

Data Analysis in R

Causality & The Basics of Statistics

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Syllabus: Data Analysis in R

1. Introduction
2. **Causality & Basics of Statistics**
3. Measurement
4. Prediction
5. Multivariate Regression
6. Probability & Uncertainty
7. Hypothesis Testing
8. Assumptions & Limits of OLS
9. Interactions & Non-Linear Effects

Table of Contents

Introduction

Causality

Statistics: The Basics

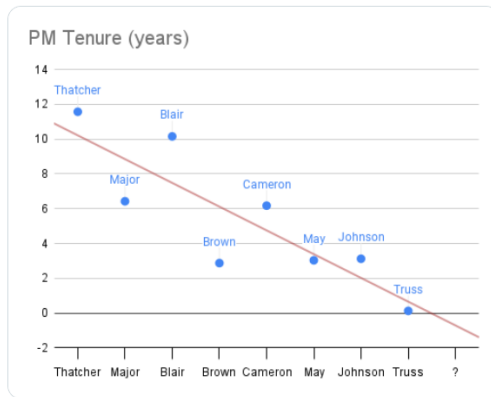
Why Do We Analyse Data?



Rob Sansom
@Sansom_Rob

...

Following current trends, the next PM will be in office for approximately minus 200 days



6:59 pm · 20 Oct 2022 · Twitter Web App

Definitions

Causality

Refers to the relationship between events where one set of events (the effects) is a direct consequence of another set of events (the causes). (Hidalgo & Sekhon 2012)

Data are Key

The process by which one can use data to make claims about causal relationships. (Hidalgo & Sekhon 2012)

Inferring causal relationships is a central task of science.

Examples

- ▶ What is the effect of peace-keeping missions on peace?
- ▶ What is the effect of church attendance on social capital?
- ▶ What is the effect of minimum wage on employment?

A Counterfactual Logic

Counterfactual Logic

If X had/had not been the case, Y would/would not have happened

Example: *Does college education increase earnings?*

- ▶ If high school grads had instead obtained a college degree, how much would their income change?
- ▶ If college grads had only obtained a high school diploma, how much would their income change?

A hypothetical example

Imagine two students who are interested in getting a very high score on their thesis. They are considering the courses they should take and they are undecided between *Data Analysis in R* or sticking with *SPSS*.

Y_i : Thesis score is the outcome variable of interest for unit i .

$$D_i = \begin{cases} 1 & \text{if unit } i \text{ received the treatment (taking Data Analysis in R)} \\ 0 & \text{otherwise.} \end{cases}$$

$$Y_{di} = \begin{cases} Y_{1i} & \text{Potential thesis score for student } i \text{ with Data Analysis in R} \\ Y_{0i} & \text{Potential thesis score for student } i \text{ without Data Analysis in R} \end{cases}$$

Q: What is the effect of taking Data Analysis in R on your thesis score?

Defining the Potential Outcomes

Definition: Treatment

D_i : Indicator of treatment status for unit i

$$D_i = \begin{cases} 1 & \text{if unit } i \text{ received the treatment} \\ 0 & \text{otherwise.} \end{cases}$$

Definition: Observed Outcome

Y_i : Observed outcome variable of interest for unit i . (Realized after the treatment has been assigned)

Defining the Potential Outcomes

Definition: Potential Outcomes

Y_{0i} and Y_{1i} : Potential Outcomes for unit i

$$Y_{di} = \begin{cases} Y_{1i} & \text{Potential outcome for unit } i \text{ with treatment} \\ Y_{0i} & \text{Potential outcome for unit } i \text{ without treatment} \end{cases}$$

The Fundamental Problem of Causal Inference

The Fundamental Problem of Causal Inference

It is impossible to observe for the same unit i the values $D_i = 1$ and $D_i = 0$ as well as the values Y_{1i} and Y_{0i} and, therefore, it is impossible to observe the effect of D on Y for unit i .

This is why we call this a **missing data problem**. We cannot observe both potential outcomes, hence we cannot estimate:

$$\tau_i = Y_{1i} - Y_{0i}$$

		Y_{i1}	Y_{i0}
Person 1	Treatment Group ($D = 1$)	Observable as Y	Counterfactual
Person 2	Control Group ($D = 0$)	Counterfactual	Observable as Y

Dealing with this is core challenge of social science research!

Causal Identification & Internal Validity

- ▶ **Association is not causation.**
- ▶ *Internal validity* refers to the concern that the difference in outcomes we observe between treated and untreated units are truly caused by the treatment.
- ▶ Some threats to internal validity are:
 - ▶ Omitted variables
 - ▶ Selection bias: Non-random selection into the treatment group
 - ▶ Endogeneity and reverse causality
- ▶ **Randomised experiments v observational studies**

Statistics: The Basics

Today, we'll briefly discuss the very basics of descriptive statistics:

- ▶ Types of variables
- ▶ Measures of central tendency
- ▶ Quantiles
- ▶ Standard Deviation

Types of Variables: Discrete Variables

A **variable** is a measurement of a characteristic of a *unit of analysis* that (usually) varies across unit in a population of units.

There are different levels of measurement:

- ▶ **Nominal:** categorical measure, with no ordering
 - ▶ e.g . Employed/Unemployed; Single/Married/Divorced
- ▶ **Ordinal:** ordered categorical measure
 - ▶ The distance between each category is unknown (strongly agree v agree)
 - ▶ e.g. many survey questions

Types of Variables: Continuous Variables

- ▶ **Interval:** numbers represent a quantitative variable
 - ▶ The distance between each level is known and uniform
 - ▶ e.g . temperatures, voting cohesion, HDI, measures of democratisation? etc.
 - ▶ We can say that it's 10 C more than yesterday
- ▶ **Ratio:** There is a meaningful zero mark - which marks complete absence of the measure
 - ▶ We can divide measures and express them as multiples
 - ▶ e.g. Age: someone might be twice as old as you are whereas this is not the case for temperature (human development?)

Descriptive Statistics

- ▶ **Descriptive statistics** are simply that: they describe a large amount of data by summarising it
 - ▶ Think of all the values of a variable, which is not very informative - but we somehow want to make sense of them
- ▶ Why descriptive stats?
 - ▶ Because we're often interested in what a typical unit (e.g .person/country/district etc.) looks like
 - ▶ Because it's useful to reduce many measurements to key indicators - either we're interested in them or as a preparatory step
- ▶ **Descriptive statistics \neq inferential statistics**

Measures of Central Tendency

- ▶ Measuring the *centre* of data - but which one?
 - ▶ **Mean:** most common, also referred to as the *average*
 - ▶ Sum of measures divided by number of observations

$$\text{mean} = \frac{x_1 + x_2 + \dots + x_n}{n}$$

- ▶ **Median:** More robust to *outliers*
 - ▶ Value at 50% mark of all observed values.
- $$\text{median} = \begin{cases} \text{middle value} & \text{if number of entries is odd} \\ \frac{\text{sum of two middle values}}{2} & \text{if number of entries is even} \end{cases}$$

Example: data = {0, 1, 2, 3, 100}, mean = 21.2, median = 2

Range & Quantiles

- ▶ Measuring the **spread** or **dispersion** of data
 - ▶ **Range:** $[\min(x), \max(x)]$
 - ▶ **Quantile:** 'Portions' of the sorted data: quartile, quantile, percentile, etc.:
 - ▶ 25 percentile = lower quartile
 - ▶ 50 percentile = median
 - ▶ 75 percentile = upper quartile
 - ▶ **Interquartile Range (IQR):** Measure of variability and dispersion of the overall variable
 - ▶ A definition of *outliers*: over 1.5 IQR above upper quartile or below lower quartile

Example:

0%	25%	50%	75%	100%
9.9	16.2	29.2	42.3	75.2

Standard Deviation

- ▶ On average, how far away are data points from their mean?

$$\text{standard deviation} = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2}$$

- ▶ **Root-Mean-Square** (RMS) of deviation from average
- ▶ Sometimes it's divided by n instead of $n-1$
- ▶ Variance = standard deviation²

Wrap Up

- ▶ Key points from today:
 - ▶ We're interested in causal effects, but can't observe counterfactuals - the fundamental problem of causal inference
 - ▶ Randomization is ideal, but possibilities with observational data - need a carefully drafted identification strategy though
 - ▶ Description also important; there are different ways to describe data
- ▶ Next time we'll be talking about:
 - ▶ Measurement and sampling
 - ▶ Summarizing relationships between two variables
 - ▶ Visualizing data and distributions