Spam or Ham message Classification

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Requiring the necessary packages-

```
require(quanteda)#natural language processing package
require(dplyr)
require(RColorBrewer)
require(ggplot2)
require(pROC)#to plot a ROC curve and find auc
```

quanteda makes it easy to manage texts in the form of a **corpus**, defined as a collection of texts that includes document-level variables specific to each text, as well as meta-data for documents and for the collection as a whole. quanteda includes tools to make it easy and fast to manuipulate the texts in a corpus, by performing the most common natural language processing tasks simply and quickly, such as tokenizing, stemming, or forming ngrams. quanteda's functions for tokenizing texts and forming multiple tokenized documents into a document-feature matrix are both extremely fast and extremely simple to use. quanteda can segment texts easily by words, paragraphs, sentences, or even user-supplied delimiters and tags.

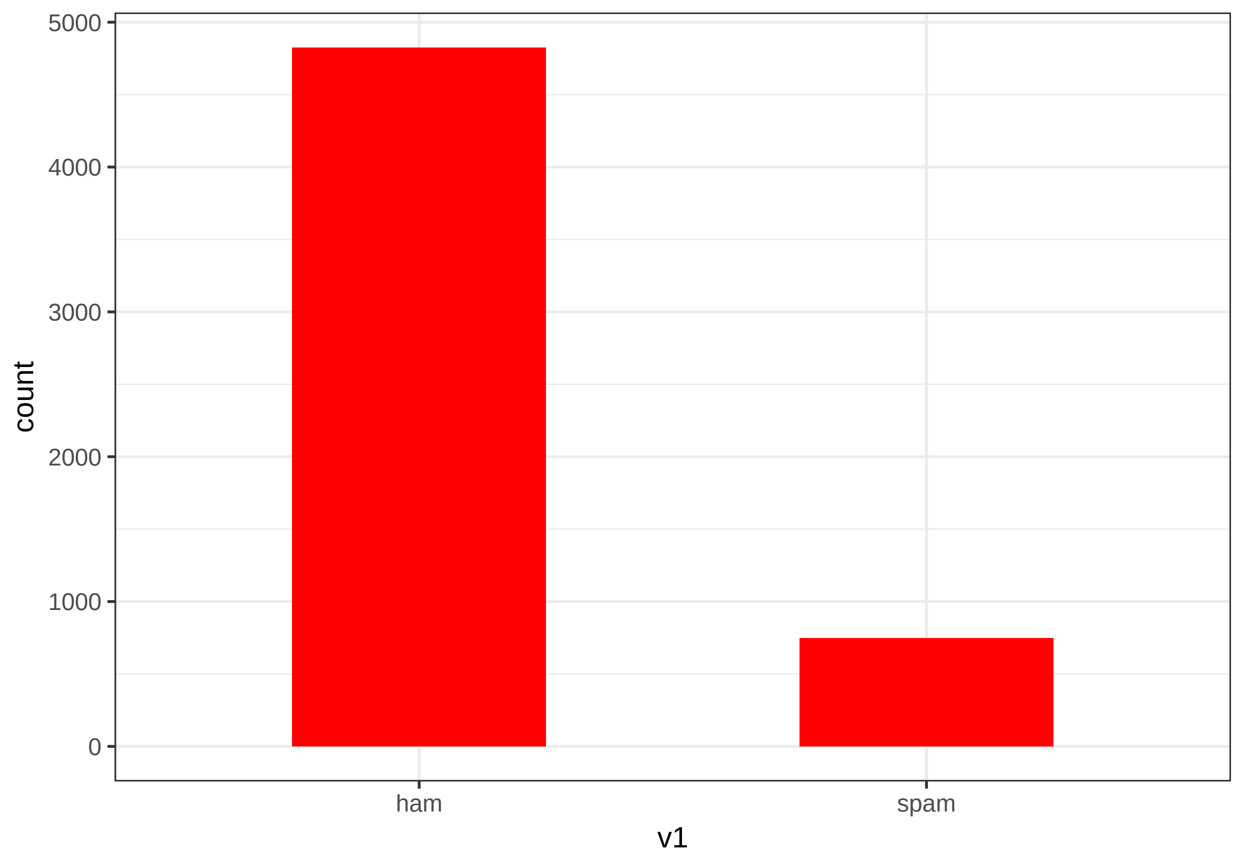
---

loading the dataset

```
spam<-read.csv("F:/PROJECTS/Datasets/spam.csv",header=TRUE, sep=",", quote='\"\"', stringsAsFactors=FALS

table(spam$v1)
```

```
##
##  ham spam
## 4825  747
```

```
#checking the distribution of type of messages
theme_set(theme_bw())
ggplot(aes(x=v1),data=spam) +
  geom_bar(fill="red",width=0.5)
```



Now let's add appropiate names to the columns.

```
names(spam)<-c("type","message")
head(spam)
```

```
##   type
## 1  ham
## 2  ham
## 3 spam
## 4  ham
## 5  ham
## 6 spam
##
## 1                                            Go until jurong point, crazy.. Available only in bugis
## 2
## 3 Free entry in 2 a wkly comp to win FA Cup final tkts 21st May 2005. Text FA to 87121 to receive en
## 4
## 5                                                                                              Nah 
## 6        FreeMsg Hey there darling it's been 3 week's now and no word back! I'd like some fun you up
##   NA NA NA
## 1
## 2
## 3
## 4
## 5
## 6
```

Now we can sample the data.We can randomize our data using the sample() command.If the data is not stored in a random distribution, this will help to ensure that we are dealing with a random draw from our data. The set.seed() is to ensure reproducable results.

```
set.seed(2012)
spam<-spam[sample(nrow(spam)),]
```

Now let's build the spam and ham Wordclouds

We'll use quanteda's corpus() command to construct a corpus from the Text field of our raw data.A corpus can be thought of as a master copy of our dataset from which we can pull subsets or observations as needed.

After this I will attach the Label field as a document variable to the corpus using the docvars() command. We attach Label as a variable directly to our corpus so that we can associate SMS messages with their respective ham/spam label later in the analysis.

```
?corpus #to search more on this method
```

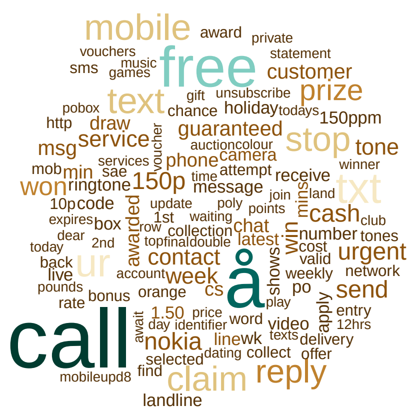
```
## starting httpd help server ... done
```

```
msg.corpus<-corpus(spam$message)
docvars(msg.corpus)<-spam$type   #ataching the label to the corpus message text
```

Let's plot the wordcloud now-

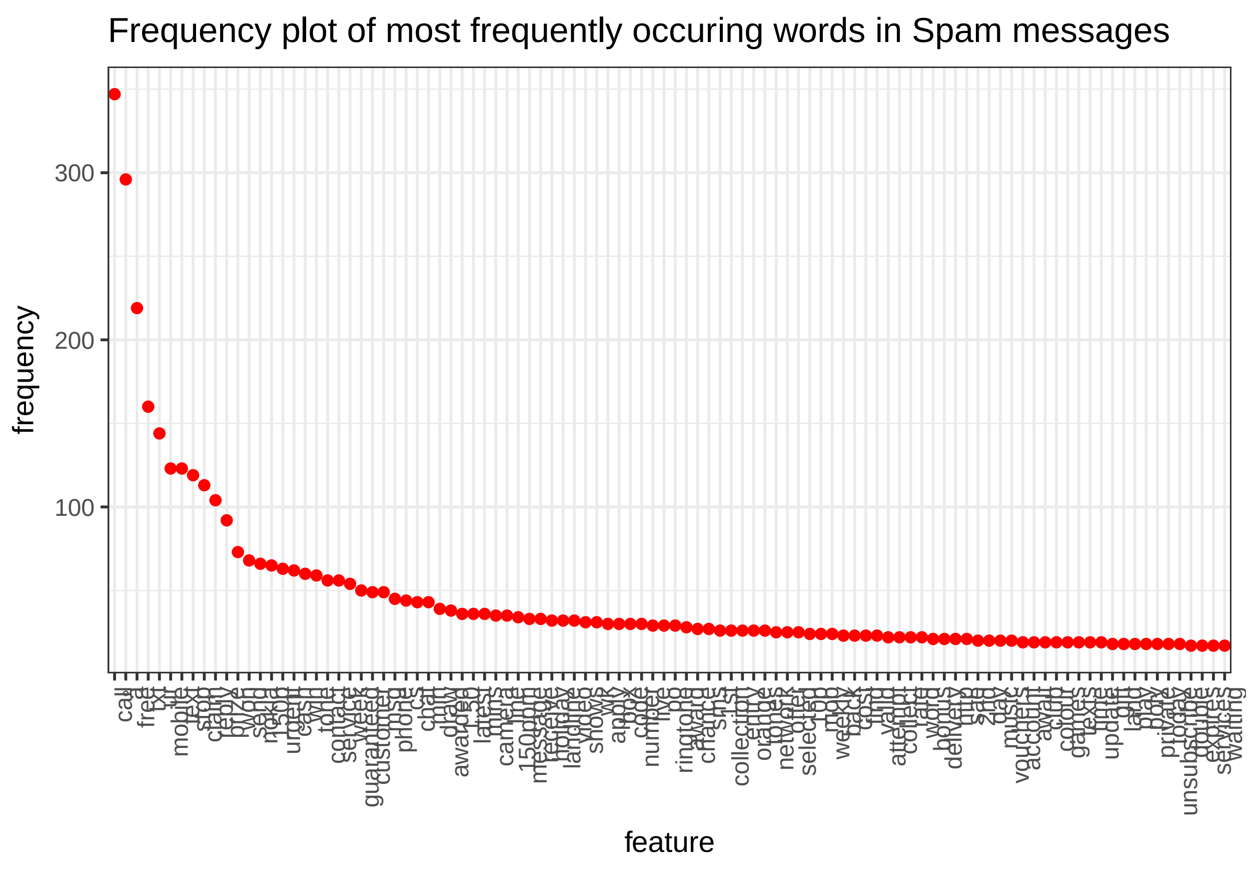
```
#subsetting only the spam messages
spam.plot<-corpus_subset(msg.corpus,docvar1=="spam")

#now creating a document-feature matrix using dfm()
spam.plot<-dfm(spam.plot, tolower = TRUE, remove_punct = TRUE, remove_twitter = TRUE, remove_numbers =

spam.col <- brewer.pal(10, "BrBG")

textplot_wordcloud(spam.plot, min.freq = 16, color = spam.col)
title("Spam Wordcloud", col.main = "grey14")
```

Spam Wordcloud



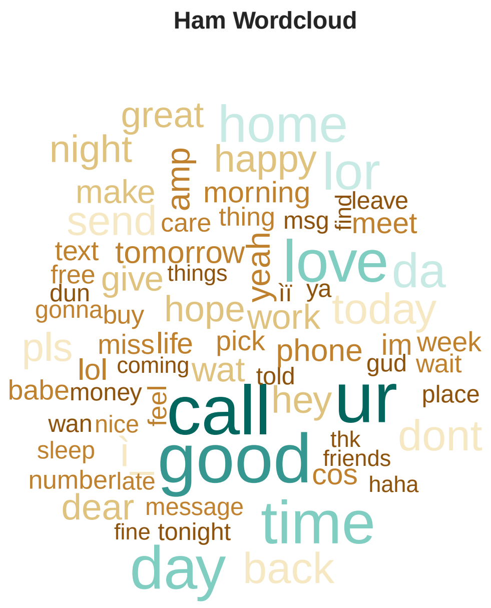
Generating a Frequency plot of most frequently occuring words in Spam messages-

```r
features_spam <- textstat_frequency(spam.plot, n = 100)

features_spam$feature <- with(features_spam, reorder(feature, -frequency))


ggplot(features_spam, aes(x = feature, y = frequency)) +
    geom_point(color="red") +
    theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
    ggtitle("Frequency plot of most frequently occuring words in Spam messages")
```



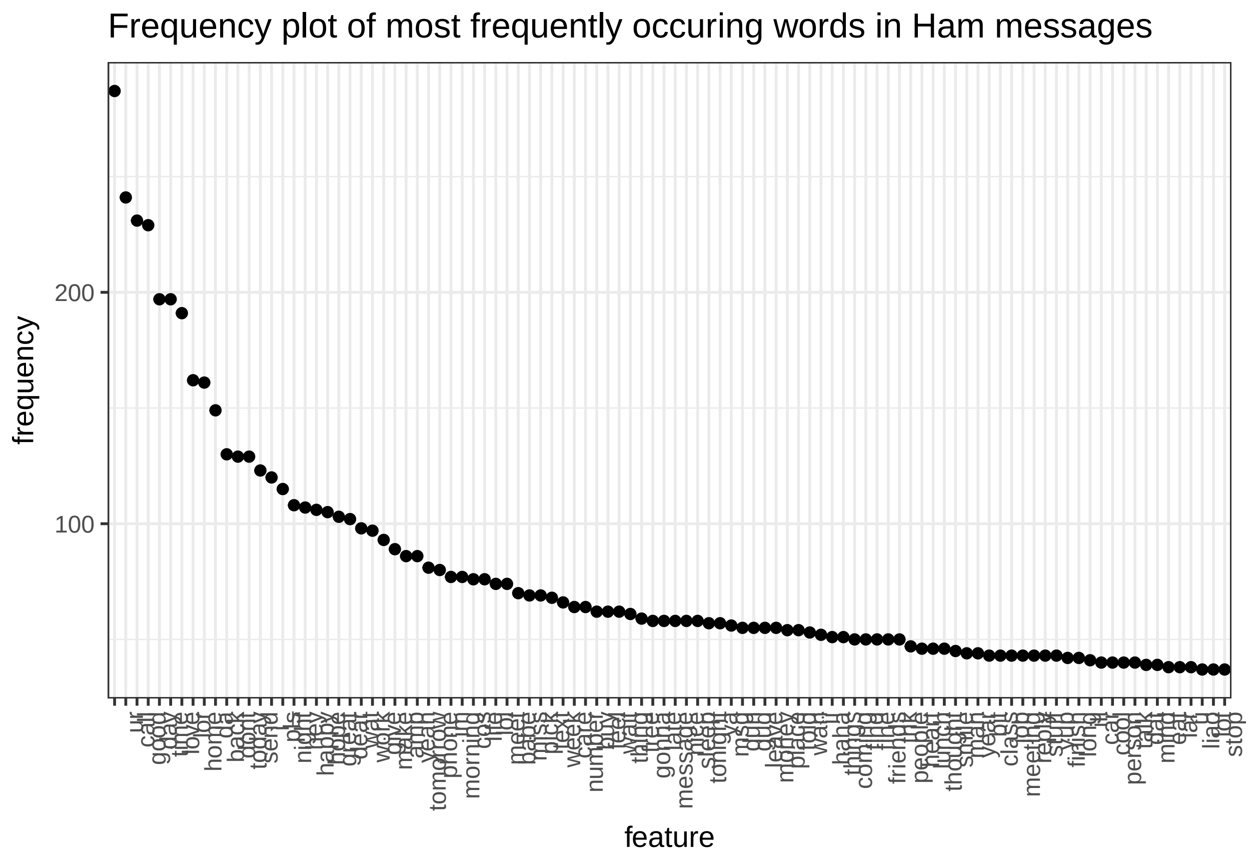
Generating the Ham wordcloud

```
ham.plot<-corpus_subset(msg.corpus,docvar1=="ham")
ham.plot<-dfm(ham.plot,tolower = TRUE, remove_punct = TRUE, remove_twitter = TRUE, remove_numbers = TRU
ham.col=brewer.pal(10, "BrBG")
textplot_wordcloud(ham.plot,min.freq=50,colors=ham.col,fixed.asp=TRUE)
title("Ham Wordcloud",col.main = "grey14")
```



Generating a Frequency plot of most frequently occuring words in Ham messages-

```
#finding the frequencies of the 100 most frequently occuring words in ham messages
features_ham <- textstat_frequency(ham.plot, n = 100)

features_ham$feature <- with(features_ham, reorder(feature, -frequency))


ggplot(features_ham, aes(x = feature, y = frequency)) +
    geom_point() +
    theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
    ggtitle("Frequency plot of most frequently occuring words in Ham messages")
```



Prediction Using Naive Bayes Classifier

Naive Bayes classifiers are a class of simple linear classifiers which are *conditional probability* models based on **Bayes** Theoram i.e

$$P(Y \in K_j|X_i) = P(X_1|Y).P(X_2|Y)......P(X_i|Y).\ P(Y \in K_j)$$

where X_i are the number of inputs and Y is discrete response variable and K_j are the number of class labels.

The special thing about Naive Bayes classifiers are that they follow *Conditional Independence Theoram* i.e the features X_i are uncorrelated and independent of each other which is often always crude.Secondly,they assume that the data samples are drawn from a identical and independent distribution- **IID** is the term which is famous in Statistics.

```r
#separating Train and test data
spam.train<-spam[1:4458,]
spam.test<-spam[4458:nrow(spam),]

msg.dfm <- dfm(msg.corpus, tolower = TRUE)  #generating document freq matrix
msg.dfm <- dfm_trim(msg.dfm, min_count = 5, min_docfreq = 3)
msg.dfm <- dfm_weight(msg.dfm, type = "tfidf")

#trining and testing data of dfm
msg.dfm.train<-msg.dfm[1:4458,]
msg.dfm.test<-msg.dfm[4458:nrow(spam),]
```

Training the Naive Bayes classifier-

```
nb.classifier<-textmodel_NB(msg.dfm.train,spam.train[,1])
nb.classifier
```

```
## Fitted Naive Bayes model:
## Call:
##  textmodel_NB.dfm(x = msg.dfm.train, y = spam.train[, 1])
##
##
## Training classes and priors:
## spam  ham
##  0.5  0.5
##
##        Likelihoods:      Class Posteriors:
## 30 x 4 Matrix of class "dgeMatrix"
##                 spam          ham       spam       ham
## you     5.001507e-03 0.0096798156 0.34067144 0.6593286
## have    4.322289e-03 0.0042303673 0.50537386 0.4946261
## 1       2.695748e-03 0.0009529526 0.73882413 0.2611759
## new     3.492485e-03 0.0010753934 0.76457487 0.2354251
## .       6.965338e-03 0.0168302131 0.29271598 0.7072840
## please  2.339097e-03 0.0011593603 0.66860811 0.3313919
## call    1.058603e-02 0.0021859571 0.82884759 0.1711524
## i       8.439760e-04 0.0112106647 0.07001254 0.9299875
## wait    1.860817e-04 0.0011538316 0.13887596 0.8611240
## for     5.699340e-03 0.0045025239 0.55865674 0.4413433
## hope    2.334040e-04 0.0017258550 0.11912872 0.8808713
## tonight 1.137075e-04 0.0011106417 0.09287182 0.9071282
## too     3.802754e-05 0.0017024748 0.02184860 0.9781514
## bad     1.232420e-04 0.0006045270 0.16934219 0.8306578
## as      1.339518e-03 0.0020699791 0.39287852 0.6071215
## well    2.938089e-04 0.0017334850 0.14492664 0.8550734
## but     2.528948e-04 0.0043933716 0.05442968 0.9455703
## rock    3.802754e-05 0.0002684845 0.12406542 0.8759346
## night   3.003905e-04 0.0017976398 0.14317739 0.8568226
## anyway  3.802754e-05 0.0005405216 0.06572915 0.9342709
## going   1.538819e-04 0.0023951976 0.06036762 0.9396324
## a       7.856726e-03 0.0064918622 0.54756091 0.4524391
## now     6.254232e-03 0.0028758075 0.68501697 0.3149830
## good    6.723203e-04 0.0030342352 0.18138681 0.8186132
## speak   8.003838e-04 0.0004728416 0.62862694 0.3713731
## to      1.113210e-02 0.0075761991 0.59503541 0.4049646
## soon    2.642059e-04 0.0010608467 0.19939274 0.8006073
## today   1.120666e-03 0.0019041688 0.37048833 0.6295117
## is      4.451802e-03 0.0058153446 0.43359683 0.5664032
## accept  3.802754e-05 0.0003188419 0.10655871 0.8934413
```

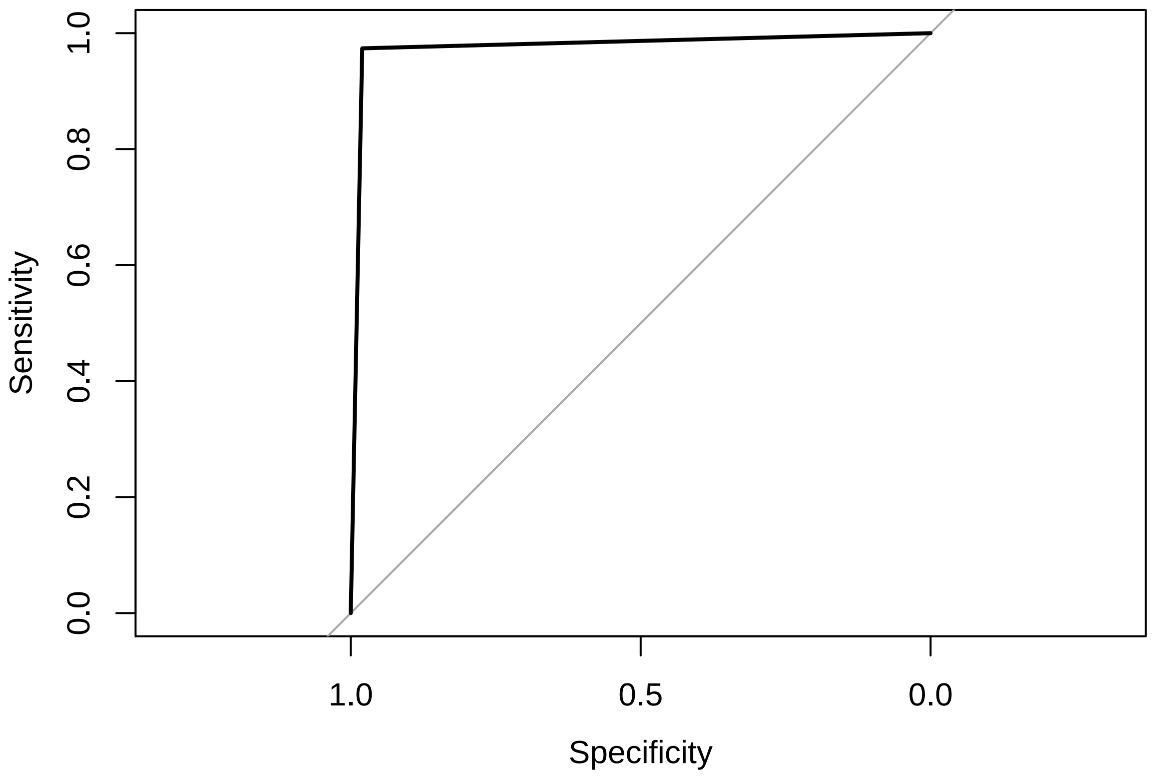
The model outputs the Probabilities of the message being Spam or ham.

Let's Test the Model

```
pred<-predict(nb.classifier,msg.dfm.test)

#generating a confusion matrix

# use pred$nb.predicted to extract the class labels
table(predicted=pred$nb.predicted,actual=spam.test[,1])
```

```
##          actual
## predicted ham spam
##      ham  943    4
##      spam  19  149
```

```
#16 wrongly classified for ham and 7 examples wrongly classified for spam

#acccuracy of the classifier on Test data
acc_nb=mean(pred$nb.predicted==spam.test[,1])*100
#accuracy of 97% on test set

prednum<-ifelse(pred$nb.predicted=="spam",1,2)

auc<-roc(as.factor(spam.test[,1]),prednum)
plot(auc)
```



```
auc$auc
```

```
## Area under the curve: 0.9771
```

```r
#Area under the curve: 0.9679
```

In the ROC curve the area under the curve is **0.9679** which is a very nice score and implies that the model can easily recognize text messages as either spam or ham. ROC curve is plotted between **Sensitivity**-i.e true positive rate(positive classes being classified correctly) vs the **Specificity**-i.e true negetive rate(negetive classes being clssified correctly)

In the Confusion matrix , the **diagonals** are the correctly classified examples while the **off-diagonals** the incorrectly classifiec examples.

Training a K-NN classifier

Now let's train the K-nearest neighbor model. K-NN is a **lazy learner**, which means we have to give it the test data point t, using which it will try to find the nearest neighbors to that test data point t from the training data, using a distance metric and classify t using the voting(mode) method.

```r
require(class)
```

```
## Loading required package: class
```

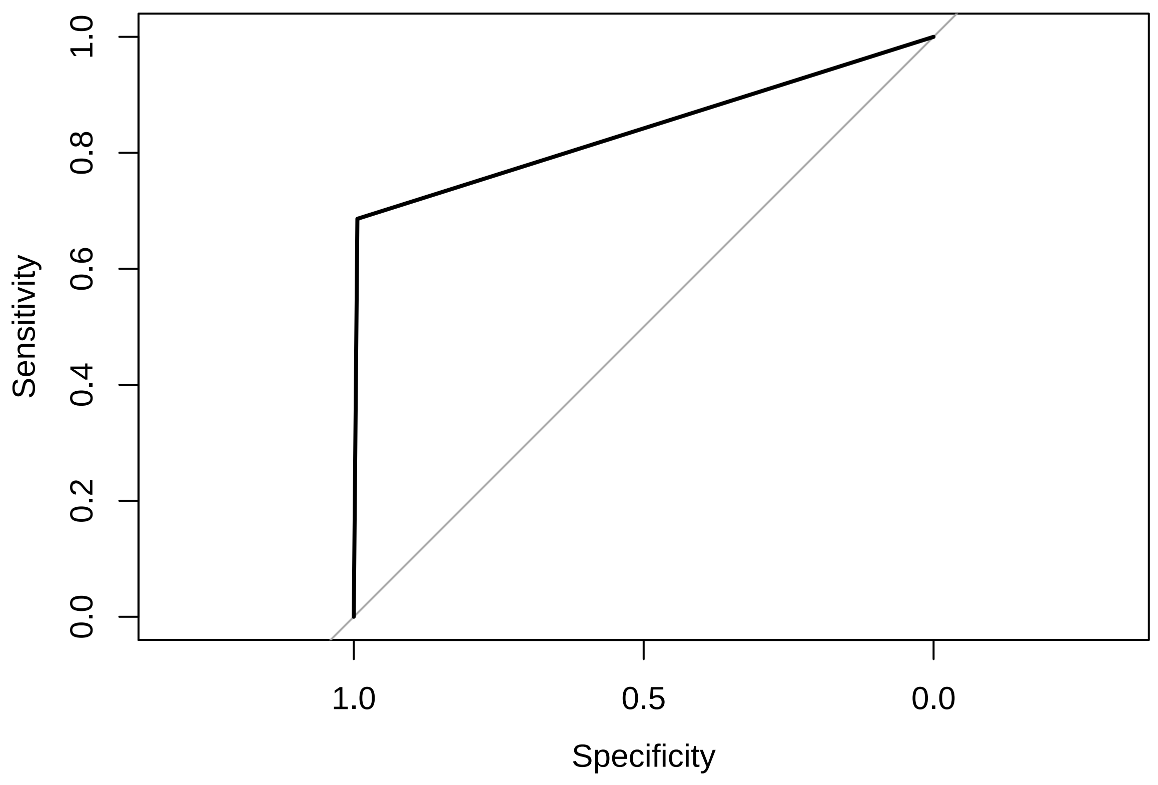
```r
#k=5 nearest neighbors model
knn.pred<-knn(msg.dfm.train,msg.dfm.test,spam.train[,1],k = 1,prob=T)

summary(knn.pred)
```

```
##  ham spam
## 1004  111
```

```r
confMat<-table( Predictions = knn.pred,Actual=spam.test[,1])
confMat
```

```
##            Actual
## Predictions ham spam
##        ham  956   48
##        spam   6  105
```

```r
#TPR = (51)/(51+96) = 0.653
#TNR = (968)/968 = 1

#accuracy of the KNN-classifier
acc_knn=mean(knn.pred==spam.test[,1])*100

#the predicted class argument of the roc() function expects a ordered factor
auc_Knn<-roc(as.factor(spam.test[,1]),ordered(knn.pred))

plot(auc_Knn)
```



```
auc_Knn$sensitivities #true positive rate-TPR- is a spam message
```

```
## [1] 1.0000000 0.6862745 0.0000000
```

```
auc_Knn$specificities #true negetive rate-TNR-not a spam message
```

```
## [1] 0.000000 0.993763 1.000000
```

```
auc_Knn$auc
```

```
## Area under the curve: 0.84
```

Hence we can observe that the K-NN classifier gave us an AUC value of **0.82**, which is not as good as the Naive Bayes text classifier trained above.

Building a SVM classifier

First starting off with some text preprocessing.

```
require(RTextTools)
```

```
## Loading required package: RTextTools
```

```
## Warning: package 'RTextTools' was built under R version 3.4.4
```

```
## Loading required package: SparseM
```

```
##
## Attaching package: 'SparseM'
## The following object is masked from 'package:base':
##
##     backsolve
```

```r
msg_matrix <- create_matrix(spam[,2], language = "English",
                                       removeNumbers = TRUE,
                                       removePunctuation = TRUE,
                                       removeStopwords = FALSE, stemWords = FALSE)


msg_container <- create_container(msg_matrix,spam$type,
                                             trainSize = 1:4458, testSize = 4458:nrow(spam),
                                             virgin = FALSE)
```

Let's traing a SVM model.

```r
svm_model <- train_model(msg_container, algorithm = "SVM")
summary(svm_model)
```

```
##
## Call:
## svm.default(x = container@training_matrix, y = container@training_codes,
##     kernel = kernel, cost = cost, cross = cross, probability = TRUE,
##     method = method)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  radial
##        cost:  100
##       gamma:  0.0001330318
##
## Number of Support Vectors:  760
##
##  ( 328 432 )
##
##
## Number of Classes:  2
##
## Levels:
##  ham spam
```

```r
#summary of the SVM model
svm_model_result <- classify_model(msg_container, svm_model) #gives a data frame with predicted class l
```

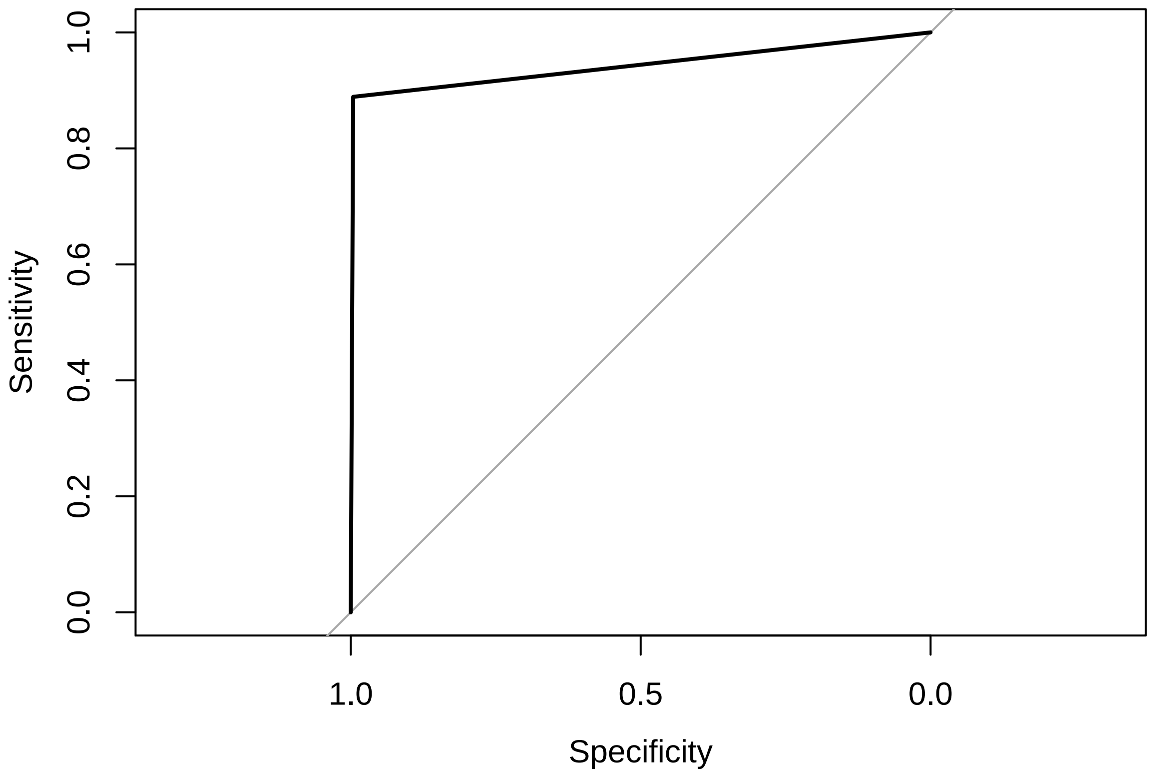
Finding AUC value and ROC curve.

```r
#let's generate a confusion matrix-
table(Pred=svm_model_result$SVM_LABEL,Actual=spam[4458:nrow(spam),1])
```

```
##       Actual
## Pred   ham spam
##   ham  958   17
##   spam   4  136
```

```r
acc_svm=mean(svm_model_result$SVM_LABEL==spam.test[,1])*100
```

```r
auc_svm<-roc(as.factor(spam.test[,1]),ordered(svm_model_result$SVM_LABEL))

plot(auc_svm) #roc curve
```



```r
auc_svm$auc #auc value is 0.95
```

```
## Area under the curve: 0.9424
```

```r
auc_svm$sensitivities
```

```
## [1] 1.0000000 0.8888889 0.0000000
```

```r
auc_svm$specificities
```

```
## [1] 0.000000 0.995842 1.000000
```

Hence SVM classifier gave us an AUC value of **0.95**, which is better than K-NN classifer but slightly lower than Naive bayes classifier.

Comparing the 3 models-

Generating a comparative evaluative table of all the 3 classifier generated for the text classification problem-

```r
eval_table<-as.data.frame(rbind(auc$auc,auc_svm$auc,auc_Knn$auc))
colnames(eval_table)<-c("AUC")
eval_table<- eval_table %>% mutate(Accuracy=c(acc_nb,acc_svm,acc_knn))
```

```r
row.names(eval_table)<- c("Naive_bayes","SVM","K-NN")

#comparative evaluation table of the 3 classifiers
eval_table
```

```
##                   AUC Accuracy
## Naive_bayes 0.9770528 97.93722
## SVM         0.9423654 98.11659
## K-NN        0.8400188 95.15695
```

Conclusion

This was a simple article on classifying text messages as ham or spam using some basic natural language processing and then building a naive Bayes text classifier.I urge the readers to implement and use the knowledge acquired from this article in making their own text classifiers and solving different problems related to text processing and NLP etc. Ofcourse,there are various other packages to do text processing and building such models.

Hope you guys liked the article , make sure to like and share it.