

# Decoding Ta-Shma's Binary Codes

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*based on joint work with*

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Junior Theorists Workshop 2020  
Northwestern

# Goal of the Talk

## Goal

Present two **efficient decoding algorithms** for Ta-Shma's codes



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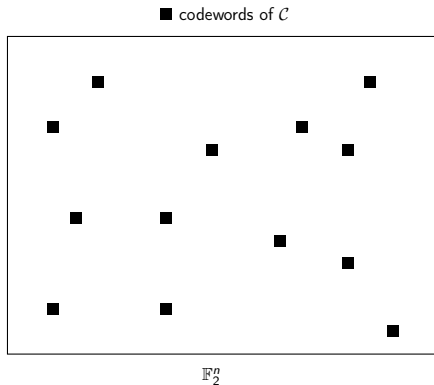
While highlighting connections among:

- Approximation and Optimization
- Pseudorandomness and Expansion
- Coding Theory

# Coding Theory Concepts

## Code

A binary code is a subset  $\mathcal{C} \subseteq \mathbb{F}_2^n$



# Coding Theory Concepts

Two fundamental parameters

## Distance

The distance  $\Delta(\mathcal{C})$  of  $\mathcal{C}$  is  $\Delta(\mathcal{C}) := \min_{z, z' \in \mathcal{C}: z \neq z'} \Delta(z, z')$

# Coding Theory Concepts

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## Rate

The rate  $r(\mathcal{C})$  of  $\mathcal{C}$  is  $\frac{\log_2(|\mathcal{C}|)}{n}$  (the fraction of information symbols)

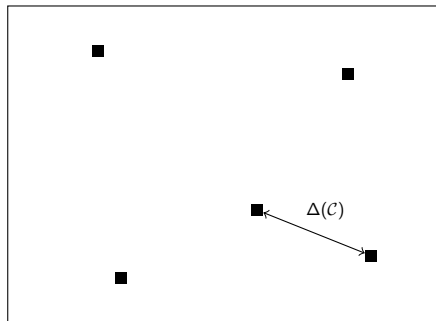
# Tension between Rate and Distance of a Code

## Tension

- Higher rate  $r(\mathcal{C})$ , lower distance  $\Delta(\mathcal{C})$
- Higher distance  $\Delta(\mathcal{C})$ , lower rate  $r(\mathcal{C})$

# Tension between Rate and Distance of a Code

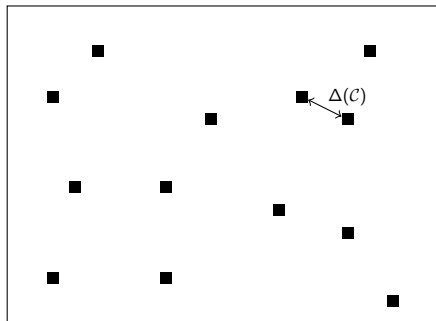
■ codewords of  $\mathcal{C}$



$\mathbb{F}_2^n$

Lower rate  $r(\mathcal{C})$

■ codewords of  $\mathcal{C}$



$\mathbb{F}_2^n$

Higher rate  $r(\mathcal{C})$



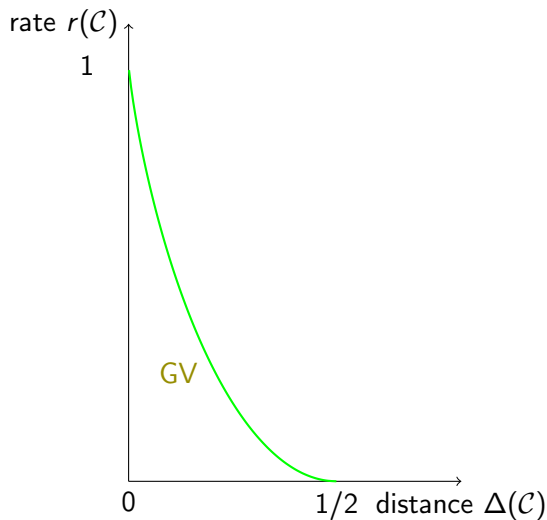
# Coding Theory Concepts

## Question

What is the best trade-off between rate  $r(\mathcal{C})$  and distance  $\Delta(\mathcal{C})$ ?

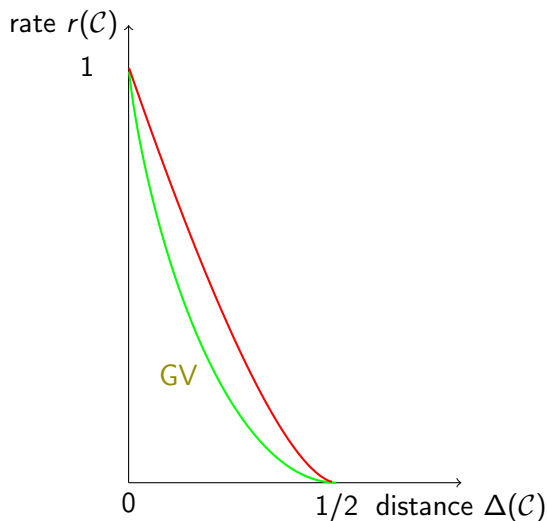
# Coding Theory Concepts

Gilbert–Varshamov existential bound (Gilbert'52, Varshamov'57)

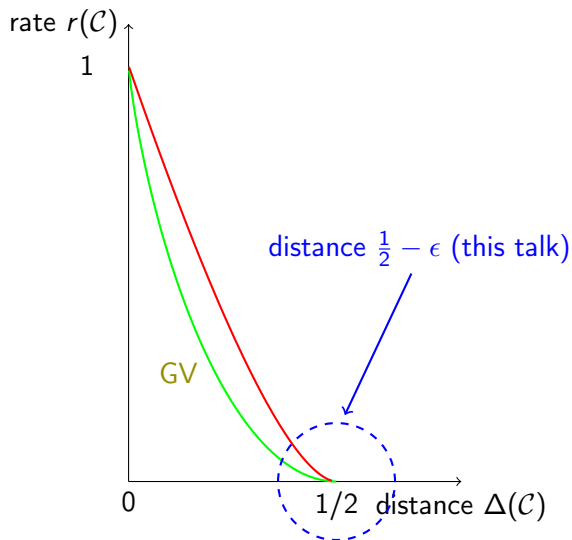


# Coding Theory Concepts

McEliece–Rodemich–Rumsey–Welch'77 impossibility bound



# Coding Theory Concepts



# Coding Theory Concepts

## Why is the Gilbert–Varshamov bound interesting?

The Gilbert–Varshamov (GV) bound is “*nearly*” optimal

For distance  $1/2 - \epsilon$

- rate  $\Omega(\epsilon^2)$  is achievable (Gilbert–Varshamov bound)
- rate better than  $O(\epsilon^2 \log(1/\epsilon))$  is impossible (McEliece *et al.*)

# Coding Theory Concepts

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Ta-Shma's Codes (60 years later!)

First **explicit** binary codes near the GV bound are due to Ta-Shma'17 with

- distance  $1/2 - \epsilon/2$  (actually  $\epsilon$ -balanced), and
- rate  $\Omega(\epsilon^{2+o(1)})$ .

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# Coding Theory Concepts

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## Theorem (this talk)

*Ta-Shma's codes are polynomial (even near-linear) time unique decodable*



# Our Contribution

## Theorem (Near-linear Time Decoding)

For every  $\epsilon > 0$ ,  $\exists$  explicit binary linear Ta-Shma codes  $\mathcal{C}_{N,\epsilon} \subseteq \mathbb{F}_2^N$  with

- 1 distance at least  $1/2 - \epsilon/2$  (actually  $\epsilon$ -balanced),
- 2 rate  $\Omega(\epsilon^{2+o(1)})$ , and
- 3 a unique decoding algorithm with running time  $\tilde{O}_\epsilon(N)$ .

# Our Contribution

Pseudorandomness approach

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# Our Contribution

Sum-of-Squares SDP hierarchy approach (SOS approach)

Theorem (J-Quintana-Srivastava-Tulsiani'20)

*Ta-Shma's codes are unique decodable in  $N^{O_\epsilon(1)}$  time*



## Related Work (a Sample)

Theorem (Guruswami–Indyk'04)

*Efficiently decodable **non-explicit** binary codes at the GV bound*

Theorem (Hemenway–Ron–Zewi–Wootters'17)

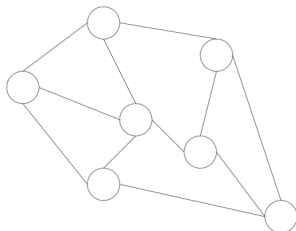
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# Towards Ta-Shma's Codes

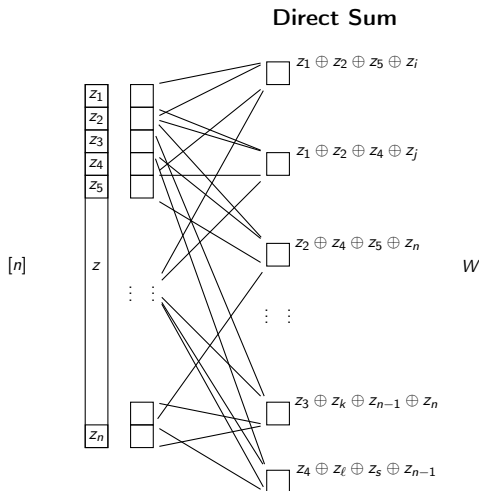
## Expander Graphs and Codes

Expanders can amplify the distance of a not so great base code  $\mathcal{C}_0$



# Expansion and Distance Amplification

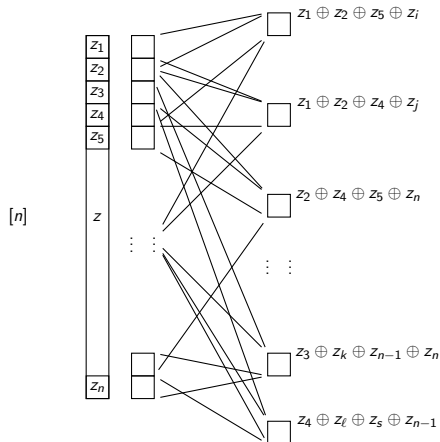
Fix a bipartite graph between  $[n]$  and  $W \subseteq [n]^k$ . Let  $z \in \mathbb{F}_2^n$ .



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## Direct Sum



$W$

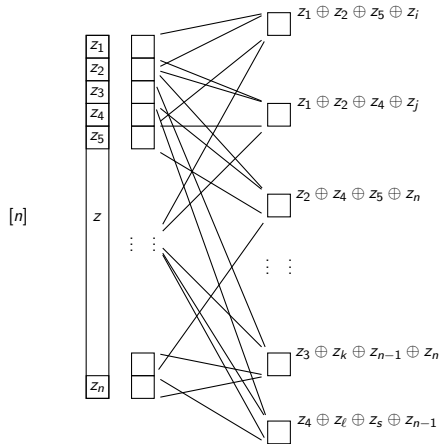
rate loss factor  $n/|W|$

distance amplification needs to be worth this loss

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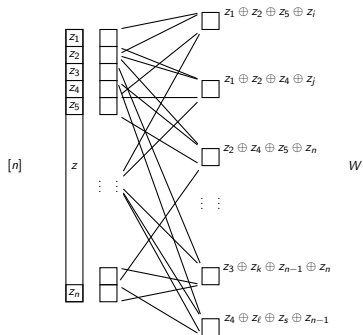
# Expansion and Distance Amplification

## Direct Sum

Let  $z \in \mathbb{F}_2^n$  and  $W \subseteq [n]^k$ . The *direct sum* of  $z$  is  $y \in \mathbb{F}_2^W$  defined as

$$y_{(i_1, \dots, i_k)} = z_{i_1} \oplus \dots \oplus z_{i_k},$$

for every  $(i_1, \dots, i_k) \in W$ . We denote  $y = \text{dsum}_W(z)$ .



# Expansion and Distance Amplification

## Bias

- Let  $z \in \mathbb{F}_2^n$ . Define  $\text{bias}(z) := |\mathbf{E}_{i \in [n]} (-1)^{z_i}|$
- $\text{bias}(\mathcal{C}) = \max_{z \in \mathcal{C} \setminus 0} \text{bias}(z)$
- If  $\text{bias}(\mathcal{C}) \leq \epsilon$ , then  $\Delta(\mathcal{C}) \geq 1/2 - \epsilon/2$  (assuming  $\mathcal{C}$  linear)

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$$\text{bias}(\underbrace{00 \dots 0}_n) = \text{bias}(\underbrace{11 \dots 1}_n) = 1$$

$$\text{bias}(\underbrace{0 \dots 0}_{n/2} \underbrace{1 \dots 1}_{n/2}) = 0$$

# Expansion and Distance Amplification

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## Definition (Parity Sampler, c.f. Ta-Shma'17)

Let  $W \subseteq [n]^k$ . We say that  $\text{dsum}_W$  is  $(\epsilon_0, \epsilon)$ -**parity sampler** iff

$$(\forall z \in \mathbb{F}_2^n) (\text{bias}(z) \leq \epsilon_0 \implies \text{bias}(\text{dsum}_W(z)) \leq \epsilon).$$

# Expanders and Distance Amplification

## Parity Samplers

Where to look for good parity samplers  $W \subseteq [n]^k$ ?

# Expanders and Distance Amplification

## A Dream Parity Sampler

Let  $z \in \mathbb{F}_2^n$  with  $\text{bias}(z) = \epsilon_0$ . Let  $W = [n]^k$ . Then

$$\text{bias}(\text{dsum}_W(z)) \leq |\mathbf{E}_{i \in [n]} (-1)^{z_i}|^k \leq \epsilon_0^k,$$

implying that  $W$  is a  $(\epsilon_0, \epsilon_0^k)$ -parity sampler (for every  $\epsilon_0$ ).

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## Issue: Vanishing Rate

$W$  is "too dense" so distance amplified code has rate  $\leq 1/n^{k-1}$

# Expanders and Distance Amplification

## Another Dream Parity Sampler

Sample a uniformly random  $W \subseteq [n]^k$  of size  $\Theta_{\epsilon_0}(n/\epsilon^2)$ .  
Then w.h.p.  $\text{dsum}_W$  is  $(\epsilon_0, \epsilon)$ -parity sampler.



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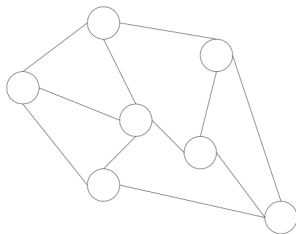
## Issue: Non-explicit

Now  $W$  has near optimal size but it is non-explicit

# Explicit Constructions of Parity Samplers

## Solution (Alon and Rozenman–Wigderson)

Take  $W \subseteq [n]^k$  to be the collection of **all** length- $(k - 1)$  walks on a sparse expander graph  $G = (V = [n], E)$



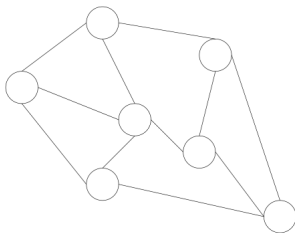
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## Solution (good but not near optimal)

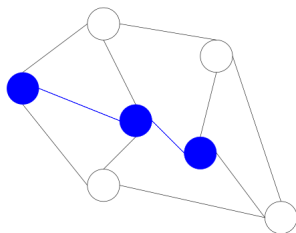
This yields codes of distance  $1/2 - \epsilon$  and rate  $\Omega(\epsilon^{4+o(1)})$



# Explicit Constructions of Parity Samplers

## Solution of Ta-Shma'17

Take  $W \subseteq [n]^k$  to be a **carefully chosen** collection of length- $(k - 1)$  walks on a **structured** sparse expander graph  $G = (V = [n], E)$



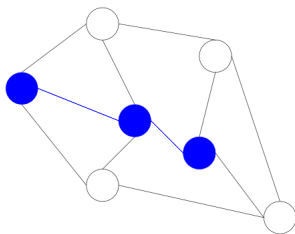
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# General Techniques for Decoding

## Decoding Direct Sum

What does decoding look like for direct sum?

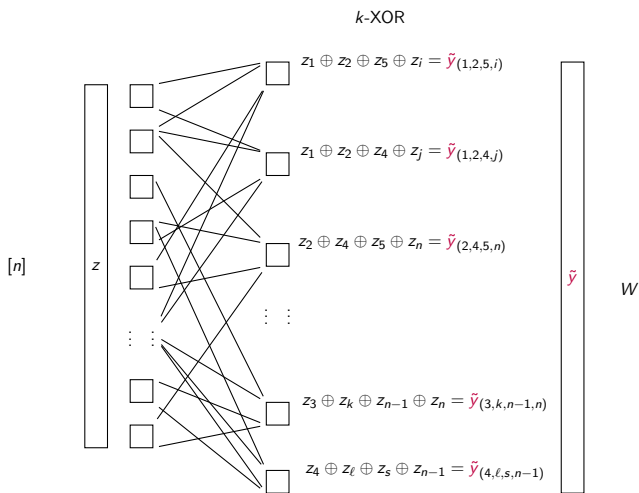
# Decoding by Solving a $k$ -CSP

## Setup (informal)

- $\mathcal{C}_0 \subseteq \mathbb{F}_2^n$  is a code of small distance
- $W \subseteq [n]^k$  for direct sum
- $\mathcal{C} = \text{dsum}_W(\mathcal{C}_0)$  is a code of large distance

# Decoding by Solving a $k$ -CSP

Suppose  $y^* \in \mathcal{C}$  is corrupted into some  $\tilde{y} \in \mathbb{F}_2^W$  in the unique decoding ball centered at  $y^*$ .





# Decoding by Solving a $k$ -CSP

## Unique Decoding Scenario: $k$ -XOR like

Unique decoding  $\tilde{y}$  amounts to solving

$$\arg \max_{z \in \mathcal{C}_0} \mathbf{E}_{(i_1, \dots, i_k) \in W} \mathbf{1}[z_{i_1} \oplus \dots \oplus z_{i_k} = \tilde{y}_{(i_1, \dots, i_k)}].$$

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## A Relaxation

Suppose that we can find  $\tilde{z} \in \mathbb{F}_2^n$  (rather than in  $\mathcal{C}_0$ ) satisfying

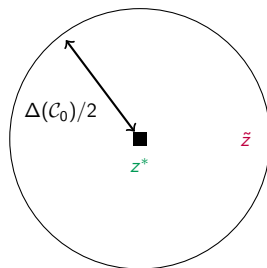
$$\mathbf{E}_{(i_1, \dots, i_k) \in W} \mathbf{1}[\tilde{z}_{i_1} \oplus \dots \oplus \tilde{z}_{i_k} = \tilde{y}_{(i_1, \dots, i_k)}] \approx \text{OPT}.$$

# Decoding by Solving a $k$ -CSP

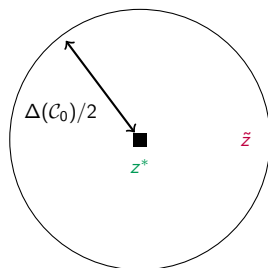
Say  $y^* = \text{dsum}(z^*)$  for some  $z^* \in \mathcal{C}_0$

## Claim (Informal)

If the parity sampler is *strong enough*, then  $\tilde{z}$  lies in the unique decoding ball centered at  $z^* \in \mathcal{C}_0$ .



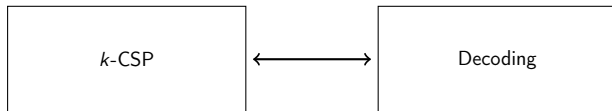
# Decoding by Solving a $k$ -CSP



## Moral

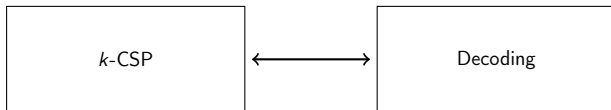
- Find approx. optimal solution  $\tilde{z} \in \mathbb{F}_2^n$  (rather than in  $\mathcal{C}_0$ ) is enough
- Use unique decoder of  $\mathcal{C}_0$  to correct  $\tilde{z}$  into  $z^*$

What do we have so far?



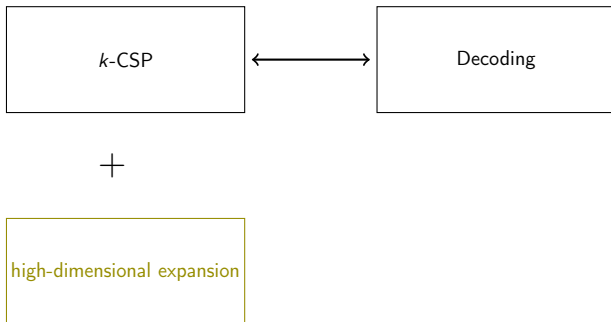
# What do we have so far?

Why can we efficiently approximate these  $k$ -CSPs?



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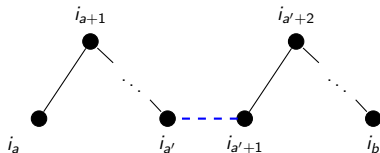
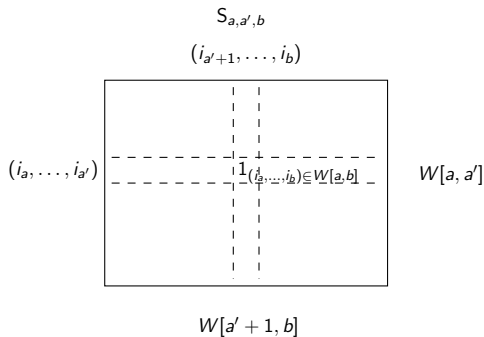
# A Notion of High-dimensional Expansion

Let  $W \subseteq [n]^k$ . Define  $W[a, b]$  for  $1 \leq a \leq b \leq k$  as

$$W[a, b] = \{(i_a, \dots, i_b) \mid (i_1, \dots, i_k) \in W\}.$$



# A Notion of High-dimensional Expansion



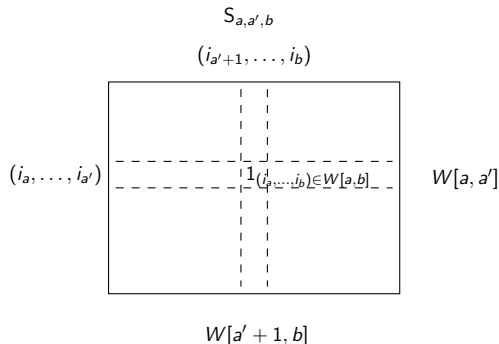
$$W[a, b] = \{(i_a, \dots, i_b) \mid (i_1, \dots, i_k) \in W\}$$

# A Notion of High-dimensional Expansion

## Definition (Splittability (informal))

A collection  $W \subseteq [n]^k$  is said to be  $\tau$ -splittable, if  $k = 1$  or for every  $1 \leq a \leq a' < b \leq k$ :

- 1 The (normalized) matrix  $S_{a,a',b} \in \mathbb{R}^{W[a,a'] \times W[a'+1,b]}$  defined as  $S_{a,a',b}(w, w') = 1_{ww' \in W[a,b]}$  satisfy  $\sigma_2(S_{a,a',b}) \leq \tau$

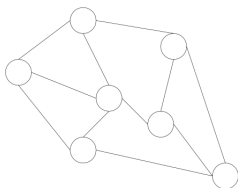


# A Notion of High-dimensional Expansion

Example of  $\tau$ -splittable structures

Lemma (Alev–J–Quintana–Srivastava–Tulsiani'20)

*The collection  $W \subseteq [n]^k$  of **all** walks on  $\tau$ -two-sided spectral expander graph  $G = (V = [n], E)$  is  $\tau$ -splittable*

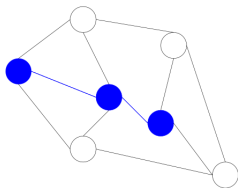


# A Notion of High-dimensional Expansion

Example of  $\tau$ -splittable structures

Lemma (J–Quintana–Srivastava–Tulsiani'20)

*A simple modification of Ta-Shma's parity sampler  $W \subseteq [n]^k$  is  $\tau$ -splittable*

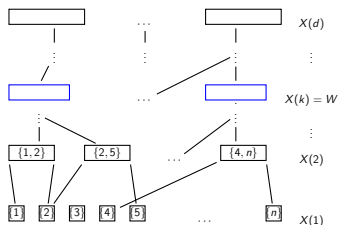


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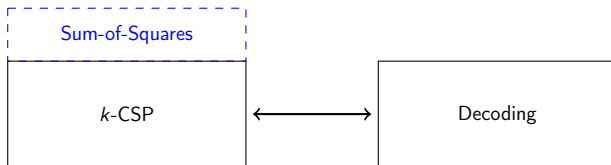
Example of  $\tau$ -splittable structures

**Theorem (Alev–J–Tulsiani'19 and Dikstein–Dinur'19)**

*The collection  $W$  of hyperedges of sufficiently expanding high-dimensional expander (link spectral HDX [Dinur–Kaufman]) is  $\tau$ -splittable*



# Sum-of-Squares Approach



+

high-dimensional expansion



# Sum-of-Squares Approach

Using the Sum-of-Squares (SOS) semi-definite programming hierarchy:

Theorem (Alev–J–Tulsiani'19 (informal))

*Instances of  $k$ -XOR supported on **expanding** ( $\tau$ -splittable) tuples  $W \subseteq [n]^k$  can be efficiently approximated*

(building on Barak–Raghavendra–Steurer'11)



# Sum-of-Squares Approach

Using the Sum-of-Squares (SOS) semi-definite programming hierarchy:

## Theorem (Alev–J–Tulsiani'19)

Let  $W \subseteq [n]^k$  be  $\tau$ -splittable. Suppose  $\mathfrak{J}$  is a  $k$ -XOR instance on  $W$ . If  $\tau \leq \text{poly}(\delta/2^k)$ , then we can find a solution  $z \in \mathbb{F}_2^n$  satisfying

$$\text{OPT}(\mathfrak{J}) - \delta,$$

fraction of the constraints of  $\mathfrak{J}$  in time  $n^{\text{poly}(2^k/\delta)}$ .

(building on Barak–Raghavendra–Steurer'11)



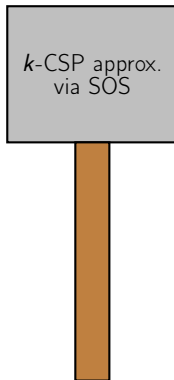
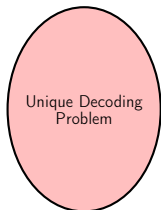


# Sum-of-Squares Approach

What are the techniques?

We will just mention the techniques at a very high-level

# Sum-of-Squares Approach



# Sum-of-Squares Approach

## Well... Our parameters...

We can only decode codes  $\mathcal{C}$  satisfying

- $\Delta(\mathcal{C}) \geq 1/2 - \epsilon$ , and
- rate  $r(\mathcal{C}) = 2^{-\text{polylog}(1/\epsilon)} \ll \epsilon^{2+o(1)}$  (not even polynomial rate)

# Sum-of-Squares Approach

## Leveraging Unique Decoding to List Decoding AJQST'20

Maximizing an entropic function  $\Psi$  while “solving” the Sum-of-Squares program of unique decoding yields a list decoding algorithm

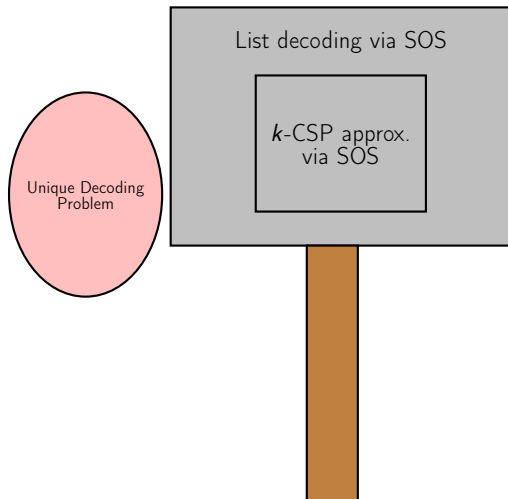
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Several independent applications in robust statistics:  
Raghavendra–Yau & Karmalkar–Klivans–Kothari to regression  
by Raghavendra–Yau & Bakshi–Kothari to subspace recovery  
by Bakshi–Kothari to clustering mixtures of Gaussians

# Sum-of-Squares Approach



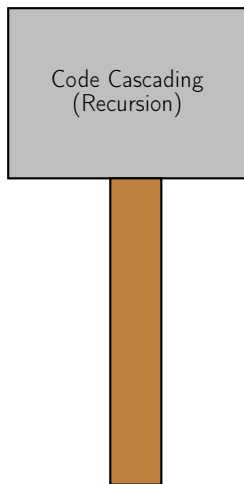
# Sum-of-Squares Approach

## Second Hammer Effect

We can only decode codes  $\mathcal{C}$  satisfying

- $\Delta(\mathcal{C}) \geq 1/2 - \epsilon$ , and
- rate  $r(\mathcal{C}) = 2^{-\text{polylog}(1/\epsilon)} \ll \epsilon^{2+o(1)}$  (not even polynomial rate)

# Sum-of-Squares Approach





# Sum-of-Squares Approach

Ta-Shma's walks admit a recursive structure

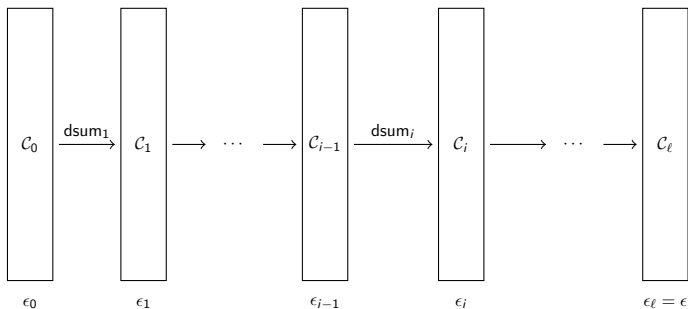
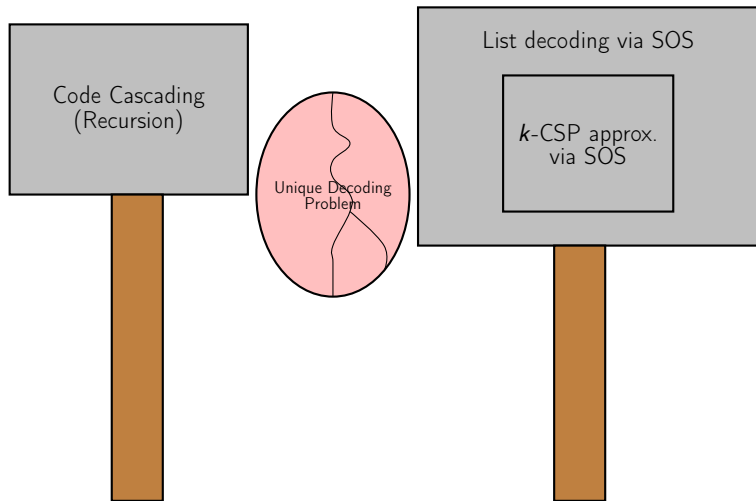
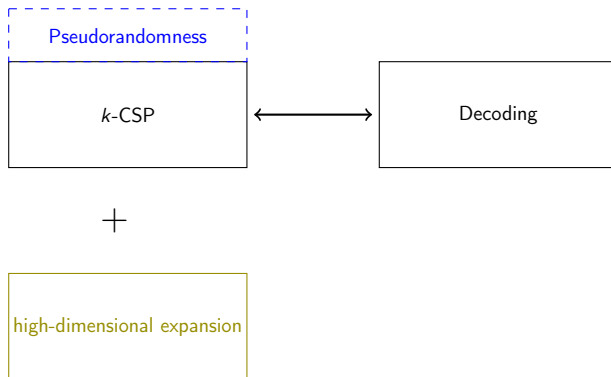


Figure: Code cascading: recursive construction of codes.

# Sum-of-Squares Approach



# Pseudorandomness Approach



# Pseudorandomness Approach

Using pseudorandomness techniques (weak regularity decompositions):

## Theorem (J–Srivastava–Tulsiani'20)

Let  $W \subseteq [n]^k$  be  $\tau$ -splittable. Suppose  $\mathfrak{J}$  is a  $k$ -XOR instance on  $W$ . If  $\tau \leq \text{poly}(\delta/k)$ , then we can find a solution  $z \in \mathbb{F}_2^n$  satisfying

$$\text{OPT}(\mathfrak{J}) - \delta,$$

fraction of the constraints of  $\mathfrak{J}$  in time  $\tilde{O}_\delta(|W|)$ .



# Weak Regularity Decomposition: Dense Graphs

We recall Frieze and Kannan'96 approach.

Let  $A$  be the adjacency matrix of a **dense** graph  $G = ([n], E)$ . Suppose we have  $A \approx \sum_{\ell=1}^L c_i \cdot 1_{S_1^i} \otimes 1_{S_2^i}$  such that

$$\max_{S, T \subseteq [n]} \left| \left\langle A - \sum_{\ell=1}^L c_i \cdot 1_{S_1^i} \otimes 1_{S_2^i}, 1_S \otimes 1_T \right\rangle \right| \leq \delta \cdot n^2,$$

and  $L = O(1/\delta^2)$ .

## Weak Regularity Decomposition: Dense Graphs

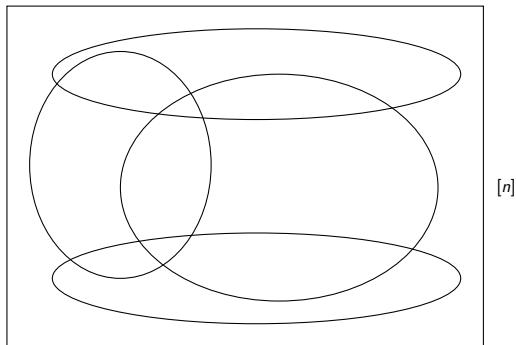
Frieze and Kannan use  $\sum_{\ell=1}^L c_i \cdot 1_{S_1^i} \otimes 1_{S_2^i}$  to approximate the **maximum cut** value of  $G$  within additive error  $\delta \cdot n^2$

$$\begin{aligned} |E(S, \bar{S})| &= \langle A, 1_S \otimes 1_{\bar{S}} \rangle \approx \left\langle \sum_{\ell=1}^L c_i \cdot 1_{S_1^i} \otimes 1_{S_2^i}, 1_S \otimes 1_{\bar{S}} \right\rangle, \\ &= \sum_{\ell=1}^L c_i \cdot |S_1^i \cap S| |S_2^i \cap \bar{S}|, \end{aligned}$$

# Weak Regularity Decomposition: Dense Graphs

$$|E(S, \bar{S})| \approx \sum_{\ell=1}^L c_i \cdot |S_1^i \cap S| |S_2^i \cap \bar{S}|$$

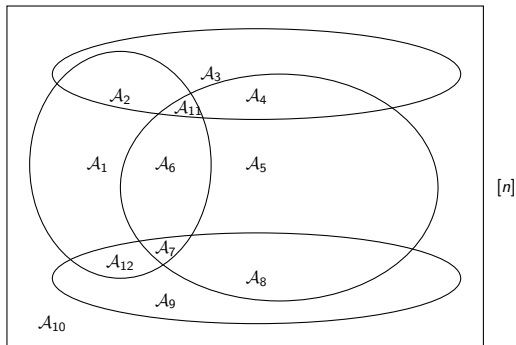
Venn diagram of sets  $S_1^i, S_2^i$  for  $i \in [L]$



# Weak Regularity Decomposition: Dense Graphs

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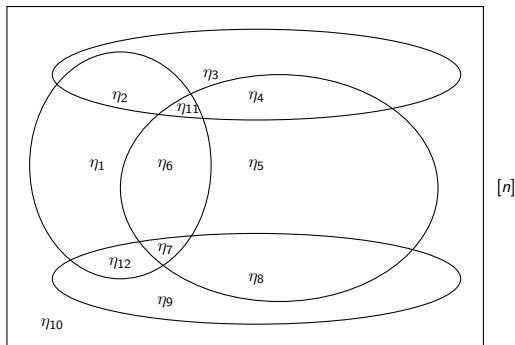
$\exp(L) = \exp(1/\delta^2)$  atoms  $\mathcal{A}_1, \mathcal{A}_2, \dots$



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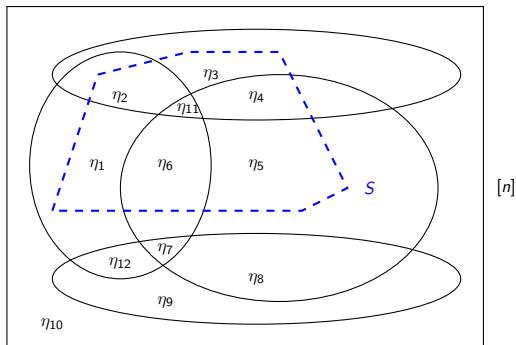
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$$\eta_j = \frac{|\mathcal{A}_j \cap S|}{|\mathcal{A}_j|} \text{ for atom } \mathcal{A}_j$$

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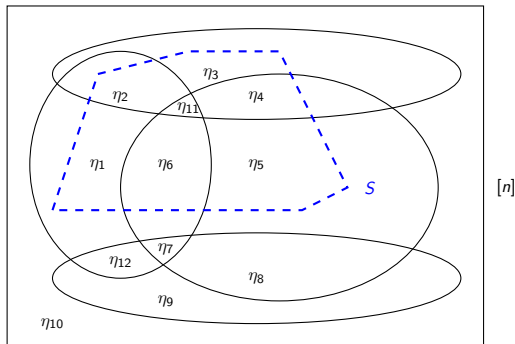
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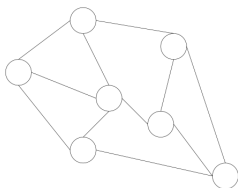
To find best  $S$  brute-force over a fine enough discretization of  $\eta_j$ 's

# Weak Regularity Decomposition: Sparse Graphs

## Theorem (Oveis Gharan and Trevisan'13)

*Expander graphs admit efficient weak regularity decompositions, so MaxCut can be approximated on them*

(their result also holds for low threshold rank graphs)



# Weak Regularity Decomposition: Sparse Tensors

## Sparse Tensors on Splittable Structures

Let  $W \subseteq [n]^k$  and  $g: W \rightarrow [-1, 1]$ . We want to find  $g \approx \sum_{\ell=1}^L c_i \cdot 1_{S_1^i} \otimes \cdots \otimes 1_{S_k^i}$  such that

$$\max_{S_1, \dots, S_k \subseteq [n]} \left| \left\langle g - \sum_{\ell=1}^L c_i \cdot 1_{S_1^i} \otimes \cdots \otimes 1_{S_k^i}, 1_{S_1} \otimes \cdots \otimes 1_{S_k} \right\rangle \right| \leq \delta \cdot |W|,$$

and  $L = O(1/\delta^2)$ .

# Weak Regularity Decomposition: Sparse Tensors

## Sparse Tensors on Splittable Structures

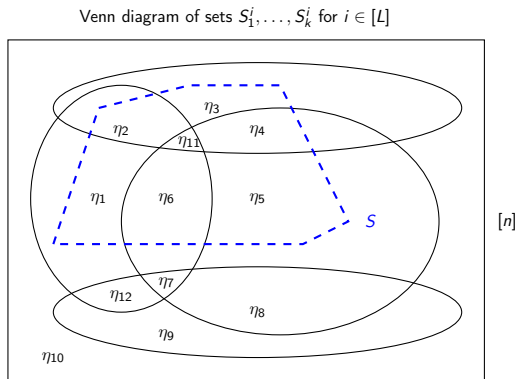
Let  $W \subseteq [n]^k$   $\tau$ -splittable and  $g: W \rightarrow [-1, 1]$ . If  $\tau \leq \text{poly}(\delta/k)$ , there exists  $\sum_{\ell=1}^L c_i \cdot 1_{S_1^i} \otimes \cdots \otimes 1_{S_k^i}$  such that

$$\max_{S_1, \dots, S_k \subseteq [n]} \left| \left\langle g - \sum_{\ell=1}^L c_i \cdot 1_{S_1^i} \otimes \cdots \otimes 1_{S_k^i}, 1_{S_1} \otimes \cdots \otimes 1_{S_k} \right\rangle \right| \leq \delta \cdot |W|,$$

and  $L = O(1/\delta^2)$ .

# Weak Regularity Decomposition: Sparse Tensors

Similar strategy works for  $k$ -CSPs (and even to list decoding)



$\exp(kL) = \exp(k/\delta^2)$  atoms  $\mathcal{A}_1, \mathcal{A}_2, \dots$

$$\eta_j = \frac{|\mathcal{A}_j \cap S|}{|\mathcal{A}_j|} \text{ for atom } \mathcal{A}_j$$

# Weak Regularity Decomposition: Sparse Tensors

## Existential regularity decomposition for splittable tensors

Showing the **existence** of  $\sum_{\ell=1}^L c_{\ell} \cdot 1_{S_1^{\ell}} \otimes \cdots \otimes 1_{S_k^{\ell}} \approx g$  is not too hard



# Weak Regularity Decomposition: Sparse Tensors

$$\text{CUT}^{\otimes k} = \{\pm 1_{S_1} \otimes \cdots \otimes 1_{S_k} \mid S_1, \dots, S_k \subseteq [n]\}$$

Let  $\mu$  be a probability measure on  $W$

---

```
1: function ExistentialWeakRegularityDecomposition( $g: W \rightarrow [-1, 1]$ )
2:    $h \leftarrow 0$ 
3:   while  $\exists f \in \text{CUT}^{\otimes k}: \langle g - h, f \rangle_\mu \geq \delta$  do
4:      $h \leftarrow h + \delta \cdot f$ 
5:   end while
6:   return  $h$ 
7: end function
```

---

# Weak Regularity Decomposition: Sparse Tensors

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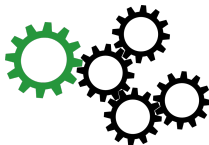
Claim:  $\|g - h\|_{\mu}^2$  decreases by  $\delta^2$  at each iteration

$$\begin{aligned} \langle g - h - \delta \cdot f, g - h - \delta \cdot f \rangle_{\mu} &= \langle g - h, g - h \rangle_{\mu} - 2\delta \langle g - h, f \rangle_{\mu} + \delta^2 \langle f, f \rangle_{\mu} \\ &\leq \langle g - h, g - h \rangle_{\mu} - \delta^2 \end{aligned}$$

# Weak Regularity Decomposition: Sparse Tensors

## Near-linear time regularity decomposition for splittable tensors

The more challenging steps are related to **algorithmically** finding a decomposition  $\sum_{\ell=1}^L c_{\ell} \cdot 1_{S_1^{\ell}} \otimes \cdots \otimes 1_{S_k^{\ell}} \approx g$  in time  $\tilde{O}_{\delta}(|W|)$  (and also proving list decoding)



# Towards List Decoding Capacity

Major Open Problem in the adversarial (Hamming) model

Find explicit efficient list decodable binary codes from radius  $1/2 - \epsilon$  having rate  $\Omega(\epsilon^2)$

(pointed by Guruswami and Sudan)



# Towards List Decoding Capacity

## Open Problem: Near List Decoding Capacity

Find explicit efficient list decodable binary codes from radius  $1/2 - \epsilon$  having rate  $\Omega(\epsilon^{2+o(1)})$

Can any of our approaches help resolve this problem?

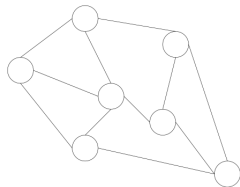


vs



# Towards List Decoding Capacity

More broadly, where else can these techniques be applied?



That's all.

Thank you!

Questions?