Sentiment Analysis for Amazon Review and Drug Review

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Contents

1 Introduction

In recent years, machine learning techniques have become increasingly popular and relevant to solving text and sentiment-related problems. It has boosted performance on several tasks and significantly reduced the necessity for human efforts. For this project, we focused on text classification, especially sentiment analysis, on two datasets, *Amazon Review* and *Drug Review*. Although the *Amazon Review* dataset is popular and was being used for many research papers and projects, most code works were carried out using Python. Therefore, we decided to explore more on implementing four classic Natural Language Processing (NLP) methods using R packages. We first replicated the R code from existing literature for the *Amazon Review* dataset. We adapted them to a newer but less popular UCI Machine Learning Repository dataset. Our goal for the project is to compare classifiers, including `BoW`, `Word2Vec`, `GloVe`, `fastText` for two different datasets.

2 Data

2.1 Dataset Overview

For the *Amazon Review* dataset, we use the dataset constructed and made available by Zhang, Zhao and LeCun (2015). The dataset contains about 1,800,000 training samples and 200,000 testing samples with three attributes, which are classification labels (1 for negative reviews and 2 for positive reviews), the title of each review text, and the review text body. Due to the limit of computer computation ability, we pulled out the first 100,000 data samples and split 80% of the data into the training set and 20% of the data into the testing set.

For the Drug dataset, we downloaded from the UCI Machine Learning Repository. The dataset has 215,063 samples with 6 attributes, including drugName, condition, review, rating (1 to 10), date, usefulCount. Similar to *Amazon Review* dataset, we split the whole dataset into training (80%) and testing (20%) datasets. In order to replicate the code, we categorized the dataset into two labels, where rating range from [1 to 4] are categorized as [1(negative)] and the rating range from [7 to 10] are categorized as [2(positive)]. We combined the text columns together and removed symbols that are not a number or a word. Moreover, we only retained the columns of rating and merged columns of review, name, condition as one text body attribute. Hence our drug dataset has the same format as *Amazon Review*.

2.2 Dataset Prepossessing

Take the code for Amazon reviews as example.

2.2.1 Amazon review

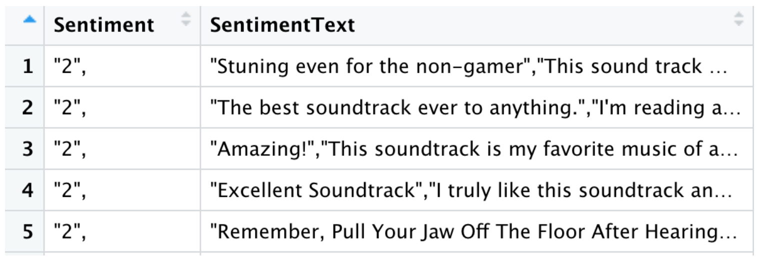
We first set seed and read the data. Note that we split the original data into training and testing according to ratio 8:2.

```r
set.seed(1)
N_amazon <- 100000
N_train_amazon <- 0.8*N_amazon
reviews_amazon <- readLines("amazon_review_polarity_csv/train.csv", n = N_amazon)
reviews_amazon <- data.frame(reviews_amazon)
```

Then we separating the sentiment and the review text.

```r
library(tidyr)
reviews_amazon <- separate(data = reviews_amazon, col = reviews_amazon,
                           into = c("Sentiment", "SentimentText"), sep = 4)
```

Here we got the data before prepossessing.



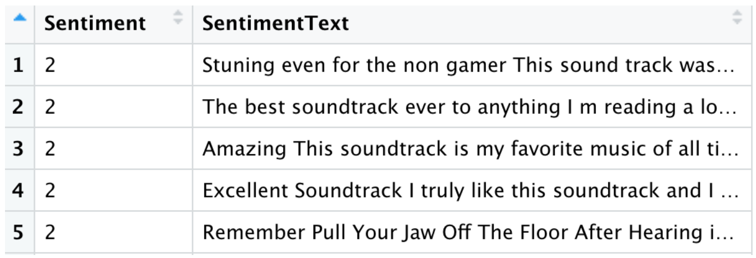
	Sentiment	SentimentText
1	"2",	"Stuning even for the non-gamer","This sound track ...
2	"2",	"The best soundtrack ever to anything.","I'm reading a...
3	"2",	"Amazing!","This soundtrack is my favorite music of a...
4	"2",	"Excellent Soundtrack","I truly like this soundtrack an...
5	"2",	"Remember, Pull Your Jaw Off The Floor After Hearing...

Figure 1: Head rows of the data before prepossessing

Since the unnecessary punctuation may cause the problem for our sentiment analysis, we remove the punctuation with the following code:

```r
# Retaining only alphanumeric values in the sentiment column
reviews_amazon$Sentiment <- gsub("[^[:alnum:] ]","",reviews_amazon$Sentiment)
# Retaining only alphanumeric values in the sentiment text
reviews_amazon$SentimentText <- gsub("[^[:alnum:] ]"," ",reviews_amazon$SentimentText)
# Replacing multiple spaces in the text with single space
reviews_amazon$SentimentText <- gsub("(?<=[\\s])\\s*|^\\s+|\\s+$", "",
                                     reviews_amazon$SentimentText, perl=TRUE)
# Writing the output to a file that can be consumed in other models
write.table(reviews_amazon,file = "Sentiment Analysis Dataset.csv",row.names = F,
            col.names = T,sep=',')
```

This will give us the following output:



	Sentiment	SentimentText
1	2	Stuning even for the non gamer This sound track was...
2	2	The best soundtrack ever to anything I m reading a lo...
3	2	Amazing This soundtrack is my favorite music of all ti...
4	2	Excellent Soundtrack I truly like this soundtrack and I ...
5	2	Remember Pull Your Jaw Off The Floor After Hearing i...

Figure 2: Head rows of the data after prepossessing

Since The fastText algorithm expects the dataset to be in a format: ___ label ___ <x> <text>, where x is the class name and text is the review text, we need to transform our data format as required.

```r
reviews_amazon <- readLines('amazon_review_polarity_csv/train.csv', n = N_amazon)
# Basic EDA to confirm that the data is read correctly
print(class(reviews_amazon))
```

```
## [1] "character"
```

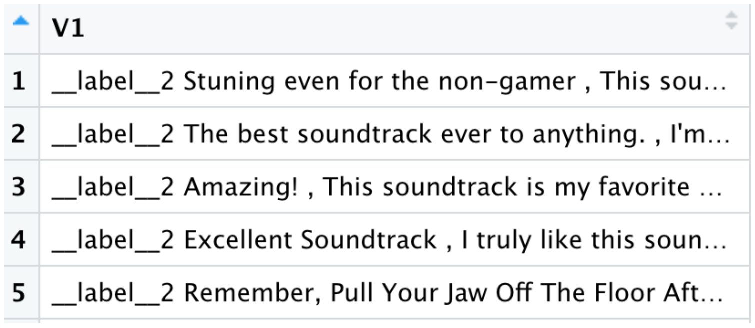
```
print(length(reviews_amazon))
```

```
## [1] 100000
```

```
# Replacing the positive sentiment value 2 with __label__2
reviews_amazon <- gsub("\\\"2\\\",","__label__2 ",reviews_amazon)
# Replacing the negative sentiment value 1 with __label__1
reviews_amazon <- gsub("\\\"1\\\",","__label__1 ",reviews_amazon)
# Removing the unnecessary \" characters
reviews_amazon <- gsub("\\\""," ",reviews_amazon)
# Replacing multiple spaces in the text with single space
reviews_amazon <- gsub("(?<=[\\s])\\s*|^\\s+|\\s+$", "", reviews_amazon, perl=TRUE)

# Writing the revamped file to the directory so we could use it with
# fastText sentiment analyzer project
fileConn <- file("Sentiment Analysis Dataset_ft.txt")
writeLines(reviews_amazon, fileConn)
close(fileConn)
```

This will give us the following dataset:



	V1
1	__label__2 Stuning even for the non-gamer , This sou…
2	__label__2 The best soundtrack ever to anything. , I'm…
3	__label__2 Amazing! , This soundtrack is my favorite …
4	__label__2 Excellent Soundtrack , I truly like this soun…
5	__label__2 Remember, Pull Your Jaw Off The Floor Aft…

Figure 3: Head rows of the prepossessing data for FastText

2.2.2 Drug Review

The prepossing method for Drug Review are similar to Amazon Review.

However we did find some problems during our training processes, which is the Drug Review are actually imbalanced. So we need to balanced our Drug Review, make them equal numbers of the positive reviews and negative reviews.

```
# Checking the summary of our label for Drug Review
(Sentimentable = table(reviews_text_Drug$Sentiment))
```

```
##
##      1      2
##  40075 106866
```

```
# Balance our Drug Review
minlabel <- names(which(Sentimentable == min(Sentimentable)))
maxlabel <- names(which(Sentimentable == max(Sentimentable)))

n_maxlabel <- min(Sentimentable)
minlabelid <- c(1:N_Drug)[reviews_text_Drug$Sentiment==minlabel]
maxlabelid <- sample(c(1:N_Drug)[reviews_text_Drug$Sentiment==maxlabel],n_maxlabel)
balanceid <- sample(c(minlabelid,maxlabelid))
reviews_text_Drug <- reviews_text_Drug[balanceid,]

N_Drug <- nrow(reviews_text_Drug)
N_train_Drug <- round(0.8*N_Drug)
```

3 BoW approach with Naive Bayes

Bag of Words (BoW) method is widely used in NLP and computer vision fields. It takes the occurrence of each word in the text regardless of grammar and makes it into "bags" to characterize the text. To implement BoW method for our dataset, *Amazon Review* and *Drug Review*, we first use `VCorpus` function and `DocumentTermMatrix` function in the `tm` package to convert text into a Document Term Matrix (DTM). By adjusting the built-in parameter in the `DocumentTermMatrix` function, we do not have to worry about cleaning the dataset with stop words. In order to make the model more precise, we removed words that do not occur in 99% of the documents by using `removeSparseTerms` function.

After finishing the process of BoW conversion, we can use the DTM to create word clouds for both positive and negative sentiment cases. And also to better interpret our word cloud, we simply use the two-sample t-test to better discriminant our words. Finally, we followed Chinnamgari (2019) and used the Naive Bayes sentiment classifier to perform predictions. Utilizing the `nb_sent_classifier` in the `e1071` package, we obtained the prediction results with approximate **81.19%** for *Amazon Review* data and **74.77%** for *Drug Review*.

3.1 Amazon review

```
library(SnowballC)
library(tm)
# Reading the transformed file as a dataframe
text_amazon <- read.table(file='Sentiment Analysis Dataset.csv', sep=',', header = TRUE)

# Transforming the text into volatile corpus
amazon_corp <- VCorpus(VectorSource(text_amazon$SentimentText))
```

```
# Creating document term matrix (DTM)
dtm_amazon <- DocumentTermMatrix(amazon_corp, control = list( tolower = TRUE,
   removeNumbers = TRUE, stopwords = TRUE, removePunctuation = TRUE, stemming = TRUE))
# Basic EDA on dtm
inspect(dtm_amazon)
```

```
## <<DocumentTermMatrix (documents: 100000, terms: 74760)>>
## Non-/sparse entries: 3399444/7472600556
## Sparsity           : 100%
## Maximal term length: 188
## Weighting          : term frequency (tf)
## Sample             :
##        Terms
## Docs    book get good great just like movi one read time
##   1250     0   0    0     0    0    0    0   0    0    0
##   56817    0   0    0     0    0    0    0   0    0    0
##   63995    0   2    1     1    0    2    0   2    0    1
##   6785     0   7    1     0    0    1    0   1    0    0
##   69262    0   0    0     0    0    0    0   0    0    0
##   73633    1   0    0     2    0    3    0   2    0    2
##   79144    0   0    0     0    0    0    0   0    0    0
##   80872    0   0    0     0    0    0    0   0    0    0
##   85894    0   1    0     0    0    1    0   1    0    0
##   87875    0   0    0     0    0    0    0   0    0    0
```

We see that the DTM is 100% sparse. Since the DTM tends to get very big, we removed sparse terms, that is, terms occurring only in very few documents, and tried to reduce the size of the matrix without losing significant relations inherent to the matrix.

```
# Removing sparse terms
dtm_amazon = removeSparseTerms(dtm_amazon, 0.99)
inspect(dtm_amazon)
```

```
## <<DocumentTermMatrix (documents: 100000, terms: 645)>>
## Non-/sparse entries: 2131029/62368971
## Sparsity           : 97%
## Maximal term length: 10
## Weighting          : term frequency (tf)
## Sample             :
##        Terms
## Docs    book get good great just like movi one read time
##   34297    0   1    0     0    2    5    0   3    0    0
##   38984    6   0    0     1    1    0    0   1    0    1
##   42051    3   0    1     0    2    1    0   3    5    1
##   56269    0   1    0     0    1    0    1   1    0    1
##   65117    0   1    1     1    1    0    0   1    0    0
##   65135    0   0    1     2    0    4    0   0    1    0
##   6785     0   7    1     0    0    1    0   1    0    0
##   80366    0   3    1     1    1    1    0   8    0    0
##   87149    6   0    1     0    0    1    0   2    1    0
##   90397    0   2    1     0    3    3    0   2    0    0
```

Using the DTM, we can create word clouds for better understanding for our sentiment text. However, we found that some of the selected words are difficult to interpret. So we decided to first filter out a vocab with words that we can interpret. We used a simple screening method, which we described in discriminant analysis before: two-sample t-test. Assume we have one-dimensional observations from two groups

$$X_1, X_2, \ldots, X_m, \quad Y_1, Y_2, \ldots, Y_n X$$

to test whether the X population and the Y population have the same mean, we computed the following two-sample t-statistic $\frac{\bar{X}-\bar{Y}}{\sqrt{\frac{s_X^2}{m}+\frac{s_Y^2}{n}}}$.

where s_X^2 denotes the sample variance of X.

Again, we used the training data from the first split. Since dtm_train is a large sparse matrix, we used commands from the R package `slam` to efficiently compute the mean and var for each column of dtm_train.

```
# Word Cloud preparing
v.size = dim(dtm_amazon)[2]
ytrain = as.numeric(text_amazon$Sentiment)
```

```
# Using two-sample t-test to find the most represent words to show our Word Cloud
library(slam)
summ = matrix(0, nrow=v.size, ncol=4)
summ[,1] = colapply_simple_triplet_matrix(
  as.simple_triplet_matrix(dtm_amazon[ytrain==2, ]), mean)
summ[,2] = colapply_simple_triplet_matrix(
  as.simple_triplet_matrix(dtm_amazon[ytrain==2, ]), var)
summ[,3] = colapply_simple_triplet_matrix(
  as.simple_triplet_matrix(dtm_amazon[ytrain==1, ]), mean)
summ[,4] = colapply_simple_triplet_matrix(
  as.simple_triplet_matrix(dtm_amazon[ytrain==1, ]), var)

n1 = sum((ytrain)-1);
n = length(ytrain)
n0 = n - n1

myp = (summ[,1] - summ[,3])/
  sqrt(summ[,2]/n1 + summ[,4]/n0)
```

We ordered words by the magnitude of their t-statistics, which are then divided into two lists: positive words and negative words.

```
words = colnames(dtm_amazon)
id = order(abs(myp), decreasing=TRUE)
pos.list = words[id[myp[id]>0]]
posvalue = myp[id][myp[id]>0][1:50]
neg.list = words[id[myp[id]<0]]
negvalue = myp[id][myp[id]<0][1:50]
```

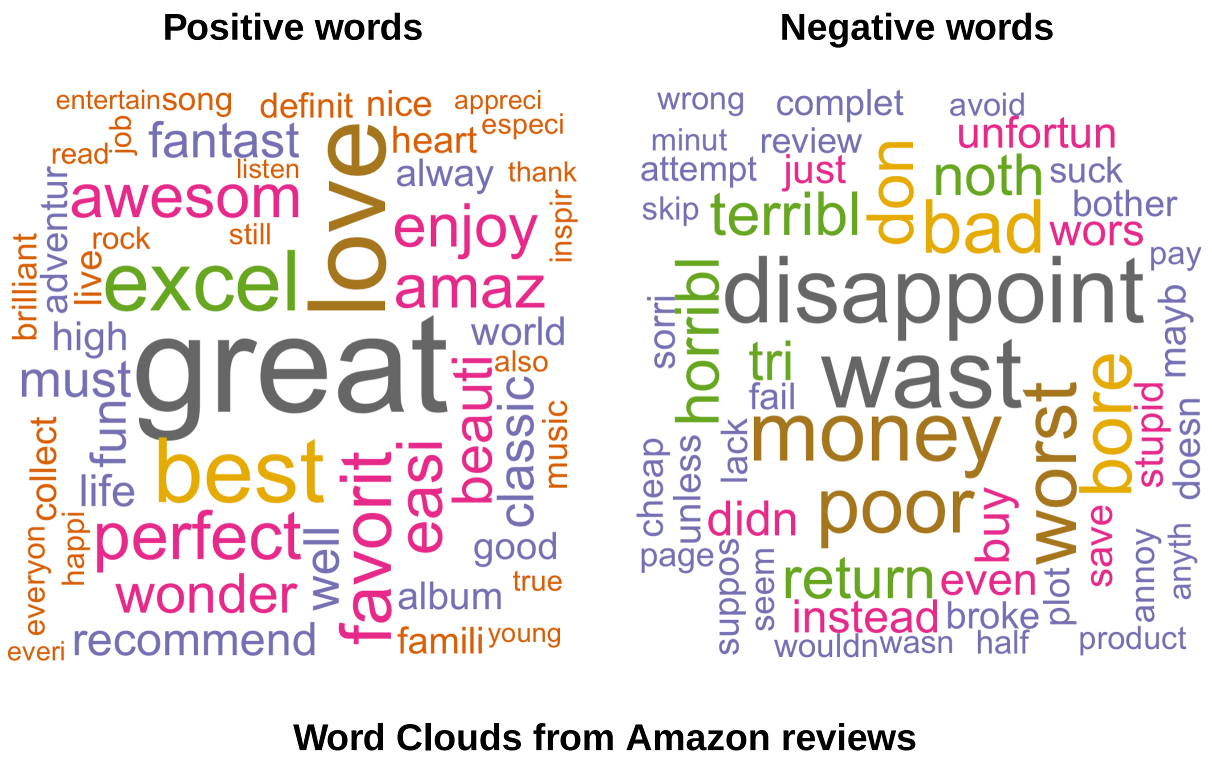
Using the `wordcloud` package to plot the Word Cloud for most represent words, both positive and negative.

```
# Word Cloud for positive words
library(wordcloud)
wordcloud(words = pos.list[1:50], freq = posvalue, scale=c(6,.2), min.freq = 5,
          random.order=FALSE, rot.per=0.35, colors = brewer.pal(8, "Dark2"))
```

```
# Word Cloud for negative words
wordcloud(words = neg.list[1:50], freq = abs(negvalue), scale=c(4.3,.2), min.freq = 5,
          random.order=FALSE, rot.per=0.35, colors = brewer.pal(8, "Dark2"))
```

```
library(png)
par(mfrow=c(1, 2), mar=c(1, 0, 3, 0))
plot.new()
plot.window(xlim=c(0, 1), ylim=c(0, 1), asp=1)
```

```
rasterImage(readPNG("amazonpos"), 0, 0, 1, 1)
title('Positive words', line = -0.5)
plot.new()
plot.window(xlim=c(0, 1), ylim=c(0, 1), asp=1)
rasterImage(readPNG("amazonneg"), 0, 0, 1, 1)
title('Negative words', line = -0.5)
title("Word Clouds from Amazon reviews", line = -22, outer = TRUE)
```



Then, we continue using the DTM that to training with machine learning classification. We divide our DTM into training (80%) and testing (20%) datasets.

```
# Splitting the train and test DTM
dtm_amazon_train <- dtm_amazon[1:N_train_amazon, ]
dtm_amazon_test <- dtm_amazon[(N_train_amazon+1):N_amazon, ]
dtm_amazon_train_labels <- as.factor(as.character(text_amazon[1:N_train_amazon, ]$Sentiment))
dtm_amazon_test_labels <- as.factor(as.character(text_amazon[(N_train_amazon+1):N_amazon, ]$Sentiment))
```

Here we use Naive Bayes to create a classifier. Since Naive Bayes is generally trained on data with nominal features, DTM need to be converted to nominal prior to feeding the dataset as input for creating the model with Naive Bayes.

```
# Convert the cell values with a non-zero value to Y, and in case of a zero we convert it to N
cellconvert<- function(x) { x <- ifelse(x > 0, "Y", "N") }

# Applying the function to rows in training and test datasets
```

```
dtm_amazon_train <- apply(dtm_amazon_train, MARGIN = 2,cellconvert)
dtm_amazon_test <- apply(dtm_amazon_test, MARGIN = 2,cellconvert)
```

Then, we proceed to build a text sentiment analysis classifier using the Naive Bayes algorithm from the `e1071` package.

```
# Training the naive bayes classifier on the training dtm
library(e1071)
nb_amazon_senti_classifier <- naiveBayes(dtm_amazon_train,dtm_amazon_train_labels)
```

Finally, we used the trained Naive Bayes model to predict sentiment on the test data DTM. The accuracy for testing *Amazon review* is

```
# Making predictions on the test data dtm
nb_amazon_predicts <- predict(nb_amazon_senti_classifier, dtm_amazon_test, type="class")

# Computing accuracy of the model
library(rminer)
print(mmetric(nb_amazon_predicts, dtm_amazon_test_labels, c("ACC")))
```

```
## [1] 81.19
```

3.2 Drug Review

The works for *Drug Review* are similar to before.

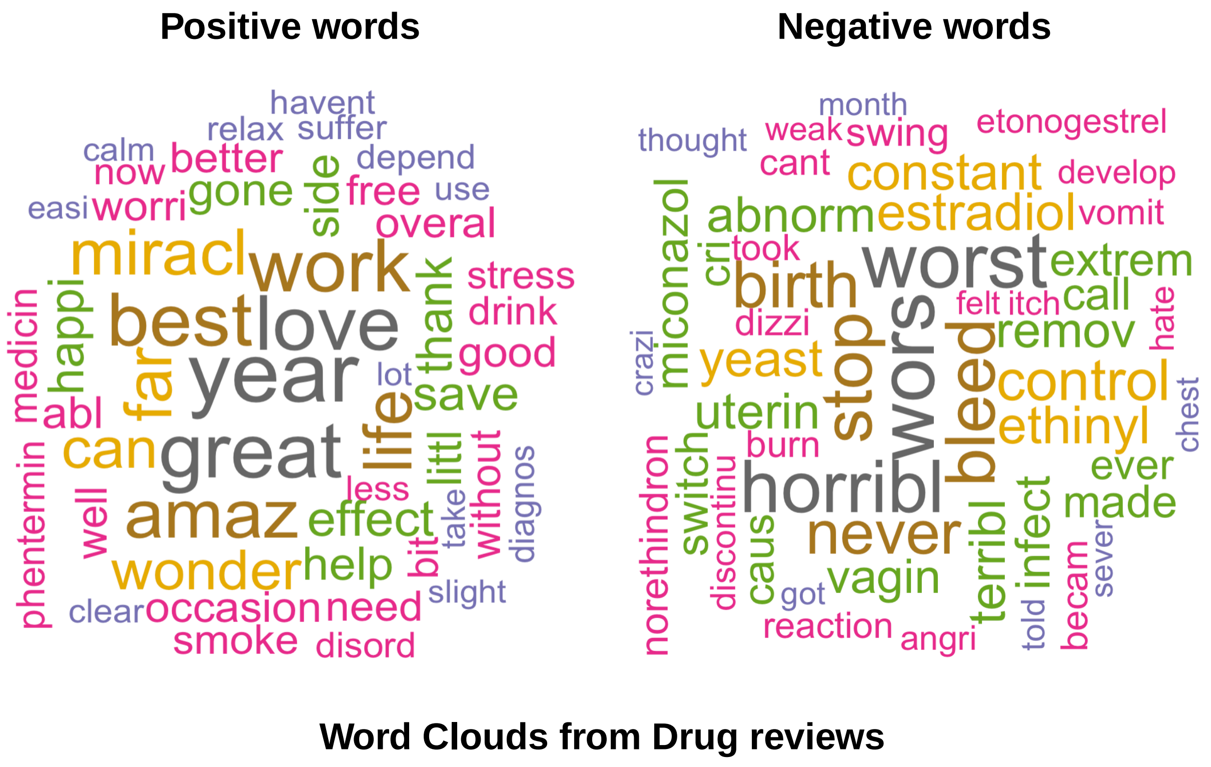
Raw DTM for *Drug Review*

```
## <<DocumentTermMatrix (documents: 80150, terms: 44610)>>
## Non-/sparse entries: 2919201/3572572299
## Sparsity           : 100%
## Maximal term length: 95
## Weighting          : term frequency (tf)
## Sample             :
##        Terms
## Docs    day effect get month pain start take week work year
##   14443   0      7   0     0    0     1    1    0    0    0
##   21739   3      4   3     1   10     4    3    5    6    1
##   32948   9      1   1     1    1     3    5    1    1    5
##   35157   7      7   4     1    3     1    6    4    4    0
##   39889   0      2   2     4    3     4    1    0    2    1
##   4810    0      7   0     0    0     1    1    0    0    0
##   48674   7      7   4     1    3     1    6    4    4    0
##   50714   7      5   3     2    0     4    9    6    2    1
##   56489   0      2   2     4    3     4    1    0    2    1
##   79862   6      0   2     0    7     0    2    0    4    2
```

DTM after removing the sparse columns

```
## <<DocumentTermMatrix (documents: 80150, terms: 645)>>
## Non-/sparse entries: 2177799/49518951
## Sparsity           : 96%
## Maximal term length: 14
## Weighting          : term frequency (tf)
## Sample             :
##        Terms
## Docs    day effect get month pain start take week work year
##   1194    2      3   4     0    0     1    3    3    1    0
##   21739   3      4   3     1   10     4    3    5    6    1
##   32948   9      1   1     1    1     3    5    1    1    5
##   35157   7      7   4     1    3     1    6    4    4    0
##   35179   2      3   4     0    0     1    3    3    1    0
##   39889   0      2   2     4    3     4    1    0    2    1
##   48674   7      7   4     1    3     1    6    4    4    0
##   50714   7      5   3     2    0     4    9    6    2    1
##   56489   0      2   2     4    3     4    1    0    2    1
##   79862   6      0   2     0    7     0    2    0    4    2
```

We also use the `wordcloud` package to plot the Word Cloud for *Drug Review*.



The accuracy for testing *Drug Review* is

```
## [1] 74.7723
```

4 Pretrained word2vec word embedding with Random Forest algorithm

`Word2vec` was developed by Mikolov *et al.* (2013) as a response to making the neural-network-based training of the embedding more efficient, and since then it has become the standard method for developing pretrained word embedding. The `softmaxreg` library in R offers pretrained `word2vec` word embedding that can be used for building our sentiment analysis engine for the sentiment reviews data. The pretrained vector is built using the word2vec model, and it is based on the Reuter_50_50 dataset UCI Machine Learning Repository.

After obtaining the word embedding, we calculated the review sentences embedding by taking the mean of all the word vectors of the words made up of the review sentences. Finally, the machine learning classification method is applied to the review sentence embeddings. In this problem, we used Random Forest algorithm to make classification and achieve an accuracy of **62.56%** on *Amazon Review* and **70.99%** on *Drug Review*.

4.1 Amazon review

First we examined the `word2vec` pretrained emdeddings.

```
library(softmaxreg)
# Importing the word2vec pretrained vector into memory
data(word2vec)
```

In order to decode the entire review, we take the mean of all the word vectors of the words that made up the review. The `softmaxreg` library offers the wordEmbed function where we could pass a sentence and ask it to compute the mean word vector for the sentence.

```
# Function to get word vector for each review
docVectors <- function(x) { wordEmbed(x, word2vec, meanVec = TRUE) }
text_amazon <- read.csv(file='Sentiment Analysis Dataset.csv', header = TRUE)
# Applying the docVector function on each of the reviews
# Storing the matrix of word vectors as temp
temp_amazon <- t(sapply(text_amazon$SentimentText, docVectors))
```

This data frame can now be used to build classification models using an ML algorithm. We first split our matrix into training (80%) and testing (20%) datasets, then applying the Random Forest algorithm for our classifier model.

```
# Splitting the dataset into train and test
temp_amazon_train <- temp_amazon[1:N_train_amazon,]
temp_amazon_test <- temp_amazon[(N_train_amazon+1):N_amazon,]
labels_amazon_train <- as.factor(as.character(text_amazon[1:N_train_amazon,]$Sentiment))
labels_amazon_test <- as.factor(as.character(text_amazon[(N_train_amazon+1):N_amazon,]$Sentiment))
library(randomForest)
# Training a model using random forest classifier with training dataset
# Observe that we are using 20 trees to create the model
rf_amazon_senti_classifier <- randomForest(temp_amazon_train, labels_amazon_train, ntree=20)
print(rf_amazon_senti_classifier)
```

```
##
## Call:
##  randomForest(x = temp_amazon_train, y = labels_amazon_train,      ntree = 20)
##                Type of random forest: classification
##                      Number of trees: 20
## No. of variables tried at each split: 4
##
##         OOB estimate of  error rate: 40%
## Confusion matrix:
##       1     2 class.error
## 1 23547 15436   0.3959675
## 2 16563 24448   0.4038673
```

The accuracy for testing *Amazon Review* is

```
# Making predictions on the dataset
rf_amazon_predicts <- predict(rf_amazon_senti_classifier, temp_amazon_test)
library(rminer)
print(mmetric(rf_amazon_predicts, labels_amazon_test, c("ACC")))
```

```
## [1] 62.555
```

4.2 Drug Review

The works for *Drug Review* are similar to before.

```
##
## Call:
##  randomForest(x = temp_train_Drug, y = labels_train_Drug, ntree = 20)
##                Type of random forest: classification
##                      Number of trees: 20
## No. of variables tried at each split: 4
##
##         OOB estimate of  error rate: 31.81%
## Confusion matrix:
##       1     2 class.error
## 1 23040  8945   0.2796623
## 2 11453 20677   0.3564581
```

The accuracy for testing *Drug Review* is

```
## [1] 70.98565
```

5 GloVe word embedding with Random Forest algorithm

Pennington, Socher and Manning (2014) developed an extension of the `word2vec` method called `GloVe Vectors` for Word Representation (`GloVe`) for efficiently learning word vectors. It combines the global statistics of matrix factorization techniques with local context-based learning in `word2vec`. Also, unlike `word2vec`, rather than using a window to define local context, `GloVe` constructs an explicit word context or word co-occurrence matrix using statistics across the whole text corpus. As an effect, the learning model yields generally better word embeddings.

The `text2vec` package in R has a `GloVe` implementation that we could use to train to obtain word embeddings from our own training corpus. Similar to the previous part, we used the `softmaxreg` library to obtain the mean word vector for each review. In this problem, we used the Random Forest algorithm to make classification and achieve an accuracy of **72.72%** on *Amazon Review* and **74.96%** on *Drug Review.*

5.1 Amazon review

The following code demonstrates how `GloVe` word embeddings can be created and used for sentiment analysis.

```r
library(text2vec)
# Reading the dataset
text_amazon <- read.csv(file='Sentiment Analysis Dataset.csv', header = TRUE)
# Subsetting only the review text so as to create Glove word embedding
wiki_amazon <- as.character(text_amazon$SentimentText)
# Create iterator over tokens
tokens_amazon <- space_tokenizer(wiki_amazon)
# Create vocabulary. Terms will be unigrams (simple words).
it_amazon <- itoken(tokens_amazon, progressbar = FALSE)
vocab_amazon <- create_vocabulary(it_amazon)
# Consider a term in the vocabulary if and only if the term has appeared at least
# three times in the dataset
vocab_amazon <- prune_vocabulary(vocab_amazon, term_count_min = 3L)
# Use the filtered vocabulary
vectorizer_amazon <- vocab_vectorizer(vocab_amazon)
# Use window of 5 for context words and create a term co-occurance matrix
tcm_amazon <- create_tcm(it_amazon, vectorizer_amazon, skip_grams_window = 5L)
# Create the glove embedding for each in the vocab and
# the dimension of the word embedding should set to 50
# x_max is the maximum number of co-occurrences to use in the weighting function
glove <- GlobalVectors$new(rank = 50, x_max = 100)
wv_main_amazon <- glove$fit_transform(tcm_amazon, n_iter = 10, convergence_tol = 0.01)
```

```
## INFO  [03:19:10.009] epoch 1, loss 0.0502
## INFO  [03:19:15.675] epoch 2, loss 0.0318
## INFO  [03:19:21.329] epoch 3, loss 0.0267
## INFO  [03:19:26.989] epoch 4, loss 0.0239
## INFO  [03:19:32.609] epoch 5, loss 0.0222
## INFO  [03:19:38.250] epoch 6, loss 0.0209
## INFO  [03:19:43.931] epoch 7, loss 0.0199
## INFO  [03:19:49.640] epoch 8, loss 0.0191
## INFO  [03:19:55.362] epoch 9, loss 0.0184
## INFO  [03:20:01.050] epoch 10, loss 0.0179
```

The following uses the `GloVe` model to obtain the combined word vector.

```r
# Glove model learns two sets of word vectors - main and context.
# Both matrices may be added to get the combined word vector
wv_context <- glove$components
word_vectors_amazon <- wv_main_amazon + t(wv_context)
# Converting the word_vector to a dataframe for visualization
word_vectors_amazon <- data.frame(word_vectors_amazon)
# The word for each embedding is set as row name by default
# Using the tibble library rownames_to_column function, the rownames is copied
# as first column of the dataframe
# We also name the first column of the dataframe as words
library(tibble)
word_vectors_amazon <- rownames_to_column(word_vectors_amazon, var = "words")
```

We used the `softmaxreg` library to obtain the mean word vector for each review.

```
library(softmaxreg)
docVectors_amazon = function(x) { wordEmbed(x, word_vectors_amazon, meanVec = TRUE) }
# Applying the function docVectors function on the entire reviews dataset
# This will result in word embedding representation of the entire reviews dataset
temp_amazon <- t(sapply(text_amazon$SentimentText, docVectors_amazon))
```

We split the dataset into 80% train and 20% test portions and used the Random Forest algorithm to build a model to train.

```
# Splitting the dataset into train and test portions
temp_amazon_train <- temp_amazon[1:N_train_amazon,]
temp_amazon_test <- temp_amazon[(N_train_amazon+1):N_amazon,]
labels_amazon_train <- as.factor(as.character(text_amazon[1:N_train_amazon,]$Sentiment))
labels_amazon_test <- as.factor(as.character(text_amazon[(N_train_amazon+1):N_amazon,]$Sentiment))
# Using randomforest to build a model on train data
library(randomForest)
rf_amazon_senti_classifier <- randomForest(temp_amazon_train, labels_amazon_train,ntree=20)
```

Finally, the accuracy for testing *Amazon Review* is

```
# Predicting labels using the randomforest model created
rf_amazon_predicts <- predict(rf_amazon_senti_classifier, temp_amazon_test)
# Estimating the accuracy from the predictions
library(rminer)
print(mmetric(rf_amazon_predicts, labels_amazon_test, c("ACC")))
```

```
## [1] 72.72
```

5.2 Drug Review

The works for *Drug Review* are similar.

```
## INFO  [03:25:59.763] epoch 1, loss 0.0755
## INFO  [03:26:02.057] epoch 2, loss 0.0487
## INFO  [03:26:04.357] epoch 3, loss 0.0401
## INFO  [03:26:06.657] epoch 4, loss 0.0354
## INFO  [03:26:08.962] epoch 5, loss 0.0324
## INFO  [03:26:11.256] epoch 6, loss 0.0302
## INFO  [03:26:13.565] epoch 7, loss 0.0285
## INFO  [03:26:15.875] epoch 8, loss 0.0273
## INFO  [03:26:18.206] epoch 9, loss 0.0262
## INFO  [03:26:20.471] epoch 10, loss 0.0254
```

```
##
## Call:
##  randomForest(x = temp_train_Drug, y = labels_train_Drug, ntree = 20)
##                Type of random forest: classification
##                      Number of trees: 20
## No. of variables tried at each split: 7
##
##         OOB estimate of  error rate: 29.08%
## Confusion matrix:
##       1     2 class.error
## 1 23380  8604   0.2690095
## 2 10039 22089   0.3124689
```

The accuracy for testing *Drug Review* is

```
## [1] 74.95945
```

6 FastText word embedding

`FastText` is also an extension of `word2vec`, `fastTextR` package is used to reach more concise predictions for the analysis. Created and open-sourced by Facebook in 2016 (Mannes, 2016), `FastText` is a more powerful tool to classify text and learn word vector representation by breaking words into several character n-grams. `FastText` can construct the vector for a word from its character n-grams, even if it doesn't appear in the training corpus; however, it is also time-consuming.

Before training the model, we convert the label in the dataset from “\\\1\\\” into “__label__1” in order to meet the format of the `FastText` algorithm. We also cleaned all multiple spaces in the text with a single space. Thereupon, we used `ft_train` function to train the model and `ft_control` to tune the hyper-parameter for our two datasets. Our best accuracy for the fastText model is **86.49%** for the *Amazon Review Dataset* and **78.69%** for the Drug dataset.

6.1 Amazon review

We used the `fastTextR` library for this problem to build a sentiment analysis engine on *Amazon Review*.

```r
library(fastTextR)
# Input reviews file
text_amazon <- readLines("Sentiment Analysis Dataset_ft.txt")
```

We divided the reviews into 80% training and 20% testing datasets.

```r
# Dividing the reviews into training and test
temp_amazon_train <- text_amazon[1:N_train_amazon]
temp_amazon_test <- text_amazon[(N_train_amazon+1):N_amazon]
```

We then created a `.txt` file for the train and test dataset.

```r
# Creating txt file for train and test dataset
fileConn <- file("train.ft.txt")
writeLines(temp_amazon_train, fileConn)
close(fileConn)
fileConn <- file("test.ft.txt")
writeLines(temp_amazon_test, fileConn)
close(fileConn)
# Creating a test file with no labels
temp_amazon_test_nolabel <- gsub("__label__1", "", temp_amazon_test, perl=TRUE)
temp_amazon_test_nolabel <- gsub("__label__2", "", temp_amazon_test_nolabel, perl=TRUE)
```

We also created no labels test dataset to a file so we can use it for testing.

```r
fileConn <- file("test_nolabel.ft.txt")
writeLines(temp_amazon_test_nolabel, fileConn)
close(fileConn)
# Training a supervised classification model with training dataset file
model_amazon <- ft_train("train.ft.txt", method = "supervised",
                control = ft_control(nthreads = 3L, seed = 1))
# Obtain all the words from a previously trained model
words_amazon <- ft_words(model_amazon)

# Obtain word vectors from a previously trained model.
word_vec_amazon <- ft_word_vectors(model_amazon, words_amazon)
```

The estimate of the accuracy for testing *Amazon Review* is

```r
# Predicting the labels for the reviews in the no labels test dataset
# Getting the predictions into a dataframe so as to compute performance measurement
ft_preds_amazon <- ft_predict(model_amazon, newdata = temp_amazon_test_nolabel)
# Reading the test file to extract the actual labels
reviewstestfile_amazon <- readLines("test.ft.txt")
# Extracting just the labels frm each line
library(stringi)
actlabels_amazon <- stri_extract_first(reviewstestfile_amazon, regex="\\w+")
# Converting the actual labels and predicted labels into factors
actlabels_amazon <- as.factor(as.character(actlabels_amazon))
ft_preds_amazon <- as.factor(as.character(ft_preds_amazon$label))
# Getting the estimate of the accuracy
library(rminer)
print(mmetric(actlabels_amazon, ft_preds_amazon, c("ACC")))
```

```
## [1] 86.51
```

6.2 Drug Review

The estimate of the accuracy for testing *Drug Review* is

```
## [1] 78.68996
```

7 Conclusion & Discussion

In conclusion, comparing all of our models after fine-tuning, the `FastText` model performs best on the *Amazon Review Dataset* with **86.49%** of accuracy and the Drug dataset with **78.69%** of accuracy. Since words passed by the `FastText` model are represented as the sum of each word's bag of character n-grams, `FastText` is much more efficient for dealing with large corpus and computing word embeddings for words unseen from the training set (Bojanowski *et al.*, 2016). With such features, `FastText` can cope with typos and different word tenses accordingly without treating them as different words. For example, "helped" and "help" are two same words but only different from tenses. However, models other than `FastText` may treat them as two different words and assign the wrong labels. Therefore, using fastText can significantly boost performance.

From the entire scope, the `Word2vec` model performs with relatively low accuracy for both models (**62.56%** for *Amazon Review* and **70.99%** for Drug). One possible reason will be the existing words-only embedding in the `word2vec` package. When encountering a sentence that its own embeddings cannot convert, the model will turn it into zero vectors, which will lose information and weaken the info of other word features. Thus, we may want to try to create and train word embedding on our own using CBOW and Continuous Skip-Gram in the future to see if any improvements can be made.

For future investigation, we can try to use BERT to better process the dataset and attempt more classification algorithms, such as XGBoost and AdaBoost, to classify the sentence embeddings. Moreover, as we only split our data into train and test datasets with 80-20, we may want to split the test set further into 10% of the validation dataset and 10% of the testing dataset so that we can select more fitting hyperparameters for the model and realize higher accuracy (**validSet?**).

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