A Sentiment Analysis Engine for Online Product Reviews

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Abstract

Nowadays online shopping has become part of our daily life and it becomes hard for customers to assess the quality of a product from the selling website. The existing mechanism rating based model takes into account a rating-based score, but not the qualitative feedback of a particular product from the valid consumers. In this paper, we are announcing a decision-making engine named Guppy for online products based on sentiments of consumer reviews. Here the reviews can be termed as an opinion and obviously, it varies from consumer to consumer for the same product. Each opinion contains the feeling, experience, and most importantly sentiments. Sentiment identifies that an expression bears whether positive attitude or negative attitude or neutral attitude. By analyzing the sentiments of opinions for product reviews, we can find out the polarity of each opinion. Most of the cases opinions vary from consumer to consumer, but the polarity of opinions may remain the same if both consumers are satisfied or disturbed with the product in the same way. By finding polarities of all the opinions we can easily decide on the product in less time. We planned Guppy as a web stage for simple availability. We kept the interfaces spotless and moderate, so clients can communicate with the stage without any problem. In the backend we have used machine learning techniques for sentiment analysis, using reviews as data (amazon.in), which is more efficient and time-saving than a customer manually going through all the reviews then decide, we prepared a Naive Bayes Classifier to group the extremity of assessments of purchaser audits that prompts ultimate conclusion.

Customers need to understand the quality of their selected products. This paper provides a comprehensive overview of the background and the underlying theory of analogy for sentiment analysis engine. Users can access the platform with https://reviewguppy.herokuapp.com for demo purposes.

Keywords: Guppy, Sentiment analysis, Naïve-Bayes-classifier, Consumer review.

1. Introduction

E-commerce platforms have brought a revolutionary change in the way people shop. Most people, in rural or urban areas, shop online. In India, the number of digital buyers in 2016 was 130.4 million and by 2020, this number is estimated to be 329.1 million. Moreover, online retail sales in India brought revenues of 38 billion dollars by 2020 India is expected to generate $100 billion in online retail revenue. So, it is obvious that online sales are set to grow four times in the coming years. The number of E-commerce platforms have brought a revolutionary change in the way people shop. Most people, in rural or urban areas, shop online. In India, the number of digital buyers in 2016 was 130.4 million and by 2020, this number is estimated to be 329.1 million. Moreover, online retail sales in India brought revenues of 38 billion dollars by 2020 India is expected to generate $100 billion in online retail revenue. So, it is obvious that online sales are set to grow four times in the coming years. The number of e-commerce platforms has increased rapidly and there are lots of products with different features. So, they categorize the products by using a rating-based model on a scale from 0 to 5. A higher rating means a better product. But the rating is just selecting a button out of five buttons. While rating a product, people don't think much and just give an average rating which does not specify the qualities of the product, for example, whether it is good or bad. On the other hand, buyers also give their reviews. Reviews of a valid user are very important as they carry the feelings, experience, and sentiment of the buyer. So, apart from the rating, buyers also read the reviews posted by a user of that product. Different users express different experiences and sentiments for a single product. So, a buyer should read almost hundreds of reviews to come up with a decision. Reading hundreds of reviews and coming up with a decision is a very tedious and time-consuming task. So, we came up with a solution to this problem by developing an intelligent system that reads all the reviews of a product and provides a decision to the buyer.

The core objectives which have been designated as fundamental to the project are: Identify and understand the sentiments of the users expressed in product reviews. Reduce human effort by analyzing reviews by an automated system. Save human time by analyzing hundreds of reviews within a few moments. Help buyers make a fast and reliable decision while purchasing online. Overall, build an intelligent decision-making system by implementing a sentiment analysis engine to give buyers a smooth online shopping experience.

The utilization of web-based business stages is expanding step by step as the number of items on those stages. Customers regularly take the rating of an item as a benchmark. In any case, there are audits posted by a client of that item. Alongside rating, customers will in general read those surveys to get thought regarding the item from a client's point of view. Since regular audits express something other than a rating. Once more, there might be some appraising which was given erroneously. On the off chance that a customer attempts to peruse all the surveys and even a few pages of audits and go to a choice, it will take a ton of time and is a misuse of human time. Thus, our foundation, Guppy, pursues openly accessible audits and breaks down the estimations of those and gives an attainable choice to that item. We will probably show that feeling the investigation of item audits can help settle on a choice, regardless of whether it very well may be purchased or can't be purchased, and sparing human time. For this reason, we have utilized Amazon **https://www.amazon.in** items and their audits for an investigation to give a demo.

2. Related work

2.1. Product Review Sentiment Analysis with Aspect Ranking [5]

Product aspect ranking framework has been used, which automatically identifies the important aspects of products from online consumer reviews, aiming at improving the usability of the numerous reviews. Important product aspects identification is based on two observations: 1) the important aspects are usually commented on by a large number of consumers and 2) overall opinions on the product is decided by opinions on important aspects of those products. In particular, consumer reviews of a product are given in textual format; first parse the reviews with natural language processor to identify the aspects of particular product then for sentiment analysis. Sentiment classifier such as Naïve Bays or SVM to classify the comments as positive and negative sentiments has been used. After sentiment analysis probabilistic aspect ranking algorithm is applied for usual aspect ranking. The process of product aspect ranking consisting of three main Steps:

- Aspect identification
- Sentiment classification on aspects
- Product aspect ranking

2.2. Stanford Sentiment System

Numerous research efforts have also studied the same task on reviews. How to use NLP techniques to categorize Amazon reviews according to their sentiment. Similarly, the Stanford Sentiment System [6] has been proposed recently in the domain of movie reviews. It contains the Stanford Tree Parser, a machine-learning model that parses the input text into the Stanford Tree format and uses some existing models, some of them being trained especially for parsing tweets. The Stanford Sentiment Classifier is at the heart of the system. This classifier takes as input Stanford Trees and outputs their classification results. The Stanford Sentiment Classifier provides also useful detailed results such as classification label and classification distribution on all the nodes in the Stanford Tree. The Stanford Sentiment System is a Recursive Neural Tensor Network trained on the Stanford Sentiment TreeBank that is the first corpus with fully labeled parse trees which makes possible training a model with large and labeled dataset. This model stores the information for compositional vector representations, its size of parameters is not very large and the computation cost is empirically tested as feasible in the movie review domain. In addition, the Stanford Sentiment System captures the meaning of longer phrases and shows a great strength in classifying negative sentences. It beats the bag of word approaches when predicting fine-grained sentiment labels.

3. The Method

We have tried to include every kind of opinion of the customers of all products in our analysis. In some cases, it was difficult and time-consuming to categorize the data but to bring accuracy in the highest possible amount, they were not compromised.

3.1. Study design

For our sentiment analysis engine, we have determined the hypothesis as Good reviews increase the chance of more sales with one discrete dependent variable CUSTOMER REVIEW, and two discrete independent variables PRODUCT QUALITY, SERVICE QUALITY. To test the hypothesis in our case we have structured an online survey. To analyze and classify the sentiment of customer reviews we could use other models also. But we have used the Bayes model to get the most efficient outcome from our sentiment analysis engine. The following table will help to understand the leveling of our engine.

Positive Review	**Negative Review**	**Neutral review**	**Decision**
100%	0%	0%	Recommended Product
0%	0%	100%	You can go for other similar Product
0%	100%	0%	Do not Buy
50%	0%	50%	Recommended Product
0%	50%	50%	Do not Buy
50%	50%	0%	You can go for other similar product

Table 3.1.1

Positive & Neutral Reviews	**Decision**
%>=90	Recommended Product
% >=75 & % < 90	Recommended Product
%>=70 & % <75	Recommended Product
%>=65 & % <70	Recommended Product
%>=55 & %<65	You can Go for other similar product
%>=45 & % <55	You can go for other similar product
%<45	Do Not buy

Table 3.1.2

3.2. Implementation

Our Sentiment Analysis Engine for Online Product Reviews (Guppy), there exist four components that helped to build the engine. The following are the components used for this analysis engine: Scraper, Natural Language Processing, Classifier, Server. We used Python as the main implementation language to build the system in the back-end and also to create servers. HTML, CSS, and JavaScript are used to build the front-end. We also used some frameworks and libraries to ease our development. Python is an interpreted high-level programming language for general-purpose programming. Python has a design philosophy that emphasizes code readability and a syntax that allows programmers to express concepts in fewer lines of code, notably using significant whitespace. Python features a dynamic type system and automatic memory management. JavaScript, is a high-level, interpreted programming language. It is a language that is also characterized as dynamic, weakly typed, prototype-based, and multi-paradigm. It is used to make webpages interactive. The majority of websites employ it, and all modern web browsers support it without the need for plug-ins employing a built-in JavaScript engine.

3.3. Model & Data Analysis

For our sentiment analysis engine, we have used Bayes' model. We trained our model with real reviews collected from Amazon (India) and analyzed them depending upon the sentiments. We have covered almost all the products from amazon. For our Analysis engine here, we used the steps of NLP to pre-process the product review: Structure extraction Converting all characters to lower case character, Split characters, Stemming or Lemmatization, Stop-words, Tokenization or Vectorization, Bag of Words Model. The libraries used in the project are NumPy, pandas, matplotlib, scikit-learn, NLTK, Beautiful Soup. And the frameworks used in the project are Flask, Semantic UI.

Our model will classify the individual review as positive or negative or neutral.

NLTK: The Natural Language Toolkit, or more commonly NLTK, is a suite of libraries and programs for symbolic and statistical natural language processing (NLP) for English written in the Python programming language. the underlying concepts behind the language processing tasks supported by the toolkit, plus a cookbook. NLTK supports classification, tokenization, stemming, tagging, parsing, and semantic reasoning functionalities.

Beautiful Soup: Beautiful Soup is a Python library for pulling data out of HTML and XML files. It works with your favorite parser to provide idiomatic ways of navigating, searching, and modifying the parse tree. It commonly saves the programmer's hours or days of work.

3.4. Procedure

Our proposed intelligent system will follow the steps:
• Get the product URL from the consumer. • Collect product information from provided URL • Gather review data of the product from provided URL • Preprocess the collected review data • Polarity classification of gathered reviews into positive or negative or neutral labels • Analyze the classified reviews to get a statistic result • Provide an efficient decision based on statistical results to help consumers in less time.

Initially product reviews were made into raw dataset using web scrappers and python scripts. Tokenization, Stemming and splitting were done on the raw dataset and it forms Effective data. Data is then classified and then passed into sentiment source where final decision has been made whether to buy the product or not or look for other same products which is latter shown to the User.

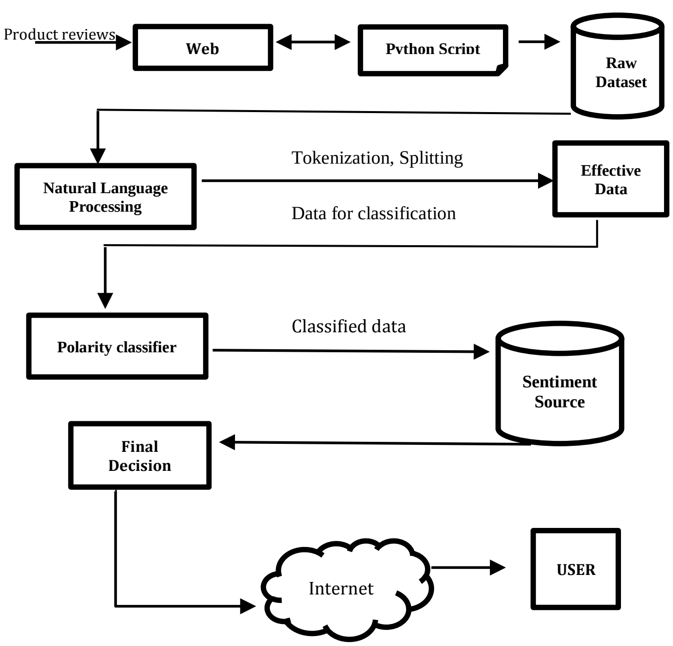

Fig: Block Diagram

User will have to open the website Guppy by using following link [https://reviewguppy.herokuapp.com/]

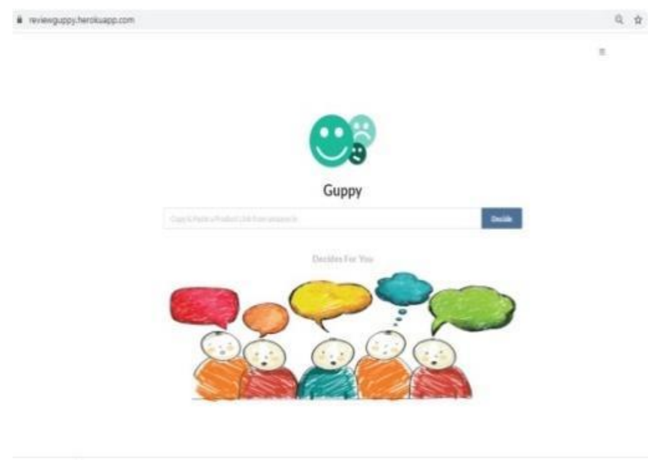

Fig: Home Page

The selected product URL will then be pasted into the bar and apply for results e.g. decision page for OnePlus5T (Midnight black, 6GB RAM, 64GB Storage) as shown

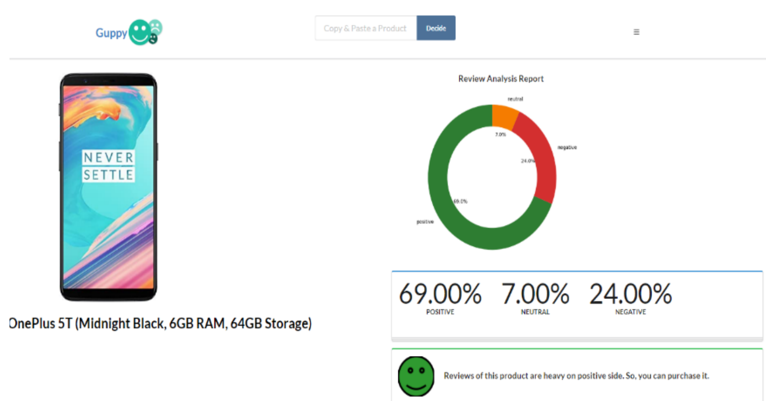

Fig: Decision page

3.5. Measures

We are measuring the sentiment of individual review of products in-terms of positivity, negativity and neutrality based on polarity of a review. The existing model (rating based) doesn't bear any feeling or experience or sentiments of the user of that product. It may be visualized as a random click on a button as the user wishes. This model is not perfect to categorize products. Moreover, some reviews are found to be inappropriate with the reviews meaning the rating doesn't match with the reviews.

4. Results

In this study, we built a system that aims to analyze reviews of e-commerce products and provide a feasible decision for consumers. So, the outcome of the system should be easily readable by consumers. Thus, we provide pellucid charts and decisions (in the simple text) in a human-readable format. In this system, we analyzed product reviews based on consumer's sentiments. This system generates charts and provides a feasible decision about the product. This is very helpful for consumers and businesses as well. The consumer can see how many people have expressed positive feelings and how many people have expressed negative and neutral reviews. The manufacturer also can use the result to improve its product. As our system is dependent on reviews, it is possible that popularity can affect product quality. What we have shown in this study is that public reviews are a very important factor in e-commerce. We implemented a way to automate decision-process about a product based on reviews. So that consumers don't have to read all the reviews wasting their time. But there are many lacunae in our system. Currently, we are analyzing the overall sentiments of reviews. It can be possible to extract sentiments for different attributes of a product. This will help to develop better decision-making rules. Manufacturers can also know which features of a product are getting negative reviews and they can improve the product quality. Guppy, which helps the buyer to decide in the fastest way about any product with an accuracy of 92.87% based on our survey. Previously, this decision making had to be done by the buyer spending a lot of time and thought in any individual product. We have used amazon.in here, but if taken approach, can be applied for any shopping website. We have presented some use cases here to verify the functionality of the website. Further work could be implemented using other issues as the budget of the buyer or individual choices.

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