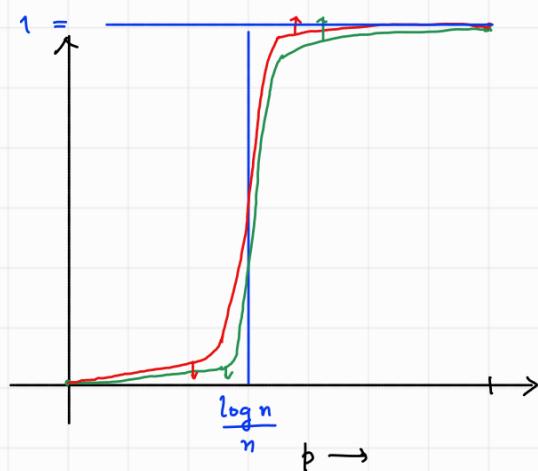


① $G(n, p)$

$$\textcircled{a} \quad \Pr(G(n, p) \text{ has no isolated vertices}) = \begin{cases} o_{c_1}(1) & p < c_1 \frac{\log n}{n}, c_1 < 1 \\ 1 - o_{c_2}(1) & p > c_2 \frac{\log n}{n}, c_2 > 1 \end{cases}$$

$$\textcircled{b} \quad \Pr(G(n, p) \text{ is connected}) = \begin{cases} o_{c_1}(1) & p < c_1 \frac{\log n}{n}, c_1 < 1 \\ 1 - o_{c_2}(1) & p > c_2 \frac{\log n}{n}, c_2 > 1 \end{cases}$$



n - fixed

- As $n \rightarrow \infty$, the red and green curves flatten

The properties of {Having no isolated pts} & {being connected} for $G(n, p)$ has a threshold at $p = \frac{\log n}{n}$

W Pr(|X - E[X]| ≥ c) ≤ o(1)

$$X = \sum_{i=1}^n X_i$$

$$c = c(n)$$

2. Exponential tail bounds

e.g. $Z \sim N(0, 1)$, $M_Z(s) = \mathbb{E} e^{sZ}$ ← moment gen f_n (MGF)
or Laplace Transform

$$M_Z(s) = e^{s^2/2}$$

$$Z \sim N(0, \sigma^2),$$

$$\sigma Z_1, \quad M_Z(s) = e^{s^2 \sigma^2/2}$$

$$sG(\sigma_i^2) \subseteq sG(\sigma_j^2)$$

Sub Gaussian Random Variables:

- ① Defn: X is said to be sub-Gaussian ($sG(\sigma^2)$) if the mgf of $X - \mathbb{E}X$ exists and

$$\mathbb{E} e^{\lambda(X-\mathbb{E}X)} \leq e^{\frac{\lambda^2 \sigma^2}{2}} \quad \left| \begin{array}{l} \text{The mgf is dominated} \\ \text{by that of a } N(0, \sigma^2). \end{array} \right.$$

- ② Tail Probabilities: $P(X - \mathbb{E}X \geq \beta) \quad , \beta > 0$

$$\begin{aligned} &= P(e^{\lambda(X-\mathbb{E}X)} \geq e^{\lambda\beta}) \quad \forall \lambda > 0 \\ &\leq e^{-\lambda\beta} \mathbb{E} e^{\lambda(X-\mathbb{E}X)} \leq e^{-\lambda\beta} + \frac{\lambda^2 \sigma^2}{2} \quad \forall \lambda > 0 \end{aligned}$$

Optimizing λ : $\lambda^* = \frac{\beta}{\sigma^2}$, we see that

$$P(X - \mathbb{E}X \geq \beta) \leq e^{-\left(\frac{\beta^2}{\sigma^2} - \frac{\beta^2}{2\sigma^2}\right)} = e^{-\frac{\beta^2}{2\sigma^2}} \quad \longrightarrow ②$$

★ Exc: Tail bounds for a Gaussian: $Z \sim N(0,1)$, for $t > 0$

$$\left(\frac{1}{t} - \frac{1}{t^3}\right) e^{-\frac{t^2}{2}} \leq P(Z \geq t) \leq \frac{1}{t} e^{-\frac{t^2}{2}}$$

- ③ Constructing sG rv's out of old:

Claim: Let $X_i \in sG(\sigma_i^2)$ are indep for $i=1, 2, \dots, n$. Then $\sum w_i X_i \sim sG$.

$$\begin{aligned} \text{Proof: } \mathbb{E} e^{s(\sum_{i=1}^n w_i X_i)} &= \prod_{i=1}^n \mathbb{E} e^{\lambda w_i X_i} \leq \prod_{i=1}^n e^{\frac{s^2 w_i^2 \sigma_i^2}{2}} \\ &= \exp\left(\frac{s^2}{2} \sum_{i=1}^n w_i^2 \sigma_i^2\right) \end{aligned}$$

$$\therefore \sum w_i X_i \sim sG\left(\sum w_i^2 \sigma_i^2\right). \quad \square$$

(4) Hoeffding's Inequality: Say $X_i \in \mathcal{G}(\sigma_i^2)$ be indep random variables and thus $\sum X_i \sim \mathcal{G}(\sum \sigma_i^2)$.

$$\therefore \boxed{\mathbb{P}\left(\sum_{i=1}^n (X_i - \mathbb{E}(X_i)) \geq t\right) \leq \exp\left(-\frac{t^2}{2 \sum \sigma_i^2}\right)} \quad \square$$

[Proof ③ + ②]

(5) Hoeffding's Lemma: All bounded rv's are subGaussian.

Q1. Say $\text{Ran}(X) \subseteq [a, b]$. Then $\text{Var}(X) \leq \frac{1}{4}(b-a)^2$.

Proof: $\left(X - \frac{a+b}{2}\right)^2 \leq \frac{1}{4}(b-a)^2 \text{ w.p. 1}$

$$\mathbb{E}\left(X - \frac{a+b}{2}\right)^2 \leq \frac{1}{4}(b-a)^2$$

$$X = \begin{cases} a & \text{w.p. } \frac{1}{2} \\ b & \text{w.p. } \frac{1}{2} \end{cases}$$

$$\text{Var}(X) = \min_c \mathbb{E}(X-c)^2 \leq \frac{1}{4}(b-a)^2. \quad \square$$

★ Change of measure:

$$(\Omega, \mathcal{F}, \mathbb{P}) \xrightarrow{\text{use } f} (\Omega, \mathcal{F}, \tilde{\mathbb{P}})$$

$$\begin{matrix} X \\ \downarrow \\ \mathbb{R} \end{matrix} \xrightarrow{f} X$$

$$f_i = f(i)$$

Discrete: \underline{X} , pmf $(p_i)_{i \in I}$, and let $f \geq 0$, $f: I \rightarrow [0, \infty)$ s.t.

$$\sum_{i \in I} f(i)p_i$$

$$I \subseteq \mathbb{R}$$

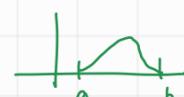
Then define $\bar{q}_i = \frac{f(i)p_i}{\sum f(i)p_i} \rightsquigarrow$ Gives another pmf.

Cont:- X rv, \mathbb{P} - pdf, and say $f: \Omega \rightarrow \mathbb{R}$ s.t. $Ef = \int_{\Omega} f(x)\mathbb{P}(dx) < \infty$

Then, $\bar{q}(x) = \frac{f(x)\mathbb{P}(x)}{Ef} \rightarrow$ Another pdf.

Used another random variable f to give a new measure for X .

[Change of Measure / Tilting]



(WLOG)

Proof of Hoeffding's Ineq: $X \in [a, b]$ a.s. and $\mathbb{E} X = 0$

$$\psi_X(s) = \log M_X(s) \quad (\text{cumulant generating fn., log-mgf})$$

$$i) \quad \psi_X(0) = \log \mathbb{E} e^0 = 0$$

$$\begin{aligned} ii) \quad \psi'_X(s) &= \frac{d}{ds} \log \mathbb{E} e^{sx} = \frac{\frac{d}{ds} \mathbb{E} e^{sx}}{\mathbb{E} e^{sx}} = \frac{1}{\mathbb{E} e^{sx}} \mathbb{E} \left[\frac{\partial}{\partial s} e^{sx} \right] \\ &= \frac{\mathbb{E}[X e^{sx}]}{\mathbb{E}[e^{sx}]} = \mathbb{E} \left[X \frac{e^{sx}}{\mathbb{E} e^{sx}} \right] \\ \psi'_X(0) &= 0 \end{aligned}$$

$$\begin{aligned} iii) \quad \psi''_X(s) &= \frac{1}{[\mathbb{E} e^{sx}]^2} \left(\mathbb{E}[e^{sx}] \mathbb{E}[x^2 e^{sx}] - (\mathbb{E}[x e^{sx}])^2 \right) \\ &= \mathbb{E} \left[X^2 \frac{e^{sx}}{\mathbb{E} e^{sx}} \right] - \left(\mathbb{E} \left[X \frac{e^{sx}}{\mathbb{E} e^{sx}} \right] \right)^2. \end{aligned}$$

Exponential Tilting
Tilting

$$= \mathbb{E}_{q_s}(x^2) - (\mathbb{E}_{q_s}(x))^2, \text{ where } q_s \text{ is the new pdf of } X.$$

$$\mathbb{E} \left[X^2 \frac{e^{sx}}{\mathbb{E} e^{sx}} \right] = \int_{\mathbb{R}} x^2 \underbrace{\left(\frac{e^{sx}}{\mathbb{E} e^{sx}} \right) \cdot p(x)}_{q_s(x)} dx = \int_{\mathbb{R}} x^2 \underbrace{q_s(x)}_{\text{new pdf}} dx$$

$$x \in [a, b]$$

$$\psi''_X(s) = \text{Var}_{q_s}(X) \leq \frac{1}{4} (b-a)^2 \rightarrow \otimes$$

∴ Integrating twice,

$$\int_0^s \int_0^{s_1} \psi''_X(s_2) ds_2 ds_1 \leq \frac{1}{4} (b-a)^2 \underbrace{\int_0^s \int_0^{s_1} ds_2 ds_1}_{=\frac{1}{2}}$$

$$\therefore \psi_X(s) \leq \frac{1}{8} (b-a)^2 s^2 \quad \square$$

$$\Rightarrow M_X(s) \leq e^{\frac{1}{2} s^2 \left(\frac{1}{4} (b-a)^2 \right)}$$

$$\text{i.e., } X \in \mathcal{L}_Y \left(\frac{1}{4} (b-a)^2 \right). \quad \square$$

[MDP – Symmetrization]

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(Hoeffding's Ineq.)

Thm: Let $X_i \in [a_i, b_i]$ be indep rv's. Then

$$\begin{aligned} \mathbb{P}\left(\sum(X_i - \mathbb{E}X_i) \geq \beta\right) &\leq \exp\left(-\frac{2\beta^2}{\sum(b_i - a_i)^2}\right) \rightarrow \star \\ \mathbb{P}\left(\sum(X_i - \mathbb{E}X_i) \leq -\beta\right) &\leq \exp\left(-\frac{2\beta^2}{\sum(b_i - a_i)^2}\right) \\ \therefore \mathbb{P}\left(\left|\sum X_i - \mathbb{E}X_i\right| \geq \beta\right) &\leq 2 \exp\left(-\frac{2\beta^2}{\sum(b_i - a_i)^2}\right) \quad \square \end{aligned}$$

e.g. X_i iid $\text{Ber}_{\pm}\left(\frac{1}{2}\right)$. $S_n = \sum_{i=1}^n X_i$ — Repr a simple random walk in 1D.

$$\begin{aligned} \mathbb{P}\left(\sum_{i=1}^n X_i \geq c\sqrt{n}\right) &\stackrel{\leq \frac{1}{c^2}}{\leq} \exp\left(-\frac{2(c\sqrt{n})^2}{4n}\right) \\ &= e^{-\frac{c^2}{2}}. \quad \sum_{i=1}^n X_i = O_p(\sqrt{n}) \\ \boxed{\sum_{i=1}^n X_i \in [-c\sqrt{n}, c\sqrt{n}] \text{ whp.}} \end{aligned}$$


$$\mathbb{P}\left(\sum X_i \geq cn^{\frac{1}{2}+\varepsilon}\right) \leq \leftarrow \text{Much sharper using Hoeffding ineq.} \quad \square$$

2. Subexponential Random Variables:

$$\textcircled{1} \quad \underline{\text{Def}}: \quad X \sim s\mathcal{E}(\gamma, \alpha) \quad \text{if} \quad \mathbb{E}e^{\lambda(X-\mathbb{E}X)} \leq \exp\left(\frac{\lambda^2\gamma}{2}\right) \quad \forall |\lambda| \leq \frac{1}{\alpha}.$$

e.g. $X \sim \text{Exp}(1)$. Then,

$$\mathbb{E}e^{sx} = \int_0^\infty e^{sx} \cdot e^{-x} dx = \lambda \left(-\frac{e^{-(1-s)}}{1-s} \right)_0^\infty = \begin{cases} \frac{1}{1-s} & \text{if } s < 1 \\ \infty & s \geq 1 \end{cases}$$

$$(2) \text{ Tail Probabilities: } X \sim s\mathcal{E}(\nu, \alpha) \quad P(X - \mathbb{E}X \geq \beta) \leq \begin{cases} e^{-\frac{\beta^2}{2\nu}} & \text{if } 0 < \beta \leq \frac{\nu}{\alpha} \\ e^{-\frac{\beta}{2\nu}} & \text{if } \beta \geq \frac{\nu}{\alpha}. \end{cases}$$

(3) Sums: $X_i \sim s\mathcal{E}(\nu_i, \alpha_i)$, then $\sum w_i X_i \sim s\mathcal{E}\left(\sum w_i^2 \nu_i, \max_{i=1}^n |w_i| \alpha_i\right)$

(4) Bernstein's Inequality: $X_i \sim sG(\nu_i, \alpha)$

$$P(|\sum (X_i - \mathbb{E}X_i)| \geq \underline{\beta}) \leq \begin{cases} 2e^{-\frac{\beta^2}{2 \sum w_i^2 \nu_i}} & \text{if } 0 < \beta \leq \frac{\nu}{\alpha} \text{ (Moderate deviations)} \\ 2e^{-\frac{\beta}{2\alpha}} & \text{if } \beta \geq \frac{\nu}{\alpha}. \text{ (Large deviations)} \end{cases}$$

(5) Result: Let $|X_i| \leq c$ a.s. and $\mathbb{E}X = \mu$, $\text{Var}X = \nu$. Then

$$X \sim s\mathcal{E}(2\nu, 2c) \xrightarrow{\text{[Reading H.W.]}}$$

(Bernstein Ineq.)

Thm: If $|X_i| \leq c \ \forall i = 1(1)n$ and X_i 's are indep, then

$$P\left(\sum_{i=1}^n (X_i - \mathbb{E}X_i) \geq \beta\right) \leq \begin{cases} \exp\left(-\frac{\beta^2}{2 \sum_{i=1}^n \text{Var}(X_i)}\right) & \text{if } 0 < \beta \leq \frac{\sum \text{Var}(X_i)}{2c} \\ \exp\left(-\frac{\beta}{4c}\right) & \text{if } \beta \geq \frac{\sum \text{Var}(X_i)}{2c} \end{cases}$$

$$P\left(\sum (X_i - \mathbb{E}X_i) \geq \beta\right) \leq \exp\left(-\frac{\beta^2}{2 \left[\frac{1}{4} \sum (b_i - a_i)^2\right]}\right) \rightarrow \textcircled{*}$$

> Upper bd to $\text{Var}(X_i)$

1) For large β , Hoeffding is better.

$$\underline{\beta} = o(1)$$

2) For moderate β : eq. $\mathbf{Y} \sim \text{Ber}(\underline{\beta})$. $\text{Var}(\mathbf{Y}) = \underline{\beta}(1-\underline{\beta}) \downarrow$
 $(b-a)^2 = 1$

\checkmark [Reading H.W. - Example 2.4.18 (Max degree of ERRL's) MDP]
Pg - 78.

Modern Discrete Prob
- Sebastian Roch.

$$p = \frac{\log n}{n}$$

e.g. X_i iid $\text{Bern}(p)$, and let β be moderate

$$\text{Hoeff: } \mathbb{P}\left(\sum(X_i - \mathbb{E}X_i) \geq \beta\right) \leq \exp\left(-\frac{2\beta^2}{n}\right)$$

$$\text{Bern: } " \leq \exp\left(-\frac{\beta^2}{2np(1-p)}\right) = \exp\left(-\frac{\beta^2}{2\log n}\right)$$

Q: X_i iid $N(0,1)$ and $\mathbb{E} \sup_{i=1}^n X_i$ - estimate.

$$\therefore \mathbb{E} \sup_{i=1}^n X_i \leq C \sqrt{\log n} \quad \xrightarrow{\text{sg rvs}} \text{extends to}$$

$$\therefore \mathbb{E} \sup_{i=1}^n X_i = \alpha^* \sqrt{\log n} - \frac{3}{2\alpha^*} \frac{\log \log n}{\sqrt{\log n}} + O\left(\frac{1}{\sqrt{\log n}}\right).$$

\curvearrowright Special to $N(0,1)$.