

Counting distinct elements in data streams

Elements arrive (a_i) from a domain $[m] = \{1..m\}$ a_1, \dots, a_n elements

Goal: Count # distinct items (F_0)

$$F_k = \sum_{i \in A} f_i^k$$

where f_i is the frequency of an item
if A is the distinct set of items.

Result: with a small amount of memory we will approximate F_0 with high probability.

$$\Pr[|\tilde{F}_0 - F_0| \leq \epsilon \cdot F_0] \geq 1 - \delta.$$

↳ error parameter

confidence parameter

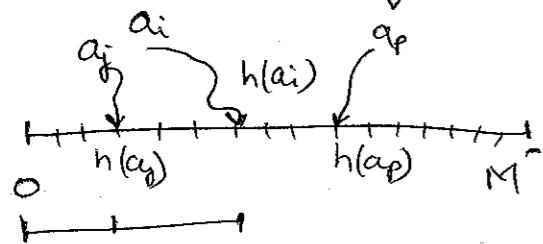
Choose a random hash function $h: [m] \rightarrow [M]$ $M = m^3$
Note: ensures that the probability of a collision is very small ($\leq \frac{1}{m}$)

Basic Idea: Let $t = \frac{c}{\epsilon^2}$ $c \equiv \text{constant. (TBD)}$

Apply $h(a_i)$, and maintain ~~min~~

$V \equiv$ max over the set of t smallest values in $\{h(a_i)\}$

Output $\tilde{F}_0 = \frac{tM}{V}$



$$\tilde{F}_0 = \frac{t \cdot M}{V}$$

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Suppose $\tilde{F}_0 > (1+\epsilon) F_0$. Let b_1, b_2, \dots, b_{F_0} be a listing of the F_0 distinct values

$\Rightarrow h(b_1), h(b_2), \dots, h(b_{F_0})$

contains $\gg t$ elements smaller than V .

$$\frac{tM}{V} > (1+\epsilon) F_0 \Rightarrow V < \frac{tM}{F_0(1+\epsilon)}$$

What is $\Pr \left[h(b_i) < \frac{tM}{F_0(1+\epsilon)} \right]$?

If $h(b_i)$ is uniformly distributed, then it is $< \frac{t}{F_0(1+\epsilon)}$

We have F_0 (pairwise indep.) events happening. Each event

has prob $p < \frac{t}{F_0(1+\epsilon)}$. What is the chance that $\gg t$ happen?

$$\text{Let } X_i = 1 \text{ iff } h(b_i) < \frac{tM}{F_0(1+\epsilon)}$$

$= 0$ otherwise

$$E[X_i] < \frac{t}{F_0(1+\epsilon)} \quad E\left[\sum_{i=1}^{F_0} X_i\right] < \frac{t}{1+\epsilon}$$

$$\text{Let } Y = \sum_{i=1}^{F_0} X_i \quad E[Y] < \frac{t}{1+\epsilon}$$

$$\text{Var}[Y] = \sum_{i=1}^{F_0} \text{Var}[X_i] \leq \frac{t}{1+\epsilon}$$

[THIS NEEDS

"PAIRWISE INDEPENDENCE"]

$$Pr(X \wedge Y) = Pr(X) \cdot Pr(Y)$$

$$E[XY] = E[X] \cdot E[Y]$$

NOT TRUE FOR

DEPENDENT VARIABLES.

Note that $\text{Var}[X_i]$ is actually $p(1-p)$.

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Use Chebyshev's Bound.

$$\Pr [|Y - E[Y]| \geq a] \leq \frac{\text{Var}[Y]}{a^2}$$

$$\Rightarrow \Pr \left[\left| Y - \frac{t}{1+\epsilon} \right| \geq a \right] \leq \frac{\frac{t}{1+\epsilon}}{a^2}$$

$$\Pr [Y \geq t] \leq \Pr \left[\left| Y - \frac{t}{1+\epsilon} \right| \geq \frac{t-\epsilon}{1+\epsilon} \right] \leq \frac{\frac{t}{1+\epsilon}}{\frac{t^2 \epsilon^2}{(1+\epsilon)^2}} = \frac{(1+\epsilon)}{t \epsilon^2}$$

since $t = \frac{c}{\epsilon^2}$ we get $\frac{1+\epsilon}{c}$.

Similar proof when $\tilde{F}_0 < (1+\epsilon) F_0$.

Defn $\text{Var}[X] = E[(X - \mu_x)^2] = E[X^2] - (\mu_x)^2$ $\mu_x = E[X]$
(easy proof)

FACT $E[XY] = E[X] \cdot E[Y]$ (if X & Y are indep)

FACT $\text{Var}[X+Y] = \text{Var}[X] + \text{Var}[Y]$ if X & Y are independent.

$$\begin{aligned} &= E[(X+Y - E[X+Y])^2] \\ &= E[(X - \mu_x + Y - \mu_y)^2] = E[(X - \mu_x)^2] + E[(Y - \mu_y)^2] \\ &\quad + 2E[(X - \mu_x)(Y - \mu_y)] \\ &= \text{Var}[X] + \text{Var}[Y] + 2 \left[E[XY - X\mu_y - Y\mu_x + \mu_x\mu_y] \right] \\ &= 2[\mu_x\mu_y - \mu_x\mu_y - \mu_y\mu_x + \mu_x\mu_y] \\ &= 0 \end{aligned}$$