

# **SDSC3001 Assignment 3**

**2024.11.28**

# Q1

1. (25 points) Design a sampling algorithm to maintain  $k$  uniform samples from a stream of elements  $x_1, x_2, x_3, \dots$ . Prove the correctness of your algorithm, that is, your algorithm can guarantee that at any time point  $t \geq k$  (the time we have received  $x_1, x_2, \dots, x_t$ ) the probability that  $x_i$  ( $i \leq t$ ) is kept as a sample is  $\frac{k}{t}$ .

## Solution:

Assume that after  $t - 1$  samples, we obtain  $S_{old} = \{s_1, s_2, \dots, s_k\}$ . And  $Pr(x_i \in S_{old}) = \frac{k}{t-1}$  for all  $i \leq t - 1$ . When  $x_t$  comes, with probability  $\frac{k}{t}$ , we add  $x_t$  to  $S_{old}$ . And we delete an  $s_j$  in  $S_{old}$  with probability  $\frac{1}{k}$ . Then we get  $S_{new} = \{s_1, s_2, \dots, s_{j-1}, s_{j+1}, \dots, s_k\} \cup \{x_t\}$ . We have:

$$Pr(x_t \in S_{new}) = \frac{k}{t}$$

For  $i \leq t - 1$ , we have:

$$\begin{aligned} Pr(x_i \in S_{new}) &= Pr(x_i \in S_{old}) \left(1 - \frac{k}{t}\right) + Pr(x_i \in S_{old}) \cdot \frac{k}{t} \cdot \left(1 - \frac{1}{k}\right) \\ &= \frac{k}{t} \end{aligned}$$

$\downarrow$  Does not add  $x_t$                        $\downarrow$  add  $x_t$                        $\downarrow$  Does not delete  $x_i$

## Q2

2. (75 points) Download the file "trans.txt" and implement a streaming algorithm for mining the top- $k$  most frequent patterns. In the data file "trans.txt", every line is a transaction represented by a set of item ids and the largest transaction contains 15 items.

a) (15 points) Prove that to mine top- $k$  most frequent patterns, we do not need to consider patterns of size greater than  $m = \lceil \log_2(k + 1) \rceil$ .

b) (60 points) Apply the idea of the Misra-Gries Algorithm to mine approximate frequent patterns by scanning each transaction only once. Specifically, implement your algorithm as follows.

(1). Maintain at most  $C$  counters. Each counter is a (key, value) pair where "key" represents a specific pattern and "value" indicates the corresponding (approximate) support of the pattern.

(2). When reading a transaction, enumerate all its subsets of size at most  $m$ . Suppose for the  $i$ -th transaction we have  $L_i$  such valid subsets and clearly,  $L_i = \sum_{j=1}^{\min(l_i, m)} \binom{l_i}{j}$  where  $l_i$  is the size of the  $i$ -th transaction. Transform the  $i$ -th transaction to a stream of  $L_i$  subsets (the order could be arbitrary) and use the Misra-Gries Algorithm to count each subset's number of appearances (support).

## Q2

a) **(15 points)** Prove that to mine top- $k$  most frequent patterns, we do not need to consider patterns of size greater than  $m = \lceil \log_2(k+1) \rceil$ .

### Solution:

If  $S = \{x_1, \dots, x_m\}$  is a frequent pattern. Then for all  $S' \subseteq S$  is a frequent pattern. The number of subsets of  $S$  is:

$$2^m - 1 = 2^{\lceil \log_2(k+1) \rceil} - 1 \geq 2^{\log_2(k+1)} - 1 = k + 1 - 1 = k$$

Note: If  $S'$  is a subset of  $S$ , then  $\text{support}(S') \geq \text{support}(S)$ .

# Q2

## Misra–Gries Algorithm

- ▶ Maintain  $k$  counters that are initialized as 0
- ▶ All counters of value 0 are considered as “available”
- ▶ Upon receiving  $a_t$ , check if there is a counter for  $a_t$ 
  - ▶ If there is one, increase the counter by 1
  - ▶ If no and there is at least one counter available, use an available counter to count  $a_t$
  - ▶ If no and no available counters, decrease each counter by 1 (decrement)

## A Running Example

- ▶  $m = 8, k = 4$

Data Stream	1	2	3	2	6	7	8	2	2	1	3	3	1	1	3
Key <sub>1</sub>	1	1	1	1	1	1	8	8	8	8	8	8	8	8	8
Value <sub>1</sub>	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1
Key <sub>2</sub>		2	2	2	2	2	2	2	2	2	2	2	2	2	2
Value <sub>2</sub>		1	1	2	2	1	1	2	3	3	3	3	3	3	3
Key <sub>3</sub>			3	3	3	3				1	1	1	1	1	1
Value <sub>3</sub>			1	1	1	0				1	1	1	2	3	3
Key <sub>4</sub>					6	6					3	3	3	3	3
Value <sub>4</sub>					1	0					1	2	2	2	3

## Q2

b.1) (8 points) Suppose in total we have  $M$  transactions. Let  $L = \sum_{i=1}^M L_i$ . Suppose  $f_S$  is the real support of a pattern  $S$  and  $\hat{f}_S$  is the approximate support maintained by your Misra-Gries Algorithm. Prove that for any pattern  $S$ , we have that  $f_S \geq \hat{f}_S \geq f_S - \frac{L}{C+1}$ .

### Solution:

$\hat{f}_S \leq f_S$  is trivial. We can prove that at time  $t$ , we have at most  $\frac{t}{C+1}$  decrements. Let  $V = \text{sum of the counters}$ . When we decrease:  $V = V - C$  and when we increase:  $V = V + 1$ . Denote  $a$  as the number of increments, and  $b$  as the number of decrements. Then:

$$a + b = t$$

$$a - Cb \geq 0 \quad (V \geq 0 \text{ always holds})$$

We have  $t - b - Cb \geq 0 \Rightarrow b \leq \frac{t}{C+1}$ .

- Case1: At any time  $t$ , if a pattern(key)  $S$  does **not** exist in the counter (so the count  $\hat{f}_S$  is 0). Then the real support  $f_S$  is less than  $\frac{t}{C+1}$ . So  $\hat{f}_S \geq f_S - \frac{t}{C+1}$ .
- Case2: At any time  $t$ , if a pattern(key)  $S$  exists in the counter, the total number of decrements applied to the count  $\hat{f}_S$  is less than  $\frac{t}{C+1}$ . So we also have  $\hat{f}_S \geq f_S - \frac{t}{C+1}$ .
- We have  $L$  streams of data (patterns), so let  $t=L$ , which leads to the proven inequality.

► Any element appearing more than  $\frac{t}{k+1}$  has a counter at time  $t$  (**Heavy-Hitters**)

Lec 7, Page 13.  $C$  is equivalent to  $k$  in Question 2 here.

## Q2

b.2) (7 points) Suppose  $S^k$  is the real  $k$ -th most frequent pattern. Let  $\hat{f}^k$  be the  $k$ -th largest (approximate) support obtained by your Misra–Gries Algorithm. Prove that

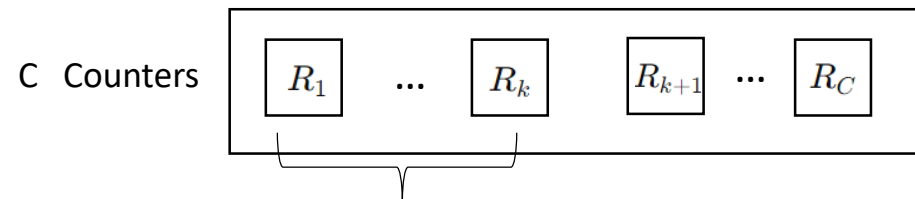
$$f_{S^k} \geq \hat{f}^k \geq f_{S^k} - \frac{L}{C+1} .$$

### Solution:

$S_1, S_2, \dots, S_k$  are the real  $k$  most frequent patterns.  $S_{k+1}, S_{k+2}, \dots$  are other patterns.

$R_1, R_2, \dots, R_k$  are the  $k$  most frequent patterns approximated using the counter.  $R_{k+1}, R_{k+2}, \dots, R_C$  are other patterns in the counter.

The approximated support of  $R_i$  is  $\hat{f}^i$ .



We hope this part is an approximation of the real top- $k$  frequent patterns.

## Q2

b.2) (7 points) Suppose  $S^k$  is the real  $k$ -th most frequent pattern. Let  $\hat{f}^k$  be the  $k$ -th largest (approximate) support obtained by your Misra–Gries Algorithm. Prove that

$$f_{S^k} \geq \hat{f}^k \geq f_{S^k} - \frac{L}{C+1} .$$

**Solution:**

Denote the key of  $\hat{f}^i$  as  $R_i, (i = 1, 2, \dots, k)$ .

$$\hat{f}^k \leq \hat{f}^i \leq f_{R_i} \Rightarrow \hat{f}^k \leq f_{S^k}$$

Let  $y_k$  be the  $k^{th}$  largest value among  $\{x_1, x_2, \dots, x_n\}$ . For a real number  $t$ , if there exist  $k$  different  $x_{i_1}, x_{i_2}, \dots, x_{i_k}$ , such that, for all  $j \in [k]$ ,

$$x_{i_j} \geq t$$

Then we have  $y_k \geq t$ .

**$k^{th}$  largest value**



## Q2

b.2) (7 points) Suppose  $S^k$  is the real  $k$ -th most frequent pattern. Let  $\hat{f}^k$  be the  $k$ -th largest (approximate) support obtained by your Misra–Gries Algorithm. Prove that

$$f_{S^k} \geq \hat{f}^k \geq f_{S^k} - \frac{L}{C+1}.$$

**Solution:**

1) When  $R_k = S^j, j \leq k$ , we have:

$$\hat{f}^k \geq f_{R_k} - \frac{L}{C+1} = f_{S^j} - \frac{L}{C+1} \geq f_{S^k} - \frac{L}{C+1}$$

2) When  $R_k = S^m, m \geq k+1$ , we have:

$$\begin{aligned} |\{S^1, S^2, \dots, S^k\} - \{R_1, R_2, \dots, R_k\}| &> 0 \\ \Leftrightarrow \exists S^j, j \leq k, S^j &\notin \{R_1, R_2, \dots, R_k\} \end{aligned}$$

2.a) When  $S^j = R_\tau, k+1 \leq \tau \leq C$ , we have:

$$\hat{f}^k \geq \hat{f}^\tau \geq f_{R_\tau} - \frac{L}{C+1} = f_{S^j} - \frac{L}{C+1} \geq f_{S^k} - \frac{L}{C+1}$$

2.b) When  $S^j \neq R_\tau$ , for  $\tau = 1, 2, \dots, C$ , then each  $S^j$  is associated with a decrement. We have:

$$\begin{aligned} f_{S^j} &\leq \frac{L}{C+1} \\ \Rightarrow \hat{f}^k &\geq 0 \geq f_{S^j} - \frac{L}{C+1} \geq f_{S^k} - \frac{L}{C+1} \end{aligned}$$

Note: In 2.a),  $S^j$  exists in the counter but is not included in the set of the top  $k$  approximate supports.

In 2.b),  $S^j$  does not exist in the counter.

we have that  $f_S \geq \hat{f}_S \geq f_S - \frac{L}{C+1}$ .

## Q2

b.3) (15 points) Since we only have the approximate supports of patterns obtained by our Misra–Gries Algorithm, we can only use such approximate supports to return approximate top- $k$  patterns. We hope to collect all the true top- $k$  patterns by returning a collection of patterns  $A = \{S \mid \hat{f}_S \geq t\}$  where  $t$  is a threshold for us to filter out non-frequent patterns. Prove that if we set  $t = \hat{f}^k - \frac{L}{C+1}$ , we can guarantee that

(1) The returned pattern collection  $A$  has 100% recall. This means that if for a pattern  $S$ ,  $f_S \geq f_{S^k}$ , then  $S \in A$ ; (6 points)

(2) The minimum support of patterns in  $A$ , denoted by  $\min Sup(A) = \min_{S \in A} f_S$ , is at least  $f_{S^k} - \frac{2L}{C+1}$ . That is,  $\min Sup(A) \geq f_{S^k} - \frac{2L}{C+1}$ . (9 points)

## Q2

### Solution:

(1) The returned pattern collection  $A$  has 100% recall. This means that if for a pattern  $S$ ,  $f_S \geq f_{S^k}$ , then  $S \in A$ ; (6 points)

Denote the key of  $\hat{f}^i$  as  $R_i$ . If  $S = R_i$ ,  $i \in \{1, 2, \dots, C\}$  and  $f_S \geq f_{S^k}$ , then:

$$\begin{aligned}\hat{f}^i &\geq f_{R_i} - \frac{L}{C+1} = f_S - \frac{L}{C+1} \\ &\geq f_{S^k} - \frac{L}{C+1} \\ &\geq \hat{f}^k - \frac{L}{C+1} = t\end{aligned}$$

So,  $S \in A$ .

we have that  $f_S \geq \hat{f}_S \geq f_S - \frac{L}{C+1}$ .

Note: We should prove that the approximate supports of the real top-k frequent sets are greater than the threshold, so that they can be recalled.

## Q2

**Solution:**

(2) The minimum support of patterns in  $A$ , denoted by  $\minSup(A) = \min_{S \in A} f_S$ , is at least  $f_{S^k} - \frac{2L}{C+1}$ . That is,  $\minSup(A) \geq f_{S^k} - \frac{2L}{C+1}$ . (9 points)

If  $S \in A$ , then:

$$\begin{aligned} f_S &\geq \hat{f}_S \geq t = \hat{f}^k - \frac{L}{C+1} \\ &\geq f_{S^k} - \frac{L}{C+1} - \frac{L}{C+1} \\ &= f_{S^k} - \frac{2L}{C+1} \end{aligned}$$

we have that  $f_S \geq \hat{f}_S \geq f_{S^k} - \frac{2L}{C+1}$ .

## Q2

b.4) (30 points) Set  $k = 500$ . Run your Misra–Gries Algorithm on the "trans.txt" dataset and report the values of  $L$  and  $\minSup(A)$  when setting  $C = 500000, 750000, 1000000$ . To compute  $\minSup(A)$ , you can refer to the file "patterns\_Apriori.txt" containing all the frequent patterns of support at least 21. Each line of "patterns\_Apriori.txt" is in the form  $id_1, id_2, \dots, id_l : sup$ , where  $id_1, id_2, \dots, id_l$  denotes a pattern  $\{id_1, id_2, \dots, id_l\}$  and  $sup$  is the support of this pattern. (Hint: the file "patterns\_Apriori.txt" contains enough information. If your algorithm returns some pattern that is not in the "patterns\_Apriori.txt" file, probably your algorithm is not implemented correctly.)

C = 500000 minSup(A) = 1037

C = 750000 minSup(A) = 1077

C = 1000000 minSup(A) = 1098