INFO-F440 - ALGORITHMS FOR BIG DATA - 202324

# Maximum Coverage in Random-Arrival Streams



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### Introduction

- Maximum Coverage Problem.
- Definition: Given a collection of m sets, each a subset of a universe  $\{1,...,n\}$ , select k sets whose union has the largest cardinality.
- Goal: Choose k sets from a collection such that their union has the largest cardinality.



### Maximum Coverage

#### ILP formulation:

maximize 
$$\sum_{e_j \in E} y_j$$
 (maximizing the sum of covered elements) subject to  $\sum_{e_j \in S_i} x_i \leq k$  (no more than  $k$  sets are selected)  $\sum_{e_j \in S_i} x_i \geq y_j$  (if  $y_j > 0$  then at least one set  $e_j \in S_i$  is selected)  $y_j \in \{0,1\}$  (if  $y_j = 1$  then  $e_j$  is covered)  $x_i \in \{0,1\}$  (if  $x_i = 1$  then  $S_i$  is selected for the cover)

### NP-Hard

(Greedy algorithm: 1-1/e approximation)

## Streaming Models

Set-Streaming Model

Edge-Streaming Model

Random-Arrival Model:

Arbitrary-Arrival Model:

**Data Stream Processing** 

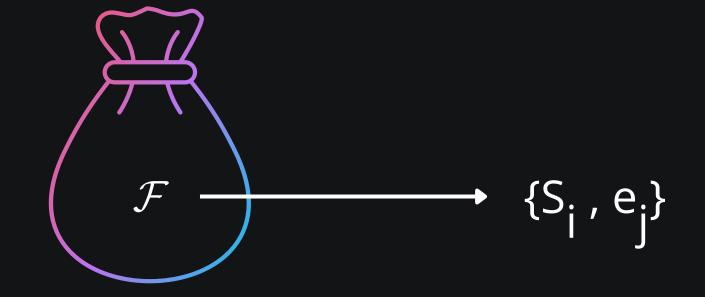


### Set-streaming model:



each set is contiguously listed

### Edge-streaming model:



Each random selection gives a pair (Set i, element j)

### What we know:

#### **Set-streaming:**

Arbitrary-arrival: 1/2 approximation is the best (low space)

Random-arrival: best approximation is between 1/2 and 1-1/e (low space)

Breaking the 1-1/e (≈0.63) approximation requires high space

The best approximation at that moment is 1/2

#### **Edge-streaming:**

 $\alpha$ -approximation in  $\tilde{O}(\alpha^2 m)$  space high space

#### The objective:

By mixing algorithms from many different papers, they aim to:

- Solve Set-streaming random-arrival model
- With a One-pass algorithm
- Using low space (polylogarithmic in n,m)
- With more than a 1/2 approximation

The main idea is to combine two algorithms to perform the maximum coverage

MV-4 for the sumbsampling of the data

ANY subroutine that computes the submodular maximization problem (e.g. SALSA)

### **MV-4**

MV-4 is a set-streaming maximum coverage algorithm designed to operate in an arbitrary-arrival model.

Approximation 
$$\rightarrow \frac{1}{2} - \epsilon$$
 using  $\tilde{O}(k\epsilon^{-3})$  space

### How MV-4 Works:

- 1 Initialization
  - **2** Processing Stream
- 3 Selection Criteria

4 Final Selection

#### k=3 and there are 100 elements (universe) Stream: {1, 2, 3}, {4, 5}, {1, 6, 7, 8}, ... Buffer: Empty Coverage: 0 elements Step 1: Buffer: {1, 2, 3} Coverage: 3 elements Step 2: Step 3: Buffer: {1, 2, 3}, {4, 5} Buffer: {1, 2, 3}, {4, 5}, {1, 6, 7, 8} Coverage: 5 elements Coverage: 8 elements (1, 2, 3, 4, 5)

(1, 2, 3, 4, 5, 6, 7, 8)

### MV-4 Example

Select Best k=3k = 3k=3 Sets from Buffer: {4, 5}, {1, 6, 7, 8}, {9, 10} Final Sets: {1, 6, 7, 8}, {4, 5}, {9, 10} Coverage: 10 elements

Step 4:

Buffer Full: Remove least valuable set
Buffer:

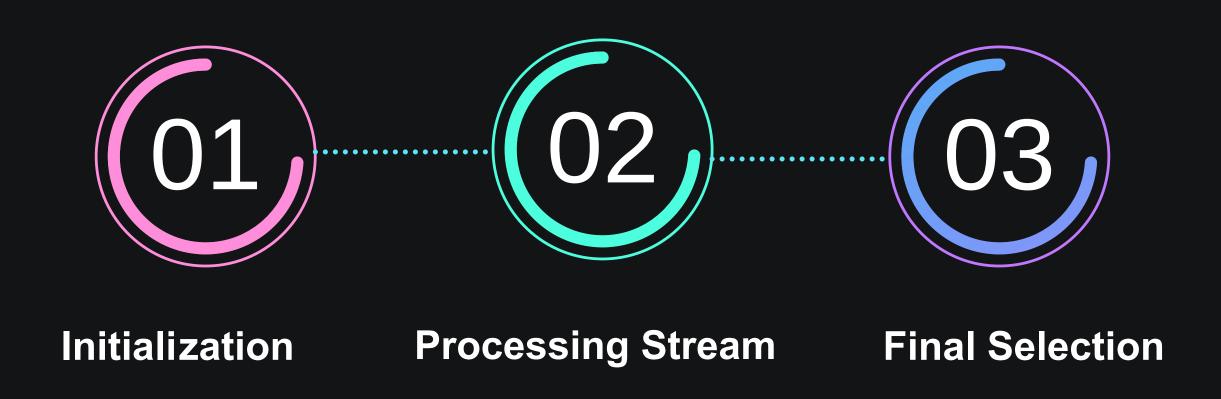
{4, 5}, {1, 6, 7, 8}, {9, 10} Coverage: 8 elements (1, 4, 5, 6, 7, 8, 9, 10)

### SALSA

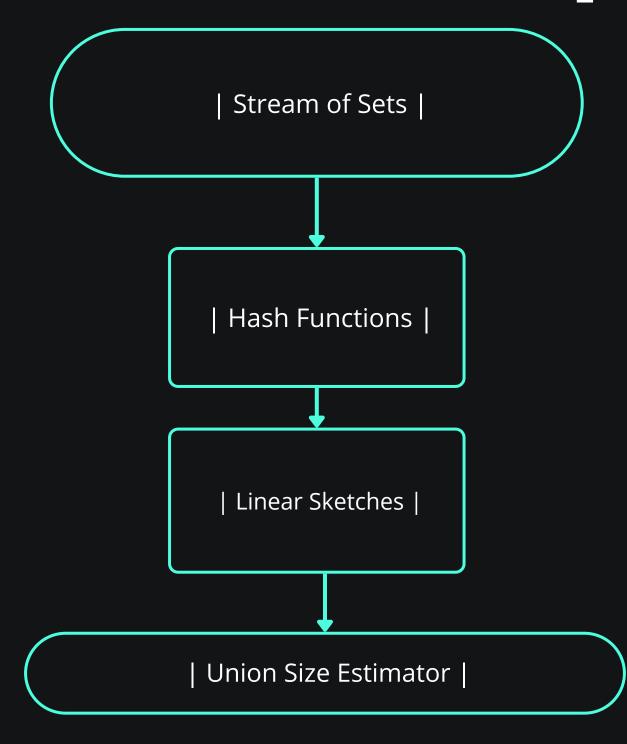
SALSA (Streaming Algorithm for Large Set Approximation) algorithm is to provide a near-optimal solution to the maximum coverage problem in a streaming context with random arrival orders.

Approximation 
$$\rightarrow 1 - \frac{1}{2} + co$$

### How SALSA Works:



### SALSA Example:



### **Assumptions:**

There is w such that:  $d/2 \le w \le d$   $(d \le OPT \le kd)$ 

There exists a family of  $\lambda$ -wise independant binary hash functions such that  $Pr(h(e)=1)=p_{w}$ 

An instantiation of B shouldn't use more than a certain amount of space, else it gets terminated

▶ **Lemma 3.** With probability at least  $1 - \varepsilon$ , for all collections of up to k sets  $S_1, \ldots, S_l \in \mathcal{F}$ ,  $|S'_1 \cup \cdots \cup S'_l| = p \cdot |S_1 \cup \cdots \cup S_l| \pm p\varepsilon d$ .

▶ Corollary 5. Let OPT' be the optimal coverage for the subsampled problem instance  $\mathcal{I}'$ . If a choice of k sets  $S_1, \ldots, S_k$  satisfies  $|S'_1 \cup \cdots \cup S'_k| \geq \beta \cdot \text{OPT'}$ , then with probability at least  $1 - \varepsilon$ ,  $|S_1 \cup \cdots \cup S_k| \geq (\beta - 2\varepsilon) \cdot \text{OPT}$ .

# Generalised Subsampling Algorithm GS(B)

Algorithm 1 The generalised subsampling algorithm  $GS(\mathcal{B})$ .

MV-4

```
1: W \leftarrow \{2^i : i \in \mathbb{N}, \ 2^i \le n\}
                                                                                                    \triangleright Guesses for d
 2: \lambda \leftarrow \lfloor 2k \log(em\varepsilon^{-1}) \rfloor
                                                                  ▶ Hash function independence parameter
 3: for w \in W do O(\log(n)
         Initialise \mathcal{B}_w, an instantiation of \mathcal{B}
         p_w \leftarrow \min\{1, 3k\varepsilon^{-2}\log(em\varepsilon^{-1})w^{-1}\}

    ▷ Subsampling rate

         Sample h_w \in \mathcal{H}_{p_w,\lambda} uniformly at random
                                                                                         ▶ Kill switch indicator
         active_w \leftarrow true
 8: for i = 1, ..., m do O(m)
                                                                        ▶ Iterate over each set in the stream
         for e \in S_i do O(d)
                                                                       ▶ Iterate over each element in the set
             for w \in W do O(\log(n)
10:
                  if d_w^* > 2p_w w(1+\varepsilon) then Too much space?
11:
                       active_w \leftarrow false
                                                                                                   \triangleright Terminate \mathcal{B}_w
12:
                  if active<sub>w</sub> and h_w(e) = 1 then
                       Supply e to the stream of \mathcal{B}_w
15: Let I_w \subset [m] be the solution returned by \mathcal{B}_w
16: w_c \leftarrow \min\{w \in W : d^*/2 \le w \le d^*\}
                                                                                        \triangleright At this point, d^* = d.
17: return I_{w_c}
```

SALSA

#### **GS-SALSA**

▶ **Theorem 2** (Generalised subsampling). Suppose  $\mathcal{B}$  achieves an approximation factor of  $\alpha$  in-expectation<sup>9</sup> for set-streaming maximum coverage using O(ds) space, where d is the maximum set size. There exists an algorithm, called  $GS(\mathcal{B})$ , which, given  $\varepsilon > 0$ , achieves an approximation factor of  $\alpha - \varepsilon$  in-expectation and uses  $\tilde{O}(k\varepsilon^{-2}s)$  space.

Space used: Õ(k²)

Running time: Õ(T<sub>B</sub>dm)

k: # of sets to select

d: size of bigest set

m: # of sets

T<sub>B</sub>: Running time of B

Here, Salsa runs in a polylogarthmic time

 $1/2 + c_1$  approximation

### What about Edge-streaming?

They prooved that  $\forall \alpha > 0$ ,  $\forall \delta > 0$ :

Any algorithm that  $\alpha$ -approximates with proba at least 1- $\delta$  requires  $\Omega(m^{1-\delta})$  space

So, no low space algorithm

#### Previous Work

MV-4:  $1/2 - \epsilon$  approximation

(Andrew McGregor and Hoa T Vu. Better streaming algorithms for the maximum coverage problem. Theory of Computing Systems, 63:1595–1619, 2019)

 $1/2 + c_0$ SALSA:

(Ashkan Norouzi-Fard, Jakub Tarnawski, Slobodan Mitrovic, Amir Zandieh, Aidasadat Mousavifar, and Ola Svensson. Beyond 1/2-approximation for submodular maximization on massive

data streams. In 35th ICML, pages 3829–3838, 2018.)

SMC:  $1 - 1/e - \varepsilon - o(1)$ 

(Shipra Agrawal, Mohammad Shadravan, and Cliff Stein. Submodular Secretary Problem with Shortlists. In 10th ITCS, pages 1:1–1:19, 2019.)

Greedy : 1-1/e (But high space)