Sentiment analysis and opinion mining on E-commerce site

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Abstract: Sentiment analysis or opinion mining help to illustrate the phrase NLP (Natural Language Processing). Sentiment analysis has been the most significant topic in recent years. The goal of this study is to solve the sentiment polarity classification challenges in sentiment analysis. A broad technique for categorizing sentiment opposition is presented, along with comprehensive process explanations. With the results of the analysis, both sentence-level classification and review-level categorization are conducted. Finally, we discuss our plans for future sentiment analysis research.

Keywords: Sentiment analysis; Sentiment polarity, e-commerce; categorization; Natural language processing; Product reviews, customers’ reviews.

I. INTRODUCTION

In the 21st century, where people communicate and express their feedback through social media and express their opinions and feedbacks. Online activities day to day life increasing rapidly and they are involved with blogging, vlogging, review posting, social networking, etc. has resulted in an incremental lot of user-generated content. Most of the reviews and feedback has done by text process. This in turn has led to increased research in automatic classification, summarization, and opinion mining from web-based data. Opinion mining is the basic method to make a decision. For a product, service, or idea this is the popular way to organize as well as categorized. But it's impossible to take data from the user because many people are not willing to submit their answers to surveys. Also, there are a huge amount of data that need to be collected; but fails to detect the most important problems here opinion mining is the best thing to identify their problems and make product decisions and improve their market value. Not only organizations but also potential buyers want to know what the value of the product they buy is. In an organization, customers are heart when the organization releases a new product to market and want to know its market value. Nowadays customers view products online, on social media, on blog sites, and so on. Retrieving market value simply lies in surveying but it is not sufficient on today’s web. We need smart search where people's opinions had a great impact on the business of an e-commerce site or any organization where mining people's opinions on product attributes indicate positive and negative sentiments Established companies develop by taking care of people’s opinions, ratings, and reviewing of products Opinion mining is the key factor because where open eyes fail but algorithm scrub it out easily.[5] Because this opinion from the user influences another user. This paper is focused on sentiment analysis in the application of e-commerce to predict the performance accuracy of the data.

Opinion can be expressed as:

Direct Opinion: “This product performance is better”.

Comparative Opinion: “This perfume is better than that in its smell”

Fig. 1. Customer review on product.

II. LITERATURE REVIEW

This section covered additional papers relating to sentiment analysis on an e-commerce site. In most circumstances, taking positive or negative feedback from customers is important in market analysis of a product not only one commerce sites but also on physical markets. Market movement is forecasted by large marketplaces such as Facebook, Amazon, Rakuten, and Walmart. Customers mostly review products using text on their websites. These sentence-based reviews are categorized using either supervised or unsupervised algorithms. The study focused on e-commerce site data, namely customer reviews, where it scrabbled the data and analyzed product favorable, negative, or neutral praises. Natural Text Processing (NLP) is also emphasized, which converts human language to machine language by eliminating emojis, punctuation, and letter gaps, among other things. [11] The research also focused on ways to enhance data sets, such as data pretreatment for the system classifier to train itself. [12] Whereas developing a recommended model that might be useful for data analysis. Deep learning is fast expanding nowadays. The most common are current research field analysis and deep learning emotion analysis. If a buyer purchases a product with favorable or bad ratings. When sentence-level data is analyzed, it is simpler to boost production and satisfy both consumers and merchants.
[16] Sentiment analysis has grown in popularity in recent years, and it is becoming more prevalent by the day. Sentiment analysis on paper for quick feedback. Developing innovative procedures and processes improves consumer reviews, which has a significant influence on the market. Online apps handle pricing, rating, comments, and so on for various items on an e-commerce site. Whereas designing an application based on sentiment analysis will place a greater emphasis on consumer product reviews. A good analysis also has an impact on the reputation of a well-established organization in order to increase its productivity globally.

III. SENTIMENT ANALYSIS

In this digital age, individuals from all over the world exchange their data on a single activity as well as their experiences. The information given might be organized or unstructured. Structured data is retrieved from an e-commerce site using a GUI that gathered the data from product feedback. Unstructured data are user remarks that cannot be categorized as good, negative, or neutral. The method of sentiment analysis is used to obtain user data via an interface. This method retrieves and categorizes all essential data from the e-commerce site.

Sentiment analysis measures the accuracy of the data by analyzing the user’s experience. Some ideas to analyze the user experience. They are product reviews [1], stock market predictions [2], and brand monitoring [3], customer feedback [4]. According to a USA survey, there are 81% of internet users are buying products from online platforms [5]. Three-level sentiment analysis about Sentence-level Sentiment Analysis (SSA), Document-level Sentiment Analysis (DSA), and Aspect-level Sentiment Analysis (ASA).

A. Sentence-level Sentiment Analysis (SSA)

SSA refers to sentiment conveyed in sentences where linguistic content is utilized to determine if something is positive, negative, or neutral. This scrapes the client attitude by using their sentences, such as reviews and comments [6]. The authors develop a phrase recursive autoencoder (PRAE) model for identifying sentiment in sentences for coarse-grained review analysis [7]. However, this sentence-level sentiment analysis is unable to extract fine-grained characteristics from the words.

B. Document-level Sentiment Analysis (DSA)

DSA refers to discussing unpleasant or happy emotions. Opinions extracted from the entire document [6][5]. The researcher presented a neural network approach to detect phrase categorization semantics [7].

C. Aspect-level Sentiment Analysis (ASA)

The polarity of emotion output of each word in input data is preset in each aspect. It captures comments such as "I adore this brand." Where it said "love" in this sentiment analysis statement For further examination of this data, sentiment polarity was also applied [6]. The researcher discusses the technique of extracting consumer preferences for air purifiers using fine-grained sentiment analysis of internet reviews [7].

IV. METHODOLOGY

Sentiment analysis is a method of recognizing and extracting sentiment information from text, audio, or databases using a computer. Sentiment analysis was also used to classify emotions, subjective impressions, and points of view [8]. This article's primary goal is to characterize customer sentiment. Whereas Fog 2 demonstrates the techniques used to assess the sentiment of customer reviews.
So many users use emojis in reviews to express their emotions. The strong way that helps people’s sentiment analysis. But these emojis should be turned into text format so that machine learning can identify the specific sentiment regarding the customer [10]. Some emojis converted into emotions are given below.

**Fig.3. Converted Emojis example**

- **Transform Cases**
  
  There are several cases in a sentence, such as upper-case and lower-case letters. For normal scenarios, converting all terms to lower case will facilitate data standardization. Data transformation improves result accuracy [11].
- **Remove stop words**
  
  The goal is to simply delete terms that appear often in all of the papers in the corpus. Articles and pronouns are typically categorized as stop words [11].
- **Removing punctuation**
  
  In a particular sentence, there also come so many punctuations like ‘!’, “’, Etc. Better accuracy in data mining it needs to remove.

V. PROPOSED MODEL

Analyze customer reviews for a particular product, a model that would be the best option for sentiment orientation classification. Regarding this issues ‘Supervised Learning Approaches” classify the sentiment orientation in a new document [12]. In this system classifier, it trains itself and classifies the opinion which are positive and which one is negative. Mentioning some popular supersized models are,

1. **Logistic regression model (LR)** [13]: In this model, the dichotomous means of two possible classes either 1 or 0 classification algorithm.
2. **Naive Bayes (NB)** [14]: For making quick predictions on a large amount of data this system of algorithms can help easily. Most effective classification system in NLP.
3. **Maximum Entropy (ME)** [14]: Deals with conditional distribution for a specific class level with a probabilistic model
4. **Support Vector Machine (SVM)** [13]: An approach for supervised machine learning called SVM can be applied to classification or regression issues. Your data is transformed using a method known as the kernel trick, and based on these modifications, it determines the best border between the potential outputs.

Creating a model for this opinion mining it’s easier to identify and solve the problems. For this approach proposed model including below,

**Fig.4. Proposed model for sentiment analysis of user**

VI. EVALUATION

After identifying the data, the confusion matrix assessment is applied. The confusion matrix table is illustrated in True Positive (TP) is the number of data points that have been labeled as positive and categorized as such by the classifier. The amount of data points labeled as positive but categorized as negative by the classifier is known as false positive (FP). True Negative (TN) is the number of data points that have been labeled as negative and categorized as such by the classifier. The number of false negatives (FN) is the number of data points that were labeled as negative but were categorized as positive by the classifier.

Actual values

| Positive | Negative |
|----------|----------|
| TP       | FP       |
| FN       | TN       |

The performance of the classifier is measured with accuracy, precision, recall, and f-measure,

\[
\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{(i)}
\]

\[
\text{Precision} = \frac{TP}{TP+FP} \quad \text{(ii)}
\]

\[
\text{Recall} = \frac{TP}{TP+FN} \quad \text{(iii)}
\]

\[
\text{F- measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad \text{(iv)}
\]

**Table-2. Confusion matrix of proposed model**

| Method      | TP | FP | TN | FN | TP  | FP  | TN  |
|-------------|----|----|----|----|-----|-----|-----|
| SVM         | 156| 15 | 86 | 46 | 136 | 16  | 94  |
| Naive Bayes | 106| 14 | 98 | 39 | 119 | 9   | 104 |
| Decision Tree | 161| 89 | 29 | 4  | 161 | 89  | 39  |
The confusion matrix is primarily used to assess paper mismeasurement, whereas the precision calculator computes performance accuracy, precision, recall, and f measure. It compares the confusion matrix of TF-IDF sentiment analysis and sentiment analysis utilizing a combination of TF-IDF and Backward Elimination in five different machine learning algorithms.

### VII. RESULT

In this paper, sentiment analysis discussing based on text type data where various types algorithm used where ML based are mostly used to identify the sentiment of user. In this graph it easy to define that algorithm SVM and Logistic Regression performed well. SVM algorithm accuracy almost 79% for this textual data analysis. It’s mainly for the text type data taken for analysis of user sentiments. Whereas it will be more accurate by using lots of data, ensemble methods, cross validation etc. Whereas using DL algorithm it will be more accurate in this result section. By using Long Short-Term Memory (LSTM) networks it will provide almost 89% accuracy.

### Table-3. ML Based accuracy

| Algorithm            | Accuracy |
|----------------------|----------|
| SVM                  | 79%      |
| Logistic Regression  | 77%      |
| Random Forest        | 76%      |
| Naïve Bayes          | 52%      |

### VIII. CONCLUSION

According to this study, the sentiment analysis technique and methodologies are based on earlier studies on e-commerce sites. Based on previous ratings, this review depicts client happiness on numerous e-commerce sites. Customers that buy things online using data analysis get a lot of trust from them. Many academics employed various ways to determine client attitudes in order to assess customer behavior. The ideal technique is to do a sentiment analysis on consumers’ opinions. As a result, there are several hurdles to improving data accuracy, which may be avoided by employing efficient and dependable ways to sentiment analysis. This study may be used in the future to compare to others with larger data sets and featured selection methods. Sentiment analysis is a very important tool for businesses since it allows them to get honest feedback from customers in an unbiased (or less biased) manner. If done properly, it has the potential to greatly increase the value of your systems, apps, or online projects.

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