TAD Project

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1.1. Preliminary Analysis - cosine similary, euclidean & manhattan distance

```
rm(list =ls())
library(quanteda)

## Package version: 1.4.0

## Parallel computing: 2 of 8 threads used.

## See https://quanteda.io for tutorials and examples.

##
## Attaching package: 'quanteda'

## The following object is masked from 'package:utils':
##
##     View

library(quanteda.corpora)
setwd("~/Desktop/GitHub/Movie_Reviews_Text_Analyzation_Project")  # set worki
ng directory
dc<- read.csv('Reviews_DC.csv')
mv<- read.csv('Reviews_Marvel.csv')
dc$review <- as.character(dc$review)
mv$review <- as.character(mv$review)

# Combine the reviwes for each into one document,and combine the two document
s into one corpus.
library(tm)

## Loading required package: NLP

##
## Attaching package: 'tm'

## The following objects are masked from 'package:quanteda':
##
##     as.DocumentTermMatrix, stopwords

dc_review <- paste(unlist(dc$review), collapse =" ")
mv_review <- paste(unlist(mv$review), collapse =" ")

dc_corpus = corpus(dc_review)
mv_corpus = corpus(mv_review)
```

```
review_corpus <- c(dc_corpus,mv_corpus)
docnames(review_corpus) <- c('DC','Marvel')

# covert to dfm and compare the cosine similary, euclidean & manhattan distan
ce between the two documents

Movielist_DC <- read.csv('Movielist_DC.csv')
Movielist_MV <- read.csv('Movielist_Marvel.csv')

Movielist_DC_token <- paste(unlist(Movielist_DC$name), collapse =" ") %>%
  as.character() %>% tolower() %>% unique() %>%
  tokens(remove_punct = TRUE, remove_numbers = TRUE) %>%
  unlist() %>% unique()

Movielist_MV_token <- paste(unlist(Movielist_MV$name), collapse =" ") %>%
  as.character() %>% tolower() %>%
  tokens(remove_punct = TRUE, remove_numbers = TRUE) %>%
  unlist() %>% unique()
Movielist_MV_token

##  [1] "captain"    "america"    "the"        "first"      "avenger"
##  [6] "iron"       "man"        "incredible" "hulk"       "thor"
## [11] "avengers"   "three"      "dark"       "world"      "winter"
## [16] "soldier"    "guardians"  "of"         "galaxy"     "vol"
## [21] "age"        "ultron"     "ant-man"    "civil"      "war"
## [26] "spider-man" "homecoming" "doctor"     "strange"    "ragnarok"
## [31] "black"      "panther"    "infinity"   "and"        "wasp"
## [36] "marvel"

review_dfm <- dfm(review_corpus, stem = TRUE, remove_punct = TRUE, remove = c
(stopwords("english"), Movielist_DC_token, Movielist_MV_token), remove_number
s = TRUE)

dim(review_dfm)

## [1]     2 51303

similarity <- textstat_simil(review_dfm, margin = "documents", method = 'cosi
ne')
as.matrix(similarity)

##              DC   Marvel
## DC     1.000000 0.950243
## Marvel 0.950243 1.000000

euclidean <- textstat_dist(review_dfm, margin = "documents", method = "euclid
ean")
as.matrix(euclidean)
```

```
##               DC    Marvel
## DC          0.00 21661.05
## Marvel 21661.05     0.00
```

```r
manhattan <- textstat_dist(review_dfm, margin = "documents", method = "manhat
tan")
as.matrix(manhattan)
```

```
##            DC Marvel
## DC          0 579873
## Marvel 579873      0
```

1.2. Preliminary Analysis - Most feaqurent terms (I used the topfearues in dfm, but this is not the only way to find top terms, should be others as well).

```r
dc_dfm <- dfm(dc_corpus, stem = TRUE, remove_punct = TRUE, remove = c(stopwor
ds("english"), Movielist_DC_token, Movielist_MV_token), remove_numbers = TRUE
)
mv_dfm <- dfm(mv_corpus, stem = TRUE, remove_punct = TRUE, remove = c(stopwor
ds("english"), Movielist_DC_token, Movielist_MV_token), remove_numbers = TRUE
)

dc_top <- topfeatures(dc_dfm, n = 300, decreasing = TRUE, scheme = "count")
mv_top <- topfeatures(mv_dfm, n = 300, decreasing = TRUE, scheme = "count")


# top terms based on counts for each document
dc_top <- names(dc_top)
mv_top <- names(mv_top)




# shared terms in the top 20 temrs
shared_terms <- intersect(dc_top,mv_top)
#shared_terms
length(shared_terms)
```

```
## [1] 237
```

```r
dc_unique_top<- setdiff(dc_top,mv_top) # in dc,not mv
dc_unique_top
```

```
##  [1] "joker"     "dc"        "reev"      "christoph" "bruce"
##  [6] "nolan"     "terribl"   "burton"    "anim"      "classic"
## [11] "kid"       "citi"      "trilog"    "adapt"     "wayn"
## [16] "richard"   "beauti"    "style"     "score"     "version"
## [21] "cut"       "portray"   "lex"       "poor"      "idea"
## [26] "tim"       "graphic"   "novel"     "cheesi"    "clark"
## [31] "minut"     "half"      "hate"      "critic"    "stupid"
## [36] "keaton"    "luthor"    "snyder"    "aw"        "loi"
```

```
## [41] "famili"    "horribl"   "greatest"  "true"      "dialogu"
## [46] "rememb"    "john"      "campi"     "silli"     "music"
## [51] "gotham"    "base"      "truli"     "face"      "wrong"
## [56] "wonder"    "donner"    "read"      "write"     "name"
## [61] "shot"      "near"      "els"
```

```r
length(dc_unique_top)
```

```
## [1] 63
```

```r
mv_unique_top <- setdiff(mv_top,dc_top) # in mv,not mv
mv_unique_top
```

```
##  [1] "mcu"          "toni"         "stark"        "cinemat"      "downey"
##  [6] "chris"        "loki"         "jr"           "robert"       "marvel"
## [11] "suit"         "peter"        "battl"        "deliv"        "next"
## [16] "wait"         "pace"         "lead"         "previous"     "twist"
## [21] "team"         "addit"        "rudd"         "paul"         "forc"
## [26] "evan"         "spiderman"    "side"         "less"         "hemsworth"
## [31] "care"         "date"         "pack"         "weak"         "impress"
## [36] "heart"        "build"        "rest"         "entri"        "studio"
## [41] "friend"       "cap"          "humour"       "introduc"     "throughout"
## [46] "stand"        "steve"        "manag"        "earth"        "banner"
## [51] "thank"        "continu"      "opinion"      "along"        "storylin"
## [56] "found"        "instead"      "holland"      "let"          "norton"
## [61] "phase"        "hand"         "predecessor"
```

```r
length(mv_unique_top)
```

```
## [1] 63
```

1.3 Preliminary Analysis - rating score for each

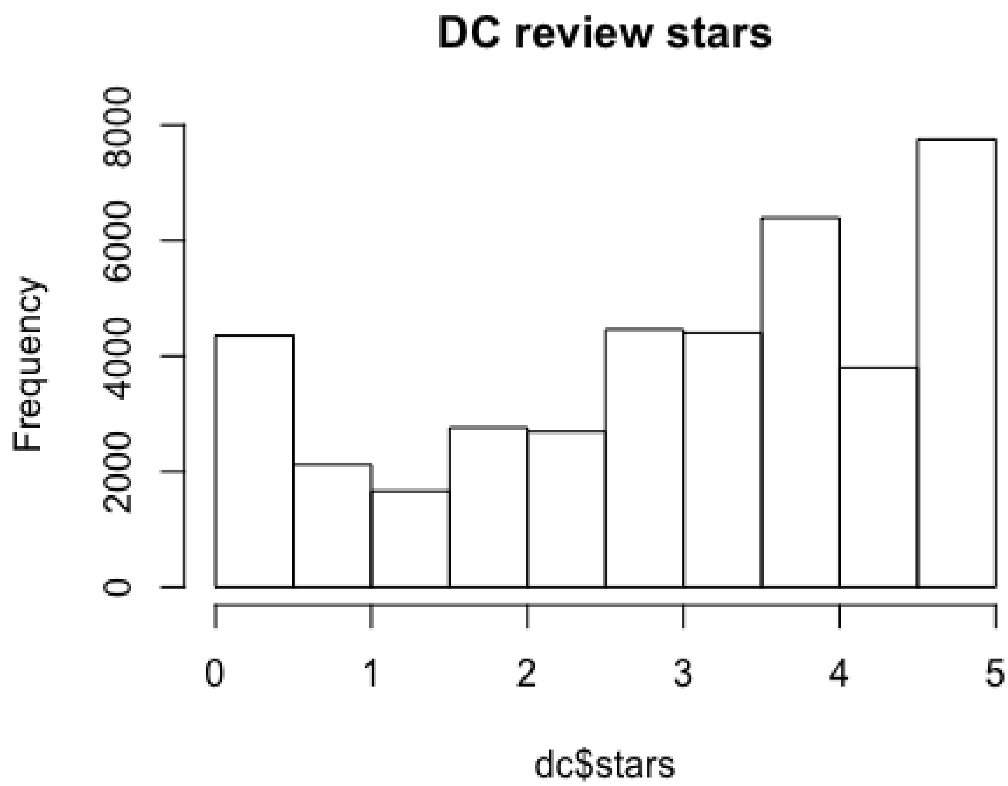
```r
median(dc$stars)
```

```
## [1] 3.5
```

```r
mean(dc$stars)
```

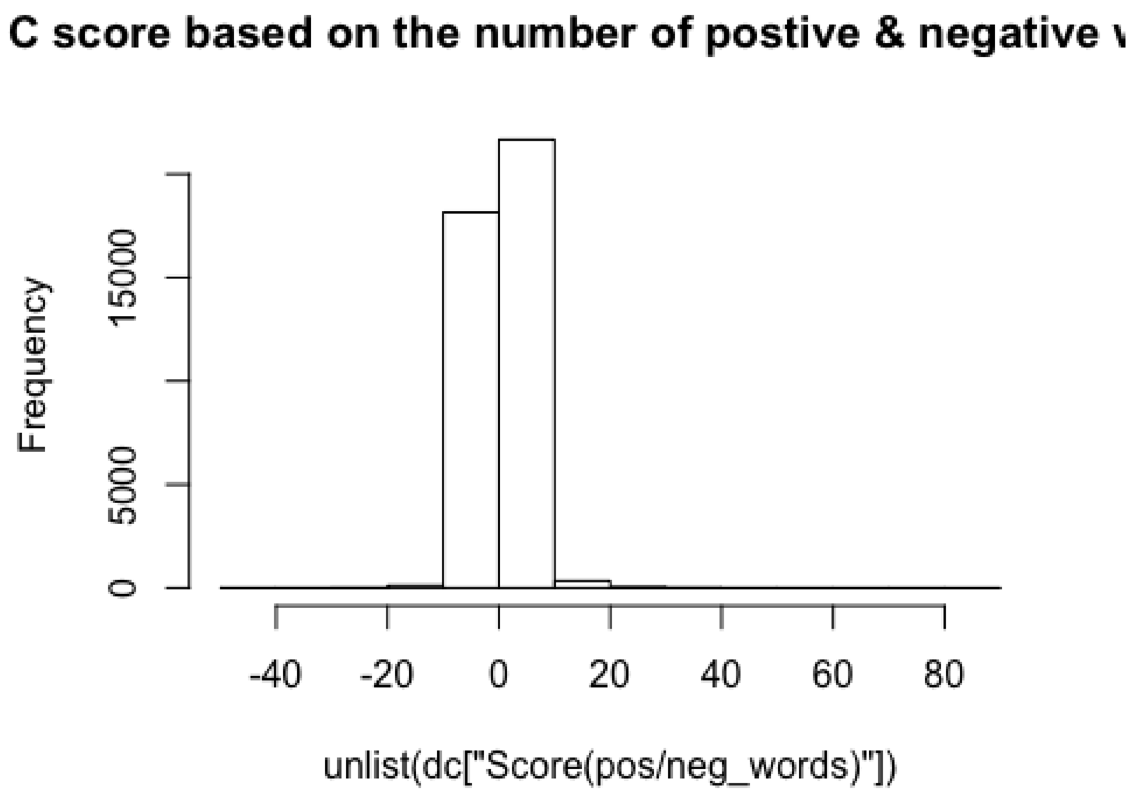
```
## [1] 3.17795
```

```r
hist(dc$stars, main = 'DC review stars')
```

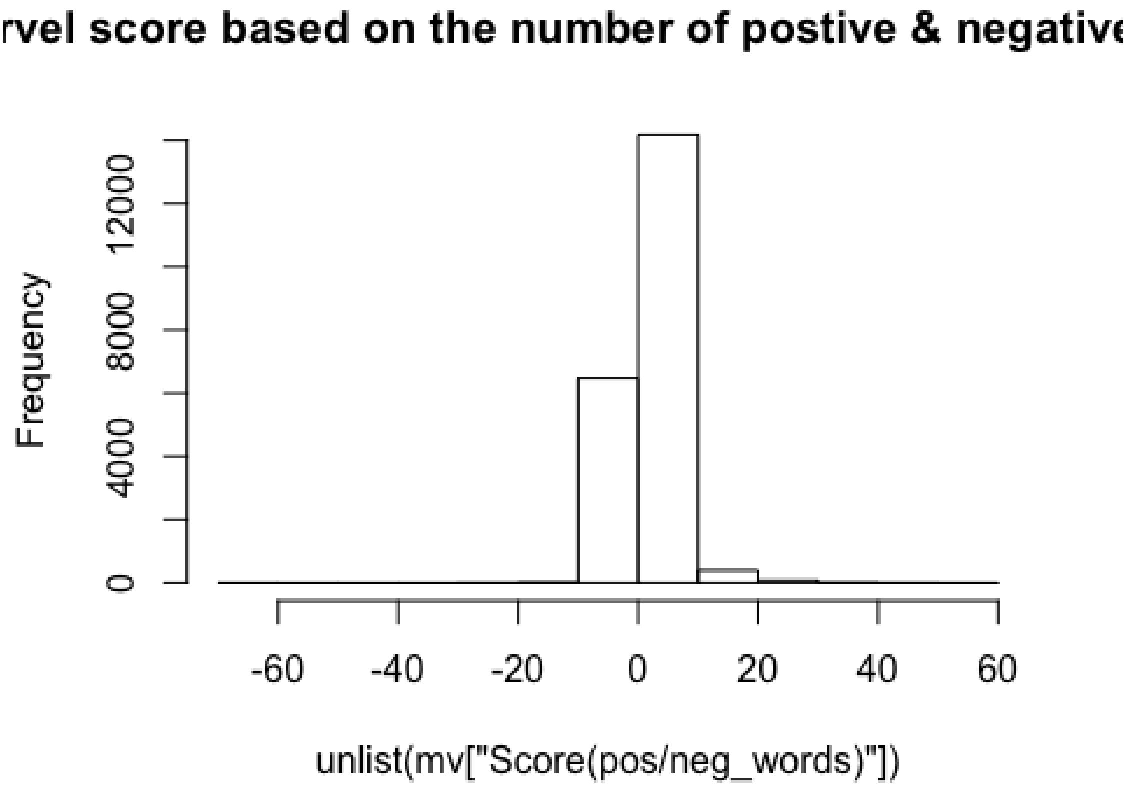



```
median(mv$stars)

## [1] 4

mean(mv$stars)

## [1] 3.582885

hist(mv$stars, main = 'Marvel review stars')
```


```r
# using the positive words and negatives words doc. given from HW2
library(stringr)
pos <- readLines('positive-words.txt')
neg <- readLines('negative-words.txt')

for (row in 1:nrow(dc)) {
    text <- tolower(dc[row, 'review'])
    words <- unlist(str_split(text, " "))
    pos.matches <- match(words, pos)
    neg.matches <- match(words, neg)
    score <- sum(!is.na(pos.matches))-sum(!is.na(neg.matches))
    dc[row, 'Score(pos/neg_words)']<-score
    }
median(unlist(dc['Score(pos/neg_words)']))

## [1] 1

mean(unlist(dc['Score(pos/neg_words)']))

## [1] 0.9554538

hist(unlist(dc['Score(pos/neg_words)']), main = 'DC score based on the number
 of postive & negative words')
```




```r
for (row in 1:nrow(mv)) {
    text <- tolower(mv[row, 'review'])
    words <- unlist(str_split(text, " "))
    pos.matches <- match(words, pos)
    neg.matches <- match(words, neg)
    score <- sum(!is.na(pos.matches))-sum(!is.na(neg.matches))
    mv[row, 'Score(pos/neg_words)']<-score
}
median(unlist(mv['Score(pos/neg_words)']))

## [1] 1

mean(unlist(mv['Score(pos/neg_words)']))

## [1] 1.93727

hist(unlist(mv['Score(pos/neg_words)']), main = 'Marvel score based on the nu
mber of postive & negative words')
```



Modeling

```
dc$Label <- "DC"
mv$Label <- "Marvel"

all_movies<- rbind(dc, mv)
head(all_movies)

##                          name
## 1 Superman and the Mole-Men
## 2 Superman and the Mole-Men
## 3 Superman and the Mole-Men
## 4 Superman and the Mole-Men
## 5 Superman and the Mole-Men
## 6 Superman and the Mole-Men
##
```

review
1

An average b-movie of the early 50s, preceding the TV series "Adventures of Superman".
2

About what you would expect. Not that much about Superman but the mole men were pretty weird.

3

A charming little tale where the villains are prejudice and paranoia and Superman's real powers are tolerance and compassion.

4

Where to even begin? For starters, this is more of a B-grade science-fiction picture that happens to feature Superman than a "Superman" movie outright. Whatever the intentions of the producers, it certainly is a product of its time. By that, and given its low budget, I mean that it's kind of what you'd expect from a sci-fi film in the 1950's: shoddy production values, questionable acting, and overt message-making. Still despite all of this there is a certain B-movie charm, and of course George Reeves has a great screen presence as the Man of Steel (not so much Clark Kent, who is played too similarly). Other than Clark Kent/Superman and Lois Lane, though, there isn't much else here that ties it to the Action Comics source material. Ergo, no Daily Planet, no Metropolis, etc. But I didn't really mind. As long as you do away with any expectations of what a Superman movie "should" be, this film can be a lot of fun. And, at 58 minutes, it never wears out its welcome. Considering the time in which this film was made, with liberal Hollywood under attack by fear-mongering by the likes of Joseph McCarthy and racial tensions coming to a boil, the message it conveys is actually quite radical (again, for its time). It basically says that as beings who inhabit this planet, we should all just get

along regardless of who we are. There are also other things you could read into it, like anti-oil drilling and gun control, but those are secondary concerns. Did I like it? Well, yes and no. It isn't my idea of what a comic movie should be, but taken as a cheesy sci-movie, it has its charms. I wouldn't bend over backwards to see this if you haven't already, but fans of George Reeves of Superman would be remiss for not checking it out.
5

terrible. superman is only in it for like 2 mins.
6

I own this as a bonus feature on the DVD and on the

```
 Blu-Ray of:* Superman (1978)and i also own it as a two part episode in the f
irst season of the "Adventures Of Superman" TV series.
##   stars               date Score(pos/neg_words) Label
## 1   2.0      April 6, 2019                    0    DC
## 2   2.0        May 7, 2017                    1    DC
## 3   3.0      June 15, 2015                   -2    DC
## 4   3.0       June 8, 2015                    0    DC
## 5   0.5 September 29, 2014                    1    DC
## 6   3.0      June 18, 2014                    1    DC

# Randomize the order of the data frame
all_movies <- all_movies[sample(1:nrow(all_movies)), ]
```

2.1 Native Based (uniform and with smooting)

```
library(readtext)
library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

set.seed(2019)
prop_train <- 0.7
index <- 1:nrow(all_movies)
train_index <- sample(index, ceiling(prop_train*length(index)), replace = FAL
SE)
test_index <- index[train_index]
train_set <- all_movies[train_index,]
test_set <- all_movies[test_index,]
train_dfm <- dfm(train_set$review, stem = TRUE, remove_punct = TRUE, remove =
 c(stopwords("english"), Movielist_DC_token, Movielist_MV_token),remove_numbe
rs = TRUE)
test_dfm <- dfm(test_set$review, stem = TRUE, remove_punct = TRUE, remove = c
(stopwords("english"), Movielist_DC_token, Movielist_MV_token),remove_numbers
 = TRUE)
test_dfm <- dfm_match(test_dfm, features = featnames(train_dfm))

# uniform and with smooting
nb_model <- textmodel_nb(train_dfm, train_set$Label, smooth = 1, prior = "uni
form")
predicted_label_uniform <- predict(nb_model, newdata = test_dfm)
baseline_acc <- max(prop.table(table(test_set$Label)))
```

```r
matrix <- table(test_set$Label, predicted_label_uniform)
matrix

##         predicted_label_uniform
##             DC Marvel
##   DC     23688   4709
##   Marvel  2254  12449

nb_acc <- sum(diag(matrix))/sum(matrix) # (TP + TN) / (TP + FP + TN + FN)
nb_recall <- matrix[2,2]/sum(matrix[2,]) #TP / (TP + FN)
nb_precision <- matrix[2,2]/sum(matrix[,2]) # TP / (TP + FP)
nb_f1 <- 2*(nb_recall*nb_precision)/(nb_recall + nb_precision)
cat(
  " Baseline Accuracy: ", baseline_acc, "\n",
  "Accuracy:",  nb_acc, "\n",
  "Recall:",  nb_recall, "\n",
  "Precision:",  nb_precision, "\n",
  "F1-score:", nb_f1)

##  Baseline Accuracy:  0.6588631
##  Accuracy: 0.8384455
##  Recall: 0.846698
##  Precision: 0.7255508
##  F1-score: 0.781457
```

2.2 Native Based (uniform and without smooting)

```r
nb_model <- textmodel_nb(train_dfm, train_set$Label, smooth = 0, prior = "uni
form")
predicted_label_uniform <- predict(nb_model, newdata = test_dfm)
baseline_acc <- max(prop.table(table(test_set$Label)))
matrix <- table(test_set$Label, predicted_label_uniform)
matrix

##         predicted_label_uniform
##             DC Marvel
##   DC     23228   5169
##   Marvel  1609  13094

nb_acc <- sum(diag(matrix))/sum(matrix) # (TP + TN) / (TP + FP + TN + FN)
nb_recall <- matrix[2,2]/sum(matrix[2,]) #TP / (TP + FN)
nb_precision <- matrix[2,2]/sum(matrix[,2]) # TP / (TP + FP)
nb_f1 <- 2*(nb_recall*nb_precision)/(nb_recall + nb_precision)
cat(
  " Baseline Accuracy: ", baseline_acc, "\n",
  "Accuracy:",  nb_acc, "\n",
  "Recall:",  nb_recall, "\n",
  "Precision:",  nb_precision, "\n",
  "F1-score:", nb_f1)

##  Baseline Accuracy:  0.6588631
##  Accuracy: 0.8427378
```

```
##  Recall: 0.8905666
##  Precision: 0.7169687
##  F1-score: 0.7943942
```

2.3 Native Based (docfreq and with smooting) # docfreq prior takes into account of the proportions of the document in training set, we have much more DC than Marvel.

```
nb_model <- textmodel_nb(train_dfm, train_set$Label, smooth = 1, prior = "doc
freq")
predicted_label_uniform <- predict(nb_model, newdata = test_dfm)
baseline_acc <- max(prop.table(table(test_set$Label)))
matrix <- table(test_set$Label, predicted_label_uniform)
matrix

##         predicted_label_uniform
##             DC Marvel
##   DC     26461   1936
##   Marvel  4233  10470

nb_acc <- sum(diag(matrix))/sum(matrix) # (TP + TN) / (TP + FP + TN + FN)
nb_recall <- matrix[2,2]/sum(matrix[2,]) #TP / (TP + FN)
nb_precision <- matrix[2,2]/sum(matrix[,2]) # TP / (TP + FP)
nb_f1 <- 2*(nb_recall*nb_precision)/(nb_recall + nb_precision)
cat(
  " Baseline Accuracy: ", baseline_acc, "\n",
  "Accuracy:",  nb_acc, "\n",
  "Recall:",  nb_recall, "\n",
  "Precision:",  nb_precision, "\n",
  "F1-score:", nb_f1)

##  Baseline Accuracy:  0.6588631
##  Accuracy: 0.8568677
##  Recall: 0.7120996
##  Precision: 0.8439465
##  F1-score: 0.7724372
```

2.1.4 Native Based (docfreq and without smooting) # docfreq prior takes into account of the proportions of the document in training set

```
nb_model <- textmodel_nb(train_dfm, train_set$Label, smooth = 0, prior = "doc
freq")
predicted_label_uniform <- predict(nb_model, newdata = test_dfm)
baseline_acc <- max(prop.table(table(test_set$Label)))
matrix <- table(test_set$Label, predicted_label_uniform)
matrix

##         predicted_label_uniform
##             DC Marvel
##   DC     26102   2295
##   Marvel  3461  11242
```

```r
nb_acc <- sum(diag(matrix))/sum(matrix) # (TP + TN) / (TP + FP + TN + FN)
nb_recall <- matrix[2,2]/sum(matrix[2,]) #TP / (TP + FN)
nb_precision <- matrix[2,2]/sum(matrix[,2]) # TP / (TP + FP)
nb_f1 <- 2*(nb_recall*nb_precision)/(nb_recall + nb_precision)
cat(
  " Baseline Accuracy: ", baseline_acc, "\n",
  "Accuracy:",  nb_acc, "\n",
  "Recall:",  nb_recall, "\n",
  "Precision:",  nb_precision, "\n",
  "F1-score:", nb_f1)

##  Baseline Accuracy:  0.6588631
##  Accuracy: 0.8664501
##  Recall: 0.7646059
##  Precision: 0.8304647
##  F1-score: 0.7961756
```

3.1 SVM

```r
#yelp_svm <- yelp[1:1000,]

library(caret)


## Loading required package: lattice

## Loading required package: ggplot2

##
## Attaching package: 'ggplot2'

## The following object is masked from 'package:NLP':
##
##     annotate

library(dplyr)

movies_svm <- all_movies[sample(1:5000),]
svm_dfm <- dfm(movies_svm$review, stem = TRUE, remove_punct = TRUE, remove_nu
mbers = TRUE, remove = c(stopwords("english"), Movielist_DC_token, Movielist_
MV_token)) %>% convert("matrix")
set.seed(2019)
baseline_acc <- max(prop.table(table(movies_svm $Label)))
baseline_acc

## [1] 0.6642

ids_train <- createDataPartition(1:nrow(svm_dfm), p = 0.8, list = FALSE, time
s = 1)
train_x <- svm_dfm[ids_train,] %>% as.data.frame() # train set data
train_y <- movies_svm$Label[ids_train] %>% as.factor()  # train set labels
test_x <- svm_dfm[-ids_train, ]  %>% as.data.frame() # test set data
```

```r
test_y <- movies_svm$Label[-ids_train] %>% as.factor() # test set labels
trctrl <-trainControl(method="cv", number=3)
svm_mod_linear <- train(x = train_x,
                        y = train_y,
                        method = "svmLinear",
                        trControl = trctrl)

## Warning in .local(x, ...): Variable(s) `' constant. Cannot scale data.

## Warning in .local(x, ...): Variable(s) `' constant. Cannot scale data.

## Warning in .local(x, ...): Variable(s) `' constant. Cannot scale data.

## Warning in .local(x, ...): Variable(s) `' constant. Cannot scale data.

svm_linear_pred <- predict(svm_mod_linear, newdata = test_x)
svm_linear_cmat <- confusionMatrix(svm_linear_pred, test_y)

length(train_x)

## [1] 12137

length(train_y)

## [1] 4000

svm_mod_radial <- train(x = train_x,
                        y = train_y,
                        method = "svmRadial",
                        trControl = trctrl)

## Warning in .local(x, ...): Variable(s) `' constant. Cannot scale data.

## Warning in .local(x, ...): Variable(s) `' constant. Cannot scale data.

## Warning in .local(x, ...): Variable(s) `' constant. Cannot scale data.

## Warning in .local(x, ...): Variable(s) `' constant. Cannot scale data.

## Warning in .local(x, ...): Variable(s) `' constant. Cannot scale data.

## Warning in .local(x, ...): Variable(s) `' constant. Cannot scale data.

## Warning in .local(x, ...): Variable(s) `' constant. Cannot scale data.

## Warning in .local(x, ...): Variable(s) `' constant. Cannot scale data.

## Warning in .local(x, ...): Variable(s) `' constant. Cannot scale data.

## Warning in .local(x, ...): Variable(s) `' constant. Cannot scale data.
```

```
## Warning in .local(x, ...): Variable(s) `' constant. Cannot scale data.

svm_radial_pred <- predict(svm_mod_radial, newdata = test_x)
svm_radial_cmat <- confusionMatrix(svm_radial_pred, test_y)

cat(
    "SVM-Linear Accuracy:",  svm_linear_cmat$overall[["Accuracy"]], "\n",
    "SVM-Radial Accuracy:",  svm_radial_cmat$overall[["Accuracy"]])

## SVM-Linear Accuracy: 0.778
##  SVM-Radial Accuracy: 0.731

svm_radial_cmat$byClass

##          Sensitivity          Specificity       Pos Pred Value
##            0.9984756            0.2209302            0.7096425
##       Neg Pred Value            Precision               Recall
##            0.9870130            0.7096425            0.9984756
##                   F1           Prevalence       Detection Rate
##            0.8296390            0.6560000            0.6550000
## Detection Prevalence    Balanced Accuracy
##            0.9230000            0.6097029
```

4. Random Forest

```
library(randomForest)

## randomForest 4.6-14

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ggplot2':
##
##     margin

## The following object is masked from 'package:dplyr':
##
##     combine

movies_rf <- all_movies[sample(1:1000),]


prop_train <- 0.8
index <- 1:nrow(movies_rf)
train_index <- sample(index, ceiling(prop_train*length(index)), replace = FAL
SE)
test_index <- index[train_index]
train_set <- movies_rf[train_index,]
test_set <- movies_rf[test_index,]
```

```r
train_dfm <- dfm(train_set$review, stem = TRUE, remove_punct = TRUE, remove_n
umbers = TRUE,remove = c(stopwords("english"), Movielist_DC_token, Movielist_
MV_token))
test_dfm <- dfm(test_set$review, stem = TRUE, remove_punct = TRUE, remove_num
bers = TRUE,remove = c(stopwords("english"), Movielist_DC_token, Movielist_MV
_token))
test_dfm <- dfm_match(test_dfm, features = featnames(train_dfm))
train_dfm  <- train_dfm %>% convert("matrix")
test_dfm <- test_dfm%>% convert("matrix")
train_set$Label <- as.factor(train_set$Label)
rf_model<- randomForest(train_dfm,train_set$Label , importance=TRUE)
rf_model
```

```
##
## Call:
##  randomForest(x = train_dfm, y = train_set$Label, importance = TRUE)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 66
##
##         OOB estimate of  error rate: 26.62%
## Confusion matrix:
##         DC Marvel class.error
## DC     506     27  0.05065666
## Marvel 186     81  0.69662921
```

```r
importance <- importance(rf_model)
import_df<- as.data.frame(importance)
import_df[order(-import_df$MeanDecreaseGini),][1:30,]
```

```
##                                   DC     Marvel MeanDecreaseAccuracy
## mcu                       29.0635182 21.0180218           27.5105662
## robert                    15.4622201 10.7776676           14.8942611
## downey                    12.2866706  8.3786462           11.5154222
## funni                     10.5621580  3.6467797            9.6041503
## univers                   16.5498838  3.0608233           14.5719110
## jr                        11.4208848  6.3044741           10.3906521
## toni                      11.5872753  3.4484565            9.9306695
## blockbust                 13.0414213  6.1874305           12.2338800
## best                       1.8200971 -0.1048438            1.4971769
## start                     10.1096684 -0.1135969            8.4974250
## 2nd                        9.9452901  0.4088955            7.1209979
## promis                     6.5873092  8.2975884            8.6552019
## film                       0.8893770 -0.1776787            0.6423440
## stark                      9.3422382  1.8120827            7.8775419
## masterpiec                 0.1807879  8.0912562            4.8277862
## good                       3.1098455 -1.4022977            2.1977198
## second                     8.6815264 -2.3916178            5.0942793
## marvel                     8.7193101  1.7124214            7.0117848
## one                        3.1583807 -2.1417825            2.2914987
```

```
## action                         2.7277861  0.4539824            2.5056133
## better                         1.6434285 -2.3744290           -0.2649316
## bucki                          8.3210945  7.4096381            8.8658164
## yasssssssssssssssssssssssssss  0.0000000  0.0000000            0.0000000
## humor                          7.6905295  0.1412295            5.9495246
## hurt                           5.7891647  0.6214035            4.1747482
## likeabl                        7.2487619  4.3953611            6.8701213
## holland                        8.5326815  4.4857102            8.0131181
## awesom                         5.5716104  0.1714180            4.1965010
## crazi                          8.5555059  3.6422970            7.2594398
## superhero                      2.4211895 -2.7706054            0.3663790
##                               MeanDecreaseGini
## mcu                                 11.2506581
## robert                               3.6420293
## downey                               2.6329089
## funni                                2.4400922
## univers                              2.1267376
## jr                                   2.0802043
## toni                                 1.8243837
## blockbust                            1.6172351
## best                                 1.4882951
## start                                1.4604186
## 2nd                                  1.4221922
## promis                               1.4089872
## film                                 1.3794697
## stark                                1.2996276
## masterpiec                           1.1877082
## good                                 1.1830800
## second                               1.1699943
## marvel                               1.1575385
## one                                  1.1376255
## action                               1.1329309
## better                               1.1049118
## bucki                                1.1047540
## yasssssssssssssssssssssssssss        1.0566533
## humor                                1.0495880
## hurt                                 1.0464935
## likeabl                              1.0347672
## holland                              1.0271858
## awesom                               0.9721958
## crazi                                0.9458343
## superhero                            0.9408893
```

```
predTest <- predict(rf_model, test_dfm , type = "class")
rf_cmat <- table(predTest, test_set$Label)
rf_cmat
```

```
##
## predTest  DC Marvel
```

```
##   DC      533     49
##   Marvel   0    218
```

```r
rf_acc <- sum(diag(rf_cmat))/sum(rf_cmat) # accuracy = (TP + TN) / (TP + FP +
 TN + FN)
rf_recall <- rf_cmat[2,2]/sum(rf_cmat[2,]) # recall = TP / (TP + FN)
rf_precision <- rf_cmat[2,2]/sum(rf_cmat[,2]) # precision = TP / (TP + FP)
rf_f1 <- 2*(rf_recall*rf_precision )/(rf_recall + rf_precision)

baseline_acc <- max(prop.table(table(test_set$Label)))

cat(
  "Baseline Accuracy: ", baseline_acc, "\n",
  "Accuracy:",  rf_acc, "\n",
  "Recall:",  rf_recall, "\n",
  "Precision:",  rf_precision, "\n",
  "F1-score:", rf_f1
)
```

```
## Baseline Accuracy:  0.66625
##  Accuracy: 0.93875
##  Recall: 1
##  Precision: 0.8164794
##  F1-score: 0.8989691
```

4.2 To see if only using the positive or negative review, can better or worse distinguish the two kinds of movie. Positive/negative review are defined by above or below the medium score.

```r
#setting pos/nega, and seperating them for both movie kinds
all_median <- median(all_movies$stars)
all_movies['pos/neg'] <- ifelse(all_movies$stars>all_median , 'positive',
                  ifelse(all_movies$stars<=all_median , 'negative','n/a'))
prop.table(table(all_movies['pos/neg']))
```

```
##
##  negative  positive
## 0.5199039 0.4800961
```

```r
mv_ <- all_movies[all_movies$Label == 'Marvel',]
prop.table(table(mv_['pos/neg']))
```

```
##
##  negative  positive
## 0.4514302 0.5485698
```

```r
dc_ <- all_movies[all_movies$Label == 'DC',]
prop.table(table(dc_['pos/neg']))
```

```
##
##  negative  positive
## 0.5558252 0.4441748
```

```r
pos_movies <-all_movies[all_movies['pos/neg'] == 'positive',]
neg_movies <-all_movies[all_movies['pos/neg'] == 'negative',]


# using only positives reviews in Random forest

movies_rf <- pos_movies[sample(1:1000),]
prop_train <- 0.8
index <- 1:nrow(movies_rf)
train_index <- sample(index, ceiling(prop_train*length(index)), replace = FAL
SE)
test_index <- index[train_index]
train_set <- movies_rf[train_index,]
test_set <- movies_rf[test_index,]
train_dfm <- dfm(train_set$review, stem = TRUE, remove_punct = TRUE, remove_n
umbers = TRUE,remove = c(stopwords("english"), Movielist_DC_token, Movielist_
MV_token))
test_dfm <- dfm(test_set$review, stem = TRUE, remove_punct = TRUE, remove_num
bers = TRUE,remove = c(stopwords("english"), Movielist_DC_token, Movielist_MV
_token))
test_dfm <- dfm_match(test_dfm, features = featnames(train_dfm))
train_dfm  <- train_dfm %>% convert("matrix")
test_dfm <- test_dfm%>% convert("matrix")
train_set$Label <- as.factor(train_set$Label)
rf_model<- randomForest(train_dfm,train_set$Label , importance=TRUE)
rf_model
```

```
##
## Call:
##  randomForest(x = train_dfm, y = train_set$Label, importance = TRUE)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 65
##
##         OOB estimate of  error rate: 27.88%
## Confusion matrix:
##         DC Marvel class.error
## DC     441     39     0.08125
## Marvel 184    136     0.57500
```

```r
importance <- importance(rf_model)
import_df<- as.data.frame(importance)
import_df[order(-import_df$MeanDecreaseGini),][1:30,]
```

```
##                     DC    Marvel MeanDecreaseAccuracy MeanDecreaseGini
## mcu         28.9364273 17.973020           26.9010607        12.326824
```

```
## univers     19.9348428  4.852438           16.9942220         3.254413
## robert      13.6444787  7.185223           12.3980777         2.821839
## film         0.9180799  4.741798            4.4648240         2.160481
## best         7.8829818 -2.878854            5.5214850         2.131198
## marvel      11.9122915  1.249142            8.9776963         1.972983
## downey      11.1353867  5.760630           10.3223369         1.953260
## charact     12.6159564 -7.415956            9.9040187         1.734362
## superhero    8.1123661 -3.058920            4.8418959         1.725687
## predict     11.4389977  5.359071            9.9217386         1.679607
## joker        5.5560164 10.487576            9.0321682         1.669459
## villain     14.1213300 -6.112685           10.7571879         1.644157
## dc           6.8293534  7.837236            8.6065933         1.595433
## second      10.0704655  1.966168            9.1973576         1.465933
## one          7.8535381 -4.218171            6.2396116         1.465267
## far         10.6920782 -2.079919            7.9588963         1.459469
## trilog       6.1355030  8.361495            8.7740633         1.375804
## good         2.0115659 -2.237442           -0.2089279         1.344491
## jr          10.0105168  4.341880            8.6298106         1.344154
## great       -2.6637582  1.416891           -1.0552151         1.328119
## cumberbatch  8.6532594  6.666563            8.7354722         1.302792
## cast        10.2494309 -4.032283            7.6659521         1.255261
## studio       8.9581050  4.482580            8.2119139         1.241325
## start        7.5039640 -1.823434            5.1655038         1.226372
## effect      12.7725563 -7.261391            6.6983707         1.199396
## adapt        1.2252326  6.649910            4.6377168         1.189738
## rudd         9.7307506  2.660515            8.0041703         1.159687
## action       4.0277657 -4.968480           -0.2217326         1.148612
## holland      8.0445865  2.804434            6.4459725         1.139986
## anim         5.0068237  7.811433            7.6201630         1.135642
```

```r
predTest <- predict(rf_model, test_dfm , type = "class")
rf_cmat <- table(predTest, test_set$Label)
rf_cmat
```

```
##
## predTest  DC Marvel
##   DC     479     48
##   Marvel   1    272
```

```r
rf_acc <- sum(diag(rf_cmat))/sum(rf_cmat) # accuracy = (TP + TN) / (TP + FP +
 TN + FN)
rf_recall <- rf_cmat[2,2]/sum(rf_cmat[2,]) # recall = TP / (TP + FN)
rf_precision <- rf_cmat[2,2]/sum(rf_cmat[,2]) # precision = TP / (TP + FP)
rf_f1 <- 2*(rf_recall*rf_precision )/(rf_recall + rf_precision)

baseline_acc <- max(prop.table(table(test_set$Label)))

cat(
  "Baseline Accuracy: ", baseline_acc, "\n",
  "Accuracy:",  rf_acc, "\n",
```

```
  "Recall:",  rf_recall, "\n",
  "Precision:",  rf_precision, "\n",
  "F1-score:", rf_f1
)

## Baseline Accuracy:  0.6
##  Accuracy: 0.93875
##  Recall: 0.996337
##  Precision: 0.85
##  F1-score: 0.9173693

# using only negative reviews in Random forest

movies_rf <- neg_movies[sample(1:1000),]
prop_train <- 0.8
index <- 1:nrow(movies_rf)
train_index <- sample(index, ceiling(prop_train*length(index)), replace = FAL
SE)
test_index <- index[train_index]
train_set <- movies_rf[train_index,]
test_set <- movies_rf[test_index,]
train_dfm <- dfm(train_set$review, stem = TRUE, remove_punct = TRUE, remove_n
umbers = TRUE,remove = c(stopwords("english"), Movielist_DC_token, Movielist_
MV_token))
test_dfm <- dfm(test_set$review, stem = TRUE, remove_punct = TRUE, remove_num
bers = TRUE,remove = c(stopwords("english"), Movielist_DC_token, Movielist_MV
_token))
test_dfm <- dfm_match(test_dfm, features = featnames(train_dfm))
train_dfm  <- train_dfm %>% convert("matrix")
test_dfm <- test_dfm%>% convert("matrix")
train_set$Label <- as.factor(train_set$Label)
rf_model<- randomForest(train_dfm,train_set$Label , importance=TRUE)
rf_model

##
## Call:
##  randomForest(x = train_dfm, y = train_set$Label, importance = TRUE)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 67
##
##         OOB estimate of  error rate: 23.38%
## Confusion matrix:
##         DC Marvel class.error
## DC     561     18  0.03108808
## Marvel 169     52  0.76470588

importance <- importance(rf_model)
import_df<- as.data.frame(importance)
import_df[order(-import_df$MeanDecreaseGini),][1:30,]
```

```
##                  DC     Marvel MeanDecreaseAccuracy MeanDecreaseGini
## mcu     25.8759699 20.7344003           25.1759296        9.1201271
## overr    6.9902618 11.5749067           10.6181234        3.0202962
## stark   14.1405822  9.0017205           13.2558234        2.9582030
## sequel  16.0953145  5.9966639           14.1560950        2.4487194
## toni    12.2135534  6.4273773           11.4656638        2.1204417
## amaz    11.6214244  5.9335423           10.4889609        1.9783348
## hype     6.6529255  7.8886376            8.5282303        1.7814915
## norton  11.5377126 10.3572171           11.8315997        1.7595783
## bore     9.1247007  0.1108950            7.4153176        1.4762834
## promis   8.1640661  0.5688166            6.4045174        1.3390305
## great    4.0901378  0.6510427            4.0515287        1.2594230
## overhyp  5.7441719  2.4085090            5.1901486        1.2351436
## dork     0.0000000  0.0000000            0.0000000        1.2239407
## holland  8.5197771  4.5630168            7.7899136        1.1935279
## good    -0.5003307  2.0633876            0.5453843        1.1605512
## loki     9.6957563  2.7413528            8.5840390        1.1270634
## place   11.3691593 -1.4424555            8.6853981        1.0916280
## okay     2.5804773 -0.3003699            1.8376744        1.0368472
## decent   6.6331208 -0.2050076            5.1298669        1.0080460
## shane    0.0000000  0.0000000            0.0000000        1.0001715
## hurt     8.6519176 -5.2684475            4.6544017        0.9599620
## chapter  7.1285657  3.4432870            6.5004291        0.9542588
## els      9.6522787 -4.3123135            6.6328543        0.9493338
## new      8.6426439 -3.2462390            6.1063240        0.9459348
## phase    7.2771591  5.1629903            7.2471985        0.9282519
## seri     4.0983069  6.6767110            6.6098620        0.9154337
## best     4.4706723 -1.1860380            3.5387710        0.9070026
## film     2.8309955  0.8551990            2.9317406        0.9027094
## generic  6.1870136  3.1916934            5.7743867        0.8905197
## plot     6.2316693 -2.8786798            4.0609697        0.8832892
```

```
predTest <- predict(rf_model, test_dfm , type = "class")
rf_cmat <- table(predTest, test_set$Label)
rf_cmat
```

```
##
## predTest  DC Marvel
##   DC     578     41
##   Marvel   1    180
```

```
rf_acc <- sum(diag(rf_cmat))/sum(rf_cmat) # accuracy = (TP + TN) / (TP + FP +
 TN + FN)
rf_recall <- rf_cmat[2,2]/sum(rf_cmat[2,]) # recall = TP / (TP + FN)
rf_precision <- rf_cmat[2,2]/sum(rf_cmat[,2]) # precision = TP / (TP + FP)
rf_f1 <- 2*(rf_recall*rf_precision )/(rf_recall + rf_precision)

baseline_acc <- max(prop.table(table(test_set$Label)))

cat(
```

```r
  "Baseline Accuracy: ", baseline_acc, "\n",
  "Accuracy:",  rf_acc, "\n",
  "Recall:",  rf_recall, "\n",
  "Precision:",  rf_precision, "\n",
  "F1-score:", rf_f1
)
```

```
## Baseline Accuracy:  0.72375
##  Accuracy: 0.9475
##  Recall: 0.9944751
##  Precision: 0.8144796
##  F1-score: 0.8955224
```