Locally Sampleable Uniform Symmetric Distributions

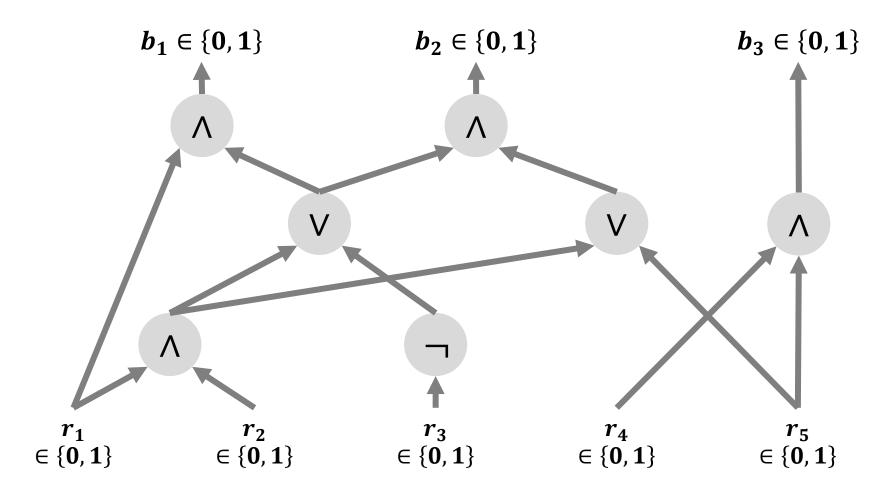
Kewen Wu (UC Berkeley)

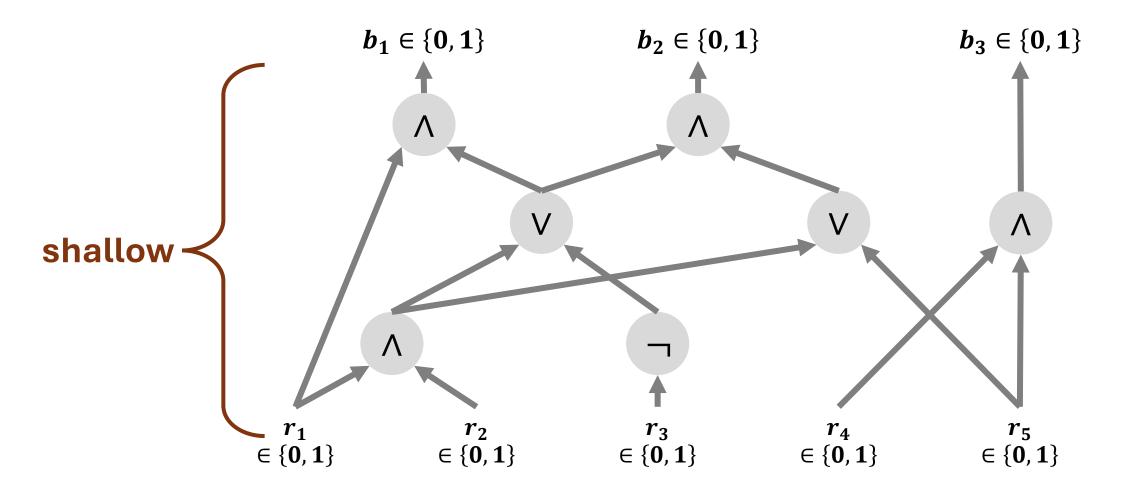


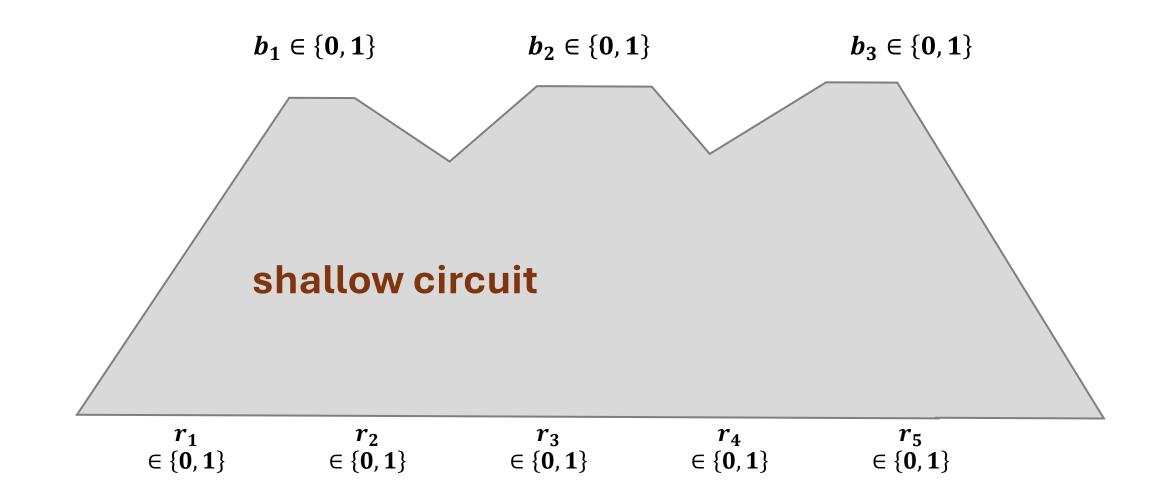
Daniel Kane UCSD

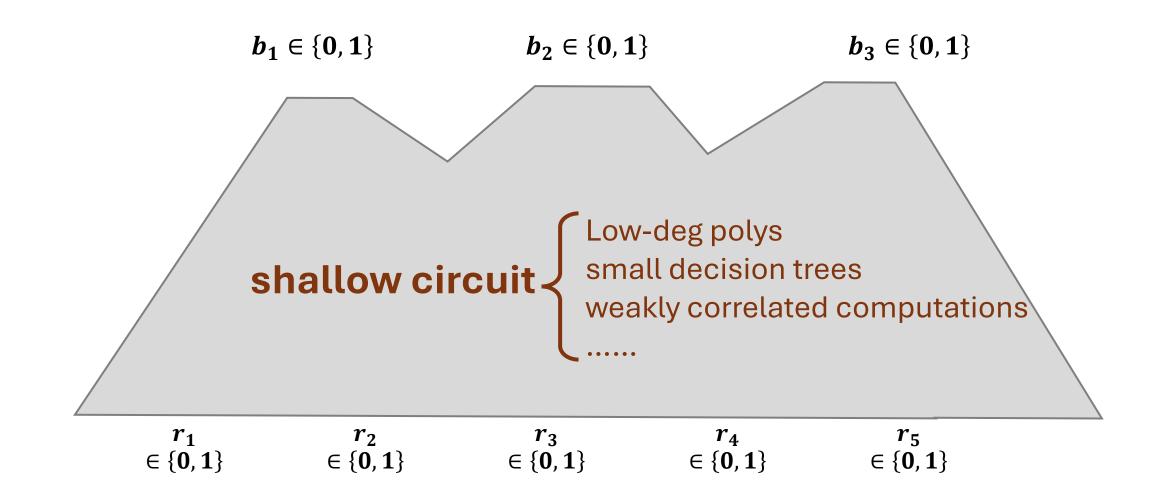


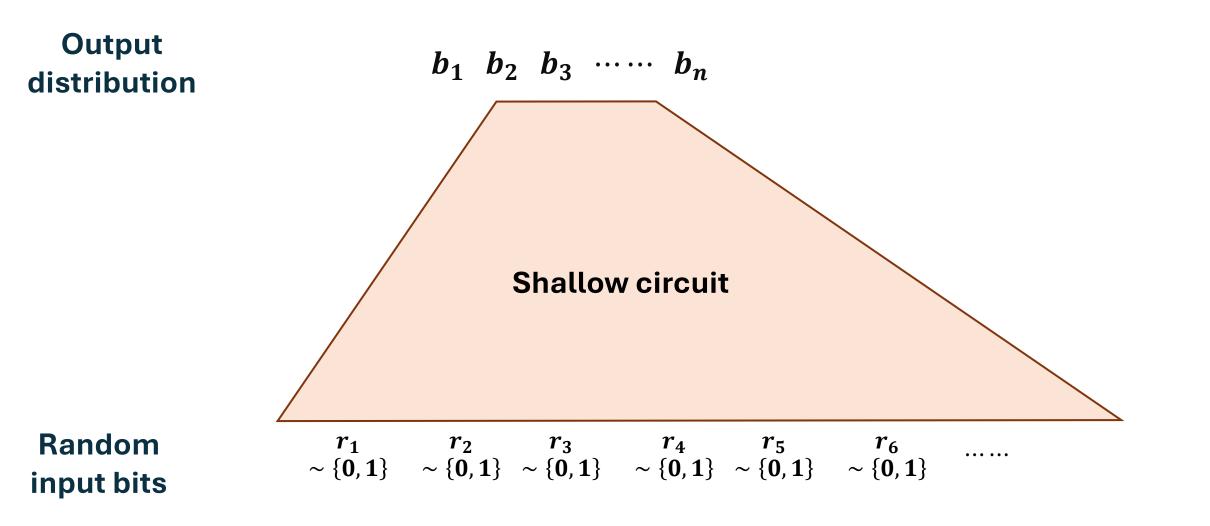
Anthony Ostuni UCSD











Output $D = (b_1, b_2, b_3, \cdots, b_n)$ over $\{0, 1\}^n$

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the support of **D** is symmetric

x in support iff $\pi(x)$ in support

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Symmetric.

the support of **D** is symmetric

x in support iff $\pi(x)$ in support

Ex / Non-Ex.

Uniform over $\{0, 1\}^n$ 1/3-biased distribution Uniform string of weight n/2Point distribution on 0^n

uniform symmetric

Motivations.

Natural question on its own

uniform symmetric

What can shallow circuits do?

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Computation.

It cannot compute

$$f(x_1, \dots, x_{n-1}) = x_1 \oplus \dots \oplus x_{n-1}$$

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Sampling.

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Sampling. It *can* sample

$$(x_1, \dots, x_{n-1}, x_1 \oplus \dots \oplus x_{n-1})$$
$$\parallel$$
$$(y_1 \oplus y_2, y_2 \oplus y_3, \dots, y_n \oplus y_1)$$

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Other examples like this?

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Other examples like this? No! [KOW'25+]

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Data structure lower bounds [Vio'12, FLRS'23, KOW'24]



Dictionary Problem.

Given an n-bit string x of weight 0 modulo 127Store it as some s-bit string h such that each x_i can be recovered <u>easily</u> from h



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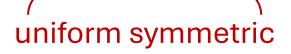
Max Efficiency. Store h = x



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Given an n-bit string x of weight 0 modulo 127Store it as some s-bit string h such that each x_i can be recovered easily from h

Max Efficiency. Store h = xs = n1 bit of h to decode x_i

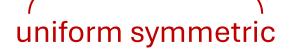


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Only $\approx 2^n/127$ possible xStore h as the index



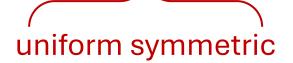
Dictionary Problem.

Given an *n*-bit string *x* of weight **0** modulo **127** Store it as some *s*-bit string *h* such that each x_i can be recovered easily from h

Max Efficiency. Min Storage. Store h = x $s = \log(2^n/127) = n - 6$ s = n1 bit of h to decode x_i

Only $\approx 2^n/127$ possible x Store **h** as the index

Read entire h to decode x_i



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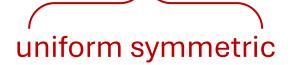
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1 bit of *h* to decode *x*_{*i*}

Can we achieve both?



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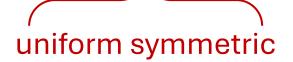
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Can we achieve both? No! [KOW'24]



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1 bit of *h* to decode *x*_{*i*}

Either read $\omega(1)$ bits of hOr h has length n

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Data structure lower bounds [Vio'12, FLRS'23, KOW'24]

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- Natural question on its own
- Data structure lower bounds [Vio'12, FLRS'23, KOW'24]
- Quantum-classical separation [BGK'18, WP'23, KOW'24]

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Can quantum shallow circuit generate distributions that are classically hard?

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Can quantum shallow circuit generate distributions that are classically hard? Yes!

Formal Set-Up

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Shallow circuit

Let $f: \{0, 1\}^m \rightarrow \{0, 1\}^n$ be a local function

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Let $f: \{0, 1\}^m \to \{0, 1\}^n$ be a **local** function each output bit depends on **constant** number of input bits Define U to be the uniform distribution over $\{0, 1\}^m$ Define f(U) be the output distribution of f under U

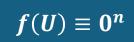
Formal Set-Up

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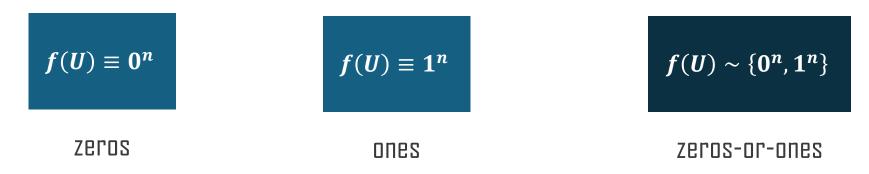
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evens-or-odds

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ZEROSONESZEROS-OF-ONESEVENSoddsevens-of-oddsUniform over weight ≤ 10 ?
Uniform over weight n/2?
Uniform over weight 0 modulo 3?Uniform over weight 0 modulo 3?

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zeros ones zeros-or-ones evens odds evens-or-odds **Conjecture** [Filmus-Leigh-Riazanov-Sokolov'23]. No other examples

Our Result

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Robust and Quantitative

Let $f: \{0, 1\}^m \to \{0, 1\}^n$ be a *d*-local function each output bit depends on *d* input bits Define *U* to be the uniform distribution over $\{0, 1\}^m$ Define *f(U)* be the output distribution of *f* under *U*

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If f(U) is ϵ -close to a uniform symmetric distribution

Robust and Quantitative

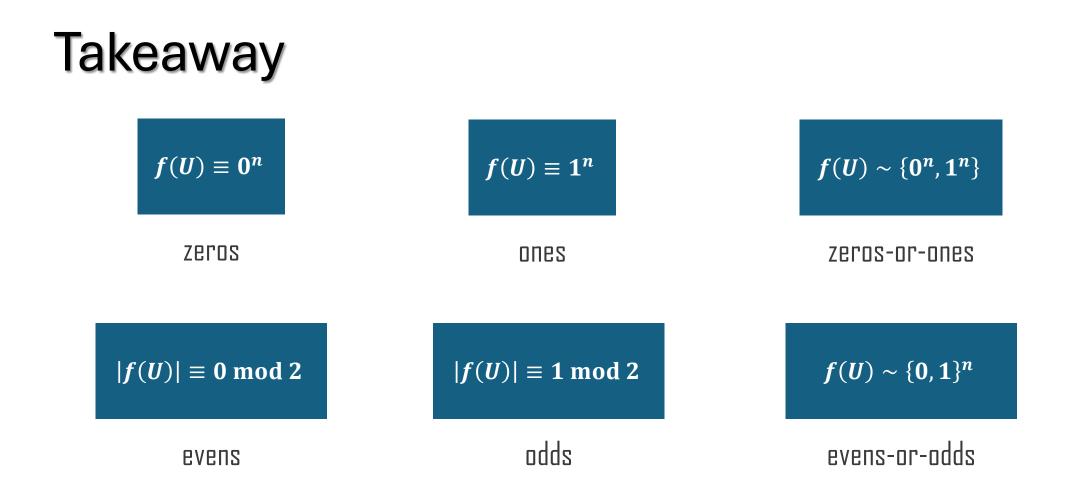
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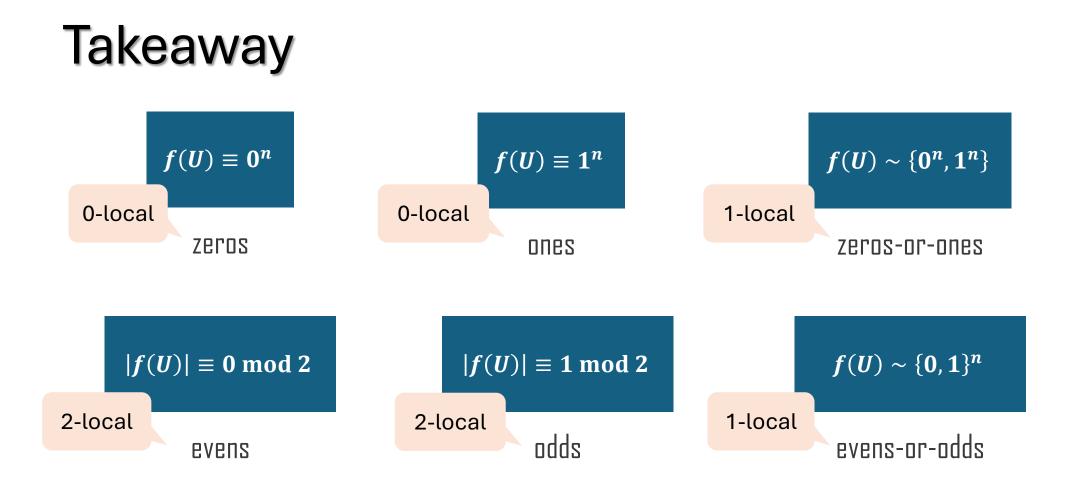
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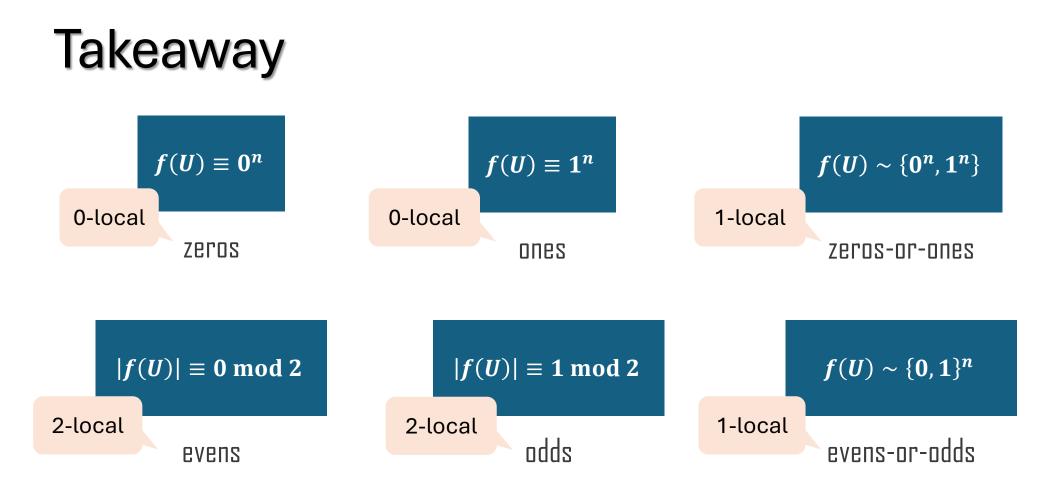
Define U to be the uniform distribution over $\{0, 1\}^m$

Define f(U) be the output distribution of f under U

Theorem [KOW'25+].If f(U) is ϵ -close to a uniform symmetric distribution,then f(U) is $O_d(\epsilon)$ -close to one of the following sixzeros ones zeros-or-ones evens odds evens-or-odds







For uniform symmetric distributions, locality of **large constant** is the same as locality of **two**

Proof Overview

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How to rule out Uniform over weight n/3Uniform over weight $\ge n/2$

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General case

 $f: \{0, 1\}^m \to \{0, 1\}^n$ is a **local** function f(U) is the output dist of f under uniform input

Why can't f(U) be uniform over n-bit strings of weight n/3?

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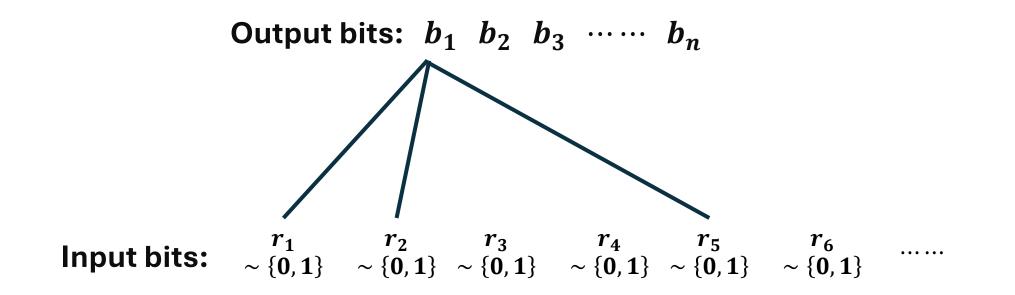
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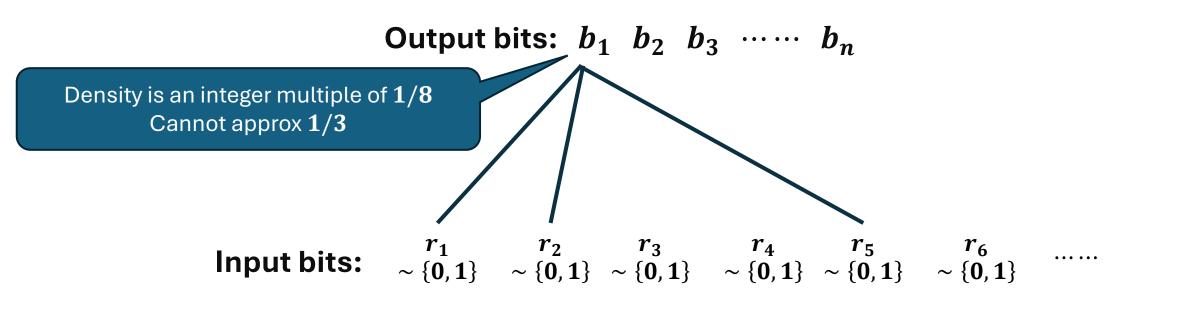
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Structural Lemma. Conditioning on o(n) input bits, we can find $\Omega(n)$ independent output bits.

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After conditioning, we have $1 - e^{-\Omega(n)}$ distance

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By union bound over $2^{o(n)}$ conditioning, the distance is $1 - 2^{o(n)} \cdot e^{-\Omega(n)} = 1 - e^{-\Omega(n)}$

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Why can't f(U) be uniform over n-bit strings of weight $\geq n/2$?

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Granularity argument does not work

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Why can't f(U) be uniform over n-bit strings of weight $\geq n/2$? Sharp cutoff!

f(U) cannot generate strong correlation to produce a sharp cutoff between < n/2 and $\ge n/2$

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Structural Lemma.

Conditioning on o(n) input bits, we can find $\Omega(n)$ independent output bits. Sum of independent bits \Rightarrow Gaussian distribution \Rightarrow No sharp cutoff

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Conditioning on o(n) input bits, we can find $\Omega(n)$ independent output bits.

Not always correct!

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Many independent bits, but total weight is always n/2

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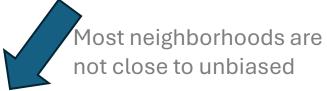
Ex.
$$x_1, \neg x_1, x_2, \neg x_2, x_3, \neg x_3, \dots, x_{n/2}, \neg x_{n/2}$$
Fix.Each neighborhood is far from unbiased
But the "weight $\geq n/2$ " distribution is

Upgraded Structural Lemma.

Conditioning on o(n) input bits, we can find $\Omega(n)$ independent output neighborhoods.

Upgraded Structural Lemma.

Conditioning on o(n) input bits, we can find $\Omega(n)$ independent output neighborhoods.



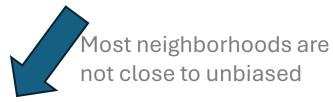
Each has $\Omega(1)$ distance



 $1 - e^{-\Omega(n)}$ distance by concentration

Upgraded Structural Lemma.

Conditioning on o(n) input bits, we can find $\Omega(n)$ independent output neighborhoods.



Each has $\Omega(1)$ distance



 $1 - e^{-\Omega(n)}$ distance by concentration



Most neighborhoods are close to unbiased

Weight distribution is like Gaussian

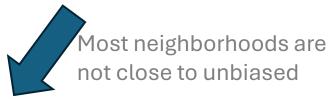


Property of Gaussians

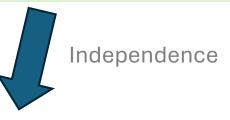
Cannot generate sharp cutoff

Upgraded Structural Lemma.

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 $1 - e^{-\Omega(n)}$ distance by concentration

Large distance either way



Most neighborhoods are close to unbiased

Weight distribution is like Gaussian



Property of Gaussians

Cannot generate sharp cutoff

To rule out any "weird" uniform symmetric distribution \boldsymbol{D}

To rule out any "weird" uniform symmetric distribution Dhave $0.5n \sim 0.5n + \sqrt{n}$, but not $0.5n - \sqrt{n} \sim 0.5n$ have n/2 and n/2 + 10, but not n/2 + 2

To rule out any "weird" uniform symmetric distribution Dhave $0.5n \sim 0.5n + \sqrt{n}$, but not $0.5n - \sqrt{n} \sim 0.5n$ have n/2 and n/2 + 10, but not n/2 + 2

Design a potential function h to witness the cutoffs $E_{x\sim D}[h(|x|)] \approx 1$ for the claimed distribution D $E_{z\sim G}[h(z)] \ll 1$ for Gaussian distributions G

To rule out any "weird" uniform symmetric distribution **D**

have $0.5n \sim 0.5n + \sqrt{n}$, but not $0.5n - \sqrt{n} \sim 0.5n$ have n/2 and n/2 + 10, but not n/2 + 2

Design a potential function h to witness the cutoffs $E_{x\sim D}[h(|x|)] \approx 1$ for the claimed distribution D $E_{z\sim G}[h(z)] \ll 1$ for Gaussian distributions G

Independent neighborhoods

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Close to correct marginal \Rightarrow weight distribution is like Gaussian \Rightarrow impossible by potential function *h*

Independent neighborhoods

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Design a potential function h to witness the priodicity subtlety that allows $E_{x\sim D}[h(|x|)] \approx 1$ for the claimed distributions $E_{z\sim G}[h(z)] \ll 1$ for Gaussian distributions G

Close to correct marginal \Rightarrow weight distribution is like Gaussian \Rightarrow impossible by potential function *h*

 \sim Far from correct marginal ⇒ large distance by concentration

Independent neighborhoods



Locally sampleable uniform symmetric distributions

zeros ones zeros-or-ones evens odds evens-or-odds



Locally sampleable uniform symmetric distributions zeros ones zeros-or-ones evens odds evens-or-odds

Locally sampleable symmetric distributions?



Locally sampleable uniform symmetric distributions

zeros ones zeros-or-ones evens odds evens-or-odds

Locally sampleable symmetric distributions? In progress: mixture of evens, odds, and p-biased p and the mixing weights should be dyadic rational with constant denominator

Summary

Locally sampleable uniform symmetric distributions

zeros ones zeros-or-ones evens odds evens-or-odds

Locally sampleable symmetric distributions? In progress: mixture of evens, adds, and p-biased p and the mixing weights should be dyadic rational with constant denominator

Improving quantitative bounds?

Let $f: \{0, 1\}^m \rightarrow \{0, 1\}^n$ be a *d*-local function

Theorem [KOW'25+]. If $n \ge tower(d)$ and f(U) is ϵ -close to a uniform symmetric distribution, then f(U) is $(\epsilon \cdot tower(d))$ -close to one of the following six zeros ones zeros-or-ones evens odds evens-or-odds

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$$tower(d) = 2^{2^{2^{\cdots}}}$$
 of height d

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Let $f: \{0, 1\}^m \rightarrow \{0, 1\}^n$ be a *d*-local function

Necessary for our structural lemma But should be exp(d)

Theorem [KOW'25+]. If $n \ge \mathbf{tower}(d)$ and f(U) is ϵ -close to a uniform symmetric distribution, then f(U) is $(\epsilon \cdot \mathbf{tower}(d))$ -close to one of the following six zeros ones zeros-or-ones evens odds evens-or-odds

Thank you!

kewen_wu@berkeley.edu https://shlw.github.io