SECTION 3 Algorithm design

Is it worth doing cardio?



heart rate = $\frac{1}{\text{lifespan}}$ \Rightarrow heartrate \times lifespan = const \Rightarrow total lifetime heartbeats = const Equivalently, $\log(\text{heartrate}) + \log(\text{lifespan}) = \text{const}$ and this is easier to see on a \log -log plot.

const

It looks like maybe

Rest Heart Rate and Life Expectancy, Herbert J. Levine, Journal of the American College of Cardiology (1997)

Is it worth doing cardio?



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Equivalently, log(heartrate) + log(lifespan) = constand this is easier to see on a log-log plot.

Rest Heart Rate and Life Expectancy, Herbert J. Levine, Journal of the American College of Cardiology (1997) Let's suppose we have a fixed number of total lifetime heartbeats. If we want to live as long as possible, how much should we exercise?

(Exercise decreases resting heartrate 👍 , but it burns through our lifetime heartbeats 👎 .)

(b)
$$x = (r, b)$$
 be the current state, $r = resting heartrate and $b = # heartbeach remaining as of roday.
(c) inserve a analel:
If we exercise:
 $r = (r - \lambda(r - 50))$
will be polled about to a floor of 50 bpm
 $b = b - (23\times60\pi r - 60\times155)$
If we don't charcise:
 $r = (r + \lambda(90 - r))$
if we heave enercise, r .
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if $r = rearrise are into a floor of $r = 155$ bpm.
If we don't charcise:
 $r = r + \lambda(90 - r)$
if $r = rearrise into a callong$
if $r = rearrise int$$$$



3.1 The Bellman equation and dynamic programming

Problem statement

programme

We're given an initial state x_0 , and we wish to choose a sequence of actions $[a_0, a_1, ...]$.

If we're in state x and we take action a, we gain $reward_{x,a}$, and move to $nextstate_{x,a}$ (unless x is a terminal state, where no further actions are possible, in which case we gain termreward_x).

We want to find the maximum possible total reward starting from x_0 .



Bellman recursion

Let v(x) be the total reward that can be gained starting in state x. Then

 $v(x) = \begin{cases} \text{termreward}_{x} & \text{if } x \text{ is terminal} \\ \max_{a \in A} \{ \text{reward}_{x,a} + v(\text{nextstate}_{x,a}) \} & \text{otherwise} \end{cases}$

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How can I frame my task as "find an optimal sequence of actions"?

- What are the actions?
- What is the value/cost that I'm optimizing?

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Example: rod cutting

A DIY supplier has a steel rod of length $n \in \mathbb{N}$, and a machine that can cut it into smaller pieces. Different lengths can be sold for different prices; a piece of length $\ell \in \mathbb{N}$ fetches p_{ℓ} .

How should it be cut, to maximize profit?

length	1	2	3	4	5	6	7	8	9	10
price	£1	£5	£8	£9	£10	£17	£17	£20	£24	£30



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How should it be cut, to maximize profit?

let v(n) = max profit I ran achieve from a rod of length n. Then $\mathbf{v}(\mathbf{I}) = \mathbf{P}_{\mathbf{I}}$ EMan $n_{7/2}$: $V(n) = P_n V max {P_c + V(n-z)}$ $A(\text{fernalizely}: \\ v(n) = \begin{cases} 0 & \text{if } n > 0 \\ \max & \{P_i + v(n-\bar{z})\} \\ \max & \{P_i + v(n-\bar{z})\} \end{cases} \text{if } n > 0.$ v (o) = 0 Sanity check: $\sqrt{(1)} = \rho_1 + \sqrt{(2)} = \rho_1$ $v(2) = (P_1 + v(1)) v (P_2 + v(0)) = (P_1 + P_1) v P_2$

Example 3.1.1 Matrix chain multiplication

The cost of multiplying two matrices depends on their dimensions:

$$\begin{bmatrix} \vdots & \vdots & \vdots \\ \ell \times m \end{bmatrix} \times \begin{bmatrix} \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ m \times n \end{bmatrix} = \begin{bmatrix} \vdots & \vdots & \vdots \\ \ell \times n \end{bmatrix}$$

 ℓmn multiplications $+ \ell (m-1)n$ additions For simplicity, let's take the total cost to be ℓmn .

If we want to compute the product of several matrices, we have a choice about the order of multiplication (because matrix multiplication is associative). For example,

$$ABCDE = (AB)((CD)E) = A(B((CD)E))$$

Find the least-cost way to compute the product $\begin{array}{cc} A_0 & A_1 & \cdots & A_{n-1} \\ d_0 \times d_1 & d_1 \times d_2 & & d_{n-1} \times d_n \end{array}$

let
$$V(i,j) = \min \operatorname{cort} af \operatorname{multiplying} A_i A_{i+1} \cdots A_{j-1}$$
.
We want to find $v(0,n)$.



Try out some simple capes:

$$v(0,1) = 0 \quad \begin{pmatrix} gince & we don't need to de aywork to compute \\ R_0 & -it'' right rhune, \\ v(0,2) = d_0 d_1 d_2 \quad \begin{pmatrix} \frac{A_0}{1-2} & \alpha_2 t & i & d_0 d_1 d_2 \end{pmatrix} \\ d_{0}xd_1 & d_1xd_2 \\ u(0,3) = \min \left\{ d_0 d_1 d_3 + v(1,3), d_0 d_2 d_3 + v(0,2) \right\} \quad \begin{pmatrix} A_0, A_1, A_2 \\ 0 & 1 & 2 & 3 \\ \end{array}$$

$$A_0 (A_1, A_2) \quad \begin{pmatrix} A_0, A_1, A_2 \\ 0 & 1 & 2 & 3 \\ \end{array}$$

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$$A_0 (A_1, A_2) \quad (A_0, A_1) A_2 \quad (A_0, A_1, A_2) \quad (A_0, A_1) A_2 \quad (A_0, A_0) \quad (A_0, A_0) A_2 \quad (A_0, A_0) \quad (A$$

General core:

$$V(\hat{i}_{j}) = \begin{cases}
if \ j=\hat{i}+1:0 \\
if \ i=\hat{i}+2: \ did_{i+1}d_{i+2} \ did_{i+1}d_{i+2} \ free third equation. \\
if \ j=\hat{i}+2: \ min \\
i \ k \ j \ did_kd_j + V(\hat{i}_{k}) + V(\hat{k}_{j}) \end{cases}$$
and we can choose any bracketing point

$$k \in \hat{i}+1, \dots, \hat{j}-1\hat{j}.$$

Example 3.1.2 Longest common subsequence

A subsequence of a string s is any string obtained by dropping zero or more characters from s. Given two strings s and t, what's the longest subsequence they have in common?



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A subsequence of a string s is any string obtained by dropping zero or more characters from s. Given two strings s and t, what's the longest subsequence they have in common?



The Translation strategy for designing algorithms

It's up to us how to translate the problem into "choose a sequence of actions". How can we make sure that our translation is legitimate?



Searching for the highest-value action sequence will find us the longest common substring, when ...

- 1. Every common substring can be achieved through some valid action sequence, and every action sequence produces a common substring.
- 2. The higher the value of the action sequence, the longer its corresponding common substring.

Extracting the programme

We've seen how to compute the value v(x) of the optimal programme (i.e. action sequence) starting from state x:



If we also want to extract an optimal programme,

```
def vp(x):
    # return a pair with optimal (value, programme)
    if is_terminal(x):
        return terminal_reward(x), []
    else:
        children = [vp(nextstate(x,a)) for a in ACTIONS]
        vals,progs = zip(*children)
        vals = [reward(x,a) + v for a,v in zip(ACTIONS,vals)]
        imax = index of max item in vals
        return vals[imax], progs[imax] with ACTIONS[imax] prepended
```



QUESTION What's the extra memory cost of extracting the programme, for a tree of height h?

What can go wrong?

The running time of naïve recursion is typically exponential in the size of the problem, making it impractical for all but the smallest problems.



Workarounds

- IA Algorithms: look at problems with a special "overlapping" structure that permits efficient solution.
- IB Artificial Intelligence: branch-and-bound, backtracking
- MPhil: Reinforcement learning, to approximate the value function
- Maths tripos: analytical methods for approximating large problems