

# Randomness and Computation

or, “Randomized Algorithms”

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(Based on slides by M. Cryan)

# Bounding deviation

We already have ...

## Theorem (3.1, Markov's Inequality)

Let  $X$  be any random variable that takes only non-negative values. Then for any  $a > 0$ ,

$$\Pr[X \geq a] \leq \frac{E[X]}{a}.$$

## Theorem (3.2, Chebyshev's Inequality)

For every  $a > 0$ ,

$$\Pr[|X - E[X]| \geq a] \leq \frac{\text{Var}[X]}{a^2}.$$

These are **generic**. Chernoff/Hoeffding bounds (specific) give tighter bounds for **sums of independent variables** and related distributions.

## Chernoff bounds — upper tail

*Poisson trials* - sequence of Bernoulli variables  $X_i$  with varying  $p_i$ s.

### Theorem (4.4, basic form)

Let  $X_1, \dots, X_n$  be independent Bernoulli random variables with parameter  $p_i$  for  $i \in [n]$ . Let  $X = \sum_{i=1}^n X_i$ , and  $\mu = E[X]$ . Then for any  $\delta > 0$ ,

$$\Pr[X \geq (1 + \delta)\mu] \leq \left( \frac{e^\delta}{(1 + \delta)^{1+\delta}} \right)^\mu.$$

For example, if  $\mu = pn$  and  $\delta = 1$ ,

$$\Pr[X \geq 2\mu] \leq \left( \frac{e}{4} \right)^{pn} = \exp(-\Omega(n)).$$

## Comparing with Chebyshev's inequality

Theorem (4.4, basic Chernoff)

$$\Pr[X \geq (1 + \delta)\mu] \leq \left( \frac{e^\delta}{(1+\delta)^{(1+\delta)}} \right)^\mu.$$

Consider the case where  $p_i = p$  and  $\mu = pn$ . Due to independence,  $\text{Var}[X_i] = p - p^2$  and  $\text{Var}[X] = (p - p^2)n = \mu(1 - p)$ . With Chebyshev's inequality

$$\begin{aligned} \Pr[X \geq (1 + \delta)\mu] &\leq \Pr[|X - \mu| \geq \delta\mu] \\ &\leq \frac{\mu(1 - p)}{\delta^2\mu^2} = \frac{1 - p}{\delta^2\mu} = O(1/n). \end{aligned}$$

Thus, Chebyshev gives an **inverse polynomial** tail whereas Chernoff gives us an **exponential** tail.

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Theorem (4.4, basic Chernoff)

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$$\begin{aligned} \Pr[X \geq (1 + \delta)\mu] &\leq \Pr[|X - \mu| \geq \delta\mu] \\ &\leq \frac{\mu(1 - p)}{\delta^2\mu^2} = \frac{1 - p}{\delta^2\mu} = O(1/n). \end{aligned}$$

Thus, Chebyshev gives an **inverse polynomial** tail whereas Chernoff gives us an **exponential** tail.

However, both give us constant concentration bound for a window of width  $O(\sqrt{n})$ , although Chernoff's constant is much better.

# Chernoff bounds — upper tail

## Lemma

Let  $X_1, \dots, X_n$  and  $X$  be the same as before and  $\mu = E[X]$ . For any  $t \in \mathbb{R}$ ,

$$E[e^{tX}] \leq e^{\mu(e^t-1)}.$$

## Proof.

Consider

$$E[e^{tX}] = E\left[e^{t(\sum_{i=1}^n X_i)}\right] = E\left[\prod_{i=1}^n e^{tX_i}\right].$$

The  $X_i$  and hence the  $e^{tX_i}$  are mutually independent, so by Thm 3.3,  $E[e^{tX}] = \prod_{i=1}^n E[e^{tX_i}]$ . Each  $e^{tX_i}$  has expectation

$$\begin{aligned} E[e^{tX_i}] &= p_i \cdot e^t + (1 - p_i) \cdot 1 \\ &= 1 + p_i(e^t - 1) \\ &\leq e^{p_i(e^t-1)} \quad (\text{by } 1 + x \leq e^x \text{ for } x \in \mathbb{R}) \end{aligned}$$

$$\Rightarrow E[e^{tX}] \leq \prod_{i=1}^n e^{p_i(e^t-1)} = e^{\sum_{i=1}^n p_i(e^t-1)} = e^{\mu(e^t-1)}. \quad \square$$

# Chernoff bounds — upper tail

## Proof of Thm 4.4.

The event of interest is

$$X \geq (1 + \delta)\mu \Leftrightarrow e^X \geq e^{(1+\delta)\mu}$$

which, in turn, is equivalent to  $e^{tX} \geq e^{t(1+\delta)\mu}$  for any  $t > 0$ .

$$\begin{aligned} \Pr[X \geq (1 + \delta)\mu] &= \Pr[e^{tX} \geq e^{t(1+\delta)\mu}] \\ &\leq \frac{\mathbf{E}[e^{tX}]}{e^{t(1+\delta)\mu}} && \text{(by Markov's Inequality)} \\ &\leq \frac{e^{\mu(e^t-1)}}{e^{t(1+\delta)\mu}} \cdot && \text{(by the last Lemma)} \end{aligned}$$

# Chernoff bounds — upper tail

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$$\begin{aligned} \Pr[X \geq (1 + \delta)\mu] &= \Pr[e^{tX} \geq e^{t(1+\delta)\mu}] \\ &\leq \frac{\mathbb{E}[e^{tX}]}{e^{t(1+\delta)\mu}} && \text{(by Markov's Inequality)} \\ &\leq \frac{e^{\mu(e^t-1)}}{e^{t(1+\delta)\mu}} && \text{(by the last Lemma)} \end{aligned}$$

This holds for any  $t > 0$ , and we want to pick  $t$  to minimize the right hand side, which is  $RHS := e^{\mu(e^t-1)-t(1+\delta)\mu}$ . Differentiate the exponent,

$$(\ln RHS)' = \mu e^t - (1 + \delta)\mu.$$

Thus,  $RHS$  decreases if  $t \leq \ln(1 + \delta)$  and increases if  $t \geq \ln(1 + \delta)$ . Its minimum is taken at  $t = \ln(1 + \delta)$ .



# Chernoff bounds — upper tail

## Proof of Thm 4.4 (cont.)

Now take  $t = \ln(1 + \delta)$  (and note this is  $> 0$ ) to see

$$\begin{aligned}\Pr[X \geq (1 + \delta)\mu] &\leq e^{\mu(e^t - 1) - t(1 + \delta)\mu} \\ &\leq \frac{e^{\mu(e^{\ln(1 + \delta)} - 1)}}{e^{\ln(1 + \delta)(1 + \delta)\mu}} \\ &= \frac{e^{\mu\delta}}{(1 + \delta)^{(1 + \delta)\mu}} = \left( \frac{e^\delta}{(1 + \delta)^{(1 + \delta)}} \right)^\mu. \quad \square\end{aligned}$$

# Chernoff bounds — upper tail

## Theorem (4.4, full)

Let  $X_1, \dots, X_n$  be independent Bernoulli random variables with parameter  $p_i$  for  $i \in [n]$ . Let  $X = \sum_{i=1}^n X_i$ , and  $\mu = E[X]$ .

1. For any  $\delta > 0$ ,

$$\Pr[X \geq (1 + \delta)\mu] \leq \left( \frac{e^\delta}{(1 + \delta)^{1+\delta}} \right)^\mu;$$

2. For any  $0 < \delta \leq 1$ ,

$$\Pr[X \geq (1 + \delta)\mu] \leq e^{-\mu\delta^2/3};$$

3. For  $R \geq 6\mu$ ,

$$\Pr[X \geq R] \leq 2^{-R}.$$

## Chernoff bounds — upper tail

### Proof of Thm 4.4 (2.)

Already have

$$\Pr[X \geq (1 + \delta)\mu] \leq \left( \frac{e^\delta}{(1 + \delta)^{(1 + \delta)}} \right)^\mu.$$

Comparing the RHS with  $\leq e^{-\mu\delta^2/3}$ , we want

$$\delta - (1 + \delta) \ln(1 + \delta) < -\delta^2/3$$

We will show the following  $f$  is always negative for  $\delta \in (0, 1)$

$$f(\delta) := \delta - (1 + \delta) \ln(1 + \delta) + \delta^2/3$$

Differentiating,

$$\begin{aligned} f'(\delta) &= 1 - \ln(1 + \delta) - (1 + \delta) \frac{1}{1 + \delta} + \frac{2\delta}{3} \\ &= -\ln(1 + \delta) + \frac{2\delta}{3}. \end{aligned}$$

# Chernoff bounds — upper tail

Proof of Thm 4.4 (2.) cont.

$$f'(\delta) = -\ln(1 + \delta) + \frac{2\delta}{3}.$$

Differentiate again

$$f''(\delta) = -\frac{1}{1 + \delta} + \frac{2}{3} = -\frac{1}{1 + \delta} + \frac{2}{3}$$

Note

$$f''(\delta) \begin{cases} < 0 & \text{for } 0 < \delta < 1/2; \\ = 0 & \text{for } \delta = 1/2; \\ > 0 & \text{for } \delta > 1/2. \end{cases}$$

# Chernoff bounds — upper tail

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$$f'(\delta) = -\ln(1 + \delta) + \frac{2\delta}{3}.$$

Differentiate again

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Also  $f'(0) = 0$ ,  $f'(1) \approx -0.026 < 0$  (check  $\delta = 1$  in top equation). Since  $f'$  decreases from 0 to 1/2 and then increases from 1/2 to 1, we have that  $f'(\delta) < 0$  on  $(0, 1)$ .

# Chernoff bounds — upper tail

Proof of Thm 4.4 (2.) cont.

$$f'(\delta) = -\ln(1 + \delta) + \frac{2\delta}{3}.$$

Differentiate again

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By  $f(0) = 0$ , this implies that  $f(\delta) \leq 0$  in all of  $[0, 1]$ .

Hence  $\delta - (1 + \delta) \ln(1 + \delta) < -\delta^2/3$ , proving (2.). □

## Chernoff bounds — upper tail

For  $R \geq 6\mu$ ,

$$\Pr[X \geq R] \leq 2^{-R}.$$

### Proof of Thm 4.4 (3.)

Let  $R = (1 + \delta)\mu$  and thus  $\delta = R/\mu - 1 \geq 5$ . By Thm 4.4 (1.)

$$\begin{aligned}\Pr[X \geq (1 + \delta)\mu] &\leq \left( \frac{e^\delta}{(1 + \delta)^{1+\delta}} \right)^\mu \\ &= \left( \frac{e^{\frac{\delta}{1+\delta}}}{1 + \delta} \right)^{(1+\delta)\mu} \leq \left( \frac{e}{1 + \delta} \right)^{(1+\delta)\mu} \\ &\leq \left( \frac{e}{6} \right)^R \leq 2^{-R}\end{aligned}$$

□

## Chernoff bounds — upper tail

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### Proof of Thm 4.4 (3.)

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$$\begin{aligned}\Pr[X \geq (1 + \delta)\mu] &\leq \left( \frac{e^\delta}{(1 + \delta)^{1+\delta}} \right)^\mu \\ &= \left( \frac{e^{\frac{\delta}{1+\delta}}}{1 + \delta} \right)^{(1+\delta)\mu} \leq \left( \frac{e}{1 + \delta} \right)^{(1+\delta)\mu} \\ &\leq \left( \frac{e}{6} \right)^R \leq 2^{-R} \quad \square\end{aligned}$$

Thm 4.4 (1.) is the strongest. The other two are slightly weaker but easy to use.



## Chernoff Bounds (lower tail)

### Theorem (4.5)

Let  $X_1, \dots, X_n$  be independent Poisson trials such that  $\Pr[X_i = 1] = p_i$  for all  $i \in [n]$ . Let  $X = \sum_{i=1}^n X_i$ , and  $\mu = E[X]$ . For any  $0 < \delta < 1$ , we have the following Chernoff bounds:

1.

$$\Pr[X \leq (1 - \delta)\mu] \leq \left( \frac{e^{-\delta}}{(1 - \delta)^{1-\delta}} \right)^\mu;$$

2.

$$\Pr[X \leq (1 - \delta)\mu] \leq e^{-\mu\delta^2/2};$$

- ▶ Proof is similar to Thm 4.4.
- ▶ Bound of (2.) is slightly *better* than the bound for  $\geq (1 + \delta)\mu$ .
- ▶ No (3.) Why?

# Concentration

## Corollary (4.6)

Let  $X_1, \dots, X_n$  be independent Bernoulli rv such that  $\Pr[X_i = 1] = p_i$  for all  $i \in [n]$ . Let  $X = \sum_{i=1}^n X_i$ , and  $\mu = E[X]$ . Then for any  $\delta, 0 < \delta < 1$ ,

$$\Pr[|X - \mu| \geq \delta\mu] \leq 2e^{-\mu\delta^2/3}.$$

- ▶ For most applications, we will want to work with a *symmetric* version like the Corollary.
- ▶ We “threw away” a bit in moving from the  $\left(\frac{e^{\pm\delta}}{(1\pm\delta)^{1\pm\delta}}\right)^\mu$  versions, but they are tricky to work with.

## Analysing a collection of coin flips

Suppose we have  $p_i = 1/2$  for all  $i \in [n]$ .

We have  $\mu = \mathbb{E}[X] = \frac{n}{2}$ ,  $\text{Var}[X] = \frac{n}{4}$ .

Consider the probability of being further than  $5\sqrt{n}$  from  $\mu$ .

$$\text{Chebyshev } \Pr[|X - \mu| \geq 5\sqrt{n}] \leq \frac{\text{Var}[X]}{25n} = \frac{1}{100}$$

## Analysing a collection of coin flips

Suppose we have  $p_i = 1/2$  for all  $i \in [n]$ .

We have  $\mu = E[X] = \frac{n}{2}$ ,  $\text{Var}[X] = \frac{n}{4}$ .

Consider the probability of being further than  $5\sqrt{n}$  from  $\mu$ .

**Chebyshev**  $\Pr[|X - \mu| \geq 5\sqrt{n}] \leq \frac{\text{Var}[X]}{25n} = \frac{1}{100}$

**Chernoff** Work out the  $\delta$  – we need  $\mu\delta = 5\sqrt{n}$ , so need  
 $\delta = 5\sqrt{n}/\mu = 10\sqrt{n}/n = \frac{10}{\sqrt{n}}$ . Then by Chernoff

$$\Pr[|X - \mu| \geq 5\sqrt{n}] \leq 2e^{-\mu\delta^2/3} = 2e^{\frac{-10^2 \cdot n}{2 \cdot 3 \cdot \sqrt{n}^2}} = 2e^{-16.6\dots}$$

This is much smaller than the Chebyshev bound (though note it doesn't depend on  $n$ ).

Get much improved bounds because Chernoff uses specialised analysis for sums of independent Bernoulli variables.

## Comparison with Chebyshev

For i.i.d. coin flips,

$$\Pr[|X - \mu| > D] \leq p$$

Deviation $p$	Constant	$O(\frac{1}{n^c})$	$\exp(-\Omega(n))$
$D$ for Chebyshev	$\Omega(\sqrt{n})$	$\Omega(\sqrt{n} \cdot n^{c/2})$	$\exp(\Omega(n))$
$D$ for Chernoff	$\Omega(\sqrt{n})$	$\Omega(\sqrt{n}(\log n)^{c/2})$	$\Omega(n)$

## Unbiased $+1/-1$ variables

In fact, for the case of unbiased variables, we can do even better than  $2e^{-\mu\delta^2/3}$ . We first switch to  $+1/-1$  variables.

### Theorem (4.7)

Let  $X_1, \dots, X_n$  be independent random variables with  $\Pr[X_i = 1] = 1/2 = \Pr[X_i = -1]$  for all  $i \in [n]$ . Let  $X = \sum_{k=1}^n X_k$ . Note  $\mu = E[X] = 0$ . Then for any  $a > 0$ ,

$$\Pr[X \geq a] \leq e^{-a^2/2n}.$$

### Proof.

We will once again consider the moment generating function  $e^{tX_i}$ :

$$E[e^{tX_i}] = \frac{e^t + e^{-t}}{2} \leq e^{t^2/2},$$

where the last estimate is due to Taylor expansion. □

# Unbiased $+1/ - 1$ variables

Proof of Thm 4.7 cont.

Use the last estimate

$$\mathbb{E} [e^{tX}] = \prod_{i=1}^n \mathbb{E} [e^{tX_i}] \leq e^{t^2 n/2};$$

## Unbiased $+1/ - 1$ variables

Proof of Thm 4.7 cont.

Use the last estimate

$$\mathbb{E} [e^{tX}] = \prod_{i=1}^n \mathbb{E} [e^{tX_i}] \leq e^{t^2 n/2};$$

$$\Pr[X \geq a] = \Pr[e^{tX} \geq e^{ta}] \leq \frac{\mathbb{E}[e^{tX}]}{e^{ta}} = e^{t^2 n/2 - ta}.$$

Once again, minimizing the exponent gives us  $t = a/n$  and

$$\Pr[X \geq a] \leq e^{-a^2/2n}.$$

□



## Unbiased $+1/ - 1$ variables

Proof of Thm 4.7 cont.

Use the last estimate

$$\mathbb{E} [e^{tX}] = \prod_{i=1}^n \mathbb{E} [e^{tX_i}] \leq e^{t^2 n/2};$$

$$\Pr[X \geq a] = \Pr[e^{tX} \geq e^{ta}] \leq \frac{\mathbb{E}[e^{tX}]}{e^{ta}} = e^{t^2 n/2 - ta}.$$

Once again, minimizing the exponent gives us  $t = a/n$  and

$$\Pr[X \geq a] \leq e^{-a^2/2n}.$$

□

The lower tail is completely symmetric. Think  $-X$ .

$$\Pr[X \leq -a] = \Pr[-X \geq a] \leq e^{-a^2/2n}.$$

## Unbiased $+1/-1$ variables

### Corollary (4.8)

Let  $X_1, \dots, X_n$  be independent random variables with  $\Pr[X_i = 1] = 1/2 = \Pr[X_i = -1]$  for all  $i \in [n]$ . Let  $X = \sum_{k=1}^n X_k$ . Note  $\mu = E[X] = 0$ . Then for any  $a > 0$ ,

$$\Pr[|X| \geq a] \leq 2e^{-a^2/2n}.$$

## Unbiased 0/1 variables

Consider  $Y_1, \dots, Y_n$  such that  $\Pr[Y_i = 1] = 1/2$  for every  $i \in [n]$ . Define  $X_i = 2Y_i - 1$  for every  $i \in [n]$ . Then

$$X_i = \begin{cases} 1 & | Y_i = 1 \\ -1 & | Y_i = 0 \end{cases}$$

Note also that for any  $t \in \mathbb{Z}$ , that

$$\sum_{i=1}^n Y_i = t \quad \Leftrightarrow \quad \sum_{i=1}^n X_i = 2t - n$$

### Corollary (4.9, 4.10)

For  $Y = \sum_{i=1}^n Y_i$ ,  $X = \sum_{i=1}^n X_i$ , we have

$$\begin{aligned} \Pr[Y \geq \frac{n}{2} + a] &= \Pr[X \geq 2a] \leq e^{-2a^2/n}; \\ \Pr[Y \leq \frac{n}{2} - a] &= \Pr[X \leq -2a] \leq e^{-2a^2/n}. \end{aligned}$$

Say  $\mu = \mathbb{E}[Y] = n/2$  and  $a = \delta\mu$ . The bound is

$$e^{-2a^2/n} = e^{-2\delta^2\mu^2/(2\mu)} = e^{-\delta^2\mu}.$$

# References

- ▶ Chapter 4 of [MU]
- ▶ We will continue with Chernoff Bounds on Friday.
- ▶ We will not have time to cover the packet routing analysis of 4.5, but it's worth reading (not examinable in the exam).