Algorithms for data streams: Streaming models, graph streams

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- We abstract the data to a particular feature, the data field of interest the label.

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- Goal Compute a function of stream, e.g., median, number of distinct elements, longest increasing sequence.

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- Theoretical Appeal:
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- Origins in 70's but has become popular in this century because of growing theory and very applicable.

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- Semi-streaming model
  - Usual for graph problems.
  - Working memory is $O(n \text{ polylog } n)$, for a graph with n vertices.
  - Enough space to store vertices but not for storing all the edges.

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- Typical approach:
  - Build up a synopsis data structure
  - It should be enough to compute answers with a high confidence level.

Streams that describe graphs

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- on $[n]$ vertices
- the stream describes the edges of G
- we assume that an edge appears only once in the stream
- We want to keep a DS that allows to answer queries about a graph property
- $O(n \log n)$ memory is reasonable as we are working on the semi-streaming model.

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Maximum matching

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procedure MMATCHING(int n, stream s, double t)
    $M = \emptyset$
    while not $s.end()$ **do**
        $(u, v) = s.read()$
        if $M \cup (u, v)$ is a matching **then**
            $M = M \cup \{(u, v)\}$
    On query, report M

Maximum matching: Analysis

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- 1 pass, $O(n \log n)$ space, $O(1)$ ops. per item
- M is a maximal matching that provides an estimation $\hat{f}$ of the size f of a maximum matching.
- $\hat{f}$ is a 2 approximation to f.

  Because, at least one vertex of each edge of M must be matched by an edge in a maximum matching.

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- Example: To compute the median packet size of some IP packets, we could just sample some and use the median of the sample as an estimate for the true median. Statistical arguments relate the size of the sample to the accuracy of the estimate.
- Challenge: But how do you take a sample from a stream of unknown length or from a sliding window?

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  - Quality?
    What is the probability that $x = x_i$ at some time $t \geq i$?

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  - Base $t = 1$: $Pr[x = x_1] = 1$.
  - Induction hypothesis: true for time steps up to $t - 1$
    - $Pr[x = x_t] = 1/t$
    - For $i < t$, $x = x_i$ only when x_t is not selected and x_i was the sampled element at step $t - 1$. By induction hypothesis we have

$$Pr[x = x_t] = \left(1 - \frac{1}{t}\right) \frac{1}{t-1} = \frac{1}{t}$$

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  - Initially $X = \{x_1, \ldots, x_k\}$.
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    - $Pr[x_t \in X] = k/t$
    - For $i < t$, $x_i \in X$ when x_t is not selected and x_i was in the sample at step $t - 1$, or when x_t is selected, x_i was in the sample at step $t - 1$ and x_i is not evicted.

$$\begin{aligned} Pr[x_i \in X] &= \left(1 - \frac{k}{t}\right) \frac{k}{t-1} + \frac{k}{t} \frac{k}{t-1} \left(1 - \frac{1}{k}\right) \\ &= \frac{k}{t-1} - \frac{k}{t} \frac{k}{t-1} \frac{1}{k} = \frac{k}{t-1} - \frac{1}{t} \frac{k}{t-1} = \frac{k}{t} \end{aligned}$$

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  - Could store the entire window but this would require $O(w)$ memory.

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- For higher values of k, run k parallel chain samples. With high probability, for large enough w, such chains will not intersect.

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- With high probability the number of updates is $O(\log m)$.