

CS7960 L11 : Streaming I Approximate Rank

Streaming Algorithms

Stream : $A = \langle a_1, a_2, \dots, a_m \rangle$

a_i in $[n]$ size $\log n$

Compute $f(A)$ in $\text{poly}(\log m, \log n)$ space

Let $f_j = |\{a_i \text{ in } A \mid a_i = j\}|$

$F_1 = \sum_j f_j = m$ == total count

Goal:

eps-RELATIVE-RANK: Build data structure S .

$\text{rank}(v) = 1 + \# \text{ items in } A \text{ smaller than } v$

$\text{relative-rank}(v) = \text{Rrank}(v) = \text{rank}(v)/|A|$ in $[0,1]$

eps-RELATIVE-RANK S returns $S(v)$ such that

$\text{Rrank}(v) - \text{eps} \leq S(v) \leq \text{Rrank}(v) + \text{eps}$

Why relative rank?

$\text{median}(A) = \{ * \mid \text{Rrank}(*) = 1/2 \}$

quantiles: $\text{Rrank}(*) = 1/4, 3/4$

- more "robust" than mean

- captures distribution

Warm Up:

Random Sampling | Reservoir Sampling S w/ $k = O(1/\text{eps}^2 \log(1/\delta))$

For any interval $I_v = (-\infty, v)$ --> $\text{Rrank}(v) = \text{count}(I)/m$

Estimate $\text{count}(I_v)$ w/ $S(v)$ s.t.

$\text{Rrank}(v) - \text{eps} < S(v)/m < \text{Rrank}(v) + \text{eps}$

correct w.p. $1-\delta$

Want S of size $\sim O(1/\text{eps})$ instead of $\sim O(1/\text{eps}^2)$

eps		.1	.01	.001
1/eps		10	100	1000
1/eps^2		100	10000	1000000

Greenwald-Kanna Algorithm [G,K '01]

min-rank(v) = smallest possible rank of v (to S's knowledge)
 max-rank(v) = largest possible rank of v (to S's knowledge)
 m = size of stream up to know
 | A = <a1, a2, ..., a_m | a_{m+1}, ... >

Maintain collection of tuples (v_i, g_i, Delta_i)

s.t. v_i <= v_{i+1}
 g_i = min-rank(v_i) - min-rank(v_{i-1})
 Delta_i = max-rank(v_i) - min-rank(v_i)

Maintain MIN = min{a_j \in A} (seen so far)

MAX = max{a_j \in A} (seen so far)

Maintain m = total count

#####

Process: a_m

Find i s.t. v_i < a_m < v_{i+1}

a_m becomes v_{i+1} (don't actually keep indices)

(v_{i+1} = a_m, g_{i+1} = 1, Delta_i = L 2 eps m J)

m <- m+1

Update {MIN, MAX} as needed

--> Delta_i = 0

Check if we can compress:

if (i s.t. g_i + g_{i+1} + Delta_{i+1} <= L 2 eps m - 1J) then

Remove (v_i, g_i, Delta_i)

Set g_{i+1} <-- g_i + g_{i+1}

#####

Query : rank(v)?

Find i s.t. v_i < v < v_{i+1}

Return (min-rank(v_i) + max-rank(v_{i+1}))/2

- min-rank(v_i) = 1 + sum_{j=1}^i g_j

- max-rank(v_{i+1}) = min-rank(v_{i+1}) + Delta_{i+1}

Error ?

- we know : max-rank(v_{i+1}) - min-rank(v_i) = g_i + g_{i+1} + Delta_{i+1}

g_i + g_{i+1} + Delta_{i+1} <= 1 + L 2 eps m - 1 J < 2 eps m

INDUCTION: Base case true on insertion

Delta < 2 eps m, by induction as well...

Insertion does not increase

Compression only allowed if above holds

2 eps m / 2 < eps m -> Rrank(v) within eps.

Space : O((1/eps) log(eps * m) log n)

- each tuple space : O(log n + log m) -> O(log n + log (eps m))

- how many tuples? O((1/eps) log (eps m))

INTUITION: <analysis quite complicated>

- Delta starts $2 \epsilon m$, but as m grows, this shrinks relative to m .
- g_i starts at 1. If $g_i + g_{i+1} < \epsilon m$, eventually will compress as Δ_{i+1} decreases relative to m .
- So $g_i + g_{i+1} > \epsilon m$ unless g_{i+1} is new (second half of stream).
<this is hard part to show, need amortized slack of $\log(\epsilon m)$ >
- if $g_i + g_{i+1} > \epsilon m$, then $g_i > i * \epsilon m / 2$
-> $\max i < 2 / \epsilon$.

So $O((1/\epsilon) * \log(\epsilon m)) * O(\log n + \log(\epsilon m))$
<second $\log(\epsilon m)$ can be absorbed into the $O((1/\epsilon) \log(\epsilon m))$ term>
--> $O((1/\epsilon) \log(\epsilon m) \log n)$

Median Exactly?

- 1-pass $O(\min\{m, n\})$ space
- 2-pass $\sim O(\sqrt{n})$ space
- p -pass $\sim O(n^{1/p})$ space

$p = O(\log n)$ passes --> $\sim O(1)$ space

2-pass set $\epsilon \sim 1/\sqrt{n}$ in GK.

- Space: $O(\sqrt{n} * \log(m/\sqrt{n})) \log n$
- Estimate rank of all elements within \sqrt{n} on pass 1
Find $\max i$ s.t. $R_{\text{rank}}(v_i) < 1/2$
 $\max j$ s.t. $R_{\text{rank}}(v_j) > 1/2$
 $I_{i,j} = (v_i, v_j)$ and $\text{count}(I_{i,j}) = O(\sqrt{n})$
- Second pass keep all elements in $I_{i,j}$ and count a in A s.t. $a < v_i$

In p -pass narrow range and approximate each pass...

A few more passes can get much more accurate!