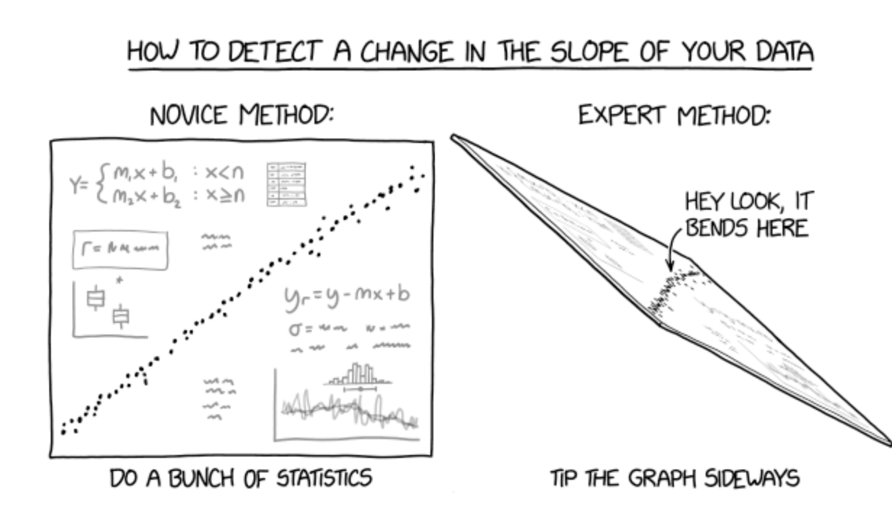
Exploratory Data Analysis

Daniel Lawson University of Bristol

Lecture 01.2 (v2.0.3)

EDA



https://xkcd.com/2701/

Signposting

This Lecture on Exploratory Data Analysis is split into two short parts:

- Slides covering the (few) abstract notions
- An RStudio session covering the details

Dataset and getting started

```
data("mtcars")
```

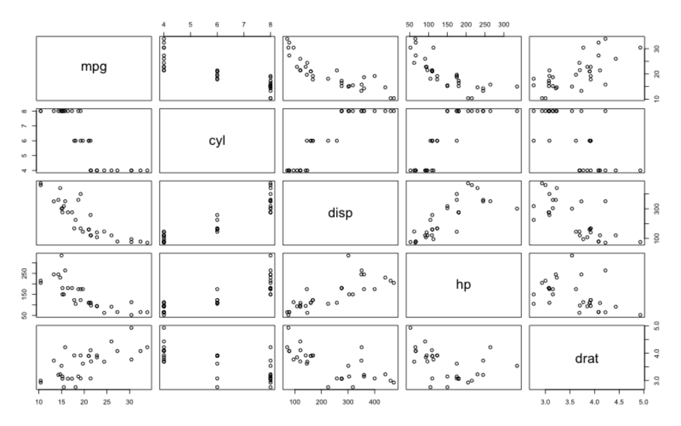
Should we at least find out what the range of each variable is?

```
> apply(mtcars,2,range)
      mpg cyl  disp  hp drat    wt qsec vs am gear carb
[1,] 10.4   4  71.1  52 2.76 1.513 14.5  0  0    3    1
[2,] 33.9   8 472.0 335 4.93 5.424 22.9  1  1    5    8
```

(luckily for us, the data are all numeric!)

Initial plot

```
> pairs(mtcars[,1:5])
```



Summaries of distributions

- Important **positional summaries**:
  - Mean (`mean(x)`)
  - Median (`median(x)`)
  - Weighted Mean (`weighted.mean(x,w)`)
- Important additional summaries:
  - Sample variance (`var(x)`)
  - Sample standard deviation (s.d.) (`sd(x)`)
  - Quantiles (`quantile(x,probs=c(0.05,0.25,0.5,0.75,0.95))`)

Summary and boxplots

The *five number summary* shows: (min, Q_1,Q_2,Q_3,max)

- **Outliers**:
  - an be defined with respect to the Normal distribution.
  - Define the interquartile range $IQR = Q_3 - Q_1$.
  - **outliers** as those observations at least $3/2IQR$ above Q_3 or below Q_1.
  - This is just a heuristic for exploratory data analysis.

Summary and boxplots (2)

```
> summary(mtcars[,1:5])
      mpg             cyl             disp             hp
 Min.   :10.40   Min.   :4.000   Min.   : 71.1   Min.   : 5
 1st Qu.:15.43   1st Qu.:4.000   1st Qu.:120.8   1st Qu.: 9
 Median :19.20   Median :6.000   Median :196.3   Median :12
 Mean   :20.09   Mean   :6.188   Mean   :230.7   Mean   :14
 3rd Qu.:22.80   3rd Qu.:8.000   3rd Qu.:326.0   3rd Qu.:18
 Max.   :33.90   Max.   :8.000   Max.   :472.0   Max.   :33
```

Standardization

- **Standardized variables** z_i are defined from data x_i using the **sample mean** $\bar{x}$ and the **sample s.d.** $\hat{s}_x$:

$$z_i = \frac{x_i - \bar{x}}{\hat{s}_x}$$

- The standardized variables have mean 0 and s.d. 1.
- z_i is also called the standard score, z-value, z-score, and the normal score.
- An individual z-score z_i gives the number of standard deviations an observation x_i is from the mean.
- The standardized score has no units.

```
# Can you guess the output of:
> summary(scale(mtcars))
```

Standardization against a reference

- In machine learning, we often use a **training** set, and a **test** set. It is essential that **both are standardized against the training data**:

$$z_i = \frac{x_i - \bar{x}_{train}}{\hat{s}_{train}}$$

- Test data may **not have** mean (close to) 0 and s.d. (close to) 1.

Types of Data

- **Quantitative Variables**
  - Quantitative variables are those for which arithmetic operations like addition and differences make sense.
  - Another name for quantitative variables is **features**.
- **Categorical Variables**
  - Categorical variables partition the individuals into classes.
  - Other names for categorical variables are levels or **factors**.
  - We often **One-Hot Encode** categorical variables to convert them to binary quantitative variables.

Further Types of Data

- Later we'll cover more complex data types, including:
  - relational tables
  - graphs
  - images
  - text
- This basic Exploratory Data Analysis still applies then, but to summaries:
  - Counts of nodes, edges
  - Tree depths
  - corpus size
  - etc

Categorical variables: Table

The most straightforward summary for categorical variables is to count them.

```
table(mtcars[,"gear"])
## from ?mtcars :
# gear  Number of forward gears
```

Var1	Freq
3	15
4	12
5	5

Two-way Table

Relationships between two categorical variables can be shown through a **two-way table** or **contingency table** (also known as cross tabulation):

```
table(mtcars[,c("vs","gear")])
#  vs    Engine (0 = V-shaped, 1 = straight)
```

	3	4	5
0	12	2	4
1	3	10	1

Types of plot

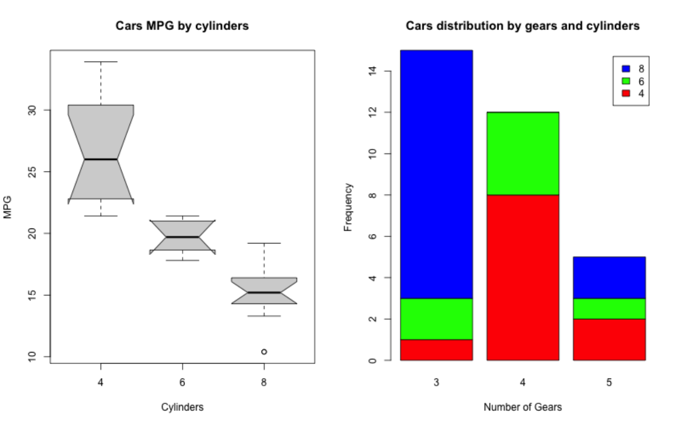
Some essential plots include[1]:

- Bar Chart
  - Segmented Bar Chart
- Heatmap
  - Highlight table
- Histograms
  - Kernel Density estimates
- Cumulative Distribution Functions

[1] Know what these are **for**. Applies to all plots we use in the course.

Boxplot example

```
combined = table(mtcars$cyl, mtcars$gear)
boxplot(mpg~cyl,data=mtcars,notch=TRUE,...)
barplot(combined,...)
```



Empirical Cumulative Distribution Function

- The **empirical cumulative distribution** function:

$$F_X(x) = Pr(X \leq x),$$

- is, for a continuous RV:

$$F_X(x) = \int_{-\infty}^{x} f_X(t)dt$$

- where $f_X(t)$ is the density function of the Random Variable X.
- For a discrete RV

$$F_X(x) = \sum_{x_i \leq X} x_i$$

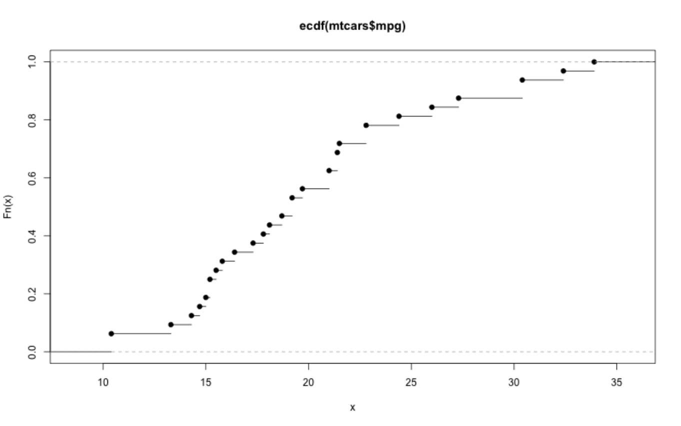
Empirical Cumulative Distribution Function

To create the empirical cumulative distribution function:

- **Sort the observations** from smallest to largest
- Next **match these up** with the integral multiples of the 1 over the number of observations
- Display it with the correct **type of line**.

ECDF

```
ecdf(mtcars$mpg)
```



Cumulative Distribution Function for categorical data

- Categorical data have a **natural ordering** too: by frequency. This allows the creation of key concepts such as $P(X < x)$.
- It is often useful to establish natural orderings, which may exist in other settings.
- One example is ordinal data.

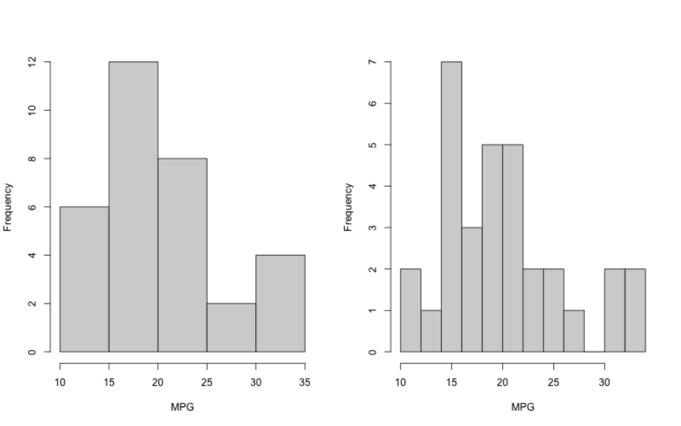
Survival Function

- It is sometimes more convenient to work with the **fraction of samples that are larger than some value**.
- The **survival function** S_X is trivially related to the ECDF:

$$S_X(x) = Pr(X > x) = 1 - F_X(x)$$

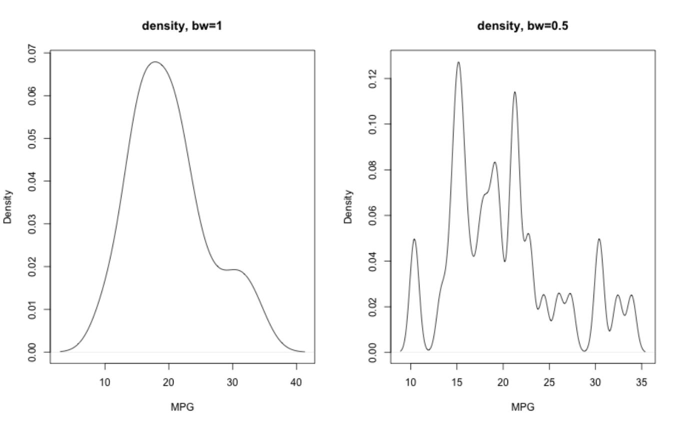
Histograms

- Histograms are a common visual representation of a quantitative variable. Histograms visual the data using **rectangles of area** to display frequencies and proportions.
- **It is critical that bins are comparable**. Many comparisons are impossible if bins are poorly chosen.



Kernel Density Estimates

- Kernel Density Estimates are sometimes used instead, fitting a mini Normal (or other) distribution around each point. But which bandwidth is appropriate?



Scatterplots

- **Scatterplots** show the relationship for **pairs of observations**.
- The values of the first variable

$$\{x_1, \dots, x_n\}$$

  are often assumed known.
- They are often called **explanatory**, predictor, or descriptor variables, and are displayed on the horizontal axis.
- The values of the second variable

$$\{y_1, \dots, y_n\}$$

  are viewed as observations with input $\{x_1, \dots, x_n\}$.
- Called the **response** variable, they are displayed on the vertical axis.

Interpretation

Interpret plots considering:

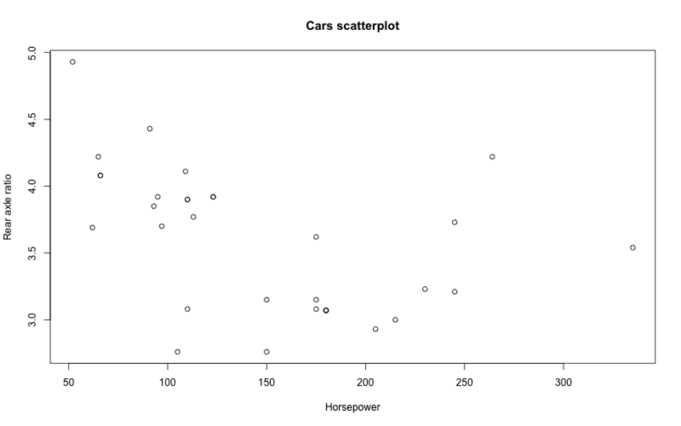
- the overall **pattern**
- the **center**
- the **spread**
- the **shape** (symmetry, skewness, peaks)
- and **deviations** from the pattern
- **outliers**
- **gaps**

Scatterplots

In describing a scatterplot, take into consideration

- positive or negative association/**trend**
- **intercept**
- **clusters**
- the **form**, for example,
  - linear
  - curved relationships
  - (uni/multi)modal conditional distributions
- magnitude of the **noise**

Scatterplots



Further reading

- R for Data Science by Hadley Wickham and Garrett Grolemund is an excellent resource!
- It uses R tidyverse. You don't have to, but look into it.
- EDA is an **art** not a science. There is no **right** way to do it.
- You should be proactive in exploring solutions that others use and keep experimenting to find a better way to represent the data.

Reflection

By the end of the course, you should:

- Be able to describe basic tools of EDA
- Be able to suggest appropriate EDA for a wide variety of data
- Be able to spot mistakes in an analysis from EDA plots
- Have practical experience to draw on to go beyond simple examples
- **However**, EDA is not proscriptive. Only general ideas are essential.

Signposting

- The Workshop Lecture 1.3.1 demonstrate these features.
- There are further workshops on background: working with RStudio, setting up a Data Science environment with GitHub, and understanding the Assessments.
- There are text notes and links in the Coursebook.
- Block 02 covers **Regression and correlations** where we say something more rigorous about the relationship between variables.