ISL-ch4 Lab and Exrecises.Rmd

```
library(tidyverse)
```

```
## -- Attaching packages --------------------------------- tidyverse 1.3.0.9000 --
```

```
## 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 ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
smarket.df = read.csv("/Users/shahrdadshadab/env/my-R-project/ISLR/Data/Smarket.csv", header=T, strings
```

```
smarket.df = as_tibble(smarket.df)
```

```
str(attributes(smarket.df))
```

```
## List of 3
##  $ names    : chr [1:10] "X" "Year" "Lag1" "Lag2" ...
##  $ row.names: int [1:1250] 1 2 3 4 5 6 7 8 9 10 ...
##  $ class    : chr [1:3] "tbl_df" "tbl" "data.frame"
```

```
str(smarket.df)
```

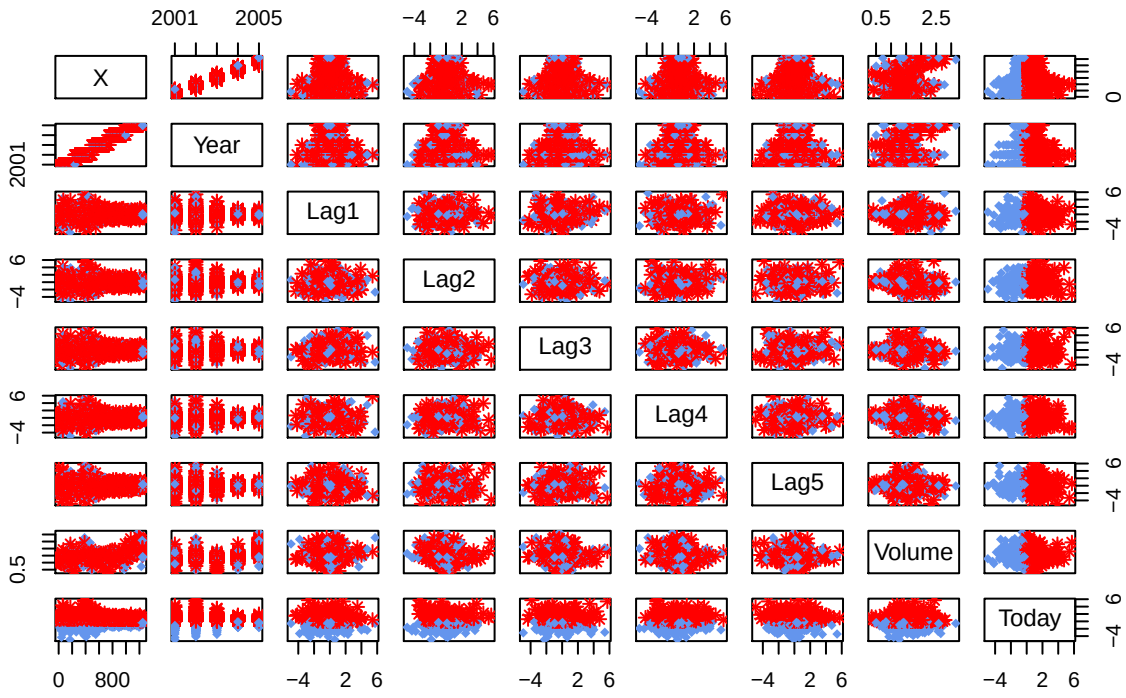
```
## tibble [1,250 x 10] (S3: tbl_df/tbl/data.frame)
##  $ X        : int [1:1250] 1 2 3 4 5 6 7 8 9 10 ...
##  $ Year     : int [1:1250] 2001 2001 2001 2001 2001 2001 2001 2001 2001 2001 ...
##  $ Lag1     : num [1:1250] 0.381 0.959 1.032 -0.623 0.614 ...
##  $ Lag2     : num [1:1250] -0.192 0.381 0.959 1.032 -0.623 ...
##  $ Lag3     : num [1:1250] -2.624 -0.192 0.381 0.959 1.032 ...
##  $ Lag4     : num [1:1250] -1.055 -2.624 -0.192 0.381 0.959 ...
##  $ Lag5     : num [1:1250] 5.01 -1.055 -2.624 -0.192 0.381 ...
##  $ Volume   : num [1:1250] 1.19 1.3 1.41 1.28 1.21 ...
##  $ Today    : num [1:1250] 0.959 1.032 -0.623 0.614 0.213 ...
##  $ Direction: Factor w/ 2 levels "Down","Up": 2 2 1 2 2 2 1 2 2 2 ...
```

```
cor(smarket.df[, -10])
```

```
##                 X       Year         Lag1         Lag2         Lag3
## X      1.00000000 0.97977289  0.035414677  0.036022487  0.038988767
## Year   0.97977289 1.00000000  0.029699649  0.030596422  0.033194581
## Lag1   0.03541468 0.02969965  1.000000000 -0.026294328 -0.010803402
## Lag2   0.03602249 0.03059642 -0.026294328  1.000000000 -0.025896670
## Lag3   0.03898877 0.03319458 -0.010803402 -0.025896670  1.000000000
## Lag4   0.04143714 0.03568872 -0.002985911 -0.010853533 -0.024051036
## Lag5   0.03502515 0.02978799 -0.005674606 -0.003557949 -0.018808338
## Volume 0.54634793 0.53900647  0.040909908 -0.043383215 -0.041823686
## Today  0.03527333 0.03009523 -0.026155045 -0.010250033 -0.002447647
```

```
##                Lag4         Lag5      Volume        Today
## X       0.041437137  0.035025152  0.54634793  0.035273325
## Year    0.035688718  0.029787995  0.53900647  0.030095229
## Lag1   -0.002985911 -0.005674606  0.04090991 -0.026155045
## Lag2   -0.010853533 -0.003557949 -0.04338321 -0.010250033
## Lag3   -0.024051036 -0.018808338 -0.04182369 -0.002447647
## Lag4    1.000000000 -0.027083641 -0.04841425 -0.006899527
## Lag5   -0.027083641  1.000000000 -0.02200231 -0.034860083
## Volume -0.048414246 -0.022002315  1.00000000  0.014591823
## Today  -0.006899527 -0.034860083  0.01459182  1.000000000
```

```r
group <- NA
group[smarket.df$Direction == "Up"] <- 1
group[smarket.df$Direction == "Down"]  <- 2
group[is.na(smarket.df$Direction)] <- 3

pairs(smarket.df[, -10],
      col = c("red", "cornflowerblue", "purple")[group],    # Change color by group
      pch = c(8, 18, 1)[group],                             # Change points by group
      main = "This is an even nicer pairs plot in R")
```




```r
# let's do the logistic regression
glm.fit <- glm (Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5 + Volume, data = smarket.df, family = bino
summary(glm.fit)
```

```
##
## Call:
## glm(formula = Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5 +
##     Volume, family = binomial, data = smarket.df)
##
## Deviance Residuals:
```

```
##    Min      1Q  Median      3Q     Max
## -1.446  -1.203   1.065   1.145   1.326
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.126000   0.240736  -0.523    0.601
## Lag1        -0.073074   0.050167  -1.457    0.145
## Lag2        -0.042301   0.050086  -0.845    0.398
## Lag3         0.011085   0.049939   0.222    0.824
## Lag4         0.009359   0.049974   0.187    0.851
## Lag5         0.010313   0.049511   0.208    0.835
## Volume       0.135441   0.158360   0.855    0.392
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1731.2  on 1249  degrees of freedom
## Residual deviance: 1727.6  on 1243  degrees of freedom
## AIC: 1741.6
##
## Number of Fisher Scoring iterations: 3
```

```
# contrats shows Direction is set to dummy variable 1 for "Up"
contrasts(smarket.df$Direction)
```

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

```
# This basically returns P(Y=1 | X) which means P(Y="Up" | X)
glm.probs <- predict(glm.fit, type="response")

# Since no data is given to predict , model is applied against the training data (i.e smarket.df)
# Thus the order of elements in the vector is the same as order of elements in smarket.df dataframe

# Let's convert probabilities to Up and down
Direction.pred <- rep("Down", nrow(smarket.df))
Direction.pred[glm.probs > 0.5] <- "Up"


# now use table to create a confusion matrix using predidted Direction vs training data Direction
(confusionMatrix <- table(Direction.pred, smarket.df$Direction))
```

```
##
## Direction.pred Down  Up
##           Down  145 141
##           Up    457 507
```

```
# Now we can calculate training error rate
(trainingErrorRate <- (confusionMatrix[1,1] + confusionMatrix[2,2])/nrow(smarket.df))
```

```
## [1] 0.5216
```

```
(trainingErrorRate2 <- nrow(smarket.df[smarket.df$Direction == Direction.pred, ]) / nrow(smarket.df))
```

```
## [1] 0.5216
```

```
stopifnot(trainingErrorRate == trainingErrorRate2)
```

```r
# We really need to test the model against test data
# Thus we need to train it on some part of the data and test it against some other part

# lets train model only on observations of year >= 2000
smarket.df.2005 <- smarket.df[smarket.df$Year >= 2005, ]
dim(smarket.df.2005) # 252 observations have year >= 2005
```

```
## [1] 252  10
```

```r
# side note
stopifnot(smarket.df.2005$Direction == smarket.df$Direction[smarket.df$Year >= 2005])

Direction.2005 <- smarket.df.2005$Direction

# now we fit the model (using subset) only to observations of year < 2005
glm.fit <- glm(Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5 + Volume,
               data = smarket.df,family = binomial, subset = smarket.df$Year < 2005)


summary(glm.fit)
```

```
##
## Call:
## glm(formula = Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5 +
##     Volume, family = binomial, data = smarket.df, subset = smarket.df$Year <
##     2005)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.302  -1.190   1.079   1.160   1.350
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.191213   0.333690   0.573    0.567
## Lag1        -0.054178   0.051785  -1.046    0.295
## Lag2        -0.045805   0.051797  -0.884    0.377
## Lag3         0.007200   0.051644   0.139    0.889
## Lag4         0.006441   0.051706   0.125    0.901
## Lag5        -0.004223   0.051138  -0.083    0.934
## Volume      -0.116257   0.239618  -0.485    0.628
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1383.3  on 997  degrees of freedom
## Residual deviance: 1381.1  on 991  degrees of freedom
## AIC: 1395.1
##
## Number of Fisher Scoring iterations: 3
```

```r
# Run the model on test data (i.e observations for which Year >= 2005)
glm.probs <- predict(glm.fit,smarket.df.2005, type="response")
stopifnot(length(glm.probs) == length(Direction.2005))
# Convert thr probabilities into Up and Down using threshold 0.5
glm.pred <- rep("Down", nrow(smarket.df.2005))
glm.pred [glm.probs > .5] = "Up"
```

```r
table(glm.pred, Direction.2005)
```

```
##         Direction.2005
## glm.pred Down Up
##     Down   77 97
##     Up     34 44
```

```r
# calculate proportion of correct prediction
mean(glm.pred == Direction.2005)
```

```
## [1] 0.4801587
```

```r
# calculate test error rate
mean(glm.pred != Direction.2005)
```

```
## [1] 0.5198413
```

```r
# clearly the test error rate is too high Lets remove predictors with highest p-value
# we obly keep Lag1 and Lag2

glm.fit <- glm(Direction ~ Lag1 + Lag2, data = smarket.df,family = binomial, subset = smarket.df$Year <
summary(glm.fit)
```

```
##
## Call:
## glm(formula = Direction ~ Lag1 + Lag2, family = binomial, data = smarket.df,
##     subset = smarket.df$Year < 2005)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.345  -1.188   1.074   1.164   1.326
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.03222    0.06338   0.508    0.611
## Lag1        -0.05562    0.05171  -1.076    0.282
## Lag2        -0.04449    0.05166  -0.861    0.389
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1383.3  on 997  degrees of freedom
## Residual deviance: 1381.4  on 995  degrees of freedom
## AIC: 1387.4
##
## Number of Fisher Scoring iterations: 3
```

```r
# get the probabilities
glm.probs <- predict(glm.fit,smarket.df.2005 , type = "response")

# convert them to up and down
glm.preds <- rep("Down", nrow(smarket.df.2005))
glm.preds[glm.probs >= 0.5] = "Up"

(conf_matrix <- table(glm.preds , Direction.2005))
```

```
##          Direction.2005
## glm.preds Down  Up
```

```
##      Down   35  35
##      Up     76 106
```

```
mean(glm.preds == Direction.2005)
```

```
## [1] 0.5595238
```

```
# test error rate
mean(glm.preds != Direction.2005)
```

```
## [1] 0.4404762
```

```
(FP_rate <- conf_matrix[2,1]/(conf_matrix[2,1] + conf_matrix[1,1]))
```

```
## [1] 0.6846847
```

```
(TP_rate <- conf_matrix[2,2]/(conf_matrix[2,2] + conf_matrix[1,2]))
```

```
## [1] 0.751773
```

```
# Now calculate Area under the curve
library(pROC)
```

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

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

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

```
roc_obj <- roc(Direction.2005, glm.probs)
```

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

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

```
auc(roc_obj)
```

```
## Area under the curve: 0.5584
```

```
# For some reason roc_obj$specificities has extra row
# roc_df <- tibble(
#   TPR=rev(roc_obj$sensitivities),
#   FPR=rev(1 - roc_obj$specificities),
#   labels=roc_obj$response,
#   scores=roc_obj$predictor)


# we can predict based on specefic values of Lag1 nd Lag2
(glm.probs <- predict(glm.fit,tibble(Lag1 = c(1.2, 1.5), Lag2 = c(1.1, -0.8)) , type = "response"))
```

```
##         1         2
## 0.4791462 0.4960939
```

```
library(tidyverse)

smarket.df = read.csv("/Users/shahrdadshadab/env/my-R-project/ISLR/Data/Smarket.csv", header=T, strings

smarket.df = as_tibble(smarket.df)
```

```r
# split to test train
smarket.df.2005 <- smarket.df[smarket.df$Year >= 2005, ]
Direction.2005 <- smarket.df.2005$Direction

# Note we use only Lag1 and Lag2 due to others predictors are even lower in statistically significance
(lda.fit <- MASS::lda(Direction ~ Lag1 + Lag2, data = smarket.df,family = binomial, subset = smarket.df$
```

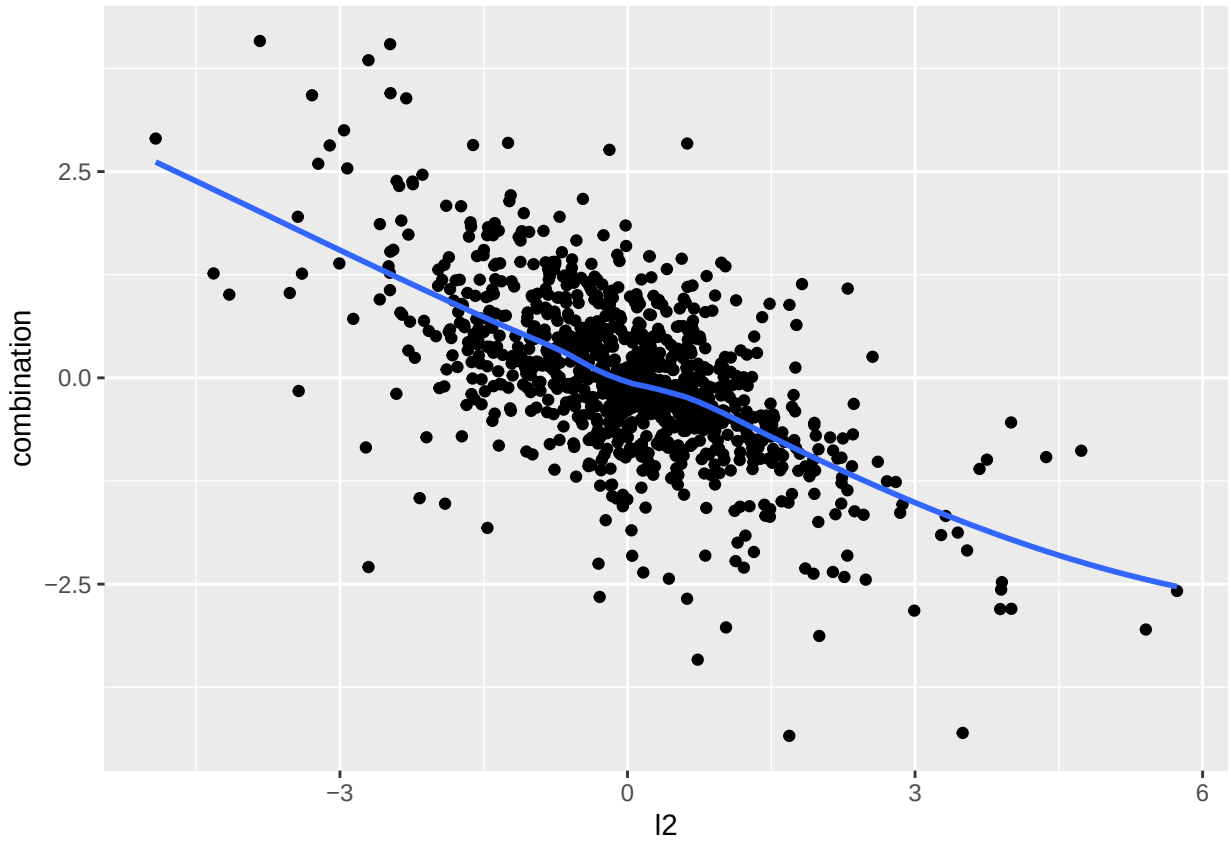
```
## Call:
## lda(Direction ~ Lag1 + Lag2, data = smarket.df, family = binomial,
##     subset = smarket.df$Year < 2005)
##
## Prior probabilities of groups:
##     Down       Up
## 0.491984 0.508016
##
## Group means:
##             Lag1        Lag2
## Down  0.04279022  0.03389409
## Up   -0.03954635 -0.03132544
##
## Coefficients of linear discriminants:
##             LD1
## Lag1 -0.6420190
## Lag2 -0.5135293
```

```r
contrasts(smarket.df$Direction)
```

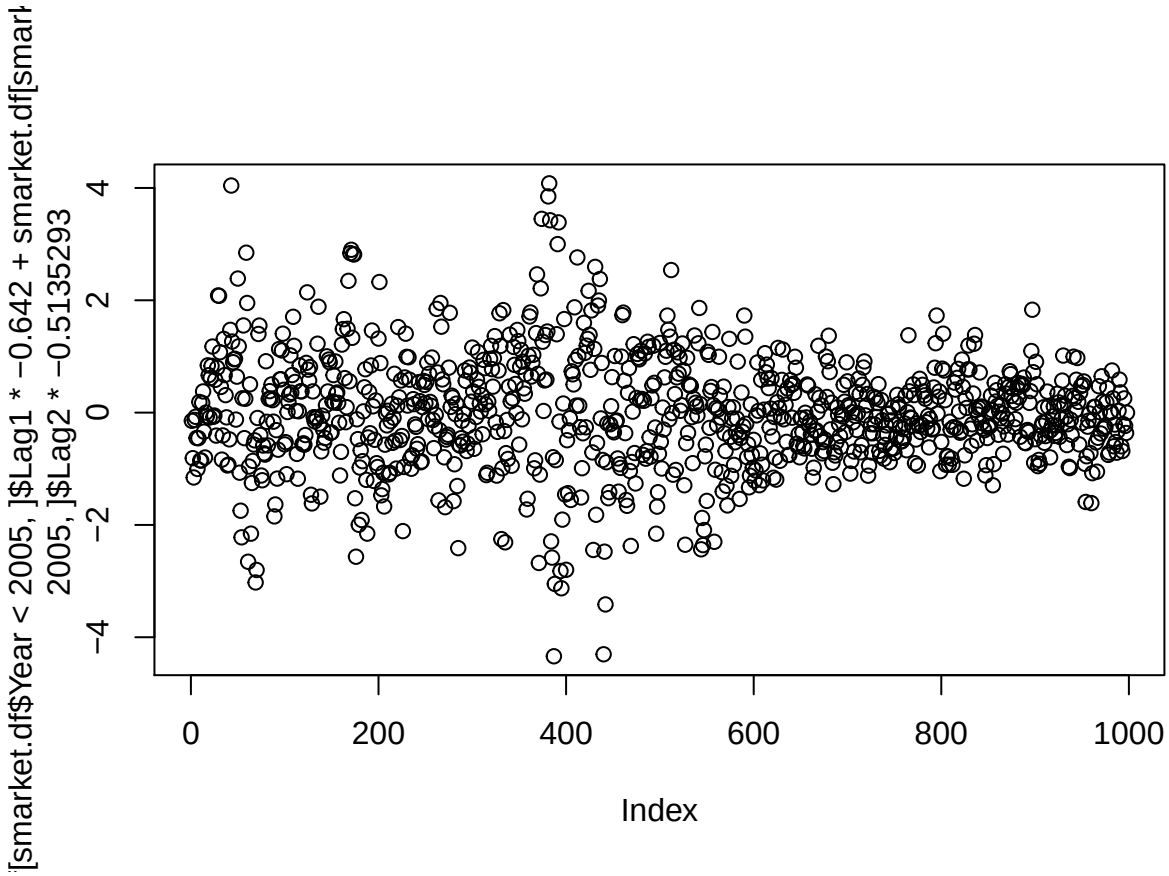
```
##      Up
## Down  0
## Up    1
```

```r
# if Lag1 * -0.642 + Lag2 * -0.5135293 is large then LDA predicts market increases otherwise it decreas
tibble(l1 = smarket.df[smarket.df$Year < 2005, ]$Lag1, l2 = smarket.df[smarket.df$Year < 2005, ]$Lag2, c
  ggplot(mapping = aes(x= l2, y = combination)) +
  geom_point()+
  geom_smooth(se=F)
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```




```
plot(smarket.df[smarket.df$Year < 2005, ]$Lag1 * -0.642 + smarket.df[smarket.df$Year < 2005, ]$Lag2 * -
```




```
# lets predict on test data using the model:
lda.pred <- predict(lda.fit, smarket.df.2005)
names(lda.pred)
```

```
## [1] "class"     "posterior" "x"
```

```
# first get class ("Up", or "Down") from lda.pred
lda.class <- lda.pred$class
lda.posterior.Down = lda.pred$posterior[,1]
lda.posterior.Up = lda.pred$posterior[,2]

table(lda.class, Direction.2005)
```

```
##          Direction.2005
## lda.class Down  Up
##      Down   35  35
##      Up     76 106
```

```
mean(lda.class == Direction.2005)
```

```
## [1] 0.5595238
```

```
# recreate the predictions contained in lda.pred$class.
sum(lda.pred$posterior[,1]>=.5)
```

```
## [1] 70
```

```
sum(lda.pred$posterior[,1]<.5)
```

```
## [1] 182
```

```
# posterior probability output by the model corresponds to "Down" probability :
# lda.pred$posterior[1:20,1]
# lda.class[1:20]

(class_prob <- tibble(probability = lda.pred$posterior[,1], cluster = lda.class))
```

```
## # A tibble: 252 x 2
##    probability cluster
##          <dbl> <fct>
##  1       0.490 Up
##  2       0.479 Up
##  3       0.467 Up
##  4       0.474 Up
##  5       0.493 Up
##  6       0.494 Up
##  7       0.495 Up
##  8       0.487 Up
##  9       0.491 Up
## 10       0.484 Up
## # ... with 242 more rows
```

```
library(pROC)
roc_obj <- roc(Direction.2005, lda.posterior.Up)
```

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

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

```
auc(roc_obj)
```

```
## Area under the curve: 0.5584
```

```
# roc_df <- tibble(
#   TPR=rev(roc_obj$sensitivities),
#   FPR=rev(1 - roc_obj$specificities),
#   labels=roc_obj$response,
#   scores=roc_obj$predictor)
```

```
library(tidyverse)

smarket.df = read.csv("/Users/shahrdadshadab/env/my-R-project/ISLR/Data/Smarket.csv", header=T, strings

smarket.df = as_tibble(smarket.df)

# split to test train
smarket.df.2005 <- smarket.df[smarket.df$Year >= 2005, ]
Direction.2005 <- smarket.df.2005$Direction

# Note we use only Lag1 and Lag2 due to others predictors are even lower in statistically significance
(qda.fit <- MASS::qda(Direction ~ Lag1 + Lag2, data = smarket.df,family = binomial, subset = smarket.df
```

```
## Call:
## qda(Direction ~ Lag1 + Lag2, data = smarket.df, family = binomial,
##     subset = smarket.df$Year < 2005)
##
## Prior probabilities of groups:
##     Down       Up
```

```
## 0.491984 0.508016
##
## Group means:
##             Lag1        Lag2
## Down  0.04279022  0.03389409
## Up   -0.03954635 -0.03132544
```

```
qda.fit
```

```
## Call:
## qda(Direction ~ Lag1 + Lag2, data = smarket.df, family = binomial,
##     subset = smarket.df$Year < 2005)
##
## Prior probabilities of groups:
##     Down       Up
## 0.491984 0.508016
##
## Group means:
##             Lag1        Lag2
## Down  0.04279022  0.03389409
## Up   -0.03954635 -0.03132544
```

```
contrasts(smarket.df$Direction)
```

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

```
qda.pred <- predict(qda.fit, smarket.df.2005)
names(qda.pred)
```

```
## [1] "class"     "posterior"
```

```
# first get class ("Up", or "Down") from lda.pred
qda.class <- qda.pred$class
qda.posterior.Down = qda.pred$posterior[,1]
qda.posterior.Up = qda.pred$posterior[,2]

table(qda.class, Direction.2005)
```

```
##          Direction.2005
## qda.class Down  Up
##      Down   30  20
##      Up     81 121
```

```
mean(qda.class == Direction.2005)
```

```
## [1] 0.5992063
```

```
# recreate the predictions contained in lda.pred$class.
sum(qda.pred$posterior[,1]>=.5)
```

```
## [1] 50
```

```
sum(qda.pred$posterior[,1]<.5)
```

```
## [1] 202
```

```
(class_prob <- tibble(probability = qda.pred$posterior[,1], cluster = qda.class))
```

```
## # A tibble: 252 x 2
##    probability cluster
##          <dbl> <fct>
##  1       0.487 Up
##  2       0.476 Up
##  3       0.464 Up
##  4       0.474 Up
##  5       0.490 Up
##  6       0.491 Up
##  7       0.492 Up
##  8       0.485 Up
##  9       0.489 Up
## 10       0.482 Up
## # ... with 242 more rows
```

```
library(pROC)
roc_obj <- roc(Direction.2005, qda.posterior.Up)
```

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

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

```
auc(roc_obj)
```

```
## Area under the curve: 0.562
```

```
# QDA predictions are accurate almost 60% of the time
# This level of accuracy is quite impressive for stock market data, which is known to be quite hard to
# However, we recommend evaluating this method's performance on a larger test set before betting that t
```

```
# knn() forms predictions using a single command
library(class)
library(tidyverse)

smarket.df = read.csv("/Users/shahrdadshadab/env/my-R-project/ISLR/Data/Smarket.csv", header=T, strings

smarket.df = as_tibble(smarket.df)

smarket.df.2005 <- smarket.df[smarket.df$Year >= 2005, ]
Direction.2005 <- smarket.df.2005$Direction

# first create train and test data
train.X <- cbind(smarket.df$Lag1,smarket.df$Lag2)[smarket.df$Year < 2005, ]
test.X <- cbind(smarket.df$Lag1,smarket.df$Lag2)[smarket.df$Year >= 2005, ]
train.Direction =smarket.df$Direction [smarket.df$Year < 2005]

# a seed must be set in order to ensure reproducibility of results.
set.seed (1)
# arg1 : matrix containing the predictors associated with the training data
# arg2 : matrix containing the predictors associated with the test data
# arg3 : A vector containing the class labels for the training observations
# arg4 : number of nearest neighbors
knn.pred=knn(train.X,test.X,train.Direction ,k=3)
str(attributes(knn.pred))
```

```
## List of 2
##  $ levels: chr [1:2] "Down" "Up"
```

```
##  $ class : chr "factor"
```

```
table(knn.pred,Direction.2005)
```

```
##         Direction.2005
## knn.pred Down Up
##     Down   48 55
##     Up     63 86
```

```
mean (knn.pred == Direction.2005)
```

```
## [1] 0.531746
```

```
library(tidyverse)
library(class)
caravan.df = read.csv("/Users/shahrdadshadab/env/my-R-project/ISLR/Data/Caravan.csv", header=T, strings

caravan.df = as_tibble(caravan.df)
dim(caravan.df)
```

```
## [1] 5822   87
```

```
names(caravan.df)
```

```
##  [1] "X"         "MOSTYPE"   "MAANTHUI" "MGEMOMV"   "MGEMLEEF" "MOSHOOFD"
##  [7] "MGODRK"    "MGODPR"    "MGODOV"   "MGODGE"    "MRELGE"   "MRELSA"
## [13] "MRELOV"    "MFALLEEN" "MFGEKIND" "MFWEKIND" "MOPLHOOG" "MOPLMIDD"
## [19] "MOPLLAAG" "MBERHOOG" "MBERZELF" "MBERBOER" "MBERMIDD" "MBERARBG"
## [25] "MBERARBO" "MSKA"      "MSKB1"    "MSKB2"    "MSKC"     "MSKD"
## [31] "MHHUUR"   "MHKOOP"    "MAUT1"    "MAUT2"    "MAUT0"    "MZFONDS"
## [37] "MZPART"   "MINKM30"   "MINK3045" "MINK4575" "MINK7512" "MINK123M"
## [43] "MINKGEM"  "MKOOPKLA" "PWAPART"  "PWABEDR"  "PWALAND"  "PPERSAUT"
## [49] "PBESAUT"  "PMOTSCO"   "PVRAAUT"  "PAANHANG" "PTRACTOR" "PWERKT"
## [55] "PBROM"    "PLEVEN"    "PPERSONG" "PGEZONG"  "PWAOREG"  "PBRAND"
## [61] "PZEILPL"  "PPLEZIER" "PFIETS"   "PINBOED"  "PBYSTAND" "AWAPART"
## [67] "AWABEDR"  "AWALAND"  "APERSAUT" "ABESAUT"  "AMOTSCO"  "AVRAAUT"
## [73] "AAANHANG" "ATRACTOR" "AWERKT"   "ABROM"    "ALEVEN"   "APERSONG"
## [79] "AGEZONG"  "AWAOREG"  "ABRAND"   "AZEILPL"  "APLEZIER" "AFIETS"
## [85] "AINBOED"  "ABYSTAND" "Purchase"
```

```
# KNN classifier predicts the class of a given test observation by identifying the observations that ar
#str(caravan.df)
summary(caravan.df$Purchase)
```

```
##   No  Yes
## 5474  348
```

```
# To use KNN we should first standardize all qualitative columns
# result of scal is a matrix
standardized.carvan <- scale(caravan.df[, -87])

# Let's break it into test and train
test = 1:1000

train.X <- standardized.carvan[-test, ]
test.X <- standardized.carvan[test, ]

# split corresponding response variable
```

```
train.Y <- caravan.df$Purchase[-test]
test.Y <-  caravan.df$Purchase[test]

# now do the KNN
set.seed(1)
knn.pred <- class::knn(train.X, test.X, train.Y, k = 2)
mean(test.Y != "No")
```

```
## [1] 0.059
```

```
(conf_matrix <- table (knn.pred, test.Y))
```

```
##         test.Y
## knn.pred  No Yes
##      No  877  48
##      Yes  64  11
```

```
# precision is high and that is what is important in this use case
(precision <- conf_matrix[2,1]/(conf_matrix[2,1] + conf_matrix[2,2]))
```

```
## [1] 0.8533333
```

```
# Use logistic regression to compare
# Note for Logistic regression we do not need to standardize the predictors

dim(caravan.df[test, ])
```

```
## [1] 1000   87
```

```
glm.fit <- glm(Purchase ~ MGEMLEEF + PPERSAUT + PLEVEN + PBRAND + PBRAND + ALEVEN + APLEZIER , data =ca
summary(glm.fit)
```

```
##
## Call:
## glm(formula = Purchase ~ MGEMLEEF + PPERSAUT + PLEVEN + PBRAND +
##     PBRAND + ALEVEN + APLEZIER, family = binomial, data = caravan.df,
##     subset = -test)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.2472  -0.3909  -0.2658  -0.1912   2.8998
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -4.38590    0.28110 -15.603  < 2e-16 ***
## MGEMLEEF     0.09825    0.07664   1.282   0.1999
## PPERSAUT     0.24328    0.02614   9.306  < 2e-16 ***
## PLEVEN      -0.20454    0.11759  -1.739   0.0820 .
## PBRAND       0.16694    0.03250   5.137 2.79e-07 ***
## ALEVEN       0.56724    0.23568   2.407   0.0161 *
## APLEZIER     1.92991    0.43595   4.427 9.56e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2187.1  on 4821  degrees of freedom
```

```
## Residual deviance: 2010.2  on 4815  degrees of freedom
## AIC: 2024.2
##
## Number of Fisher Scoring iterations: 6
```

```
glm.probs <- predict(glm.fit, caravan.df[test, ], type =  "response")
stopifnot(length(glm.probs) == length(test.Y))
glm.pred <- ifelse(glm.probs > 0.05 , "Yes", "No")
table(glm.pred, test.Y)
```

```
##         test.Y
## glm.pred  No Yes
##      No  500  14
##      Yes 441  45
```

```
library(tidyverse)
library(class)
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)
#names(weekly.df)
dim(weekly.df)
```

```
## [1] 1089    9
```

```
#str(weekly.df)

# a) Let's take some summary
summary(weekly.df)
```

```
##       Year           Lag1               Lag2               Lag3
##  Min.   :1990   Min.   :-18.1950   Min.   :-18.1950   Min.   :-18.1950
##  1st Qu.:1995   1st Qu.: -1.1540   1st Qu.: -1.1540   1st Qu.: -1.1580
##  Median :2000   Median :  0.2410   Median :  0.2410   Median :  0.2410
##  Mean   :2000   Mean   :  0.1506   Mean   :  0.1511   Mean   :  0.1472
##  3rd Qu.:2005   3rd Qu.:  1.4050   3rd Qu.:  1.4090   3rd Qu.:  1.4090
##  Max.   :2010   Max.   : 12.0260   Max.   : 12.0260   Max.   : 12.0260
##       Lag4               Lag5              Volume            Today
##  Min.   :-18.1950   Min.   :-18.1950   Min.   :0.08747   Min.   :-18.1950
##  1st Qu.: -1.1580   1st Qu.: -1.1660   1st Qu.:0.33202   1st Qu.: -1.1540
##  Median :  0.2380   Median :  0.2340   Median :1.00268   Median :  0.2410
##  Mean   :  0.1458   Mean   :  0.1399   Mean   :1.57462   Mean   :  0.1499
##  3rd Qu.:  1.4090   3rd Qu.:  1.4050   3rd Qu.:2.05373   3rd Qu.:  1.4050
##  Max.   : 12.0260   Max.   : 12.0260   Max.   :9.32821   Max.   : 12.0260
##  Direction
##  Down:484
##  Up  :605
##
##
##
##
```

```
cor(weekly.df[, -9])
```

```
##               Year         Lag1        Lag2        Lag3         Lag4
## Year    1.00000000 -0.032289274 -0.03339001 -0.03000649 -0.031127923
## Lag1   -0.03228927  1.000000000 -0.07485305  0.05863568 -0.071273876
```

```
## Lag2   -0.03339001 -0.074853051  1.00000000 -0.07572091  0.058381535
## Lag3   -0.03000649  0.058635682 -0.07572091  1.00000000 -0.075395865
## Lag4   -0.03112792 -0.071273876  0.05838153 -0.07539587  1.000000000
## Lag5   -0.03051910 -0.008183096 -0.07249948  0.06065717 -0.075675027
## Volume  0.84194162 -0.064951313 -0.08551314 -0.06928771 -0.061074617
## Today  -0.03245989 -0.075031842  0.05916672 -0.07124364 -0.007825873
##                Lag5      Volume        Today
## Year   -0.030519101  0.84194162 -0.032459894
## Lag1   -0.008183096 -0.06495131 -0.075031842
## Lag2   -0.072499482 -0.08551314  0.059166717
## Lag3    0.060657175 -0.06928771 -0.071243639
## Lag4   -0.075675027 -0.06107462 -0.007825873
## Lag5    1.000000000 -0.05851741  0.011012698
## Volume -0.058517414  1.00000000 -0.033077783
## Today   0.011012698 -0.03307778  1.000000000
```

```
# percentage of up and down classification:
table(weekly.df$Direction)/sum(table(weekly.df$Direction))
```

```
##
##      Down        Up
## 0.4444444 0.5555556
```

```
# The only correlation is between Year and Volume which is 0.84194162
group <- NA
group[weekly.df$Direction == "Up"] <- 1
str(group)
```

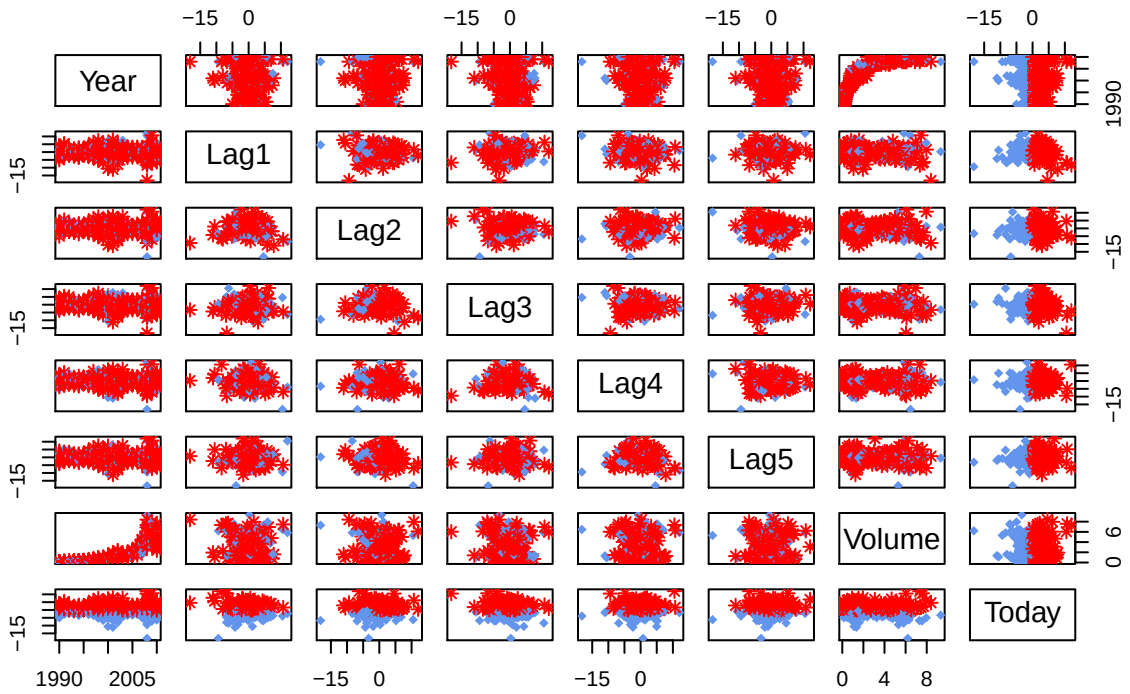
```
##  num [1:1089] NA NA 1 1 1 NA 1 1 1 NA ...
```

```
group[weekly.df$Direction == "Down"]  <- 2
str(group)
```

```
##  num [1:1089] 2 2 1 1 1 2 1 1 1 2 ...
```

```
group[is.na(weekly.df$Direction)] <- 3

pairs(weekly.df[, -9],
      col = c("red", "cornflowerblue", "purple")[group],   # Change color by group
      pch = c(8, 18, 1)[group],                            # Change points by group
      main = "correlation between oairs of predictors in weekly stock")
```

correlation between oairs of predictors in weekly stock




```
# b) Logistic regression using full data set:
glm.fit <- glm(Direction ~ . -Year -Today, data = weekly.df, family = binomial)
summary(glm.fit)
```

```
##
## Call:
## glm(formula = Direction ~ . - Year - Today, family = binomial,
##     data = weekly.df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6949  -1.2565   0.9913   1.0849   1.4579
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.26686    0.08593   3.106   0.0019 **
## Lag1        -0.04127    0.02641  -1.563   0.1181
## Lag2         0.05844    0.02686   2.175   0.0296 *
## Lag3        -0.01606    0.02666  -0.602   0.5469
## Lag4        -0.02779    0.02646  -1.050   0.2937
## Lag5        -0.01447    0.02638  -0.549   0.5833
## Volume      -0.02274    0.03690  -0.616   0.5377
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1496.2  on 1088  degrees of freedom
## Residual deviance: 1486.4  on 1082  degrees of freedom
## AIC: 1500.4
```

```
##
## Number of Fisher Scoring iterations: 4
```

```
# Lag2 is the only predictor that is ststistically significant

# How well our model fits depends on the difference between the model and the observed data.
# One approach for binary data is to implement a Hosmer Lemeshow goodness of fit test:

library(ResourceSelection)
```

```
## ResourceSelection 0.3-5   2019-07-22
```

```
hoslem.test(weekly.df$Direction, fitted(glm.fit))
```

```
## Warning in Ops.factor(1, y): '-' not meaningful for factors
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  weekly.df$Direction, fitted(glm.fit)
## X-squared = 1089, df = 8, p-value < 2.2e-16
```

```
# c) confusion matrix

# 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.fit, weekly.df, type =  "response")
glm.predict <- ifelse(glm.probs > 0.5 , "Up", "Down")
(confusion_table <- table(glm.predict, weekly.df$Direction))
```

```
##
## glm.predict Down  Up
##        Down   54  48
##        Up    430 557
```

```
# overall fraction of correct predictions:
sprintf("overall fraction of correct predictions: %s", mean(glm.predict == weekly.df$Direction))
```

```
## [1] "overall fraction of correct predictions: 0.561065197428834"
```

```
# Null classifier:
sprintf("Null classifier : %s ", (48 + 557)/(48 + 557 + 430 + 54) )
```

```
## [1] "Null classifier : 0.555555555555556 "
```

```
# FP rate:
sprintf("FP rate (TypeI error, 1 - specificity) : %s", confusion_table[2,1]/(confusion_table[2,1]+ confu
```

```
## [1] "FP rate (TypeI error, 1 - specificity) : 0.888429752066116"
```

```
# TP rate:
sprintf("TP rate (1-TypeII error, power, sensetivity, recall) : %s", confusion_table[2,2]/(confusion_tab
```

```
## [1] "TP rate (1-TypeII error, power, sensetivity, recall) : 0.920661157024793"
```

```
# precision:
sprintf("precision: %s", confusion_table[2,2] / (confusion_table[2,2] + confusion_table[2,1]))
```

```
## [1] "precision: 0.564336372847011"
```

```
# specificity 1-FP/N:
sprintf("specificity 1-FP/N: %s", 1 - confusion_table[2,1]/(confusion_table[2,1]+ confusion_table[1,1]))
```

```
## [1] "specificity 1-FP/N: 0.111570247933884"
```

```
# d)

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

glm.fit <- glm(Direction ~ Lag2, data = weekly.df, family = binomial, subset = train)
sprintf("summary of logistic regression: ")
```

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

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

```
##
## Call:
## glm(formula = Direction ~ Lag2, family = binomial, data = weekly.df,
##     subset = train)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.536  -1.264   1.021   1.091   1.368
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.20326    0.06428   3.162  0.00157 **
## Lag2         0.05810    0.02870   2.024  0.04298 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1354.7  on 984  degrees of freedom
## Residual deviance: 1350.5  on 983  degrees of freedom
## AIC: 1354.5
##
## Number of Fisher Scoring iterations: 4
```

```
glm.probs <- predict(glm.fit, test.X, type =  "response")
# again 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 scenario
glm.pred <- ifelse(glm.probs > 0.5, "Up", "Down")

stopifnot(length(glm.pred) == length(test.Y))
```

```r
(confusion_table <- table(glm.pred, test.Y))
```

```
##         test.Y
## glm.pred Down Up
##     Down    9  5
##     Up     34 56
```

```r
# Null classifier:
sprintf("Logistic Regression : Null classifier : %s ", (5 + 56)/(5 + 56 + 9 + 34) )
```

```
## [1] "Logistic Regression : Null classifier : 0.586538461538462 "
```

```r
# overall fraction of correct predictions:
sprintf("Logistic Regression : overall fraction of correct predictions: %s", mean(glm.pred == test.Y))
```

```
## [1] "Logistic Regression : overall fraction of correct predictions: 0.625"
```

```r
# FP rate:
sprintf("Logistic Regression : FP rate (TypeI error, 1 - specificity) : %s", confusion_table[2,1]/(confu
```

```
## [1] "Logistic Regression : FP rate (TypeI error, 1 - specificity) : 0.790697674418605"
```

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

```
## [1] "Logistic Regression : TP rate (1-TypeII error, power, sensetivity, recall) : 0.918032786885246"
```

```r
# precision:
sprintf("Logistic Regression : precision: %s", confusion_table[2,2] / (confusion_table[2,2] + confusion_
```

```
## [1] "Logistic Regression : precision: 0.622222222222222"
```

```r
# specificity 1-FP/N:
sprintf("Logistic Regression : specificity 1-FP/N: %s", 1 - confusion_table[2,1]/(confusion_table[2,1]+
```

```
## [1] "Logistic Regression : specificity 1-FP/N: 0.209302325581395"
```

```r
library(pROC)
roc_obj <- roc(test.Y, glm.probs)
```

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

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

```r
auc(roc_obj)
```

```
## Area under the curve: 0.4537
```

```r
# ------------------------------
# e) repeat part (d) using LDA

lda.fit <- MASS::lda(Direction ~ Lag2, data = weekly.df,family = binomial, subset = train)

# contrasts shows 1 is adssigned to Up
contrasts(weekly.df$Direction)
```

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

```r
# lets predict on test data using the model:
lda.pred <- predict(lda.fit, test.X, type =  "response")
names(lda.pred)
```

```
## [1] "class"     "posterior" "x"
```

```r
stopifnot(length (lda.pred$class) == length(test.Y))
(confusion_table <- table(lda.pred$class, test.Y))
```

```
##       test.Y
##        Down Up
##   Down    9  5
##   Up     34 56
```

```r
# Null classifier:
sprintf("LDA: Null classifier : %s ", (5 + 56)/(5 + 56 + 9 + 34) )
```

```
## [1] "LDA: Null classifier : 0.586538461538462 "
```

```r
# overall fraction of correct predictions:
sprintf("LDA: overall fraction of correct predictions: %s", mean(lda.pred$class == test.Y))
```

```
## [1] "LDA: overall fraction of correct predictions: 0.625"
```

```r
# FP rate:
sprintf("LDA: FP rate (TypeI error, 1 - specificity) : %s", confusion_table[2,1]/(confusion_table[2,1]+
```

```
## [1] "LDA: FP rate (TypeI error, 1 - specificity) : 0.790697674418605"
```

```r
# TP rate:
sprintf("LDA: TP rate (1-TypeII error, power, sensetivity, recall) : %s", confusion_table[2,2]/(confusi
```

```
## [1] "LDA: TP rate (1-TypeII error, power, sensetivity, recall) : 0.918032786885246"
```

```r
# precision:
sprintf("LDA: precision: %s", confusion_table[2,2] / (confusion_table[2,2] + confusion_table[2,1]))
```

```
## [1] "LDA: precision: 0.622222222222222"
```

```r
# specificity 1-FP/N:
sprintf("LDA: specificity 1-FP/N: %s", 1 - confusion_table[2,1]/(confusion_table[2,1]+ confusion_table[
```

```
## [1] "LDA: specificity 1-FP/N: 0.209302325581395"
```

```r
# Below is the corresponding posterior probabilities of tests
colnames(lda.pred$posterior)
```

```
## [1] "Down" "Up"
```

```r
lda.pred$posterior[1:10, "Up"]
```

```
##         1         2         3         4         5         6         7         8
## 0.5263445 0.6441383 0.4867140 0.4857052 0.5200273 0.5402414 0.6228883 0.4815276
##         9        10
## 0.4519603 0.4853882
```

```r
lda.pred$posterior[1:10, "Down"]
```

```
##         1         2         3         4         5         6         7         8
## 0.4736555 0.3558617 0.5132860 0.5142948 0.4799727 0.4597586 0.3771117 0.5184724
##         9        10
## 0.5480397 0.5146118
```

```
library(pROC)
roc_obj <- roc(test.Y, lda.pred$posterior[, "Up"])
```

```
## Setting levels: control = Down, case = Up
## Setting direction: controls > cases
```

```
auc(roc_obj)
```

```
## Area under the curve: 0.4537
```

```
# ----------------------------
# f) repeat part (d) using QDA

qda.fit <- MASS::qda(Direction ~ Lag2, data = weekly.df,family = binomial, subset = train)

# contrasts shows 1 is adssigned to Up
contrasts(weekly.df$Direction)
```

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

```
# lets predict on test data using the model:
qda.pred <- predict(qda.fit, test.X, type =  "response")
names(qda.pred)
```

```
## [1] "class"     "posterior"
```

```
stopifnot(length (qda.pred$class) == length(test.Y))
(confusion_table <- table(qda.pred$class, test.Y))
```

```
##       test.Y
##        Down Up
##   Down    0  0
##   Up     43 61
```

```
# Null classifier:
sprintf("QDA: Null classifier : %s ", 61/(61+43) )
```

```
## [1] "QDA: Null classifier : 0.586538461538462 "
```

```
# overall fraction of correct predictions:
sprintf("QDA: overall fraction of correct predictions: %s", mean(qda.pred$class == test.Y))
```

```
## [1] "QDA: overall fraction of correct predictions: 0.586538461538462"
```

```
# FP rate:
sprintf("QDA: FP rate (TypeI error, 1 - specificity) : %s", confusion_table[2,1]/(confusion_table[2,1]+
```

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

```
# TP rate:
sprintf("QDA: TP rate (1-TypeII error, power, sensetivity, recall) : %s", confusion_table[2,2]/(confusi
```

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

```
# precision:
sprintf("QDA: precision: %s", confusion_table[2,2] / (confusion_table[2,2] + confusion_table[2,1]))
```

```
## [1] "QDA: precision: 0.586538461538462"
```

```r
# specificity 1-FP/N:
sprintf("QDA: specificity 1-FP/N: %s", 1 - confusion_table[2,1]/(confusion_table[2,1]+ confusion_table[
```

```
## [1] "QDA: specificity 1-FP/N: 0"
```

```r
# Below is the corresponding posterior probabilities of tests
colnames(qda.pred$posterior)
```

```
## [1] "Down" "Up"
```

```r
qda.pred$posterior[1:10, "Up"]
```

```
##         1         2         3         4         5         6         7         8
## 0.5215370 0.7306048 0.5264584 0.5270882 0.5197265 0.5290087 0.6714698 0.5299634
##         9        10
## 0.5625713 0.5272914
```

```r
qda.pred$posterior[1:10, "Down"]
```

```
##         1         2         3         4         5         6         7         8
## 0.4784630 0.2693952 0.4735416 0.4729118 0.4802735 0.4709913 0.3285302 0.4700366
##         9        10
## 0.4374287 0.4727086
```

```r
library(pROC)
roc_obj <- roc(test.Y, qda.pred$posterior[, "Up"])
```

```
## Setting levels: control = Down, case = Up
## Setting direction: controls > cases
```

```r
auc(roc_obj)
```

```
## Area under the curve: 0.4914
```

```r
# ------------------------------
# g) repeat part (d) using KNN where K = 1

# First remove NAs

# Now find a subset of records that have at least one NA
# dfSubsetWithNa <- weekly.df[rowSums(is.na(weekly.df)) > 0,]
# head(dfSubsetWithNa)

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

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


# To use KNN first we need to standardize the predictor Lag2

standardized.weekly <- scale(weekly.df[, c("Lag2")])
names(standardized.weekly)
```

```
## NULL
```

```r
# now split it into to train and test
# First make a dataframe
helperDf <- tibble(Year = weekly.df$Year, Direction = weekly.df$Direction
                , Lag2 = standardized.weekly[,1])
head(helperDf)
```

```
## # A tibble: 6 x 3
##    Year Direction   Lag2
##   <int> <fct>      <dbl>
## 1  1990 Down       0.603
## 2  1990 Down       0.282
## 3  1990 Up        -0.179
## 4  1990 Up        -1.16
## 5  1990 Up         1.43
## 6  1990 Down       0.238
```

```r
# Let's break helper into test and train

train.X <- helperDf[train, "Lag2"]
train.Y <- helperDf[train, ]$Direction
test.X <- helperDf[!train, "Lag2"]
test.Y <- helperDf[!train, ]$Direction

# now do the KNN
set.seed(1)
knn.pred <- class::knn(train.X, test.X, train.Y, k = 1)

(confusion_table <- table (knn.pred, test.Y))
```

```
##         test.Y
## knn.pred Down Up
##     Down   21 31
##     Up     22 30
```

```r
stopifnot(length (knn.pred) == length(test.Y))

# Null classifier:
sprintf("KNN: Null classifier : %s ", (31+30)/(21+22+31+30) )
```

```
## [1] "KNN: Null classifier : 0.586538461538462 "
```

```r
# overall fraction of correct predictions:
sprintf("KNN: overall fraction of correct predictions: %s", mean(knn.pred == test.Y))
```

```
## [1] "KNN: overall fraction of correct predictions: 0.490384615384615"
```

```r
# FP rate:
sprintf("KNN: FP rate (TypeI error, 1 - specificity) : %s", confusion_table[2,1]/(confusion_table[2,1]+
```

```
## [1] "KNN: FP rate (TypeI error, 1 - specificity) : 0.511627906976744"
```

```r
# TP rate:
sprintf("KNN: TP rate (1-TypeII error, power, sensetivity, recall) : %s", confusion_table[2,2]/(confusi
```

```
## [1] "KNN: TP rate (1-TypeII error, power, sensetivity, recall) : 0.491803278688525"
```

```r
# precision:
sprintf("KNN: precision: %s", confusion_table[2,2] / (confusion_table[2,2] + confusion_table[2,1]))
```

```
## [1] "KNN: precision: 0.576923076923077"
```

```
# specificity 1-FP/N:
sprintf("KNN: specificity 1-FP/N: %s", 1 - confusion_table[2,1]/(confusion_table[2,1]+ confusion_table[
```

```
## [1] "KNN: specificity 1-FP/N: 0.488372093023256"
```

```
print ("LDA and QDA are best classifiers with 62% of overall correct prediction.")
```

```
## [1] "LDA and QDA are best classifiers with 62% of overall correct prediction."
```

```
library(tidyverse)
library(class)
car.df = read.csv("/Users/shahrdadshadab/env/my-R-project/ISLR/Data/datasets/Auto.csv",
                      header=T, stringsAsFactors = T, na.strings = "?")
car.df = tibble(car.df)
dim(car.df)
```

```
## [1] 392   9
```

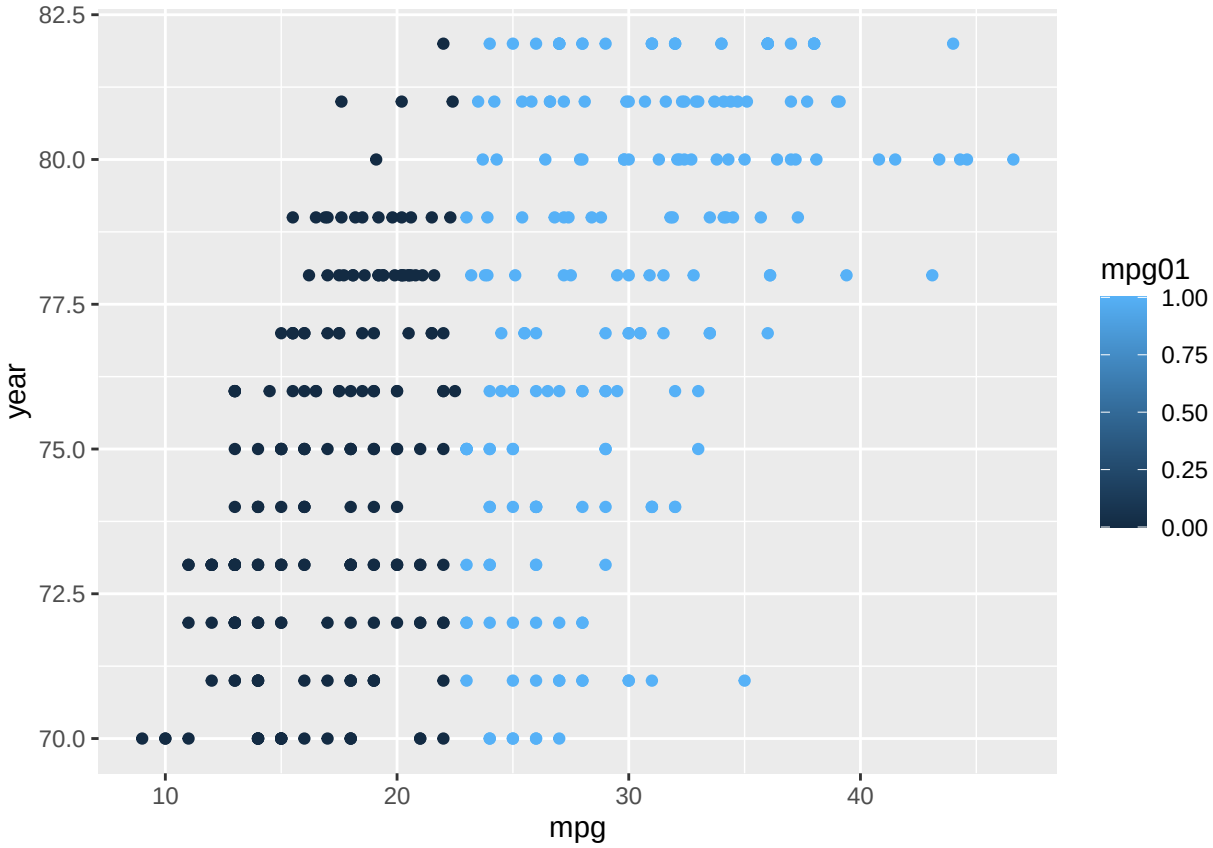
```
# a)
car.df <- car.df %>%
  mutate(mpg01 = ifelse (mpg > median(mpg), 1, 0))
colnames(car.df)
```

```
##  [1] "mpg"          "cylinders"    "displacement" "horsepower"   "weight"
##  [6] "acceleration" "year"         "origin"       "name"         "mpg01"
```

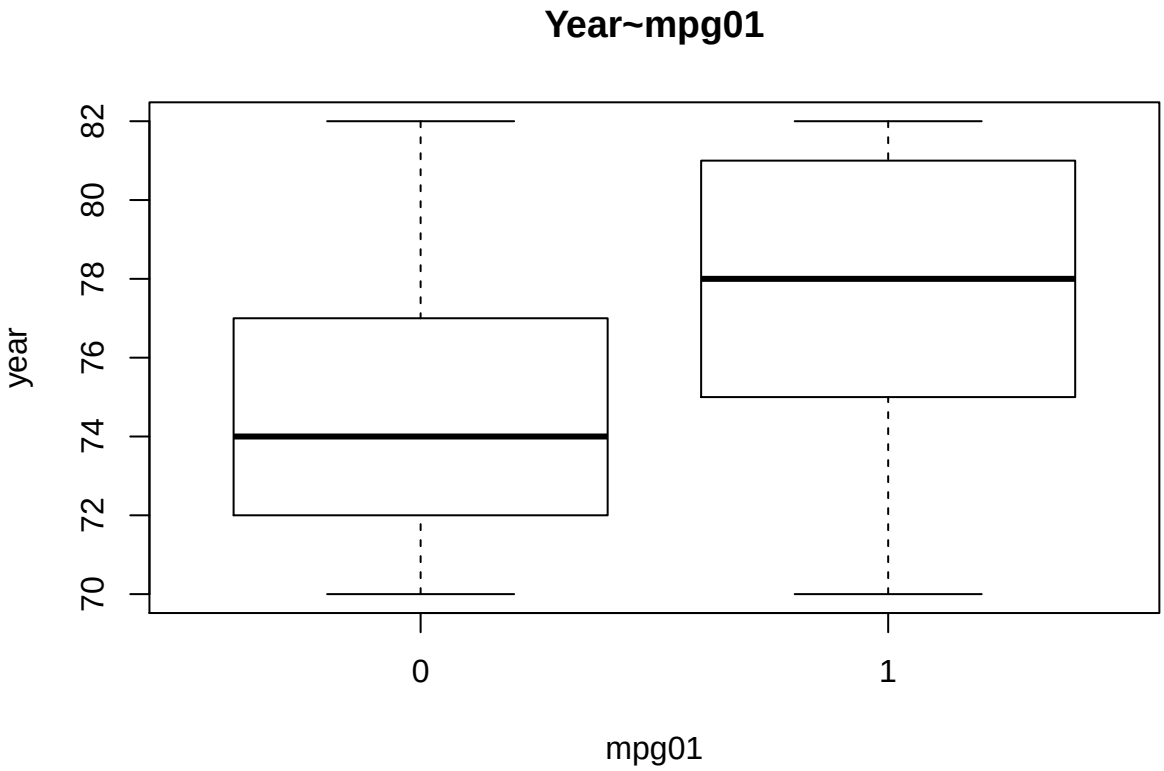
```
median(car.df$mpg)
```

```
## [1] 22.75
```

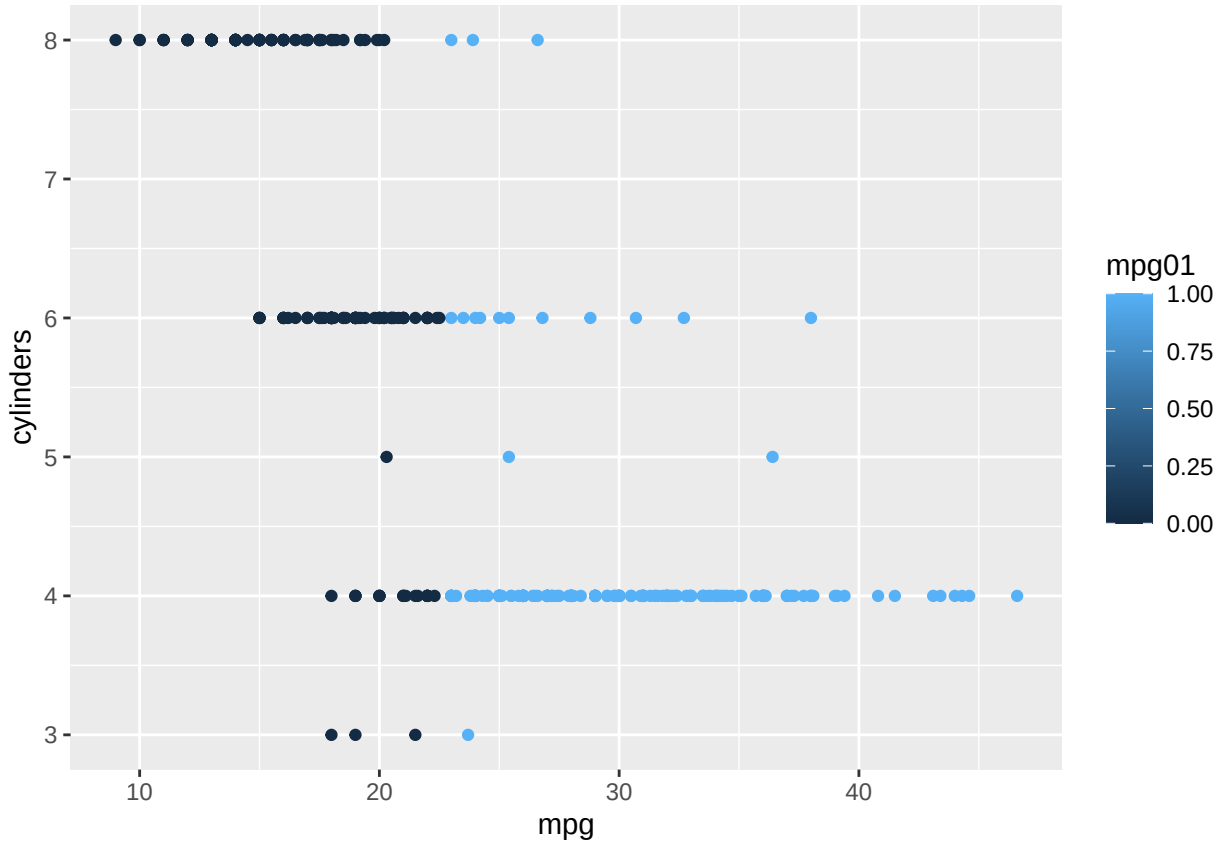
```
# b) Explore the data graphically

# group <- NA
# group[car.df$mpg01 == "0"] <- 1
# group[car.df$mpg01 == "1"]  <- 2
#
# pairs(car.df[, c("mpg01", "year")],
#       col = c("red", "cornflowerblue", "purple")[group],   # Change color by group
#       pch = c(8, 18, 1)[group],                            # Change points by group
#       main = "correlation between mpg01 and other predictors ")
#

car.df %>%
  ggplot() +
   geom_point(mapping = aes(x = mpg, y = year, color = mpg01))
```



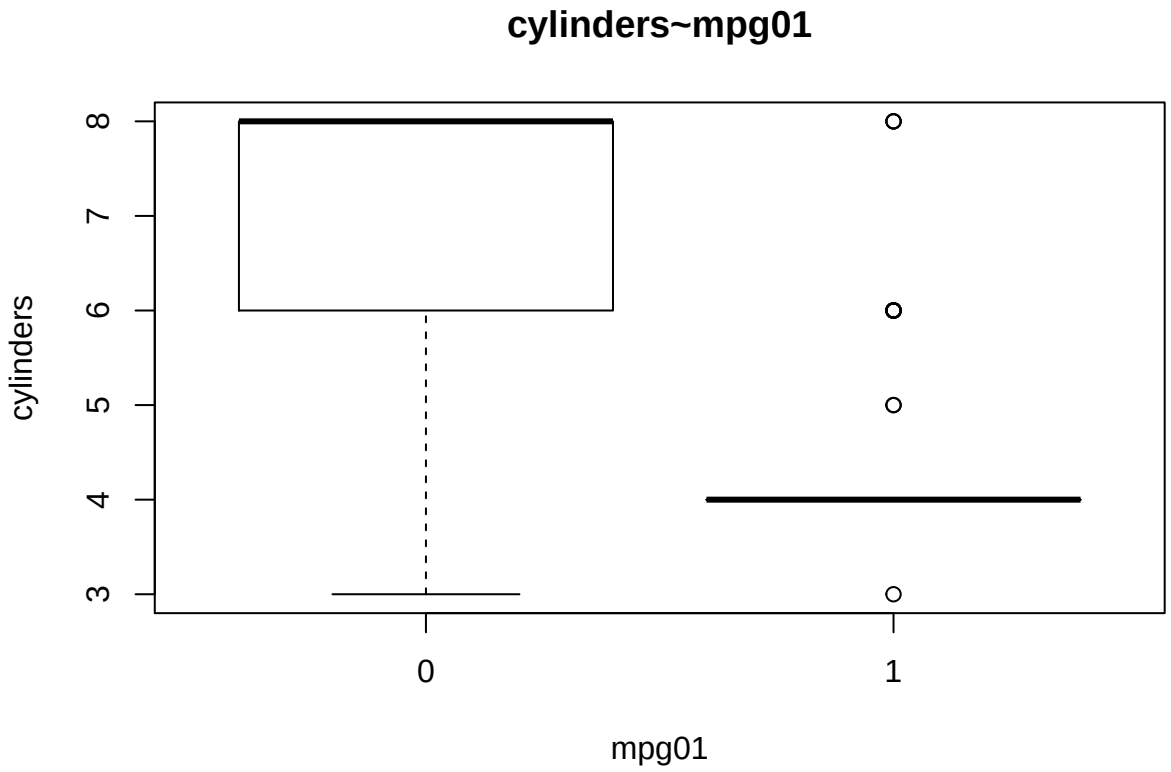

```
boxplot(year~mpg01,car.df,main="Year~mpg01")
```



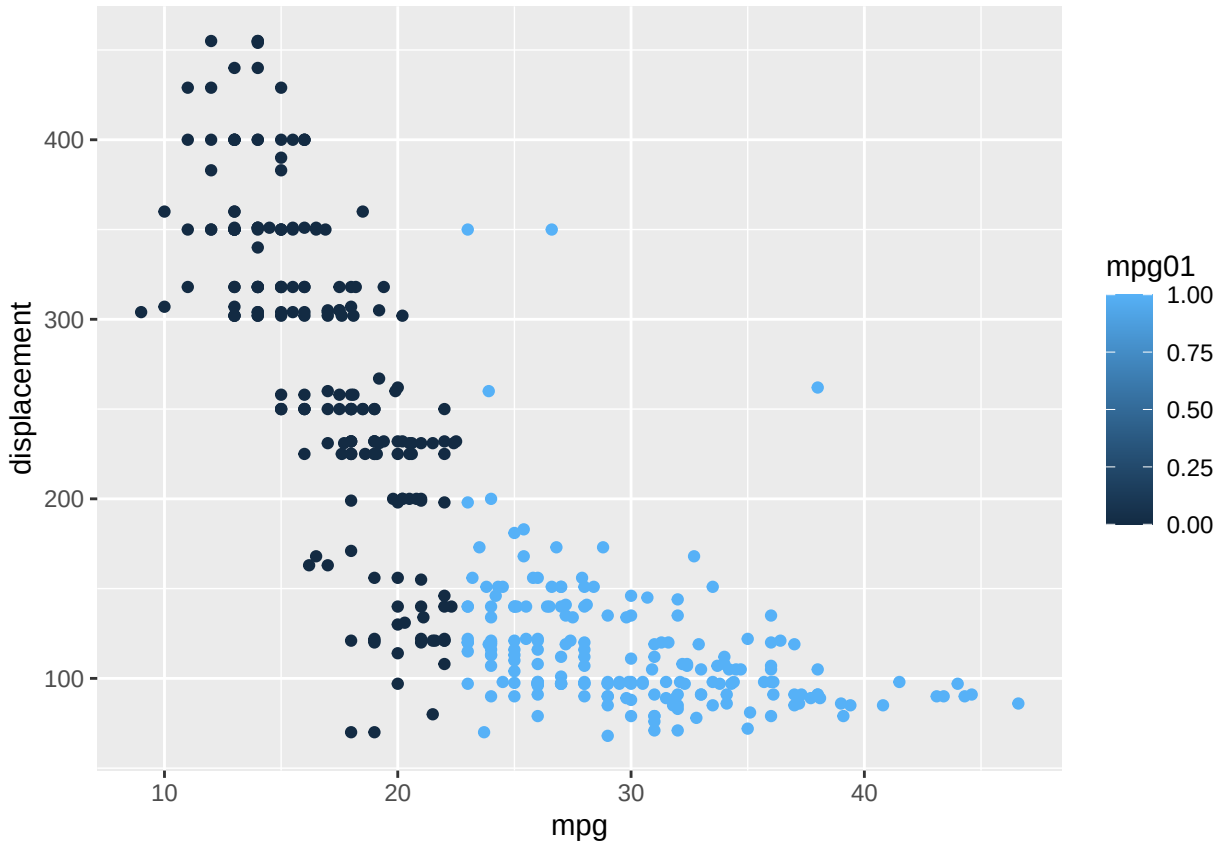
```
car.df %>%
  ggplot() +
   geom_point(mapping = aes(x = mpg, y = cylinders, color = mpg01))
```



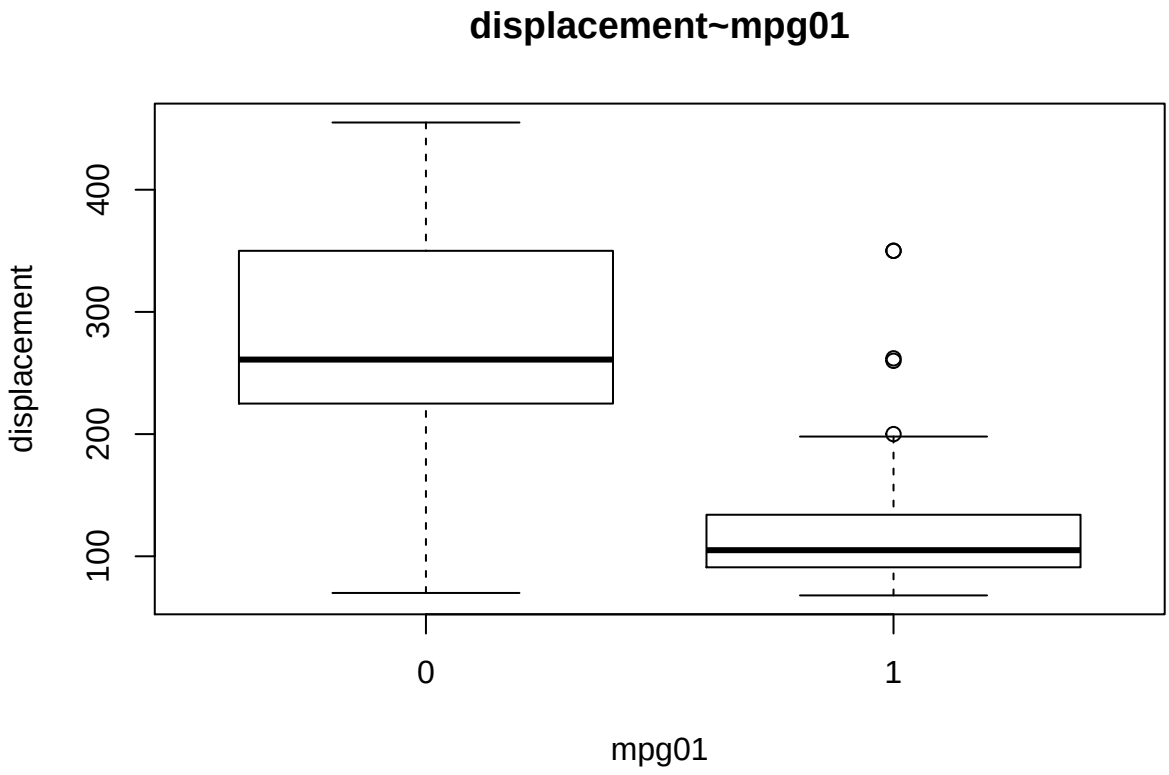

```
boxplot(cylinders~mpg01,car.df,main="cylinders~mpg01")
```



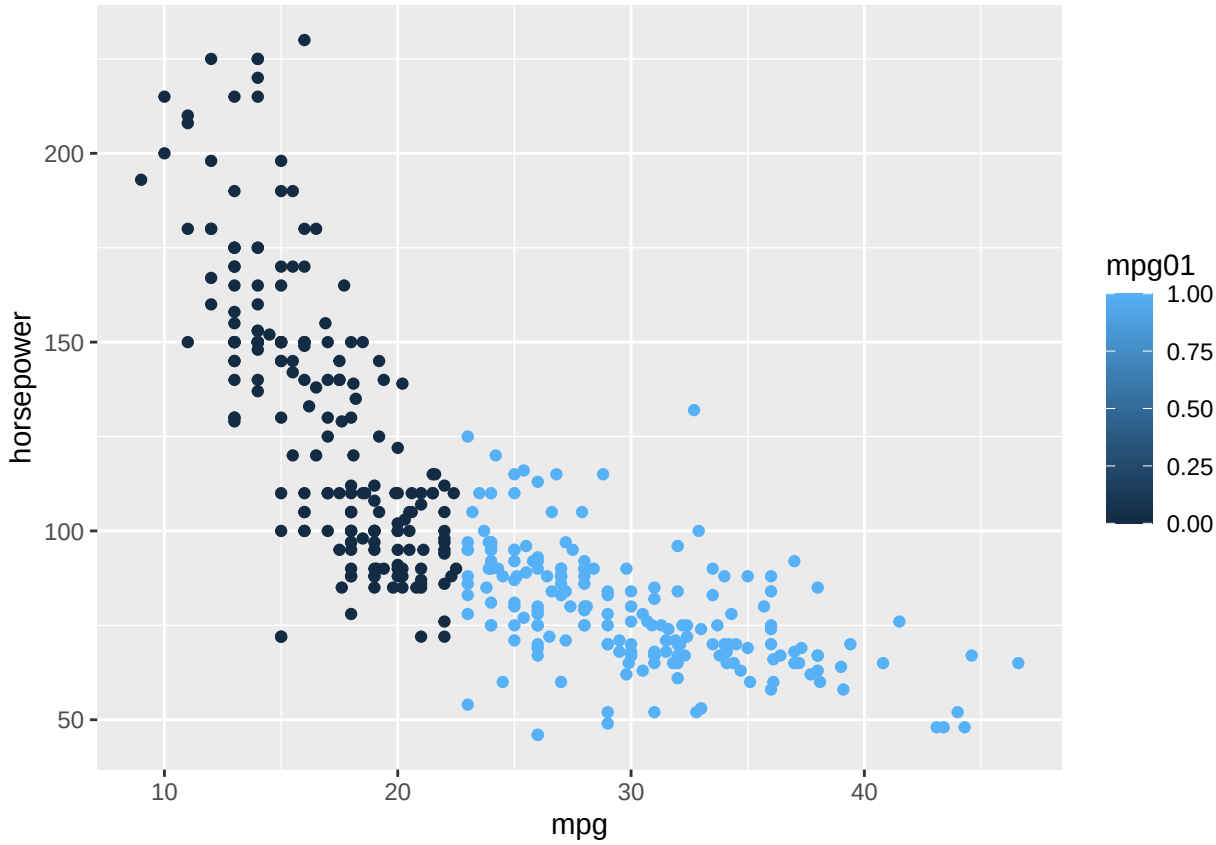

```
car.df %>%
  ggplot() +
   geom_point(mapping = aes(x = mpg, y = displacement, color = mpg01))
```



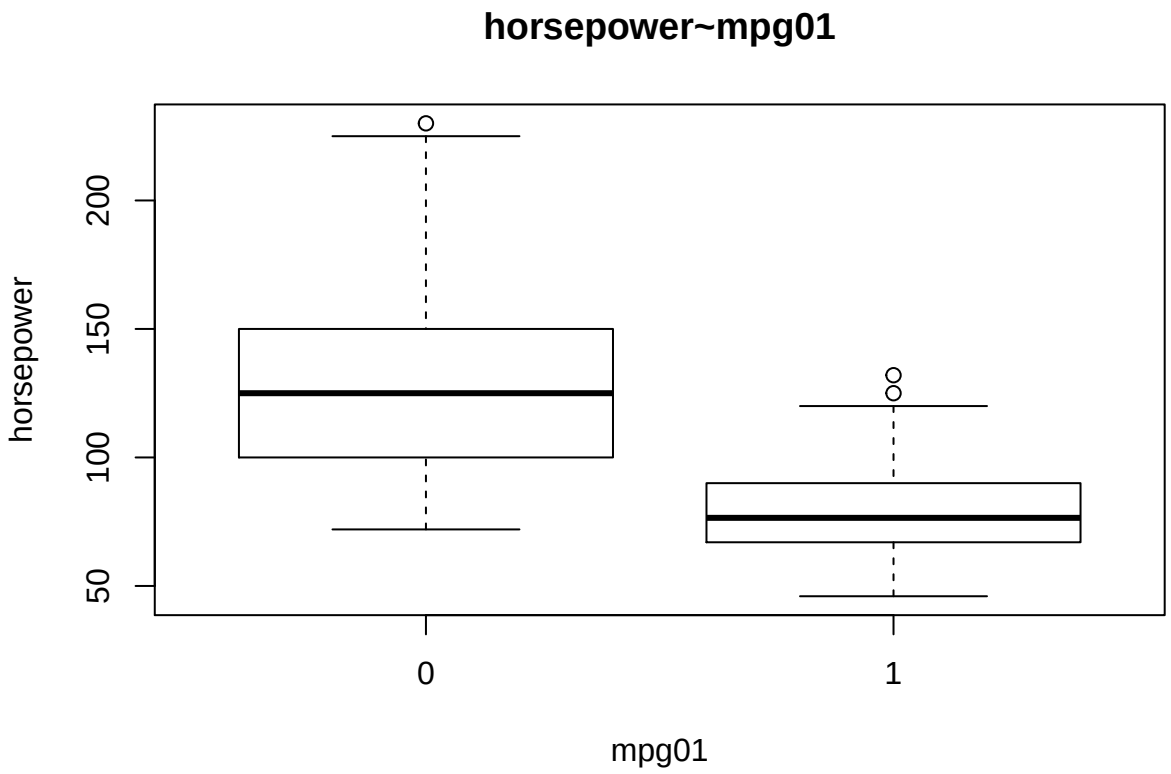

```
boxplot(displacement~mpg01,car.df,main="displacement~mpg01")
```



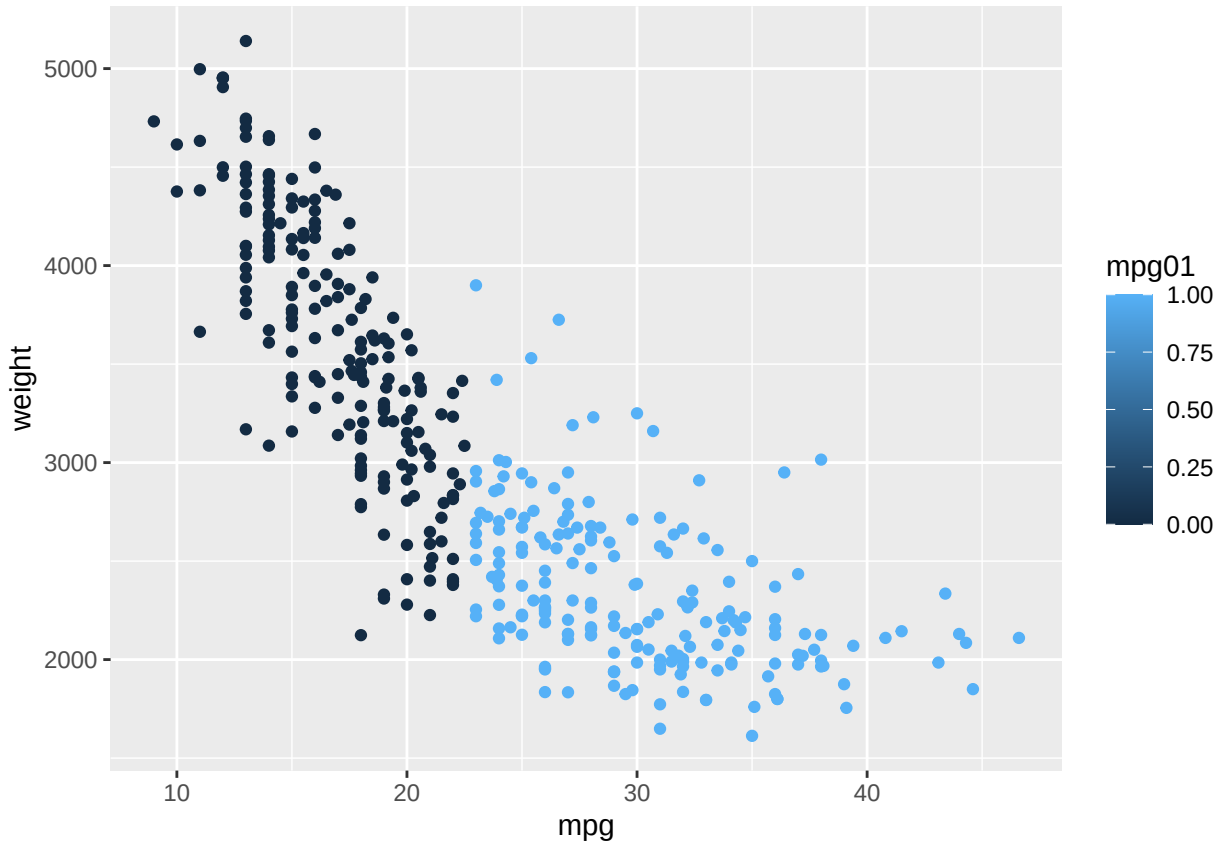
```
car.df %>%
  ggplot() +
   geom_point(mapping = aes(x = mpg, y = horsepower, color = mpg01))
```



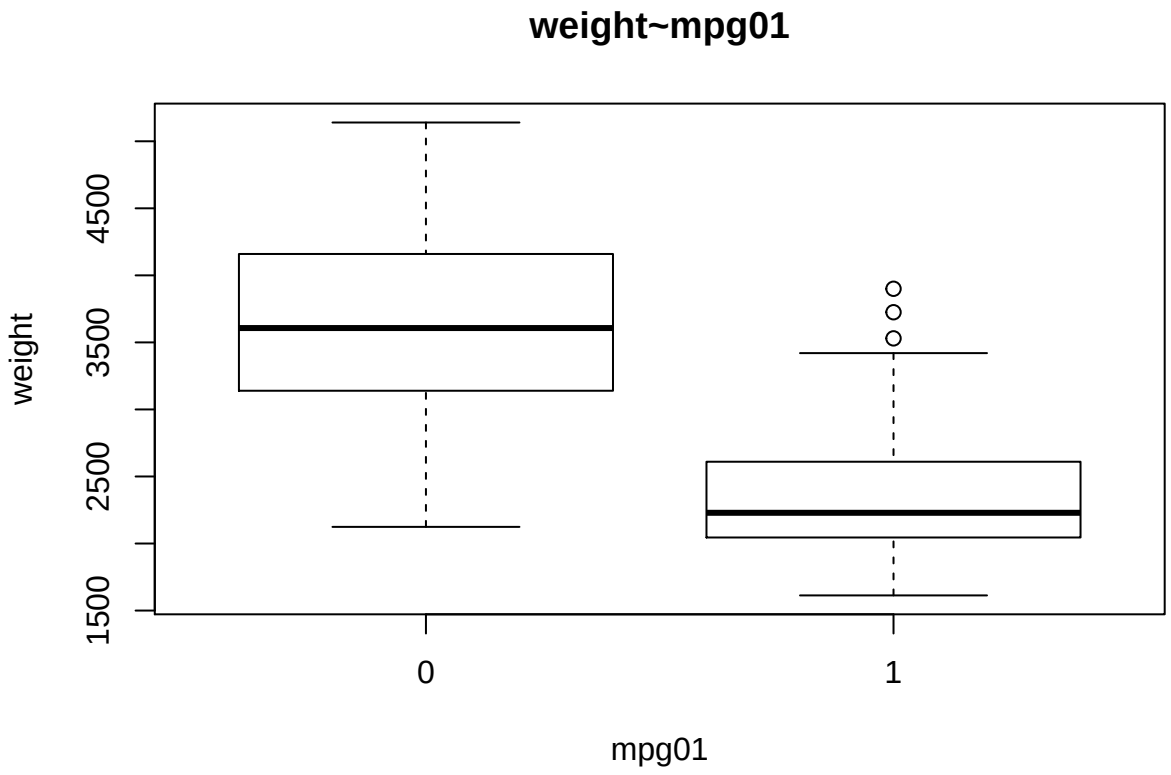

```
boxplot(horsepower~mpg01,car.df,main="horsepower~mpg01")
```



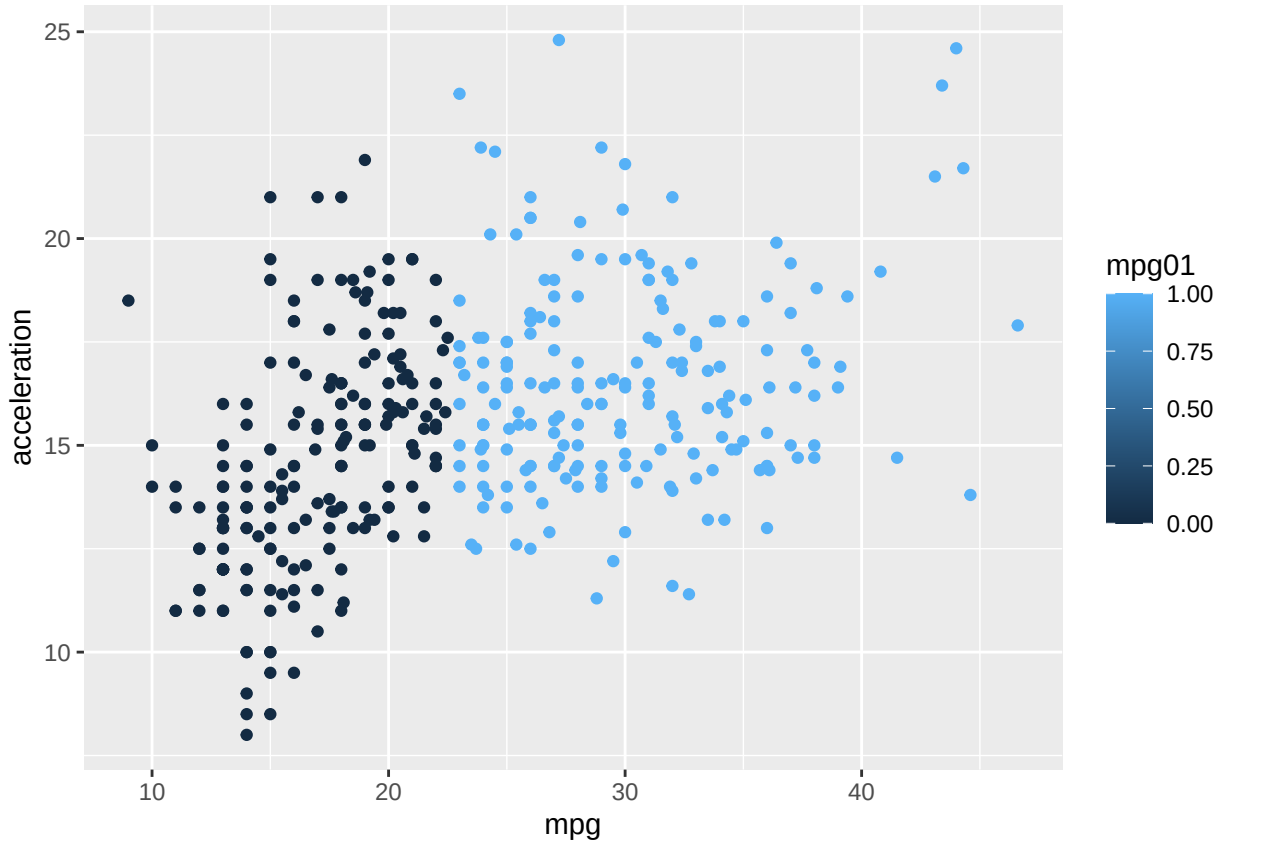

```
car.df %>%
  ggplot() +
   geom_point(mapping = aes(x = mpg, y = weight, color = mpg01))
```



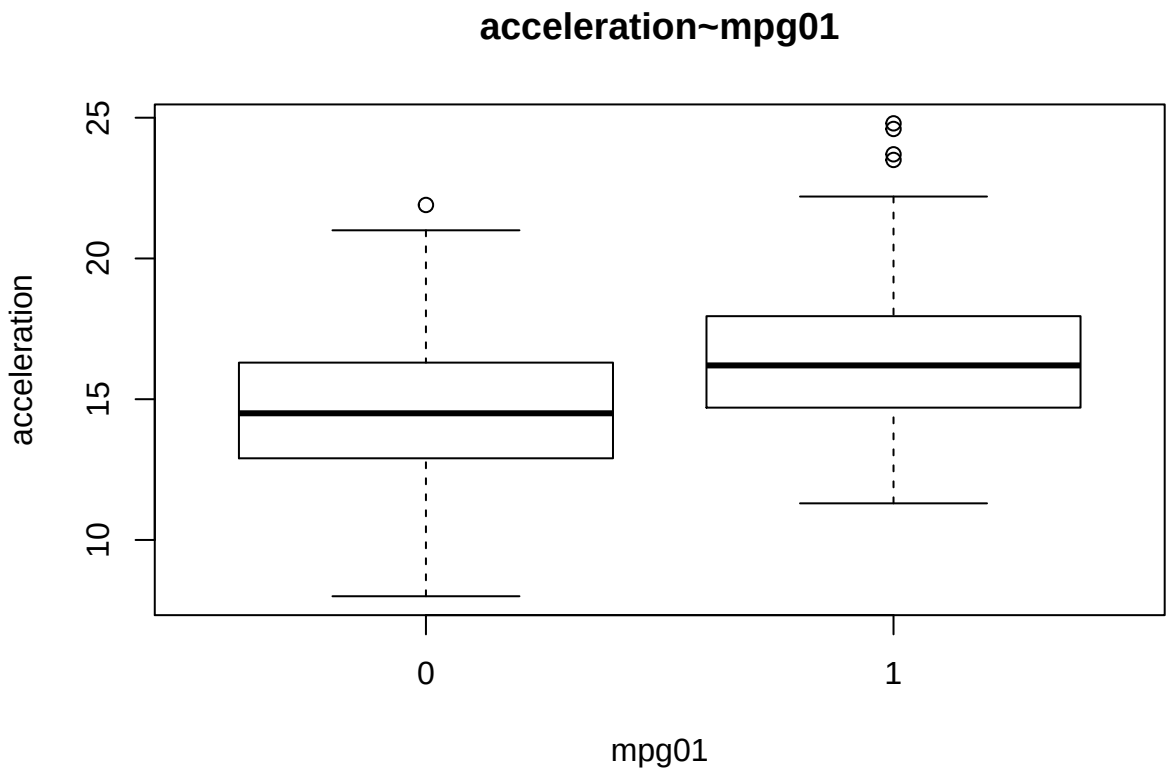

```
boxplot(weight~mpg01,car.df,main="weight~mpg01")
```



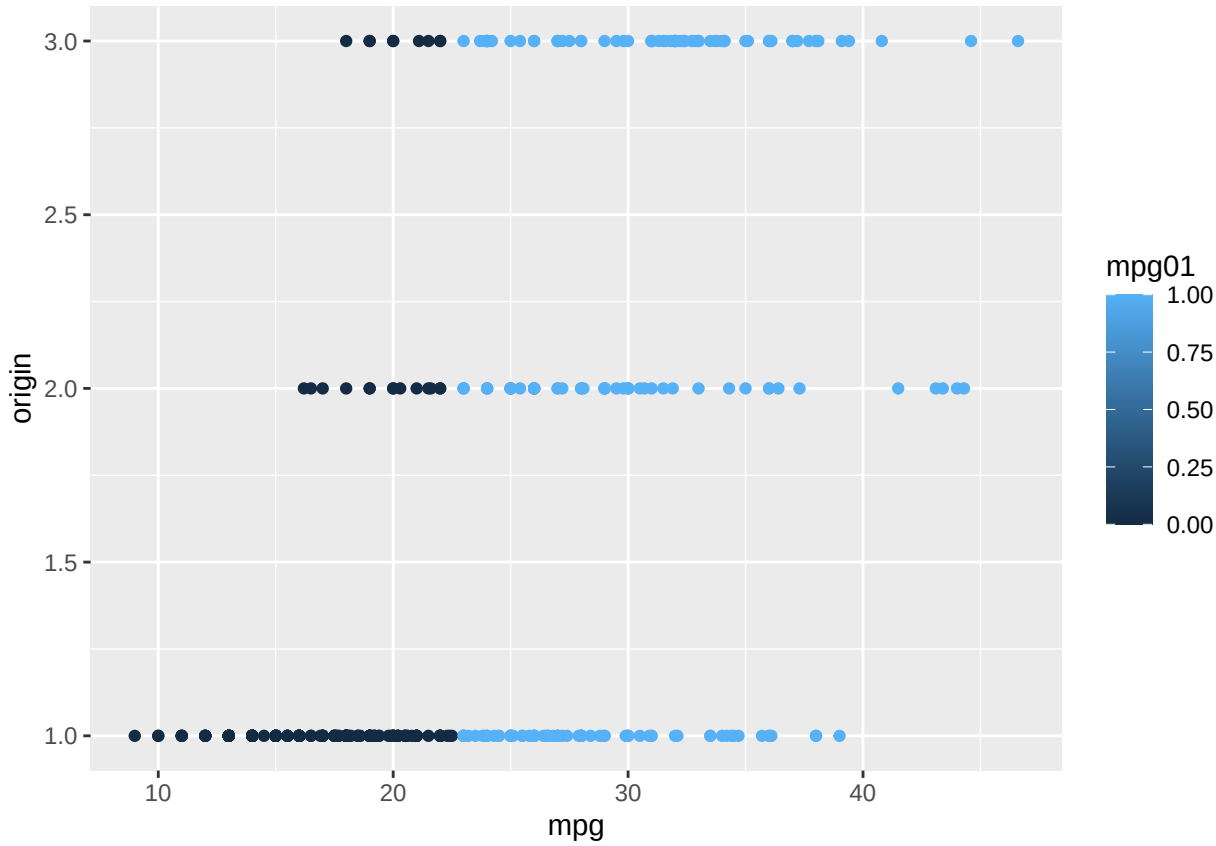
```
car.df %>%
  ggplot() +
   geom_point(mapping = aes(x = mpg, y = acceleration, color = mpg01))
```



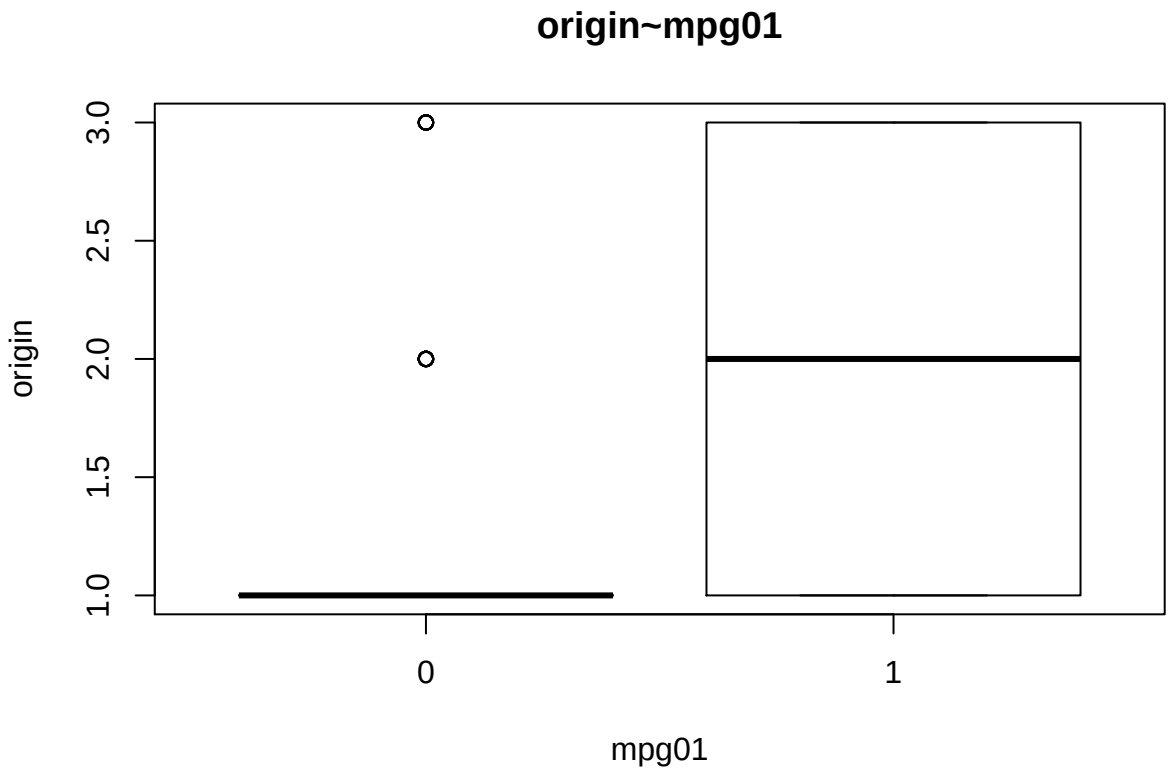

```
boxplot(acceleration~mpg01,car.df,main="acceleration~mpg01")
```




```
car.df %>%
  ggplot() +
   geom_point(mapping = aes(x = mpg, y = origin, color = mpg01))
```




```
boxplot(origin~mpg01,car.df,main="origin~mpg01")
```



```
#
# car.df %>%
#   filter(mpg01 == 0) %>%
#   ggplot(mapping = aes(x = mpg01, y = year)) +
#   geom_boxplot()
#
#
# car.df %>%
#   filter(mpg01 != 0) %>%
#   ggplot(mapping = aes(x = mpg01, y = year)) +
#   geom_boxplot()
#

# ggplot(data = car.df) +
#   geom_point(mapping = aes(x = mpg01, y = year, size = cylinders))

sprintf("Features : year, cylinders, displacement, horsepower, weight, origin")
```

```
## [1] "Features : year, cylinders, displacement, horsepower, weight, origin"
```

```
# c) Split the data into training and test

# car.df %>%
#   group_by(year) %>%
#   summarize(n())

train <- (car.df$year <= 78)
# train.Y <- car.df[train, "mpg01"]
# test.Y <- car.df[!train, "mpg01"]
train.Y <- car.df[train, ]$mpg01
test.Y <- car.df[!train, ]$mpg01
test.X <- car.df[!train, ]

# d) Perform LDA
lda.fit <- MASS::lda(mpg01 ~ year + cylinders + displacement + horsepower + weight + origin, data = car

# lets predict on test data using the model:
lda.pred <- predict(lda.fit, test.X, type =  "response")

stopifnot(length (lda.pred$class) == length(test.Y))
(confusion_table <- table(lda.pred$class, test.Y))
```

```
##    test.Y
##      0  1
##   0 17 13
##   1  1 83
```

```
# Null classifier:
sprintf("LDA: Null classifier : %s ", (13+83)/(17+1+13+83) )
```

```
## [1] "LDA: Null classifier : 0.842105263157895 "
```

```
# overall fraction of correct predictions:
sprintf("LDA: overall fraction of correct predictions: %s", mean(lda.pred$class == test.Y))
```

```
## [1] "LDA: overall fraction of correct predictions: 0.87719298245614"
```

```r
# FP rate:
sprintf("LDA: FP rate (TypeI error, 1 - specificity) : %s", confusion_table[2,1]/(confusion_table[2,1]+
```

```
## [1] "LDA: FP rate (TypeI error, 1 - specificity) : 0.0555555555555556"
```

```r
# TP rate:
sprintf("LDA: TP rate (1-TypeII error, power, sensetivity, recall) : %s", confusion_table[2,2]/(confusi
```

```
## [1] "LDA: TP rate (1-TypeII error, power, sensetivity, recall) : 0.864583333333333"
```

```r
# precision:
sprintf("LDA: precision: %s", confusion_table[2,2] / (confusion_table[2,2] + confusion_table[2,1]))
```

```
## [1] "LDA: precision: 0.988095238095238"
```

```r
# specificity 1-FP/N:
sprintf("LDA: specificity 1-FP/N: %s", 1 - confusion_table[2,1]/(confusion_table[2,1]+ confusion_table[
```

```
## [1] "LDA: specificity 1-FP/N: 0.944444444444444"
```

```r
sprintf("test Error is about %s", mean(lda.pred$class != test.Y))
```

```
## [1] "test Error is about 0.12280701754386"
```

```r
# e) Perform QDA
qda.fit <- MASS::qda(mpg01 ~ year + cylinders + displacement + horsepower + weight + origin, data = car

# lets predict on test data using the model:
qda.pred <- predict(qda.fit, test.X, type =  "response")

stopifnot(length (qda.pred$class) == length(test.Y))
(confusion_table <- table(qda.pred$class, test.Y))
```

```
##    test.Y
##      0  1
##   0 17 19
##   1  1 77
```

```r
# Null classifier:
sprintf("QDA: Null classifier : %s ",(77+19)/(77+19+1+17) )
```

```
## [1] "QDA: Null classifier : 0.842105263157895 "
```

```r
# overall fraction of correct predictions:
sprintf("QDA: overall fraction of correct predictions: %s", mean(qda.pred$class == test.Y))
```

```
## [1] "QDA: overall fraction of correct predictions: 0.824561403508772"
```

```r
# FP rate:
sprintf("QDA: FP rate (TypeI error, 1 - specificity) : %s", confusion_table[2,1]/(confusion_table[2,1]+
```

```
## [1] "QDA: FP rate (TypeI error, 1 - specificity) : 0.0555555555555556"
```

```r
# TP rate:
sprintf("QDA: TP rate (1-TypeII error, power, sensetivity, recall) : %s", confusion_table[2,2]/(confusi
```

```
## [1] "QDA: TP rate (1-TypeII error, power, sensetivity, recall) : 0.802083333333333"
```

```r
# precision:
sprintf("QDA: precision: %s", confusion_table[2,2] / (confusion_table[2,2] + confusion_table[2,1]))
```

```
## [1] "QDA: precision: 0.987179487179487"
```

```r
# specificity 1-FP/N:
sprintf("QDA: specificity 1-FP/N: %s", 1 - confusion_table[2,1]/(confusion_table[2,1]+ confusion_table[
```

```
## [1] "QDA: specificity 1-FP/N: 0.944444444444444"
```

```r
sprintf("test Error is about %s", mean(qda.pred$class != test.Y))
```

```
## [1] "test Error is about 0.175438596491228"
```

```r
# f) Perform Logistic regrssion
glm.fit <- glm(mpg01 ~ year + cylinders + displacement + horsepower + weight + origin, data = car.df, fa
sprintf("summary of logistic regression: ")
```

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

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

```
##
## Call:
## glm(formula = mpg01 ~ year + cylinders + displacement + horsepower +
##     weight + origin, family = binomial, data = car.df, subset = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4231  -0.1160  -0.0028   0.1674   2.2930
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.583967   7.769287  -0.075  0.94008
## year          0.241226   0.111557   2.162  0.03059 *
## cylinders    -0.454012   0.636865  -0.713  0.47592
## displacement -0.006523   0.017002  -0.384  0.70123
## horsepower   -0.042541   0.025010  -1.701  0.08894 .
## weight       -0.003957   0.001326  -2.985  0.00283 **
## origin       -0.030567   0.423935  -0.072  0.94252
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 363.21  on 277  degrees of freedom
## Residual deviance: 101.47  on 271  degrees of freedom
## AIC: 115.47
##
## Number of Fisher Scoring iterations: 8
```

```r
glm.probs <- predict(glm.fit, test.X, type =  "response")

glm.pred <- ifelse(glm.probs > 0.5, 1, 0)

stopifnot(length(glm.pred) == length(test.Y))


(confusion_table <- table(glm.pred, test.Y))
```

```
##         test.Y
## glm.pred  0  1
```

```
##        0 17 14
##        1  1 82
```

```
# Null classifier:
sprintf("Logistic Regression : Null classifier : %s ", (14+82)/(14+82+1+17) )
```

```
## [1] "Logistic Regression : Null classifier : 0.842105263157895 "
```

```
# overall fraction of correct predictions:
sprintf("Logistic Regression : overall fraction of correct predictions: %s", mean(glm.pred == test.Y))
```

```
## [1] "Logistic Regression : overall fraction of correct predictions: 0.868421052631579"
```

```
# FP rate:
sprintf("Logistic Regression : FP rate (TypeI error, 1 - specificity) : %s", confusion_table[2,1]/(confu
```

```
## [1] "Logistic Regression : FP rate (TypeI error, 1 - specificity) : 0.0555555555555556"
```

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

```
## [1] "Logistic Regression : TP rate (1-TypeII error, power, sensetivity, recall) : 0.854166666666667"
```

```
# precision:
sprintf("Logistic Regression : precision: %s", confusion_table[2,2] / (confusion_table[2,2] + confusion_
```

```
## [1] "Logistic Regression : precision: 0.987951807228916"
```

```
# specificity 1-FP/N:
sprintf("Logistic Regression : specificity 1-FP/N: %s", 1 - confusion_table[2,1]/(confusion_table[2,1]+
```

```
## [1] "Logistic Regression : specificity 1-FP/N: 0.944444444444444"
```

```
sprintf("Logistic Regression : Test Error Rate: %s", mean(glm.pred != test.Y))
```

```
## [1] "Logistic Regression : Test Error Rate: 0.131578947368421"
```

```
library(pROC)
roc_obj <- roc(test.Y, glm.probs)
```

```
## Setting levels: control = 0, case = 1
```

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

```
auc(roc_obj)
```

```
## Area under the curve: 0.9624
```

```
# g) Perform KNN
# First scale the data
str(car.df)
```

```
## tibble [392 x 10] (S3: tbl_df/tbl/data.frame)
##  $ mpg         : num [1:392] 18 15 18 16 17 15 14 14 14 15 ...
##  $ cylinders   : int [1:392] 8 8 8 8 8 8 8 8 8 8 ...
##  $ displacement: num [1:392] 307 350 318 304 302 429 454 440 455 390 ...
##  $ horsepower  : int [1:392] 130 165 150 150 140 198 220 215 225 190 ...
##  $ weight      : int [1:392] 3504 3693 3436 3433 3449 4341 4354 4312 4425 3850 ...
##  $ acceleration: num [1:392] 12 11.5 11 12 10.5 10 9 8.5 10 8.5 ...
##  $ year        : int [1:392] 70 70 70 70 70 70 70 70 70 70 ...
##  $ origin      : int [1:392] 1 1 1 1 1 1 1 1 1 1 ...
##  $ name        : Factor w/ 301 levels "amc ambassador brougham",..: 49 36 230 14 160 141 54 222 240 1
```

```
##  $ mpg01       : num [1:392] 0 0 0 0 0 0 0 0 0 0 ...
```

```
scaled.car.df <- scale(car.df[, -9])
colnames(scaled.car.df)
```

```
## [1] "mpg"          "cylinders"    "displacement" "horsepower"   "weight"
## [6] "acceleration" "year"         "origin"       "mpg01"
```

```
(helperDF <- tibble(year = car.df$year, mpg01 = car.df$mpg01 , cylinders = scaled.car.df[, "cylinders"]
                    displacement = scaled.car.df[, "displacement"], horsepower = scaled.car.df[, "horsep
                    weight = scaled.car.df[,"weight"], origin = scaled.car.df[, "origin"]))
```

```
## # A tibble: 392 x 7
##     year mpg01 cylinders displacement horsepower weight origin
##    <int> <dbl>     <dbl>        <dbl>      <dbl>  <dbl>  <dbl>
##  1    70     0      1.48         1.08      0.663  0.620 -0.716
##  2    70     0      1.48         1.49      1.57   0.842 -0.716
##  3    70     0      1.48         1.18      1.18   0.540 -0.716
##  4    70     0      1.48         1.05      1.18   0.536 -0.716
##  5    70     0      1.48         1.03      0.923  0.555 -0.716
##  6    70     0      1.48         2.24      2.43   1.61  -0.716
##  7    70     0      1.48         2.48      3.00   1.62  -0.716
##  8    70     0      1.48         2.35      2.87   1.57  -0.716
##  9    70     0      1.48         2.49      3.13   1.70  -0.716
## 10    70     0      1.48         1.87      2.22   1.03  -0.716
## # ... with 382 more rows
```

```
train.X <- helperDF[train, c("cylinders", "displacement", "horsepower", "weight", "origin")]
train.Y <- helperDF[train, ]$mpg01
test.X <- helperDF[!train, c("cylinders", "displacement", "horsepower", "weight", "origin")]
test.Y <- helperDF[!train, ]$mpg01

# now do the KNN
set.seed(1)
knn.pred <- class::knn(train.X, test.X, train.Y, k = 15)

(confusion_table <- table (knn.pred, test.Y))
```

```
##         test.Y
## knn.pred  0  1
##        0 17 14
##        1  1 82
```

```
stopifnot(length (knn.pred) == length(test.Y))

# Null classifier:
sprintf("KNN: Null classifier : %s ", (24+72)/(24+72+17+1) )
```

```
## [1] "KNN: Null classifier : 0.842105263157895 "
```

```
# overall fraction of correct predictions:
sprintf("KNN: overall fraction of correct predictions: %s", mean(knn.pred == test.Y))
```

```
## [1] "KNN: overall fraction of correct predictions: 0.868421052631579"
```

```
# FP rate:
sprintf("KNN: FP rate (TypeI error, 1 - specificity) : %s", confusion_table[2,1]/(confusion_table[2,1]+
```

```
## [1] "KNN: FP rate (TypeI error, 1 - specificity) : 0.0555555555555556"
```

```r
# TP rate:
sprintf("KNN: TP rate (1-TypeII error, power, sensetivity, recall) : %s", confusion_table[2,2]/(confusi
```

```
## [1] "KNN: TP rate (1-TypeII error, power, sensetivity, recall) : 0.854166666666667"
```

```r
# precision:
sprintf("KNN: precision: %s", confusion_table[2,2] / (confusion_table[2,2] + confusion_table[2,1]))
```

```
## [1] "KNN: precision: 0.987951807228916"
```

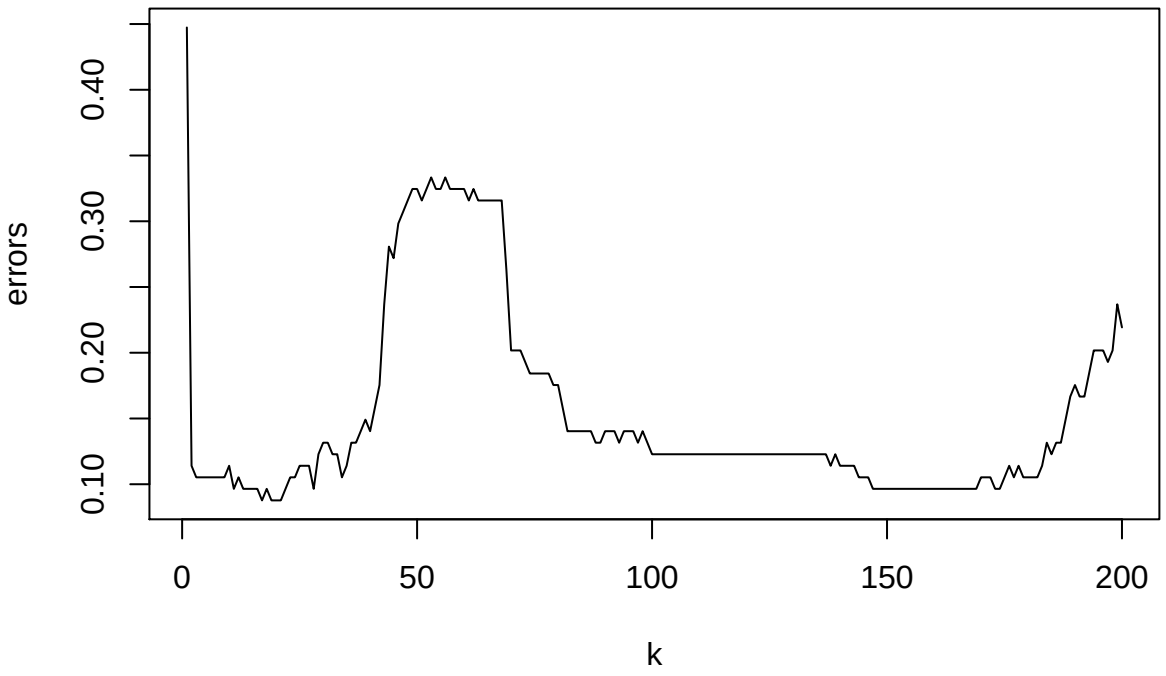
```r
# specificity 1-FP/N:
sprintf("KNN: specificity 1-FP/N: %s", 1 - confusion_table[2,1]/(confusion_table[2,1]+ confusion_table[
```

```
## [1] "KNN: specificity 1-FP/N: 0.944444444444444"
```

```r
# test error rate
sprintf("KNN: Test error rate: %s", mean(knn.pred != test.Y))
```

```
## [1] "KNN: Test error rate: 0.131578947368421"
```

```r
# accumulate errors:
errors <- c()
maxK <- 200
step <- 1
for(k in seq(1,maxK,step)){
  knn.pred <- class::knn(train.X, test.X, train.Y, k)
  (confusion_table <- table (knn.pred, test.Y))
  errors <- c(mean(knn.pred != test.Y), errors)
}

data <- cbind(seq(1,maxK,step),errors)
plot(data,type="l",xlab="k")
```




```r
#a)
```

```r
Power <- function(){
  2 ^ 3
}

Power()
```

```
## [1] 8
```

```r
# b)
Power2 <- function(x, a) { x^a }
Power2(2,3)
```

```
## [1] 8
```

```r
# c)
Power2(10,3)
```

```
## [1] 1000
```

```r
Power2(8,17)
```

```
## [1] 2.2518e+15
```

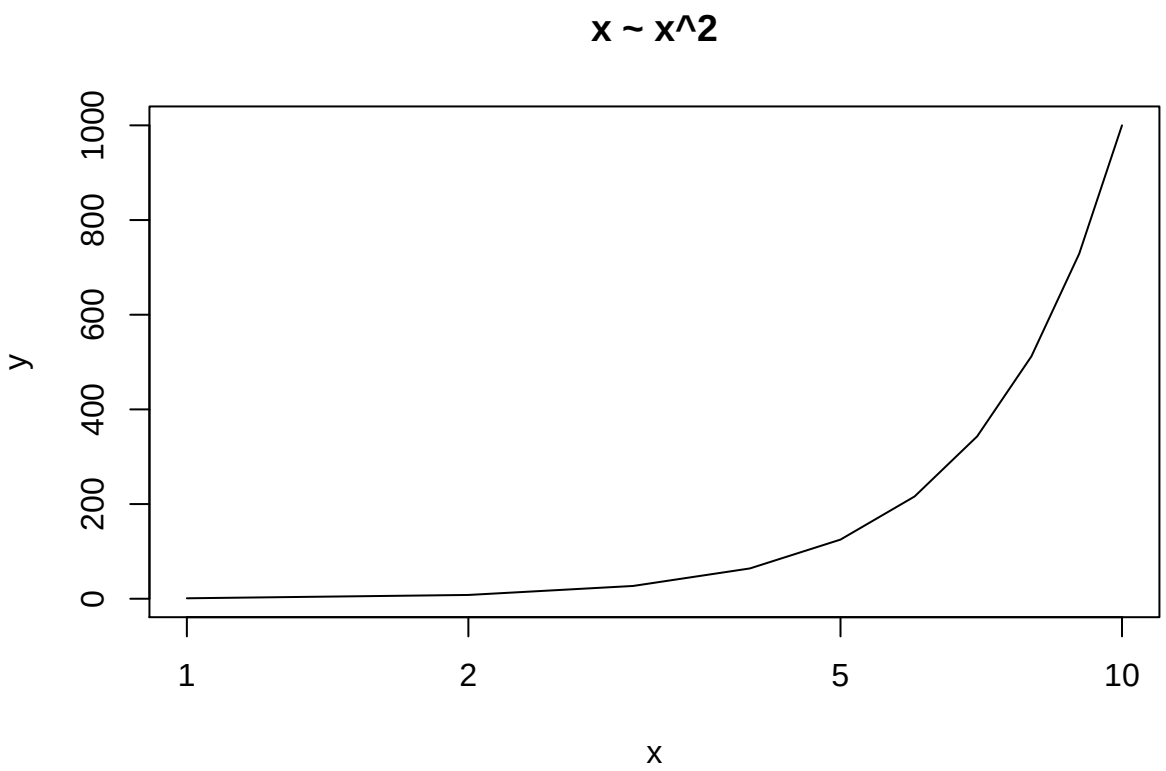
```r
Power2(131,3)
```

```
## [1] 2248091
```

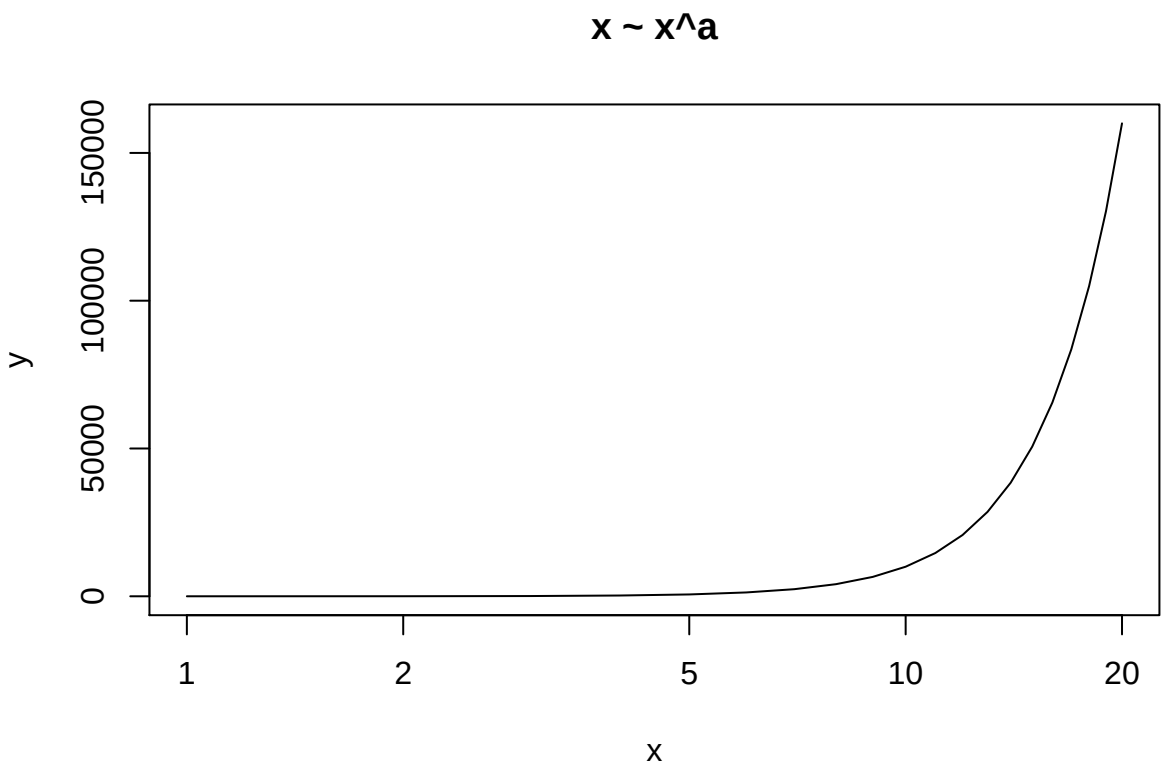
```r
# d)
Power3 <- function(x, a){
  result <- x^a
  return (result)
}

Power3(2,3)
```

```
## [1] 8
```

```r
# e)

x = 1:10
y = sapply(x,function(x){Power3(x,3)})

plot(x,y,log='x',main='x ~ x^2',type='l')
```




```
# f)

PlotPower <- function(x, a){

  y = sapply(x,function(x){Power3(x,a)})

  plot(x,y,log='x',main='x ~ x^a',type='l')

}
PlotPower(1:20,4)
```




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

```
## [1] 506  14
```

```
names(boston.df)
```

```
##  [1] "crim"    "zn"      "indus"   "chas"    "nox"     "rm"      "age"
##  [8] "dis"     "rad"     "tax"     "ptratio" "b"       "lstat"   "medv"
```

```
boston.df <- boston.df %>%
  mutate (crim01 = ifelse (crim >= median(crim), 1, 0))

# split the data into test and train
train <- (boston.df$age <= 90)
test.X <- boston.df[!train,]
test.Y <- boston.df[!train,]$crim01
train.Y <- boston.df[train,]$crim01

 # first use Logistic refression to calculate P(crime01=1 | X):
glm.fit <- glm(crim01 ~ . , data = boston.df, family = binomial, subset = train)
```

```
## Warning: glm.fit: algorithm did not converge
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
sprintf("summary of logistic regression: ")
```

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

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

```
##
## Call:
## glm(formula = crim01 ~ ., family = binomial, data = boston.df,
##     subset = train)
##
## Deviance Residuals:
##        Min          1Q      Median          3Q         Max
## -1.277e-03  -2.000e-08  -2.000e-08   2.000e-08   1.306e-03
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -6.541e+02  1.207e+05  -0.005    0.996
## crim         1.077e+03  3.057e+04   0.035    0.972
## zn           2.079e+00  3.823e+02   0.005    0.996
## indus       -2.053e+00  1.537e+03  -0.001    0.999
## chas        -6.263e+01  2.256e+04  -0.003    0.998
## nox          1.120e+02  1.715e+05   0.001    0.999
## rm           4.531e+01  9.435e+03   0.005    0.996
## age          1.654e-01  7.844e+01   0.002    0.998
## dis         -8.349e-01  3.747e+03   0.000    1.000
## rad          1.379e+00  5.268e+03   0.000    1.000
## tax         -3.621e-02  2.026e+02   0.000    1.000
## ptratio      2.826e+00  2.921e+03   0.001    0.999
## b            2.910e-02  3.482e+01   0.001    0.999
## lstat        1.904e+00  4.980e+02   0.004    0.997
## medv        -1.369e+00  8.238e+02  -0.002    0.999
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 4.2502e+02  on 337  degrees of freedom
## Residual deviance: 5.5710e-06  on 323  degrees of freedom
## AIC: 30
##
## Number of Fisher Scoring iterations: 25
```

```r
glm.probs <- predict(glm.fit, test.X, type =  "response")

glm.pred <- ifelse(glm.probs > 0.5, 1, 0)

stopifnot(length(glm.pred) == length(test.Y))


(confusion_table <- table(glm.pred, test.Y))
```

```
##         test.Y
## glm.pred   0   1
##        0  21   1
##        1   3 143
```

```r
# Null classifier:
sprintf("Logistic Regression : Null classifier : %s ", (1+143)/(1+143+21+3) )
```

```
## [1] "Logistic Regression : Null classifier : 0.857142857142857 "
```

```r
# overall fraction of correct predictions:
sprintf("Logistic Regression : overall fraction of correct predictions: %s", mean(glm.pred == test.Y))
```

```
## [1] "Logistic Regression : overall fraction of correct predictions: 0.976190476190476"
```

```r
# FP rate:
sprintf("Logistic Regression : FP rate (TypeI error, 1 - specificity) : %s", confusion_table[2,1]/(confu
```

```
## [1] "Logistic Regression : FP rate (TypeI error, 1 - specificity) : 0.125"
```

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

```
## [1] "Logistic Regression : TP rate (1-TypeII error, power, sensetivity, recall) : 0.993055555555556"
```

```r
# precision:
sprintf("Logistic Regression : precision: %s", confusion_table[2,2] / (confusion_table[2,2] + confusion_
```

```
## [1] "Logistic Regression : precision: 0.979452054794521"
```

```r
# specificity 1-FP/N:
sprintf("Logistic Regression : specificity 1-FP/N: %s", 1 - confusion_table[2,1]/(confusion_table[2,1]+
```

```
## [1] "Logistic Regression : specificity 1-FP/N: 0.875"
```

```r
sprintf("Logistic Regression : Test Error Rate: %s", mean(glm.pred != test.Y))
```

```
## [1] "Logistic Regression : Test Error Rate: 0.0238095238095238"
```

```r
library(pROC)
roc_obj <- roc(test.Y, glm.probs)
```

```
## Setting levels: control = 0, case = 1
```

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

```r
auc(roc_obj)
```

```
## Area under the curve: 0.9988
```

```r
# Now lets do the LDA
lda.fit <- MASS::lda(crim01 ~ . , data = boston.df, family = binomial, subset = train)

# lets predict on test data using the model:
lda.pred <- predict(lda.fit, test.X, type =  "response")

stopifnot(length (lda.pred$class) == length(test.Y))
(confusion_table <- table(lda.pred$class, test.Y))
```

```
##    test.Y
##       0   1
##   0  24  36
##   1   0 108
```

```r
# Null classifier:
sprintf("LDA: Null classifier : %s ", (36+108)/(36+108+24+0) )
```

```
## [1] "LDA: Null classifier : 0.857142857142857 "
```

```r
# overall fraction of correct predictions:
sprintf("LDA: overall fraction of correct predictions: %s", mean(lda.pred$class == test.Y))
```

```
## [1] "LDA: overall fraction of correct predictions: 0.785714285714286"
```

```
# FP rate:
sprintf("LDA: FP rate (TypeI error, 1 - specificity) : %s", confusion_table[2,1]/(confusion_table[2,1]+
```

```
## [1] "LDA: FP rate (TypeI error, 1 - specificity) : 0"
```

```
# TP rate:
sprintf("LDA: TP rate (1-TypeII error, power, sensetivity, recall) : %s", confusion_table[2,2]/(confusi
```

```
## [1] "LDA: TP rate (1-TypeII error, power, sensetivity, recall) : 0.75"
```

```
# precision:
sprintf("LDA: precision: %s", confusion_table[2,2] / (confusion_table[2,2] + confusion_table[2,1]))
```

```
## [1] "LDA: precision: 1"
```

```
# specificity 1-FP/N:
sprintf("LDA: specificity 1-FP/N: %s", 1 - confusion_table[2,1]/(confusion_table[2,1]+ confusion_table[
```

```
## [1] "LDA: specificity 1-FP/N: 1"
```

```
sprintf("test Error is about %s", mean(lda.pred$class != test.Y))
```

```
## [1] "test Error is about 0.214285714285714"
```

```
library(pROC)
roc_obj <- roc(test.Y, glm.probs)
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```
auc(roc_obj)
```

```
## Area under the curve: 0.9988
```

```
# Now lets do the KNN

# First scala the predictors
scaled_boston <- scale(boston.df)
colnames(scaled_boston)
```

```
##  [1] "crim"    "zn"      "indus"   "chas"    "nox"     "rm"      "age"
##  [8] "dis"     "rad"     "tax"     "ptratio" "b"       "lstat"   "medv"
## [15] "crim01"
```

```
helperDF <- tibble(age = boston.df$age, crim01 = boston.df$crim01,
                   zn = scaled_boston[,  "zn"], indus = scaled_boston[, "indus"], chas = scaled_boston[
                   nox = scaled_boston[, "nox"], rm = scaled_boston[, "rm"], medv = scaled_boston[, "me
                   dis = scaled_boston[, "dis"], rad = scaled_boston[, "rad"], tax = scaled_boston[, "t
                   ptratio = scaled_boston[, "ptratio"], b = scaled_boston[, "b"], lstat = scaled_bosto

train.X <- helperDF[train, c("zn", "indus", "chas", "nox", "rm","age","dis","rad","tax","ptratio","b","
train.Y <- helperDF[train, ]$crim01
test.X <-  helperDF[!train, c("zn", "indus", "chas", "nox", "rm","age","dis","rad","tax","ptratio","b",
test.Y <- helperDF[!train, ]$crim01

set.seed(1)
knn.pred <- class::knn(train.X, test.X, train.Y, k = 85)

(confusion_table <- table (knn.pred, test.Y))
```

```
##          test.Y
## knn.pred   0   1
##        0   0   0
##        1  24 144
```

```r
stopifnot(length (knn.pred) == length(test.Y))

# Null classifier:
sprintf("KNN: Null classifier : %s ", (144)/(144+24) )
```

```
## [1] "KNN: Null classifier : 0.857142857142857 "
```

```r
# overall fraction of correct predictions:
sprintf("KNN: overall fraction of correct predictions: %s", mean(knn.pred == test.Y))
```

```
## [1] "KNN: overall fraction of correct predictions: 0.857142857142857"
```

```r
# FP rate:
sprintf("KNN: FP rate (TypeI error, 1 - specificity) : %s", confusion_table[2,1]/(confusion_table[2,1]+
```

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

```r
# TP rate:
sprintf("KNN: TP rate (1-TypeII error, power, sensetivity, recall) : %s", confusion_table[2,2]/(confusi
```

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

```r
# precision:
sprintf("KNN: precision: %s", confusion_table[2,2] / (confusion_table[2,2] + confusion_table[2,1]))
```

```
## [1] "KNN: precision: 0.857142857142857"
```

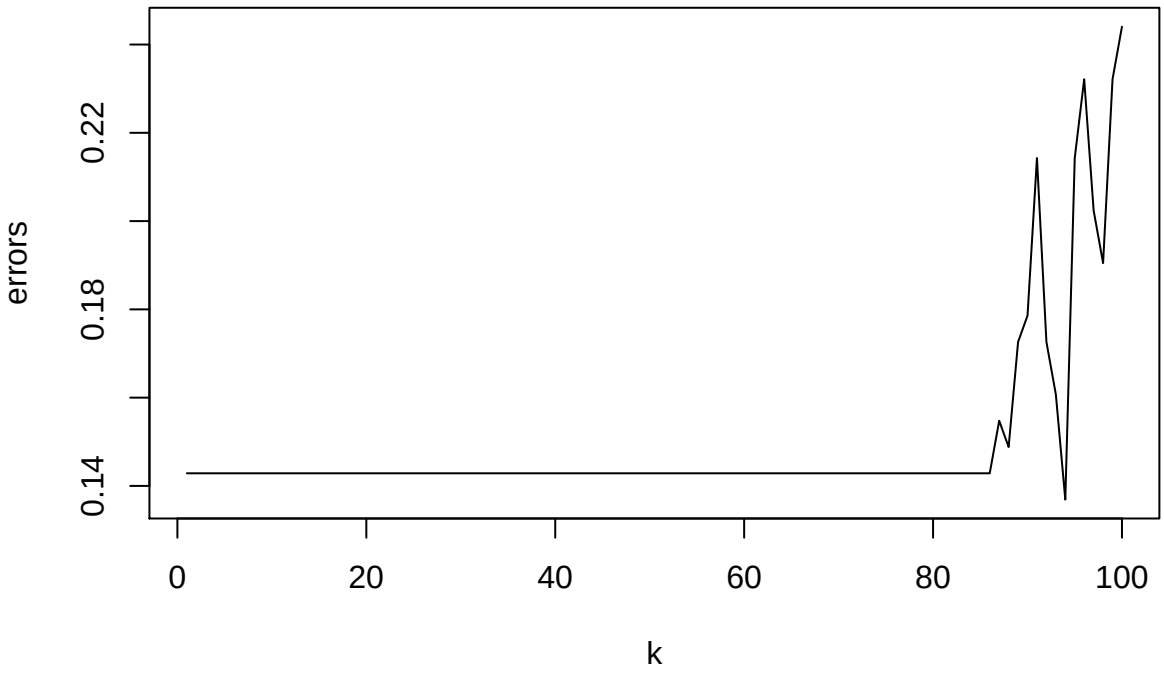
```r
# specificity 1-FP/N:
sprintf("KNN: specificity 1-FP/N: %s", 1 - confusion_table[2,1]/(confusion_table[2,1]+ confusion_table[
```

```
## [1] "KNN: specificity 1-FP/N: 0"
```

```r
# test error rate
sprintf("KNN: Test error rate: %s", mean(knn.pred != test.Y))
```

```
## [1] "KNN: Test error rate: 0.142857142857143"
```

```r
# accumulate errors:
errors <- c()
maxK <- 100
step <- 1
for(k in seq(1,maxK,step)){
  knn.pred <- class::knn(train.X, test.X, train.Y, k)
  (confusion_table <- table (knn.pred, test.Y))
  errors <- c(mean(knn.pred != test.Y), errors)
}

data <- cbind(seq(1,maxK,step),errors)
plot(data,type="l",xlab="k")
```


errors
0.14
0.18
0.22
0
20
40
60
80
100
k