

Concentration.

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We have seen Chebyshev's inequality:

$$\mathbb{P}[|X - \mathbb{E}X| > \beta] \leq \frac{\text{Var} X}{\beta^2}$$

- Today: more concentration inequalities.
 - Chernoff-Cramér bound \Rightarrow large deviation
 - Bernstein inequality / Hoeffding inequality (sum of independent)
 - Azuma-Hoeffding inequality / bounded difference estimates (Martingale)

Applications:

- norm bound of random matrices
- first-passage percolation
- chromatic number of graph.

- Chernoff-Cramér: $\mathbb{P}[X \geq \beta] \leq e^{-s\beta} \mathbb{E}[e^{sX}]$, $\forall s \geq 0$
 proof: Markov inequality. moment generating function (MGF)
 $= \sum_{k=0}^{\infty} \frac{s^k \mathbb{E}[X^k]}{k!}$
- Useful for sum of independent:
 MGF factors: $\mathbb{E}[e^{\sum_{i=1}^m sX_i}] = \prod_{i=1}^m \mathbb{E}[e^{sX_i}]$

• Example: Large deviation

Legendre transform: $\Lambda_*(x) = \sup_s sx - \Lambda(s)$ constant-generating function $\left[\begin{array}{l} \Lambda \text{ convex} \\ \Lambda_* \text{ convex} \end{array} \right]$
 $\Lambda(s) = \log \mathbb{E}[e^{sX}]$ $\Lambda_*(\bar{x}) = 0$ since $\Lambda(0) = 0$ ($\bar{x} = \mathbb{E}X$)
 $\Lambda_*(\bar{x}) = 0$, since $\Lambda(s) = \log \mathbb{E}[e^{sX}] \geq \mathbb{E}[sX] = s\bar{x}$
 (Cramér) $-\frac{1}{m} \log(\mathbb{P}[A_m \in I]) \rightarrow \inf_{x \in I} \Lambda_*(x)$ as $m \rightarrow \infty$

proof. Upper bound: $\mathbb{P}[A_m \in I] \leq \exp(-m \inf_{x \in I} \Lambda_*(x))$

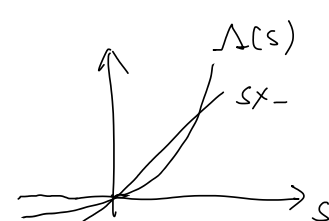
If $\bar{x} \in I$, obvious
 Assume $\inf I = x_- > \bar{x}$
 $\mathbb{P}[A_m \geq x_-] \leq \exp(-smx_- + m\Lambda(s))$, $\forall s \geq 0$
 $\leq \exp(-m\Lambda_*(x_-))$ [Here $x_- - \Lambda(s)$ maximized when $s \geq 0$, since $\Lambda'(0) = \mathbb{E}X = \bar{x} < x_-$]

Lower bound: $\mathbb{P}[A_m \in I] \geq \exp(-m\Lambda_*(x_+))$ for any $x_+ \in I$.

change of measure: $\frac{\tilde{\mu}}{\mu}(x) = \exp(sx - \Lambda(s))$

$$\mathbb{P}[A_m \in (x_-, x_+)] \geq \mathbb{E}[\exp(-m\tilde{\Lambda}_*(x_+)) \mathbb{1}[A_m \in (x_-, x_+)]] \approx \exp(-m(x_+ - \Lambda(s))) \mathbb{P}[\tilde{A}_m \in (x_-, x_+)]$$

choose s such that $\mathbb{P}[\tilde{A}_m \in (x_-, x_+)] \rightarrow 1$ ($\mathbb{E}_{\tilde{\mu}} X = 0$)



• Some concentration inequalities

Take X_1, \dots, X_n independent, with $\mu_i = \mathbb{E}X_i$, $\sigma_i^2 = \text{Var}(X_i)$ and $|X_i - \mu_i| \leq c_i$, $c = \max c_i$
 For $T = X_1 + \dots + X_n \Rightarrow \mathbb{P}[|T - \mathbb{E}T| > \beta] < \begin{cases} \exp(-\beta^2 / (2 \sum \sigma_i^2)) & 0 \leq \beta \leq \frac{\sum \sigma_i^2}{c} \\ \exp(-\beta/c) & \beta > \frac{\sum \sigma_i^2}{c} \end{cases} \Bigg/ \exp(-\frac{\beta^2}{2 \sum \sigma_i^2 + 2c\beta})$
 (Bernstein)

$$\mathbb{P}[|T - \mathbb{E}T| > \beta] < \exp(-\frac{\beta^2}{2 \sum \sigma_i^2}) \quad (\text{Hoeffding}) \quad (\text{Both for sub-Gaussian as well})$$

proof Using Chernoff-Cramér; need: compute MGF

(Bernstein) $\mathbb{E} \exp(s(X_i - \mu_i)) = \sum_{k=0}^{\infty} \frac{s^k \mathbb{E}(X_i - \mu_i)^k}{k!} \leq 1 + \sum_{k=2}^{\infty} \frac{s^k}{k!} \sigma_i^2 \cdot c^{k-2} \leq 1 + \frac{s^2 \sigma_i^2}{2} + \frac{s^3 \sigma_i^2}{6} \sum_{k=3}^{\infty} (sc)^{k-2} = 1 + \frac{s^2 \sigma_i^2}{2} (1 + \frac{sc}{3}) \leq 1 + s^2 \sigma_i^2 \leq \exp(s^2 \sigma_i^2)$ when $s \leq \frac{1}{c}$

(Hoeffding) $\mathbb{E} \exp(s(X_i - \mu_i)) \leq \frac{1}{2}(e^{cs} + e^{-cs}) \leq e^{2c^2 s^2}$

• Operator norm for random matrices

$X = (X_{ij})$ $m \times n$ random matrix,

$$\|X\|_2 = \sup_{\|u\|_2 = \|v\|_2 = 1} u^T X v$$

Suppose X_{ij} iid Rademacher ($\mathbb{P}[X_{ij} = 1] = \mathbb{P}[X_{ij} = -1] = \frac{1}{2}$)

Claim: $\mathbb{P}[\|X\|_2 \geq C(\sqrt{m} + \sqrt{n} + t)] < e^{-t^2}$ ($C > 0$ is some constant)

proof. ① Bound $u^T X v$ for fixed u, v

$$u^T X v = \sum_{i=1}^m \sum_{j=1}^n u_i v_j X_{ij}$$

$$\mathbb{P}[u^T X v \geq C(\sqrt{m} + \sqrt{n} + t)] < \exp(-\frac{2t^2}{\sum_{i=1}^m \sum_{j=1}^n u_i^2 v_j^2}) = \exp(-2t^2 / (\sum u_i^2 + \sum v_j^2)) \leq \exp(-2t^2 / (m+n+t^2))$$

② For S^{m+1} (i.e. $\{u \in \mathbb{R}^m : \|u\|_2 = 1\}$)

$$\exists P_m \subseteq S^{m+1}, |P_m| = 2^m, \forall x \in P_m, \sum_{i=1}^m x_i^2 \geq \frac{m}{4}$$

$$\Rightarrow \mathbb{P}[\max_{u \in P_m, v \in P_n} u^T X v \geq C(\sqrt{m} + \sqrt{n} + t)] < e^{-t^2} \quad (\text{union bound})$$

③ $\forall u \in P_m, v \in P_n, \tilde{u} \in S^{m+1}, \tilde{v} \in S^{n+1}, \|u - \tilde{u}\|_2 \leq \frac{1}{4}, \|v - \tilde{v}\|_2 \leq \frac{1}{4}$

$$|u^T X v - \tilde{u}^T X \tilde{v}| \leq |(u - \tilde{u})^T X v| + |\tilde{u}^T X (v - \tilde{v})| \leq \frac{1}{4} \|X\|_2 + \frac{1}{4} \|X\|_2 = \frac{1}{2} \|X\|_2$$

$$\Rightarrow \tilde{u}^T X \tilde{v} \leq \frac{1}{2} \|X\|_2 + C(\sqrt{m} + \sqrt{n} + t), \text{ with prob } > 1 - e^{-t^2}$$

$$\Rightarrow \|X\|_2 \leq 2C(\sqrt{m} + \sqrt{n} + t), \text{ with prob } > 1 - e^{-t^2}$$

Martingale concentration

Recall: Martingale $Z_1, Z_2, \dots, Z_n, \dots$

st. $\mathbb{E}|Z_n| < \infty$

$$\mathbb{E}[Z_n | Z_1, \dots, Z_{n-1}] = Z_n$$

(A_i, B_i can depend on X_1, \dots, X_{i-1})

Azuma/Azuma-Hoeffding ineq: $A_i \leq Z_i - Z_{i-1} \leq B_i, B_i - A_i \leq c_i$ (but c_i is constant)

$$\mathbb{P}[\max_{0 \leq i \leq n} Z_i - Z_0 \geq \beta] \leq \exp(-\frac{\beta^2}{2 \sum_{i=1}^n c_i^2})$$

proof $\mathbb{P}[\max_{0 \leq i \leq n} Z_i - Z_0 \geq \beta]$

$$\leq \mathbb{P}[\max_{0 \leq i \leq n} \exp(s(Z_i - Z_0)) \geq e^{s\beta}]$$

$$\leq \mathbb{E}[\exp(s\beta - Z_0)] e^{-s\beta}$$

$\tau = \min\{t : Z_t - Z_0 \geq \beta\}$ or n (stopping time)

$$\leq \mathbb{E}[\exp(s\beta - Z_0)] e^{-s\beta} = \mathbb{E}[\exp(s \sum_{i=1}^{\tau} (Z_i - Z_{i-1}))] e^{-s\beta}$$

Then Chernoff-Cramér.

• Bounded difference estimates:

X_1, X_2, \dots, X_n independent

each $X_i \in \Omega_i$

$f: \Omega_1 \times \dots \times \Omega_n \rightarrow \mathbb{R}$

$$D_i = \max_{x_1, \dots, x_n} |f(x_1, \dots, x_i, \dots, x_n) - f(x_1, \dots, \tilde{x}_i, \dots, x_n)|$$

Let $Z_i = \mathbb{E}[f(X_1, \dots, X_n) | X_1, \dots, X_i]$

(McDiarmid's ineq)

$$\Rightarrow A_i \leq Z_i - Z_{i-1} \leq B_i, B_i - A_i \leq D_i$$

$$\Rightarrow \mathbb{P}[f(X_1, \dots, X_n) - \mathbb{E}f(X_1, \dots, X_n) \geq \beta] \leq \exp(-\frac{\beta^2}{\sum_{i=1}^n D_i^2})$$

• Example: First-Passage Percolation

$w_e \sim \text{Unif}[0, 1]$, $\forall e \in E$ (edge weights)

$$T_n = \min_{\gamma} \sum_{e \in \gamma} w_e$$

γ : up-right path from $(0,0)$ to (n,n)

scaling limit of T_n as $n \rightarrow \infty$?

$T_{2n} \leq T_n + T_n$ (sub-additivity)

$$\Rightarrow \mathbb{E}T_{2n} \leq \mathbb{E}T_n + \mathbb{E}T_n, \frac{1}{n} \mathbb{E}T_n \text{ converges as } n \rightarrow \infty$$

(Exercise: $\lim_{n \rightarrow \infty} \frac{1}{n} \mathbb{E}T_n > 0$, by large deviation)

By bounded difference estimates,

(X_i : w_e for e between x_{i-1} and x_i)

$$\mathbb{P}[T_n - \mathbb{E}T_n \geq \beta] \leq \exp(-\frac{\beta^2}{4n}) \quad (D_i = D_2 = \dots = D_n = 1)$$

(In particular, $\text{var}(T_n)$ is $O(n)$)

(KPZ universality conjecture: $\text{var}(T_n)$ is of order $O(n^{\frac{1}{3}})$)

(state of art: $\log(n) < \text{var}(T_n) < \frac{1}{10} \log(n)$) (Newman-Pisa) (Benjamini-Kalai-Sudakov)

Example: • Pattern matching

X_1, X_2, \dots, X_n iid, each uniform from $\{1, \dots, s\}$

For $a = (a_1, \dots, a_k) \in \{1, \dots, s\}^k$

$N_n = \#\{i \text{ such that } (X_i, \dots, X_{i+k-1}) = (a_1, \dots, a_k)\}$

$$\mathbb{E}N_n = (n-k+1) s^{-k}$$

$$\mathbb{P}[|N_n - \mathbb{E}N_n| \geq b\sqrt{n}] \leq 2 \exp(-\frac{2b^2 \mathbb{E}N_n}{kn}) \leq 2e^{-2b^2}$$

$D_i \leq k$

• Chromatic number

Take Erdős-Rényi graph $G(n, p)$

χ : minimum number of colors to properly color $G(n, p)$

$$X_i = \#\{j : (i, j) \in G(n, p)\} \text{ is } \text{Bin}(n-1, p)$$

Claim: change X_i alters χ by ≤ 1

$$(D_i \leq 1)$$

$$\Rightarrow \mathbb{P}[|\chi - \mathbb{E}\chi| \geq b\sqrt{n}] \leq 2 \exp(-\frac{2b^2}{n-1}) = 2e^{-2b^2}$$

