

# The Hardest Halfspace

Alexander Sherstov

UCLA

# Approximation by polynomials

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

DEFINITION.

$E(f, d)$  is the minimum error to which  $f$  can be approximated in  $l_\infty$  norm by a polynomial  $p \in \mathbf{R}[x_1, x_2, \dots, x_n]$  of degree  $\leq d$ :

$$E(f, d) = \min_{p: \deg p \leq d} \|f - p\|_\infty$$

$$E(f, n) = 0$$

$$E(f, d) \in [0, 1]$$


# Motivation

- **Circuit complexity**  
[PS94, SRK94, BRS95, ABFR94, KP97, KP98, S09, BH12]
- **Quantum query complexity**  
[BBC+01, BCWZ99, AS04, A05, A05, KŠW07, BKT17]
- **Communication complexity**  
[BW01, R02, BVW07, S09, S11, RS10, LS09, CA08, S08, BH12, S14, S16]
- **Learning theory**  
[TT99, KS04, KOS04, KKMS08, OS10, ACR+10]
- **Algorithm design**  
[LN90, KLS96, S09]
- **Differential privacy**  
[TUV12, CTUW14]

# Our problem

What is the worst-case  $E(h, d)$  for a halfspace  $h : \{0,1\}^n \rightarrow \{-1,+1\}$ ,  
 $h(x) = \text{sgn}(\sum_{i=1}^n z_i x_i - \theta)$ ?

Bound	Reference
$E(h, 1) \leq 1 - 2^{-O(n \log n)}$	Folklore
$E(h, 1) \geq 1 - 2^{-\Omega(n)}$	Folklore
$E(h, 1) \geq 1 - 2^{-\Omega(n \log n)}$	Håstad (1994)
$E(h, \varepsilon n) \geq 1/3$	Paturi (1992)
$E(h, d) \geq 1 - 2^{-\Omega(n/d^2)}$	Beigel (1994)
$E(h, \varepsilon n) \geq 1 - 2^{-\Omega(n)}$ , <b>NOT EXPLICIT</b>	[S. 2010]



# Main result

MAIN RESULT.

There is an explicitly given halfspace  $h : \{0,1\}^n \rightarrow \{-1,+1\}$  such that:

$$E(h, d) \geq 1 - \exp(-\Omega(n)) \quad \text{for } d = 0, 1, \dots, \varepsilon n$$

$$R(h, d) \geq 1 - \exp(-\Omega(n/d)) \quad \text{for } d = 0, 1, \dots, \varepsilon n$$

**approximation by rational functions**

- Optimal for both  $E$  and  $R$
- Quadratic improvement on previous explicit constructions

# Main result

COROLLARY.

There are explicitly given halfspaces  $h_1, h_2 : \{0,1\}^n \rightarrow \{-1,+1\}$  such that:

$$E(h_1 \wedge h_2, \Omega(n)) = 1$$

$$R(h_1 \wedge h_2, \Omega(n)) = 1$$

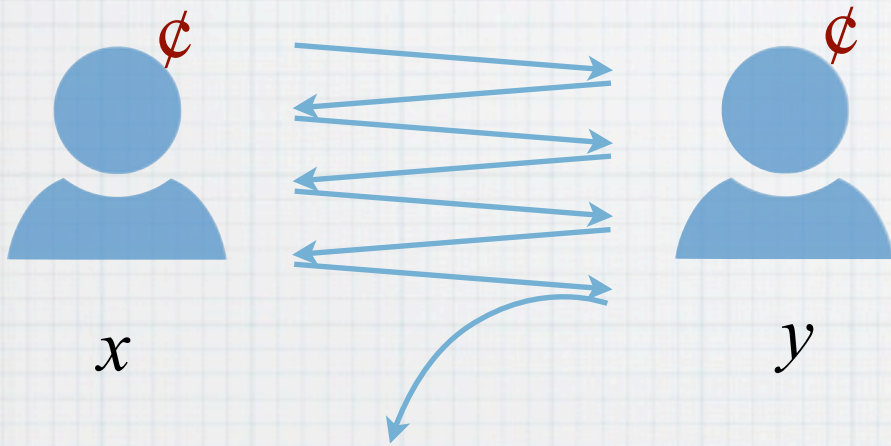
- Optimal for both  $E$  and  $R$
- Quadratic improvement on previous explicit constructions

**Application 1:**

**Unbounded-error  
communication**

# UPP versus PP

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



$R_\epsilon(f)$  = minimum cost of an  $\epsilon$ -error protocol for  $f$

$$\text{UPP}(f) = \min_{0 < \epsilon < 1/2} R_\epsilon(f)$$

**a.k.a. sign-rank**

$$\text{PP}(f) = \min_{0 < \epsilon < 1/2} \left\{ R_\epsilon(f) + \log \frac{1}{\frac{1}{2} - \epsilon} \right\}$$

**a.k.a. discrepancy**



# UPP versus PP

$$\text{UPP} = \{\{f_n\}_{n=1}^{\infty} : \text{UPP}(f_n) = \log^{O(1)} n\}$$

$$\text{PP} = \{\{f_n\}_{n=1}^{\infty} : \text{PP}(f_n) = \log^{O(1)} n\}$$

Babai, Frankl, & Simon (1986):  $\text{PP} \subsetneq \text{UPP}?$

# UPP versus PP

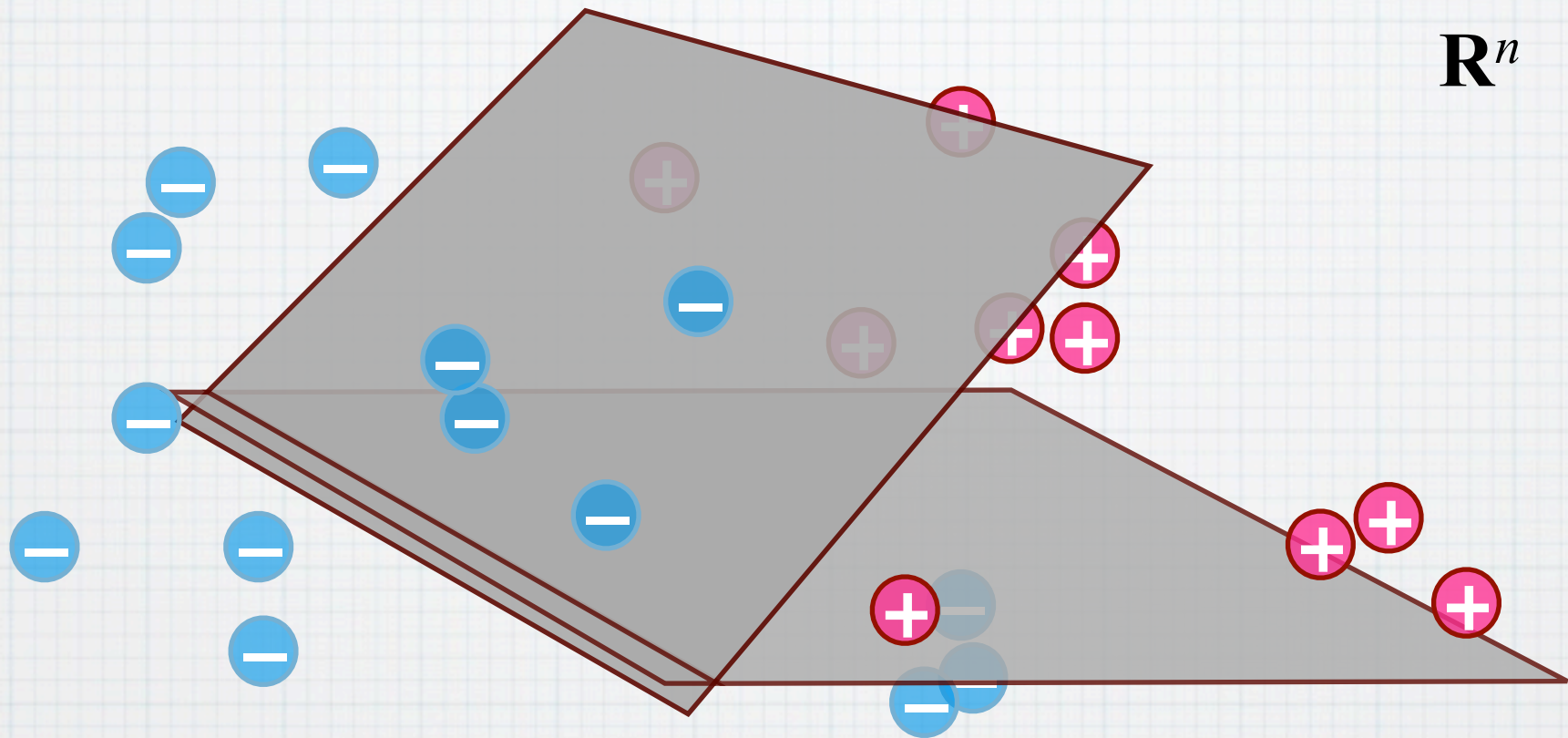
Babai, Frankl, & Simon (1986):  $PP \subsetneq UPP?$

UPP vs. PP	Reference
$O(\log n)$ vs. $\Omega(n^{1/3})$	[Buhrman et al., 2007]
$O(\log n)$ vs. $\Omega(n^{1/2})$	[S. 2007]
$O(\log n)$ vs. $\Omega(n^{2/5})$	[Thaler, 2016]
$O(\log n)$ vs. $\Omega(n)$	This work

# Application 2:

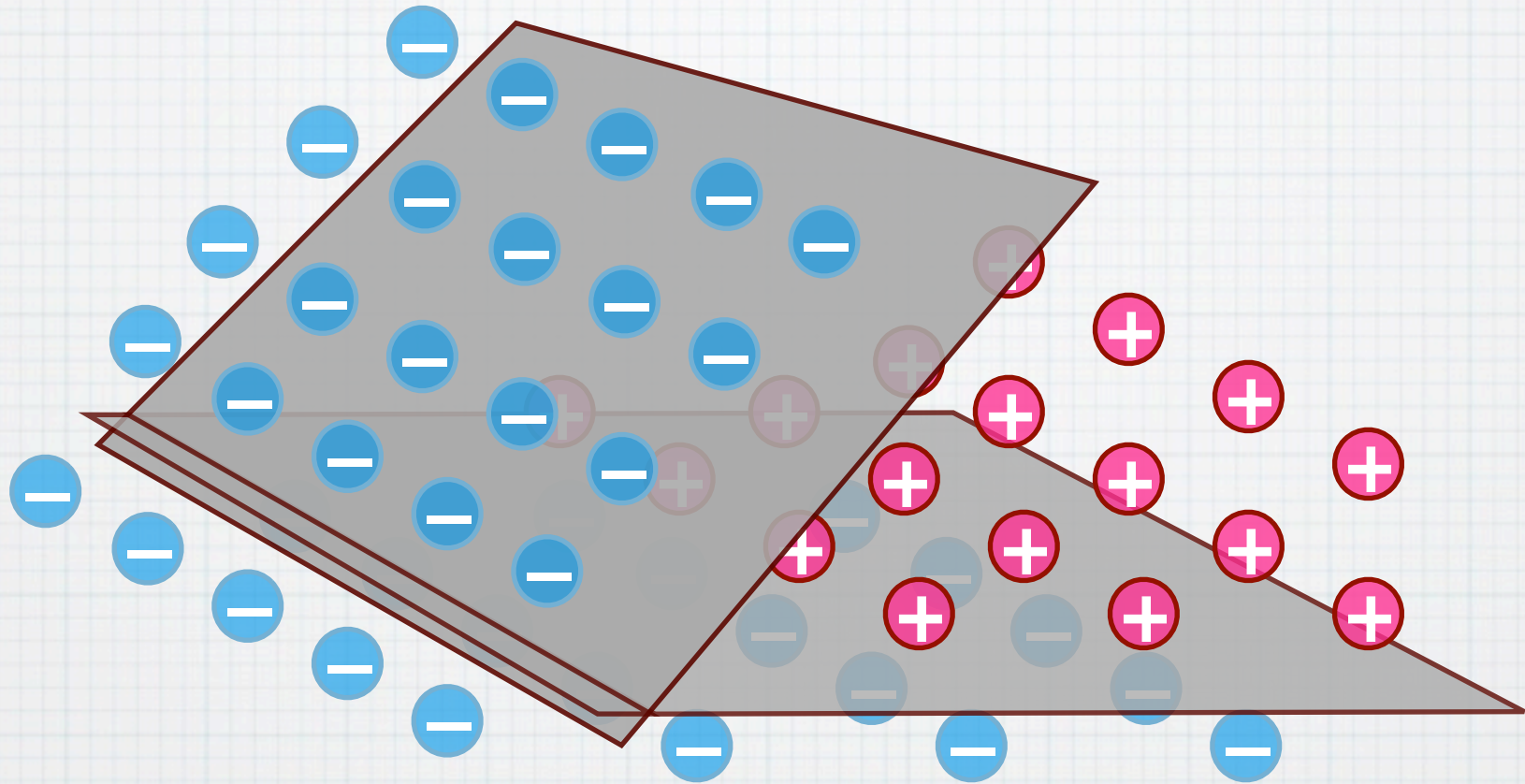
## Learning intersections of halfspaces

# The problem



Learn intersection from examples.

# Restricted distributions



Symmetric on  $\mathbf{R}^n$

Uniform on  $\mathbf{S}^{n-1}$

Uniform on  $\{0,1\}^n$

Log-concave on  $\mathbf{R}^n$

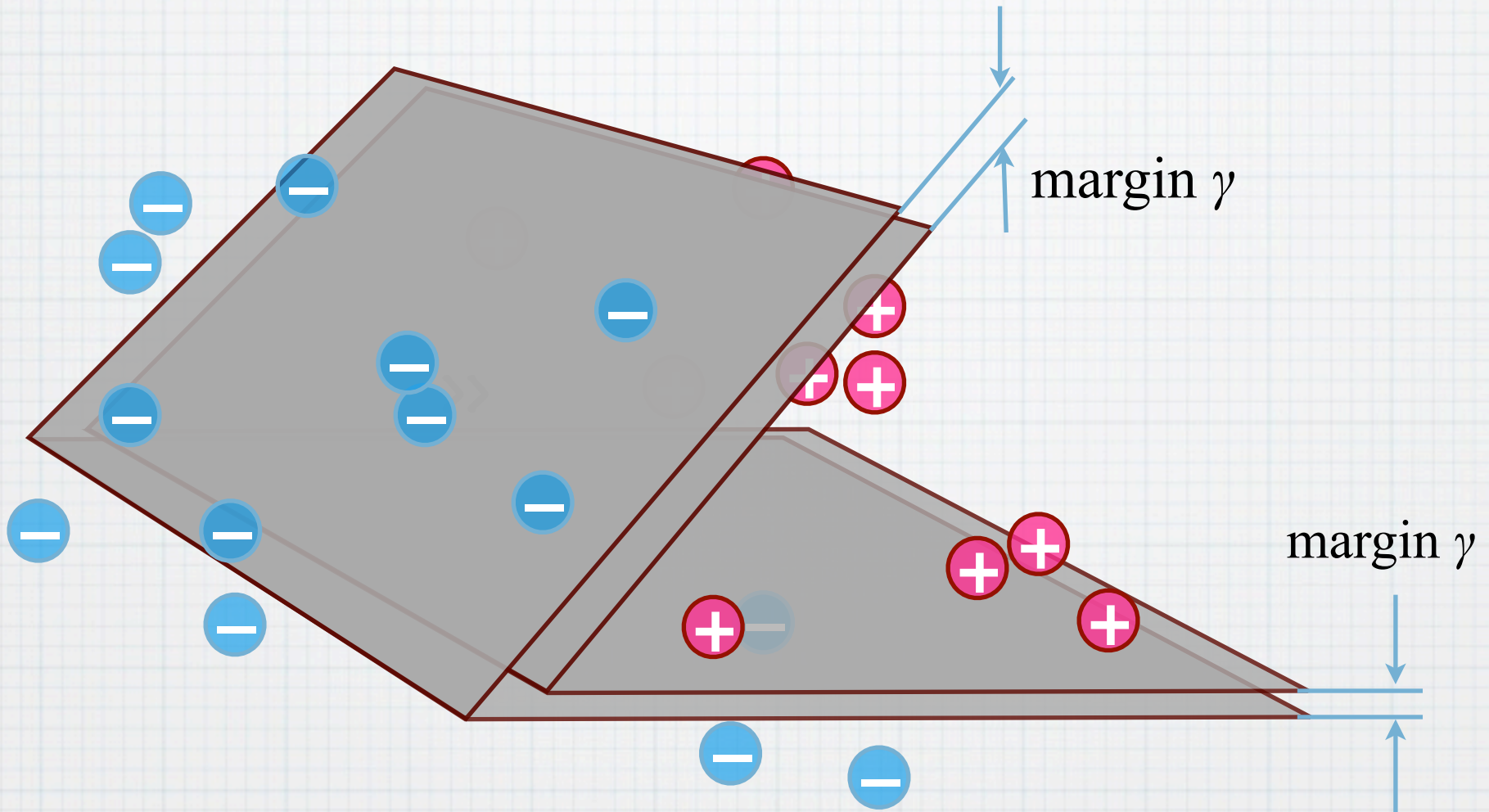
[Baum 90]

[Blum & Kannan '93, Vempala, '97]

[Klivans, O'Donnell, & Servedio, '02]

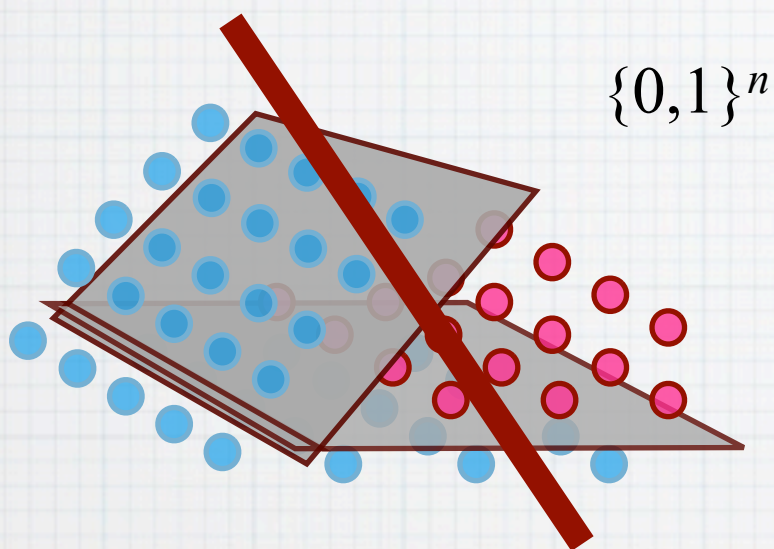
[Klivans, Long, & Tang, '09]

# Large margin



Random projection [Arriaga & Vempala '99]  
[Klivans & Servedio '04]

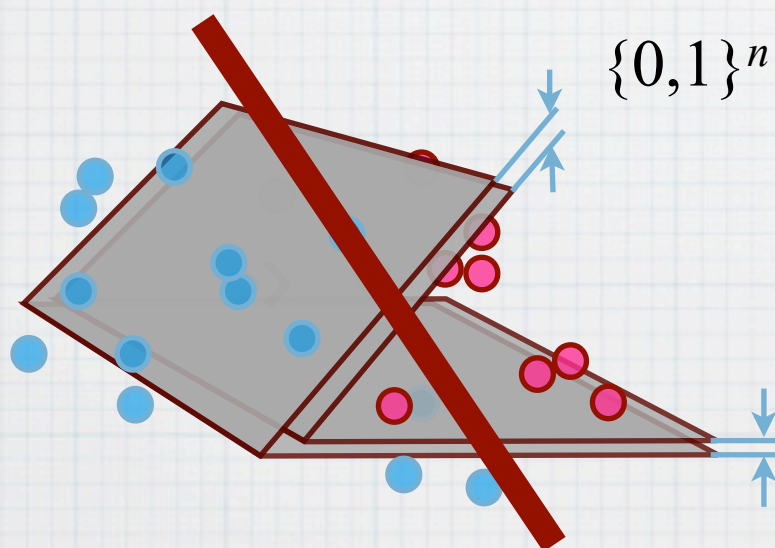
# What about general case?



No algorithm better than  $2^{\Theta(n)}$ .

Hardness:

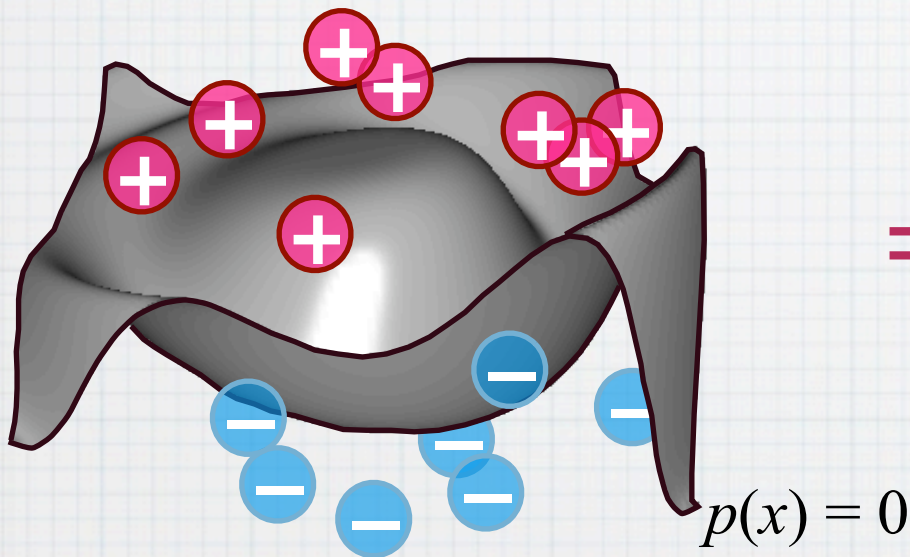
- NP-hardness for proper learning  
[Blum and Rivest, '88]  
[Alekhovich, Braverman, Feldman, Klivans, and Pitassi, '04]  
[Khot and Saket, '08]
- Cryptographic hardness for  $n^\epsilon$  halfspaces  
[Klivans and S., '07], using [Regev'05]
- Lower bounds for  $n^\epsilon$  halfspaces in SQ model  
[Klivans and S., '06]



# The polynomial method

Low-degree polynomial  $p : \{0,1\}^n \rightarrow \mathbf{R}$

Can learn  $f(x) = \text{sgn } p(x)$   
in time  $n^{O(\deg p)}$  w.r.t. any distribution.

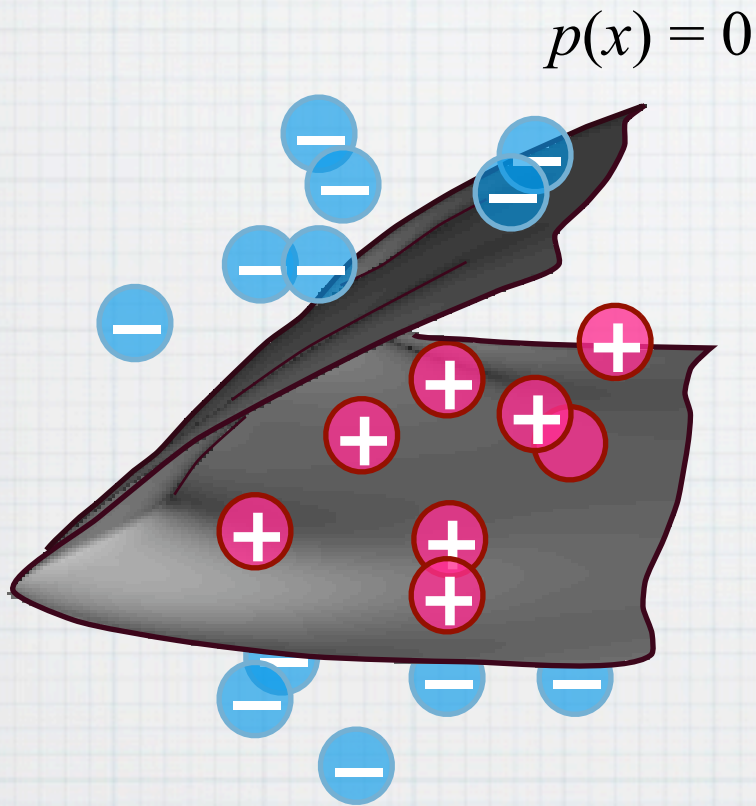


- $\exp(n^{1/3})$ -time algorithm for DNF  
[Klivans and Servedio, 03]
- $\exp(n^{1/2})$ -time algorithm for read-once formulas  
[O'Donnell and Servedio, 03]  
[Ambainis, Childs, Reichardt, Spalek, Zhang, '07]



# Intersection of two halfspaces

**Klivans (2002):** What is the worst-case threshold degree?



Bound	Reference
$\omega(1)$	[Minsky & Papert, 1969]
$\Omega\left(\frac{\log n}{\log \log n}\right)$	[O'Donnell & Servedio, 2002]
$\Omega(n^{1/2})$	[S. 2009]
$\Omega(n)$ <b>NOT EXPLICIT</b>	[S. 2010]
$\Omega(n)$ , explicit	This work

# Proof strategy

# Proof strategy

Given:  $f(x) = \text{sgn}(\sum z_i x_i - \theta)$  for some fixed  $z_1, \dots, z_n, \theta$

Black-box approximants:  $S(\sum z_i x_i - \theta)$  for some polynomial  $S$  or rational function  $S$

**Optimal** if  $z_1 = z_2 = \dots = z_n$  (Minsky & Papert 1968)

**Pathetic** in general:

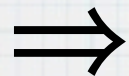
$$f(x) = \text{sgn} \left( \sum_{i=1}^n (-2)^i x_i + 1 \right) \equiv \lim_{M \rightarrow \infty} \frac{\sum_{i=1}^n (-M)^i x_i + 1}{\sum_{i=1}^n M^i x_i + 1}$$

degree 1!

# Proof strategy

Will construct  $z_1, \dots, z_n, \theta$  such that:

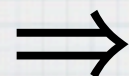
- range of sum  $\sum z_i x_i - \theta$  contains  $\{\pm 1, \pm 2, \dots, \pm 2^{\Omega(n)}\}$
- for approximants of degree  $\leq \varepsilon n$ , weighted sum is as good as individual bits.



Any approximant of degree  $\leq \varepsilon n$  for

$$f(x) = \text{sgn}(\sum z_i x_i - \theta)$$

gives a univariate approximant for  $\text{sgn}$  on  $\{\pm 1, \pm 2, \dots, \pm 2^{\Omega(n)}\}$ .



$$\begin{aligned} E(f, d) &\geq 1 - \exp(-\Omega(n)) && \text{for } d = 0, 1, \dots, \varepsilon n, \\ R(f, d) &\geq 1 - \exp(-\Omega(n/d)) && \text{for } d = 0, 1, \dots, \varepsilon n. \end{aligned}$$

# Step 1: Discrepancy mod $m$

# Discrepancy defined

$Z = \{z_1, z_2, \dots, z_n\}$ , multiset of integers

DEFINITION (DISCREPANCY MOD  $m$ ).

$$\text{disc}_m(Z) = \max_{k=1,2,\dots,m-1} \left| \frac{1}{n} \sum_{i=1}^n \omega^{kz_i} \right|,$$

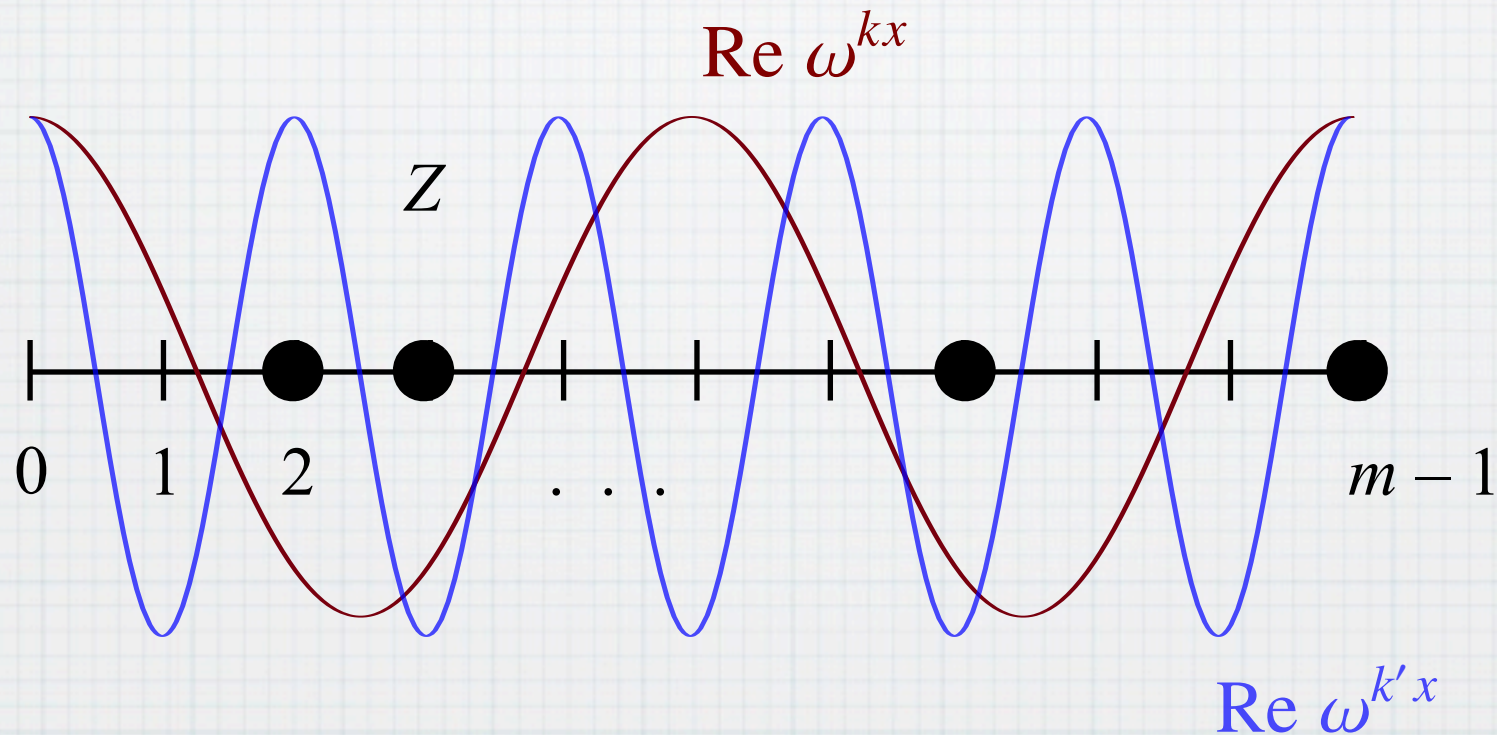
where  $\omega$  is any  $m$ -th root of unity.

maximum magnitude  
of a nonconstant  
Fourier coefficient of  
the frequency vector  
of  $Z$

- $\text{disc}_m(Z) = \text{disc}_m(Z \bmod m)$
- $\text{disc}_m(\{0, 1, 2, \dots, m-1\}) = 0$

# Discrepancy pictorially

*Intuition:*  $\text{disc}_m(Z)$  measures aperiodicity/balancedness



# A nonconstructive bound

tight (simultaneous  
diophantine  
approximation)

FACT.

Choose  $z_1, z_2, \dots, z_{O(\frac{1}{\epsilon^2} \log m)} \in \{0, 1, 2, \dots, m-1\}$   
uniformly at random. Then w.h.p.,

$$\text{disc}_m \left( \left\{ z_1, z_2, \dots, z_{O(\frac{1}{\epsilon^2} \log m)} \right\} \right) < \epsilon.$$

PROOF: Hoeffding + union bound.  $\square$



# Explicit construction

ITERATION LEMMA (AJTAI ET AL).

Take  $P, R$  with  $P^2(R + 1) \leq m$ . Fix a set  $Z_p \in \{1, 2, \dots, p - 1\}$  for each prime  $p \in (P/2, P]$  with  $p \nmid m$ , such that all  $Z_p$  have the same cardinality. Let

$$Z_m = \{(r + s \cdot (p^{-1})_m) \bmod m : \text{distinct mod } m, \\ r = 1, 2, \dots, R; \quad p \in (P/2, P] \text{ prime with } p \nmid m; \quad s \in Z_p\}.$$

Then

$$\text{disc}(Z_m) = O\left(\frac{1}{\sqrt{R}} + \frac{\ln m}{\ln \ln m} \cdot \frac{\ln P}{P} + \max_p \text{disc}_p(Z_p)\right).$$

# Explicit construction

THEOREM (AJTAI ET AL).

For each  $m$ , there is an explicit set  $Z_m$  with

$$|Z_m| \leq \log^{1+o(1)} m,$$

$$\text{disc}_m(Z_m) = o(1).$$

PROOF: recursively apply Iteration Lemma.  $\square$

# Explicit construction

THEOREM.

For each  $m$  and  $\epsilon > 0$ , there is an explicit set  $Z_m$  with

$$|Z_m| = O_\epsilon(\log m),$$

$$\text{disc}_m(Z_m) < \epsilon.$$

PROOF: apply Iteration Lemma twice, then use brute force search.  $\square$

**Step 2:**  
**A random walk on  $Z_m$**

# A random walk on $\mathbb{Z}_m$

Fix  $z_1, z_2, \dots, z_n \in \{0, 1, 2, \dots, m-1\}$ . *Think  $m = 2^{\Omega(n)}$ .*

For  $x \in \{0, 1\}^n$ , analyze distribution of

$$\left( \sum_{i=1}^n z_i x_i \right) \bmod m.$$

*n*-step random walk  
on  $\mathbb{Z}_m$

# A random walk on $Z_m$

$$\frac{1}{2} \begin{bmatrix} 1 & & & & & & \\ & 1 & & & & & \\ & & 1 & & & & \\ & & & 1 & & & \\ & & & & \ddots & & \\ & & & & & 1 & \\ & & & & & & 1 \end{bmatrix} + \frac{1}{2} \begin{bmatrix} & & \overbrace{z_j \bmod m} & & & & \\ & & & 1 & & & \\ & & & & 1 & & \\ & & & & & \ddots & \\ & & & & & & 1 \\ 1 & & & & & & \\ & \ddots & & & & & \\ & & & 1 & & & \end{bmatrix}$$

# A random walk on $\mathbb{Z}_m$

$$\prod_{i=1}^n \left( \frac{1}{2} \begin{bmatrix} 1 & & & & \\ & 1 & & & \\ & & 1 & & \\ & & & 1 & \\ & & & & \ddots \\ & & & & & 1 \\ & & & & & & 1 \end{bmatrix} + \frac{1}{2} \begin{bmatrix} & & & & \overbrace{1}^{z_j \bmod m} & & \\ & & & & & 1 & \\ & & & & & & 1 \\ & & & & & & \ddots \\ & & & & & & & 1 \\ & & & & & & & & 1 \\ & & & & & & & & & 1 \end{bmatrix} \right)$$

$$= \prod_{i=1}^n U \operatorname{diag} \left( 1, \frac{1 + \omega^{z_i}}{2}, \frac{1 + \omega^{2z_i}}{2}, \dots, \frac{1 + \omega^{(m-1)z_i}}{2} \right) U^*$$

# A random walk on $Z_m$

$$= \prod_{i=1}^n U \operatorname{diag} \left( 1, \frac{1 + \omega^{z_i}}{2}, \frac{1 + \omega^{2z_i}}{2}, \dots, \frac{1 + \omega^{(m-1)z_i}}{2} \right) U^*$$

$$= U \operatorname{diag} \left( 1, \prod_{i=1}^n \frac{1 + \omega^{z_i}}{2}, \prod_{i=1}^n \frac{1 + \omega^{2z_i}}{2}, \dots, \prod_{i=1}^n \frac{1 + \omega^{(m-1)z_i}}{2} \right) U^*$$

bound by  $\left( \frac{1 + \operatorname{disc}_m(\{z_1, z_2, \dots, z_n\})}{2} \right)^{n/2}$



# A random walk on $Z_m$

This sketches:

LEMMA. For any integers  $z_1, z_2, \dots, z_n, s$ ,

$$\left| \mathbf{P}_{x \in \{0,1\}^n} \left[ \sum_{j=1}^n z_j x_j \equiv s \pmod{m} \right] - \frac{1}{m} \right| \leq \left( \frac{1 + \text{disc}_m(Z)}{2} \right)^{n/2}.$$

# Step 3: Fooling distributions

# Fooling distributions

Given:  $\epsilon = \frac{1}{2018}$

$$m = 2^{\epsilon n}$$

$$z_1, z_2, \dots, z_n \in \mathbb{Z}_m \text{ with } \text{disc}_m(\{z_1, z_2, \dots, z_n\}) < \epsilon$$

---

Define  $L: \{0, 1\}^n \rightarrow \mathbb{Z}_m$  by  $L(x) = \sum z_i x_i$

---

By Step 2:

$$\mathbf{E}_{L^{-1}(0)} p \approx \mathbf{E}_{L^{-1}(1)} p \approx \mathbf{E}_{L^{-1}(2)} p \approx \dots \approx \mathbf{E}_{L^{-1}(m-1)} p$$

for every polynomial  $p$  of degree  $\leq \epsilon n$ .

# Fooling distributions

Given:  $\epsilon = \frac{1}{2018}$

$$m = 2^{\epsilon n}$$

$$z_1, z_2, \dots, z_n \in \mathbb{Z}_m \text{ with } \text{disc}_m(\{z_1, z_2, \dots, z_n\}) < \epsilon$$

---

Define  $L: \{0, 1\}^n \rightarrow \mathbb{Z}_m$  by  $L(x) = \sum z_i x_i$

---

By Step 2 **and perturbation argument:**

$$\mathbf{E}_{\mu_0} p \approx \mathbf{E}_{\mu_1} p \approx \mathbf{E}_{\mu_2} p \approx \dots \approx \mathbf{E}_{\mu_{m-1}} p$$

for every polynomial  $p$  of degree  $\leq \epsilon n$ , **where  $\text{supp } \mu_i \subseteq L^{-1}(i)$**

# Step 4: Univariatization

# Univariattization

Define  $F : \{0,1\}^n \times \{0, 1, \dots, n\} \rightarrow \{-1,+1\}$  by

$$F(x, t) = \text{sgn}(\sum z_i x_i - 2^{\varepsilon n} t)$$

halfspace on  
 $\{0,1\}^{2n}$

Fix  $\delta$ -error approximant  $P/Q$  for  $F$   
( $\deg P, \deg Q \leq \varepsilon n$ ;  $Q > 0$ ).

Distributions  $\mu_s$  for  $s = \pm 1, \pm 2, \dots, \pm 2^{\varepsilon n-1}$ .  
 $\text{supp } \mu_s \subseteq \{x : \sum z_i x_i \equiv s \pmod{2^{\varepsilon n}}\}$

For  $x \in \text{supp } \mu_s$ :

$$2^{-\varepsilon n} (\sum z_i x_i - s) \in \{0, 1, \dots, n\}.$$

$$(1 - \delta)Q(x, t)$$

$$< P(x, t)F(x, t)$$

$$< (1 + \delta)Q(x, t)$$

# Univariatization

Define  $F : \{0,1\}^n \times \{0, 1, \dots, n\} \rightarrow \{-1,+1\}$  by

$$F(x, t) = \text{sgn}(\sum z_i x_i - 2^{\varepsilon n} t)$$

halfspace on  $\{0,1\}^{2n}$

Fix  $\delta$ -error approximant  $P/Q$  for  $F$   
 (deg  $P$ , deg  $Q \leq \varepsilon n$ ;  $Q > 0$ ).

Distributions  $\mu_s$  for  $s = \pm 1, \pm 2, \dots, \pm 2^{\varepsilon n-1}$ .  
 $\text{supp } \mu_s \subseteq \{x : \sum z_i x_i \equiv s \pmod{2^{\varepsilon n}}\}$

For  $x \in \text{supp } \mu_s$ :  
 $2^{-\varepsilon n} (\sum z_i x_i - s) \in \{0,1, \dots, n\}$ .

$$(1 - \delta)Q\left(x, 2^{-\varepsilon n} (\sum z_i x_i - s)\right)$$

$$< P\left(x, 2^{-\varepsilon n} (\sum z_i x_i - s)\right)F\left(x, 2^{-\varepsilon n} (\sum z_i x_i - s)\right)$$

$$< (1 + \delta)Q\left(x, 2^{-\varepsilon n} (\sum z_i x_i - s)\right)$$

$x \in \text{supp } \mu_s$

# Univariattization

Define  $F : \{0,1\}^n \times \{0, 1, \dots, n\} \rightarrow \{-1,+1\}$  by

$$F(x, t) = \text{sgn}(\sum z_i x_i - 2^{\varepsilon n} t)$$

halfspace on  $\{0,1\}^{2n}$

Fix  $\delta$ -error approximant  $P/Q$  for  $F$   
 (deg  $P$ , deg  $Q \leq \varepsilon n$ ;  $Q > 0$ ).

Distributions  $\mu_s$  for  $s = \pm 1, \pm 2, \dots, \pm 2^{\varepsilon n - 1}$ .  
 $\text{supp } \mu_s \subseteq \{x : \sum z_i x_i \equiv s \pmod{2^{\varepsilon n}}\}$

For  $x \in \text{supp } \mu_s$ :  
 $2^{-\varepsilon n} (\sum z_i x_i - s) \in \{0, 1, \dots, n\}$ .

$$\begin{aligned} & (1 - \delta)Q\left(x, 2^{-\varepsilon n} (\sum z_i x_i - s)\right) \\ & < P\left(x, 2^{-\varepsilon n} (\sum z_i x_i - s)\right) \text{sgn } s \\ & < (1 + \delta)Q\left(x, 2^{-\varepsilon n} (\sum z_i x_i - s)\right) \end{aligned}$$

}  $x \in \text{supp } \mu_s$



# Univariattization

Define  $F : \{0,1\}^n \times \{0, 1, \dots, n\} \rightarrow \{-1,+1\}$  by

$$F(x, t) = \text{sgn}(\sum z_i x_i - 2^{\varepsilon n} t)$$

halfspace on  
 $\{0,1\}^{2n}$

Fix  $\delta$ -error approximant  $P/Q$  for  $F$   
( $\deg P, \deg Q \leq \varepsilon n$ ;  $Q > 0$ ).

Distributions  $\mu_s$  for  $s = \pm 1, \pm 2, \dots, \pm 2^{\varepsilon n-1}$ .  
 $\text{supp } \mu_s \subseteq \{x : \sum z_i x_i \equiv s \pmod{2^{\varepsilon n}}\}$

For  $x \in \text{supp } \mu_s$ :

$$2^{-\varepsilon n} (\sum z_i x_i - s) \in \{0, 1, \dots, n\}.$$

$$\begin{aligned} & (1 - \delta) \mathbf{E} \left[ Q \left( x, 2^{-\varepsilon n} (\sum z_i x_i - s) \right) \right] \\ & < \mathbf{E} \left[ P \left( x, 2^{-\varepsilon n} (\sum z_i x_i - s) \right) \right] \text{sgn } s \\ & < (1 + \delta) \mathbf{E} \left[ Q \left( x, 2^{-\varepsilon n} (\sum z_i x_i - s) \right) \right] \end{aligned}$$

expectation  
w.r.t.  
 $x \sim \text{supp } \mu_s$

# Univariatization

Define  $F : \{0,1\}^n \times \{0, 1, \dots, n\} \rightarrow \{-1,+1\}$  by

$$F(x, t) = \text{sgn}(\sum z_i x_i - 2^{\varepsilon n} t)$$

halfspace on  
 $\{0,1\}^{2n}$

Fix  $\delta$ -error approximant  $P/Q$  for  $F$   
( $\deg P, \deg Q \leq \varepsilon n$ ;  $Q > 0$ ).

Distributions  $\mu_s$  for  $s = \pm 1, \pm 2, \dots, \pm 2^{\varepsilon n - 1}$ .  
 $\text{supp } \mu_s \subseteq \{x : \sum z_i x_i \equiv s \pmod{2^{\varepsilon n}}\}$

For  $x \in \text{supp } \mu_s$ :

$$2^{-\varepsilon n} (\sum z_i x_i - s) \in \{0, 1, \dots, n\}.$$

$$\begin{aligned} (1 - \delta) q(s) &< p(s) \text{sgn } s \\ &< (1 + \delta) q(s) \end{aligned}$$

for every  
 $s = \pm 1, \pm 2, \dots, \pm 2^{\varepsilon n - 1}$ .

$p/q$  approximates  $\text{sgn}$  on  $\{\pm 1, \pm 2, \dots, \pm 2^{\varepsilon n - 1}\}$ .

# Summary

THEOREM.

Any rational approximant of degree  $d \leq \varepsilon n$  for  $F$  gives a degree- $d$  univariate rational approximant for  $\text{sgn}$  on  $\{\pm 1, \pm 2, \dots, \pm 2^{\Omega(n)}\}$ , with the same error.

COROLLARY.

$$\begin{aligned} E(F, d) &\geq 1 - \exp(-\Omega(n)) && \text{for } d = 0, 1, \dots, \varepsilon n, \\ R(F, d) &\geq 1 - \exp(-\Omega(n/d)) && \text{for } d = 0, 1, \dots, \varepsilon n. \end{aligned}$$

COROLLARY.  $E(F \wedge F, \Omega(n)) = 1,$   
 $R(F \wedge F, \Omega(n)) = 1.$

# Open Problems

- Is UPP closed under intersection? Equivalently, does the intersection of two halfspaces have high sign-rank?
- Determine the *statistical query dimension* of the intersection of two halfspaces.