# Data Analysis in R

## Causality & The Basics of Statistics

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31st October 2024

# Syllabus: Data Analysis in R

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# Why Do We Analyse Data?

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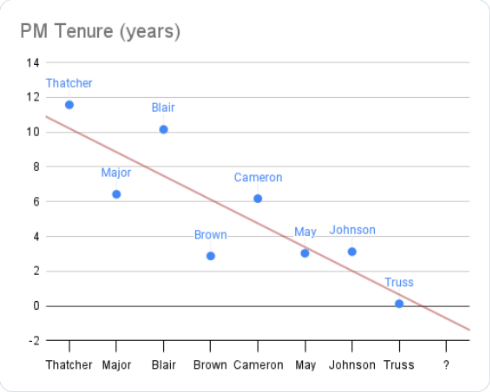
Following current trends, the next PM will be in office for approximately minus 200 days

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# 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:

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

| | | $Y_{1i}$ | $Y_{0i}$ |
|---|---|---|---|
| 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 - where we can quantify distances
  - 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

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

- **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 quantile
  - **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 deviation$^2$

# 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 carefuly 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