Summary Part 1: Probabilistic Methods for Non-Asymptotic Analysis

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Contents

1 Basic Inequalities

1.1 Arithmetic, Calculus and Algebra

- **Remark** (***Basic Inequalities***)
  1. ***Arithmetic Mean-Geometric Mean Inequality***:
  $$\sum_{i=1}^{n} \alpha_i x_i \ge \prod_{i=1}^{n} x_i^{\alpha_i}$$
  where $\sum_{i=1}^{n} \alpha_i = 1$ and $\alpha_i \ge 0$. Simple case, $\frac{a+b}{2} \ge \sqrt{ab}$
  2. $a^2 + b^2 \ge \pm 2ab$; Also $a + b \ge 2\sqrt{ab}$. Similarly, $\frac{a}{x} + bx \ge 2\sqrt{ab}$
  3. $(a+b)^2 \le 2(a^2 + b^2)$; Also $(\sqrt{a} + \sqrt{b})^2 \le 2(a+b)$
  4. $x + 1 \le e^x$
  5. $\log x \le x - 1$ for $x > 0$
  6. $e^s - e^t \le e^t(s - t)$ for $s \ge t$
  7. $$h(x) := (x+1)\log(x+1) - x \ge \frac{x^2}{2(1 + x/3)}, \qquad \text{for } x > 0$$
  8. $$-\log(1-x) - x \le \frac{x^2}{2(1-x)}, \qquad \text{for } x \in (0,1)$$
  9. $$h_1(x) := 1 + x - \sqrt{1+2x} \ge \frac{x^2}{2(1+x)}, \qquad \text{for } x > 0.$$
  10. ***Log-Sum Inequality***:
  For non-negative numbers $a_1, \ldots, a_n$ and $b_1, \ldots, b_n$,
  $$\sum_{i=1}^{n} a_i \log\frac{a_i}{b_i} \ge \left(\sum_{i=1}^{n} a_i\right) \log\frac{\sum_{i=1}^{n} a_i}{\sum_{i=1}^{n} b_i}$$
  with equality if and only if $\frac{a_i}{b_i}$ is constant.
  11. (Le Cam) For positive sequences a_i and b_i, such that $\sum_i a_i = \sum_i b_i = 1$,
  $$\sum_i \min\{a_i, b_i\} \ge \frac{1}{2}\left(\sum_i \sqrt{a_i b_i}\right)^2$$

12. (Devorye and Gyorfi) For non-negative sequences a_i and b_i, such that $\sum_i a_i = \sum_i b_i = 1$,

$$\sum_i \sqrt{a_i b_i} \leq 1 - \frac{\left(\sum_i |a_i - b_i|\right)^2}{8}$$

13. Taylor series:

$$\begin{aligned}
e^x &:= \sum_{n=0}^{\infty} \frac{x^n}{n!} = 1 + x + \frac{x^2}{2} + \dots, \quad \forall x \\
\log(1+x) &:= \sum_{n=1}^{\infty} \frac{(-1)^{n+1}}{n} x^n = x - \frac{x^2}{2} + \dots, \quad |x| < 1 \\
\frac{1}{1-x} &:= \sum_{n=0}^{\infty} x^n = 1 + x + x^2 + \dots, \quad |x| < 1 \\
(1+x)^{\alpha} &:= \sum_{n=0}^{\infty} \binom{\alpha}{n} x^n
\end{aligned}$$

1.2 Function Space, Convexity and Duality

- **Proposition 1.1** ***(Jensen's inequality)*** *[Vershynin, 2018]*
  Let $(\Omega, \mathscr{F}, \mathbb{P})$ be a probability space. Let $f : \Omega \to \mathbb{R}$ be a $\mathbb{P}$-measurable function and $\varphi : \mathbb{R} \to \mathbb{R}$ be ***convex function****. Then*

$$\varphi\left(\mathbb{E}\left[X\right]\right) := \varphi\left(\int X d\mathbb{P}\right) \leq \int \varphi \circ X d\mathbb{P} := \mathbb{E}\left[\varphi\left(X\right)\right]. \tag{1}$$

- **Remark** As a simple consequence of Jensen's inequality, $\|X\|_{L^p}$ is an ***increasing function in*** p, that is

$$\|X\|_{L^p} \leq \|X\|_{L^q} \quad \text{for any } 1 \leq p \leq q \leq \infty \tag{2}$$

  This inequality follows since $\varphi(x) = x^{q/p}$ is a *convex function* if $q/p \geq 1$.

- **Proposition 1.2** ***(Minkowski's inequality)*** *[Vershynin, 2018]*
  For any $p \in [1, \infty]$, $X, Y \in L^p(\Omega, \mathbb{P})$,

$$\|X + Y\|_{L^p} \leq \|X\|_{L^p} + \|Y\|_{L^p}, \tag{3}$$

  which implies that $\|\cdot\|_{L^p}$ is a norm.

- **Proposition 1.3** ***(Cauchy-Schwarz inequality)*** *[Vershynin, 2018]*
  For any random variables $X, Y \in L^2(\Omega, \mathbb{P})$, the following inequality is satisfied:

$$|\langle X\,,\, Y\rangle_{L^2}| := |\mathbb{E}\left[XY\right]| \leq \|X\|_{L^2}\,\|Y\|_{L^2}. \tag{4}$$

  This inequalities can be extended to *conjugate spaces* L^p and L^q

Proposition 1.4 ***(Hölder's inequality)*** *[Vershynin, 2018]*
For $p, q \in (1, \infty)$, $1/p + 1/q = 1$, then the random variables $X \in L^p(\Omega, \mathbb{P})$, $Y \in L^q(\Omega, \mathbb{P})$ satisfy

$$|\langle X\,,\,Y\rangle_{L^2}| := |\mathbb{E}\left[XY\right]| \leq \|X\|_{L^p}\,\|Y\|_{L^q}\,. \tag{5}$$

- **Definition** (***Legendre Transform***)
  Let $\mathcal{X} \subset \mathbb{R}^n$ be a ***convex set***, and $f : \mathcal{X} \to \mathbb{R}$ a ***convex*** function; then its ***Legendre transform*** is the function $f^* : \mathcal{X}^* \to \mathbb{R}$ defined by

  $$f^*(x^*) = \sup_{x\in\mathcal{X}}(\langle x^*\,,\,x\rangle - f(x)), \quad x^* \in \mathcal{X}^*$$

  where sup denotes the supremum, and the domain $\mathcal{X}^*$ is

  $$\mathcal{X}^* = \left\{x^* \in \mathbb{R}^n : \sup_{x\in\mathcal{X}}(\langle x^*\,,\,x\rangle - f(x)) < \infty\right\}.$$

  The function f^* is called *the **convex conjugate function*** of f.

- **Theorem 1.5** ***(Fenchel's Inequality / Fenchel-Young Inequality)***
  Suppose $f^* : \mathcal{X}^* \to \mathbb{R}$ is the convex conjugate of function $f : \mathcal{X} \to \mathbb{R}$. For every $x \in \mathcal{X}$ and $p \in \mathcal{X}^*$, i.e., independent (x, p) pairs,

  $$\langle p\,,\,x\rangle \leq f(x) + f^*(p). \tag{6}$$

- **Theorem 1.6** ***(Young's Convolution Inequality)***
  Suppose f is in the Lebesgue space $L^p(\mathbb{R}^d)$ and g is in $L^q(\mathbb{R}^d)$ and $1/p + 1/q = 1/r + 1$ with $1 \leq p, q, r \leq \infty$. Then

  $$\|f * g\|_r \leq \|f\|_p\,\|g\|_q\,. \tag{7}$$

  *Here the star denotes **convolution**:*

  $$(f * g)(t) = \int_{\mathbb{R}^d} f(t-\tau)g(\tau)d\tau$$

1.3 Probability Theory

- Assume a probability space $(\Omega, \mathscr{F}, \mathbb{P})$ and a random variable $X : \Omega \to \mathbb{R}$ is a real-valued measurable function on Ω.

- For a random variable X, the ***expectation*** and ***variance*** are denoted as

  $$\mathbb{E}\left[X\right] = \int X d\mathbb{P}$$
  $$Var(X) = \mathbb{E}\left[(X - \mathbb{E}\left[X\right])^2\right]$$

- The ***moment generating function*** of X and its ***logarithm*** are denoted as

  $$M_X(\lambda) := \mathbb{E}\left[e^{\lambda X}\right]$$
  $$\psi_X(\lambda) := \log\mathbb{E}\left[e^{\lambda X}\right]$$

- For $p > 0$, ***the p-th moment** of X* is defined as $\mathbb{E}[X^p]$, and the ***p-th absolute moment*** is $\mathbb{E}[|X|^p]$.
- The L^p ***norm*** of X is

$$\|X\|_{L^p} := \mathbb{E}[|X|^p]^{1/p}$$

where $1 \leq p < \infty$. Note that the L^p space is a *Banach space*, which is defined as

$$L^p(\Omega, \mathbb{P}) := \{X : \|X\|_{L^p} < \infty\}.$$

- *The* ***essential supremum*** of $|X|$ is the L^∞ ***norm*** of X

$$\|X\|_{L^\infty} := \text{ess sup}\,|X|$$

Similarly, L^∞ is a Banach space as well

$$L^\infty(\Omega, \mathbb{P}) := \{X : \|X\|_{L^\infty} < \infty\}.$$

- For $p = 2$, L^2 space is a *Hilbert space* with inner product between random variables $X, Y \in L^2(\Omega, \mathbb{P})$

$$\langle X\,,\,Y\rangle_{L^2} := \mathbb{E}[XY] = \int XY d\mathbb{P}$$

The ***standard deviation*** is

$$\sigma(X) = (Var(X))^{1/2} = \|X - \mathbb{E}[X]\|_{L^2}.$$

The ***covariance*** is defined as

$$\begin{aligned} cov(X,Y) &:= \langle X - \mathbb{E}[X]\,,\,Y - \mathbb{E}[Y]\rangle \\ &= \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])] \end{aligned}$$

When we consider random variables as vectors in the Hilbert space L^2, the identity above gives a ***geometric interpretation** of the notion of covariance.* The more the vectors $X - \mathbb{E}[X]$ and $Y - \mathbb{E}[Y]$ are aligned with each other, the bigger their inner product and covariance are.

- The ***cumulative distribution function (CDF)*** is defined as

$$F_X(t) := \mathbb{P}[X \leq t], \quad t \in \mathbb{R}.$$

The following result is important

Lemma 1.7 ***(Integral Identity)****. [Vershynin, 2018]*
Let X be a **non-negative** *random variable. Then*

$$\mathbb{E}[X] = \int_0^\infty \mathbb{P}[X > t]\,dt. \tag{8}$$

The two sides of this identity are either finite or infinite simultaneously.

- **Theorem 1.8** *(**Central Limit Theorem, Linderberg-Levý**)*
  *Let $X_1, \dots, X_n$ be **independent identically distributed** random variables with mean $\mathbb{E}[X_i] = 0$ and variance $Var(X_i) = 1$. Then*

$$\frac{1}{\sqrt{n}} \sum_{i=1}^{n} X_i \xrightarrow{d} N(0,1) \tag{9}$$

$$i.e. \;\; \lim_{n \to \infty} \sup_{t \in \mathbb{R}} \left| \mathbb{P}\left\{ \frac{1}{\sqrt{n}} \sum_{i=1}^{n} X_i \le t \right\} - \Phi(t) \right| = 0$$

  where $\Phi(t) = \int_{-\infty}^{t} \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du = \mathbb{P}\{g \le t\}$ for some Gaussian variable g.

- **Theorem 1.9** *(**Central Limit Theorem, Nonasymptotic, Berry-Esseen**) [Vershynin, 2018]*
  *Let $X_1, \dots, X_n$ be **independent identically distributed** random variables with mean $\mathbb{E}[X_i] = 0$, variance $Var(X_i) = \sigma^2$ and $\rho := \mathbb{E}\left[|X_i|^3\right] < \infty$. Then with some constant $C > 0$,*

$$\sup_{t \in \mathbb{R}} \left| \mathbb{P}\left\{ \frac{1}{\sigma\sqrt{n}} \sum_{i=1}^{n} X_i \le t \right\} - \Phi(t) \right| \le \frac{C}{\sigma^3 \sqrt{n}} \rho \tag{10}$$

  where $\Phi(t) = \int_{-\infty}^{t} \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du = \mathbb{P}\{g \le t\}$ for some Gaussian variable g.

- **Remark** The *Berry-Esseen* version of *central limit theorem* is ***non-asymptotic*** and it has a bound

$$\mathbb{P}\left\{ \frac{1}{\sqrt{n}} \sum_{i=1}^{n} X_i \le t \right\} \le \mathbb{P}\{g \le t\} + \frac{C}{\sqrt{n}} \rho = \int_{-\infty}^{t} \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du + \frac{C}{\sqrt{n}} \rho$$

  This bound is ***sharp***, i.e. the equality is attained when $X_i \sim \text{Bernoulli}(1/2)$.

- **Theorem 1.10** *(**Poisson Limit Theorem**). [Vershynin, 2018]*
  Let $X_{N,i}$, $1 \le i \le N$, be independent random variables $X_{N,i} \sim Ber(p_{N,i})$, and let $S_N = \sum_{i=1}^{N} X_{N,i}$. Assume that, as $N \to \infty$

$$\max_{i \le N} p_{N,i} \to 0 \quad \text{and} \quad \mathbb{E}[S_N] = \sum_{i=1}^{N} p_{N,i} \to \lambda < \infty,$$

  Then, as $N \to \infty$,

$$S_N = \sum_{i=1}^{N} X_{N,i} \xrightarrow{d} Pois(\lambda)$$

1.4 Information Theory

- **Definition** (***Shannon Entropy***) [Cover and Thomas, 2006]
  Let $(\Omega, \mathscr{F}, \mathbb{P})$ be a probability space and $X : \mathbb{R} \to \mathcal{X}$ be a random variable. Define $p(x)$ as *the*

probability density function of X with respect to a base measure μ on $\mathcal{X}$. ***The Shannon Entropy*** is defined as

$$\begin{aligned} H(X) &:= \mathbb{E}_p \left[-\log p(X) \right] \\ &= \int_{\Omega} -\log p(X(\omega)) d\mathbb{P}(\omega) \\ &= -\int_{\mathcal{X}} p(x) \log p(x) d\mu(x) \end{aligned}$$

- **Definition** (***Conditional Entropy***) [Cover and Thomas, 2006]
  If a pair of random variables (X, Y) follows the joint probability density function $p(x, y)$ with respect to a base product measure μ on $\mathcal{X} \times \mathcal{Y}$. Then ***the joint entropy*** of (X, Y), denoted as $H(X, Y)$, is defined as

$$H(X, Y) := \mathbb{E}_{X,Y} \left[-\log p(X, Y) \right] = -\int_{\mathcal{X} \times \mathcal{Y}} p(x, y) \log p(x, y) d\mu(x, y)$$

  Then ***the conditional entropy*** $H(Y|X)$ is defined as

$$\begin{aligned} H(Y|X) &:= \mathbb{E}_{X,Y} \left[-\log p(Y|X) \right] = -\int_{\mathcal{X} \times \mathcal{Y}} p(x, y) \log p(y|x) d\mu(x, y) \\ &= \mathbb{E}_X \left[\mathbb{E}_Y \left[-\log p(Y|X) \right] \right] = \int_{\mathcal{X}} p(x) \left(-\int_{\mathcal{Y}} p(y|x) \log p(y|x) d\mu(y) \right) d\mu(x) \end{aligned}$$

- **Proposition 1.11** *(**Properties of Shannon Entropy**) [Cover and Thomas, 2006]*
  Let X, Y, Z be random variables.

  1. *(**Non-negativity**) $H(X) \geq 0$;*
  2. *(**Concavity**) $H(p) := \mathbb{E}_p \left[-\log p(X) \right]$ is a concave function in terms of p.d.f. p, i.e.*

$$H(\lambda p_1 + (1-\lambda) p_2) \geq \lambda H(p_1) + (1-\lambda) H(p_2)$$

     for any two p.d.fs p_1, p_2 on $\mathcal{X}$ and any $\lambda \in [0, 1]$.

- **Definition** (***Relative Entropy / Kullback-Leibler Divergence***) [Cover and Thomas, 2006]
  Suppose that P and Q are *probability measures* on a measurable space $\mathcal{X}$, and P is *absolutely continuous* with respect to Q, then ***the relative entropy*** or ***the Kullback-Leibler divergence*** is defined as

$$\mathbb{KL}\left(P \,\|\, Q \right) := \mathbb{E}_P \left[\log \left(\frac{dP}{dQ} \right) \right] = \int_{\mathcal{X}} \log \left(\frac{dP(x)}{dQ(x)} \right) dP(x)$$

  where $\frac{dP}{dQ}$ is *the Radon-Nikodym derivative* of P with respect to Q. Equivalently, the KL-divergence can be written as

$$\mathbb{KL}\left(P \,\|\, Q \right) = \int_{\mathcal{X}} \left(\frac{dP(x)}{dQ(x)} \right) \log \left(\frac{dP(x)}{dQ(x)} \right) dQ(x)$$

  which is *the entropy of P relative to Q*. Furthermore, if μ is a base measure on $\mathcal{X}$ for which densities p and q with $dP = p(x) d\mu$ and $dQ = q(x) d\mu$ exist, then

$$\mathbb{KL}\left(P \,\|\, Q \right) = \int_{\mathcal{X}} p(x) \log \left(\frac{p(x)}{q(x)} \right) d\mu(x)$$

- **Definition** (***Mutual Information***) [Cover and Thomas, 2006]
  Consider two random variables X, Y on $\mathcal{X} \times \mathcal{Y}$ with joint probability distribution $P_{(X,Y)}$ and marginal distribution P_X and P_Y. ***The mutual information*** $I(X;Y)$ is *the relative entropy* between *the joint distribution* $P_{(X,Y)}$ and *the product distribution* $P_X \otimes P_Y$:

$$I(X;Y) = \mathbb{KL}\left(P_{(X,Y)} \,\|\, P_X \otimes P_Y\right) = \mathbb{E}_{P_{(X,Y)}}\left[\log \frac{dP_{(X,Y)}}{dP_X \otimes dP_Y}\right]$$

  If $P_{(X,Y)}$ has a probability density function $p(x,y)$ with respect to a base measure μ on $\mathcal{X} \times \mathcal{Y}$, then

$$I(X;Y) = \int_{\mathcal{X}\times\mathcal{Y}} p(x,y) \log\left(\frac{p(x,y)}{p_X(x)p_Y(y)}\right) d\mu(x,y)$$

- **Proposition 1.12** ***(Properties of Relative Entropy and Mutual Information)*** *[Cover and Thomas, 2006]*
  Let X, Y be random variables.

  1. *(**Non-negativity**) Let $p(x), q(x)$ be probability density function of P, Q.*

$$\mathbb{KL}\left(P \,\|\, Q\right) \geq 0$$

     with equality if and only if $p(x) = q(x)$ almost surely. Therefore, the mutual information is non-negative as well:

$$I(X;Y) \geq 0$$

     with equality if and only if X and Y are independent.

  2. *(**Symmetry**) $I(X;Y) = I(Y;X)$*

  3. *(**Information Gain via Conditioning**) The mutual information $I(X;Y)$ is the reduction in the uncertainty of X due to the knowledge of Y (and vice versa)*

$$\begin{aligned} I(X;Y) &= H(X) - H(X|Y) \qquad (11) \\ &= H(Y) - H(Y|X) \\ &= H(X) + H(Y) - H(X,Y) \end{aligned}$$

  4. *(**Shannon Entropy as Self-Information**) $I(X;X) = H(X)$*

  5. *(**Joint Convexity of Relative Entropy**) The relative entropy $\mathbb{KL}\left(p \,\|\, q\right)$ is **convex** in the pair (p,q); that is, if (p_1, q_1) and (p_2, q_2) are two pairs of probability density functions, then for $\lambda \in [0,1]$,*

$$\mathbb{KL}\left(\lambda p_1 + (1-\lambda)p_2 \,\|\, \lambda q_1 + (1-\lambda)q_2\right) \leq \lambda \mathbb{KL}\left(p_1 \,\|\, q_1\right) + (1-\lambda)\mathbb{KL}\left(p_2 \,\|\, q_2\right) \qquad (12)$$

- **Proposition 1.13** ***(Conditioning Reduces Entropy)*** *[Cover and Thomas, 2006]*
  From non-negativity of mutual information, we see that the entropy of X is non-increasing when conditioning on Y

$$H(X|Y) \leq H(X) \qquad (13)$$

  where equality holds if and only if X and Y are independent.

- **Proposition 1.14** *(**Chain Rule for Entropy**) [Cover and Thomas, 2006]*
  Let $X_1, X_2, \dots, X_n$ be drawn according to $p(x_1, x_2, \dots, x_n)$. Then

$$H(X_1, X_2, \dots, X_n) = \sum_{i=1}^{n} H(X_i | X_{i-1}, \dots, X_1) \tag{14}$$

- **Proposition 1.15** *(**Sub-Additivity of Entropy**) [Cover and Thomas, 2006]*
  Let $X_1, X_2, \dots, X_n$ be drawn according to $p(x_1, x_2, \dots, x_n)$. Then

$$H(X_1, X_2, \dots, X_n) \le \sum_{i=1}^{n} H(X_i) \tag{15}$$

  with equality if and only if the X_i are independent.

- **Proposition 1.16** *(**Chain Rule for Relative Entropy**) [Cover and Thomas, 2006]*
  *Let $P_{(X,Y)}$ and $Q_{(X,Y)}$ be two probability measures on product space $\mathcal{X} \times \mathcal{Y}$ and $P \ll Q$. Denote the marginal distributions P_X, Q_X and P_Y, Q_Y on $\mathcal{X}$ and $\mathcal{Y}$, respectively. $P_{Y|X}$ and $Q_{Y|X}$ are conditional distributions (Note that $P_{Y|X} \ll Q_{Y|X}$). Define **the conditional relative entropy** as*

$$\mathbb{E}_X \left[\mathbb{KL} \left(P_{Y|X} \,\|\, Q_{Y|X} \right) \right] := \mathbb{E}_X \left[\mathbb{E}_{P_{Y|X}} \left[\log \left(\frac{dP_{Y|X}}{dQ_{Y|X}} \right) \right] \right].$$

  Then the relative entropy of joint distribution $P_{(X,Y)}$ with respect to $Q_{(X,Y)}$ is

$$\mathbb{KL} \left(P_{(X,Y)} \,\|\, Q_{(X,Y)} \right) = \mathbb{KL} \left(P_X \,\|\, Q_X \right) + \mathbb{E}_X \left[\mathbb{KL} \left(P_{Y|X} \,\|\, Q_{Y|X} \right) \right] \tag{16}$$

  In addition, let P and Q denote two joint distributions for $X_1, X_2, \dots, X_n$, let $P_{1:i}$ and $Q_{1:i}$ denote the marginal distributions of $X_1, X_2, \dots, X_i$ under P and Q, respectively. Let $P_{X_i|1\dots i-1}$ and $Q_{X_i|1\dots i-1}$ denote the conditional distribution of X_i with respect to $X_1, X_2, \dots, X_{i-1}$ under P and under Q.

$$\mathbb{KL} \left(P \,\|\, Q \right) = \sum_{i=1}^{n} \mathbb{E}_{P_{1:i-1}} \left[\mathbb{KL} \left(P_{X_i|1\dots i-1} \,\|\, Q_{X_i|1\dots i-1} \right) \right] \tag{17}$$

- **Proposition 1.17** *(**Han's Inequality**) [Cover and Thomas, 2006, Boucheron et al., 2013]*
  Let $X_1, X_2, \dots, X_n$ be random variables. Then

$$H(X_1, X_2, \dots, X_n) \le \frac{1}{n-1} \sum_{i=1}^{n} H(X_1, \dots, X_{i-1}, X_{i+1}, \dots, X_n) \tag{18}$$

$$\Leftrightarrow H(X) \le \frac{1}{n-1} \sum_{i=1}^{n} H(X_{(-i)})$$

2 Summary: General Proof Stratgy for Concentration Problem

There are many proof techniques introduced. We can summarize them as follows:

1. ***The Cramér-Chernoff Method***:
   This class of methods essentially apply ***the Markov inequality*** on ***exponential transform*** $e^{\lambda X}$ with parameter λ. The key is to ***bound*** the ***log-moment generating function*** from above and then use ***the Legendre transform*** to find the concentration bound.

   Specifically, for a real-valued random variable X, any $\lambda \geq 0$, the following inequality holds

   $$\mathbb{P}\{X \geq t\} = \mathbb{P}\left\{e^{\lambda X} \geq e^{\lambda t}\right\} \leq e^{-\lambda t}\mathbb{E}\left[e^{\lambda X}\right] = \exp\left(-\lambda t + \psi_X(\lambda)\right)$$

   where $\psi_X(\lambda) := \log \mathbb{E}\left[e^{\lambda X}\right]$. One can choose optimal λ^* that ***minimizes*** *the upper bound above*. Since $\psi_X(\lambda)$ is a ***convex function***, we can define its ***Legendre transform***

   $$\psi_X^*(t) := \sup_{\lambda \in \mathbb{R}} \left\{\lambda\, t - \psi_X(\lambda)\right\}.$$

   The expression of the right-hand side is known as the ***convex conjugate*** of ψ_X. The Legendre transform of log-moment generating function is also its *convex conjugate*. Thus we have

   $$\mathbb{P}\{X \geq t\} \leq \exp\left\{-\psi_X^*(t)\right\}$$

   The lower bound can be found by applying above formula to $-X$.

   In other word, in order to prove concentration around mean

   $$\mathbb{P}\{f(X) \geq \mathbb{E}[f(X)] + t\} \;\text{ or }\; \mathbb{P}\{f(X) \leq \mathbb{E}[f(X)] - t\}$$

   using ***the Cramér-Chernoff Method***, we just need to find ***the upper bound*** $\phi(\lambda)$ of ***the logarithmic moment generating function*** $\psi(\lambda)$

   $$\psi(\lambda) := \log \mathbb{E}\left[e^{\lambda(f(X) - \mathbb{E}[f(X)])}\right] \leq \phi(\lambda).$$

   Remark (***Advantages and Disadvantages of Cramér-Chernoff Method***)
   There are several advantages for this method:

   (a) The derivation is ***distribution-free***, since ***Markov inequality*** is based on fundamental properties of *measure and integration theory*. Moreover, *the bounds on logarithmic moment generating function* $\psi(\lambda)$ can be used to ***characterize different distributions*** in terms of *their concentration behavior*.

   (b) This method is ***widely applicable***. Most of techniques we learned here is to compute *the upper bound* for $\psi(\lambda)$ and then apply the *Cramér-Chernoff method*.

   (c) The formula is ***easy to compute*** if the ***simple bounds*** on *logarithmic moment generating function* is *computed*. Then it will compute the rate via ***Legendre transform*** *of upper bound of* $\psi(\lambda)$.

   (d) The function $\psi(\lambda)$ easily handles *product measures* $\mathbb{P} = \otimes_{k=1}^n \mathbb{P}_k$ (i.e. ***independent variables***).

   $$\psi_Z(\lambda) = \log \mathbb{E}\left[e^{\lambda \sum_{i=1}^n X_i}\right] = \log \prod_{i=1}^n \mathbb{E}\left[e^{\lambda X_i}\right] = n\,\psi_X(\lambda)$$

and consequently,

$$\psi_Z^*(t) = n\, \psi_X^* \left(\frac{t}{n}\right).$$

For ***martingale difference sequence***, we see that by conditioning on previous input

$$\begin{aligned}
\mathbb{E}\left[\exp\left\{\lambda\left(\sum_{k=1}^{n} D_k\right)\right\}\right] &= \mathbb{E}\left[\mathbb{E}\left[\exp\left\{\lambda\left(\sum_{k=1}^{n} D_k\right)\right\} \;\middle|\; \mathscr{B}_{n-1}\right]\right] \\
&= \mathbb{E}\left[\exp\left\{\lambda\left(\sum_{k=1}^{n-1} D_k\right)\right\} \mathbb{E}\left[\exp\left\{\lambda D_n\right\} \;\middle|\; \mathscr{B}_{n-1}\right]\right]
\end{aligned}$$

If we can control each martingale difference by

$$\log \mathbb{E}\left[\exp\left\{\lambda D_n\right\} \;\middle|\; \mathscr{B}_{n-1}\right] \le \phi(\lambda)$$

then we have

$$\begin{aligned}
\psi_Z(\lambda) &\le \log \mathbb{E}\left[\exp\left\{\lambda\left(\sum_{k=1}^{n-1} D_k\right)\right\}\right] + \phi(\lambda) \\
&\le \ldots \\
&\le n\phi(\lambda).
\end{aligned}$$

The main disadvantage is that the Chernoff bound is ***not necessarily sharp***, since the Markov inequality is not necessarily sharp.

2. ***Entropy Method***:
The entropy method focus on *the* <u>***tensorization property***</u> *of the* ***entropy functional*** $\mathrm{Ent}(X)$

$$\mathrm{Ent}(X) := \mathbb{E}\left[X \log X\right] - \mathbb{E}\left[X\right] \log\left(\mathbb{E}\left[X\right]\right).$$

Specifically, let $Z_1, Z_2, \ldots, Z_n$ be *independent random variables* taking values in $\mathcal{X}$, and let $f : \mathcal{X}^n \to [0, \infty)$ be a measurable function. Letting $X = f(Z_1, Z_2, \ldots, Z_n)$ such that $\mathbb{E}\left[X \log X\right] < \infty$, we have

$$\mathrm{Ent}(X) \le \mathbb{E}\left[\sum_{i=1}^{n} \mathrm{Ent}_{(-i)}(X)\right].$$

where $\mathbb{E}_{(-i)}\left[\cdot\right]$ is the conditional expectation operator conditioning on $Z_{(-i)}$, which is equal to Z after dropping i-component. In other word, the ***key strategy*** for proving concentration using entropy method is to *find* <u>***the upper bound***</u> *for each* <u>***single variable***</u> ***entropy functional***

$$\mathrm{Ent}_{(-i)}(X) := \mathbb{E}_{(-i)}\left[X \log X\right] - \mathbb{E}_{(-i)}\left[X\right] \log\left(\mathbb{E}_{(-i)}\left[X\right]\right) \equiv H_{\Phi}(\mathbb{P}_i).$$

Note that for independent random variables Z, this term ***depends only on distribution of*** Z_i, since the rest $Z_{(-i)}$ are ***controlled*** by the conditioning. For distributions such as *Gaussian, Bernoulli and Poisson*, one can use <u>***the logarithmic Sobolev inequalities***</u> to derive *the upper bound of the entropy functional* via ***norm of gradients***.

To obtain *the concentraion bound*, we use ***the Herbst's argument***; that is, the find the bound

$$\mathrm{Ent}(e^{\lambda X}) \le \mathbb{E}\left[e^{\lambda X}\right]\phi(\lambda)$$

and using the differential equation for the log-moment generating function ψ

$$\frac{\mathrm{Ent}(e^{\lambda Z})}{\mathbb{E}\left[e^{\lambda Z}\right]} = \lambda\, \psi'(\lambda) - \psi(\lambda) = \lambda^2 \left(\frac{\psi(\lambda)}{\lambda}\right)',$$

we can obtain the upper bound for $\psi(\lambda)$:

$$\begin{aligned}
\left(\frac{\psi(\lambda)}{\lambda}\right)' &\le \lambda^{-2}\phi(\lambda) \\
\left(\frac{\psi(\lambda)}{\lambda}\right) &\le \lim_{\lambda\to 0}\left(\frac{\psi(\lambda)}{\lambda}\right) + \int_0^\lambda s^{-2}\phi(s)ds \\
\psi(\lambda) &\le \lambda\left(\mathbb{E}\left[X\right] + \int_0^\lambda s^{-2}\phi(s)ds\right).
\end{aligned}$$

Finally, we apply *the Chernoff bound*.

In general, ***the key advantage*** of the ***entropy method*** is that the tensorization property allows us to ***generalize*** *the concentration result from* 1***-dimensional distribution*** *to* n***-dimensional product distribution***.

The main effort is to find a concentration inequality for ***entropy of single variable distribution***. One way to find such concentration is to use ***the logarithmic Sobelev inequalities***.

3. ***Transportation Method***:
   The transportation method is closed related to various *statistical divergence* esp. ***the Kullback-Leibler divergence*** and ***the information inequality***. The centrial part of the proof is to show that for *given distribution* $\mathbb{P}$ of concern, ***the transportation cost inequality*** holds:

   $$\mathcal{W}_1^d(\mathbb{Q},\mathbb{P}) := \min_{\gamma\in\Pi(\mathbb{Q},\mathbb{P})} \mathbb{E}_\gamma\left[d(Y,X)\right] \le \phi^{*-1}\left(\mathbb{KL}\left(\mathbb{Q}\,\|\,\mathbb{P}\right)\right) \quad \forall \text{ distribution } \mathbb{Q}$$

   where $\Pi(\mathbb{Q},\mathbb{P}) = \{\gamma \in \mathcal{P}(\mathcal{X}\times\mathcal{X}) : Y_{\#}\gamma = \mathbb{Q},\ X_{\#}\gamma = \mathbb{P}\}$ i.e. γ is a ***coupling*** of marginal distribution $\mathbb{Q}$ and $\mathbb{P}$. And, for every $s \ge 0$,

   $$\phi^{*-1}(s) = \inf\{t \in \mathrm{dom}(\phi^*) : \phi^*(t) > s\}$$

   is defined as the ***the generalized inverse*** of *the Legendre transform* $\phi^* = \sup_{\lambda\in(0,b)}(\lambda x - \phi(\lambda))$.

   There are *two ways to proceed*:

   (a) Based on *the duality of* 1*-Wasserstein distance*, this *transportation cost inequality* implies that for any 1*-Lipschitz function* $f : \mathcal{X} \to \mathbb{R}$ with respect to metric d

   $$\mathbb{E}_{\mathbb{Q}}\left[f(Y)\right] - \mathbb{E}_{\mathbb{P}}\left[f(X)\right] = \mathbb{E}_\gamma\left[f(Y) - f(X)\right] \le \mathcal{W}_1^d(\mathbb{Q},\mathbb{P}) \le \phi^{*-1}\left(\mathbb{KL}\left(\mathbb{Q}\,\|\,\mathbb{P}\right)\right).$$

(b) Or, we use *the Cauchy-Schwartz inequality*

$$\mathbb{E}_{\mathbb{Q}}\left[f(Y)\right] - \mathbb{E}_{\mathbb{P}}\left[f(X)\right] = \mathbb{E}_{\gamma}\left[f(Y) - f(X)\right] \le \sum_{i=1}^{n} \alpha_i \mathbb{E}_{\gamma}\left[d(Y_i, X_i)\right]$$
$$\le \left(\sum_{i=1}^{n} \alpha_i^2\right)^{1/2} \left(\sum_{i=1}^{n} (\mathbb{E}_{\gamma}\left[d(Y_i, X_i)\right])^2\right)^{1/2}$$

If we can show that the quadratic of transportation cost

$$\min_{\gamma \in \Pi(\mathbb{Q},\mathbb{P})} \sum_{i=1}^{n} (\mathbb{E}_{\gamma}\left[d(Y_i, X_i)\right])^2 \le \varphi\left(\mathbb{KL}\left(\mathbb{Q} \,\|\, \mathbb{P}\right)\right)$$

Then

$$\mathbb{E}_{\mathbb{Q}}\left[f(Y)\right] - \mathbb{E}_{\mathbb{P}}\left[f(X)\right] \le \left(\left(\sum_{i=1}^{n} \alpha_i^2\right) \varphi\left(\mathbb{KL}\left(\mathbb{Q} \,\|\, \mathbb{P}\right)\right)\right)^{1/2}$$

Finally by the ***transportation lemma***, we can show that

$$\psi_{f(X)}(\lambda) := \mathbb{E}_{\mathbb{P}}\left[e^{\lambda(f(X) - \mathbb{E}[f(X)])}\right] \le \phi(\lambda).$$

The concentration follows from *Chernoff bound* with rate function $\phi^*(t)$.

Note that the transportation cost inequality has ***the tensorization property*** as well. This allows us to generalize the the inequality from 1-dimension distribution to product distributions.

Remark (***Advantages and Disadvantages of Transportation Method***)
There are several advantages for this method:

(a) *The optimal transport problem* and *the Wasserstein distance* is closely related to ***the information geometry*** of probability space $\mathcal{P}(\mathcal{X})$. In particular, the transportation cost inequality relates the optimal transport cost to the relative entropy:

$$\mathcal{W}_p^d(\mathbb{Q}, \mathbb{P}) \le \varphi\left(\mathbb{KL}\left(\mathbb{Q} \,\|\, \mathbb{P}\right)\right).$$

This provides an alternative ***information theoretical interpretation*** of the concentration behavior of independent random variables.

(b) *The low optimal transportation cost* is closely associated with ***the concentration of measure*** in $\mathbb{P} \in \mathcal{P}(\mathcal{X})$. In fact, we can bound the concentration function $\alpha_{\mathbb{P},(\mathcal{X},d)}(t)$ from above by the upper bound of optimal transport cost.

(c) ***The dual formulation*** naturally leads to *the concentration of Lipschitz function* or other *strong uniform continuous functions.*

(d) The concept of ***coupling*** $\gamma \in \Pi(\mathbb{Q}, \mathbb{P})$ allows us to extend the concentration results to ***dependent variables***, such as *Markov chains, Markov random field* etc. In those cases, we can separate the conditional distribution $\mathbb{P}(X_i | X_{1:i-1})$ and the marginal distributions $\mathbb{P}(X_{1:i-1})$.

4. ***Concentration of Measure and Isoperimetric Inequalities***:
The applicablity of ***isoperimetric Inequalities*** are *limited* to a few cases such as ***Gaussian measure***, ***Bernoulli measure*** (or *the uniform distribution on* ***binary hypercube***, *compact manifolds*, *Lebesgue measure* on $\mathbb{R}^n$, *graph vertex and edge boundaries* etc.).

The key is to derive the upper bound for ***the concentration function***:

$$\alpha_{\mathbb{P},(\mathcal{X},d)} := \sup\left\{\mathbb{P}\left\{A_t^c\right\} : A \subset \mathcal{X}, \mathbb{P}(A) \geq \frac{1}{2}\right\}.$$

Note that for $d(x,A) := \inf_{y\in A} d(x,y)$, the *t-blowup of* A is defined as

$$\mathbb{P}\left\{A_t^c\right\} := \mathbb{P}\left\{d(X,A) \geq t\right\}.$$

Then the goal is to find ***the isopermetric inequality***

$$\alpha_{\mathbb{P},(\mathcal{X},d)} \leq \exp\left(-\phi(t)\right) \quad \Leftrightarrow \quad \mathbb{P}(A)\mathbb{P}\left(A_t^c\right) := \mathbb{P}(A)\mathbb{P}\left\{d(X,A) \geq t\right\} \leq \exp\left(-\phi(t)\right).$$

By Levy's inequality, for *Lipschitz function* $f : \mathcal{X} \to \mathbb{R}$, let $A := \{x : f(x) \leq \mathrm{Med}(f(X))\}$, so that $\mathbb{P}(A) \geq 1/2$, and the complement of t-blowup of A becomes

$$\mathbb{P}\left(A_t^c\right) = \mathbb{P}\left\{f(X) \geq \mathrm{Med}(f(X)) + t\right\}$$

Then the above isopermetric inequality is equivalent to

$$\begin{aligned}\mathbb{P}\left\{f(X) \geq \mathrm{Med}(f(X)) + t\right\} &\leq 2\exp\left(-\phi(t)\right)\\ \mathbb{P}\left\{f(X) \leq \mathrm{Med}(f(X)) - t\right\} &\leq 2\exp\left(-\phi(t)\right).\end{aligned}$$

Besides the existing result for *Gaussian and Bernoulli random variables*, the Talagrand's ***convex distance inequality*** is very useful to derive such isopermetric inequality based on *weighted Hamming distance.*

$$\mathbb{P}(A)\mathbb{P}\left\{\sup_{\alpha\in\mathbb{R}_+^n:\|\alpha\|_2=1}\inf_{y\in A}\sum_{i=1}^{n}\alpha_i \mathbb{1}\left\{x_i \neq y_i\right\} \geq t\right\} \leq \exp\left(-\frac{t^2}{4}\right).$$

Note that if A is a convex set,

$$d(x,A) := \inf_{y\in A}\|x-y\|_2 \leq d_T(x,A) := \sup_{\alpha\in\mathbb{R}_+^n:\|\alpha\|_2=1}\inf_{y\in A}\sum_{i:x_i\neq y_i}\alpha_i$$

If ***isoperimetric theorem*** exists ***for given distribution or space***, then the derived concentration bound is known to be ***sharp*** due to ***the concentration of measure phenomenon***. This is the main ***advantage*** of using isoperimetric inequalities. However, proving ***isoperimetric theorem*** is extremely hard and thus is not widely available.

Transportation methods and *logarithmic Sobolev inequalities* can also use to show *isoperimetric inequalities.*

3 Summary: Distribution-Free Concentration Inequality

- **Remark** (***Distribution-Free Concentration Inequality***)
  Some concentration results are based on ***assumption*** *on specific underling distributions* such as *Gaussian, Bernoulli, Poisson, sub-Gaussian, sub-Gamma* etc. On the other hand, some concentration results are based on assumption on specific function class such as *bounded (actually is sub-Gaussian), Lipschitz function, bounded difference, convex function* etc. The latter results do not rely on specific distribution assumption, so it is called ***the distribution-free concentration inequality***.

  We list out several important inequalities:

  1. **Theorem 3.1** *(**Markov's Inequality**). [Vershynin, 2018]*
     *For any **non-negative** random variable X and $t > 0$, we have*
     $$\mathbb{P}\left\{X \geq t\right\} \leq \frac{\mathbb{E}\left[X\right]}{t}$$

  2. **Theorem 3.2** *(**Chebyshev's Inequality**). [Vershynin, 2018]*
     Let X be a random variable with mean μ and variance σ^2. Then, for any $t > 0$, we have
     $$\mathbb{P}\left\{|X - \mu| \geq t\right\} \leq \frac{\sigma^2}{t^2}.$$

  3. **Theorem 3.3** *(**Chernoff's inequality**) [Boucheron et al., 2013]*
     *Let X be a real-valued random variable. For $\lambda \geq 0$, $\psi_X(\lambda)$ is the **the logarithm of moment generating function** of X and $\psi_X^*(t)$ is its **Legendre (Cramér) transform**. Then*
     $$\mathbb{P}\left\{X \geq t\right\} \leq \exp\left(-\psi_X^*(t)\right).$$

  4. **Theorem 3.4** *(**Hoeffding's inequality**) [Boucheron et al., 2013]*
     *Let $X_1, \ldots, X_n$ be independent random variables such that X_i takes its values in $[a_i, b_i]$ **almost surely** for all $i \leq n$. Then for every $t > 0$,*
     $$\mathbb{P}\left\{\sum_{i=1}^{n}\left(X_i - \mathbb{E}\left[X_i\right]\right) \geq t\right\} \leq \exp\left(-\frac{2t^2}{\sum_{i=1}^{n}(b_i - a_i)^2}\right).$$

  5. **Corollary 3.5** *(**Azuma-Hoeffding Inequality**)[Wainwright, 2019]*
     *Let $\{(D_k, \mathscr{B}_k), k \geq 1\}$ be a **martingale difference sequence** for which there are constants $\{(a_k, b_k)\}_{k=1}^{n}$ such that $D_k \in [a_k, b_k]$ almost surely for all $k = 1, \ldots, n$. Then, for all $t \geq 0$,*
     $$\mathbb{P}\left\{\left|\sum_{k=1}^{n} D_k\right| \geq t\right\} \leq 2\exp\left(-\frac{2t^2}{\sum_{k=1}^{n}(b_k - a_k)^2}\right)$$

  6. **Theorem 3.6** *(**McDiarmid's Inequality / Bounded Differences Inequality**)[Boucheron et al., 2013, Wainwright, 2019]*

*Suppose that f satisfies **the bounded difference property** (50) with parameters $(L_1, \ldots, L_n)$ i.e. for each index $k = 1, 2, \ldots, n$,*

$$\left|f(x_1, \ldots, x_n) - f(x_1, \ldots, x_{i-1}, x_i', x_{i+1}, \ldots, x_n)\right| \le L_k, \quad \textit{for all } x, x' \in \mathcal{X}^n.$$

*Assume that the random vector $X = (X_1, X_2, \ldots, X_n)$ has **independent** components. Then*

$$\mathbb{P}\left\{|f(X) - \mathbb{E}\left[f(X)\right]| \ge t\right\} \le 2\exp\left(-\frac{2t^2}{\sum_{k=1}^{n} L_k^2}\right).$$

Note that *functions with bounded difference property* are ***Lipschitz function*** *with respect to **Hamming distance**.*

7. **Theorem 3.7** *(**Concentration of Separately Convex Lipschitz Functions**) [Boucheron et al., 2013]*
*Let $Z := (Z_1, \ldots, Z_n)$ be independent random variables, each taking values in the interval $[a_i, b_i]$ and let $f : \mathbb{R}^n \to \mathbb{R}$ be a **separately convex function** (i.e. f is **convex in each coordinate** while the **others** are **fixed**) such that*

$$|f(x) - f(y)| \le L\,\|x - y\| \quad \textit{for all } x, y \in [0, 1]^n.$$

Then $X = f(Z_1, \ldots, Z_n)$ satisfies, for all $t > 0$,

$$\mathbb{P}\left\{f(Z) - \mathbb{E}\left[f(Z)\right] \ge t\right\} \le \exp\left(-\frac{t^2}{2L^2\sum_{k=1}^{n}(b_k - a_k)^2}\right).$$

Convex Lipschitz assumption is ***stronger*** than bounded difference assumption.

8. **Theorem 3.8** *(**Concentration of Quasi-Convex Lipschitz Functions**) [Boucheron et al., 2013]*
*Let $Z := (Z_1, \ldots, Z_n)$ be independent random variables taking values in the interval $[0, 1]$ and let $f : [0, 1]^n \to \mathbb{R}$ be a **quasi-convex function**; that is*

$$\{z : f(z) \le s\} \;\; \textit{is convex set for all } s \in \mathbb{R}.$$

Moreover, f is Lipschitz function satisfying

$$|f(x) - f(y)| \le \|x - y\| \quad \textit{for all } x, y \in [0, 1]^n.$$

Then $X = f(Z_1, \ldots, Z_n)$ satisfies, for all $t > 0$,

$$\mathbb{P}\left\{f(Z) \ge \mathit{Med}(f(Z)) + t\right\} \le 2\exp\left(-\frac{t^2}{4}\right),$$
$$\mathbb{P}\left\{f(Z) \le \mathit{Med}(f(Z)) - t\right\} \le 2\exp\left(-\frac{t^2}{4}\right).$$

4 Comparison: Gaussian Tail Bound vs. Poisson Tail Bound

- **Remark** (***Gaussian Tail Bound*** *vs.* ***Poisson Tail Bound***)
  Based on Chernoff bound, we can derive the tail bound for two important class of distributions:

  1. ***Gaussian tail bound***: for any $t > 0$,

  $$\mathbb{P}\left\{X \geq t\right\} \leq \exp\left(-\frac{t^2}{2\nu}\right),$$

     where $\nu > 0$.

  2. ***Poisson tail bound***: for any $t > \mathbb{E}\left[X\right] = \nu$,

  $$\mathbb{P}\left\{X \geq t\right\} \leq \exp\left(-\nu h\left(\frac{t}{\nu}\right)\right) = e^{-\nu}\left(\frac{e\nu}{t+\nu}\right)^{t+\nu}$$

     where $h(x) = (1+x)\log(1+x) - x$ for all $x \geq -1$ and $\nu > 0$.

     Note that for ***small deviation*** *around the mean*, the *tail of Poisson distribution* $\text{Pois}(\nu)$ behaves like *Gaussian* $\mathcal{N}(\nu, \nu)$:

  $$\mathbb{P}\left\{|X - \nu| \geq t\right\} \leq 2\exp\left(-\frac{ct^2}{\nu}\right)$$

     But in *the* ***large deviation*** *regime*, the Poisson tail is ***heavier*** *than Gaussian*. Such distribution is a ***sub-Gamma distribution***.

- **Remark** 1. ***The Bennet inequality*** captures ***the Poisson tail bevarior***: for sum of n independent random variables X_i such that $X_i \leq b$ almost surely with zero mean, finite variance $\nu = \sum_{i=1}^{n} \mathbb{E}\left[X_i^2\right]$. The Bennet inequality provides a tail bound as

  $$\mathbb{P}\left\{\sum_{i=1}^{n} X_i \geq t\right\} \leq \exp\left(-\frac{\nu}{b^2} h\left(\frac{bt}{\nu}\right)\right)$$

  In small deviation regime, where $u := bt/\nu \ll 1$, $h(u) \approx u^2$, the Bennet inequality gives a Gaussian tail bound $\approx \exp\left(-t^2/\nu\right)$.

  In large deviation regime, $u \gg bt/\nu \geq 2$, $h(u) \geq \frac{1}{2} u\log(u)$, thus the Bennet inequality gives a Poisson tail bound $\approx (\nu/b^2 t)^{t/(2b^2)}$

  2. ***The Bernstein inequality*** captures ***the Exponential tail bevarior***

  3. Let X_i, $1 \leq i \leq n$, be *independent centred random variables a.s.* ***bounded*** by $c < \infty$ in absolute value. Set $\sigma^2 = 1/n \sum_{i=1}^{n} \mathbb{E}\left[X_i^2\right]$ and $S_n = \sum_{i=1}^{n} X_i$. Then, for all $t \geq 0$,

  $$\begin{aligned} \mathbb{P}\left\{S_n \geq t\right\} &\leq \exp\left(-\frac{n\sigma^2}{c^2} h\left(\frac{ct}{n\sigma^2}\right)\right) && (\textit{Bennett inequality}) \\ &\leq \exp\left(-\frac{3t}{4c}\log\left(1 + \frac{2ct}{3n\sigma^2}\right)\right) && (\textit{Prokhorov inequality}) \\ &\leq \exp\left(-\frac{t^2}{2n\sigma^2 + 2ct/3}\right) && (\textit{Bernstein inequality}) \end{aligned}$$

5 The Cramér-Chernoff Method

5.1 From Markov Inequality to Cramér-Chernoff Method

- **Proposition 5.1** *(**Markov's Inequality**). [Vershynin, 2018]*
  *For any **non-negative** random variable X and $t > 0$, we have*

$$\mathbb{P}\{X \geq t\} \leq \frac{\mathbb{E}[X]}{t} \tag{19}$$

- **Proposition 5.2** *(**Chebyshev's Inequality**). [Vershynin, 2018]*
  Let X be a random variable with mean μ and variance σ^2. Then, for any $t > 0$, we have

$$\mathbb{P}\{|X - \mu| \geq t\} \leq \frac{\sigma^2}{t^2}. \tag{20}$$

- **Remark** (***Cramér-Chernoff Method***)
  In this section we describe and formalize the Cramér-Chernoff bounding method. This method determines *the best possible bound* for a ***tail probability*** that one can possibly obtain using *Markov's inequality* with an exponential function $\phi(t) = e^{\lambda t}$.

  Recall that for a real-valued random variable X, any $\lambda \geq 0$, the following inequality holds

$$\mathbb{P}\{X \geq t\} \leq e^{-\lambda t}\mathbb{E}\left[e^{\lambda X}\right] = \exp\left(-\lambda t + \psi_X(\lambda)\right)$$

  where $\psi_X(\lambda) := \log \mathbb{E}\left[e^{\lambda X}\right]$. One can choose optimal λ^* that ***minimizes** the upper bound above*. Since $\psi_X(\lambda)$ is a ***convex function***, we can define its ***Legendre transform***

$$\psi_X^*(t) := \sup_{\lambda \in \mathbb{R}} \left\{\lambda\, t - \psi_X(\lambda)\right\}.$$

  The expression of the right-hand side is known as the ***Fenchel-Legendre dual function*** (or the ***convex conjugate***) of ψ_X. The Legendre transform of log-moment generating function is also its convex conjugate.

  In other word, in order to prove concentration around mean

$$\mathbb{P}\{f(X) \geq \mathbb{E}[f(X)] + t\} \;\text{ or }\; \mathbb{P}\{f(X) \leq \mathbb{E}[f(X)] - t\}$$

  using ***the Cramér-Chernoff Method***, we just need to find *the upper bound* of *the logarithmic moment generating function*

$$\psi(\lambda) := \log \mathbb{E}\left[e^{\lambda(f(X) - \mathbb{E}[f(X)])}\right] \leq \phi(\lambda)$$

- **Proposition 5.3** *(**Chernoff's inequality**) [Boucheron et al., 2013]*
  *Let X be a real-valued random variable. For $\lambda \geq 0$, $\psi_X(\lambda)$ is the **the logarithm of moment generating function** of X and $\psi_X^*(t)$ is its **Legendre (Cramér) transform**. Then*

$$\mathbb{P}\{X \geq t\} \leq \exp\left(-\psi_X^*(t)\right). \tag{21}$$

- **Remark** The ***Legendre transform*** is also called ***the Cramér transform*** [Boucheron et al., 2013].

  Since $\psi_X(0) = 0$, its *Legendre transform* $\psi_X^*(t)$ is ***nonnegative***.

- **Definition** (***The Rate Function***)
  <u>***The rate function***</u> is defined as ***the Legendre transformation*** of *the logarithm of the moment generating function* of a random variable. That is,

$$\psi_X^*(t) := \sup_{\lambda \in \mathbb{R}} \{\lambda\, t - \psi_X(\lambda)\}, \tag{22}$$

  where $\psi_X(\lambda) := \log \mathbb{E}\left[e^{\lambda X}\right]$. Thus, by *Chernoff's inequality*, we can bound *the tail probabilities* of random variables via *its rate function*.

- **Remark** (***Sums of independent random variables***)
  The reason why Chernoff's inequality became popular is that it is very simple to use when applied to a sum of independent random variables. As an illustration, assume that $Z := X_1 + \ldots + X_n$ where $X_1, \ldots, X_n$ are ***independent*** *and* ***identically distributed*** *real-valued random variables*. Denote the logarithm of the moment-generating function of the X_i by $\psi_X(\lambda) = \log \mathbb{E}\left[e^{\lambda X_i}\right]$, and the corresponding *Legendre transform* by $\psi_X^*(t)$. Then, by independence, for all λ for which $\psi_X(\lambda) < \infty$,

$$\psi_Z(\lambda) = \log \mathbb{E}\left[e^{\lambda \sum_{i=1}^n X_i}\right] = \log \prod_{i=1}^{n} \mathbb{E}\left[e^{\lambda X_i}\right] = n\, \psi_X(\lambda)$$

  and consequently,

$$\psi_Z^*(t) = n\, \psi_X^*\left(\frac{t}{n}\right).$$

  Thus *the Chernoff's inequality* states that

$$\mathbb{P}\{Z \geq t\} \leq \exp\left(-\psi_Z^*(t)\right) = \exp\left(-n\, \psi_X^*\left(\frac{t}{n}\right)\right).$$

- **Example** (***Normal Distribution***)
  Let X be a ***centered normal random variable*** with variance σ^2. Then

$$\psi_X(\lambda) = \frac{\lambda^2 \sigma^2}{2}, \quad \lambda_t = \frac{t}{\sigma^2}$$

  and, therefore for every $t > 0$,

$$\psi_X^*(t) = \frac{t^2}{2\sigma^2}.$$

  Hence, *Chernoff's inequality* implies, for all $t > 0$,

$$\mathbb{P}\{X \geq t\} \leq \exp\left(-\frac{t^2}{2\sigma^2}\right).$$

  Chernoff's inequality appears to be quite sharp in this case. In fact, one can show that it cannot be improved uniformly by more than a factor of 1/2. ∎

- **Example** (***Poisson Distribution***)
  Let X be a ***Poisson random variable*** with parameter ν, that is, $\mathbb{P}\{X = k\} = \frac{1}{k!}e^{\nu}\nu^k$ for all $k = 0, 1, 2, \ldots$ Let $Z = X - \nu$ be the *corresponding centered variable.* Then by direct calculation,

$$\psi_Z(\lambda) = \nu\left(e^{\lambda} - \lambda - 1\right), \quad \lambda_t = \log\left(1 + \frac{t}{\nu}\right)$$

  Therefore *the Legendre transform* equals, for every $t > 0$,

$$\psi^*_Z(t) = \nu h\left(\frac{t}{\nu}\right).$$

  where the function h is defined, for all $x \geq -1$, by $h(x) = (1 + x)\log(1 + x) - x$. Similarly, for every $t \leq \nu$,

$$\psi^*_{-Z}(t) = \nu h\left(-\frac{t}{\nu}\right).$$

- **Example** (***Bernoulli Distribution***)
  Let X be a ***Bernoulli random variable*** with probability of success p, that is, $\mathbb{P}\{X = 1\} = 1 - \mathbb{P}\{X = 0\} = p$. Let $Z = X - p$ be the *corresponding centered variable.* If $0 < t < 1 - p$, we have

$$\psi_Z(\lambda) = \log\left(pe^{\lambda} + 1 - p\right) - p\,\lambda, \quad \lambda_t = \log\frac{(1-p)(p+t)}{p(1-p-t)}$$

  and therefore, for every $t \in (0, 1 - p)$,

$$\psi^*_Z(t) = (1 - p - t)\log\frac{1-p-t}{1-p} + (p + t)\log\frac{p+t}{p}.$$

  Equivalently, setting $a = t + p$ for every $a \in (p, 1)$,

$$\psi^*_Z(t) = h_p(a) = (1 - a)\log\frac{1-a}{1-p} + a\log\frac{a}{p}.$$

  We note here that $h_p(a)$ is just the ***Kullback-Leibler divergence*** $\mathbb{KL}\left(\mathbb{P}_a \,\|\, \mathbb{P}_p\right)$ between a Bernoulli distribution $\mathbb{P}_a$ of parameter a and a Bernoulli distribution $\mathbb{P}_p$ of parameter p.

$$\mathbb{P}\{X \geq t\} \leq \exp\left(-\mathbb{KL}\left(\mathbb{P}_{p+t} \,\|\, \mathbb{P}_p\right)\right)$$

5.2 Sub-Gaussian Random Variables

- **Definition** (***Sub-Gaussian Random Variable***)
  A ***centered*** random variable X is said to be ***sub-Gaussian** with **variance factor** ν* if

$$\psi_X(\lambda) \leq \frac{\lambda^2\nu}{2}, \quad \text{for every } \lambda \in \mathbb{R}. \tag{23}$$

  We denote the collection of such random variables by $\mathcal{G}(\nu)$.

- **Proposition 5.4** ***(Moment Characterization of Sub-Gaussian Random Variables)*** *[Boucheron et al., 2013]*
  Let X be a random variable with $\mathbb{E}[X] = 0$. If for some $\nu > 0$

$$\mathbb{P}\{X > t\} \vee \mathbb{P}\{-X > t\} \le \exp\left(-\frac{t^2}{2\nu}\right), \quad \text{for all } t > 0 \tag{24}$$

  then for every integer $q \ge 1$,

$$\mathbb{E}\left[X^{2q}\right] \le 2q!(2\nu)^q \le q!(4\nu)^q. \tag{25}$$

  ***Conversely**, if for some positive constant C*

$$\mathbb{E}\left[X^{2q}\right] \le q!C^q,$$

  then $X \in \mathcal{G}(4C)$ (and therefore (25) holds with $\nu = 4C$).

- **Proposition 5.5** ***(Equivalent Definitions for Sub-Gaussian Random Variables)**. [Vershynin, 2018]*
  *Let X be a random variable. Then the following properties are **equivalent**; the parameters $K_i > 0$ appearing in these properties differ from each other by at most an absolute constant factor.*

  1. *The **tails** of X satisfy*

  $$\mathbb{P}\{|X| \ge t\} \le 2\exp\left(-t^2/K_1^2\right) \quad \text{for all } t \ge 0.$$

  2. *The **moments** of X satisfy*

  $$\|X\|_{L^p} = \left(\mathbb{E}\left[|X|^p\right]\right)^{1/p} \le K_2\sqrt{p} \quad \text{for all } p \ge 1.$$

  3. *The **moment-generating function (MGF)** of X^2 satisfies*

  $$\mathbb{E}\left[\exp(\lambda^2 X^2)\right] \le \exp(K_3^2\,\lambda^2) \quad \text{for all } \lambda \text{ such that } |\lambda| \le \frac{1}{K_3}$$

  4. *The **MGF** of X^2 is **bounded** at some point, namely*

  $$\mathbb{E}\left[\exp(X^2/K_4^2)\right] \le 2.$$

  *Moreover, if $\mathbb{E}[X] = 0$ then properties (1)-(4) are also **equivalent** to the following one.*

  5. *The **MGF** of X satisfies*

  $$\mathbb{E}\left[\exp(\lambda X)\right] \le \exp(K_5^2\,\lambda^2) \quad \text{for all } \lambda \in \mathbb{R}.$$

- **Definition** (***Sub-Gaussian Norm***)
  The ***sub-gaussian norm*** of X, denoted $\|X\|_{\psi_2}$, is defined to be the ***smallest*** K_4 that satisfies

$$\mathbb{E}\left[\exp(X^2/K_4^2)\right] \le 2.$$

  In other words, we define

$$\|X\|_{\psi_2} = \inf\left\{t > 0 : \mathbb{E}\left[\exp(X^2/t^2)\right] \le 2\right\}. \tag{26}$$

- **Remark** (***Sub-Gaussian Characterizations via Sub-Gaussian Norm***)
We can restate the properties of sub-gaussian random variables in terms of sub-gaussian norm:

$$\begin{aligned}
\mathbb{P}\{|X| \geq t\} \leq 2\exp\left(-ct^2/\|X\|_{\psi_2}^2\right) \quad &\text{for all } t \geq 0; \\
\|X\|_{L^p} \leq C\,\|X\|_{\psi_2}\sqrt{p} \quad &\text{for all } p \geq 1; \\
\mathbb{E}\left[\exp(X^2/\|X\|_{\psi_2}^2)\right] \leq 2; \\
\text{if } \mathbb{E}[X] = 0, \quad \text{then } \mathbb{E}[\exp(\lambda X)] \leq \exp(C\lambda^2\,\|X\|_{\psi_2}^2) \quad &\text{for all } \lambda \in \mathbb{R}.
\end{aligned}$$

- **Example** Here are some classical examples of sub-gaussian distributions.

  1. (***Gaussian***): As we already noted, $X \sim N(0,1)$ is a sub-gaussian random variable with $\|X\|_{\psi_2} \leq C$, where C is an absolute constant. More generally, if $X \sim N(0,\sigma^2)$ then X is sub-gaussian with
  $$\|X\|_{\psi_2} \leq C\sigma \tag{27}$$
  2. (***Bernoulli***): Let X be a random variable with ***symmetric Bernoulli distribution***. Since $|X| = 1$, it follows that X is a sub-gaussian random variable with
  $$\|X\|_{\psi_2} \leq \frac{1}{\sqrt{\log 2}} \tag{28}$$
  3. (***Bounded***): More generally, any ***bounded random variable*** X is sub-gaussian with
  $$\|X\|_{\psi_2} \leq C\,\|X\|_{\infty} \tag{29}$$
  where $C = 1/\sqrt{\log 2}$.

5.3 Sub-Exponential and Sub-Gamma Random Variables

- **Remark** For *exponential distribution* $X \sim \exp(a)$ with *rate* a (*inverse* of *scale parameter*), the p.d.f. and moment generating function

$$\begin{aligned}
f_X(x) &= ae^{-ax}, \quad x > 0 \\
M_X(\lambda) &= \frac{1}{1-\lambda/a}, \quad 0 < \lambda < a
\end{aligned}$$

For *Gamma distribution* $X \sim \Gamma(a, 1/b)$ with *shape parameter* a and *scale parameter* b, the p.d.f. and the moment generating function

$$\begin{aligned}
f_X(x) &= \frac{1}{\Gamma(a)\,b^a}x^{a-1}e^{-x/b}, \quad x > 0 \\
M_X(\lambda) &= \left(\frac{1}{1-b\lambda}\right)^a, \quad 0 < \lambda < 1/b
\end{aligned}$$

Also $\mathbb{E}[X] = ab$ and $\mathrm{Var}(X) = ab^2$.

- **Definition** (***Sub-Exponential Random Variables***)
  A ***nonnegative*** random variable X has a ***sub-exponential distribution*** if there exists a constant $a > 0$ such that

$$
\begin{aligned}
&\mathbb{E}\left[e^{\lambda X}\right] \le \frac{1}{1-\lambda/a} \quad \text{for every } \lambda \text{ such that } 0 < \lambda < a \\
\text{or} \quad &\psi_X(\lambda) \le \log\left(\frac{1}{1-\lambda/a}\right)
\end{aligned}
$$

- **Definition** (***Sub-Gamma Random Variables***)
  A real-valued ***centered*** *random variable* X is said to be ***sub-gamma*** *on* ***the right tail*** *with* ***variance factor*** ν *and* ***scale parameter*** c if

$$
\psi_X(\lambda) \le \frac{\lambda^2 \nu}{2(1-c\lambda)} \quad \text{for every } \lambda \text{ such that } 0 < \lambda < 1/c
$$

  We denote the collection of such random variables by $\Gamma_+(\nu, c)$.

  Similarlly, a real-valued centered random variable X is said to be ***sub-gamma*** *on* ***the left tail*** *with* ***variance factor*** ν *and* ***scale parameter*** c if $-X$ is ***sub-gamma on the right tail*** *with variance factor* ν *and tail parameter* c. We denote the collection of such random variables by $\Gamma_-(\nu, c)$.

  Finally, X is simply said to be ***sub-gamma*** *with* ***variance factor*** ν *and* ***scale parameter*** c if X is *sub-gamma* ***both*** *on the right and left tails* with ***the same*** *variance factor* ν and *scale parameter* c. The collection of such random variables is denoted by $\Gamma(\nu, c)$.

  Observe that $\Gamma(\nu, 0) = \mathcal{G}(\nu)$.

- **Remark** To derive the definition fo sub-gamma distribution, we see that *the variance factor* $\nu := ab^2$ and $c := b$. Also $\mathbb{E}[X] = ab$. The logarithmic moment generating function of Gamma distribution $\Gamma(a, 1/b) = \Gamma(\nu/c^2, 1/c)$ is

$$
\psi_{X-\mathbb{E}[X]}(\lambda) = a \log\left(\frac{1}{1-b\lambda}\right) - \lambda ab \le \frac{\lambda^2 b^2 a}{2(1-b\lambda)} \equiv \frac{\lambda^2 \nu}{2(1-c\lambda)}
$$

  The last inequality is due to

$$
\log\left(\frac{1}{1-u}\right) - u \le \frac{u^2}{2(1-u)}
$$

- **Remark** Note that the sum of n i.i.d. random variables with exponential distribution $\exp(1/b)$ have the Gamma distribution $\Gamma(n, 1/b)$. So ***the sub-gamma distributed*** random variable follows ***the sub-exponential distribution*** as well (with shape parameter = 1).

- **Proposition 5.6** ***(Equivalent Definitions for Sub-Exponential Random Variables).*** *[Vershynin, 2018]*
  Let X be a random variable. Then the following properties are ***equivalent****; the parameters $K_i > 0$ appearing in these properties differ from each other by at most an absolute constant factor.*

  1. *The* ***tails*** *of X satisfy*

$$
\mathbb{P}\left\{|X| \ge t\right\} \le 2\exp\left(-t/K_1\right) \quad \textit{for all } t \ge 0.
$$

*2. The **moments** of X satisfy*

$$\|X\|_{L^p} = \left(\mathbb{E}\left[|X|^p\right]\right)^{1/p} \le K_2\, p \quad \textit{for all } p \ge 1.$$

*3. The **moment-generating function (MGF)** of $|X|$ satisfies*

$$\mathbb{E}\left[\exp(\lambda\,|X|)\right] \le \exp(K_3\,\lambda) \quad \textit{for all } \lambda \textit{ such that } 0 \le \lambda \le \frac{1}{K_3}$$

*4. The **MGF** of $|X|$ is **bounded** at some point, namely*

$$\mathbb{E}\left[\exp(|X|/K_4)\right] \le 2.$$

*Moreover, if $\mathbb{E}[X] = 0$ then properties (1)-(4) are also **equivalent** to the following one.*

*5. The **MGF** of X satisfies*

$$\mathbb{E}\left[\exp(\lambda X)\right] \le \exp(K_5^2\,\lambda^2) \quad \textit{for all } \lambda \textit{ such that } |\lambda| \le \frac{1}{K_5}.$$

- **Definition** (***Sub-Exponential Norm***)
  The ***sub-exponential norm*** of X, denoted $\|X\|_{\psi_1}$, is defined to be the ***smallest*** K_4 that satisfies

  $$\mathbb{E}\left[\exp(|X|/K_4)\right] \le 2.$$

  In other words, we define

  $$\|X\|_{\psi_1} = \inf\left\{t > 0 : \mathbb{E}\left[\exp(|X|/t)\right] \le 2\right\}. \tag{30}$$

- **Remark** Sub-gaussian and sub-exponential distributions are closely related.

  1. First, *any sub-gaussian distribution is clearly sub-exponential.*
  2. Second, *the **square** of a **sub-gaussian random variable** is **sub-exponential***:

     Lemma 5.7 *(**Sub-exponential is Sub-gaussian Squared**). [Vershynin, 2018]*
     *A random variable X is **sub-gaussian** if and only if X^2 is **sub-exponential**. Moreover,*

     $$\left\|X^2\right\|_{\psi_1} = \|X\|_{\psi_2}^2$$

     More generally, *the **product** of two **sub-gaussian random variables** is **sub-exponential***:

     Lemma 5.8 *(**Product of Sub-Gaussians is Sub-Exponential**). [Vershynin, 2018]*
     *Let X and Y be **sub-gaussian random variables**. Then XY is **sub-exponential**. Moreover,*

     $$\|XY\|_{\psi_1} \le \|X\|_{\psi_2}\,\|Y\|_{\psi_2}.$$

- **Proposition 5.9** *(**Moment Characterization of Sub-Exponential Random Variables**) [Boucheron et al., 2013]*

Let X be a nonnegative random variable. If X is sub-exponential distributed with parameter $a > 0$ then for every integer $q \geq 1$,

$$\mathbb{E}\left[X^q\right] \leq 2^{q+1}\frac{q!}{a^q}. \tag{31}$$

Conversely*, if there exists a constant $a > 0$ in order that for every positive integer q,*

$$\mathbb{E}\left[X^q\right] \leq \frac{q!}{a^q},$$

then X is sub-exponential. More precisely, for any $0 < \lambda < a$,

$$\mathbb{E}\left[e^{\lambda X}\right] \leq \frac{1}{1 - \lambda/a}.$$

- **Remark** (***Concentration Inequalities for Sub-Gamma Distribution***)
  Similarly to the *sub-Gaussian property*, the ***sub-gamma property*** can be characterized in terms of *tail or moment conditions.* We start by computing ***the Fenchel-Legendre dual function*** of

$$\psi(\lambda) = \frac{\lambda^2 \nu}{2(1 - c\lambda)}.$$

Setting

$$h_1(u) = 1 + u - \sqrt{1 + 2u} \text{ for } u > 0,$$

it follows by elementary calculation that for every $t > 0$,

$$\psi^*(t) = \sup_{\lambda \in (0, 1/c)} \left\{ t\lambda - \frac{\lambda^2 \nu}{2(1 - c\lambda)} \right\} = \frac{\nu}{c^2} h_1\left(\frac{c\,t}{\nu}\right).$$

Since h_1 is an increasing function from $(0, \infty)$ onto $(0, \infty)$ with ***inverse function***

$$h^{-1}(u) = u + \sqrt{2u} \text{ for } u > 0,$$

we finally get

$$\psi^{*-1}(u) = \sqrt{2\nu u} + cu.$$

Hence, *Chernoff's inequality* implies that whenever X is a *sub-gamma random variable on the right tail* with *variance factor* ν and *scale parameter* c, for every $t > 0$, we have

$$\mathbb{P}\left\{X > t\right\} \leq \exp\left(\frac{\nu}{c^2} h_1\left(\frac{c\,t}{\nu}\right)\right), \tag{32}$$

or equivalently, for every $t > 0$,

$$\mathbb{P}\left\{X > \sqrt{2\nu t} + ct\right\} \leq e^{-t}. \tag{33}$$

Therefore, if X belongs to $\Gamma(\nu, c)$, then for every $t > 0$,

$$\mathbb{P}\left\{X > \sqrt{2\nu t} + ct\right\} \vee \mathbb{P}\left\{-X > \sqrt{2\nu t} + ct\right\} \leq e^{-t}. \quad \blacksquare$$

5.4 Hoeffding's Inequality

- **Remark** (***Bounded Variables***)
  Bounded variables are an important class of *sub-Gaussian random variables.* The *sub-Gaussian property* of *bounded random variables* is established by the following lemma:

- **Lemma 5.10** ***(Hoeffding's Lemma)*** *[Boucheron et al., 2013]*
  Let X be a random variable with $\mathbb{E}[X] = 0$, taking values in a ***bounded interval*** *$[a, b]$ and let $\psi_X(\lambda) := \log \mathbb{E}\left[e^{\lambda X}\right]$. Then*

$$\psi_X''(\lambda) \le \frac{(b-a)^2}{4}$$

  and $X \in \mathcal{G}((b-a)^2/4)$.

- **Proposition 5.11** ***(Hoeffding's inequality)*** *[Boucheron et al., 2013]*
  Let $X_1, \ldots, X_n$ be independent random variables such that X_i takes its values in $[a_i, b_i]$ ***almost surely*** *for all $i \le n$. Let*

$$S = \sum_{i=1}^{n} (X_i - \mathbb{E}[X_i]) .$$

  Then for every $t > 0$,

$$\mathbb{P}\{S \ge t\} \le \exp\left(-\frac{2t^2}{\sum_{i=1}^{n}(b_i - a_i)^2}\right). \tag{34}$$

- **Proposition 5.12** ***(General Hoeffding's inequality)*** *[Vershynin, 2018]*
  Let $X_1, \ldots, X_n$ be ***independent sub-gaussian*** *random variables. Let*

$$S = \sum_{i=1}^{n} (X_i - \mathbb{E}[X_i]) .$$

  Then for every $t > 0$,

$$\mathbb{P}\{S \ge t\} \le \exp\left(-\frac{c\,t^2}{\sum_{i=1}^{n}\|X_i\|_{\psi_2}}\right). \tag{35}$$

5.5 Bernstein's Inequality

- **Definition** (***Bernstein's Condition***)
  Given a *random variable X* with mean $\mu = \mathbb{E}[X]$ we say that ***<u>Bernstein's condition</u>*** *with parameter ν, c* holds if the *variance* $\mathrm{Var}(X) = \mathbb{E}\left[X^2\right] - \mu^2 \le \nu$, and

$$\sum_{i=1}^{n} \mathbb{E}\left[(X-\mu)_+^q\right] \le \frac{q!}{2}\nu c^{q-2}, \quad \text{for all integers } q \ge 2,$$

  where $(x)_+ = \max\{x, 0\}$.

- **Remark** If X is *bounded*, then it satisfies *the Bernstein's condition*.

  If X satisfies *the Bernstein's condition*, X follows a ***sub-gamma distribution***.

- **Proposition 5.13** ***(Bernstein's Condition*** $\Rightarrow$ ***Sub-Gamma Distribution)**. [Boucheron et al., 2013]*
  *Let $X_1, \ldots, X_n$ be independent real-valued random variables and each X_i satisfies **the Bernstein's condition** with parameter ν and c. If $S = \sum_{i=1}^{n} (X_i - \mathbb{E}[X_i])$, then for all $\lambda \in (0, 1/c)$ and $t > 0$*

$$\psi_S(\lambda) \le \frac{\lambda^2 \nu}{2(1 - c\lambda)}$$

  and

$$\psi_S^*(t) \ge \frac{\nu}{c^2} h_1\left(\frac{ct}{\nu}\right),$$

  where $h_1(u) = 1 + u - \sqrt{1 + 2u}$ for $u > 0$. In particular, for all $t > 0$,

$$\mathbb{P}\left\{S \ge \sqrt{2\nu t} + ct\right\} \le e^{-t}. \quad (36)$$

- **Proposition 5.14** ***(Bernstein's Inequality)**. [Boucheron et al., 2013]*
  *Let $X_1, \ldots, X_n$ be independent real-valued random variables satisfying **the Bernstein's conditions** above and let $S = \sum_{i=1}^{n} (X_i - \mathbb{E}[X_i])$. Then for all $t > 0$,*

$$\mathbb{P}\{S \ge t\} \le \exp\left(-\frac{t^2}{2(\nu + ct)}\right). \quad (37)$$

- **Corollary 5.15** ***(Bernstein's Inequality for Bounded Distributions)**. [Vershynin, 2018]*
  *Let $X_1, \ldots, X_n$ be **independent, mean zero** random variables, such that $|X_i| \le b$ all i. Then, for every $t \ge 0$, we have*

$$\mathbb{P}\left\{\left|\frac{1}{n}\sum_{i=1}^{n} X_i\right| \ge t\right\} \le 2\exp\left(-\frac{t^2}{2(\nu + bt/3)}\right). \quad (38)$$

  Here $\nu = \sum_{i=1}^{n} \mathbb{E}\left[X_i^2\right]$ is the variance of the sum.

- **Corollary 5.16** ***(Bernstein's Inequality)**. [Vershynin, 2018]*
  *Let $X_1, \ldots, X_n$ be **independent, mean zero, sub-exponential random variables**. Then, for every $t \ge 0$, we have*

$$\mathbb{P}\left\{\left|\sum_{i=1}^{n} X_i\right| \ge t\right\} \le 2\exp\left[-c\min\left\{\frac{t^2}{\sum_{i=1}^{n} \|X_i\|_{\psi_2}^2}, \frac{t}{\max_i \|X_i\|_{\psi_1}}\right\}\right] \quad (39)$$

  where $c > 0$ is an absolute constant.

- **Proposition 5.17** ***(Bernstein's Inequality, Linear Combination Form)**. [Vershynin, 2018]*

*Let $X_1, \ldots, X_n$ be **independent, mean zero, sub-exponential random variables**, and $a = (a_1, \ldots, a_n) \in \mathbb{R}^n$. Then, for every $t \geq 0$, we have*

$$\mathbb{P}\left\{\left|\sum_{i=1}^{n} a_i X_i\right| \geq t\right\} \leq 2\exp\left[-c\min\left\{\frac{t^2}{K^2\,\|a\|_2^2}, \frac{t}{K\,\|a\|_\infty}\right\}\right] \tag{40}$$

where $c > 0$ is an absolute constant and $K = \max_i \|X_i\|_{\psi_1}$.

- **Corollary 5.18** *(**Bernstein's Inequality, Average Form**). [Vershynin, 2018]*
*Let $X_1, \ldots, X_n$ be **independent, mean zero, sub-exponential random variables**. Then, for every $t \geq 0$, we have*

$$\mathbb{P}\left\{\left|\frac{1}{n}\sum_{i=1}^{n} X_i\right| \geq t\right\} \leq 2\exp\left[-c\min\left\{\frac{t^2}{K^2}, \frac{t}{K}\right\}n\right] \tag{41}$$

where $K = \max_i \|X_i\|_{\psi_1}$.

5.6 Bennett's Inequality

- **Remark** Our starting point is the fact that *the logarithmic moment-generating function* of an *independent sum* equals *the sum of the logarithmic moment-generating functions of the centered summands*, that is,

$$\psi_S(\lambda) = \sum_{i=1}^{n}\left(\log \mathbb{E}\left[e^{\lambda X_i}\right] - \lambda \mathbb{E}\left[X_i\right]\right).$$

Using $\log u \leq u - 1$ for $u > 0$,

$$\psi_S(\lambda) \leq \sum_{i=1}^{n} \mathbb{E}\left[e^{\lambda X_i} - \lambda X_i - 1\right]. \tag{42}$$

Both Bennett's and Bernstein's inequalities may be derived from this bound, under different integrability conditions for the X_i.

- **Proposition 5.19** *(**Bennett's Inequality**) [Boucheron et al., 2013]*
*Let $X_1, \ldots, X_n$ be independent random variables with **finite variance** such that $X_i \leq b$ for some $b > 0$ **almost surely** for all $i \leq n$. Let*

$$S = \sum_{i=1}^{n}\left(X_i - \mathbb{E}\left[X_i\right]\right)$$

and $\nu = \sum_{i=1}^{n} \mathbb{E}\left[X_i^2\right]$. If we write $\phi(u) = e^u - u - 1$ for $u \in \mathbb{R}$, then, for all $\lambda > 0$,

$$\log \mathbb{E}\left[e^{\lambda S}\right] \leq n\log\left(1 + \frac{\nu}{nb^2}\phi(b\lambda)\right) \leq \frac{\nu}{b^2}\,\phi(b\lambda),$$

and for any $t > 0$,

$$\mathbb{P}\left\{S \geq t\right\} \leq \exp\left(-\frac{\nu}{b^2}h\left(\frac{b\,t}{\nu}\right)\right) \tag{43}$$

where $h(u) = (1+u)\log(1+u) - u$ for $u > 0$.

- **Remark** This bound can be analyzed in two different regimes:
  1. *In the **small deviation regime***, where $u := bt/\nu \ll 1$, we have *asymptotically* $h(u) \approx u^2$ and *Bennett's inequality* gives *approximately the Gaussian tail bound* $\approx \exp(-t^2/\nu)$.
  2. *In the **large deviations regime***, say where $u := bt/\nu \geq 2$, we have $h(u) \geq \frac{1}{2} u \log u$, and *Bennett's inequality* gives a ***Poisson-like tail*** $(\nu/bt)^{t/2b}$.

5.7 The Johnson-Lindenstrauss Lemma

- **Remark** (***Overview of The Johnson-Lindenstrauss Lemma***)
  The celebrated ***Johnson-Lindenstrauss lemma*** states roughly that, given an arbitrary set of *n points* in a (high-dimensional) Euclidean space, there exists a ***linear embedding*** of these points in a *d-dimensional Euclidean space* such that ***all pairwise distances are preserved*** within a factor of $1 \pm \epsilon$ if d is proportional to $(\log n)/\epsilon^2$. It is remarkable that *this result* ***does not involve the dimension of the space*** to which the n points belong. In fact, the dimension of this space may even be *infinite*.

- **Definition** (***ϵ-Isometry***)
  Consider an arbitrary set $A \subset \mathbb{R}^D$ or $A \subset \mathcal{H}$ for *separable Hilbert space $\mathcal{H}$*. Given $\epsilon \in (0, 1)$, a map $f : \mathbb{R}^D \to \mathbb{R}^d$ is called an ***ϵ-isometry on** A* if for every pair $a, a' \in A$, we have

$$(1-\epsilon)\left\|a - a'\right\|_2^2 \leq \left\|f(a) - f(a')\right\|_2^2 \leq (1+\epsilon)\left\|a - a'\right\|_2^2.$$

- **Remark** (***Problem Statement***)
  A natural question is to find ***the smallest possible value of*** d for which *a linear ϵ-isometry exists on A*. *The Johnson-Lindenstrauss lemma*, stated and proved below, ensures that when A is a ***finite set*** with cardinality n, a *linear ϵ-isometry* exists whenever $d \geq \kappa\epsilon^{-2}\log(n)$, where κ is an absolute constant.

- **Remark** (***Gaussian Random Projection***)
  The basic idea is to construct a ***random projection*** $W : \mathbb{R}^D \to \mathbb{R}^d$ (i.e. a *linear mapping*) that is an exact ***isometry*** "***in expectation***," that is, for every $\alpha \in \mathbb{R}^D$,

$$\mathbb{E}\left[\|W(\alpha)\|_2^2\right] = \mathbb{E}\left[\|\alpha\|_2^2\right].$$

  In other words, denoting by $L^{2,d}$ the space of *square-integrable $\mathbb{R}^d$-valued random vectors*, W is an ***isometry*** from $\mathbb{R}^D$ into $L^{2,d}$.

  To construct W, let $X_{i,j}$, $i = 1, \ldots, d$, $j = 1, \ldots, D$ be *independent and identically distributed* real-valued random variables such that $\mathbb{E}[X_{i,j}] = 0$ and $\mathrm{Var}(X_{i,j}) = 1$. For every $\alpha = (\alpha_1, \ldots, \alpha_D) \in \mathbb{R}^D$ and $i \in \{1, \ldots, d\}$, define

$$W_i(\alpha) := \sum_{j=1}^{D} \alpha_j X_{i,j}$$

$W_i(\alpha)/\sqrt{d}$ is the i-th component of the random vector $W(\alpha)$, that is, W is defined by

$$W(\alpha) := \left(\frac{1}{\sqrt{d}}\sum_{j=1}^{D}\alpha_j X_{i,j}\right)_{i=1}^{d}$$
$$\Rightarrow W(\alpha) := \frac{1}{\sqrt{d}}X\alpha^T.$$

Observe that by independence of the $X_{i,j}$, for every $i = 1, \ldots, d$,

$$\mathbb{E}\left[W_i(\alpha)^2\right] = \mathbb{E}\left[\left(\sum_{j=1}^{D}\alpha_j X_{i,j}\right)^2\right] = \sum_{j=1}^{D}\alpha_i^2\mathbb{E}\left[X_{i,j}^2\right] = \mathbb{E}\left[\|\alpha\|_2^2\right].$$

Therefore, for every $\alpha \in \mathbb{R}^D$,

$$\mathbb{E}\left[\|W(\alpha)\|_2^2\right] = \frac{1}{d}\sum_{i=1}^{d}\mathbb{E}\left[W_i(\alpha)^2\right] = \mathbb{E}\left[\|\alpha\|_2^2\right].$$

and indeed, W is an *isometry* from $\mathbb{R}^D$ into $L^{2,d}$.

- **Theorem 5.20** ***(The Johnson-Lindenstrauss Lemma)*** *[Boucheron et al., 2013]*
  Let A be a ***finite subset*** *of $\mathbb{R}^D$ with cardinality n. Assume that for some $\nu \geq 1$, $X = [X_{i,j}]$ where $X_{i,j}$ are i.i.d with zero mean sub-Gaussian random variables with variance less than or equal to ν^2, i.e. $X_{i,j} \in \mathcal{G}(\nu)$ and let $\epsilon, \delta \in (0,1)$. If*

  $$d \geq 100\frac{\nu^2\log\left(\frac{n}{\sqrt{\delta}}\right)}{\epsilon^2},$$

  then with probability at least $1-\delta$, W is an ***ϵ-isometry*** *on A. That is, for every pair $a, a' \in A$, with probability $1-\delta$ we have*

  $$(1-\epsilon)\left\|a - a'\right\|_2^2 \leq \left\|\frac{1}{\sqrt{d}}Xa^T - \frac{1}{\sqrt{d}}X(a')^T\right\|_2^2 \leq (1+\epsilon)\left\|a-a'\right\|_2^2.$$

6 Martingale Method

6.1 Martingale and Martingale Difference Sequence

- **Definition** (***Martingale***) [Resnick, 2013]
  Let $\{X_n, n \geq 0\}$ be a stochastic process on $(\Omega, \mathscr{F})$ and $\{\mathscr{F}_n, n \geq 0\}$ be a ***filtration***; that is, $\{\mathscr{F}_n, n \geq 0\}$ is an *increasing sub σ-fields* of $\mathscr{F}$

  $$\mathscr{F}_0 \subseteq \mathscr{F}_1 \subseteq \mathscr{F}_2 \subseteq \ldots \subseteq \mathscr{F}.$$

  Then $\{(X_n, \mathscr{F}_n), n \geq 0\}$ is a ***martingale (mg)*** if

  1. X_n is ***adapted*** in the sense that for each n, $X_n \in \mathscr{F}_n$; that is, X_n is $\mathscr{F}_n$-measurable.
  2. $X_n \in L_1$; that is $\mathbb{E}\left[|X_n|\right] < \infty$ for $n \geq 0$.

3. For $0 \leq m < n$

$$\mathbb{E}[X_n \mid \mathscr{F}_m] = X_m, \quad \text{a.s.} \tag{44}$$

If the equality of (44) is replaced by $\geq$; that is, things are getting better on the average:

$$\mathbb{E}[X_n \mid \mathscr{F}_m] \geq X_m, \quad \text{a.s.} \tag{45}$$

then $\{X_n\}$ is called a ***sub-martingale (submg)*** while if things are getting worse on the average

$$\mathbb{E}[X_n \mid \mathscr{F}_m] \leq X_m, \quad \text{a.s.} \tag{46}$$

$\{X_n\}$ is called a ***super-martingale (supermg)***.

- **Remark** $\{X_n\}$ is ***martingale*** if it is *both* a ***sub*** and ***supermartingale***. $\{X_n\}$ is a ***super-martingale*** if and only if $\{-X_n\}$ is a ***submartingale***.

- **Remark** If $\{X_n\}$ is a ***martingale***, then $\mathbb{E}[X_n]$ is *constant*. In the case of a ***submartingale***, *the mean increases* and for a ***supermartingale***, *the mean decreases*.

- **Proposition 6.1** *[Resnick, 2013]*
  *If $\{(X_n, \mathscr{F}_n), n \geq 0\}$ is a **(sub, super) martingale**, then*

  $$\{(X_n, \sigma(X_0, X_1, \ldots, X_n)), n \geq 0\}$$

  *is also a **(sub, super) martingale**.*

- **Definition** (***Martingale Differences***). [Resnick, 2013]
  $\{(d_j, \mathscr{B}_j), j \geq 0\}$ is a ***(sub, super) martingale difference sequence*** or a ***(sub, super) fair sequence*** if

  1. For $j \geq 0$, $\mathscr{B}_j \subset \mathscr{B}_{j+1}$.
  2. For $j \geq 0$, $d_j \in L_1$, $d_j \in \mathscr{B}_j$; that is, d_j is *absolutely integrable* and $\mathscr{B}_j$*-measurable*.
  3. For $j \geq 0$,

  $$\begin{aligned} \mathbb{E}[d_{j+1} | \mathscr{B}_j] &= 0, && (\textit{martingale difference / fair sequence}); \\ &\geq 0, && (\textit{submartingale difference / subfair sequence}); \\ &\leq 0, && (\textit{supmartingale difference / supfair sequence}) \end{aligned}$$

- **Proposition 6.2** *(**Construction of Martingale From Martingale Difference**)[Resnick, 2013]*
  *If $\{(d_j, \mathscr{B}_j), j \geq 0\}$ is **(sub, super) martingale difference sequence**, and*

  $$X_n = \sum_{j=0}^{n} d_j,$$

  *then $\{(X_n, \mathscr{B}_n), n \geq 0\}$ is a **(sub, super) martingale**.*

- **Proposition 6.3** ***(Construction of Martingale Difference From Martingale)*** *[Resnick, 2013]*
  Suppose $\{(X_n, \mathscr{B}_n), n \geq 0\}$ is a ***(sub, super) martingale****. Define*

$$d_0 := X_0 - \mathbb{E}[X_0]$$
$$d_j := X_j - X_{j-1}, \quad j \geq 1.$$

  Then $\{(d_j, \mathscr{B}_j), j \geq 0\}$ is a ***(sub, super) martingale difference sequence****.*

- **Proposition 6.4** ***(Orthogonality of Martingale Differences)****. [Resnick, 2013]*
  If $\{(X_n, \mathscr{B}_n), n \geq 0\}$ is a ***martingale*** *where X_n can be decomposed as*

$$X_n = \sum_{j=0}^{n} d_j,$$

  d_j is $\mathscr{B}_j$-measurable and $\mathbb{E}[d_j^2] < \infty$ for $j \geq 0$, then $\{d_j\}$ are ***orthogonal****:*

$$\mathbb{E}[d_i\, d_j] = 0 \quad i \neq j.$$

- **Example** (***Smoothing as Martingale***)
  Suppose $X \in L_1$ and $\{\mathscr{B}_n, n \geq 0\}$ is an increasing family of sub σ-algebra of $\mathscr{B}$. Define for $n \geq 0$

$$X_n := \mathbb{E}[X|\mathscr{B}_n].$$

  Then $(X_n, \mathscr{B}_n)$ is a ***martingale***. From this result, we see that $\{(d_n, \mathscr{B}_n), n \geq 0\}$ is a ***martingale difference sequence*** when

$$d_n := \mathbb{E}[X|\mathscr{B}_n] - \mathbb{E}[X|\mathscr{B}_{n-1}], \quad n \geq 1. \tag{47}$$

- **Example** (***Sums of Independent Random Variables***)
  Suppose that $\{Z_n, n \geq 0\}$ is an ***independent*** *sequence of integrable random variables* satisfying for $n \geq 0$, $\mathbb{E}[Z_n] = 0$. Set

$$X_0 := 0,$$
$$X_n := \sum_{i=1}^{n} Z_i, \quad n \geq 1$$
$$\mathscr{B}_n := \sigma(Z_0, \ldots, Z_n).$$

  Then $\{(X_n, \mathscr{B}_n), n \geq 0\}$ is a ***martingale*** since $\{(Z_n, \mathscr{B}_n), n \geq 0\}$ is a ***martingale difference sequence***.

- **Example** (***Likelihood Ratios***).
  Suppose $\{Y_n, n \geq 0\}$ are ***independent identically distributed*** random variables and suppose *the true density* of Y_n is f_0 (The word "*density*" can be understood with respect to some fixed reference measure μ.) Let f_1 be *some other probability density*. For simplicity suppose $f_0(y) > 0$, for all y. For $n \geq 0$, define the likelihood ratio

$$X_n := \frac{\prod_{i=0}^{n} f_1(Y_i)}{\prod_{i=0}^{n} f_0(Y_i)}$$
$$\mathscr{B}_n := \sigma(Y_0, \ldots, Y_n)$$

  Then $(X_n, \mathscr{B}_n)$ is a ***martingale***.

6.2 Bernstein Inequality for Martingale Difference Sequence

- **Proposition 6.5** ***(Bernstein Inequality, Martingale Difference Sequence Version)*** *[Wainwright, 2019]*
  Let $\{(D_k, \mathscr{B}_k), k \geq 1\}$ be a ***martingale difference sequence****, and suppose that*

$$\mathbb{E}\left[\exp\left(\lambda D_k\right)|\mathscr{B}_{k-1}\right] \leq \exp\left(\frac{\lambda^2 \nu_k^2}{2}\right)$$

  almost surely for any $|\lambda| < 1/\alpha_k$. Then the following hold:

  1. *The sum $\sum_{k=1}^n D_k$ is* ***sub-exponential*** *with* ***parameters*** $\left(\sqrt{\sum_{k=1}^n \nu_k^2}\ ,\ \alpha_*\right)$ *where $\alpha_* := \max_{k=1,\ldots,n} \alpha_k$. That is, for any $|\lambda| < 1/\alpha_*$,*

$$\mathbb{E}\left[\exp\left\{\lambda\left(\sum_{k=1}^n D_k\right)\right\}\right] \leq \exp\left(\frac{\lambda^2 \sum_{k=1}^n \nu_k^2}{2}\right)$$

  2. *The sum satisfies* ***the concentration inequality***

$$\mathbb{P}\left\{\left|\sum_{k=1}^n D_k\right| \geq t\right\} \leq \begin{cases} 2\exp\left(-\frac{t^2}{2\sum_{k=1}^n \nu_k^2}\right) & \text{if } 0 \leq t \leq \frac{\sum_{k=1}^n \nu_k^2}{\alpha_*} \\ 2\exp\left(-\frac{t}{\alpha_*}\right) & \text{if } t > \frac{\sum_{k=1}^n \nu_k^2}{\alpha_*}. \end{cases} \tag{48}$$

6.3 Azuma-Hoeffding Inequality

- **Corollary 6.6** ***(Azuma-Hoeffding Inequality)****[Wainwright, 2019]*
  Let $\{(D_k, \mathscr{B}_k), k \geq 1\}$ be a ***martingale difference sequence*** *for which there are constants $\{(a_k, b_k)\}_{k=1}^n$ such that $D_k \in [a_k, b_k]$ almost surely for all $k = 1, \ldots, n$. Then, for all $t \geq 0$,*

$$\mathbb{P}\left\{\left|\sum_{k=1}^n D_k\right| \geq t\right\} \leq 2\exp\left(-\frac{2t^2}{\sum_{k=1}^n (b_k - a_k)^2}\right) \tag{49}$$

6.4 Bounded Difference Inequality

- An important application of *Azuma-Hoeffding Inequality* concerns functions that satisfy a *bounded difference property.*

  Definition (***Functions with Bounded Difference Property***)
  Given vectors $x, x' \in \mathcal{X}^n$ and an index $k \in \{1, 2, \ldots, n\}$, we define a new vector $x^{(-k)} \in \mathcal{X}^n$ via

$$x_j^{(-k)} = \begin{cases} x_j & j \neq k \\ x_k' & j = k \end{cases}$$

  With this notation, we say that $f : \mathcal{X}^n \to \mathbb{R}$ satisfies ***the bounded difference inequality*** with parameters $(L_1, \ldots, L_n)$ if, for each index $k = 1, 2, \ldots, n$,

$$\left|f(x) - f(x^{(-k)})\right| \leq L_k, \quad \text{for all } x, x' \in \mathcal{X}^n. \tag{50}$$

- **Corollary 6.7** ***(McDiarmid's Inequality / Bounded Differences Inequality)****[Wainwright, 2019]*
  Suppose that f satisfies ***the bounded difference property*** (50) *with parameters* $(L_1, \ldots, L_n)$ *and that the random vector $X = (X_1, X_2, \ldots, X_n)$ has* ***independent*** *components. Then*

$$\mathbb{P}\left\{|f(X) - \mathbb{E}\left[f(X)\right]| \geq t\right\} \leq 2\exp\left(-\frac{2t^2}{\sum_{k=1}^{n} L_k^2}\right). \tag{51}$$

7 Bounding Variance

7.1 Mean-Median Deviation

- **Definition** (***Median of Random Variable***)
  The ***median*** of a random variable $X \in \mathcal{X}$ with distribution $\mathbb{P}$ is a constant m such that

$$\mathbb{P}\left\{X \geq m\right\} \geq \frac{1}{2} \quad \wedge \quad \mathbb{P}\left\{X \leq m\right\} \geq \frac{1}{2}$$

- **Proposition 7.1** ***(Mean-Median Deviation, Variance Bound)*** *[Boucheron et al., 2013]*
  Let $X \in \mathcal{X}$ be a random variable with distribution $\mathbb{P}$, m be the ***median*** *of X and $\mu = \mathbb{E}[X]$ be the* ***mean*** *of X. If $Var(X) = \sigma^2 < \infty$, then*

$$|m - \mu| \leq \sqrt{Var(X)} = \sigma \tag{52}$$

  (proof by Jenson's inequality $|m - \mu| = |\mathbb{E}[X - m]| \leq \mathbb{E}[|X - m|] \leq \mathbb{E}[|X - \mu|] \leq \sqrt{\mathbb{E}\left[|X - \mu|^2\right]}$)

- **Exercise 7.2** ***(Mean-Median Deviation via Concentration Inequality)*** *[Boucheron et al., 2013]*
  Let X be a random variable with ***median*** *m such that positive constants a and b exist so that for all $t > 0$,*

$$\mathbb{P}\left\{|X - m| \geq t\right\} \leq a\exp\left(-\frac{t^2}{b}\right)$$

  Show that

$$|m - \mu| \leq \min\left\{\sqrt{ab},\ \frac{a}{2}\sqrt{b\pi}\right\}.$$

- **Exercise 7.3** ***(Concentration Inequality Around Medians and Means)*** *[Wainwright, 2019]*
  Given a scalar random variable X, suppose that there are positive constants c_1, c_2 such that for all $t \geq 0$,

$$\mathbb{P}\left\{|X - \mathbb{E}[X]| \geq t\right\} \leq c_1\exp\left(-c_2 t^2\right) \tag{53}$$

  1. *Prove that $Var(X) \leq \frac{c_1}{c_2}$*

2. *Let m_X be the a* ***median*** *of X. Show that* ***whenever the mean concentration bound*** (53) ***holds****, then for* ***any median*** *m_X, we have, for all $t \geq 0$,* ***the median concentration***

$$\mathbb{P}\left\{|X - m_X| \geq t\right\} \leq c_3 \exp\left(-c_4 t^2\right) \tag{54}$$

where $c_3 := 4c_1$ and $c_4 := \frac{c_2}{8}$.

3. *Conversely, show that* ***whenever the median concentration bound*** (54) ***holds****, then* ***mean concentration*** (53) *holds with $c_1 = 2c_3$ and $c_2 = \frac{c_4}{4}$.*

7.2 The Efron-Stein Inequality and Jackknife Estimation

- **Remark** (***Variance of Smoothing Martingale Difference Sequence***)
  Suppose $X \in L_1$ and $\{\mathscr{B}_n, n \geq 0\}$ is an increasing family of sub σ-algebra of $\mathscr{B}$ formed by

$$\mathscr{B}_n := \sigma\left(Z_1, \ldots, Z_n\right).$$

  For $n \geq 1$, define

$$\begin{aligned}
d_0 &:= \mathbb{E}\left[X\right] \\
d_n &:= \mathbb{E}\left[X|\mathscr{B}_n\right] - \mathbb{E}\left[X|\mathscr{B}_{n-1}\right] \\
&= \mathbb{E}\left[X|Z_1, \ldots, Z_n\right] - \mathbb{E}\left[X|Z_1, \ldots, Z_{n-1}\right].
\end{aligned}$$

  From (47) we see that $(d_n, \mathscr{B}_n)$ is a martingale difference sequence. By *orthogonality of martingale difference*, we see that

$$\mathbb{E}\left[d_i\, d_j\right] = 0 \quad i \neq j.$$

  Therefore, based on the decomposition

$$X - EX = \sum_{i=1}^{n} d_i$$

  we have

$$\begin{aligned}
\mathrm{Var}(X) = \mathbb{E}\left[\left(\sum_{i=1}^{n} d_i\right)^2\right] &= \sum_{i=1}^{n} \mathbb{E}\left[d_i^2\right] + 2\sum_{i>j} \mathbb{E}\left[d_i\, d_j\right] \\
&= \sum_{i=1}^{n} \mathbb{E}\left[d_i^2\right].
\end{aligned} \tag{55}$$

- **Remark** (***Variance of General Functions of Independent Random Variables***)
  Then above formula (55) holds when $X = f\left(Z_1, \ldots, Z_n\right)$ for general function $f : \mathbb{R}^n \to \mathbb{R}$ with n independent random variables $(Z_1, \ldots, Z_n)$. By *Fubini's theorem*,

$$\mathbb{E}\left[X|Z_1, \ldots, Z_i\right] = \int_{\mathcal{Z}^{n-i}} f(Z_1, \ldots, Z_i, z_{i+1}, \ldots, z_n)\; d\mu_{i+1}(z_{i+1}) \ldots d\mu_n(z_n)$$

  where μ_j is the probability distribution of Z_j for $j \geq 1$.

Let $Z_{(-i)} := (Z_1, \ldots, Z_{i-1}, Z_{i+1}, \ldots, Z_n)$ be all random variables $(Z_1, \ldots, Z_n)$ ***except for*** Z_i. Denote $\mathbb{E}_{(-i)}[\cdot]$ as the conditional expectation of X given $Z_{(-i)}$

$$\begin{aligned}\mathbb{E}_{(-i)}[X] &:= \mathbb{E}[X|Z_1, \ldots, Z_{i-1}, Z_{i+1}, \ldots, Z_n] \\ &= \int_{\mathcal{Z}} f(Z_1, \ldots, Z_{i-1}, z_i, Z_{i+1}, \ldots, Z_n)\; d\mu_i(z_i).\end{aligned}$$

Then, again by *Fubini's theorem* (*smoothing properties of conditional expectation*),

$$\mathbb{E}\left[\mathbb{E}_{(-i)}[X]\,|Z_1, \ldots, Z_i\right] = \mathbb{E}[X|Z_1, \ldots, Z_{i-1}] \tag{56}$$

- **Proposition 7.4** *(**Efron-Stein Inequality**) [Boucheron et al., 2013]*
*Let $Z_1, \ldots, Z_n$ be **independent random variables** and let $X = f(Z)$ be a square-integrable function of $Z = (Z_1, \ldots, Z_n)$. Then*

$$Var(X) \le \sum_{i=1}^{n} \mathbb{E}\left[\left(X - \mathbb{E}_{(-i)}[X]\right)^2\right] := \nu. \tag{57}$$

*Moreover, if $Z'_1, \ldots, Z'_n$ are **independent** copies of $Z_1, \ldots, Z_n$ and if we define, for every $i = 1, \ldots, n$,*

$$X'_i := f\left(Z_1, \ldots, Z_{i-1}, Z'_i, Z_{i+1}, \ldots, Z_n\right),$$

then

$$\nu = \frac{1}{2}\sum_{i=1}^{n} \mathbb{E}\left[\left(X - X'_i\right)^2\right] = \sum_{i=1}^{n} \mathbb{E}\left[\left(X - X'_i\right)_+^2\right] = \sum_{i=1}^{n} \mathbb{E}\left[\left(X - X'_i\right)_-^2\right]$$

*where $x_+ = \max\{x, 0\}$ and $x_- = \max\{-x, 0\}$ denote the **positive** and **negative** parts of a real number x. Also,*

$$\nu = \inf_{X_i} \sum_{i=1}^{n} \mathbb{E}\left[(X - X_i)^2\right],$$

where the infimum is taken over the class of all $Z_{(-i)}$-measurable and square-integrable variables X_i, $i = 1, \ldots, n$.

- **Example** (***The Jackknife Estimate***)
We should note here that the Efron-Stein inequality was first motivated by the study of the so-called ***jackknife estimate*** *of* ***statistics***.

To describe this estimate, assume that $Z_1, \ldots, Z_n$ are i.i.d. random variables and one wishes to *estimate a functional θ of the distribution* of the Z_i by a function $X = f(Z_1, \ldots, Z_n)$ of the data. The quality of the estimate is often measured by its bias $\mathbb{E}[X] - \theta$ and its variance $\mathrm{Var}(X)$. Since the distribution of the Z_i's is unknown, one needs to *estimate* the bias and variance ***from the same sample***. ***The jackknife estimate*** of ***the bias*** is defined by

$$(n-1)\left(\frac{1}{n}\sum_{i=1}^{n} X_i - X\right) \tag{58}$$

where X_i is an appropriately defined function of $Z_{(-i)} := (Z_1, \ldots, Z_{i-1}, Z_{i+1}, \ldots, Z_n)$. $Z_{(-i)}$ is often called ***the i-th jackknife sample*** while X_i is the so-called ***jackknife replication of*** X. In an analogous way, ***the jackknife estimate** of the **variance*** is defined by

$$\sum_{i=1}^{n} (X - X_i)^2 \tag{59}$$

Using this language, ***the Efron-Stein inequality*** simply states that ***the jackknife estimate of the variance*** *is* ***always positively biased***. In fact, this is how Efron and Stein originally formulated their inequality.

7.3 Functions with Bounded Differences

- **Corollary 7.5** *[Boucheron et al., 2013]*
  *If f has the **bounded differences property** with parameters $(L_1, \ldots, L_n)$, then*

$$Var(f(Z)) \leq \frac{1}{4} \sum_{i=1}^{n} L_i^2.$$

7.4 Convex Poincaré Inequality

- **Theorem 7.6** ***(Convex Poincaré Inequality)*** *[Boucheron et al., 2013]*
  *Let $Z_1, \ldots, Z_n$ be **independent** random variables taking values in the interval $[0,1]$ and let $f : [0,1]^n \to \mathbb{R}$ be a **separately convex function** whose partial derivatives exist; that is, for every $i = 1, \ldots, n$ and fixed $z_1, \ldots, z_{i-1}, z_{i+1}, \ldots, z_n$, f is a convex function of its i-th variable. Then $f(Z) = f(Z_1, \ldots, Z_n)$ satisfies*

$$Var(f(Z)) \leq \mathbb{E}\left[\|\nabla f(Z)\|_2^2\right]. \tag{60}$$

7.5 Gaussian Poincaré Inequality

- **Theorem 7.7** ***(Gaussian Poincaré Inequality)*** *[Boucheron et al., 2013]*
  *Let $Z = (Z_1, \ldots, Z_n)$ be a vector of **i.i.d. standard Gaussian** random variables (i.e. Z is a Gaussian vector with **zero mean** vector and **identity covariance matrix**). Let $f : \mathbb{R}^n \to \mathbb{R}$ be any **continuously differentiable** function. Then*

$$Var(f(Z)) \leq \mathbb{E}\left[\|\nabla f(Z)\|_2^2\right]. \tag{61}$$

8 Entropy Method

8.1 Entropy Functional and Φ-Entropy

- **Definition** (Φ-***Entropy***)[Boucheron et al., 2013]
  Let $\Phi : [0, \infty) \to \mathbb{R}$ be a ***convex*** function, and assign, to every ***non-negative*** *integrable*

random variable X, ***the* Φ*-entropy*** of X is defined as

$$H_{\Phi}(X) = \mathbb{E}\left[\Phi(X)\right] - \Phi(\mathbb{E}\left[X\right]). \tag{62}$$

- **Remark** The Φ-entropy is a ***functional*** of *distribution* P_X instead of a function of X.
- **Remark** By Jenson's inequality, the Φ-entropy is *non-negative*

$$\begin{aligned} &\Phi(\mathbb{E}\left[X\right]) \le \mathbb{E}\left[\Phi(X)\right] \\ &\Rightarrow H_{\Phi}(X) = \mathbb{E}\left[\Phi(X)\right] - \Phi(\mathbb{E}\left[X\right]) \ge 0. \end{aligned}$$

- **Example** (***Special Examples for* Φ*-Entropy***)
  1. For $\Phi(x) = x^2$, *the* Φ*-entropy* of X is *the* ***variance*** of X:

$$H_{\Phi}(X) = \mathbb{E}\left[X^2\right] - (\mathbb{E}\left[X\right])^2 = \mathrm{Var}(X).$$

  2. For $\Phi(x) = -\log(x)$, *the* Φ*-entropy* of $Y = e^{\lambda X}$ is *the* ***logarithm of moment generating function*** of $X - \mathbb{E}\left[X\right]$:

$$H_{\Phi}(e^{\lambda X}) = -\lambda \mathbb{E}\left[X\right] + \log\left(\mathbb{E}\left[e^{\lambda X}\right]\right) = \log \mathbb{E}\left[e^{\lambda(X - \mathbb{E}[X])}\right] := \psi_{X-\mathbb{E}[X]}(\lambda). \tag{63}$$

  3. For $\Phi(x) = x\log x$, *the* Φ*-entropy* of X is defined as the ***entropy functional*** of X

$$H_{\Phi}(X) = \mathrm{Ent}(X) := \mathbb{E}\left[X \log X\right] - \mathbb{E}\left[X\right] \log\left(\mathbb{E}\left[X\right]\right). \tag{64}$$

  Let $(\Omega, \mathscr{B})$ be measurable space, and P and Q are probability measures on Ω with $P \ll Q$. Define a random variable X by the *Radon-Nikodym derivative* of P with respect to Q; that is,

$$X(\omega) := \begin{cases} \frac{dP}{dQ}(\omega) & Q(\omega) > 0 \\ 0 & \text{o.w.} \end{cases}.$$

  We see that X is Q-measurable and $dP = X\,dQ$ with $\mathbb{E}_Q\left[X\right] = 1$. Then the entropy of X is the relative entropy of P with respect to Q.

$$\mathrm{Ent}(X) = \mathbb{KL}\left(P \,\|\, Q\right) \tag{65}$$

8.2 Dual Formulation

- **Lemma 8.1** *The* ***Legendre transform*** *(or* ***convex conjugate****) of* $\Phi(x) = x\log(x)$ *is* e^{u-1}*. That is,*

$$\sup_{x>0} \{u\,x - x\log(x)\} = e^{u-1}$$

- **Proposition 8.2** ***(Duality Formula of Entropy)*** *[Boucheron et al., 2013]*
Let X *be a non-negative random variable defined on a probability space* $(\Omega, \mathscr{A}, P)$ *such that* $\mathbb{E}\left[\Phi(X)\right] < \infty$*. Then we have* ***the duality formula***

$$\mathit{Ent}(X) = \sup_{U \in \mathcal{U}} \mathbb{E}\left[U\,X\right] \tag{66}$$

where the supremum is taken over the set $\mathcal{U}$ of all random variables $U : \Omega \to \mathbb{R} \cup \{\infty\}$ with $\mathbb{E}\left[e^U\right] = 1$. Moreover, if U is such that $\mathbb{E}[UX] \le$ Ent(X) for all non-negative random variable X such that $\Phi(X)$ is integrable and $\mathbb{E}[X] = 1$, then $\mathbb{E}\left[e^U\right] \le 1$.

- **Corollary 8.3** *(**Alternative Duality Formula of Entropy**) [Boucheron et al., 2013]*

$$\mathit{Ent}(X) = \sup_T \mathbb{E}\left[X\left(\log(T) - \log\left(\mathbb{E}[T]\right)\right)\right] \tag{67}$$

where the supremum is taken over all non-negative and integrable random variables.

- **Corollary 8.4** *(**Duality Formula of Log-MGF**) [Cover and Thomas, 2006, Boucheron et al., 2013]*
Let X be a real-valued integrable random variable. Then for every $\lambda \in \mathbb{R}$,

$$\log \mathbb{E}_{\mathbb{P}}\left[e^{\lambda(X - \mathbb{E}[X])}\right] = \sup_{\mathbb{Q} \ll \mathbb{P}} \left\{\lambda\left(\mathbb{E}_{\mathbb{Q}}[X] - \mathbb{E}_{\mathbb{P}}[X]\right) - \mathbb{KL}\left(\mathbb{Q} \,\|\, \mathbb{P}\right)\right\}, \tag{68}$$

where the supremum is taken over all probability measures $\mathbb{Q}$ absolutely continuous with respect to $\mathbb{P}$.

- **Corollary 8.5** *(**Duality Formula of Kullback-Leibler Divergence**) [Cover and Thomas, 2006, Boucheron et al., 2013]*
Let $\mathbb{P}$ and $\mathbb{Q}$ be two probability distributions on the same space.Then

$$\mathbb{KL}\left(\mathbb{Q} \,\|\, \mathbb{P}\right) = \sup_X \left\{\mathbb{E}_{\mathbb{Q}}[X] - \log \mathbb{E}_{\mathbb{P}}\left[e^X\right]\right\}, \tag{69}$$

where the supremum is taken over all random variables such that $\mathbb{E}_{\mathbb{P}}[\exp(X)] < \infty$.

- **Definition** (***Bregman Divergence***)
Let $F : \mathcal{X} \to \mathbb{R}$ be a *continuously-differentiable*, ***strictly convex*** function defined on a convex set $\mathcal{X}$. The ***Bregman divergence*** associated with F for points $p, q \in \mathcal{X}$ is the difference between the value of F at point p and the value of the *first-order Taylor expansion* of F around point q evaluated at point p:

$$\mathbb{D}^F\left(p \,\|\, q\right) = F(p) - F(q) - \langle \nabla F(q)\,,\, p - q\rangle \tag{70}$$

- **Theorem 8.6** *(**The Expected Value Minimizes Expected Bregman Divergence**) [Boucheron et al., 2013]*
*Let $I \subseteq \mathbb{R}$ be an open interval and let $f : I \to \mathbb{R}$ be **convex** and **differentiable**. For any $x, y \in I$, **the Bregman divergence** of f from x to y is $f(y) - f(x) - f'(x)(y - x)$. Let X be an I-valued random variable. Then*

$$\mathbb{E}\left[f(X) - f(\mathbb{E}[X])\right] = \inf_{a \in I} \mathbb{E}\left[f(X) - f(a) - f'(a)(X - a)\right] \tag{71}$$

- **Corollary 8.7** *(**Duality Formula of Entropy via Bregman Divergence**) [Boucheron et al., 2013]*
Let X be a non-negative random variable such that $\mathbb{E}[\Phi(X)] < \infty$. Then

$$\mathit{Ent}(X) = \inf_{u > 0} \mathbb{E}\left[X\left(\log(X) - \log(u)\right) - (X - u)\right] \tag{72}$$

8.3 Tensorization Property

- **Proposition 8.8** ***(Sub-Additivity of The Entropy / Tensorization Property)*** *[Boucheron et al., 2013]*
  Let $\Phi(x) = x \log x$, for $x > 0$ and $\Phi(0) = 0$. Let $Z_1, Z_2, \ldots, Z_n$ be independent random variables taking values in $\mathcal{X}$, and let $f : \mathcal{X}^n \to [0, \infty)$ be a measurable function. Letting $X = f(Z_1, Z_2, \ldots, Z_n)$ such that $\mathbb{E}[X \log X] < \infty$, we have

$$
\mathit{Ent}(X) := \mathbb{E}[\Phi(X)] - \Phi(\mathbb{E}[X]) \le \sum_{i=1}^{n} \mathbb{E}\left[\mathbb{E}_{(-i)}[\Phi(X)] - \Phi(\mathbb{E}_{(-i)}[X])\right], \qquad (73)
$$

  where $\mathbb{E}_{(-i)}[\cdot]$ is the conditional expectation operator conditioning on $Z_{(-i)}$. Introducing the notation $\mathit{Ent}_{(-i)}(X) = \mathbb{E}_{(-i)}[\Phi(X)] - \Phi(\mathbb{E}_{(-i)}[X])$, this can be re-written as

$$
\mathit{Ent}(X) \le \mathbb{E}\left[\sum_{i=1}^{n} \mathit{Ent}_{(-i)}(X)\right]. \qquad (74)
$$

8.4 Herbst's Argument

- **Remark** (***Entropy Functional for Moment Generating Function***)
  Let $X = e^{\lambda Z}$ where Z is a random variable. The entropy function of X becomes

$$
\mathrm{Ent}(e^{\lambda Z}) = \mathbb{E}\left[\lambda Z e^{\lambda Z}\right] - \mathbb{E}\left[e^{\lambda Z}\right] \log\left(\mathbb{E}\left[e^{\lambda Z}\right]\right)
$$

  Denote $\psi_{Z-\mathbb{E}[Z]}(\lambda) := \log \mathbb{E}\left[e^{\lambda(Z-\mathbb{E}[Z])}\right]$. Then we have

$$
\frac{\mathrm{Ent}(e^{\lambda Z})}{\mathbb{E}[e^{\lambda Z}]} = \lambda\, \psi'_{Z-\mathbb{E}[Z]}(\lambda) - \psi_{Z-\mathbb{E}[Z]}(\lambda). \qquad (75)
$$

  Our strategy is based on using (75) ***the sub-additivity of entropy*** and then univariate calculus to derive ***upper bounds*** *for the* ***derivative*** *of* $\psi(\lambda)$. By solving the obtained ***differential inequality***, we obtain tail bounds via *Chernoff's bounding*.

  For example, if

$$
\begin{aligned}
\frac{\mathrm{Ent}(e^{\lambda Z})}{\mathbb{E}[e^{\lambda Z}]} &\le \frac{\nu \lambda^2}{2} \\
\Leftrightarrow \lambda\, \psi'_{Z-\mathbb{E}[Z]}(\lambda) - \psi_{Z-\mathbb{E}[Z]}(\lambda) &\le \frac{\nu \lambda^2}{2}, \\
\Leftrightarrow \frac{1}{\lambda}\psi'_{Z-\mathbb{E}[Z]}(\lambda) - \frac{1}{\lambda^2}\psi_{Z-\mathbb{E}[Z]}(\lambda) &\le \frac{\nu}{2}.
\end{aligned}
$$

  Setting $G(\lambda) = \lambda^{-1}\psi_{Z-\mathbb{E}[Z]}(\lambda)$, we see that the differential inequality becomes

$$
G'(\lambda) \le \frac{\nu}{2}.
$$

  Since $G(\lambda) \to 0$ as $\lambda \to 0$, which implies that

$$
G(\lambda) \le \frac{\nu \lambda}{2},
$$

  and the result follows.

- **Proposition 8.9** ***(Herbst's Argument)*** *[Boucheron et al., 2013, Wainwright, 2019]*
Let Z be an integrable random variable such that for some $\nu > 0$, we have, for every $\lambda > 0$,

$$\frac{Ent(e^{\lambda Z})}{\mathbb{E}\left[e^{\lambda Z}\right]} \le \frac{\nu \lambda^2}{2} \tag{76}$$

Then, for every $\lambda > 0$, the logarithmic moment generating function of centered random variable $(Z - \mathbb{E}[Z])$ satisfies

$$\psi_{Z-\mathbb{E}[Z]}(\lambda) := \log \mathbb{E}\left[e^{\lambda(Z-\mathbb{E}[Z])}\right] \le \frac{\nu\lambda^2}{2}.$$

8.5 Association Inequalities

- **Proposition 8.10** ***(Chebyshev's Association Inequalities)*** *[Boucheron et al., 2013]*
*Let f and g be **nondecreasing** real-valued functions defined on the real line. If X is a real-valued random variable and Y is a **nonnegative** random variable, then*

$$\mathbb{E}[Y]\,\mathbb{E}[Y f(X) g(X)] \ge \mathbb{E}[Y f(X)]\,\mathbb{E}[Y g(X)] \tag{77}$$

*If f is **nonincreasing** and g is **nondecreasing** then*

$$\mathbb{E}[Y]\,\mathbb{E}[Y f(X) g(X)] \le \mathbb{E}[Y f(X)]\,\mathbb{E}[Y g(X)] \tag{78}$$

- **Proposition 8.11** ***(Harris's Inequalities)*** *[Boucheron et al., 2013]*
*Let $f, g : \mathbb{R}^n \to \mathbb{R}$ be **nondecreasing** functions. Let $Z_1, \ldots, Z_n$ be **independent** real-valued random variables and define the random vector $Z = (Z_1, \ldots, Z_n)$ taking values in $\mathbb{R}^n$. Then*

$$\mathbb{E}[f(X)g(X)] \ge \mathbb{E}[f(X)]\,\mathbb{E}[g(X)] \tag{79}$$

*If f is **nonincreasing** and g is **nondecreasing** then*

$$\mathbb{E}[f(X)g(X)] \le \mathbb{E}[f(X)]\,\mathbb{E}[g(X)] \tag{80}$$

8.6 Connection to Variance Bounds

- **Proposition 8.12** ***(A Modified Logarithmic Sobolev Inequalities for Moment Generating Function)*** *[Boucheron et al., 2013]*
Consider independent random variables $Z_1, \ldots, Z_n$ taking values in $\mathcal{X}$, a real-valued function $f : \mathcal{X}^n \to \mathbb{R}$ and the random variable $X = f(Z_1, \ldots, Z_n)$. Also denote $Z_{(-i)} = (Z_1, \ldots, Z_{i-1}, Z_{i+1}, \ldots, Z_n)$ and $X_{(-i)} = f_i(Z_{(-i)})$ where $f_i : \mathcal{X}^{n-1} \to \mathbb{R}$ is an arbitrary function. Let $\phi(x) = e^x - x - 1$. Then for all $\lambda \in \mathbb{R}$,

$$Ent(e^{\lambda X}) := \mathbb{E}\left[\lambda X e^{\lambda X}\right] - \mathbb{E}\left[e^{\lambda X}\right] \log \mathbb{E}\left[e^{\lambda X}\right] \le \sum_{i=1}^{n} \mathbb{E}\left[e^{\lambda X} \phi(-\lambda(X - X_{(-i)}))\right] \tag{81}$$

- **Proposition 8.13** ***(Symmetrized Modified Logarithmic Sobolev Inequalities)*** *[Boucheron et al., 2013]*

Consider independent random variables $Z_1, \ldots, Z_n$ taking values in $\mathcal{X}$, a real-valued function $f : \mathcal{X}^n \to \mathbb{R}$ and the random variable $X = f(Z_1, \ldots, Z_n)$. Also denote $\widetilde{X}^{(i)} = f(Z_1, \ldots, Z_{i-1}, Z'_i, Z_{i+1}, \ldots, Z_n)$. Let $\phi(x) = e^x - x - 1$. Then for all $\lambda \in \mathbb{R}$,

$$\lambda \mathbb{E}\left[X e^{\lambda X}\right] - \mathbb{E}\left[e^{\lambda X}\right] \log \mathbb{E}\left[e^{\lambda X}\right] \le \sum_{i=1}^{n} \mathbb{E}\left[e^{\lambda X} \phi(-\lambda(X - \widetilde{X}^{(i)}))\right] \tag{82}$$

Moreover, denoting $\tau(x) = x(e^x - 1)$, for all $\lambda \in \mathbb{R}$,

$$\lambda \mathbb{E}\left[X e^{\lambda X}\right] - \mathbb{E}\left[e^{\lambda X}\right] \log \mathbb{E}\left[e^{\lambda X}\right] \le \sum_{i=1}^{n} \mathbb{E}\left[e^{\lambda X} \tau(-\lambda(X - \widetilde{X}^{(i)})_+)\right],$$

$$\lambda \mathbb{E}\left[X e^{\lambda X}\right] - \mathbb{E}\left[e^{\lambda X}\right] \log \mathbb{E}\left[e^{\lambda X}\right] \le \sum_{i=1}^{n} \mathbb{E}\left[e^{\lambda X} \tau(\lambda(\widetilde{X}^{(i)} - X)_-)\right].$$

- **Remark** In the proof, we have

$$\begin{aligned}
\mathrm{Ent}_{\mu_i}(e^{\lambda X}) &\le \mathbb{E}_{\mu_i}\left[e^{\lambda X}(\log e^{\lambda X} - \log e^{\lambda X'_i}) - (e^{\lambda X} - e^{\lambda X'_i})\right] \\
&= \mathbb{E}_{\mu_i}\left[e^{\lambda X}(\lambda(X - X'_i) - (e^{\lambda X} - e^{\lambda X'_i})\right] \\
&\le \mathbb{E}_{\mu_i}\left[(e^{\lambda X} - e^{\lambda X'_i})(\lambda(X - X'_i)_+)\right] \\
&\le \lambda^2 \mathbb{E}_{\mu_i}\left[(X - X'_i)_+^2\right]
\end{aligned}$$

  Using the convexity of e^x, we have $e^s - e^t \le e^t(s - t)$ if $s > t$. Thus

$$\mathrm{Ent}(e^{\lambda X}) \le \lambda^2 \sum_{i=1}^{n} \mathbb{E}\left[\left(X - X'_i\right)_+^2\right].$$

  From Efron-Stein inequality, if we can bound

$$\sum_{i=1}^{n} \mathbb{E}\left[\left(X - X'_i\right)_+^2\right] \le \nu,$$

  then we can bound both the variance $\mathrm{Var}(X)$ and entropy $\mathrm{Ent}(e^{\lambda X})$.

9 Transportation Method

9.1 Optimal Transport, Wasserstein Distance and its Dual

- **Definition** (***Pushforward Measure***) [Peyr and Cuturi, 2019]
  Let $(\mathcal{X}, \mathscr{B}_X)$ and $(\mathcal{Y}, \mathscr{B}_Y)$ be two topological measurable spaces. Denote the spaces of *general (Radon) measures* on $\mathcal{X}, \mathcal{Y}$ as $\mathcal{M}(\mathcal{X})$ and $\mathcal{M}(\mathcal{Y})$. Also let $\mathcal{C}(\mathcal{X})$ be space of continuous functions on $\mathcal{X}$. For a *continous* map $T : \mathcal{X} \to \mathcal{Y}$, the ***push-forward operator*** is defined as $T_{\#} : \mathcal{M}(\mathcal{X}) \to \mathcal{M}(\mathcal{Y})$ that satisfies

$$\forall\, h \in \mathcal{C}(\mathcal{X}), \quad \int_{\mathcal{Y}} h(y)\, d\left(T_{\#}\alpha\right)(y) = \int_{\mathcal{X}} h(T(x))\, d\alpha(x). \tag{83}$$

$$\text{or equivalently,} \quad \left(T_{\#}\alpha\right)(B) := \alpha\left(\{x : T(x) \in B \subset \mathcal{Y}\}\right) = \alpha(T^{-1}(B)) \tag{84}$$

where the ***push-forward measure*** $\beta := T_{\#}\alpha \in \mathcal{M}(\mathcal{Y})$ of some $\alpha \in \mathcal{M}(\mathcal{X})$, $T^{-1}(\cdot)$ is the pre-image of T.

- **Remark** (***Density Function of Pushforward Measure***)
  Assume that (α, β) have densities $(\rho_\alpha, \rho_\beta)$ with respect to a fixed measure, and $\beta = T_{\#}\alpha$. We see that $T_{\#}$ acts on a density ρ_α linearly to a density ρ_β as a change of variable, i.e.

$$\rho_\alpha(\boldsymbol{x}) = \left|\det(T'(\boldsymbol{x}))\right| \rho_\beta(T(\boldsymbol{x})) \tag{85}$$
$$\left|\det(T'(\boldsymbol{x}))\right| = \frac{\rho_\alpha(\boldsymbol{x})}{\rho_\beta(T(\boldsymbol{x}))}$$

- **Definition** (***Optimal Transport Problem, Monge Problem***) [Villani, 2009, Santambrogio, 2015, Peyr and Cuturi, 2019]
  Let $(\mathcal{X}, \mathscr{B}_X)$ and $(\mathcal{Y}, \mathscr{B}_Y)$ be two measurable spaces, where $\mathcal{X}$ and $\mathcal{Y}$ are *complete separable metric spaces*. Denote $\mathcal{P}(\mathcal{X})$ and $\mathcal{P}(\mathcal{Y})$ as the space of probabiilty measures on $\mathcal{X}$ and $\mathcal{Y}$. Define a ***cost function*** $c : \mathcal{X} \times \mathcal{Y} \to \mathbb{R}_+$ as non-negative real-valued measurable functions on $\mathcal{X} \times \mathcal{Y}$. ***The optimal transport problem*** by *Monge* (i.e. ***Monge Problem***) is defined as follows: given two probability measures $\mathbb{P} \in \mathcal{P}(\mathcal{X})$ and $\mathbb{Q} \in \mathcal{P}(\mathcal{Y})$, find a *continuous measurable map* $T : \mathcal{X} \to \mathcal{Y}$ so that

$$\inf_T \int_{\mathcal{X}} c(x, T(x)) d\mathbb{P}(x)$$
$$\text{s.t. } \mathbb{Q} = T_{\#}\mathbb{P}$$

  The optimal solution T is also called an ***optimal transportation plan***.

- **Definition** (***Optimal Transport Problem, Kantorovich Relaxation***) [Villani, 2009, Santambrogio, 2015, Peyr and Cuturi, 2019]
  The optimal transport problem by *Kantorovich* (i.e. ***Kantorovich Relxation***) is defined as follows: given two probability measures $\mathbb{P} \in \mathcal{P}(\mathcal{X})$ and $\mathbb{Q} \in \mathcal{P}(\mathcal{Y})$, find a *joint probability measure* $\gamma \in \Pi(\mathbb{P}, \mathbb{Q})$ so that

$$\inf_\gamma \int_{\mathcal{X}\times\mathcal{Y}} c(x, y) d\gamma(x, y)$$
$$\text{s.t. } \gamma \in \Pi(\mathbb{P}, \mathbb{Q}) := \{\gamma \in \mathcal{P}(\mathcal{X} \times \mathcal{Y}) : \pi_{\mathcal{X},\#}\gamma = \mathbb{P},\ \pi_{\mathcal{Y},\#}\gamma = \mathbb{Q}\}$$

  where $\mathcal{P}(\mathcal{X} \times \mathcal{Y})$ is the space of joint probability measure on $\mathcal{X} \times \mathcal{Y}$, $\pi_{\mathcal{X}}$ and $\pi_{\mathcal{Y}}$ are the coordinate projection onto $\mathcal{X}$ and $\mathcal{Y}$. $\pi_{\mathcal{X},\#}\gamma = \mathbb{P}$ means that $\mathbb{P}$ is the marginal distribution of γ on $\mathcal{X}$. Similarly $\mathbb{Q}$ is the marginal distribution of γ on $\mathcal{Y}$.

  Equivalently, let X and Y are *random variables* taking values in $\mathcal{X}$ and $\mathcal{Y}$. The *joint distribution* of (X, Y) is γ with marginal distribution of X and Y being $\mathbb{P}$ and $\mathbb{Q}$. Then the problem is

$$\min_{\gamma \in \Pi(\mathbb{P},\mathbb{Q})} \mathbb{E}_\gamma \left[c(X, Y)\right]$$

  The joint distribution $\gamma \in \Pi(\mathbb{P}, \mathbb{Q})$ such that $X_{\#}\gamma = \mathbb{P}$ and $Y_{\#}\gamma = \mathbb{Q}$ is called ***a coupling***.

- **Definition** (***Dual Problem of Kantorovich Problem***) [Villani, 2009, Santambrogio, 2015, Peyr and Cuturi, 2019]

The ***dual problem*** of *Kantorovich problem* is described as below:

$$\mathcal{L}_c(\mathbb{P},\mathbb{Q}) = \max_{(\varphi,\psi)\in\mathcal{C}(\mathcal{X})\times\mathcal{C}(\mathcal{Y})} \int_{\mathcal{X}} \varphi(x)d\mathbb{P}(x) + \int_{\mathcal{Y}} \psi(y)d\mathbb{Q}(y)$$
$$\text{s.t. } \varphi(x)+\psi(y) \le c(x,y), \quad \forall x\in\mathcal{X}, y\in\mathcal{Y},$$

Here, (φ,ψ) is a pair of *continuous functions* on $\mathcal{X}$ and $\mathcal{Y}$ respectively and they are also the ***Kantorovich potentials***. The feasible region is

$$\mathcal{R}(c) := \{(\varphi,\psi)\in\mathcal{C}(\mathcal{X})\times\mathcal{C}(\mathcal{Y}) : \varphi\oplus\psi \le c\}$$

where $(\varphi\oplus\psi)(x,y) = \varphi(x)+\psi(y)$.

In other words, the dual optimization problem is

$$\max_{(\varphi,\psi)\in\mathcal{R}(c)} \mathbb{E}_{\mathbb{P}}\left[\varphi(X)\right] + \mathbb{E}_{\mathbb{Q}}\left[\psi(Y)\right]$$

- **Proposition 9.1** ***(Strong Duality)*** *[Santambrogio, 2015]*
  Let $\mathcal{X},\mathcal{Y}$ be ***complete separable spaces****, and $c:\mathcal{X}\times\mathcal{Y}\to\mathbb{R}_+$ be* ***lower semi-continuous and bounded from below****. Then the optimal value of* primal *and* dual problems *are the same*

  $$\min_{X\sim\mathbb{P},Y\sim\mathbb{Q}} \mathbb{E}\left[c(X,Y)\right] = \mathcal{L}_c(\mathbb{P},\mathbb{Q}) = \max_{(\varphi,\psi)\in\mathcal{R}(c)} \mathbb{E}_{\mathbb{P}}\left[\varphi(X)\right] + \mathbb{E}_{\mathbb{Q}}\left[\psi(Y)\right].$$

- **Definition** (***Wasserstein Distance***)
  Let $((\mathcal{X},d),\mathscr{B})$ be *a metric measurable space* with *Borel σ-algebra* induced by metric d. Let X,Y be two random variables taking values in $\mathcal{X}$ with distribution $\mathbb{P}$ and $\mathbb{Q}$. ***The Wasserstein distance*** between *probability distributions* $\mathbb{P}$ and $\mathbb{Q}$ induced by d is defined as

  $$\mathcal{W}_1(\mathbb{P},\mathbb{Q}) \equiv \mathcal{W}_d(\mathbb{P},\mathbb{Q}) := \min_{X\sim\mathbb{P},Y\sim\mathbb{Q}} \mathbb{E}\left[d(X,Y)\right] \tag{86}$$

  In general, for $p\in[1,\infty)$, we can define ***Wasserstein p-distance*** as

  $$\mathcal{W}_p(\mathbb{P},\mathbb{Q}) \equiv \mathcal{W}_{p,d}(\mathbb{P},\mathbb{Q}) := \left(\min_{X\sim\mathbb{P},Y\sim\mathbb{Q}} \mathbb{E}\left[(d(X,Y))^p\right]\right)^{1/p}. \tag{87}$$

- **Remark** Not to confuse the 2-***Wasserstein distance*** with ***the Wasserstein distance induced by L_2 norm***:

  $$\mathcal{W}_{\|\cdot\|_2}(\mathbb{P},\mathbb{Q}) \equiv \mathcal{W}_{1,\|\cdot\|_2}(\mathbb{P},\mathbb{Q}) := \min_{X\sim\mathbb{P},Y\sim\mathbb{Q}} \mathbb{E}\left[\|X-Y\|_2\right]$$
  $$\mathcal{W}_2(\mathbb{P},\mathbb{Q}) \equiv \mathcal{W}_{2,d}(\mathbb{P},\mathbb{Q}) := \sqrt{\min_{X\sim\mathbb{P},Y\sim\mathbb{Q}} \mathbb{E}\left[d(X,Y)^2\right]}$$

- **Remark** (***Wasserstein p-Distance is a Metric in $\mathcal{P}(\mathcal{X})$***)
  The ***Wasserstein p-distance*** $\mathcal{W}_{p,d}(\mathbb{P},\mathbb{Q}) := \left(\min_{X\sim\mathbb{P},Y\sim\mathbb{Q}} \mathbb{E}\left[(d(X,Y))^p\right]\right)^{1/p}$ is a well-defined *metric* in $\mathcal{P}(\mathcal{X})$: for all $\mathbb{P},\mathbb{Q},\mathbb{M}\in\mathcal{P}(\mathcal{X})$,

  1. (*Non-Negativity*): $\mathcal{W}_{p,d}(\mathbb{P},\mathbb{Q}) \ge 0$.

2. (*Definiteness*): $\mathcal{W}_{p,d}(\mathbb{P}, \mathbb{Q}) = 0$ iff $\mathbb{P} = \mathbb{Q}$
3. (*Symmetric*): $\mathcal{W}_{p,d}(\mathbb{P}, \mathbb{Q}) = \mathcal{W}_{p,d}(\mathbb{Q}, \mathbb{P})$
4. (*Triangular inequality*): $\mathcal{W}_{p,d}(\mathbb{P}, \mathbb{Q}) \le \mathcal{W}_{p,d}(\mathbb{P}, \mathbb{M}) + \mathcal{W}_{p,d}(\mathbb{M}, \mathbb{Q})$

- **Definition** (***Total Variation / Variational Distance***)
Let P, Q be two probability measures on measurable space $(\Omega, \mathscr{F})$. The ***total variation*** or ***variational distance*** between P and Q is defined by
$$V(P, Q) := \sup_{A \in \mathscr{F}} |P(A) - Q(A)| \tag{88}$$

- **Remark** (***Equivalent Formulation of Total Variation***)
It is a well-known and simple fact that the total variation is half the L_1-distance, that is, if μ is a *common dominating measure* of P and Q and $p(x) = dP/d\mu$ and $q(x) = dQ/d\mu$ denote their respective densities, then
$$V(P, Q) := P(A^*) - Q(A^*) = \frac{1}{2}\int_{\Omega} |p(x) - q(x)|\, d\mu(x), \tag{89}$$
where $A^* = \{x : p(x) \ge q(x)\}$.

- **Remark** (***Total Variation via Optimal Coupling of Two Measures***)
We note that another important interpretation of *the variational distance* is related to *the best coupling of the two measures*
$$V(P, Q) = \min P\{X \neq Y\} \tag{90}$$
where the minimum is taken over *all pairs of joint distributions* for the random variables (X, Y) whose marginal distributions are $X \sim P$ and $Y \sim Q$.

- **Proposition 9.2** ***(Pinsker's Inequality)*** *[Cover and Thomas, 2006, Boucheron et al., 2013]*
Let P, Q be two probability distributions on measurable space $(\Omega, \mathscr{F})$ such that $P \ll Q$. Then
$$V(P, Q)^2 \le \frac{1}{2}\mathbb{KL}\left(P \,\|\, Q\right). \tag{91}$$

- **Remark** (***Total Variation as*** 1***-Wasserstein Distance***)
The total variation between P and Q is ***the Wasserstein distance*** induced by ***the Hamming distance*** $d(x, y) = \#\{i : x_i \neq y_i\}$.
$$V(P, Q) = \mathcal{W}_1(P, Q).$$
Thus *the Pinsker's inequality* (91) is the special case of *transportation cost inequality* (93).

- **Theorem 9.3** ***(Kantorovich-Rubenstein Duality)*** *[Villani, 2009]*
Let $\mathcal{X}$ be a ***Polish space****, i.e. $\mathcal{X}$ a* ***complete separable metric*** *space equipped with a Borel σ-algebra induced by metric d, and $\mathbb{P}$ and $\mathbb{Q}$ be probability measures on $\mathcal{X}$. For fixed $p \in [1, \infty)$, let Lip_1 be the space of all* 1-***Lipschitz*** *function with respect to metric d such that*
$$\|f\|_L := \sup_{x,y \in \mathcal{X}} \left\{ \frac{|f(x) - f(y)|}{d(x, y)} \right\} \le 1.$$
Then
$$\mathcal{W}_d(\mathbb{P}, \mathbb{Q}) \equiv \mathcal{W}_{1,d}(\mathbb{P}, \mathbb{Q}) = \sup_{f \in Lip_1} \left\{ \mathbb{E}_{\mathbb{P}}\left[f(X)\right] - \mathbb{E}_{\mathbb{Q}}\left[f(Y)\right] \right\}. \tag{92}$$

9.2 Concentration via Transportation Cost

- **Lemma 9.4** *(**Transportation Lemma**) [Boucheron et al., 2013]*
  *Let X be a real-valued integrable random variable. Let ϕ be a **convex** and **continuously differentiable** function on a (possibly unbounded) interval $[0, b)$ and assume that $\phi(0) = \phi'(0) = 0$. Define, for every $x \geq 0$, **the Legendre transform** $\phi^*(x) = \sup_{\lambda \in (0,b)}(\lambda x - \phi(\lambda))$, and let, for every $t \geq 0$, $\phi^{*-1}(t) = \inf\{x \geq 0 : \phi^*(x) > t\}$, i.e. the **the generalized inverse** of ϕ^*. Then the following two statements are equivalent:*

  1. *for every $\lambda \in (0, b)$,*
  $$\psi_{X-\mathbb{E}[X]}(\lambda) \leq \phi(\lambda)$$
  where $\psi_X(\lambda) := \log \mathbb{E}_Q\left[e^{\lambda X}\right]$ is the logarithm of moment generating function;
  2. *for any probability measure P absolutely continuous with respect to Q such that $\mathbb{KL}\left(P \,\|\, Q\right) < \infty$,*
  $$\mathbb{E}_P\left[X\right] - \mathbb{E}_Q\left[X\right] \leq \phi^{*-1}\left(\mathbb{KL}\left(P \,\|\, Q\right)\right). \tag{93}$$

  In particular, given $\nu > 0$, X follows a sub-Gaussian distribution, i.e.
  $$\psi_{X-\mathbb{E}[X]}(\lambda) \leq \frac{\nu\lambda^2}{2}$$
  *for every $\lambda > 0$ **if and only if** for any probability measure P absolutely continuous with respect to Q and such that $\mathbb{KL}\left(P \,\|\, Q\right) < \infty$,*
  $$\mathbb{E}_P\left[X\right] - \mathbb{E}_Q\left[X\right] \leq \sqrt{2\nu \mathbb{KL}\left(P \,\|\, Q\right)}. \tag{94}$$

- **Remark** (***Transportation Method***)
  Let $\mathbb{P} = \otimes_{i=1}^n \mathbb{P}_i$ be the product measure for $Z := (Z_1, \ldots, Z_n)$ on $\mathcal{X}^n$ and $f : \mathcal{X}^n \to \mathbb{R}$ be 1-*Lipschitz function*. Consider a probability measure $\mathbb{Q}$ on $\mathcal{X}^n$, absolutely continuous with respect to $\mathbb{P}$ and let Y be a random variable (defined on the same probability space as $\mathcal{X}$) such that Y has distribution $\mathbb{Q}$.

  The lemma above suggests that one may prove *sub-Gaussian concentration inequalities* for $X = f(Z_1, \ldots, Z_n)$ by proving a "*transportation*" *inequality* as above. The key to achieving this relies on *coupling*. In particular, *the Kantorovich-Rubenstein duality* for $\mathcal{W}_{1,d}$ suggests that
  $$\mathbb{E}_{\mathbb{Q}}\left[f(Y)\right] - \mathbb{E}_{\mathbb{P}}\left[f(Z)\right] \leq \min_{\gamma \in \Pi(\mathbb{Q},\mathbb{P})} \mathbb{E}_\gamma\left[d(Y, Z)\right] := \mathcal{W}_{1,d}(\mathbb{Q}, \mathbb{P})$$
  Thus, it suffices to *upper bound* the 1-*Wasserstein distance* between $\mathbb{Q}$ and $\mathbb{P}$.

- **Definition** (d-***Transportation Cost Inequality***) [Wainwright, 2019]
  Let $(\mathcal{X}, d)$ be a *metric space* with metric d, and $(\mathcal{X}, \mathscr{B})$ be a *measurable space*, where $\mathscr{B}$ is *the Borel σ-algebra* induced by metric d, ***the probability measure*** $\mathbb{P}$ is said to satisfy a ***d-transportation cost inequality*** with parameter $\nu > 0$ if
  $$\mathcal{W}_{1,d}(\mathbb{Q}, \mathbb{P}) \leq \sqrt{2\nu \mathbb{KL}\left(\mathbb{Q} \,\|\, \mathbb{P}\right)} \tag{95}$$
  for all probability measure $\mathbb{Q} \ll \mathbb{P}$ on $\mathscr{B}$.

- **Theorem 9.5** ***(Isoperimetric Inequality via Transportation Cost)****[Wainwright, 2019]*
Consider a metric measure space $(\mathcal{X}, \mathscr{B}, \mathbb{P})$ *with metric* d*, and suppose that* $\mathbb{P}$ *satisfies the* d***-transportation cost inequality*** *in* (95) *Then its* ***concentration function*** *satisfies the bound*

$$\alpha_{\mathbb{P},(\mathcal{X},d)}(t) \le \exp\left(-\frac{(t-t_0)_+^2}{2\nu}\right), \text{ for } t \ge t_0 \tag{96}$$

where $t_0 := \sqrt{2\nu \log 2}$*. Moreover, for any* $Z \sim \mathbb{P}$ *and any* L*-Lipschitz function* $f : \mathcal{X} \to \mathbb{R}$*, we have the* ***concentration inequality***

$$\mathbb{P}\left\{|f(Z) - \mathbb{E}\left[f(Z)\right]| \ge t\right\} \le 2\exp\left(-\frac{t^2}{2\nu L^2}\right). \tag{97}$$

9.3 Tensorization for Transportation Cost

- **Proposition 9.6** ***(Tensorization for Transportation Cost)*** *[Boucheron et al., 2013]*
Suppose that, for each $k = 1, 2, \ldots, n$*, the univariate distribution* $\mathbb{P}_k$ *satisfies a* d_k***-transportation cost inequality*** *with parameter* ν_k*. Then* ***the product distribution*** $\mathbb{P} = \otimes_{k=1}^n \mathbb{P}_k$ *satisfies the transportation cost inequality*

$$\mathcal{W}_{1,d}(\mathbb{Q}, \mathbb{P}) = \sqrt{2\left(\sum_{k=1}^n \nu_k\right) \mathbb{KL}\left(\mathbb{Q} \,\|\, \mathbb{P}\right)}, \qquad \text{for all distributions } \mathbb{Q} \ll \mathbb{P} \tag{98}$$

where the Wasserstein metric is defined using the distance $d(x, y) := \sum_{k=1}^n d_k(x_k, y_k)$*.*

9.4 Induction Lemma

- **Lemma 9.7** *[Boucheron et al., 2013]*
Let $\mathbb{P} = \otimes_{i=1}^n \mathbb{P}_i$ *be a* ***product probability measure*** *on a product measurable space* $\mathcal{X}^n$ *and let* $\mathbb{Q}$ *be a probability measure absolutely continuous with respect to* $\mathbb{P}$ *(i.e.* $\mathbb{Q} \ll \mathbb{P}$*). Let* $w : \mathcal{X} \times \mathcal{X} \to [0, \infty)$ *be a measurable function and let* $\phi : [0, \infty) \to [0, \infty)$ *be a* ***convex function****. Suppose that for every* $i = 1, \ldots, n$ *and for every probability measure* $\nu \ll \mathbb{P}_i$ *which is absolutely continuous with respect to* $\mathbb{P}_i$*,*

$$\min_{\gamma \in \Pi(\mathbb{P}_i, \nu)} \phi\left(\mathbb{E}_\gamma\left[w(X_i, Y_i)\right]\right) \le \mathbb{KL}\left(\nu \,\|\, \mathbb{P}_i\right)$$

Then

$$\min_{\gamma \in \Pi(\mathbb{P}, \mathbb{Q})} \sum_{i=1}^n \phi\left(\mathbb{E}_\gamma\left[w(X_i, Y_i)\right]\right) \le \mathbb{KL}\left(\mathbb{Q} \,\|\, \mathbb{P}\right).$$

9.5 Marton's Transportation Inequality

- **Theorem 9.8** ***(Marton's Transportation Inequality)*** *[Boucheron et al., 2013]*
Let $\mathbb{P} = \otimes_{k=1}^n \mathbb{P}_k$ *be a product probability measure on* $\mathcal{X}^n$*, and let* $\mathbb{Q}$ *be a probability measure*

absolutely continuous with respect to $\mathbb{P}$. Define two random vectors $X = (X_1, \ldots, X_n), Y = (Y_1, \ldots, Y_n)$ in $\mathcal{X}^n$ with distribution $\mathbb{P}$ and $\mathbb{Q}$ respectively. Then

$$\mathcal{W}_{2,d_H}(\mathbb{Q},\mathbb{P}) := \sqrt{\min_{\gamma\in\Pi(\mathbb{Q},\mathbb{P})} \sum_{i=1}^{n} \gamma^2\left\{X_i \neq Y_i\right\}} \le \sqrt{\frac{1}{2}\mathbb{KL}\left(\mathbb{Q}\,\|\,\mathbb{P}\right)} \tag{99}$$

$$\Leftrightarrow \min_{\gamma\in\Pi(\mathbb{Q},\mathbb{P})} \sum_{i=1}^{n} \gamma^2\left\{X_i \neq Y_i\right\} \le \frac{1}{2}\mathbb{KL}\left(\mathbb{Q}\,\|\,\mathbb{P}\right)$$

- **Theorem 9.9** ***(Marton's Conditional Transportation Inequality)*** *[Boucheron et al., 2013]*
  Let $\mathbb{P} = \otimes_{k=1}^{n}\mathbb{P}_k$ be a product probability measure on $\mathcal{X}^n$, and let $\mathbb{Q}$ be a probability measure absolutely continuous with respect to $\mathbb{P}$. Define two random vectors $X = (X_1, \ldots, X_n), Y = (Y_1, \ldots, Y_n)$ in $\mathcal{X}^n$ with distribution $\mathbb{P}$ and $\mathbb{Q}$ respectively. Then

$$\min_{\gamma\in\Pi(\mathbb{Q},\mathbb{P})} \mathbb{E}_{\gamma}\left[\sum_{i=1}^{n}(\gamma^2\left\{X_i \neq Y_i | X_i\right\} + \gamma^2\left\{X_i \neq Y_i | Y_i\right\})\right] \le 2\mathbb{KL}\left(\mathbb{Q}\,\|\,\mathbb{P}\right) \tag{100}$$

- **Proposition 9.10** ***(Concentration of Lipschitz Function with Function Weighted Hamming Distance)*** *[Boucheron et al., 2013]*
  Let $f : \mathcal{X}^n \to \mathbb{R}$ be a measurable function and let $Z_1, \ldots, Z_n$ be independent random variables taking their values in $\mathcal{X}$. Define $X = f(Z_1, \ldots, Z_n)$. Assume that there exist ***measurable functions*** *$c_i : \mathcal{X}_n \to [0, \infty)$ such that for all $x, y \in \mathcal{X}^n$,*

$$f(y) - f(z) \le \sum_{i=1}^{n} c_i(z)\mathbb{1}\left\{y_i \neq z_i\right\}.$$

  Setting

$$\nu = \mathbb{E}\left[\sum_{i=1}^{n} c_i^2(Z)\right] \qquad \textit{and} \qquad \nu_{\infty} = \sup_{z\in\mathcal{X}^n}\sum_{i=1}^{n} c_i^2(z)$$

  for all $\lambda > 0$, we have

$$\psi_{X-\mathbb{E}[X]}(\lambda) \le \frac{\nu\lambda^2}{2} \qquad \textit{and} \qquad \psi_{-X+\mathbb{E}[X]}(\lambda) \le \frac{\nu_{\infty}\lambda^2}{2}$$

  In particular, for all $t > 0$,

$$\mathbb{P}\left\{X \ge \mathbb{E}\left[X\right] + t\right\} \le \exp\left(-\frac{t^2}{2\nu}\right)$$
$$\mathbb{P}\left\{X \le \mathbb{E}\left[X\right] - t\right\} \le \exp\left(-\frac{t^2}{2\nu_{\infty}}\right). \tag{101}$$

- **Remark** The condition in above proposition covers
  1. *Lipschitz functions* such as *functions with bounded difference*,

2. ***self-bounding functions*** including ***configuration functions***: Let f be such a configuration function. For any $z \in \mathcal{X}^n$, fix a *maximal sub-sequence* $(z_{i,1}, \ldots, z_{i,m})$ satisfying property Π (so that $f(z) = m$). Let $c_i(z)$ denote *the indicator that* z_i *belongs to the sub-sequence* $(z_{i,1}, \ldots, z_{i,m})$. Thus,

$$\sum_{i=1}^{n} c_i^2(z) = \sum_{i=1}^{n} c_i(z) = f(z).$$

It follows from the definition of a configuration function that for all $z, y \in \mathcal{X}^n$,

$$f(y) \geq f(z) - \sum_{i=1}^{n} c_i(z) \mathbb{1}\left\{z_i \neq y_i\right\}$$

So $g = -f$ satisfies the condition in above proposition.

3. ***weakly self-bounding functions***

4. ***convex distance function***

$$d_T(z, A) := \sup_{\alpha \in \mathbb{R}_+^n : \|\alpha\|_2 = 1} \inf_{y \in A} \sum_{i=1}^{n} \alpha_i \mathbb{1}\left\{z_i \neq y_i\right\}$$

Denote by $c(z) = (c_1(z), \ldots, c_n(z)) = \alpha^*$ the vector of nonnegative components *in the unit ball* for which *the supremum is achieved.* Thus

$$\begin{aligned} d_T(z, A) - d_T(y, A) &\leq \inf_{z' \in A} \sum_{i=1}^{n} c_i(z) \mathbb{1}\left\{z_i \neq z_i'\right\} - \inf_{y' \in A} \sum_{i=1}^{n} c_i(z) \mathbb{1}\left\{y_i \neq y_i'\right\} \\ &\leq \sum_{i=1}^{n} c_i(z) \mathbb{1}\left\{z_i \neq y_i\right\} \end{aligned}$$

9.6 Talagrand's Gaussian Transportation Inequality

- **Theorem 9.11** *(**Talagrand's Gaussian Transportation Inequality**) [Boucheron et al., 2013]*
  Let $\mathbb{P}$ be be the standard Gaussian probability measure on $\mathbb{R}^n$, and let $\mathbb{Q}$ be a probability measure absolutely continuous with respect to $\mathbb{P}$. Define two random vectors $X = (X_1, \ldots, X_n), Y = (Y_1, \ldots, Y_n)$ in $\mathcal{X}^n$ with distribution $\mathbb{P}$ and $\mathbb{Q}$ respectively. Then

$$\begin{aligned} \mathcal{W}_{2,d}(\mathbb{Q}, \mathbb{P}) := \sqrt{\min_{\gamma \in \Pi(\mathbb{Q}, \mathbb{P})} \sum_{i=1}^{n} \mathbb{E}_\gamma\left[(X_i - Y_i)^2\right]} &\leq \sqrt{2\mathbb{KL}\left(\mathbb{Q} \,\|\, \mathbb{P}\right)} \qquad (102) \\ \Leftrightarrow \min_{\gamma \in \Pi(\mathbb{Q}, \mathbb{P})} \sum_{i=1}^{n} \mathbb{E}_\gamma\left[(X_i - Y_i)^2\right] &\leq 2\mathbb{KL}\left(\mathbb{Q} \,\|\, \mathbb{P}\right) \end{aligned}$$

10 Proofs of Bounded Difference Inequality

- **Theorem 10.1** *(**McDiarmid's Inequality / Bounded Differences Inequality**)[Boucheron et al., 2013, Wainwright, 2019]*

Suppose that f satisfies **the bounded difference property** (50) *with parameters* $(L_1, \ldots, L_n)$ *i.e. for each index* $k = 1, 2, \ldots, n$,

$$\left|f(x_1, \ldots, x_n) - f(x_1, \ldots, x_{i-1}, x_i', x_{i+1}, \ldots, x_n)\right| \le L_k, \quad \textit{for all } x, x' \in \mathcal{X}^n.$$

Assume that the random vector $X = (X_1, X_2, \ldots, X_n)$ *has* ***independent*** *components. Then*

$$\mathbb{P}\left\{|f(X) - \mathbb{E}\left[f(X)\right]| \ge t\right\} \le 2\exp\left(-\frac{2t^2}{\sum_{k=1}^n L_k^2}\right).$$

10.1 Martingale Method

- **Proof:** Consider the associated *martingale difference sequence*

$$D_k := \mathbb{E}\left[f(X)|X_1, \ldots, X_k\right] - \mathbb{E}\left[f(X)|X_1, \ldots, X_{k-1}\right].$$

We claim that D_k lies in *an interval of length at most L_k almost surely.* In order to prove this claim, define the random variables

$$\begin{aligned} A_k &:= \inf_x \left\{\mathbb{E}\left[f(X)|X_1, \ldots, X_{k-1}, x\right]\right\} - \mathbb{E}\left[f(X)|X_1, \ldots, X_{k-1}\right] \\ B_k &:= \sup_x \left\{\mathbb{E}\left[f(X)|X_1, \ldots, X_{k-1}, x\right]\right\} - \mathbb{E}\left[f(X)|X_1, \ldots, X_{k-1}\right]. \end{aligned}$$

On one hand, we have

$$D_k - A_k = \mathbb{E}\left[f(X)|X_1, \ldots, X_k\right] - \inf_x \left\{\mathbb{E}\left[f(X)|X_1, \ldots, X_{k-1}, x\right]\right\},$$

so that $D_k \ge A_k$ *almost surely.* A similar argument shows that $D_k \le B_k$ *almost surely.* We now need to show that $B_k - A_k \le L_k$ *almost surely.* Observe that by the independence of $\{X_k\}_{k=1}^n$, we have

$$\mathbb{E}\left[f(X)\,|\,x_1, \ldots, x_k\right] = \mathbb{E}_{(k+1)}\left[f(x_1, \ldots, x_k, X_{k+1}, \ldots, X_n)\right], \text{ for any } (x_1, \ldots, x_k),$$

where $\mathbb{E}_{(k+1)}\left[\cdot\right]$ denote the expectation over $(X_{k+1}, \ldots, X_n)$. Consequently, we have

$$\begin{aligned} B_k - A_k &= \sup_x \mathbb{E}_{(k+1)}\left[f(X_1, \ldots, X_{k-1}, x, X_{k+1}, \ldots, X_n)\right] \\ &\quad - \inf_x \mathbb{E}_{(k+1)}\left[f(X_1, \ldots, X_{k-1}, x, X_{k+1}, \ldots, X_n)\right] \\ &\le \sup_{x,y} \left\{\mathbb{E}_{(k+1)}\left[f(X_{1:k-1}, x, X_{k+1:n})\right] - \mathbb{E}_{(k+1)}\left[f(X_{1:k-1}, y, X_{k+1:n})\right]\right\} \\ &\le L_k, \end{aligned}$$

using *the bounded differences assumption.* Thus, the variable D_k lies within an interval of length L_k at most surely, so that the claim follows as a corollary of *the Azuma-Hoeffding inequality.* ∎

10.2 Entropy Method

- **Proof:** Recall that for a random variable Y taking its values in $[a, b]$, then we know from *Hoeffding's Lemma* that the logarithmic moment generating functions $\psi(\lambda)$ satisfies

$$\psi(\lambda)'' = \mathrm{Var}(Y) \le \frac{(b-a)^2}{4}$$

for every $\lambda \in \mathbb{R}$. Hence, Hoeffding's inequality is obtained since

$$\frac{\mathrm{Ent}(e^{\lambda Y})}{\mathbb{E}\left[e^{\lambda Y}\right]} = \lambda\psi'(\lambda) - \psi(\lambda) = \int_0^\lambda s\psi''(s)ds \le \frac{(b-a)^2}{4}\int_0^\lambda sds = \frac{(b-a)^2\lambda^2}{8},$$

Note that by the bounded differences assumption, given $X_{(-i)}$, $f(X)$ is a random variable whose range is in an interval of length at most L_i, so

$$\frac{\mathrm{Ent}_{(-i)}(e^{\lambda f(X)})}{\mathbb{E}_{(-i)}\left[e^{\lambda f(X)}\right]} \le \frac{L_i^2\lambda^2}{8}$$

From the tensorization property of entropy, we can bound the entropy of total function

$$\mathrm{Ent}(e^{\lambda f(X)}) \le \mathbb{E}\left[\sum_{i=1}^n \mathrm{Ent}_{(-i)}(e^{\lambda f(X)})\right] \le \sum_{i=1}^n \frac{L_i^2\lambda^2}{8}\mathbb{E}\left[\mathbb{E}_{(-i)}\left[e^{\lambda f(X)}\right]\right]$$
$$\frac{\mathrm{Ent}(e^{\lambda f(X)})}{\mathbb{E}\left[e^{\lambda f(X)}\right]} \le \frac{\sum_{i=1}^n L_i^2\lambda^2}{8} \equiv \frac{\nu\lambda^2}{2},$$

where $\nu := \frac{1}{4}\sum_{i=1}^n L_i^2$. Using *Herbst's argument*, it leads to the bound of logarithmic moment generating function:

$$\psi_{f(X)}(\lambda) \le \frac{\nu\lambda^2}{2}.$$

Finally, we apply *the Chernoff's inequality*

$$\mathbb{P}\left\{f(X) - \mathbb{E}\left[f(X)\right] \ge t\right\} \le \inf_{\lambda>0} \exp\left(\psi_{f(X)}(\lambda) - \lambda t\right) \le \exp\left(-\frac{t^2}{2\nu}\right). \quad \blacksquare$$

10.3 Isoperimetric Inequality on Binary Hypercube

- **Definition** (***Vertex Boundary of Graph***) [Boucheron et al., 2013]
Consider a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ and let $\mathcal{A} \subset \mathcal{V}$ be a set of its vertices. ***The vertex boundary*** of $\mathcal{A}$ is defined as *the set of those vertices*, ***not in*** $\mathcal{A}$, which are ***connected*** to *some vertex in* $\mathcal{V}$ by *an edge*. We denote *the vertex boundary of* $\mathcal{A}$ by $\partial V(\mathcal{A})$.

- **Remark** (***Binary Hypercube as Nearest Neighbor Graph with Hamming Distance***)
Consider the graph as binary hypercube $\{-1, +1\}^n$ in which two vertices are connected by an edge if and only if their ***Hamming distance*** *equals* 1. Define the *norm* as the *Hamming distance* to $-1^n = (-1, \ldots, -1)$

$$\|x\|_H := \sum_{i=1}^n \mathbb{1}\left\{x_i = 1\right\} = d_H(x, -1^n)$$

Theorem 10.2 ***(Harp's Vertex Isoperimetric Theorem)*** *[Boucheron et al., 2013]*
For $N = \sum_{i=0}^{k}\binom{n}{i}$, *for* $k = 0, , \ldots, n$, *let* S_N *is a* ***Hamming ball*** *centered at the vector* $-1^n = (-1\,, \ldots,\, -1)$, *i.e.*

$$S_N = \{x \in \{-1, +1\}^n : d_H(x, -1^n) \le k\} = B_H(-1^n, k).$$

For any subset $A \subset \{-1, +1\}^n$, *where* $|A| = |S_N|$,

$$|\partial V(A)| \ge |\partial V(S_N)|$$

- **Definition** (***t-Blowup of Set A in Binary Hypercube***)
For any $A \subset \{-1, +1\}^n$ and $x \in \{-1, +1\}^n$, let $d_H(x, A) = \min_{y \in A} d_H(x, y)$ be the *Hamming distance* of x to the set A. Also, denote by

$$A_t := \{x \in \{-1, +1\}^n : d_H(x, A) < t\}$$

the *t-blowup of the set A*, that is, the set of points whose Hamming distance from A is at most t.

- **Corollary 10.3** ***(Isoperimetric Inequality in Binary Hypercube)*** *[Boucheron et al., 2013]*
Let $A \subset \{-1, +1\}^n$ *such that* $|A| \ge \sum_{i=0}^{k}\binom{n}{i}$. *Then for any* $t = 1, 2\,, \ldots, n - k + 1$,

$$|A_t| \ge \sum_{i=0}^{k+1-t}\binom{n}{i}. \tag{103}$$

In particular, if $|A|/2^n \ge 1/2$ *then we may take* $k = \lfloor n/2 \rfloor$ *in the corollary above and*

$$\frac{|A_t|}{2^n} \ge \mathbb{P}\{X < \mathbb{E}[X] + t\} \ge 1 - \exp\left(-\frac{2t^2}{n}\right) \tag{104}$$

where $X \sim Ber(1/2)$ *is a symmetric Bernoulli random variable taking values in* $\{-1, +1\}$ *with* $\mathbb{P}\{X = 1\} = \mathbb{P}\{X = -1\} = 1/2$.

- **Proof:** (***Proof of Bounded Difference Inequality on Binary Hypercube***)
Note that any function with ***bounded difference property*** is ***Lipschitz function*** with respect to ***Hamming distance***.

$$\begin{aligned}
&\sup_{x \in \mathcal{X}^n, y_i \in \mathcal{X}} |f(x_1\,, \ldots, x_n) - f(x_1\,, \ldots, x_{i-1}, y_i, x_{i+1}\,, \ldots, x_n)| \\
&\le c_i = c_i\, d_H((x_1\,, \ldots, x_n), (x_1\,, \ldots, x_{i-1}, y_i, x_{i+1}\,, \ldots, x_n)), \quad 1 \le i \le n \\
\Rightarrow |f(x) - f(y)| &= \left|\sum_{i=1}^{n}(f(x_{(i-1)}) - f(x_{(i)}))\right| \\
&\le \sum_{i=1}^{n}\left|f(x_{(i-1)}) - f(x_{(i)})\right| \\
&\le \sum_{i=1}^{n} L_i \mathbb{1}\left\{x_{(i-1)}[i] \neq x_{(i)}[i]\right\} \\
&\le \left(\sum_{i}^{n} L_i^2\right)^{1/2} d_H(x, y)
\end{aligned}$$

where $x_{(i)}$ is replicate of $x_{(i-1)}$ except for i-th component, which is replaced by y_i. Note that $x_{(0)} = x$ and $x_{(n)} = y$.

The Harp's isoperimetric theorem suggests that the concentration function

$$\alpha_{\mathbb{P},(\{-1,+1\}^n, d_{H,L})}(t) := \sup_{A:\mathbb{P}\{A\}\geq 1/2} \mathbb{P}\{A_t\} \leq \exp\left(-\frac{2t^2}{\sum_i^n L_i^2}\right)$$

where $\mathbb{P}$ is uniform distribution on $\{-1,+1\}^n$. Thus by *Levy's inequality*, we prove that for $Z \in \{-1,1\}^n$ and Lipschitz function $f : \{-1,1\}^n \to \mathbb{R}$ with respect to weighted Hamming distance $d_{H,L}$,

$$\mathbb{P}\{|f(Z) - \mathrm{Med}(f(Z))| \geq t\} \leq 2\exp\left(-\frac{2t^2}{\sum_i^n L_i^2}\right). \quad \blacksquare$$

10.4 Transportation Method

- **Proof:** Any function with ***bounded difference property*** is ***Lipschitz function*** with respect to ***Hamming distance***. This implies that for all $x, y \in \mathcal{X}^n$,

$$f(y) - f(x) \leq \sum_{i=1}^n L_i \mathbb{1}\{x_i \neq y_i\} \equiv d_{H,L}(x,y).$$

Note that for coupling $\gamma \in \Pi(\mathbb{Q},\mathbb{P})$ where $Y \sim \mathbb{Q}$ and $X \sim \mathbb{P}$,

$$\begin{aligned}
\mathbb{E}_{\mathbb{Q}}[f(Y)] - \mathbb{E}_{\mathbb{P}}[f(X)] &= \mathbb{E}_\gamma[f(Y) - f(X)] \\
&\leq \sum_{i=1}^n L_i \mathbb{E}_\gamma[\mathbb{1}\{X_i \neq Y_i\}] \\
&\leq \left(\sum_{i=1}^n L_i^2\right)^{1/2} \left(\sum_{i=1}^n (\mathbb{E}_\gamma[\mathbb{1}\{X_i \neq Y_i\}])^2\right)^{1/2}
\end{aligned}$$

We want to prove the concentration using transportation cost inequality. That is, to bound the term

$$\min_{\gamma\in\Pi(\mathbb{Q},\mathbb{P})} \sum_{i=1}^n (\mathbb{E}_\gamma[\mathbb{1}\{X_i \neq Y_i\}])^2 = \min_{\gamma\in\Pi(\mathbb{Q},\mathbb{P})} \sum_{i=1}^n \gamma^2\{X_i \neq Y_i\}.$$

We have shown that

$$\min_{\gamma\in\Pi(\mathbb{Q},\mathbb{P})} \gamma\{X \neq Y\} = \mathcal{W}_{1,d_H}(\mathbb{Q},\mathbb{P}) = \sup_{A\in\mathcal{X}} |\mathbb{Q}(A) - \mathbb{P}(A)| \equiv \|\mathbb{Q} - \mathbb{P}\|_{TV}.$$

For each independent variable X_i, Y_i, and their marginal distribution $\mathbb{P}_i, \mathbb{Q}_i$ where $\mathbb{Q}_i \ll \mathbb{P}_i$, by Pinsker's inequality,

$$\left[\min_{\gamma\in\Pi(\mathbb{Q},\mathbb{P})} \gamma\{X_i \neq Y_i\}\right]^2 = \|\mathbb{Q} - \mathbb{P}\|_{TV}^2 \leq \frac{1}{2}\mathbb{KL}(\mathbb{Q}_i \,\|\, \mathbb{P}_i)$$

$$\min_{\gamma\in\Pi(\mathbb{Q},\mathbb{P})} \gamma^2\{X_i \neq Y_i\} \leq \left[\min_{\gamma\in\Pi(\mathbb{Q},\mathbb{P})} \gamma\{X_i \neq Y_i\}\right]^2 \leq \frac{1}{2}\mathbb{KL}(\mathbb{Q}_i \,\|\, \mathbb{P}_i)$$

Thus by induction lemma,

$$\min_{\gamma \in \Pi(\mathbb{Q},\mathbb{P})} \sum_{i=1}^{n} \gamma^2 \{X_i \neq Y_i\} \leq \frac{1}{2} \mathbb{KL}\left(\mathbb{Q} \,\|\, \mathbb{P}\right)$$

which is the *Marton's transportation inequality*. Finally, we have

$$\begin{aligned}
\mathbb{E}_{\mathbb{Q}}\left[f(Y)\right] - \mathbb{E}_{\mathbb{P}}\left[f(X)\right] &\leq \left(\sum_{i=1}^{n} L_i^2\right)^{1/2} \left(\sum_{i=1}^{n} (\mathbb{E}_{\gamma}\left[\mathbb{1}\{X_i \neq Y_i\}\right])^2\right)^{1/2} \\
&\leq \sqrt{\frac{\left(\sum_{i=1}^{n} L_i^2\right)}{2} \mathbb{KL}\left(\mathbb{Q} \,\|\, \mathbb{P}\right)}.
\end{aligned}$$

Then we can apply the transportation lemma with $\nu := \frac{1}{4}\sum_{i=1}^{n} L_i^2$, which proves the bounded difference inequality. ∎

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