"algorithms for Big Data"

Lecture 1: Intro + Streaming

Slides at http://grigory.us/big-data-csclub.html

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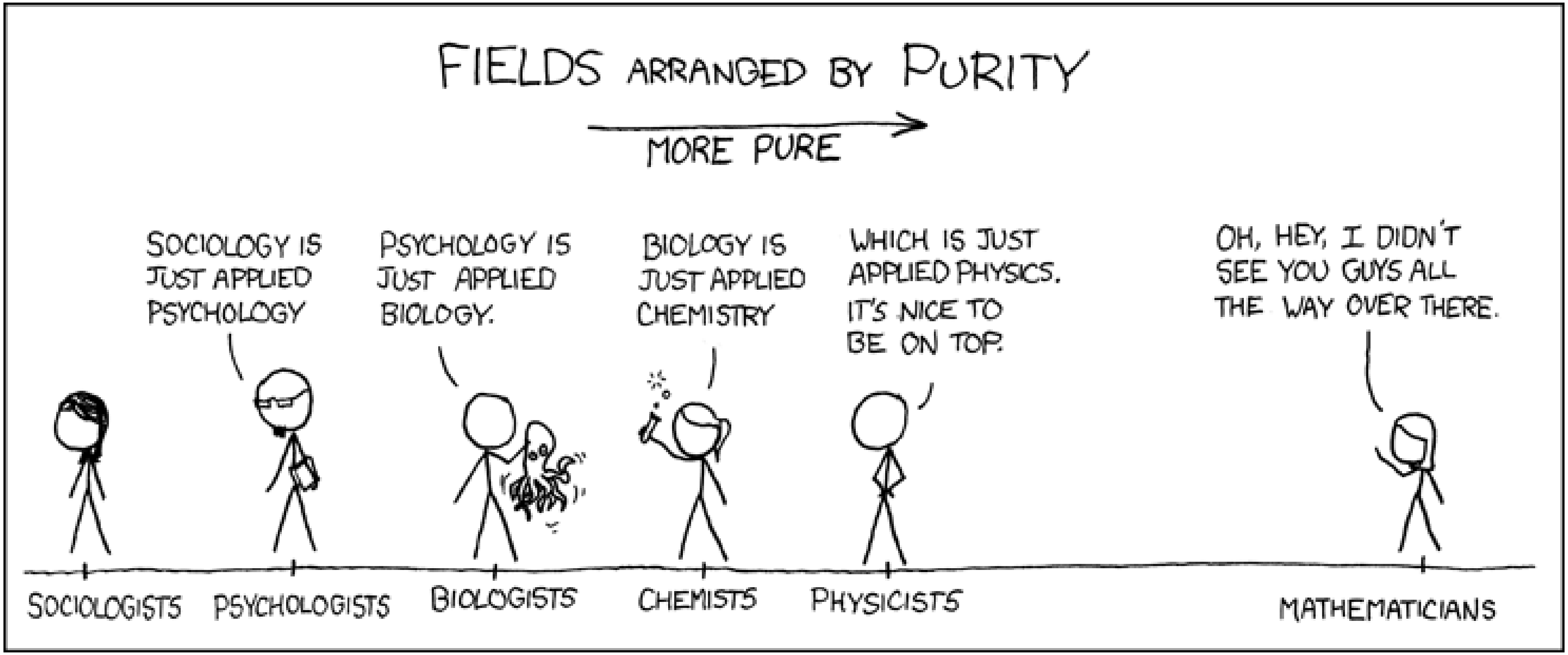
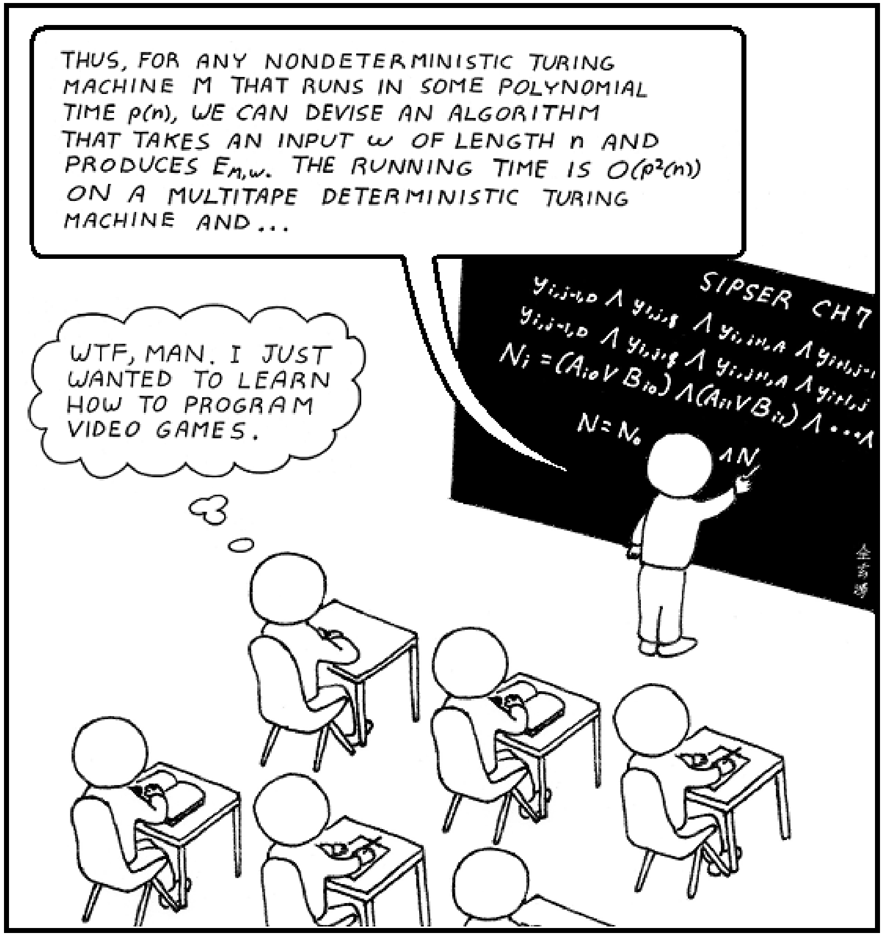
Disclaimers

- A lot of Math!



Disclaimers

- No programming!

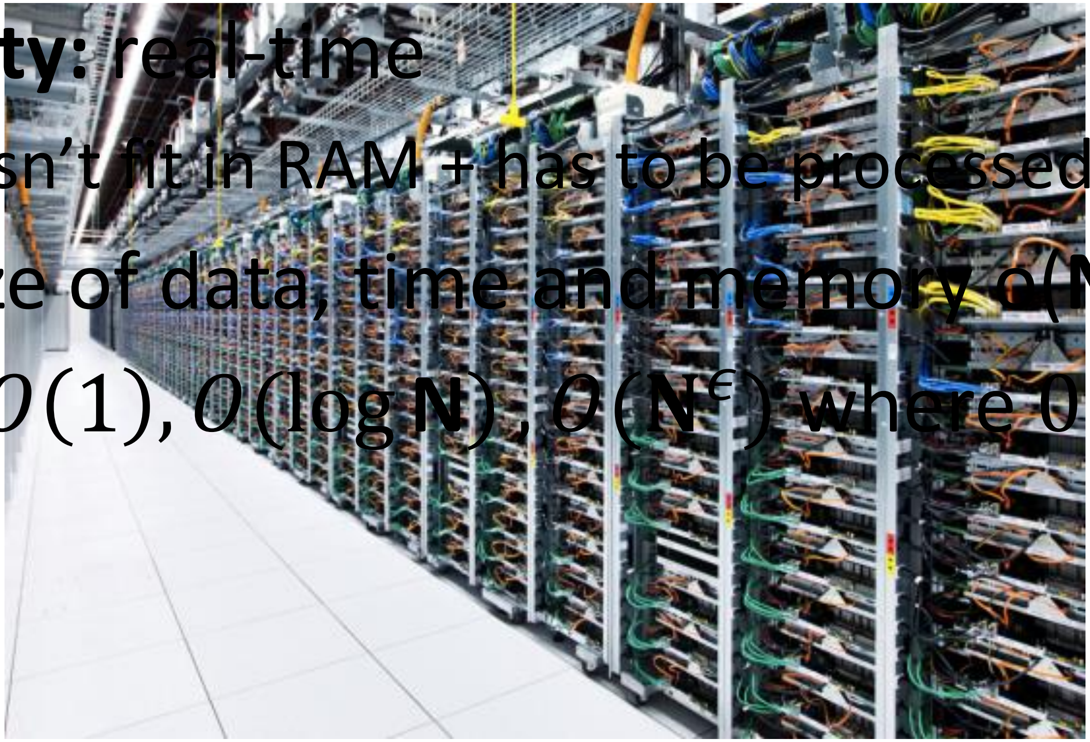


What is this class about?

- Not about the band (https://en.wikipedia.org/wiki/Big_Data_(band))

What is this class about?

- The four V's: **volume**, **velocity**, variety, veracity
- **Volume:** "Big Data" = too big to fit in RAM
  - If 16GB $\approx$ 100\$ => "big" starts at terabytes
- **Velocity:** real-time
  - Doesn't fit in RAM + has to be processed on the fly
- **N** = size of data, time and memory o(**N**)
- o(**N**): $O(1)$, $O(\log \mathbf{N})$, $O(\mathbf{N}^{\epsilon})$ where $0 < \epsilon < 1$



Getting hands dirty

- Cloud computing platforms (all offer free trials):
  - Amazon EC2 (1 CPU/12mo)
  - Microsoft Azure ($200/1mo)
  - Google Compute Engine ($200/2mo)
- Distributed Google Code Jam
  - First time in 2015:
    https://code.google.com/codejam/distributed_index.html
  - Caveats:
    - Very basic aspects of distributed algorithms (few rounds)
    - Small data ($\sim 1\ GB$, with hundreds MB RAM)
    - Fast query access ($\sim 0.01\ ms$ per request), "data with queries"

Outline

- Part 1: Streaming Algorithms

STORM

Highlights:

- Approximate counting
- # Distinct Elements
- Median
- Frequency moments
- Heavy hitters
- Graph sketching

Outline

- Part 2: Massively Parallel Algorithms

Highlights:

- Computational Model
- Sorting (Terasort)
- Connectivity, MST
- Filtering dense graphs
- Euclidean MST

Outline

- Part 3: Sublinear Time Algorithms

Highlights:

- "Data with queries"
- Sublinear approximation
- Property Testing
- Testing images, sortedness, connectedness
- Testing noisy data

Today

- Approximate counting: Morris' algorithm
- Approximate Median
- Alon-Mathias-Szegedy Sampling
- Frequency Moments
- Distinct Elements
- Count-Min

Recap

- (Markov) For every $c > 0$ (and non-negative $\boldsymbol{X}$):

$$\Pr\left[\boldsymbol{X} \geq c\ \mathbb{E}[\boldsymbol{X}]\right] \leq \frac{1}{c}$$

- (Chebyshev) For every $c > 0$:

$$\Pr\left[|\boldsymbol{X} - \mathbb{E}[\boldsymbol{X}]| \geq c\ \mathbb{E}[\boldsymbol{X}]\right] \leq \frac{Var[\boldsymbol{X}]}{(c\ \mathbb{E}[\boldsymbol{X}])^2}$$

- (Chernoff) Let $\boldsymbol{X}_1 \ldots \boldsymbol{X}_{\boldsymbol{t}}$ be independent and identically distributed r.vs with range [0, c] and expectation μ. Then if $X = \frac{1}{\boldsymbol{t}} \sum_i X_i$ and $1 > \delta > 0$,

$$\Pr[|X - \mu| \geq \delta\mu] \leq 2 \exp\left(-\frac{\boldsymbol{t}\mu\delta^2}{3c}\right)$$

Morris's Algorithm

- (**Hard puzzle, "Count the number of items"**)
  - You have items coming arriving one by one
  - What is the total number of items up to error $\pm\, \epsilon n$?
  - You have $O(\log\log n\, / \epsilon^2)$ space and can be completely wrong with some small probability

Morris's Algorithm: Alpha-version

Maintains a counter X using $\log\log n$ bits

- Initialize X to 0
- When an item arrives, increase X by 1 with probability $\frac{1}{2^X}$
- When the stream is over, output $2^X - 1$

Claim: $\mathbb{E}[2^X] = n + 1$

Morris's Algorithm: Alpha-version

Maintains a counter X using $\log\log n$ bits

- Initialize X to 0, when an item arrives, increase X by 1 with probability $\frac{1}{2^X}$

Claim: $\mathbb{E}[2^X] = n + 1$

- Let the value after seeing n items be X_n

$$\mathbb{E}[2^{X_n}] = \sum_{j=0}^{\infty} \Pr[X_{n-1} = j\,]\mathbb{E}[2^{X_n} | X_{n-1} = j]$$

$$= \textstyle\sum_{j=0}^{\infty} \Pr[X_{n-1} = j\,]\left(\frac{1}{2^j}\,2^{j+1} + \left(1 - \frac{1}{2^j}\right)2^j\right)$$

$$= \textstyle\sum_{j=0}^{\infty} \Pr[X_{n-1} = j\,]\left(2^j + 1\right) = 1 + \mathbb{E}[2^{X_{n-1}}]$$

Morris's Algorithm: Alpha-version

Maintains a counter X using $\log \log n$ bits

- Initialize X to 0, when an item arrives, increase X by 1 with probability $\frac{1}{2^X}$

Claim: $\mathbb{E}[2^{2X}] = \frac{3}{2}n^2 + \frac{3}{2}n + 1$

$$\mathbb{E}[2^{2X_n}] = \sum_{j=0}^{\infty} \Pr[2^{X_{n-1}} = j\,]\mathbb{E}[2^{2X_n} | 2^{X_{n-1}} = j]$$

$$= \sum_{j=0}^{\infty} \Pr[2^{X_{n-1}} = j\,]\left(\frac{1}{j}\,4\,j^2 + \left(1\, - \frac{1}{j}\right)j^2\right)$$

$$= \sum_{j=0}^{\infty} \Pr[2^{X_{n-1}} = j\,](j^2 + 3j) = \mathbb{E}[2^{2X_{n-1}}] + 3\mathbb{E}[2^{X_{n-1}}]$$

$$= 3\,\frac{(\mathrm{n}-1)^2}{2} + 3(\mathrm{n} - 1)/2\ + 1 + 3\mathrm{n} = \frac{3}{2}n^2 + \frac{3}{2}n + 1$$

Morris's Algorithm: Alpha-version

Maintains a counter X using $\log\log n$ bits

- Initialize X to 0, when an item arrives, increase X by 1 with probability $\frac{1}{2^X}$
- $\mathbb{E}[2^X] = \mathrm{n} + 1, Var[2^X] = O(n^2)$
- Is this good?

Morris's Algorithm: Beta-version

Maintains t counters $X^1, \ldots, X^t$ ($\log \log n$ bits each)

- Initialize X^i to 0, when an item arrives, increase each X^i by 1 independently with probability $\frac{1}{2^{X^i}}$
- Output $\mathrm{Z} = \frac{1}{t}\left(\sum_{i=1}^{t} 2^{X^i} - 1\right)$
- $\mathbb{E}[2^{X_i}] = \mathrm{n} + 1, Var[2^{X_i}] = O(n^2)$
- $Var[Z] = Var\left(\frac{1}{t}\sum_{j=1}^{t} 2^{X^j} - 1\right) = O\left(\frac{n^2}{t}\right)$
- Claim: If $t \geq \frac{c}{\epsilon^2}$ then $\Pr[|Z - n| > \epsilon n] < 1/3$

Morris's Algorithm: Beta-version

Maintains t counters $X^1, \ldots, X^t$

- Output $\mathrm{Z} = \frac{1}{t}\left(\sum_{i=1}^{t} 2^{X^i} - 1\right)$
- $Var[Z] = Var\left(\frac{1}{t}\sum_{j=1}^{t} 2^{X^j} - 1\right) = O\left(\frac{n^2}{t}\right)$
- Claim: If $t \geq \frac{c}{\epsilon^2}$ then $\Pr[|Z - n| > \epsilon n] < 1/3$
  - $\Pr[|Z - n| > \epsilon\, n] < \frac{Var[Z]}{\epsilon^2 n^2} = O\left(\frac{n^2}{t}\right) \cdot \frac{1}{\epsilon^2 n^2}$
  - If $t \geq \frac{c}{\epsilon^2}$ we can make this at most $\frac{1}{3}$

Morris's Algorithm: Final

- What if I want the probability of error to be really small, i.e. $\Pr[|Z - n| > \epsilon\, n] \leq \delta$?
- Same Chebyshev-based analysis: $t = O\left(\frac{1}{\epsilon^2 \delta}\right)$
- Do these steps $m = O\left(\log\frac{1}{\delta}\right)$ times independently in parallel and output the median answer.
- Total space: $O\left(\frac{\log\log n \cdot \log\frac{1}{\delta}}{\epsilon^2}\right)$

Morris's Algorithm: Final

- Do these steps $m = O\left(\log\frac{1}{\delta}\right)$ times independently in parallel and output the median answer

$$Z^{med} = median(Z_1, \dots, Z_m)$$

- Each Z_i computed as before:

Maintain t counters $X^1, \dots, X^t$ using $\log\log n$ bits for each

- Initialize $X^{i'}s$ to 0, when an item arrives, increase each X^i by 1 independently with probability $\frac{1}{2^{X^i}}$
- Output Z $= \frac{1}{t}(\sum_{i=1}^{t} 2^{X^i} - 1)$

Morris's Algorithm: Final Analysis

Claim: $\Pr\left[\left|Z^{med} - n\right| > \epsilon\, n\right] \le \delta$

- Let Y_i be an indicator r.v. for the event that $|Z_i - n| \le \epsilon n$, where Z_i is the i-th trial.
- Let $Y = \sum_i Y_i$.
- $\Pr\left[\left|Z^{med} - n\right| > \epsilon n\right] \le \Pr\left[Y \le \frac{m}{2}\right] \le \Pr\left[|Y - \mathbb{E}[Y]| \ge \frac{m}{6}\right] \le \Pr\left[|Y - \mathbb{E}[Y]| \ge \frac{\mu}{4}\right] \le \exp\left(-c\,\frac{1}{4^2}\frac{2m}{3}\right) < \exp\left(-c' \log\frac{1}{\delta}\right) < \delta$

Data Streams

- Stream: $\boldsymbol{m}$ elements from universe $[\boldsymbol{n}] = \{1, 2, \ldots, \boldsymbol{n}\}$, e.g.

$$\langle x_1, x_2, \ldots, x_{\boldsymbol{m}} \rangle = \langle 5, 8, 1, 1, 1, 4, 3, 5, \ldots, 10 \rangle$$

Approximate Median

- $S = \{x_1, \dots, x_m\}$ (all distinct) and let
$$rank(y) = |x \in S : x \leq y|$$
- Problem: Find ϵ-approximate median, i.e. y:
$$\frac{m}{2} - \epsilon m < rank(y) < \frac{m}{2} + \epsilon m$$
- Exercise: Can we approximate the value of the median with additive error $\pm\epsilon n$ in sublinear time?
- Algorithm: Return the median of a sample of size t taken from S (with replacement).

Approximate Median

- Problem: Find ϵ-approximate median, i.e. y:
$$\frac{m}{2} - \epsilon m < rank(y) < \frac{m}{2} + \epsilon m$$
- Algorithm: Return the median of a sample of size t taken from S (with replacement).
- Claim: If $t = \frac{7}{\epsilon^2} \log \frac{2}{\delta}$ then this algorithm gives ϵ-median with probability $1 - \delta$

Approximate Median

- Partition S into 3 groups

$$\boldsymbol{S_L} = \left\{x \in S: rank(x) \le \frac{m}{2} - \epsilon m\right\}$$
$$\boldsymbol{S_M} = \left\{x \in S: \frac{m}{2} - \epsilon m \le rank(x) \le \frac{m}{2} + \epsilon m\right\}$$
$$\boldsymbol{S_U} = \left\{x \in S: rank(x) \ge \frac{m}{2} + \epsilon m\right\}$$

- **Key fact**: If less than $\frac{t}{2}$ elements from each of $\boldsymbol{S_L}$ and $\boldsymbol{S_U}$ are in sample then its median is in $\boldsymbol{S_M}$
- Let $\boldsymbol{X}_i = 1$ if i-th sample is in $\boldsymbol{S_L}$ and 0 otherwise.
- Let $\boldsymbol{X} = \sum_i \boldsymbol{X}_i$. By Chernoff, if $t > \frac{7}{\epsilon^2} \log \frac{2}{\delta}$

$$\Pr\left[\boldsymbol{X} \ge \frac{t}{2}\right] \le \Pr[\boldsymbol{X} \ge (1+\epsilon)\mathbb{E}[\boldsymbol{X}]] \le e^{-\frac{\epsilon^2\left(\frac{1}{2}-\epsilon\right)t}{3}} \le \frac{\delta}{2}$$

- Same for $\boldsymbol{S_U}$ + union bound $\Rightarrow$ error probability $\le \delta$

Data Streams

- Stream: $\boldsymbol{m}$ elements from universe $[\boldsymbol{n}] = \{1, 2, \ldots, \boldsymbol{n}\}$, e.g.

$$\langle x_1, x_2, \ldots, x_{\boldsymbol{m}} \rangle = \langle 5, 8, 1, 1, 1, 4, 3, 5, \ldots, 10 \rangle$$

- f_i = frequency of i in the stream = # of occurrences of value i

$$f = \langle f_1, \ldots, f_{\boldsymbol{n}} \rangle$$

AMS Sampling

- Problem: Estimate $\sum_{i \in [n]} g(f_i)$, for an arbitrary function g with $g(0) = 0$.
- Estimator: Sample $x_{\boldsymbol{J}}$, where $\boldsymbol{J}$ is sampled uniformly at random from $[m]$ and compute:

$$r = \left|\{j \geq \boldsymbol{J} : x_j = x_{\boldsymbol{J}}\}\right|$$

Output: $\boldsymbol{X} = m(g(r) - g(r-1))$

- Expectation:

$$\mathbb{E}[\boldsymbol{X}] = \sum_i \Pr\left[x_{\boldsymbol{J}} = i\right] \mathbb{E}[\boldsymbol{X} | x_{\boldsymbol{J}} = i]$$

$$= \sum_i \frac{f_i}{m} \left(\sum_{r=1}^{f_i} \frac{m\left(g(r) - g(r-1)\right)}{f_i} \right) = \sum_i g(f_i)$$

Frequency Moments

- Define $F_k = \sum_i f_i^k$ for $k \in \{0,1,2,\ldots\}$
  - $F_0 =$ # number of distinct elements
  - $F_1 =$ # elements
  - F_2 = "Gini index", "surprise index"

Frequency Moments

- Define $F_k = \sum_i f_i^k$ for $k \in \{0,1,2,\dots\}$
- Use AMS estimator with $\boldsymbol{X} = m\left(r^k - (r-1)^k\right)$
$$\mathbb{E}[\boldsymbol{X}] = F_k$$
- Exercise: $0 \le \boldsymbol{X} \le m\, k\, f_*^{k-1}$, where $f_* = \max_i f_i$
- Repeat t times and take average $\widehat{\boldsymbol{X}}$. By Chernoff:
$$\Pr\left[\left|\widehat{\boldsymbol{X}} - F_k\right| \ge \epsilon F_k\right] \le 2\exp\left(-\frac{tF_k\epsilon^2}{3m\, k\, f_*^{k-1}}\right)$$
- Taking $t = \frac{3mkf_*^{k-1}\log\frac{1}{\delta}}{\epsilon^2 F_k}$ gives $\Pr\left[\left|\widehat{\boldsymbol{X}} - F_k\right| \ge \epsilon F_k\right] \le \delta$

Frequency Moments

- Lemma:

$$\frac{m f_*^{k-1}}{F_k} \leq n^{1-1/k}$$

- Result:

$$t = \frac{3mk f_*^{k-1} \log\frac{1}{\delta}}{\epsilon^2 F_k} = O\left(\frac{kn^{1-\frac{1}{k}} \log\frac{1}{\delta}}{\epsilon^2} (\log n + \log m)\right)$$

memory suffices for (ϵ, δ)-approximation of F_k

- Question: What if we don't know m?
  - Then we can use probabilistic guessing (similar to Morris's algorithm), replacing $\log n$ with $\log nm$.

Frequency Moments

- Lemma:

$$\frac{m f_*^{k-1}}{F_k} \leq n^{1-1/k}$$

- Exercise: $F_k \geq n \left(\frac{m}{n}\right)^k$ (Hint: worst-case when $f_1 = \cdots = f_n = \frac{m}{n}$. Use convexity of $g(x) = x^k$).
- Case 1: $f_*^k \leq n \left(\frac{m}{n}\right)^k$

$$\frac{m f_*^{k-1}}{F_k} \leq \frac{m n^{1-\frac{1}{k}} \left(\frac{m}{n}\right)^{k-1}}{n \left(\frac{m}{n}\right)^k} = n^{1-\frac{1}{k}}$$

Frequency Moments

- Lemma:

$$\frac{mf_*^{k-1}}{F_k} \leq n^{1-1/k}$$

- Case 2: $f_*^k \geq n\left(\frac{m}{n}\right)^k$

$$\frac{mf_*^{k-1}}{F_k} \leq \frac{mf_*^{k-1}}{f_*^k} = \frac{m}{f_*} \leq \frac{m}{n^{\frac{1}{k}}\left(\frac{m}{n}\right)} = n^{1-\frac{1}{k}}$$

Hash Functions

- Definition: A family H of functions from $A \to B$ is k-wise independent if for any distinct $x_1, \dots, x_k \in A$ and $i_1, \dots i_k \in B$:

$$\Pr_{h \in_R H}[h(x_1) = i_1, h(x_2) = i_2, \dots, h(x_k) = i_k] = \frac{1}{|B|^k}$$

- Example: If $A \subseteq \{0, \dots, p-1\}, B = \{0, \dots, p-1\}$ for prime p

$$H = \left\{ h(x) = \sum_{i=0}^{k-1} a_i x^i \ mod\, p : 0 \le a_0, a_1, \dots, a_{k-1} \le p-1 \right\}$$

is a k-wise independent family of hash functions.

Linear Sketches

- Sketching algorithm: picks a random matrix $Z \in R^{k \times n}$, where $k \ll n$ and computes Zf.
- Can be incrementally updated:
  - We have a sketch Zf
  - When i arrives, new frequencies are $f' = f + e_i$
  - Updating the sketch:

  $Zf' = Z(f + e_i) = Zf + Ze_i = Zf$ +(i-th column of Z)
- Need to choose random matrices carefully

F_2

- Problem: (ϵ, δ)-approximation for $F_2 = \sum_i f_i^2$
- Algorithm:
  - Let $Z \in \{-1,1\}^{k \times n}$, where entries of each row are 4-wise independent and rows are independent
  - Don't store the matrix: k 4-wise independent hash functions σ
  - Compute Zf, average squared entries "appropriately"
- Analysis:
  - Let s be any entry of Zf.
  - Lemma: $\mathbb{E}[s^2] = F_2$
  - Lemma: $\mathrm{Var}[s^2] \leq 2F_2^2$

F_2: Expectaton

- Let σ be a row of Z with entries $\sigma_i \in_R \{-1,1\}$.

$$\mathbb{E}[s^2] = \mathbb{E}\left[\left(\sum_{i=1}^{n} \sigma_i f_i\right)^2\right]$$

$$= \mathbb{E}\left(\sum_{i=1}^{n} \sigma_i^2 f_i^2 + \sum_{i \neq j} \mathbb{E}[\sigma_i \sigma_j f_i f_j]\right)$$

$$= \mathbb{E}\left(\sum_{i=1}^{n} f_i^2 + \sum_{i \neq j} \mathbb{E}[\sigma_i \sigma_j] f_i f_j\right)$$

$$= F_2 + \textstyle\sum_{i \neq j} \mathbb{E}[\sigma_i]\mathbb{E}[\sigma_j]\, f_i \; f_j = F_2$$

- We used 2-wise independence for $\mathbb{E}[\sigma_i \sigma_j] = \mathbb{E}[\sigma_i]\mathbb{E}[\sigma_j]$.

F_2: Variance

$$\mathbb{E}[(X^2 - \mathbb{E}X^2)^2] = \mathbb{E}\left(\sum_{i \neq j} \sigma_i \sigma_j f_i f_j\right)^2$$

$$= \mathbb{E}\left(2 \sum_{i \neq j} \sigma_i^2 \sigma_j^2 f_i^2 f_j^2 + 4 \sum_{i \neq j \neq k} \sigma_i^2 \sigma_j \sigma_k f_i^2 f_j f_k\right.$$

$$\left. + 24 \sum_{i<j<k<l} \sigma_i \sigma_j \sigma_k \sigma_l f_i f_j f_k f_l\right)$$

$$= 2 \sum_{i \neq j} f_i^2 f_j^2 + 4 \sum_{i \neq j \neq k} \mathbb{E}\left[\sigma_j \sigma_k\right] f_i^2 f_j f_k$$

$$+ 24 \sum_{i<j<k<l} \mathbb{E}[\sigma_i \sigma_j \sigma_k \sigma_l] f_i f_j f_k f_l \leq 2\, F_2^2$$

- $\mathbb{E}\left[\sigma_i \sigma_j \sigma_k \sigma_l\right] = \mathbb{E}\left[\sigma_i\right] \mathbb{E}\left[\sigma_j\right] \mathbb{E}\left[\sigma_k\right] \mathbb{E}\left[\sigma_l\right] = 0$ by 4-wise independence

F_0: Distinct Elements

- Problem: (ϵ, δ)-approximation for $F_0 = \sum_i f_i^0$
- Simplified: For fixed $T > 0$, with prob. $1 - \delta$ distinguish:

$$F_0 > (1+\epsilon)T \text{ vs. } F_0 < (1-\epsilon)T$$

- Original problem reduces by trying $O\left(\frac{\log n}{\epsilon}\right)$ values of T:

$$T = 1, (1+\epsilon), (1+\epsilon)^2, \ldots, n$$

F_0: Distinct Elements

- Simplified: For fixed $T > 0$, with prob. $1 - \delta$ distinguish:

$$F_0 > (1+\epsilon)T \text{ vs. } F_0 < (1-\epsilon)T$$

- Algorithm:
  - Choose random sets $S_1, \dots, S_k \subseteq [n]$ where $\Pr[i \in S_j] = \frac{1}{T}$
  - Compute $s_j = \sum_{i \in S_j} f_i$
  - If at least k/e of the values s_j are zero, output $F_0 < (1-\epsilon)T$

$F_0 > (1+\epsilon)T$ vs. $F_0 < (1-\epsilon)T$

- Algorithm:
  - Choose random sets $S_1, \ldots, S_k \subseteq [n]$ where $\Pr[i \in S_j] = \frac{1}{T}$
  - Compute $s_j = \sum_{i \in S_j} f_i$
  - If at least k/e of the values s_j are zero, output $F_0 < (1-\epsilon)T$
- Analysis:
  - If $F_0 > (1+\epsilon)T$, then $\Pr[s_j = 0] < \frac{1}{e} - \frac{\epsilon}{3}$
  - If $F_0 < (1-\epsilon)T$, then $\Pr[s_j = 0] > \frac{1}{e} + \frac{\epsilon}{3}$
  - Chernoff: $k = O\left(\frac{1}{\epsilon^2} \log \frac{1}{\delta}\right)$ gives correctness w.p. $1-\delta$

$F_0 > (1+\epsilon)T$ vs. $F_0 < (1-\epsilon)T$

- Analysis:
  - If $F_0 > (1+\epsilon)T$, then $\Pr[s_j = 0] < \frac{1}{e} - \frac{\epsilon}{3}$
  - If $F_0 < (1-\epsilon)T$, then $\Pr[s_j = 0] > \frac{1}{e} + \frac{\epsilon}{3}$
- If T is large and ϵ is small then:

$$\Pr[s_j = 0] = \left(1 - \frac{1}{T}\right)^{F_0} \approx e^{-\frac{F_0}{T}}$$

- If $F_0 > (1+\epsilon)T$:

$$e^{-\frac{F_0}{T}} \le e^{-(1+\epsilon)} \le \frac{1}{e} - \frac{\epsilon}{3}$$

- If $F_0 < (1-\epsilon)T$:

$$e^{-\frac{F_0}{T}} \ge e^{-(1-\epsilon)} \ge \frac{1}{e} + \frac{\epsilon}{3}$$

Count-Min Sketch

- https://sites.google.com/site/countminsketch/
- Stream: $\boldsymbol{m}$ elements from universe $[\boldsymbol{n}] = \{1, 2, \ldots, \boldsymbol{n}\}$, e.g.

  $\langle x_1, x_2, \ldots, x_{\boldsymbol{m}} \rangle = \langle 5, 8, 1, 1, 1, 4, 3, 5, \ldots, 10 \rangle$
- f_i = frequency of i in the stream = # of occurrences of value i, $f = \langle f_1, \ldots, f_{\boldsymbol{n}} \rangle$
- Problems:
  - Point Query: For $i \in [n]$ estimate f_i
  - Range Query: For $i, j \in [n]$ estimate $f_i + \cdots + f_j$
  - Quantile Query: For $\phi \in [0,1]$ find j with $f_1 + \cdots + f_j \approx \phi m$
  - Heavy Hitters: For $\phi \in [0,1]$ find all i with $f_i \geq \phi m$

Count-Min Sketch: Construction

- Let $H_1, \dots, H_d : [n] \to [w]$ be 2-wise independent hash functions
- We maintain $d \cdot w$ counters with values:

  $c_{i,j} =$ # elements e in the stream with $H_i(e) = j$
- For every x the value $c_{i,H_i(x)} \geq f_x$ and so:

$$f_x \leq \widetilde{f_x} = \min(c_{1,H_1(x)}, \dots, c_{d,H_d(x)})$$

- If $w = \frac{2}{\epsilon}$ and $d = \log_2 \frac{1}{\delta}$ then:

$$\Pr\left[f_x \leq \widetilde{f_x} \leq f_x + \epsilon m\right] \geq 1 - \delta.$$

Count-Min Sketch: Analysis

- Define random variables $\boldsymbol{Z}_1 \dots, \boldsymbol{Z}_k$ such that $c_{i,H_i(x)} = f_x + \boldsymbol{Z}_i$

$$\boldsymbol{Z}_i = \sum_{y \neq x, H_i(y) = H_i(x)} f_y$$

- Define $\boldsymbol{X}_{i,y} = 1$ if $H_i(y) = H_i(x)$ and 0 otherwise:

$$\boldsymbol{Z}_i = \sum_{y \neq x} f_y \boldsymbol{X}_{i,y}$$

- By 2-wise independence:

$\mathbb{E}[\boldsymbol{Z}_i] = \sum_{y \neq x} f_y \, \mathbb{E}\left[\boldsymbol{X}_{i,y}\right] = \sum_{y \neq x} f_y \Pr[H_i(y) = H_i(x)] \leq \frac{m}{w}$

- By Markov inequality,

$$\Pr[\boldsymbol{Z}_i \geq \epsilon m] \leq \frac{1}{w\,\epsilon} = \frac{1}{2}$$

Count-Min Sketch: Analysis

- All Z_i are independent

$$\Pr[Z_i \geq \epsilon m \quad for\ all \quad 1 \leq i \leq d\,] \leq \left(\frac{1}{2}\right)^d = \delta$$

- With prob. $1 - \delta$ there exists j such that $Z_j \leq \epsilon m$

$$\widetilde{f_x} = \min\left(c_{1,H_1(x)}, \ldots, c_{d,H_d(x)}\right) =$$
$$= \min(f_x, +Z_1 \ \ldots, f_x + Z_d) \leq f_x + \epsilon m$$

- CountMin estimates values f_x up to $\pm\epsilon m$ with total memory $O\left(\frac{\log m \log\frac{1}{\delta}}{\epsilon}\right)$`

Dyadic Intervals

- Define $\log n$ partitions of $[n]$:

$I_0 = \{1,2,3, \dots n\}$
$I_1 = \{\{1,2\}, \{3,4\}, \dots, \{n-1, n\}\}$
$I_2 = \{\{1,2,3,4\}, \{5,6,7,8\}, \dots, \{n-3, n-2, n-1, n\}\}$
…
$\mathrm{I}_{\log n} = \{\{1, 2,3, \dots, n\}\}$

- Exercise: Any interval (i, j) can be written as a disjoint union of at most $2 \log n$ such intervals.
- Example: For $n = 256$: $[48,107] = [48,48] \cup [49,64] \cup [65,96] \cup [97,104] \cup [105,106] \cup [107,107]$

Count-Min: Range Queries and Quantiles

- Range Query: For $i, j \in [n]$ estimate $f_i + \cdots f_j$
- Approximate median: Find j such that:

$$f_1 + \cdots + f_j \geq \frac{m}{2} + \epsilon m \text{ and}$$
$$f_1 + \cdots + f_{j-1} \leq \frac{m}{2} - \epsilon m$$

Count-Min: Range Queries and Quantiles

- Algorithm: Construct $\log n$ Count-Min sketches, one for each I_i such that for any $I \in I_i$ we have an estimate $\tilde{f_l}$ for f_l such that:
$$\Pr\left[f_l \leq \widetilde{f_l} \leq f_l + \epsilon m\right] \geq 1 - \delta$$
- To estimate $[i, j]$, let $I_1 \ldots, I_k$ be decomposition:
$$\widetilde{f_{[i,j]}} = \widetilde{f_{I_1}} + \cdots + \widetilde{f_{I_k}}$$
- Hence,
$$\Pr\left[f_{[i,j]} \leq \widetilde{f_{[i,j]}} \leq 2\,\epsilon m \log n\right] \geq 1 \ - 2\delta \log n$$

Count-Min: Heavy Hitters

- Heavy Hitters: For $\phi \in [0,1]$ find all i with $f_i \geq \phi m$ but no elements with $f_i \leq (\phi - \epsilon)m$
- Algorithm:
  - Consider binary tree whose leaves are [n] and associate internal nodes with intervals corresponding to descendant leaves
  - Compute Count-Min sketches for each I_i
  - Level-by-level from root, mark children I of marked nodes if $\widetilde{f_l} \geq \phi m$
  - Return all marked leaves
- Finds heavy-hitters in $O(\phi^{-1} \log n)$ steps