

# Sublinear Time and Space Algorithms 2026A – Lecture 4

## Precision Sampling and High Frequency Moments\*

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### 1 Precision Sampling

**Sum Estimation:** Suppose the input is  $a_1, \dots, a_n \in [0, 1]$ , and we want to estimate its sum  $S = \sum_i a_i$  using low-accuracy readings of the  $a_i$ 's.

**The Subsampling Model:** Read only a random subset  $J \subset [n]$  of size  $|J| = m$ , and output  $\tilde{S} = \frac{n}{m} \sum_{j \in J} a_j$ .

We analyze instead sampling elements from  $[n]$  with replacement, i.e.,  $J$  is a multiset. Then  $\mathbb{E}[\tilde{S}] = S$  and

$$\text{Var}(\tilde{S}) \leq \frac{n^2}{m^2} |J| = \frac{n^2}{m}$$

because this is just like averaging  $m$  copies of a basic estimator, which samples one element and scales it by  $n$ , with standard deviation  $n$ . By Chebyshev's inequality  $\Pr[\tilde{S} \in S \pm 2n/\sqrt{m}] \geq 3/4$ . For example, to achieve additive error  $O(1)$  this analysis gives nothing better than the trivial  $m = n$ .

**Exer:** Prove similar bounds for subsampling  $m$  elements without replacement, and also for subsampling each element independently with probability  $m/n$ .

**Exer:** Show that  $\Omega(n)$  samples are really needed, even if we allow both additive error 10 and multiplicative error 1.1.

Hint: Consider  $S$  with  $O(1)$  nonzeros.

**The Precision Model:** The algorithm gets a non-accurate reading  $\hat{a}_i$  for every  $a_i$ . The algorithm chooses in advance (non-adaptively) some precisions  $u_i$  and then it is guaranteed additive approximation  $|\hat{a}_i - a_i| \leq u_i$ . The algorithm's cost is inverse proportional to precisions and defined as  $\frac{1}{n} \sum_i \frac{1}{u_i}$ .

Comparison with subsampling explains the scaling by  $\frac{1}{n}$ : no information about item  $i$  means  $u_i = 1$  and costs  $\frac{1}{nu_i} = 1/n \approx 0$ , and nearly-full information means  $u_i = 1/n$  and costs  $\frac{1}{n} \cdot n = 1$ .

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\*These notes summarize the material covered in class, usually skipping proofs, details, examples and so forth, and possibly adding some remarks, or pointers. The exercises are for self-practice and need not be handed in. In the interest of brevity, most references and credits were omitted.

**High-level idea:** We will choose the  $u_i$ 's at random, iid from the exponential distribution  $\text{Exp}(1)$ , which is continuous with pdf  $e^{-x}$  on  $(0, \infty)$ . Intuition: its discrete analogue is the geometric distribution; indeed, both are memoryless.

This will magically translate an  $\ell_1$ -problem (estimate the sum) into  $\ell_\infty$ -problem (evaluate the max), of a related input.

**Precision Sampling Lemma [Andoni, Krauthgamer and Onak, 2011]:**

Fix an integer  $n \geq 2$ , and consider iid  $u_1, \dots, u_n \sim \text{Exp}(1)$  (called precisions). Then for every  $a_1, \dots, a_n \in [0, 1]$ , and estimates  $\hat{a}_1, \dots, \hat{a}_n \in [0, 1]$  that satisfy  $|\hat{a}_i - a_i| \leq u_i$ , the estimator  $\hat{S} = \max_i \hat{a}_i / u_i$  satisfies

$$\Pr_{u_i} \left[ \frac{1}{4}S - 1 \leq \hat{S} \leq 4S + 1 \right] \geq 3/4.$$

In addition, with high probability the PSL estimator has total cost  $O(\log n)$ .

**Proof:** Was seen in class, using the fact that the exponential distribution is min-stable.

**Remark:** To achieve additive error  $\varepsilon$ , it suffices to require that each  $|\hat{a}_i - a_i| \leq \varepsilon u_i$ .

Furthermore, by scaling, we can extend the lemma to  $a_i \in [0, M]$  if we require  $|\hat{a}_i - a_i| \leq (\varepsilon u_i)M$ . Notice that the algorithm does not change (it does not need to know  $M$ ).

**Exer:** Can you improve the multiplicative error to  $1 + \varepsilon$ ? How would it increase the estimator cost?

Hint: Use independent repetitions.

## 2 High Frequency Moments

Let  $x \in \mathbb{R}^n$  be the frequency vector of the input stream.

**Theorem [Indyk and Woodruff, 2005]:** For every  $p \in (2, \infty)$ , one can estimate  $\text{norm}_p^p$  within factor  $1 + \varepsilon$  with high probability using a linear sketch of dimension  $s = O(n^{1-2/p} (\frac{1}{\varepsilon} \log n)^{O(1)})$ . It implies a streaming algorithm using  $O(s \log n)$  bits of storage.

We will see a different algorithm that relies on Precision Sampling, due to [Andoni, Krauthgamer and Onak, 2011]. We will see in class a simplified version, due to Andoni, that achieves only  $O(1)$  approximation, and omits discussion of randomness (how to replace full independence with limited independence).

Intuition: Both the PSL and CountSketch apply linear maps, which can be combined into one linear sketch of  $x$ . The output step raises it to power  $p$ , so effectively we get information about  $|x_i|^p$  instead of  $x_i$ .

**Algorithm PSLsketch:**

1. Init: pick a random hash function  $h : [n] \rightarrow [w]$  for  $w = O(n^{1-2/p} \log^{O(1)} n)$
2. pick independent signs  $r_1, \dots, r_n \in \{\pm 1\}$  and random  $u_1, \dots, u_n \sim \text{Exp}(1)$

3. Update: maintain vector  $S = [S_1, \dots, S_w]$  where  $S_j = \sum_{i:h(i)=j} r_i x_i / u_i^{1/p}$ .
4. Output: to estimate  $\|x\|_p^p$  report  $\max_{j \in [w]} |S_j|^p$

The sketch  $S$  is linear, hence can be updated easily.

Storage requirement:  $O(w \log n)$  bits, not counting storing the randomness.

**Correctness:**

To use the PSL, let  $a_i = |x_i|^p$ , then  $\sum_i a_i = \|x\|_p^p$ , and let  $\hat{a}_i = |S_{h(i)}|^p \cdot u_i$ .

Suppose we could show that WHP (over the signs  $r_i$  and hash  $h$ ) for every  $i \in [n]$ ,

$$|\hat{a}_i - a_i| \leq \varepsilon \|x\|_p^p \cdot u_i \quad \Leftrightarrow \quad \left| |S_{h(i)}|^p - \frac{|x_i|^p}{u_i} \right| \leq \varepsilon \|x\|_p^p.$$

Then we could use the PSL (with the range  $[0, 1]$  scaled by  $M = \|x\|_p^p$ ), and then WHP (over the precisions  $u_i$ ) the algorithm's output is

$$\max_{j \in [w]} |S_j|^p = \max_i \frac{\hat{a}_i}{u_i} \in [1/4 - \varepsilon, 4 + \varepsilon] \cdot \|x\|_p^p.$$

The heart of the proof is the following weaker bound.

**Lemma:** For every  $i \in [n]$ , with probability at least 0.9,

$$\left| S_{h(i)} - \frac{r_i x_i}{u_i^{1/p}} \right|^p \leq \varepsilon \|x\|_p^p.$$

**Proof of lemma:** Was seen in class. It uses the norm-comparison inequality  $\|x\|_2 \leq n^{1/2-1/p} \|x\|_p$ , which follows from Holder's inequality.

**Exer:** Prove this norm-comparison inequality, i.e., that  $\|x\|_2 \leq n^{1/2-1/p} \|x\|_p$  for  $p \geq 2$ .

Hint: Use Holder's inequality which generalizes the Cauchy-Schwartz inequality and asserts that for all  $p, q \in [1, \infty]$  satisfying  $1/p + 1/q = 1$ ,

$$\forall a, b \in \mathbb{R}^n, \quad \langle a, b \rangle \leq \|a\|_p \|b\|_q.$$

Use  $a_i = x_i^2$  and  $b_i = 1$ .

**Exer:** Design a streaming algorithm for  $\ell_p$  point query with space  $\tilde{O}(\alpha^{-2} n^{1-2/p})$ .

**Finishing the theorem:** The lemma is not enough because (1) it has error probability 10% separately for every  $i$ , which is too big for a union bound over all  $i$ ; and (2) we actually need to bound the difference  $|S_{h(i)}|^p - \frac{|x_i|^p}{u_i}$ .

To overcome (1) we use a slightly bigger  $w$  and a concentration bound. To overcome (2), we split into two cases, whether  $|C| \geq \varepsilon' \frac{|x_i|}{u_i^{1/p}}$ , and either use the lemma above or extend the PSL to  $\hat{a}_i$  that have multiplicative errors.

We will not cover this in the course.