

TTIC 31150/CMSC 31150
Mathematical Toolkit (Fall 2024)

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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,*

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

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 $\mu = \mathbb{E}[X] = \sum_i p_i$.

Q: how can we use mutual independence to show that it is very unlikely that X will be *too* far from its expectation?

Intuition: Let's say all $p_i = 0.5$. $X = \#$ heads in a sequence of fair coin flips. Want to show it's unlikely we'll have many more heads than tails.

- Consider this random walk: starting at 1, on heads multiply by $1 + \epsilon$ and on tails multiply by $1 - \epsilon$. Final position $Y = \prod_i Y_i$, where $\Pr[Y_i = 1 + \epsilon] = \Pr[Y_i = 1 - \epsilon] = 0.5$.
- By mutual independence, $\mathbb{E}[Y] = \prod_i \mathbb{E}[Y_i] = \prod_i 1 = 1$.
- By Markov, $\Pr[Y > 1,000,000] < .000001$. But since Y grows multiplicatively, it doesn't take *too* many more heads than tails for Y to get large. (Caveat: $(1 + \epsilon)(1 - \epsilon) = 1 - \epsilon^2$)

Chernoff-Hoeffding bounds

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Now, let's do this for real...

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 for $\lambda > 0$

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

Let's analyze the numerator:

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

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

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

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

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

Chernoff-Hoeffding bounds

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

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Chernoff-Hoeffding bounds

So, $\mathbb{P}[X \geq (1 + \delta)\mu] \leq e^{(e^\lambda - 1)\mu - \lambda(1 + \delta)\mu}$. Set λ 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: $\mathbb{P}[|X - \mu| \geq \delta\mu] \leq \frac{\text{Var}[X]}{\delta^2\mu^2} = \frac{n/4}{\delta^2(n/2)^2} = \frac{1}{\delta^2 n}$.
 - Chernoff/Hoeffding: $\mathbb{P}[|X - \mu| \geq \delta\mu] \leq 2e^{-\delta^2 n/6}$.
- Using $\delta = k/\sqrt{n}$, get $\mathbb{P}[|X - \mu| \geq k\sigma] = e^{-O(k^2)}$.

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, $|\langle v_i, v_j \rangle| = O(\sqrt{n \log m})$ 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:

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

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.

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

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

- 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 .