Randomised Algorithms

Lecture 1: Introduction to Course & Introduction to Chernoff Bounds

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UNIVERSITY OF CAMBRIDGE

Outline

Randomised Algorithms

What? Randomised Algorithms utilise random bits to compute their output.

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But often: simple algorithm at the cost of a sophisticated analysis!

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How? This course aims to strengthen your knowledge of probability theory and apply this to analyse examples of randomised algorithms.

What if I (initially) don't care about randomised algorithms?
Many of the techniques in this course (Markov Chains, Concentration of Measure, Spectral Theory) are very relevant to other popular areas of research and employment such as Data Science and Machine Learning.

Some stuff you should know...

In this course we will assume some basic knowledge of probability:

- random variable
- computing expectations and variances
- notions of independence
- "general" idea of how to compute probabilities (manipulating, counting and **estimating**)

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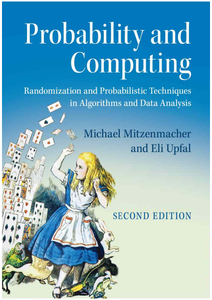
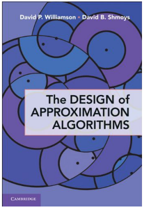
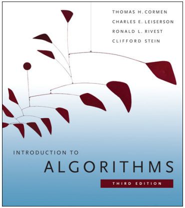
You should also be familiar with basic computer science, mathematics knowledge such as:

- graphs
- basic algorithms (sorting, graph algorithms etc.)
- matrices, norms and vectors

Textbooks







- **($\star$) Michael Mitzenmacher and Eli Upfal. Probability and Computing: Randomized Algorithms and Probabilistic Analysis, Cambridge University Press, 2nd edition, 2017**
- David P. Williamson and David B. Shmoys. The Design of Approximation Algorithms, Cambridge University Press, 2011
- Cormen, T.H., Leiserson, C.D., Rivest, R.L. and Stein, C. Introduction to Algorithms. MIT Press (3rd ed.), 2009
  (We will adopt some of the labels (e.g., Theorem 35.6) from this book in Lectures 6-10)

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1 Introduction (Lecture)

- Intro to Randomised Algorithms; Logistics; Recap of Probability; Examples.

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Lectures 2-5 focus on probabilistic tools and techniques.

2–3 Concentration (Lectures)

- Concept of Concentration; Recap of Markov and Chebyshev; Chernoff Bounds and Applications; Extensions: Hoeffding's Inequality and Method of Bounded Differences; Applications.

4 Markov Chains and Mixing Times (Lecture)

- Recap; Stopping and Hitting Times; Properties of Markov Chains; Convergence to Stationary Distribution; Variation Distance and Mixing Time

5 Hitting Times and Application to 2-SAT (Lecture)

- Reversible Markov Chains and Random Walks on Graphs; Cover Times and Hitting Times on Graphs (Example: Paths and Grids); A Randomised Algorithm for 2-SAT Algorithm

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Lectures 6-8 introduce linear programming, a (mostly) deterministic but very powerful technique to solve various optimisation problems.

6–7 Linear Programming (Lectures)

- Introduction to Linear Programming, Applications, Standard and Slack Forms, Simplex Algorithm, Finding an Initial Solution, Fundamental Theorem of Linear Programming

8 Travelling Salesman Problem (Interactive Demo)

- Hardness of the general TSP problem, Formulating TSP as an integer program; Classical TSP instance from 1954; Branch & Bound Technique to solve integer programs using linear programs

We then see how we can efficiently combine linear programming with randomised techniques, in particular, rounding:

9–10 **Randomised Approximation Algorithms** (Lectures)

- MAX-3-CNF and Guessing, Vertex-Cover and Deterministic Rounding of Linear Program, Set-Cover and Randomised Rounding, Concluding Example: MAX-CNF and Hybrid Algorithm

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Lectures 11-12 cover a more advanced topic with ML flavour:

11–12 **Spectral Graph Theory and Spectral Clustering** (Lectures)

- Eigenvalues, Eigenvectors and Spectrum; Visualising Graphs; Expansion; Cheeger's Inequality; Clustering and Examples; Analysing Mixing Times

Outline

Introduction

Topics and Syllabus

A (Very) Brief Reminder of Probability Theory

Basic Examples

Introduction to Chernoff Bounds

Recap: Probability Space

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Components of the Probability Space $(\Omega, \Sigma, \mathbf{P})$

- The Sample Space Ω contains all the possible outcomes $\omega_1, \omega_2, \ldots$ of the experiment.
- The Event Space Σ is the power-set of Ω containing events, which are combinations of outcomes (subsets of Ω including $\emptyset$ and Ω).
- The Probability Measure $\mathbf{P}$ is a function from Σ to $\mathbb{R}$ satisfying
  (i) $0 \leq \mathbf{P}[\mathcal{E}] \leq 1$, for all $\mathcal{E} \in \Sigma$
  (ii) $\mathbf{P}[\Omega] = 1$
  (iii) If $\mathcal{E}_1, \mathcal{E}_2, \ldots \in \Sigma$ are pairwise disjoint ($\mathcal{E}_i \cap \mathcal{E}_j = \emptyset$ for all $i \neq j$) then

$$\mathbf{P}\left[\bigcup_{i=1}^{\infty} \mathcal{E}_i\right] = \sum_{i=1}^{\infty} \mathbf{P}[\mathcal{E}_i].$$

Recap: Random Variables

A random variable X on $(\Omega, \Sigma, \mathbf{P})$ is a function $X : \Omega \to \mathbb{R}$ mapping each sample "outcome" to a real number.

Intuitively, random variables are the "observables" in our experiment.

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- The indicator random variable $\mathbf{1}_{\mathcal{E}}$ of an event $\mathcal{E} \in \Sigma$ given by

$$\mathbf{1}_{\mathcal{E}}(\omega) = \begin{cases} 1 & \text{if } \omega \in \mathcal{E} \\ 0 & \text{otherwise.} \end{cases}$$

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- The number of sixes of two dice throws $X_1, X_2 \in \{1, 2, \ldots, 6\}$ is

$$\mathbf{1}_{X_1=6} + \mathbf{1}_{X_2=6}$$

Recap: Boole's Inequality (Union Bound)

Union Bound

Let $\mathcal{E}_1, \ldots, \mathcal{E}_n$ be a collection of events in Σ. Then

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3. It is clear that $\mathbf{1}_{\bigcup_{i=1}^{n} \mathcal{E}_i} \leq \sum_{i=1}^{n} \mathbf{1}_{\mathcal{E}_i}$ (**Check this**)
4. Taking expectation completes the proof.

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A Randomised Algorithm for MAX-CUT (1/2)

$E(A, B)$: set of edges with one endpoint in $A \subseteq V$ and the other in $B \subseteq V$.

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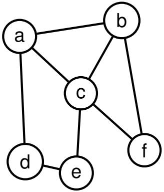

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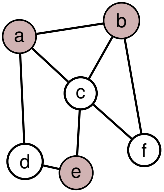

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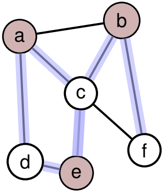

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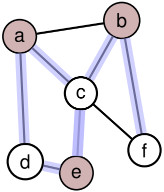
Applications:



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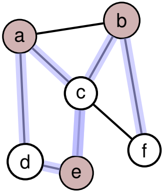
- clustering, statistical physics



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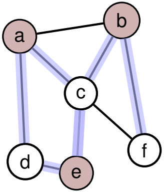
Comments:

- This problem will appear again in the course
- MAX-CUT is NP-hard
- It is different from the clustering problem, where we want to find a sparse cut
- Note that the MIN-CUT problem is solvable in polynomial time!



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A Randomised Algorithm for MAX-CUT (2/2)

RANDMAXCUT(G)

1: Start with $S \leftarrow \emptyset$
2: **For** each $v \in V$, add v to S with probability $1/2$
3: **Return** S

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RANDMAXCUT(G)

This kind of "random guessing" will appear often in this course!

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Question:

1. What is the sample space Ω here?
2. Which quantity do we need to analyse?

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Proposition

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Proof:

- We need to analyse the expectation of $e(S, S^c)$:

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More details on approximation algorithms from Lecture 9 onwards!

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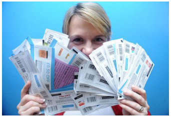

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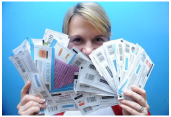

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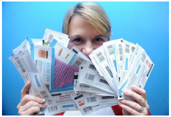

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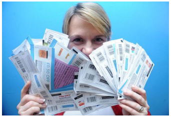

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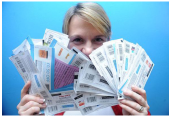

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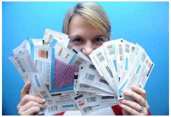

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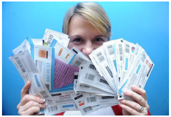

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2. Use Union Bound to prove that the probability it takes more than $n \log n + cn$ boxes to collect all n coupons is $\leq e^{-c}$.

   Hint: It is useful to remember that $1 - x \leq e^{-x}$ for all x

Outline

Concentration Inequalities

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  1. **Randomised Algorithms:** Easy to Design and Implement
  2. **Deterministic Algorithms:** They do what they claim

Chernoff Bounds: A Tool for Concentration (1952)

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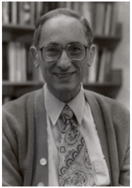

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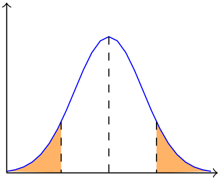

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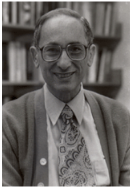

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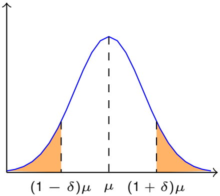

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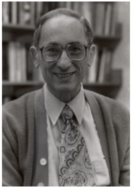

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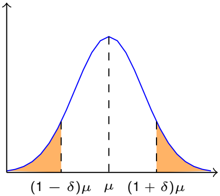

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Chebyshev's inequality (or Markov) can be obtained by chosing $f(X) := (X - \mu)^2$ (or $f(X) := X$, respectively).

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We can consider the first, second, third and more moments! That is the basic idea behind the Chernoff Bounds

Our First Chernoff Bound

Chernoff Bounds (General Form, Upper Tail)

Suppose $X_1, \ldots, X_n$ are independent Bernoulli random variables with parameter p_i. Let $X = X_1 + \ldots + X_n$ and $\mu = \mathbf{E}[X] = \sum_{i=1}^{n} p_i$. Then, for any $\delta > 0$ it holds that

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This implies that for any $t > \mu$,

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What about a concrete value of n, say $n = 100$?

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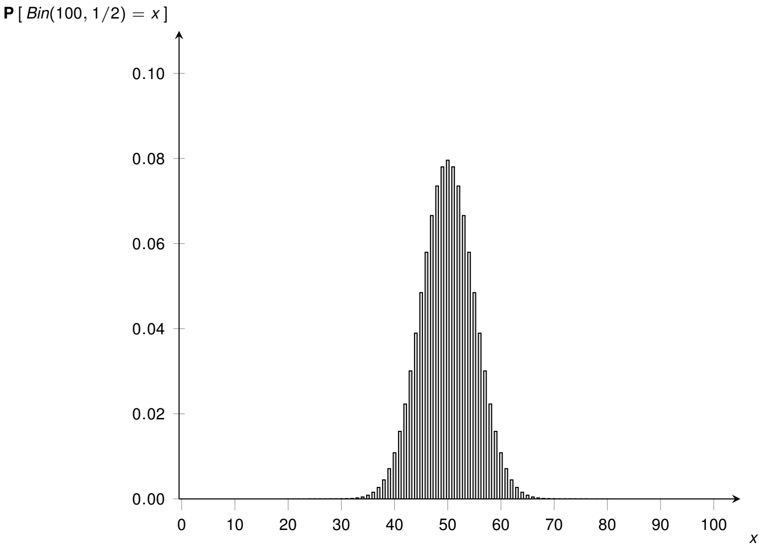

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- Markov's inequality: $\mathbf{E}[X] = 100/2 = 50$.

$$\mathbf{P}[X \geq 3/2 \cdot \mathbf{E}[X]] \leq 2/3 = \mathbf{0.666}.$$

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Consider $n = 100$ independent coin flips. We wish to find an upper bound on the probability that the number of heads is greater or equal than 75.

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- Remark: The exact probability is **0.00000028 ...**

Chernoff bound yields a much better result (but needs independence!)

Randomised Algorithms

Lecture 2: Concentration Inequalities, Application to Balls-into-Bins

Thomas Sauerwald (tms41@cam.ac.uk)

Lent 2024

UNIVERSITY OF CAMBRIDGE

Outline

How to Derive Chernoff Bounds

Application 1: Balls into Bins

General Recipe for Deriving Chernoff Bounds

Recipe

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2. Compute an upper bound for $\mathbf{E}\left[\, e^{\lambda X} \,\right]$ (using independence)
3. Optimise value of λ to obtain best tail bound

Chernoff Bound: Proof

Chernoff Bound (General Form, Upper Tail)

Suppose $X_1, \ldots, X_n$ are independent Bernoulli random variables with parameter p_i. Let $X = X_1 + \ldots + X_n$ and $\mu = \mathbf{E}[X] = \sum_{i=1}^n p_i$. Then, for any $\delta > 0$ it holds that

$$\mathbf{P}[X \geq (1+\delta)\mu] \leq \left[\frac{e^{\delta}}{(1+\delta)^{(1+\delta)}}\right]^{\mu}.$$

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5. Choose $\lambda = \log(1+\delta) > 0$ to get the result.

Chernoff Bounds: Lower Tails

We can also use Chernoff Bounds to show a random variable is **not too small** compared to its mean:

Chernoff Bounds (General Form, Lower Tail)

Suppose $X_1, \ldots, X_n$ are independent Bernoulli random variables with parameter p_i. Let $X = X_1 + \ldots + X_n$ and $\mu = \mathbf{E}[X] = \sum_{i=1}^{n} p_i$. Then, for any $0 < \delta < 1$ it holds that

$$\mathbf{P}[X \leq (1-\delta)\mu] \leq \left[\frac{e^{-\delta}}{(1-\delta)^{1-\delta}}\right]^{\mu},$$

and thus, by substitution, for any $t < \mu$,

$$\mathbf{P}[X \leq t] \leq e^{-\mu}\left(\frac{e\mu}{t}\right)^{t}.$$

Exercise on Supervision Sheet

Hint: multiply both sides by -1 and repeat the proof of the Chernoff Bound

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- For all $t > 0$,

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All upper tail bounds hold even under a relaxed independence assumption: For all $1 \leq i \leq n$ and $x_1, x_2, \ldots, x_{i-1} \in \{0, 1\}$,

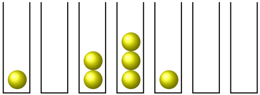
$$\mathbf{P}[X_i = 1 \mid X_1 = x_1, \ldots, X_{i-1} = x_{i-1}] \leq p_i.$$

Outline

How to Derive Chernoff Bounds

Application 1: Balls into Bins

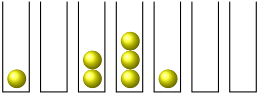
Balls into Bins



Balls into Bins Model

You have m balls and n bins. Each ball is allocated in a bin picked independently and uniformly at random.

Balls into Bins



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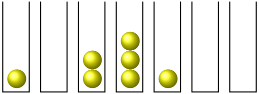

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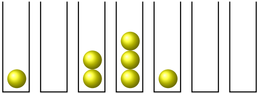

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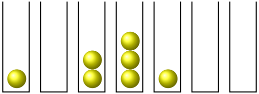

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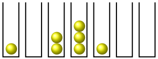
Exercise: Think about the relation between the Balls into Bins Model and the Coupon Collector Problem.

Balls into Bins: Bounding the Maximum Load (1/4)



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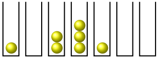

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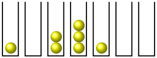

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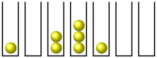

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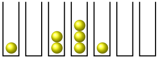

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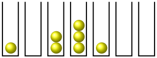

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- Since $m = 2n \log n$, then $\mu = \mathbf{E}[X] = 2 \log n$
- By the Chernoff Bound,

$$\mathbf{P}[X \geq t] \leq e^{-\mu}(e\mu/t)^t$$

$$\mathbf{P}[X \geq 6 \log n] \leq e^{-2 \log n} \left(\frac{2e \log n}{6 \log n}\right)^{6 \log n} \leq e^{-2 \log n} = n^{-2}$$

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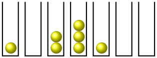

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here we could have used the "nicer" bounds as well!

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- Let $\mathcal{E}_j := \{X(j) \geq 6 \log n\}$, that is, bin j receives at least $6 \log n$ balls.

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We just proved that

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- As mentioned on the to prove that whp at least one bin receives at least $c \log n / \log \log n$ balls, for some constant $c > 0$.

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$\Rightarrow$ for $m = n$ this gives a maximum load of $\log_2 \log n + \Theta(1)$ w.p. $1 - 1/n$.

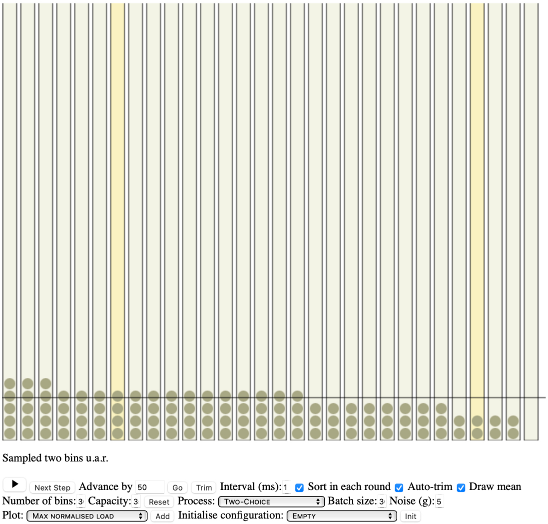
This is called the **power of two choices**: It is a common technique to improve the performance of randomised algorithms (covered in Chapter 17 of the textbook by Mitzenmacher and Upfal)

ACM Paris Kanellakis Theory and Practice Award 2020

For "the discovery and analysis of balanced allocations, known as the power of two choices, and their extensive applications to practice."

"These include i-Google's web index, Akamai's overlay routing network, and highly reliable distributed data storage systems used by Microsoft and Dropbox, which are all based on variants of the power of two choices paradigm. There are many other software systems that use balanced allocations as an important ingredient."

Simulation



https://www.dimitrioslos.com/balls_and_bins/visualiser.html

Randomised Algorithms

Lecture 3: Concentration Inequalities, Application to Quick-Sort, Extensions

Thomas Sauerwald (tms41@cam.ac.uk)

Lent 2024

UNIVERSITY OF CAMBRIDGE

Outline

Application 2: Randomised QuickSort

Extensions of Chernoff Bounds

Applications of Method of Bounded Differences

Appendix: More on Moment Generating Functions (non-examinable)

QuickSort

QuickSort (Input $A[1], A[2], \ldots, A[n]$)

Pick an element from the array, the so-called pivot
If $|A| = 0$ or $|A| = 1$ **then**
  return A
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  Create two subarrays A_1 and A_2 (without the pivot) such that:
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We will now give a proof of this “well-known” result!

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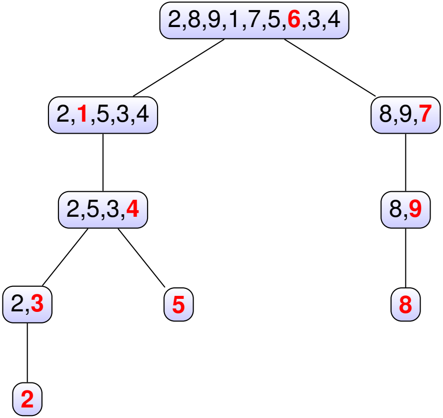

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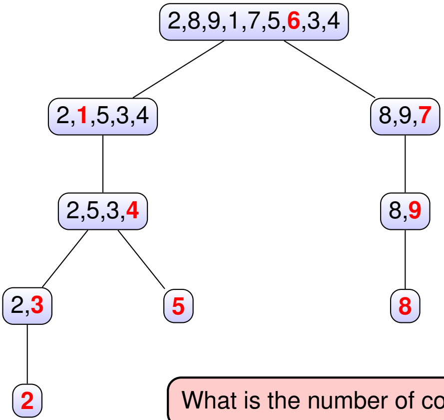

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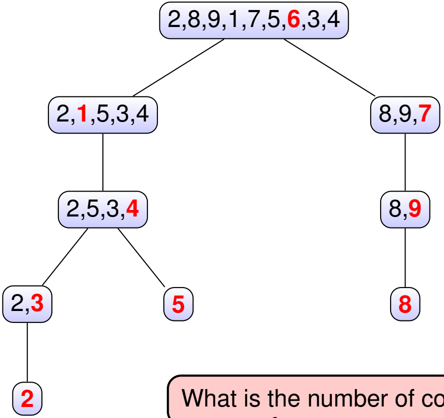

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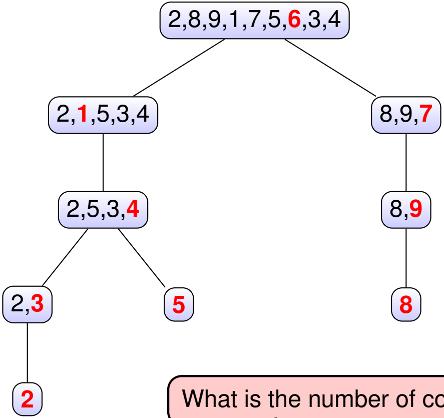

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$$0 + 1 + 1 + 2 + 2 + 3 + 3 + 3 + 4 = 19.$$

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4. Actually, we will prove sth slightly stronger:

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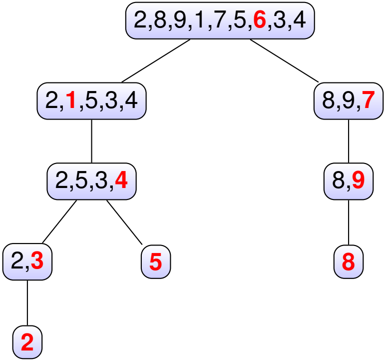

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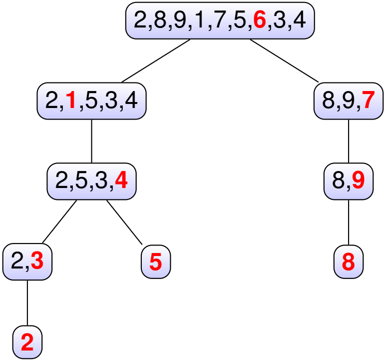

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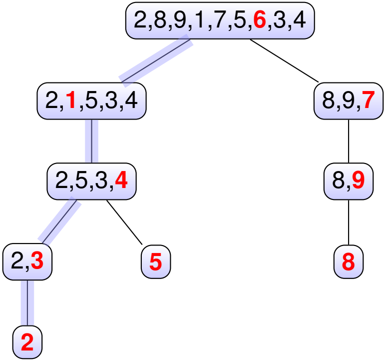

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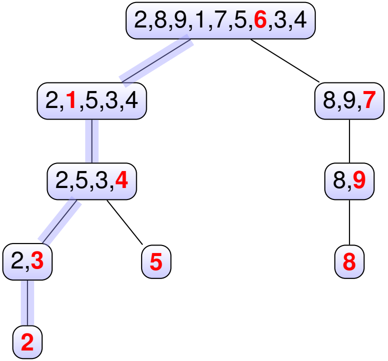

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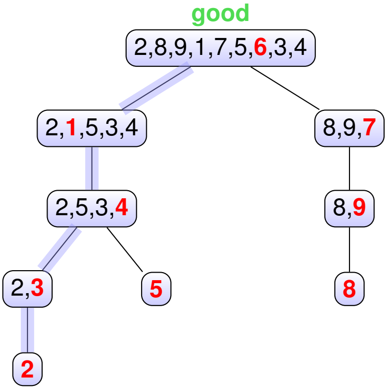

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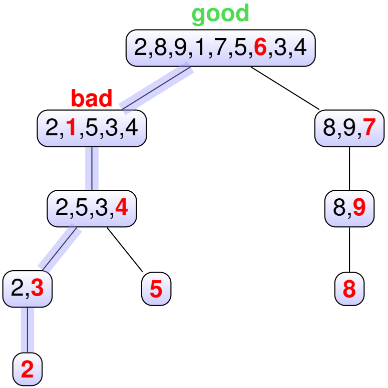

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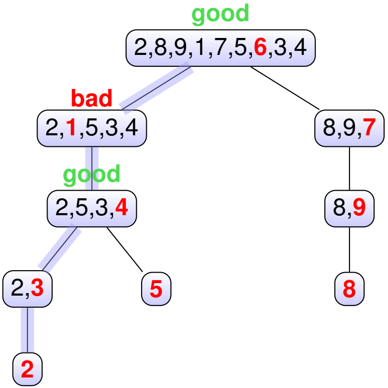

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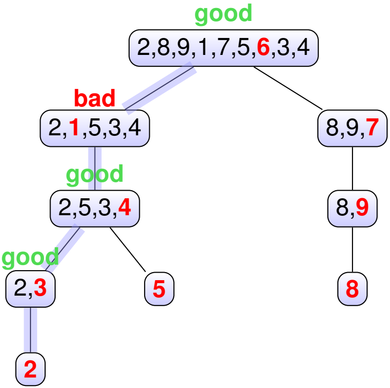

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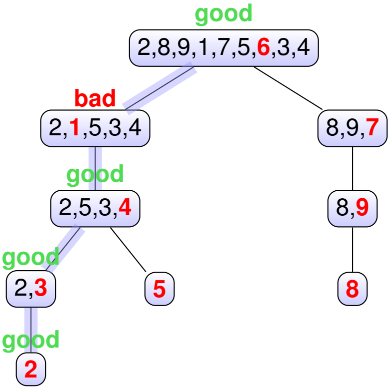

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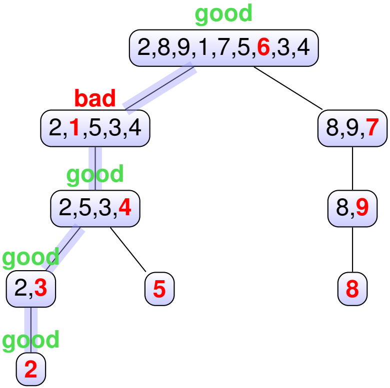

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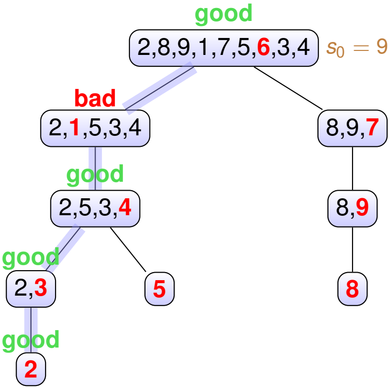

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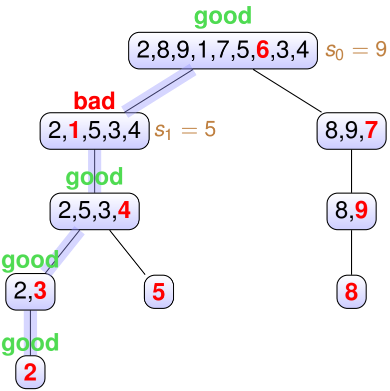

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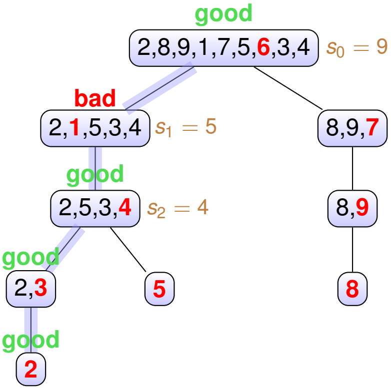

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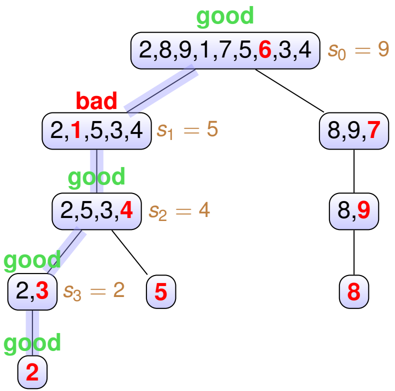

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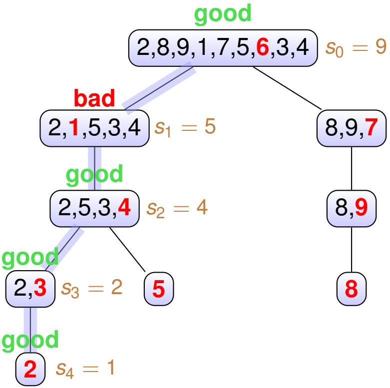

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Let us now upper bound the probability that this “bad event” happens!

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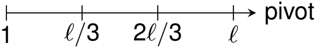

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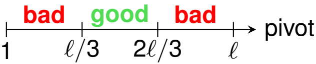

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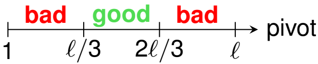

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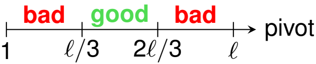

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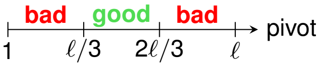

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Answer: We can then simply define X_j as 0 (deterministically).

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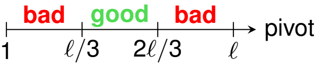

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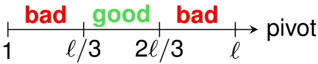

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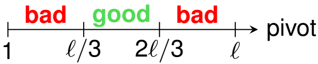

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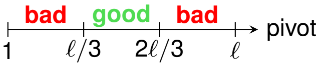

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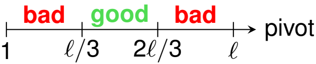

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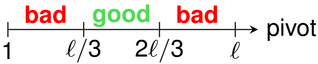

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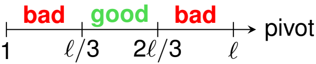

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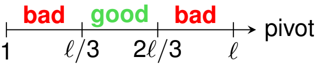

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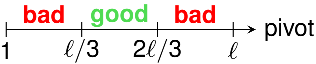

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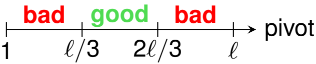

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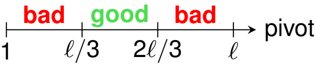

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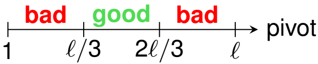

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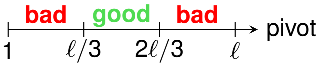

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Exercise: *[Ex 2-3.6]* Our upper bound of $O(n \log n)$ whp also immediately implies a $O(n \log n)$ bound on the expected number of comparisons!

- It is possible to deterministically find the best pivot element that divides the array into two subarrays of the same size.
- The latter requires to compute the median of the array in linear time, which is not easy...
- The presented randomised algorithm for QuickSort is much easier to implement!

Outline

Application 2: Randomised QuickSort

Extensions of Chernoff Bounds

Applications of Method of Bounded Differences

Appendix: More on Moment Generating Functions (non-examinable)

Hoeffding's Extension

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Let X be a random variable with mean 0 such that $a \leq X \leq b$. Then for all $\lambda \in \mathbb{R}$,

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We omit the proof of this lemma!

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Let $X_1, \ldots, X_n$ be independent random variable with mean μ_i such that $a_i \leq X_i \leq b_i$. Let $X = X_1 + \ldots + X_n$, and let $\mu = \mathbf{E}[X] = \sum_{i=1}^{n} \mu_i$. Then for any $t > 0$

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This is not magic! you just need to optimise λ!

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Framework

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In all those cases (and more) we can easily prove concentration of $f(X_1, \ldots, X_n)$ around its mean by the so-called **Method of Bounded Differences**.

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A function f is called Lipschitz with parameters $\mathbf{c} = (c_1, \ldots, c_n)$ if for all $i = 1, 2, \ldots, n$,

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- Notice the similarity with Hoeffding's inequality! *[Exercise 2/3.14]*

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and

$$\mathbf{P}[X \leq \mu - t] \leq \exp\left(-\frac{2t^2}{\sum_{i=1}^n c_i^2}\right).$$

- Notice the similarity with Hoeffding's inequality! *[Exercise 2/3.14]*
- The proof is omitted here (it requires the concept of martingales).

Outline

Application 2: Randomised QuickSort

Extensions of Chernoff Bounds

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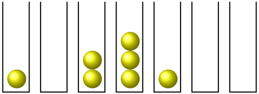
Appendix: More on Moment Generating Functions (non-examinable)

Application 3: Balls into Bins (again...)



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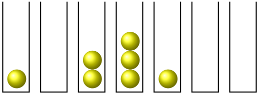

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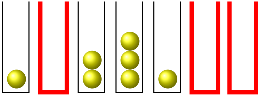

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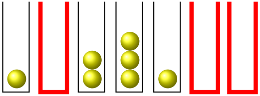

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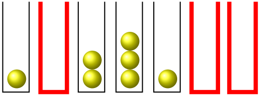

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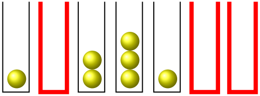

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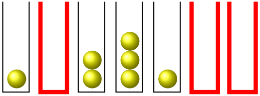

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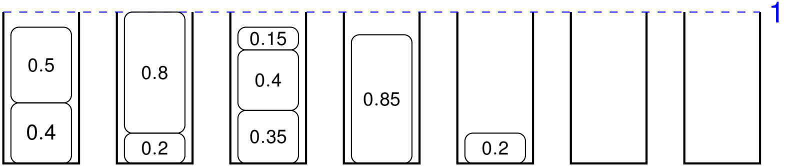
This is a decent bound, but for some values of m it is far from tight and stronger bounds are possible through a refined analysis.

Application 4: Bin Packing



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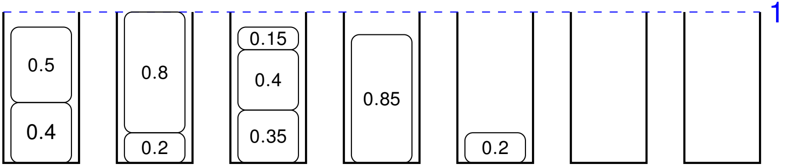

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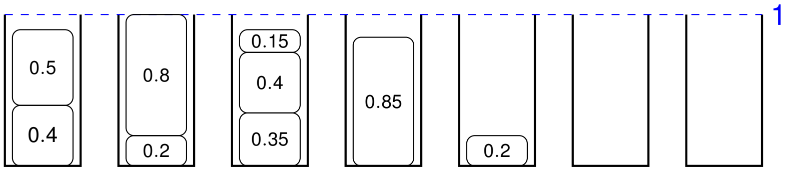

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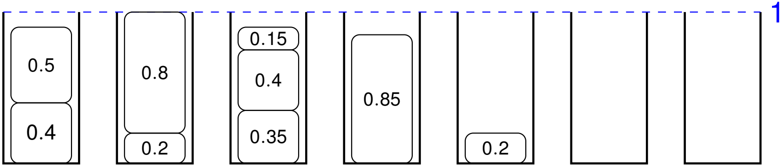

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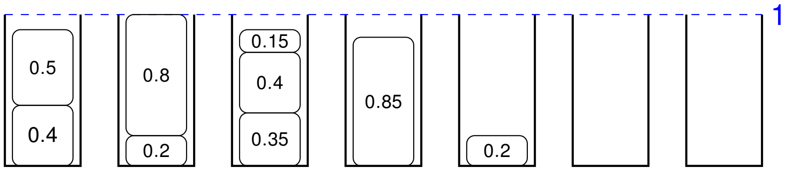

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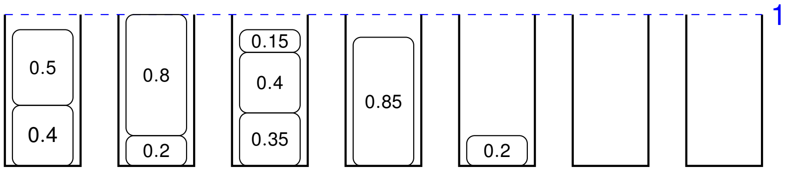

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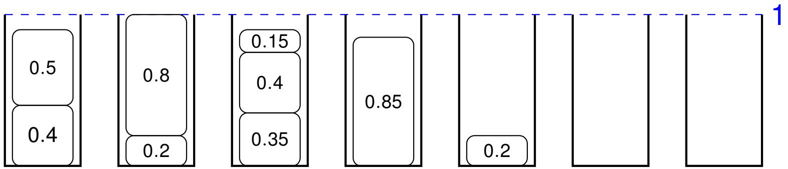

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This is a typical example where proving concentration is much easier than calculating (or estimating) the expectation!

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Appendix: More on Moment Generating Functions (non-examinable)

Moment Generating Functions (non-examinable)

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1. If X and Y are two r.v.'s with $M_X(t) = M_Y(t)$ for all $t \in (-\delta, +\delta)$ for some $\delta > 0$, then the distributions X and Y are identical.
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Proof of 2:

$$M_{X+Y}(t) = \mathbf{E}\left[e^{t(X+Y)}\right] = \mathbf{E}\left[e^{tX} \cdot e^{tY}\right] \stackrel{(!)}{=} \mathbf{E}\left[e^{tX}\right] \cdot \mathbf{E}\left[e^{tY}\right] = M_X(t)M_Y(t) \qquad \square$$

Randomised Algorithms

Lecture 4: Markov Chains and Mixing Times

Thomas Sauerwald (tms41@cam.ac.uk)

Lent 2024

UNIVERSITY OF CAMBRIDGE

Outline

Recap of Markov Chain Basics

Irreducibility, Periodicity and Convergence

Total Variation Distance and Mixing Times

Application 1: Card Shuffling

Application 2: Markov Chain Monte Carlo (non-examin.)

Appendix: Remarks on Mixing Time (non-examin.)

Applications of Markov Chains in Computer Science

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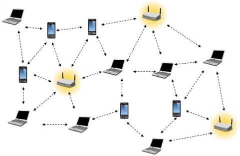
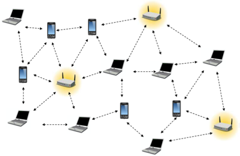


Broadcasting

Applications of Markov Chains in Computer Science



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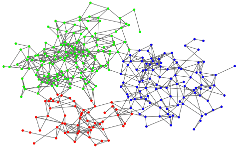

Clustering

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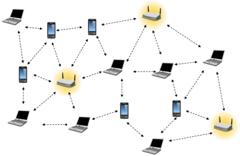

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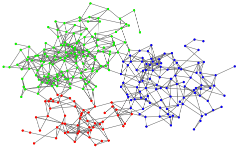

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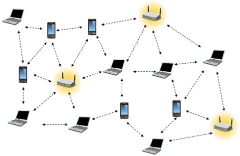

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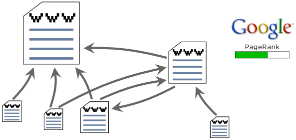
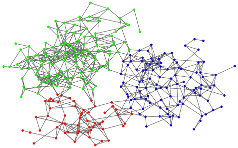


Ranking Websites



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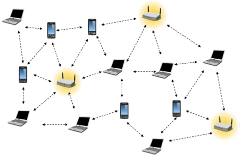

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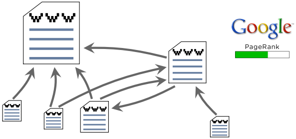

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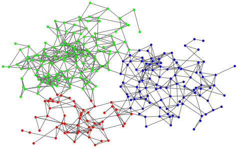

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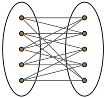

Sampling and Optimisation

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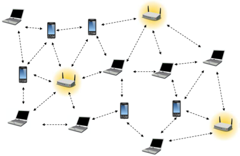

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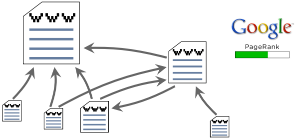

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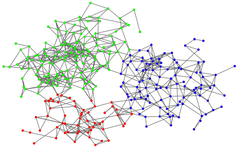

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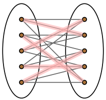

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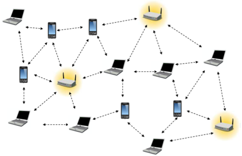

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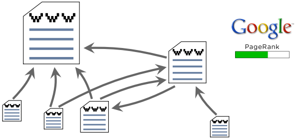

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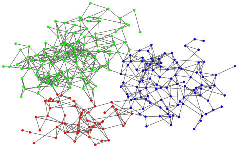

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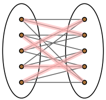

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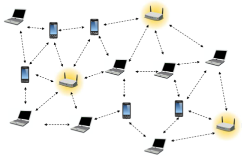

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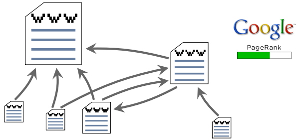

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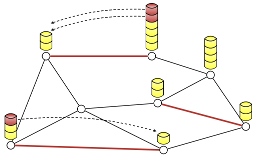
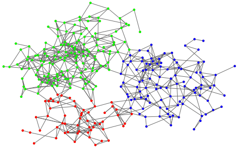


Load Balancing



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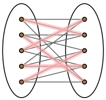

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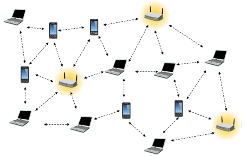

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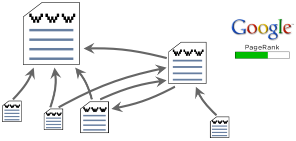

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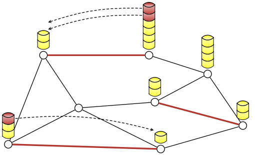

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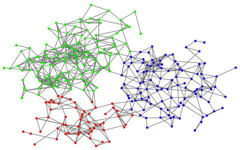

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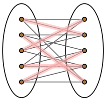
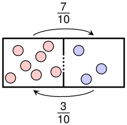


$$A = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Sampling and Optimisation



Particle Processes

Markov Chains

Markov Chain (Discrete Time and State, Time Homogeneous)

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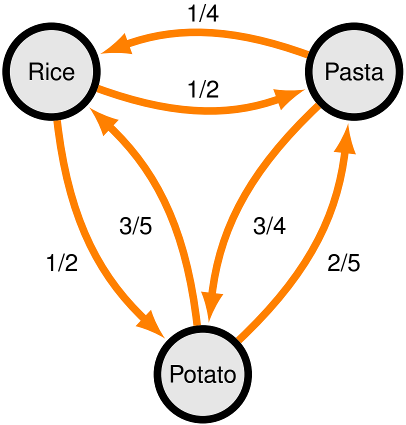
- For all $0 \leq t_1 < t_2, x \in \Omega$,

$$\mathbf{P}[X_{t_2} = x] = \sum_{y \in \Omega} \mathbf{P}[X_{t_2} = x \mid X_{t_1} = y] \cdot \mathbf{P}[X_{t_1} = y].$$

What does a Markov Chain Look Like?

Example: the carbohydrate served with lunch in the college cafeteria.



This has transition matrix:

	Rice	Pasta	Potato	
	0	1/2	1/2	Rice
	1/4	0	3/4	Pasta
	3/5	2/5	0	Potato

$$P = \begin{bmatrix} 0 & 1/2 & 1/2 \\ 1/4 & 0 & 3/4 \\ 3/5 & 2/5 & 0 \end{bmatrix}$$

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$\Rightarrow$ can replace ρ by any (load) vector and view P as a balancing matrix!

Stopping and Hitting Times

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Some distinguish between $\tau_y^+ = \min\{t \geq 1 \colon X_t = y\}$ and $\tau_y = \min\{t \geq 0 \colon X_t = y\}$

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A Useful Identity

Hitting times are the solution to a set of linear equations:

$$h(x, y) \stackrel{\text{Markov Prop.}}{=} 1 + \sum_{z \in \Omega \setminus \{y\}} P(x, z) \cdot h(z, y) \qquad \forall x \neq y \in \Omega.$$

Outline

Recap of Markov Chain Basics

Irreducibility, Periodicity and Convergence

Total Variation Distance and Mixing Times

Application 1: Card Shuffling

Application 2: Markov Chain Monte Carlo (non-examin.)

Appendix: Remarks on Mixing Time (non-examin.)

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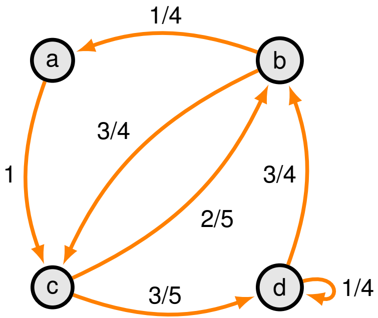

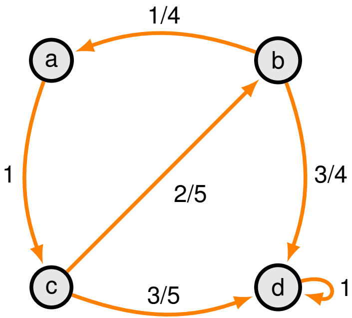

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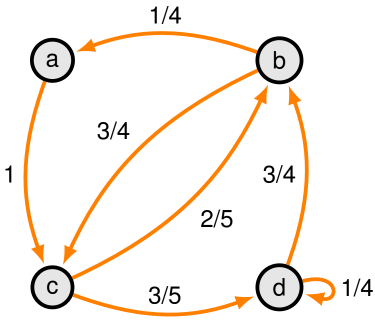

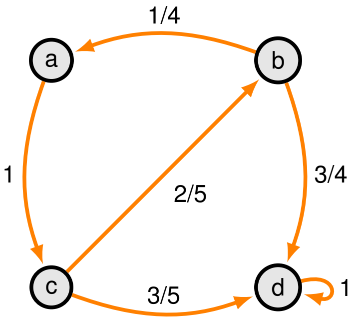

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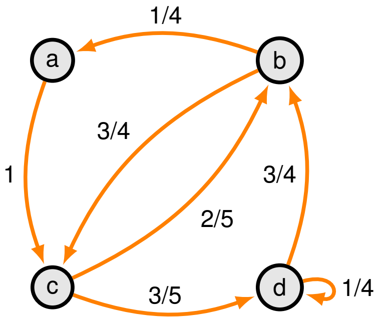

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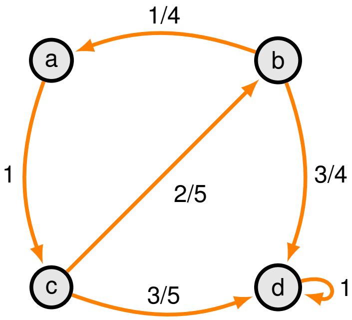

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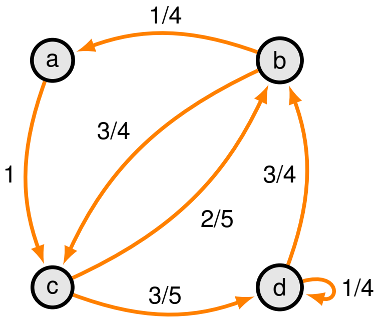

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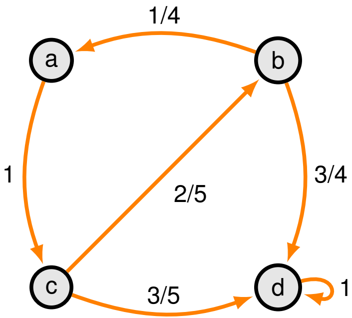

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Finite Hitting Time Theorem

For any states x and y of a finite irreducible Markov Chain $h(x, y) < \infty$.

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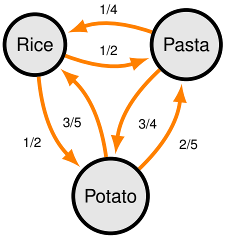

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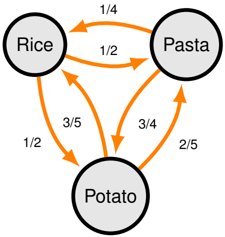

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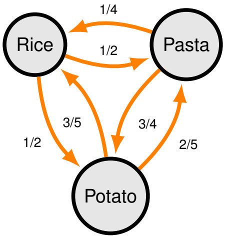

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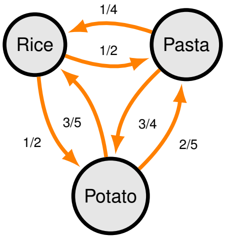

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Existence and Uniqueness of a Positive Stationary Distribution

Let P be finite, irreducible M.C., then there exists a unique probability distribution π on Ω such that $\pi = \pi P$ and $\pi(x) = 1/h(x,x) > 0$, $\forall x \in \Omega$.

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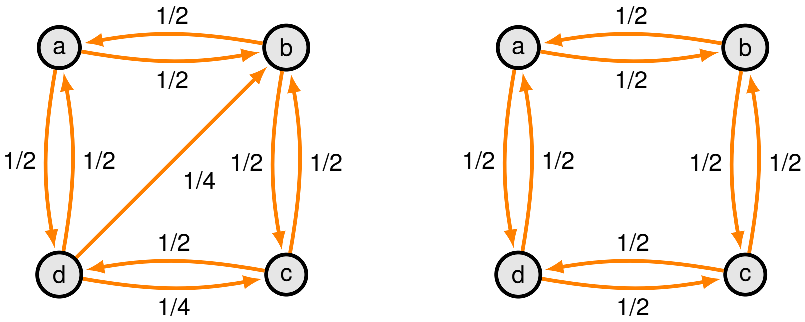

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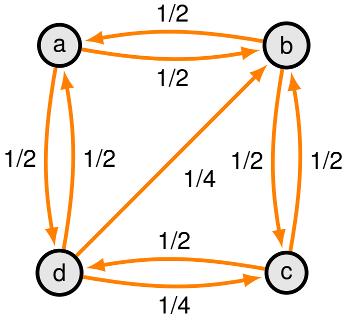

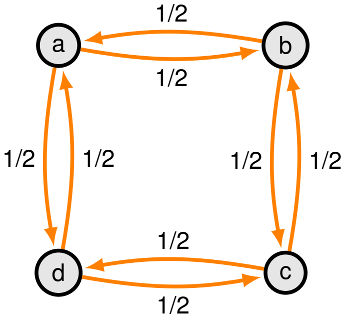

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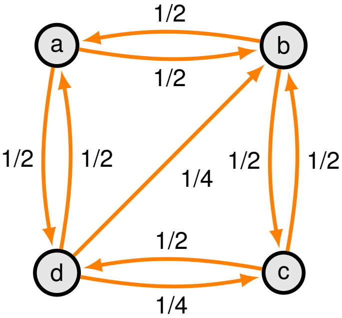

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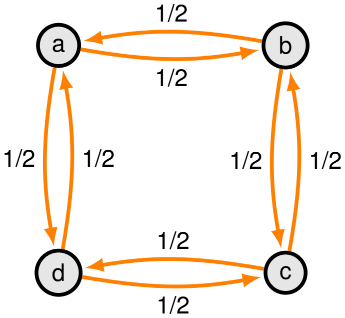

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Let P be any finite, irreducible, aperiodic Markov Chain with stationary distribution π. Then for any $x, y \in \Omega$,

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- We will prove a simpler version of the Convergence Theorem after introducing Spectral Graph Theory.

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- Markov Chain: stays put with $1/2$ and moves left (or right) w.p. $1/4$
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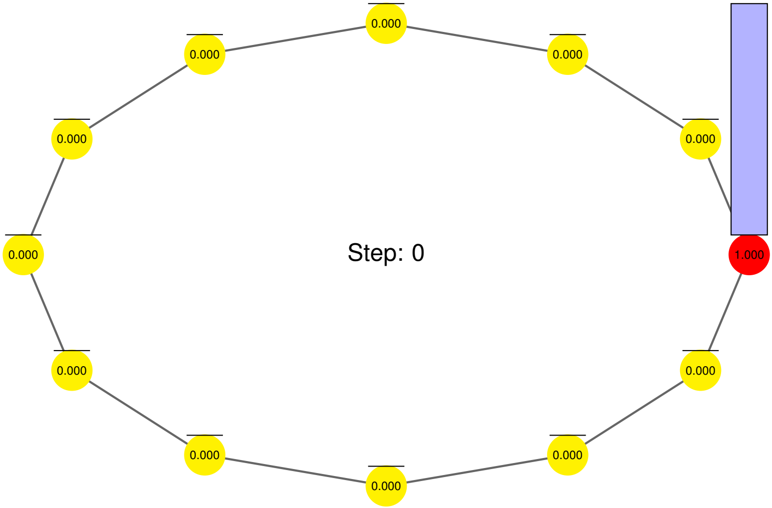

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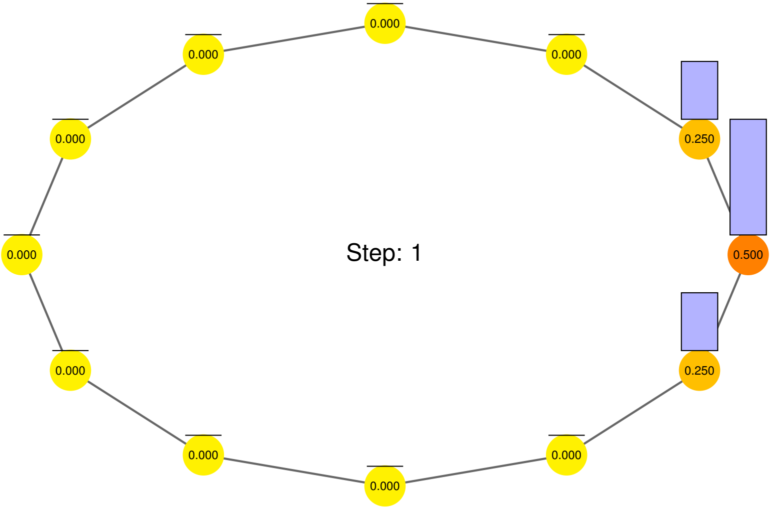

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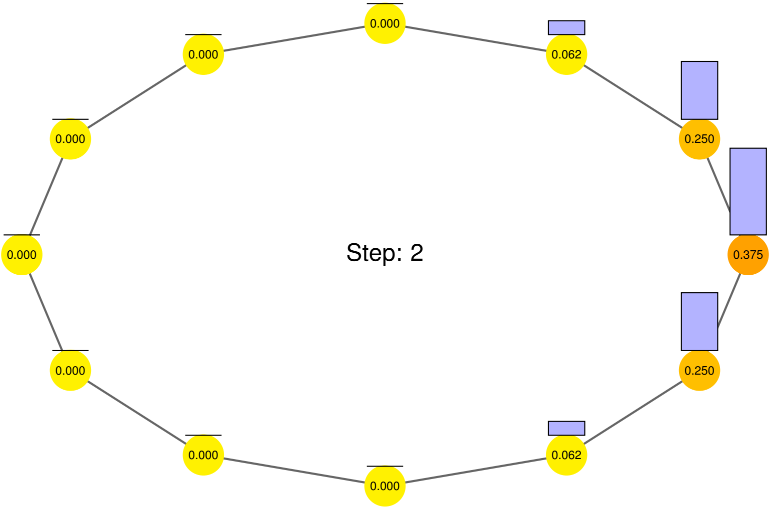

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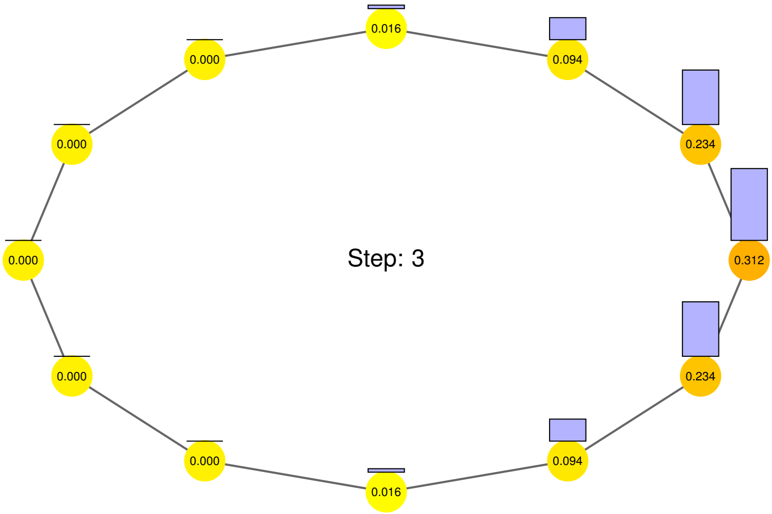

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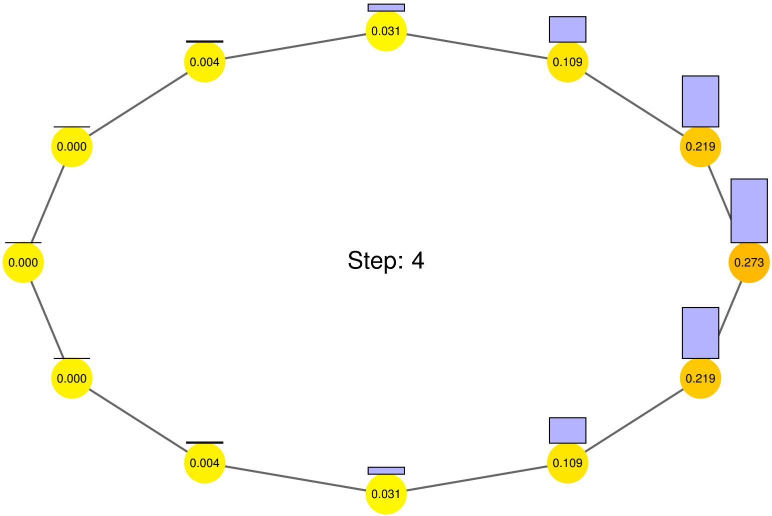

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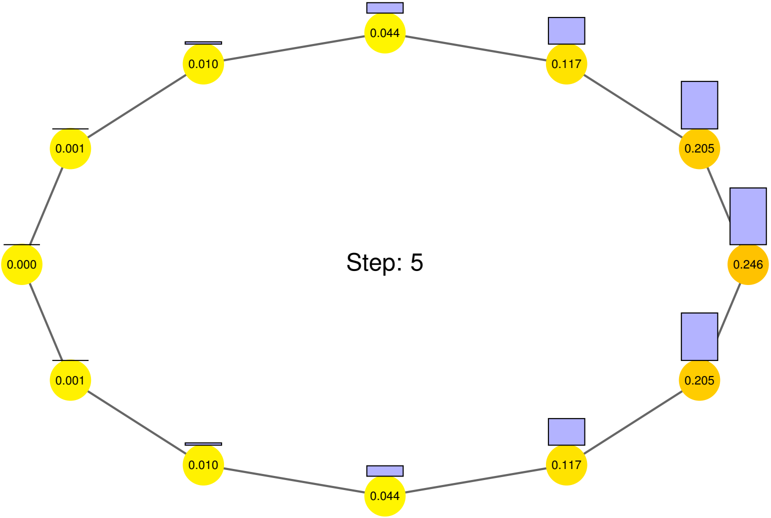

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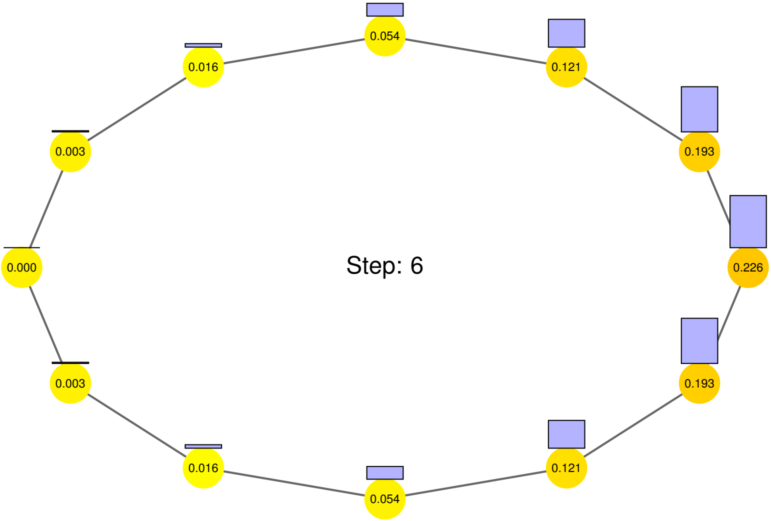

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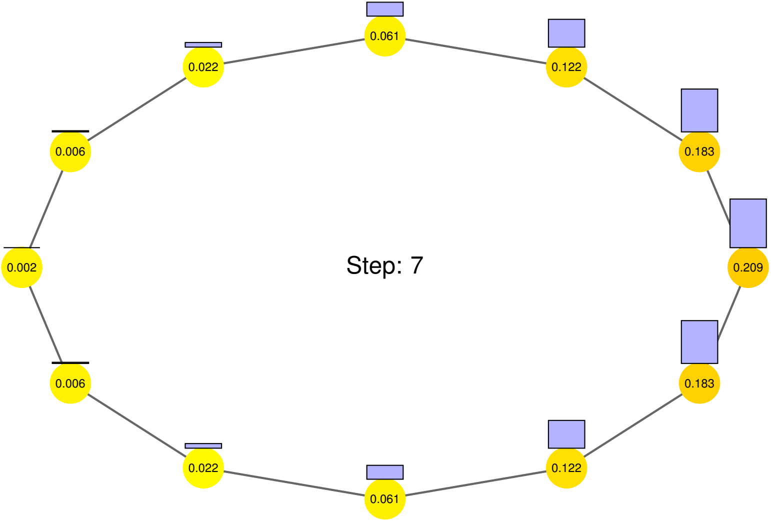

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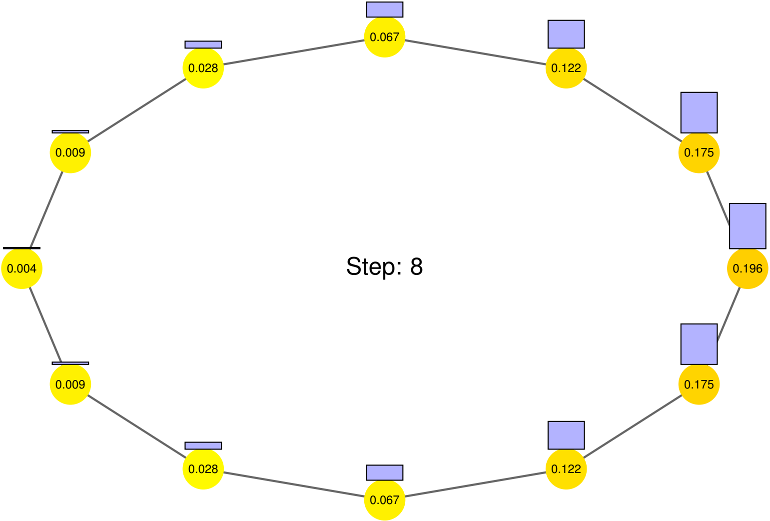

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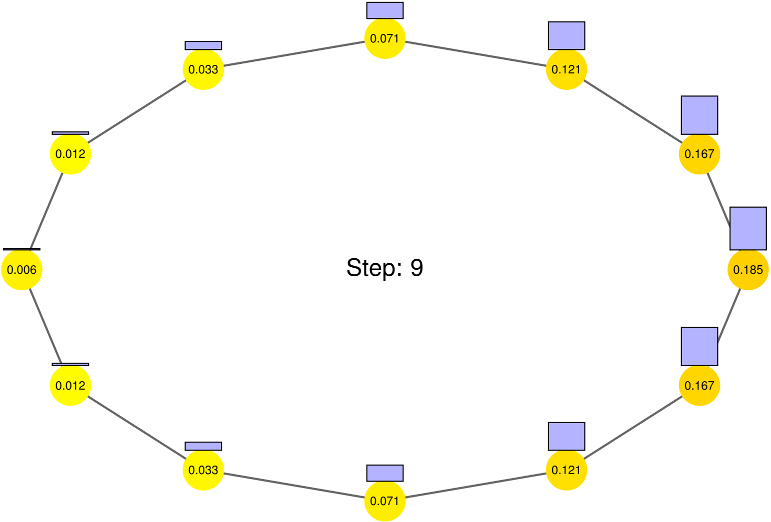

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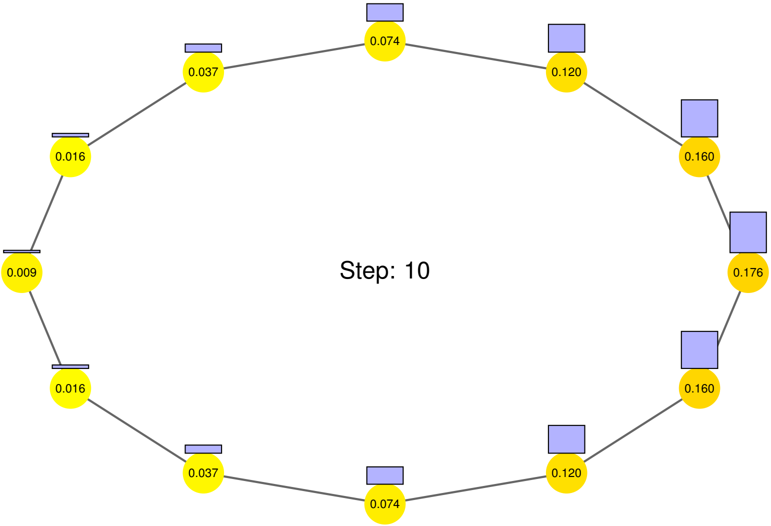

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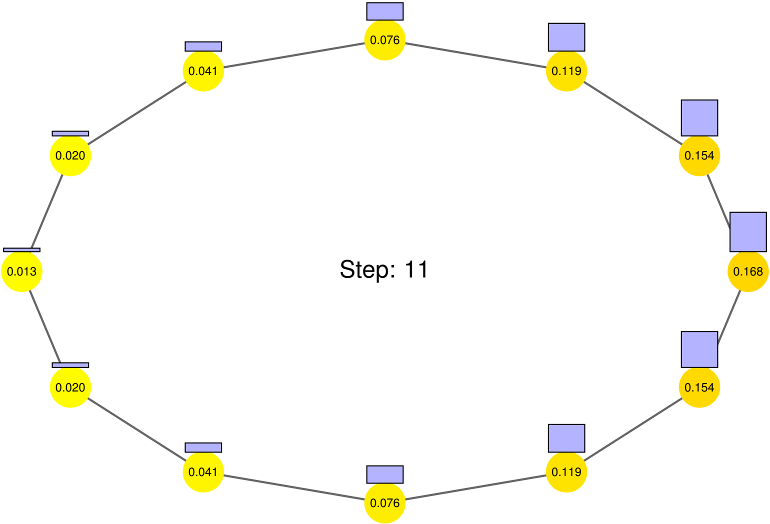

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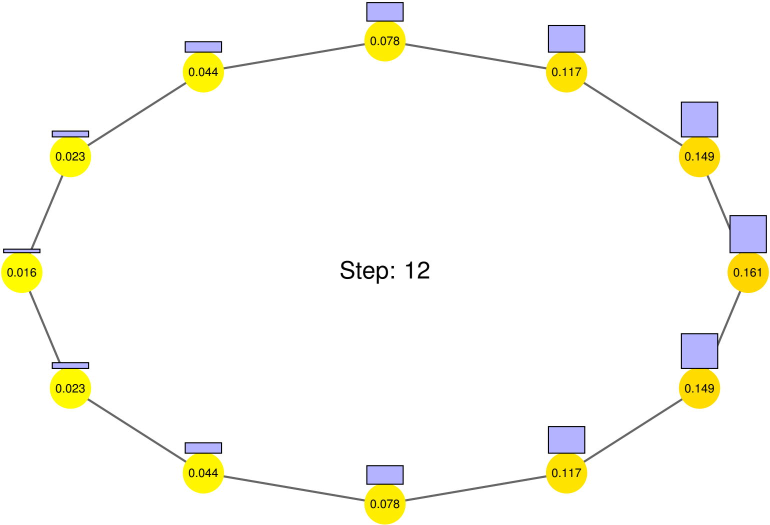

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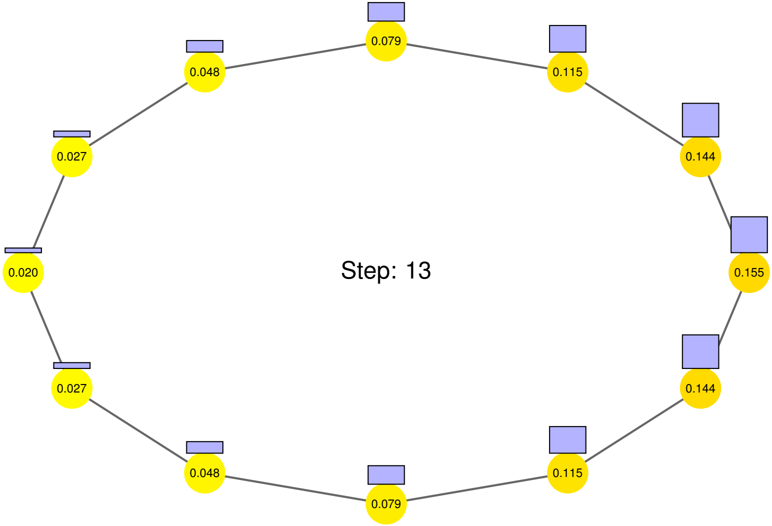

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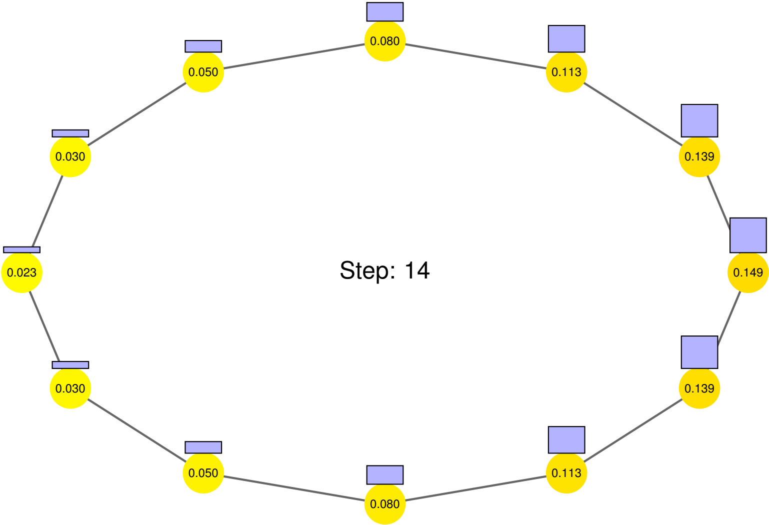

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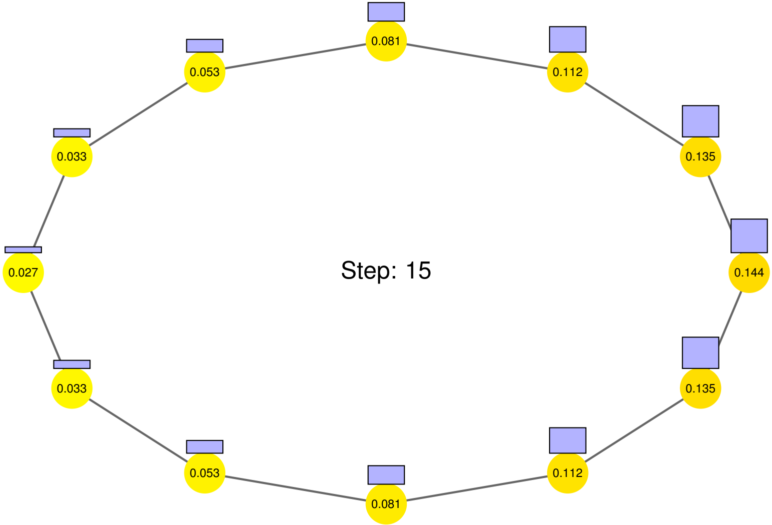

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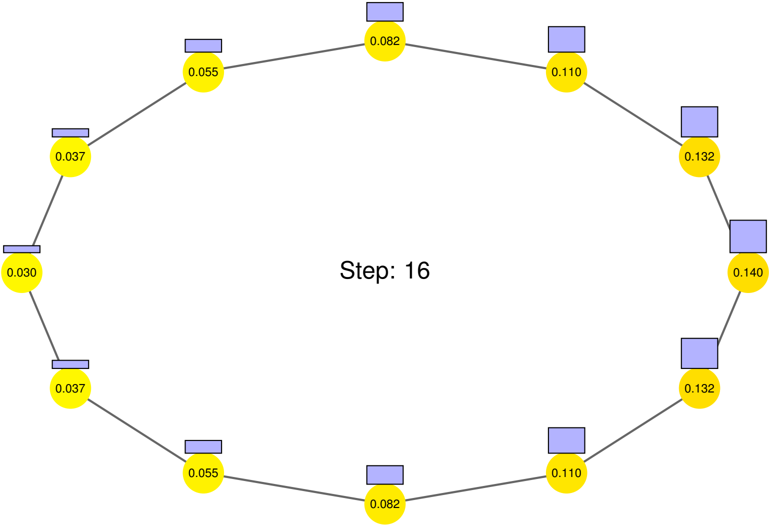

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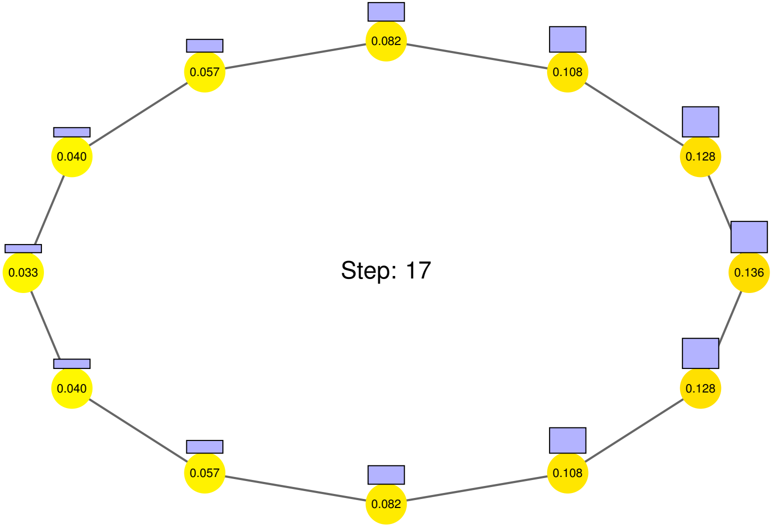

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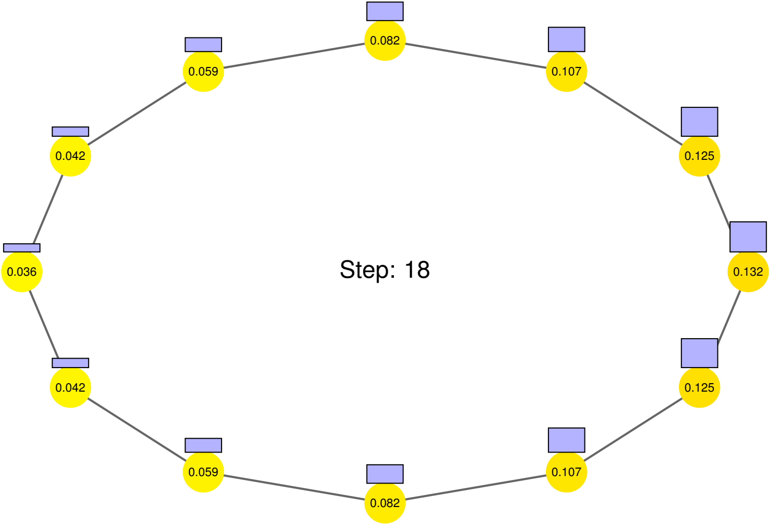

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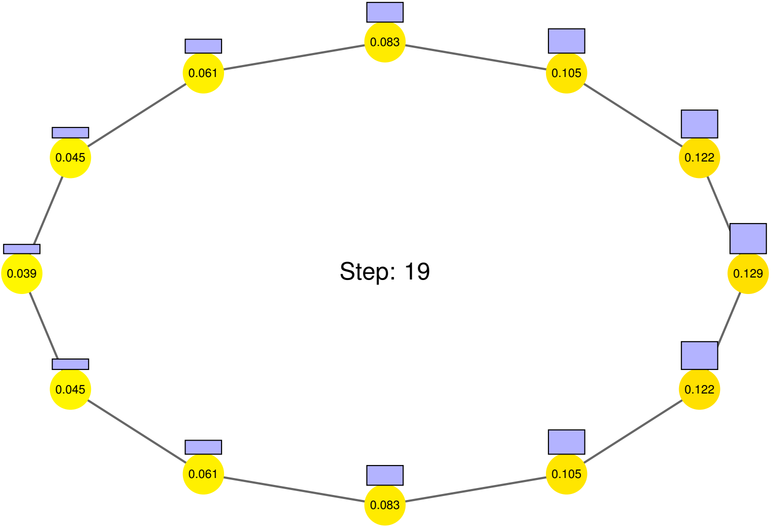

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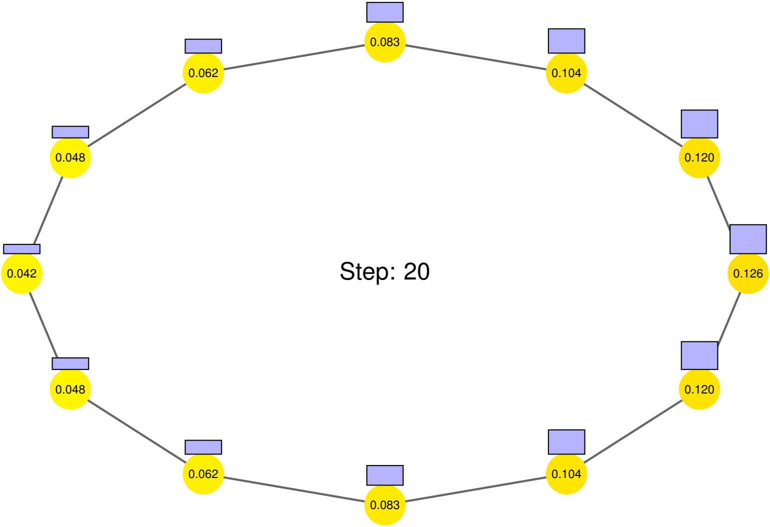

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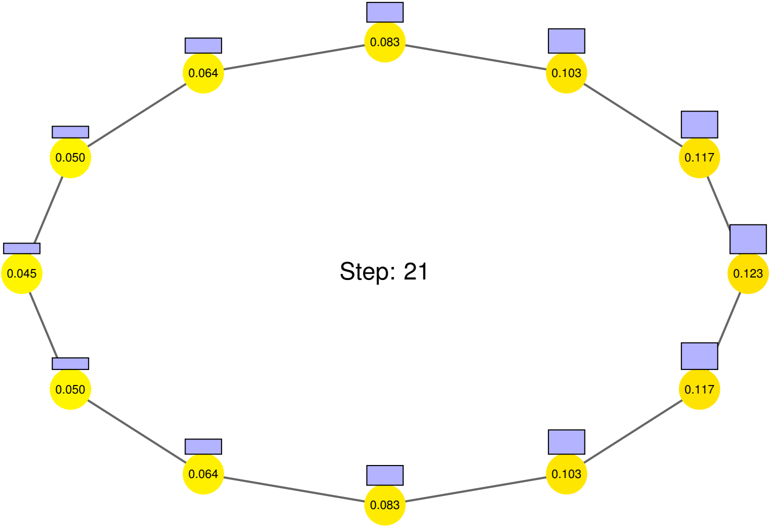

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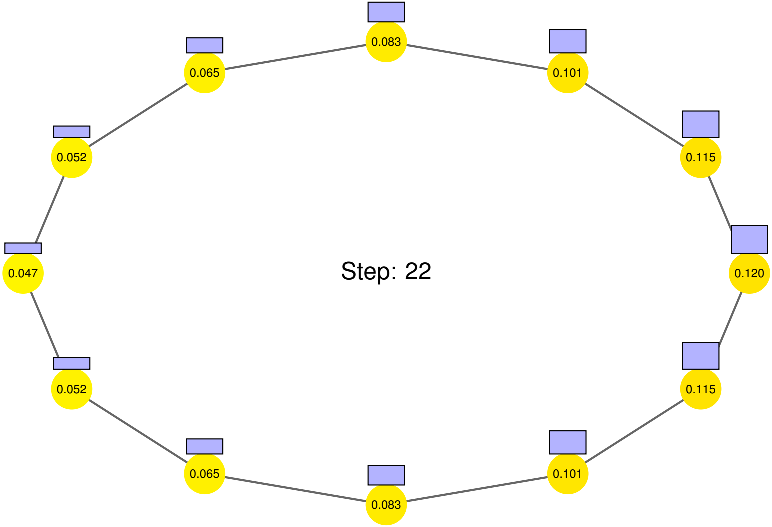

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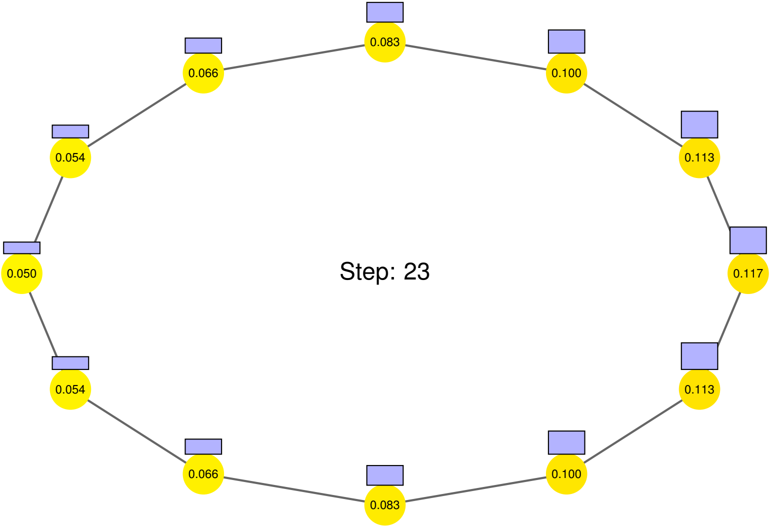

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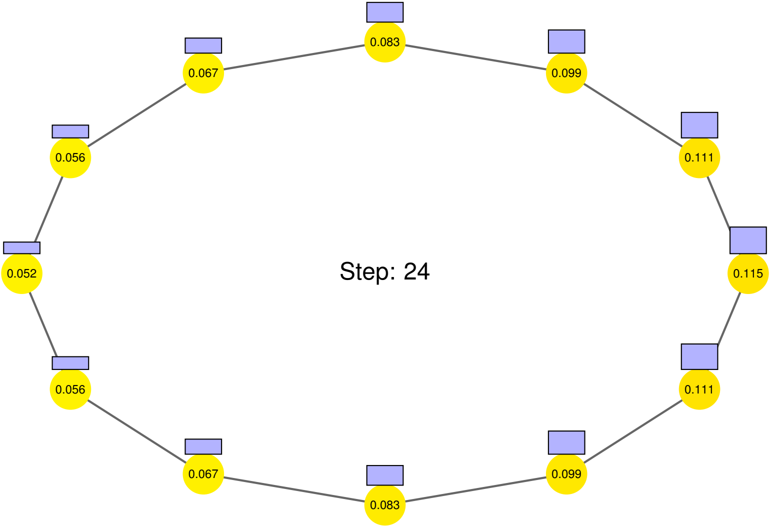

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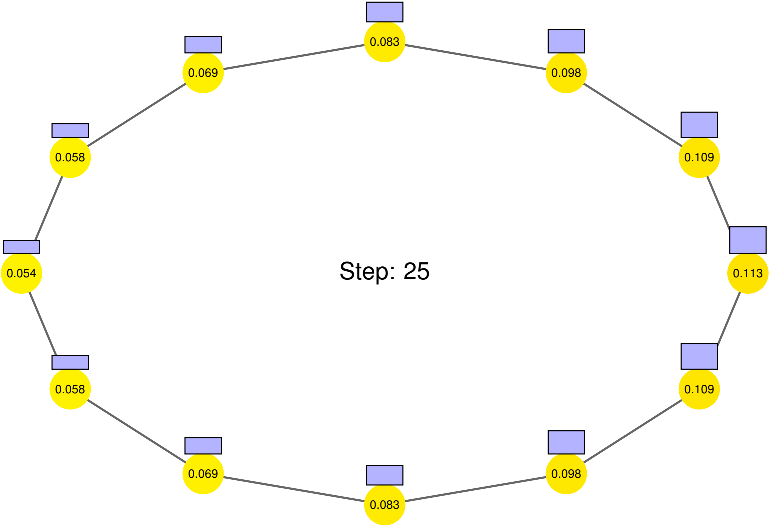

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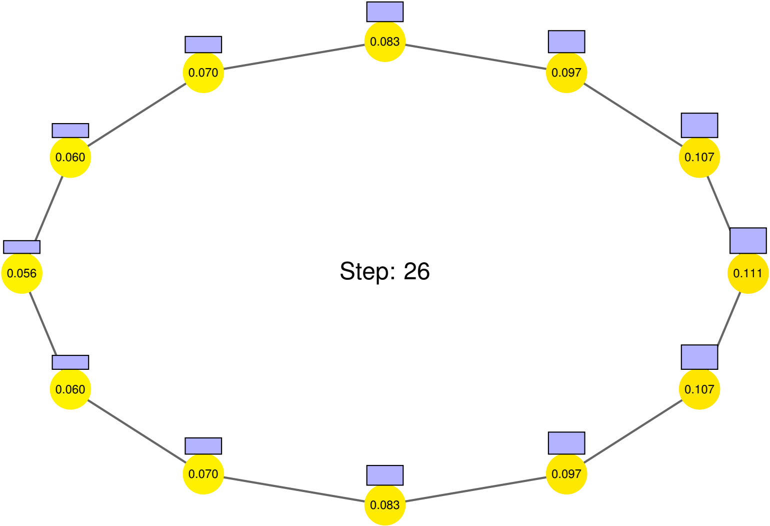

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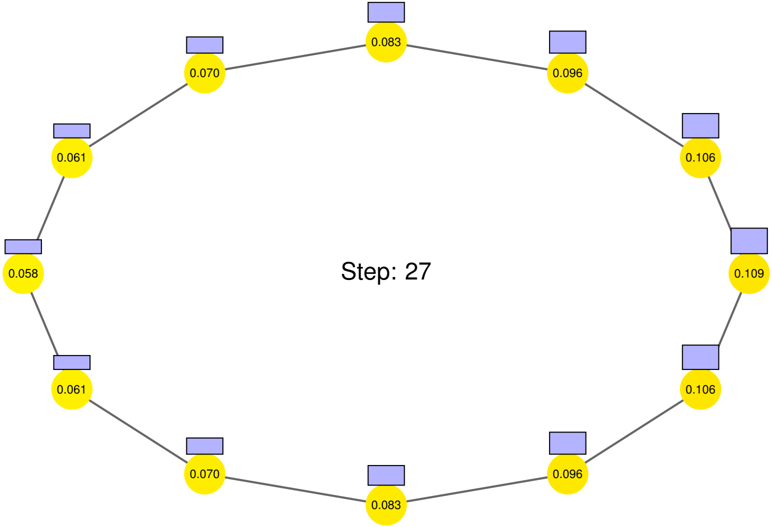

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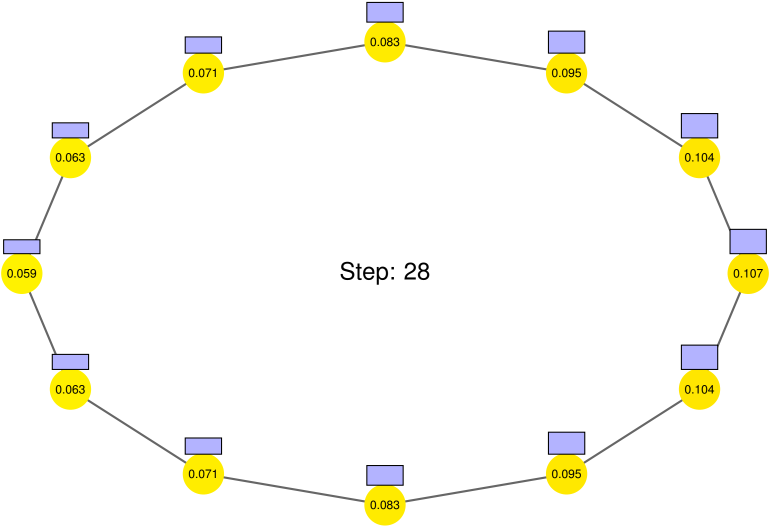

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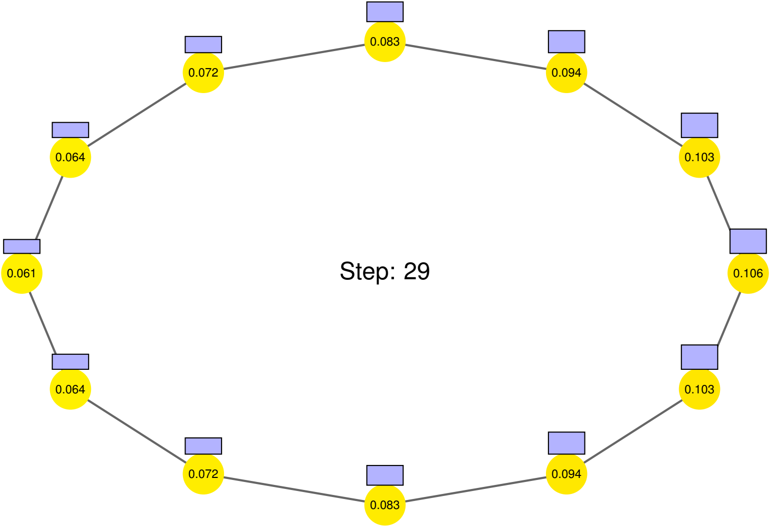

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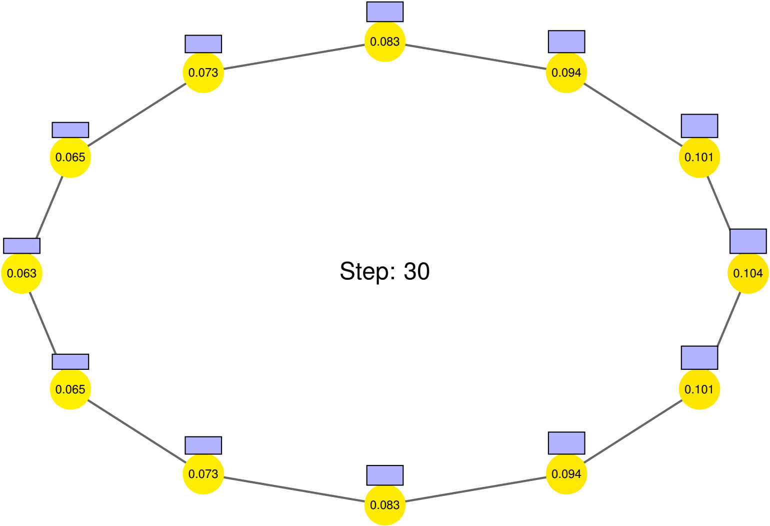

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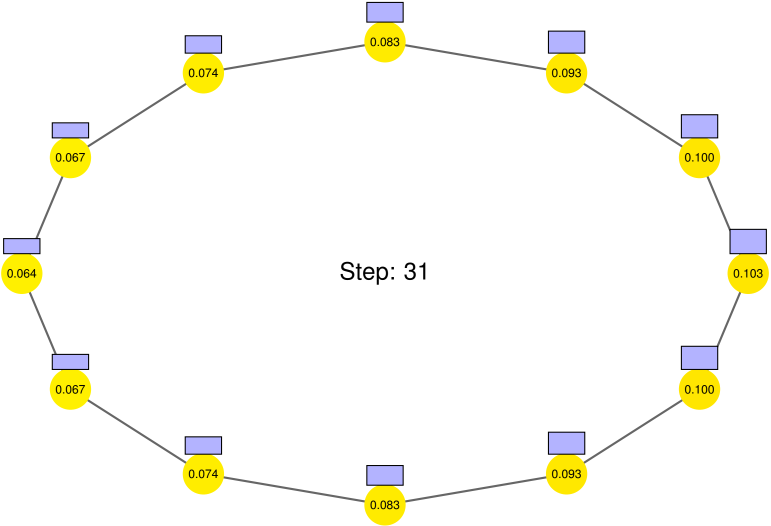

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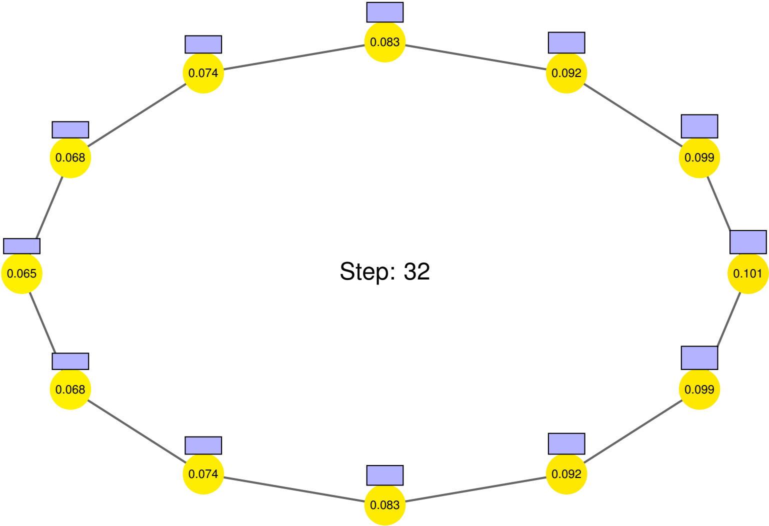

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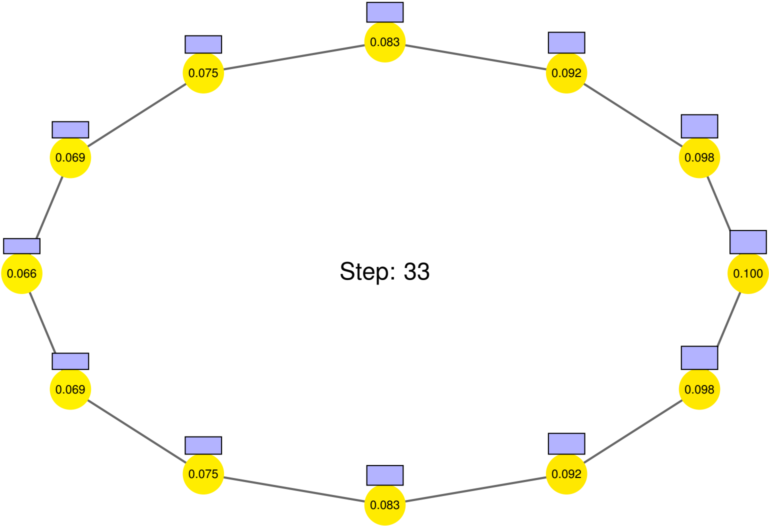

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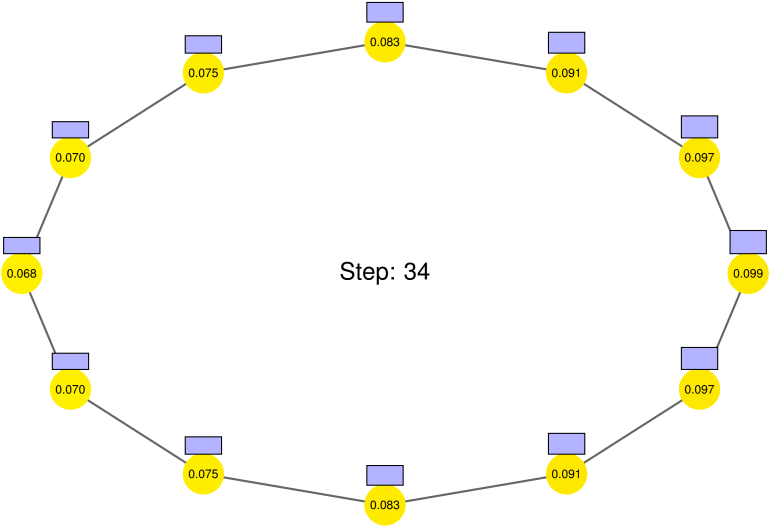

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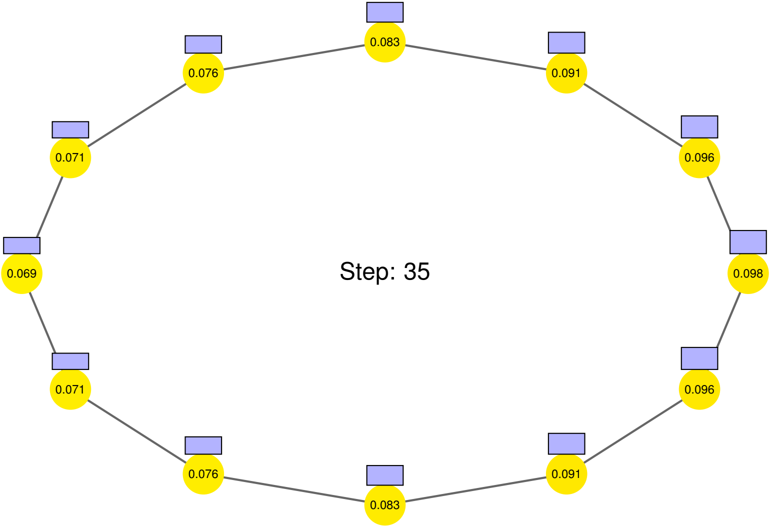

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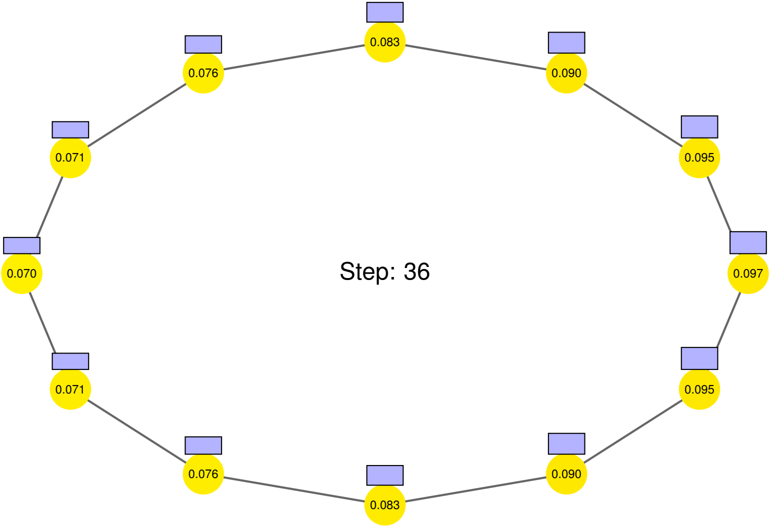

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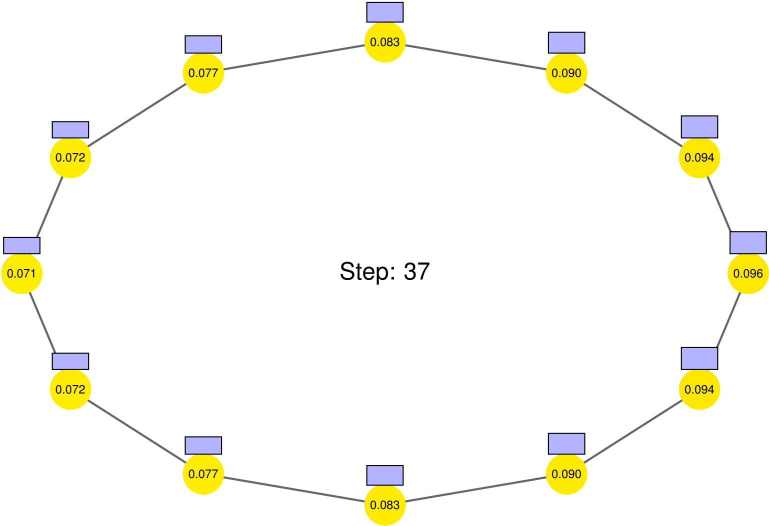

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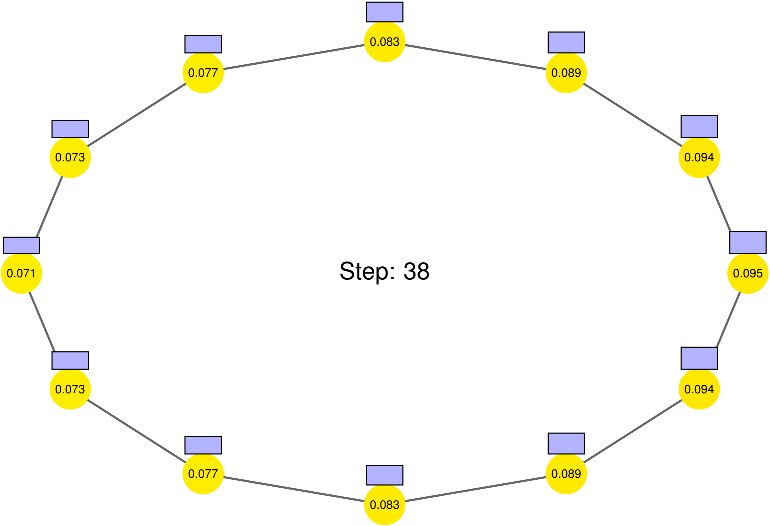

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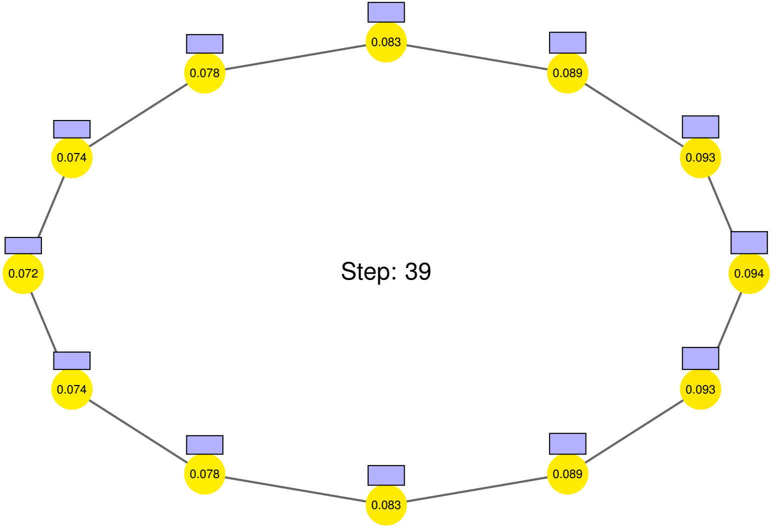

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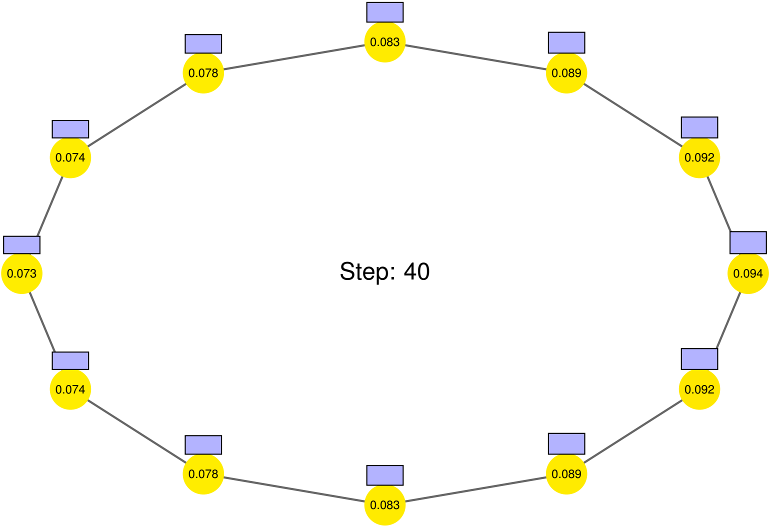

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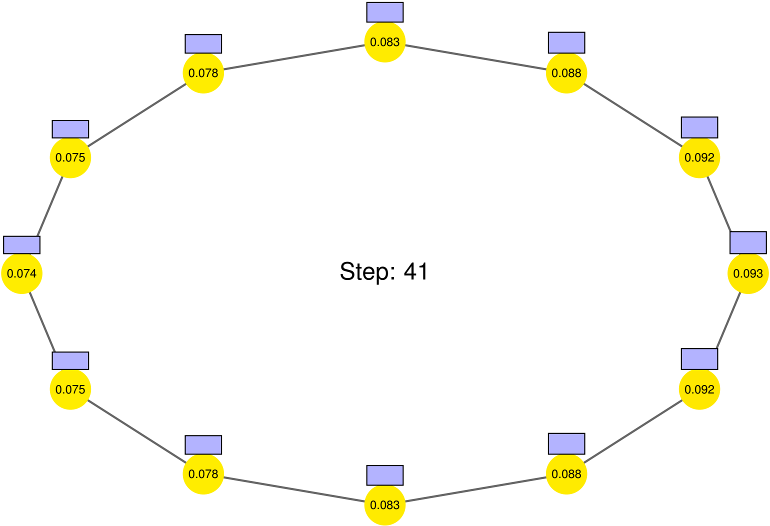

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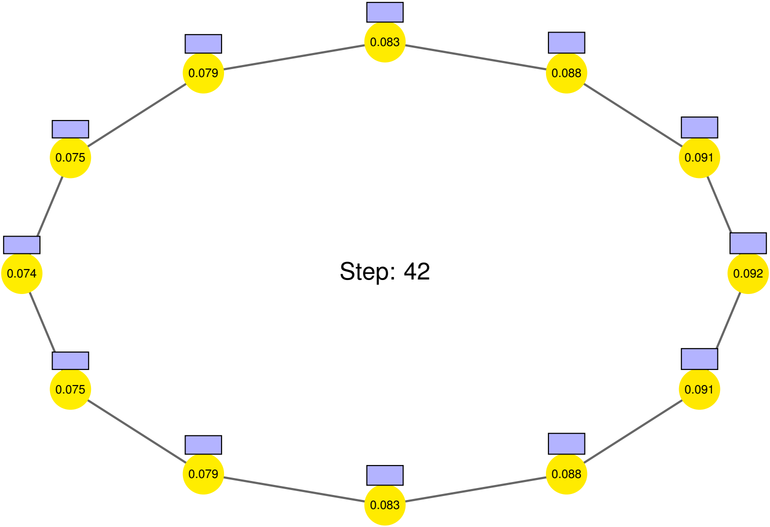

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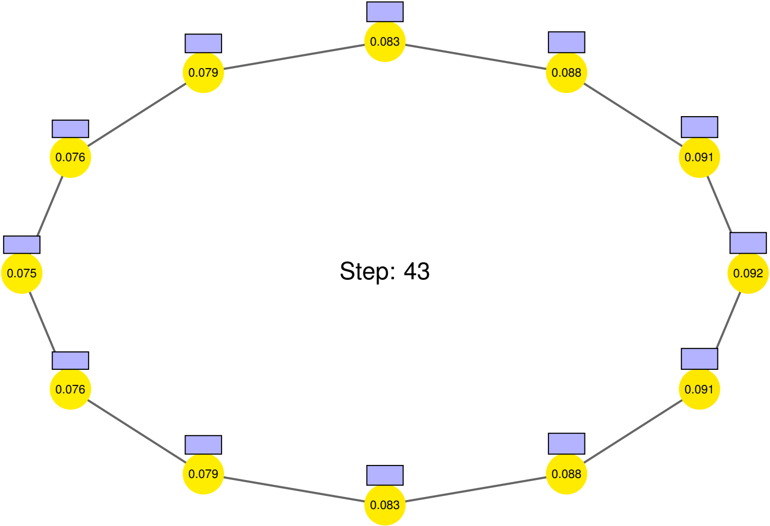

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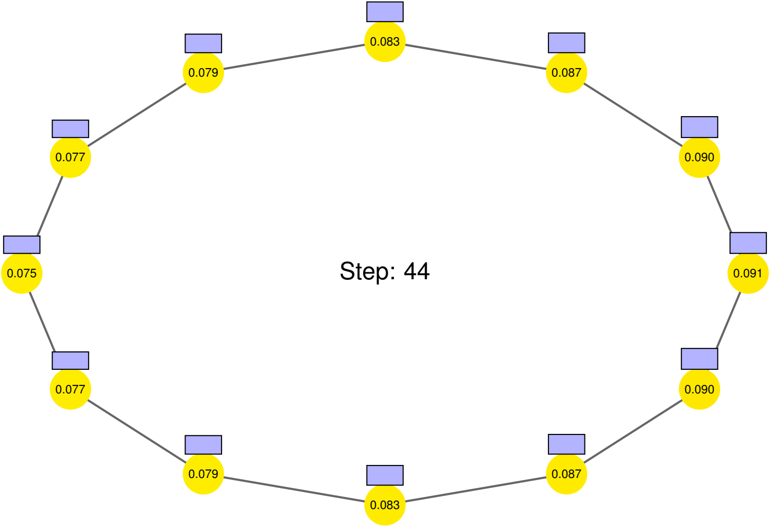

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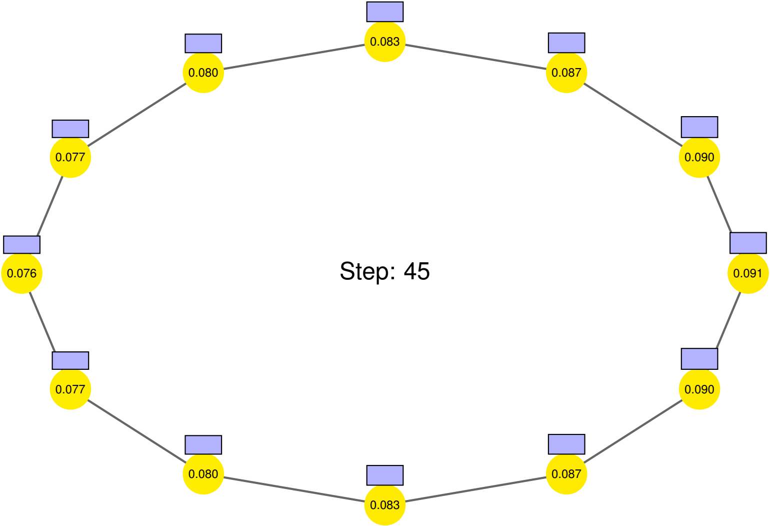

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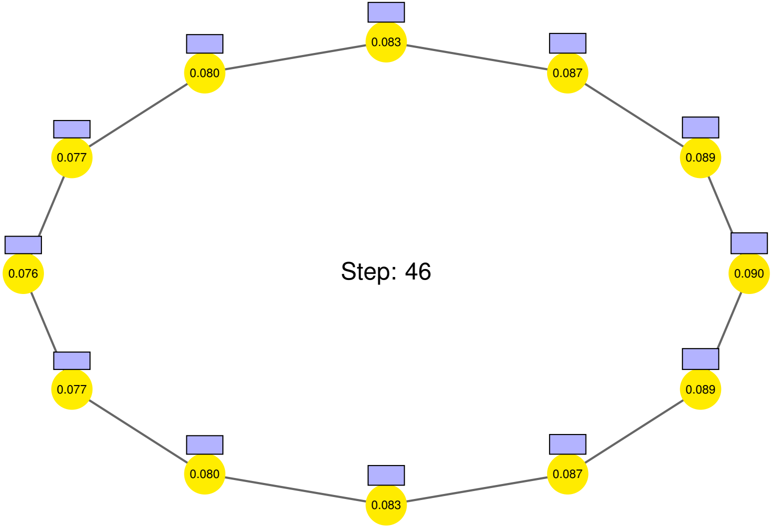

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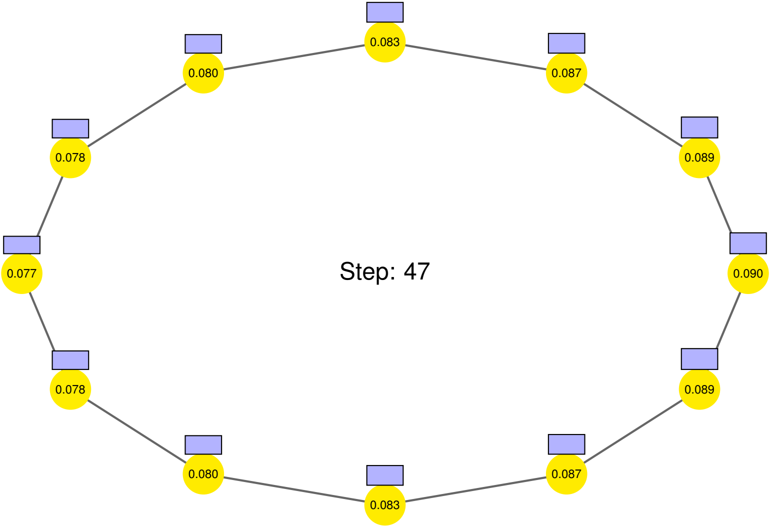

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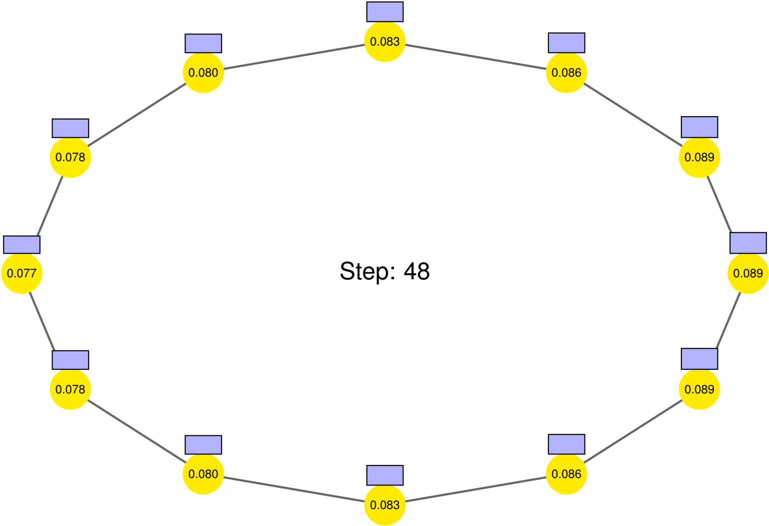

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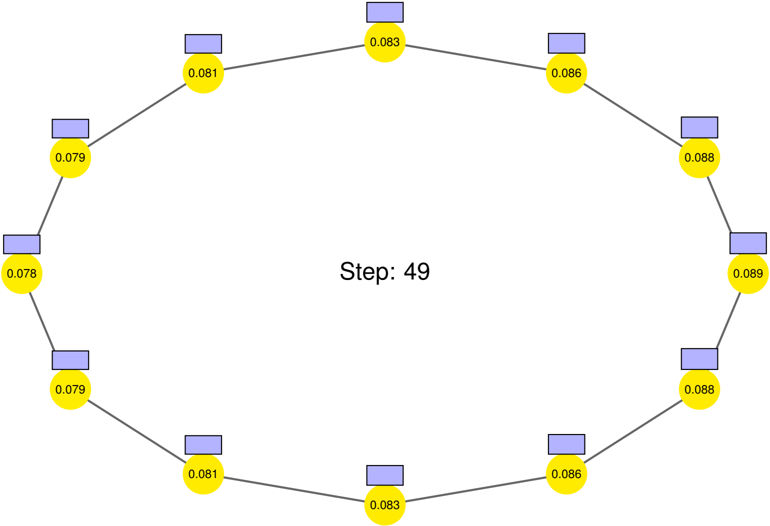

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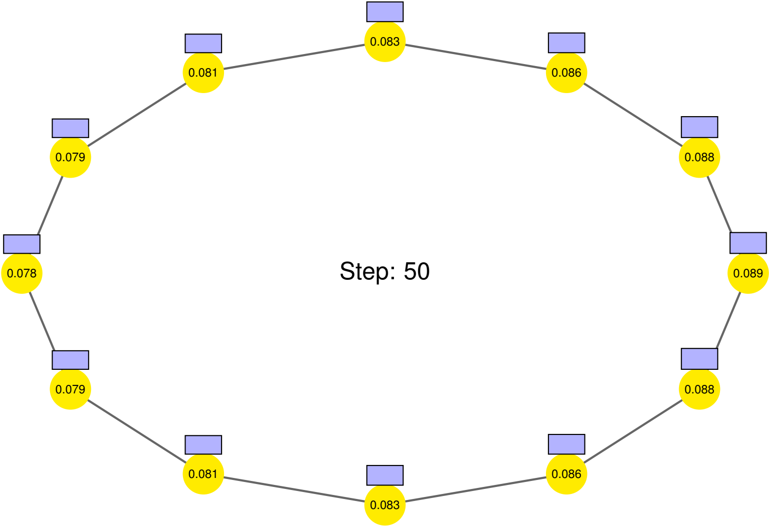

Outline

Recap of Markov Chain Basics

Irreducibility, Periodicity and Convergence

Total Variation Distance and Mixing Times

Application 1: Card Shuffling

Application 2: Markov Chain Monte Carlo (non-examin.)

Appendix: Remarks on Mixing Time (non-examin.)

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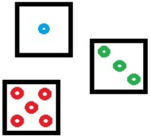

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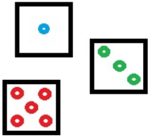

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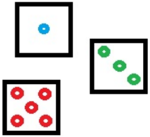

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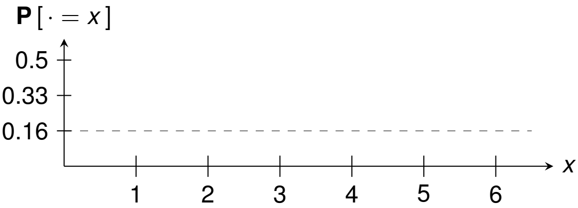

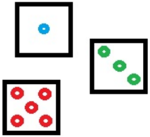

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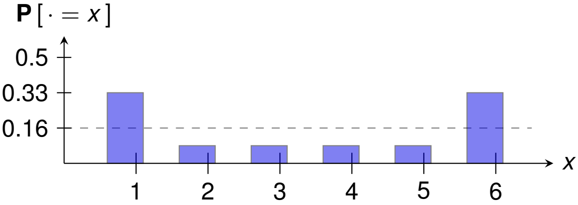

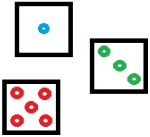

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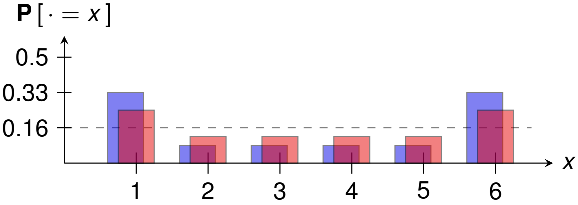

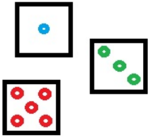

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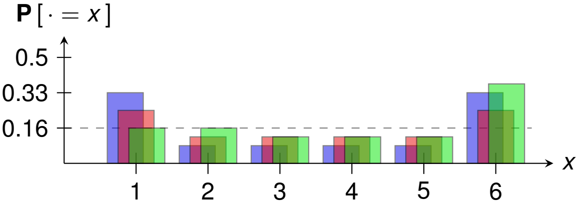

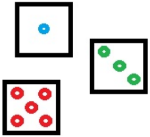

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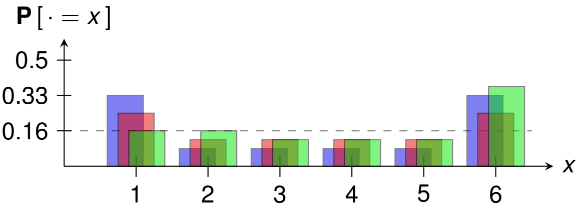

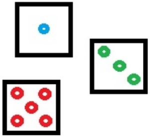

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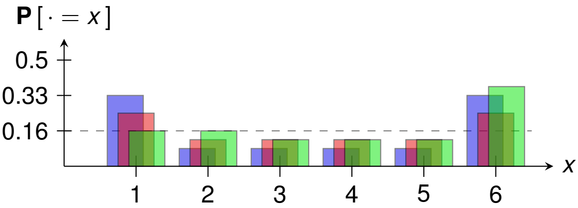

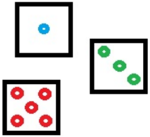

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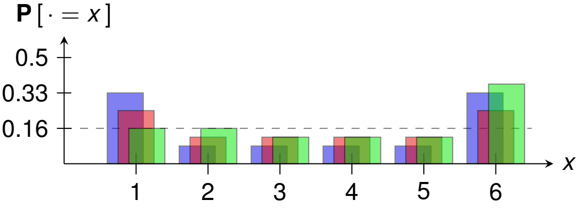

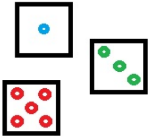

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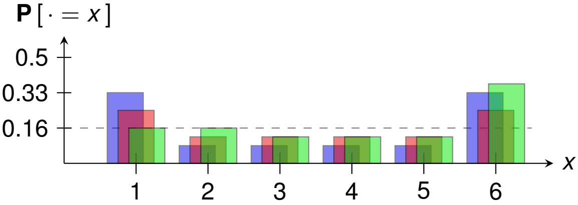
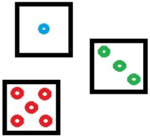
We need a formal "fairness measure" to compare probability distributions!





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Thus

$$\|D - B\|_{tv} = \|D - C\|_{tv} \quad \text{and} \quad \|D - B\|_{tv}, \|D - C\|_{tv} < \|D - A\|_{tv}.$$

So A is the least “fair”, however B and C are equally “fair” (in TV distance).

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We will see a similar result later after introducing spectral techniques (Lecture 12)!

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- This is how long we need to wait until we are "ϵ-close" to stationarity

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$$\tau_x(\epsilon) = \min\left\{t \geq 0 \colon \left\| P_x^t - \pi \right\|_{tv} \leq \epsilon \right\},$$

and,

$$\tau(\epsilon) = \max_x \tau_x(\epsilon).$$

- This is how long we need to wait until we are “ϵ-close” to stationarity
- We often take $\epsilon = 1/4$, indeed let $t_{mix} := \tau(1/4)$

Mixing Time of a Markov Chain

Convergence Theorem: "Nice" Markov Chains converge to stationarity.

Question: How fast do they converge?

Mixing Time

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See final slides for some comments on why we choose $1/4$.

Outline

Recap of Markov Chain Basics

Irreducibility, Periodicity and Convergence

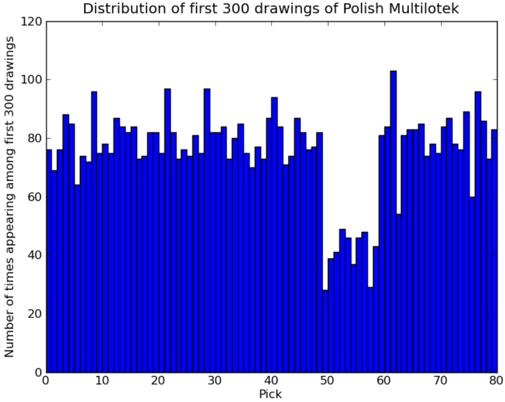
Total Variation Distance and Mixing Times

Application 1: Card Shuffling

Application 2: Markov Chain Monte Carlo (non-examin.)

Appendix: Remarks on Mixing Time (non-examin.)

Experiment Gone Wrong...



Thanks to Krzysztof Onak (pointer) and Eric Price (graph)

Source: Slides by Ronitt Rubinfeld

What is Card Shuffling?

Source: wikipedia

How long does it take to shuffle a deck of 52 cards?

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Persi Diaconis (Professor of Statistics and former Magician)

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One of the leading experts in the field who has related card shuffling to many other mathematical problems.

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Here we will focus on one shuffling scheme which is easy to analyse.

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Here we will focus on one shuffling scheme which is easy to analyse.

How long does it take to shuffle a deck of 52 cards?

How quickly do we converge to the uniform distribution over all $n!$ permutations?

One of the leading experts in the field who has related card shuffling to many other mathematical problems.

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Source: `www.soundcloud.com`

The Card Shuffling Markov Chain

TOPTORANDOMSHUFFLE (Input: A pile of n cards)

```
For t = 1, 2, ...
    Pick i ∈ {1, 2, ..., n} uniformly at random
    Take the top card and insert it behind the i-th card
```

The Card Shuffling Markov Chain

TopToRandomShuffle (Input: A pile of n cards)

1: **For** $t = 1, 2, \ldots$
2: Pick $i \in \{1, 2, \ldots, n\}$ uniformly at random
3: Take the top card and insert it behind the i-th card

This is a slightly informal definition, so let us look at a small example...

The Card Shuffling Markov Chain

TOPTORANDOMSHUFFLE (Input: A pile of n cards)

For $t = 1, 2, \ldots$
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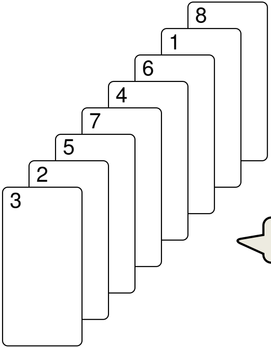
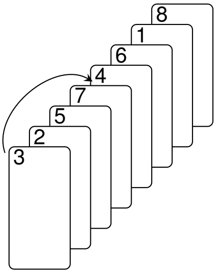


We will focus on this "small" set of cards ($n = 8$)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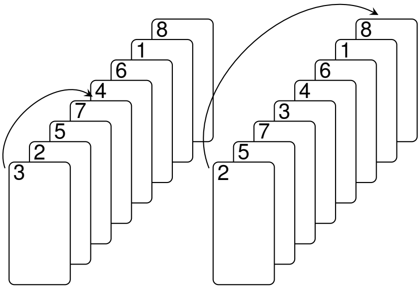
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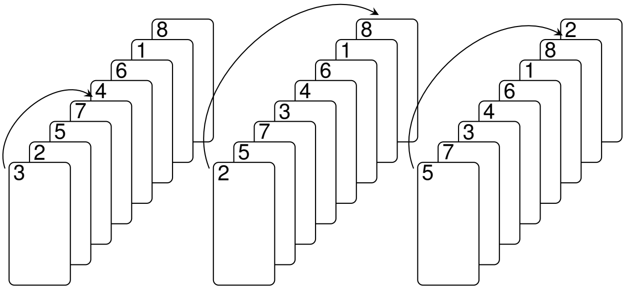
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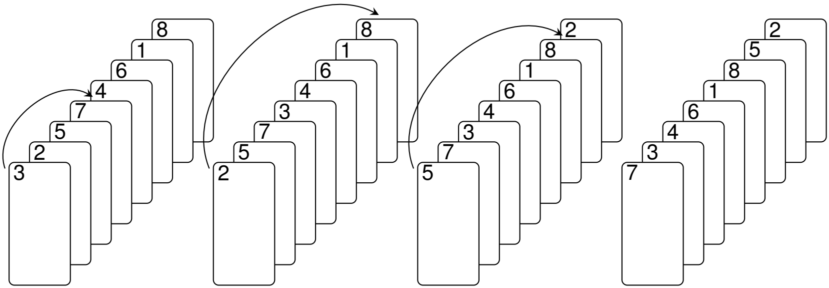

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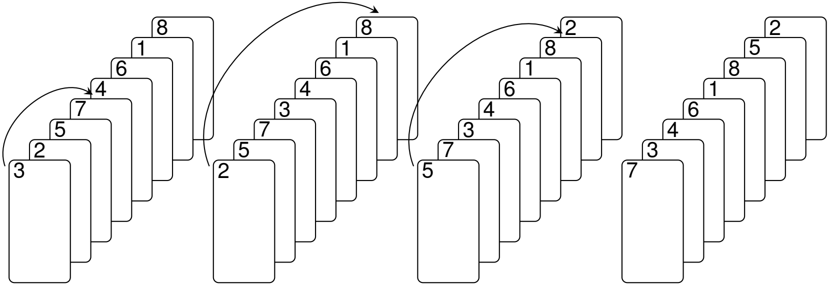
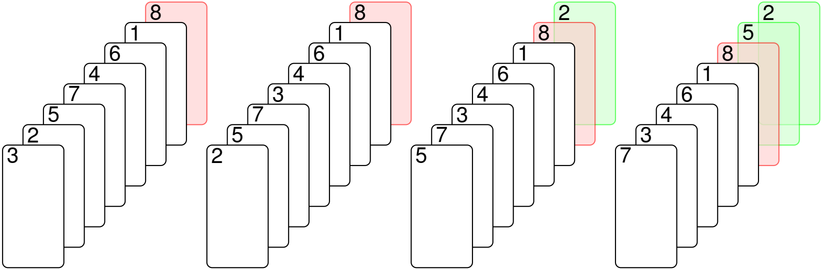


Even if we know which set of cards come after 8, every permutation is equally likely!



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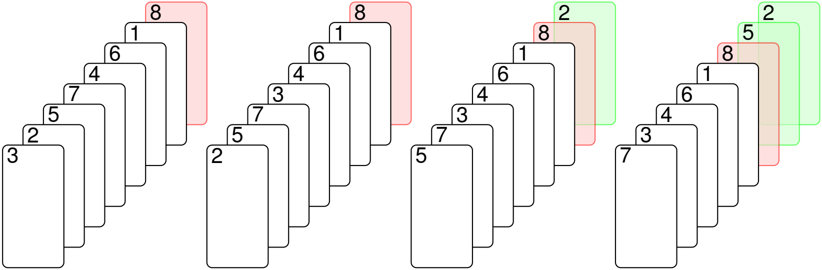

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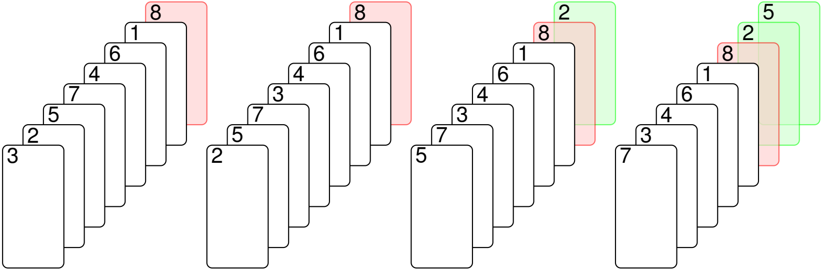

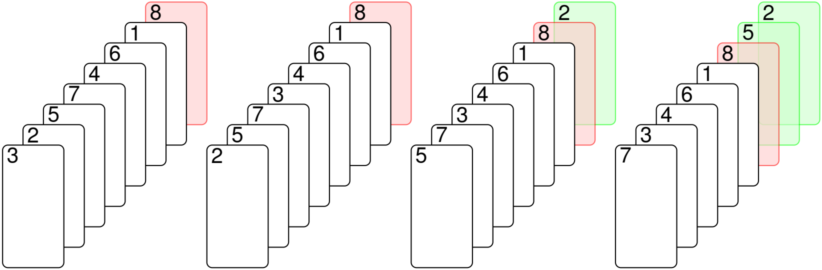

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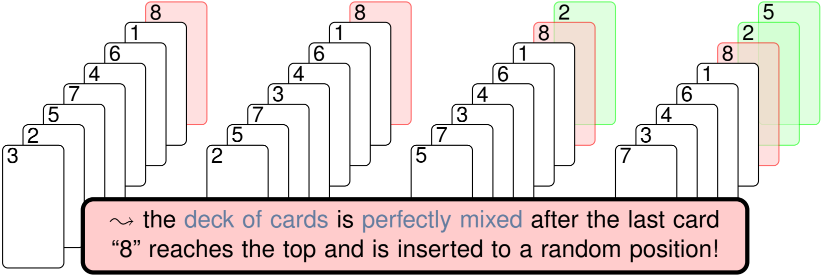
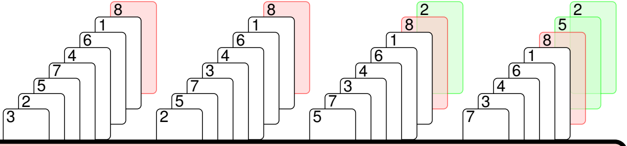


$\rightsquigarrow$ the deck of cards is perfectly mixed after the last card "8" reaches the top and is inserted to a random position!

Analysing the Mixing Time (Intuition)



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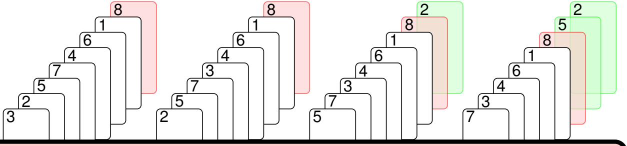

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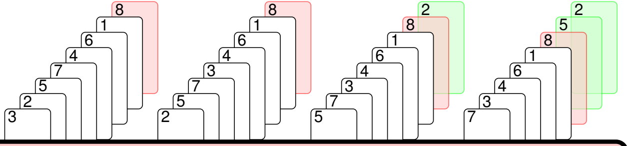

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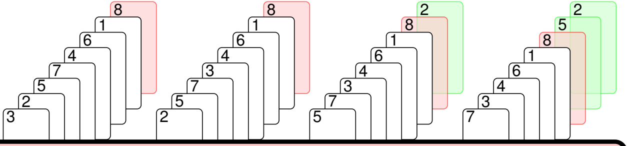

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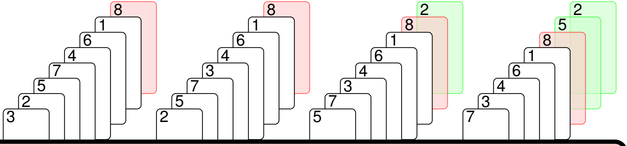

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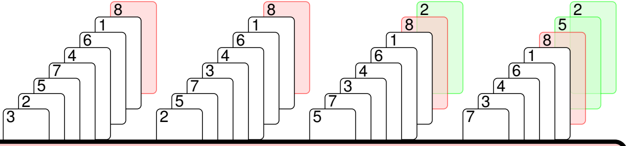

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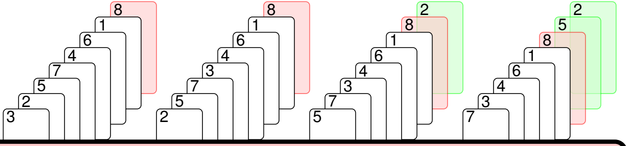

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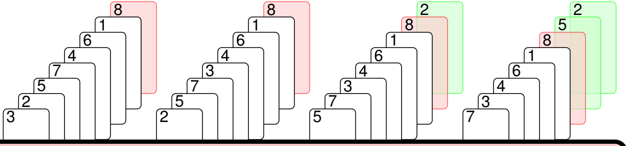

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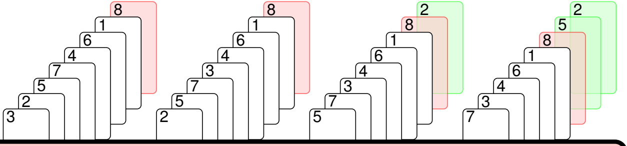

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This is a **"reversed" coupon collector** process with n cards, which takes $n \log n$ in expectation.

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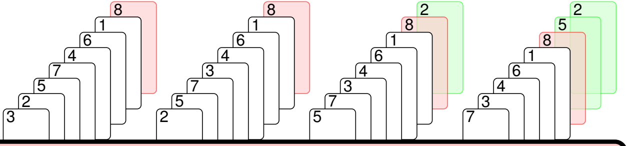

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Using the so-called coupling method, one could prove $t_{mix} \leq n \log n$.

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1. Split a deck of n cards into two piles (thus the size of each portion will be Binomial)

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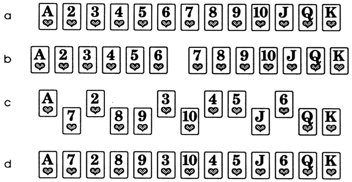

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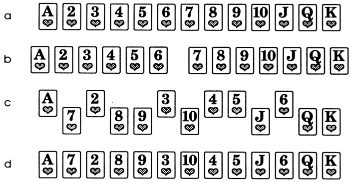

t	1	2	3	4	5	6	7	8	9	10
$\|\|P^t - \pi\|\|_{tv}$	1.000	1.000	1.000	1.000	0.924	0.614	0.334	0.167	0.085	0.043

Figure: Total Variation Distance for t riffle shuffles of 52 cards.

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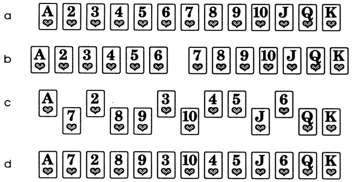

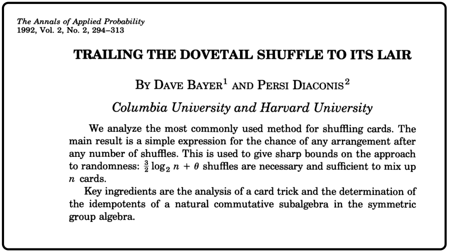

The Annals of Applied Probability
1992, Vol. 2, No. 2, 294–313

TRAILING THE DOVETAIL SHUFFLE TO ITS LAIR

By Dave Bayer[1] and Persi Diaconis[2]

Columbia University and Harvard University

We analyze the most commonly used method for shuffling cards. The main result is a simple expression for the chance of any arrangement after any number of shuffles. This is used to give sharp bounds on the approach to randomness: $\frac{3}{2}\log_2 n + \theta$ shuffles are necessary and sufficient to mix up n cards.

Key ingredients are the analysis of a card trick and the determination of the idempotents of a natural commutative subalgebra in the symmetric group algebra.

t	1	2	3	4	5	6	7	8	9	10
$\lVert P^t - \pi \rVert_{tv}$	1.000	1.000	1.000	1.000	0.924	0.614	0.334	0.167	0.085	0.043

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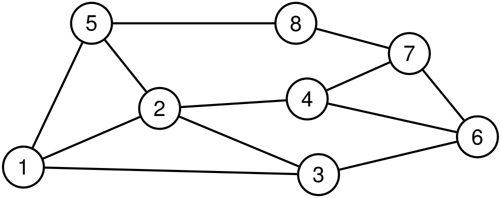
Application 2: Markov Chain Monte Carlo (non-examin.)

Appendix: Remarks on Mixing Time (non-examin.)

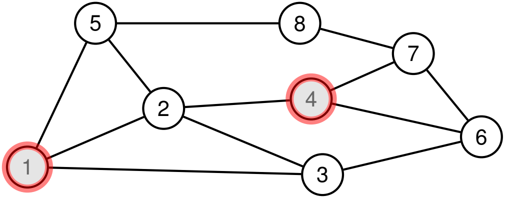
Markov Chain for Sampling Independent Sets (1/2) (non-examin.)



Independent Set

Given an undirected graph $G = (V, E)$, an independent set is a subset $S \subseteq V$ such that there are no two vertices $u, v \in S$ with $\{u, v\} \in E(G)$.

Markov Chain for Sampling Independent Sets (1/2) (non-examin.)



$S = \{1, 4\}$ is an independent set ✓

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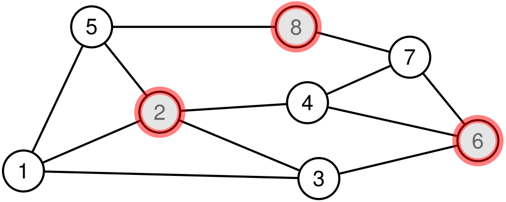

$S = \{2, 6, 8\}$ is an independent set ✓

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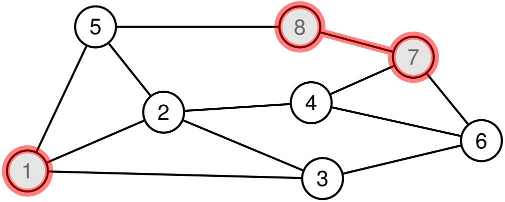

$S = \{1, 7, 8\}$ is **not** an independent set ×

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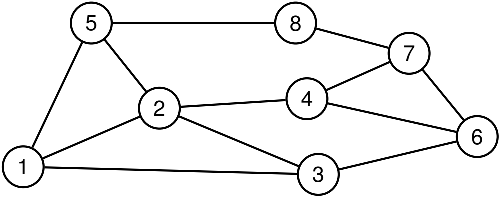

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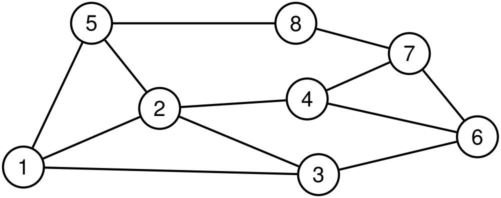

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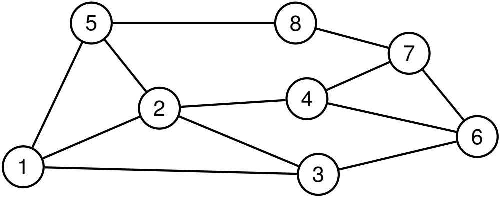
How can we take a sample from the space of all independent sets?

Markov Chain for Sampling Independent Sets (1/2) (non-examin.)



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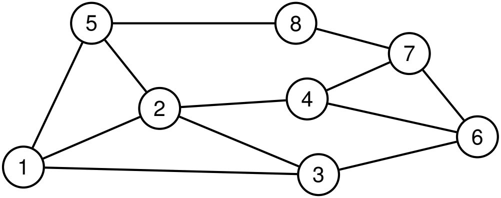

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We can use a generic Markov Chain Monte Carlo approach to tackle this problem!

Markov Chain for Sampling Independent Sets (2/2) (non-examin.)

INDEPENDENTSETSAMPLER

Let X_0 be an arbitrary independent set in G
For $t = 0, 1, 2, \ldots$:
  Pick a vertex $v \in V(G)$ uniformly at random
  If $v \in X_t$ **then** $X_{t+1} \leftarrow X_t \setminus \{v\}$
  elif $v \notin X_t$ **and** $X_t \cup \{v\}$ is an independent set **then** $X_{t+1} \leftarrow X_t \cup \{v\}$
  else $X_{t+1} \leftarrow X_t$

Markov Chain for Sampling Independent Sets (2/2) (non-examin.)

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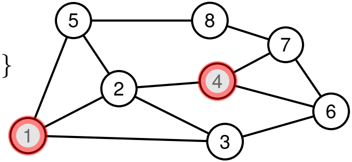

Markov Chain for Sampling Independent Sets (2/2) (non-examin.)

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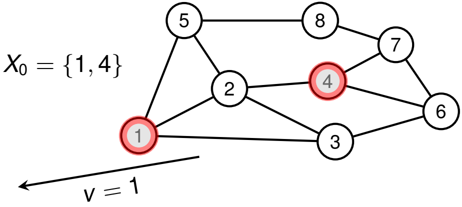

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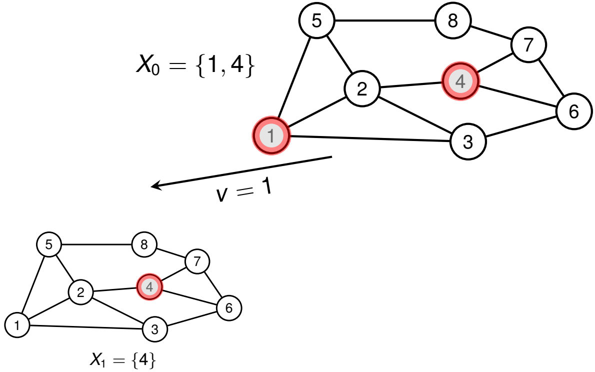

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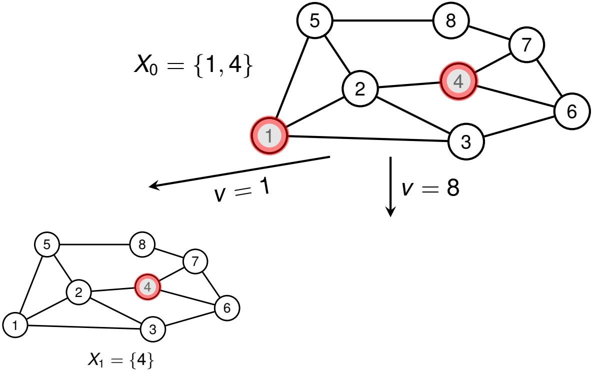

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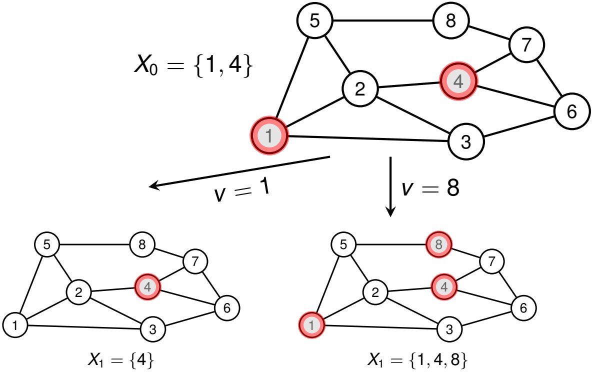

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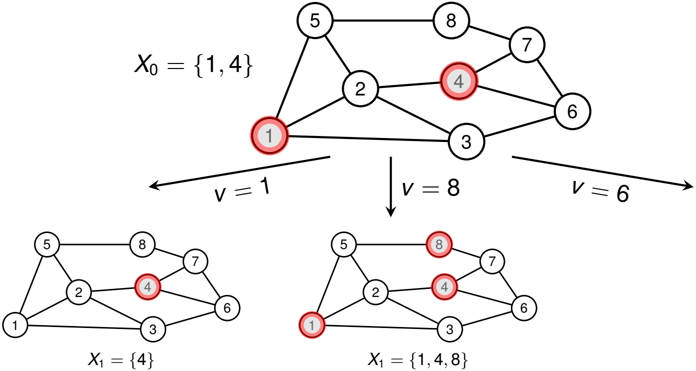

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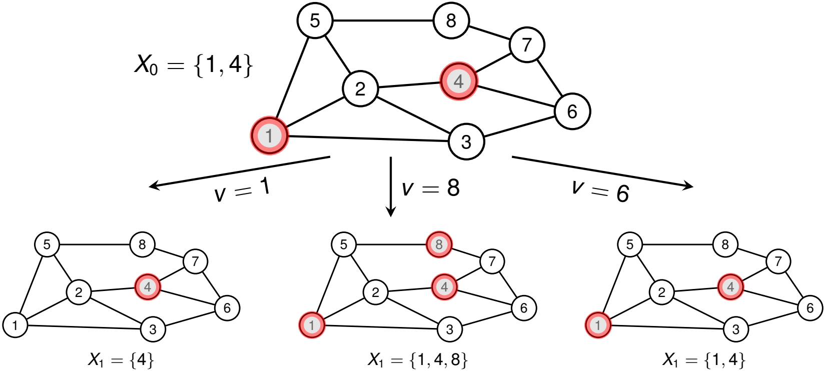

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- This is a local definition (no explicit definition of P!)

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Markov Chain for Sampling Independent Sets (2/2) (non-examin.)

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- This chain is aperiodic (Check!)

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Key Question: What is the mixing time of this Markov Chain?

Markov Chain for Sampling Independent Sets (2/2) (non-examin.)

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2: **For** $t = 0, 1, 2, \ldots$:
3: Pick a vertex $v \in V(G)$ uniformly at random
4: **If** $v \in X_t$ **then** $X_{t+1} \leftarrow X_t \setminus \{v\}$
5: **elif** $v \notin X_t$ **and** $X_t \cup \{v\}$ is an independent set **then** $X_{t+1} \leftarrow X_t \cup \{v\}$
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Remark

- This is a local definition (no explicit definition of P!)
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Key Question: What is the mixing time of this Markov Chain?

not covered here, see the textbook by Mitzenmacher and Upfal

Outline

Recap of Markov Chain Basics

Irreducibility, Periodicity and Convergence

Total Variation Distance and Mixing Times

Application 1: Card Shuffling

Application 2: Markov Chain Monte Carlo (non-examin.)

Appendix: Remarks on Mixing Time (non-examin.)

Further Remarks on the Mixing Time (non-examin.)

- One can prove $\max_x \left\| P_x^t - \pi \right\|_{tv}$ is non-increasing in t (this means if the chain is "ϵ-mixed" at step t, then this also holds in future steps) *[Mitzenmacher, Upfal, 12.3]*

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- We chose $t_{mix} := \tau(1/4)$, but other choices of ϵ are perfectly fine too (e.g, $t_{mix} := \tau(1/e)$ is often used); in fact, any constant $\epsilon \in (0, 1/2)$ is possible.

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Remark: This freedom on how to pick ϵ relies on the sub-multiplicative property of a (version) of the variation distance. First, let

$$d(t) := \max_x \left\| P_x^t - \pi \right\|_{tv}$$

be the variation distance after t steps when starting from the worst state. Further, define

$$\overline{d}(t) := \max_{\mu,\nu} \left\| P_\mu^t - P_\nu^t \right\|_{tv}.$$

These quantities are related by the following double inequality

$$d(t) \leq \overline{d}(t) \leq 2d(t).$$

Further, $\overline{d}(t)$ is sub-multiplicative, that is for any $s, t \geq 1$,

$$\overline{d}(s+t) \leq \overline{d}(s) \cdot \overline{d}(t).$$

Hence for any fixed $0 < \epsilon < \delta < 1/2$ it follows from the above that

$$\tau(\epsilon) \leq \left\lceil \frac{\ln \epsilon}{\ln(2\delta)} \right\rceil \tau(\delta).$$

In particular, for any $\epsilon < 1/4$

$$\tau(\epsilon) \leq \left\lceil \log_2 \epsilon^{-1} \right\rceil \tau(1/4).$$

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Hence smaller constants $\epsilon < 1/4$ only increase the mixing time by some constant factor.

Randomised Algorithms

Lecture 5: Random Walks, Hitting Times and Application to 2-SAT

Thomas Sauerwald (tms41@cam.ac.uk)

Lent 2024

UNIVERSITY OF CAMBRIDGE

Outline

The Ehrenfest Markov Chain

Ehrenfest Model

- A simple model for the exchange of molecules between two boxes

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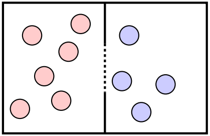

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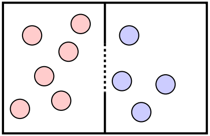

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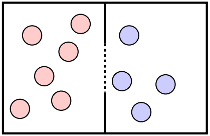

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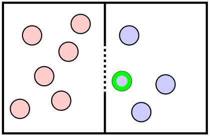

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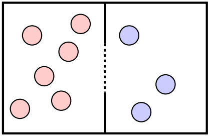

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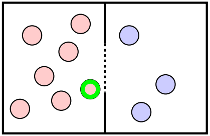

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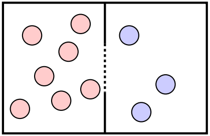

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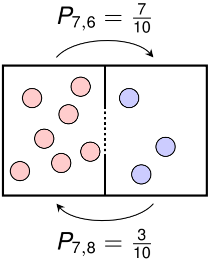

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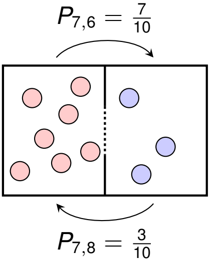

Let us now enlarge the state space by looking at each particle individually!

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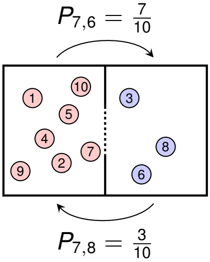

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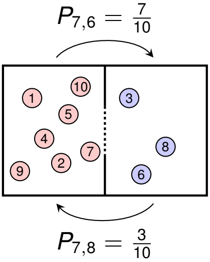

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Random Walk on the Hypercube

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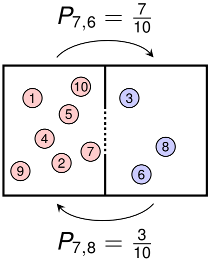

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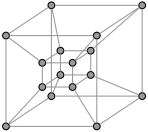
Random Walk on the Hypercube

- For each particle an indicator variable $\Rightarrow \Omega = \{0, 1\}^d$



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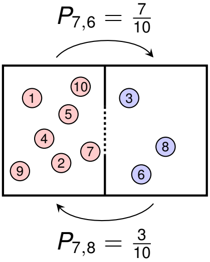
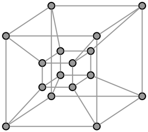


Let us now enlarge the state space by looking at each particle individually!

Random Walk on the Hypercube

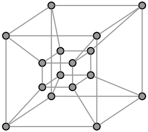
- For each particle an indicator variable $\Rightarrow \Omega = \{0, 1\}^d$
- At each step: pick a random coordinate in $[d]$ and flip it



Analysis of the Mixing Time

(Non-Lazy) Random Walk on the Hypercube

- For each particle an indicator variable $\Rightarrow \Omega = \{0,1\}^d$
- At each step: pick a random coordinate in $[d]$ and flip it

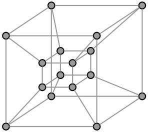


Analysis of the Mixing Time

(Non-Lazy) Random Walk on the Hypercube

- For each particle an indicator variable $\Rightarrow \Omega = \{0,1\}^d$
- At each step: pick a random coordinate in $[d]$ and flip it

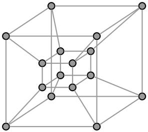
Problem: This Markov Chain is periodic, as the number of ones always switches between odd to even!



Analysis of the Mixing Time

(Non-Lazy) Random Walk on the Hypercube

- For each particle an indicator variable $\Rightarrow \Omega = \{0, 1\}^d$
- At each step: pick a random coordinate in $[d]$ and flip it



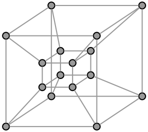
Problem: This Markov Chain is periodic, as the number of ones always switches between odd to even!

Solution: Add self-loops to break periodic behaviour!

Analysis of the Mixing Time

(Non-Lazy) Random Walk on the Hypercube

- For each particle an indicator variable $\Rightarrow \Omega = \{0, 1\}^d$
- At each step: pick a random coordinate in $[d]$ and flip it



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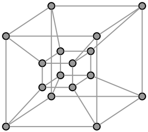
Lazy Random Walk (1st Version)

Analysis of the Mixing Time

(Non-Lazy) Random Walk on the Hypercube

- For each particle an indicator variable $\Rightarrow \Omega = \{0,1\}^d$
- At each step: pick a random coordinate in $[d]$ and flip it



Problem: This Markov Chain is periodic, as the number of ones always switches between odd to even!

Solution: Add self-loops to break periodic behaviour!

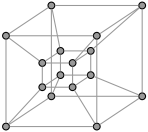
Lazy Random Walk (1st Version)

- At each step $t = 0, 1, 2 \ldots$

Analysis of the Mixing Time

(Non-Lazy) Random Walk on the Hypercube

- For each particle an indicator variable $\Rightarrow \Omega = \{0,1\}^d$
- At each step: pick a random coordinate in $[d]$ and flip it



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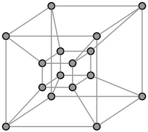
Lazy Random Walk (1st Version)

- At each step $t = 0, 1, 2 \ldots$
  - Pick a random coordinate in $[d]$

Analysis of the Mixing Time

(Non-Lazy) Random Walk on the Hypercube

- For each particle an indicator variable $\Rightarrow \Omega = \{0,1\}^d$
- At each step: pick a random coordinate in $[d]$ and flip it



Problem: This Markov Chain is periodic, as the number of ones always switches between odd to even!

Solution: Add self-loops to break periodic behaviour!

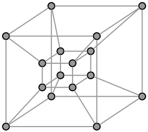
Lazy Random Walk (1st Version)

- At each step $t = 0, 1, 2 \dots$
  - Pick a random coordinate in $[d]$
  - With prob. $1/2$ flip coordinate.

Analysis of the Mixing Time

(Non-Lazy) Random Walk on the Hypercube

- For each particle an indicator variable $\Rightarrow \Omega = \{0,1\}^d$
- At each step: pick a random coordinate in $[d]$ and flip it



Problem: This Markov Chain is periodic, as the number of ones always switches between odd to even!

Solution: Add self-loops to break periodic behaviour!

Lazy Random Walk (1st Version)

- At each step $t = 0, 1, 2 \ldots$
  - Pick a random coordinate in $[d]$
  - With prob. $1/2$ flip coordinate.

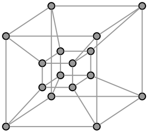
Lazy Random Walk (2nd Version)

- At each step $t = 0, 1, 2 \ldots$
  - Pick a random coordinate in $[d]$

Analysis of the Mixing Time

(Non-Lazy) Random Walk on the Hypercube

- For each particle an indicator variable $\Rightarrow \Omega = \{0,1\}^d$
- At each step: pick a random coordinate in $[d]$ and flip it



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  - Pick a random coordinate in $[d]$
  - With prob. $1/2$ flip coordinate.

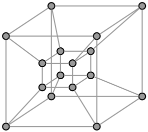
Lazy Random Walk (2nd Version)

- At each step $t = 0, 1, 2 \ldots$
  - Pick a random coordinate in $[d]$
  - Set coordinate to $\{0, 1\}$ uniformly.

Analysis of the Mixing Time

(Non-Lazy) Random Walk on the Hypercube

- For each particle an indicator variable $\Rightarrow \Omega = \{0, 1\}^d$
- At each step: pick a random coordinate in $[d]$ and flip it



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Lazy Random Walk (1st Version)

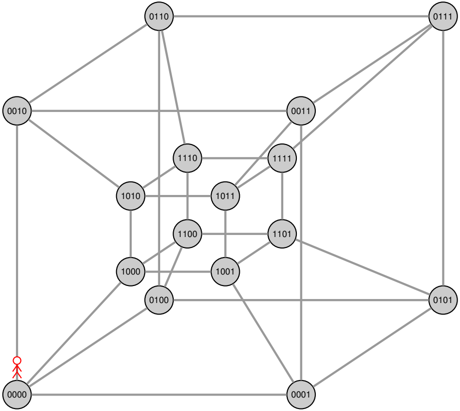
- At each step $t = 0, 1, 2 \ldots$
  - Pick a random coordinate in $[d]$
  - With prob. $1/2$ flip coordinate.

Lazy Random Walk (2nd Version)

- At each step $t = 0, 1, 2 \ldots$
  - Pick a random coordinate in $[d]$
  - Set coordinate to $\{0, 1\}$ uniformly.

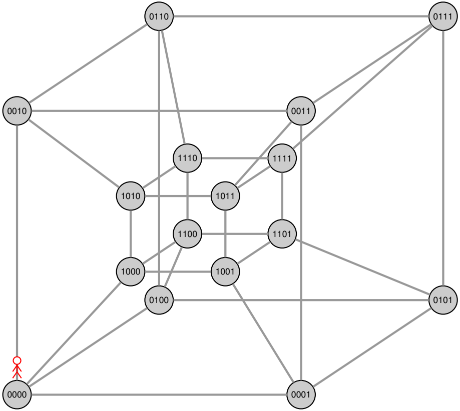
These two chains are equivalent!

Example of a Random Walk on a 4-Dimensional Hypercube



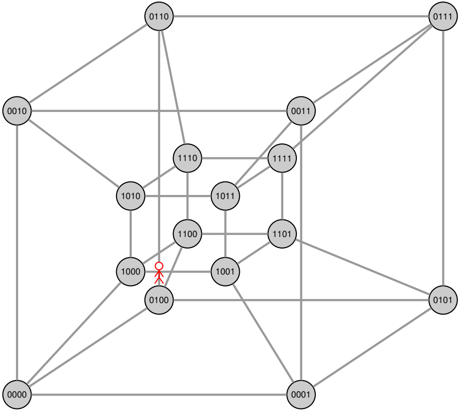
t	Coord.	X_t
0		0 0 0 0

Example of a Random Walk on a 4-Dimensional Hypercube



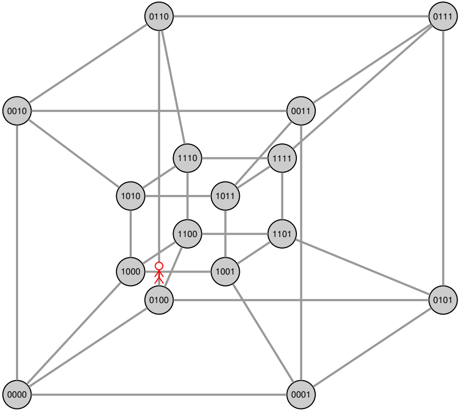
t	Coord.	X_t			
0	2	0	0	0	0
1		0	?	0	0

Example of a Random Walk on a 4-Dimensional Hypercube



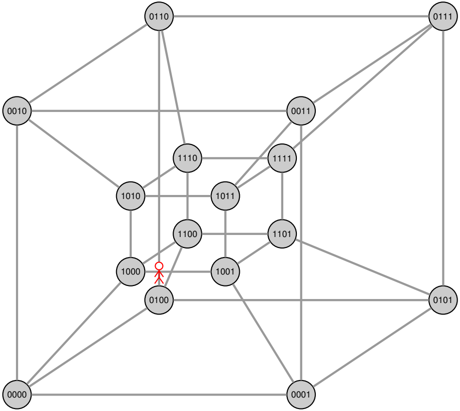
t	Coord.	X_t			
0	2	0	0	0	0
1		0	1	0	0

Example of a Random Walk on a 4-Dimensional Hypercube



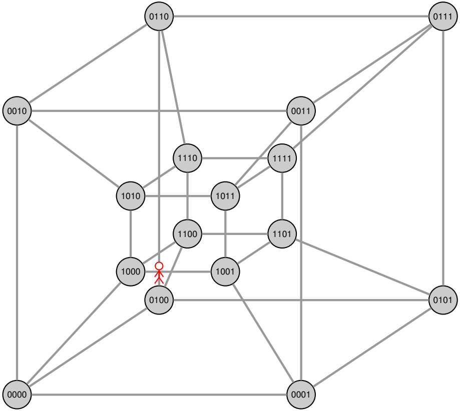
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2		0	1	?	0

Example of a Random Walk on a 4-Dimensional Hypercube



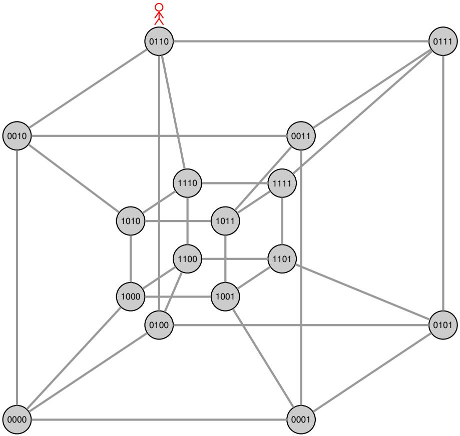
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2		0	1	0	0

Example of a Random Walk on a 4-Dimensional Hypercube



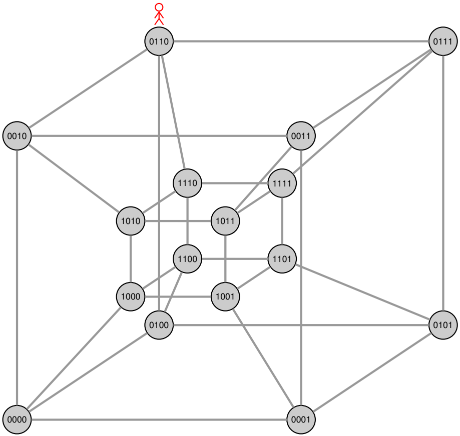
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3		0	1	?	0

Example of a Random Walk on a 4-Dimensional Hypercube



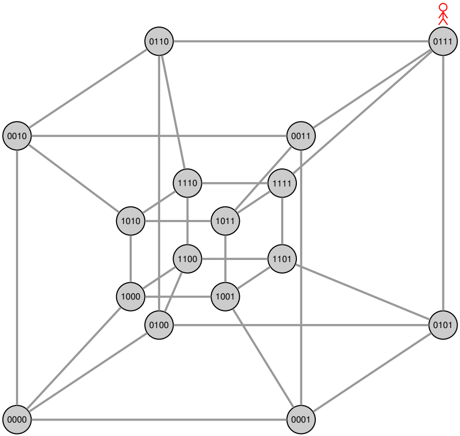
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3		0	1	1	0

Example of a Random Walk on a 4-Dimensional Hypercube



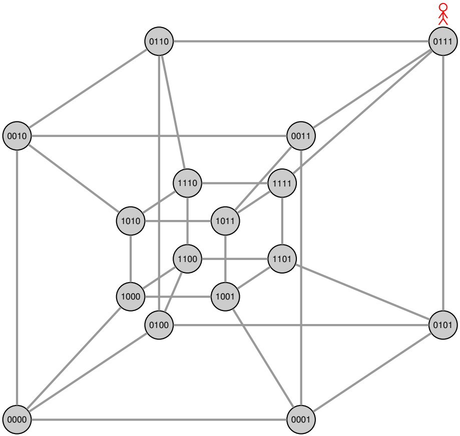
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3	4	0	1	1	0
4		0	1	1	?

Example of a Random Walk on a 4-Dimensional Hypercube



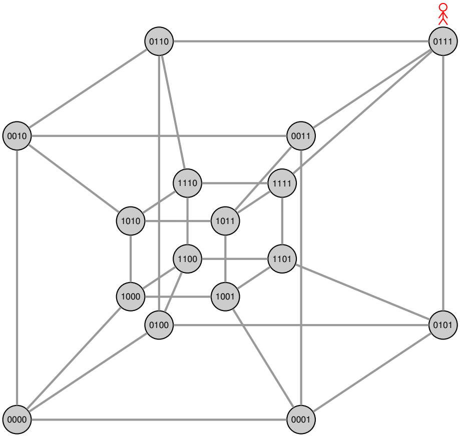
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3	4	0	1	1	0
4		0	1	1	1

Example of a Random Walk on a 4-Dimensional Hypercube



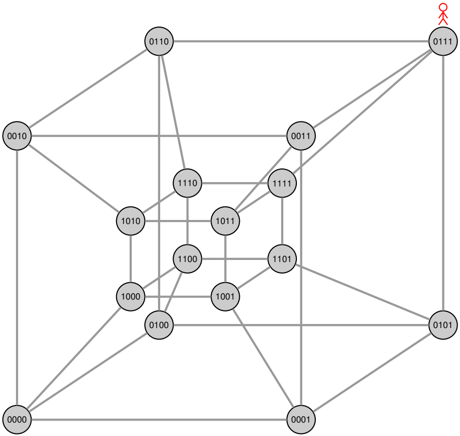
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3	4	0	1	1	0
4	2	0	1	1	1
5		0	?	1	1

Example of a Random Walk on a 4-Dimensional Hypercube



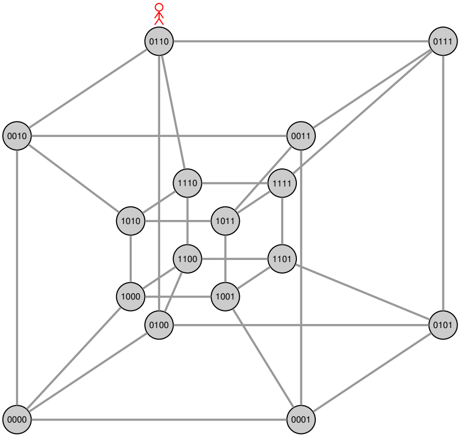
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3	4	0	1	1	0
4	2	0	1	1	1
5		0	1	1	1

Example of a Random Walk on a 4-Dimensional Hypercube



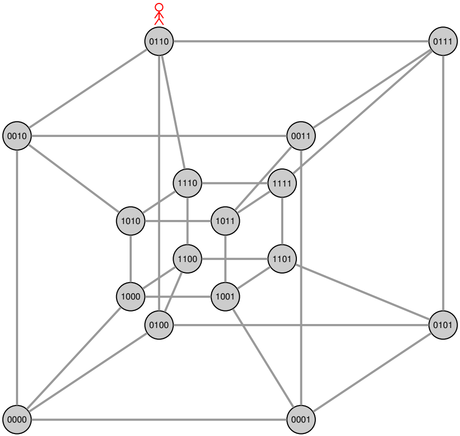
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3	4	0	1	1	0
4	2	0	1	1	1
5	4	0	1	1	1
6		0	1	1	?

Example of a Random Walk on a 4-Dimensional Hypercube



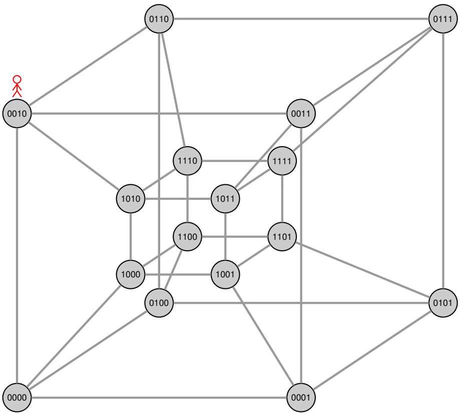
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3	4	0	1	1	0
4	2	0	1	1	1
5	4	0	1	1	1
6		0	1	1	0

Example of a Random Walk on a 4-Dimensional Hypercube



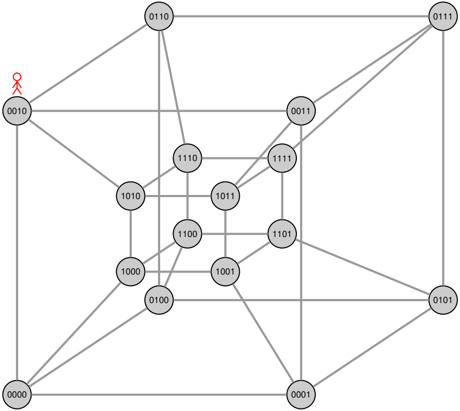
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3	4	0	1	1	0
4	2	0	1	1	1
5	4	0	1	1	1
6	2	0	1	1	0
7		0	?	1	0

Example of a Random Walk on a 4-Dimensional Hypercube



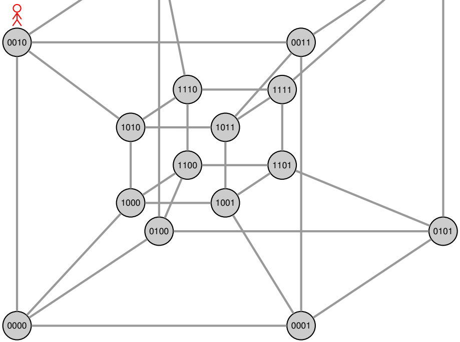
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3	4	0	1	1	0
4	2	0	1	1	1
5	4	0	1	1	1
6	2	0	1	1	0
7		0	0	1	0

Example of a Random Walk on a 4-Dimensional Hypercube



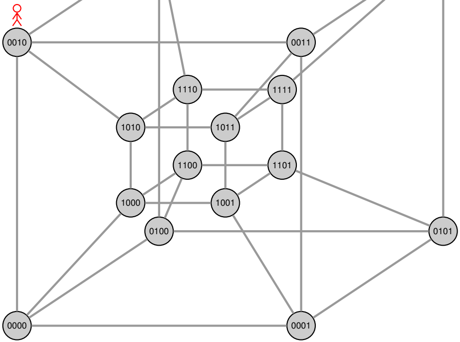
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3	4	0	1	1	0
4	2	0	1	1	1
5	4	0	1	1	1
6	2	0	1	1	0
7	4	0	0	1	0
8		0	0	1	?

Example of a Random Walk on a 4-Dimensional Hypercube



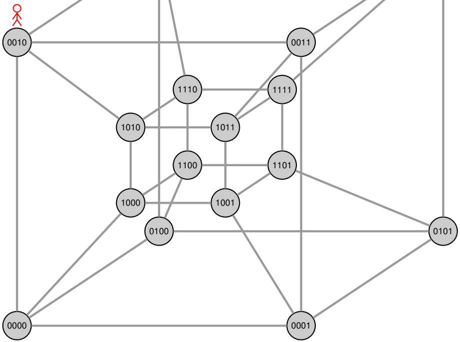
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3	4	0	1	1	0
4	2	0	1	1	1
5	4	0	1	1	1
6	2	0	1	1	0
7	4	0	0	1	0
8		0	0	1	0

Example of a Random Walk on a 4-Dimensional Hypercube



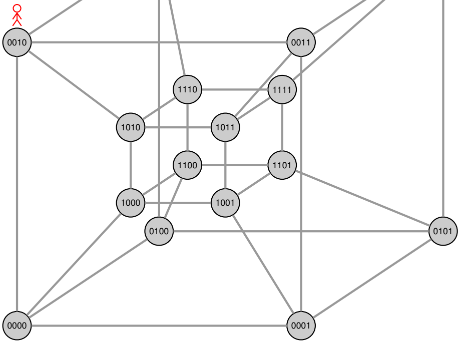
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3	4	0	1	1	0
4	2	0	1	1	1
5	4	0	1	1	1
6	2	0	1	1	0
7	4	0	0	1	0
8	3	0	0	1	0
9		0	0	?	0

Example of a Random Walk on a 4-Dimensional Hypercube



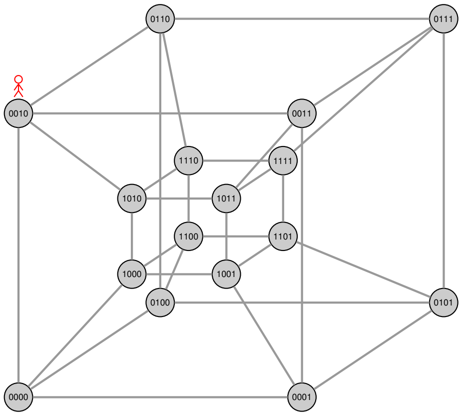
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3	4	0	1	1	0
4	2	0	1	1	1
5	4	0	1	1	1
6	2	0	1	1	0
7	4	0	0	1	0
8	3	0	0	1	0
9		0	0	1	0

Example of a Random Walk on a 4-Dimensional Hypercube



t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3	4	0	1	1	0
4	2	0	1	1	1
5	4	0	1	1	1
6	2	0	1	1	0
7	4	0	0	1	0
8	3	0	0	1	0
9	1	0	0	1	0
10	done!	?	0	1	0

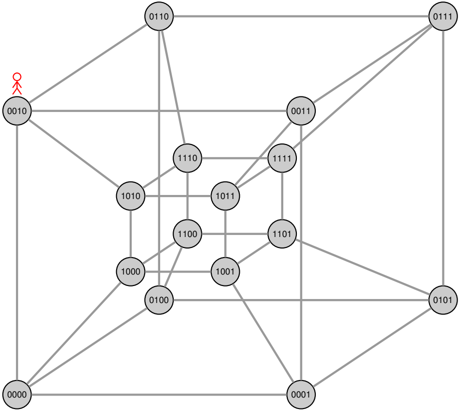
Example of a Random Walk on a 4-Dimensional Hypercube



Once all coordinates have been picked at least once, the state is uniformly at random in $\{0,1\}^d$.

t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3	4	0	1	1	0
4	2	0	1	1	1
5	4	0	1	1	1
6	2	0	1	1	0
7	4	0	0	1	0
8	3	0	0	1	0
9	1	0	0	1	0
10	done!	0	0	1	0

Example of a Random Walk on a 4-Dimensional Hypercube

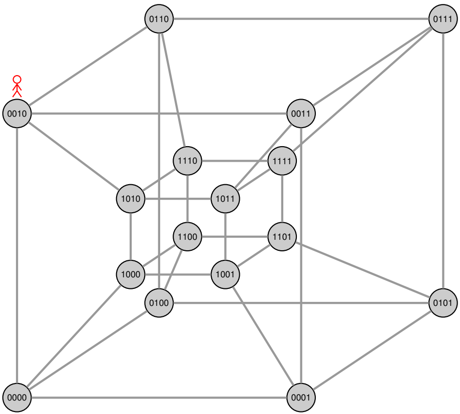


t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3	4	0	1	1	0
4	2	0	1	1	1
5	4	0	1	1	1
6	2	0	1	1	0
7	4	0	0	1	0
8	3	0	0	1	0
9	1	0	0	1	0
10	done!	0	0	1	0

Once all coordinates have been picked at least once, the state is uniformly at random in $\{0,1\}^d$.

Coupon Collector $\rightsquigarrow$ mixing time should be $O(d \log d)$

Example of a Random Walk on a 4-Dimensional Hypercube



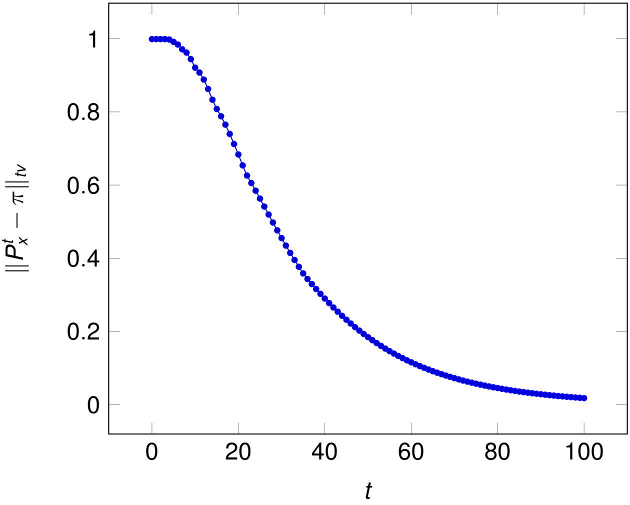
t	Coord.	X_t			
0	2	0	0	0	0
1	3	0	1	0	0
2	3	0	1	0	0
3	4	0	1	1	0
4	2	0	1	1	1
5	4	0	1	1	1
6	2	0	1	1	0
7	4	0	0	1	0
8	3	0	0	1	0
9	1	0	0	1	0
10	done!	0	0	1	0

Once all coordinates have been picked at least once, the state is uniformly at random in $\{0,1\}^d$.

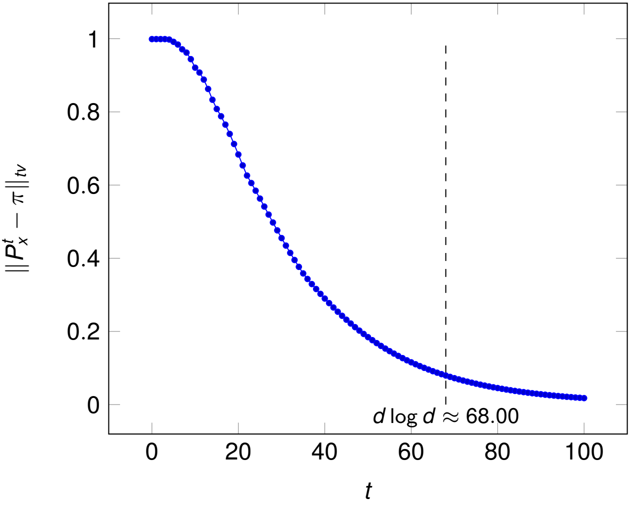
Coupon Collector $\rightsquigarrow$ mixing time should be $O(d \log d)$

We won't formalise this argument here (see *[Ex. 4/5.11]*)

Total Variation Distance of Random Walk on Hypercube $(d = 22)$



Total Variation Distance of Random Walk on Hypercube ($d = 22$)



Theoretical Results (by Diaconis, Graham and Morrison)

RANDOM WALK ON A HYPERCUBE 53

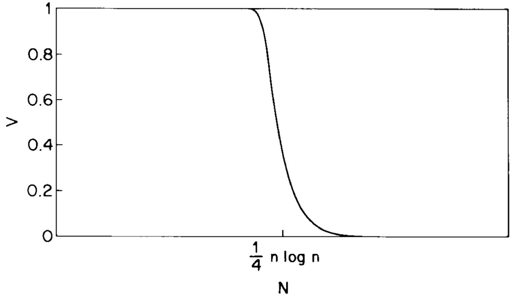


Fig. 1. The variation distance V as a function of N, for $n = 10^{12}$.

Source: "Asymptotic analysis of a random walk on a hypercube with many dimensions", P. Diaconis, R.L. Graham, J.A. Morrison; Random Structures & Algorithms, 1990.

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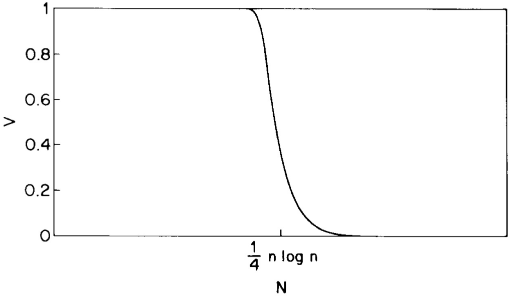

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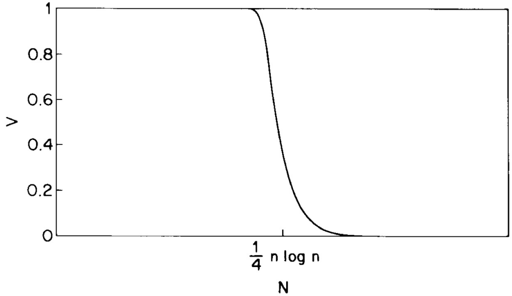

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- This is a numerical plot of a theoretical bound, where $d = 10^{12}$
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- The variation distance exhibits a so-called cut-off phenomena:
  - Distance remains close to its maximum value 1 until step $\frac{1}{4} n \log n - \Theta(n)$
  - Then distance moves close to 0 before step $\frac{1}{4} n \log n + \Theta(n)$

Outline

Application 3: Ehrenfest Chain and Hypercubes

Random Walks on Graphs, Hitting Times and Cover Times

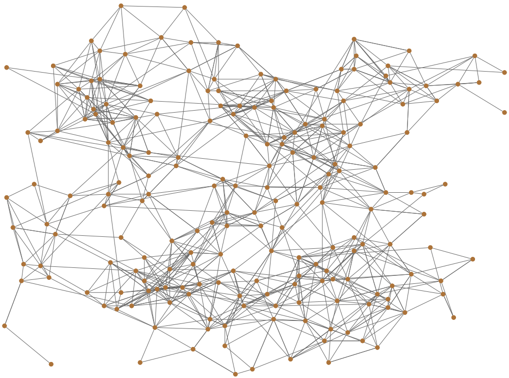
Random Walks on Paths and Grids

SAT and a Randomised Algorithm for 2-SAT

Random Walks on Graphs

A Simple Random Walk (SRW) on a graph G is a Markov chain on $V(G)$ with

$$P(u,v) = \begin{cases} \frac{1}{\deg(u)} & \text{if } \{u,v\} \in E, \\ 0 & \text{if } \{u,v\} \notin E. \end{cases}, \qquad \text{and} \qquad \pi(u) = \frac{\deg(u)}{2|E|}$$



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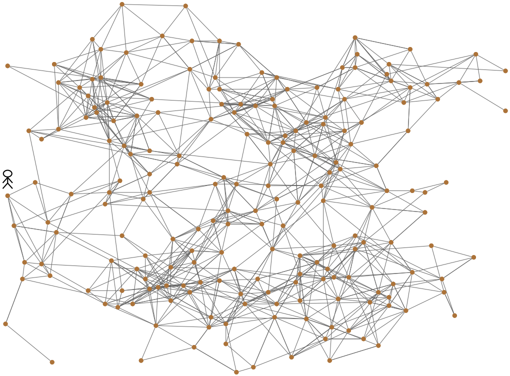

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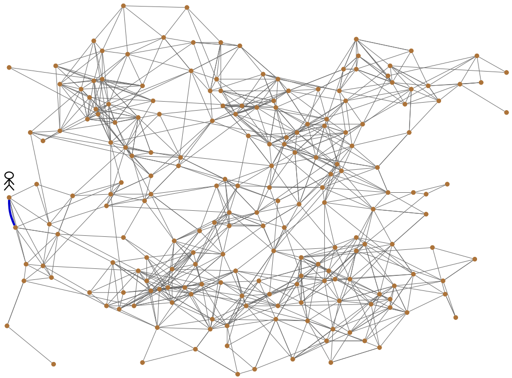

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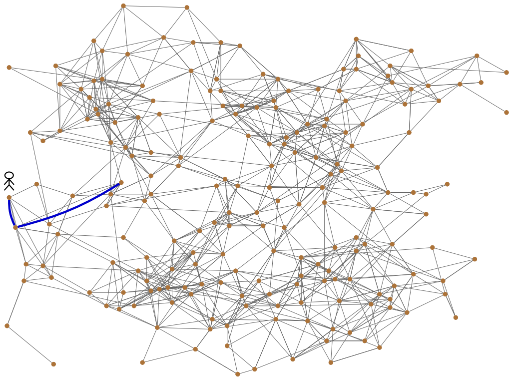

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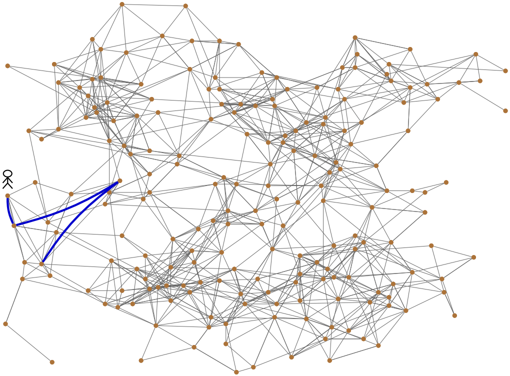

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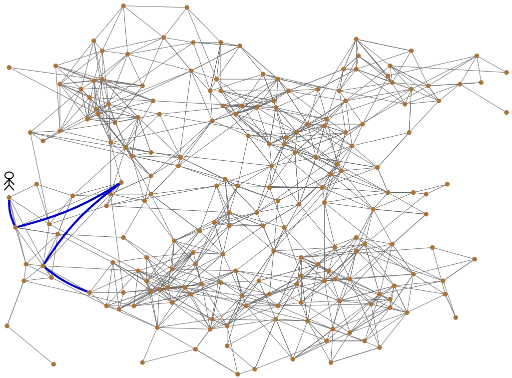

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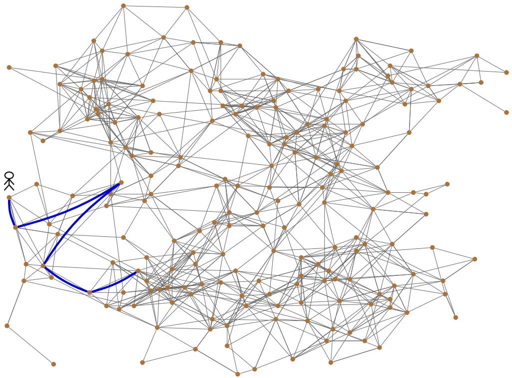

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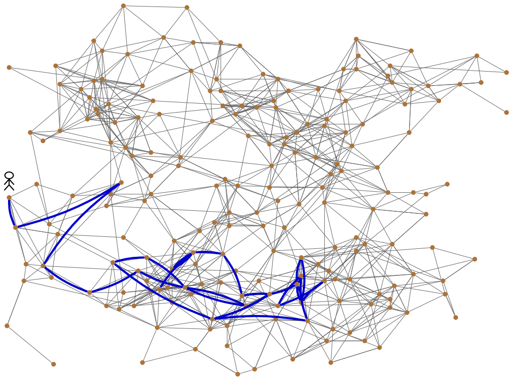

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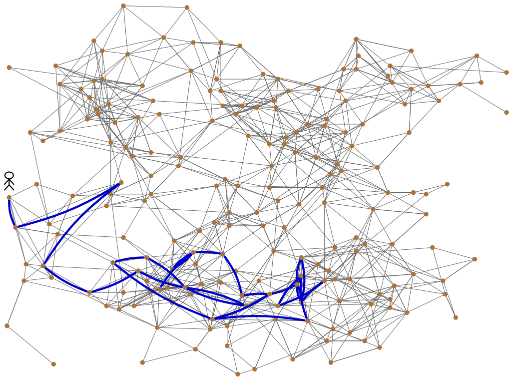
Recall: $h(u,v) = \mathbf{E}_u[\min\{t \geq 1 : X_t = v\}]$ is the hitting time of v from u.



Lazy Random Walks and Periodicity

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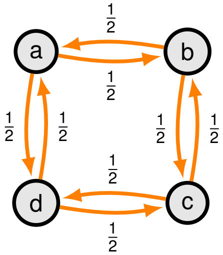

SRW on C_4, *Periodic*

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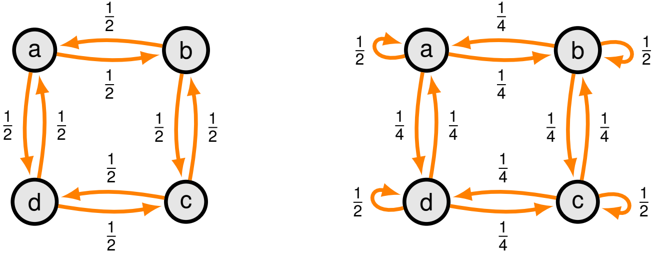

SRW on C_4, *Periodic* LRW on C_4, *Aperiodic*

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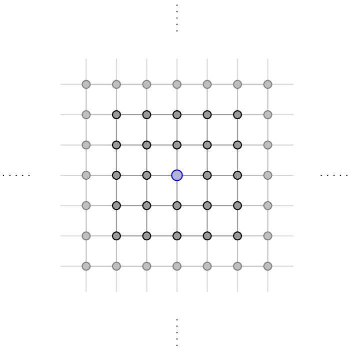

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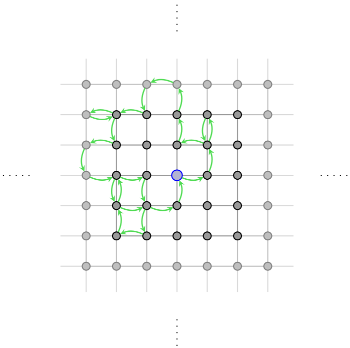

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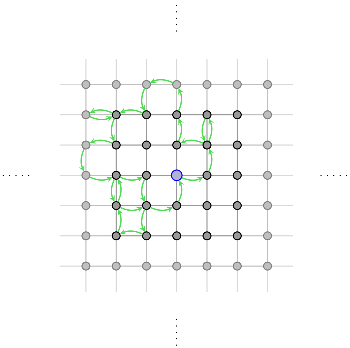

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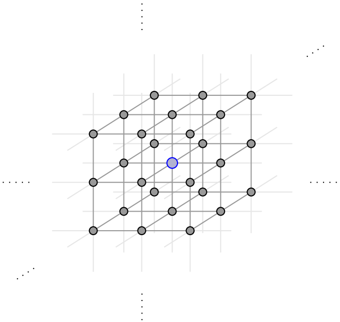

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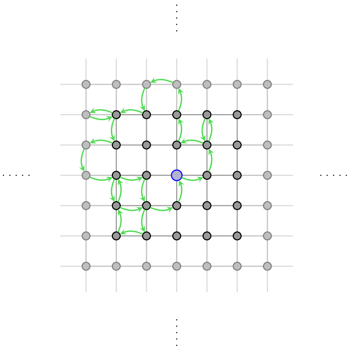

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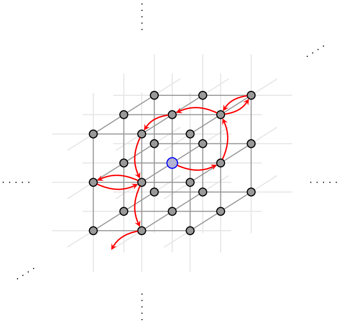

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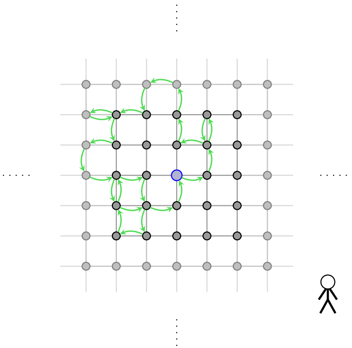

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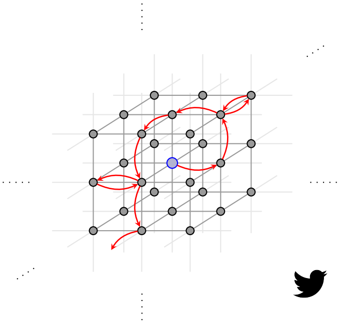

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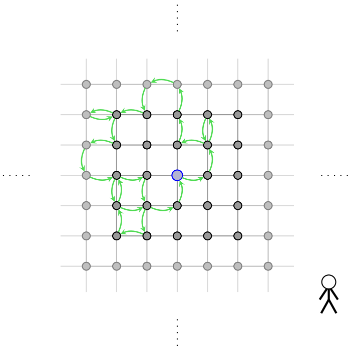

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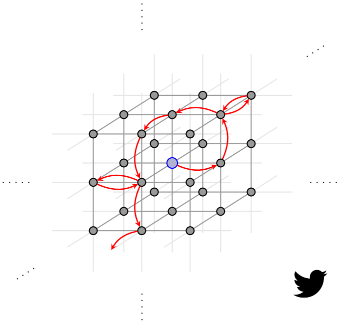

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But for any regular (finite) graph, the expected return time to u is $1/\pi(u) = n$

SRW Random Walk on Two-Dimensional Grids: Animation

Random Walk on a Path (1/2)

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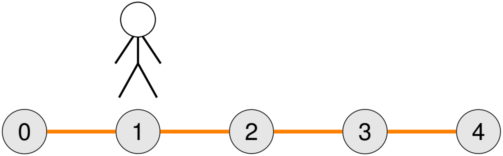

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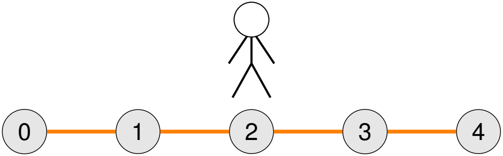

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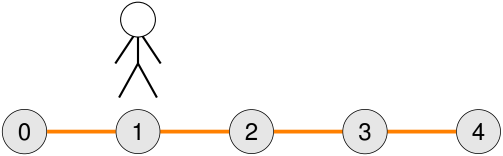

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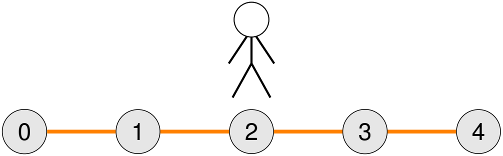

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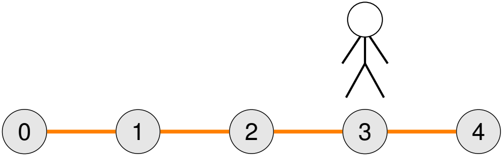

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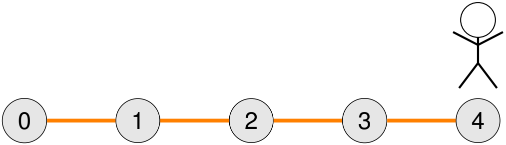

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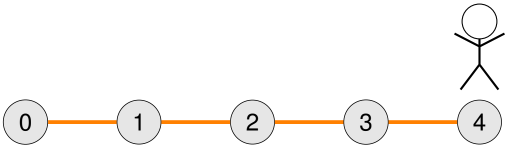

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Exercise: *[Exercise 4/5.15]* What happens for the LRW on P_n?

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System of n independent equations in n unknowns, so has a unique solution.

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and for any $1 \leq k \leq n-1$ we have,

$$f(k) = 1 + \frac{n^2 - (k-1)^2}{2} + \frac{n^2 - (k+1)^2}{2} = n^2 - k^2. \qquad \square$$

Outline

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  - → Design of experiments
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2-SAT

RANDOMISED-2-SAT (Input: a 2-SAT-Formula)

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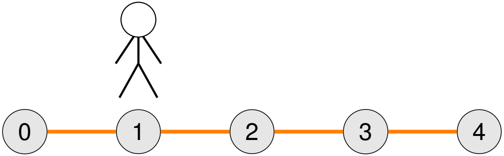
F T T T F F F T F T

$$\alpha = (\mathtt{T}, \mathtt{T}, \mathtt{F}, \mathtt{T}).$$



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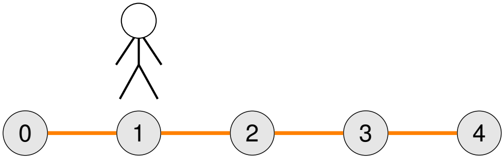

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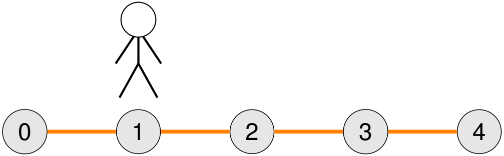

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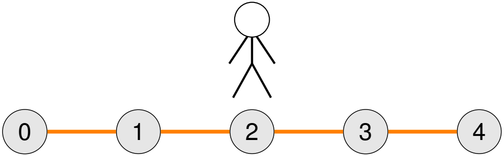

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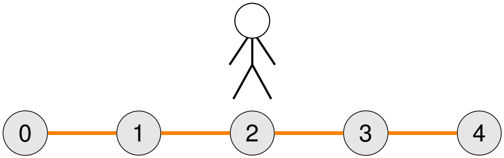

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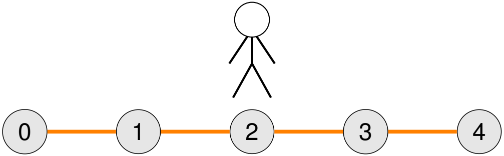

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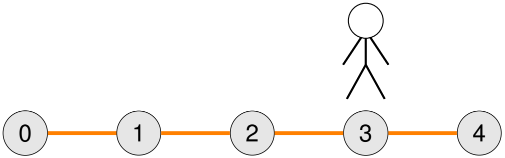

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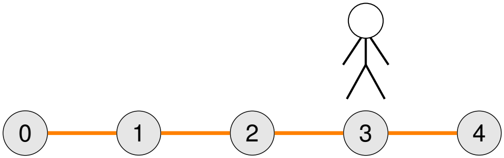

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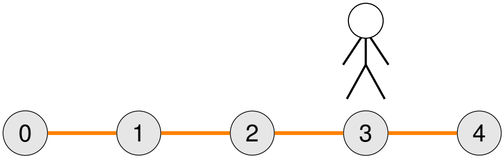

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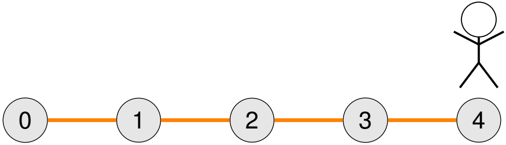

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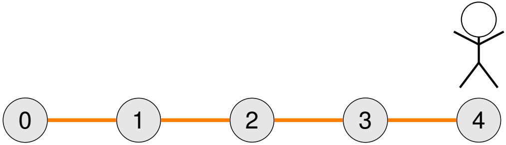

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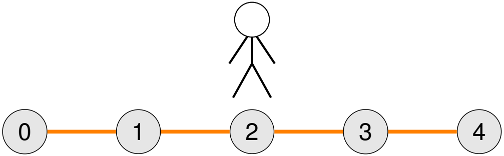

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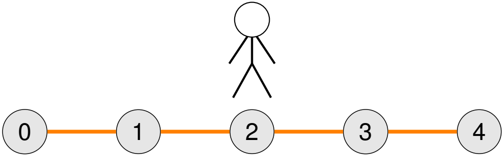

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RANDOMISED-2-SAT (Input: a 2-SAT-Formula)

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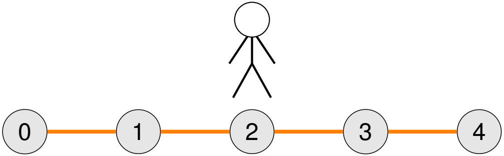
$$(x_1 \lor \overline{x_2}) \land (\overline{x_1} \lor \overline{x_3}) \land (x_1 \lor x_2) \land (x_4 \lor x_3) \land (x_4 \lor \overline{x_1})$$

F T T T F F F F F T

$$\alpha = (\mathtt{T}, \mathtt{F}, \mathtt{F}, \mathtt{T}).$$



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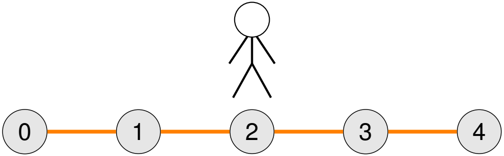

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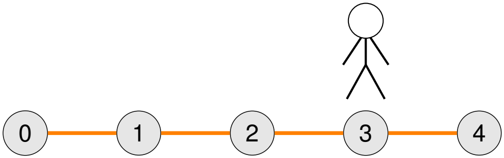

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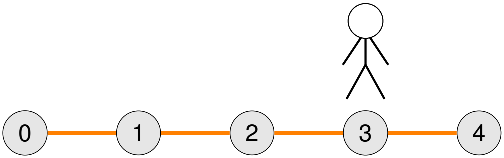

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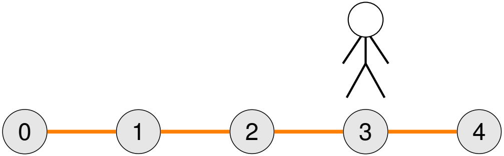

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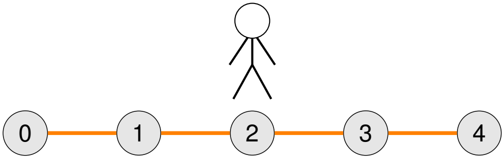

t	x_1	x_2	x_3	x_4
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1	F	F	F	T
2	F	T	F	T

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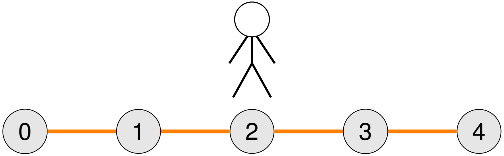

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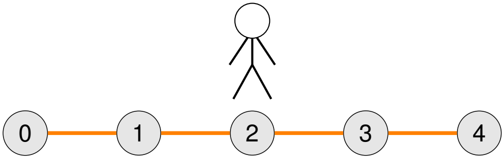

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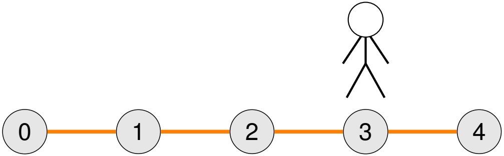

t	x_1	x_2	x_3	x_4
0	F	F	F	F
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Example 2 : (Another) Solution Found

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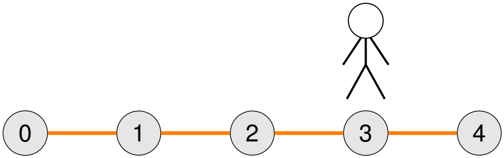

2-SAT and the SRW on the Path

Expected iterations of (2) in RANDOMISED-2-SAT

If the formula is satisfiable, then the expected number of steps before RANDOMISED-2-SAT outputs a valid solution is at most n^2.

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2-SAT and the SRW on the Path

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Proposition

Provided a solution exists, RANDOMISED-2-SAT will return a valid solution in $O(n^2)$ steps with probability at least $1/2$.

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□

Exercise: (difficult, beyond this course) What happens to the above analysis if we apply the same algorithm to 3-SAT?

Boosting Success Probabilities

Boosting Lemma

Suppose a randomised algorithm succeeds with probability (at least) p. Then for any $C \geq 1$, $\lceil \frac{C}{p} \cdot \log n \rceil$ repetitions are sufficient to succeed (in at least one repetition) with probability at least $1 - n^{-C}$.

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$$\begin{aligned} \mathbf{P}[\, t \text{ runs all fail} \,] &\leq (1-p)^t \\ &\leq e^{-pt} \\ &\leq n^{-C}, \end{aligned}$$

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RANDOMISED-2-SAT

There is a $O(n^2 \log n)$-step algorithm for 2-SAT which succeeds w.h.p.

Randomised Algorithms

Lecture 6: Linear Programming: Introduction

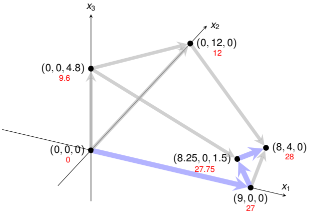
Thomas Sauerwald (tms41@cam.ac.uk)

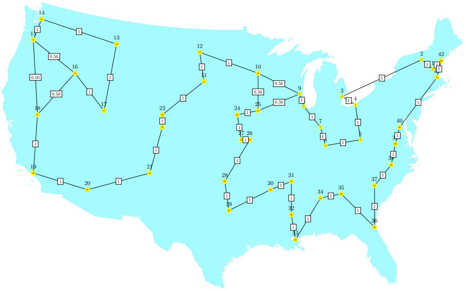
Lent 2024

UNIVERSITY OF CAMBRIDGE

Outline

Introduction





- linear programming is a powerful tool in optimisation
- inspired more sophisticated techniques such as quadratic optimisation, convex optimisation, integer programming and semi-definite programming
- we will later use the connection between linear and integer programming to tackle several problems (Vertex-Cover, Set-Cover, TSP, satisfiability)

Outline

What are Linear Programs?

Linear Programming (informal definition)

- maximise or minimise an objective, given limited resources (competing constraint)
- constraints are specified as (in)equalities
- objective function and constraints are linear

A Simple Example of a Linear Optimisation Problem

- Laptop

A Simple Example of a Linear Optimisation Problem

- Laptop
  - selling price to retailer: 1,000 GBP

A Simple Example of a Linear Optimisation Problem

- Laptop
  - selling price to retailer: 1,000 GBP
  - glass: 4 units

A Simple Example of a Linear Optimisation Problem

- Laptop
  - selling price to retailer: 1,000 GBP
  - glass: 4 units
  - copper: 2 units

A Simple Example of a Linear Optimisation Problem

- Laptop
  - selling price to retailer: 1,000 GBP
  - glass: 4 units
  - copper: 2 units
  - rare-earth elements: 1 unit

A Simple Example of a Linear Optimisation Problem

- Laptop
  - selling price to retailer: 1,000 GBP
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- Smartphone

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- Smartphone
  - selling price to retailer: 1,000 GBP
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- You have a daily supply of:

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- You have a daily supply of:
  - glass: 20 units

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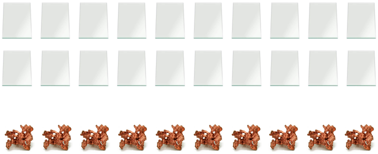

- You have a daily supply of:
  - glass: 20 units
  - copper: 10 units

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  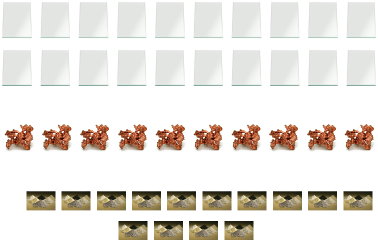
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  - glass: 20 units
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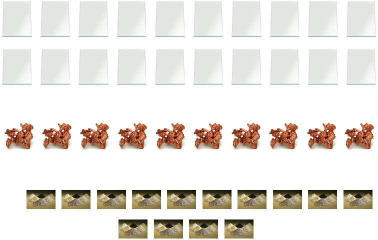

- You have a daily supply of:
  - glass: 20 units
  - copper: 10 units
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  - (and enough of everything else...)

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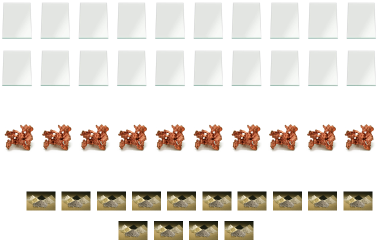

How to maximise your daily earnings?

The Linear Program

Linear Program for the Production Problem

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\begin{array}{lrcrcr}
\text{maximise} & x_1 & + & x_2 & & \\
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The solution of this linear program yields the optimal production schedule.

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Formal Definition of Linear Program

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$$f(x_1, x_2, \ldots, x_n) = a_1 x_1 + a_2 x_2 + \cdots + a_n x_n.$$

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- Linear Equality: $f(x_1, x_2, \ldots, x_n) = b$
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Linear Constraints

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Linear Constraints

- Linear-Progamming Problem: either minimise or maximise a linear function subject to a set of linear constraints

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Any setting of x_1 and x_2 satisfying all constraints is a feasible solution

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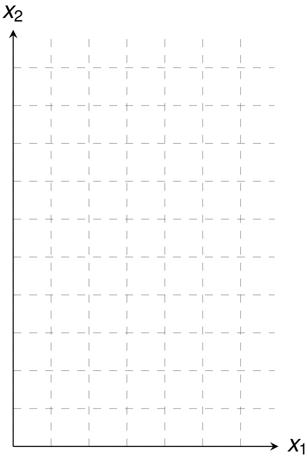

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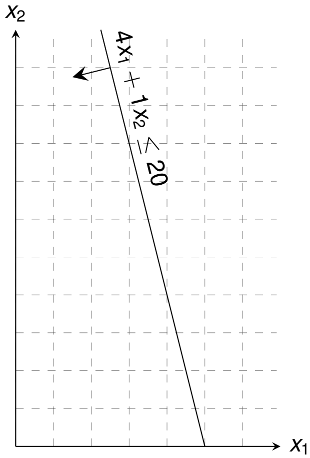

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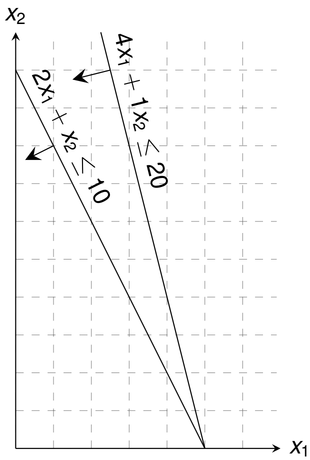

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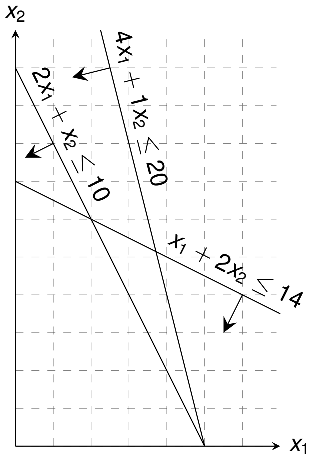

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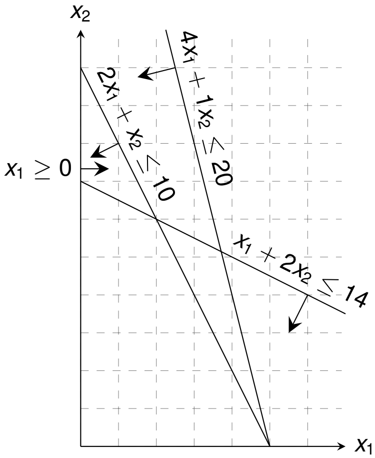

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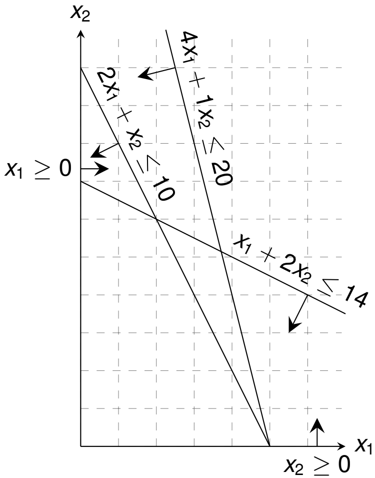

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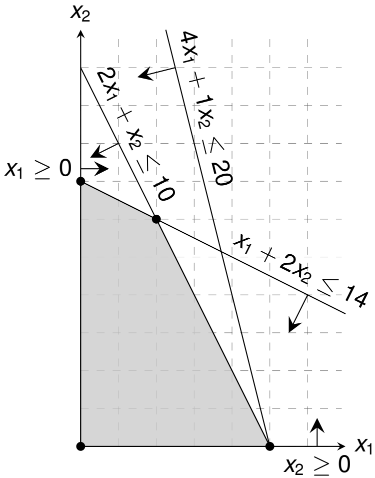

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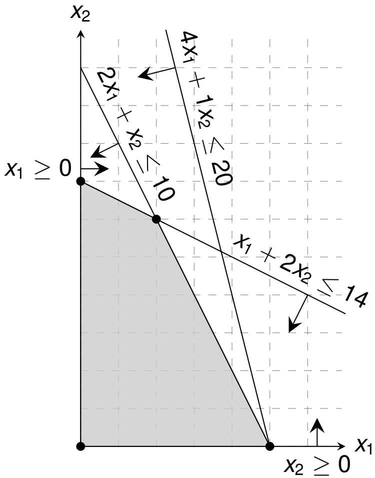
Graphical Procedure: Move the line $x_1 + x_2 = z$ as far up as possible.



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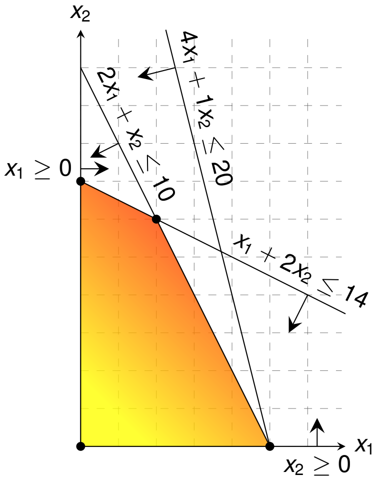

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subject to					
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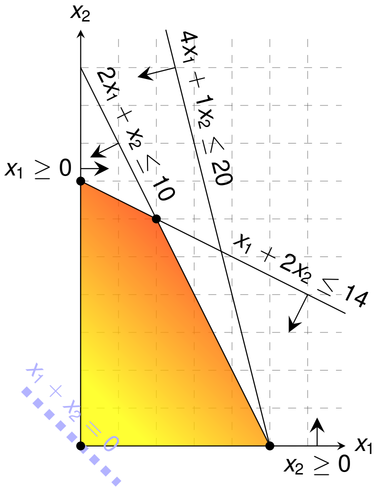

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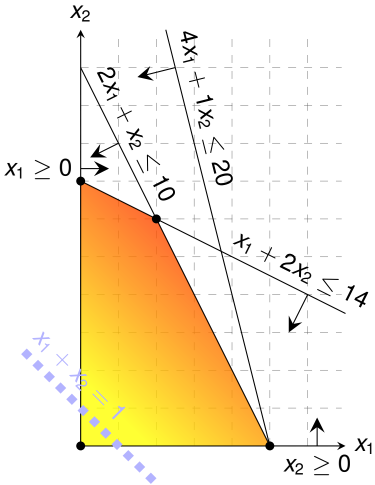

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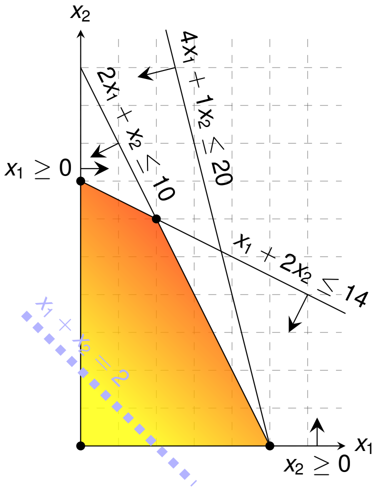

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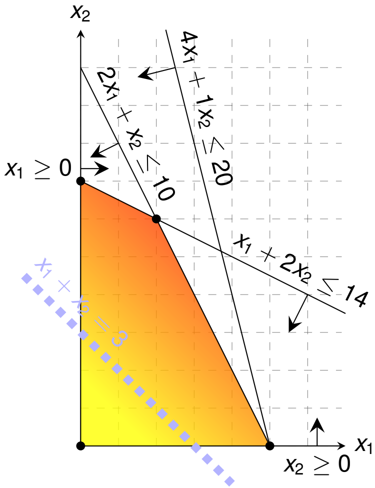

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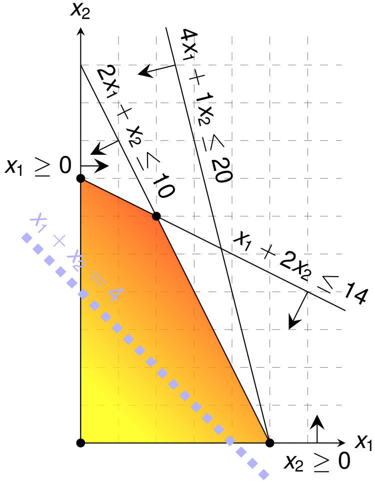

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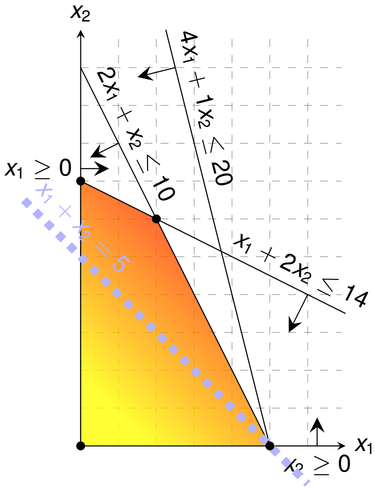

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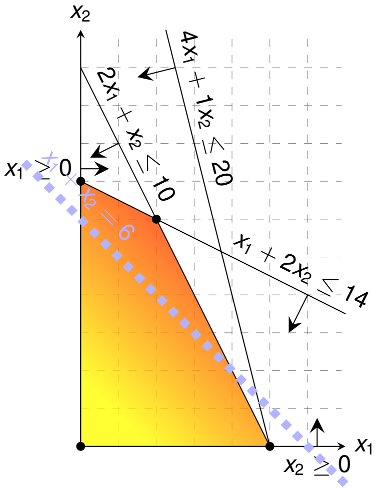
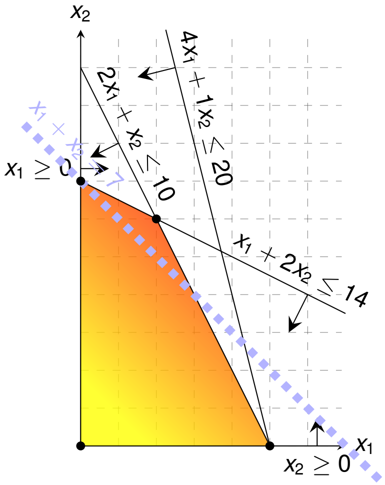


Finding the Optimal Production Schedule

maximise	x_1	$+$	x_2		
subject to					
	$4x_1$	$+$	x_2	$\leq$	20
	$2x_1$	$+$	x_2	$\leq$	10
	x_1	$+$	$2x_2$	$\leq$	14
	x_1, x_2			$\geq$	0

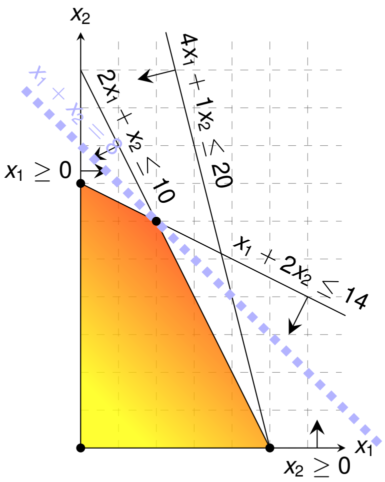
Graphical Procedure: Move the line $x_1 + x_2 = z$ as far up as possible.



Finding the Optimal Production Schedule

$$\begin{array}{lrcrcr} \text{maximise} & x_1 & + & x_2 & & \\ \text{subject to} & & & & & \\ & 4x_1 & + & x_2 & \leq & 20 \\ & 2x_1 & + & x_2 & \leq & 10 \\ & x_1 & + & 2x_2 & \leq & 14 \\ & x_1, x_2 & & & \geq & 0 \end{array}$$

Graphical Procedure: Move the line $x_1 + x_2 = z$ as far up as possible.



Finding the Optimal Production Schedule

$$
\begin{array}{llcll}
\text{maximise} & x_1 & + & x_2 & \\
\text{subject to} & & & & \\
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& 2x_1 & + & x_2 & \leq 10 \\
& x_1 & + & 2x_2 & \leq 14 \\
& x_1, x_2 & & & \geq 0
\end{array}
$$

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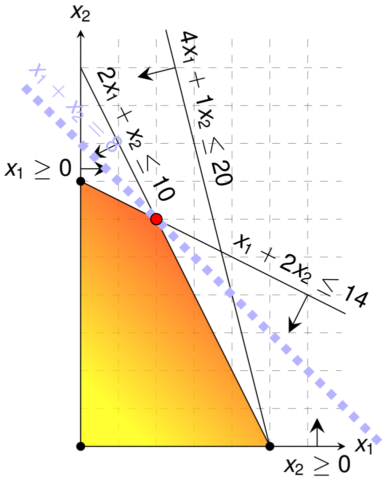

Finding the Optimal Production Schedule

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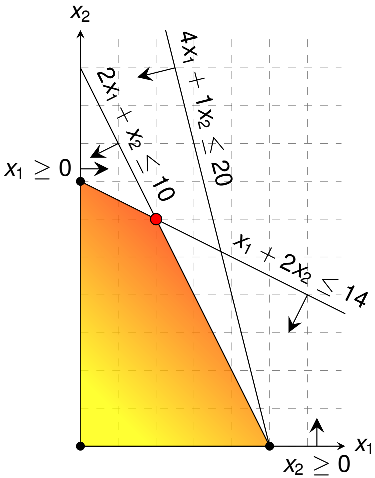

Graphical Procedure: Move the line $x_1 + x_2 = z$ as far up as possible.

Question: Which aspect did we ignore in the formulation of the linear program?

Finding the Optimal Production Schedule

$$
\begin{array}{lrcrcr}
\text{maximise} & x_1 & + & x_2 & & \\
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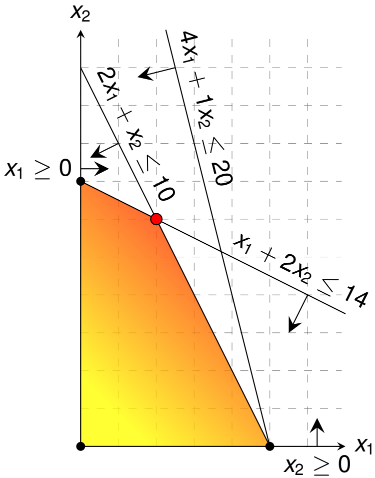


Graphical Procedure: Move the line $x_1 + x_2 = z$ as far up as possible.

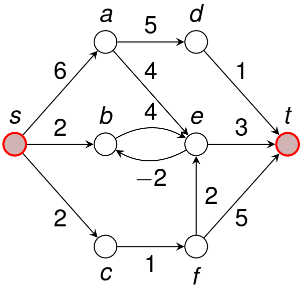
While the same approach also works for higher-dimensions, we need to take a more systematic and algebraic procedure.

Outline

Shortest Paths

Single-Pair Shortest Path Problem

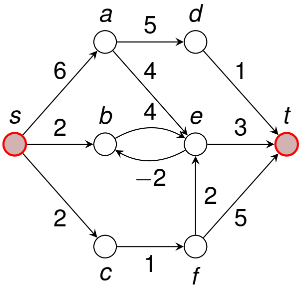
- Given: directed graph $G = (V, E)$ with edge weights $w : E \to \mathbb{R}$, pair of vertices $s, t \in V$



Shortest Paths

Single-Pair Shortest Path Problem

- Given: directed graph $G = (V, E)$ with edge weights $w : E \to \mathbb{R}$, pair of vertices $s, t \in V$
- Goal: Find a path of minimum weight from s to t in G



Shortest Paths

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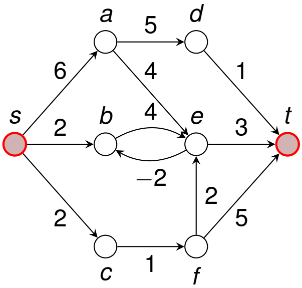
$p = (v_0 = s, v_1, \ldots, v_k = t)$ such that $w(p) = \sum_{i=1}^{k} w(v_{k-1}, v_k)$ is minimised.



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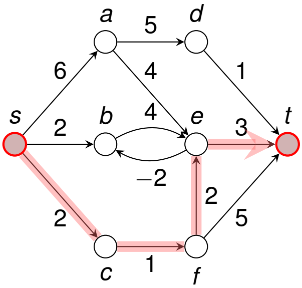

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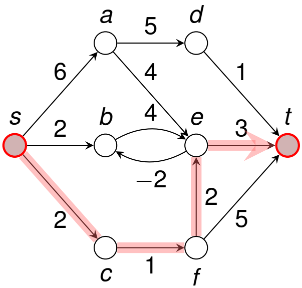
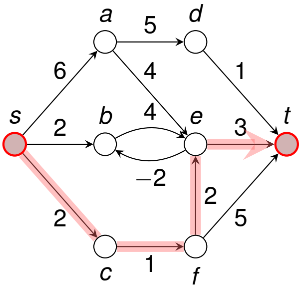


Exercise: Translate the SPSP problem into a linear program!

Shortest Paths



Single-Pair Shortest Path Problem

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Shortest Paths as LP

subject to

Shortest Paths

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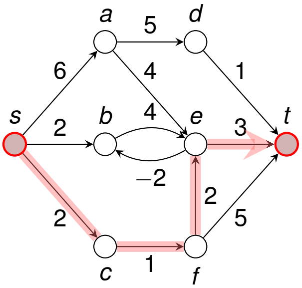

Shortest Paths as LP

subject to

$$\begin{aligned} d_v &\leq d_u + w(u,v) \quad \text{for each edge } (u,v) \in E, \\ d_s &= 0. \end{aligned}$$

Shortest Paths

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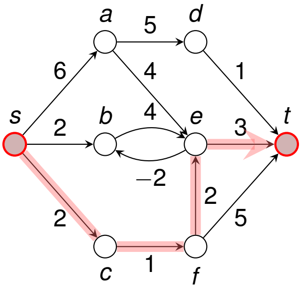

Shortest Paths as LP

maximise d_t

subject to

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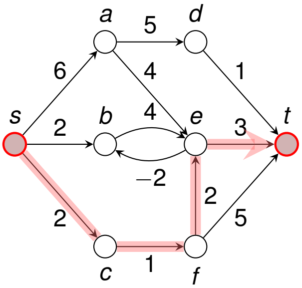

Shortest Paths as LP

$$
\begin{array}{lllll}
\text{maximise} & d_t & & & \\
\text{subject to} & & & & \\
 & d_v \leq d_u + w(u, v) & & & \text{for each edge } (u, v) \in E, \\
 & d_s = 0. & & &
\end{array}
$$

this is a maximisation problem!

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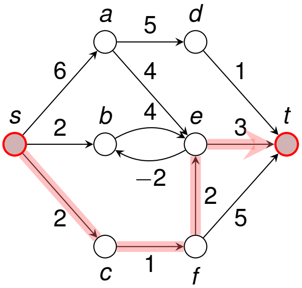

Shortest Paths as LP

maximise d_t

subject to

$$d_v \leq d_u + w(u, v) \quad \text{for each edge } (u, v) \in E,$$
$$d_s = 0.$$

Recall: When BELLMAN-FORD terminates, all these inequalities are satisfied.

this is a maximisation problem!

Shortest Paths

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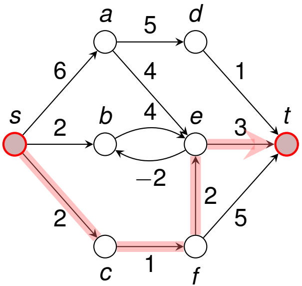

Shortest Paths as LP

$$
\begin{array}{llcllll}
\text{maximise} & d_t & & & & & \\
\text{subject to} & & & & & & \\
 & d_v & \leq & d_u & + & w(u,v) & \text{for each edge } (u,v) \in E, \\
 & d_s & = & 0. & & &
\end{array}
$$

Recall: When BELLMAN-FORD terminates, all these inequalities are satisfied.

this is a maximisation problem!

Solution $\overline{d}$ satisfies $\overline{d}_v = \min_{u:\,(u,v)\in E} \{\overline{d}_u + w(u,v)\}$

Maximum Flow

Maximum Flow Problem

- Given: directed graph $G = (V, E)$ with edge capacities $c : E \to \mathbb{R}^+$ (recall $c(u, v) = 0$ if $(u, v) \notin E$), pair of vertices $s, t \in V$

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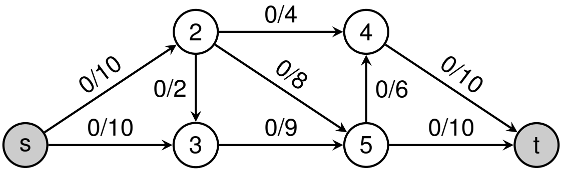

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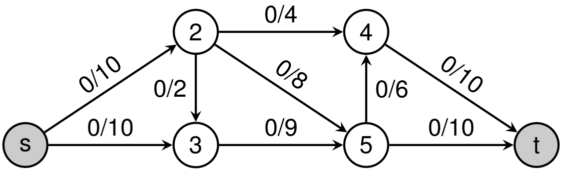
- Goal: Find a maximum flow $f : V \times V \to \mathbb{R}$ from s to t which satisfies the capacity constraints and flow conservation



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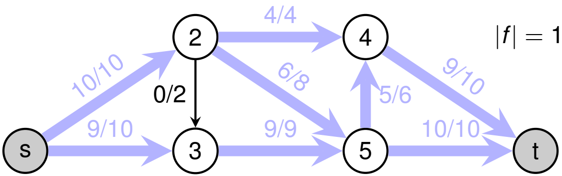

$|f| = 19$

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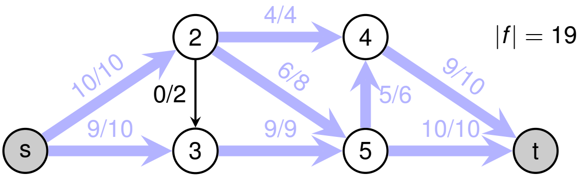

Maximum Flow as LP

maximise $\sum_{v \in V} f_{sv} - \sum_{v \in V} f_{vs}$

subject to

$$
\begin{aligned}
f_{uv} &\leq c(u, v) && \text{for each } u, v \in V, \\
\sum_{v \in V} f_{vu} &= \sum_{v \in V} f_{uv} && \text{for each } u \in V \setminus \{s, t\}, \\
f_{uv} &\geq 0 && \text{for each } u, v \in V.
\end{aligned}
$$

Minimum-Cost Flow

Extension of the Maximum Flow Problem

Minimum-Cost-Flow Problem

Minimum-Cost Flow

Extension of the Maximum Flow Problem

Minimum-Cost-Flow Problem

- Given: directed graph $G = (V, E)$ with capacities $c : E \to \mathbb{R}^+$, pair of vertices $s, t \in V$, cost function $a : E \to \mathbb{R}^+$, flow demand of d units

Minimum-Cost Flow

Extension of the Maximum Flow Problem

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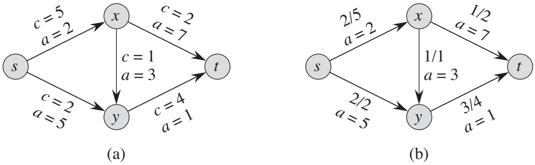

Figure 29.3 **(a)** An example of a minimum-cost-flow problem. We denote the capacities by c and the costs by a. Vertex s is the source and vertex t is the sink, and we wish to send 4 units of flow from s to t. **(b)** A solution to the minimum-cost flow problem in which 4 units of flow are sent from s to t. For each edge, the flow and capacity are written as flow/capacity.

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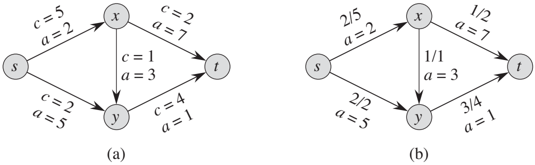
Optimal Solution with total cost:
$\sum_{(u,v)\in E} a(u,v) f_{uv} = (2\cdot 2)+(5\cdot 2)+(3\cdot 1)+(7\cdot 1)+(1\cdot 3) = 27$



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Minimum Cost Flow as a LP

Minimum Cost Flow as LP

$$
\begin{array}{llrcll}
\text{minimise} & \sum_{(u,v)\in E} a(u,v) f_{uv} & & & & \\
\text{subject to} & & & & & \\
& & f_{uv} & \leq & c(u,v) & \text{for } u,v \in V, \\
& & \sum_{v\in V} f_{vu} - \sum_{v\in V} f_{uv} & = & 0 & \text{for } u \in V \setminus \{s,t\}, \\
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$$

Minimum Cost Flow as a LP

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minimise $\sum_{(u,v)\in E} a(u,v) f_{uv}$

subject to

$$
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\sum_{v\in V} f_{sv} - \sum_{v\in V} f_{vs} &= d\ , && \\
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\end{aligned}
$$

Real power of Linear Programming comes from the ability to solve **new problems**!

Outline

Introduction

A Simple Example of a Linear Program

Formulating Problems as Linear Programs

Standard and Slack Forms

Standard and Slack Forms

Standard Form

maximise $\sum_{j=1}^{n} c_j x_j$

subject to

$$\sum_{j=1}^{n} a_{ij} x_j \leq b_i \qquad \text{for } i = 1, 2, \ldots, m$$

$$x_j \geq 0 \qquad \text{for } j = 1, 2, \ldots, n$$

Standard and Slack Forms

Standard Form

maximise $\sum_{j=1}^{n} c_j x_j$ — Objective Function

subject to

$$\sum_{j=1}^{n} a_{ij} x_j \leq b_i \qquad \text{for } i = 1, 2, \ldots, m$$

$$x_j \geq 0 \qquad \text{for } j = 1, 2, \ldots, n$$

Standard and Slack Forms

Standard Form

$$\text{maximise} \quad \sum_{j=1}^{n} c_j x_j$$

Objective Function

subject to

$$\left\{ \begin{aligned} \sum_{j=1}^{n} a_{ij} x_j &\leq b_i \qquad \text{for } i = 1, 2, \ldots, m \\ x_j &\geq 0 \qquad \text{for } j = 1, 2, \ldots, n \end{aligned} \right.$$

$n + m$ constraints

Standard and Slack Forms

Standard Form

$$\text{maximise} \quad \sum_{j=1}^{n} c_j x_j$$

Objective Function

subject to

$$\begin{cases} \displaystyle\sum_{j=1}^{n} a_{ij} x_j \leq b_i & \text{for } i = 1, 2, \ldots, m \\ x_j \geq 0 & \text{for } j = 1, 2, \ldots, n \end{cases}$$

$n + m$ constraints

Non-Negativity Constraints

Standard and Slack Forms

Standard Form

$$\text{maximise} \quad \sum_{j=1}^{n} c_j x_j$$

Objective Function

subject to

$$\begin{cases} \sum_{j=1}^{n} a_{ij} x_j \leq b_i & \text{for } i = 1, 2, \ldots, m \\ x_j \geq 0 & \text{for } j = 1, 2, \ldots, n \end{cases}$$

$n + m$ constraints

Non-Negativity Constraints

Standard Form (Matrix-Vector-Notation)

$$\text{maximise} \quad c^T x$$

Inner product of two vectors

subject to

$$Ax \leq b$$

Matrix-vector product

$$x \geq 0$$

Converting Linear Programs into Standard Form

Reasons for a LP not being in standard form:

1. The objective might be a minimisation rather than maximisation.
2. There might be variables without nonnegativity constraints.
3. There might be equality constraints.
4. There might be inequality constraints (with $\geq$ instead of $\leq$).

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Goal: Convert linear program into an equivalent program which is in standard form

Equivalence: a correspondence (not necessarily a bijection) between solutions.

Converting into Standard Form (1/5)

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Converting into Standard Form (1/5)

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1. The objective might be a minimisation rather than maximisation.

$$\begin{array}{lrcrcr} \text{minimise} & -2x_1 & + & 3x_2 & & \\ \text{subject to} & & & & & \\ & x_1 & + & x_2 & = & 7 \\ & x_1 & - & 2x_2 & \leq & 4 \\ & x_1 & & & \geq & 0 \end{array}$$

Converting into Standard Form (1/5)

Reasons for a LP not being in standard form:

1. The objective might be a minimisation rather than maximisation.

$$\begin{array}{lrcrcl} \text{minimise} & -2x_1 & + & 3x_2 & & \\ \text{subject to} & & & & & \\ & x_1 & + & x_2 & = & 7 \\ & x_1 & - & 2x_2 & \leq & 4 \\ & x_1 & & & \geq & 0 \end{array}$$

↓ Negate objective function

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1. The objective might be a minimisation rather than maximisation.

$$\begin{array}{lrcrcr} \text{minimise} & -2x_1 & + & 3x_2 & & \\ \text{subject to} & & & & & \\ & x_1 & + & x_2 & = & 7 \\ & x_1 & - & 2x_2 & \leq & 4 \\ & x_1 & & & \geq & 0 \end{array}$$

Negate objective function

$$\begin{array}{lrcrcr} \text{maximise} & 2x_1 & - & 3x_2 & & \\ \text{subject to} & & & & & \\ & x_1 & + & x_2 & = & 7 \\ & x_1 & - & 2x_2 & \leq & 4 \\ & x_1 & & & \geq & 0 \end{array}$$

Converting into Standard Form (2/5)

Reasons for a LP not being in standard form:

2. There might be variables without nonnegativity constraints.

Converting into Standard Form (2/5)

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$$
\begin{array}{lrcrcl}
\text{maximise} & 2x_1 & - & 3x_2 & & \\
\text{subject to} & & & & & \\
& x_1 & + & x_2 & = & 7 \\
& x_1 & - & 2x_2 & \leq & 4 \\
& \boxed{x_1} & & & \geq & 0
\end{array}
$$

Converting into Standard Form (2/5)

Reasons for a LP not being in standard form:

2. There might be variables without nonnegativity constraints.

$$
\begin{array}{lrcrcr}
\text{maximise} & 2x_1 & - & 3x_2 & & \\
\text{subject to} & & & & & \\
 & x_1 & + & x_2 & = & 7 \\
 & x_1 & - & 2x_2 & \leq & 4 \\
 & x_1 & & & \geq & 0
\end{array}
$$

Replace x_2 by two non-negative variables x_2' and x_2''

Converting into Standard Form (2/5)

Reasons for a LP not being in standard form:

2. There might be variables without nonnegativity constraints.

$$
\begin{array}{ll}
\text{maximise} & 2x_1 - 3x_2 \\
\text{subject to} & \\
& x_1 + x_2 = 7 \\
& x_1 - 2x_2 \leq 4 \\
& x_1 \geq 0
\end{array}
$$

Replace x_2 by two non-negative variables x_2' and x_2''

$$
\begin{array}{ll}
\text{maximise} & 2x_1 - 3x_2' + 3x_2'' \\
\text{subject to} & \\
& x_1 + x_2' - x_2'' = 7 \\
& x_1 - 2x_2' + 2x_2'' \leq 4 \\
& x_1, x_2', x_2'' \geq 0
\end{array}
$$

Converting into Standard Form (3/5)

Reasons for a LP not being in standard form:

3. There might be equality constraints.

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$$\begin{array}{lrcrcrcr}
\text{maximise} & 2x_1 & - & 3x_2' & + & 3x_2'' & & \\
\text{subject to} & & & & & & & \\
& x_1 & + & x_2' & - & x_2'' & = & 7 \\
& x_1 & - & 2x_2' & + & 2x_2'' & \leq & 4 \\
& x_1, x_2', x_2'' & & & & & \geq & 0
\end{array}$$

Converting into Standard Form (3/5)

Reasons for a LP not being in standard form:

3. There might be equality constraints.

$$
\begin{array}{lrcrcrcr}
\text{maximise} & 2x_1 & - & 3x_2' & + & 3x_2'' & & \\
\text{subject to} & & & & & & & \\
& x_1 & + & x_2' & - & x_2'' & = & 7 \\
& x_1 & - & 2x_2' & + & 2x_2'' & \leq & 4 \\
& & & x_1, x_2', x_2'' & & & \geq & 0
\end{array}
$$

Replace each equality by two inequalities.

Converting into Standard Form (3/5)

Reasons for a LP not being in standard form:

3. There might be equality constraints.

$$\begin{array}{ll} \text{maximise} & 2x_1 - 3x_2' + 3x_2'' \\ \text{subject to} & \\ & x_1 + x_2' - x_2'' = 7 \\ & x_1 - 2x_2' + 2x_2'' \leq 4 \\ & x_1, x_2', x_2'' \geq 0 \end{array}$$

Replace each equality by two inequalities.

$$\begin{array}{ll} \text{maximise} & 2x_1 - 3x_2' + 3x_2'' \\ \text{subject to} & \\ & x_1 + x_2' - x_2'' \leq 7 \\ & x_1 + x_2' - x_2'' \geq 7 \\ & x_1 - 2x_2' + 2x_2'' \leq 4 \\ & x_1, x_2', x_2'' \geq 0 \end{array}$$

Converting into Standard Form (4/5)

Reasons for a LP not being in standard form:

4. There might be inequality constraints (with $\geq$ instead of $\leq$).

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$$
\begin{array}{lrcrcrcr}
\text{maximise} & 2x_1 & - & 3x_2' & + & 3x_2'' & & \\
\text{subject to} & & & & & & & \\
& x_1 & + & x_2' & - & x_2'' & \leq & 7 \\
& x_1 & + & x_2' & - & x_2'' & \geq & 7 \\
& x_1 & - & 2x_2' & + & 2x_2'' & \leq & 4 \\
& & & x_1, x_2', x_2'' & & & \geq & 0
\end{array}
$$

Converting into Standard Form (4/5)

Reasons for a LP not being in standard form:

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$$
\begin{array}{lrcrcrcr}
\text{maximise} & 2x_1 & - & 3x_2' & + & 3x_2'' & & \\
\text{subject to} & & & & & & & \\
& x_1 & + & x_2' & - & x_2'' & \leq & 7 \\
& x_1 & + & x_2' & - & x_2'' & \geq & 7 \\
& x_1 & - & 2x_2' & + & 2x_2'' & \leq & 4 \\
& & x_1, x_2', x_2'' & & & & \geq & 0
\end{array}
$$

Negate respective inequalities.

Converting into Standard Form (4/5)

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4. There might be inequality constraints (with $\geq$ instead of $\leq$).

$$\begin{array}{lrcrcrcr} \text{maximise} & 2x_1 & - & 3x_2' & + & 3x_2'' & & \\ \text{subject to} & & & & & & & \\ & x_1 & + & x_2' & - & x_2'' & \leq & 7 \\ & x_1 & + & x_2' & - & x_2'' & \geq & 7 \\ & x_1 & - & 2x_2' & + & 2x_2'' & \leq & 4 \\ & x_1, x_2', x_2'' & & & & & \geq & 0 \end{array}$$

Negate respective inequalities.

$$\begin{array}{lrcrcrcr} \text{maximise} & 2x_1 & - & 3x_2' & + & 3x_2'' & & \\ \text{subject to} & & & & & & & \\ & x_1 & + & x_2' & - & x_2'' & \leq & 7 \\ & -x_1 & - & x_2' & + & x_2'' & \leq & -7 \\ & x_1 & - & 2x_2' & + & 2x_2'' & \leq & 4 \\ & x_1, x_2', x_2'' & & & & & \geq & 0 \end{array}$$

Converting into Standard Form (5/5)

$$\begin{array}{lrcrcrcr}
\text{maximise} & 2x_1 & - & 3x_2 & + & 3x_3 & & \\
\text{subject to} & & & & & & & \\
& x_1 & + & x_2 & - & x_3 & \leq & 7 \\
& -x_1 & - & x_2 & + & x_3 & \leq & -7 \\
& x_1 & - & 2x_2 & + & 2x_3 & \leq & 4 \\
& & & x_1, x_2, x_3 & & & \geq & 0
\end{array}$$

Converting into Standard Form (5/5)

Rename variable names (for consistency).

$$\begin{array}{lrcrcrcr}
\text{maximise} & 2x_1 & - & 3x_2 & + & 3x_3 & & \\
\text{subject to} & & & & & & & \\
& x_1 & + & x_2 & - & x_3 & \leq & 7 \\
& -x_1 & - & x_2 & + & x_3 & \leq & -7 \\
& x_1 & - & 2x_2 & + & 2x_3 & \leq & 4 \\
& & x_1, x_2, x_3 & & & & \geq & 0
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\begin{array}{lrcrcrcr}
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\text{subject to} & & & & & & & \\
& x_1 & + & x_2 & - & x_3 & \leq & 7 \\
& -x_1 & - & x_2 & + & x_3 & \leq & -7 \\
& x_1 & - & 2x_2 & + & 2x_3 & \leq & 4 \\
& x_1, x_2, x_3 & & & & & \geq & 0
\end{array}
$$

It is always possible to convert a linear program into standard form.

Converting Standard Form into Slack Form (1/3)

Goal: Convert standard form into slack form, where all constraints except for the non-negativity constraints are equalities.

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Introducing Slack Variables

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- Introduce a slack variable s by

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- Let $\sum_{j=1}^{n} a_{ij}x_j \leq b_i$ be an inequality constraint
- Introduce a slack variable s by

$$s = b_i - \sum_{j=1}^{n} a_{ij}x_j$$

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$$s \geq 0.$$

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s measures the slack between the two sides of the inequality.

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$$s \geq 0.$$

s measures the slack between the two sides of the inequality.

- Denote slack variable of the i-th inequality by x_{n+i}

Converting Standard Form into Slack Form (2/3)

$$
\begin{array}{lrcrcrcr}
\text{maximise} & 2x_1 & - & 3x_2 & + & 3x_3 & & \\
\text{subject to} & & & & & & & \\
 & x_1 & + & x_2 & - & x_3 & \leq & 7 \\
 & -x_1 & - & x_2 & + & x_3 & \leq & -7 \\
 & x_1 & - & 2x_2 & + & 2x_3 & \leq & 4 \\
 & & & x_1, x_2, x_3 & & & \geq & 0
\end{array}
$$

Converting Standard Form into Slack Form (2/3)

$$\begin{array}{lrcrcrcr}
\text{maximise} & 2x_1 & - & 3x_2 & + & 3x_3 & & \\
\text{subject to} & & & & & & & \\
& x_1 & + & x_2 & - & x_3 & \leq & 7 \\
& -x_1 & - & x_2 & + & x_3 & \leq & -7 \\
& x_1 & - & 2x_2 & + & 2x_3 & \leq & 4 \\
& & x_1, x_2, x_3 & & & & \geq & 0
\end{array}$$

↓ Introduce slack variables

Converting Standard Form into Slack Form (2/3)

$$
\begin{array}{lrcrcrcr}
\text{maximise} & 2x_1 & - & 3x_2 & + & 3x_3 & & \\
\text{subject to} & & & & & & & \\
& x_1 & + & x_2 & - & x_3 & \leq & 7 \\
& -x_1 & - & x_2 & + & x_3 & \leq & -7 \\
& x_1 & - & 2x_2 & + & 2x_3 & \leq & 4 \\
& & x_1, x_2, x_3 & & & & \geq & 0
\end{array}
$$

Introduce slack variables

subject to

$$
x_4 = 7 - x_1 - x_2 + x_3
$$

Converting Standard Form into Slack Form (2/3)

$$\begin{array}{lrcrcrcr} \text{maximise} & 2x_1 & - & 3x_2 & + & 3x_3 & & \\ \text{subject to} & & & & & & & \\ & x_1 & + & x_2 & - & x_3 & \leq & 7 \\ & -x_1 & - & x_2 & + & x_3 & \leq & -7 \\ & x_1 & - & 2x_2 & + & 2x_3 & \leq & 4 \\ & x_1, x_2, x_3 & & & & & \geq & 0 \end{array}$$

↓ Introduce slack variables

subject to

$$\begin{array}{rcrcrcrcr} x_4 & = & 7 & - & x_1 & - & x_2 & + & x_3 \\ x_5 & = & -7 & + & x_1 & + & x_2 & - & x_3 \end{array}$$

Converting Standard Form into Slack Form (2/3)

$$
\begin{array}{lrcrcrcr}
\text{maximise} & 2x_1 & - & 3x_2 & + & 3x_3 & & \\
\text{subject to} & & & & & & & \\
& x_1 & + & x_2 & - & x_3 & \leq & 7 \\
& -x_1 & - & x_2 & + & x_3 & \leq & -7 \\
& x_1 & - & 2x_2 & + & 2x_3 & \leq & 4 \\
& & x_1, x_2, x_3 & & & & \geq & 0
\end{array}
$$

Introduce slack variables

subject to

$$
\begin{array}{rcrcrcrcr}
x_4 & = & 7 & - & x_1 & - & x_2 & + & x_3 \\
x_5 & = & -7 & + & x_1 & + & x_2 & - & x_3 \\
x_6 & = & 4 & - & x_1 & + & 2x_2 & - & 2x_3
\end{array}
$$

Converting Standard Form into Slack Form (2/3)

$$\begin{array}{lrcrcrcr} \text{maximise} & 2x_1 & - & 3x_2 & + & 3x_3 & & \\ \text{subject to} & & & & & & & \\ & x_1 & + & x_2 & - & x_3 & \leq & 7 \\ & -x_1 & - & x_2 & + & x_3 & \leq & -7 \\ & x_1 & - & 2x_2 & + & 2x_3 & \leq & 4 \\ & & x_1, x_2, x_3 & & & & \geq & 0 \end{array}$$

Introduce slack variables

subject to

$$\begin{array}{rcrcrcrcr} x_4 & = & 7 & - & x_1 & - & x_2 & + & x_3 \\ x_5 & = & -7 & + & x_1 & + & x_2 & - & x_3 \\ x_6 & = & 4 & - & x_1 & + & 2x_2 & - & 2x_3 \\ & & \multicolumn{3}{c}{x_1, x_2, x_3, x_4, x_5, x_6} & \geq & 0 & & \end{array}$$

Converting Standard Form into Slack Form (2/3)

$$\begin{array}{lrcrcrcr}
\text{maximise} & 2x_1 & - & 3x_2 & + & 3x_3 & & \\
\text{subject to} & & & & & & & \\
& x_1 & + & x_2 & - & x_3 & \leq & 7 \\
& -x_1 & - & x_2 & + & x_3 & \leq & -7 \\
& x_1 & - & 2x_2 & + & 2x_3 & \leq & 4 \\
& & & x_1, x_2, x_3 & & & \geq & 0
\end{array}$$

Introduce slack variables

$$\begin{array}{lrcrcrcrcr}
\text{maximise} & 2x_1 & - & 3x_2 & + & 3x_3 & & & & \\
\text{subject to} & & & & & & & & & \\
& x_4 & = & 7 & - & x_1 & - & x_2 & + & x_3 \\
& x_5 & = & -7 & + & x_1 & + & x_2 & - & x_3 \\
& x_6 & = & 4 & - & x_1 & + & 2x_2 & - & 2x_3 \\
& & & x_1, x_2, x_3, x_4, x_5, x_6 & & \geq & & 0 & &
\end{array}$$

Converting Standard Form into Slack Form (3/3)

$$
\begin{array}{lrcrcrcrcr}
\text{maximise} & 2x_1 & - & 3x_2 & + & 3x_3 & & & & \\
\text{subject to} & & & & & & & & & \\
 & x_4 & = & 7 & - & x_1 & - & x_2 & + & x_3 \\
 & x_5 & = & -7 & + & x_1 & + & x_2 & - & x_3 \\
 & x_6 & = & 4 & - & x_1 & + & 2x_2 & - & 2x_3 \\
 & \multicolumn{4}{c}{x_1, x_2, x_3, x_4, x_5, x_6} & & \geq & 0 & &
\end{array}
$$

Converting Standard Form into Slack Form (3/3)

$$
\begin{array}{ll}
\text{maximise} & 2x_1 - 3x_2 + 3x_3 \\
\text{subject to} & \\
& x_4 = 7 - x_1 - x_2 + x_3 \\
& x_5 = -7 + x_1 + x_2 - x_3 \\
& x_6 = 4 - x_1 + 2x_2 - 2x_3 \\
& x_1, x_2, x_3, x_4, x_5, x_6 \geq 0
\end{array}
$$

Use variable z to denote objective function and omit the nonnegativity constraints.

Converting Standard Form into Slack Form (3/3)

$$
\begin{array}{ll}
\text{maximise} & 2x_1 - 3x_2 + 3x_3 \\
\text{subject to} & \\
& x_4 = 7 - x_1 - x_2 + x_3 \\
& x_5 = -7 + x_1 + x_2 - x_3 \\
& x_6 = 4 - x_1 + 2x_2 - 2x_3 \\
& x_1, x_2, x_3, x_4, x_5, x_6 \geq 0
\end{array}
$$

Use variable z to denote objective function and omit the nonnegativity constraints.

$$
\begin{array}{rcl}
z & = & 2x_1 - 3x_2 + 3x_3 \\
x_4 & = & 7 - x_1 - x_2 + x_3 \\
x_5 & = & -7 + x_1 + x_2 - x_3 \\
x_6 & = & 4 - x_1 + 2x_2 - 2x_3
\end{array}
$$

Converting Standard Form into Slack Form (3/3)

$$\begin{array}{lrcrcrcrcr} \text{maximise} & 2x_1 & - & 3x_2 & + & 3x_3 \\ \text{subject to} \end{array}$$

$$\begin{array}{rcrcrcrcr} x_4 & = & 7 & - & x_1 & - & x_2 & + & x_3 \\ x_5 & = & -7 & + & x_1 & + & x_2 & - & x_3 \\ x_6 & = & 4 & - & x_1 & + & 2x_2 & - & 2x_3 \\ \end{array}$$

$$x_1, x_2, x_3, x_4, x_5, x_6 \geq 0$$

Use variable z to denote objective function and omit the nonnegativity constraints.

$$\begin{array}{rcrcrcrcr} z & = & & & 2x_1 & - & 3x_2 & + & 3x_3 \\ x_4 & = & 7 & - & x_1 & - & x_2 & + & x_3 \\ x_5 & = & -7 & + & x_1 & + & x_2 & - & x_3 \\ x_6 & = & 4 & - & x_1 & + & 2x_2 & - & 2x_3 \end{array}$$

This is called slack form.

Basic and Non-Basic Variables

$$
\begin{array}{rcrcrcrcr}
z & = & & & 2x_1 & - & 3x_2 & + & 3x_3 \\
x_4 & = & 7 & - & x_1 & - & x_2 & + & x_3 \\
x_5 & = & -7 & + & x_1 & + & x_2 & - & x_3 \\
x_6 & = & 4 & - & x_1 & + & 2x_2 & - & 2x_3
\end{array}
$$

Basic and Non-Basic Variables

$$\begin{array}{rcrcrcrcr} z & = & & & 2x_1 & - & 3x_2 & + & 3x_3 \\ x_4 & = & 7 & - & x_1 & - & x_2 & + & x_3 \\ x_5 & = & -7 & + & x_1 & + & x_2 & - & x_3 \\ x_6 & = & 4 & - & x_1 & + & 2x_2 & - & 2x_3 \end{array}$$

Basic Variables: $B = \{4, 5, 6\}$

Basic and Non-Basic Variables

$$\begin{array}{rcrcrcrcr} z & = & & & 2x_1 & - & 3x_2 & + & 3x_3 \\ x_4 & = & 7 & - & x_1 & - & x_2 & + & x_3 \\ x_5 & = & -7 & + & x_1 & + & x_2 & - & x_3 \\ x_6 & = & 4 & - & x_1 & + & 2x_2 & - & 2x_3 \end{array}$$

Basic Variables: $B = \{4, 5, 6\}$

Non-Basic Variables: $N = \{1, 2, 3\}$

Basic and Non-Basic Variables

$$
\begin{array}{rcrcrcrcr}
z & = & & & 2x_1 & - & 3x_2 & + & 3x_3 \\
x_4 & = & 7 & - & x_1 & - & x_2 & + & x_3 \\
x_5 & = & -7 & + & x_1 & + & x_2 & - & x_3 \\
x_6 & = & 4 & - & x_1 & + & 2x_2 & - & 2x_3
\end{array}
$$

Basic Variables: $B = \{4, 5, 6\}$

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Slack Form (Formal Definition)

Slack form is given by a tuple (N, B, A, b, c, v) so that

$$z = v + \sum_{j \in N} c_j x_j$$

$$x_i = b_i - \sum_{j \in N} a_{ij} x_j \qquad \text{for } i \in B,$$

and all variables are non-negative.

Basic and Non-Basic Variables

$$
\begin{array}{rcrcrcrcr}
z & = & & & 2x_1 & - & 3x_2 & + & 3x_3 \\
x_4 & = & 7 & - & x_1 & - & x_2 & + & x_3 \\
x_5 & = & -7 & + & x_1 & + & x_2 & - & x_3 \\
x_6 & = & 4 & - & x_1 & + & 2x_2 & - & 2x_3
\end{array}
$$

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and all variables are non-negative.

Variables/Coefficients on the right hand side are indexed by B and N.

Slack Form (Example)

$$
\begin{array}{rcrcrcrcr}
z & = & 28 & - & \frac{x_3}{6} & - & \frac{x_5}{6} & - & \frac{2x_6}{3} \\
x_1 & = & 8 & + & \frac{x_3}{6} & + & \frac{x_5}{6} & - & \frac{x_6}{3} \\
x_2 & = & 4 & - & \frac{8x_3}{3} & - & \frac{2x_5}{3} & + & \frac{x_6}{3} \\
x_4 & = & 18 & - & \frac{x_3}{2} & + & \frac{x_5}{2} & &
\end{array}
$$

Slack Form (Example)

$$\begin{aligned} z &= 28 - \frac{x_3}{6} - \frac{x_5}{6} - \frac{2x_6}{3} \\ x_1 &= 8 + \frac{x_3}{6} + \frac{x_5}{6} - \frac{x_6}{3} \\ x_2 &= 4 - \frac{8x_3}{3} - \frac{2x_5}{3} + \frac{x_6}{3} \\ x_4 &= 18 - \frac{x_3}{2} + \frac{x_5}{2} \end{aligned}$$

Slack Form Notation

Slack Form (Example)

$$
\begin{aligned}
z &= 28 - \frac{x_3}{6} - \frac{x_5}{6} - \frac{2x_6}{3} \\
x_1 &= 8 + \frac{x_3}{6} + \frac{x_5}{6} - \frac{x_6}{3} \\
x_2 &= 4 - \frac{8x_3}{3} - \frac{2x_5}{3} + \frac{x_6}{3} \\
x_4 &= 18 - \frac{x_3}{2} + \frac{x_5}{2}
\end{aligned}
$$

Slack Form Notation

- $B = \{1, 2, 4\}$, $N = \{3, 5, 6\}$

Slack Form (Example)

$$
\begin{aligned}
z &= 28 - \frac{x_3}{6} - \frac{x_5}{6} - \frac{2x_6}{3} \\
x_1 &= 8 + \frac{x_3}{6} + \frac{x_5}{6} - \frac{x_6}{3} \\
x_2 &= 4 - \frac{8x_3}{3} - \frac{2x_5}{3} + \frac{x_6}{3} \\
x_4 &= 18 - \frac{x_3}{2} + \frac{x_5}{2}
\end{aligned}
$$

Slack Form Notation

- $B = \{1, 2, 4\}$, $N = \{3, 5, 6\}$
- $$A = \begin{pmatrix} a_{13} & a_{15} & a_{16} \\ a_{23} & a_{25} & a_{26} \\ a_{43} & a_{45} & a_{46} \end{pmatrix} = \begin{pmatrix} -1/6 & -1/6 & 1/3 \\ 8/3 & 2/3 & -1/3 \\ 1/2 & -1/2 & 0 \end{pmatrix}$$

Slack Form (Example)

$$
\begin{aligned}
z &= 28 - \frac{x_3}{6} - \frac{x_5}{6} - \frac{2x_6}{3} \\
x_1 &= 8 + \frac{x_3}{6} + \frac{x_5}{6} - \frac{x_6}{3} \\
x_2 &= 4 - \frac{8x_3}{3} - \frac{2x_5}{3} + \frac{x_6}{3} \\
x_4 &= 18 - \frac{x_3}{2} + \frac{x_5}{2}
\end{aligned}
$$

Slack Form Notation

- $B = \{1, 2, 4\}$, $N = \{3, 5, 6\}$
- $$A = \begin{pmatrix} a_{13} & a_{15} & a_{16} \\ a_{23} & a_{25} & a_{26} \\ a_{43} & a_{45} & a_{46} \end{pmatrix} = \begin{pmatrix} -1/6 & -1/6 & 1/3 \\ 8/3 & 2/3 & -1/3 \\ 1/2 & -1/2 & 0 \end{pmatrix}$$
- $$b = \begin{pmatrix} b_1 \\ b_2 \\ b_4 \end{pmatrix} = \begin{pmatrix} 8 \\ 4 \\ 18 \end{pmatrix},$$

Slack Form (Example)

$$
\begin{aligned}
z &= 28 - \frac{x_3}{6} - \frac{x_5}{6} - \frac{2x_6}{3} \\
x_1 &= 8 + \frac{x_3}{6} + \frac{x_5}{6} - \frac{x_6}{3} \\
x_2 &= 4 - \frac{8x_3}{3} - \frac{2x_5}{3} + \frac{x_6}{3} \\
x_4 &= 18 - \frac{x_3}{2} + \frac{x_5}{2}
\end{aligned}
$$

Slack Form Notation

- $B = \{1, 2, 4\}$, $N = \{3, 5, 6\}$
- $$A = \begin{pmatrix} a_{13} & a_{15} & a_{16} \\ a_{23} & a_{25} & a_{26} \\ a_{43} & a_{45} & a_{46} \end{pmatrix} = \begin{pmatrix} -1/6 & -1/6 & 1/3 \\ 8/3 & 2/3 & -1/3 \\ 1/2 & -1/2 & 0 \end{pmatrix}$$
- $$b = \begin{pmatrix} b_1 \\ b_2 \\ b_4 \end{pmatrix} = \begin{pmatrix} 8 \\ 4 \\ 18 \end{pmatrix}, \quad c = \begin{pmatrix} c_3 \\ c_5 \\ c_6 \end{pmatrix} = \begin{pmatrix} -1/6 \\ -1/6 \\ -2/3 \end{pmatrix}$$

Slack Form (Example)

$$
\begin{array}{rcrcrcrcr}
z & = & 28 & - & \frac{x_3}{6} & - & \frac{x_5}{6} & - & \frac{2x_6}{3} \\
x_1 & = & 8 & + & \frac{x_3}{6} & + & \frac{x_5}{6} & - & \frac{x_6}{3} \\
x_2 & = & 4 & - & \frac{8x_3}{3} & - & \frac{2x_5}{3} & + & \frac{x_6}{3} \\
x_4 & = & 18 & - & \frac{x_3}{2} & + & \frac{x_5}{2} & &
\end{array}
$$

Slack Form Notation

- $B = \{1, 2, 4\}$, $N = \{3, 5, 6\}$
- $$A = \begin{pmatrix} a_{13} & a_{15} & a_{16} \\ a_{23} & a_{25} & a_{26} \\ a_{43} & a_{45} & a_{46} \end{pmatrix} = \begin{pmatrix} -1/6 & -1/6 & 1/3 \\ 8/3 & 2/3 & -1/3 \\ 1/2 & -1/2 & 0 \end{pmatrix}$$
- $$b = \begin{pmatrix} b_1 \\ b_2 \\ b_4 \end{pmatrix} = \begin{pmatrix} 8 \\ 4 \\ 18 \end{pmatrix}, \quad c = \begin{pmatrix} c_3 \\ c_5 \\ c_6 \end{pmatrix} = \begin{pmatrix} -1/6 \\ -1/6 \\ -2/3 \end{pmatrix}$$
- $v = 28$

Randomised Algorithms

Lecture 7: Linear Programming: Simplex Algorithm

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Lent 2024

UNIVERSITY OF CAMBRIDGE

Outline

Simplex Algorithm by Example

Details of the Simplex Algorithm

Finding an Initial Solution

Appendix: Cycling and Termination (non-examinable)

Simplex Algorithm: Introduction

Simplex Algorithm

- classical method for solving linear programs (Dantzig, 1947)
- usually fast in practice although worst-case runtime not polynomial
- iterative procedure somewhat similar to Gaussian elimination

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Simplex Algorithm

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Basic Idea:

- Each iteration corresponds to a “basic solution” of the slack form
- All non-basic variables are 0, and the basic variables are determined from the equality constraints
- Each iteration converts one slack form into an equivalent one while the objective value will not decrease
- Conversion (“pivoting”) is achieved by switching the roles of one basic and one non-basic variable

Simplex Algorithm: Introduction

Simplex Algorithm

- classical method for solving linear programs (Dantzig, 1947)
- usually fast in practice although worst-case runtime not polynomial
- iterative procedure somewhat similar to Gaussian elimination

Basic Idea:

- Each iteration corresponds to a “basic solution” of the slack form
- All non-basic variables are 0, and the basic variables are determined from the equality constraints
- Each iteration converts one slack form into an equivalent one while the objective value will not decrease
- Conversion (“pivoting”) is achieved by switching the roles of one basic and one non-basic variable

In that sense, it is a greedy algorithm.

Extended Example: Conversion into Slack Form

$$
\begin{array}{lrcrcrcr}
\text{maximise} & 3x_1 & + & x_2 & + & 2x_3 & & \\
\text{subject to} & & & & & & & \\
 & x_1 & + & x_2 & + & 3x_3 & \leq & 30 \\
 & 2x_1 & + & 2x_2 & + & 5x_3 & \leq & 24 \\
 & 4x_1 & + & x_2 & + & 2x_3 & \leq & 36 \\
 & & & x_1, x_2, x_3 & & & \geq & 0
\end{array}
$$

Extended Example: Conversion into Slack Form

$$
\begin{array}{lrcrcrcr}
\text{maximise} & 3x_1 & + & x_2 & + & 2x_3 & & \\
\text{subject to} & & & & & & & \\
 & x_1 & + & x_2 & + & 3x_3 & \leq & 30 \\
 & 2x_1 & + & 2x_2 & + & 5x_3 & \leq & 24 \\
 & 4x_1 & + & x_2 & + & 2x_3 & \leq & 36 \\
 & & & x_1, x_2, x_3 & & & \geq & 0
\end{array}
$$

↓ Conversion into slack form

Extended Example: Conversion into Slack Form

$$
\begin{array}{lrcrcrcr}
\text{maximise} & 3x_1 & + & x_2 & + & 2x_3 & & \\
\text{subject to} & & & & & & & \\
& x_1 & + & x_2 & + & 3x_3 & \leq & 30 \\
& 2x_1 & + & 2x_2 & + & 5x_3 & \leq & 24 \\
& 4x_1 & + & x_2 & + & 2x_3 & \leq & 36 \\
& & & x_1, x_2, x_3 & & & \geq & 0
\end{array}
$$

Conversion into slack form

$$
\begin{array}{rcrcrcrcr}
z & = & & & 3x_1 & + & x_2 & + & 2x_3 \\
x_4 & = & 30 & - & x_1 & - & x_2 & - & 3x_3 \\
x_5 & = & 24 & - & 2x_1 & - & 2x_2 & - & 5x_3 \\
x_6 & = & 36 & - & 4x_1 & - & x_2 & - & 2x_3
\end{array}
$$

Extended Example: Iteration 1

$$
\begin{array}{rcrcrcrcr}
z & = & & & 3x_1 & + & x_2 & + & 2x_3 \\
x_4 & = & 30 & - & x_1 & - & x_2 & - & 3x_3 \\
x_5 & = & 24 & - & 2x_1 & - & 2x_2 & - & 5x_3 \\
x_6 & = & 36 & - & 4x_1 & - & x_2 & - & 2x_3
\end{array}
$$

Extended Example: Iteration 1

$$\begin{aligned}
z &= & & 3x_1 &+& x_2 &+& 2x_3 \\
x_4 &= 30 &-& x_1 &-& x_2 &-& 3x_3 \\
x_5 &= 24 &-& 2x_1 &-& 2x_2 &-& 5x_3 \\
x_6 &= 36 &-& 4x_1 &-& x_2 &-& 2x_3
\end{aligned}$$

Basic solution: $(\overline{x_1}, \overline{x_2}, \ldots, \overline{x_6}) = (0, 0, 0, 30, 24, 36)$

Extended Example: Iteration 1

$$
\begin{aligned}
z &= & & 3x_1 &+& x_2 &+& 2x_3 \\
x_4 &= 30 &-& x_1 &-& x_2 &-& 3x_3 \\
x_5 &= 24 &-& 2x_1 &-& 2x_2 &-& 5x_3 \\
x_6 &= 36 &-& 4x_1 &-& x_2 &-& 2x_3
\end{aligned}
$$

Basic solution: $(\overline{x_1}, \overline{x_2}, \ldots, \overline{x_6}) = (0, 0, 0, 30, 24, 36)$

This basic solution is **feasible**

Extended Example: Iteration 1

$$
\begin{array}{rcrcrcrcr}
z & = & & & 3x_1 & + & x_2 & + & 2x_3 \\
x_4 & = & 30 & - & x_1 & - & x_2 & - & 3x_3 \\
x_5 & = & 24 & - & 2x_1 & - & 2x_2 & - & 5x_3 \\
x_6 & = & 36 & - & 4x_1 & - & x_2 & - & 2x_3
\end{array}
$$

Basic solution: $(\overline{x_1}, \overline{x_2}, \ldots, \overline{x_6}) = (0, 0, 0, 30, 24, 36)$

This basic solution is **feasible**

Objective value is 0.

Extended Example: Iteration 1

Increasing the value of x_1 would increase the objective value.

$$
\begin{array}{rclcrcrcr}
z & = & & & 3x_1 & + & x_2 & + & 2x_3 \\
x_4 & = & 30 & - & x_1 & - & x_2 & - & 3x_3 \\
x_5 & = & 24 & - & 2x_1 & - & 2x_2 & - & 5x_3 \\
x_6 & = & 36 & - & 4x_1 & - & x_2 & - & 2x_3
\end{array}
$$

Basic solution: $(\overline{x_1}, \overline{x_2}, \ldots, \overline{x_6}) = (0, 0, 0, 30, 24, 36)$

This basic solution is **feasible**

Objective value is 0.

Extended Example: Iteration 1

Increasing the value of x_1 would increase the objective value.

$$
\begin{array}{rcrcrcrcr}
z & = & & & 3x_1 & + & x_2 & + & 2x_3 \\
x_4 & = & 30 & - & x_1 & - & x_2 & - & 3x_3 \\
x_5 & = & 24 & - & 2x_1 & - & 2x_2 & - & 5x_3 \\
x_6 & = & 36 & - & 4x_1 & - & x_2 & - & 2x_3
\end{array}
$$

The third constraint is the tightest and limits how much we can increase x_1.

Extended Example: Iteration 1

Increasing the value of x_1 would increase the objective value.

$$
\begin{aligned}
z &= & & 3x_1 &+& x_2 &+& 2x_3 \\
x_4 &= 30 &-& x_1 &-& x_2 &-& 3x_3 \\
x_5 &= 24 &-& 2x_1 &-& 2x_2 &-& 5x_3 \\
x_6 &= 36 &-& 4x_1 &-& x_2 &-& 2x_3
\end{aligned}
$$

The third constraint is the tightest and limits how much we can increase x_1.

Switch roles of x_1 and x_6:

Extended Example: Iteration 1

Increasing the value of x_1 would increase the objective value.

$$\begin{array}{rcrcrcrcr} z & = & & & 3x_1 & + & x_2 & + & 2x_3 \\ x_4 & = & 30 & - & x_1 & - & x_2 & - & 3x_3 \\ x_5 & = & 24 & - & 2x_1 & - & 2x_2 & - & 5x_3 \\ x_6 & = & 36 & - & 4x_1 & - & x_2 & - & 2x_3 \end{array}$$

The third constraint is the tightest and limits how much we can increase x_1.

Switch roles of x_1 and x_6:

- Solving for x_1 yields:

$$x_1 = 9 - \frac{x_2}{4} - \frac{x_3}{2} - \frac{x_6}{4}.$$

Extended Example: Iteration 1

Increasing the value of x_1 would increase the objective value.

$$\begin{array}{rclcrcrcr}
z & = & & & 3x_1 & + & x_2 & + & 2x_3 \\
x_4 & = & 30 & - & x_1 & - & x_2 & - & 3x_3 \\
x_5 & = & 24 & - & 2x_1 & - & 2x_2 & - & 5x_3 \\
x_6 & = & 36 & - & 4x_1 & - & x_2 & - & 2x_3
\end{array}$$

The third constraint is the tightest and limits how much we can increase x_1.

Switch roles of x_1 and x_6:

- Solving for x_1 yields:

$$x_1 = 9 - \frac{x_2}{4} - \frac{x_3}{2} - \frac{x_6}{4}.$$

- Substitute this into x_1 in the other three equations

Extended Example: Iteration 2

$$
\begin{array}{rclcrcrcr}
z & = & 27 & + & \frac{x_2}{4} & + & \frac{x_3}{2} & - & \frac{3x_6}{4} \\
x_1 & = & 9 & - & \frac{x_2}{4} & - & \frac{x_3}{2} & - & \frac{x_6}{4} \\
x_4 & = & 21 & - & \frac{3x_2}{4} & - & \frac{5x_3}{2} & + & \frac{x_6}{4} \\
x_5 & = & 6 & - & \frac{3x_2}{2} & - & 4x_3 & + & \frac{x_6}{2}
\end{array}
$$

Extended Example: Iteration 2

$$
\begin{array}{rclcccccc}
z & = & 27 & + & \frac{x_2}{4} & + & \frac{x_3}{2} & - & \frac{3x_6}{4} \\
x_1 & = & 9 & - & \frac{x_2}{4} & - & \frac{x_3}{2} & - & \frac{x_6}{4} \\
x_4 & = & 21 & - & \frac{3x_2}{4} & - & \frac{5x_3}{2} & + & \frac{x_6}{4} \\
x_5 & = & 6 & - & \frac{3x_2}{2} & - & 4x_3 & + & \frac{x_6}{2}
\end{array}
$$

Basic solution: $(\overline{x_1}, \overline{x_2}, \ldots, \overline{x_6}) = (9, 0, 0, 21, 6, 0)$ with objective value 27

Extended Example: Iteration 2

Increasing the value of x_3 would increase the objective value.

$$
\begin{aligned}
z &= 27 + \frac{x_2}{4} + \frac{x_3}{2} - \frac{3x_6}{4} \\
x_1 &= 9 - \frac{x_2}{4} - \frac{x_3}{2} - \frac{x_6}{4} \\
x_4 &= 21 - \frac{3x_2}{4} - \frac{5x_3}{2} + \frac{x_6}{4} \\
x_5 &= 6 - \frac{3x_2}{2} - 4x_3 + \frac{x_6}{2}
\end{aligned}
$$

Basic solution: $(\overline{x_1}, \overline{x_2}, \ldots, \overline{x_6}) = (9, 0, 0, 21, 6, 0)$ with objective value 27

Extended Example: Iteration 2

Increasing the value of x_3 would increase the objective value.

$$
\begin{aligned}
z &= 27 + \frac{x_2}{4} + \frac{x_3}{2} - \frac{3x_6}{4} \\
x_1 &= 9 - \frac{x_2}{4} - \frac{x_3}{2} - \frac{x_6}{4} \\
x_4 &= 21 - \frac{3x_2}{4} - \frac{5x_3}{2} + \frac{x_6}{4} \\
x_5 &= 6 - \frac{3x_2}{2} - 4x_3 + \frac{x_6}{2}
\end{aligned}
$$

The third constraint is the tightest and limits how much we can increase x_3.

Extended Example: Iteration 2

Increasing the value of x_3 would increase the objective value.

$$\begin{array}{rcrcrcrcr}
z & = & 27 & + & \frac{x_2}{4} & + & \frac{x_3}{2} & - & \frac{3x_6}{4} \\
x_1 & = & 9 & - & \frac{x_2}{4} & - & \frac{x_3}{2} & - & \frac{x_6}{4} \\
x_4 & = & 21 & - & \frac{3x_2}{4} & - & \frac{5x_3}{2} & + & \frac{x_6}{4} \\
x_5 & = & 6 & - & \frac{3x_2}{2} & - & 4x_3 & + & \frac{x_6}{2}
\end{array}$$

The third constraint is the tightest and limits how much we can increase x_3.

Switch roles of x_3 and x_5:

Extended Example: Iteration 2

Increasing the value of x_3 would increase the objective value.

$$
\begin{aligned}
z &= 27 + \frac{x_2}{4} + \frac{x_3}{2} - \frac{3x_6}{4} \\
x_1 &= 9 - \frac{x_2}{4} - \frac{x_3}{2} - \frac{x_6}{4} \\
x_4 &= 21 - \frac{3x_2}{4} - \frac{5x_3}{2} + \frac{x_6}{4} \\
x_5 &= 6 - \frac{3x_2}{2} - 4x_3 + \frac{x_6}{2}
\end{aligned}
$$

The third constraint is the tightest and limits how much we can increase x_3.

Switch roles of x_3 and x_5:

- Solving for x_3 yields:

$$x_3 = \frac{3}{2} - \frac{3x_2}{8} - \frac{x_5}{4} - \frac{x_6}{8}.$$

Extended Example: Iteration 2

Increasing the value of x_3 would increase the objective value.

$$\begin{array}{rclcccccc}
z & = & 27 & + & \frac{x_2}{4} & + & \frac{x_3}{2} & - & \frac{3x_6}{4} \\
x_1 & = & 9 & - & \frac{x_2}{4} & - & \frac{x_3}{2} & - & \frac{x_6}{4} \\
x_4 & = & 21 & - & \frac{3x_2}{4} & - & \frac{5x_3}{2} & + & \frac{x_6}{4} \\
x_5 & = & 6 & - & \frac{3x_2}{2} & - & 4x_3 & + & \frac{x_6}{2}
\end{array}$$

The third constraint is the tightest and limits how much we can increase x_3.

Switch roles of x_3 and x_5:

- Solving for x_3 yields:

$$x_3 = \frac{3}{2} - \frac{3x_2}{8} - \frac{x_5}{4} - \frac{x_6}{8}.$$

- Substitute this into x_3 in the other three equations

Extended Example: Iteration 3

$$
\begin{aligned}
z &= \frac{111}{4} + \frac{x_2}{16} - \frac{x_5}{8} - \frac{11x_6}{16} \\
x_1 &= \frac{33}{4} - \frac{x_2}{16} + \frac{x_5}{8} - \frac{5x_6}{16} \\
x_3 &= \frac{3}{2} - \frac{3x_2}{8} - \frac{x_5}{4} + \frac{x_6}{8} \\
x_4 &= \frac{69}{4} + \frac{3x_2}{16} + \frac{5x_5}{8} - \frac{x_6}{16}
\end{aligned}
$$

Extended Example: Iteration 3

$$\begin{aligned}
z &= \frac{111}{4} + \frac{x_2}{16} - \frac{x_5}{8} - \frac{11x_6}{16} \\
x_1 &= \frac{33}{4} - \frac{x_2}{16} + \frac{x_5}{8} - \frac{5x_6}{16} \\
x_3 &= \frac{3}{2} - \frac{3x_2}{8} - \frac{x_5}{4} + \frac{x_6}{8} \\
x_4 &= \frac{69}{4} + \frac{3x_2}{16} + \frac{5x_5}{8} - \frac{x_6}{16}
\end{aligned}$$

Basic solution: $(\overline{x_1}, \overline{x_2}, \ldots, \overline{x_6}) = (\frac{33}{4}, 0, \frac{3}{2}, \frac{69}{4}, 0, 0)$ with objective value $\frac{111}{4} = 27.75$

Extended Example: Iteration 3

Increasing the value of x_2 would increase the objective value.

$$
\begin{array}{rcrcrcrcr}
z & = & \frac{111}{4} & + & \frac{x_2}{16} & - & \frac{x_5}{8} & - & \frac{11x_6}{16} \\
x_1 & = & \frac{33}{4} & - & \frac{x_2}{16} & + & \frac{x_5}{8} & - & \frac{5x_6}{16} \\
x_3 & = & \frac{3}{2} & - & \frac{3x_2}{8} & - & \frac{x_5}{4} & + & \frac{x_6}{8} \\
x_4 & = & \frac{69}{4} & + & \frac{3x_2}{16} & + & \frac{5x_5}{8} & - & \frac{x_6}{16}
\end{array}
$$

Basic solution: $(\overline{x_1}, \overline{x_2}, \ldots, \overline{x_6}) = (\frac{33}{4}, 0, \frac{3}{2}, \frac{69}{4}, 0, 0)$ with objective value $\frac{111}{4} = 27.75$

Extended Example: Iteration 3

Increasing the value of x_2 would increase the objective value.

$$
\begin{array}{rcrcrcrcr}
z & = & \frac{111}{4} & + & \frac{x_2}{16} & - & \frac{x_5}{8} & - & \frac{11x_6}{16} \\
x_1 & = & \frac{33}{4} & - & \frac{x_2}{16} & + & \frac{x_5}{8} & - & \frac{5x_6}{16} \\
x_3 & = & \frac{3}{2} & - & \frac{3x_2}{8} & - & \frac{x_5}{4} & + & \frac{x_6}{8} \\
x_4 & = & \frac{69}{4} & + & \frac{3x_2}{16} & + & \frac{5x_5}{8} & - & \frac{x_6}{16}
\end{array}
$$

The second constraint is the tightest and limits how much we can increase x_2.

Extended Example: Iteration 3

Increasing the value of x_2 would increase the objective value.

$$
\begin{aligned}
z &= \frac{111}{4} + \frac{x_2}{16} - \frac{x_5}{8} - \frac{11x_6}{16} \\
x_1 &= \frac{33}{4} - \frac{x_2}{16} + \frac{x_5}{8} - \frac{5x_6}{16} \\
x_3 &= \frac{3}{2} - \frac{3x_2}{8} - \frac{x_5}{4} + \frac{x_6}{8} \\
x_4 &= \frac{69}{4} + \frac{3x_2}{16} + \frac{5x_5}{8} - \frac{x_6}{16}
\end{aligned}
$$

The second constraint is the tightest and limits how much we can increase x_2.

Switch roles of x_2 and x_3:

Extended Example: Iteration 3

Increasing the value of x_2 would increase the objective value.

$$
\begin{aligned}
z &= \frac{111}{4} + \frac{x_2}{16} - \frac{x_5}{8} - \frac{11x_6}{16} \\
x_1 &= \frac{33}{4} - \frac{x_2}{16} + \frac{x_5}{8} - \frac{5x_6}{16} \\
x_3 &= \frac{3}{2} - \frac{3x_2}{8} - \frac{x_5}{4} + \frac{x_6}{8} \\
x_4 &= \frac{69}{4} + \frac{3x_2}{16} + \frac{5x_5}{8} - \frac{x_6}{16}
\end{aligned}
$$

The second constraint is the tightest and limits how much we can increase x_2.

Switch roles of x_2 and x_3:

- Solving for x_2 yields:

$$x_2 = 4 - \frac{8x_3}{3} - \frac{2x_5}{3} + \frac{x_6}{3}.$$

Extended Example: Iteration 3

Increasing the value of x_2 would increase the objective value.

$$
\begin{aligned}
z &= \frac{111}{4} + \frac{x_2}{16} - \frac{x_5}{8} - \frac{11x_6}{16} \\
x_1 &= \frac{33}{4} - \frac{x_2}{16} + \frac{x_5}{8} - \frac{5x_6}{16} \\
x_3 &= \frac{3}{2} - \frac{3x_2}{8} - \frac{x_5}{4} + \frac{x_6}{8} \\
x_4 &= \frac{69}{4} + \frac{3x_2}{16} + \frac{5x_5}{8} - \frac{x_6}{16}
\end{aligned}
$$

The second constraint is the tightest and limits how much we can increase x_2.

Switch roles of x_2 and x_3:

- Solving for x_2 yields:

$$x_2 = 4 - \frac{8x_3}{3} - \frac{2x_5}{3} + \frac{x_6}{3}.$$

- Substitute this into x_2 in the other three equations

Extended Example: Iteration 4

$$
\begin{aligned}
z &= 28 - \frac{x_3}{6} - \frac{x_5}{6} - \frac{2x_6}{3} \\
x_1 &= 8 + \frac{x_3}{6} + \frac{x_5}{6} - \frac{x_6}{3} \\
x_2 &= 4 - \frac{8x_3}{3} - \frac{2x_5}{3} + \frac{x_6}{3} \\
x_4 &= 18 - \frac{x_3}{2} + \frac{x_5}{2}
\end{aligned}
$$

Extended Example: Iteration 4

$$
\begin{aligned}
z &= 28 - \frac{x_3}{6} - \frac{x_5}{6} - \frac{2x_6}{3} \\
x_1 &= 8 + \frac{x_3}{6} + \frac{x_5}{6} - \frac{x_6}{3} \\
x_2 &= 4 - \frac{8x_3}{3} - \frac{2x_5}{3} + \frac{x_6}{3} \\
x_4 &= 18 - \frac{x_3}{2} + \frac{x_5}{2}
\end{aligned}
$$

Basic solution: $(\overline{x_1}, \overline{x_2}, \ldots, \overline{x_6}) = (8, 4, 0, 18, 0, 0)$ with objective value 28

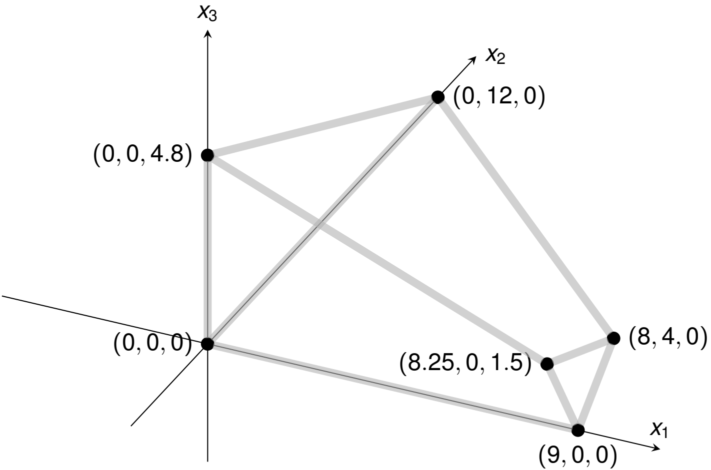
Extended Example: Iteration 4

All coefficients are negative, and hence this basic solution is **optimal**!

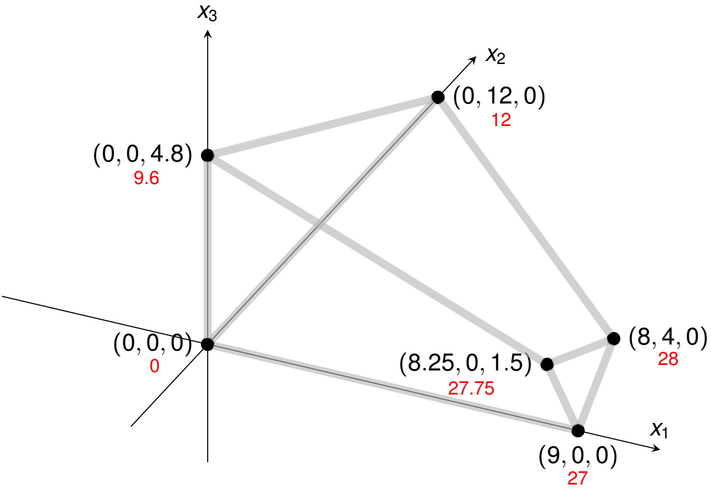
$$
\begin{aligned}
z &= 28 - \frac{x_3}{6} - \frac{x_5}{6} - \frac{2x_6}{3} \\
x_1 &= 8 + \frac{x_3}{6} + \frac{x_5}{6} - \frac{x_6}{3} \\
x_2 &= 4 - \frac{8x_3}{3} - \frac{2x_5}{3} + \frac{x_6}{3} \\
x_4 &= 18 - \frac{x_3}{2} + \frac{x_5}{2}
\end{aligned}
$$

Basic solution: $(\overline{x_1}, \overline{x_2}, \ldots, \overline{x_6}) = (8, 4, 0, 18, 0, 0)$ with objective value 28

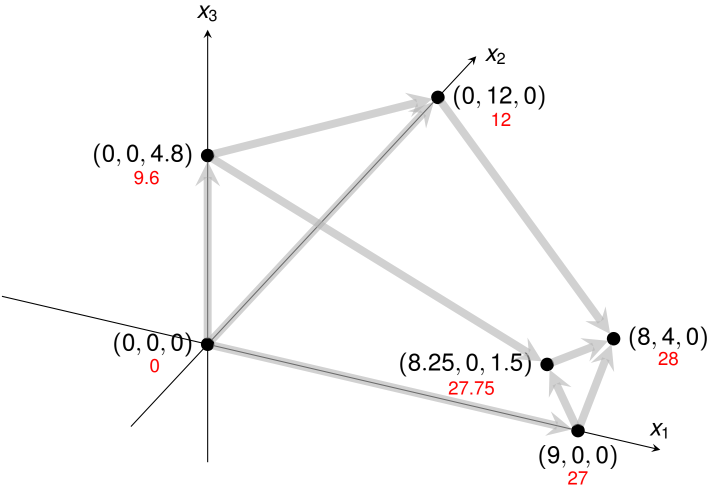
Extended Example: Visualization of SIMPLEX



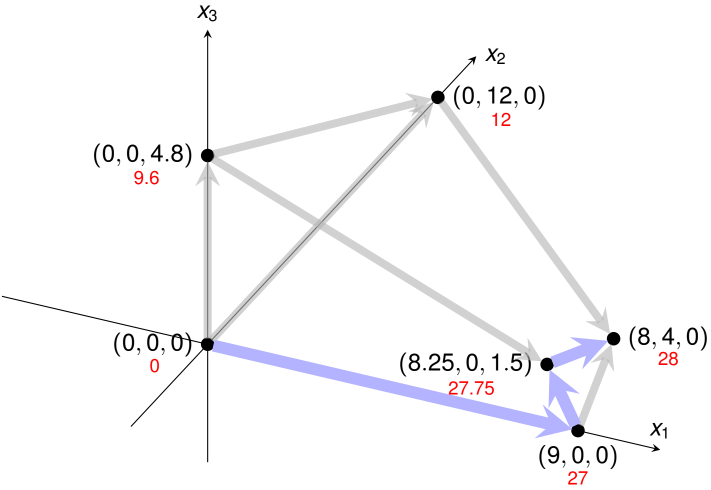
Extended Example: Visualization of SIMPLEX



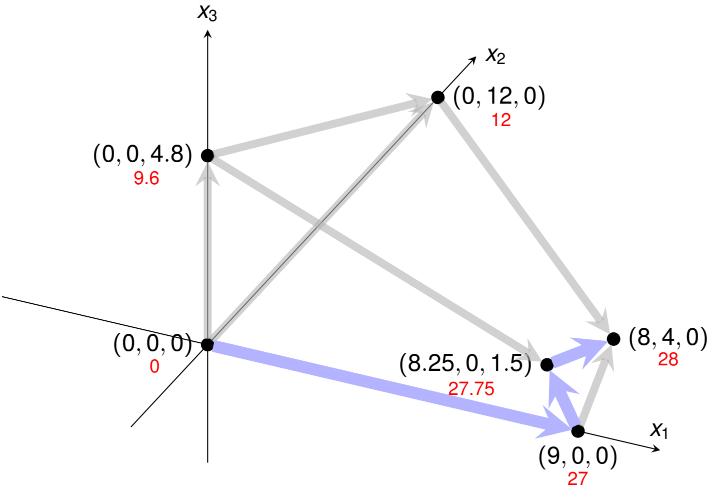
Extended Example: Visualization of SIMPLEX



Extended Example: Visualization of SIMPLEX



Extended Example: Visualization of SIMPLEX



Exercise: *[Ex. 6/7.6]* How many basic solutions (including non-feasible ones) are there?

Extended Example: Alternative Runs (1/2)

$$
\begin{array}{rclllllll}
z & = & & & 3x_1 & + & x_2 & + & 2x_3 \\
x_4 & = & 30 & - & x_1 & - & x_2 & - & 3x_3 \\
x_5 & = & 24 & - & 2x_1 & - & 2x_2 & - & 5x_3 \\
x_6 & = & 36 & - & 4x_1 & - & x_2 & - & 2x_3
\end{array}
$$

Extended Example: Alternative Runs (1/2)

$$\begin{array}{rcrcrcrcr}
z & = & & & 3x_1 & + & x_2 & + & 2x_3 \\
x_4 & = & 30 & - & x_1 & - & x_2 & - & 3x_3 \\
x_5 & = & 24 & - & 2x_1 & - & 2x_2 & - & 5x_3 \\
x_6 & = & 36 & - & 4x_1 & - & x_2 & - & 2x_3
\end{array}$$

↓ Switch roles of x_2 and x_5

Extended Example: Alternative Runs (1/2)

$$
\begin{array}{lllllllll}
z & = & & & 3x_1 & + & x_2 & + & 2x_3 \\
x_4 & = & 30 & - & x_1 & - & x_2 & - & 3x_3 \\
x_5 & = & 24 & - & 2x_1 & - & 2x_2 & - & 5x_3 \\
x_6 & = & 36 & - & 4x_1 & - & x_2 & - & 2x_3
\end{array}
$$

Switch roles of x_2 and x_5

$$
\begin{array}{lllllllll}
z & = & 12 & + & 2x_1 & - & \frac{x_3}{2} & - & \frac{x_5}{2} \\
x_2 & = & 12 & - & x_1 & - & \frac{5x_3}{2} & - & \frac{x_5}{2} \\
x_4 & = & 18 & - & x_2 & - & \frac{x_3}{2} & + & \frac{x_5}{2} \\
x_6 & = & 24 & - & 3x_1 & + & \frac{x_3}{2} & + & \frac{x_5}{2}
\end{array}
$$

Extended Example: Alternative Runs (1/2)

$$\begin{aligned}
z &= && 3x_1 + x_2 + 2x_3 \\
x_4 &= 30 &-& x_1 - x_2 - 3x_3 \\
x_5 &= 24 &-& 2x_1 - 2x_2 - 5x_3 \\
x_6 &= 36 &-& 4x_1 - x_2 - 2x_3
\end{aligned}$$

Switch roles of x_2 and x_5

$$\begin{aligned}
z &= 12 + 2x_1 - \frac{x_3}{2} - \frac{x_5}{2} \\
x_2 &= 12 - x_1 - \frac{5x_3}{2} - \frac{x_5}{2} \\
x_4 &= 18 - x_2 - \frac{x_3}{2} + \frac{x_5}{2} \\
x_6 &= 24 - 3x_1 + \frac{x_3}{2} + \frac{x_5}{2}
\end{aligned}$$

Switch roles of x_1 and x_6

Extended Example: Alternative Runs (1/2)

$$
\begin{array}{rcrcrcrcr}
z & = & & & 3x_1 & + & x_2 & + & 2x_3 \\
x_4 & = & 30 & - & x_1 & - & x_2 & - & 3x_3 \\
x_5 & = & 24 & - & 2x_1 & - & 2x_2 & - & 5x_3 \\
x_6 & = & 36 & - & 4x_1 & - & x_2 & - & 2x_3
\end{array}
$$

Switch roles of x_2 and x_5

$$
\begin{array}{rcrcrcrcr}
z & = & 12 & + & 2x_1 & - & \frac{x_3}{2} & - & \frac{x_5}{2} \\
x_2 & = & 12 & - & x_1 & - & \frac{5x_3}{2} & - & \frac{x_5}{2} \\
x_4 & = & 18 & - & x_2 & - & \frac{x_3}{2} & + & \frac{x_5}{2} \\
x_6 & = & 24 & - & 3x_1 & + & \frac{x_3}{2} & + & \frac{x_5}{2}
\end{array}
$$

Switch roles of x_1 and x_6

$$
\begin{array}{rcrcrcrcr}
z & = & 28 & - & \frac{x_3}{6} & - & \frac{x_5}{6} & - & \frac{2x_6}{3} \\
x_1 & = & 8 & + & \frac{x_3}{6} & + & \frac{x_5}{6} & - & \frac{x_6}{3} \\
x_2 & = & 4 & - & \frac{8x_3}{3} & - & \frac{2x_5}{3} & + & \frac{x_6}{3} \\
x_4 & = & 18 & - & \frac{x_3}{2} & + & \frac{x_5}{2} & &
\end{array}
$$

Extended Example: Alternative Runs (2/2)

$$
\begin{aligned}
z &= & & & 3x_1 &+ & x_2 &+ & 2x_3 \\
x_4 &= & 30 &- & x_1 &- & x_2 &- & 3x_3 \\
x_5 &= & 24 &- & 2x_1 &- & 2x_2 &- & 5x_3 \\
x_6 &= & 36 &- & 4x_1 &- & x_2 &- & 2x_3
\end{aligned}
$$

Extended Example: Alternative Runs (2/2)

$$\begin{array}{rcrcrcrcr} z & = & & & 3x_1 & + & x_2 & + & 2x_3 \\ x_4 & = & 30 & - & x_1 & - & x_2 & - & 3x_3 \\ x_5 & = & 24 & - & 2x_1 & - & 2x_2 & - & 5x_3 \\ x_6 & = & 36 & - & 4x_1 & - & x_2 & - & 2x_3 \end{array}$$

↓ Switch roles of x_3 and x_5

Extended Example: Alternative Runs (2/2)

$$
\begin{array}{rcrcrcrcr}
z & = & & & 3x_1 & + & x_2 & + & 2x_3 \\
x_4 & = & 30 & - & x_1 & - & x_2 & - & 3x_3 \\
x_5 & = & 24 & - & 2x_1 & - & 2x_2 & - & 5x_3 \\
x_6 & = & 36 & - & 4x_1 & - & x_2 & - & 2x_3
\end{array}
$$

Switch roles of x_3 and x_5

$$
\begin{array}{rcrcrcrcr}
z & = & \frac{48}{5} & + & \frac{11x_1}{5} & + & \frac{x_2}{5} & - & \frac{2x_5}{5} \\
x_4 & = & \frac{78}{5} & + & \frac{x_1}{5} & + & \frac{x_2}{5} & + & \frac{3x_5}{5} \\
x_3 & = & \frac{24}{5} & - & \frac{2x_1}{5} & - & \frac{2x_2}{5} & - & \frac{x_5}{5} \\
x_6 & = & \frac{132}{5} & - & \frac{16x_1}{5} & - & \frac{x_2}{5} & + & \frac{2x_3}{5}
\end{array}
$$

Extended Example: Alternative Runs (2/2)

$$
\begin{array}{lcrcrcrcr}
z & = & & & 3x_1 & + & x_2 & + & 2x_3 \\
x_4 & = & 30 & - & x_1 & - & x_2 & - & 3x_3 \\
x_5 & = & 24 & - & 2x_1 & - & 2x_2 & - & 5x_3 \\
x_6 & = & 36 & - & 4x_1 & - & x_2 & - & 2x_3
\end{array}
$$

Switch roles of x_3 and x_5

$$
\begin{array}{lcrcrcrcr}
z & = & \frac{48}{5} & + & \frac{11x_1}{5} & + & \frac{x_2}{5} & - & \frac{2x_5}{5} \\
x_4 & = & \frac{78}{5} & + & \frac{x_1}{5} & + & \frac{x_2}{5} & + & \frac{3x_5}{5} \\
x_3 & = & \frac{24}{5} & - & \frac{2x_1}{5} & - & \frac{2x_2}{5} & - & \frac{x_5}{5} \\
x_6 & = & \frac{132}{5} & - & \frac{16x_1}{5} & - & \frac{x_2}{5} & + & \frac{2x_3}{5}
\end{array}
$$

Switch roles of x_1 and x_6

Extended Example: Alternative Runs (2/2)

$$\begin{array}{rclcrcrcr}
z & = & & & 3x_1 & + & x_2 & + & 2x_3 \\
x_4 & = & 30 & - & x_1 & - & x_2 & - & 3x_3 \\
x_5 & = & 24 & - & 2x_1 & - & 2x_2 & - & 5x_3 \\
x_6 & = & 36 & - & 4x_1 & - & x_2 & - & 2x_3
\end{array}$$

Switch roles of x_3 and x_5

$$\begin{array}{rclcrcrcr}
z & = & \frac{48}{5} & + & \frac{11x_1}{5} & + & \frac{x_2}{5} & - & \frac{2x_5}{5} \\
x_4 & = & \frac{78}{5} & + & \frac{x_1}{5} & + & \frac{x_2}{5} & + & \frac{3x_5}{5} \\
x_3 & = & \frac{24}{5} & - & \frac{2x_1}{5} & - & \frac{2x_2}{5} & - & \frac{x_5}{5} \\
x_6 & = & \frac{132}{5} & - & \frac{16x_1}{5} & - & \frac{x_2}{5} & + & \frac{2x_3}{5}
\end{array}$$

Switch roles of x_1 and x_6

$$\begin{array}{rclcrcrcr}
z & = & \frac{111}{4} & + & \frac{x_2}{16} & - & \frac{x_5}{8} & - & \frac{11x_6}{16} \\
x_1 & = & \frac{33}{4} & - & \frac{x_2}{16} & + & \frac{x_5}{8} & - & \frac{5x_6}{16} \\
x_3 & = & \frac{3}{2} & - & \frac{3x_2}{8} & - & \frac{x_5}{4} & + & \frac{x_6}{8} \\
x_4 & = & \frac{69}{4} & + & \frac{3x_2}{16} & + & \frac{5x_5}{8} & - & \frac{x_6}{16}
\end{array}$$

Extended Example: Alternative Runs (2/2)

$$\begin{aligned}
z &= && 3x_1 + x_2 + 2x_3 \\
x_4 &= 30 &&- x_1 - x_2 - 3x_3 \\
x_5 &= 24 &&- 2x_1 - 2x_2 - 5x_3 \\
x_6 &= 36 &&- 4x_1 - x_2 - 2x_3
\end{aligned}$$

Switch roles of x_3 and x_5

$$\begin{aligned}
z &= \frac{48}{5} + \frac{11x_1}{5} + \frac{x_2}{5} - \frac{2x_5}{5} \\
x_4 &= \frac{78}{5} + \frac{x_1}{5} + \frac{x_2}{5} + \frac{3x_5}{5} \\
x_3 &= \frac{24}{5} - \frac{2x_1}{5} - \frac{2x_2}{5} - \frac{x_5}{5} \\
x_6 &= \frac{132}{5} - \frac{16x_1}{5} - \frac{x_2}{5} + \frac{2x_3}{5}
\end{aligned}$$

Switch roles of x_1 and x_6

Switch roles of x_2 and x_3

$$\begin{aligned}
z &= \frac{111}{4} + \frac{x_2}{16} - \frac{x_5}{8} - \frac{11x_6}{16} \\
x_1 &= \frac{33}{4} - \frac{x_2}{16} + \frac{x_5}{8} - \frac{5x_6}{16} \\
x_3 &= \frac{3}{2} - \frac{3x_2}{8} - \frac{x_5}{4} + \frac{x_6}{8} \\
x_4 &= \frac{69}{4} + \frac{3x_2}{16} + \frac{5x_5}{8} - \frac{x_6}{16}
\end{aligned}$$

Extended Example: Alternative Runs (2/2)

$$
\begin{array}{rcrcrcrcr}
z & = & & & 3x_1 & + & x_2 & + & 2x_3 \\
x_4 & = & 30 & - & x_1 & - & x_2 & - & 3x_3 \\
x_5 & = & 24 & - & 2x_1 & - & 2x_2 & - & 5x_3 \\
x_6 & = & 36 & - & 4x_1 & - & x_2 & - & 2x_3
\end{array}
$$

Switch roles of x_3 and x_5

$$
\begin{array}{rcrcrcrcr}
z & = & \frac{48}{5} & + & \frac{11x_1}{5} & + & \frac{x_2}{5} & - & \frac{2x_5}{5} \\
x_4 & = & \frac{78}{5} & + & \frac{x_1}{5} & + & \frac{x_2}{5} & + & \frac{3x_5}{5} \\
x_3 & = & \frac{24}{5} & - & \frac{2x_1}{5} & - & \frac{2x_2}{5} & - & \frac{x_5}{5} \\
x_6 & = & \frac{132}{5} & - & \frac{16x_1}{5} & - & \frac{x_2}{5} & + & \frac{2x_3}{5}
\end{array}
$$

Switch roles of x_1 and x_6

$$
\begin{array}{rcrcrcrcr}
z & = & \frac{111}{4} & + & \frac{x_2}{16} & - & \frac{x_5}{8} & - & \frac{11x_6}{16} \\
x_1 & = & \frac{33}{4} & - & \frac{x_2}{16} & + & \frac{x_5}{8} & - & \frac{5x_6}{16} \\
x_3 & = & \frac{3}{2} & - & \frac{3x_2}{8} & - & \frac{x_5}{4} & + & \frac{x_6}{8} \\
x_4 & = & \frac{69}{4} & + & \frac{3x_2}{16} & + & \frac{5x_5}{8} & - & \frac{x_6}{16}
\end{array}
$$

Switch roles of x_2 and x_3

$$
\begin{array}{rcrcrcrcr}
z & = & 28 & - & \frac{x_3}{6} & - & \frac{x_5}{6} & - & \frac{2x_6}{3} \\
x_1 & = & 8 & + & \frac{x_3}{6} & + & \frac{x_5}{6} & - & \frac{x_6}{3} \\
x_2 & = & 4 & - & \frac{8x_3}{3} & - & \frac{2x_5}{3} & + & \frac{x_6}{3} \\
x_4 & = & 18 & - & \frac{x_3}{2} & + & \frac{x_5}{2} & &
\end{array}
$$

Outline

The Pivot Step Formally

PIVOT(N, B, A, b, c, v, l, e)

// Compute the coefficients of the equation for new basic variable x_e.
let $\widehat{A}$ be a new $m \times n$ matrix
$\widehat{b}_e = b_l / a_{le}$
for each $j \in N - \{e\}$
    $\widehat{a}_{ej} = a_{lj} / a_{le}$
$\widehat{a}_{el} = 1 / a_{le}$
// Compute the coefficients of the remaining constraints.
for each $i \in B - \{l\}$
    $\widehat{b}_i = b_i - a_{ie} \widehat{b}_e$
    for each $j \in N - \{e\}$
        $\widehat{a}_{ij} = a_{ij} - a_{ie} \widehat{a}_{ej}$
    $\widehat{a}_{il} = -a_{ie} \widehat{a}_{el}$
// Compute the objective function.
$\widehat{v} = v + c_e \widehat{b}_e$
for each $j \in N - \{e\}$
    $\widehat{c}_j = c_j - c_e \widehat{a}_{ej}$
$\widehat{c}_l = -c_e \widehat{a}_{el}$
// Compute new sets of basic and nonbasic variables.
$\widehat{N} = N - \{e\} \cup \{l\}$
$\widehat{B} = B - \{l\} \cup \{e\}$
return $(\widehat{N}, \widehat{B}, \widehat{A}, \widehat{b}, \widehat{c}, \widehat{v})$

The Pivot Step Formally

PIVOT(N, B, A, b, c, v, l, e)

// Compute the coefficients of the equation for new basic variable x_e.
let $\widehat{A}$ be a new $m \times n$ matrix
$\widehat{b}_e = b_l / a_{le}$
for each $j \in N - \{e\}$
    $\widehat{a}_{ej} = a_{lj} / a_{le}$
$\widehat{a}_{el} = 1 / a_{le}$
// Compute the coefficients of the remaining constraints.
for each $i \in B - \{l\}$
    $\widehat{b}_i = b_i - a_{ie} \widehat{b}_e$
    for each $j \in N - \{e\}$
        $\widehat{a}_{ij} = a_{ij} - a_{ie} \widehat{a}_{ej}$
    $\widehat{a}_{il} = -a_{ie} \widehat{a}_{el}$
// Compute the objective function.
$\widehat{v} = v + c_e \widehat{b}_e$
for each $j \in N - \{e\}$
    $\widehat{c}_j = c_j - c_e \widehat{a}_{ej}$
$\widehat{c}_l = -c_e \widehat{a}_{el}$
// Compute new sets of basic and nonbasic variables.
$\widehat{N} = N - \{e\} \cup \{l\}$
$\widehat{B} = B - \{l\} \cup \{e\}$
return $(\widehat{N}, \widehat{B}, \widehat{A}, \widehat{b}, \widehat{c}, \widehat{v})$

Rewrite “tight” equation for enterring variable x_e.

The Pivot Step Formally

PIVOT(N, B, A, b, c, v, l, e)

// Compute the coefficients of the equation for new basic variable x_e.
let $\widehat{A}$ be a new $m \times n$ matrix
$\widehat{b}_e = b_l / a_{le}$
for each $j \in N - \{e\}$
    $\widehat{a}_{ej} = a_{lj} / a_{le}$
$\widehat{a}_{el} = 1 / a_{le}$
// Compute the coefficients of the remaining constraints.
for each $i \in B - \{l\}$
    $\widehat{b}_i = b_i - a_{ie}\widehat{b}_e$
    for each $j \in N - \{e\}$
        $\widehat{a}_{ij} = a_{ij} - a_{ie}\widehat{a}_{ej}$
    $\widehat{a}_{il} = -a_{ie}\widehat{a}_{el}$
// Compute the objective function.
$\widehat{v} = v + c_e\widehat{b}_e$
for each $j \in N - \{e\}$
    $\widehat{c}_j = c_j - c_e\widehat{a}_{ej}$
$\widehat{c}_l = -c_e\widehat{a}_{el}$
// Compute new sets of basic and nonbasic variables.
$\widehat{N} = N - \{e\} \cup \{l\}$
$\widehat{B} = B - \{l\} \cup \{e\}$
return $(\widehat{N}, \widehat{B}, \widehat{A}, \widehat{b}, \widehat{c}, \widehat{v})$

Rewrite "tight" equation for enterring variable x_e.

Substituting x_e into other equations.

The Pivot Step Formally

PIVOT(N, B, A, b, c, v, l, e)

// Compute the coefficients of the equation for new basic variable x_e.
let $\widehat{A}$ be a new $m \times n$ matrix
$\widehat{b}_e = b_l / a_{le}$
for each $j \in N - \{e\}$
    $\widehat{a}_{ej} = a_{lj} / a_{le}$
$\widehat{a}_{el} = 1/a_{le}$
// Compute the coefficients of the remaining constraints.
for each $i \in B - \{l\}$
    $\widehat{b}_i = b_i - a_{ie}\widehat{b}_e$
    for each $j \in N - \{e\}$
        $\widehat{a}_{ij} = a_{ij} - a_{ie}\widehat{a}_{ej}$
    $\widehat{a}_{il} = -a_{ie}\widehat{a}_{el}$
// Compute the objective function.
$\widehat{v} = v + c_e\widehat{b}_e$
for each $j \in N - \{e\}$
    $\widehat{c}_j = c_j - c_e\widehat{a}_{ej}$
$\widehat{c}_l = -c_e\widehat{a}_{el}$
// Compute new sets of basic and nonbasic variables.
$\widehat{N} = N - \{e\} \cup \{l\}$
$\widehat{B} = B - \{l\} \cup \{e\}$
return $(\widehat{N}, \widehat{B}, \widehat{A}, \widehat{b}, \widehat{c}, \widehat{v})$

Rewrite “tight” equation for enterring variable x_e.

Substituting x_e into other equations.

Substituting x_e into objective function.

The Pivot Step Formally

PIVOT(N, B, A, b, c, v, l, e)

// Compute the coefficients of the equation for new basic variable x_e.
let $\widehat{A}$ be a new $m \times n$ matrix
$\widehat{b}_e = b_l / a_{le}$
for each $j \in N - \{e\}$
  $\widehat{a}_{ej} = a_{lj} / a_{le}$
$\widehat{a}_{el} = 1 / a_{le}$
// Compute the coefficients of the remaining constraints.
for each $i \in B - \{l\}$
  $\widehat{b}_i = b_i - a_{ie} \widehat{b}_e$
  for each $j \in N - \{e\}$
    $\widehat{a}_{ij} = a_{ij} - a_{ie} \widehat{a}_{ej}$
  $\widehat{a}_{il} = -a_{ie} \widehat{a}_{el}$
// Compute the objective function.
$\widehat{v} = v + c_e \widehat{b}_e$
for each $j \in N - \{e\}$
  $\widehat{c}_j = c_j - c_e \widehat{a}_{ej}$
$\widehat{c}_l = -c_e \widehat{a}_{el}$
// Compute new sets of basic and nonbasic variables.
$\widehat{N} = N - \{e\} \cup \{l\}$
$\widehat{B} = B - \{l\} \cup \{e\}$
return $(\widehat{N}, \widehat{B}, \widehat{A}, \widehat{b}, \widehat{c}, \widehat{v})$

Rewrite "tight" equation for enterring variable x_e.

Substituting x_e into other equations.

Substituting x_e into objective function.

Update non-basic and basic variables

The Pivot Step Formally

PIVOT(N, B, A, b, c, v, l, e)

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return $(\widehat{N}, \widehat{B}, \widehat{A}, \widehat{b}, \widehat{c}, \widehat{v})$

Need that $a_{le} \neq 0$!

Rewrite "tight" equation for enterring variable x_e.

Substituting x_e into other equations.

Substituting x_e into objective function.

Update non-basic and basic variables

Effect of the Pivot Step (extra material, non-examinable)

Lemma 29.1

Consider a call to $\textsc{Pivot}(N, B, A, b, c, v, l, e)$ in which $a_{le} \neq 0$. Let the values returned from the call be $(\widehat{N}, \widehat{B}, \widehat{A}, \widehat{b}, \widehat{c}, \widehat{v})$, and let $\overline{x}$ denote the basic solution after the call. Then

Effect of the Pivot Step (extra material, non-examinable)

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1. $\overline{x}_j = 0$ for each $j \in \widehat{N}$.
2. $\overline{x}_e = b_l / a_{le}$.
3. $\overline{x}_i = b_i - a_{ie}\widehat{b}_e$ for each $i \in \widehat{B} \setminus \{e\}$.

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Proof:

Effect of the Pivot Step (extra material, non-examinable)

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2. $\overline{x}_e = b_l / a_{le}$.
3. $\overline{x}_i = b_i - a_{ie}\widehat{b}_e$ for each $i \in \widehat{B} \setminus \{e\}$.

Proof:

1. holds since the basic solution always sets all non-basic variables to zero.
2. When we set each non-basic variable to 0 in a constraint
$$x_i = \widehat{b}_i - \sum_{j \in \widehat{N}} \widehat{a}_{ij} x_j,$$
we have $\overline{x}_i = \widehat{b}_i$ for each $i \in \widehat{B}$. Hence $\overline{x}_e = \widehat{b}_e = b_l / a_{le}$.
3. After substituting into the other constraints, we have
$$\overline{x}_i = \widehat{b}_i = b_i - a_{ie}\widehat{b}_e.$$

Effect of the Pivot Step (extra material, non-examinable)

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Consider a call to PIVOT(N, B, A, b, c, v, l, e) in which $a_{le} \neq 0$. Let the values returned from the call be $(\widehat{N}, \widehat{B}, \widehat{A}, \widehat{b}, \widehat{c}, \widehat{v})$, and let $\overline{x}$ denote the basic solution after the call. Then

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3. After substituting into the other constraints, we have
$$\overline{x}_i = \widehat{b}_i = b_i - a_{ie}\widehat{b}_e. \qquad \square$$

Formalizing the Simplex Algorithm: Questions

Questions:

- How do we determine whether a linear program is feasible?
- What do we do if the linear program is feasible, but the initial basic solution is not feasible?
- How do we determine whether a linear program is unbounded?
- How do we choose the entering and leaving variables?

Formalizing the Simplex Algorithm: Questions

Questions:

- How do we determine whether a linear program is feasible?
- What do we do if the linear program is feasible, but the initial basic solution is not feasible?
- How do we determine whether a linear program is unbounded?
- How do we choose the entering and leaving variables?

Example before was a particularly nice one!

The formal procedure SIMPLEX

```
SIMPLEX(A, b, c)
(N, B, A, b, c, v) = INITIALIZE-SIMPLEX(A, b, c)
let Δ be a new vector of length m
while some index j ∈ N has c_j > 0
    choose an index e ∈ N for which c_e > 0
    for each index i ∈ B
        if a_ie > 0
            Δ_i = b_i / a_ie
        else Δ_i = ∞
    choose an index l ∈ B that minimizes Δ_i
    if Δ_l == ∞
        return "unbounded"
    else (N, B, A, b, c, v) = PIVOT(N, B, A, b, c, v, l, e)
for i = 1 to n
    if i ∈ B
        x̄_i = b_i
    else x̄_i = 0
return (x̄_1, x̄_2, ..., x̄_n)
```

The formal procedure SIMPLEX

Returns a slack form with a feasible basic solution (if it exists)

```
SIMPLEX(A, b, c)
(N, B, A, b, c, v) = INITIALIZE-SIMPLEX(A, b, c)
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        x̄_i = b_i
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return (x̄_1, x̄_2, ..., x̄_n)
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let Δ be a new vector of length m
while some index $j \in N$ has $c_j > 0$
    choose an index $e \in N$ for which $c_e > 0$
    for each index $i \in B$
        if $a_{ie} > 0$
            $\Delta_i = b_i / a_{ie}$
        else $\Delta_i = \infty$
    choose an index $l \in B$ that minimizes Δ_i
    if $\Delta_l == \infty$
        return "unbounded"
    else $(N, B, A, b, c, v) = $ PIVOT(N, B, A, b, c, v, l, e)
for $i = 1$ **to** n
    if $i \in B$
        $\bar{x}_i = b_i$
    else $\bar{x}_i = 0$
return $(\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_n)$

Returns a slack form with a feasible basic solution (if it exists)

Main Loop:

The formal procedure SIMPLEX

SIMPLEX(A, b, c)

1 $(N, B, A, b, c, v) =$ INITIALIZE-SIMPLEX(A, b, c)
2 let Δ be a new vector of length m
3 **while** some index $j \in N$ has $c_j > 0$
4   choose an index $e \in N$ for which $c_e > 0$
5   **for** each index $i \in B$
6   **if** $a_{ie} > 0$
7             $\Delta_i = b_i / a_{ie}$
8   **else** $\Delta_i = \infty$
9   choose an index $l \in B$ that minimizes Δ_i
10   **if** $\Delta_l == \infty$
11   **return** "unbounded"
12   **else** $(N, B, A, b, c, v) =$ PIVOT(N, B, A, b, c, v, l, e)
13 **for** $i = 1$ **to** n
14   **if** $i \in B$
15         $\bar{x}_i = b_i$
16   **else** $\bar{x}_i = 0$
17 **return** $(\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_n)$

Returns a slack form with a feasible basic solution (if it exists)

Main Loop:

- terminates if all coefficients in objective function are non-positive
- Line 4 picks enterring variable x_e with positive coefficient
- Lines 6 – 9 pick the tightest constraint, associated with x_l
- Line 11 returns "unbounded" if there are no constraints
- Line 12 calls PIVOT, switching roles of x_l and x_e

The formal procedure SIMPLEX

SIMPLEX(A, b, c)

1 $(N, B, A, b, c, v) = \text{INITIALIZE-SIMPLEX}(A, b, c)$
2 let Δ be a new vector of length m
3 **while** some index $j \in N$ has $c_j > 0$
4   choose an index $e \in N$ for which $c_e > 0$
5   **for** each index $i \in B$
6   **if** $a_{ie} > 0$
7             $\Delta_i = b_i / a_{ie}$
8   **else** $\Delta_i = \infty$
9   choose an index $l \in B$ that minimizes Δ_i
10   **if** $\Delta_l == \infty$
11   **return** "unbounded"
12   **else** $(N, B, A, b, c, v) = \text{PIVOT}(N, B, A, b, c, v, l, e)$
13 **for** $i = 1$ **to** n
14   **if** $i \in B$
15         $\bar{x}_i = b_i$
16   **else** $\bar{x}_i = 0$
17 **return** $(\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_n)$

Returns a slack form with a feasible basic solution (if it exists)

Main Loop:

- terminates if all coefficients in objective function are non-positive
- Line 4 picks enterring variable x_e with positive coefficient
- Lines 6 – 9 pick the tightest constraint, associated with x_l
- Line 11 returns "unbounded" if there are no constraints
- Line 12 calls PIVOT, switching roles of x_l and x_e

Return corresponding solution.

The formal procedure SIMPLEX

Returns a slack form with a feasible basic solution (if it exists)

```
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1  (N, B, A, b, c, v) = INITIALIZE-SIMPLEX(A, b, c)
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10     if Δ_l == ∞
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12     else (N, B, A, b, c, v) = PIVOT(N, B, A, b, c, v, l, e)
13 for i = 1 to n
14     if i ∈ B
15         x̄_i = b_i
16     else x̄_i = 0
17 return (x̄_1, x̄_2, ..., x̄_n)
```

Lemma 29.2

Suppose the call to INITIALIZE-SIMPLEX in line 1 returns a slack form for which the basic solution is feasible. Then if SIMPLEX returns a solution, it is a feasible solution. If SIMPLEX returns "unbounded", the linear program is unbounded.

The formal procedure SIMPLEX

```
SIMPLEX(A, b, c)
1  (N, B, A, b, c, v) = INITIALIZE-SIMPLEX(A, b, c)
2  let Δ be a new vector of length m
3  while some index j ∈ N has c_j > 0
4      choose an index e ∈ N for which c_e > 0
5      for each index i ∈ B
6          if a_ie > 0
7              Δ_i = b_i / a_ie
8          else Δ_i = ∞
9      choose an index l ∈ B that minimizes Δ_i
10     if Δ_l == ∞
11         return "unbounded"
```

Returns a slack form with a feasible basic solution (if it exists)

Proof is based on the following three-part loop invariant:

Lemma 29.2

Suppose the call to INITIALIZE-SIMPLEX in line 1 returns a slack form for which the basic solution is feasible. Then if SIMPLEX returns a solution, it is a feasible solution. If SIMPLEX returns "unbounded", the linear program is unbounded.

The formal procedure SIMPLEX

Returns a slack form with a feasible basic solution (if it exists)

SIMPLEX(A, b, c)

1 $(N, B, A, b, c, \nu) =$ INITIALIZE-SIMPLEX(A, b, c)
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8   **else** $\Delta_i = \infty$
9   choose an index $l \in B$ that minimizes Δ_i
10   **if** $\Delta_l == \infty$
11   **return** "unbounded"

Proof is based on the following three-part loop invariant:

1. the slack form is always equivalent to the one returned by INITIALIZE-SIMPLEX,
2. for each $i \in B$, we have $b_i \geq 0$,
3. the basic solution associated with the (current) slack form is feasible.

Lemma 29.2

Suppose the call to INITIALIZE-SIMPLEX in line 1 returns a slack form for which the basic solution is feasible. Then if SIMPLEX returns a solution, it is a feasible solution. If SIMPLEX returns "unbounded", the linear program is unbounded.

Outline

Simplex Algorithm by Example

Details of the Simplex Algorithm

Finding an Initial Solution

Appendix: Cycling and Termination (non-examinable)

Finding an Initial Solution

$$
\begin{array}{lrcrcr}
\text{maximise} & 2x_1 & - & x_2 & & \\
\text{subject to} & & & & & \\
& 2x_1 & - & x_2 & \leq & 2 \\
& x_1 & - & 5x_2 & \leq & -4 \\
& & x_1, x_2 & & \geq & 0
\end{array}
$$

Finding an Initial Solution

$$\begin{array}{lrcrcr}
\text{maximise} & 2x_1 & - & x_2 & & \\
\text{subject to} & & & & & \\
& 2x_1 & - & x_2 & \leq & 2 \\
& x_1 & - & 5x_2 & \leq & -4 \\
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\end{array}$$

↓ Conversion into slack form

Finding an Initial Solution

$$\begin{array}{lrcrcr} \text{maximise} & 2x_1 & - & x_2 & & \\ \text{subject to} & & & & & \\ & 2x_1 & - & x_2 & \leq & 2 \\ & x_1 & - & 5x_2 & \leq & -4 \\ & & x_1, x_2 & & \geq & 0 \end{array}$$

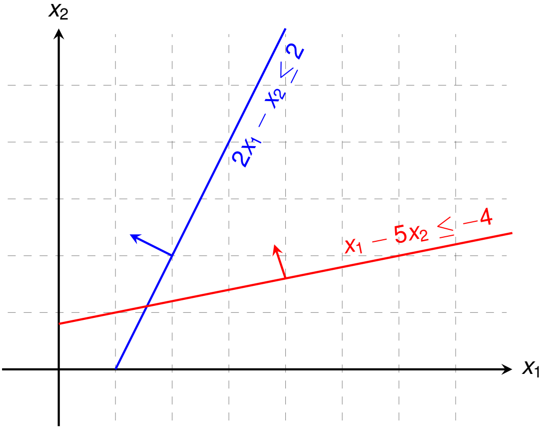
Conversion into slack form

$$\begin{array}{rcrcrcr} z & = & & & 2x_1 & - & x_2 \\ x_3 & = & 2 & - & 2x_1 & + & x_2 \\ x_4 & = & -4 & - & x_1 & + & 5x_2 \end{array}$$

Basic solution $(x_1, x_2, x_3, x_4) = (0, 0, 2, -4)$ is not feasible!

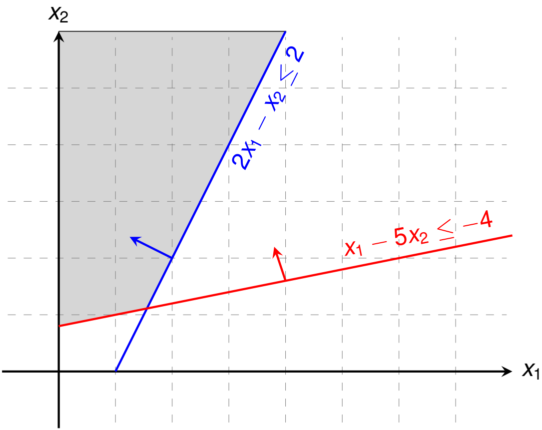
Geometric Illustration

$$\begin{array}{lrcrcr}
\text{maximise} & 2x_1 & - & x_2 & & \\
\text{subject to} & & & & & \\
 & 2x_1 & - & x_2 & \leq & 2 \\
 & x_1 & - & 5x_2 & \leq & -4 \\
 & & x_1, x_2 & & \geq & 0
\end{array}$$



Geometric Illustration

$$\begin{array}{lrcrcr} \text{maximise} & 2x_1 & - & x_2 & & \\ \text{subject to} & & & & & \\ & 2x_1 & - & x_2 & \leq & 2 \\ & x_1 & - & 5x_2 & \leq & -4 \\ & & x_1, x_2 & & \geq & 0 \end{array}$$

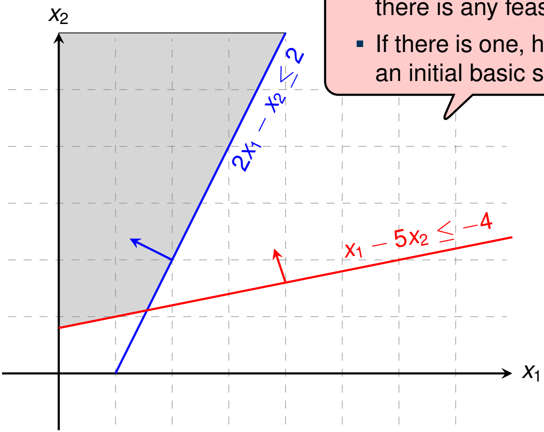


Geometric Illustration

$$
\begin{array}{lrcrcr}
\text{maximise} & 2x_1 & - & x_2 & & \\
\text{subject to} & & & & & \\
& 2x_1 & - & x_2 & \leq & 2 \\
& x_1 & - & 5x_2 & \leq & -4 \\
& & x_1, x_2 & & \geq & 0
\end{array}
$$

Questions:

- How to determine whether there is any feasible solution?
- If there is one, how to determine an initial basic solution?



Formulating an Auxiliary Linear Program

maximise $\sum_{j=1}^{n} c_j x_j$

subject to

$$\begin{aligned} \sum_{j=1}^{n} a_{ij} x_j &\leq b_i \quad \text{for } i = 1, 2, \ldots, m, \\ x_j &\geq 0 \quad \text{for } j = 1, 2, \ldots, n \end{aligned}$$

Formulating an Auxiliary Linear Program

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↓ Formulating an Auxiliary Linear Program

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↓ Formulating an Auxiliary Linear Program

maximise $-x_0$

subject to

$$\begin{aligned} \sum_{j=1}^{n} a_{ij} x_j - x_0 &\leq b_i \quad \text{for } i = 1, 2, \ldots, m, \\ x_j &\geq 0 \quad \text{for } j = 0, 1, \ldots, n \end{aligned}$$

Formulating an Auxiliary Linear Program

$$
\begin{array}{ll}
\text{maximise} & \sum_{j=1}^{n} c_j x_j \\
\text{subject to} & \\
& \begin{array}{rcll}
\sum_{j=1}^{n} a_{ij} x_j & \leq & b_i & \text{for } i = 1, 2, \ldots, m, \\
x_j & \geq & 0 & \text{for } j = 1, 2, \ldots, n
\end{array}
\end{array}
$$

↓ Formulating an Auxiliary Linear Program

$$
\begin{array}{ll}
\text{maximise} & -x_0 \\
\text{subject to} & \\
& \begin{array}{rcll}
\sum_{j=1}^{n} a_{ij} x_j - x_0 & \leq & b_i & \text{for } i = 1, 2, \ldots, m, \\
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\end{array}
\end{array}
$$

Lemma 29.11

Let L_{aux} be the auxiliary LP of a linear program L in standard form. Then L is feasible if and only if the optimal objective value of L_{aux} is 0.

Formulating an Auxiliary Linear Program

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↓ Formulating an Auxiliary Linear Program

$$\begin{array}{ll} \text{maximise} & -x_0 \\ \text{subject to} & \end{array}$$

$$\begin{aligned} \sum_{j=1}^{n} a_{ij} x_j - x_0 &\leq b_i \quad \text{for } i = 1, 2, \ldots, m, \\ x_j &\geq 0 \quad \text{for } j = 0, 1, \ldots, n \end{aligned}$$

Lemma 29.11

Let L_{aux} be the auxiliary LP of a linear program L in standard form. Then L is feasible if and only if the optimal objective value of L_{aux} is 0.

Proof. Exercise!

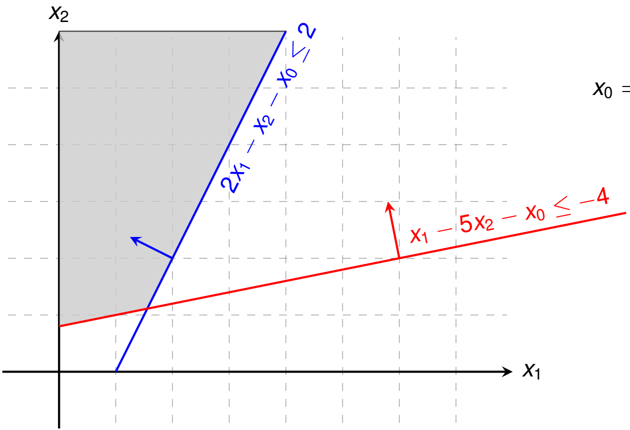
- Let us illustrate the role of x_0 as "distance from feasibility"

- Let us illustrate the role of x_0 as "distance from feasibility"
- We'll also see that increasing x_0 enlarges the feasible region

Geometric Illustration

maximise $-x_0$
subject to

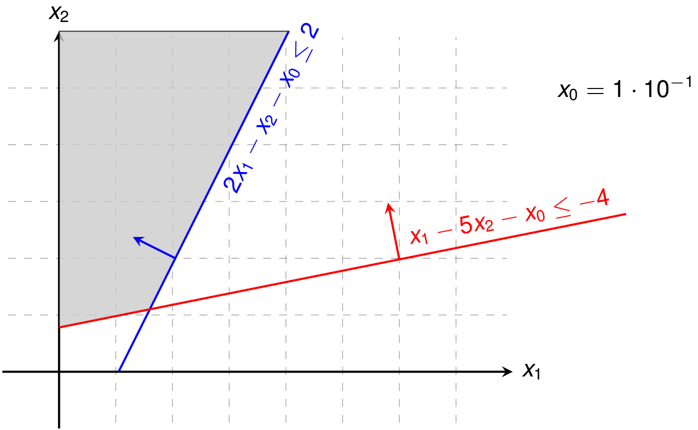
$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



$x_0 = 0$

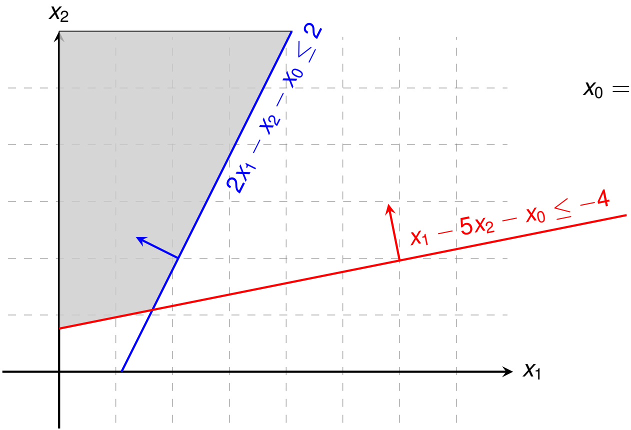
Geometric Illustration

$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 & & & & & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & x_0, x_1, x_2 & & & & & \geq & 0 \end{array}$$



Geometric Illustration

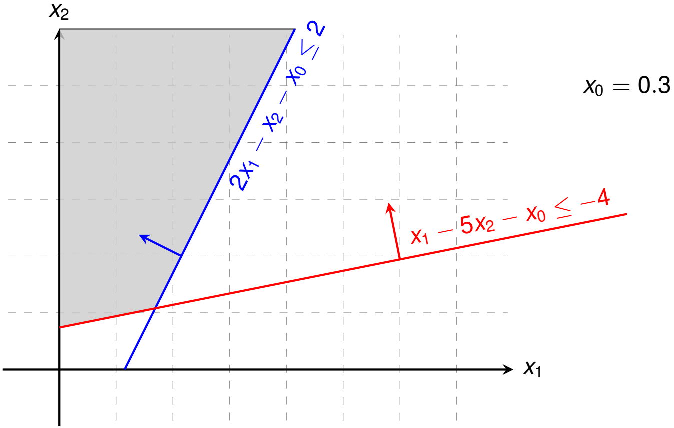
$$\begin{array}{llrcrcrcr} \text{maximise} & & -x_0 & & & & & & \\ \text{subject to} & & & & & & & & \\ & & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & & & \geq & 0 \end{array}$$



$x_0 = 0.2$

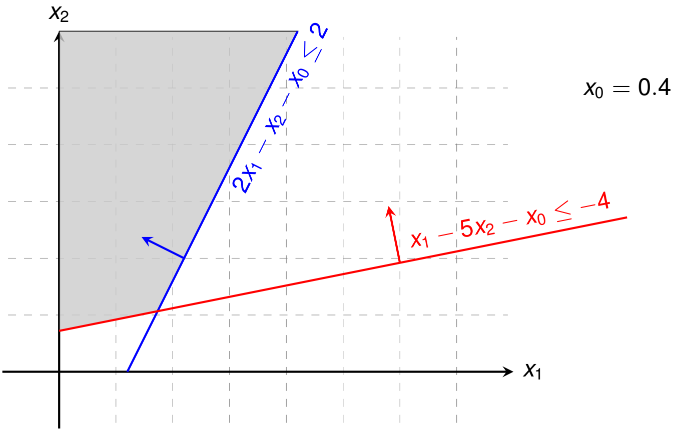
Geometric Illustration

$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 & & & & & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & x_0, x_1, x_2 & & & & & \geq & 0 \end{array}$$



Geometric Illustration

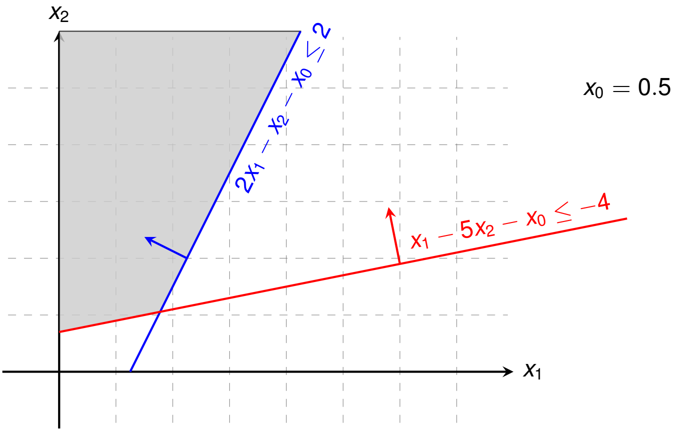
$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



Geometric Illustration

maximise $-x_0$
subject to

$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$

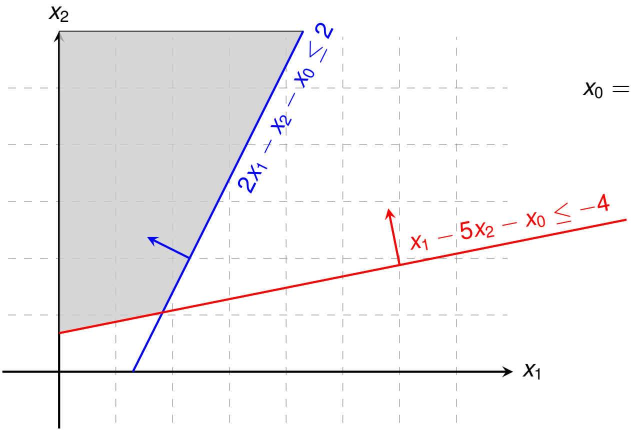


Geometric Illustration

maximise $-x_0$

subject to

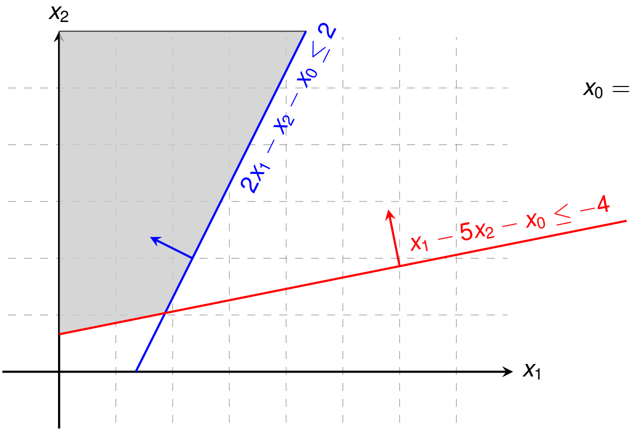
$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



$x_0 = 0.6$

Geometric Illustration

$$\begin{array}{llcrcrcl}
\text{maximise} & -x_0 \\
\text{subject to} \\
& 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\
& x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\
& x_0, x_1, x_2 & & & & & \geq & 0
\end{array}$$

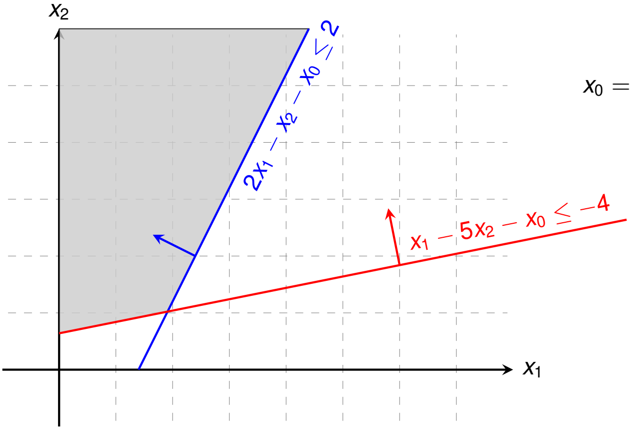


$x_0 = 0.7$

Geometric Illustration

maximise $-x_0$
subject to

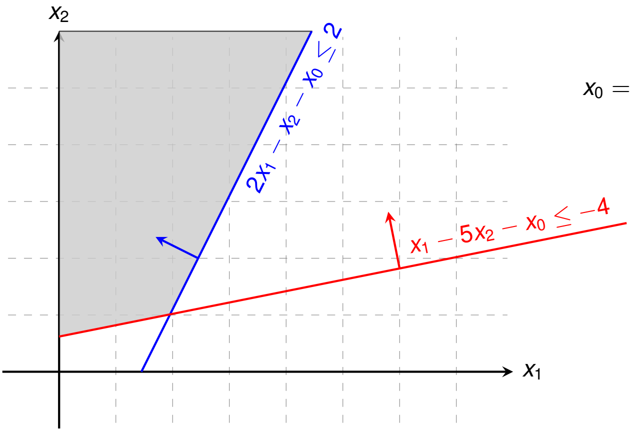
$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



$x_0 = 0.8$

Geometric Illustration

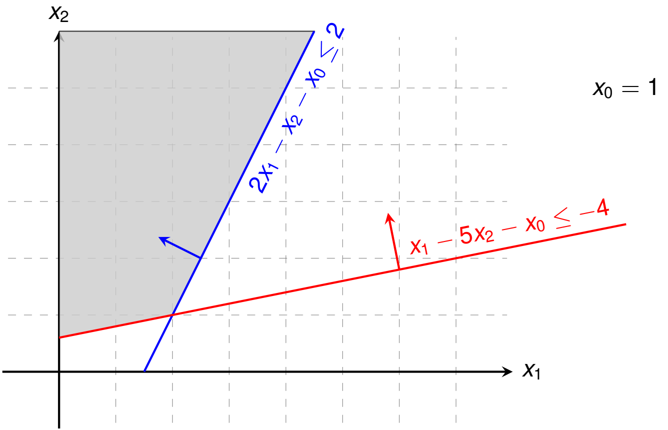
$$\begin{array}{llrcrcrcr}
\text{maximise} & -x_0 & & & & & & & \\
\text{subject to} & & & & & & & & \\
& & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\
& & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\
& & x_0, x_1, x_2 & & & & & \geq & 0
\end{array}$$



$x_0 = 0.9$

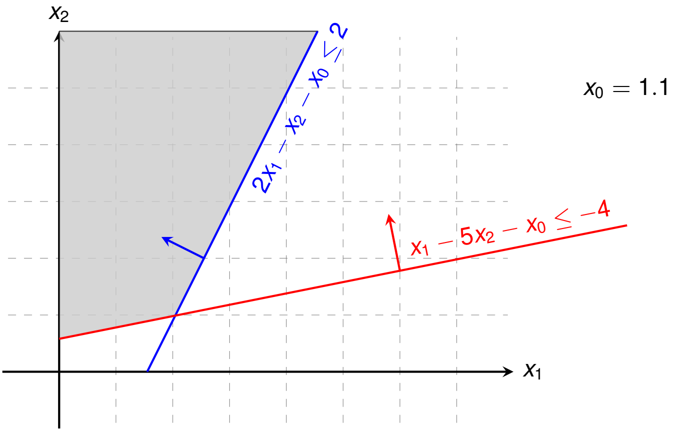
Geometric Illustration

$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



Geometric Illustration

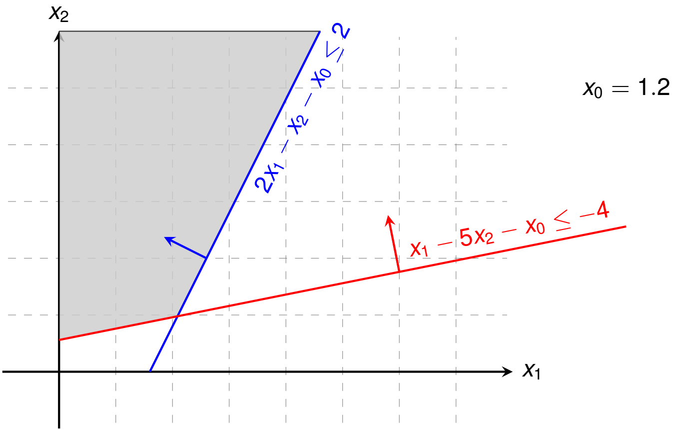
$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



Geometric Illustration

maximise $-x_0$
subject to

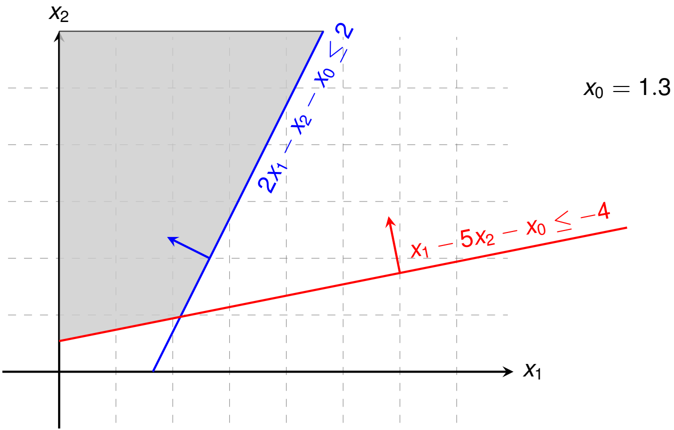
$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



Geometric Illustration

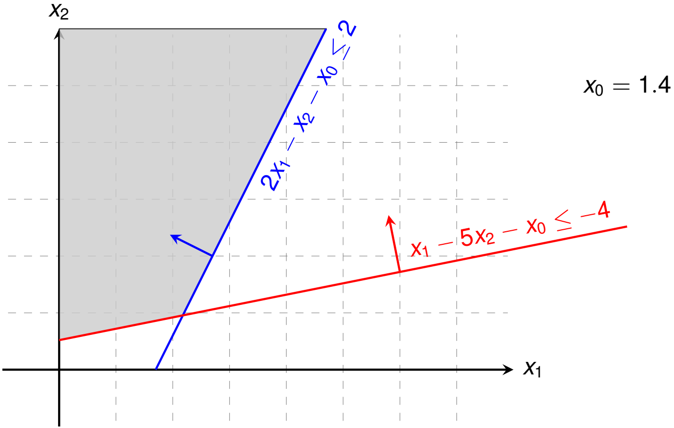
maximise $-x_0$
subject to

$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & & x_0, x_1, x_2 & & \geq & 0 \end{array}$$



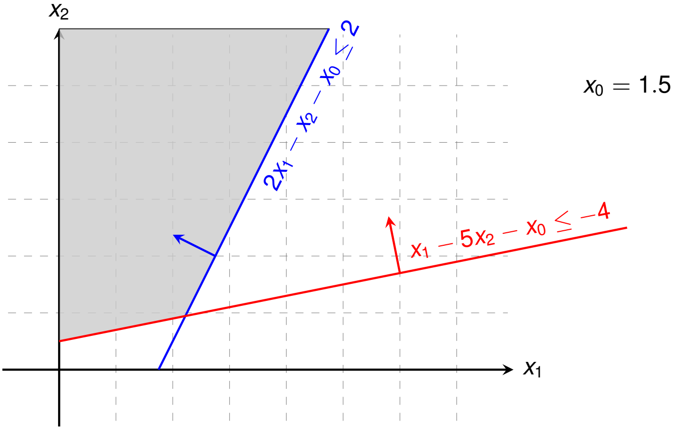
Geometric Illustration

$$\begin{array}{llrrrrrrr}
\text{maximise} & -x_0 \\
\text{subject to} \\
& 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\
& x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\
& x_0, x_1, x_2 & & & & & \geq & 0
\end{array}$$



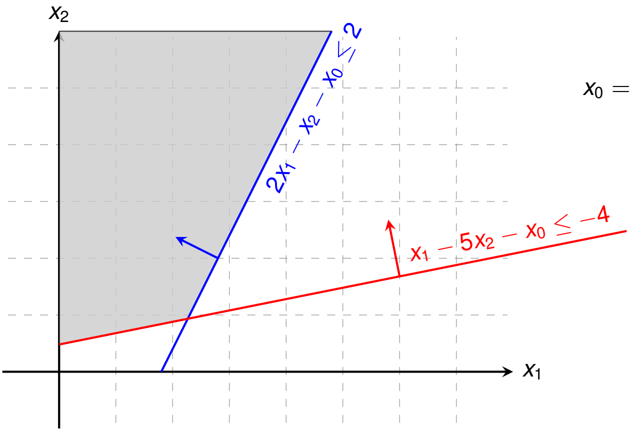
Geometric Illustration

$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & x_0, x_1, x_2 & & & & & \geq & 0 \end{array}$$



Geometric Illustration

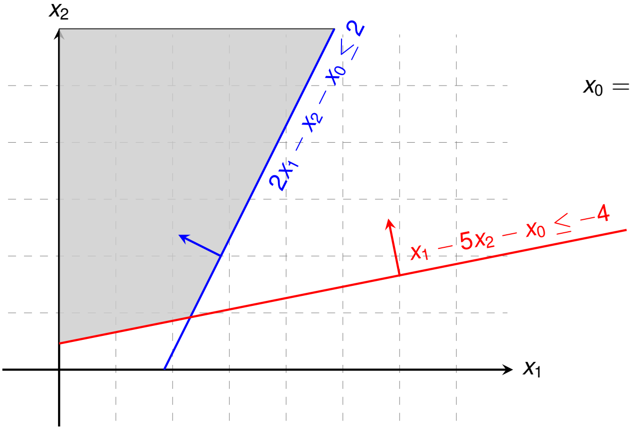
$$
\begin{array}{lrcrcrcr}
\text{maximise} & -x_0 \\
\text{subject to} \\
& 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\
& x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\
& x_0, x_1, x_2 & & & & & \geq & 0
\end{array}
$$



$x_0 = 1.6$

Geometric Illustration

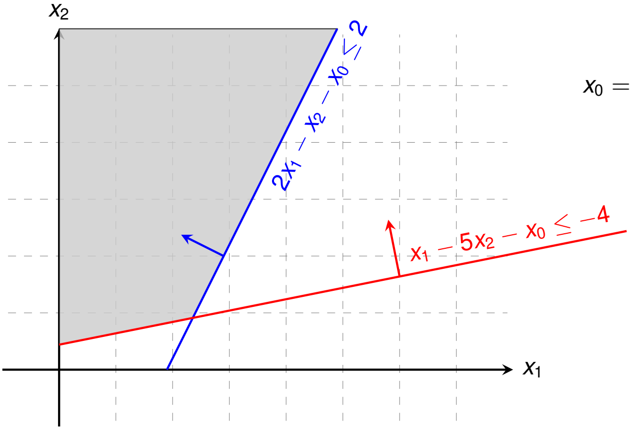
$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



$x_0 = 1.7$

Geometric Illustration

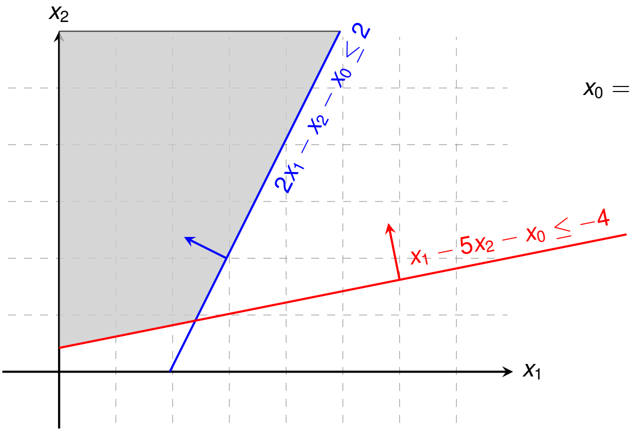
$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 & & & & & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



$x_0 = 1.8$

Geometric Illustration

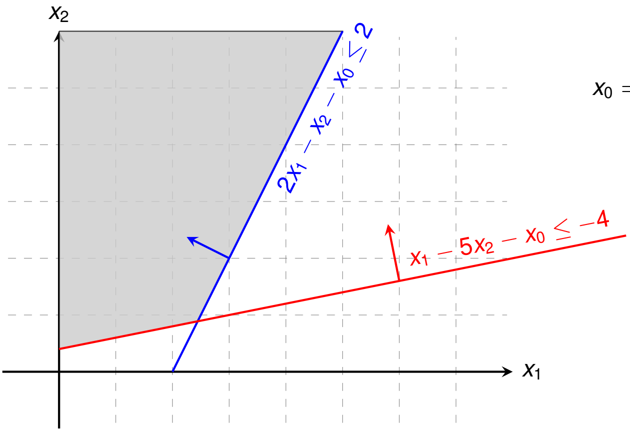
$$
\begin{array}{ll}
\text{maximise} & -x_0 \\
\text{subject to} & \\
& \begin{array}{rcrcrcr}
2x_1 & - & x_2 & - & x_0 & \leq & 2 \\
x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\
& & x_0, x_1, x_2 & & & \geq & 0
\end{array}
\end{array}
$$



$x_0 = 1.9$

Geometric Illustration

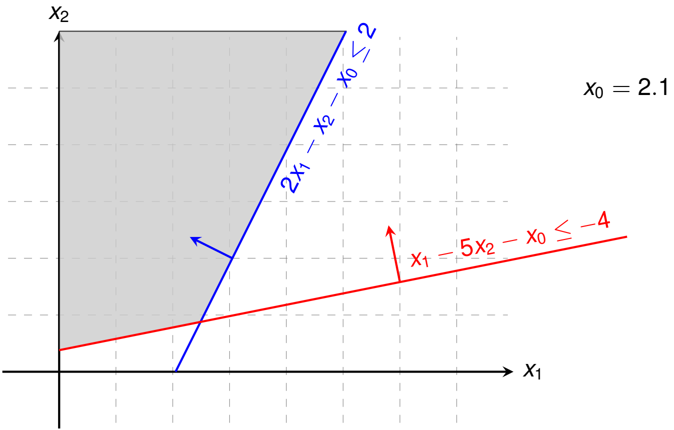
$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



$x_0 = 2$

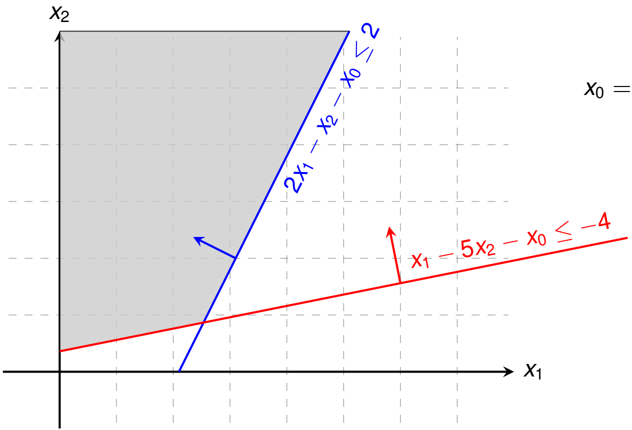
Geometric Illustration

$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



Geometric Illustration

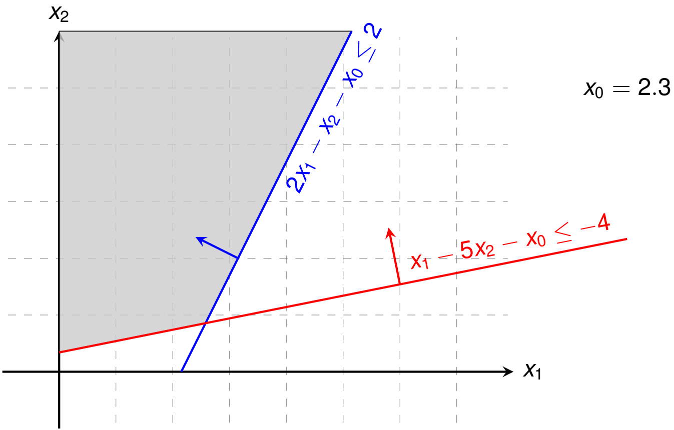
$$\begin{array}{ll} \text{maximise} & -x_0 \\ \text{subject to} & \\ & \begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array} \end{array}$$



$x_0 = 2.2$

Geometric Illustration

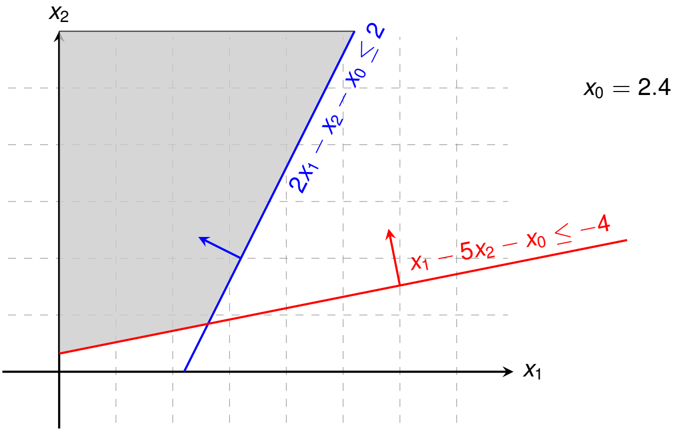
$$
\begin{array}{lrcrcrcr}
\text{maximise} & -x_0 \\
\text{subject to} \\
& 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\
& x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\
& & x_0, x_1, x_2 & & & & \geq & 0
\end{array}
$$



Geometric Illustration

maximise $-x_0$
subject to

$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$

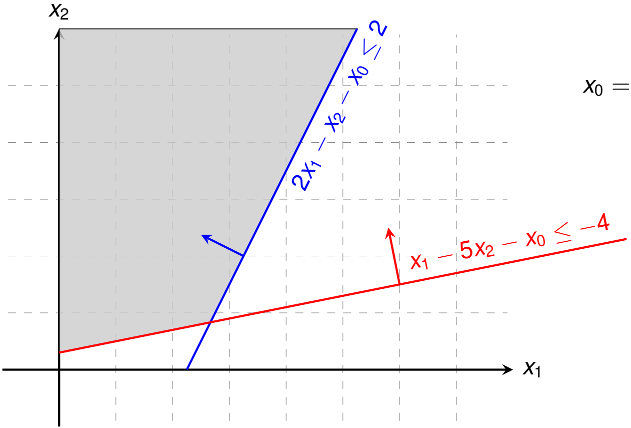


Geometric Illustration

maximise $\quad -x_0$

subject to

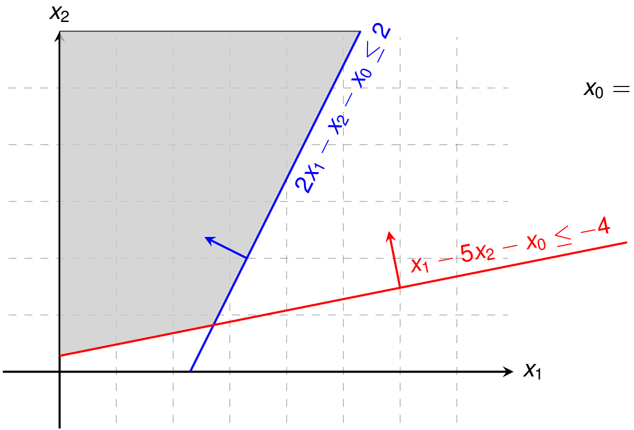
$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



$x_0 = 2.5$

Geometric Illustration

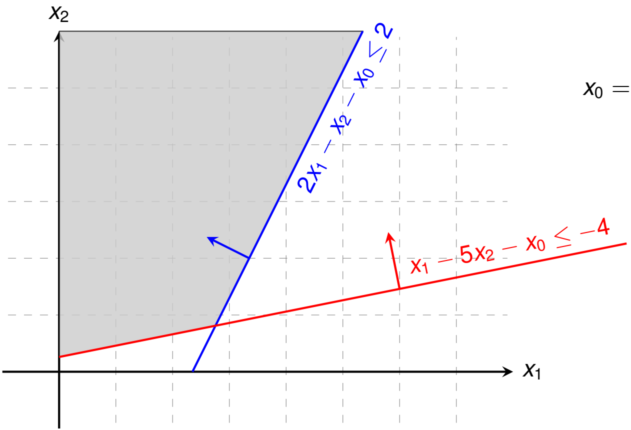
$$
\begin{array}{llrcrcrcr}
\text{maximise} & -x_0 \\
\text{subject to} \\
& 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\
& x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\
& x_0, x_1, x_2 & & & & & \geq & 0
\end{array}
$$



$x_0 = 2.6$

Geometric Illustration

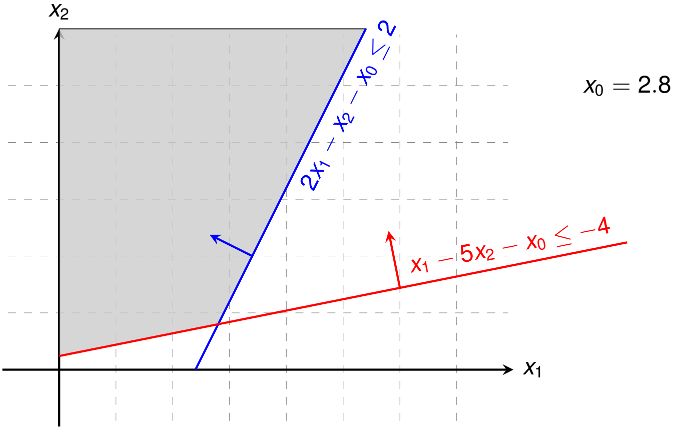
$$\begin{array}{lrcrcrcr}
\text{maximise} & -x_0 \\
\text{subject to} \\
& 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\
& x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\
& x_0, x_1, x_2 & & & & & \geq & 0
\end{array}$$



$x_0 = 2.7$

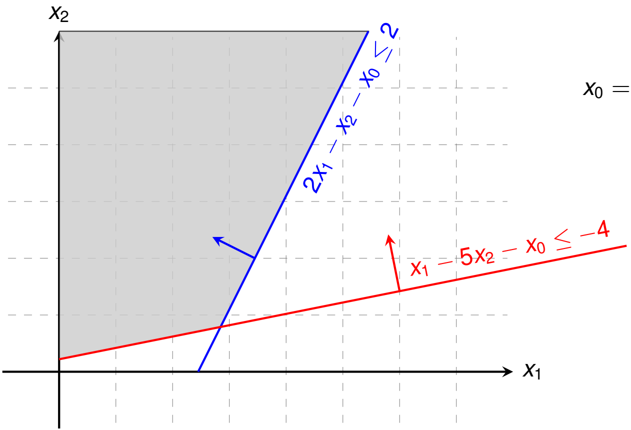
Geometric Illustration

$$\begin{array}{llrrrr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & x_0, x_1, x_2 & & & & & \geq & 0 \end{array}$$



Geometric Illustration

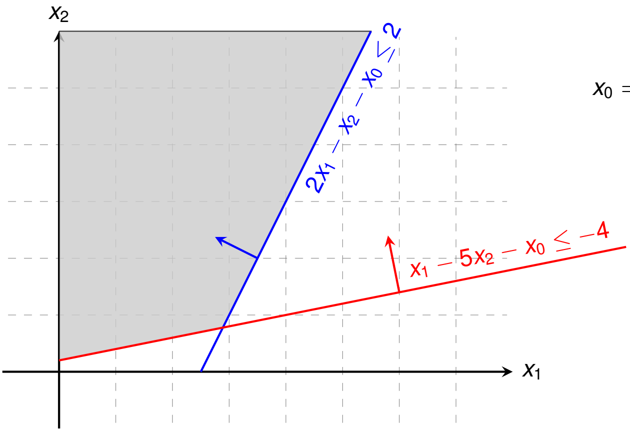
$$\begin{array}{lrcrcrcr}
\text{maximise} & -x_0 & & & & & & \\
\text{subject to} & & & & & & & \\
& 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\
& x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\
& x_0, x_1, x_2 & & & & & \geq & 0
\end{array}$$



$x_0 = 2.9$

Geometric Illustration

$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & x_0, x_1, x_2 & & & & & \geq & 0 \end{array}$$



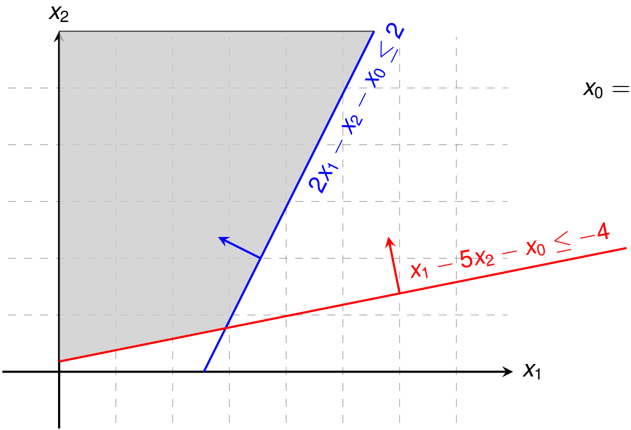
$x_0 = 3$

Geometric Illustration

maximise $\quad -x_0$

subject to

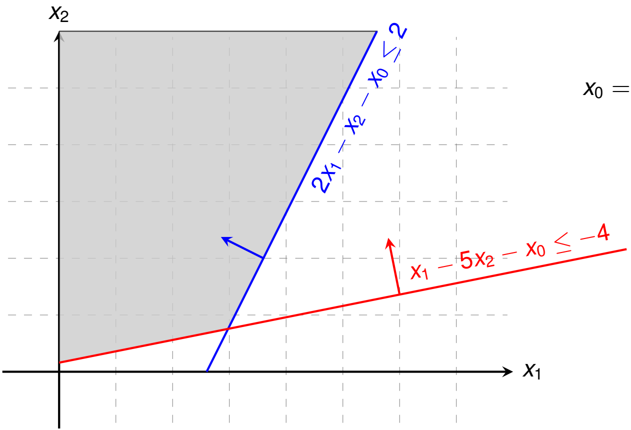
$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



$x_0 = 3.1$

Geometric Illustration

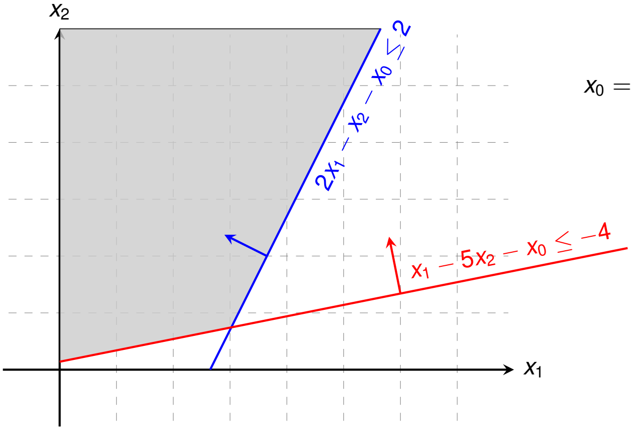
$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



$x_0 = 3.2$

Geometric Illustration

$$\begin{array}{llrrrrrcr}
\text{maximise} & -x_0 \\
\text{subject to} \\
& 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\
& x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\
& x_0, x_1, x_2 & & & & & \geq & 0
\end{array}$$

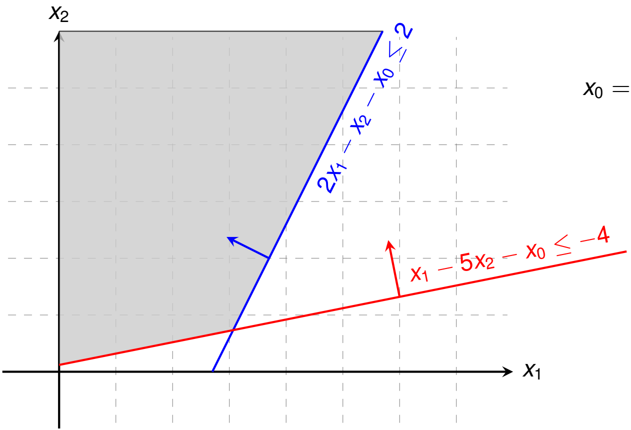


$x_0 = 3.3$

Geometric Illustration

maximise $-x_0$
subject to

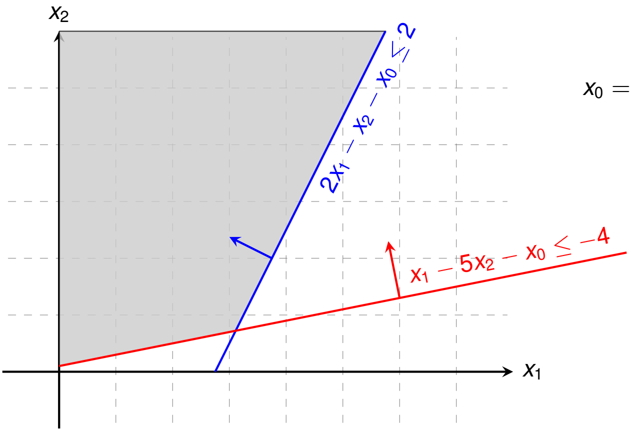
$$
\begin{array}{rcrcrcr}
2x_1 & - & x_2 & - & x_0 & \leq & 2 \\
x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\
 & & x_0, x_1, x_2 & & & \geq & 0
\end{array}
$$



$x_0 = 3.4$

Geometric Illustration

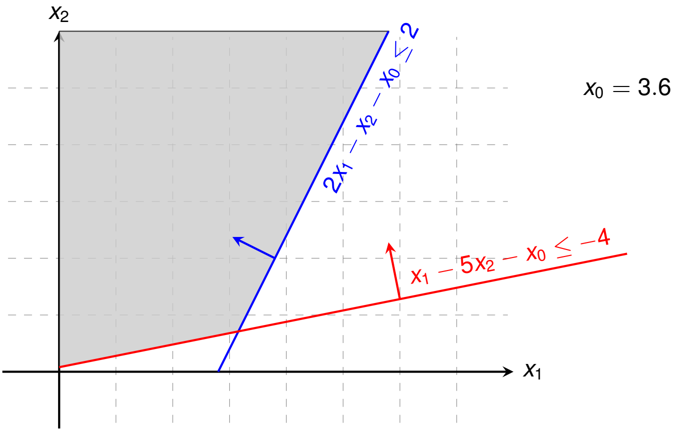
$$\begin{array}{llrcrcrcr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & x_0, x_1, x_2 & & & & & \geq & 0 \end{array}$$



$x_0 = 3.5$

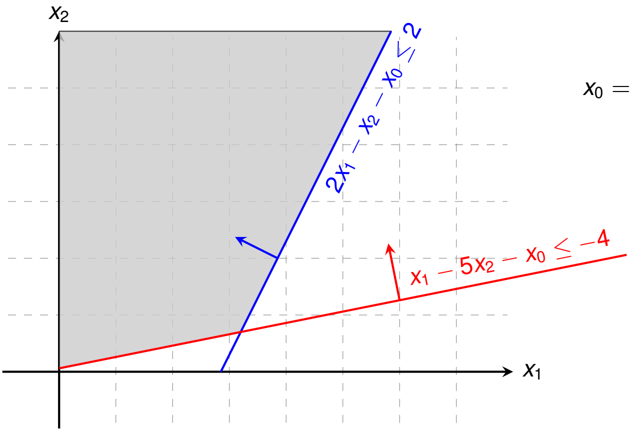
Geometric Illustration

$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 & & & & & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & x_0, x_1, x_2 & & & & & \geq & 0 \end{array}$$



Geometric Illustration

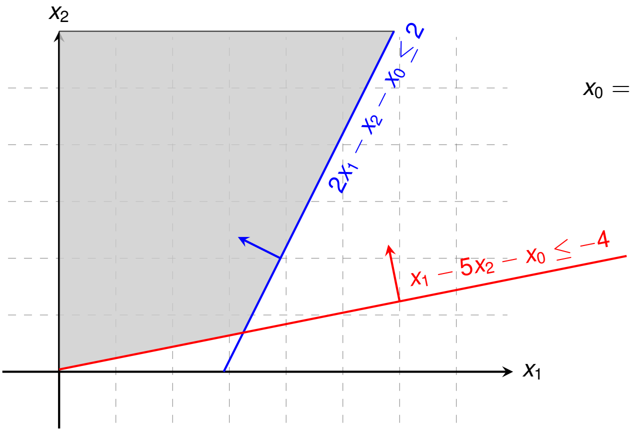
$$\begin{array}{llrrrrrrr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & x_0, x_1, x_2 & & & & & \geq & 0 \end{array}$$



$x_0 = 3.7$

Geometric Illustration

$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & x_0, x_1, x_2 & & & & & \geq & 0 \end{array}$$

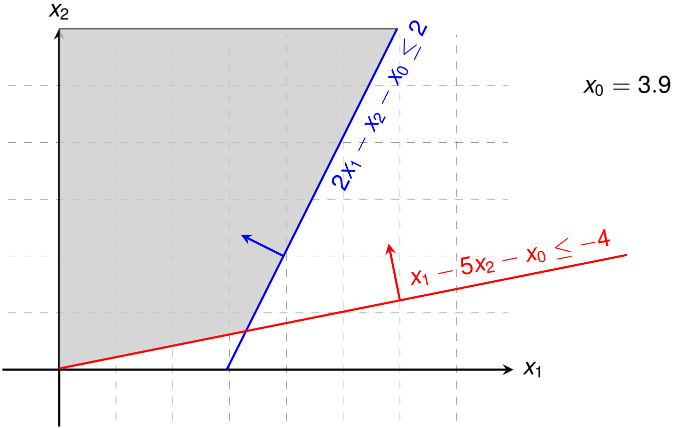


$x_0 = 3.8$

Geometric Illustration

maximise $-x_0$
subject to

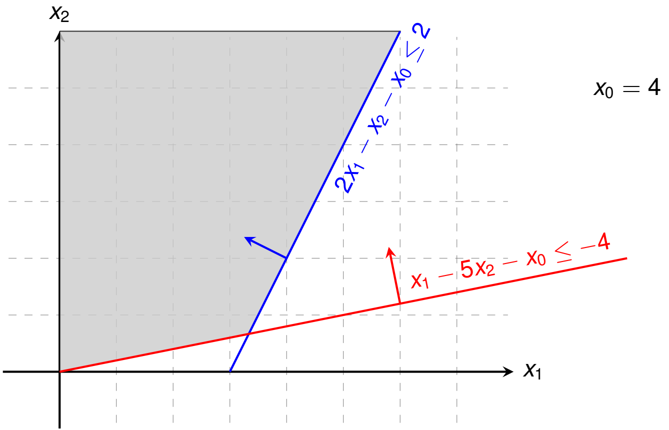
$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



Geometric Illustration

maximise $-x_0$
subject to

$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



- Let us now modify the original linear program so that it is not feasible

- Let us now modify the original linear program so that it is not feasible

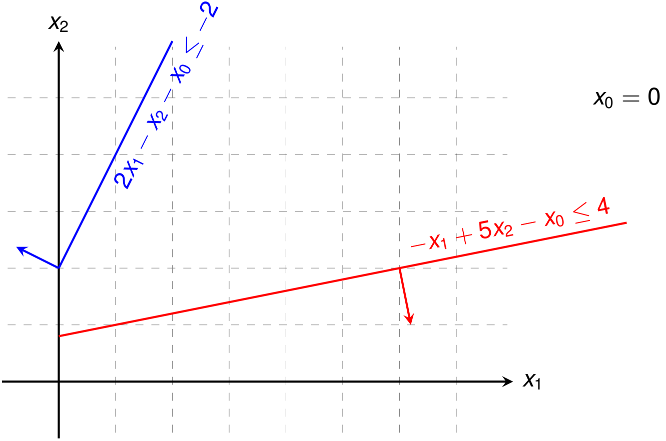
$\Rightarrow$ Hence the auxiliary linear program has only a solution for a sufficiently large $x_0 > 0$!

Geometric Illustration

maximise $-x_0$

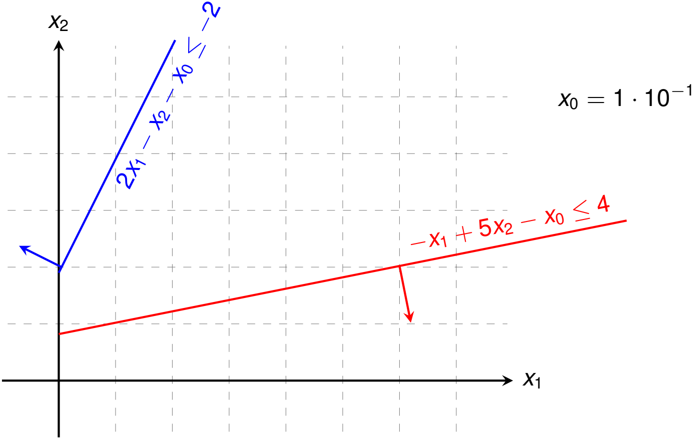
subject to

$$
\begin{array}{rcrcrcr}
2x_1 & - & x_2 & - & x_0 & \leq & -2 \\
-x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\
 & x_0, x_1, x_2 & & & & \geq & 0
\end{array}
$$



Geometric Illustration

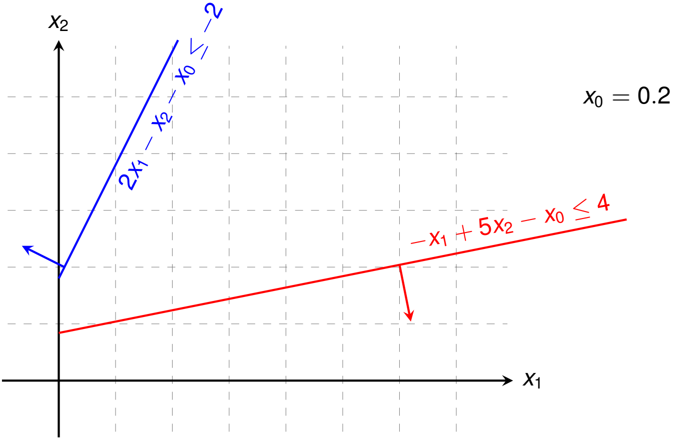
$$\begin{array}{llrrrl} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



Geometric Illustration

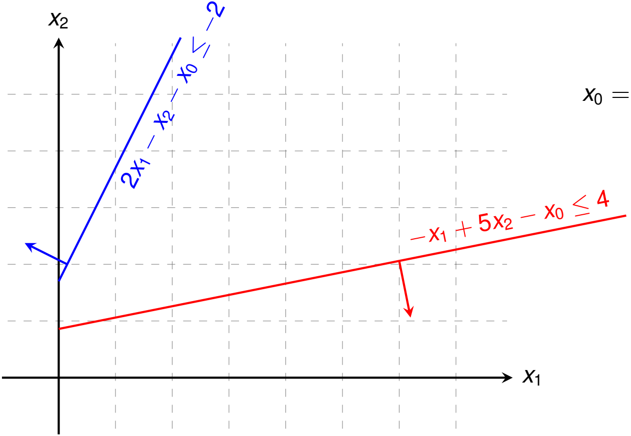
maximise $-x_0$
subject to

$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



Geometric Illustration

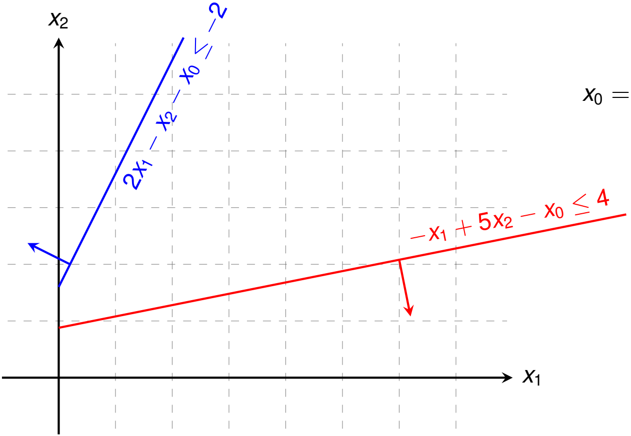
$$\begin{array}{llrrrrrrl} \text{maximise} & -x_0 \\ \text{subject to} \\ & & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



$x_0 = 0.3$

Geometric Illustration

$$\begin{array}{ll} \text{maximise} & -x_0 \\ \text{subject to} & \\ & \begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array} \end{array}$$

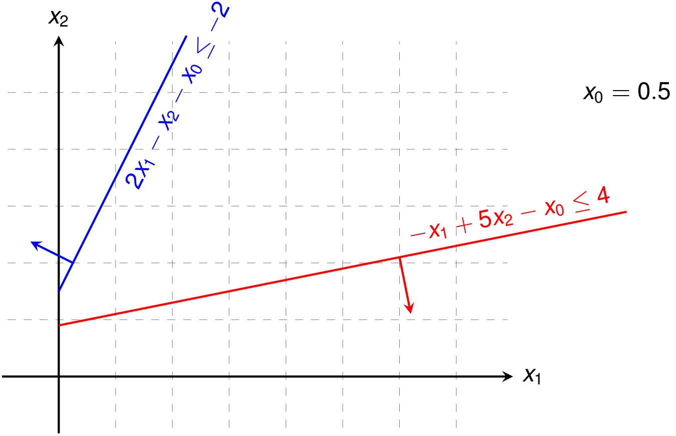


$x_0 = 0.4$

Geometric Illustration

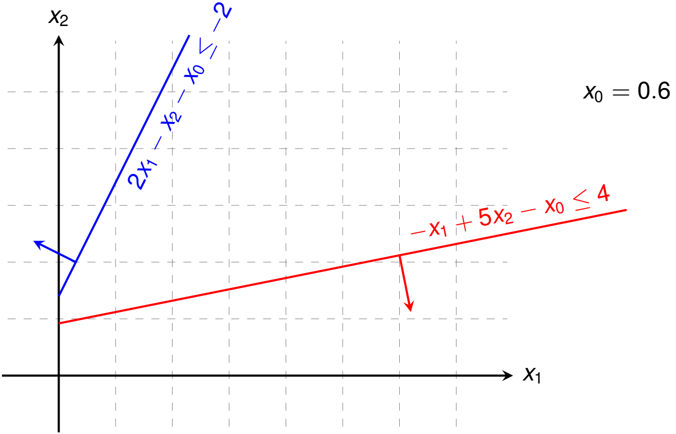
maximise $-x_0$
subject to

$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



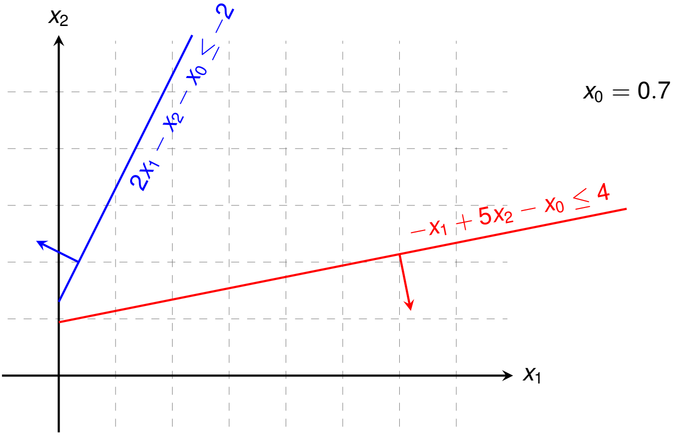
Geometric Illustration

$$\begin{array}{llcrcrcl}
\text{maximise} & -x_0 \\
\text{subject to} \\
& 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\
& -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\
& & x_0, x_1, x_2 & & & & \geq & 0
\end{array}$$



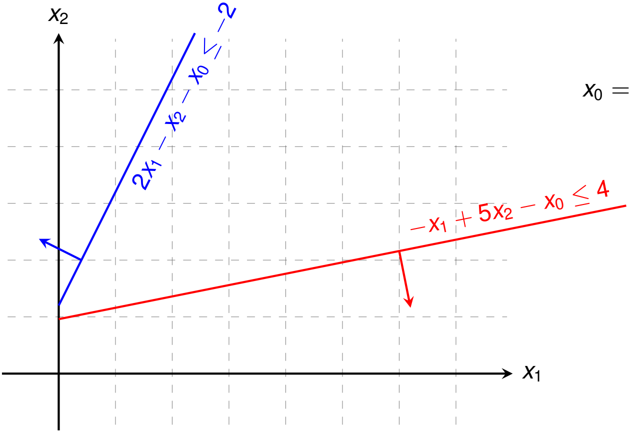
Geometric Illustration

$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 & & & & & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



Geometric Illustration

$$
\begin{array}{lrrrrrrrrr}
\text{maximise} & -x_0 \\
\text{subject to} \\
& 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\
& -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\
& & x_0, x_1, x_2 & & & & \geq & 0
\end{array}
$$

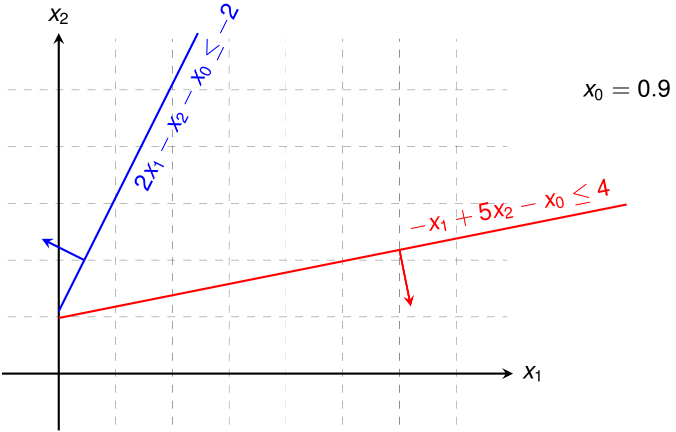


$x_0 = 0.8$

Geometric Illustration

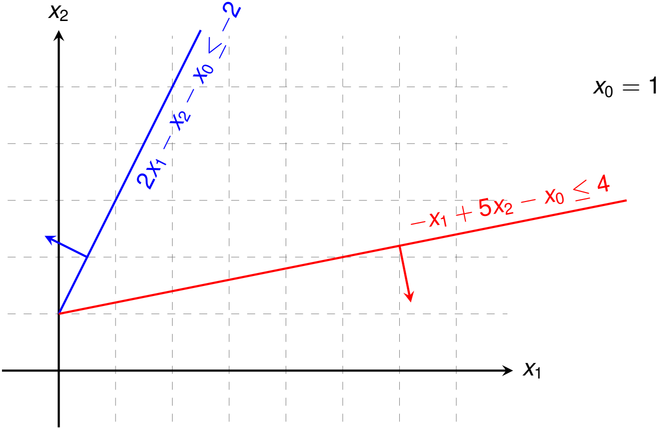
maximise $-x_0$
subject to

$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



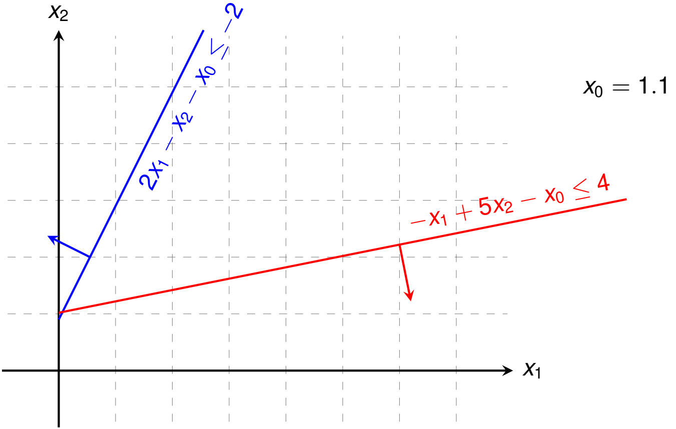
Geometric Illustration

$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



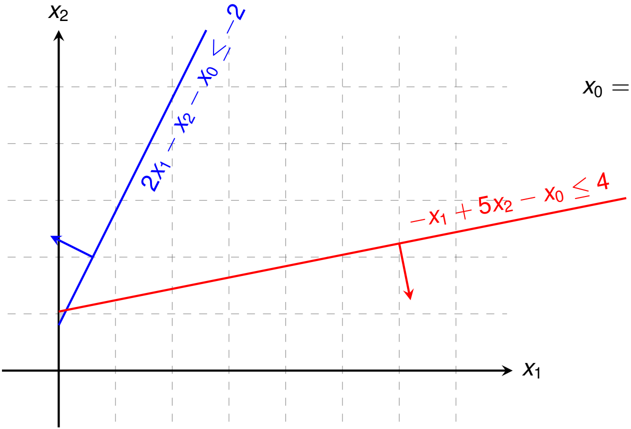
Geometric Illustration

$$\begin{array}{llrcrcrcr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



Geometric Illustration

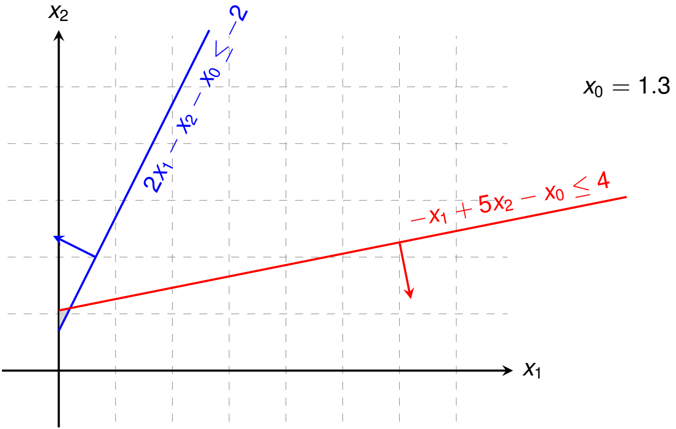
$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 & & & & & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



$x_0 = 1.2$

Geometric Illustration

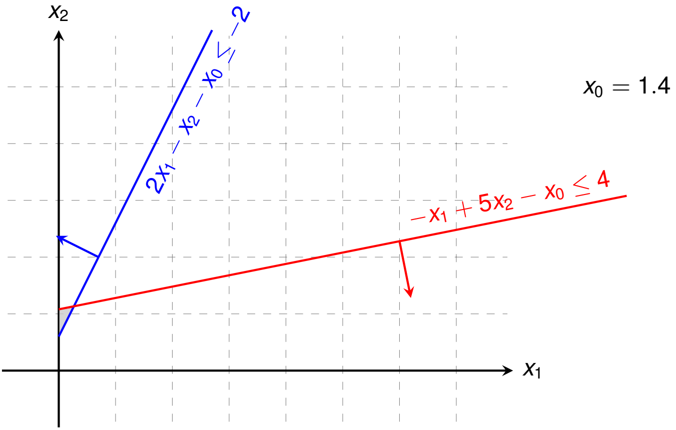
$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



Geometric Illustration

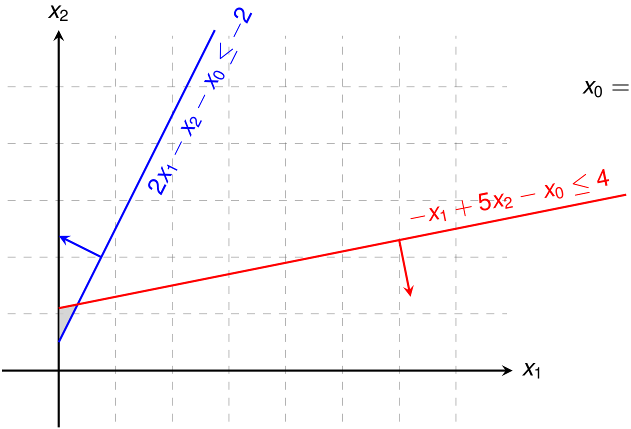
maximise $-x_0$
subject to

$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



Geometric Illustration

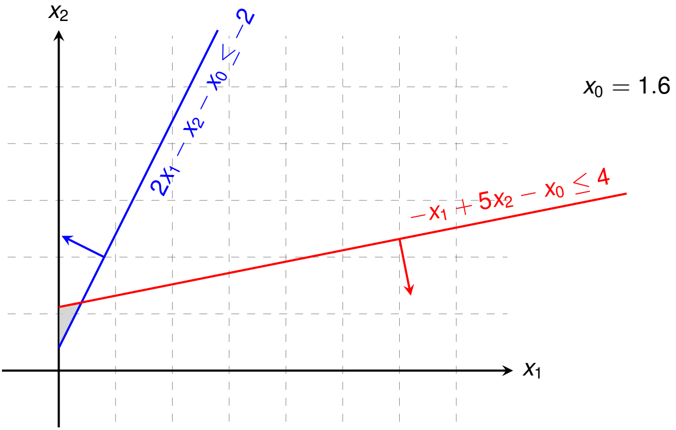
$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 & & & & & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & x_0, x_1, x_2 & & & & & \geq & 0 \end{array}$$



$x_0 = 1.5$

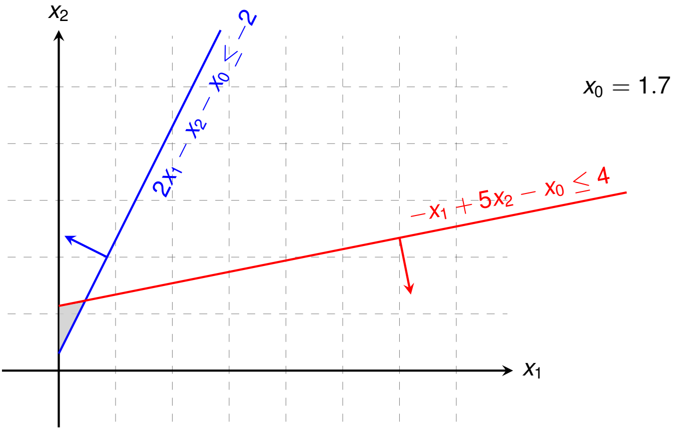
Geometric Illustration

$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 & & & & & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



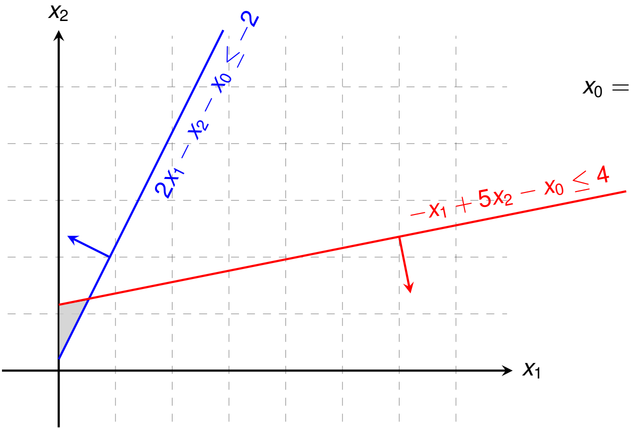
Geometric Illustration

$$\begin{array}{ll} \text{maximise} & -x_0 \\ \text{subject to} & \\ & \begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & x_0, x_1, x_2 & & & & \geq & 0 \end{array} \end{array}$$



Geometric Illustration

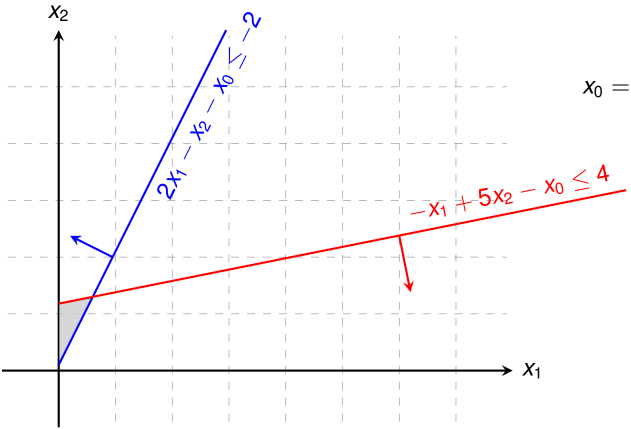
$$\begin{array}{llrrrcr} \text{maximise} & -x_0 & & & & & \\ \text{subject to} & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & x_0, x_1, x_2 & & & & & \geq & 0 \end{array}$$



$x_0 = 1.8$

Geometric Illustration

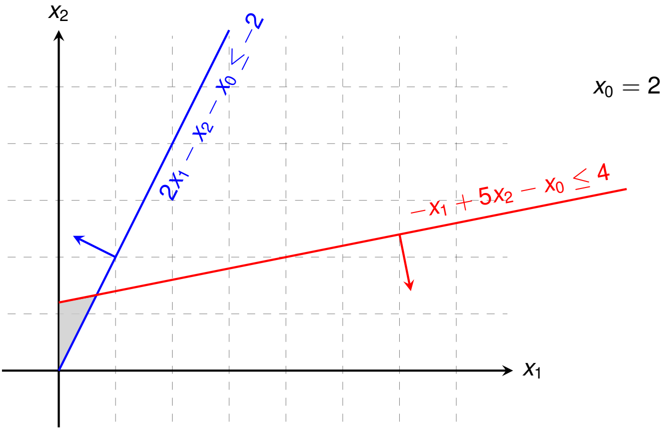
$$\begin{array}{llcrcrcl}
\text{maximise} & -x_0 & & & & & & \\
\text{subject to} & & & & & & & \\
& 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\
& -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\
& x_0, x_1, x_2 & & & & & \geq & 0
\end{array}$$



$x_0 = 1.9$

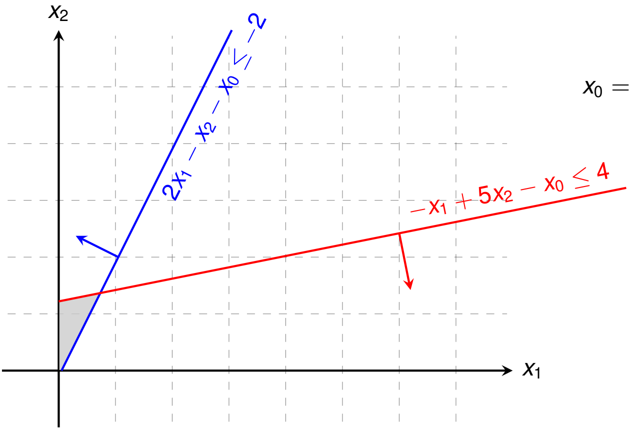
Geometric Illustration

$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 & & & & & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



Geometric Illustration

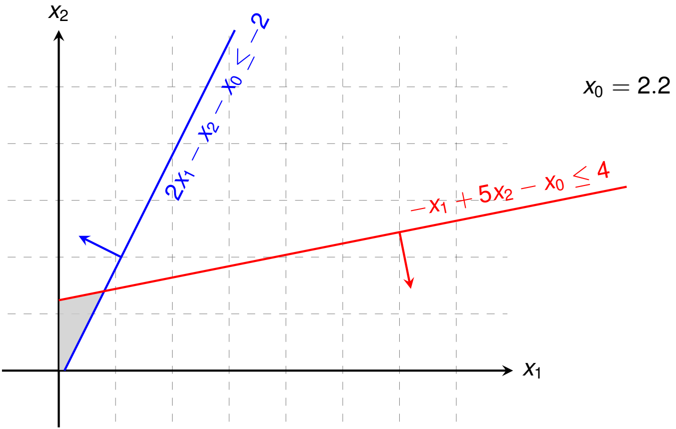
$$
\begin{array}{llcrcrcl}
\text{maximise} & -x_0 \\
\text{subject to} \\
& 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\
& -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\
& x_0, x_1, x_2 & & & & & \geq & 0
\end{array}
$$



$x_0 = 2.1$

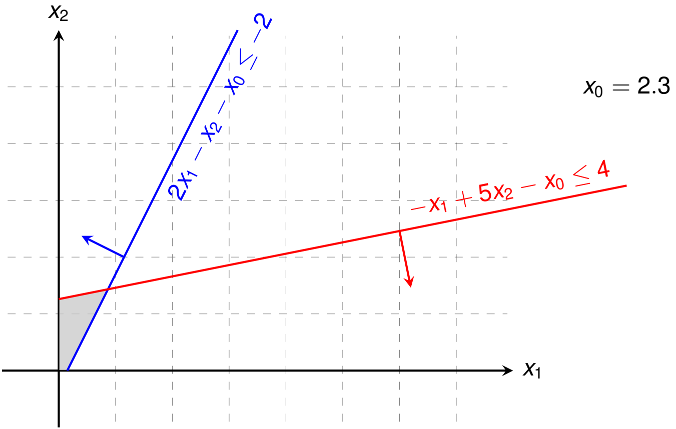
Geometric Illustration

$$\begin{array}{llllllll} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



Geometric Illustration

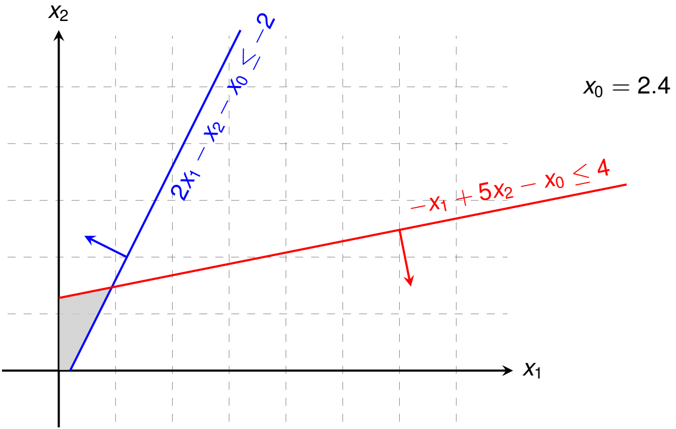
$$\begin{array}{llcccccccc} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



Geometric Illustration

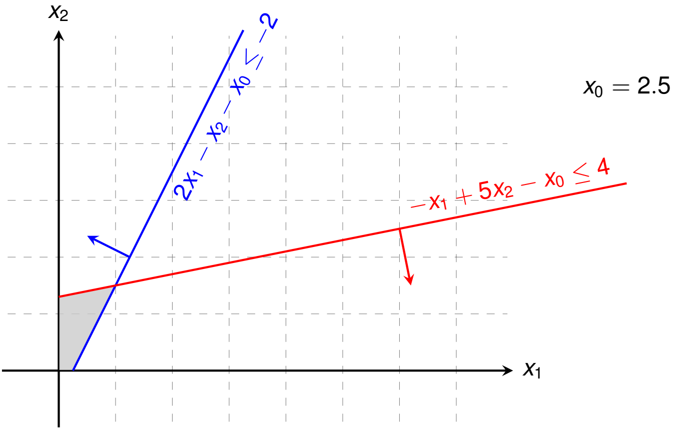
maximise $-x_0$
subject to

$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



Geometric Illustration

$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 & & & & & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & x_0, x_1, x_2 & & & & & \geq & 0 \end{array}$$

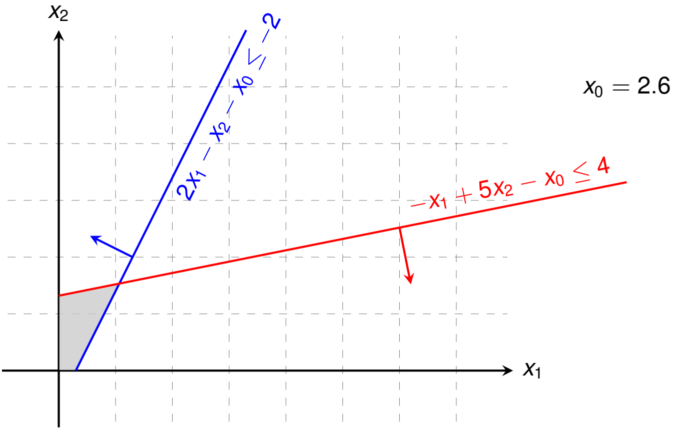


Geometric Illustration

maximise $-x_0$

subject to

$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$

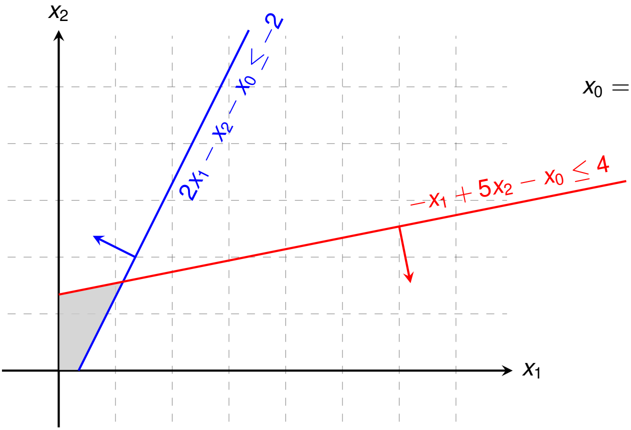


Geometric Illustration

maximise $-x_0$

subject to

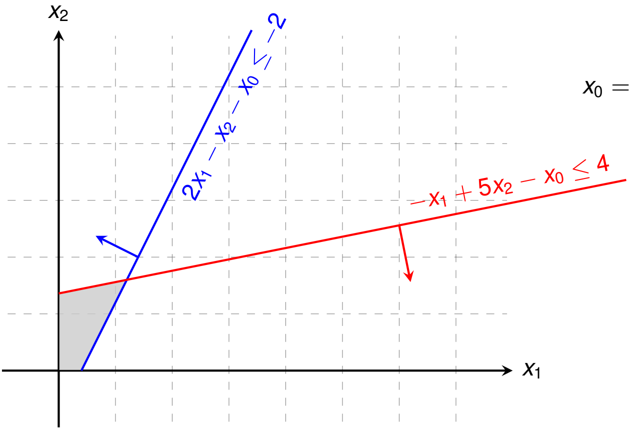
$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



$x_0 = 2.7$

Geometric Illustration

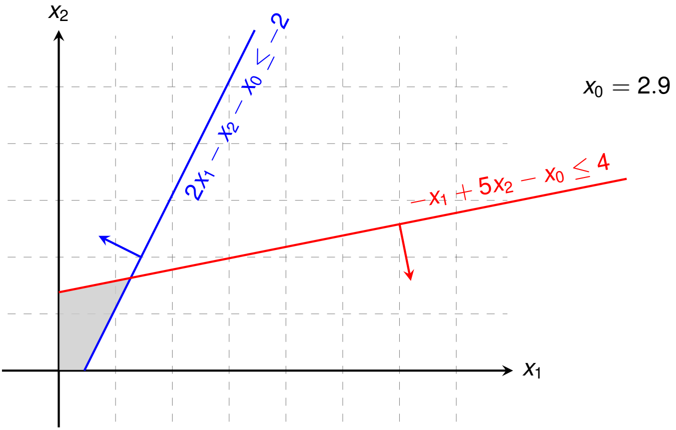
$$\begin{array}{ll} \text{maximise} & -x_0 \\ \text{subject to} & \\ & \begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & x_0, x_1, x_2 & & & & \geq & 0 \end{array} \end{array}$$



$x_0 = 2.8$

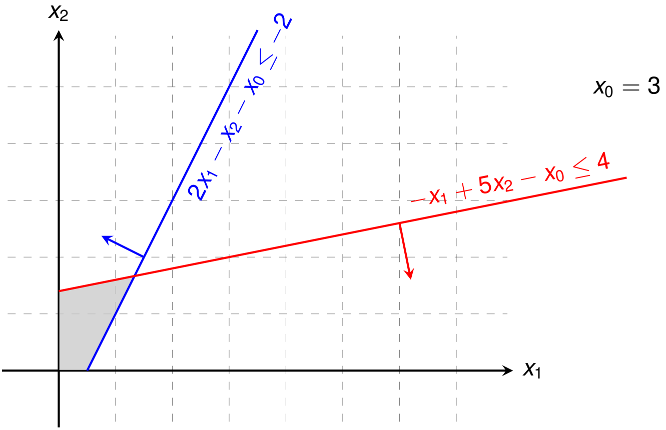
Geometric Illustration

$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



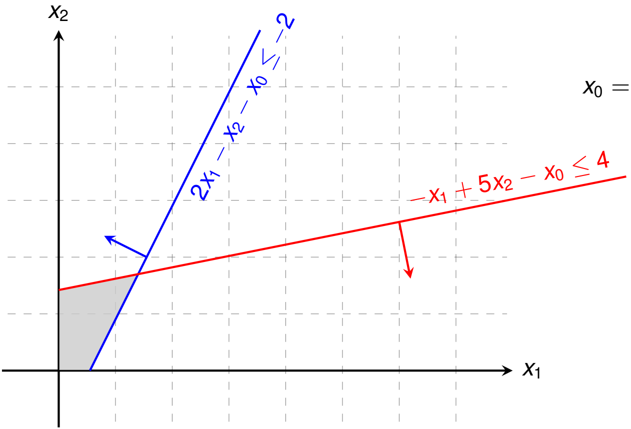
Geometric Illustration

$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 & & & & & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



Geometric Illustration

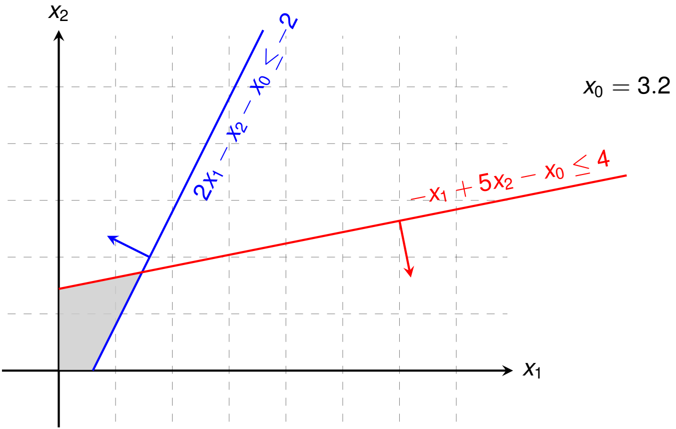
$$\begin{array}{llcccccc} \text{maximise} & -x_0 & & & & & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$



$x_0 = 3.1$

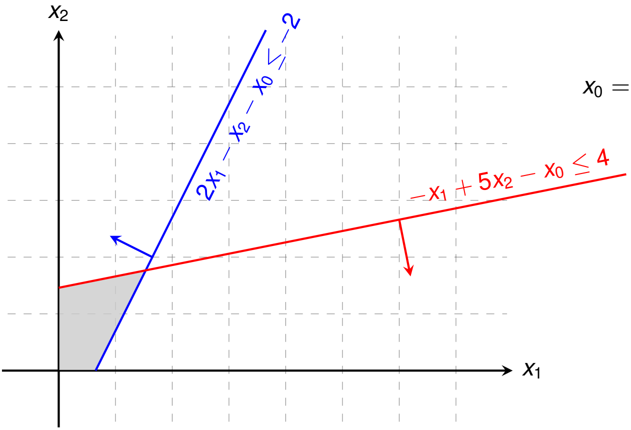
Geometric Illustration

$$\begin{array}{llcccccl} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



Geometric Illustration

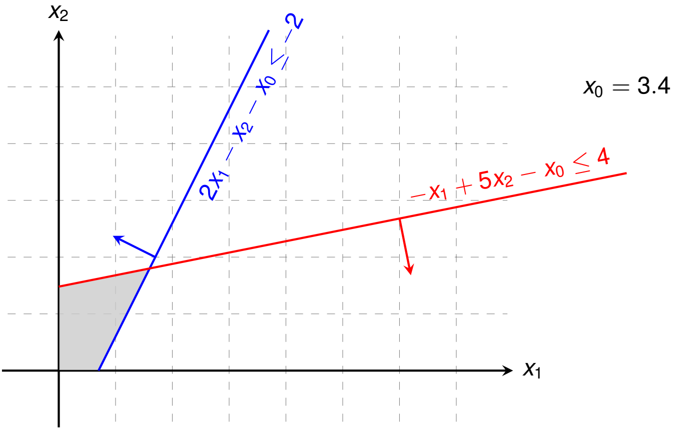
$$\begin{array}{llcrcrcl} \text{maximise} & -x_0 & & & & & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & x_0, x_1, x_2 & & & & & \geq & 0 \end{array}$$



$x_0 = 3.3$

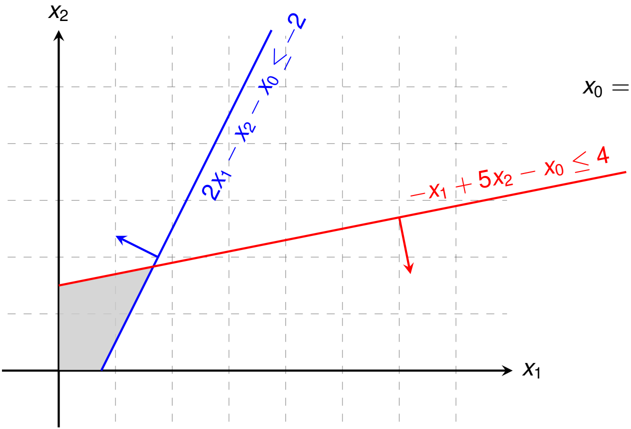
Geometric Illustration

$$\begin{array}{llcrcrcl} \text{maximise} & -x_0 & & & & & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & x_0, x_1, x_2 & & & & & \geq & 0 \end{array}$$



Geometric Illustration

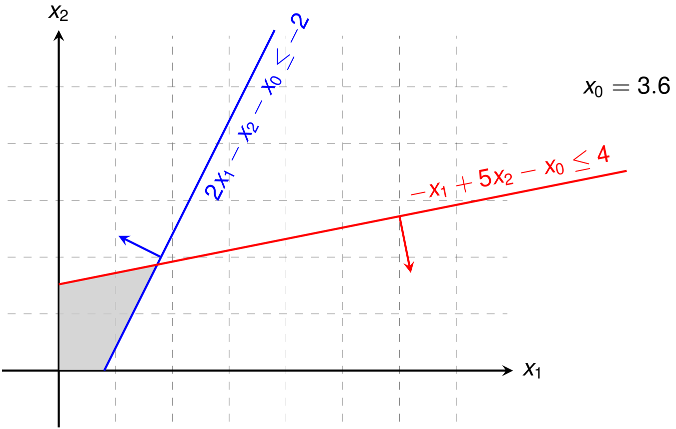
$$\begin{array}{llcccccl} \text{maximise} & -x_0 & & & & & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



$x_0 = 3.5$

Geometric Illustration

$$\begin{array}{ll} \text{maximise} & -x_0 \\ \text{subject to} & \\ & \begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array} \end{array}$$

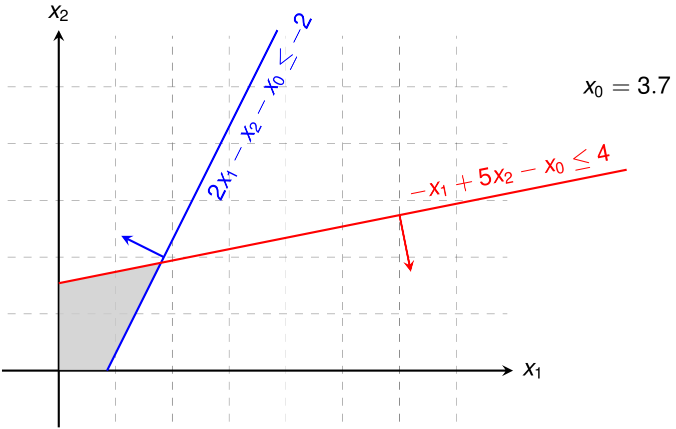


Geometric Illustration

maximise $-x_0$

subject to

$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & \geq & 0 \end{array}$$

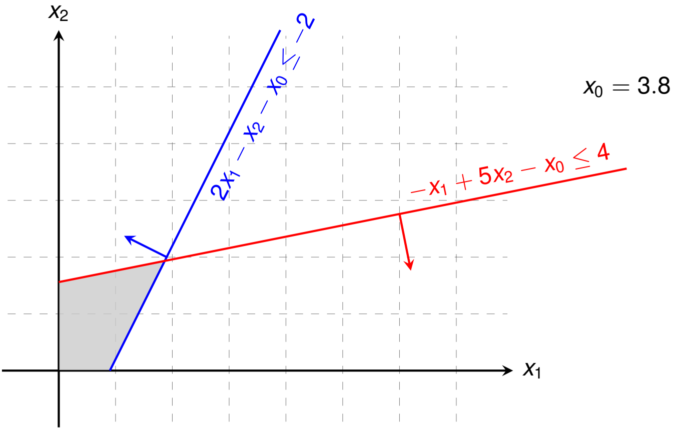


Geometric Illustration

maximise $\quad -x_0$

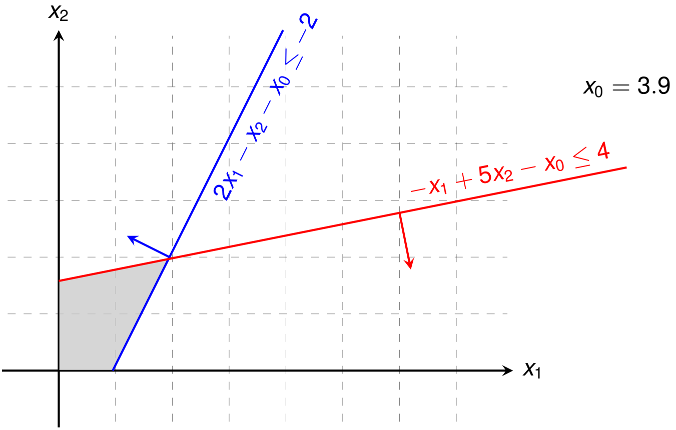
subject to

$$\begin{array}{rcrcrcr} 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



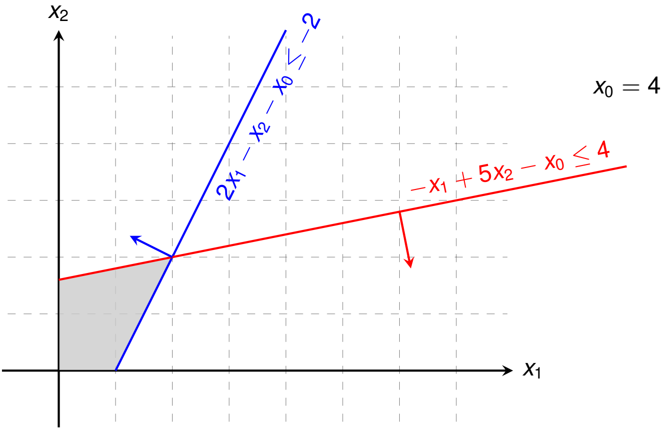
Geometric Illustration

$$\begin{array}{lrcrcrcr} \text{maximise} & -x_0 & & & & & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



Geometric Illustration

$$\begin{array}{llllllll} \text{maximise} & -x_0 \\ \text{subject to} \\ & 2x_1 & - & x_2 & - & x_0 & \leq & -2 \\ & -x_1 & + & 5x_2 & - & x_0 & \leq & 4 \\ & & x_0, x_1, x_2 & & & & \geq & 0 \end{array}$$



INITIALIZE-SIMPLEX(A, b, c)

let k be the index of the minimum b_i
if $b_k \geq 0$ // is the initial basic solution feasible?
    return $(\{1, 2, \ldots, n\}, \{n+1, n+2, \ldots, n+m\}, A, b, c, 0)$
form L_{aux} by adding $-x_0$ to the left-hand side of each constraint
    and setting the objective function to $-x_0$
let (N, B, A, b, c, ν) be the resulting slack form for L_{aux}
$l = n + k$
// L_{aux} has $n + 1$ nonbasic variables and m basic variables.
$(N, B, A, b, c, \nu) =$ PIVOT$(N, B, A, b, c, \nu, l, 0)$
// The basic solution is now feasible for L_{aux}.
iterate the **while** loop of lines 3–12 of SIMPLEX until an optimal solution
    to L_{aux} is found
if the optimal solution to L_{aux} sets $\bar{x}_0$ to 0
    if $\bar{x}_0$ is basic
        perform one (degenerate) pivot to make it nonbasic
    from the final slack form of L_{aux}, remove x_0 from the constraints and
        restore the original objective function of L, but replace each basic
        variable in this objective function by the right-hand side of its
        associated constraint
    return the modified final slack form
else return "infeasible"

Test solution with $N = \{1, 2, \ldots, n\}$, $B = \{n + 1, n + 2, \ldots, n + m\}$, $\overline{x}_i = b_i$ for $i \in B$, $\overline{x}_i = 0$ otherwise.

```
INITIALIZE-SIMPLEX(A, b, c)
let k be the index of the minimum b_i
if b_k ≥ 0                        // is the initial basic solution feasible?
    return ({1, 2, ..., n}, {n + 1, n + 2, ..., n + m}, A, b, c, 0)
form L_aux by adding −x_0 to the left-hand side of each constraint
    and setting the objective function to −x_0
let (N, B, A, b, c, ν) be the resulting slack form for L_aux
l = n + k
// L_aux has n + 1 nonbasic variables and m basic variables.
(N, B, A, b, c, ν) = PIVOT(N, B, A, b, c, ν, l, 0)
// The basic solution is now feasible for L_aux.
iterate the while loop of lines 3–12 of SIMPLEX until an optimal solution
    to L_aux is found
if the optimal solution to L_aux sets x̄_0 to 0
    if x̄_0 is basic
        perform one (degenerate) pivot to make it nonbasic
    from the final slack form of L_aux, remove x_0 from the constraints and
        restore the original objective function of L, but replace each basic
        variable in this objective function by the right-hand side of its
        associated constraint
    return the modified final slack form
else return "infeasible"
```

INITIALIZE-SIMPLEX

Test solution with $N = \{1, 2, \ldots, n\}$, $B = \{n+1, n+2, \ldots, n+m\}$, $\overline{x}_i = b_i$ for $i \in B$, $\overline{x}_i = 0$ otherwise.

INITIALIZE-SIMPLEX(A, b, c)

let k be the index of the minimum b_i
if $b_k \geq 0$ // is the initial basic solution feasible?
  return $(\{1, 2, \ldots, n\}, \{n+1, n+2, \ldots, n+m\}, A, b, c, 0)$
form L_{aux} by adding $-x_0$ to the left-hand side of each constraint
  and setting the objective function to $-x_0$
let (N, B, A, b, c, v) be the resulting slack form for L_{aux}
$l = n + k$
// L_{aux} has $n+1$ nonbasic variables and m basic variables.
$(N, B, A, b, c, v) = $ PIVOT$(N, B, A, b, c, v, l, 0)$
// The basic solution is now feasible for L_{aux}.
iterate the **while** loop of lines 3–12 of SIMPLEX until an optimal solution
  to L_{aux} is found
if the optimal solution to L_{aux} sets $\bar{x}_0$ to 0
  if $\bar{x}_0$ is basic
    perform one (degenerate) pivot to make it nonbasic
  from the final slack form of L_{aux}, remove x_0 from the constraints and
    restore the original objective function of L, but replace each basic
    variable in this objective function by the right-hand side of its
    associated constraint
  return the modified final slack form
else return "infeasible"

ℓ will be the leaving variable so that x_ℓ has the most negative value.

INITIALIZE-SIMPLEX

Test solution with $N = \{1, 2, \ldots, n\}$, $B = \{n+1, n+2, \ldots, n+m\}$, $\overline{x}_i = b_i$ for $i \in B$, $\overline{x}_i = 0$ otherwise.

INITIALIZE-SIMPLEX(A, b, c)

let k be the index of the minimum b_i
if $b_k \geq 0$ // is the initial basic solution feasible?
    return $(\{1, 2, \ldots, n\}, \{n+1, n+2, \ldots, n+m\}, A, b, c, 0)$
form L_{aux} by adding $-x_0$ to the left-hand side of each constraint
    and setting the objective function to $-x_0$
let (N, B, A, b, c, ν) be the resulting slack form for L_{aux}
$l = n + k$
// L_{aux} has $n + 1$ nonbasic variables and m basic variables.
$(N, B, A, b, c, \nu) = \text{PIVOT}(N, B, A, b, c, \nu, l, 0)$
// The basic solution is now feasible for L_{aux}.
iterate the **while** loop of lines 3–12 of SIMPLEX until an optimal solution
    to L_{aux} is found
if the optimal solution to L_{aux} sets $\bar{x}_0$ to 0
    if $\bar{x}_0$ is basic
        perform one (degenerate) pivot to make it nonbasic
    from the final slack form of L_{aux}, remove x_0 from the constraints and
        restore the original objective function of L, but replace each basic
        variable in this objective function by the right-hand side of its
        associated constraint
    return the modified final slack form
else return "infeasible"

ℓ will be the leaving variable so that x_ℓ has the most negative value.

Pivot step with x_ℓ leaving and x_0 entering.

Test solution with $N = \{1, 2, \ldots, n\}$, $B = \{n+1, n+2, \ldots, n+m\}$, $\overline{x}_i = b_i$ for $i \in B$, $\overline{x}_i = 0$ otherwise.

INITIALIZE-SIMPLEX(A, b, c)

let k be the index of the minimum b_i
if $b_k \geq 0$ // is the initial basic solution feasible?
    return $(\{1, 2, \ldots, n\}, \{n+1, n+2, \ldots, n+m\}, A, b, c, 0)$
form L_{aux} by adding $-x_0$ to the left-hand side of each constraint
    and setting the objective function to $-x_0$
let (N, B, A, b, c, ν) be the resulting slack form for L_{aux}
$l = n + k$
// L_{aux} has $n + 1$ nonbasic variables and m basic variables.
$(N, B, A, b, c, \nu) = \text{PIVOT}(N, B, A, b, c, \nu, l, 0)$
// The basic solution is now feasible for L_{aux}.
iterate the **while** loop of lines 3–12 of SIMPLEX until an optimal solution
    to L_{aux} is found
if the optimal solution to L_{aux} sets $\bar{x}_0$ to 0
    if $\bar{x}_0$ is basic
        perform one (degenerate) pivot to make it nonbasic
    from the final slack form of L_{aux}, remove x_0 from the constraints and
        restore the original objective function of L, but replace each basic
        variable in this objective function by the right-hand side of its
        associated constraint
    return the modified final slack form
else return "infeasible"

ℓ will be the leaving variable so that x_ℓ has the most negative value.

Pivot step with x_ℓ leaving and x_0 entering.

This pivot step does not change the value of any variable.

Example of INITIALIZE-SIMPLEX (1/3)

$$
\begin{array}{lrcrcr}
\text{maximise} & 2x_1 & - & x_2 & & \\
\text{subject to} & & & & & \\
& 2x_1 & - & x_2 & \leq & 2 \\
& x_1 & - & 5x_2 & \leq & -4 \\
& & x_1, x_2 & & \geq & 0
\end{array}
$$

Example of INITIALIZE-SIMPLEX (1/3)

$$
\begin{array}{llcrcr}
\text{maximise} & 2x_1 & - & x_2 & & \\
\text{subject to} & & & & & \\
 & 2x_1 & - & x_2 & \leq & 2 \\
 & x_1 & - & 5x_2 & \leq & -4 \\
 & & x_1, x_2 & & \geq & 0
\end{array}
$$

↓ Formulating the auxiliary linear program

Example of INITIALIZE-SIMPLEX (1/3)

$$\begin{array}{lrcrcr} \text{maximise} & 2x_1 & - & x_2 & & \\ \text{subject to} & & & & & \\ & 2x_1 & - & x_2 & \leq & 2 \\ & x_1 & - & 5x_2 & \leq & -4 \\ & & x_1, x_2 & & \geq & 0 \end{array}$$

↓ Formulating the auxiliary linear program

$$\begin{array}{lrcrcrcr} \text{maximise} & & & & - & x_0 & & \\ \text{subject to} & & & & & & & \\ & 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\ & x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\ & & x_1, x_2, x_0 & & & & \geq & 0 \end{array}$$

Example of INITIALIZE-SIMPLEX (1/3)

maximise $2x_1 - x_2$

subject to

$$
\begin{array}{rcrcr}
2x_1 & - & x_2 & \leq & 2 \\
x_1 & - & 5x_2 & \leq & -4 \\
 & x_1, x_2 & & \geq & 0
\end{array}
$$

↓ Formulating the auxiliary linear program

maximise $-x_0$

subject to

$$
\begin{array}{rcrcrcr}
2x_1 & - & x_2 & - & x_0 & \leq & 2 \\
x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\
 & x_1, x_2, x_0 & & & & \geq & 0
\end{array}
$$

↓ Converting into slack form

Example of Initialize-Simplex (1/3)

$$\begin{array}{lrcrcr}
\text{maximise} & 2x_1 & - & x_2 & & \\
\text{subject to} & & & & & \\
& 2x_1 & - & x_2 & \leq & 2 \\
& x_1 & - & 5x_2 & \leq & -4 \\
& & x_1, x_2 & & \geq & 0
\end{array}$$

Formulating the auxiliary linear program

$$\begin{array}{lrcrcrcr}
\text{maximise} & & & & - & x_0 & & \\
\text{subject to} & & & & & & & \\
& 2x_1 & - & x_2 & - & x_0 & \leq & 2 \\
& x_1 & - & 5x_2 & - & x_0 & \leq & -4 \\
& & x_1, x_2, x_0 & & & & \geq & 0
\end{array}$$

Converting into slack form

$$\begin{array}{rcrcrcrcr}
z & = & & & & & & - & x_0 \\
x_3 & = & 2 & - & 2x_1 & + & x_2 & + & x_0 \\
x_4 & = & -4 & - & x_1 & + & 5x_2 & + & x_0
\end{array}$$

Example of INITIALIZE-SIMPLEX (1/3)

$$\begin{array}{ll} \text{maximise} & 2x_1 - x_2 \\ \text{subject to} & \\ & 2x_1 - x_2 \leq 2 \\ & x_1 - 5x_2 \leq -4 \\ & x_1, x_2 \geq 0 \end{array}$$

Formulating the auxiliary linear program

$$\begin{array}{ll} \text{maximise} & -x_0 \\ \text{subject to} & \\ & 2x_1 - x_2 - x_0 \leq 2 \\ & x_1 - 5x_2 - x_0 \leq -4 \\ & x_1, x_2, x_0 \geq 0 \end{array}$$

Basic solution $(0, 0, 0, 2, -4)$ not feasible!

Converting into slack form

$$\begin{aligned} z &= -x_0 \\ x_3 &= 2 - 2x_1 + x_2 + x_0 \\ x_4 &= -4 - x_1 + 5x_2 + x_0 \end{aligned}$$

Example of INITIALIZE-SIMPLEX (2/3)

$$
\begin{array}{rcrcrcrcr}
z & = & & & & & & - & x_0 \\
x_3 & = & 2 & - & 2x_1 & + & x_2 & + & x_0 \\
x_4 & = & -4 & - & x_1 & + & 5x_2 & + & x_0
\end{array}
$$

Example of INITIALIZE-SIMPLEX (2/3)

$$\begin{array}{rcrcrcrcr} z & = & & & & & & - & x_0 \\ x_3 & = & 2 & - & 2x_1 & + & x_2 & + & x_0 \\ x_4 & = & -4 & - & x_1 & + & 5x_2 & + & x_0 \end{array}$$

↓ Pivot with x_0 entering and x_4 leaving

Example of INITIALIZE-SIMPLEX (2/3)

$$\begin{array}{rcrcrcrcr} z & = & & & & & & - & x_0 \\ x_3 & = & 2 & - & 2x_1 & + & x_2 & + & x_0 \\ x_4 & = & -4 & - & x_1 & + & 5x_2 & + & x_0 \end{array}$$

Pivot with x_0 entering and x_4 leaving

$$\begin{array}{rcrcrcrcr} z & = & -4 & - & x_1 & + & 5x_2 & - & x_4 \\ x_0 & = & 4 & + & x_1 & - & 5x_2 & + & x_4 \\ x_3 & = & 6 & - & x_1 & - & 4x_2 & + & x_4 \end{array}$$

Example of INITIALIZE-SIMPLEX (2/3)

$$
\begin{aligned}
z &= & & & & & & -x_0 \\
x_3 &= 2 & &- 2x_1 & &+ x_2 & &+ x_0 \\
x_4 &= -4 & &- x_1 & &+ 5x_2 & &+ x_0
\end{aligned}
$$

Pivot with x_0 entering and x_4 leaving

$$
\begin{aligned}
z &= -4 & &- x_1 & &+ 5x_2 & &- x_4 \\
x_0 &= 4 & &+ x_1 & &- 5x_2 & &+ x_4 \\
x_3 &= 6 & &- x_1 & &- 4x_2 & &+ x_4
\end{aligned}
$$

Basic solution $(4, 0, 0, 6, 0)$ is feasible!

Example of INITIALIZE-SIMPLEX (2/3)

$$\begin{aligned} z &= & & & & & & - x_0 \\ x_3 &= 2 & - & 2x_1 & + & x_2 & + & x_0 \\ x_4 &= -4 & - & x_1 & + & 5x_2 & + & x_0 \end{aligned}$$

Pivot with x_0 entering and x_4 leaving

$$\begin{aligned} z &= -4 & - & x_1 & + & 5x_2 & - & x_4 \\ x_0 &= 4 & + & x_1 & - & 5x_2 & + & x_4 \\ x_3 &= 6 & - & x_1 & - & 4x_2 & + & x_4 \end{aligned}$$

Basic solution $(4, 0, 0, 6, 0)$ is feasible!

Pivot with x_2 entering and x_0 leaving

Example of INITIALIZE-SIMPLEX (2/3)

$$\begin{aligned} z &= && && && - x_0 \\ x_3 &= 2 &- 2x_1 &+ x_2 &+ x_0 \\ x_4 &= -4 &- x_1 &+ 5x_2 &+ x_0 \end{aligned}$$

Pivot with x_0 entering and x_4 leaving

$$\begin{aligned} z &= -4 &- x_1 &+ 5x_2 &- x_4 \\ x_0 &= 4 &+ x_1 &- 5x_2 &+ x_4 \\ x_3 &= 6 &- x_1 &- 4x_2 &+ x_4 \end{aligned}$$

Basic solution $(4, 0, 0, 6, 0)$ is feasible!

Pivot with x_2 entering and x_0 leaving

$$\begin{aligned} z &= && - x_0 \\ x_2 &= \frac{4}{5} &- \frac{x_0}{5} &+ \frac{x_1}{5} &+ \frac{x_4}{5} \\ x_3 &= \frac{14}{5} &+ \frac{4x_0}{5} &- \frac{9x_1}{5} &+ \frac{x_4}{5} \end{aligned}$$

Example of INITIALIZE-SIMPLEX (2/3)

$$\begin{aligned} z &= -x_0 \\ x_3 &= 2 - 2x_1 + x_2 + x_0 \\ x_4 &= -4 - x_1 + 5x_2 + x_0 \end{aligned}$$

Pivot with x_0 entering and x_4 leaving

$$\begin{aligned} z &= -4 - x_1 + 5x_2 - x_4 \\ x_0 &= 4 + x_1 - 5x_2 + x_4 \\ x_3 &= 6 - x_1 - 4x_2 + x_4 \end{aligned}$$

Basic solution $(4, 0, 0, 6, 0)$ is feasible!

Pivot with x_2 entering and x_0 leaving

$$\begin{aligned} z &= -x_0 \\ x_2 &= \frac{4}{5} - \frac{x_0}{5} + \frac{x_1}{5} + \frac{x_4}{5} \\ x_3 &= \frac{14}{5} + \frac{4x_0}{5} - \frac{9x_1}{5} + \frac{x_4}{5} \end{aligned}$$

Optimal solution has $x_0 = 0$, hence the initial problem was feasible!

Example of INITIALIZE-SIMPLEX (3/3)

$$
\begin{aligned}
z &= & & - & x_0 & & & & \\
x_2 &= & \frac{4}{5} & - & \frac{x_0}{5} & + & \frac{x_1}{5} & + & \frac{x_4}{5} \\
x_3 &= & \frac{14}{5} & + & \frac{4x_0}{5} & - & \frac{9x_1}{5} & + & \frac{x_4}{5}
\end{aligned}
$$

Example of INITIALIZE-SIMPLEX (3/3)

$$
\begin{aligned}
z &= & & - & x_0 & & & & \\
x_2 &= & \frac{4}{5} & - & \frac{x_0}{5} & + & \frac{x_1}{5} & + & \frac{x_4}{5} \\
x_3 &= & \frac{14}{5} & + & \frac{4x_0}{5} & - & \frac{9x_1}{5} & + & \frac{x_4}{5}
\end{aligned}
$$

Set $x_0 = 0$ and express objective function by non-basic variables

Example of INITIALIZE-SIMPLEX (3/3)

$$\begin{aligned} z &= & & - & x_0 \\ x_2 &= \frac{4}{5} & - & \frac{x_0}{5} & + & \frac{x_1}{5} & + & \frac{x_4}{5} \\ x_3 &= \frac{14}{5} & + & \frac{4x_0}{5} & - & \frac{9x_1}{5} & + & \frac{x_4}{5} \end{aligned}$$

$2x_1 - x_2 = 2x_1 - (\frac{4}{5} - \frac{x_0}{5} + \frac{x_1}{5} + \frac{x_4}{5})$

Set $x_0 = 0$ and express objective function by non-basic variables

$$\begin{aligned} z &= -\frac{4}{5} & + & \frac{9x_1}{5} & - & \frac{x_4}{5} \\ x_2 &= \frac{4}{5} & + & \frac{x_1}{5} & + & \frac{x_4}{5} \\ x_3 &= \frac{14}{5} & - & \frac{9x_1}{5} & + & \frac{x_4}{5} \end{aligned}$$

Example of INITIALIZE-SIMPLEX (3/3)

$$
\begin{aligned}
z &= & & - & x_0 & & & & \\
x_2 &= \frac{4}{5} & & - & \frac{x_0}{5} & + & \frac{x_1}{5} & + & \frac{x_4}{5} \\
x_3 &= \frac{14}{5} & & + & \frac{4x_0}{5} & - & \frac{9x_1}{5} & + & \frac{x_4}{5}
\end{aligned}
$$

$2x_1 - x_2 = 2x_1 - (\frac{4}{5} - \frac{x_0}{5} + \frac{x_1}{5} + \frac{x_4}{5})$

Set $x_0 = 0$ and express objective function by non-basic variables

$$
\begin{aligned}
z &= -\frac{4}{5} & + & \frac{9x_1}{5} & - & \frac{x_4}{5} \\
x_2 &= \frac{4}{5} & + & \frac{x_1}{5} & + & \frac{x_4}{5} \\
x_3 &= \frac{14}{5} & - & \frac{9x_1}{5} & + & \frac{x_4}{5}
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Basic solution $(0, \frac{4}{5}, \frac{14}{5}, 0)$, which is feasible!

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Basic solution $(0, \frac{4}{5}, \frac{14}{5}, 0)$, which is feasible!

Lemma 29.12

If a linear program L has no feasible solution, then INITIALIZE-SIMPLEX returns "infeasible". Otherwise, it returns a valid slack form for which the basic solution is feasible.

Fundamental Theorem of Linear Programming

Theorem 29.13 (Fundamental Theorem of Linear Programming)

For any linear program L, given in standard form, either:

1. L is infeasible $\Rightarrow$ SIMPLEX returns "infeasible".
2. L is unbounded $\Rightarrow$ SIMPLEX returns "unbounded".
3. L has an optimal solution with a finite objective value
   $\Rightarrow$ SIMPLEX returns an optimal solution with a finite objective value.

Small Technicality: need to equip SIMPLEX with an "anti-cycling strategy" (see extra slides)

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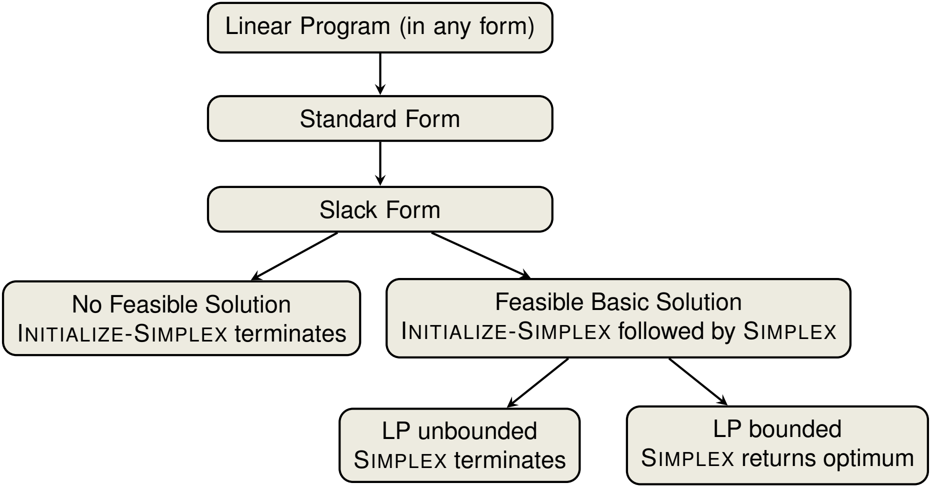
Proof requires the concept of duality, which is not covered in this course (for details see CLRS3, Chapter 29.4)

Workflow for Solving Linear Programs



Linear Programming and Simplex: Summary and Outlook

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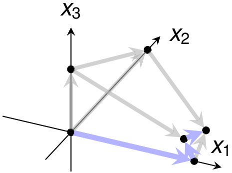
Simplex Algorithm

- In practice: usually terminates in polynomial time, i.e., $O(m+n)$



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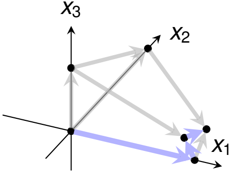

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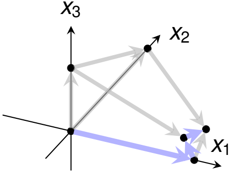

Research Problem: Is there a pivoting rule which makes SIMPLEX a polynomial-time algorithm?

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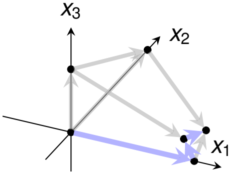

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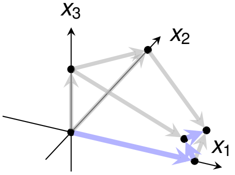
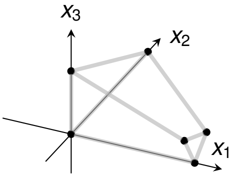


Polynomial-Time Algorithms

- Interior-Point Methods: traverses the interior of the feasible set of solutions (not just vertices!)



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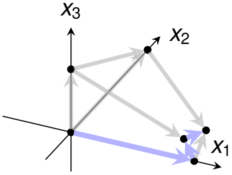

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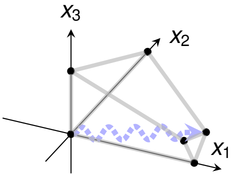

Outlook: Alternatives to Worst Case Analysis (non-examinable)

1.2 Famous Failures and the Need for Alternatives

For many problems a bit beyond the scope of an undergraduate course, the downside of worst-case analysis rears its ugly head. This section reviews four famous examples in which worst-case analysis gives misleading or useless advice about how to solve a problem. These examples motivate the alternatives to worst-case analysis that are surveyed in Section 1.4 and described in detail in later chapters of the book.

1.2.1 The Simplex Method for Linear Programming

Perhaps the most famous failure of worst-case analysis concerns linear programming, the problem of optimizing a linear function subject to linear constraints (Figure 1.1). Dantzig proposed in the 1940s an algorithm for solving linear programs called the *simplex method*. The simplex method solves linear programs using greedy local

Source: “Beyond the Worst-Case Analysis of Algorithms” by Tim Roughgarden, 2020

Outline

Termination

Degeneracy: One iteration of SIMPLEX leaves the objective value unchanged.

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$$\begin{aligned} z &= x_1 + x_2 + x_3 \\ x_4 &= 8 - x_1 - x_2 \\ x_5 &= x_2 - x_3 \end{aligned}$$

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$$\begin{aligned} z &= && x_1 + x_2 + x_3 \\ x_4 &= 8 &-& x_1 - x_2 \\ x_5 &= && \phantom{x_1 - {}} x_2 - x_3 \end{aligned}$$

Pivot with x_1 entering and x_4 leaving

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\end{aligned}
$$

Pivot with x_3 entering and x_5 leaving

Cycling: If additionally slack form at two iterations are identical, SIMPLEX fails to terminate!

$$
\begin{aligned}
z &= 8 + x_2 - x_4 - x_5 \\
x_1 &= 8 - x_2 - x_4 \\
x_3 &= x_2 - x_5
\end{aligned}
$$

Exercise: Execute one more step of the Simplex Algorithm on the tableau from the previous slide.

Termination and Running Time

Cycling: SIMPLEX may fail to terminate.

Termination and Running Time

It is theoretically possible, but very rare in practice.

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Replace each b_i by $\widehat{b_i} = b_i + \epsilon_i$, where $\epsilon_i \gg \epsilon_{i+1}$ are all small.

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Every set B of basic variables uniquely determines a slack form, and there are at most $\binom{n+m}{m}$ unique slack forms.

Randomised Algorithms

Lecture 8: Solving a TSP Instance using Linear Programming

Thomas Sauerwald (tms41@cam.ac.uk)

Lent 2024

UNIVERSITY OF CAMBRIDGE

Outline

The Traveling Salesman Problem (TSP)

Given a set of cities along with the cost of travel between them, find the cheapest route visiting all cities and returning to your starting point.

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- Given: A complete undirected graph $G = (V, E)$ with nonnegative integer cost $c(u, v)$ for each edge $(u, v) \in E$

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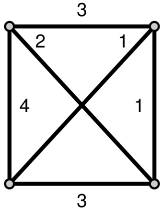

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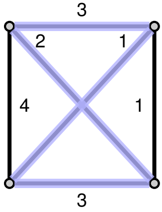

$3 + 2 + 1 + 3 = 9$

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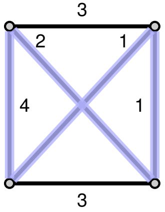

$2 + 4 + 1 + 1 = 8$

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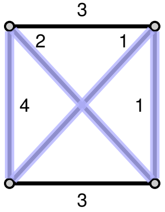

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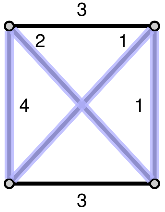

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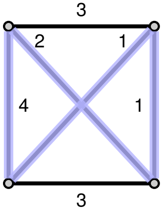

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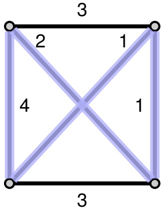

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$$\forall u, v, w \in V: \qquad c(u, w) \leq c(u, v) + c(v, w).$$

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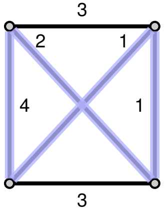

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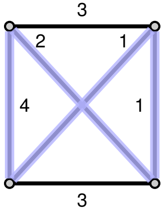

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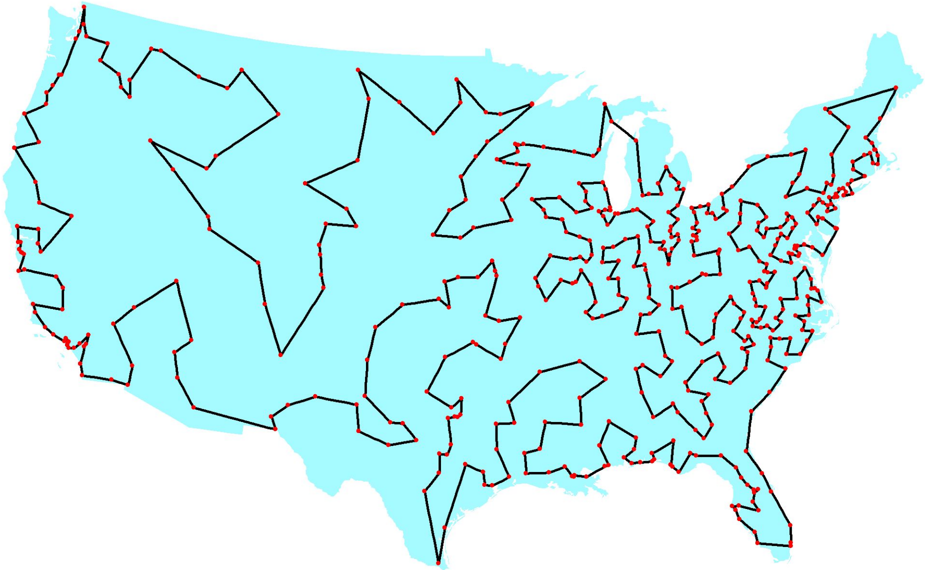
- Euclidean TSP: cities are points in the Euclidean space, costs are equal to their (rounded) Euclidean distance

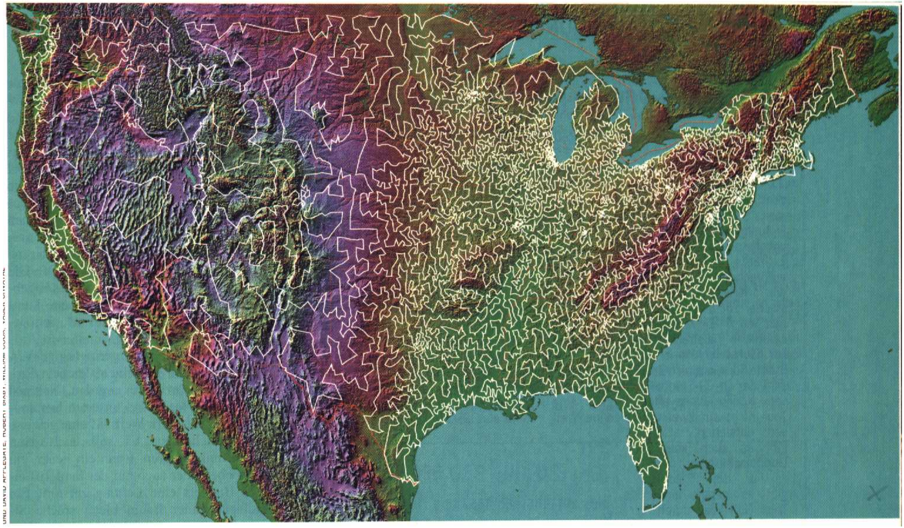
Outline

33 city contest (1964)

532 cities (1987 [Padberg, Rinaldi])



13,509 cities (1999 [Applegate, Bixby, Chavatal, Cook])



SOLUTION OF A LARGE-SCALE TRAVELING-SALESMAN PROBLEM*

G. DANTZIG, R. FULKERSON, AND S. JOHNSON

The Rand Corporation, Santa Monica, California

(Received August 9, 1954)

It is shown that a certain tour of 49 cities, one in each of the 48 states and Washington, D. C., has the shortest road distance.

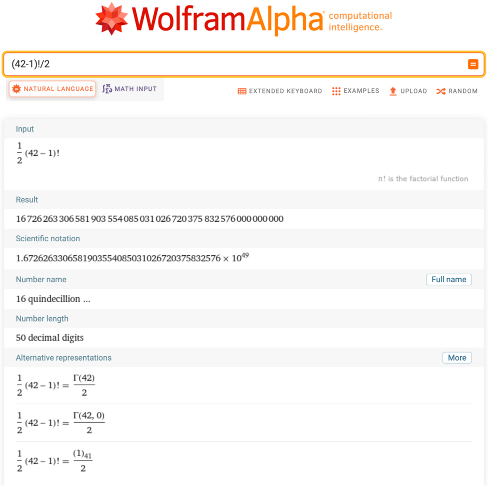
THE TRAVELING-SALESMAN PROBLEM might be described as follows: Find the shortest route (tour) for a salesman starting from a given city, visiting each of a specified group of cities, and then returning to the original point of departure. More generally, given an n by n symmetric matrix $D=(d_{IJ})$, where d_{IJ} represents the 'distance' from I to J, arrange the points in a cyclic order in such a way that the sum of the d_{IJ} between consecutive points is minimal. Since there are only a finite number of possibilities (at most $\frac{1}{2}(n-1)!$) to consider, the problem is to devise a method of picking out the optimal arrangement which is reasonably efficient for fairly large values of n. Although algorithms have been devised for problems of similar nature, e.g., the optimal assignment problem,[3,7,8] little is known about the traveling-salesman problem. We do not claim that this note alters the situation very much; what we shall do is outline a way of approaching the problem that sometimes, at least, enables one to find an optimal path and prove it so. In particular, it will be shown that a certain arrangement of 49 cities, one in each of the 48 states and Washington, D. C., is best, the d_{IJ} used representing road distances as taken from an atlas.

The 42 (49) Cities

1. Manchester, N. H.
2. Montpelier, Vt.
3. Detroit, Mich.
4. Cleveland, Ohio
5. Charleston, W. Va.
6. Louisville, Ky.
7. Indianapolis, Ind.
8. Chicago, Ill.
9. Milwaukee, Wis.
10. Minneapolis, Minn.
11. Pierre, S. D.
12. Bismarck, N. D.
13. Helena, Mont.
14. Seattle, Wash.
15. Portland, Ore.
16. Boise, Idaho
17. Salt Lake City, Utah
18. Carson City, Nev.
19. Los Angeles, Calif.
20. Phoenix, Ariz.
21. Santa Fe, N. M.
22. Denver, Colo.
23. Cheyenne, Wyo.
24. Omaha, Neb.
25. Des Moines, Iowa
26. Kansas City, Mo.
27. Topeka, Kans.
28. Oklahoma City, Okla.
29. Dallas, Tex.
30. Little Rock, Ark.
31. Memphis, Tenn.
32. Jackson, Miss.
33. New Orleans, La.
34. Birmingham, Ala.
35. Atlanta, Ga.
36. Jacksonville, Fla.
37. Columbia, S. C.
38. Raleigh, N. C.
39. Richmond, Va.
40. Washington, D. C.
41. Boston, Mass.
42. Portland, Me.

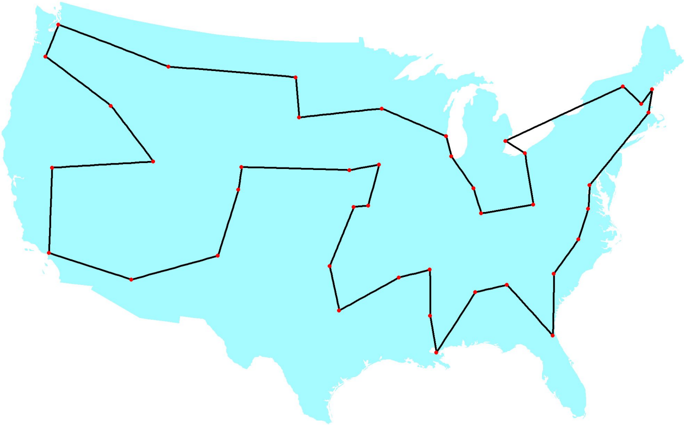
A. Baltimore, Md.
B. Wilmington, Del.
C. Philadelphia, Penn.
D. Newark, N. J.
E. New York, N. Y.
F. Hartford, Conn.
G. Providence, R. I.

Combinatorial Explosion



Solution of this TSP problem

Dantzig, Fulkerson and Johnson found an optimal tour through 42 cities.



`http://www.math.uwaterloo.ca/tsp/history/img/dantzig_big.html`

Road Distances

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11	103	107	62	67	72	63	57	46	41	23																															
12	108	117	66	71	77	68	61	51	46	26	11																														
13	145	149	104	108	114	106	99	88	84	63	49	40																													
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17	142	146	101	104	111	97	91	85	86	75	51	59	29	53	48	21																									
18	174	178	133	138	143	129	123	117	118	107	83	84	54	46	35	26	31																								
19	185	186	142	143	140	130	126	124	128	118	93	101	72	69	58	58	43	26																							
20	164	165	120	123	124	106	106	105	110	104	86	97	71	93	82	62	42	45	22																						
21	137	139	94	96	94	80	78	77	84	77	56	64	65	90	87	58	36	68	50	30																					
22	117	122	77	80	83	68	62	60	61	50	34	42	49	82	77	60	30	62	70	49	21																				
23	114	118	73	78	84	69	63	57	59	48	28	36	43	77	72	45	27	59	69	55	27	5																			
24	85	89	44	48	53	41	34	28	29	22	23	35	69	105	102	74	56	88	99	81	54	32	29																		
25	77	80	36	40	46	34	27	19	21	14	29	40	77	114	111	84	64	96	107	87	60	40	37	8																	
26	87	89	44	46	46	30	28	29	32	27	36	47	78	116	112	84	66	98	95	75	47	36	39	12	11																
27	91	93	48	50	48	34	32	33	36	30	34	45	77	115	110	83	63	97	91	72	44	32	36	9	15	3															
28	105	106	62	63	64	47	46	49	54	48	46	59	85	119	115	88	66	98	79	59	31	36	42	28	33	21	20														
29	111	113	69	71	66	51	53	56	61	57	59	71	96	130	126	98	75	98	85	62	38	47	53	39	42	29	30	12													
30	91	92	50	51	46	30	34	38	43	49	60	71	103	141	136	109	90	115	99	81	53	61	62	36	34	24	28	20	20												
31	83	85	42	43	38	22	26	32	36	51	63	75	106	142	140	112	93	126	108	88	60	64	66	39	36	27	31	28	28	8											
32	89	91	55	55	50	34	39	44	49	63	76	87	120	155	150	123	100	123	109	86	62	71	78	52	49	39	44	35	24	15	12										
33	95	97	64	63	56	42	49	56	60	75	86	97	126	160	155	128	104	128	113	90	67	76	82	62	59	49	53	40	29	25	23	11									
34	74	81	44	43	35	23	30	39	44	62	78	89	121	159	155	127	108	136	124	101	75	79	81	54	50	42	46	43	39	23	14	14	21								
35	67	69	42	41	31	25	32	41	46	64	83	90	130	164	160	133	114	146	134	111	85	84	86	59	52	47	51	53	49	32	24	24	30	9							
36	74	76	61	60	42	44	51	60	66	83	102	110	147	185	179	155	133	159	146	122	98	105	107	79	71	66	70	70	60	48	40	36	33	25	18						
37	57	59	46	41	25	30	36	47	52	71	93	98	136	172	172	148	126	158	147	124	121	97	99	71	65	59	63	67	62	46	38	37	43	23	13	17					
38	45	46	41	34	20	34	38	48	53	73	96	99	137	176	178	151	131	163	159	135	108	102	103	73	67	64	69	75	72	54	46	49	54	34	24	29	12				
39	35	37	35	26	18	34	36	46	51	70	93	97	134	171	176	151	129	161	163	139	118	102	101	71	65	65	70	84	78	58	50	56	62	41	32	38	21	9			
40	29	33	30	21	18	35	33	40	45	65	87	91	117	166	171	144	125	157	156	139	113	95	97	67	60	62	67	79	82	62	53	59	66	45	38	45	27	15	6		
41	3	11	41	37	47	57	55	58	63	83	105	109	147	186	188	164	144	176	182	161	134	119	116	86	78	84	88	101	108	88	80	86	92	71	64	71	54	41	32	25	
42	5	12	55	41	53	64	61	61	66	84	111	113	150	186	192	166	147	180	188	167	140	124	119	90	87	90	94	107	114	77	86	92	98	80	74	77	60	48	38	32	6
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**

Road Distances

Hence this is an instance of the Metric TSP, but not Euclidean TSP.

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Modelling TSP as a Linear Program Relaxation

Idea: Indicator variable $x(i,j)$, $i > j$, which is one if the tour includes edge $\{i,j\}$ (in either direction)

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minimize $\sum_{i=1}^{42} \sum_{j=1}^{i-1} c(i,j)x(i,j)$

subject to

$$\sum_{j<i} x(i,j) + \sum_{j>i} x(j,i) = 2 \qquad \text{for each } 1 \leq i \leq 42$$

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  - Return best of these two solutions

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Bound-Step: If the best known integral solution so far is better than the solution of a LP, no need to explore branch further!

Outline

Introduction

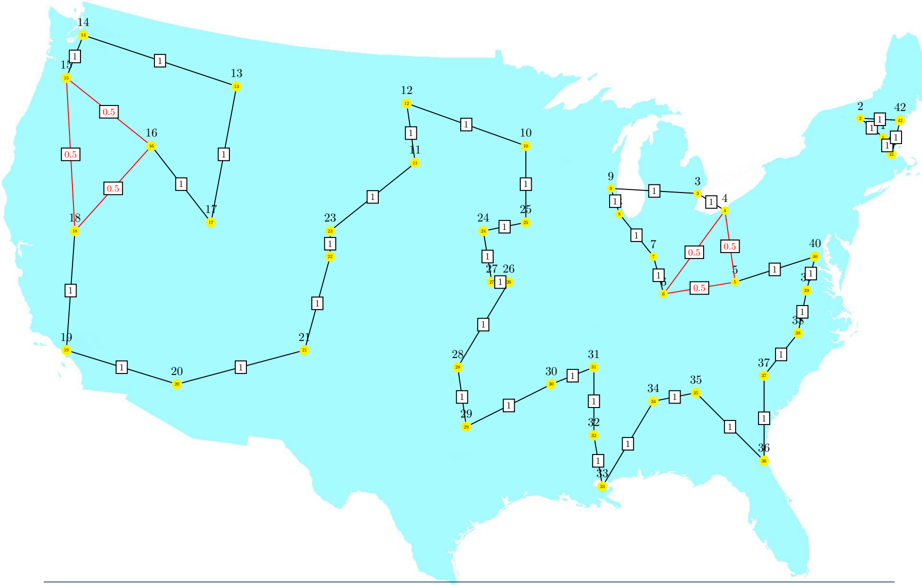
Examples of TSP Instances

Demonstration

In the following, there are a few different runs of the demo.

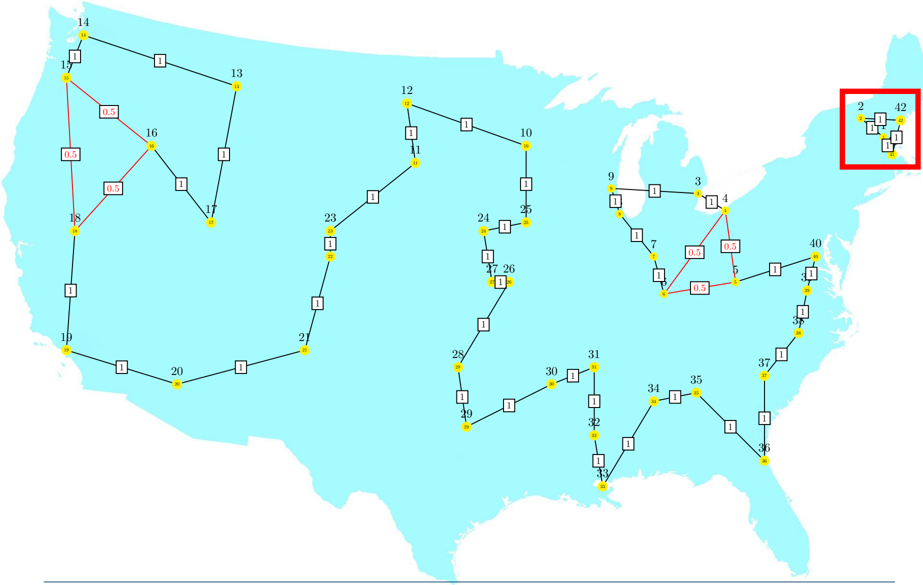
Iteration 1:

Objective value: -641.000000, 861 variables, 945 constraints, 1809 iterations



Iteration 1: Eliminate Subtour $1, 2, 41, 42$

Objective value: -641.000000, 861 variables, 945 constraints, 1809 iterations



Iteration 1: Eliminate Subtour $1, 2, 41, 42$

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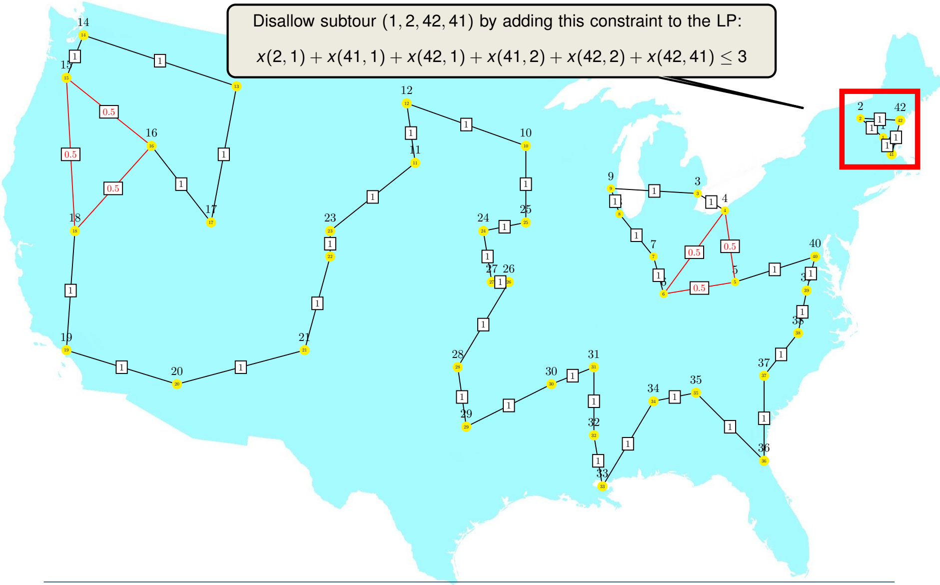
Disallow subtour $(1, 2, 42, 41)$ by adding this constraint to the LP:

$$x(2,1) + x(41,1) + x(42,1) + x(41,2) + x(42,2) + x(42,41) \leq 3$$



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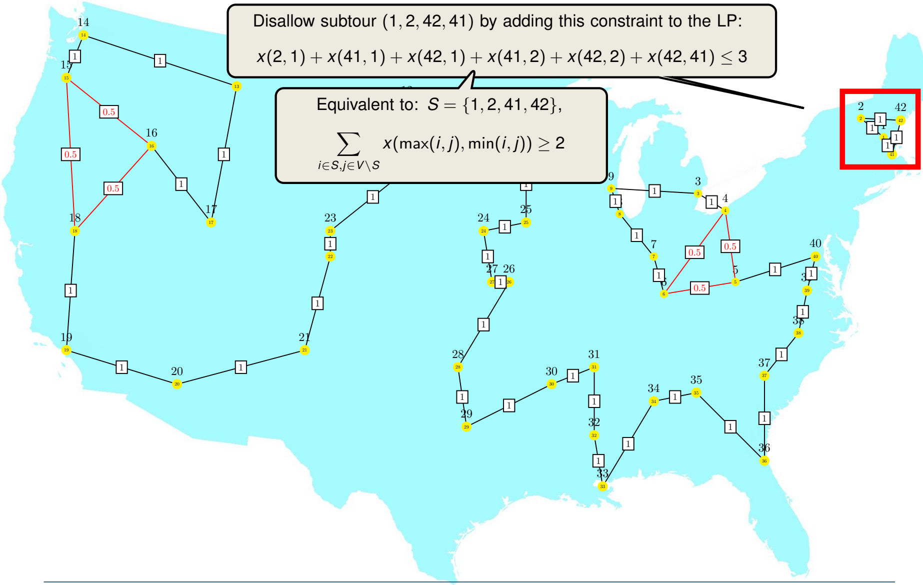
$$x(2,1) + x(41,1) + x(42,1) + x(41,2) + x(42,2) + x(42,41) \leq 3$$

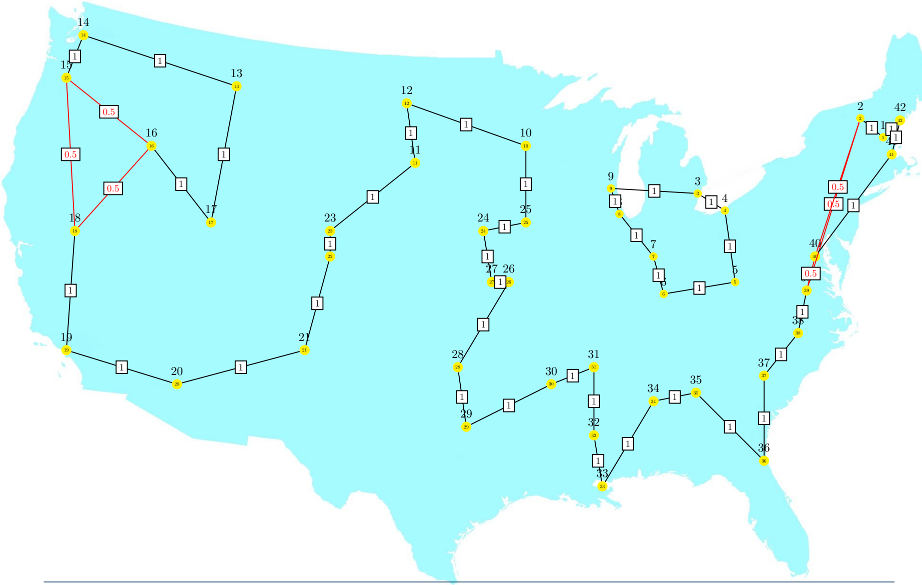
Equivalent to: $S = \{1, 2, 41, 42\}$,

$$\sum_{i \in S, j \in V \setminus S} x(\max(i,j), \min(i,j)) \geq 2$$



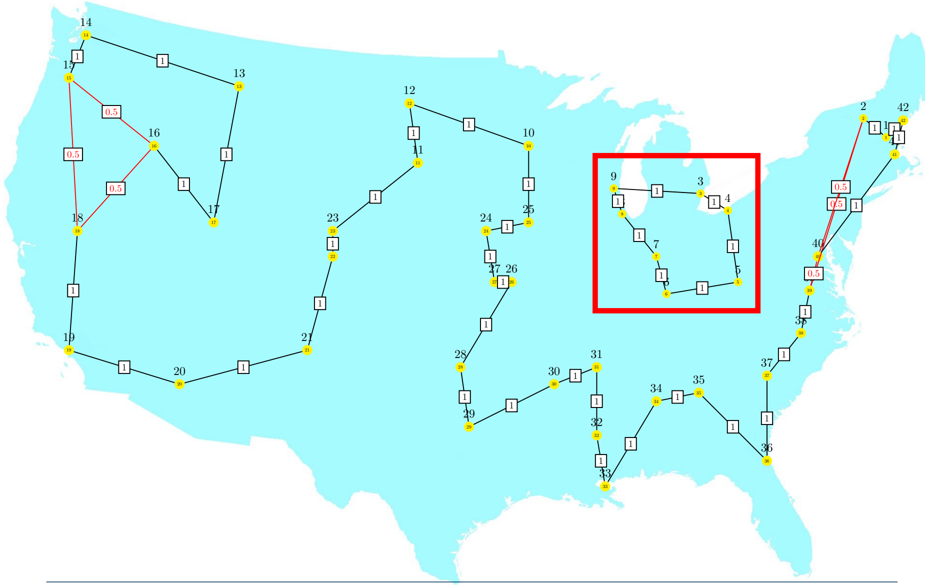
Iteration 2:

Objective value: -676.000000, 861 variables, 946 constraints, 1802 iterations



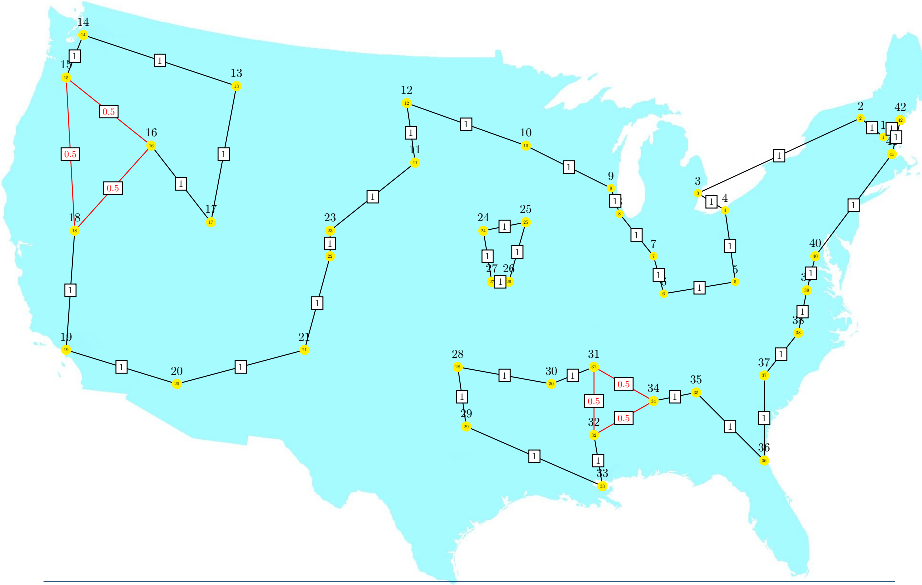
Iteration 2: Eliminate Subtour $3 - 9$

Objective value: -676.000000, 861 variables, 946 constraints, 1802 iterations



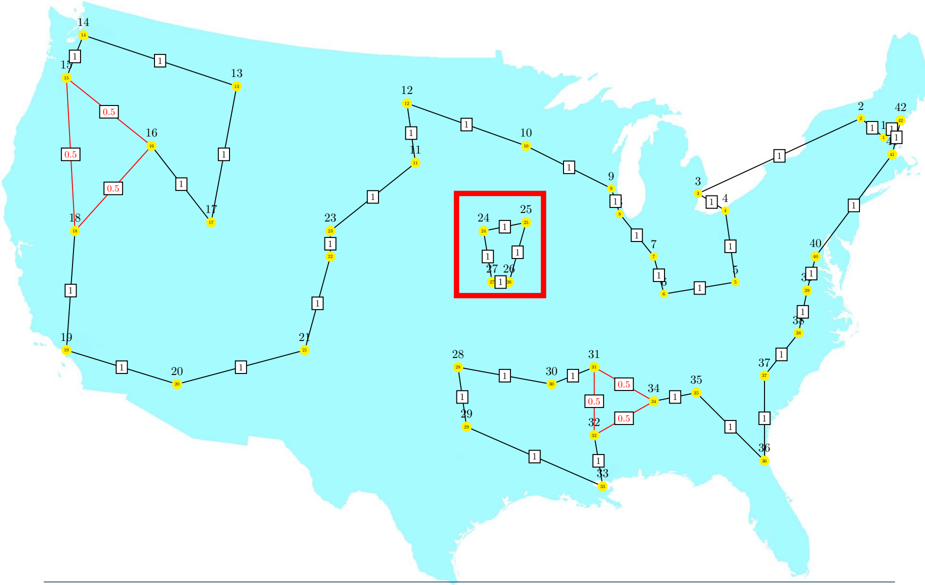
Iteration 3:

Objective value: -681.000000, 861 variables, 947 constraints, 1984 iterations



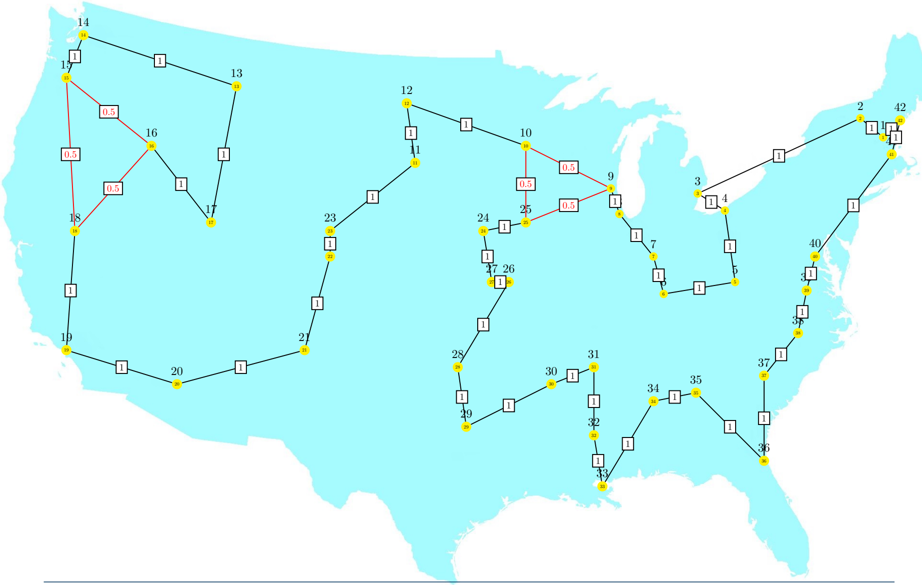
Iteration 3: Eliminate Subtour $24, 25, 26, 27$

Objective value: −681.000000, 861 variables, 947 constraints, 1984 iterations



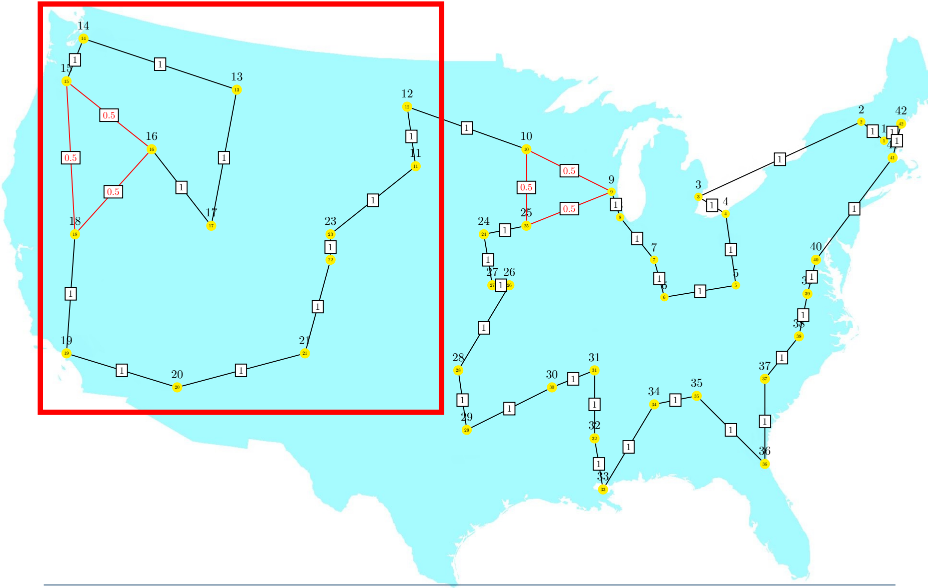
Iteration 4:

Objective value: -682.500000, 861 variables, 948 constraints, 1492 iterations



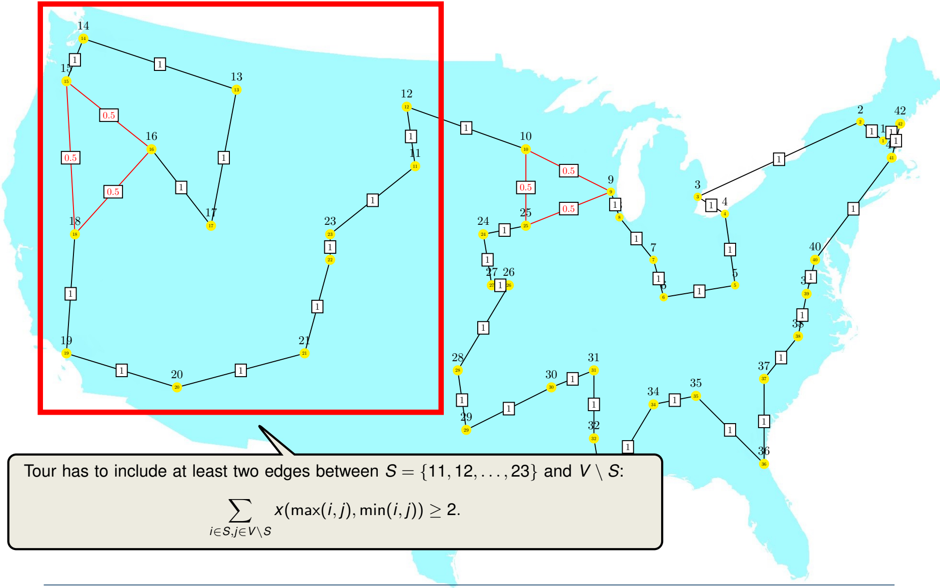
Iteration 4: Eliminate Cut $11 - 23$

Objective value: -682.500000, 861 variables, 948 constraints, 1492 iterations



Iteration 4: Eliminate Cut $11 - 23$

Objective value: -682.500000, 861 variables, 948 constraints, 1492 iterations

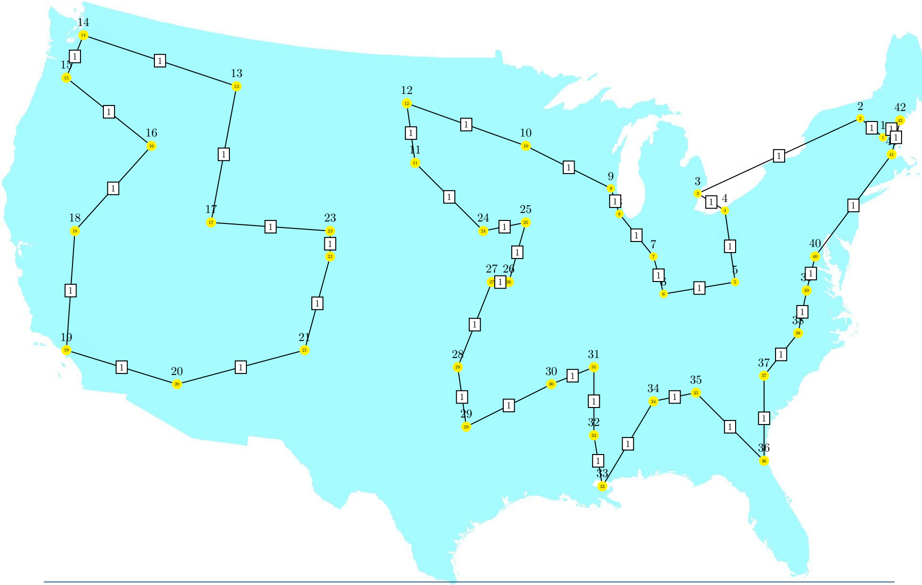


Tour has to include at least two edges between $S = \{11, 12, \dots, 23\}$ and $V \setminus S$:

$$\sum_{i \in S, j \in V \setminus S} x(\max(i,j), \min(i,j)) \geq 2.$$

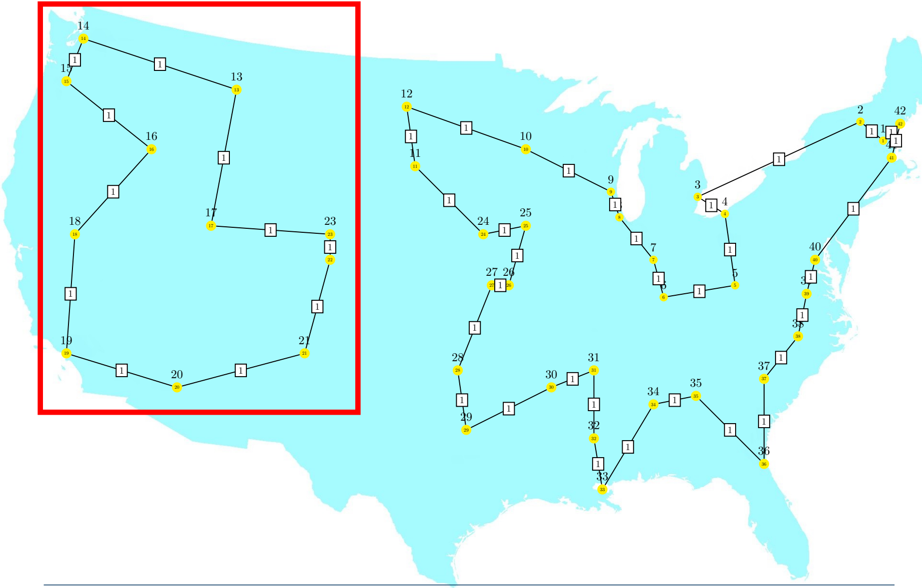
Iteration 5:

Objective value: −686.000000, 861 variables, 949 constraints, 2446 iterations



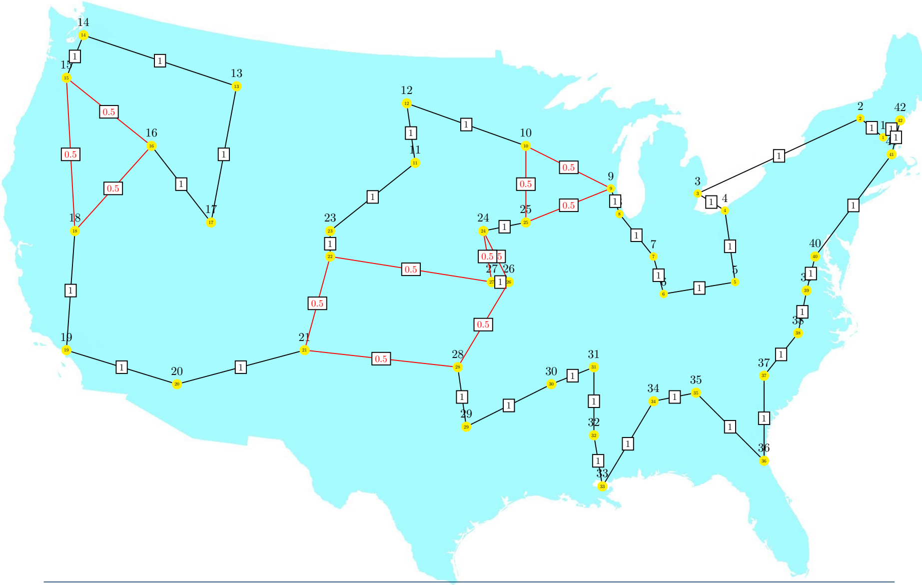
Iteration 5: Eliminate Subtour $13 - 23$

Objective value: -686.000000, 861 variables, 949 constraints, 2446 iterations



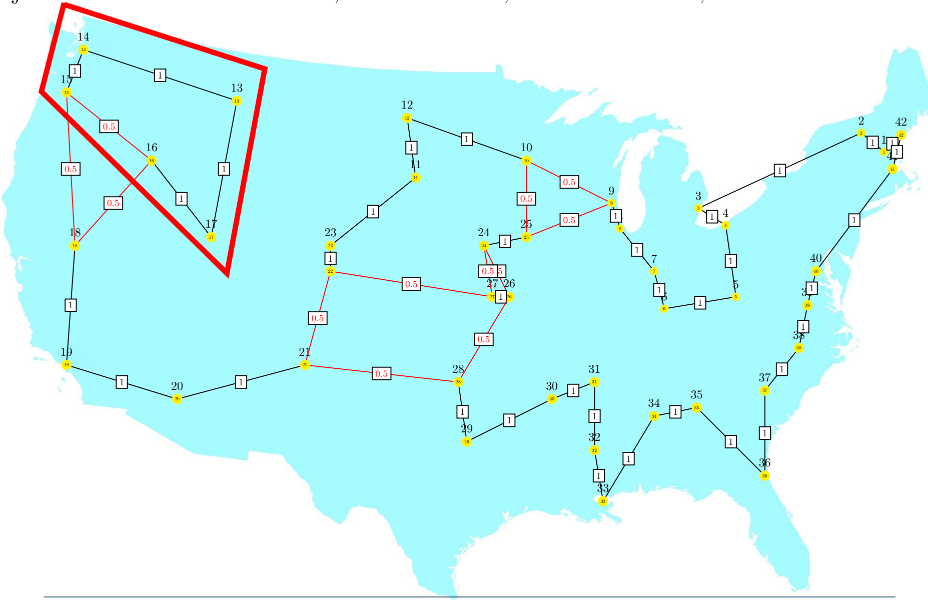
Iteration 6:

Objective value: -694.500000, 861 variables, 950 constraints, 1690 iterations



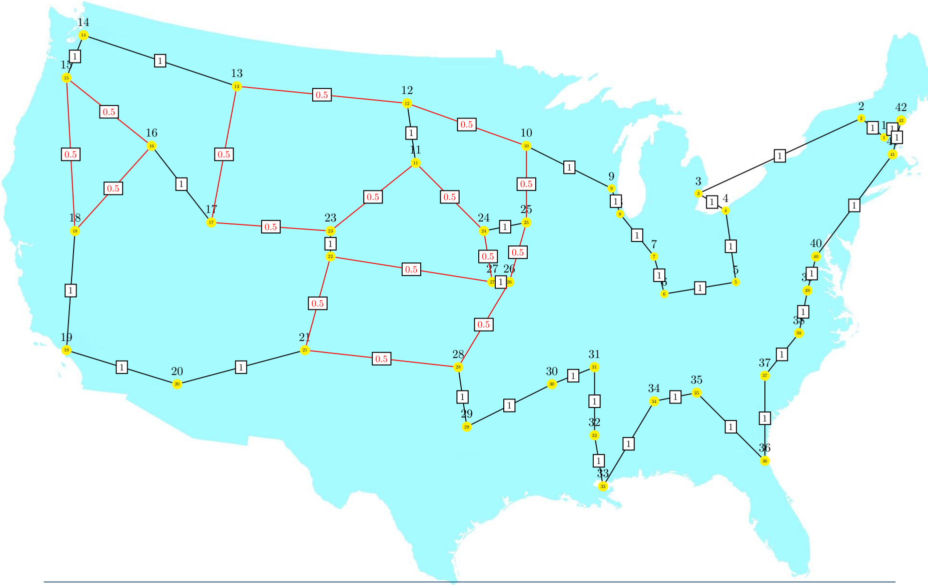
Iteration 6: Eliminate Cut $13 - 17$

Objective value: -694.500000, 861 variables, 950 constraints, 1690 iterations



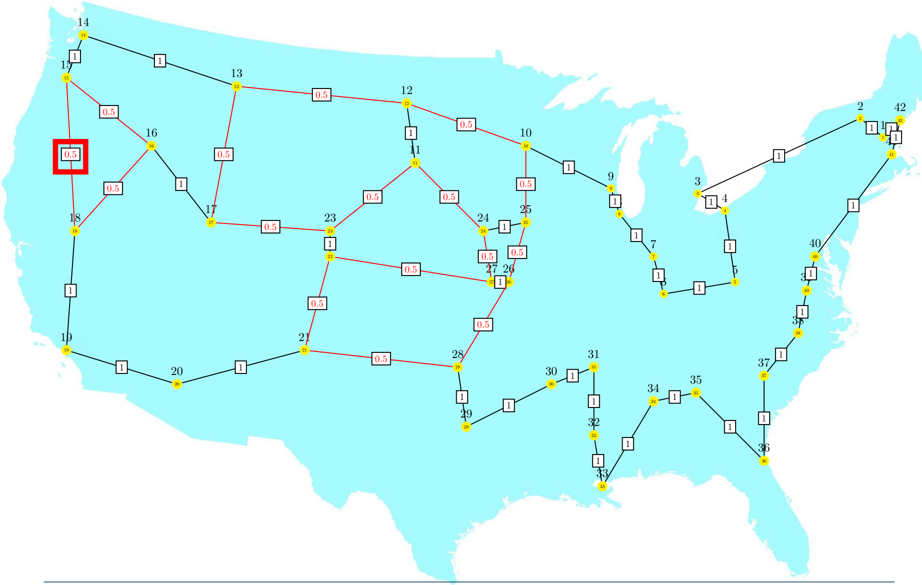
Iteration 7:

Objective value: -697.000000, 861 variables, 951 constraints, 2212 iterations



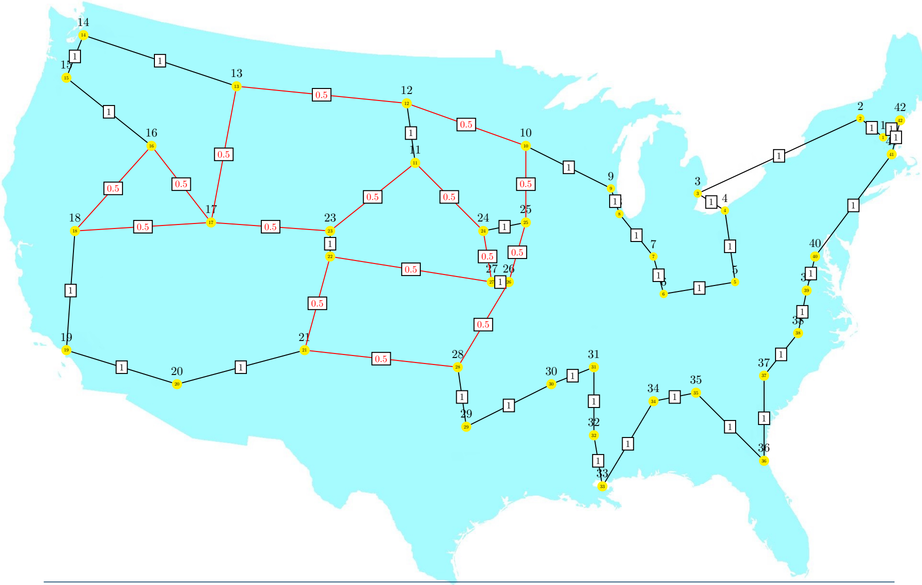
Iteration 7: Branch 1a $x_{18,15} = 0$

Objective value: −697.000000, 861 variables, 951 constraints, 2212 iterations



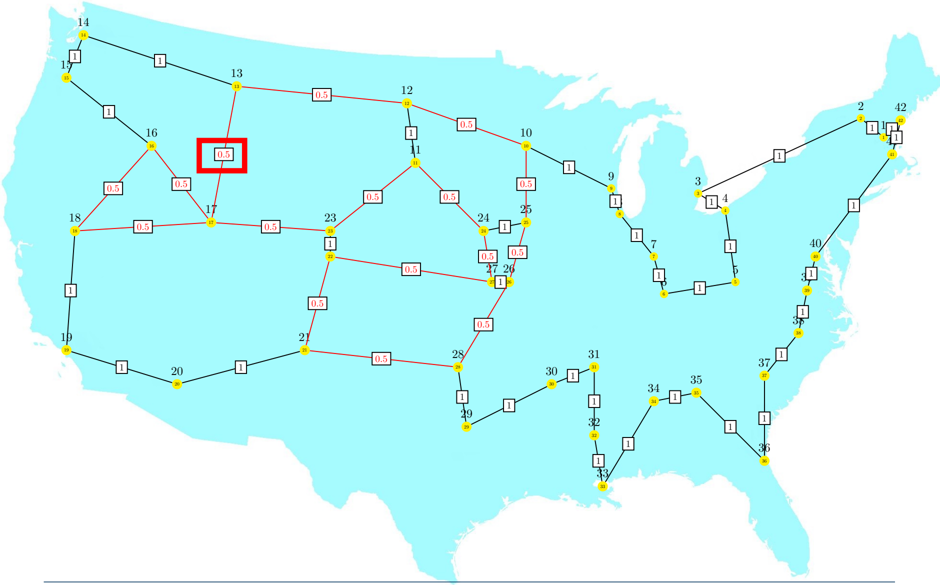
Iteration 8:

Objective value: −698.000000, 861 variables, 952 constraints, 1878 iterations



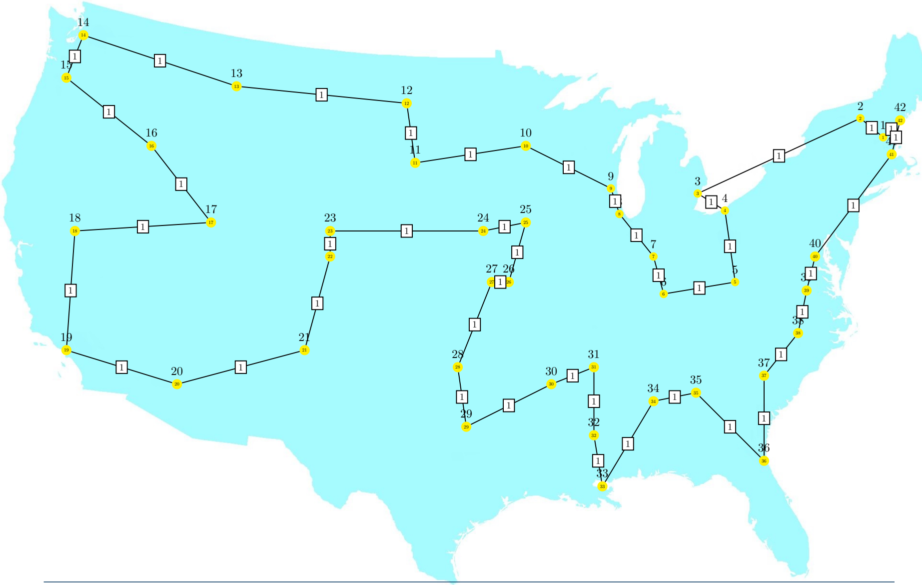
Iteration 8: Branch 2a $x_{17,13} = 0$

Objective value: -698.000000, 861 variables, 952 constraints, 1878 iterations



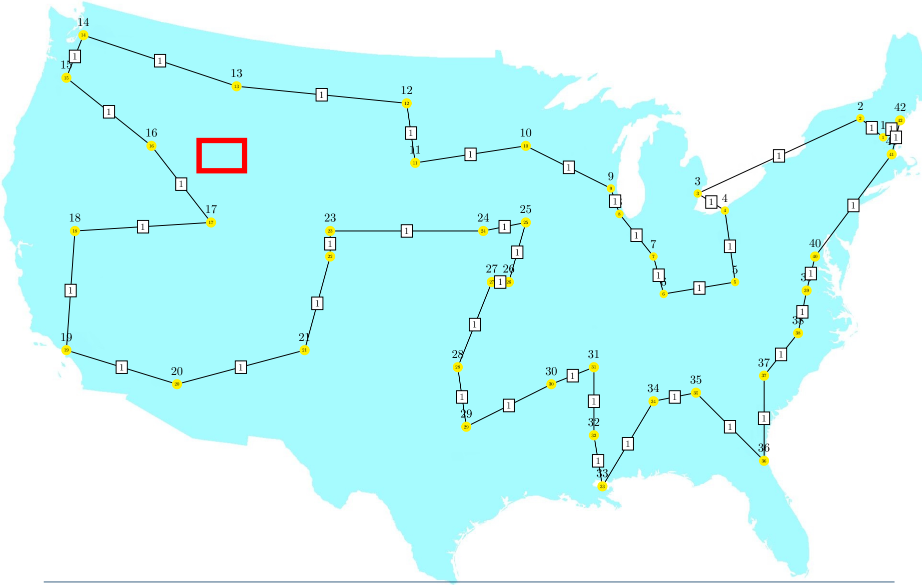
Iteration 9:

Objective value: −699.000000, 861 variables, 953 constraints, 2281 iterations



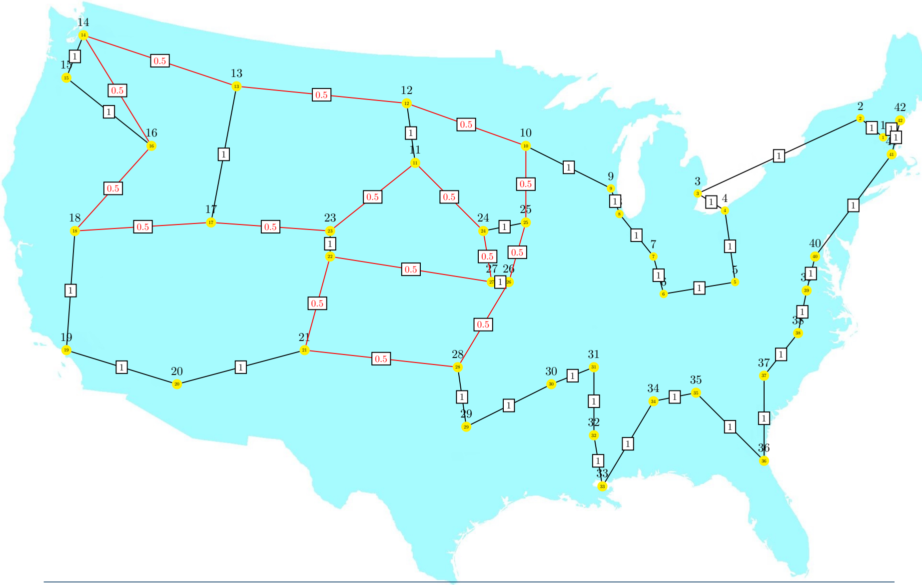
Iteration 9: Branch 2b $x_{17,13} = 1$

Objective value: -699.000000, 861 variables, 953 constraints, 2281 iterations



Iteration 10:

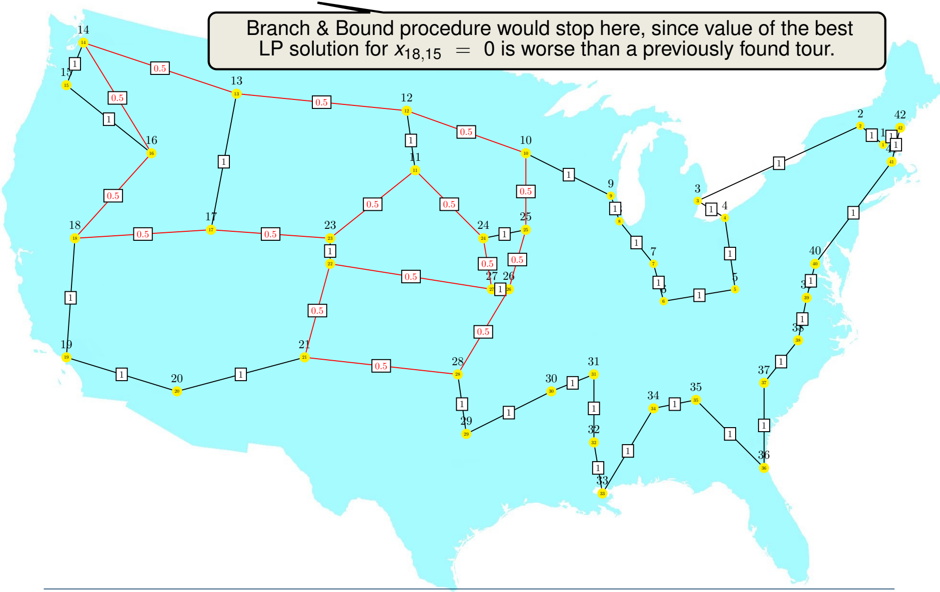
Objective value: −700.000000, 861 variables, 954 constraints, 2398 iterations



Iteration 10:

Objective value: −700.000000, 861 variables, 954 constraints, 2398 iterations

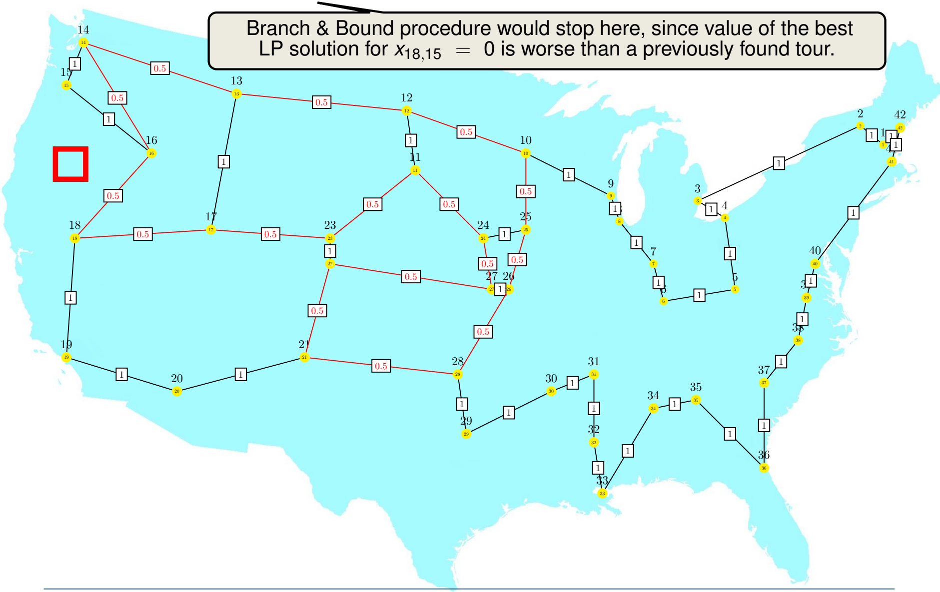
Branch & Bound procedure would stop here, since value of the best LP solution for $x_{18,15} = 0$ is worse than a previously found tour.



Iteration 10: Branch 1b $x_{18,15} = 1$

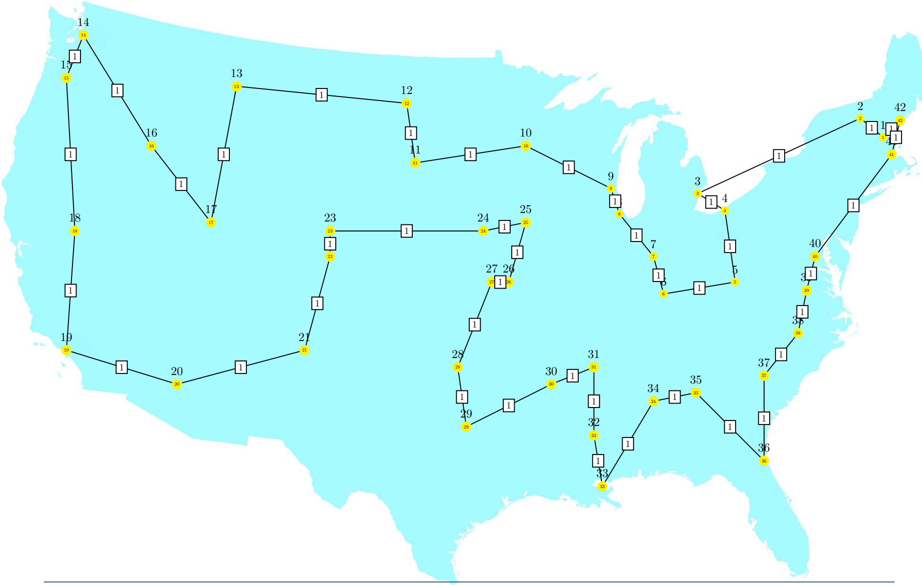
Objective value: -700.000000, 861 variables, 954 constraints, 2398 iterations

Branch & Bound procedure would stop here, since value of the best LP solution for $x_{18,15} = 0$ is worse than a previously found tour.



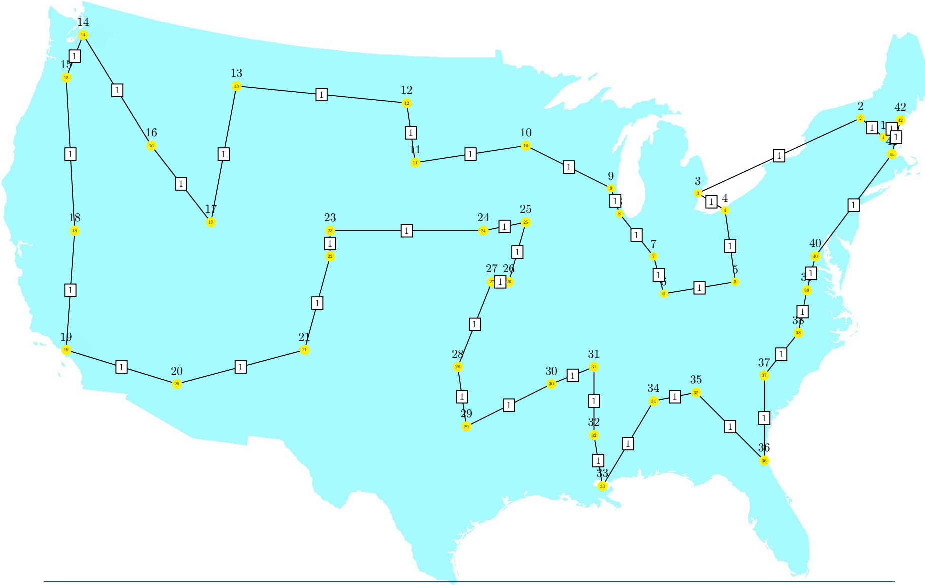
Iteration 11:

Objective value: -701.000000, 861 variables, 953 constraints, 2506 iterations



Iteration 11: Branch & Bound terminates

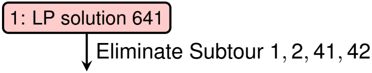
Objective value: -701.000000, 861 variables, 953 constraints, 2506 iterations



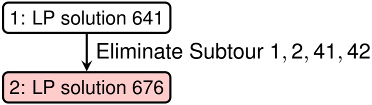
Branch & Bound Overview

1: LP solution 641

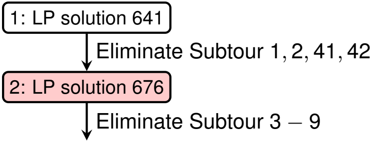
Branch & Bound Overview



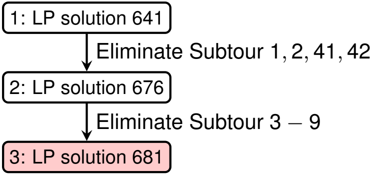
Branch & Bound Overview



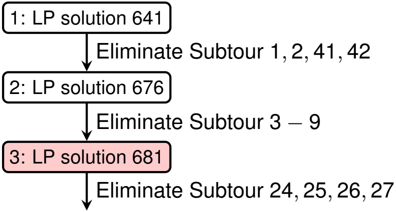
Branch & Bound Overview



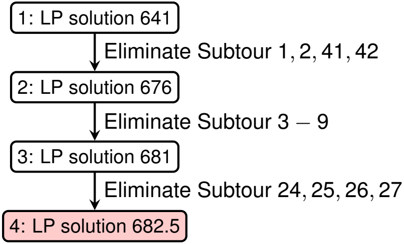
Branch & Bound Overview



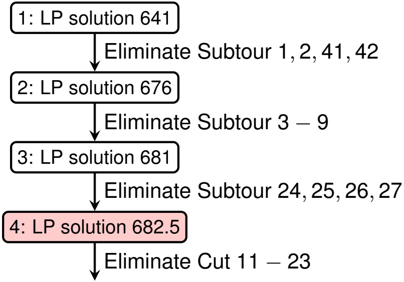
Branch & Bound Overview



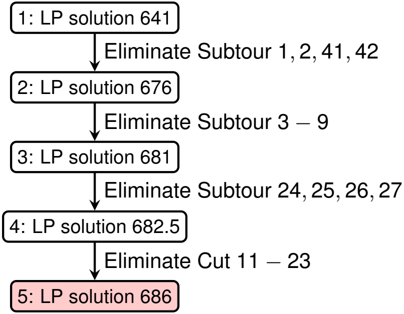
Branch & Bound Overview



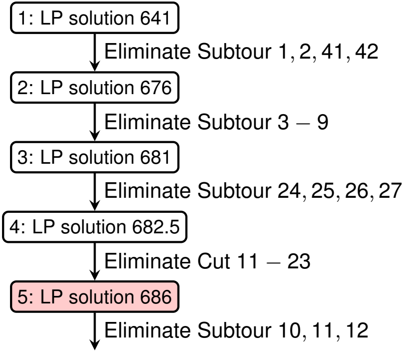
Branch & Bound Overview



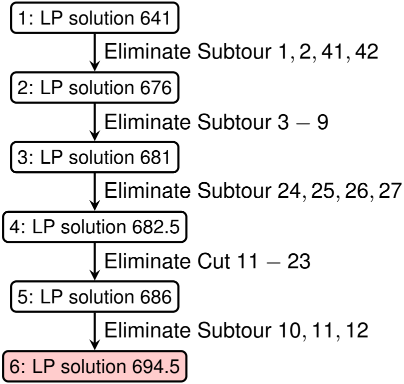
Branch & Bound Overview



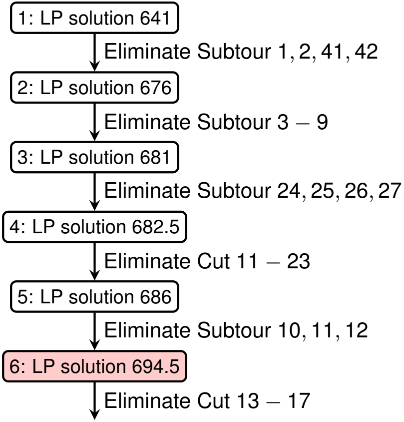
Branch & Bound Overview



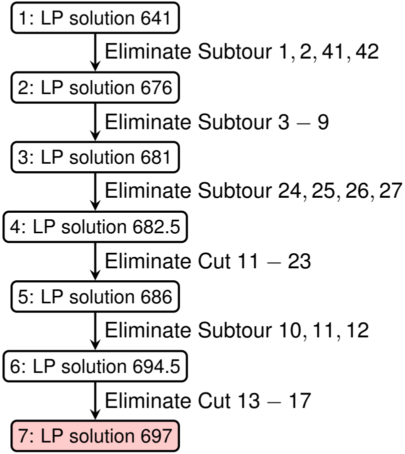
Branch & Bound Overview



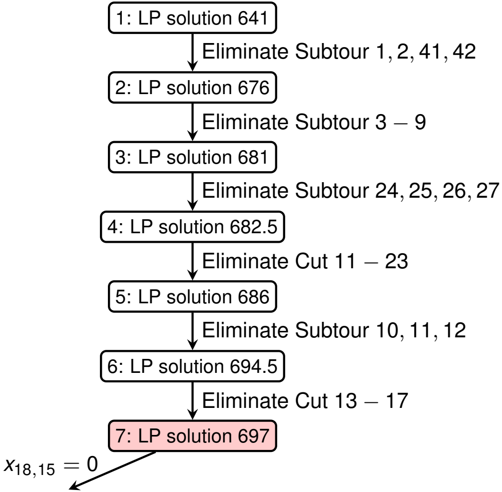
Branch & Bound Overview



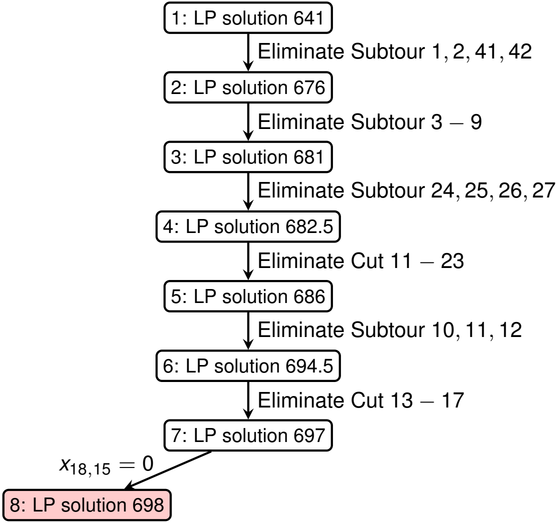
Branch & Bound Overview



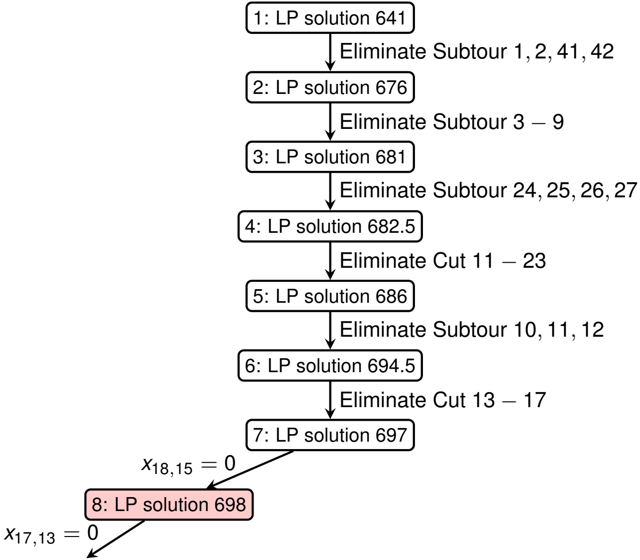
Branch & Bound Overview



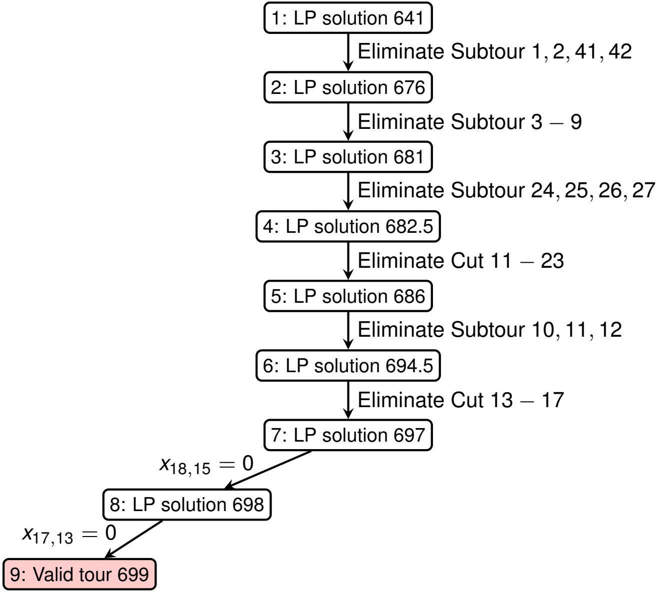
Branch & Bound Overview



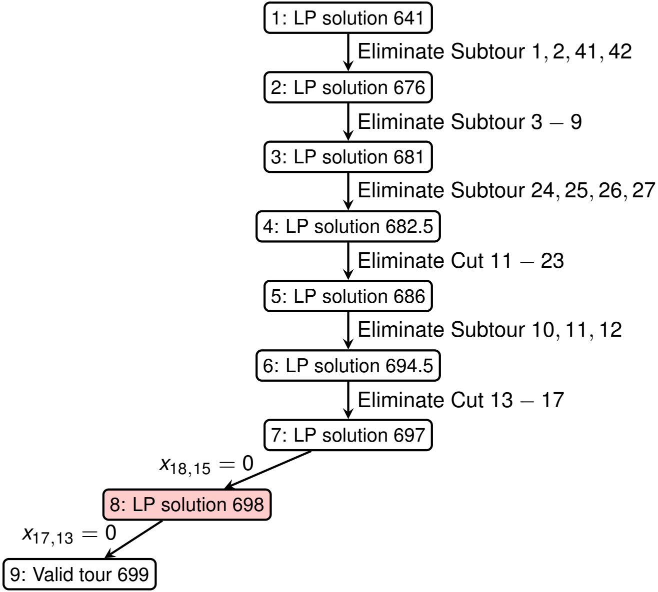
Branch & Bound Overview



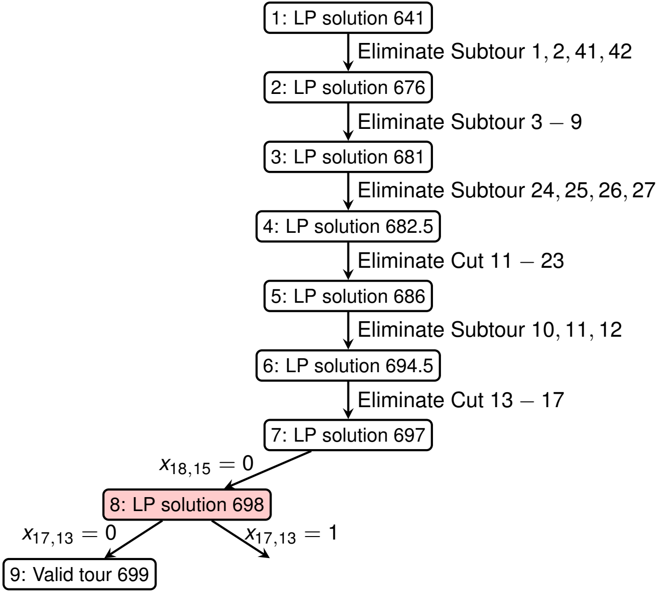
Branch & Bound Overview



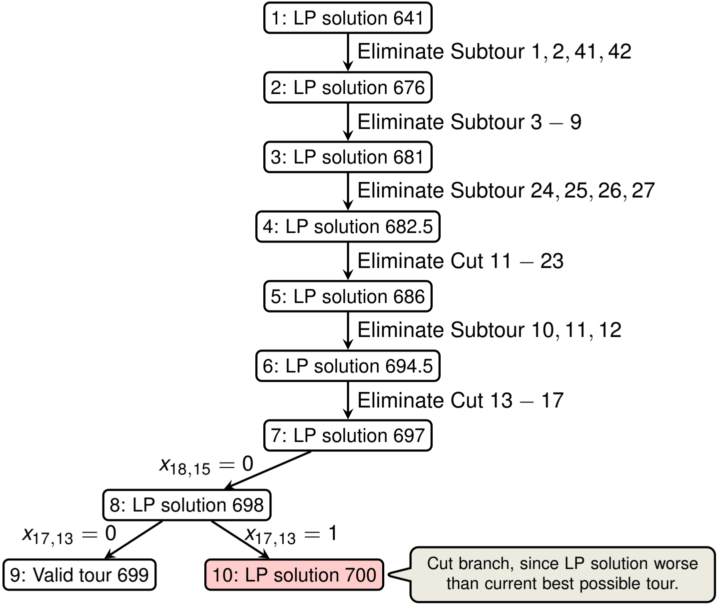
Branch & Bound Overview



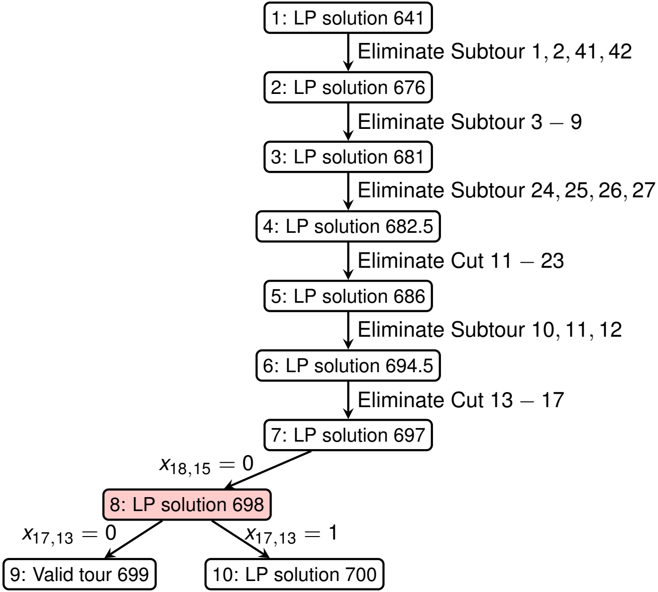
Branch & Bound Overview



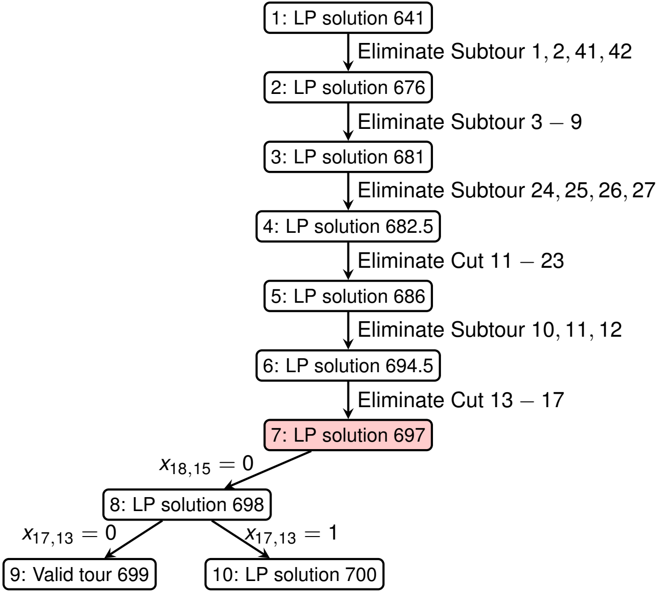
Branch & Bound Overview



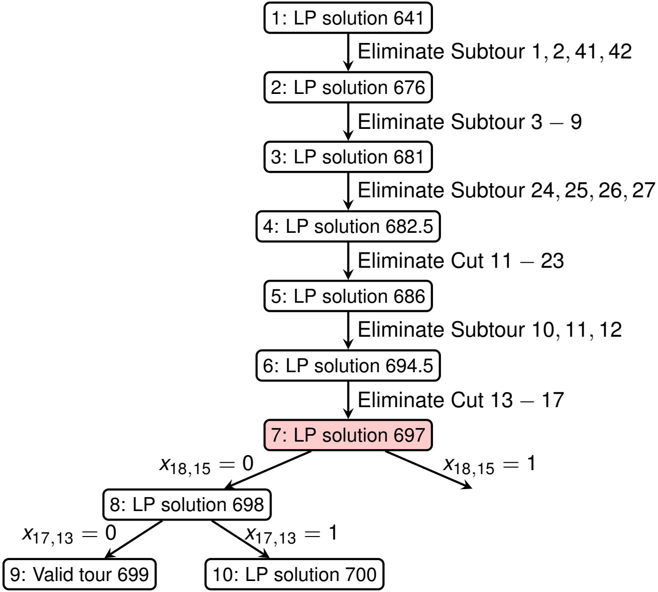
Branch & Bound Overview



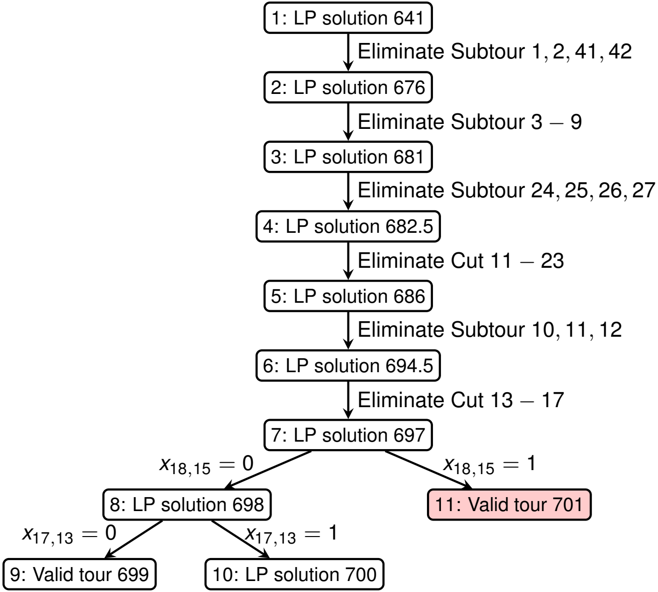
Branch & Bound Overview



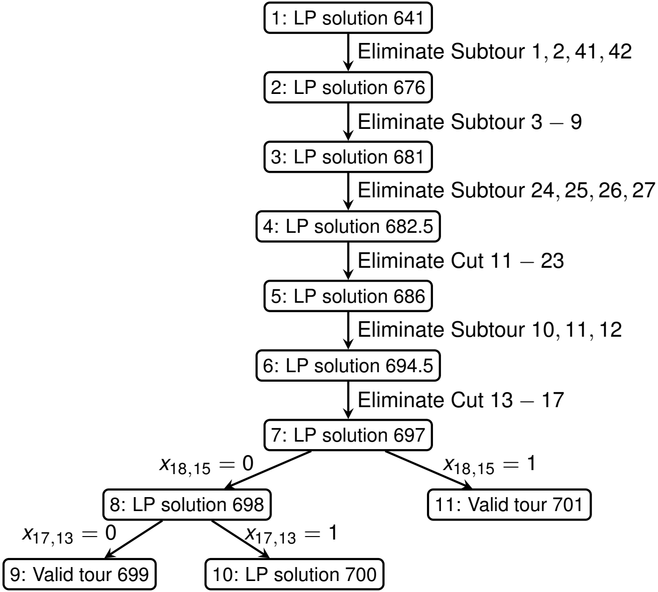
Branch & Bound Overview



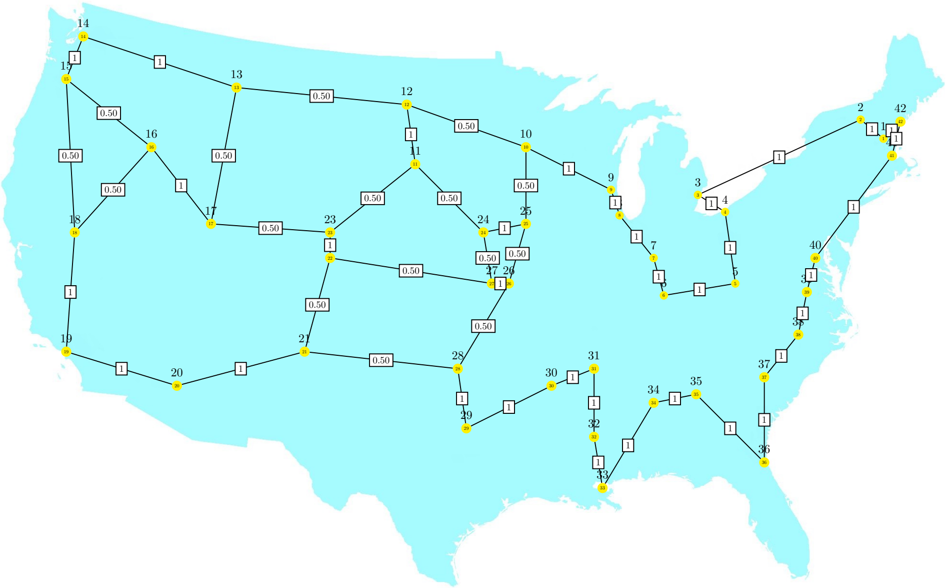
Branch & Bound Overview



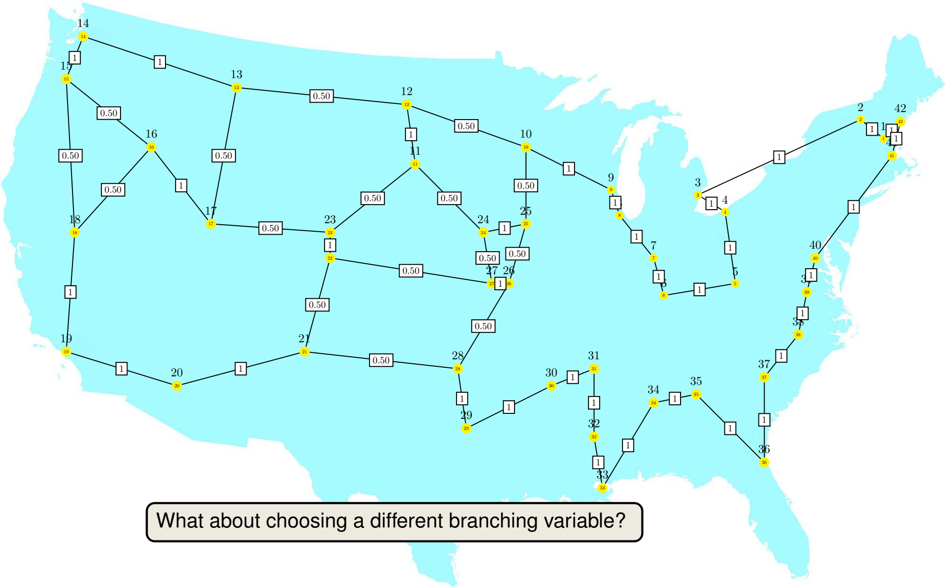
Branch & Bound Overview



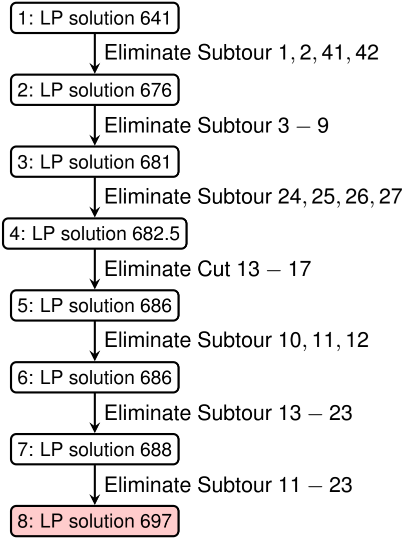
Iteration 7: Objective 697



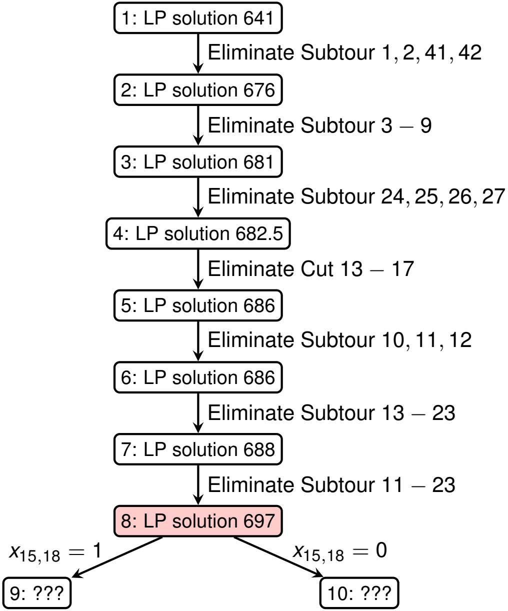
Iteration 7: Objective 697



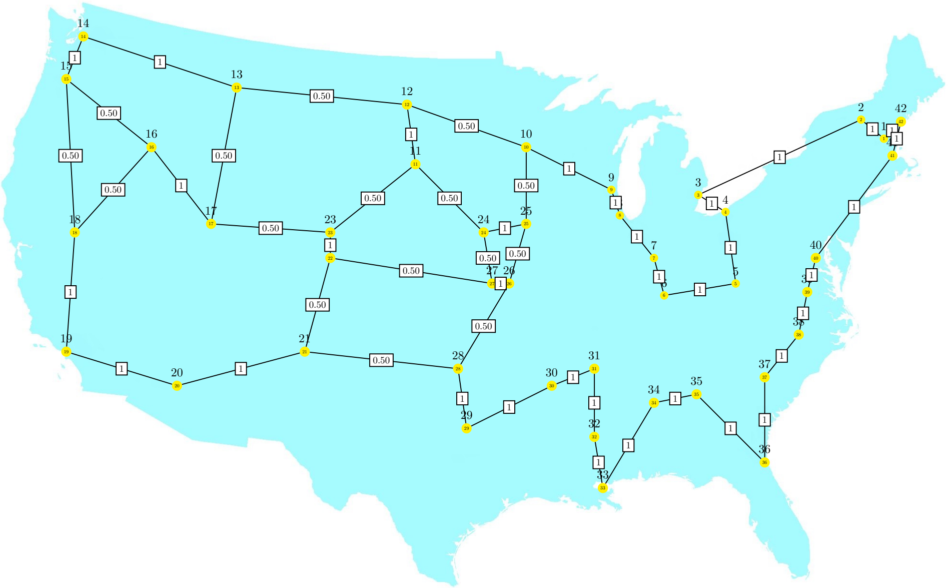
Solving Progress (Alternative Branch 1)



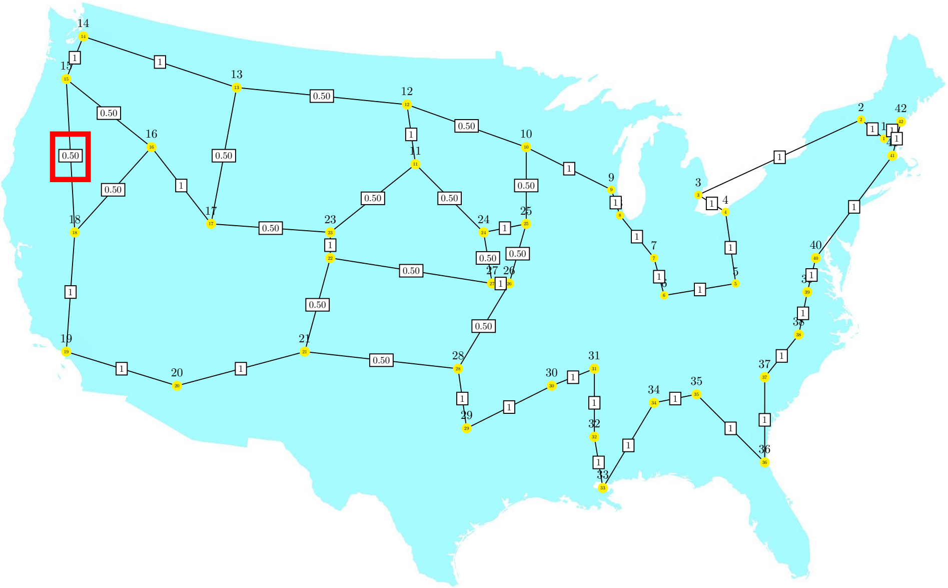
Solving Progress (Alternative Branch 1)



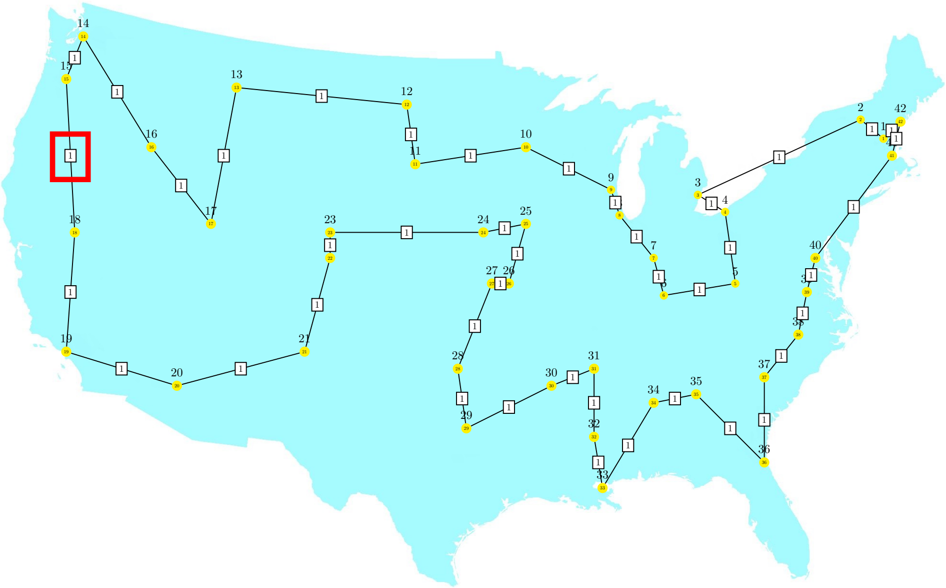
Alternative Branch 1: $x_{18,15}$, Objective 697



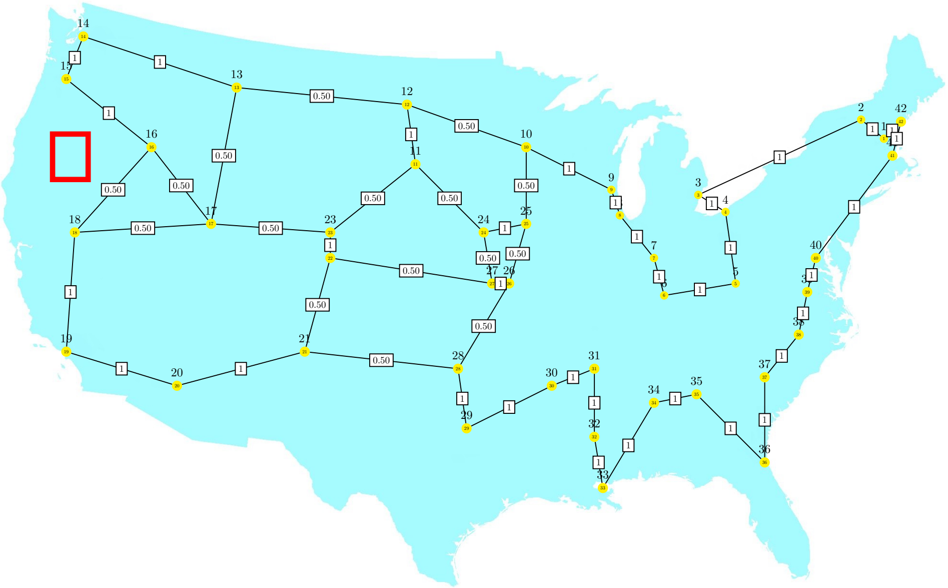
Alternative Branch 1: $x_{18,15}$, Objective 697



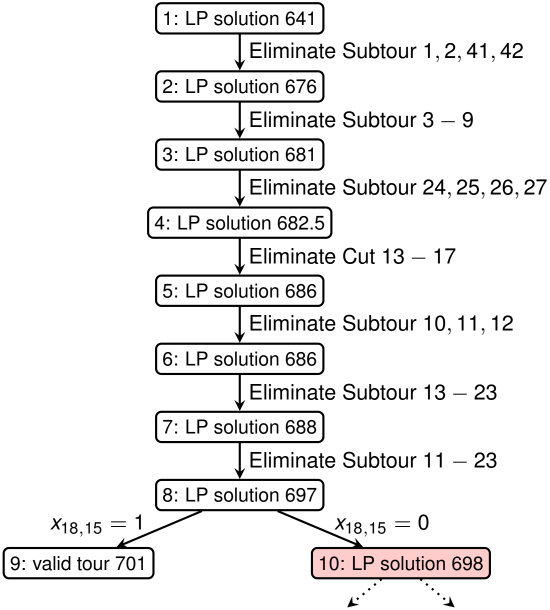
Alternative Branch 1a: $x_{18,15} = 1$, Objective 701 (Valid Tour)



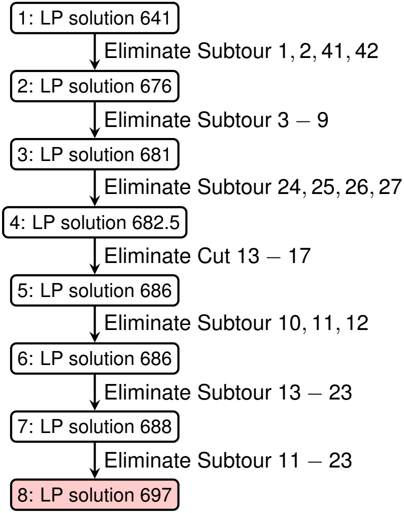
Alternative Branch 1b: $x_{18,15} = 0$, Objective 698



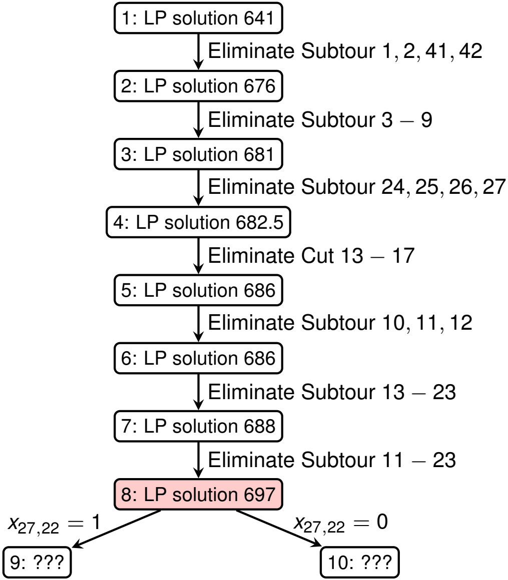
Solving Progress (Alternative Branch 1)



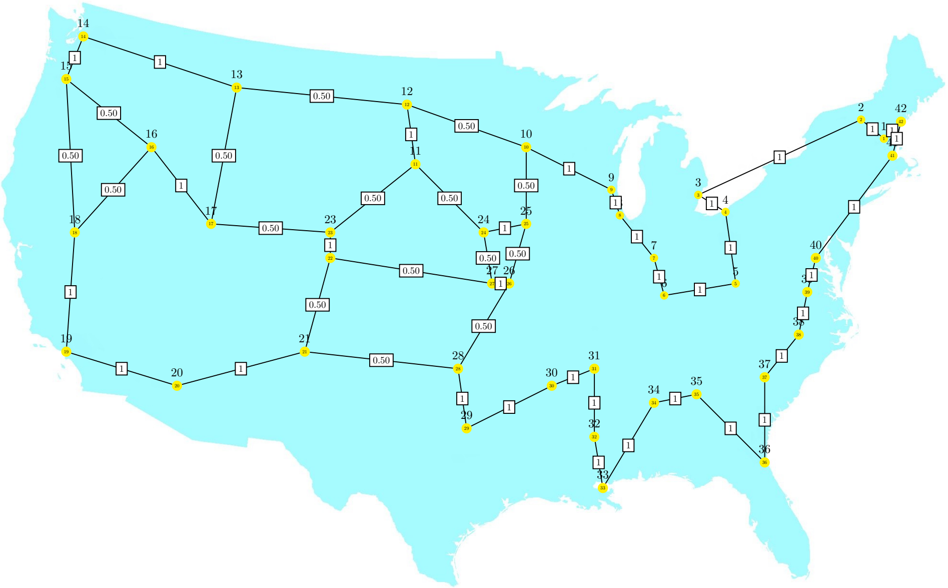
Solving Progress (Alternative Branch 2)



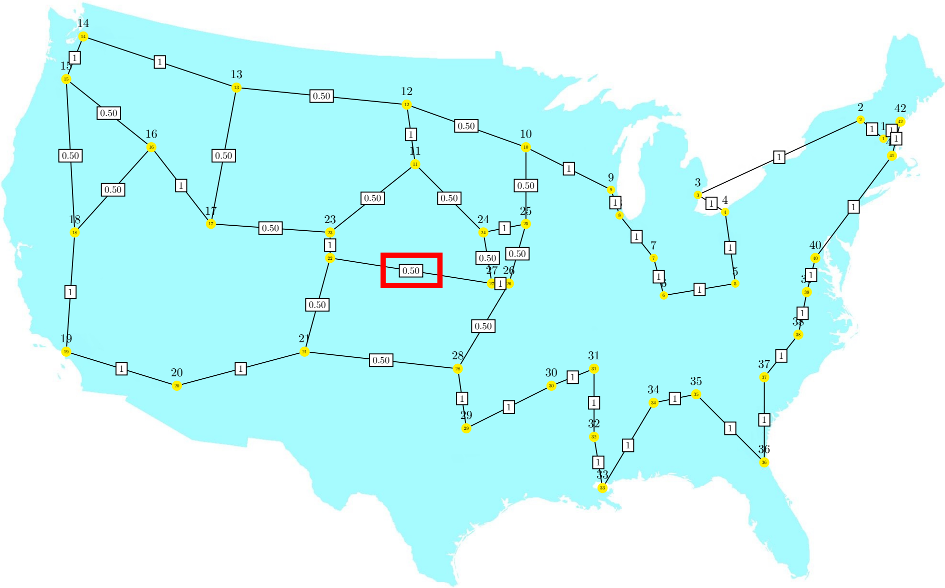
Solving Progress (Alternative Branch 2)



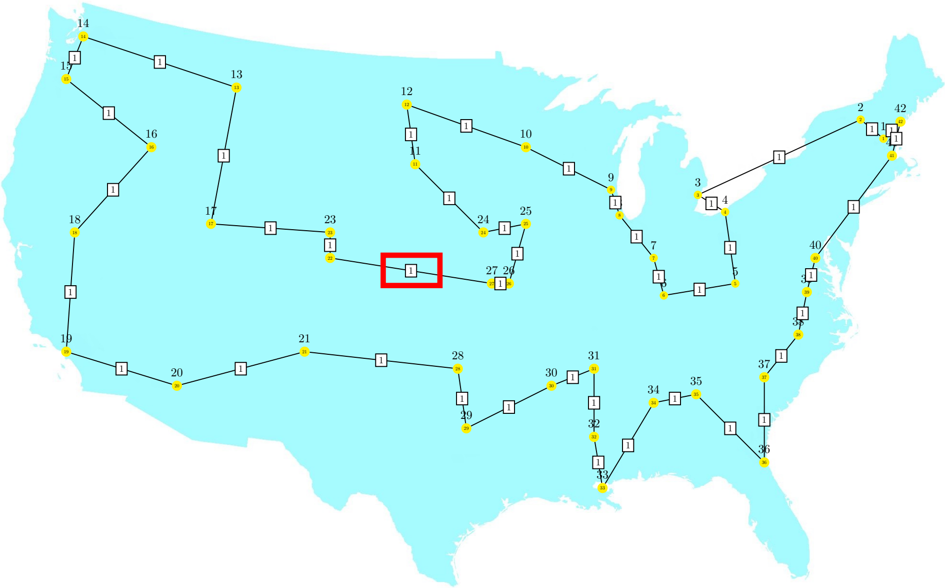
Alternative Branch 2: $x_{27,22}$, Objective 697



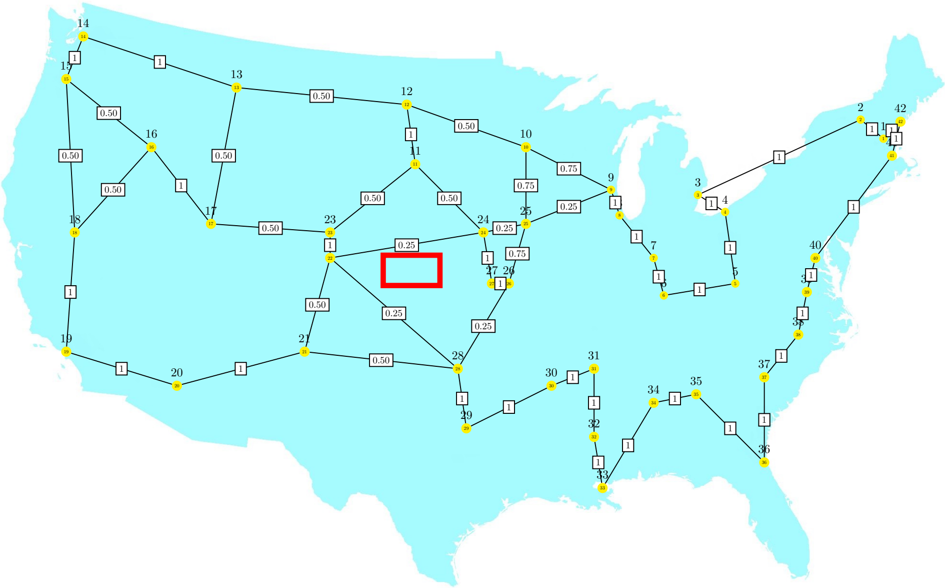
Alternative Branch 2: $x_{27,22}$, Objective 697



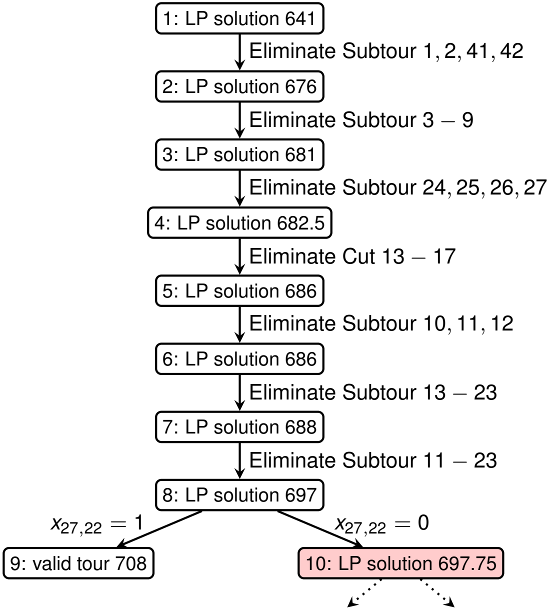
Alternative Branch 2a: $x_{27,22} = 1$, Objective 708 (Valid tour)



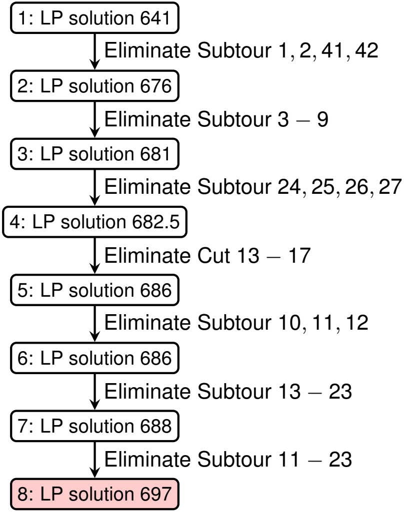
Alternative Branch 2b: $x_{27,22} = 0$, Objective 697.75



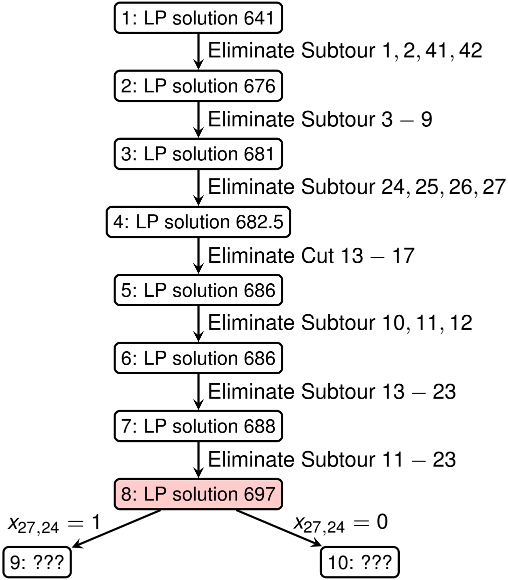
Solving Progress (Alternative Branch 2)



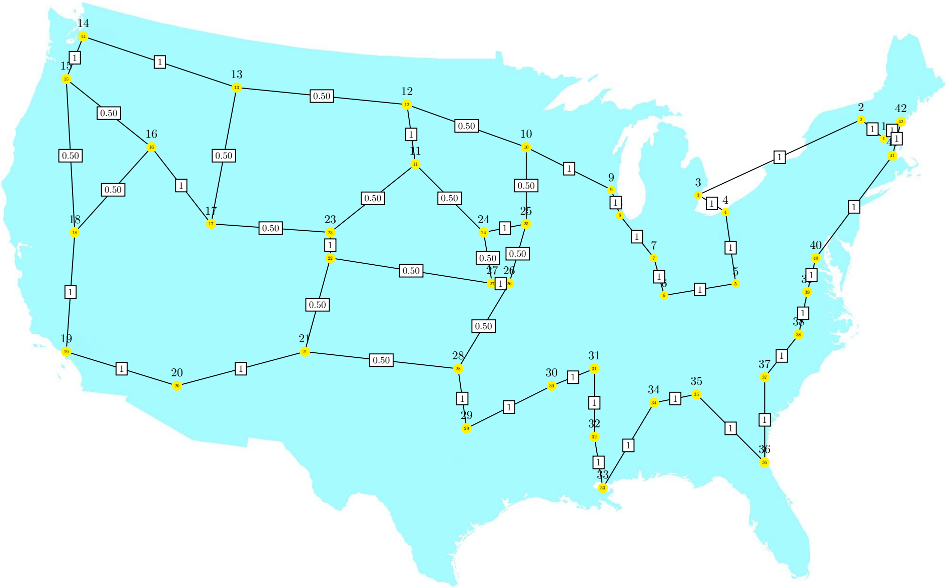
Solving Progress (Alternative Branch 3)



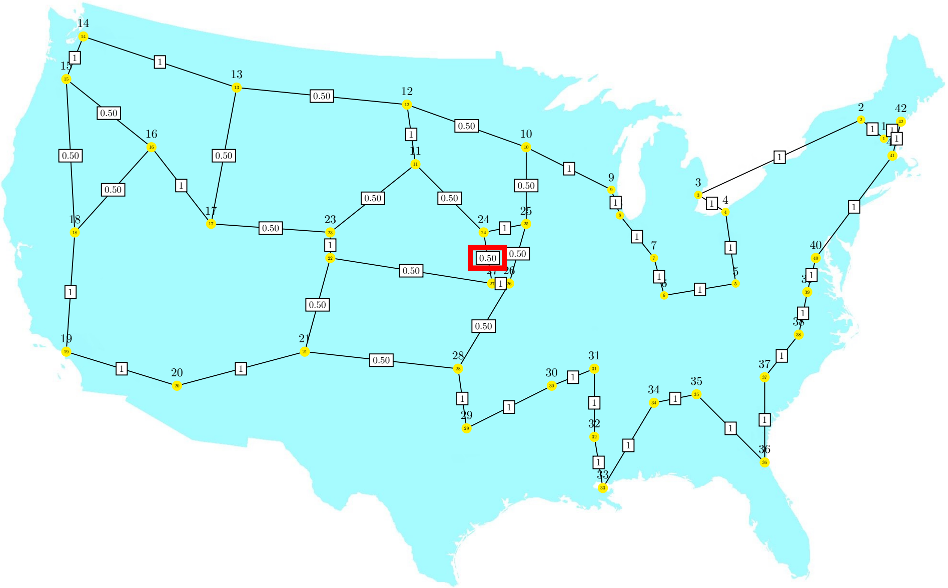
Solving Progress (Alternative Branch 3)



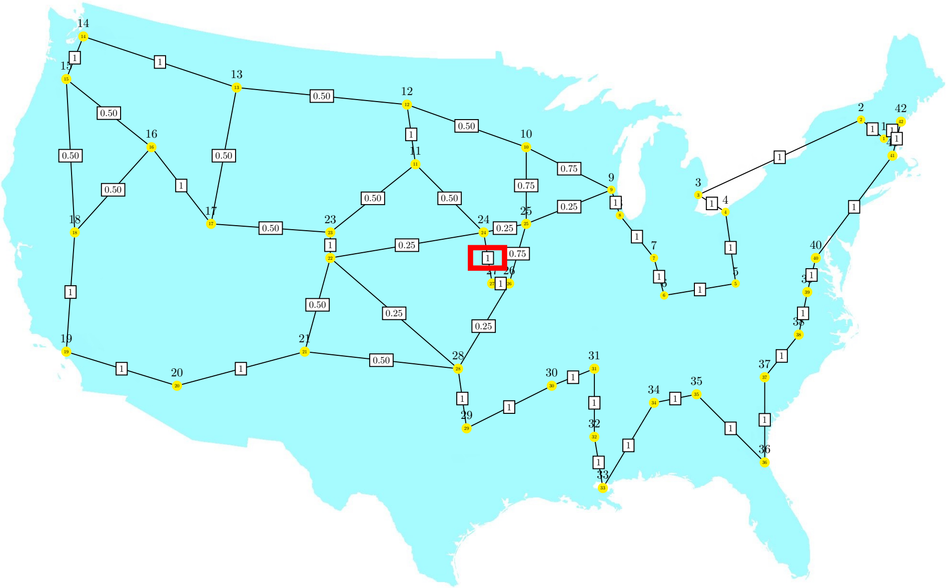
Alternative Branch 3: $x_{27,24}$, Objective 697



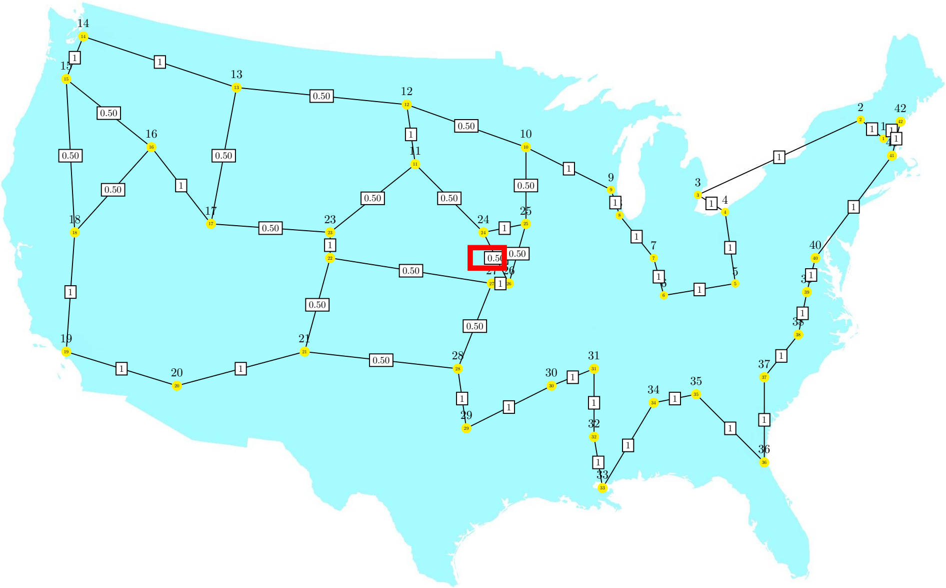
Alternative Branch 3: $x_{27,24}$, Objective 697



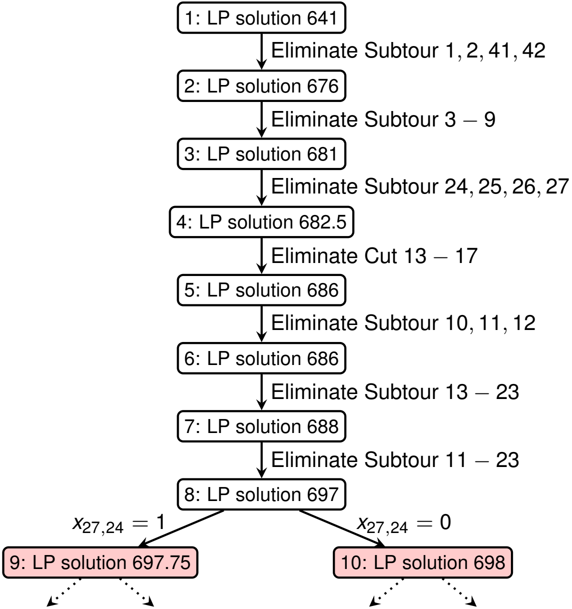
Alternative Branch 3a: $x_{27,24} = 1$, Objective 697.75



Alternative Branch 3b: $x_{27,24} = 0$, Objective 698



Solving Progress (Alternative Branch 3)



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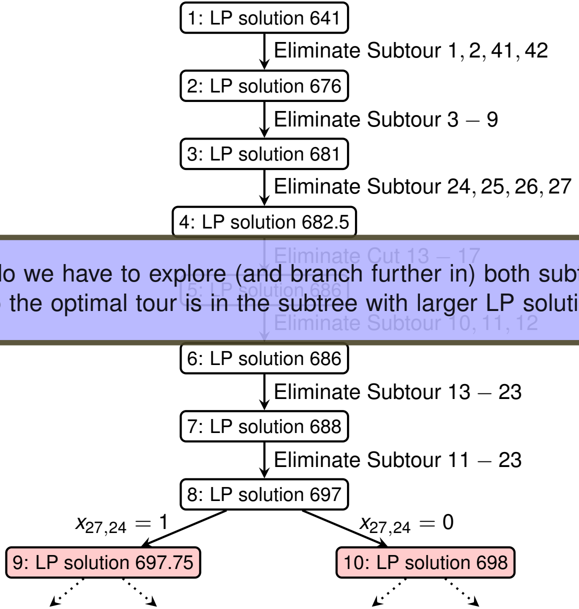

Not only do we have to explore (and branch further in) both subtrees, but also the optimal tour is in the subtree with larger LP solution!

Conclusion (1/2)

- How can one generate these constraints automatically?

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  Small Cuts: Finding the Minimum Cut in Weighted Graphs

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  BFS may be more attractive, even though it might need more memory.

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  BFS may be more attractive, even though it might need more memory.

CONCLUDING REMARK

It is clear that we have left unanswered practically any question one might pose of a theoretical nature concerning the traveling-salesman problem; however, we hope that the feasibility of attacking problems involving a moderate number of points has been successfully demonstrated, and that perhaps some of the ideas can be used in problems of similar nature.

Conclusion (2/2)

- Eliminate Subtour $1, 2, 41, 42$
- Eliminate Subtour $3 - 9$
- Eliminate Subtour $10, 11, 12$
- Eliminate Subtour $11 - 23$
- Eliminate Subtour $13 - 23$
- Eliminate Cut $13 - 17$
- Eliminate Subtour $24, 25, 26, 27$

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THE 49-CITY PROBLEM*

The optimal tour $\bar{x}$ is shown in Fig. 16. The proof that it is optimal is given in Fig. 17. To make the correspondence between the latter and its programming problem clear, we will write down in addition to 42 relations in non-negative variables (2), a set of 25 relations which suffice to prove that $D(x)$ is a minimum for $\bar{x}$. We distinguish the following subsets of the 42 cities:

$S_1 = \{1, 2, 41, 42\}$ $\quad$ $S_5 = \{13, 14, \cdots, 23\}$
$S_2 = \{3, 4, \cdots, 9\}$ $\quad$ $S_6 = \{13, 14, 15, 16, 17\}$
$S_3 = \{1, 2, \cdots, 9, 29, 30, \cdots, 42\}$ $\quad$ $S_7 = \{24, 25, 26, 27\}$.
$S_4 = \{11, 12, \cdots, 23\}$

CPLEX

en.wikipedia.org/wiki/CPLEX

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The Free Encyclopedia

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CPLEX

From Wikipedia, the free encyclopedia

IBM ILOG CPLEX Optimization Studio (often informally referred to as simply as CPLEX) is an optimization software package. In 2004, the work on CPLEX earned the first INFORMS Impact Prize.

CPLEX	
Developer(s)	IBM
Stable release	12.6
Development status	Active
Type	Technical computing
License	Proprietary
Website	ibm.com/software/products/ibmilogcpleoptistud/

The CPLEX Optimizer was named for the simplex method as implemented in the C programming language, although today it also supports other types of mathematical optimization and offers interfaces other than just C. It was originally developed by Robert E. Bixby and was offered commercially starting in 1988 by CPLEX Optimization Inc., which was acquired by ILOG in 1997; ILOG was subsequently acquired by IBM in January 2009.[1] CPLEX continues to be actively developed under IBM.

The IBM ILOG CPLEX Optimizer solves integer programming problems, very large[2] linear programming problems using either primal or dual variants of the simplex method or the barrier interior

```
Welcome to IBM(R) ILOG(R) CPLEX(R) Interactive Optimizer 12.6.1.0
  with Simplex, Mixed Integer & Barrier Optimizers
5725-A06 5725-A29 5724-Y48 5724-Y49 5724-Y54 5724-Y55 5655-Y21
Copyright IBM Corp. 1988, 2014.  All Rights Reserved.

Type 'help' for a list of available commands.
Type 'help' followed by a command name for more
information on commands.

CPLEX> read tsp.lp
Problem 'tsp.lp' read.
Read time = 0.00 sec. (0.06 ticks)
CPLEX> primopt
Tried aggregator 1 time.
LP Presolve eliminated 1 rows and 1 columns.
Reduced LP has 49 rows, 860 columns, and 2483 nonzeros.
Presolve time = 0.00 sec. (0.36 ticks)

Iteration log . . .
Iteration:     1    Infeasibility =            33.999999
Iteration:    26    Objective     =          1510.000000
Iteration:    90    Objective     =           923.000000
Iteration:   155    Objective     =           711.000000

Primal simplex - Optimal:  Objective =  6.9900000000e+02
Solution time =    0.00 sec.  Iterations = 168 (25)
Deterministic time = 1.16 ticks  (288.86 ticks/sec)

CPLEX> █
```

```
CPLEX> display solution variables -
Variable Name           Solution Value
x_2_1                         1.000000
x_42_1                        1.000000
x_3_2                         1.000000
x_4_3                         1.000000
x_5_4                         1.000000
x_6_5                         1.000000
x_7_6                         1.000000
x_8_7                         1.000000
x_9_8                         1.000000
x_10_9                        1.000000
x_11_10                       1.000000
x_12_11                       1.000000
x_13_12                       1.000000
x_14_13                       1.000000
x_15_14                       1.000000
x_16_15                       1.000000
x_17_16                       1.000000
x_18_17                       1.000000
x_19_18                       1.000000
x_20_19                       1.000000
x_21_20                       1.000000
x_22_21                       1.000000
x_23_22                       1.000000
x_24_23                       1.000000
x_25_24                       1.000000
x_26_25                       1.000000
x_27_26                       1.000000
x_28_27                       1.000000
x_29_28                       1.000000
x_30_29                       1.000000
x_31_30                       1.000000
x_32_31                       1.000000
x_33_32                       1.000000
x_34_33                       1.000000
x_35_34                       1.000000
x_36_35                       1.000000
x_37_36                       1.000000
x_38_37                       1.000000
x_39_38                       1.000000
x_40_39                       1.000000
x_41_40                       1.000000
x_42_41                       1.000000
All other variables in the range 1-861 are 0.
```

Randomised Algorithms

Lecture 9: Approximation Algorithms: MAX-3-CNF and Vertex-Cover

Thomas Sauerwald (tms41@cam.ac.uk)

Lent 2024

UNIVERSITY OF CAMBRIDGE

Outline

Randomised Approximation

MAX-3-CNF

Weighted Vertex Cover

Approximation Ratio for Randomised Approximation Algorithms

Approximation Ratio

A randomised algorithm for a problem has approximation ratio $\rho(n)$, if for any input of size n, the expected cost (value) $\mathbf{E}[C]$ of the returned solution and optimal cost C^* satisfy:

$$\max\left(\frac{\mathbf{E}[C]}{C^*}, \frac{C^*}{\mathbf{E}[C]}\right) \leq \rho(n).$$

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- Maximisation problem: $\frac{C^*}{\mathbf{E}[C]} \geq 1$
- Minimisation problem: $\frac{\mathbf{E}[C]}{C^*} \geq 1$

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not covered here (non-examinable)

Randomised Approximation Schemes

An approximation scheme is an approximation algorithm, which given any input and $\epsilon > 0$, is a $(1+\epsilon)$-approximation algorithm.

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not covered here (non-examinable)

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An approximation scheme is an approximation algorithm, which given any input and $\epsilon > 0$, is a $(1+\epsilon)$-approximation algorithm.

- It is a polynomial-time approximation scheme (PTAS) if for any fixed $\epsilon > 0$, the runtime is polynomial in n. For example, $O(n^{2/\epsilon})$.
- It is a fully polynomial-time approximation scheme (FPTAS) if the runtime is polynomial in both $1/\epsilon$ and n. For example, $O((1/\epsilon)^2 \cdot n^3)$.

Outline

Randomised Approximation

MAX-3-CNF

Weighted Vertex Cover

MAX-3-CNF Satisfiability

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- Given: 3-CNF formula, e.g.: $(x_1 \vee x_3 \vee \overline{x_4}) \wedge (x_2 \vee \overline{x_3} \vee \overline{x_5}) \wedge \cdots$

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Relaxation of the satisfiability problem. Want to compute how "close" the formula to being satisfiable is.

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Example:

$$(x_1 \vee x_3 \vee \overline{x_4}) \wedge (x_1 \vee \overline{x_3} \vee \overline{x_5}) \wedge (x_2 \vee \overline{x_4} \vee x_5) \wedge (\overline{x_1} \vee x_2 \vee \overline{x_3})$$

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$x_1 = 1$, $x_2 = 0$, $x_3 = 1$, $x_4 = 0$ and $x_5 = 1$ satisfies 3 (out of 4 clauses)

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Idea: What about assigning each variable uniformly and independently at random?

Analysis

Theorem 35.6

Given an instance of MAX-3-CNF with n variables $x_1, x_2, \ldots, x_n$ and m clauses, the randomised algorithm that sets each variable independently at random is a randomised $8/7$-approximation algorithm.

Analysis

Theorem 35.6

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Linearity of Expectations

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$$\mathbf{P}[\,\text{clause } i \text{ is not satisfied}\,] = \frac{1}{2} \cdot \frac{1}{2} \cdot \frac{1}{2} = \frac{1}{8}$$

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$$\Rightarrow \quad \mathbf{E}[\,Y_i\,] = \mathbf{P}[\,Y_i = 1\,] \cdot 1 = \frac{7}{8}.$$

- Let $Y := \sum_{i=1}^{m} Y_i$ be the number of satisfied clauses. Then,

$$\mathbf{E}[\,Y\,] = \mathbf{E}\left[\sum_{i=1}^{m} Y_i\right] = \sum_{i=1}^{m} \mathbf{E}[\,Y_i\,] = \sum_{i=1}^{m} \frac{7}{8}$$

Linearity of Expectations

Analysis

Theorem 35.6

Given an instance of MAX-3-CNF with n variables $x_1, x_2, \ldots, x_n$ and m clauses, the randomised algorithm that sets each variable independently at random is a randomised $8/7$-approximation algorithm.

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Linearity of Expectations

maximum number of satisfiable clauses is m

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Linearity of Expectations

maximum number of satisfiable clauses is m

Interesting Implications

Theorem 35.6

Given an instance of MAX-3-CNF with n variables $x_1, x_2, \ldots, x_n$ and m clauses, the randomised algorithm that sets each variable independently at random is a polynomial-time randomised $8/7$-approximation algorithm.

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For any instance of MAX-3-CNF, there exists an assigment which satisfies at least $\frac{7}{8}$ of all clauses.

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Any instance of MAX-3-CNF with at most 7 clauses is satisfiable.

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Follows from the previous Corollary.

Expected Approximation Ratio

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Expected Approximation Ratio

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Given an instance of MAX-3-CNF with n variables $x_1, x_2, \ldots, x_n$ and m clauses, the randomised algorithm that sets each variable independently at random is a polynomial-time randomised $8/7$-approximation algorithm.

One could prove that the probability to satisfy $(7/8) \cdot m$ clauses is at least $1/(8m)$

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$$\mathbf{E}[\,Y\,] = \frac{1}{2} \cdot \mathbf{E}[\,Y \mid x_1 = 1\,] + \frac{1}{2} \cdot \mathbf{E}[\,Y \mid x_1 = 0\,].$$

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One of the two conditional expectations is at least $\mathbf{E}[\,Y\,]$

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Algorithm: Assign x_1 so that the conditional expectation is maximised and recurse.

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GREEDY-3-CNF(ϕ, n, m)

for $j = 1, 2, \ldots, n$
  Compute $\mathbf{E}[\,Y \mid x_1 = v_1 \ldots, x_{j-1} = v_{j-1}, x_j = 1\,]$
  Compute $\mathbf{E}[\,Y \mid x_1 = v_1, \ldots, x_{j-1} = v_{j-1}, x_j = 0\,]$
  Let $x_j = v_j$ so that the conditional expectation is maximised
return the assignment $v_1, v_2, \ldots, v_n$

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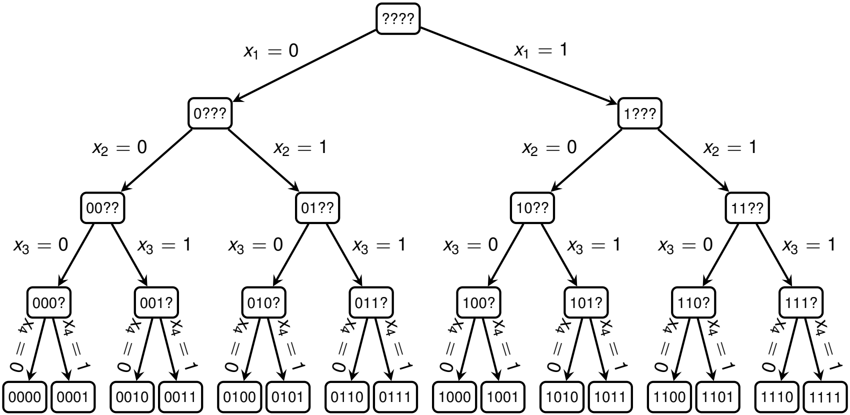
Skip Analysis

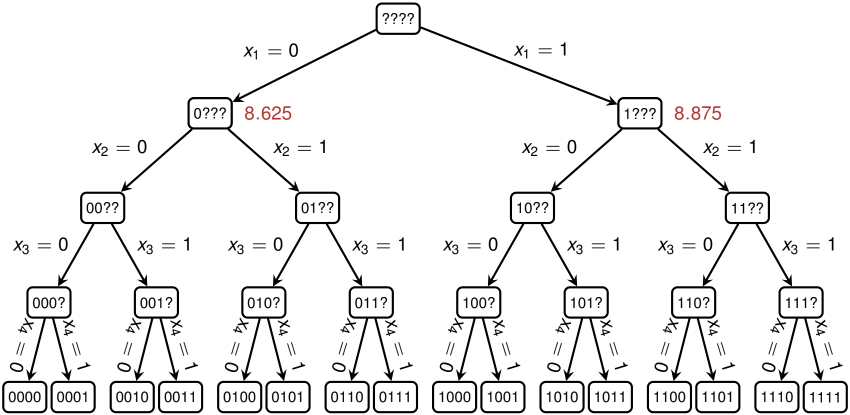
Run of GREEDY-3-CNF(φ, n, m)

$(x_1 \vee x_2 \vee x_3) \wedge (x_1 \vee \overline{x_2} \vee \overline{x_4}) \wedge (x_1 \vee x_2 \vee \overline{x_4}) \wedge (\overline{x_1} \vee \overline{x_3} \vee x_4) \wedge (x_1 \vee x_2 \vee \overline{x_4}) \wedge (\overline{x_1} \vee \overline{x_2} \vee \overline{x_3}) \wedge (\overline{x_1} \vee x_2 \vee x_3) \wedge (\overline{x_1} \vee \overline{x_2} \vee x_3) \wedge (x_1 \vee x_3 \vee x_4) \wedge (x_2 \vee \overline{x_3} \vee \overline{x_4})$



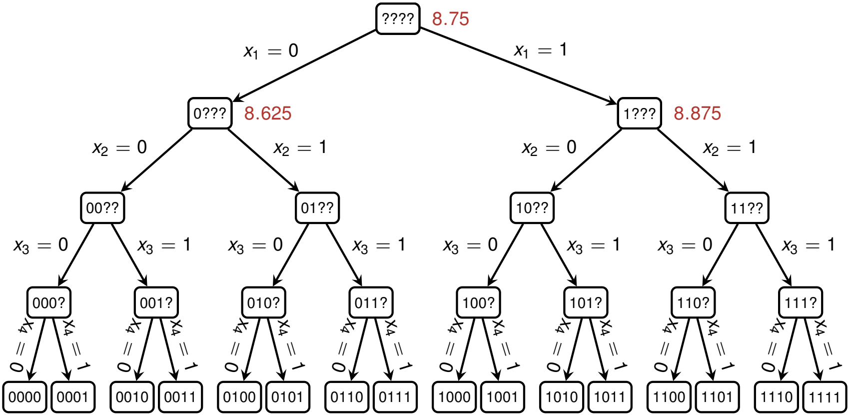
Run of GREEDY-3-CNF(φ, n, m)

$(x_1 \vee x_2 \vee x_3) \wedge (x_1 \vee \overline{x_2} \vee \overline{x_4}) \wedge (x_1 \vee x_2 \vee \overline{x_4}) \wedge (\overline{x_1} \vee \overline{x_3} \vee x_4) \wedge (x_1 \vee x_2 \vee \overline{x_4}) \wedge (\overline{x_1} \vee \overline{x_2} \vee \overline{x_3}) \wedge (\overline{x_1} \vee x_2 \vee x_3) \wedge (\overline{x_1} \vee \overline{x_2} \vee x_3) \wedge (x_1 \vee x_3 \vee x_4) \wedge (x_2 \vee \overline{x_3} \vee \overline{x_4})$



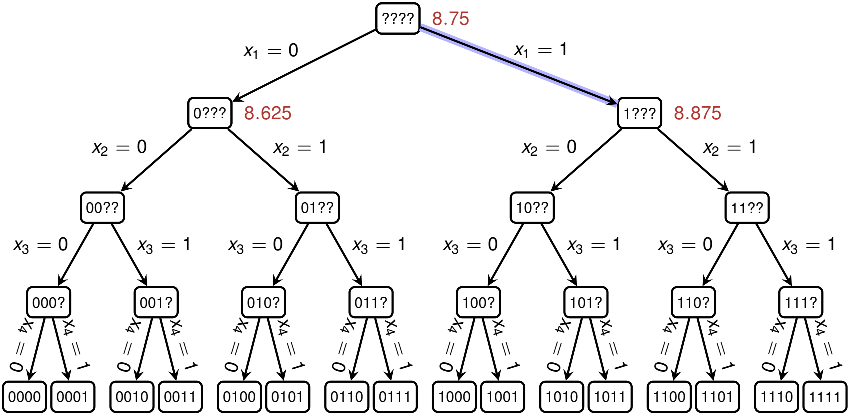
Run of GREEDY-3-CNF(φ, n, m)

$$(x_1 \vee x_2 \vee x_3) \wedge (x_1 \vee \overline{x_2} \vee \overline{x_4}) \wedge (x_1 \vee x_2 \vee \overline{x_4}) \wedge (\overline{x_1} \vee \overline{x_3} \vee x_4) \wedge (x_1 \vee x_2 \vee \overline{x_4}) \wedge (\overline{x_1} \vee \overline{x_2} \vee \overline{x_3}) \wedge (\overline{x_1} \vee x_2 \vee x_3) \wedge (\overline{x_1} \vee \overline{x_2} \vee x_3) \wedge (x_1 \vee x_3 \vee x_4) \wedge (x_2 \vee \overline{x_3} \vee \overline{x_4})$$



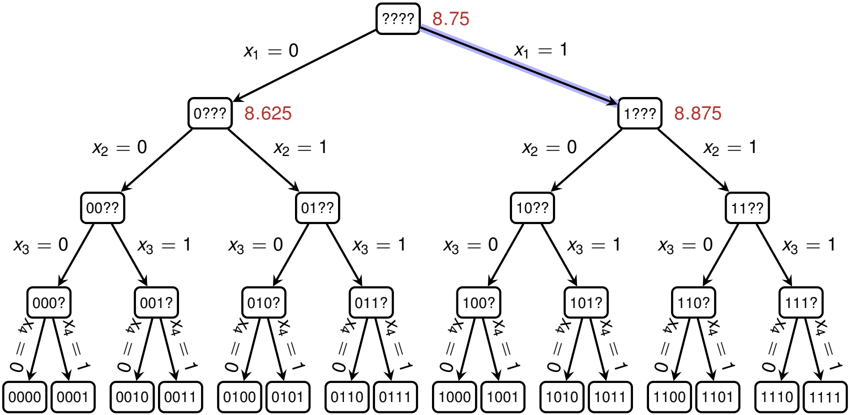
Run of GREEDY-3-CNF(φ, n, m)

$(x_1 \vee x_2 \vee x_3) \wedge (x_1 \vee \overline{x_2} \vee \overline{x_4}) \wedge (x_1 \vee x_2 \vee \overline{x_4}) \wedge (\overline{x_1} \vee \overline{x_3} \vee x_4) \wedge (x_1 \vee x_2 \vee \overline{x_4}) \wedge (\overline{x_1} \vee \overline{x_2} \vee \overline{x_3}) \wedge (\overline{x_1} \vee x_2 \vee x_3) \wedge (\overline{x_1} \vee \overline{x_2} \vee x_3) \wedge (x_1 \vee x_3 \vee x_4) \wedge (x_2 \vee \overline{x_3} \vee \overline{x_4})$



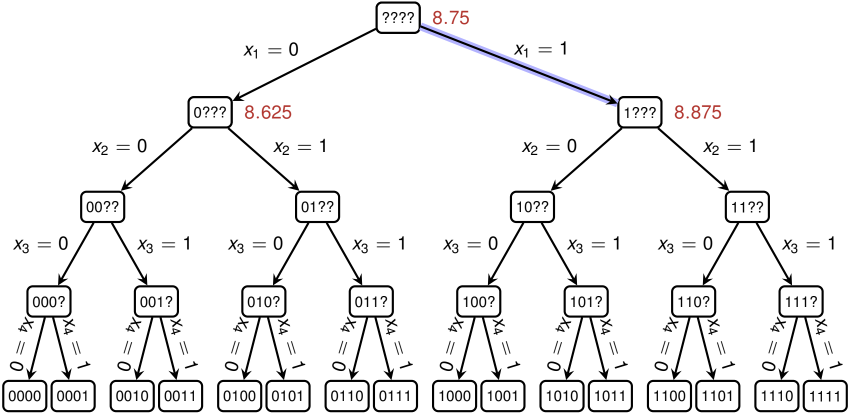
Run of GREEDY-3-CNF(φ, n, m)

$(x_1 \lor x_2 \lor \overline{x_3}) \land (x_1 \lor \overline{x_2} \lor \overline{x_4}) \land (x_1 \lor x_2 \lor \overline{x_4}) \land (\overline{x_1} \lor \overline{x_3} \lor x_4) \land (x_1 \lor x_2 \lor \overline{x_4}) \land (\overline{x_1} \lor \overline{x_2} \lor \overline{x_3}) \land (\overline{x_1} \lor x_2 \lor x_3) \land (\overline{x_1} \lor \overline{x_2} \lor x_3) \land (x_1 \lor x_3 \lor \overline{x_4}) \land (x_2 \lor \overline{x_3} \lor \overline{x_4})$



Run of GREEDY-3-CNF(φ, n, m)

$$1 \wedge 1 \wedge 1 \wedge (\overline{x_3} \vee x_4) \wedge 1 \wedge (\overline{x_2} \vee \overline{x_3}) \wedge (x_2 \vee x_3) \wedge (\overline{x_2} \vee x_3) \wedge 1 \wedge (x_2 \vee \overline{x_3} \vee \overline{x_4})$$



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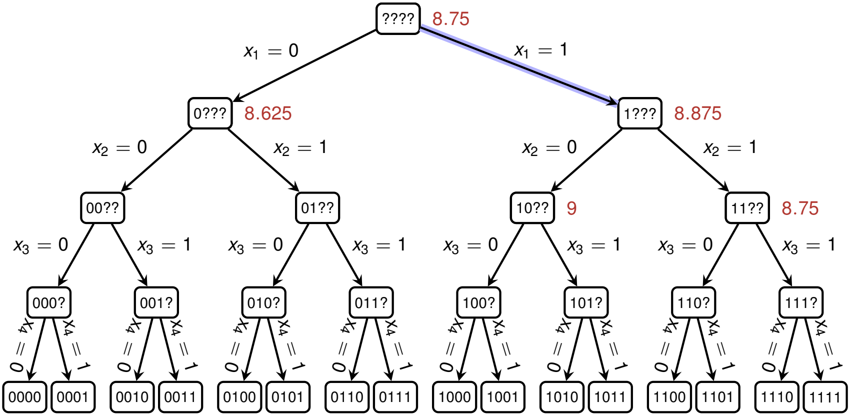

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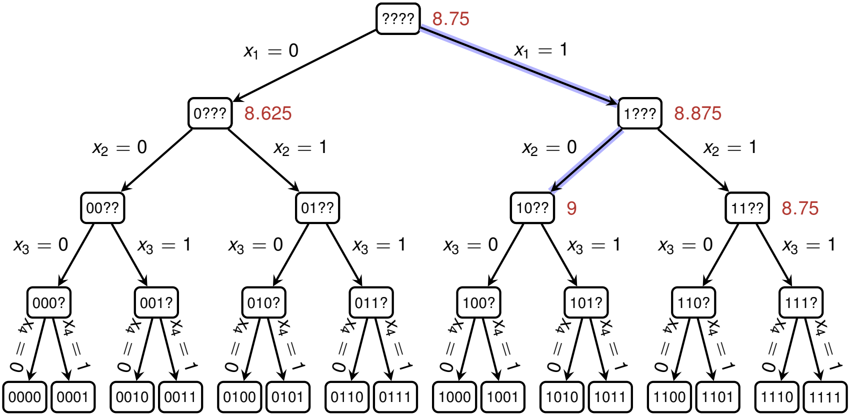
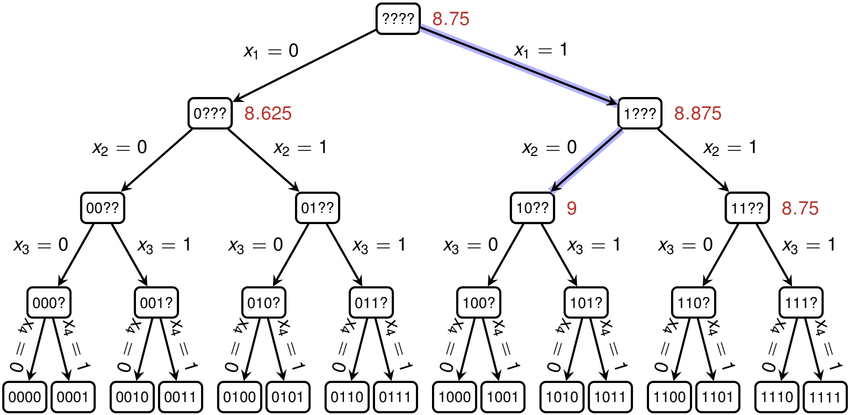
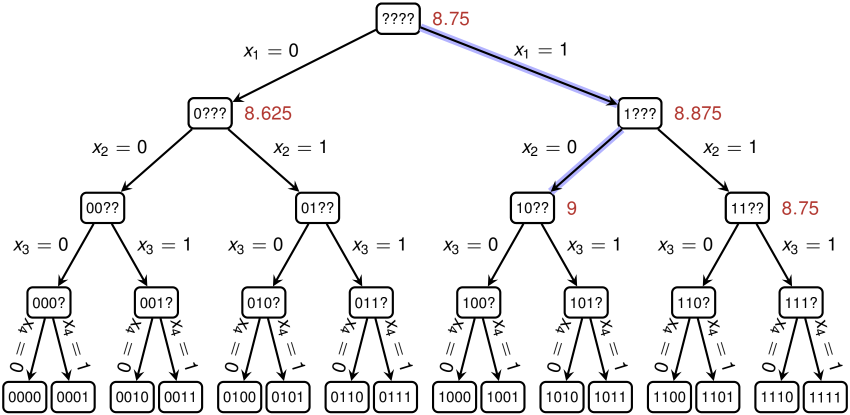


Run of GREEDY-3-CNF(φ, n, m)

$$1 \wedge 1 \wedge 1 \wedge (\overline{x_3} \vee x_4) \wedge 1 \wedge \cancel{(\overline{x_2} \vee \overline{x_3})} \wedge (\cancel{x_2} \vee x_3) \wedge \cancel{(\overline{x_2} \vee x_3)} \wedge 1 \wedge (\cancel{x_2} \vee \overline{x_3} \vee \overline{x_4})$$



$$1 \wedge 1 \wedge 1 \wedge (\overline{x_3} \vee x_4) \wedge 1 \wedge 1 \wedge (x_3) \wedge 1 \wedge 1 \wedge (\overline{x_3} \vee \overline{x_4})$$



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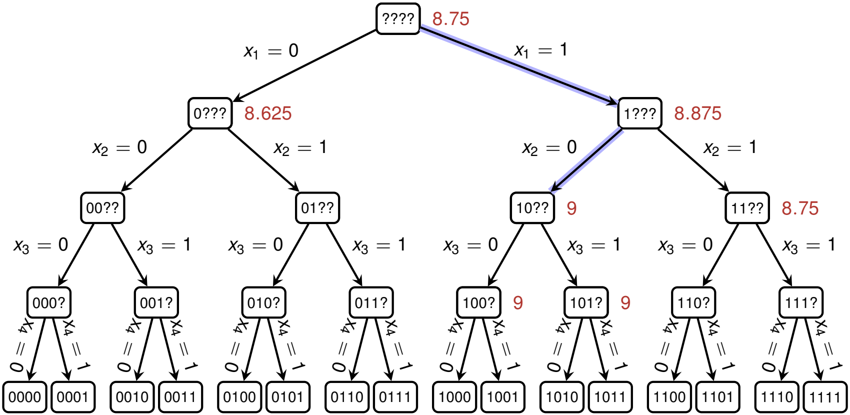

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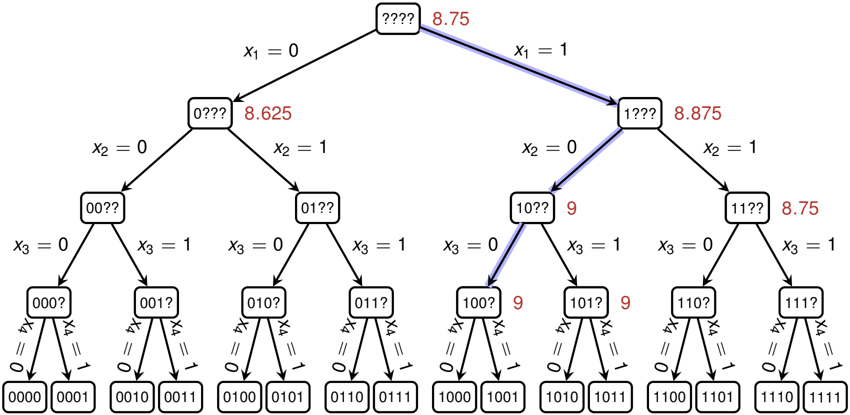
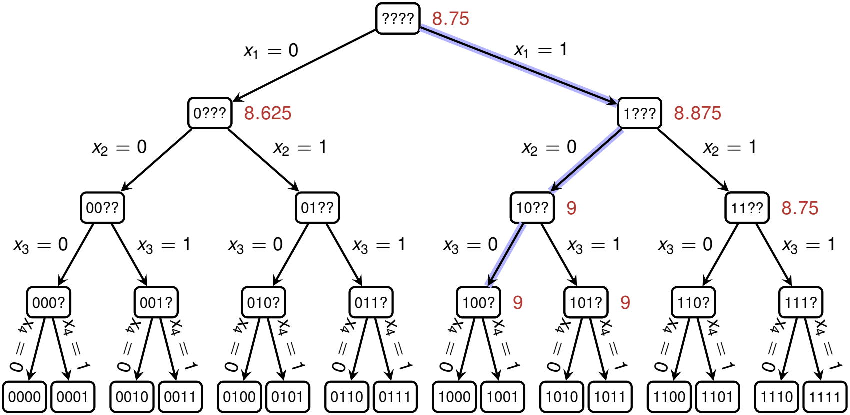


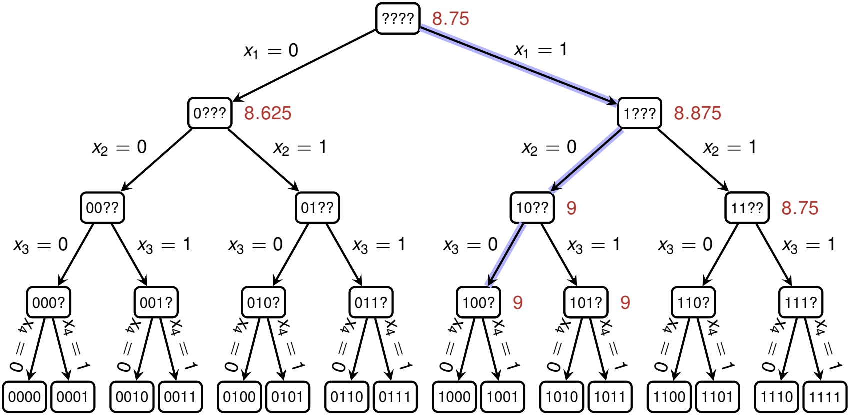
Run of GREEDY-3-CNF(φ, n, m)

$$1 \wedge 1 \wedge 1 \wedge \cancel{(\overline{x_3} \vee x_4)} \wedge 1 \wedge 1 \wedge \cancel{(x_3)} \wedge 1 \wedge 1 \wedge (\cancel{\overline{x_3}} \vee \overline{x_4})$$

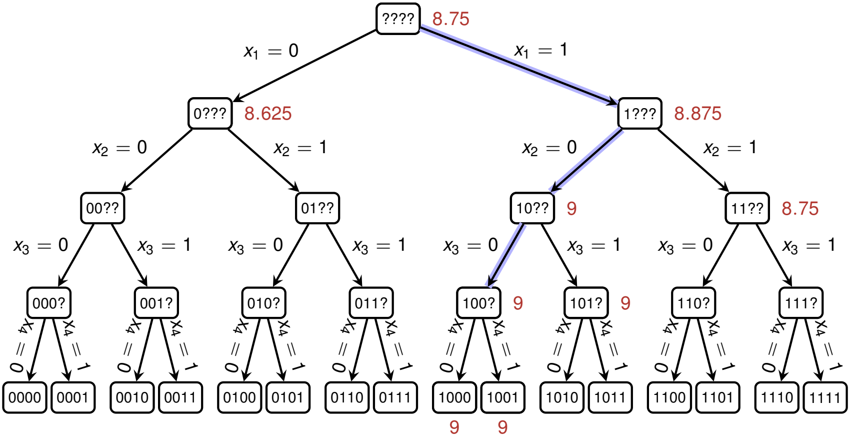


Run of GREEDY-3-CNF(φ, n, m)

$1 \wedge 1 \wedge 1 \wedge 1 \wedge 1 \wedge 1 \wedge 0 \wedge 1 \wedge 1 \wedge 1$

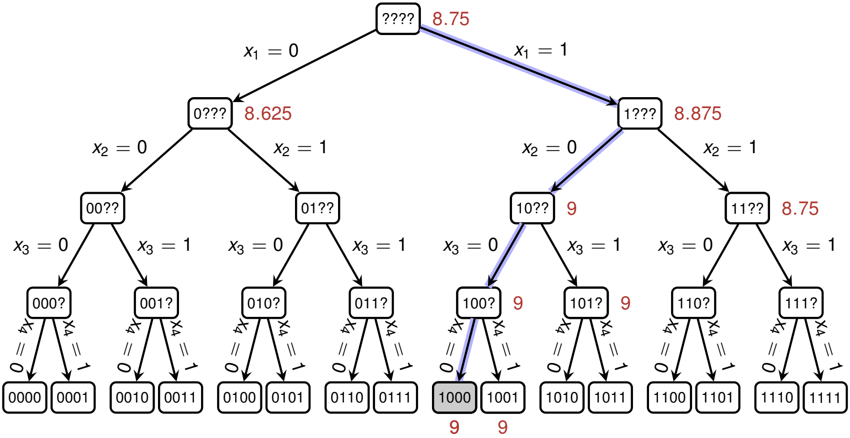


$1 \wedge 1 \wedge 1 \wedge 1 \wedge 1 \wedge 1 \wedge 0 \wedge 1 \wedge 1 \wedge 1$



Run of GREEDY-3-CNF(φ, n, m)

$1 \wedge 1 \wedge 1 \wedge 1 \wedge 1 \wedge 1 \wedge 0 \wedge 1 \wedge 1 \wedge 1$



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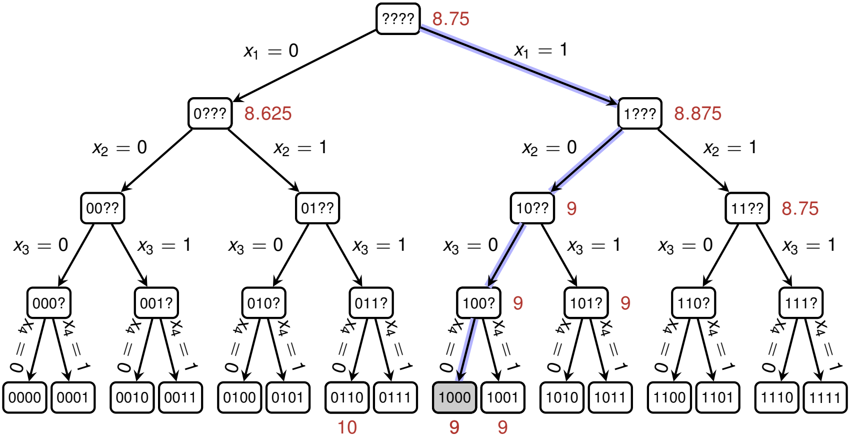
$1 \wedge 1 \wedge 1 \wedge 1 \wedge 1 \wedge 1 \wedge 0 \wedge 1 \wedge 1 \wedge 1$



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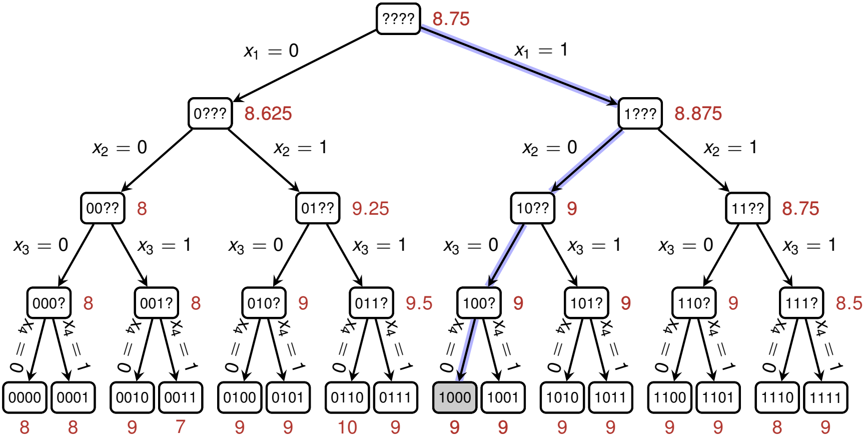
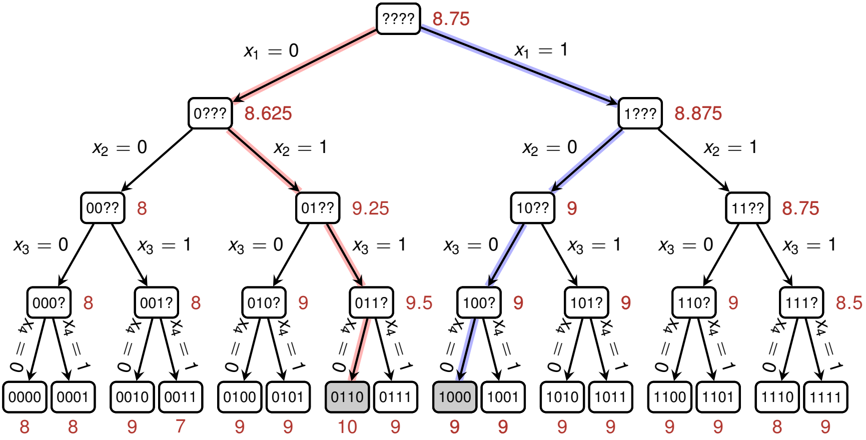
$1 \wedge 1 \wedge 1 \wedge 1 \wedge 1 \wedge 1 \wedge 0 \wedge 1 \wedge 1 \wedge 1$



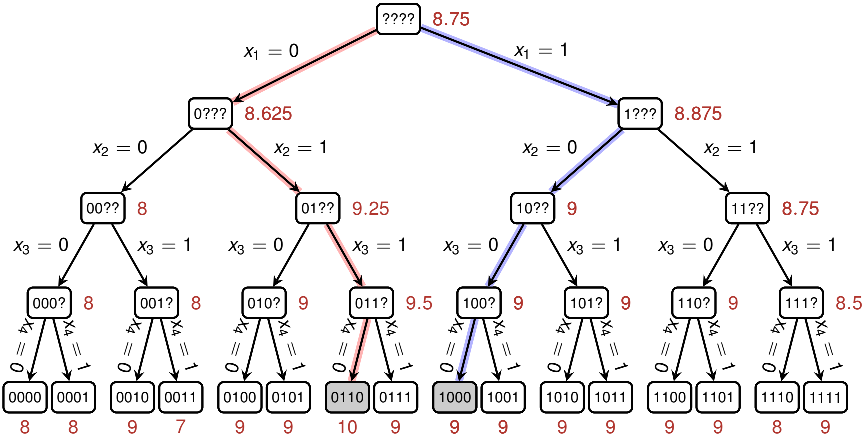
Run of GREEDY-3-CNF(φ, n, m)

$1 \wedge 1 \wedge 1 \wedge 1 \wedge 1 \wedge 1 \wedge 0 \wedge 1 \wedge 1 \wedge 1$



Run of GREEDY-3-CNF(φ, n, m)

$1 \wedge 1 \wedge 1 \wedge 1 \wedge 1 \wedge 1 \wedge 0 \wedge 1 \wedge 1 \wedge 1$



Returned solution satisfies 9 out of 10 clauses, but the formula is satisfiable.

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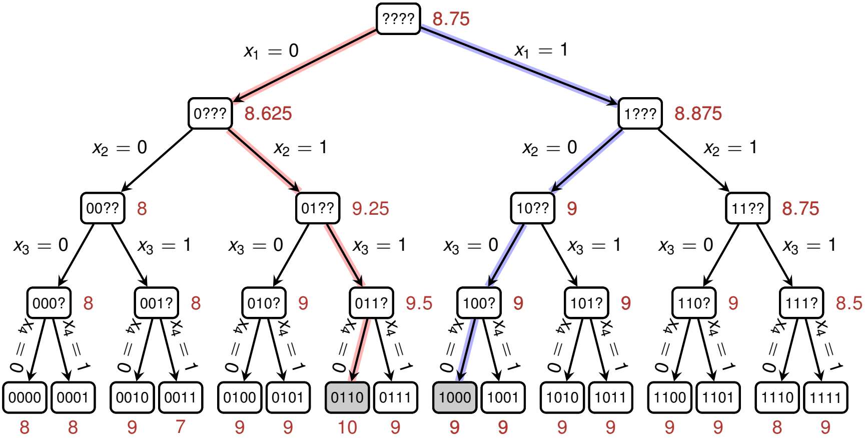

Go to Analysis

Analysis of GREEDY-3-CNF(ϕ, n, m)

Theorem

GREEDY-3-CNF(ϕ, n, m) is a polynomial-time $8/7$-approximation.

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Go to Conclusion

MAX-3-CNF: Concluding Remarks

Theorem 35.6

Given an instance of MAX-3-CNF with n variables $x_1, x_2, \ldots, x_n$ and m clauses, the randomised algorithm that sets each variable independently at random is a randomised $8/7$-approximation algorithm.

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Theorem (Hastad'97)

For any $\epsilon > 0$, there is no polynomial time $8/7 - \epsilon$ approximation algorithm of MAX3-CNF unless P=NP.

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Essentially there is nothing smarter than just guessing!

Source of Image: Stefan Szeider, TU Vienna

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Outline

Randomised Approximation

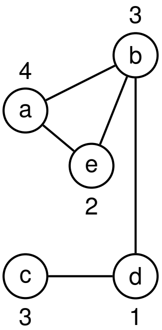
MAX-3-CNF

Weighted Vertex Cover

The Weighted Vertex-Cover Problem

Vertex Cover Problem

- Given: Undirected, vertex-weighted graph $G = (V, E)$
- Goal: Find a minimum-weight subset $V' \subseteq V$ such that if $\{u, v\} \in E(G)$, then $u \in V'$ or $v \in V'$.



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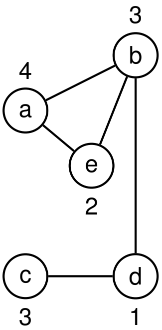

Question: How can we deal with graphs that have **negative** weights?

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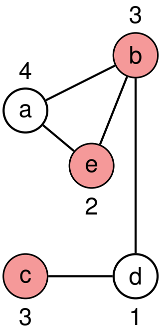

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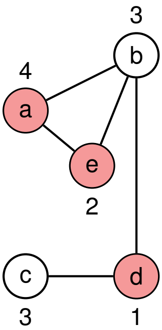

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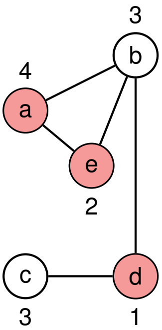

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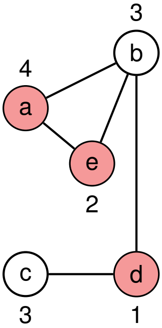

Applications:

The Weighted Vertex-Cover Problem

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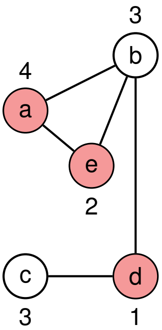

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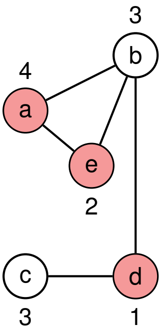

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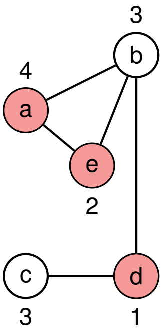

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- Perform all tasks with the minimal amount of resources

A Greedy Approach working for Unweighted Vertex Cover

APPROX-VERTEX-COVER(G)

```
C = ∅
E' = G.E
while E' ≠ ∅
    let (u, v) be an arbitrary edge of E'
    C = C ∪ {u, v}
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This algorithm is a 2-approximation for **unweighted graphs**!

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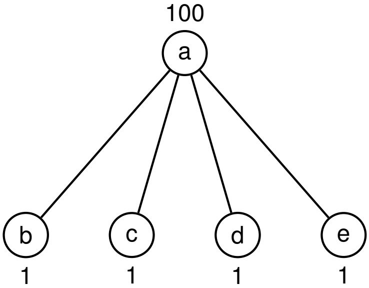

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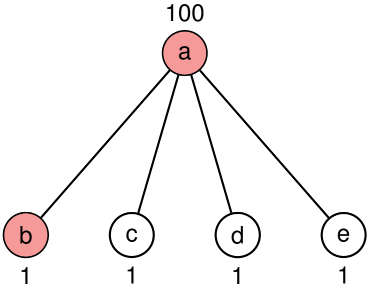
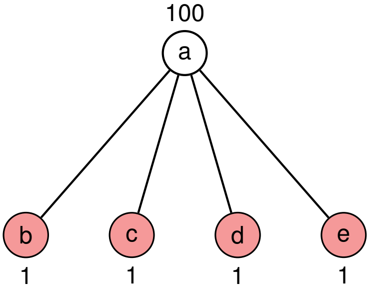


Computed solution has weight 101

A Greedy Approach working for Unweighted Vertex Cover

APPROX-VERTEX-COVER(G)

```
C = ∅
E' = G.E
while E' ≠ ∅
    let (u, v) be an arbitrary edge of E'
    C = C ∪ {u, v}
    remove from E' every edge incident on either u or v
return C
```



Optimal solution has weight 4

Invoking an (Integer) Linear Program

Idea: Round the solution of an associated linear program.

Invoking an (Integer) Linear Program

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0-1 Integer Program

$$\begin{array}{llcll} \text{minimize} & \sum_{v \in V} w(v)x(v) & & & \\ \text{subject to} & x(u) + x(v) & \geq & 1 & \text{for each } (u,v) \in E \\ & x(v) & \in & \{0,1\} & \text{for each } v \in V \end{array}$$

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$$\begin{array}{llcll} \text{minimize} & \sum_{v \in V} w(v)x(v) & & & \\ \text{subject to} & x(u) + x(v) & \geq & 1 & \text{for each } (u,v) \in E \\ & x(v) & \in & [0,1] & \text{for each } v \in V \end{array}$$

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optimum is a lower bound on the optimal weight of a minimum weight-cover.

Linear Program

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Rounding Rule: if $x(v) \geq 1/2$ then round up, otherwise round down.

The Algorithm

APPROX-MIN-WEIGHT-VC(G, w)

$C = \emptyset$
compute $\bar{x}$, an optimal solution to the linear program
for each $v \in V$
    if $\bar{x}(v) \geq 1/2$
        $C = C \cup \{v\}$
return C

The Algorithm

APPROX-MIN-WEIGHT-VC(G, w)

```
C = ∅
compute x̄, an optimal solution to the linear program
for each v ∈ V
    if x̄(v) ≥ 1/2
        C = C ∪ {v}
return C
```

Theorem 35.7

APPROX-MIN-WEIGHT-VC is a polynomial-time 2-approximation algorithm for the minimum-weight vertex-cover problem.

The Algorithm

APPROX-MIN-WEIGHT-VC(G, w)

```
C = ∅
compute x̄, an optimal solution to the linear program
for each v ∈ V
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return C
```

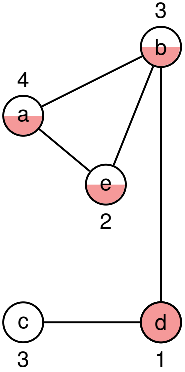
Theorem 35.7

APPROX-MIN-WEIGHT-VC is a polynomial-time 2-approximation algorithm for the minimum-weight vertex-cover problem.

is polynomial-time because we can solve the linear program in polynomial time

Example of APPROX-MIN-WEIGHT-VC

$\overline{x}(a) = \overline{x}(b) = \overline{x}(e) = \frac{1}{2}, \overline{x}(d) = 1, \overline{x}(c) = 0$



fractional solution of LP
with weight $= 5.5$

Example of APPROX-MIN-WEIGHT-VC

$\overline{x}(a) = \overline{x}(b) = \overline{x}(e) = \frac{1}{2}, \overline{x}(d) = 1, \overline{x}(c) = 0$

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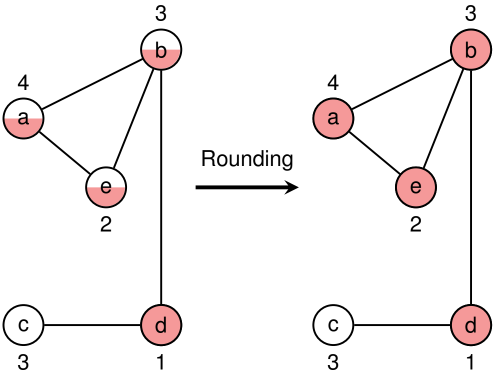
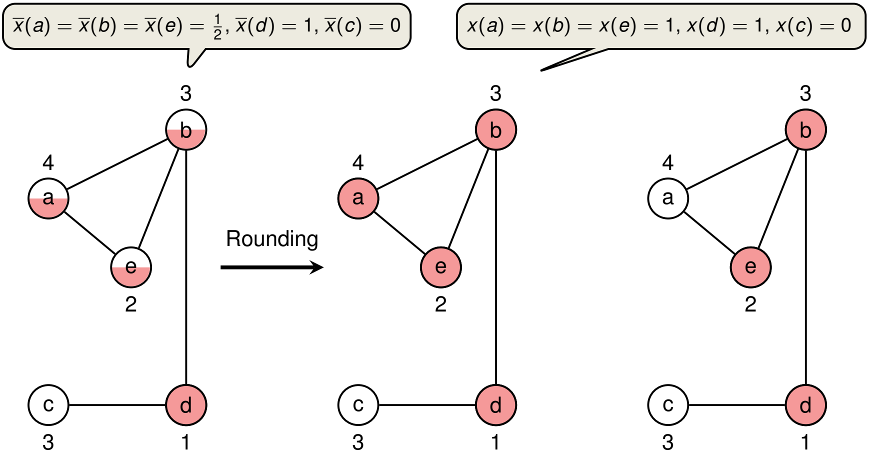


fractional solution of LP
with weight $= 5.5$

rounded solution of LP
with weight $= 10$

Example of APPROX-MIN-WEIGHT-VC



fractional solution of LP with weight $= 5.5$

rounded solution of LP with weight $= 10$

optimal solution with weight $= 6$

Approximation Ratio

Proof (Approximation Ratio is 2 and Correctness):

Approximation Ratio

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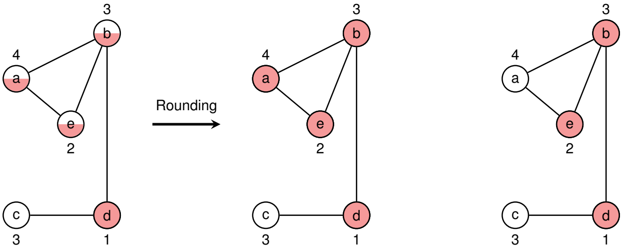

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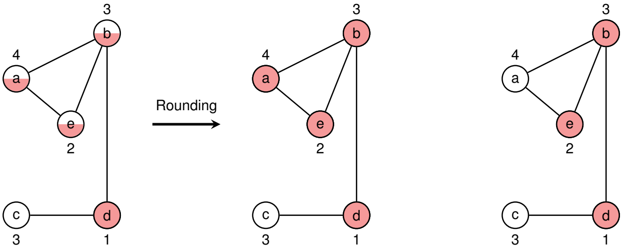

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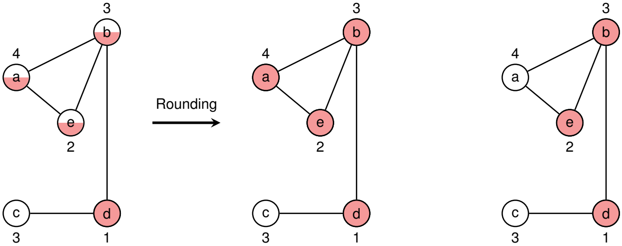

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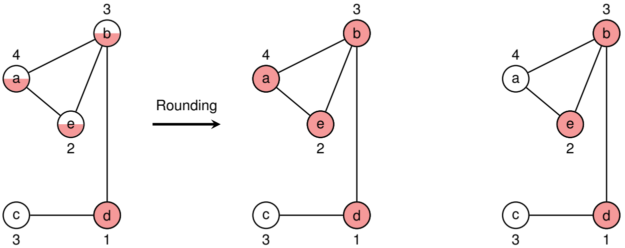

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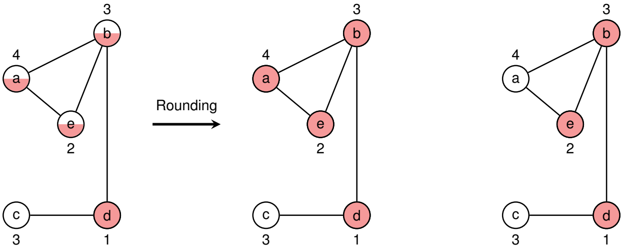

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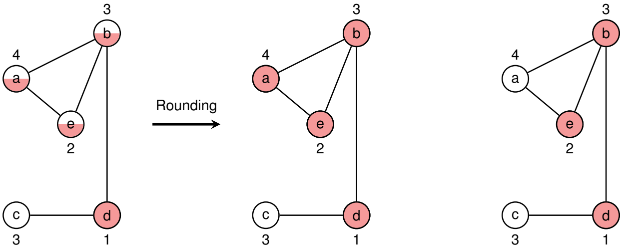

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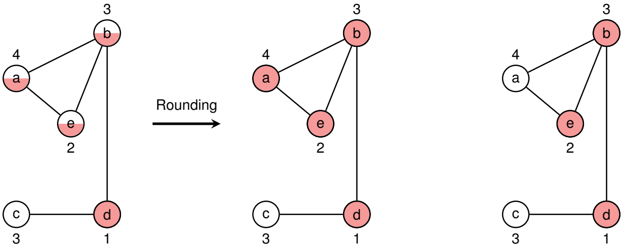

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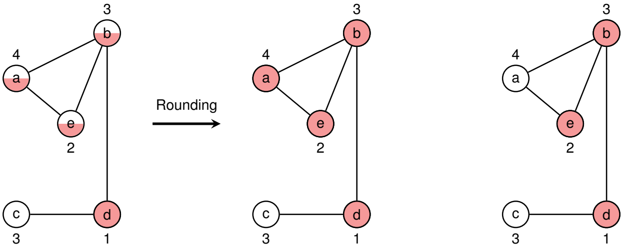

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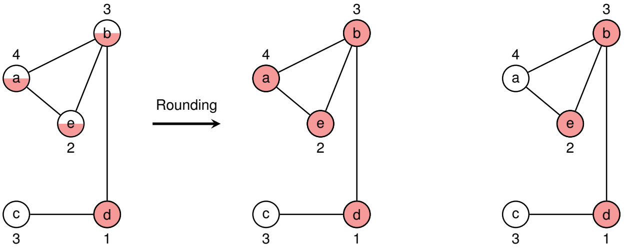

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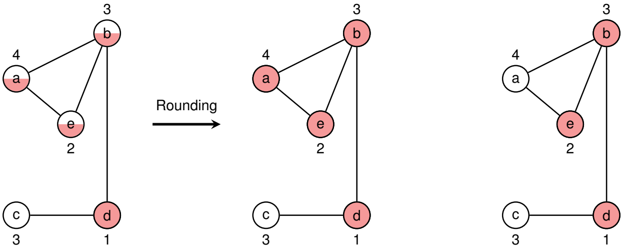

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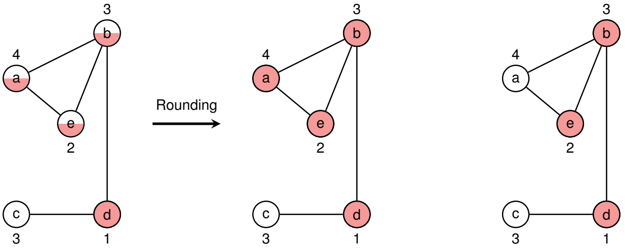

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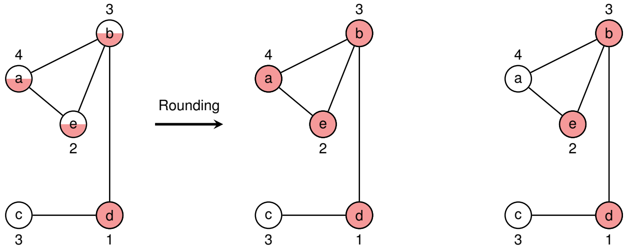

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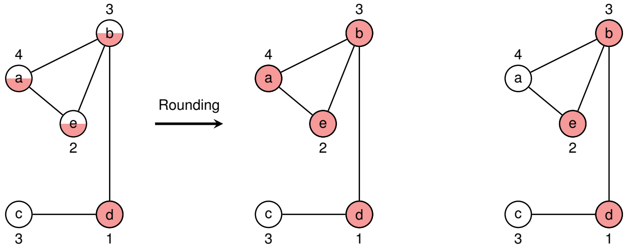

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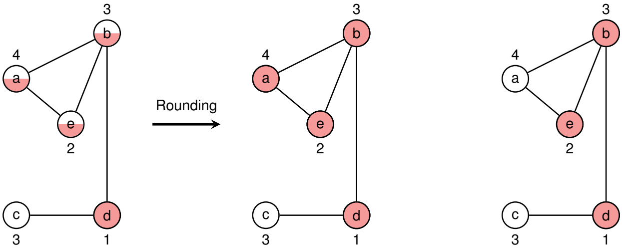

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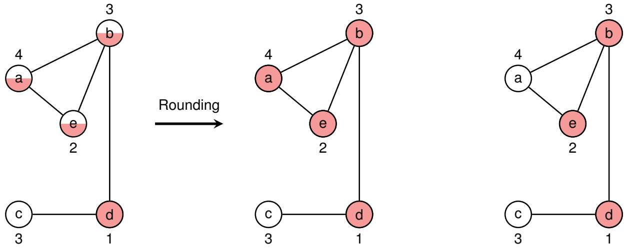

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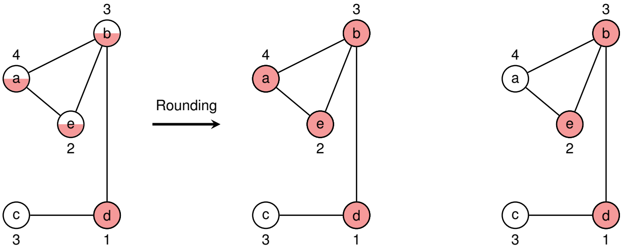

Randomised Algorithms

Lecture 10: Approximation Algorithms: Set-Cover and MAX-CNF

Thomas Sauerwald (tms41@cam.ac.uk)

Lent 2024

UNIVERSITY OF CAMBRIDGE

Outline

Weighted Set Cover

MAX-CNF

The Weighted Set-Cover Problem

Set Cover Problem

- Given: set X and a family of subsets $\mathcal{F}$, and a cost function $c : \mathcal{F} \to \mathbb{R}^+$
- Goal: Find a minimum-cost subset $\mathcal{C} \subseteq \mathcal{F}$

$$\text{s.t.} \qquad X = \bigcup_{S \in \mathcal{C}} S.$$

The Weighted Set-Cover Problem

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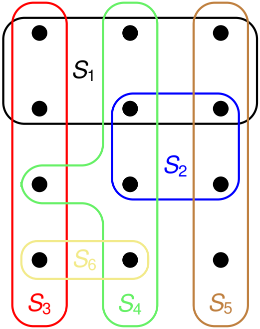
Sum over the costs of all sets in $\mathcal{C}$



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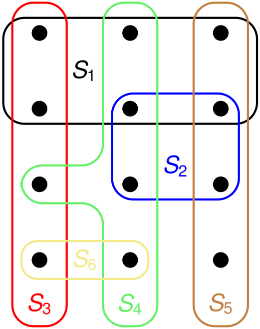

	S_1	S_2	S_3	S_4	S_5	S_6
c :	2	3	3	5	1	2

The Weighted Set-Cover Problem

Set Cover Problem

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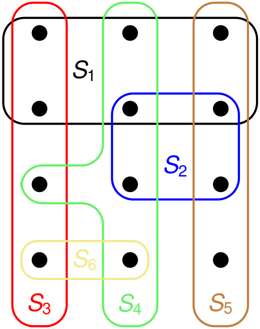

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Remarks:

- generalisation of the weighted Vertex-Cover problem
- models resource allocation problems

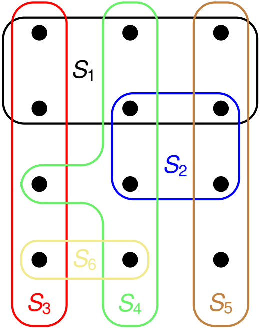
The Weighted Set-Cover Problem

Set Cover Problem

- Given: set X and a family of subsets $\mathcal{F}$, and a cost function $c : \mathcal{F} \to \mathbb{R}^+$
- Goal: Find a minimum-cost subset $\mathcal{C} \subseteq \mathcal{F}$

s.t. $$X = \bigcup_{S \in \mathcal{C}} S.$$

Sum over the costs of all sets in $\mathcal{C}$



	S_1	S_2	S_3	S_4	S_5	S_6
c :	2	3	3	5	1	2

???

Question: How can we reduce the Vertex-Cover problem to the Set-Cover problem?

Remarks:

- generalisation of the weighted Vertex-Cover problem
- models resource allocation problems

Setting up an Integer Program

Question: Try to formulate the integer program and linear program of the weighted SET-COVER problem (solution on next slide!)

Setting up an Integer Program

0-1 Integer Program

$$\begin{array}{llcll}
\text{minimize} & \displaystyle\sum_{S \in \mathcal{F}} c(S) y(S) & & & \\
\text{subject to} & \displaystyle\sum_{S \in \mathcal{F}\colon\, x \in S} y(S) & \geq & 1 & \text{for each } x \in X \\
& y(S) & \in & \{0, 1\} & \text{for each } S \in \mathcal{F}
\end{array}$$

Setting up an Integer Program

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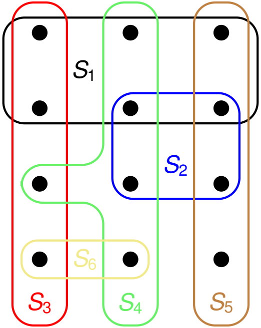
Linear Program

$$\begin{array}{llcll} \text{minimize} & \sum_{S \in \mathcal{F}} c(S)y(S) & & & \\ \text{subject to} & \sum_{S \in \mathcal{F}:\, x \in S} y(S) & \geq & 1 & \text{for each } x \in X \\ & y(S) & \in & [0,1] & \text{for each } S \in \mathcal{F} \end{array}$$

Back to the Example



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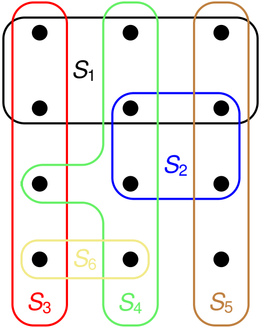

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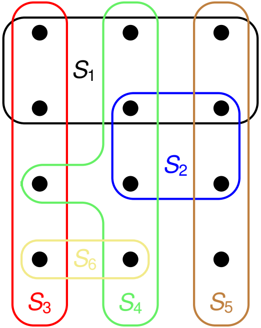

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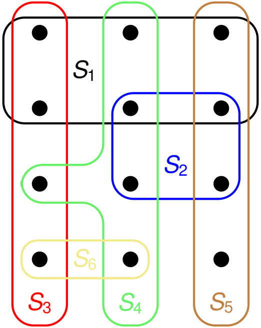

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The strategy employed for Vertex-Cover would take all 6 sets!

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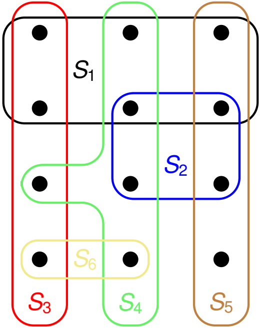

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The strategy employed for Vertex-Cover would take all 6 sets!

Even worse: If all $\overline{y}$'s were below $1/2$, we would not even return a valid cover!

Randomised Rounding

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Idea: Interpret the $\overline{y}$-values as probabilities for picking the respective set.

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- Let $\mathcal{C} \subseteq \mathcal{F}$ be a random set with each set S being included independently with probability $\overline{y}(S)$.
- More precisely, if $\overline{y}$ denotes the optimal solution of the LP, then we compute an integral solution y by:

$$y(S) = \begin{cases} 1 & \text{with probability } \overline{y}(S) \\ 0 & \text{otherwise.} \end{cases} \qquad \text{for all } S \in \mathcal{F}.$$

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- Therefore, $\mathbf{E}[\, y(S) \,] = \overline{y}(S)$.

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$$\mathbf{P}[\,x \notin \cup_{S \in \mathcal{C}} S\,] = \prod_{S \in \mathcal{F}\colon x \in S} \mathbf{P}[\,S \notin \mathcal{C}\,] = \prod_{S \in \mathcal{F}\colon x \in S} (1 - \overline{y}(S))$$

$$\leq \prod_{S \in \mathcal{F}\colon x \in S} e^{-\overline{y}(S)}$$

$$= e^{-\sum_{S \in \mathcal{F}\colon x \in S} \overline{y}(S)} \leq e^{-1}$$

$1 + x \leq e^x$ for any $x \in \mathbb{R}$

$\overline{y}$ solves the LP!

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Lemma

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C = ∅
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clearly runs in polynomial-time!

Analysis of WEIGHTED SET COVER-LP

Theorem

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Hence with probability at least $1 - \frac{1}{n} - \frac{1}{2} > \frac{1}{3}$, solution is valid and within a factor of $4\ln(n)$ of the optimum.

probability could be further increased by repeating

Typical Approach for Designing Approximation Algorithms based on LPs

Analysis of WEIGHTED SET COVER-LP

Theorem

- With probability at least $1 - \frac{1}{n}$, the returned set $\mathcal{C}$ is a valid cover of X.
- The expected approximation ratio is $2\ln(n)$.

By Markov's inequality, $\mathbf{P}[\, c(\mathcal{C}) \leq 4\ln(n) \cdot c(\mathcal{C}^*) \,] \geq 1/2$.

Hence with probability at least $1 - \frac{1}{n} - \frac{1}{2} > \frac{1}{3}$, solution is valid and within a factor of $4\ln(n)$ of the optimum.

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Typical Approach for Designing Approximation Algorithms based on LPs

[Exercise Question (9/10).10] gives a different perspective on the amplification procedure through non-linear randomised rounding.

Outline

Weighted Set Cover

MAX-CNF

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Recall:

MAX-3-CNF Satisfiability

- Given: 3-CNF formula, e.g.: $(x_1 \vee x_3 \vee \overline{x_4}) \wedge (x_2 \vee \overline{x_3} \vee \overline{x_5}) \wedge \cdots$
- Goal: Find an assignment of the variables that satisfies as many clauses as possible.

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Why study this generalised problem?

- Allowing arbitrary clause lengths makes the problem more interesting (we will see that simply guessing is not the best!)
- a nice concluding example where we can practice previously learned approaches

Approach 1: Guessing the Assignment

Assign each variable true or false uniformly and independently at random.

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- First statement as in the proof of Theorem 35.6. For clause i not to be satisfied, all ℓ occurring variables must be set to a specific value.
- As before, let $Y := \sum_{i=1}^{m} Y_i$ be the number of satisfied clauses. Then,

$$\mathbf{E}[Y] = \mathbf{E}\left[\sum_{i=1}^{m} Y_i\right] = \sum_{i=1}^{m} \mathbf{E}[Y_i] \geq \sum_{i=1}^{m} \frac{1}{2} = \frac{1}{2} \cdot m. \qquad \square$$

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First solve a linear program and use fractional values for a **biased** coin flip.

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\begin{aligned}
\text{maximize} \quad & \sum_{i=1}^{m} z_i \\
\text{subject to} \quad & \sum_{j \in C_i^+} y_j + \sum_{j \in C_i^-} (1 - y_j) \geq z_i && \text{for each } i = 1, 2, \ldots, m \\
& z_i \in \{0, 1\} && \text{for each } i = 1, 2, \ldots, m \\
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C_i^+ is the index set of the un-negated variables of clause i.

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- In the corresponding LP each $\in \{0, 1\}$ is replaced by $\in [0, 1]$
- Let $(\overline{y}, \overline{z})$ be the optimal solution of the LP
- Obtain an integer solution y through randomised rounding of $\overline{y}$

Analysis of Randomised Rounding

Lemma

For any clause i of length ℓ,

$$\mathbf{P}\left[\,\text{clause } i \text{ is satisfied}\,\right] \geq \left(1 - \left(1 - \frac{1}{\ell}\right)^{\ell}\right) \cdot \overline{z}_i.$$

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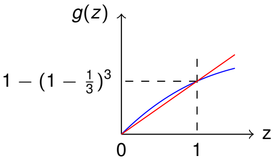

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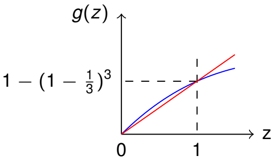

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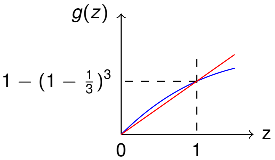

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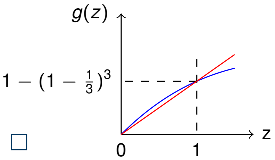

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- Then the expected number of satisfied clauses is:

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Analysis of Randomised Rounding

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LP solution at least as good as optimum

Approach 3: Hybrid Algorithm

Summary

- Approach 1 (Guessing) achieves better guarantee on longer clauses
- Approach 2 (Rounding) achieves better guarantee on shorter clauses

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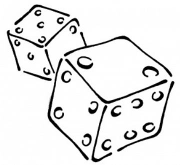
Let $b \in \{0, 1\}$ be the flip of a fair coin
If $b = 0$ **then** perform random guessing
If $b = 1$ **then** perform randomised rounding
return the computed solution



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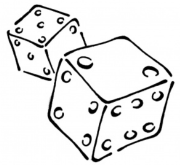

Algorithm sets each variable x_i to TRUE with prob. $\frac{1}{2} \cdot \frac{1}{2} + \frac{1}{2} \cdot \overline{y}_i$.
Note, however, that variables are **not** independently assigned!

Analysis of Hybrid Algorithm

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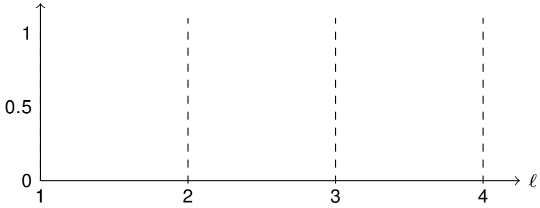

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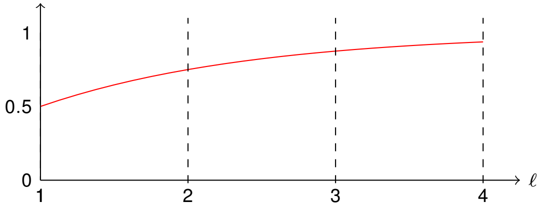

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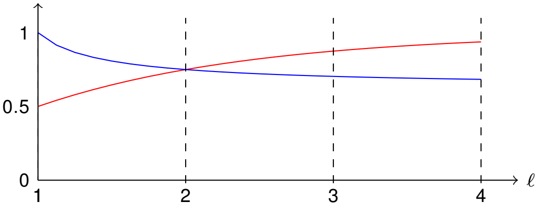

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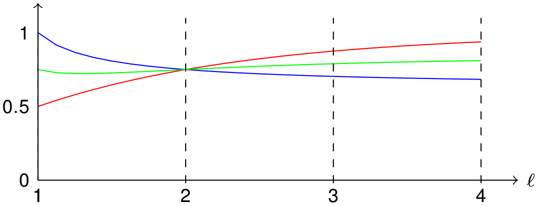

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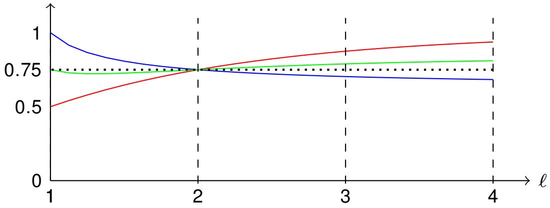

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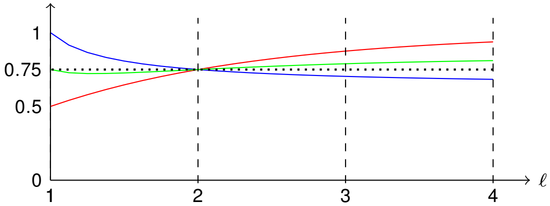


MAX-CNF Conclusion

Summary

- Since $\alpha_2 = \beta_2 = 3/4$, we cannot achieve a better approximation ratio than $4/3$ by combining Algorithm 1 & 2 in a different way
- The $4/3$-approximation algorithm can be easily derandomised
  - Idea: use the conditional expectation trick for both Algorithm 1 & 2 and output the better solution
- The $4/3$-approximation algorithm applies unchanged to a weighted version of MAX-CNF, where each clause has a non-negative weight
- Even MAX-2-CNF (every clause has length 2) is NP-hard!

Randomised Algorithms

Lecture 11: Spectral Graph Theory

Thomas Sauerwald (tms41@cam.ac.uk)

Lent 2024

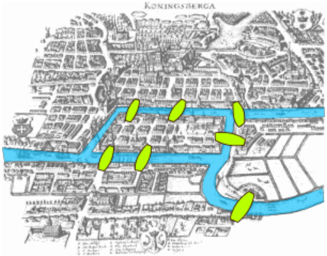
Outline

Introduction to (Spectral) Graph Theory and Clustering

Matrices, Spectrum and Structure

A Simplified Clustering Problem

Origin of Graph Theory



Source: Wikipedia

Seven Bridges at Königsberg 1737

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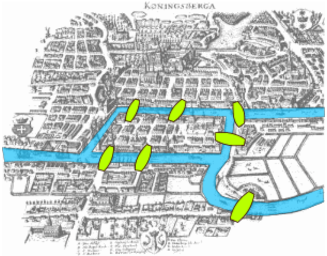

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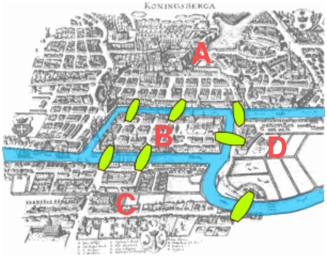

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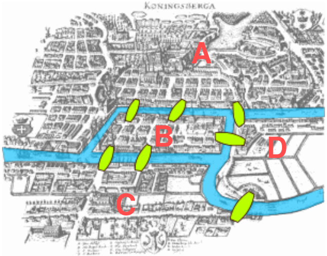

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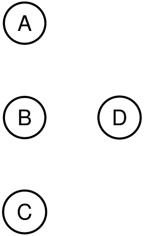

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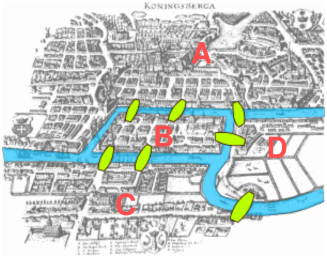

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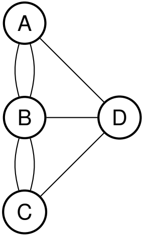

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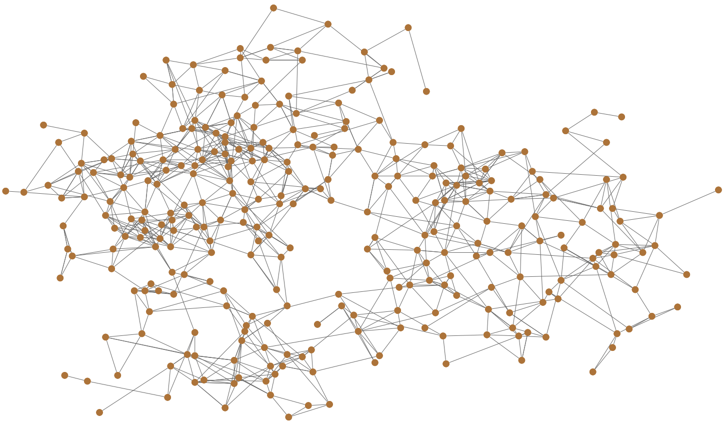
Graphs Nowadays: Clustering



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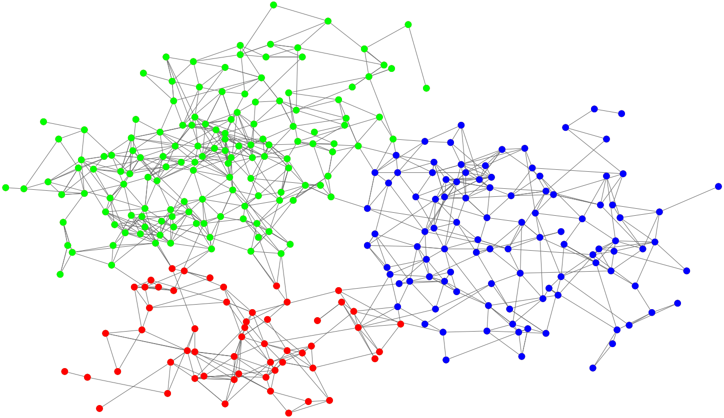

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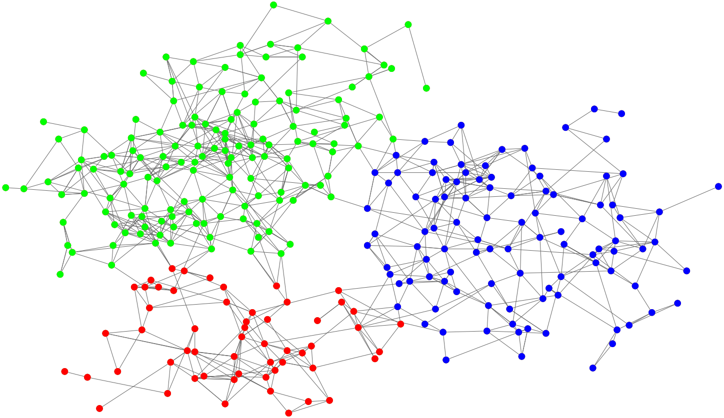

Goal: Use spectrum of graphs (unstructured data) to extract clustering (communitites) or other structural information.

Graph Clustering (applications)

- Applications of Graph Clustering
  - Community detection
  - Group webpages according to their topics
  - Find proteins performing the same function within a cell
  - Image segmentation
  - Identify bottlenecks in a network
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Graphs and Matrices

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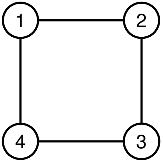

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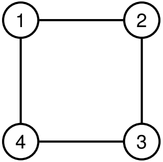

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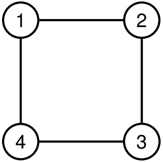

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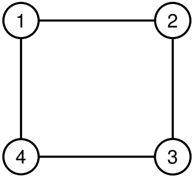

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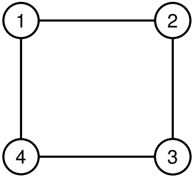

$$\mathbf{A} = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{pmatrix}$$

Properties of $\mathbf{A}$:

- The sum of elements in each row/column i equals the degree of the corresponding vertex i, $\deg(i)$
- Since G is undirected, $\mathbf{A}$ is symmetric

Eigenvalues and Graph Spectrum of A

Eigenvalues and Eigenvectors

Let $\mathbf{M} \in \mathbb{R}^{n \times n}$, $\lambda \in \mathbb{C}$ is an eigenvalue of $\mathbf{M}$ if and only if there exists $x \in \mathbb{R}^n \setminus \{\mathbf{0}\}$ such that

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= orthogonal and normalised

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Remark: For symmetric matrices we have algebraic multiplicity $=$ geometric multiplicity (otherwise $\geq$)

Example 1

Question: What are the Eigenvalues and Eigenvectors?

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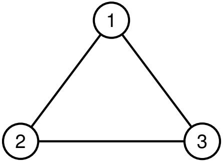

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Bonus: Can you find a short-cut to $\det(\mathbf{A} - \lambda \cdot \mathbf{I})$?

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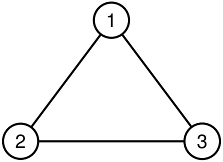

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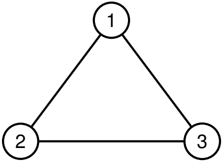

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Solution:

- The three eigenvalues are $\lambda_1 = \lambda_2 = -1, \lambda_3 = 2$.
- The three eigenvectors are (for example):

$$f_1 = \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix}, \quad f_2 = \begin{pmatrix} -\frac{1}{2} \\ 1 \\ -\frac{1}{2} \end{pmatrix}, \quad f_3 = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}.$$

Laplacian Matrix

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Let $G = (V, E)$ be a d-regular undirected graph. The (normalised) Laplacian matrix of G is the n by n matrix $\mathbf{L}$ defined as

$$\mathbf{L} = \mathbf{I} - \frac{1}{d}\mathbf{A},$$

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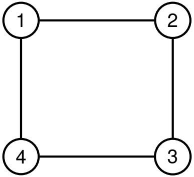

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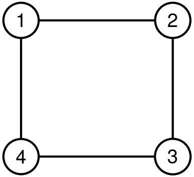

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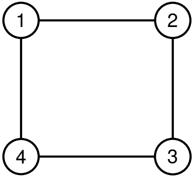

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- The sum of elements in each row/column equals zero
- $\mathbf{L}$ is symmetric

Relating Spectrum of Adjacency Matrix and Laplacian Matrix

Correspondence between Adjacency and Laplacian Matrix

A and **L** have the same set of eigenvectors.

Exercise: Prove this correspondence. Hint: Use that $\mathbf{L} = \mathbf{I} - \frac{1}{d}\mathbf{A}$.
[Exercise 11/12.1]

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Useful Facts of Graph Spectrum

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The proof of these properties is based on a powerful characterisation of eigenvalues/vectors!

A Min-Max Characterisation of Eigenvalues and Eigenvectors

Courant-Fischer Min-Max Formula

Let $\mathbf{M}$ be an n by n symmetric matrix with eigenvalues $\lambda_1 \leq \cdots \leq \lambda_n$. Then,

$$\lambda_k = \min_{\substack{x^{(1)},\ldots,x^{(k)} \in \mathbb{R}^n \setminus \{\mathbf{0}\}, \\ x^{(i)} \perp x^{(j)}}} \max_{i \in \{1,\ldots,k\}} \frac{{x^{(i)}}^T \mathbf{M} x^{(i)}}{{x^{(i)}}^T x^{(i)}}.$$

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Lemma

Let $\mathbf{L}$ be the Laplacian matrix of a d-regular graph $G = (V, E)$ with n vertices. For any $x \in \mathbb{R}^n$,

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Proof:

$$\begin{aligned} x^T \mathbf{L} x = x^T \left(\mathbf{I} - \frac{1}{d} \mathbf{A} \right) x &= x^T x - \frac{1}{d} x^T \mathbf{A} x \\ &= \sum_{u \in V} x_u^2 - \frac{2}{d} \sum_{\{u,v\} \in E} x_u x_v \\ &= \frac{1}{d} \sum_{\{u,v\} \in E} (x_u^2 + x_v^2 - 2 x_u x_v) \\ &= \sum_{\{u,v\} \in E} \frac{(x_u - x_v)^2}{d}. \end{aligned}$$

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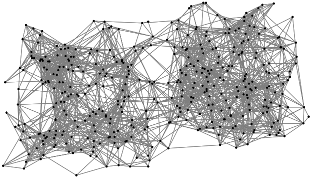

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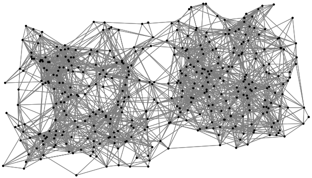
Embedding onto Line

Coordinates given by x



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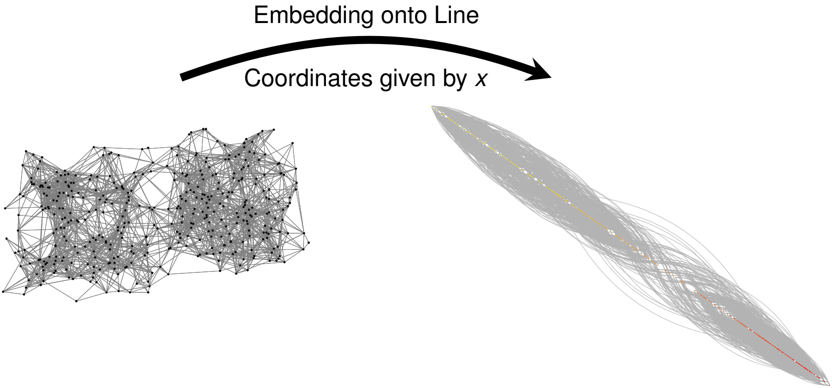

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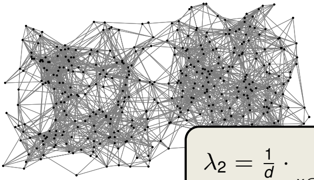

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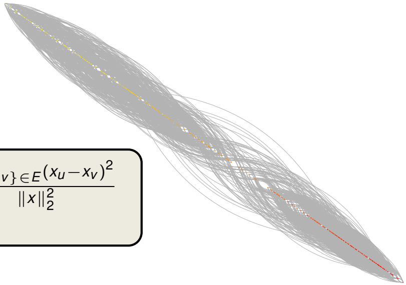

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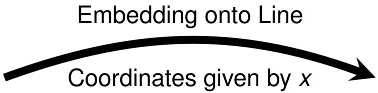

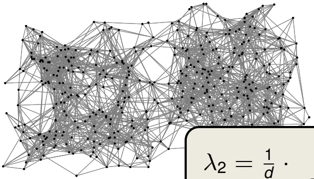

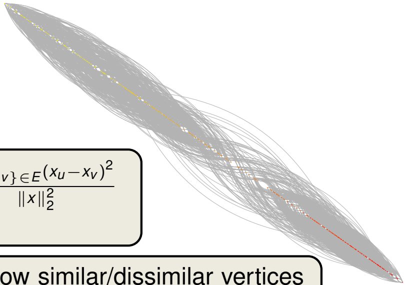

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The coordinates in the vector **x** indicate how similar/dissimilar vertices are. Edges between dissimilar vertices are penalised quadratically.

Outline

Introduction to (Spectral) Graph Theory and Clustering

Matrices, Spectrum and Structure

A Simplified Clustering Problem

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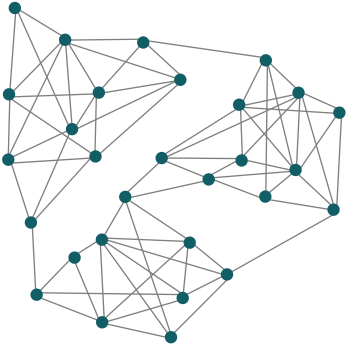
Partition the graph into ***connected components*** *so that any pair of vertices in the same component is connected, but vertices in different components are not.*



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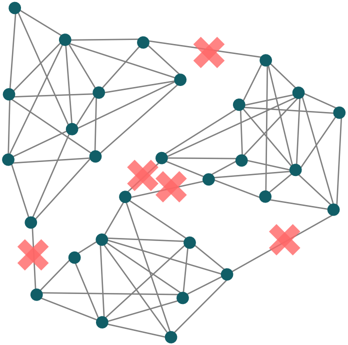

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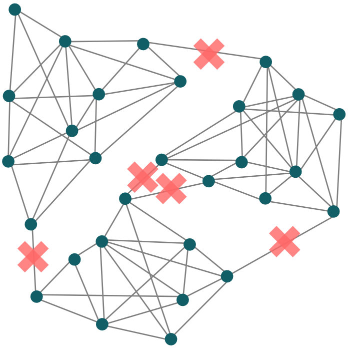

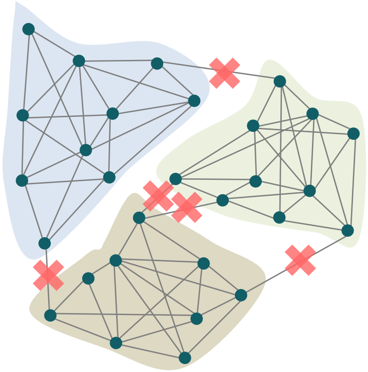

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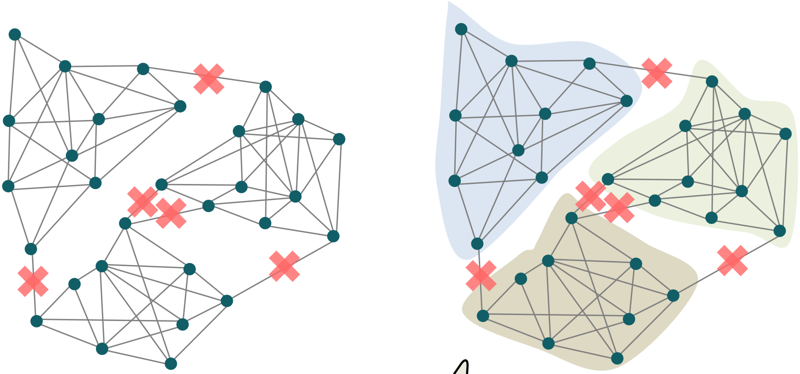

We could obviously solve this easily using DFS/BFS, but let's see how we can tackle this using the spectrum of **L**!

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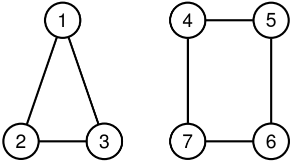

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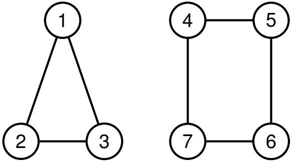

$$\mathbf{A} = \begin{pmatrix} 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 & 0 \end{pmatrix}$$

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Example 2

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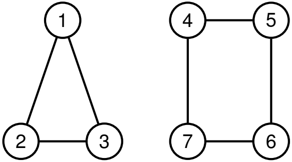

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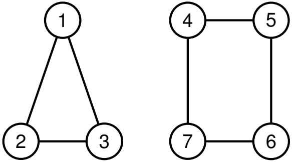

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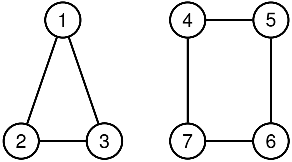

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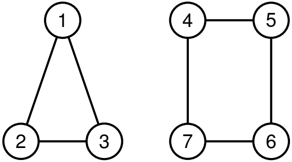

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Next Lecture: A fine-grained approach works even if the clusters are **sparsely** connected!

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$\square$

Randomised Algorithms

Lecture 12: Spectral Graph Clustering

Thomas Sauerwald (tms41@cam.ac.uk)

Lent 2024

Outline

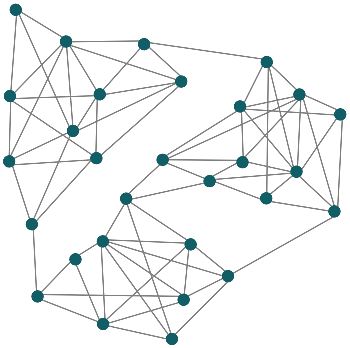
Conductance, Cheeger's Inequality and Spectral Clustering

Illustrations of Spectral Clustering and Extension to Non-Regular Graphs

Appendix: Relating Spectrum to Mixing Times (non-examinable)

Graph Clustering

*Partition the graph into **pieces (clusters)** so that vertices in the same piece have, on average, more connections among each other than with vertices in other clusters*



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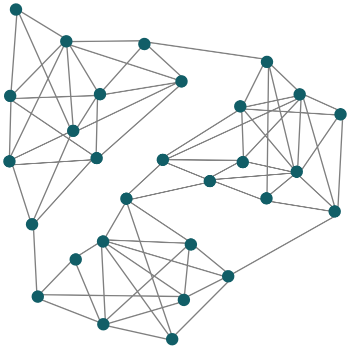

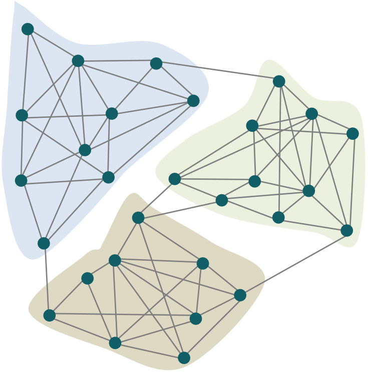

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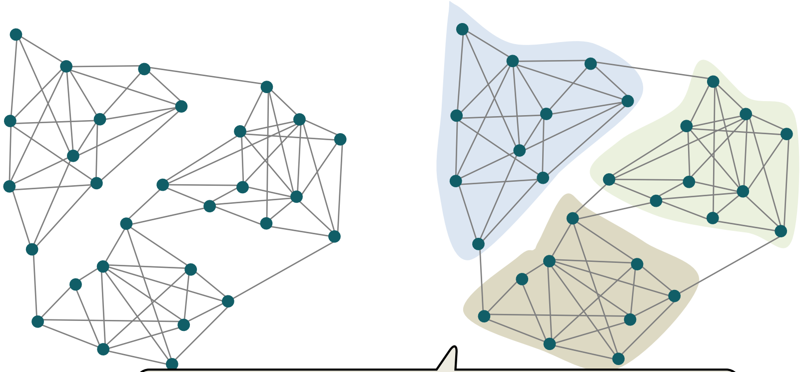

Let us for simplicity focus on the case of **two clusters**!

Conductance

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Let $G = (V, E)$ be a d-regular and undirected graph and $\emptyset \neq S \subsetneq V$. The conductance (edge expansion) of S is

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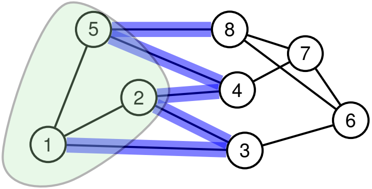

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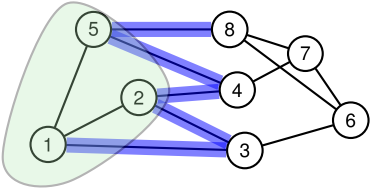

- $\phi(S) = ??$

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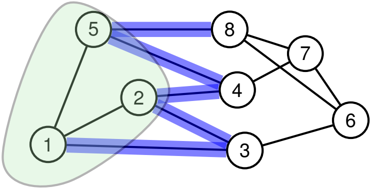

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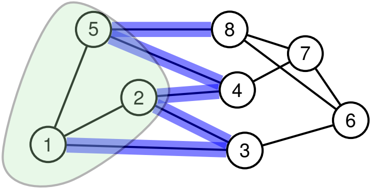

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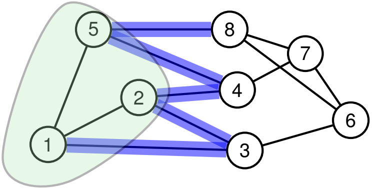

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- If G is a complete graph, then $e(S, V \setminus S) = |S| \cdot (n - |S|)$ and $\phi(G) \approx 1/2$.

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Moreover, the conductance (edge expansion) of the graph G is

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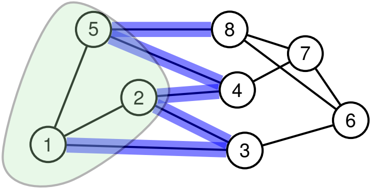
NP-hard to compute!

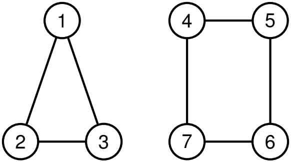


- $\phi(S) = \frac{5}{9}$
- $\phi(G) \in [0, 1]$ and $\phi(G) = 0$ iff G is disconnected
- If G is a complete graph, then $e(S, V \setminus S) = |S| \cdot (n - |S|)$ and $\phi(G) \approx 1/2$.

λ_2 versus Conductance (1/2)

G is disconnected

λ_2 versus Conductance (1/2)



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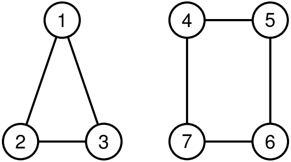

$$\phi(G) = 0 \quad \Leftrightarrow \quad G \text{ is disconnected}$$

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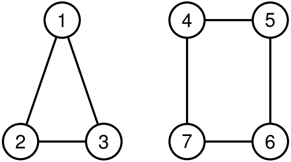

$$\phi(G) = 0 \quad \Leftrightarrow \quad G \text{ is disconnected} \quad \Leftrightarrow \quad \lambda_2(G) = 0$$

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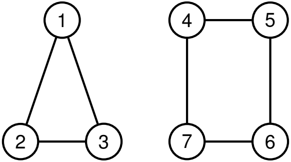
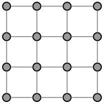
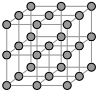


$$\phi(G) = 0 \quad \Leftrightarrow \quad G \text{ is disconnected} \quad \Leftrightarrow \quad \lambda_2(G) = 0$$

What is the relationship between $\phi(G)$ and $\lambda_2(G)$ for **connected** graphs?

λ_2 versus Conductance (2/2)

1D Grid (Path)	2D Grid	3D Grid
		
$\lambda_2 \sim n^{-2}$	$\lambda_2 \sim n^{-1}$	$\lambda_2 \sim n^{-2/3}$
$\phi \sim n^{-1}$	$\phi \sim n^{-1/2}$	$\phi \sim n^{-1/3}$

λ_2 versus Conductance (2/2)

1D Grid (Path)

$$\lambda_2 \sim n^{-2}$$
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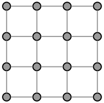
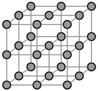
2D Grid



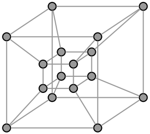
$$\lambda_2 \sim n^{-1}$$
$$\phi \sim n^{-1/2}$$

3D Grid



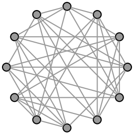
$$\lambda_2 \sim n^{-2/3}$$
$$\phi \sim n^{-1/3}$$

Hypercube



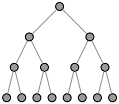
$$\lambda_2 \sim (\log n)^{-1}$$
$$\phi \sim (\log n)^{-1}$$

Random Graph (Expanders)



$$\lambda_2 = \Theta(1)$$
$$\phi = \Theta(1)$$

Binary Tree



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Relating λ_2 and Conductance

Cheeger's inequality

Let G be a d-regular undirected graph and $\lambda_1 \leq \cdots \leq \lambda_n$ be the eigenvalues of its Laplacian matrix. Then,

$$\frac{\lambda_2}{2} \leq \phi(G) \leq \sqrt{2\lambda_2}.$$

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- no constant factor worst-case guarantee, but usually works well in practice (see examples later!)
- very fast: can be implemented in $O(|E| \log |E|)$ time

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Proof (of the easy direction):

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- By the Courant-Fischer Formula,

$$\lambda_2 = \min_{\substack{x \in \mathbb{R}^n \\ x \neq 0, x \perp 1}} \frac{x^T \mathbf{L} x}{x^T x}$$

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- Since $y \perp 1$, it follows that

$$\lambda_2 \leq \frac{1}{d} \cdot \frac{\sum_{u \sim v} (y_u - y_v)^2}{\sum_u y_u^2} = \frac{1}{d} \cdot \frac{|E(S, V \setminus S)| \cdot (\frac{1}{|S|} + \frac{1}{|V \setminus S|})^2}{\frac{1}{|S|} + \frac{1}{|V \setminus S|}}$$

$$= \frac{1}{d} \cdot |E(S, V \setminus S)| \cdot \left(\frac{1}{|S|} + \frac{1}{|V \setminus S|} \right)$$

$$\leq \frac{1}{d} \cdot \frac{2 \cdot |E(S, V \setminus S)|}{|S|} = 2 \cdot \phi(G). \qquad \square$$

Outline

Conductance, Cheeger's Inequality and Spectral Clustering

Illustrations of Spectral Clustering and Extension to Non-Regular Graphs

Appendix: Relating Spectrum to Mixing Times (non-examinable)

Illustration on a small Example

$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} \qquad \mathbf{L} = \begin{pmatrix} 1 & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & 1 & 0 & 0 & -\frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} & 0 \\ -\frac{1}{3} & 0 & 1 & -\frac{1}{3} & 0 & 0 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & 0 & -\frac{1}{3} & 1 & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & -\frac{1}{3} & 0 & 0 & 1 & -\frac{1}{3} & 0 & -\frac{1}{3} \\ 0 & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 1 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & 0 & -\frac{1}{3} & 0 & 0 & 1 & 0 \\ 0 & 0 & -\frac{1}{3} & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 1 \end{pmatrix}$$

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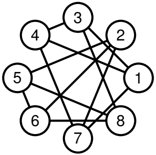

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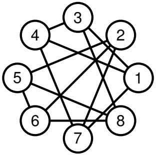

$$\lambda_2 = 1 - \sqrt{5}/3 \approx 0.25$$

$$v = (-0.425, +0.263, -0.263, -0.425, +0.425, +0.425, -0.263, +0.263)^T$$

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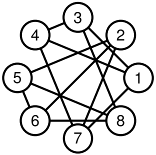

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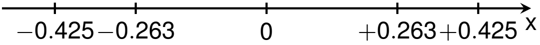

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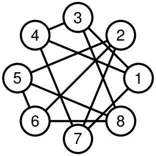

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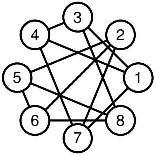
$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} \quad \mathbf{L} = \begin{pmatrix} 1 & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & 1 & 0 & 0 & -\frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} & 0 \\ -\frac{1}{3} & 0 & 1 & -\frac{1}{3} & 0 & 0 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & 0 & -\frac{1}{3} & 1 & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & -\frac{1}{3} & 0 & 0 & 1 & -\frac{1}{3} & 0 & -\frac{1}{3} \\ 0 & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 1 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & 0 & -\frac{1}{3} & 0 & 0 & 1 & 0 \\ 0 & 0 & -\frac{1}{3} & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 1 \end{pmatrix}$$

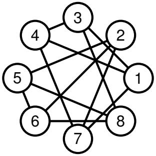


$$\lambda_2 = 1 - \sqrt{5}/3 \approx 0.25$$

$$v = (-0.425, +0.263, -0.263, -0.425, +0.425, +0.425, -0.263, +0.263)^T$$

Illustration on a small Example

$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} \quad \mathbf{L} = \begin{pmatrix} 1 & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & 1 & 0 & 0 & -\frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} & 0 \\ -\frac{1}{3} & 0 & 1 & -\frac{1}{3} & 0 & 0 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & 0 & -\frac{1}{3} & 1 & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & -\frac{1}{3} & 0 & 0 & 1 & -\frac{1}{3} & 0 & -\frac{1}{3} \\ 0 & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 1 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & 0 & -\frac{1}{3} & 0 & 0 & 1 & 0 \\ 0 & 0 & -\frac{1}{3} & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 1 \end{pmatrix}$$



$$\lambda_2 = 1 - \sqrt{5}/3 \approx 0.25$$

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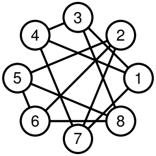
Illustration on a small Example

$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} \qquad \mathbf{L} = \begin{pmatrix} 1 & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & 1 & 0 & 0 & -\frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} & 0 \\ -\frac{1}{3} & 0 & 1 & -\frac{1}{3} & 0 & 0 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & 0 & -\frac{1}{3} & 1 & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & -\frac{1}{3} & 0 & 0 & 1 & -\frac{1}{3} & 0 & -\frac{1}{3} \\ 0 & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 1 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & 0 & -\frac{1}{3} & 0 & 0 & 1 & 0 \\ 0 & 0 & -\frac{1}{3} & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 1 \end{pmatrix}$$



$$\lambda_2 = 1 - \sqrt{5}/3 \approx 0.25$$

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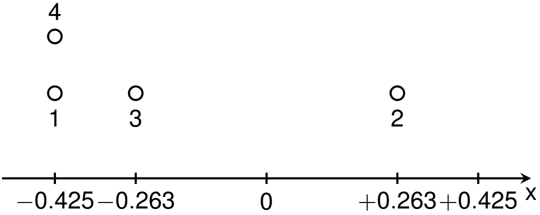
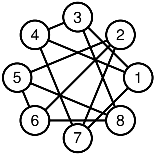


Illustration on a small Example

$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} \qquad \mathbf{L} = \begin{pmatrix} 1 & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & 1 & 0 & 0 & -\frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} & 0 \\ -\frac{1}{3} & 0 & 1 & -\frac{1}{3} & 0 & 0 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & 0 & -\frac{1}{3} & 1 & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & -\frac{1}{3} & 0 & 0 & 1 & -\frac{1}{3} & 0 & -\frac{1}{3} \\ 0 & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 1 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & 0 & -\frac{1}{3} & 0 & 0 & 1 & 0 \\ 0 & 0 & -\frac{1}{3} & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 1 \end{pmatrix}$$



$$\lambda_2 = 1 - \sqrt{5}/3 \approx 0.25$$

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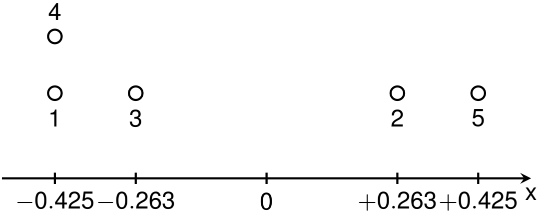
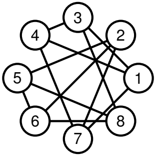


Illustration on a small Example

$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} \quad \mathbf{L} = \begin{pmatrix} 1 & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & 1 & 0 & 0 & -\frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} & 0 \\ -\frac{1}{3} & 0 & 1 & -\frac{1}{3} & 0 & 0 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & 0 & -\frac{1}{3} & 1 & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & -\frac{1}{3} & 0 & 0 & 1 & -\frac{1}{3} & 0 & -\frac{1}{3} \\ 0 & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 1 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & 0 & -\frac{1}{3} & 0 & 0 & 1 & 0 \\ 0 & 0 & -\frac{1}{3} & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 1 \end{pmatrix}$$



$$\lambda_2 = 1 - \sqrt{5}/3 \approx 0.25$$

$$v = (-0.425, +0.263, -0.263, -0.425, +0.425, +0.425, -0.263, +0.263)^T$$

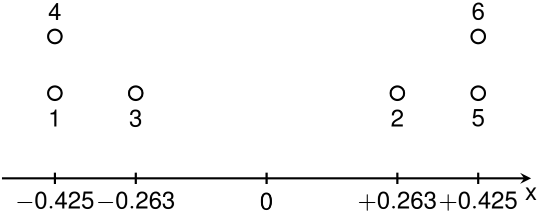
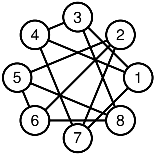


Illustration on a small Example

$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} \quad \mathbf{L} = \begin{pmatrix} 1 & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & 1 & 0 & 0 & -\frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} & 0 \\ -\frac{1}{3} & 0 & 1 & -\frac{1}{3} & 0 & 0 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & 0 & -\frac{1}{3} & 1 & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & -\frac{1}{3} & 0 & 0 & 1 & -\frac{1}{3} & 0 & -\frac{1}{3} \\ 0 & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 1 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & 0 & -\frac{1}{3} & 0 & 0 & 1 & 0 \\ 0 & 0 & -\frac{1}{3} & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 1 \end{pmatrix}$$



$$\lambda_2 = 1 - \sqrt{5}/3 \approx 0.25$$

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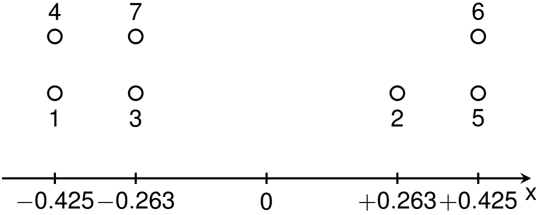
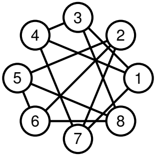


Illustration on a small Example

$$\mathbf{A} = \begin{pmatrix} 0&0&1&1&0&0&1&0\\ 0&0&0&0&1&1&1&0\\ 1&0&0&1&0&0&0&1\\ 1&0&1&0&0&0&1&0\\ 0&1&0&0&0&1&0&1\\ 0&1&0&0&1&0&0&1\\ 1&1&0&1&0&0&0&0\\ 0&0&1&0&1&1&0&0 \end{pmatrix} \quad \mathbf{L} = \begin{pmatrix} 1&0&-\frac{1}{3}&-\frac{1}{3}&0&0&-\frac{1}{3}&0\\ 0&1&0&0&-\frac{1}{3}&-\frac{1}{3}&-\frac{1}{3}&0\\ -\frac{1}{3}&0&1&-\frac{1}{3}&0&0&0&-\frac{1}{3}\\ -\frac{1}{3}&0&-\frac{1}{3}&1&0&0&-\frac{1}{3}&0\\ 0&-\frac{1}{3}&0&0&1&-\frac{1}{3}&0&-\frac{1}{3}\\ 0&-\frac{1}{3}&0&0&-\frac{1}{3}&1&0&-\frac{1}{3}\\ -\frac{1}{3}&-\frac{1}{3}&0&-\frac{1}{3}&0&0&1&0\\ 0&0&-\frac{1}{3}&0&-\frac{1}{3}&-\frac{1}{3}&0&1 \end{pmatrix}$$



$$\lambda_2 = 1 - \sqrt{5}/3 \approx 0.25$$

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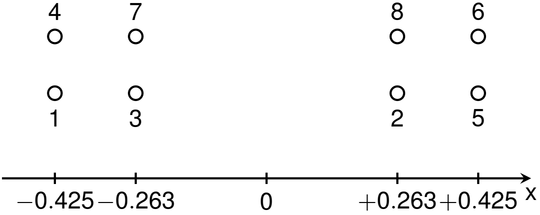
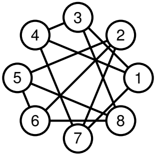


Illustration on a small Example

$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} \quad \mathbf{L} = \begin{pmatrix} 1 & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & 1 & 0 & 0 & -\frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} & 0 \\ -\frac{1}{3} & 0 & 1 & -\frac{1}{3} & 0 & 0 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & 0 & -\frac{1}{3} & 1 & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & -\frac{1}{3} & 0 & 0 & 1 & -\frac{1}{3} & 0 & -\frac{1}{3} \\ 0 & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 1 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & 0 & -\frac{1}{3} & 0 & 0 & 1 & 0 \\ 0 & 0 & -\frac{1}{3} & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 1 \end{pmatrix}$$



$$\lambda_2 = 1 - \sqrt{5}/3 \approx 0.25$$

$$v = (-0.425, +0.263, -0.263, -0.425, +0.425, +0.425, -0.263, +0.263)^T$$

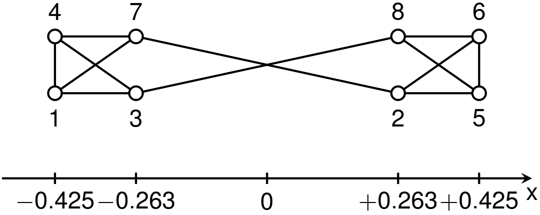
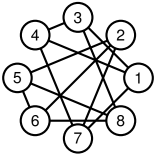


Illustration on a small Example

$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} \qquad \mathbf{L} = \begin{pmatrix} 1 & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & 1 & 0 & 0 & -\frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} & 0 \\ -\frac{1}{3} & 0 & 1 & -\frac{1}{3} & 0 & 0 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & 0 & -\frac{1}{3} & 1 & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & -\frac{1}{3} & 0 & 0 & 1 & -\frac{1}{3} & 0 & -\frac{1}{3} \\ 0 & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 1 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & 0 & -\frac{1}{3} & 0 & 0 & 1 & 0 \\ 0 & 0 & -\frac{1}{3} & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 1 \end{pmatrix}$$



$$\lambda_2 = 1 - \sqrt{5}/3 \approx 0.25$$

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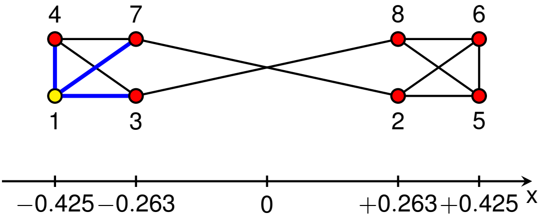
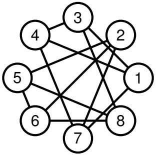


Sweep: 1

Conductance: 1

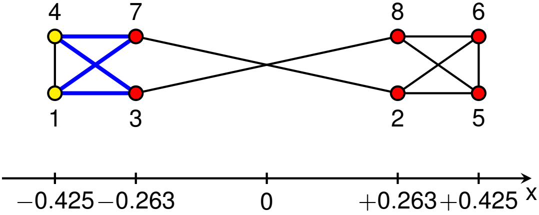
Illustration on a small Example

$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} \qquad \mathbf{L} = \begin{pmatrix} 1 & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & 1 & 0 & 0 & -\frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} & 0 \\ -\frac{1}{3} & 0 & 1 & -\frac{1}{3} & 0 & 0 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & 0 & -\frac{1}{3} & 1 & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & -\frac{1}{3} & 0 & 0 & 1 & -\frac{1}{3} & 0 & -\frac{1}{3} \\ 0 & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 1 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & 0 & -\frac{1}{3} & 0 & 0 & 1 & 0 \\ 0 & 0 & -\frac{1}{3} & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 1 \end{pmatrix}$$



$$\lambda_2 = 1 - \sqrt{5}/3 \approx 0.25$$

$$v = (-0.425, +0.263, -0.263, -0.425, +0.425, +0.425, -0.263, +0.263)^T$$

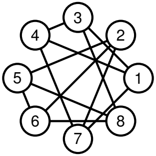


Sweep: 2

Conductance: 0.666

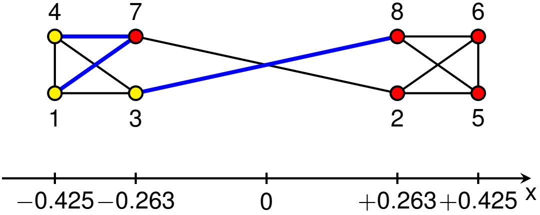
Illustration on a small Example

$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} \quad \mathbf{L} = \begin{pmatrix} 1 & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & 1 & 0 & 0 & -\frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} & 0 \\ -\frac{1}{3} & 0 & 1 & -\frac{1}{3} & 0 & 0 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & 0 & -\frac{1}{3} & 1 & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & -\frac{1}{3} & 0 & 0 & 1 & -\frac{1}{3} & 0 & -\frac{1}{3} \\ 0 & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 1 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & 0 & -\frac{1}{3} & 0 & 0 & 1 & 0 \\ 0 & 0 & -\frac{1}{3} & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 1 \end{pmatrix}$$



$$\lambda_2 = 1 - \sqrt{5}/3 \approx 0.25$$

$$v = (-0.425, +0.263, -0.263, -0.425, +0.425, +0.425, -0.263, +0.263)^T$$

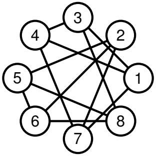


Sweep: 3

Conductance: 0.333

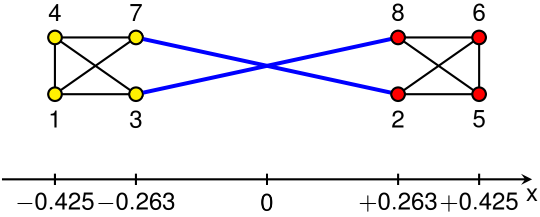
Illustration on a small Example

$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} \qquad \mathbf{L} = \begin{pmatrix} 1 & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & 1 & 0 & 0 & -\frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} & 0 \\ -\frac{1}{3} & 0 & 1 & -\frac{1}{3} & 0 & 0 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & 0 & -\frac{1}{3} & 1 & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & -\frac{1}{3} & 0 & 0 & 1 & -\frac{1}{3} & 0 & -\frac{1}{3} \\ 0 & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 1 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & 0 & -\frac{1}{3} & 0 & 0 & 1 & 0 \\ 0 & 0 & -\frac{1}{3} & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 1 \end{pmatrix}$$



$$\lambda_2 = 1 - \sqrt{5}/3 \approx 0.25$$

$$v = (-0.425, +0.263, -0.263, -0.425, +0.425, +0.425, -0.263, +0.263)^T$$

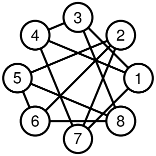


Sweep: 4

Conductance: 0.166

Illustration on a small Example

$$\mathbf{A} = \begin{pmatrix} 0&0&1&1&0&0&1&0\\ 0&0&0&0&1&1&1&0\\ 1&0&0&1&0&0&0&1\\ 1&0&1&0&0&0&1&0\\ 0&1&0&0&0&1&0&1\\ 0&1&0&0&1&0&0&1\\ 1&1&0&1&0&0&0&0\\ 0&0&1&0&1&1&0&0 \end{pmatrix} \qquad \mathbf{L} = \begin{pmatrix} 1&0&-\frac{1}{3}&-\frac{1}{3}&0&0&-\frac{1}{3}&0\\ 0&1&0&0&-\frac{1}{3}&-\frac{1}{3}&-\frac{1}{3}&0\\ -\frac{1}{3}&0&1&-\frac{1}{3}&0&0&0&-\frac{1}{3}\\ -\frac{1}{3}&0&-\frac{1}{3}&1&0&0&-\frac{1}{3}&0\\ 0&-\frac{1}{3}&0&0&1&-\frac{1}{3}&0&-\frac{1}{3}\\ 0&-\frac{1}{3}&0&0&-\frac{1}{3}&1&0&-\frac{1}{3}\\ -\frac{1}{3}&-\frac{1}{3}&0&-\frac{1}{3}&0&0&1&0\\ 0&0&-\frac{1}{3}&0&-\frac{1}{3}&-\frac{1}{3}&0&1 \end{pmatrix}$$



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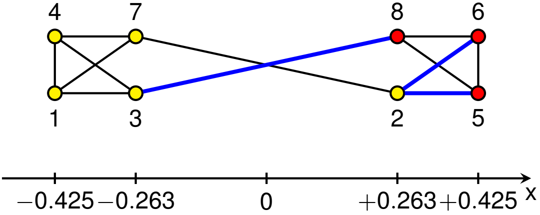
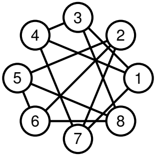


Sweep: 5

Conductance: 0.333

Illustration on a small Example

$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} \qquad \mathbf{L} = \begin{pmatrix} 1 & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & 1 & 0 & 0 & -\frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} & 0 \\ -\frac{1}{3} & 0 & 1 & -\frac{1}{3} & 0 & 0 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & 0 & -\frac{1}{3} & 1 & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & -\frac{1}{3} & 0 & 0 & 1 & -\frac{1}{3} & 0 & -\frac{1}{3} \\ 0 & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 1 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & 0 & -\frac{1}{3} & 0 & 0 & 1 & 0 \\ 0 & 0 & -\frac{1}{3} & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 1 \end{pmatrix}$$



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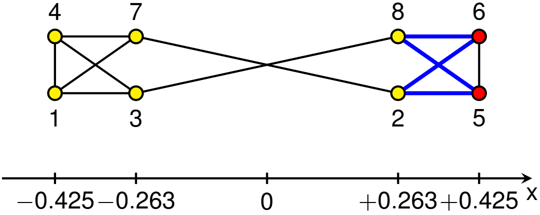
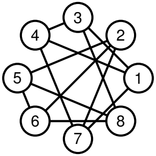


Sweep: 6

Conductance: 0.666

Illustration on a small Example

$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} \qquad \mathbf{L} = \begin{pmatrix} 1 & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & 1 & 0 & 0 & -\frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} & 0 \\ -\frac{1}{3} & 0 & 1 & -\frac{1}{3} & 0 & 0 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & 0 & -\frac{1}{3} & 1 & 0 & 0 & -\frac{1}{3} & 0 \\ 0 & -\frac{1}{3} & 0 & 0 & 1 & -\frac{1}{3} & 0 & -\frac{1}{3} \\ 0 & -\frac{1}{3} & 0 & 0 & -\frac{1}{3} & 1 & 0 & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & 0 & -\frac{1}{3} & 0 & 0 & 1 & 0 \\ 0 & 0 & -\frac{1}{3} & 0 & -\frac{1}{3} & -\frac{1}{3} & 0 & 1 \end{pmatrix}$$



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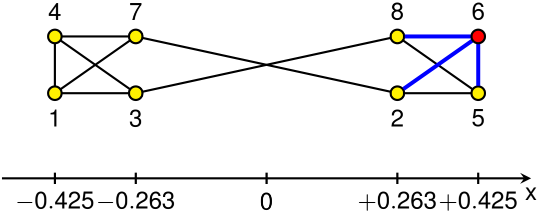

Sweep: 7

Conductance: 1

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Let us now look at an example of a non-regular graph!

The Laplacian Matrix (General Version)

The (normalised) Laplacian matrix of $G = (V, E, w)$ is the n by n matrix

$$\mathbf{L} = \mathbf{I} - \mathbf{D}^{-1/2}\mathbf{A}\mathbf{D}^{-1/2}$$

where $\mathbf{D}$ is a diagonal $n \times n$ matrix such that $\mathbf{D}_{uu} = deg(u) = \sum_{v:\ \{u,v\} \in E} w(u, v)$, and $\mathbf{A}$ is the weighted adjacency matrix of G.

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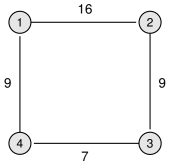

$$\mathbf{L} = \begin{pmatrix} 1 & -16/25 & 0 & -9/20 \\ -16/25 & 1 & -9/20 & 0 \\ 0 & -9/20 & 1 & -7/16 \\ -9/20 & 0 & -7/16 & 1 \end{pmatrix}$$

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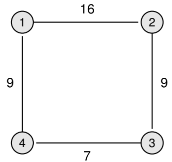

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- $\mathbf{L}_{uv} = -\frac{w(u,v)}{\sqrt{d_u d_v}}$ for $u \neq v$
- $\mathbf{L}$ is symmetric
- If G is d-regular, $\mathbf{L} = \mathbf{I} - \frac{1}{d} \cdot \mathbf{A}$.

Conductance and Spectral Clustering (General Version)

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Let $G = (V, E, w)$ and $\emptyset \subsetneq S \subsetneq V$. The conductance (edge expansion) of S is

$$\phi(S) := \frac{w(S, S^c)}{\min\{\mathrm{vol}(S), \mathrm{vol}(S^c)\}},$$

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3. Try all $n - 1$ sweep cuts of the form $(\{1, 2, \ldots, k\}, \{k + 1, \ldots, n\})$ and return the one with smallest conductance

Stochastic Block Model and 1D-Embedding

Stochastic Block Model

$G = (V, E)$ with clusters $S_1, S_2 \subseteq V$, $0 \leq q < p \leq 1$

$$\mathbf{P}[\{u, v\} \in E] = \begin{cases} p & \text{if } u, v \in S_i, \\ q & \text{if } u \in S_i, v \in S_j, i \neq j. \end{cases}$$

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Here:

- $|S_1| = 80$,
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- $p = 0.08$
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```
Number of Vertices: 200
Number of Edges:  919
Eigenvalue  1  :  -1.1968431479565368e-16
Eigenvalue  2  :  0.1543784937248489
Eigenvalue  3  :  0.37049909753568877
Eigenvalue  4  :  0.39770640242147404
Eigenvalue  5  :  0.4316114413430584
Eigenvalue  6  :  0.44379221120189777
Eigenvalue  7  :  0.4564011652684181
Eigenvalue  8  :  0.4632911204500282
Eigenvalue  9  :  0.474638606357877
Eigenvalue  10  :  0.4814019607292904
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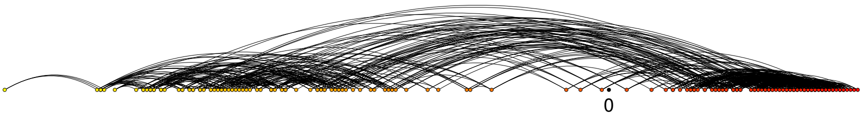
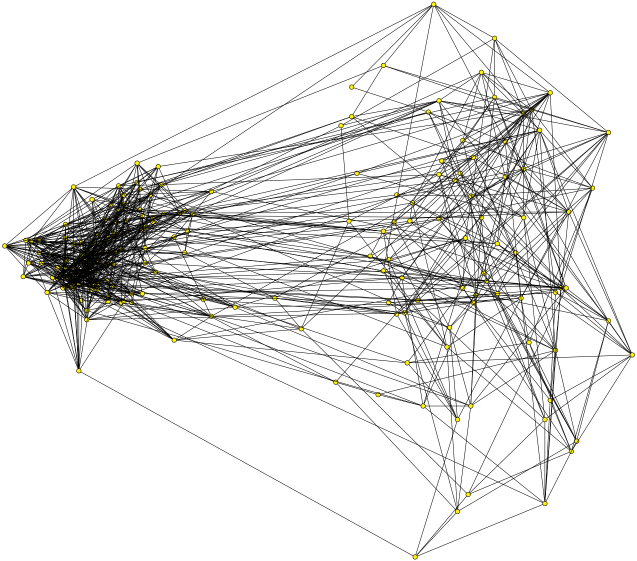
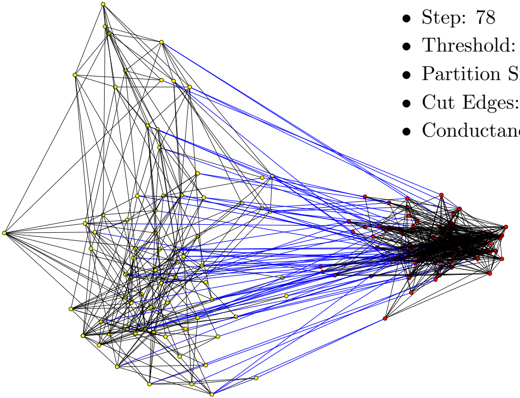


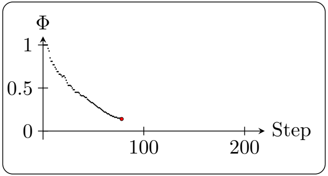
Drawing the 2D-Embedding



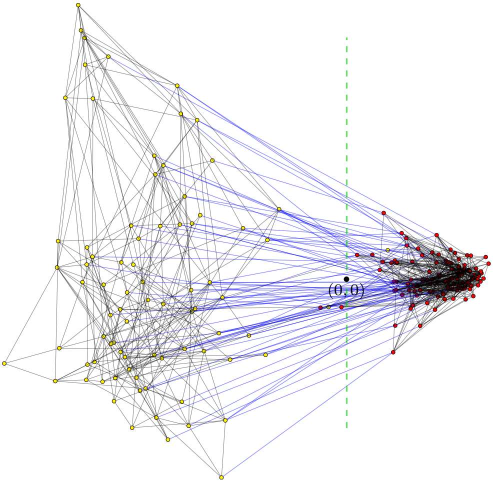
Best Solution found by Spectral Clustering



- Step: 78
- Threshold: −0.027
- Partition Sizes: 78/122
- Cut Edges: 84
- Conductance: 0.145



Clustering induced by Blocks



- Step: 1
- Threshold: 0
- Partition Sizes: 80/120
- Cut Edges: 88
- Conductance: 0.1486

Additional Example: Stochastic Block Models with 3 Clusters

Graph $G = (V, E)$ with clusters
$S_1, S_2, S_3 \subseteq V; \quad 0 \leq q < p \leq 1$

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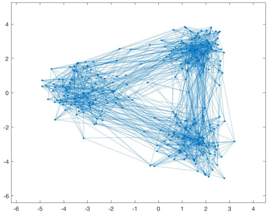

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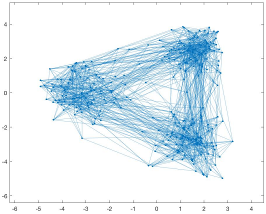
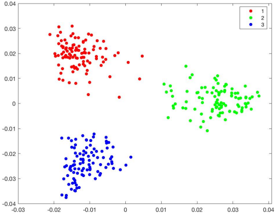


Spectral embedding



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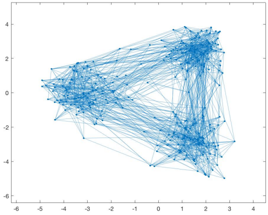

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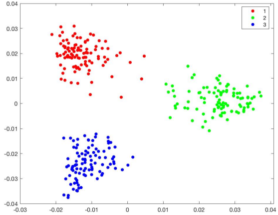
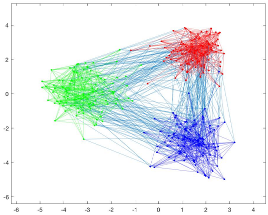


Output of Spectral Clustering



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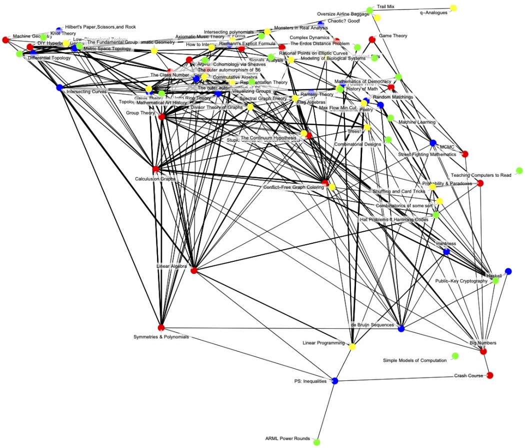
- For $k = 2$ use sweep-cut extract clusters. For $k \geq 3$ use embedding in k-dimensional space and apply k-means (geometric clustering)

Another Example



(many thanks to Kalina Jasinska)

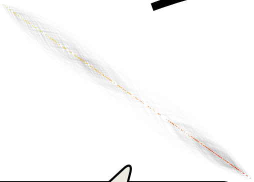
- nodes represent math topics taught within 4 weeks of a Mathcamp
- node colours represent to the week in which they thought
- teachers were asked to assign weights in $0 - 10$ indicating how closely related two classes are

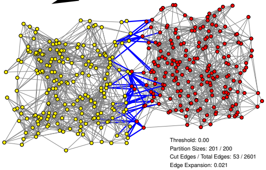
Summary: Spectral Clustering

Spectral Embedding onto Line

Compute Sweep Cuts

$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \end{pmatrix}$$





$$\min_{\substack{x \in \mathbb{R}^n \setminus \{\mathbf{0}\} \\ x \perp \mathbf{1}}} \frac{\sum_{u \sim v} (x_u - x_v)^2}{\sum_u x_u^2}$$

- Given any graph (adjacency matrix)
- Graph Spectrum (computable in poly-time)
  - λ_2 (relates to connectivity)
  - λ_n (relates to bipartiteness)

  ...
- Cheeger's Inequality
  - relates λ_2 to conductance
  - unbounded approximation ratio
  - effective in practice

Outline

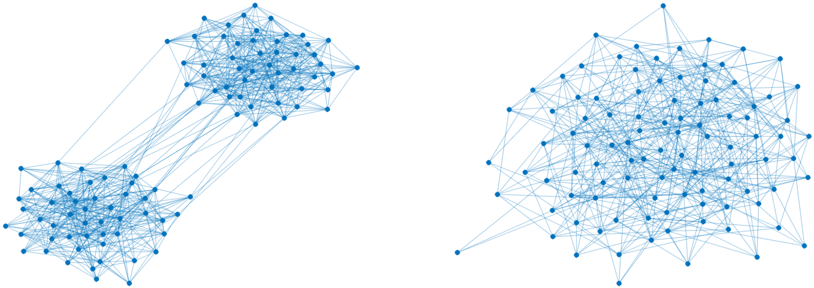
Conductance, Cheeger's Inequality and Spectral Clustering

Illustrations of Spectral Clustering and Extension to Non-Regular Graphs

Appendix: Relating Spectrum to Mixing Times (non-examinable)

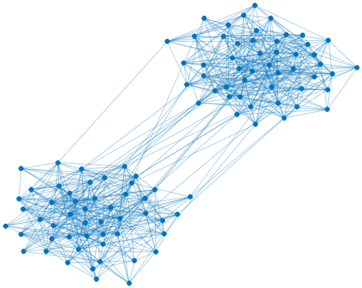
Relation between Clustering and Mixing (non-examinable)

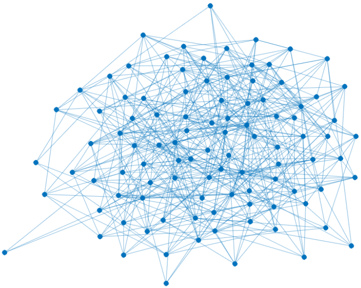
- Which graph has a "cluster-structure"?



Relation between Clustering and Mixing (non-examinable)

- Which graph has a “cluster-structure”?
- Which graph mixes faster?





Convergence of Random Walk (non-examinable)

Recall: If the underlying graph G is connected, undirected and d-regular, then the random walk converges towards the stationary distribution $\pi = (1/n, \ldots, 1/n)$, which satisfies $\pi \mathbf{P} = \pi$.

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$$\left\| x\mathbf{P}^t - \pi \right\|_2 \leq \lambda^t,$$

with $1 = \lambda_1 > \lambda_2 \geq \cdots \geq \lambda_n$ as eigenvalues and $\lambda := \max\{|\lambda_2|, |\lambda_n|\}$.

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$\Rightarrow$ This implies for $t = \mathcal{O}\left(\frac{\log n}{\log(1/\lambda)}\right) = \mathcal{O}\left(\frac{\log n}{1-\lambda}\right)$,

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$$\left\| x\mathbf{P}^t - \pi \right\|_{tv} \leq \frac{1}{4}.$$

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$\|x - \pi\|_2^2 + \|\pi\|_2^2 = \|x\|_2^2 \leq 1$

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The End...

Thank you and Best Wishes for the Exam!