Weekly Assignment 5

Loic Roldan Waals & Kimberly Cheng

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Question 1

In this question we just need the text part of last week's assignment. Before we answer the sub-questions, we first import the data and make a *corpus* and *document term matrix* (DTM). these will then be used for the next questions.

Amongst the words that were removed were the search terms *artificial, intelligence* and *artificialintelligence*, and several usernames.

```r
#---------------------------------------
# Load Relevant Packages & Tweets
#---------------------------------------
library(readr)
library(wordcloud)
library(jsonlite)
library(tm)
library(SnowballC)

AITweets <- read_delim("AITweets.csv",
                       ">", escape_double = FALSE, trim_ws = TRUE)

# Remove emoji's
AITweets$text <- sapply(AITweets$text, function(row) iconv(row, "latin1", "ASCII", sub = ""))

#---------------------------------------
# Create Corpus and Clean Textual Data
#---------------------------------------

# Create Corpus
vecdata <- VectorSource(AITweets$text)
myCorpus <- VCorpus(vecdata)


# Remove the links
removeLinks <- function (x) {
  gsub("http [^[:blank:]]+","",x)
}
myCorpus <- tm_map (myCorpus, content_transformer(removeLinks))

# Only lower case
tweets_corpus_clean <- tm_map(myCorpus, content_transformer(tolower))

# Remove punctuation
tweets_corpus_clean <- tm_map(tweets_corpus_clean, removePunctuation)

# Remove numbers
tweets_corpus_clean <- tm_map(tweets_corpus_clean, removeNumbers)
```

```
# Remove stopwords
tweets_corpus_clean <- tm_map(tweets_corpus_clean, removeWords, stopwords("english"))
tweets_corpus_clean <- tm_map(tweets_corpus_clean, removeWords, c("userexperienceu", "artificial", "int

# Remove unnecessary white space
tweets_corpus_clean <- tm_map(tweets_corpus_clean, stripWhitespace)

#stemming
tweets_corpus_clean <- tm_map(tweets_corpus_clean, stemDocument, language = "english")

myCorpus <- tweets_corpus_clean

#---------------------------------------
# Create Term Frequency Matrix
#---------------------------------------

dtm <- TermDocumentMatrix(tweets_corpus_clean)
dtm
```

```
## <<TermDocumentMatrix (terms: 2467, documents: 1021)>>
## Non-/sparse entries: 9078/2509729
## Sparsity           : 100%
## Maximal term length: 42
## Weighting          : term frequency (tf)
```

Part (a)

Because euclidean distance is normally used to calculate distance with k-means clustering (https://www.mailman.columbia.edu/research/population-health-methods/cluster-analysis-using-k-means) and because the dataset does not suffer too much from high dimensionality, euclidean distance was used to measure the distance.

We first remove the spare items to allow for a more easily understandable analysis. Then we plot a cluster dendrogram to see if we can see any natural clusters forming. Again, the euclidean distance metric was used. It appears that 3 groups have formed, these were labeled with the red boxes.

The first cluster appears to discuss machine learning and the new capabilities of robots (thanks to artificial intelligence). The second cluster is solely defined by the word *human*. This cluster could be encoding the comparison between humans and AI (e.g. when they become smarter than us, if they can mimic our behavior). The final cluster on the right seems to be about the (potential) behavior of AI, but this is highly speculative.

Finally the elbow method is used to determine whether our choice of 3 clusters seems reasonable. Plotting the within groups sum of squares against the number of clusters shows different values every time, but the large drop is always between 2 and 5 clusters. This means our choice of k=3 is reasonable.

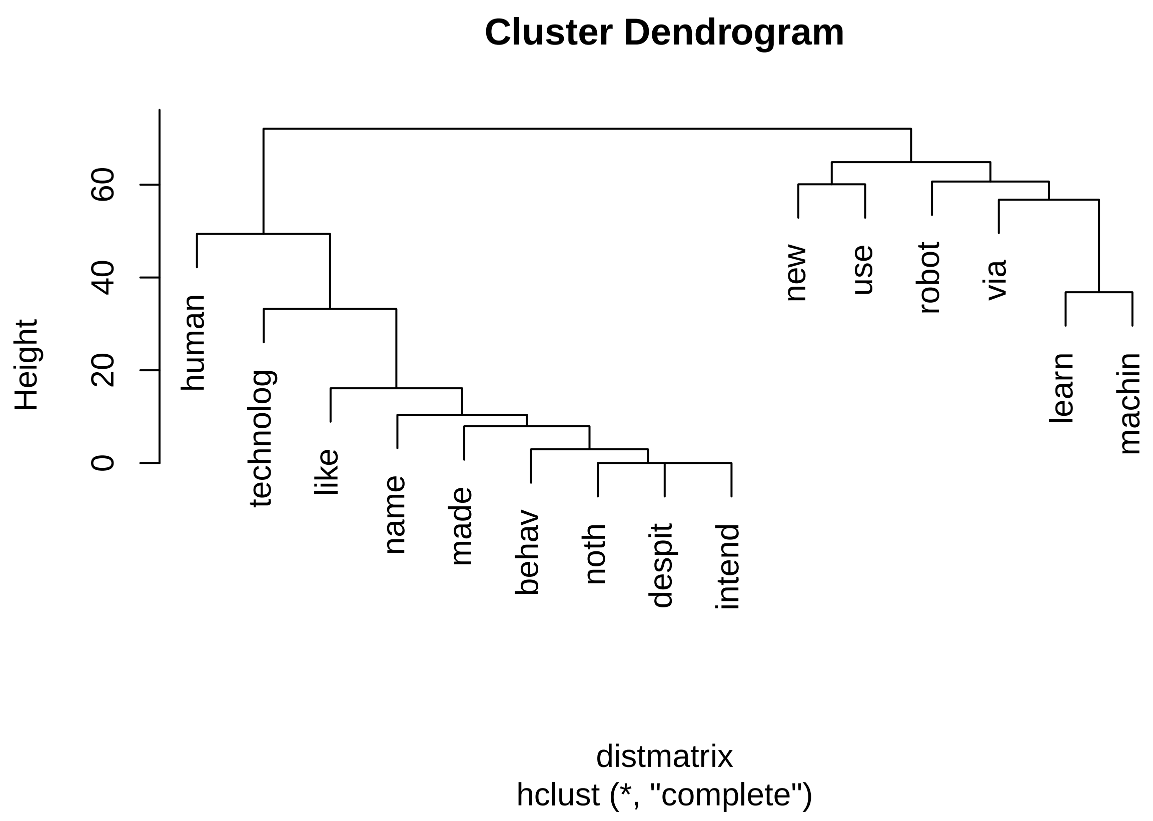
We finally finish with a cluster plot that shows that two components explain 67.9% of the point variability. Additionally, there is not much overlap between the clusters. A decision tree will also be created to show how each cluster can be attained.

```
set.seed(156)

#---------------------------------------
# Load Relevant Packages
```

```r
#---------------------------------------
library(cluster)

# Remove sparse words
dtm2 <- removeSparseTerms(dtm, sparse = 0.95)
dtm2
```

```
## <<TermDocumentMatrix (terms: 15, documents: 1021)>>
## Non-/sparse entries: 1193/14122
## Sparsity           : 92%
## Maximal term length: 9
## Weighting          : term frequency (tf)
```

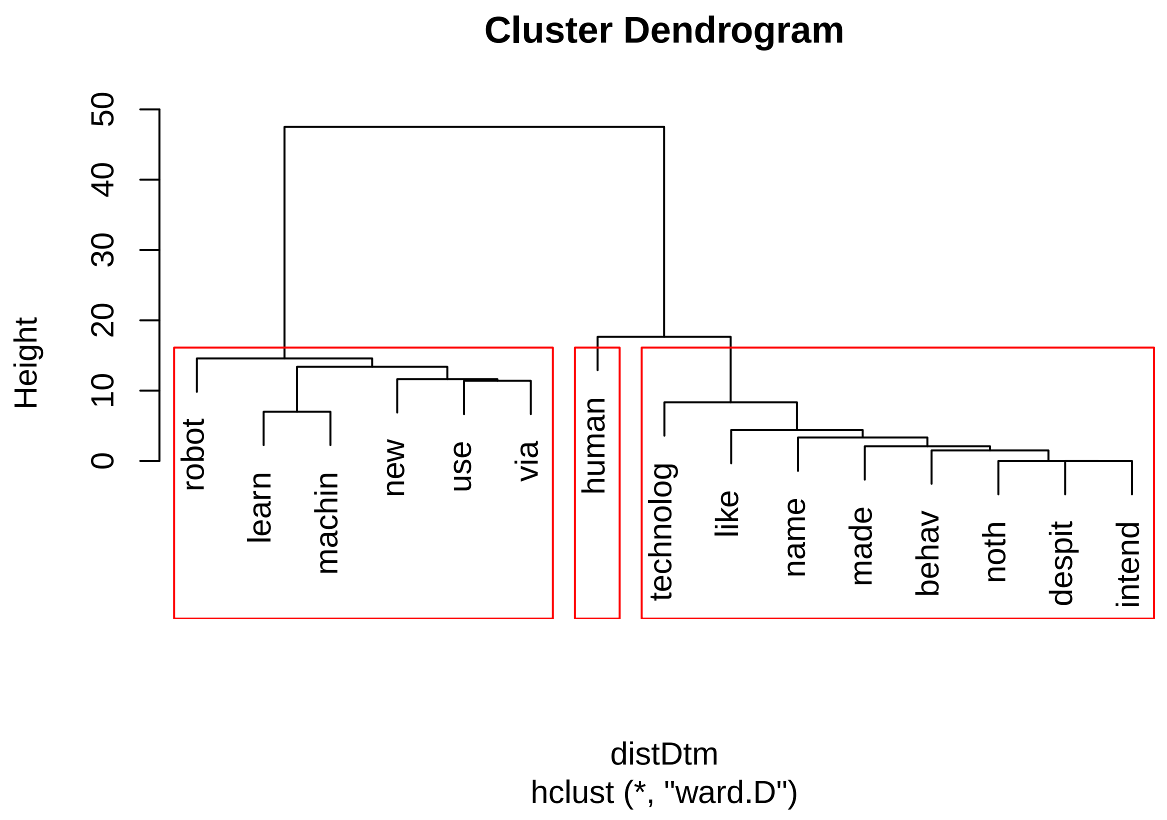
```r
dtm2 <- as.matrix(dtm2)
distmatrix <- dist(scale(dtm2))

#---------------------------------------
# Plot Dendrogram
#---------------------------------------
fit <- hclust(distmatrix)

plot(fit)
```



```r
clusters = 3


#----------------------------------------
# K-Means Clustering
#----------------------------------------
distDtm <- dist(dtm2 , method = "euclidean")

groups <- hclust(distDtm, method = "ward.D")
groups
```

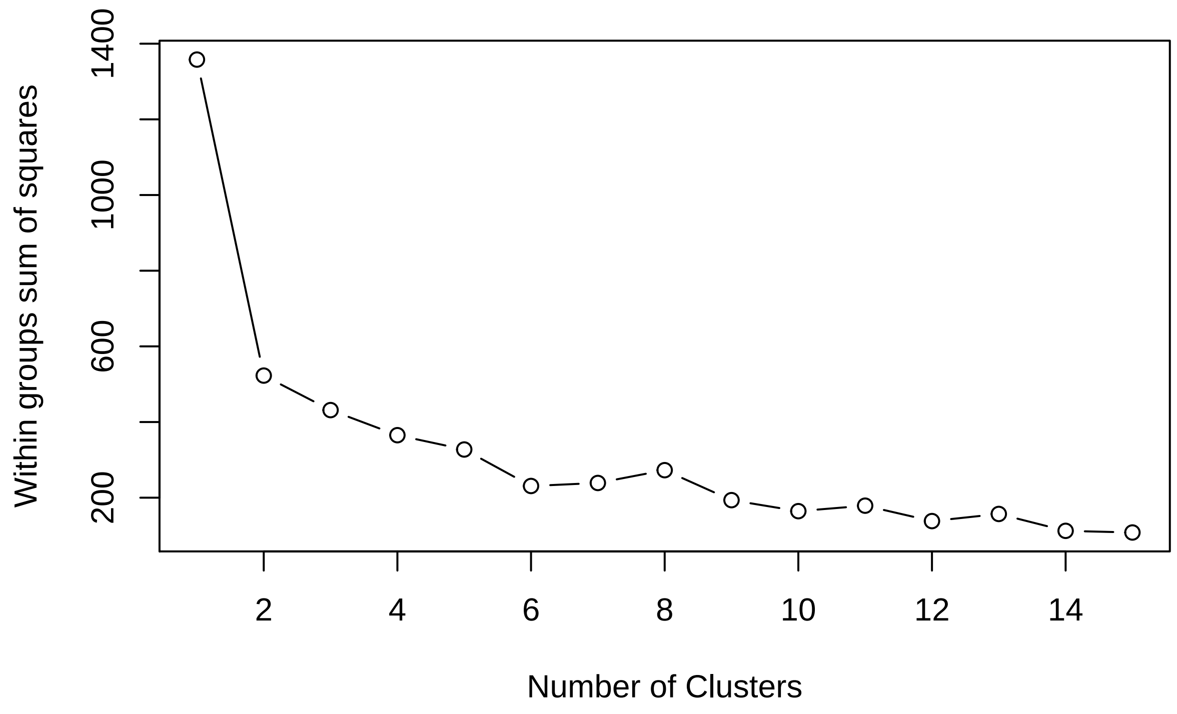
```
##
## Call:
## hclust(d = distDtm, method = "ward.D")
##
## Cluster method   : ward.D
## Distance         : euclidean
## Number of objects: 15
```

```r
plot(groups)
rect.hclust(groups, k=clusters)
```

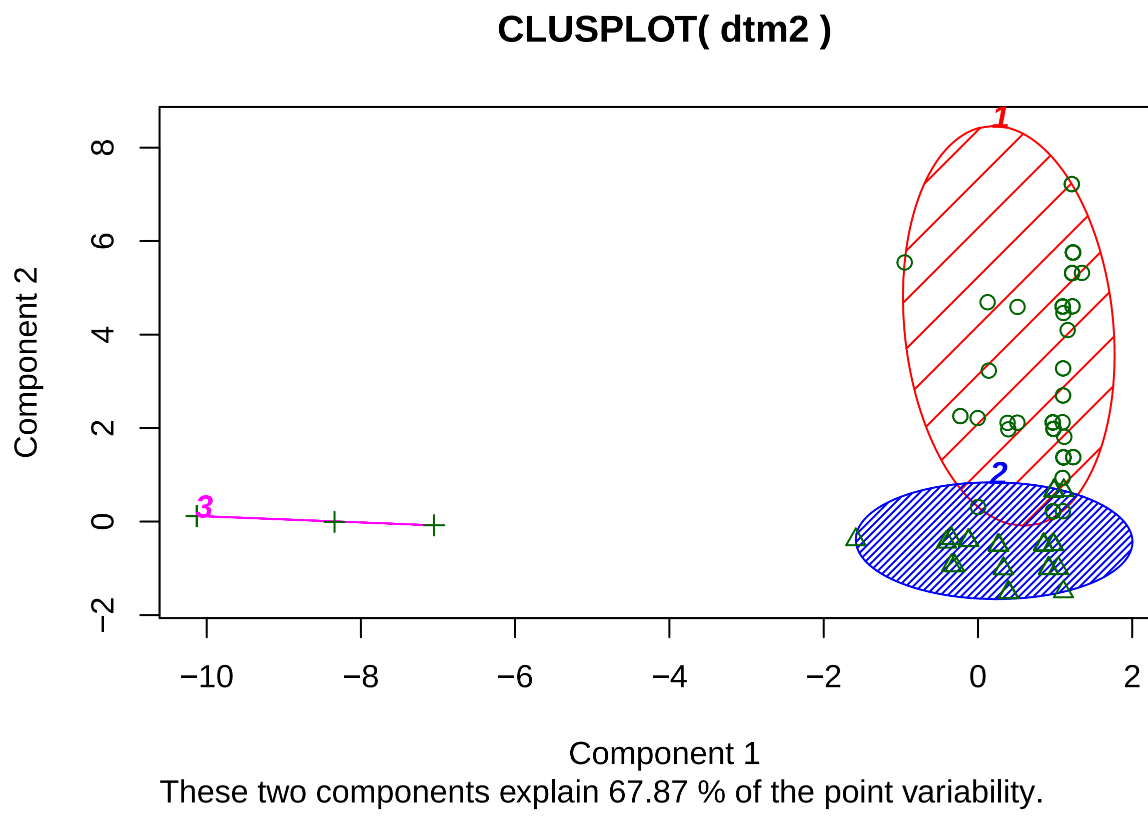


```r
dtm2 <- t(dtm2)
```

```r
#---------------------------------------
# Elbow Method
#---------------------------------------
# Using elbow method to determine number of clusters
x <- data.frame(dtm2)
wss <- (nrow(x)-1)*sum(apply(x,2,var))
for (i in 2:15) wss[i] <- sum(kmeans(x, centers = i)$withinss)

plot(1:15, wss, type="b", xlab="Number of Clusters", ylab="Within groups sum of squares")
```

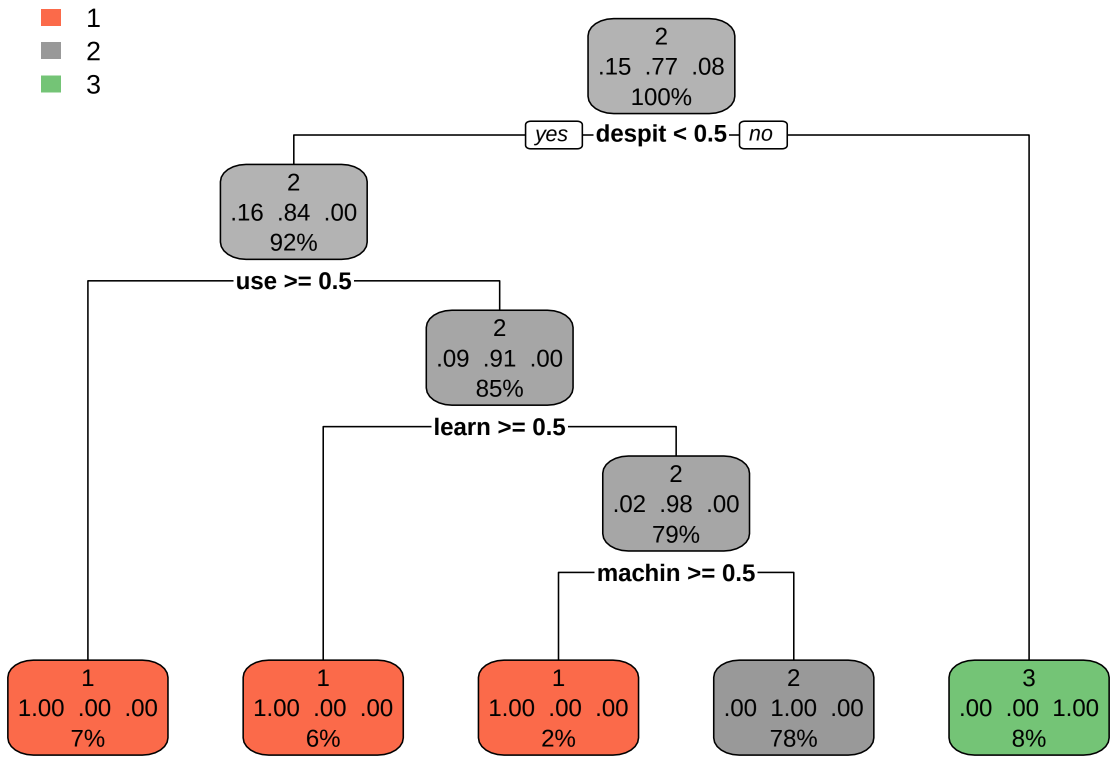


```r
#---------------------------------------
# Cluster Plot Principle Component Analysis
#---------------------------------------
rsltKmeans <- kmeans(dtm2, clusters)
clusplot(dtm2, rsltKmeans$cluster, color = TRUE, shade = TRUE, labels = 4, lines = 0)
```



It seems like the model checks whether the stem word *despit* is used, in which case it belongs to the third cluster.Then it checks Whether any of the words *use, learn* or *machin* are being used, if any of them are used, it belongs to the first cluster. Anything else and it belongs to the second cluster, the one that solely contained the word *human*.

```r
#---------------------------------------
# Load Relevant Packages
#---------------------------------------
library(rpart)
library(rpart.plot)

#---------------------------------------
# Plot Decision Tree
#---------------------------------------

#add clusters to the existing dataframe
dfcluster <- data.frame(dtm2, k = as.factor(rsltKmeans$cluster))

#train the tree
tree <- rpart(k ~ ., data = dfcluster, method = "class")
rpart.plot(tree)
```



Part (b)

We will now proceed with the sentiment analysis for twitter. We first import the file and clean the text in the same way as in **Part (a)**. After we have obtained the DTM we append the manual sentiment labels to create a data frame that contains the usage of the terms and the sentiment as columns. Here we find the first variable where we have a choice, *sparsity*. Using a trail an error method, we found that the optimal value for this is 0.96.

We then apply ten fold cross validation. Here we find the second variable we can tweak, the threshold of the prediction for the Naive Bayes model. Again, using the trail and error method we found a optimal threshold of 0.7. Finally to evaluate the performance we use accuracy and a confusion matrix. The code below was used:

```r
#load libraries

#----------------------------------------
# Load Relevant Packages
#----------------------------------------
library("e1071")
library("plyr")
library(naivebayes)
library(caret)
library(pROC)

# Set the values for the sparsity and the threshold for NB (easier tweaking).
```

```r
spar = 0.96
nbt = 0.7

#---------------------------------------
# Convert to Corpus and Clean Text Data
#---------------------------------------

# Import the dataset and create corpus
AITweets <- read_delim("C:/Users/Loic RW/Google Drive/Big Data and Business Analytics/Assignments/Assig

AITweets$sentiment <- as.factor(AITweets$sentiment)

# Remove emoji's
AITweets$text <- sapply(AITweets$text, function(row) iconv(row, "latin1", "ASCII", sub = ""))

# Create corpus
vecdata <- VectorSource(AITweets$text)
myCorpus <- VCorpus(vecdata)

# Remove the links
removeLinks <- function (x) {
  gsub("http [^[:blank:]]+","",x)
}
myCorpus <- tm_map (myCorpus, content_transformer(removeLinks))

# Only lower case
tweets_corpus_clean <- tm_map(myCorpus, content_transformer(tolower))

# Remove punctuation
tweets_corpus_clean <- tm_map(tweets_corpus_clean, removePunctuation)

# Remove numbers
tweets_corpus_clean <- tm_map(tweets_corpus_clean, removeNumbers)

# Remove stopwords
tweets_corpus_clean <- tm_map(tweets_corpus_clean, removeWords, stopwords("english"))
tweets_corpus_clean <- tm_map(tweets_corpus_clean, removeWords,
                              c("userexperienceu", "artificial", "intelligence", "artificialintelligenc
                                "murthaburk", "will", "dbrainio"))

# Remove unnecessary white space
tweets_corpus_clean <- tm_map(tweets_corpus_clean, stripWhitespace)

# Stemming
tweets_corpus_clean <- tm_map(tweets_corpus_clean, stemDocument, language = "english")

myCorpus <- tweets_corpus_clean

#---------------------------------------
# Make Term Frequency Matrix
#---------------------------------------

# Make term frequency matrix
```

```r
dtm <- TermDocumentMatrix(tweets_corpus_clean)
dtm2 <- removeSparseTerms(dtm, sparse = spar)
dtm2 <- t(as.matrix(dtm2))

# Turn the dtm into a data frame
dfsentiment <- data.frame(dtm2)
dfsentiment$target <- as.factor(AITweets$sentiment)

# Delete any potential missing values due to improper manual labeling
dfsentiment <- dfsentiment[complete.cases(dfsentiment),]

# Randomize the data
dfsentiment <- dfsentiment[sample(1:nrow(dfsentiment)), ]

#--------------------------------------
# 10-Fold Cross Validation & Naive Bayes Model
#--------------------------------------

# Create 10 equally sized folds
nFolds <- 10
folds <- cut(seq(1, nrow(dfsentiment)),
             breaks = nFolds,
             labels = FALSE)

# Vectors to store the results initialized with zeros
pdNB <- NULL
actual <- NULL

# Define the model
mdl <- as.factor(target) ~ .

# Perform 10 fold cross validation
for(i in 1:nFolds){

  #Segment the data by fold using which-function
  testIndexes <- which(folds == i, arr.ind = FALSE)
  testData <- dfsentiment[testIndexes, ]
  trainData <- dfsentiment[-testIndexes, ]

  #train the model
  rsltNB <- naiveBayes(mdl, data = trainData)

  #Make predictions on the test set
  NBClass <- predict(rsltNB, testData, type="class", threshold = nbt)

  #save the results to calculate accuracy later on
  pdNB <- c(as.character(pdNB), as.character(NBClass))
  actual <- c(actual, as.character(testData$target))
}

meanAccNB = mean(pdNB == actual)
meanAccNB
```

```
## [1] 0.6967509
```

```
actual <- as.factor(actual)
pdNB <- as.factor(pdNB)

confusionMatrix(pdNB, actual, positive = "1")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  -1   0   1
##         -1   0   4   4
##         0   11 144  40
##         1    1  24  49
##
## Overall Statistics
##
##                Accuracy : 0.6968
##                  95% CI : (0.6389, 0.7503)
##     No Information Rate : 0.6209
##     P-Value [Acc > NIR] : 0.005062
##
##                   Kappa : 0.3574
##  Mcnemar's Test P-Value : 0.028418
##
## Statistics by Class:
##
##                      Class: -1 Class: 0 Class: 1
## Sensitivity            0.00000   0.8372   0.5269
## Specificity            0.96981   0.5143   0.8641
## Pos Pred Value         0.00000   0.7385   0.6622
## Neg Pred Value         0.95539   0.6585   0.7833
## Prevalence             0.04332   0.6209   0.3357
## Detection Rate         0.00000   0.5199   0.1769
## Detection Prevalence   0.02888   0.7040   0.2671
## Balanced Accuracy      0.48491   0.6757   0.6955
```

As can be seen the accuracy of the model is 69.8%, simply choosing the most common factor would result in an accuracy of 62.1%. This shows that our model does not show great performance, but it is better than simply predicting neutral all the time. In the confusion matrix we see that the model classifies 0 most of the time correctly (83.7%). The sensitivity class 1 and -1 is poor, with 52.7% and 0% respectively.

Question 2

First we collect all the data with *newsapi*, these are then put into data frames and saved for later use.

Part (a)

```r
#---------------------------------------
# Load Relevant Files and Packages
#---------------------------------------
load(file = "cars.rda")

# Read lines of Positive and Negative Words
positive_words <- readLines("positive_words.txt")
negative_words <- readLines("negative_words.txt")

library(stringi) #to more cleanly transform to lower


#---------------------------------------
# Prepare Corpus and Clean Textual Data
#---------------------------------------

# Remove links Function
removeLinks <- function (x) {
  gsub("http [^[:blank:]]+","",x)
}

# Create a function to convert all strings to UTF
convertUTF <- function(d) {
  d$description <- iconv(d$description, "latin1", "ASCII")
  d$description <- iconv(d$description, "ASCII", "UTF-8")
  # Extract only complete cases
  d <- d[complete.cases(d), ]
}

# Create a function to Clean each Corpus
clean_corpus <- function(x) {

  x <- convertUTF(x)

  vecData <- VectorSource(x$description)
  myCorpus <- VCorpus(vecData)

  # Remove Links
  myCorpus <- tm_map(myCorpus, content_transformer(removeLinks))

  # Convert words to lowercase
  myCorpus <- tm_map(myCorpus, content_transformer(stri_trans_tolower))

  # Remove punctuation
  myCorpus <- tm_map(myCorpus, removePunctuation)

  # Remove numbers
  myCorpus <- tm_map(myCorpus, removeNumbers)

  # Remove stop-words
  myCorpus <- tm_map(myCorpus, removeWords, stopwords("english"))

  # Remove extra white spaces
  myCorpus <- tm_map(myCorpus, stripWhitespace)

  # Stemming
  myCorpus<- tm_map(myCorpus, stemDocument, language = "english")

}

# Run function to clean corpus
myCorpus.Volkswagen <- clean_corpus(df.Volkswagen)
myCorpus.Toyota <- clean_corpus(df.Toyota)
myCorpus.Honda <- clean_corpus(df.Honda)
myCorpus.BMW <- clean_corpus(df.BMW)
myCorpus.Ford <- clean_corpus(df.Ford)
myCorpus.MercedesBenz <- clean_corpus(df.MercedesBenz)
myCorpus.Volvo <- clean_corpus(df.Volvo)
myCorpus.Tesla <- clean_corpus(df.Tesla)
```

```r
#--------------------------------------
# Score Each Corpus
#--------------------------------------

# Create a function to Score each Corpus

score_corpus <- function(y) {
  # Initiate the Score Topic
  scoreTopic <- 0

  #Start a loop over the documents
  for(ifold in 1: length(y)) {
    terms <- unlist(strsplit(y[[ifold]]$content, " "))
    pos_matches <- sum(terms %in% positive_words)
    neg_matches <- sum(terms %in% negative_words)
    scoreTopic[ifold] <- pos_matches - neg_matches
  } # End of the for loop

  df <- data.frame(text = sapply(y, paste, collapse = " "), stringsAsFactors = FALSE)
  df$score_topic <- scoreTopic
}

score.Volkswagen <- score_corpus(myCorpus.Volkswagen)
score.Toyota <- score_corpus(myCorpus.Toyota)
score.Honda <- score_corpus(myCorpus.Honda)
score.BMW <- score_corpus(myCorpus.BMW)
score.Ford <- score_corpus(myCorpus.Ford)
score.MercedesBenz <- score_corpus(myCorpus.MercedesBenz)
score.Volvo <- score_corpus(myCorpus.Volvo)
score.Tesla <- score_corpus(myCorpus.Tesla)
```

```r
# Merge all scores to plot
df <- cbind(score.Tesla, score.BMW, score.Ford, score.Honda,
            score.Toyota, score.MercedesBenz, score.Volkswagen, score.Volvo)

#--------------------------------------
```

```r
# Evaluate Sentiment
#---------------------------------------

# Total Sum of Scores of Topics (Positive Words - Negative Words) / Mean of Scores of TOpics
sums <- data.frame(Sums = colSums(df, na.rm = TRUE))
sums
```

```
               Sums
```

score.Tesla -13 score.BMW -20 score.Ford 64 score.Honda 27 score.Toyota 78 score.MercedesBenz 108 score.Volkswagen 37 score.Volvo -32

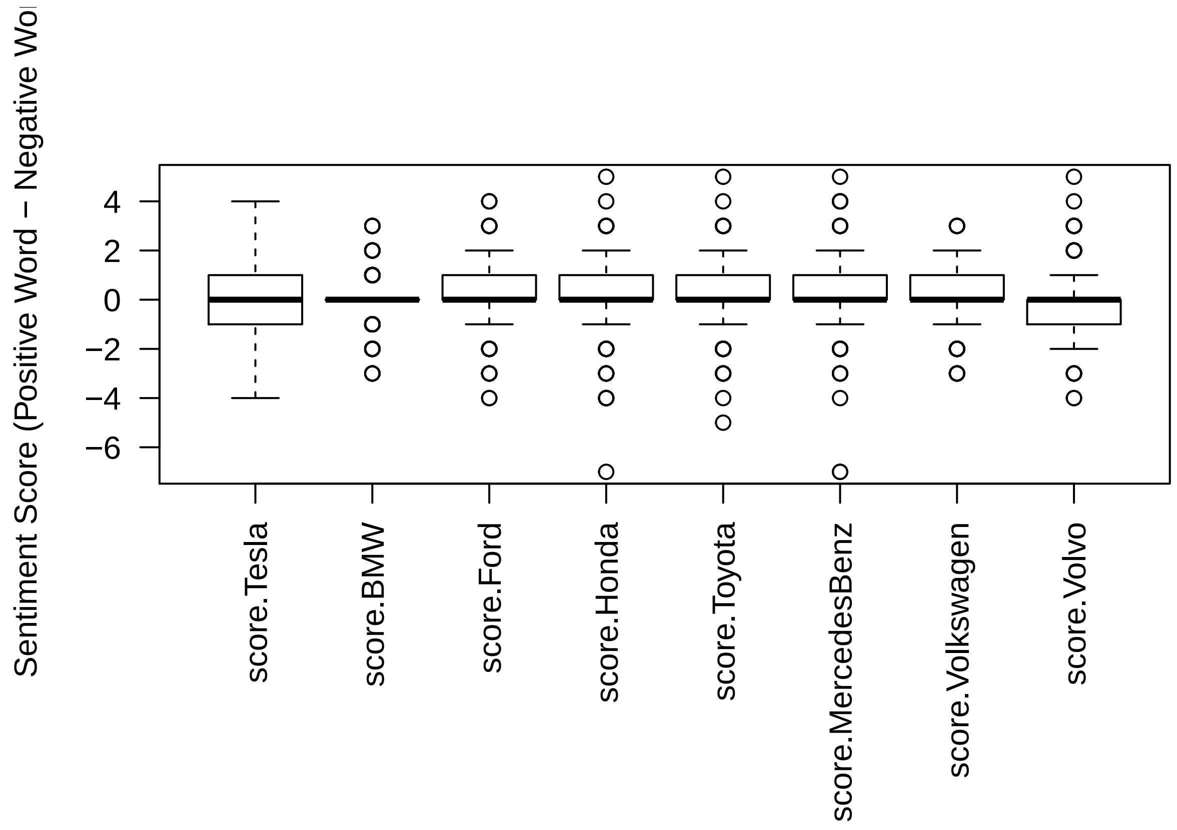
```r
means <- data.frame(Means = colMeans(df, na.rm = TRUE))
means
```

```
                     Means
```

score.Tesla -0.02233677 score.BMW -0.03436426 score.Ford 0.10996564 score.Honda 0.04639175 score.Toyota 0.13402062 score.MercedesBenz 0.18556701 score.Volkswagen 0.06357388 score.Volvo -0.05498282

When evaluating which brand has the most positive sentiment, we initially evaluated the sum of the sentiment where *sentiment = positive words - negative words*. The highest in this data is Mercedes Benz with a sentiment score from the whole corpus of 108. This means that Mercedes Benz has the most positive terms relative to negative terms out of all brands. When evaluating the average sentiment score per document, it is seen that again Mercedes Benz has the largest score with an average 0.18 score out of all documents within the corpus. In order to get better visualization of the distribution of these sentiment scores, a box plot was plotted.

```r
#---------------------------------------
# Plot Boxplot
#---------------------------------------
par(mar = c(10,4,4,2) + 0.1)
boxplot(df, ylab =  "Sentiment Score (Positive Word - Negative Word)", las = 2)
```



From the box plot, it is visible that the median sentiment score for the documents within each corpus all fall around the same range ~0. The distribution of sentiment scores appear to be largely skewed with only Tesla showing a relatively normal distribution. Ford, Honda, Toyota, Mercedes-Benz, and Volkswagen are all more negatively-skewed, while Volvo is positively-skewed. Additionally, BMW appears to have the most consistent score.

Part (b)

Here we simply chose a value of 0 for the cutoff. This means that a document with a sentiment score higher than 0 will be labeled as 1, while the ones with a sentiment score of less than 0 will be labeled as -1, the rest is labeled as 0.

```
#---------------------------------------
# Prepare Term Frequency Matix into Data Frame
#---------------------------------------

# Create a Function to convert the corpus to a data frame
# with the calculated sentiment scores

convert2DF <- function(a, b) {
  df <- cbind(data.frame(text = sapply(a, paste, collapse = " "),
                         stringsAsFactors = FALSE), score_topic = b)
}

# Run the functions for each brand
df.Volkswagen.Corp <- convert2DF(myCorpus.Volkswagen, score.Volkswagen)
```

```r
df.Toyota.Corp <- convert2DF(myCorpus.Toyota, score.Toyota)
df.Honda.Corp <- convert2DF(myCorpus.Honda, score.Honda)
df.BMW.Corp <- convert2DF(myCorpus.BMW, score.BMW)
df.MercedesBenz.Corp <- convert2DF(myCorpus.MercedesBenz, score.MercedesBenz)
df.Ford.Corp <- convert2DF(myCorpus.Ford, score.Ford)
df.Volvo.Corp <- convert2DF(myCorpus.Volvo, score.Volvo)
df.Tesla.Corp <- convert2DF(myCorpus.Tesla, score.Tesla)


# Merge all dataframes
df <- rbind(df.Volkswagen.Corp, df.Toyota.Corp,
            df.Honda.Corp, df.Ford.Corp, df.BMW.Corp,
            df.MercedesBenz.Corp, df.Tesla.Corp, df.Volvo.Corp)

# Classify Sentiment based on cutoffs
# Cutoffs ( > 1 is "1", < 1 is "-1", and 0 is "0")
df$sentiment[df$score_topic > 0] <- 1
df$sentiment[df$score_topic < 0] <- -1
df$sentiment[df$score_topic == 0] <- 0

# Convert Back to Corpus
vecData <- VectorSource(df$text)
myCorpus <- VCorpus(vecData)

# Convert to Document Term Matrix -
dtm <- DocumentTermMatrix(myCorpus)

# Remove Sparse Terms
dtm2 <- removeSparseTerms(dtm, sparse = 0.99)
dtm2 <- as.matrix(dtm2)

# Create Data Frame for Predictions
df.news <- data.frame(cbind(dtm2, sentiment = df$sentiment))
df.news$sentiment <- as.factor(df.news$sentiment)

#-----------------------------------
# 10-Fold Cross Validation - Prep
#-----------------------------------

# Prepare Cross Validation
# 1 - Randomize the order of the observations
df.news <- df.news[sample(1:nrow(df.news)), ]

# 2 - Create 10 equally sized folds - (10 = K)
n.Folds <- 10
Folds<- cut(seq(1, nrow(df.news)),
            breaks = n.Folds,
            labels = FALSE)
```

```r
#-----------------------------------
# Naive Bayes Classifier
#-----------------------------------
```

```r
library(caret)
library(e1071)

# Define the Model

mdl.news <- sentiment ~ .

# Create Empty Vectors to Collect Results
accuracy.NB <- rep(NA, n.Folds)
accuracy.SVM <- rep(NA, n.Folds)

# Perform the 10-fold cross validation for Naive Bayes
#Set a threshold
nbt = 0.5

for(i in 1: n.Folds) {

  testIndexes <- which(Folds == i, arr.ind = TRUE)
  df.news.test <- df.news[testIndexes, ]
  df.news.train <- df.news[-testIndexes, ]

  #Fit NB Model
  rslt.NB <- naiveBayes(mdl.news, data = df.news.train)
  #Fit SVM Model
  rslt.SVM <- svm(mdl.news, data = df.news.train, type = "C-classification", probability = TRUE)

  #Predicted Classification Test Set
  pred.NB <- predict(rslt.NB, df.news.test, type = "class", threshold = nbt)
  pred.SVM <- predict(rslt.SVM, df.news.test, type = "response")

  #Accuracy
  accuracy.NB[i] <- mean(pred.NB == df.news.test$sentiment)
  accuracy.SVM[i] <- mean(pred.SVM == df.news.test$sentiment)

}

# Calculate Results for Naive Bayes Model: Accuracy
JSONAccNB <- mean(accuracy.NB)
JSONAccNB
```

```
## [1] 0.5899393
```

```r
JSONAccSVM <- mean(accuracy.SVM)
JSONAccSVM
```

```
## [1] 0.7192802
```

In this data, SVM has the highest accuracy in predicting the sentiment for the news articles based on textual data with a mean accuracy of `mean(accuracy.SVM)` over a Naive Bayes which has a mean accuracy of `mean(accuracy.SVM)`.