



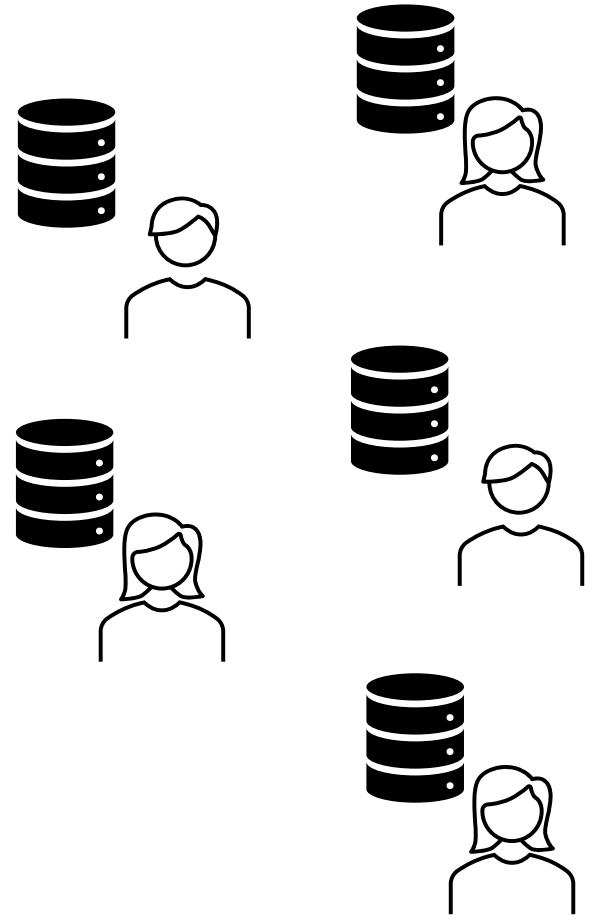
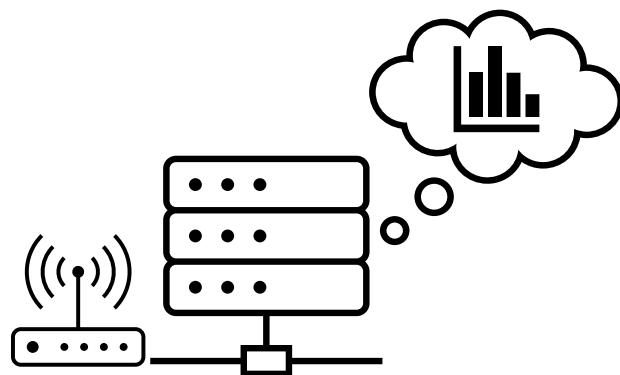
Domain Compression and its Applications to Distribution Testing

Clément Canonne, University of Sydney

CIS Seminar (U Melbourne), 10/05/2022

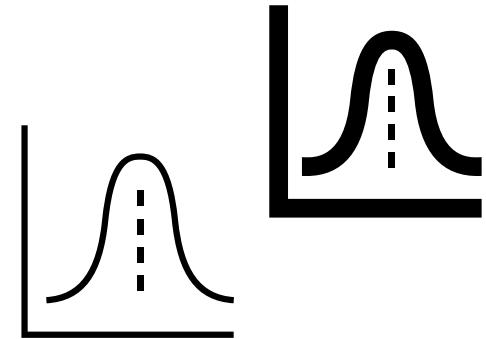
The (distributed) setting

- Users have **data** (observations)
- Center wants to perform **hypothesis testing**



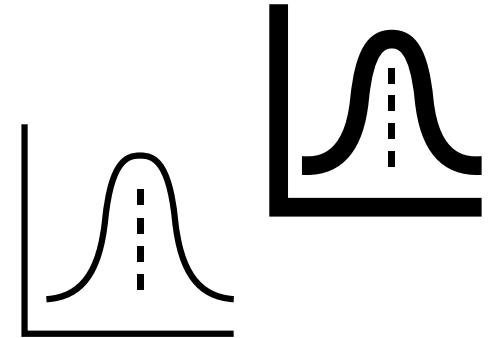
The (distributed) setting: example

- Users have **data** (observations) X_1, \dots, X_n i.i.d. from some p
- Does the data distribution p **fit the model** q ?
 - $H_0: p=q$
 - $H_1: TV(p,q) > \varepsilon$



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One-sample testing [Stats]
(One-sample) goodness-of-fit [Stats/ML]
Identity testing [Computer Science]

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$$TV(p, q) = \sup_S (p(S) - q(S))$$

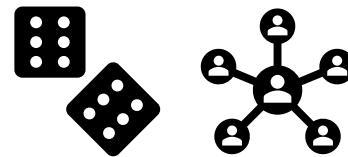
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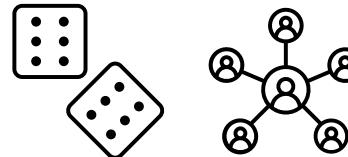
- Users have **data** (observations) X_1, \dots, X_n i.i.d. from some p
- Users have **constraints**: privacy, bandwidth, memory, ...
- Center has **goals**: e.g., minimise number of users n (maximise utility)

The (distributed) setting: more!

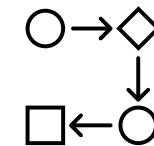
- Private-coin protocols



- Public-coin protocols



- Sequentially interactive protocols

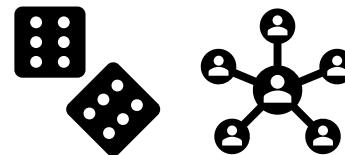


- Blackboard protocols

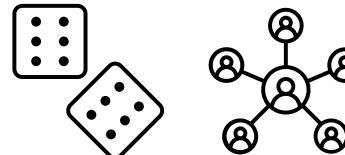


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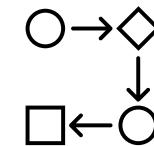
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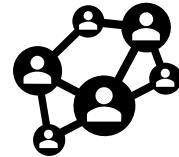
- Public-coin protocols



- Sequentially interactive protocols



- Blackboard protocols



Back to our example: identity testing

n i.i.d. samples from unknown p over $[k] = \{1, 2, \dots, k\}$

known reference q over $[k]$

Distance parameter ϵ in $(0, 1]$

$$\mathcal{H}_0: p = q \quad \text{vs.} \quad \mathcal{H}_1: \text{TV}(p, q) > \epsilon$$

How large must n be to distinguish with probability at least $2/3$?

Back to our example: identity testing

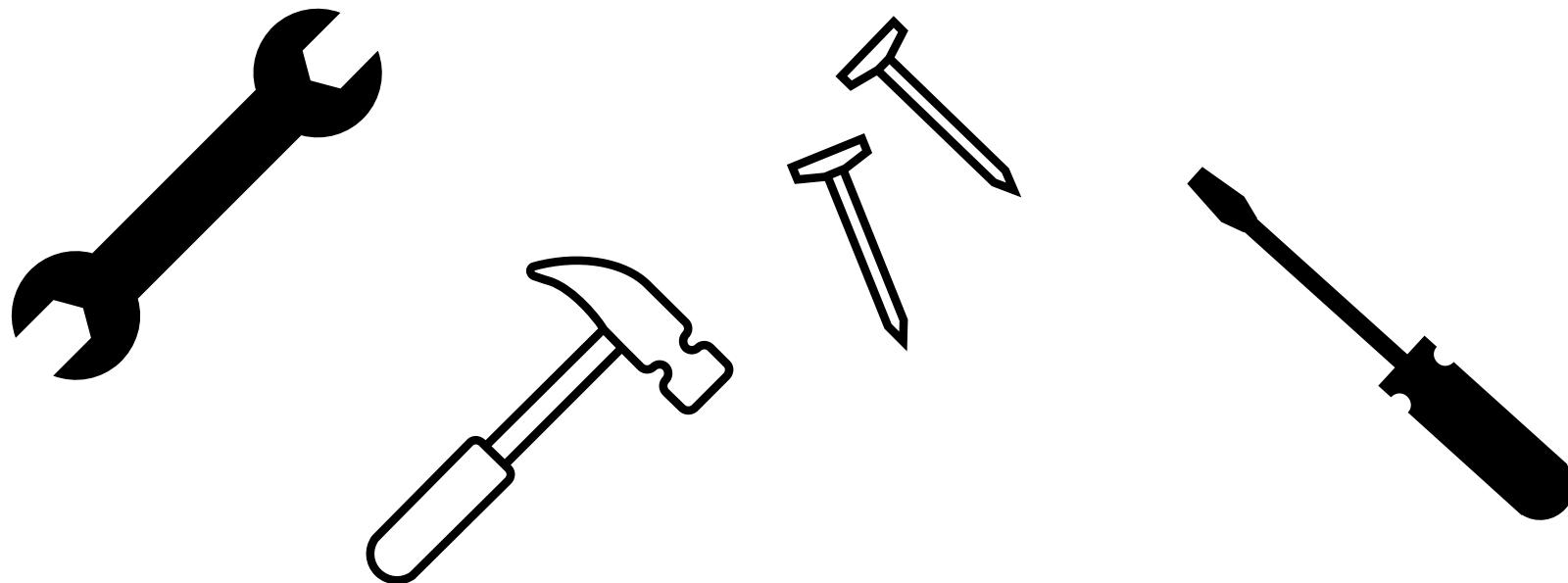
	Private-Coin	Public-Coin
Centralised		$k^{1/2}/\epsilon^2$
Local privacy	$k^{3/2}/(\epsilon^2\rho^2)$	$k/(\epsilon^2\rho^2)$
Shuffle privacy*	$k^{3/4}/(\epsilon\rho) + k^{1/2}/\epsilon^2$	$k^{2/3}/(\epsilon^{4/3}\rho^{2/3}) + k^{1/2}/\epsilon^2 + k^{1/2}/(\epsilon\rho)$
Bandwidth	$k^{3/2}/(\epsilon^22^\ell) + k^{1/2}/\epsilon^2$	$k/(\epsilon^22^{\ell/2}) + k^{1/2}/\epsilon^2$

Back to our example: identity testing

	Private-Coin	Public-Coin
Centralised	$k^{1/2}/\epsilon^2$	
Local privacy	$k^{3/2}/(\epsilon^2 \rho^2)$?
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Bandwidth	$k^{3/2}/(\epsilon^2 2^\ell) + k^{1/2}/\epsilon^2$?

Claim: all the public-coin bounds are “immediate”

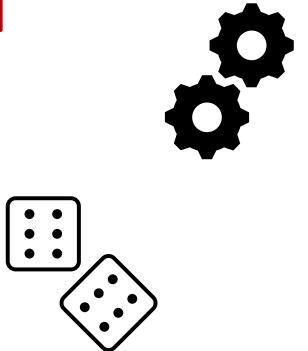
(For every hard-earned upper bound, the second is free!)



Domain Compression

[Acharya–Canonne–Han–Sun–Tyagi'20], [Amin–Joseph–Mao'20]

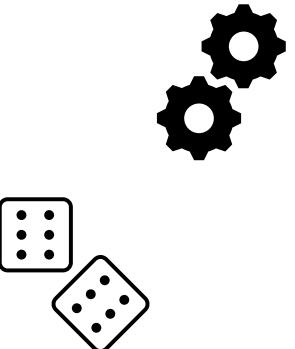
- trade **domain size** for statistical distance using **shared randomness**
- develop a "private-coin" protocol, get a "public-coin" one for free!



Domain Compression

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- trade **domain size** for statistical distance using **shared randomness**
- develop a "private-coin" protocol, get a "public-coin" one for free!



Theorem 2.12 (Domain Compression Lemma). There exist absolute constants $c_1, c_2 > 0$ such that the following holds. For any $2 \leq L \leq k$ and any $\mathbf{p}, \mathbf{q} \in \Delta_k$,

$$\Pr_{\Pi} \left[d_{\text{TV}}(\mathbf{p}_{\Pi}, \mathbf{q}_{\Pi}) \geq c_1 \sqrt{\frac{L}{k}} d_{\text{TV}}(\mathbf{p}, \mathbf{q}) \right] \geq c_2,$$

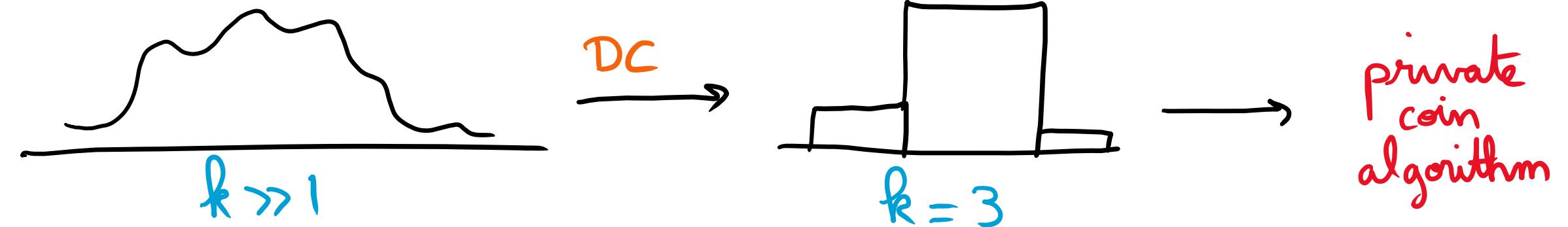
where $\Pi = (\Pi_1, \dots, \Pi_L)$ is a uniformly random partition of $[k]$ in L subsets, and $\mathbf{p}_{\Pi} \in \Delta_L$ denotes the probability distribution on $[L]$ induced by \mathbf{p} and Π via $\mathbf{p}_{\Pi}(i) = \mathbf{p}(\Pi_i)$.

Domain Compression

Use **public randomness** to convert a testing instance (k, ϵ) to a testing instance $(L, \epsilon\sqrt{L/k})$, for your choice of $2 \leq L \leq k$.

(Fine print: need to repeat $O(1)$ times to amplify success probability.)

Now, what could that be good for?



Let's see: identity testing

	Private-Coin	Public-Coin
Centralised		$k^{1/2}/\epsilon^2$
Local privacy	$k^{3/2}/(\epsilon^2 \rho^2)$?
Shuffle privacy*	$k^{3/4}/(\epsilon \rho) + k^{1/2}/\epsilon^2$?
Bandwidth	$k^{3/2}/(\epsilon^2 2^\ell) + k^{1/2}/\epsilon^2$?

Local privacy

$$\frac{k^{3/2}}{\epsilon^2 \rho^2} \xrightarrow{DC}$$

Local privacy

$$\frac{k^{3/2}}{\epsilon^2 \rho^2} \xrightarrow{DC} \frac{L^{3/2}}{\left(\epsilon \sqrt{\frac{L}{k}}\right)^2 \rho^2} = \frac{L^{1/2} k}{\epsilon^2 \rho^2}$$

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Minimised for $L^* = 2$

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Minimised for $L^* = 2$

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Just a
fluke?

Shuffle privacy

$$\frac{k^{3/4}}{\epsilon\rho} + \frac{k^{1/2}}{\epsilon^2} \xrightarrow{DC}$$

Shuffle privacy

$$\frac{k^{3/4}}{\epsilon \rho} + \frac{k^{1/2}}{\epsilon^2} \xrightarrow{DC} \frac{L^{3/4}}{\epsilon \sqrt{\frac{L}{k}} \rho} + \frac{L^{1/2}}{\left(\epsilon \sqrt{\frac{L}{k}}\right)^2}$$

Shuffle privacy

$$\frac{k^{3/4}}{\epsilon\rho} + \frac{k^{1/2}}{\epsilon^2} \xrightarrow{DC} \frac{L^{1/4}k^{1/2}}{\epsilon\rho} + \frac{k}{\epsilon^2 L^{1/2}}$$

Shuffle privacy

$$\frac{k^{3/4}}{\epsilon\rho} + \frac{k^{1/2}}{\epsilon^2} \xrightarrow{DC} \frac{L^{1/4}\rho^{1/2}}{\epsilon\rho} + \frac{k}{\epsilon^2 L^{1/2}}$$

Minimised for $L^* \approx \frac{k^{2/3}\rho^{4/3}}{\epsilon^{4/3}}$

Shuffle privacy

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Minimised for $L^* \approx k^{2/3} \frac{\rho^{4/3}}{\epsilon^{4/3}}$

(but careful: we need $2 \leq L \leq k$)

Shuffle privacy

Case 1 $L^* \leq 2$ Take $L = 2$.

$$\frac{L^{1/4}k^{1/2}}{\epsilon\rho} + \frac{k}{\epsilon^2 L^{1/2}} \asymp \frac{k^{1/2}}{\epsilon\rho} + \frac{k}{\epsilon^2}$$

Shuffle privacy

$$k \lesssim \frac{\epsilon^2}{\rho^2}$$

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$$\frac{L^{1/4} \rho^{1/2}}{\epsilon \rho} + \frac{k}{\epsilon^2 L^{1/2}} \lesssim \frac{k^{1/2}}{\epsilon \rho} + \frac{k}{\epsilon^2} \lesssim \frac{k^{1/2}}{\epsilon \rho} + \frac{k^{2/3}}{\epsilon^{4/3} \rho^{2/3}}$$

$= \frac{k^{2/3}}{\epsilon^2} \cdot \rho^{1/3}$

Shuffle privacy

$$k \lesssim \frac{\epsilon^2}{\rho^2}$$

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$\boxed{= \frac{k^{2/3}}{\epsilon^2} \cdot \rho^{1/3}}$

Good!

Shuffle privacy

Case 2 $L^* \geq k$ Take $L = k$.

$$\frac{L^{1/4}k^{1/2}}{\epsilon\rho} + \frac{k}{\epsilon^2 L^{1/2}} \asymp \frac{k^{3/4}}{\epsilon\rho} + \frac{\sqrt{k}}{\epsilon^2}$$

Shuffle privacy

$$k \leq \frac{\rho^4}{\varepsilon^4}$$

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$$\frac{L^{1/4}R^{1/2}}{\varepsilon\rho} + \frac{k}{\varepsilon^2 L^{1/2}} \stackrel{?}{=} \frac{k^{3/4}}{\varepsilon\rho} + \frac{\sqrt{k}}{\varepsilon^2} \leq 2 \frac{\sqrt{k}}{\varepsilon^2}$$

$\boxed{= \frac{\sqrt{k}}{\varepsilon\rho} \cdot k^{1/4}}$

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Good!

Shuffle privacy

Case 3 $2 \leq L^* \leq k$. Take $L = L^* \approx \frac{k^{2/3}}{\epsilon^{4/3}}$

$$\frac{L^{1/4}k^{1/2}}{\epsilon\rho} + \frac{k}{\epsilon^2 L^{1/2}} \approx \frac{k^{2/3}}{\epsilon^{4/3} \rho^{2/3}}$$

Shuffle privacy

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Good!

Shuffle privacy

Summary

$$\frac{\sqrt{k}}{\varepsilon^2} + \frac{\sqrt{k}}{\varepsilon\rho} + \frac{k^{2/3}}{\varepsilon^{4/3}\rho^{2/3}}$$

suffices.

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One more time?

Bandwidth (each user sends ℓ bits)

$$\frac{k^{3/2}}{\varepsilon^2 2^\ell} + \frac{k^{1/2}}{\varepsilon^2} \xrightarrow{DC}$$

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$$\frac{\ell^{3/2}}{\varepsilon^2 2^\ell} + \frac{\ell^{1/2}}{\varepsilon^2} \xrightarrow{DC} \frac{\ell^{3/2}}{\left(\varepsilon \sqrt{\frac{\ell}{R}}\right)^2 2^\ell} + \frac{\ell^{1/2}}{\left(\varepsilon \sqrt{\frac{\ell}{R}}\right)^2}$$

Bandwidth (each user sends ℓ bits)

$$\frac{k^{3/2}}{\varepsilon^2 2^\ell} + \frac{k^{1/2}}{\varepsilon^2} \xrightarrow{DC} \frac{L^{1/2} k}{\varepsilon^2 2^\ell} + \frac{k}{L^{1/2} \varepsilon^2}$$

Minimised for $L^* = 2^\ell$

Bandwidth (each user sends ℓ bits)

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Minimised for $L^* = 2^\ell$

(again, we need $2 \leq L \leq k$)

Bandwidth (each user sends ℓ bits)

Case 1: $L^* \geq R$. Take $L = R$

$$\frac{L'^{\frac{1}{2}}k}{\varepsilon^2 2^\ell} + \frac{k}{L'^{\frac{1}{2}} \varepsilon^2} = \frac{k}{\varepsilon^2 2^\ell} + \frac{\sqrt{k}}{\varepsilon^2} \asymp \frac{\sqrt{k}}{\varepsilon^2}$$

\uparrow
 $2^\ell = L^* \geq R$

Bandwidth (each user sends ℓ bits)

Case 1: $L^* \geq k$. Take $L = k$

$$\frac{L'^2 k}{\varepsilon^2 2^\ell} + \frac{k}{L'^2 \varepsilon^2} = \frac{k}{\varepsilon^2 2^\ell} + \frac{\sqrt{k}}{\varepsilon^2} \asymp \frac{\sqrt{k}}{\varepsilon^2}$$

Case 2 $L^* \leq k$. Take $L = L^* = 2^\ell$.

$$\frac{L'^2 k}{\varepsilon^2 2^\ell} + \frac{k}{L'^2 \varepsilon^2} \asymp \frac{k}{\varepsilon^2 2^{\ell/2}}$$

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Great!

We've seen: identity testing

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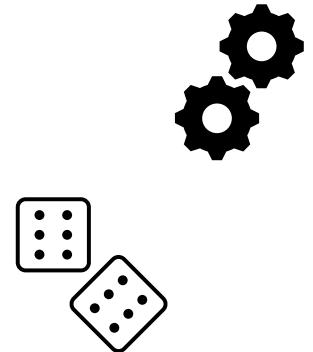
Domain
Compression

Domain Compression: let's prove it

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where $\Pi = (\Pi_1, \dots, \Pi_L)$ is a uniformly random partition of $[k]$ in L subsets, and $\mathbf{p}_{\Pi} \in \Delta_L$ denotes the probability distribution on $[L]$ induced by \mathbf{p} and Π via $\mathbf{p}_{\Pi}(i) = \mathbf{p}(\Pi_i)$.



Domain Compression: The Plan

- Prove the case $L=2$ (“one-bit isometry”) for the ℓ_2 norm (*not* TV)
- For general L :
 - partition the domain in L parts
 - apply the one-bit isometry separately to each of them
 - invoke a “simple” probability lemma about additivity of tails to conclude

Part I: One-bit isometry

Theorem. There exist $c_1, c_2 > 0$ s.t. for all $p, q \in [0,1]^k$,

$$P\{|p(s) - q(s)| \geq c_1 \|p - q\|_2\} \geq c_2,$$

where $S \subseteq [k]$ is uniformly random.

not necessarily proba. distr.!

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Prof. Set $\delta := p - q$, and $X_1, \dots, X_k \stackrel{\text{iid}}{\sim} \text{Bern}\left(\frac{1}{2}\right)$.

$$Z^2 := (p(S) - q(S))^2 = \left(\sum_{i=1}^k \delta_i X_i\right)^2 = \sum_i \delta_i^2 X_i^2 + \sum_{i \neq j} \delta_i \delta_j X_i X_j$$

so $E[Z^2] = \frac{1}{2} \|\delta\|_2^2 + \frac{1}{4} \sum_{i \neq j} \delta_i \delta_j$

Proof. Set $\delta := p - q$, and X_1, \dots, X_k iid $\text{Bern}\left(\frac{1}{2}\right)$.

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so $\mathbb{E}[Z^2] = \frac{1}{2} \|\delta\|_2^2 + \frac{1}{4} \sum_{i \neq j} \delta_i \delta_j = \frac{1}{2} \|\delta\|_2^2 + \frac{1}{4} \left(\left(\sum_i \delta_i \right)^2 - \sum_i \delta_i^2 \right)$

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$$\begin{aligned} \text{so } \mathbb{E}[Z^2] &= \frac{1}{2} \|\delta\|_2^2 + \frac{1}{4} \sum_{i \neq j} \delta_i \delta_j = \frac{1}{2} \|\delta\|_2^2 + \frac{1}{4} \left(\left(\sum_i \delta_i \right)^2 - \|\delta\|_2^2 \right) \\ &= \frac{1}{4} \|\delta\|_2^2 + \frac{1}{4} \underbrace{\left(\sum_i \delta_i \right)^2}_{(\mathbb{E} Z)^2} \geq \frac{1}{4} \|\delta\|_2^2 \end{aligned}$$

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$$\text{so } \mathbb{E}[Z^2] \geq \frac{1}{4} \|\delta\|_2^2 + \frac{1}{4} (\mathbb{E} Z)^2 \geq \frac{1}{4} \|\delta\|_2^2$$

Suffices now to prove

$$\Pr\left\{ Z^2 \geq \frac{1}{2} \mathbb{E}[Z^2] \right\} \geq \Omega(1)$$

(anticoncentration)

Proof. $Z^2 := \left(\sum_{i=1}^k \delta_i X_i \right)^2$ where X_1, \dots, X_k iid $\text{Bern}\left(\frac{1}{2}\right)$.

By Paley-Zygmund,

$$P\left\{ Z^2 \geq \frac{1}{2} E[Z^2] \right\} \geq \frac{1}{4} \frac{E[Z^2]^2}{E[Z^4]}$$

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\nearrow

\nearrow this is scary

Nice trick: MGF.

$$E e^{\lambda Z} = \prod_{i=1}^k E e^{\lambda \delta_i X_i} \stackrel{HL}{\leq} \prod_{i=1}^k e^{\lambda \frac{\delta_i}{2} + \frac{\lambda^2 \delta_i^2}{8}} = e^{\frac{\lambda}{2} E[Z] + \frac{\lambda^2 \| \delta \|_2^2}{8}}$$

Proof. So $\mathbb{E} e^{\lambda(Z - \mathbb{E} Z)}$ ^{symmetric} $\leq e^{\frac{1}{8}\lambda^2\|\delta\|_2^2}$, and "so"

$$\frac{\lambda^4}{24} \mathbb{E}[(Z - \mathbb{E} Z)^4] \leq e^{\frac{1}{8}\lambda^2\|\delta\|_2^2}$$

Choosing $\lambda = \frac{1}{\|\delta\|_2}$, we get

$$\mathbb{E}[(Z - \mathbb{E} Z)^4] \leq 28 \|\delta\|_2^4$$

Almost there!

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$$\mathbb{E}[Z^4] \leq \mathbb{E}[8(Z - \mathbb{E}Z)^4 + 8\mathbb{E}[Z]^4] \leq 224 \|\delta\|_2^4 + 8\mathbb{E}[Z]^4$$

which is... something.

Proof.

By Paley-Zygmund,

$$P\left\{ Z^2 \geq \frac{1}{2} E[Z^2] \right\} \geq \frac{1}{4} \frac{E[Z^2]^2}{E[Z^4]} = \Omega(1)$$

\nearrow

$$\geq \frac{1}{4} \|\delta\|_2^2$$

\nwarrow

$$\lesssim \|\delta\|_2^4 + E[Z]^4$$

and we are done!

□

Part II: General L

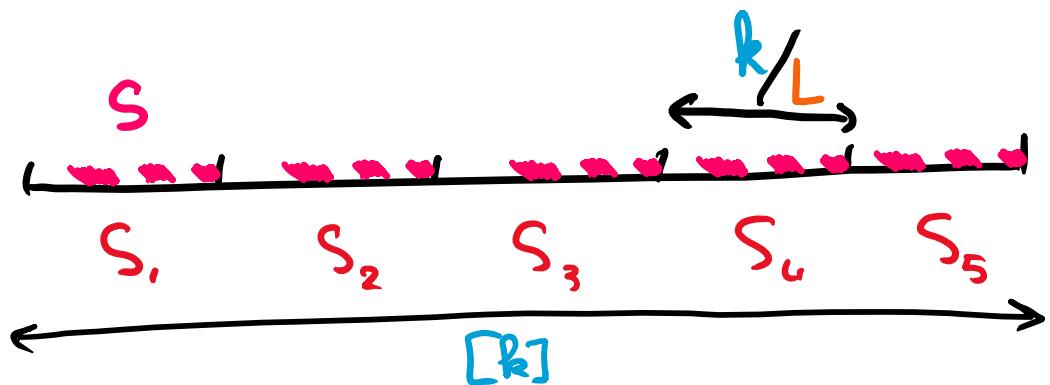
Divide $\lceil k \rceil$ in L parts of equal size, and apply
the 1-bit isometry to the L subvectors separately:

Part II: General L

Divide $[k]$ in L parts of equal size, and apply the 1-bit isometry to the L subvectors separately:

$$\forall j \in [L], \quad \Pr_S \left\{ |p^j(S) - q^j(S)| \geq \frac{c_1}{\sqrt{\frac{k}{L}}} \|p^j - q^j\|_1 \right\} \geq c_2$$

$$c_1 \leq \frac{\|p^j - q^j\|_2}{\sqrt{\frac{k}{L}}}$$



Pick $S \subseteq [\frac{k}{L}]$ u.a.r, translate it in all L parts.

Part II: General L

Divide $[k]$ in L parts of equal size:

$$\forall j \in [L], \quad \underset{S}{\mathbb{P}} \left\{ |p^j(S) - q^j(S)| \geq \frac{c_1}{\sqrt{\frac{k}{L}}} \|p^j - q^j\|_1 \right\} \geq c_2$$

“Then”

$$\underset{S}{\mathbb{P}} \left\{ \sum_{j=1}^L |p^j(S) - q^j(S)| \geq \frac{c'_1}{\sqrt{\frac{k}{L}}} \sum_{j=1}^L \|p^j - q^j\|_1 \right\} \geq c'_2$$

and we are done.



Part II: General L

What was that “Then”?

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$$\Pr\left[Y_1 + \dots + Y_m \geq c \cdot \frac{a_1 + \dots + a_m}{2}\right] \geq \frac{c}{2 - c}.$$

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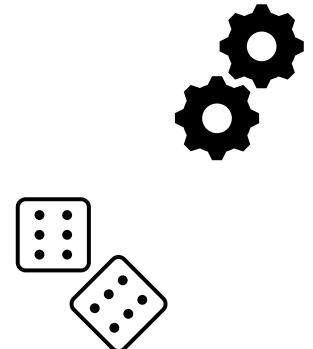
No independence of
 Y_1, \dots, Y_m required!

Domain Compression: we proved it

Theorem 2.12 (Domain Compression Lemma). There exist absolute constants $c_1, c_2 > 0$ such that the following holds. For any $2 \leq L \leq k$ and any $\mathbf{p}, \mathbf{q} \in \Delta_k$,

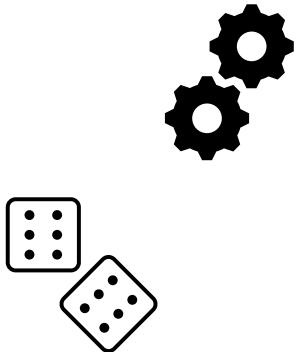
$$\Pr_{\Pi} \left[d_{\text{TV}}(\mathbf{p}_{\Pi}, \mathbf{q}_{\Pi}) \geq c_1 \sqrt{\frac{L}{k}} d_{\text{TV}}(\mathbf{p}, \mathbf{q}) \right] \geq c_2,$$

where $\Pi = (\Pi_1, \dots, \Pi_L)$ is a uniformly random partition of $[k]$ in L subsets, and $\mathbf{p}_{\Pi} \in \Delta_L$ denotes the probability distribution on $[L]$ induced by \mathbf{p} and Π via $\mathbf{p}_{\Pi}(i) = \mathbf{p}(\Pi_i)$.



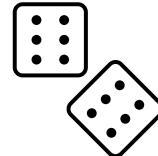
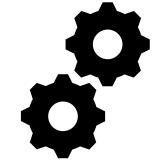
Domain Compression: comments

- Optimal, up to the constants
- Can generalise to other than uniformly random partition
 - E.g., equipartition
- Proof via Paley-Zygmund: only requires 4th moments
 - This means 4-wise independent Bernoulli suffice!
 - This means $O(\log k)$ bits of shared randomness suffice!



Domain Compression: comments

- Optimal, up to the constants
- Can generalise to other than uniformly random partition
 - E.g., equipartition
- Proof via Paley-Zygmund: only requires 4^{th} moments
 - This means 4-wise independent Bernoulli suffice!
 - This means $O(\log k)$ bits of shared randomness suffice!
- But **we can do better**. General statement with s bits of randomness
 - Proof of the one-bit isometry much more involved
 - Cute derandomisation ideas involved
 - Check [Acharya–Canonne–Han–Sun–Tyagi’20]



<https://arxiv.org/abs/1907.08743>

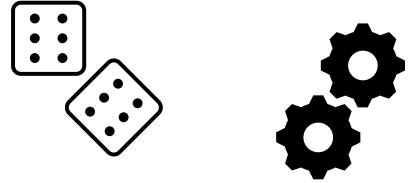
Once more: identity testing

	Private-Coin	Public-Coin
Centralised		$k^{1/2}/\epsilon^2$
Local privacy	$k^{3/2}/(\epsilon^2\rho^2)$	$k/(\epsilon^2\rho^2)$
Shuffle privacy*	$k^{3/4}/(\epsilon\rho) + k^{1/2}/\epsilon^2$	$k^{2/3}/(\epsilon^{4/3}\rho^{2/3}) + k^{1/2}/\epsilon^2 + k^{1/2}/(\epsilon\rho)$
Bandwidth	$k^{3/2}/(\epsilon^2 2^\ell) + k^{1/2}/\epsilon^2$	$k/(\epsilon^2 2^{\ell/2}) + k^{1/2}/\epsilon^2$

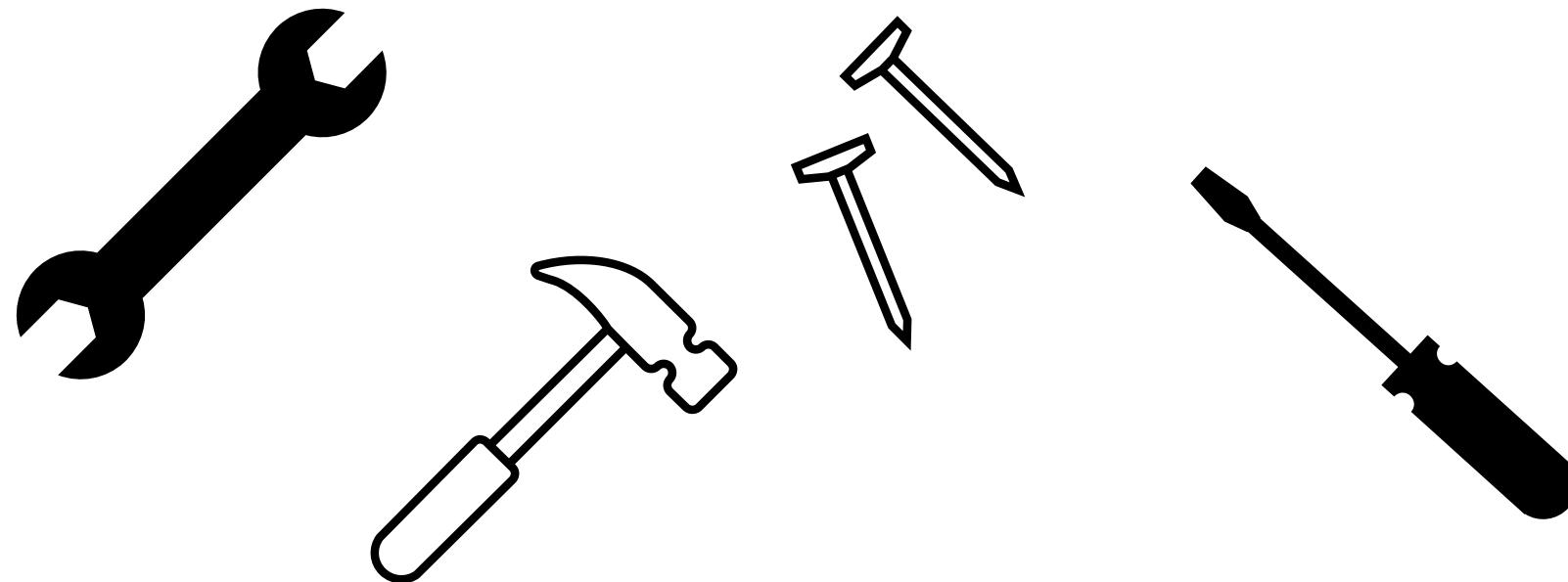
↳ Domain compression with s public coins:

$$\frac{\sqrt{k}}{\epsilon^2} \sqrt{\frac{k}{2} \ell^{v_1}} \sqrt{\frac{k}{2^{s+\ell}} \ell^{v_1}}$$

Conclusion



Domain compression is a versatile **primitive**! More applications?



Thank you.

An example

