

Lecture 5

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Review: * From tensorization of variance to tensorization of Ψ_X :

$$\text{Var}\left(\sum_{i=1}^n X_i\right) = \sum_{i=1}^n \text{Var}(X_i) \quad \Bigg| \quad \Psi_{\sum_{i=1}^n X_i}(\lambda) = \sum_{i=1}^n \Psi_{X_i}(\lambda)$$

* SubGaussian tails:

$$\Psi_X(\lambda) \leq \frac{\lambda^2 v}{2} \longrightarrow \mathbb{P}\left(\sum_{i=1}^n X_i > \sqrt{2n v \log \frac{1}{\delta}}\right) \leq \delta$$

* Less than subGaussian tails:

- (a) Poisson-tail (right) $\Psi_X(\lambda) \leq v(e^\lambda - 1 - \lambda)$
 (b) χ^2 -tail (right)
 (c) Exponential
- } $\mathbb{P}\left(\sum_{i=1}^n X_i > \log \frac{1}{\delta} + \sqrt{cn v \log \frac{1}{\delta}}\right) \leq \delta$

$$\Psi_X(\lambda) \leq \frac{\lambda^2 v}{2}, \text{ for all } \lambda < \frac{c_1}{\sqrt{v}} \longrightarrow \mathbb{P}\left(\sum_{i=1}^n X_i > \sqrt{cn v} \log \frac{1}{\delta}\right) \leq \delta$$

* Concentration bounds from tensorization of $\Psi_X(\lambda)$

I. Hoeffding inequality: $X_1, \dots, X_n$ indep, $\mathbb{E}[X_i] = 0$

Suppose $X_i \in [a_i, b_i]$. Then,

$$\mathbb{P}\left(\sum_{i=1}^n X_i > t\right) \leq \exp\left(-\frac{2t^2}{\sum_{i=1}^n (b_i - a_i)^2}\right).$$

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II. Bennett inequality

$$|X_i| < C, \quad \sigma^2 = \frac{1}{n} \cdot \sum_{i=1}^n \text{Var}(X_i)$$

$$P\left(\sum_{i=1}^n X_i > t\right) \leq \exp\left(\frac{-t^2}{2\sigma^2 n + \frac{2Ct}{3}}\right).$$

* Concentration using multiplicative property
(martingale difference)

I. Azuma inequality

$X_1, \dots, X_n$ are zero-mean and mutually uncorrelated

$$|X_i| < c_i, \quad 1 \leq i \leq n$$

$$P\left(\sum_{i=1}^n X_i > t\right) \leq \exp\left(-\frac{t^2}{2 \sum_{i=1}^n c_i^2}\right)$$

II. McDiarmid inequality

$$f: \mathcal{X}_1 \times \dots \times \mathcal{X}_n \rightarrow \mathbb{R}$$

$X_1, \dots, X_n$ are indep, denote $X = (X_1, \dots, X_n)$

Assume: f satisfies BDP with $c = (c_1, \dots, c_n)$, i.e.,

$$f(x) - f(x') \leq \sum_{i=1}^n c_i \mathbb{1}_{\{x_i \neq x'_i\}}$$

$$P(f(X) - \mathbb{E}f(X) > t) \leq \exp\left(-\frac{t^2}{2 \sum_{i=1}^n c_i^2}\right)$$

Agenda: Applications

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- [A] A bound for $\mathbb{E}[\max_i X_i]$ for subGaussian X_i
- [B] - longest increasing subsequence
- longest common subsequence
- chromatic number of Erdős-Rényi random graphs
- [C] Balls and bins

- [D] Concentration empirical measures
 - introduction to chaining
 - VC theory
 - Glivenko-Cantelli theorem

} next lecture

[A] A maximal inequality

Suppose $X_1, \dots, X_n$ are subGaussian with variance parameter σ^2 . (no independence assumption!)

By Jensen's inequality, for $\lambda > 0$,

$$\lambda \mathbb{E}[\max_i X_i] \leq \log \mathbb{E}[e^{\lambda \max_i X_i}].$$

Further,

$$\begin{aligned} \mathbb{E}[e^{\lambda \max_i X_i}] &= \mathbb{E}[\max_i e^{\lambda X_i}] \leq \mathbb{E}[\sum_{i=1}^n e^{\lambda X_i}] \\ &= \sum_{i=1}^n \mathbb{E}[e^{\lambda X_i}]. \end{aligned}$$

Thus,

$$\begin{aligned} \lambda \mathbb{E}[\max_i X_i] &\leq \log n \cdot e^{\lambda^2 \sigma^2 / 2} \\ &= \log n + \frac{\lambda^2 \sigma^2}{2}, \end{aligned}$$

i.e., $\mathbb{E}[\max_i X_i] \leq \frac{\log n}{\lambda} + \frac{\lambda \sigma^2}{2} \leq \sigma \sqrt{\frac{\log n}{2}}$

[B] Concentration of some interesting quantities

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(a) Longest Common Sequence

Applications of
McDiarmid

Let $X_1, \dots, X_n, Y_1, \dots, Y_n$ be iid P_{XY} . ($X_i, Y_i \in \mathcal{X}$)

$$L = \max \{k \mid \exists i_1 < i_2 < \dots < i_k \text{ and } j_1 < j_2 < \dots < j_k \text{ s.t. } X_{i_\ell} = Y_{j_\ell}, 1 \leq \ell \leq k\}$$

Claim: $P(|L - \mathbb{E}L| > t) \leq 2e^{-t^2/8n}$

Pf. By changing any one pair (X_i, Y_i) , L can change by at most 2. Use Hoeffding inequality.

Remark. $\mathbb{E}L = \frac{n}{|\mathcal{X}|^2}$ (check: Chvatal-Sankoff)

(b) Longest increasing sequence

$X_1, \dots, X_n$ are iid P_X

$$f(X^n) = \max \{k \mid \exists i_1 < i_2 < \dots < i_k, X_{i_1} < X_{i_2} < \dots < X_{i_k}\}$$

f satisfies BDP with $(1, \dots, 1)$.

(c) Erdős-Rényi random graphs

$G(n, p)$: Graph on n vertices, $(i, j) \in E$ with prob. p
- indep. for all pairs (i, j)

$$X_{ij} = \mathbf{1}(\exists \text{ edge b/w } i \text{ and } j), \quad 1 \leq i < j \leq n$$

A coloring of G is an assignment of colors to the vertices of G s.t. no two adjacent vertices have the same color.

The chromatic number of G is the min. # of colors required for coloring G .

$X(G(n, p)) \equiv \text{chromatic \# of } G(n, p)$

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Claim: $P(|X(G(n, p)) - \mathbb{E} X(G(n, p))| > t) \leq 2 e^{-\frac{t^2}{2n}}$.

Remark: $\mathbb{E} X(G(n, p)) \approx \begin{cases} \frac{n}{\log n} & \text{when } p > \frac{\log n}{n} \\ c & \text{when } p < \frac{\log n}{n} \end{cases}$

[C] Balls and bins

* Throw m balls independently and uniformly at random into n bins

$Z = \# \text{ of empty bins}$

$$= \sum_{i=1}^n \underbrace{\mathbb{1}(\text{bin } i \text{ is empty})}_{X_i}$$

$$\mathbb{E} Z = n P(X_i = 1) = n \left(1 - \frac{1}{n}\right)^m \leq e^{-\frac{m}{n} + \log n}$$

Thus, $\mathbb{E} Z \geq 1$ roughly only when $m \ll n \log n$.

Note that $X_1, \dots, X_n$ are not indep.

Let $B_j = \text{index of the bin where ball } j \text{ falls}$

$$\in \{1, \dots, n\}, \text{ for } 1 \leq j \leq m.$$

Then, $Z = f(B_1, \dots, B_m)$. Clearly, f satisfies BDP with $(1, \dots, 1)$. Thus, by McDiarmid's inequality,

$$P(Z - \mathbb{E} Z > t) \leq \exp\left(-\frac{t^2}{2m}\right).$$

that is

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$$P\left(Z > \mathbb{E}Z + \sqrt{2m \log \frac{1}{\delta}}\right) \leq \delta$$

$$\Leftrightarrow P\left(Z \leq \mathbb{E}Z + \sqrt{2m \log \frac{1}{\delta}}\right) \geq 1 - \delta.$$

To study the max. m s.t. no bin is empty, it is better to consider

$Z' = \#$ of non-empty bins

and bound $P(Z' \geq n)$. As before

$$P\left(Z' - \mathbb{E}Z' > \sqrt{2m \log \frac{1}{\delta}}\right) \leq \delta$$

Also

$$\mathbb{E}Z' = n \left(1 - \left(1 - \frac{1}{n}\right)^m\right) \approx m$$

Thus,

$P(Z' \geq n)$ is small if (roughly)

$$m + \sqrt{m} \leq n. \quad \left(\begin{array}{l} m + \sqrt{m} \leq (\sqrt{m} + 0.5)^2 \leq n \\ \Leftrightarrow \sqrt{m} \leq \sqrt{n} - 0.5 \\ \Leftarrow \sqrt{m} \leq \frac{\sqrt{n}}{2} \end{array} \right)$$

$\uparrow$
 $m \leq \frac{n}{c}$

That is, up to $m = \frac{n}{c}$ there is at least one nonempty bin.

Also, similarly, $P\left(Z' < \mathbb{E}Z - \sqrt{2m \log \frac{1}{\delta}}\right) \leq \delta$.

Thus, if $m - \sqrt{m} > n$, $P(Z' < n) \leq \delta$. This again holds once $m \geq c'n$.

* What happens for $m = n$?

We seek to study the max. load in this regime.

$X_i^{(m)}$ def # of balls in bin i

$$X_i^{(m)} \sim \text{Bin}\left(m, \frac{1}{n}\right)$$

$$\text{Thus, } P\left(\max_i X_i^{(m)} > t\right) \leq n P\left(X_i^{(m)} > t\right) \quad (\text{by union bound})$$

By Bennett inequality,

$$P\left(X_i^{(m)} - \frac{m}{n} > t\right) \leq \exp\left(-\frac{t^2}{2\frac{m}{n} + \frac{2t}{3}}\right)$$

In particular, for $m=n$,

$$P\left(X_i^{(n)} - 1 > c \log \frac{n}{\delta}\right) \leq \frac{\delta}{n}$$

$$\Rightarrow P\left(\max_{1 \leq i \leq n} X_i^{(n)} > 1 + c \log \frac{n}{\delta}\right) \leq \delta$$

$$\text{Max. load} = O(\log n)$$

Reading assignment: Poisson approximation
(Mittchenmacher and Upfal, "Probability and computing")