Counting different items in a stream

QT Curs 2020-2021

RA-MIRI Data streams

Image: A matrix and a matrix

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 where f_i is the frequency of the j in the stream s
- In order to solve the problem using sublinear space, we need to use probabilistic algorithms/data structure and some adequate notion of approximation.

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When δ = 0, A must be deterministic.
 When ε = 0, A must be an exact algorithm.



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- Algorithm:
 - 1: **procedure** COUNT-DIF(stream *s*)
 - 2: Choose a random hash function $h: [n] \rightarrow [n]$ form a universal family

3: int
$$z = 0$$

5:
$$j = s.read()$$

6: **if**
$$zeros(h(j)) > z$$
 then

7:
$$z = \operatorname{zeros}(h(j))$$

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- Algorithm:
 - 1: **procedure** COUNT-DIF(stream *s*)
 - 2: Choose a random hash function $h: [n] \rightarrow [n]$ form a universal family
 - 3: int z = 0
 - 4: while not s.end() do
 - 5: j = s.read()
 - 6: **if** $\operatorname{zeros}(h(j)) > z$ **then**
 - 7: $z = \operatorname{zeros}(h(j))$
 - 8: Return $2^{z+\frac{1}{2}}$
- Assuming that there are d distinct elements, the algorithm computes max zeros(h(j)) as a good approximation of log d.

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• Since *h*(*j*) is uniformly distributed over the log *n*-bit strings,

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• Random variables Y_r are pairwise independent, as they come from a universal hash family.

$$Var[Y_r] = \sum_{j|f_j>0} Var[X_{r,j}] \le \sum_{j|f_j>0} E[X_{r,j}^2] = \sum_{j|f_j>0} E[X_{r,j}] = \frac{d}{2r}$$

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• Using Markov's and Chebyshev's inequalities,

$$Pr[Y_r > 0] = Pr[Y_r \ge 1] \le \frac{E[Y_r]}{1} = \frac{d}{2^r}.$$

$$Pr[Y_r = 0] = Pr[|Y_r - E[Y_r]| \ge \frac{d}{2^r}] \le \frac{Var[Y_r]}{(d/2^r)^2} \le \frac{2^r}{d}.$$

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• Let b be the largest integer so that $2^{b+\frac{1}{2}} \leq 3d$,

$$Pr[\hat{d} \le 3d] = Pr[t \le b] = Pr[Y_{b+1} = 0] \le \frac{2^{b+1}}{d} \le \frac{\sqrt{2}}{3}.$$

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- By standard Chernoff bounds, the median exceed 3d with probability $2^{-\Omega(k)}$ and the median is below 3d with probability $2^{-\Omega(k)}$.
- Choosing k = Θ(log(1/δ)), we can make the sum to be at most δ. So we get a (2, δ)-approximation. However, the used memory is now O(log(1/δ) log n).

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