



Sublinear Algorithms

Lecture 03: Streaming III



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Recap: Distinct Elements

approximate the number of distinct items among $x_1, ..., x_m \in [n]$



Idealized Setting: FM (Flajolet,Martin 1985) 1) Pick random function $h: [n] \rightarrow [0,1]$ 2) On update(): Maintain $X = \min_{i} h(x_i)$ 3) On query(): Output $\tilde{t} = 1/X - 1$

Let $y_1, ..., y_t$ be the distinct items in the stream Suppose that $y_1, ..., y_t$ are *random* in [0,1] Then we expect $1/\min_i y_i \approx t$

Recap: Distinct Elements

approximate the number of distinct items among $x_1, ..., x_m \in [n]$

Theoretical Variant: (Bar-Yossef et al. 2002)

- 1) Pick a prime m with $n^3 \le m \le n^{O(1)}$
- 2) Pick pairwise independent hash function $h': [n] \rightarrow [m]$
- 3) Denote $h(x) \coloneqq h'(x)/m \in (0,1]$

4) Maintain a set *L* containing the $k \coloneqq [36/\varepsilon^2]$ smallest distinct values among $h(x_1), \dots, h(x_m)$

5) On query(): If |L| < k: Output $\tilde{t} = |L|$ Otherwise: Output $\tilde{t} = k / \max(L)$ Idealized Setting: FM (Flajolet,Martin 1985) 1) Pick random function $h: [n] \rightarrow [0,1]$ 2) On update(): Maintain $X = \min_{i} h(x_i)$ 3) On query(): Output $\tilde{t} = 1/X - 1$

Space usage:
$$O\left(\frac{1}{\varepsilon^2}\log n\right)$$

Recap: Pairwise Independence

Random variables $X_1, ..., X_n$ are **independent** if for any $j_1, ..., j_n$ we have

 $\mathbb{P}[X_1 = j_1 \text{ and } \dots \text{ and } X_n = j_n] = \mathbb{P}[X_1 = j_1] \cdot \dots \cdot \mathbb{P}[X_n = j_n]$

k = N

Random variables $X_1, ..., X_n$ are **pairwise independent** if for any $i \neq i'$ the random variables X_i and $X_{i'}$ are independent.

Lem: For pairwise independent X_1, \ldots, X_n we have

$$Var[X_1 + \dots + X_n] = Var[X_1] + \dots + Var[X_n]$$

Random variables X_1, \ldots, X_n are k-wise independent if

for any distinct $i_1, ..., i_k$ the random variables $X_{i_1}, ..., X_{i_k}$ are independent.

Recap: Pairwise Independent Hash Function

Let p be a prime with $p \ge n$, and pick $h \in \mathcal{H}$ uniformly at random

Let \mathcal{H} be the set of all functions $h: [n] \to [m]$ of the form

 $h(i) = (a \cdot i + b) \mod p$ where $a, b \in [p]$

Each hash value h(i) is **uniformly distributed** in [m]

The random variables $h(1), \dots, h(n)$ are **pairwise independent**

A function $h \in \mathcal{H}$ can be represented by the pair $(a, b) \in [p]^2$, using $2\lceil \log p \rceil$ bits We can sample a function $h \in \mathcal{H}$ in time O(1)

k-wise Independent Hash Function

Let p be a prime with $p \ge n$, and pick $h \in \mathcal{H}$ uniformly at random

Let
$$\mathcal{H}$$
 be the set of all functions $h: [n] \to [p]$ of the form

 $h(i) = (a_0 + a_1 \cdot i + \dots + a_{k-1} \cdot i^{k-1}) \mod p \text{ where } a_0, \dots, a_{k-1} \in [p]$

Each hash value h(i) is **uniformly distributed** in [m]

The random variables h(1), ..., h(n) are *k***-wise independent**

A function $h \in \mathcal{H}$ can be represented by the tuple $(a_0, \dots, a_{k-1}) \in [p]^k$, using $k \lceil \log p \rceil$ bits We can sample a function $h \in \mathcal{H}$ in time O(k)

k-wise Independent Hash Function

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Let p be a prime with $p \ge n$, and pick $h \in \mathcal{H}$ uniformly at random

Let
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 be the set of all functions $h: [n] \to [p]$ of the form
 $h(i) = (a_0 + a_1 \cdot i + \dots + a_{k-1} \cdot i^{k-1}) \mod p$ where $a_0, \dots, a_{k-1} \in [p]$

Arbitrary Codomain: Can we get codomain $Y = \{y_1, ..., y_t\}$ for $t \ll p$?

$$\sigma(i) \coloneqq y_{h(i) \mod t}$$
 is almost uniform, that is, $\mathbb{P}[\sigma(i) = y_j] = 1/t \pm O(1/p)$

Lem: Fix k. For any n and Y, there is a family \mathcal{H} of functions from [n] to Y such that

- $-h \in \mathcal{H}$ can be stored using $O(\log(n + |Y|))$ bits, and sampled in time O(1),
- for random $h \in \mathcal{H}$ and fixed *i*, the value h(i) is (almost) uniformly distributed in *Y*,

- for random $h \in \mathcal{H}$, the random variables h(1), ..., h(n) are k-wise independent.

Outline

1) Turnstile Model + Moment Estimation

2) Point Query + Heavy Hitters

Generalized Streaming Model

maintain a vector $x \in \mathbb{Z}^n$ under updates of the form $x_i = x_i + \Delta$



maintain vector $x \in \mathbb{Z}^n$

update(*i*, Δ): $x_i = x_i + \Delta$

query(): approximate f(x)

Insertion-only:

Each update has $\Delta = 1$

This is what we studied so far

(E.g. distinct elements: #non-zero x_i 's)

 $z_{1r}, z_m \in [n]$ $X_i = | \{ j \mid z_j = i \} |$

Generalized Streaming Model

maintain a vector $x \in \mathbb{Z}^n$ under updates of the form $x_i = x_i + \Delta$



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approximate $F_2 = ||x||_2^2 = \sum_{i=1}^n x_i^2$ for a vector $x \in \mathbb{Z}^n$ given in turnstile model

Data structure problem:

maintain vector $x \in \mathbb{Z}^n$

update(*i*, Δ): $x_i = x_i + \Delta$

query(): output \tilde{F}_2 with

 $\mathbb{P}\big[\big|\widetilde{F}_2 - F_2\big| \ge \varepsilon F_2\big] \le \delta$

initially x = (0, ..., 0)assume $|\Delta| = n^{O(1)}$ AMS Sketch: (Alon, Matias, Szegedy 1999) 1) Pick 4-wise independent hash function $\sigma: [n] \rightarrow \{-1,1\}$ 2) Maintain $y = \sum_{i=1}^{n} \sigma(i) \cdot x_i$ 3) Output y^2

Goal: $O(\log n)$ space

so entries of x are $O(\log n)$ -bit integers

approximate $F_2 = \|x\|_2^2 = \sum_{i=1}^n x_i^2$ for a vector $x \in \mathbb{Z}^n$ given in turnstile model

Standard Approach:

Lem: AMS Sketch is an unbiased estimator, that is, $\mathbb{E}[y^2] = ||x||_2^2$ **AMS Sketch:** (Alon, Matias, Szegedy 1999) 1) Pick <u>4-wise independent</u> $\sigma: [n] \rightarrow \{-1,1\}$

2) Maintain $y = \sum_{i=1}^{n} \sigma(i) \cdot x_i$

3) Output y^2

Proof: $\mathbb{E}[y^{2}] = \mathbb{E}[(\sum_{i=1}^{n} \sigma(i)x_{i})^{2}]$ $= \mathbb{E}[\sum_{i,j} \sigma(i)\sigma(j)x_{i}x_{j}] \qquad \text{indegendent} \qquad y^{2} = \sum_{i} x_{i}^{2} + \sum_{i\neq j} \sigma(i)\sigma(j)x_{i}x_{j}$ $= \sum_{i} \mathbb{E}[\sigma(i)^{2}]x_{i}^{2} + \sum_{i\neq j} \mathbb{E}[\sigma(i)\sigma(j)]x_{i}x_{j}$ $= \sum_{i} x_{i}^{2} \qquad x_{i}^{2} \qquad$

approximate $F_2 = \|x\|_2^2 = \sum_{i=1}^n x_i^2$ for a vector $x \in \mathbb{Z}^n$ given in turnstile model

Standard Approach: AMS Sketch: (Alon, Matias, Szegedy 1999) 1) Pick 4-wise independent $\sigma: [n] \rightarrow \{-1,1\}$ Lem: AMS Sketch is an unbiased estimator, 2) Maintain $y = \sum_{i=1}^{n} \sigma(i) \cdot x_i$ that is, $\mathbb{E}[y^2] = ||x||_2^2$ 3) Output y^2 We have $\mathbb{E}[y^4] \leq 3\mathbb{E}[y^2]^2$. Lem: **Proof:** $\mathbb{E}[y^4] = \mathbb{E}[(\sum_{i=1}^n \sigma(i)x_i)^4] \stackrel{\checkmark}{=} \sum_{i=1}^n \mathbb{E}[(\sigma(i)x_i)^4] + 6\sum_{i<j} \mathbb{E}[(\sigma(i)x_i)^2] \cdot \mathbb{E}\left[\left(\sigma(j)x_j\right)^2\right]$...since σ is 4-wise independent and has expectation 0, see Exercise Sheet 1

$$= \sum_{i=1}^{n} x_i^4 + 6 \sum_{i < j} x_i^2 \cdot x_j^2 \le 3 \left(\sum_{i=1}^{n} x_i^4 + 2 \sum_{i < j} x_i^2 \cdot x_j^2 \right) = 3 \left(\sum_{i=1}^{n} x_i^2 \right)^2 = 3 \mathbb{E}[y^2]^2$$

approximate $F_2 = \|x\|_2^2 = \sum_{i=1}^n x_i^2$ for a vector $x \in \mathbb{Z}^n$ given in turnstile model



approximate $F_2 = ||x||_2^2 = \sum_{i=1}^n x_i^2$ for a vector $x \in \mathbb{Z}^n$ given in turnstile model



Space usage: ()

$$O\left(\frac{1}{\varepsilon^2}\log\left(\frac{1}{\delta}\right)\log n\right) \frac{1}{\delta}$$

AMS Sketch: (Alon, Matias, Szegedy 1999) 1) Pick 4-wise independent $\sigma: [n] \rightarrow \{-1,1\}$ 2) Maintain $y = \sum_{i=1}^{n} \sigma(i) \cdot x_i$ 3) Output y^2

AMS+: average over $O(1/\varepsilon^2)$ runs of AMS

AMS++: median of $O(\log(1/\delta))$ runs of AMS+

Remark 1: Moment Estimation

approximate $F_p = ||x||_p^p = \sum_{i=1}^n |x_i|^p$ for a vector $x \in \mathbb{Z}^n$ given in turnstile model

For $0 \le p \le 2$ and constant δ : There is streaming algorithm using $poly(\varepsilon^{-1} \log n)$ space. For p > 2 and constant ε, δ : Space complexity is $n^{1-2/p}$ up to logfactors.

[Alon, Matias, Szegedy'99, Bar-Yossef, Jayram, Kumar, Sivakumar'04, Indyk, Woodruff'05, Indyk'06]

Remark 2: Linear Sketch

... is an algorithm that maintains $\prod \chi$, for some matrix $\Pi \in \mathbb{R}^{m \times n}$



We cannot store Π explicitly!

Implicit representation of Π : Given *i*, *j* we can efficiently compute the entry $\Pi_{i,j}$

On update (i, Δ) : $y = y + \Delta \cdot \Pi_i$, where Π_i is the *i*-th column of $\Pi \rightarrow \text{time } O(m)$

 Π may be **randomized** (that is, chosen from some probability distribution)

Remark 2: Linear Sketch

... is an algorithm that maintains $\prod x$, for some matrix $\Pi \in \mathbb{R}^{m \times n}$

Want to maintain vector $x \in \mathbb{Z}^n$

Pick a suitable matrix Π and instead maintain $y \in \mathbb{Z}^m$ with $y = \Pi x$



Any algorithm in strict/general turnstile model can be converted into a linear sketch, at the cost of at most a logarithmic factor in the space bound.

[Li,Nguyen,Woodruff'14]

Remark 2: Linear Sketch

approximate $F_2 = ||x||_2^2 = \sum_{i=1}^n x_i^2$ for a vector $x \in \mathbb{Z}^n$ given in turnstile model



AMS+ Sketch: (Alon, Matias, Szegedy 1999) 1) Pick 4-wise independent hash functions $\sigma_1, ..., \sigma_s$: $[n] \rightarrow \{-1,1\}$ 2) Maintain $y_j = \sum_{i=1}^n \sigma_j(i) \cdot x_i$ 3) Output $\frac{1}{s} \sum_{j=1}^s y_j^2$

This is a linear sketch!

$$(\gamma_{A_{I'}}, \gamma_{S}) = y = \Pi x \text{ with } \Pi_{j,i} = \sigma_{j}(i)$$

 $\boldsymbol{\Pi}$ is implicitly represented

Outline

1) Turnstile Model + Moment Estimation

2) Point Query + Heavy Hitters

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Point Query

Goal: $O(\log n)$ space

approximate $x_i \pm \varepsilon \|x\|_1$ for a vector $x \in \mathbb{Z}^n$ given in turnstile model

Data structure problem:

maintain vector $x \in \mathbb{Z}^n$

update(*i*, Δ): $x_i = x_i + \Delta$

query(*i*): output \tilde{x}_i with

 $\mathbb{P}[|\tilde{x}_i - x_i| \ge \varepsilon \|x\|_1] \le \delta$

CountMin Sketch: (Cormode, Muthukrishnan'05) 1) Pick 2-wise independent hash function $h: [n] \rightarrow [t]$ for $t = [4/\varepsilon]$ 2) Maintain counters $C_j = \sum_{i \text{ s.t. } h(i)=j} x_i$ That is, initially $C_1, \dots, C_t = 0$ On update(*i*, Δ): Add Δ to $C_{h(i)}$ 3) On query(*i*): output $C_{h(i)}$



IM-Ziki Point Query

approximate $x_i \pm \varepsilon \|x\|_1$ for a vector $x \in \mathbb{Z}^n$ given in turnstile model

Lem: $\mathbb{P}[|C_{h(i)} - x_i| > \varepsilon ||x||_1] \le 1/4$

Proof: Fix *i*. For $j \neq i$: $Z_j = \begin{cases} 1, & \text{if } h(j) = h(i) \\ 0, & \text{otherwise} \end{cases}$ $\mathbb{E}[Z_i] = \mathbb{P}[Z_i = 1] = 1/t$ $C_{h(i)} = x + \sum_{i=1}^{n} x_{i}$ $\left|C_{h(i)} - x_{i}\right| \leq \sum_{i \neq i} |x_{i}| \cdot Z_{i}$ $\mathbb{P}\left[\left|C_{h(i)}-x_{i}\right| \geq \varepsilon \|x\|_{1}\right] \leq \mathbb{P}\left[\sum_{j\neq i} |x_{j}| \cdot Z_{j} > \varepsilon \|x\|_{1}\right] \leq \frac{\sum_{j\neq i} |x_{j}|/t}{\varepsilon \|x\|_{1}} \leq \frac{1}{\varepsilon t} \leq \frac{1}{4} \mathsf{I}$

CountMin Sketch: (Cormode, Muthukrishnan'05) 1) Pick 2-wise independent hash function $h: [n] \rightarrow [t]$ for $t = [4/\varepsilon]$ 2) Maintain counters $C_i = \sum_{i \text{ s.t. } h(i)=i} x_i$ That is, initially $C_1, \ldots, C_t = 0$ On update(*i*, Δ): Add Δ to $C_{h(i)}$

3) On query(*i*): output $C_{h(i)}$

Point Query

approximate $x_i \pm \varepsilon ||x||_1$ for a vector $x \in \mathbb{Z}^n$ given in turnstile model

Data structure problem:

maintain vector $x \in \mathbb{Z}^n$

update(*i*, Δ): $x_i = x_i + \Delta$

query(*i*): output \tilde{x}_i with

 $\mathbb{P}[|\tilde{x}_i - x_i| \ge \varepsilon \|x\|_1] \le \delta$

Space usage: $O\left(\frac{1}{\varepsilon}\log\left(\frac{1}{\delta}\right)\log n\right)$

In **strict** turnstile model we can use *minimum* instead of *median*

CountMin Sketch: (Cormode, Muthukrishnan'05) 1) Pick 2-wise independent hash function $h: [n] \rightarrow [t]$ for $t = [4/\varepsilon]$ 2) Maintain counters $C_j = \sum_{i \text{ s.t. } h(i)=j} (x_i)$ That is, initially $C_1, \ldots, C_t = 0$ On update(*i*, Δ): Add Δ to $C_{h(i)}$ 3) On query(*i*): output $C_{h(i)}$

CM++: median of $O(\log(1/\delta))$ runs of CM



compute all *i* with $x_i \ge \varepsilon ||x||_1$ for a vector $x \in \mathbb{Z}^n$ given in strict turnstile model





compute all *i* with $x_i \ge \varepsilon ||x||_1$ for a vector $x \in \mathbb{Z}^n$ given in **strict** turnstile model

Level
$$\ell$$
 corresponds to vector $x^{\ell} \in \mathbb{Z}^{2^{\ell}}$ with
 $x_i^{\ell} = x_{(i-1)n/2^{\ell}+1} + \dots + x_{in/2^{\ell}}$
Store a CM++ sketch for every vector x^{ℓ}
with $\mathbb{P}\left[\left|\tilde{x}_i^{\ell} - x_i^{\ell}\right| \ge \frac{\varepsilon}{4} \left\|x^{\ell}\right\|_1\right] \le \frac{\delta\varepsilon}{4\log n}$





compute all *i* with $x_i \ge \varepsilon ||x||_1$ for a vector $x \in \mathbb{Z}^n$ given in **strict** turnstile model

Level
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Store a CM++ sketch for every vector x^{ℓ}
with $\mathbb{P}\left[\left| \tilde{x}_i^{\ell} - x_i^{\ell} \right| \ge \frac{\varepsilon}{4} \left\| x^{\ell} \right\|_1 \right] \le \frac{\delta \varepsilon}{4 \log n}$

On update(i, Δ):

- Affects one entry of every vector x^{ℓ}
- So perform $O(\log n)$ updates of CM++





compute all *i* with $x_i \ge \varepsilon ||x||_1$ for a vector $x \in \mathbb{Z}^n$ given in **strict** turnstile model

Level
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Store a CM++ sketch for every vector x^{ℓ}
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DFS x_i^{ℓ}): Use CM++ sketch to decide if $x_i^{\ell} \ge \frac{3}{4} \varepsilon ||x||_1$ If CM++ says "larger": $//x_i^{\ell}$, $\int t_{eary}$ helter If x_i^{ℓ} is a leaf: add i to result RElse: run DFS($x_{2i-1}^{\ell+1}$) and DFS($x_{2i}^{\ell+1}$)

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On query():

Same norm on every level: $||x^{\ell}||_1 = ||x||_1 \rightarrow \text{sylch}$ Every node is less than or equal to its parent So all heavy hitters on all levels form a **subtree** There are $O(1/\varepsilon)$ heavy hitters on each level

compute all *i* with $x_i \ge \varepsilon ||x||_1$ for a vector $x \in \mathbb{Z}^n$ given in **strict** turnstile model

Level ℓ corresponds to vector $x^{\ell} \in \mathbb{Z}^{2^{\ell}}$ with

 $x_i^{\ell} = x_{(i-1)n/2^{\ell}+1} + \dots + x_{in/2^{\ell}}$

Store a CM++ sketch for every vector x^ℓ

with $\mathbb{P}\left[\left|\tilde{x}_{i}^{\ell}-x_{i}^{\ell}\right|\geq\frac{\varepsilon}{4}\left\|x^{\ell}\right\|_{1}\right]\leq\frac{\delta\varepsilon}{4\log n}$

On query():

Assuming correctness of CM++: CM++ says "larger" only if $x_i^{\ell} \ge \frac{\varepsilon}{2} ||x||_1$ On each level we explore the children of $\le 2/\varepsilon$ nodes

So $\leq \frac{4}{\varepsilon} \log n$ calls to CM++, so error probability δ

DFS (x_i^{ℓ}) : Use CM++ sketch to decide if $x_i^{\ell} \ge \frac{3}{2i} \varepsilon ||x||_1$ If CM++ says "larger": If x_i^{ℓ} is a leaf: add *i* to result *R* Else: run DFS $(x_{2i-1}^{\ell+1})$ and DFS $(x_{2i}^{\ell+1})$



compute all *i* with $x_i \ge \varepsilon ||x||_1$ for a vector $x \in \mathbb{Z}^n$ given in **strict** turnstile model

Level
$$\ell$$
 corresponds to vector $x^{\ell} \in \mathbb{Z}^{2^{\ell}}$ with
 $x_i^{\ell} = x_{(i-1)n/2^{\ell}+1} + \dots + x_{in/2^{\ell}}$
Store a CM++ sketch for every vector x^{ℓ}
with $\mathbb{P}\left[|\tilde{x}_i^{\ell} - x_i^{\ell}| \ge \frac{\varepsilon}{4} ||x^{\ell}||_1\right] \le \frac{\delta \varepsilon}{4 \log n}$
CMMT: $O\left(\frac{1}{\varepsilon} \int \frac{\delta \varepsilon}{4 \log n}\right) \log n$ bits
 $= O\left(\frac{1}{\varepsilon} \log^2 n \left(\log \log n + \log\left(\frac{1}{\delta \varepsilon}\right)\right)\right)$

Heavy Hitters

Goal: *O*(polylog *n*) space

compute all *i* with $x_i \ge \varepsilon ||x||_1$ for a vector $x \in \mathbb{Z}^n$ given in **strict** turnstile model

Data structure problem: maintain vector $x \in \mathbb{Z}^n$ update(*i*, Δ): $x_i = x_i + \Delta$ query(): output a set R s.t. *R* contains **all** *i* with $x_i \ge \varepsilon \|x\|_1$ *R* contains **no** *i* with $x_i < \frac{\varepsilon}{2} ||x||_1$ with failure probability δ

Space:
$$O\left(\frac{1}{\varepsilon}\log^2 n\left(\log\log n + \log\left(\frac{1}{\delta\varepsilon}\right)\right)\right)$$
 bits

Level ℓ corresponds to vector $x^{\ell} \in \mathbb{Z}^{2^{\ell}}$ with $x_i^{\ell} = x_{(i-1)n/2^{\ell}+1} + \dots + x_{in/2^{\ell}}$ Store a CM++ sketch for every vector x^{ℓ} with $\mathbb{P}\left[\left|\tilde{x}_{i}^{\ell}-x_{i}^{\ell}\right|\geq\frac{\varepsilon}{4}\left\|x^{\ell}\right\|_{1}\right]\leq\frac{\delta\varepsilon}{4\log n}$ $CM \leftrightarrow O(y^{\prime} \delta)$ Update time: $O\left(\log n \left(\log \log n + \log \left(\frac{1}{\delta \varepsilon}\right)\right)\right)$ **Query time:** $O\left(\frac{1}{\varepsilon}\log n\left(\log\log n + \log\left(\frac{1}{\delta\varepsilon}\right)\right)\right)$

More Material

Moment estimation, AMS Sketch:

[Alon, Matias, Szegedy "The space complexity of approximating the drequency moments" 1999]

Point Query + Heavy Hitters, CountMin Sketch:

[Cormode, Muthukrishnan "An improved data stream summary: the count-min sketch and its applications" 2005]

- − Course Website \rightarrow Material \rightarrow Link to Summer School on Streaming by Jelani Nelson
- Exercise Sheet 1 due on Friday, May 22

Nect lecture by Vasileios Nakos on May 28!