

# Sublinear Algorithms for Big Data

**Grigory Yaroslavtsev**

<http://grigory.us>



# Part 0: Introduction

- Disclaimers
- Logistics
- Materials
- ...

# Name

Correct:

- Grigory
- Gregory (easiest and highly recommended!)

Also correct:

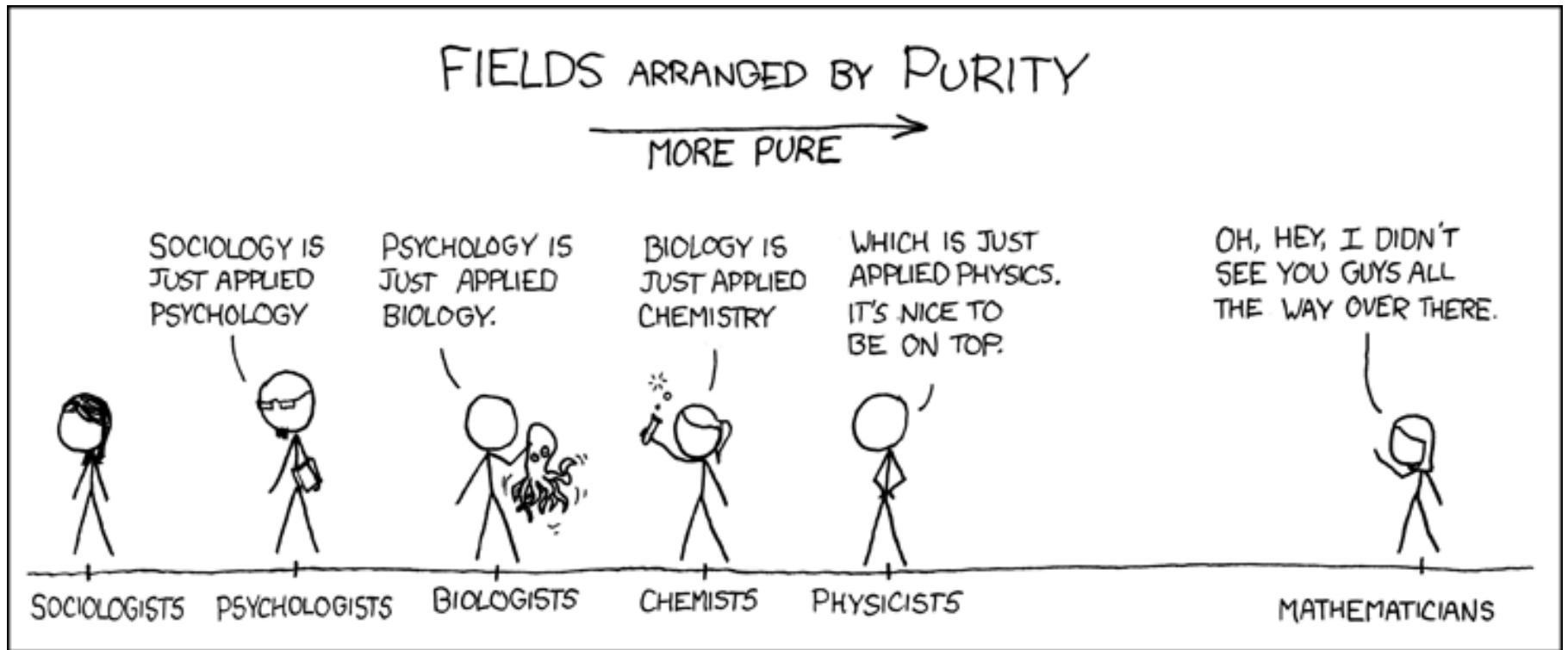
- Dr. Yaroslavtsev (I bet it's difficult to pronounce)

Wrong:

- Prof. Yaroslavtsev (Not any easier)

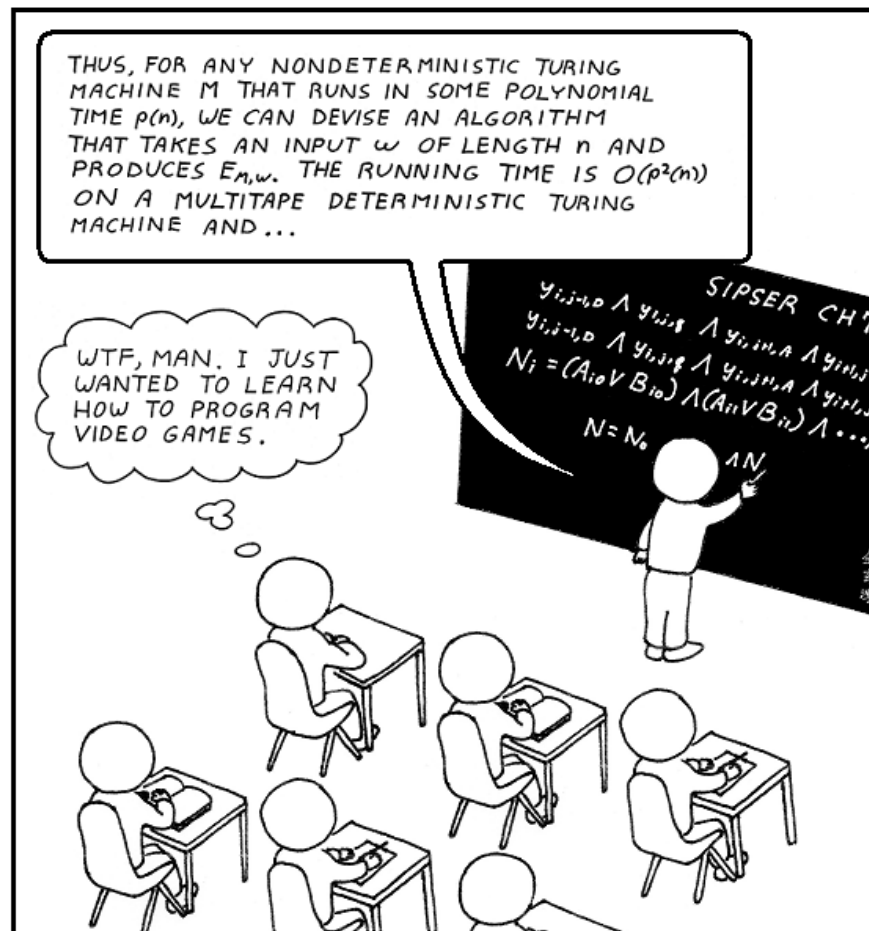
# Disclaimers

- A lot of Math!



# Disclaimers

- No programming!



# Disclaimers

- 10-15 times longer than “Fuerza Bruta”, soccer game, milonga...

# Big Data

- Data
- Programming and Systems
- **Algorithms**
- **Probability and Statistics**

# Sublinear Algorithms

$n$  = size of the data, we want  $o(n)$ , not  $O(n)$

- Sublinear Time
  - Queries
  - Samples
- Sublinear Space
  - Data Streams
  - Sketching
- Distributed Algorithms
  - Local and distributed computations
  - MapReduce-style algorithms



# Why is it useful?

- Algorithms for big data used by big companies (ultra-fast (randomized algorithms for approximate decision making)
  - Networking applications (counting and detecting patterns in small space)
  - Distributed computations (small sketches to reduce communication overheads)
- Aggregate Knowledge: startup doing streaming algorithms, acquired for \$150M
- Today: Applications to soccer



# Course Materials

- Will be posted at the class homepage:  
<http://grigory.us/big-data.html>
- Related and further reading:
  - **Sublinear Algorithms** (MIT) by Indyk, Rubinfeld
  - **Algorithms for Big Data** (Harvard) by Nelson
  - **Data Stream Algorithms** (University of Massachusetts) by McGregor
  - **Sublinear Algorithms** (Penn State) by Raskhodnikova

# Course Overview

- Lecture 1
- Lecture 2
- Lecture 3
- Lecture 4
- Lecture 5

3 hours = 3 x (45-50 min lecture + 10-15 min break).

# Puzzles



You see a sequence of values  $a_1, \dots, a_n$ , arriving one by one:

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

**1**

8

5

**11**



3

9

2

6

**7**

4

Which number was missing?



# Puzzle #1



You see a sequence of values  $a_1, \dots, a_n$ , arriving one by one:

- **(Easy, “Find a missing player”)**
  - If all  $a_i$ 's are different and have values between 1 and  $n + 1$ , which value is missing?
  - You have  $O(\log n)$  space
- **Example:**
  - There are 11 soccer players with numbers 1, ..., 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  $a_1, \dots, a_n$ , arriving one by one:

- **(Harder, “Keep a random team”)**
  - How can you maintain a uniformly random sample of  $S$  values out of those you have seen so far?
  - You can store exactly  $S$  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  $a_1, \dots, a_n$ , arriving one by one:

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

# Puzzles



You see a sequence of values  $a_1, \dots, a_n$ , arriving one by one:

- **(Easy, “Find a missing player”)**
  - If all  $a_i$ 's are different and have values between 1 and  $n + 1$ , which value is missing?
  - You have  $O(\log n)$  space
- **(Harder, “Keep a random team”)**
  - How can you maintain a uniformly random sample of  $S$  values out of those you have seen so far?
  - You can store exactly  $S$  items at any time
- **(Very hard, “Count the number of players”)**
  - What is the total number of values up to error  $\pm \epsilon n$ ?
  - You have  $O(\log \log n / \epsilon^2)$  space and can be completely wrong with some small probability

# Part 1: Probability 101

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

- Basic Spanish: Hola, Gracias, Bueno, Por favor, Bebida, Comida, Jamon, Queso, Gringo, Chica, Amigo, ...
- Basic Probability:
  - Probability, events, random variables
  - Expectation, variance / standard deviation
  - Conditional probability, independence, pairwise independence, mutual independence

# Expectation

- $X$  = 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):

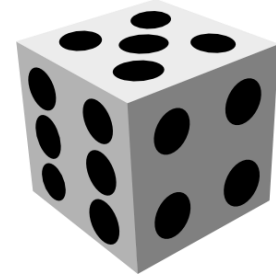
$$\mathbb{E}[cX] = c\mathbb{E}[X]$$

$$\mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y]$$

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

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

# Expectation



- Example: dice has values 1, 2, ..., 6 with probability 1/6

$$\begin{aligned}\mathbb{E}[\text{Value}] &= \\ \sum_{i=1}^6 i \cdot \Pr[\text{Value} = i] \\ &= \frac{1}{6} \sum_{i=1}^6 i = \frac{21}{6} = 3.5\end{aligned}$$

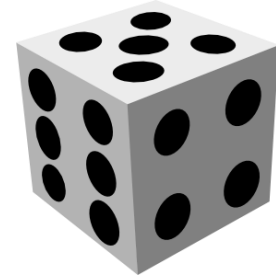
# Variance

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

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

- $\mathbb{E}[X]$  is some fixed value (a constant)
- $2 \mathbb{E}[X \cdot \mathbb{E}[X]] = 2 \mathbb{E}[X] \cdot \mathbb{E}[X] = 2 \mathbb{E}^2[X]$
- $\mathbb{E}[\mathbb{E}[X]^2] = \mathbb{E}^2[X]$
- $Var[X] = \mathbb{E}[X^2] - 2 \mathbb{E}^2[X] + \mathbb{E}^2[X] = \mathbb{E}[X^2] - \mathbb{E}^2[X]$
- Corollary:  $Var[cX] = c^2 Var[X]$

# Variance



- Example (Variance of a fair dice):

$$\mathbb{E}[Value] = 3.5$$

$$Var[Value] = \mathbb{E}[(Value - \mathbb{E}[Value])^2]$$

$$= \mathbb{E}[(Value - 3.5)^2]$$

$$= \sum_{i=1}^6 (i - 3.5)^2 \cdot Pr[Value = i]$$

$$= \frac{1}{6} \sum_{i=1}^6 (i - 3.5)^2$$

$$= \frac{1}{6} [(1 - 3.5)^2 + (2 - 3.5)^2 + (3 - 3.5)^2 \\ + (4 - 3.5)^2 + (5 - 3.5)^2 + (6 - 3.5)^2]$$

$$= \frac{1}{6} [6.25 + 2.25 + 0.25 + 0.25 + 2.25 + 6.25]$$

$$= \frac{8.75}{3} \approx 2.917$$



# 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  $i, j$

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

# Independence: Example



Independent or not?

- Event  $E_1$  = Argentina wins the World Cup
- Event  $E_2$  = Messi becomes the best striker

Independent or not?

- Event  $E_1$  = Argentina wins against Netherlands in the semifinals
- Event  $E_2$  = Germany wins against Brazil in the semifinals

# Independence: Example

- Ratings of mortgage securities
  - AAA = 1% probability of default (over X years)
  - AA = 2% probability of default
  - A = 5% probability of default
  - B = 10% probability of default
  - C = 50% probability of default
  - D = 100% probability of default
- You are a portfolio holder with 1000 AAA securities?
  - Are they all independent?
  - Is the probability of default  $(0.01)^{1000} = 10^{-2000}$ ?

# Conditional Probabilities

- For two events  $E_1$  and  $E_2$ :

$$\Pr[E_2|E_1] = \frac{\Pr[E_1 \text{ and } E_2]}{\Pr[E_1]}$$

- If two random variables (r.vs) are independent

$$\begin{aligned} & \Pr[X_2 = x_2 | X_1 = x_1] \\ &= \frac{\Pr[X_1 = x_1 \text{ and } X_2 = x_2]}{\Pr[X_1 = x_1]} \quad (\text{by definition}) \\ &= \frac{\Pr[X_1 = x_1] \Pr[X_2 = x_2]}{\Pr[X_1 = x_1]} \quad (\text{by independence}) \\ &= \Pr[X_2 = x_2] \end{aligned}$$

# Union Bound

For any events  $E_1, \dots, E_k$ :

$$\begin{aligned} & \Pr[E_1 \text{ or } E_2 \text{ or } \dots \text{ or } E_k] \\ & \leq \Pr[E_1] + \Pr[E_2] + \dots + \Pr[E_k] \end{aligned}$$

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

$$\Pr[E_1 \text{ or } E_2 \text{ or } \dots \text{ or } E_k] = 1 - \prod_{i=1}^k (1 - \Pr[E_i])$$

# Union Bound: Example



Events “Argentina wins the World Cup” and “Messi becomes the best striker” are **not independent**, but:

$$\begin{aligned} &\Pr[\text{“Argentina wins the World Cup” or} \\ &\quad \text{“Messi becomes the best striker”}] \leq \\ &\Pr[\text{“Argentina wins the World Cup”}] + \\ &\Pr[\text{“Messi becomes the best striker”}] \end{aligned}$$

# Independence and Linearity of Expectation/Variance

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

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

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

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

## Part 2: Inequalities

- Markov inequality
- Chebyshev inequality
- Chernoff bound



# Markov's Inequality

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

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

$$\geq \sum_{i=c\mathbb{E}[X]}^{\infty} i \cdot \Pr[X = i] \quad (\text{pick only some } i\text{'s})$$

$$\geq \sum_{i=c\mathbb{E}[X]}^{\infty} c\mathbb{E}[X] \cdot \Pr[X = i] \quad (i \geq c\mathbb{E}[X])$$

$$= c\mathbb{E}[X] \sum_{i=c\mathbb{E}[X]}^{\infty} \Pr[X = i] \quad (\text{by linearity})$$

$$= c\mathbb{E}[X] \Pr[X \geq c \mathbb{E}[X]] \quad (\text{same as above})$$

$$> \mathbb{E}[X] \quad (\text{by assumption } \Pr[X \geq c \mathbb{E}[X]] > \frac{1}{c})$$

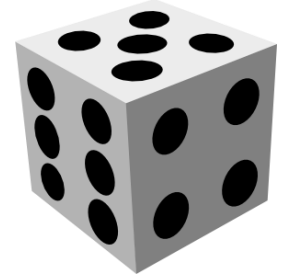
# Markov's Inequality

- For every  $c > 0$ :  $\Pr[\mathbf{X} \geq c \mathbb{E}[\mathbf{X}]] \leq \frac{1}{c}$
- **Corollary** ( $c' = c \mathbb{E}[\mathbf{X}]$ ) :

For every  $c' > 0$ :  $\Pr[\mathbf{X} \geq c' ] \leq \frac{\mathbb{E}[\mathbf{X}]}{c'}$

- **Pro**: always works!
- **Cons**:
  - Not very precise
  - Doesn't work for the lower tail:  $\Pr[\mathbf{X} \leq c \mathbb{E}[\mathbf{X}]]$

# Markov Inequality: Example



Markov 1: For every  $c > 0$ :

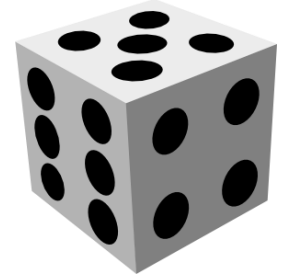
$$\Pr[\mathbf{X} \geq c \mathbb{E}[\mathbf{X}]] \leq \frac{1}{c}$$

- Example:

$$\begin{aligned} \Pr[\textit{Value} \geq 1.5 \cdot \mathbb{E}[\textit{Value}]] &= \Pr[\textit{Value} \geq 1.5 \cdot 3.5] = \\ \Pr[\textit{Value} \geq 5.25] &\leq \frac{1}{1.5} = \frac{2}{3} \end{aligned}$$

$$\begin{aligned} \Pr[\textit{Value} \geq 2 \cdot \mathbb{E}[\textit{Value}]] &= \Pr[\textit{Value} \geq 2 \cdot 3.5] \\ &= \Pr[\textit{Value} \geq 7] \leq \frac{1}{2} \end{aligned}$$

# Markov Inequality: Example



Markov 2: For every  $c > 0$ :

$$\Pr[X \geq c] \leq \frac{\mathbb{E}[X]}{c}$$

- Example:

$$\Pr[Value \geq 4] \leq \frac{\mathbb{E}[Value]}{4} = \frac{3.5}{4} = 0.875 (= 0.5)$$

$$\Pr[Value \geq 5] \leq \frac{\mathbb{E}[Value]}{5} = \frac{3.5}{5} = 0.7 \quad (\approx 0.33)$$

$$\Pr[Value \geq 6] \leq \frac{\mathbb{E}[Value]}{6} = \frac{3.5}{6} \approx 0.58 \quad (\approx 0.17)$$

$$\Pr[Value \geq 3] \leq \frac{\mathbb{E}[Value]}{3} = \frac{3.5}{3} \approx 1.17 \quad (= 1)$$

# Markov Inequality: Example



Markov 2: For every  $c > 0$ :

$$\Pr[X \geq c] \leq \frac{\mathbb{E}[X]}{c}$$

- $\Pr[Value \leq z] = \Pr[(7 - Value) \geq z]$ :

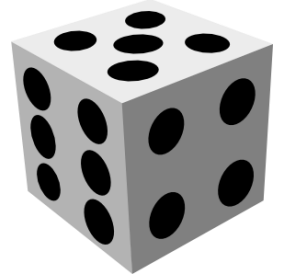
$$\Pr[Value \leq 3] \leq \frac{\mathbb{E}[7 - Value]}{4} = \frac{3.5}{4} = 0.875 \quad (= \mathbf{0.5})$$

$$\Pr[Value \leq 2] \leq \frac{\mathbb{E}[7 - Value]}{5} = \frac{3.5}{5} = 0.7 \quad (\approx \mathbf{0.33})$$

$$\Pr[Value \leq 1] \leq \frac{\mathbb{E}[7 - Value]}{6} = \frac{3.5}{6} \approx 0.58 \quad (\approx \mathbf{0.17})$$

$$\Pr[Value \leq 4] \leq \frac{\mathbb{E}[7 - Value]}{3} = \frac{3.5}{3} \approx 1.17 \quad (= \mathbf{1})$$

# Markov + Union Bound: Example



Markov 2: For every  $c > 0$ :

$$\Pr[\mathbf{X} \geq c] \leq \frac{\mathbb{E}[\mathbf{X}]}{c}$$

- Example:

$$\begin{aligned} \Pr[\textit{Value} \geq 4 \textit{ or } \textit{Value} \leq 3] &\leq \\ \Pr[\textit{Value} \geq 4] + \Pr[\textit{Value} \leq 3] &= 2 \cdot 0.875 = 1.75 \\ &(\mathbf{= 1}) \end{aligned}$$

$$\begin{aligned} \Pr[\textit{Value} \geq 5 \textit{ or } \textit{Value} \leq 2] &\leq 2 \cdot 0.7 = 1.4 \\ &(\mathbf{\approx 0.66}) \end{aligned}$$

$$\begin{aligned} \Pr[\textit{Value} \geq 6 \textit{ or } \textit{Value} \leq 1] &\leq 2 \cdot 0.58 \approx 1.16 \\ &(\mathbf{\approx 0.33}) \end{aligned}$$

# Chebyshev's Inequality

- For every  $c > 0$ :

$$\Pr \left[ |\mathbf{X} - \mathbb{E}[\mathbf{X}]| \geq c \sqrt{\text{Var}[\mathbf{X}]} \right] \leq \frac{1}{c^2}$$

- Proof:

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

# Chebyshev's Inequality

- For every  $c > 0$ :

$$\Pr \left[ |\mathbf{X} - \mathbb{E}[\mathbf{X}]| \geq c \sqrt{\text{Var}[\mathbf{X}]} \right] \leq \frac{1}{c^2}$$

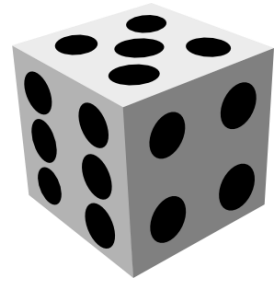
- **Corollary** ( $c' = c \sqrt{\text{Var}[\mathbf{X}]}$ ):

For every  $c' > 0$ :

$$\Pr[|\mathbf{X} - \mathbb{E}[\mathbf{X}]| \geq c'] \leq \frac{\text{Var}[\mathbf{X}]}{c'^2}$$



# Chebyshev: Example



- For every  $c' > 0$ :  $\Pr[|X - \mathbb{E}[X]| \geq c'] \leq \frac{\text{Var}[X]}{c'^2}$

$$\mathbb{E}[\text{Value}] = 3.5; \text{Var}[\text{Value}] \approx 2.91$$

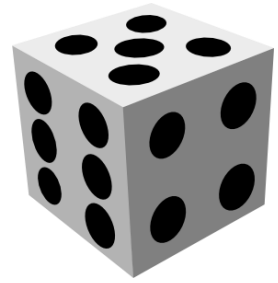
$$\Pr[\text{Value} \geq 4 \text{ or } \text{Value} \leq 3] =$$

$$\Pr[|\text{Value} - 3.5| > 0.5] \leq \frac{2.91}{0.5^2} \approx 11.64 (= \mathbf{1})$$

$$\Pr[\text{Value} \geq 5 \text{ or } \text{Value} \leq 2] \leq \frac{2.91}{1.5^2} \approx 1.29 \quad (\approx \mathbf{0.66})$$

$$\Pr[\text{Value} \geq 6 \text{ or } \text{Value} \leq 1] \leq \frac{2.91}{2.5^2} \approx 0.47 \quad (\approx \mathbf{0.33})$$

# Chebyshev: Example



- Roll a dice 10 times:

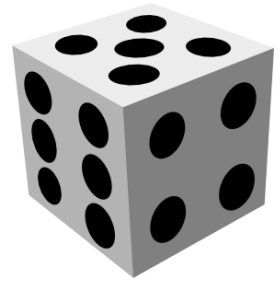
$Value_{10}$  = Average value over 10 rolls

$\Pr[Value_{10} \geq 4 \text{ or } Value_{10} \leq 3] = ?$

- $X_i$  = value of the  $i$ -th roll,  $\mathbf{X} = \frac{1}{10} \sum_{i=1}^{10} X_i$
- Variance (= by linearity for **independent** r.vs):

$$\begin{aligned} Var[\mathbf{X}] &= Var\left[\frac{1}{10} \sum_{i=1}^{10} X_i\right] = \frac{1}{100} Var\left[\sum_{i=1}^{10} X_i\right] \\ &= \frac{1}{100} \sum_{i=1}^{10} Var[X_i] \approx \frac{1}{100} \cdot 10 \cdot 2.91 = 0.291 \end{aligned}$$

# Chebyshev: Example



- Roll a dice 10 times:

$Value_{10}$  = Average value over 10 rolls

$\Pr[Value_{10} \geq 4 \text{ or } Value_{10} \leq 3] = ?$

- $Var[Value_{10}] = 0.291$  (if  $n$  rolls then  $2.91 / n$ )
- $\Pr[Value_{10} \geq 4 \text{ or } Value_{10} \leq 3] \leq \frac{0.291}{0.5^2} \approx 1.16$
- $\Pr[Value_n \geq 4 \text{ or } Value_n \leq 3] \leq \frac{2.91}{n \cdot 0.5^2} \approx \frac{11.6}{n}$

# Chernoff bound

- Let  $X_1 \dots X_t$  be independent and identically distributed r.v.s with range  $[0,1]$  and expectation  $\mu$ .
- Then if  $X = \frac{1}{t} \sum_i X_i$  and  $1 > \delta > 0$ ,

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

# Chernoff bound (corollary)

- Let  $X_1 \dots X_t$  be independent and identically distributed r.v.s with range  $[0, \mathbf{c}]$  and expectation  $\mu$ .

- Then if  $X = \frac{1}{t} \sum_i X_i$  and  $1 > \delta > 0$ ,

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

# Chernoff: Example



- $\Pr[|X - \mu| \geq \delta\mu] \leq 2 \exp\left(-\frac{\mu t \delta^2}{3c}\right)$
- Roll a dice 10 times:
  - $Value_{10}$  = Average value over 10 rolls
  - $\Pr[Value_{10} \geq 4 \text{ or } Value_{10} \leq 3] = ?$
  - $X = Value_{10}, t = 10, c = 6$
  - $\mu = \mathbb{E}[X_i] = 3.5$
  - $\delta = \frac{0.5}{3.5} = \frac{1}{7}$
- $\Pr[Value_{10} \geq 4 \text{ or } Value_{10} \leq 3] \leq 2 \exp\left(-\frac{3.5 \cdot 10}{3 \cdot 6 \cdot 49}\right) = 2 \exp\left(-\frac{35}{882}\right) \approx 2 \cdot 0.96 = 1.92$

# Chernoff: Example



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

- Roll a dice 1000 times:

$Value_{1000}$  = Average value over 1000 rolls

$$\Pr[Value_{1000} \geq 4 \text{ or } Value_{1000} \leq 3] = ?$$

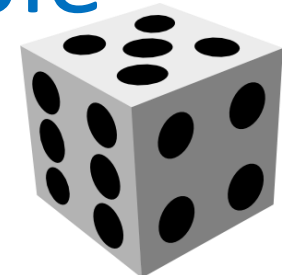
- $X = Value_{1000}$ ,  $t = 1000$ ,  $c = 6$

- $\mu = \mathbb{E}[X_i] = 3.5$

- $\delta = \frac{0.5}{3.5} = \frac{1}{7}$

- $\Pr[Value_{10} \geq 4 \text{ or } Value_{10} \leq 3] \leq$   
 $2 \exp\left(-\frac{3.5 \cdot 1000}{3 \cdot 6 \cdot 49}\right) = 2 \exp\left(-\frac{3500}{882}\right) \approx$   
 $2 \cdot \exp(-3.96) \approx 2 \cdot 0.02 = 0.04$

# Chernoff v.s Chebyshev: Example



Let  $\sigma = \text{Var}[X_i]$  :

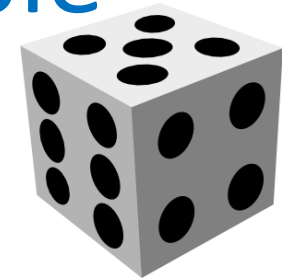
- Chebyshev:  $\Pr[|\mathbf{X} - \mu| \geq c'] \leq \frac{\text{Var}[\mathbf{X}]}{c'^2} = \frac{\sigma}{t c'^2}$
- Chernoff:  $\Pr[|X - \mu| \geq \delta\mu] \leq 2 \exp\left(-\frac{\mu t \delta^2}{3c}\right)$

If  $t$  is very big:

- Values  $\mu, \sigma, \delta, c, c'$  are all constants!
  - Chebyshev:  $\Pr[|\mathbf{X} - \mu| \geq z] = O\left(\frac{1}{t}\right)$
  - Chernoff:  $\Pr[|\mathbf{X} - \mu| \geq z] = e^{-\Omega(t)}$



# Chernoff v.s Chebyshev: Example



Large values of  $t$  is exactly what we need!

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

So is Chernoff always better for us?

- Yes, if we have i.i.d. variables.
- No, if we have dependent or only pairwise independent random variables.
- If the variables are not identical – Chernoff-type bounds exist.

# Answers to the puzzles

You see a sequence of values  $a_1, \dots, a_n$ , arriving one by one:

- **(Easy)**
  - If all  $a_i$ 's are different and have values between 1 and  $n + 1$ , which value is missing?
  - You have  $O(\log n)$  space
  - **Answer:** missing value =  $\sum_{i=1}^n i - \sum_{i=1}^n a_i$
- **(Harder)**
  - How can you maintain a uniformly random sample of  $S$  values out of those you have seen so far?
  - You can store exactly  $S$  values at any time
  - **Answer:** Store first  $a_1, \dots, a_S$ . When you see  $a_i$  for  $i > S$ , with probability  $S/i$  replace random value from your storage with  $a_i$ .

## Part 3: Morris's Algorithm

- **(Very hard, “Count the number of players”)**
  - What is the total number of values 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  $X_n$

$$\begin{aligned}\mathbb{E}[2^{X_n}] &= \sum_{j=0}^{\infty} \Pr[X_{n-1} = j] \mathbb{E}[2^{X_n} | X_{n-1} = j] \\ &= \sum_{j=0}^{\infty} \Pr[X_{n-1} = j] \left( \frac{1}{2^j} 2^{j+1} + \left(1 - \frac{1}{2^j}\right) 2^j \right) \\ &= \sum_{j=0}^{\infty} \Pr[X_{n-1} = j] (2^j + 1) = 1 + \mathbb{E}[2^{X_{n-1}}]\end{aligned}$$

# 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  $\frac{1}{2^X}$

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

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

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

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

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

# 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  $\frac{1}{2^X}$
- $\mathbb{E}[2^X] = n + 1, \text{Var}[2^X] = O(n^2)$
- Is this good?

# Morris's Algorithm: Beta-version

Maintains  $t$  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  $Z = \frac{1}{t} (\sum_{i=1}^t 2^{X^i} - 1)$
- $\mathbb{E}[2^{X^i}] = n + 1, \text{Var}[2^{X^i}] = O(n^2)$
- $\text{Var}[Z] = \text{Var} \left( \frac{1}{t} \sum_{j=1}^t 2^{X^j} - 1 \right) = O \left( \frac{n^2}{t} \right)$
- Claim: If  $t \geq \frac{c}{\epsilon^2}$  then  $\Pr[|Z - n| > \epsilon n] < 1/3$



# Morris's Algorithm: Beta-version

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

- Output  $Z = \frac{1}{t} (\sum_{i=1}^t 2^{X^i} - 1)$
- $Var[Z] = Var \left( \frac{1}{t} \sum_{j=1}^t 2^{X^j} - 1 \right) = O \left( \frac{n^2}{t} \right)$
- 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  $Z^m$ .

Maintains  $t$  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:  $\Pr[|Z^m - n| > \epsilon n] \leq \delta$

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

# Thank you!

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