Introduction to Data Science (11372 & G 11516)

Semester 2 2020

UNIVERSITY OF CANBERRA

INTRODUCTION TO DATA SCIENCE

Lecture 9

Dr. Ibrahim Radwan

DISTINCTIVE BY DESIGN

OUTLINE

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- Data Wrangling, a recap
- Exploratory Data Analysis
- Data Visualisation
- Grammar of Graphics
- EDA; Univariate Analysis

DATA WRANGLING

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Transform

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Import → Transform → Visualise

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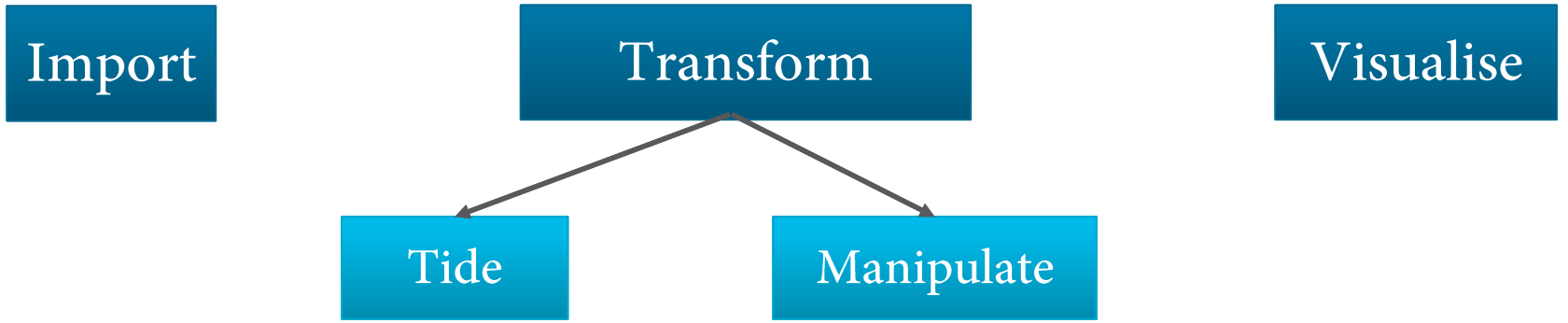

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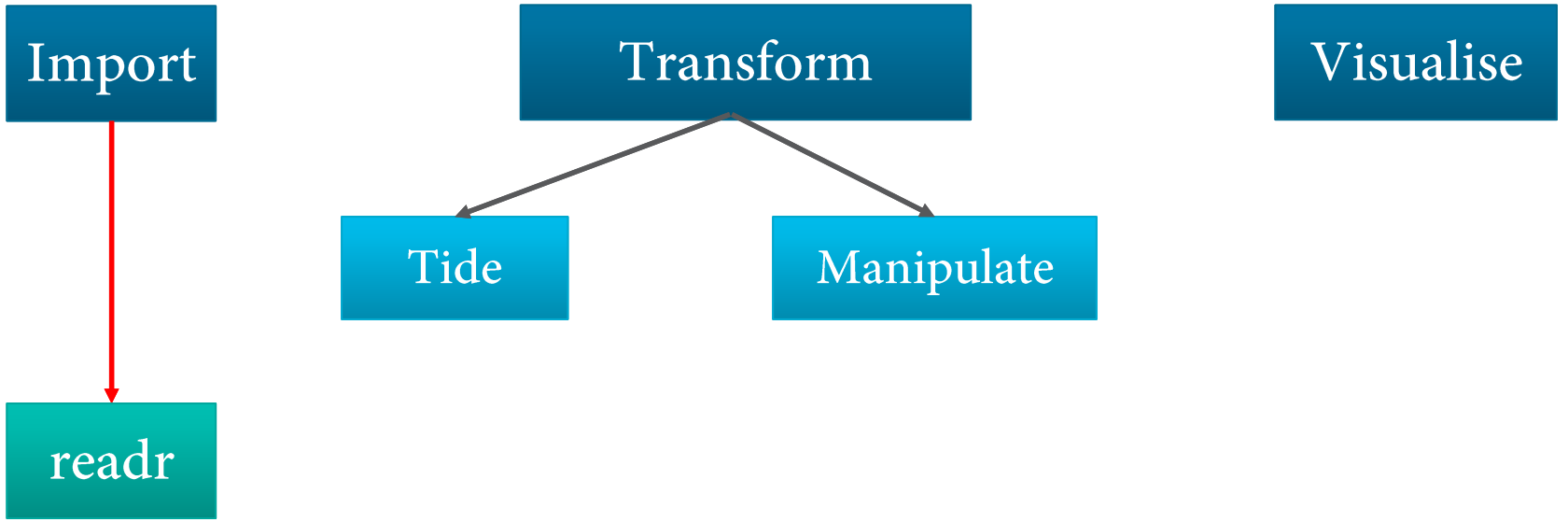

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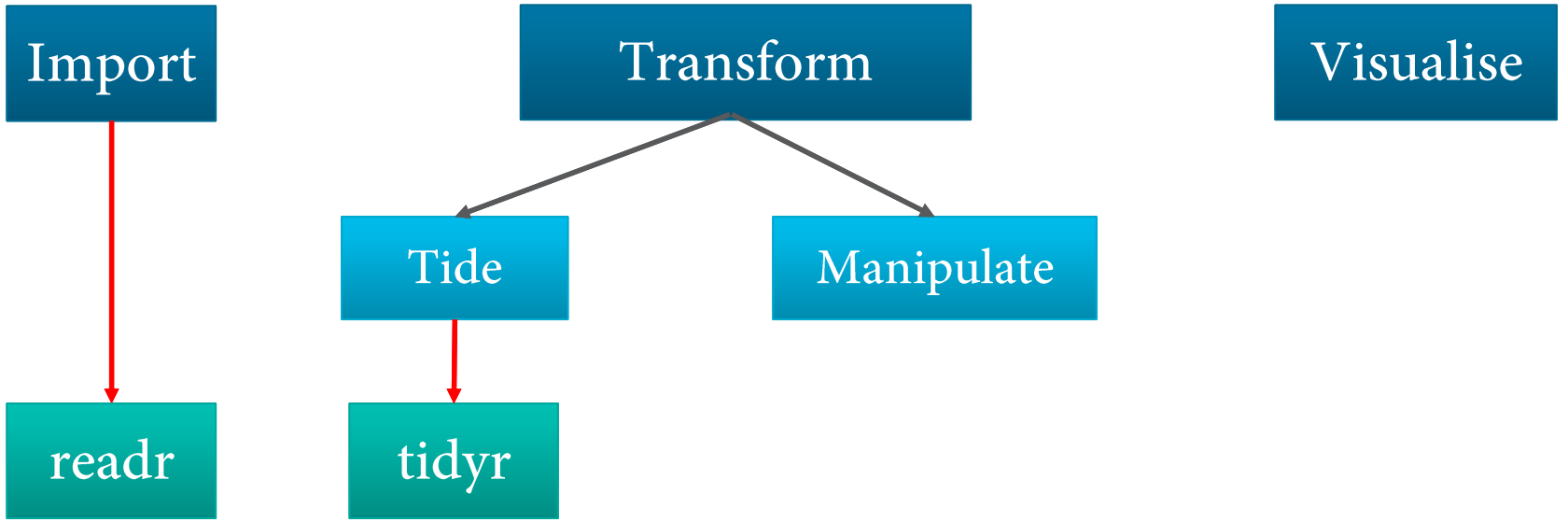

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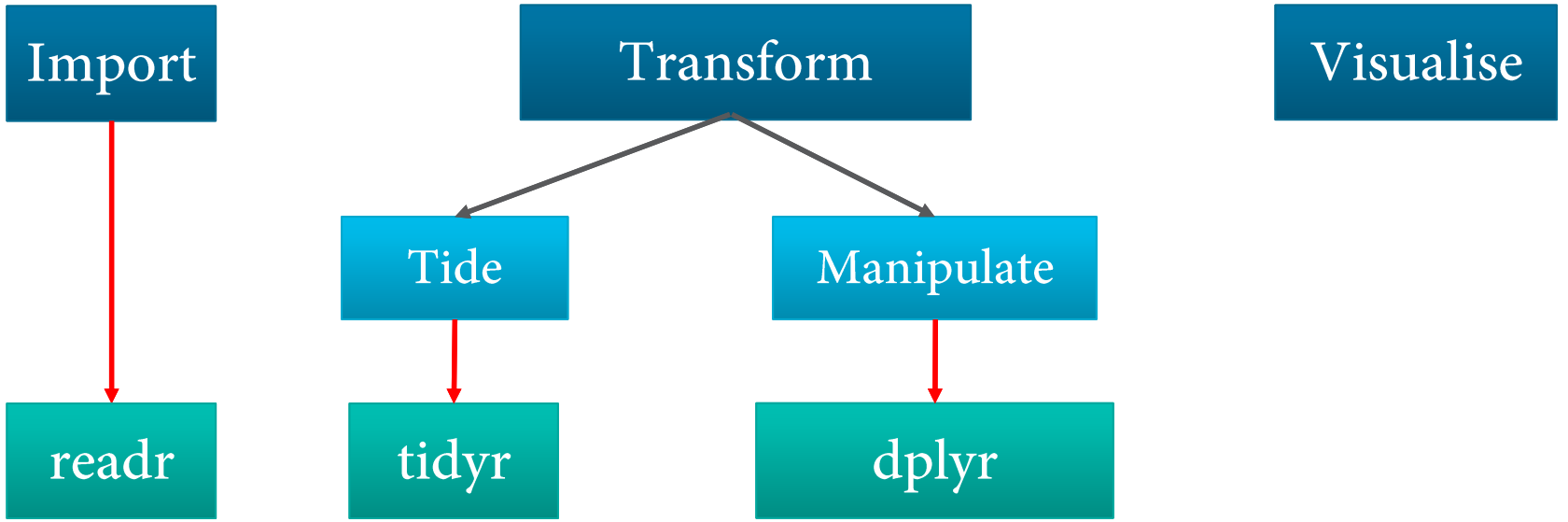

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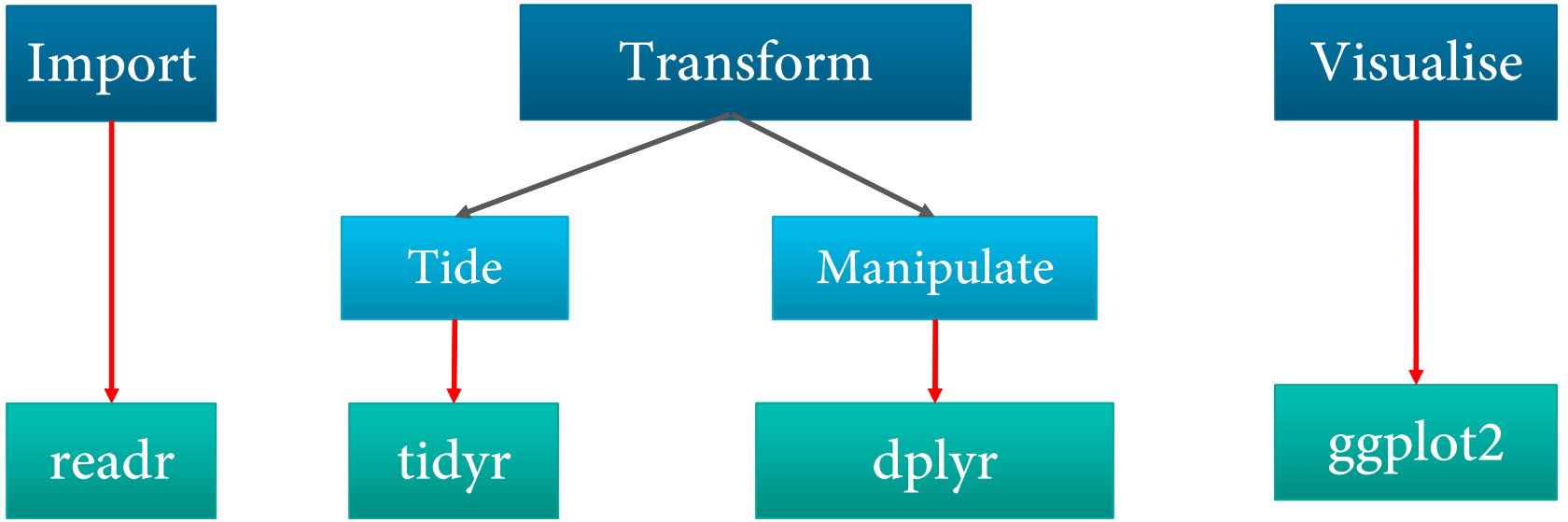

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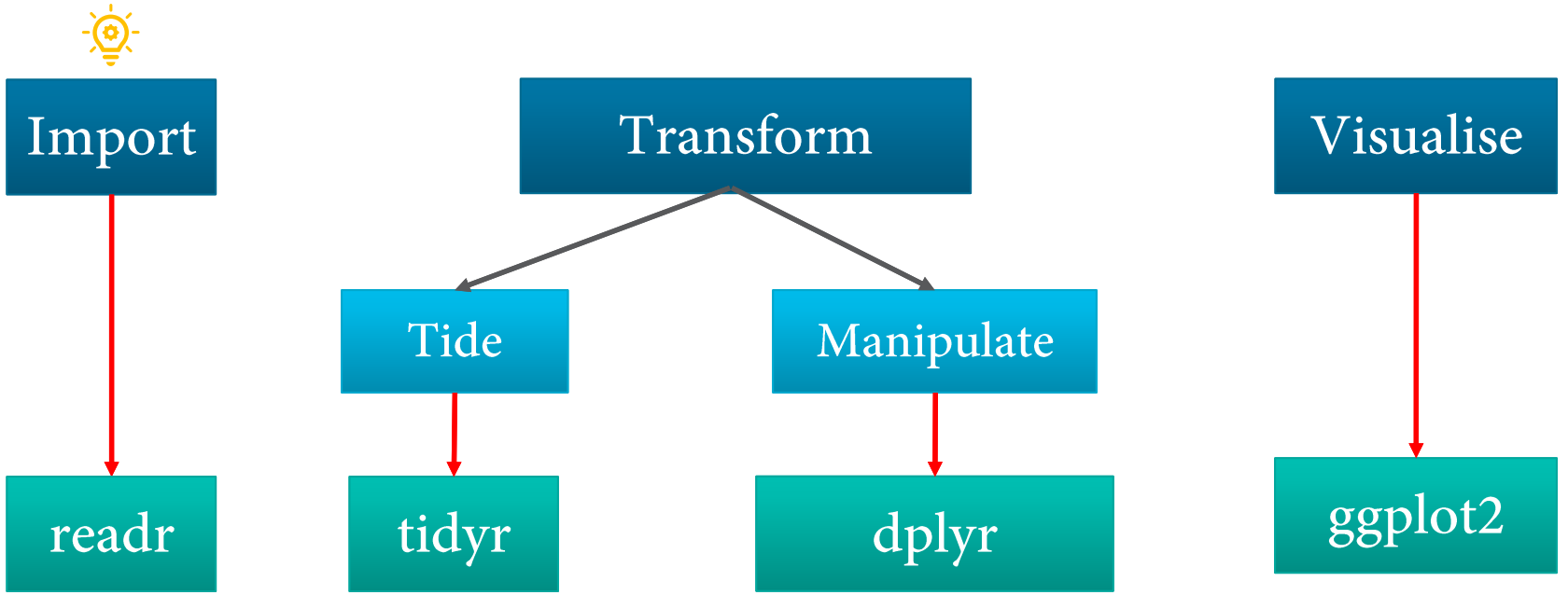

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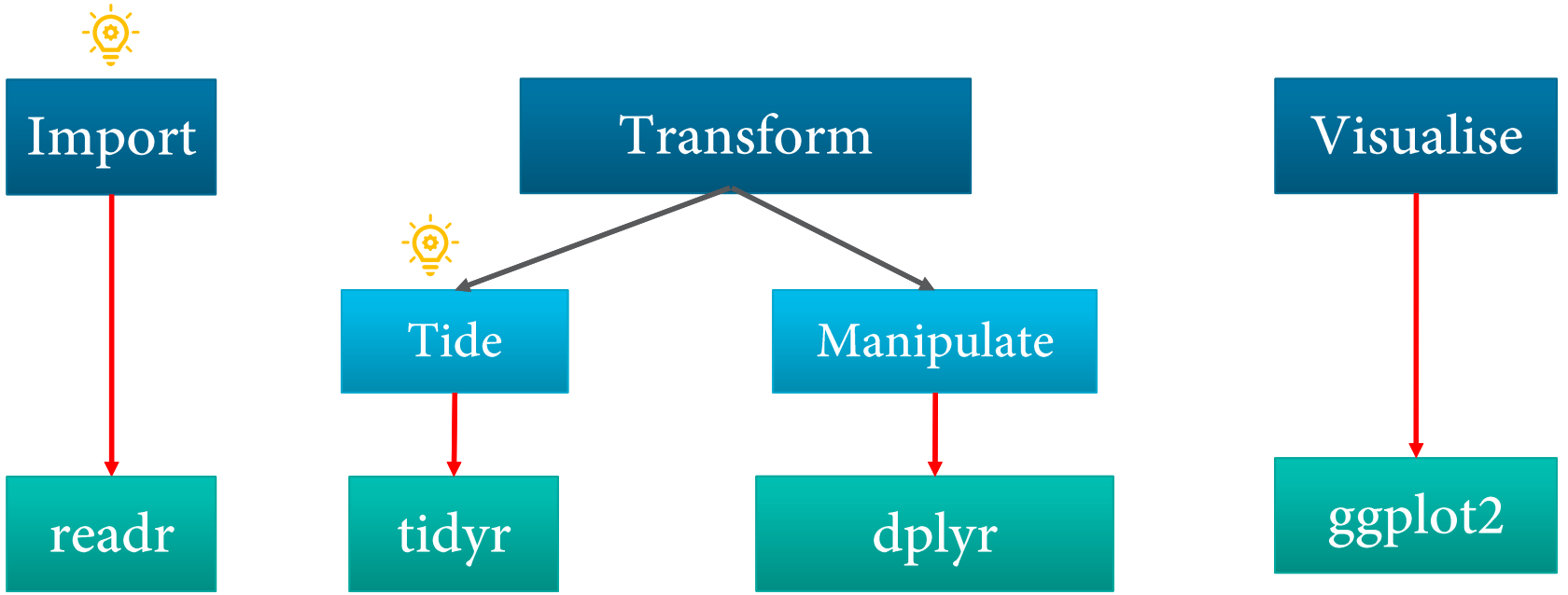

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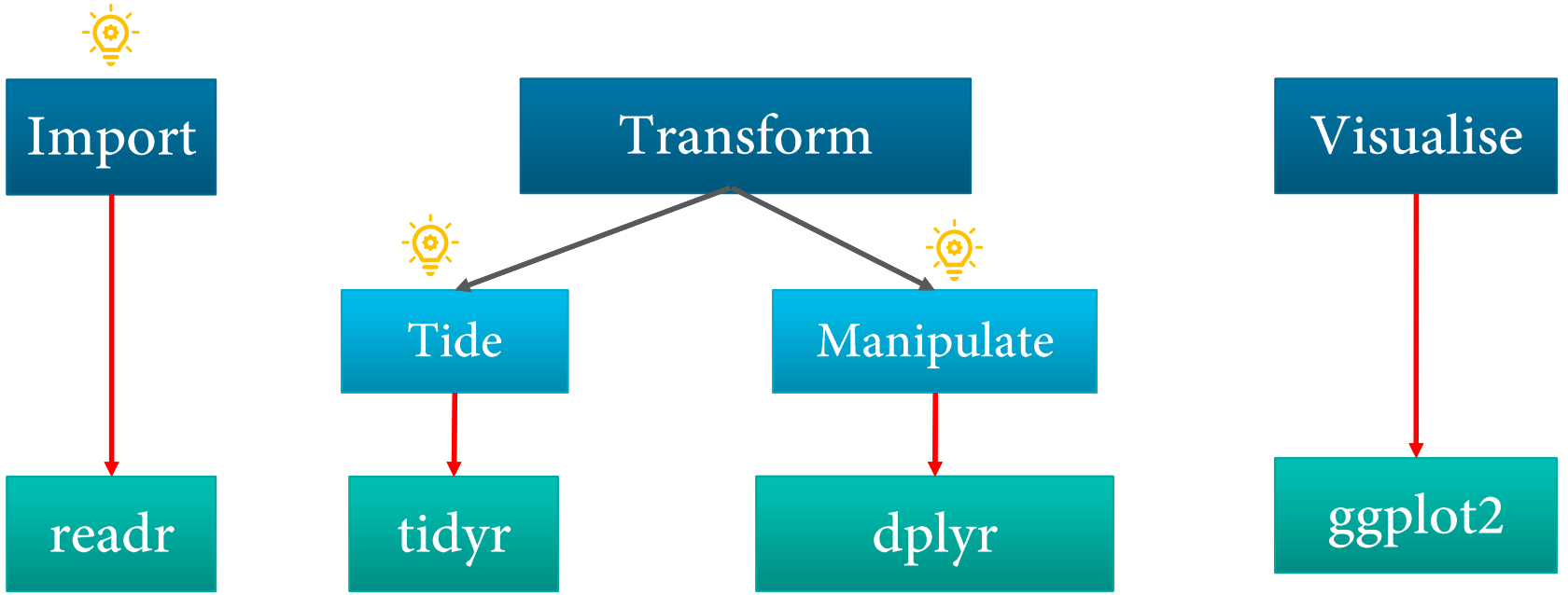

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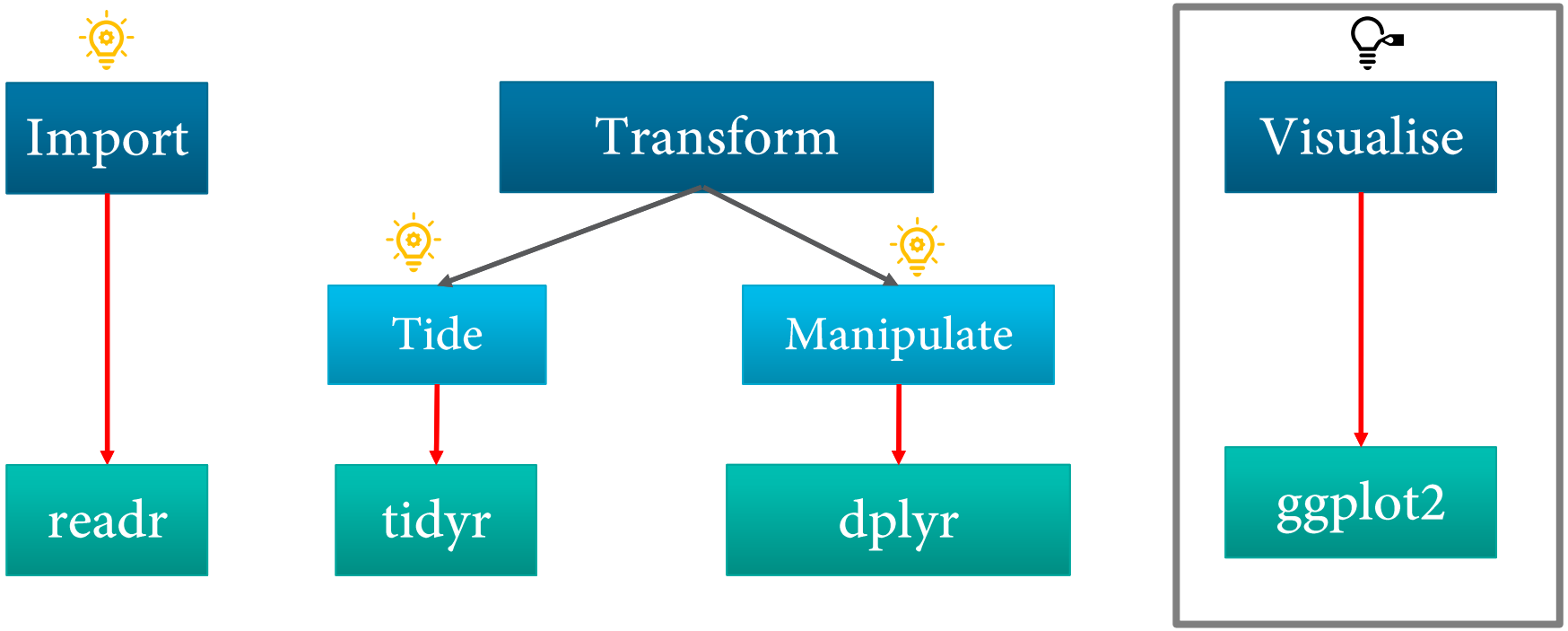

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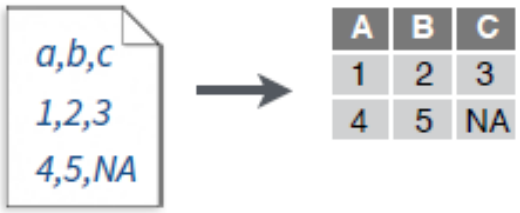

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Comma Delimited Files

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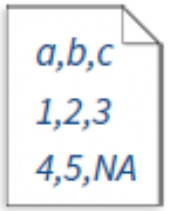

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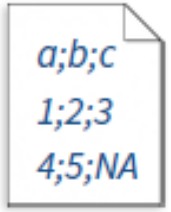

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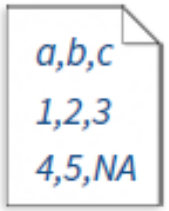

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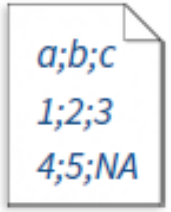

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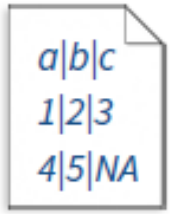

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Files with Any Delimiter

read_delim("file.txt", delim = "|"**)**

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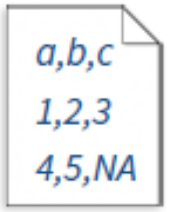

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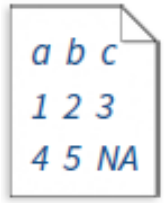

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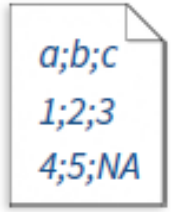

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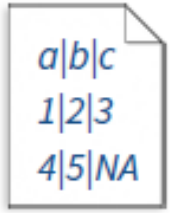

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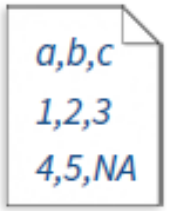

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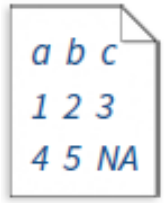

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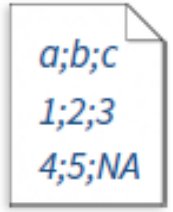

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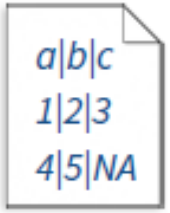

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To save data into csv or txt file

Comma delimited file
write_csv(x, path, na = "NA", append = FALSE, col_names = !append**)**
File with arbitrary delimiter
write_delim(x, path, delim = " ", na = "NA", append = FALSE, col_names = !append**)**

DATA MANIPULATION (RECAP)

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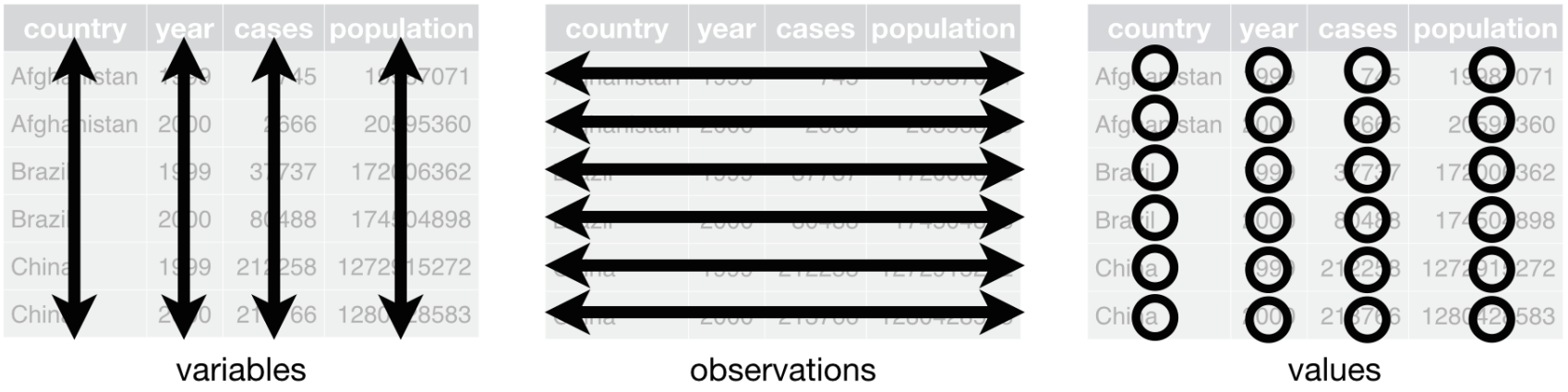

Credit: R for Data Science

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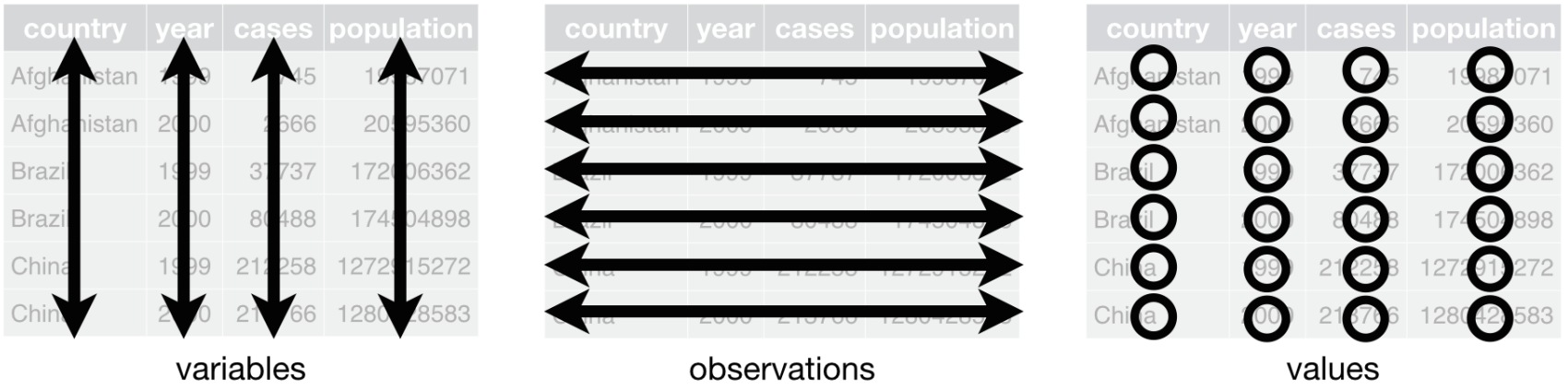
Having your data in a tidy format is crucial for data manipulation and exploring



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TIDY DATA (RECAP) – 2

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- The `*tidyr*` package presents four main *verbs/functions* to tide up the data:
    1. gather() collapses multiple columns into key-value pairs. It produces a "long" data format from a "wide" one.
    2. spread() takes two columns (key & value), and spreads into multiple columns: it makes "long" data wider. This is the reverse of gather.
    3. unite() unites multiple columns into one
    4. separate() takes a column and divides it into multiple columns
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DATA VISUALISATION

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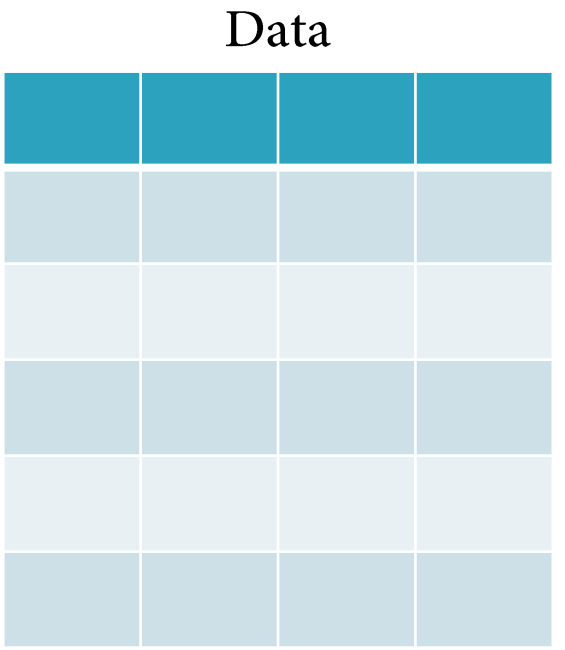

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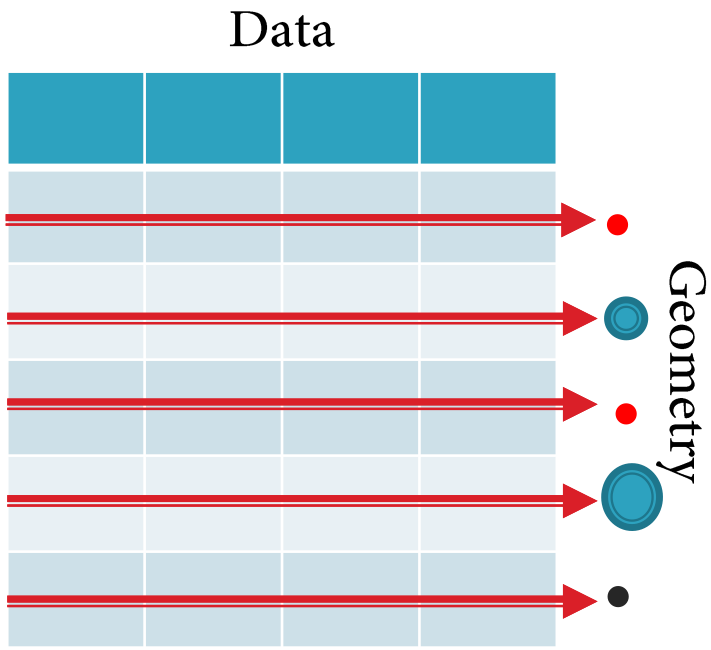

GRAPH COMPONENTS

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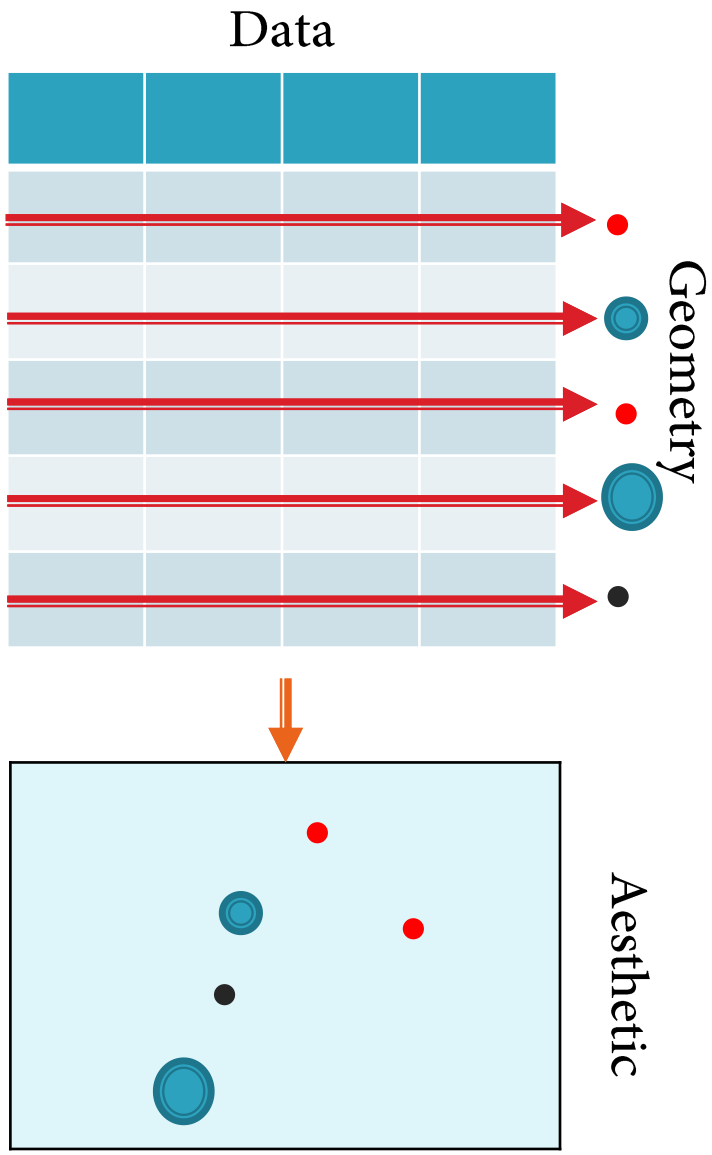
3. **Aesthetic mapping**: the coordinate map and the other visual cues, such as size, scale and color.



BUILD GRAPHS IN R

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We will be focusing on using this method to build the graphs

BUILD GRAPHS IN R (2)

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- The ggplot2 is one of the core members of the `*tidyverse*` library, so you will be able to use its functions when loading the `tidyverse` library.
  - *library(tidyverse)*

GRAPHS IN R - EXAMPLE

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GRAPHS IN R – EXAMPLE (2)

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GRAPHS IN R – EXAMPLE (2)

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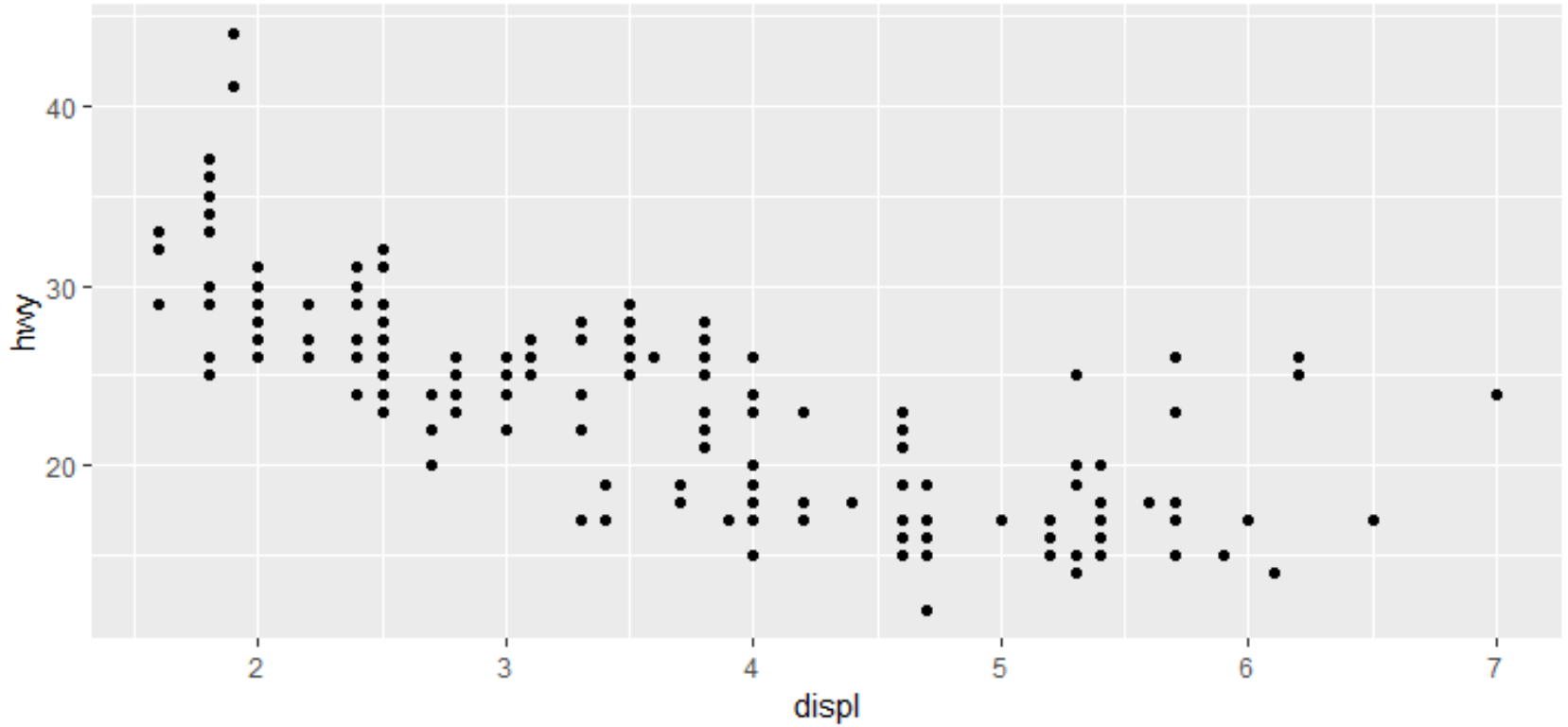

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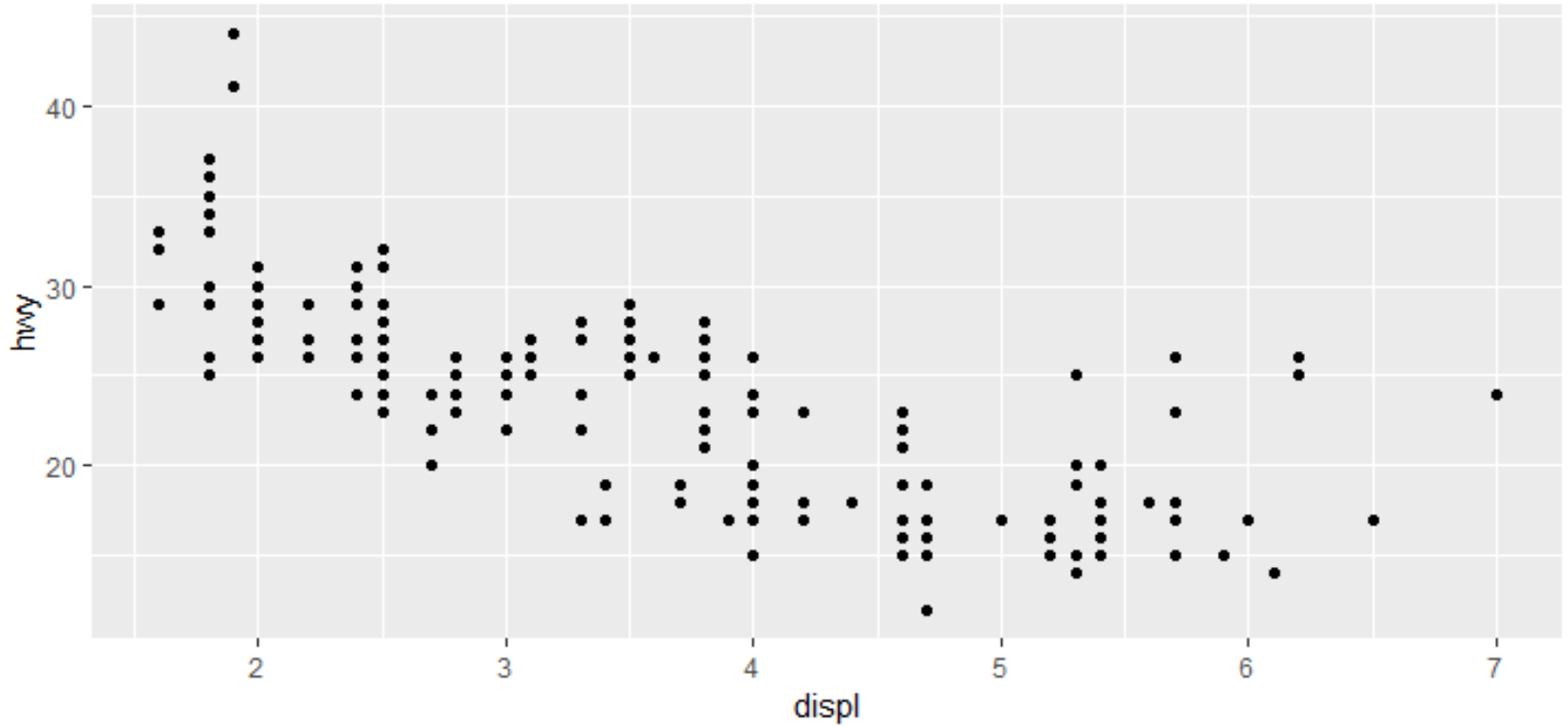
You may add as many layers as needed



GRAPHS IN R – EXAMPLE (3)

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```
ggplot(data = mpg) +
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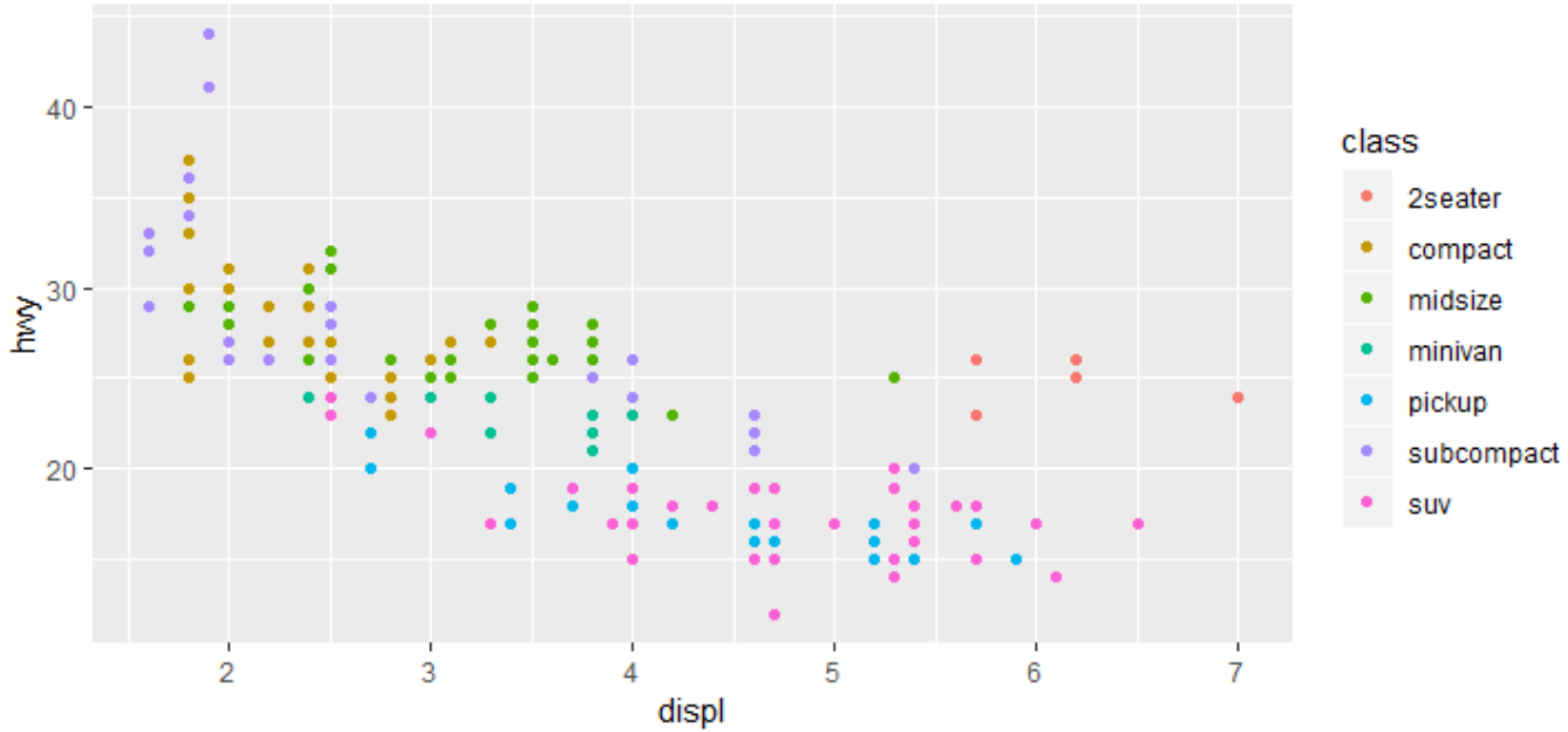

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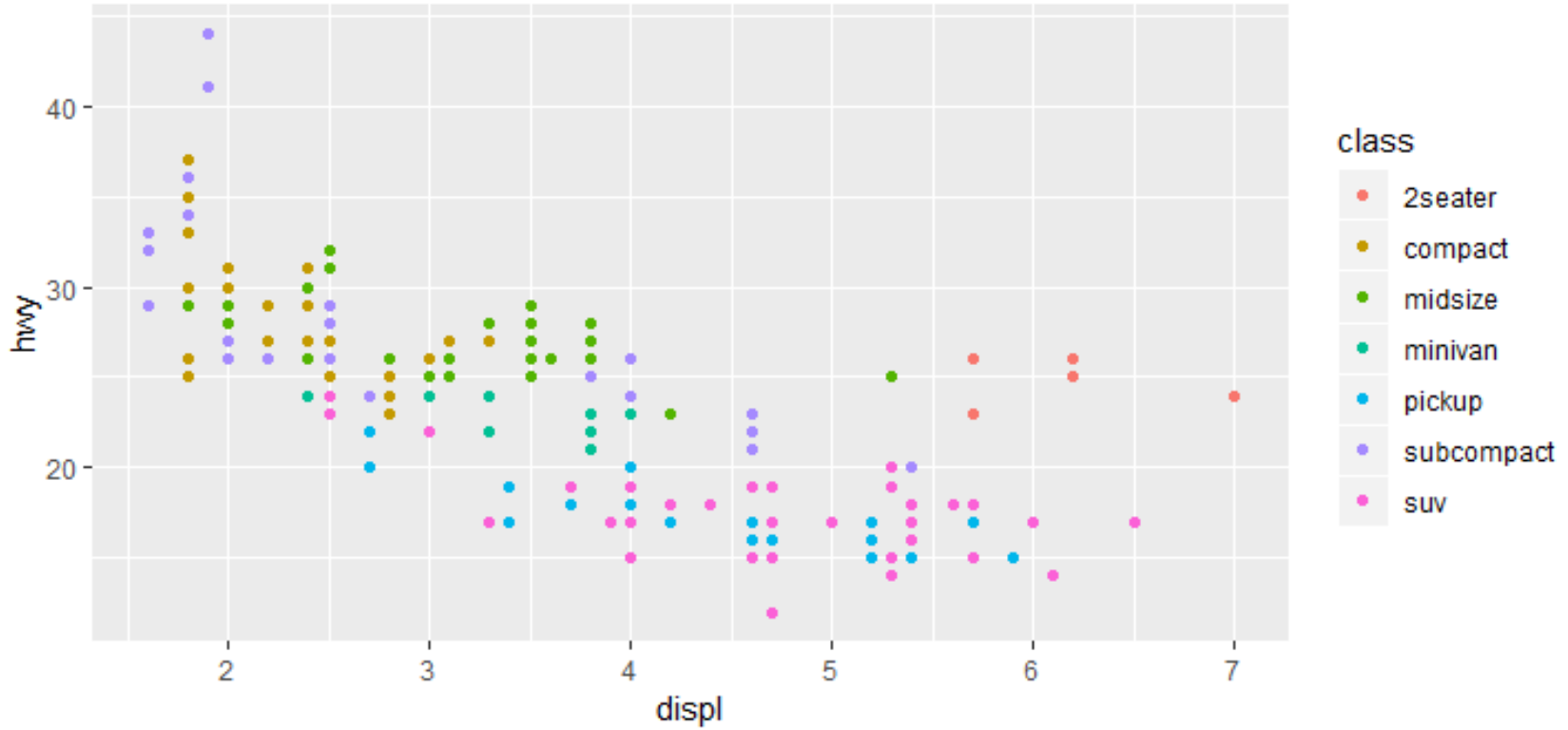

Three variables are represented in the 2D graph

GRAPHS IN R – EXAMPLE (4)

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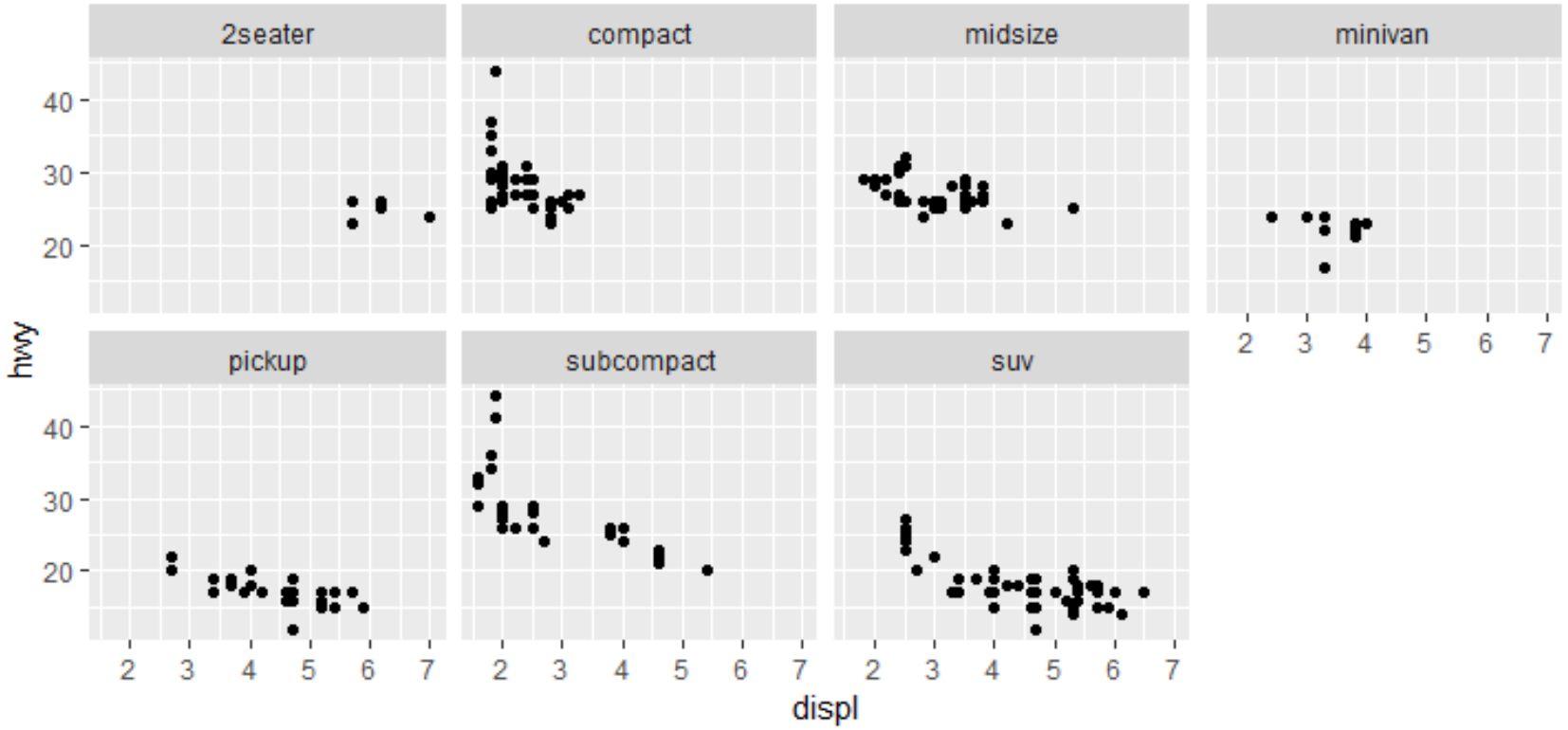

GRAPHS IN R – EXAMPLE (5)

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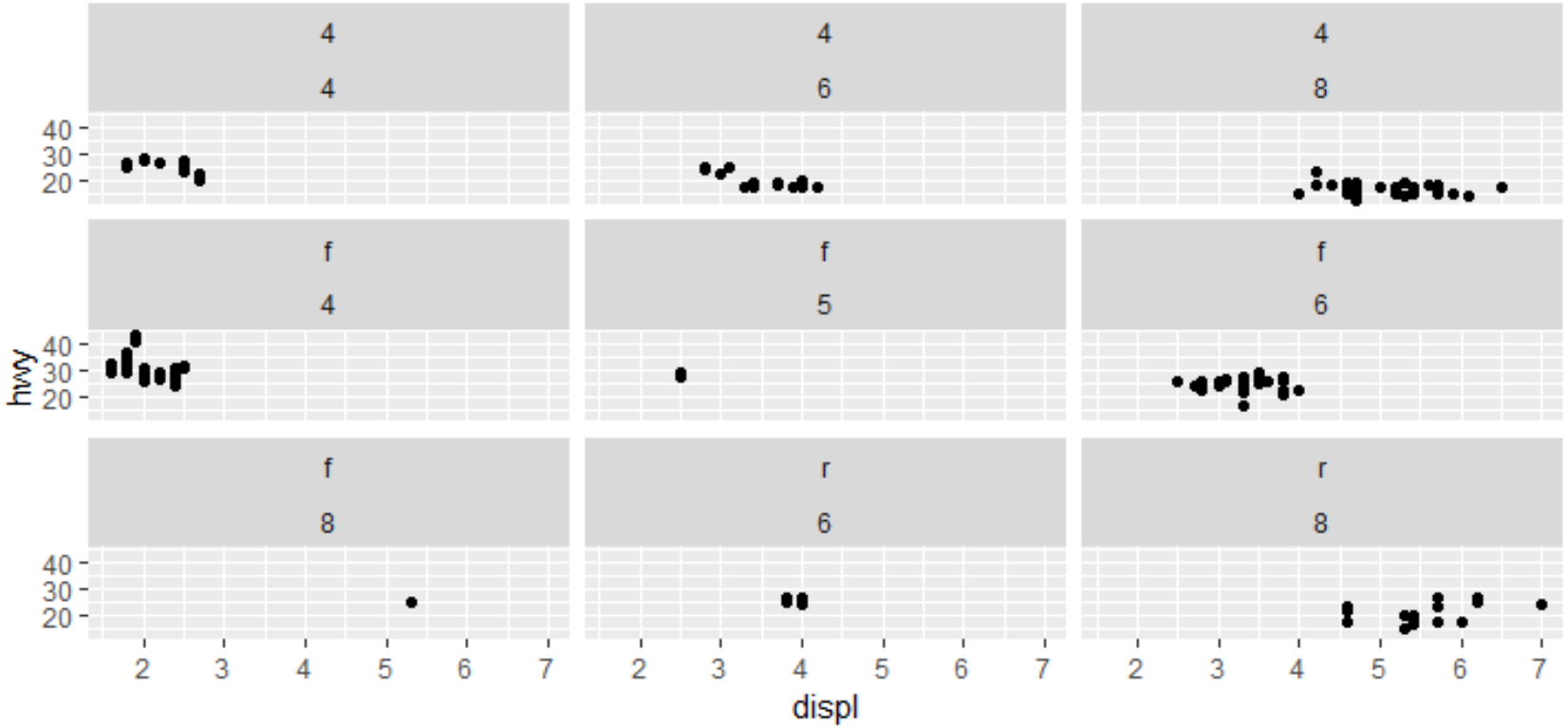

EXPLORATORY DATA ANALYSIS (EDA)

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- To understand the variables in a dataset, we may transform these variables into other format or extract their summaries (e.g. mean, variance, etc.) or to get insights about the distribution of these variables.
- The most elegant way to understand relationships with-in a variable or between variables is by ***visualising*** these relationships.

EXPLORATORY DATA ANALYSIS (EDA) – 2

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  - Uni-variate analysis
    - Discover the variations of the data into **one** variable
  - Multi-variate analysis
    - Discover the co-variation of **multiple** variables
    - Bi-variate analysis is a special type of this analysis with only **two** variables.

EXPLORATORY DATA ANALYSIS (EDA) – 3

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- EDA
  - Uni-variate analysis
    - Discrete
    - Continuous
  - Bi-variate analysis (can be extended to multi-variate analysis)
    - Discrete
    - Continuous

EXPLORATORY DATA ANALYSIS (EDA) – 3

UNIVERSITY OF CANBERRA

- EDA
  - Uni-variate analysis
    - Discrete
    - Continuous
  - Bi-variate analysis (can be extended to multi-variate analysis)
    - Discrete
    - Continuous

We will start by using the visualisation to do the EDA for both of the univariate and bi-variate analysis.

EDA – UNIVARIATE

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- There are two types of visualization-based univariate analysis:
  - Visualising variation of continuous variable
  - Visualising variation of discrete variable
- Examples of univariate continuous :
  - Histograms, etc.
- Examples of univariate discrete:
  - bar plots, etc.

EDA – UNIVARIATE, CONTINUOUS

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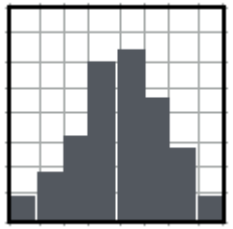

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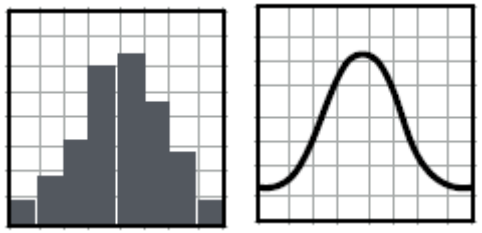

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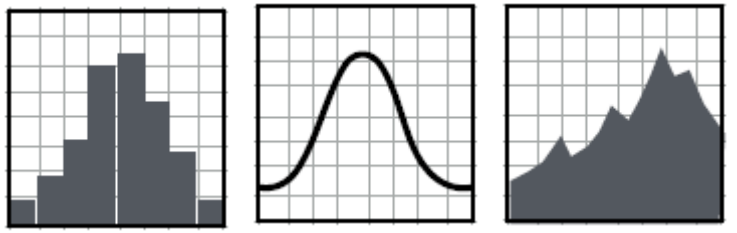

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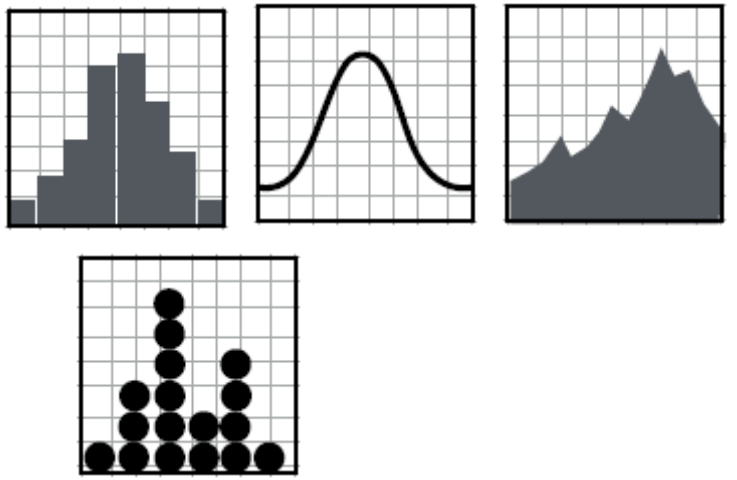

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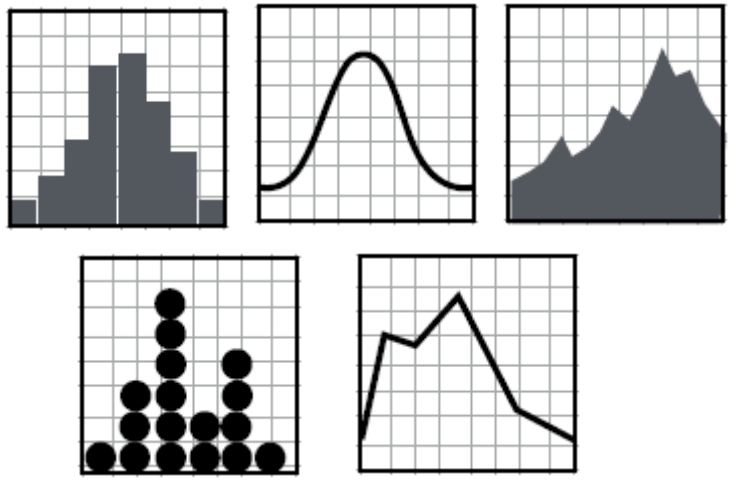
  - *geom_freqpoly(),* for a frequency polygon



HISTOGRAMS

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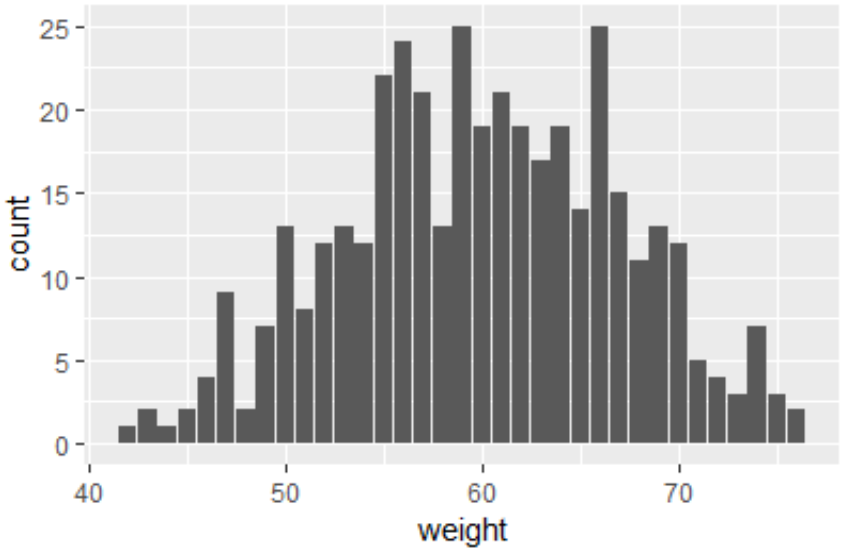
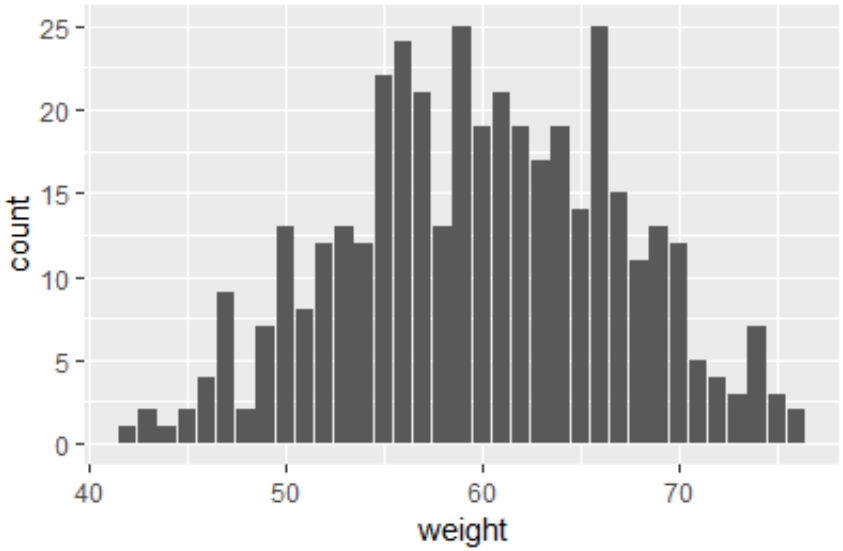
- Summarise the variable by extracting a 1-D distribution of the variation in the data within this variable.



HISTOGRAMS

UNIVERSITY OF CANBERRA

- Summarise the variable by extracting a 1-D distribution of the variation in the data within this variable.
- The data are summarised using suitable binwidths.



HISTOGRAMS

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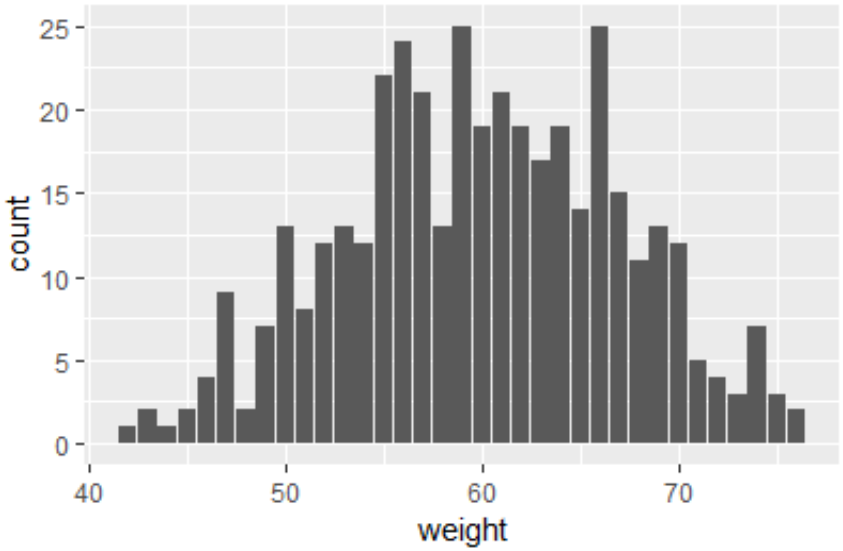
- Summarise the variable by extracting a 1-D distribution of the variation in the data within this variable.
- The data are summarised using suitable binwidths.
- A histogram plot shows properties, such as:



HISTOGRAMS

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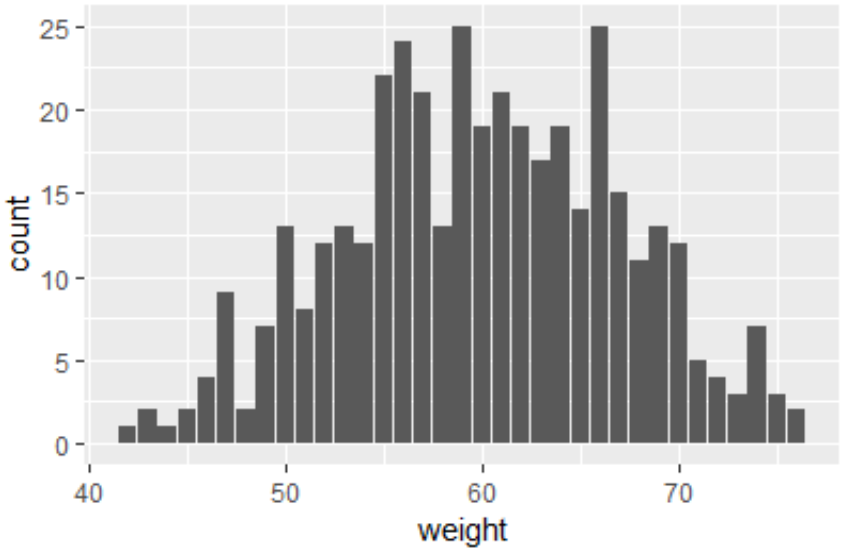

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UNIVERSITY OF CANBERRA

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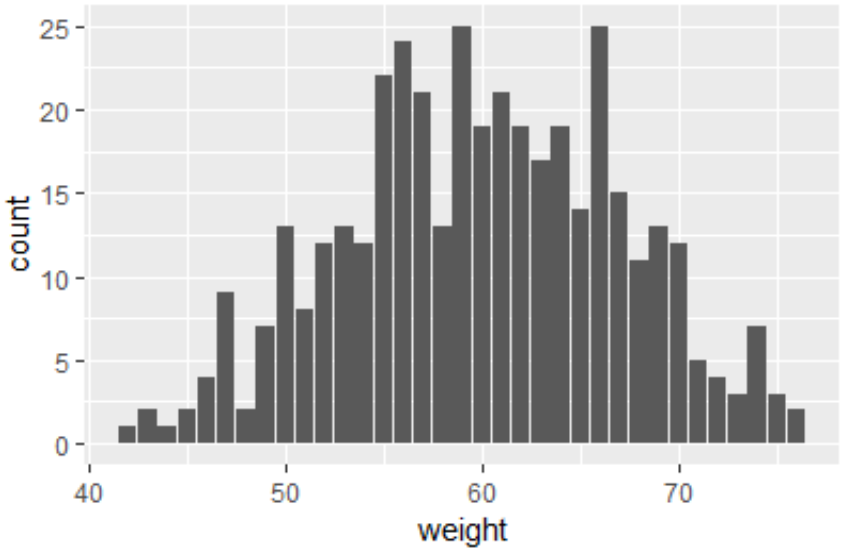

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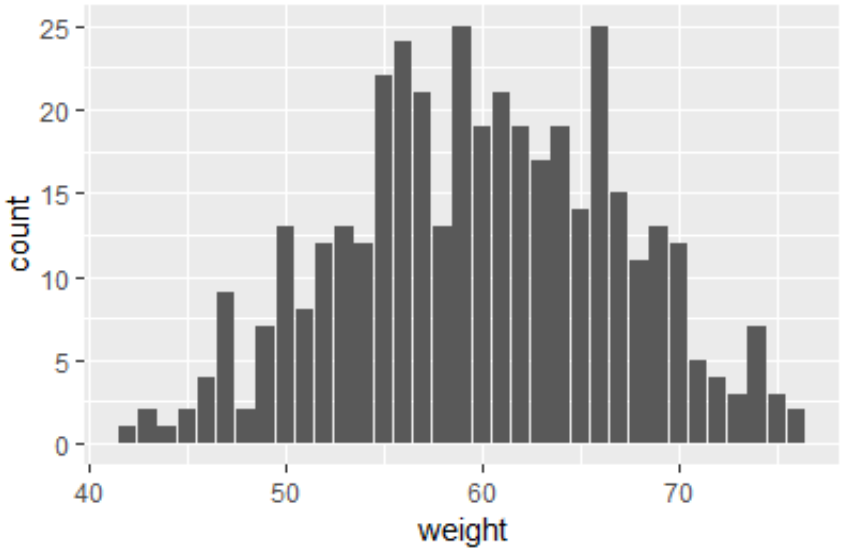

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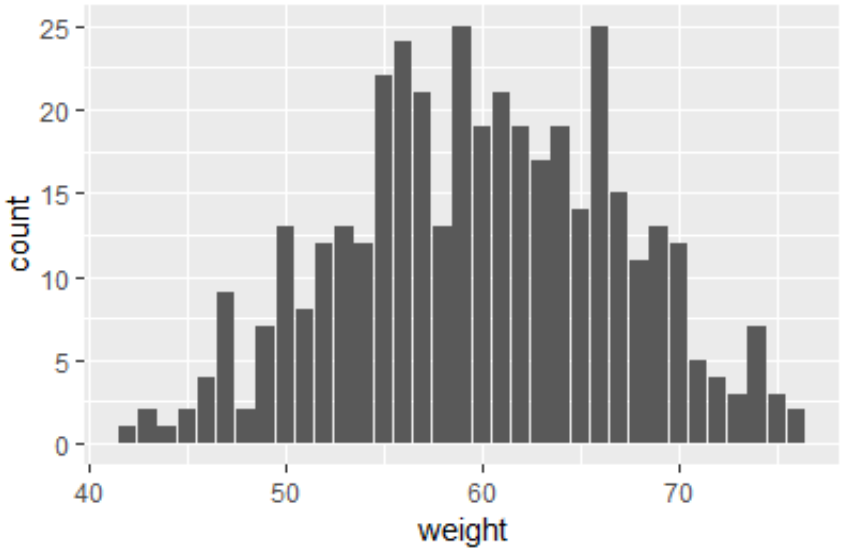

HISTOGRAMS (2)

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HISTOGRAMS (2)

UNIVERSITY OF CANBERRA

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HISTOGRAMS (2)

UNIVERSITY OF CANBERRA

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HISTOGRAMS (2)

UNIVERSITY OF CANBERRA

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HISTOGRAMS (2)

UNIVERSITY OF CANBERRA

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HISTOGRAMS (2)

UNIVERSITY OF CANBERRA

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BUILDING A HISTOGRAM

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BUILDING A HISTOGRAM

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BUILDING A HISTOGRAM

UNIVERSITY OF CANBERRA

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```

EXAMPLE

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EXAMPLE

UNIVERSITY OF CANBERRA

Basic histogram visualization

EXAMPLE

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Basic histogram visualization

```
ggplot(data= airquality, aes(x = Ozone)) +
  geom_histogram() +
  xlab("Ozone per billion") +
  ylab("Count") +
  ggtitle("Ozone Histogram")
```

EXAMPLE

UNIVERSITY OF CANBERRA

Basic histogram visualization

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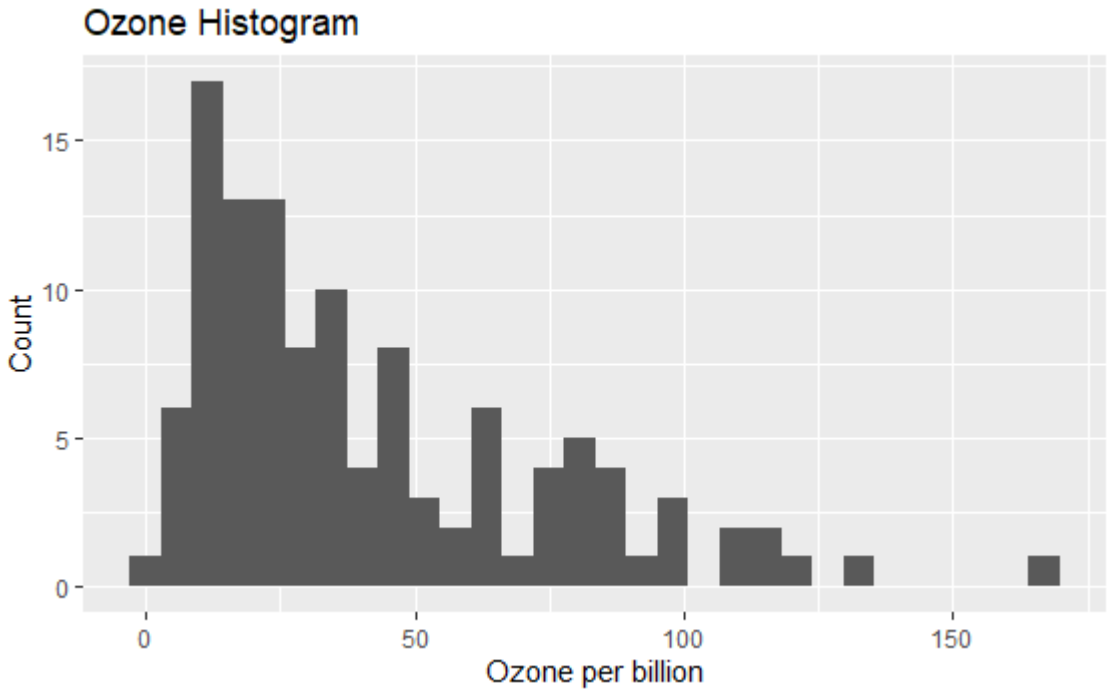
```



EXAMPLE (2)

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UNIVERSITY OF CANBERRA

Adding extra visual cues and more options

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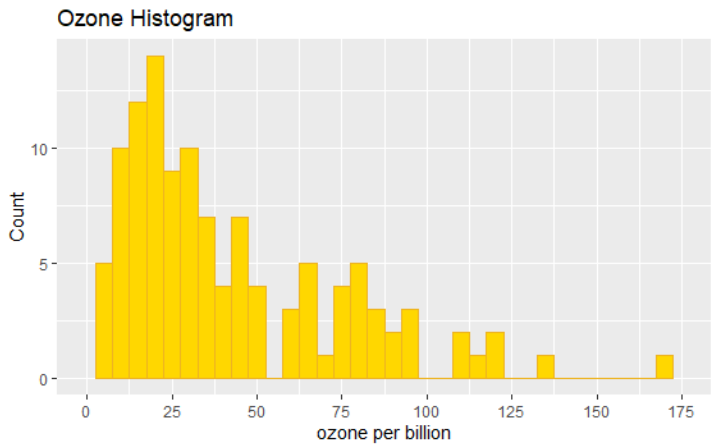
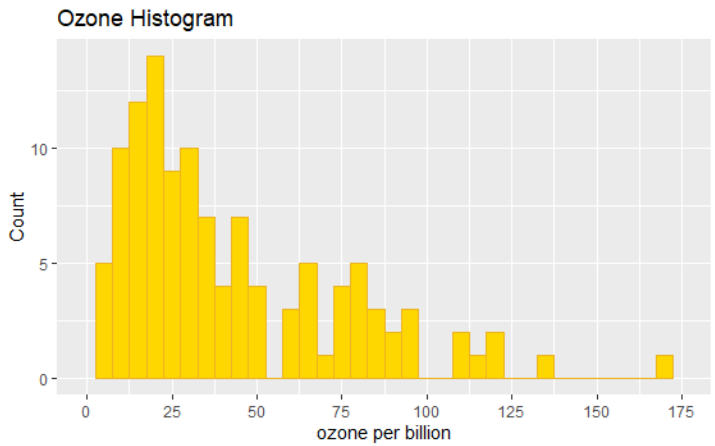
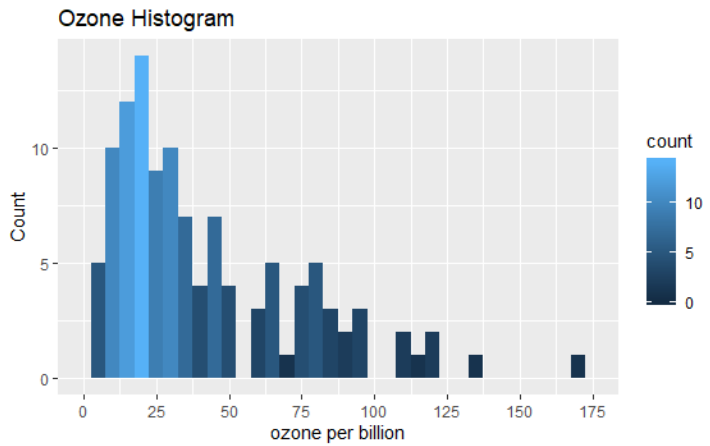


EXAMPLE (2)

UNIVERSITY OF CANBERRA

Adding extra visual cues and more options





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UNIVERSITY OF CANBERRA

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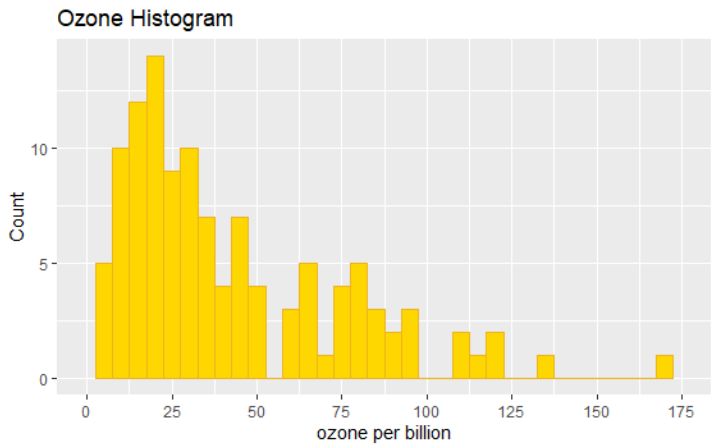

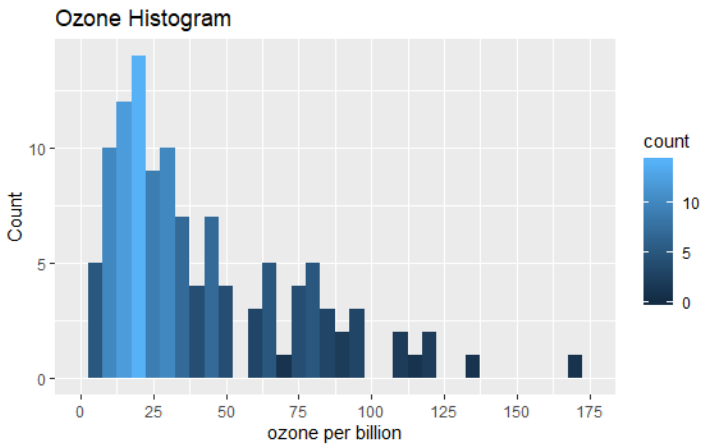

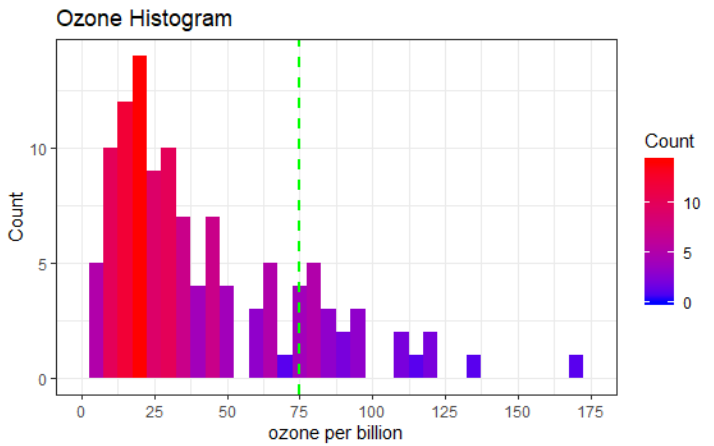

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UNIVERSITY OF CANBERRA

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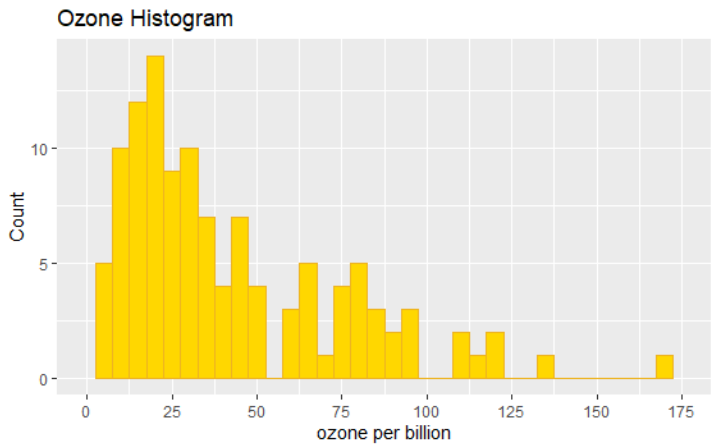

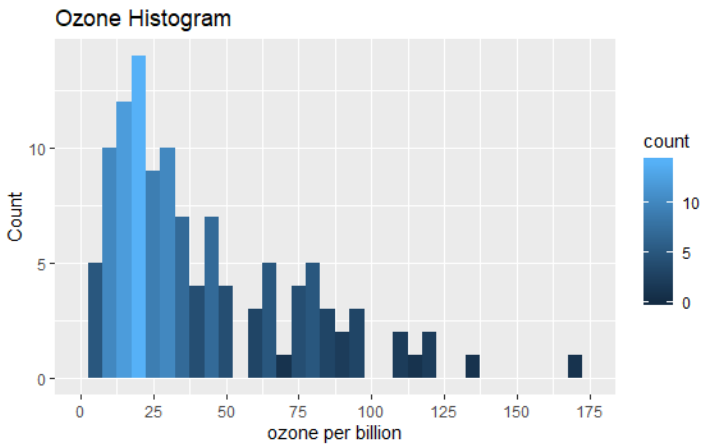

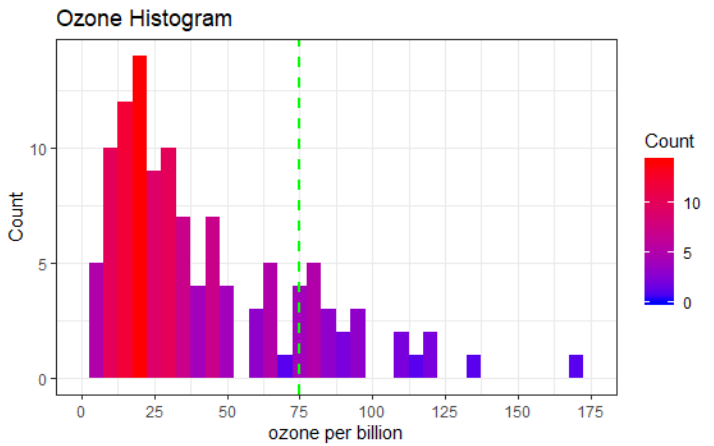

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HISTOGRAM INTERPRETATION

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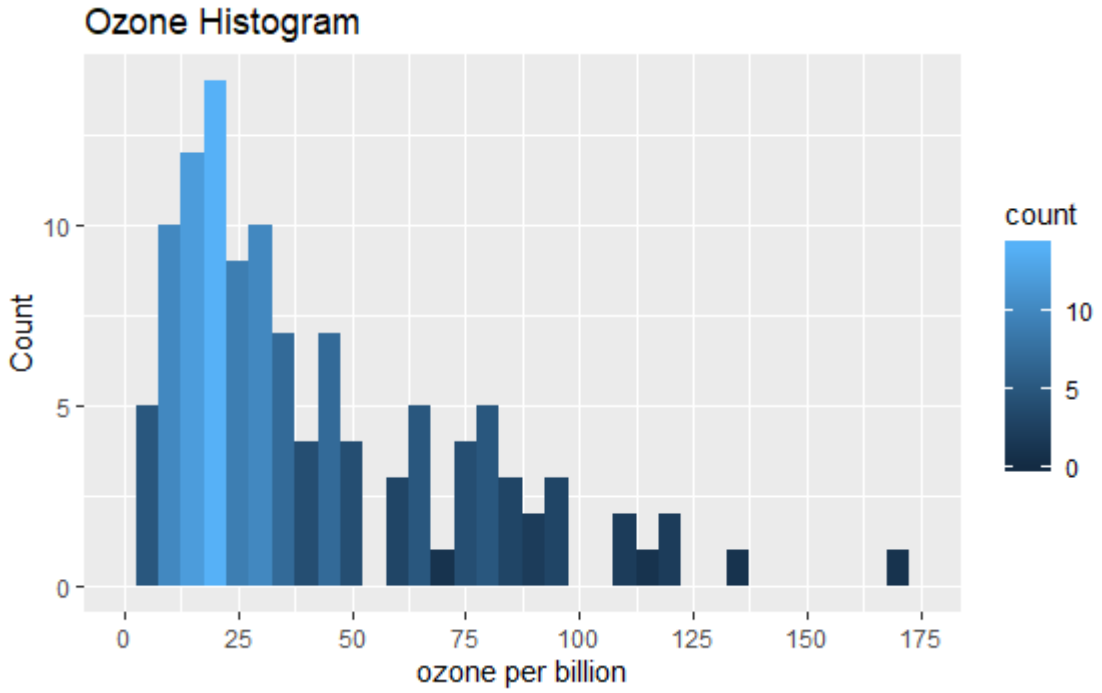
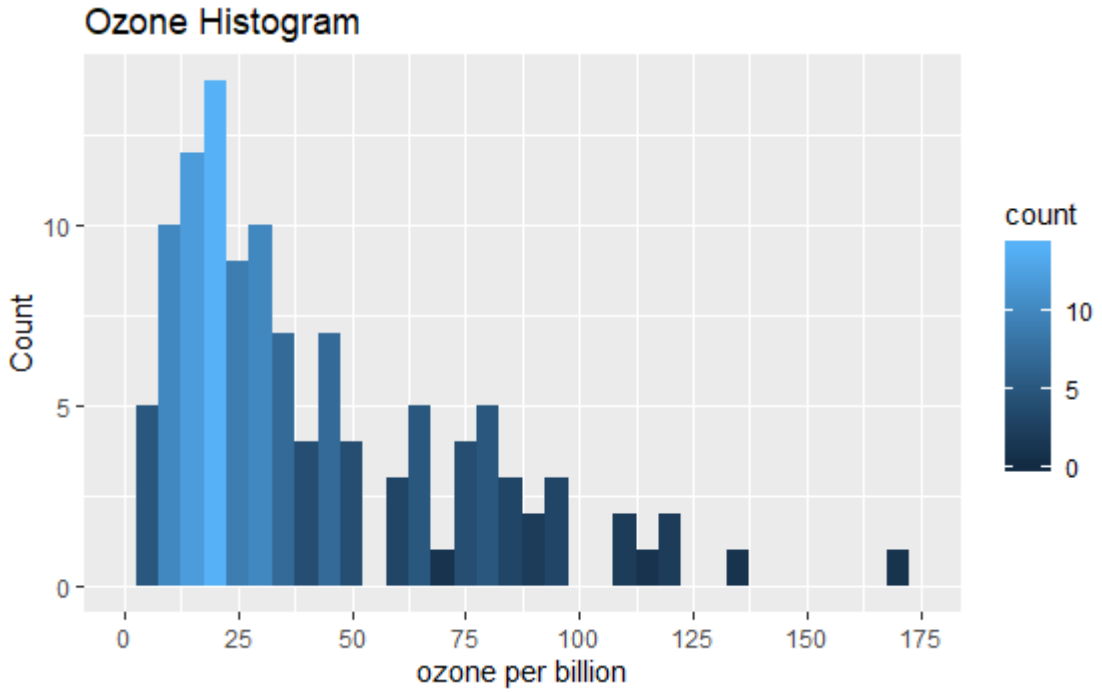


HISTOGRAM INTERPRETATION



Back to our questions...

- What kind of distribution do the data come from?
- How spread out are the data?
- Are the data symmetric or skewed?
- Are there outliers in the data?

The data is right skewed and there are clearly outliers as the graph stretches on the scale to175 Ozone per billion. It seems the median is around the 20 Ozone per billion.

EDA – UNIVARIATE, DISCRETE

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- The analysis is done based on just one variable, where it is a discrete (i.e. categorical) variable.

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EDA – UNIVARIATE, DISCRETE

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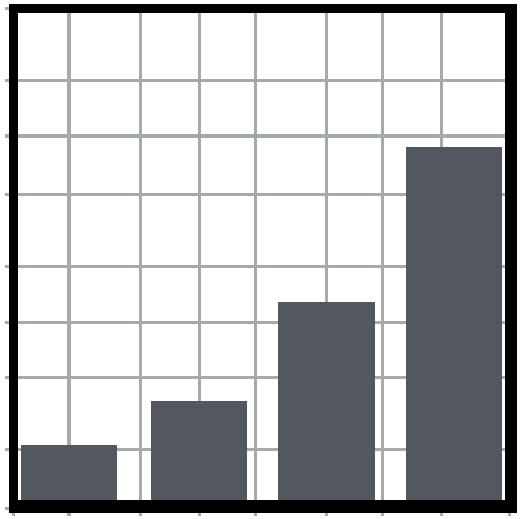
- The analysis is done based on just one variable, where it is a discrete (i.e. categorical) variable.
- ggplot2 provides one functions to plot the variation of the univariate discrete, which is:
  - *geom_bar()*, for a bar plot



UNIVARIATE BAR PLOT

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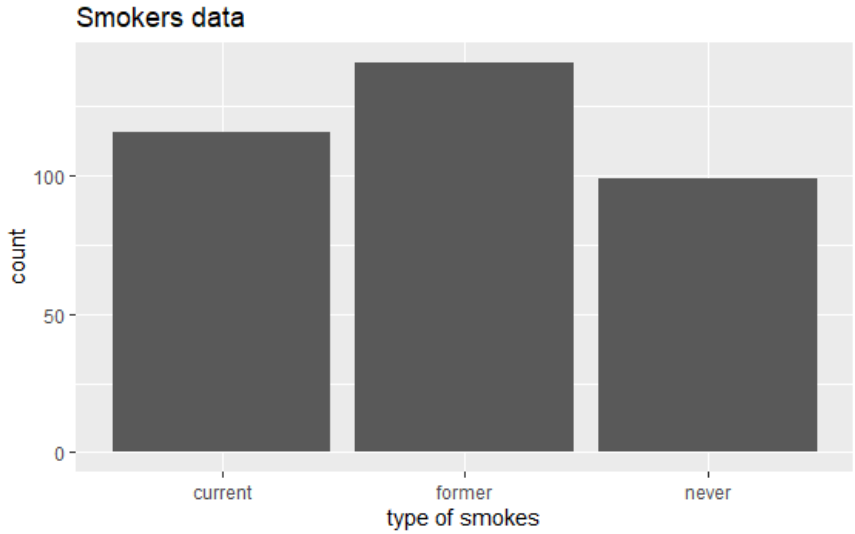
UNIVERSITY OF CANBERRA

- Summarise the variable by extracting a frequency of each level/category of the univariate variable.



UNIVARIATE BAR PLOT

UNIVERSITY OF CANBERRA

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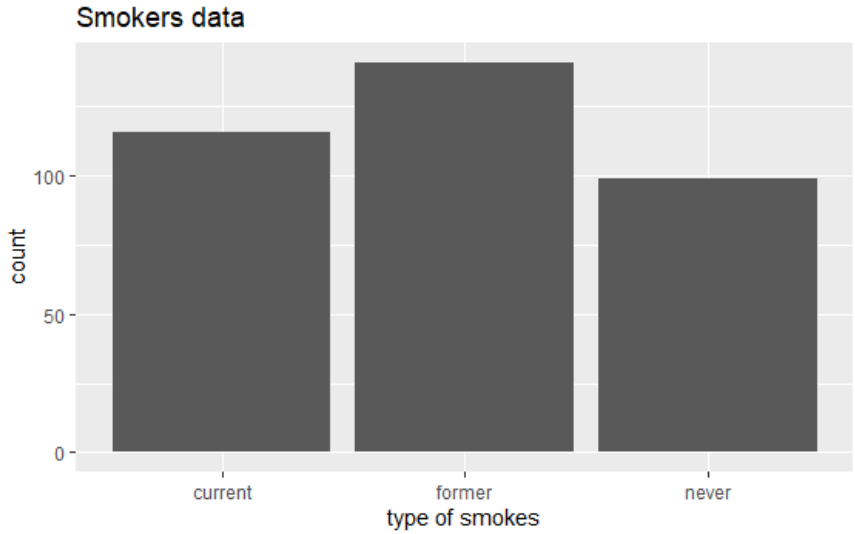
- The x-axis represents the levels/categories of the data



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UNIVERSITY OF CANBERRA

- Summarise the variable by extracting a frequency of each level/category of the univariate variable.
- The x-axis represents the levels/categories of the data
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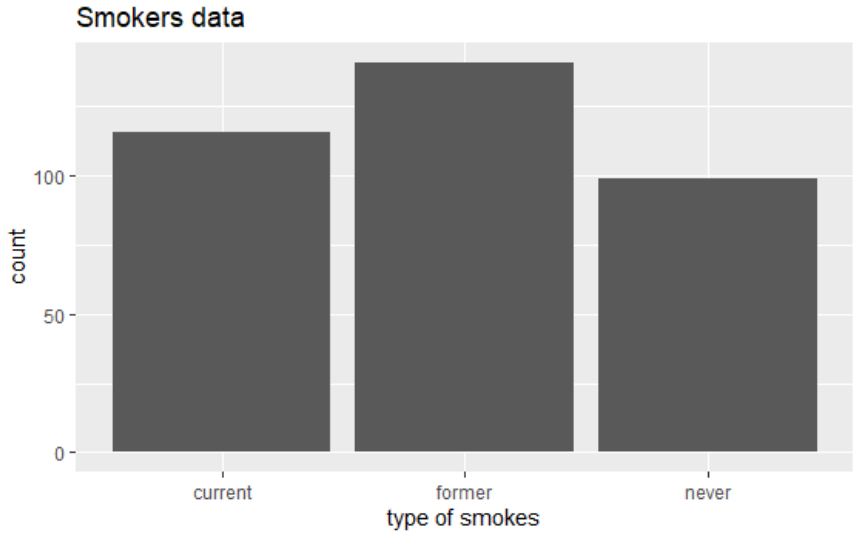

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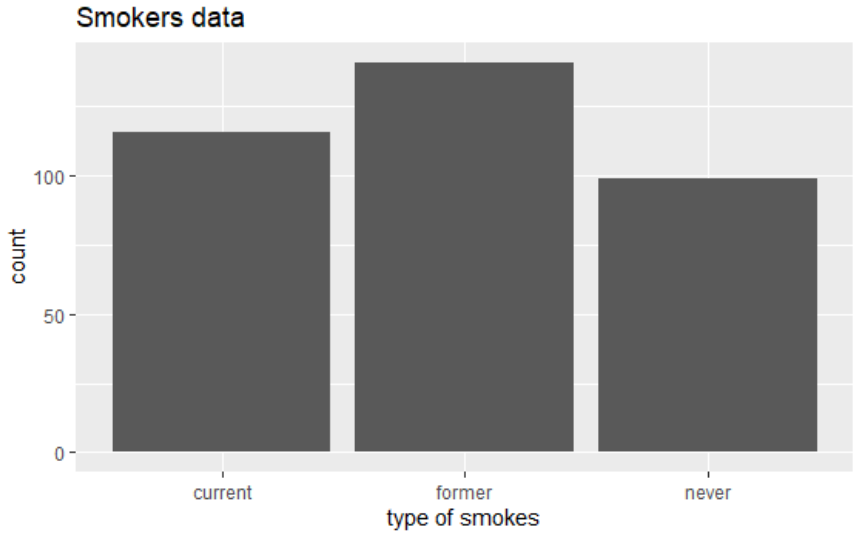

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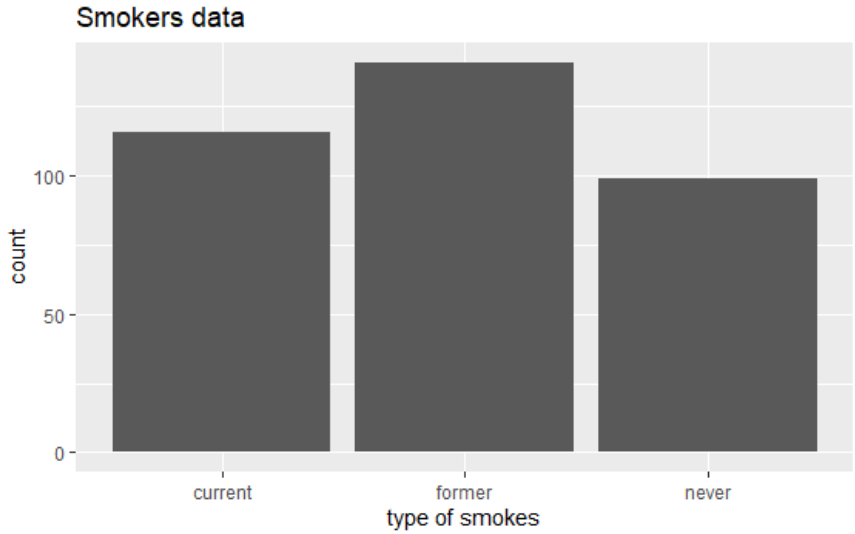

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UNIVERSITY OF CANBERRA

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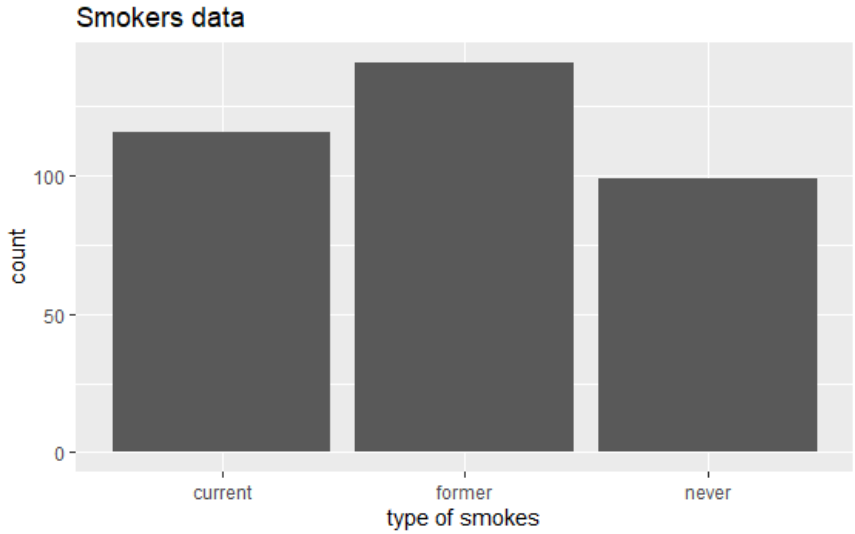

BUILDING A BAR PLOT

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BUILDING A BAR PLOT

UNIVERSITY OF CANBERRA

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UNIVERSITY OF CANBERRA

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UNIVERSITY OF CANBERRA

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EXAMPLE

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EXAMPLE

UNIVERSITY OF CANBERRA

Basic bar plot visualization

EXAMPLE

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Basic bar plot visualization

```
ggplot(data, aes(x = Smoke)) +
  geom_bar()+
  xlab("type of smokes") +
  ylab("count") +
  ggtitle("Smokers data")
```

EXAMPLE

UNIVERSITY OF CANBERRA

Basic bar plot visualization

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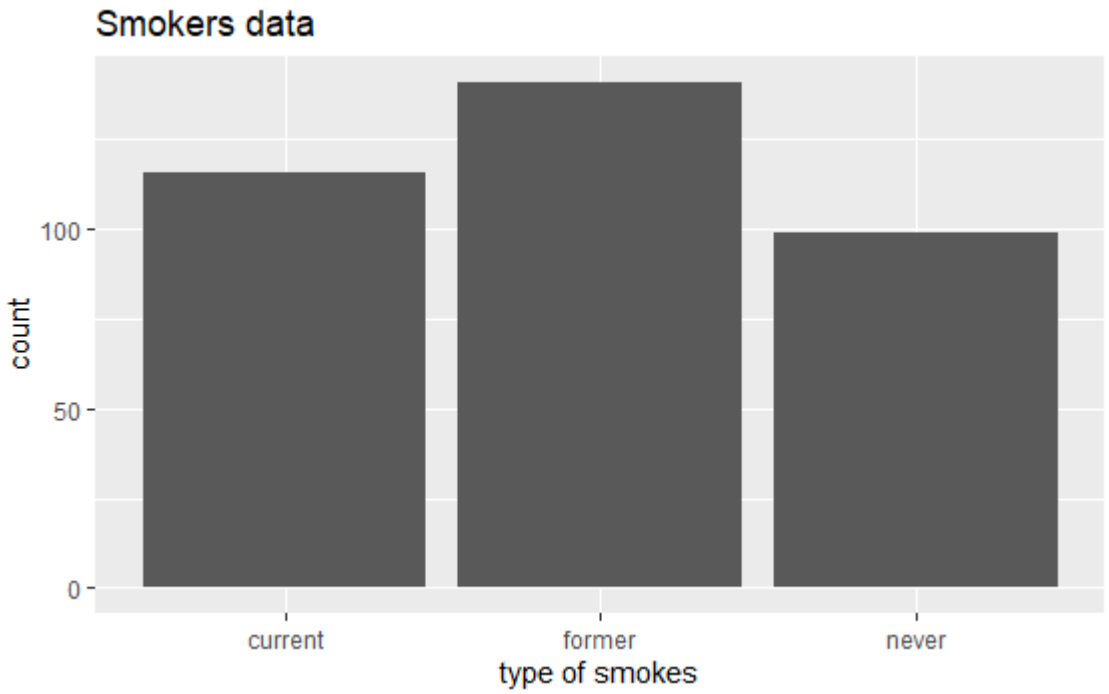

EXAMPLE (2)

UNIVERSITY OF CANBERRA

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UNIVERSITY OF CANBERRA

Adding extra visual cues and more options

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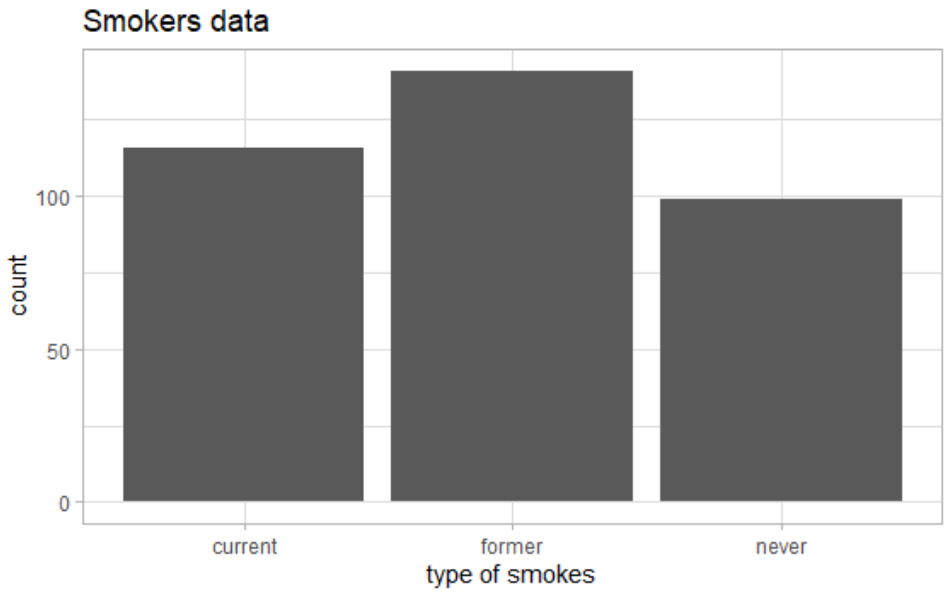

EXAMPLE (2)

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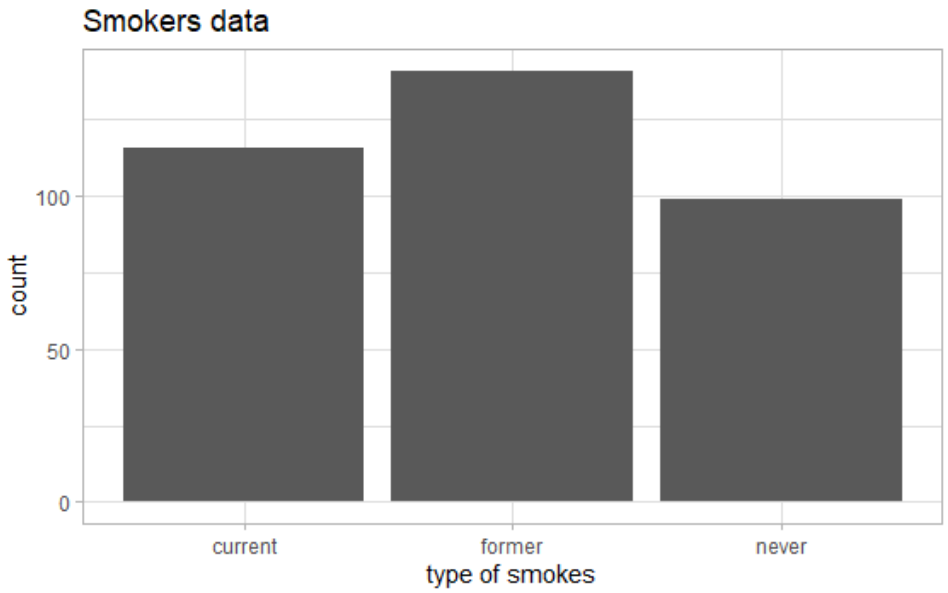

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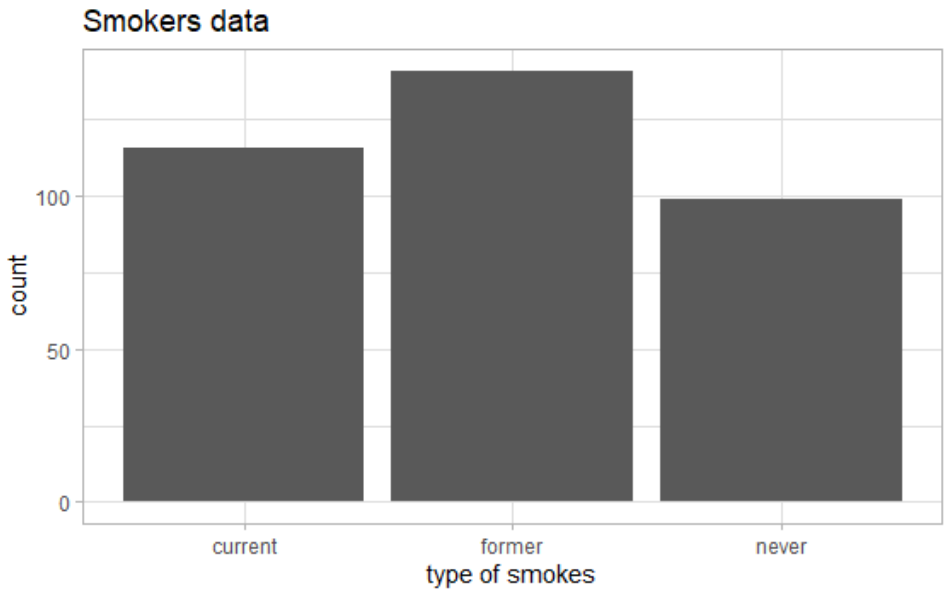

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BAR PLOT INTERPRETATION

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BAR PLOT INTERPRETATION

BAR PLOT INTERPRETATION

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Back to our questions...

What is the spread of observations between levels of the data? Which level has the most observations or least observations etc. ?

Former smokers are more than the current, etc.

RECOMMENDED READING

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- You are recommended to read chapters 3 from the *"R for Data Science"* book:
  - https://r4ds.had.co.nz/data-visualisation.html

ANNOUNCEMENT

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- This week online test has been released since yesterday and is due this Sunday.
  - One attempt
  - 60 minutes long
  - Weights 20%