

# Massive Data Algorithmics

## The Streaming Model

### Lecture 15: Frequent Items via Sketching

# The Problem

- Frequency
  - Input: the stream  $\sigma = \langle a_1, \dots, a_m \rangle$  where  $a_i \in [n]$
  - Frequent number of item  $j$ :  $f_j = |\{i : a_i = j\}|$ ,
  - Frequency vector:  $F = (f_1, f_2, \dots, f_n)$
  - Frequency moments:  $F_k = \|F\|_k^k = \sum_{j=1}^n f_j^k$
  - $F_0$ : the number of distinct items
  - $F_1$ : the number of items (i.e.  $m$ )
- Problem: Estimating the frequent number
  - Input: the stream  $\sigma = \langle a_1, \dots, a_m \rangle$  where  $a_i \in [n]$ , and  $k$
  - Output for a query  $a$ :  $\hat{f}_a$ , an estimator of  $f_a$

# Misra-Gries Algorithm

- Let  $\hat{f}_a$  be the output of Misra-Gries Algorithm. We showed  $f_a - m/k \leq \hat{f}_a \leq f_a$ .
- Let  $MG(\sigma)$  denote the data structure (the set of  $k - 1$  keys and their counters) computed by Misra-Gries algorithm.
- One drawback of this data structure is that there is no general way to compute  $MG(\sigma_1 \cdot \sigma_2)$  from  $MG(\sigma_1)$  and  $MG(\sigma_2)$  where  $\sigma_1 \cdot \sigma_2$  is the concatenation of  $\sigma_1$  and  $\sigma_2$ .

# Sketch

- A data structure  $DS(\sigma)$  computed in streaming fashion by processing a stream  $\sigma$  is called a sketch if there is a space-efficient combining algorithm COMB such that, for every two stream  $\sigma_1$  and  $\sigma_2$ , we have

$$\text{COMB}(DS(\sigma_1), DS(\sigma_2)) = DS(\sigma_1 \cdot \sigma_2)$$

# The Algorithm

**Initialize** :

- 1  $C[1 \dots k] \leftarrow \vec{0}$ , where  $k := 3/\varepsilon^2$  ;
- 2 Choose a random hash function  $h : [n] \rightarrow [k]$  from a 2-universal family ;
- 3 Choose a random hash function  $g : [n] \rightarrow \{-1, 1\}$  from a 2-universal family ;

**Process**  $(j, c)$ :

- 4  $C[h(j)] \leftarrow C[h(j)] + cg(j)$  ;

**Output** :

- 5 On query  $a$ , report  $\hat{f}_a = g(a)C[h(a)]$  ;

# Analysis

- $X = \hat{f}_a$
- Let  $Y_j$  be the indicator for the event " $h(j) = h(a)$ ".
- Token  $j$  contributes to the counter  $C[h(a)]$  iff  $h(j) = h(a)$  and the amount of the contribution is its frequency times sign  $g(j)$ .
- $X = g(a) \sum_{j=1}^n f_j g(j) Y_j = f_a + \sum_{j \in [n] - \{a\}} f_j g(a) g(j) Y_j$
- $E(g(j) Y_j) = E(g(j)) E(Y_j) = 0 \cdot E(Y_j) = 0$
- $E(X) = f_a + \sum_{j \in [n] - \{a\}} f_j g(a) E(g(j) Y_j) = f_a$
- We need to show that  $X$  is unlikely to deviate too much from its mean. For this, we analyze its variance.

# Analysis

- For  $j \in [n] - \{a\}$ , we have

$$E(Y_j^2) = E(Y_j) = \Pr(h(j) = h(a)) = 1/k$$

- For all  $i, j \in [n]$  and  $i \neq j$ , we have

$$E(g(i)g(j)Y_iY_j) = E(g(i))E(g(j))E(Y_iY_j) = 0 \cdot 0 \cdot E(Y_iY_j) = 0$$

- $$\begin{aligned} \text{Var}(X) &= 0 + g(a)^2 \text{Var}(\sum_{j \in [n] - \{a\}} f_j g(j) Y_j) = E(\sum_{j \in [n] - \{a\}} f_j^2 Y_j^2 + \\ &\sum_{i, j \in [n] - \{a\}, i \neq j} f_i f_j g(i) g(j) Y_i Y_j) - (\sum_{j \in [n] - \{a\}} f_j E(g(j) Y_j))^2 = \\ &\sum_{j \in [n] - \{a\}} \frac{f_j^2}{k} + 0 - 0 = \frac{\|F\|_2^2 - f_a^2}{k} \end{aligned}$$

# Analysis

- $\Pr(|\hat{f}_a - f_a| \geq \varepsilon \sqrt{\|F\|_2^2 - f_a^2}) = \Pr(|X - E(X)| \geq \varepsilon \sqrt{\|F\|_2^2 - f_a^2}) \leq \frac{\text{Var}(X)}{\varepsilon^2(\|F\|_2^2 - f_a^2)} = \frac{1}{k\varepsilon^2} = \frac{1}{3}$
- For  $j \in [n]$ , let us define  $F_{-j}$  to be the  $(n-1)$ -dimensional vector obtained by dropping the  $j$ -th entry of  $F$ . Then,  $\|F_{-j}\|_2^2 = \|F\|_2^2 - f_j^2$ .
- We can rewrite the above statement in the following more memorable form

$$\Pr(|\hat{f}_a - f_a| \geq \varepsilon \|F_{-a}\|_2) \leq \frac{1}{3}$$



# The Final Sketch

- Apply the median trick to bring its probability down to  $\delta$

**Initialize** :

- 1  $C[1 \dots t][1 \dots k] \leftarrow \vec{0}$ , where  $k := 3/\epsilon^2$  and  $t := O(\log(1/\delta))$  ;
- 2 Choose  $t$  independent hash functions  $h_1, \dots, h_t : [n] \rightarrow [k]$ , each from a 2-universal family ;
- 3 Choose  $t$  independent hash functions  $g_1, \dots, g_t : [n] \rightarrow [k]$ , each from a 2-universal family ;

**Process** ( $j, c$ ):

- 4 **for**  $i = 1$  **to**  $t$  **do**  $C[i][h_i(j)] \leftarrow C[i][h_i(j)] + c g_i(j)$  ;

**Output** :

- 5 On query  $a$ , report  $\hat{f}_a = \text{median}_{1 \leq i \leq t} g_i(a) C[i][h_i(a)]$  ;

# Analysis

- $\Pr(|\hat{f}_a - f_a| \geq \epsilon \|F_{-a}\|_2) \leq \delta$
- space:  $O(\frac{1}{\epsilon^2} \log \frac{1}{\delta} (\log n + \log m))$

# The Algorithm

**Initialize** :

- 1  $C[1 \dots t][1 \dots k] \leftarrow \vec{0}$ , where  $k := 2/\varepsilon$  and  $t := \lceil \log(1/\delta) \rceil$  ;
- 2 Choose  $t$  independent hash functions  $h_1, \dots, h_t : [n] \rightarrow [k]$ , each from a 2-universal family

**Process** ( $j, c$ ):

- 3 **for**  $i = 1$  **to**  $t$  **do**  $C[i][h_i(j)] \leftarrow C[i][h_i(j)] + c$  ;

**Output** :

- 4 On query  $a$ , report  $\hat{f}_a = \min_{1 \leq i \leq t} C[i][h_i(a)]$  ;

# Analysis

- space:  $O(\frac{1}{\epsilon} \log \frac{1}{\delta} (\log n + \log m))$
- It is clear  $f_a \leq \hat{f}_a$
- We analyze the excess in (i.e.  $\hat{f}_a - f_a$ ) for counter  $C[i][h_i(a)]$ .
- Let  $X_i$  be this excess.
- For  $j \in [n] - \{a\}$ , let  $Y_{i,j}$  be the indicator of the event " $h_i(j) = h_i(a)$ ".
- $j$  makes a contribution to the counter iff  $Y_{i,j} = 1$  and when it does contribute, it causes  $f_j$  to be added to this counter.
- $X_i = \sum_{j \in [n] - \{a\}} f_j Y_{i,j}$
- $E(Y_{i,j}) = 1/k$
- $E(X_i) = \sum_{j \in [n] - \{a\}} \frac{f_j}{k} = \frac{\|F\|_1 - f_a}{k} = \frac{\|F_{-a}\|_1}{k}$

# Analysis

- $\Pr(X_i \geq \epsilon \|F_{-a}\|_1) \leq \frac{\|F_{-a}\|_1}{k\epsilon \|F_{-a}\|_1} = \frac{1}{2}$
- $\Pr(\hat{f}_a - f_a \geq \epsilon \|F_{-a}\|_1) = \Pr(\min(X_1, \dots, X_t) \geq \epsilon \|F_{-a}\|_1) = \Pr(\bigwedge_{i=1}^t (X_i \geq \epsilon \|F_{-a}\|_1)) = \prod_{i=1}^t \Pr(X_i \geq \epsilon \|F_{-a}\|_1) \leq \frac{1}{2^t} \leq \delta$
- $f_a \leq \hat{f}_a \leq f_a + \epsilon \|F_{-a}\|_1$
- The deviation  $\epsilon \|F_{-a}\|_1$  is weaker than the deviation  $\epsilon \|F_{-a}\|_2$  of the count sketch.

# Comparison of Frequency Estimation Methods

Method	$\hat{f}_a - f_a \in \dots$	Space	Error Probability
Misra-Gries	$[-\varepsilon \ \mathbf{f}_{-a}\ _1, 0]$	$O\left(\frac{1}{\varepsilon}(\log m + \log n)\right)$	0 (deterministic)
Count Sketch	$[-\varepsilon \ \mathbf{f}_{-a}\ _2, \varepsilon \ \mathbf{f}_{-a}\ _2]$	$O\left(\frac{1}{\varepsilon^2} \log \frac{1}{\delta} \cdot (\log m + \log n)\right)$	$\delta$ (overall)
Count-Min Sketch	$[0, \varepsilon \ \mathbf{f}_{-a}\ _1]$	$O\left(\frac{1}{\varepsilon} \log \frac{1}{\delta} \cdot (\log m + \log n)\right)$	$\delta$ (upper bound only)
Count/Median	$[-\varepsilon \ \mathbf{f}_{-a}\ _1, \varepsilon \ \mathbf{f}_{-a}\ _1]$	$O\left(\frac{1}{\varepsilon} \log \frac{1}{\delta} \cdot (\log m + \log n)\right)$	$\delta$ (overall)

## References

- **Data Stream Algorithms** (Chapter 4)  
Lecture notes by A. Chakrabbarti and D. College