# Communication Complexity with Small Advantage 

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Classic results
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## Classic results

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\text { R(InNer-Product) } & =\Theta(n) \\
\text { R(Set-Intersection) } & =\Theta(n) \\
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Small advantage:
$\mathrm{R}_{1 / 2+\epsilon}=$ randomized c.c., success probability $\geq 1 / 2+\epsilon$

## Classic results — revisited

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other functions?

## Climbing the polynomial hierarchy

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(information complexity) (corruption)

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Small advantage: open

## Function definitions

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Tribes:


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- Fails in general (Gap-Hamming)


## Our approach for Tribes

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Information complexity:

- $\Omega(1)$-advantage for Tribes [JKS'03]


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4-step approach:

1. Conditioning and direct sum
2. Uniformly covering a pair of gadgets
3. Relating information and probabilities for inputs
4. Relating information and probabilities for transcripts

## Preliminaries

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Idea from $\left[B M^{\prime} 13\right]:$





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Idea from [BM'13]: $\square$





Idea from $\left[B M^{\prime} 13\right]$ : $\square$


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Idea from [BM'13]:
Suffices to use 3EQ gadget instead of And gadget

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Usual info complexity proofs:

- mutual info $\rightarrow$ Hellinger distance $\rightarrow$ statistical distance
- quadratic loss-very roughly:
- info cost: quadratic terms (in small parameters)
- probabilities: quadratic and linear terms

3EQ has nice symmetry properties

- Exploit to get linear terms to perfectly cancel


## 1. Conditioning and direct sum

info cost $O(\epsilon \cdot n)$

$\leadsto$
info cost $o(\epsilon)$


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Want to show: advantage $\leq O$ (info cost)
2. Uniformly covering a pair of gadgets
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Uniformly cover


## 2. Uniformly covering a pair of gadgets

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Lemma: Linear combination of acceptance probabilities $\leq O\left(\sum\right.$ four contributions to info cost)

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with


Lemma: Linear combination of acceptance probabilities $\leq O\left(\sum\right.$ four contributions to info cost) $\Downarrow$ adv $\leq\left(\sum_{\text {light gray }}\right.$ acc prob $)-\left(\sum_{\text {white }}\right.$ acc prob $)$ $\leq O$ (info cost)
3. Relating information and probabilities for inputs


Lemma: Linear combination of acceptance probabilities $\leq O$ ( $\sum$ four contributions to info cost)

## 3. Relating information and probabilities for inputs



Lemma: Linear combination of acceptance probabilities $\leq O\left(\sum\right.$ four contributions to info cost)

Prove for individual transcripts?
contribution to lin comb of acc prob $\leq O$ (contribution to info costs)

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[BM'13] setting: yes Our setting: ....
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Our transcript lemma:
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$\forall$ transcript:
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accepting
rejecting

rejecting

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accepting
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(2) -1

rejecting

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lin comb of probabilities
$=2 \cdot$ green area
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contribution to info costs
$=\Theta\left(\delta^{2}+\gamma^{2}\right)$

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for decision trees

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for decision trees open:
$\Omega(\sqrt{\epsilon} \cdot m)$
for communication?

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[ $n$ ] is partitioned into $\ell$ equal-size parts
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Also: Simplified proof of UP $\cap$ coUP $\nsubseteq$ BPP [Klauck, CCC'03]


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