

Applied Data Analysis for Public Policy Studies

Summarising, Visualizing and Tidying Data

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Recap from last week

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- Basic data wrangling:
 - `View`, `str`, `names`, `nrow`, `ncol`
 - *subsetting*: `murders[row condition, "column name"]`
 - *variable creation*: `murders$total_percap = (murders$total / murders$population) * 10000`



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 - *variable creation*: `murders$total_percap = (murders$total / murders$population) * 10000`

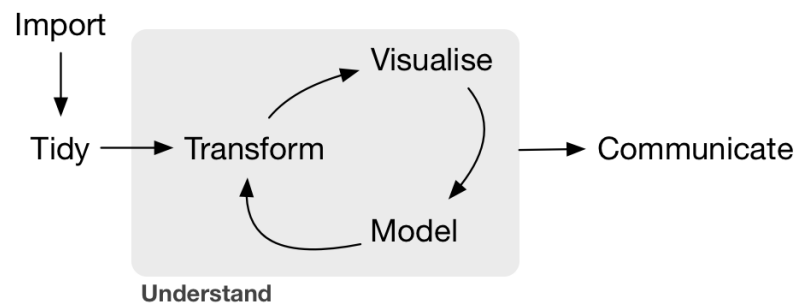
Today

- Deeper dive into data wrangling with R:
 - **summarizing** data,
 - **visualisation** data,
 - **tidying** data



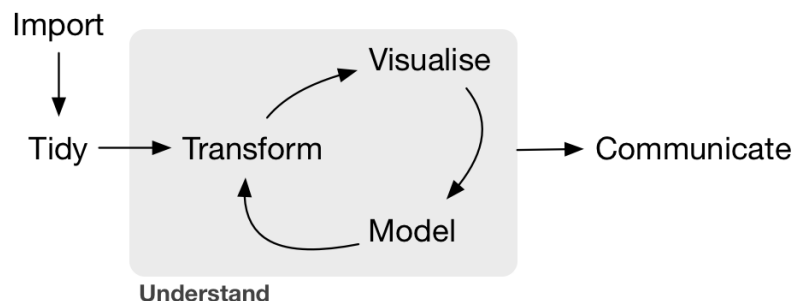
Working With Data

- Econometrics is about **data**.



Working With Data

- Econometrics is about **data**.



- According a to **2014 NYTimes article**, "data scientists [...] spend from **50 percent to 80 percent of their time** mired in this more mundane labor of collecting and preparing unruly digital data, before it can be explored for useful nuggets."
- In the next two lectures you will learn the **basics** of summarizing, visualising and tidying data



The gapminder dataset: Overview

- Let's first load a dataset with these commands:

```
library(dslabs)
gapminder <- gapminder
```

- Here are the first 3 rows

```
head(gapminder, n = 3)
```

```
##   country year infant_mortality life_expectancy fertility population
## 1 Albania 1960          115.4           62.87         6.19    1636054
## 2 Algeria 1960          148.2           47.50         7.65    11124892
## 3  Angola 1960          208.0           35.98         7.32     5270844
##           gdp continent      region
## 1           NA    Europe Southern Europe
## 2 13828152297    Africa Northern Africa
## 3           NA    Africa  Middle Africa
```



The gapminder dataset: Overview

- What variables does this dataset contain?

```
names(gapminder)
```

```
## [1] "country"      "year"          "infant_mortality" "life_expectancy"  
## [5] "fertility"    "population"    "gdp"             "continent"  
## [9] "region"
```

- `tail` gives you the last (6) rows.

```
tail(gapminder)
```



The gapminder dataset: Datatypes

- It's important to know how the data is stored.
- We can use `str` for that:

```
str(gapminder)
```

```
## 'data.frame':    10545 obs. of  9 variables:
## $ country      : Factor w/ 185 levels "Albania","Algeria",...: 1 2 3 4 5 6 7 8 9 10 ...
## $ year         : int  1960 1960 1960 1960 1960 1960 1960 1960 1960 1960 ...
## $ infant_mortality: num  115.4 148.2 208 NA 59.9 ...
## $ life_expectancy : num  62.9 47.5 36 63 65.4 ...
## $ fertility     : num  6.19 7.65 7.32 4.43 3.11 4.55 4.82 3.45 2.7 5.57 ...
## $ population    : num  1636054 11124892 5270844 54681 20619075 ...
## $ gdp           : num  NA 1.38e+10 NA NA 1.08e+11 ...
## $ continent     : Factor w/ 5 levels "Africa","Americas",...: 4 1 1 2 2 3 2 5 4 3 ...
## $ region        : Factor w/ 22 levels "Australia and New Zealand",...: 19 11 10 2 15 21 2 1 22 21 ...
```



Task 1 (7 minutes)

- Create a new variable called `gdppercap` corresponding to `gdp` divided by `population`
- Which countries had a 2011 GDP per capita greater than 30.000?
- Filter the dataset to only keep the year 2015: `gapminder_2015`
- How many countries have an infant mortality in 2015 greater than 90 (per 1000)?
- What is the average life expectancy in Africa in 2015?



Summarizing

Summarizing Data

- One can learn only a limited amount from **looking** at a `data.frame`. 🔍



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- Even if you *could* see all rows of the dataset, you would not know very much **about it**.



Summarizing Data

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- Even if you *could* see all rows of the dataset, you would not know very much **about it**.
- We need to **summarize** the data for us to learn from it.



Summarizing Data

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- In general, we can compute summary statistics, or visualize the data with plots.



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- Let's start with some statistics first!



Summarizing Data

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- Even if you *could* see all rows of the dataset, you would not know very much **about it**.
- We need to **summarize** the data for us to learn from it.
- In general, we can compute summary statistics, or visualize the data with plots.
- Let's start with some statistics first!
- Let's look at two features: *central tendency* and *spread*.



Central Tendency

1. `mean(x)`: the average of all values in `x`.

$$\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i$$

```
x <- c(1,2,2,2,2,100)
mean(x)
```

```
## [1] 18.16667
```

```
mean(x) == sum(x) / length(x)
```

```
## [1] TRUE
```

Your turn: What's the mean of `infant_mortality` in 1960? Read the help for `mean` to remove NAs.



Central Tendency

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Your turn: What's the mean of `infant_mortality` in 1960? Read the help for `mean` to remove NAs.

1. `median`: the value x_j below and above which 50% of the values in `x` lie. m is the median if

$$\Pr(X \leq m) \geq 0.5 \text{ and } \Pr(X \geq m) \geq 0.5$$

2. The median is robust against *outliers*.
🤔? (later).

```
median(x)
```

```
## [1] 2
```

Your turn: What's the median of `infant_mortality` in 1960?



Missing Values: NA

- Whenever a value is *missing*, we code it as NA.

```
x <- NA
```

- R propagates NA through operations:

```
NA > 5
```

```
## [1] NA
```

```
NA + 10
```

```
## [1] NA
```

- the function `is.na(x)` returns TRUE if x is an NA.

```
is.na(x)
```

```
## [1] TRUE
```



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- the function `is.na(x)` returns TRUE if x is an NA.

```
is.na(x)
```

```
## [1] TRUE
```

- What is confusing is that

```
NA == NA
```

```
## [1] NA
```

- It's easy to illustrate like that:

```
# Let x be Mary's age. We don't know how old she is
x <- NA
```

```
# Let y be John's age. We don't know how old he is
y <- NA
```

```
# Are John and Mary the same age?
x == y
```

```
## [1] NA
```

```
#> [1] NA
# We don't know!
```



Spread

- Another interesting feature is how much a variable is *spread out* about its center (the mean in this case).
- The *variance* is such a measure.

$$\text{Var}(X) = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2$$

- Consider two normal distributions with equal mean at 0:

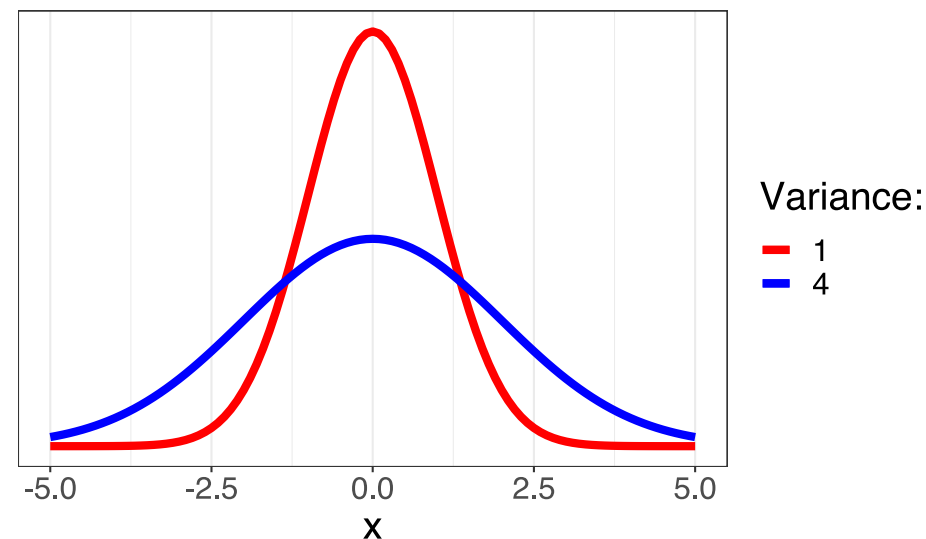


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- Consider two normal distributions with equal mean at 0:



- Compute with:

```
var(x)  
range(x) # range
```



Example: the Weight of Women and Men¹

- Men weight 65 kg and women 55 kg on average. The variance is 25.

```
# Generate a random dataset
set.seed(1234) # `set.seed` allows replicating random numbers
df <- data.frame(
  sex=factor(rep(c("F", "M"), each=200)),
  weight=round(c(rnorm(200, mean=55, sd=5), # ?
                 rnorm(200, mean=65, sd=5))))
```

- Plot the overall density

```
ggplot(df, aes(x=weight)) + geom_density() + theme_minimal()
```

- Plot separated densities

```
# Change density plot line colors by groups
ggplot(df, aes(x=weight, color=sex)) + geom_density()
```



Example: the Weight of Women and Men¹

- Men weight 65 kg and women 55 kg on average. The variance is 25.

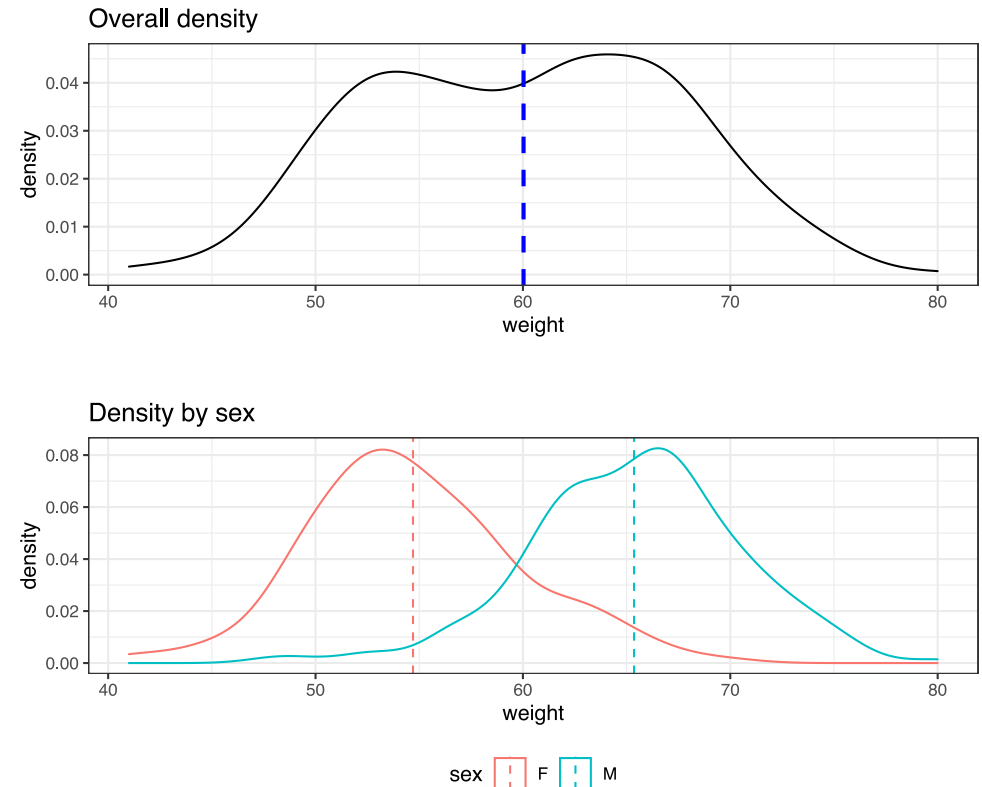
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                rnorm(200, mean=65, sd=5))))
```

- Plot the overall density

```
ggplot(df, aes(x=weight)) + geom_density() + theme_minimal()
```

- Plot separated densities

```
# Change density plot line colors by groups
ggplot(df, aes(x=weight, color=sex)) + geom_density()
```



[1]: This example is taken from sthda.com.



The `table` function

- `table(x)` is a useful function that counts the occurrence of each unique value in `x`:

```
table(gapminder$continent)
```

```
##  
## Africa Americas Asia Europe Oceania  
## 2907 2052 2679 2223 684
```

```
table(gapminder$region)
```

```
##  
## Australia and New Zealand Caribbean Central America  
## 114 741 456  
## Central Asia Eastern Africa Eastern Asia  
## 285 912 342  
## Eastern Europe Melanesia Micronesia  
## 570 285 114  
## Middle Africa Northern Africa Northern America  
## 456 342 171  
## Northern Europe Polynesia South America  
## 570 171 684  
## South-Eastern Asia Southern Africa Southern Asia  
## 570 285 456  
## Southern Europe Western Africa Western Asia  
## 684 912 1026  
## Western Europe  
## 399
```



Crosstables

- Given two vectors, `table` produces a contingency table:

```
gapminder_2015 <- subset(gapminder, year == 2015)
gapminder_2015$fertility_above_2 = (gapminder_2015$fertility > 2.1) # dummy variable for fertility rate above 2.1
table(gapminder_2015$fertility_above_2, gapminder_2015$continent)
```

```
##
##      Africa Americas Asia Europe Oceania
## FALSE      2      15  20    39      4
##  TRUE     49      20  27     0      8
```



Crosstables

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table(gapminder_2015$fertility_above_2, gapminder_2015$continent)
```

```
##
##      Africa Americas Asia Europe Oceania
## FALSE      2      15  20    39      4
##  TRUE     49      20  27     0      8
```

- With `prop.table`, we can get proportions:

```
# proportions by row
prop.table(table(gapminder_2015$fertility_above_2, gapminder_2015$continent), margin = 1)
# proportions by column
prop.table(table(gapminder_2015$fertility_above_2, gapminder_2015$continent), margin = 2)
```

- ⚠ To obtain `tables` with `NA`s, use the `useNA = "always"` or `useNA = "ifany"`



Plotting

Plotting

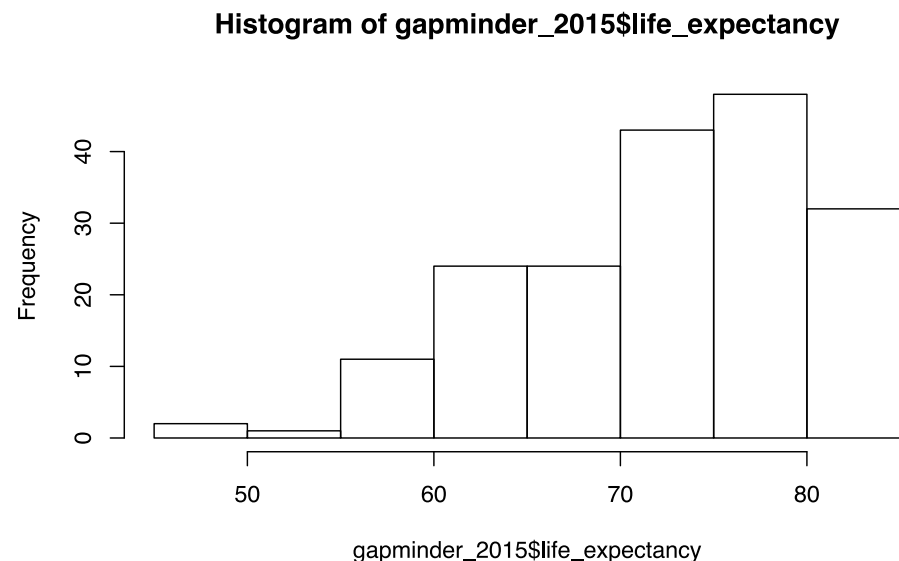
- R base plotting is fairly good.
- There is an extremely powerful alternative in package `ggplot2`. We'll see both.
- First example: *histograms*. A histogram counts how many observations fall within a certain bin.



Plotting

- **R** base plotting is fairly good.
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- First example: *histograms*. A histogram counts how many observations fall within a certain bin.

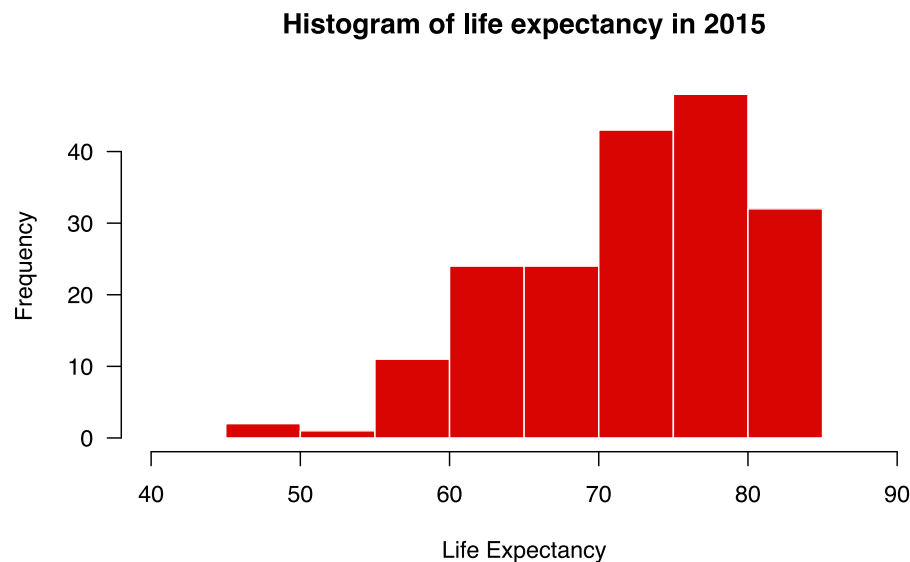
```
gapminder_2015 <- gapminder[gapminder$year == 2015,]  
hist(gapminder_2015$life_expectancy)
```



A Nicer Histogram

- We can give additional arguments to `hist`.
- Look at `?hist` for more.

```
hist(gapminder_2015$life_expectancy,  
     xlab  = "Life Expectancy",  
     main  = "Histogram of life expectancy in 2015",  
     breaks = seq(from = 40, to = 90, by = 5),  
     las = 1, # horizontal y-axis values  
     col   = "#d90502",  
     border = "white")
```

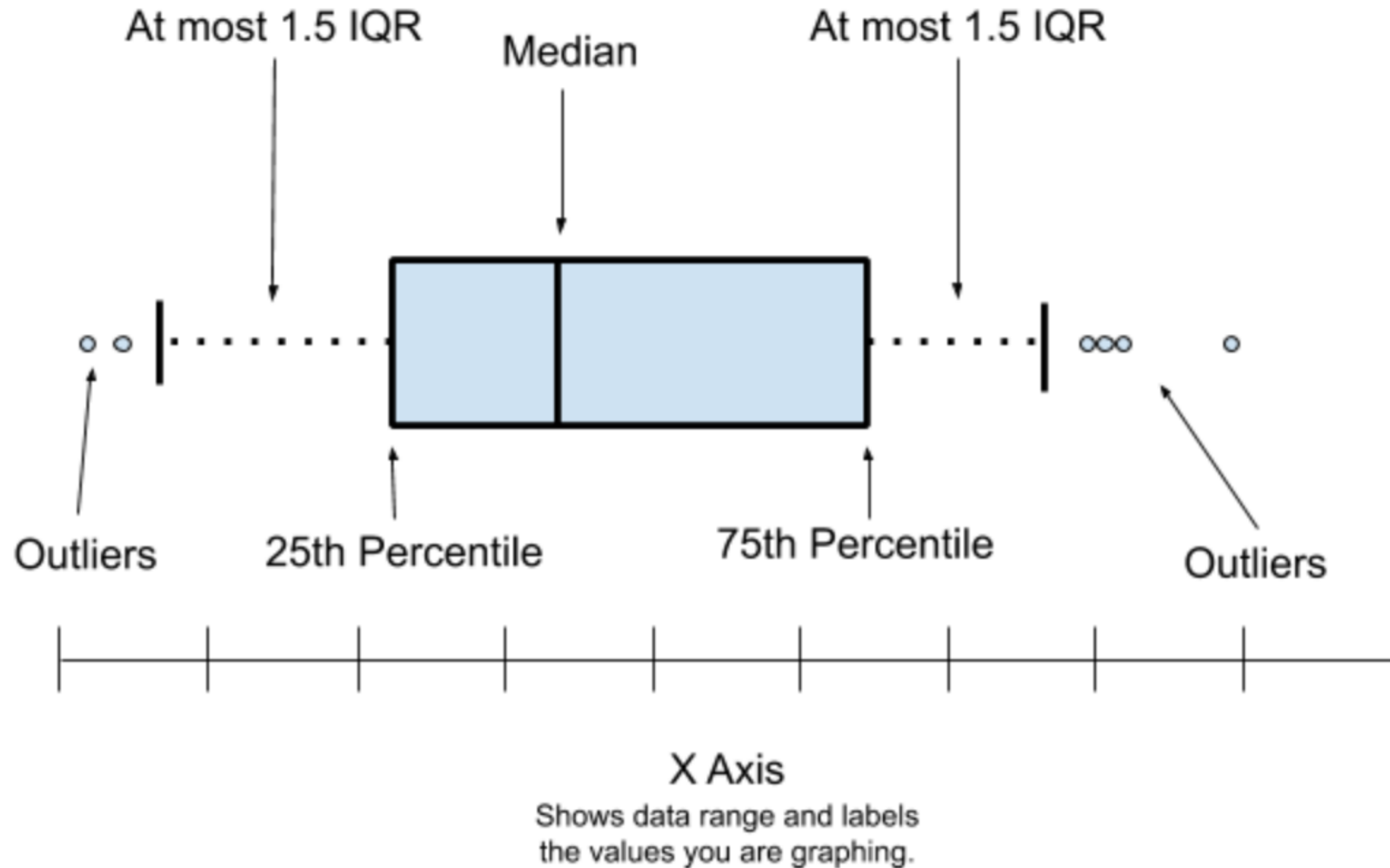


Looking for Outliers: Boxplots

- An *outlier* is a datapoint far removed from the center of a distribution.
- Boxplots are an effective way to visualise the distribution of a variable.
- The *box* typically denotes the **interquartile range** (observations between 25th pctile and 75th pctile).
- The *thick line* corresponds to the **median**.
- The *dots* are **outliers** (⚠ no universally accepted definition).



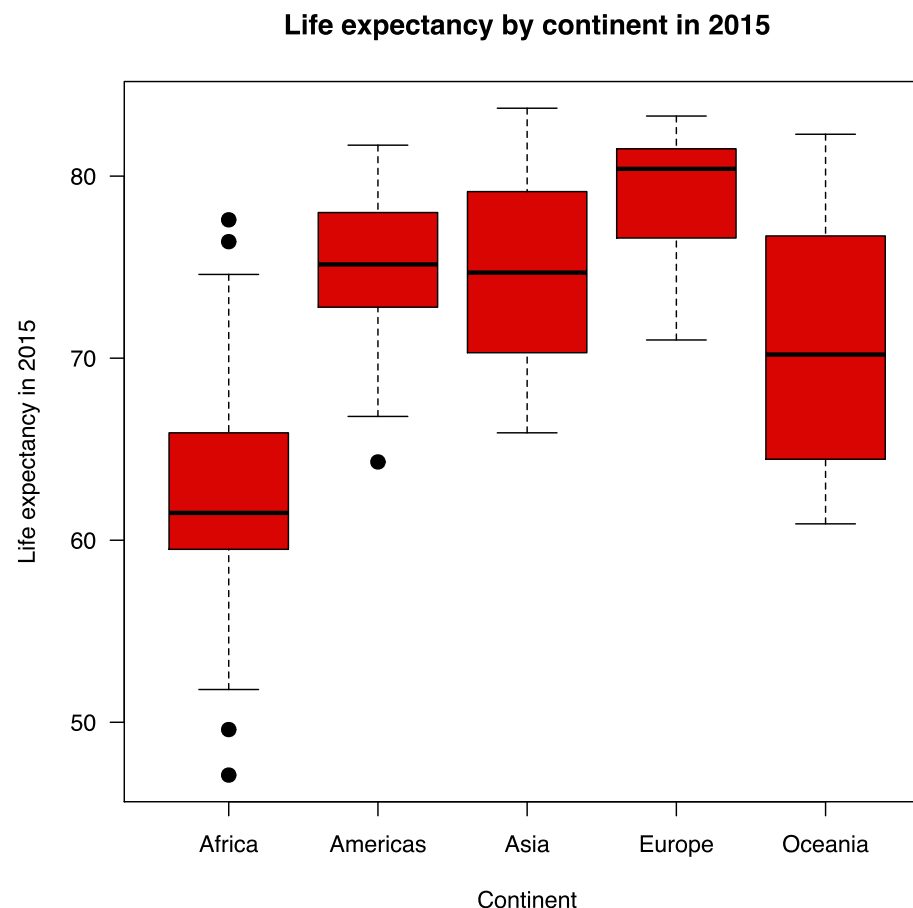
Looking for Outliers: Boxplots



Looking for Outliers: Boxplots

```
boxplot(life_expectancy ~ continent,  
  data = gapminder_2015,  
  xlab = "Continent",  
  ylab = "Life expectancy in 2015",  
  main = "Life expectancy by continent in 2015",  
  pch = 20, cex = 2, # colour and size of outliers  
  col = "#d90502", border = "black", las = 1)
```

- see `?boxplot` for more options



Scatter Plots

- Two variables x and y



Scatter Plots

- Two variables x and y
- Natural to ask: How often do certain pairs of (x_i, y_i) occur?

```
head(gapminder_2015[,c("fertility", "infant_mortality")])
```

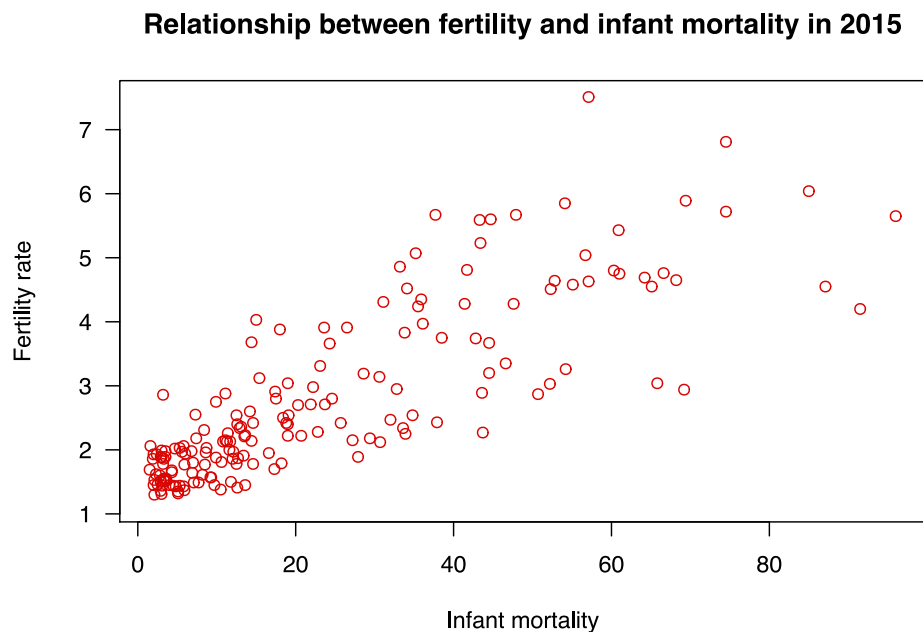
```
##      fertility infant_mortality
## 10176      1.78             12.5
## 10177      2.71             21.9
## 10178      5.65             96.0
## 10179      2.06              5.8
## 10180      2.15             11.1
## 10181      1.41             12.6
```

- That's what a scatter plots shows.



Scatter Plots

```
plot(fertility ~ infant_mortality,  
     data = gapminder_2015,  
     xlab = "Infant mortality",  
     ylab = "Fertility rate",  
     main = "Relationship between fertility and infant mortality",  
     col = "#d90502",  
     las = 1)
```

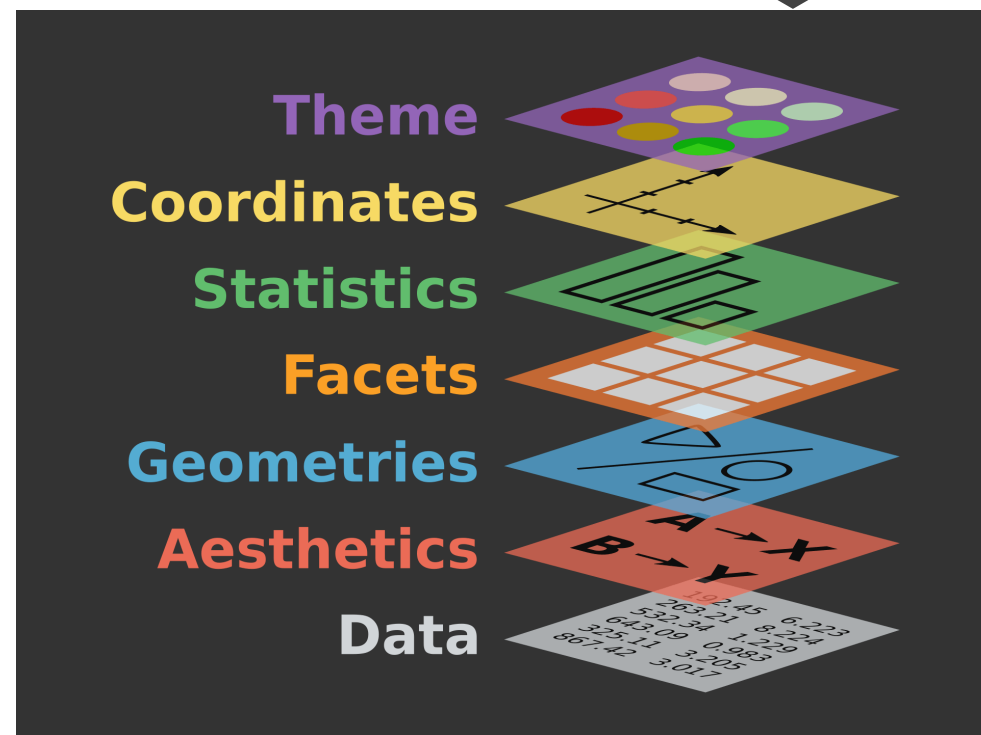
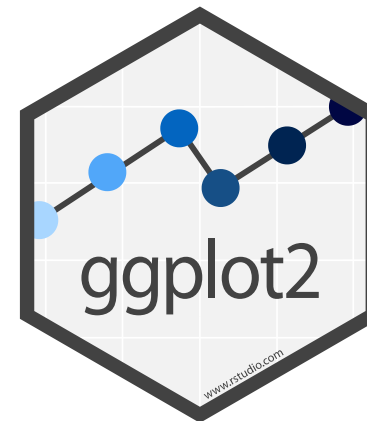


- Each dot is one pair (x_i, y_i) .
- We often call it one *observation*.
- Corresponding to one *row* of the `data.frame`.
- Why do some dots appear *darker* than others here?



Quick `ggplot2` Intro

- Excellent cheatsheet on [project website](#).
- Great intro to `ggplot2` [here](#).
- Based on *The Grammar of Graphics* (hence `ggplot`).
- More powerful than base R plotting
- Let's reproduce the previous graphs in `ggplot`



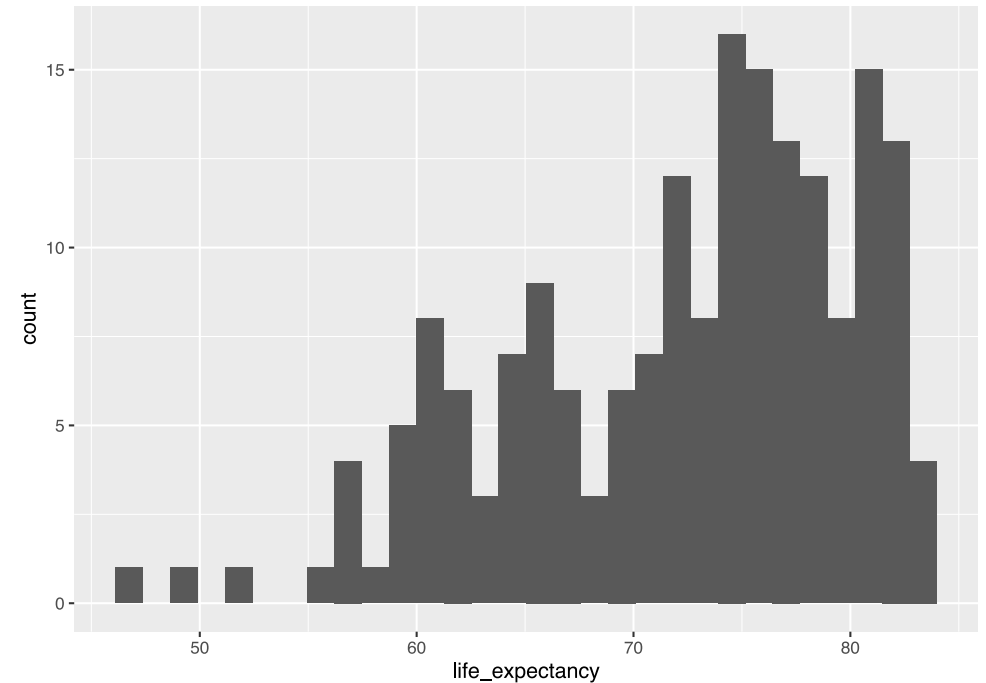
source: **BloggoType**



ggplot2: Basic Histogram

```
library(ggplot2)

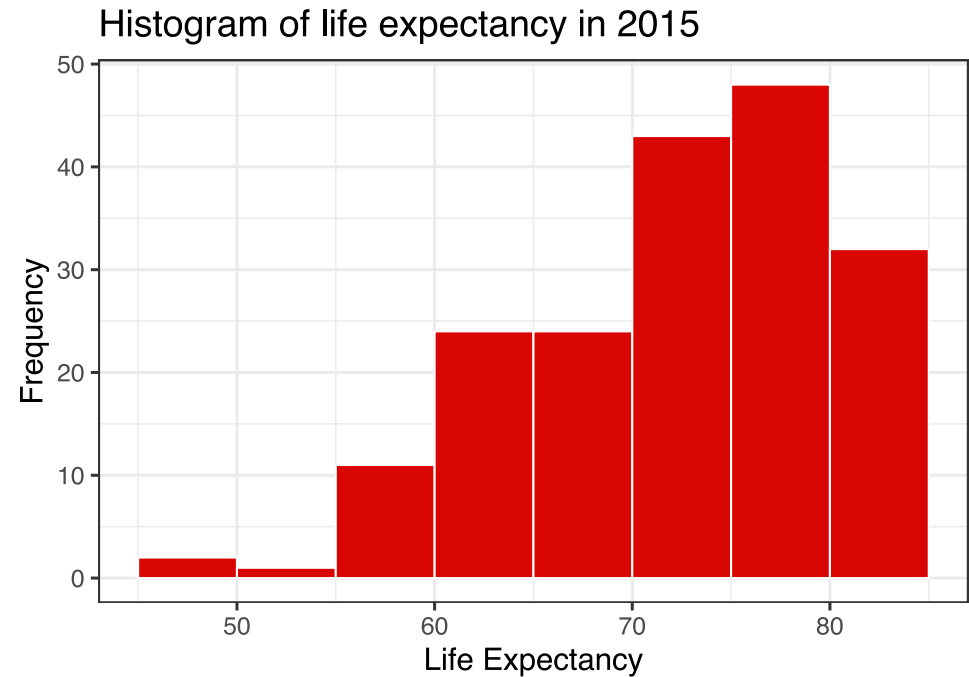
ggplot(gapminder_2015,
       aes(x = life_expectancy)) +
  geom_histogram()
```



ggplot2: Fancy Histogram

```
library(ggplot2)

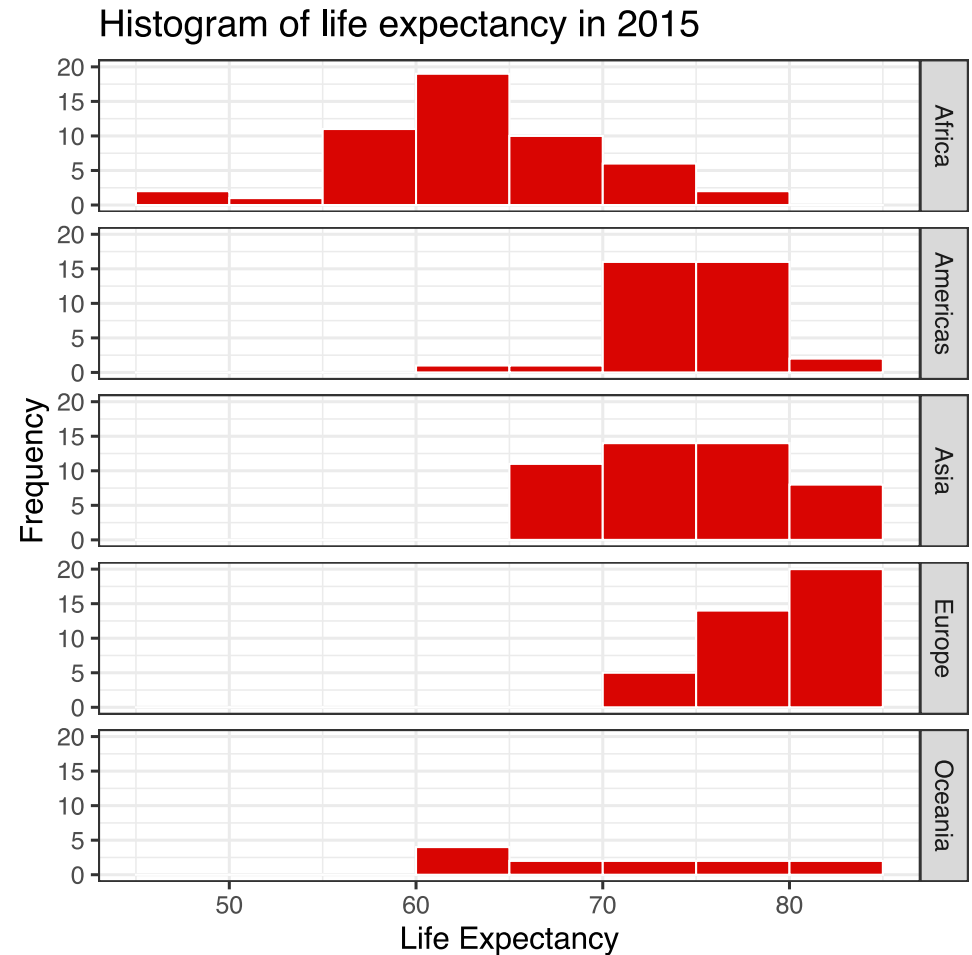
ggplot(gapminder_2015,
       aes(x = life_expectancy)) +
  geom_histogram(binwidth = 5,
                 boundary = 45,
                 colour = "white",
                 fill = "#d90502") +
  labs(x = "Life Expectancy",
       y = "Frequency",
       title = "Histogram of life expectancy in 2015",
       theme_bw(base_size = 16))
```



ggplot2: Fancy Histogram with facet_grid()

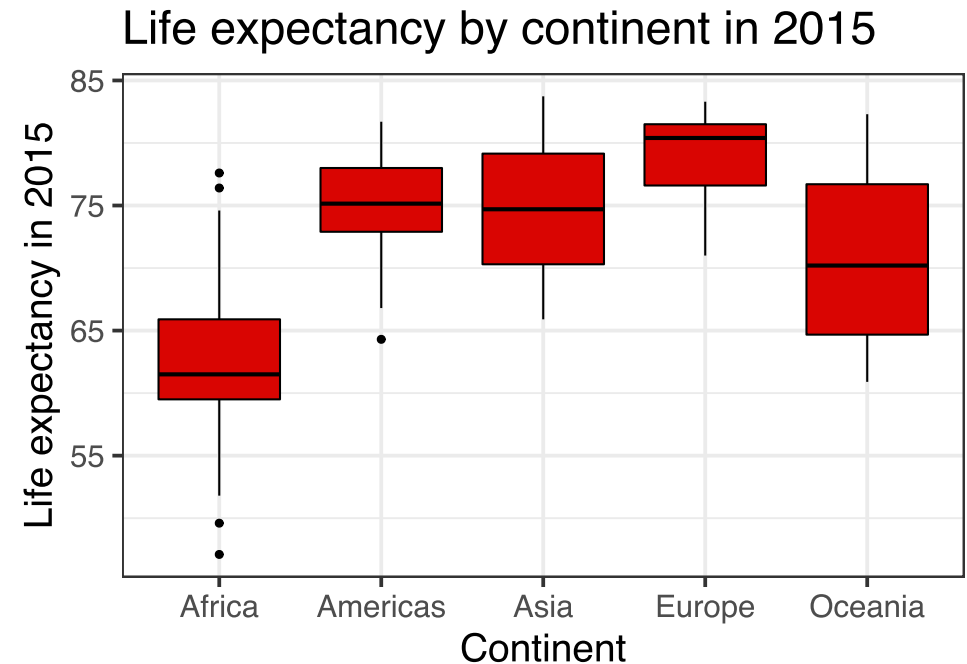
```
library(ggplot2)

ggplot(gapminder_2015,
       aes(x = life_expectancy)) +
  geom_histogram(binwidth = 5,
                 boundary = 45,
                 colour = "white",
                 fill = "#d90502") +
  labs(x = "Life Expectancy",
       y = "Frequency",
       title = "Histogram of life expectancy in 2015") +
  theme_bw(base_size = 16) +
  facet_grid(rows = vars(continent))
```



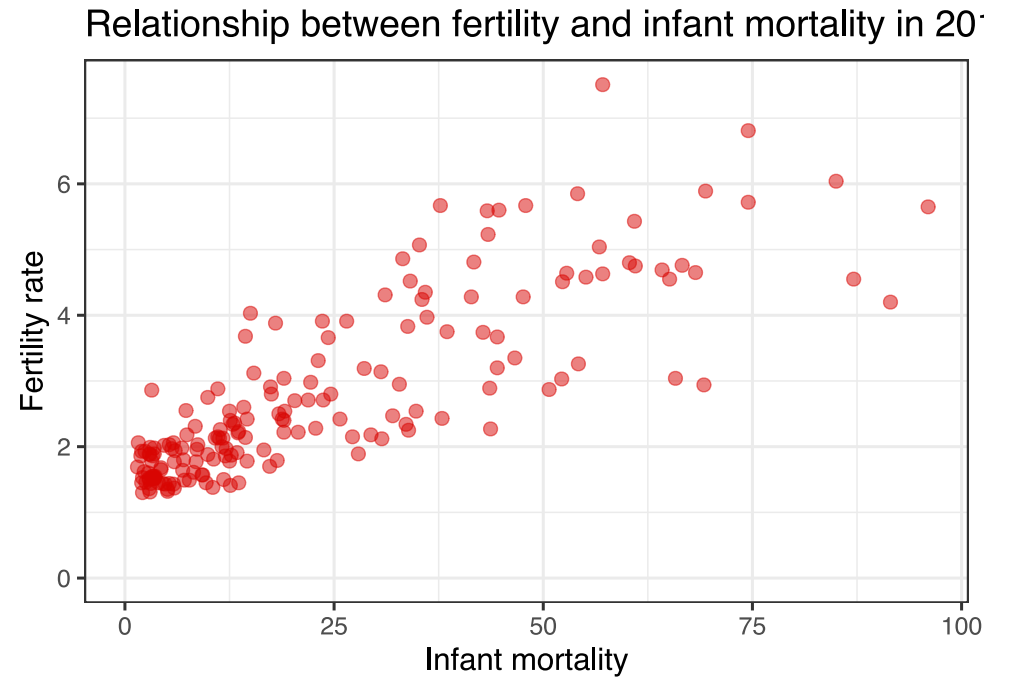
ggplot2: Boxplots

```
ggplot(gapminder_2015,  
       aes(x = continent, y = life_expectancy)) +  
  geom_boxplot(colour = "black",  
               fill = "#d90502") +  
  labs(x = "Continent",  
       y = "Life expectancy in 2015",  
       title = "Life expectancy by continent in 2015",  
       theme_bw(base_size = 20))
```



ggplot2: Scatter Plots

```
ggplot(gapminder_2015,  
      aes(x = infant_mortality,  
          y = fertility)) +  
  geom_point(size = 3,  
            alpha = 0.5,  
            colour = "#d90502") +  
  expand_limits(x = 0, y = 0) +  
  labs(x = "Infant mortality",  
       y = "Fertility rate",  
       title = "Relationship between fertility and infant mortality",  
       theme_bw(base_size = 16))
```



It's Tutorial Time!



Tutorial 1 (10 minutes)

Time for our first tutorial!!

Type this into your **RStudio** console:

```
library(ScPoEconometrics)  
runTutorial('chapter2')
```

If you have trouble with the interactive doc, try this version (no interactive content):

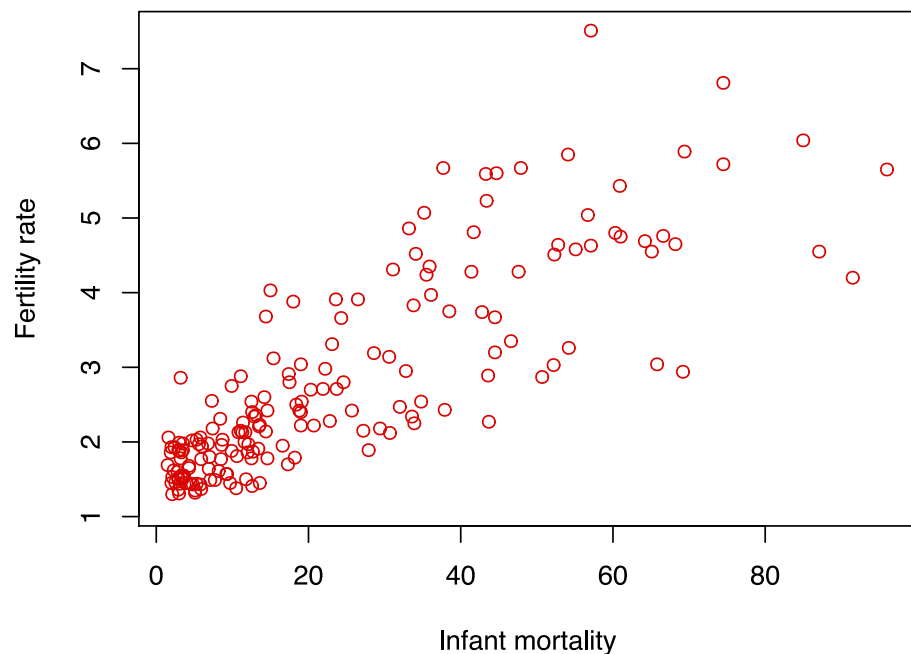
```
ScPoEconometrics::runTutorial('chapter2-script')
```



How are x and y related? Covariance and Correlation

- **This** is the relevant section in the book about Covariance.

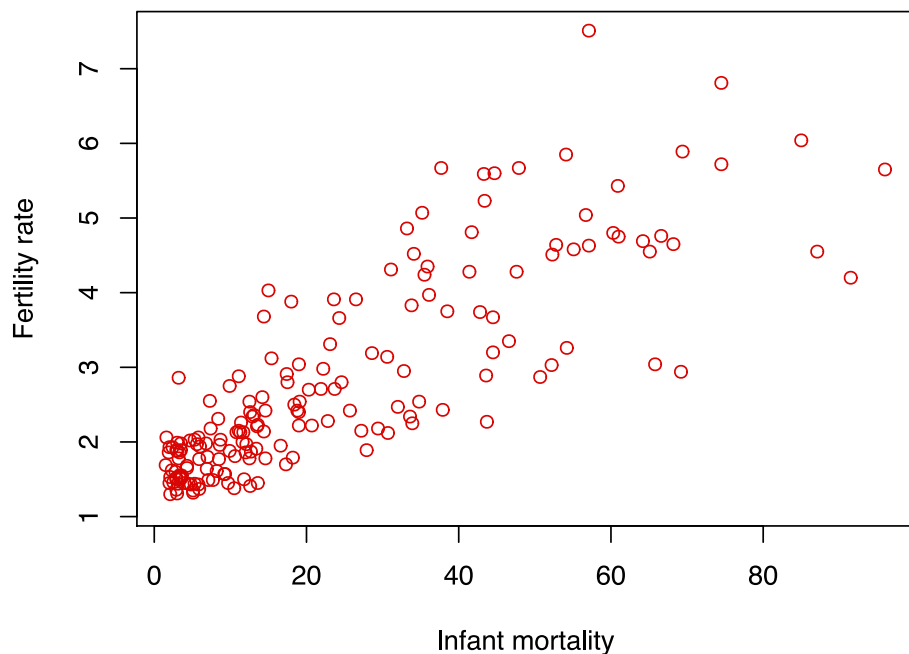
Relationship between fertility and infant mortality in 2015



How are x and y related? Covariance and Correlation

- **This** is the relevant section in the book about Covariance.

Relationship between fertility and infant mortality in 2015



- The covariance is a measure of **joint variability** of two variables.

$$Cov(x, y) = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})$$

[1] 24.21146

- The correlation is a measure of the strenght of the **linear association** between two variables.

$$Cor(x, y) = \frac{Cov(x, y)}{\sqrt{Var(x)}\sqrt{Var(y)}}$$

[1] 0.8286402



Correlation App

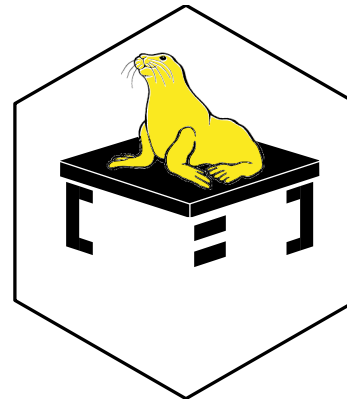
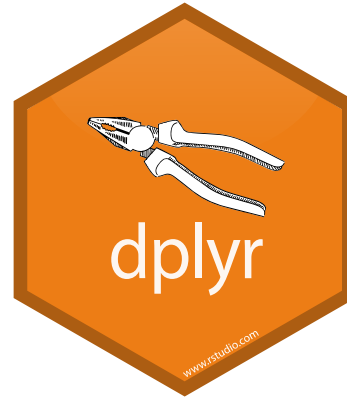
```
library(ScPoEconometrics)  
runTutorial('correlation')
```



Wrangling

Intro to `dplyr`

- `dplyr` is part of the **tidyverse** package family.
- `data.table` is an alternative. Very fast but a bit more difficult.
- Both have pros and cons. We'll start you off with `dplyr`.



dplyr Overview

- You *must* read through **Hadley Wickham's chapter**. It's concise.
- The package is organized around a set of **verbs**, i.e. *actions* to be taken.
- We operate on `data.frames` or `tibbles` (*nicer looking data.frames.*)
- All *verbs*: First argument is a data.frame, subsequent arguments describe what to do, returns another data.frame.



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- All *verbs*: First argument is a data.frame, subsequent arguments describe what to do, returns another data.frame.

Verbs

1. `filter()`: Choose observations based on a certain value (i.e. subset)
2. `arrange()`: Reorder rows
3. `select()`: Select variables by name
4. `mutate()`: Create new variables out of existing ones
5. `summarise()`: Summarise variables



Data on 2016 US election polls from the `ds1abs` package

- This dataset contains **real** data on polls made during the 2016 US Presidential elections and compiled by **fivethirtyeight**

```
library(ds1abs)
library(dplyr)
data(polls_us_election_2016) # this data is from fivethirtyeight.com
polls_us_election_2016 <- as_tibble(polls_us_election_2016)
head(polls_us_election_2016[,1:6], n = 6) # show first 6 lines of first 6 variables
```

```
## # A tibble: 6 x 6
##   state startdate   enddate   pollster      grade samplesize
##   <fct> <date>     <date>     <fct>      <fct>      <int>
## 1 U.S.  2016-11-03 2016-11-06 ABC News/Washington Post A+         2220
## 2 U.S.  2016-11-01 2016-11-07 Google Consumer Surveys B          26574
## 3 U.S.  2016-11-02 2016-11-06 Ipsos      A-         2195
## 4 U.S.  2016-11-04 2016-11-07 YouGov     B          3677
## 5 U.S.  2016-11-03 2016-11-06 Gravis Marketing B-        16639
## 6 U.S.  2016-11-03 2016-11-06 Fox News/Anderson Robbins Resear... A          1295
```

🚩 This is a `tibble` (more informative than `data.frame`)

What variables does this dataset contain?



`filter()`: subset a data.frame

- `filter` has the same purpose as `subset`
- Example: Which A graded poll with at least 2,000 people had Trump win at least 45% of the vote?

```
filter(polls_us_election_2016,  
       grade == "A" & samplesize > 2000 & rawpoll_trump > 45)
```



filter(): subset a data.frame

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```
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```

```
## # A tibble: 1 x 15  
##   state startdate   enddate   pollster grade samplesize population  
##   <fct> <date>       <date>       <fct>    <fct>      <int> <chr>  
## 1 Indi... 2016-04-26 2016-04-28 Marist ... A          2149 rv  
## # ... with 8 more variables: rawpoll_clinton <dbl>, rawpoll_trump <dbl>,  
## #   rawpoll_johnson <dbl>, rawpoll_mcmullin <dbl>, adjpoll_clinton <dbl>,  
## #   adjpoll_trump <dbl>, adjpoll_johnson <dbl>, adjpoll_mcmullin <dbl>
```



Create a Filter: Comparisons and Logical Operators

- We have a standard suite of comparison operators:

- `>`: greater than,
- `<`: smaller than,
- `>=`: greater than or equal to,
- `<=`: smaller than or equal to,
- `!=`: not equal to,
- `==`: equal to.

- Construct more complex filters with logical operators

1. `x & y`: `x` **and** `y`
2. `x | y`: `x` **or** `y`
3. `!y`: **not** `y`

- R has the convenient `x %in% y` operator (conversely `!(x %in% y)`), `TRUE` if `x` is a *member of* `y`.

```
3 %in% 1:3
```

```
## [1] TRUE
```

```
c(2,5) %in% 2:10 # also vectorized
```

```
## [1] TRUE TRUE
```

```
c("S", "Po") %in% c("Sciences", "Po") # also string
```

```
## [1] FALSE TRUE
```



mutate(): create new variables

- *Example:* What was
 1. the combined vote share of Trump and Clinton for each poll?
 2. the difference between Trump's raw poll vote share and 538's adjusted vote share?

```
mutate(polls_us_election_2016,  
       trump_clinton_tot = rawpoll_trump + rawpoll_clinton,  
       trump_raw_adj_diff = rawpoll_trump - adjpoll_trump)
```

select(): only keep some variables

- *Example:* Only keep the variables
state, startdate, enddate, pollster, rawpoll_clinton, rawpoll_trump

```
select(polls_us_election_2016,  
       state, startdate, enddate, pollster, rawpoll_clinton, rawpoll_trump)
```



Task 2 (10 minutes)

1. Which polls had more vote intentions for Trump than for Clinton.
2. How many polls have a missing `grade`?
3. Which polls were (i) polled by American Strategies, GfK Group or Merrill Poll, *and* (ii) had a sample size greater than 1,000, *and* (iii) started on October 20th, 2016?

For the following questions you should use `filter` and `mutate`.

1. Which polls (i) did not have missing poll data for Johnson, (ii) had a combined raw poll vote share for Trump and Clinton greater than 95% *and* (iii) had a sample size greater than 1,000.?
2. Which polls (i) did not poll for vote intentions for Johnson, (ii) had a difference in raw poll vote shares between Trump and Clinton greater than 5, *and* (iii) were done in the state of Iowa?



Split-Apply-Combine

- Often we do *some* operation **by** some group in our dataset:
 - Mean vote share for Clinton by pollster grade.
 - Maximum vote share for Trump by poll month, etc
- For this, we need to
 1. Split the data **by** group
 2. Apply to each group the operation
 3. Recombine all groups into one table
- In `dplyr`, this is achieved with `group_by()` and `summarise`.



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- In `dplyr`, this is achieved with `group_by()` and `summarise`.

1. `group_by(polls_us_election_2016, grade)` groups/splits `polls_us_election_2016` by pollster grade:

```
polls_grade = group_by(polls_us_election_2016, gr
```

2. `summarise` each chunk and re-combine

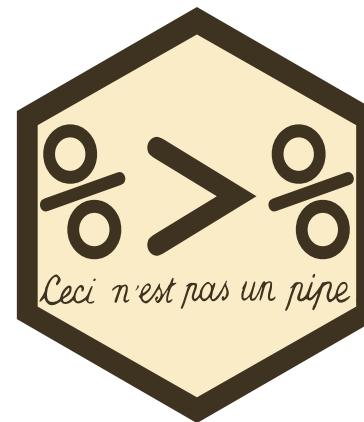
```
summarise(polls_grade, mean_vote_clinton = mean(r
```

```
##   mean_vote_clinton  
## 1                41.99086
```

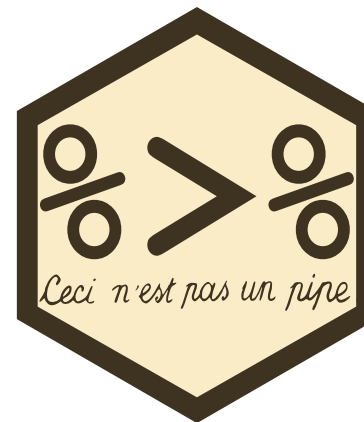


Chaining Commands Together: The Pipe

- The `magrittr` package gives us the *pipe* `%>%`.
- `x %>% f(y)` becomes `f(x,y)`.
- With the *pipe* you construct data *pipelines*.



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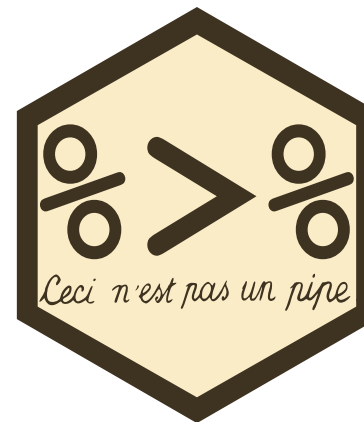
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polls_us_election_2016 %>%  
  group_by(grade) %>%  
  summarise(  
    mean_vote_clinton = mean(rawpoll_clinton)  
  )
```

which is equivalent to, but nicer than:

```
summarise(  
  group_by(polls_us_election_2016, grade),  
  mean_vote_clinton = mean(rawpoll_clinton))
```



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```
summarise(  
  group_by(polls_us_election_2016, grade),  
  mean_vote_clinton = mean(rawpoll_clinton))
```

Works for all `dplyr` verbs:

```
polls_us_election_2016 %>%  
  mutate(trump_clinton_diff = rawpoll_trump-rawpoll_c.  
  filter(trump_clinton_diff>5 &  
    state == "Iowa" &  
    is.na(rawpoll_johnson)) %>%  
  select(pollster)
```

```
## # A tibble: 3 x 1  
##   pollster  
##   <fct>  
## 1 Ipsos  
## 2 Ipsos  
## 3 Ipsos
```



SEE YOU IN TWO WEEKS!

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