Towards Sample-Optimal Methods for Solving Random Quadratic Equations with Structure

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Problem Setup

Random Quadratic Equations

- Unknown vector of parameters, $\mathbf{x}^* \in \mathbb{R}^n$
- Observations $\mathbf{y} \in \mathbb{R}^m$ of the form:

$$y_i = |\langle \mathbf{a}_i, \mathbf{x}^* \rangle|^p, \quad i = [m], \quad \text{s.t.} \quad \mathbf{x}^* \in \mathcal{M}_s$$

- $\mathcal{M}_s \subset \mathbb{R}^n$ is a *model* set that reflects the structural constraints on $\mathbf{x}^*$.
- Under-determined Gaussian observations, $\mathcal{A} = [\mathbf{a}_1 \ldots \mathbf{a}_i \ldots \mathbf{a}_m]^\top \in \mathbb{R}^{m \times n}$ with $m < n$.

Task: Estimate $\mathbf{x}^*$ from either absolute-value ($p = 1$) or quadratic ($p = 2$) measurements $\mathbf{y}$.

Applications

- Phase retrieval.
  - Fourier imaging.
  - Sub-diffraction imaging (eg. Ptychography).

- Polynomial neural networks with quadratic activation functions.

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Observation Model

Model: $\mathbf{x} \in \mathbb{C}^n$

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Goal: Recover **x** from **y.**

(Statistical)

How many measurements do we need for stable recovery?

(Computational)

How quickly can we perform the recovery?

What is known

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Challenges:

- High sample complexity ($\mathcal{O}(n)$ measurements for Gaussian operator $\mathcal{A}$; can be huge if n is large).
- High running time; algorithms are not scalable.

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Solution:

- Utilize inherent structure of **x**!
  - Most images to be acquired have *underlying (structured) sparsity*!
  - Weights of teacher network to be learned can be sparse.

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Given:

$$\mathbf{y} = |\mathcal{A}(\mathbf{x})|, \qquad \mathcal{A} : \mathbb{R}^n \to \mathbb{R}^m, \quad m \ll n$$

Recover: $\mathbf{x}$, such that $\|\mathbf{x}\|_0 \leq s$.

Sample complexity

Algorithm	Initialization Sample complexity	Convergence Sample complexity	Running time	Assumptions
AltMin	$\mathcal{O}\left(n\log^3 n\right)$	$\mathcal{O}(n)$	$\mathcal{O}\left(n^2\log^3 n\right)$	none
AltMinSparse	$\mathcal{O}\left(s^2\log^3 n\right)$	$\mathcal{O}(s)$	$\mathcal{O}\left(s^2 n\log n\right)$	s-sparse $x^*_{\min} \approx \frac{c}{\sqrt{s}}\left\|\mathbf{x}^*\right\|_2$
ℓ_1-PhaseLift	–	$\mathcal{O}\left(s^2\log n\right)$	$\mathcal{O}\left(\frac{n^3}{\epsilon^2}\right)$	s-sparse
SPARTA	$\mathcal{O}\left(s^2\log n\right)$	$\mathcal{O}\left(s\log n/s\right)$	$\mathcal{O}\left(s^2 n\log n\right)$	s-sparse $x^*_{\min} \approx \frac{c}{\sqrt{s}}\left\|\mathbf{x}^*\right\|_2$
CoPRAM	$\mathcal{O}\left(s^2\log n\right)$	$\mathcal{O}\left(s\log n/s\right)$	$\mathcal{O}\left(s^2 n\log n\right)$	s-sparse

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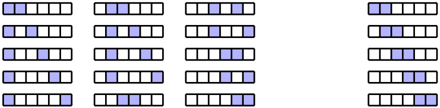
Is sparsity the only prior that can be used?

Modeling Sparsity

- Block/group sparsity.



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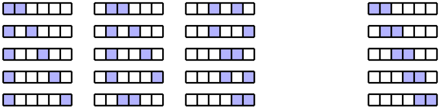
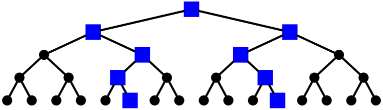


- Tree sparsity.



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CoPRAM	$\mathcal{O}\left(s^2 \log n\right)$	$\mathcal{O}\left(s \log n/s\right)$	s-sparse
Model-based CoPRAM	??	$\mathcal{O}\left(s + \log(\mathrm{card}(\mathbb{M}_{4s}))\right)$	model sparse $\mathcal{M}_s$
Block CoPRAM	$\mathcal{O}\left(s^2/b \log n\right)$	$\mathcal{O}\left(s + (s/b) \log n\right)$	model sparse $\mathcal{M}_s^b$ s-sparse, block length b
Tree CoPRAM	??	$\mathcal{O}\left(s\right)$	model sparse $\mathcal{M}_s$ s-tree sparse

Our contributions

Sample-optimal methods

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3. Novel initialization strategy.

Contributions (I) : Sparse signal and phase recovery

The signal estimate can be posed as the solution to the non-convex optimization problem:

$$\min_{\mathbf{x}\in\mathcal{M}_s, \mathbf{p}\in\mathcal{P}} \|\mathbf{A}\mathbf{x} - \mathbf{p}\circ\mathbf{y}\|_2$$

- $\mathbf{x} \in \mathbb{R}^n$ is a sparse signal (or weight vector),
- Let $\mathbb{M}_s$ denote the set of all allowable supports $\{S_1 \dots S_i \dots S_N\}$, such that $|S_i| \leq s$, then $\mathcal{M}_s = \{\mathbf{x} \in \mathbb{R}^n | \, \mathrm{supp}(\mathbf{x}) \in \mathbb{M}_s\}$,
- $\mathbf{A} \in \mathbb{R}^{m\times n}$ is a measurement operator with $a_{ij} \sim \mathcal{N}(0, 1)$,
- $\mathbf{p} \in \mathbb{R}^m$ is a vector that stores the missing sign information with entries constrained to be in $\{-1, 1\}$ $(:= \mathcal{P})$,
- $\mathbf{y} \in \mathbb{R}^m$ are observations or labels.

Contributions (I) : Model-based CoPRAM Framework

Utilize the CoPRAM (Compressive Phase Retrieval with Alternating Minimization) framework [Jagatap, Hegde '17]:

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- Set: $\hat{S} \leftarrow \textsc{ModelApprox}(\text{diag}(\mathbf{M}))$.
- $\mathbf{v} \in \mathbb{R}^n \leftarrow$ top s.v. of $\mathbf{M}_{\hat{S}} = \frac{1}{m}\sum_{i=1}^{m} y_i^2 \mathbf{a}_{i_{\hat{S}}} \mathbf{a}_{i_{\hat{S}}}^T$ for $\hat{S}$, and $\mathbf{0}$ for $\hat{S}^c$.
- Compute: $\mathbf{x^0} \leftarrow \phi\mathbf{v}$, with $\phi^2 = \frac{1}{m}\sum_{i=1}^{m} y_i^2$.

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For $t = 0, \ldots, T$, alternate:

- Phase estimation: $\mathbf{p}^t = \text{sign}(\mathbf{A}\mathbf{x}^t)$.
- Signal estimation: $\mathbf{x}^t = \text{argmin}_{\mathbf{x}' \in \mathcal{M}_s} \left\|\mathbf{A}\mathbf{x}' - \mathbf{p}^t \circ \mathbf{y}\right\|_2$.

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Key features

- Utilizes Model-based CoSaMP [Baraniuk et. al. '10] to recover (structured) sparse signal estimate $\mathbf{x}^t$
  $\implies$ reduced sample complexity.
- Initialization strategy for *faster* convergence.
- No tuning parameters!

Contributions (II) - Convergence guarantees

Theorem

Given an initialization $\mathbf{x^0} \in \mathcal{M}_s$ *satisfying* $\operatorname{dist}\left(\mathbf{x}^0, \mathbf{x}^*\right) \leq \delta_0 \left\|\mathbf{x}^*\right\|_2$, *for* $0 < \delta_0 < 1$, *if we have number of Gaussian measurements,*

$$m > C\left(s + \log(\operatorname{card}(\mathbb{M}_{4s}))\right),$$

then the iterates $\mathbf{x}^{t+1}$ *of model-based CoPRAM satisfy:*

$$\operatorname{dist}\left(\mathbf{x}^{t+1}, \mathbf{x}^*\right) \leq \rho_0 \operatorname{dist}\left(\mathbf{x}^t, \mathbf{x}^*\right),$$

where $\mathbf{x}^t, \mathbf{x}^{t+1}, \mathbf{x}^* \in \mathcal{M}_s$, *and* $0 < \rho_0 < 1$ *is a constant, with probability greater than* $1 - e^{-\gamma m}$, *for positive constant* γ.

Contributions (II) - Convergence guarantees

Proof outline

- Per-iteration error for the t^{th} iteration of model-based CoPRAM, with L iterations of model-based CoSaMP:

$$\left\|\mathbf{x}^{t+1} - \mathbf{x}^*\right\|_2 \leq (\rho_1\rho_3)^L \left\|\mathbf{x}^* - \mathbf{x}^t\right\|_2 + \frac{(\rho_1\rho_4 + \rho_2)}{(1 - \rho_1\rho_3)} \left\|E_{ph}\right\|_2$$

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  - $\rho_1, \rho_2, \rho_3, \rho_4$ are appropriate constants, and E_{ph} is the error in estimating phase in the t^{th} run of Model-based CoPRAM.

- Bound the phase error term $\left\|E_{ph}\right\|_2$ via Lemma III.2 as:

$$\left\|E_{ph}\right\|_2^2 = \frac{4}{m}\sum_{i=1}^{m}\left(\mathbf{a}_i{}^\top \mathbf{x}^*\right)^2 \cdot \mathbf{1}_{\{\text{sign}(\mathbf{a}_i\mathbf{x}^t)\,\text{sign}(\mathbf{a}_i\mathbf{x}^*) = -1\}} < \rho_5^2 \left\|\mathbf{x}^t - \mathbf{x}^*\right\|_2^2.$$

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- Convergence criterion of the form (for $\rho_0 < 1$):

$$\mathrm{dist}\left(\mathbf{x}^{t+1}, \mathbf{x}^*\right) \leq \rho_0 \mathrm{dist}\left(\mathbf{x}^t, \mathbf{x}^*\right).$$

as long as $\mathbf{x^0}$ satisfies $\mathrm{dist}\left(\mathbf{x^0}, \mathbf{x}^*\right) \leq \delta_0 \left\|\mathbf{x}^*\right\|_2$,

  - $\mathrm{dist}\left(\mathbf{x}_1, \mathbf{x}_2\right) := \min\left\{\left\|\mathbf{x}_1 - \mathbf{x}_2\right\|_2, \left\|\mathbf{x}_1 + \mathbf{x}_2\right\|_2\right\}$.

Contributions (II) - Convergence guarantees

Key Lemma

Lemma

(Lemma III.2) As long as the initial estimate is a small distance away from the true signal $\mathbf{x}^* \in \mathcal{M}_s$, $\mathrm{dist}\left(\mathbf{x}^{\mathbf{0}}, \mathbf{x}^*\right) \leq \delta_0 \|\mathbf{x}^*\|_2$, *and subsequently,* $\mathrm{dist}\left(\mathbf{x}^t, \mathbf{x}^*\right) \leq \delta_0 \|\mathbf{x}^*\|_2$, *where* $\mathbf{x}^t$ *is the* t^{th} *update of model-based CoPRAM, then the following bound holds,*

$$\frac{4}{m} \sum_{i=1}^{m} \left(\mathbf{a}_i{}^\top \mathbf{x}^*\right)^2 \cdot \mathbf{1}_{\left\{(\mathbf{a}_i{}^\top \mathbf{x}^t)(\mathbf{a}_i{}^\top \mathbf{x}^*) \leq 0\right\}} \leq \rho_5^2 \left\|\mathbf{x}^t - \mathbf{x}^*\right\|_2^2,$$

with probability greater than $1 - e^{-\gamma_2 m}$, *where* γ_2 *is a positive constant, as long as* $m > C\left(s + \log(\mathrm{card}(\mathbb{M}_{4s}))\right)$ *and* $\rho_5^2(\delta_0) < 1$.

Contributions (II) - Convergence guarantees

Corollary for tree sparse signals

Corollary

As a consequence of Theorem 1, if $\mathcal{M}_s$ is a model representing rooted tree sparse signals with sparsity s, then Tree CoPRAM is linearly convergent and requires a Gaussian sample complexity of $m > Cs$, as long as the initialization $\mathbf{x}^0$ satisfies $\mathrm{dist}\left(\mathbf{x}^0, \mathbf{x}^*\right) \leq \delta_0 \left\|\mathbf{x}^*\right\|_2$.

- $m = O(s)$ samples are necessary for reconstructing any s-sparse parameter vector even in the linear case (where perfect phase information is available).
- Implies information-theoretic optimality (up to constants) of our proposed approach.

Contributions (III) - Initialization Strategy

- Spectral initialization [Wang et al '17, Jagatap, Hegde '17].
- Construct signal *marginal* matrix: $\mathbf{M} = \frac{1}{m}\sum_{i=1}^{m} y_i^2 \mathbf{a}_i \mathbf{a}_i^\top$.
- The j^{th} signal coefficient can be estimated from the the diagonal term $M_{jj} = \frac{1}{m}\sum_{i=1}^{m} y_i^2 a_{ij}^2$, and the set of all M_{jj}'s can be calculated in $\mathcal{O}(mn)$ time.
- Approximate support estimate $\hat{S}$ via approximate model projection algorithm (for eg. [Hegde et. al. '14] for tree sparsity) on the diag($\mathbf{M}$).
- Spectral initialization on sub-matrix $\mathbf{M}_{\hat{S}}$.

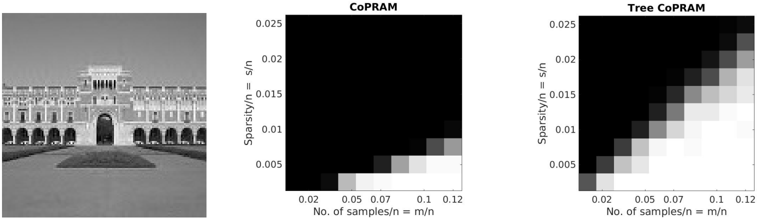
Initialization

Intuition

- Diagonal elements of the expectation matrix $\mathbb{E}[\mathbf{M}]$ are given by $\mathbb{E}\left[M_{jj}\right] = \|\mathbf{x}^*\|^2 + 2x_j^{*2}$.
- The signal marginals M_{jj} corresponding to $j \in S$ are larger, in *expectation*, than those corresponding to $j \in S^c$, where $S \in \mathbb{M}_s$.

Experimental validation

Ground truth



(a) (b) (c)

Figure: (a) Image considered for simulations, resized to 32×32 and 64×64 pixels, considered to be sparse in Haar basis. Phase transition diagrams for (b) CoPRAM (c) Tree CoPRAM on signal of dimension $n = 4096$.

Simulation results

Phase transitions

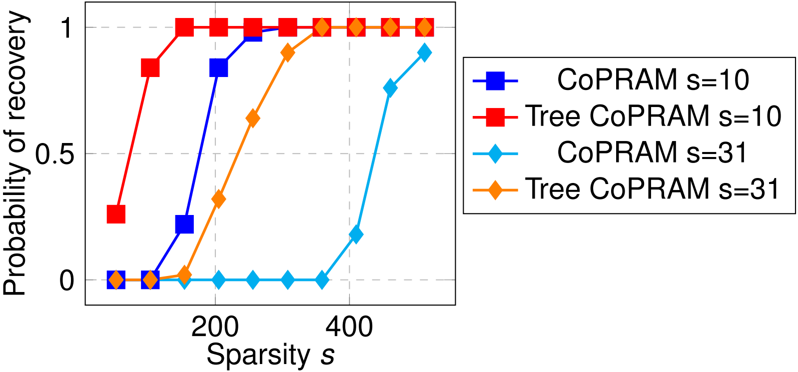


Figure: *Phase transitions for CoPRAM and Tree CoPRAM for sparsities s=10 and s=31 on an n=1024 dimensional signal.*

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- Sample optimal convergence analysis.

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- Sample optimal convergence analysis.

Open questions:

- Theoretical guarantees on initializaiton.

Questions?

Interested in knowing more?
Check our project website:

https://gaurijagatap.github.io/phase-retrieval-of-structured-signals/