# Estimating Frequency Moments $F_{0}$ and $F_{2}$ 

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Frequency Moments

## Frequency Moments

## Definition

Let $A=\left(a_{1}, a_{2}, \ldots, a_{n}\right)$ be a stream, where elements are from universe $U=\{1, \ldots, u\}$. Let $m_{i}=\#$ of elements in $A$ that are equal to $i$. The $k$-th frequency moment $F_{k}=\sum_{i=1}^{u} m_{i}^{k}$, where $0^{0}=0$.

## Example: $F_{k}=\sum_{i=1}^{u} m_{i}^{k}$

$A=(3,2,4,7,2,2,3,2,2,1,4,2,2,2,1,1,2,3,2)$ and $m_{1}=m_{3}=3, m_{2}=10$, $m_{4}=2, m_{7}=1, m_{5}=m_{6}=0$
$F_{0}=\sum_{i=1}^{7} m_{i}^{0}=3^{0}+10^{0}+3^{0}+2^{0}+0^{0}+0^{0}+1^{0}=5$
(\# of Distinct Elements in $A$ )
$F_{1}=\sum_{i=1}^{7} m_{i}^{1}=3^{1}+10^{1}+3^{1}+2^{1}+0^{1}+0^{1}+1^{1}=19$
(\# of Elements in $A$ )
$F_{2}=\sum_{i=1}^{7} m_{i}^{2}=3^{2}+10^{2}+3^{2}+2^{2}+0^{2}+0^{2}+1^{2}=123$
(Surprise Number)

## Streaming Problem

## Find frequency moments in a stream

Input: A stream $A$ consisting of $n$ elements from universe $U=\{1, \ldots, u\}$.
Output: Estimate Frequency Moments $F_{k}$ 's for different values of $k$.

Our Task: Estimate $F_{0}$ and $F_{2}$ using sublinear space

Reference: The space complexity of estimating frequency moments by Noga Alon, Yossi Matias, and Mario Szegedy, Journal of Computer Systems and Science, 1999.

## Estimating $F_{0}$

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## Computation of $F_{0}$

Input: Stream $A=\left(a_{1}, a_{2}, \ldots, a_{n}\right)$, where each $a_{i} \in U=\{1, \ldots, u\}$.
Output: An estimate $\hat{F}_{0}$ of number of distinct elements $F_{0}$ in $A$ such that $\operatorname{Pr}\left(\frac{1}{c} \leq \frac{\hat{F}_{0}}{F_{0}} \leq c\right) \geq 1-\frac{2}{c}$ for some constant $c$ using sublinear space.

## Algorithm

## Algorithm for Estimating $F_{0}$

Input: Stream $A$ and a hash function $h: U \rightarrow U$
Output: Estimate $\hat{F}_{0}$

Step 1: Initialize $R:=0$
Step 2: For each elements $a_{i} \in A$ do:

1. Compute binary representation of $h\left(a_{i}\right)$
2. Let $r$ be the location of the rightmost 1 in the binary representation
3. if $r>R, R:=r$

Step 3: Return $\hat{F}_{0}=2^{R}$

Space Requirements $=O(\log u)$ bits

## Correctness

## Observation 1

Let $d$ to be smallest integer such that $2^{d} \geq u$ ( $d$-bits are sufficient to represent numbers in $U$ )

## Observation 1

$$
\operatorname{Pr}\left(\text { rightmost } 1 \text { in } h\left(a_{i}\right) \text { is at location } \geq r+1\right)=\frac{1}{2^{r}}
$$

Proof: For that to happen the last $r$ bits in $h\left(a_{i}\right)$ must be 0 . Since $h$ is a hash function from universal family of hash functions, this happens with probability $\left(\frac{1}{2}\right)^{r}$.

## Observations 2

## Observation 2

For $a_{i} \neq a_{j}, \operatorname{Pr}$ (rightmost 1 in $h\left(a_{i}\right) \geq r+1$ and rightmost 1 in
$\left.h\left(a_{j}\right) \geq r+1\right)=\frac{1}{2^{2 r}}$
Proof: $h\left(a_{i}\right)$ and $h\left(a_{j}\right)$ are independent as $a_{i} \neq a_{j}$.
$\operatorname{Pr}\left(\right.$ rightmost 1 in $h\left(a_{i}\right) \geq r+1$ and rightmost 1 in $\left.h\left(a_{j}\right) \geq r+1\right)=\operatorname{Pr}\left(\right.$ rightmost 1 in $\left.h\left(a_{i}\right) \geq r+1\right) \times \operatorname{Pr}($ rightmost 1 in $\left.h\left(a_{j}\right) \geq r+1\right)=\frac{1}{2^{r}} \times \frac{1}{2^{r}}=\frac{1}{2^{2 r}}$

## Observations 3

Fix $r \in\{1, \ldots, d\} . \forall x \in A$, define indicator r.v:

$$
I_{x}^{r}= \begin{cases}1, & \text { if the rightmost } 1 \text { is at location } \geq r+1 \text { in } h(x) \\ 0, & \text { otherwise }\end{cases}
$$

Let $Z^{r}=\sum I_{x}^{r}$ (sum is over distinct elements of $A$ )

## Observation 3

The following holds:

1. $E\left[I_{x}^{r}\right]=\frac{1}{2^{r}}$
2. $\operatorname{Var}\left[I_{x}^{r}\right]=\frac{1}{2^{r}}\left(1-\frac{1}{2^{r}}\right)$
3. $E\left[Z^{r}\right]=\frac{F_{0}}{2^{r}}$
4. $\operatorname{Var}\left[Z^{r}\right] \leq E\left[Z^{r}\right]$

## Observation 3.1

## Observation 3.1

$$
E\left[I_{x}^{r}\right]=\frac{1}{2^{r}}
$$

$$
\text { Proof: } E\left[I_{x}^{r}\right]=1 \times \operatorname{Pr}\left(I_{x}^{r}=1\right)+0 \times \operatorname{Pr}\left(I_{x}^{r}=0\right)=\frac{1}{2^{r}}
$$

Note that $\operatorname{Pr}\left(I_{x}^{r}=1\right)$ corresponds to
$\operatorname{Pr}($ rightmost 1 in $h(x)$ is at location $\geq r+1)=\frac{1}{2^{r}}$ by Observation 1 .

## Observation 3.2

## Observation 3.2

$$
\operatorname{Var}\left[I_{x}^{r}\right]=E\left[I_{x}^{r 2}\right]-E\left[I_{x}^{r}\right]^{2}=\frac{1}{2^{r}}\left(1-\frac{1}{2^{r}}\right)
$$

Proof: Note that the variance of a random variable $X$ is given by $\operatorname{Var}[X]=E\left[(X-E[X])^{2}\right]=E\left[X^{2}\right]-E[X]^{2}$.
$E\left[I_{x}^{r 2}\right]=1^{2} \operatorname{Pr}\left(I_{x}^{r}=1\right)=\frac{1}{2^{r}}$
Then $E\left[I_{x}^{r}{ }^{2}\right]-E\left[I_{x}^{r}\right]^{2}=\frac{1}{2^{r}}-\left(\frac{1}{2^{r}}\right)^{2}=\frac{1}{2^{r}}\left(1-\frac{1}{2^{r}}\right)$

## Observation 3.3

## Observation 3.3

$$
E\left[Z^{r}\right]=\frac{F_{0}}{2^{r}}
$$

Proof: Let $A^{\prime} \subseteq A$ be the set of distinct elements of $A$.
Note that $F_{0}=\left|A^{\prime}\right|$.
By definition $Z^{r}=\sum_{x \in A^{\prime}} I_{x}^{r}$
Then, $E\left[Z^{r}\right]=E\left[\sum_{x \in A^{\prime}} I_{x}^{r}\right]=\sum_{x \in A^{\prime}} E\left[I_{x}^{r}\right]=\sum_{x \in A^{\prime}} \frac{1}{2^{r}}=\frac{F_{0}}{2^{r}}$

## Observation 3.4

## Observation 3.4

$\operatorname{Var}\left[Z^{r}\right]=\frac{F_{0}}{2^{r}}\left(1-\frac{1}{2^{r}}\right) \leq \frac{F_{0}}{2^{r}}=E\left[Z^{r}\right]$
Proof: $\operatorname{Var}\left[Z^{r}\right]=\operatorname{Var}\left[\sum_{x \in A^{\prime}} I_{x}^{r}\right]$
For two independent random variables $X$ and $Y$,
$\operatorname{Var}[X+Y]=\operatorname{Var}[X]+\operatorname{Var}[Y]$.
$\operatorname{Var}\left[Z^{r}\right]=\operatorname{Var}\left[\sum_{x \in A^{\prime}} I_{x}^{r}\right]=\sum_{x \in A^{\prime}} \operatorname{Var}\left[I_{x}^{r}\right]=F_{0} \frac{1}{2^{r}}\left(1-\frac{1}{2^{r}}\right) \leq \frac{F_{0}}{2^{r}}=E\left[Z^{r}\right]$

## Observation 4

## Observation 4

```
If }\mp@subsup{2}{}{r}>c\mp@subsup{F}{0}{},\operatorname{Pr}(\mp@subsup{Z}{}{r}>0)<\frac{1}{c
```

Proof: Recall Markov's inequality for a random variable $X$, $\operatorname{Pr}(X \geq s) \leq \frac{E[X]}{s}$, where $s>0$ and $X$ takes positive values.
What is the number of distinct elements $x \in A$, whose hash map $h(x)$ has its rightmost 1 in position $\geq r+1$ ?
$=Z^{r}=\sum_{x \in A^{\prime}} I_{x}^{r}$
What is $\operatorname{Pr}\left(Z^{r}>0\right) ? \Leftrightarrow$ What is $\operatorname{Pr}\left(Z^{r} \geq 1\right)$.
By Markov's inequality: $\operatorname{Pr}\left(Z^{r} \geq 1\right) \leq \frac{E\left[Z^{r}\right]}{1}=E\left[Z^{r}\right]=\frac{F_{0}}{2^{r}}<\frac{1}{c}$.

## Chebyshev's Inequality

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$$
\operatorname{Pr}(|X-E[X]| \geq \alpha) \leq \frac{\operatorname{Var}[X]}{\alpha^{2}}
$$

Proof: Recall Markov's inequality for a random variable $X$, $\operatorname{Pr}(X \geq s) \leq \frac{E[X]}{s}$, where $s>0$ and $X$ takes positive values.

Now

$$
\begin{aligned}
\operatorname{Pr}(|X-E[X]| \geq \alpha) & =\operatorname{Pr}\left((X-E[X])^{2} \geq \alpha^{2}\right) \\
& \leq \frac{E\left[(X-E[X])^{2}\right]}{\alpha^{2}} \\
& =\frac{\operatorname{Var}[X]}{\alpha^{2}}
\end{aligned}
$$

## Observation 5

## Observation 5

If $c 2^{r}<F_{0}, \operatorname{Pr}\left(Z^{r}=0\right)<\frac{1}{c}$
Proof: Recall Chebyshev's inequality $\operatorname{Pr}(|X-E[X]| \geq \alpha) \leq \frac{\operatorname{Var}[X]}{\alpha^{2}}$.
For a random variable $X, \operatorname{Pr}(X=0) \leq \operatorname{Pr}(|X-E[X]| \geq E[X])$, as the event $|X-E[X]| \geq E[X]$ includes $X \leq 0$ and $X \geq 2 E[X]$.

Now, $\operatorname{Pr}\left(Z^{r}=0\right) \leq \operatorname{Pr}\left(\left|Z^{r}-E\left[Z^{r}\right]\right| \geq E\left[Z^{r}\right]\right)$.

$$
\begin{aligned}
\operatorname{Pr}\left(Z^{r}=0\right) & \leq \operatorname{Pr}\left(\left|Z^{r}-E\left[Z^{r}\right]\right| \geq E\left[Z^{r}\right]\right) \\
& \leq \frac{\operatorname{Var}\left[Z^{r}\right]}{E\left[Z^{r}\right]^{2}} \\
& \leq \frac{E\left[Z^{r}\right]}{E\left[Z^{r}\right]^{2}} \\
& =\frac{1}{E\left[Z^{r}\right]}=\frac{2^{r}}{F_{0}}<\frac{1}{c}
\end{aligned}
$$

## Observation 6

## Claim

Set $\hat{F}_{0}=2^{R}$. We have $\operatorname{Pr}\left(\frac{1}{c} \leq \frac{\hat{F}_{0}}{F_{0}} \leq c\right) \geq 1-\frac{2}{c}$
Proof We have that
Observation 4: if $2^{r}>c F_{0}, \operatorname{Pr}\left(Z^{r}>0\right)<\frac{1}{c}$
Observation 5, if $c 2^{r}<F_{0}, \operatorname{Pr}\left(Z^{r}=0\right)<\frac{1}{c}$
When do we produce a wrong answer?
Case 1: $\hat{F}_{0}=2^{R}>c F_{0}$, but this happens with $\operatorname{Pr}\left(Z^{R}>0\right)<\frac{1}{c}$
Case 2: $c 2^{R}=c \hat{F}_{0}<F_{0}$, but this happens with $\operatorname{Pr}\left(Z^{R}=0\right)<\frac{1}{c}$
Therefore, with probability $\leq \frac{2}{c}$, we produce a wrong answer.
$\Longrightarrow$ with probability $\geq 1-\frac{2}{c}$, we produce the right answer, i.e.,

$$
\operatorname{Pr}\left(\frac{1}{c} \leq \frac{\hat{F}_{0}}{F_{0}} \leq c\right) \geq 1-\frac{2}{c}
$$

## Further Improvements

## Improving success probability

Execute the algorithm $s$ times in parallel
(with independent hash functions)
Let $R$ to the median value among these runs
Return $\hat{F}_{0}=2^{R}$
Note: Algorithm uses $O(s \log u)$ bits.

## Claim

For $c>4$, there exists $s=O\left(\log \frac{1}{\epsilon}\right), \epsilon>0$, such that $\operatorname{Pr}\left(\frac{1}{c} \leq \frac{\hat{F}_{0}}{F_{0}} \leq c\right) \geq 1-\epsilon$.

Technique: Median + Chernoff Bounds

## Improving success probability (contd.)

$i$-th Run of the Algorithm:
Step 1: Initialize $R_{i}:=0$
Step 2: For each elements $a_{i} \in A$ do:

1. Compute binary representation of $h\left(a_{i}\right)$
2. Let $r$ be the location of the rightmost 1 in the binary representation
3. if $r>R_{i}, R_{i}:=r$

Step 3: Return $R_{i}$

Let $R=\operatorname{Median}\left(R_{1}, R_{2}, \ldots, R_{s}\right)$

## Indicator Random Variables

Define $X_{1}, \ldots, X_{s}$ be indicator random variables:

$$
X_{i}= \begin{cases}0, & \text { if success, i.e. } \frac{1}{c} \leq \frac{2^{R_{i}}}{F_{0}} \leq c \\ 1, & \text { otherwise }\end{cases}
$$

1. $E\left[X_{i}\right]=\operatorname{Pr}\left(X_{i}=1\right) \leq \frac{2}{c}=\beta<\frac{1}{2}($ Since $c>4)$
2. Let $X=\sum_{i=1}^{s} X_{i}=$ Number of failures in $s$ runs
3. $E[X] \leq s \beta<\frac{s}{2}$
4. If $X<\frac{s}{2}$, then $\frac{1}{c} \leq \frac{2^{R}}{F_{0}} \leq c$ $\left(R=\operatorname{Median}\left(R_{1}, R_{2}, \ldots, R_{s}\right)\right)$

## Chernoff Bounds

## Chernoff Bounds

If r.v. $X$ is sum of independent identical indicator r.v. and $0<\delta<1$, $\operatorname{Pr}(X \geq(1+\delta) E[X]) \leq e^{-\frac{\delta^{2} E[X]}{3}}$

Proof: See my notes
An example: Toss a fair coin $n$-times. Let $X$ be the total number of heads obtained in these $n$-trials. Evaluate $\operatorname{Pr}\left(X \geq \frac{3}{4} n\right)$

$$
\begin{aligned}
\operatorname{Pr}\left(X \geq \frac{3}{4} n\right) & =\operatorname{Pr}\left(X \geq\left(1+\frac{1}{2}\right) \frac{n}{2}\right) \\
& =\operatorname{Pr}\left(X \geq\left(1+\frac{1}{2}\right) E[X]\right) \\
& \leq e^{-\frac{\left(\frac{1}{2}\right)^{2} E[X]}{3}} \\
& =e^{-\frac{n}{24}}
\end{aligned}
$$

## Main Result

## Claim

For any $\epsilon>0$, if $s=O\left(\log \frac{1}{\epsilon}\right), \operatorname{Pr}\left(X<\frac{s}{2}\right) \geq 1-\epsilon$
Proof: We show that $\operatorname{Pr}\left(X \geq \frac{s}{2}\right)<\epsilon$.

$$
E[X]=s \beta<\frac{s}{2}
$$

$$
\begin{aligned}
\operatorname{Pr}\left(X \geq \frac{s}{2}\right) & =\operatorname{Pr}\left(X-E[X] \geq \frac{s}{2}-E[X]\right) \\
& =\operatorname{Pr}\left(X-E[X] \geq \frac{s}{2}-s \beta\right) \\
& =\operatorname{Pr}\left(X-E[X] \geq \frac{\frac{1}{2}-\beta}{\beta} s \beta\right) \\
& =\operatorname{Pr}\left(X-E[X] \geq \frac{\frac{1}{2}-\beta}{\beta} E[X]\right) \\
& =\operatorname{Pr}\left(X \geq\left(1+\frac{\frac{1}{2}-\beta}{\beta}\right) E[X]\right)
\end{aligned}
$$

## Proof (contd.)

$$
\begin{aligned}
& \qquad \begin{aligned}
& \operatorname{Pr}\left(X \geq \frac{s}{2}\right)=\operatorname{Pr}\left(X \geq\left(1+\frac{\frac{1}{2}-\beta}{\beta}\right) E[X]\right) \\
& \leq e^{-\frac{1}{3}\left(\frac{\frac{1}{2}-\beta}{\beta}\right)^{2} E[X]} \\
& \text { We want } e^{-\frac{1}{3}\left(\frac{\frac{1}{2}-\beta}{\beta}\right)^{2} E[X]} \leq \epsilon
\end{aligned}
\end{aligned}
$$

Substitute $E[X]=s \beta$ and we have
$-\frac{1}{3}\left(\frac{\frac{1}{2}-\beta}{\beta}\right)^{2} s \beta \leq \ln \epsilon$
$\Leftrightarrow s \geq \frac{3}{\beta}\left(\frac{\beta}{\frac{1}{2}-\beta}\right)^{2} \ln \frac{1}{\epsilon}$
$\Longrightarrow$ if $s \in O\left(\ln \frac{1}{\epsilon}\right), \operatorname{Pr}\left(X \geq \frac{s}{2}\right)<\epsilon$.

Estimating $F_{2}$

## Estimating $F_{2}$

Input: Stream $A$ and hash function $h: U \rightarrow\{-1,+1\}$
Output: Estimate $\hat{F}_{2}$ of $F_{2}=\sum_{i=1}^{u} m_{i}^{2}$

## Algorithm (Tug of War)

Step 1: Initialize $Y:=0$.
Step 2: For each element $x \in U$, evaluate $r_{x}=h(x)$.
Step 3: For each element $a_{i} \in A, Y:=Y+r_{a_{i}}$
Step 4: Return $\hat{F}_{2}=Y^{2}$

## Correctness

## Observation 1

## Observation 1

$E\left[r_{i}\right]=0$
Proof: $E\left[r_{i}\right]=-1 \times \frac{1}{2}+1 \times \frac{1}{2}=0$

## Observation 2

## Observation 2

$$
\begin{aligned}
& \text { Let } Y=\sum_{i=1}^{u} r_{i} m_{i} \\
& E\left[Y^{2}\right]=\sum_{i=1}^{u} m_{i}^{2}=F_{2}
\end{aligned}
$$

## Proof:

$$
\begin{aligned}
E\left[Y^{2}\right] & =E\left[\sum_{i=1}^{u} r_{i} m_{i} \sum_{j=1}^{u} r_{j} m_{j}\right] \\
& =E\left[\sum_{i=1}^{u} r_{i}^{2} m_{i}^{2}+\sum_{i, j: i \neq j} r_{i} r_{j} m_{i} m_{j}\right] \\
& =\sum_{i=1}^{u} E\left[r_{i}^{2} m_{i}^{2}\right]+\sum_{i, j: i \neq j} E\left[r_{i} r_{j} m_{i} m_{j}\right] \\
& =\sum_{i=1}^{u} E\left[m_{i}^{2}\right]+\sum_{i, j: i \neq j} m_{i} m_{j} E\left[r_{i}\right] E\left[r_{j}\right] \\
& =\sum_{i=1}^{u} m_{i}^{2}=F_{2}
\end{aligned}
$$

## Observation 3

## Observation 3

$\operatorname{Pr}\left(\left|Y^{2}-E\left[Y^{2}\right]\right| \geq \sqrt{2} c E\left[Y^{2}\right]\right) \leq \frac{1}{c^{2}}$ for any positive constant c. (I.e., $Y^{2}$ approximates $F_{2}=E\left[Y^{2}\right]$ within a constant factor with $\operatorname{Pr} \geq 1-\frac{1}{c^{2}}$ )

Proof: Recall Chebyshev's inequality $\operatorname{Pr}(|X-E[X]| \geq \alpha) \leq \frac{\operatorname{Var}[X]}{\alpha^{2}}$.
Now, $\operatorname{Pr}\left(\left|Y^{2}-E\left[Y^{2}\right]\right| \geq \sqrt{2} c E\left[Y^{2}\right]\right) \leq \frac{\operatorname{Var}\left[Y^{2}\right]}{\left(\sqrt{2} c E\left[Y^{2}\right]\right)^{2}}$.
$\operatorname{Var}\left[Y^{2}\right]=E\left[Y^{4}\right]-E\left[Y^{2}\right]^{2}$

$$
\begin{aligned}
E\left[Y^{4}\right] & =E\left[\sum_{i=1}^{u} r_{i} m_{i} \sum_{j=1}^{u} r_{j} m_{j} \sum_{k=1}^{u} r_{k} m_{k} \sum_{l=1}^{u} r_{l} m_{l}\right] \\
& =\sum_{i=1}^{u} E\left[r_{i}^{4} m_{i}^{4}\right]+6 \sum_{1 \leq i<j \leq u} E\left[r_{i}^{2} r_{j}^{2} m_{i}^{2} m_{j}^{2}\right] \\
& =\sum_{i=1}^{u} m_{i}^{4}+6 \sum_{1 \leq i<j \leq u} m_{i}^{2} m_{j}^{2}
\end{aligned}
$$

## Observation 4 contd.

$$
\begin{aligned}
\operatorname{Var}\left[Y^{2}\right] & =E\left[Y^{4}\right]-E\left[Y^{2}\right]^{2} \\
& =\sum_{i=1}^{u} m_{i}^{4}+6 \sum_{1 \leq i<j \leq u} m_{i}^{2} m_{j}^{2}-\left(\sum_{i=1}^{u} m_{i}^{2}\right)^{2} \\
& =4 \sum_{1 \leq i<j \leq u} m_{i}^{2} m_{j}^{2} \\
& \leq 2 F_{2}^{2}
\end{aligned}
$$

Now, $\frac{\operatorname{Var}\left[Y^{2}\right]}{\left(\sqrt{2} c E\left[Y^{2}\right]\right)^{2}}=\frac{2 F_{2}^{2}}{\left(\sqrt{2} c E\left[Y^{2}\right]\right)^{2}}=\frac{2 F_{2}^{2}}{2 c^{2} F_{2}^{2}}=\frac{1}{c^{2}}$
Thus, $\operatorname{Pr}\left(\left|Y^{2}-E\left[Y^{2}\right]\right| \geq \sqrt{2} c E\left[Y^{2}\right]\right) \leq \frac{\operatorname{Var}\left[Y^{2}\right]}{\left(\sqrt{2} c E\left[Y^{2}\right]\right)^{2}}=\frac{1}{c^{2}}$

## Improving Variance

## Improving the Variance

Execute the algorithm $k$ times (using independent hash functions) resulting in $Y_{1}^{2}, Y_{2}^{2}, \ldots, Y_{k}^{2}$.
Output $\bar{Y}^{2}=\frac{1}{k} \sum_{i=1}^{k} Y_{i}^{2}$
Observations:

1. $E\left[\bar{Y}^{2}\right]=E\left[Y^{2}\right]=F_{2}$
2. $\operatorname{Var}\left[\bar{Y}^{2}\right]=\frac{1}{k} \operatorname{Var}\left[Y^{2}\right]$
(Note: $\operatorname{Var}[c X]=c^{2} \operatorname{Var}[X]$ )
3. $\operatorname{Pr}\left(\left|\bar{Y}^{2}-E\left[\bar{Y}^{2}\right]\right| \geq \sqrt{\frac{2}{k}} c E\left[\bar{Y}^{2}\right]\right) \leq \frac{1}{c^{2}}$
4. Set $k=O\left(\frac{1}{\epsilon^{2}}\right)$, we have

$$
\operatorname{Pr}\left(\left|\bar{Y}^{2}-E\left[\bar{Y}^{2}\right]\right| \geq \epsilon c E\left[\bar{Y}^{2}\right]\right) \leq \frac{1}{c^{2}}
$$

## Complexity

## Space Complexity

## Algorithm (Tug of War)

Step 1: Initialize $Y:=0$.
Step 2: For each element $x \in U$, evaluate $r_{x}=h(x)$.
Step 3: For each element $a_{i} \in A, Y:=Y+r_{a_{i}}$
Step 4: Return $\hat{F}_{2}=Y^{2}$

- Need to store $Y$ and $\left(r_{1}, r_{2}, \ldots, r_{u}\right)$. $Y$ requires $O(\log n)$ bits.
- We needed $r_{i}$ 's to be 2 -wise and 4 -wise independent hash functions.
- 4 -wise independent functions can be maintained using $O(\log u)$ bits.
- Total space required is $O(\log n+\log u)$.


## References

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