PeerReview_4

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0. Load packages

```
#install.packages("tm")
#install.packages("SnowballC")
#install.packages("wordcloud")
#install.packages("e1071")
#install.packages("klaR")

library(tm)

## Loading required package: NLP

library(SnowballC)
library(wordcloud)

## Loading required package: RColorBrewer

library(e1071)
library(gmodels)
library(klaR)

## Loading required package: MASS
```

Problem 1

1. Read in data file

```
sms_raw <- read.csv("da5030.spammsgdataset.csv", stringsAsFactors = FALSE)</pre>
```

2. Get the overall information of the data

```
# check the structure of the data
str(sms_raw)

## 'data.frame': 5574 obs. of 2 variables:
## $ type: chr "ham" "ham" "spam" "ham" ...
```

\$ text: chr "Go until jurong point, crazy.. Available only in bugis n great world la e buffet... C

```
# convert type column to factor
sms_raw$type <- factor(sms_raw$type)</pre>
# check the type column and count the number in each type
str(sms raw$type)
## Factor w/ 2 levels "ham", "spam": 1 1 2 1 1 2 1 1 2 2 ...
table(sms_raw$type)
##
## ham spam
## 4827 747
  3. Create corpus
# create sms corpus
sms corpus <- VCorpus(VectorSource(sms raw$text))</pre>
# print the corpus to check
print(sms_corpus)
## <<VCorpus>>
## Metadata: corpus specific: 0, document level (indexed): 0
## Content: documents: 5574
  4. Clean the dataset
# convert text string to all lower case
sms_corpus_clean <- tm_map(sms_corpus, content_transformer(tolower))</pre>
# remove numbers from text
sms_corpus_clean <- tm_map(sms_corpus_clean, removeNumbers)</pre>
# remove stop words such as "to", "and", and "or"
sms_corpus_clean <- tm_map(sms_corpus_clean, removeWords, stopwords())</pre>
# remove punctuation
sms_corpus_clean <- tm_map(sms_corpus_clean, removePunctuation)</pre>
# only keep the stems of the word
sms_corpus_clean <- tm_map(sms_corpus_clean, stemDocument)</pre>
# remove the blank spaces due to the cleaning
sms_corpus_clean <- tm_map(sms_corpus_clean, stripWhitespace)</pre>
  5. Splitting text documents into words, create a sparse matrix
sms_dtm <- DocumentTermMatrix(sms_corpus_clean)</pre>
```

6. Create training data and testing data

```
# split the data by row number
sms_dtm_train <- sms_dtm[1:4169, ]</pre>
sms_dtm_test <- sms_dtm[4170:5559, ]
# get the type information from the original dataset
sms_train_labels <- sms_raw[1:4169, ]$type</pre>
sms_test_labels <- sms_raw[4170:5559, ]$type</pre>
# check the portion of ham and span in training and testing data
prop.table(table(sms_train_labels))
```

```
## sms_train_labels
## ham spam
## 0.8647158 0.1352842

prop.table(table(sms_test_labels))

## sms_test_labels
## ham spam
## 0.8697842 0.1302158
```

7. Create word cloud 7.1 Create a word cloud for the entire dataset

```
wordcloud(sms_corpus_clean, min.freq = 50, random.order = FALSE)
```

```
tonight
                                   minut
               gonna
                    finish use wishsomeon 
ent even babe urgent money
         offerhelp sent even babe urgent mone plan realli claim
     collect number later phone night everi
      sleep wattri home sendwork feelaward thank mean
 checkfirst pls Stop show
                               txt text pleas nokia
  mani thingtoday
                                                   wan wäğ' repli
place give One
                                               dont<sup>minlate</sup>
a won Sorrinice
                                  OVE need let contact
   čhat much
                             good mobil leav so back ask hey so meet yes as page 1
      cashmake
   word pick newtime
   personfriend Week
              year miss live
              alreaditione hope meet
    special
                                   B morn P
                   gudtomorrow
                          servic Servic wenthour
               guarante around wein
```

7.2 Create word cloud for spam data and ham data respectively

```
# separate span and ham data
spam <- subset(sms_raw, type == "spam")
ham <- subset(sms_raw, type == "ham")
# create word cloud for each
wordcloud(spam$text, max.words = 40, scale = c(3, 0.5))

## Warning in tm_map.SimpleCorpus(corpus, tm::removePunctuation): transformation
## drops documents</pre>
```

```
## Warning in tm_map.SimpleCorpus(corpus, function(x) tm::removeWords(x,
## tm::stopwords())): transformation drops documents
```



```
wordcloud(ham$text, max.words = 40, scale = c(2, 0.5))
```

```
## Warning in tm_map.SimpleCorpus(corpus, tm::removePunctuation): transformation
## drops documents
## Warning in tm_map.SimpleCorpus(corpus, tm::removePunctuation): transformation
## drops documents
```

Jike oday

goodhome of got

later time call got

its want ill thinklor love

will of see of send just

know back on OW today

know back on OW today

come how get of going odont

well of sorry ocan

8. Get the most frequent words

```
# only keep the words that appeared at least 5 times
sms_freq_words <- findFreqTerms(sms_dtm_train, 5)
str(sms_freq_words)

## chr [1:1157] "£wk" "abiola" "abl" "abt" "accept" "access" "account" ...

# only keep the columns that have the frequent words
sms_dtm_freq_train <- sms_dtm_train[ , sms_freq_words]
sms_dtm_freq_test <- sms_dtm_test[ , sms_freq_words]</pre>
```

9. Convert counts to yes/no for Naive Bayes

```
# create the function
convert_counts <- function(x){
   x <- ifelse(x > 0, "Yes", "No")
}
# apply the function to both training and testing data
sms_train <- apply(sms_dtm_freq_train, MARGIN = 2, convert_counts)
sms_test <- apply(sms_dtm_freq_test, MARGIN = 2, convert_counts)</pre>
```

10. Apply the Naive Bayes

```
sms_classifier <- naiveBayes(sms_train, sms_train_labels)
sms_test_pred <- predict(sms_classifier, sms_test)</pre>
```

11. Evaluate the prediction

```
CrossTable(sms_test_pred, sms_test_labels, prop.chisq = FALSE, prop.t = FALSE, dnn = c("predicted", "ac
```

```
##
##
##
   Cell Contents
## |-----|
## |
         N / Row Total |
        N / Col Total |
## |
##
##
## Total Observations in Table: 1390
##
##
##
          | actual
##
   predicted | ham |
                      spam | Row Total |
## -----|-----|
                      20 |
##
       ham |
              1200 |
                               1220
##
        - 1
              0.984 |
                     0.016 |
                              0.878 |
##
          0.993 |
                     0.110 |
  -----|-----|
##
              9 |
                       161 |
       spam |
                               170 |
       0.053 |
                     0.947 |
                               0.122 |
##
##
          - 1
              0.007 |
                     0.890 |
 -----|-----|------|
              1209 |
## Column Total |
                       181 |
                              1390 l
   0.870 | 0.130 |
##
    -----|-----|
##
##
##
```

As the table above, 1390 predictions were made, the accuracy is (1200 + 161) / 1390 = 97.9%

12. Improve the model

Cell Contents ## |-----|

```
# set laplace as 1
sms_classifier2 <- naiveBayes(sms_train, sms_train_labels, laplace = 1)
sms_test_pred2 <- predict(sms_classifier2, sms_test)
# evaluate the prediction
CrossTable(sms_test_pred2, sms_test_labels, prop.chisq = FALSE, prop.t = FALSE, prop.r = FALSE, dnn = c
##
##
##</pre>
```

```
## |
       N / Col Total |
## |
  |-----|
##
##
## Total Observations in Table: 1390
##
##
##
            | actual
                 ham |
##
    predicted |
                          spam | Row Total |
                        -----|----|
                          10 |
##
        ham |
                1182 |
                                   1192 |
                         0.055 l
                0.978 |
##
  -----|----|
##
                         171 |
##
                  27 |
        spam |
##
                0.022 |
                         0.945 |
##
                1209 |
                                   1390
  Column Total |
                          181 |
    1
##
                0.870 |
                         0.130 |
   -----|----|
##
##
##
```

As the table above, the accuracy is (1182 + 171) / 1390

Problem 2

1. Load and check dataset

```
# load data
data(iris)
# get an overview of the data
nrow(iris)
## [1] 150
```

summary(iris)

```
##
     Sepal.Length
                     Sepal.Width
                                    Petal.Length
                                                     Petal.Width
##
   Min.
          :4.300
                    Min.
                          :2.000
                                    Min.
                                         :1.000
                                                    Min.
                                                         :0.100
                    1st Qu.:2.800
##
   1st Qu.:5.100
                                    1st Qu.:1.600
                                                    1st Qu.:0.300
   Median :5.800
##
                   Median :3.000
                                    Median :4.350
                                                    Median :1.300
         :5.843
##
   Mean
                    Mean :3.057
                                    Mean
                                         :3.758
                                                    Mean
                                                         :1.199
##
   3rd Qu.:6.400
                    3rd Qu.:3.300
                                    3rd Qu.:5.100
                                                    3rd Qu.:1.800
##
         :7.900
                   Max. :4.400
                                    Max. :6.900
                                                    Max. :2.500
##
         Species
##
   setosa
             :50
   versicolor:50
##
##
   virginica:50
##
##
##
```

head(iris)

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

2. split the dataset

```
# get all the row number that can be devided by 5
testidx <- which(1:length(iris[, 1]) %% 5 == 0)
# split the data
iristrain <- iris[-testidx, ]
iristest <- iris[testidx, ]</pre>
```

3. Apply Naive Bayes and make the prediction

```
nbmodel <- NaiveBayes(Species~., data = iristrain)
prediction <- predict(nbmodel, iristest[ , -5])</pre>
```

4. Evaluate the prediction

```
table(prediction$class, iristest[ , 5])
```

```
##
##
                 setosa versicolor virginica
##
                      10
                                   0
     setosa
                                              2
##
                       0
                                  10
     versicolor
                       0
                                   0
                                              8
     virginica
```

As the table above, the predict accuracy is (10 + 10 + 8) / (10 + 10 + 2 + 8) = 0.93