

# Limitations in Approximating RIP

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# RIP Definition

## Definition

A vector  $x$  is  $k$ -sparse if it has at most  $k$  nonzero components

## Definition

An matrix  $V$  satisfies the Restricted Isometry Property with order  $k$  and Restricted Isometry Constant  $\delta$  if for every  $k$ -sparse vector  $x$ ,

$$(1 - \delta)\|x\|^2 \leq \|Vx\|^2 \leq (1 + \delta)\|x\|^2$$

# Alternate Definition

## Definition

A matrix  $V$  is RIP- $k, \delta$  if for every submatrix  $A$  created by selecting  $k$  columns from  $V$  and every  $k$ -dimensional vector  $x$ ,

$$(1 - \delta)\|x\|^2 \leq \|Ax\|^2 \leq (1 + \delta)\|x\|^2$$

# Compressive Sensing

- Given a compressible (sparse) signal vector and a few measurements with noise, can we reconstruct the original signal accurately? (Candès and Tao)

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- Given a compressible (sparse) signal vector and a few measurements with noise, can we reconstruct the original signal accurately? (Candès and Tao)
- If the sensing matrix satisfies RIP with  $\delta = \sqrt{2} - 1$ , we can recover the original

# Random Construction

- Draw elements from certain sufficiently concentrated distributions e.g.  $\mathcal{N}\left(0, \frac{1}{\sqrt{n}}\right)$
- This (almost) always works in theory, but is non-deterministic (Baraniuk et al.)
- Deterministic algorithms currently don't achieve the same bounds

# Certification

- Random construction succeeds with very high probability, but is not guaranteed
- A certification algorithm to verify generated matrices would be useful



# Naive Algorithm

- To verify RIP- $k, \delta$  for a matrix  $V$ , check every  $k$ -column submatrix  $A$  of  $V$
- Inspect eigenvalues of  $A^T A$
- Requires time exponential in  $k$

# Naive Algorithm

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- Inspect eigenvalues of  $A^T A$
- Requires time exponential in  $k$
- Certification is actually NP-Hard

# Adversarial Matrices

- We can alter the generation process to produce matrices that "look" random
- We try to fool a decision algorithm: try to plant a large eigenvalue and break RIP

# Breaking RIP with Singular Values

- Large eigenvalues in  $V^T V$  correspond to large singular values of  $V$
- We leave most of  $V$  completely random, fix  $k$  columns to have a large singular value

$$V = [ Q \mid QM ]$$

$$V^T V = \left[ \begin{array}{c|c} Q^T Q & Q^T QM \\ \hline M^T Q^T Q & M^T Q^T QM \end{array} \right]$$

# Hiding Singular Values

- We plant a large eigenvalue in  $M^T Q^T Q M$
- $M$  must have a large singular value
- We can manipulate the singular value decomposition of  $M$ :
  - 1 Decompose random matrix as  $U\Sigma V^T$  where  $U$  and  $V$  are unitary
  - 2 Construct  $\Sigma'$  by setting first diagonal entry of  $\Sigma$  to a planted singular value, setting the rest to something convenient
  - 3 Reconstruct  $M$  as  $U\Sigma'V^T$

# Statistical Analysis

- Elements of the matrix  $Q$  are independent, identically distributed Gaussian,  $\mathcal{N}\left(0, \frac{1}{\sqrt{n}}\right)$
- Distribution of elements of  $Q^T Q$  is highly concentrated: within  $O\left(\frac{\log n}{n}\right)$
- Elements of  $M^T Q^T Q M$  follow the same bounds with high probability

# Distinguishing Random from Planted

- Inspecting elements directly give no indication
- Inspecting eigenvalues of full matrix detects this implementation of planted model

# Proof of hardness

An oracle that certifies RIP would be enable an efficient solution to Spark, and therefore subset sum.

Theorem (Bandeira et al.)

*Certifying RIP for arbitrary  $k$  and  $\delta$  is NP-Hard*



# Limitations of proof

- Weak result: shows hardness only for arbitrary matrix
- Says nothing about approximability

# Reductions

- Small set expansion: if approximating SSE is hard, then approximating RIP is hard (Natrajan and Wu)
- Densest  $k$ -subgraph: if detecting an  $n^{\frac{1}{2}-\epsilon}$  clique in a random graph  $G(n, \frac{1}{2})$  is hard, approximating RIP is hard (Koiran and Zouzias)

# Sum Of Squares

- SOS: a framework for proving statements using the trivial inequality and basic rules of algebra
- A degree- $2n$  SOS proof proves a statement using only intermediate inequalities of polynomials of degree at most  $2n$
- Unbounded degree SOS is a complete proof system, bounded is not
- Max clique with an  $n^{\frac{1}{3}}$  clique embedded in a random graph  $G(n, \frac{1}{2})$  is unsolvable by degree-4 SOS
- For this particular implementation of the planted model, degree 2 SOS proof is sufficient

# Sum of Squares Approximation

## Theorem (Koiran and Souzias)

*Assume a matrix  $\Phi$  has unit column vectors and satisfies RIP of order  $k$  and parameter  $\epsilon$ . For  $m \geq k$ ,  $\Phi$  also satisfies RIP of order  $m$  and parameter  $\epsilon \left( \frac{m-1}{k-1} \right)$ .*

We can set  $n = m$  and examine the matrix's eigenvalues to get a very coarse approximation.

## Theorem

*Sum of squares of degree 2 can differentiate between a matrix that is RIP of order  $k$  with parameter  $\delta$  and one that is not RIP of order  $k$  with parameter  $\delta \left( \frac{n-1}{k-1} \right)$ .*

# Future Research

## Conjecture

*Planted model is complete - planted framework can be improved in order to prove any hardness results.*

## Conjecture

*Degree-4 SOS is insufficient to approximate RIP to within any constant factor.*

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