

TTIC 31150/CMSC 31150  
Mathematical Toolkit (Spring 2023)

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Lecture 12: Tail inequalities 2

# Recap

- The probabilistic method, coupon collector problem, DeMillo-Lipton-Schwartz-Zippel lemma, polynomial identity testing, application of DLSZ to finding perfect matchings.
- Basic tail inequalities: Markov's inequality and Chebyshev's inequality.
- Properties of variance:  $Var(\sum_i X_i) = \sum_i Var(X_i)$  if **pairwise** independent.
- Markov vs Chebyshev for coin flips.
- Threshold phenomena in random graphs.

# Markov and Chebyshev

**Proposition 1.1 (Markov's Inequality)** *Let  $X$  be non-negative variable. Then,*

$$\mathbb{P} [X \geq t] \leq \frac{\mathbb{E} [X]}{t}. \quad (1)$$

*Equivalently,*

$$\mathbb{P} [X \geq a \cdot \mathbb{E} [X]] \leq \frac{1}{a}. \quad (2)$$

**Proposition 1.2 (Chebyshev's inequality)** *Let  $X$  be a random variable and let  $\mu = \mathbb{E} [X]$ . Then,*

$$\mathbb{P} [ |X - \mu| \geq t ] \leq \frac{\text{Var} [X]}{t^2} = \frac{\mathbb{E} [(X - \mu)^2]}{t^2}. \quad (3)$$

# Threshold phenomena in Random Graphs

Consider a graph  $G$  on  $n$  vertices where each possible edge is placed into the graph independently with probability  $p$ . This is called the  $G_{n,p}$  random graph model.

It turns out that many graph properties have “threshold phenomena”: for some function  $f(n)$ , for  $p \ll f(n)$  the graph will almost surely not have the property and for  $p \gg f(n)$  the graph almost surely will have the property (or vice-versa).

One example: the property of containing a 4-clique.

# Threshold phenomena in Random Graphs

**Theorem 3.1** *Let  $G$  be generated randomly according to the model  $\mathcal{G}_{n,p}$  graph. Then,*

1. *If  $p \ll n^{-2/3}$ , then  $\mathbb{P}[G \text{ contains a 4-clique}] \rightarrow 0$  as  $n \rightarrow \infty$ .*
2. *If  $p \gg n^{-2/3}$ , then  $\mathbb{P}[G \text{ contains a 4-clique}] \rightarrow 1$  as  $n \rightarrow \infty$ .*

(1) Is the easier case, so let's start with that:

- For each set  $S$  of 4 vertices, define indicator R.V.  $X_S$  for the event that  $S$  is a clique.
- Let  $X = \sum_S X_S$  denote the number of 4-cliques in the graph.
- We have  $\mathbb{E}[X] = \sum_S \mathbb{E}[X_S] = O(n^4 p^6) = o(1)$  for  $p \ll n^{-2/3}$ .
- So, by Markov's inequality,  $\mathbb{P}[X \geq 1] \leq \mathbb{E}[X]/1 = o(1)$ .

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For (2), we have  $\mathbb{E}[X] = \Theta(n^4 p^6) \rightarrow \infty$ , but this is not sufficient to get  $\mathbb{P}[X = 0] = o(1)$ .

For this, we will use Chebyshev's inequality with  $t = \mathbb{E}[X]$ , giving:

$$\mathbb{P}[X = 0] \leq \frac{\text{Var}[X]}{\mathbb{E}[X]^2}$$

Second Moment method

So, if we can show that  $\text{Var}[X] = o(\mathbb{E}[X]^2)$ , we will be done.

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We can write variance as:  $Var[X] = \mathbb{E}[X^2] - \mathbb{E}[X]^2 = \sum_{S,S'} \mathbb{E}[X_S X_{S'}] - \mathbb{E}[X]^2$ .

Let's now consider a few cases for  $S, S'$ :

- If  $S, S'$  share at most 1 vertex in common, then  $X_S$  and  $X_{S'}$  are independent, so  $\mathbb{E}[X_S X_{S'}] = \mathbb{E}[X_S] \mathbb{E}[X_{S'}]$  and the sum over all of these is at most  $\mathbb{E}[X]^2$ . We can therefore cover these using the  $-\mathbb{E}[X]^2$  term.

So, if we can show that  $Var[X] = o(\mathbb{E}[X]^2)$ , we will be done.

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Let's now consider a few cases for  $S, S'$ :

- If  $S, S'$  share 2 vertices in common, there are at most  $O(n^6)$  such cases and each one has  $\mathbb{E}[X_S X_{S'}] = p^{11}$ . So, overall, we get  $O(n^6 p^{11}) = o(n^8 p^{12}) = o(\mathbb{E}[X]^2)$ .

So, if we can show that  $Var[X] = o(\mathbb{E}[X]^2)$ , we will be done.



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Let's now consider a few cases for  $S, S'$ :

- If  $S, S'$  share 3 vertices in common, there are at most  $O(n^5)$  such cases and each one has  $\mathbb{E}[X_S X_{S'}] = p^9$ . So, overall, we get  $O(n^5 p^9) = o(n^8 p^{12}) = o(\mathbb{E}[X]^2)$ .

So, if we can show that  $Var[X] = o(\mathbb{E}[X]^2)$ , we will be done.

# Threshold phenomena in Random Graphs

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We can write variance as:  $Var[X] = \mathbb{E}[X^2] - \mathbb{E}[X]^2 = \sum_{S,S'} \mathbb{E}[X_S X_{S'}] - \mathbb{E}[X]^2$ .

Let's now consider a few cases for  $S, S'$ :

- And finally, if  $S, S'$  share all 4 vertices in common, then the total is just  $\mathbb{E}[X] = o(\mathbb{E}[X]^2)$ .
- So, overall we have  $Var[X] = o(\mathbb{E}[X]^2)$  as desired.

So, if we can show that  $Var[X] = o(\mathbb{E}[X]^2)$ , we will be done.

# Chernoff-Hoeffding bounds

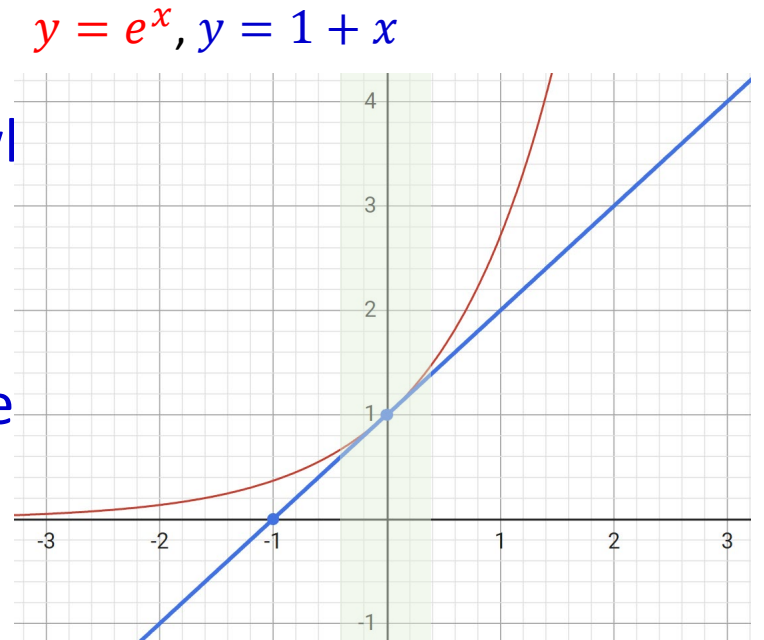
Consider  $n$  mutually independent Bernoulli R.V.s  $X_1, \dots, X_n$ , w/

- Let  $X = \sum_i X_i$ , and let  $\mu = \mathbb{E}[X] = \sum_i p_i$ .

Q: how can we use mutual independence to show that it is ve far from its expectation?

Idea: Define  $Y_i = e^{\lambda X_i}$  for some small  $\lambda > 0$ .

- So, if  $X_i = 0$  then  $Y_i = 1$ , and if  $X_i = 1$  then  $Y_i \approx 1 + \lambda$ .  $\mathbb{E}[Y_i] \approx 1 + p_i \lambda \approx e^{p_i \lambda}$ .
- Now, consider **product**  $Y$  of the  $Y_i$ .  $\mathbb{E}[Y] = \prod_i \mathbb{E}[Y_i] \approx e^{\lambda \sum_i p_i} = e^{\lambda \mathbb{E}[X]}$ .
- By Markov,  $\mathbb{P}[Y \geq k \mathbb{E}[Y]] \leq \frac{1}{k}$ . But since  $X = \frac{\ln Y}{\lambda}$ , this means  $\mathbb{P}\left[X \geq \frac{\ln \mathbb{E}[Y]}{\lambda} + \frac{\ln k}{\lambda}\right] \leq \frac{1}{k}$ .
- And for small  $\lambda$ ,  $\frac{\ln \mathbb{E}[Y]}{\lambda} \approx \mathbb{E}[X]$ . So, even for large  $k$ ,  $X$  is just a little bit larger than  $\mathbb{E}[X]$ .



# Chernoff-Hoeffding bounds

Consider  $n$  mutually independent Bernoulli R.V.s  $X_1, \dots, X_n$ , where  $\mathbb{P}(X_i = 1) = p_i$ .

- Let  $X = \sum_i X_i$ , and let  $\mu = \mathbb{E}[X] = \sum_i p_i$ .

But, we are cheating: these “ $\approx$ ” are not exact and require small  $\lambda$ . So, let's now do this carefully.

Idea: Define  $Y_i = e^{\lambda X_i}$  for some small  $\lambda > 0$ .

- So, if  $X_i = 0$  then  $Y_i = 1$ , and if  $X_i = 1$  then  $Y_i \approx 1 + \lambda$ .  $\mathbb{E}[Y_i] \approx 1 + p_i \lambda \approx e^{p_i \lambda}$ .
- Now, consider **product**  $Y$  of the  $Y_i$ .  $\mathbb{E}[Y] = \prod_i \mathbb{E}[Y_i] \approx e^{\lambda \sum_i p_i} = e^{\lambda \mathbb{E}[X]}$ .
- By Markov,  $\mathbb{P}[Y \geq k \mathbb{E}[Y]] \leq \frac{1}{k}$ . But since  $X = \frac{\ln Y}{\lambda}$ , this means  $\mathbb{P}\left[X \geq \frac{\ln \mathbb{E}[Y]}{\lambda} + \frac{\ln k}{\lambda}\right] \leq \frac{1}{k}$ .
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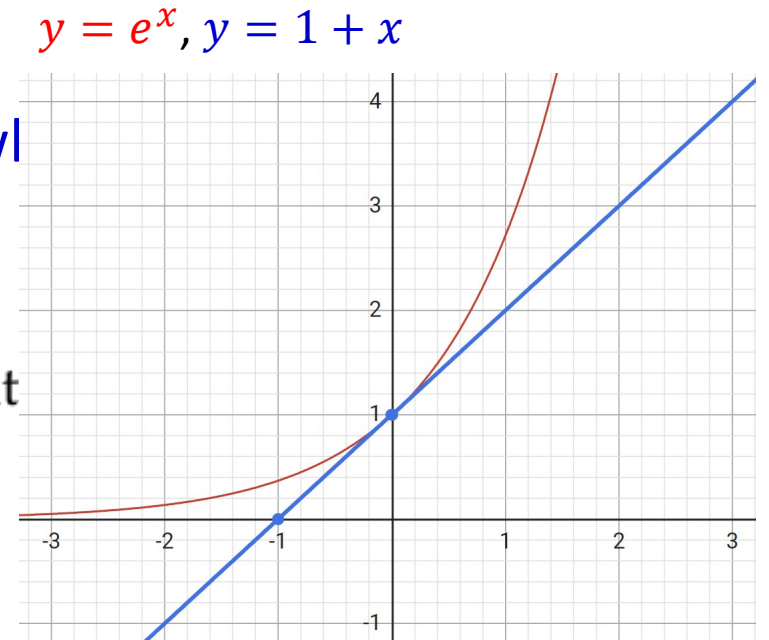
# Chernoff-Hoeffding bounds

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- Let  $X = \sum_i X_i$ , and let  $\mu = \mathbb{E}[X] = \sum_i p_i$ .

Using the fact that the function  $e^x$  is strictly increasing, we get that

$$\mathbb{P}[X \geq (1 + \delta)\mu] = \mathbb{P}[e^{\lambda X} \geq e^{\lambda(1+\delta)\mu}] \stackrel{\text{(Markov)}}{\leq}$$



Let's analyze the numerator:

$$\mathbb{E}[e^{\lambda X}] = \mathbb{E}[e^{\lambda(X_1 + \dots + X_n)}] = \mathbb{E}\left[\prod_{i=1}^n e^{\lambda X_i}\right] \stackrel{\text{(independence)}}{=} \prod_{i=1}^n \mathbb{E}[e^{\lambda X_i}]$$

Now use  $1 + x \leq e^x$  to get

$$\mathbb{E}[e^{\lambda X}] \leq e^{\sum_i p_i(e^\lambda - 1)} = e^{(e^\lambda - 1)\mu}$$

$$= \prod_{i=1}^n [p_i e^\lambda + (1 - p_i)]$$

$$= \prod_{i=1}^n [1 + p_i(e^\lambda - 1)] \leq \prod_{i=1}^n e^{p_i(e^\lambda - 1)}$$

# Chernoff-Hoeffding bounds

So,  $\mathbb{P}[X \geq (1 + \delta)\mu] \leq e^{(e^\lambda - 1)\mu - \lambda(1 + \delta)\mu}$ . Set  $\lambda$  to minimize ( $e^\lambda = 1 + \delta$ ,  $\lambda = \ln(1 + \delta)$ )

Using the fact that the function  $e^x$  is strictly increasing, we get that for  $\lambda > 0$

$$\mathbb{P}[X \geq (1 + \delta)\mu] = \mathbb{P}[e^{\lambda X} \geq e^{\lambda(1 + \delta)\mu}] \stackrel{\text{(Markov)}}{\leq} \frac{\mathbb{E}[e^{\lambda X}]}{e^{\lambda(1 + \delta)\mu}}.$$

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$$= \prod_{i=1}^n [p_i e^\lambda + (1 - p_i)]$$

$$= \prod_{i=1}^n [1 + p_i(e^\lambda - 1)].$$

# Chernoff-Hoeffding bounds

So,  $\mathbb{P}[X \geq (1 + \delta)\mu] \leq e^{(e^\lambda - 1)\mu - \lambda(1 + \delta)\mu}$ . Set  $\lambda$  to minimize ( $e^\lambda = 1 + \delta$ ,  $\lambda = \ln(1 + \delta)$ )

$$\text{Get: } \mathbb{P}[X \geq (1 + \delta)\mu] \leq e^{\mu(\delta - (1 + \delta) \ln(1 + \delta))} = \left( \frac{e^\delta}{(1 + \delta)^{1 + \delta}} \right)^\mu.$$

$$\text{Similarly, } \mathbb{P}[X \leq (1 - \delta)\mu] \leq \left( \frac{e^{-\delta}}{(1 - \delta)^{1 - \delta}} \right)^\mu.$$

For  $\delta \in [0, 1]$  can use Taylor series to simplify to:

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

$$\blacktriangleright \mathbb{P}[X \leq (1 - \delta)\mu] \leq e^{-\delta^2 \mu / 2}$$

$$\begin{aligned} & e^{\delta - (1 + \delta) \ln(1 + \delta)} \\ & \leq e^{\delta - (1 + \delta) \left( \delta - \frac{\delta^2}{2} + \frac{\delta^3}{3} - \frac{\delta^4}{4} + \dots \right)} \\ & = e^{-\frac{\delta^2}{2} + \frac{\delta^3}{6} - \frac{\delta^4}{12} + \dots} \leq e^{-\frac{\delta^2}{3}} \end{aligned}$$

# Comparing vs Chebyshev on fair coin tosses

Consider  $n$  independent fair coin flips  $X_1, \dots, X_n$ ,  $\mathbb{P}(X_i = 1) = \frac{1}{2}$ ,  $X = \sum_i X_i$ ,  $\mu = \mathbb{E}[X] = \frac{n}{2}$

- Chebyshev:  $\mathbb{P}[|X - \mu| \geq \delta\mu] \leq \frac{\text{Var}[X]}{\delta^2\mu^2} = \frac{n/4}{\delta^2(n/2)^2} = \frac{1}{\delta^2n}$ .

- Chernoff/Hoeffding:  $\mathbb{P}[|X - \mu| \geq \delta\mu] \leq 2e^{-\delta^2n/6}$ .

➤ Using  $\delta = k/\sqrt{n}$ , get  $\mathbb{P}[|X - \mu| \geq k\sigma] = e^{-O(k^2)}$ .

**$n = 1000, \mu = 500$**

- Markov  $\mathbb{P}[X > 600] \leq 5/6 \approx \mathbf{0.83}$

- Chebyshev  $\mathbb{P}[X > 600] \leq \mathbb{P}[|X - 500| > 0.2 \times 500] \leq 250/(0.2 \times 500)^2 \approx \mathbf{0.025}$

- Chernoff  $\mathbb{P}[X > 600] \leq \mathbb{P}[|X - 500| > 0.2 \times 500] \leq 2e^{-.2^2 \times 1000/6} \approx \mathbf{0.001}$



# Random Vectors

Suppose we pick  $m$  random vectors  $v_1, \dots, v_m \in \{-1, 1\}^n$ . Clearly,  $\langle v_i, v_i \rangle = n$ .

What about  $\langle v_i, v_j \rangle$  for  $i \neq j$ ? Claim: whp,  $|\langle v_i, v_j \rangle| = O\left(\sqrt{n \log m}\right)$  for all  $i \neq j$ .

So, even though can only have  $n$  truly orthogonal vectors, can have a much larger number of **nearly-orthogonal** vectors.

# Random Vectors

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What about  $\langle v_i, v_j \rangle$  for  $i \neq j$ ? Claim: whp,  $|\langle v_i, v_j \rangle| = O(\sqrt{n \log m})$  for all  $i \neq j$ .

Proof: First, fix some  $i, j$  s.t.  $i \neq j$  (then will do a union bound over all  $\binom{m}{2}$  such pairs).

- For  $k \in \{1, \dots, n\}$  let  $X_k$  be indicator RV for event that  $k$ th coordinate of  $v_i, v_j$  are equal.

- Let  $X = \sum_k X_k$ . By Chernoff/Hoeffding,  $\mathbb{P}\left(\left|X - \frac{n}{2}\right| \geq \frac{\delta n}{2}\right) \leq 2e^{-\delta^2 n/6}$ .

- Notice that  $|\langle v_i, v_j \rangle| = 2\left|X - \frac{n}{2}\right|$ . So, using  $\delta = 6\sqrt{\frac{\ln m}{n}}$  we get:

$$\mathbb{P}\left(|\langle v_i, v_j \rangle| \geq 6\sqrt{n \ln m}\right) = \mathbb{P}\left(2\left|X - \frac{n}{2}\right| \geq 2\frac{\delta n}{2}\right) \leq 2e^{-6 \ln m} = 2m^{-6}.$$

Finally, do a union bound over all  $\binom{m}{2}$  pairs. Overall prob of failure  $\leq m^{-4}$ .

# Balls and Bins revisited

We saw earlier that if we toss balls independently at random into  $n$  bins, it will take an expected  $\Theta(n \log n)$  tosses until there are no empty bins.

Other statistics:

- If toss  $n$  balls into  $n$  bins, what is the expected fraction of empty bins?
  - Let  $X_i$  be indicator R.V. for event that bin  $i$  is empty.  $\mathbb{E}[X_i] = \left(1 - \frac{1}{n}\right)^n \approx \frac{1}{e}$ . So, expected fraction of empty bins is  $\approx 1/e$ .
- If toss  $n$  balls into  $n$  bins, how loaded will the most-loaded bin be?

# Balls and Bins revisited

Claim: if we toss  $n$  balls into  $n$  bins, whp no bin will have more than  $t = \frac{3 \ln n}{\ln \ln n}$  balls.

Proof:

- Let  $X_{ij}$  be indicator RV for event that ball  $j$  is in bin  $i$ . Let  $Z_i = \sum_j X_{ij}$ . What is  $\mathbb{E}[Z_i]$ ?
- $\mathbb{E}[Z_i] = 1$  and is a sum of independent Bernoulli R.V.s, so can apply Chernoff/Hoeffding.

- $\mathbb{P}[Z_i \geq t] \leq \frac{e^{t-1}}{t^t} \leq \left(\frac{e}{t}\right)^t.$

$$\mathbb{P}[Z_i \geq \underbrace{(1 + \delta)\mu}_{=t}] \leq \left(\frac{e^\delta}{(1 + \delta)^{1+\delta}}\right)^\mu$$

- For  $t = \frac{3 \ln n}{\ln \ln n}$  we have  $\left(\frac{e}{t}\right)^t \leq \left(\frac{\ln \ln n}{\ln n}\right)^t = O\left(\left(\frac{1}{\ln n}\right)^{0.9t}\right) = O(e^{-2.7 \ln n}) = O(n^{-2.7}).$

- Now do a union bound over all  $i$ .