SYRACUSE UNIVERSITY
SCHOOL OF INFORMATION TECHNOLOGY

IST 707: DATA ANALYTICS

DATA ANALYSIS PROJECT:
PATIENTS REVIEWS ON SPECIFIC DRUGS

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1.0 Introduction

Social media is playing a crucial role in this era nearly in every field like education, health, medical sciences, marketing, finance, travel, demographics, etc. With the growth of online social networks, everyone can easily interact and engage through different modes and mediums of communication with each other and get the latest updates of information on different fields. The pharmaceutical industry for example has benefited from this era of social media and technological advancement, by bringing customers together to share a common interest about the numerous pharmaceutical products that are made available to the public.

Through online social networking, the communication is vastly improved and different interest of information is available on internet easily at the open pace. Different kind of information needs to share to chronicle highlights of potential benefits and harms and availability of utilities of certain insights, items, people behaviors, products, etc. One of the important fields is the medical and health sciences to consider social aspects through online discussions, blogs, reviews, and online survey. The health-related content shared through various online feedbacks or reviews contains hidden sentiment patterns that need to be identified and extracted through different sources ranging from statistical analysis and machine learning algorithm.

In this regard, the online mechanism is very popular these days for online shopping, different products through different websites like online purchasing of medicine at door step. After purchases, several websites and blogs offer customers rate their products according to their satisfaction and quality of products and services and also by providing feedback facility by which customer can comment on a particular medicine or on quality of services.

With the context of health and pharmacological sciences, the patients are able to share their reviews and experiences of signs and impact of a medicine so that it can help to rate the medicine according to its usage, cost and chronic effects. Several studies have been carried out to concentrate on the patient's information and their related matters particularly reviewing patient's medication data with varying costs and usage of a drug. One of these websites that such reviews about pharmaceutical products are found is the drug.com

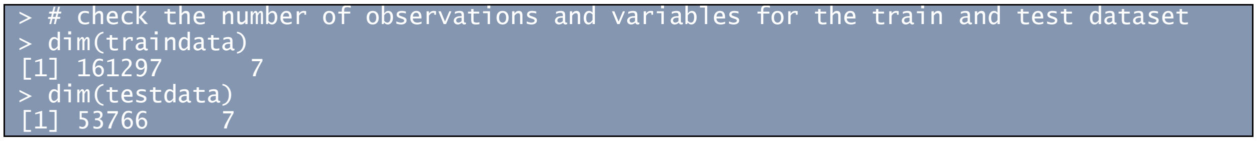
2.0 Analysis and Models

2.1 About the Data

The dataset for our analysis is the Drug Review Dataset (Drug.com). It was data from https://archive.ics.uci.edu/ml/datasets/Drug+Review+Dataset+%28Drugs.com%29 and crawled reviews from online pharmaceutical review sites.

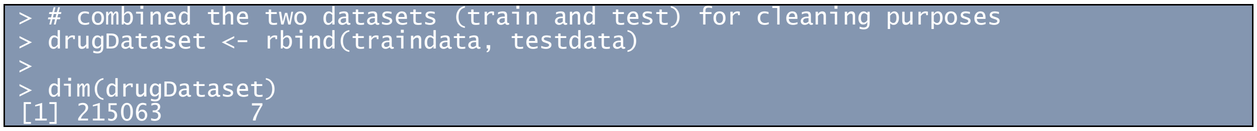
The dataset provides patient reviews on specific drugs along with related conditions and a 10-star patient rating reflecting overall patient satisfaction. Our intention is to study the sentiment analysis of drug experience over multiple facets. That is sentiments learned on specific aspects such as effectiveness and side effects. We also intend to use the dataset in developing different models to be used to predict areas of the dataset as well the correlation between ratings, conditions, drugs and drugs usefulness.

We first started by loading the two datasets (train and test) into R-studio for data exploration, understanding and cleaning of the dataset.



```
> # check the number of observations and variables for the train and test dataset
> dim(traindata)
[1] 161297      7
> dim(testdata)
[1] 53766     7
```

We then combined the two datasets to one dataset for easy cleaning and exploration using the rbind() which allows for two datasets to be combined base on rows.



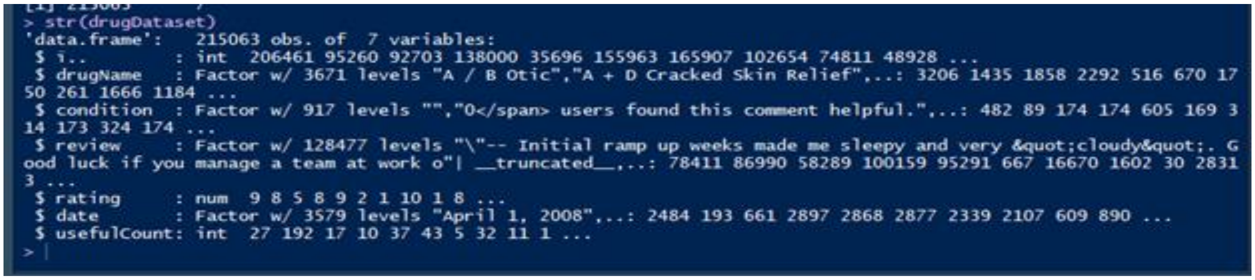
```
> # combined the two datasets (train and test) for cleaning purposes
> drugDataset <- rbind(traindata, testdata)
>
> dim(drugDataset)
[1] 215063      7
```

This is the result of looking at the data through the head () command. There are six variables except for the unique ID that identifies the individual, and review is the key variable.

```
> View(head(drugDataset, 15))>
```

Below details are additional explanations for variables in the dataset.

- drugName (categorical): name of drug
- condition (categorical): name of condition
- review (text): patient review
- rating (numerical): 10-star patient rating
- date (date): date of review entry
- usefulCount (numerical): number of users who found review useful



```
[1] 215063       7
> str(drugDataset)
'data.frame':   215063 obs. of  7 variables:
 $ i..        : int  206461 95260 92703 138000 35696 155963 165907 102654 74811 48928 ...
 $ drugName   : Factor w/ 3671 levels "A / B Otic","A + D Cracked Skin Relief",..: 3206 1435 1858 2292 516 670 17
50 261 1666 1184 ...
 $ condition  : Factor w/ 917 levels "","0</span> users found this comment helpful.",..: 482 89 174 174 605 169 3
14 173 324 174 ...
 $ review     : Factor w/ 128477 levels "\"-- Initial ramp up weeks made me sleepy and very &quot;cloudy&quot;. G
ood luck if you manage a team at work o"| __truncated__,..: 78411 86990 58289 100159 95291 667 16670 1602 30 2831
3 ...
 $ rating     : num  9 8 5 8 9 2 1 10 1 8 ...
 $ date       : Factor w/ 3579 levels "April 1, 2008",..: 2484 193 661 2897 2868 2877 2339 2107 609 890 ...
 $ usefulCount: int  27 192 17 10 37 43 5 32 11 1 ...
> |
```

The structure of the data is that a patient with a unique ID purchases a drug that meets his condition and writes a review and rating for the drug he/she purchased on the date. Afterwards, if the others read that review and find it helpful, they will click usefulCount, which will add 1 for the variable.

```
> # fetching the name of all columns/variables
> colnames(drugDataset)
[1] "ï.."    "drugName"    "condition"    "review"    "rating"    "date"    "usefulCount"
```

First, we will start exploring variables, starting from uniqueID which was initially in the form (‘i..’) as above. We compared the unique number of unique IDs and the length of the train data to see if the same customer has written multiple reviews, and there weren't more than one reviews for one customer.

```
> # checking the counting of unique numbers in the uinqueID column and comparing it
with total count of observations
> length(unique(drugDataset$uniqueID))
[1] 215063
> dim(drugDataset)
[1] 215063      7
```

This confirms no customer reviewed a drug multiple time.

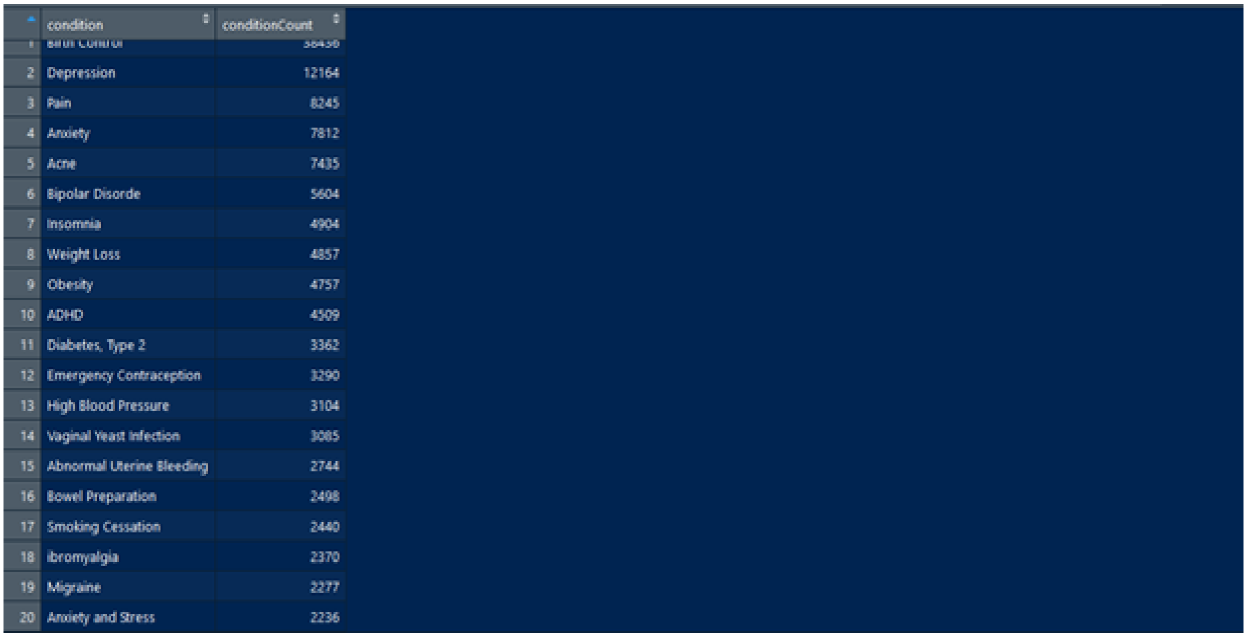
3.0 Results

The ideas of the preliminary data exploration were

- Most common conditions
- Overall best and worst reviewed drugs
- The curability of each disease
- Best drugs for each condition
- Most useful reviews
- Usefulness vs review score
- Bias in reviews
- Users tend to review things they really liked or really disliked, fewer reviews in the middle

The exploration began with the installation of or calling the r library, the sqldf and ggplot2 packages. A script was developed to generate or fetch the most common conditions in the dataset.

```
> # using sqldf package/library to extract common conditions and frequency in the
dataset
> condition_SQL <- sqldf("SELECT DISTINCT(condition), count(condition) AS
conditionCount +                    FROM drugDataset +                    GROUP BY
condition +                   ORDER BY conditionCount DESC")
> View(head(condition_SQL, n=20))
```



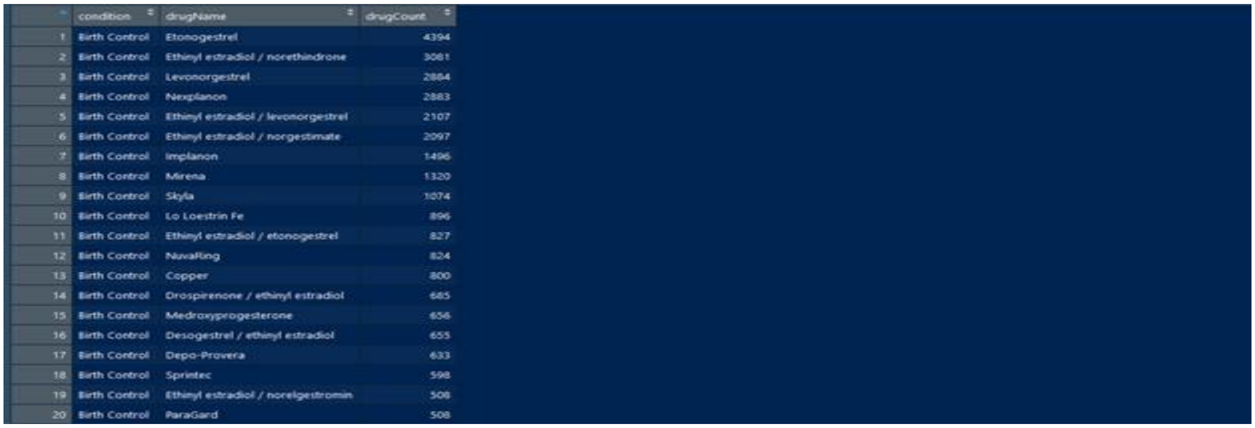
	condition	conditionCount
1	Birth Control	38436
2	Depression	12164
3	Pain	8245
4	Anxiety	7812
5	Acne	7435
6	Bipolar Disorde	5604
7	Insomnia	4904
8	Weight Loss	4857
9	Obesity	4757
10	ADHD	4509
11	Diabetes, Type 2	3362
12	Emergency Contraception	3290
13	High Blood Pressure	3104
14	Vaginal Yeast Infection	3085
15	Abnormal Uterine Bleeding	2744
16	Bowel Preparation	2498
17	Smoking Cessation	2440
18	ibromyalgia	2370
19	Migraine	2277
20	Anxiety and Stress	2236

Conditions like Birth Control, Depression, Pain (in various forms), Anxiety and Acne are among the top five conditions in the drug review dataset.

Since Birth Control happens to be the top condition, further understanding and exploration to the condition was done to have insight of drugs that were taken and reviewed in relation to this condition.

Using the sqldf package, the various drugs used for birth control condition was extracted.

```
> # exploring birth Control and Drug Name
> TestQuery <- sqldf("SELECT DISTINCT(condition), drugName, count(drugName) AS
drugCount +                   FROM drugDataset +
                              WHERE Condition = 'Birth Control'+
                              GROUP BY condition, drugName+
                              ORDER BY drugCount DESC")
>
> drugs_BC <- (TestQuery[1:20,])
>
> View(head(drugs_BC, n=20))
```

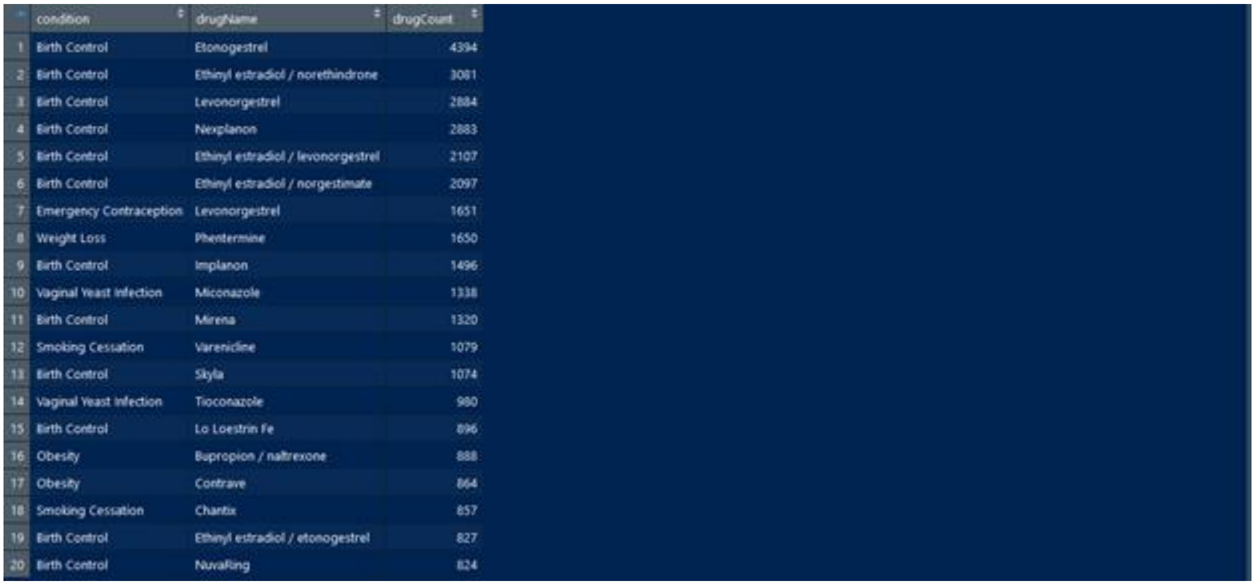


	condition	drugName	drugCount
1	Birth Control	Etonogestrel	4394
2	Birth Control	Ethinyl estradiol / norethindrone	3081
3	Birth Control	Levonorgestrel	2884
4	Birth Control	Nexplanon	2883
5	Birth Control	Ethinyl estradiol / levonorgestrel	2107
6	Birth Control	Ethinyl estradiol / norgestimate	2097
7	Birth Control	Implanon	1496
8	Birth Control	Mirena	1320
9	Birth Control	Skyla	1074
10	Birth Control	Lo Loestrin Fe	896
11	Birth Control	Ethinyl estradiol / etonogestrel	827
12	Birth Control	NuvaRing	824
13	Birth Control	Copper	800
14	Birth Control	Drospirenone / ethinyl estradiol	685
15	Birth Control	Medroxyprogesterone	656
16	Birth Control	Desogestrel / ethinyl estradiol	655
17	Birth Control	Depo-Provera	633
18	Birth Control	Sprintec	598
19	Birth Control	Ethinyl estradiol / norelgestromin	508
20	Birth Control	ParaGard	508

It can be noticed that common birth control drugs are Etonogestrel, Ethinyl estradiol/norethindrone, Levonorgestrel, Nexplanon and Ethinyl estradiol/ Levonorgestrel are among the top five birth control drugs used and reviewed by customers.

The next area that was explored was top drugs or commonly used drugs and the condition that these drugs relate to.

```
> # Exploring TOP 20 Drugs per conditions by Customers
> TestQuery <- sqldf("SELECT DISTINCT(condition), drugName, count(drugName) AS
drugCount +                        FROM drugDataset +                     GROUP BY
condition, drugName+                         ORDER BY drugCount DESC")
>
> drug_conditionTOP20 <- head(TestQuery, 20)
>
> View(drug_conditionTOP20)
```



	condition	drugName	drugCount
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4	Birth Control	Nexplanon	2883
5	Birth Control	Ethinyl estradiol / levonorgestrel	2107
6	Birth Control	Ethinyl estradiol / norgestimate	2097
7	Emergency Contraception	Levonorgestrel	1651
8	Weight Loss	Phentermine	1650
9	Birth Control	Implanon	1496
10	Vaginal Yeast Infection	Miconazole	1338
11	Birth Control	Mirena	1320
12	Smoking Cessation	Varenicline	1079
13	Birth Control	Skyla	1074
14	Vaginal Yeast Infection	Tioconazole	980
15	Birth Control	Lo Loestrin Fe	896
16	Obesity	Bupropion / naltrexone	888
17	Obesity	Contrave	864
18	Smoking Cessation	Chantix	857
19	Birth Control	Ethinyl estradiol / etonogestrel	827
20	Birth Control	NuvaRing	824

Notice the first five common drugs relate to birth control. Other common drugs are Levonorgestrel, Phentermine for weight loss, Miconazole for vaginal yeast infection, and varenicline for smoking cessation.

Rating Distribution

```
> RatingQuery <- sqldf("SELECT rating, count(rating) ratingCount +
FROM drugDataset +
                      GROUP BY rating+
                      ORDER BY rating DESC, ratingCount DESC")
> (RatingQuery)
  rating ratingCount
1   10    68005
2    9    36708
3    8    25046
4    7    12547
5    6     8462
6    5    10723
7    4     6671
8    3     8718
9    2     9265
10   1    28918
```

The highest rating that most of the patients or customers gave for the various drugs was 10 and a rating of 4 being the least rating from customers.

```
> ################  UsefulCount and Rating Distributing
> # using SQL Query to extract rating distribution
> usefulQuery <- sqldf("SELECT usefulCount, rating+
                        FROM drugDataset +
                        ORDER BY usefulCount DESC, rating DESC")
```

```
> ############       Average UsefulCount vs Rating
> AveUsefulQuery <- sqldf("SELECT rating, AVG(usefulCount) avgUsefulCount +
FROM drugDataset +                    GROUP BY rating+                    ORDER BY
rating DESC")
> (AveUsefulQuery)
   rating avgUsefulCount
1      10       37.47466
2       9       33.78939
3       8       29.29190
4       7       23.19965
5       6       19.92224
6       5       17.20153
7       4       16.52541
8       3       16.13283
9       2       16.33632
10      1       15.67076
```

This was graphed to determine whether there is a relationship between ratings and useful counts provided by the customers.

2.2 Cleaning and Pre-processing

Based on the understanding attained from the prior data exploration and understanding, the next action taken was to clean the data and process it for analysis.

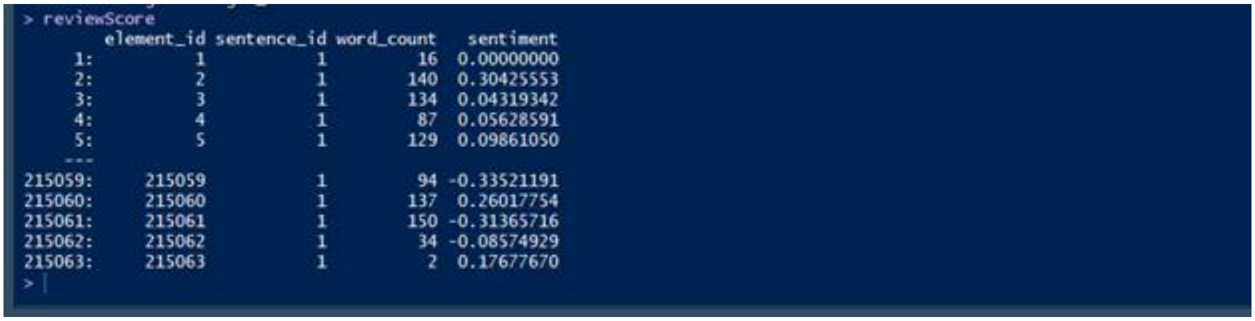
The column uniqueID was removed from the dataset since it has no significant impact on the general analysis of the dataset.

Another column, “label”, was added to the dataset. All the Ratings were either labeled as “positive” or “negative” depending on the range between which the rating fell. This was done by using the function cut() to group the ratings into two. Ratings from 1 – 5 were labeled as “negative” and 6 – 10 were labeled as “positive”.

Initial cleaning of the reviews started with removing punctuations and digits. This allowed for sentiment analysis to be performed on the dataset.

The sentimentr package was installed and called from library to be used for this analysis. A sentiment score was developed using the sentment() function in the sentimentr package.

```
> # developing sentiment scores for each review
> reviewScore <- sentiment(drugData$review)
```



```
> reviewScore
        element_id sentence_id word_count   sentiment
     1:          1           1         16  0.00000000
     2:          2           1        140  0.30425553
     3:          3           1        134  0.04319342
     4:          4           1         87  0.05628591
     5:          5           1        129  0.09861050
    ---
215059:     215059           1         94 -0.33521191
215060:     215060           1        137  0.26017754
215061:     215061           1        150 -0.31365716
215062:     215062           1         34 -0.08574929
215063:     215063           1          2  0.17677670
> |
```

The above data depicts the first and last five rows in the dataset with their respective sentiment scores. The sentiment() function for each row determines the score for the reviews base on the count of words in that review. Scare range from –1 to 1. A score of zero(0) being neutral.

Sentiment_by() function provides a more detailed of sentiment scores in the reviews columns. It allows to create sentiment scores base on averages.

```
> # create a score base on averages for each review
> aveScores <- sentiment_by(drugData$review)
```

Since the object “aveScores” is a data frame, it was saved is a “aveScoresdf” for further process. The negative and positive label was added to the sentiment scores data frame(aveScoresdf). Both the Id and sd columns were removed.

Using the **Naïve Bayes model**

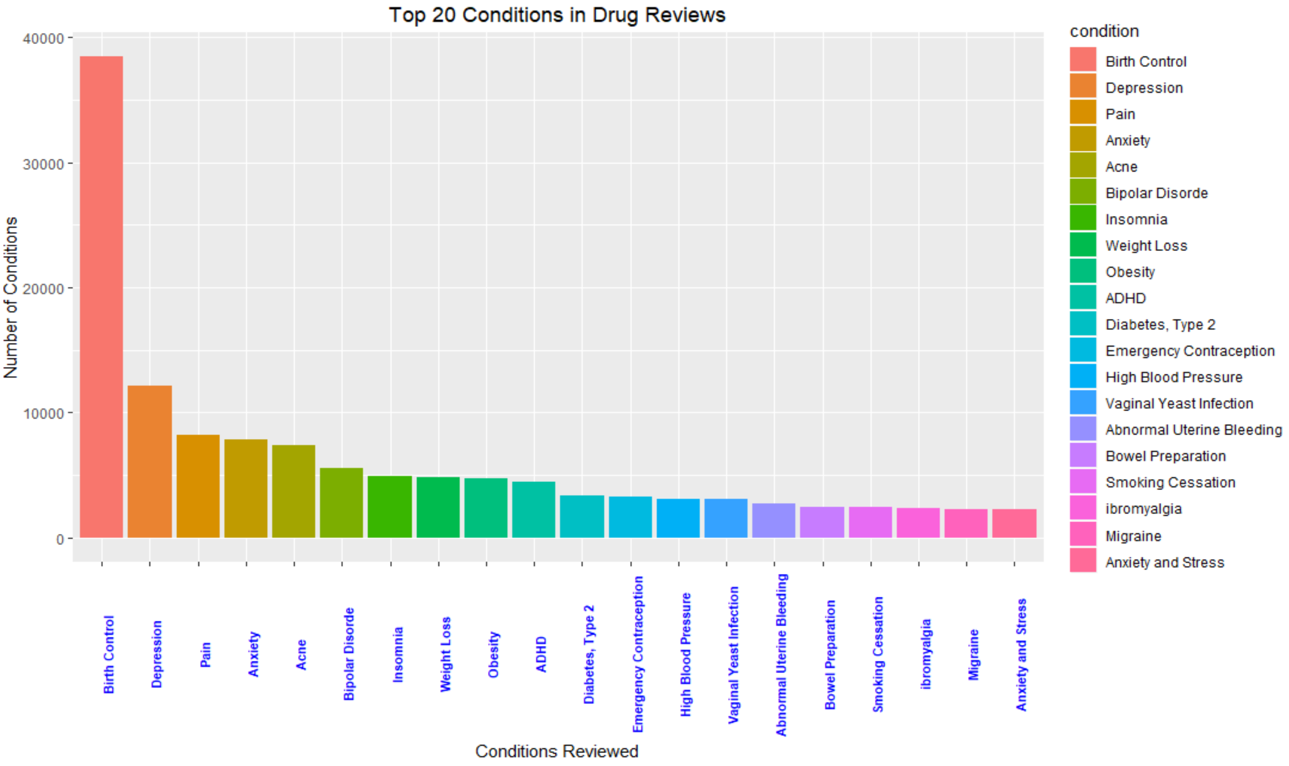
```
> model_nbNaive Bayes Classifier for Discrete Predictors
Call:
naiveBayes.default(x = X, y = Y, laplace = laplace)
A-priori probabilities:
Y
negative positive
0.2988596 0.7011404
Conditional probabilities:
     word_count
Y    [,1]     [,2]
negative 82.82742 45.48749
positive 85.66210 45.01827
    ave_sentiment
Y    [,1]       [,2]
  negative -0.24509008 0.3351107
  positive  0.01033591 0.3313749
```

3.0 Visualization

Common Conditions

```
> # visualizing the TOP 20 conditions in the dataset
> ggplot(data=commonConditions, aes(x=condition, y=conditionCount, fill =
condition)) ++  geom_bar(position ='stack', stat="identity") + theme(axis.text.x =
element_text(face = "bold", color = "blue", +  size = 8, angle = 90)) + ggtitle('Top
20 Conditions in Drug Reviews') + +  theme(plot.title = element_text(hjust = 0.5)) +
xlab('Conditions Reviewed') + ylab('Number of Conditions')
```

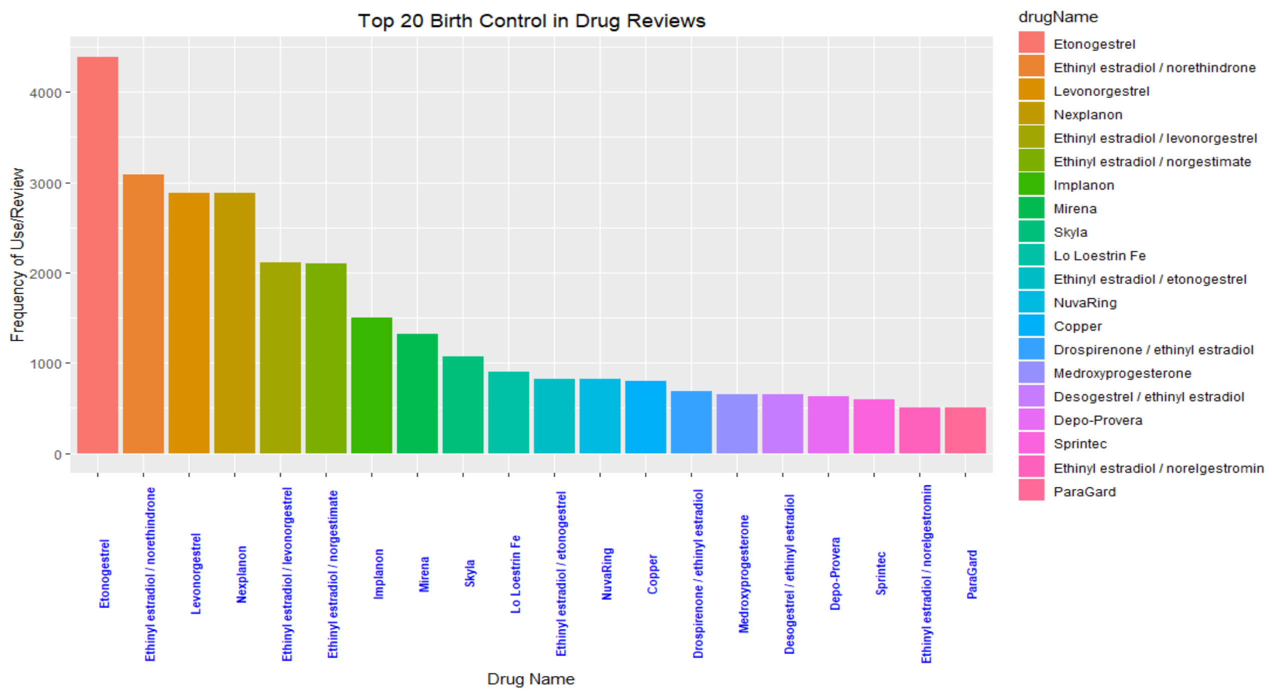
The graph depicting the top 20 Conditions in the Drug Review Dataset



Common Birth Control Drugs

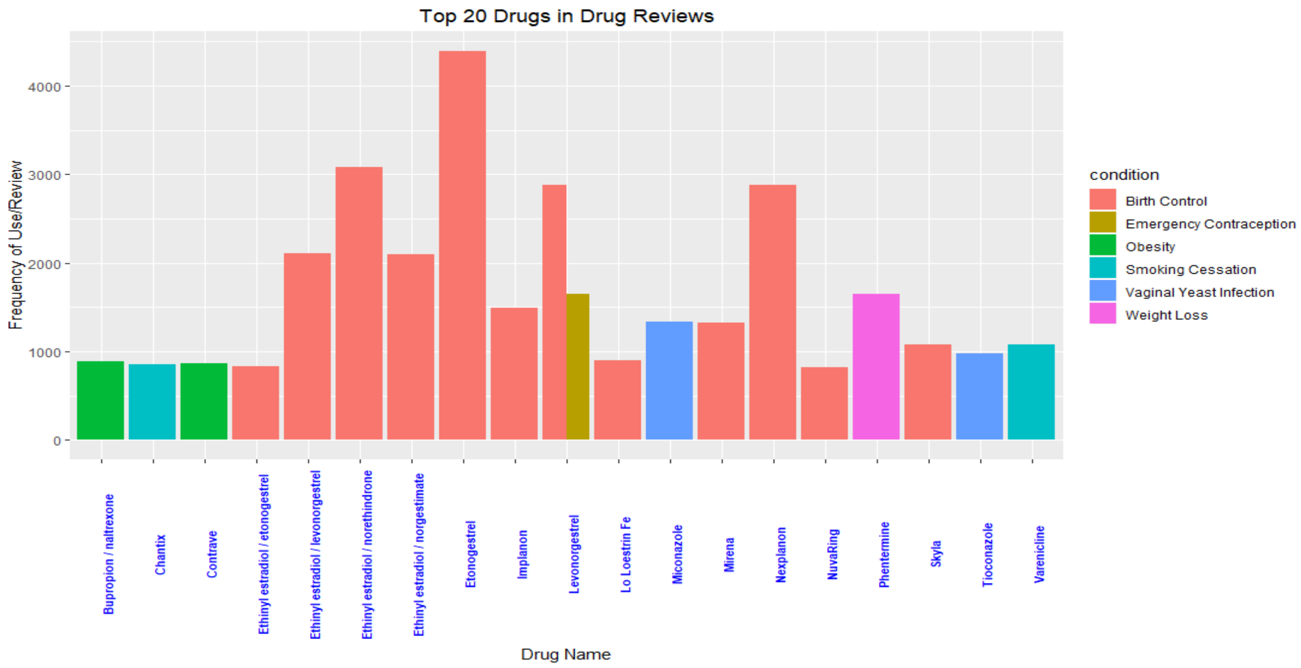
```
> #graph the TOP 20 BIRTH CONTROL drugs distribution by customers> ggplot(drugs_BC,
aes(x=drugName, y=drugCount, fill=drugName)) +  geom_bar(position ='stack',
stat="identity") ++  theme(axis.text.x = element_text(face = "bold", color = "blue",
+                                     size = 8, angle = 90)) + ggtitle('Top 20 Birth
Control in Drug Reviews') + +  theme(plot.title = element_text(hjust = 0.5)) +
xlab('Drug Name') +  ylab('Frequency of Use/Review')
```

The graph depicting the top 20 birth control drugs in Drug Review Dataset.



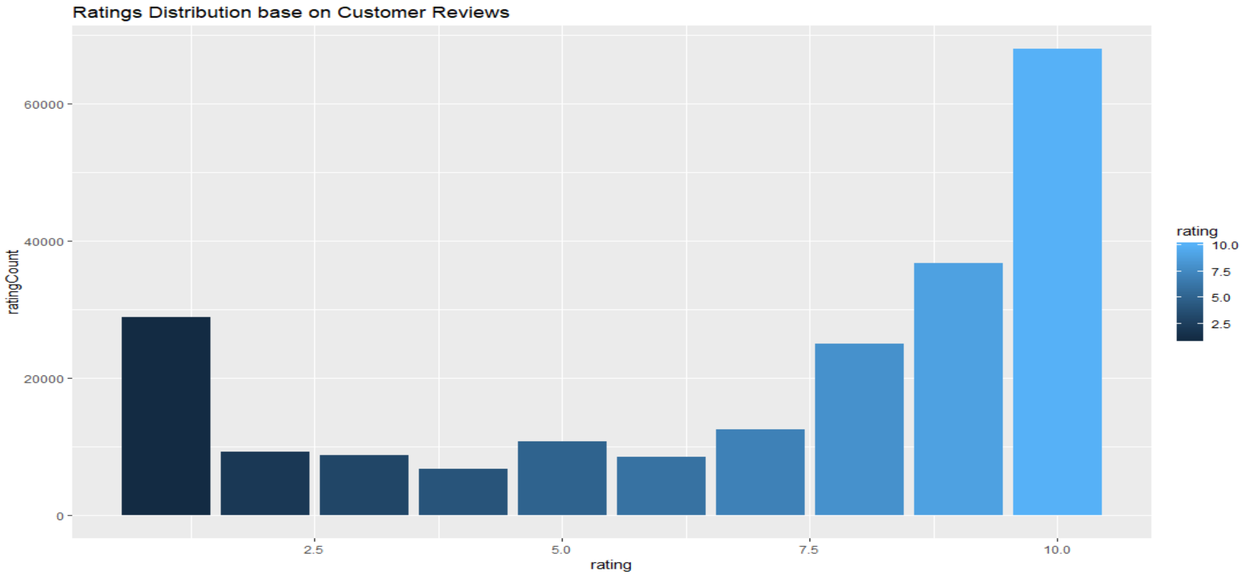
```
> #graph the TOP 20 drugs and Conditions drug distribution of customers
> ggplot(drug_conditionTOP20, aes(x=drugName, y=drugCount, fill=condition)) +
geom_bar(position ='dodge', stat="identity") ++  theme(axis.text.x =
element_text(face = "bold", color = "blue", +                          size
= 8, angle = 90)) + ggtitle('Top 20 Drugs in Drug Reviews') + +  theme(plot.title =
element_text(hjust = 0.5)) + xlab('Drug Name') +  ylab('Frequency of Use/Review')
```

The graph showing the top 20 commonly used drugs in Drug Review Dataset.



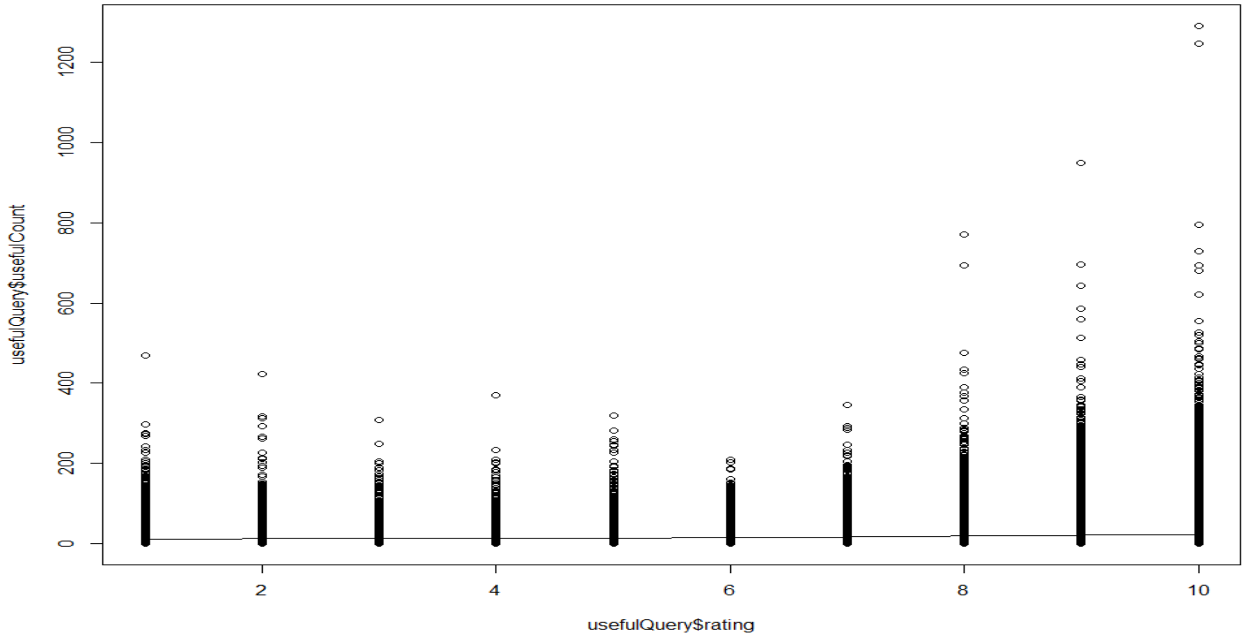
```
> # Graph the rating distribution
> ggplot(RatingQuery, aes(x=rating, y=ratingCount, fill=rating)) +
geom_bar(stat="identity") ++                      ggtitle('Ratings Distribution base
on Customer Reviews') + theme_classic(base_size = 10)
```

The graph showing the Rating distribution base on Customer reviews in Drug Review Dataset.



```
> scatter.smooth(usefulQuery$rating, usefulQuery$usefulCount)
```

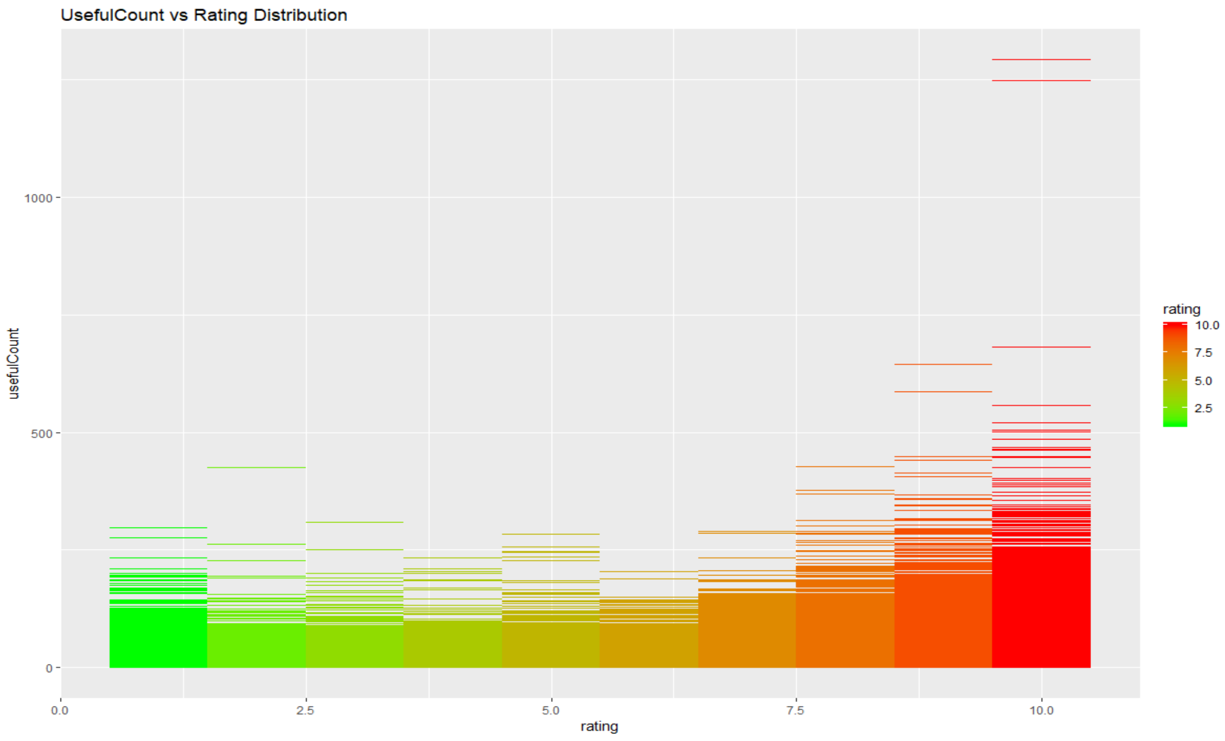
A Scatter plot showing various ratings and useful counts in drugs in Drug Review Dataset.



```
> # Graph the usefulCount and ratings distribution using heatmap
> ggplot(usefulQuery, aes(x=rating, y=usefulCount)) + geom_tile(aes(fill=rating)) +
+                       scale_fill_gradient(low="green", high="red") +
+                       ggtitle('UsefulCount vs Rating Distribution')
>
```

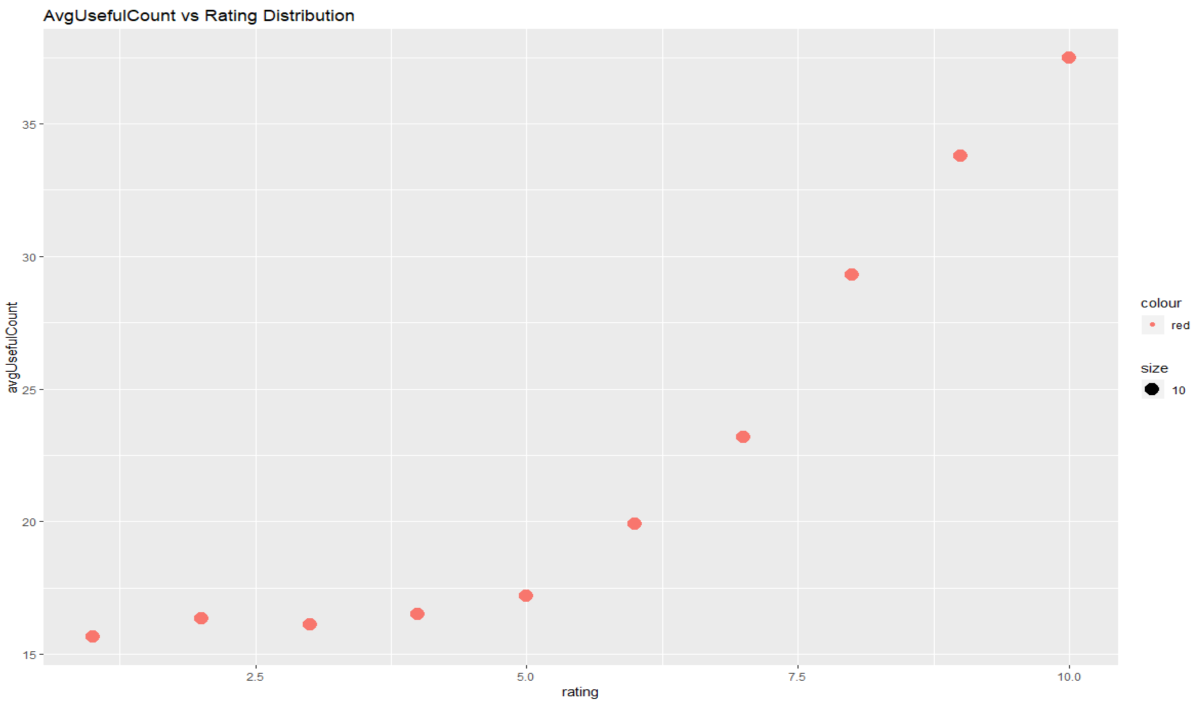
Using heatmap to depict the various ratings base on useful counts.

Notice the higher the rating the more it becomes useful to others.



```
> ggplot(AveUsefulQuery) +  geom_point(aes(x=rating, y=avgUsefulCount, color='red',
size=10)) +
+  ggtitle('AvgUsefulCount vs Rating Distribution')
```

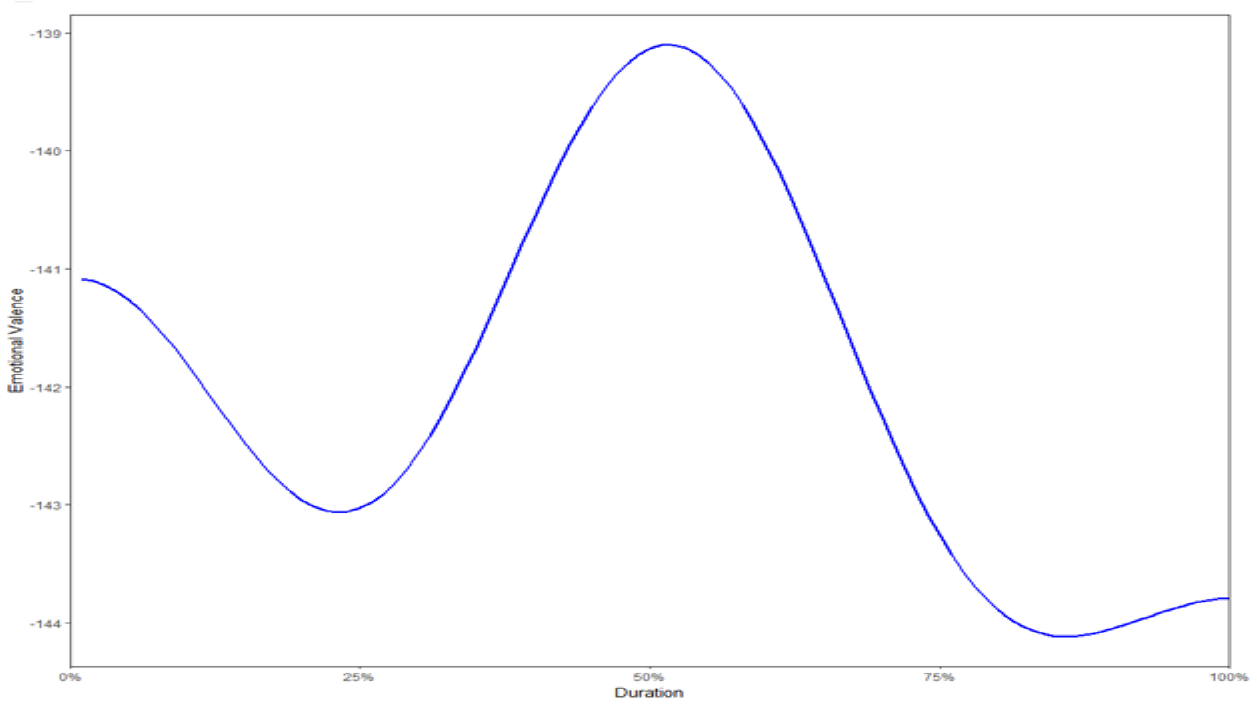
Noticed there is a linear relationship between customer ratings and the usefulness(usefulcount) to other customers.



Sentiment Analysis

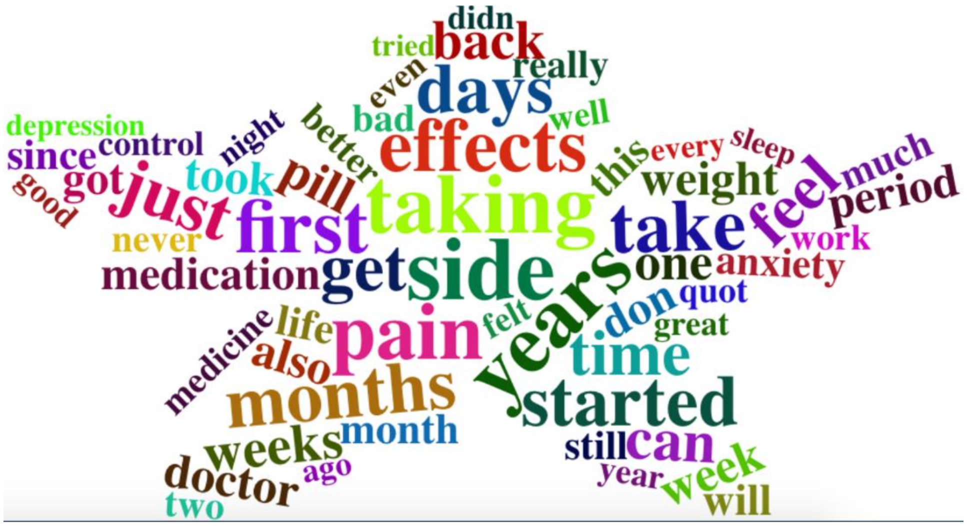
```
> # Graph the reviews base on the sentiments
> plot(reviewScore)
```

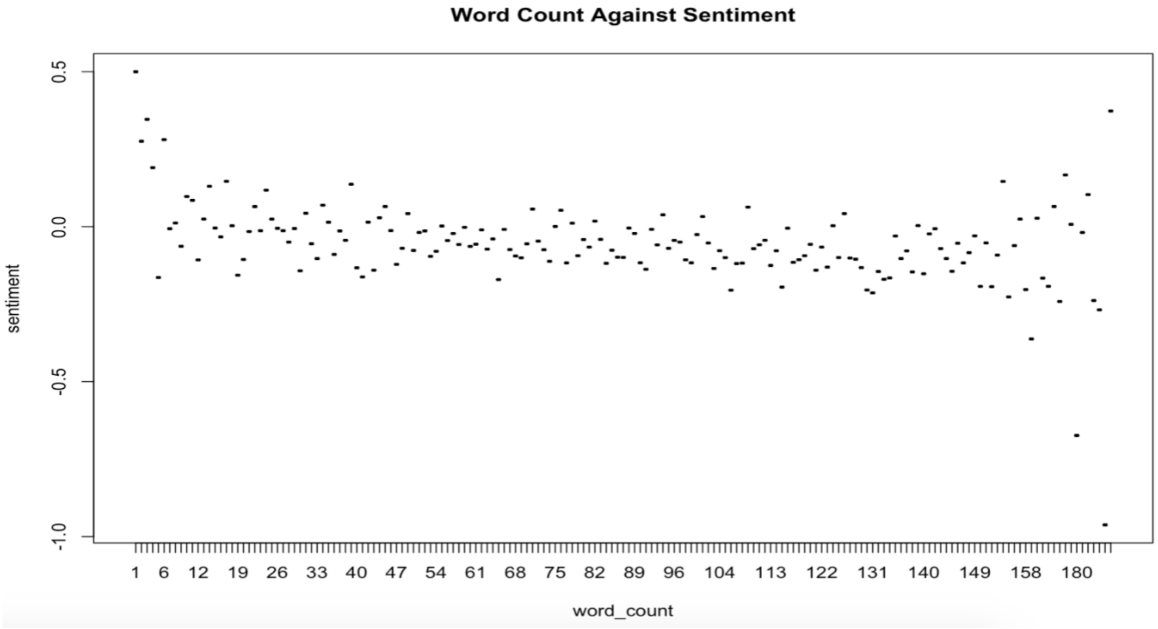
The graph depicting the sentiments in the reviews of customers.



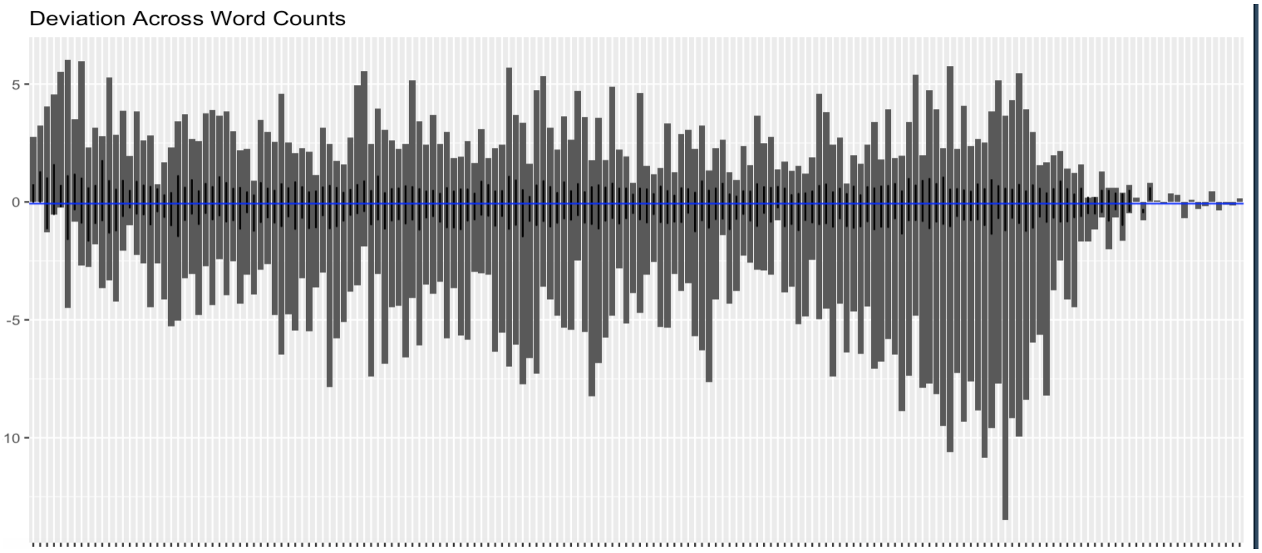
For the drug prediction scoring we wanted to use our sentiment scores to see how and where we would be able to predict what drugs would be appropriate for revision or promotion based on the drugs performance. We wanted to first figure out what would be categorized as “Positive” or “Negative feedback. Giving our sentiment scoring a categorization of “Positive” when it was greater than 0, and negative when it was below 0. Using this we ran through Naïve Bayes, SVM, and Random forest methods to predict the positive and negative outcomes on our sentiment analysis.

Corpus Word Cloud:

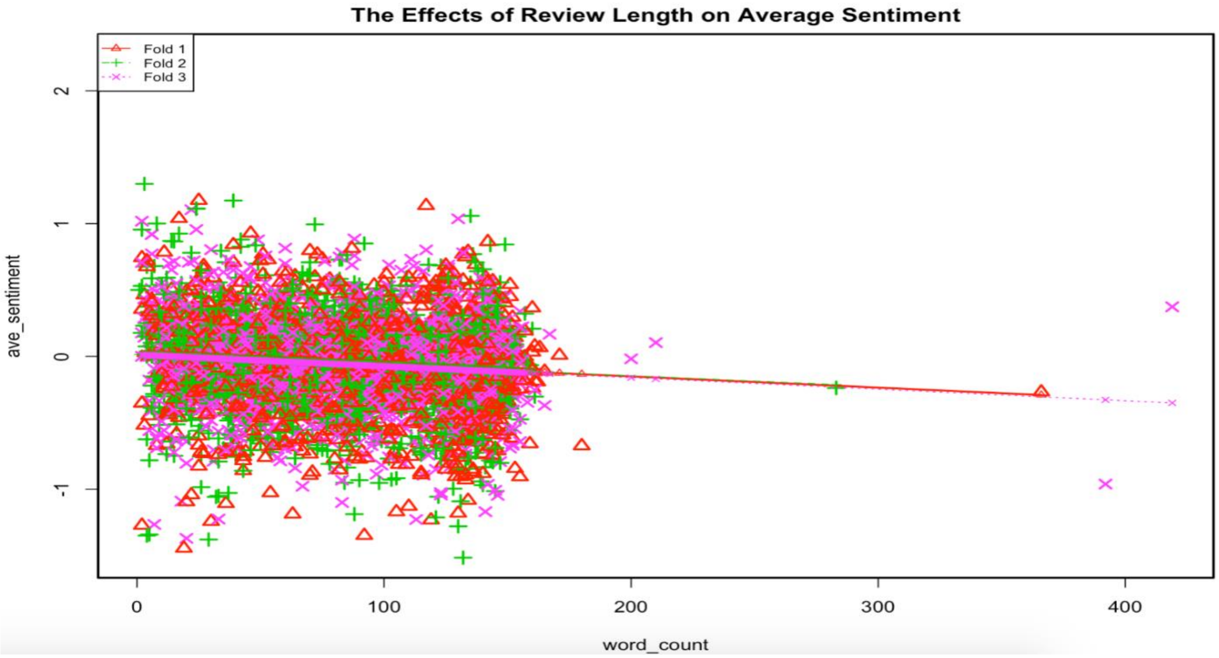




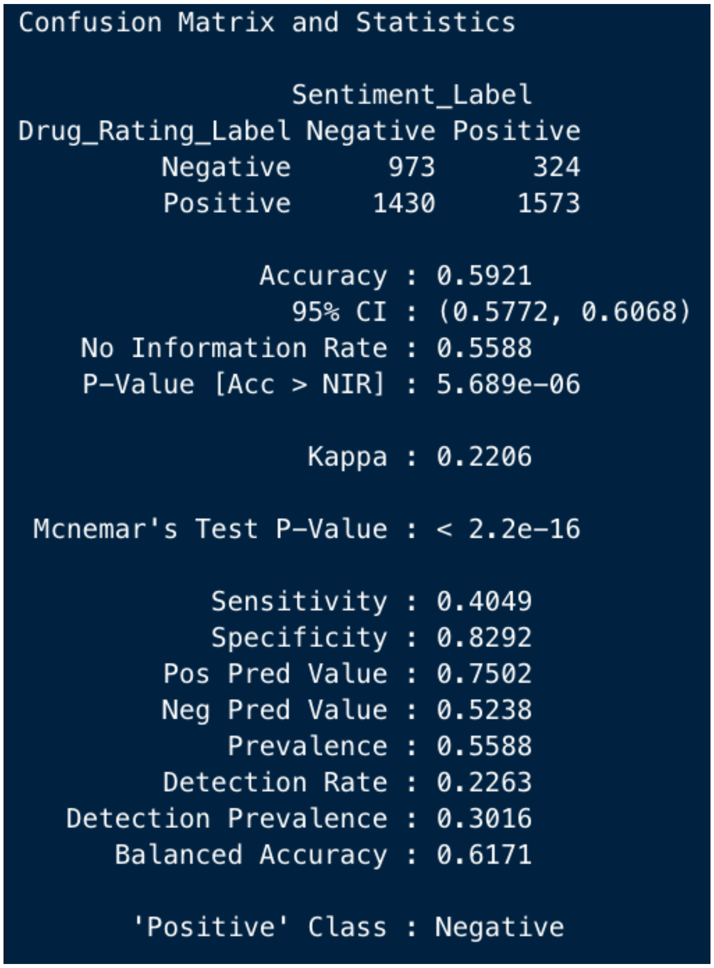
In our first analysis we found that the average sentiment of our drug reviews allows us to see that as work count of a review increases, we found that the average sentiment takes a down turn. We also see that the deviation away from 0 increases around the extreme values. At the beginning we see a more positive sentiment spread. And at around 150 words the deviation spread becomes more negative. To test our hypothesis of the positive and negative sentiment we used a Cross-Validation plot to see how



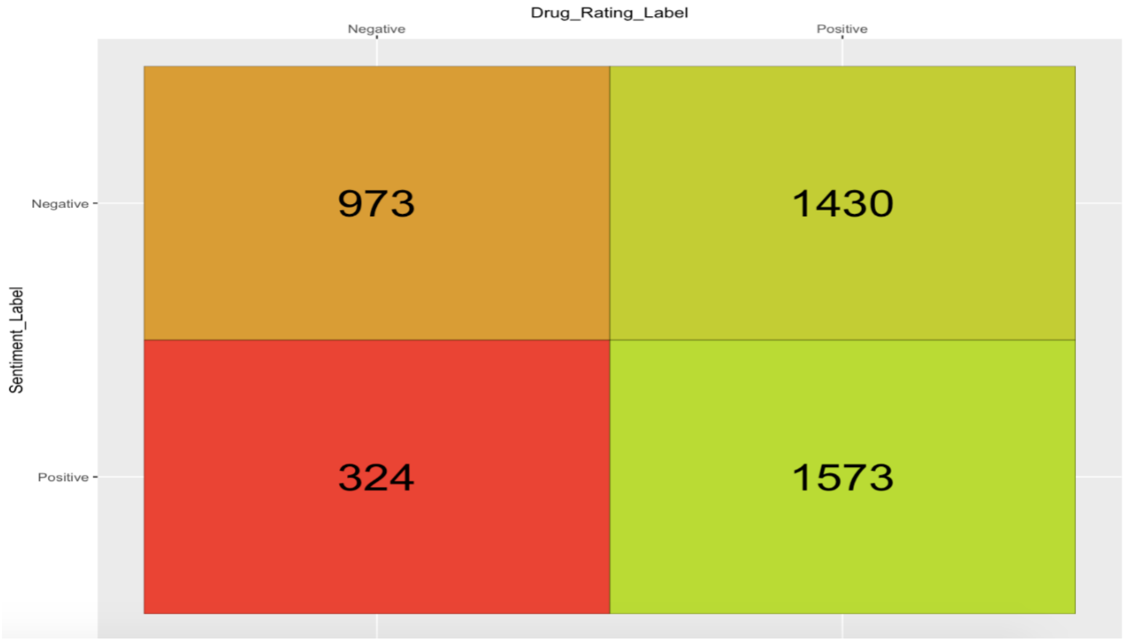
By summing the average sentiment of each entry, above is a plot of the summed average sentiment for each entry. What we can take away from this article is that there is a higher more positive deviation in reviews with fewer than 50 words. And a higher more negative deviation in reviews that contain more than 150 words.



To test our hypothesis of the positive and negative sentiment we used a Cross-Validation plot to see how the sentiment varied over the word count of reviews. There was a very negative slope based on the average sentiment scores within each observed review. By combining this with our sub-set data we can consider the incoming drug reviews that are extremely long would be able to more negative.

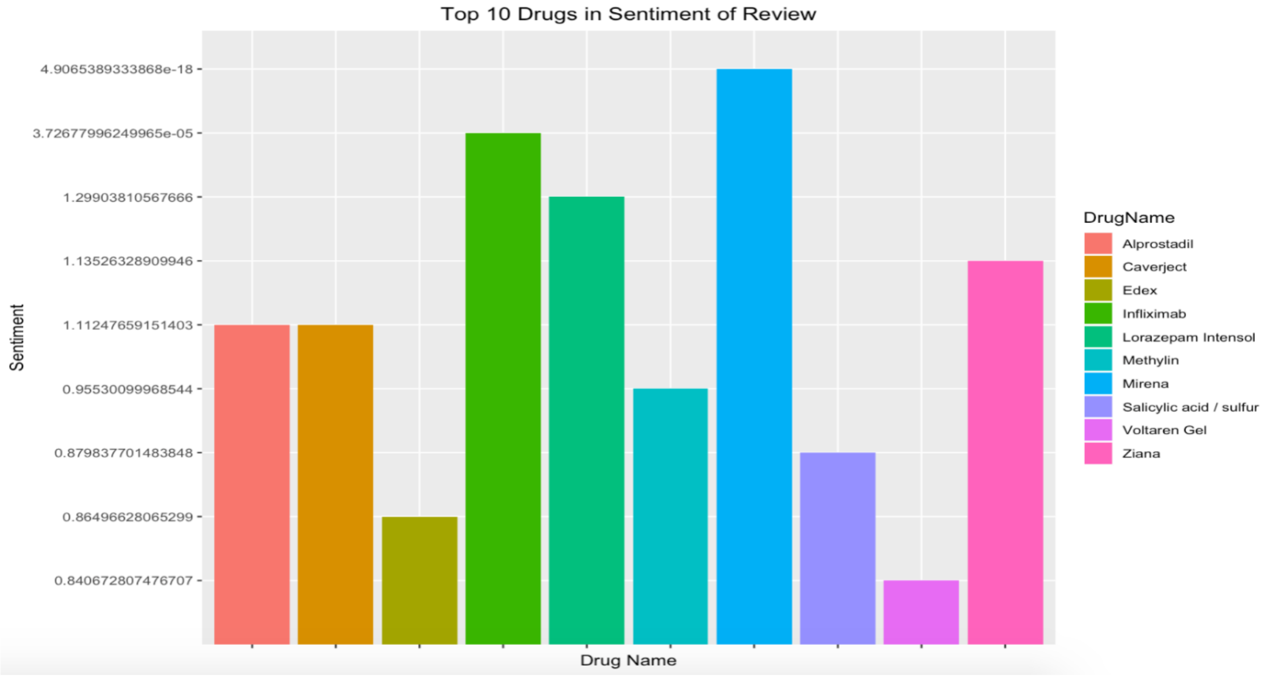


```
Confusion Matrix and Statistics

                 Sentiment_Label
Drug_Rating_Label Negative Positive
         Negative      973      324
         Positive     1430     1573

               Accuracy : 0.5921
                 95% CI : (0.5772, 0.6068)
    No Information Rate : 0.5588
    P-Value [Acc > NIR] : 5.689e-06

                  Kappa : 0.2206

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.4049
            Specificity : 0.8292
         Pos Pred Value : 0.7502
         Neg Pred Value : 0.5238
             Prevalence : 0.5588
         Detection Rate : 0.2263
   Detection Prevalence : 0.3016
      Balanced Accuracy : 0.6171

       'Positive' Class : Negative
```

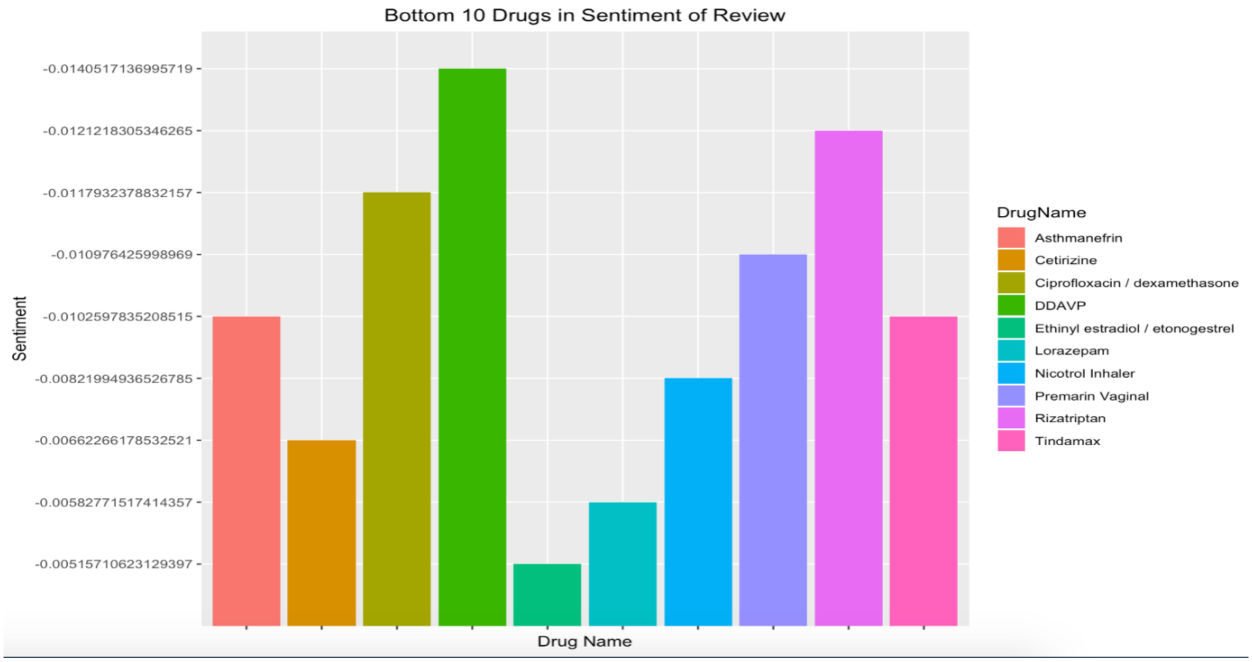


Within our data we were given the actual rating of the drug. So what we wanted to do was to see how well we could predict sentiment based on the Rating label that we created using:

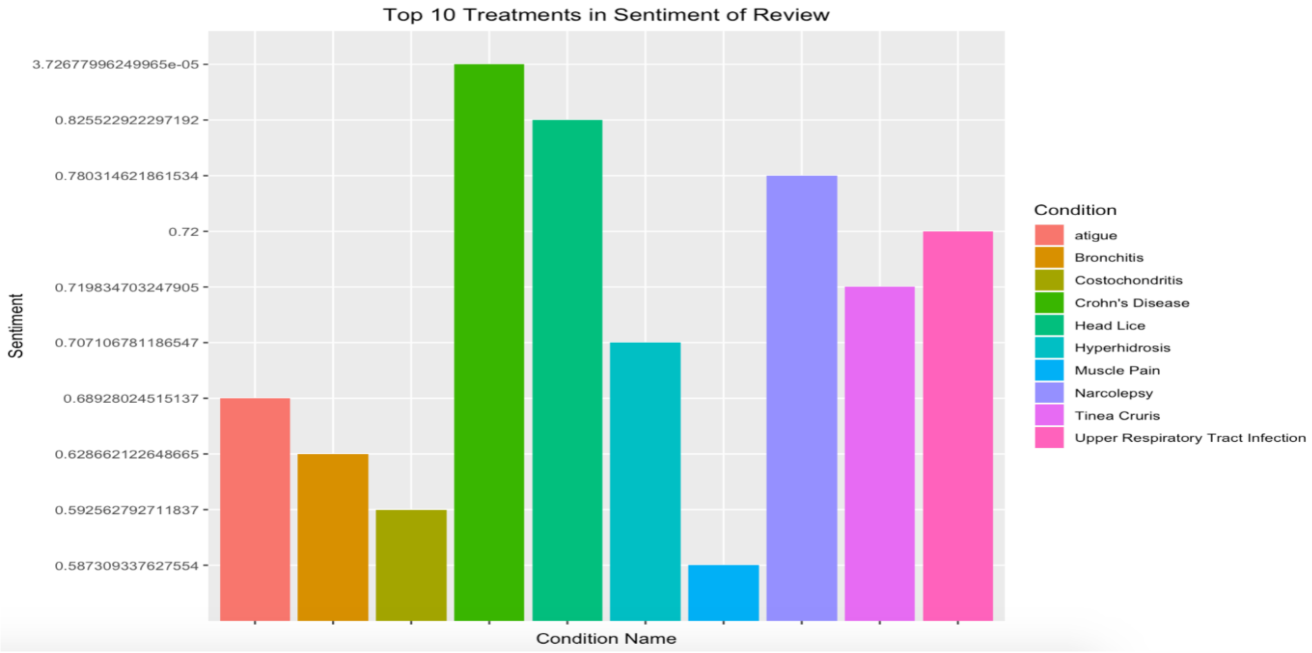
From here the plan was to take it to the business side of things. Given that we had found the top and bottom drugs based on rating. We wanted to predict what we could based on our sentiment levels from the ratings. What we get is the following.



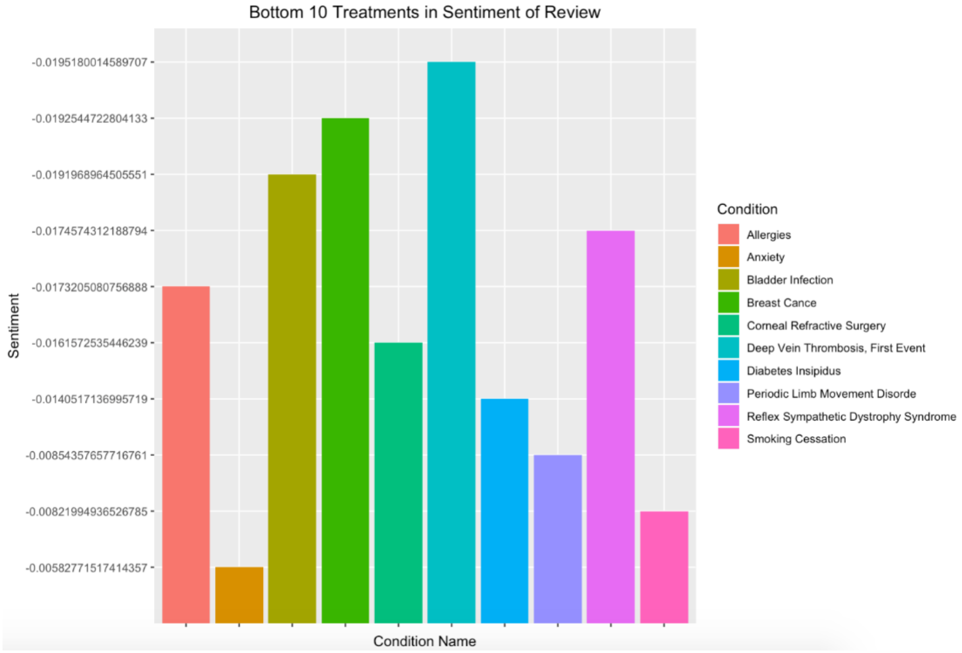
Above is the top 10 drugs based on an aggregated sentiment score. By aggregating our set were able to see that the drugs had very high sentiment scores based off our scoring system. In this case you marketing could narrow its scope down to now specifically focus on these drugs since they have the highest rated reviews.



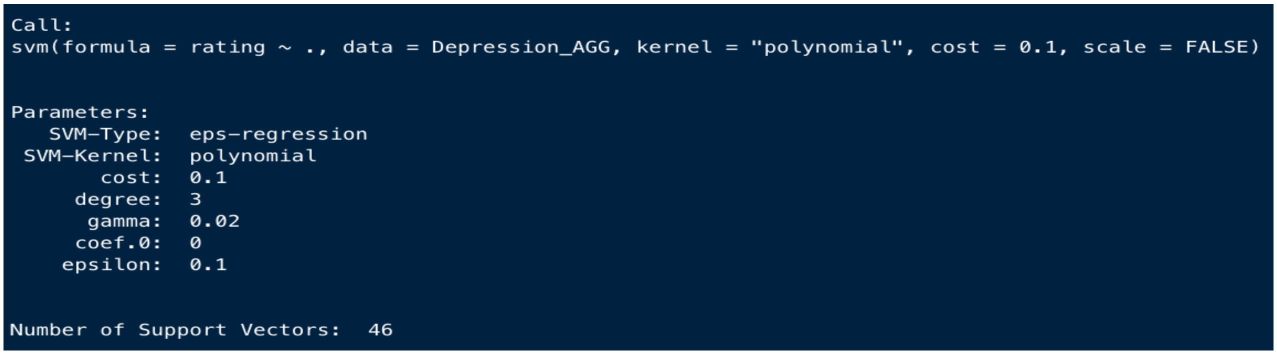
Maybe more interestingly is the graphic with the bottom 10 drugs in drug sentiment. We see that Asthamnefrin, Cetrizine, Ciprofloxacin / dexamethasone, DDAVP, Ethinyl Estradiol, Lorazepam, Nicotrol, Premarin, Rizitriptan, and Tindamax all had the worst aggregated sentiment scores running through our analysis. From a marketing perspective this would be valuable to prove what drugs are the least approved by people. Using the actual review sentiment you would be able to pick out what drugs that need to either be modified or dropped.



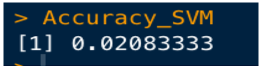
Where the analysis lead us was to now figure out what were the top and bottom conditions that were being treated. The above graphic depicts what conditions that are being treated the best based on their aggregated sentiment score. Chromes Disease, Head Lice and Narcolepsy are among the Top 10 treatments with their diseases. From a marketing perspective you can see how valuable understanding the top performers based on customer review can be to a company. Having great customer reviews could get a drug being picked up by distributors and become a value-add a company.



The above graphic is representing the worst 10 treated conditions based on sentiment review. Diabetes Insipididus, Breast Cancer, and Bladder Infections are among the worst reviewed treatments based on our aggregated sentiment review. This is more important than our drug review since we can understand and change the treatment methods. Of course, some of these are issues that can’t be avoided like treatment for breast cancer, but it gives a marketing or pharmaceutical company a benchmark as to what drugs can be worked on.



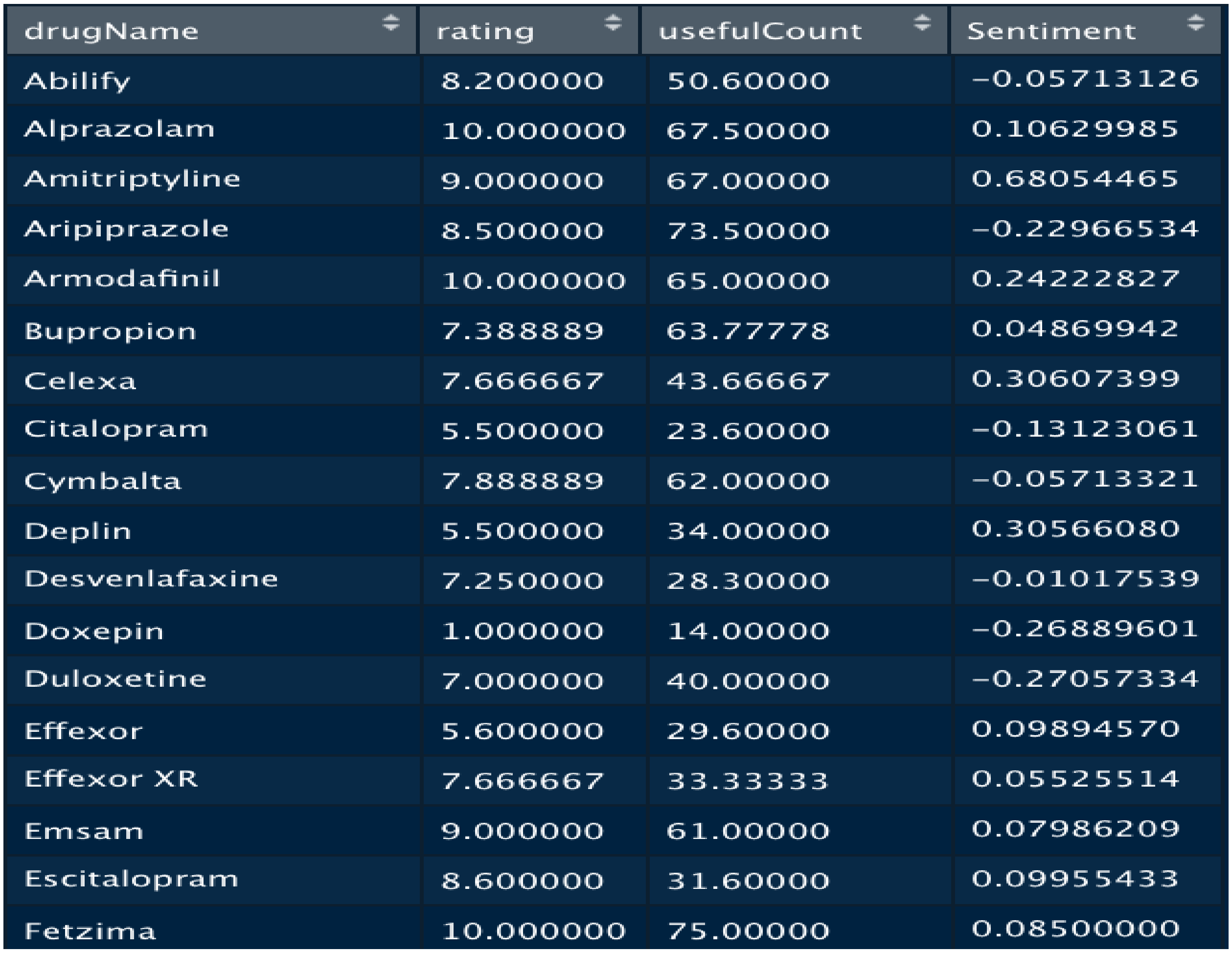
```
Call:
svm(formula = rating ~ ., data = Depression_AGG, kernel = "polynomial", cost = 0.1, scale = FALSE)


Parameters:
   SVM-Type:  eps-regression
 SVM-Kernel:  polynomial
       cost:  0.1
     degree:  3
      gamma:  0.02
     coef.0:  0
    epsilon:  0.1


Number of Support Vectors:  46
```



```
> Accuracy_SVM
[1] 0.02083333
```

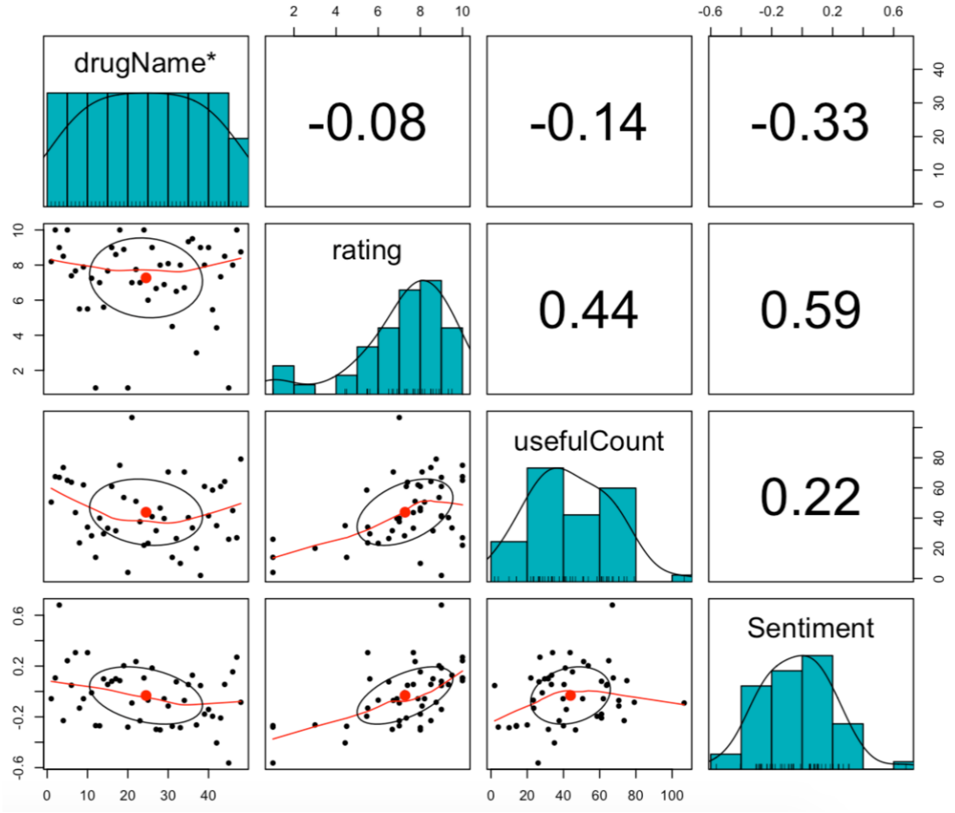
Our initial SVM model we took a grouping of our columns to figure out whether we could successfully predict the rating based on our sentiment score, drugName, condition, and useful count. As you can tell there is little possibility of us accepting the accuracy of around 2%.

From there we wanted to see if we could dive deeper into one of these categories and figure out what exactly we needed to look at from a marketing perspective. We wanted to figure out what specific drugs are working. For a model we decided to look into all of the drugs used to treat Depression. By aggregating all of the different drugs and instances that account for the treatment of depression these are the average ‘Rating’ ‘UsefulCount’ and ‘Sentiment of the different drugs within our data.

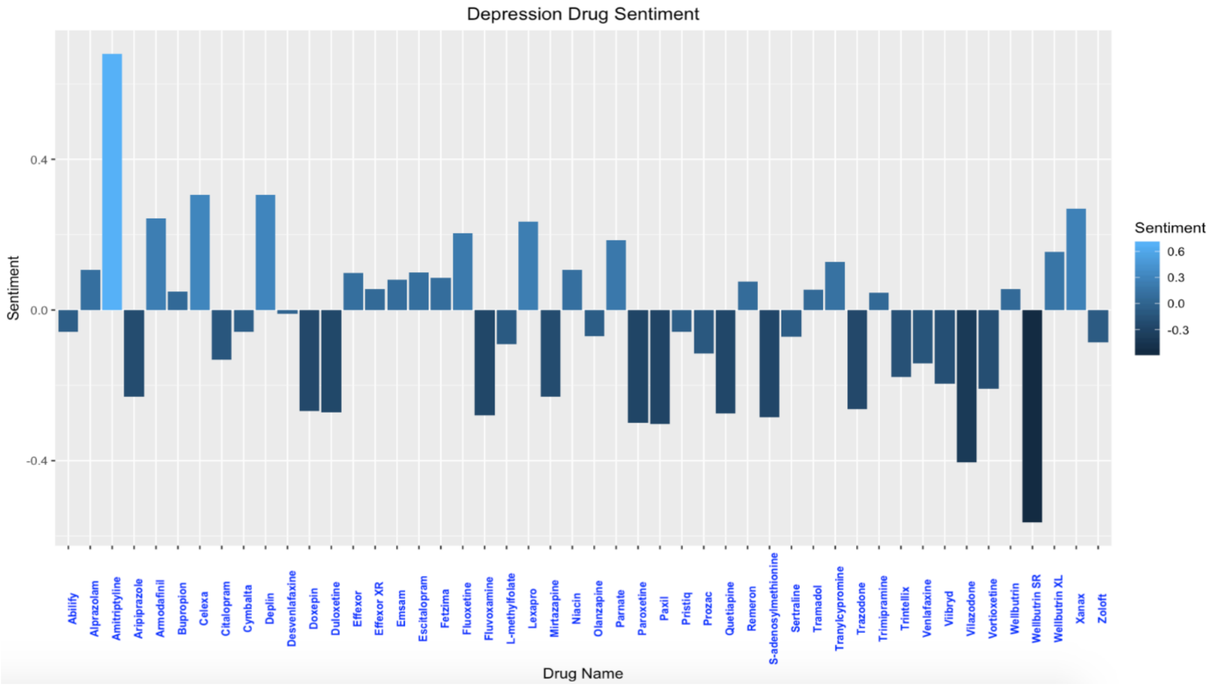


drugName	rating	usefulCount	Sentiment
Abilify	8.200000	50.60000	−0.05713126
Alprazolam	10.000000	67.50000	0.10629985
Amitriptyline	9.000000	67.00000	0.68054465
Aripiprazole	8.500000	73.50000	−0.22966534
Armodafinil	10.000000	65.00000	0.24222827
Bupropion	7.388889	63.77778	0.04869942
Celexa	7.666667	43.66667	0.30607399
Citalopram	5.500000	23.60000	−0.13123061
Cymbalta	7.888889	62.00000	−0.05713321
Deplin	5.500000	34.00000	0.30566080
Desvenlafaxine	7.250000	28.30000	−0.01017539
Doxepin	1.000000	14.00000	−0.26889601
Duloxetine	7.000000	40.00000	−0.27057334
Effexor	5.600000	29.60000	0.09894570
Effexor XR	7.666667	33.33333	0.05525514
Emsam	9.000000	61.00000	0.07986209
Escitalopram	8.600000	31.60000	0.09955433
Fetzima	10.000000	75.00000	0.08500000

By combining all the entries for the different conditions, we can pinpoint specific values for each drug being used. You can see the different columns, all being referenced to treat Depression, average rating, average useful count, and average sentiment for each aggregated drug.



Using our aggregated dataset that contained specific treatment drugs for depression, above is how the correlation of the variables impacted one another. UsefulCount and sentiment had a positive correlation of .22. Sentiment and rating had a positive .59 correlation, so on and so forth.



Above is the graphic that we really would like to focus on. This is a breakdown of how each sentiment was dispersed for each of the different drugs that are treating depression. Very interesting as we see a couple are considered outliers with Wellbutrin SR has an average sentiment of review of around –0.45. One recommendation that we would have to have with this would be to work on those drugs or just drop them from being used.

4.0 Conclusion

In the analysis of our data, it was noticed that no customer provided more than one review. In line with that, the most common conditions whose drugs were reviewed relate to Birth Control, Depression, Pain, Acne, Anxiety, Bipolar Disorders, and Insomnia.

Based on the sentiment placement for each drug for treatment it is safe to use the prediction method for customer preference. By analyzing the sentiment scores for the drug reviews, we can see the breakdown of each drug for a treatment, some with a high score for the treatment, and some with low scores for the treatment. You can see consumer preference which allow pharmaceutical companies to adjust defective drugs that get low review scores.

It was also evident that the useful count of a review is determined by the rating of the drug. Thus, there a linear relationship between useful counts and drug ratings. Most reviews that expressed positive sentiments were of high ratings and reviews with low rating were more less had negative sentiment score.