Sentiment analysis

Sara Sarrafan Chaharsoughi
Student, Masters in Applied Computing
Wilfrid Laurier University

***Abstract*— Every day, billions of pieces of text, whether from forums, blogs, social media, or review sites, flood the internet. Previously unstructured data can be turned into more structured data via sentiment analysis, making this data more useful information. The information can be used to describe public perceptions of products, brands, community services, services, politics, or other topics. Sentiment analysis is a branch of Natural Language Processing (NLP) that develops algorithms for recognising and retrieving text-based opinions. The idea is to extract emotions or 'feelings' from a set of texts or sentences at the most fundamental level. The discipline of sentiment analysis, often known as 'opinion mining,' always involves some sort of data mining to obtain the text that will later be used to carry out the learning process in the machine learning that will be constructed. In This study We did the project in four phases:**

1-predicting using title only 2- predicting using review text only 3-predicting using title and review text only 4- Predicting using Title and Review Text where Positive Feedback Count is greater than 1 and for every phase we did the algorithm of Naive Bayes, Support Vector Machin and K-Nearest Neighbor and Random Forest.

We conduct sentimental analysis with data from Kaggle The accuracy of measurements in this study, for the fourth phase for SVM is 80% and for Naive Bayes 79% which are good accuracies.

***Keywords*— Sentiment analysis, NLP, Opinion mining, Customer satisfaction, KNN, Random Forest, SVM, Naive Bayes.**

I. Introduction

The dataset that will be analyzed later can be sourced from the comment's column, netizens tweets on Twitter, and various sources of uploads from people related to their opinions or sentiment on a matter. Sentiment analysis is part of text mining, and the dataset that will be analyzed later can be sourced from the comment's column, netizens tweets on Twitter, and various sources of uploads from people related to their opinions or sentiment on a matter. People who work in data science may come across the term sentiment analysis on a regular basis. Sentiment analysis is also a procedure that involves examining diverse data in the form of views or opinions in order to draw conclusions from a variety of current viewpoints. Sentiment analysis can yield a proportion of positive, negative, or neutral sentiment as a result.

Human-computer interaction practitioners and researchers, as well as those from subjects such as sociology, marketing and advertising, psychology, economics, and political science, can benefit from sentiment analysis.

Natural Language Processing (NLP), a branch of computer science that approaches the analysis and representation of naturally occurring text with the goal of achieving a computerized human-like understanding of it, is an area of research quickly growing in popularity [1]. Within NLP is the subfield of sentiment analysis, a machine learning approach to classifying the sentimental polarity of a text according to the opinions it contains. Sentiment analysis has received attention in large part for its application as a tool for business analytics via online reviews of their products or services. With the rapidly growing e-commerce market, it's not difficult to see the appeal of a tool that can sort through an abundance of reviews to extract the overall sentiment, and do so exponentially faster than any human, benefiting market research, product analytics, reputation-monitoring, and more, making it incredibly useful to industry [2]. It has additional applications in research, lending to its popularity, such as mining public opinion to create intervention strategies and public service announcements that are most beneficial given the current state of affairs. A more recent example addressed the global COVID-19 pandemic by mining twitter posts from users in Nepal to assess the mental state of the people [3].

Specifically, however, this paper tackles the problem of automating a sentiment classification system for e-commerce women's clothing reviews. The goal is to assign each review a class labeled by numerical rating from one to five where one is a strong negative opinion and five is a strong positive opinion. Previous work in the domain of sentiment analysis for e-commerce product reviews has yielded strong results,
ML algorithms are being employed in RSs to deliver better recommendations to users, as previously indicated. The
by anyone because there aren't any user ratings to utilise to compute the prediction [38].

II. Sentiment Analysis

Sentiment analysis is a procedure that uses Natural Language Processing to extract attitudes, opinions, perspectives, and emotions from text, audio, tweets, and database sources (NLP). Sentiment analysis is the process of categorizing textual opinions into categories such as "positive," "negative," or "neutral." Subjectivity analysis, opinion mining, and assessment extraction are other terms for it.

Although the terms opinion, feeling, view, and belief are sometimes used interchangeably, there are some distinctions.

Opinion: A conclusion that is open to debate (since different experts have differing viewpoints).
Belief: deliberate acceptance and intellectual assent
View: subjective opinion
Sentiment: is an opinion that represents one's feelings.
Sentiment analysis encompasses a wide range of activities, including sentiment extraction, sentiment classification subjectivity categorization, opinion summarization, and

opinion spam detection, to name a few. Its goal is to examine people's feelings, attitudes, views, and emotions regarding things including products, people, subjects, organizations, and services.

III. Related Works

In recent years a lot of work has been done in the field of "Sentiment Analysis on Twitter"by number of researchers. In its early stage it was intended for binary classification which assigns opinions or reviews to bipolar classes such as positive or negative only.

Pak and Paroubek (2010) [22] suggested a strategy for categorising tweets into objective, positive, and negative categories. They constructed a Twitter corpus by using the Twitter API to gather tweets and automatically annotating them with emoticons. They created a sentiment classifier based on the multinomial Naive Bayes algorithm and features like Ngram and POS-tags using that corpus. The training set they utilised was ineffective since it only included tweets with emoticons.

(Nasukawa and Yi, 2003) may have been the first to use the term sentiment analysis, while (Dave, Lawrence, and Pennock, 2003) may have been the first to use the term opinion mining. Das and Chen, 2001; Morinaga et al., 2002; Pang, Lee, and Vaithyanathan, 2002; Tong, 2001; Turney, 2002; Wiebe, 2000) published earlier research on attitudes and opinions. We use the phrases sentiment analysis and opinion mining interchangeably in this work. To classify tweets, Parikh and Movassate(2009) used two models: a Naive Bayes bigram model and a Maximum Entropy model. They discovered that Naive Bayes classifiers outperformed the Maximum Entropy model.[23]

Go and L.Huang (2009) proposed employing distant supervision to solve sentiment analysis for twitter data, with their training set consisting of tweets with emoticons that functioned as noisy labels. They use Naive Bayes, MaxEnt, and Support Vector Machines to create models (SVM). Unigrams, bigrams, and POS made up their feature space. SVM outperformed other models, and unigrams were more effective as features, they concluded.[24]

Barbosa et al. (2010) developed a two-phase automatic sentiment analysis approach for categorising tweets. They classified tweets as objective or subjective, and then the subjective tweets were categorised as positive or negative in the second phase. Retweets, hashtags, links, punctuation, and exclamation marks were employed in combination with features like preceding polarity of words and POS [25] Bifet and Frank (2010) employed Twitter streaming data given by Firehouse API, which offered all publicly available messages from every user in real-time. Multinomial naive Bayes, stochastic gradient descent, and the Hoeffding tree were all used. They came to the conclusion that the SGD-based model was superior to the others when applied with an acceptable learning rate [26].

IV. Sentiment Analysis Applications

Opinions have a crucial role in practically all human activities since they shape our actions. We seek out the opinions of others whenever we need to make a decision. Businesses and organisations in the real world are continuously looking for customer or public feedback on their products and services. Individual customers also want to know what other people think about a product before buying it, and what other people think about political candidates before voting in a political election. When a person wanted advice in the past, he or she turned to friends and family. When a company or organisation sought public or customer feedback, they conducted surveys, polls, and focus groups.

For marketing, public relations, and political campaign firms, obtaining public and consumer opinions has long been a lucrative business.

Individuals and organisations are increasingly using the content in social media (e.g., reviews, forum discussions, blogs, microblogs, Twitter, comments, and postings in social network sites) for decision making, thanks to the explosive growth of social media (e.g., reviews, forum discussions, blogs, microblogs, Twitter, comments, and postings in social network sites) on the Web. If you want to buy a consumer goods, you are no longer confined to asking your friends and family for their opinions because there are many user reviews and debates about the product on public forums on the Internet.

Because there is an abundance of publicly available information, surveys, opinion polls, and focus groups may no longer be essential for an organisation to acquire public viewpoints. Due to the growth of different sites, locating and monitoring opinion sites on the Internet, as well as distilling the information contained in them, remains a difficult undertaking. Each site often contains a large amount of opinion text, which might be difficult to comprehend in lengthy blogs and forum posts. The normal human reader will struggle to find relevant sites and extract and summarise the thoughts contained within them. As a result, automated sentiment analysis tools are required.

Agarwal et al. (2011) created a three-way model for separating positive, negative, and neutral mood. They tried out models like the unigram, feature-based models, and tree kernel-based models.

They used a tree kernel-based model to represent tweets.

The feature-based model employs 100 features, while the unigram model employs around 10,000. They came to the conclusion that features that combine a word's prior polarity with its parts-of-speech(pos) tags are the most crucial and play a significant influence in the classification task. The model based on tree kernels outperformed the other two[27].

Using punctuation, single words, n-grams, and patterns as different feature types, Davidov et al. (2010) suggested a method to use Twitter user-defined hastags in tweets as a classification of sentiment type, which is then integrated into a single feature vector for sentiment classification. They constructed a feature vector for each example in the training and test sets and used the K-Nearest Neighbor approach to assign sentiment labels [28].

Po-Wei Liang et al.(2014) collected twitter data using the Twitter API. Their training data is divided into three types (camera, movie, mobile). The data is divided into three categories: favourable, negative, and non-opinions. Opinion-based tweets were censored. The Naive Bayes simplified independence assumption was used with the Unigram Naive Bayes model. They also used the Mutual Information and Chi Square feature extraction methods to reduce unnecessary features. Finally, the tweet's orientation is projected. i.e. if it is favourable or bad [29].

Pablo et al. proposed Naive Bayes classifier modifications for identifying polarity in English tweets. Baseline (trained to identify tweets as positive, negative, and neutral) and Binary (makes use of a polarity lexicon and classifies as positive and negative) Naive Bayes classifiers were created. Neutral tweets go unnoticed). Classifiers took into account Lemmas (nouns, verbs, adjectives, and adverbs), Polarity Lexicons, Multiword from various sources, and Valence Shifters [30].

Turney et al employed the bag-of-words method for sentiment analysis, which ignores word relationships and treats a document as a collection of words. To estimate the overall sentiment of the paper, the sentiments of each word were determined, and the results were then combined using aggregation methods [32].

The lexical database WordNet was utilised by Kamps et al. to determine the emotional content of a word along various dimensions. They used WordNet to build a distance metric and estimate the semantic polarity of adjectives [33].

For Sentiment Classification, Xia et al. employed an ensemble framework that was created by merging several feature sets and classification approaches. They used two types of feature sets (Part-of-speech information and Word relations) as well as three different basic classifiers (Naive Bayes, Maximum Entropy, and Support Vector Machines) in their research. They improved sentiment classification accuracy by using ensemble approaches such as fixed combination, weighted combination, and Meta-classifier combination.[34]

The problems and effective strategies for mining opinions from Twitter tweets were emphasised by Luoet al. Opinion retrieval on Twitter is difficult due of spam and widely differing wording.[35]

V. RESULT AND DISCUSSION

A. *Training*

For tackling categorization difficulties, supervised learning is a useful strategy. The classifier may be trained to produce better predictions for unknown data in the future.

B. *Classification*

1) *Naive Bayes:*

Naive Bayes is a probabilistic classifier that can learn the pattern of reviewing a collection of categorized texts [36]. It compares the contents of the documents to a list of words to assign them to the appropriate category or class.

2) *Support vector machine*

The support vector machine examines the data, defines the decision boundaries, and performs computations in input space using kernels [37]. The input data consists of two sets of m-dimensional vectors. After that, each piece of data that is represented as a vector is assigned to a class. Following that, we discover a margin between the two classes that is unrelated to any document. The margin of the classifier is defined by the distance; boosting the margin lowers indecisive decisions. SVM also supports classification and regression, which are useful in statistical learning theory, and it aids in detecting the factors that must be considered in order to properly comprehend it.

3) *K Nearest Neighbor*

Because of its ease of implementation and superior performance, the K Nearest Neighbor (kNN) approach is frequently utilized in data mining and machine learning applications. However, in the previous kNN techniques, putting all test data to the same k value has been shown to render these methods impracticable in real-world applications. On data with a huge example size, such as approaching infinity, the kNN classifier has shown outstanding performance, with its error rate nearing the Bayes optimum under relatively moderate conditions. However, various issues, such as the choice of the k value, the choice of distance measures, and so on, can have an impact on the kNN classification's performance.

4) *Random Forest*

Random forest is an ensemble learning-based supervised machine learning technique. Ensemble learning is a sort of learning in which numerous versions of the same algorithm are combined to produce a more effective prediction model. The random forest algorithm combines several methods of the same sort, such as numerous decision trees, to create a forest of trees, hence the name "Random Forest." Both regression and classification jobs can benefit from the random forest approach. A group of tree structured classifiers can be described as an RF classifier. It's a more complex variant of Bagging that incorporates randomization [39]. RF splits each node using the best split among a group of predictors randomly picked at that node, rather than the best split among all variables. With replacement, a new training data set is constructed from the original data set. Then, using random feature selection, a tree is grown. Trees that have reached maturity are not pruned [39], [40]. This technique gives RF unrivalled precision [41]. RF is also quick, resistant to overfitting, and allows the user to create as many trees as they wish.

C. *Dataset*

There are 23486 rows and 10 feature variables in this dataset. Each row is a customer review and contains the following variables:

Clothing ID: Integer Categorical variable that refers to the specific piece being reviewed.

•Age: Positive Integer variable of the reviewer’s age.
•Title: String variable for the title of the review.
•Review Text: String variable for the review body.
•Rating: Positive Ordinal Integer variable for the product score granted by the customer from 1 Worst to 5 Best.

•Recommended IND: Binary variable stating where the customer recommends the product where 1 is recommended, 0 is not recommended.

•Positive Feedback Count: Positive Integer documenting the number of other customers who found this review positive.

•Division Name: Categorical name of the product high level division.

•Department Name: Categorical name of the product department name.

•Class Name: Categorical name of the product class name.

D. A General looking at the data

	Unnamed: 0	Clothing ID	Age	Title	Review Text	Rating	Recommended IND	Positive Feedback Count	Division Name	Department Name	Class Name
0	0	767	33	NaN	Absolutely wonderful - silky and sexy and comf...	4	1	0	Initmates	Intimate	Intimates
1	1	1080	34	NaN	Love this dress! it's sooo pretty. i happene...	5	1	4	General	Dresses	Dresses
2	2	1077	60	Some major design flaws	I had such high hopes for this dress and reall...	3	0	0	General	Dresses	Dresses
3	3	1049	50	My favorite buy!	I love, love, love this jumpsuit. it's fun, fl...	5	1	0	General Petite	Bottoms	Pants
4	4	847	47	Flattering shirt	This shirt is very flattering to all due to th...	5	1	6	General	Tops	Blouses

E. Data cleaning

In data cleaning We Removed First Unnamed Column, and removed all null values because it is less than 30% of the whole data.

	Clothing ID	Age	Title	Review Text	Rating	Recommended IND	Positive Feedback Count	Division Name	Department Name	Class Name
0	767	33	NaN	Absolutely wonderful - silky and sexy and comf...	4	1	0	Initmates	Intimate	Intimates
1	1080	34	NaN	Love this dress! it's sooo pretty. i happene...	5	1	4	General	Dresses	Dresses
2	1077	60	Some major design flaws	I had such high hopes for this dress and reall...	3	0	0	General	Dresses	Dresses
3	1049	50	My favorite buy!	I love, love, love this jumpsuit. it's fun, fl...	5	1	0	General Petite	Bottoms	Pants
4	847	47	Flattering shirt	This shirt is very flattering to all due to th...	5	1	6	General	Tops	Blouses

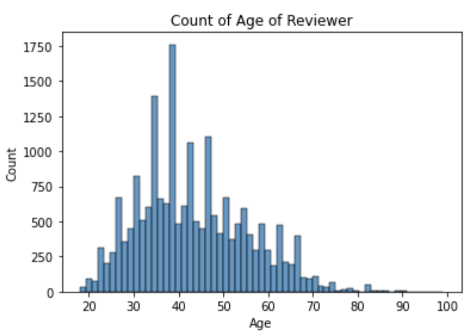
F. Describe Dataset

1- show the count, mean, standard deviation, minimum, maximum, 25%, 50% and 75% percentiles.

	Clothing ID	Age	Rating	Recommended IND	Positive Feedback Count
count	19662.000000	19662.000000	19662.000000	19662.000000	19662.000000
mean	921.297274	43.260808	4.183145	0.818177	2.652477
std	200.227528	12.258122	1.112224	0.385708	5.834285
min	1.000000	18.000000	1.000000	0.000000	0.000000
25%	861.000000	34.000000	4.000000	1.000000	0.000000
50%	936.000000	41.000000	5.000000	1.000000	1.000000
75%	1078.000000	52.000000	5.000000	1.000000	3.000000
max	1205.000000	99.000000	5.000000	1.000000	122.000000

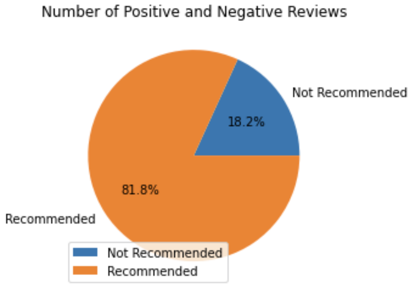
2- Count of Age of Reviewer:

As it is clear from the plot most ranges of the age belong to between about 32 to 42 years.



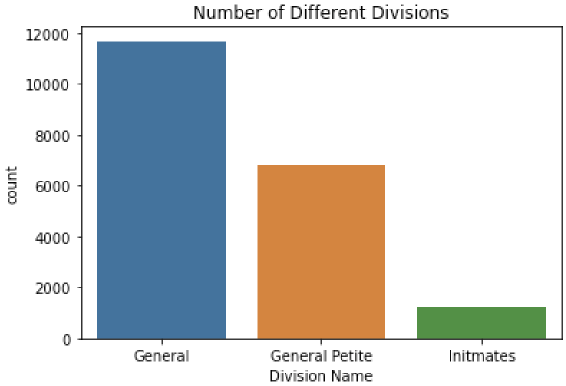
3- Number of Customer's Positive and Negative Recommendation:

As the pie chart shows, 81.8 % of the reviewer recommended the goods and just about 18.2 % of them didn't recommend the products.



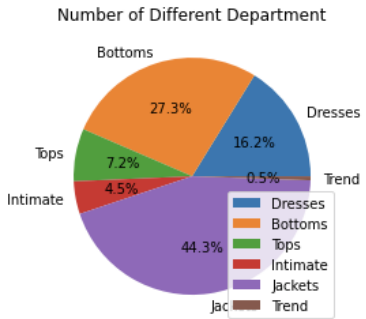
4- Number of different divisions:

As the number of different divisions show the general part is 11664, the general petit is 6778 and intimates are 1220.



5- Number of Different Department:

As the bellow pie chart shows the percentage of different department in the dataset.



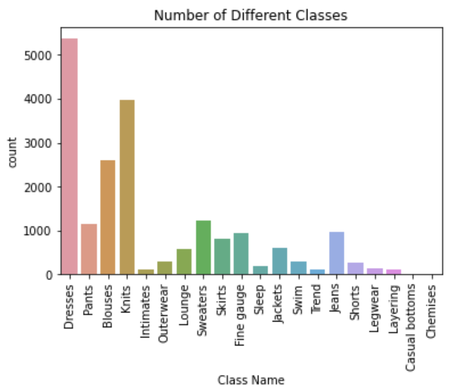
6- Number of different classes

It shows that first one in amount are knits, after that are dresses and blouses. Casual bottoms and chemises have the least number (1).

Class Name	
Blouses	2587
Casual bottoms	1
Chemises	1
Dresses	5371
Fine gauge	927
Intimates	120
Jackets	598
Jeans	970
Knits	3981
Layering	115
Legwear	131
Lounge	574
Outerwear	281
Pants	1157
Shorts	260
Skirts	796
Sleep	174
Sweaters	1218
Swim	293
Trend	107

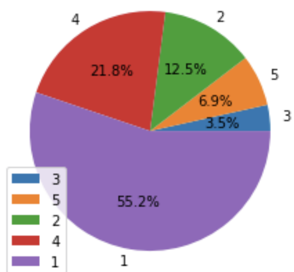
7- Number of Different Classes

The bellow chart shows the number of different classes the most one is dresses and knits and blouses, and the least ones are chemises, casual bottoms and trend.



8- Number of customer's rating from 1 to 5

The bellow chart shows the number of ratings from 0 to 4, as it is obvious the most number of rating belongs to 1 and after that 4.

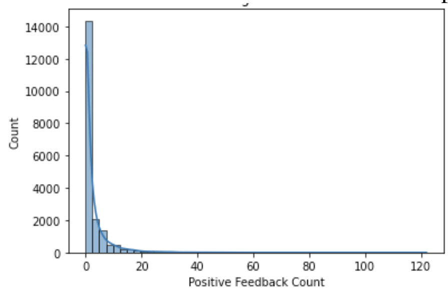


9- Number of positive feedback

Positive Feedback Count	
0	8930
1	3502
2	1923
3	1258
4	803
...	
95	1
98	1
99	1
108	1
122	1

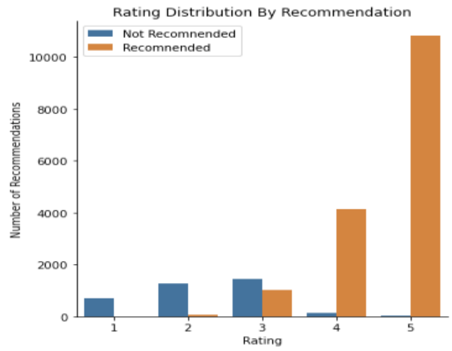
10- Count of positive

The below chart shows the count of positive feedback



11- Rating distribution by recommendation

The bellow chart shows the rating distribution by recommendation.



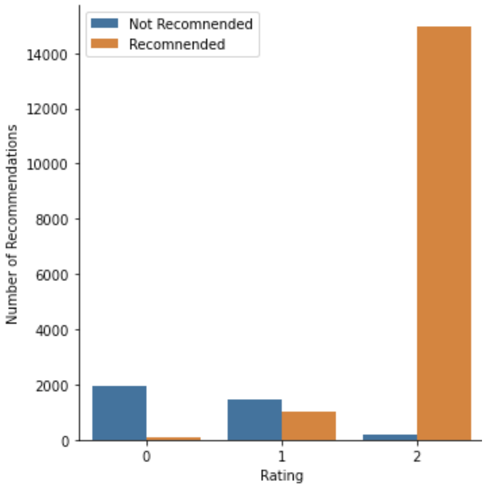
12- Most frequent words

The below chart shows the most frequent words that reputed more than 2000 times.

13- Frequent words in positive Recommendation

14- Frequent words in negative Recommendation

15- Changed rating compared by recommendation



VI. OUR METHOD

First, we combined the title and review text column and put it in a new column called: “Title Review”.

We did the project in four phases:

1- predicting using title only
2- predicting using review text only
3- predicting using title and review text only
4- Predicting using Title and Review Text where Positive Feedback Count is greater than 1

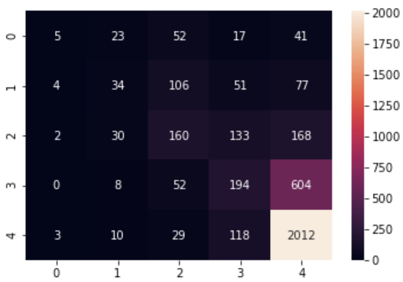
and for every phase we did the algorithm of Naive Bayes, Support Vector Machin and K-Nearest Neighbor and Random Forest.

First, we split the dataset into 80% Training set and 20% Testing set and convert them inti vectorized form.

A. Predicting Using Title Only

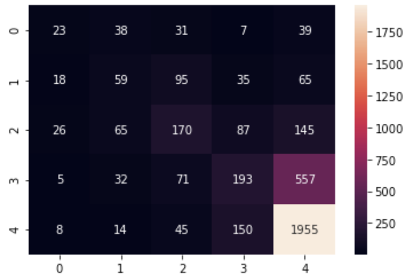
1) Navie bayes

After using the Naive Bayes classification, we ha ve the accuracy of Naive Bayes: 0.61, then We draw the hea tmap for confusion matrix as bellow:



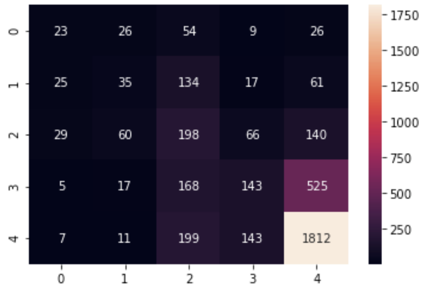
2) Support vectore machine(SVM)

After using the SVM classification, we have the accuracy of SVM: 0.61, then We draw the heatmap for conf usion matrix as bellow:



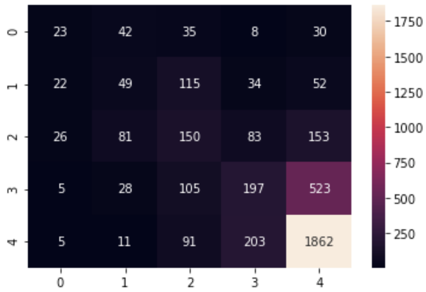
3) K Nearest Neighbor (KNN)

After using the K-NN classification, we have the accuracy of KNN: 0.56, then We draw the heatmap for conf usion matrix as bellow:



4) Random Forest

After using the Random Forest classification, we have the accuracy of Random Forest: 0.58, then We draw th e heatmap for confusion matrix as bellow:



In the table below we have the accuracy of predictions for algorithms using title only.

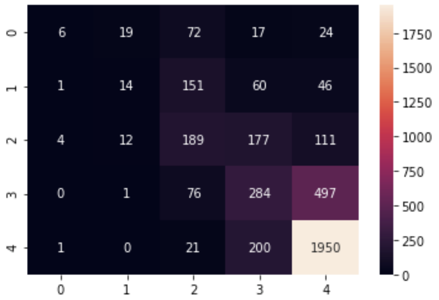
Algorithm	Accuracy
Naive Bayes	61 %
SVM	61 %
KNN	56 %
Random Forest	58 %

Table1 for the accuracy of predictions for algorithms using title only

B. predicting using review text only

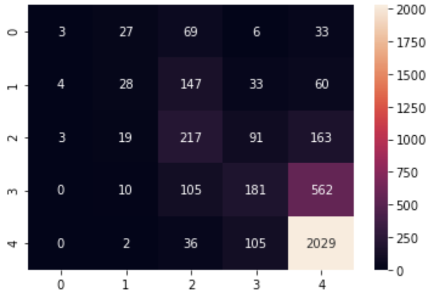
1) Navie bayes

After using the Naive Bayes classification, we ha ve the accuracy of Naive Bayes: 0.62, then We draw the hea tmap for confusion matrix as bellow:



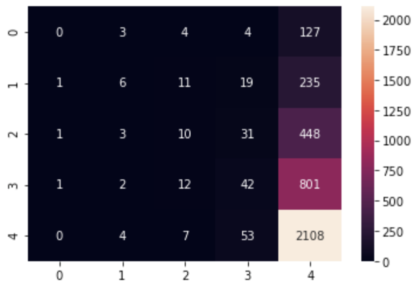
2) *Support vectore machine(SVM)*

After using the SVM classification, we have the accuracy of SVM: 0.62, then We draw the heatmap for confusion matrix as bellow:



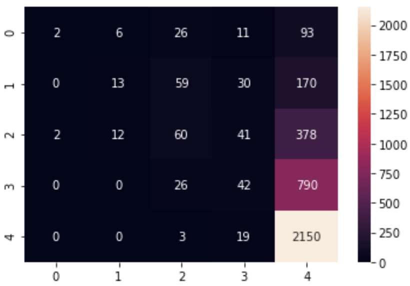
3) *K Nearest Neighbor (KNN)*

After using the K-NN classification, we have the accuracy of KNN: 0.55, then We draw the heatmap for confusion matrix as bellow:



4) *Random Forest*

After using the Random Forest classification, we have the accuracy of Random Forest: 0.58, then We draw the heatmap for confusion matrix as bellow:



In the table below we have the accuracy of predictions for algorithms using review text only.

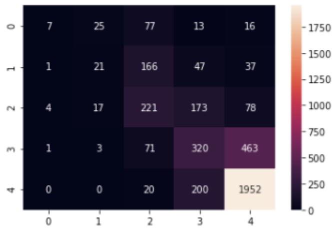
Algorithm	Accuracy
Naive Bayes	62 %
SVM	62 %
KNN	55 %
Random Forest	58 %

Table 2 for the accuracy of predictions for algorithms using review text only

C. *predicting using title and review text only*

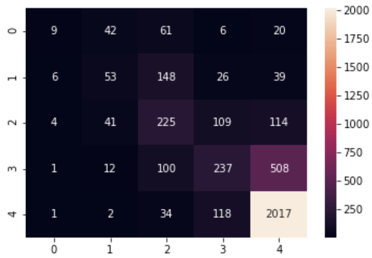
1) *Navie bayes*

After using the Naive Bayes classification, we have the accuracy of Naive Bayes: 0.64, then We draw the heatmap for confusion matrix as bellow:



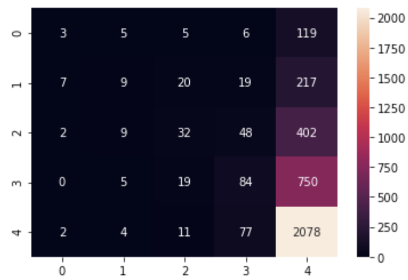
2) *Support vectore machine(SVM)*

After using the SVM classification, we have the accuracy of SVM: 0.65, then We draw the heatmap for confusion matrix as bellow:



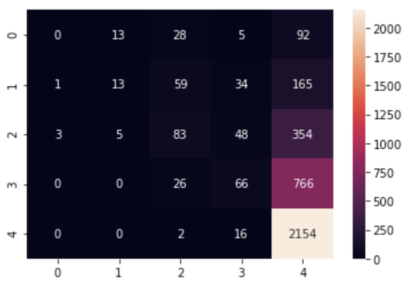
3) *K Nearest Neighbor (KNN)*

After using the K-NN classification, we have the accuracy of KNN: 0.56, then We draw the heatmap for confusion matrix as bellow:



4) *Random Forest*

After using the Random Forest classification, we have the accuracy of Random Forest: 0.59, then We draw the heatmap for confusion matrix as bellow:



In the table below we have the accuracy of predictions for algorithms using Title and review text .

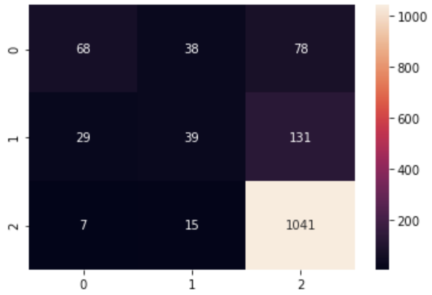
Algorithm	Accuracy
Naive Bayes	64 %
SVM	65 %
KNN	56 %
Random Forest	59 %

Table 3 for the accuracy of predictions for algorithms using Title and review text

D. Predicting using Title and Review Text where Positive Feedback Count is greater than 1

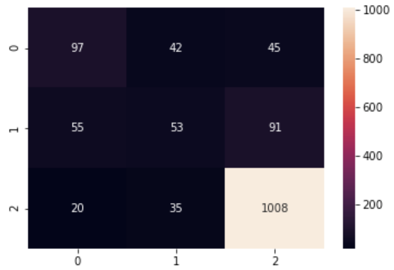
1) Navie bayes

After using the Naive Bayes classification, we ha ve the accuracy of Naive Bayes: 0.79, then We draw the hea tmap for confusion matrix as bellow:



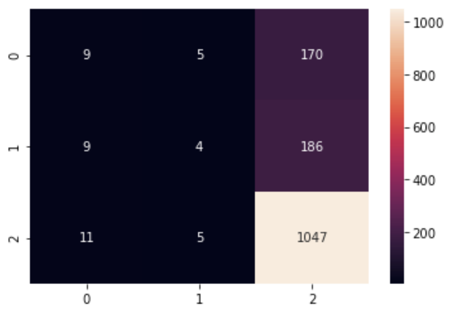
2) Support vectore machine(SVM)

After using the SVM classification, we have the accuracy of SVM: 0.80, then We draw the heatmap for conf usion matrix as bellow:



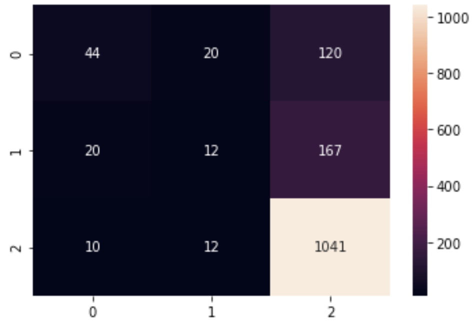
3) K Nearest Neighbor (KNN)

After using the K-NN classification, we have the accuracy of KNN: 0.73, then We draw the heatmap for confusion matrix as bellow:



4) Random Forest

After using the Random Forest classification, we have the accuracy of Random Forest: 0.76, then We draw the heatmap for confusion matrix as bellow:



Algorithm	Accuracy
Naive Bayes	79 %
SVM	80 %
KNN	73 %
Random Forest	76 %

Table 4 for the accuracy of predictions for algorithms using Title and review text where positive feedback count is greater than 1

Conclusion

We used sentiment analysis in this research to assess whether the product is recommended or not. To generate more accurate predictions, We did the project in three phases:1- predicting using title only 2- predicting by using review text only 3- predicting by using title and review text only 4- Predicting using Title and Review Text where Positive Feedback Count is greater than 1, and We used four Machine learning algorithms: Naive Bayes, Support Vector Machine (SVM), Random Forest, and K-Nearest Neighbor (KNN). We got the dataset from the Kaggle website's Woman Clothing Review. The accuracy of Naive Bayes and SVM appear better than the scores of other models in each phase. With Predicting using Title and Review Text where Positive Feedback Count is greater than 1, We got better accuracy 79 % and 80 % for SVM and Naive Bayes algorithms. There is no clear answer to the question of which algorithms are superior; each performs better in different data sets and under different conditions. Each modelling algorithm has its own set of advantages and disadvantages. As a result, we might choose one of these algorithms based on our requirements for accuracy or precision.

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