Erasmus
School of
Economics

Statistics for Data Science
Lecture 1

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Erasmus University Rotterdam

Who am I

Dennis Fok

- PhD in Econometrics
- Professor of *Econometrics and Data Science*
- Director of Econometric Institute, Erasmus School of Economics
- Research interests:
  - Modeling individual behavior
  - Marketing models
  - Panel data models
  - Simulation-based estimation methods
  - High-dimensional data
- Publications:
  - Marketing (*Marketing Science*, *Journal of Marketing Research*, *International Journal of Research in Marketing*)
  - Econometrics (*Journal of Econometrics*, *Journal of Applied Econometrics*)

Course setup

Background of this course

Statistics:

- Most scary course –or– exiting and fun?
- Basis for many courses to follow!

Goals:

- (Re-)introduce statistics
- Apply everything in Python (or R)
- Not just know *how* to do things: also understand *why*!
- Critical thinking!

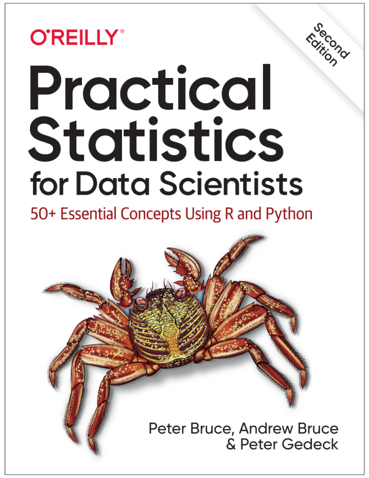
Setup of course

People involved

- Me!
- + (technical) assistant

Material

- Handouts of slides (most important)
- Book: Bruce, Bruce, and Gedeck, "Practical Statistics for Data Scientists" (we do chapters 1 – 5)
- Additional exercises



Study advice

Steps to take:

1. Preparation: read book
2. Lectures
   - Theory
   - In-class practice
3. After lecture:
   - Reread book (try out code examples in book)
   - Practice
     - Weekly assignment
     - Apply methods in own work environment!
4. "Final" assignment is to be submitted in parts
5. Questions and discussions
   - During class
   - Through *Discussions* on Canvas

Outline of course

1. Basics of statistics and inference
2. Distributions, descriptive statistics and hypothesis testing
3. Testing for differences
4. Linear regression model
5. Diagnostics for multiple regression + model selection
6. Generalized linear models (logistical regression)
7. Bayesian statistics

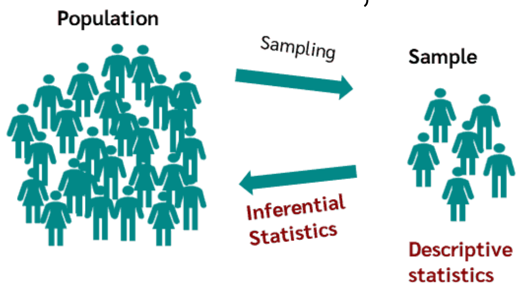
Statistics

Goal of statistics

Goals:

1. Summarize properties of data } Descriptive statistics
2. Make statements on (differences across) datasets
   → Statistical hypothesis testing
3. Estimate properties of (assumed) data generating process

} Inferential statistics



Inference/Inferential statistics

Usually statements on the **population** are the target!

Two important things to keep in mind:

1. How good are these statements?
2. Estimation uncertainty will always be present
3. **All** methods have associated assumptions (also ML/AI methods)!
   - Properties of methods derived under these assumptions
   - What if assumptions are not correct?

Some key concepts in statistics

1. Data and variables
2. Samples and population
3. Variation and uncertainty
4. Models

Key concept 1: Data

Key starting point is always: data or dataset → collection of observed variables or features

Classification of data/variables

- Role in the analysis
  - Dependent/Response/Outcome variable
  - Independent/Explanatory variable
- Measurement type
  - Numeric
    - Continuous (eg. temperature)
    - Discrete (eg. a count)
  - Categorical (aka: *factor with levels*)
    - Binary (eg. yes/no)
    - Nominal (no ordering: eg. color)
    - Ordinal (with ordering: eg. disagree/neutral/agree)

Notes:

- No clear dependent variable → *Exploratory statistics*
- Measurement type (dependent) variable → Determines *type of statistical analysis*
- In R/Python: data type may determine "actions" by functions

Data sets

Terminology

- Data frame: `DataFrame` objects
  → Data like a spreadsheet
  → Structured, rectangular data
- Other data shapes: possible, but more advanced material

Key concept 2: samples and population

- Source of data
  - Experimental
  - Observational
- Independent observations?
  - Repeated observations?
  - Hierarchical clustering? (eg. Children within a Class within a School)
- Random sample from population?
  - What is the population of interest?
  - What effects to control for?

Beware of *selective sampling / sampling bias*

Question

How (not) to get random sample for political survey?

Examples of non-random samples

- Survey on "random" people at the local market
- Response to a (e)mail/or online survey (response rate matters)
- ...

→ Compare "population" to "sample" to spot (potentially big) problems

Key concept 3: Variation and uncertainty

- Variation across samples is always expected
  - measurement error
  - different respondents
  - random variation
  - ...

  → When is variation larger than expected?
- Comparing (assumed) truth (=unobserved) versus measurement/estimation (=observed)
  - Expectations vs. (sample) means
- Statistical concept: significance
  - A difference (*assumed* truth − observed) is significant:
    → Size of found difference is *unlikely* under the assumed truth
  - Not significant:
    → The found difference is not larger than what can be expected by chance alone
  - Not significant does not mean no true difference!
    (and other way around?)

Key concept 4: Models

Statistical/Econometric models:

- Set of assumptions made about the *data generating process*
- Allow for description and prediction (and sometimes prescription)
- Important for all statistical procedures (even for "just testing")
- "All models are wrong, but some are useful" (Box & Draper, 1987)
- Know which assumptions are crucial!
- Model choice and testing of assumptions are important
- How to fix things?

Models in Python (sneak preview)

Many models are available in Python packages (eg in statsmodels), examples:

- Linear model `m = smf.ols(..)`
- Generalized linear model `m = smf.glm(..)`
- Linear mixed effects `m = smf.mixedlm(..)`
- etc.

Most models allow for a large range of functions/results

- `r = m.fit()`: fit the model to data and get result named `r`
- `r.summary()`: print summary
- `r.predict()`: give fitted values
- `r.params`: give coefficients
- `sm.stats.anova_lm(r)`: analysis of variance of fitted model
- etc

(after `import statsmodels.api as sm` and
`import statsmodels.formula.api as smf`)

Organization of (statistical) analysis in Python

Steps to take:

- Import data (using pandas DataFrame: `import pandas as pd`)
  - Create a data frame directly: `data = pd.DataFrame(..)`
  - Load from file, eg. `data = pd.read_csv("file.csv")`
- Select and transform data (if necessary)
- Explore data (spot & fix errors)
  - `data.plot(title="Title text", ..)`
  - `data.describe()`
- Perform statistical calculations
- Present results

Organize all of this in a script, such that the results can be replicated!
→ See programming course for more info

In-class assignment

Assignment

- See the file `Day-1-AssignmentPython.pdf` on canvas.
- Do exercise 1.1

Descriptive statistics

Explore data

Use descriptive statistics to understand your data

Graphical:

- various plots: `dataname.plot.scatter(..)`,
  for example `dataname.plot.scatter('xvar', 'yvar')`
- histograms: `dataname.seriesname.plot.hist()`
- density: `dataname.seriesname.plot.density()`
- boxplots: `dataname.boxplot('varname')`

where `dataname` refers to a dataframe and `seriesname` to a variable within the data)

Things to look for

- Degree of variation in variables
- Shape of distributions
- Signs of relations between variables (eg. correlation)
- Strange observations: Outliers!

Summary statistics

- Graphical summaries of data are useful
- Numerical summaries → basis for further analysis

Consider n observations on a variable: $X_1, X_2, \ldots, X_n$

Measures of location/central tendency

- Mode (`dataname.seriesname.mode()`): most frequently observed value
- Mean (`.mean()` or `np.mean(..)` from `import numpy as np`)
  (note `dataname.seriesname` should come before the `.` or instead of the `..`)

$$\frac{X_1 + X_2 + \ldots + X_n}{n} = \frac{\sum_{i=1}^{n} X_i}{n} = \bar{X}$$

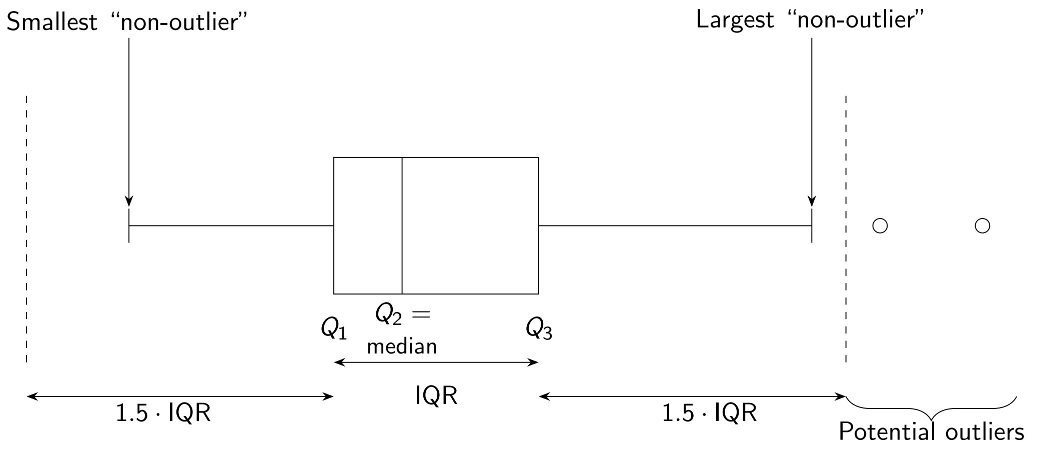
- Median=50%quantile (`.median()`): 50% of observations is smaller
  (median is much less sensitive to outliers than mean)

Measures of variation

Possible measures of variation

- Range (max-min): use `.min()` and `.max()`
- Inter-quantile range
  - 75% quantile – 25% quantile *or*
  - 3rd quartile – 1st quartile)
  - `.quantile(0.75) - .quantile(0.25)`
  - Also useful to detect outliers
    → Common definition of outlier: obs. more than 1.5×IQR below 1st or above 3rd quartile

Putting some things together: Boxplots



Other measures of variation

- Mean deviation from mean? → will always be zero
- Mean absolute deviation from mean?
  - Very useful (robust to outliers) *but*
  - Absolute values are mathematically difficult

→ Use mean *squared* deviation from mean

Mean squared deviation & Degrees of freedom

The mean squared deviation is a crucial tool in statistics!
Given a sample $X_1, \dots, X_n$. Define sum of squares $= \sum_i (X_i - \bar{X})^2$

Important detail: how to define "mean"?

- Naive definition: sum over all i (all observations) and divide by n
- However: we used the data to calculate $\bar{X}$!
- Here we know that $\sum_i (X_i - \bar{X}) = 0$
  → We "loose" the information of one observation, degrees of freedom becomes $n - 1$
- Estimated variance of X (`.var()`)

$$s^2 = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \bar{X})^2$$

- In general: degrees of freedom = no. obs − no. estimated parameters
- Standard deviation $= \sqrt{\text{Variance}}$ (`.std()`)

In-class assignment

Assignment

- See the file `Day-1-AssignmentPython.pdf` on canvas.
- Do exercise 1.2

Estimation uncertainty

Sample mean $\frac{1}{n}\sum_i X_i$ and sample variance $\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2$ are both estimates!

Therefore:

- Different sample $\rightarrow$ different findings
- There is estimation uncertainty

Estimates of what?
$\rightarrow$ Corresponding *population* concepts (remember the concept *inferential statistics*)

- Expected value: $\mathrm{E}[X]$
- (Population) variance: $\mathrm{Var}[X] = \mathrm{E}[(X - \mathrm{E}[X])^2]$

Higher order moments

Until now:

- Central tendency (eg. mean)
- Measures of variation (eg. variance)

Moments of a random variable X

- First moment: $\mathrm{E}[X] = \mu$
- Second (central) moment: $\mathrm{E}[(X - \mu)^2] = \mathrm{Var}[X] = \sigma^2$
- Third (standardized) moment: $\mathrm{E}[\frac{(X-\mu)^3}{\sigma^3}] = \text{skewness}$
- Fourth (standardized) moment: $\mathrm{E}[\frac{(X-\mu)^4}{\sigma^4}] = \text{kurtosis}$

$\rightarrow$ Can estimate all of these using data

`.skew()` or `.kurtosis()`
(do check exact definition of what is calculated!)

Moments for normal distribution

If $X \sim N(\mu, \sigma^2)$

- mean=E$[X] = \mu$
  $\rightarrow$ location
- variance=E$[(X-\mu)^2] = \sigma^2$
  $\rightarrow$ spread/variation
- skewness=E$[\frac{(X-\mu)^3}{\sigma^3}] = 0$
  $\rightarrow$ skewed or symmetric?
- kurtosis= E$[\frac{(X-\mu)^4}{\sigma^4}] = 3$
  $\rightarrow$ "peakedness"

Notes

- Often we look at excess kurtosis = kurtosis - 3
- Can test moments against values for normal distribution (more in later lectures)

Overview of descriptive statistics

Getting a quick overview

- `dataframename.describe()` from `pandas` package
- Various packages will give you options for descriptive statistics
- If you do not have a package yet:
  - Install it first (see programming course). This is needed only once.
  - Next load it with `import packagename` (in each session where you use it)
  - Abbreviate the package name (for later use): use eg `import pandas as pd` instead

Also possible: bivariate (or multivariate) descriptives

- scatter plot
- conditional boxplot
- correlation
- contingency table/cross table
- ...

Assignment

Before next time

Assignment for next week

- Read
  - Chapter 1 (this week's material)
  - Chapter 2 (next week)
- Try some examples in the book yourself (see here for data and code)
- Finish today's assignments (1.1 - 1.4)
- Continue to practice using own data (or the housing data)
  - Create simple plots
  - Calculate summary statistics
  - Inspect distributions of some variables (also consider transformations of variables)
  - Visualize relations between variables
- Optional: Exercise 2 (Volkswagen prices)