

List Decoding of Direct Sum Codes

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joint work with

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Outline

- 1 Motivation and Background
- 2 Distance Amplification

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- 3 Main Results

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- 4 Unique Decoding Techniques

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- 5 List Decoding Techniques

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- 2 Distance Amplification
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- 5 List Decoding Techniques

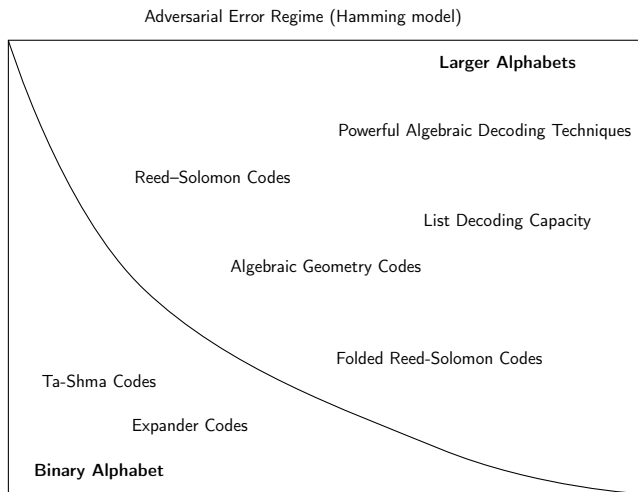
Context

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Binary codes are not that well understood compared to larger alphabet codes. We lack:

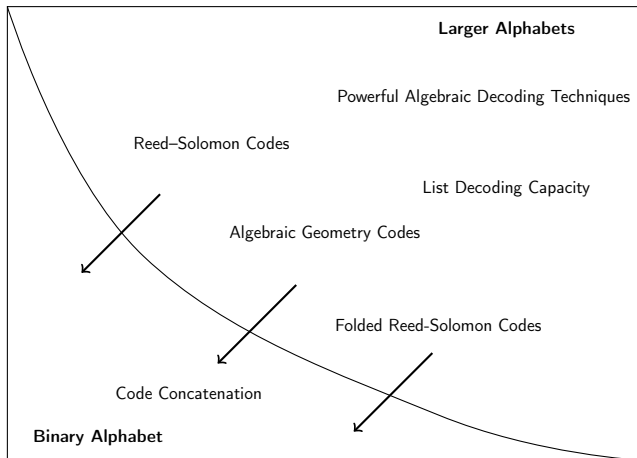
- algorithmic tools,
- explicit constructions, and
- impossibility results.

Context



Context

Popular approach: obtain results by concatenating with binary codes



Context

This work

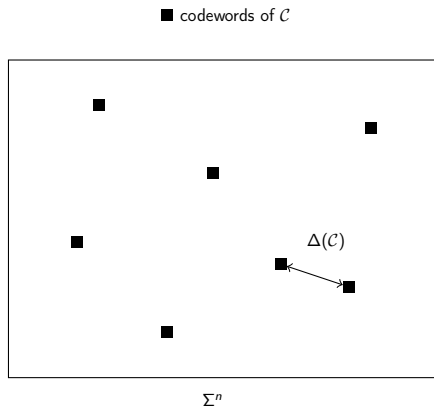
We make partial progress on the **algorithmic tool** front by providing a list decoding framework to handle *direct sum codes* on some (sparse) “expanding structures”.

Notation

Notation

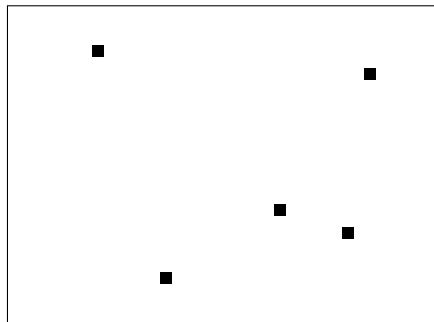
- Let Σ be a finite alphabet.
- A code is a subset $\mathcal{C} \subseteq \Sigma^n$ (where n the block length).
- The (normalized) Hamming distance between $z, z' \in \Sigma^n$ is $\Delta(z, z') := |\{i \mid z_i \neq z'_i\}|/n$.
- The distance $\Delta(\mathcal{C})$ of \mathcal{C} is $\min_{z, z' \in \mathcal{C}: z \neq z'} \Delta(z, z')$.
- The rate $r(\mathcal{C})$ of \mathcal{C} is $\log_{|\Sigma|}(\mathcal{C})/n$.

Notation



Notation

■ codewords of \mathcal{C}

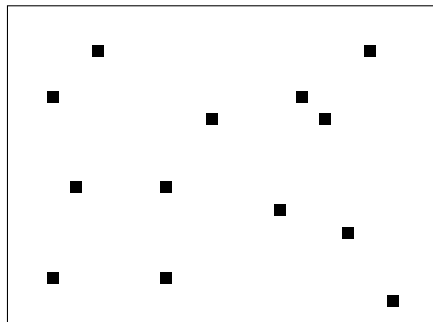


Σ^n

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

Notation

■ codewords of \mathcal{C}



Σ^n

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

Background

We digress a bit to provide some background.

Expander and Codes

Expander graphs and codes have had a synergetic relationship. There are two major approaches:

- **Distance amplification:** use pseudorandom properties to boost distance ([ABNNR92], [AEL95], [GI03], [DHKNT19], etc).
- **Parity Check Matrix:** adjacency of a bipartite expander is used to define a parity check matrix ([Sipser–Spielman94], [Zémor01], LDPCs, etc).

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Expansion and Distance Amplification

Direct Product

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

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

for every $(i_1, \dots, i_k) \in X(k)$.

Expansion and Distance Amplification

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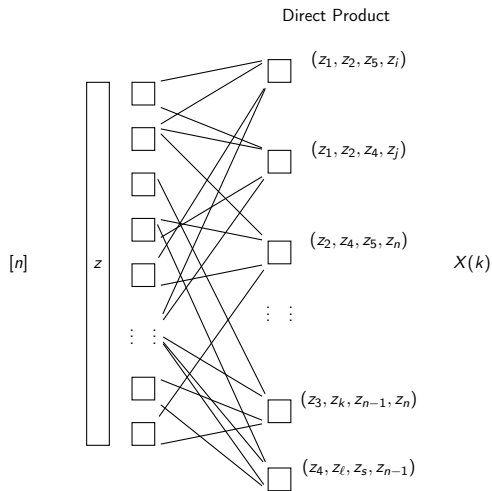
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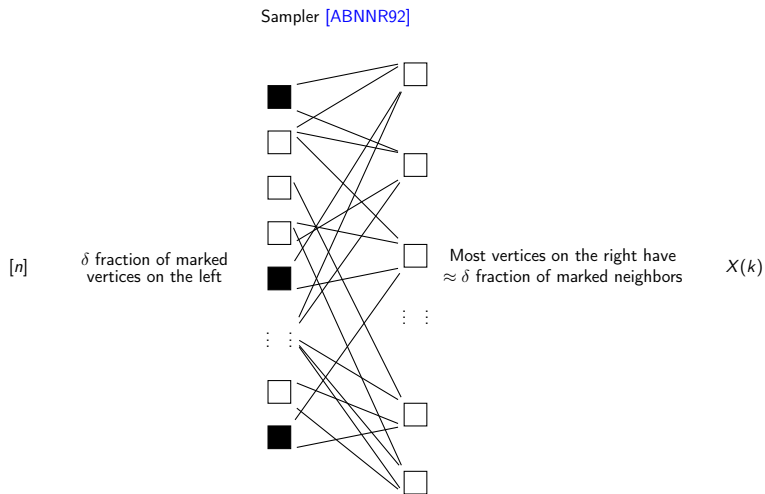
Shortcoming

Resulting alphabet is no longer binary.

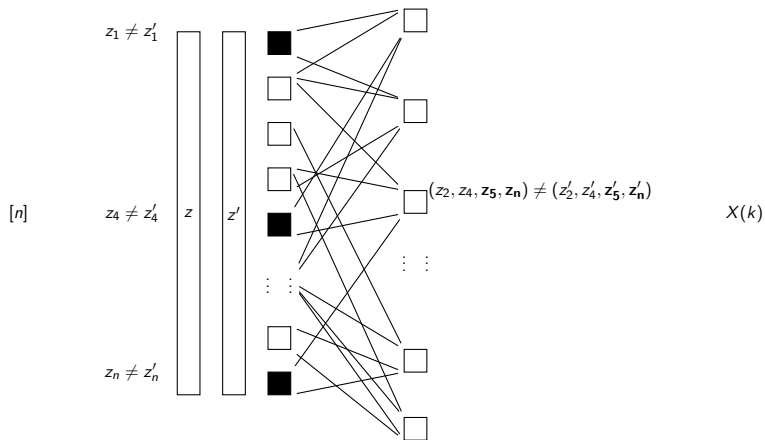
Expansion and Distance Amplification



Expansion and Distance Amplification



Expansion and Distance Amplification



Expansion and Distance Amplification

Theorem (Dinur, Harsha, Kaufman, Navon and Ta-Shma'19)

*For every $\beta > 0$, there is a family of explicit (non-binary) **direct product** codes list decodable from radius $1 - \beta$ with rate $\exp(-\exp(\text{poly}(1/\beta)))$ in polynomial time. (The construction relies on “double samplers”).*

Expansion and Distance Amplification

Direct Sum

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

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

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

Expansion and Distance Amplification

Direct Sum

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Advantage

The resulting alphabet is binary.

Expansion and Distance Amplification

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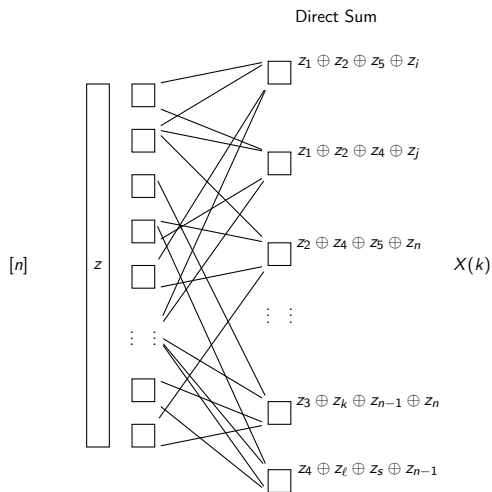
Advantage

The resulting alphabet is binary.

Further Motivation

Ta-Shma [Ta-Shma'17] found explicit binary codes “near” the Gilbert–Varshamov bound using direct sum.

Expansion and Distance Amplification



Expansion and Distance Amplification

Further Notation

- Let $z \in \mathbb{F}_2^n$. Define $\text{bias}(z) := |\mathbf{E}_{i \in [n]} (-1)^{z_i}|$.
- Let $\mathcal{C} \subseteq \mathbb{F}_2^n$. Define $\text{bias}(\mathcal{C}) := \max_{z \in \mathcal{C} \setminus \{0\}} \text{bias}(z)$.

Definition

Let $X \subseteq [n]^k$. We say that dsum_X is (β_0, β) -**parity sampler** iff

$$(\forall z \in \mathbb{F}_2^n) (\text{bias}(z) \leq \beta_0 \implies \text{bias}(\text{dsum}_X(z)) \leq \beta).$$

Expansion and Distance Amplification

A Dream Parity Sampler

Let $z \in \mathbb{F}_2^n$ with $\text{bias}(z) \leq \beta_0 < 1$. Let $X(k) = [n]^k$ (i.e., all k -tuples of $[n]$). Then

$$\text{bias}(\text{dsum}_{X(k)}(z)) \leq |\mathbf{E}_{i \in [n]} (-1)^{z_i}|^k \leq \beta_0^k.$$

Expansion and Distance Amplification

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Issue

$X(k)$ is "too dense". The code $\text{dsum}_{X(k)}(\mathcal{C})$ has **vanishing rate**.

Expansion and Distance Amplification

Explicit Sparse Expanding Structures

Two explicit **sparse** “expanding” structures for parity sampling:

- (sparse) **High-dimensional expanders** [[this work](#)], and
- $X(k) \subseteq [n]^k$ from length- $(k - 1)$ walks on expander graph $G = ([n], E)$ [[Ta-Shma'17](#)].

Expansion and Distance Amplification

High-dimensional expander (informal) definition

A γ -spectral high-dimensional expander X is a hypergraph s.t.

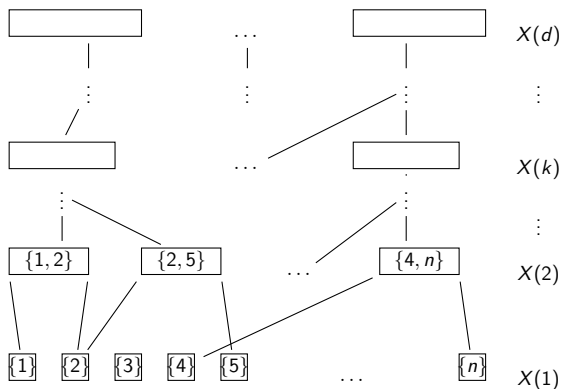
- **Downward-close**: if $s \in X$ and $t \subseteq s$, then $t \in X$.
- **“Multiscale expansion”**: all sub-expander graphs are γ -two sided spectral expanders.

Expansion and Distance Amplification

Intuition

- Expander graph: “sparse approximation” of a complete graph
- High-dimensional expander: “sparse approximation” of $\binom{[n]}{\leq d}$

Expansion and Distance Amplification



High-dimensional expansion adjacency by containment.

Expansion and Distance Amplification

High-dimensional Expander as Parity Sampler

- High-dimensional expander \approx complete hypergraph $\binom{[n]}{\leq d}$.
- Complete hypergraph $\binom{[n]}{\leq d}$ is a parity sampler.
- Follows that high-dimensional expander is a parity sampler.

Main Results

Theorem (Direct Sum High-dimensional Expanders)

*For every $\beta > 0$, there is a family of explicit **binary** direct sum codes based on high-dimensional expanders list decodable from radius $1/2 - \beta$ with rate $\exp(-\text{poly}(1/\beta))$ in time $n^{\text{poly}(1/\beta)}$, where n is the block length.*

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Corollary (Direct Product High-dimensional Expanders)

For every $\beta > 0$, there is a family of explicit (non-binary) direct product codes based on high-dimensional expanders list decodable from radius $1 - \beta$ with rate $\exp(-\text{poly}(1/\beta))$ in time $n^{\text{poly}(1/\beta)}$, where n is the block length.

Main Results

Theorem (Direct Sum Expander Walks)

*For every $\beta > 0$, there is a family of explicit **binary** direct sum codes based on walks on expanders list decodable from radius $1/2 - \beta$ with (**quasipolynomial**) rate $\exp(-\text{polylog}(1/\beta))$ in time $n^{\text{poly}(1/\beta)}$, where n is the block length.*

Bird's-eye view of Techniques

Very High-level Strategy

- Start with a unique decoding algorithm for direct sum codes.
- Enhance this algorithm with list decoding capabilities.

Bird's-eye view of Techniques

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- Start with a unique decoding algorithm for direct sum codes.
- Enhance this algorithm with list decoding capabilities.

First Step: Dealing with k -XOR

We first describe this unique decoding algorithm and how it is naturally related to k -XOR.

Bird's-eye view of Techniques: Unique Decoding

Setup

- $\mathcal{C} \subseteq \mathbb{F}_2^n$ a β_0 -biased code,
- $X \subseteq [n]^k$ for direct sum, and
- $\mathcal{C}' = \text{dsum}_X(\mathcal{C})$ a β -biased code.

Bird's-eye view of Techniques: Unique Decoding

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

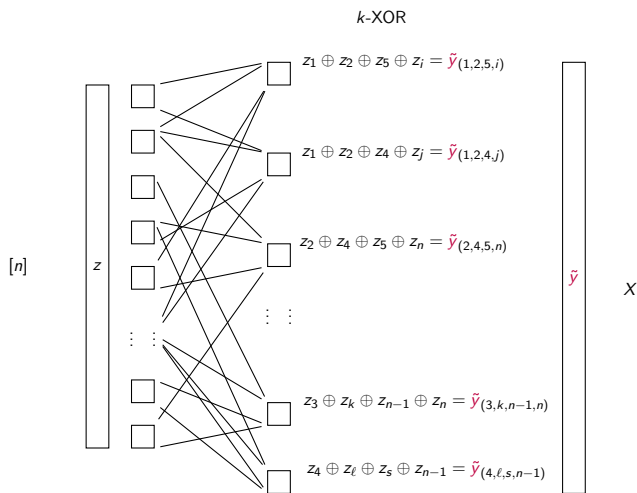
Unique Decoding Scenario: k -XOR

Unique decoding \tilde{y} amounts to solving

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

which is a MAX k -XOR instance \mathfrak{J} with the additional constraint that the solution z must lie in \mathcal{C} .

Bird's-eye view of Techniques: Unique Decoding



Bird's-eye view of Techniques: Unique Decoding

Let $z^* \in \mathcal{C}$ be s.t. $y^* = \text{dsum}_X(z^*)$.

Optimal Value

Since \tilde{y} is in the unique decoding ball centered at y^* , we have

$$\mathbf{E}_{(i_1, \dots, i_k) \in X} \mathbf{1}[z^*_{i_1} \oplus \dots \oplus z^*_{i_k} \neq \tilde{y}_{(i_1, \dots, i_k)}] = \Delta(y^*, \tilde{y}) < \Delta(\mathcal{C}')/2$$

Thus,

$$\text{OPT}(\mathcal{J}) \geq \mathbf{E}_{(i_1, \dots, i_k) \in X} \mathbf{1}[z^*_{i_1} \oplus \dots \oplus z^*_{i_k} = \tilde{y}_{(i_1, \dots, i_k)}] > 1 - \Delta(\mathcal{C}')/2$$

Bird's-eye view of Techniques: Unique Decoding

Optimal Solution

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

$$\mathbf{E}_{(i_1, \dots, i_k) \in X} \mathbf{1}[\tilde{z}_{i_1} \oplus \dots \oplus \tilde{z}_{i_k} = \tilde{y}_{(i_1, \dots, i_k)}] = \text{OPT}(\mathfrak{J}) > 1 - \Delta(\mathcal{C}')/2$$

Thus, $\Delta(\text{dsum}_X(\tilde{z}), \tilde{y}) < \Delta(\mathcal{C}')/2$

Bird's-eye view of Techniques: Unique Decoding

By triangle inequality,

$$\Delta(\text{dsum}_X(\tilde{z}), \text{dsum}_X(z^*)) \leq \Delta(\text{dsum}_X(\tilde{z}), \tilde{y}) + \Delta(\tilde{y}, \text{dsum}_X(z^*)) < \Delta(C') \leq 1/2 - \beta/2,$$

implying

$$\text{bias}(\text{dsum}_X(\tilde{z}) \oplus \text{dsum}_X(z^*)) = \text{bias}(\text{dsum}_X(\tilde{z} \oplus z^*)) > \beta$$

“Nontrivial bias”

Bird's-eye view of Techniques: Unique Decoding

Claim

If dsum_χ is a “strong enough” parity sampler, then either \tilde{z} or $\tilde{z} \oplus 1$ lie in the unique decoding ball of \mathcal{C} centered at z^* .

Bird's-eye view of Techniques: Unique Decoding

Claim

If dsum_X is a $(1/2 + \beta_0/2, \beta)$ -parity sampler, then either \tilde{z} or $\tilde{z} \oplus 1$ lie in the unique decoding ball of \mathcal{C} centered at z^* .

Proof

Towards a contradiction, suppose

$$\Delta(\mathcal{C})/2 \leq \Delta(\tilde{z}, z^*) \leq 1 - \Delta(\mathcal{C})/2,$$

implying that $\text{bias}(\tilde{z} \oplus z^*) \leq 1 - \Delta(\mathcal{C}) \leq 1/2 + \beta_0/2$. “not too large”
Using the $(1/2 + \beta_0/2, \beta)$ -parity sampler assumption,

$$\text{bias}(\text{dsum}_X(\tilde{z} \oplus z^*)) \leq \beta, \quad \text{“small”}$$

contradicting $\text{bias}(\text{dsum}_X(\tilde{z} \oplus z^*)) > \beta$ “Nontrivial bias” from before.

Bird's-eye view of Techniques: Unique Decoding

Moral

- Find solution $\tilde{z} \in \mathbb{F}_2^n$ (rather than in \mathcal{C}) is enough.
- Unique decoder of \mathcal{C} : correct \tilde{z} into z^* .

Bird's-eye view of Techniques: Unique Decoding

Need to resolve the following assumption.

Optimal Solution

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

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

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Possible issue?

MAX k-XOR is NP-hard, right?

Bird's-eye view of Techniques: Unique Decoding

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MAX k-XOR is NP-hard, right?

Not an issue

Right, it can be NP-hard in general. However, for **expanding** instances we can find an **approximate** solution (and that is enough).

Bird's-eye view of Techniques: Unique Decoding

Not an issue

Right, it can be NP-hard in general. However, for **expanding** instances we can find an **approximate** solution (and that is enough).

Using a better spectral analysis of Dinur–Dikstein'19.

Theorem (Alev–J–Tulsiani'19)

Let X be a γ -spectral high-dimensional expander on n vertices. Let \mathfrak{J} be a k -CSP on $X(k)$ with alphabet size q .

If $\gamma \leq \text{poly}(\epsilon/q^k)$, then we can find a solution $z \in [q]^n$ satisfying

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

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

Bird's-eye view of Techniques: Unique Decoding

Theorem (this work)

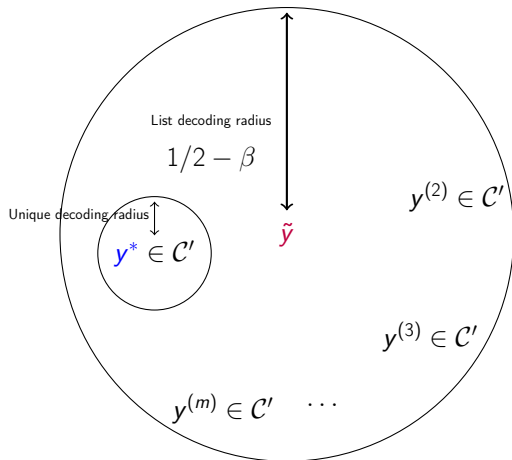
Alev-J-Tulsiani'19 also holds when $X(k)$ is the collection of length- $(k - 1)$ walks on a γ -two-sided spectral expander graph G .

Bird's-eye view of Techniques: List Decoding

List Decoding

How about our main goal of list decoding?

Bird's-eye view of Techniques: List Decoding



Bird's-eye view of Techniques: List Decoding

List Decoding Task

Given \tilde{y} promised to satisfy $\Delta(\tilde{y}, \mathcal{C}') \leq 1/2 - \beta$, we want to find

$$\mathcal{L}(\tilde{y}) := \left\{ y \in \mathcal{C}' \mid \Delta(y, \tilde{y}) \leq \frac{1}{2} - \beta \right\}.$$

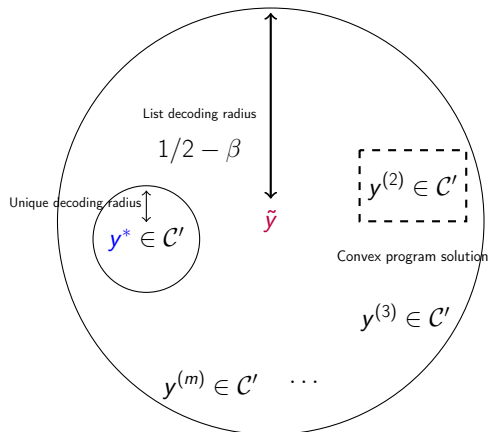
Bird's-eye view of Techniques: List Decoding

CSP Algorithms

We will need to understand a bit more the preceding CSP algorithms for expanding structures which are based on the *Sum-of-Squares* (SOS) semidefinite programming hierarchy.

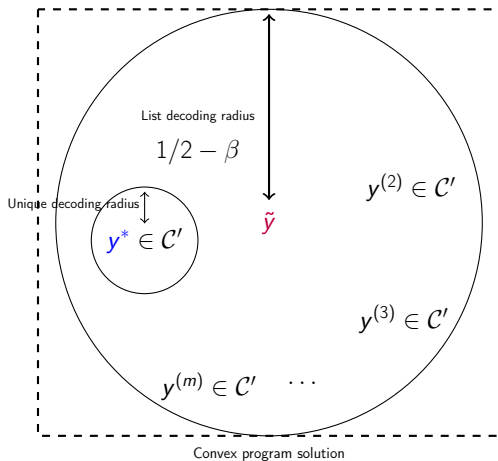
Bird's-eye view of Techniques: List Decoding

Issue: "Low Entropy" convex program solution



Bird's-eye view of Techniques: List Decoding

Want: "High Entropy" convex program solution



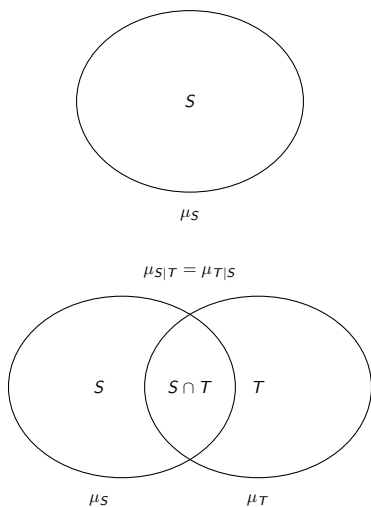
Bird's-eye view of Techniques: List Decoding

Sum-of-Square Solution: PSD ensemble

A t -local PSD ensemble is a collection $\mathbf{Z}_1, \dots, \mathbf{Z}_n$ of “local random variables” taking value in $\{\pm 1\}$ and satisfying:

- for $S \subseteq [n]$ with $|S| \leq t$, the variable \mathbf{Z}_S has a distribution μ_S .
- for $S, T \subseteq [n]$ with $|S|, |T| \leq t$, $\mu_{S|T} = \mu_{T|S}$.
- a global PSD property (we won't have time to describe).

Bird's-eye view of Techniques: List Decoding



Bird's-eye view of Techniques: List Decoding

Pseudo-expectation

$\tilde{\mathbb{E}}$ will denote the “expectation” w.r.t. the local random variables.

Bird's-eye view of Techniques: List Decoding

maximize $\mathbb{E}_{(i_1, \dots, i_k) \in X} \tilde{\mathbb{E}} [\mathbf{1}[\mathbf{Z}_{i_1} \cdots \mathbf{Z}_{i_k} = \tilde{\mathbf{y}}_{(i_1, \dots, i_k)}]]$ (Objective)

subject to

$\mathbf{Z}_1, \dots, \mathbf{Z}_n$ being t -local PSD ensemble

Table: k -XOR unique decoding SOS formulation for $\tilde{\mathbf{y}}$.

Bird's-eye view of Techniques: List Decoding

Recall the SOS program. Do you see the issue for list decoding?

$$\begin{aligned} & \text{maximize} && \mathbf{E}_{(i_1, \dots, i_k) \in \mathcal{X}} \tilde{\mathbf{E}} [\mathbf{1}[\mathbf{Z}_{i_1} \cdots \mathbf{Z}_{i_k} = \tilde{\mathbf{y}}_{(i_1, \dots, i_k)}]] && \text{(Objective)} \\ & \text{subject to} && && \\ & && \mathbf{Z}_1, \dots, \mathbf{Z}_n \text{ being } t\text{-local PSD ensemble} && \end{aligned}$$

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Issue

The objective function “forces” the solution to agree with $\tilde{\mathbf{y}}$ as much as possible.

Bird's-eye view of Techniques: List Decoding

Direct Sum of the PSD ensemble

Let $X \subseteq [n]^k$. For $\mathfrak{s} = (i_1, \dots, i_k) \in X$, define the local random variable (we are working with $\{\pm 1\}$ variables now)

$$\mathbf{Y}_{\mathfrak{s}} := \mathbf{Z}_{i_1} \cdots \mathbf{Z}_{i_k}.$$

$\{\mathbf{Y}_{\mathfrak{s}}\}_{\mathfrak{s} \in X}$ is also a PSD ensemble.

Bird's-eye view of Techniques: List Decoding

List Decoding Attempt

Drop the objective function and add a constraint?

$$\mathbf{E}_{\mathfrak{s} \in X(k)} \tilde{\mathbf{E}}[\tilde{\mathbf{y}}_{\mathfrak{s}} \cdot \mathbf{Y}_{\mathfrak{s}}] \geq 2\beta \quad (\text{Agreement Constraint})$$

$$\mathbf{Y}_{\mathfrak{s}} := \mathbf{Z}_{i_1} \cdots \mathbf{Z}_{i_k} \quad (\forall \mathfrak{s} = (i_1, \dots, i_k) \in X(k))$$

$\mathbf{Z}_1, \dots, \mathbf{Z}_n$ being t -local PSD ensemble

Bird's-eye view of Techniques: List Decoding

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$\mathbf{Z}_1, \dots, \mathbf{Z}_n$ being t -local PSD ensemble

Issue

SOS solution may not be “diverse” enough. In particular, a delta distribution with any single element in $\mathcal{L}(\tilde{\mathfrak{y}})$ is a feasible solution.

Bird's-eye view of Techniques: List Decoding

Issue

SOS solution may not be “diverse” enough. In particular, a delta distribution with any single element in $\mathcal{L}(\tilde{y})$ is a feasible solution.

The goal

Make the SOS solution richer (“high entropy”) somehow.

Bird's-eye view of Techniques: List Decoding

Solution: use a proxy for negative entropy to enforce diversity in the SOS solution.

Definition (Entropic Proxy)

Let $\mathbf{Y} = \{\mathbf{Y}_s\}_{s \in X(k)}$ be a t -local PSD ensemble. Define $\Psi = \Psi(\{\mathbf{Y}_s\}_{s \in X(k)})$ as

$$\Psi := \mathbf{E}_{s,t \in X(k)} \left(\tilde{\mathbf{E}}[\mathbf{Y}_s \mathbf{Y}_t] \right)^2.$$

Bird's-eye view of Techniques: List Decoding

Solution: use a proxy for negative entropy to enforce diversity in the SOS solution.

Definition (Entropic Proxy)

Let $\mathbf{Y} = \{\mathbf{Y}_s\}_{s \in X(k)}$ be a t -local PSD ensemble. Define $\Psi = \Psi(\{\mathbf{Y}_s\}_{s \in X(k)})$ as

$$\Psi := \mathbf{E}_{s,t \in X(k)} \left(\tilde{\mathbf{E}}[\mathbf{Y}_s \mathbf{Y}_t] \right)^2.$$

A similar idea was independently used by Raghavendra–Yau'19 and Karmalkar–Klivans–Kothari'19 both in the context of learning regression.

Bird's-eye view of Techniques: List Decoding

$$\text{minimize} \quad \Psi(\{\mathbf{Y}_s\}_{s \in X(k)}) \quad (\text{Negative Entropy Proxy})$$

subject to

$$\mathbf{E}_{s \in X(k)} \tilde{\mathbf{E}}[\tilde{\mathbf{y}}_s \cdot \mathbf{Y}_s] \geq 2\beta \quad (\text{Agreement Constraint})$$

$$\mathbf{Y}_s := \mathbf{Z}_{i_1} \cdots \mathbf{Z}_{i_k} \quad (\forall s = (i_1, \dots, i_k) \in X(k))$$

$\mathbf{Z}_1, \dots, \mathbf{Z}_n$ being t -local PSD ensemble

Table: List decoding SOS formulation for $\tilde{\mathbf{y}}$.

Bird's-eye view of Techniques: List Decoding

Why does Ψ enforce diversity in the SOS solution?

If SOS solution contains a single codeword

$$\begin{array}{|c|c|c|c|} \hline 1 & -1 & 1 & \dots \\ \hline s & t & & y^{(i)} \\ \hline \end{array}$$

$$y^{(i)} \in \mathcal{L}(\tilde{y})$$

$$\Psi = \mathbf{E}_{s,t \in X(k)} \left(\tilde{\mathbf{E}}[\mathbf{Y}_s \mathbf{Y}_t] \right)^2 = 1 \text{ (as large as possible)}$$

Bird's-eye view of Techniques: List Decoding

Why does Ψ enforce diversity in the SOS solution?

If SOS solution is uniform on two codewords

$$\boxed{1 \mid -1 \mid 1 \mid \dots \mid y^{(i)}} \quad y^{(i)}, y^{(j)} \in \mathcal{L}(\tilde{y})$$

$$\boxed{1 \mid 1 \mid -1 \mid \dots \mid y^{(j)}}$$

$s \quad t$

$$\Psi = \mathbf{E}_{s,t \in X(k)} \left(\tilde{\mathbf{E}}[\mathbf{Y}_s \mathbf{Y}_t] \right)^2 < 1$$

Bird's-eye view of Techniques: List Decoding

Propagation Rounding Algorithm

- Choose $\ell \in [t/k]$.
- Sample $S \sim \binom{X}{\ell}$.
- Sample an assignment $\eta \sim \mathbf{Y}_S$.
- Sample $z_i \sim \{\mathbf{Z}_i | \mathbf{Y}_S = \eta\}$ independently for $i \in [n]$.
- Return assignment (z_1, \dots, z_n) .

Bird's-eye view of Techniques: List Decoding

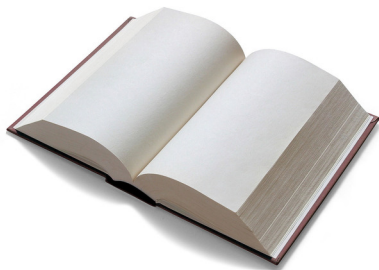
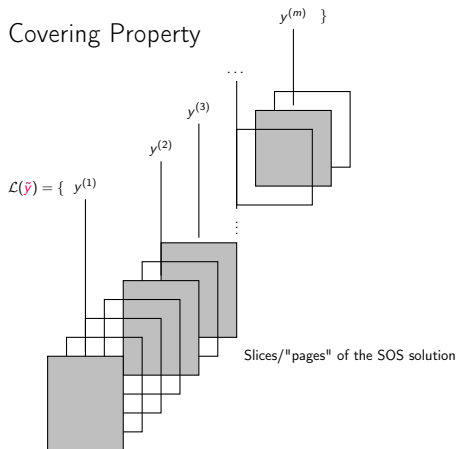


Figure: SOS solution is like a book. Each choice of S and η lead to a “page” (or set of pages), i.e., solution(s).

Bird's-eye view of Techniques: List Decoding



Questions

How far can we push this technique?

- Can we get rate $\Omega(\beta^{O(1)})$?
- Can we decode Ta-Shma's construction?
- Can we do better than the (algebraic) state-of-the-art rate $\Omega(\beta^3)$?

That's all.

Thank you!