STREAMING ALGORITHMS

- Streaming Model of Computation
- Streaming Algorithms and DFA
- Stream: Motivation and Applications
- Synopsis: Sliding Window, Histogram, Wavelets
- Sampling from Stream: Reservoir Sampling
- Linear Sketch
- Count-Min Sketch
- AMS Sketch

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Synopsis: Linear Sketch

Synopsis: Linear Sketch

- Sample is a general purpose synopsis
- Process sample only no advantage from observing the whole stream
- Sketches are specific to a particular purpose (query)
- Sketches (also histograms and wavelets) take advantage from the fact the processor see the whole stream (though can't remember all)

A linear sketch interprets a stream as defining the frequency vector

IP	Frequency
160.39.142.2	3
18.9.22.69	2
80.97.56.20	2

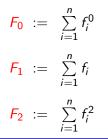
$$S: a_1, a_2, a_3, a_4, \dots, a_m \qquad \mathbf{F}: \begin{array}{c|c} 1 & 2 & 3 & & n \\ \hline f_1 & f_2 & f_3 & & \dots & f_n \end{array}$$
$$a_i \in [n] \qquad \qquad f_j = |\{a_i \in S: a_i = j\}| \quad (\text{frequency of } j \text{ in } S) \end{array}$$

$$\begin{aligned} \mathcal{S} &: 2, 5, 6, 7, 8, 2, 1, 2, 7, 5, 5, 4, 2, 8, 8, 9, 5, 6, 4, 4, 2, 5, 5 \\ \mathbf{F} &: 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 \\ \hline 1 & 5 & 0 & 3 & 6 & 2 & 2 & 3 & 1 \\ \end{aligned}$$

Linear Sketch: Frequency Moments

Often we are interested in frequency moments of a stream

$$S: a_1, a_2, a_3, a_4, \dots, a_m \qquad \mathbf{F}: \begin{bmatrix} 1 & 2 & 3 & & n \\ f_1 & f_2 & f_3 & & \dots & f_n \end{bmatrix}$$
$$a_i \in [n] \qquad \qquad f_j = |\{a_i \in S : a_i = j\}| \quad \text{(frequency of } j \text{ in } S \text{)}$$



> number of distinct elements

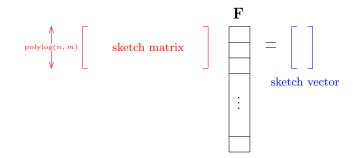
▷ length of stream, *m*

▷ second frequency moment

Synopsis: Linear Sketch

Linear sketch is a synopsis that can be computed as a linear transform of ${\bf F}$

- Best suited for data streams, highly parallelizable
- Very good for our problems of computing norms of F
- Can be readily extended to variations of the basic stream model



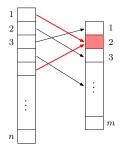
Linear Sketch: Hash Functions

Hash function is an efficient way to implement the Dictionary ADT

Hash functions map keys $A \subset U$ to m buckets labeled $\{0, 1, 2, \dots, m-1\}$ $\triangleright A$ is not known in advance and |A| = n

Desired properties of hash functions

- Fewer collisions
- Small range (m)
- Small space complexity to store hash function
- Easy to evaluate hash value for any key



Linear Sketch: Universal Hash Functions

Universal hash functions have probabilistic guarantees on collision

A family \mathcal{H} of hash functions of the form $h: U \mapsto [m]$ is 2-universal if

for any distinct keys $x, y \in U$, $\Pr_{h \in_{\mathcal{R}} \mathcal{H}} [h(x) = h(y)] \leq \frac{1}{m}$

 \triangleright Source of randomness is picking *h* (at random) from the family

Linear Congruential Generators for $U = \mathbb{Z}$

- Pick a prime number p > m
- For any two integers a and b $(1 \le a \le p-1)$, $(0 \le b \le p-1)$
- A hash function $h_{a,b}: U \mapsto [m]$ is defined as

 $h_{a,b}(x) = (ax+b) \pmod{p} \pmod{m}$

 $\mathcal{H} := \{h_{a,b} : 1 \le a \le p-1, 0 \le b \le p-1\}$ is 2-universal

Picking a random $h \in \mathcal{H}$ amounts to picking random a and b

Linear Sketch: Universal Hash Functions

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