SciencesPo
DEPARTMENT OF ECONOMICS

ScPoEconometrics

Tidying, Visualising and Summarising Data

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SciencesPo Paris
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Quick "Quiz" on Last Week's Material

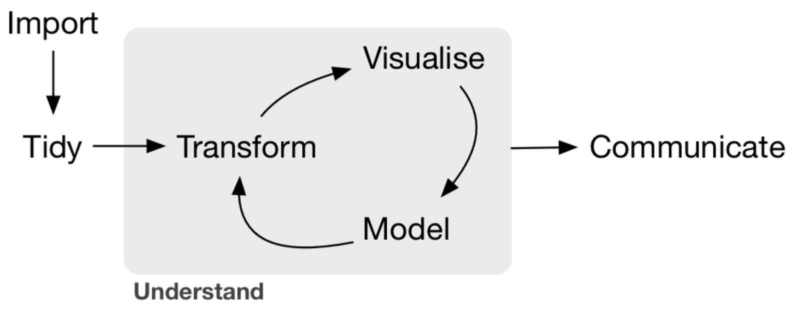
1. From your ***computer*** 👉 connect to ***www.wooclap.com/SCPOINTRO***

   OR

2. From your ***phone*** 👉 flash QR code below

Working With Data

- Econometrics is about `data`.



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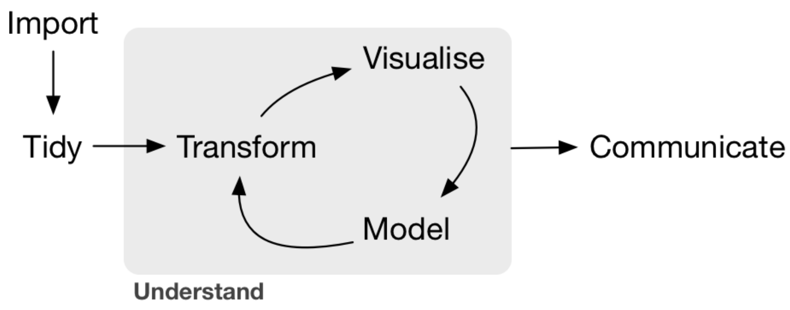

- According a to 2014 NYTimes article, "data scientists [...] spend from ***50 percent to 80 percent of their time*** mired in this more mundane labor of collecting and preparing unruly digital data, before it can be explored for useful nuggets."

- In the next two lectures you will learn the basics of ***tidying***, ***visualising*** and ***summarising*** data

Tidying Data

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

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- All *verbs* work as follows:

$$\text{verb}(\underbrace{\text{data.frame}}_{\text{1st argument}}, \underbrace{\text{what to do}}_{\text{2nd argument}})$$

- Alternatively you can (should) use the `pipe` operator `%>%`:

$$\underbrace{\text{data.frame}}_{\text{1st argument}} \quad \underbrace{\%{>}\%}_{\text{"pipe" operator}} \quad \text{verb}(\underbrace{\text{what to do}}_{\text{2nd argument}})$$

Main `dplyr` Verbs

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5. `summarise()`: Collapse data to a single summary
6. `group_by()`: All the above can be used in conjunction with `group_by()` to use function on groups rather than entire data

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

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

```
library(dslabs)
library(tidyverse)
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]) # 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 Research/Shaw & Company Resea… A   1295
```

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

What variables does this dataset contain?

`dplyr` Verbs

Filter observations

```
filter()
```

Example: Which A graded poll with at least 2,000 people had Trump win at least 45% of the vote?

dplyr Verbs

Filter observations

```
filter()
```

Example: Which A graded poll with at least 2,000 people had Trump win at least 45% of the vote?

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

```
## # A tibble: 1 x 15
##   state startdate  enddate    pollster grade samplesize population rawpoll_clinton rawp
##   <fct> <date>     <date>     <fct>    <fct>      <int> <chr>                <dbl>
## 1 Indi… 2016-04-26 2016-04-28 Marist … A           2149 rv                      41
## # … with 6 more variables: rawpoll_johnson <dbl>, rawpoll_mcmullin <dbl>, adjpoll_clin
## #   adjpoll_trump <dbl>, adjpoll_johnson <dbl>, adjpoll_mcmullin <dbl>
```

`dplyr` Verbs

Filter observations

```
filter()
```

Standard suite of comparison operators:

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

Logical operators:

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

`dplyr` Verbs

Filter observations

```
filter()
```

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

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

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

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

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

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

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

`dplyr` Verbs

Filter

Create new variable(s)

```
mutate()
```

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?

`dplyr` Verbs

Filter

Create new variable(s)

```
mutate()
```

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?

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

```
##  [1] "state"              "startdate"          "enddate"            "pollster"
##  [5] "grade"              "samplesize"         "population"         "rawpoll_clinton"
##  [9] "rawpoll_trump"      "rawpoll_johnson"    "rawpoll_mcmullin"   "adjpoll_clinton"
## [13] "adjpoll_trump"      "adjpoll_johnson"    "adjpoll_mcmullin"   "trump_clinton_tot
## [17] "trump_raw_adj_diff"
```

`dplyr` Verbs

Filter

Mutate

Keep some variable(s)

```
select()
```

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

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

```
## [1] "state"           "startdate"       "enddate"         "pollster"        "rawpoll_c
## [6] "rawpoll_trump"
```

`dplyr` Verbs

Filter

Mutate

Select

Compute statistic

```
summarise()
```

Example: What is the maximum vote share for Trump?

```
polls_us_election_2016 %>%
  summarise(max_trump = max(rawpoll_trump))
```

```
## # A tibble: 1 x 1
##   max_trump
##       <dbl>
## 1        68
```

`dplyr` Verbs

Filter

Mutate

Select

Summarise

Apply function by group

```
group_by()
```

Example: What is the average vote share for Clinton by poll grade?

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

```
## # A tibble: 11 x 2
##    grade mean_vote_clinton
##    <fct>             <dbl>
##  1 D                  46.7
##  2 C-                 43.2
##  3 C                  41.8
##  4 C+                 44.2
##  5 B-                 43.9
##  6 B                  37.3
##  7 B+                 44.1
##  8 A-                 43.0
##  9 A                  45.3
## 10 A+                 45.8
## 11 <NA>               43.2
```

Chaining 🔗 Commands Together

Works for all `dplyr` verbs:

```
polls_us_election_2016 %>%
  mutate(trump_clinton_diff = rawpoll_trump-rawpoll_clinton) %>%
  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
```

Chaining 🔗 Commands Together

Works for all `dplyr` verbs:

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polls_us_election_2016 %>%
  mutate(trump_clinton_diff = rawpoll_trump-rawpoll_clinton) %>%
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```

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

But also with other `R` commands:

```
polls_us_election_2016$samplesize %>% mean(na.rm = T)
```

```
## [1] 1148.216
```

Chaining 🔗 Commands Together

Works for all `dplyr` verbs:

```
polls_us_election_2016 %>%
  mutate(trump_clinton_diff = rawpoll_trump-rawpoll_clinton) %>%
  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
```

But also with other `R` commands:

```
polls_us_election_2016$samplesize %>% mean(na.rm = T)
```

```
## [1] 1148.216
```

```
polls_us_election_2016 %>% count()
```

```
## # A tibble: 1 x 1
##       n
##   <int>
## 1  4208
```

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
```

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

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

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

Missing Values: `NA`

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NA > 5
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```

```r
NA + 10
```

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

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

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

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

- What is confusing is that

```r
NA == NA
```

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

- It's easy to illustrate like that:

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

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

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

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

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

Task 1

10:00

Load the data as explained on slide 8.

1. How many polls have a missing `grade`?

2. Which polls were (i) polled by American Strategies, GfK Group or Merrill Poll, (ii) had a sample size greater than 1,000, *and* (iii) started on October 20th, 2016?

3. 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?

4. 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?

5. Which state had the highest average Trump vote share for polls which had at least a sample size of 2,000? (*Hint: you'll have to use* `filter`, `group_by`, `summarise` *and* `arrange`. *To obtain ranking in descending order check* `arrange`*'s help page.*)

Visualising Data

Base `R` and `ggplot2`

- Base `R` plotting is fairly good.
- There is an extremely powerful alternative: `ggplot2` (part of the `tidyverse` suite) $\rightarrow$ what we'll be using
- Let's go back to the `gapminder` dataset to run the examples.

The `gapminder` dataset: Overview

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

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

The `gapminder` dataset: Overview

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

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

- Here are the first 3 rows and last 2 rows.

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

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

```r
tail(gapminder, n = 2)
```

```
##        country year infant_mortality life_expectancy fertility population gdp continent         region
## 10544   Zambia 2016               NA           57.10        NA         NA  NA    Africa Eastern Africa
## 10545 Zimbabwe 2016               NA           61.69        NA         NA  NA    Africa Eastern Africa
```

Task 2

05:00

1. What variables does this dataset contain?

2. How are the data stored?

3. Create a new variable called `gdppercap` corresponding to `gdp` divided by `population`.

4. Compute the average population per continent per year, `mean_pop`, removing missing values and assign the output to a new object `gapminder_new`.

gg is for Grammar of Graphics[1]

[1]: The following slides are taken from Garrick Aden-Buie's wonderful Gentle Guide to the Grammar of Graphics with `ggplot2`

gg is for Grammar of Graphics

Data

```
data %>%
  ggplot()
```

or

```
ggplot(data)
```

gg is for Grammar of Graphics

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```
ggplot(data)
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Tidy Data

1. Each variable forms a ***column***
2. Each observation forms a ***row***
3. Each observational unit forms a table

gg is for Grammar of Graphics

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```
ggplot(data)
```

Tidy Data

1. Each variable forms a ***column***
2. Each observation forms a ***row***
3. Each observational unit forms a table

Start by asking

1. What information do I want to use in my visualization?
2. Is that data contained in ***one column/row*** for a given data point?

gg is for Grammar of Graphics

Data

Aesthetics

```
+ aes()
```

Map data to visual elements or parameters

- year
- population
- country

gg is for Grammar of Graphics

Data

Aesthetics

```
+ aes()
```

Map data to visual elements or parameters

- year → **x**
- population → **y**
- country → *shape*, *color*, etc.

gg is for Grammar of Graphics

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```
+ aes()
```

Map data to visual elements or parameters

```
aes(
  x = year,
  y = population,
  color = country
)
```

gg is for Grammar of Graphics

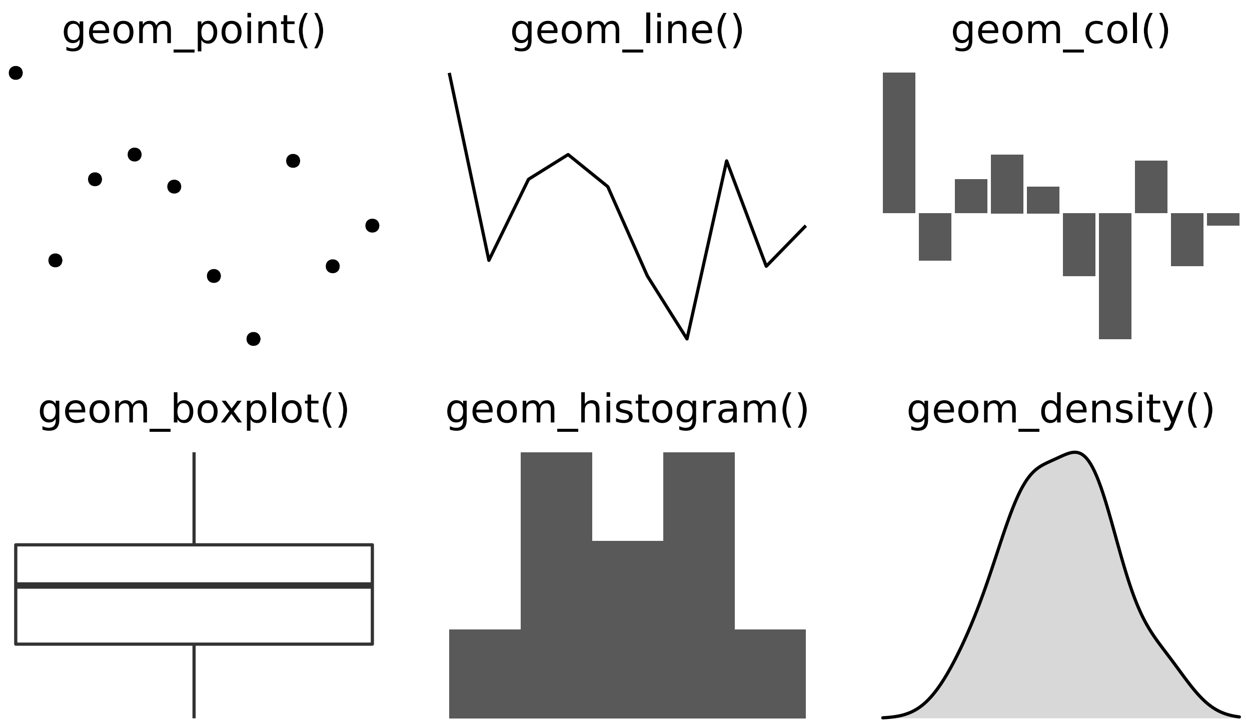
Data

Aesthetics

Geoms

```
+ geom_*()
```

Geometric objects displayed on the plot



gg is for Grammar of Graphics

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Aesthetics

Geoms

```
+ geom_*()
```

Here are the some of the most widely used geoms

Type	Function
Point	`geom_point()`
Line	`geom_line()`
Bar	`geom_bar()`, `geom_col()`
Histogram	`geom_histogram()`
Regression	`geom_smooth()`
Boxplot	`geom_boxplot()`
Text	`geom_text()`
Vert./Horiz. Line	`geom_{vh}line()`
Count	`geom_count()`
Density	`geom_density()`

https://eric.netlify.com/2017/08/10/most-popular-ggplot2-geoms/

gg is for Grammar of Graphics

Data

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Geoms

```
+ geom_*()
```

Just start typing `geom_` in `RStudio` to see all the options

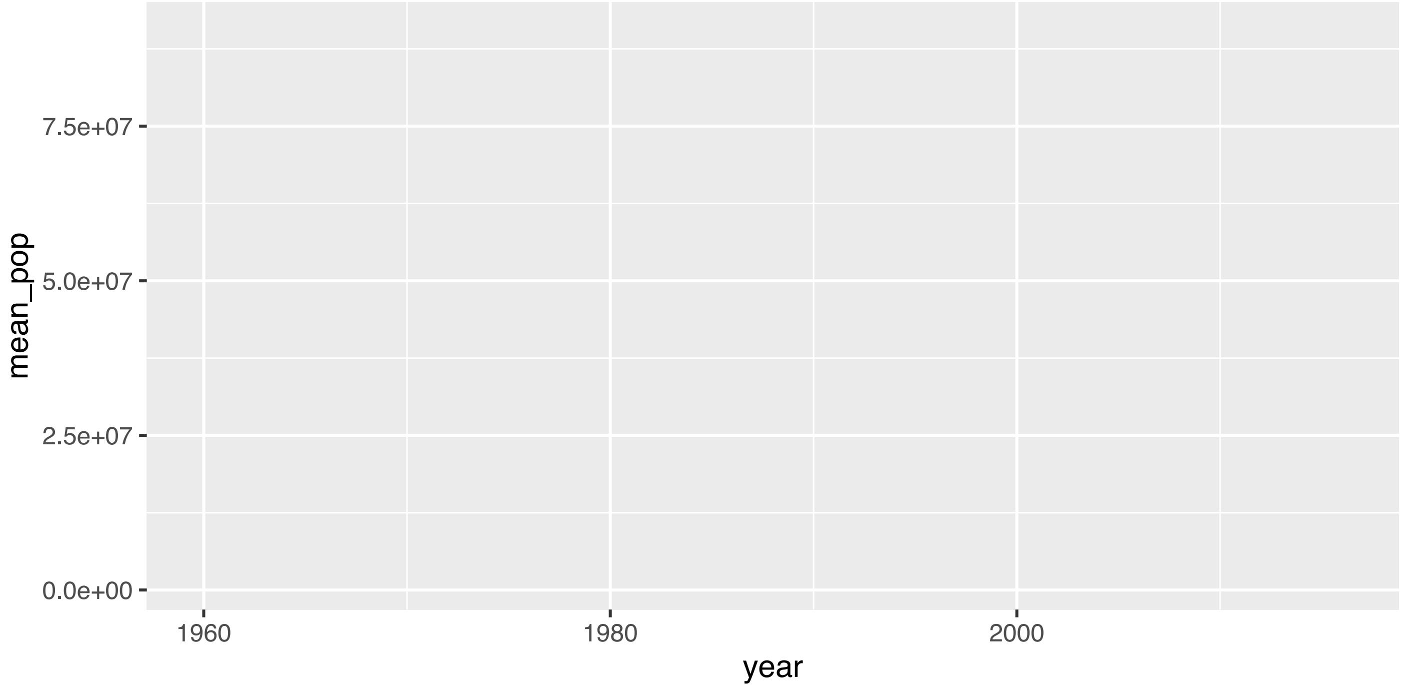
```
ggplot(df_geom) +
  aes(x, y) +
  
```

(Y)Our first plot!

```
gapminder_mean %>%
  ggplot()
```

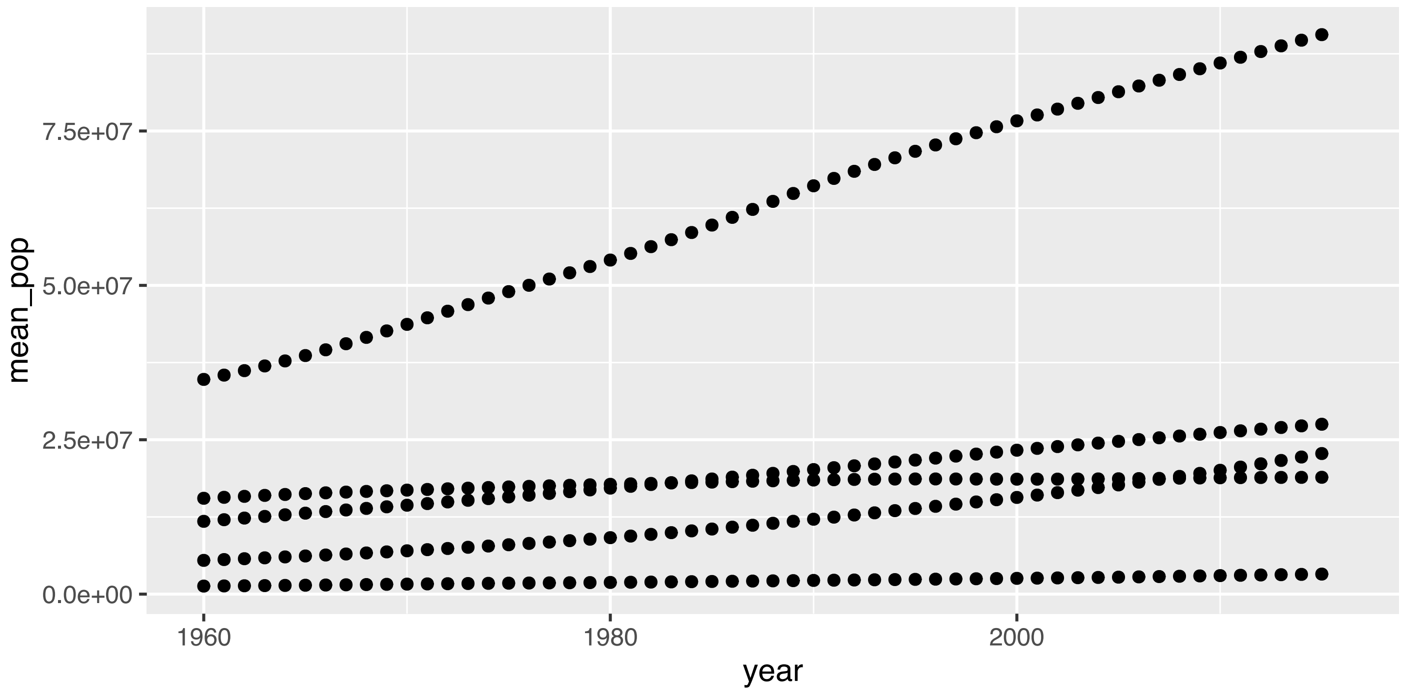
(Y)Our first plot!

```
gapminder_mean %>%
  ggplot() +
  aes(x = year,
      y = mean_pop)
```



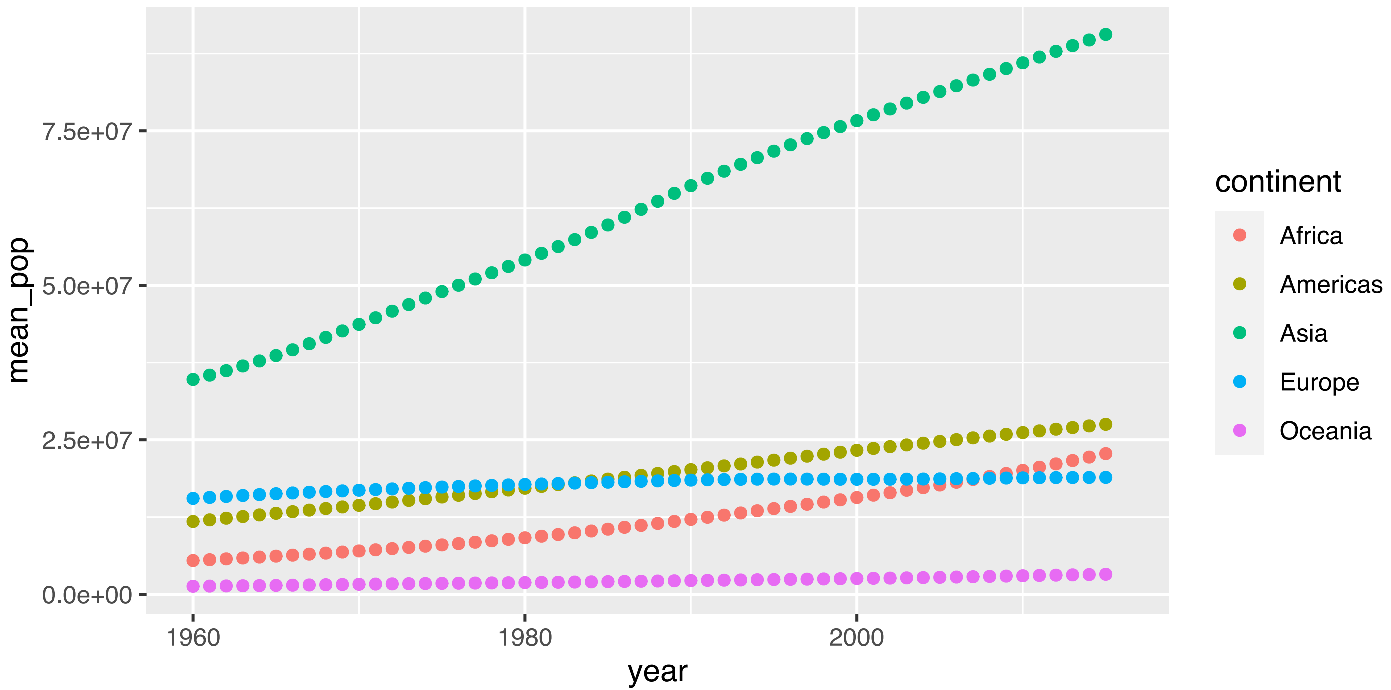
(Y)Our first plot!

```
gapminder_mean %>%
  ggplot() +
  aes(x = year,
      y = mean_pop) +
  geom_point()
```



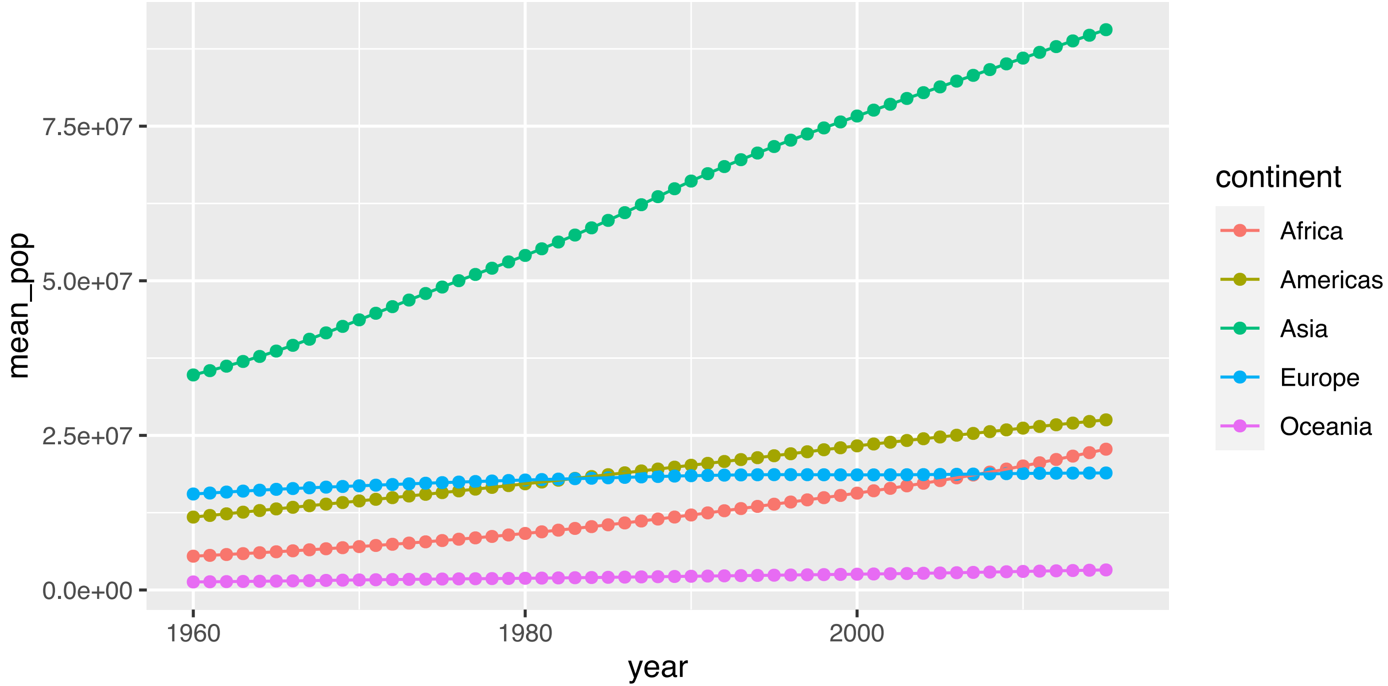
(Y)Our first plot!

```
gapminder_mean %>%
  ggplot() +
  aes(x = year,
      y = mean_pop,
      color = continent) +
  geom_point()
```



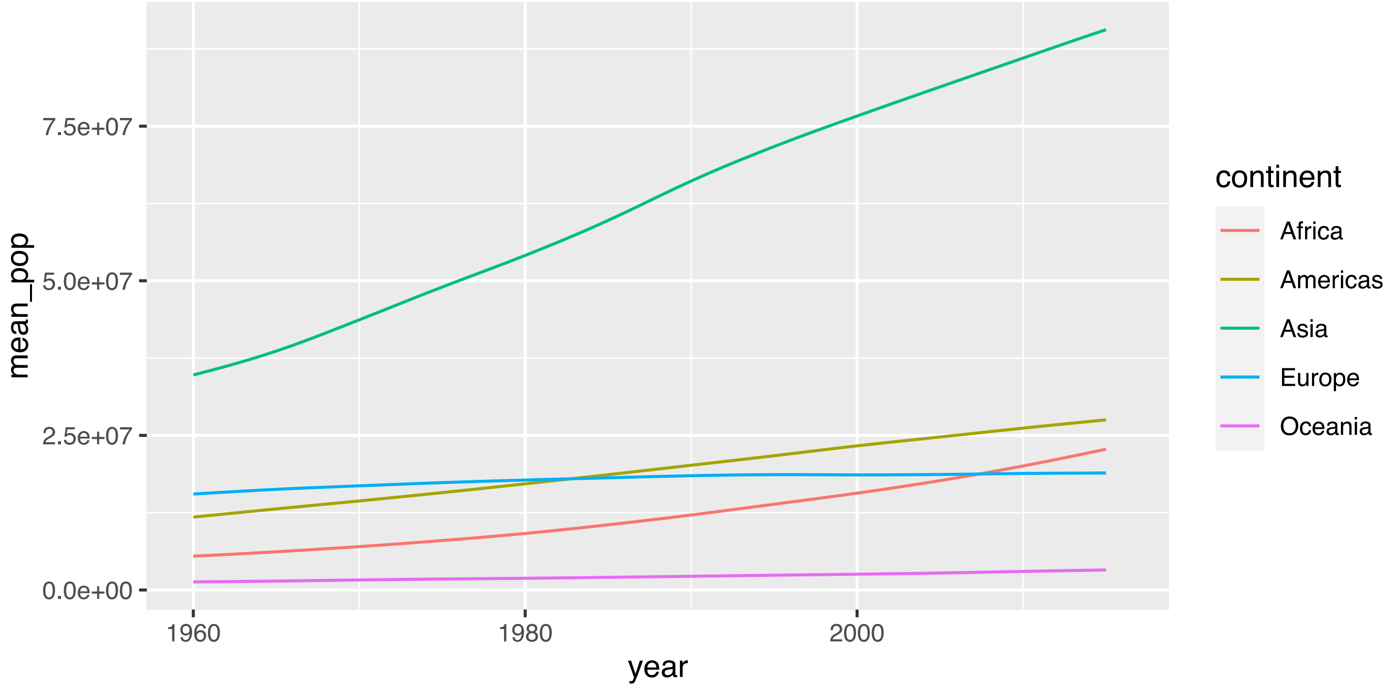
(Y)Our first plot!

```
gapminder_mean %>%
  ggplot() +
  aes(x = year,
      y = mean_pop,
      color = continent) +
  geom_point() +
  geom_line()
```



(Y)Our first plot!

```
gapminder_mean %>%
  ggplot() +
  aes(x = year,
      y = mean_pop,
      color = continent) +
  # geom_point() +
  geom_line()
```



gg is for Grammar of Graphics

Data

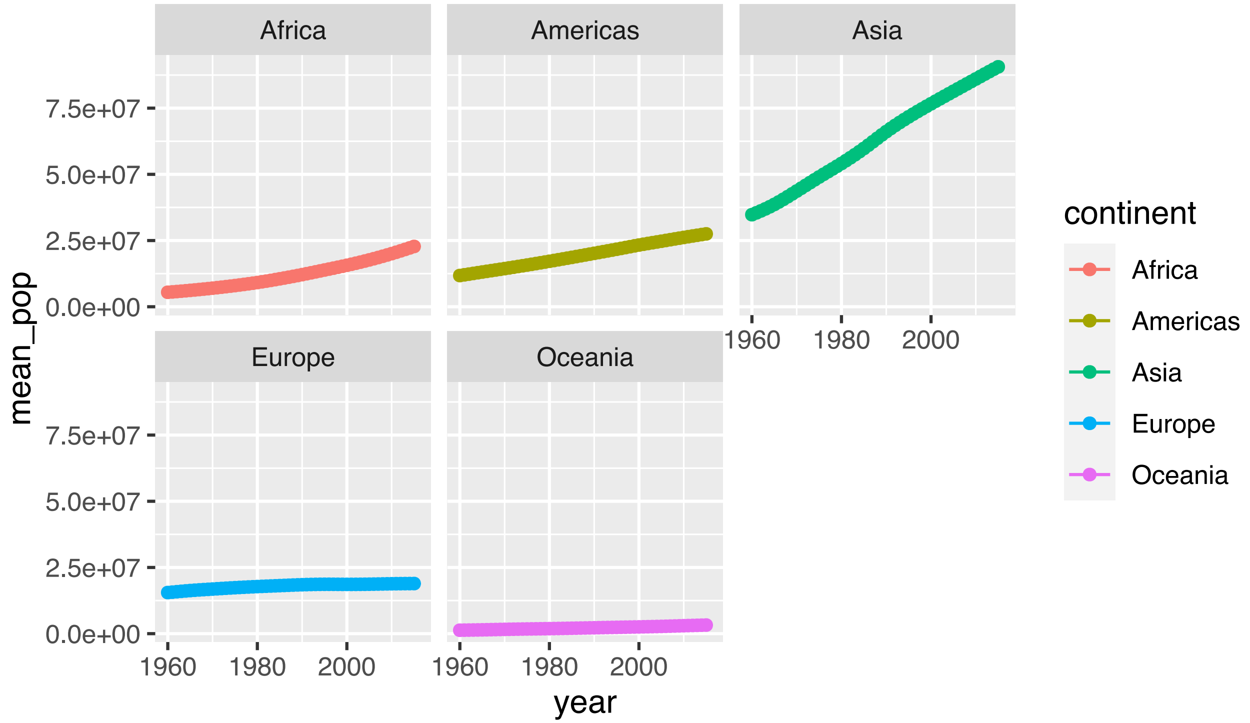
Aesthetics

Geoms

Facet

```
+ facet_wrap()
+ facet_grid()
```

```
g + facet_wrap(~ continent)
```



gg is for Grammar of Graphics

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Aesthetics

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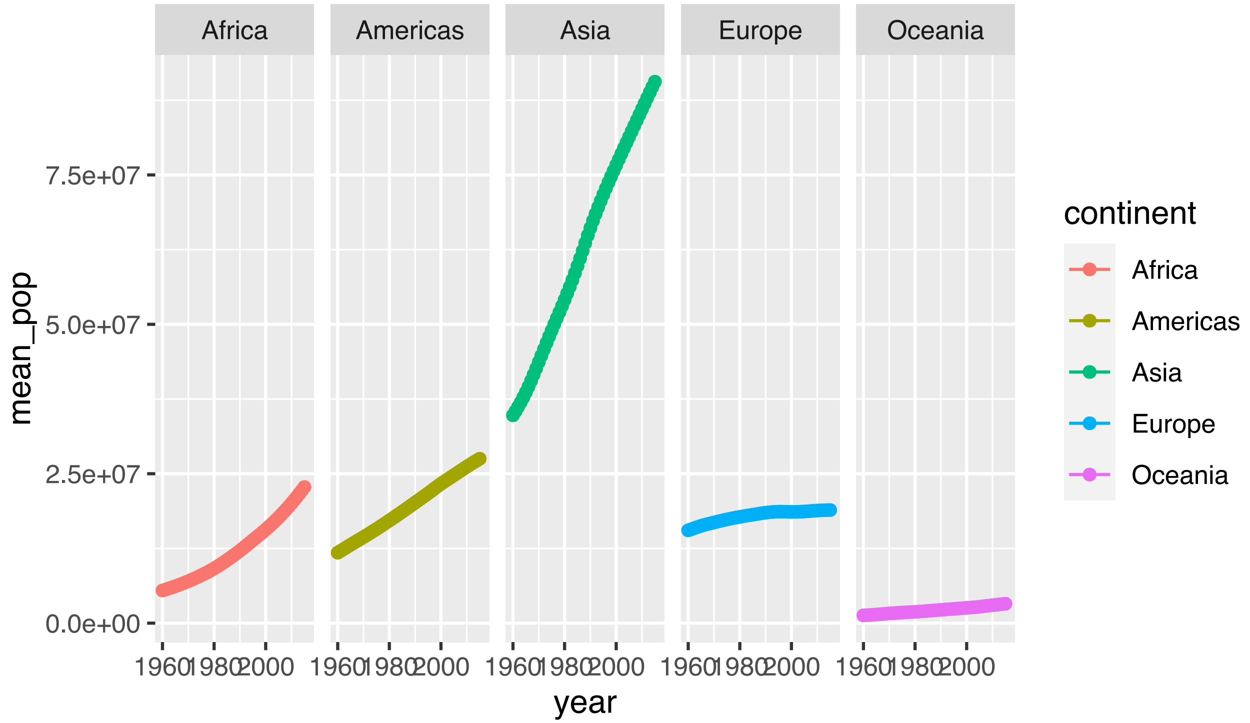
Facet

```
+ facet_wrap()
+ facet_grid()
```

```
g + facet_grid(~ continent)
```



gg is for Grammar of Graphics

Data

Aesthetics

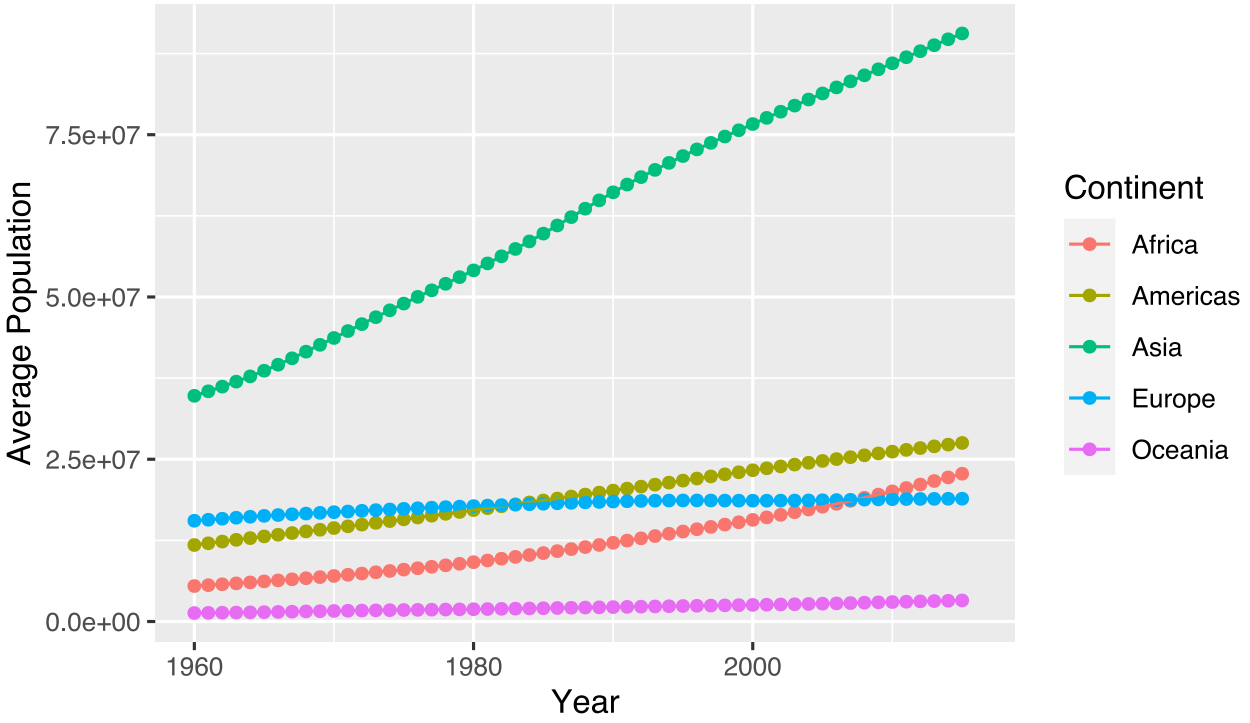
Geoms

Facet

Labels

```
+ labs()
```

```
g + labs(x = "Year", y = "Average Population", color = "Continent")
```



gg is for Grammar of Graphics

Data

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Facet

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Scales

```
+ scale_*_*()
```

`scale` + `_` + `<aes>` + `_` + `<type>` + `()`

What parameter do you want to adjust? → `<aes>`
What type is the parameter? → `<type>`

- I want to change my discrete x-axis
  `scale_x_discrete()`
- I want to change range of point sizes from continuous variable
  `scale_size_continuous()`
- I want to rescale y-axis as log
  `scale_y_log10()`
- I want to use a different color palette
  `scale_fill_discrete()`
  `scale_color_manual()`

gg is for Grammar of Graphics

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Facet

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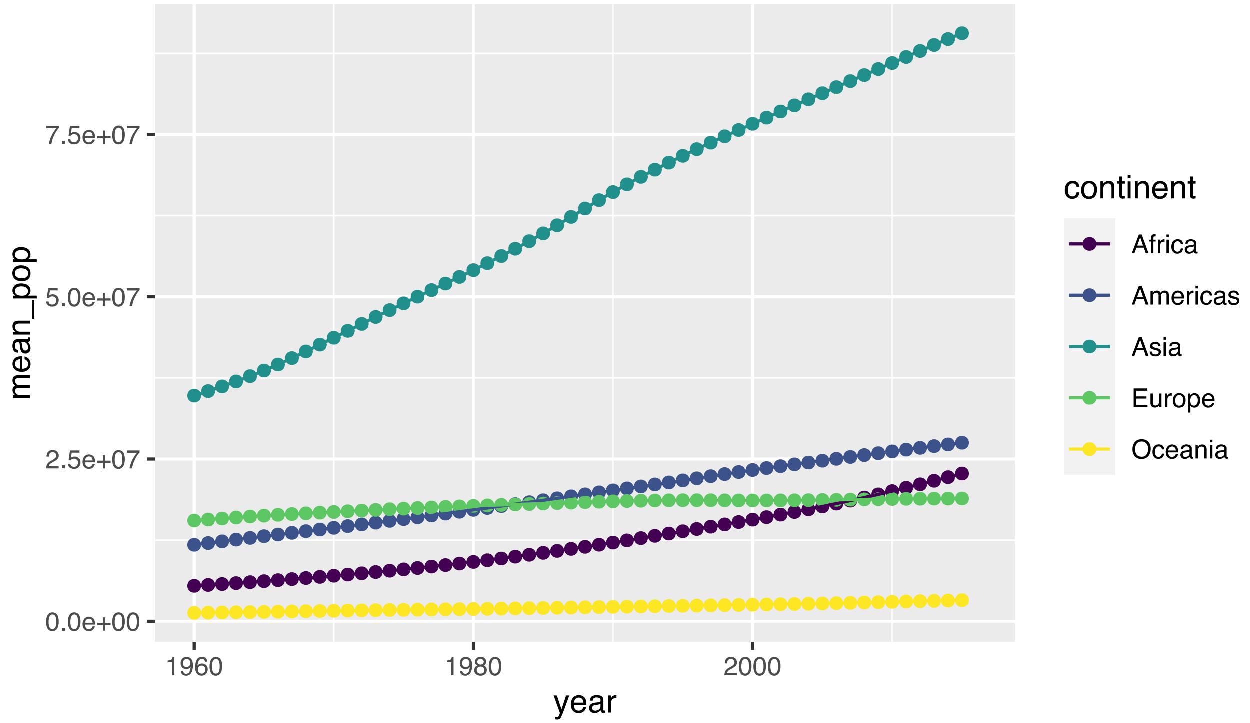
Scales

```
+ scale_*_*()
```

```
g + scale_color_viridis_d()
```



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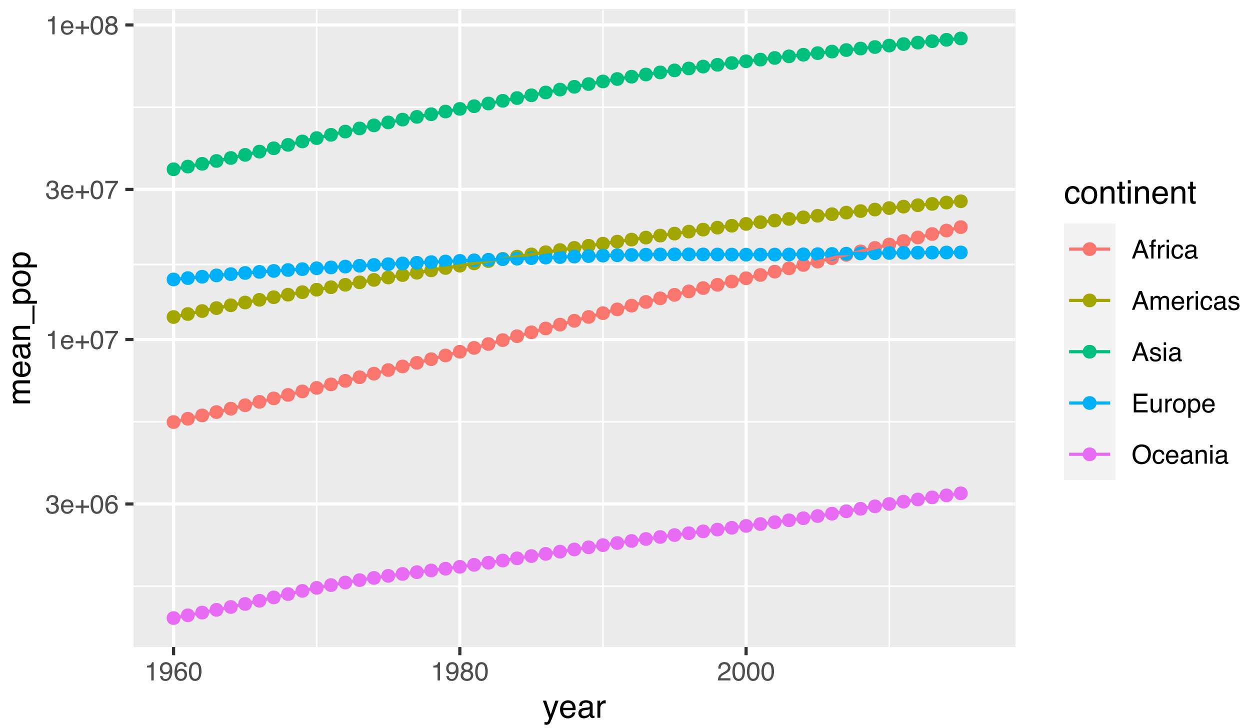
```
+ scale_*_*()
```

```
g + scale_y_log10()
```



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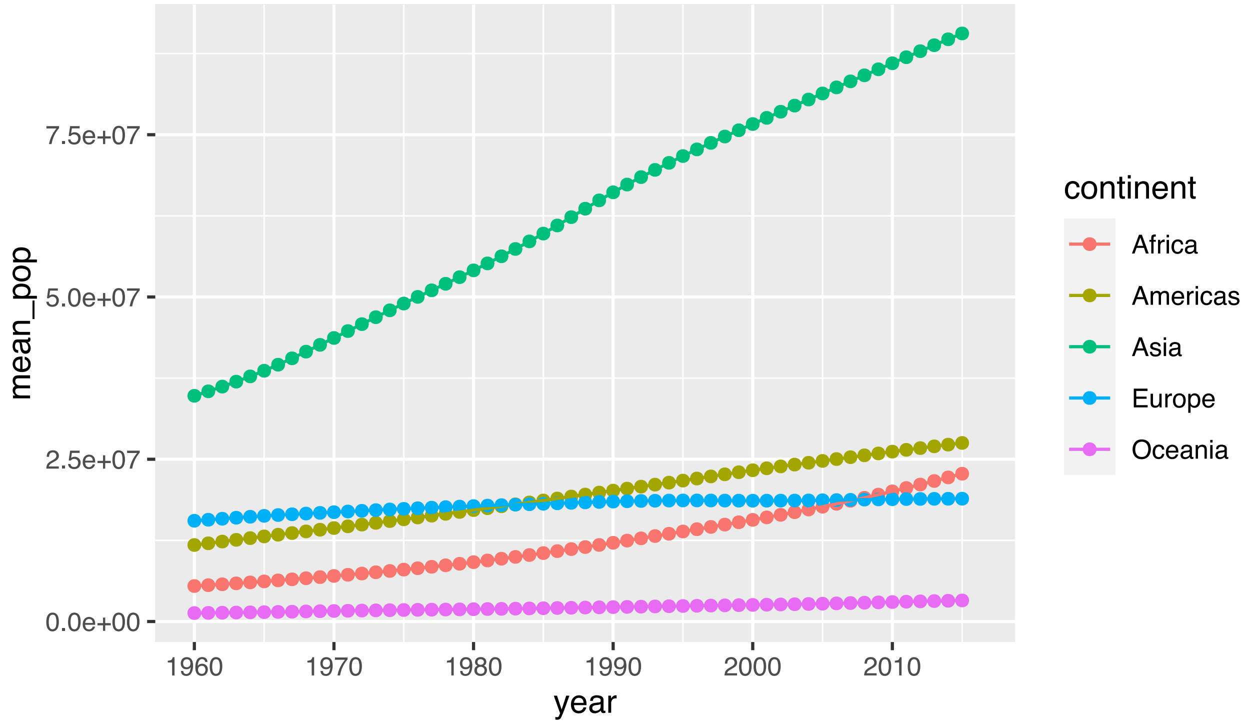
Scales

```
+ scale_*_*()
```

```
g + scale_x_continuous(breaks = seq(1950, 2020, 10))
```



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- Garrick Aden-Buie's wonderful Gentle Guide to the Grammar of Graphics with `ggplot2` from which the previous slides were taken from.

Types of Plots

Histograms: counts how many observations fall within a certain bin.

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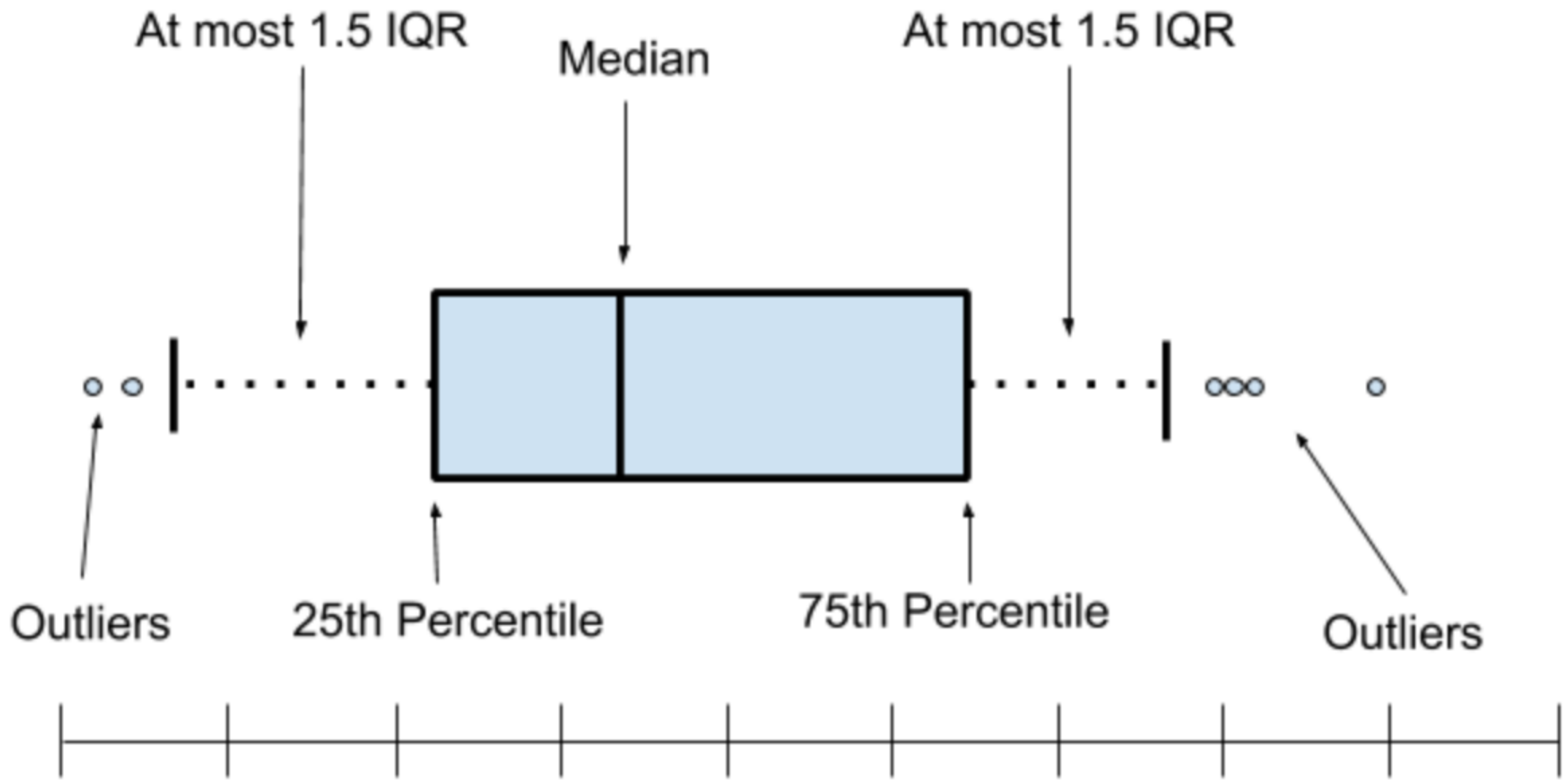

Types of Plots

Histograms: counts how many observations fall within a certain bin.

Boxplots: displays the distribution of a variable.

Scatter plots: shows the association between two variables.

Task 3

10:00

Using the `gapminder` data, create the following plots using `ggplot2`. Don't forget to label the axes.

1. A histogram of life expectancy in 2015. Within the appropriate `geom_*` set: `binwidth` to 5, `boundary` to 45, `colour` to "white" and `fill` to "#d90502".

2. Using the previous graph, facet it by continent such that each continent's plot is a new row. (*Hint: check the help for `facet_grid`*.)

3. A boxplot of average life expectancy per year by continent (removing missing values). Within the appropriate `geom_*` set: `colour` to "black" and `fill` to "#d90502". (*Hint: you need to group by both `continent` and `year`*.)

4. A scatter plot of fertility rate (y-axis) with respect to infant mortality (x-axis) in 2015. Within the appropriate `geom_*` set: `size` to 3, `alpha` to 0.5, `colour` to "#d90502".

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- In general, we can compute summary statistics and/or visualise the data with plots.
- Let's now turn to summary statistics!
- In particular, let's look at two features: *central tendency* and *spread*.

Central Tendency

`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
```

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

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

The median is robust against *outliers*.

```
median(x)
```

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

Spread

Another interesting feature is how much a variable is *spread out* about it's center (the mean in this case).

The *variance* is such a measure.

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

Consider two `normal distributions` with equal mean at `0`:

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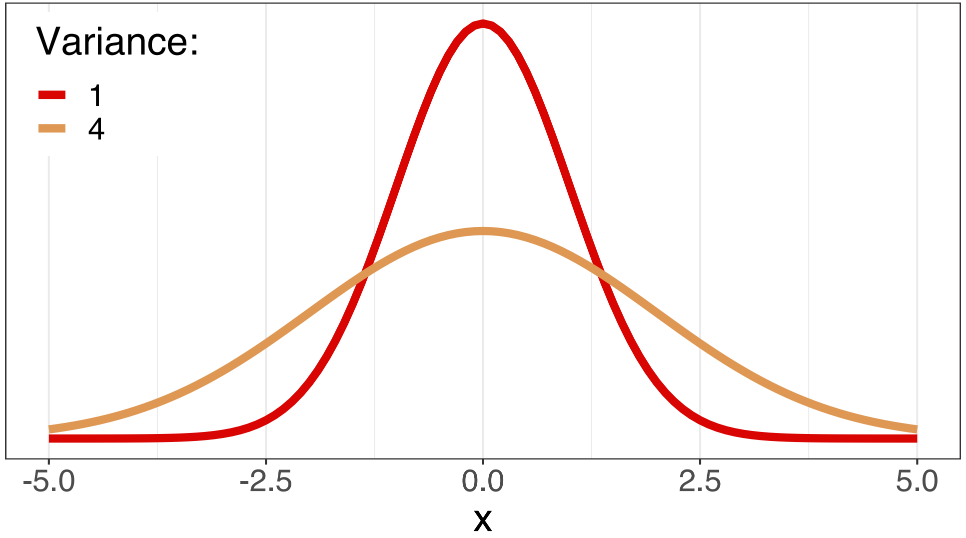

Compute with:

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

Tabulating Data

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

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

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

Tabulating Data

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```

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

The same can be achieved using the `count` function (from `dplyr`)

```
gapminder %>% count(continent)
```

```
##   continent    n
## 1    Africa 2907
## 2  Americas 2052
## 3      Asia 2679
## 4    Europe 2223
## 5   Oceania  684
```

Tabulating Data

Given two variables, `table` produces a contingency table:

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

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

Tabulating Data

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```

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

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

Tabulating Data

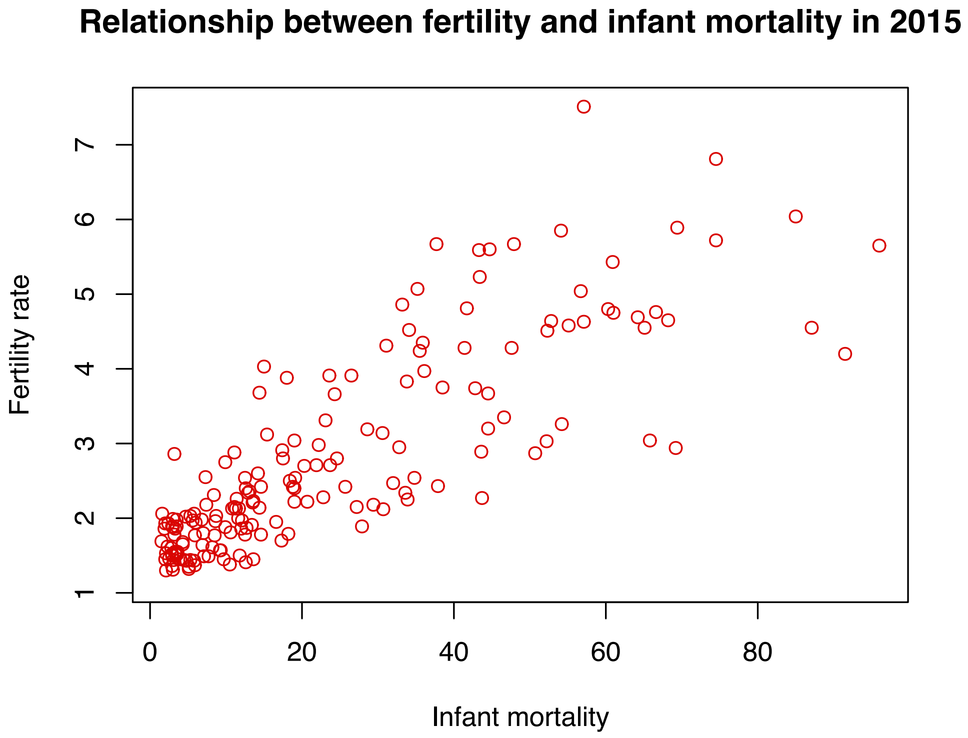
Again the `count` function can get you there as well:

```
gapminder_new %>%
  count(continent, fertility_above_2)
```

```
##    continent fertility_above_2  n
## 1     Africa             FALSE  2
## 2     Africa              TRUE 49
## 3   Americas             FALSE 15
## 4   Americas              TRUE 20
## 5   Americas                NA  1
## 6       Asia             FALSE 20
## 7       Asia              TRUE 27
## 8     Europe             FALSE 39
## 9    Oceania             FALSE  4
## 10   Oceania              TRUE  8
```

Note that `count` will display `NA`s only if there are some.

How are x and y related? Covariance and Correlation



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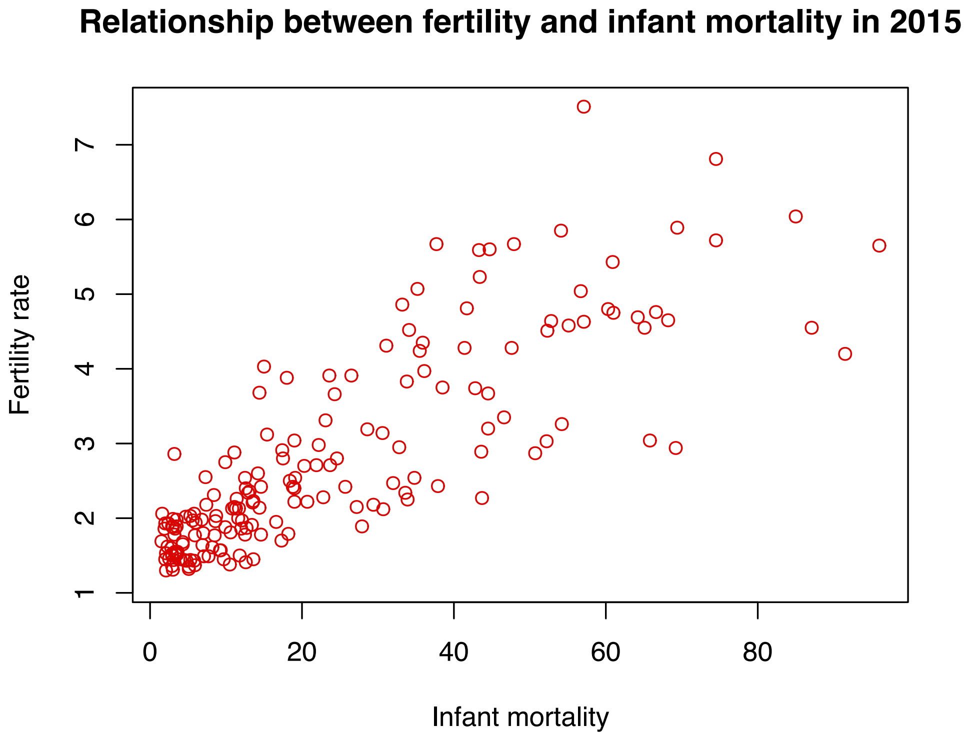

- The covariance is a measure of **joint variability** of two variables.

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

```
## [1] 24.21146
```

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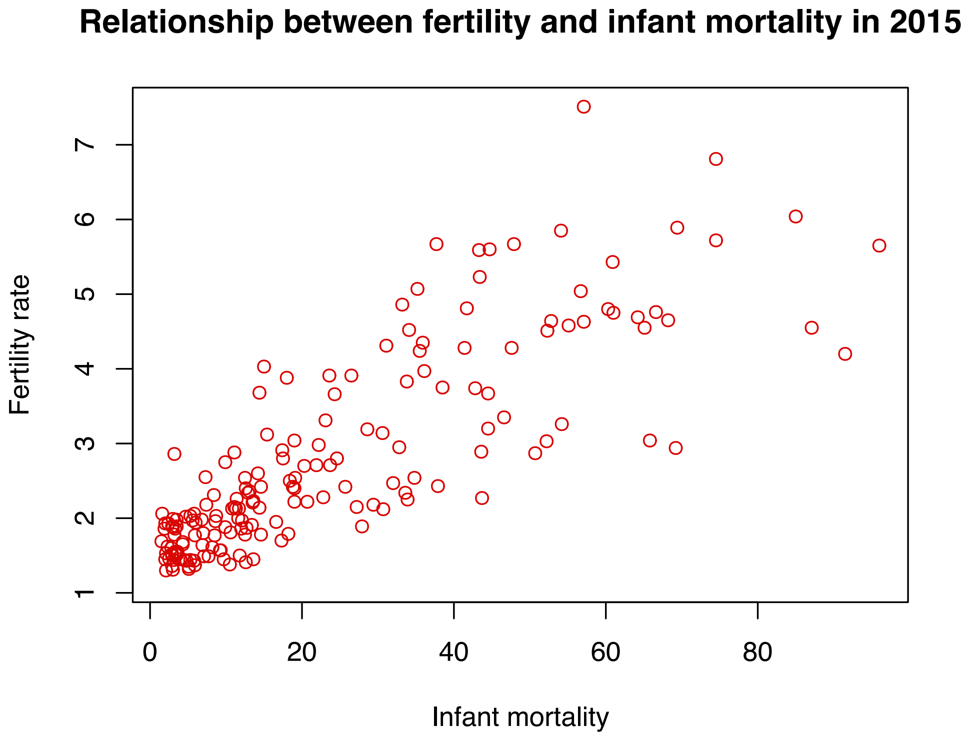

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## [1] 24.21146
```

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

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

```
## [1] 0.8286402
```

Task 4

10:00

1. Compute the mean of population in 1960 and assign to object `mean`. Read the help for `mean` to remove `NA`s.

2. Compute the median of population in 1960 and assign to object `median`. Is it greater or smaller than the average?

3. Create of density plot using `geom_density` of population in 1960. A density plot is a way of representing the distribution of a numeric variable. Add a vertical line containing the value of `mean` and another one containing the value of `median`. Use `geom_vline` to do so and use `as.numeric` around `mean` and `median`. What do you observe?

4. Compute the correlation between fertility rate and infant mortality in 2015. To drop `NA`s in either variable set the argument `use` to "pairwise.complete.obs" in your `cor()` function. Is this correlation consistent with the graph you produced in Task 3?

In your free time, you can do this tutorial:

```
library(ScPoApps)
runTutorial('chapter2')
```

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