

## Lecture 5 — September 22, 2014

Prof. Piotr Indyk

Scribe: Zhengyu Wang

## 1 Introduction

In this lecture, we give an  $O(k \log n)$ -time sparse Fourier transform algorithm (for the exactly  $k$ -sparse case) that works even for worst case inputs, based on the *pseudo-random spectrum permutation* technique (to permute coefficients randomly so that it is as if the average case) and *flat window functions* (to bin coefficients in an efficient and desirable way) that we discussed in the previous lecture. We follow the idea of Section 5 in Lecture 4, and give a complete proof of Theorem 7 in Lecture 4.

The result mentioned in the lecture first appears in [1].

## 2 $O(k \log n)$ -time Algorithm

We assume that  $n$  is a power of 2, and  $\hat{a}_u$  contains at most  $k$  non-zero coefficients with “polynomial precision” (For example, one simple way is to assume that  $\hat{a}_u$  in  $\{-n^{O(1)}, \dots, n^{O(1)}\}$ ). And the proposed algorithm outputs at most  $k$  potential coefficients, and each actual non-zero coefficient of  $\hat{a}$  is output correctly with probability  $1 - p$  for some constant  $p > 0$ .

We first show a basic block of the  $O(k \log n)$ -time algorithm in Algorithm 1. Basically, the function of the algorithm is to recover most coefficients of  $\hat{a}$ . For the parameters, we have the relations that  $B = 1/(2\varepsilon)$ ,  $\varepsilon' = (1 - \gamma)\varepsilon$  and  $\delta = 1/n^{O(1)}$ .  $B$  is the number of bins, and  $\varepsilon, \varepsilon', \delta$  altogether specify the parameters of the flat window function used as the filter function on input signal  $a$ .

Now we give some explanations for Algorithm 1. Line 2 randomly picks a linear permutation where  $\sigma$  is uniformly chosen from odd numbers in  $[n]$ , and  $\beta$  is uniformly chosen from  $[n]$ . Line 6 to Line 13 do the binning, i.e., it puts the coefficients of  $\hat{a} - \hat{e}$  into  $B$  bins, where  $\hat{e}$  is the signal already recovered and stored in list. We do the binning for  $\hat{a}$  on Line 6-7, and subtract the binning for  $\hat{e}$  on Line 8-13. Binning is the bottleneck of our algorithm, so we should carefully design it.

**Discussion.** In order to compute  $\hat{c}_{j_{n/B}}, j = 0, \dots, B - 1$  (on Line 6 in Algorithm 1), we have two options.

- The direct option is to compute the DFT of  $(a \times g)_{-w/2}, \dots, (a \times g)_{w/2}$  where  $w = O(k \log(n)/\gamma)$ . However, it runs in  $O((k \log(n)/\gamma) \cdot \log n)$  time, and it computes too many samples of  $\hat{a} * \hat{g}$ . So we will not adopt this option.
- The second option is to alias  $a \times g$  into  $B$  bins first. That is, first to compute  $b_i = \sum_t (a \times g)_{i+tB}$ , and then to compute the DFT of  $b_0, \dots, b_{B-1}$ . It runs in  $O(k \log(n)/\gamma) + O(B \log B) = O(k \log(n)/\gamma)$  time. We will compute in this way.

Line 14-18 do the updates. We will prove later, that after the updates,  $\text{supp}(\hat{a} - \hat{e})$  shrinks by a constant fraction with good probability.

Now we give the  $O(k \log n)$ -time algorithm in Algorithm 2. It basically repeats Algorithm 1 with carefully chosen parameters.

---

**Algorithm 1** Basic Block for  $O(k \log n)$ -time Sparse Fourier Transformation.

---

```
1: function PARTIAL-RECOVERY( $B, \gamma, k, \text{list}$ )
2:   Choose random  $\sigma, \beta$ 
3:   Define  $a'_j = a_{\sigma j} \omega^{-j\beta}$  ▷ so that  $\widehat{a}'_u = \widehat{a}_{1/\sigma(u+\beta)}$ 
4:   Define  $a''_j = a'_{j+1}$  ▷ so that  $\widehat{a}''_u = \widehat{a}'_u \omega^u$ 
5:   Let  $g$  to be the  $(\varepsilon, \varepsilon', \delta, O(k \log n / \gamma))$  flat window function constructed in Lecture 4
6:   Compute  $\widehat{c}'_{jn/B}, j = 0, \dots, B-1$ , where  $\widehat{c}' = \widehat{a}' * \widehat{g}$  ▷ see discussion
7:   Compute  $\widehat{c}''_{jn/B}, j = 0, \dots, B-1$ , where  $\widehat{c}'' = \widehat{a}'' * \widehat{g}$  ▷ similar to previous line
8:   for each (val, pos) in list do
9:      $u = \sigma \cdot \text{pos} - \beta$ 
10:    let  $j$  be the closest bin to  $u$ 
11:     $\text{off} = u - jn/B$ 
12:     $\widehat{c}'_{jn/B} = \widehat{c}'_{jn/B} - \text{val} \cdot \widehat{g}_{\text{off}}$ 
13:     $\widehat{c}''_{jn/B} = \widehat{c}''_{jn/B} - \text{val} \cdot \omega^u \cdot \widehat{g}_{\text{off}}$ 
14:   for  $j \leftarrow 0, \dots, B-1$  do
15:     if  $|\widehat{c}'_{jn/B}| > 1/2$  then
16:        $\text{val} = \widehat{c}'_{jn/B}$ 
17:        $\text{pos} = 1/\sigma(\text{round}(\text{phase}(\widehat{c}''_{jn/B}/\widehat{c}'_{jn/B})) + \beta)$ 
18:       Add (val, pos) to outputList
19:   return outputList
```

---

---

**Algorithm 2**  $O(k \log n)$ -time Sparse Fourier Transformaion.

---

```
1: function MAIN
2:   list =  $\emptyset$ 
3:   for  $t \leftarrow 1, \dots, \log k/3$  do
4:      $k_t = k/8^{t-1}, B_t = Ck/4^t, \gamma_t = 1/(C2^t)$  (this defines  $\varepsilon_t$  and  $\varepsilon'_t$ )
5:     list = list + Partial-Recovery( $B_t, \gamma_t, k_t, \text{list}$ )
6:   return list
```

---

### 3 Analysis

We start the analysis with two claims for Algorithm 1.

**Claim 1.** *At most  $k$  entries in  $\hat{c}_0, \dots, \hat{c}_{B-1}$  have magnitudes  $> 1/2$ , and therefore are reported.*

This is true because each spectrum to be recovered contributes to exactly one entry in  $\hat{c}_0, \dots, \hat{c}_{B-1}$ , whose values are negligible otherwise.

**Claim 2.** *For each  $u$  in  $\text{supp}(\hat{a})$ , the probability  $u$  is not correctly reported is at most  $O(k\varepsilon + \gamma)$ .*

*Proof.*  $u$  will be not correctly reported either because it collides with other coefficients or because subsampling hits its “slope part” instead of the “flat peak”.

- The probability of being mapped within  $O(\varepsilon n)$  of some other coefficient is  $O(k\varepsilon)$ . This is because there are at most  $k$  other coefficients, and the probability to collide is  $O(\varepsilon)$  (Lemma 2 in Lecture 4).
- Probability that the coefficient is not sampled properly is at most  $O(\gamma)$  since the position of the center of the “flat peak” is chosen uniformly at random.

□

Now we prove correctness and run time guarantee.

#### 3.1 Correctness

Let  $\hat{e}_t$  be the contents of list at the end of stage  $t$  in Algorithm 2. Define a “good” event  $E_t$  to be

$$r_t = \|\hat{a}_t - \hat{e}_t\|_0 < k/8^t.$$

By Claim 2, conditioned on  $E_{t-1}$ , for any  $u$ , the probability of failure to recover  $u$  is at most the sums of

$$r_{t-1}\varepsilon_t = O(k/8^{t-1} \cdot 1/(Ck/4^t)) = O(1)/C \cdot 1/2^t$$

and

$$\gamma_t = 1/(C2^{t-1}).$$

Therefore,

$$\mathbb{P}[\bar{E}_t | E_{t-1}] < \mathbb{P}[\text{fraction of failures} > 1/(3 \times 8)] < O(1)/C \cdot 2^{-t}$$

and

$$\mathbb{P}[\bar{E}_1 \vee \bar{E}_2 \vee \dots \vee \bar{E}_{\log k/3}] < O(1)/C \cdot (1/2 + 1/4 + \dots) = O(1)/C.$$

### 3.2 Run Time Guarantee

The time for binning is

$$\sum_{t=1}^{\log k/3} O(k_t \log n / \gamma_t) = O(k \cdot \log n) + O(k/4 \cdot \log n) + \dots = O(k \log n).$$

And the time for list operations is also bounded by

$$O(\log n) \cdot k.$$

### References

- [1] H. Hassanieh, P. Indyk, D. Katabi, and E. Price. Near-optimal algorithm for sparse Fourier transform. *STOC*, 2012.