# Amplification of One-Way Information Complexity via Codes and Noise Sensitivity 

Presenter: Omri Weinstein (NYU)

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## COMMUNICATION MODEL

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- 2 deterministic players: Alice has input $a$ and Bob input $b$
- Joint function $f$



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Ex: $x, y \in\{0,1\}^{n}$, want to output $x \stackrel{?}{=} y$
Want small communication from Alice to Bob

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Our goal: Lower bound one-way product complexity


$$
\begin{array}{lccccc}
\text { a4 } \begin{array}{cc}
1 & 0 \\
& 0 \\
\text { b1 } & \text { b2 }
\end{array} \text { b3 } & \text { b4 } & \text { b5 }
\end{array}
$$

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## ROWS AS METRIC SPACE (1/2)

We can see the rows of matrix $f$ as a metric space:

- Each row is 0-1 vector
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metric space view of $f$ :


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## Idea for lower bound:

If protocol has low error (orange points close to green) and rows of $f$ are far apart...
$\Rightarrow$ can use protocol's output to recover Alice's input
$\Rightarrow$ protocol reveals a lot of information
$\Rightarrow$ protocol has large communication!
metric space view:

## protocol produces approximate row a1

## LOWER BOUND VIA CODES

First result: Suppose the rows of $f$ form a $(\delta, \beta)$-code (far apart). Then

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Obs: Readily recovers lower bound of Dasgupta-KumarSivakumar '12 on Sparse Set Disjointness function

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Thm: [KNRgg] Let VC be the VC-dimension of rows of $f$. Then

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V C *(1-H(\delta)) \leq D_{\times, \delta}(f) \leq V C * O\left(\frac{1}{\delta} \log \frac{1}{\delta}\right)
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Thm (oversimplified): Suppose the rows of $f$ form a $(\delta, \beta)$ code. Then computing $g(f)$ with error $N S_{\delta}(g)$ needs comm.

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Ex: $g=$ XOR, Similar to noise sensitivity of $g$ :
$(\alpha, \beta)$-codes $\mathrm{g} \approx$ probability that $g^{\prime}$ 's output changes if we flip communicatio inputs with probability $\delta$

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Corollary: For any function $f$

$$
D_{x, 1 / 4}(X O R(f)) \geq n * D_{\times, \frac{1}{n}}(f)
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Given one pass over a stream $v_{1} \ldots v_{n}$ of vectors in $[ \pm \boldsymbol{M}]^{d}$ decide whether:

1. For all $i \neq j$ it holds that $\left|\left|v^{i}-v^{j}\right|_{p}^{p} \geq(1+\boldsymbol{\epsilon}) \theta\right.$
2. There exist $i \neq j$ such that $\left|\left|v^{i}-v^{j}\right|_{p}^{p} \leq(1-\boldsymbol{\epsilon}) \theta\right.$

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Theorem (simplified):
Any streaming algorithms for approximate closest pair problem $\ell_{\boldsymbol{p}}(\boldsymbol{n}, \boldsymbol{d}, \boldsymbol{M}, \boldsymbol{\epsilon}, \boldsymbol{\theta})$ with error $\delta$ takes space:

$$
\Omega\left(\frac{\boldsymbol{n}}{\boldsymbol{\epsilon}^{2}} \log \frac{\boldsymbol{n}}{\delta}(\log \boldsymbol{d}+\log \boldsymbol{M})\right)
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Given one pass over a stream representing entries of a matrix $\boldsymbol{A} \in[ \pm \boldsymbol{M}]^{\boldsymbol{n} \times \boldsymbol{n}}$ construct an $\boldsymbol{n} \times \boldsymbol{d}$ sketch matrix $S$ such that for any $\boldsymbol{B} \in[ \pm \boldsymbol{M}]^{n \times n}$ from $A S$ and $B$ only it is possible to compute whether:

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Theorem (simplified):
Number of bits to specify linear sketch $A S$ :

$$
\Omega\left(\frac{\boldsymbol{n}}{\boldsymbol{\epsilon}^{2}} \log \frac{\boldsymbol{n}}{\delta}(\log \boldsymbol{d}+\log \boldsymbol{M})\right)
$$

(matching upper bounds for this and streaming via JL).

## THANK YOU!

