# Testing and Learning Convex Sets in the Ternary Hypercube

ITCS 24





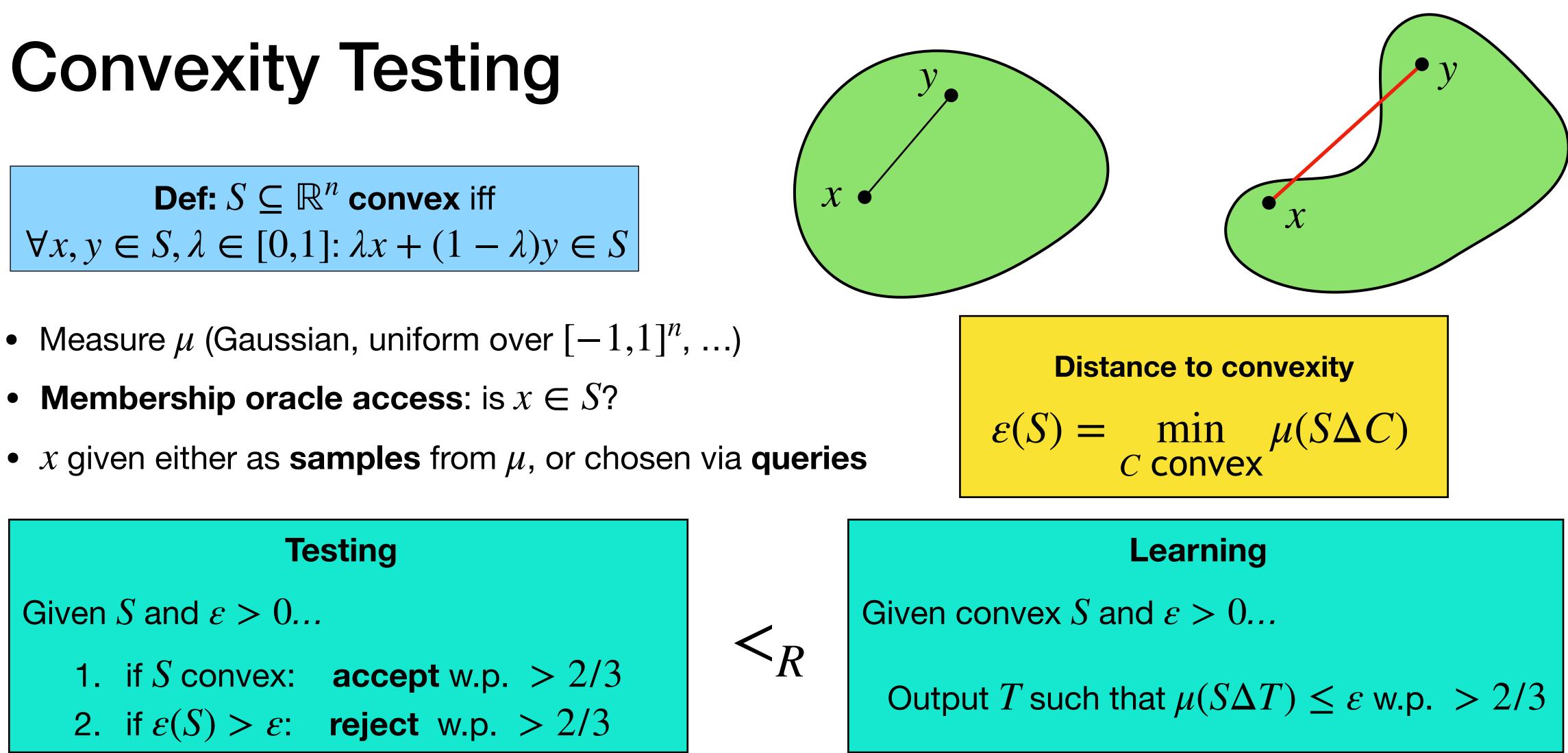
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**Def:**  $S \subseteq \mathbb{R}^n$  **convex** iff



How hard is it to test convexity with queries in n dimensions?

## Question

# Prior Work on Convexity Testing

- Klivans-O'Donnell-Servedio [08]:  $2^{\widetilde{O}(n^{1/2})}$  for **learning** with **samples** under Gaussian
- Chen-Freilich-Servedio-Sun [17]:  $2^{\Theta(n^{1/2})}$  for **testing** with **samples** under Gaussian
- Schmeltz [92], Raskhodnikova [03], Berman-Murzabulatov-Raskhodnikova [19],[19],[22]: Testing and learning over  $[m]^2$  and  $[0,1]^2$

## What about queries in high dimensions?

Rademacher-Vempala [04], Blais-Bommireddi [20]: testers that spot check for violations require  $2^{\Omega(n)}$  queries 

Query-based high-dimensional convexity testing is a wide open problem

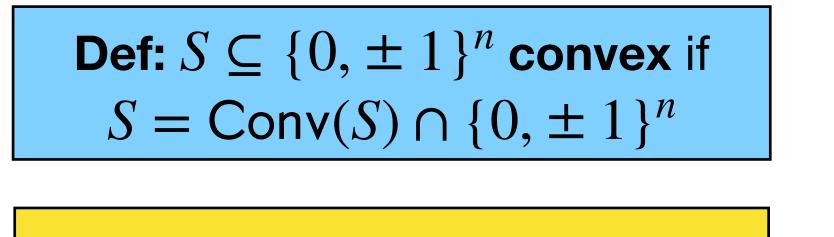
### ???



# The Ternary Hypercube

Black-Blais-Harms **[ITCS 24]** 

• We consider sets in the **ternary hypercube**  $\{-1,0,1\}^n$ 

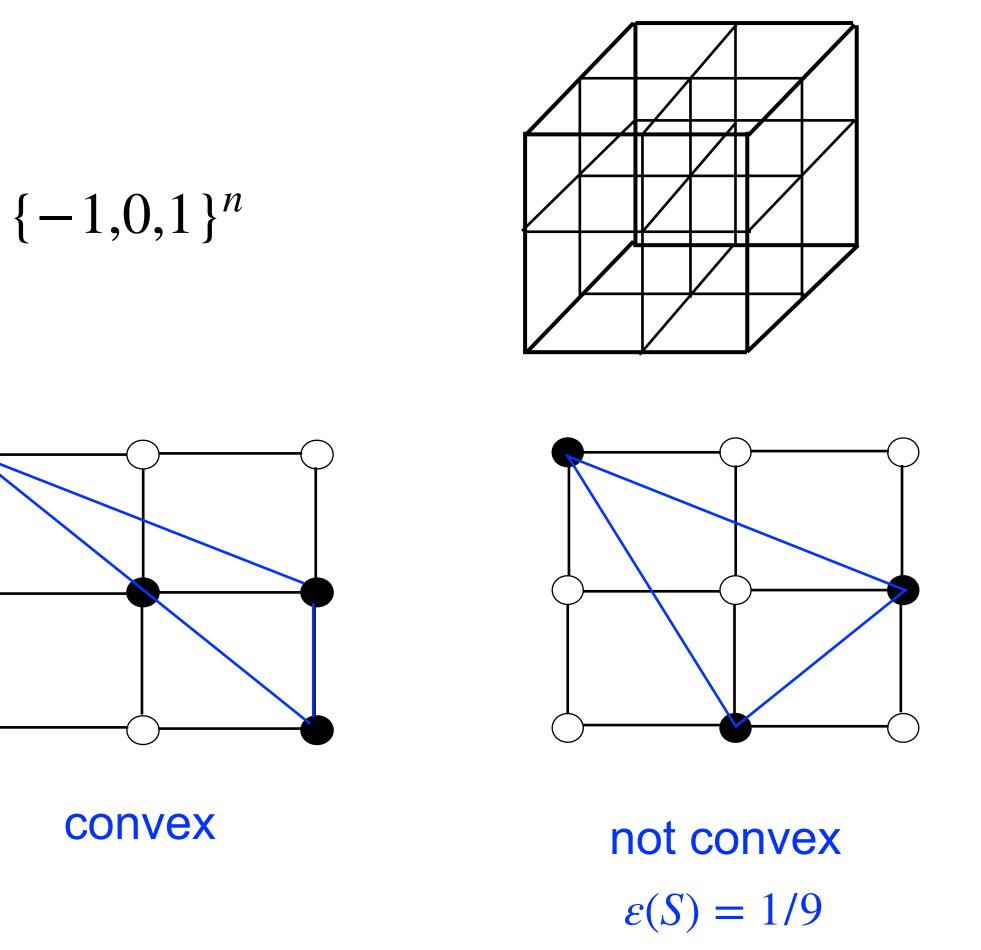


**Distance to convexity** 

$$\varepsilon(S) = \min_{C \text{ convex}} 3^{-n} |S\Delta C|$$

### Why the ternary cube?

• 
$$Z \approx \frac{1}{\sqrt{k}} \sum_{i=1}^{k} X_i$$
 where  $Z \sim \mathcal{N}(0,1)$  and  $X_i \sim$ 



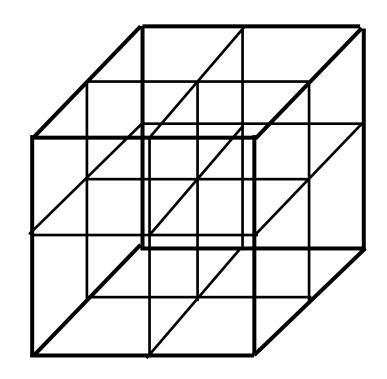
• simplest high-dimensional domain where convexity is a non-trivial property (all sets in  $\{\pm 1\}^n$  are convex)

 $unif(\{-1,0,1\})$ 



# **Our Results**

Black-Blais-Harms [ITCS 24]



**Computational**:



Learning and testing with samples:  $2^{\widetilde{O}(n^{3/4})}$ 

Learning and testing with samples:  $2^{\Omega(n^{1/2})}$ 

Structural:



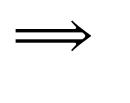
All convex sets satisfy  $I(S) \leq O(n^{3/4})$ 

There exists a convex set with  $I(S) \ge \Omega(n^{3/4})$ 

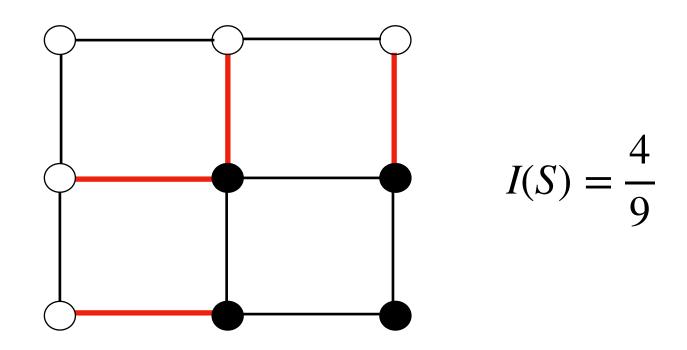


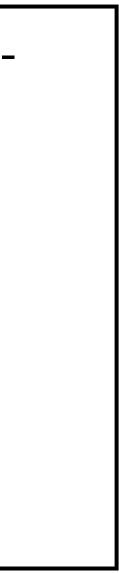
 Uses the "Low-Degree Algorithm" of Linial-Mansour-Nisan 93

$$I(S) \le B \implies \sum_{T: |T| > B/\varepsilon} \widehat{S}(T)^2 \le \varepsilon$$



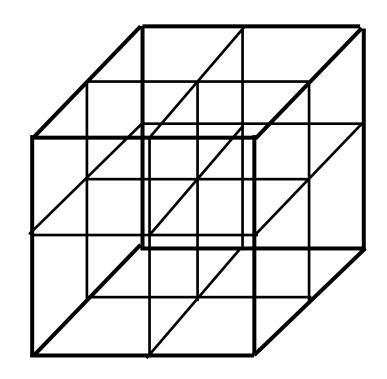
Can learn *S* to error  $\varepsilon$  with poly( $n^B$ , 1/ $\varepsilon$ ) samples





# **Our Results**

Black-Blais-Harms [ITCS 24]



**Computational**:



Learning and testing with samples:  $2^{\widetilde{O}(n^{3/4})}$ 

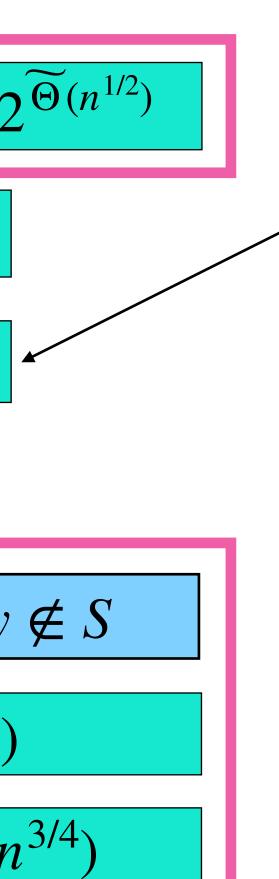
Learning and testing with samples:  $2^{\Omega(n^{1/2})}$ 

Structural:



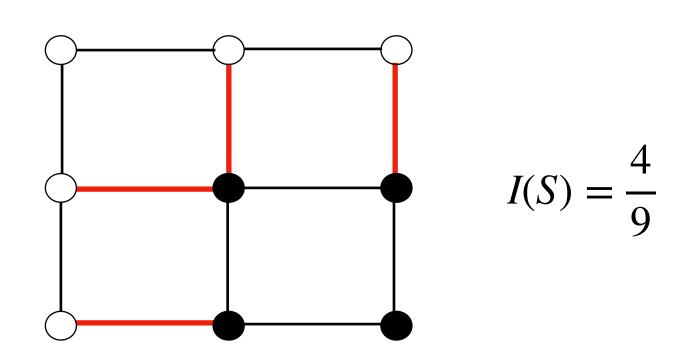
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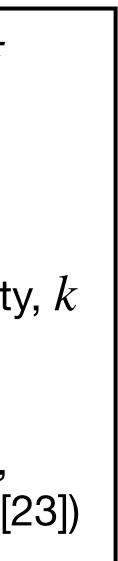
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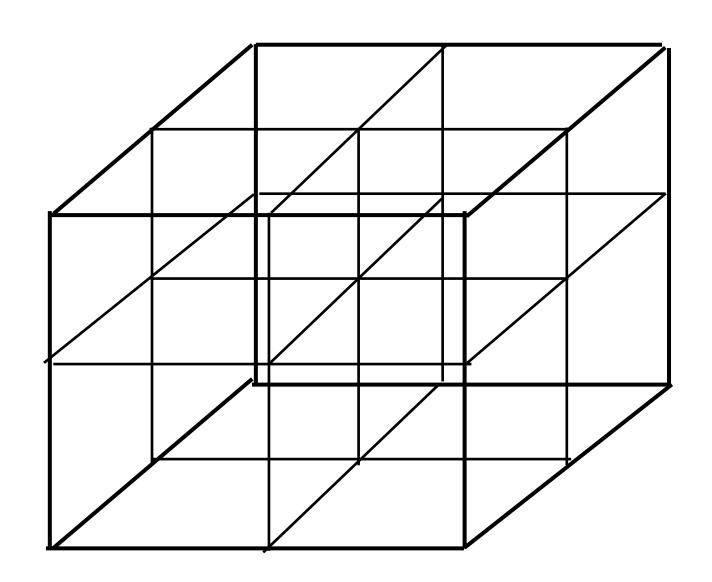
- Uses a version of Talagrand's random DNF (Talagrand [96]) adapted to  $\{0, \pm 1\}^n$
- Talagrand's random DNF has been used to prove lower bounds for testing monotonicity, k -monotonicity, and unateness in {±1}<sup>n</sup>

(Belovs-Blais [16], Chen-Waingarten-Xie [17], Chen-De-Li-Nadimpalli-Servedio [23], Black [23])





# The Influence of Convex Sets

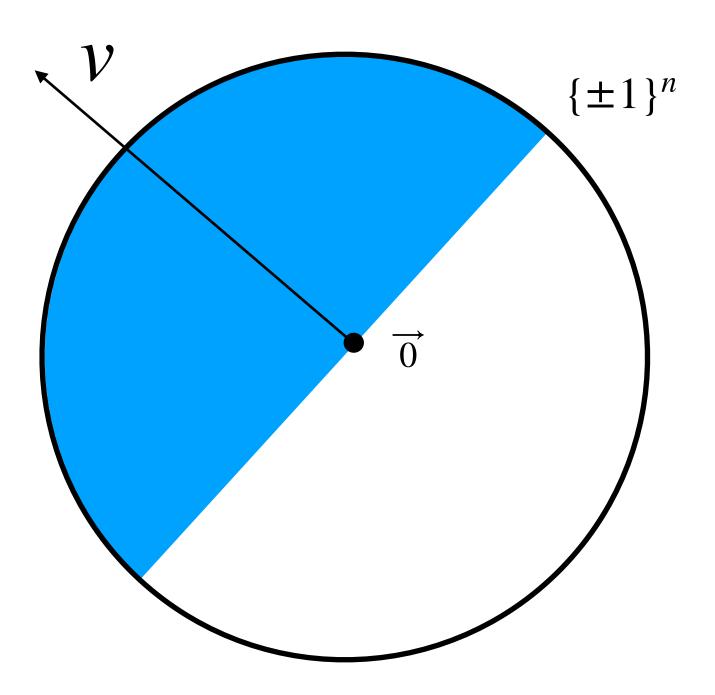


The maximum influence of convex sets in  $\{0, \pm 1\}^n$  is  $\widetilde{\Theta}(n^{3/4})$ 





## Halfspace $H = \{x \colon \langle x, \overrightarrow{1} \rangle \ge 0\}$



**Def:**  $I(S) = 3^{-n} \cdot \#$  edges  $(x, y) : x \in S, y \notin S$ 

 $= \mathbb{E}_{x}[\# edges (x, y) \colon x \in S, y \notin S]$ 

$$I(H) \approx \mathbb{P}_{x}[\langle x, \overrightarrow{1} \rangle = 0] \cdot \Theta(n)$$

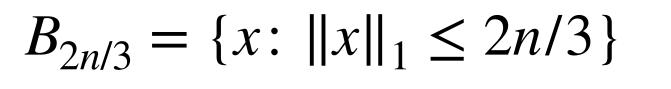
$$\approx \mathbb{P}_x \left[ \sum_i x_i = 0 \right] \cdot \Theta(n)$$

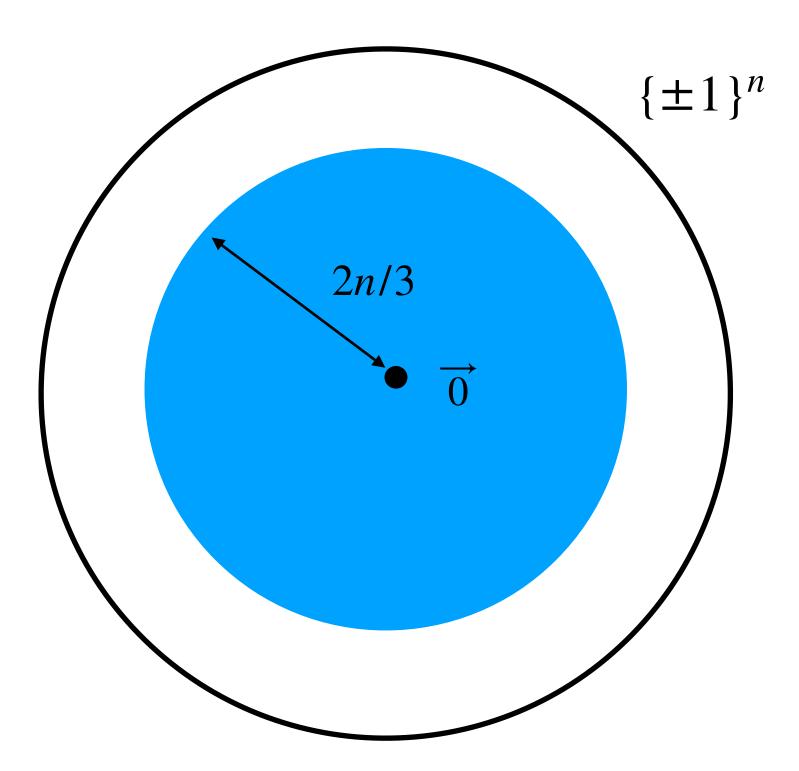
 $\approx \Theta(n^{1/2})$ 

## Examples









**Def:**  $I(S) = 3^{-n} \cdot \#$  edges  $(x, y) : x \in S, y \notin S$ 

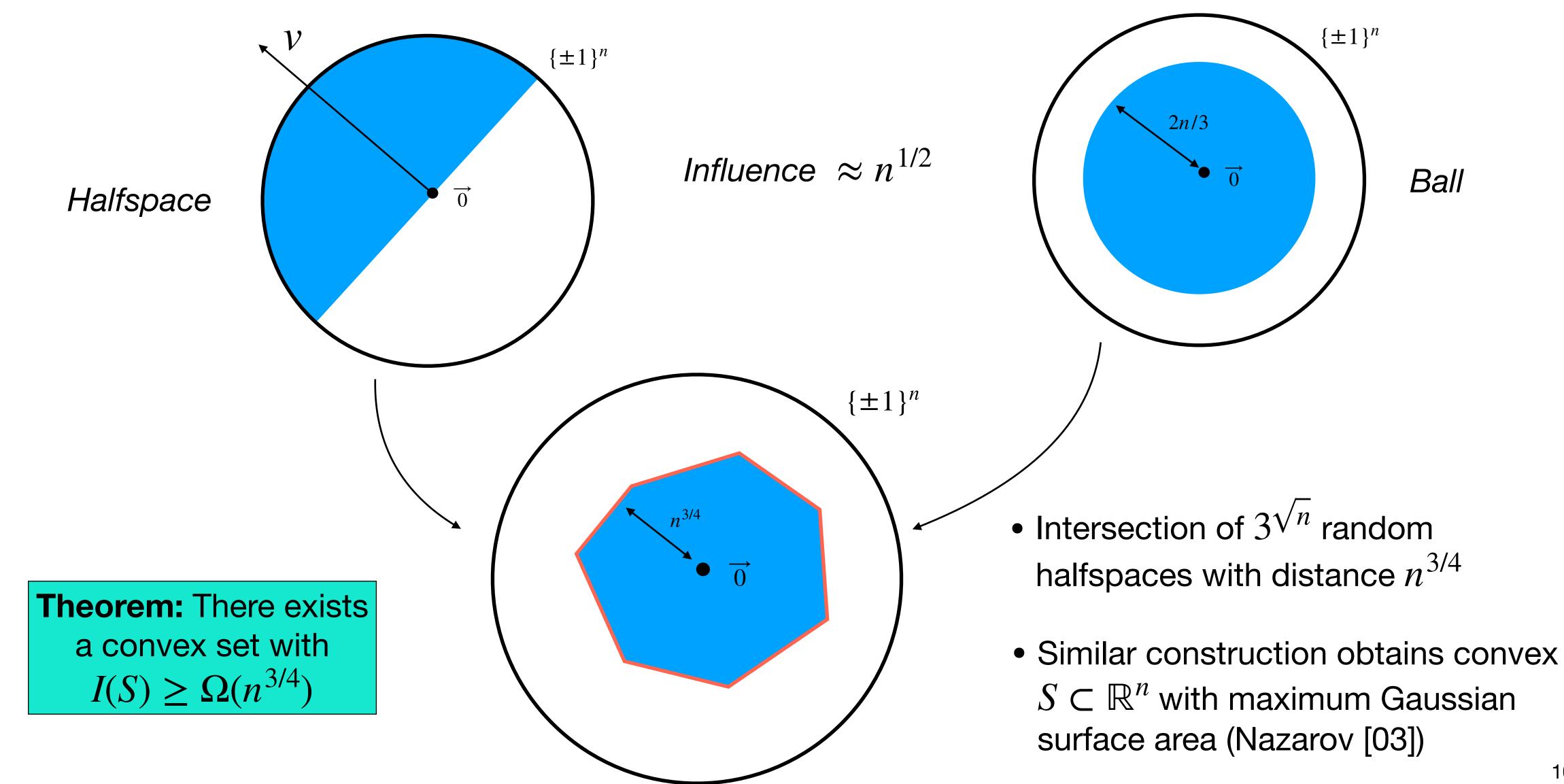
 $= \mathbb{E}_{x}[\# edges (x, y) \colon x \in S, y \notin S]$ 

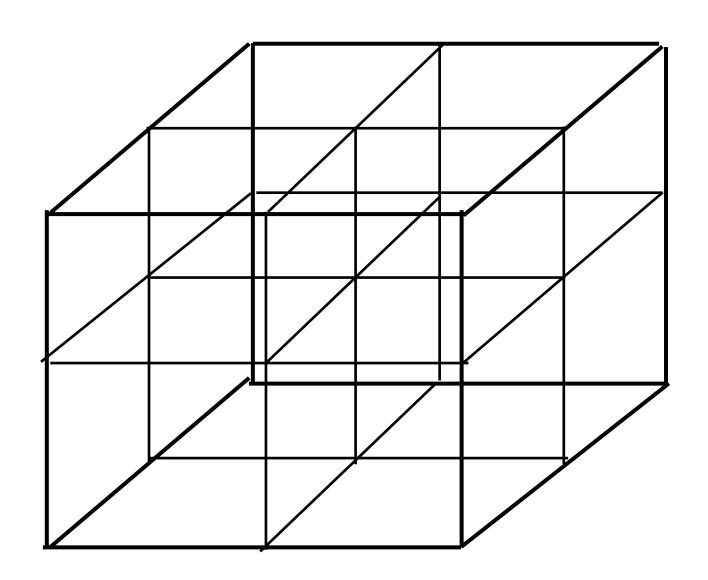
$$I(B_{2n/3}) = \mathbb{P}_{x}[\|x\|_{1} = 2n/3] \cdot 2n/3$$

$$=\frac{1}{3^n}\binom{n}{2n/3}\cdot 2^{2n/3}\cdot\Theta(n)$$

 $\approx \Theta(n^{1/2})$ 

# High Influence Set





# **Proof Sketch**

All convex sets satisfy  $I(S) \le O(n^{3/4})$ 

# The Edge-Boundary of Convex Sets

**Def:**  $I(S) = 3^{-n} \cdot \# \text{ edges } (x, y) : S(x) \neq S(y)$   $\approx n \cdot \mathbb{P}_{(x,y)}[S(x) \neq S(y)]$ 

### **Distribution** *D* **over edges**:

- Perform a **directed** random walk of length  $m \approx \sqrt{n/\log n}$  in the middle  $\sqrt{n\log n}$  layers
- Return a random edge (x, y) from the walk

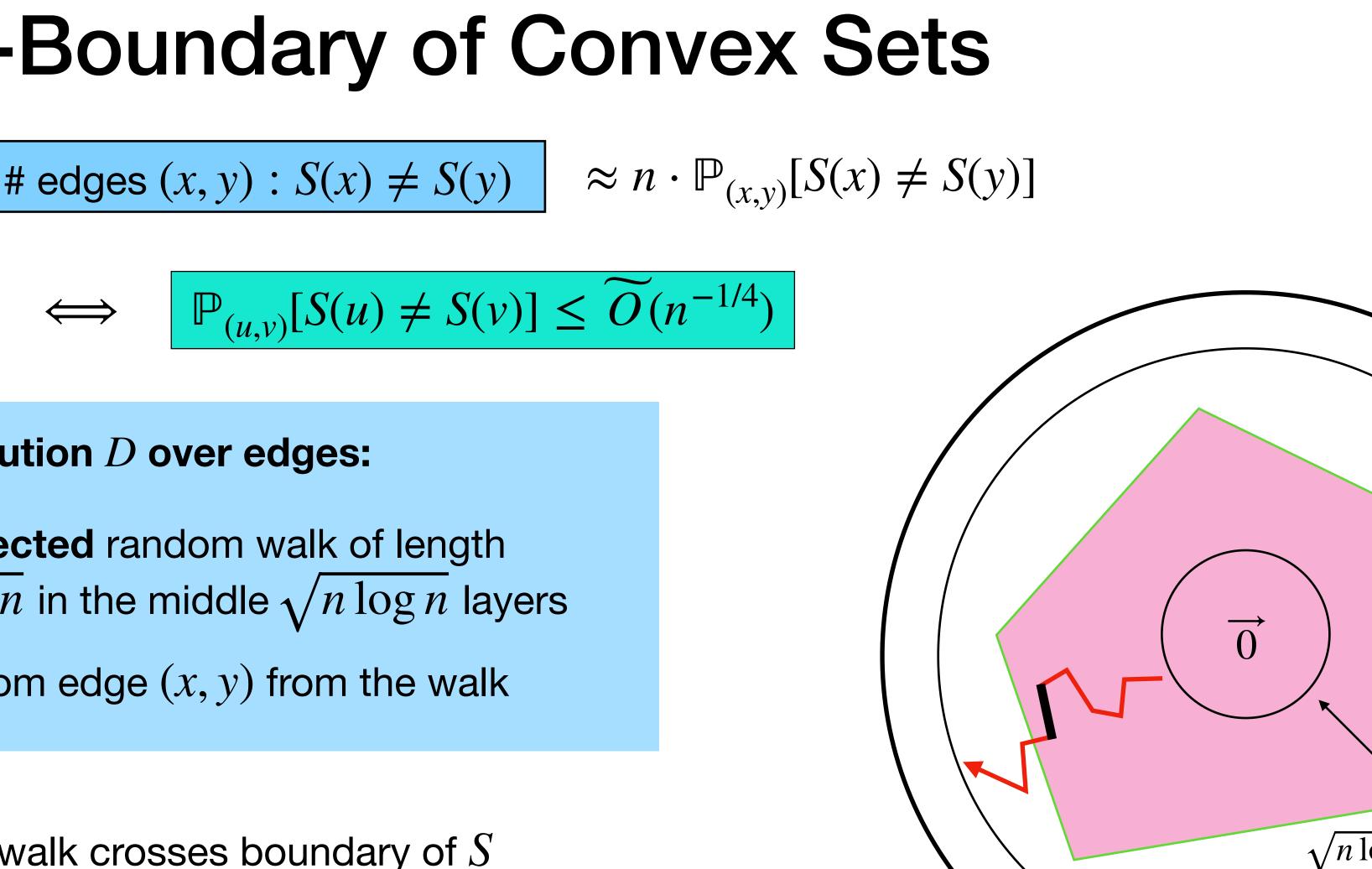
Let C = # times walk crosses boundary of S

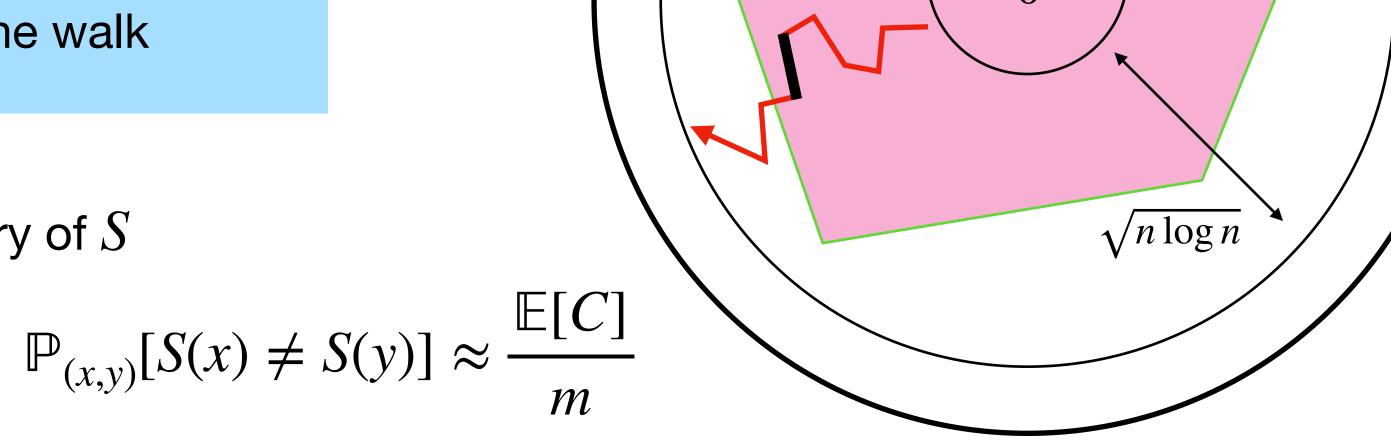
**1)** D is "close" to uniform  $\implies$ 

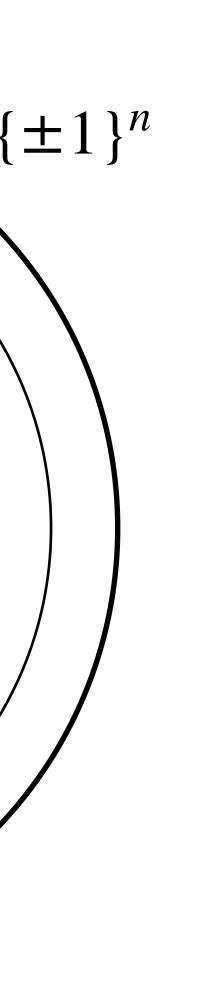
**2)**  $\mathbb{E}[C] \leq O(\sqrt{m})$ 

 $I(S) \leq \widetilde{O}(n^{3/4})$ 









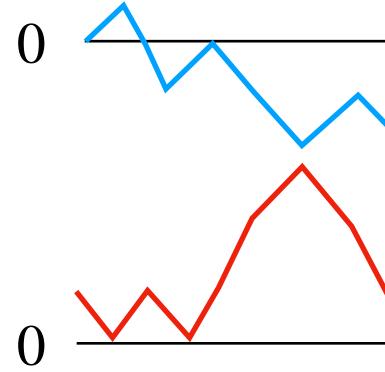
# Halfspaces and 1-D Walks

Lemma:  $\mathbb{E}[C] \leq O(\sqrt{m})$ 

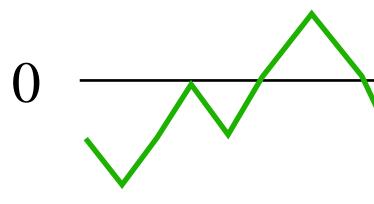
 $S \text{ convex} \implies S = \bigcap^{k} H_i$  where  $H_i = \{x \colon \langle x, v_i \rangle < \tau_i\}$ i=1

 $w_1(t) = \langle z^{(t)}, v_1 \rangle - \tau_1$ 

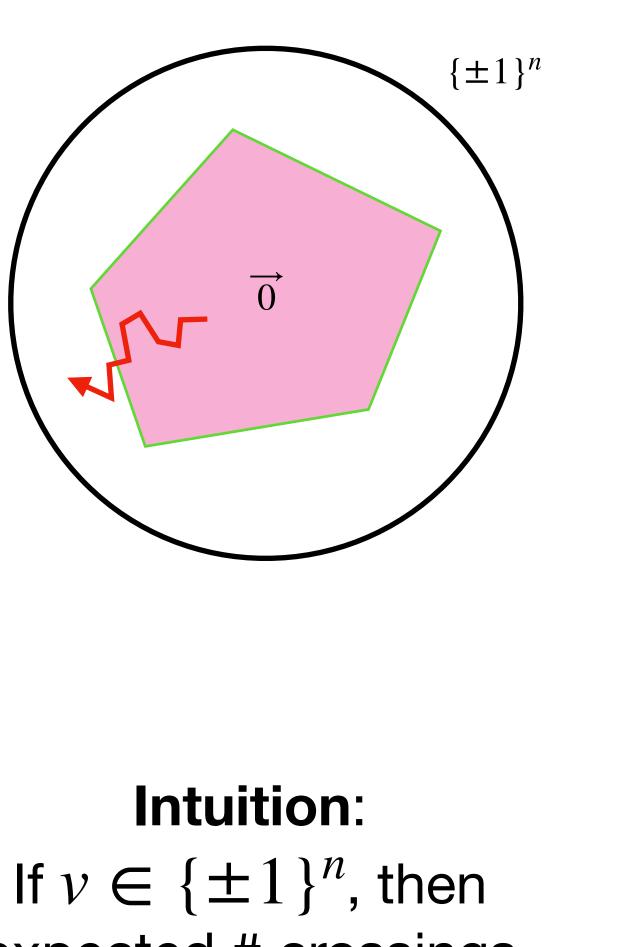
 $w_2(t) = \langle z^{(t)}, v_2 \rangle - \tau_2$ 



$$w_k(t) = \langle z^{(t)}, v_k \rangle - \tau_k$$



т  $\mathcal{M}$ M



expected # crossings for a single walk is

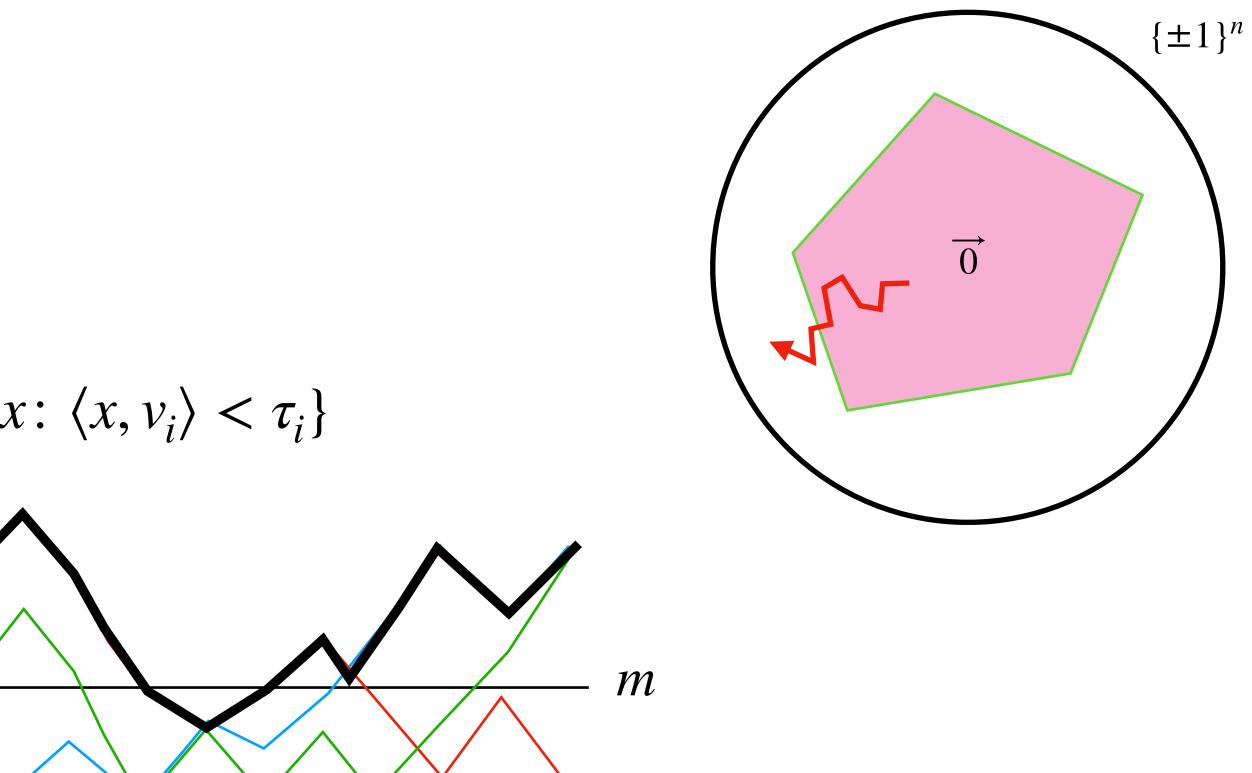
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**The Max-Walk**  
Lemma: 
$$\mathbb{E}[C] \le O(\sqrt{m})$$
  
 $S \text{ convex} \implies S = \bigcap_{i=1}^{k} H_i \quad \text{where } H_i = \{x, y_i\} = \{x_i\}$   
 $W(t) = \max_{i \in [k]} \langle z^{(t)}, v_i \rangle - \tau_i = 0$ 

C = # times max walk crosses the origin

### **Challenges:**

- $v_i$ 's can be arbitrary vectors in  $\mathbb{R}^n$
- Analyzing max-walk for arbitrary real vectors is tricky

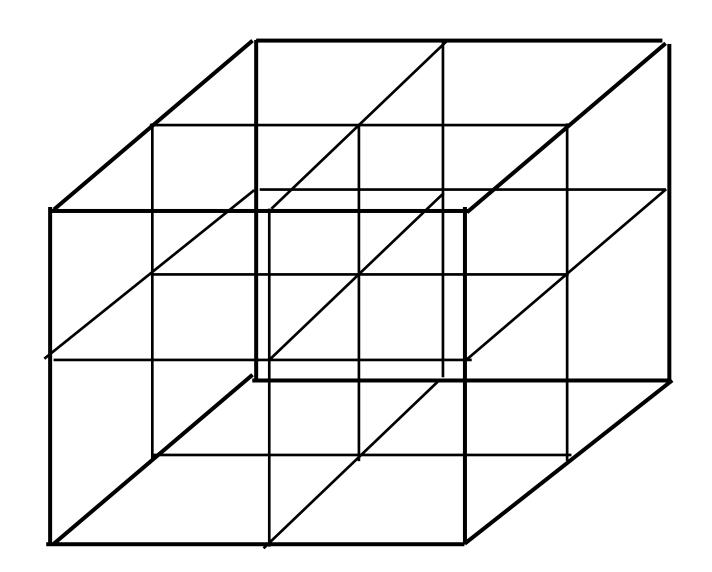


Key tool: Sparre Andersen's fluctuation theorem [Sparre '54]



# **Testing with Queries**

# 1-sided non-adaptive **query**-based testing: $2^{\widetilde{\Theta}(n^{1/2})}$



# **Testing with Queries**

Given *S* and  $\varepsilon > 0...$ 2. if  $\varepsilon(S) > \varepsilon$ : reject w.p. > 2/3

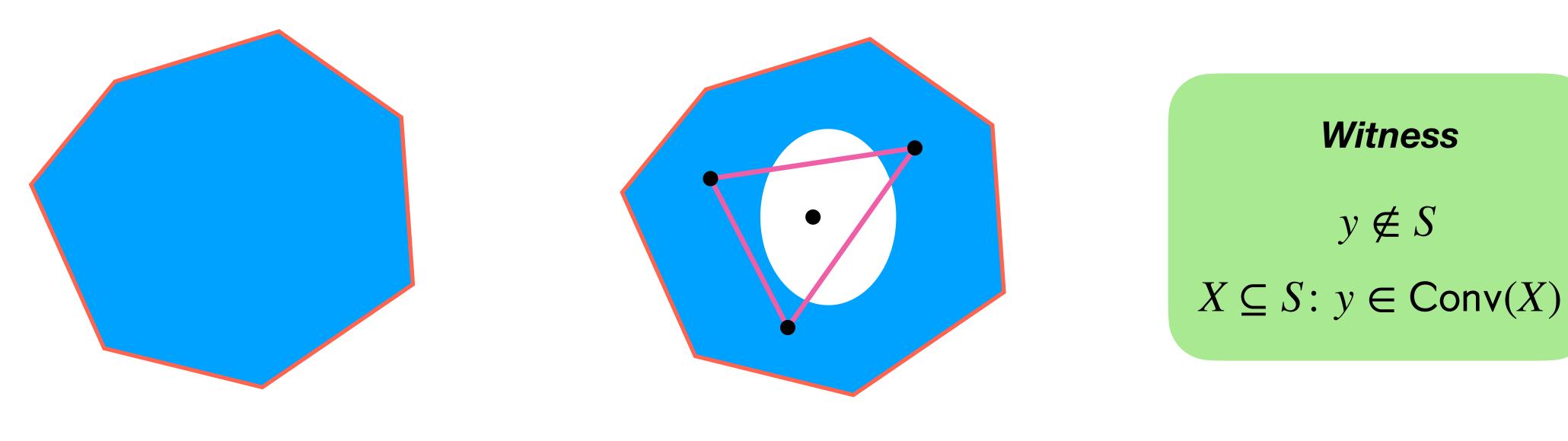
# 1-sided non-adaptive **query**-based testing: $2^{\Theta(n^{1/2})}$

### **Testing**

1. if *S* convex: **accept** w.p. 1

## **Testing with Queries**

# 1-sided non-adaptive **query**-based testing: $2^{\Theta(n^{1/2})}$



Always accept

Find a witness of non-convexity with probability > 2/3

How many queries to find a witness when S if  $\varepsilon$ -far from convex?

## Question

# Special Structure of $\{0, \pm 1\}^n$

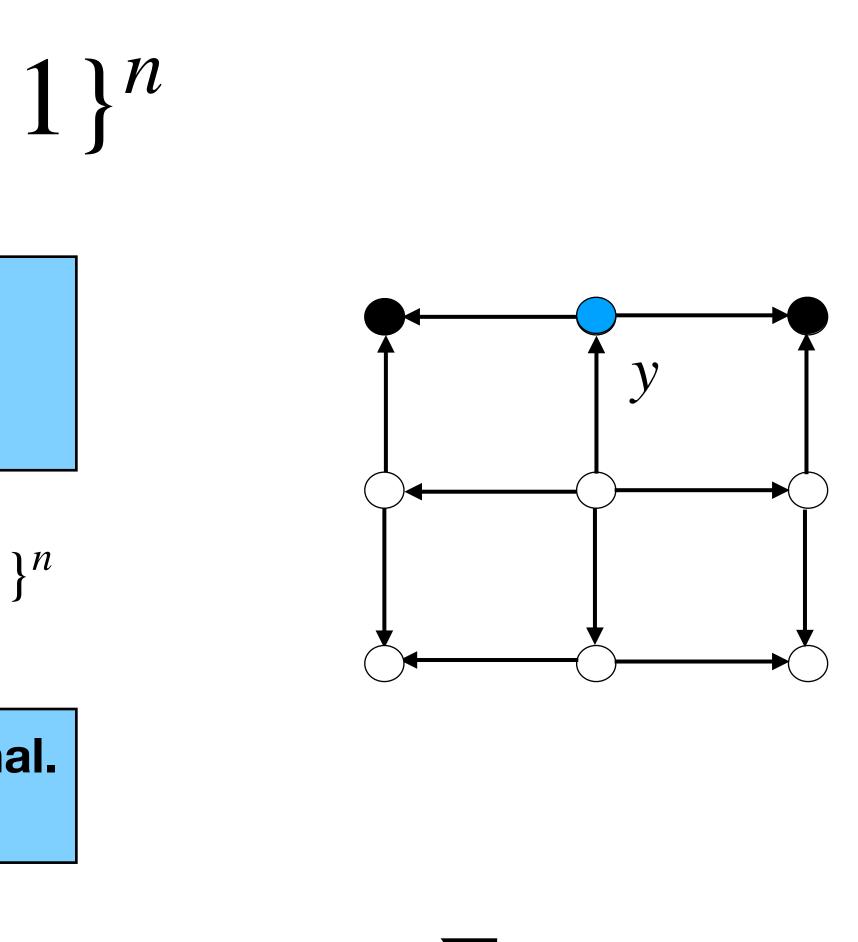
**Def:** Outward-oriented poset on  $\{0, \pm 1\}^n$ 

$$y \prec x \text{ iff } y_i \neq 0 \implies x_i = y_i$$

Minimal point:  $\vec{0}$  Maximal points:  $\{\pm 1\}^n$ 

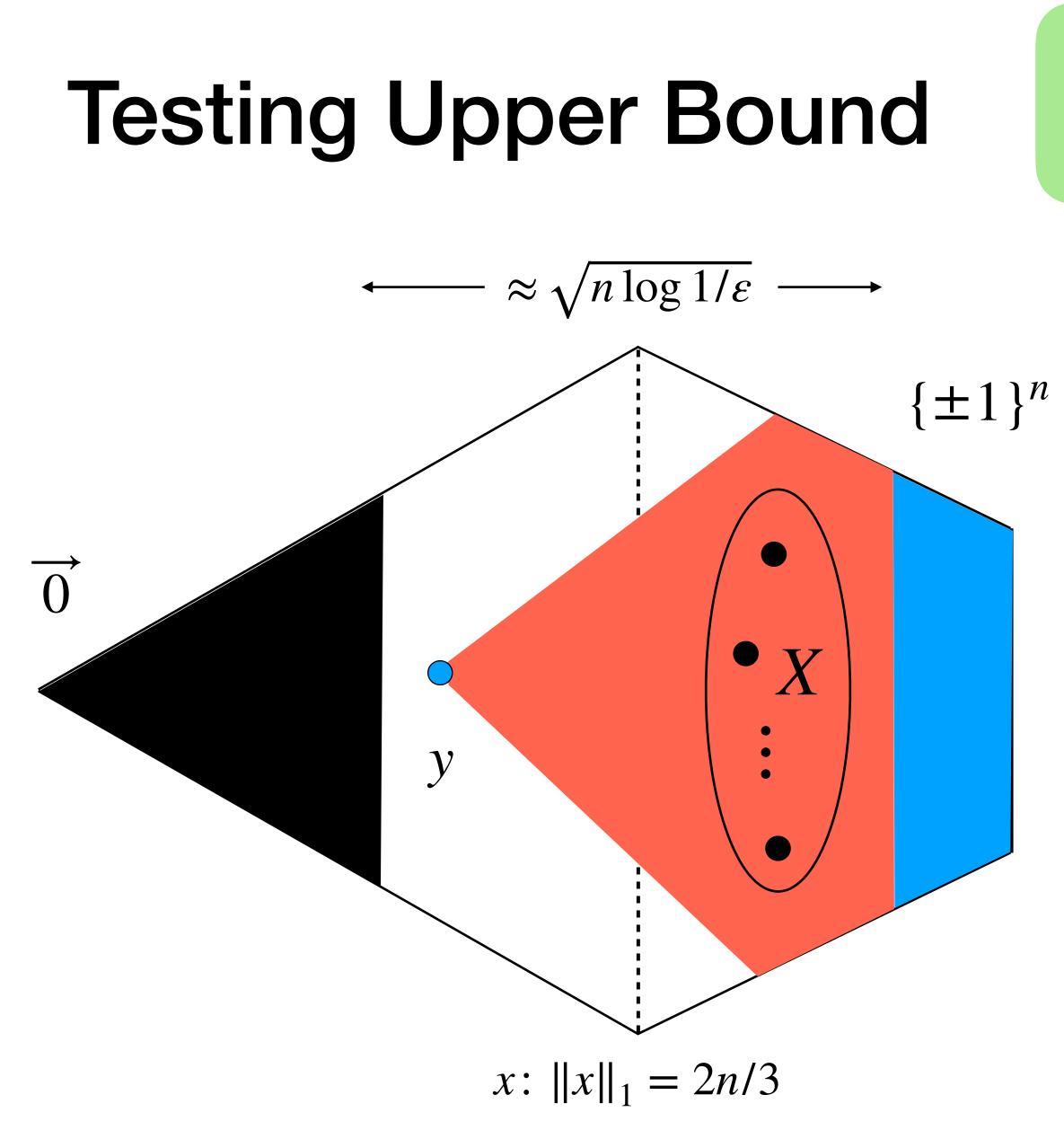
**Fact:** Suppose  $y \in Conv(X)$  and X is **minimal.** Then  $y \prec x$  for all  $x \in X$ 

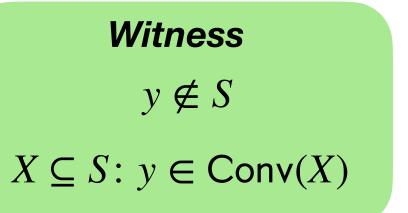
Proof:
$$y = \sum_{x \in X} \lambda_x x$$
Suppose  $y_i$  $X minimal \Longrightarrow \lambda_x > 0$  for all  $x$ If  $x_i \neq y_i$  for some  $x$ , then  $\sum_{x \in X} \lambda_x x_i$ 



= 1... *i.e.*,  $\sum \lambda_x x_i = 1$ *x*∈*X* 

 $x_i < 1$ . Contradiction.





**Fact:** Suppose  $y \in Conv(X)$ and X is **minimal**. Then  $y \prec x$  for all  $x \in X$ 

## $3^{-n} |\operatorname{Conv}(S) \setminus S| \ge \varepsilon(S) > \varepsilon$ $\implies$ $\Pr_{v}[y \in \operatorname{Conv}(S) \setminus S] \ge \varepsilon$

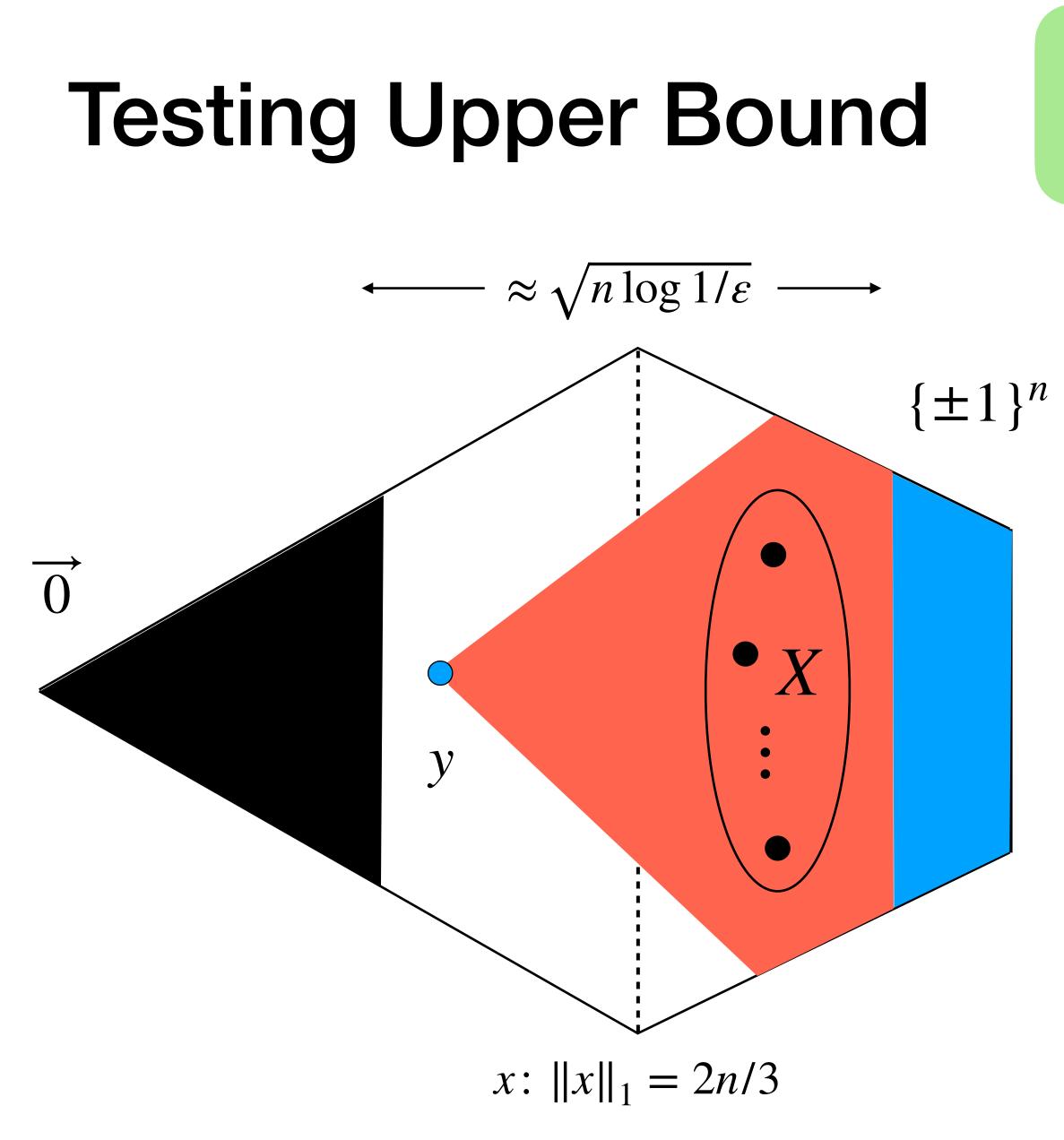
If we can find  $X \subset S$  such that  $y \in Conv(X)$ , then we win

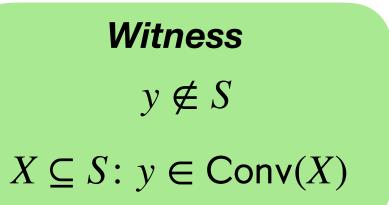
**Obs 1:** By Fact,  $\exists$  such an *X* where  $y \prec x \forall x \in X$ 

**Obs 2:** By concentration bounds, it suffices to query only *x* such that  $\|x\|_1 \le 2n/3 + O(\sqrt{n\log 1/\varepsilon})$ 

# of points satisfying (1) and (2)  $\sqrt{n\log 1/\varepsilon}$  $\begin{pmatrix} \#i \colon y_i = 0 \\ \ell \end{pmatrix} \cdot 2^{\ell} \leq 2^{\widetilde{O}(\sqrt{n \log 1/\varepsilon})}$ 







Fact: Suppose  $y \in Conv(X)$ and X is minimal. Then  $y \prec x$  for all  $x \in X$ 

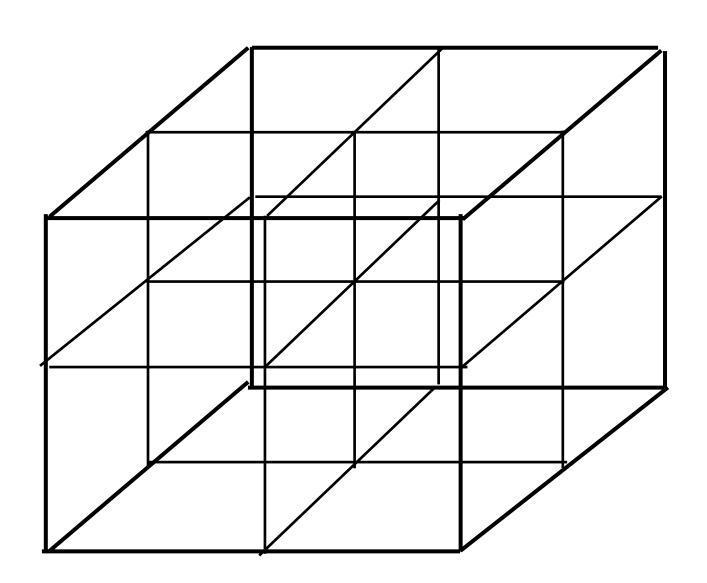
## Tester

**Repeat**  $O(1/\varepsilon)$  **times:** 

- Query  $y \in \{0, \pm 1\}^n$  uniformly at random
- If  $||y||_1 > 2n/3 \widetilde{O}(\sqrt{n})$ , then query all of  $U_y = \{x > y : ||x||_1 \le 2n/3 + \widetilde{O}(\sqrt{n})\}$
- If  $y \notin S$  and there exists  $X \subset U_y \cap S$ such that  $y \in Conv(X)$ , then **reject**



# 1-sided non-adaptive **query**-based testing: $2^{\Omega(n^{1/2})}$



# **Proof Sketch**

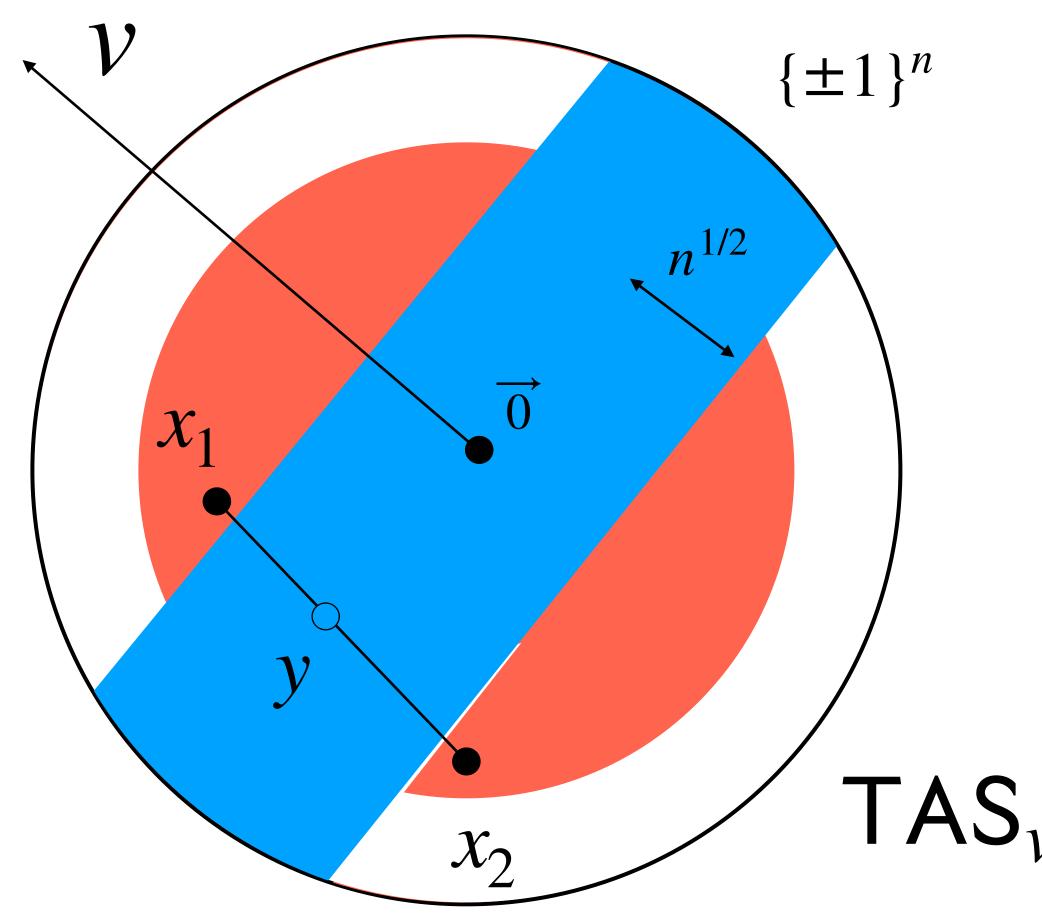
# Hard Family of Sets: Truncated Anti-Slabs

**Def:** Given 
$$v \in \{\pm 1\}^n$$
, let  
Slab<sub>v</sub> =  $\{x: |\langle x, v \rangle | < n^{1/2}\}$ 

$$\mathsf{TAS}_{v} = \overline{\mathsf{Slab}_{v}} \cup \left\{ x \colon \|x\|_{1} < \frac{2n}{3} - 0.6n^{1/2} \right\}$$
$$\setminus \left\{ x \colon \|x\|_{1} > \frac{2n}{3} + 0.6n^{1/2} \right\}$$

### Fact: $\varepsilon(TAS_v) = \Omega(1)$

$$\exists x \in \{x_1, x_2\}:$$
(A)  $|\langle x - y, v \rangle| > n^{1/2}$ 
(B)  $y \prec x \implies ||x - y||_1 < 1.2n^{1/2}$ 





# Witnesses of Non-Convexity

Let T be a 1-sided non-adaptive tester

- Query set:  $Q \subset \{0, \pm 1\}^n$
- *T* rejects  $\mathsf{TAS}_v \implies \exists x, y \in Q$

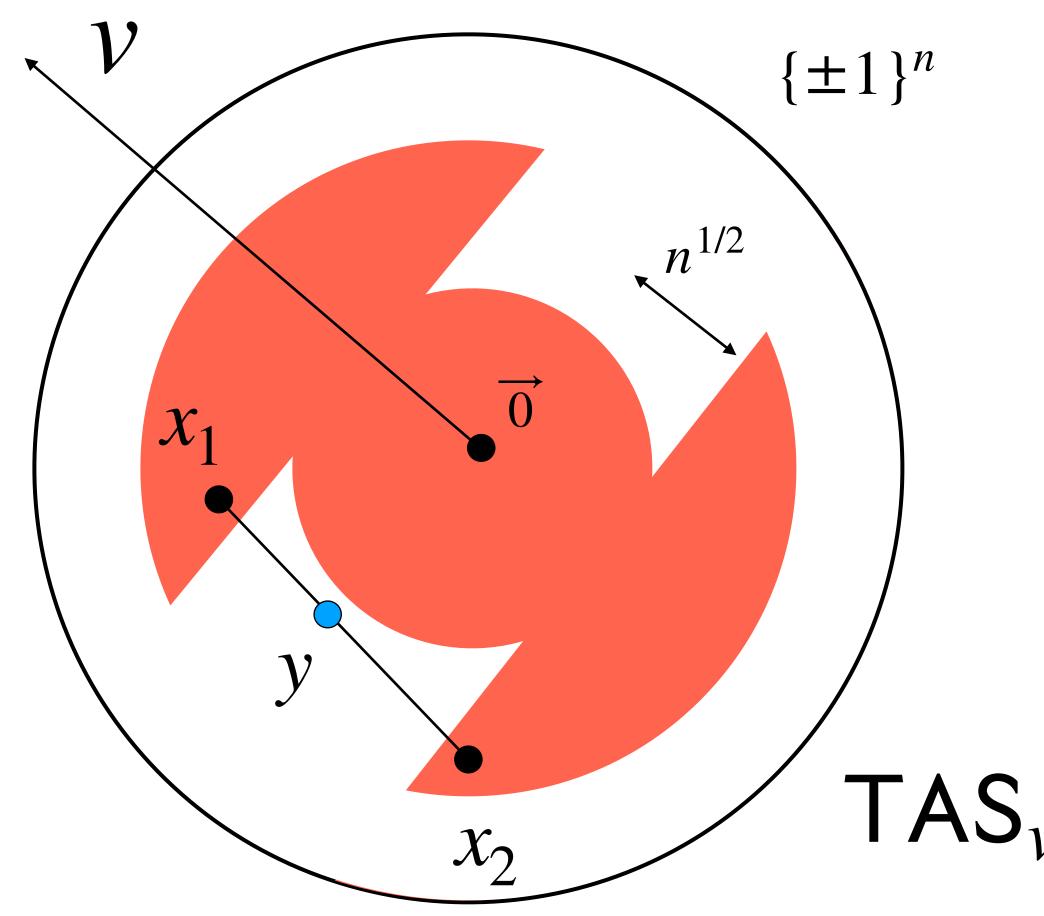
(A) 
$$|\langle x - y, v \rangle| > n^{1/2}$$
  
(B)  $||x - y||_1 < 1.2n^{1/2}$ 

### **Question**:

If **(B)** holds for *x*, *y*, then for how many  $v \in \{\pm 1\}^n$  can (A) hold?

> Answer: at most  $2^{n-0.08n^{1/2}}$







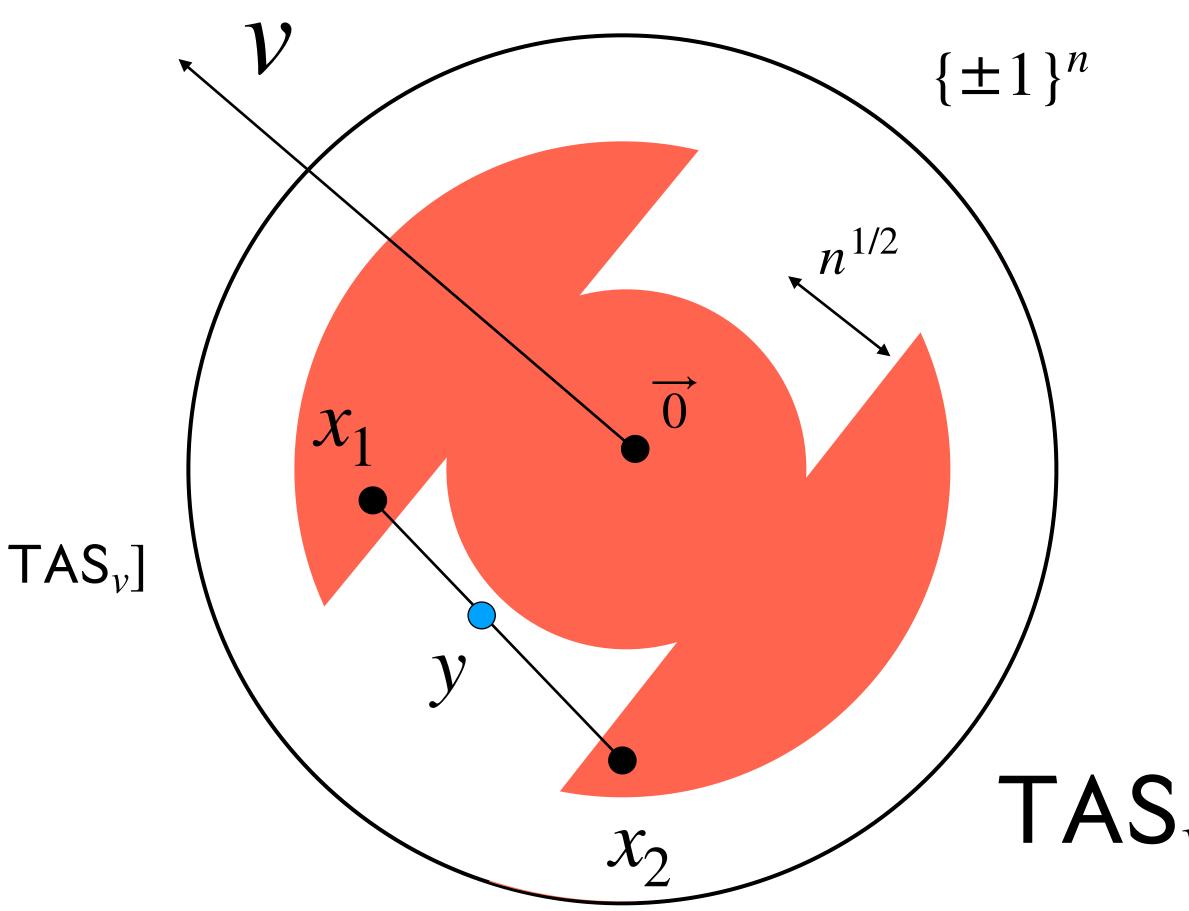
# Lower Bound Proof

Let T be a 1-sided non-adaptive tester

 $w(Q) = \# v : Q \text{ witnesses non-convexity of TAS}_{v}$  $\leq \|Q\|^{2} \cdot 2^{n-0.08n^{1/2}}$ 

 $\frac{2}{3} \cdot 2^{n} \leq \sum_{\nu \in \{\pm 1\}^{n}} \mathbb{P}_{Q}[T \text{ rejects } \mathsf{TAS}_{\nu}]$  $\leq \sum_{\nu \in \{\pm 1\}^{n}} \mathbb{P}_{Q}[T \text{ contains a witness for } \mathsf{TAS}_{\nu}]$  $= \mathbb{E}_{Q}[w(Q)] \leq |Q|^{2} \cdot 2^{n-0.08n^{1/2}}$ 

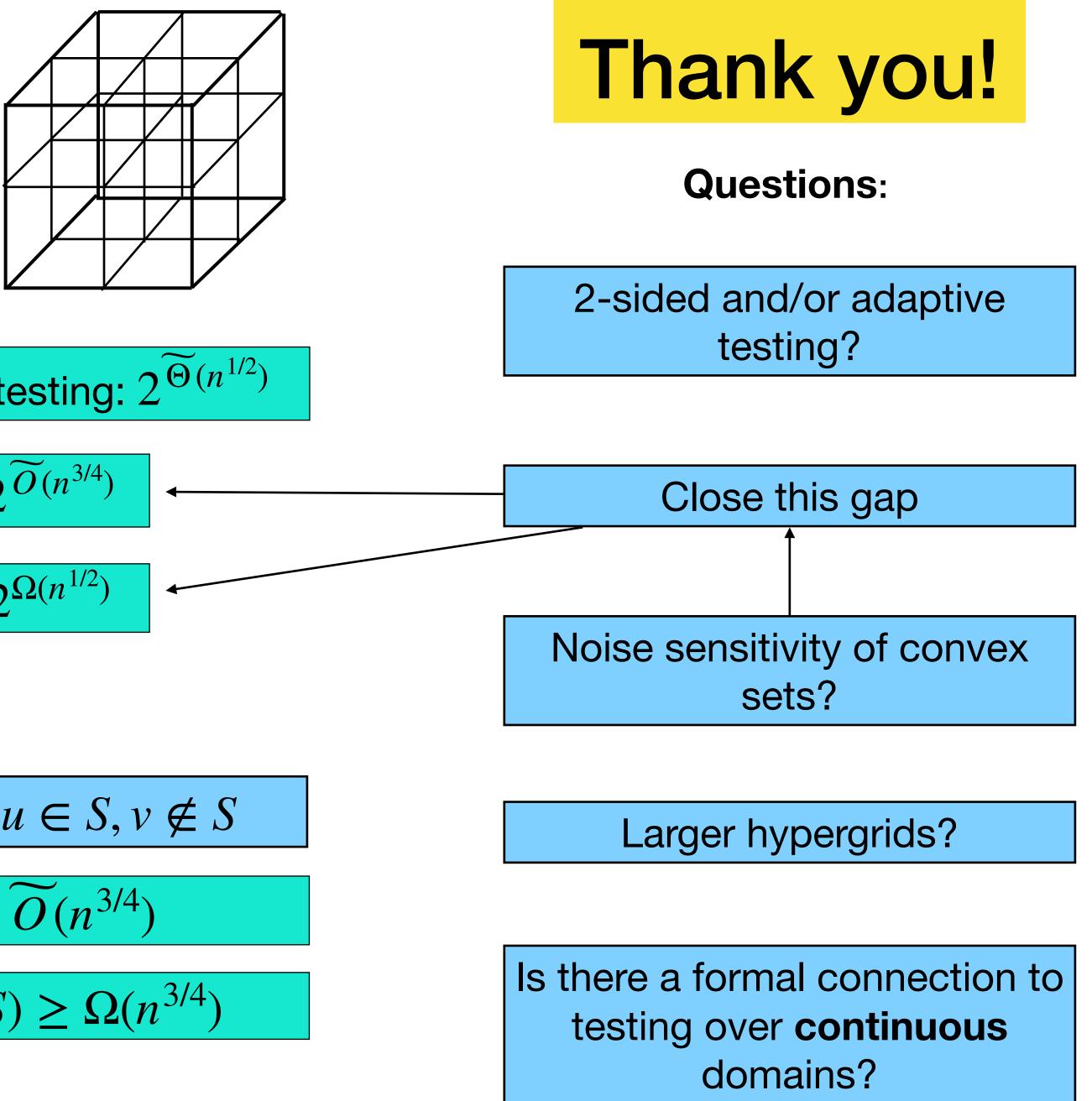
 $\implies |Q| > 2^{0.03n^{1/2}}$ 





# **Future Directions**

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**Computational**:

Learning and testing with samples:  $2^{\Omega(n^{1/2})}$ 

Structural:

