

Lecture Notes: Statistical Modelling

L3 MIDO

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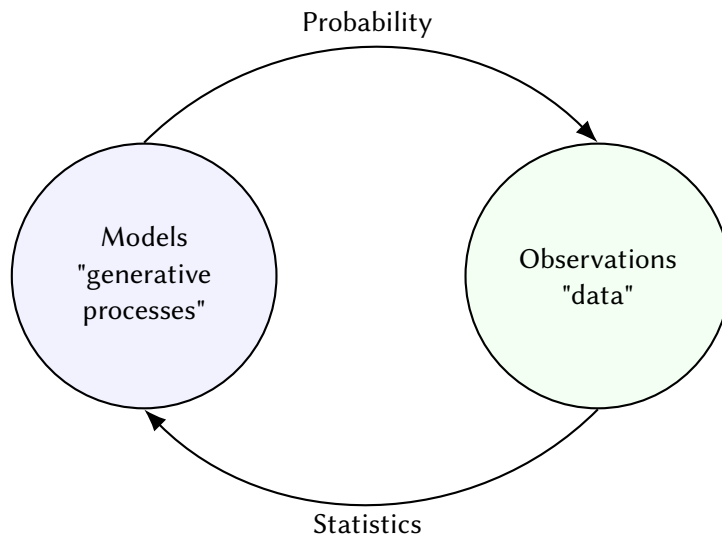
Contents

Chapter 1: Introduction to Statistical Modelling	3
I. Data.	3
II. Statistical Modelling	4
Chapter 2: Models	6
I. What is a statistical model?.	6
II. Parametric Model	7
III. Identifiability	7
IV. Empirical Distribution Function	9
Chapter 3: Point estimators and MLE	11
I. Point Estimators	11
II. Quadratic Risk, Bias.	11
III. Empirical Distribution Function	15
IV. Consistency	19
Chapter 4: Maximum Likelihood Estimation	23
I. The Likelihood	23
II. Kullback-Leibler Divergence (K.L)	24
III. Exponential Families.	32
IV. Sufficient Condition for Consistency of MLE	36
V. Using Asymptotic Normality to Compute Confidence Regions	36
VI. Delta method and confidence intervals.	37
VI.1 Delta method	37
VI.2 Confidence intervals	39

Chapter 5: Bayesian statistics.	41
I. In Bayesian statistics.	41
II. Bayesian decision theory: Risks	43
II.1 Posterior and integrated risks	43

Chapter 1: Introduction to Statistical Modelling

Introduction Schema



I. Data

1) $n = \#$ L3 MIDO students

- Were students in Dauphine in L2?
- $\text{Data} \in \{0, 1\}^n$:
 - 1: in L2 in Dauphine.
 - 0: not in L2 in Dauphine.
- $x = (0, 0, 1, 1, 0, \dots)$
- $\downarrow \text{sum}(x)$

$\implies x$ is a distribution of n independent experiences of Bernoulli of parameter p .

$$x \sim \text{Ber}(p)^{\otimes n} \quad (\text{i.i.d.})$$

$$\implies \text{sum}(x) \sim \text{Bin}(n, p)$$

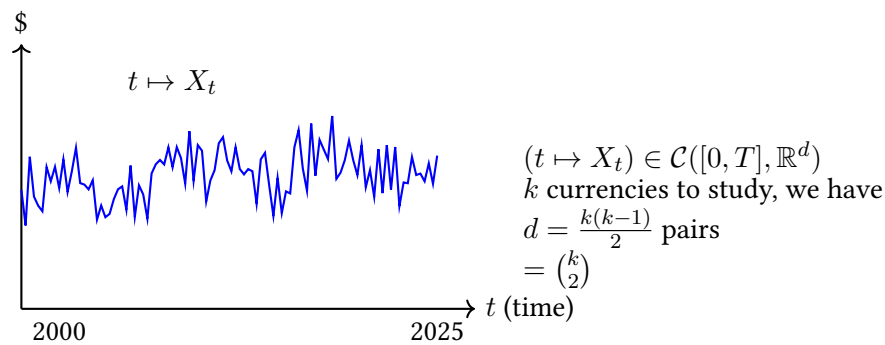
2) INSEE (economy)

Example: Employment rate between 2005 & 2025.

Male ♂	2005	2006	...	2025		Female ♀	2005	...
15-24 yo	α	α	α	α		15-24	α	α
25-49 yo	α	56%	α	α		25-49	α	α
50 +	α		α	α		50 +	α	α

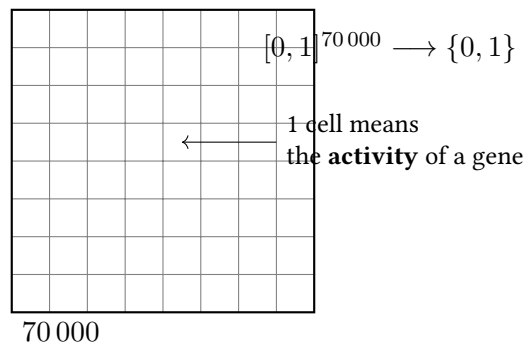
\implies **Tensor:** multiple entries array.

3) Financial data



\Rightarrow Brownian motion. \Rightarrow Diffusion processes.

4) Microarrays



- Compute a big space into a smaller one: the cells of an individual translated to *healthy* or *not*.
- $[0, 1]$ measures the activity of one cell. One person has 70 000 cells.

II. Statistical Modelling

1) Stat models with words

To each set of data, we must associate a scientific question/objective.

To answer that question, we must have at our disposition:

- A methodology.
- A quantitative mathematical (probabilistic) model that accounts for the properties of the data.
- Well suited methods (mathematical) that combine... and...

2) Abstract (simple) example

We toss a coin 18 times and observe ($n = 18, H = 0, T = 1$).

$(0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0)$

\equiv Data (raw).

- **Statistical model:** We observe $n = 18$ random variables X_i ; that are independent and that have the same distribution.

- $\mathbb{P}(X_i = 1) = 1 - \mathbb{P}(X_i = 0) = \theta$.
- $\text{Ber}(\theta)$ where $\theta \in \Theta = [0, 1]$.
- θ is the **unknown parameter**.

Questions:

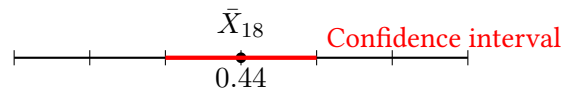
1) What is a good (the best) estimation of θ ?

- A good (?) estimator:

$$\underbrace{\bar{X}_n}_{\substack{\text{notation} \\ \text{of the mean}}} = \frac{1}{n} \sum_{i=1}^n X_i$$

$$= \frac{1}{18} \sum_{i=1}^{18} X_i = \frac{8}{18} = 0.44$$

- What is my accuracy of estimation?



\implies We want:

1. Small length.
 2. Good coverage.
- 2) Is the coin fair?

For instance, we compare \bar{X}_{18} to 0.5. If $|\bar{X}_{18} - 0.5|$ is small, we accept the idea that the coin is fair, otherwise we reject that hypothesis.

Chapter 2: Models

I. What is a statistical model?

Definition 1: Statistical Model

Let $X = (X_1, \dots, X_n) \in \mathcal{X}^n$ be a vector of n random variables, where each variable $X_i \in \mathcal{X}$ and \mathcal{X} is a measurable space.

A **model** for X is a set \mathcal{P} of probability distributions on \mathcal{X}^n .

Statistical inference will consist in estimating P (the distribution of X) or $F(P)$, with $P \in \mathcal{P}$.

Examples

i) Let X_1, \dots, X_n be i.i.d. $\mathcal{N}(\mu, \sigma^2)$.

Notation: $X_i \underset{i.i.d.}{\sim} \mathcal{N}(\mu, \sigma^2)$ (Gaussian distribution with parameters μ and σ^2). The density is

given by: $x \mapsto \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$.

Here, $\mathcal{X} = \mathbb{R}$. The model is defined as:

$$\mathcal{P} = \{\mathcal{N}(\mu, \sigma^2)^{\otimes n}, (\mu, \sigma^2) \in \mathbb{R} \times (0, +\infty)\}$$

Remark

Notations: If (X_1, X_2) is a random vector of \mathbb{R}^2 , with $X_1 \sim P_1$ and $X_2 \sim P_2$.

(By the way: $X \sim P$ means that P is the distribution of $X \in \mathbb{R}$, meaning: $\forall A \in \mathcal{B}(\mathbb{R}), P(A) = \mathbb{P}(X \in A) = \mathbb{P}(X^{-1}(A))$.)

$$(\Omega, \mathcal{F}, \mathbb{P}) \xrightarrow{X} (\mathbb{R}, \mathcal{B}(\mathbb{R}), P)$$

P is defined via: $\forall A \in \mathcal{B}(\mathbb{R}), P(A) = \mathbb{P}(X^{-1}(A)) = \mathbb{P}(\{\omega \in \Omega, X(\omega) \in A\})$.

If $X_1 \sim P_1, X_2 \sim P_2$ and $X_1 \perp\!\!\!\perp X_2$ (X_1 and X_2 are independent):

$$\mathbb{P}(X_1 \in A, X_2 \in B) = \mathbb{P}(X_1 \in A) \cdot \mathbb{P}(X_2 \in B)$$

$\forall A, B \in \mathcal{B}(\mathbb{R})$, the distribution of (X_1, X_2) is defined on $(\mathbb{R}^2, \mathcal{B}(\mathbb{R}^2))$ and is denoted by $P_1 \otimes P_2$.

Computation formula:

$$P_1 \otimes P_2(A \times B) = P_1(A) \cdot P_2(B) = \mathbb{P}(X_1 \in A) \cdot \mathbb{P}(X_2 \in B)$$

In our example, saying $(X_1, \dots, X_n) \sim \mathcal{N}(\mu, \sigma^2)^{\otimes n}$ exactly means:

$$\begin{aligned} \mathbb{P}(X_1 \in A_1, \dots, X_n \in A_n) &= \prod_{i=1}^n \mathbb{P}(X_i \in A_i) \\ &= \prod_{i=1}^n \int_{A_i} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x_i-\mu)^2}{2\sigma^2}} dx_i \\ &= \int_{A_1} \dots \int_{A_n} \frac{1}{(2\pi\sigma^2)^{n/2}} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2\right) dx_1 \dots dx_n \end{aligned}$$

ii) $X_i \in \{0, 1\}, \forall i = 1, \dots, n$, independently with same distribution $\text{Ber}(p), p \in [0, 1]$.

$$\mathcal{P} = \{\text{Ber}(p)^{\otimes n}, p \in [0, 1]\}, \quad \mathcal{X}^n = \{0, 1\}^n$$

Model Comparison and Types

Let us consider models of the form $\mathcal{P} = \{P^{\otimes n}, P \in \mathcal{P}_0\}$.

- Example (1): $\mathcal{P}_0 = \{\mathcal{N}(\mu, \sigma^2), (\mu, \sigma^2) \in \mathbb{R} \times (0, +\infty)\}$ (Parametric).
- Example (2): $\mathcal{P}_0 = \{\text{Ber}(p), p \in [0, 1]\}$.
- Example (3): $\mathcal{P}_0 = \{\text{All distributions on } (\mathbb{R}, \mathcal{B}(\mathbb{R}))\}$ (Huge model).

Which is the best model? Generally, the best model is the one where the set of parameter values is the **smallest** (Parsimony principle).

Remark

In the 3 examples considered above, all observations are **i.i.d.** But, in many situations, this is not the case.

Example of a very standard non-i.i.d. model:

$$X_0 = x_0; \quad X_t = \rho X_{t-1} + \sigma \varepsilon_t, \quad t = 1, \dots, T$$

We observe (X_1, \dots, X_T) . They are not i.i.d. Here $\rho \in \mathbb{R}$, $\sigma > 0$ (Volatility), and $\varepsilon_t \stackrel{i.i.d.}{\sim} \mathcal{N}(0, 1)$. X_t could represent the log price of a financial asset.

In this course, we will mainly focus on the i.i.d. case.

II. Parametric Model

Definition 2: Parametric Model

Let there be data $(X_1, \dots, X_n) \in \mathcal{X}^n$. A model \mathcal{P} for (X_1, \dots, X_n) is called **parametric** if:

$$\mathcal{P} = \{P_\theta, \theta \in \Theta\}$$

with $\Theta \subset \mathbb{R}^d$ for some $d \geq 1$. Here P_θ is a distribution on \mathcal{X}^n .

Definition 3: Nuisance Parameters

Let $X = (X_1, \dots, X_n)$ i.i.d. with model $\mathcal{P} = \{P_\theta, \theta \in \Theta\}$. If $\Theta = (\theta_1, \theta_2)$, and if we only are interested in estimating or predicting θ_1 and we don't care about θ_2 , we say that:

- θ_1 is the **parameter of interest**.
- θ_2 is the **nuisance parameter**.

III. Identifiability

Context: We have a statistical model for $X = (X_1, \dots, X_n)$. $X_i \sim P_\theta$, $\theta \in \Theta \subset \mathbb{R}^d$. So $\mathcal{P} = \{P_\theta^{\otimes n}, \theta \in \Theta\}$.

Aim: Can we learn/estimate θ from X ? This is only possible if we can learn θ from $P_\theta^{\otimes n}$ or P_θ .

Definition 4: Identifiability

A statistical model $\{P_\theta, \theta \in \Theta\}$ is **identifiable** (for θ) if:

$$P_{\theta_1} = P_{\theta_2} \implies \theta_1 = \theta_2$$

(i.e., the map $\theta \mapsto P_\theta$ is injective).

Examples

Example 1: Exponential Distribution

Let $(P_\theta, \theta \in \Theta) = (\mathcal{E}(\theta), \theta > 0)$. P_θ has density $f_\theta(x) = \theta e^{-\theta x} \mathbb{1}_{\{x>0\}}$.

If $P_{\theta_1} = P_{\theta_2}$, then for every $x \in \mathbb{R}$:

$$f_{\theta_1}(x) = f_{\theta_2}(x) \implies \theta_1 e^{-\theta_1 x} = \theta_2 e^{-\theta_2 x} \quad \text{whenever } x > 0$$

Take $x \rightarrow 0$ (or $x = 0$ in the limit), we get $\theta_1 = \theta_2$. Thus, the model is identifiable.

Example 2: Gaussian Distribution

Let $\theta = (\mu, \sigma^2) \in \Theta = \mathbb{R} \times (0, +\infty)$.

$$P_\theta = \mathcal{N}(\mu, \sigma^2)$$

$$f_{\mu, \sigma^2}(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \quad \forall x \in \mathbb{R}$$

Injectivity? Assume $P_{\theta_1} = P_{\theta_2}$. Then $\forall x \in \mathbb{R}$:

$$\frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}} = \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{(x-\mu_2)^2}{2\sigma_2^2}}$$

Take $x = \mu_1$, then:

$$\frac{1}{\sigma_1} = \frac{1}{\sigma_2} e^{-\frac{(\mu_1-\mu_2)^2}{2\sigma_2^2}}$$

Take $x = \mu_2$, then:

$$\frac{1}{\sigma_1} e^{-\frac{(\mu_2-\mu_1)^2}{2\sigma_1^2}} = \frac{1}{\sigma_2}$$

This implies:

$$\begin{aligned} \frac{\sigma_2}{\sigma_1} &= e^{-\frac{(\mu_1-\mu_2)^2}{2\sigma_2^2}} \leq 1 \quad (\text{because } e^{-\cdot} \leq 1) \\ &= e^{\frac{(\mu_1-\mu_2)^2}{2\sigma_1^2}} \geq 1 \quad (\text{because } e^{\cdot} \geq 1) \end{aligned}$$

Hence:

$$\frac{\sigma_2}{\sigma_1} = 1 \implies \sigma_1 = \sigma_2$$

And substituting back:

$$e^{-\frac{(\mu_1-\mu_2)^2}{2\sigma^2}} = 1 \implies \frac{(\mu_1-\mu_2)^2}{2\sigma^2} = 0 \implies \mu_1 = \mu_2$$

Thus $\theta_1 = \theta_2$. The model is identifiable.

Proposition 1: Identifiability via CDF and Density

- If P_θ admits a cumulative distribution function (CDF) F_θ , the model is identifiable $\iff (\forall \theta_1, \theta_2, F_{\theta_1} = F_{\theta_2} \implies \theta_1 = \theta_2)$.
- If P_θ admits a density f_θ , the model is identifiable $\iff (\forall \theta_1, \theta_2, f_{\theta_1} = f_{\theta_2} \implies \theta_1 = \theta_2)$.

Example 3: Non-identifiable Model (Mixture)

Let $Y_1 \sim \text{Ber}(p_1)$, $Y_2 \sim \text{Ber}(p_2)$. $Y_1 \in \{0, 1\}$. $\mathbb{P}(Y_1 = 1) = p_1$.

Let X be defined as:

$$X = \begin{cases} Y_1 & \text{with proba } \pi \\ Y_2 & \text{with proba } 1 - \pi \end{cases}$$

$$\begin{aligned} \mathbb{P}(X = 1) &= \mathbb{P}(X = 1 | X = Y_1) \mathbb{P}(X = Y_1) + \mathbb{P}(X = 1 | X = Y_2) \mathbb{P}(X = Y_2) \\ &= \mathbb{P}(Y_1 = 1) \times \pi + \mathbb{P}(Y_2 = 1) \times (1 - \pi) \\ &= p_1 \pi + p_2 (1 - \pi) \end{aligned}$$

We have a model with 3 parameters (p_1, p_2, π) . $X \sim \text{Ber}(p)$ with $p = p_1 \pi + p_2 (1 - \pi)$.

Knowing $\mathbb{P}(X = 1)$ gives limited information on the law of X .

Numeric Examples:

- $\pi = 1/2, p_1 = 0.6, p_2 = 0.2$. $\mathbb{P}(X = 1) = 0.6 \times 0.5 + 0.2 \times 0.5 = 0.4$.
- $\pi = 0.6, p_1 = 1/2, p_2 = 0.25$. $\mathbb{P}(X = 1) = 0.6 \times 0.5 + 0.4 \times 0.25 = 0.3 + 0.1 = 0.4$.

We have different parameters but the same distribution \implies **Not identifiable**.

IV. Empirical Distribution Function

Model: We observe X_1, \dots, X_n i.i.d. P . We set $F(t) =$ Cumulative distribution function of P at t

$$= \mathbb{P}(X_i \leq t), \quad \forall i$$

Remark

Reminder:

- F is non-decreasing.
- F is càdlàg (right-continuous with left limits).
- $\lim_{t \rightarrow -\infty} F(t) = 0$ and $\lim_{t \rightarrow +\infty} F(t) = 1$.

Definition 5: Empirical CDF

$$\hat{F}_n(t) = \frac{1}{n} \sum_{i=1}^n \mathbb{1}_{\{X_i \leq t\}}$$

It is a good idea since when $n \rightarrow +\infty$: Fix t : $\hat{F}_n(t) \xrightarrow[n \rightarrow \infty]{} \mathbb{E}[Y_i]$ in probability (Weak Law of Large

Numbers).

$$\frac{1}{n} \sum_{i=1}^n Y_i$$

with $Y_i = \mathbb{1}_{\{X_i \leq t\}}$. The Y_i are i.i.d., $\mathbb{E}[|Y_i|] < +\infty$.

$$\mathbb{E}[Y_1] = \mathbb{P}(X_1 \leq t) = F(t)$$

So, we have: $\hat{F}_n(t) \rightarrow F(t)$ in probability.

Examples

1. $X_i = \begin{cases} 1 & \text{if I have an accident on day } i \\ 0 & \text{otherwise} \end{cases}$ $X_i \stackrel{i.i.d.}{\sim} \text{Ber}(p); p = \mathbb{P}(\text{avoir un accident}).$

$$\hat{p} = \frac{1}{n} \sum_{i=1}^n X_i \xrightarrow[n \rightarrow \infty]{\mathbb{P}} p \quad (\text{Law of Large Numbers})$$

($\xrightarrow{\mathbb{P}}$ en probabilité).

2. X_1, \dots, X_n i.i.d. $X_i = \text{Lifetime of computer } i.$

We want to estimate the function $t \mapsto F(t) = \mathbb{P}(X_i \leq t)$. To estimate F , we use at time t , $\hat{F}_n(t) = \frac{1}{n} \sum_{i=1}^n \mathbb{1}_{\{X_i \leq t\}}.$

Chapter 3: Point estimators and MLE

I. Point Estimators

We consider a parametric model $(X_1, \dots, X_n) \stackrel{i.i.d.}{\sim} P_\theta$, with $\theta \in \Theta \subset \mathbb{R}^d$.

Goal: Constructions of estimators for θ or for $g(\theta)$ with $g : \Theta \rightarrow \mathbb{R}^p$.

Definition 6: Point Estimator

A **point estimator** for θ is a quantity $\hat{\theta}$ which depends **only** on X_1, \dots, X_n (the data).

Examples:

- We observe $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \text{Ber}(\theta)$.

$$\hat{\theta}_n = \frac{1}{n} \sum_{i=1}^n X_i \quad \text{is a point estimator of } \theta.$$

- We observe $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \mathcal{N}(\theta, 1)$.

$$\hat{\theta}_n = \bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i \quad \text{is an estimator of } \theta.$$

- We observe $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \mathcal{E}(\theta)$.

$$\hat{\theta}_n = \frac{1}{\frac{1}{n} \sum_{i=1}^n X_i} = \frac{1}{\bar{X}_n}$$

Recall: If $X \sim \mathcal{E}(\theta)$, $\theta > 0$:

$$E[X] = \frac{1}{\theta}$$

$$\frac{1}{\hat{\theta}_n} \xrightarrow{n \rightarrow \infty} \frac{1}{\theta}$$

$$\frac{1}{\hat{\theta}_n} = \frac{1}{n} \sum_{i=1}^n X_i$$

By the Weak Law of Large Numbers (WLLN), $\hat{\theta}_n \xrightarrow[n \rightarrow \infty]{\mathbb{P}} \theta$.

For this last example, if we want to estimate $g(\theta) = \frac{1}{\theta}$, in this case, $\hat{g} = \frac{1}{\hat{\theta}_n} = \frac{1}{n} \sum_{i=1}^n X_i$ is a "good estimator".

II. Quadratic Risk, Bias

Measure of error = Loss function. The most common loss function is the **quadratic loss**:

$$l(\hat{\theta}, \theta) = (\hat{\theta}_n - \theta)^2$$

We cannot compute $l(\hat{\theta}_n, \theta)$ since we do not know θ .

Definition 7: Quadratic Risk (Mean Squared Error)

We call **quadratic risk** (or mean squared error):

$$R(\hat{\theta}_n, \theta) = \mathbb{E}[(\hat{\theta}_n - \theta)^2]$$

Definition 8: Bias

Let $\hat{\theta}_n$ be an estimator of θ in a statistical model $(X_i)_{i \leq n} \stackrel{i.i.d.}{\sim} P_\theta, \theta \in \Theta$.

- (i) We say that $\hat{\theta}_n$ is **unbiased** at θ iff $\mathbb{E}_\theta(\hat{\theta}_n) = \theta$.
- (ii) We say that $\hat{\theta}_n$ is **unbiased** over Θ iff it is unbiased at all $\theta \in \Theta$.

The **bias** is defined as:

$$b(\theta) = \mathbb{E}_\theta(\hat{\theta}_n) - \theta$$

Theorem 1: Bias-Variance Decomposition

In a statistical model $(X_i)_{i \leq n}$ i.i.d. $P_\theta, \theta \in \Theta$. If $\hat{\theta}_n$ is an estimator of θ , then:

$$R(\hat{\theta}_n, \theta) = b(\theta)^2 + \mathbb{V}_\theta(\hat{\theta}_n)$$

where $\mathbb{V}_\theta(\hat{\theta}_n)$ is the variance of $\hat{\theta}_n$ assuming that $X_i \stackrel{i.i.d.}{\sim} P_\theta$.

Proof.

$$R(\hat{\theta}_n, \theta) = \mathbb{E}_\theta[(\hat{\theta}_n - \theta)^2]$$

Add and subtract $\mathbb{E}_\theta(\hat{\theta}_n)$:

$$= \mathbb{E}_\theta[(\hat{\theta}_n - \mathbb{E}_\theta(\hat{\theta}_n) + \mathbb{E}_\theta(\hat{\theta}_n) - \theta)^2]$$

Let $A = \hat{\theta}_n - \mathbb{E}_\theta(\hat{\theta}_n)$ and $B = \mathbb{E}_\theta(\hat{\theta}_n) - \theta = b(\theta)$.

$$\begin{aligned} &= \mathbb{E}_\theta[(A + B)^2] = \mathbb{E}_\theta[A^2 + B^2 + 2AB] \\ &= \underbrace{\mathbb{E}_\theta(A^2)}_{\mathbb{V}_\theta(\hat{\theta}_n)} + \underbrace{\mathbb{E}_\theta(B^2)}_{b(\theta)^2 \text{ (constant)}} + \underbrace{2\mathbb{E}_\theta[(\hat{\theta}_n - \mathbb{E}_\theta(\hat{\theta}_n)) \cdot b(\theta)]}_0 \end{aligned}$$

The cross term is zero because:

$$2b(\theta)\mathbb{E}_\theta(\hat{\theta}_n - \mathbb{E}_\theta(\hat{\theta}_n)) = 2b(\theta)(\mathbb{E}_\theta(\hat{\theta}_n) - \mathbb{E}_\theta(\hat{\theta}_n)) = 0$$

Hence:

$$R(\hat{\theta}_n, \theta) = b(\theta)^2 + \mathbb{V}_\theta(\hat{\theta}_n)$$

(Q.E.D)

□

Examples of Risk Calculation:

Example 4: Normal Mean

$X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \mathcal{N}(\theta, 1)$. Estimator $\hat{\theta}_n = \frac{1}{n} \sum X_i = \bar{X}_n$.

$$R(\hat{\theta}_n, \theta) = \mathbb{E}[(\hat{\theta}_n - \theta)^2]$$

$$\begin{aligned}
&= \mathbb{E}[(\bar{X}_n - \theta)^2] \\
&= \text{Var}(\bar{X}_n) \quad (\text{as } \mathbb{E}[\bar{X}_n] = \theta, \text{ it is unbiased}) \\
&= \frac{1}{n} \text{Var}(X_1) = \frac{1}{n}
\end{aligned}$$

Example 5: Bernoulli Mean

We observe $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \text{Ber}(\theta)$.

$$\begin{aligned}
\hat{\theta}_n &= \bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i \\
R(\hat{\theta}_n, \theta) &= \mathbb{E}[(\hat{\theta}_n - \theta)^2] \\
&= \mathbb{E}[(\bar{X}_n - \theta)^2] \\
&= \text{Var}(\bar{X}_n) = \frac{\text{Var}(X_1)}{n} = \frac{\theta(1 - \theta)}{n}
\end{aligned}$$

Remark

The function $x \in [0, 1] \mapsto x(1 - x)$ attains its maximum at $x = 1/2$.

$$\implies \forall \theta \in [0, 1], \quad \theta(1 - \theta) \leq \frac{1}{4}$$

$$\implies R(\hat{\theta}_n, \theta) \leq \frac{1}{4n}$$

Reminders on Convergence

Definitions

Definition 9: Convergence in Probability

$$X_n \xrightarrow{\mathbb{P}} X \iff \forall \varepsilon > 0, \mathbb{P}(|X_n - X| > \varepsilon) \xrightarrow{n \rightarrow \infty} 0.$$

Definition 10: Convergence in L^p

$$X_n \xrightarrow{L^p} X \iff \mathbb{E}(|X_n - X|^p) \xrightarrow{n \rightarrow \infty} 0.$$

Definition 11: Convergence in Distribution

$$\begin{aligned} X_n \xrightarrow{\mathcal{D}} X &\iff \forall x \text{ (where } F_X \text{ is continuous), } F_{X_n}(x) \xrightarrow{n \rightarrow \infty} F_X(x) \\ &\iff \forall g \text{ continuous and bounded: } \mathbb{E}(g(X_n)) \xrightarrow{n \rightarrow \infty} \mathbb{E}(g(X)) \end{aligned}$$

Main Theorems

Theorem 2: Law of Large Numbers (Weak)

If $(X_n)_n$ are i.i.d. random variables such that $\mathbb{E}(|X_n|) < \infty$, then:

$$\frac{1}{n} \sum_{i=1}^n X_i \xrightarrow[n \rightarrow \infty]{\mathbb{P}} \mathbb{E}(X_1)$$

Theorem 3: Central Limit Theorem (CLT)

If $(X_n)_n$ are i.i.d. such that $\mathbb{E}(X_n^2) < \infty$, then:

$$\sqrt{n}(\bar{X}_n - \mu) \xrightarrow{\mathcal{D}} \mathcal{N}(0, \sigma^2)$$

where $\bar{X}_n = \frac{1}{n} \sum X_i$, $\mu = \mathbb{E}(X_1)$, $\sigma^2 = \text{Var}(X_1)$.

Theorem 4: Continuity Mapping Theorem

- i) If $X_n \xrightarrow{\mathbb{P}} X$ and if g is continuous, then $g(X_n) \xrightarrow{\mathbb{P}} g(X)$.
- ii) If $X_n \xrightarrow{L^p} X$, $p \geq 1$, then $X_n \xrightarrow{L^q} X$ for all $1 \leq q \leq p$.
- iii) If $X_n \xrightarrow{\mathcal{D}} X$, and if g is continuous and bounded, then $g(X_n) \xrightarrow{\mathcal{D}} g(X)$. (Actually holds for any continuous g).

Theorem 5: Delta Method

If $(Y_n)_n$ are like $\sqrt{n}(Y_n - \mu) \xrightarrow{\mathcal{D}} \mathcal{N}(0, \sigma^2)$. If g is \mathcal{C}^1 at μ so that $|g'(\mu)| > 0$, then:

$$\sqrt{n}(g(Y_n) - g(\mu)) \xrightarrow{\mathcal{D}} \mathcal{N}(0, g'(\mu)^2 \sigma^2)$$

Sketch of proof. Taylor expansion of $g(Y_n)$ around μ :

$$g(Y_n) \approx g(\mu) + g'(\mu)(Y_n - \mu)$$

$$\sqrt{n}(g(Y_n) - g(\mu)) \approx g'(\mu)\sqrt{n}(Y_n - \mu)$$

Since $\sqrt{n}(Y_n - \mu) \xrightarrow{\mathcal{D}} \mathcal{N}(0, \sigma^2)$, the result follows. \square

Remark

If $\sqrt{n}(Y_n - \mu) \xrightarrow{\mathcal{D}} \mathcal{N}(0, \sigma^2)$, then $Y_n \xrightarrow{\mathbb{P}} \mu$.

III. Empirical Distribution Function

Definition 12: Dirac Mass

Dirac mass at $a \in \mathbb{R}$ is the distribution defined by:

$$\forall A \subset \mathbb{R}, \quad \delta_{\{a\}}(A) = \begin{cases} 1 & \text{if } a \in A \\ 0 & \text{if } a \notin A \end{cases}$$

Let $\mathbb{P}_n = \frac{1}{n} \sum_{i=1}^n \delta_{\{X_i\}}$.

Definition 13: Empirical CDF

F_n = Empirical Cumulative Distribution Function (CDF) for $(X_i)_i$ i.i.d. with distribution P_X .

$$F_n(x) = \frac{1}{n} \sum_{i=1}^n \mathbb{1}_{\{X_i \leq x\}} = \mathbb{P}_n((-\infty, x])$$

Remark: F_n is the CDF of \mathbb{P}_n .

Theorem 6: Asymptotic Normality of Empirical CDF

$$\forall x, \quad \sqrt{n}(F_n(x) - F_X(x)) \xrightarrow[n \rightarrow \infty]{\mathcal{D}} \mathcal{N}(0, F_X(x)(1 - F_X(x)))$$

Where F_X is the CDF of P_X .

Proof.

$$F_n(x) = \frac{1}{n} \sum_{i=1}^n \underbrace{\mathbb{1}_{\{X_i \leq x\}}}_{=Y_i}$$

The variables Y_i are i.i.d. Bernoulli variables:

$$Y_i \sim \text{Ber}(p) \quad \text{with } p = \mathbb{P}(X_i \leq x) = F_X(x)$$

$$\mathbb{E}[Y_i^2] < \infty$$

Applying CLT:

$$\sqrt{n}(\bar{Y}_n - \mathbb{E}(Y_1)) \xrightarrow{\mathcal{D}} \mathcal{N}(0, \text{Var}(Y_1))$$

Here $\bar{Y}_n = F_n(x)$ and $\mathbb{E}(Y_1) = F_X(x)$.

$$\text{Var}(Y_1) = F_X(x)(1 - F_X(x))$$

(Q.E.D)

□

More on Quadratic Risk

Expression of Risk using Density:

$$R(\hat{\theta}_n, \theta) = \mathbb{E}_\theta[(\hat{\theta}_n - \theta)^2]$$

Under the model $X_i \stackrel{i.i.d.}{\sim} P_\theta$:

$$= \begin{cases} \int (\hat{\theta}_n(x_1, \dots, x_n) - \theta)^2 \prod_{i=1}^n f_\theta(x_i) dx_i & \text{if continuous (density } f_\theta) \\ \sum_{x_1, \dots, x_n} (\hat{\theta}_n(x_1, \dots, x_n) - \theta)^2 \prod_{i=1}^n P_\theta(X = x_i) & \text{if discrete observations} \end{cases}$$

Example: Exponential Family

Example 2 (from beginning): $X_i \stackrel{i.i.d.}{\sim} \mathcal{E}(\theta), \theta > 0$.

X_i are continuous random variables with density $f_\theta(x) = \theta e^{-\theta x} \mathbb{1}_{\{x>0\}}$

Estimator:

$$\hat{\theta}_n = \frac{1}{\bar{X}_n}; \quad \bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$$

If $X \sim \mathcal{E}(\theta)$, $\mathbb{E}_\theta(X) = \frac{1}{\theta}$. What is $R(\hat{\theta}_n, \theta)$? What is $b(\theta)$?

We need to calculate $\mathbb{E}_\theta(\hat{\theta}_n) = \mathbb{E}_\theta\left(\frac{1}{\bar{X}_n}\right)$.

Recall:

- $\mathbb{E}(h(X)) = \int h(x)f_X(x)dx$ (if continuous).
- We write: $\mathbb{E}(h(X)) = \int h(x)dF_X(x) = \int h(x)dP_X(x)$.
- If $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \Gamma(a, b)$, then $\sum_{i=1}^n X_i \sim \Gamma(na, b)$.

Gamma distribution $\Gamma(a, b)$: \mathcal{C}^0 distribution on \mathbb{R}^+ with density:

$$f_{a,b}(x) = \frac{b^a}{\Gamma(a)} x^{a-1} e^{-bx} \mathbb{1}_{\{x>0\}}$$

Note: $\mathcal{E}(\theta) = \Gamma(1, \theta)$.

$$\implies \sum_{i=1}^n X_i \sim \Gamma(n, \theta).$$

Let $Z_n = \sum_{i=1}^n X_i$. Then $\hat{\theta}_n = \frac{n}{Z_n}$.

We want to compute $\mathbb{E}_\theta\left(\frac{n}{Z_n}\right) = n\mathbb{E}_\theta\left(\frac{1}{Z_n}\right)$.

$$\begin{aligned}\mathbb{E}_\theta \left(\frac{1}{Z_n} \right) &= \int_0^{+\infty} \frac{1}{z} \cdot \frac{\theta^n}{\Gamma(n)} z^{n-1} e^{-\theta z} dz \\ &= \frac{\theta^n}{\Gamma(n)} \int_0^{+\infty} z^{n-2} e^{-\theta z} dz\end{aligned}$$

Remark

Let $f_{n-1,\theta}(z) = \frac{\theta^{n-1}}{\Gamma(n-1)} z^{n-2} e^{-\theta z}$ be the density of a $\Gamma(n-1, \theta)$.

$$\begin{aligned}\implies \int_0^{+\infty} z^{n-2} e^{-\theta z} dz \times \frac{\theta^{n-1}}{\Gamma(n-1)} &= 1 \\ \implies \int_0^{+\infty} z^{n-2} e^{-\theta z} dz &= \frac{\Gamma(n-1)}{\theta^{n-1}}\end{aligned}$$

Back to the expectation:

$$\mathbb{E}_\theta(\hat{\theta}_n) = \frac{n\theta^n}{\Gamma(n)} \times \frac{\Gamma(n-1)}{\theta^{n-1}}$$

And we have: $\Gamma(x+1) = x\Gamma(x)$ if $x > 0$. So $\Gamma(n) = (n-1)\Gamma(n-1)$.

$$\implies \mathbb{E}_\theta(\hat{\theta}_n) = \frac{n}{n-1}\theta$$

$$\implies b(\theta) = \mathbb{E}_\theta(\hat{\theta}_n) - \theta = \frac{n}{n-1}\theta - \theta = \frac{\theta}{n-1}$$

Now, let's compute the quadratic risk. We need $\mathbb{E}_\theta(\hat{\theta}_n^2) = n^2 \mathbb{E}(\frac{1}{Z_n^2})$.

$$\mathbb{E} \left(\frac{1}{Z_n^2} \right) = \int y^{n-3} e^{-\theta y} dy \frac{\theta^n}{\Gamma(n)}$$

Using the same trick (identification with $\Gamma(n-2, \theta)$) for $n > 2$:

$$\begin{aligned}&= \frac{\theta^n}{\Gamma(n)} \cdot \frac{\Gamma(n-2)}{\theta^{n-2}} = \frac{\theta^2 \Gamma(n-2)}{(n-1)(n-2)\Gamma(n-2)} = \frac{\theta^2}{(n-1)(n-2)} \\ \implies \mathbb{E}_\theta(\hat{\theta}_n^2) &= \frac{n^2 \theta^2}{(n-1)(n-2)}\end{aligned}$$

$$R(\theta, \hat{\theta}_n) = \underbrace{\frac{n^2 \theta^2}{(n-1)(n-2)}}_{\mathbb{E}(\hat{\theta}_n^2)} - \underbrace{\left(\frac{n\theta}{n-1} \right)^2}_{\mathbb{E}(\hat{\theta}_n)^2} + \underbrace{\frac{\theta^2}{(n-1)^2}}_{b(\theta)^2}$$

(Using variance decomposition $\mathbb{V}(\hat{\theta}_n) = \mathbb{E}(\hat{\theta}_n^2) - \mathbb{E}(\hat{\theta}_n)^2$). Actually, let's calculate directly:

$$R(\theta, \hat{\theta}_n) = \frac{n^2 \theta^2}{(n-1)(n-2)} - 2\theta \frac{n\theta}{n-1} + \theta^2$$

Simplifying (algebra):

$$\begin{aligned}&= \frac{\theta^2 n^2}{n-1} \left(\frac{1}{n-2} - \frac{1}{n-1} \right) + \frac{\theta^2}{(n-1)^2} \\ &= \frac{\theta^2}{(n-1)^2} \left[\frac{n^2}{n-2} + 1 \right]\end{aligned}$$

Unbiased estimator

We can construct an unbiased estimator $\tilde{\theta}_n$:

$$\tilde{\theta}_n = \hat{\theta}_n \times \left(\frac{n-1}{n} \right) \implies \mathbb{E}_\theta(\tilde{\theta}_n) = \mathbb{E}_\theta(\hat{\theta}_n) \times \frac{n-1}{n} = \theta.$$

Risk of the unbiased estimator:

$$\begin{aligned} R(\theta, \tilde{\theta}_n) &= \mathbb{V}_\theta(\tilde{\theta}_n) = \left(\frac{n-1}{n} \right)^2 \mathbb{V}_\theta(\hat{\theta}_n) \\ &= \frac{(n-1)^2}{n^2} \times \frac{n^2 \theta^2}{(n-1)^2 (n-2)} = \frac{\theta^2}{n-2} \end{aligned}$$

We observe that:

$$\forall \theta, R(\theta, \tilde{\theta}_n) < R(\hat{\theta}_n, \theta) \implies \tilde{\theta}_n \text{ is better than } \hat{\theta}_n.$$

Remark

Unbiased estimators are not necessarily better than biased estimators.

Example 6: Empirical Variance

$X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \mathcal{N}(0, \sigma^2).$

$$S_n^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X}_n)^2 \quad (\text{Empirical variance})$$

We know that $S_n^2 = \frac{1}{n} \sum X_i^2 - \bar{X}_n^2.$

$$\mathbb{E}_{\sigma^2} \left(\frac{1}{n} \sum X_i^2 \right) = \sigma^2$$

Since $\bar{X}_n \sim \mathcal{N}(0, \frac{\sigma^2}{n})$, $\mathbb{E}_{\sigma^2}(S_n^2) = \sigma^2 - \frac{\sigma^2}{n} = \sigma^2 \frac{n-1}{n}.$

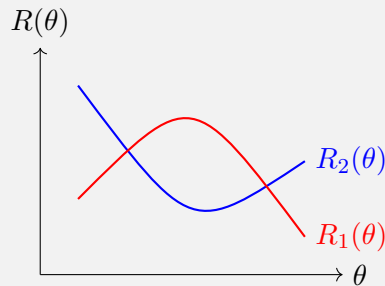
Define $\tilde{\sigma}_n^2 = S_n^2 \cdot \frac{n}{n-1} = \frac{1}{n-1} \sum (X_i - \bar{X}_n)^2.$

$$\implies \mathbb{E}_{\sigma^2}(\tilde{\sigma}_n^2) = \sigma^2 \implies \text{Unbiased.}$$

Exercise: Compute $R(\sigma^2, S_n^2)$ and $R(\sigma^2, \tilde{\sigma}_n^2)$ and show that $\forall \sigma > 0, R(\sigma^2, S_n^2) < R(\sigma^2, \tilde{\sigma}_n^2).$

Remark

In most cases, if $\hat{\theta}_{n,1}$ and $\hat{\theta}_{n,2}$ are 2 estimators of θ , then risk functions $R_1(\theta) = R(\theta, \hat{\theta}_{n,1})$ and $R_2(\theta, \hat{\theta}_{n,2})$ cross.



$\implies \hat{\theta}_{n,1}$ and $\hat{\theta}_{n,2}$ cannot be compared uniformly.

Example 7: Normal Mean Estimators

$X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \mathcal{N}(\theta, 1)$.

$$\hat{\theta}_{n,1} = \bar{X}_n$$

$$\hat{\theta}_{n,2} = \frac{n\bar{X}_n}{n + \tau^2} \quad \text{with } \tau > 0$$

Compute their risks and show that they are not comparable.

Admissibility

Definition 14: Admissibility

An estimator $\hat{\theta}_n$ is **not admissible** iff $\exists \tilde{\theta}_n$, another estimator such that:

- $\forall \theta, R(\theta, \tilde{\theta}_n) \leq R(\theta, \hat{\theta}_n)$
- and $\exists \theta_0, R(\theta_0, \tilde{\theta}_n) < R(\theta_0, \hat{\theta}_n)$.

$\hat{\theta}_n$ is **admissible** iff it is not non-admissible.

IV. Consistency

Example 8: Bernoulli Consistency

$X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \text{Ber}(p)$. $\theta = p \in]0, 1[$. $\bar{X}_n = \hat{\theta}_n$ is a possible estimator for θ .

$$\bar{X}_n \xrightarrow[n \rightarrow \infty]{P_\theta} \theta = \mathbb{E}_\theta(X_1) \quad (\text{LLN})$$

Question: $R(\theta, \hat{\theta}_n) \xrightarrow[n \rightarrow \infty]{} 0, \forall \theta?$

$$R(\theta, \hat{\theta}_n) = \mathbb{E}_\theta[(\bar{X}_n - \theta)^2] = \mathbb{V}_\theta(\bar{X}_n) = \frac{1}{n^2} n \mathbb{V}_\theta(X_1)$$

$$= \frac{\theta(1 - \theta)}{n} \leq \frac{1}{4n}$$

So $\sup_{\theta \in (0,1)} R(\theta, \hat{\theta}_n) \xrightarrow[n \rightarrow \infty]{} 0$.

Can I say something like: $\hat{\theta}_{n,1} \leq \theta \leq \hat{\theta}_{n,2}$ with proba ≈ 0.95 ?

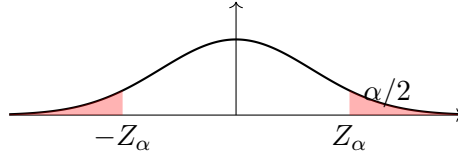
$$\sqrt{n}(\bar{X}_n - \theta) \xrightarrow[n \rightarrow \infty]{\mathcal{D}} \mathcal{N}(0, \theta(1 - \theta)) \quad (\text{CLT})$$

$$\implies \frac{\sqrt{n}(\bar{X}_n - \theta)}{\sqrt{\theta(1 - \theta)}} \xrightarrow[n \rightarrow \infty]{\mathcal{D}} \mathcal{N}(0, 1)$$

Since $\bar{X}_n \xrightarrow{\mathbb{P}} \theta$, by Slutsky's lemma (replacing θ with \bar{X}_n in the denominator):

$$\frac{\sqrt{n}(\bar{X}_n - \theta)}{\sqrt{\bar{X}_n(1 - \bar{X}_n)}} \xrightarrow[n \rightarrow \infty]{\mathcal{D}} \mathcal{N}(0, 1)$$

Let Z_α be such that $\mathbb{P}(|\mathcal{N}(0, 1)| \leq Z_\alpha) = 1 - \alpha$. (Usually $1 - \alpha = 0.95 \implies Z_\alpha \approx 1.96$).



$$\begin{aligned} &\implies \mathbb{P}_\theta \left(-Z_\alpha \leq \frac{\sqrt{n}(\bar{X}_n - \theta)}{\sqrt{\bar{X}_n(1 - \bar{X}_n)}} \leq Z_\alpha \right) \xrightarrow{n \rightarrow \infty} 1 - \alpha \\ &\implies \mathbb{P}_\theta \left(\underbrace{\bar{X}_n - \frac{\sqrt{\bar{X}_n(1 - \bar{X}_n)}Z_\alpha}{\sqrt{n}}}_{\hat{\theta}_{n,1}} \leq \theta \leq \bar{X}_n + \underbrace{\frac{Z_\alpha \sqrt{\bar{X}_n(1 - \bar{X}_n)}}{\sqrt{n}}}_{\hat{\theta}_{n,2}} \right) \rightarrow 1 - \alpha \end{aligned}$$

With probability under $P_\theta \approx 1 - \alpha$, $\hat{\theta}_{n,1} \leq \theta \leq \hat{\theta}_{n,2}$.

Definition 15: Consistency

1. We say that an estimator $\hat{\theta}_n$ is **consistent in probability** at θ iff $\hat{\theta}_n \xrightarrow[n \rightarrow \infty]{P_\theta} \theta$.
2. $\hat{\theta}_n$ is consistent **over** Θ if it is consistent at $\theta, \forall \theta \in \Theta$.
3. $\hat{\theta}_n$ converges in **quadratic mean** at θ iff $R(\hat{\theta}_n, \theta) \xrightarrow[n \rightarrow \infty]{} 0$ (Notation: $\hat{\theta}_n \xrightarrow[n \rightarrow \infty]{q.m.} \theta$).
4. $\hat{\theta}_n$ converges in quadratic mean over Θ iff $\hat{\theta}_n \xrightarrow[n \rightarrow \infty]{q.m.} \theta, \forall \theta \in \Theta$.
5. $\hat{\theta}_n$ is **asymptotically normal** at θ with rate $\frac{1}{\sqrt{n}}$ iff $\exists V > 0$ s.t. $\sqrt{n}(\hat{\theta}_n - \theta) \xrightarrow[n \rightarrow \infty]{\mathcal{D}} \mathcal{N}(0, V)$.

Estimation of $g(\theta)$

$X_1, \dots, X_n \stackrel{i.i.d.}{\sim} P_\theta, \theta \in \Theta$.

Examples:

1. $P_\theta \sim \text{Ber}(\theta)$. Interested in estimating $\eta = \log(\frac{\theta}{1-\theta})$.
2. $X_i \stackrel{i.i.d.}{\sim} \mathcal{N}(\mu, \sigma^2), \theta = (\mu, \sigma^2)$. $g_1(\theta) = \mu$. $g_2(\theta) = \mathbb{P}_\theta(X > 1)$.

If $\hat{\theta}$ is an estimator of θ , then we can use $g(\hat{\theta})$ as an estimator of $g(\theta)$ (one possibility among others).

Theorem 7: Plug-in Consistency

Let $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} P_\theta, \theta \in \Theta \subset \mathbb{R}^d$. Let $\hat{\theta}_n$ be an estimator of θ and $g : \Theta \rightarrow \mathbb{R}^p$. Then:

- i) If $\hat{\theta}_n$ is consistent at θ in probability and g is \mathcal{C}^0 (continuous), then $\hat{\eta}_n = g(\hat{\theta}_n)$ is consistent in probability at $\eta = g(\theta)$.
- ii) If $\hat{\theta}_n \xrightarrow{L^2} \theta$ and g is \mathcal{C}^0 and **bounded**, then $g(\hat{\theta}_n) \xrightarrow{L^2(P_\theta)} g(\theta), \forall p \geq 1$.

iii) If $\sqrt{n}(\hat{\theta}_n - \theta) \xrightarrow[n \rightarrow \infty]{\mathcal{L}(P_\theta)} \mathcal{N}(0, \sigma^2)$ and g is \mathcal{C}^1 with $g'(\theta) \neq 0$ (or $\nabla g(\theta)$ of full rank), then $\sqrt{n}(g(\hat{\theta}_n) - g(\theta)) \xrightarrow[n \rightarrow \infty]{\mathcal{L}(P_\theta)} \mathcal{N}(0, g'(\theta)^2 \sigma^2)$.

Remark

$\hat{\theta}_n$ is unbiased $\nRightarrow g(\hat{\theta}_n)$ is unbiased.

Proof for (ii). $\forall \varepsilon > 0$,

$$\mathbb{E}_\theta(|g(\hat{\theta}_n) - g(\theta)|^p) = \mathbb{E}_\theta(|g(\hat{\theta}_n) - g(\theta)|^p \mathbb{1}_{|g(\hat{\theta}_n) - g(\theta)| > \varepsilon}) + \mathbb{E}_\theta(|g(\hat{\theta}_n) - g(\theta)|^p \mathbb{1}_{|g(\hat{\theta}_n) - g(\theta)| \leq \varepsilon})$$

The second term is $\leq \varepsilon^p$. The first term:

$$\begin{aligned} &\leq \mathbb{E}_\theta((2\|g\|_\infty)^p \mathbb{1}_{|g(\hat{\theta}_n) - g(\theta)| > \varepsilon}) \\ &= (2\|g\|_\infty)^p \mathbb{P}_\theta(|g(\hat{\theta}_n) - g(\theta)| > \varepsilon) \xrightarrow[n \rightarrow \infty]{} 0 \end{aligned}$$

Because $g(\hat{\theta}_n) \xrightarrow[n \rightarrow \infty]{\mathbb{P}} g(\theta)$ (from point (i), continuous mapping theorem).

Thus $\mathbb{E}_\theta(|g(\hat{\theta}_n) - g(\theta)|^p) \leq \varepsilon^p + 2\|g\|_\infty^p \times (\dots \rightarrow 0)$. Taking limit $n \rightarrow \infty$ then $\varepsilon \rightarrow 0$ yields the result. \square

The Multivariate Case

$X_i \stackrel{i.i.d.}{\sim} P_\theta, \theta \in \Theta \subset \mathbb{R}^d, \theta = (\theta_1, \dots, \theta_d)$.

$$\begin{aligned} \hat{\theta}_n \xrightarrow[n \rightarrow \infty]{\mathbb{P}} \theta &\iff \forall \varepsilon > 0, \mathbb{P}_\theta(\|\hat{\theta}_n - \theta\| > \varepsilon) \xrightarrow[n \rightarrow \infty]{} 0 \\ &\iff \forall j \leq d, \hat{\theta}_{n,j} \xrightarrow[n \rightarrow \infty]{\mathbb{P}_\theta} \theta_j \end{aligned}$$

Because:

- If $\forall \varepsilon > 0, \mathbb{P}_\theta(\|\hat{\theta}_n - \theta\| > \varepsilon) \rightarrow 0$. Let $j \leq d, \forall \varepsilon > 0, \|\hat{\theta}_n - \theta\| \geq |\hat{\theta}_{n,j} - \theta_j|$.

$$\mathbb{P}_\theta(|\hat{\theta}_{n,j} - \theta_j| > \varepsilon) \leq \mathbb{P}_\theta(\|\hat{\theta}_n - \theta\| > \varepsilon) \xrightarrow[n \rightarrow \infty]{} 0$$

- **Reverse:** If $\forall j \leq d, \mathbb{P}_\theta(|\hat{\theta}_{n,j} - \theta_j| > \varepsilon) \rightarrow 0$.

$$\|\hat{\theta}_n - \theta\|^2 = \sum_j |\hat{\theta}_{n,j} - \theta_j|^2 \leq d \cdot \max_j |\hat{\theta}_{n,j} - \theta_j|^2$$

$$\mathbb{P}_\theta(\|\hat{\theta}_n - \theta\| > \varepsilon) \leq \mathbb{P}_\theta\left(\max_j |\hat{\theta}_{n,j} - \theta_j| > \frac{\varepsilon}{\sqrt{d}}\right)$$

$$= \mathbb{P}_\theta\left(\bigcup_{j=1}^d \{|\hat{\theta}_{n,j} - \theta_j| > \frac{\varepsilon}{\sqrt{d}}\}\right)$$

$$\leq \sum_{j=1}^d \mathbb{P}_\theta\left(\{|\hat{\theta}_{n,j} - \theta_j| > \frac{\varepsilon}{\sqrt{d}}\}\right)$$

$$\xrightarrow[n \rightarrow \infty]{} 0 \quad \text{because } d \text{ is fixed.}$$

→ Similarly, show that $\hat{\theta}_n \xrightarrow{q.m} \theta \iff \forall j, \hat{\theta}_{n,j} \xrightarrow{q.m} \theta_j$.

But, if $\sqrt{n}(\hat{\theta}_{n,j} - \theta_j) \xrightarrow{\mathcal{L}(P_\theta)} \mathcal{N}(0, \sigma_j^2)$, it does **NOT** imply directly the joint normality.

$$\implies \sqrt{n}(\hat{\theta}_n - \theta) \xrightarrow{\mathcal{L}(P_\theta)} \mathcal{N}(\mathbf{0}, \Sigma)$$

(Multivariate Central Limit Theorem required).

Chapter 4: Maximum Likelihood Estimation

I. The Likelihood

Model: $X_i \stackrel{i.i.d.}{\sim} P_\theta, \theta \in \Theta$.

Observations: (x_1, \dots, x_n) , where x_i is a realisation of X_i .

- If P_θ is **discrete**, then proba mass function of $X_1 \sim P_\theta$:

$$x \in \mathcal{X}, \quad f_\theta(x) = P_\theta(X_1 = x)$$

(\rightarrow density with respect to counting measure).

- If P_θ is a **continuous** distribution, then it has density f_θ on \mathbb{R} (or \mathbb{R}^d) with respect to Lebesgue measure.

$$\int_A f_\theta(x) dx = P_\theta(X \in A)$$

In both cases, there is a density, with respect to either Lebesgue or counting measure, denoted f_θ .

Definition 16: Likelihood

Let $(X_i)_{i=1}^n \stackrel{i.i.d.}{\sim} P_\theta, \theta \in \Theta$ with $\{P_\theta, \theta \in \Theta\}$ either discrete or continuous. Let f_θ be the density of P_θ (or probability mass function). We call the **likelihood** at (x_1, \dots, x_n) (realisations of (X_1, \dots, X_n)) the function:

$$L_n : \Theta \rightarrow \mathbb{R}_+$$

$$\theta \mapsto \prod_{i=1}^n f_\theta(x_i)$$

Examples

1. $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \mathcal{P}(\lambda), \lambda > 0$ (Poisson). Observations $(x_1, \dots, x_n), \forall x \in \mathbb{N}, f_\lambda(x) = \frac{e^{-\lambda} \lambda^x}{x!}$.

$$L_n(\lambda) = \prod_{i=1}^n f_\lambda(x_i) = \prod_{i=1}^n \frac{e^{-\lambda} \lambda^{x_i}}{x_i!}$$

$$= \frac{e^{-n\lambda} \lambda^{\sum_{i=1}^n x_i}}{\prod_{i=1}^n x_i!}$$

2. $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \mathcal{E}(\theta), \theta > 0$. Observations $(x_1, \dots, x_n), x_i > 0, \forall i$.

$$\forall x > 0, f_\theta(x) = \theta e^{-\theta x}$$

$$L_n(\theta) = \prod_{i=1}^n \theta e^{-\theta x_i} \mathbb{1}_{\{x_i > 0\}}$$

$$= \theta^n e^{-\theta \sum_{i=1}^n x_i} \mathbb{1}_{\{\min_i x_i > 0\}}$$

Remark

In the **discrete** case, $\forall \theta, L_n(\theta) = \prod_{i=1}^n f_\theta(x_i) = \prod_{i=1}^n \mathbb{P}_\theta(X_i = x_i) = \mathbb{P}_\theta(X_1 = x_1, \dots, X_n = x_n)$.

But, in the **continuous** case, it is different:

$$L_n(\theta) = \prod_{i=1}^n f_\theta(x_i) \neq \mathbb{P}_\theta(X_1 = x_1, \dots, X_n = x_n) = 0$$

(Probability of exact points in continuous case is 0).

If $L_n(\theta)$ is large, it means that the observations are highly likely for θ . "There is a good fit between (x_1, \dots, x_n) and P_θ ".

Exercise 1: Show that if $P_\theta \sim \mathcal{N}(\mu, \sigma^2)$, $\theta = (\mu, \sigma^2)$, then:

$$L_n(\theta) = \frac{e^{-n \frac{(\bar{x}_n - \mu)^2}{2\sigma^2}}}{(2\pi\sigma^2)^{n/2}} e^{-\sum_{i=1}^n \frac{(x_i - \bar{x}_n)^2}{2\sigma^2}}$$

II. Kullback-Leibler Divergence (K.L)

2nd interpretation: Kullback-Leibler divergence.

Definition 17: Kullback-Leibler Divergence

Let P and Q be 2 probabilities.

- If P, Q are **discrete** on \mathcal{X} , then:

$$\begin{aligned} KL(P, Q) &= \sum_{x \in \mathcal{X}} P(x) \ln \left(\frac{P(x)}{Q(x)} \right) \\ &= \mathbb{E}_P \left(\ln \left(\frac{P(X)}{Q(X)} \right) \right) \end{aligned}$$

(where $P(x) = \mathbb{P}(X = x)$, $Q(x) = \mathbb{Q}(X = x)$).

- If P and Q are **continuous** with density f_P and f_Q (resp), then:

$$\begin{aligned} KL(P, Q) &= \int_{\mathcal{X}} f_P(x) \ln \left(\frac{f_P(x)}{f_Q(x)} \right) dx \\ &= \mathbb{E}_P \left(\ln \left(\frac{f_P(X)}{f_Q(X)} \right) \right) \end{aligned}$$

Proposition 2: Properties of KL

- i) $\forall P, Q, \quad KL(P, Q) \geq 0$.
- ii) $KL(P, Q) = 0 \iff P = Q$.

But, $KL(P, Q) \neq KL(Q, P)$ (Not symmetric).

Proof. Assume that P, Q are continuous.

i)

$$\begin{aligned} KL(P, Q) &= \int_{\mathcal{X}} f_P(x) \ln \left(\frac{f_P(x)}{f_Q(x)} \right) dx \\ &= \int_{\mathcal{X}} f_P(x) \left[-\ln \left(\frac{f_Q(x)}{f_P(x)} \right) \right] dx \end{aligned}$$

By Jensen's inequality:

$$\begin{aligned} &\geq -\ln \left[\int_{\mathcal{X}} f_P(x) \frac{f_Q(x)}{f_P(x)} dx \right] \\ &= -\ln \left[\int_{\mathcal{X}} f_Q(x) dx \right] = -\ln(1) = 0 \end{aligned}$$

(Because $x \mapsto -\ln(x)$ is strictly convex on \mathbb{R}).

ii) Since $-\ln(\cdot)$ is strictly convex:

$$\mathbb{E}_P(-\ln(R(X))) > -\ln(\mathbb{E}_P(R(X))) \quad \text{with } R(x) = \frac{f_Q(x)}{f_P(x)}$$

if $\forall c, \mathbb{P}(R(X) = c) < 1$ ($R(X)$ is not constant).

$R(x) = \frac{f_Q(x)}{f_P(x)}$ is constant iff $\exists c \neq 0$ so that:

$$\begin{aligned} f_Q(x) &= cf_P(x), \quad \forall x \in \mathcal{X} \\ \implies c &= 1 \quad (\text{since } \int f_P = \int f_Q = 1) \end{aligned}$$

$$R(x) = \frac{f_Q(x)}{f_P(x)} \text{ is constant iff } f_Q = f_P \iff P = Q. \quad \square$$

Links with the likelihood

$\forall \theta, \theta_0 \in \Theta$:

$$\begin{aligned} &\ln(L_n(\theta)) - \ln(L_n(\theta_0)) \\ &= \ln \left(\prod_{i=1}^n f_{\theta}(x_i) \right) - \ln \left(\prod_{i=1}^n f_{\theta_0}(x_i) \right) \\ &= \sum_{i=1}^n \ln(f_{\theta}(x_i)) - \sum_{i=1}^n \ln(f_{\theta_0}(x_i)) \\ &= \sum_{i=1}^n \ln \left(\frac{f_{\theta}(x_i)}{f_{\theta_0}(x_i)} \right) \end{aligned}$$

If $(x_i)_{i=1}^n$ are the realisations of $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} P_{\theta_0}$. Then when $X_i \stackrel{i.i.d.}{\sim} P_{\theta_0}$:

$$\frac{1}{n} \sum_{i=1}^n \ln \left(\frac{f_{\theta}(X_i)}{f_{\theta_0}(X_i)} \right) \underbrace{\text{converges under } P_{\theta_0}}_{n \rightarrow \infty} \text{ to } \mathbb{E}_{\theta_0} \left(\ln \left(\frac{f_{\theta}(X)}{f_{\theta_0}(X)} \right) \right)$$

as soon as $\mathbb{E}_{\theta_0} \left(\left| \ln \frac{f_{\theta}(X)}{f_{\theta_0}(X)} \right| \right) < \infty$.

\implies if $\mathbb{E}_{\theta_0}(\dots) < \infty$, then we have:

$$\begin{aligned} &\frac{1}{n} (\ln(L_n(\theta)) - \ln(L_n(\theta_0))) \xrightarrow[n \rightarrow \infty]{P_{\theta_0}} \mathbb{E}_{\theta_0} \left[\ln \left(\frac{f_{\theta}(X)}{f_{\theta_0}(X)} \right) \right] \\ &= -KL(P_{\theta_0}, P_{\theta}) \end{aligned}$$

- θ_0 minimizes $KL(P_{\theta_0}, P_\theta)$ over θ .
- θ_0 maximizes $-KL(P_{\theta_0}, P_\theta)$ over θ .

We cannot maximize $-KL(P_{\theta_0}, P_\theta)$ because it depends on θ_0 unknown. \implies We maximize:

$$\mathbb{E}_{P_n} \left[-\ln \left(\frac{f_\theta(X)}{f_{\theta_0}(X)} \right) \right] = \frac{1}{n} [\ln(L_n(\theta)) - \ln(L_n(\theta_0))]$$

(Empirical version of $-KL(P_{\theta_0}, P_\theta)$).

Maximizing in θ , $\ln(L_n(\theta)) - \ln(L_n(\theta_0))$ is equivalent to maximizing in θ , $\ln L_n(\theta)$.

Definition 18: Maximum Likelihood Estimator (MLE)

Let $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} P_\theta$, $\theta \in \Theta$, the model P_θ with density (or probability mass function) f_θ . We call **Maximum Likelihood Estimator** any selection $\hat{\theta}_n$ (when it exists) such that:

$$\hat{\theta}_n \in \operatorname{argmax}_{\theta \in \Theta} \{\ln(L_n(\theta))\}$$

$$\iff \log(L_n(\hat{\theta}_n)) \geq \log(L_n(\theta)), \forall \theta \in \Theta$$

Examples of Calculations

1) Bernoulli Model

$X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \text{Ber}(\theta)$ ($\theta \in]0, 1[$).

$$\begin{aligned} L_n(\theta) &= \prod_{i=1}^n P_\theta(X_i = x_i) \\ &= \prod_{i=1}^n \theta^{x_i} (1 - \theta)^{1-x_i} \\ &= \theta^{\sum x_i} (1 - \theta)^{n - \sum x_i} \end{aligned}$$

Define $l(\theta) = \log(L_n(\theta))$.

$$l(\theta) = \left(\sum_{i=1}^n x_i \right) \log(\theta) + \left(n - \sum_{i=1}^n x_i \right) \log(1 - \theta)$$

$\hat{\theta}_n$ maximizes $l(\theta)$ in θ . Let $\bar{x}_n = \frac{1}{n} \sum x_i$.

$$l(\theta) = n\bar{x}_n \log(\theta) + n(1 - \bar{x}_n) \log(1 - \theta)$$

Derivative:

$$l'(\theta) = \frac{n\bar{x}_n}{\theta} - \frac{n(1 - \bar{x}_n)}{1 - \theta}$$

Second derivative:

$$l''(\theta) = -\frac{n\bar{x}_n}{\theta^2} - \frac{n(1 - \bar{x}_n)}{(1 - \theta)^2} < 0$$

So $\theta \mapsto l(\theta)$ is **concave**. $\implies \hat{\theta}_n$ is the solution of $l'(\theta) = 0$.

$$l'(\theta) = 0 \iff \frac{n\bar{x}_n}{\theta} = \frac{n(1 - \bar{x}_n)}{1 - \theta} \iff \theta = \bar{x}_n$$

$\implies \hat{\theta}_n = \bar{x}_n$ is the MLE (Maximum Likelihood Estimator)

2) Exponential Model

$X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \mathcal{E}(\theta), \theta > 0.$

$$X \sim \mathcal{E}(\theta) \iff f_\theta(x) = \theta e^{-\theta x} \mathbb{1}_{\{x>0\}}$$

$$L_n(\theta) = \theta^n e^{-n\theta \bar{x}_n} \prod_{i=1}^n \mathbb{1}_{\{x_i>0\}}$$

$$l(\theta) = \log(L_n(\theta)) = n \log(\theta) - n\bar{x}_n \theta \quad (\text{if } \forall i, x_i > 0)$$

Exercise: Show that $\theta \mapsto l(\theta)$ is concave and that $\hat{\theta}_n = \frac{1}{\bar{x}_n}$.

Remark

1. The log likelihood as a function is not necessarily concave, therefore, $\hat{\theta}_n$ does not always exist and is not always unique.
2. In practice: how do we compute $\hat{\theta}_n$?

$$\hat{\theta}_n \in \operatorname{argmax}\{l(\theta), \theta \in \Theta\}$$

Algorithms such as gradient descent, Newton-Raphson.

Summary:

- **Model:** $f_\theta(\cdot), \theta \in \Theta$ density or proba mass function. $X_i \stackrel{i.i.d.}{\sim} f_\theta$.
- **Log-likelihood:** $l(\theta) = \log(L_n(\theta)) = \sum_{i=1}^n \log(f_\theta(x_i))$.
- **MLE:** $\hat{\theta}_n$ such that $l(\hat{\theta}_n) \geq l(\theta), \forall \theta \in \Theta$.

Proposition 3: Invariance

If $\eta = g(\theta)$, where g is invertible (\iff new parametrization).

For instance: $X_i \stackrel{i.i.d.}{\sim} \text{Ber}(p), \theta = p \in]0, 1[$.

$$\eta = \log\left(\frac{p}{1-p}\right) \in \mathbb{R}$$

Let $\tilde{l}(\eta) = \sum_{i=1}^n \log(f_{g^{-1}(\eta)}(x_i))$. Let $l(\theta) = \sum_{i=1}^n \log(f_\theta(x_i))$.

- If $\hat{\eta}_n$ is the MLE of \tilde{l} ($\iff \tilde{l}(\eta) \leq \tilde{l}(\hat{\eta}_n), \forall \eta$).
- If $\hat{\theta}_n$ is the MLE of l ($\iff l(\theta) \leq l(\hat{\theta}_n), \forall \theta$).

Then:

$$\hat{\eta}_n = g(\hat{\theta}_n)$$

Proof. Note: $\hat{\eta}_n = g(\hat{\theta}_n)$. We verify that $\tilde{l}(\hat{\eta}_n) \geq \tilde{l}(\eta), \forall \eta$, that is, it will imply that $\hat{\eta}_n$ is an MLE of \tilde{l} .

Indeed:

$$\tilde{l}(\eta) = l(g^{-1}(\eta)) \leq l(\hat{\theta}_n), \forall \eta$$

And:

$$\tilde{l}(\hat{\eta}_n) = l(g^{-1}(g(\hat{\theta}_n))) = l(\hat{\theta}_n)$$

$$\implies \forall \eta, \tilde{l}(\eta) \leq \tilde{l}(\hat{\eta}_n). \quad (\text{Q.E.D})$$

□

Examples

MLE for $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \text{Ber}(p)$.

$$l(p) = p^{\sum x_i} (1-p)^{n-\sum x_i}$$

x_1, \dots, x_n are the observations.

$$\hat{p}_n = \frac{1}{n} \sum_{i=1}^n x_i \rightarrow \text{MLE}$$

$$\eta = \log\left(\frac{p}{1-p}\right) \implies \hat{\eta}_n = \log\left(\frac{\hat{p}_n}{1-\hat{p}_n}\right) \text{ is the MLE of } \eta.$$

Asymptotic Normality of the MLE

Under which conditions on the model is the MLE asymptotically normal?

Definition 19: Regular Model

The model $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} f_\theta, \theta \in \Theta \subset \mathbb{R}^k$ (either density or probability mass function) is **regular** on Θ iff:

- (i) Θ is an open set and the model is identifiable.
- (ii) $\theta \mapsto \log(f_\theta(x))$ is $\mathcal{C}^2, \forall x \in \mathcal{X}$.
- (iii) $\forall \theta \in \Theta, \mathbb{E}_\theta(\|\nabla_\theta \log(f_\theta(X))\|^2) < +\infty$ and $\exists \delta > 0, \mathbb{E}_\theta(\sup_{|\theta' - \theta| < \delta} \|D_\theta^2 \log(f_{\theta'}(X))\|) < +\infty$.
- (iv) $\forall \theta, I(\theta) = \mathbb{E}_\theta(\nabla_\theta \log(f_\theta(X)) \cdot \nabla_\theta \log(f_\theta(X))^T)$ is positive definite.

Fisher Information

$I(\theta)$ is called the **Fisher Information Matrix**.

Notations: $D^2 \log(f_\theta(x))$ is the matrix:

$$(D^2 \log(f_\theta(x)))_{i,j} = \frac{\partial^2 \log(f_\theta(x))}{\partial \theta_i \partial \theta_j}$$

$$\nabla_\theta \log(f_\theta(x)) = \left(\frac{\partial}{\partial \theta_j} \log(f_\theta(x)) \right)_{j=1, \dots, k}$$

Lemma 1: Properties of Score and Fisher Information

If the model is regular:

- a) $\forall \theta \in \Theta, \mathbb{E}_\theta(\nabla_\theta \log(f_\theta(X))) = 0$. $S(\theta, x) = \nabla_\theta \log(f_\theta(x))$ is called the **score function**.
- b) $I(\theta) = -\mathbb{E}_\theta(D^2 \log(f_\theta(X)))$.

Proof. **a)** The model is regular $\implies \nabla_\theta \log(f_\theta(X))$ exists and is integrable. And:

$$\nabla_\theta \log(f_\theta(X)) = \frac{\nabla_\theta f_\theta(X)}{f_\theta(X)}$$

$$\mathbb{E}_\theta(\nabla_\theta \log(f_\theta(X))) = \begin{cases} \int_{\mathcal{X}} \frac{\nabla_\theta f_\theta(x)}{f_\theta(x)} f_\theta(x) dx & \text{if } X_i\text{'s are continuous} \\ \sum_{x \in \mathcal{X}} \frac{\nabla_\theta f_\theta(x)}{f_\theta(x)} f_\theta(x) & \text{if } X_i\text{'s are discrete} \end{cases}$$

We have, if the X_i 's are continuous:

$$\int_{\mathcal{X}} \frac{\partial}{\partial \theta_j} f_\theta(x) dx = \frac{\partial}{\partial \theta_j} \int_{\mathcal{X}} f_\theta(x) dx$$

Because $\mathbb{E}_\theta(\|\nabla_\theta f_\theta(X)\|) < +\infty$. Also $\forall \theta, \int_{\mathcal{X}} f_\theta(x) dx = 1 \implies \frac{\partial}{\partial \theta_j} (\int f_\theta(x) dx) = 0$.

$$\text{So } \mathbb{E}_\theta \left(\frac{\partial}{\partial \theta_j} \frac{f_\theta(X)}{f_\theta(X)} \right) = 0.$$

$$\implies \mathbb{E}_\theta(\nabla_\theta \log(f_\theta(X))) = 0$$

If f is discrete \rightarrow same argument.

$$\sum_x \frac{\partial}{\partial \theta_j} f_\theta(x) = \frac{\partial}{\partial \theta_j} \sum_x f_\theta(x) = \frac{\partial}{\partial \theta_j} (1) = 0$$

(Q.E.D)

b) Show that $I(\theta) = -\mathbb{E}_\theta(D_\theta^2 \log(f_\theta(X)))$.

$$\begin{aligned} \frac{\partial^2 \log(f_\theta(x))}{\partial \theta_i \partial \theta_j} &= \frac{\partial}{\partial \theta_j} \left(\frac{\frac{\partial}{\partial \theta_i} f_\theta(x)}{f_\theta(x)} \right) \\ &= \frac{\frac{\partial^2}{\partial \theta_i \partial \theta_j} f_\theta(x)}{f_\theta(x)} - \left(\frac{\frac{\partial}{\partial \theta_i} f_\theta(x)}{f_\theta(x)} \right) \left(\frac{\frac{\partial}{\partial \theta_j} f_\theta(x)}{f_\theta(x)} \right) \end{aligned}$$

Similarly to before:

$$\begin{aligned} \mathbb{E}_\theta \left(\frac{\frac{\partial^2}{\partial \theta_i \partial \theta_j} f_\theta(X)}{f_\theta(X)} \right) &= \int_{\mathcal{X}} \frac{\frac{\partial^2}{\partial \theta_i \partial \theta_j} f_\theta(x)}{f_\theta(x)} f_\theta(x) dx \\ &= \int_{\mathcal{X}} \frac{\partial^2}{\partial \theta_i \partial \theta_j} f_\theta(x) dx = \frac{\partial^2}{\partial \theta_i \partial \theta_j} \int_{\mathcal{X}} f_\theta(x) dx = 0 \end{aligned}$$

$$\begin{aligned} J(\theta)_{i,j} &= -\mathbb{E}_\theta(D_\theta^2 \log(f_\theta(X))) \\ &= -\mathbb{E}_\theta \left(\frac{\partial^2}{\partial \theta_i \partial \theta_j} \log(f_\theta(X)) \right) \\ &= - \left(-\mathbb{E}_\theta \left(\frac{\frac{\partial f}{\partial \theta_i}}{f} \cdot \frac{\frac{\partial f}{\partial \theta_j}}{f} \right) \right) \\ &= I_{i,j}(\theta) \end{aligned}$$

So $J(\theta) = I(\theta)$. (Q.E.D)

□

Theorem 8: Asymptotic Normality of MLE

Let (x_1, \dots, x_n) be observations from the model $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} f_\theta, \theta \in \Theta \subset \mathbb{R}^k$. Assume the model is **regular**.

(i) **Score Convergence:** For all $\theta \in \Theta$, let $S_n(\theta) = \frac{1}{\sqrt{n}} \sum_{i=1}^n \nabla_{\theta} \log(f_{\theta}(X_i))$. Then:

$$S_n(\theta) \xrightarrow[n \rightarrow \infty]{\mathcal{L}_{P_{\theta}}} \mathcal{N}(0, I(\theta))$$

(ii) **MLE Convergence:** If in addition the MLE $\hat{\theta}_n$ is **consistent** over Θ (in probability), then:

$$\sqrt{n}(\hat{\theta}_n - \theta) \xrightarrow[n \rightarrow \infty]{\mathcal{L}_{P_{\theta}}} \mathcal{N}(0, I^{-1}(\theta))$$

$\implies I^{-1}(\theta)$ is the asymptotical variance of $\sqrt{n}(\hat{\theta}_n - \theta)$.

Remark

Cramer-Rao Lower Bound: For the variance of a regular estimator is $\frac{I^{-1}(\theta)}{n}$.

Multivariate Gaussians Reminder

$X \sim \mathcal{N}(\mu, \Sigma)$, $X \in \mathbb{R}^k$, $\mu \in \mathbb{R}^k$. Σ symmetric, positive semi-definite.
 \iff its density (w.r.t Lebesgue)

$$f_{\mu, \Sigma}(x) = \frac{e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)}}{(2\pi)^{k/2} (\det(\Sigma))^{1/2}}$$

$\iff \forall a \in \mathbb{R}^d, a^T X \sim \mathcal{N}(a^T \mu, a^T \Sigma a)$.

Proof of the Theorem

Objective: Show that $\sqrt{n}(\hat{\theta}_n - \theta) \xrightarrow{\mathcal{L}_{P_{\theta}}} \mathcal{N}(0, I^{-1}(\theta))$.

$\hat{\theta}_n$ is defined by $l(\hat{\theta}_n) \geq l(\theta)$ and verifies $\nabla_{\theta} l(\hat{\theta}_n) = 0$. The rest of the proof is done with $k = 1$.
 $\theta \mapsto l(\theta) = \sum \log(f_{\theta}(x_i))$ is \mathcal{C}^2 .

Taylor expansion:

$$l'(\theta) = l'(\hat{\theta}_n) + (\theta - \hat{\theta}_n) l''(\tilde{\theta}_n) \quad \text{with } \tilde{\theta}_n \in]\theta, \hat{\theta}_n[$$

$$\implies l'(\theta) = (\theta - \hat{\theta}_n) l''(\tilde{\theta}_n) \quad (\text{since } l'(\hat{\theta}_n) = 0)$$

$$\frac{l''(\tilde{\theta}_n)}{n} = \frac{1}{n} \sum_{i=1}^n \frac{\partial^2}{\partial \theta^2} \log(f_{\tilde{\theta}_n}(x_i))$$

$$\frac{l''(\tilde{\theta}_n) - l''(\theta)}{n} = \Delta_n(\theta)$$

So:

$$l'(\theta) = (\theta - \hat{\theta}_n)(l''(\theta) + \Delta_n(\theta) \times n)$$

And $\frac{l'(\theta)}{\sqrt{n}} = -S_n(\theta)$.

$$S_n(\theta) = \sqrt{n}(\theta - \hat{\theta}_n) \left(\frac{l''(\theta)}{n} + \Delta_n(\theta) \right)$$

We examine the terms:

$$\frac{l''(\theta)}{n} = \frac{1}{n} \sum_{i=1}^n D^2 \log(f_\theta(x_i)) \xrightarrow[n \rightarrow \infty]{P_\theta} \mathbb{E}_\theta(D^2 \log(f_\theta(X))) = -I(\theta)$$

$$\implies S_n(\theta) = \sqrt{n}(\hat{\theta}_n - \theta)(-I(\theta) + \Delta_n(\theta) + B_n(\theta))$$

where $B_n(\theta) = \frac{l''(\theta)}{n} + I(\theta) \xrightarrow{P_\theta} 0$.

We need to handle $S_n(\theta)$ and $\Delta_n(\theta)$.

(i) Behavior of $S_n(\theta)$:

$$\forall \theta \in \Theta, S_n(\theta) = \frac{1}{\sqrt{n}} \sum_{i=1}^n \nabla_\theta \log(f_\theta(x_i)) \xrightarrow{\mathcal{L}} \mathcal{N}(0, I(\theta))$$

Proof for (i):

$$S_n(\theta) = \frac{1}{\sqrt{n}} \sum_{i=1}^n s_1(\theta, x_i)$$

And $\forall \theta, (s_1(\theta, x_i))_{i=1, \dots, n}$ are i.i.d. because (x_i) are i.i.d. And $\mathbb{E}_\theta(s_1(\theta, X_i)) = 0$ (Lemma). And $\mathbb{E}_\theta(\|s_1(\theta, X)\|^2) < +\infty$ (Assumption).

By the CLT:

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n s_1(\theta, X_i) \xrightarrow[n \rightarrow \infty]{\mathcal{L}} \mathcal{N}(0, \text{Var}_\theta(s_1(\theta, X)))$$

Also $\text{Var}_\theta(s_1(\theta, X)) = \mathbb{E}_\theta(s_1(\theta, X)s_1(\theta, X)^T) = I(\theta)$.

(ii) Behavior of $\Delta_n(\theta)$: We show that $\Delta_n(\theta) \xrightarrow[n \rightarrow \infty]{P_\theta} 0$. Because when $|\hat{\theta}_n - \theta| \leq \delta$:

$$|\Delta_n(\theta)| \leq \frac{1}{n} \sum \sup_{|\theta' - \theta| \leq \delta} |D_{\theta'}^2 \log(f_{\theta'}(x_i)) - D_\theta^2 \log(f_\theta(x_i))|$$

LLN:

$$\begin{aligned} & \frac{1}{n} \sum \sup_{|\theta' - \theta| \leq \delta} |D_{\theta'}^2 \log(f_{\theta'}(x_i)) - D_\theta^2 \log(f_\theta(x_i))| \\ & \xrightarrow{P_\theta} \mathbb{E}_\theta \left(\sup_{|\theta' - \theta| \leq \delta} |D_{\theta'}^2 \log(f_{\theta'}(x)) - D_\theta^2 \log(f_\theta(x))| \right) \end{aligned}$$

By the dominated convergence theorem:

$$\mathbb{E}_\theta \left(\sup_{|\theta' - \theta| \leq \delta} |D_{\theta'}^2 \log(f_{\theta'}(x)) - D_\theta^2 \log(f_\theta(x))| \right) \xrightarrow{\delta \rightarrow 0} 0$$

$\forall \varepsilon > 0, \exists \delta_\varepsilon > 0, \forall \delta \leq \delta_\varepsilon$, this expectation is $< \varepsilon$.

We know that $\hat{\theta}_n \xrightarrow{P_\theta} \theta$. $\forall \delta > 0, \mathbb{P}_\theta(|\hat{\theta}_n - \theta| > \delta) \xrightarrow[n \rightarrow \infty]{} 0$.

Also $\theta \mapsto D_\theta^2 \log(f_\theta(x))$ is continuous. $\implies \limsup_{\delta \rightarrow 0} \sup_{|\theta' - \theta| \leq \delta} |D_{\theta'}^2 \log(f_{\theta'}(x)) - D_\theta^2 \log(f_\theta(x))| = 0$ (almost surely). Let $\delta_p \rightarrow 0, \delta_p \downarrow$.

$$\begin{aligned} & \sup_{|\theta' - \theta| \leq \delta_p} |D_{\theta'}^2 \log(f_{\theta'}(x)) - D_\theta^2 \log(f_\theta(x))| \\ & \leq \sup_{|\theta' - \theta| \leq \delta_0} |D_{\theta'}^2 \log(f_{\theta'}(x)) - D_\theta^2 \log(f_\theta(x))| \end{aligned}$$

And $\mathbb{E}_\theta(H(X)) < +\infty$ (by assumption).

So $\Delta_n(\theta) \xrightarrow{P_\theta} 0$.

Conclusion of Proof:

$$S_n(\theta) = \sqrt{n}(\hat{\theta}_n - \theta)(-I(\theta) + \Delta_n(\theta) + B_n(\theta))$$

$$B_n(\theta) = \frac{l''(\theta)}{n} + I(\theta) \xrightarrow{P_\theta} 0$$

$$\Delta_n(\theta) \xrightarrow{P_\theta} 0$$

$$S_n(\theta) \xrightarrow[n \rightarrow \infty]{\mathcal{L}} \mathcal{N}(0, I(\theta))$$

$$\implies \sqrt{n}(\hat{\theta}_n - \theta) = \frac{S_n(\theta)}{I(\theta)(1 + \mu_n)} \xrightarrow{\mathcal{L}} \mathcal{N}\left(0, \frac{I(\theta)}{I^2(\theta)}\right) = \mathcal{N}(0, I^{-1}(\theta))$$

With $\mu_n \xrightarrow{P_\theta} 0$.

III. Exponential Families

Definition 20: Exponential Family

Model $X \in \mathbb{R}^d \sim P_\theta$, $\theta \in \Theta \subset \mathbb{R}^k$ is an **exponential family** iff P_θ has density (or proba mass function) f_θ and:

- $\exists h : \mathbb{R}^d \rightarrow \mathbb{R}_+$
- $\exists A : \Theta \rightarrow \mathbb{R}^k$
- $\exists S : \mathbb{R}^d \rightarrow \mathbb{R}^k$
- $\exists C : \Theta \rightarrow \mathbb{R}$

Such that:

$$f_\theta(x) = h(x) \exp(A(\theta)^T S(x) - C(\theta))$$

It's a **canonical exponential family** iff $A(\theta) = \theta$.

Remark

Cramer-Rao Lower Bound: For the variance of a regular estimator, the lower bound is $\frac{I^{-1}(\theta)}{n}$. What are regular models? Exponential families are a prime example.

Theorem 9: Properties of Exponential Families

Let P_θ be an exponential family. If $f_\theta(x) = h(x) \exp(A(\theta)^T S(x) - C(\theta))$ and if $\Theta = \{\theta, f_\theta(x) \text{ exists}\}$ is an open set, then:

- (i) If $A(\theta) = \theta$, then the model is **regular**.
- (ii) $\exp(C(\theta)) = \int_{\mathbb{R}^d} h(x) e^{A(\theta)^T S(x)} dx$ (if continuous) or $\sum_{x \in \mathcal{X}} h(x) e^{A(\theta)^T S(x)}$ (if discrete).

(iii) If $A(\theta) = \theta$, then $\theta \mapsto C(\theta)$ is \mathcal{C}^∞ on Θ and:

$$\mathbb{E}_\theta(S(X)) = \nabla_\theta C(\theta)$$

$$\mathbb{V}_\theta(S(X)) = \frac{\partial^2 C(\theta)}{\partial \theta^2} = D^2 C(\theta)$$

(iv) If A is invertible and \mathcal{C}^2 , and A^{-1} is \mathcal{C}^2 , then the model is regular.

Remark

" f_θ exists" means:

- If P_θ is continuous: $\int_{\mathbb{R}^d} e^{A(\theta)^T S(x)} h(x) dx < +\infty$.
- If P_θ is discrete: $\sum_{x \in \mathcal{X}} e^{A(\theta)^T S(x)} h(x) < +\infty$.

Heuristic of the proof (Continuous case)

(ii) We know that $\int_{\mathbb{R}^d} f_\theta(x) dx = 1$.

$$\iff \int_{\mathbb{R}^d} h(x) e^{A(\theta)^T S(x) - C(\theta)} dx = 1$$

$$\iff \int_{\mathbb{R}^d} h(x) e^{A(\theta)^T S(x)} dx = e^{C(\theta)}$$

(iii) If $A(\theta) = \theta$.

$$e^{C(\theta)} = \int_{\mathbb{R}^d} e^{\theta^T S(x)} h(x) dx$$

And $\{\theta, \int_{\mathbb{R}^d} e^{\theta^T S(x)} h(x) dx < +\infty\}$ is open.

Differentiation:

$$\frac{\partial}{\partial \theta} e^{\theta^T S(x)} = S(x) e^{\theta^T S(x)}$$

If $k = 1$:

$$\begin{aligned} \frac{d}{d\theta} e^{C(\theta)} &= C'(\theta) e^{C(\theta)} = \int_{\mathbb{R}^d} S(x) e^{\theta^T S(x)} h(x) dx \\ \implies C'(\theta) &= e^{-C(\theta)} \int_{\mathbb{R}^d} S(x) e^{\theta^T S(x)} h(x) dx \\ &= \int_{\mathbb{R}^d} S(x) \underbrace{e^{\theta^T S(x) - C(\theta)} h(x)}_{f_\theta(x)} dx = \mathbb{E}_\theta(S(X)) \end{aligned}$$

Second derivative:

$$\begin{aligned} \frac{d^2}{d\theta^2} e^{C(\theta)} &= C''(\theta) e^{C(\theta)} + (C'(\theta))^2 e^{C(\theta)} = \int_{\mathbb{R}^d} S(x)^2 e^{\theta^T S(x)} h(x) dx \\ \implies C''(\theta) &= - \underbrace{C'(\theta)^2}_{\mathbb{E}_\theta(S(X))^2} + \underbrace{\int_{\mathbb{R}^d} S(x)^2 e^{\theta^T S(x) - C(\theta)} h(x) dx}_{\mathbb{E}_\theta(S(X)^2)} \\ &= \mathbb{E}_\theta(S(X)^2) - \mathbb{E}_\theta(S(X))^2 = \mathbb{V}_\theta(S(X)) \end{aligned}$$

Remark

Using properties of the log-likelihood:

$$\frac{d^2}{d\theta^2} \log(f_\theta(x)) = -\frac{d^2}{d\theta^2} C(\theta)$$

Or $I(\theta) = -\mathbb{E}_\theta \left(\frac{d^2}{d\theta^2} \log f_\theta(X) \right) = \frac{d^2}{d\theta^2} C(\theta).$

Justification for differentiation under the integral sign (Proof details): If $\theta \in \Theta$, $\theta + \varepsilon \in \Theta$ and $\theta - \varepsilon \in \Theta$ (since open).

$$\implies \int e^{(\theta+\varepsilon)S(x)} h(x) dx < +\infty \quad \text{and} \quad \int e^{(\theta-\varepsilon)S(x)} h(x) dx < +\infty$$

$$|S(x)|e^{\theta S(x)} \leq e^{\theta S(x)} + \varepsilon |S(x)|e^{\theta S(x)} \dots$$

Wait, actually we use convexity arguments.

$$|S(x)|e^{\theta S(x)} \leq e^{(\theta+\varepsilon)S(x)} + e^{(\theta-\varepsilon)S(x)}$$

This bound (integrable function) allows the use of the Dominated Convergence Theorem.

$$\implies \int |S(x)|e^{\theta S(x)} h(x) dx < +\infty$$

Proposition 4: Stability of Exponential Families

If $\{P_\theta, \theta \in \Theta\}$ is an exponential family and $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} P_\theta$, then the joint distribution is also an exponential family.

$$f_\theta^{(n)}(x_1, \dots, x_n) = e^{A(\theta)^T \sum_{i=1}^n S(x_i) - nC(\theta)} \prod_{i=1}^n h(x_i)$$

This is an exponential family with:

$$A_n(\theta) = A(\theta), \quad S_n(x_1, \dots, x_n) = \sum_{i=1}^n S(x_i), \quad C_n(\theta) = nC(\theta)$$

Proof.

$$\begin{aligned} f_\theta^{(n)}(x_1, \dots, x_n) &= \prod_{i=1}^n f_\theta(x_i) \\ &= \prod_{i=1}^n \left(h(x_i) e^{A(\theta)^T S(x_i) - C(\theta)} \right) \\ &= \left(\prod_{i=1}^n h(x_i) \right) e^{A(\theta)^T \sum S(x_i) - nC(\theta)} \end{aligned}$$

□

Examples

Example 9: Binomial Distribution

$X \sim \text{Bin}(n, p)$, $p = \theta$. Probability mass function:

$$\begin{aligned} f_p(x) &= \binom{n}{x} p^x (1-p)^{n-x}, \quad x \in \{0, \dots, n\} \\ &= \underbrace{\binom{n}{x}}_{h(x)} \exp \left(\underbrace{\log \left(\frac{p}{1-p} \right)}_{A(p)} x + \underbrace{n \log(1-p)}_{-C(p)} \right) \end{aligned}$$

Here $S(x) = x$.

Canonical Parametrisation:

$$\eta = \log \left(\frac{p}{1-p} \right) \implies p = \frac{e^\eta}{1 + e^\eta}$$

$$\tilde{f}_\eta(x) = \binom{n}{x} \exp(\eta x - n \log(1 + e^\eta))$$

With $C(\eta) = n \log(1 + e^\eta)$.

$$\Theta = \mathbb{R} \text{ (open)}$$

Moments check:

$$\mathbb{E}_\eta(X) = C'(\eta) = n \frac{e^\eta}{1 + e^\eta} = np$$

$$\mathbb{V}_\eta(X) = C''(\eta) = n \frac{e^\eta(1 + e^\eta) - e^\eta e^\eta}{(1 + e^\eta)^2} = n \frac{e^\eta}{(1 + e^\eta)^2} = np(1 - p)$$

Remark: In a canonical exponential family, if Θ is an open set, then $I(\theta) = \frac{d^2 C(\theta)}{d\theta^2}$.

Proof:

$$\begin{aligned} \log(f_\theta(x)) &= \theta^T S(x) - C(\theta) + \log(h(x)) \\ \implies \frac{d}{d\theta} \log(f_\theta(x)) &= S(x) - \nabla C(\theta) \\ \implies \frac{d^2}{d\theta^2} \log(f_\theta(x)) &= -\frac{d^2}{d\theta^2} C(\theta) \\ \implies I(\theta) &= -\mathbb{E}_\theta \left[\frac{d^2}{d\theta^2} \log(f_\theta(X)) \right] \quad (\text{see Lemma 1}) \\ &= \frac{d^2}{d\theta^2} C(\theta) \end{aligned}$$

Example 10: Exponential Distribution

$X \sim \mathcal{E}(\theta)$, $\theta > 0$.

$$f_\theta(x) = \theta e^{-\theta x} \mathbb{1}_{x>0} = \mathbb{1}_{x>0} e^{-\theta x + \log(\theta)}$$

$h(x) = \mathbb{1}_{x>0}$. $A(\theta) = \theta$ (or $-\theta$). $S(x) = -x$. $C(\theta) = -\log(\theta)$. Canonical exponential family.

IV. Sufficient Condition for Consistency of MLE

Theorem 10: Consistency of MLE

If Θ is compact,

If (i) $\sup_{\theta \in \Theta} \left| \frac{\ln(L_n(\theta)) - \ln(L_n(\theta_0))}{n} + KL(\theta_0, \theta) \right| \xrightarrow[n \rightarrow \infty]{P_{\theta_0}} 0$

If (ii) $\forall \varepsilon > 0, \exists \delta > 0$ such that $\inf_{|\theta - \theta_0| > \varepsilon} KL(\theta_0, \theta) > \delta$.

Then the MLE is consistent.

Where:

$$KL(\theta_0, \theta) = \mathbb{E}_{\theta_0}[\log f_{\theta_0}(X) - \log f_{\theta}(X)]$$

(Kullback-Leibler divergence between f_{θ_0} and f_{θ}).

Proof.

$$KL(\theta_0, \theta) = \mathbb{E}_{\theta_0}[\log(f_{\theta_0}(X)) - \log(f_{\theta}(X))]$$

Idea of the proof: Prove that $\forall \varepsilon > 0, P_{\theta_0} \left[\sup_{|\theta - \theta_0| > \varepsilon} \ln(\theta) < \sup_{\theta \in \Theta} \ln(\theta) \right] \rightarrow 1$ as $n \rightarrow \infty$. (where $\ln(\theta)$ denotes the log-likelihood).

Because if $\sup_{|\theta - \theta_0| > \varepsilon} \ln(\theta) < \sup_{\theta \in \Theta} \ln(\theta)$, then $|\hat{\theta}_n - \theta_0| \leq \varepsilon$ (since $\hat{\theta}_n$ maximizes the likelihood). Show that:

$$P_{\theta_0} \left(\sup_{|\theta - \theta_0| > \varepsilon} (\ln(\theta) - \ln(\theta_0)) < 0 \right) \xrightarrow[n \rightarrow \infty]{} 1$$

$$\sup_{|\theta - \theta_0| > \varepsilon} \left[\frac{\ln(\theta) - \ln(\theta_0)}{n} + KL(\theta_0, \theta) - KL(\theta_0, \theta) \right]$$

We have:

$$\frac{\ln(\theta) - \ln(\theta_0)}{n} = - \left[\frac{1}{n} \sum_{i=1}^n \log \left(\frac{f_{\theta_0}(x_i)}{f_{\theta}(x_i)} \right) \right]$$

By LLN $\rightarrow -\mathbb{E}_{\theta_0} \left[\log \left(\frac{f_{\theta_0}(X)}{f_{\theta}(X)} \right) \right] = -KL(\theta_0, \theta)$.

By assumption (i):

$$\sup_{|\theta - \theta_0| > \varepsilon} \left| \frac{\ln(\theta) - \ln(\theta_0)}{n} + KL(\theta_0, \theta) \right| \xrightarrow[n \rightarrow \infty]{P_{\theta_0}} 0$$

And using (ii):

$$\sup_{|\theta - \theta_0| > \varepsilon} -KL(\theta_0, \theta) = - \inf_{|\theta - \theta_0| > \varepsilon} KL(\theta_0, \theta) < -\delta$$

So:

$$\sup_{|\theta - \theta_0| > \varepsilon} \frac{\ln(\theta) - \ln(\theta_0)}{n} < -\delta + o(1)$$

Which is < 0 for n large enough. □

V. Using Asymptotic Normality to Compute Confidence Regions

$\theta \in \Theta \subset \mathbb{R}$. Model $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} P_{\theta}$. $\hat{\theta}_n = \text{MLE}$.

We know:

$$\sqrt{n}(\hat{\theta}_n - \theta_0) \xrightarrow[n \rightarrow \infty]{\mathcal{L}_{P_{\theta_0}}} \mathcal{N}(0, I^{-1}(\theta_0))$$

We want $I_n = [\hat{\theta}_{n,1}, \hat{\theta}_{n,2}]$ such that:

$$P_{\theta_0}(\theta_0 \in I_n) \geq 1 - \alpha$$

Then I_n is a $(1 - \alpha)$ confidence interval for θ_0 .

I_n is an **asymptotic** $(1 - \alpha)$ confidence interval if $P_{\theta_0}(\theta_0 \in I_n) \xrightarrow{n \rightarrow \infty} 1 - \alpha$.

Exercise: Construct I_n .

VI. Delta method and confidence intervals

VI.1 Delta method

Remark

Reminder: If $\sqrt{n}(X_n - \mu) \xrightarrow{\mathcal{L}} \mathcal{N}(0, V_0)$, with $X_n \in \mathbb{R}^{d_1}$ and if $g : \mathbb{R}^{d_1} \rightarrow \mathbb{R}^{d_2}$ is \mathcal{C}^1 and s.t (sub-tangent/standard) ($d_1 \leq d_2$), $\nabla g(\mu) \in \mathbb{R}^{d_2 \times d_1}$ is of rank d_2

Then:

$$\sqrt{n}(g(X_n) - g(\mu)) \xrightarrow{\mathcal{L}} \mathcal{N}(0, \nabla g(\mu) V_0 \nabla g(\mu)^\top)$$

Proof. Case $d_1 = d_2 = 1$.

Taylor expansion:

$$g(X_n) = g(X_n - \mu + \mu) = g(\mu) + (X_n - \mu)g'(\bar{\mu}_n)$$

where $\bar{\mu}_n \in]X_n, \mu[$.

This implies:

$$\begin{aligned} \sqrt{n}(g(X_n) - g(\mu)) &= \sqrt{n}(X_n - \mu)g'(\bar{\mu}_n) \\ &= \sqrt{n}(X_n - \mu)(g'(\mu) + o_p(1)) \end{aligned}$$

We know that $\sqrt{n}(X_n - \mu)g'(\mu) \xrightarrow{\mathcal{L}} \mathcal{N}(0, g'(\mu)^2 V_0)$.

And $\sqrt{n}(X_n - \mu)(g'(\bar{\mu}_n) - g'(\mu)) \xrightarrow{\mathbb{P}} 0$. □

Remark

Reminders:

- $X_n = O_p(1) \iff \lim_{C \rightarrow \infty} \limsup_n \mathbb{P}(|X_n| > C) = 0$.
- $X_n = o_p(1) \iff X_n \xrightarrow{\mathbb{P}} 0$.
- If $X_n \xrightarrow{\mathcal{L}} Q$ (where Q is a probability distribution), then $X_n = O_p(1)$.

Application to the MLE

If $\hat{\theta}_n$ is the MLE and if $\hat{\eta}_n = g(\hat{\theta}_n)$ with $g \in \mathcal{C}^1$, $\hat{\theta}_n \in \mathbb{R}^d$, $g : \mathbb{R}^d \rightarrow \mathbb{R}^k$.

If $\sqrt{n}(\hat{\theta}_n - \theta_0) \xrightarrow[\mathbb{P}_{\theta_0}]{\mathcal{L}} \mathcal{N}(0, I^{-1}(\theta_0))$ with $\nabla g(\theta_0)$ of rank k .

Then:

$$\sqrt{n}(\hat{\eta}_n - g(\theta_0)) \xrightarrow[\mathbb{P}_{\theta_0}]{\mathcal{L}} \mathcal{N}(0, \nabla g(\theta_0) I^{-1}(\theta_0) \nabla g(\theta_0)^\top)$$

Example 11: Bernoulli

$X_1, \dots, X_n \stackrel{i.i.d}{\sim} \text{Ber}(p)$ under \mathbb{P}_{p_0} .

MLE: $\hat{p}_n = \bar{X}_n$ and $\sqrt{n}(\hat{p}_n - p_0) \xrightarrow{\mathcal{L}} \mathcal{N}(0, p_0(1 - p_0))$.

Let $\eta = \log(\frac{p}{1-p})$ and $g(p) = \log(\frac{p}{1-p})$.

$g :]0, 1[\rightarrow \mathbb{R}$ is invertible. For $x \in \mathbb{R}$, $g^{-1}(x) = \frac{e^x}{1+e^x}$.

Derivative:

$$g'(p) = \frac{1}{p} + \frac{1}{1-p} = \frac{1}{p(1-p)}$$

$\forall p_0 \in]0, 1[, g'(p_0) \neq 0$.

$$\sqrt{n}(\hat{\eta}_n - \eta) \xrightarrow[\mathbb{P}_{p_0}]{\mathcal{L}} \mathcal{N}\left(0, \frac{1}{p_0(1-p_0)}\right)$$

Note: $\frac{1}{p_0(1-p_0)} = \frac{(1+e^{\eta_0})^2}{e^{\eta_0}}$.

Example 12: Normal Distribution

$X_1, \dots, X_n \stackrel{i.i.d}{\sim} \mathcal{N}(\mu, \sigma^2)$.

$\theta = (\mu, \sigma^2) \in \mathbb{R} \times \mathbb{R}^{+*}$.

MLE: $\hat{\theta}_n = (\bar{X}_n, S_n^2)$ where $S_n^2 = \frac{1}{n} \sum_{k=1}^n (X_k - \bar{X}_n)^2$.

Canonical parameters:

$$\frac{e^{-\frac{(x-\mu)^2}{2\sigma^2}}}{\sqrt{2\pi}\sigma} = \frac{e^{-\frac{x^2}{2\sigma^2} - \frac{x\mu}{\sigma^2} - \frac{\mu^2}{2\sigma^2} - \frac{\log(\sigma^2)}{2}}}{\sqrt{2\pi}}$$

$$\implies \eta_1 = \frac{\mu}{\sigma^2}, \quad \eta_2 = \frac{-1}{2\sigma^2}$$

$$\implies \sqrt{n}(\hat{\eta}_n - \eta) \rightarrow \mathcal{N}(0, \tilde{V}_0)$$

Let $g(\eta) = \sigma^2$. We have $\sigma^2 = -\frac{1}{2\eta_2}$.

Gradient:

$$\nabla g(\eta) = \left(\frac{\partial g}{\partial \eta_1}, \frac{\partial g}{\partial \eta_2} \right) = \left(0, \frac{1}{2\eta_2^2} \right)$$

$$\implies \sqrt{n}(S_n^2 - \sigma^2) \xrightarrow{\mathcal{L}} \mathcal{N}\left(0, (0, \frac{1}{2\eta_2^2}) \tilde{V}_0 \begin{pmatrix} 0 \\ \frac{1}{2\eta_2^2} \end{pmatrix}\right)$$

Where $\tilde{V}_0 = \frac{d^2 c}{d^2 \eta}(\eta_0)$ and $c(\eta_0) = \frac{\eta_1^2}{8\eta_2} + \frac{1}{2} \log(-\frac{1}{2\eta_2})$.

$$\implies c'' = \dots$$

VI.2 Confidence intervals

Definition 21: Confidence Region

A confidence region of level α for an estimator of $g(\theta)$ is any region $C_\alpha(X_1, \dots, X_n)$ verifying:

$$\forall \theta \in \Theta, \quad \mathbb{P}_\theta[g(\theta) \in C_\alpha(X_1, \dots, X_n)] \geq 1 - \alpha$$

We can use asymptotic normality of an estimator to construct asymptotic confidence regions.

Example 13: Construction using MLE

$X_1, \dots, X_n \stackrel{i.i.d}{\sim} \mathbb{P}_\theta, \theta \in \Theta \subset \mathbb{R}$.

If the MLE verifies:

$$\sqrt{n}(\hat{\theta}_n - \theta) \xrightarrow[\mathbb{P}_\theta]{\mathcal{L}} \mathcal{N}(0, I_\theta^{-1})$$

We look for:

$$C_\alpha(X_1, \dots, X_n) = [\hat{\theta}_{n,1}, \hat{\theta}_{n,2}]$$

s.t.

$$\mathbb{P}_\theta[\theta \in [\hat{\theta}_{n,1}, \hat{\theta}_{n,2}]] \xrightarrow[n \rightarrow \infty]{} 1 - \alpha$$

$$\hat{\theta}_{n,1} \leq \theta \leq \hat{\theta}_{n,2} \iff \sqrt{n}(\hat{\theta}_{n,1} - \hat{\theta}_n) \leq \sqrt{n}(\theta - \hat{\theta}_n) \leq \sqrt{n}(\hat{\theta}_{n,2} - \hat{\theta}_n)$$

But:

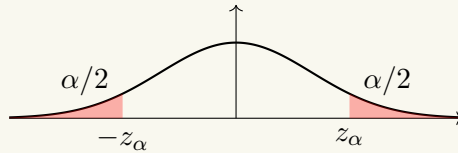
$$\begin{aligned} \sqrt{n}(\theta - \hat{\theta}_n) &\xrightarrow{\mathcal{L}} \mathcal{N}(0, I_\theta^{-1}) \\ \implies \sqrt{n}I_\theta^{1/2}(\theta - \hat{\theta}_n) &\xrightarrow{\mathcal{L}} \mathcal{N}(0, 1) \end{aligned}$$

Since $\hat{\theta}_n \xrightarrow{\mathbb{P}_\theta} \theta \implies I_{\hat{\theta}_n} \xrightarrow{\mathbb{P}_\theta} I_\theta$.

$$\implies \sqrt{n}I_{\hat{\theta}_n}^{1/2}(\theta - \hat{\theta}_n) \xrightarrow[\mathbb{P}_\theta]{\mathcal{L}} \mathcal{N}(0, 1)$$

If z_α is the $1 - \frac{\alpha}{2}$ quantile of a $\mathcal{N}(0, 1)$:

$$\iff \Phi(z_\alpha) = 1 - \frac{\alpha}{2}, \quad \Phi = \text{CDF of } \mathcal{N}(0, 1)$$



By symmetry: $\Phi(-z_\alpha) = \frac{\alpha}{2}$.

$$\implies \lim_{n \rightarrow \infty} \mathbb{P}_\theta \left(-z_\alpha \leq \sqrt{n}I_{\hat{\theta}_n}^{1/2}(\theta - \hat{\theta}_n) \leq z_\alpha \right) = 1 - \alpha$$

$$\iff \lim_{n \rightarrow \infty} \mathbb{P}_\theta \left(\frac{-z_\alpha}{I_{\hat{\theta}_n}^{1/2}} \leq \sqrt{n}(\theta - \hat{\theta}_n) \leq \frac{z_\alpha}{I_{\hat{\theta}_n}^{1/2}} \right) = 1 - \alpha$$

So if:

$$\hat{\theta}_{n,1} = \hat{\theta}_n - \frac{z_\alpha}{\sqrt{n}\sqrt{I_{\hat{\theta}_n}}} \quad ; \quad \hat{\theta}_{n,2} = \hat{\theta}_n + \frac{z_\alpha}{\sqrt{I_{\hat{\theta}_n}}\sqrt{n}}$$

Then:

$$\mathbb{P}_\theta(\hat{\theta}_{n,1} \leq \theta \leq \hat{\theta}_{n,2}) \xrightarrow[n \rightarrow \infty]{} 1 - \alpha$$

Chapter 5: Bayesian statistics

Model: $X_1, \dots, X_n \stackrel{i.i.d}{\sim} \mathbb{P}_\theta$.
 $\hat{\theta}_n \rightarrow \mathcal{R}(\theta, \hat{\theta}_n) = \mathbb{E}[(\theta - \hat{\theta}_n)^2] = \text{Quadratic risk.}$

I. In Bayesian statistics

θ = unknown \rightarrow Modelled as a random variable.

Definition 22: Prior Distribution

We call prior distribution on θ , a probability distribution over Θ .

Model:

$X_1, \dots, X_n | \theta \stackrel{i.i.d}{\sim} \mathbb{P}_\theta$: Conditional distribution of (X_1, \dots, X_n) given θ .

Prior Marginal Probability over Θ :

$\theta \sim \Pi$ Probability on Θ .

\Rightarrow **Joint distribution** on $(X_1, \dots, X_n, \theta)$.

IF \mathbb{P}_θ is continuous, with density f_θ (wrt Lebesgue measure).

Theorem 11: Bayes Theorem

The conditional distribution of θ given (X_1, \dots, X_n) has density wrt ν :

$$\Pi_n(\theta | X_1, \dots, X_n) = \frac{\Pi(\theta) \prod_{i=1}^n f_\theta(x_i)}{\int_{\Theta} \Pi(\theta) \prod_{i=1}^n f_\theta(x_i) d\nu(\theta)}$$

If π is the density of Π wrt ν , it is called the **posterior distribution**.

Definition 23: Bayesian Model

In Bayesian statistics, the Bayesian model is defined by:

- i) $[X|\theta] \sim \mathbb{P}_\theta$ with likelihood $L(\theta)$, $\theta \in \Theta$.
- ii) Prior distribution Π on Θ .

Then the inference is made by the **posterior distribution** defined as the conditional distribution of θ given X . If π is the density of Π (wrt a measure ν), then the posterior distribution has density (wrt ν) given by:

$$\Pi(\theta | X) = \frac{L(\theta)\Pi(\theta)}{\int_{\Theta} L(\theta)\Pi(\theta)d\nu(\theta)}$$

where

$$\int_{\Theta} L(\theta)\Pi(\theta)d\nu(\theta) = \begin{cases} \int L(\theta)\Pi(\theta)d\nu(\theta) & \text{if } \Pi \text{ continuous} \\ \sum_{\theta \in \Theta} L(\theta)\Pi(\theta) & \text{if } \Pi \text{ discrete} \end{cases}$$

Remark

- If \mathbb{P}_θ is continuous:
 $L(\theta) = f_\theta(x)$ = density at the observations when θ is the parameter.
- If \mathbb{P}_θ is discrete:

$$L(\theta) = f_\theta(x) = \mathbb{P}_\theta(X = x).$$

$$\Pi(\theta|X = x) = \frac{f_\theta(x)\Pi(\theta)}{\int_{\Theta} f_\theta(x)\Pi(\theta)d\nu(\theta)}$$

Example 14: Poisson - Gamma

$X = (X_1, \dots, X_n)$ and $X_i \stackrel{i.i.d}{\sim} \mathcal{P}(\theta), \theta > 0$.

Prior: $\theta \sim \Gamma(a, b)$, Π is a $\Gamma(a, b)$.

$$f_\theta(x) = \prod_{i=1}^n f_\theta(x_i)$$

$$\Rightarrow \Pi(\theta|X_1, \dots, X_n) = \frac{\prod_{i=1}^n f_\theta(x_i)\theta^{a-1}e^{-b\theta}}{\int_{\Theta} \prod_{i=1}^n f_\theta(x_i)\theta^{a-1}e^{-b\theta}d\theta}$$

Normalization constant (denominator) implies:

$$\begin{aligned} \Pi(\theta|X_1, \dots, X_n) &\propto e^{-n\theta} \prod_{i=1}^n \frac{\theta^{x_i}}{x_i!} \times \theta^{a-1}e^{-b\theta} \\ &\propto e^{-(n+b)\theta} \theta^{a+\sum_{i=1}^n x_i-1} \end{aligned}$$

(Recall: $f_\theta(x_i) = e^{-\theta} \frac{\theta^{x_i}}{x_i!}$).

$\Pi(\cdot)$ is a density $\Rightarrow \frac{f(\theta)}{g(\theta)}$ is a constant implies $\exists c \neq 0, f(\theta) = cg(\theta)$.
 $\exists C > 0$ s.t.

$$\Pi(\theta|X_1, \dots, X_n) = Ce^{-(b+n)\theta} \theta^{\sum_{i=1}^n x_i + a - 1}$$

We recognize the kernel of a Gamma distribution $\Gamma(\sum_{i=1}^n x_i + a, b + n)$.

$$\Rightarrow \Pi(\theta|X_1, \dots, X_n) = \frac{e^{-(b+n)\theta} \theta^{\sum_{i=1}^n x_i + a - 1} (b + n)^{a + \sum x_i}}{\Gamma(a + \sum_{i=1}^n x_i)}$$

Posterior distribution is $\Gamma(\sum x_i + a, b + n)$.

Note regarding the constant:

$$\begin{aligned} g(\theta) &= \theta^{b-1} e^{-b\theta} \times c \\ \int_{\mathbb{R}^+} g(\theta) d\theta &= 1 \iff c = \frac{b^a}{\Gamma(a)} \end{aligned}$$

Example 15: Normal - Normal

Bayesian model: $X_1, \dots, X_n | \mu \stackrel{i.i.d}{\sim} \mathcal{N}(\mu, 1), \mu \in \mathbb{R}$.

Prior: $\mu \sim \mathcal{N}(a, b^2), a \in \mathbb{R}, b > 0$.

Posterior distribution? Continuous with density.

$$\Pi(\mu|X_1, \dots, X_n) \propto \prod_{i=1}^n \frac{e^{-\frac{(x_i - \mu)^2}{2}}}{\sqrt{2\pi}} \frac{e^{-\frac{(\mu - a)^2}{2b^2}}}{\sqrt{2\pi}b}$$

$$\propto \exp \left(-\frac{n}{2} \{ \mu^2 + \bar{X}_n^2 - 2\mu\bar{X}_n \} - \frac{1}{2b^2} \{ \mu^2 + a^2 - 2a\mu \} \right)$$

Because:

$$\begin{aligned} \sum_{i=1}^n (X_i - \mu)^2 &= \sum_{i=1}^n [(X_i - \bar{X}_n)^2 + (\bar{X}_n - \mu)^2 + 2(\bar{X}_n - \mu)(X_i - \bar{X}_n)] \\ &= n(\bar{X}_n - \mu)^2 + \sum_{i=1}^n (X_i - \bar{X}_n)^2 \end{aligned}$$

$$\Pi(\mu | X_1, \dots, X_n) \propto e^{-\frac{1}{2}(n + \frac{1}{b^2}) \left(\mu - \frac{\frac{a}{b^2} + n\bar{X}_n}{n + \frac{1}{b^2}} \right)^2}$$

\Rightarrow Posterior distribution is:

$$a \mathcal{N} \left(\frac{\frac{a}{b^2} + n\bar{X}_n}{n + \frac{1}{b^2}}, \frac{1}{n + \frac{1}{b^2}} \right)$$

Definition 24: Marginal Likelihood

In a Bayesian model $X|\theta \sim f_\theta(x)$, $\theta \in \Theta$ (Likelihood) and prior $\theta \sim \Pi$ with density π wrt ν . The quantity:

$$m(x) = \int_{\Theta} f_\theta(x) \Pi(\theta) d\nu(\theta)$$

is called the **marginal likelihood**.

II. Bayesian decision theory: Risks

II.1 Posterior and integrated risks

Recall: Quadratic Risk:

$$\mathcal{R}(\theta, \delta) = \begin{cases} \int (\theta - \delta(x))^2 f_\theta(x) dx \\ \sum_x (\theta - \delta(x))^2 \mathbb{P}_\theta(X = x) \end{cases}$$

Definition 25: Loss Function

A loss function is a function:

$$l : \Theta \times \mathcal{D} \rightarrow \mathbb{R}^+$$

where \mathcal{D} is the set of decisions (i.e., estimators).

Example 16: Examples of Loss Functions

1. If $\mathcal{D} = \Theta$.
 - a) The quadratic loss $l(\theta, \delta) = (\theta - \delta)^2$.
 - b) The L_1 loss $l(\theta, \delta) = |\theta - \delta|$.
2. $\mathcal{D} = \{0, 1\}$, $\theta \in [0, 1]$.

Aim is testing if $\theta > \frac{1}{2}$ (choosing 1) or $\theta \leq \frac{1}{2}$ (choosing 0).

0-1 loss function defined by:

$$l(\theta, \delta) = 1 \quad \text{if } \theta < \frac{1}{2} \text{ and } \delta = 1 \text{ (wrong decision)}$$

$$\quad \text{if } \theta > \frac{1}{2} \text{ and } \delta = 0 \text{ (wrong decision)}$$

$$l(\theta, \delta) = 0 \quad \text{else (correct decision)}$$

Definition 26: Risks

In a Bayesian model $X|\theta \sim f_\theta(x)$, $\theta \sim \Pi$ with a loss function $l : \Theta \times \mathcal{D} \rightarrow \mathbb{R}^+$. where:

a) We call the **posterior risk**:

$$l(\Pi, \delta|X) = \int_{\Theta} l(\theta, \delta) \Pi(\theta|X_1, \dots, X_n) d\nu(\theta)$$

b) We call the **integrated risk**:

$$r(\Pi, \delta) = \begin{cases} \int_{\mathcal{X}} l(\Pi, \delta|X = x) m(x) dx & \text{if } X \text{ continuous} \\ \sum_{x \in \mathcal{X}} l(\Pi, \delta|X = x) m(x) & \text{if } X \text{ discrete} \end{cases}$$

Example 17: Calculation of Posterior Risk

1) Bayesian model, $X_1, \dots, X_n|\theta \sim \mathcal{P}(\theta)$, $\theta > 0$.

Prior: $\theta \sim \Gamma(a, b)$.

Loss function: Quadratic. $\mathcal{D} = \Theta = \mathbb{R}_+$.

$\forall \theta > 0, \delta > 0$, $l(\theta, \delta) = (\theta - \delta)^2$.

Posterior risk:

Posterior distribution: $\Gamma(a + \sum_{i=1}^n X_i, b + n)$.

$$\Pi(\theta|X_1, \dots, X_n) = \frac{(b + n)^{n\bar{X}_n + a} e^{-(b+n)\theta} \theta^{n\bar{X}_n + a - 1}}{\Gamma(a + n\bar{X}_n)}$$

With $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$.

$\forall \delta > 0$:

$$l(\Pi, \delta|X_1, \dots, X_n) = \int_0^\infty (\theta - \delta)^2 \Pi(\theta|X_1, \dots, X_n) d\theta$$

$$= \int_0^\infty \theta^2 \Pi(\theta|X_1, \dots, X_n) d\theta + \delta^2 - 2\delta \int_0^\infty \theta \Pi(\theta|X_1, \dots, X_n) d\theta$$

$$\implies l(\Pi, \delta|X_1, \dots, X_n) = \frac{a'(a' + 1)}{b'^2} + \delta^2 - 2\delta \frac{a'}{b'}$$

where $a' = a + n\bar{X}_n$ and $b' = b + n$. (Using moments of Gamma distribution).

\rightarrow Can be minimized in δ .

$\delta(X_1, \dots, X_n) = \text{minimizer of } l(\Pi, \delta|X_1, \dots, X_n)$.

Show that:

$$\delta(X_1, \dots, X_n) = \frac{a'}{b'} = \frac{a + n\bar{X}_n}{b + n}$$