

CIS 700: “algorithms for Big Data”

Lecture 1: Intro

Slides at <http://grigory.us/big-data-class.html>

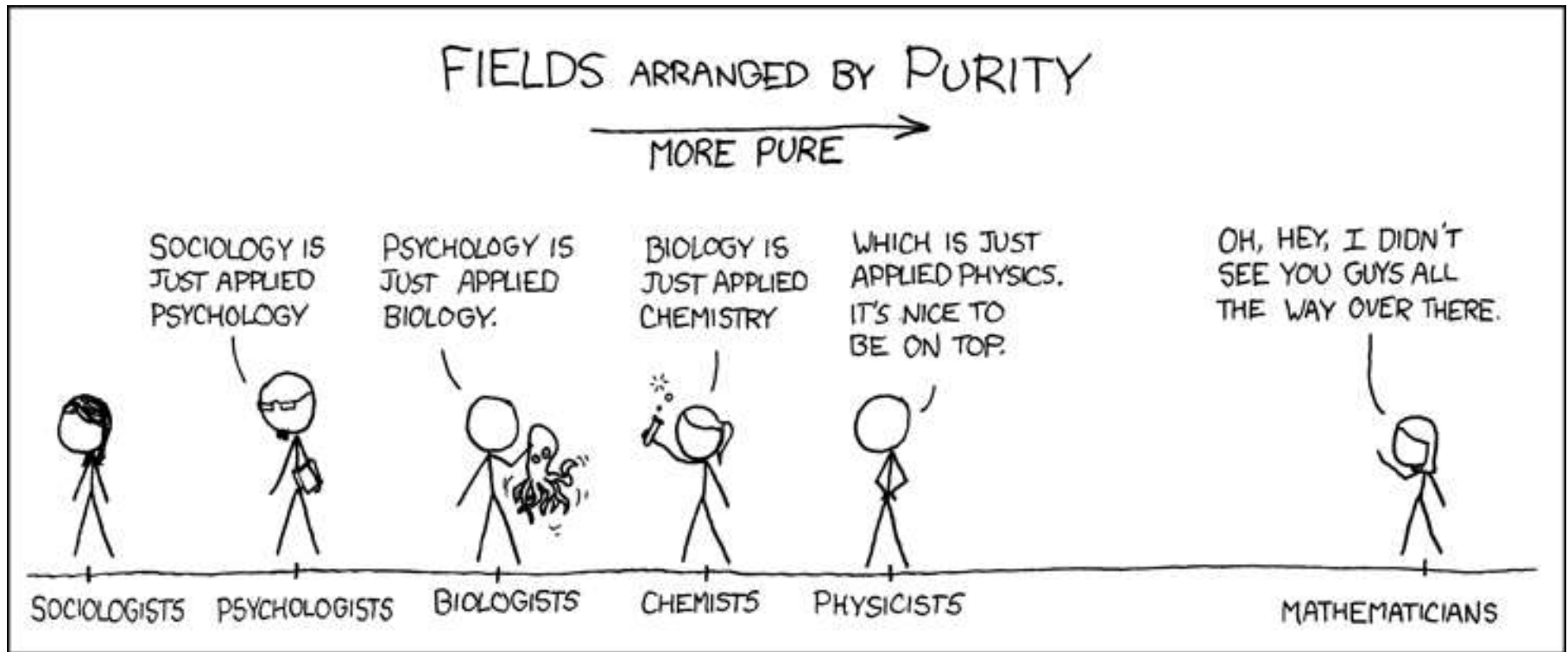
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<http://grigory.us>



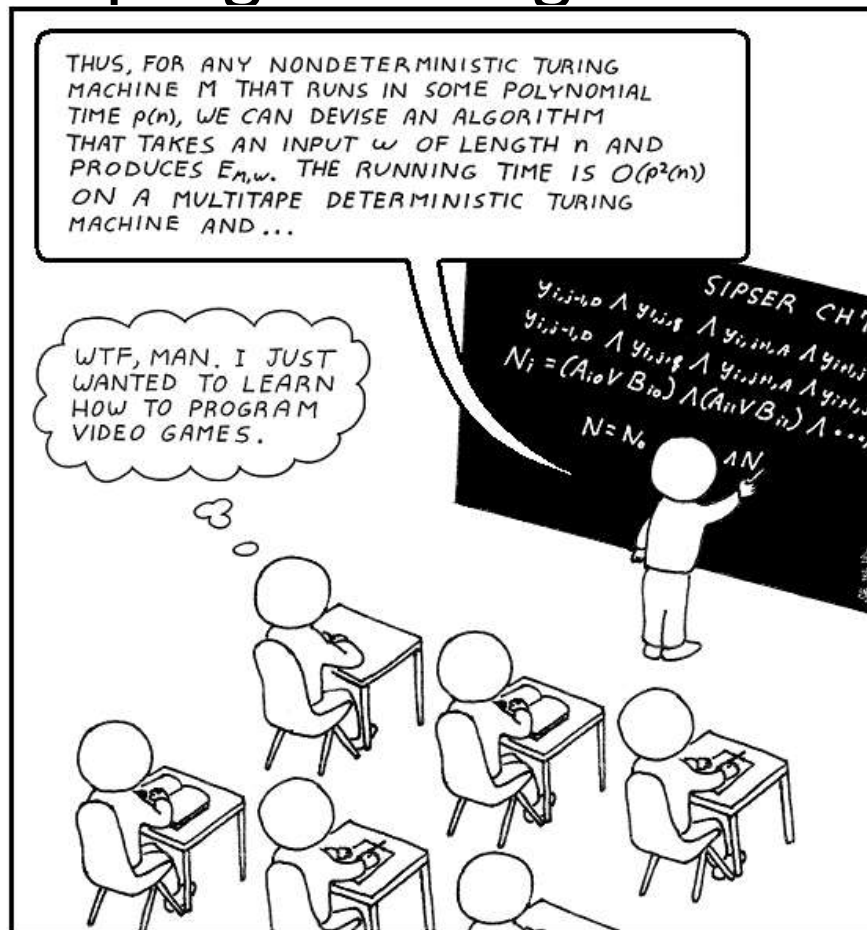
Disclaimers

- A lot of Math!



Disclaimers

- (Almost) no programming!



Class info

- MW 10:30 – 12:00, Towne 307
- Grading:
 - 1-2 homework assignments (40%)
 - Project (60%)
- Office hours by appointment
- Slides will be posted

What is this class about?

- Not about the band

([https://en.wikipedia.org/wiki/Big_Data_\(band\)](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
 - Today 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 $o(N)$

- $o(N)$: (1) , $(\log N)$, (\dots) where $0 < \dots < 1$



Getting hands dirty

- Cloud computing platforms (all offer free trials):

- Amazon EC2 (1 CPU/12mo)



- Microsoft Azure (\$200/1mo)



- Google Compute Engine (\$200/2mo)



Windows Azure

- 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 (~ 1 MB, with hundreds MB RAM)
- Fast query access (~ 0.01 s per request), “data with queries”

Outline

- Part 1: Streaming Algorithms



Highlights:

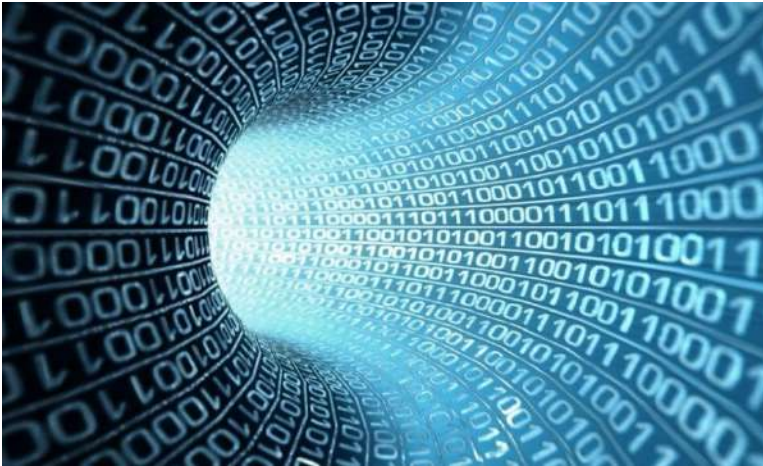
- Approximate counting
- # Distinct Elements, Hyperloglog
- Median
- Frequency moments
- Heavy hitters
- Graph sketching

Outline

- Part 2: Algorithms for numerical linear algebra

Highlights:

- Dimension reduction
- Nearest neighbor search
- Linear sketching
- Linear regression
- Low rank approximation



Outline

- Part 3: Massively Parallel Algorithms



Highlights:

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

Outline

- Part 4: Sublinear Time Algorithms



Highlights:

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

Today

Puzzles



You see a sequence of values $1, \dots$, arriving one by one:

- **(Easy, “Find a missing player”)**
 - If all a_i are different and have values between 1 and $n + 1$, which value is missing?
 - You have $(\log n)$ space
- **Example:**
 - There are 11 soccer players with numbers $1, \dots, 11$.
 - You see 10 of them one by one, which one is missing? You can only remember a single number.

1

8

5

1 1

3

9

2

6

7

4

Which number was missing?



Puzzle #1



You see a sequence of values $1, \dots$, arriving one by one:

- **(Easy, “Find a missing player”)**
 - If all i are different and have values between 1 and $n + 1$, which value is missing?
 - You have $(\log n)$ space
- **Example:**
 - There are 11 soccer players with numbers $1, \dots, 11$.
 - You see 10 of them one by one, which one is missing? You can only remember a single number.

Puzzle #2



You see a sequence of values v_1, \dots, v_n , arriving one by one:

- **(Harder, “Keep a random team”)**
 - How can you maintain a uniformly random sample of k values out of those you have seen so far?
 - You can store exactly k items at any time
- **Example:**
 - You want to have a team of 11 players randomly chosen from the set you have seen.
 - Players arrive one at a time and you have to decide whether to keep them or not.

Puzzle #3



You see a sequence of values x_1, \dots, x_n , arriving one by one:

- **(Very hard, “Count the number of players”)**
 - What is the total number of values up to error $\pm \epsilon$?
 - You have $(\log \log n / \epsilon^2)$ space and can be completely wrong with some small probability

Puzzles



You see a sequence of values $1, \dots$, arriving one by one:

- **(Easy, “Find a missing player”)**
 - If all are different and have values between 1 and $+ 1$, which value is missing?
 - You have (\log) space
- **(Harder, “Keep a random team”)**
 - How can you maintain a uniformly random sample of values out of those you have seen so far?
 - You can store exactly items at any time
- **(Very hard, “Count the number of players”)**
 - What is the total number of values up to error \pm ?

Part 1: Probability 101

“The bigger the data the better you should know your Probability”

- Basic Probability:

- Probability, events, random variables
- Expectation, variance / standard deviation
- Conditional probability, independence, pairwise independence, mutual independence

Expectation

- = random variable with values x_1, \dots, x_n, \dots

- Expectation $\mathbb{E}[X]$

$$\mathbb{E}[X] = \sum_{i=1}^{\infty} x_i \cdot \Pr[X = x_i]$$

- Properties (linearity):

$$\mathbb{E}[aX + b] = a\mathbb{E}[X] + b$$

- Useful fact: if all $x_i \geq 0$ and integer then

$$\mathbb{E}[X] = \sum_{i=1}^{\infty} \Pr[X \geq i]$$

Variance

- Variance
$$[] = \mathbb{E}[(\mathbf{X} - \mathbb{E}[\mathbf{X}])^2]$$

$$\begin{aligned} &= \mathbb{E} [\quad] = \mathbb{E}[(\mathbf{X} - \mathbb{E}[\mathbf{X}])^2] = \\ &= \mathbb{E} [\quad^2 - 2 \quad \cdot \mathbb{E}[\mathbf{X}] + \mathbb{E}[\mathbf{X}]^2] \\ &= \mathbb{E} [\quad^2] - 2\mathbb{E} [\quad \cdot \mathbb{E}[\mathbf{X}]] + \mathbb{E}[\mathbb{E}[\mathbf{X}]^2] \end{aligned}$$

- $\mathbb{E}[\mathbf{X}]$ is some fixed value (a constant)
- $2 \mathbb{E} [\quad \cdot \mathbb{E}[\mathbf{X}]] = 2 \mathbb{E}[\mathbf{X}] \cdot \mathbb{E}[\mathbf{X}] = 2 \mathbb{E}^2 [\quad]$
- $\mathbb{E}[\mathbb{E}[\mathbf{X}]^2] = \mathbb{E}^2[\mathbf{X}]$

Independence

- Two random variables X and Y are **independent** if and only if (iff) for every x, y :

$$\Pr[X = x, Y = y] = \Pr[X = x] \cdot \Pr[Y = y]$$

- Variables X_1, \dots, X_n are **mutually independent** iff

$$\Pr[X_1 = x_1, \dots, X_n = x_n] = \prod_{i=1}^n \Pr[X_i = x_i]$$

- Variables X_1, \dots, X_n are **pairwise independent** iff for all pairs i, j

$$\Pr[X_i = x_i, X_j = x_j] = \Pr[X_i = x_i] \Pr[X_j = x_j]$$

Conditional Probabilities

- For two events A_1 and A_2 :

$$\Pr [A_2 | A_1] = \frac{\Pr [A_1 \cap A_2]}{\Pr [A_1]}$$

- If two random variables (r.v.s) are independent

$$\Pr [A_2 = a_2 | A_1 = a_1] = \frac{\Pr [A_1 = a_1 \cap A_2 = a_2]}{\Pr [A_1 = a_1]} \quad (\text{by definition})$$

$$= \frac{\Pr [A_1 = a_1] \Pr [A_2 = a_2]}{\Pr [A_1 = a_1]} \quad (\text{by independence})$$

Union Bound

For any events A_1, A_2, \dots, A_n :

$$\Pr[A_1 \cup A_2 \cup \dots \cup A_n] \leq \Pr[A_1] + \Pr[A_2] + \dots + \Pr[A_n]$$

- **Pro:** Works even for dependent variables!
- **Con:** Sometimes very loose, especially for **mutually**

Independence and Linearity of Expectation/Variance

- Linearity of expectation (even for dependent variables!):

$$\mathbb{E} \left[\sum_{i=1}^n X_i \right] = \sum_{i=1}^n \mathbb{E}[X_i]$$

- Linearity of variance (only for **pairwise independent** variables!)

$$\text{Var} \left[\sum_{i=1}^n X_i \right] = \sum_{i=1}^n \text{Var}[X_i]$$

Part 2: Inequalities

- Markov inequality
- Chebyshev inequality
- Chernoff bound

Markov's Inequality

- For every $\epsilon > 0$: $\Pr[X \geq \epsilon] \leq \frac{1}{\epsilon}$
- **Proof (by contradiction)** $\Pr[X \geq \epsilon] > \frac{1}{\epsilon}$

$$E[X] = \sum_i x_i \cdot \Pr[X = x_i] \quad (\text{by definition})$$

$$\geq \sum_{x_i \geq \epsilon} x_i \cdot \Pr[X = x_i] \quad (\text{pick only some } i\text{'s})$$

Markov's Inequality

- For every $\epsilon > 0$: $Pr[X \geq \epsilon] \leq \frac{1}{\epsilon}$

- **Corollary** ($c' = \epsilon$):

For every $\epsilon' > 0$: $Pr[X \geq \epsilon'] \leq \frac{[]}{\epsilon'}$

- **Pro**: always works!

- **Cons**:

- Not very precise

- Doesn't work for the lower tail: $Pr[X \leq []]$

Chebyshev's Inequality

- For every $\epsilon > 0$:

$$\Pr \left[\left| \bar{X} - \mu \right| \geq \sqrt{\frac{\text{Var}(\bar{X})}{\epsilon^2}} \right] \leq \frac{1}{\epsilon^2}$$

- Proof:

$$\begin{aligned} & \Pr \left[\left| \bar{X} - \mu \right| \geq \sqrt{\frac{\text{Var}(\bar{X})}{\epsilon^2}} \right] \\ &= \Pr \left[\left| \bar{X} - \mu \right|^2 \geq \frac{\text{Var}(\bar{X})}{\epsilon^2} \right] \quad (\text{by squaring}) \\ &= \Pr \left[\left| \bar{X} - \mu \right|^2 \geq \frac{\text{Var}(\bar{X})}{\epsilon^2} \mid \left| \bar{X} - \mu \right|^2 \right] \quad (\text{def. of Var}) \\ &\leq \frac{1}{\epsilon^2} \quad (\text{by Markov's inequality}) \end{aligned}$$

Chebyshev's Inequality

- For every $\epsilon > 0$:

$$\Pr \left[\left| \bar{X} - \mu \right| \geq \sqrt{\frac{\sigma^2}{n}} \right] \leq \frac{1}{2}$$

- **Corollary** ($\epsilon = \sqrt{\frac{\sigma^2}{n}}$):

For every $\epsilon' > 0$:

$$\Pr \left[\left| \bar{X} - \mu \right| \geq \epsilon' \right] \leq \frac{\frac{\sigma^2}{n}}{\epsilon'^2}$$

Chernoff bound

- Let X_1, \dots, X_n be independent and identically distributed r.v.s with range $[0,1]$ and expectation μ .

- Then if $S_n = \sum_{i=1}^n X_i$ and $1 > \delta > 0$,

$$\Pr \left[\left| S_n - n\mu \right| \geq \delta n \right] \leq 2 \exp \left(-\frac{\delta^2 n}{3} \right)$$

Chernoff bound (corollary)

- Let X_1, \dots, X_n be independent and identically distributed r.v.s with range $[0, c]$ and expectation μ .

- Then if $S_n = \sum_{i=1}^n X_i$ and $1 - \delta > 0$,

$$\Pr \left[\left| S_n - n\mu \right| \geq \delta n\mu \right] \leq 2 \exp \left(-\frac{\delta^2}{3} \right)$$

Chernoff v.s Chebyshev

Large values of t is exactly what we need!

Let X_1, \dots, X_n be independent and identically distributed r.v.s with

range $[0,1]$ and expectation μ . Let $S_n = \sum_{i=1}^n X_i$.

- Chebyshev: $\Pr [|S_n - n\mu| \geq t] = O\left(\frac{1}{t^2}\right)$
- Chernoff: $\Pr [|S_n - n\mu| \geq t] = e^{-\Omega(t)}$

So is Chernoff always better for us?

- Yes, if we have i.i.d. variables

Answers to the puzzles

You see a sequence of values $1, \dots$, arriving one by one:

- **(Easy)**

- If all x_i are different and have values between 1 and $n + 1$, which value is missing?
- You have $(\log n)$ space

- **Answer:** missing value = $\sum_{i=1}^n x_i - \sum_{i=1}^n i$

- **(Harder)**

- How can you maintain a uniformly random sample of values out of those you have seen so far?

Part 3: Morris's Algorithm

- **(Very hard, “Count the number of players”)**
 - What is the total number of values up to error $\pm \epsilon$?
 - You have $(\log \log n / \epsilon^2)$ space and can be completely wrong with some small probability

Morris's Algorithm: Alpha-version

Maintains a counter X using $\log \log f_0$ 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: $E[2^X] = f_0 + 1$

Morris's Algorithm: Alpha-version

Maintains a counter X using $\log \log f_0$ bits

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

Claim: $E[X] = \sqrt{2 \log f_0}$

- Let the value after seeing n items be X_n

$$E[X_n] = \sum_{k=0}^{\infty} \Pr[X_n = k] E[X_n | X_n = k]$$

$$= \sum_{k=0}^{\infty} \Pr[X_n = k] \left(\frac{1}{2^k} + 1 + \left(\frac{1}{2^k} + 1 \right) E[X_n] \right)$$

Morris's Algorithm: Alpha-version

Maintains a counter using $\log \log f_0$ bits

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

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

$$E[X^2] = \sum_{i=0}^{\infty} \Pr[X=i] (i^2 - 1) = \sum_{i=0}^{\infty} \Pr[X=i] (i^2 - 1)$$

$$= \sum_{i=0}^{\infty} \Pr[X=i] (i^2 - 1) = \sum_{i=0}^{\infty} \Pr[X=i] \left(\frac{1}{4} i^2 + \left(1 - \frac{1}{4}\right) i \right)$$

Morris's Algorithm: Alpha-version

Maintains a counter X using $\log_2 \log_2 f_0$ bits

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

Morris's Algorithm: Beta-version

Maintains counters x_1, \dots, x_n using $\log \log f_0$ bits for each

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

- Output $Z = \frac{1}{n} \left(\sum_{i=1}^n 2^{x_i} - 1 \right)$

- $\mathbb{E}[Z] = n + 1, \quad \mathbb{E}[Z^2] = \binom{2}{2}$

Morris's Algorithm: Beta-version

Maintains counters $1, \dots, f_0$ using $\log \log f_0$ bits for each

- Output $Z = \frac{1}{-} \left(\sum_{=1} 2 - 1 \right)$

- $[] = \left(\frac{1}{-} \sum_{=1} 2 - 1 \right) = \left(\frac{2}{-} \right)$

- Claim: If $\geq \frac{1}{2}$ then $\Pr [| - | >] < 1/3$

$$[] = \left(\frac{2}{-} \right) = 1$$

Morris's Algorithm: Final

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

Morris's Algorithm: Final

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

Maintains counters $1, \dots$, using $\log \log f_0$ bits for each

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

Morris's Algorithm: Final Analysis

Claim: $\Pr \left[\left| \sum_{i=1}^n X_i - \sum_{i=1}^n \mu_i \right| > \epsilon \right] \leq$

- Let X_i be an indicator r.v. for the event that

$\left| \sum_{j=1}^k X_{ij} - \sum_{j=1}^k \mu_{ij} \right| \leq \epsilon / k$, where X_{ij} is the i -th trial.

- Let $Y_i = \sum_{j=1}^k X_{ij}$.

- $\Pr \left[\left| \sum_{i=1}^n Y_i - \sum_{i=1}^n \mu_i \right| > \epsilon \right] \leq \Pr \left[\sum_{i=1}^n Y_i \leq \frac{\sum_{i=1}^n \mu_i}{2} \right]$

Thank you!

- Questions?
- **Next time:**
 - More streaming algorithms