

# Property Testing of Boolean Functions

Erik Waingarten (Penn)

**My goal:** Definitions and some important ideas.

- **Linearity**  
(most of the talk)
- **Monotonicity**
- **Juntas**

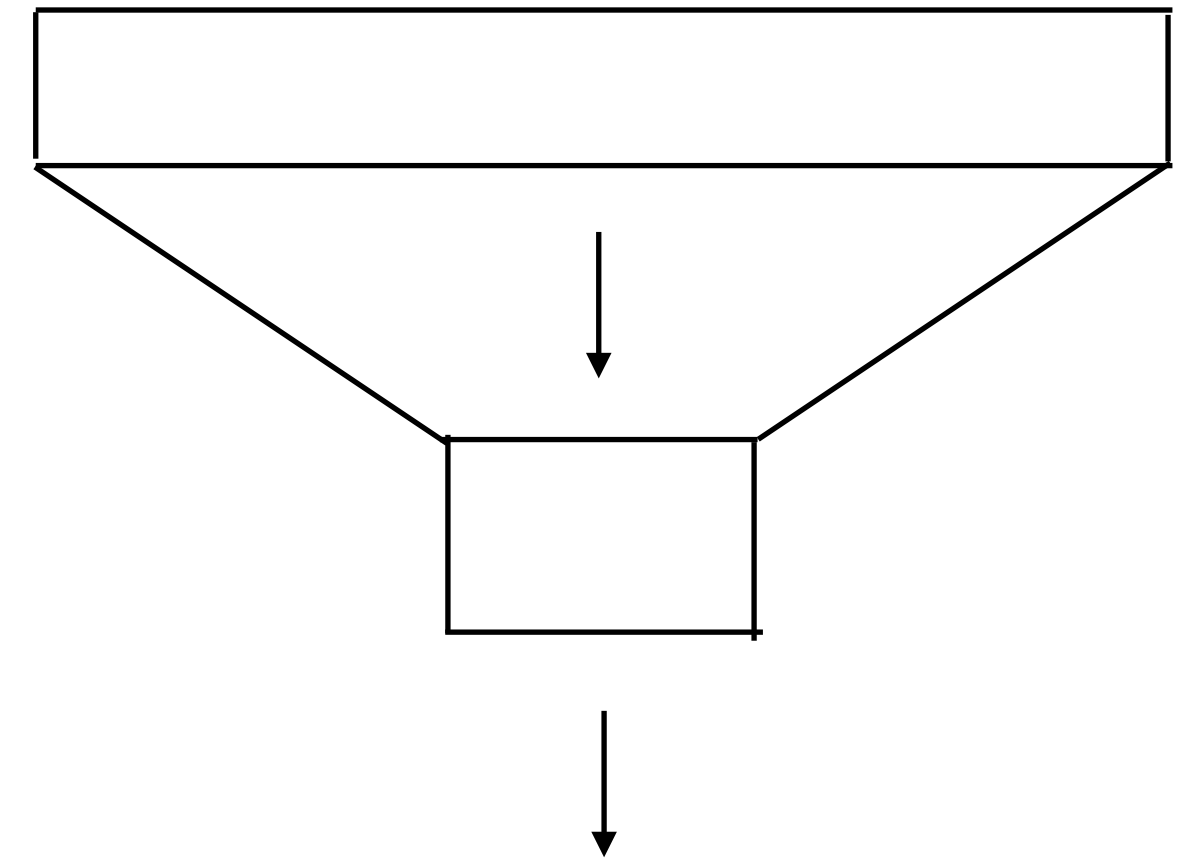
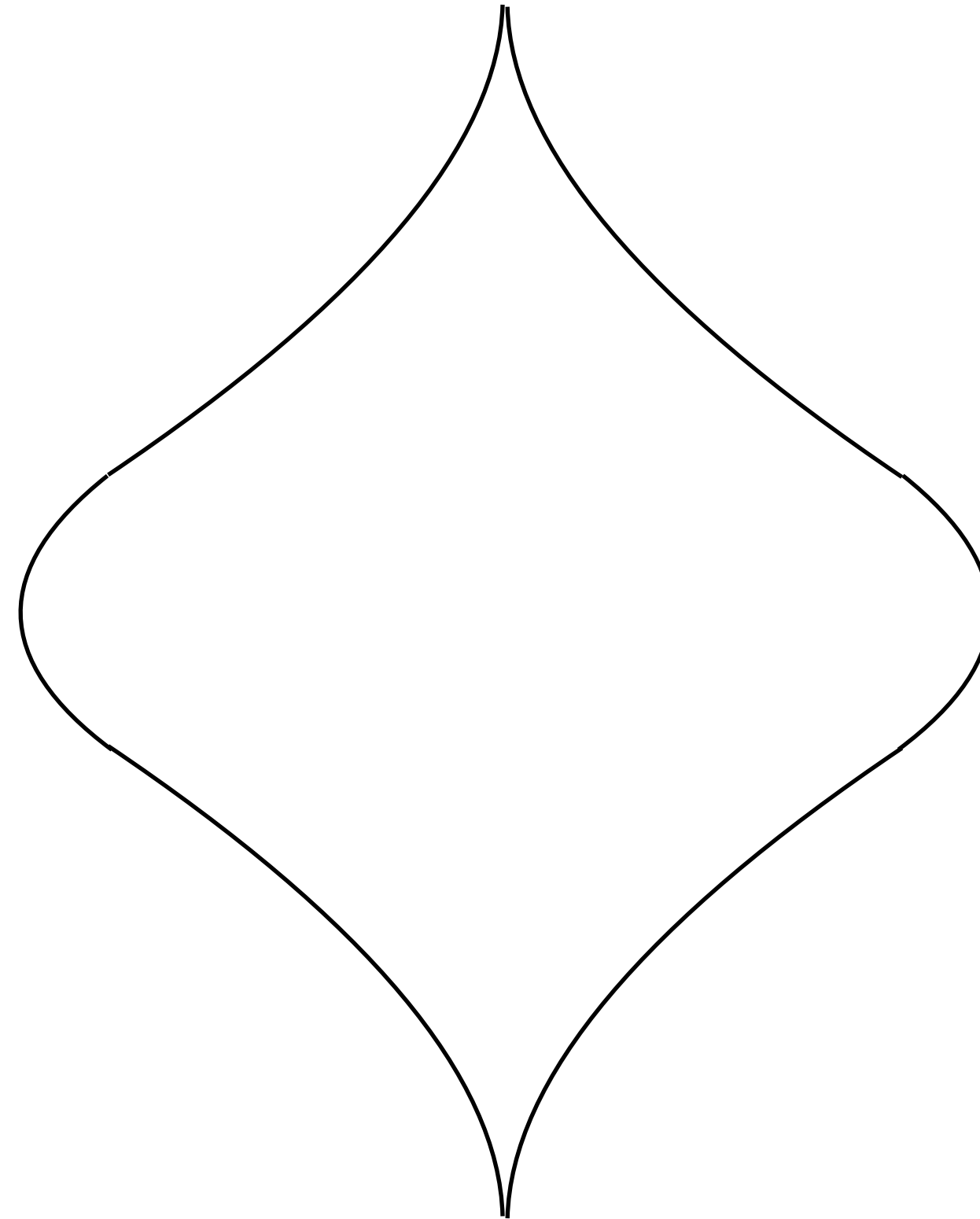
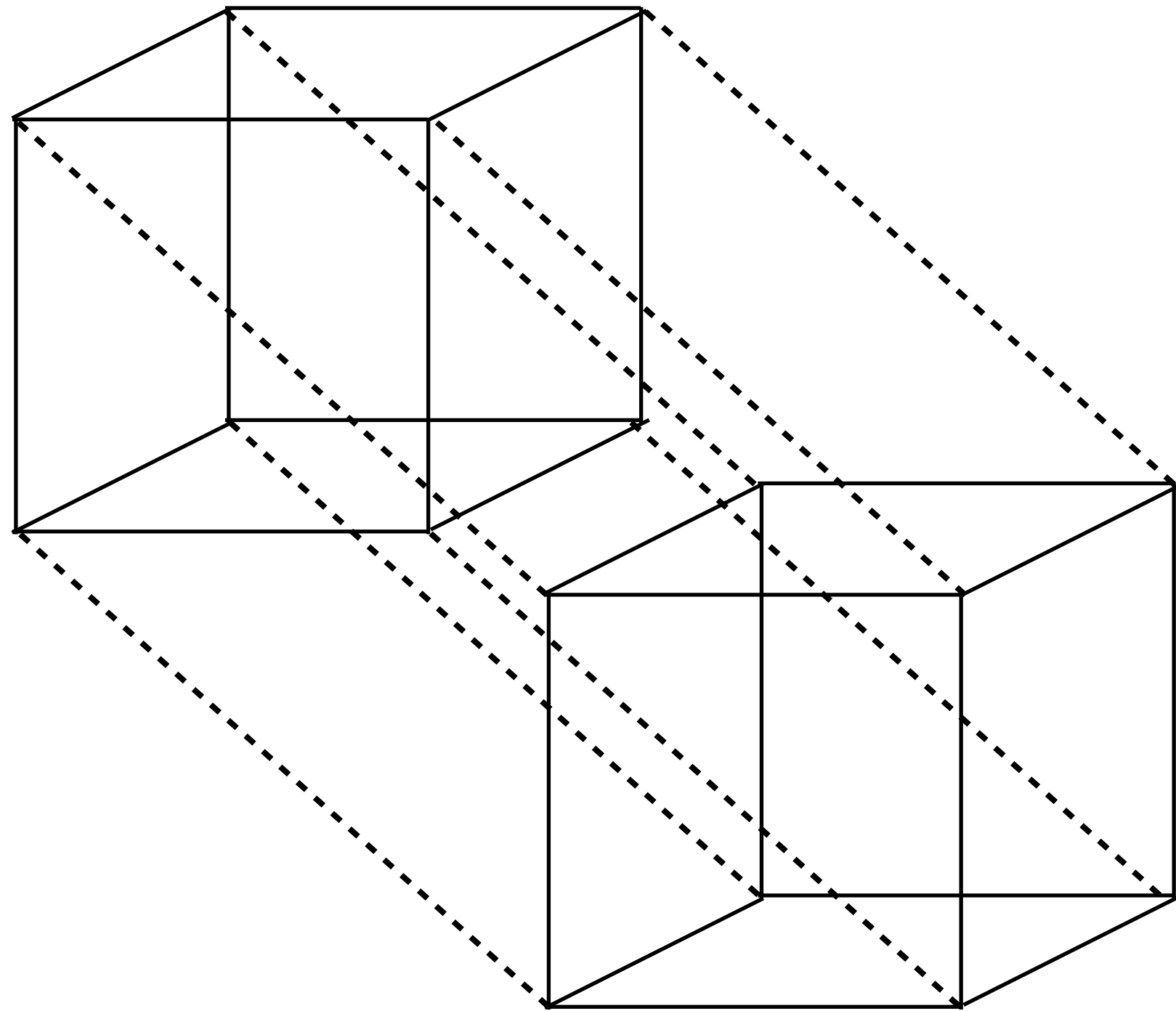
Reference: “Introduction to Property Testing” by Goldreich ‘17

“Algorithmic and Analysis Techniques in Property Testing” by Ron ‘10

# A Boolean function encodes a set of its domain.

- This talk: domain is Boolean hypercube.

$$f : \{0, 1\}^n \rightarrow \{0, 1\}$$



A property testing algorithm decides whether a function has a particular property (approximately).

Does the function have a particular property?

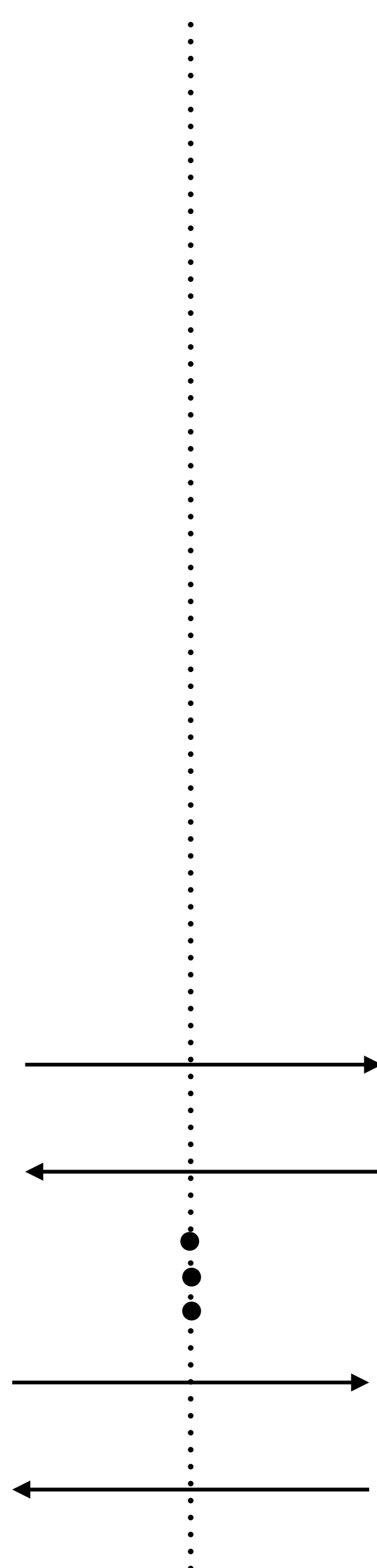


YES or NO

$x_1 \in \{0, 1\}^n$  →

⋮

$x_q \in \{0, 1\}^n$  →

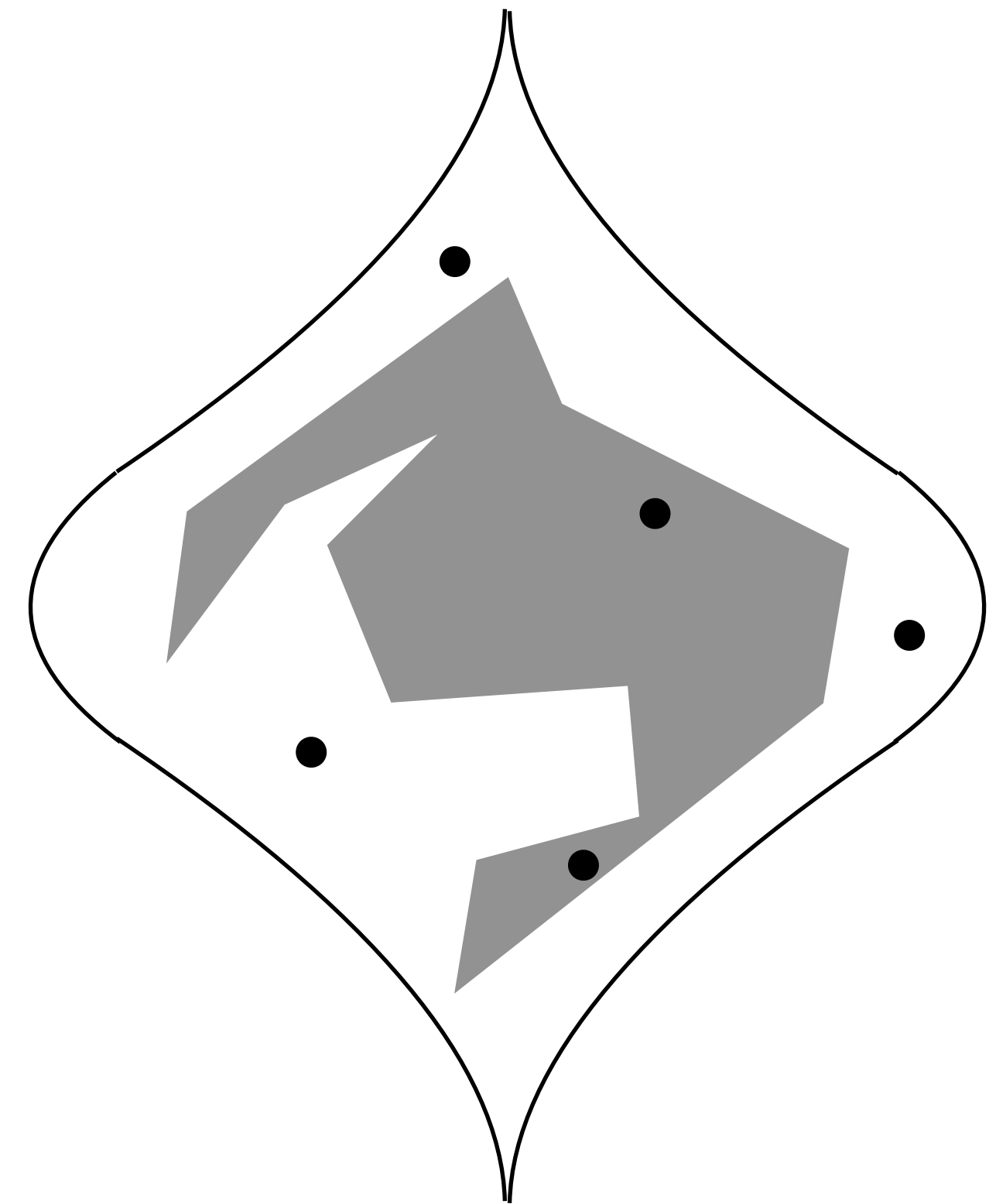


$f(x_1)$

⋮

$f(x_q)$

$$f : \{0, 1\}^n \rightarrow \{0, 1\}$$





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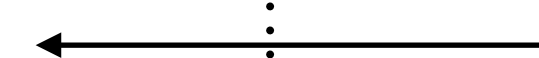


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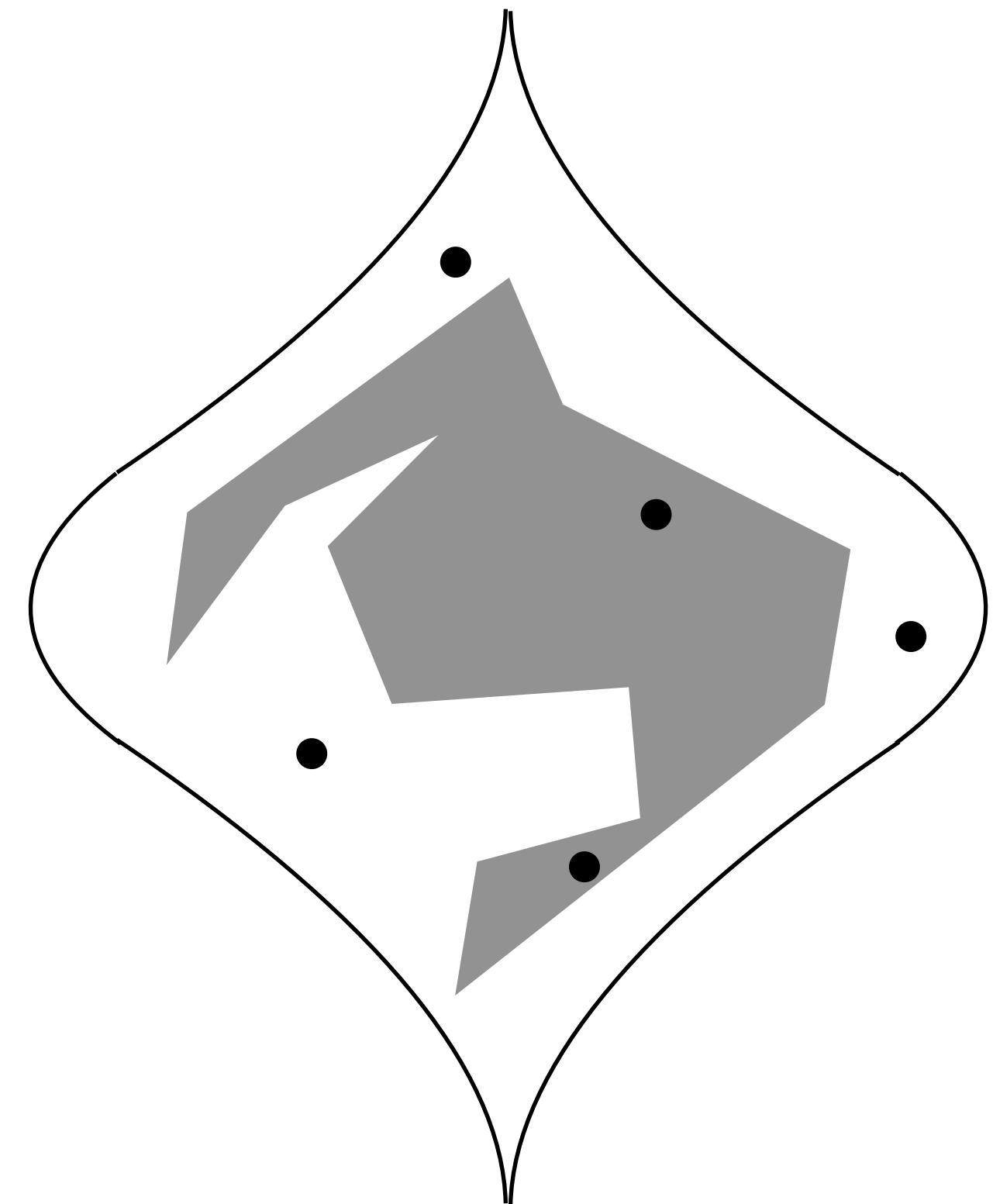


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Is the function always 0?

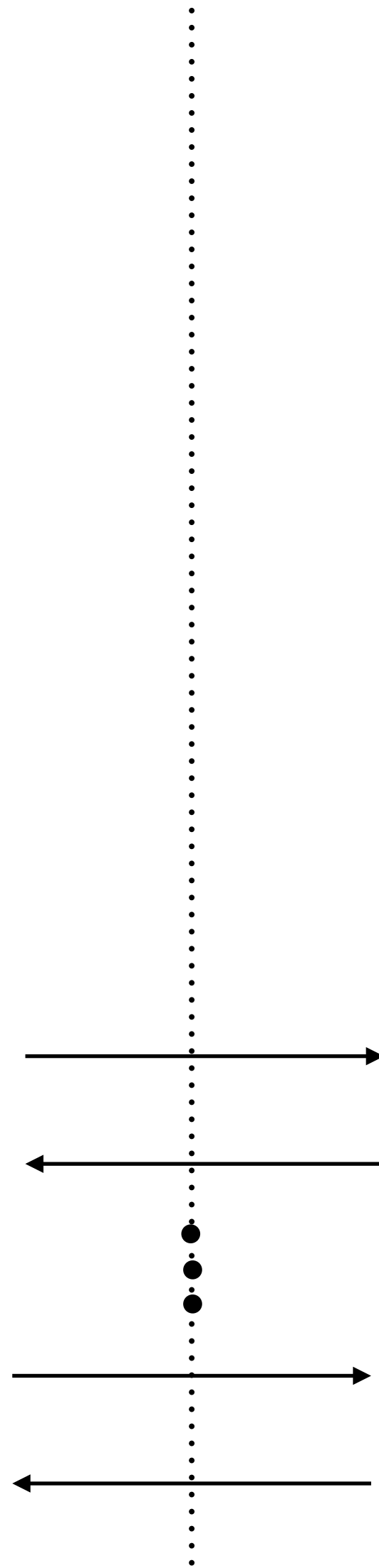


YES or NO

$x_1 \in \{0, 1\}^n$   $\longrightarrow$

$\vdots$

$x_q \in \{0, 1\}^n$   $\longrightarrow$

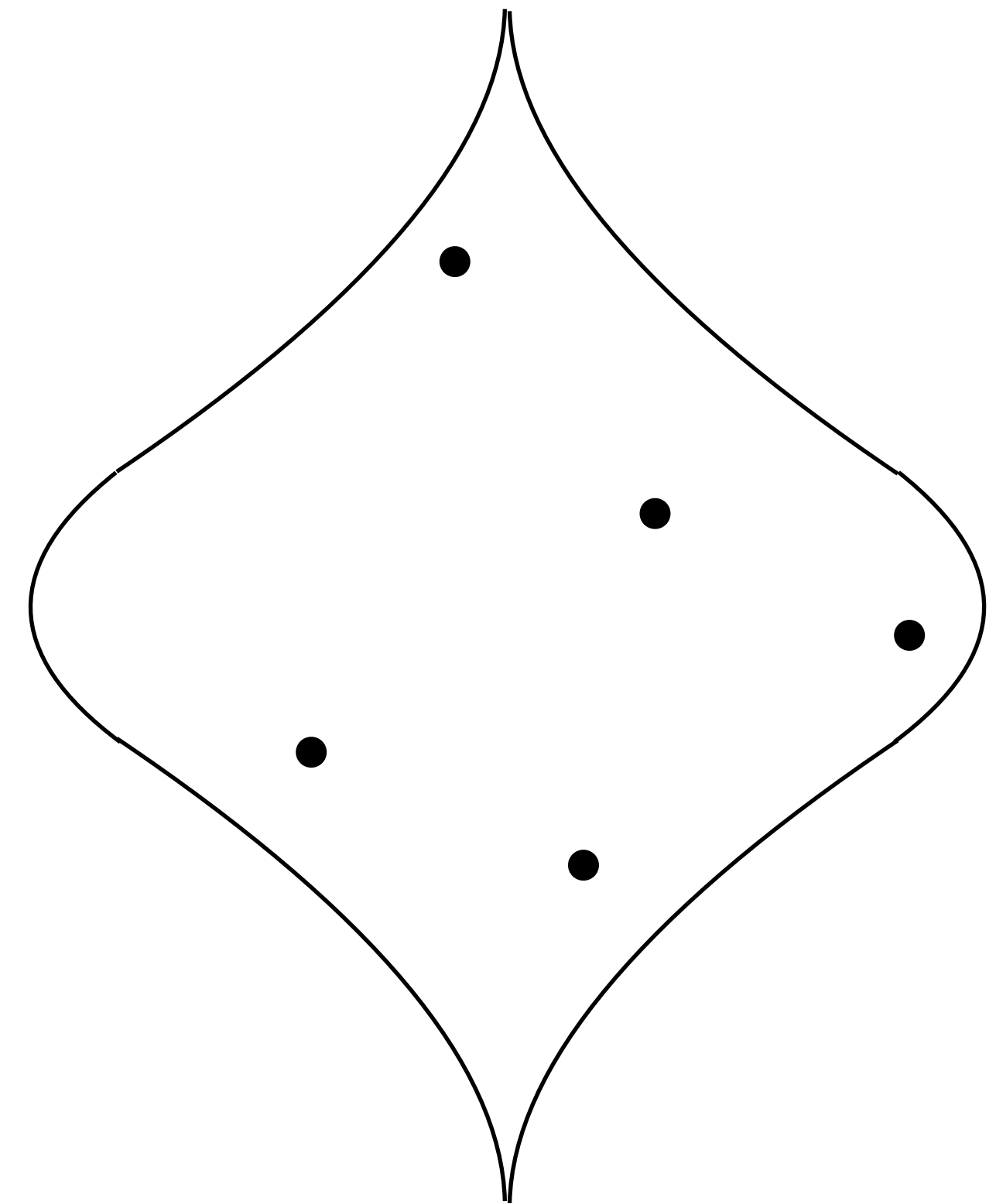


0

$\vdots$

0

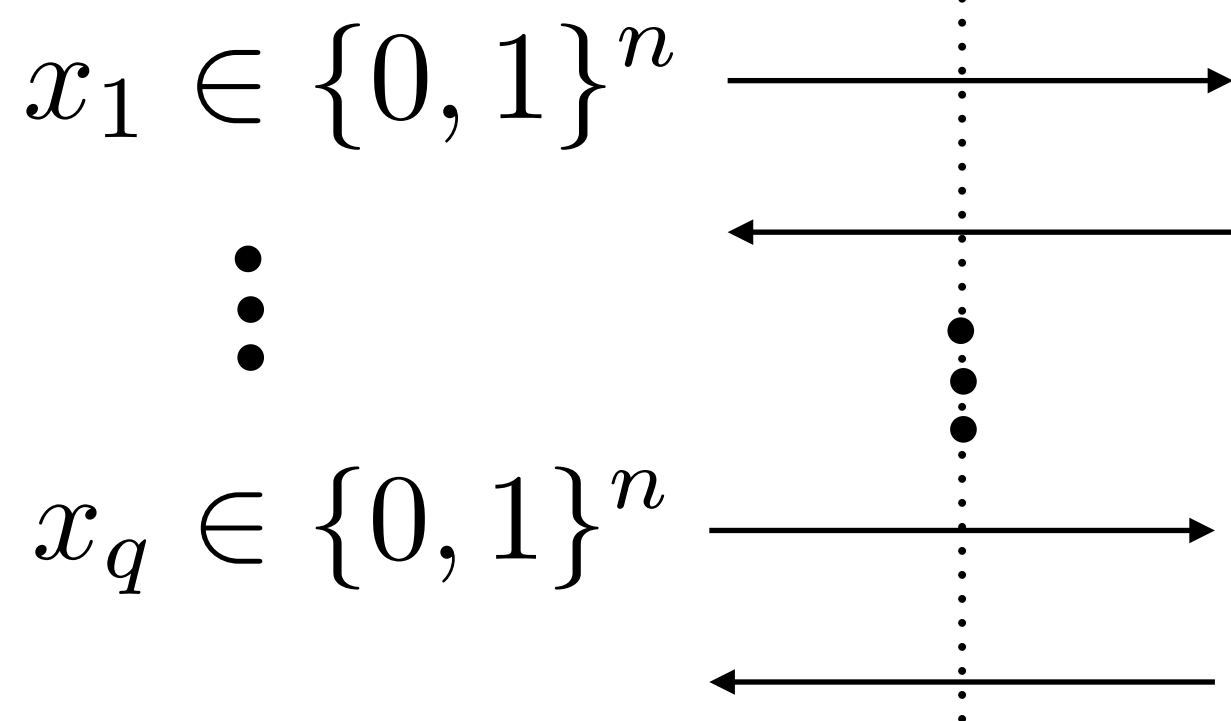
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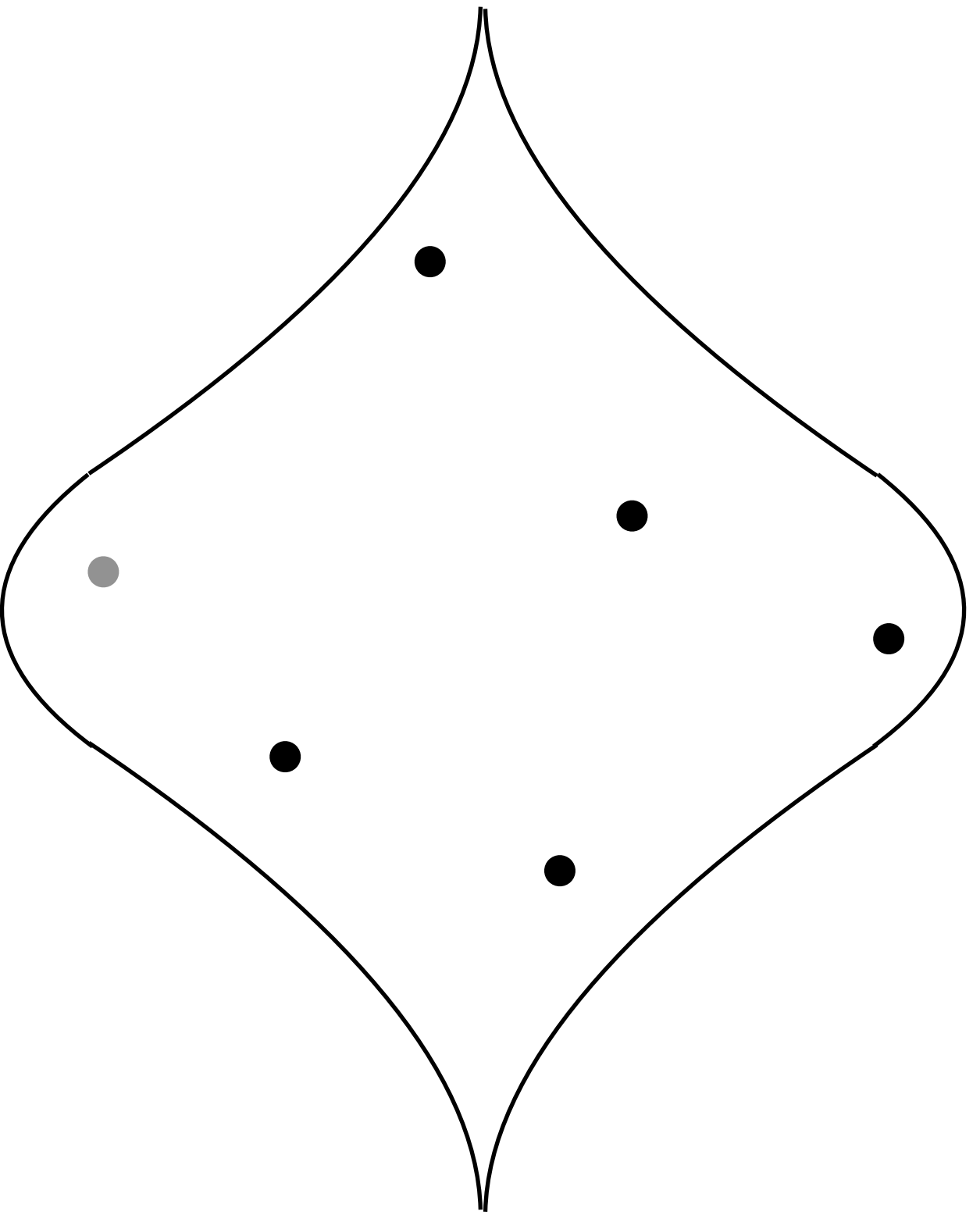


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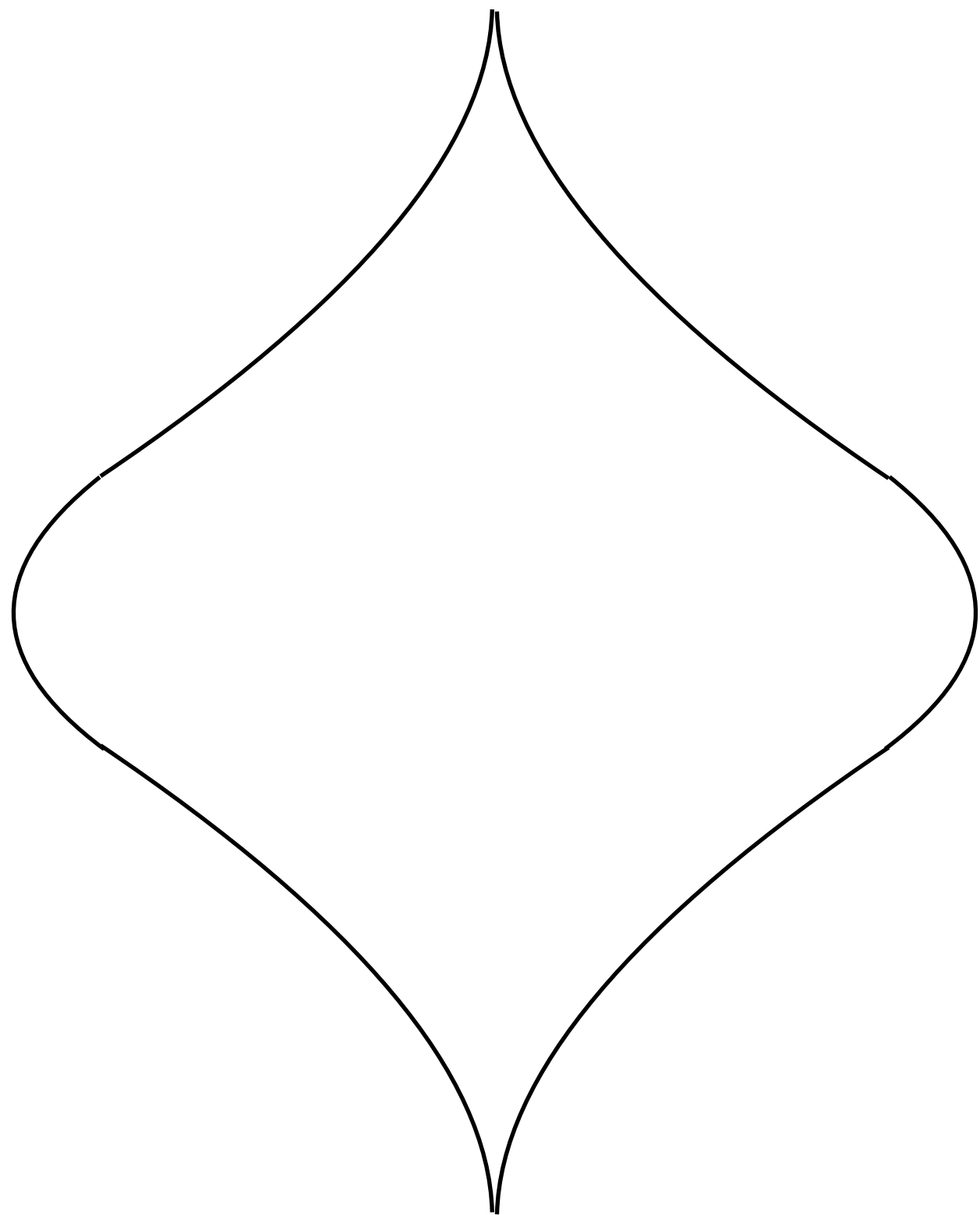
0  
⋮  
0

$$\tilde{f}: \{0, 1\}^n \rightarrow \{0, 1\}$$

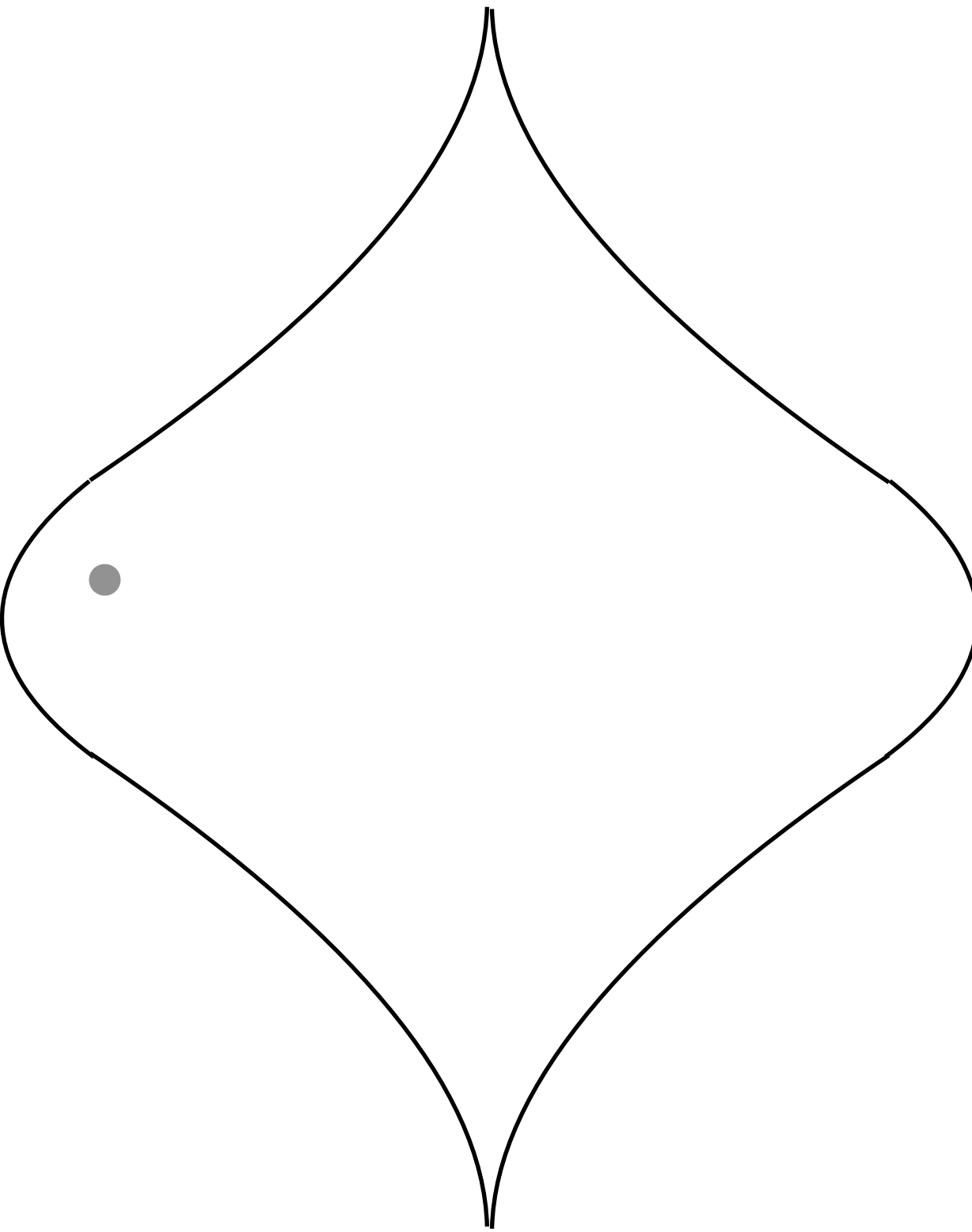


Unless Alice queries hidden point, looks like constant 0 function.

$$f: \{0, 1\}^n \rightarrow \{0, 1\}$$



$$\tilde{f}: \{0, 1\}^n \rightarrow \{0, 1\}$$



Query Complexity  
Lower Bound  
 $\Omega(2^n)$

# Property Testing as Approximate Decision Making:

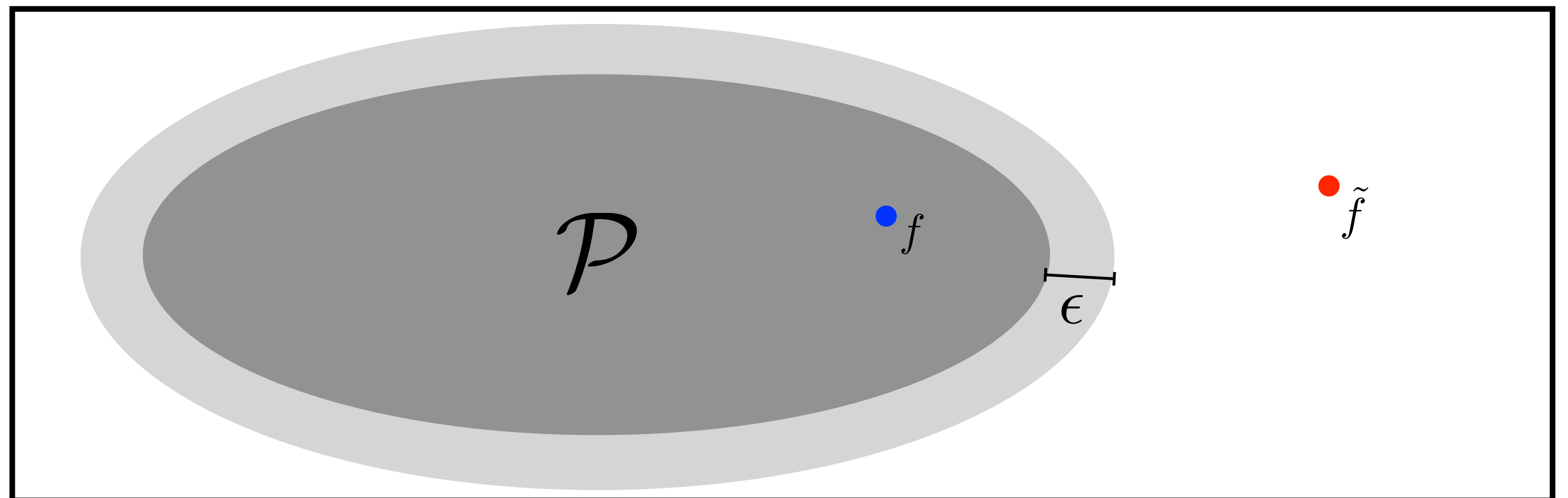
**Definition:** A property testing algorithm for a property  $\mathcal{P}$  is a randomized algorithm which receives query access to an unknown function  $f: \{0, 1\}^n \rightarrow \{0, 1\}$ :

- If  $f \in \mathcal{P}$ , the algorithm output YES w.p at least  $2/3$ .
- If  $f$  is  $\epsilon$ -far from  $\mathcal{P}$ , the algorithm outputs NO w.p at least  $2/3$ .



$f$  output YES w.p  $2/3$

$\tilde{f}$  output NO w.p  $2/3$



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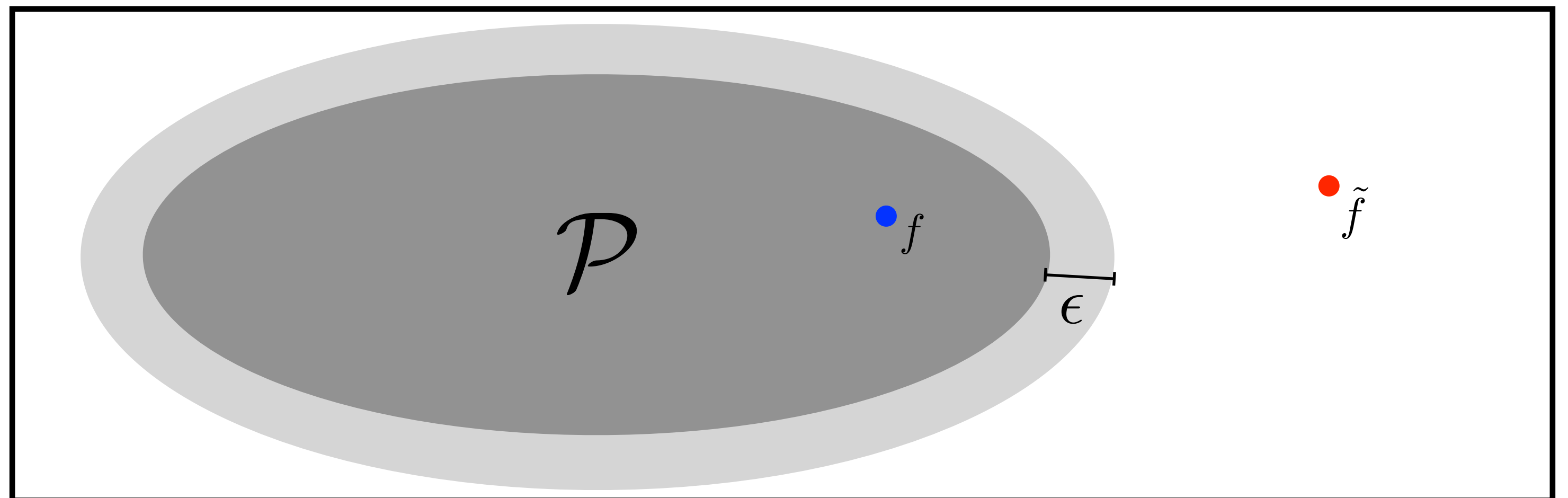
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- If algorithm outputs YES w.p at least  $1/3$ , then  $d(f, \mathcal{P}) \leq \epsilon$ .



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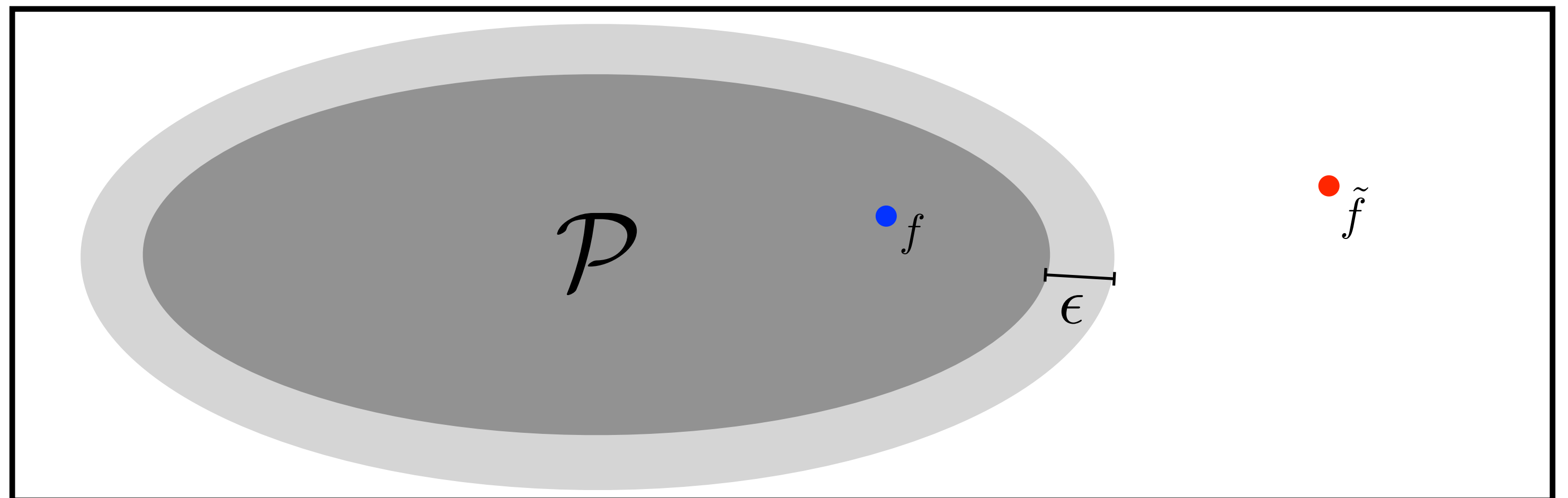


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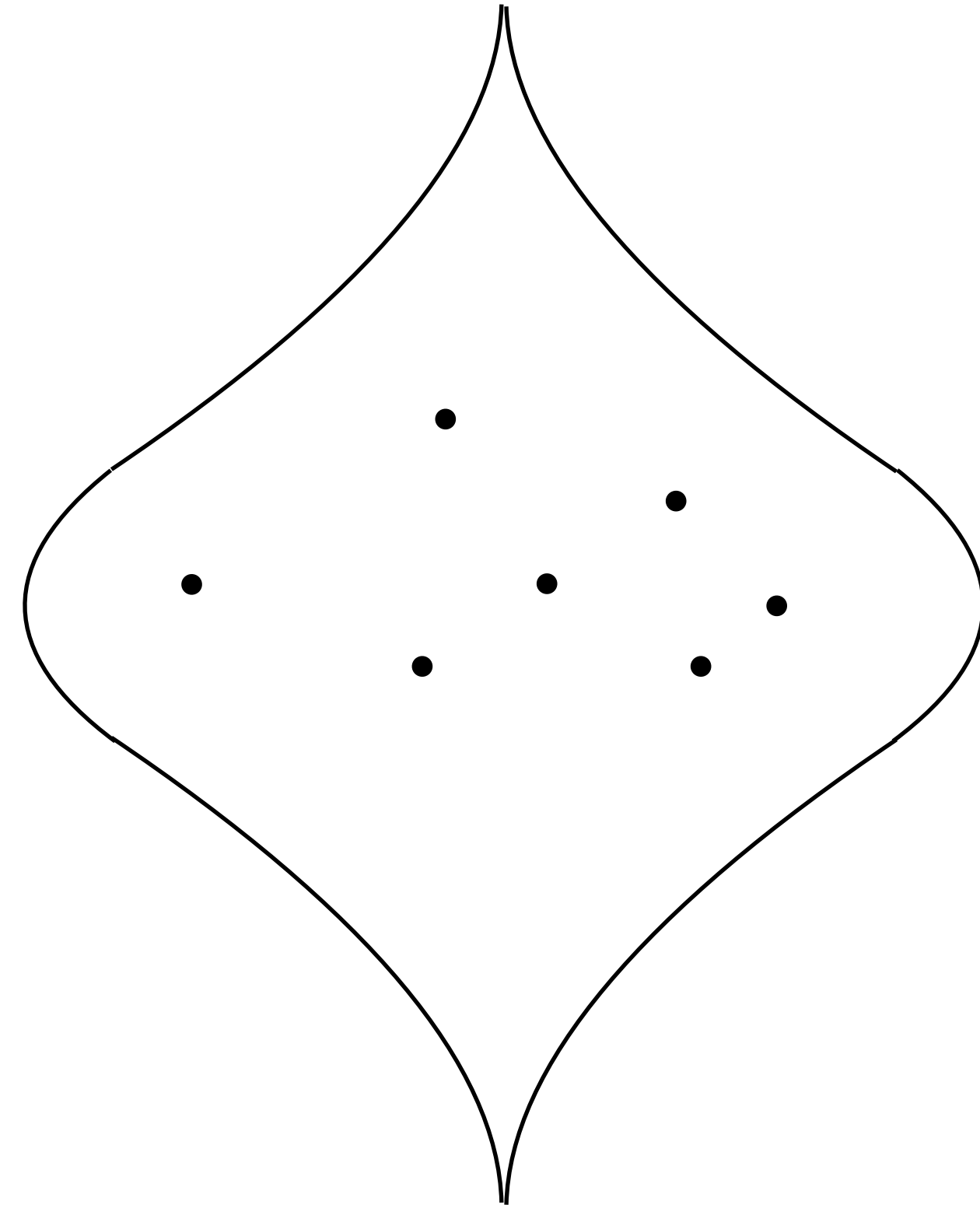
- If  $f \in \mathcal{P}$ , the algorithm output YES w.p at least  $2/3$ .
- If algorithm outputs YES w.p at least  $1/3$ , then  $d(f, \mathcal{P}) \leq \epsilon$ .

$$d(f, \mathcal{P}) = \min_{g \in \mathcal{P}} \Pr_{\mathbf{x} \sim \{0,1\}^n} [f(\mathbf{x}) \neq g(\mathbf{x})]$$



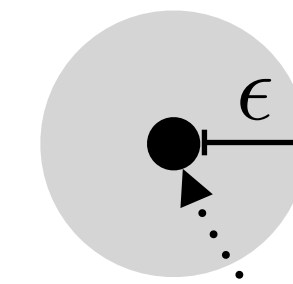


# Formal Analysis for $\mathcal{P} = \{f = 0\}$ : Direction 1



## Algorithm

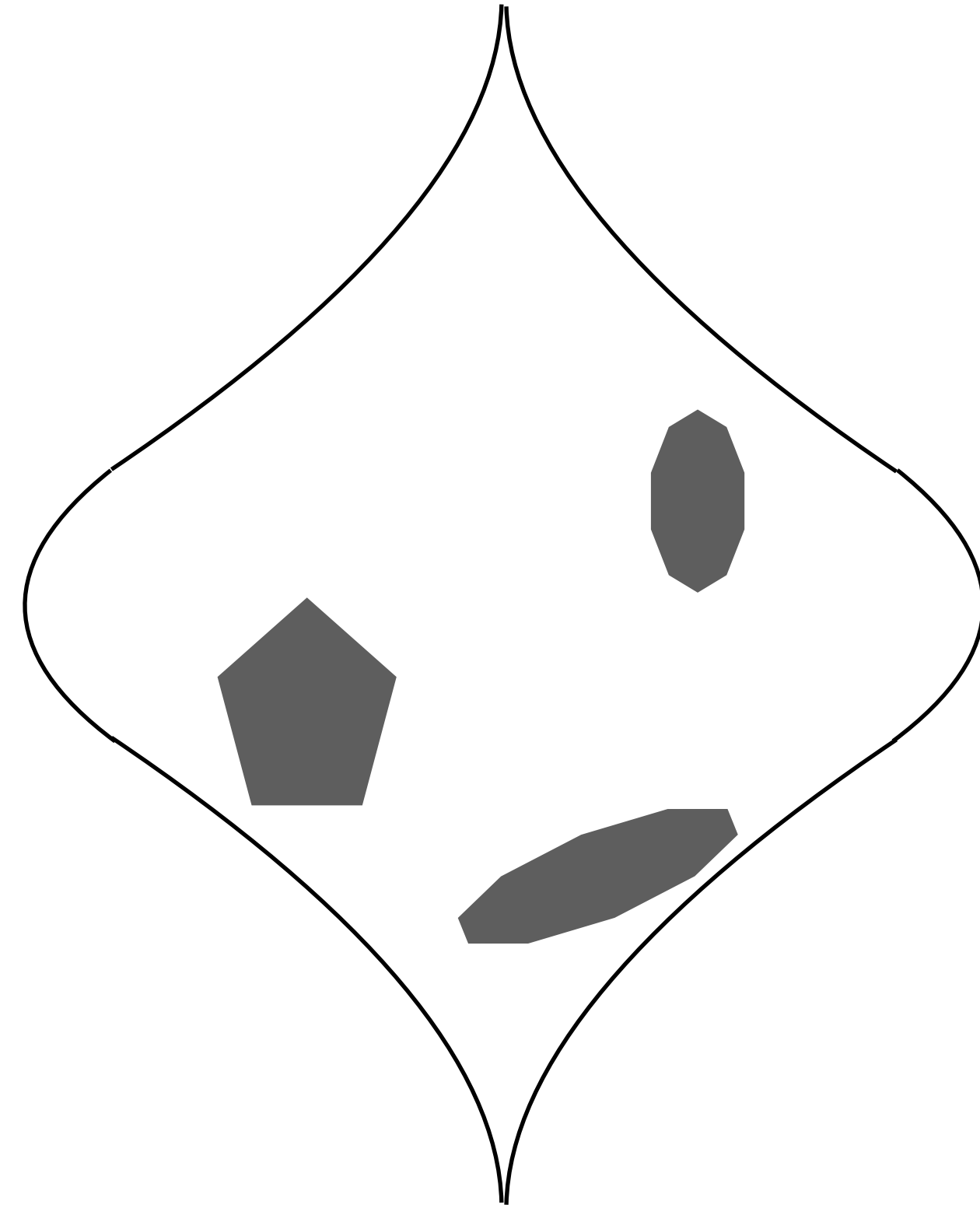
1. Sample  $q$  inputs  $x_1, \dots, x_q \sim \{0, 1\}^n$
2. Query all inputs.
3. Output **YES** iff always 0.



$$\mathcal{P} = \{f = 0\}$$



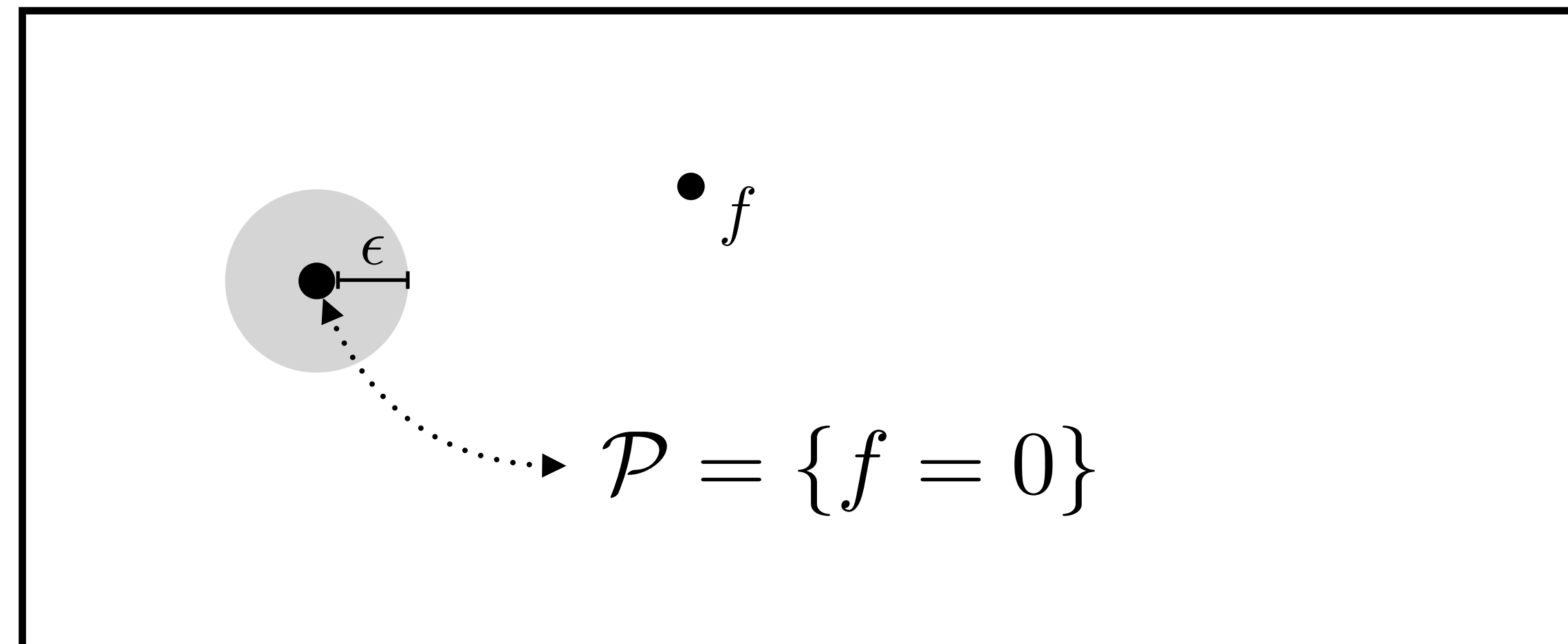
# Formal Analysis for $\mathcal{P} = \{f = 0\}$ : Direction 2



Algorithm outputs **YES**:

$$\Pr_{\mathbf{x}_1, \dots, \mathbf{x}_q} [\forall i \in [q] : f(\mathbf{x}_i) = 0] \leq \left(1 - \frac{|\{x : f(x) = 1\}|}{2^n}\right)^q$$

$$\frac{|\{x : f(x) = 1\}|}{2^n} = d(f, \mathcal{P}) \geq \epsilon.$$



# Is the function always 0?

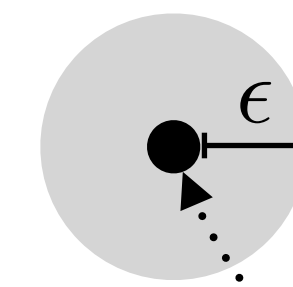
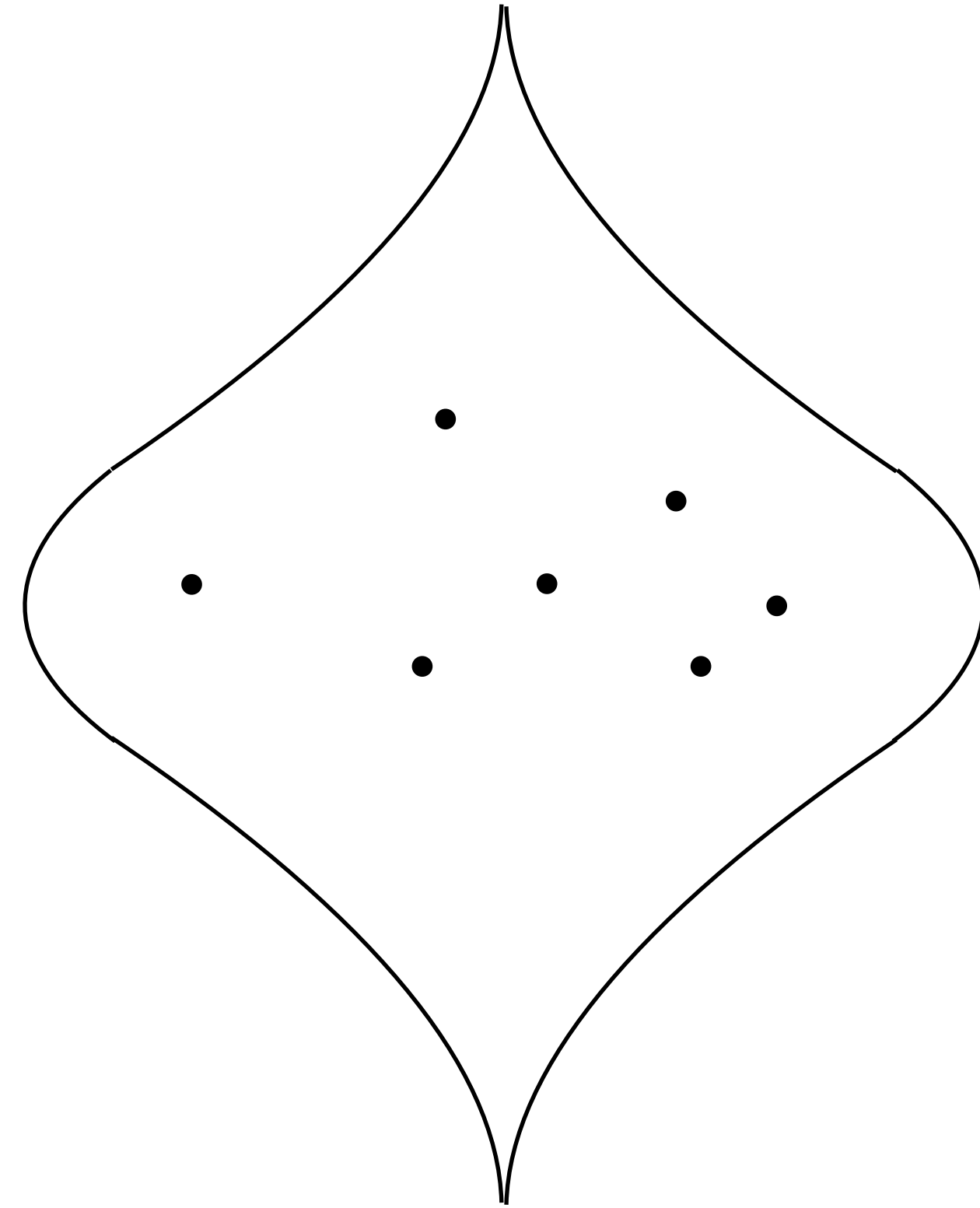


## Algorithm

1. Sample  $O(1/\epsilon)$  inputs  $\mathbf{x}_1, \dots, \mathbf{x}_q \sim \{0, 1\}^n$
2. Query all inputs.
3. Output **YES** iff always 0.

### Additional Properties:

Non-adaptive and one-sided error



$\epsilon$

$$\mathcal{P} = \{f = 0\}$$

One can always test properties of few functions.



**Observation:** For any property  $\mathcal{P}$ , there exists an algorithm which tests that property of query complexity  $O(\log |\mathcal{P}|/\epsilon)$ .

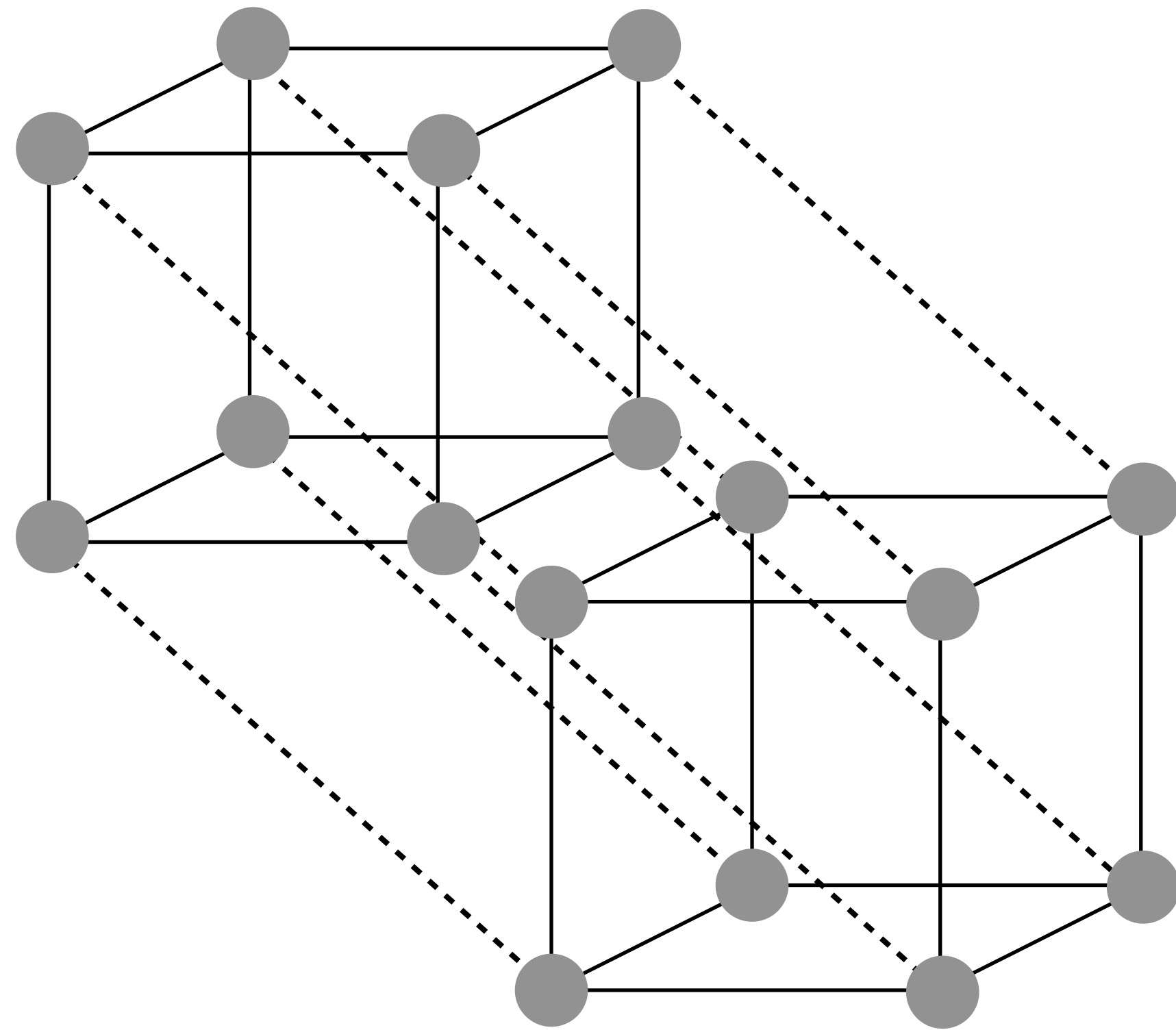
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**Observation:** For any property  $\mathcal{P}$ , there exists an algorithm which tests that property of query complexity  $O(\log |\mathcal{P}|/\epsilon)$ .

- \* Can be quite bad, number of functions is  $2^{2^n}$ .
- \* Actually, *learns* a close function in  $\mathcal{P}$ .
- \* Completely generic.

# Blum-Luby-Rubinfeld '93: Is my function linear?

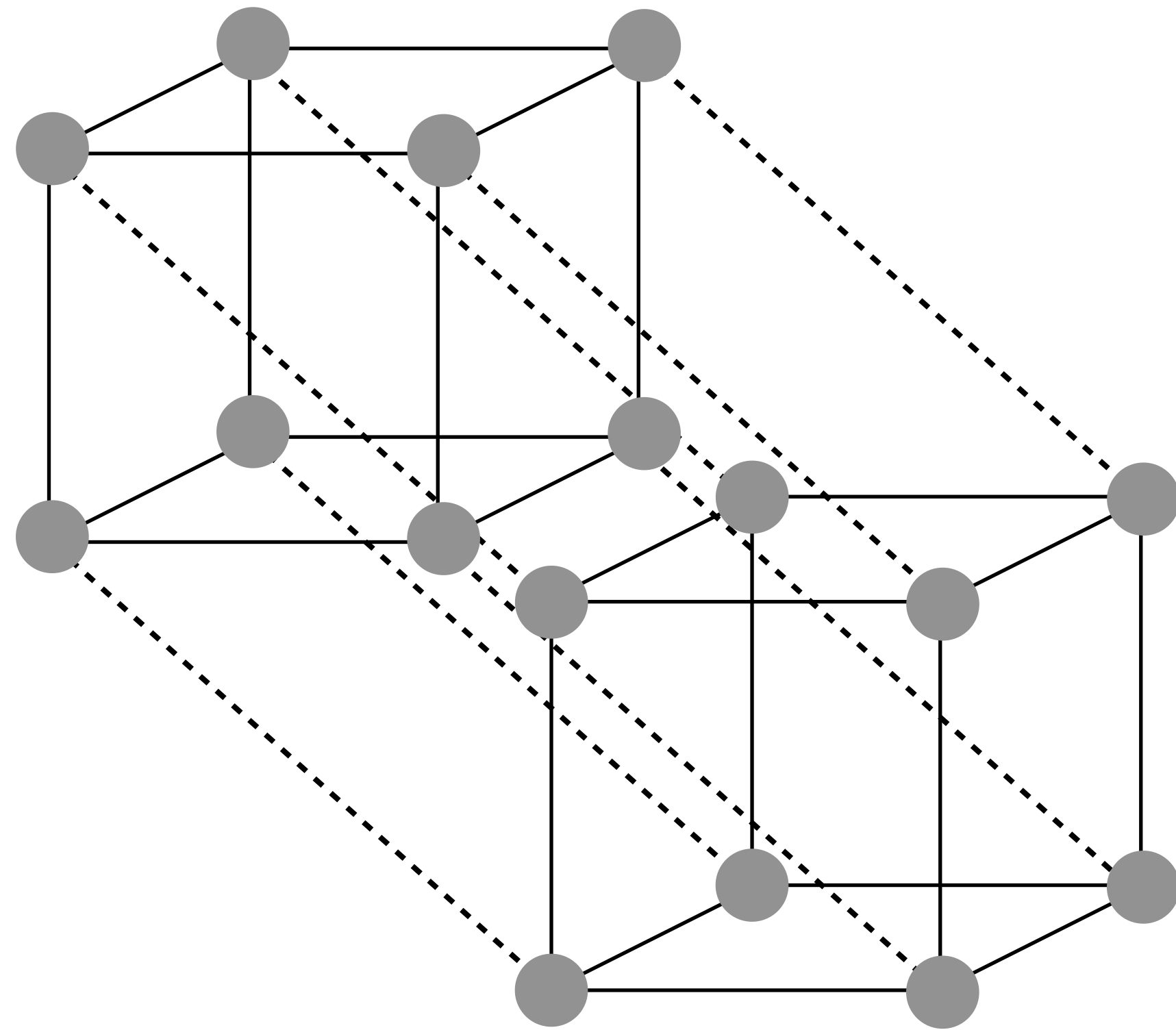


**Definition:** a function  $f: \{0, 1\}^n \rightarrow \{0, 1\}$  is linear (in  $\mathbb{F}_2$ ) if

$$f(x) = \sum_{i=1}^n a_i \cdot x_i \pmod{2}$$

for some  $a \in \{0, 1\}^n$ .

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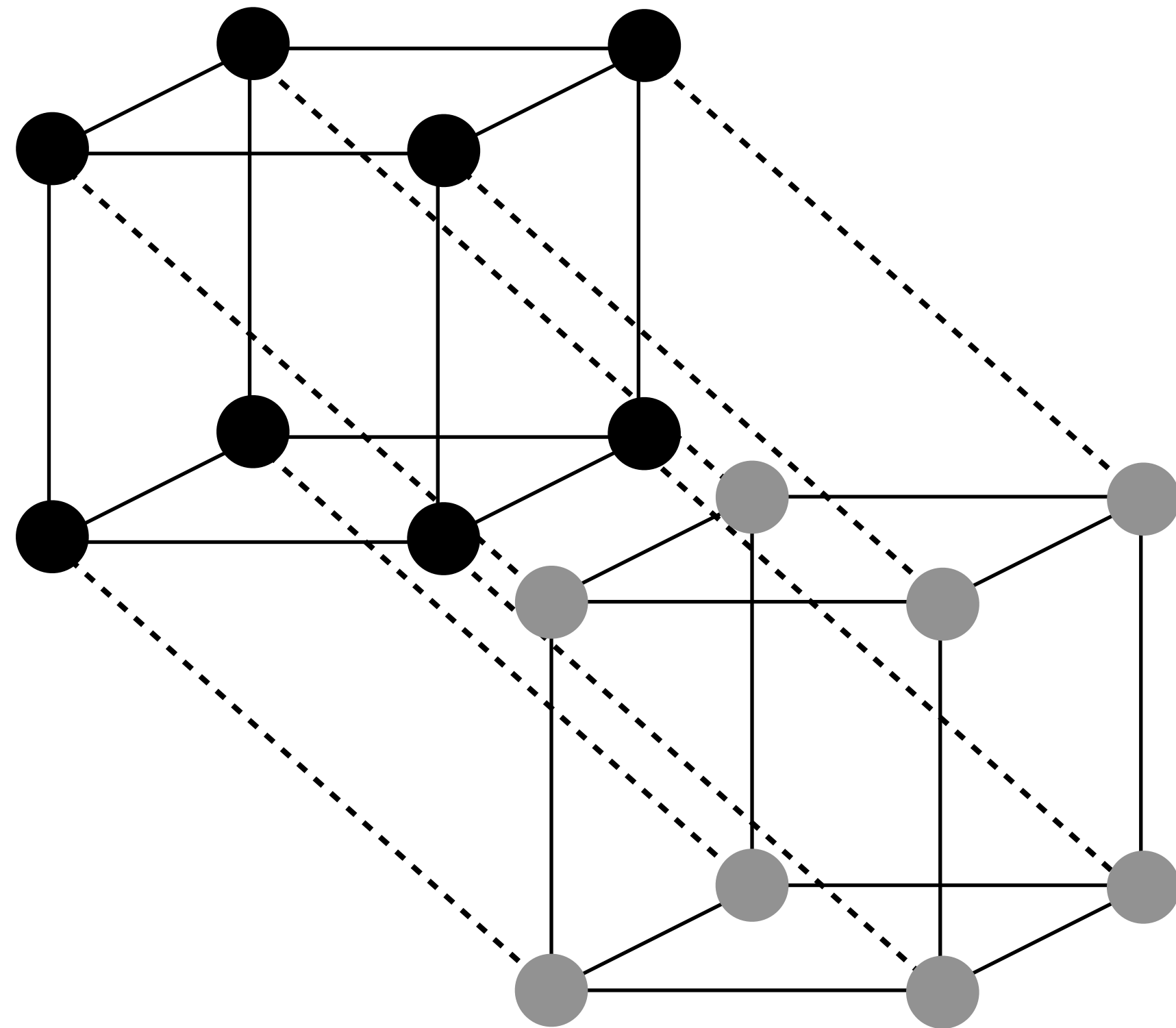
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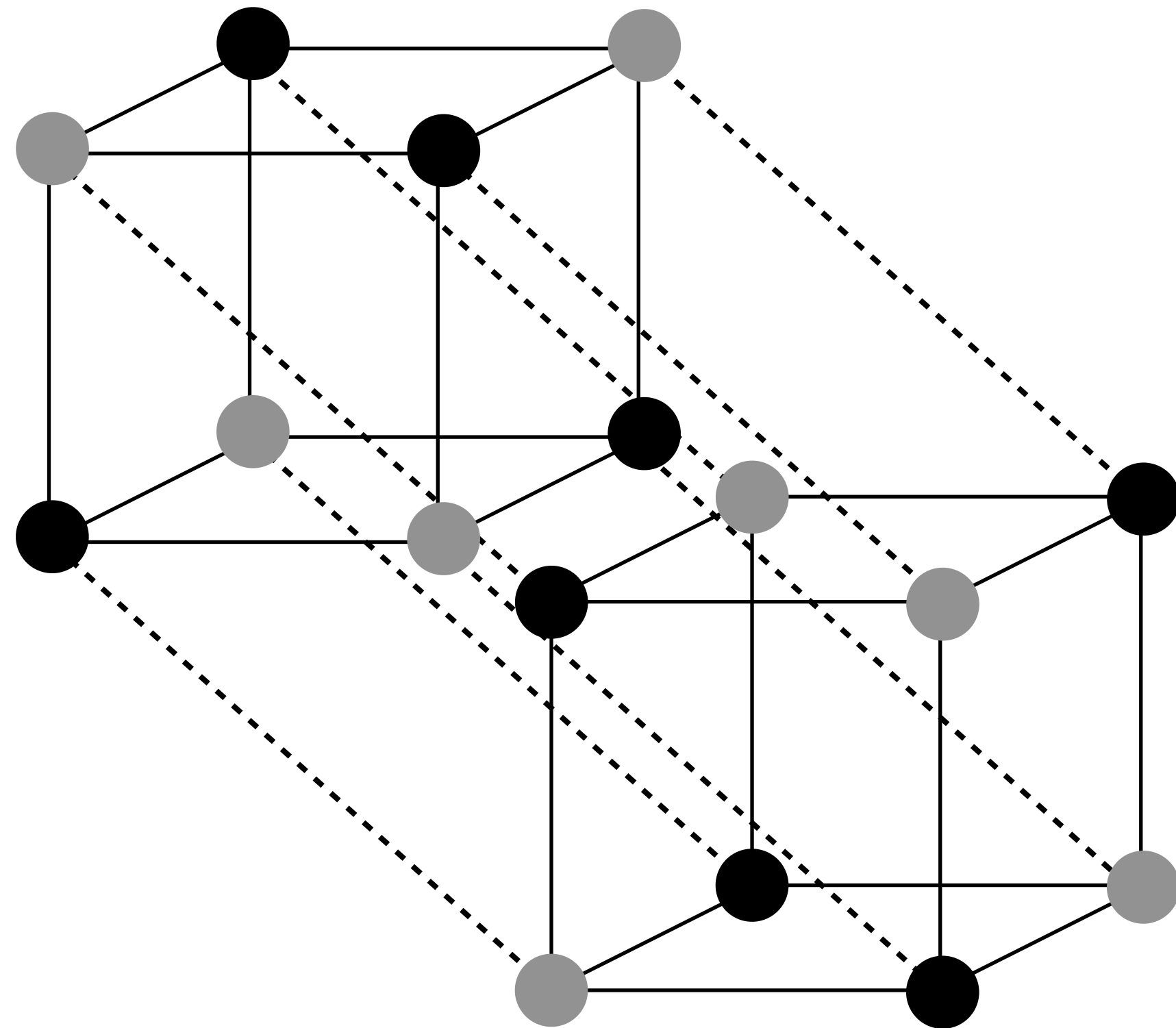
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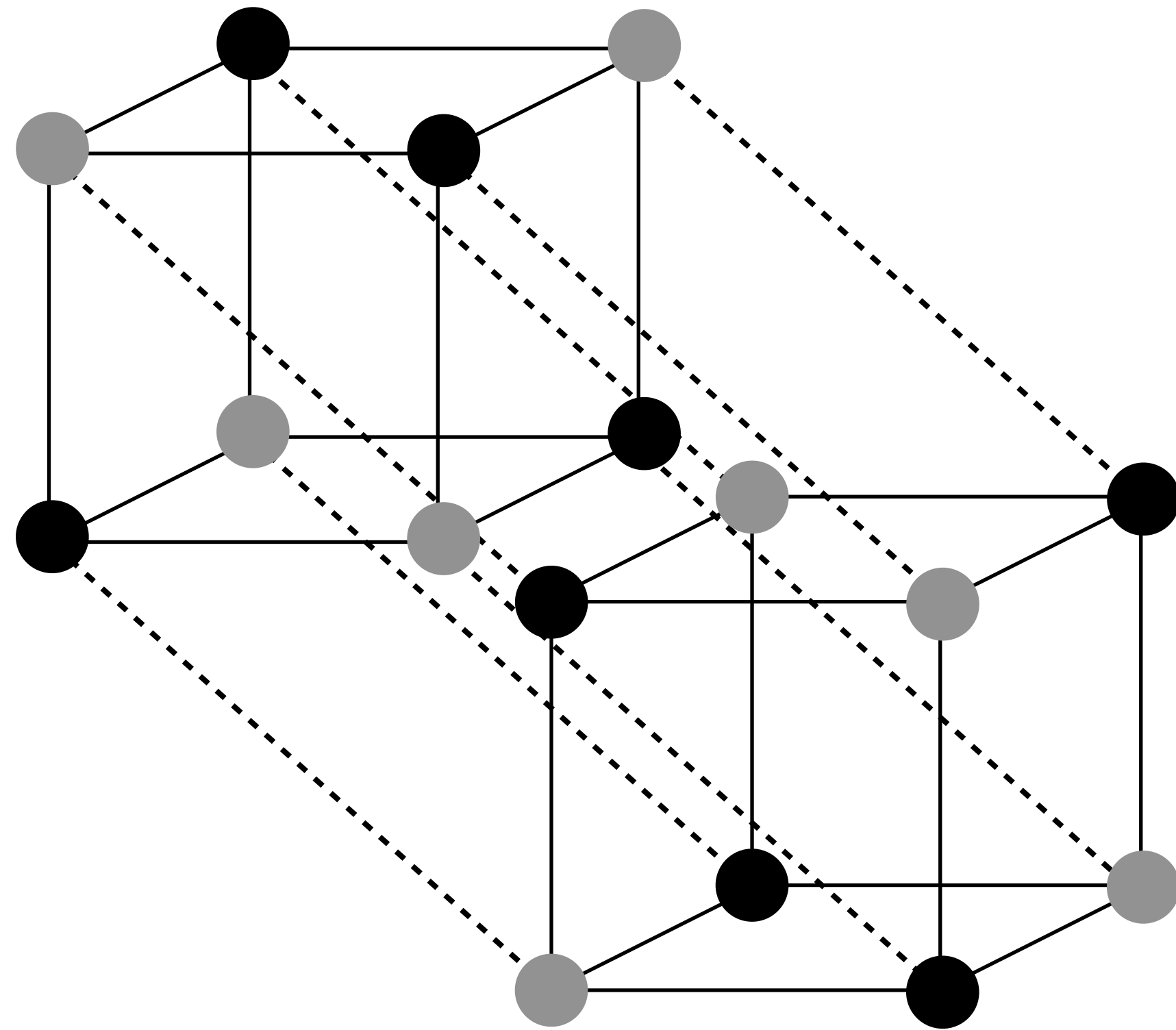
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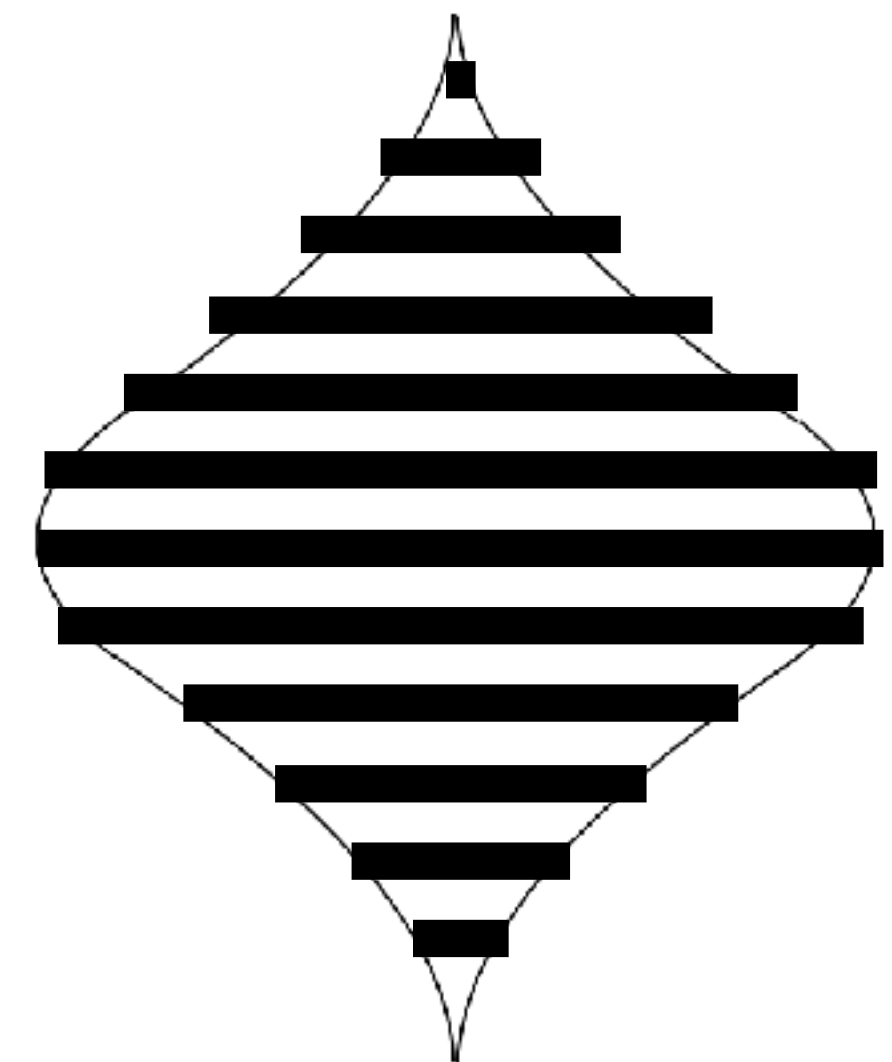
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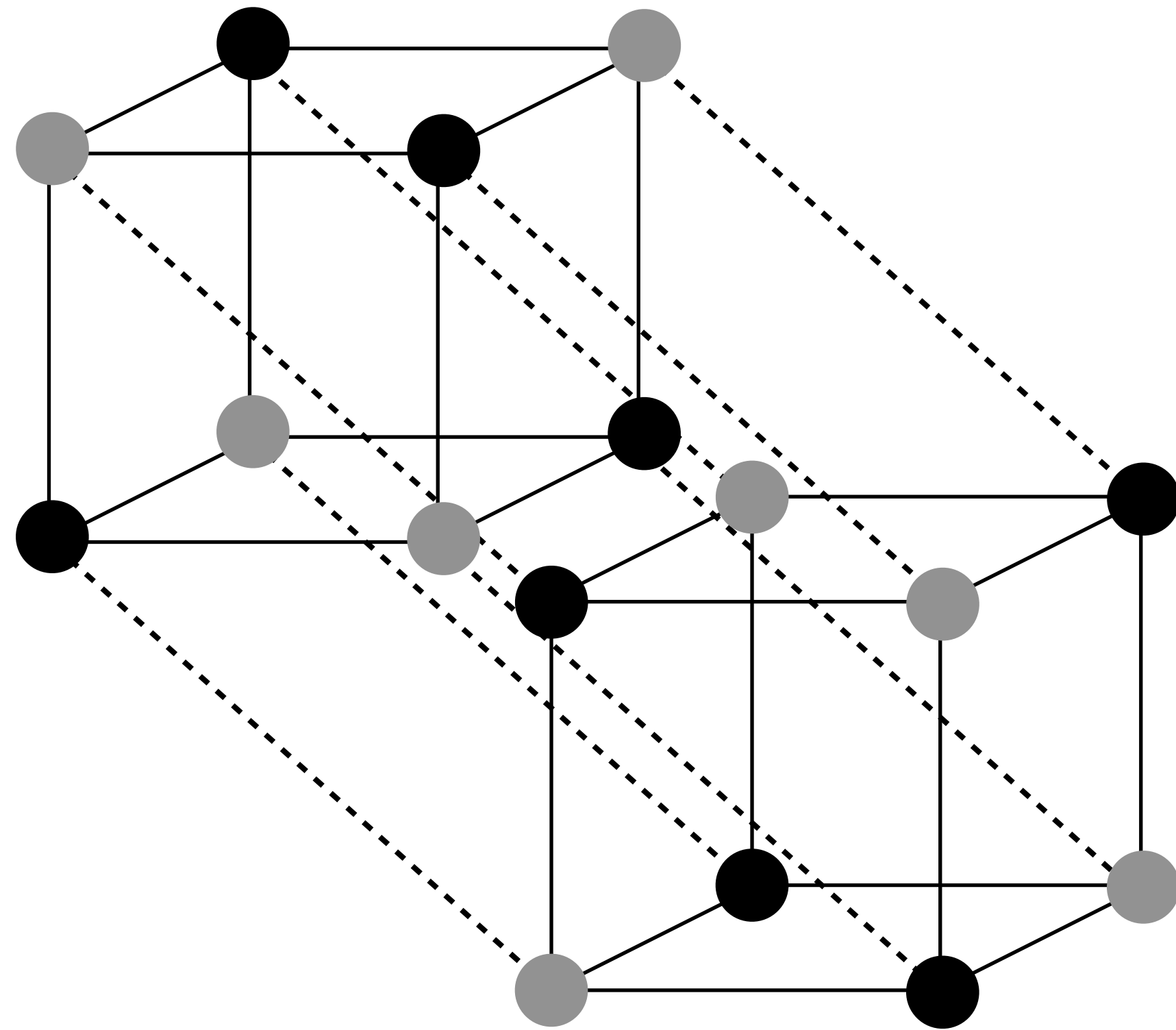
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Naive Benchmark:  $|\mathcal{P}| = 2^n$   $O(n/\varepsilon)$

# Blum-Luby-Rubinfeld '93: Is my function linear?

Slight improvement:

1. Query  $f(e_i) = \hat{a}_i, \forall i$
2. Check if

$$f \stackrel{?}{=} \sum_{i=1}^n \hat{a}_i \cdot x_i$$

by querying  $O(1/\epsilon)$   
random inputs.

$$n + O(1/\epsilon)$$

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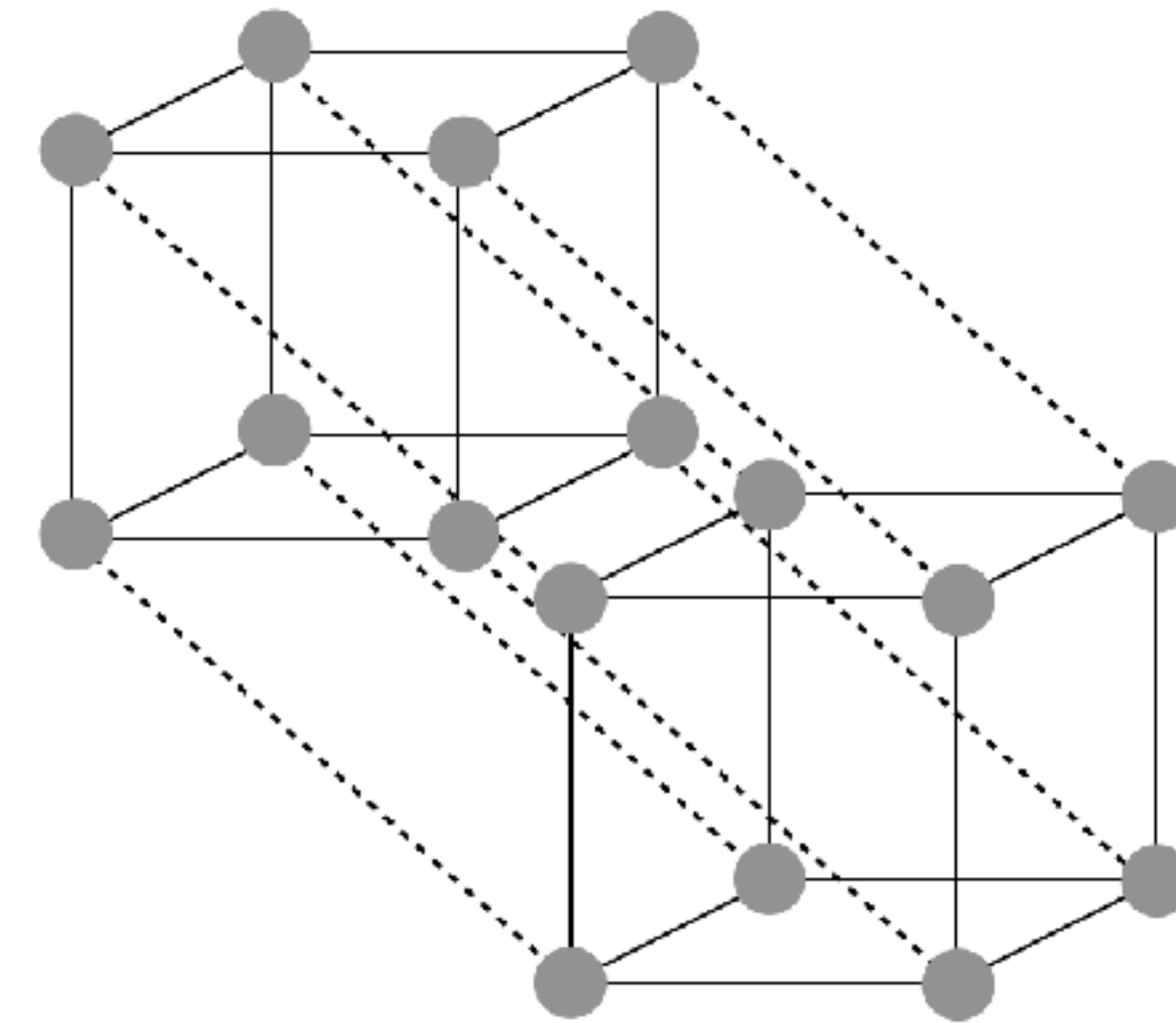
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# A different definition of linearity and a natural consistency test.

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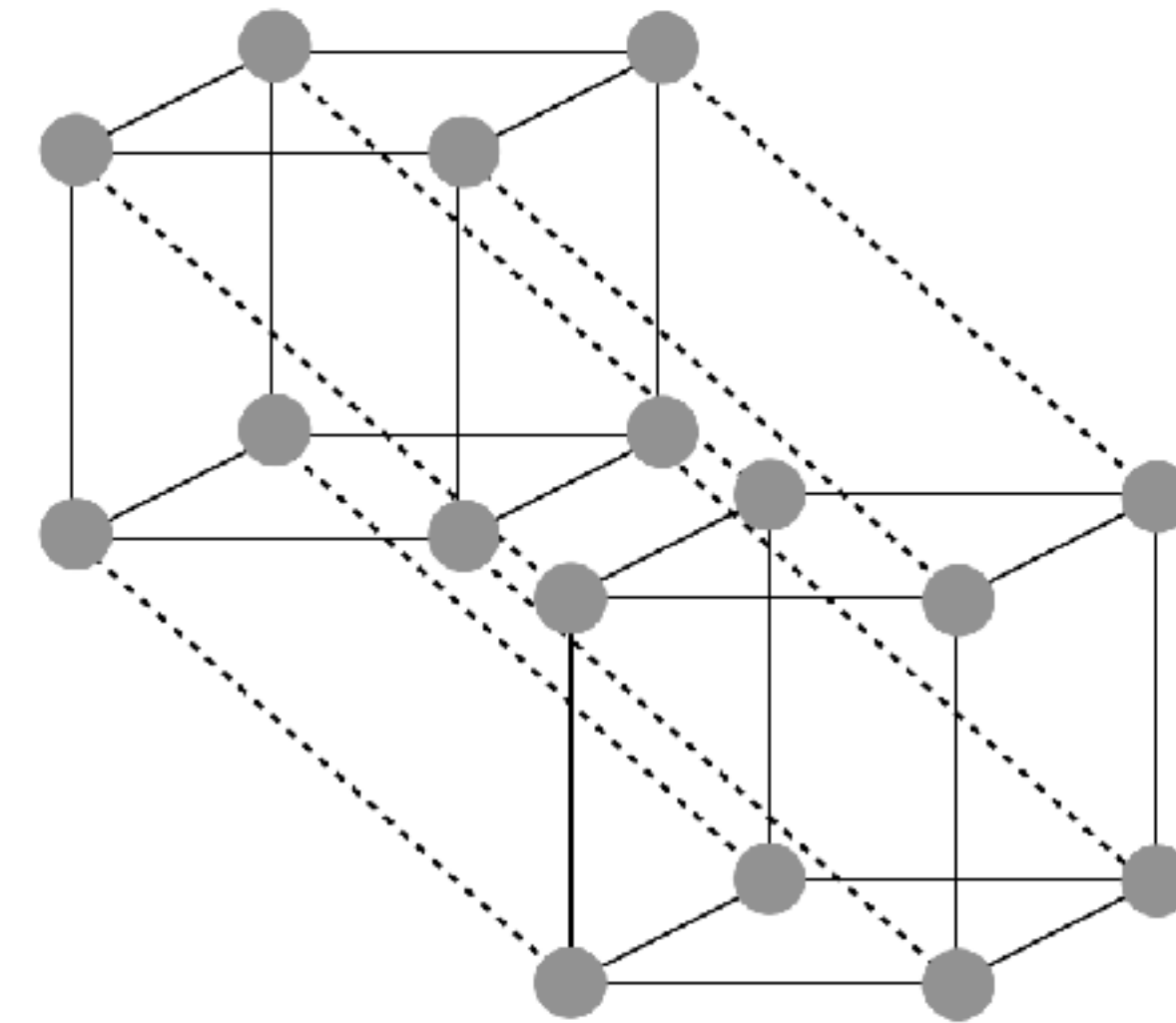
$$f(x) + f(y) = f(x + y) \quad \forall x, y \in \mathbb{F}_2$$



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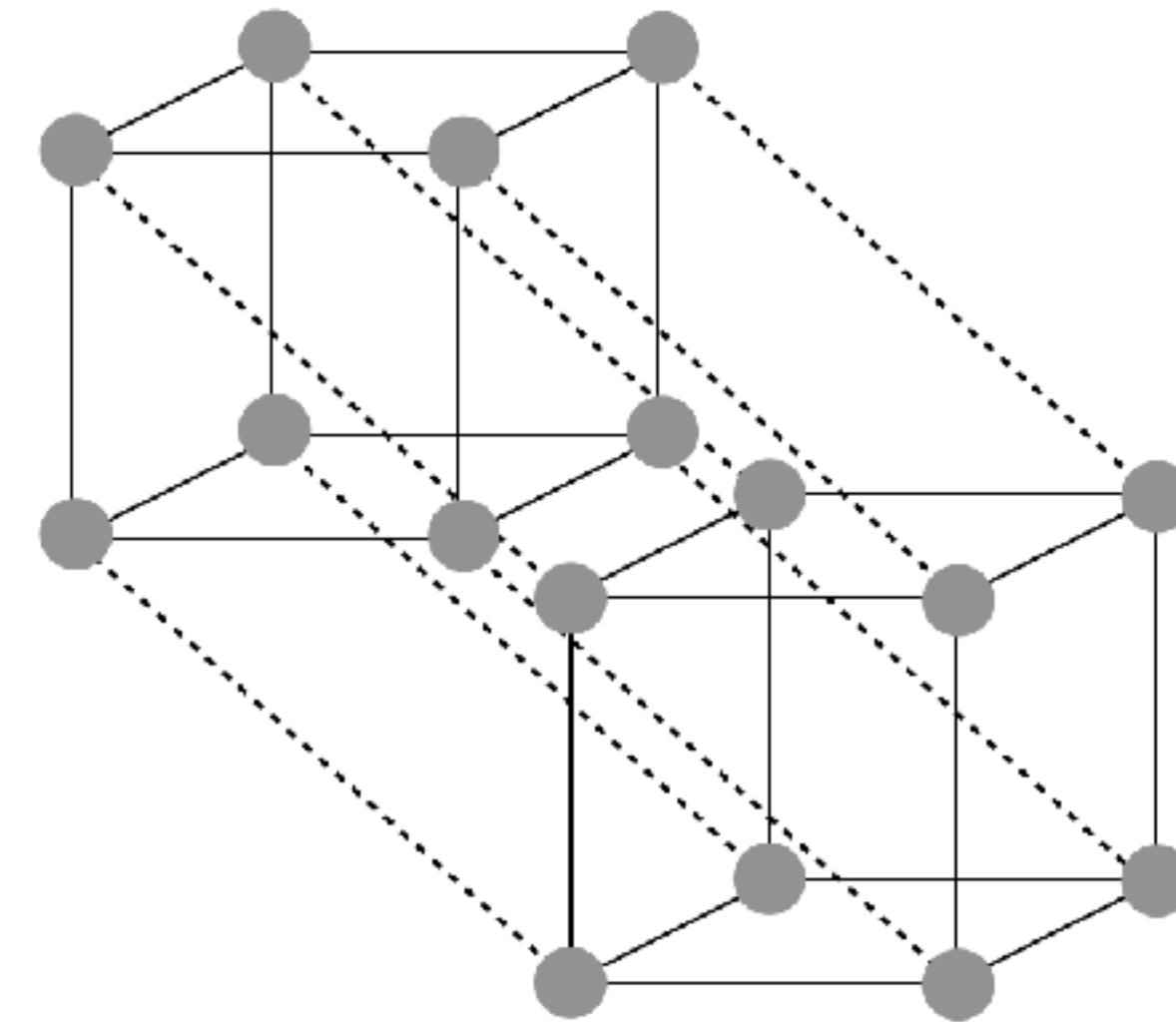
## Natural Algorithm (Check Consistency)

1. Sample pairs of inputs  $x_i, y_i \sim \{0, 1\}^n$
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3. Output **YES** iff always pass check.

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A low-query algorithm cannot check  $\forall x, y$ . Can “closeness” be derived from probabilistic guarantee?

# What could possibly go wrong?

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- Bad Case 1: *Portions* of function are linear for *different* reasons.
- Bad Case 2: Even though far, *evidence* is hard to find.

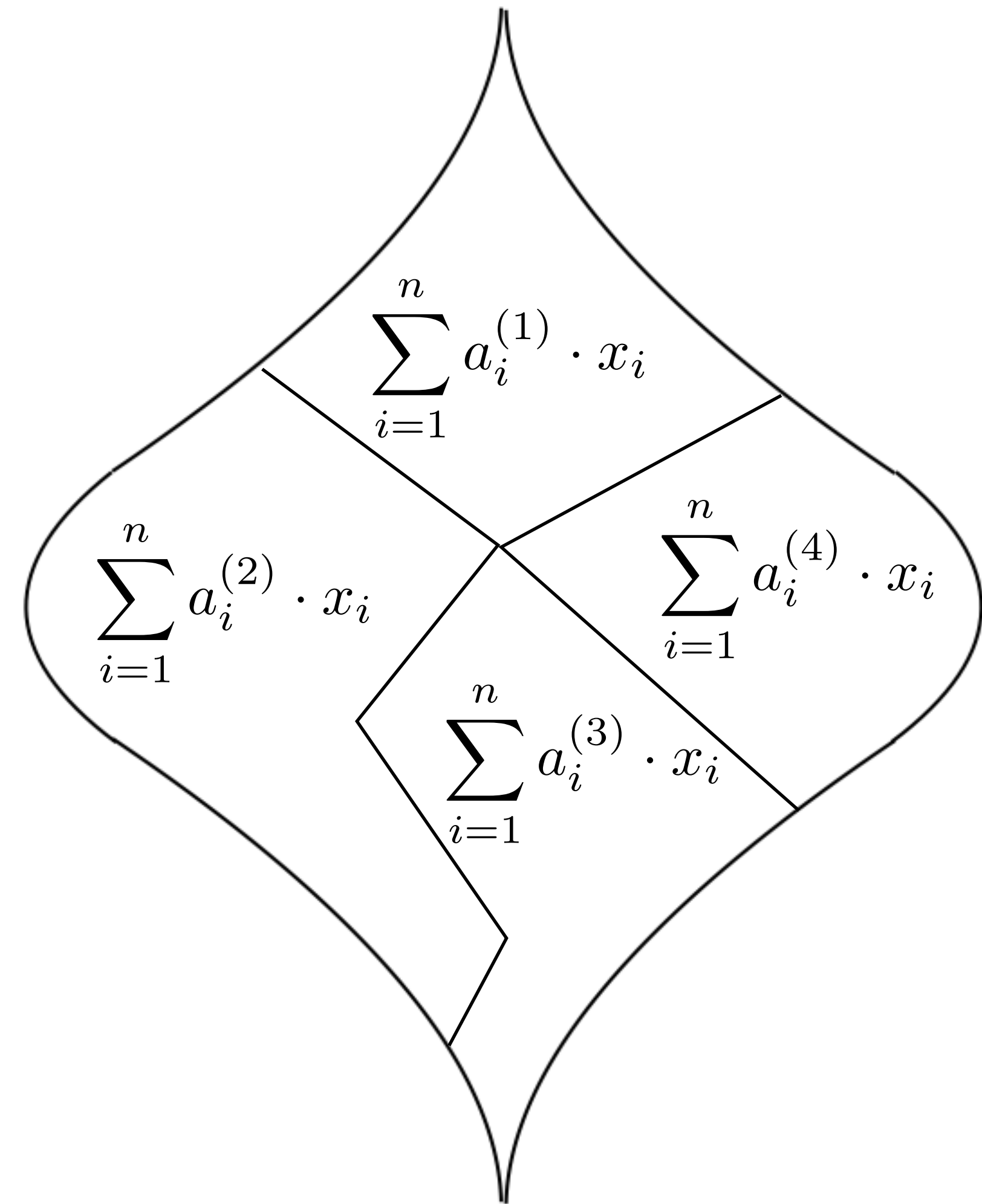


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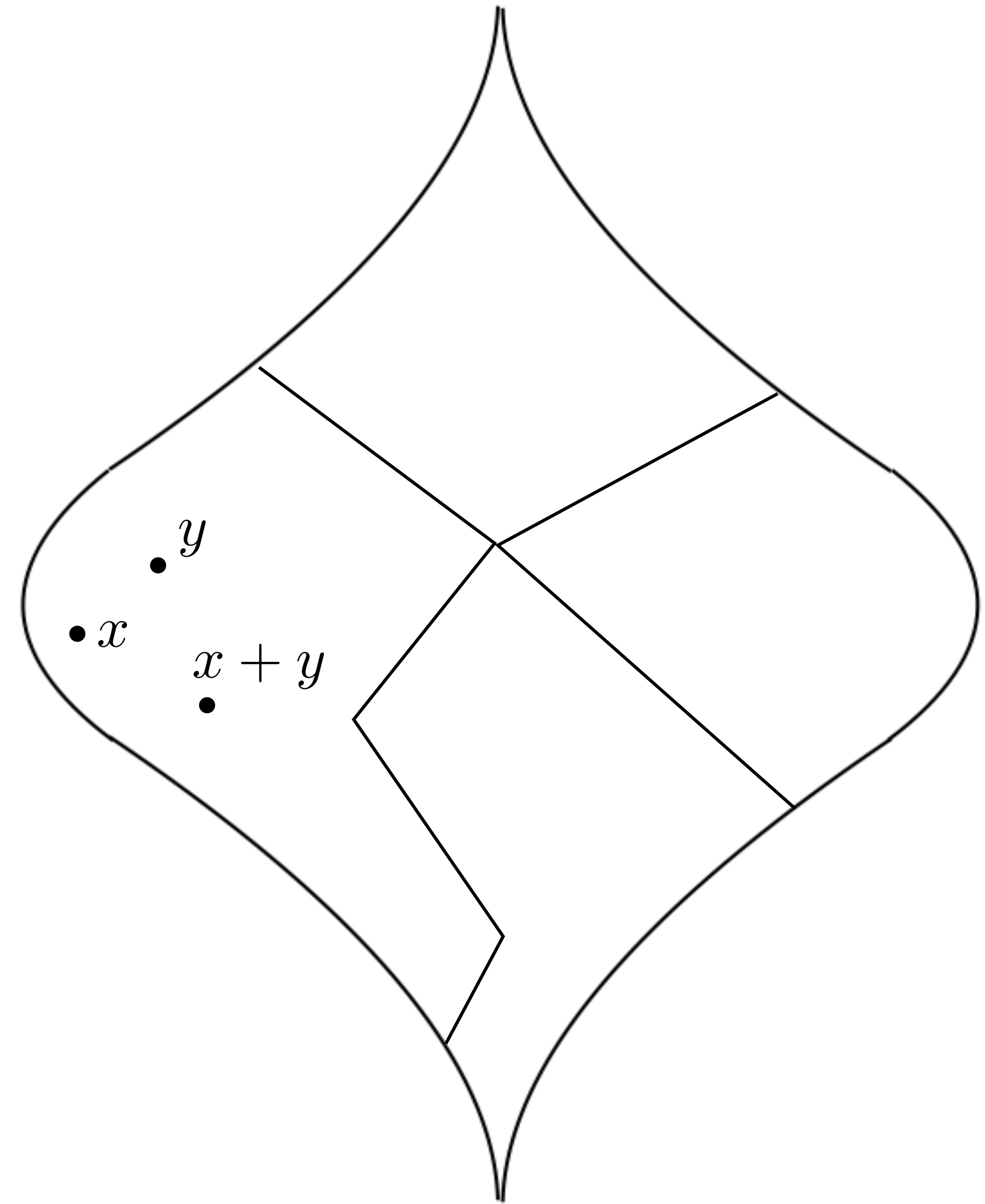


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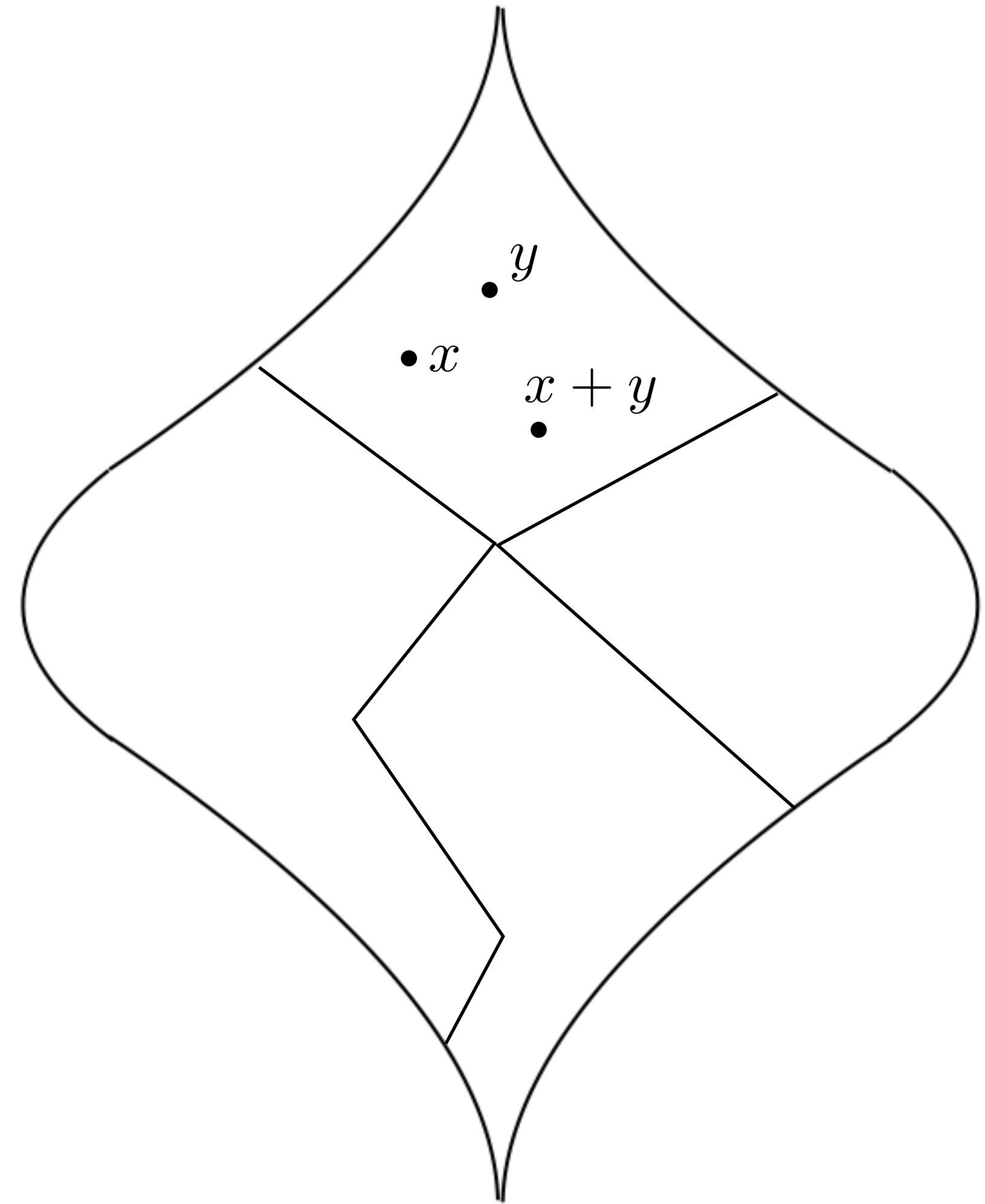


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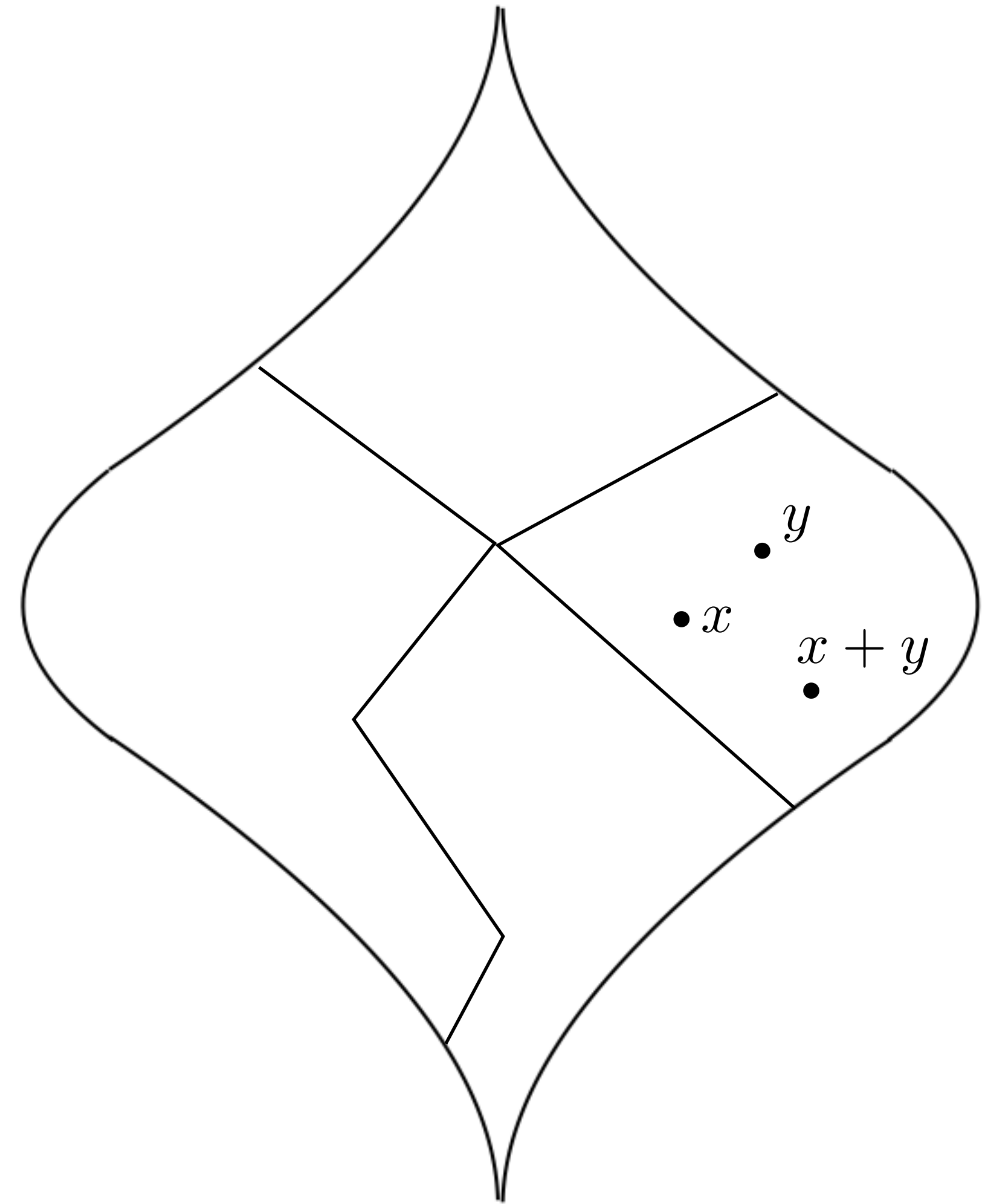


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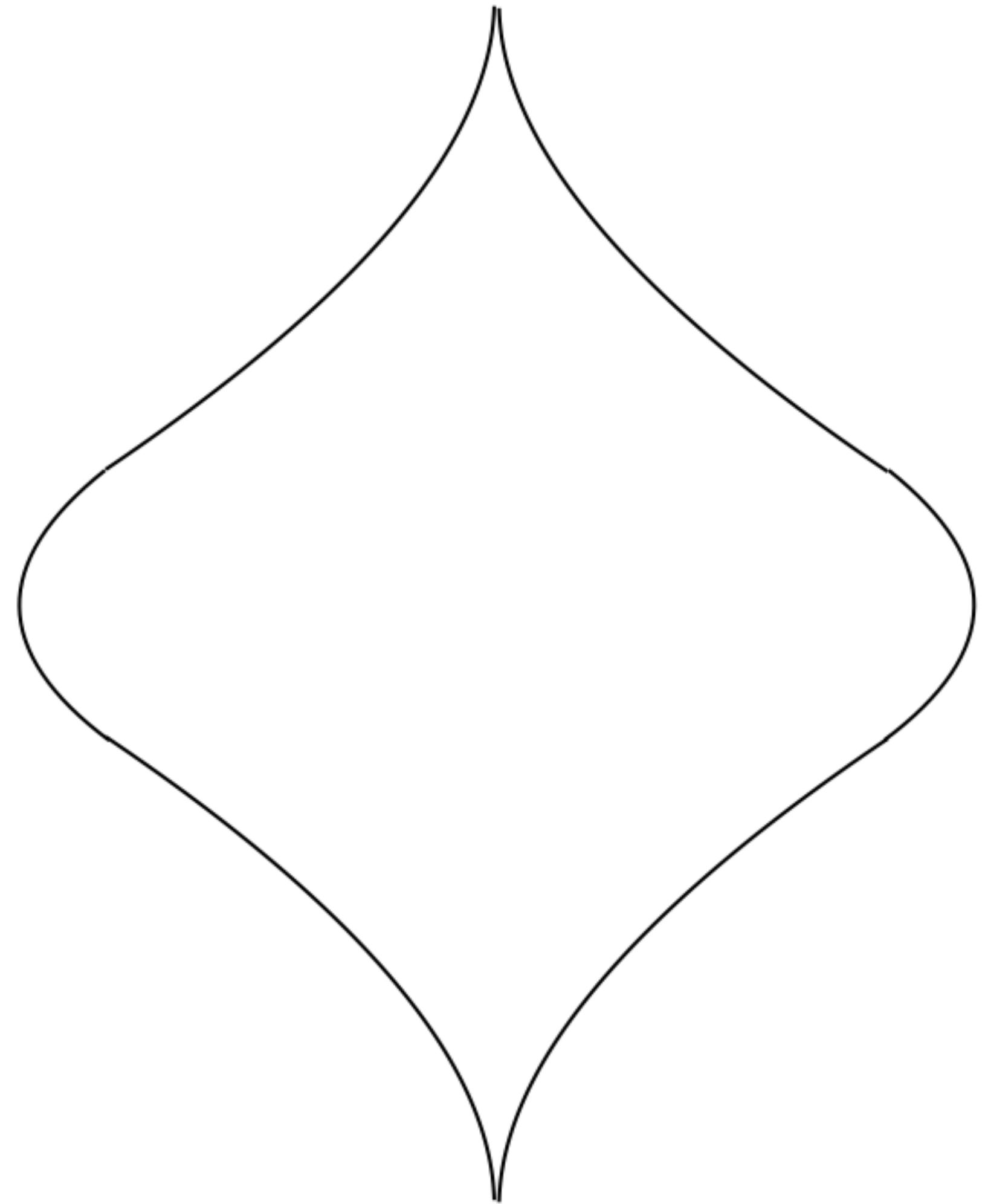


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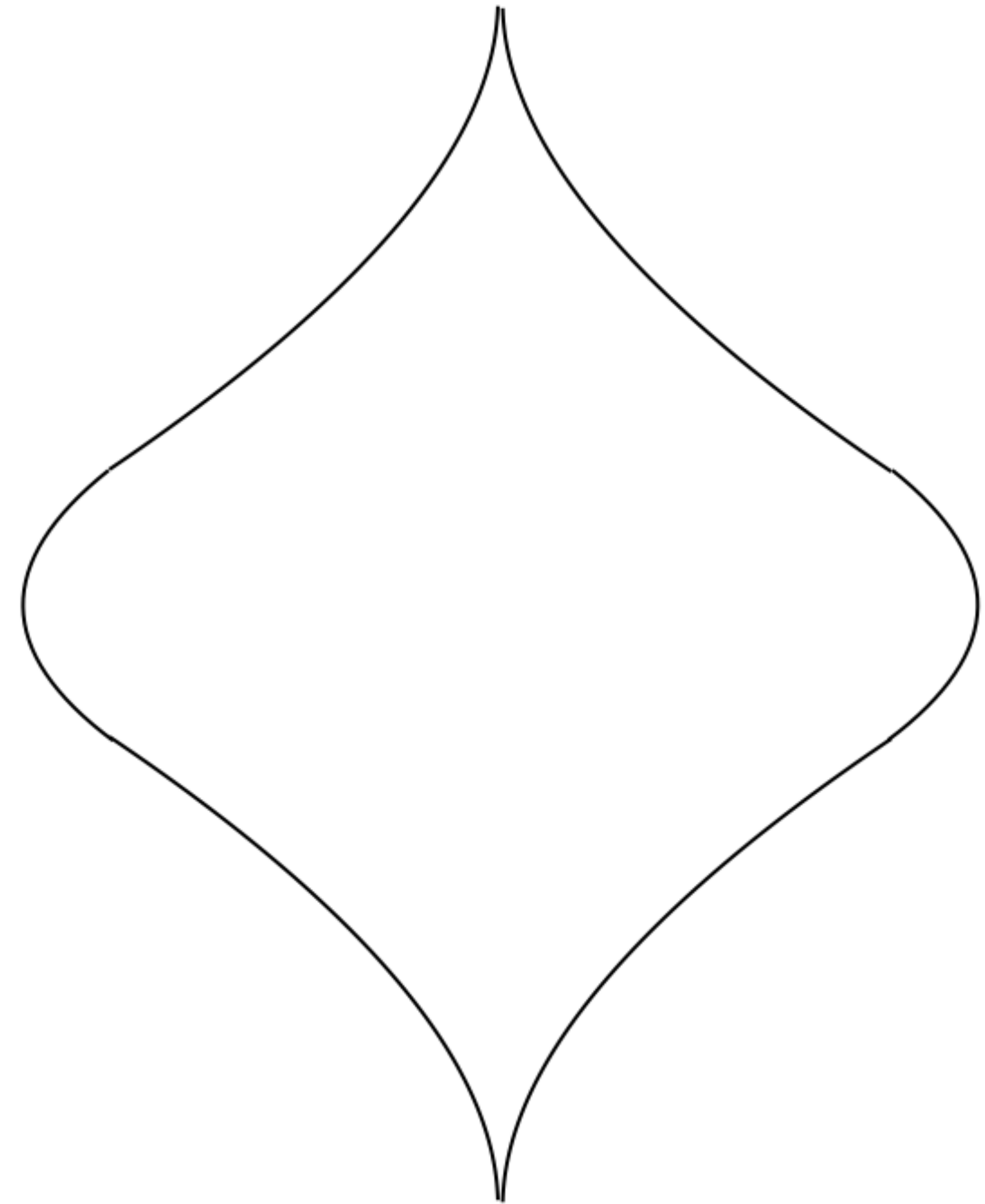
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**Theorem [BLR'93]:** Test works with query complexity  $O(1/\epsilon)$



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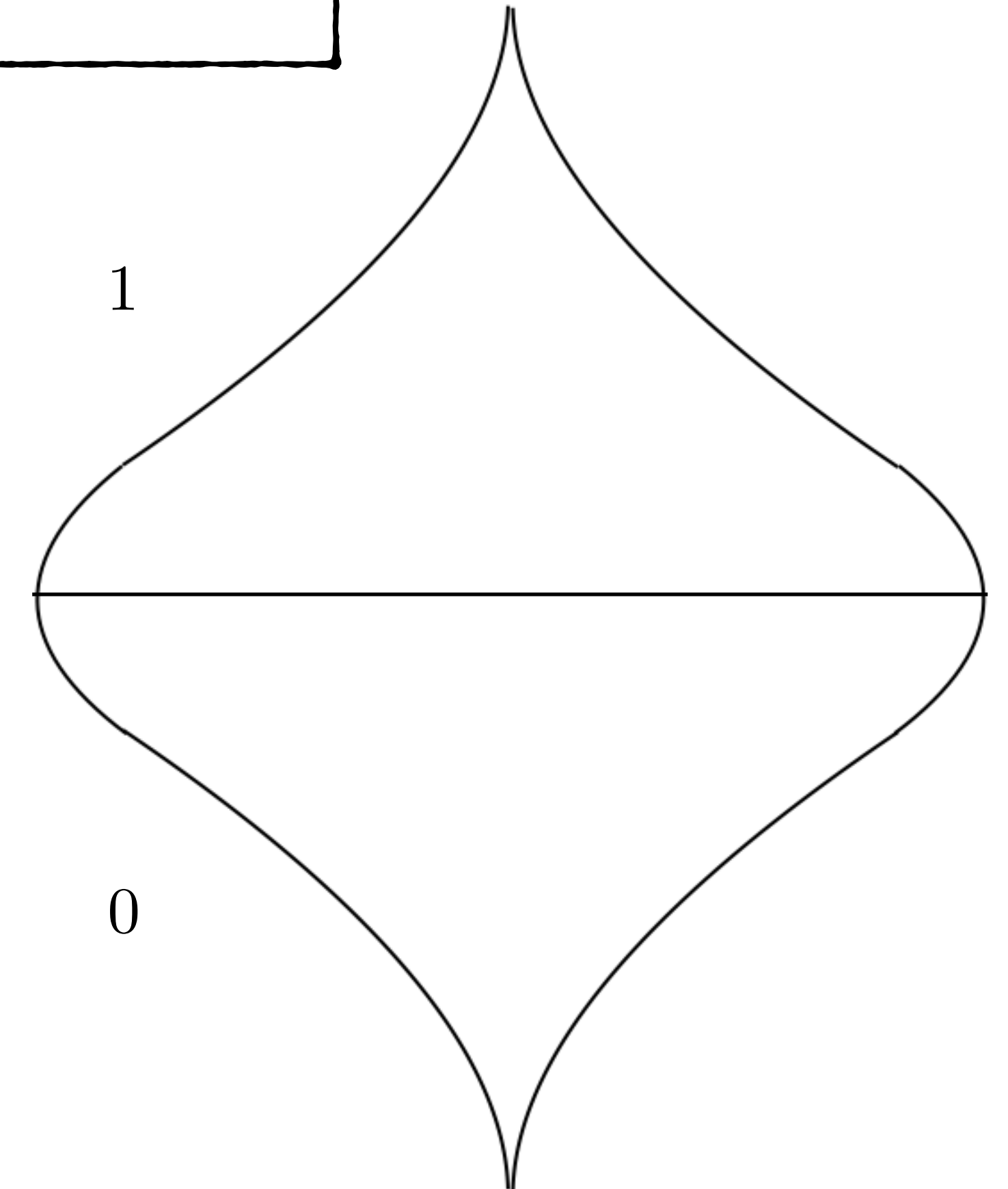
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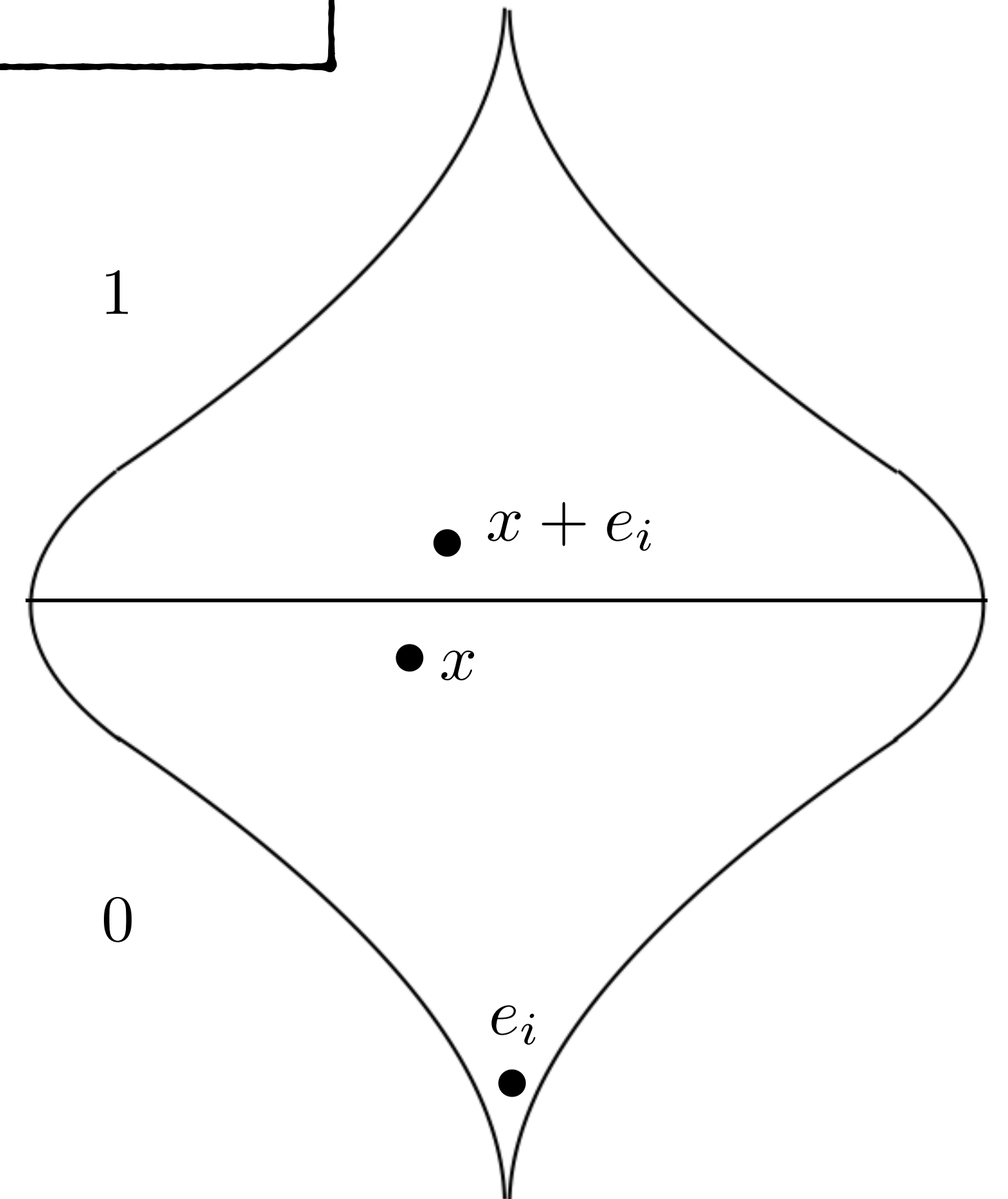
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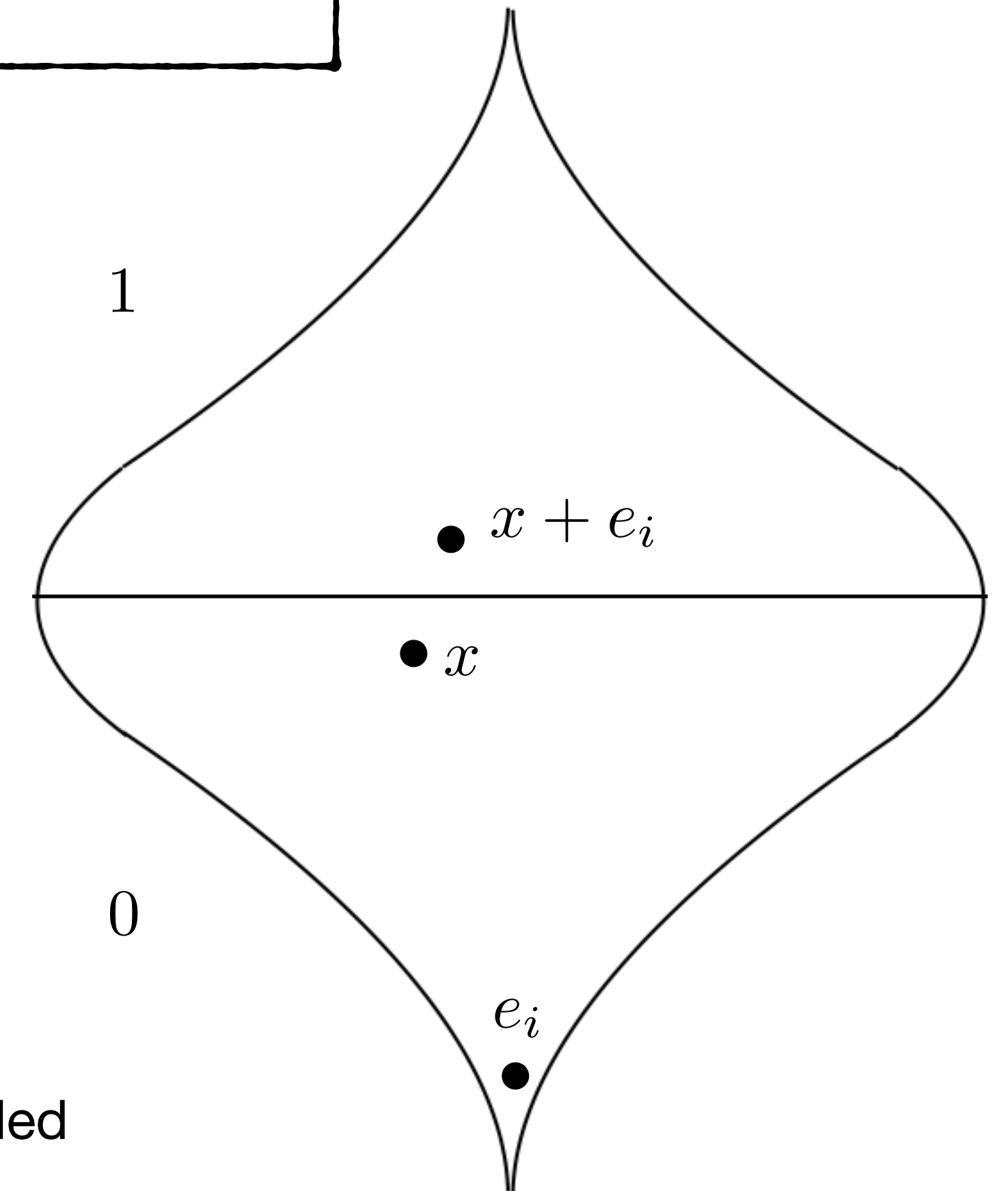
### Natural Algorithm (Check Consistency)

1. Sample  $x \sim \{0, 1\}^n, i \sim [n]$
2. Query and check  $f(x) + f(e_i) = f(x + e_i)$
3. Output **YES** iff always pass check.

# Bad Case 2: Even though $\epsilon$ -far from linear, hard to find evidence.

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## Natural Algorithm (Check Consistency)

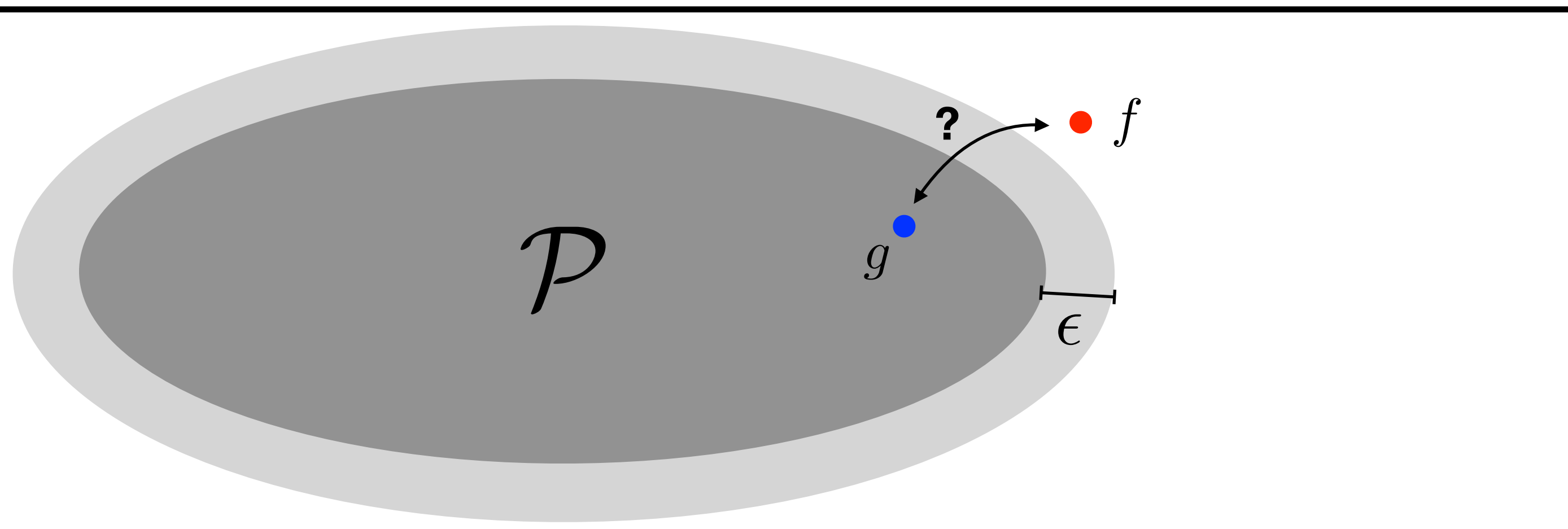
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$\Omega(\sqrt{n})$  queries needed

Thm [BLR'93]:  $O(1/\epsilon)$  repetitions suffice. Efficient test without learning.

### Natural Algorithm (Check Consistency)

1. Sample pairs of inputs  $\mathbf{x}_i, \mathbf{y}_i \sim \{0, 1\}^n$
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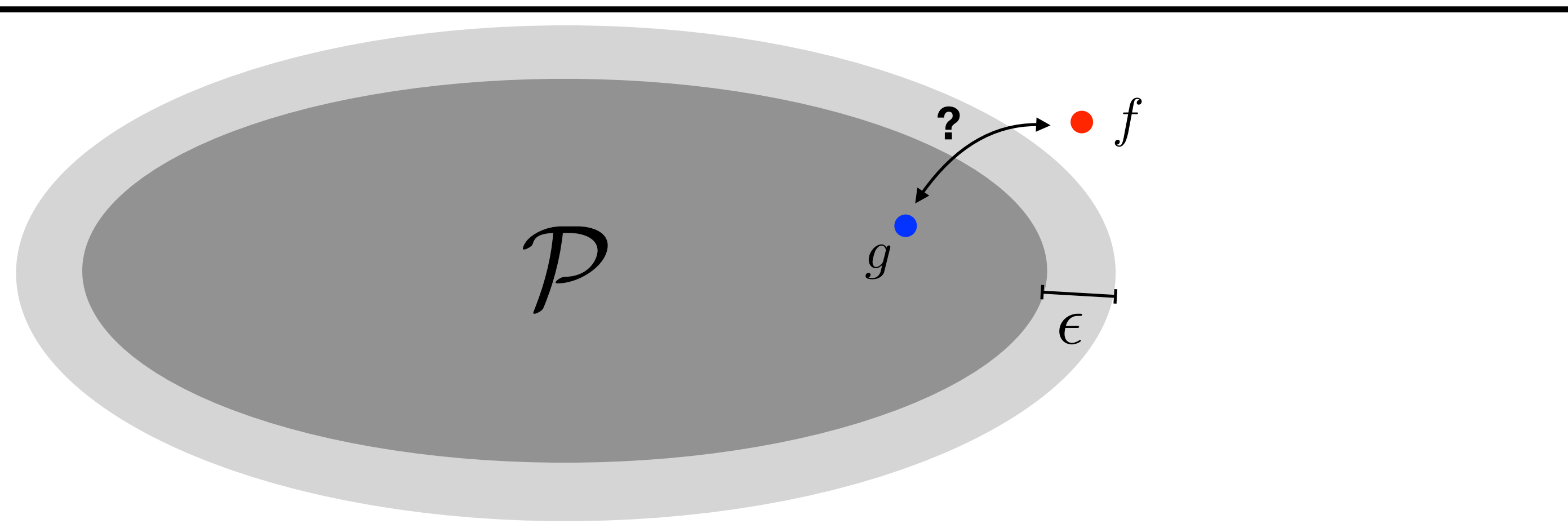
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**Voting Function:**

$$g(x) = \begin{cases} 0 & \Pr_{\mathbf{y}} [f(x + \mathbf{y}) - f(\mathbf{y}) = 0] \geq 1/2 \\ 1 & \Pr_{\mathbf{y}} [f(x + \mathbf{y}) - f(\mathbf{y}) = 1] > 1/2 \end{cases}$$

(what should  $x$  be in order to “pass” often)





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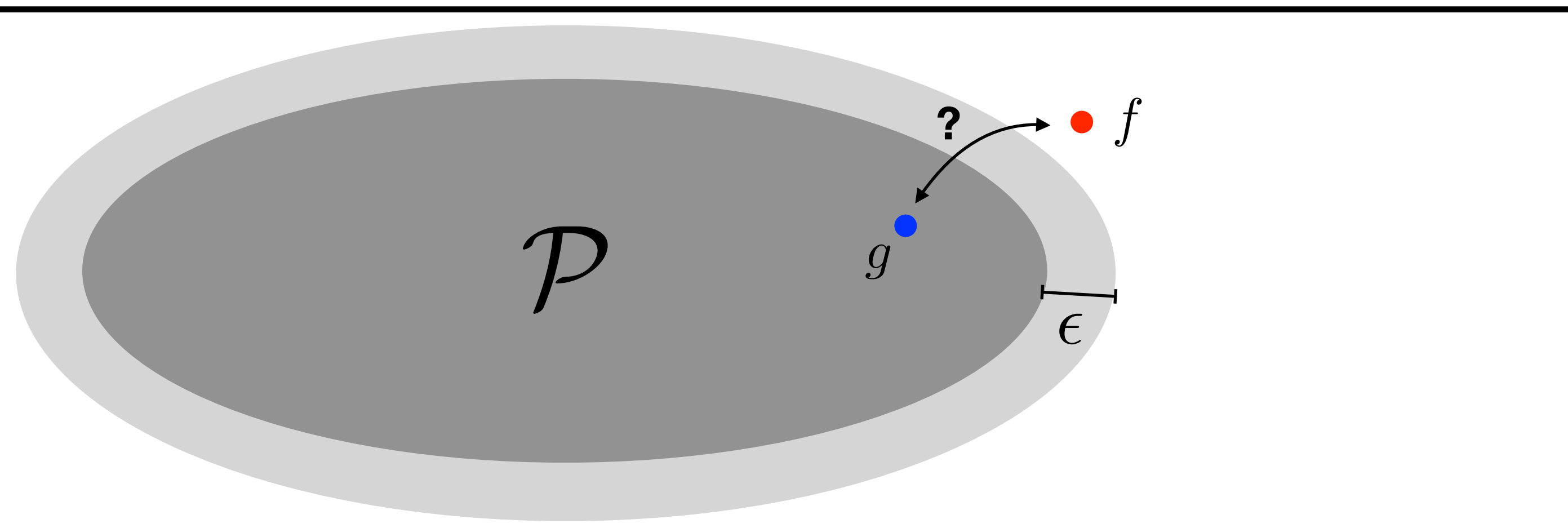
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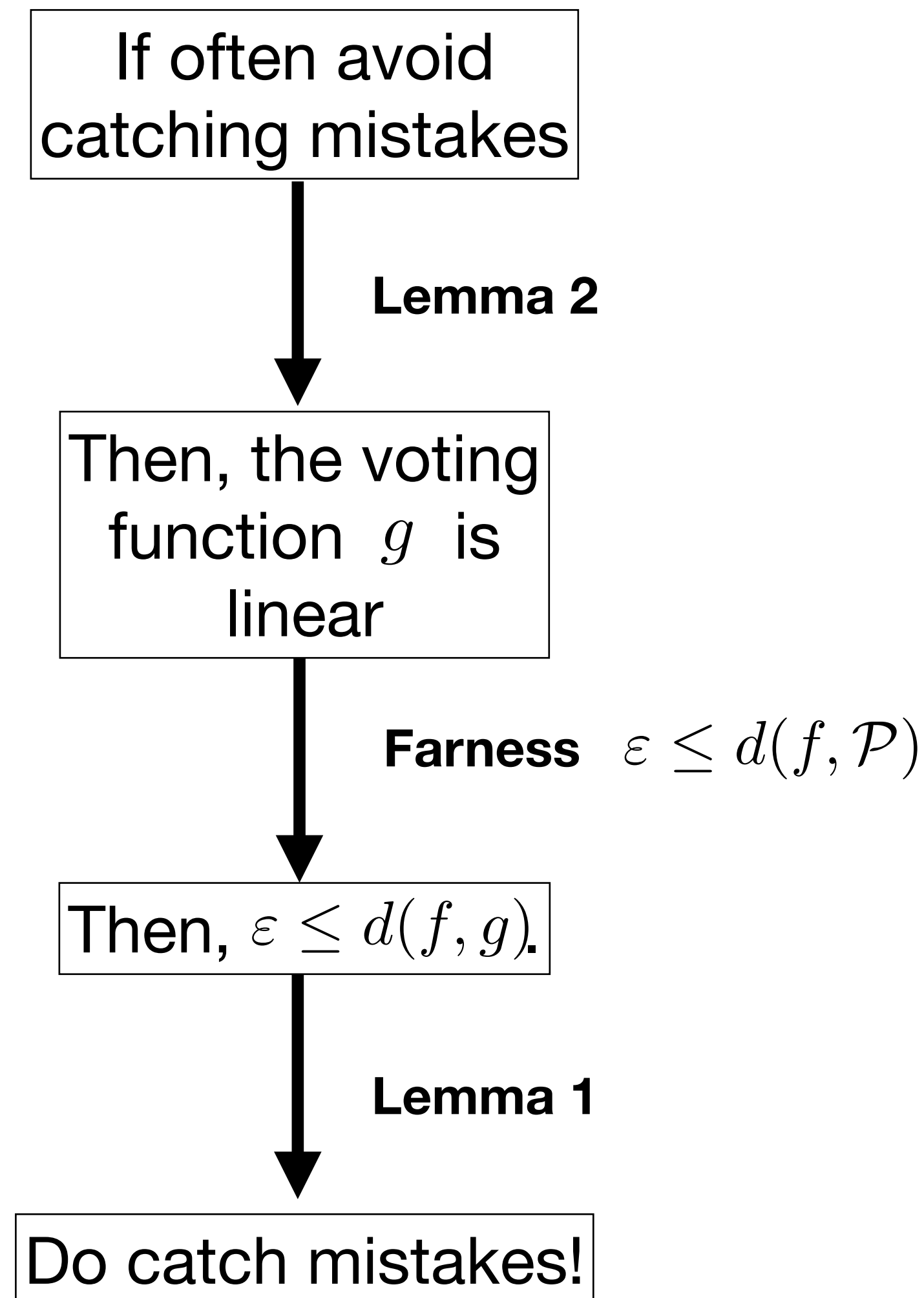


**Lemma 1:** If  $f(x) \neq g(x)$ , the battle is almost won.

$$\Rightarrow d(f, g) \cdot (1/2) \leq \Pr_{\mathbf{x}, \mathbf{y}} [\text{catch mistake!}]$$

**Lemma 2:** If  $f$  oftentimes passes test, then  $g$  is linear.

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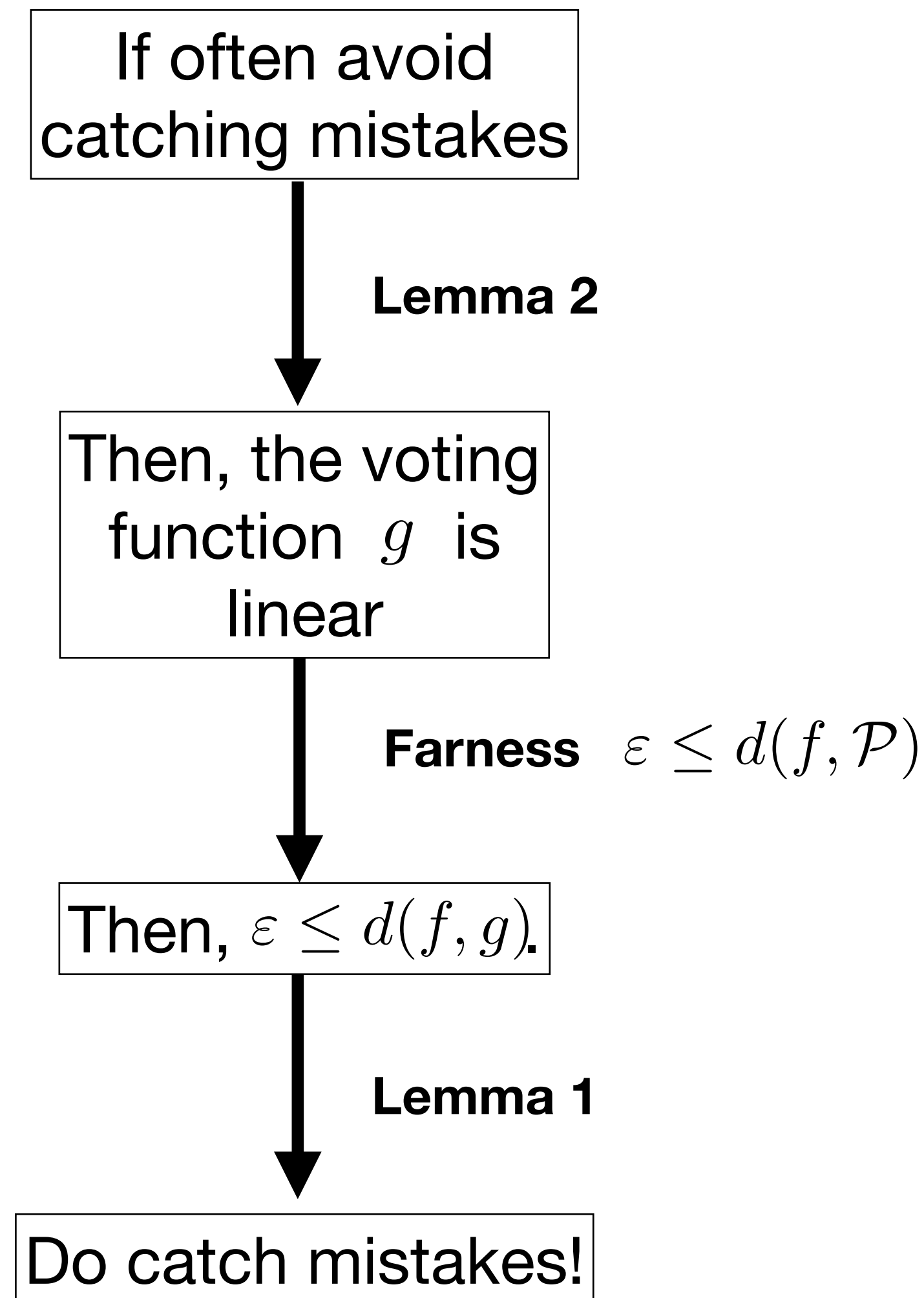
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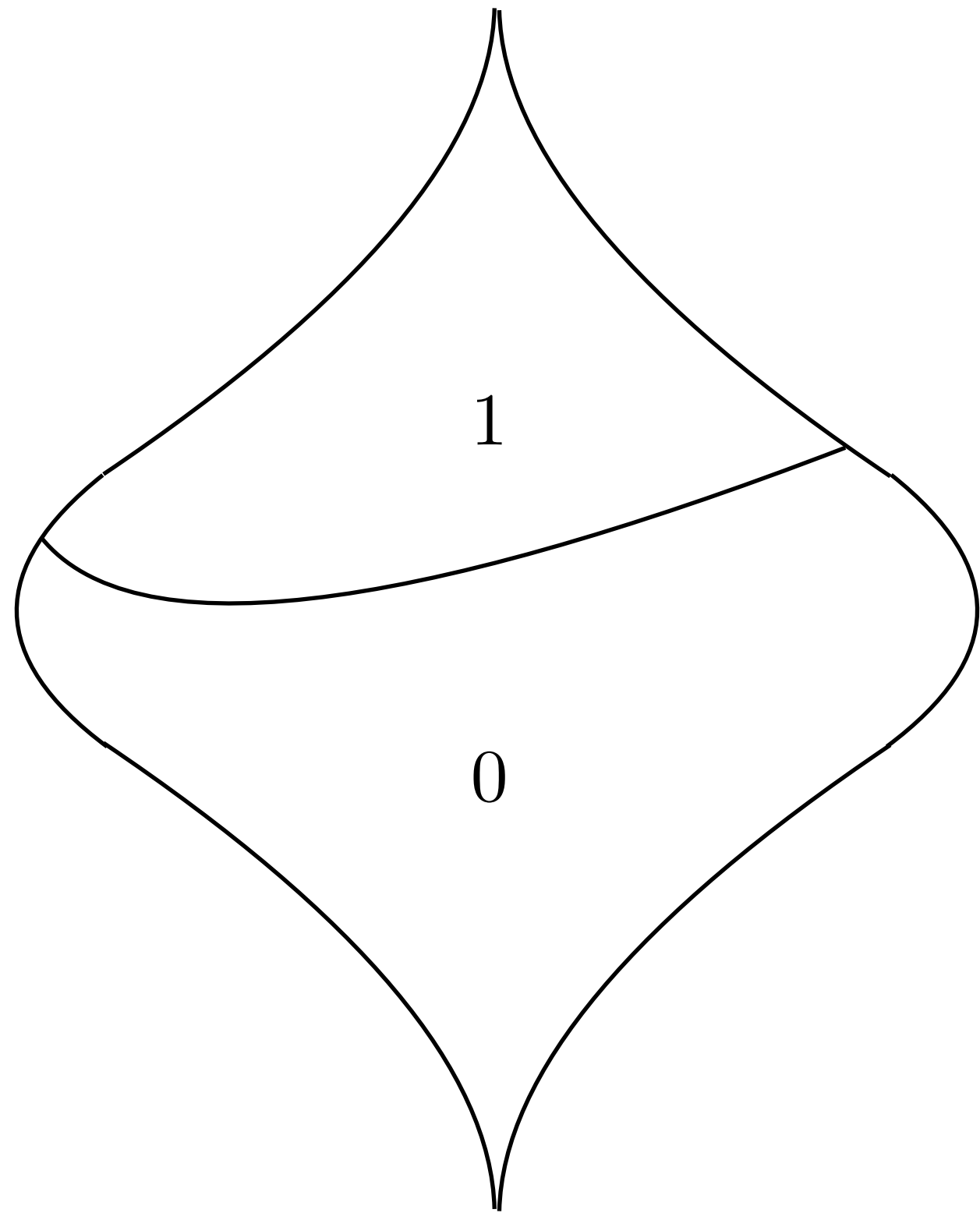
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# Quick Digest of Important Ideas

- Definition of approx. in property testing and why its necessary.
- Generic  $O(\log |\mathcal{P}|/\varepsilon)$ -query tester for any property via naive learning.
- Linearity testing definition:
  1. An algorithm via *learning* using  $n + O(1/\varepsilon)$  queries.
  2. Not all “local” definitions are equally good.
  3. Process getting to linear function (*self-correction*)
- Different Fourier-analytic proof [Bellare, Coppersmith, Håstad, Kiwi, Sudan '96] in O'Donnel's book on “Analysis of Boolean Functions”

# Is my function monotone? [Goldreich, Goldwasser, Lehman, Ron, Samorodnitsky '00]



**Definition:** a function  $f: \{0, 1\}^n \rightarrow \{0, 1\}$  is monotone iff

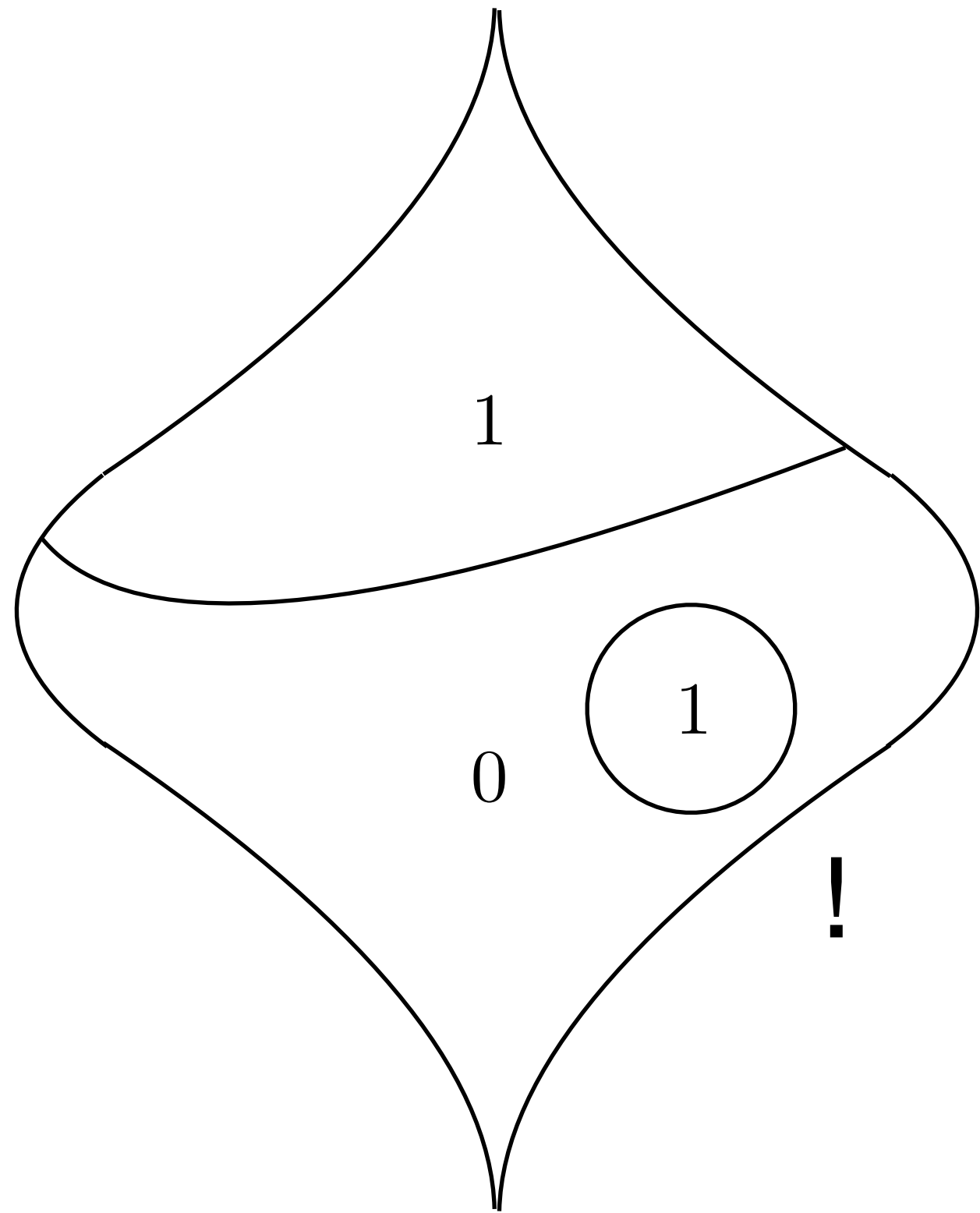
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for any  $x \preceq y$ .

Examples:  $f(x) = x_i$

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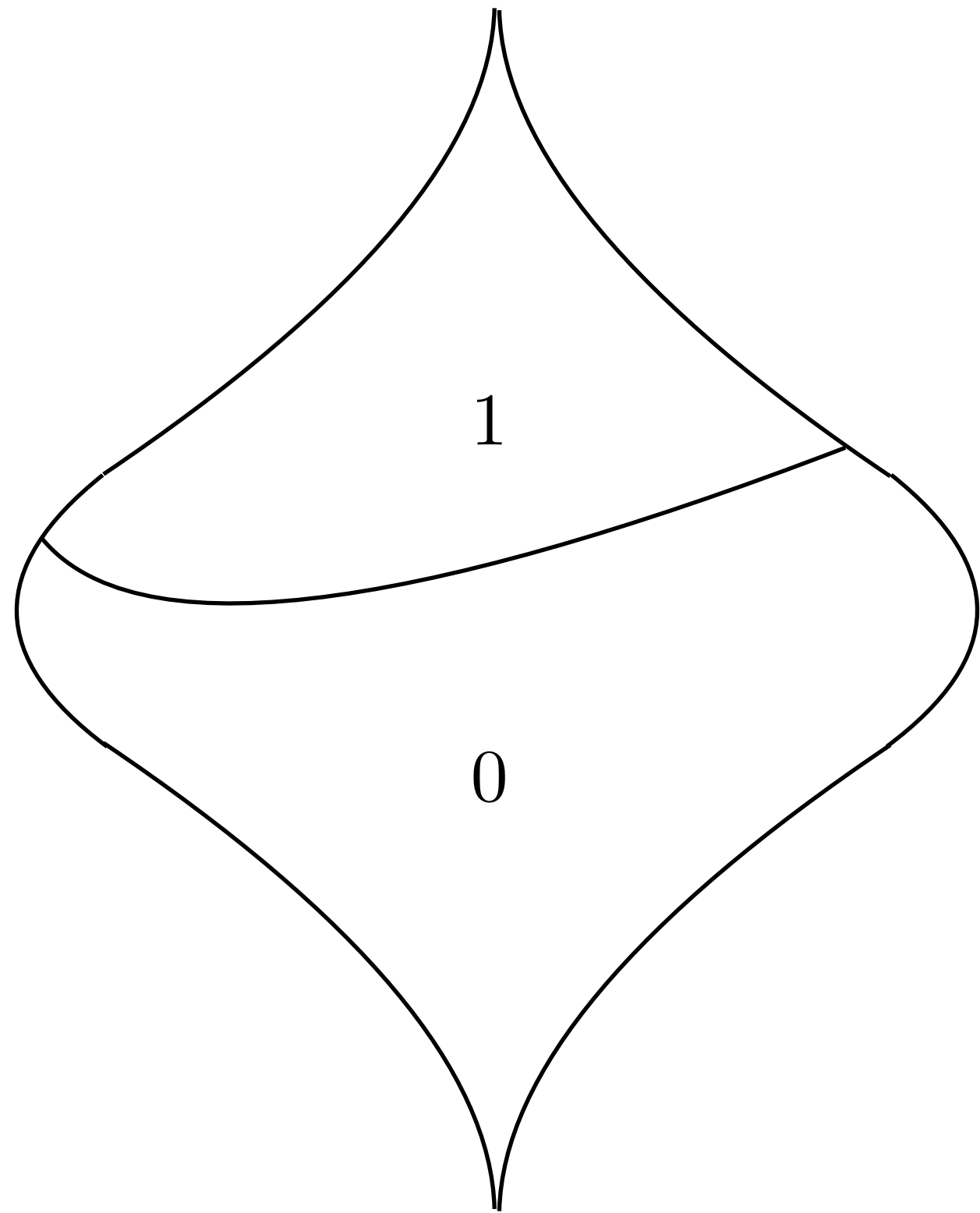
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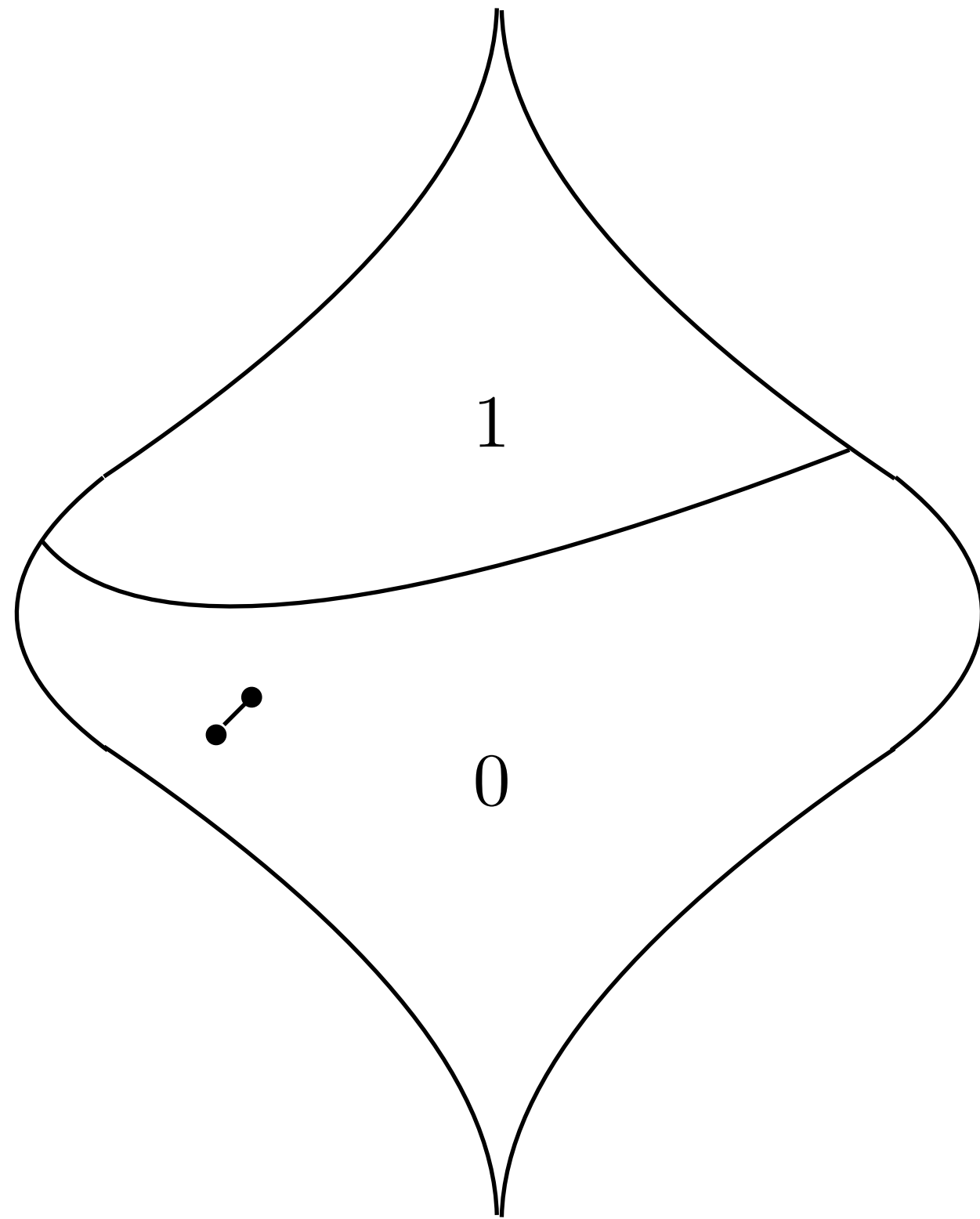
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**Generic:**  $O(\log |\mathcal{P}|/\varepsilon) = O\left(\binom{n}{n/2}/\varepsilon\right)$

**Examples:**  $f(x) = x_i$   
 $f(x) = \text{MAJ}(x)$

**Learning:**  $2^{\tilde{O}(\sqrt{n}/\varepsilon)}$  [Bshouty, Tamon '96]

# A different definition leads to the **Edge Tester**.



**Definition:** a function  $f: \{0, 1\}^n \rightarrow \{0, 1\}$  is monotone iff

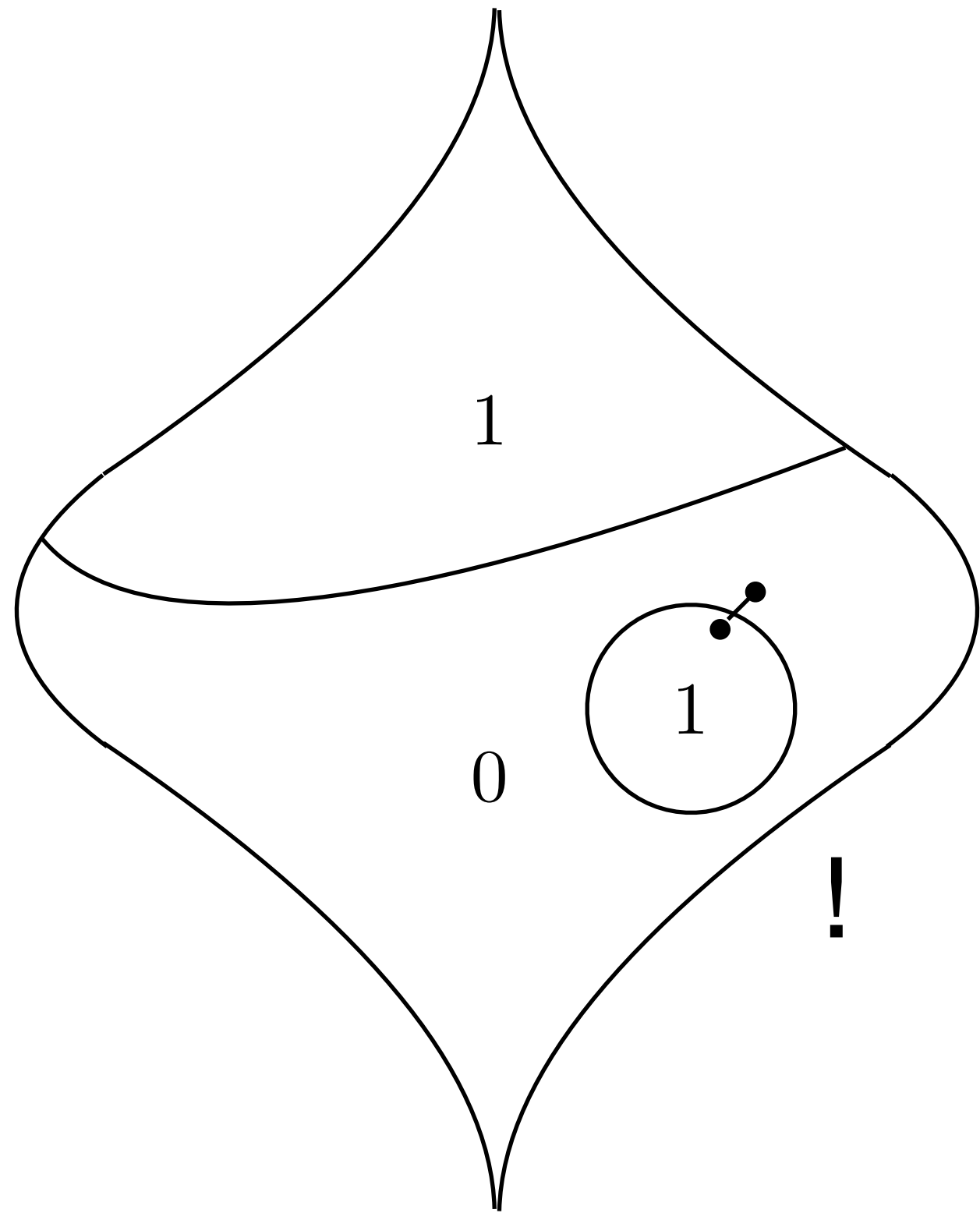
$$f(x^{(i \rightarrow 0)}) \leq f(x^{(i \rightarrow 1)})$$

for any  $x$  and  $i$ .

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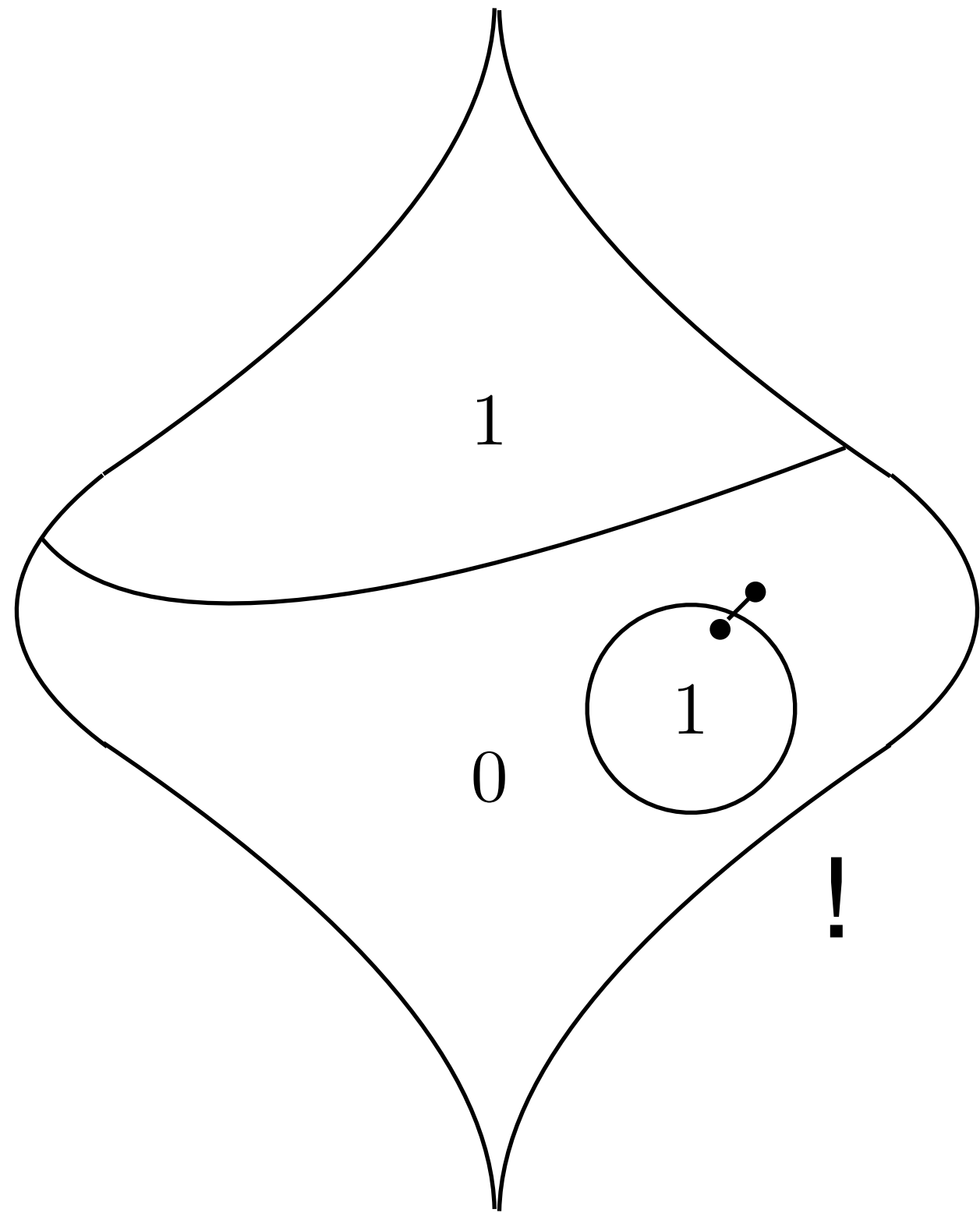
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**Theorem [GGLRS'00]:**  $O(n/\varepsilon)$  suffice.

[GGLRS'00] Far from monotone functions have a lot of “edge” evidence.

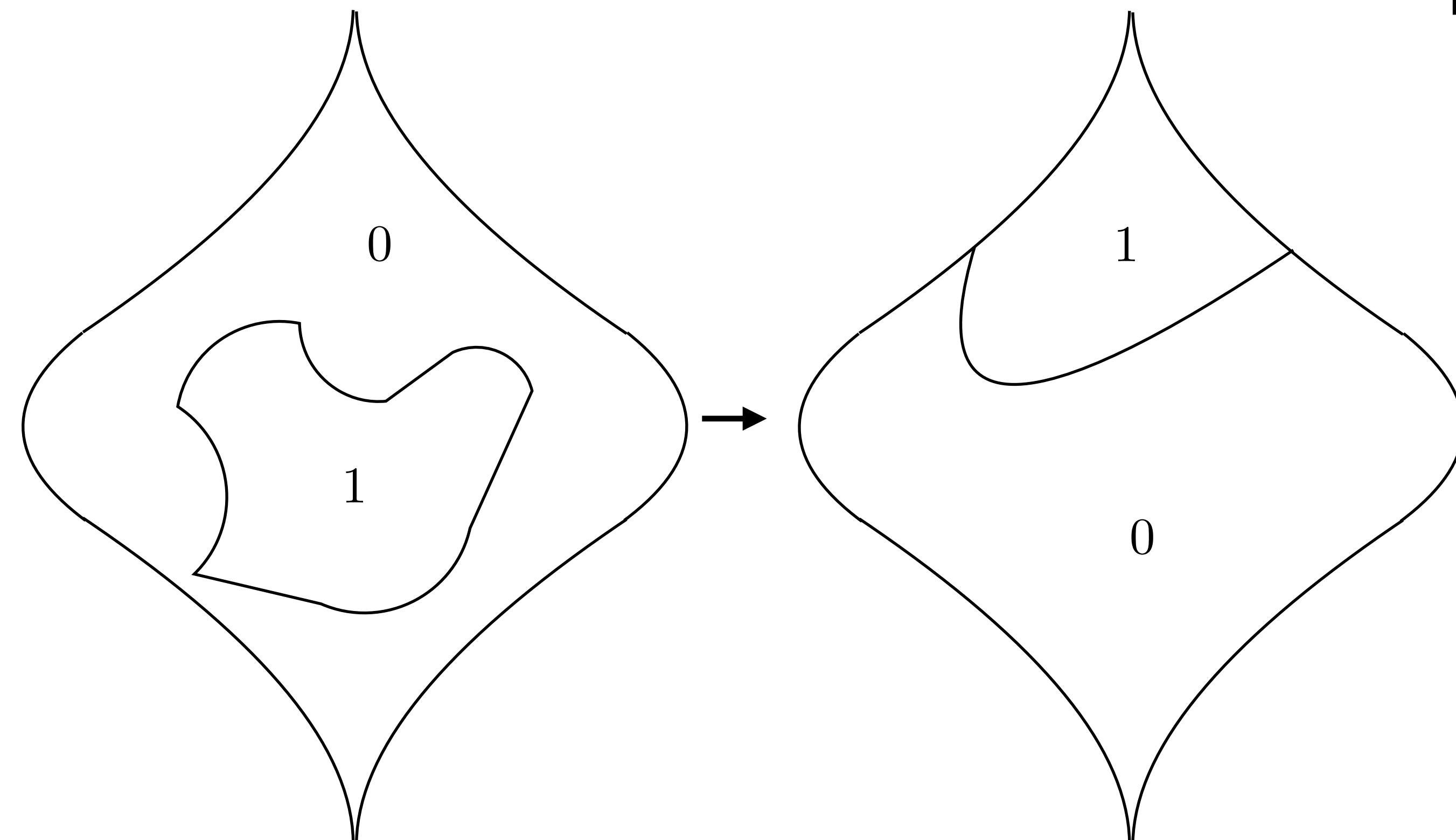
**Structural Theorem:**

If  $f$  is far from monotone, there is a lot of *structured evidence* of non-monotonicity.

**Transformed function:**

$$g(x) = S_1(S_2(S_3(\dots(S_n(f))\dots))(x)$$

is a monotone function, where changes from  $f$  came from non-monotone edges.



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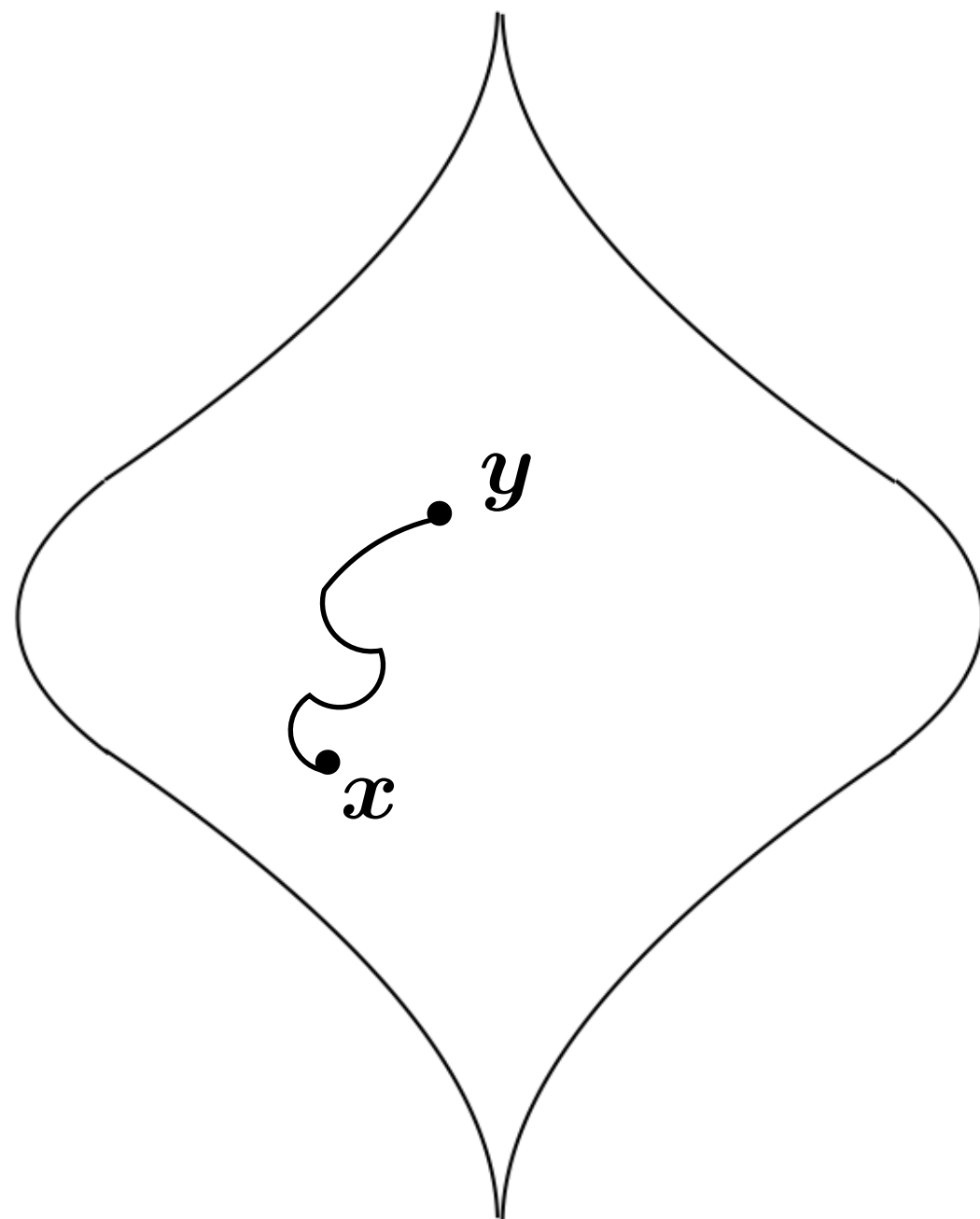


# A different **path** for monotonicity testing

[Chakrabarty, Seshadhri '13, Chen, Tan, Servedio '14, Khot, Minzer, Safra '15]

## Structural Theorem:

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## Path Tester

1. Sample  $(x, y) \sim \mathcal{D}$ .
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**Theorem [KMS'15]:**  $\tilde{O}(\sqrt{n}/\varepsilon^2)$  suffice.

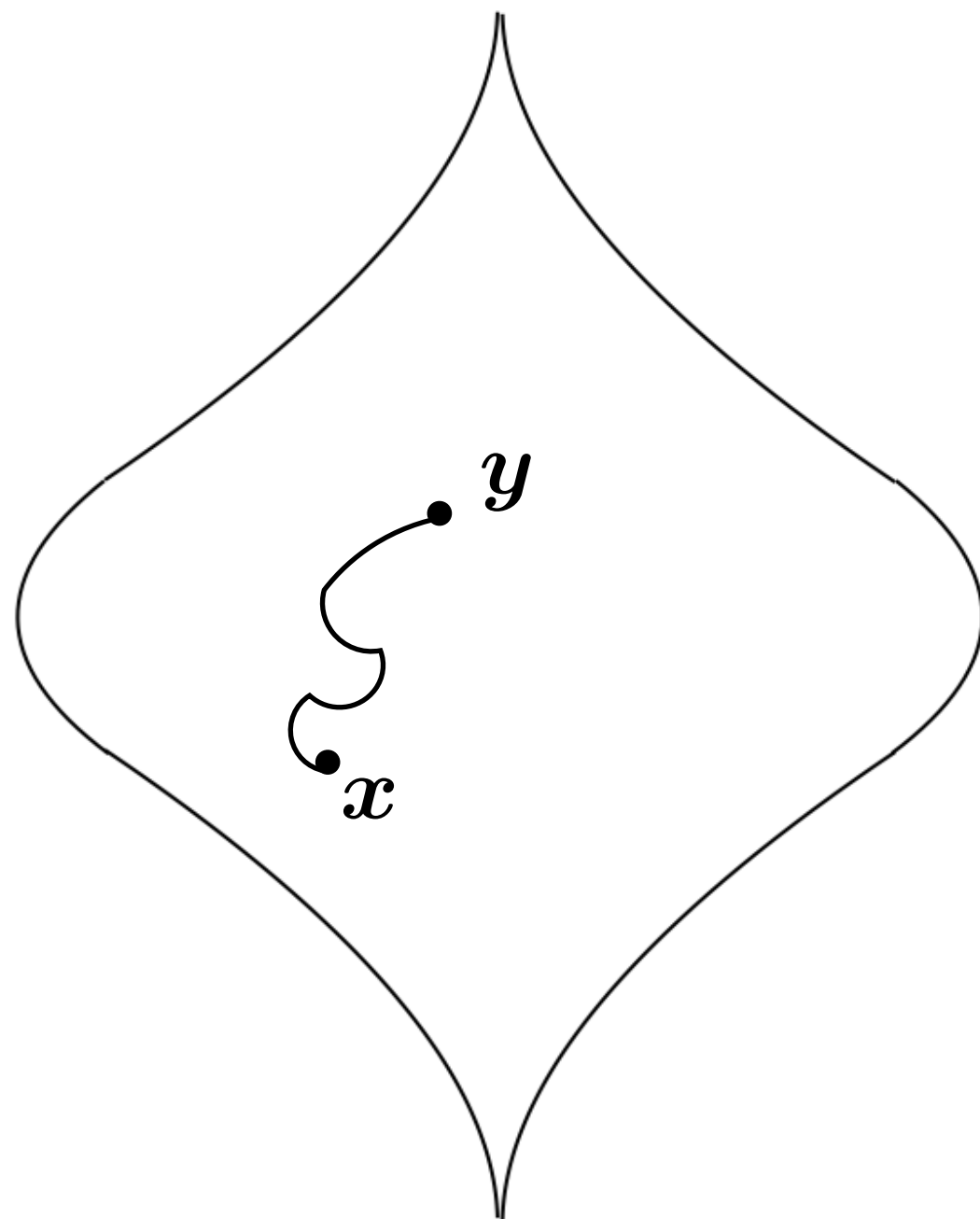
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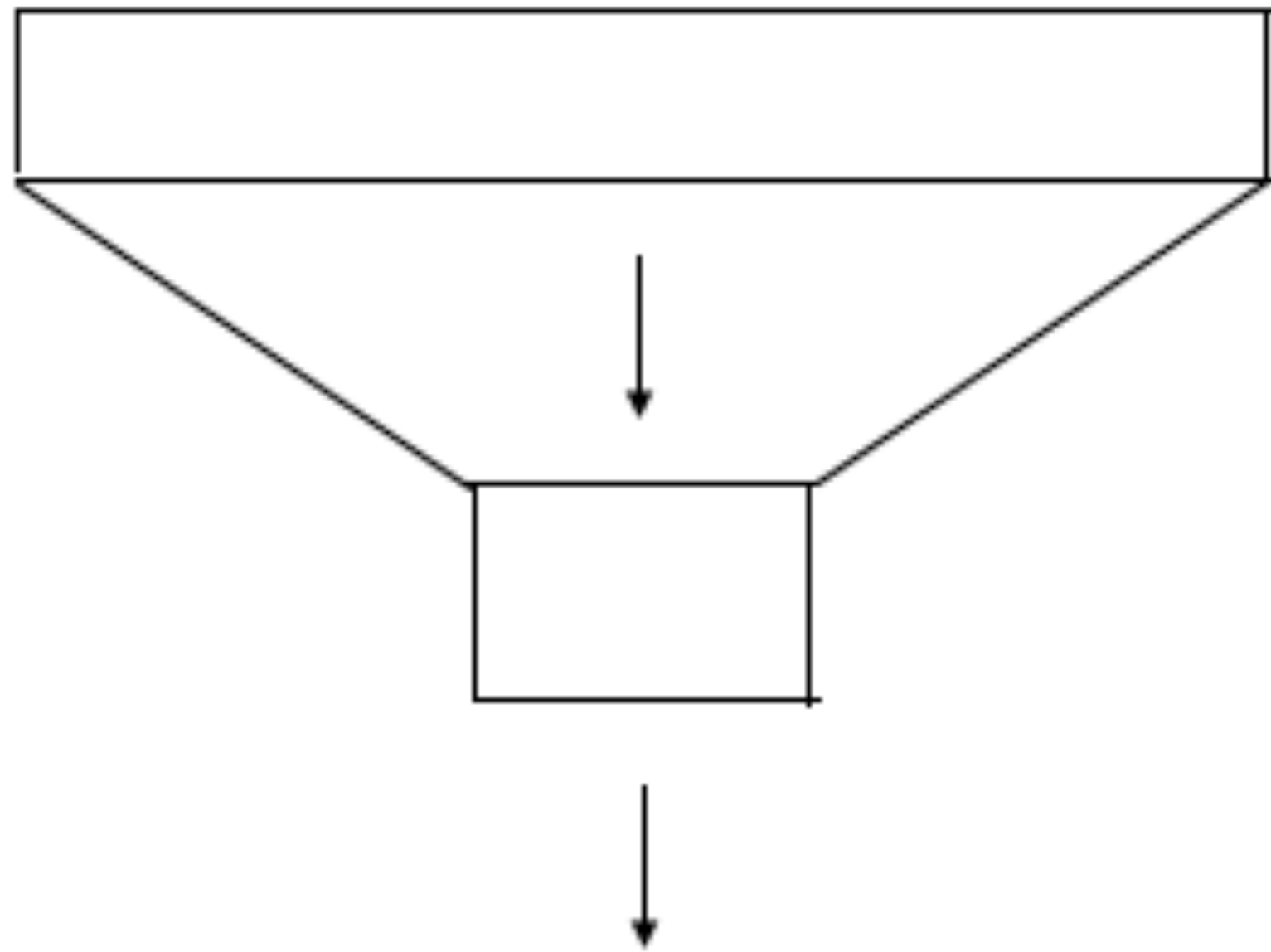
[Black, Chakrabarty, Seshadhri '23] for hypergrids

[Chen-W-Xie '18] query lower bounds

[Black, Kalemaj, Raskhodnikova '23, Pinto '24]

real-valued functions

# Is my function a junta? [Fischer, Kindler, Ron, Safra, Samorodnitsky '03]



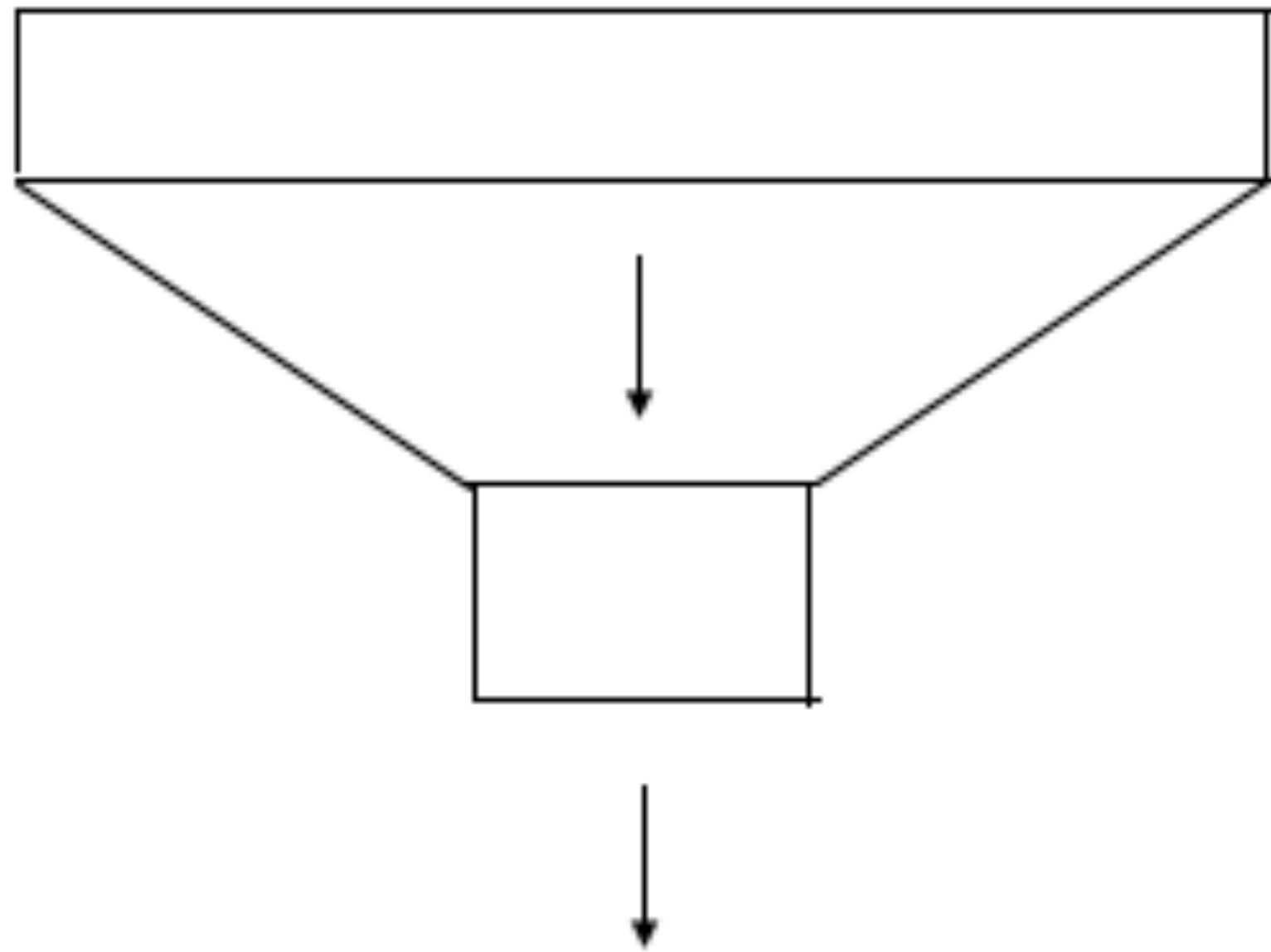
**Definition:** a function  $f: \{0, 1\}^n \rightarrow \{0, 1\}$  is a  $k$ -junta if there is a set  $S \subset [n]$  of size  $k$  such that

$$f(x) = g(x_S)$$

for some  $g: \{0, 1\}^k \rightarrow \{0, 1\}$ .

Examples:  $f(x) = x_i$  is a 1-junta.

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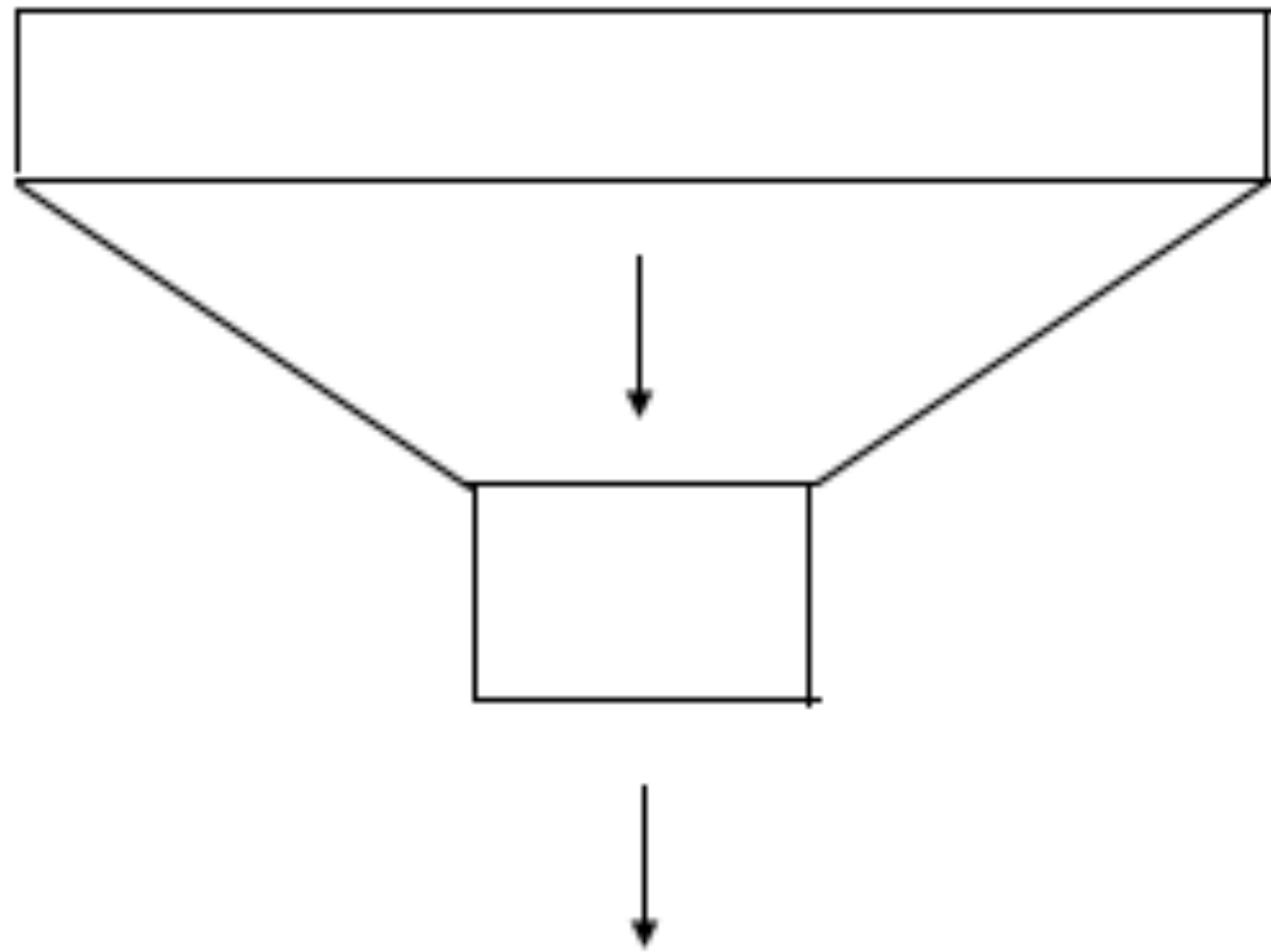
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By learning variables:

$$O(k \log n + k \log k/\epsilon)$$

**Theorem [Blais '10]:**  $O(k \log k + k/\epsilon)$

# Is my function almost a junta? (Tolerant testing)

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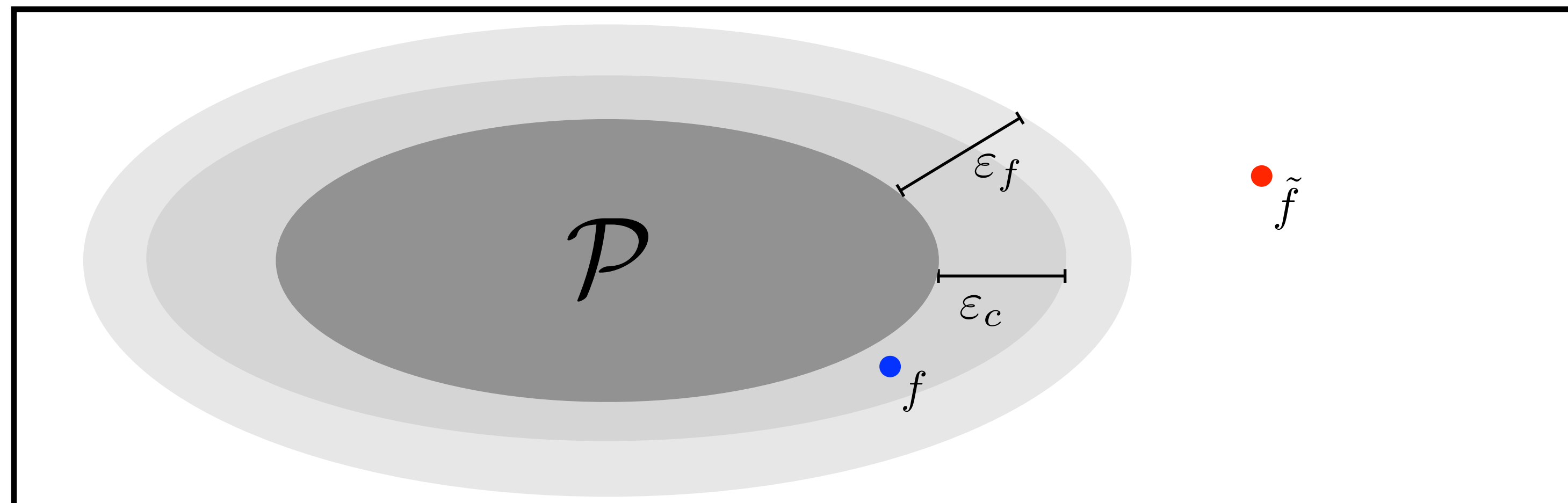
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$f$  output **YES** w.p 2/3

$\tilde{f}$  output **NO** w.p 2/3





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[Blais, Canonne, Eden, Levi, Ron '19]

[De, Mossel, Neeman '19]

[Iyer, Tal, Whitmeyer '21]

[Nadimpalli, Patel '24]

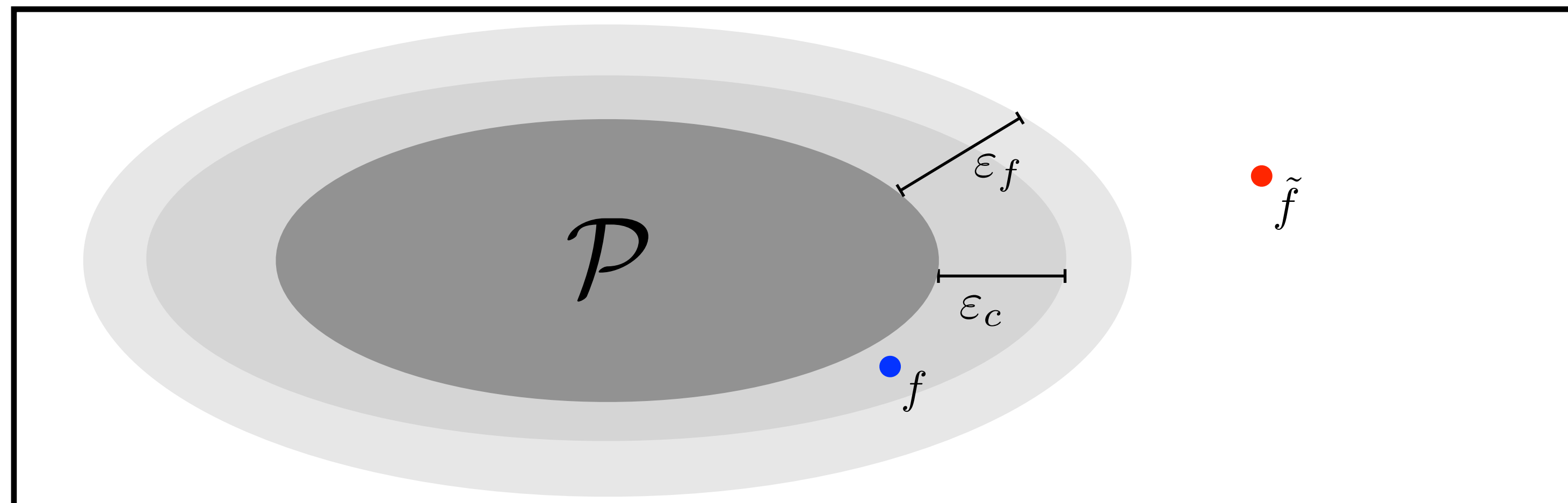
$$2^{\tilde{O}(\sqrt{k \log(1/(\varepsilon_f - \varepsilon_c))})}$$

*near-optimal for non-adaptive algorithms.*



$f$  output **YES** w.p 2/3

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# Is my function a junta, w.r.t this distribution? (Distribution-free)

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[Chen, Liu, Servedio, Sheng, Xie '18]  
[Bshouty '19]

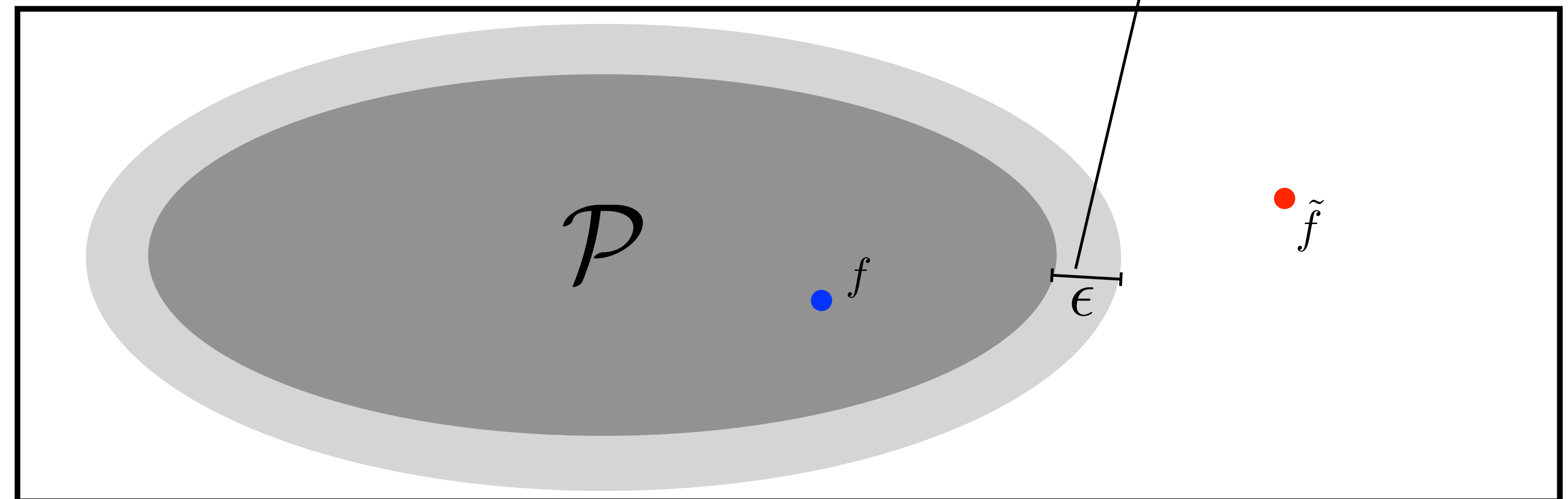
$$\tilde{O}(k/\epsilon)$$

$$d(f, g) = \Pr_{x \sim \mathcal{D}} [f(x) \neq g(x)]$$



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$\tilde{f}$  output NO w.p 2/3



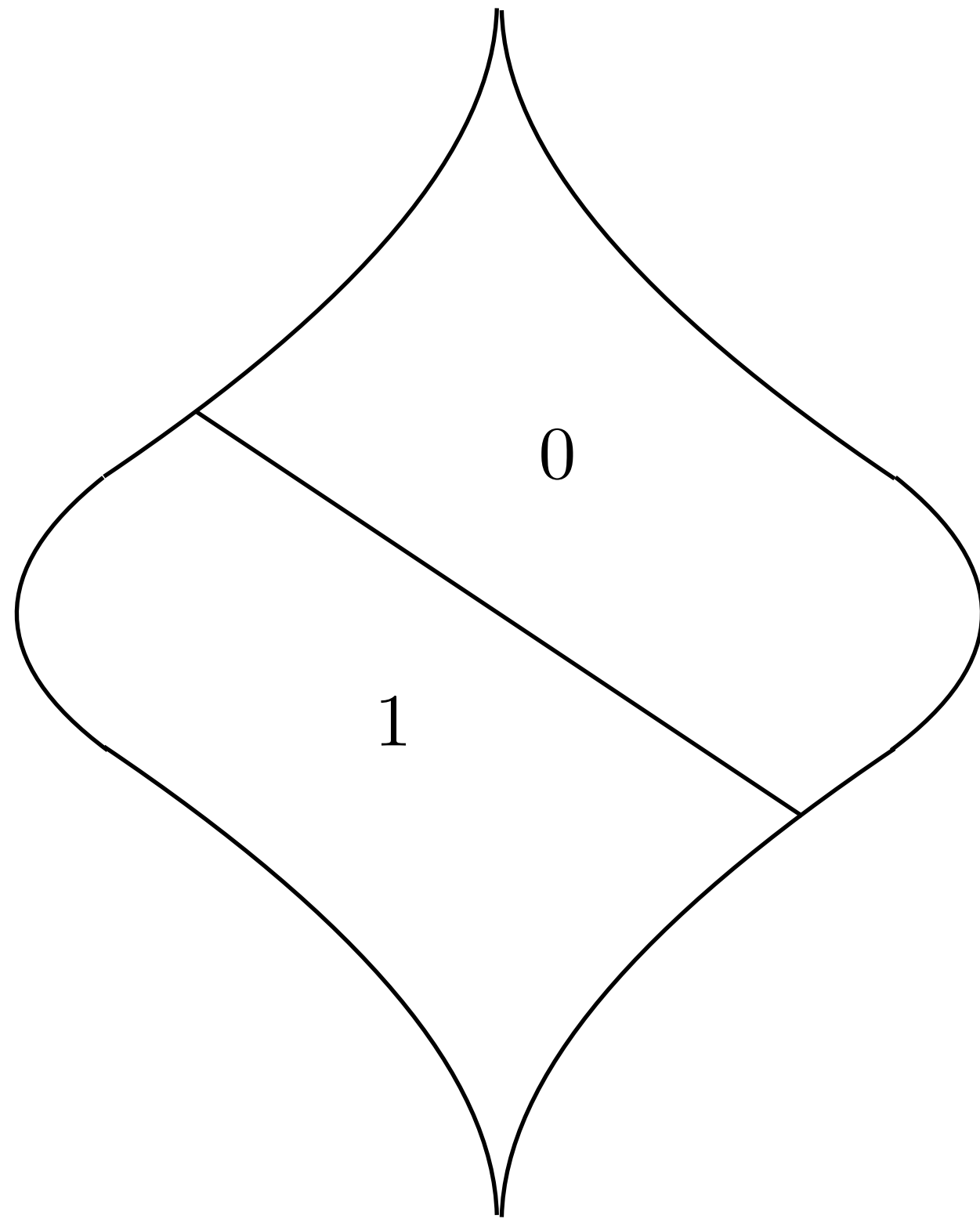


# Thanks

Reference: “Introduction to Property Testing” by Goldreich ‘17

“Algorithmic and Analysis Techniques in Property Testing” by Ron ‘10

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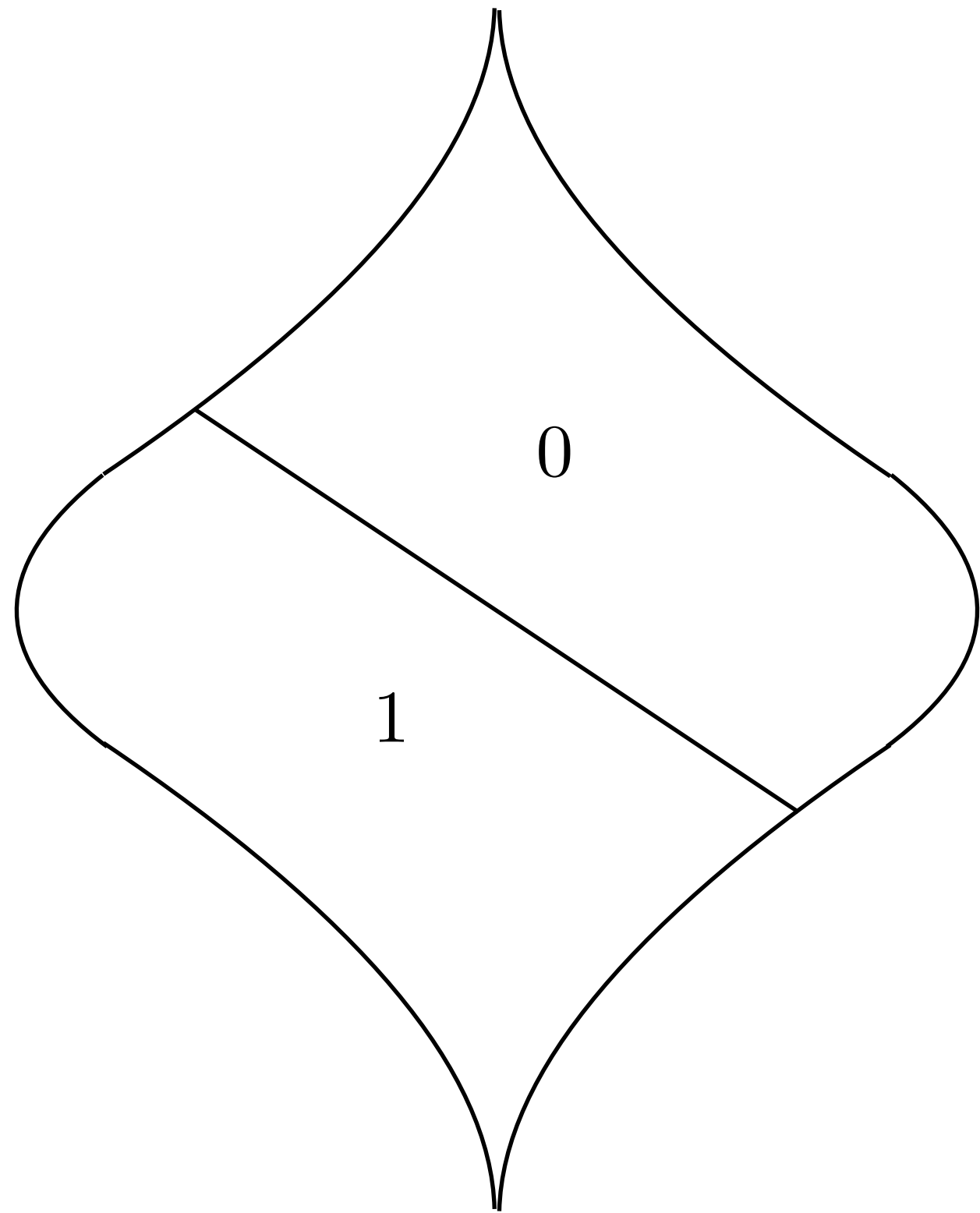
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