# Sub-linear time Compressed Sensing and Group Testing via sparse-graph codes

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## Compressed Sensing(CS)

Recover a sparse signal  $\mathbf{x}$  from  $\mathbf{y}$ :  $\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{w}$ 

- $\mathbf{x} N \times 1$  sparse signal
- $\mathbf{A} M \times N$  measurement matrix
- w -additive Gaussian noise
- $\mathbf{y} M \times 1$  measurement vector
- $|\{i: x_i \neq 0\}| = K$ . K << N

Metric of interest:

• Prob. of failure of support recovery  $\mathbb{P}_F := \Pr(\operatorname{supp}(\hat{\mathbf{x}}) \neq \operatorname{supp}(\mathbf{x}))$ 

# Group Testing(GT)

Recover a sparse signal  $\mathbf{x}$  from  $\mathbf{y}$ :  $\mathbf{y} = \mathbf{A} \odot \mathbf{x}$ 

- **x**, **y**, **A** are binary vectors/matrix respectively
- ①: Matrix multiplication with "binary OR" instead of addition
- y-  $M \times 1$  measurement vector

Metric of interest:

• Prob. of missing defective item:  $\mathbb{P}_m := \Pr(\hat{x}_i = 0, x_i = 1)$ 

#### **Known Bounds**

- In 2007, Wainwright gave information theoretic limits for compressed sensing: support recovery
- For sub-linear sparsity, K = o(N),  $M = \Theta\left(K \log(\frac{N}{K})\right)$  is shown to be necessary and sufficient.
- In the linear sparse regime,  $K = \alpha N$ , it was shown that  $M = \Theta(N)$  measurements are sufficient. [1]

#### Main Result (CS)

Sub-linear sparsity: For a given SNR, our scheme has

- Sample complexity of  $M = c_1 K \log(\frac{c_2 N}{K})$
- Decoding complexity of  $O\left(K\log(\frac{N}{K})\right)$
- $\mathbb{P}_{\mathrm{F}} \to 0$  asymptotically in K

Linear sparsity: Our scheme has

- Sample complexity of  $M = c_3 K \log K$
- Decoding complexity of  $O(K \log(K))$
- $\mathbb{P}_{\mathrm{F}} \to 0$  asymptotically in K

#### Bounds for Group Testing

- We assume all the  $\binom{N}{K}$  K-sparse sets are equi-probable
- At least  $\log_2 \binom{N}{K}$  tests are necessary
- For large K and N,  $\log_2 \binom{N}{K} \approx K \log_2 (\frac{N}{K})$

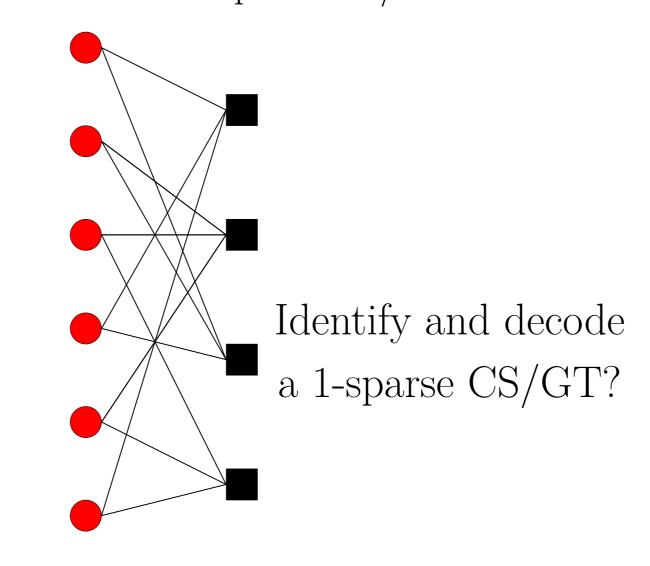
#### Main Result (GT)

Sub-linear sparsity: Let  $K \in o(N^{\frac{p}{p+1}})$ , for some  $p \in \mathbb{Z}$ 

- Number of tests  $M = 2(p+1)c(\epsilon) K \log_2(\frac{c_1N}{K})$
- Decoding complexity of  $O\left(K\log(\frac{N}{K})\right)$
- $\mathbb{P}_m \leq \epsilon$  asymptotically in K
- e.g. for  $\epsilon = 10^{-5}$ ,  $c(\epsilon) = 9.63$

### Idea: Divide-and-Conquer

- $\bullet$  Original problem is K-sparse CS/GT
- ullet Divide N nodes into random (non-disjoint) bins
- Can you solve for 1-sparse CS/GT at a bin?



K-sparse CS/GT

# Divide: $(\ell, r)$ Bipartite Graph

- N Variable(left) nodes:  $x_i$ . Each node has (left) degree:  $\ell$
- Bin(right) nodes: Choose  $M_1 = cK$  bins (sub problems)
- Each bin has (right) degree r. Gives  $r = \frac{N\ell}{cK}$
- Connections between  $N\ell$  edges on each side at random

## Conquer: 1-sparse CS

ullet At each bin, use code words of error control code  ${\cal C}$ :

$$\mathbf{y}_i = x_{i1}\mathbf{c}_1 + x_{i2}\mathbf{c}_2 + \dots x_{ir}\mathbf{c}_r + \mathbf{w}_i$$

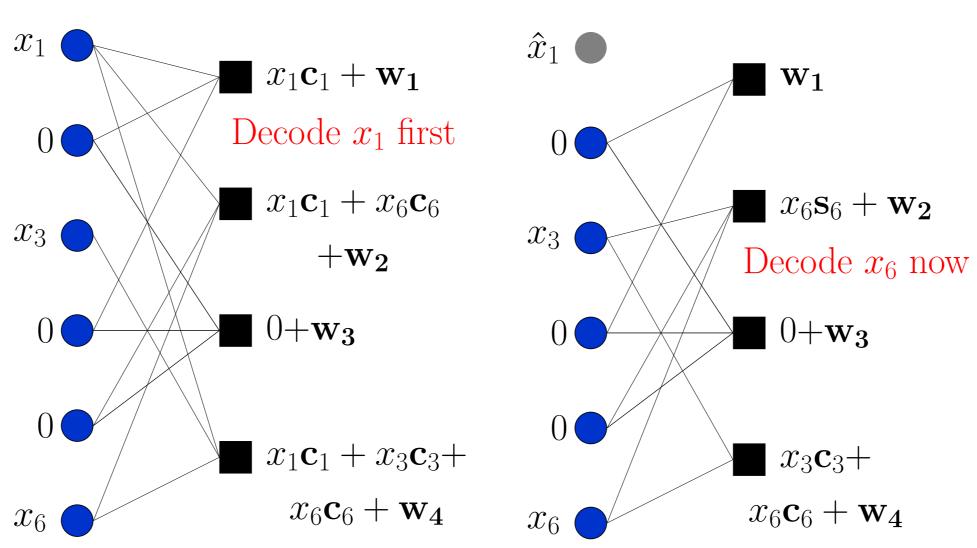
• If it is 1-sparse, only one  $x_{ik} \neq 0$ , (call it singleton):

$$\mathbf{y}_i = x_{ik}\mathbf{c}_k + \mathbf{w}_i$$

- A channel coding problem if  $sign(x_{ik})$  is known
- From channel coding,  $\dim(\mathbf{c}_j) > \frac{\log r}{C_{Sh}} \approx \Theta(\log \frac{N}{K})$
- After decoding index k, need to decode the value of  $x_{ik}$
- Let  $x \in \mathcal{X} := \{ \pm A : A \in \mathcal{A} \}$  be a discrete and finite set
- We decode  $\hat{x}_{ik} \in \mathcal{X}$  to be the value that best fits  $\mathbf{y}_i \mathbf{c}_k^{\dagger} / ||\mathbf{c}_k||^2$

#### Reconstruction via Peeling

- Assume we can conquer the 1-sparse sub-problem
- If a singleton bin is found is found, decode it
- Peel off the variable node decoded from other bins



- Continue peeling iteratively until no new singletons are found
- $\exists$  threshold  $c_*$  such that for  $M_1 > c_*K$  bins, all nodes are recovered asymptotically

## Conquer: 1 and 2-sparse GT

- Let  $\mathbf{b}_k$  be the binary expansion of k;  $\overline{\mathbf{b}}_k$  it's complement
- At each bin, test result vector would be:

$$\mathbf{y}_i = x_{i1} \begin{bmatrix} \mathbf{b}_1 \\ \overline{\mathbf{b}}_1 \end{bmatrix} \lor x_{i2} \begin{bmatrix} \mathbf{b}_2 \\ \overline{\mathbf{b}}_2 \end{bmatrix} \lor \ldots \lor x_{ir} \begin{bmatrix} \mathbf{b}_r \\ \overline{\mathbf{b}}_r \end{bmatrix}$$

• If it is 1-sparse i.e. only one  $x_{ij} = 1$ , trivial to decode j:

$$\mathbf{y}_i = egin{bmatrix} \mathbf{b}_k \ \mathbf{b}_k \end{bmatrix}$$

- Non-linear OR operation poses problem in peeling; can't remove a decoded variable node from connected bins
- If a bin is 2-sparse i.e.  $x_{ij}, x_{ik} = 1$  and an index j is known: refer to as resolvable double-ton

$$\mathbf{y}_i = egin{bmatrix} \mathbf{b}_j \ \hline \mathbf{b}_j \end{bmatrix} ee egin{bmatrix} \mathbf{b}_k \ \hline \mathbf{b}_k \end{bmatrix}$$

- bins with more than 2 non-zero variables (multi-ton) are unusable due to OR
- For  $M_1 > c(\epsilon)K$  bins, just using singletons and double-tons, peeling like iterative decoder recovers  $1 \epsilon$  fraction of nodes asymptotically

#### Conlusions

Compressed Sensing: We propose a scheme that has

- order optimal sample complexity of  $O(K \log(\frac{N}{K}))$
- sub-linear optimal decoding complexity:  $O(K \log(\frac{N}{K}))$

Group testing: We propose a scheme that achieves

- order optimal testing complexity:  $O(K \log(\frac{N}{K}))$
- sub-linear optimal decoding complexity:  $O(K \log(\frac{N}{K}))$

#### References

- M. Wainwright, "Information-Theoretic Limits on Sparsity Recovery in the High-Dimensional and Noisy Setting." *IEEE Trans. Inform Theory*, vol. 55, no. 12, pp. 5728-5741, 2009.
- [2] K. Lee, R. Pedarsani, and K. Ramchandran, "Saffron: A fast, efficient, and robust framework for group testing based on sparse-graph codes", arXiv preprint, arXiv:1508.04485, 2015.
- [3] X. Li, S. Pawar, and K. Ramchandran, "Sub-linear time compressed sensing using sparse-graph codes", in *Proc. Int. Symp. Inform. Theory*, pp. 1645-1649, 2015.