Sentimental Analysis for Amazon Product Reviews

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DAB 402

DATA ANALYTICS FOR BUSINESS

in

Data Analysis

ST CLAIR COLLEGE ACE ACUMEN

Mississauga, ONTARIO, CANADA

SUBMITTED TO

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Abstract

Sentiment Analysis also well-known as Opinion Mining refers to the use of natural language processing, text analysis to analytically identify, extract, quantify, and study affective states and subjective information. Sentiment analysis is usually utilized to reviews and survey responses, online and social media, and healthcare materials for applications that range from marketing to customer service to clinical medicine. As A Result, Online Purchasing has expanded, and that has led to Growth in Online Customer Reviews of Products. The Inferred Opinions in Customer Reviews Have a Massive Influence on Customer's Decision Purchasing, Since the Customer's Opinion About the Product is Influenced by Other Consumers' Recommendations or Complaints. This research provides an analysis of the Amazon Reviews dataset and examines sentiment ranking using various machine learning approaches. First, the Reviews were Transformed into Vector Representation using different Techniques, I.E., word tokenization, pos tagging, Tf-Idf, and more. Then, we Trained Various Machine Learning Algorithms, I.E., Logistic Regression, Random Forest, Naïve Bayes, KNN. Afterward, We Calculated the Models using Accuracy, F1-Score, Precision, Recall. Then, We Analyzed the Best Performance Model in Order to Investigate Its Sentiment Classification.

In this project, we intend to implement Sentiment Analysis of product-based reviews. Data used in this project are online product reviews collected from "amazon.com" using web scraping.

Chapter 1 Introduction

1.1 Introduction

E-Commerce has become one of the largest industries with a massive change from offline shopping to online shopping. This tendency is imagining an exponential increase andmore people choose online shopping for some reasons such as suitability and low-priced.

With new products bursting into the market regular clients very well on customer reviews of products on eCommerce sites to make up determinations about their purchase. It is vital for brand name to appear into the kind of feedbacks on products make and how these influence the way the product works in the market.

Sentiment analysis well-known as opinion mining. Using sentimental analysis, we can pick up people's opinions. People usually express their feelings, attitudes, and feedbacks on social media for various topics, products, and other things.

1.2 Problem Statement

The problem faced implied classifying an Amazon review with a positive or negative sentiment, exclusively. For example, given the following review: 'Super comfortable and extremely lightweight. Great for crossfit!' Using machine learning and natural language processing is a must to identify whether the review implies a positive or negative sentiment. This involves breaking each review down into its most relevant components and then applying machine learning techniques to assign weighted sentiment scores to the samples. Also, the example review given previously was tokenized into the following list of sentimentally relevant words:

[super, comfort, extreme, great]. Training your model on a refined list of the most relevant tokens is central to the problem of sentiment analysis and will result in a more accurate model.

1.3 Research Questions

- 1. How users are reacting to product which is new customers willing to buy?
- 2. Product from which company has had maximum positive reviews?
- 3. Analyze rating from customers for different products.

Chapter 2 Dataset

2.1 About the dataset

For this project, we extract data from Amazon using web scraping. It includes product name, review title, review date, review rating and reviews of various mobile companies. For web scraping, we used beautiful soup function.

2.2 Review data

Dataset contains 45,912 rows and 5 columns.

Table 1 Data attributes and corresponding data types

S. No	Column Name	Column Description	Туре
1	Product	It represents product name	object
2	Title	A header of review text	String
3	Date	It represents the date of the review that the customer gave feedback on this date	object
4	Rating	It contains review between 1 to 5	Int
5	Review	It shows review text for product	String

Chapter 3 Literature review & Methodology

3.1 Literature Survey

It is profound to note that businesses maximize sentiment analysis to enhance business processes and improve customer retention. **H. Gupta, L. Tiwari. et. al (2019)** asserted that an analysis of product reviews enables a business to understand customer experiences. A customer can post a review to show whether they are satisfied or unsatisfied with a specific product or service. However, most of the product reviews fail to indicate the extent of customer satisfaction. As a result, they conducted a study to categorize the extent of customer satisfaction based on online reviews. They created a method of categorizing customer satisfaction based on acoustic and linguistic features. They proposed a model of categorizing customer reviews as positive, and negative (H. Gupta, L. Tiwari. et. al, 2019). They used Bag of word technique known as natural language processing to extract feature from text. we should use this bag of wordtechnique for my existing project so we can extract feature from the text.

Meire et al. (2019) contended that social media is a trending platform for markets to drive customer engagement today. Customer engagement plans enable businesses to boost their emotional bonds with customers located in different parts of the world. Product reviews also shape customer engagement. An analysis of the product reviews enables the business to gain insights into how customers feel about their products. According to Schoenmueller, Netzer, and Stahl (2020), online consumer reviews play a critical role in shaping Amazon Reviews using Sentiment Analysis 7 customers' purchasing decisions online. A business must concentrate on analyzing and understanding these reviews to succeed in today's business environment

Sentiment analysis is divided into three different levels which are sentence level, document level and feature level. The purpose is to classify the opinion either from sentence, document or features into positive and negative sentiment (N. Mishra, and C. K. Jha. 2012). There are 2 main methods of sentiment analysis that have been identified which are a machine learning approach and lexicon-based approach. As a result, Govindaraj and Gopalakrishnan (2016) conducted a study to categorize the extent of customer satisfaction based on online reviews. They created a method of categorizing customer satisfaction based on acoustic and linguistic features. They proposed a model of categorizing customer reviews as highly positive, positive, neutral, and highly negative (Govindaraj and Gopalakrishnan, 2016). This study's results are consistent with previous research conducted by Ghasemaghaei et al. (2018) on the impact of the length of reviews and online sentiments. Customers tend to concentrate on extensive and detailed product reviews before making the final purchase (Singla, Randhawa, and Jain, 2017). Therefore, for an accurate decision based on online Amazon Reviews using Sentiment Analysis 9 product reviews, companies need to investigate the actual extent of customer satisfaction with their products and services.

R. Safrin, K.R.Sharmila, et. al (2017) described two methods for the find positive and negative prefix. One is Parts of Speech Tagging (POST) which is mainly for positive phrases. To find the phrases with negative prefixes we use Negation Phrase Identification algorithm. They used K-means cluster to classify the positive and negative words. They labeled '0' as positive and '1' as negative word. For the evaluation of dataset, they represented some technique such as recall, precision and accuracy.

For the Recall = tp/(tp+fn)

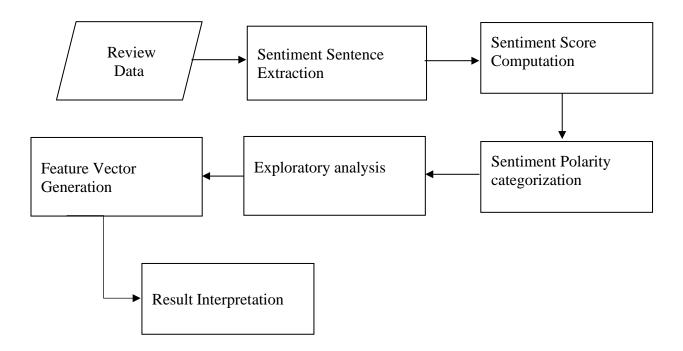
For the Precision = tp / (tp+fp)

For Accuracy = (tp+tn)/(tp+tn+fp+fn)

tp= True Positive

fp= False Positive

3.2 Methodology



Chapter 4 Data Preprocessing

4.1 Fill NA Values

Here, we use fillna() function to replace null value. First, we find NA value of reviews, which replaced with review title.

Table 2 Fill NA value of review

Company	Product	Title	Date	Rating	Review
Apple	Apple	Everything was	15-	4	Everything was
	iPhone XS,	fine	Nov-21		fine
	US Version,				
	64GB, Space				
	Gray				
Samsung	Samsung	I loved this	3-May-	5	I loved this
	Galaxy S21	phone	22		phone
	FE 5G Cell				
	Phone,				
	Factory				
Samsung	Samsung	This phone	21-	1	This phone
	Galaxy S21	have a screen	Aug-21		have a screen
	FE 5G Cell	problem, as			problem, as
	Phone,	soon as I			soon as I
	Factory				

After that, we find NA value of both reviews and titles. we filled both with a 'good' wordbecause both reviews and titles has rating 4 or above.

Table 3 Fill NA value of title and review

Company	Product	Title	Date	Rating	Review
Apple	Apple iPhone 8 Plus, 64GB, Space Gray	good	16-Apr-22	4	good
Samsung	Samsung Galaxy S21 FE 5G Cell Phone, Factory	good	1-Jan-21	5	good

4.2 Removing Punctuation and emojis

Eliminating unnecessary and special characters, including punctuation, is a crucial step in text normalization. The fundamental justification for this is that, even though punctuation can offer helpful insights on the tone of a review. It is usual practice to remove the punctuation because it tends to confuse the models rather than aiding them in predicting the correct class. In my project, we removed both punctuation and emojis.

Moreover, only spaces and alphanumeric characters are kept by replacing all RegEx pattern [^\w\s] matches with a whitespace

Table 4 Remove Punctuation

Title	Clean_Title
Honestly, it was worth it	Honestly it was worth it
Eh wouldn't buy again	Eh wouldnt buy again
Beautiful, lovely, practically brand new iPhon	Beautiful lovely practically brand new iPhone XS
Phone not working	Phone not working
May be defective one	May be defective one

Table 5 Remove Emojis

Review	Clean_Review
I absolutely love my new iPhone XS! It arrived	I absolutely love my new iPhone XS It arrived
Perfect, like new ## #RECELL	Perfect like new RECELL

4.3 Tokenization

Tokenization is the method of tokenizing or separating a string. Tokens are subunits of segments of a text document. They be able to be words, sentences, phrases etc. In our analysis we have used the method of nltk for tokenization.

There is a pre-defined word_tokenize function in nltk library. Using that function, it can separate words from sentences.

we used NLTK library for the tokenization in my project. Also, there is a pre-defined word_tokenize function that we applied for word tokenization.

Table 6 Tokenization

Review	Clean_Review	Title	Clean_Title
One - It comes in a weird boxTwo it had more s	[one, it, comes, in, a, weird, boxtwo, it, had	Eh wouldn't buy again	[eh, wouldnt, buy, again]
Suddenly Wifi is not working properly and i co	[suddenly, wifi, is, not, working, properly, a	May be defective one	[may, be, defective, one]

4.4 Removing Stopwords

Stopwords are normally words that end up occurring the most if you gathered any corpus of text based on singular tokens and checked their frequencies. Articles (a, the ,an), Pronouns (you,them,they,me), Prepositions and so on are stopwords. They have not much or no significance. They are usually removed from text during processing to retain words having maximum importance and context.

Using NLTK library, we import stopwords in my project. Then make one function and applied iton my dataframe. we got output as shown below.

Table 7 Remove Stopwords

Review	Clean_Review	Title	Clean_Title	
One - It comes in a weird boxTwo it had more s	[one, comes, weird, boxtwo, scuffs, scratches,	Eh wouldn't buy again	[eh, wouldnt, buy]	
DO NOT BUY A PHONE FROM THIS COMPANY! The phon	[buy, phone, company, phone, worked, fine, rig	BEWARE!!!	[beware]	

4.5 POS Tagging

A POS tag (or part-of-speech tag) is a specific label given to every token (word) in a text corpus to signify the part of speech and often also other grammatical groups such as tense, number (plural/singular), case etc. there are different types of POS tag categories which shown in below image:

CC conjunction, coordinating CD numeral, cardinal CD determiner CX existential there CX exist
DT determiner EX existential there FW foreign word IN preposition or conjunction, subordinating JJ adjective or numeral, ordinal JJR adjective, comparative JJS adjective, superlative LRB left round bracket LS list item marker MD modal auxiliary NNP noun, proper, singular NNPS noun, proper, plural RBR adverb, comparative RBS adverb, superlative RRB right round bracket SYM symbol TO "to" as preposition or infinitive marker UH interjection VB verb, base form VBD verb, past tense VBD verb, present participle or gerund VBN verb, past participle VBP verb, present tense, not 3rd person singular VBZ verb, present tense, 3rd person singular
EX existential there FW foreign word IN preposition or conjunction, subordinating JJ adjective or numeral, ordinal JJR adjective, comparative JJS adjective, superlative LRB left round bracket LS list item marker MD modal auxiliary NNP noun, proper, singular NNPS noun, proper, plural RBS adverb, superlative RRB right round bracket RRB right round bracket RRB right round bracket RRB right round bracket RBS adverb, superlative RRB right round bracket RBS adverb, superlative RRB right round bracket RBS adverb, superlative RRB right round bracket We'to as preposition or infinitive marker UH interjection VBD verb, base form VBD verb, past tense VBG verb, present participle or gerund VBN verb, past participle VBP verb, present tense, not 3rd person singular VBZ verb, present tense, 3rd person singular
FW foreign word IN preposition or conjunction, subordinating JJ adjective or numeral, ordinal JJR adjective, comparative JJS adjective, superlative UH interjection LRB left round bracket US verb, base form LS list item marker MD modal auxiliary NNP noun, common, singular or mass NNPS noun, proper, singular NNPS noun, proper, plural RRB right round bracket SYM symbol TO "to" as preposition or infinitive marker UH interjection VB verb, base form VBD verb, past tense VBG verb, present participle or gerund VBN verb, past participle VBP verb, present tense, not 3rd person singular VBZ verb, present tense, 3rd person singular
IN preposition or conjunction, subordinating JJ adjective or numeral, ordinal JJR adjective, comparative JJS adjective, superlative UH interjection LRB left round bracket UB verb, base form LS list item marker MD modal auxiliary NNP noun, common, singular or mass NNP noun, proper, singular NNPS noun, proper, plural RRB right round bracket SYM symbol TO "to" as preposition or infinitive marker UH interjection VB verb, base form VBD verb, past tense VBG verb, present participle or gerund VBN verb, past participle VBP verb, present tense, not 3rd person singular VBZ verb, present tense, 3rd person singular
JJ adjective or numeral, ordinal JJR adjective, comparative JJS adjective, superlative LRB left round bracket LS list item marker MD modal auxiliary NN noun, common, singular or mass NNP noun, proper, singular NNPS noun, proper, plural SYM symbol TO "to" as preposition or infinitive marker UH interjection VB verb, base form VBD verb, past tense VBG verb, present participle or gerund VBN verb, past participle VBP verb, present tense, not 3rd person singular VBZ verb, present tense, 3rd person singular
JJR adjective, comparative JJS adjective, superlative UH interjection UB verb, base form UB verb, past tense WB verb, present participle or gerund VBN verb, past participle VBN verb, past participle VBN verb, present tense, not 3rd person singular VBZ verb, present tense, 3rd person singular
JJS adjective, superlative LRB left round bracket VB verb, base form VBD verb, past tense WBC verb, present participle or gerund NN noun, common, singular or mass NNP noun, proper, singular NNPS noun, proper, plural VBI interjection VB verb, past form VBD verb, past tense VBN verb, present tense, not 3rd person singular VBZ verb, present tense, 3rd person singular
LRB left round bracket LS list item marker MD modal auxiliary NN noun, common, singular or mass NNP noun, proper, singular NNPS noun, proper, plural VB verb, base form VBD verb, past tense VBC verb, present participle or gerund VBN verb, past participle VBP verb, present tense, not 3rd person singular VBZ verb, present tense, 3rd person singular
LS list item marker VBD verb, past tense MD modal auxiliary VBG verb, present participle or gerund NN noun, common, singular or mass VBN verb, past participle NNP noun, proper, singular VBP verb, present tense, not 3rd person singular NNPS noun, proper, plural VBZ verb, present tense, 3rd person singular
MD modal auxiliary VBG verb, present participle or gerund VBN noun, common, singular or mass VBN verb, past participle VBN verb, present tense, not 3rd person singular VBZ verb, present tense, and person singular VBZ verb, present tense, 3rd person singular
NN noun, common, singular or mass VBN verb, past participle VBP verb, present tense, not 3rd person singular NNPS noun, proper, plural VBZ verb, present tense, 3rd person singular
NNP noun, proper, singular NNPS noun, proper, plural VBP verb, present tense, not 3rd person singular VBZ verb, present tense, 3rd person singular
NNPS noun, proper, plural VBZ verb, present tense, 3rd person singular
NING many common plant
NNS noun, common, plural WDT WH-determiner
PDT pre-determiner WP WH-pronoun
POS genitive marker WP\$ WH-pronoun, possessive
PRP pronoun, personal WRB Wh-adverb

Figure 1 POS Tagging Categories

For the pos tagging, we import pos_tag using NLTK. Tag library. After, make a function and applyit on my dataframe. The output has shown below:

Table 8 POS Tagging

Review	Clean_Review	Title	Clean_Title
One - It comes in a weird boxTwo it had more s	[(one, CD), (comes, VBZ), (weird, JJ), (boxtwo	Eh wouldn't buy again	[(eh, NN), (wouldnt, NN), (buy, VB)]
Good condition	[(good, JJ), (condition, NN)]	Good	[(good, JJ)]

4.6 Lemmatization

Lemmatization is a grammatical term which indicates grouping all together words with the similar origin or lemma but with distinct accents or derivatives of sense so they can be analyzed as one item. The aim is to take away inflectional suffixes and begins to take out the word's dictionary form.

For instance, to lemmatize the words "dogs," "dog's," means bringing away the suffixes "s," "'s," and "s" to bring out the root word "dog."

we import WordNetLemmatizer from NLTK library in my project. It returns dictionary form ofword based on pos tag.

For the lemmatization, we make function using for loop and applied it on dataframe. The outputhas shown in below:

Table 9 Lemmatization

Company	Product	Title	Date	Rating	Review	Clean_Title	Clean_Review
Apple	Apple	Honestly, it	22-	5	I was very	honestly	hesitant buying
	iPhone	was worth	Jun-		hesitant	worth	iphone amazon
	XS, US	it	19		about		disappoint come
	Version,				buying an		
	64GB,				iPhone		
	Space				off		
	Gray						

Company	Product	Title	Date	Rating	Review	Clean_Title	Clean_Review
Apple	Apple iPhone XS, US Version, 64GB, Space Gray	Eh wouldn't buy again	30- Jun- 19	1	One - It comes in a weird boxTwo it had more s	eh wouldnt buy	one come weird boxtwo scuff scratch id like pr
Apple	Apple iPhone XS, US Version, 64GB, Space Gray	Beautiful, lovely, practically brand new iPhon	4- Feb- 20	5	absolutely love my new iPhone XS! It arrived	beautiful lovely practically brand new iphone x	absolutely love new iphone x arrive time pract
Apple	Apple iPhone XS, US Version, 64GB, Space Gray	Phone not working	25- Dec- 18	4	The phone is froze up and unable to use. Very	phone work	phone froze unable use poor productedit within
Apple	Apple iPhone XS, US Version, 64GB, Space Gray	May be defective one	2- Jul- 19	1	Suddenly Wifi is not working properly and i co	may defective one	suddenly wifi work properly could see phone fe

4.7 TF-IDF

We used TfidfVectorizer method for converting textual data to numerical form so we can use it to our models. It's transferring text data into vectors as the models can process only numerical data.

For Term Frequency-Inverse Document Frequency the product of Term frequency and inverse document frequency used. Term frequency is in what way commonly a term has occurred in a document.

Term Frequency =
$$f/d$$
.

IDF is inverse document frequency. If a corpus contains N documents and the term of our concern exists only in D documents, then IDF is:

$$IDF = log(N/D)$$
.

In this project, using this TF-IDF method we got different types of features from the clean reviews, which has around 30,000. After that, remove all the without dictionary words and update stopwords, So we got proper words which we used for word cloud.

Chapter 5 Sentimental Analysis

5.1 Vader Sentiment

(Valence Aware Dictionary and Sentiment Reasoner) is a lexicon and rule-based sentiment

analysis tool that is specifically attuned to sentiments expressed in social media and works well

on texts from other domains. It's a Rule-based Model for Sentiment Analysis of social media

Text. This analyzer calculates text sentiment and produces four different classes of output

scores: positive, negative, neutral, and compound. A compound score is the aggregate of the

score of a word, or precisely, the sum of all words in the lexicon, normalized between -1 and 1.

Positive sentiment: compound score ≥ 0.05

Neutral sentiment: (compound score > -0.05) and (compound score < 0.05)

Negative sentiment: compound score <= -0.05

Compound Score: The compound score is computed by summing the valence scores of each

word in the lexicon, adjusted according to the rules, and then normalized to be between -1 (most

extreme negative) and +1 (most extreme positive).

we import SentimentIntensityAnalyzer from vadersentiment library. It applied on dataframe.

Theoutput has shown below

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Table 10 Sentiment Analysis

Comp any	Prod uct	Da te	Rati ng	Clean_ Title	Clean_R eview	cleaned_title _review	Posit ive	Nega tive	Neut ral	Compo und	Senti ment
Apple	Appl e iPho ne XS, US Versi on, 64G B, Spac e Gray	22- Ju n- 19	5	honestl y worth	hesitant buying iphone amazon disappoin t come	honestly worth hesitant buying iphone amazon d	0.24	0.197	0.55	0.6901	positiv e
Apple	Appl e iPho ne XS, US Versi on, 64G B, Spac e Gray	30- Ju n- 19	1	eh wouldnt buy	one come weird boxtwo scuff scratch id like pr	eh wouldnt buy one come weird boxtwo scuff scr	0.17	0.279	0.54 8	-0.3536	negati ve
Apple	Appl e iPho ne XS, US Versi on, 64G B, Spac e Gray	4- Fe b- 20	5	beautifu l lovely practica lly brand new iphone x	absolutel y love new iphone x arrive time pract	beautiful lovely practically brand new iphone	0.32	0.033	0.64	0.9896	positiv e
Apple	Appl e iPho ne XS, US Versi on, 64G B, Spac	25- De c- 18	4	phone work	phone froze unable use poor producted it within	phone work phone froze unable use poor product	0.26	0.133	0.60	0.2732	positiv e

Comp	Prod uct	Da te	Rati ng	Clean_ Title	Clean_R eview	cleaned_title _review	Posit ive	Nega tive	Neut ral	Compo und	Senti ment
	e Gray										
Apple	Appl e iPho ne XS, US Versi on, 64G B, Spac e Gray	2- Jul -19	1	may defectiv e one	suddenly wifi work properly could see phone fe	may defective one suddenly wifi work properly	0.12	0.232	0.64	-0.3415	negati ve

Chapter 6 Visualizations

1) Count of rating

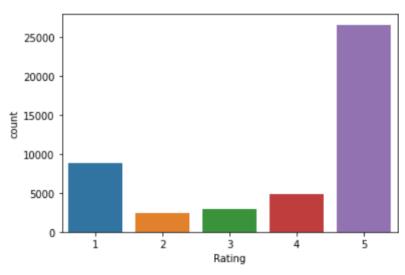


Figure 2 Count of rating

The above picture depicts count of total rating of products. It shows rating 5 has the highest count in whole dataset, while rating 2 has the lowest count.

2) Sentiment by company

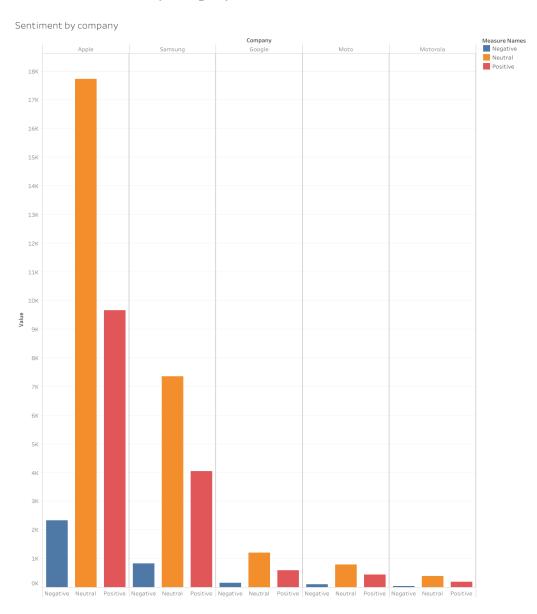


Figure 3 Sentiment by company

The bar chart represents positive, negative, and neutral sentiment by five different mobile companies. Neutral sentiment has the highest value among the all the sentiment. Apple has the maximum positive review among all the companies, whilst Motorola has the lowest sentiment in all three categories.

3) count of rating by company

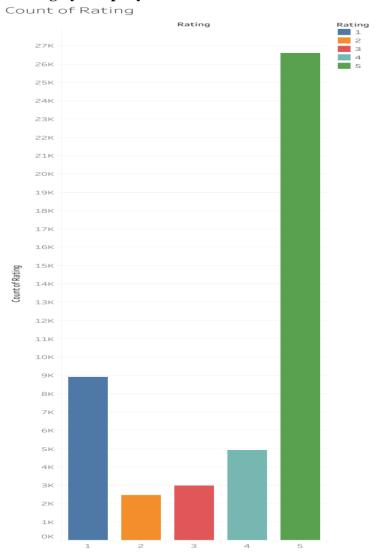


Figure 4 Count of Rating by company

The bar graph demonstrates count of rating by five different mobile companies. Apple has the top rating among all companies. Apple has the maximum rating of 5 amongst all mobile firms.

4) Word Clouds

Wordcloud is an image composed by many words that implies the contents of the document of analysis. The words are presented in various shapes and colors according to the frequency of occurrence and importance of words in the document. The larger the text form, the more the number of occurrences. Wordcloud is used in sentiment analysis to find out the frequency of dominant words and then draw conclusions according to the topic and condition of the study.

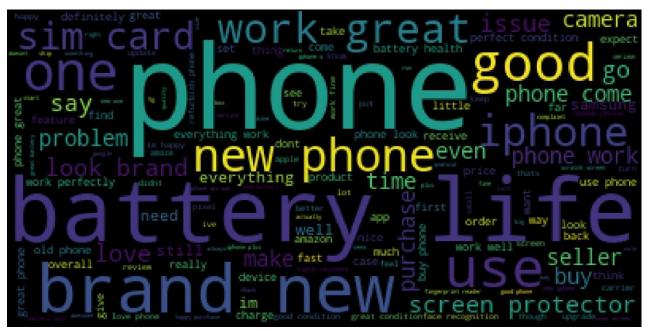


Figure 5 Positive review wordcloud

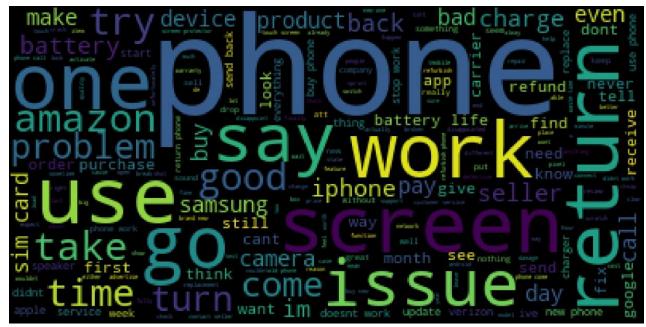


Figure 6 Negative review wordcloud

Chapter 7 Experiment Results

In all models implemented below we have implemented selection of k highest scored features of the data to passthrough our model.

Further on we have tried to tune parameters of previously executed models and tested it using both CountVectorizerand TF-IDF Tokenizer.

7.1 Navies Byes

Bayes' Theorem provides a way that we can calculate the probability of a piece of data belonging to a target class using past knowledge. Bayes' Theorem is stated as:

P(class|data) = (P(data|class) * P(class)) / P(data)

Where P(class|data) is the probability of class given the provided data. Naive Bayes is a classification algorithm for binary (two-class) and multiclass classification problems. Probabilities for each class are simplified i.e they are considered independent of each other. Using Navies Byes, we got 82% accuracy.

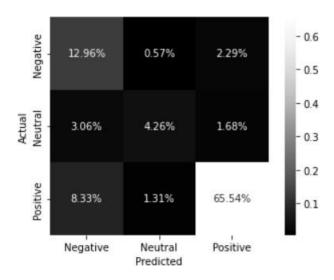


Figure 7 Confusion Matrix of Navies Byes

7.2 SVM

SVM is a supervised machine learning algorithm that can be used for both classification or regression challenges. However, it is mostly used in classification problems. In the SVM algorithm, we plot each data item as a point in n-dimensional space (where n is several features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiates the two classes very well (look at the below snapshot). Using SVM model, we got 90.67% accuracy.

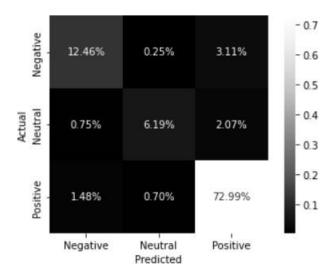


Figure 8 Confusion Matrix of SVM

7.3 KNN

KNN is one of the simplest forms of machine learning algorithms mostly used for classification. It classifies the data point on how its neighbor is classified. KNN classifies the new data points based on the similarity measure of the earlier stored data points. Using KNN algorithm, we got only 29% accuracy.

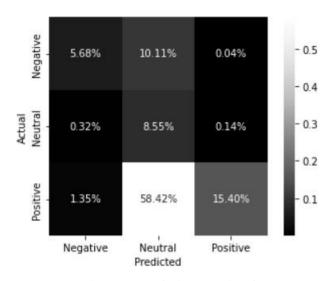
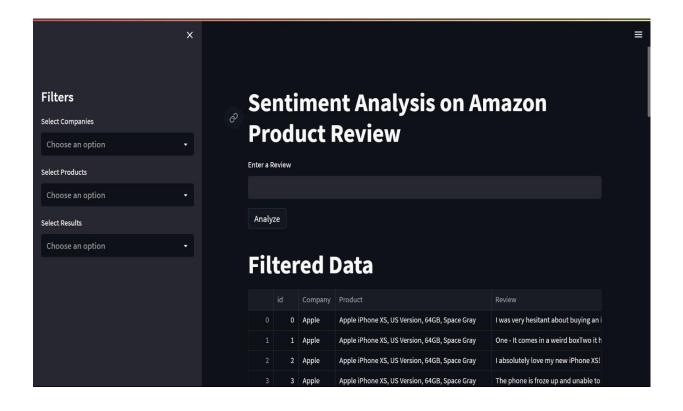


Figure 9 Confusion Matrix of KNN

FrontEnd



Conclusion

After multiple model iterations and testing, we believe that the SVM classifier does the best job at estimating the sentiment of a review, with an accuracy of almost 91%. Even though the entire testing and analysis was done at a very basic level, we consider that this will be worthwhile in various fields of product and user relationship analysis. A good application of this would be in recommendation systems, where users can be clustered based on the similar reviews that they give on sites like amazon.

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