

## 18.650 – Fundamentals of Statistics

### **3. Methods for estimation**

# Goals

In the kiss example, the estimator was **intuitively** the right thing to do:  $\hat{p} = \bar{X}_n$ .

In view of LLN, since  $p = \mathbb{E}[X]$ , we have  $\bar{X}_n$  so  $\hat{p} \approx p$  for  $n$  large enough.

If the parameter is  $\theta \neq \mathbb{E}[X]$ ? How do we perform?

1. Maximum likelihood estimation: a generic approach with very good properties
2. Method of moments: a (fairly) generic and easy approach
3. M-estimators: a flexible approach, close to machine learning

# Total variation distance

Let  $(E, (\mathbb{P}_\theta)_{\theta \in \Theta})$  be a statistical model associated with a sample of i.i.d. r.v.  $X_1, \dots, X_n$ . Assume that there exists  $\theta^* \in \Theta$  such that  $X_1 \sim \mathbb{P}_{\theta^*}$ :  $\theta^*$  is the **true** parameter.

**Statistician's goal:** given  $X_1, \dots, X_n$ , find an estimator  $\hat{\theta} = \hat{\theta}(X_1, \dots, X_n)$  such that  $\mathbb{P}_{\hat{\theta}}$  is close to  $\mathbb{P}_{\theta^*}$  for the true parameter  $\theta^*$ .

This means:  $\left| \int_A \mathbb{P}_{\hat{\theta}} - \mathbb{P}_{\theta^*} \right|$  is **small** for all  $A \subset E$ .

## Definition

The *total variation distance* between two probability measures  $\mathbb{P}_\theta$  and  $\mathbb{P}_{\theta'}$  is defined by

$$\text{TV}(\mathbb{P}_\theta, \mathbb{P}_{\theta'}) = \max_{A \subset E} \left| \int_A \mathbb{P}_\theta - \mathbb{P}_{\theta'} \right|.$$

# Total variation distance between discrete measures

Assume that  $E$  is discrete (i.e., finite or countable). This includes Bernoulli, Binomial, Poisson, ...

Therefore  $X$  has a PMF (probability mass function):

$\mathbb{P}_\theta(X = x) = p_\theta(x)$  for all  $x \in E$ ,

$$p_\theta(x) \geq 0, \quad \sum_{x \in E} p_\theta(x) = 1$$

The total variation distance between  $\mathbb{P}_\theta$  and  $\mathbb{P}_{\theta'}$  is a simple function of the PMF's  $p_\theta$  and  $p_{\theta'}$ :

$$\text{TV}(\mathbb{P}_\theta, \mathbb{P}_{\theta'}) = \frac{1}{2} \sum_{x \in E} |p_\theta(x) - p_{\theta'}(x)|.$$

# Total variation distance between continuous measures

Assume that  $E$  is continuous. This includes Gaussian, Exponential, ...

Assume that  $X$  has a density  $\mathbb{P}_\theta(X \in A) = \int_A f_\theta(x)dx$  for all  $A \subset E$ .

$$f_\theta(x) \geq 0, \quad \int f_\theta(x)dx = 1.$$

The total variation distance between  $\mathbb{P}_\theta$  and  $\mathbb{P}_{\theta'}$  is a simple function of the densities  $f_\theta$  and  $f_{\theta'}$ :

$$\text{TV}(\mathbb{P}_\theta, \mathbb{P}_{\theta'}) = \frac{1}{2} \int |f_\theta(x) - f_{\theta'}(x)| dx.$$

# Properties of Total variation

- ▶  $\text{TV}(\mathbb{P}_\theta, \mathbb{P}_{\theta'}) =$  (symmetric)
- ▶  $\text{TV}(\mathbb{P}_\theta, \mathbb{P}_{\theta'}) \geq$  (positive)
- ▶ If  $\text{TV}(\mathbb{P}_\theta, \mathbb{P}_{\theta'}) = 0$  then (definite)
- ▶  $\text{TV}(\mathbb{P}_\theta, \mathbb{P}_{\theta'}) \leq$  (triangle inequality)

These imply that the total variation is a  
probability distributions.

between

## Exercises

Compute:

**a)**  $\text{TV}(\text{Ber}(0.5), \text{Ber}(0.1)) =$

**b)**  $\text{TV}(\text{Ber}(0.5), \text{Ber}(0.9)) =$

**c)**  $\text{TV}(\text{Exp}(1), \text{Unif}[0, 1]) =$

**d)**  $\text{TV}(X, X + a) =$   
for any  $a \in (0, 1)$ , where  $X \sim \text{Ber}(0.5)$

**e)**  $\text{TV}(2\sqrt{n}(\bar{X}_n - 1/2), Z) =$   
where  $X_i \stackrel{i.i.d}{\sim} \text{Ber}(0.5)$  and  $Z \sim \mathcal{N}(0, 1)$

## An estimation strategy

Build an estimator  $\widehat{\text{TV}}(\mathbb{P}_\theta, \mathbb{P}_{\theta^*})$  for all  $\theta \in \Theta$ . Then find  $\hat{\theta}$  that *minimizes* the function  $\theta \mapsto \widehat{\text{TV}}(\mathbb{P}_\theta, \mathbb{P}_{\theta^*})$ .

**problem:** Unclear how to build  $\widehat{\text{TV}}(\mathbb{P}_\theta, \mathbb{P}_{\theta^*})$ !



# Kullback-Leibler (KL) divergence

There are **many** distances between probability measures to replace total variation. Let us choose one that is more convenient.

## Definition

The *Kullback-Leibler*<sup>1</sup> (KL) divergence between two probability measures  $\mathbb{P}_\theta$  and  $\mathbb{P}_{\theta'}$  is defined by

$$\text{KL}(\mathbb{P}_\theta, \mathbb{P}_{\theta'}) = \begin{cases} \sum_{x \in E} p_\theta(x) \log \left( \frac{p_\theta(x)}{p_{\theta'}(x)} \right) & \text{if } E \text{ is discrete} \\ & \text{if } E \text{ is continuous} \end{cases}$$

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<sup>1</sup>KL-divergence is also known as “relative entropy”

# Properties of KL-divergence

- ▶  $\text{KL}(\mathbb{P}_\theta, \mathbb{P}_{\theta'}) \neq \text{KL}(\mathbb{P}_{\theta'}, \mathbb{P}_\theta)$  in general
- ▶  $\text{KL}(\mathbb{P}_\theta, \mathbb{P}_{\theta'}) \geq 0$
- ▶ If  $\text{KL}(\mathbb{P}_\theta, \mathbb{P}_{\theta'}) = 0$  then  $\mathbb{P}_\theta = \mathbb{P}_{\theta'}$  (definite)
- ▶  $\text{KL}(\mathbb{P}_\theta, \mathbb{P}_{\theta'}) \not\leq \text{KL}(\mathbb{P}_\theta, \mathbb{P}_{\theta''}) + \text{KL}(\mathbb{P}_{\theta''}, \mathbb{P}_{\theta'})$  in general

**Not a distance.**

This is called a

Asymmetry is the key to our ability to estimate it!

# Maximum likelihood estimation

## Estimating the KL

$$\begin{aligned}\text{KL}(\mathbb{P}_{\theta^*}, \mathbb{P}_{\theta}) &= \mathbb{E}_{\theta^*} \left[ \log \left( \frac{p_{\theta^*}(X)}{p_{\theta}(X)} \right) \right] \\ &= \mathbb{E}_{\theta^*} [\log p_{\theta^*}(X)] -\end{aligned}$$

So the function  $\theta \mapsto \text{KL}(\mathbb{P}_{\theta^*}, \mathbb{P}_{\theta})$  is of the form:

“constant” –

Can be estimated:  $\mathbb{E}_{\theta^*}[h(X)] \rightsquigarrow \frac{1}{n} \sum_{i=1}^n h(X_i)$  (by LLN)

$$\widehat{\text{KL}}(\mathbb{P}_{\theta^*}, \mathbb{P}_{\theta}) = \text{“constant”} - \frac{1}{n} \sum_{i=1}^n \log p_{\theta}(X_i)$$

# Maximum likelihood

$$\widehat{\text{KL}}(\mathbb{P}_{\theta^*}, \mathbb{P}_{\theta}) = \text{"constant"} - \frac{1}{n} \sum_{i=1}^n \log p_{\theta}(X_i)$$

$$\min_{\theta \in \Theta} \widehat{\text{KL}}(\mathbb{P}_{\theta^*}, \mathbb{P}_{\theta}) \quad \Leftrightarrow \quad \min_{\theta \in \Theta} -\frac{1}{n} \sum_{i=1}^n \log p_{\theta}(X_i)$$

$$\Leftrightarrow$$

$$\Leftrightarrow$$

$$\Leftrightarrow \max_{\theta \in \Theta} \prod_{i=1}^n p_{\theta}(X_i)$$

This is the **maximum likelihood principle**.

# Likelihood, Discrete case (1)

Let  $(E, (\mathbb{P}_\theta)_{\theta \in \Theta})$  be a statistical model associated with a sample of i.i.d. r.v.  $X_1, \dots, X_n$ . Assume that  $E$  is discrete (i.e., finite or countable).

## Definition

The *likelihood* of the model is the map  $L_n$  (or just  $L$ ) defined as:

$$\begin{aligned} L_n : \quad E^n \times \Theta &\rightarrow \mathbb{R} \\ (x_1, \dots, x_n, \theta) &\mapsto \mathbb{P}_\theta[X_1 = x_1, \dots, X_n = x_n]. \end{aligned}$$

# Likelihood for the Bernoulli model

**Example 1 (Bernoulli trials):** If  $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Ber}(p)$  for some  $p \in (0, 1)$ :

- ▶  $E = \{0, 1\}$ ;
- ▶  $\Theta = (0, 1)$ ;
- ▶  $\forall (x_1, \dots, x_n) \in \{0, 1\}^n, \quad \forall p \in (0, 1),$

$$\begin{aligned} L(x_1, \dots, x_n, p) &= \prod_{i=1}^n \mathbb{P}_p[X_i = x_i] \\ &= \prod_{i=1}^n \\ &= p \quad (1 - p) \quad . \end{aligned}$$

# Likelihood for the Poisson model

## Example 2 (Poisson model):

If  $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Poiss}(\lambda)$  for some  $\lambda > 0$ :

- ▶  $E = \mathbb{N}$ ;
- ▶  $\Theta = (0, \infty)$ ;
- ▶  $\forall (x_1, \dots, x_n) \in \mathbb{N}^n, \quad \forall \lambda > 0,$

$$L(x_1, \dots, x_n, p) = e^{-n\lambda} \frac{\lambda^{\sum_{i=1}^n x_i}}{x_1! \dots x_n!}.$$



## Likelihood, Continuous case

Let  $(E, (\mathbb{P}_\theta)_{\theta \in \Theta})$  be a statistical model associated with a sample of i.i.d. r.v.  $X_1, \dots, X_n$ . Assume that all the  $\mathbb{P}_\theta$  have density  $f_\theta$ .

### Definition

The *likelihood* of the model is the map  $L$  defined as:

$$\begin{aligned} L : \quad E^n \times \Theta &\rightarrow \mathbb{R} \\ (x_1, \dots, x_n, \theta) &\mapsto \prod_{i=1}^n f_\theta(x_i). \end{aligned}$$

# Likelihood for the Gaussian model

**Example 1 (Gaussian model):** If  $X_1, \dots, X_n \stackrel{iid}{\sim} \mathcal{N}(\mu, \sigma^2)$ , for some  $\mu \in \mathbb{R}, \sigma^2 > 0$ :

- ▶  $E = \mathbb{R}$ ;
- ▶  $\Theta = \mathbb{R} \times (0, \infty)$
- ▶  $\forall (x_1, \dots, x_n) \in \mathbb{R}^n, \quad \forall (\mu, \sigma^2) \in \mathbb{R} \times (0, \infty),$

$$L(x_1, \dots, x_n, \mu, \sigma^2) = \frac{1}{(\sigma\sqrt{2\pi})^n} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2\right).$$

# Exercises

Let  $(E, (\mathbb{P}_\theta)_{\theta \in \Theta})$  be a statistical model associated with  $X_1, \dots, X_n \sim \text{Exp}(\lambda)$ .

**a)** What is  $E$ ?

**b)** What is  $\Theta$ ?

**c)** Find the likelihood of the model.

## Exercise

Let  $(E, (\mathbb{P}_\theta)_{\theta \in \Theta})$  be a statistical model associated with  $X_1, \dots, X_n \sim \text{Unif}[0, b]$  for some  $b > 0$ .

**a)** What is  $E$ ?

**b)** What is  $\Theta$ ?

**c)** Find the likelihood of the model.

# Maximum likelihood estimator

Let  $X_1, \dots, X_n$  be an i.i.d. sample associated with a statistical model  $(E, (\mathbb{P}_\theta)_{\theta \in \Theta})$  and let  $L$  be the corresponding likelihood.

## Definition

The *maximum likelihood estimator* of  $\theta$  is defined as:

$$\hat{\theta}_n^{MLE} = \operatorname{argmax}_{\theta \in \Theta} L(X_1, \dots, X_n, \theta),$$

provided it exists.

**Remark (log-likelihood estimator):** In practice, we use the fact that

$$\hat{\theta}_n^{MLE} = \operatorname{argmax}_{\theta \in \Theta} L(X_1, \dots, X_n, \theta).$$

## Interlude: maximizing/minimizing functions

Note that

$$\min_{\theta \in \Theta} -h(\theta) \quad \Leftrightarrow \quad \max_{\theta \in \Theta} h(\theta)$$

In this class, we focus on **maximization**.

Maximization of arbitrary functions can be difficult:

Example:  $\theta \mapsto \prod_{i=1}^n (\theta - X_i)$

# Concave and convex functions

## Definition

A function twice differentiable function  $h : \Theta \subset \mathbb{R} \rightarrow \mathbb{R}$  is said to be *concave* if its second derivative satisfies

$$h''(\theta) \leq 0, \quad \forall \theta \in \Theta$$

It is said to be *strictly concave* if the inequality is strict:  $h''(\theta) < 0$

Moreover,  $h$  is said to be (strictly) *convex* if  $-h$  is (strictly) concave, i.e.  $h''(\theta) \geq 0$  ( $h''(\theta) > 0$ ).

Examples:

- ▶  $\Theta = \mathbb{R}, h(\theta) = -\theta^2,$
- ▶  $\Theta = (0, \infty), h(\theta) = \sqrt{\theta},$
- ▶  $\Theta = (0, \infty), h(\theta) = \log \theta,$
- ▶  $\Theta = [0, \pi], h(\theta) = \sin(\theta)$
- ▶  $\Theta = \mathbb{R}, h(\theta) = 2\theta - 3$

## Multivariate concave functions

More generally for a *multivariate* function:  $h : \Theta \subset \mathbb{R}^d \rightarrow \mathbb{R}$ ,  $d \geq 2$ , define the

► *gradient* vector:  $\nabla h(\theta) = \begin{pmatrix} \phantom{\frac{\partial h}{\partial \theta_1}} \\ \phantom{\frac{\partial h}{\partial \theta_2}} \\ \phantom{\frac{\partial h}{\partial \theta_d}} \end{pmatrix} \in \mathbb{R}^d$

► *Hessian* matrix:

$$\mathbf{H}h(\theta) = \begin{pmatrix} \frac{\partial^2 h}{\partial \theta_1 \partial \theta_1}(\theta) & \cdots & \frac{\partial^2 h}{\partial \theta_1 \partial \theta_d}(\theta) \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 h}{\partial \theta_d \partial \theta_d}(\theta) & \cdots & \frac{\partial^2 h}{\partial \theta_d \partial \theta_d}(\theta) \end{pmatrix} \in \mathbb{R}^{d \times d}$$

$h$  is concave  $\Leftrightarrow x^\top \mathbf{H}h(\theta)x \leq 0 \quad \forall x \in \mathbb{R}^d, \theta \in \Theta$ .

$h$  is strictly concave  $\Leftrightarrow x^\top \mathbf{H}h(\theta)x < 0 \quad \forall x \in \mathbb{R}^d, \theta \in \Theta$ .

Examples:

- $\Theta = \mathbb{R}^2$ ,  $h(\theta) = -\theta_1^2 - 2\theta_2^2$  or  $h(\theta) = -(\theta_1 - \theta_2)^2$
- $\Theta = (0, \infty)$ ,  $h(\theta) = \log(\theta_1 + \theta_2)$ ,



## Optimality conditions

Strictly concave functions are easy to maximize: if they have a maximum, then it is **unique**. It is the unique solution to

$$h'(\theta) = 0 ,$$

or, in the multivariate case

$$= 0 \in \mathbb{R}^d .$$

There are many algorithms to find it numerically: this is the theory of “convex optimization”. In this class, often a **closed form formula** for the maximum.

# Exercises

**a)** Which one of the following functions are concave on  $\Theta = \mathbb{R}^2$ ?

1.  $h(\theta) = -(\theta_1 - \theta_2)^2 - \theta_1\theta_2$

2.  $h(\theta) = -(\theta_1 - \theta_2)^2 + \theta_1\theta_2$

3.  $h(\theta) = (\theta_1 - \theta_2)^2 - \theta_1\theta_2$

4. Both 1. and 2.

5. All of the above

6. None of the above

**b)** Let  $h : \Theta \subset \mathbb{R}^d \rightarrow \mathbb{R}$  be a function whose hessian matrix  $\mathbf{H}h(\theta)$  has a positive diagonal entry for some  $\theta \in \Theta$ . Can  $h$  be concave? Why or why not?

# Examples of maximum likelihood estimators

- ▶ Bernoulli trials:  $\hat{p}_n^{MLE} = \bar{X}_n$ .
- ▶ Poisson model:  $\hat{\lambda}_n^{MLE} = \bar{X}_n$ .
- ▶ Gaussian model:  $(\hat{\mu}_n, \hat{\sigma}_n^2) = (\bar{X}_n, \hat{S}_n)$ .

# Consistency of maximum likelihood estimator

Under mild regularity conditions, we have

$$\hat{\theta}_n^{MLE} \xrightarrow[n \rightarrow \infty]{\mathbb{P}} \theta^*$$

This is because for all  $\theta \in \Theta$

$$\frac{1}{n} L(X_1, \dots, X_n, \theta) \xrightarrow[n \rightarrow \infty]{\mathbb{P}} \text{“constant”} -$$

Moreover, the minimizer of the right-hand side is if the parameter is .

Technical conditions allow to transfer this convergence to the minimizers.

# Covariance

How about asymptotic normality?

In general, when  $\theta \in \mathbb{R}^d$ ,  $d \geq 2$ , its coordinates are not necessarily


.

The **covariance** between two random variables  $X$  and  $Y$  is

$$\begin{aligned}\text{Cov}(X, Y) &= \\ &= \mathbb{E}[X \cdot Y] - \\ &= \mathbb{E}[X \cdot ( \quad )]\end{aligned}$$

# Properties

- ▶  $\text{Cov}(X, Y) =$
- ▶  $\text{Cov}(X, Y) = \text{Cov}(Y, X)$
- ▶ If  $X$  and  $Y$  are independent, then  $\text{Cov}(X, Y) =$

 In general, the **converse is not true** except if  $(X, Y)^\top$  is a **Gaussian vector**<sup>2</sup>:  $\alpha X + \beta Y$  is Gaussian for all nonzero  $(\alpha, \beta)$ .

Take  $X \sim \mathcal{N}(0, 1)$ ,  $B \sim \text{Ber}(1/2)$ ,  $R = 2B - 1 \sim \text{Rad}(1/2)$ . Then

$$Y = R \cdot X \sim$$

If  $\alpha = \beta = 1$ , we get  $X + Y = \begin{cases} & \text{with prob. } 1/2 \\ & \text{with prob. } 1/2 \end{cases}$

Actually  $\text{Cov}(X, Y) = 0$  but they are not independent:  $|X| = |Y|$

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<sup>2</sup>This is stronger than “ $X$  and  $Y$  are Gaussian individually”

## Covariance matrix

The covariance matrix of a random vector  $X = (X^{(1)}, \dots, X^{(d)})^\top \in \mathbb{R}^d$  is given by

$$\Sigma = \mathbf{Cov}(X) = \mathbb{E}[(X - \mathbb{E}(X))(X - \mathbb{E}(X))^\top]$$

This is a matrix of size

The term on the  $i$ th row and  $j$ th column is

$$\Sigma_{ij} = \mathbb{E}[(X^{(i)} - \mathbb{E}(X^{(i)}))(X^{(j)} - \mathbb{E}(X^{(j)}))] =$$

In particular, on the diagonal, we have

$$\Sigma_{ii} =$$

Recall that for  $X \in \mathbb{R}$ ,  $\text{Var}(aX + b) =$   
 $X \in \mathbb{R}^d$  and  $A, B$  are matrices:

. Actually, if

$$\text{Cov}(AX + B) =$$

# The multivariate Gaussian distribution

If  $(X, Y)^\top$  is a Gaussian vector then its pdf depends on 5 parameters:

$$\text{and } \text{Cov}(X, Y)$$

More generally, a Gaussian vector<sup>3</sup>  $X \in \mathbb{R}^d$ , is completely determined by its expected value and  $\mathbb{E}[X] = \mu \in \mathbb{R}^d$  covariance matrix  $\Sigma$ . We write

$$X \sim \mathcal{N}_d(\mu, \Sigma).$$

It has pdf over  $\mathbb{R}^d$  given by:

$$\frac{1}{\sqrt{(2\pi)^d \det(\Sigma)}} \exp \left( -\frac{1}{2} (x - \mu)^\top \Sigma^{-1} (x - \mu) \right)$$

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<sup>3</sup>As before, this means that  $\alpha^\top X$  is Gaussian for any  $\alpha \in \mathbb{R}^d, \alpha \neq 0$ .



# The multivariate CLT

The CLT may be generalized to averages or random vectors (also vectors of averages).

Let  $X_1, \dots, X_n \in \mathbb{R}^d$  be independent copies of a random vector  $X$  such that  $\mathbb{E}[X] = \mu$ ,  $\text{Cov}(X) = \Sigma$ ,

$$\sqrt{n}(\bar{X}_n - \mu) \xrightarrow[n \rightarrow \infty]{(d)}$$

Equivalently

$$\xrightarrow[n \rightarrow \infty]{(d)} \mathcal{N}_d(0, I_d)$$

## Multivariate Delta method

Let  $(T_n)_{n \geq 1}$  sequence of random vectors in  $\mathbb{R}^d$  such that

$$\sqrt{n}(T_n - \theta) \xrightarrow[n \rightarrow \infty]{(d)} \mathcal{N}_d(0, \Sigma),$$

for some  $\theta \in \mathbb{R}^d$  and some covariance  $\Sigma \in \mathbb{R}^{d \times d}$ .

Let  $g : \mathbb{R}^d \rightarrow \mathbb{R}^k$  ( $k \geq 1$ ) be continuously differentiable at  $\theta$ .  
Then,

$$\sqrt{n}(g(T_n) - g(\theta)) \xrightarrow[n \rightarrow \infty]{(d)} \mathcal{N}_k\left(0, \begin{pmatrix} \nabla g(\theta) \Sigma \nabla g(\theta)^T \end{pmatrix}\right),$$

where  $\nabla g(\theta) = \frac{\partial g}{\partial \theta}(\theta) = \left( \frac{\partial g_j}{\partial \theta_i} \right)_{\substack{1 \leq i \leq d \\ 1 \leq j \leq k}} \in \mathbb{R}^{d \times k}$ .

# Fisher Information

## Definition: Fisher information

Define the log-likelihood for one observation as:

$$\ell(\theta) = \log L_1(X, \theta), \quad \theta \in \Theta \subset \mathbb{R}^d$$

Assume that  $\ell$  is a.s. twice differentiable. Under some regularity conditions, the *Fisher information* of the statistical model is defined as:

$$I(\theta) = \mathbb{E}[\nabla \ell(\theta) \nabla \ell(\theta)^\top] - \mathbb{E}[\nabla \ell(\theta)] \mathbb{E}[\nabla \ell(\theta)]^\top = -\mathbb{E}[\mathbf{H}\ell(\theta)].$$

If  $\Theta \subset \mathbb{R}$ , we get:

$$I(\theta) = \text{var}[\ell'(\theta)] = -\mathbb{E}[\ell''(\theta)]$$

# Fisher information of the Bernoulli experiment

Let  $X \sim \text{Ber}(p)$ .

$$\ell(p) =$$

$$\ell'(p) =$$

$$\text{var}[\ell'(p)] =$$

$$\ell''(p) =$$

$$- \mathbb{E}[\ell''(p)] =$$

# Asymptotic normality of the MLE

## Theorem

Let  $\theta^* \in \Theta$  (the *true* parameter). Assume the following:

1. The parameter is identifiable.
2. For all  $\theta \in \Theta$ , the support of  $\mathbb{P}_\theta$  does not depend on  $\theta$ ;
3.  $\theta^*$  is not on the boundary of  $\Theta$ ;
4.  $I(\theta)$  is invertible in a neighborhood of  $\theta^*$ ;
5. A few more technical conditions.

Then,  $\hat{\theta}_n^{MLE}$  satisfies:

- ▶  $\hat{\theta}_n^{MLE} \xrightarrow[n \rightarrow \infty]{\mathbb{P}} \theta^* \quad \text{w.r.t. } \mathbb{P}_{\theta^*};$
- ▶  $\sqrt{n} \left( \hat{\theta}_n^{MLE} - \theta^* \right) \xrightarrow[n \rightarrow \infty]{(d)} \mathcal{N} \left( 0, I^{-1}(\theta^*) \right) \quad \text{w.r.t. } \mathbb{P}_{\theta^*}.$

# The method of moments

# Moments

Let  $X_1, \dots, X_n$  be an i.i.d. sample associated with a statistical model  $(E, (\mathbb{P}_\theta)_{\theta \in \Theta})$ .

- ▶ Assume that  $E \subseteq \mathbb{R}$  and  $\Theta \subseteq \mathbb{R}^d$ , for some  $d \geq 1$ .
- ▶ *Population moments*: Let  $m_k(\theta) = \mathbb{E}_\theta[X_1^k]$ ,  $1 \leq k \leq d$ .
- ▶ *Empirical moments*: Let  $\hat{m}_k = \overline{X_n^k} = \frac{1}{n} \sum_{i=1}^n X_i^k$ ,  $1 \leq k \leq d$ .
- ▶ From LLN,

$$\hat{m}_k \xrightarrow[n \rightarrow \infty]{\mathbb{P}/a.s.}$$

More compactly, we say that the whole vector converges:

$$(\hat{m}_1, \dots, \hat{m}_d) \xrightarrow[n \rightarrow \infty]{\mathbb{P}/a.s.}$$

# Moments estimator

Let

$$\begin{aligned} M &: \Theta \rightarrow \mathbb{R}^d \\ \theta &\mapsto M(\theta) = (m_1(\theta), \dots, m_d(\theta)). \end{aligned}$$

Assume  $M$  is one to one:

$$\theta = M^{-1}(m_1(\theta), \dots, m_d(\theta)).$$

## Definition

Moments estimator of  $\theta$ :

$$\hat{\theta}_n^{MM} = M^{-1}(\quad),$$

provided it exists.



# Statistical analysis

- ▶ Recall  $M(\theta) = (m_1(\theta), \dots, m_d(\theta))$ ;
- ▶ Let  $\hat{M} = (\hat{m}_1, \dots, \hat{m}_d)$ .
- ▶ Let  $\Sigma(\theta) = \text{Cov}_\theta(X_1, X_1^2, \dots, X_1^d)$  be the covariance matrix of the random vector  $(X_1, X_1^2, \dots, X_1^d)$ , which we assume to exist.
- ▶ Assume  $M^{-1}$  is continuously differentiable at  $M(\theta)$ .

## Method of moments (5)

**Remark:** The method of moments can be extended to more general moments, even when  $E \not\subset \mathbb{R}$ .

- ▶ Let  $g_1, \dots, g_d : E \rightarrow \mathbb{R}$  be given functions, chosen by the practitioner.
- ▶ Previously,  $g_k(x) = x^k$ ,  $x \in E = \mathbb{R}$ , for all  $k = 1, \dots, d$ .
- ▶ Define  $m_k(\theta) = \mathbb{E}_\theta[g_k(X)]$ , for all  $k = 1, \dots, d$ .
- ▶ Let  $\Sigma(\theta) = \text{Cov}_\theta(g_1(X_1), g_2(X_1), \dots, g_d(X_1))$  be the covariance matrix of the random vector  $(g_1(X_1), g_2(X_1), \dots, g_d(X_1))$ , which we assume to exist.
- ▶ Assume  $M$  is one to one and  $M^{-1}$  is continuously differentiable at  $M(\theta)$ .

# Generalized method of moments

Applying the multivariate CLT and Delta method yields:

## Theorem

$$\sqrt{n} \left( \hat{\theta}_n^{MM} - \theta \right) \xrightarrow[n \rightarrow \infty]{(d)} \mathcal{N}(0, \Gamma(\theta)) \quad (\text{w.r.t. } \mathbb{P}_\theta),$$

$$\text{where } \Gamma(\theta) = \left[ \frac{\partial M^{-1}}{\partial \theta}(M(\theta)) \right]^\top \Sigma(\theta) \left[ \frac{\partial M^{-1}}{\partial \theta}(M(\theta)) \right].$$

# MLE vs. Moment estimator

- ▶ Comparison of the quadratic risks: In general, the MLE is more accurate.
- ▶ MLE still gives good results if model is misspecified
- ▶ Computational issues: Sometimes, the MLE is intractable but MM is easier (polynomial equations)

# M-estimation

# M-estimators

## Idea:

- ▶ Let  $X_1, \dots, X_n$  be i.i.d with some unknown distribution  $\mathbb{P}$  in some sample space  $E$  ( $E \subseteq \mathbb{R}^d$  for some  $d \geq 1$ ).
- ▶ No statistical model needs to be assumed (similar to ML).
- ▶ Goal: estimate some parameter  $\mu^*$  associated with  $\mathbb{P}$ , e.g. its mean, variance, median, other quantiles, the true parameter in some statistical model...
- ▶ Find a function  $\rho : E \times \mathcal{M} \rightarrow \mathbb{R}$ , where  $\mathcal{M}$  is the set of all possible values for the unknown  $\mu^*$ , such that:

$$Q(\mu) := \mathbb{E} [\rho(X_1, \mu)]$$

achieves its minimum at  $\mu = \mu^*$ .

# Examples (1)

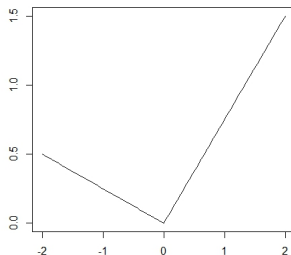
- ▶ If  $E = \mathcal{M} = \mathbb{R}$  and  $\rho(x, \mu) = (x - \mu)^2$ , for all  $x \in \mathbb{R}, \mu \in \mathbb{R}$ :  
 $\mu^* =$
- ▶ If  $E = \mathcal{M} = \mathbb{R}^d$  and  $\rho(x, \mu) = \|x - \mu\|_2^2$ , for all  
 $x \in \mathbb{R}^d, \mu \in \mathbb{R}^d$ :  $\mu^* =$
- ▶ If  $E = \mathcal{M} = \mathbb{R}$  and  $\rho(x, \mu) = |x - \mu|$ , for all  $x \in \mathbb{R}, \mu \in \mathbb{R}$ :  
 $\mu^*$  is a                      of  $\mathbb{P}$ .

## Examples (2)

If  $E = \mathcal{M} = \mathbb{R}$ ,  $\alpha \in (0, 1)$  is fixed and  $\rho(x, \mu) = C_\alpha(x - \mu)$ , for all  $x \in \mathbb{R}, \mu \in \mathbb{R}$  :  $\mu^*$  is a  $\alpha$ -quantile of  $\mathbb{P}$ .

Check function

$$C_\alpha(x) = \begin{cases} -(1 - \alpha)x & \text{if } x < 0 \\ \alpha x & \text{if } x \geq 0. \end{cases}$$





# MLE is an M-estimator

Assume that  $(E, \{\mathbb{P}_\theta\}_{\theta \in \Theta})$  is a statistical model associated with the data.

## Theorem

Let  $\mathcal{M} = \Theta$  and  $\rho(x, \theta) = -\log L_1(x, \theta)$ , provided the likelihood is positive everywhere. Then,

$$\mu^* = \theta^*,$$

where  $\mathbb{P} = \mathbb{P}_{\theta^*}$  (i.e.,  $\theta^*$  is the true value of the parameter).

# Definition

- ▶ Define  $\hat{\mu}_n$  as a minimizer of:

$$\mathcal{Q}_n(\mu) := \frac{1}{n} \sum_{i=1}^n \rho(X_i, \mu).$$

- ▶ Examples: Empirical mean, empirical median, empirical quantiles, MLE, etc.

# Statistical analysis

- ▶ Let  $J(\mu) = -\frac{\partial^2 Q}{\partial \mu \partial \mu^\top}(\mu)$  ( $= -\mathbb{E} \left[ \frac{\partial^2 \rho}{\partial \mu \partial \mu^\top}(X_1, \mu) \right]$  under some regularity conditions).

- ▶ Let  $K(\mu) = \text{Cov} \left[ \frac{\partial \rho}{\partial \mu}(X_1, \mu) \right]$ .

- ▶ **Remark:** In the log-likelihood case (write  $\mu = \theta$ ),

$$J(\theta) = K(\theta) =$$

# Asymptotic normality

Let  $\mu^* \in \mathcal{M}$  (the *true* parameter). Assume the following:

1.  $\mu^*$  is the only minimizer of the function  $Q$ ;
2.  $J(\mu)$  is invertible for all  $\mu \in \mathcal{M}$ ;
3. A few more technical conditions.

Then,  $\hat{\mu}_n$  satisfies:

$$\blacktriangleright \hat{\mu}_n \xrightarrow[n \rightarrow \infty]{\mathbf{P}} \mu^*;$$

$$\blacktriangleright \sqrt{n} (\hat{\mu}_n - \mu^*) \xrightarrow[n \rightarrow \infty]{(d)} \mathcal{N} \left( 0, \quad K(\mu^*) \quad \right).$$

# M-estimators in robust statistics

## Example: Location parameter

If  $X_1, \dots, X_n$  are i.i.d. with density  $f(\cdot - m)$ , where:

- ▶  $f$  is an unknown, positive, even function (e.g., the Cauchy density);
- ▶  $m$  is a real number of interest, a *location parameter*;

How to estimate  $m$  ?

- ▶ M-estimators: empirical mean, empirical median, ...
- ▶ Compare their risks or asymptotic variances;
- ▶ The empirical median is more *robust*.

# Recap

- ▶ Three principled methods for estimation: maximum likelihood, Method of moments, M-estimators
- ▶ Maximum likelihood is an example of  $M$ -estimation
- ▶ Method of moments inverts the function that maps parameters to moments
- ▶ All methods yield to asymptotic normality under regularity conditions
- ▶ Asymptotic covariance matrix can be computed using multivariate  $\Delta$ -method
- ▶ For MLE, asymptotic covariance matrix is the inverse Fisher information matrix