

## Overview

- Likelihood principle (11 lectures)
- Bayesian inference (2 lectures)
- Decision theory (3 lectures)
- Multivariate analysis (2 lectures)
- Nonparametric inference & Monte Carlo techniques (6 lectures)

Books:

- Theory of point estimation - Lehmann & Casella
- “Asymptotic Statistics” - van der Vaart
- “Statistical Inference” - Casella & Berger
- “Intro to Multivariate Statistical Analysis” - Anderson

## Introduction

Goal: Make inference about unknown probability distributions based on access to random samples.

Consider a real valued random variable  $X$  on a probability space  $\Omega$  with distribution function

$$F(t) = \mathbb{P}(\omega \in \Omega : X(\omega) \leq t) \quad \forall t \in \mathbb{R}$$

When  $X$  is discrete,  $F(t) = \sum_{x \leq t} f(x)$ , where  $f$  is the pmf of  $X$ .

When  $X$  is continuous,  $F(t) = \int_{-\infty}^t f(s)ds$ , where  $f$  is the pdf of  $X$ .

For all the results in this course, we assume either pdf or pmf exists.

Often, the distribution of  $X$  is parameterised by an unknown value  $\theta$ . The goal is to infer something about  $\theta$  based on (iid) samples  $X_1, \dots, X_n$ .

**Definition.** A *statistical model* for a sample from  $X$  is any family of probability distributions  $\{P_\theta : \theta \in \Theta\}$  for the law of  $X$ . When  $P_\theta$  has a pmf (pdf)  $f(\cdot, \theta)$ , this is also written as  $\{f(\cdot, \theta) : \theta \in \Theta\}$ . The index set  $\Theta$  is the *parameter space*.

**Example.**

- (i)  $\mathcal{N}(\theta, 1); \theta \in \Theta = \mathbb{R}$ .
- (ii)  $\mathcal{N}(\mu, \sigma^2), \theta = (\mu, \sigma^2) \in \Theta = \mathbb{R} \times (0, \infty)$ .
- (iii)  $\text{Exp}(\theta); \theta \in \Theta = (0, \infty)$ .

(iv)  $\mathcal{N}(\theta, 1)$ ;  $\theta \in \Theta = [-1, 1]$ .

**Remark:** for a variable  $X$  with distribution  $P$ , the model  $\{P_\theta : \theta \in \Theta\}$  is *correctly specified* if there exists  $\theta \in \Theta$  such that  $P = P_\theta$ . For instance, if  $X \sim \mathcal{N}(2, 1)$ , the model in (i) is correctly specified, but the model in (iv) is not.

In the case of a correctly specified model, we often use  $\theta_0$  to denote the “true value” of the parameter. We also say  $\{X_1, \dots, X_n\}$  are iid from a model  $\{P_\theta : \theta \in \Theta\}$  in the case of a correctly specified model.

**Statistical goals:**

- Estimation: construct  $\hat{\theta} = \hat{\theta}(X_1, \dots, X_n)$  such that  $\hat{\theta}$  is close to  $\theta_0$  when  $X_i \sim P_{\theta_0}$ .
- Hypothesis testing: determine whether the null hypothesis  $H_0 : \theta = \theta_0$  or the alternative hypothesis  $H_1 : \theta \neq \theta_0$  is true, using a test  $\psi_n = \psi(X_1, \dots, X_n)$  such that  $\psi_n = 0$  when  $H_0$  is true and  $\psi_n = 1$  when  $H_1$  is true, with high probability.
- Inference: find confidence intervals (confidence sets)  $\mathcal{C}_n = \mathcal{C}(X_1, \dots, X_n)$  such that for some  $0 < \alpha < 1$  we have  $\mathbb{P}_\theta(\theta \in \mathcal{C}_n) \geq 1 - \alpha$ , for all  $\theta \in \Theta$ , where  $\alpha$  is the significance level.

## 1 The Likelihood Principle

Suppose  $X_1, \dots, X_n$  are iid from a Poisson model  $\{\text{Poi}(\theta) : \theta \geq 0\}$  with numerical values  $X_i = x_i$ , for all  $1 \leq i \leq n$ . The joint distribution of the sample is

$$f(x_1, \dots, x_n; \theta) = \mathbb{P}_\theta(X_1 = x_1, \dots, X_n = x_n) = \prod_{i=1}^n \left( e^{-\theta} \frac{\theta^{x_i}}{x_i!} \right) = e^{-n\theta} \prod_{i=1}^n \frac{\theta^{x_i}}{x_i!} = L_n(\theta)$$

We can think of  $L_n(\theta)$  as a random function from  $\Theta$  to  $\mathbb{R}$ , where the randomness comes from  $\{X_i\}_{i=1}^n$ . This is the probability of occurrence of the observed sample  $(X_1 = x_1, \dots, X_n = x_n)$ , as a function of the unknown parameter  $\theta$ .

The idea of the likelihood principle is to find  $\theta$  which maximises  $L_n(\theta)$ , or equivalently  $l_n(\theta) = \log L_n(\theta)$ . In the example, we have

$$l_n(\theta) = -n\theta + \log(\theta) \sum_{i=1}^n x_i - \sum_{i=1}^n \log(x_i!)$$

Setting  $l'_n(\theta) = 0$  gives

$$-n + \frac{1}{\theta} \sum_{i=1}^n x_i = 0$$

and the solution is  $\hat{\theta}_{\text{mle}} = \frac{1}{n} \sum_{i=1}^n x_i$ , which is the sample mean. One can also check that  $l_n''(\theta) < 0$  for all  $\theta > 0$ . When all  $X_i$ 's are 0, one can check that maximising  $l_n(\theta)$  is equivalent to maximising  $-n\theta$ , so  $\hat{\theta}_{\text{mle}} = 0$  in this case.

## Maximum likelihood estimator

Suppose  $\{f(\cdot, \theta) : \theta \in \Theta\}$  is a statistical model of pdfs/pmfs for the distribution of a random variable  $X$ , and  $X_1, \dots, X_n$  are iid copies of  $X$ .

Define the *likelihood function*

$$L_n(\theta) = \prod_{i=1}^n f(x_i, \theta)$$

the *log likelihood function*

$$l_n(\theta) = \log L_n(\theta) = \sum_{i=1}^n \log f(x_i, \theta)$$

and the *normalised log likelihood function*

$$\bar{l}_n(\theta) = \frac{1}{n} l_n(\theta) = \frac{1}{n} \sum_{i=1}^n \log f(x_i, \theta)$$

**Definition.** The *maximum likelihood estimator* is any element  $\hat{\theta} = \hat{\theta}_{\text{mle}} = \hat{\theta}_{\text{mle}}(X_1, \dots, X_n) \in \Theta$  for which  $L_n(\hat{\theta}) = \max_{\theta \in \Theta} L_n(\theta)$ .

**Remark:** the definition of MLE can be generalised to non-iid data, provided a joint pdf/pmf of  $(X_1, \dots, X_n)$  can be specified.

**Example.**

- (i) For  $X_i \sim \text{Poi}(\theta)$ ,  $\theta \geq 0$ , we calculated  $\hat{\theta}_{\text{mle}} = \frac{1}{n} \sum_{i=1}^n X_i = \bar{X}_n$ .
- (ii) For  $X_i \sim \mathcal{N}(\mu, \sigma^2)$ ,  $\theta = (\mu, \sigma^2) \in \mathbb{R} \times (0, \infty)$ , we have  $\hat{\mu}_{\text{mle}} = \bar{X}_n$  and  $\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X}_n)^2$  (see Example sheet).
- (iii) In the Gaussian linear model  $Y = X\theta + \varepsilon$ , with a known  $X \in \mathbb{R}^{n \times p}$ , unknown  $\theta \in \mathbb{R}^p$ , and  $\varepsilon \sim \mathcal{N}(0, I_n)$ , the observations  $(Y_1, \dots, Y_n)$  are not iid, but a joint distribution  $f(Y_1, \dots, Y_n; \theta)$  can still be specified. The MLE is the least squares estimator (see Example sheet).

**Definition.** For  $\Theta \subseteq \mathbb{R}^p$  and  $l_n$  differentiable at  $\theta$ , the *score function*  $S_n$  is

$$S_n(\theta) = \begin{pmatrix} \frac{\partial}{\partial \theta_1} l_n(\theta) \\ \vdots \\ \frac{\partial}{\partial \theta_p} l_n(\theta) \end{pmatrix}$$

Solving for a root of  $S_n(\theta)$  is a common heuristic for maximising  $l_n(\theta)$ . In many cases, it is a necessary and sufficient condition.

**Note:** derivatives are taken with respect to  $\theta$ , not the  $x_i$ 's.

### Information geometry

Recall that if  $X$  is a random variable with distribution  $P_\theta$  on some space  $\mathcal{X} \subseteq \mathbb{R}^d$ , and  $g : \mathcal{X} \rightarrow \mathbb{R}$  is a function, then

$$E_\theta[g(X)] = \int_{\mathcal{X}} g(x) dP_\theta(x) = \int_{\mathcal{X}} g(x) f(x, \theta) dx$$

if  $X$  has a pdf  $f(x, \theta)$ , and

$$\mathbb{E}_\theta[g(X)] = \sum_{x \in \mathcal{X}} g(x) f(x, \theta)$$

if  $X$  has a pmf  $f(x, \theta)$

**Theorem 1.1.** Consider a model  $\{f(\cdot, \theta) : \theta \in \Theta\}$ , where  $f(\cdot, \theta)$  is a pdf/pmf and  $f(x, \theta) > 0$  for all  $x, \theta$ . Also suppose the model is correctly specified, with  $\theta_0$  equal to the true parameter, and  $\mathbb{E}_{\theta_0}[|\log(f(X, \theta))|] < \infty$  for all  $\theta \in \Theta$ . Then the function defined by  $l(\theta) = \mathbb{E}_{\theta_0}[\log(f(X, \theta))]$  is maximised at  $\theta_0$ .

*Proof.* Consider the case when  $X$  has a pdf (discrete case is analogous). For all  $\theta \in \Theta$ , we have

$$\begin{aligned} l(\theta) - l(\theta_0) &= \mathbb{E}_{\theta_0}[\log(f(X, \theta))] - \mathbb{E}_{\theta_0}[\log(f(X, \theta_0))] \\ &= \mathbb{E}_{\theta_0} \left[ \log \left( \frac{f(X, \theta)}{f(X, \theta_0)} \right) \right] \end{aligned}$$

Jensen's inequality:  $\mathbb{E}[\varphi(Z)] \leq \varphi(\mathbb{E}[Z])$  for any random variable  $Z$  and concave function  $\varphi$ .

Since  $\log$  is concave,

$$\begin{aligned} l(\theta) - l(\theta_0) &\leq \log \left( \mathbb{E}_{\theta_0} \left[ \frac{f(X, \theta)}{f(X, \theta_0)} \right] \right) \\ &= \log \left( \int_{\mathcal{X}} \frac{f(x, \theta)}{f(x, \theta_0)} f(x, \theta_0) dx \right) = \log 1 = 0 \end{aligned} \quad (*)$$

□

**Remark:** under the assumption of “strict identifiability of the model parameterisation”, i.e.,

$$f(\cdot, \theta) = f(\cdot, \theta') \iff \theta = \theta'$$

the inequality (\*) is strict, since equality occurs in Jensen only when  $\varphi$  is linear or  $Z$  is constant.

**Remark:** the quantity  $l(\theta_0) - l(\theta)$  computed above can be written as

$$\text{KL}(P_{\theta_0}, P_{\theta}) = \int_{\mathcal{X}} f(x, \theta_0) \log \left( \frac{f(x, \theta_0)}{f(x, \theta)} \right) dx$$

and is the Kullback-Leibler divergence in information theory. It is a “distance” between distributions. Maximising  $l(\theta)$  is equivalent to minimising KL.

## Fisher information

We consider the gradient and Hessian of the likelihood function.

**Theorem 1.2.** *For a parametric model  $\{f(\cdot, \theta) : \theta \in \Theta\}$ , “regular enough” so integration and differentiation can be interchanged, we have  $\mathbb{E}_{\theta}[\nabla_{\theta} \log(f(X, \theta))] = 0$  for all  $\theta \in \text{int}(\Theta)$ .*

*Proof.* We write the expectation

$$\begin{aligned} \mathbb{E}_{\theta}[\nabla_{\theta} \log(f(X, \theta))] &= \int_{\mathcal{X}} (\nabla_{\theta} \log f(x, \theta)) f(x, \theta) dx \\ &= \int_{\mathcal{X}} \frac{\nabla_{\theta} f(x, \theta)}{f(x, \theta)} f(x, \theta) dx \\ &= \nabla_{\theta} \left( \int_{\mathcal{X}} f(x, \theta) dx \right) = \nabla_{\theta}(1) = 0 \end{aligned}$$

□

**Remark:** in particular, when  $\theta_0 \in \text{int}(\Theta)$ , then  $\mathbb{E}_{\theta_0}[\nabla_{\theta} \log(f(X, \theta))] = 0$ .

**Definition.** For a parameter space  $\Theta \subseteq \mathbb{R}^p$ , the *Fisher information* matrix is defined by

$$I(\theta) = \mathbb{E}_{\theta} \left[ (\nabla_{\theta} \log f(X, \theta)) (\nabla_{\theta} \log f(X, \theta))^T \right], \quad \forall \theta \in \text{int}(\Theta)$$

in other words,

$$I_{ij}(\theta) = \mathbb{E}_{\theta} \left[ \frac{\partial}{\partial \theta_i} \log f(X, \theta) \frac{\partial}{\partial \theta_j} \log f(X, \theta) \right]$$

**Remark:** in 1 dimension, we have

$$I(\theta) = \mathbb{E}_{\theta} \left[ \left( \frac{d}{d\theta} \log f(X, \theta) \right)^2 \right] = \text{Var}_{\theta} \left[ \frac{d}{d\theta} \log f(X, \theta) \right]$$

Thus  $I_{\theta_0}$  describes random variations of  $S_n(\theta_0)$  about its mean. This in turn will help quantify the precision of  $\hat{\theta}$ , a zero of  $S_n(\hat{\theta}) = 0$ , about  $\theta_0$ .

**Theorem 1.3.** *Under the same regularity assumptions as the previous theorem*

$$I(\theta) = -\mathbb{E}_{\theta} [\nabla_{\theta}^2 \log(f(X, \theta))], \quad \forall \theta \in \text{int}(\Theta)$$

i.e.,

$$I_{ij}(\theta) = -\mathbb{E}_{\theta} \left[ \frac{\partial^2}{\partial \theta_i \partial \theta_j} \log f(X, \theta) \right]$$

*Proof.* We write

$$\nabla_{\theta}^2 \log f(X, \theta) = \nabla_{\theta} \left( \frac{\nabla_{\theta} f(X, \theta)}{f(X, \theta)} \right) = \frac{\nabla_{\theta}^2 f(X, \theta)}{f(X, \theta)} - \frac{\nabla_{\theta} f(X, \theta) \nabla_{\theta} f(X, \theta)^T}{f(X, \theta)^2}$$

note that

$$\mathbb{E} \left[ \frac{\nabla_{\theta}^2 f(X, \theta)}{f(X, \theta)} \right] = \int_{\mathcal{X}} \nabla_{\theta}^2 f(X, \theta) dx = \nabla_{\theta}^2 \int_{\mathcal{X}} f(X, \theta) dx = 0$$

Therefore

$$\begin{aligned} -\mathbb{E}_{\theta} [\nabla_{\theta}^2 \log f(X, \theta)] &= \mathbb{E}_{\theta} \left[ \frac{\nabla_{\theta} f(X, \theta) \nabla_{\theta} f(X, \theta)^T}{f^2(X, \theta)} \right] \\ &= \mathbb{E} \left[ \frac{\nabla_{\theta} f(X, \theta)}{f(X, \theta)} \left( \frac{\nabla_{\theta} f(X, \theta)}{f(X, \theta)} \right)^T \right] \\ &= \mathbb{E}_{\theta} [(\nabla_{\theta} \log f(X, \theta))(\nabla_{\theta} \log f(X, \theta))^T] \\ &= I(\theta) \end{aligned}$$

□

**Remark:** continuing the previous remark, in 1 dimension

$$\text{Var}_{\theta} \left[ \frac{d}{d\theta} \log f(X, \theta) \right] = I(\theta) = -\mathbb{E}_{\theta} \left[ \frac{d^2}{d\theta^2} \log f(X, \theta) \right]$$

this relates the variance of the score function and the curvature of  $l$ , both of which are relevant to describing the quality of the MLE  $\hat{\theta}$  as an approximation to  $\theta_0$ .

Suppose now  $X = (X_1, \dots, X_n)$  is a vector of iid copies of a random variable. Let  $I(\theta) = \mathbb{E}_\theta[(\nabla_\theta \log f(X_{i_1}, \theta))(\nabla_\theta \log f(X_{i_1}, \theta))^T]$  be the Fisher information of one copy of the random variable, and let

$$I_n(\theta) = \mathbb{E}_\theta[(\nabla_\theta \log f(X_1, \dots, X_n, \theta))(\nabla_\theta \log f(X_1, \dots, X_n, \theta))^T]$$

denotes the Fisher information of the random vector  $X$ .

**Theorem 1.4.** *In the setting described above, the Fisher information “tensorizes”*

$$I_n(\theta) = nI(\theta)$$

*Proof.* By independence,  $f(X_1, \dots, X_n, \theta) = \prod_{i=1}^n f(X_i, \theta)$ . Then  $\log f(X_1, \dots, X_n, \theta) = \sum_{i=1}^n \log f(X_i, \theta)$ . We write

$$\begin{aligned} I_n(\theta) &= \mathbb{E}_\theta[(\nabla_\theta \log f(X_1, \dots, X_n, \theta))(\nabla_\theta \log f(X_1, \dots, X_n, \theta))^T] \\ &= \mathbb{E}_\theta \left[ \left( \sum_{i=1}^n \nabla_\theta \log f(X_i, \theta) \right) \left( \sum_{i=1}^n \nabla_\theta \log f(X_i, \theta) \right)^T \right] \end{aligned}$$

Recall that  $\mathbb{E}_\theta[\nabla_\theta \log f(X_i, \theta)] = 0$ . Thus, by independence, all but the “diagonal” terms of the product remain, so

$$I_n(\theta) = \sum_{i=1}^n \mathbb{E}_\theta[(\nabla_\theta \log f(X_i, \theta))(\nabla_\theta \log f(X_i, \theta))^T] = nI(\theta)$$

□

## Cramer-Rao bound

**Theorem 1.5** (Cramer-Rao bound). *Let  $\{f(\cdot, \theta) : \theta \in \Theta\}$  be a “regular” statistical model with  $\Theta \subseteq \mathbb{R}$ . Let  $\tilde{\theta} = \tilde{\theta}(X_1, \dots, X_n)$  be an unbiased estimator of  $\theta$  based on  $n$  iid observations from the model. For all  $\theta \in \text{int}(\Theta)$ , we have*

$$\text{Var}_\theta(\tilde{\theta}) = \mathbb{E}_\theta[(\tilde{\theta} - \theta)^2] \geq \frac{1}{nI(\theta)}$$

*Proof.* Recall the Cauchy-Schwarz inequality:

$$(\mathbb{E}[YZ])^2 \leq \mathbb{E}[Y]^2 \mathbb{E}[Z]^2$$

for random variables  $Y, Z$ . In particular, we will take  $Y = \tilde{\theta} - \theta$  and  $Z = \frac{d}{d\theta} \log f(X_1, \dots, X_n, \theta)$ .

Note that  $\mathbb{E}_\theta[Y^2] = \mathbb{E}_\theta[(\tilde{\theta} - \theta)^2]$ . Also, by the previous theorem,

$$\mathbb{E}_\theta[Z^2] = I_n(\theta) = nI(\theta)$$

Furthermore,

$$\begin{aligned}\mathbb{E}_\theta[YZ] &= \mathbb{E}_\theta \left[ \tilde{\theta} \frac{d}{d\theta} \log f(X_1, \dots, X_n, \theta) \right] - \underbrace{\theta \mathbb{E}_\theta \left[ \frac{d}{d\theta} \log f(X_1, \dots, X_n, \theta) \right]}_{=0} \\ &= \int_{\mathcal{X}} \tilde{\theta}(X_1, \dots, X_n) \frac{\frac{d}{d\theta} f(X_1, \dots, X_n, \theta)}{f(X_1, \dots, X_n, \theta)} f(X_1, \dots, X_n) dx_1 \dots dx_n \\ &= \frac{d}{d\theta} \int_{\mathcal{X}} \tilde{\theta}(X_1, \dots, X_n) f(X_1, \dots, X_n, \theta) dx_1 \dots dx_n = \frac{d}{d\theta} \mathbb{E}_\theta[\tilde{\theta}] = 1\end{aligned}$$

and the result follows from Cauchy-Schwarz.  $\square$

**Remark:** if  $\tilde{\theta}$  is not unbiased, the same proof shows that

$$\text{Var}_\theta(\tilde{\theta}) \geq \frac{\left( \frac{d}{d\theta} \mathbb{E}_\theta[\tilde{\theta}] \right)^2}{nI(\theta)}$$

The Cramer-Rao bound is about a variance of an estimate, hence is univariate in nature. Here is one multivariate generalisation. Suppose  $\Theta \subseteq \mathbb{R}^p$  and  $\Phi : \Theta \rightarrow \mathbb{R}$  is differentiable. Suppose  $\tilde{\Phi}$  is an unbiased estimator of  $\Phi(\theta)$  based on iid observations  $(X_1, \dots, X_n)$  from a model  $\{f(\cdot, \theta) : \theta \in \Theta\}$ .

**Theorem 1.6.** For all  $\theta \in \text{int}(\Theta)$ , we have

$$\text{Var}_\theta(\tilde{\Phi}) \geq \frac{1}{n} \nabla_\theta \Phi(\theta)^T (I^{-1}(\theta)) \nabla_\theta \Phi(\theta)$$

*Proof.* Omitted. Can be derived using Cauchy-Schwarz.  $\square$

**Example.** Suppose  $\Phi(\theta) = \alpha^T \theta$ . Then  $\nabla_\theta \Phi(\theta) = \alpha$  so the lower bound is

$$\text{Var}_\theta(\tilde{\Phi}) \geq \frac{1}{n} \alpha^T I^{-1}(\theta) \alpha$$

In the example sheet, we will consider the special case of  $\begin{pmatrix} X_1 \\ X_2 \end{pmatrix} \sim \mathcal{N}(\theta, \Sigma)$

where  $\theta = \begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix} \in \mathbb{R}^2$  and  $\Sigma \in \mathbb{R}^{2 \times 2}$  is a known matrix. Let the sample size be  $n = 1$ .

Case 1: consider estimating  $\theta_1$  when  $\theta_2$  is known. This is a one-dimensional estimation problem, and we denote the Fisher information  $I_1(\theta)$ .

Case 2: consider estimating  $\theta_1$  when  $\theta_2$  is unknown. We can take  $\Phi(\theta) = \theta_1 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}^T \theta$  in the theorem above to obtain a lower bound

$$I_\Phi(\theta) = \nabla_\theta \Phi(\theta)^T I(\theta)^{-1} \nabla_\theta \Phi(\theta)$$



of the variance of an unbiased estimator.

We will show that  $I_1(\theta)^{-1} < I_\Phi(\theta)$ , unless  $X_1$  and  $X_2$  are independent (i.e. unless  $\Sigma$  is diagonal).

## Asymptotic theory of the MLE

Cramer-Rao is concerned with unbiased estimators, but not all estimators, even MLE's are unbiased.

On the other hand, a reasonable property to expect is *asymptotic unbiasedness*:  $\mathbb{E}_\theta[\tilde{\theta}_n] \rightarrow \theta$  as  $n \rightarrow \infty$ , when  $\tilde{\theta}_n$  is computed from  $n$  iid samples from  $P_\theta$ .

A stronger but related concept is *consistency*:  $\tilde{\theta}_n \rightarrow \theta$  as  $n \rightarrow \infty$  (where convergence is defined in a precise way to be discussed later).

For consistent estimators, a reasonable optimality criterion is *asymptotic efficiency*:  $n \text{Var}_\theta(\tilde{\theta}_n) \rightarrow I(\theta)^{-1}$  as  $n \rightarrow \infty$ , when  $\tilde{\theta}_n$  is computed from  $n$  iid samples from  $P_\theta$  (and  $p = 1$ ).

Note that Cramer-Rao does not imply that  $\liminf_{n \rightarrow \infty} n \operatorname{Var}_{\theta}(\tilde{\theta}_n) \geq I(\theta)^{-1}$  for any consistent estimator. However, this is true under appropriate regularity conditions.

Now, we will show that the MLE is always (under regularity conditions) asymptotically efficient. In fact

$$\hat{\theta}_{\text{mle}} \approx \mathcal{N}\left(\theta, \frac{I(\theta)^{-1}}{n}\right), \text{ for any } \theta \in \operatorname{int}(\Theta) \text{ and } n \text{ sufficiently large}$$

## Stochastic Convergence

We now introduce several basic definitions/results that will be used without proof.

**Definition.** Let  $\{X_n\}_{n \geq 0}$  and  $X$  be random vectors in  $\mathbb{R}^k$ , defined on a probability space  $(\Omega, \mathcal{A}, \mathbb{P})$ . So  $X : \Omega \rightarrow \mathbb{R}^k$ ,  $\mathcal{A}$  is the set of measurable sets (“events”).

1. We say  $X_n$  converges to  $X$  *almost surely*, or  $X_n \xrightarrow{\text{a.s.}} X$  as  $n \rightarrow \infty$ , if

$$\begin{aligned} \mathbb{P}(\omega \in \Omega : \|X_n(\omega) - X(\omega)\|_2 \rightarrow 0 \text{ as } n \rightarrow \infty) \\ = \mathbb{P}(\|X_n - X\|_2 \rightarrow 0 \text{ as } n \rightarrow \infty) = 1 \end{aligned}$$

2. We say that  $X_n$  converges to  $X$  *in probability*, or  $X_n \xrightarrow{P} X$  as  $n \rightarrow \infty$ , if for all  $\varepsilon > 0$ ,

$$\mathbb{P}(\|X_n - X\|_2 > \varepsilon) \rightarrow 0$$

3. We say that  $X_n$  converges to  $X$  *in distribution*, or  $X_n \xrightarrow{d} X$  as  $n \rightarrow \infty$ , if

$$\mathbb{P}(X_n \prec t) \rightarrow \mathbb{P}(X \prec t), \quad \forall t \text{ where } t \mapsto \mathbb{P}(X \prec t) \text{ is continuous}$$

we write  $\{X \prec t\}$  as a shorthand for  $\{X_{(1)} \leq t_1, \dots, X_{(k)} \leq t_k\}$ . For  $k = 1$ , this simply means

$$\mathbb{P}(X_n \leq t) \rightarrow \mathbb{P}(X \leq t)$$

i.e convergence of the usual cdf.

**Theorem 1.7.** *Almost sure convergence implies convergence in probability, which implies convergence in distribution. i.e*

$$X_n \xrightarrow{\text{a.s.}} X \implies X_n \xrightarrow{P} X \implies X_n \xrightarrow{d} X$$

*Proof.* See Probability & Measure. □

**Theorem 1.8** (Continuous mapping theorem). *If  $\{X_n\}$  and  $X$  take values in  $\mathcal{X} \subseteq \mathbb{R}^d$  and  $g : \mathcal{X} \rightarrow \mathbb{R}$  is continuous, then*

$$X_n \xrightarrow{\text{a.s./P/d}} X \implies g(X_n) \xrightarrow{\text{a.s./P/d}} g(X)$$

*Proof.* See Probability & Measure.  $\square$

**Theorem 1.9** (Slutsky's lemma). *Let  $X_n \xrightarrow{d} X$  and  $Y_n \xrightarrow{d} c$ , where  $c$  is deterministic (i.e non-stochastic). As  $n \rightarrow \infty$ , we have*

1.  $Y_n \xrightarrow{P} c$
2.  $X_n + Y_n \xrightarrow{d} X + c$
3. When  $Y_n$  is one-dimensional,  $X_n Y_n \xrightarrow{d} cX$ , and if  $c \neq 0$ ,  $\frac{X_n}{Y_n} \xrightarrow{d} \frac{X}{c}$
4. If  $\{A_n\}_{n \geq 0}$  are random matrices such that  $\{A_n\}_{ij} \xrightarrow{P} A_{ij}$  for all  $(i, j)$ , where  $A$  is deterministic, then  $A_n X_n \xrightarrow{d} AX$

*Proof.* See Probability & Measure.  $\square$

**Theorem 1.10.** *If  $X_n \xrightarrow{d} X$  as  $n \rightarrow \infty$ , then  $\{X_n\}_{n \geq 0}$  is bounded in probability, or  $X_n = O_p(1)$ : for all  $\varepsilon > 0$ , there exists  $M(\varepsilon) < \infty$  such that for all  $n \geq 0$*

$$\mathbb{P}(\|X_n\|_2 > M(\varepsilon)) < \varepsilon$$

*Proof.* See Probability & Measure.  $\square$

## Law of Large Numbers (LLN)

Many results in statistics are based on convergence of averages of iid random variables.

**Theorem 1.11** (Weak LLN). *Let  $X_1, \dots, X_n$  be iid copies of  $X$  with  $\text{Var}(X) < \infty$ . As  $n \rightarrow \infty$ , we have  $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i \xrightarrow{P} \mathbb{E}(X)$ .*

**Theorem 1.12** (Strong LLN). *Let  $X_1, \dots, X_n$  be iid copies of  $X \sim P$  on  $\mathbb{R}^k$ , such that  $\mathbb{E}[\|X\|_2] < \infty$ . Then as  $n \rightarrow \infty$  we have*

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i \xrightarrow{a.s.} \mathbb{E}[X]$$

We only prove the weak law or large numbers:

*Proof.* We will apply Chebyshev's inequality:

$$\mathbb{P}(|Z - \mu| \geq \varepsilon) \leq \frac{\text{Var}(Z)}{\varepsilon^2}$$

where  $\mu = \mathbb{E}[Z]$ . Take  $Z_n = \frac{1}{n} \sum_{i=1}^n (X_i - \mathbb{E}(X))$  for a fixed  $\varepsilon > 0$ . Then

$$\mathbb{P}(|\bar{X}_n - \mathbb{E}(X)| \geq \varepsilon) = \mathbb{P}(|Z_n| \geq \varepsilon) \leq \frac{\text{Var}(Z_n)}{\varepsilon^2}$$

So it suffices to show  $\text{Var}(Z_n) \rightarrow 0$ . By independence of the  $X_i$ 's, we have

$$\text{Var}(Z_n) = \frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i) = \frac{\text{Var}(X)}{n} \rightarrow 0$$

since  $\text{Var}(X) < \infty$ .  $\square$

## Central Limit Theorem (CLT)

We now present a finer-grained characterisation of the behaviour of  $\bar{X}_n$ . The stochastic fluctuations of  $\bar{X}_n$  around  $\mathbb{E}(X)$  are of the order  $\frac{1}{\sqrt{n}}$  and look normally distributed.

**Theorem 1.13** (CLT). *Let  $X_1, \dots, X_n$  be iid copies of  $X \sim P$  on  $\mathbb{R}$ , such that  $\text{Var}(X) = \sigma^2 < \infty$ . As  $n \rightarrow \infty$ , we have*

$$\sqrt{n} \left( \frac{1}{n} \sum_{i=1}^n X_i - \mathbb{E}(X) \right) \xrightarrow{d} \mathcal{N}(0, \sigma^2)$$

*Proof.* Omitted. □

**Remark:** the CLT is useful for constructing confidence intervals. Suppose  $X_1, \dots, X_n$  is a sequence of iid copies of a random variable with mean  $\mu_0$  and variance  $\sigma^2$ , and let  $\alpha \in (0, 1)$ . Define the confidence region

$$\mathcal{C}_n = \left\{ \mu \in \mathbb{R} : |\mu - \bar{X}_n| \leq \frac{\sigma z_\alpha}{\sqrt{n}} \right\}$$

where  $z_\alpha$  is defined such that  $\mathbb{P}(|Z| \leq z_\alpha) = 1 - \alpha$ , for  $Z \in \mathcal{N}(0, 1)$ . Then we can compute

$$\begin{aligned} \mathbb{P}(\mu_0 \in \mathcal{C}_n) &= \mathbb{P} \left( \left| \frac{1}{n} \sum_{i=1}^n \frac{X_i - \mu_0}{\sigma} \right| \leq \frac{z_\alpha}{\sqrt{n}} \right) \\ &= \mathbb{P} \left( \sqrt{n} \left| \frac{1}{n} \sum_{i=1}^n \tilde{X}_i - \mathbb{E}(\tilde{X}) \right| \leq z_\alpha \right) \\ &\rightarrow \mathbb{P}(|Z| \leq z_\alpha) = 1 - \alpha \end{aligned}$$

where  $\tilde{X}_i = \frac{X_i - \mu_0}{\sigma}$ , is a zero mean, variance 1 random variable. So  $\mathcal{C}_n$  is an asymptotic level  $(1 - \alpha)$  confidence interval.

**Theorem 1.14** (Multivariate CLT). *Let  $X_1, \dots, X_n$  be iid copies of  $X \sim P$  on  $\mathbb{R}^k$ , such that  $\text{Cov}(X) = \Sigma$  is positive definite. As  $n \rightarrow \infty$  we have*

$$\sqrt{n} \left( \frac{1}{n} \sum_{i=1}^n X_i - \mathbb{E}(X) \right) \xrightarrow{d} \mathcal{N}(0, \Sigma)$$

**Remark:** recall that a random vector  $X \in \mathbb{R}^k$  has a normal distribution with mean  $\mu \in \mathbb{R}^k$  and covariance  $\Sigma \in \mathbb{R}^{k \times k}$ , denoted by  $X \sim \mathcal{N}(\mu, \Sigma)$ , if the pdf is

$$f(x) = \frac{1}{(2\pi)^{k/2}} \frac{1}{|\det(\Sigma)|^{1/2}} \exp \left( -\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) \right)$$

**Remark:** as a consequence of one of the theorems above, we also have

$$\frac{1}{n} \sum_{i=1}^n X_i - \mathbb{E}(X) = \mathcal{O}_p \left( \frac{1}{\sqrt{n}} \right)$$

## Consistency of the MLE

**Definition.** Consider iid draws  $X_1, \dots, X_n$  from the parametric model  $\{P_\theta : \theta \in \Theta\}$ . An estimator  $\tilde{\theta}_n = \tilde{\theta}_n(X_1, \dots, X_n)$  is *consistent* if  $\tilde{\theta}_n \xrightarrow{P} \theta$  as  $n \rightarrow \infty$ , whenever the  $X_i$ 's are drawn from  $P_\theta$ . We also write  $\tilde{\theta}_n \xrightarrow{P_\theta} \theta$ .

We will show that the MLE is unique and consistent under the following regularity assumptions:

Let  $\{f(\cdot, \theta) : \theta \in \Theta\}$  be a statistical model of pdf's/pmf's on  $\mathcal{X} \subseteq \mathbb{R}^d$  such that

1.  $f(x, \theta) > 0$  for all  $x \in \mathcal{X}$ ,  $\theta \in \Theta$
2. The function  $f(x, \cdot) : \theta \mapsto f(x, \theta)$  is continuous for all  $x \in \mathcal{X}$ .
3. The set  $\Theta \subseteq \mathbb{R}^p$  is compact.
4. For any  $\theta, \theta' \in \Theta$ ,  $f(\cdot, \theta) = f(\cdot, \theta')$  if and only if  $\theta = \theta'$  (strict identifiability)
5.  $\mathbb{E}_\theta [\sup_{\theta'} |\log f(X, \theta')|] < \infty$  for all  $\theta \in \Theta$ .

These will be referred to as “the usual regularity conditions” in this course and its Examples sheets/Exams.

### Remarks:

- Assumptions 1 and 4 are required to apply the strict version of Jensen's inequality to deduce that  $\theta_0$  is the unique maximum of  $l(\theta) = \mathbb{E}_{\theta_0} [\log f(X, \theta)]$ .
- Assumption 5 implies that continuity of the function  $\theta \mapsto \log f(x, \theta)$  carries over to continuity of  $\theta \mapsto \mathbb{E}_\theta [\log f(X, \theta)] = l(\theta)$ , according to the Dominated Convergence Theorem.

**Theorem 1.15** (\*Dominated Convergence Theorem\*). *If a sequence of (measurable) functions  $\{f_n\}$  converges pointwise to a function  $f : \mathcal{X} \rightarrow \mathbb{R}$  such that  $|f_n(x)| \leq g(x)$  for all  $x \in \mathcal{X}$ , for some function  $g : \mathcal{X} \rightarrow \mathbb{R}$  such that  $\mathbb{E}[|g(X)|] < \infty$ , where  $X$  is a random variable taking values in  $\mathcal{X}$ , then*

$$\mathbb{E}|f_n(X) - f(X)| \rightarrow 0 \text{ as } n \rightarrow \infty$$

In particular, for any sequence  $\theta_n \rightarrow \theta$  in  $\Theta$ , we can define  $f_n(x) = \log(f(x, \theta_n))$  and  $g(x) = \sup_{\theta'} |\log f(x, \theta')|$  and conclude that  $l(\theta_n) \rightarrow l(\theta)$ .

**Theorem 1.16.** *Let  $X_1, \dots, X_n$  be iid samples of a model  $\{f(\cdot, \theta) : \theta \in \Theta\}$  satisfying the above assumptions. Then an MLE exists, and any MLE is consistent.*

*Proof.* Note that the mapping  $\theta \mapsto \bar{l}_n(\theta) = \frac{1}{n} \sum_{i=1}^n \log f(x_i, \theta)$  is continuous on the compact set  $\Theta$ . Thus a maximiser exists, so the MLE is well-defined.

To prove consistency, let  $\theta_0$  denote the true parameter. We use (without proof) the fact that under the regularity assumptions, we have the uniform convergence

$$\sup_{\theta \in \Theta} |\bar{l}_n(\theta) - l(\theta)| \xrightarrow{P_{\theta_0}} 0$$

(This is somewhat stronger than the LLN, which concerns convergence just at fixed  $\theta$ )

Now define  $\Theta_\varepsilon = \{\theta \in \Theta : \|\theta - \theta_0\|_2 \geq \varepsilon\}$ , for arbitrary  $\varepsilon > 0$ . We will show that for any sequence of MLE's  $\{\hat{\theta}_n\}$ , we have  $\mathbb{P}(\hat{\theta}_n \in \Theta_\varepsilon) \rightarrow 0$  as  $n \rightarrow \infty$ .

Note that since  $\Theta_\varepsilon$  is the intersection of  $\Theta$  with a closed set, it is also compact. Thus, there exists  $\theta_\varepsilon \in \Theta_\varepsilon$  such that  $l(\theta_\varepsilon) = \sup_{\theta \in \Theta_\varepsilon} l(\theta) := c(\varepsilon) < l(\theta_0)$ , since  $\theta_0$  is the unique maximiser of  $l$ .

Let  $\delta(\varepsilon) > 0$  be such that  $\delta(\varepsilon) < \frac{l(\theta_0) - c(\varepsilon)}{2}$ . We now write

$$\begin{aligned} \sup_{\theta \in \Theta_\varepsilon} \bar{l}_n(\theta) &\leq \sup_{\theta \in \Theta_\varepsilon} l(\theta) + \sup_{\theta \in \Theta_\varepsilon} (\bar{l}_n(\theta) - l(\theta)) \\ &\leq \sup_{\theta \in \Theta_\varepsilon} l(\theta) + \sup_{\theta \in \Theta} |\bar{l}_n(\theta) - l(\theta)| \end{aligned}$$

Consider the sequence of events

$$A_n(\varepsilon) = \left\{ \sup_{\theta \in \Theta} |\bar{l}_n(\theta) - l(\theta)| \leq \delta(\varepsilon) \right\}$$

By the assumed uniform convergence statement, we have  $\mathbb{P}(A_n(\varepsilon)) \rightarrow 1$  as  $n \rightarrow \infty$ .

We now argue that  $A_n(\varepsilon) \subseteq \{\hat{\theta}_n \notin \Theta_\varepsilon\}$ , which then implies the desired result.

Indeed, on the events  $\{A_n(\varepsilon)\}$ , we have

$$\sup_{\theta \in \Theta_\varepsilon} \bar{l}_n(\theta) \leq c(\varepsilon) + \delta(\varepsilon) < l(\theta_0) - \delta(\varepsilon) \leq \bar{l}_n(\theta_0)$$

Thus, the MLE cannot lie in  $\Theta_\varepsilon$ , completing the proof.  $\square$

**Remark:** the proof can be simplified under additional properties of the likelihood function, such as differentiability and/or uniqueness of zeros. This can be useful in situations where  $\Theta$  is not compact (see Example sheet).

## Uniform Law of Large Numbers

In the proof of consistency of the MLE, we assumed

$$\sup_{\theta \in \Theta} |\bar{l}_n(\theta) - l(\theta)| \xrightarrow{P_{\theta_0}} 0$$

**Theorem 1.17** (ULLN). *Let  $\Theta$  be a compact set in  $\mathbb{R}^p$  and let  $q : \mathcal{X} \times \Theta \rightarrow \mathbb{R}$  be continuous in  $\theta$  for all  $x$ . Suppose  $\mathbb{E}[\sup_{\theta \in \Theta} |q(X, \theta)|] < \infty$ , where  $X$  is a random variable defined over  $\mathcal{X}$ . Suppose  $X_1, \dots, X_n$  are drawn iid according to the distribution of  $X$ . Then as  $n \rightarrow \infty$*

$$\sup_{\theta \in \Theta} \left| \frac{1}{n} \sum_{i=1}^n q(X_i, \theta) - \mathbb{E}[q(X, \theta)] \right| \xrightarrow{a.s.} 0$$

We now discuss the proof of the theorem (\*Non-examinable\*). The main idea is that since  $\Theta$  is compact, it can be covered by a finite subcover up to a fixed precision (Heine-Borel Theorem).

### \*Beginning of non-examinable section\*

*\*Proof\**. It is relatively easy to show that for a finite set  $\{\theta_1, \dots, \theta_M\} \subseteq \Theta$ , we have

$$\max_{1 \leq j \leq M} \left| \frac{1}{n} \sum_{i=1}^n q(X_i, \theta_j) - \mathbb{E}[q(X, \theta_j)] \right| \xrightarrow{a.s.} 0 \quad (*)$$

Let  $h_j(\cdot) = q(\cdot, \theta_j)$ . Let  $A_j$  be the event that  $\frac{1}{n} \sum_{i=1}^n h_j(X_i) - \mathbb{E}[h_j(X)] \rightarrow 0$ . Then  $\mathbb{P}(A_j) = 1$  by the Strong LLN. Letting  $A = \bigcap_{j=1}^M A_j$ , we have

$$\mathbb{P}(A^c) = \mathbb{P}\left(\bigcup_{j=1}^M A_j^c\right) \leq \sum_{j=1}^M \mathbb{P}(A_j^c) = 0$$

For a general class  $\mathcal{H}$  of functions  $h : \mathcal{X} \rightarrow \mathbb{R}$ , we say that a family of *brackets*  $\{[\underline{h}_j, \bar{h}_j]\}_{j=1}^N$  covers  $\mathcal{H}$  if for all  $h \in \mathcal{H}$ , there exists  $j$  such that

$$\underline{h}_j(x) \leq h(x) \leq \bar{h}_j(x), \quad \forall x \in \mathcal{X}$$

□

**Theorem 1.18.** *Suppose  $\mathcal{H}$  is a class of functions such that for all  $\varepsilon > 0$ , there exist finitely many brackets  $\{[\underline{h}_j, \bar{h}_j]\}_{j=1}^{N(\varepsilon)}$  which cover  $\mathcal{H}$ , and such that for all  $1 \leq j \leq N(\varepsilon)$*

1.  $\mathbb{E}|\underline{h}_j(X)| < \infty, \mathbb{E}|\bar{h}_j(X)| < \infty$
2.  $\mathbb{E}|\bar{h}_j(X) - \underline{h}_j(X)| < \varepsilon$



If  $X_1, \dots, X_n$  are iid copies of  $X$ , then

$$\sup_{h \in \mathcal{H}} \left| \frac{1}{n} \sum_{i=1}^n h(X_i) - \mathbb{E}[h(X)] \right| \xrightarrow{a.s.} 0$$

*Proof.* For a given  $\varepsilon > 0$ , consider the set of  $N := N(\varepsilon/3)$  brackets guaranteed to exist by the hypothesis of the theorem. By the convergence result (\*), we know that almost surely we have

$$\max_{1 \leq j \leq N} \left| \frac{1}{n} \sum_{i=1}^n \bar{h}_j(X) - \mathbb{E}[\bar{h}_j(X)] \right| < \frac{\varepsilon}{3}$$

$$\max_{1 \leq j \leq N} \left| \frac{1}{n} \sum_{i=1}^n \underline{h}_j(X) - \mathbb{E}[\underline{h}_j(X)] \right| < \frac{\varepsilon}{3}$$

For  $n \geq n_0(\varepsilon)$ . Now take  $h \in \mathcal{H}$  arbitrarily. From the above inequalities, we have (for some  $j$ )

$$\begin{aligned} \frac{1}{n} \sum_{i=1}^n h(X_i) - \mathbb{E}[h(X)] &\leq \frac{1}{n} \sum_{i=1}^n \bar{h}_j(X) - \mathbb{E}[\bar{h}_j(X)] + (\mathbb{E}[\bar{h}_j(X)] - \mathbb{E}[h(X)]) \\ &\leq \frac{1}{n} \sum_{i=1}^n \bar{h}_j(X) - \mathbb{E}[\bar{h}_j(X)] + (\mathbb{E}[\bar{h}_j(X)] - \mathbb{E}[\underline{h}_j(X)]) \\ &< \frac{\varepsilon}{3} + \mathbb{E}[\bar{h}_j(X) - \underline{h}_j(X)] \\ &< \frac{2\varepsilon}{3} \end{aligned}$$

Similarly,

$$\begin{aligned} \frac{1}{n} \sum_{i=1}^n h(X_i) - \mathbb{E}[h(X)] &\geq \frac{1}{n} \sum_{i=1}^n \underline{h}_j(X) - \mathbb{E}[\underline{h}_j(X)] + (\mathbb{E}[\underline{h}_j(X)] - \mathbb{E}[h(X)]) \\ &\geq -\frac{\varepsilon}{3} - \mathbb{E}[\bar{h}_j(X) - \underline{h}_j(X)] > -\frac{2\varepsilon}{3} \end{aligned}$$

So almost surely,

$$\sup_{h \in \mathcal{H}} \left| \frac{1}{n} \sum_{i=1}^n h(x_i) - \mathbb{E}[h(X)] \right| < \frac{2\varepsilon}{3} < \varepsilon, \quad \text{for } n \geq n_0(\varepsilon)$$

Since  $\varepsilon$  was arbitrary, this implies the result.  $\square$

To move from the preceding theorem to the proof of the ULLN, we need to find an appropriate bracketing cover for the set of functions  $\mathcal{H} = \{q(\cdot, \theta) : \theta \in \Theta\}$ .

We define the open balls

$$B_\eta(\theta) = \{\theta' \in \Theta : \|\theta - \theta'\|_2 < \eta\}$$

Now define the functions

$$u_\eta(x, \theta) = \sup_{\theta' \in B_\eta(\theta)} q(x, \theta')$$

$$l_\eta(x, \theta) = \inf_{\theta' \in B_\eta(\theta)} q(x, \theta')$$

By assumption,  $\mathbb{E}[|u_\eta(X, \theta)|] < \infty$  and  $\mathbb{E}[|l_\eta(X, \theta)|] < \infty$  for each  $\theta, \eta$ . Furthermore, by continuity of  $q(X, \cdot)$ , together with the Dominated Convergence Theorem, we can choose a radius  $\eta_\varepsilon(\theta)$  for each  $\theta$  such that the (expected) width of the corresponding brackets is bounded by  $\varepsilon$ .

Then by compactness of  $\Theta$ , we can define a finite set  $\{\theta_1, \dots, \theta_N\} \subseteq \Theta$  constituting a subcover of  $\Theta$ . Applying the preceding theorem completes the proof.

**\*End of non-examinable section\***

## Asymptotic normality of the MLE

**Assumptions:** Let  $\{f(\cdot, \theta) : \theta \in \Theta\}$  be a statistical model of pdfs/pmfs on  $\mathcal{X} \subseteq \mathbb{R}^d$  such that, in addition to the assumptions stated for consistency of the MLE, we have

1. The true  $\theta_0$  belongs to  $\text{int}(\Theta)$ .
2. There exists an open set  $U \subseteq \Theta$  containing  $\theta_0$  such that  $\theta \mapsto f(x, \theta)$  is twice continuously differentiable with respect to  $\theta \in U$ , for each  $x \in \mathcal{X}$ .
3. The Fisher information matrix  $I(\theta_0) \in \mathbb{R}^{p \times p}$  is non-singular, and

$$\mathbb{E}_{\theta_0} [||(\nabla_{\theta} \log f(X, \theta))||_{\theta=\theta_0}] < \infty$$

4. There exists a compact ball  $K \subseteq U$  with  $\text{int}(K) \neq \emptyset$  centred at  $\theta_0$ , such that

$$\mathbb{E}_{\theta_0} \left[ \sup_{\theta \in K} ||\nabla_{\theta}^2 \log f(X, \theta)||_2 \right] < \infty$$

$$\int_{\mathcal{X}} \sup_{\theta \in K} ||\nabla_{\theta} \log f(X, \theta)||_2 dx < \infty$$

$$\int_{\mathcal{X}} \sup_{\theta \in K} ||\nabla_{\theta}^2 \log f(X, \theta)||_2 dx < \infty$$

These assumptions are stated only for rigor, and are \*non-examinable\*.

**Theorem 1.19.** Suppose the statistical model  $\{f(\cdot, \theta) : \theta \in \Theta\}$  satisfies the above regularity conditions, and let  $\hat{\theta}_n$  be an MLE based on  $n$  iid observations  $X_1, \dots, X_n$  with distribution  $P_{\theta_0}$ . As  $n \rightarrow \infty$ , we have  $\sqrt{n}(\hat{\theta}_n - \theta_0) \xrightarrow{d} \mathcal{N}(0, I(\theta_0)^{-1})$ .

*Proof.* Idea: “Mean Value Theorem + Central Limit Theorem”.

Define  $\varepsilon > 0$  such that the ball of radius  $\varepsilon$  around  $\theta_0$  is contained in  $K$ . Let  $E_n = \{||\hat{\theta}_n - \theta_0||_2 \leq \varepsilon\}$ . Then  $\mathbb{P}(E_n) \rightarrow 1$  since  $\hat{\theta}_n \xrightarrow{P_{\theta_0}} \theta_0$ .

We can focus on these events  $\{E_n\}$  for the rest of the proof, since we are trying to show something about convergence of cdf’s. On these events, the regularity assumptions imply  $\nabla_{\theta} \bar{l}_n(\hat{\theta}_n) = 0$ , by the first-order optimality condition. Applying the Mean Value Theorem coordinate-wise between  $\theta_0$  and  $\hat{\theta}_n$ , we have

$$0 = \nabla_{\theta} \bar{l}_n(\hat{\theta}_n) = \nabla_{\theta} \bar{l}_n(\theta_0) + \bar{A}_n (\hat{\theta}_n - \theta_0)$$

where  $\bar{A}_n$  is defined coordinate-wise as

$$(\bar{A}_n)_{ij} = \frac{\partial^2}{\partial \theta_i \partial \theta_j} \bar{l}_n(\theta^{(i)}), \text{ for some } \theta^{(i)} \in [\theta_0, \hat{\theta}_n]$$

Rearranging gives

$$\sqrt{n}(\hat{\theta}_n - \theta_0) = (-\bar{A}_n^{-1}) \sqrt{n} \nabla_{\theta} \bar{l}_n(\theta_0)$$

Note that

$$\sqrt{n} \nabla_{\theta} \bar{l}_n(\theta_0) = \frac{1}{\sqrt{n}} \sum_{i=1}^n \left( \nabla_{\theta} \log f(X_i, \theta) - \underbrace{\mathbb{E}_{\theta_0} [\nabla_{\theta} \log f(X, \theta_0)]}_{=0} \right)$$

Thus, by the multivariate CLT

$$\sqrt{n} \nabla_{\theta} \bar{l}_n(\theta_0) \xrightarrow{d} \mathcal{N}(0, \text{Cov}_{\theta_0}(\nabla_{\theta} \log f(X, \theta_0))) = \mathcal{N}(0, I(\theta_0))$$

Now it suffices to show

$$\bar{A}_n \xrightarrow{P} \mathbb{E}_{\theta_0} [\nabla_{\theta}^2 \bar{l}_n(\theta_0)] = -I(\theta_0)$$

Since then by the continuous mapping theorem  $(\bar{A}_n)^{-1} \xrightarrow{P} -I(\theta_0)^{-1}$ . Then by Slutsky's Lemma

$$\sqrt{n} \nabla_{\theta} \bar{l}_n(\theta_0) \xrightarrow{d} I(\theta_0)^{-1}(0, I(\theta_0)) = \mathcal{N}(0, I(\theta_0)^{-1})$$

The rest of this proof is \*non-examinable\*. It suffices to prove the convergence  $\bar{A}_n \xrightarrow{P} I(\theta_0)$  for each entry of  $\bar{A}_n$ .

For each entry, we write

$$\begin{aligned} (\bar{A}_n)_{jk} &= \frac{1}{n} \sum_{i=1}^n \left( \frac{\partial^2}{\partial \theta_j \partial \theta_k} \log f(X_i, \theta^{(j)}) - \mathbb{E}_{\theta_0} \left[ \frac{\partial^2}{\partial \theta_j \partial \theta_k} \log f(X, \theta^{(j)}) \right] \right) \\ &\quad + \mathbb{E}_{\theta_0} \left[ \frac{\partial^2}{\partial \theta_j \partial \theta_k} \log f(X, \theta^{(j)}) \right] - \mathbb{E}_{\theta_0} \left[ \frac{\partial^2}{\partial \theta_j \partial \theta_k} \log f(X, \theta_0) \right] + (-I(\theta_0))_{jk} \end{aligned}$$

Denoting  $q(X, \theta) = \frac{\partial^2}{\partial \theta_j \partial \theta_k} \log f(x, \theta)$ , the regularity assumptions imply continuity of  $q(x, \theta)$  and  $\mathbb{E}_{\theta_0}[q(x, \theta)]$  for all  $x \in \mathcal{X}$ . We can then conclude by the ULLN that

$$\frac{1}{n} \sum_{i=1}^n \left( \frac{\partial^2}{\partial \theta_j \partial \theta_k} \log f(X_i, \theta^{(j)}) - \mathbb{E}_{\theta_0} \left[ \frac{\partial^2}{\partial \theta_j \partial \theta_k} \log f(X, \theta^{(j)}) \right] \right) \xrightarrow{\text{a.s.}} 0$$

(and so also converges in probability). Now note

$$|\mathbb{E}_{\theta_0}[q(X, \theta^{(j)})] - \mathbb{E}_{\theta_0}[q(X, \theta_0)]| \xrightarrow{P} 0$$

using the fact that  $\theta^{(j)} \xrightarrow{P} \theta_0$  (by consistency of  $\hat{\theta}_n$  and the continuous mapping theorem).  $\square$

By the theorem, we conclude that the MLE is both asymptotically normal and asymptotically efficient.

**Definition.** In a parametric model  $\{f(\cdot, \theta) : \theta \in \Theta\}$ , a consistent estimator  $\tilde{\theta}_n$  is *asymptotically efficient* if  $n \text{Var}_\theta(\tilde{\theta}_n) \rightarrow I(\theta)^{-1}$  for all  $\theta \in \text{int}(\Theta)$  (if  $p = 1$ ) or when  $p > 1$   $n \text{Cov}_\theta(\tilde{\theta}_n) \rightarrow I(\theta)^{-1}$  for all  $\theta \in \text{int}(\Theta)$ .

**Remarks:**

1. At the expense of more complicated proofs, can reduce the regularity conditions required for the function  $\theta \mapsto f(x, \theta)$ . In particular, this allows us to consider Laplace distributions, where the log-likelihood is not everywhere differentiable, since the pdf is proportional to  $\exp(-|x - \theta|)$ .
2. Some notion of regularity is required: the uniform distribution on  $[0, \theta]$  with density  $f(x, \theta) = \frac{1}{\theta} 1_{[0, \theta]}$ , the likelihood is discontinuous. The asymptotic theory breaks down in this case (see Example sheet).
3. For  $\theta_0$  at the boundary of  $\Theta$ , asymptotics also might not be normal. In the case of the model  $\mathcal{N}(\theta, 1)$  for  $\theta \in [0, \infty)$ , when  $\theta_0 = 0$  (see Example sheet).
4. Although it can be shown that the optimal asymptotic variance for a “regular” estimator is indeed  $\frac{1}{n} I^{-1}(\theta_0)$ , estimators outside this class could have smaller variances. For example, Hodge’s estimator: let  $\hat{\theta}_n$  be the MLE. Consider

$$\tilde{\theta}_n = \begin{cases} \hat{\theta}_n & |\hat{\theta}_n| > n^{-1/4} \\ 0 & \text{otherwise} \end{cases}$$

This is not a very sensible estimator and does not satisfy the regularity assumptions. However it is “superefficient”, i.e has smaller asymptotic variance than the MLE under the above  $\mathcal{N}(\theta, 1)$  model for certain values in  $\Theta$  (see Example sheet).

However the Hodges’ estimator does worse than the MLE in terms of another criterion, the minimax risk.

## Plug-in MLE & Delta Method

Now consider the following estimation problem: for a parametric model  $\{f(\cdot, \theta) : \theta \in \Theta\}$ , we wish to estimate  $\Phi(\theta)$ , where  $\Phi : \Theta \rightarrow \mathbb{R}^k$  and  $\Theta \subseteq \mathbb{R}^p$ . First consider a special case, and introduce the following definition:

**Definition.** For  $\Theta = \Theta_1 \times \Theta_2$ , and  $\theta = \begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix}$ , define the *profile likelihood*, for  $\Phi(\theta) = \theta_1$  by  $L^{(p)}(\theta_1) = \sup_{\theta_2 \in \Theta_2} L(\theta_1, \theta_2)$ .

Note that maximising  $L^{(p)}$  is equivalent to maximising  $L$  and taking the first argument of the maximiser.

**Example.**  $\mathcal{N}(\mu, \sigma^2)$ , where  $\theta = (\mu, \sigma^2) \in \mathbb{R} \times (0, \infty)$ . Recall (from the Example sheet)  $\hat{\mu}_{\text{MLE}} = \bar{X}_n$  and  $\hat{\sigma}_{\text{MLE}}^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X}_n)^2$ .

For general function  $\Phi$ , can show that if  $\Phi$  is injective, an MLE in the new parameterisation in  $\phi$ , given by  $\{f(\cdot, \phi) : \phi = \Phi(\theta), \theta \in \Theta\}$ , is obtained by taking  $\Phi(\hat{\theta}_{\text{MLE}})$  (see Example sheet). For the above example, could take  $\Phi : (\mu, \sigma^2) \mapsto (\mu, \sigma)$ .

In fact when  $\Phi$  is not injective, can also define an MLE for  $\phi$  and state a similar result:  $\Phi(\hat{\theta}_{\text{MLE}})$  is always an MLE for the *induced likelihood function*  $L^*(\phi) = \sup_{\theta: \Phi(\theta)=\phi} L(\theta)$  - e.g see the profile likelihood above.

**Definition.** For a statistical model  $\{f(\cdot, \theta) : \theta \in \Theta\}$  and a function  $\Phi : \Theta \rightarrow \mathbb{R}^k$ , the *plug-in MLE* of  $\Phi$  is the estimator  $\Phi(\hat{\theta}_{\text{MLE}})$ .

**Theorem 1.20** (Delta Method). *Let  $\Phi : \Theta \rightarrow \mathbb{R}$  be continuously differentiable at  $\theta_0$ , with gradient satisfying  $\nabla_{\theta}\Phi(\theta_0) \neq 0$ . Let  $\{\hat{\theta}_n\}$  be a sequence of estimators such that  $\sqrt{n}(\hat{\theta}_n - \theta_0) \xrightarrow{d} Z$ , where  $Z$  is a random vector in  $\mathbb{R}^p$ . Then*

$$\sqrt{n}(\Phi(\hat{\theta}_n) - \Phi(\theta_0)) \xrightarrow{d} \nabla_{\theta}\Phi(\theta_0)^T Z$$

*Proof.* By the MVT, for some  $\tilde{\theta}_n$  in the line segment  $[\theta_0, \hat{\theta}_n]$ , we have

$$\sqrt{n}(\Phi(\hat{\theta}_n) - \Phi(\theta_0)) = \nabla_{\theta}\Phi(\tilde{\theta}_n)^T \sqrt{n}(\hat{\theta}_n - \theta_0)$$

Since  $\sqrt{n}(\hat{\theta}_n - \theta_0) \xrightarrow{d} Z$ , we have  $\sqrt{n}(\hat{\theta}_n - \theta_0) = \mathcal{O}_p(1)$ . Thus, for any  $\varepsilon, \delta > 0$  there exists  $M(\delta)$  such that

$$\mathbb{P}\left(\sqrt{n}\|\hat{\theta}_n - \theta_0\|_2 > M(\delta)\right) < \delta, \quad \forall n \in \mathbb{N}$$

So if we choose  $n$  large enough such that  $\frac{M(\delta)}{\sqrt{n}} < \varepsilon$ , we have

$$\mathbb{P}\left(\|\tilde{\theta}_n - \theta_0\|_2 > \varepsilon\right) \leq \mathbb{P}\left(\|\hat{\theta}_n - \theta_0\|_2 > \varepsilon\right) \leq \mathbb{P}\left(\|\hat{\theta}_n - \theta_0\|_2 > \frac{M(\delta)}{\sqrt{n}}\right)$$

Implying that  $\tilde{\theta}_n \xrightarrow{P} \theta_0$ . By the Continuous Mapping Theorem, we have  $\nabla_{\theta}\Phi(\tilde{\theta}_n) \xrightarrow{P} \nabla_{\theta}\Phi(\theta_0)$ . The result then follows by Slutsky's Lemma.  $\square$

**Remarks:**

1. The Delta Method can be generalised to other estimators, taking a sequence  $r_n \rightarrow \infty$  instead of  $\sqrt{n}$  (obvious from the proof).
2. In the case of the MLE, combining with the theorem about asymptotic normality, we have

$$\sqrt{n} \left( \Phi(\hat{\theta}_n) - \Phi(\theta_0) \right) \xrightarrow{d} \mathcal{N}(0, \nabla_{\theta}\Phi(\theta_0)^T I^{-1}(\theta_0) \nabla_{\theta}\Phi(\theta_0))$$

So when  $\theta$  is one-dimensional

$$\sqrt{n} \left( \Phi(\hat{\theta}_n) - \Phi(\theta_0) \right) \xrightarrow{d} \mathcal{N}\left(0, \frac{\Phi'(\theta_0)^2}{I(\theta_0)}\right)$$

3. The previous calculation also shows that the plug-in MLE is asymptotically efficient. Recall the “multivariate” Cramer-Rao lower bound from before:

$$\text{Var}_{\theta_0} \left( \Phi(\hat{\theta}_n) \right) \geq \frac{1}{n} \nabla_{\theta}\Phi(\theta_0)^T I^{-1}(\theta_0) \nabla_{\theta}\Phi(\theta_0)$$

4. We don't really use the fact that  $\nabla_{\theta}\Phi(\theta_0) \neq 0$  in the proof. But in that case, we have convergence in distribution to 0, so this is not very informative (so should rescale by something bigger than  $\sqrt{n}$ )
5. The proof of the Delta Method extends to multivariate functions in a straightforward manner.

**Example.** Consider the model  $\mathcal{N}(\theta, 1)$ ,  $\Theta = \mathbb{R}$ . Then  $\hat{\theta}_{\text{MLE}} = \bar{X}_n$ . SO  $\sqrt{n}(\hat{\theta}_{\text{MLE}} - \theta_0) \xrightarrow{d} \mathcal{N}(0, 1)$ . Suppose  $\Phi(\theta) = \theta^2$ . Then the Delta Method implies  $\sqrt{n}(\hat{\theta}_{\text{MLE}}^2 - \theta_0^2) \xrightarrow{d} 2\theta_0 \mathcal{N}(0, 1) = \mathcal{N}(0, 4\theta_0^2)$ . Consider the distribution of  $n(\bar{X}_n^2 - 0)$ . Then  $n\bar{X}_n^2 = \left(\frac{X_1 + \dots + X_n}{\sqrt{n}}\right)^2 \xrightarrow{d} \chi_1^2$ , by the CLT and continuous mapping theorem.

## Asymptotic Inference

For the MLE  $\hat{\theta}_n$ , under regularity assumptions,

$$\sqrt{n}(\hat{\theta}_n - \theta_0) \xrightarrow{d} \mathcal{N}(0, I(\theta_0)^{-1})$$

Let  $e_j$  denote the  $j$ th canonical basis vector. Then

$$\sqrt{n}(\hat{\theta}_j - (\theta_0)_j) = e_j^T \sqrt{n}(\hat{\theta} - \theta_0) \xrightarrow{d} \mathcal{N}(0, e_j^T I(\theta_0)^{-1} e_j) = \mathcal{N}(0, (I(\theta_0)^{-1})_{jj})$$

Let

$$\mathcal{C}_n = \left\{ \nu \in \mathbb{R} : |\nu - \hat{\theta}_{n,j}| \leq \frac{(I(\theta_0)^{-1})_{jj}^{1/2}}{\sqrt{n}} z_\alpha \right\}$$

Where  $z_\alpha$  is such that  $\mathbb{P}(Z \leq z_\alpha) = 1 - \alpha$ . This is a valid asymptotic confidence interval since

$$\mathbb{P}_{\theta_0}(\theta_{0,j} \in \mathcal{C}_n) = \mathbb{P}_{\theta_0} \left( \sqrt{n}(I(\theta_0)^{-1})_{jj}^{-1/2} |\hat{\theta}_{n,j} - \theta_{0,j}| \leq z_\alpha \right) \rightarrow \mathbb{P}(Z \leq z_\alpha) = 1 - \alpha$$

In order to construct this confidence interval, we need to evaluate  $I(\theta)$  at  $\theta_0$ . But we don't know  $\theta_0$ ! Instead we will estimate the required quantity by plugging in  $\hat{\theta}_{\text{MLE}}$ .

**Definition.** The *observed Fisher information* is the  $p \times p$  matrix

$$i_n(\theta) = \frac{1}{n} \sum_{i=1}^n (\nabla_\theta \log f(X_i, \theta)) (\nabla_\theta \log f(X_i, \theta))^T$$

It is common to use  $\hat{i}_n = i_n(\hat{\theta}_{\text{MLE}})$  as an estimator of  $I(\theta_0)$ .

**Theorem 1.21.** Under the usual regularity conditions, we have  $\hat{i}_n \xrightarrow{P_{\theta_0}} I(\theta_0)$  as  $n \rightarrow \infty$ . In particular, a confidence interval based on  $\hat{i}_n$  will be asymptotically valid.

*Proof.* Let  $q(X, \theta) = (\nabla_\theta \log f(X, \theta)) (\nabla_\theta \log f(X, \theta))^T$ . For all  $\theta \in \Theta$  we have

$$i_n(\theta) = \frac{1}{n} \sum_{i=1}^n q(X_i, \theta), \quad I(\theta) = \mathbb{E}_{\theta_0}[q(X, \theta)]$$

Thus

$$\hat{i}_n - I(\theta_0) = \left( i_n(\hat{\theta}_{\text{MLE}}) - I(\hat{\theta}_{\text{MLE}}) \right) + \left( I(\hat{\theta}_{\text{MLE}}) - I(\theta_0) \right)$$



The first term is upper bounded by

$$\left| i_n(\hat{\theta}_{\text{MLE}}) - I(\hat{\theta}_{\text{MLE}}) \right| \leq \sup_{\theta \in \Theta} \left| \frac{1}{n} \sum_{i=1}^n q(X_i, \theta) - \mathbb{E}_{\theta_0} [q(X_i, \theta)] \right| \xrightarrow{P_{\theta_0}} 0$$

by the ULLN. The second term also converges in probability to 0, by consistency of the MLE combined with the continuous mapping theorem.  $\square$

**Remark:** it is also possible to use  $\hat{j}_n(\theta) = j_n(\hat{\theta}_{\text{MLE}})$ , where

$$j_n(\theta) = -\frac{1}{n} \sum_{i=1}^n \nabla_{\theta}^2 \log f(X_i, \theta)$$

This is also a consistent estimator of  $I(\theta_0)$  with a similar proof.

**Definition.** For all  $\theta \in \Theta$ , we define the *Wald statistic* as

$$W_n(\theta) = n \left( \hat{\theta}_{\text{MLE}} - \theta \right)^T \hat{i}_n \left( \hat{\theta}_{\text{MLE}} - \theta \right)$$

The Wald statistic is a quadratic form with positive semi-definite  $\hat{i}_n$ , so its level sets are ellipsoids that can be used to construct confidence sets for  $\theta_0$ .

**Theorem 1.22.** Let  $\theta_0$  be  $p$ -dimensional. Under the usual regularity conditions, the confidence region

$$\mathcal{C}_n = \{ \theta : W_n(\theta) \leq \xi_{\alpha} \}$$

where  $\xi_{\alpha}$  is such that

$$\mathbb{P}(\chi_p^2 \leq \xi_{\alpha}) \leq 1 - \alpha$$

is an asymptotically valid confidence region for  $\theta_0$ .

*Proof.* Compute

$$\mathbb{P}(\theta_0 \in \mathcal{C}_n) = \mathbb{P}_{\theta_0} (W_n(\theta_0) \leq \xi_{\alpha})$$

Under the assumptions, we have  $\sqrt{n}(\hat{\theta}_n - \theta_0) \xrightarrow{d} \mathcal{N}(0, I(\theta_0)^{-1})$ , and  $\hat{i}_n \xrightarrow{P_{\theta_0}} I(\theta_0)$ . We can decompose the Wald statistic as

$$W_n(\theta_0) = \sqrt{n}(\hat{\theta}_n - \theta_0)^T I(\theta_0) \sqrt{n}(\hat{\theta}_n - \theta_0) + \sqrt{n}(\hat{\theta}_n - \theta_0)^T \left( \hat{i}_n - I(\theta_0) \right) \sqrt{n}(\hat{\theta}_n - \theta_0)$$

By the continuous mapping theorem, the first term converges in distribution to  $U^T U = U_1^2 + \dots + U_p^2$ , with  $U \sim \mathcal{N}(0, I_p)$ , hence has a  $\chi_p^2$  distribution.

The second term is a product of  $\sqrt{n}(\hat{\theta}_n - \theta_0)^T (\hat{i}_n - I(\theta_0))$  which converges in distribution (hence also in probability) to 0 by Slutsky's lemma, and applying Slutsky's lemma again the whole of the second term goes to 0. So  $W_n(\theta_0) \xrightarrow{d} \chi_p^2$ .  $\square$

**Remark:** the Wald statistic can also be used to design a test for

$$\begin{aligned} H_0 : \theta &= \theta_0 \\ H_1 : \theta &\in \Theta \setminus \{ \theta_0 \} \end{aligned}$$

where  $H_0$  is rejected when  $W_n(\theta_0) > \xi_{\alpha}$ , since  $\mathbb{P}_{\theta_0}(W_n(\theta_0) > \xi_{\alpha}) \rightarrow \alpha$ .

## Likelihood Ratio Test

Now consider a general “nested” hypothesis testing problem:

$$\begin{aligned} H_0 &: \theta \in \Theta_0 \\ H_1 &: \theta \in \Theta \setminus \Theta_0 \end{aligned}$$

Where  $\Theta_0 \subseteq \Theta \subseteq \mathbb{R}^p$ . We want to find a decision rule  $\Psi_n$  which is a function of the observed data, mapping into  $\{0, 1\}$ , which outputs 0 with high probability under  $H_0$  and 1 with high probability under  $H_1$ .

**Definition.** We have the following types of error:

- *Type I error:* (false positive)  $\mathbb{P}_\theta(\Psi_n = 1) = \mathbb{E}_\theta[\Psi_n]$ , for  $\theta \in \Theta_0$
- *Type II error:* (false negative)  $\mathbb{P}_\theta(\Psi_n = 0) = \mathbb{E}[1 - \Psi_n]$ , for  $\theta \in \Theta \setminus \Theta_0$ .

**Definition.** The *likelihood ratio statistic* is defined as

$$\Lambda_n(\Theta, \Theta_0) = 2 \log \left( \frac{\sup_{\theta \in \Theta} \prod_{i=1}^n f(X_i, \theta)}{\sup_{\theta \in \Theta_0} \prod_{i=1}^n f(X_i, \theta)} \right) = 2 \log \left( \frac{\prod_{i=1}^n f(X_i, \hat{\theta}_{\text{MLE}})}{\prod_{i=1}^n f(X_i, \hat{\theta}_{\text{MLE},0})} \right)$$

Where  $\hat{\theta}_{\text{MLE},0}$  is the MLE over the subset  $\Theta_0$ .

Note that  $\Lambda_n(\Theta, \Theta_0) \geq 0$ , and we should reject  $H_0$  when  $\Lambda_n$  is large.

**Theorem 1.23** (Wilks’ Theorem). *Let  $\{f(\cdot, \theta) : \theta \in \Theta\}$  be a statistical model satisfying the usual regularity conditions, where  $\Theta \subseteq \mathbb{R}^p$ , and consider a hypothesis testing problem where  $\Theta_0 = \{\theta_0\}$ , for some fixed  $\theta_0 \in \text{int}(\Theta)$ . As  $n \rightarrow \infty$  we have*

$$\Lambda_n(\Theta, \Theta_0) \xrightarrow{d} \chi_p^2$$

*Proof.* Let  $\varepsilon > 0$  be such that the ball of radius  $\varepsilon$  around  $\theta_0$  is contained in  $\Theta$ . Define  $E_n = \{\|\hat{\theta}_n - \theta_0\|_2 \leq \varepsilon\}$ , where  $\hat{\theta}_n$  is the MLE. Then  $\mathbb{P}(E_n) \rightarrow 1$  since  $\hat{\theta}_n \xrightarrow{P} \theta_0$ . Thus, on the events  $\{E_n\}$  we have  $\hat{\theta}_n \in \text{int}(\Theta)$ . It suffices to restrict our attention to these events since we are talking about convergence in distribution.

By definition of the likelihood ratio

$$\Lambda_n(\Theta, \Theta_0) = 2l_n(\hat{\theta}_n) - 2l_n(\theta_0) = 2\nabla_{\theta} l_n(\hat{\theta}_n)^T (\hat{\theta}_n - \theta_0) - (\hat{\theta}_n - \theta_0)^T \bar{B}_n (\hat{\theta}_n - \theta_0)$$

Where  $\bar{B}_n$  is defined using a Taylor approximation with remainder:

$$\bar{B}_n = -\nabla_{\theta}^2 l_n(\bar{\theta}_n), \text{ where } \bar{\theta}_n \in [\theta_0, \hat{\theta}_n]$$

The first term in the Taylor approximation is 0 since  $\hat{\theta}_n$  is an MLE. Note that the second term can be written as

$$\sqrt{n} \left( \hat{\theta}_n - \theta_0 \right)^T j_n(\bar{\theta}_n) \sqrt{n} (\hat{\theta}_n - \theta_0)$$

where  $j_n$  is as defined previously. Using the same proof technique as before, we can show (via a ULLN) that  $j_n(\bar{\theta}_n) \xrightarrow{P_{\theta_0}} I(\theta_0)$ :

$$j_n(\bar{\theta}_n) - I(\theta_0) = \underbrace{\left( j_n(\bar{\theta}_n) - I(\bar{\theta}_n) \right)}_{\text{ULLN}} + \underbrace{\left( I(\bar{\theta}_n) - I(\theta_0) \right)}_{\text{CMT}}$$

Applying Slutsky's lemma implies  $\Lambda_n(\Theta, \Theta_0) \xrightarrow{d} \chi_p^2$ . □

**Remarks:**

1. As a result,  $\Psi_n = 1\{\Lambda_n(\Theta, \Theta_0) \geq \xi_\alpha\}$  is a valid hypothesis test at level  $\alpha$ .
2. Wilks' Theorem can be generalised to certain settings with composite null hypotheses, in which case the limiting distribution is a  $\chi^2_{p-p_0}$  random variable where  $p_0 \leq p$  is the “degrees of freedom” in  $\Theta_0$ . For example,  $\Theta_0$  might be the hypothesis that fixes  $k$  values of the coordinates of  $\theta$ , in which case  $p_0 = p - k$ .

## Bayesian inference

For a given parametric model  $\{f(\cdot, \theta) : \theta \in \Theta\}$ , there are situations where it is convenient to consider  $\theta$  as a random variable with distribution  $\pi$  on  $\Theta$ .

For example, consider a finite parameter space  $\Theta = \{\theta_1, \dots, \theta_k\}$ , and possible hypotheses  $H_i : \theta = \theta_i$  for  $1 \leq i \leq k$ , with prior beliefs  $\pi_i = \mathbb{P}(H_i)$ . If the true hypothesis is  $H_i$ , then the distribution of an observation is

$$\mathbb{P}(X = x | H_i) = f_i(x)$$

By Bayes' rule, when observing  $X = x$  we have

$$\mathbb{P}(H_i | X = x) = \frac{\mathbb{P}(X = x \text{ and } H_i)}{\mathbb{P}(X = x)} = \frac{\pi_i f_i(x)}{\sum_{j=1}^k \pi_j f_j(x)}$$

Thus, we “should” prefer  $H_i$  over  $H_j$ , given the observation  $X = x$  if

$$\frac{\mathbb{P}(H_i | X = x)}{\mathbb{P}(H_j | X = x)} = \frac{f_i(x)}{f_j(x)} \frac{\pi_i}{\pi_j} \geq 1$$

If all the  $\pi_i$ 's were equal, this would be a likelihood ratio test based on  $\frac{f_i(x)}{f_j(x)}$ . In the more general case, we have a weighted ratio and may want to update the  $\pi_i$ 's.

**Definition.** For a statistical model  $\{f(\cdot, \theta) : \theta \in \Theta\}$ , we will say that the *law of  $X$  given  $\theta$*  is given by  $X | \theta \sim f(x, \theta)$ . The *posterior distribution* is defined as the law of  $\theta | X$ .

Let  $\{f(\cdot, \theta) : \theta \in \Theta\}$  be a statistical model.

**Definition.** For a sample space  $\mathcal{X}$  of the observation  $X$ , consider the product space  $\mathcal{X} \times \Theta$  with corresponding pdf/pmf  $q(x, \theta) = f(x, \theta)\pi(\theta)$ . The distribution  $\pi$  is the *prior distribution* of  $\theta$ . The *posterior distribution* is the conditional probability

$$\theta|X \sim \frac{f(x, \theta)\pi(\theta)}{\int_{\Theta} f(x, \theta')\pi(\theta')d\theta'} := \Pi(\theta|X)$$

Note that the conditional probability of  $X$  given  $\theta$  is

$$X|\theta \sim \frac{f(x, \theta)\pi(\theta)}{\int_{\mathcal{X}} f(x', \theta)\pi(\theta)dx'} = f(x, \theta)$$

Also, if  $X_1, \dots, X_n$  are iid samples with common law  $f(x, \theta)$ , then

$$\theta|X_1, \dots, X_n \sim \frac{\prod_{i=1}^n f(x_i, \theta)\pi(\theta)}{\int_{\Theta} \prod_{i=1}^n f(x_i, \theta')\pi(\theta')d\theta'} := \Pi(\theta|X_1, \dots, X_n)$$

The last expression is just a reweighted and renormalised version of the likelihood function. In fact, the denominator is often ignored in calculations.

**Example.** Suppose  $X|\theta \sim \mathcal{N}(0, 1)$ , with prior  $\theta \sim \mathcal{N}(0, 1)$ . The numerator of the posterior distribution  $\theta|X_1, \dots, X_n$  is proportional to (as a function of  $\theta$ )

$$\begin{aligned} \exp\left(-\frac{\theta^2}{2}\right) \prod_{i=1}^n \exp\left(-\frac{(X_i - \theta)^2}{2}\right) &\propto \exp\left(n\theta\bar{X} - \frac{n\theta^2}{2} - \frac{\theta^2}{2}\right) \\ &= \exp\left(n\theta\bar{X} - \frac{(n+1)\theta^2}{2}\right) \\ &\propto \exp\left(-\frac{\left(\theta\sqrt{n+1} - \frac{n\bar{X}}{\sqrt{n+1}}\right)^2}{2}\right) \\ &= \exp\left(-\frac{\left(\theta - \frac{n\bar{X}}{n+1}\right)^2}{\frac{2}{n+1}}\right) \end{aligned}$$

Thus,  $\theta|X_1, \dots, X_n \sim \mathcal{N}\left(\frac{1}{n+1} \sum_{i=1}^n X_i, \frac{1}{n+1}\right)$ . For the more general case of  $\mathcal{N}(\theta, \sigma^2)$  with prior  $\mathcal{N}(\mu, \nu^2)$ , see Example sheet.

Note that in the above example, the posterior distribution is in the same distribution class as the prior (both normal), except the parameters have been updated based on the  $X_i$ 's.

**Definition.** In a statistical model  $\{f(\cdot, \theta) : \theta \in \Theta\}$ , if the prior  $\pi(\theta)$  and posterior  $\pi(\theta|X)$  belong to the same family of distributions, then  $\pi(\theta)$  is a *conjugate prior*.

The following examples of conjugate priors are in the Example sheet:

1. Normal prior and normal sampling - gives normal posterior
2. Beta prior and binomial sampling - gives beta posterior
3. Gamma prior and Poisson sampling - gives Gamma posterior

**Definition.** A prior non-negative function with indefinite integral  $\int_{\Theta} f(x, \theta) \pi(\theta) d\theta$  is an *improper prior*.

As an example, consider the prior  $\pi(\theta) = 1$  for all  $\theta$ . But as long as the posterior is a valid pdf, a prior such as the uniform prior can still be used for estimation.

### Jeffreys prior

A potential issue with the uniform prior is that it is not invariant to reparametrisation. Suppose  $X|\theta \sim \text{Binomial}(n, \theta)$ . Suppose the prior on  $\theta$  is Uniform $[0, 1]$ . However, suppose we reparametrise with  $\phi = \theta^{100}$ .

**Definition.** The prior  $\pi(\theta)$  proportional to  $\sqrt{\det(I(\theta))}$  is called the Jeffreys prior.

Consider a monotonic function  $h$ , and let  $\phi = h(\theta)$ . We can write the Fisher information as

$$\begin{aligned}
 I_{\phi}(\phi) &= -\mathbb{E} \left[ \frac{d^2 \log p(x|\phi)}{d\phi^2} \right] \\
 &= -\mathbb{E} \left[ \frac{d^2 \log p(X|\phi)}{d\theta^2} \left( \frac{d\theta}{d\phi} \right)^2 + \frac{d \log p(X, \theta)}{d\theta} \frac{d^2 \theta}{d\phi^2} \right] \\
 &= -\mathbb{E} \left[ \frac{d^2 \log p(X, \theta)}{d\theta^2} \right] \left( \frac{d\theta}{d\phi} \right)^2 - \underbrace{\mathbb{E} \left[ \frac{d \log p(X, \theta)}{d\theta} \right]}_{=0} \frac{d^2 \theta}{d\phi^2} \\
 &= I_{\theta}(\theta) \left( \frac{d\theta}{d\phi} \right)^2 \\
 &= \frac{I_{\theta}(\theta)}{(h'(\theta))^2}
 \end{aligned}$$

(assuming that  $\theta, \phi$  are univariate). Thus  $\pi_{\phi}(\phi) = \frac{\pi_{\theta}(\theta)}{|h'(\theta)|} \propto \frac{\sqrt{I_{\theta}(\theta)}}{|h'(\theta)|} = \sqrt{I_{\phi}(\phi)}$ .

As a concrete example, the Example sheet considers the  $\mathcal{N}(\mu, \sigma^2)$  model with  $\theta = \begin{pmatrix} \mu \\ \sigma^2 \end{pmatrix} \in \mathbb{R} \times (0, \infty)$ . Then the Fisher information matrix is  $I(\theta) =$

$\begin{pmatrix} \frac{1}{\sigma^2} & 0 \\ 0 & \frac{2}{\sigma^2} \end{pmatrix}$  so the Jeffreys prior is  $\pi(\theta) \sim \frac{1}{\sigma^2}$ , which is constant in  $\mu$ , and therefore improper. However the posterior marginal of  $\mu$  (conditioned on  $\sigma^2$ ) is  $\mathcal{N}(\bar{X}_n, \frac{\sigma^2}{n})$ , which makes sense as a posterior. This can be compared with the posterior under the prior  $\pi \sim \mathcal{N}(\theta, 1)$ , which would be  $\mathcal{N}\left(\frac{\bar{X}_n + \frac{\sigma^2}{n}}{1 + \frac{\sigma^2}{n}}, \frac{\sigma^2}{n + \sigma^2}\right)$ .

Other priors motivated by other notions of “low-informativeness” lead to different families of reference priors.

### Statistical inference with the posterior

The distribution  $\pi(\cdot | X_1, \dots, X_n)$  is a random probability measure on the parameter space  $\Theta$ .

The posterior can be used for various tasks such as estimation, uncertainty quantification, and hypothesis testing (from a Bayesian perspective).

## Statistical inference with the posterior

Based on the posterior distribution  $\Pi(\cdot|X_1, \dots, X_n)$ , we might address the following statistical questions:

1. Estimation: posterior mean  $\bar{\theta}(X_1, \dots, X_n) = \mathbb{E}_\Pi[\theta|X_1, \dots, X_n]$ .
2. Uncertainty quantification: take a subset  $\mathcal{C}_n \subseteq \Theta$  such that  $\Pi(\mathcal{C}_n|X_1, \dots, X_n) = 1 - \alpha$ . This is a *credible set*.
3. Hypothesis testing: as in the motivating example from Lecture 10, the Bayes factor is defined as

$$\frac{\Pi(\Theta_0|X_1, \dots, X_n)}{\Pi(\Theta|X_1, \dots, X_n)} = \frac{\int_{\Theta_0} \prod_{i=1}^n f(X_i, \theta) \pi(\theta) d\theta}{\int_{\Theta} \prod_{i=1}^n f(X_i, \theta) \pi(\theta) d\theta}$$

## Frequentist behaviour of credible sets

Suppose  $X_i \sim^{\text{iid}} f(x, \theta_0)$ . We will discuss the behaviour of  $\mathcal{C}_n$  as  $n \rightarrow \infty$ . As an example, suppose  $X|\theta \sim \mathcal{N}(\theta, 1)$  and we take the prior  $\theta \sim \mathcal{N}(0, 1)$ .

We have seen that

$$\theta|X_1, \dots, X_n \sim \mathcal{N}\left(\frac{1}{n+1} \sum_{i=1}^n X_i, \frac{1}{n+1}\right)$$

Thus the posterior mean is

$$\bar{\theta}_n = \mathbb{E}_\pi[\theta|X_1, \dots, X_n] = \frac{1}{n+1} \sum_{i=1}^n X_i$$

This is not the MLE, but it is very close. Also, it is consistent: if  $X_i \sim^{\text{iid}} \mathcal{N}(\theta_0, 1)$ , then  $\bar{\theta}_n = \frac{n}{n+1} \frac{1}{n} \sum_{i=1}^n X_i \xrightarrow{P} \theta_0$  by the LLN and Slutsky's lemma.

Now take  $\sqrt{n}(\bar{\theta}_n - \theta_0)$ . If we write

$$\sqrt{n}(\bar{\theta}_n - \theta_0) = \sqrt{n}(\hat{\theta}_n - \theta_0) + \sqrt{n}(\bar{\theta}_n - \hat{\theta}_n)$$

We see that  $\sqrt{n}(\hat{\theta}_n - \theta_0) \xrightarrow{d} \mathcal{N}(0, 1)$  and

$$\sqrt{n}(\bar{\theta}_n - \hat{\theta}_n) = \sqrt{n}\left(\frac{1}{n+1} - \frac{1}{n}\right) \sum_{i=1}^n X_i = -\frac{\sqrt{n}}{n+1} \bar{X}_n \xrightarrow{P} 0$$

Since  $\bar{X}_n \xrightarrow{P} \theta_0$  and  $\frac{\sqrt{n}}{n+1} \rightarrow 0$  so apply Slutsky's lemma. So altogether we have  $\sqrt{n}(\bar{\theta}_n - \theta_0) \xrightarrow{d} \mathcal{N}(0, 1)$ . Thus, we could construct frequentist confidence intervals of the form

$$\mathcal{C}_n = \left\{ \nu : |\nu - \bar{\theta}_n| \leq \frac{z_\alpha}{\sqrt{n}} \right\}$$

i.e  $\hat{\theta}_n$  is replaced by  $\bar{\theta}_n$  as the centre of the confidence interval.

However, in Bayesian analysis, credible sets are based on the posterior distribution, not the asymptotic distribution of an estimator.

We should build a set of the form  $\mathcal{C}_n = \{\nu : |\nu - \bar{\theta}_n| \leq \frac{R_n}{\sqrt{n}}\}$  where  $R_n$  is taken such that  $\Pi(\mathcal{C}_n | X_1, \dots, X_n) = 1 - \alpha$ . Note that  $R_n$  is in general a random variable based on the  $X_i$ 's.

The main result we will show is that under appropriate assumptions,  $\mathbb{P}_{\theta_0}(\theta_0 \in \mathcal{C}_n) \rightarrow 1 - \alpha$  as  $n \rightarrow \infty$ , when  $\mathcal{C}_n$  is a credible set, so these are valid frequentist confidence intervals.

**Theorem 1.24** (Bernstein - von Mises). *Consider a parametric model  $\{f(\cdot, \theta) : \theta \in \Theta\}$  for  $\Theta \subseteq \mathbb{R}$  satisfying the usual regularity conditions, a prior with continuous density  $\pi$  at  $\theta_0$  with  $\pi(\theta_0) > 0$ , and the associated posterior  $\Pi(\cdot | X_1, \dots, X_n)$ . Let  $\hat{\phi}_n$  denote the random distribution  $\mathcal{N}(\hat{\theta}_n, \frac{I(\theta_0)^{-1}}{n})$  (where  $\hat{\theta}_n$  is the MLE). As  $n \rightarrow \infty$  under  $P_{\theta_0}$ , we have*

$$\left\| \Pi_n - \hat{\phi}_n \right\|_{TV} = \int_{\Theta} |\Pi_n(\theta) - \hat{\phi}_n| d\theta \xrightarrow{a.s} 0$$

**Remark:** total variation distance (TV), integrates the absolute difference between two pdf's.

*Proof.* We will only prove the special case  $X|\theta \sim \mathcal{N}(0, 1)$  and  $\theta \sim \mathcal{N}(0, 1)$ . The proof for the more general result is beyond the scope of the course.

Note that since  $\Pi_n$  and  $\hat{\phi}_n$  are probability distributions, they both integrate to 1, so  $\int_{\Theta} (\Pi_n(\theta) - \hat{\phi}_n(\theta)) d\theta = 0$ . Thus the integrals of the positive and negative parts are the same, so

$$\begin{aligned} \int_{\Theta} |\Pi_n(\theta) - \hat{\phi}_n(\theta)| d\theta &= 2 \int_{\Theta} (\hat{\phi}_n(\theta) - \Pi_n(\theta))^+ d\theta \\ &= 2 \int_{\Theta} \left( 1 - \frac{\Pi_n(\theta)}{\hat{\phi}_n(\theta)} \right)^+ \hat{\phi}_n(\theta) d\theta \end{aligned}$$

In this specific setting, the distribution of  $\hat{\phi}_n$  is  $\mathcal{N}(\bar{X}_n, \frac{1}{n})$  and the distribution of  $\Pi_n$  is  $\mathcal{N}(\bar{\theta}_n, \frac{1}{n+1}) = \mathcal{N}(\frac{n}{n+1} \bar{X}_n, \frac{1}{n+1})$ .

Thus

$$\frac{\Pi_n(\theta)}{\hat{\phi}_n(\theta)} = \frac{\frac{1}{\sqrt{\frac{2\pi}{n+1}}} \exp\left(-\frac{n+1}{2} (\theta - \bar{\theta}_n)^2\right)}{\frac{1}{\sqrt{\frac{2\pi}{n}}} \exp\left(-\frac{n}{2} (\theta - \bar{\theta}_n)^2\right)}$$



Making the substitution  $v = \sqrt{n}(\theta - \hat{\theta}_n)$ , we can write the integral as

$$2 \int_{\Theta} \left( 1 - \sqrt{\frac{n+1}{n}} \exp \left( -\frac{n+1}{2n} \left( v + \sqrt{n}(\hat{\theta}_n - \bar{\theta}_n) \right)^2 + \frac{v^2}{2} \right) \right)^+ \frac{1}{\sqrt{2\pi}} \exp \left( -\frac{v^2}{2} \right) dv$$

Since the function  $x \mapsto (1-x)^+$  is bounded by 1 for  $x \geq 0$ , if it can be shown that almost surely (with respect to  $P_{\theta_0}$ ) the inner term converges to 0 for all  $v$ , then the dominated convergence theorem implies convergence to 0.

As argued before,  $\sqrt{n}(\bar{\theta}_n - \hat{\theta}_n) \xrightarrow{\text{a.s.}} 0$ . Thus it is easy to see that for any fixed  $v$ , the term in the exponential converges to 0, concluding the proof.  $\square$

**Theorem 1.25.** *Under the same assumptions as the Bernstein - von Mises theorem, for any  $\alpha \in (0, 1)$ , we have  $\mathbb{P}_{\theta_0}(\theta_0 \in \mathcal{C}_n) \rightarrow 1 - \alpha$  as  $n \rightarrow \infty$  where  $\mathcal{C}_n = \{\nu : |\nu - \hat{\theta}_n| \leq \frac{R_n}{\sqrt{n}}\}$  and  $R_n$  is chosen such that  $\Pi_n(\mathcal{C}_n) = 1 - \alpha$ .*

*Proof.* We will prove this in the general case (not just for normal distributions). First we will show that  $R_n \xrightarrow{\text{a.s.}} \Phi_0^{-1}(1 - \alpha)$ , where  $\Phi_0$  is the cdf of a standard normal. Concretely,  $\Phi_0$  is defined by  $\Phi_0(t) = \mathbb{P}(|Z_0| \leq t) = \int_{-t}^t \varphi_0(x) dx$ , where  $Z_0 \sim \mathcal{N}(0, I(\theta_0)^{-1})$ . Note that  $\Phi_0$  has a well-defined, continuous inverse denoted  $\Phi_0^{-1}$ .

We can write

$$\Phi_0(R_n) = \int_{-R_n}^{R_n} \varphi_0(v) dv = \int_{\hat{\theta}_n - \frac{R_n}{\sqrt{n}}}^{\hat{\theta}_n + \frac{R_n}{\sqrt{n}}} \hat{\phi}_n(\theta) d\theta = \hat{\phi}_n(\mathcal{C}_n)$$

Where we made the substitution  $\theta = \hat{\theta}_n + \frac{v}{\sqrt{n}}$  and  $\hat{\phi}_n$  is the pdf of  $\mathcal{N}(\hat{\theta}_n, \frac{I(\theta_0)^{-1}}{n})$ .

Furthermore,  $\hat{\phi}_n(\mathcal{C}_n) = (\hat{\phi}_n(\mathcal{C}_n) - \Pi_n(\mathcal{C}_n)) + 1 - \alpha$ . By the Bernstein - von Mises theorem,  $\hat{\phi}_n(\mathcal{C}_n) - \Pi_n(\mathcal{C}_n) \xrightarrow{\text{a.s.}} 0$ . Therefore  $\Phi_0(R_n) \xrightarrow{\text{a.s.}} 1 - \alpha$ . So by the Continuous Mapping Theorem,  $R_n \xrightarrow{\text{a.s.}} \Phi_0^{-1}(1 - \alpha)$ .

Next, using Slutsky's lemma and noting that  $\Phi_0^{-1}(1 - \alpha) > 0$ , we have  $\frac{\Phi_0^{-1}(1 - \alpha)}{R_n} \sqrt{n}(\hat{\theta}_n - \theta_0) \xrightarrow{d} \mathcal{N}(0, I(\theta_0)^{-1})$ . Thus

$$\begin{aligned} \mathbb{P}_{\theta_0}(\theta_0 \in \mathcal{C}_n) &= \mathbb{P}_{\theta_0} \left( |\hat{\theta}_n - \theta_0| \leq \frac{R_n}{\sqrt{n}} \right) \\ &= \mathbb{P}_{\theta_0} \left( \frac{\Phi_0^{-1}(1 - \alpha)}{R_n} \sqrt{n} |\hat{\theta}_n - \theta_0| \leq \Phi_0^{-1}(1 - \alpha) \right) \\ &\rightarrow \mathbb{P}(|Z_0| \leq \Phi_0^{-1}(1 - \alpha)) \\ &= \Phi_0(\Phi_0^{-1}(1 - \alpha)) \\ &= 1 - \alpha \end{aligned}$$

□

## Decision Theory

Given a statistical model  $\{f(\cdot, \theta) : \theta \in \Theta\}$ , and an observed sample  $X \in \mathcal{X}$ , we can phrase many statistical problems as decision problems, with an *action space*  $\mathcal{A}$  and *decision rules*  $\delta : \mathcal{X} \rightarrow \mathcal{A}$ .

**Examples:**

1. Hypothesis testing:  $\mathcal{A} = \{0, 1\}$  and the decision  $\delta(X)$  is a test
2. Estimation:  $\mathcal{A} = \Theta$  and  $\delta(x) = \hat{\theta}(X)$  is an estimator

3. Inference:  $\mathcal{A} = \mathcal{P}(\Theta)$  (powerset of  $\Theta$ ) and  $\delta(X) = \mathcal{C}(X)$  is a confidence set

The performance of a decision rule is assessed by a *loss function*  $L : \mathcal{A} \times \Theta \rightarrow [0, \infty)$ . For example, in hypothesis testing, the answer is right or wrong, so taking  $\theta \in \{0, 1\}$  representing the index of the hypothesis, we could have  $L(a, \theta) = 1\{a \neq \theta\}$  (0-1 loss).

In an estimation problem, we might take  $L(a, \theta) = |a - \theta|$ , or  $(a - \theta)^2$  (in one dimension).

**Definition.** For a loss  $L$ , and a decision rule  $\delta(X)$ , with  $X \sim P_\theta$ , we define the *risk*  $R(\delta, \theta) = \mathbb{E}_\theta[L(\delta(X), \theta)] = \int_{\mathcal{X}} L(\delta(x), \theta) f(x, \theta) dx$ .

**Examples:**

1. In hypothesis testing,  $R(\delta, \theta) = \mathbb{E}_\theta[1\{\delta(X) \neq \theta\}] = \mathbb{P}_\theta(\delta(X) \neq \theta)$ . This is the probability of type I/type II error.
2. In estimation, the quadratic risk corresponds to the mean squared error (MSE):  $R(\hat{\theta}, \theta) = \mathbb{E}_\theta[(\hat{\theta}(X) - \theta)^2]$ .

As a special case, for  $X \sim \text{Bin}(n, \theta)$  and  $\theta \in [0, 1]$ , if we take  $\hat{\theta}(X) = \frac{X}{n}$ , we can check that  $R(\hat{\theta}, \theta) = \frac{\theta(1-\theta)}{n}$ . If we instead consider the estimator  $\hat{\eta}(X) = \frac{1}{2}$ , we have

$$R(\hat{\eta}, \theta) = \mathbb{E}_\theta[(\hat{\eta}(X) - \theta)^2] = \left(\theta - \frac{1}{2}\right)^2$$

From this we can see that it is generally impossible to uniformly compare two estimators, with respect to the risk function.

**Definition.** Given a prior  $\pi$  on  $\Theta$ , the  $\pi$ -Bayes risk of  $\delta$  for the loss function  $L$  is defined by

$$R_\pi(\delta) = \mathbb{E}_\pi[R(\delta, \theta)] = \int_\Theta R(\delta, \theta) \pi(\theta) d\theta = \int_\Theta \int_{\mathcal{X}} L(\delta(x), \theta) \pi(\theta) f(x, \theta) dx d\theta$$

A  $\pi$ -Bayes decision rule  $\delta_\pi$  is any decision rule that minimises the  $\pi$ -Bayes risk  $R_\pi(\delta)$ .

**Example:** for the binomial example above, if we take the uniform prior on  $[0, 1]$  for  $\pi$ , then the  $\pi$ -Bayes risk is

$$R_\pi\left(\frac{X}{n}\right) = \mathbb{E}_\pi\left[\frac{\theta(1-\theta)}{n}\right] = \frac{1}{n} \int_0^1 \theta(1-\theta) d\theta = \frac{1}{6n}$$

**Definition.** For a Bayesian model, the *posterior risk* is defined as the average loss under the posterior distribution for an observation  $x \in \mathcal{X}$ :

$$\mathbb{E}_\Pi[L(\delta(x), \theta)|x] = \int_\Theta L(\delta(x), \theta) \Pi(\theta|x) d\theta$$

**Theorem 1.26.** *An estimator  $\delta$  that minimises the  $\Pi$ -posterior risk also minimises the  $\pi$ -Bayes risk  $R_\pi$ .*

*Proof.* The  $\pi$ -Bayes risk may be written as

$$\begin{aligned} R_\pi(\delta) &= \int_{\mathcal{X}} \int_{\Theta} L(\delta(x), \theta) f(x, \theta) \pi(\theta) d\theta dx \\ &= \int_{\mathcal{X}} \int_{\Theta} L(\delta(x), \theta) \underbrace{\frac{f(x, \theta) \pi(\theta)}{\int_{\Theta} f(x, \theta') \pi(\theta') d\theta'}}_{\Pi(\theta|X)} \underbrace{\int_{\Theta} f(x, \theta') \pi(\theta') d\theta'}_{:=m(x) \geq 0} d\theta dx \\ &= \int_{\mathcal{X}} \mathbb{E}_{\Pi}[L(\delta(x), \theta)|x] m(x) dx \end{aligned}$$

If  $\delta_{\Pi}$  is a decision rule minimising posterior risk, then for any other decision rule  $\delta$ , and for all  $x \in \mathcal{X}$ , we have

$$\mathbb{E}_{\Pi}[L(\delta_{\Pi}(x), \theta)|x] \leq \mathbb{E}_{\Pi}[L(\delta(x), \theta)|x]$$

Multiplying by  $m(x)$  and integrating with respect to  $x$ , shows

$$R_{\Pi}(\delta_{\Pi}) \leq R_{\Pi}(\delta)$$

□

**Example.** For the quadratic risk (with squared loss), the posterior risk can be written as

$$\mathbb{E}_{\Pi}[(\delta(x) - \theta)^2|x] = \mathbb{E}_{\Pi}[\delta(x)^2 - 2\delta(x)\theta + \theta^2|x] = \delta(x)^2 - 2\delta(x)\mathbb{E}_{\Pi}[\theta|x] + \mathbb{E}_{\Pi}[\theta^2|x]$$

Since this is a quadratic in  $\delta(x)$ , the posterior risk is minimised by taking the posterior mean

$$\delta_{\Pi}(x) = \mathbb{E}_{\Pi}[\theta|x]$$

Other losses give other ways to minimise the posterior risk, leading to other decision rules. One can also show that this is the unique  $\pi$ -Bayes rule for the quadratic risk (see Example sheet).

The following theorem shows that unbiased estimators are typically disjoint from Bayes estimators.

**Theorem 1.27.** *Let  $\delta$  be an unbiased decision rule for  $\theta$ , i.e.  $\mathbb{E}_{\theta}[\delta(X)] = \theta$  for all  $\theta \in \Theta$ . If  $\delta$  is also a Bayes rule for some prior  $\pi$  in the quadratic risk, then  $\mathbb{E}_Q[(\delta(X) - \theta)^2] = 0$  where  $\mathbb{E}_Q$  is the expectation taken with respect to the joint distribution  $q(x, \theta) = f(x, \theta)\pi(\theta)$ . In particular,  $\delta(X) = \theta$  with probability 1 under  $Q$ .*

*Proof.* Recall that for any random variable  $Z(X, \theta)$ , by applying the “tower rule” of expectation in two different ways, we have

$$\mathbb{E}_Q[Z(X, \theta)] = \mathbb{E}[\mathbb{E}_{\Pi}[Z(X, \theta)|X]] = \mathbb{E}[\mathbb{E}_{\theta}[Z(X, \theta)]] \quad (*)$$

From the calculation in the previous example, the unique  $\pi$ -Bayes rule (which minimises  $\mathbb{E}_Q[(\delta(X) - \theta)^2]$ ) is given by  $\delta(X) = \mathbb{E}_\Pi[\theta|X]$ . Taking  $Z(X, \theta) = \theta\delta(X)$  in (\*), we have

$$\mathbb{E}_Q[\theta\delta(X)] = \mathbb{E}[\mathbb{E}_\Pi[\theta\delta(X)|X]] = \mathbb{E}[\delta(X)\mathbb{E}_\Pi[\theta|X]] = \mathbb{E}[\delta(X)^2]$$

$$\mathbb{E}_Q[\theta\delta(X)] = \mathbb{E}[\mathbb{E}_\theta[\theta\delta(X)]] = \mathbb{E}[\theta\mathbb{E}_\theta[\delta(X)]] = \mathbb{E}[\theta^2]$$

Hence

$$\mathbb{E}_Q[(\delta(X) - \theta)^2] = \mathbb{E}_Q[\delta(X)^2] - 2\mathbb{E}_Q[\theta\delta(X)] + \mathbb{E}_Q[\theta^2] = 0$$

□

**Remark:** the following statements can be derived from the above theorem

1. In a  $\mathcal{N}(\theta, 1)$  model, the MLE  $\bar{X}_n$  is not a Bayes estimator for any prior  $\pi$ .
2. In a binomial model, the MLE  $\frac{X}{n}$  is only Bayes in degenerate cases (see Example sheet).

## Minimax Risk

Bayes risk takes the average risk of a decision rule with respect to a prior. We might alternatively be interested in worst-case risk.

**Definition.** The *maximal risk* of the decision rule  $\delta$  over the parameter space  $\Theta$  is defined by  $R_m(\delta, \Theta) = \sup_{\theta \in \Theta} R(\delta, \theta)$ . The *minimax risk* is defined as the infimum of the maximum risk:

$$\inf_{\delta} \sup_{\theta \in \Theta} R(\delta, \theta) = \inf_{\delta} R_m(\delta, \Theta)$$

A decision rule that attains the minimax risk is called *minimax*.

Going back to the  $X \sim \text{Binom}(n, \theta)$  example from before, let  $\Theta = [0, 1]$  and  $\hat{\theta}(X) = \frac{X}{n}$  and  $\hat{\eta} = \frac{1}{2}$ .

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

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

Thus  $R_m(\hat{\theta}, \Theta) = \frac{1}{4n}$  and  $R_m(\hat{\eta}, \Theta) = \frac{1}{4}$ .

**Theorem 1.28.** For any prior  $\pi$  and decision rule  $\delta$ , we have

$$R_\pi(\delta) \leq R_m(\delta, \Theta)$$

*Proof.*  $R_\pi = \mathbb{E}_\pi[R(\delta, \theta)] \leq \sup_{\theta \in \Theta} R(\delta, \theta) = R_m(\delta, \Theta)$  (i.e average is bounded above by worst case). □

**Definition.** A prior  $\lambda$  is *least favourable* if for every prior  $\lambda'$ , we have

$$R_\lambda(\delta_\lambda) \geq R_{\lambda'}(\delta_{\lambda'})$$

where  $\delta_\lambda$  and  $\delta_{\lambda'}$  are Bayes estimators with respect to the priors  $\lambda$  and  $\lambda'$ .

**Theorem 1.29.** Let  $\lambda$  be a prior on  $\Theta$  such that  $R_\lambda(\delta_\lambda) = \sup_{\theta \in \Theta} R(\delta_\lambda, \theta)$ , where  $\delta_\lambda$  is a  $\lambda$ -Bayes rule. Then

1.  $\delta_\lambda$  is minimax
2. If  $\delta_\lambda$  is the unique  $\lambda$ -Bayes rule, then it is the unique minimax rule
3. The prior  $\lambda$  is least favourable

**Corollary 1.30.** If a (unique) Bayes rule  $\delta_\lambda$  has constant risk in  $\theta$ , then it is the (unique) minimax rule.

*Proof.* If a Bayes rule  $\delta_\lambda$  has constant risk, then

$$R_\lambda(\delta_\lambda) = \mathbb{E}_\lambda[R(\delta_\lambda, \theta)] = \sup_{\theta \in \Theta} R(\delta_\lambda, \theta)$$

so the hypothesis of the previous theorem is satisfied.  $\square$

*Proof of Theorem.* We want to show that  $\inf_\delta \sup_{\theta \in \Theta} R(\delta, \theta) = \sup_{\theta \in \Theta} R(\delta_\lambda, \theta)$

1. Let  $\delta$  be any decision rule. Then

$$\sup_{\theta \in \Theta} R(\delta, \theta) \geq \mathbb{E}_\lambda[R(\delta, \theta)] \geq R_\lambda(\delta_\lambda) = \sup_{\theta \in \Theta} R(\delta_\lambda, \theta) \quad (*)$$

Thus  $\inf_\delta \sup_{\theta \in \Theta} R(\delta, \theta) \geq \sup_{\theta \in \Theta} R(\delta_\lambda, \theta)$ . Hence  $\inf_\delta \sup_{\theta \in \Theta} R(\delta, \theta) = \sup_{\theta \in \Theta} R(\delta_\lambda, \theta)$ , so  $\delta_\lambda$  is minimax.

2. If  $\delta_\lambda$  is the unique  $\lambda$ -Bayes rule, then the 2nd inequality in (\*) is strict for any  $\lambda' \neq \lambda$ , so  $\sup_{\theta \in \Theta} R(\delta', \theta) > \sup_{\theta \in \Theta} R(\delta_\lambda, \theta)$  and  $\delta'$  is not minimax.
3. For any prior  $\lambda'$ , we have

$$R_{\lambda'}(\delta_{\lambda'}) = \mathbb{E}_{\lambda'}[R(\delta_{\lambda'}, \theta)] \leq \mathbb{E}_{\lambda'}[R(\delta_\lambda, \theta)] \leq \sup_{\theta \in \Theta} R(\delta_\lambda, \theta) = \mathbb{E}_\lambda[R(\delta_\lambda, \theta)]$$

So  $\delta_\lambda$  is least favourable.  $\square$

**Example.** In a  $\text{Bin}(n, \theta)$  model, let  $\pi_{a,b}$  be a  $\text{Beta}(a, b)$  prior on  $\theta \in [0, 1]$ . It can be shown that the unique Bayes rule for  $\pi_{a,b}$  over the quadratic risk is the posterior mean  $\delta_{a,b} = \bar{\theta}_{a,b}$ . If we solve the equation  $R(\delta_{a,b}, \theta) = \text{constant}$  over all  $\theta \in [0, 1]$ , we can find a prior  $\pi_{a^*, b^*}$  and corresponding Bayes rule  $\delta_{a^*, b^*}$  of constant risk. Therefore it is minimax (see Example Sheet).

In this example, the minimax rule is unique and different from the MLE. However, in the next section we will show that in a  $\mathcal{N}(\theta, 1)$  model, the MLE  $\bar{X}_n$  is minimax.

## Admissibility

**Definition.** A decision rule  $\delta$  is *inadmissible* if there exists  $\delta'$  such that

$$R(\delta', \theta) \leq R(\delta, \theta), \quad \forall \theta \in \Theta$$

and  $R(\delta', \theta) < R(\delta, \theta)$  for some  $\theta \in \Theta$ . In this case,  $\delta'$  is said to *dominate*  $\delta$ .

**Theorem 1.31.**

1. A unique Bayes rule is admissible
2. If  $\delta$  is admissible and has constant risk, then it is minimax

*Proof.* Example Sheet. □

We now study a case where an estimator which is not Bayes with respect to any prior can be proved to be admissible.

**Theorem 1.32.** Let  $X_1, \dots, X_n$  be iid samples from a  $\mathcal{N}(\theta, \sigma^2)$  model, where  $\sigma^2$  is known and  $\theta \in \Theta = \mathbb{R}$ . Then  $\hat{\theta}_{MLE} = \bar{X}_n$  is admissible and minimax for estimating  $\theta$  in quadratic risk.

*Proof.* For simplicity, let  $\sigma^2 = 1$ , the general case is analogous. Note that the MLE has constant risk:

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

Thus by the previous theorem, it remains to show that  $\bar{X}_n$  is admissible.

For any decision rule  $\delta$  we have

$$R(\delta, \theta) = \mathbb{E}_\theta[(\delta(X) - \theta)^2] = (\mathbb{E}_\theta[\delta(X)] - \theta)^2 + \text{Var}_\theta(\delta(X))$$

(“Bias-Variance decomposition of MSE”). Let  $B(\theta) = \mathbb{E}_\theta[\delta(X)] - \theta$  denote the bias. Recall the general Cramer-Rao lower bound

$$\text{Var}_\theta(\delta(X)) \geq \frac{\left(\frac{d}{d\theta} \mathbb{E}_\theta[\delta(X)]\right)^2}{nI(\theta)} = \frac{(1 + B'(\theta))^2}{n}$$

Hence if  $\delta$  dominates  $\bar{X}_n$  we have  $R(\delta, \theta) \leq \frac{1}{n}$  for all  $\theta \in \mathbb{R}$ , hence

$$B(\theta)^2 + \frac{(1 + B'(\theta))^2}{n} \leq \frac{1}{n} \quad (*)$$

(Differentiability of  $B$  can be justified using regularity of the Gaussian model). From  $(*)$ , we can see that  $B(\theta)$  is bounded above and below, and  $B'(\theta) \leq 0$  for all  $\theta$ , so  $B$  is (non-strictly) decreasing.

Now we can argue that  $B(\theta) = 0$  for all  $\theta \in \mathbb{R}$ : we construct two sequences  $\{\theta_n\}_{n \geq 1}$ , one going to  $+\infty$ , and one going to  $-\infty$ , such that  $B'(\theta_n) \rightarrow 0$ . Otherwise,  $B'(\theta)$  would be bounded away from 0 for  $\theta$  small or large enough, making  $B(\theta)$  unbounded. By  $(*)$  we have  $B(\theta_n) \rightarrow 0$  for both sequences. Since  $B$  is non-increasing, this means  $B(\theta) = 0$  for all  $\theta$ .

Thus, plugging into the usual Cramer-Rao bound gives  $\text{Var}_\theta(\delta(X)) \geq \frac{1}{n}$ , implying that  $R(\delta, \theta) \geq \frac{1}{n}$  for all  $\theta$ . Thus  $\bar{X}_n$  is admissible.  $\square$

**Remark:** the decision rule studied here is not Bayes for any prior. However, it is the limit of the Bayes rule  $\delta_{\nu^2}$  for priors  $\mathcal{N}(0, \nu^2)$  when  $\nu \rightarrow \infty$ . It can be shown that all minimax rules are limits of Bayes rules (a result of Wald).

The result shown in the theorem can be extended to dimension  $p = 2$ , with the model  $\mathcal{N}(\theta, I_2)$ , where  $\theta \in \Theta = \mathbb{R}^2$ . However it is false for  $p > 2$ , leading to “Stein’s paradox”.

### James-Stein phenomenon

Consider the model  $X \sim \mathcal{N}(\theta, I_p)$  where  $p \geq 3$ . We will consider the case of a single observation for simplicity.

**Definition.** For a vector  $X \in \mathbb{R}^p$ , the *James-Stein estimator* is

$$\delta^{\text{JS}}(X) = \left(1 - \frac{p-2}{\|X\|_2^2}\right) X$$



We will show that the James-Stein estimator dominates the MLE in this model.

First we calculate the risk of the MLE:

$$R(\hat{\theta}, \theta) = \mathbb{E}_\theta[\|X - \theta\|_2^2] = \sum_{j=1}^p \mathbb{E}[(X_j - \theta_j)^2] = p$$

We now explicitly calculate the risk of  $\delta^{\text{JS}}$  and show that  $R(\delta^{\text{JS}}, \theta) < R(\hat{\theta}_{\text{MLE}}, \theta)$  for all  $\theta$ .

**Lemma 1.33** (Stein's Lemma). *Let  $X \sim \mathcal{N}(\theta, 1)$  and let  $g : \mathbb{R} \rightarrow \mathbb{R}$  be a bounded differentiable function such that  $\mathbb{E}[|g'(X)|] < \infty$ . Then  $\mathbb{E}[(X - \theta)g(X)] = \mathbb{E}[g'(X)]$*

*Proof.* Write (using integration by parts)

$$\begin{aligned} & \mathbb{E}[(X - \theta)g(X)] \\ &= \int_{\mathbb{R}} g(x)(x - \theta) \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(x - \theta)^2}{2}\right) dx \\ &= - \int_{\mathbb{R}} g(x) \left( \frac{d}{dx} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(x - \theta)^2}{2}\right) \right) dx \\ &= - \left[ g(x) \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(x - \theta)^2}{2}\right) \right]_{-\infty}^{\infty} + \int_{\mathbb{R}} g'(x) \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(x - \theta)^2}{2}\right) dx \\ &= \mathbb{E}[g'(X)] \end{aligned}$$

Where in the final step, the first term vanishes since  $g$  is bounded.  $\square$

**Remark:** Stein's Lemma is the basis of a proof technique in probability theory called "Steins method". It turns out that  $X$  must be normally distributed if it satisfies the equality in Steins lemma for all such  $g$ . In fact, this is also "approximately" true, which can be used, e.g, to show that sums of dependent random variables converge to a normal distribution.

**Theorem 1.34.** *Let  $X \sim \mathcal{N}(\theta, I_p)$ , for  $p \geq 3$ . Then the risk of the James-Stein estimator satisfies  $R(\delta^{\text{JS}}, \theta) < p$  for all  $\theta \in \mathbb{R}^p$ .*

*Proof.* We write

$$\begin{aligned} R(\delta^{\text{JS}}, \theta) &= \mathbb{E}_\theta[\|\delta^{\text{JS}} - \theta\|_2^2] \\ &= \mathbb{E}_\theta \left[ \left\| X - \theta - \frac{p-2}{\|X\|_2^2} X \right\|_2^2 \right] \\ &= \mathbb{E}_\theta[\|X - \theta\|_2^2] + (p-2)^2 \mathbb{E}_\theta \left[ \left\| \frac{X}{\|X\|_2^2} \right\|_2^2 \right] - 2(p-2) \mathbb{E}_\theta \left[ \frac{X^T(X - \theta)}{\|X\|_2^2} \right] \\ &= p + (p-2)^2 \mathbb{E}_\theta \left[ \frac{1}{\|X\|_2^2} \right] - 2(p-2) \mathbb{E}_\theta \left[ \frac{X^T(X - \theta)}{\|X\|_2^2} \right] \end{aligned}$$

For the last term:

$$\mathbb{E}_\theta \left[ \frac{X^T(X - \theta)}{\|X\|_2^2} \right] = \sum_{j=1}^p \mathbb{E}_\theta \left[ \frac{X_j(X_j - \theta_j)}{\|X\|_2^2} \right] = \sum_{j=1}^p \mathbb{E}_\theta \left[ \mathbb{E}_j \left[ \frac{X_j(X_j - \theta_j)}{X_j^2 + \sum_{i \neq j} X_i^2} \middle| X_{(-j)} \right] \right]$$

where we use the tower property of expectation and condition on

$$X_{(-j)} = (X_1, \dots, X_{j-1}, X_{j+1}, \dots, X_p)$$

Now we write

$$\mathbb{E}_j \left[ \frac{X_j(X_j - \theta_j)}{X_j^2 + \sum_{i \neq j} X_i^2} \middle| X_{(-j)} \right] = \mathbb{E}[(X_j - \theta_j)g_j(X_j)]$$

Where  $X_j \sim \mathcal{N}(\theta_j, 1)$  and  $g_j(x) = \frac{x}{x^2 + \sum_{i \neq j} X_i^2}$  is bounded as long as  $\sum_{i \neq j} X_i^2 \neq 0$ , which happens with probability 1. We can also check that the derivative of  $g_j$  is bounded, so  $\mathbb{E}|g'_j(X)| < \infty$ . Now Stein's lemma implies

$$\mathbb{E}[(X_j - \theta_j)g_j(X_j)] = \mathbb{E}[g'_j(X_j)] = \mathbb{E}_j \left[ \frac{X_j^2 + \sum_{i \neq j} X_i^2 - 2X_j^2}{(X_j^2 + \sum_{i \neq j} X_i^2)^2} \middle| X_{(-j)} \right]$$

Thus

$$\begin{aligned} \mathbb{E}_\theta \left[ \mathbb{E}_j \left[ \frac{X_j(X_j - \theta_j)}{X_j^2 + \sum_{i \neq j} X_i^2} \middle| X_{(-j)} \right] \right] &= \mathbb{E}_\theta \left[ \frac{X_j^2 + \sum_{i \neq j} X_i^2 - 2X_j^2}{(X_j^2 + \sum_{i \neq j} X_i^2)^2} \middle| X_{(-j)} \right] \\ &= \mathbb{E}_\theta \left[ \frac{1}{\|X\|_2^2} - \frac{2X_j^2}{\|X\|_2^4} \right] \end{aligned}$$

Summing from 1 to  $p$  gives

$$\mathbb{E}_\theta \left[ \frac{X^T(X - \theta)}{\|X\|_2^2} \right] = \sum_{i=1}^p \mathbb{E}_\theta \left[ \frac{1}{\|X\|_2^2} - \frac{2X_i^2}{\|X\|_2^4} \right] = (p-2) \mathbb{E}_\theta \left[ \frac{1}{\|X\|_2^2} \right]$$

Putting everything together gives

$$\begin{aligned} R(\delta^{\text{JS}}, \theta) &= p + (p-2)^2 \mathbb{E}_\theta \left[ \frac{1}{\|X\|_2^2} \right] - 2(p-2)^2 \mathbb{E}_\theta \left[ \frac{1}{\|X\|_2^2} \right] \\ &= p - (p-2)^2 \mathbb{E}_\theta \left[ \frac{1}{\|X\|_2^2} \right] < p \end{aligned}$$

□

**Remarks:**

1. One can lower-bound the term  $\mathbb{E}_\theta \left[ \frac{1}{\|X\|_2^2} \right]$  as follows: let  $\phi$  be the pdf of the  $p$ -variate standard normal. Then

$$\begin{aligned} \mathbb{E}_\theta \left[ \frac{1}{\|X\|_2^2} \right] &= \int_{\mathbb{R}^p} \frac{1}{\|x\|_2^2} \phi(x - \theta) dx \\ &\geq \int_{c_1 \leq \|x\|_2 \leq c_2} \frac{1}{\|x\|_2^2} \phi(x - \theta) dx \\ &\geq \frac{1}{c_2^2} \mathbb{P}_\theta (\|X\|_2 \in [c_1, c_2]) \end{aligned}$$

On the Example sheet, a similar type of argument can be used to upper bound  $\mathbb{E}_\theta \left[ \frac{1}{\|X\|_2^2} \right]$ , which can be used to show that  $R(\delta^{\text{JS}}, \theta) \rightarrow p$  as  $\|\theta\|_2 \rightarrow \infty$ . This result then implies that even though  $\hat{\theta}_{\text{MLE}}$  is not admissible,  $\hat{\theta}_{\text{MLE}}$  and  $\delta^{\text{JS}}$  have the same maximal risk.

2. The James-Stein estimator is also itself not admissible. It is dominated by

$$\delta^{\text{JS}+}(X) = \left( 1 - \frac{p-2}{\|X\|_2^2} \right)^+ X$$

However, even  $\delta^{\text{JS}+}$  is inadmissible, since it can be shown that admissible estimators must satisfy a certain smoothness condition.

3. In practice, the MLE  $X$  can be much easier to work with, e.g., designing hypothesis tests or constructing confidence regions.
4. It might seem counterintuitive that one can design a better estimator in multiple dimensions by using other coordinates to estimate a certain coordinate. One explanation of Stein's paradox can be made via the "bias-variance tradeoff":  $\text{MSE} = \text{Bias}^2 + \text{Var}$

$$\sum_{j=1}^p \mathbb{E}[(\hat{\theta}_j - \theta_j)^2] = \sum_{j=1}^p \left( \mathbb{E}[\hat{\theta}_j] - \theta_j \right)^2 + \sum_{j=1}^p \mathbb{E} \left[ \left( \hat{\theta}_j - \mathbb{E}[\hat{\theta}_j] \right)^2 \right]$$

If we consider  $\hat{\theta}_\lambda = \lambda X$ , we can check that the terms are

$$\text{MSE}(\hat{\theta}_\lambda) = (\lambda - 1)\|\theta\|_2^2 + \lambda^2 p$$

If  $\lambda = 1$ , bias is 0 but variance is  $p$ . For large  $p$ , shrinking the estimator may decrease MSE.