MTH 995-003: Intro to CS and Big Data

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## 1 Overview

In this lecture, we present the algorithm for fast support identification. We want to design measurements that allow us to quickly find an  $S \subset [N]$  such that  $S_0(k) \subset S$  for  $\vec{x} \in \mathbb{C}^N$ .

## 2 Notational review

Let  $A \in \{0,1\}^{m \times N}$  and  $B_N$  be the  $N^{th}$  bit testing matrix. Let  $\{\vec{b}_0, \vec{b}_1, \dots, \vec{b}_{\lceil \log_2 N \rceil}\} \in \{0,1\}^N$  be the rows of  $B_N$ . Given  $(A \otimes B_N)\vec{x}$  we also get  $(A \otimes \vec{b}_i)\vec{x} \in \mathbb{C}^m$ ,  $\forall i = 0 \dots \lceil \log_2 N \rceil$ . This means that we get  $A\vec{x}$  as well as  $(A(K, n) \otimes \vec{b}_i)\vec{x}, \forall n \in [N]$  and  $\forall i = 0 \dots \lceil \log_2 N \rceil$ .

Note that  $(A(K,n) \otimes \vec{b}_i) \in \{0,1\}^{K \times N}$  is exactly the matrix A(K,n) with its  $l^{\text{th}}$ -column set to zero-vector if and only if  $l \in [N]$  has a zero in its  $i^{th}$  bit when written in binary.

## Example 1.

$$\left(\begin{array}{rrrr} 1 & 1 & 1 & 1 \\ 2 & 2 & 2 & 2 \end{array}\right) \otimes \left(\begin{array}{rrrr} 1 & 0 & 1 & 0 \end{array}\right) = \left(\begin{array}{rrrr} 1 & 0 & 1 & 0 \\ 2 & 0 & 2 & 0 \end{array}\right)$$

Let  $n \in [N]$  and assume that matrix A is  $(K, \alpha)$ -coherent with  $K > \frac{4\tilde{k}\alpha}{\varepsilon}$ , where  $\varepsilon \in (0, 1)$  for sparsity  $\tilde{k}$ . Theorem 1 (Lecture 27) tells us that more than 1/2 of the  $j \in [K]$  satisfy  $(A(K, n)\vec{x})_j \in B(x_n, \delta)$ , where

$$\delta := \frac{\varepsilon}{\tilde{k}} \left\| \vec{x} - \vec{x}_{S_0\left(\frac{\tilde{k}}{\varepsilon}\right)} \right\|_1 \qquad \tilde{k} \in [N], \forall \varepsilon \in (0, 1)$$

$$\tag{1}$$

**Definition 1.** Given  $\vec{x} \in \mathbb{C}^{\mathbb{N}}$ , let  $|\vec{x}| \in \mathbb{R}^{\mathbb{N}}$  be such that  $|\vec{x}|_j := |\vec{x}_j|, \forall j \in [N]$ .

Note that  $\delta$  is the same for both  $\vec{x}$  and  $|\vec{x}|$ .

Now let's let  $\vec{a}_j' \in \{0,1\}^N$  be the  $j^{th}$  row of A(K,n) and suppose that

(i) 
$$\langle \vec{a}'_j, |\vec{x}| \rangle \in B(|x_n|, \delta)$$
, and

(ii) 
$$|x_n| > \delta$$
.

From Theorem 1 (Lecture 27) we know that more than 1/2 of the rows,  $\vec{a}'_j$ , of A(K, n) will satisfy (i). Supposing that  $|x_n| > \delta$  and that the  $i^{th}$  bit of n in binary is 1:

$$\begin{split} \left\langle \vec{a}_{j}^{\prime} \otimes \vec{b}_{i}, \vec{x} \right\rangle \Big| &\geq |x_{n}| - \sum_{\substack{l \in supp(\vec{a}_{j}^{\prime}) \ s.t. \ l \neq n; \\ i^{th} \ bit \ of \ l=1}} |x_{l}| \\ &\geq \delta - \sum_{\substack{l \in supp(\vec{a}_{j}^{\prime}) \ s.t. \ l \neq n; \\ i^{th} \ bit \ of \ l=1}} |x_{l}| \\ &\geq \sum_{\substack{l \in supp(\vec{a}_{j}^{\prime}) \ s.t. \ l \neq n; \\ i^{th} \ bit \ of \ l=0}} |x_{l}| \\ &\geq \left| \left\langle \vec{a}_{j}^{\prime} - \vec{a}_{j}^{\prime} \otimes \vec{b}_{i}, \vec{x} \right\rangle \right| \end{split}$$
(2)

Essentially the same argument shows that  $\left|\langle \vec{a}'_j - \vec{a}'_j \otimes \vec{b}_i, \vec{x} \rangle\right| > \left|\langle \vec{a}'_j \otimes \vec{b}_i \rangle, \vec{x}\right|$ , whenever the  $i^{th}$  bit of n is zero. We have now shown that the algorithm below will identify all  $n \in [N]$  with  $|x_n| > \delta$  more than K/2 times appice.

- 1.  $S = \emptyset$
- 2. For  $j \in [m]$
- 3. **For**  $i = 0 \dots \lceil \log_2 N \rceil 1$
- 4. If  $\left| \langle \vec{a}'_j \otimes \vec{b}_i, \vec{x} \rangle \right| > \left| \langle \vec{a}'_j \vec{a}'_j \otimes \vec{b}_i, \vec{x} \rangle \right|$ Set  $n_i = 1$
- 5. Else Set  $n_i = 0$
- 6. End For
- 7. Set  $n = \sum_{i=0}^{\lceil \log_2 N \rceil 1} n_i \cdot 2^i$  (translate from binary to decimal);

8. 
$$S = S \cup \{n\}$$

9. End For

It takes  $O(m \log N)$  operations to go through steps 1 to 9. Also, we know that, e.g.,  $m = K^2$  is possible (from Lecture 26). Therefore, the total runtime of Algorithm 1 is generally sublinear in N. For example,

$$m = O\left(\frac{\tilde{k}^2 \log^3 N}{\varepsilon^2}\right) \ll N \tag{3}$$

works.

Measurements m can be randomized/reduced to get the total runtime of  $O\left(\tilde{k}\log\left(\frac{N}{1-p}\right)\log\tilde{k}\right)$ , which has the same accuracy as the deterministic variant with probability at least p.

It is true that  $|S| \leq m$ , but we also know that every  $n \in [N]$  such that  $|x_n| > \delta$  is recovered at least K/2 times. Therefore, |S| = O(K), and we expect  $S \supset S_0\left(\frac{2\tilde{k}}{\varepsilon}\right)$ , which follows from the Lemma below.

**Lemma 1.** Suppose that  $|x_n| > \delta$ . Then,  $n \in S_0\left(\frac{2\tilde{k}}{\varepsilon}\right)$ . As a result, Algorithm 1 finds all  $n \in S_0\left(\frac{2\tilde{k}}{\varepsilon}\right)$  with  $|x_n| > \delta$ .

Note that  $n \in S_0\left(\frac{2\tilde{k}}{\varepsilon}\right)$  with  $|x_n| \leq \delta$  are "OK to miss".

Next time we will use results from Lectures 28 and 29 to help construct Sparse Fast Fourier Transforms (SFFTs).