# Lecture 13-14: Sublinear-Time Algorithms 

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## Outline

## Introduction

# Upper Bounds on Testing Uniformity 

## Lower Bounds on Testing Uniformity

## Extensions

## Sublinear Algorithms Overview

Sublinear Algorithms: Algorithms that return reasonably good approximate answers without scanning or storing the entire input

Usually these algorithms are randomised!

Sublinear-(Time) Algorithms
Algorithm may only inspect a small fraction of the whole input

## Sublinear Algorithms



## Motivation

Goal: Estimate properties of big probability distributions
big means that the domain of the finite probability distribution is very large!

- Lottery (are numbers equally likely?)
- Birthday Distribution (is the birthday distribution uniform over 365 days?)
- Shopping patterns (are distributions the same or different?)
- Physical Experiment (is the observed distribution close to the prediction?)
- Health (are there correlations between zip code and health condition?)


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

Transactions of 20-30 yr olds Transactions of 30-40 yr olds


## Testing Probability Distribution (Formal Model)

## Model

- Given one (or more) probability distribution $p=\left(p_{1}, p_{2}, \ldots, p_{n}\right)$
- distribution(s) are unknown, but can obtain independent samples
- also known: $n$ (or a good estimate of it)


Cost: number of samples (queries)

## Questions:

1. Is the distribution $p$ close to the uniform distribution $\boldsymbol{u}$ ?
2. Is the distribution $p$ close to some other distribution $q$ ?
3. What is $\max _{1 \leq i \leq n} p_{i}$ (heavy hitter)?
4. Are the distributions $p$ and $q$ independent?

## Testing Uniformity

Testing Uniformity: Is the distribution $p$ close to the uniform distribution $u$ ?

## Distance between Discrete Distributions

Let $p$ and $q$ be any two distributions over $\{1,2, \ldots, n\}$. Then:

1. $L_{1}$-distance: $\|p-q\|_{1}=\sum_{i=1}^{n}\left|p_{i}-q_{i}\right| \in[0,2]$,
2. $L_{2}$-distance: $\|p-q\|_{2}=\sqrt{\sum_{i=1}^{n}\left(p_{i}-q_{i}\right)^{2}} \in[0, \sqrt{2}]$,
3. $L_{\infty}$-distance: $\|p-q\|_{\infty}=\max _{i=1}^{n}\left|p_{i}-q_{i}\right| \in[0,1]$.

## Examples:

1. $p=(1,0, \ldots, 0), q=(0,1,0, \ldots, 0)$. Then $\|p-q\|_{1}=2,\|p-q\|_{2}=\sqrt{2}$ and $\|p-q\|_{\infty}=1$.
2. $p=(1,0, \ldots, 0), q=(1 / n, 1 / n, \ldots, 1 / n)$. Then $\|p-q\|_{1}=2-2 / n$, $\|p-q\|_{2}=\sqrt{1 \cdot(1-1 / n)^{2}+(n-1) \cdot(1 / n)^{2}}=\sqrt{1-1 / n}$ and $\|p-q\|_{\infty}=1-1 / n$.
3. $p=(\underbrace{2 / n, \ldots, 2 / n}_{n / 2 \text { times }}, 0, \ldots, 0)$ and $q=(0, \ldots, 0, \underbrace{2 / n, \ldots, 2 / n}_{n / 2 \text { times }})$. Then $\|p-q\|_{1}=2$, $\|p-q\|_{2}=\sqrt{2 \cdot(n / 2) \cdot(2 / n)^{2}}=\sqrt{4 / n}$ and $\|p-q\|_{\infty}=2 / n$. and $L_{\infty}$ distances are small!

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## Introduction

Upper Bounds on Testing Uniformity

## Lower Bounds on Testing Uniformity

## Extensions

## Testing Uniformity in the $L_{1}$-distance

## Objective

Find an efficient tester such that

- Given any probability distribution $p$ and $\epsilon \in(0,1)$
- If $p$ is the uniform distribution, then $P[A C C E P T] \geq 2 / 3$,
- If $p$ is $\epsilon$-far from uniform ( $\sum_{i=1}^{n}\left|p_{i}-1 / n\right| \geq \epsilon$ ), then $\mathbf{P}[$ REJECT $] \geq 2 / 3$.
- tester efficient (sub-linear) $\rightsquigarrow$ different from standard statistical tests!
- tester is allowed to have two-sided error
- there is a "grey area" when $p$ is different from but close to uniform, where the tester may give any result


Recall: $L_{1}$-distance is

$$
\sum_{i=1}^{n}\left|p_{i}-\frac{1}{n}\right|
$$

First Idea might be to approximate each $p_{i}-\frac{1}{n}$, but this takes at least $\Omega(n)$ queries.

## Birthday Paradox:

- If $p$ is (close to) uniform, expect to see collisions after $\approx \sqrt{n}$ samples
- If $p$ is far from uniform, expect to see collisions with ??



## Collision Probability and $L_{2}$-distance

$$
\|p-u\|_{2}^{2}=\sum_{i=1}^{n}\left(p_{i}-1 / n\right)^{2}=\sum_{i=1}^{n} p_{i}^{2}-2 \cdot \sum_{i=1}^{n} p_{i} \cdot \frac{1}{n}+\sum_{i=1}^{n}\left(\frac{1}{n}\right)^{2}=\|p\|_{2}^{2}-\frac{1}{n}
$$

$$
\text { Hence }\|p\|_{2}^{2}=\sum_{i=1}^{n} p_{i}^{2} \text { captures the } L_{2} \text {-distance to the uniform distribution }
$$

## APPROXIMATE $\|p\|_{2}^{2}$ number of samples $r$ will be specified later!

1. Sample $r$ elements from $p, x_{1}, x_{2}, \ldots, x_{r} \in\{1, \ldots, n\}$
2. For each $1 \leq i<j \leq r$,

$$
\sigma_{i, j}:= \begin{cases}1 & \text { if } x_{i}=x_{j} \\ 0 & \text { otherwise }\end{cases}
$$

3. Output $Y:=\frac{1}{\binom{r}{2}} \cdot \sum_{1 \leq i<j \leq r} \sigma_{i, j}$.

## Runtime Analysis

- Sampling/Query Complexity is obviously $r$
- Time Complexity??
- Evaluating $\sum_{1 \leq i<j \leq r} \sigma_{i, j}$ directly takes time quadratic in $r$
- Linear-Time Solution:

1. Maintain array $A=\left(a_{1}, a_{2}, \ldots, a_{n}\right)$, where $a_{i} \in[0, r]$ counts the frequency of samples of item $i$
2. Use formula

$$
\sum_{1 \leq i<j \leq r} \sigma_{i, j} \stackrel{(\star)}{=} \sum_{k=1}^{n}\binom{a_{k}}{2}
$$

3. Since at most $O(r)$ elements in $A$ will be non-zero, using hash-function allows computation in time $O(r)$
Proof of ( $*$ ):

$$
\begin{aligned}
\sum_{1 \leq i<j \leq r} \sigma_{i, j} & =\sum_{1 \leq i<j \leq r} \mathbf{1}_{x_{i}=x_{j}} \\
& =\sum_{1 \leq i<j \leq r} \sum_{k=1}^{n} \mathbf{1}_{x_{i}=x_{j}=k}=\sum_{k=1}^{n} \sum_{1 \leq i<j \leq r} \mathbf{1}_{x_{i}=x_{j}=k}=\sum_{k=1}^{n}\binom{a_{k}}{2}
\end{aligned}
$$

## Approximation Analysis

Analysis
For any value $r \geq 30 \cdot \frac{\sqrt{n}}{\epsilon^{2}}$, the algorithm returns a value $Y$ such that

$$
\mathbf{P}\left[\left|Y-\|p\|_{2}^{2}\right| \geq \epsilon \cdot\|p\|_{2}^{2}\right] \leq 1 / 3 .
$$

## Proof (1/5):

- Let us start by computing $\mathbf{E}[Y$ ]:

$$
\begin{aligned}
\mathbf{E}[Y] & =\frac{1}{\binom{r}{2}} \cdot \sum_{1 \leq i<j \leq r} \mathbf{E}\left[\sigma_{i, j}\right] \\
& =\frac{1}{\binom{r}{2}} \cdot \sum_{1 \leq i<j \leq r} \sum_{k=1}^{n} \mathbf{P}\left[x_{i}=k\right] \cdot \mathbf{P}\left[x_{j}=k\right] \\
& =\frac{1}{\binom{r}{2}} \cdot \sum_{1 \leq i<j \leq r} \sum_{k=1}^{n} p_{k}^{2}=\|p\|_{2}^{2} .
\end{aligned}
$$

- Analysis of the deviation more complex (see next slides):
- requires a careful analysis of the variance (note that the $\sigma_{i, j}$ 's are not even pairwise independent! - Exercise)
- final step is an application of Chebysheff's inequality


## Approximation Analysis

Analysis
For any value $r \geq 30 \cdot \frac{\sqrt{n}}{\epsilon^{2}}$, the algorithm returns a value $Y$ such that

$$
\mathbf{P}\left[\left|Y-\|p\|_{2}^{2}\right| \geq \epsilon \cdot\|p\|_{2}^{2}\right] \leq 1 / 3 .
$$

## Proof (2/5):

- Define $\widehat{\sigma}_{i, j}:=\sigma_{i, j}-\mathbf{E}\left[\sigma_{i, j}\right]$. Note $\mathbf{E}\left[\widehat{\sigma}_{i, j}\right]=0, \widehat{\sigma}_{i, j} \leq \sigma_{i, j}$ and
$\operatorname{Var}\left[\sum_{1 \leq i<j \leq r} \sigma_{i, j}\right]=\mathbf{E}\left[\left(\sum_{1 \leq i<j \leq r} \sigma_{i, j}-\sum_{1 \leq i<j \leq r} \mathbf{E}\left[\sigma_{i, j}\right]\right)^{2}\right]=\mathbf{E}\left[\left(\sum_{1 \leq i<j \leq r} \widehat{\sigma}_{i, j}\right)^{2}\right]$.
- Expanding yields:

$$
\underbrace{\sum_{1 \leq i<j \leq r} \mathbf{E}\left[\widehat{\sigma}_{i, j}^{2}\right]}_{=A}+\underbrace{\sum_{i, j, k, \ell \text { diff. }} \mathbf{E}\left[\widehat{\sigma}_{i, j} \cdot \widehat{\sigma}_{k, \ell}\right]+4 \cdot \underbrace{\sum_{1 \leq i<j<k \leq r} \mathbf{E}\left[\widehat{\sigma}_{i, j} \cdot \widehat{\sigma}_{j, k}\right]}_{=C} . . . \underbrace{1 \leq j}}_{=B}
$$

## Approximation Analysis

Analysis
For any value $r \geq 30 \cdot \frac{\sqrt{n}}{\epsilon^{2}}$, the algorithm returns a value $Y$ such that

$$
\mathbf{P}\left[\left|Y-\|p\|_{2}^{2}\right| \geq \epsilon \cdot\|p\|_{2}^{2}\right] \leq 1 / 3 .
$$

## Proof (3/5):

$$
\begin{aligned}
& A=\sum_{1 \leq i<j \leq r} \mathbf{E}\left[\widehat{\sigma}_{i, j}^{2}\right] \leq \sum_{1 \leq i<j \leq r} \mathbf{E}\left[\sigma_{i, j}^{2}\right]=\sum_{1 \leq i<j \leq r} \mathbf{E}\left[\sigma_{i, j}\right]=\binom{r}{2} \cdot\|p\|_{2}^{2} . \\
& B=\sum_{i, j, k, \ell \text { diff. }} \mathbf{E}\left[\widehat{\sigma}_{i, j} \cdot \widehat{\sigma}_{k, \ell}\right]=\sum_{i, j, k, \ell, \text { diff. }} \mathbf{E}\left[\widehat{\sigma}_{i, j}\right] \cdot \mathbf{E}\left[\widehat{\sigma}_{k, \ell}\right]=0 . \\
& \text { Covariance Formula: } \mathbf{E}[(X-\mathbf{E}[X])(Y-\mathbf{E}[Y])]=\mathbf{E}[X Y]-\mathbf{E}[X] \mathbf{E}[Y] \\
& C=\sum_{1 \leq i<j<k \leq r} \mathbf{E}\left[\widehat{\sigma}_{i, j} \hat{\sigma}_{i, k}\right] \leq \sum_{1 \leq i<j<k \leq r} \mathbf{E}\left[\sigma_{i, j} \sigma_{i, k}\right] \\
& =\sum_{1 \leq i<j<k \leq r} \sum_{\ell \in[n]} \mathbf{P}\left[X_{i}=X_{j}=X_{k}=\ell\right]=\binom{r}{3} \cdot \sum_{\ell \in[n]} p_{\ell}^{3} \leq \frac{\sqrt{3}}{2}\left(\binom{r}{2}\|p\|_{2}^{2}\right)^{3 / 2}
\end{aligned}
$$

## Approximation Analysis

## Analysis

For any value $r \geq 30 \cdot \frac{\sqrt{n}}{\epsilon^{2}}$, the algorithm returns a value $Y$ such that

$$
\mathbf{P}\left[\left|Y-\|p\|_{2}^{2}\right| \geq \epsilon \cdot\|p\|_{2}^{2}\right] \leq 1 / 3 .
$$

## Proof (4/5):

- We have just shown that:

$$
\begin{aligned}
\operatorname{Var}\left[\sum_{1 \leq i<j \leq r} \sigma_{i, j}\right] & =A+B+4 C \\
& =\binom{r}{2} \cdot\|p\|_{2}^{2}+0+4 \cdot \frac{\sqrt{3}}{2}\left(\binom{r}{2}\|p\|_{2}^{2}\right)^{3 / 2} \\
& \leq 5\left(\binom{r}{2}\|p\|_{2}^{2}\right)^{3 / 2}
\end{aligned}
$$

## Approximation Analysis

## Analysis

For any value $r \geq 30 \cdot \frac{\sqrt{n}}{\epsilon^{2}}$, the algorithm returns a value $Y$ such that

$$
\mathbf{P}\left[\left|Y-\|p\|_{2}^{2}\right| \geq \epsilon \cdot\|p\|_{2}^{2}\right] \leq 1 / 3 .
$$

## Proof (5/5):

- Applying Chebyshef's inequality to $Y:=\frac{1}{\binom{r}{2}} \cdot \sum_{1 \leq i<j \leq r} \sigma_{i, j}$ yields:

$$
\begin{aligned}
\mathbf{P}\left[|Y-\mathbf{E}[Y]| \geq \epsilon \cdot\|p\|_{2}^{2}\right] & \leq \frac{\operatorname{Var}[Y]}{\epsilon^{2} \cdot\|p\|_{2}^{4}} \\
& \leq \frac{\frac{1}{\binom{r}{2}^{2}} \cdot 5\left(\binom{r}{2} \cdot\|p\|_{2}^{2}\right)^{3 / 2}}{\epsilon^{2} \cdot\|p\|_{2}^{4}} \\
& \leq \frac{10}{r \cdot\|p\|_{2} \cdot \epsilon^{2}} \\
& \leq \frac{10}{r \cdot(1 / \sqrt{n}) \cdot \epsilon^{2}}
\end{aligned}
$$

## Approximation of $\|p-u\|_{1}$ using $\|p\|_{2}^{2}$

## UNIFORM-TEST

1. Run APPROXIMATE $\|p\|_{2}^{2}$ with $r=30 \cdot \frac{\sqrt{n}}{\left(\epsilon^{2} / 4\right)^{2}}=\mathcal{O}\left(\frac{\sqrt{n}}{\epsilon^{4}}\right)$ samples to get a value $Y$ such that

$$
\mathbf{P}\left[|Y-\mathbf{E}[Y]| \geq \epsilon^{2} / 4 \cdot\|p\|_{2}^{2}\right] \leq 1 / 3
$$

2. If $Y \geq \frac{1+\epsilon^{2} / 2}{n}$, then REJECT.
3. Otherwise, ACCEPT.

Correctness Analysis

- If $p=u$, then $\mathbf{P}[$ ACCEPT $] \geq 2 / 3$.
- If $p$ is $\epsilon$-far from $u$, i.e., $\sum_{i=1}^{n}\left|p_{i}-\frac{1}{n}\right| \geq \epsilon$ ), then $\mathrm{P}[$ REJECT $] \geq 2 / 3$.

Exercise: Prove that any testing algorithm in this model will have a two-sided error!

## Analysis of UNIFORM-TEST (1/2)

Case 1: $p$ is uniform.
In this case

$$
\|p\|_{2}^{2}=\frac{1}{n}
$$

and the approximation guarantee on $Y$ implies

$$
\mathbf{P}\left[Y \geq\|p\|_{2}^{2} \cdot\left(1+\epsilon^{2} / 4\right)\right] \leq 1 / 3
$$

which means that the algorithm will ACCEPT with probability at least $2 / 3$.

## Analysis of UNIFORM-TEST (2/2)

Case 2: $p$ is $\epsilon$-far from $u$.
We will show that if $\mathbf{P}[$ REJECT ] $\leq 2 / 3$, then $p$ is $\epsilon$-close to $u$. $\mathbf{P}[$ REJECT $] \leq 2 / 3$ implies

$$
\begin{equation*}
\mathbf{P}\left[Y>\frac{1+\epsilon^{2} / 2}{n}\right]<2 / 3 \tag{1}
\end{equation*}
$$

From line 1 of the algorithm we know that

$$
\begin{equation*}
\mathbf{P}\left[Y>\left(1-\epsilon^{2} / 4\right) \cdot\|p\|_{2}^{2}\right] \geq 2 / 3 \tag{2}
\end{equation*}
$$

Combining (1) and (2) yields, and rearranging yields

Hence,

$$
\|p\|_{2}^{2}<\frac{1}{n} \cdot\left(1+\epsilon^{2} / 2\right) \cdot \frac{1}{1-\epsilon^{2} / 4} \leq \frac{1+\epsilon^{2}}{n}
$$

$$
\|p-u\|_{2}^{2}=\|p\|_{2}^{2}-\frac{1}{n}<\frac{\epsilon^{2}}{n} \quad \Rightarrow \quad\|p-u\|_{2}<\frac{\epsilon}{\sqrt{n}}
$$

Since $\|\cdot\|_{2} \geq \frac{1}{\sqrt{n}} \cdot\|\cdot\|_{1}$,

$$
\|p-u\|_{1} \leq \sqrt{n} \cdot\|p-u\|_{2}<\epsilon
$$

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## Upper Bounds on Testing Uniformity

Lower Bounds on Testing Uniformity

## Extensions

## Lower Bound

## Theorem

Let $0<\epsilon<1$. There is no algorithm with the following three properties:

1. The algorithm samples at most $r:=\frac{1}{64} \sqrt{n / \epsilon}$ times from $p$,
2. If $p=u$, then $\mathbf{P}[\mathrm{ACCEPT}] \geq \frac{2}{3}$,
3. If $\|p-u\|_{1} \geq \epsilon$, then $\mathbf{P}[$ REJECT $] \geq \frac{2}{3}$.

Exercise: Can you see why is it important to choose $\mathcal{I}$ randomly?

## Proof Outline.

- Generate a distribution $p$ randomly as follows:
- Pick a set $\mathcal{I} \subseteq\{1, \ldots, \epsilon \cdot n\}$ of size $\epsilon \cdot n / 2$ uniformly at random.
- Then define:

$$
p_{i}= \begin{cases}\frac{2}{n} & \text { if } i \in \mathcal{I}, \\ 0 & \text { if } i \in\{1, \ldots, \epsilon \cdot n\} \backslash \mathcal{I} \\ \frac{1}{n} & \text { if } \epsilon \cdot n<i<n\end{cases}
$$

- Then $\|p-u\|_{1}=\epsilon \cdot n \cdot 1 / n=\epsilon$.
- E.g., $n=16, \epsilon=1 / 4, \mathcal{I}=\{1,4\}$ :

Idea is that algorithm needs enough samples of the first $\epsilon \cdot n$ elements to see any collisions!

$$
p=(\underbrace{\frac{2}{n}, 0,0, \frac{2}{n}}_{\epsilon n=4 \text { elements }}, \underbrace{\frac{1}{n}, \frac{1}{n}, \frac{1}{n}, \frac{1}{n}, \frac{1}{n}, \frac{1}{n}, \frac{1}{n}, \frac{1}{n}, \frac{1}{n}, \frac{1}{n}, \frac{1}{n}, \frac{1}{n}}_{12 \text { elements }})
$$

## Outline

## Introduction

# Upper Bounds on Testing Uniformity 

## Lower Bounds on Testing Uniformity

Extensions

## Extension 1: Testing Closeness of Arbitrary Distributions (1/2)

$$
\begin{aligned}
\|p-q\|_{2}^{2} & =\sum_{i=1}^{n}\left(p_{i}-q_{i}\right)^{2}=\sum_{i=1}^{n} p_{i}^{2}+\sum_{i=1}^{n} q_{i}^{2}-2 \cdot \sum_{i=1}^{n} p_{i} \cdot q_{i} \\
& =\|p\|_{2}^{2}+\|q\|_{2}^{2}-2 \cdot\langle p, q\rangle
\end{aligned}
$$

We already know how to estimate $\|p\|_{2}^{2}$ and $\|q\|_{2}^{2!}$

APPROXIMATE $\langle p, q\rangle$

1. Sample $r$ elements from $p, x_{1}, x_{2}, \ldots, x_{r} \in[n]$, and sample $r$ elements from $q, y_{1}, y_{2}, \ldots, y_{r} \in[n]$
2. For each $1 \leq i<j \leq r$,

$$
\tau_{i, j}:= \begin{cases}1 & \text { if } x_{i}=y_{j} \\ 0 & \text { otherwise }\end{cases}
$$

3. Output $Y:=\frac{1}{r^{2}} \sum_{1 \leq i, j \leq r} \tau_{i, j}$.

## Extension 1: Testing Closeness of Arbitrary Distributions (2/2)

Theorem (Batu, Fortnow, Rubinfeld, Smith, White; JACM 60(1), 2013)
There exists an algorithm using $\mathcal{O}\left(1 / \epsilon^{4}\right)$ samples such that if the distributions $p$ and $q$ satisfy $\|p-q\|_{2} \leq \epsilon / 2$, then the algorithm accepts with probability at least $2 / 3$. If $\|p-q\|_{2} \geq \epsilon$, then the algorithm rejects with probability at least 2/3.

Theorem (Batu, Fortnow, Rubinfeld, Smith, White; JACM 60(1), 2013)
There exists an algorithm using $\mathcal{O}\left(1 / \epsilon^{4} \cdot n^{2 / 3} \log n\right)$ samples such that if the distributions $p$ and $q$ satisfy $\|p-q\|_{1} \leq \max \left\{\frac{\epsilon^{2}}{32 \sqrt[3]{n}}, \frac{\epsilon}{4 \sqrt{n}}\right\}$, then the algorithm accepts with probability at least $2 / 3$. If $\|p-q\|_{1} \geq \epsilon$, then the algorithm rejects with probability at least $2 / 3$.

|  | $L_{2}$-distance | $L_{1}$-distance |
| :---: | :---: | :---: |
| Testing uniformity $\\|p-u\\|$ | $\Theta(1)$ | $\Theta(\sqrt{n})$ |
| Testing closeness $\\|p-q\\|$ | $\Theta(1)$ | $\in\left[\Omega\left(n^{2 / 3}\right), \mathcal{O}\left(n^{2 / 3} \log n\right)\right]$ |

Figure: Overview of the known sampling complexities for constant $\epsilon \in(0,1)$.

## Extension 2: Testing Conductance of Graphs

## Testing Conductance of Graphs

- Idea: Start several random walks from the same vertex
- Count the number of pairwise collisions
- If the number of collisions high, graphs is not an expander
- If the number of collisions is sufficiently small, graph is an expander


