University of Wrocław: Algorithms for Big Data (Fall'19)

02/12/2019

Lecture 8: Sparse FFT

Lecturer: Przemysław Uznański

Scribe: -

# 1 Sparse FFT - no noise [Kui92]

Assume wlog n is power of two.

**Plan of solution:** Define  $p_{d,\ell}(x) = \sum_{i:i \text{ mod } 2^\ell = d} \hat{a}_i x^i$ , and for short  $p(x) = p_{0,0}(x) = \sum_i \hat{a}_i x^i$ . and for a polynomial f(x) we write for any polynomial  $||f||_2^2 = \sum_i f_i^2$ .

- 1. Define  $S_{\ell} = \{i : ||p_{i,\ell}||^2 > 0\}$
- 2. Given  $S_{\ell}$ , compute  $S_{\ell+1}$ : for each  $d \in S_{\ell}$ , test for  $e \in \{d, d+2^{\ell}\}$  whether  $||p_{e,\ell+1}||^2 > 0$  and if so, add e to  $S_{\ell+1}$ .
- 3.  $p_{i,\log n}(1) = \hat{a}_i$

The idea is to start at level 0 and proceed. The size of each  $S_{\ell}$  is bounded by k, thus the total number of steps (2) done is  $\mathcal{O}(k \log n)$ .

### A few identities:

By inverse Fourier transform

$$p(\omega^t)/\sqrt{n} = \frac{1}{\sqrt{n}} \sum_i \hat{a}_i \omega^{it} = a_{-t}$$

By Parseval's theorem

$$||p||_2^2 = \sum_i \hat{a}_i^2 = \sum_i a_i^2 = \frac{1}{n} \sum_i |p(\omega^i)|^2$$

SO

$$||p_{d,\ell}||_2^2 = \frac{1}{n} \sum_{i=0}^{n-1} |p_{d,\ell}(\omega^i)|^2$$

Additionally

$$\frac{1}{2^{\ell}} \sum_{i=0}^{2^{\ell}-1} p(\omega^{t+i\frac{n}{2^{\ell}}}) \omega^{-di\frac{n}{2^{\ell}}} = \frac{1}{2^{\ell}} \sum_{i=0}^{2^{\ell}-1} \sum_{j=0}^{n-1} \hat{a}_{j} (\omega^{t+i\frac{n}{2^{\ell}}})^{j} \omega^{-di\frac{n}{2^{\ell}}}$$

$$= \sum_{j=0}^{n-1} \hat{a}_{j} \omega^{tj} \frac{1}{2^{\ell}} \sum_{i=0}^{2^{\ell}-1} \omega^{i(j-d)\frac{n}{2^{\ell}}}$$

$$= \sum_{j=0}^{n-1} \hat{a}_{j} \omega^{tj} [j - d = 0 \mod 2^{\ell}]$$

$$= p_{d,\ell}(\omega^{t})$$

Estimating sum via sampling: Lets say we have  $a_1, \ldots, a_n$  such that  $|a_i| \leq H$ . We can use  $\mathcal{O}(H^2/\varepsilon^2)$ .  $\log n$ ) samples to obtain  $\pm \varepsilon$  estimate of  $\frac{1}{n} \sum_{i} a_{i}$ , or equivalently  $\pm n\varepsilon$  estimate of  $\sum_{i} a_{i}$ , with proof via Hoeffding bound.

First solution: Denote  $L = \max |\hat{a}_i|$  and  $H = \max |p(\omega^t)|$ . Observe that  $p_{d,\ell}(\omega^t) \leq H$ . Since  $p(\omega^t) = \max |p(\omega^t)|$  $\sum_{j} \hat{a}_{j} \omega^{-tj}$ , we have  $H \leq kL$ .

- 1. Estimate  $A_{d,\ell,t} \approx p_{d,\ell}(\omega^t)$  using  $\mathcal{O}(H^4 \log n)$  samples of  $a_{-t-i\frac{n}{2\ell}}\omega^{-di\frac{n}{2\ell}}$ , up to error  $\pm \frac{1}{16H}$ .
- 2.  $|A_{d,\ell,t}|^2 |p_{d,\ell}(\omega^t)|^2 \le (|A_{d,\ell,t}| |p_{d,\ell}(\omega^t)|)(|A_{d,\ell,t}| + |p_{d,\ell}(\omega^t)|) \le \frac{1}{16H} \cdot 2H \le \frac{1}{4}$
- 3.  $||p_{d,\ell}||_2^2 = \frac{1}{n} \sum_{t=0}^{n-1} |p_{d,\ell}(\omega^t)|^2 = \frac{1}{n} \sum_{t=0}^{n-1} (|A_{d,\ell,t}|^2 \pm \frac{1}{4}) = (\sum_{t=0}^{n-1} |A_{d,\ell,t}|^2) \pm 1/4$
- 4. We have  $|A_{d,\ell,t}|^2 = \mathcal{O}(H^2)$ .
- 5. We sample  $\mathcal{O}(H^4 \log n)$  of  $|A_{d,\ell,t}|^2$  to estimate  $||p_{d,\ell}||_2^2$  up to  $\pm \frac{1}{2}$ .
- 6. In total  $\mathcal{O}(H^8 \log^2 n) = \mathcal{O}(k^8 L^8 \log^2 n)$  samples to compute such estimate.

Applying to our tree-traversal, we get  $\mathcal{O}(k^9L^8\log^3 n)$  complexity. Once we have the indices of non-zero coefficients, we extract the exact values:

$$\hat{a}_d = p_{d,\log n}(\omega^0) = \frac{1}{n} \sum_{i=0}^{n-1} a_i \omega^{di}$$

via sampling.

**Second solution:** Let T be a support of  $\hat{a}_i$ , that is  $i \in T$  iff  $\hat{a}_i \neq 0$ . Using  $\mathcal{O}(k^8 \log^2 n)$  samples we estimate  $||p_{d,\ell}||_2^2$  up to  $\pm \frac{L^2}{16}$ . Using  $\mathcal{O}(k^9 \log^3 n)$  samples we find  $T' \subseteq T$  such that if  $|\hat{a}_i| \ge L/4$  then  $i \in T'$ , and  $\hat{a}_i' = \hat{a}_i \pm L/4$ ,

where  $\hat{a}'_i$  is defined only over T'.

Recurse on  $(\hat{a}'_i - \hat{a}_i)$ . Specifically, this sequence is also k-sparse, and max-value is L/2.

This makes it so the total complexity is  $\mathcal{O}(k^9 \log^3 n \cdot \log_2 L)$ .

## 2 Another algorithm, noisy case [LLL16] [EC18]

#### **2.1** k = 1

There is some heavy  $\hat{a}_u$  such that  $\sum_{u'\neq u} |\hat{a}_{u'}|^2 \leq \varepsilon |\hat{a}_u|^2$ , for some small constant  $\varepsilon$ . Idea: extract u bit-by-bit.

**No noise:** If  $u = 2v + b_0$  for  $b_0 \in \{0, 1\}$ , then  $a_{n/2} = \frac{1}{\sqrt{n}} \hat{a}_u \omega^{un/2} = \frac{1}{\sqrt{n}} \hat{a}_u \omega^{vn + b_0 n/2} = \frac{1}{\sqrt{n}} \hat{a}_u \omega^{b_0 n/2} = \frac{1}{\sqrt{n}} \hat{a}_u (-1)^{b_0}$ . Then,  $a_0 = \frac{1}{\sqrt{n}} \hat{a}_u$ . Thus we can use following test:

$$b_0 = 0$$
 iff  $|a_0 - a_{n/2}| \le |a_0 + a_{n/2}|$ 

How to test for older bits? Assume wlog that  $b_0 = 0$ , since if  $b_0 = 1$ , we can always consider signal a' defined as  $a'_j = a_j \cdot \omega^j$ , where  $\hat{a}'_j = \hat{a}_{j-1}$ . So  $u = 4v' + 2b_1$ , where  $b_1 \in \{0, 1\}$ . We then observe that  $a_{n/4} = \frac{1}{\sqrt{n}} \hat{a}_u (-1)^{b_1}$ , so the test is then

$$b_1 = 0$$
 iff  $|a_0 - a_{n/4}| \le |a_0 + a_{n/4}|$ 

So we can proceed with all the bits in this manner.

**Noisy case:** Consider test for bit 0. If the noise is concentrated around  $a_0$  and  $a_{n/2}$ , then such test fails. But we know that on average the noise is small. Thus we replace the test with a randomized one: pick  $0 \le r < n$  at random, and test:

$$b_0 = 0$$
 iff  $|a_r - a_{r+n/2}| \le |a_r + a_{r+n/2}|$ 

(we can do many tests and pick majority vote) and in general

$$b_{i-1} = 0$$
 iff  $|a_r - a_{r+n/2i}| \le |a_r + a_{r+n/2i}|$ 

of course assuming  $b_0 = b_1 = ... = b_{i-2} = 0$ , and changing the signal accordingly.

Why does it work?

Let  $\hat{a}'$  be the output. We show that with ppb at least 3/4 there is  $\|\hat{a} - \hat{a}'\|_2 \le \varepsilon \|\hat{a} - \hat{a}^{(1)}\|_2$ , where  $\hat{a}^{(1)}$  is the top coefficient, so  $\hat{a} - \hat{a}^{(1)}$  is the noise.

We rewrite

$$a_j = \frac{1}{\sqrt{n}} \hat{a}_u \omega^{uj} + \frac{1}{\sqrt{n}} \sum_{u' \neq u} \hat{a}_{u'} \omega^{u'j} = \frac{1}{\sqrt{n}} \hat{a}_u \omega^{uj} + \mu_j$$

SO

$$a = F^{-1}\hat{a}^{(1)} + \mu$$

Looking at the error

$$\sum_{j=0}^{n-1} |\mu_j|^2 = \|\mu\|_2^2 = \|F^{-1}(\hat{a} - \hat{a}^{(1)})\|_2^2 = \|\hat{a} - \hat{a}^{(1)}\|_2^2 = \sum_{u' \neq u} |\hat{a}_{u'}|^2$$

Algorithm at single step compares  $|a_k - a_\ell|$  vs  $|a_k + a_\ell|$ . We have

$$a_k - a_\ell = \frac{1}{\sqrt{n}} \hat{a}_u (\omega^{uk} - \omega^{u\ell}) + (\mu_k - \mu_\ell)$$

$$a_k + a_\ell = \frac{1}{\sqrt{n}}\hat{a}_u(\omega^{uk} + \omega^{u\ell}) + (\mu_k + \mu_\ell)$$

We know that  $|\omega^{uk} \pm \omega^{u\ell}| \in \{0,2\}$  so for the comparison to be done correctly, it is enough that  $|\mu_k - \omega^{uk}|$  $|\mu_{\ell}| + |\mu_k + \mu_{\ell}| \le 2\frac{1}{\sqrt{n}}\hat{a}_u$ , so  $|\mu_k| + |\mu_{\ell}| \le \frac{1}{\sqrt{n}}\hat{a}_u$ . We now have, since each index is picked with a random shift,

$$\mathbb{E}[|\mu_k|^2] = \frac{1}{n} \sum_{j=0}^{n-1} |\mu_j|^2 = \frac{1}{n} \sum_{u' \neq u} |\hat{a}_{u'}|^2 \le \frac{1}{n} \varepsilon |\hat{a}_u|^2$$

so

$$\Pr[|\mu_k| \le \frac{1}{2\sqrt{n}}|\hat{a}_u|] \le \frac{\frac{1}{n}\varepsilon|\hat{a}_u|^2}{\frac{1}{4n}|\hat{a}_u|^2} = \frac{\varepsilon}{4}$$

So picking  $\varepsilon = 1/2$  gives us by union bound 1/4 ppb of success.

Now the trick is to amplify the ppb by repeating each test  $\mathcal{O}(\log \log n)$  times and do the majority vote. This amplifies the ppb to  $1/(4 \log n)$ , so by union bound the whole procedure is ok with 3/4 ppb.

**Not covered:** how to extract the value of  $\hat{a}_u$ .

### References

- Esra Sengun Ermeydan and Ilyas Çankaya. Sparse fast fourier transform for exactly sparse signals and signals with additive gaussian noise. Signal, Image and Video Processing, 12(3):445– 452, 2018.
- [Kui92] W. Kuich, editor. Randomized interpolation and approximation of sparse polynomials: Preliminary version, Berlin, Heidelberg, 1992. Springer Berlin Heidelberg.
- [LLL16] Pierre-David Letourneau, M. Harper Langston, and Richard Lethin. A sparse multi-dimensional fast fourier transform with stability to noise in the context of image processing and change detection. In 2016 IEEE High Performance Extreme Computing Conference, HPEC 2016, Waltham, MA, USA, September 13-15, 2016, pages 1-6. IEEE, 2016.