CSCE 689: Special Topics in Modern Algorithms for Data Science

Lecture 12

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Presentation Schedule

- September 25: Team DAP, Team Bokun, Team Jason
- September 27: Galaxy AI, Team STMI
- September 29: Jung, Anmol, Chunkai

Last Time: (ε, k) -Frequent Items Problem

- Goal: Given a set S of m elements from [n], an accuracy parameter $\varepsilon \in (0, 1)$, and a parameter k, output a list that includes:
 - The items from [n] that have frequency at least $\frac{m}{k}$
 - No items with frequency less than $(1 \varepsilon) \frac{m}{k}$

(ε, k) -Frequent Items Problem

- Goal: Given a set S of m elements from [n] that induces a frequency vector $f \in \mathbb{R}^n$, an accuracy parameter $\varepsilon \in (0, 1)$, and a parameter k, output a list that includes:
 - The items from [n] that have frequency at least $\frac{\|f\|_1}{k}$
 - No items with frequency less than $(1 \varepsilon) \frac{\|f\|_1}{k}$

CountMin

- Initalization: Create b buckets of counters and use a random hash function $h: [n] \to [b]$
- Algorithm: For each update x_i , increment the counter $h(x_i)$

c_1	c_2	c_3	c_4
0	0	0	0

• At the end of the stream, output the counter $h(x_i)$ as the estimate for x_i

CountMin for (ε, k) -Frequent Items Problem

• Claim: For all estimated frequencies \hat{f}_i by CountMin, we have

$$f_i \le \widehat{f}_i \le f_i + \frac{\varepsilon \|f\|_1}{k}$$

- If $f_i \geq \frac{\|f\|_1}{k}$, then $\widehat{f}_i \geq f_i \frac{\varepsilon \|f\|_1}{k}$ and if $f_i < (1-\varepsilon) \cdot \frac{\|f\|_1}{k}$, then $\widehat{f}_i < f_i \frac{\varepsilon \|f\|_1}{k}$
- Returning coordinates V_t with $c_t \ge (1 \varepsilon) \cdot \frac{\|f\|_1}{k}$ means:
 - i with $f_i \ge \frac{\|f\|_1}{k}$ will be returned
 - NO i with $f_i < (1 \varepsilon) \cdot \frac{\|f\|_1}{k}$ will be returned

CountMin for (ε, k) -Frequent Items Problem

• Summary: CountMin can be used to solve the (ε, k) -frequent items problem on an insertion-deletion stream

• CountMin uses $O\left(\frac{k}{\varepsilon}\log n\right)$ bits of space

CountMin is a deterministic algorithm

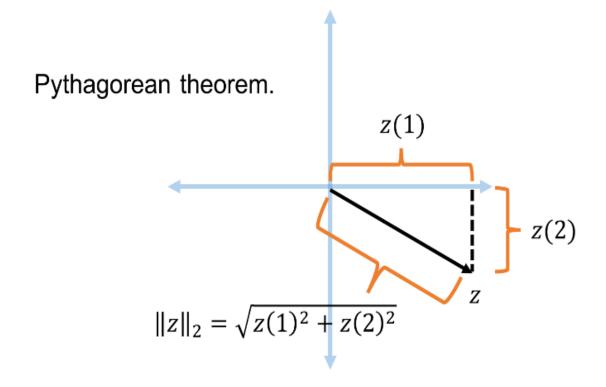
• CountMin *never* underestimates the true frequency for insertiononly streams

Recall: Euclidean Space and L_2 Norm

• For $z \in \mathbb{R}^n$, the L_2 norm of z is denoted by $||z||_2$ and defined as:

$$||z||_2 = \sqrt{z_1^2 + z_2^2 + \dots + z_n^2}$$

• For $x, y \in \mathbb{R}^n$, the distance function D is denoted by $\|\cdot\|_2$ and defined as $\|x - y\|_2$



Trivia Question #7 (Norms)

• For $x \in \mathbb{R}^n$, which of the following is (the most) true?

- $||x||_2 > ||x||_1$
- $||x||_2 \ge ||x||_1$
- $||x||_2 = ||x||_1$
- $||x||_2 \le ||x||_1$
- $||x||_2 < ||x||_1$
- None of these are true characterizations of the relationship between $\|x\|_2$ and $\|x\|_1$

Trivia Question #8 (Norms)

• For $x \in \mathbb{R}^n$, how much large can $||x||_1/||x||_2$ be?

- $\bullet O(n)$
- $O(\sqrt{n})$
- $O(\log n)$
- *0*(1)

(ε, k) -Frequent Items Problem

- Goal: Given a set S of m elements from [n] that induces a frequency vector $f \in \mathbb{R}^n$, an accuracy parameter $\varepsilon \in (0,1)$, and a parameter k, output a list that includes:
 - The items from [n] that have frequency at least $\frac{\|f\|_1}{k}$
 - No items with frequency less than $(1 \varepsilon) \frac{\|f\|_1}{k}$

L_2 Heavy-Hitters

- Goal: Given a set S of m elements from [n] that induces a frequency vector $f \in \mathbb{R}^n$, an accuracy parameter $\varepsilon \in (0,1)$, and a parameter k, output a list that includes:
 - The items from [n] that have frequency at least $\frac{\|f\|_2}{k}$
 - No items with frequency less than $(1 \varepsilon) \frac{\|f\|_2}{k}$

L_2 Heavy-Hitters

- Goal: Given a set S of m elements from [n] that induces a frequency vector $f \in \mathbb{R}^n$ and a threshold parameter $\varepsilon \in (0, 1)$, output a list that includes:
 - The items from [n] that have frequency at least $\varepsilon \cdot ||f||_2$
 - No items with frequency less than $\frac{\varepsilon}{2} \cdot \|f\|_2$

L_2 Estimation

• Goal: Given a set S of m elements from [n] that induces a frequency vector $f \in \mathbb{R}^n$ and an accuracy parameter $\varepsilon \in (0,1)$, output a $(1 + \varepsilon)$ -approximation to $||f||_2$

- Find Z such that $(1 \varepsilon) \cdot ||f||_2 \le Z \le (1 + \varepsilon) \cdot ||f||_2$
- Find Z' such that $(1 \varepsilon) \cdot ||f||_2^2 \le Z' \le (1 + \varepsilon) \cdot ||f||_2^2$

L_2 Estimation

• How to do?

L_2 Estimation

• How to do?

• Sorry, won't reveal until next lecture (wait, don't we already have a tool for this)?

• Assume for now we are given $||f||_2$

Revisiting CountMin

- Initalization: Create b buckets of counters and use a random hash function $h: [n] \to [b]$
- Algorithm: For each insertion (or deletion) to x_i , increment (or decrement) the counter $h(x_i)$

c_1	c_2	c_3	c_4
0	0	0	0

• At the end of the stream, output the counter $h(x_i)$ as the estimate for x_i

CountMin and the Power of Random Signs

- Initalization: Create b buckets of counters and use a random hash function $h: [n] \to [b]$ and a uniformly random sign function $s: [n] \to \{-1, +1\}$, i.e., $\Pr[s(i) = +1] = \Pr[s(i) = -1] = \frac{1}{2}$
- Algorithm: For each insertion (or deletion) to x_i , change the counter $h(x_i)$ by $s(x_i)$ (or $-s(x_i)$)

c_1	c_2	c_3	c_4
0	0	0	0

• At the end of the stream, output the quantity $s(x_i) \cdot h(x_i)$ as the estimate for x_i

f_1	f_2	f_3	f_4	f_5	f_6	f_7
0	0	0	0	0	0	0

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c_1	c_2	c_3	c_4
0	0	0	0

f_1	f_2	f_3	f_4	f_5	f_6	f_7
1	0	0	0	0	0	0

$$h(x) = 3x + 2 \pmod{4}$$

 $s(x) = +1 \text{ for } x \in \{1,2,3\}$
 $s(x) = -1 \text{ for } x \in \{4,5\}$



c_1	c_2	c_3	c_4
0	0	0	0

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1	0	0	0	0	0	0

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1	0	1	1

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1	1	1	0	0	0	0

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1	0	1	1

f_1	f_2	f_3	f_4	f_5	f_6	f_7
2	1	1	0	0	0	0

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1	0	1	1

f_1	f_2	f_3	f_4	f_5	f_6	f_7
2	1	1	0	1	0	0

- What is the estimation for f_4 ?
- What about f_3 ?
- What about f_5 ? What about f_1 ?

$h(x) = 3x + 2 \pmod{4}$
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