# Sublinear Time and Space Algorithms 2024A - Lecture 3 $\ell_{1}$ and $\ell_{2}$ Point Queries, Amplifying success probability* 

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## $1 \ell_{1}$ Point Query via CountMin

Problem Definition: Let $x \in \mathbb{R}^{n}$ be the frequency vector of the input stream, and let $\|x\|_{p}=$ $\left(\sum_{i}\left|x_{i}\right|^{p}\right)^{1 / p}$ be its $\ell_{p}$-norm. Let $\alpha \in(0,1)$ and $p \geq 1$ be parameters known in advance.

The goal is to estimate every coordinate with additive error, namely, given query $i \in[n]$, report $\tilde{x}_{i}$ such that WHP

$$
\tilde{x}_{i} \in x_{i} \pm \alpha\|x\|_{p}
$$

Observe: $\|x\|_{1} \geq\|x\|_{2} \geq \ldots \geq\|x\|_{\infty}$, hence higher norms (larger $p$ ) give better accuracy. We will see an algorithm for $\ell_{1}$, which is the easiest.
Exer: Show that the $\ell_{1}$ and $\ell_{2}$ norms differ by at most a factor of $\sqrt{n}$, and that this is tight. Do the same for $\ell_{2}$ and $\ell_{\infty}$.
It is not difficult to see that $\ell_{\infty}$ point query is hard. For instance, with $\alpha<1 / 2$ we could recover an arbitrary binary vector $x \in\{0,1\}^{n}$, which (at least intuitively) requires $\Omega(n)$ bits to store.
Theorem 1 [Cormode-Muthukrishnan, 2005]: There is a streaming algorithm for $\ell_{1}$ point queries that uses a (linear) sketch of $O\left(\alpha^{-1} \log n\right)$ memory words to achieve accuracy $\alpha$ with success probability $1-1 / n^{2}$.
We will initially assume all $x_{i} \geq 0$.

## Algorithm CountMin:

(Assume all $x_{i} \geq 0$.)

1. Init: set $w=4 / \alpha$ and choose a random hash function $h:[n] \rightarrow[w]$.
2. Update: maintain vector $S=\left[S_{1}, \ldots, S_{w}\right]$ where $S_{j}=\sum_{i: h(i)=j} x_{i}$.
3. Output: to estimate $x_{i}$ report $\tilde{x}_{i}=S_{h(i)}$
[^0]Once again, the update step can be implemented in a streaming fashion because it is some linear map $L: \mathbb{R}^{n} \rightarrow \mathbb{R}^{w}$ (observe that $S_{j}=\sum_{i} \mathbb{1}_{\{h(i)=j\}} x_{i}$ ).

We call $S$ a sketch to emphasize it is a succinct version of the input, and $L$ a sketching matrix.
Analysis (correctness): We saw in class that $\tilde{x}_{i} \geq x_{i}$ and $\operatorname{Pr}\left[\tilde{x}_{i} \geq x_{i}+\alpha\|x\|_{1}\right] \leq 1 / 4$.

## Algorithm CountMin+:

1. Run $k=\log n$ independent copies of algorithm CountMin, keeping in memory the vectors $S^{1}, \ldots, S^{k}$ (and functions $h^{1}, \ldots, h^{k}$ )
2. Output: the minimum of all estimates $\hat{x}_{i}=\min _{l \in[k]} \tilde{x}_{i}^{l}$

Analysis (correctness): As before, $\hat{x}_{i} \geq x_{i}$ and

$$
\operatorname{Pr}\left[\hat{x}_{i}>x_{i}+\alpha\|x\|_{1}\right] \leq(1 / 4)^{k}=1 / n^{2} .
$$

By a union bound, with probability at least $1-1 / n$, for all $i \in[n]$ we will have $x_{i} \leq \hat{x}_{i} \leq x_{i}+\alpha\|x\|_{1}$.
Space requirement: $O\left(\alpha^{-1} \log n\right)$ words (for success probability $\left.1-1 / n^{2}\right)$, without counting memory used to represent/store the hash functions.

Exer: Let $x \in \mathbb{R}^{n}$ be the frequency vector of a stream of $m$ items (insertions only). Show how to use the CountMin+ sketch seen in class (for $\ell_{1}$ point queries) to estimate the median of $x$, which means to report an index $j \in[n]$ that with high probability satisfies $\sum_{i=1}^{j} x_{i} \in\left(\frac{1}{2} \pm \varepsilon\right) m$.

## General $x$ (allowing negative entries):

Observe that Algorithm CountMin actually extends to general $x$ that might be negative, and achieves the guarantee

$$
\operatorname{Pr}\left[\tilde{x}_{i} \notin x_{i} \pm \alpha\|x\|_{1}\right] \leq 1 / 4 .
$$

Exer: complete the proof.

## 2 Amplifying Success Probability

To amplify the success probability of Algorithm CountMin (in general case), we use median of independent repetitions (instead of minimum), and analyze it using the standard concentration bounds, as follows.

## Algorithm CountMin++:

1. Run $k=O(\log n)$ independent copies of algorithm CountMin, keeping in memory the vectors $S^{1}, \ldots, S^{k}$ (and functions $h^{1}, \ldots, h^{k}$ )
2. Output: To estimate $x_{i}$ report the median of all basic estimates, i.e., $\hat{x}_{i}=\operatorname{median}_{l \in[k]} \tilde{x}_{i}^{l}$

## Lemma:

$$
\operatorname{Pr}\left[\hat{x}_{i} \in x_{i} \pm \alpha\|x\|_{1}\right] \leq 1 / n^{2} .
$$

Proof: as seen in class, we define an indicator $Y_{l}$ for the event that copy $l \in[k]$ succeeds, then use one of the concentration bounds below.

Chernoff-Hoeffding concentration bounds: Let $X=\sum_{i \in[n]} X_{i}$ where $X_{i} \in[0,1]$ for $i \in[n]$ are independently distributed random variables. Then

$$
\begin{array}{rc}
\forall t>0, & \operatorname{Pr}[|X-\mathbb{E}[X]| \geq t] \leq 2 e^{-2 t^{2} / n} . \\
\forall 0<\varepsilon \leq 1, & \operatorname{Pr}[X \leq(1-\varepsilon) \mathbb{E}[X]] \leq e^{-\varepsilon^{2} \mathbb{E}[X] / 2} . \\
\forall 0<\varepsilon \leq 1, & \operatorname{Pr}[X \geq(1+\varepsilon) \mathbb{E}[X]] \leq e^{-\varepsilon^{2} \mathbb{E}[X] / 3} . \\
\forall t \geq 2 e \mathbb{E}[X], & \operatorname{Pr}[X \geq t] \leq 2^{-t} .
\end{array}
$$

Exer: Use these concentration bounds to amplify the success probability of the algorithms we saw for Distinct Elements (say from constant to $1-1 / n^{2}$ ).

Hint: use independent repetitions + median.

## $3 \quad \ell_{2}$ Point Query via CountSketch

The idea is to hash coordinates to buckets (similar to algorithm CountMin), but furthermore use tug-of-war inside each bucket (as in algorithm AMS). The analysis will show it is a good estimate with error proportional to $\|x\|_{2}$ instead of $\|x\|_{1}$.

Theorem 2 [Charikar, Chen and Farach-Colton, 2003]: One can estimate $\ell_{2}$ point queries within error $\alpha$ with constant high probability, using a linear sketch of dimension $O\left(\alpha^{-2}\right)$. It implies, in particular, a streaming algorithm.

This algorithm achieves better accuracy than CountMin ( $\ell_{2}$ instead of $\ell_{1}$ ), but requires more storage ( $1 / \alpha^{2}$ instead of $1 / \alpha$ ).

## Algorithm CountSketch:

1. Init: Set $w=4 / \alpha^{2}$ and choose a hash function $h:[n] \rightarrow[w]$
2. Choose random signs $r_{1}, \ldots, r_{n} \in\{-1,+1\}$
3. Update: Maintain vector $S=\left[S_{1}, \ldots, S_{w}\right]$ where $S_{j}=\sum_{i: h(i)=j} r_{i} x_{i}$.
4. Output: To estimate $x_{i}$ return $\tilde{x}_{i}=r_{i} \cdot S_{h(i)}$.

Storage requirement: $O(w)=O\left(\alpha^{-2}\right)$ words, not counting storage of the random bits.
Correctness: We saw in class that $\operatorname{Pr}\left[\left|\tilde{x}_{i}-x_{i}\right|^{2} \geq \alpha^{2}\|x\|_{2}^{2}\right] \leq 1 / 4$, i.e., with high (constant) probability, $\tilde{x}_{i} \in x_{i} \pm \alpha\|x\|_{2}$.
Exer: Explain how to amplify the success probability to $1-1 / n^{2}$ using the median of $O(\log n)$ independent copies.


[^0]:    *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.

