# CS60021: Scalable Data Mining 

## Streaming Algorithms

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## Count distinct

## Streaming problem: distinct count

- Universe is $U$, number of distinct elements $=m$, stream size is $n$
- Example: $U=$ all IP addresses
10.1.21.10, 10.93.28,1,.....,98.0.3.1,.....10.93.28.1.....
- IPs can repeat
- Want to estimate the number of distinct elements in the stream


## Other applications

- Universe = set of all k-grams, stream is generated by document corpus
- need number of distinct k-grams seen in corpus
- Universe = telephone call records, stream generated by tuples (caller, callee)
- need number of phones that made $>0$ calls


## Solutions

- Seen $n$ elements from stream with elements from $U$.
- Naïve solution: $O(n \log |U|)$ space
- Store all elements, sort and count distinct
- Store a hashmap, insert if not present
- Bit array: O(|U|) space:
- Bits initialized to 1 only if element seen in stream
- Can we do this in less space ?


## Approximations

- $(\epsilon, \delta)$-approximations
- Algorithm will use random hash functions
- Will return an answer $\hat{n}$ such that

$$
(1-\epsilon) n \leq \hat{n} \leq(1+\epsilon) n
$$

- This will happen with probability $1-\delta$ over the randomness of the algorithm


## First effort

- Stream length: $n$, distinct elements: $m$
- Proposed algo: Given space $s$, sample $s$ items from the stream
- Find the number of distinct elements in this set: $\widehat{m}$
- return $\mathrm{m}=\widehat{m} \times \frac{n}{s}$
- Not a constant factor approximation
$-1,1,1,1, \ldots ., 1,2,3,4, \ldots ., m-1$

$$
n-m+1
$$

## Linear Counting

- Bit array $B$ of size $m$, initialized to all zero
- Hash function $h: U \rightarrow[m]$
- When seeing item $x$, set $B[h(x)]=1$


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- Bit array $B$ of size $m$, initialized to all zero
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- When seeing item $x$, set $B[h(x)]=1$
- $z_{m}=$ fraction of zero entries
- Return estimate $-\mathrm{m} \log \left(\frac{z_{m}}{m}\right)$


## Linear Counting Analysis

- $\operatorname{Pr}[$ position remaining 0$]=\left(1-\frac{1}{m}\right)^{n} \approx e^{-\frac{n}{m}}$
- Expected number of positions at zero: $\mathrm{E}\left[\mathrm{z}_{\mathrm{m}}\right]=m e^{-n / m}$
- Using tail inequalities we can show this is concentrated
- Typically useful only for $m=\Theta(n)$, often useful in practice


## Flajolet Martin Sketch

## Flajolet Martin Sketch

- Components
- "random" hash function $h: U \rightarrow 2^{\ell}$ for some large $\ell$
- $h(x)$ is a $\ell$-length bit string
- initially assume it is completely random, can relax
- zero $(v)=$ position of rightmost 1 in bit representation of $v$
$=\max \left\{i, 2^{i}\right.$ divides $\left.v\right\}$
$-\operatorname{zeros}(10110)=1, \quad \operatorname{zeros}(110101000)=3$


## Flajolet Martin Sketch

## Initialize:

- Choose a "random" hash function $h: U \rightarrow 2^{\ell}$
$-z \leftarrow 0$


## Process(x)

- if $\operatorname{zeros}(h(x))>z, \quad \mathrm{z} \leftarrow \operatorname{zeros}(h(x))$

Estimate:

- return $2^{z+1 / 2}$


## Example



## Space usage

- We need $\ell \geq C \log (n)$ for some $C \geq 3$, say
- by birthday paradox analysis, no collisions with high prob
- Sketch : $z$, needs to have only $O(\log \log n)$ bits
- Total space usage $=O(\log n+\log \log n)$


## Intuition

- Assume hash values are uniformly distributed
- The probability that a uniform bit-string
- is divisible by 2 is $1 / 2$
- is divisible by 4 is $1 / 4$
- is divisible by $2^{k}$ is $\frac{1}{2^{k}}$
- We don't expect any of them to be divisible by $2^{\log _{2}(n)+1}$


## Formalizing intuition

- $S=$ set of elements that appeared in stream
- For any $r \in[\ell], j \in[n], \quad X_{r j}=$ indicator of $\operatorname{zeros}(h(j)) \geq r$
- $Y_{r}=$ number of $j \in U$ such that $\operatorname{zeros}(h(j)) \geq r$

$$
Y_{r}=\sum_{j \in S} X_{r j}
$$

- Let $\hat{z}$ be final value of $z$ after the algorithm has seen all data


## Proof of FM

- $Y_{r}>0 \leftrightarrow \hat{z} \geq r$, equivalently, $Y_{r}=0 \leftrightarrow \hat{z}<r$
- $E\left[Y_{r}\right]=\sum_{j \in S} E\left[X_{r j}\right] \quad X_{r j}=\left\{\begin{array}{c}1 \text { with prob } \frac{1}{2^{r}} \\ 0 \quad \text { ese }\end{array}\right.$
- $E\left[Y_{r}\right]=\frac{n}{2^{r}}$
- $\operatorname{var}\left(Y_{r}\right)=\sum_{j \in S} \operatorname{var}\left(X_{r j}\right) \leq \sum_{j \in S} E\left[X_{r j}^{2}\right]$


## Proof of FM

- $\operatorname{var}\left(Y_{r}\right) \leq \sum_{j \in S} E\left[X_{r j}^{2}\right] \leq n / 2^{r}$

$$
\begin{gathered}
\operatorname{Pr}\left[Y_{r}>0\right]=\operatorname{Pr}\left[Y_{r} \geq 1\right] \leq \frac{E\left[Y_{r}\right]}{1}=\frac{n}{2^{r}} \\
\operatorname{Pr}\left[Y_{r}=0\right] \leq \operatorname{Pr}\left[\left|Y_{r}-E\left[Y_{r}\right]\right| \geq E\left[Y_{r}\right]\right] \leq \frac{\operatorname{var}\left(Y_{r}\right)}{E\left[Y_{r}\right]^{2}} \leq \frac{2^{r}}{n}
\end{gathered}
$$

## Upper bound

Returned estimate $\hat{n}=2^{\hat{z}+1 / 2}$
$a=$ smallest integer with $2^{a+1 / 2} \geq 4 n$

$$
\operatorname{Pr}[\hat{n} \geq 4 n]=\operatorname{Pr}[\hat{z} \geq a]=\operatorname{Pr}\left[Y_{a}>0\right] \leq \frac{n}{2^{a}} \leq \frac{\sqrt{2}}{4}
$$

## Lower bound

Returned estimate $\hat{n}=2^{\hat{z}+1 / 2}$
$b=$ largest integer with $2^{b+1 / 2} \leq n / 4$

$$
\operatorname{Pr}\left[\hat{n} \leq \frac{n}{4}\right]=\operatorname{Pr}[\hat{z} \leq b]=\operatorname{Pr}\left[Y_{b+1}=0\right] \leq \frac{2^{b+1}}{n} \leq \frac{\sqrt{2}}{4}
$$

## Understanding the bound

- By union bound, with prob $1-\frac{\sqrt{2}}{2}$,

$$
\frac{n}{4} \leq \hat{n} \leq 4 n
$$

- Can get somewhat better constants
- Need only 2-wise independent hash functions, since we only used variances


## Improving the probabilities

- To improve the probabilities, a common trick: median of estimates
- Create $\widehat{z_{1}}, \widehat{z_{2}}, \ldots ., \widehat{z_{k}}$ in parallel
- return median
- Expect at most $\frac{\sqrt{2}}{4} k$ of them to exceed $4 n$
- But if median exceeds $4 n$, then $\frac{k}{2}$ of them does exceed $4 n$
$\rightarrow$ using this prob is $\exp (-\Omega(k))$


## Improving the probabilities

- To improve the probabilities, a common trick: median of estimates
- Create $\widehat{z_{1}}, \widehat{z_{2}}, \ldots ., \widehat{z_{k}}$ in parallel
- return median
- Using Chernoff bound, can show that median will lie in $\left[\frac{n}{4}, 4 n\right]$ with probability $1-\exp (-\Omega(k))$.
- Given error prob $\delta$, choose $k=0\left(\log \left(\frac{1}{\delta}\right)\right)$


## k-minimum value Sketch

## k-MV sketch

- Developed in an effort to get better accuracy
- Flajolet Martin only give multiplicative accuracy
- Additional capabilities for estimating cardinalities of union and intersection of streams
- If $S_{1}$ and $S_{2}$ are two streams, can compute their union sketch from individual sketches of $S_{1}$ and $S_{2}$
[kMV sketch slides courtesy Cohen-Wang]


## Intuition

- Suppose $h: U \rightarrow[0,1]$ is random hash function such that $h(x) \sim U[0,1]$ for all $x \in U$
- Maintain min-hash value $y$
- initialize $y \leftarrow 1$
- For each item $x_{i}, y \leftarrow \min \left(y, h\left(x_{i}\right)\right)$
- Expectation of minimum is $E\left[\min _{i} h\left(x_{i}\right)\right]=\frac{1}{n+1}$


# Why is expectation of $\min =\frac{1}{n+1} ?$ 

Intuition:

- You have sampled $n$ points uniformly at random in interval [0,1]
- $n+1$ intervals are formed.
- Expected length of each interval is $\frac{1}{n+1}$
- Value of $\mathrm{E}\left[\min _{i} X_{i}\right]$ is the length of an interval.


## Why is expectation of $\min =\frac{1}{n+1} ?$

Assuming a $X_{i}=U(0,1)$, we have:

$$
P\left(\min _{i} X_{i} \leq x\right)=1-P\left(\min _{i} X_{i} \geq x\right)=1-(1-x)^{n}
$$

So, the density function is: $f(x)=n(1-x)^{n-1}$

Hence,

$$
E\left[\min _{i} X_{i}\right]=\int_{0}^{1} x f(x) d x=n \int_{0}^{1} x(1-x)^{n-1} d x=\frac{1}{n+1}
$$

## $k$-minimum value sketch

Initialize:
$-y_{1}, \ldots, y_{k} \leftarrow 1, \ldots 1$

- Uniform random hash functions $h_{1}, \ldots, h_{k}, h_{i}: U \rightarrow[0,1]$

Process $(x)$ :

- For all $j \in[k], y_{j} \leftarrow \min \left(y_{j}, h_{j}\left(x_{i}\right)\right)$

Estimate:

- return median-of-means $\left(\frac{1}{y_{1}}, \ldots, \frac{1}{y_{k}}\right)$


## Example

|  | h1 | h2 | h3 | h4 |
| :---: | :---: | :---: | :---: | :---: |
| .45 | .19 | .10 | .92 |  |
| 0 | .35 | .51 | .71 | .20 |
| 0 | .21 | .07 | .93 | .18 |
| $\mathbf{O}$ | .14 | .70 | .50 | .25 |

## Median-of-means

- Given $(\epsilon, \delta)$, choose $k=\frac{c}{\epsilon^{2}} \log \left(\frac{1}{\delta}\right)$
- Group $t_{1}, \ldots t_{k}$ into $\log \left(\frac{1}{\delta}\right)$ groups of size $\frac{c}{\epsilon^{2}}$ each
- Find mean $\left(t_{i}\right)$ for each group: $Z_{1}, \ldots, Z_{\log \left(\frac{1}{\delta}\right)}$
- Return $\hat{n}=$ median of $Z_{1}, \ldots Z_{\log \left(\frac{1}{\delta}\right)}$


## Complexity

- Total space required $=$ $O(k \log n)=O\left(\frac{1}{\epsilon^{2}} \log n \log \left(\frac{1}{\delta}\right)\right)$
- can be improved
- don't need floating points, can use $h: U \rightarrow 2^{\ell}$ as before
- Update time per item $=O(k)$
- However, can show that most items will not result in updates


## Theoretical Guarantees

With probability $1-\delta$, returns $\hat{n}$ satisfies

$$
(1-\epsilon) n \leq \hat{n} \leq(1+\epsilon) n
$$

Proof: Apply Chebychef's inequality

$$
P\left(\left|X_{N}-\mu_{X}\right| \geq \epsilon\right) \leq \frac{\sigma_{X}^{2}}{N \epsilon^{2}} \Rightarrow N \geq \frac{\sigma_{X}^{2}}{\epsilon^{2}}
$$

followed by Chernoff bounding.

## Merging

- For two stream $S_{1}$ and $S_{2}$ use same set of hash functions
- Stream $S_{i}$ has sketch $\left(y_{1}^{i}, \ldots, y_{k}^{i}\right)$
- For each $\mathrm{j} \in[k]$, find the combined sketch as:
$-\mathrm{y}_{\mathrm{j}}=\min \left(y_{j}^{1}, y_{j}^{2}\right)$
- Gives estimate of $\left|S_{1} \cup S_{2}\right|$


## References:

- Primary reference for this lecture
- Lecture notes by Amit Chakrabarti: http://www.cs.dartmouth.edu/~ac/Teach/data-streams-lecnotes.pdf

