

# On the Power of Interactive Proofs for Learning<sup>STOC'24</sup>

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August 1, 2024

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- ▶ The interactive version was first discussed in [GRSY21]<sup>1</sup>
- ▶ [GRSY21] use  $\text{poly}(t, n)$  random examples
- ▶ Our work:  $\text{poly}(t)$  random examples

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# The Standard Goldreich-Levin Algorithm

# Goldreich-Levin Algorithm

## Learning Fourier coefficients

**Input** Oracle access to a function  $f : \{0,1\}^n \rightarrow \{0,1\}$ , and  $0 < \tau < 1$

**Output** Find all Fourier coefficients with  $|\hat{f}| > \tau$ .

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- 1 Break the domain of Fourier coefficients ( $\{0,1\}^n$ ) to subcubes by fixing coordinates.
- 2 If a subcube has low Fourier weight, simply discard it. Otherwise keep splitting until we get singletons.

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## Query Complexity

- ▶ We fix coordinates until we get singletons.
- ▶ We need to fix  $n$  coordinates.

$\implies$  Query complexity depends on  $n$ , and requires *membership* queries.

## Goldreich-Levin Algorithm cont.

Subcube notation:  $0\mathbf{10**} = \{2\}, \{2, 4\}, \{2, 5\}, \{2, 4, 5\}.$

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### Weight of Subcube

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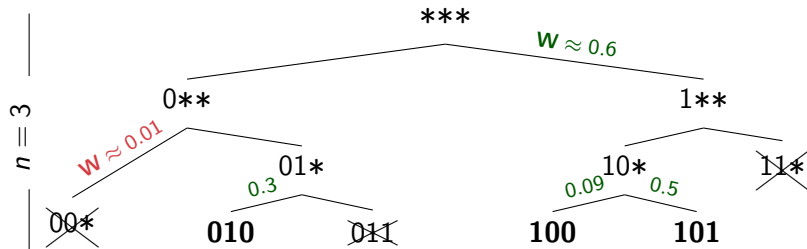
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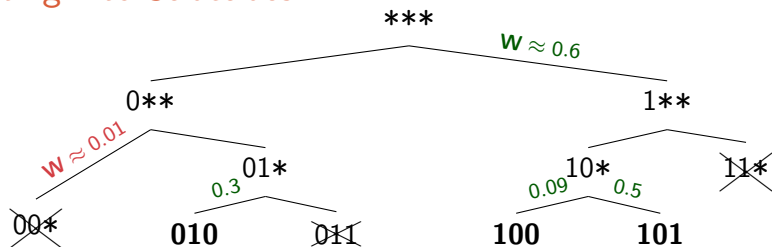
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**Input**  $f : \{0, 1\}^3 \rightarrow \{0, 1\}$ , and  $\tau = 0.1$



# Splitting into Subcubes



$x_1 = 0$	$x_1 = 1$

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## Main Theorem

There is an interactive protocol for finding top  $t$  Fourier coefficients of a function  $f : \{0, 1\}^n \rightarrow \{0, 1\}$  with error parameter  $\varepsilon$ , where the Verifier uses  $\text{poly}(t, 1/\varepsilon)$  *random examples*, *independent of  $n$* .

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- ▶ Our output  $\Lambda = \{\gamma_1, \dots, \gamma_t\}$  is correct with error parameter  $\varepsilon$  if for all  $\gamma \in \Lambda$  and all  $\beta \notin \Lambda$ , it holds that  $|\hat{f}(\gamma)| + \varepsilon \geq |\hat{f}(\beta)|$ .

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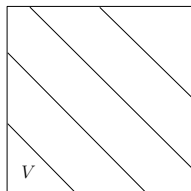
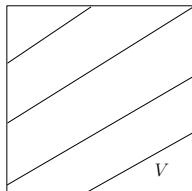
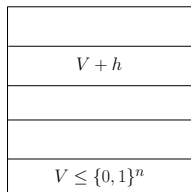
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- ▶ This means if we want  $\{\gamma : |\hat{f}(\gamma)| \geq \tau\}$ , then we can set  $t = 4/\tau^2$ ,  $\varepsilon = \tau/2$ . Thus  $\text{poly}(1/\tau)$  random examples.

# Splitting the Domain (in Affine Ways)

# Splitting into Affine Subspaces

View  $\{0, 1\}^n$  as  $\mathbb{F}_2^n$ . Choose some subspace  $V$ . [GOSSW11]<sup>1</sup>

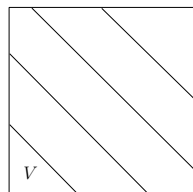
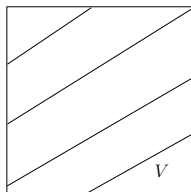
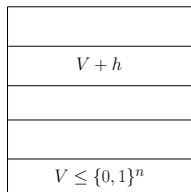


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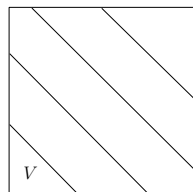
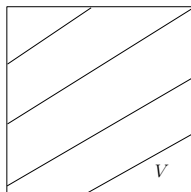
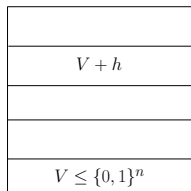
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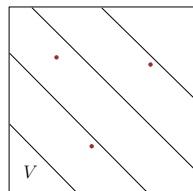
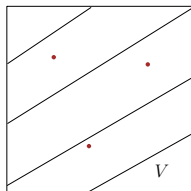
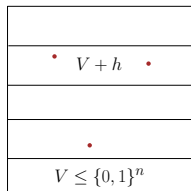
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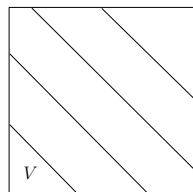
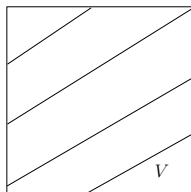
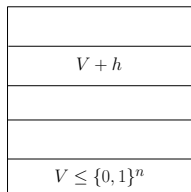


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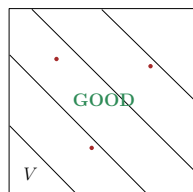
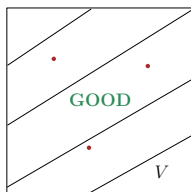
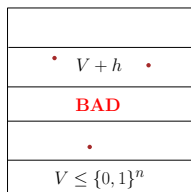


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# How the Splitting is Actually Done

## Linear functions

Let  $r, \gamma \in \{0, 1\}^n$ . Then  $\langle r, \gamma \rangle = r_1\gamma_1 + \cdots + r_n\gamma_n$ .

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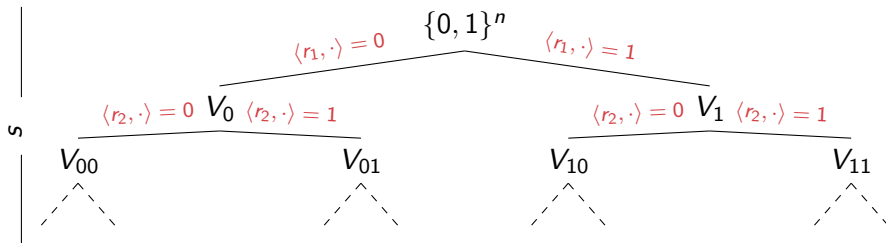
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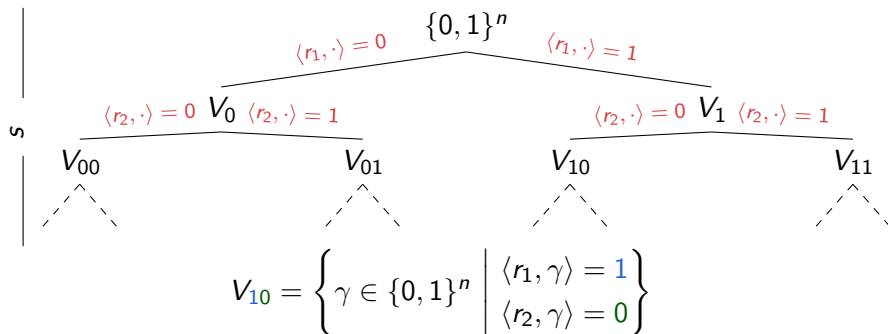
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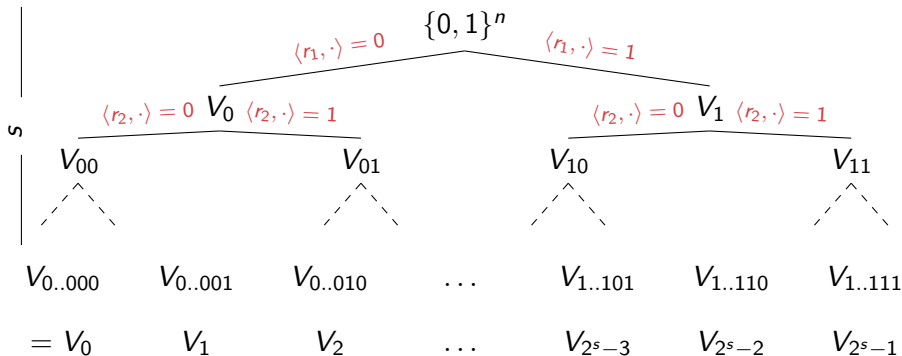
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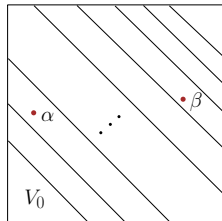
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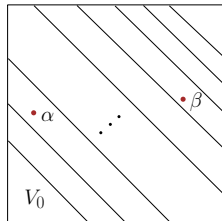
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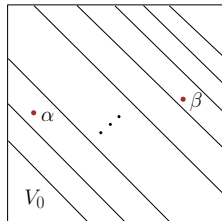
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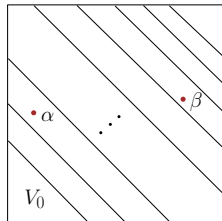
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- 2  $\left( \sum_{\gamma \in V+h} \hat{f}(\gamma)^4 \right)^{1/4}$  is close to the *maximum* coefficients in  $V + h$ .

# Algorithm for Computing Top $t$ Coefficient Values

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## Theorem

There is an algorithm such that given (membership) query access to a function  $f : \{0, 1\}^n \rightarrow \{0, 1\}$ , and parameters  $t \in \mathbb{N}, \varepsilon > 0$ , makes  $\text{poly}(t, 1/\varepsilon)$  queries to  $f$  and outputs  $t$  real numbers  $c_1, \dots, c_t \in \mathbb{R}^+$  that correspond to top  $t$  Fourier coefficient values of  $f$ .

# Finding Largest $t$ Coefficients

## Task - Non-Interactive

**Input** Oracle  $f : \{0,1\}^n \rightarrow \{0,1\}$ , and  $t \in \mathbb{N}, \varepsilon > 0$

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Let  $\Lambda_t = \{\gamma_1, \dots, \gamma_t\}$  be the correct set.

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All  $\gamma_i$ 's belong to different cosets w.h.p.; Here  $s \approx \log(t + 1/\varepsilon)$ .
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- ▶ The query complexity is  $\text{poly}(t, 1/\varepsilon)$ , *independent of  $n$* ;
- ▶ The characters  $\gamma_i$ 's are still unknown!

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## Interactive Protocol - $\text{poly}(t, 1/\varepsilon)$ samples

- P** Sends a set  $\Lambda'_t = \{\gamma'_1, \dots, \gamma'_t\}$  of **large** coefficients
- V** Estimates the coefficients  $c'_1, \dots, c'_t$
- V** Splits the domain into  $V_0, \dots, V_{2^s-1}$   
W.h.p. all of  $\gamma'_i$  and  $\gamma_i$  are separated;
- V** Reject if  $\gamma'_i$ s cannot be matched with high-weight cosets.

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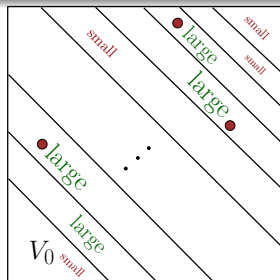
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## Interactive Protocol - $\text{poly}(t, 1/\varepsilon)$ samples

- P** Sends a set  $\Lambda'_t = \{\gamma'_1, \dots, \gamma'_t\}$  of **large** coefficients
- V** Estimates the coefficients  $c'_1, \dots, c'_t$
- V** Splits the domain into  $V_0, \dots, V_{2^s-1}$   
W.h.p. all of  $\gamma'_i$  and  $\gamma_i$  are separated;
- V** Reject if  $\gamma'_i$ 's cannot be matched with high-weight cosets.



Honest Prover

# Use Prover to Find $\gamma_i$ 's

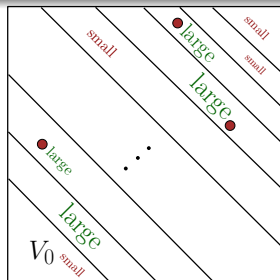
## Task - Interactive

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Cheating Prover

# IP for Finding Top $t$ Fourier Coefficients

## Theorem

There is an interactive protocol for finding top  $t$  Fourier coefficients of a function  $f : \{0, 1\}^n \rightarrow \{0, 1\}$  with error parameter  $\varepsilon$ , where the Verifier uses  $\text{poly}(t, 1/\varepsilon)$  *membership queries*, *independent of  $n$* .

*Can we use random examples instead?*

# Our Result

## Main Theorem - Random Examples

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# Query-to-Sample Reduction

## Random Example

$(x, f(x))$  where  $x \sim \{0, 1\}^n$ .

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- ▶ Idea: Prover will answer Verifier's membership queries.

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- ▶ Idea: Prover will answer Verifier's membership queries.
- ▶  $P_M$ : IP with  $q$  membership queries  $\rightarrow P_R$ : IP with  $O(q)$  random examples

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## Recall

$$\sum_{\gamma \in V+h} \hat{f}(\gamma)^4 = \mathbf{E}_{\substack{x,y,z \sim \{0,1\}^n \\ w \sim V^\perp}} [\chi_h(w) \cdot f(x) \cdot f(y) \cdot f(z) \cdot f(x+y+z+w)].$$

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$$\mathbf{E}_{\substack{x, y, z \sim \{0, 1\}^n \\ w \sim V^\perp}} \left[ \chi_h(w) \cdot f(\underbrace{x}_{\text{query}}) \cdot f(\underbrace{y}_{\text{query}}) \cdot f(\underbrace{z}_{\text{query}}) \cdot f(\underbrace{x + y + z + w}_{\text{query}}) \right].$$

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## Observation

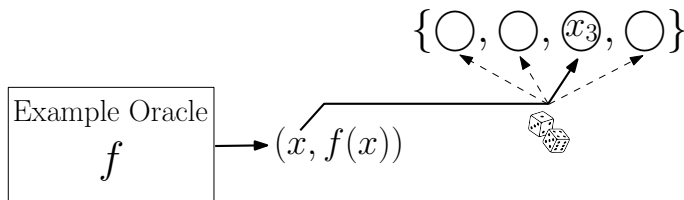
$$\mathbf{E}_{\substack{x, y, z \sim \{0, 1\}^n \\ w \sim V^\perp}} [\chi_h(w) \cdot f(\underbrace{x}_{\text{uniform}}) \cdot f(\underbrace{y}_{\text{uniform}}) \cdot f(\underbrace{z}_{\text{uniform}}) \cdot f(\underbrace{x + y + z + w}_{\text{uniform}})].$$

# Embedding a Random Example

- ▶ Our query set is  $\{x, y, z, x + y + z + w\} \sim \mathcal{D}$ .

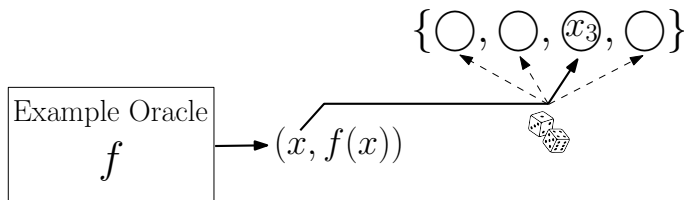
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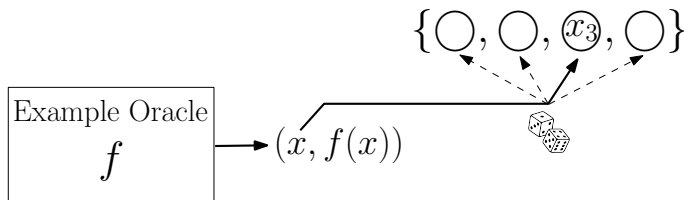
- ▶ Our query set is  $\{x, y, z, x + y + z + w\} \sim \mathcal{D}$ .



- ▶ We extend  $\{O, O, x_3, O\}$  to  $\{x_1, x_2, x_3, x_4\} \sim \mathcal{D}$ .

# Embedding a Random Example

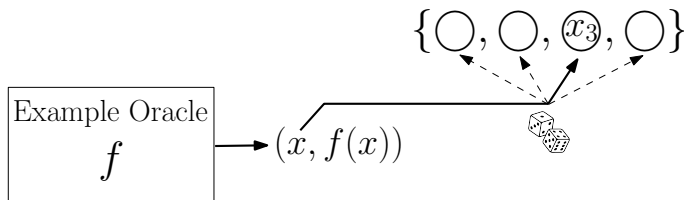
- ▶ Our query set is  $\{x, y, z, x + y + z + w\} \sim \mathcal{D}$ .



- ▶ We extend  $\{\bigcirc, \bigcirc, x_3, \bigcirc\}$  to  $\{x_1, x_2, x_3, x_4\} \sim \mathcal{D}$ .
- ▶ Note that the Verifier knows  $f(x_3)$ .

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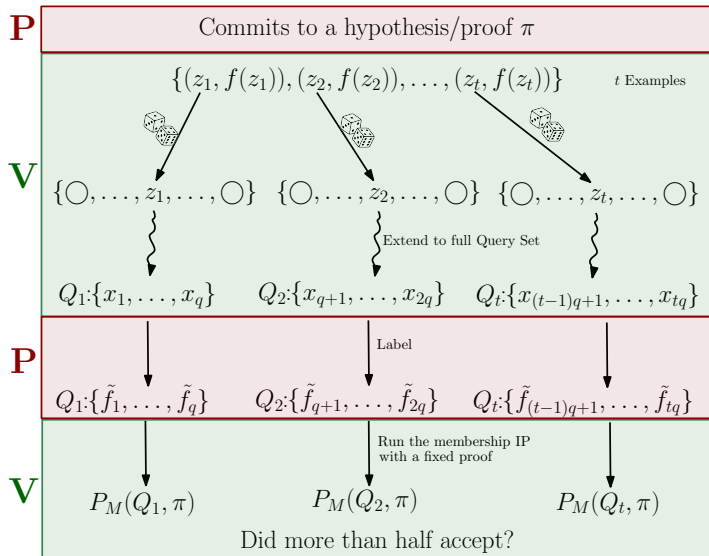


- ▶ We extend  $\{\circ, \circ, \circledast_3, \circ\}$  to  $\{x_1, x_2, x_3, x_4\} \sim \mathcal{D}$ .
- ▶ Note that the Verifier knows  $f(x_3)$ .
- ▶ Now, if the Prover cheats in labeling this set, the Verifier catches him with probability  $1/4$ .

# Query-to-Sample Reduction: Details

- ▶  $P_M$ : MA-like *membership protocol*;
- ▶  $\pi$ : The proof (hypothesis) sent by the prover;
- ▶  $q$ : Number of Verifier's queries.
- ▶ Let  $t = O(q)$ , large enough

# Query-to-Sample Reduction: Details



# Interactive Proofs for Learning top Fourier Coefficients

## Main Theorem

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We have also other results

- ▶ Learning  $k$ -juntas
- ▶ Learning  $\text{AC}^0[\oplus]$
- ▶ Some results for arbitrary classes

Thank you for listening!