

Chernoff Bounds

CSC 473 Advanced Algorithms



Variance and Chebyshev

- Let $X_1, \dots, X_n \in \{0,1\}$ be independent random variables
 - Not necessarily uniform or identically distributed

- Remember, for $X = \sum_{i=1}^n X_i$:

$$\mathbb{E}[X] = \sum_{i=1}^n \mathbb{E}[X_i] \quad \text{Var}(X) = \sum_{i=1}^n \text{Var}(X_i) \leq \mathbb{E}[X]$$

- By Chebyshev's inequality:

$$\mathbb{P}(X \geq (1 + \delta)\mathbb{E}[X]) \leq \frac{\text{Var}(X)}{\delta^2 \mathbb{E}[X]^2} \leq \frac{1}{\delta^2 \mathbb{E}[X]}$$



The Chernoff Bound

- Let $X_1, \dots, X_n \in \{0,1\}$ be independent random variables
 - Not necessarily uniform or identically distributed

- Chernoff Bound: if $X = \sum_{i=1}^n X_i$ and $\mathbb{E}[X] \leq \mu$

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

- For $0 \leq \delta \leq 1$, the right hand side is $\leq e^{-\delta^2\mu/3}$
 - Compare with $\frac{1}{\delta^2\mu}$ from Chebyshev.



Proof Idea

- “Chernoff trick”: for any $t \geq 0$, by Markov’s inequality

$$\mathbb{P}(X \geq (1 + \delta)\mathbb{E}[X]) = \mathbb{P}(e^{tX} \geq e^{t(1+\delta)\mathbb{E}[X]}) \leq \frac{\mathbb{E}[e^{tX}]}{e^{t(1+\delta)\mathbb{E}[X]}}$$

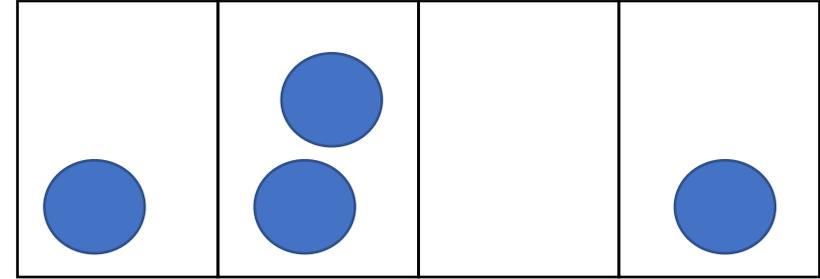
- By independence of X_1, \dots, X_n

$$\mathbb{E}[e^{tX}] = \mathbb{E}[e^{t(X_1 + \dots + X_n)}] = \mathbb{E}\left[\prod_{i=1}^n e^{tX_i}\right] = \prod_{i=1}^n \mathbb{E}[e^{tX_i}]$$

- Using $1 + z \leq e^z$, $\mathbb{E}[e^{tX_i}] \leq e^{\mathbb{E}[X_i](e^t - 1)}$, so $\mathbb{E}[e^{tX}] \leq e^{\mathbb{E}[X](e^t - 1)}$
 - Choosing $t = \ln(1 + \delta)$ gives the best bound.



Balls and Bins



- Suppose we throw n balls into n bins
 - Each ball lands in a uniformly random bin, independently from the others
- **Theorem** With prob. $\geq \frac{1}{2}$, no bin has more than $O\left(\frac{\log n}{\log \log n}\right)$ balls
- $X_{ij} = 1 \Leftrightarrow$ ball j lands in bin i . $X_i = \sum_{j=1}^n X_{ij}$ number of balls in bin i .
 - $\mathbb{E}[X_{ij}] = \mathbb{P}(X_{ij} = 1) = \frac{1}{n}$, so $\mathbb{E}[X_i] = 1$.
- **Chernoff**: $\mathbb{P}\left(X_i \geq \frac{c \ln n}{\ln \ln n}\right) \leq \frac{1}{2n}$ for all large enough c, n
 - Use $\mu = 1$, $1 + \delta = \frac{c \ln n}{\ln \ln n}$. Then $\left(\frac{e^\delta}{(1+\delta)}\right)^{(1+\delta)} \approx e^{-c \ln n} = n^{-c}$
- **Union bound**: $\mathbb{P}\left(\exists i: X_i \geq \frac{c \ln n}{\ln \ln n}\right) \leq n \cdot \frac{1}{2n} = \frac{1}{2}$

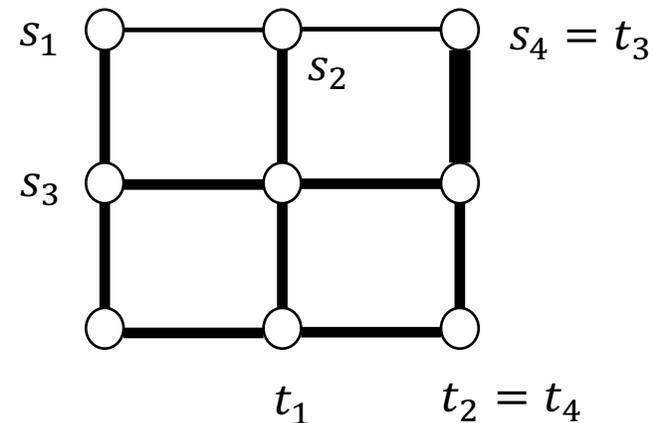
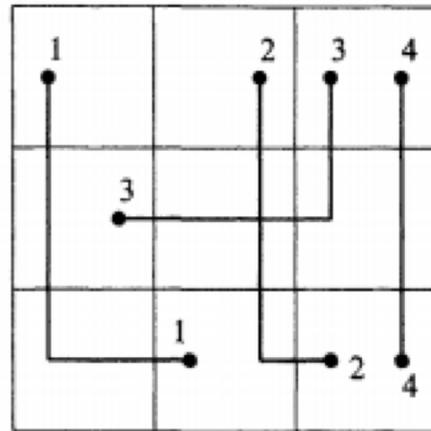


Multicommodity Flow Problem

- Motivation: given a chip with “wire channels”, connect locations with wires, so that no channel is overloaded
- **Multicommodity Flow:** Given an undirected graph $G = (V, E)$, and vertices $s_1, t_1, \dots, s_k, t_k$, find paths P_i in G connecting s_i and t_i so that the maximum number of paths going through any edge is minimized.

Squares -> vertices

Boundaries -> edges



LP Relaxation

- $\mathcal{P}_i =$ all paths between s_i and t_i . $\mathcal{P} = \bigcup_{i=1}^k \mathcal{P}_i$
- Exponential size relaxation: introduce a variable x_P for every $P \in \mathcal{P}$

No edge used by more than W paths

One path between s_i and t_i for each i .

$$\begin{array}{l} \min W \\ \text{s.t.} \\ \sum_{P \in \mathcal{P}: e \in P} x_P \leq W \quad \forall e \in E \\ \sum_{P \in \mathcal{P}_i} x_P = 1 \quad \forall i \in [k] \\ x_P \in \{0,1\} \quad \forall P \in \mathcal{P} \end{array}$$

$$\begin{array}{l} \min W \\ \text{s.t.} \\ \sum_{P \in \mathcal{P}: e \in P} y_P \leq W \quad \forall e \in E \\ \sum_{P \in \mathcal{P}_i} y_P = 1 \quad \forall i \in [k] \\ y_P \geq 0 \quad \forall P \in \mathcal{P} \end{array}$$

- Can be solved in polynomial time, and only poly-many y_P are not 0



Randomized Rounding

- Solve the LP to get optimal y_P , with value $LP = W$
- $\{y_P : P \in \mathcal{P}_i\}$ give a probability distribution over \mathcal{P}_i
- Independently for each $i \in [k]$:
 - Sample $P_i \in \mathcal{P}_i$ with probability y_P
- $Z_{e,i} = 1 \Leftrightarrow e \in P_i$. $Z_e = \sum_{i=1}^k Z_{e,i}$ is the load on edge e
- $\mathbb{E}[Z_e] = \sum_{P \in \mathcal{P}: e \in P} y_P \leq LP \leq OPT$
- **Theorem.** With prob. $\geq \frac{1}{2}$, $\max_{e \in E} Z_e = O\left(\frac{\log n}{\log \log n}\right) \cdot OPT$
 - Same calculation as Balls & Bins, with $\mu = OPT \geq 1$.

$$\begin{array}{l} \min W \\ \text{s.t.} \\ \sum_{P \in \mathcal{P}: e \in P} y_P \leq W \quad \forall e \in E \\ \sum_{P \in \mathcal{P}_i} y_P = 1 \quad \forall i \in [k] \\ y_P \geq 0 \quad \forall P \in \mathcal{P} \end{array}$$



More on Multicommodity Flow

- Much better approximation if LP (or OPT) is large
- E.g., if $LP \geq 10 \ln n$, then, with prob. $\geq 1/2$, randomized rounding finds a solution with value $\leq LP + \sqrt{10 LP \ln n} < 2 LP$.
- Under an assumption slightly stronger than $P \neq NP$ (NP doesn't have randomized algorithms running in expected time $n^{\log^{O(1)} n}$), the $O\left(\frac{\log n}{\log \log n}\right)$ approximation is best possible in the worst case.

