
Data Programming Course Exercises

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Chapter 1

Introduction

In this document you will find some exercises about these sections:

- *Data Manipulation with dplyr*
- *Data Visualization with ggplot2*
- *Writing R functions*

Chapter 2

Data Manipulation with dplyr

Load dplyr package, supposing it is already installed.

```
require(dplyr)
```

2.1 Data

All the following exercises are based on the `nycflights13` data, taken from the `nycflights13` package.

So first of all, install and load this package

```
install.packages("nycflights13")  
require(nycflights13)
```

The `nycflights13` package contains information about all flights that departed from NYC (e.g. EWR, JFK and LGA) in 2013: 336,776 flights in total.

```
ls(pos = "package:nycflights13")  
  
## [1] "airlines" "airports" "flights"  "planes"   "weather"
```

To help understand what causes delays, it includes a number of useful datasets:

- `flights`: information about all flights that departed from NYC
- `weather`: hourly meteorological data for each airport;
- `planes`: construction information about each plane;
- `airports`: airport names and locations;

- **airlines**: translation between two letter carrier codes and names.

Let us explore the features of **flights** datasets, which will be used in the following exercises.

```
data("flights")
```

2.1.1 flights

This dataset contains on-time data for all flights that departed from NYC (i.e. JFK, LGA or EWR) in 2013. The data frame has 16 variables and 336776 observations. The variables are organised as follow:

- Date of departure: **year**, **month**, **day**;
- Departure and arrival times (local tz): **dep_time**, **arr_time**;
- Departure and arrival delays, in minutes: **dep_delay**, **arr_delay** (negative times represent early departures/arrivals);
- Time of departure broken in to hour and minutes: **hour**, **minute**;
- Two letter carrier abbreviation: **carrier**;
- Plane tail number: **tailnum**;
- Flight number: **flight**;
- Origin and destination: **origin**, **dest**;
- Amount of time spent in the air: **air_time**;
- Distance flown: **distance**.

```
dim(flights)
```

```
## [1] 336776      16
```

```
head(flights)
```

```
##   year month day dep_time dep_delay arr_time arr_delay carrier tailnum flight
## 1 2013     1   1      517         2      830         11      UA  N14228  1545
## 2 2013     1   1      533         4      850         20      UA  N24211  1714
## 3 2013     1   1      542         2      923         33      AA  N619AA  1141
## 4 2013     1   1      544        -1     1004        -18      B6  N804JB   725
## 5 2013     1   1      554        -6      812        -25      DL  N668DN   461
## 6 2013     1   1      554        -4      740         12      UA  N39463  1696
##   origin dest air_time distance hour minute
## 1   EWR  IAH      227     1400     5      17
## 2   LGA  IAH      227     1416     5      33
```



```
## 3    JFK  MIA      160    1089    5    42
## 4    JFK  BQN      183    1576    5    44
## 5    LGA  ATL      116     762    5    54
## 6    EWR  ORD      150     719    5    54
```

```
str(flights)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':  336776 obs. of  16 variables:
## $ year      : int  2013 2013 2013 2013 2013 2013 2013 2013 2013 2013 ...
## $ month     : int   1  1  1  1  1  1  1  1  1  1 ...
## $ day       : int   1  1  1  1  1  1  1  1  1  1 ...
## $ dep_time  : int  517 533 542 544 554 554 555 557 557 558 ...
## $ dep_delay: num    2  4  2 -1 -6 -4 -5 -3 -3 -2 ...
## $ arr_time  : int  830 850 923 1004 812 740 913 709 838 753 ...
## $ arr_delay: num   11 20 33 -18 -25 12 19 -14 -8 8 ...
## $ carrier   : chr  "UA" "UA" "AA" "B6" ...
## $ tailnum   : chr  "N14228" "N24211" "N619AA" "N804JB" ...
## $ flight    : int  1545 1714 1141 725 461 1696 507 5708 79 301 ...
## $ origin    : chr  "EWR" "LGA" "JFK" "JFK" ...
## $ dest      : chr  "IAH" "IAH" "MIA" "BQN" ...
## $ air_time  : num  227 227 160 183 116 150 158 53 140 138 ...
## $ distance  : num  1400 1416 1089 1576 762 ...
## $ hour      : num   5  5  5  5  5  5  5  5  5 ...
## $ minute    : num  17 33 42 44 54 54 55 57 57 58 ...
```

2.2 Select

2.2.1 Exercise 1

Extract the following information:

- month;
- day;
- air_time;
- distance.

```
select(flights, month, day, air_time, distance)
```

```
## Source: local data frame [336,776 x 4]
##
##   month   day air_time distance
##   (int) (int)   (dbl)   (dbl)
## 1     1     1     227     1400
## 2     1     1     227     1416
## 3     1     1     160     1089
## 4     1     1     183     1576
## 5     1     1     116       762
## 6     1     1     150       719
## 7     1     1     158     1065
## 8     1     1      53       229
## 9     1     1     140       944
## 10    1     1     138       733
## ..    ...    ...     ...     ...
```

```
# flights %>% select(month, day, air_time, distance)
```

2.2.2 Exercise 2

Extract all information about `flights` except hour and minute.

```
select(flights, -c(hour, minute))
```

```
## Source: local data frame [336,776 x 14]
##
##   year month   day dep_time dep_delay arr_time arr_delay carrier tailnum
##   (int) (int) (int)   (int)     (dbl)   (int)     (dbl)   (chr)   (chr)
## 1  2013     1     1     517         2     830         11     UA   N14228
## 2  2013     1     1     533         4     850        20     UA   N24211
```

```
## 3 2013 1 1 542 2 923 33 AA N619AA
## 4 2013 1 1 544 -1 1004 -18 B6 N804JB
## 5 2013 1 1 554 -6 812 -25 DL N668DN
## 6 2013 1 1 554 -4 740 12 UA N39463
## 7 2013 1 1 555 -5 913 19 B6 N516JB
## 8 2013 1 1 557 -3 709 -14 EV N829AS
## 9 2013 1 1 557 -3 838 -8 B6 N593JB
## 10 2013 1 1 558 -2 753 8 AA N3ALAA
## .. ... .. ... .. ... .. ... ..
## Variables not shown: flight (int), origin (chr), dest (chr), air_time (dbl),
## distance (dbl)
```

```
# flights %>% select(-c(hour, minute))
```

2.2.3 Exercise 3

Extract `tailnum` variable and rename it into `tail_num`

```
select(flights, tail_num=tailnum)

## Source: local data frame [336,776 x 1]
##
##   tail_num
##   (chr)
## 1 N14228
## 2 N24211
## 3 N619AA
## 4 N804JB
## 5 N668DN
## 6 N39463
## 7 N516JB
## 8 N829AS
## 9 N593JB
## 10 N3ALAA
## .. ...
```

```
# flights %>% select(tail_num=tailnum)
```

2.3 Filter

2.3.1 Exercise 1

Select all flights which delayed more than 1000 minutes at departure.

```
filter(flights, dep_delay > 1000)

## Source: local data frame [5 x 16]
##
##   year month   day dep_time dep_delay arr_time arr_delay carrier tailnum
##   (int) (int) (int)   (int)     (dbl)   (int)     (dbl)   (chr)   (chr)
## 1  2013     1     9     641      1301    1242      1272     HA   N384HA
## 2  2013     1    10    1121      1126    1239      1109     MQ   N517MQ
## 3  2013     6    15    1432      1137    1607      1127     MQ   N504MQ
## 4  2013     7    22     845      1005    1044       989     MQ   N665MQ
## 5  2013     9    20    1139      1014    1457      1007     AA   N338AA
## Variables not shown: flight (int), origin (chr), dest (chr), air_time (dbl),
##   distance (dbl), hour (dbl), minute (dbl)

# flights %>% filter(dep_delay > 1000)
```

2.3.2 Exercise 2

Select all flights which delayed more than 1000 minutes at departure or at arrival.

```
filter(flights, dep_delay > 1000 | arr_delay >1000)

## Source: local data frame [5 x 16]
##
##   year month   day dep_time dep_delay arr_time arr_delay carrier tailnum
##   (int) (int) (int)   (int)     (dbl)   (int)     (dbl)   (chr)   (chr)
## 1  2013     1     9     641      1301    1242      1272     HA   N384HA
## 2  2013     1    10    1121      1126    1239      1109     MQ   N517MQ
## 3  2013     6    15    1432      1137    1607      1127     MQ   N504MQ
## 4  2013     7    22     845      1005    1044       989     MQ   N665MQ
## 5  2013     9    20    1139      1014    1457      1007     AA   N338AA
## Variables not shown: flight (int), origin (chr), dest (chr), air_time (dbl),
##   distance (dbl), hour (dbl), minute (dbl)

# flights %>% filter(dep_delay > 1000 | arr_delay >1000)
```

2.3.3 Exercise 3

Select all flights which took off from “EWR” and landed in “IAH”.

```
filter(flights, origin == "EWR" & dest == "IAH")
```

```
## Source: local data frame [3,973 x 16]
##
##   year month   day dep_time dep_delay arr_time arr_delay carrier tailnum
##   (int) (int) (int)   (int)    (dbl)   (int)    (dbl)   (chr)   (chr)
## 1  2013     1     1     517         2     830        11     UA   N14228
## 2  2013     1     1     739         0    1104        26     UA   N37408
## 3  2013     1     1     908         0    1228         9     UA   N12216
## 4  2013     1     1    1044        -1    1352         1     UA   N667UA
## 5  2013     1     1    1205         5    1503        -2     UA   N39418
## 6  2013     1     1    1356         6    1659        19     UA   N26906
## 7  2013     1     1    1527        12    1854        44     UA   N69059
## 8  2013     1     1    1620         0    1945        23     UA   N18119
## 9  2013     1     1    1725         5    2045        24     UA   N17122
## 10 2013     1     1    1959        -1    2310         3     UA   N76514
## .. ... ..
## Variables not shown: flight (int), origin (chr), dest (chr), air_time (dbl),
##   distance (dbl), hour (dbl), minute (dbl)

# flights %>% filter(origin == "EWR" & dest == "IAH")
```

2.4 Arrange

2.4.1 Exercise 1

Sort the flights in chronological order.

```
arrange(flights, year, month, day)

## Source: local data frame [336,776 x 16]
##
##   year month   day dep_time dep_delay arr_time arr_delay carrier tailnum
##   (int) (int) (int)   (int)     (dbl)   (int)     (dbl)   (chr)   (chr)
## 1  2013     1     1     517         2     830         11     UA   N14228
## 2  2013     1     1     533         4     850         20     UA   N24211
## 3  2013     1     1     542         2     923         33     AA   N619AA
## 4  2013     1     1     544        -1    1004        -18     B6   N804JB
## 5  2013     1     1     554        -6     812        -25     DL   N668DN
## 6  2013     1     1     554        -4     740         12     UA   N39463
## 7  2013     1     1     555        -5     913         19     B6   N516JB
## 8  2013     1     1     557        -3     709        -14     EV   N829AS
## 9  2013     1     1     557        -3     838         -8     B6   N593JB
## 10 2013     1     1     558        -2     753          8     AA   N3ALAA
## .. ... ..
## Variables not shown: flight (int), origin (chr), dest (chr), air_time (dbl),
##   distance (dbl), hour (dbl), minute (dbl)

# flights %>% arrange(year, month, day)
```

2.4.2 Exercise 2

Sort the flights by decreasing arrival delay.

```
arrange(flights, desc(arr_delay))

## Source: local data frame [336,776 x 16]
##
##   year month   day dep_time dep_delay arr_time arr_delay carrier tailnum
##   (int) (int) (int)   (int)     (dbl)   (int)     (dbl)   (chr)   (chr)
## 1  2013     1     9     641    1301    1242    1272     HA   N384HA
## 2  2013     6    15    1432    1137    1607    1127     MQ   N504MQ
## 3  2013     1    10    1121    1126    1239    1109     MQ   N517MQ
## 4  2013     9    20    1139    1014    1457    1007     AA   N338AA
## 5  2013     7    22     845    1005    1044     989     MQ   N665MQ
## 6  2013     4    10    1100     960    1342     931     DL   N959DL
## 7  2013     3    17    2321     911     135     915     DL   N927DA
```

```
## 8 2013 7 22 2257 898 121 895 DL N6716C
## 9 2013 12 5 756 896 1058 878 AA N5DMAA
## 10 2013 5 3 1133 878 1250 875 MQ N523MQ
## .. ... .. ... .. ... .. ... ..
## Variables not shown: flight (int), origin (chr), dest (chr), air_time (dbl),
## distance (dbl), hour (dbl), minute (dbl)
```

```
# flights %>% arrange(desc(arr_delay))
```

2.4.3 Exercise 3

Sort the flights by origin (in alphabetical order) and decreasing arrival delay.

```
arrange(flights, origin, desc(arr_delay))

## Source: local data frame [336,776 x 16]
##
##   year month   day dep_time dep_delay arr_time arr_delay carrier tailnum
##   (int) (int) (int)   (int)     (dbl)   (int)     (dbl)   (chr)   (chr)
## 1  2013     1    10    1121     1126    1239     1109     MQ   N517MQ
## 2  2013    12     5     756     896    1058     878     AA   N5DMAA
## 3  2013     5     3    1133     878    1250     875     MQ   N523MQ
## 4  2013    12    19     734     849    1046     847     DL   N375NC
## 5  2013    12    17     705     845    1026     846     AA   N5EMAA
## 6  2013    11     3     603     798     829     796     DL   N990AT
## 7  2013     2    24    1921     786    2135     773     DL   N348NW
## 8  2013    10    14    2042     702    2255     688     DL   N943DL
## 9  2013     7    21    1555     580    1955     645     AA   N3EMAA
## 10 2013     7     7    2123     653     17     632     VX   N521VA
## .. ... .. ... .. ... .. ... ..
## Variables not shown: flight (int), origin (chr), dest (chr), air_time (dbl),
## distance (dbl), hour (dbl), minute (dbl)
```

```
# flights %>% arrange(origin, desc(arr_delay))
```

2.5 Mutate

2.5.1 Exercise 1

Add the following new variable to the `flights` dataset:

- the speed in miles per hour, named `speed` (`distance / air_time * 60`).

Consider that times are in minutes and distances are in miles.

```
mutate(flights, speed = distance / air_time * 60)

## Source: local data frame [336,776 x 17]
##
##   year month   day dep_time dep_delay arr_time arr_delay carrier tailnum
##   (int) (int) (int)   (int)    (dbl)   (int)    (dbl)   (chr)   (chr)
## 1  2013     1     1     517        2     830        11     UA   N14228
## 2  2013     1     1     533        4     850        20     UA   N24211
## 3  2013     1     1     542        2     923        33     AA   N619AA
## 4  2013     1     1     544       -1    1004       -18     B6   N804JB
## 5  2013     1     1     554       -6     812       -25     DL   N668DN
## 6  2013     1     1     554       -4     740        12     UA   N39463
## 7  2013     1     1     555       -5     913        19     B6   N516JB
## 8  2013     1     1     557       -3     709       -14     EV   N829AS
## 9  2013     1     1     557       -3     838        -8     B6   N593JB
## 10 2013     1     1     558       -2     753         8     AA   N3ALAA
## .. ... ..
## Variables not shown: flight (int), origin (chr), dest (chr), air_time (dbl),
##   distance (dbl), hour (dbl), minute (dbl), speed (dbl)

# flights %>% mutate(speed = distance / air_time * 60)
```

2.5.2 Exercise 2

Add the following new variables to the `flights` dataset:

- the gained time in minutes (named `gain`), defined as the difference between delay at departure and delay at arrival;
- the gain time per hours, defined as `gain / (air_time / 60)`

```
mutate(flights, gain = arr_delay - dep_delay,
       gain_per_hour = gain / (air_time / 60))

## Source: local data frame [336,776 x 18]
##
##   year month   day dep_time dep_delay arr_time arr_delay carrier tailnum
##   (int) (int) (int)   (int)    (dbl)   (int)    (dbl)   (chr)   (chr)
## 1  2013     1     1     517        2     830        11     UA   N14228
## 2  2013     1     1     533        4     850        20     UA   N24211
## 3  2013     1     1     542        2     923        33     AA   N619AA
## 4  2013     1     1     544       -1    1004       -18     B6   N804JB
## 5  2013     1     1     554       -6     812       -25     DL   N668DN
## 6  2013     1     1     554       -4     740        12     UA   N39463
```



```
## 7 2013 1 1 555 -5 913 19 B6 N516JB
## 8 2013 1 1 557 -3 709 -14 EV N829AS
## 9 2013 1 1 557 -3 838 -8 B6 N593JB
## 10 2013 1 1 558 -2 753 8 AA N3ALAA
## .. ... .. ... .. ... .. ... ..
## Variables not shown: flight (int), origin (chr), dest (chr), air_time (dbl),
## distance (dbl), hour (dbl), minute (dbl), gain (dbl), gain_per_hour (dbl)

# flights %>% mutate(gain = arr_delay - dep_delay,
# gain_per_hour = gain / (air_time / 60))
```

2.6 Summarise

2.6.1 Exercise 1

Calculate minimum, mean and maximum delay at arrival. Remember to add `na.rm=TRUE` option to all calculations.

```
summarise(flights, min_delay = min(arr_delay, na.rm=TRUE),
           mean_delay = mean(arr_delay, na.rm=TRUE),
           max_delay = max(arr_delay, na.rm=TRUE))

## Source: local data frame [1 x 3]
##
##   min_delay mean_delay max_delay
##   (dbl)      (dbl)      (dbl)
## 1     -86    6.895377    1272

# flights %>% summarise(min_delay = min(arr_delay, na.rm=TRUE),
#   mean_delay = mean(arr_delay, na.rm=TRUE),
#   max_delay = max(arr_delay, na.rm=TRUE))
```

2.7 Group_by

2.7.1 Exercise 1

Calculate number of flights, minimum, mean and maximum delay at departure for flights by month.

Remember to add `na.rm=TRUE` option to all calculations.

```
by_month <- group_by(flights, month)
```

```
summarise(by_month, min_delay = min(dep_delay, na.rm=TRUE),
          mean_delay = mean(dep_delay, na.rm=TRUE),
          max_delay = max(dep_delay, na.rm=TRUE))
```

```
## Source: local data frame [12 x 4]
##
##   month min_delay mean_delay max_delay
##   (int)   (dbl)     (dbl)     (dbl)
## 1     1      -30  10.036665     1301
## 2     2      -33  10.816843      853
## 3     3      -25  13.227076      911
## 4     4      -21  13.938038      960
## 5     5      -24  12.986859      878
## 6     6      -21  20.846332     1137
## 7     7      -22  21.727787     1005
## 8     8      -26  12.611040      520
## 9     9      -24   6.722476     1014
## 10    10      -25   6.243988      702
## 11    11      -32   5.435362      798
## 12    12      -43  16.576688      896
```

```
# flights %>% group_by(month) %>%
#   summarise(min_delay = min(dep_delay, na.rm=TRUE),
#   mean_delay = mean(dep_delay, na.rm=TRUE),
#   max_delay = max(dep_delay, na.rm=TRUE))
```

2.7.2 Exercise 2

Calculate number of flights (using `n()` operator), mean delay at departure and at arrival for flights by origin.

Remember to add `na.rm=TRUE` option to mean calculations.

```
by_origin <- group_by(flights, origin)

summarise(by_origin, n_flights = n(),
          mean_dep_delay = mean(dep_delay, na.rm=TRUE),
          mean_arr_delay = mean(arr_delay, na.rm=TRUE))
```

```
## Source: local data frame [3 x 4]
##
##   origin n_flights mean_dep_delay mean_arr_delay
##   (chr)   (int)     (dbl)         (dbl)
## 1   EWR    120835   15.10795         1109
## 2   JFK    111279   12.11216         1272
## 3   LGA    104662   10.34688          915
```

```
# flights %>% group_by(origin) %>%
#   summarise(n_flights = n(),
#   mean_dep_delay = mean(dep_delay, na.rm=TRUE),
#   mean_arr_delay = max(arr_delay, na.rm=TRUE))
```

2.8 Chain multiple operations (%>%)

2.8.1 Exercise 1

Calculate number of flights, minimum, mean and maximum delay at departure for flights by month.

Remember to add `na.rm=TRUE` option to all calculations.

```
flights %>% group_by(month) %>%
  summarise(min_delay = min(dep_delay, na.rm=TRUE),
  mean_delay = mean(dep_delay, na.rm=TRUE),
  max_delay = max(dep_delay, na.rm=TRUE))
```

```
## Source: local data frame [12 x 4]
##
##   month min_delay mean_delay max_delay
##   (int)   (dbl)      (dbl)      (dbl)
## 1     1      -30  10.036665    1301
## 2     2      -33  10.816843     853
## 3     3      -25  13.227076     911
## 4     4      -21  13.938038     960
## 5     5      -24  12.986859     878
## 6     6      -21  20.846332    1137
## 7     7      -22  21.727787    1005
## 8     8      -26  12.611040     520
## 9     9      -24   6.722476    1014
## 10    10      -25   6.243988     702
## 11    11      -32   5.435362     798
## 12    12      -43  16.576688     896
```

2.8.2 Exercise 2

Calculate the monthly mean gained time in minutes, where the gained time is defined as the difference between delay at departure and delay at arrival. Remember to add `na.rm=TRUE` option to mean calculations.

```
flights %>% group_by(month) %>%
  mutate(gain = dep_delay - arr_delay) %>%
  summarise(mean_gain = mean(gain, na.rm=TRUE))
```

```
## Source: local data frame [12 x 2]
##
##   month mean_gain
##   (int)      (dbl)
## 1     1  3.855519
## 2     2  5.147220
## 3     3  7.356713
## 4     4  2.673124
## 5     5  9.370201
## 6     6  4.244284
## 7     7  4.810872
## 8     8  6.529872
## 9     9 10.648649
## 10    10  6.400238
## 11    11  4.958993
## 12    12  1.611806
```

2.8.3 Exercise 3

For each destination, select all days where the mean delay at arrival is greater than 30 minutes. Remember to add `na.rm=TRUE` option to mean calculations.

```
flights %>% group_by(dest) %>%
  summarise(mean_arr_delay = mean(arr_delay, na.rm=TRUE)) %>%
  filter(mean_arr_delay > 30)

## Source: local data frame [3 x 2]
##
##   dest mean_arr_delay
##   (chr)      (dbl)
## 1  CAE      41.76415
## 2  OKC      30.61905
## 3  TUL      33.65986
```

Chapter 3

Data Visualization with ggplot2

Load ggplot2 package, supposing it is already installed.

```
require(ggplot2)
```

3.1 Data

3.1.1 iris

Almost all the following exercises are based on the `iris` dataset, taken from the `datasets` package.

It is a base package so it is already installed and loaded.

```
data("iris")
```

This dataset gives the measurements in centimeters of length and width of sepal and petal, respectively, for 50 flowers from each of 3 species of iris. The species are *Iris setosa*, *versicolor*, and *virginica*.

`iris` dataset contains the following variables:

- `Sepal.Length`: length of iris sepal
- `Sepal.Width`: width of iris sepal
- `Petal.Length`: length of iris petal
- `Petal.Width`: width of iris petal
- `Species`: species of iris

```
dim(iris)
```

```
## [1] 150 5
```

```
head(iris)
```

```
##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1         5.1         3.5         1.4         0.2   setosa
## 2         4.9         3.0         1.4         0.2   setosa
## 3         4.7         3.2         1.3         0.2   setosa
## 4         4.6         3.1         1.5         0.2   setosa
## 5         5.0         3.6         1.4         0.2   setosa
## 6         5.4         3.9         1.7         0.4   setosa
```

```
str(iris)
```

```
## 'data.frame':   150 obs. of  5 variables:
##  $ Sepal.Length: num  5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
##  $ Sepal.Width : num  3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
##  $ Petal.Length: num  1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
##  $ Petal.Width : num  0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
##  $ Species     : Factor w/ 3 levels "setosa","versicolor",...: 1 1 1 1 1 1 1 1 1 1 ...
```

3.1.2 mpg

Some of the exercises are based on `mpg` dataset, taken from the `ggplot2` package.

```
data("mpg")
```

This dataset contains the fuel economy data from 1999 and 2008 for 38 popular models of car. `mpg` dataset contains the following variables:

- `manufacturer`
- `model`
- `displ`: engine displacement, in litres
- `year`
- `cyl`: number of cylinders
- `trans`: type of transmission
- `drv`: drivetrain type, f = front-wheel drive, r = rear wheel drive, 4 = 4wd
- `cty`: city miles per gallon

- hwy: highway miles per gallon
- fl: fuel type

```
dim(mpg)
```

```
## [1] 234 11
```

```
head(mpg)
```

```
##   manufacturer model displ year cyl      trans drv  cty   hwy fl    class
## 1          audi   a4    1.8 1999   4   auto(l5)  f   18   29  p compact
## 2          audi   a4    1.8 1999   4 manual(m5)  f   21   29  p compact
## 3          audi   a4    2.0 2008   4 manual(m6)  f   20   31  p compact
## 4          audi   a4    2.0 2008   4   auto(av)  f   21   30  p compact
## 5          audi   a4    2.8 1999   6   auto(l5)  f   16   26  p compact
## 6          audi   a4    2.8 1999   6 manual(m5)  f   18   26  p compact
```

```
str(mpg)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':   234 obs. of  11 variables:
## $ manufacturer: chr  "audi" "audi" "audi" "audi" ...
## $ model       : chr  "a4" "a4" "a4" "a4" ...
## $ displ       : num  1.8 1.8 2 2 2.8 2.8 3.1 1.8 1.8 2 ...
## $ year        : int  1999 1999 2008 2008 1999 1999 2008 1999 1999 2008 ...
## $ cyl         : int  4 4 4 4 6 6 6 4 4 4 ...
## $ trans       : chr  "auto(l5)" "manual(m5)" "manual(m6)" "auto(av)" ...
## $ drv         : chr  "f" "f" "f" "f" ...
## $ cty         : int  18 21 20 21 16 18 18 18 16 20 ...
## $ hwy         : int  29 29 31 30 26 26 27 26 25 28 ...
## $ fl         : chr  "p" "p" "p" "p" ...
## $ class       : chr  "compact" "compact" "compact" "compact" ...
```

3.2 Scatterplot

Let us consider `iris` dataset.

3.2.1 Exercise 1

- a. Generate a scatterplot to analyze the relationship between `Sepal.Width` and `Sepal.Length` variables.
- b. Set the size of the point as 3 and their colour (`colour` and `fill` arguments as “green”).

```
pl <- ggplot(data = iris, mapping = aes(x=Sepal.Width, y=Sepal.Length)) +  
  geom_point(size=3, colour="green", fill="green")  
pl
```

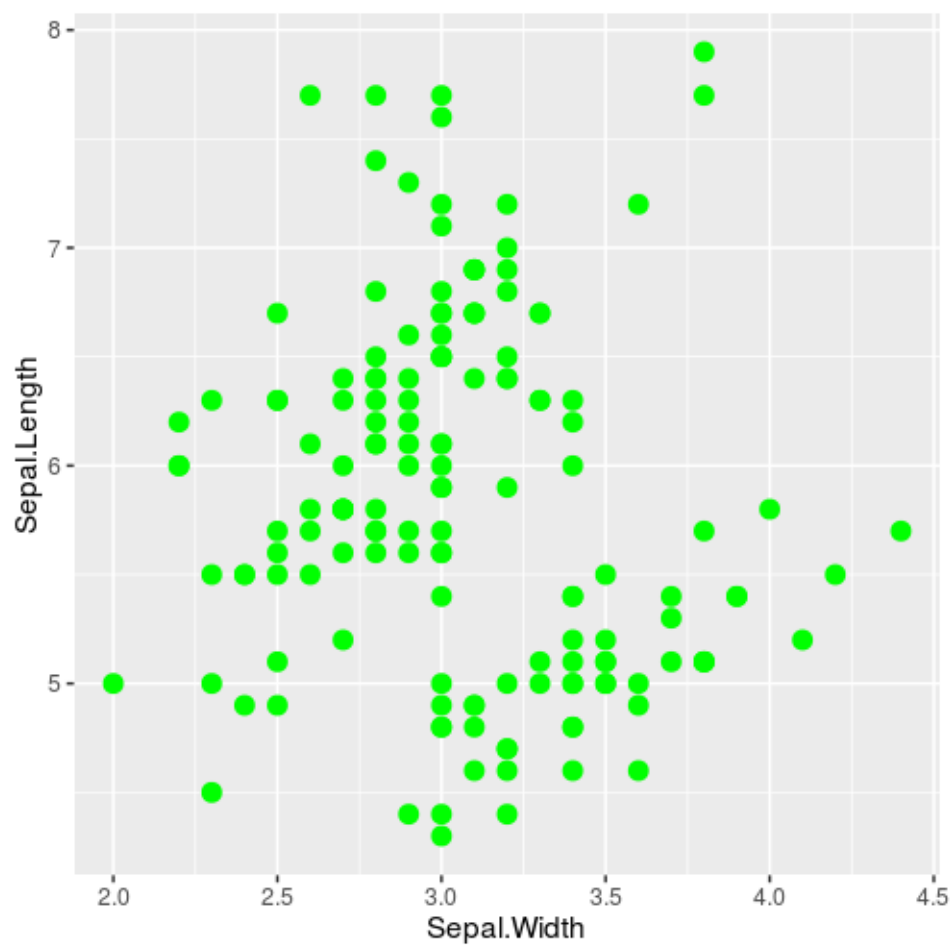



Figure 3.1:

3.2.2 Exercise 2

- a. Generate a scatterplot to analyze the relationship between `Petal.Width` and `Petal.Length` variables according to iris species, mapped as `colour` aes.

```
p1 <- ggplot(data = iris, mapping = aes(x=Sepal.Width, y=Sepal.Length, colour=Species)) +  
  geom_point()  
p1
```

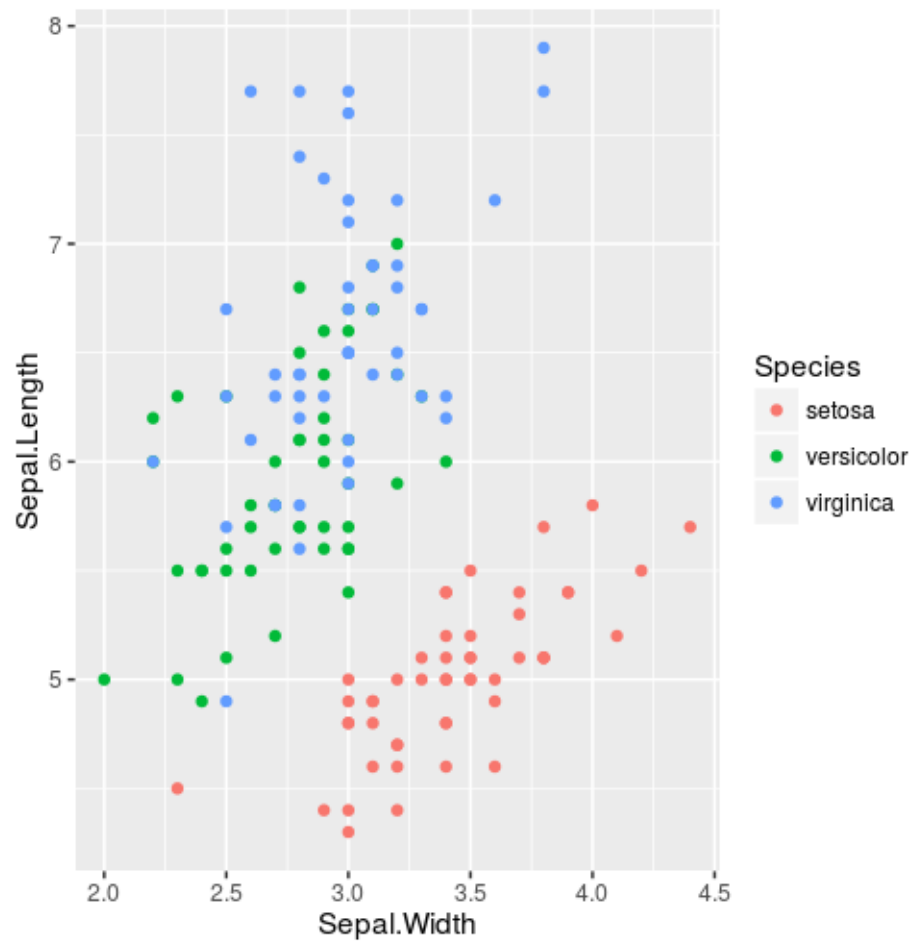


Figure 3.2:

3.3 Box Plot

Let us consider `iris` dataset.

3.3.1 Exercise 1

- Build a box plot to compare the differences of sepal width accordingly to the type of iris species.
- Set the fill colour of boxes as “#00FFFF”, the lines colour of boxes as “#0000FF” and the outliers colour as “red”.
- Add the plot title: “Boxplot of Sepal.Width vs Species”

```
p1 <- ggplot(data=iris, aes(x=Species, y=Sepal.Width)) +  
  geom_boxplot(fill="#00FFFF", colour="#0000FF", outlier.colour = "red") +  
  ggtitle("Boxplot of Sepal.Width vs Species")  
p1
```

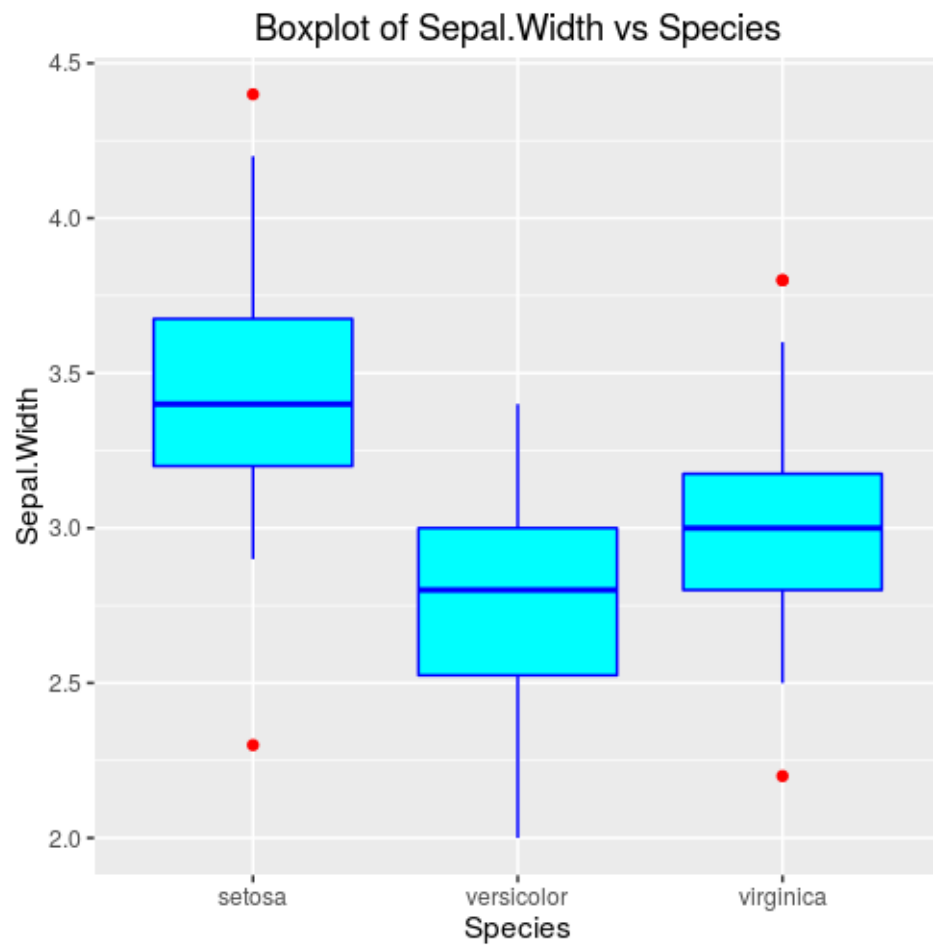


Figure 3.3:

3.4 Histogram

Let us consider `iris` dataset.

3.4.1 Exercise 1

- Represent the distribution of `Sepal.Length` variable with an histogram.
- Set bins fill colour as “hotpink” and bins line colour as “deeppink”.
- Set the number of bins as 15.

```
p1 <- ggplot(data=iris, aes(x=Sepal.Length)) +  
  geom_histogram(fill="hotpink", colour="deeppink", bins=15)  
p1
```

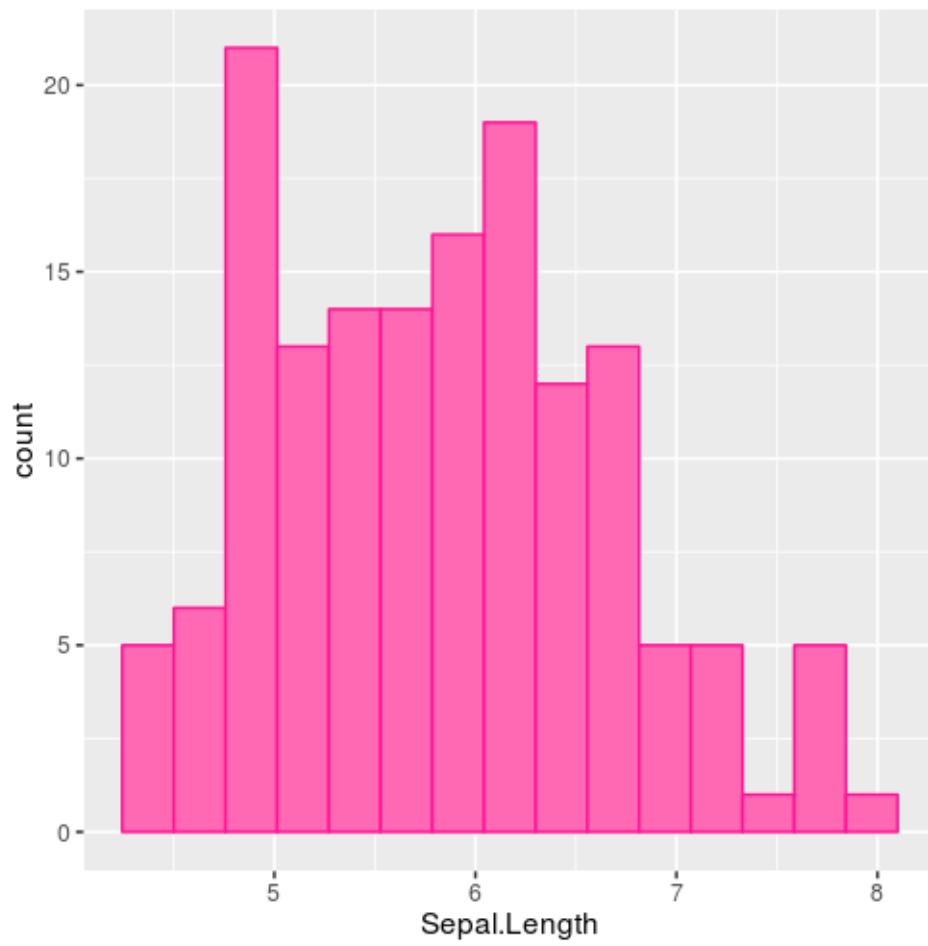


Figure 3.4:

3.5 Line graph

3.5.1 Exercise 1

Let us suppose that the observations on `iris` are taken along time.

So let us consider the following dataset, named `iris2`, in which `time` variable is added:

```
require(dplyr)
iris2 <- iris %>% mutate(time=1:150)
```

- Build a line graph to visualize the measures of `Sepal.Length` variable along time.

```
ggplot(data = iris2, mapping = aes(y=Sepal.Width, x= time)) + geom_line()
```

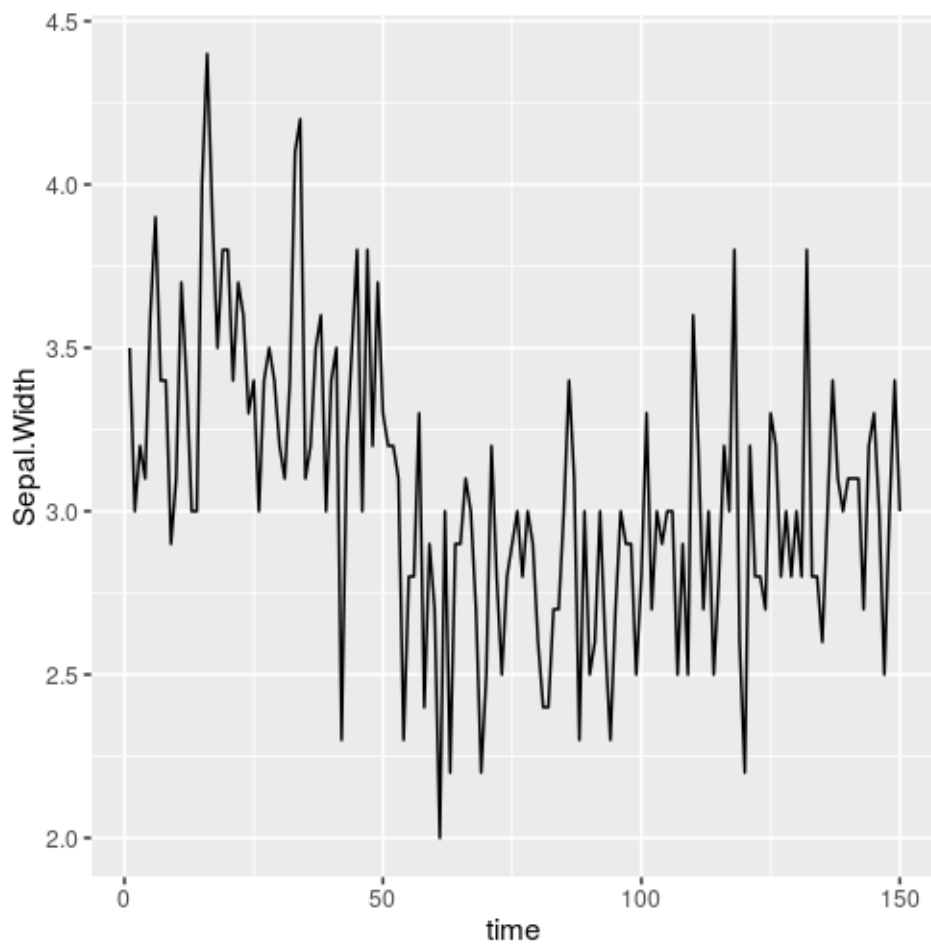


Figure 3.5:

3.5.2 Exercise 2

Let us suppose that the observations on `iris` are taken along time.

So let us consider the following dataset, named `iris3`, in which `time` variable is added:

```
iris3 <- iris %>% mutate(time=rep(1:50, times=3))
```

- Build a line graph to visualize the measures of `Sepal.Length` variable along time, according to the `Species` variable, mapped as `colour` aes.
- Set `linetype` as “twodash”.

```
ggplot(data = iris3, mapping = aes(y=Sepal.Length, x= time, colour=Species)) +  
  geom_line(linetype=6)
```

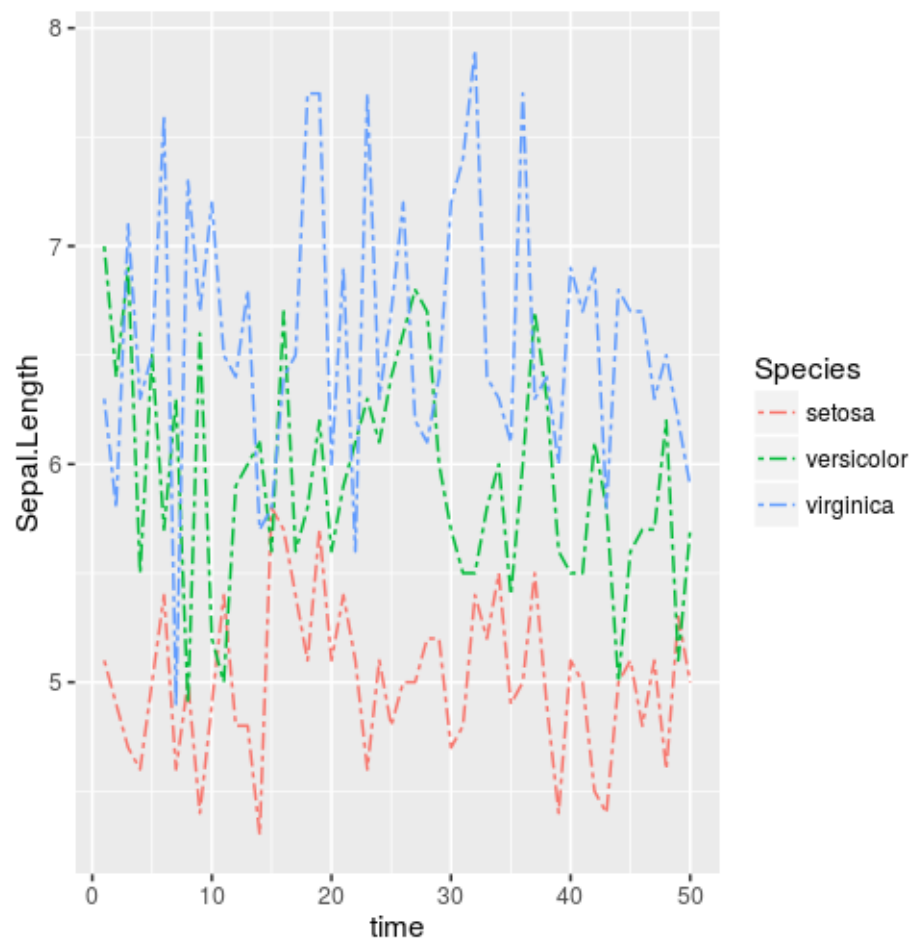


Figure 3.6:

3.6 Bar graph

Let us consider mpg dataset.

3.6.1 Exercise 1

- Represent graphically with a bar graph how many cars there are for each class.
- Represent horizontal bars and set bars width as 0.6.

```
p1 <- ggplot(mpg, aes(class)) +  
  coord_flip() +  
  geom_bar(width=0.6)  
p1
```

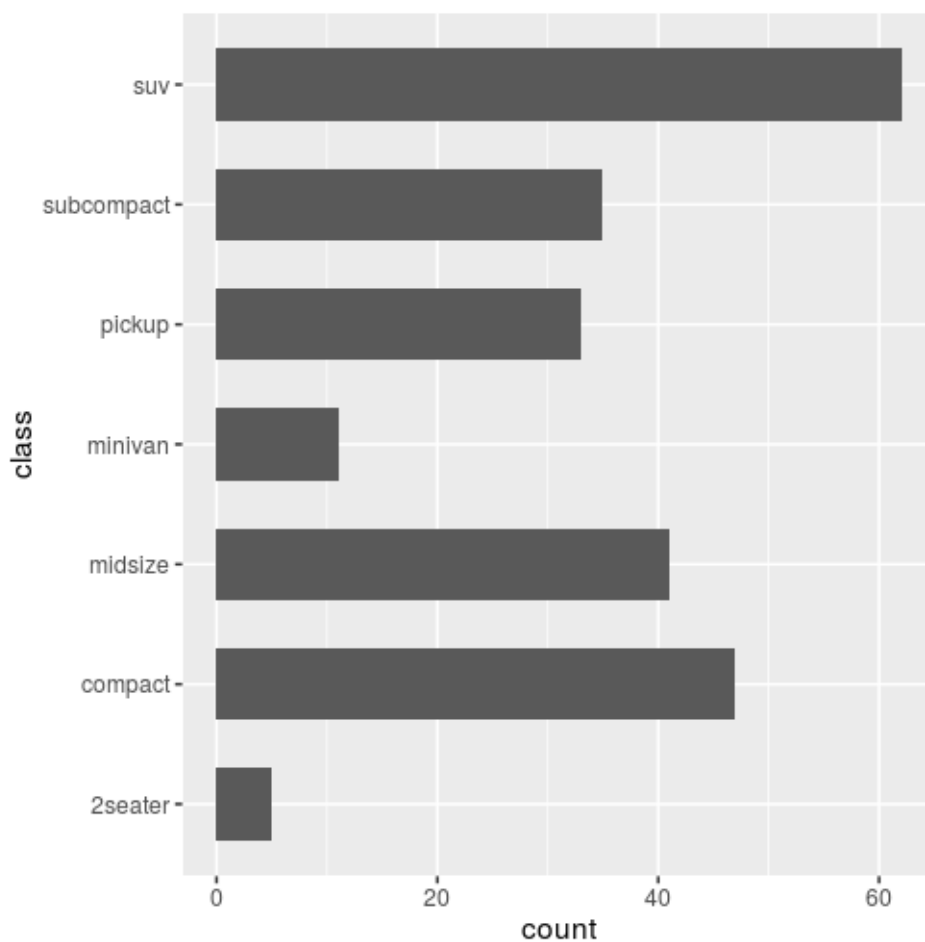


Figure 3.7:

3.6.2 Exercise 2

- a. Represent graphically with a bar graph how many cars there are for each class according to manufacturer.

```
p1 <- ggplot(mpg, aes(class, fill=manufacturer)) +  
  geom_bar()  
p1
```

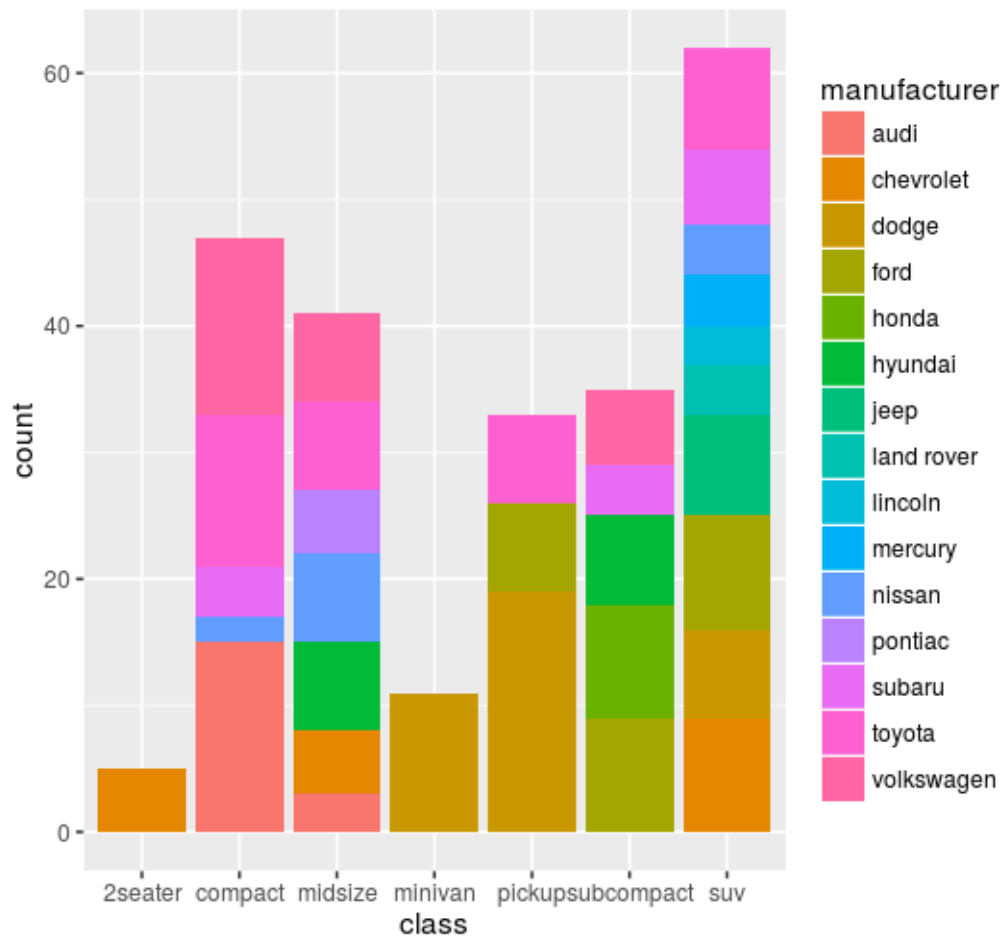


Figure 3.8:

- b. Represent graphically with a bar graph, the distribution of manufacturer for each class (set position argument of `geom_bar`).

```
p1 <- ggplot(mpg, aes(class, fill=manufacturer)) +  
  geom_bar(position = "fill")  
p1
```

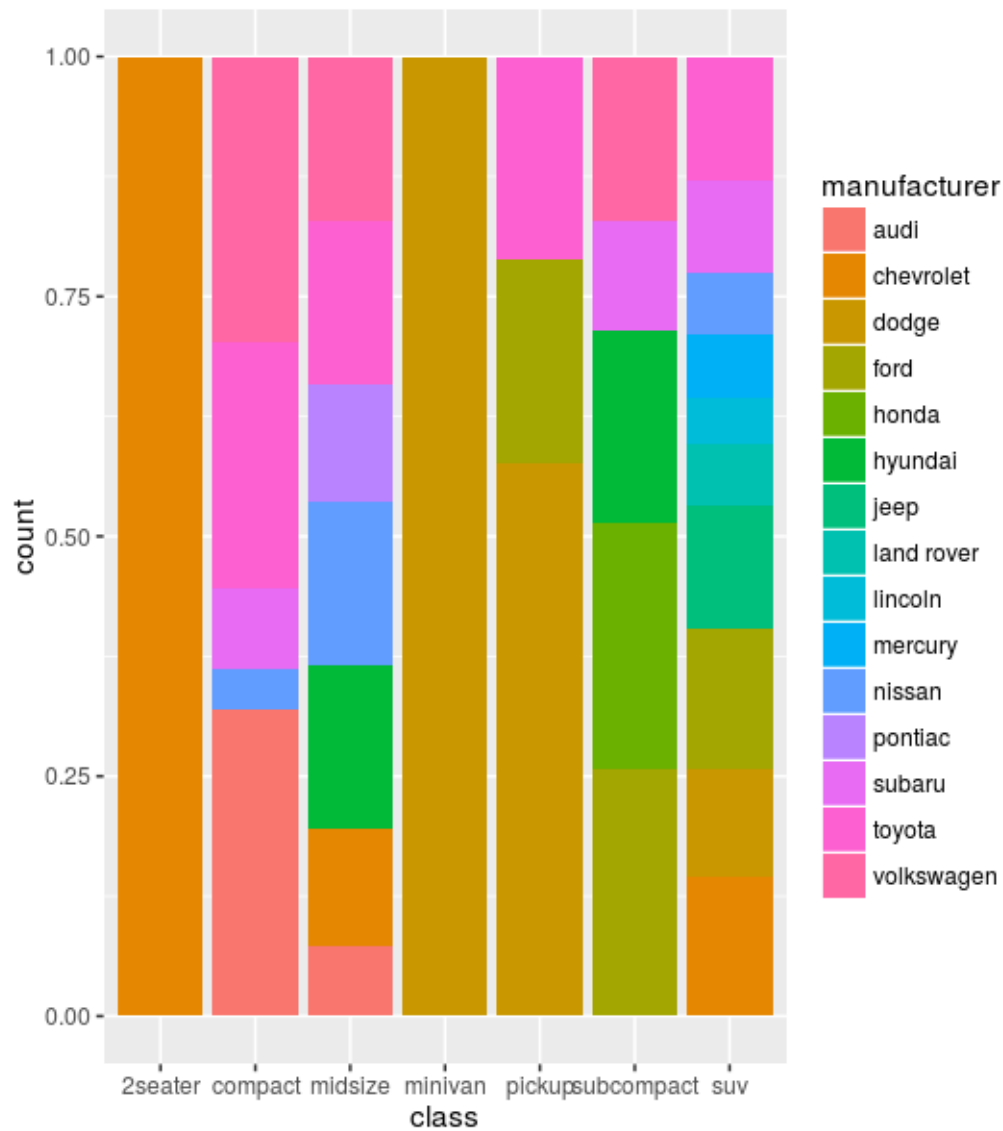


Figure 3.9:

Chapter 4

Writing R functions

4.1 Exercise 1

Write a function, named `compute_summary`, which computes: sum, subtraction, multiplication and division of two numbers. The function arguments should be the two numbers, named as: `x` and `y`. The function should return all amounts computed.

```
compute_summary <- function(x, y){  
  sum_op <- x+y  
  sub_op <- x-y  
  mul_op <- x*y  
  div_op <- x/y  
  return(list(sum_op=sum_op, sub_op=sub_op, mul_op=mul_op, div_op=div_op))  
}
```

```
compute_summary(x=4, y=2)
```

```
## $sum_op  
## [1] 6  
##  
## $sub_op  
## [1] 2  
##  
## $mul_op  
## [1] 8  
##  
## $div_op  
## [1] 2
```

```
compute_summary(x=3, y=7)
```

```
## $sum_op
## [1] 10
##
## $sub_op
## [1] -4
##
## $mul_op
## [1] 21
##
## $div_op
## [1] 0.4285714
```

4.2 Exercise 2

Write a function, named `compute_gain`, which computes the income by multiplying the amount produced for sale price and then computes the gain by subtracting the costs to income. The function arguments should be: `amount`, `price`, and `costs`; `price` should have a default value equal to 5. The function should return the gain.

```
compute_gain <- function(amount, costs, price=5){
  income = amount * price
  gain = income - costs
  return(gain)
}

compute_gain(amount = 40, costs = 50)

## [1] 150

compute_gain(amount = 100, costs = 70, price = 1)

## [1] 30
```