

CSSS/POLS 510 - Maximum Likelihood Estimation

Lab 2: Probability Distributions, Statistical Inference, and Ordinary Least Squares

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Preview

- ▶ Statistical Inference
- ▶ Probability Distributions
- ▶ Least Squares Estimation

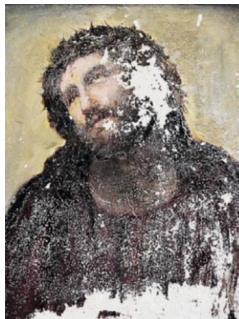
Statistical inference: estimation

- ▶ In statistical inference, we are concerned with making **predictions** (inferences) about a **DGP** or *population* based on information obtained from a *sample*.
- ▶ This involves the following key concepts:
 - ▶ **Estimand**: The **quantity of interest** from the data-generating process that we aim to estimate or infer.
 - ▶ **Estimator**: A statistical **method** or **formula** used to estimate the estimand based on sample data.
 - ▶ **Estimate**: it is the calculated value that serves as the **best guess** or approximation of the estimand based on the available information from the sample.

Estimand, estimator, and estimate

- ▶ Statistical inference involves using **estimators** to obtain **estimates** of **estimands** from sample data to make predictions about the population.

- ▶ Analogy (from Spain):
have you ever heard about the *ecce homo*?
 - ▶ explanation: [1 min. YouTube video](#).



Statistical inference: estimation

Estimand



Statistical inference: estimation

Estimand



Estimator



Statistical inference: estimation

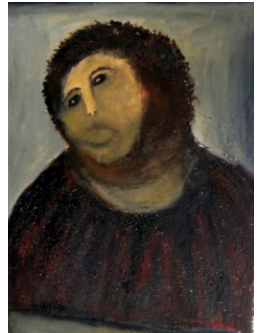
Estimand



Estimator



Estimate



Statistical inference: Plug-in moment estimator.

The **plug-in principle** states that a feature of a given distribution can be approximated by the same feature of the **empirical distribution**, based on a sample of observations drawn from that distribution.

Estimand

$$\mu$$

Estimator

$$\hat{\mu} = \bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$$

Estimate

$$\hat{\mu} = 3.6$$

Statistical inference: Ordinary Least Squares

We could be interested in a **controlled association** (β) between two predictors \mathbf{X} and an outcome \mathbf{y} .

Estimand

$$\beta$$

Estimator

$$(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

Estimate

$$\hat{\beta} = \begin{bmatrix} 3.4 \\ -0.20 \end{bmatrix}$$

Statistical inference: Generalized Method of Moments

GMM estimators find parameter values (θ) that minimize the distance between **sample** moments (from data) and **theoretical** moments (from the model) using a **weighting matrix** (\mathcal{W}). This method, often used in *dynamic panel* settings, relies on **moment conditions** but does not require full **distributional assumptions**.

Estimand

$$E[\mathbf{g}(Y_i, \theta)] = \mathbf{0}$$

Estimator

$$\hat{\mathbf{g}}_n(\theta)^T \mathcal{W}_n \hat{\mathbf{g}}_n(\theta)$$

Estimate

$$\hat{\theta} = \begin{bmatrix} 0.5 \\ -0.3 \\ 1.2 \end{bmatrix}$$

Estimand, estimator, and estimate

- ▶ **Estimates** are *best guesses*, but they never return you the “*true*”.



Maximum Likelihood Inference

- ▶ **1. Choose a Probability Model:** Select a **pdf** (e.g., normal, binomial) that best describes the DGP.

Maximum Likelihood Inference

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Maximum Likelihood Inference

- ▶ **1. Choose a Probability Model:** Select a **pdf** (e.g., normal, binomial) that best describes the DGP.
- ▶ **2. Maximize the Likelihood:** Estimate the **parameters** by maximizing the **likelihood** or **log-likelihood** function using observed data.
- ▶ **3. Evaluate the Fit:** Use the **estimated parameters** to compute probabilities, perform hypothesis tests, and make inferences about the population.

How do we evaluate our estimators

- ▶ **Bias:** Measures the **difference between the expected value** of the estimator and the true parameter. An **unbiased estimator** has $E[\hat{\theta}] = \theta$.
- ▶ **Efficiency:** Compares **variance** among unbiased estimators; the **most efficient estimator** has the **smallest variance** and thus provides **more precise estimates**.
- ▶ **Consistency:** Ensures that the estimator **converges to the true parameter** as the sample size increases ($\hat{\theta} \rightarrow \theta$ as $n \rightarrow \infty$), indicating **reliability** with large samples.

Chris will cover all these in detail next week in class!

sample() Function in R:

- ▶ Generates a **random sample** from a specified vector or a set of integers.
- ▶ **Syntax:** `sample(x, size, replace = FALSE, prob = NULL)`
 - ▶ **x:** The vector to sample from (e.g., `1:10`).
 - ▶ **size:** Number of elements to sample.
 - ▶ **replace:** If `TRUE`, allows **sampling with replacement**.
 - ▶ **prob:** A vector of **probabilities** for sampling each element.
- ▶ **Example:** `sample(1:5, 3, replace = TRUE)` might return 4, 1, 2.

for Loops in R:

- ▶ Executes a block of code **repeatedly** for each element in a sequence.
- ▶ **Basic Syntax:**

```
for (index in sequence) {  
  # Code to execute  
}
```

- ▶ **index:** Loop or control variable that takes values from the sequence.
- ▶ **sequence:** A vector or list of elements to iterate over.

for Loops in R:

► Example:

```
# Use a for loop to iterate over numbers 1 to 5  
for (i in 1:5) {  
  print(paste("Index:", i, "Value:", i))  
}
```

```
## [1] "Index: 1 Value: 1"  
## [1] "Index: 2 Value: 2"  
## [1] "Index: 3 Value: 3"  
## [1] "Index: 4 Value: 4"  
## [1] "Index: 5 Value: 5"
```

function() in R:

- ▶ Creates a **custom function** to encapsulate code and perform specific tasks.
- ▶ **Basic Syntax:**

```
function_name <- function(arg1, arg2, ...) {  
  # Code to execute  
  return(result)  
}
```

- ▶ `arg1, arg2, ...`: Function arguments.
- ▶ `return()`: Specifies the output.

function() in R:

► Example:

```
add_numbers <- function(x, y) {  
  sum <- x + y  
  return(sum)  
}
```

use the function

```
add_numbers(3, 4)
```

```
## [1] 7
```

Open lab 2

- ▶ Open the `lab2.Rmd` file and follow the explanations and code.
- ▶ We will then work on the `Lab2_practice.Rmd` file.
 - ▶ If we don't finish all the exercises today, we'll continue from where we left off next week.

FIN