Session #3 - Exercises

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04/03/2020

INSTRUCTIONS

There are different segment with emphasis on data manipulation and visualization, each covering questions that increase in difficulty. Fill in the answer within the code chunk. When you wish to test the code chunk, press the *green play button* on the right side of the code chunk to see your output.

Cheatsheets are provided where you can find clues for solving the questions. In more difficult cases, actual hints will be given as to which functions are required. You can access further information with *?x* where x is the function name, e.g. ?print().

Also check this page, specifically sections 8.3 and 10.2 for additional help.

We encourage to write code in the spirit of tidyverse, which improves readability. For instance, compare the two codes below that filter the mtcars dataset for automatic cars, then categorizes them per cyl capaticy, and compute the average horse power.

```
suppressPackageStartupMessages( library(dplyr) )

# base code
summarise(group_by(filter(mtcars, am == 1), cyl), hp = mean(hp))

# tidyverse code
mtcars %>%
  filter(am == 1) %>%
  group_by(cyl) %>%
  summarise(hp = mean(hp))
```

The main dataset that we will be exploring the coronavirus dataset, which comes from the like-named {coronavirus} library. To showcase that ggplot2 can also be used to visualize data on the world map. For this, let us walk through this example.

EXAMPLE: coronavirus over the world during the last 24 hours

First, we install/upload the necessary packages. The {coronavirus} package provides an up-to-date dataset of confirmed, recovered and dead cases of coronavirus.

```
devtools::install_github("RamiKrispin/coronavirus")
```

```
## Skipping install of 'coronavirus' from a github remote, the SHA1 (c7a08321) has not changed since las
##   Use `force = TRUE` to force installation
```

```
suppressPackageStartupMessages( library(coronavirus) )
suppressPackageStartupMessages( library(tidyverse) )
suppressPackageStartupMessages( library(viridis) ) # install.packages("viridis")
```

We load in the data. And make some minor adjustments, for consistency with other packages.

```
coronavirus
```

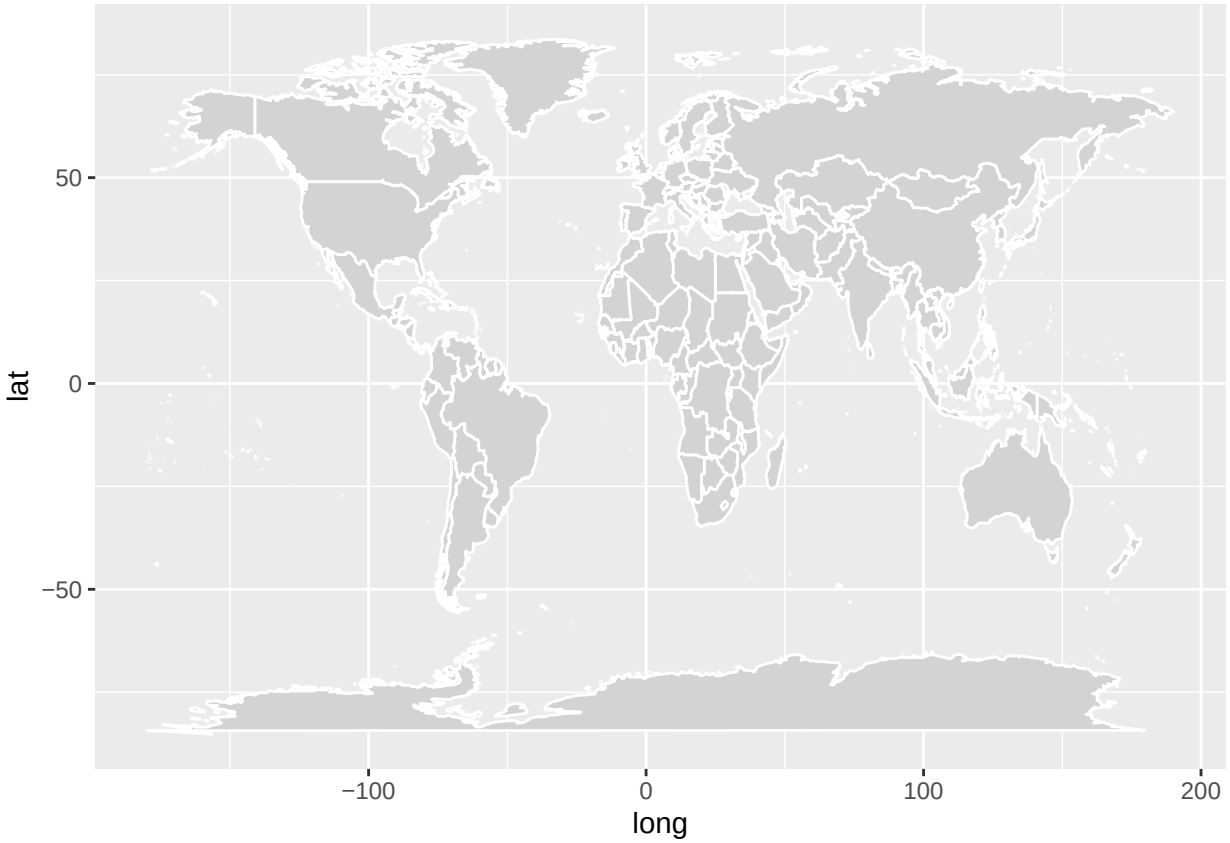
```
## # A tibble: 2,582 x 7
##    Province.State Country.Region   Lat  Long date       cases type
##    <chr>          <chr>          <dbl> <dbl> <date>     <int> <chr>
##  1 ""             Japan           36    138  2020-01-22     2 confirmed
##  2 ""             South Korea     36    128  2020-01-22     1 confirmed
##  3 ""             Thailand        15    101  2020-01-22     2 confirmed
##  4 "Anhui"        Mainland China  31.8  117. 2020-01-22     1 confirmed
##  5 "Beijing"      Mainland China  40.2  116. 2020-01-22    14 confirmed
##  6 "Chongqing"    Mainland China  30.1  108. 2020-01-22     6 confirmed
##  7 "Fujian"       Mainland China  26.1  118. 2020-01-22     1 confirmed
##  8 "Guangdong"    Mainland China  23.3  113. 2020-01-22    26 confirmed
##  9 "Guangxi"      Mainland China  23.8  109. 2020-01-22     2 confirmed
## 10 "Guizhou"      Mainland China  26.8  107. 2020-01-22     1 confirmed
## # ... with 2,572 more rows
```

```
coronavirus <- coronavirus %>%
  mutate(Country.Region = case_when(
    Country.Region == "US" ~ "USA",
    Country.Region %in% c("Mainland China","Macau","Hong Kong") ~ "China",
    Country.Region == "North Macedonia" ~ "Macedonia",
    TRUE ~ as.character(Country.Region)
  ))

max(coronavirus$date) # check whether the dataset is up to date (i.e. yesterday)
```

```
## [1] "2020-03-02"
```

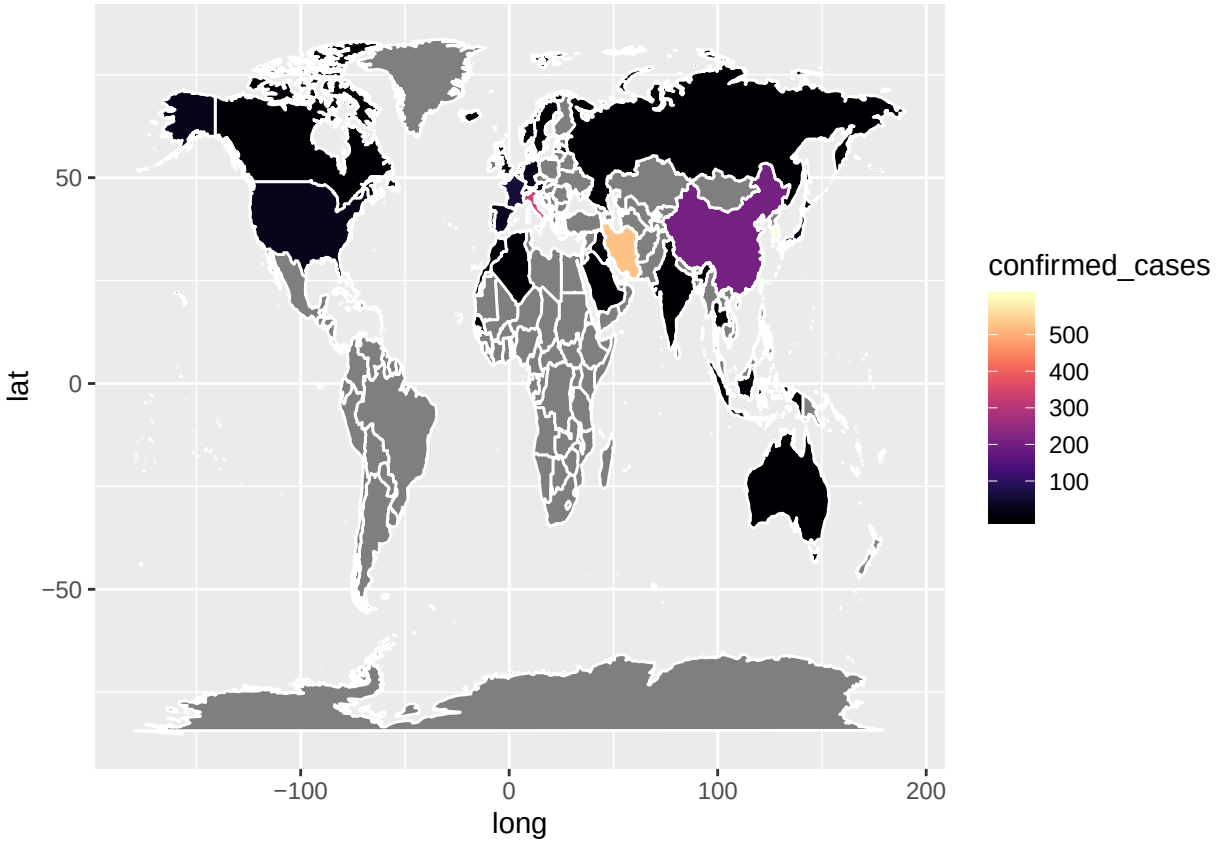
With {ggplot2}, we can construct the world map. This map is constructed through a dataset "world" that contains all the longitudes and latitudes of all the country boundaries. In the code below we construct an ordinary world map.

```
suppressPackageStartupMessages( library(maps) )
suppressPackageStartupMessages( library(ggplot2) )

world_map <- map_data("world")
ggplot(world_map, aes(x = long, y = lat, group = group)) +
  geom_polygon(fill = "lightgray", color = "white")
```



This world map can now be filled with more statistical information. Let's augment it with information on the number of confirmed cases yesterday.

```
yesterday <- coronavirus %>%
  filter(date == max(date)) %>% # get only data from yesterday
  filter(type == "confirmed") %>% # only confirmed cases
  select(Country.Region, cases) %>%
  group_by(Country.Region) %>%
  summarise(confirmed_cases = sum(cases)) %>%
  arrange(desc(confirmed_cases))

merged_map <- left_join(world_map, yesterday, by = c("region" = "Country.Region"))

ggplot(merged_map, aes(long, lat, group = group)) +
  geom_polygon(aes(fill = confirmed_cases), color = "white") +
  scale_fill_viridis(option = "magma")
```



The world map now shows the new confirmed cases from only yesterday. Fascinating, right? Now it is your turn, to explore this (and other) datasets with {dplyr} and {ggplot2}!

EXERCISES

data manipulations {dplyr}

```
suppressPackageStartupMessages( library(dplyr) )
suppressPackageStartupMessages( library(tidyr) )
suppressPackageStartupMessages( library(lubridate) )
```

In the following questions, you will perform exploratory analysis on the coronavirus. This dataset is contained in the like-named {coronavirus} library.

```
# devtools::install_github("RamiKrispin/coronavirus")
suppressPackageStartupMessages( library(coronavirus) )
```

1. Worldwide, how many confirmed cases of coronavirus have been found?

```
coronavirus %>%
    filter(type == "confirmed") %>%
    summarise(worldwide_confirmed = sum(cases))
```

```
## # A tibble: 1 x 1
##   worldwide_confirmed
```

```
##                 <int>
## 1               90313
```

2. Worldwide, how many people died from coronavirus?

```
coronavirus %>%
    filter(type == "death") %>%
    summarise(worldwide_confirmed = sum(cases))
```

```
## # A tibble: 1 x 1
##   worldwide_confirmed
##                 <int>
## 1                3085
```

3. Which are the top 5 countries with the most cases of confirmed coronavirus?

```
coronavirus %>%
    filter(type == "confirmed") %>%
    group_by(Country.Region) %>%
    summarise(confirmed = sum(cases)) %>%
    arrange(desc(confirmed)) %>%
    head(5)
```

```
## # A tibble: 5 x 2
##   Country.Region confirmed
##   <chr>              <int>
## 1 China              80136
## 2 South Korea         4335
## 3 Italy               2036
## 4 Iran                1501
## 5 Others               705
```

4. From which country is the last confirmed case?

```
coronavirus %>%
    filter(type == "confirmed") %>%
    arrange(desc(date)) %>%
    head(1)
```

```
## # A tibble: 1 x 7
##   Province.State Country.Region   Lat  Long date       cases type
##   <chr>          <chr>          <dbl> <dbl> <date>     <int> <chr>
## 1 ""             Algeria         28.0  1.66 2020-03-02     2 confirmed
```

5. From which country were the latest recovered cases?

```
coronavirus %>%
    filter(type == "recovered") %>%
    arrange(desc(date)) %>%
    head(1)
```

```
## # A tibble: 1 x 7
##   Province.State Country.Region   Lat  Long date       cases type
##   <chr>          <chr>          <dbl> <dbl> <date>     <int> <chr>
## 1 ""             Iran              32    53 2020-03-02   116 recovered
```

6. When and where were the most confirmed cases detected on a single day?

```
coronavirus %>%
    filter(type == "confirmed") %>%
```

```
    arrange(desc(cases)) %>%
    head(1)
```

```
## # A tibble: 1 x 7
##   Province.State Country.Region   Lat  Long date       cases type
##   <chr>          <chr>          <dbl> <dbl> <date>     <int> <chr>
## 1 Hubei          China           31.0  112. 2020-02-13 14840 confirmed
```

7. Were there any false positive confirmed cases?

```
coronavirus %>%
    filter(type == "confirmed") %>%
    filter(cases < 0)
```

```
## # A tibble: 8 x 7
##   Province.State             Country.Region   Lat   Long date       cases type
##   <chr>                      <chr>          <dbl>  <dbl> <date>     <int> <chr>
## 1 ""                         Japan           36    138   2020-01-23    -1 confi~
## 2 "Queensland"               Australia      -28.0  153.  2020-01-31    -1 confi~
## 3 "Queensland"               Australia      -28.0  153.  2020-02-02    -1 confi~
## 4 ""                         Japan           36    138   2020-02-07   -20 confi~
## 5 "Lackland, TX (From Diamo~ USA             29.4  -98.6 2020-02-24    -2 confi~
## 6 "Omaha, NE (From Diamond ~ USA             41.3  -96.0 2020-02-24   -11 confi~
## 7 "Travis, CA (From Diamond~ USA             38.3 -122.  2020-02-24    -5 confi~
## 8 "From Diamond Princess"    Australia       35.4  140.  2020-02-29    -8 confi~
```

8. Which are the top 3 countries that have more than 20 deaths?

```
coronavirus %>%
    filter(type == "death") %>%
    group_by(Country.Region) %>%
    summarise(death = sum(cases)) %>%
    filter(death > 20) %>%
    arrange(desc(death))
```

```
## # A tibble: 4 x 2
##   Country.Region death
##   <chr>          <int>
## 1 China           2914
## 2 Iran              66
## 3 Italy             52
## 4 South Korea       28
```

9. How many countries have a recovered-confirmed ratio of more than 0.60?

```
coronavirus %>%
    filter(type %in% c("confirmed", "recovered")) %>%
    group_by(Country.Region, type) %>%
    summarise(cases = sum(cases)) %>%

    # from {tidyr}: to have values put in separate columns
    pivot_wider(names_from = "type", values_from = "cases") %>%
    mutate(recovered = ifelse(is.na(recovered), 0, recovered)) %>%
    mutate(proportion = recovered / confirmed) %>%
    filter(proportion > 0.60) %>%
    arrange(desc(proportion))
```

```
## # A tibble: 8 x 4
```

```
## # Groups:   Country.Region [8]
##   Country.Region confirmed recovered proportion
##   <chr>              <int>     <dbl>      <dbl>
## 1 Cambodia               1         1      1
## 2 Nepal                  1         1      1
## 3 Sri Lanka              1         1      1
## 4 Vietnam               16        16      1
## 5 Singapore            108        78      0.722
## 6 Thailand              43        31      0.721
## 7 Russia                 3         2      0.667
## 8 Malaysia              29        18      0.621
```

10. What is the recovery-confirmed ratio for Italy?

```
coronavirus %>%
    filter(Country.Region == "Italy") %>%
    filter(type %in% c("confirmed", "recovered")) %>%
    group_by(type) %>%
    summarise(cases = sum(cases)) %>%

    # from {tidyr}: to have values put in separate columns
    pivot_wider(names_from = "type", values_from = "cases") %>%
    mutate(proportion = recovered / confirmed)
```

```
## # A tibble: 1 x 3
##   confirmed recovered proportion
##       <int>     <int>      <dbl>
## 1      2036       149     0.0732
```

11. How many confirmed, recovered and dead cases were there in only the month February?

```
coronavirus %>%
    filter(between(date, as.Date("2020-02-01"), as.Date("2020-02-29"))) %>%
    group_by(type) %>%
    summarise(cases_in_february = sum(cases))
```

```
## # A tibble: 3 x 2
##   type      cases_in_february
##   <chr>                 <int>
## 1 confirmed             76086
## 2 death                  2728
## 3 recovered             39560
```

```
# alternatively
coronavirus %>%
    # specific date functions are in the {lubridate} package
    filter(month(date) == 2) %>%
    group_by(type) %>%
    summarise(cases_in_february = sum(cases))
```

```
## # A tibble: 3 x 2
##   type      cases_in_february
##   <chr>                 <int>
## 1 confirmed             76086
## 2 death                  2728
## 3 recovered             39560
```

12. How many cases are still existing worldwide? (= confirmed - death - recovered)

```r
coronavirus %>%
  group_by(date, type) %>%
  summarise(cases = sum(cases)) %>%
  pivot_wider(names_from = type, values_from = cases) %>%
  mutate(exist = confirmed - death - recovered) %>%
  ungroup() %>% summarise(exist = sum(exist))
```

```
## # A tibble: 1 x 1
##   exist
##   <int>
## 1 41624
```

In the following questions, you will explore the popularity of certain babynames. This dataset can be found in the like-named {babynames} library.

```r
suppressPackageStartupMessages( library(babynames) )
```

1. What is the proportion of female babies that are called "Anna" in 1880 and 2017?

```r
babynames %>%
    filter(sex == "F" & name == "Anna") %>%
    filter(year %in% c(1880,2017))
```

```
## # A tibble: 2 x 5
##    year sex   name      n    prop
##   <dbl> <chr> <chr> <int>   <dbl>
## 1  1880 F     Anna   2604 0.0267
## 2  2017 F     Anna   4520 0.00241
```

2. From 1880-1900, which was the most popular name for boys and girls?

```r
babynames %>%
    filter(between(year, 1880, 1900)) %>%
    group_by(name, sex) %>%
    summarise(n = sum(n)) %>%
    arrange(desc(n)) %>%
    group_by(sex) %>%
    slice(1)
```

```
## # A tibble: 2 x 3
## # Groups:   sex [2]
##   name  sex        n
##   <chr> <chr>  <int>
## 1 Mary  F     239510
## 2 John  M     180444
```

3. From 1880-1900, which was the least popular name for boys and girls?

```r
babynames %>%
    filter(between(year, 1880, 1900)) %>%
    group_by(name, sex) %>%
    summarise(n = sum(n)) %>%
    arrange(n) %>%
    group_by(sex) %>%
    slice(1)
```

```
## # A tibble: 2 x 3
```

```
## # Groups:   sex [2]
##   name    sex       n
##   <chr>   <chr> <int>
## 1 Abelina F         5
## 2 Abron   M         5
```

4. From 2000-2017, which was the most popular name for boys and girls?

```
babynames %>%
    filter(between(year, 2000, 2017)) %>%
    group_by(name, sex) %>%
    summarise(n = sum(n)) %>%
    arrange(desc(n)) %>%
    group_by(sex) %>%
    slice(1)
```

```
## # A tibble: 2 x 3
## # Groups:   sex [2]
##   name  sex        n
##   <chr> <chr>  <int>
## 1 Emma  F     339802
## 2 Jacob M     413884
```

5. From 2000-2017, which was the least popular name for boys and girls?

```
babynames %>%
    filter(between(year, 2000, 2017)) %>%
    group_by(name, sex) %>%
    summarise(n = sum(n)) %>%
    arrange(n) %>%
    group_by(sex) %>%
    slice(1)
```

```
## # A tibble: 2 x 3
## # Groups:   sex [2]
##   name  sex       n
##   <chr> <chr> <int>
## 1 Aada  F         5
## 2 Aabir M         5
```

6. For girls, what were the most popular name in 1880, 1917, 1943 and 2017?

```
babynames %>%
    filter(sex == "F") %>%
    filter(year %in% c(1880,1917,1943,2017)) %>%
    group_by(year,name) %>%
    summarise(n = sum(n)) %>%
    ungroup() %>% arrange(year, desc(n)) %>%
    group_by(year) %>%
    slice(1)
```

```
## # A tibble: 4 x 3
## # Groups:   year [4]
##    year name      n
##   <dbl> <chr> <int>
## 1  1880 Mary   7065
## 2  1917 Mary  64281
## 3  1943 Mary  66169
```

```
## 4  2017 Emma  19738
```

7. How many different boy names were there between 1880-1900?

```
babynames %>%
    filter(sex == "M") %>%
    filter(between(year,1880,1900)) %>%
    pull(name) %>%
    unique() %>%
    length()
```

```
## [1] 2411
```

8. How many different boy names were there between 2000-2017? Did we diversify compared to the previous era?

```
babynames %>%
    filter(sex == "M") %>%
    filter(between(year,2000,2017)) %>%
    pull(name) %>%
    unique() %>%
    length()
```

```
## [1] 30118
```

9. What is the popularity of your own name in 2017?

```
babynames %>%
    filter(name == "Adrian" & year == 2017)
```

```
## # A tibble: 2 x 5
##    year sex   name        n      prop
##   <dbl> <chr> <chr>   <int>     <dbl>
## 1  2017 F     Adrian    114 0.0000608
## 2  2017 M     Adrian   6203 0.00316
```

In the following questions, you will perform exploratory analysis on the flight schedule of airplanes arriving and departing from NYC in 2013. This dataset (flights) is contained in the {nycflights13} library.

```
suppressPackageStartupMessages( library(nycflights13) )
```

1. How many flights have an arrival delay of more than 2 hours? HINT: **tally()**

```
flights %>%
  filter(arr_delay >= 120) %>%
  tally()
```

```
## # A tibble: 1 x 1
##       n
##   <int>
## 1 10200
```

2. How many flights flew to Houston (IAH or HOU)?

```
flights %>%
  filter(dest %in% c("IAH", "HOU")) %>%
  tally()
```

```
## # A tibble: 1 x 1
```

```
##       n
##   <int>
## 1  9313
```

3. How many flights were operated by UA, AA and DL separately?

```
flights %>%
  filter(carrier %in% c("UA","AA","DL")) %>%
  group_by(carrier) %>%
  summarise(n = n())
```

```
## # A tibble: 3 x 2
##   carrier     n
##   <chr>   <int>
## 1 AA      32729
## 2 DL      48110
## 3 UA      58665
```

4. How many flights departed in the months July, August and September separately?

```
flights %>%
  filter(between(month,7,9)) %>%
  tally()
```

```
## # A tibble: 1 x 1
##       n
##   <int>
## 1 86326
```

5. How many flights arrived with more than 2 hours delay, but left on time?

```
flights %>%
  filter(arr_delay > 120 & dep_delay == 0) %>%
  tally()
```

```
## # A tibble: 1 x 1
##       n
##   <int>
## 1     3
```

6. How many flights departed between midnight and 6 am (inclusive)?

```
flights %>%
  filter(between(dep_time, 0, 600)) %>%
  tally()
```

```
## # A tibble: 1 x 1
##       n
##   <int>
## 1  9344
```

7. How many flights have a missing dep_time? What other variables are missing? What might these rows represent?

```
# example row
flights %>%
  filter(is.na(dep_time)) %>%
  head(1)
```

```
## # A tibble: 1 x 19
```

```
##    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
## 1  2013     1     1       NA           1630        NA       NA           1815
## # ... with 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
## #   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
## #   hour <dbl>, minute <dbl>, time_hour <dttm>
```

```
flights %>%
  filter(is.na(dep_time)) %>%
  tally()
```

```
## # A tibble: 1 x 1
##       n
##   <int>
## 1  8255
```

8. Sort flights to find the most delayed departure flights.

```
flights %>%
  arrange(desc(dep_delay))
```

```
## # A tibble: 336,776 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
##  1  2013     1     9      641            900      1301     1242           1530
##  2  2013     6    15     1432           1935      1137     1607           2120
##  3  2013     1    10     1121           1635      1126     1239           1810
##  4  2013     9    20     1139           1845      1014     1457           2210
##  5  2013     7    22      845           1600      1005     1044           1815
##  6  2013     4    10     1100           1900       960     1342           2211
##  7  2013     3    17     2321            810       911      135           1020
##  8  2013     6    27      959           1900       899     1236           2226
##  9  2013     7    22     2257            759       898      121           1026
## 10  2013    12     5      756           1700       896     1058           2020
## # ... with 336,766 more rows, and 11 more variables: arr_delay <dbl>,
## #   carrier <chr>, flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dttm>
```

9. Find the flights that flew the longest distance.

```
flights %>%
  arrange(desc(distance))
```

```
## # A tibble: 336,776 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
##  1  2013     1     1      857            900        -3     1516           1530
##  2  2013     1     2      909            900         9     1525           1530
##  3  2013     1     3      914            900        14     1504           1530
##  4  2013     1     4      900            900         0     1516           1530
##  5  2013     1     5      858            900        -2     1519           1530
##  6  2013     1     6     1019            900        79     1558           1530
##  7  2013     1     7     1042            900       102     1620           1530
##  8  2013     1     8      901            900         1     1504           1530
##  9  2013     1     9      641            900      1301     1242           1530
## 10  2013     1    10      859            900        -1     1449           1530
## # ... with 336,766 more rows, and 11 more variables: arr_delay <dbl>,
```

```
## #   carrier <chr>, flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dttm>
```

10. Select from flights the following columns: dep_time, dep_delay, arr_time, arr_delay

```
flights %>%
  select(dep_time, dep_delay, arr_time, arr_delay)
```

```
## # A tibble: 336,776 x 4
##    dep_time dep_delay arr_time arr_delay
##       <int>     <dbl>    <int>     <dbl>
##  1      517         2      830        11
##  2      533         4      850        20
##  3      542         2      923        33
##  4      544        -1     1004       -18
##  5      554        -6      812       -25
##  6      554        -4      740        12
##  7      555        -5      913        19
##  8      557        -3      709       -14
##  9      557        -3      838        -8
## 10      558        -2      753         8
## # ... with 336,766 more rows
```

```
# alternatively
flights %>%
  select(starts_with("dep"), starts_with("arr"))
```

```
## # A tibble: 336,776 x 4
##    dep_time dep_delay arr_time arr_delay
##       <int>     <dbl>    <int>     <dbl>
##  1      517         2      830        11
##  2      533         4      850        20
##  3      542         2      923        33
##  4      544        -1     1004       -18
##  5      554        -6      812       -25
##  6      554        -4      740        12
##  7      555        -5      913        19
##  8      557        -3      709       -14
##  9      557        -3      838        -8
## 10      558        -2      753         8
## # ... with 336,766 more rows
```

11. How many cancelled flights are there per month day?

```
flights %>%
  filter(is.na(dep_time)) %>%
  group_by(day) %>%
  tally()
```

```
## # A tibble: 31 x 2
##      day     n
##    <int> <int>
##  1     1   246
##  2     2   250
##  3     3   109
##  4     4    82
##  5     5   226
```

```
##  6     6   296
##  7     7   318
##  8     8   921
##  9     9   593
## 10    10   535
## # ... with 21 more rows
```

12. Which carrier has the most cancelled flights?

```
flights %>%
  filter(is.na(dep_time)) %>%
  group_by(carrier) %>%
  tally() %>%
  arrange(desc(n)) %>%
  head(5) # top 5
```

```
## # A tibble: 5 x 2
##   carrier     n
##   <chr>   <int>
## 1 EV       2817
## 2 MQ       1234
## 3 9E       1044
## 4 UA        686
## 5 US        663
```

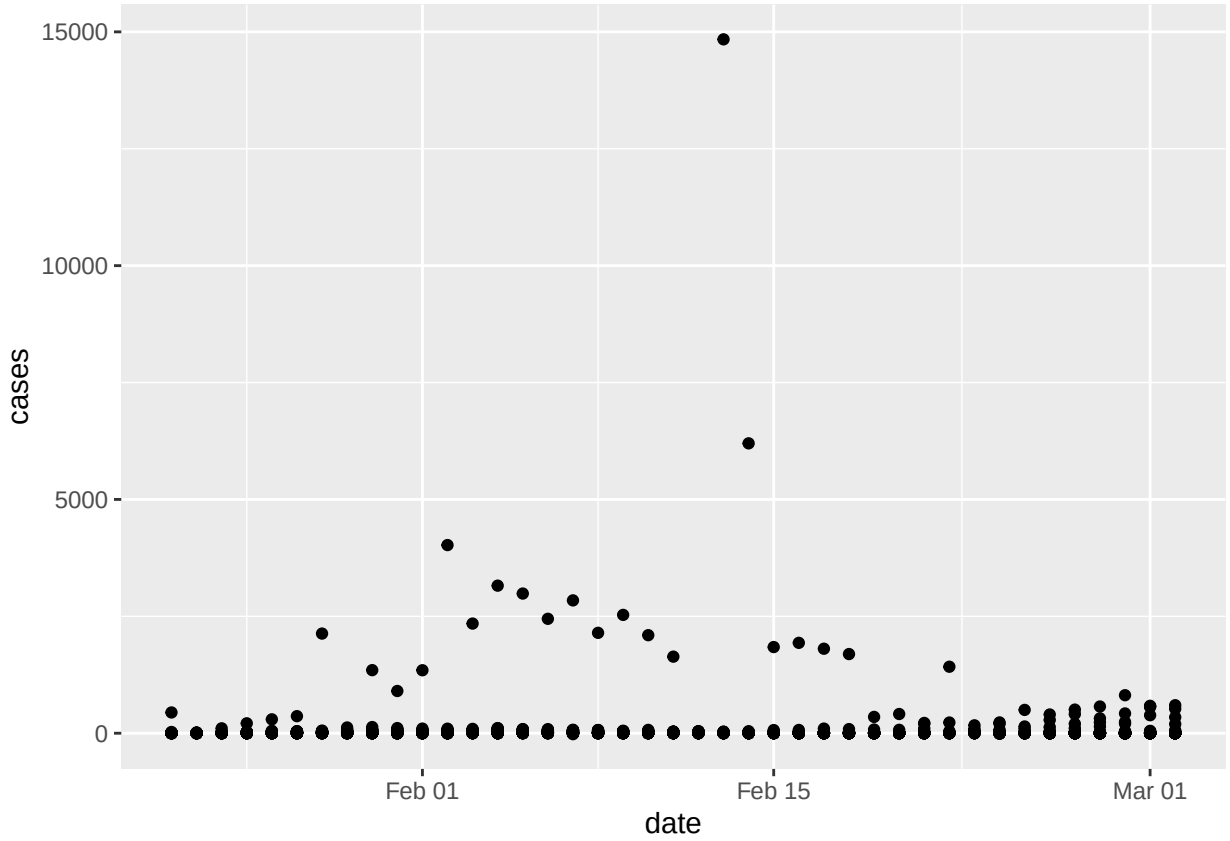
data visualizations {ggplot2}

```
suppressPackageStartupMessages( library(ggplot2) )
suppressPackageStartupMessages( library(forcats) )
```

In the following questions, you will perform exploratory analysis on the coronavirus. This dataset is contained in the like-named {coronavirus} library.

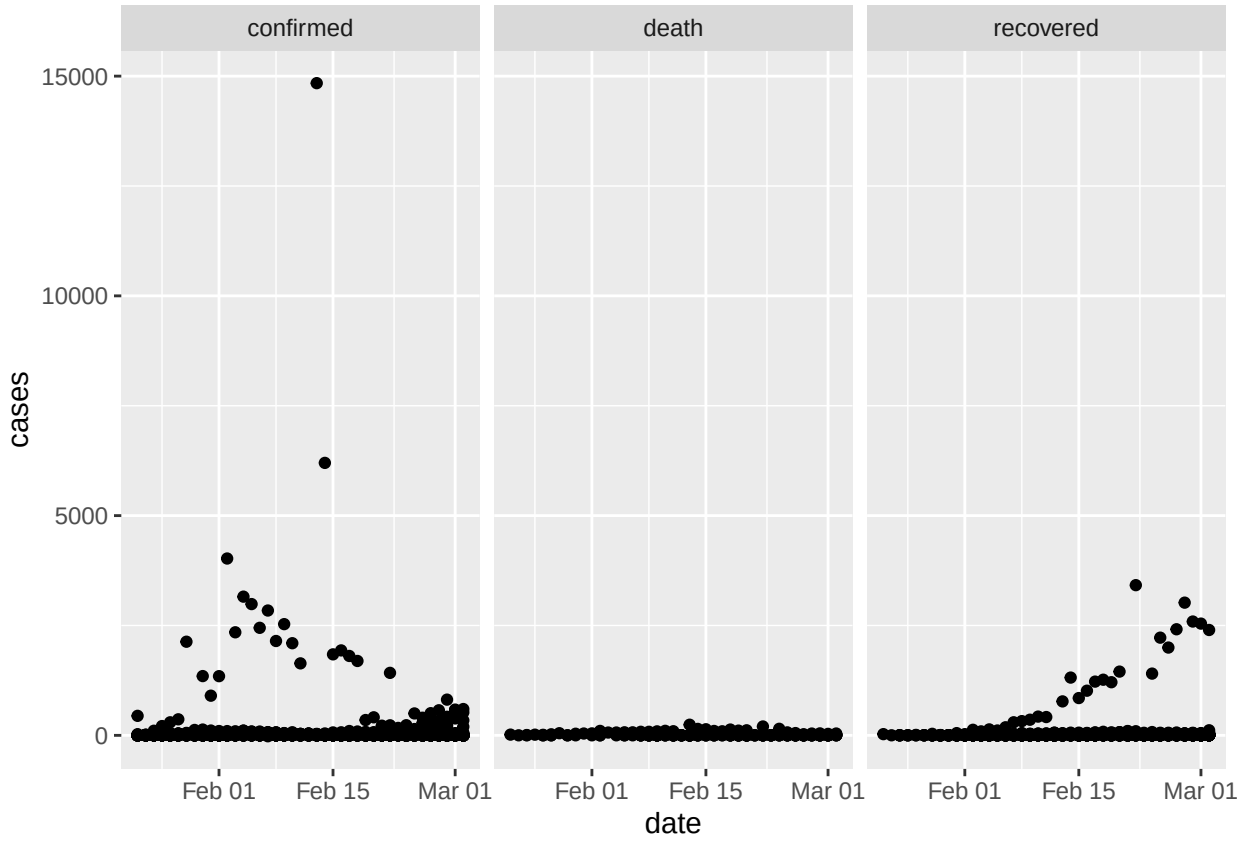
1. Plot the confirmed coronavirus cases over time.

```
coronavirus %>%
  filter(type == "confirmed") %>%
  ggplot(., aes(date, cases)) +
  geom_point()
```



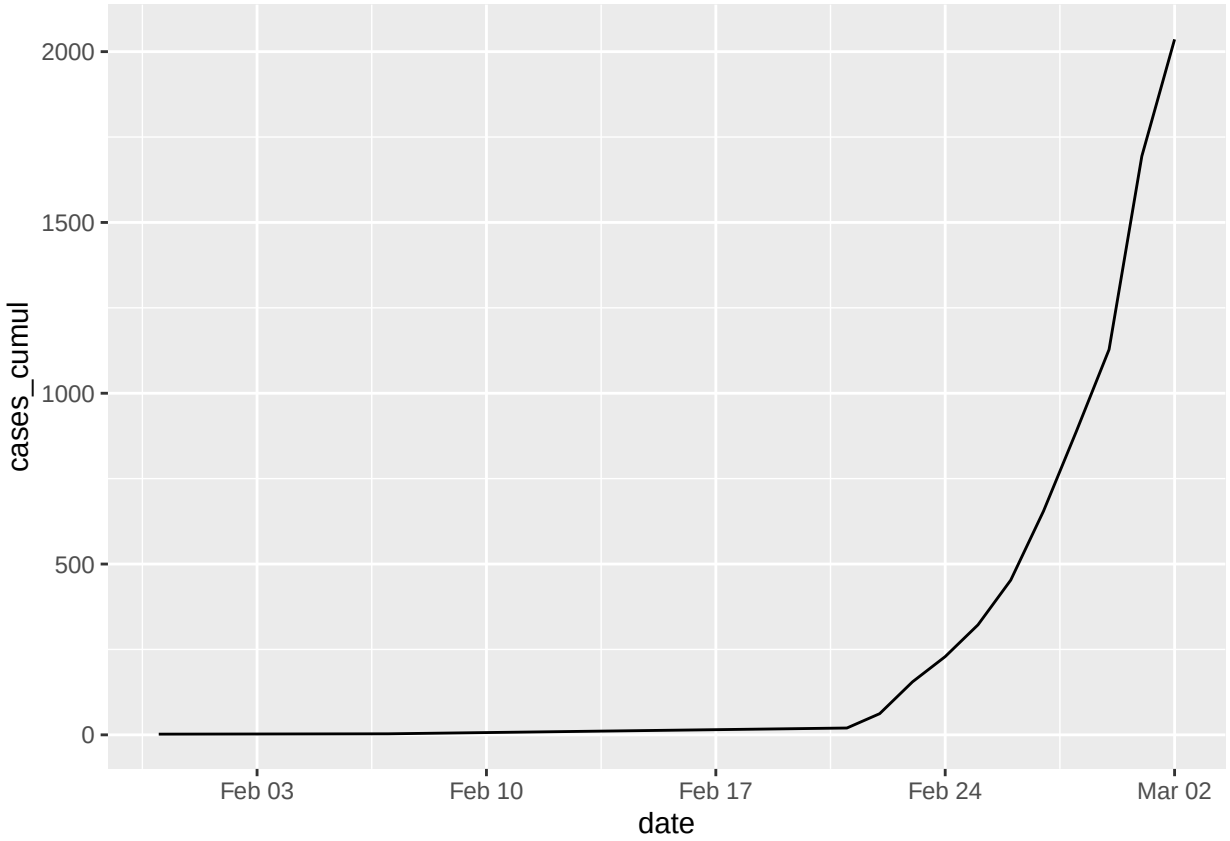
2. Plot the confirmed cases over time, as well as recovered from and death by coronavirus in side-by-side plots

```
coronavirus %>%
  ggplot(., aes(date, cases)) +
  geom_point() +
  facet_wrap(~ type)
```



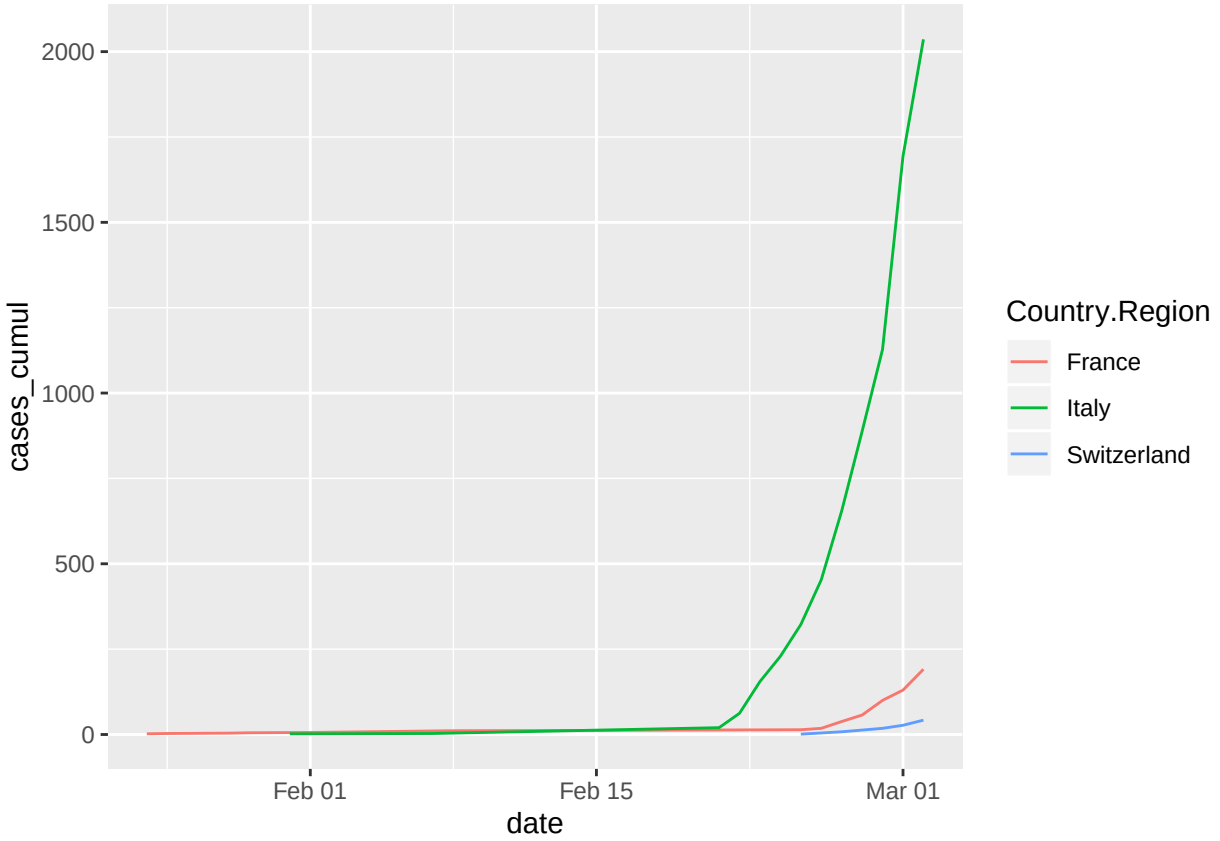
3. Plot the cumulative frequency of confirmed cases in Italy. HINT: **cumsum()**

```
coronavirus %>%
  filter(Country.Region == "Italy") %>%
  filter(type == "confirmed") %>%
  mutate(cases_cumul = cumsum(cases)) %>%
  ggplot(., aes(date, cases_cumul)) +
  geom_line()
```



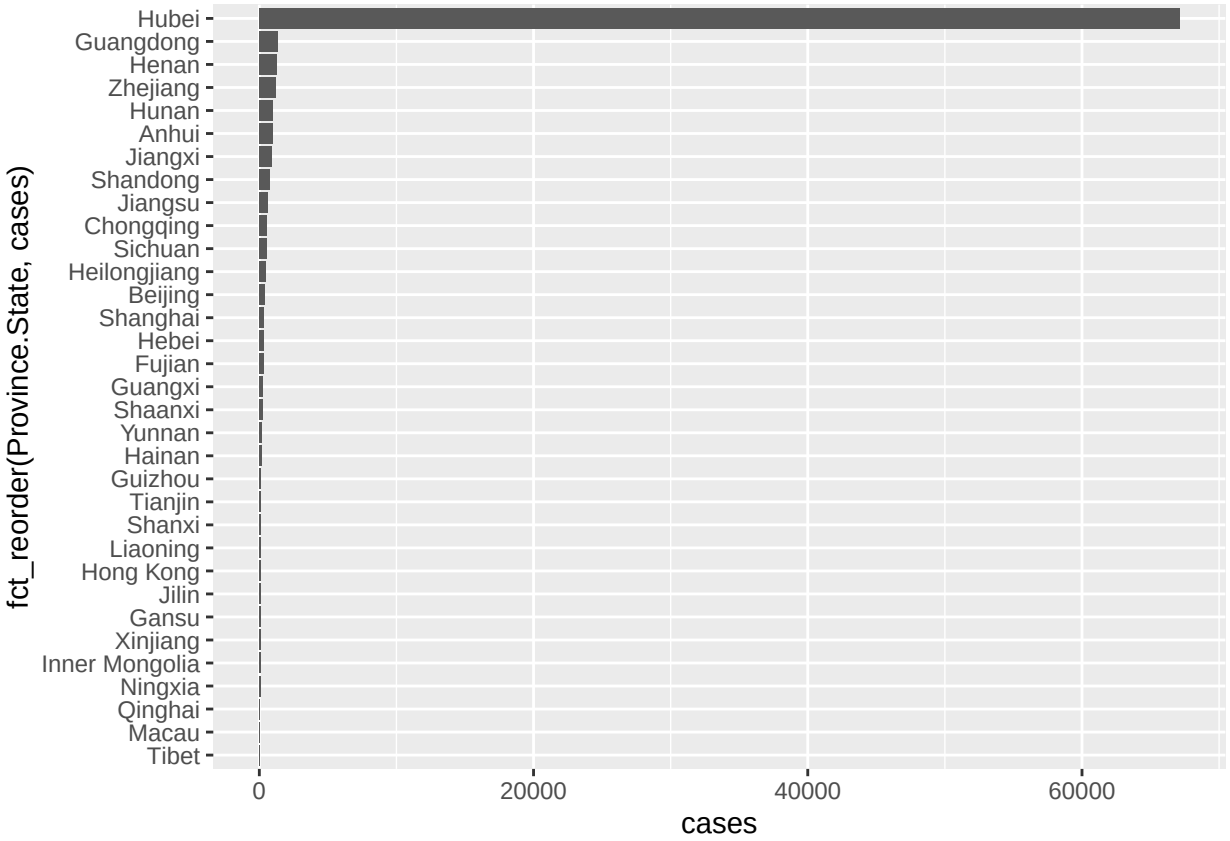
4. Plot the cumulative frequency of confirmed cases in Italy as well as its neighbouring countries (France and Switzerland). Plot the progression in one plot, but with differently colored lines. HINT: **cumsum()**

```
coronavirus %>%
  filter(Country.Region %in% c("Italy","Switzerland","France")) %>%
  filter(type == "confirmed") %>%
  group_by(Country.Region) %>%
  mutate(cases_cumul = cumsum(cases)) %>%
  ggplot(., aes(date, cases_cumul, color = Country.Region)) +
  geom_line()
```



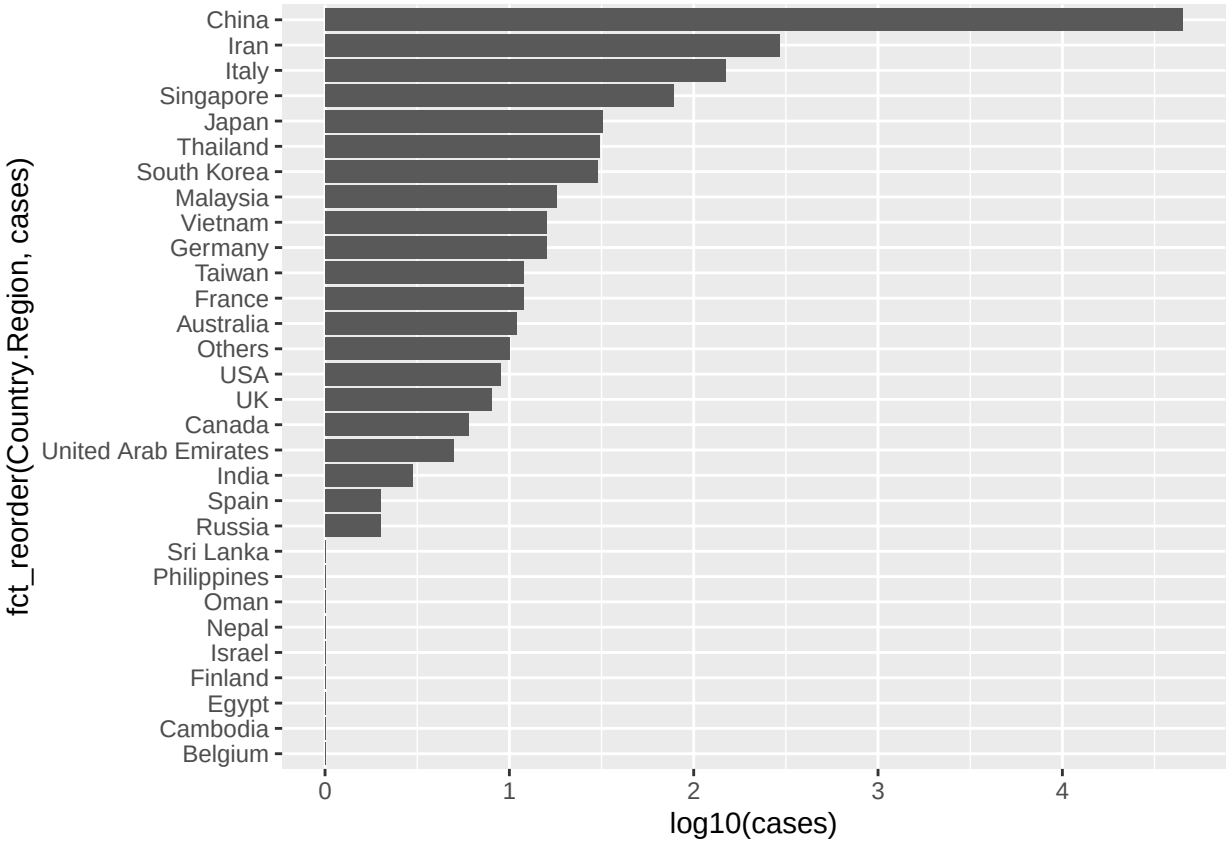
5. Selectively for China, which province has shown the most confirmed cases? Plot with bars, and sorted in decreasing severity. HINT: **fct_reorder()** from the {forcats} library and **coord_flip()**

```
coronavirus %>%
  filter(Country.Region == "China") %>%
  filter(type == "confirmed") %>%
  group_by(Province.State) %>%
  summarise(cases = sum(cases)) %>%
  ggplot(., aes(fct_reorder(Province.State, cases), cases)) +
  geom_col() +
  coord_flip()
```



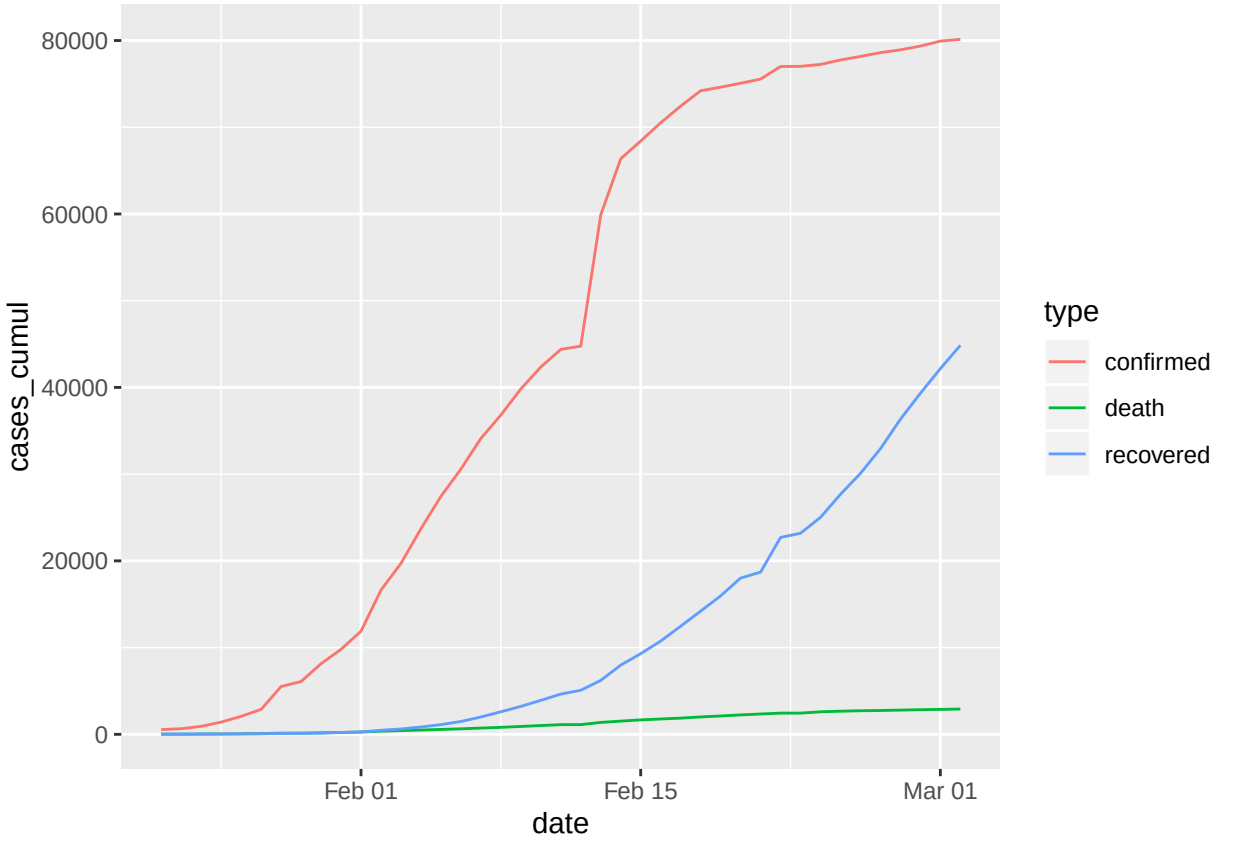
6. In the coronavirus dataset, filter for recovered cases, and show per country the total amount of recovered cases. Plot with bars, and sorted in decreasing severity. Also, normalize the number of cases with log10 (to reduce the saturation from China).

```
coronavirus %>%
  filter(type == "recovered") %>%
  group_by(Country.Region) %>%
  summarise(cases = sum(cases)) %>%
  ggplot(., aes(fct_reorder(Country.Region, cases), log10(cases))) +
  geom_col() +
  coord_flip()
```



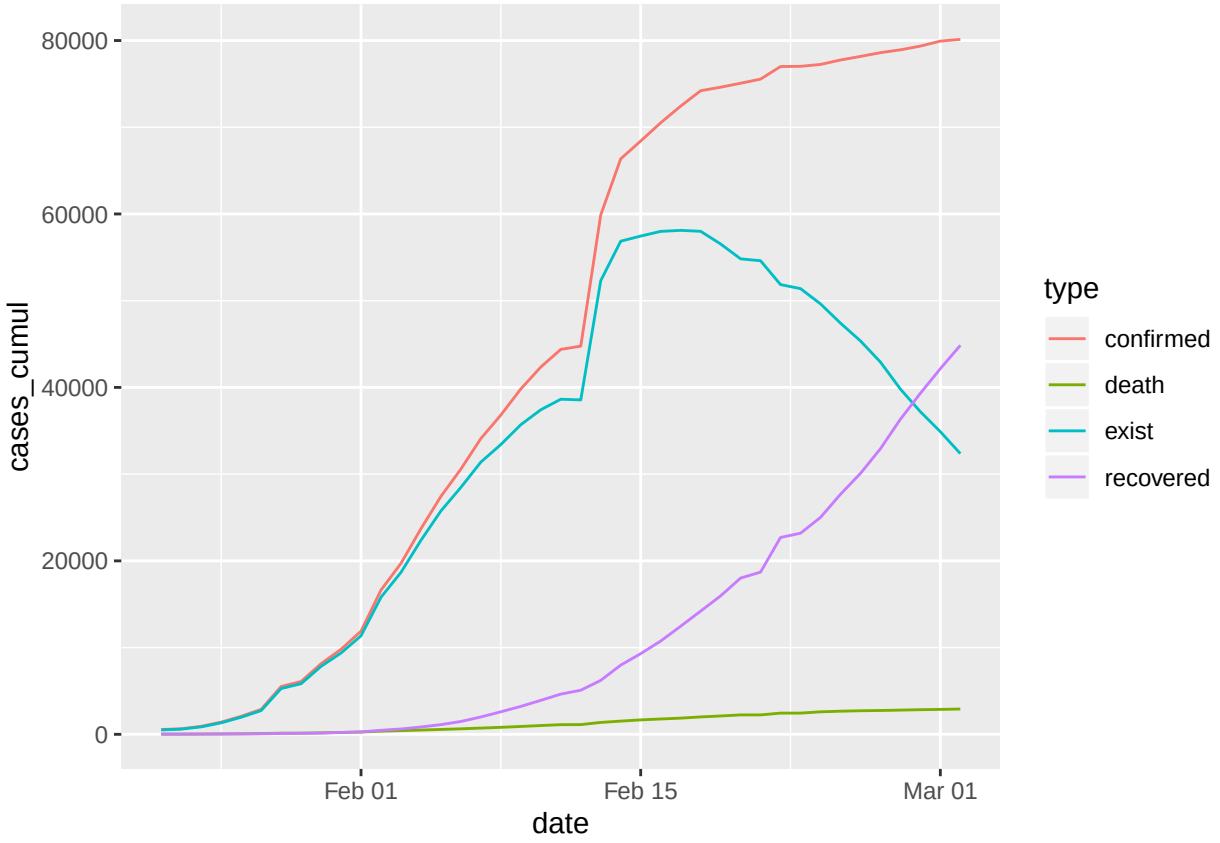
7. Selectively for China, plot the cumulative frequency of confirmed cases, as well as recovered and dead cases. Place in one plot, but with differently colored lines.

```
coronavirus %>%
  filter(Country.Region == "China") %>%
  group_by(type, date) %>%
  summarise(cases = sum(cases)) %>%
  ungroup() %>% group_by(type) %>%
  mutate(cases_cumul = cumsum(cases)) %>%
  ggplot(., aes(date, cases_cumul, color = type)) +
  geom_line()
```



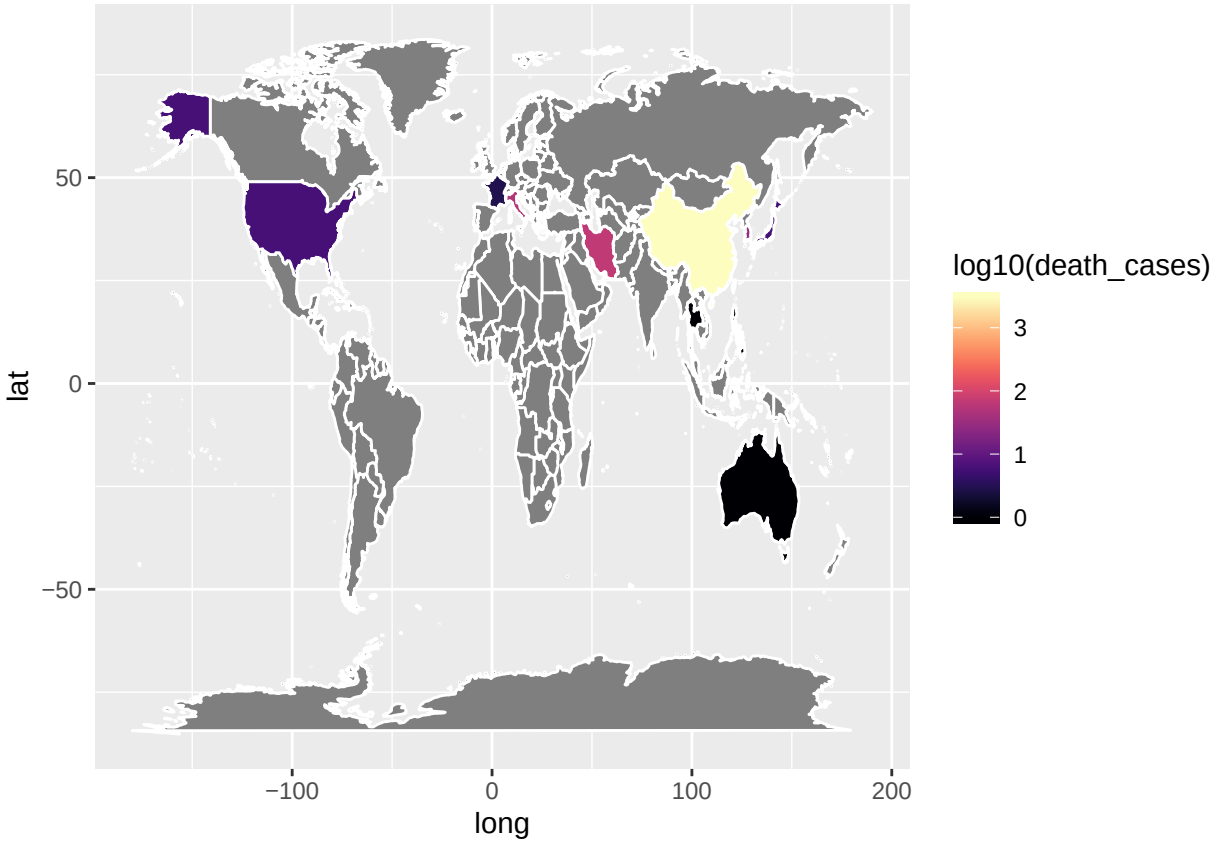
8. Continue from the previous question. Add another line that shows the number of existing cases. What can we observe?

```
coronavirus %>%
  filter(Country.Region == "China") %>%
  group_by(type, date) %>%
  summarise(cases = sum(cases)) %>%
  pivot_wider(names_from = type, values_from = cases) %>%
  mutate(
    confirmed = ifelse(is.na(confirmed), 0, confirmed),
    death = ifelse(is.na(death), 0, death), # if there are NAs, these have to be turned to 0
    recovered = ifelse(is.na(recovered), 0, recovered),
  ) %>%
  mutate(exist = confirmed - death - recovered) %>%
  pivot_longer(-date, names_to = "type", values_to = "cases") %>%
  ungroup() %>% group_by(type) %>%
  mutate(cases_cumul = cumsum(cases)) %>%
  ggplot(., aes(date, cases_cumul, color = type)) +
  geom_line()
```



9. Plot the log10 number of death cases by coronavirus on the world map.

```
world_map <- map_data("world")

world_death <- coronavirus %>%
  filter(type == "death") %>%
  group_by(Country.Region) %>%
  summarise(death_cases = sum(cases)) %>%
  arrange(desc(death_cases))

merged_map <- left_join(world_map, world_death, by = c("region" = "Country.Region"))

ggplot(merged_map, aes(long, lat, group = group)) +
  geom_polygon(aes(fill = log10(death_cases)), color = "white") +
  scale_fill_viridis(option = "magma")
```

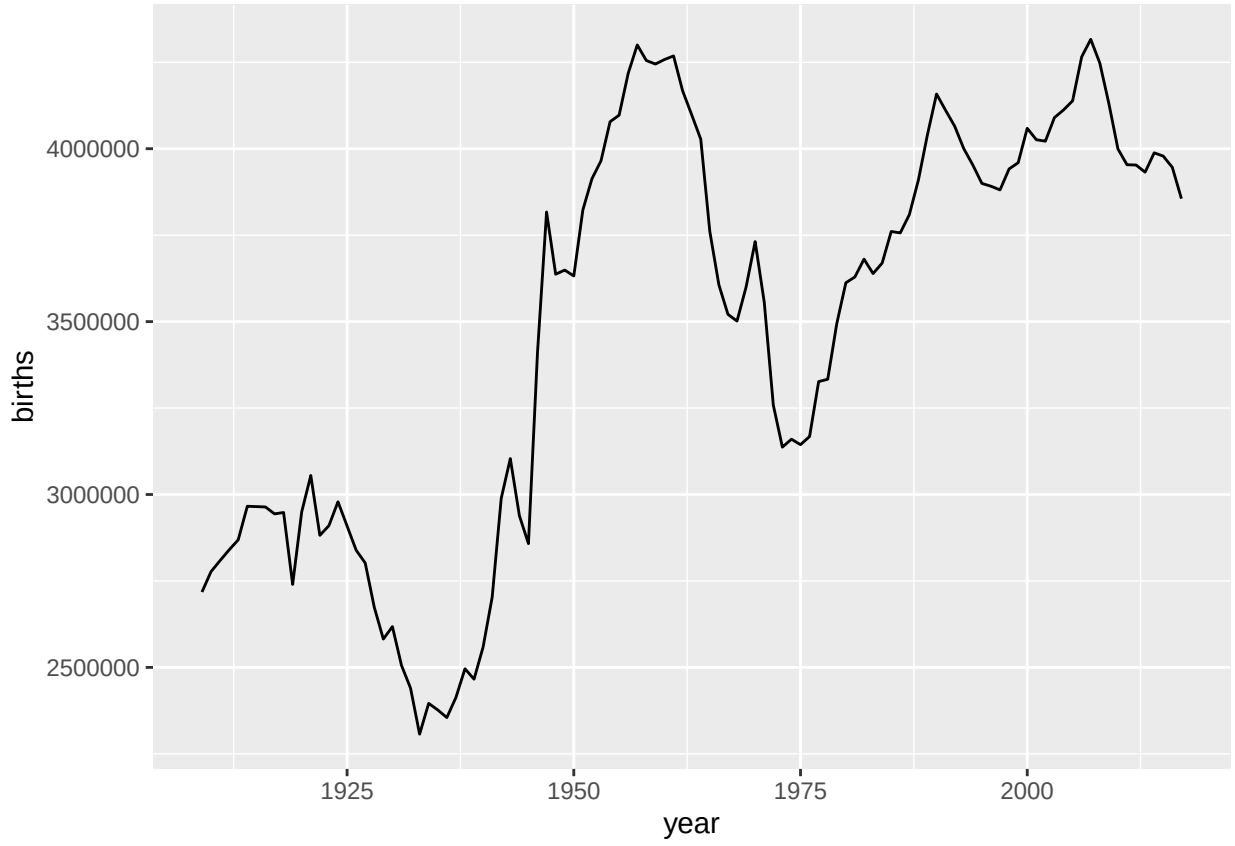


In the following questions, you will visualize the popularity of certain babynames as well as the number of births. This dataset can be found in the like-named {babynames} library.

```
suppressPackageStartupMessages( library(babynames) )
```

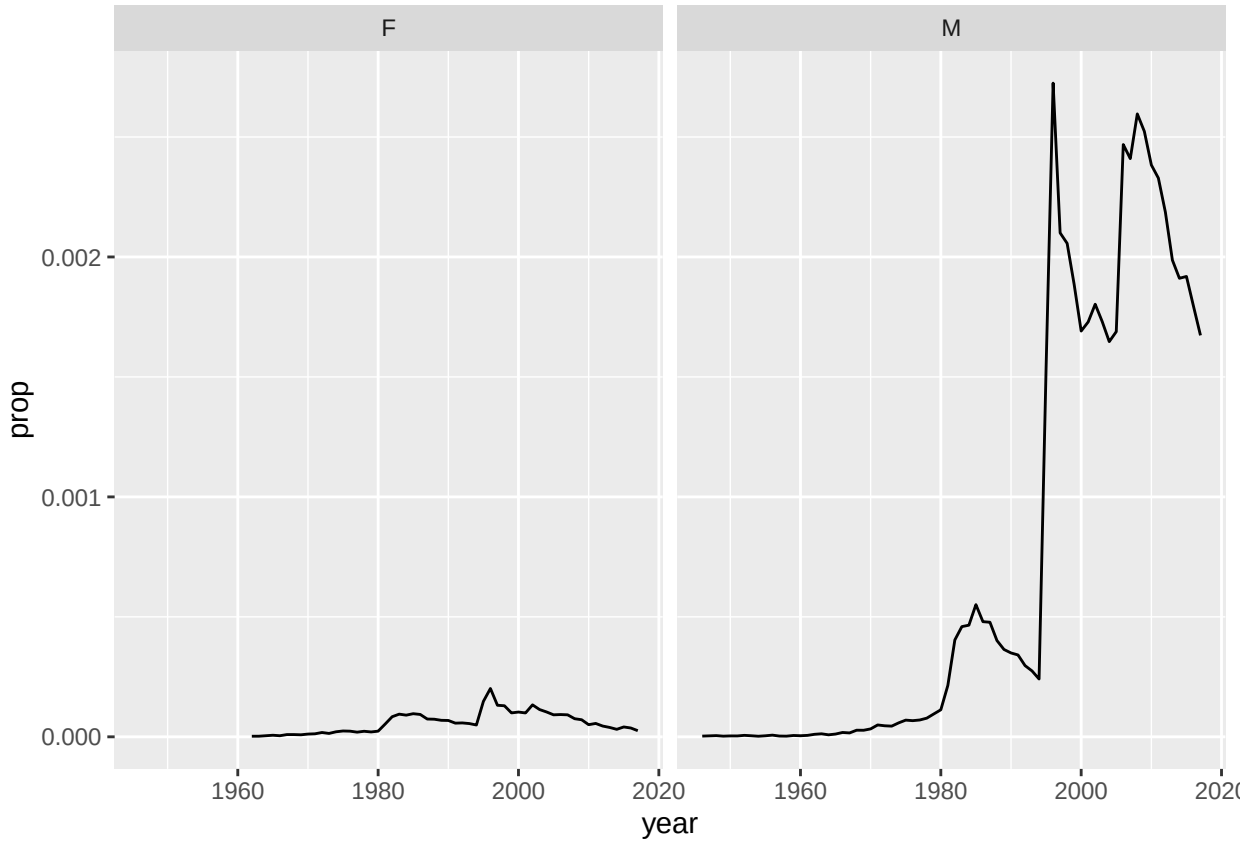
1. Plot the number of birth over time from the births dataset.

```
births %>%
    ggplot(., aes(year, births)) + geom_line()
```



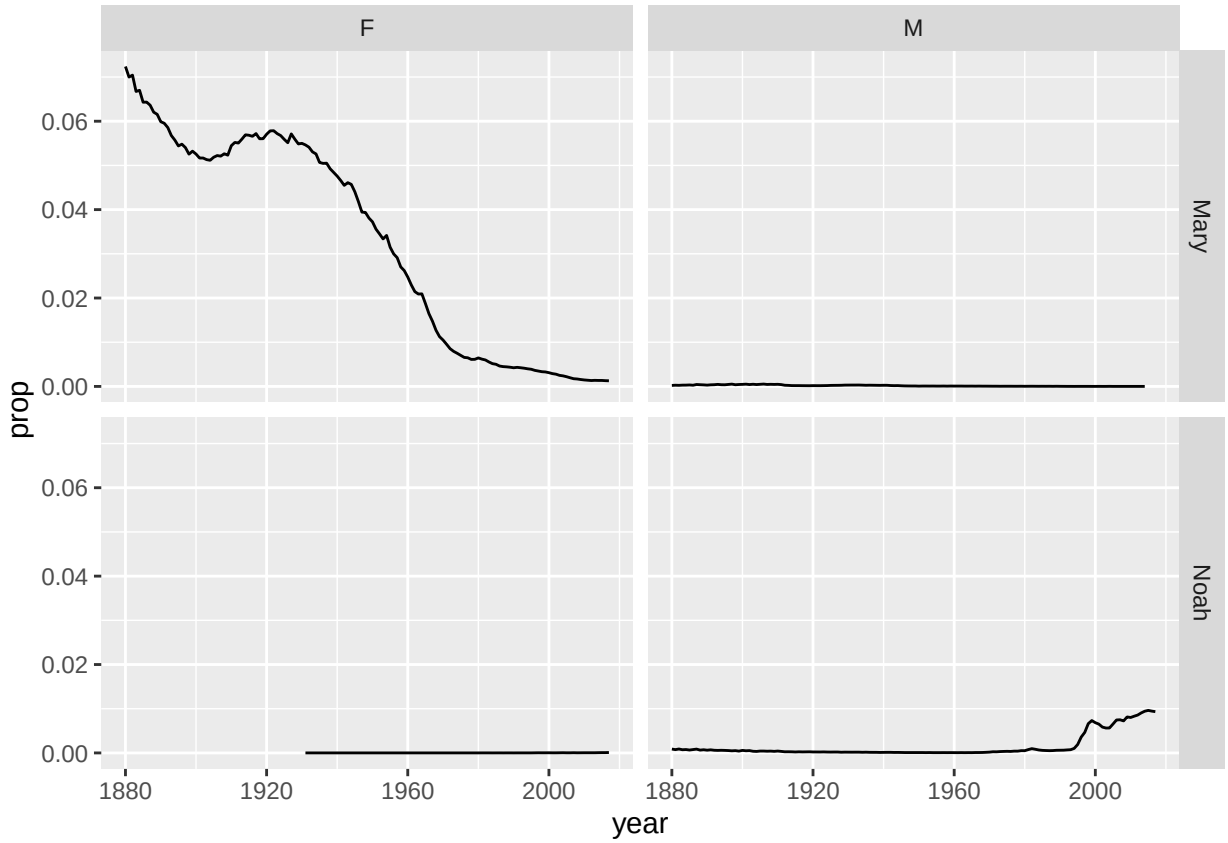
2. Plot the development of the name "Tristan" over time for each sex from the babynames dataset.

```
babynames %>%
    filter(name == "Tristan") %>%
    ggplot(., aes(year, prop)) +
    geom_line() +
    facet_wrap(~ sex)
```



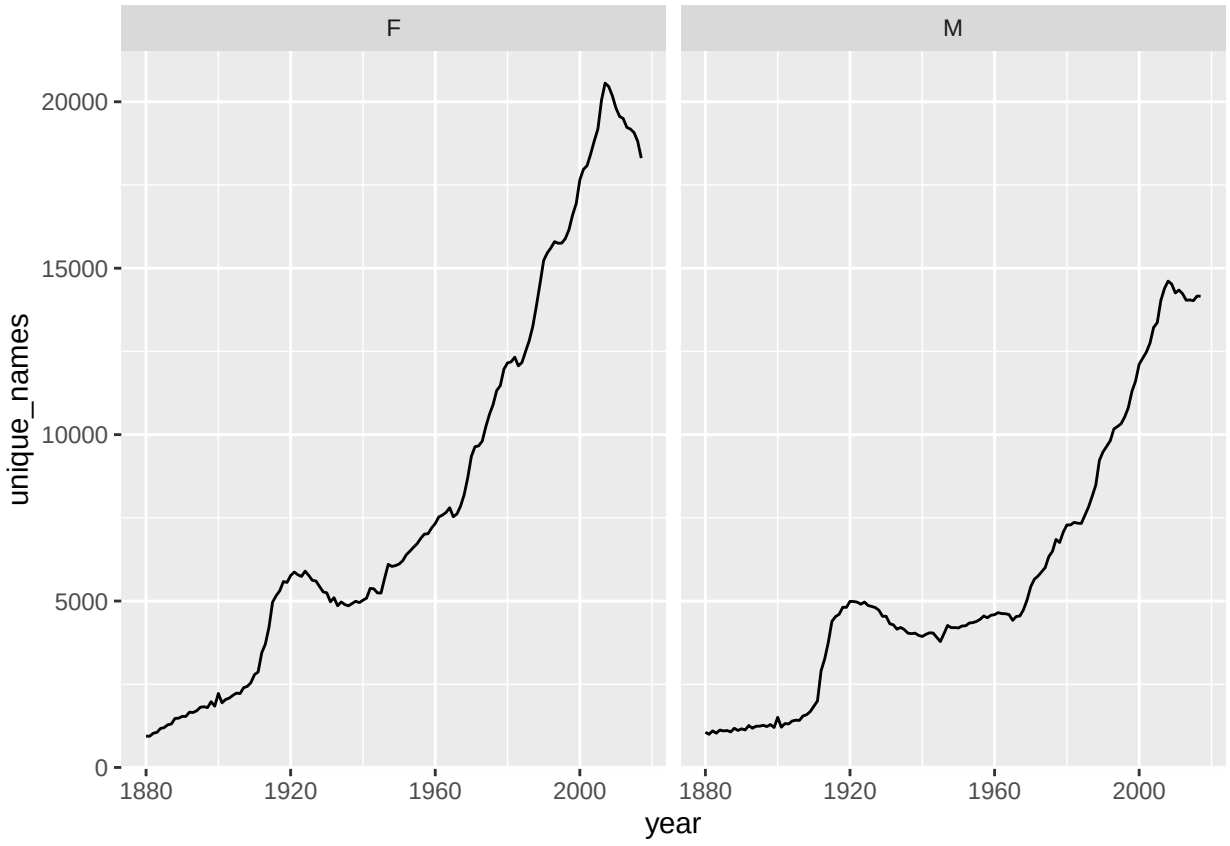
3. Plot the development of the name "Mary" and "Noah" over time for each sex. What can you say about the development of these names?

```
babynames %>%
    filter(name %in% c("Mary","Noah")) %>%
    ggplot(., aes(year, prop)) +
    geom_line() +
    facet_grid(name ~ sex)
```



4. Extract from the babynames dataset for each year, the number of unique names for boys and girls. Plot these over time side-by-side. What is the trend? Which sex has more diversified names? Any peculiar trends?

```
babynames %>%
    group_by(year, sex) %>%
    summarise(unique_names = n()) %>%
    ggplot(., aes(year, unique_names)) +
    geom_line() +
    facet_grid(. ~ sex)
```

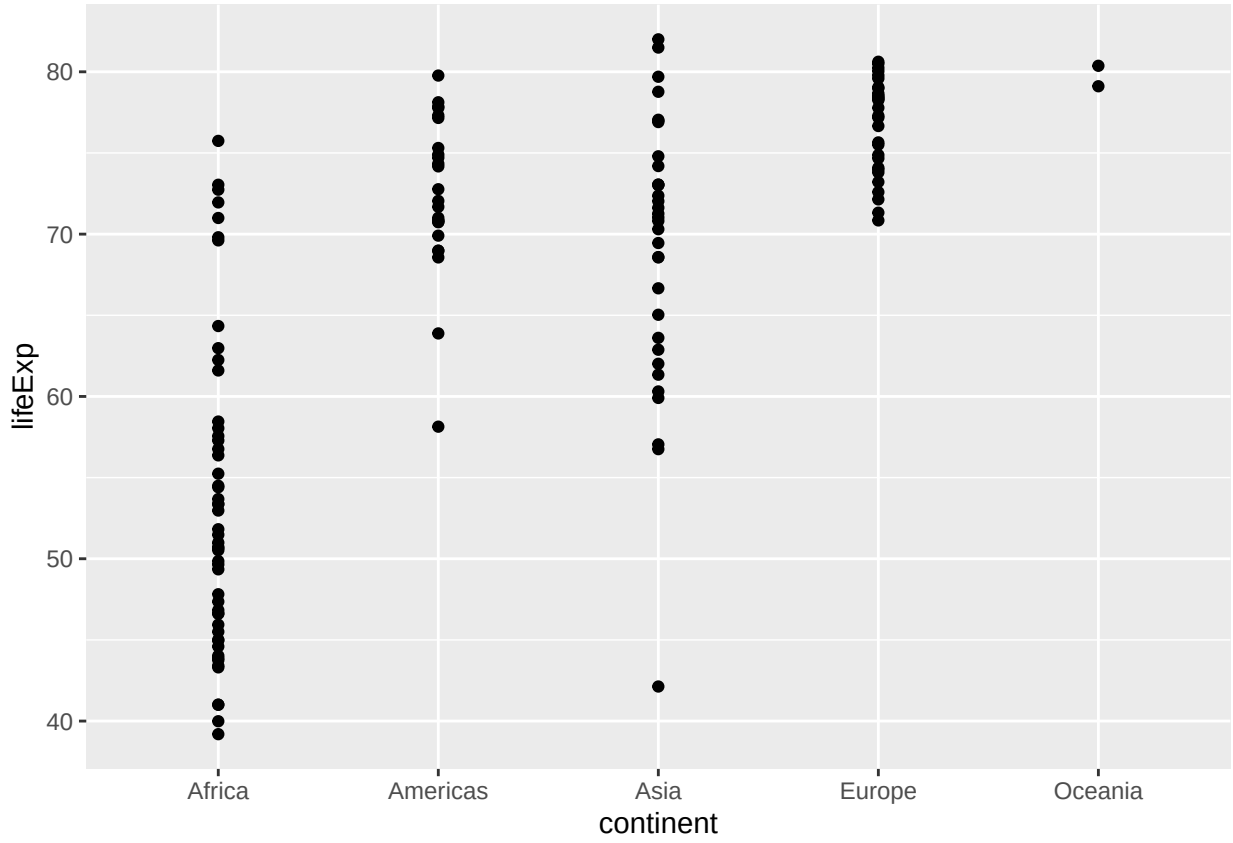


In the following questions, you will visualize the economic parameteres from the gapminder dataset. This dataset can be found in the like-named {gapminder} library.

```
suppressPackageStartupMessages( library(gapminder) )
```

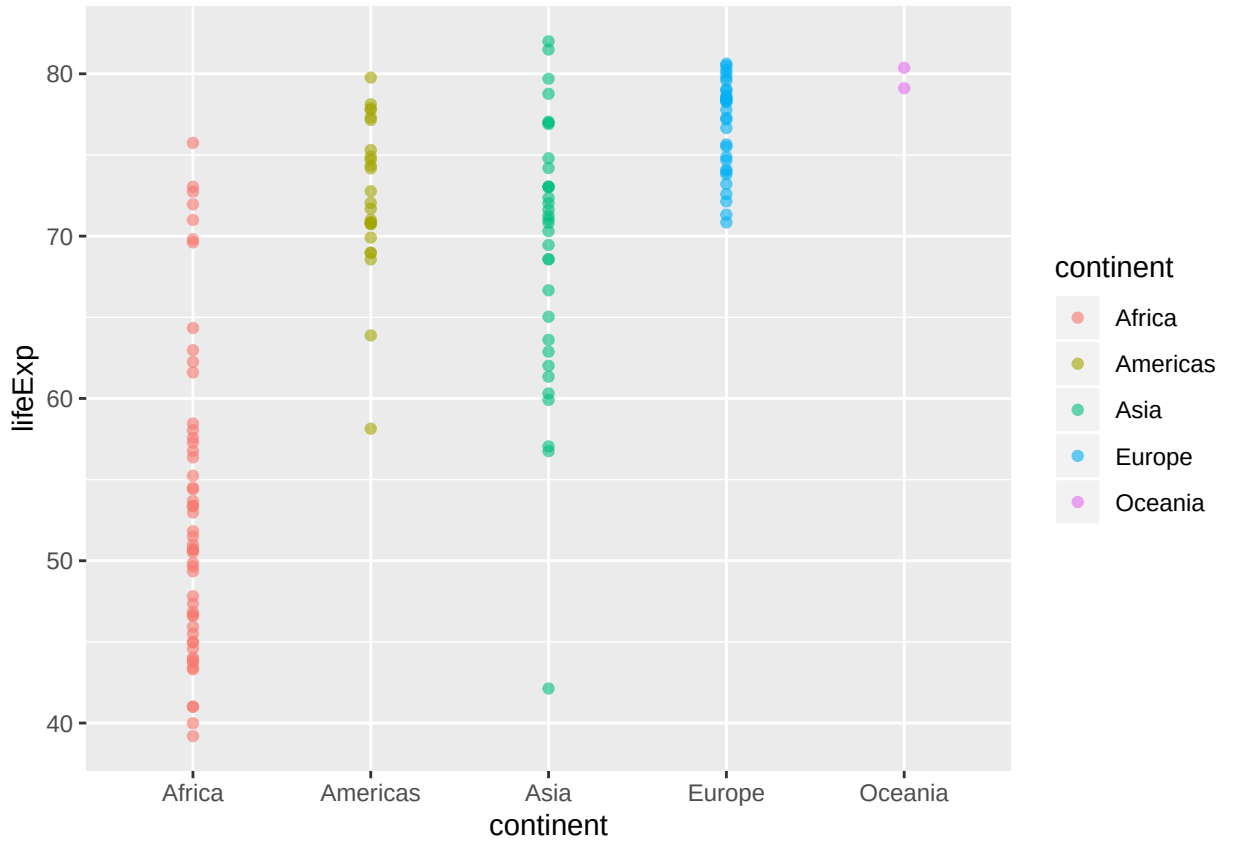
1. Plot the life expectancy for each continent from the year 2002 as individual points

```
gapminder %>%
    filter(year == 2002) %>%
    ggplot(., aes(continent, lifeExp)) +
    geom_point()
```



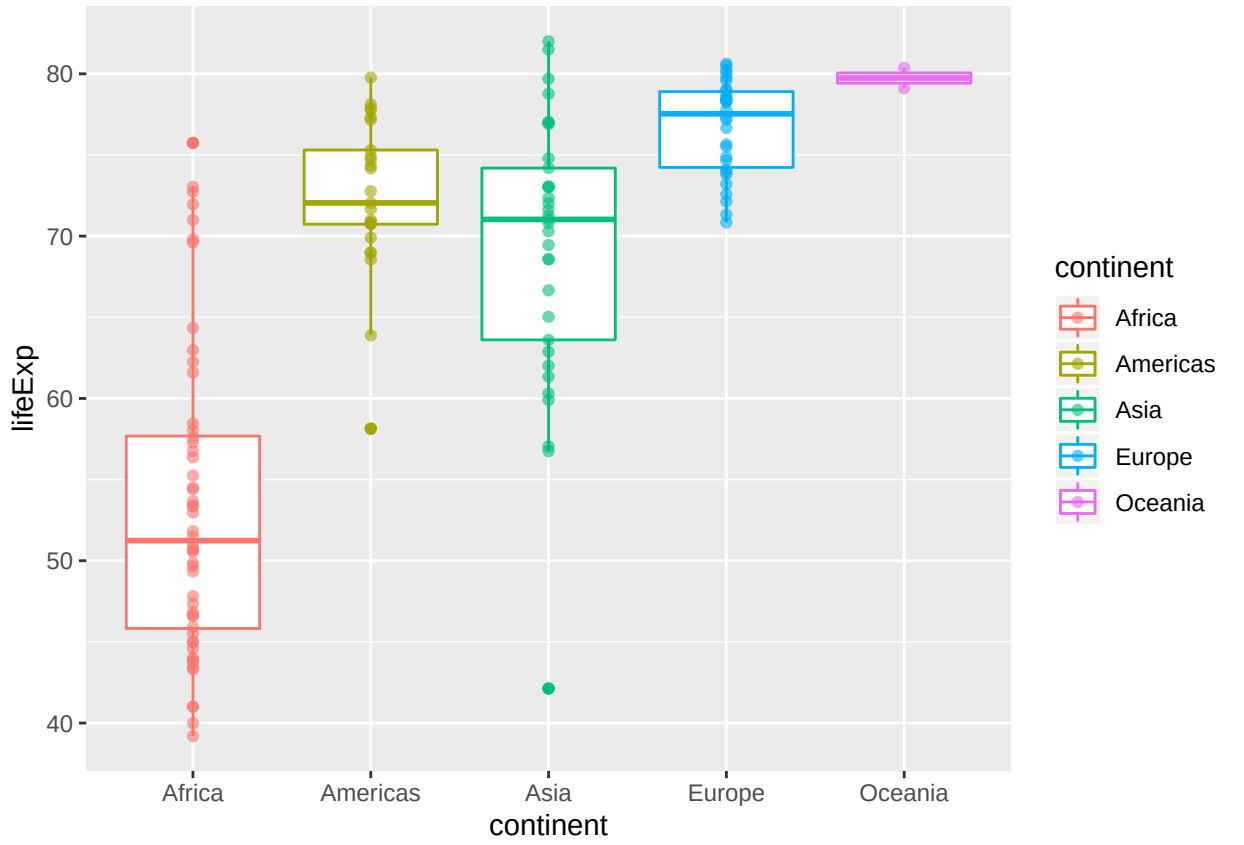
2. Continue from the previous question: add some transparency in the dots and give each continent a different color.

```
gapminder %>%
    filter(year == 2002) %>%
    ggplot(., aes(continent, lifeExp, color = continent)) +
    geom_point(alpha = 0.60)
```



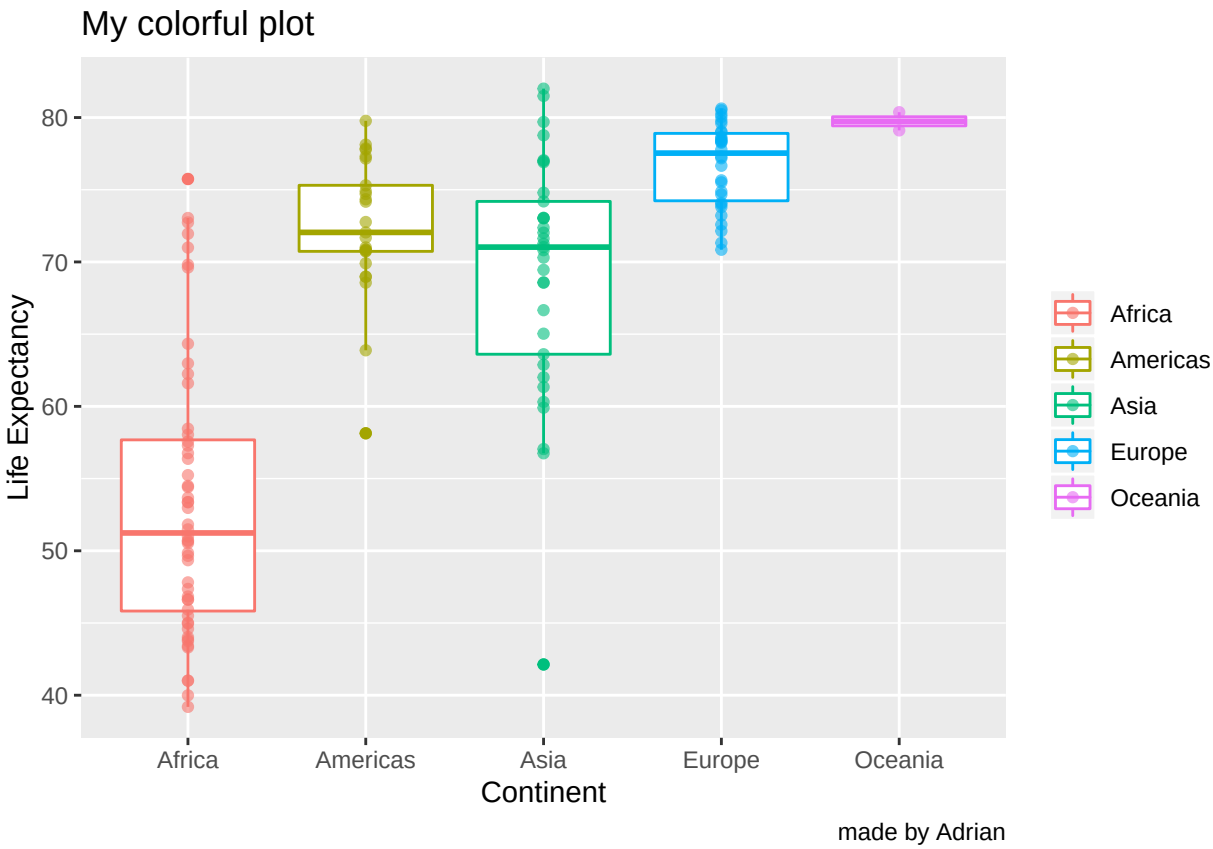
3. Continue from the previous question: add a boxplot to the graph. Add it in such a way that the individual points will still be visible.

```
gapminder %>%
    filter(year == 2002) %>%
    ggplot(., aes(continent, lifeExp, color = continent)) +
    geom_boxplot() +
    geom_point(alpha = 0.60)
```



4. Continue from the previous question: Adjust the labels so they are more presentable. Change the title on the y-axis to "Life Expectancy", and the title on the x-axis to "Continent". Add a title "My colorful plot". Also add a caption with "made by {your name}". Finally, remove the legend title.

```
gapminder %>%
    filter(year == 2002) %>%
    ggplot(., aes(continent, lifeExp, color = continent)) +
    geom_boxplot() +
    geom_point(alpha = 0.60) +
    labs(x = "Continent", y = "Life Expectancy",
         title = "My colorful plot", caption = "made by Adrian") +
    theme(legend.title = element_blank())
```


My colorful plot
Life Expectancy
80
70
60
50
40
Africa
Americas
Asia
Europe
Oceania
Continent
made by Adrian
Africa
Americas
Asia
Europe
Oceania