ISL Ch5 Lab and Exercises

```
library(tidyverse)
```

```
## -- Attaching packages ---------------------------------------------------------------------------
## v ggplot2 3.3.0     v purrr   0.3.3
## v tibble  3.0.1     v dplyr   0.8.5
## v tidyr   1.0.2     v stringr 1.4.0
## v readr   1.3.1     v forcats 0.5.0
## -- Conflicts ------------------------------------------------------------------------------------
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
set.seed(1)
x <- 1:12
# a random permutation
is.integer(sample(x))
```

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

```
# bootstrap resampling -- only if length(x) > 1 !
sample(x, replace = TRUE)
```

```
##  [1]  5 10  6 10  7  9  5  5  9  9  5  5
```

```
# 100 Bernoulli trials
sample(c(0,1), 100, replace = TRUE)
```

```
##   [1] 1 1 1 0 1 0 0 1 0 1 1 1 1 0 1 1 1 1 1 0 0 1 0 1 1 0 0 1 1 1 0 0 1 1 1 1 1
##  [38] 1 0 1 1 1 1 0 0 0 1 1 0 0 1 1 1 0 0 0 1 0 1 0 1 0 0 1 1 0 0 0 1 1 0 1 1 1
##  [75] 0 0 0 0 1 0 0 0 0 0 1 1 1 1 0 1 1 1 1 0 0 1 0 0 1 1
```

```
# create divide a dataframe into folds using samples:

(theDf <- tibble(x=1:56))
```

```
## # A tibble: 56 x 1
##        x
##    <int>
##  1     1
##  2     2
##  3     3
##  4     4
##  5     5
##  6     6
##  7     7
##  8     8
##  9     9
## 10    10
## # ... with 46 more rows
```

```r
k = 10
folds <- sample(1:k, size = nrow(theDf), replace = T) #10 fold CV
table(folds)
```

```
## folds
##  1  2  3  4  5  6  7  8  9 10
##  8  6 10  3  4  5  5  5  4  6
```

```r
# folds with same size
sameSizefolds <- sample(rep(1:k, length.out = nrow(theDf)), size = nrow(theDf), replace = F)
table(sameSizefolds)
```

```
## sameSizefolds
##  1  2  3  4  5  6  7  8  9 10
##  6  6  6  6  6  6  5  5  5  5
```

```r
# train data set
theDf[folds != 3, ]
```

```
## # A tibble: 46 x 1
##        x
##    <int>
##  1     1
##  2     2
##  3     3
##  4     4
##  5     5
##  6     6
##  7     7
##  8     8
##  9     9
## 10    10
## # ... with 36 more rows
```

```r
# test data set
theDf[folds == 3, ]
```

```
## # A tibble: 10 x 1
##        x
##    <int>
##  1    13
##  2    15
##  3    23
##  4    25
##  5    27
##  6    28
##  7    41
##  8    43
##  9    53
## 10    56
```

```r
## More careful bootstrapping --  Consider this when using sample()
## programmatically (i.e., in your function or simulation)!

# sample()'s surprise -- example
# x <- 1:10
#     sample(x[x >  8]) # length 2
```

```
#     sample(x[x >  9]) # oops -- length 10: If x has length 1, is numeric and x >= 1, sampling via sam
#     sample(x[x > 10]) # length 0
#
# ## safer version:
# x[sample.int(length(x)) >  8] # length 2
# x[sample.int(length(x)) >  9] # length 1
# x[sample.int(length(x)) >  10] # length 0
#
# ## R 3.x.y only
# sample.int(1e10, 12, replace = TRUE)
# sample.int(1e10, 12) # not that there is much chance of duplicates
```

```
library(tidyverse)
# Sample fixed number per group
auto.df = read.csv("/Users/shahrdadshadab/env/my-R-project/ISLR/Data/Auto.csv", header=T, stringsAsFact

(auto.df = as_tibble(auto.df))
```

```
## # A tibble: 397 x 9
##      mpg cylinders displacement horsepower weight acceleration  year origin
##    <dbl>     <int>        <dbl>      <int>  <int>        <dbl> <int>  <int>
##  1    18         8          307        130   3504         12      70      1
##  2    15         8          350        165   3693         11.5    70      1
##  3    18         8          318        150   3436         11      70      1
##  4    16         8          304        150   3433         12      70      1
##  5    17         8          302        140   3449         10.5    70      1
##  6    15         8          429        198   4341         10      70      1
##  7    14         8          454        220   4354          9      70      1
##  8    14         8          440        215   4312          8.5    70      1
##  9    14         8          455        225   4425         10      70      1
## 10    15         8          390        190   3850          8.5    70      1
## # ... with 387 more rows, and 1 more variable: name <fct>
```

```
(by_cyl <- auto.df %>%
  group_by(year))
```

```
## # A tibble: 397 x 9
## # Groups:   year [13]
##      mpg cylinders displacement horsepower weight acceleration  year origin
##    <dbl>     <int>        <dbl>      <int>  <int>        <dbl> <int>  <int>
##  1    18         8          307        130   3504         12      70      1
##  2    15         8          350        165   3693         11.5    70      1
##  3    18         8          318        150   3436         11      70      1
##  4    16         8          304        150   3433         12      70      1
##  5    17         8          302        140   3449         10.5    70      1
##  6    15         8          429        198   4341         10      70      1
##  7    14         8          454        220   4354          9      70      1
##  8    14         8          440        215   4312          8.5    70      1
##  9    14         8          455        225   4425         10      70      1
## 10    15         8          390        190   3850          8.5    70      1
## # ... with 387 more rows, and 1 more variable: name <fct>
```

```
sample_n(auto.df, 10)
```

```
## # A tibble: 10 x 9
```

```
##      mpg cylinders displacement horsepower weight acceleration  year origin
##    <dbl>     <int>        <dbl>      <int>  <int>        <dbl> <int>  <int>
##  1  29           4           97         75   2171         16      75      3
##  2  36.4         5          121         67   2950         19.9    80      2
##  3  15           8          350        145   4082         13      73      1
##  4  33.7         4          107         75   2210         14.4    81      3
##  5  19           4          122         85   2310         18.5    73      1
##  6  29           4           97         78   1940         14.5    77      2
##  7  19           4          121        112   2868         15.5    73      2
##  8  15           8          304        150   3892         12.5    72      1
##  9  10           8          307        200   4376         15      70      1
## 10  14           8          351        153   4154         13.5    71      1
## # ... with 1 more variable: name <fct>
```

```
sample_n(auto.df, 50, replace = TRUE)
```

```
## # A tibble: 50 x 9
##      mpg cylinders displacement horsepower weight acceleration  year origin
##    <dbl>     <int>        <dbl>      <int>  <int>        <dbl> <int>  <int>
##  1  24           4          113         95   2372         15      70      3
##  2  31.9         4           89         71   1925         14      79      2
##  3  21           4          122         86   2226         16.5    72      1
##  4  32           4          144         96   2665         13.9    82      3
##  5  32           4           71         65   1836         21      74      3
##  6  16           6          225        105   3439         15.5    71      1
##  7  36           4          107         75   2205         14.5    82      3
##  8  34.5         4          100         NA   2320         15.8    81      2
##  9  18           4          121        112   2933         14.5    72      2
## 10  12           8          400        167   4906         12.5    73      1
## # ... with 40 more rows, and 1 more variable: name <fct>
```

```
sample_n(auto.df, 10, weight = as.integer(mpg))
```

```
## # A tibble: 10 x 9
##      mpg cylinders displacement horsepower weight acceleration  year origin
##    <dbl>     <int>        <dbl>      <int>  <int>        <dbl> <int>  <int>
##  1  24           4          140         92   2865         16.4    82      1
##  2  17           8          260        110   4060         19      77      1
##  3  38           4           91         67   1995         16.2    82      3
##  4  20.5         6          200         95   3155         18.2    78      1
##  5  21.5         6          231        115   3245         15.4    79      1
##  6  27           4          112         88   2640         18.6    82      1
##  7  27.2         4          119         97   2300         14.7    78      3
##  8  25.1         4          140         88   2720         15.4    78      1
##  9  14           8          340        160   3609          8      70      1
## 10  32           4           91         67   1965         15.7    82      3
## # ... with 1 more variable: name <fct>
```

```
sample_n(by_cyl, 3)
```

```
## # A tibble: 39 x 9
## # Groups:   year [13]
##      mpg cylinders displacement horsepower weight acceleration  year origin
##    <dbl>     <int>        <dbl>      <int>  <int>        <dbl> <int>  <int>
##  1    14         8          455        225   4425         10      70      1
##  2    26         4           97         46   1835         20.5    70      2
```

```
##  3    15         8          350        165   3693         11.5    70      1
##  4    19         6          232        100   2634         13      71      1
##  5    14         8          400        175   4464         11.5    71      1
##  6    28         4          140         90   2264         15.5    71      1
##  7    18         4          121        112   2933         14.5    72      2
##  8    28         4           98         80   2164         15      72      1
##  9    23         4           97         54   2254         23.5    72      2
## 10    24         4          121        110   2660         14      73      2
## # ... with 29 more rows, and 1 more variable: name <fct>
```

```
sample_n(by_cyl, 10, replace = TRUE)
```

```
## # A tibble: 130 x 9
## # Groups:   year [13]
##      mpg cylinders displacement horsepower weight acceleration  year origin
##    <dbl>     <int>        <dbl>      <int>  <int>        <dbl> <int>  <int>
##  1    18         8          318        150   3436         11      70      1
##  2    15         8          390        190   3850          8.5    70      1
##  3    15         8          429        198   4341         10      70      1
##  4    11         8          318        210   4382         13.5    70      1
##  5    14         8          454        220   4354          9      70      1
##  6    18         6          199         97   2774         15.5    70      1
##  7    18         8          307        130   3504         12      70      1
##  8    25         4          104         95   2375         17.5    70      2
##  9    18         8          307        130   3504         12      70      1
## 10    18         8          318        150   3436         11      70      1
## # ... with 120 more rows, and 1 more variable: name <fct>
```

```
sample_n(by_cyl, 3, weight = mpg / mean(mpg))
```

```
## # A tibble: 39 x 9
## # Groups:   year [13]
##      mpg cylinders displacement horsepower weight acceleration  year origin
##    <dbl>     <int>        <dbl>      <int>  <int>        <dbl> <int>  <int>
##  1    22         6          198         95   2833         15.5    70      1
##  2    10         8          307        200   4376         15      70      1
##  3    15         8          400        150   3761          9.5    70      1
##  4    35         4           72         69   1613         18      71      3
##  5    19         6          232        100   2634         13      71      1
##  6    26         4           91         70   1955         20.5    71      1
##  7    28         4           98         80   2164         15      72      1
##  8    21         4          120         87   2979         19.5    72      2
##  9    12         8          350        160   4456         13.5    72      1
## 10    14         8          318        150   4237         14.5    73      1
## # ... with 29 more rows, and 1 more variable: name <fct>
```

```
# Sample fixed fraction per group
# Default is to sample all data = randomly resample rows
sample_frac(auto.df)
```

```
## # A tibble: 397 x 9
##      mpg cylinders displacement horsepower weight acceleration  year origin
##    <dbl>     <int>        <dbl>      <int>  <int>        <dbl> <int>  <int>
##  1  29           4           90         70   1937         14      75      2
##  2  14           8          454        220   4354          9      70      1
##  3  18           3           70         90   2124         13.5    73      3
```

```
##  4  10           8          307        200   4376         15      70      1
##  5  30.5         4           97         78   2190         14.1    77      2
##  6  23           8          350        125   3900         17.4    79      1
##  7  20.2         6          200         85   2965         15.8    78      1
##  8  18           6          225        105   3613         16.5    74      1
##  9  13           8          350        175   4100         13      73      1
## 10  13           8          400        175   5140         12      71      1
## # ... with 387 more rows, and 1 more variable: name <fct>
```

```
sample_frac(auto.df, 0.1)
```

```
## # A tibble: 40 x 9
##      mpg cylinders displacement horsepower weight acceleration  year origin
##    <dbl>     <int>        <dbl>      <int>  <int>        <dbl> <int>  <int>
##  1  26.4         4          140         88   2870         18.1    80      1
##  2  32.2         4          108         75   2265         15.2    80      3
##  3  16           8          351        149   4335         14.5    77      1
##  4  28           4          116         90   2123         14      71      2
##  5  27.5         4          134         95   2560         14.2    78      3
##  6  27           4           97         60   1834         19      71      2
##  7  27.2         4          141         71   3190         24.8    79      2
##  8  20           6          156        122   2807         13.5    73      3
##  9  19           4          121        112   2868         15.5    73      2
## 10  25           4          104         95   2375         17.5    70      2
## # ... with 30 more rows, and 1 more variable: name <fct>
```

```
sample_frac(auto.df, 1.5, replace = TRUE)
```

```
## # A tibble: 596 x 9
##      mpg cylinders displacement horsepower weight acceleration  year origin
##    <dbl>     <int>        <dbl>      <int>  <int>        <dbl> <int>  <int>
##  1  44           4           97         52   2130         24.6    82      2
##  2  18           4          121        112   2933         14.5    72      2
##  3  25           4          140         92   2572         14.9    76      1
##  4  27.5         4          134         95   2560         14.2    78      3
##  5  19           4          122         85   2310         18.5    73      1
##  6  21           6          155        107   2472         14      73      1
##  7  22           6          225        100   3233         15.4    76      1
##  8  32.3         4           97         67   2065         17.8    81      3
##  9  15.5         8          350        170   4165         11.4    77      1
## 10  30.5         4           98         63   2051         17      77      1
## # ... with 586 more rows, and 1 more variable: name <fct>
```

```
sample_frac(auto.df, 0.1, weight = 1 / mpg)
```

```
## # A tibble: 40 x 9
##      mpg cylinders displacement horsepower weight acceleration  year origin
##    <dbl>     <int>        <dbl>      <int>  <int>        <dbl> <int>  <int>
##  1  26           4           97         46   1950         21      73      2
##  2  28.4         4          151         90   2670         16      79      1
##  3  16           6          250        100   3278         18      73      1
##  4  25           4          116         81   2220         16.9    76      2
##  5  15           8          350        165   3693         11.5    70      1
##  6  16           6          225        105   3439         15.5    71      1
##  7  24           4          134         96   2702         13.5    75      3
##  8  18           6          171         97   2984         14.5    75      1
```

```
##  9  29.8         4          134         90   2711         15.5    80      3
## 10  20          8          262        110   3221         13.5    75      1
## # ... with 30 more rows, and 1 more variable: name <fct>
```

```
sample_frac(by_cyl, 0.2)
```

```
## # A tibble: 81 x 9
## # Groups:   year [13]
##      mpg cylinders displacement horsepower weight acceleration  year origin
##    <dbl>     <int>        <dbl>      <int>  <int>        <dbl> <int>  <int>
##  1    15         8          429        198   4341         10      70      1
##  2    24         4          113         95   2372         15      70      3
##  3    26         4          121        113   2234         12.5    70      2
##  4    15         8          390        190   3850          8.5    70      1
##  5    27         4           97         88   2130         14.5    70      3
##  6    15         8          383        170   3563         10      70      1
##  7    35         4           72         69   1613         18      71      3
##  8    14         8          400        175   4464         11.5    71      1
##  9    25         4          113         95   2228         14      71      3
## 10    13         8          400        170   4746         12      71      1
## # ... with 71 more rows, and 1 more variable: name <fct>
```

```
sample_frac(by_cyl, 1, replace = TRUE)
```

```
## # A tibble: 397 x 9
## # Groups:   year [13]
##      mpg cylinders displacement horsepower weight acceleration  year origin
##    <dbl>     <int>        <dbl>      <int>  <int>        <dbl> <int>  <int>
##  1    14         8          455        225   4425         10      70      1
##  2    15         8          350        165   3693         11.5    70      1
##  3    14         8          455        225   4425         10      70      1
##  4    15         8          383        170   3563         10      70      1
##  5    14         8          440        215   4312          8.5    70      1
##  6    26         4          121        113   2234         12.5    70      2
##  7    15         8          429        198   4341         10      70      1
##  8    16         8          304        150   3433         12      70      1
##  9    10         8          307        200   4376         15      70      1
## 10    15         8          390        190   3850          8.5    70      1
## # ... with 387 more rows, and 1 more variable: name <fct>
```

```
library(tidyverse)

auto.df = read.csv("/Users/shahrdadshadab/env/my-R-project/ISLR/Data/Auto.csv", header=T, stringsAsFacto
(auto.df = as_tibble(auto.df))
```

```
## # A tibble: 397 x 9
##      mpg cylinders displacement horsepower weight acceleration  year origin
##    <dbl>     <int>        <dbl>      <int>  <int>        <dbl> <int>  <int>
##  1    18         8          307        130   3504         12      70      1
##  2    15         8          350        165   3693         11.5    70      1
##  3    18         8          318        150   3436         11      70      1
##  4    16         8          304        150   3433         12      70      1
##  5    17         8          302        140   3449         10.5    70      1
##  6    15         8          429        198   4341         10      70      1
##  7    14         8          454        220   4354          9      70      1
##  8    14         8          440        215   4312          8.5    70      1
```

```
##  9    14         8          455        225   4425         10      70      1
## 10    15         8          390        190   3850          8.5    70      1
## # ... with 387 more rows, and 1 more variable: name <fct>
```

```
# Check a particular column that has NA and include the record
# dfSubsetWithNaInOneCol <- auto.df[is.na(auto.df$Directions), ]
# head(dfSubsetWithNaInOneCol)

# get a subset of records in dataframe with no NA in any column:
auto.df <- auto.df[rowSums(is.na(auto.df)) == 0, ]

# Now find a subset of records that have at least one NA
auto.df[rowSums(is.na(auto.df)) > 0,]
```

```
## # A tibble: 0 x 9
## # ... with 9 variables: mpg <dbl>, cylinders <int>, displacement <dbl>,
## #   horsepower <int>, weight <int>, acceleration <dbl>, year <int>,
## #   origin <int>, name <fct>
```

```
set.seed(1)

train <- sample(dim(auto.df)[1],196) # choose a sample of size 196 from row indices of dataframe auto.d

lm.fit <- lm(mpg ~ horsepower, data = auto.df, subset = train)

# test error MSE
mean((auto.df$mpg - predict(lm.fit, auto.df))[-train]^2, na.rm = T)
```

```
## [1] 23.26601
```

```
# claculate test.mse for polynimial regression

lm.fit2 <- lm(mpg~poly(horsepower, 2), data=auto.df, subset = train)

# test error MSE
mean((auto.df$mpg - predict(lm.fit2, auto.df))[-train]^2, na.rm = T)
```

```
## [1] 18.71646
```

```
# claculate test.mse for  cubic regression

lm.fit3 <- lm(mpg~poly(horsepower, 3), data=auto.df, subset = train)

# test error MSE
mean((auto.df$mpg - predict(lm.fit3, auto.df))[-train]^2, na.rm = T)
```

```
## [1] 18.79401
```

```
# if we sample again and create another traing sample MSE values will be different
train <- sample(dim(auto.df)[1],196) # choose a sample of size 196 from row indices of dataframe auto.d

lm.fit <- lm(mpg ~ horsepower, data = auto.df, subset = train)

# test error MSE
mean((auto.df$mpg - predict(lm.fit, auto.df))[-train]^2, na.rm = T)
```

```
## [1] 26.83974
```

```r
# claculate test.mse for polynimial regression

lm.fit2 <- lm(mpg~poly(horsepower, 2), data=auto.df, subset = train)

# test error MSE
mean((auto.df$mpg - predict(lm.fit2, auto.df))[-train]^2, na.rm = T)
```

```
## [1] 19.56785
```

```r
# claculate test.mse for  cubic regression

lm.fit3 <- lm(mpg~poly(horsepower, 3), data=auto.df, subset = train)

# test error MSE
mean((auto.df$mpg - predict(lm.fit3, auto.df))[-train]^2, na.rm = T)
```

```
## [1] 19.62272
```

```r
library(tidyverse)
library(boot)

auto.df = read.csv("/Users/shahrdadshadab/env/my-R-project/ISLR/Data/Auto.csv", header=T, stringsAsFacto
auto.df = as_tibble(auto.df)

# remove NAs
# is.na(auto.df)
is.matrix(is.na(auto.df))
```

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

```r
# rowSums(is.na(auto.df))

auto.df <- auto.df[rowSums(is.na(auto.df)) == 0,]

# now fit the data on the whole data
glm.fit <- glm(mpg ~ horsepower, data = auto.df)

cv.err <- cv.glm(auto.df, glm.fit)
str(cv.err)
```

```
## List of 4
##  $ call : language cv.glm(data = auto.df, glmfit = glm.fit)
##  $ K    : num 392
##  $ delta: num [1:2] 24.2 24.2
##  $ seed : int [1:626] 10403 583 1654269195 -1877109783 -961256264 1403523942 124639233 261424787 183
```

```r
cv.err$delta
```

```
## [1] 24.23151 24.23114
```

```r
# redo this for polynomials and save the results in a vector
cv.error <- NULL
for (i in 1:5){
  glm.fit <- glm(mpg ~ poly(horsepower,i), data = auto.df)
  cv.error <- rbind(cv.error, cv.glm(auto.df, glm.fit)$delta)
}
cv.error
```

```
##          [,1]     [,2]
## [1,] 24.23151 24.23114
## [2,] 19.24821 19.24787
## [3,] 19.33498 19.33448
## [4,] 19.42443 19.42371
## [5,] 19.03321 19.03242
```

```
library(tidyverse)
library(class)
library(boot)

set.seed(17)
weekly.df = read.csv("/Users/shahrdadshadab/env/my-R-project/ISLR/Data/datasets/Weekly.csv",
                     header=T, stringsAsFactors = T, na.strings = "?")
weekly.df = tibble(weekly.df)

# create k-fold
k <- 10
threshold <- 0.5

folds <- sample(1:k, size = nrow(weekly.df), replace = T) #10 fold CV
table(folds)
```

```
## folds
##   1   2   3   4   5   6   7   8   9  10
## 100 106 106 116 111 107 108  99 111 125
```

```
# folds with same size
# sameSizefolds <- sample(rep(1:k, length.out = nrow(weekly.df)), size = nrow(weekly.df), replace = F)
# table(sameSizefolds)

# Run the model by making the model on 9 folds and predicting on the hold out:

results <- lapply(1:k, function(x){  # x is the index of test portion, the rest are for training
  glm.fit <- glm(Direction ~ Lag2, data = weekly.df[folds != x,], family = binomial)
  glm.probs <- predict(glm.fit, weekly.df[folds == x,], type =  "response")
  # since contrasts(weekly.df$Direction) shows dummy variable 1 asigned to 'Up'
  # and since P(y=1|x) is glm.probs what we get is prosterior of probability of 'Up' case
  glm.pred <- ifelse(glm.probs > threshold, "Up", "Down")
  return(data.frame(probs = glm.probs, predicted = glm.pred, real = weekly.df[folds == x, ]$Direction ))
})

# calculate confusion table and other measeres

missclassificationRate = NULL
nullClassificationRate = NULL
FP_rates = NULL
TP_rates = NULL
precisions = NULL
specificities = NULL
confusionTables = NULL
aucs = NULL

library(pROC)
```

```
## Type 'citation("pROC")' for a citation.
```

```
##
## Attaching package: 'pROC'
```

```
## The following objects are masked from 'package:stats':
##
##     cov, smooth, var
```

```
for( df in results){
  confusion_table <- table(df$predicted, df$real)

  nullClassifier <- max(
    (confusion_table[1,1] + confusion_table[2,1])/(confusion_table[1,1] + confusion_table[2,1]+ confusi
    (confusion_table[1,2] + confusion_table[2,2])/(confusion_table[1,1] + confusion_table[2,1]+ confusi

  nullClassificationRate <- c(nullClassificationRate, nullClassifier)

  roc_obj <- roc(df$real, df$probs)
  aucs <- c(aucs, auc(roc_obj))

  confusionTables  <- cbind(confusionTables, confusion_table)
  missclassificationRate <- c(missclassificationRate, mean(df$predicted != df$real))
  FP_rates <- c(FP_rates, confusion_table[2,1]/(confusion_table[2,1]+ confusion_table[1,1]))
  TP_rates <- c(TP_rates, confusion_table[2,2]/(confusion_table[2,2]+ confusion_table[1,2]))
  precisions <- c(precisions, confusion_table[2,2] / (confusion_table[2,2] + confusion_table[2,1]))
  specificities <- c(specificities , 1 - confusion_table[2,1]/(confusion_table[2,1]+ confusion_table[1,

  # overall fraction of wrong predictions:
  # print(confusion_table)
}
```

```
## Setting levels: control = Down, case = Up
```

```
## Setting direction: controls > cases
```

```
## Setting levels: control = Down, case = Up
```

```
## Setting direction: controls > cases
```

```
## Setting levels: control = Down, case = Up
```

```
## Setting direction: controls > cases
```

```
## Setting levels: control = Down, case = Up
```

```
## Setting direction: controls < cases
```

```
## Setting levels: control = Down, case = Up
```

```
## Setting direction: controls < cases
```

```
## Setting levels: control = Down, case = Up
```

```
## Setting direction: controls < cases
```

```
## Setting levels: control = Down, case = Up
```

```
## Setting direction: controls < cases
```

```
## Setting levels: control = Down, case = Up
```

```
## Setting direction: controls > cases
```

```
## Setting levels: control = Down, case = Up
```

```
## Setting direction: controls < cases
```

```
## Setting levels: control = Down, case = Up
```

```
## Setting direction: controls < cases
```

```
# average missclassification error rate
sprintf("Logistic Regression : Missclassification error rate : %s", mean(missclassificationRate))
```

```
## [1] "Logistic Regression : Missclassification error rate : 0.436181472329902"
```

```
sprintf("Logistic regression : Null Classifier: %s", mean(nullClassificationRate))
```

```
## [1] "Logistic regression : Null Classifier: 0.562748219282808"
```

```
sprintf("Logistic Regression AUC: %s", mean (aucs))
```

```
## [1] "Logistic Regression AUC: 0.545318579186755"
```

```
# FP rate:
sprintf("Logistic Regression : FP rate (TypeI error, 1 - specificity) : %s", mean(FP_rates))
```

```
## [1] "Logistic Regression : FP rate (TypeI error, 1 - specificity) : 0.935210201833379"
```

```
# TP rate:
sprintf("Logistic Regression : TP rate (1-TypeII error, power, sensetivity, recall) : %s", mean(TP_rates
```

```
## [1] "Logistic Regression : TP rate (1-TypeII error, power, sensetivity, recall) : 0.962289778137507"
```

```
# precision:
sprintf("Logistic Regression : precision: %s", mean(precisions))
```

```
## [1] "Logistic Regression : precision: 0.562532496546535"
```

```
# specificity 1-FP/N:
sprintf("Logistic Regression : specificity 1-FP/N: %s", mean(specificities))
```

```
## [1] "Logistic Regression : specificity 1-FP/N: 0.0647897981666212"
```

```
library(tidyverse)
library(class)
library(boot)


weekly.df = read.csv("/Users/shahrdadshadab/env/my-R-project/ISLR/Data/datasets/Weekly.csv",
                     header=T, stringsAsFactors = T, na.strings = "?")
weekly.df = tibble(weekly.df)


# train <- (weekly.df$Year >= 1990 & weekly.df$Year <= 2008)
# test.Y <- weekly.df[!train,]$Direction
# test.X <- weekly.df[!train,]
# train.Y <- weekly.df[train, ]$Direction
#
# train.X <- weekly.df[train,]

boot.fn <- function (df, index){
  lda.fit <- MASS::lda(Direction ~ Lag2, data = df,family = binomial, subset = index)
  lda.fit$scaling
}
```

```r
# First estimate the coefficients on the full set
boot.fn(weekly.df,1:nrow(weekly.df))
```

```
##            LD1
## Lag2 0.4251523
```

```r
# we can use the function to create bootstrap estimate for LDA coefficient
# by randomly sampling from among the observations with replacement
set.seed(17)
boot.fn(weekly.df, sample(nrow(weekly.df),nrow(weekly.df), replace=T))
```

```
##           LD1
## Lag2 0.402531
```

```r
boot.fn(weekly.df, sample(nrow(weekly.df),nrow(weekly.df), replace=T))
```

```
##            LD1
## Lag2 0.4010238
```

```r
boot.fn(weekly.df, sample(nrow(weekly.df),nrow(weekly.df), replace=T))
```

```
##            LD1
## Lag2 0.4339658
```

```r
boot.fn(weekly.df, sample(nrow(weekly.df),nrow(weekly.df), replace=T))
```

```
##            LD1
## Lag2 0.4161635
```

```r
# next we plugin the function into 'boot()' to compute SE[] of 1000 bootstrap estimates for the LDA coe
boot(data=weekly.df, statistic = boot.fn, R = 1000)
```

```
##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot(data = weekly.df, statistic = boot.fn, R = 1000)
##
##
## Bootstrap Statistics :
##      original      bias    std. error
## t1* 0.4251523 0.001264081  0.01746007
```

```r
library(tidyverse)
library(class)
library(boot)
set.seed(1)

default.df = read.csv("/Users/shahrdadshadab/env/my-R-project/ISLR/Data/Default.csv",
                      header=T, stringsAsFactors = T, na.strings = "?")
default.df = tibble(default.df)
colnames(default.df)
```

```
## [1] "default" "student" "balance" "income"
```

```r
str(default.df)
```

```
## tibble [10,000 x 4] (S3: tbl_df/tbl/data.frame)
```

```
##  $ default: Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 1 1 1 1 ...
##  $ student: Factor w/ 2 levels "No","Yes": 1 2 1 1 1 2 1 2 1 1 ...
##  $ balance: num [1:10000] 730 817 1074 529 786 ...
##  $ income : num [1:10000] 44362 12106 31767 35704 38463 ...
```

```
# a)

glm.fit <- glm(default ~ balance + income, data = default.df, family = binomial)
sprintf("summary of logistic regression: ")
```

```
## [1] "summary of logistic regression: "
```

```
summary(glm.fit)
```

```
##
## Call:
## glm(formula = default ~ balance + income, family = binomial,
##     data = default.df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4725  -0.1444  -0.0574  -0.0211   3.7245
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.154e+01  4.348e-01 -26.545  < 2e-16 ***
## balance      5.647e-03  2.274e-04  24.836  < 2e-16 ***
## income       2.081e-05  4.985e-06   4.174 2.99e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2920.6  on 9999  degrees of freedom
## Residual deviance: 1579.0  on 9997  degrees of freedom
## AIC: 1585
##
## Number of Fisher Scoring iterations: 8
```

```
# b)
# get a random sample
train <- sample(nrow(default.df), nrow(default.df)/2)

# let's create a function that get the full data and a subset of indices as training set
# and return the miss classification error rate on the validation set
classify <- function(df , train.indices){

  # train on random set
  glm.fit <- glm(default ~ balance + income, data = default.df, family = binomial, subset=train.indices

  # obtain the prediction of default in validation set
  contrasts(default.df$default)

  # since contrasts(default.df$default) shows dummy variable 1 asigned to "Yes"
  # since P(y=1|x) is actually glm.probs what we get is prosterior of probability of defauly = Yes
```

```
  glm.probs <- predict(glm.fit, default.df[-train.indices, ], type =  "response")

  # convert posterior probabilities into "Yes" and "No"
  glm.pred <- ifelse(glm.probs > 0.5, "Yes", "No")
  stopifnot(length(glm.pred) == length(default.df[-train.indices, ]$default))

  (confusion_matrix <- table(glm.pred, default.df[-train.indices, ]$default))

  # validation set missclassification error rate
  mean(glm.pred != default.df[-train.indices, ]$default)

}

classify(default.df, train)
```

```
## [1] 0.0254
```

```
# c)

train <- sample(nrow(default.df), nrow(default.df)/3)
classify(default.df, train)
```

```
## [1] 0.02759862
```

```
train <- sample(nrow(default.df), 2*nrow(default.df)/3)
classify(default.df, train)
```

```
## [1] 0.0284943
```

```
train <- sample(nrow(default.df), 4*nrow(default.df)/5)
classify(default.df, train)
```

```
## [1] 0.026
```

```
train <- sample(nrow(default.df), nrow(default.df)/5)
classify(default.df, train)
```

```
## [1] 0.026625
```

```
# in general all error rates are around 0.025

# d)
classify1 <- function(df , train.indices){

  # train on random set
  glm.fit <- glm(default ~ balance + income + student,
                 data = default.df, family = binomial, subset=train.indices)

  # obtain the prediction of default in validation set
  contrasts(default.df$default)

  # since contrasts(default.df$default) shows dummy variable 1 asigned to "Yes"
  # since P(y=1|x) is actually glm.probs what we get is prosterior of probability of defauly = Yes

  glm.probs <- predict(glm.fit, default.df[-train.indices, ], type =  "response")

  # convert posterior probabilities into "Yes" and "No"
```

```
  glm.pred <- ifelse(glm.probs > 0.5, "Yes", "No")
  stopifnot(length(glm.pred) == length(default.df[-train.indices, ]$default))

  (confusion_matrix <- table(glm.pred, default.df[-train.indices, ]$default))

  # validation set missclassification error rate
  mean(glm.pred != default.df[-train.indices, ]$default)

}

train <- sample(nrow(default.df), nrow(default.df)/2)
classify(default.df, train)
```

```
## [1] 0.0274
```

```
# adding student actually increased the error rate
```

```
library(tidyverse)
library(class)
library(boot)
set.seed(1)

default.df = read.csv("/Users/shahrdadshadab/env/my-R-project/ISLR/Data/Default.csv",
                      header=T, stringsAsFactors = T, na.strings = "?")
default.df = tibble(default.df)
colnames(default.df)
```

```
## [1] "default" "student" "balance" "income"
```

```
glm.fit <- glm(default ~ balance + income ,data = default.df, family = binomial)

# a)
summary(glm.fit)
```

```
##
## Call:
## glm(formula = default ~ balance + income, family = binomial,
##     data = default.df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4725  -0.1444  -0.0574  -0.0211   3.7245
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.154e+01  4.348e-01 -26.545  < 2e-16 ***
## balance      5.647e-03  2.274e-04  24.836  < 2e-16 ***
## income       2.081e-05  4.985e-06   4.174 2.99e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2920.6  on 9999  degrees of freedom
## Residual deviance: 1579.0  on 9997  degrees of freedom
## AIC: 1585
```

```
##
## Number of Fisher Scoring iterations: 8
```

```
# b)
boot.fn <- function(df, index) {
  glm.fit <- glm(default ~ balance + income ,data = default.df, family = binomial, subset = index)
  coefficients(glm.fit)
}

# c)
# next we plugin the boot.fn function into 'boot()' to compute SE[] of 1000
# bootstrap estimates for the logistic regression coefficients
(result <- boot(data=weekly.df, statistic = boot.fn, R = 100))
```

```
##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot(data = weekly.df, statistic = boot.fn, R = 100)
##
##
## Bootstrap Statistics :
##          original        bias     std. error
## t1* -1.170135e+01 -4.555716e-01 1.337812e+00
## t2*  5.662070e-03  2.097998e-04 6.699781e-04
## t3*  3.355312e-05  2.448351e-06 1.542786e-05
```

```
print("--------------- Here are the values by capturing output:-------------------- ")
```

```
## [1] "--------------- Here are the values by capturing output:-------------------- "
```

```
library(stringr)

(x <- capture.output(result)) # store the output as text
```

```
##  [1] ""
##  [2] "ORDINARY NONPARAMETRIC BOOTSTRAP"
##  [3] ""
##  [4] ""
##  [5] "Call:"
##  [6] "boot(data = weekly.df, statistic = boot.fn, R = 100)"
##  [7] ""
##  [8] ""
##  [9] "Bootstrap Statistics :"
## [10] "         original        bias     std. error"
## [11] "t1* -1.170135e+01 -4.555716e-01 1.337812e+00"
## [12] "t2*  5.662070e-03  2.097998e-04 6.699781e-04"
## [13] "t3*  3.355312e-05  2.448351e-06 1.542786e-05"
```

```
(x <- str_extract(x ,"^t1.*$")) # grab the line that starts with t1
```

```
##  [1] NA
##  [2] NA
##  [3] NA
##  [4] NA
##  [5] NA
```

```
##  [6] NA
##  [7] NA
##  [8] NA
##  [9] NA
## [10] NA
## [11] "t1* -1.170135e+01 -4.555716e-01 1.337812e+00"
## [12] NA
## [13] NA
```

```
(x <- x[!is.na(x)]) # remove all the lines we don't need
```

```
## [1] "t1* -1.170135e+01 -4.555716e-01 1.337812e+00"
```

```
# (se <- as.numeric(unlist(str_extract_all(x, '[0-9.]+$')))) # extract the final value (se)


# d)

# For balance SE is shrink from 0.005647 to 0.000709
# For income  SE is changed from 2.081e-05 to 1.443805e-05 not much change
```

```
library(tidyverse)
library(class)
weekly.df = read.csv("/Users/shahrdadshadab/env/my-R-project/ISLR/Data/datasets/Weekly.csv", header=T, s
weekly.df = tibble(weekly.df)


# a) Logistic regression using full data set:
glm.fit1 <- glm(Direction ~ Lag1 + Lag2, data = weekly.df, family = binomial)

# b) Logistic regression using full data set but the first observation:

glm.fit2 <- glm(Direction ~ Lag1 + Lag2, data = weekly.df, family = binomial, subset=(1:nrow(weekly.df)

# c) Predict first observation using model b

# first lets see the contrasts of Direction to know what is assigned to 1 and which is 2
contrasts(weekly.df$Direction)
```

```
##      Up
## Down  0
## Up    1
```

```
# Contrasts shows Down is 0 and Up is 1
# Since Posterior is P(Y=1|X) Tuse if posterior > 0.5 it should be "Up"

glm.probs <- predict(glm.fit2, weekly.df[1,], type =  "response")
(glm.predict <- ifelse(glm.probs > 0.5 , "Up", "Down"))
```

```
##    1
## "Up"
```

```
weekly.df[1,]$Direction
```

```
## [1] Down
## Levels: Down Up
```

```r
# d)
# First observation is not correctly classified
# errors
errorList = NULL

for(i in 1:nrow(weekly.df)){
  glm.fit <- glm(Direction ~ Lag1 + Lag2, data = weekly.df, family = binomial, subset = (1:nrow(weekly.
  # Predict ith observation using model that is trained on all records but the ith one
  glm.probs <- predict(glm.fit, weekly.df[i,], type =  "response")
  (glm.predict <- ifelse(glm.probs > 0.5 , "Up", "Down"))

  # accumulate errors
  errorList <-c(errorList , glm.predict != weekly.df[i,]$Direction)
}

# e)
sprintf("average LOOC error rate: %s", mean(errorList) )
```

```
## [1] "average LOOC error rate: 0.449954086317723"
```

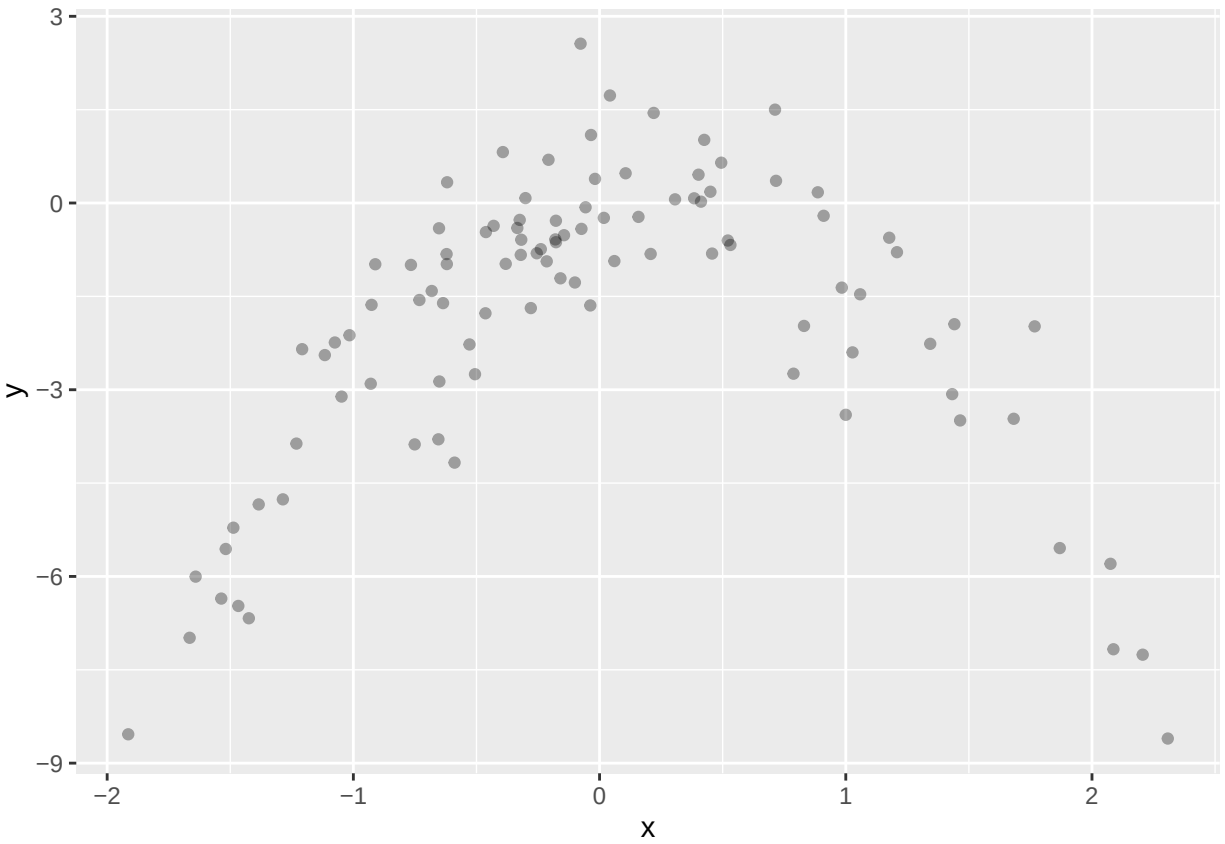
```r
library(tidyverse)
library(class)
library(boot)

# a ) generate simulated data set:
set.seed(1)
y <- rnorm(100)
x <- rnorm(100)
y <- x - 2*x^2+rnorm(100)

df <- tibble(y = y, x = x)
head(df)
```

```
## # A tibble: 6 x 2
##        y       x
##    <dbl>   <dbl>
## 1 -0.981 -0.620
## 2  1.73   0.0421
## 3 -0.984 -0.911
## 4 -0.223  0.158
## 5 -3.80  -0.655
## 6 -1.98   1.77
```

```r
# b)
df %>%
  ggplot(mapping = aes(x=x, y=y))+
  geom_point(alpha=1/3)
```




```
# c)
set.seed(1)
errors <- NULL
for (i in 1:4){
  glm.fit <- glm(y ~ poly(x, i), data=df)
  errors <- rbind(errors, cv.glm(df, glm.fit)$delta)
}
errors
```

```
##           [,1]     [,2]
## [1,] 5.890979 5.888812
## [2,] 1.086596 1.086326
## [3,] 1.102585 1.102227
## [4,] 1.114772 1.114334
```

```
# d) repeat c with another random seed
set.seed(17)
errors <- NULL
for (i in 1:4){
  glm.fit <- glm(y ~ poly(x, i), data=df)
  summary(glm.fit)
  errors <- rbind(errors, cv.glm(df, glm.fit)$delta)
}
errors
```

```
##           [,1]     [,2]
## [1,] 5.890979 5.888812
## [2,] 1.086596 1.086326
```

```
## [3,] 1.102585 1.102227
## [4,] 1.114772 1.114334
```

```r
# The result is the same for different seed vlues becuse there is no random
# componenet in LOOC procedure

# f)

for (i in 1:4){
  glm.fit <- glm(y ~ poly(x, i), data=df)
  print("---------- Ploy Model of oder -------------- ")
  print(i)

  print(summary(glm.fit))
}
```

```
## [1] "---------- Ploy Model of oder -------------- "
## [1] 1
##
## Call:
## glm(formula = y ~ poly(x, i), data = df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -7.3469  -0.9275   0.8028   1.5608   4.3974
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -1.8277     0.2362  -7.737 9.18e-12 ***
## poly(x, i)    2.3164     2.3622   0.981    0.329
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 5.580018)
##
##     Null deviance: 552.21  on 99  degrees of freedom
## Residual deviance: 546.84  on 98  degrees of freedom
## AIC: 459.69
##
## Number of Fisher Scoring iterations: 2
##
## [1] "---------- Ploy Model of oder -------------- "
## [1] 2
##
## Call:
## glm(formula = y ~ poly(x, i), data = df)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.89884  -0.53765   0.04135   0.61490   2.73607
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -1.8277     0.1032 -17.704   <2e-16 ***
## poly(x, i)1   2.3164     1.0324   2.244   0.0271 *
```

```
## poly(x, i)2 -21.0586     1.0324 -20.399   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 1.06575)
##
##     Null deviance: 552.21  on 99  degrees of freedom
## Residual deviance: 103.38  on 97  degrees of freedom
## AIC: 295.11
##
## Number of Fisher Scoring iterations: 2
##
## [1] "---------- Ploy Model of oder -------------- "
## [1] 3
##
## Call:
## glm(formula = y ~ poly(x, i), data = df)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.87250  -0.53881   0.02862   0.59383   2.74350
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -1.8277     0.1037 -17.621   <2e-16 ***
## poly(x, i)1   2.3164     1.0372   2.233   0.0279 *
## poly(x, i)2 -21.0586     1.0372 -20.302   <2e-16 ***
## poly(x, i)3  -0.3048     1.0372  -0.294   0.7695
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 1.075883)
##
##     Null deviance: 552.21  on 99  degrees of freedom
## Residual deviance: 103.28  on 96  degrees of freedom
## AIC: 297.02
##
## Number of Fisher Scoring iterations: 2
##
## [1] "---------- Ploy Model of oder -------------- "
## [1] 4
##
## Call:
## glm(formula = y ~ poly(x, i), data = df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.8914  -0.5244   0.0749   0.5932   2.7796
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -1.8277     0.1041 -17.549   <2e-16 ***
## poly(x, i)1   2.3164     1.0415   2.224   0.0285 *
## poly(x, i)2 -21.0586     1.0415 -20.220   <2e-16 ***
```

```
## poly(x, i)3  -0.3048     1.0415  -0.293   0.7704
## poly(x, i)4  -0.4926     1.0415  -0.473   0.6373
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 1.084654)
##
##     Null deviance: 552.21  on 99  degrees of freedom
## Residual deviance: 103.04  on 95  degrees of freedom
## AIC: 298.78
##
## Number of Fisher Scoring iterations: 2
```

```
# Clearly in all the models only beta 1 and beta 2 are statistically signifocant which matches
# The result from LOOCV that shows ploynomial of order 2 has smallest error
```

```
library(tidyverse)
library(class)
library(boot)
boston.df = read.csv("/Users/shahrdadshadab/env/my-R-project/ISLR/Data/Boston.csv",
                     header=T, stringsAsFactors = T, na.strings = "?")
boston.df = tibble(boston.df)
str(boston.df)
```

```
## tibble [506 x 14] (S3: tbl_df/tbl/data.frame)
##  $ crim   : num [1:506] 0.00632 0.02731 0.02729 0.03237 0.06905 ...
##  $ zn     : num [1:506] 18 0 0 0 0 0 12.5 12.5 12.5 12.5 ...
##  $ indus  : num [1:506] 2.31 7.07 7.07 2.18 2.18 2.18 7.87 7.87 7.87 7.87 ...
##  $ chas   : int [1:506] 0 0 0 0 0 0 0 0 0 0 ...
##  $ nox    : num [1:506] 0.538 0.469 0.469 0.458 0.458 0.458 0.524 0.524 0.524 0.524 ...
##  $ rm     : num [1:506] 6.58 6.42 7.18 7 7.15 ...
##  $ age    : num [1:506] 65.2 78.9 61.1 45.8 54.2 58.7 66.6 96.1 100 85.9 ...
##  $ dis    : num [1:506] 4.09 4.97 4.97 6.06 6.06 ...
##  $ rad    : int [1:506] 1 2 2 3 3 3 5 5 5 5 ...
##  $ tax    : int [1:506] 296 242 242 222 222 222 311 311 311 311 ...
##  $ ptratio: num [1:506] 15.3 17.8 17.8 18.7 18.7 18.7 15.2 15.2 15.2 15.2 ...
##  $ black  : num [1:506] 397 397 393 395 397 ...
##  $ lstat  : num [1:506] 4.98 9.14 4.03 2.94 5.33 ...
##  $ medv   : num [1:506] 24 21.6 34.7 33.4 36.2 28.7 22.9 27.1 16.5 18.9 ...
```

```
# a)
(muHat <- mean (boston.df$medv))
```

```
## [1] 22.53281
```

```
# b)
(SE_of_muHat <- sd(boston.df$medv) / sqrt(nrow(boston.df)))
```

```
## [1] 0.4088611
```

```
#c)
boot.fn <- function(df, index) mean (df[index, ]$medv)

(result <- boot(data=boston.df, statistic = boot.fn, R = 1000))
```

```
##
## ORDINARY NONPARAMETRIC BOOTSTRAP
```

```
##
##
## Call:
## boot(data = boston.df, statistic = boot.fn, R = 1000)
##
##
## Bootstrap Statistics :
##     original      bias    std. error
## t1* 22.53281 -0.01080613    0.416494
```

```
# comparing with part b) , bootstrap error is a bit larger

# d)
# lets calculate 95% confedence interval for the muHat estimator:
# [muHat - 2*SE[muHat], muHat + 2*SE[muHat]]
(leftBound <- 22.53281 - 2 * 0.4251931)
```

```
## [1] 21.68242
```

```
(rightBound <- 22.53281 + 2 * 0.4251931)
```

```
## [1] 23.3832
```

```
# e) provide an estimate for median value of the population based on the data set
(muHatMed <- median(boston.df$medv))
```

```
## [1] 21.2
```

```
# f) calculate SE of muhatMed using bootstrap

boot.fn <- function(df, index) median(df[index, ]$medv)
(result <- boot(data=boston.df, statistic = boot.fn, R = 1000))
```

```
##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot(data = boston.df, statistic = boot.fn, R = 1000)
##
##
## Bootstrap Statistics :
##     original   bias    std. error
## t1*     21.2 -0.00995   0.3755923
```

```
# g) 10th percentile
percentiles <- quantile(boston.df$medv,  probs = c(10, 25, 50, 75, 100)/100)
print("-------- 10th percentile mdev: ------------- ")
```

```
## [1] "-------- 10th percentile mdev: ------------- "
```

```
(muHat01 <- percentiles[1])
```

```
##   10%
## 12.75
```

```
# h) use bootstrap to find SE error for t0th percentile
boot.fn <- function(df, index) quantile(df[index,]$medv,  probs = c(10, 25, 50, 75, 100)/100)[1]
print("-------- bootstrap 10th percentile mdev: ------------- ")
```

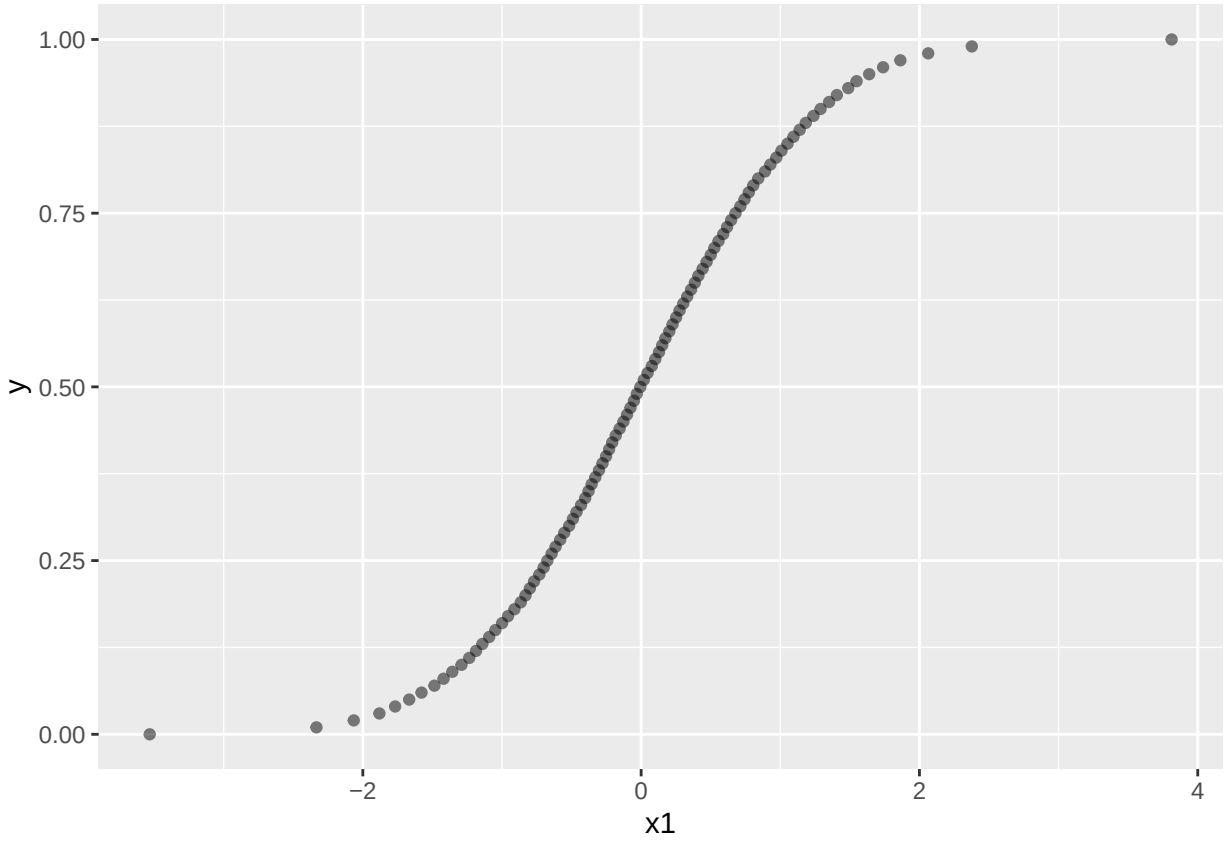
```
## [1] "-------- bootstrap 10th percentile mdev: ------------- "
```

```
(result <- boot(data=boston.df, statistic = boot.fn, R = 10000))
```

```
##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot(data = boston.df, statistic = boot.fn, R = 10000)
##
##
## Bootstrap Statistics :
##     original   bias    std. error
## t1*    12.75 0.000315    0.497474
```

```
set.seed(10)
x <- rnorm(10000)

tibble(x1 = quantile(x,  probs = seq(0,1,0.01), type=1), y = seq(0,1,0.01)) %>%
  ggplot(mapping = aes(x=x1, y=y))+
  geom_point(alpha=1/2)
```




```
quantile(x) # Extremes & Quartiles by default
```

```
##           0%          25%          50%          75%         100%
## -3.531562865 -0.673447402 -0.005305007  0.678582296  3.812580336
```

```
quantile(x,  probs = c(0, 0.1, 0.5, 1, 2, 5, 10, 25, 50, 75, 100)/100)
```

```
##           0%         0.1%         0.5%           1%           2%           5%
## -3.531562865 -3.011770339 -2.600016820 -2.329913624 -2.061742013 -1.665475833
##          10%          25%          50%          75%         100%
## -1.290686953 -0.673447402 -0.005305007  0.678582296  3.812580336
```

```
### Compare different types
quantAll <- function(x, prob, ...)
  t(vapply(1:9, function(typ) quantile(x, prob=prob, type = typ, ...), quantile(x, prob, type=1)))
p <- c(0.1, 0.5, 1, 2, 5, 10, 50)/100
signif(quantAll(x, p), 4)
```

```
##         0.1%   0.5%     1%     2%     5%    10%       50%
##  [1,] -3.012 -2.601 -2.333 -2.065 -1.667 -1.291 -0.005325
##  [2,] -3.012 -2.600 -2.332 -2.063 -1.666 -1.291 -0.005305
##  [3,] -3.012 -2.601 -2.333 -2.065 -1.667 -1.291 -0.005325
##  [4,] -3.012 -2.601 -2.333 -2.065 -1.667 -1.291 -0.005325
##  [5,] -3.012 -2.600 -2.332 -2.063 -1.666 -1.291 -0.005305
##  [6,] -3.012 -2.601 -2.333 -2.065 -1.667 -1.291 -0.005305
##  [7,] -3.012 -2.600 -2.330 -2.062 -1.665 -1.291 -0.005305
##  [8,] -3.012 -2.600 -2.332 -2.064 -1.666 -1.291 -0.005305
##  [9,] -3.012 -2.600 -2.332 -2.064 -1.666 -1.291 -0.005305
```

```
## for complex numbers:
z <- complex(re=x, im = -10*x)
signif(quantAll(z, p), 4)
```

```
##                0.1%         0.5%            1%            2%            5%
##  [1,] -3.01+30.12i -2.6+26.01i -2.33+23.33i -2.07+20.65i -1.67+16.67i
##  [2,] -3.01+30.12i -2.6+26.00i -2.33+23.32i -2.06+20.63i -1.67+16.66i
##  [3,] -3.01+30.12i -2.6+26.01i -2.33+23.33i -2.07+20.65i -1.67+16.67i
##  [4,] -3.01+30.12i -2.6+26.01i -2.33+23.33i -2.07+20.65i -1.67+16.67i
##  [5,] -3.01+30.12i -2.6+26.00i -2.33+23.32i -2.06+20.63i -1.67+16.66i
##  [6,] -3.01+30.12i -2.6+26.01i -2.33+23.33i -2.07+20.65i -1.67+16.67i
##  [7,] -3.01+30.12i -2.6+26.00i -2.33+23.30i -2.06+20.62i -1.67+16.65i
##  [8,] -3.01+30.12i -2.6+26.00i -2.33+23.32i -2.06+20.64i -1.67+16.66i
##  [9,] -3.01+30.12i -2.6+26.00i -2.33+23.32i -2.06+20.64i -1.67+16.66i
##                 10%               50%
##  [1,] -1.29+12.91i -0.00533+0.05325i
##  [2,] -1.29+12.91i -0.00531+0.05305i
##  [3,] -1.29+12.91i -0.00533+0.05325i
##  [4,] -1.29+12.91i -0.00533+0.05325i
##  [5,] -1.29+12.91i -0.00531+0.05305i
##  [6,] -1.29+12.91i -0.00531+0.05305i
##  [7,] -1.29+12.91i -0.00531+0.05305i
##  [8,] -1.29+12.91i -0.00531+0.05305i
##  [9,] -1.29+12.91i -0.00531+0.05305i
```