

HDP Session 6

Recall

- 1. Doob's Ineq: If $(M_n)_n$ is subM, then

$$\mathbb{P}\left(\sup_{0 \leq s \leq t} M_s \geq a\right) \leq \frac{\mathbb{E} M_t}{a} \quad \forall a > 0$$

- 2. Kolmogorov's Ineq: If $(M_n)_n$ Martingale and $\mathbb{E} M_n^2 < \infty$ and $\mathbb{E} M_n = 0$

$$\mathbb{P}\left(\sup_{0 \leq s \leq t} |M_s| \geq a\right) \leq \frac{\text{Var}(M_t)}{a^2}.$$

3. Hoeffding's lemma: $\text{Ran}(X) \subseteq [a, b]$, then $X \in \text{sg}\left(\frac{1}{4}(b-a)^2\right)$

1. Azuma-Hoeffding Inequality:

- Let $(M_n)_n$ be a Martingale and $\exists (A_n)_n, (B_n)_n$ predictable processes s.t. $A_n \leq M_n - M_{n-1} \leq B_n$ and $\exists$ constants $c_n > 0$ s.t. $B_n - A_n \leq c_n$ a.s.. Then

$$\mathbb{P}\left(\sup_{0 \leq i \leq t} (M_i - M_0) \geq \beta\right) \leq \exp\left(-\frac{2\beta^2}{\sum_{n=1}^t c_n^2}\right)$$

Proof: $\mathbb{P}\left(\sup_{0 \leq i \leq t} (M_i - M_0) \geq \beta\right) = \mathbb{P}\left(\sup_{0 \leq i \leq t} e^{\lambda(M_i - M_0)} \geq e^{\lambda\beta}\right)$

$$\leq e^{-\lambda\beta} \mathbb{E}\left[e^{\lambda(M_t - M_0)}\right]$$

$$\mathcal{F}_i = X_1, X_2, \dots, X_i$$

$$= e^{-\lambda\beta} \mathbb{E}\left[\underbrace{\mathbb{E}\left[e^{\lambda(M_{t-1} - M_0)} e^{\lambda(M_t - M_{t-1})}\right]}_{\text{const.}} \middle| \mathcal{F}_{t-1}\right]$$

$$= e^{-\lambda\beta} \mathbb{E}\left[e^{\lambda(M_{t-1} - M_0)} \underbrace{\mathbb{E}\left[e^{\lambda(M_t - M_{t-1})}\right]}_{\mathbb{E}(M_i | \mathcal{F}_{i-1})} \middle| \mathcal{F}_{t-1}\right]$$

$$\leq e^{-\lambda\beta} e^{\frac{\lambda^2 c_t^2}{8}}$$

$$\leq e^{-\lambda\beta} e^{\frac{\lambda^2 c_t^2}{8}} \mathbb{E}\left[e^{\lambda(M_{t-1} - M_0)}\right]$$

(Hoeffding's lemma)

$$\text{(By Induction)} \quad \leq e^{-\lambda\beta} e^{\frac{\lambda^2 \sum c_n^2}{8}} \quad \checkmark$$

Optimising: $\lambda = \frac{4\beta}{\sum c_n^2}$, we have

$$\mathbb{P}(M_t - M_0 \geq \beta) \leq \mathbb{P}\left(\sup_{0 \leq i \leq t} M_i - M_0 \geq \beta\right) \leq \exp\left(-\frac{2\beta^2}{\sum c_n^2}\right) \quad \square$$

Our purpose: $\mathbb{P}\left(f(\underline{x}) - \mathbb{E}f(\underline{x}) \geq \beta\right) \leq o(1)$.

(Range(X_i) = X_i)

$X_1, X_2, \dots, X_n$ are independent

2. Method of Bounded Difference:

Let $M_i = \mathbb{E}[f(\underline{x}) | \mathcal{F}_i]$ - martingale

$\underline{x} = (X_1, \dots, X_n)$

$$\rightarrow f(\underline{x}) - \mathbb{E}f(\underline{x}) = \sum_{i=1}^n (M_i - M_{i-1}) \quad \begin{cases} M_n = f(\underline{x}) \\ M_0 = \mathbb{E}f(\underline{x}) \end{cases}$$

Def: $D_i f$ is a random variable

$$D_i f(x_1, \dots, \hat{x}_i, \dots, x_n) = \text{ess sup}_{y \in X_i} f(x_1, \dots, y, \dots, x_n) - \text{ess inf}_{y \in X_i} f(x_1, \dots, y, \dots, x_n)$$

Random var. $\Rightarrow \{X_1, X_2, \dots, X_n\} \setminus X_i$ [ignore measure zero events]

$$M_i - M_{i-1} = \mathbb{E}[f(\underline{x}) | \mathcal{F}_i] - \mathbb{E}[f(\underline{x}) | \mathcal{F}_{i-1}]$$

$$\begin{aligned} &= \mathbb{E}[f(\underline{x}) | \mathcal{F}_i] - \mathbb{E}[f(x^{(i)}) | \mathcal{F}_i] \\ \rightarrow &= \mathbb{E}[f(\underline{x}) - f(x^{(i)}) | \mathcal{F}_i] \end{aligned}$$

$x^{(i)} = (x_1, \dots, x_{i-1}, x'_i, x_{i+1}, \dots, x_n)$
 $x'_i \stackrel{d}{=} x_i$ and $x_i \perp x'_i$

$$|M_i - M_{i-1}| \leq \mathbb{E}[|f(\underline{x}) - f(x^{(i)})| | \mathcal{F}_i]$$

$$\leq \text{ess sup } |D_i f(x_1, \hat{x}_i, x_n)| = \|D_i f\|_\infty$$

$$\|D_i f\|_\infty \leq M_i - M_{i-1} \leq \|D_i f\|_\infty$$

[H.W.: Improve by a factor of 4]

$$\Rightarrow \mathbb{P}\left(f(\underline{x}) - \mathbb{E}f(\underline{x}) \geq \beta\right) \leq \exp\left(-\frac{2\beta^2}{2 \sum \|D_i f\|_\infty^2}\right) \quad \square$$

McDiarmid's Inequality

Barely any improvement.

$$\bullet \quad \text{Var} (f(X) - \mathbb{E}f(X)) = \sum_{i=1}^n \mathbb{E} (M_i - M_{i-1})^2$$

$$\boxed{\text{Var } f(X) \leq \sum_{i=1}^n \|\underline{D_i f}\|_{\infty}^2} \longrightarrow \text{Can be Improved.}$$

⊛ Improving the variance bound:

$$\text{Var} (f(X, Y)) \stackrel{\text{(ANOVA)}}{=} \mathbb{E} \left[\underbrace{\text{Var} (f(X, Y) | X)}_{g_i} \right] + \text{Var} \left[\mathbb{E} [f(X, Y) | X] \right].$$

$$\star \text{ Lemma: } \mathbb{E} \left[\mathbb{E} [f(X) | \underbrace{X_1, \dots, \hat{X}_i, \dots, X_n}_{g_i}] \mid \underbrace{X_1, \dots, X_i}_{\mathcal{F}_i} \right] = \mathbb{E} [f(X) | X_1, \dots, X_{i-1}]$$

$$\begin{aligned} \therefore (M_i - M_{i-1})^2 &= \left(\mathbb{E} [f(X) | \mathcal{F}_i] - \mathbb{E} [f(X) | \mathcal{F}_{i-1}] \right)^2 \\ &= \left(\mathbb{E} [f(X) | \mathcal{F}_i] - \mathbb{E} [\mathbb{E} [f(X) | g_i] | \mathcal{F}_i] \right)^2 \\ &\leq \mathbb{E} \left((f(X) - \mathbb{E} (f(X) | g_i))^2 \mid \mathcal{F}_i \right) \end{aligned}$$

$$\begin{aligned} \text{Var} (f(X)) &= \sum_{i=1}^n \mathbb{E} (M_i - M_{i-1})^2 \leq \sum_{i=1}^n \mathbb{E} \left(f(X) - \mathbb{E} [f(X) | g_i] \right)^2 \checkmark \\ &= \sum_{i=1}^n \mathbb{E} \left[\mathbb{E} \left[(f(X) - \mathbb{E} (f(X) | g_i))^2 \mid g_i \right] \right] \\ &= \sum_{i=1}^n \mathbb{E} [\text{Var} (f(X) | g_i)] \end{aligned}$$

$\text{Var} (Y | X) := \mathbb{E} [(Y - \mathbb{E}(Y|X))^2 | X]$

$$\boxed{\text{Var } f(X) \leq \sum_{i=1}^n \mathbb{E} [\text{Var} (f(X) | g_i)]} \longrightarrow \text{Efron Stein Ineq.}$$

ES1

Lemma: $\text{Var } X = \frac{1}{2} \mathbb{E} (X - X')^2$, X' is an indep copy of X

Proof:

$$\begin{aligned} \mathbb{E} (X - X')^2 &= \mathbb{E} ((X - \mathbb{E}X) - (X' - \mathbb{E}X'))^2 \\ &= \mathbb{E} (X - \mathbb{E}X)^2 + \mathbb{E} (X' - \mathbb{E}X')^2 \\ &= 2 \text{Var}(X). \end{aligned}$$

$$\text{Var}(f(X) | \mathcal{G}_i) = \frac{1}{2} \mathbb{E} \left[(f(X) - f(X^{(i)}))^2 | \mathcal{G}_i \right]$$

$$\begin{aligned} \therefore \text{Var } f(X) &\leq \frac{1}{2} \sum_{i=1}^n \mathbb{E} \left[\mathbb{E} \left[(f(X) - f(X^{(i)}))^2 | \mathcal{G}_i \right] \right] \\ &= \frac{1}{2} \sum_{i=1}^n \mathbb{E} \left[(f(X) - f(X^{(i)}))^2 \right] \quad [\text{ES2}] \end{aligned}$$

Bounded Difference Inequality:

$$|D_i f| \leq c_i$$

$$\begin{aligned} \text{Var } f(X) &\leq \sum_{i=1}^n \mathbb{E} [\text{Var}(f(X) | \mathcal{G}_i)] \\ &\leq \frac{1}{4} \sum_{i=1}^n \mathbb{E} [(D_i f(X))^2] \quad \square \end{aligned}$$

☆ Quick Summary:

1. Azuma-Hoeffding: $\mathbb{P} \left(\sup_{1 \leq i \leq t} M_i - M_0 \geq \beta \right) \leq \exp \left(- \frac{\beta^2}{\sum c_n^2} \right)$

exp bounds $\left\{ \begin{array}{l} 2. \text{ McDiarmid's Ineq: } \mathbb{P} \left(f(X) - \mathbb{E} f(X) \geq \beta \right) \leq \exp \left(- \frac{2 \beta^2}{\sum_{i=1}^n \|D_i f\|_\infty^2} \right) \end{array} \right.$

3. Obvious: $\rightarrow \text{Var } f(X) \leq \sum_{i=1}^n \|D_i f\|_\infty^2 \quad \leftarrow$

ES: $\text{Var } f(X) \leq \sum_{i=1}^n \mathbb{E} [\text{Var}(f(X) | \mathcal{G}_i)] = \frac{1}{2} \sum_{i=1}^n \text{Var} ((f(X) - f(X^{(i)}))^2 | \mathcal{G}_i)$

$\rightarrow$ Bounded diff: $\text{Var } f(X) \leq \frac{1}{4} \sum_{i=1}^n \mathbb{E} [(D_i f(X))^2] \quad \leftarrow \text{☆}$

★ Examples

1. Balls and Bins — Suppose we have m - balls
 n - bins

$Z_{n,m}$ = # empty bins

$$\mathbb{E} Z_{n,m} = \mathbb{E} \left(\sum_{i=1}^n \mathbb{1}_{B_i} \right) = \sum_{i=1}^n \left(1 - \frac{1}{n} \right)^m = n \left(1 - \frac{1}{n} \right)^m$$

Generating r.v.s: $X_i = j$ if i^{th} ball lands in B_j

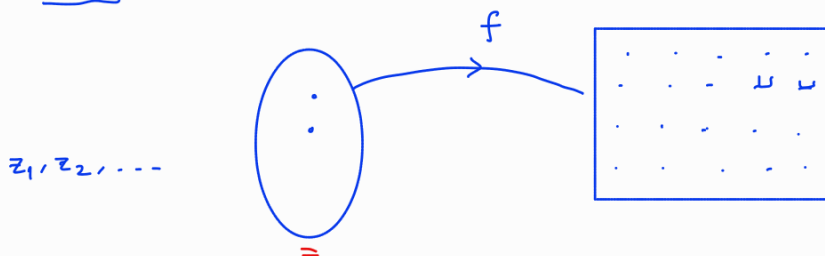
$$Z_{n,m} = Z_{n,m}(X_1, X_2, \dots, X_m)$$

• $\|D_i Z_{n,m}(X_1, \dots, X_m)\|_{\infty} \leq 2 \rightarrow (Z_{n,m} \text{ does not depend too much of any of the } X_i\text{'s})$

$$\mathbb{P}(|Z_{n,m} - \mathbb{E} Z_{n,m}| \geq \beta) \leq 2 \exp \left(- \frac{2\beta^2}{\sum_{i=1}^m \|D_i f\|_{\infty}^2} \right)$$

$$\Rightarrow \mathbb{P} \left(\left| Z_{n,m} - \underbrace{n \left(1 - \frac{1}{n} \right)^m}_{\substack{m \sim n \\ m = n^2}} \right| \geq \underbrace{\beta \sqrt{m}}_{\substack{\sim \sqrt{n} \\ n \cdot \frac{1}{e}}} \right) \leq 2 \exp \left(- \frac{\beta^2}{2} \right)$$

Hashing:



H.W. Find $\mathbb{P}(\text{collisions})$ and $\forall m \in \mathbb{N}$, find n s.t. $\mathbb{P}(\text{collisions}) < \frac{1}{2}$.

2. $X_1, X_2, X_3, \dots, X_n$ — random in a set S $|S|=s$, $(a_1, a_2, \dots, a_k)$ — given string $\in S^k$
 $\underbrace{\quad}_{\underline{a}} \quad \underbrace{\quad}_{\underline{a}} \quad \downarrow$
 Set of alphabets

• $\mathbb{P}(\underline{X} \text{ contains } \underline{a}) \leftarrow \text{Conc. of \# occurrences of } \underline{a} \text{ in } \underline{X}.$

• $E_i = \text{Event that } (X_i \dots, X_{i+k-1}) = \underline{a}$

$$N = \sum_{i=1}^{n-k+1} \mathbb{1}_{E_i} \leftarrow \text{Could be highly correlated}$$

$$\mathbb{E}N = (n-k+1) \left(\frac{1}{s}\right)^k$$

Consider $\|D_i N(X_1, \dots, X_n)\|_\infty \leq k$ (local corr)

$$\mathbb{P}\left((N - \mathbb{E}N) \geq \beta k \sqrt{n}\right) \leq e^{-2\beta^2}. \quad \square$$

[H.W.] Q: We have a random string of length n . For what k is a given seq.

$$\mathbb{P}((a_1, \dots, a_k) \in \underline{X}) \geq \varepsilon.$$

• Conc. of measure of $\{0,1\}^n$.