

# High Dimensional Probability Notes

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# 1 Random variables

## 1.1 Basic Inequalities

First, we revisit the definition of a random variable as well as some basic inequalities that we learned in introductory statistics.

**Definition 1.1** (Random variable).

Let  $(\Omega, \Sigma, \mathbb{P})$  be a probability space. A random variable  $X$  is defined as a mapping from the sample space  $\Omega$  to  $\mathbb{R}$ :

$$X : \Omega \rightarrow \mathbb{R} \quad (1)$$

$\Sigma$  is the  $\sigma$ -algebra containing the possible events (collection of subsets of  $\Omega$ ) and  $\mathbb{P}$  is a probability measure that assigns events with probabilities:

$$\mathbb{P} : \Sigma \rightarrow [0, 1] \quad (2)$$

For a given probability space  $(\Omega, \Sigma, \mathbb{P})$  and a random variable  $X : \Omega \rightarrow \mathbb{R}$ , we will use the following basic notations throughout this note:

- $\|X\|_{L^p}$  - The  $p^{th}$  root of the  $p^{th}$  moment of the random variable  $X$ .

$$\|X\|_{L^p} = (\mathbb{E}|X|^p)^{1/p}, \quad p \in (0, \infty) \quad (3)$$

$$\|X\|_{L^\infty} = \text{ess sup } |X| \quad (4)$$

- $L^p(\Omega, \Sigma, \mathbb{P})$  - The space of random variables  $X$  satisfying:

$$L^p(\Omega, \Sigma, \mathbb{P}) = \left\{ X : \Omega \rightarrow \mathbb{R} \mid \|X\|_{L^p} < \infty \right\} \quad (5)$$

Some basic inequalities and identities:

- **1. Jensen's Inequality** - For a random variable  $X$  and a convex function  $\varphi : \mathbb{R} \rightarrow \mathbb{R}$ , we have:

$$\varphi(\mathbb{E}X) \leq \mathbb{E}\varphi(X) \quad (6)$$

- **2. Monotonicity of  $L^p$  norm** - For a random variable  $X$ :

$$\|X\|_{L^p} \leq \|X\|_{L^q}, \quad 0 \leq p \leq q \leq \infty. \quad (7)$$

- **3. Minkowski's Inequality** - For  $1 \leq p \leq \infty$  and two random variables  $X, Y$  in  $L^p(\Omega, \Sigma, \mathbb{P})$  space:

$$\|X + Y\|_{L^p} \leq \|X\|_{L^p} + \|Y\|_{L^p}. \quad (8)$$

- **4. Holder's Inequality** - For  $p, q \in [1, \infty]$  such that  $1/p + 1/q = 1$ . Then, for random variables  $X \in L^p(\Omega, \Sigma, \mathbb{P})$  and  $Y \in L^q(\Omega, \Sigma, \mathbb{P})$ , we have:

$$|\mathbb{E}XY| \leq \|X\|_{L^p} \cdot \|Y\|_{L^q}. \quad (9)$$

- **5. Markov's Inequality** - For a non-negative random variable  $X$  and  $t > 0$ , we have:

$$\mathbb{P}(X \geq t) \leq \frac{\mathbb{E}X}{t}. \quad (10)$$

We can also generalize Markov's Inequality for  $p^{th}$  moment:

$$\mathbb{P}(|X| \geq t) \leq \frac{\mathbb{E}[|X|^p]}{t^p}, \quad \forall t > 0, p \in [2, \infty). \quad (11)$$

- **6. Chebyshev's Inequality** - For a random variable  $X$  with mean  $\mu$  and variance  $\sigma^2$ . Then, for any  $t > 0$ , we have:

$$\mathbb{P}(|X - \mu| \geq t) \leq \frac{\sigma^2}{t^2}. \quad (12)$$

- **7. Integral Identity** - Let  $X$  be a non-negative random variable, we have:

$$\mathbb{E}X = \int_0^\infty \mathbb{P}(X > t) dt. \quad (13)$$

## Exercises

### Exercise 1.1.1: Generalized Integral Identity

Let  $X$  be a random variable (not necessarily non-negative). Prove the following identity:

$$\mathbb{E}X = \int_0^\infty \mathbb{P}(X > t) dt - \int_{-\infty}^0 \mathbb{P}(X < t) dt. \quad (14)$$

**Solution** (Exercise 1.1.1).

For  $x \in \mathbb{R}$ , using the basic integral identity, we have:

$$|x| = \int_0^\infty \mathbf{1}\{t < |x|\} dt$$

We consider the following cases:

- When  $x < 0 \implies x = -|x|$ :

$$x = - \int_0^\infty \mathbf{1}\{t < |x|\} dt = - \int_0^\infty \mathbf{1}\{t < -x\} dt = - \int_0^\infty \mathbf{1}\{-t > x\} dt = - \int_{-\infty}^0 \mathbf{1}\{t > x\} dt.$$

- When  $x \geq 0 \implies x = |x|$ :

$$x = \int_0^\infty \mathbf{1}\{t < |x|\} dt = \int_0^\infty \mathbf{1}\{t < x\} dt.$$

Therefore, for  $x \in \mathbb{R}$ , we can write:

$$x = \int_0^\infty \mathbf{1}\{t < x\} dt - \int_{-\infty}^0 \mathbf{1}\{t > x\} dt.$$

Therefore, for a random variable  $X$  not necessarily non-negative, we have:

$$\begin{aligned} \mathbb{E}X &= \mathbb{E} \left[ \int_0^\infty \mathbf{1}\{t < X\} dt - \int_{-\infty}^0 \mathbf{1}\{t > X\} dt \right] \\ &= \mathbb{E} \int_0^\infty \mathbf{1}\{t < X\} dt - \mathbb{E} \int_{-\infty}^0 \mathbf{1}\{t > X\} dt \\ &= \int_0^\infty \mathbb{E} \mathbf{1}\{t < X\} dt - \int_{-\infty}^0 \mathbb{E} \mathbf{1}\{t > X\} dt \\ &= \int_0^\infty \mathbb{P}(t < X) dt - \int_{-\infty}^0 \mathbb{P}(t > X) dt. \end{aligned}$$

□.

**Exercise 1.1.2:  $p^{th}$ -moments via tails**

Let  $X$  be a random variable and  $p \in (0, \infty)$ . Show that:

$$\mathbb{E}|X|^p = \int_0^\infty pt^{p-1}\mathbb{P}(|X| > t)dt. \quad (15)$$

**Solution** (Exercise 1.1.2). \_\_\_\_\_

Let  $X$  be a random variable that is not necessarily non-negative. Using the integral identity, we have:

$$\mathbb{E}|X|^p = \int_0^\infty \mathbb{P}(u < |X|^p)du.$$

Let  $t^p = u \implies pt^{p-1}dt = du$ . Since we integrate  $u$  from  $0 \rightarrow \infty$ , we also integrate  $t$  from  $0 \rightarrow \infty$  when changing the variables. Hence, we have:

$$\mathbb{E}|X|^p = \int_0^\infty \mathbb{P}(t^p < |X|^p)pt^{p-1}dt = \int_0^\infty \mathbb{P}(t < |X|)pt^{p-1}dt.$$

Hence, we obtained the desired identity.  $\square$ .

**1.2 Limit Theorems****1.2.1 Weak Law of Large Numbers****Theorem 1.1: Weak Law of Large Numbers (WLLN)**

Let  $X_1, \dots, X_N$  be *i.i.d* random variables with mean  $\mu$ . Consider the sum:

$$S_N = X_1 + \dots + X_N$$

Then, the sample mean **converges to  $\mu$  in probability** ( $S_N/N \xrightarrow{p} \mu$ ):

$$\lim_{N \rightarrow \infty} \mathbb{P}\left(|S_N/N - \mu| > \epsilon\right) = 0, \quad \forall \epsilon > 0 \quad (16)$$

**Proof** (Weak Law of Large Numbers (WLLN)). \_\_\_\_\_

We split the proof into two sections corresponding to the assumptions of finite variance and non-finite variance.

1. **Finite variance case:** Suppose that  $\text{Var}X_i = \sigma^2 < \infty$  for all  $1 \leq i \leq N$ . Let  $\bar{X} = S_N/N$ . Then,  $\bar{X}$  is a random variable with the following mean and variance:

$$\mathbb{E}\bar{X} = \mu \quad \text{and} \quad \text{Var}\bar{X} = \frac{\sigma^2}{N}.$$

Hence, by the Chebyshev's inequality, we have:

$$\mathbb{P}\left(|S_N/N - \mu| > \epsilon\right) = \mathbb{P}\left(|\bar{X} - \mu| > \epsilon\right) \leq \frac{\sigma^2}{N\epsilon^2}.$$

Therefore, we have:

$$\lim_{N \rightarrow \infty} \mathbb{P}\left(|S_N/N - \mu| > \epsilon\right) \leq \lim_{N \rightarrow \infty} \frac{\sigma^2}{N\epsilon^2} = 0.$$

Hence, we have  $\lim_{N \rightarrow \infty} \mathbb{P}\left(|S_N/N - \mu| > \epsilon\right) = 0$  and we obtained **(WLLN)**.

2. **Non-finite variance case:** In this case, we rely on the Levy Continuity Theorem (**LCT**), which relies on the convergence of the characteristic function. For  $n \geq 1$ , define the sequence of random variable  $Y_n = S_n/n$ . Hence, we have:

$$\begin{aligned}\varphi_{Y_n}(t) &= \varphi_{S_n/n}(t) \\ &= \varphi_{S_n}(t/n) \\ &= \prod_{i=1}^n \varphi_{X_i}(t/n) = \left[ \varphi_X(t/n) \right]^n,\end{aligned}$$

Where  $X = X_1 = \dots = X_n$ . By Taylor's expansion, we have:

$$\varphi_X(t/n) = 1 + \frac{it\mathbb{E}[X]}{n} + \mathcal{O}(1/n^2) = 1 + \frac{it\mu}{n} + \mathcal{O}(1/n^2).$$

Hence, we have:

$$\lim_{n \rightarrow \infty} \varphi_{Y_n}(t) = \lim_{n \rightarrow \infty} \left( 1 + \frac{it\mu}{n} + \mathcal{O}(1/n^2) \right)^n = e^{it\mu}.$$

Therefore, by (**LCT**), we have  $Y_n \xrightarrow{p} \mu$ .

**Remark 1.1** (Taylor expansion of Moment Generating and Characteristic Functions). —————  
Given a random variable  $X$ . For reference, the following are the Taylor expansions of the Moment Generating Function  $M_X(t)$  and the Characteristic Function  $\varphi_X(t)$ :

$$\begin{aligned}M_X(t) &= \mathbb{E}[e^{tX}] = 1 + \sum_{n=1}^{\infty} \frac{t^n}{n!} \mathbb{E}[X^n], \\ \varphi_X(t) &= \mathbb{E}[e^{itX}] = 1 + \sum_{n=1}^{\infty} \frac{(it)^n}{n!} \mathbb{E}[X^n].\end{aligned}\tag{17}$$

For the sake of my laziness, here are the Taylor expansion for the first three terms of both the MGF and the CF:

$$\begin{aligned}M_X(t) &= 1 + t\mathbb{E}[X] + \frac{t^2}{2}\mathbb{E}[X^2] + \mathcal{O}(t^3), \\ \varphi_X(t) &= 1 + it\mathbb{E}[X] - \frac{t^2}{2}\mathbb{E}[X^2] + \mathcal{O}(t^3).\end{aligned}\tag{18}$$

□.

### Theorem 1.2: Levy Continuity Theorem (**LCT**)

Let  $X_1, X_2, \dots$  be *i.i.d* random variables. Then:

$$\forall t \in \mathbb{R} : \lim_{n \rightarrow \infty} \varphi_{X_n}(t) = \varphi_X(t) \iff X_n \xrightarrow{d} X,\tag{19}$$

for some random variable  $X$ . In a special case where  $X = c$  for some  $c \in \mathbb{R}$ , we have:

$$\forall t \in \mathbb{R} : \lim_{n \rightarrow \infty} \varphi_{X_n}(t) = e^{itc} \iff X_n \xrightarrow{p} c.\tag{20}$$

**Proof** (Levy Continuity Theorem (**LCT**)). —————  
The proof for (**LCT**) can be found in Gut 2004, Section 9.1, Theorem 9.1 and Collorary 9.1 □.

### 1.2.2 Strong Law of Large Numbers

#### Theorem 1.3: Strong Law of Large Numbers (SLLN)

Let  $X_1, \dots, X_N$  be *i.i.d* random variables with mean  $\mu < \infty$ . Consider the sum:

$$S_N = X_1 + \dots + X_N$$

Then, the sample mean **converges to  $\mu$  almost surely** ( $S_N/N \xrightarrow{a.s} \mu$ ):

$$\mathbb{P}\left(\limsup_{N \rightarrow \infty} |S_N/N - \mu| > \epsilon\right) = 0, \quad \forall \epsilon > 0 \quad (21)$$

**Proof** (Strong Law of Large Numbers (SLLN)).

For the sake of simplicity, we will present the proof for (SLLN) with an additional assumption that  $\mathbb{E}[|X_n|^4] < \infty, \forall n \geq 1$ . The proof for the general case of (SLLN) (also called the Kolmogorov Strong Law) can be found in Gut 2004, Section 6, Theorem 6.1. For convenience, we assume the following:

1.  $\mathbb{E}[|X_n|^4] = K < \infty$ .
2.  $\mathbb{E}[X_n] = 0$ . For non-zero mean case, we can set  $Y_n = X_n - \mu$  and repeat the same arguments made below.

We aim to prove that  $\mathbb{P}\left(\limsup_{N \rightarrow \infty} |S_N/N| > \epsilon\right) = 0$  for any  $\epsilon > 0$ . Firstly, use the Multinomial formula to expand  $\mathbb{E}[S_n]$ . The expansion will contain the terms in the following forms:

$$X_i^2, X_i^3 X_j, X_i^2 X_j^2, X_i^2 X_j X_k, X_i X_j X_k X_\ell,$$

where  $i, j, k, \ell$  are distinct indices. By independence, we have:

$$\mathbb{E}[X_i^3 X_j] = \mathbb{E}[X_i^2 X_j X_k] = \mathbb{E}[X_i X_j X_k X_\ell] = 0.$$

As a result, we have the following remaining terms by the Multinomial formula:

$$\begin{aligned} \mathbb{E}[S_n^4] &= \sum_{i=1}^n \mathbb{E}[X_i^4] + \binom{4}{2} \sum_{1 \leq i < j \leq n} \mathbb{E}[X_i^2 X_j^2] \\ &= \sum_{i=1}^n \mathbb{E}[X_i^4] + 6 \underbrace{\sum_{1 \leq i < j \leq n} \mathbb{E}[X_i^2 X_j^2]}_{n(n-1)/2 \text{ terms}} \\ &= nK + 3n(n-1)\mathbb{E}[X_i^2 X_j^2]. \end{aligned}$$

By independence, we have  $\mathbb{E}[X_i^2 X_j^2] = \mathbb{E}[X_i^2] \mathbb{E}[X_j^2]$  and for any  $1 \leq i \leq n$ . Furthermore, we have  $\mathbb{E}[X_i^2] = \text{Var}(X_i) + \mu^2 = \sigma^2 + \mu^2$ . Therefore:

$$\mathbb{E}[S_n^4] = nK + 3n(n-1)(\sigma^2 + \mu^2) < nK + 3n^2(\sigma^2 + \mu^2).$$

Applying Markov's Inequality with the fourth moment, we have:

$$\begin{aligned} \mathbb{P}(|S_n/n| \geq \epsilon) &= \mathbb{P}(|S_n| \geq n\epsilon) \\ &\leq \frac{\mathbb{E}[S_n^4]}{n^4 \epsilon^4} \\ &< \frac{K}{n^3 \epsilon^4} + \frac{3(\sigma^2 + \mu^2)}{n^2}. \end{aligned}$$

Therefore, we have:

$$\sum_{n=1}^{\infty} \mathbb{P}(|S_n/n| \geq \epsilon) < \frac{K}{\epsilon^4} \sum_{n=1}^{\infty} n^{-3} + 3(\sigma^2 + \mu^2) \sum_{n=1}^{\infty} n^{-2} < \infty \quad (22)$$

Finally, by the Borel-Cantelli Lemma (**BCL**), we have:

$$\mathbb{P}\left(\limsup_{n \rightarrow \infty} |S_n/n| \geq \epsilon\right) = 0, \quad \forall \epsilon > 0.$$

□.

#### Theorem 1.4: Borel-Cantelli Lemma (**BCL**)

**1. First Borel-Cantelli Lemma:** Given a probability space  $(X, \mathcal{S}, \mathbb{P})$  and a sequence  $\{A_n\}_{n=1}^{\infty} \subset \mathcal{S}$ . If  $\sum_{n=1}^{\infty} \mathbb{P}(A_n) < \infty$ , we have:

$$\mathbb{P}\left(\limsup_{n \rightarrow \infty} A_n\right) = 0. \quad (23)$$

**2. Second Borel-Cantelli Lemma:** On the other hand, if  $\sum_{n=1}^{\infty} \mathbb{P}(E_n) = \infty$ , we have:

$$\mathbb{P}\left(\limsup_{n \rightarrow \infty} A_n\right) = 1. \quad (24)$$

**Proof** (Borel-Cantelli Lemma (**BCL**)).

We focus on proving the first Borel-Cantelli lemma. We define another sequence of  $\mathcal{S}$ -measurable sets  $\{B_n\}_{n=1}^{\infty}$  such that:

$$B_n = \bigcup_{k=n}^{\infty} A_k.$$

Hence, we have  $B_{\ell+1} \subset B_{\ell}$  for every  $\ell \geq 1$ . In other words,  $B_n$  is a decreasing sequence of  $\mathcal{S}$ -measurable sets. By continuity of measure, we have:

$$\begin{aligned} \mathbb{P}\left(\lim_{n \rightarrow \infty} B_n\right) &= \lim_{n \rightarrow \infty} \mathbb{P}(B_n) \\ &= \lim_{n \rightarrow \infty} \sum_{k=n}^{\infty} \mathbb{P}(A_k) \quad (\text{By additivity}) \\ &= \sum_{i=1}^{\infty} \mathbb{P}(A_i) - \lim_{n \rightarrow \infty} \sum_{k=1}^n \mathbb{P}(A_k) \\ &= 0. \end{aligned}$$

Furthermore, we have:

$$\mathbb{P}\left(\lim_{n \rightarrow \infty} B_n\right) = \mathbb{P}\left(\lim_{n \rightarrow \infty} \bigcup_{k=n}^{\infty} A_k\right) = \mathbb{P}\left(\bigcap_{n=1}^{\infty} \bigcup_{k=n}^{\infty} A_k\right) = \mathbb{P}\left(\limsup_{n \rightarrow \infty} A_n\right).$$

Hence proved the first Borel-Cantelli Lemma. To prove the second Borel-Cantelli Lemma, we prove the following:

$$\begin{aligned} 1 - \mathbb{P}\left(\limsup_{n \rightarrow \infty} A_n\right) &= \mathbb{P}\left(\left\{\limsup_{n \rightarrow \infty} A_n\right\}^c\right) \\ &= \mathbb{P}\left(\liminf_{n \rightarrow \infty} A_n^c\right) = 0. \end{aligned}$$

□.

### 1.2.3 Uniform Law of Large Numbers

The Uniform Law of Large Numbers (**ULLN**) provides a convergence result for collection of estimators where the convergence is uniform in the parameters space.

#### Theorem 1.5: Uniform Law of Large Numbers (**ULLN**)

Let  $\mathbf{X} = (X_1, \dots, X_n)$  be a random sample from a distribution  $p_{\theta}$  over  $\mathcal{X}$  that depends on the true parameters  $\theta$ . Let  $\Theta \subset \mathbb{R}^m$  be the parameters space and  $f_{\theta} : \mathcal{X} \rightarrow \mathbb{R}$  be a function indexed by  $\theta \in \Theta$  that satisfies the following conditions:

1.  $\theta \in \Theta$  and  $\Theta$  is compact.
2.  $\mathbb{E}_{\theta}[\sup_{\theta \in \Theta} |f_{\theta}(X)|] < \infty^a$ .
3.  $f_{\theta}(x)$  is continuous in  $\theta$  for all  $x \in \mathcal{X}$ .

Then, we have:

$$\sup_{\theta \in \Theta} \left| \frac{1}{n} \sum_{i=1}^n f_{\theta}(X_i) - \mathbb{E}_{\theta}[f_{\theta}(X)] \right| \xrightarrow{p} 0. \quad (25)$$

<sup>a</sup> $\mathbb{E}_{\theta}$  denotes the expectation taken over the distribution described by  $p_{\theta}$ .

**Proof** (Theorem 1.5).

A nice proof is provided in Ferguson 1996, Theorem 16, Page 111. However, we will conduct our own version of the proof relying on results in learning theory. For  $\theta \in \Theta$ , define the following function:

$$\phi_{\theta}(\mathbf{X}) = \left| \frac{1}{n} \sum_{i=1}^n \left( f_{\theta}(X_i) - \mathbb{E}_{\theta}[f_{\theta}(X)] \right) \right| \quad (26)$$

We have to prove that  $\mathbb{P}(\sup_{\theta \in \Theta} |\phi_{\theta}(\mathbf{X})| \geq \epsilon) \rightarrow 0$  for all  $\epsilon > 0$ . For  $\epsilon > 0$ , we have:

$$\begin{aligned} \mathbb{P}\left(\sup_{\theta \in \Theta} |\phi_{\theta}(\mathbf{X})| \geq \epsilon\right) &= \mathbb{P}\left(\left\{\sup_{\theta \in \Theta} \phi_{\theta}(\mathbf{X}) \geq \epsilon\right\} \cup \left\{\sup_{\theta \in \Theta} (-\phi_{\theta}(\mathbf{X})) \geq \epsilon\right\}\right) \\ &\leq \mathbb{P}\left(\sup_{\theta \in \Theta} \phi_{\theta}(\mathbf{X}) \geq \epsilon\right) + \mathbb{P}\left(\sup_{\theta \in \Theta} (-\phi_{\theta}(\mathbf{X})) \geq \epsilon\right) \\ &\leq \frac{1}{\epsilon} \left( \mathbb{E}\left[\sup_{\theta \in \Theta} \phi_{\theta}(\mathbf{X})\right] + \mathbb{E}\left[\sup_{\theta \in \Theta} (-\phi_{\theta}(\mathbf{X}))\right] \right) \quad (\text{Markov's Inequality}) \end{aligned}$$

Now, we need to bound the expectations on the right-hand-side. To do so, we use the symmetrization trick. Specifically, given a sequence of i.i.d random variables  $S = \{Z_1, \dots, Z_n\} \sim \rho^n$  sampled from a distribution  $\rho$  and a class of functions  $\mathcal{F}$ . Let  $S' = \{Z'_1, \dots, Z'_n\} \sim \rho^n$  be a another sample



from the same distribution  $\rho$  (which we called the phantom sample), we have:

$$\begin{aligned}
& \mathbb{E}_S \left[ \sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n (f(Z_i) - \mathbb{E}_S[f(Z_i)]) \right] \\
&= \mathbb{E}_S \left[ \sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n (f(Z_i) - \mathbb{E}_{S'}[f(Z'_i)]) \right] \\
&= \mathbb{E}_S \left[ \sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n f(Z_i) - \frac{1}{n} \sum_{i=1}^n \mathbb{E}_{S'}[f(Z'_i)] \right] \\
&= \mathbb{E}_S \left[ \sup_{f \in \mathcal{F}} \mathbb{E}_{S'} \left[ \frac{1}{n} \sum_{i=1}^n (f(Z_i) - f(Z'_i)) \right] \right] \\
&\leq \mathbb{E}_{S, S'} \left[ \sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n (f(Z_i) - f(Z'_i)) \right] \quad (\text{Jensen's Inequality}) \\
&= \mathbb{E}_{S, S', \sigma} \left[ \sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n \sigma_i (f(Z_i) - f(Z'_i)) \right] \quad (\sigma \sim \text{Rad}^n, f(Z_i) - f(Z'_i) \text{ is symmetric}) \\
&\leq \mathbb{E}_{S, \sigma} \left[ \sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n \sigma_i f(Z_i) \right] + \mathbb{E}_{S', \sigma} \left[ \sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n (-\sigma_i) f(Z'_i) \right] \\
&= \mathbb{E}_{S, \sigma} \left[ \sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n \sigma_i f(Z_i) \right] + \mathbb{E}_{S', \sigma} \left[ \sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n \sigma_i f(Z'_i) \right] \quad (\text{Rademacher variables are symmetric}) \\
&= 2\mathbb{E}_{S, \sigma} \left[ \sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n \sigma_i f(Z_i) \right] \quad (S \text{ and } S' \text{ are identically distributed}) \\
&= 2\mathfrak{R}_n(\mathcal{F}).
\end{aligned} \tag{27}$$

Using the same argument, we can also have:

$$\mathbb{E}_S \left[ \sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n (\mathbb{E}_S[f(Z_i)] - f(Z_i)) \right] \leq 2\mathfrak{R}_n(\mathcal{F}). \tag{28}$$

Using equations 27 and 28 to bound  $\mathbb{P}(\sup_{\theta \in \Theta} |\phi_\theta(S)| \geq \epsilon)$ , we have:

$$\mathbb{P} \left( \sup_{\theta \in \Theta} |\phi_\theta(S)| \geq \epsilon \right) \leq \frac{4\mathfrak{R}_n(\mathcal{F}_\Theta)}{\epsilon}, \quad \text{where } \mathcal{F}_\Theta = \{f_\theta : \theta \in \Theta\}.$$

To complete the proof, we have to show that the Rademacher complexity  $\mathfrak{R}_n(\mathcal{F}_\Theta) \rightarrow 0$  as  $n \rightarrow \infty$ . By the definition of Rademacher Complexity, we have:

$$\mathfrak{R}_n(\mathcal{F}_\Theta) = \mathbb{E}_{\mathbf{X} \sim p_\theta^n} \mathbb{E}_\sigma [\hat{\mathfrak{R}}_{\mathbf{X}}(\mathcal{F}_\Theta)],$$

It is sufficient to prove that the Empirical Rademacher Complexity  $\hat{\mathfrak{R}}_{\mathbf{X}}(\mathcal{F}_\Theta) \rightarrow 0$  as  $n \rightarrow \infty$ . Using Dudley's Entropy Integral Bartlett et al. 2017, Lemma A.5, we have:

$$\hat{\mathfrak{R}}_{\mathbf{X}}(\mathcal{F}_\Theta) \leq \frac{12}{\sqrt{n}} \int_\alpha^M \sqrt{\log \mathcal{N}(\mathcal{F}_\Theta, \epsilon, L_2(\mathbf{X}))} d\epsilon, \quad \alpha > 0, \tag{29}$$

where  $M < \infty$  is a constant such that  $|f_\theta(x)| \leq M$   $p_\theta$ -(almost everywhere) on  $\mathcal{X}$  for all  $\theta \in \Theta^1$ . Now, we need to construct a cover in  $L_2$  norm for the class  $\mathcal{F}_\Theta$ . Since  $f_\theta(x)$  is continuous in  $\theta$  for all  $x \in \mathcal{X}$ , for all  $\epsilon > 0$ , there exists  $\delta_x > 0$  such that  $\|\theta - \theta'\|_2 < \delta_x \implies |f_\theta(x) - f_{\theta'}(x)| < \epsilon$ . Define  $\delta > 0$  as follows:

$$\delta = \min_{1 \leq i \leq n} \delta_{X_i}, \quad X_i \in \mathbf{X}. \tag{30}$$

---

<sup>1</sup>M exists because we have  $\mathbb{E}_\theta [\sup_{\theta \in \Theta} |f_\theta(X)|] < \infty$ .

Due to continuity, constructing an  $\epsilon$ -cover in  $\mathcal{F}_\Theta$  is equivalent to constructing a  $\delta$ -cover for  $\Theta$  with respect to the Euclidean norm. Since  $\Theta$  is compact, there exists  $N \in \mathbb{N}$  and a sequence of open balls  $\{\mathcal{B}(y_j, r_j)\}_{j=1}^N$  where  $y_j \in \Theta$  for all  $1 \leq j \leq N$  such that:

$$\Theta \subseteq \bigcup_{j=1}^N \mathcal{B}(y_j, r_j). \quad (31)$$

By Long et al. 2020, Lemma A.8, we have:

$$\log \mathcal{N}(\mathcal{B}(y_j, r_j), \delta, \|\cdot\|_2) \leq m \log \left( \frac{3r_j}{\delta} \right). \quad (32)$$

Therefore, we have:

$$\log \mathcal{N}(\Theta, \delta, \|\cdot\|_2) \leq \sum_{j=1}^N \log \mathcal{N}(\mathcal{B}(y_j, r_j), \delta, \|\cdot\|_2) \leq mN \log \left( \frac{\prod_{j=1}^N r_j}{\delta^N} \right). \quad (33)$$

From the above covering number bound, we can see that  $\log \mathcal{N}(\Theta, \delta, \|\cdot\|_2)$  does not grow with  $n$  and therefore,  $\log \mathcal{N}(\mathcal{F}_\Theta, \epsilon, L_2(\mathbf{X}))$  does not grow with  $n$ . Therefore, we have  $\hat{\mathfrak{R}}_{\mathbf{X}}(\mathcal{F}_\Theta) \in \mathcal{O}(1/\sqrt{n})$  and  $\hat{\mathfrak{R}}_{\mathbf{X}}(\mathcal{F}_\Theta) \rightarrow 0$  as  $n \rightarrow \infty$ .  $\square$ .

#### 1.2.4 Central Limit Theorem

##### Theorem 1.6: Central Limit Theorem (CLT)

Let  $X_1, \dots, X_n$  be a sequence of *i.i.d* random variables with expected value  $\mu$  and finite variance  $\sigma^2$ . Then, we have:

$$\frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} \xrightarrow{d} \mathcal{N}(0, 1) \quad \text{as } n \rightarrow \infty, \quad (34)$$

where  $\bar{X}_n = S_n/n$  and  $\mathcal{N}(0, 1)$  is the standard normal distribution.

**Proof** (Central Limit Theorem (CLT)).

We prove this via the Characteristic Function. Let  $\bar{Z}_n = \frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}}$ , notice that:

$$\bar{Z}_n = \frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} = \frac{1}{\sqrt{n}} \sum_{i=1}^n \frac{X_i - \mu}{\sigma},$$

Let  $Z_i = X_i - \mu$  for  $1 \leq i \leq n$  and suppose  $Z = Z_1 = \dots = Z_n$ , we have:

$$\begin{aligned} \varphi_{\bar{Z}_n}(t) &= \varphi_{\sum_{i=1}^n Z_i} \left( \frac{t}{\sqrt{n}} \right) = \left[ \varphi_Z \left( \frac{t}{\sqrt{n}} \right) \right]^n \\ &= \left[ 1 + \frac{it\mathbb{E}[Z]}{\sqrt{n}} - \frac{t^2}{2n} \mathbb{E}[Z^2] + \mathcal{O}(1/n) \right]^n \quad (\text{Taylor's Expansion}) \\ &= \left[ 1 - \frac{t^2}{2n} + \mathcal{O}(1/n) \right]^n. \end{aligned}$$

The final equality comes from the fact that  $\mathbb{E}[Z] = 0$  and  $\mathbb{E}[Z^2] = \mathbb{E}[Z]^2 + \text{Var}(Z) = 1$ . Finally, we have:

$$\lim_{n \rightarrow \infty} \varphi_{\bar{Z}_n}(t) = \lim_{n \rightarrow \infty} \left[ 1 - \frac{t^2}{2n} + \mathcal{O}(1/n) \right]^n = e^{-t^2/2}.$$

Since  $e^{-t^2/2}$  is the Characteristic Function of the standard normal distribution, by **(LCT)**, we have  $\bar{Z}_n \xrightarrow{d} \mathcal{N}(0, 1)$ .  $\square$ .

### 1.3 Convergence of Random Variables

In this section, we revise the modes of convergence in random variables.

#### 1.3.1 Convergence in Distribution

**Definition 1.2** (Convergence in Distribution). 

---

Given a sequence of real-valued random variables  $X_1, X_2, \dots$  with CDFs  $F_1, F_2, \dots$ . We say that the sequence converges in distribution to a random variable  $X$  with CDF  $F$ , denoted  $X_n \xrightarrow{d} X$  if:

$$\lim_{n \rightarrow \infty} F_n(x) = F(x), \quad (35)$$

for all  $x \in \mathbb{R}$  at which  $F$  is continuous. Convergence in distribution can also be referred to as weak convergence in measure theory.

#### Theorem 1.7: Slutsky's Theorem **(SLUTSKY)**

Let  $X_n$  and  $Y_n$  be two sequences of random variables such that  $X_n \xrightarrow{d} X$  and  $Y_n \xrightarrow{d} c$  where  $c < \infty$  is a constant. Then, we have:

1.  $X_n + Y_n \xrightarrow{d} X + c$ .
2.  $X_n Y_n \xrightarrow{d} cX$ .
3.  $X_n/Y_n \xrightarrow{d} X/c$  if  $c \neq 0$ .

**Proof** (Theorem 1.7). 

---

$\square$ .

#### 1.3.2 Convergence in Probability

**Definition 1.3** (Convergence in Probability). 

---

Given a sequence of real-valued random variables  $X_1, X_2, \dots$ . We say that the sequence converges in probability to a random variable  $X$ , denoted  $X_n \xrightarrow{p} X$  if:

$$\lim_{n \rightarrow \infty} \mathbb{P}(|X_n - X| \geq \epsilon) = 0, \quad \forall \epsilon > 0. \quad (36)$$

We also refer to convergence in probability as convergence in measure in measure theory.

#### Proposition 1.1: $X_n \xrightarrow{p} X \implies X_n \xrightarrow{d} X$

Let  $X$  and the sequence  $X_1, X_2, \dots$  be real-valued random variables. If  $X_n \xrightarrow{p} X$ , then  $X_n \xrightarrow{d} X$ .

**Proof** (Proposition 1.1). 

---

We first prove the following claim: Let  $X, Y$  be random variables,  $a \in \mathbb{R}$  and  $\epsilon > 0$ , the inequality

$\mathbb{P}(Y \leq a) \leq \mathbb{P}(X \leq a + \epsilon) + \mathbb{P}(|Y - X| \geq \epsilon)$  holds. We have:

$$\begin{aligned} \mathbb{P}(Y \leq a) &= \mathbb{P}(Y \leq a, X \leq a + \epsilon) + \mathbb{P}(Y \leq a, X \geq a + \epsilon) \\ &\leq \mathbb{P}(X \leq a + \epsilon) + \mathbb{P}(Y - X \leq a - X, a - X \leq -\epsilon) \\ &\leq \mathbb{P}(X \leq a + \epsilon) + \mathbb{P}(Y - X \leq -\epsilon) \\ &\leq \mathbb{P}(X \leq a + \epsilon) + \mathbb{P}(Y - X \leq -\epsilon) + \mathbb{P}(Y - X \geq \epsilon) \\ &= \mathbb{P}(X \leq a + \epsilon) + \mathbb{P}(|Y - X| \geq \epsilon). \end{aligned}$$

Using the above inequality, we have:

$$\mathbb{P}(X \leq a - \epsilon) - \mathbb{P}(|X_n - X| \geq \epsilon) \leq \mathbb{P}(X_n \leq a) \leq \mathbb{P}(X \leq a + \epsilon) + \mathbb{P}(|X_n - X| \geq \epsilon).$$

Taking limits as  $n \rightarrow \infty$  from both sides, we have:

$$F_X(a - \epsilon) \leq \lim_{n \rightarrow \infty} F_{X_n}(a) \leq F_X(a + \epsilon).$$

Taking  $\epsilon \rightarrow 0^+$ , we have  $\lim_{n \rightarrow \infty} F_{X_n}(a) = F_X(a)$ .  $\square$ .

**Proposition 1.2:**  $X_n \xrightarrow{d} c \iff X_n \xrightarrow{p} c$

Let  $c \in \mathbb{R}$  be a constant and  $X_1, X_2, \dots$  be a sequence of real-valued random variables. Then,  $X_n \xrightarrow{d} c \iff X_n \xrightarrow{p} c$ .

**Proof** (Proposition 1.2, Pishro-Nik 2014).  $\square$ .

Since  $X_n \xrightarrow{d} c$ , we immediately have the following:

$$\begin{aligned} \lim_{n \rightarrow \infty} F_{X_n}(c - \epsilon) &= 0, \\ \lim_{n \rightarrow \infty} F_{X_n}(c + \epsilon/2) &= 1. \end{aligned}$$

Then, for any  $\epsilon > 0$ , we have:

$$\begin{aligned} \lim_{n \rightarrow \infty} \mathbb{P}(|X_n - c| \geq \epsilon) &= \lim_{n \rightarrow \infty} \mathbb{P}[\mathbb{P}(X_n \leq c - \epsilon) + \mathbb{P}(X_n \geq c + \epsilon)] \\ &= \underbrace{\lim_{n \rightarrow \infty} F_{X_n}(c - \epsilon)}_{=0} + \lim_{n \rightarrow \infty} \mathbb{P}(X_n \geq c + \epsilon) \\ &\leq \lim_{n \rightarrow \infty} \mathbb{P}(X_n \geq c + \epsilon/2) \\ &= 1 - \underbrace{\lim_{n \rightarrow \infty} F_{X_n}(c + \epsilon/2)}_{=1} \\ &= 0. \end{aligned}$$

From the above, we have  $\lim_{n \rightarrow \infty} \mathbb{P}(|X_n - c| \geq \epsilon) = 0$  and  $X_n \xrightarrow{p} c$ .  $\square$ .

### 1.3.3 Convergence in $L^p$ norm

**Definition 1.4** (Convergence in  $L^p$  norm).  $\square$ .

Given a sequence of random variables  $X_1, X_2, \dots$  and a real number  $p \in [1, \infty)$ . We say that the sequence converges in  $L^p$  norm to a random variable  $X$ , denoted as  $X_n \xrightarrow{L^p} X$  if:

$$\lim_{n \rightarrow \infty} \mathbb{E}|X_n - X|^p = 0. \quad (37)$$

**Proposition 1.3:**  $X_n \xrightarrow{L^p} X \implies X_n \xrightarrow{p} X$

Let  $p \geq 1$  and  $X_1, X_2, \dots$  be a sequence of real-valued random variables. Let  $X$  be a random variable, then,  $X_n \xrightarrow{L^p} X \implies X_n \xrightarrow{p} X$ .

**Proof** (Proposition 1.3). \_\_\_\_\_

Let  $\epsilon > 0$ , we have:

$$\begin{aligned} \mathbb{P}(|X_n - X| \geq \epsilon) &= \mathbb{P}(|X_n - X|^p \geq \epsilon^p) \quad (p \geq 1) \\ &\leq \frac{\mathbb{E}|X_n - X|^p}{\epsilon^p}. \quad (\text{Markov's Inequality}) \end{aligned}$$

Taking the limits from both sides, we have  $\lim_{n \rightarrow \infty} \mathbb{P}(|X_n - X| \geq \epsilon) = 0$  and  $X_n \xrightarrow{p} X$ .  $\square$ .

### 1.3.4 Almost-sure Convergence

**Definition 1.5** (Convergence almost-surely). \_\_\_\_\_

Let  $X_1, X_2, \dots$  be a sequence of real-valued random variables that map from a sample space  $\Omega$ . Let  $X$  also be a real-valued random variable. We say that  $X_n$  converges almost surely to  $X$ , denoted as  $X_n \xrightarrow{a.s.} X$ , if:

$$\mathbb{P}\left(\limsup_{n \rightarrow \infty} E_n\right) = 0 \quad \text{where} \quad E_n = \left\{\omega \in \Omega : |X_n(\omega) - X(\omega)| \geq \epsilon\right\}.$$

**Remark 1.2** (Consequence of **(BCL)**). \_\_\_\_\_

$$\sum_{n=1}^{\infty} \mathbb{P}(E_n) < \infty \implies X_n \xrightarrow{a.s.} X. \quad (38)$$

**Proposition 1.4:**  $X_n \xrightarrow{a.s.} X \implies X_n \xrightarrow{p} X$

Let  $X_1, X_2, \dots$  be a sequence of real-valued random variables and also let  $X$  be a real valued random variables. If  $X_n \xrightarrow{a.s.} X$  then  $X_n \xrightarrow{p} X$ .

**Proof** (Proposition 1.4). \_\_\_\_\_

Let  $f_n : \Omega \rightarrow \mathbb{R}_+$  be a sequence of nonnegative Borel-measurable functions such that  $f_n(\omega) = |X_n(\omega) - X(\omega)|$ . By Fatou's Lemma (reverse), we have:

$$\begin{aligned} \underbrace{\mathbb{P}\left(\limsup_{n \rightarrow \infty} \{\omega \in \Omega : |X_n(\omega) - X(\omega)| \geq \epsilon\}\right)}_{=0} &= \int f_n d\mathbb{P} \\ &\geq \limsup_{n \rightarrow \infty} \mathbb{P}(|X_n - X| \geq \epsilon) \\ &\geq \lim_{n \rightarrow \infty} \mathbb{P}(|X_n - X| \geq \epsilon). \end{aligned}$$

Hence, we have  $\lim_{n \rightarrow \infty} \mathbb{P}(|X_n - X| \geq \epsilon) = 0$  and  $X_n \xrightarrow{p} X$ .  $\square$ .

**Theorem 1.8: Continuous Mapping Theorem (CMT)**

Let  $f : \mathbb{R} \rightarrow \mathbb{R}$  be a continuous function and  $X_1, X_2, \dots$  be a sequence of real-valued random variables. Then, the following statements hold true:

1.  $X_n \xrightarrow{d} X \implies f(X_n) \xrightarrow{d} f(X)$ .
2.  $X_n \xrightarrow{p} X \implies f(X_n) \xrightarrow{p} f(X)$ .
3.  $X_n \xrightarrow{a.s.} X \implies f(X_n) \xrightarrow{a.s.} f(X)$ .

**Proof** (Continuous Mapping Theorem (CMT)).

Since almost-sure convergence implies the other two modes of convergence, we only have to handle the almost-sure convergence case. Since  $f$  is continuous, for any  $\omega \in \Omega$  such that  $X_n(\omega) \rightarrow X(\omega)$ , we have  $f(X_n(\omega)) \rightarrow f(X(\omega))$ . Therefore, we have:

$$\left\{ \omega \in \Omega : X_n(\omega) \rightarrow X(\omega) \right\} \subseteq \left\{ \omega \in \Omega : f(X_n(\omega)) \rightarrow f(X(\omega)) \right\}.$$

Therefore, we have:

$$\begin{aligned} & \mathbb{P} \left( \limsup_{n \rightarrow \infty} \left\{ \omega \in \Omega : |f(X_n(\omega)) - f(X(\omega))| \leq \epsilon \right\} \right) \\ & \geq \mathbb{P} \left( \limsup_{n \rightarrow \infty} \left\{ \omega \in \Omega : |X_n(\omega) - X(\omega)| \leq \epsilon \right\} \right) = 1, \end{aligned}$$

for all  $\epsilon > 0$ . Therefore, we have  $f(X_n) \xrightarrow{a.s.} f(X)$ .

□.

## 2 Statistical Inference

### 2.1 Sufficiency & Likelihood Principles

#### 2.1.1 Sufficiency

**Definition 2.1** (Sufficient Statistics). 

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Let  $\mathbf{X} = (X_1, \dots, X_n) \sim p(\cdot; \theta)$  be a random sample drawn i.i.d from a distribution with parameters  $\theta$ . Let  $\mathbf{U} = T(\mathbf{X})$  be a statistic, then it is called a sufficient statistic if the conditional distribution  $p_{\mathbf{X}|\mathbf{U}}$  does not depend on  $\theta$ .

**Example 2.1** (Bernoulli random variables). 

---

Let  $\mathbf{X} = (X_1, \dots, X_n) \sim \text{Bernoulli}(\theta)$  be a random sample from the Bernoulli distribution. Let  $\mathbf{U} = \frac{1}{n} \sum_{i=1}^n X_i$ , then  $\mathbf{U}$  is a sufficient statistic of  $\theta$ . To illustrate this, suppose that  $\mathbf{x} = (x_1, \dots, x_n)$  is an observation of the random sample  $\mathbf{X}$  and  $\mathbf{u} = \frac{1}{n} \sum_{i=1}^n x_i$ . We have:

$$\begin{aligned} \mathbb{P}(\mathbf{X} = \mathbf{x} | \mathbf{U} = \mathbf{u}) &= \frac{\mathbb{P}(\mathbf{X} = \mathbf{x}, \mathbf{U} = \mathbf{u})}{\mathbb{P}(\mathbf{U} = \mathbf{u})} \\ &= \frac{\mathbb{P}(X_1 = x_1, \dots, X_n = x_n, \sum_{i=1}^n X_i = \sum_{i=1}^n x_i)}{\mathbb{P}(\sum_{i=1}^n X_i = \sum_{i=1}^n x_i)} \\ &= \frac{\mathbb{P}(X_1 = x_1, \dots, X_n = x_n)}{\mathbb{P}(\sum_{i=1}^n X_i = \sum_{i=1}^n x_i)} \\ &= \frac{\theta^{\sum_{i=1}^n x_i} (1 - \theta)^{n - \sum_{i=1}^n x_i}}{\mathbb{P}(\sum_{i=1}^n X_i = \sum_{i=1}^n x_i)}. \end{aligned}$$

Now, setting  $k = \sum_{i=1}^n x_i$ , The denominator is basically the probability that the Bernoulli variables sums up to  $k$ . Hence, we can calculate the denominator as follows:

$$\mathbb{P}\left(\sum_{i=1}^n X_i = k\right) = \binom{n}{k} \theta^k (1 - \theta)^{n-k}.$$

Therefore, we have:

$$\mathbb{P}(\mathbf{X} = \mathbf{x} | \mathbf{U} = \mathbf{u}) = \frac{\theta^k (1 - \theta)^{n-k}}{\binom{n}{k} \theta^k (1 - \theta)^{n-k}} = \frac{1}{\binom{n}{k}}.$$

Therefore, the conditional distribution does not depend on  $\theta$  and  $\mathbf{U}$  is a sufficient statistic.

**Definition 2.2** (Sufficiency Principle). 

---

If  $\mathbf{U} = T(\mathbf{X})$  is a sufficient statistic for  $\theta$ , then any inference about  $\theta$  should only depend on the sample  $\mathbf{X}$  through  $\mathbf{U}$ . In other words, if we estimate  $\theta$  using an estimator  $\hat{\theta}$ , only  $\mathbf{U}$  shows up in the formula of  $\hat{\theta}$ , not the sample  $\mathbf{X}$  itself. We will see why this is the case in the Factorisation Theorem (**FacT**), which states that we can factorise the density function into a function of  $\mathbf{U}, \theta$  and a function of the observations  $\mathbf{x}$  and thus, the inference about  $\theta$  is independent of the observations  $\mathbf{x}$ .

**Theorem 2.1: Factorisation Theorem (FactT)**

Let  $\mathbf{X} = (X_1, \dots, X_n)$  be a random sample with joint density function  $p(\mathbf{x}; \boldsymbol{\theta})$  over  $\mathcal{X}^n$ . The statistic  $\mathbf{U} = T(\mathbf{X})$  is sufficient for the parameters  $\boldsymbol{\theta}$  if and only if we can find functions  $h, g$  such that:

$$p(\mathbf{x}; \boldsymbol{\theta}) = g(T(\mathbf{x}), \boldsymbol{\theta})h(\mathbf{x}),$$

for all  $\mathbf{x} \in \mathbb{R}^n$  and  $\boldsymbol{\theta} \in \Theta$ .

**Proof** (Factorisation Theorem (FactT)).

We have to conduct the proof in both directions.

- $T(\mathbf{X})$  is sufficient  $\implies$  Factorisation exists: Let  $\mathbf{U} = T(\mathbf{X})$  be a sufficient statistics and  $\mathbf{u} = T(\mathbf{x})$  be the statistics evaluated on the observations  $\mathbf{x}$ . Then, we have:

$$\begin{aligned} p(\mathbf{x}; \boldsymbol{\theta}) &= \mathbb{P}(\mathbf{X} = \mathbf{x}; \boldsymbol{\theta}) \\ &= \mathbb{P}(\mathbf{X} = \mathbf{x} | \mathbf{U} = \mathbf{u}; \boldsymbol{\theta}) \mathbb{P}(\mathbf{U} = \mathbf{u}; \boldsymbol{\theta}). \end{aligned}$$

Since  $\mathbf{U} = T(\mathbf{X})$  is a sufficient statistics,  $\mathbb{P}(\mathbf{X} = \mathbf{x} | \mathbf{U} = \mathbf{u}; \boldsymbol{\theta})$  does not depend on  $\boldsymbol{\theta}$ . Hence, we denote  $h(\mathbf{x}) = \mathbb{P}(\mathbf{X} = \mathbf{x} | \mathbf{U} = \mathbf{u}; \boldsymbol{\theta})$ . Furthermore,  $\mathbb{P}(\mathbf{U} = \mathbf{u}; \boldsymbol{\theta})$  is a function of  $\mathbf{u}$  and  $\boldsymbol{\theta}$ . We denote this function as  $g(\mathbf{u}, \boldsymbol{\theta})$  and conclude that the factorisation  $p(\mathbf{x}; \boldsymbol{\theta}) = h(\mathbf{x})g(T(\mathbf{x}), \boldsymbol{\theta})$  indeed exists.

- Factorisation exists  $\implies T(\mathbf{X})$  is sufficient: Suppose that there exists  $g, h$  such that  $p(\mathbf{x}; \boldsymbol{\theta}) = g(T(\mathbf{x}), \boldsymbol{\theta})h(\mathbf{x})$ . We then have:

$$\mathbb{P}(\mathbf{X} = \mathbf{x} | \mathbf{U} = \mathbf{u}; \boldsymbol{\theta}) = \frac{p(\mathbf{x}; \boldsymbol{\theta})}{\mathbb{P}(\mathbf{U} = \mathbf{u}; \boldsymbol{\theta})} = \frac{g(\mathbf{u}, \boldsymbol{\theta})h(\mathbf{x})}{\mathbb{P}(\mathbf{U} = \mathbf{u}; \boldsymbol{\theta})}.$$

We denote  $A_{\mathbf{u}} = \{\tilde{\mathbf{x}} \in \mathcal{X}^n : T(\tilde{\mathbf{x}}) = \mathbf{u}\}$ . We have:

$$\begin{aligned} \mathbb{P}(\mathbf{U} = \mathbf{u}; \boldsymbol{\theta}) &= \sum_{\tilde{\mathbf{x}} \in A_{\mathbf{u}}} \mathbb{P}(\mathbf{X} = \tilde{\mathbf{x}}) \\ &= \sum_{\tilde{\mathbf{x}} \in A_{\mathbf{u}}} p(\tilde{\mathbf{x}}; \boldsymbol{\theta}) = \sum_{\tilde{\mathbf{x}} \in A_{\mathbf{u}}} g(T(\tilde{\mathbf{x}}), \boldsymbol{\theta})h(\tilde{\mathbf{x}}) \\ &= g(\mathbf{u}, \boldsymbol{\theta}) \sum_{\tilde{\mathbf{x}} \in A_{\mathbf{u}}} h(\tilde{\mathbf{x}}). \end{aligned}$$

From the above, we have:

$$\mathbb{P}(\mathbf{X} = \mathbf{x} | \mathbf{U} = \mathbf{u}; \boldsymbol{\theta}) = \frac{h(\mathbf{x})}{\sum_{\tilde{\mathbf{x}} \in A_{\mathbf{u}}} h(\tilde{\mathbf{x}})},$$

and the above expression does not depend on  $\boldsymbol{\theta}$ . Hence,  $T(\mathbf{X})$  is a sufficient statistics.

**2.1.2 Likelihood**

**Definition 2.3** (Likelihood Function).

Let  $\mathbf{X} = (X_1, \dots, X_n)$  be a random sample from a distribution  $p(\cdot | \theta)$  that depends on parameters  $\theta \in \Theta$ . Let  $\mathbf{x} = (x_1, \dots, x_n)$  be an observation of the random sample  $\mathbf{X}$ . Then, the likelihood function  $L(\theta; \mathbf{x})$  is defined as follows:

$$L(\theta; \mathbf{x}) = \prod_{i=1}^n p(x_i; \theta), \quad \theta \in \Theta. \quad (39)$$



In some cases, we also use the log-likelihood function:

$$\ell(\theta; \mathbf{x}) = \log L(\theta; \mathbf{x}) = \sum_{i=1}^n \log p(x_i; \theta), \quad \theta \in \Theta. \quad (40)$$

Essentially,  $L(\theta; \mathbf{x})$  quantifies the likelihood that  $\theta$  generates the observations  $\mathbf{x}$ . In a way, it is the inverse of probability density (mass) functions, we can see the contrast as follows:

- **Probability Density Function:** The parameters are fixed but the observations are random.
- **Likelihood Function:** The observations are fixed but the parameters are variable.

**Definition 2.4** (Maximum Likelihood Estimator). \_\_\_\_\_

Given  $\mathbf{X} = (X_1, \dots, X_n)$  be a random sample from a distribution  $p(\cdot; \theta)$  that depends on  $\theta \in \Theta$  and  $\mathbf{x} = (x_1, \dots, x_n)$  be an observation of  $\mathbf{X}$ . The Maximum Likelihood Estimator  $\theta_{MLE} \in \Theta$  is the parameter that maximizes the likelihood function:

$$\theta_{MLE} = \arg \max_{\theta \in \Theta} L(\theta; \mathbf{x}). \quad (41)$$

In the subsequent propositions, we will discuss some of the key properties of MLE.

#### Proposition 2.1: Consistency of MLE

Let  $\mathbf{X} = (X_1, \dots, X_n)$  be a random sample from a distribution  $p(\cdot; \theta)$  over  $\mathcal{X}$  dependent on a true set of parameters  $\theta$ . Let  $\Theta$  be the parameters space. Then, the Maximum Likelihood Estimator  $\theta_{MLE} = \arg \max_{\theta \in \Theta} L(\theta; \mathbf{X})$ , which is a random variable, is consistent, meaning  $\theta_{MLE} \xrightarrow{P} \theta$ , provided that the following conditions are met:

1.  $\theta \in \Theta$  and  $\Theta$  is a compact space.
2. If  $\theta_1 \neq \theta_2$  then  $p(x; \theta_1) \neq p(x; \theta_2)$ ,  $\forall x \in \mathcal{X}$ .
3.  $\log p(x; \theta)$  is continuous in  $\theta$  for almost all  $x \in \mathcal{X}$ .
4.  $\mathbb{E}_\theta[\sup_{\theta \in \Theta} |\log(X; \theta)|] < \infty$ .

Furthermore, we can also show that  $\theta_{MLE}$  is asymptotically unbiased. In other words,  $\lim_{n \rightarrow \infty} \mathbb{E}[\theta_{MLE}] = \theta$ .

**Proof** (Proposition 2.1). \_\_\_\_\_

A proof for consistency of MLE can be found in “Chapter 36 Large sample estimation and hypothesis testing” 1994, Theorem 2.5. In this section, we briefly go through the proof again.  $\square$ .

#### Proposition 2.2: Asymptotic Normality of MLE

Let  $\mathbf{X} = (X_1, \dots, X_n)$  be a random sample from a distribution  $p(\cdot; \theta)$  dependent on a true set of parameters  $\theta$ . Let  $\Theta$  be the parameters space. Then, the Maximum Likelihood Estimator  $\theta_{MLE} = \arg \max_{\theta \in \Theta} L(\theta; \mathbf{X})$  is asymptotically normal:

$$\frac{\theta_{MLE} - \theta}{\sqrt{\text{Var}(\theta_{MLE})/n}} \xrightarrow{d} \mathcal{N}(0, 1). \quad (42)$$

Proof (Proposition 2.2).

□.

## 2.2 Point Estimation

### 2.2.1 Bias, Variance, Consistency and MSE

### 2.2.2 Sufficient Statistics & Rao-Blackwell Theorem

*Theorem 2.2: Rao-Blackwell Theorem (RB)*

### 2.2.3 Estimator Variance & Cramer-Rao Lower Bound

**Definition 2.5** (Fisher Information).

Let  $\mathbf{X} = (X_1, \dots, X_n) \sim p(\cdot; \boldsymbol{\theta})$  be a random sample from a distribution parameterized by  $\boldsymbol{\theta}$ . The (total) Fisher Information about  $\theta$  in the random sample  $\mathbf{X}$  is defined as follows:

$$\mathcal{I}_{\mathbf{X}}(\boldsymbol{\theta}) = \mathbb{E}_{\mathbf{X}} \left[ \left( \frac{\partial}{\partial \theta} \log L(\theta; \mathbf{X}) \right)^2 \mid \boldsymbol{\theta} \right]. \quad (43)$$

The Fisher Information is the total information about  $\boldsymbol{\theta}$  contained in the sample  $\mathbf{X}$ .

*Theorem 2.3: Cramer-Rao Lower Bound (CRLB)*

### 2.2.4 Maximum Likelihood Estimation (MLE)

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## C Important Propositions

1.1	$X_n \xrightarrow{p} X \implies X_n \xrightarrow{d} X$	11
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## D References

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