Classification and Summarization of Amazon Product Reviews

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Abstract - *Feedback of the customer is the secret behind the growth of the companies like Google, Amazon. On analyzing the feedback of the customer on a product, the quality and service of marketing has been increasing. Reviews collected from online shopping sites (such as Amazon) helps both the customer and manufacturer to know the advantages and disadvantages of the product. One should go through all the reviews to know about a particular product. But it is hard for a person to read all the reviews as the product may have thousands of reviews. This project aims at classifying and summarizing the product reviews in real time. Dataset consisting of large number of data are used for training process. The dataset which includes product details and reviews of the product are collected from Amazon.com. The fetched reviews are classified into positive and negative and the classified output is represented in the form of pie-chart using sentiment analysis. The classified reviews are summarized and the short description of positive and negative reviews are displayed. The implementation of this system is achieved by using Python and Django. The statistical results that are generated by the system are visualized with React. This project can be further developed to analyze the reviews of other e- commerce websites.*

***Key Words*: Feedback of the customer, Dataset from Amazon.com, Sentiment analysis, Positive and negative classification, Summarization.**

1. INTRODUCTION

Now a days, online shopping zone plays a major part in marketing and best example is Amazon. When a customer buys a product on the internet, he/she will be provided with many choices based on the brand, colour, prize, etc. Multiple collection of new products, new brands new business strategies happen daily. This may lead a customer confused to make best choices of product. Online shopping sites customer post their reviews of the product. Amazon provides the overall rating of the product. But based on the rating one cannot decide the all the features of the product. Let us consider a scenario, a person searched for air conditioner. While searching for the product, person tends to see the overall ratings of the product. For a particular brand with affordable prize the overall rating is 4. But on going through the reviews many were not happy about few features. On the other scenario, for bad packaging of the product many customers gave less than 2 stars. In such scenario, rating is not reliable to conclude on the quality of the product. On the other hand seller wants to know exact feedback of the customer to improve the quality of the product. Fetching reviews on the major features of the product helps to improve the marketing of the product. The solution for these problems is to go through all the text reviews to understand which feature of the product needs to be modified. As each product may have thousands of reviews that makes the work difficult. So, a system is built to that work.

2. LITERATURE SURVEY

The related work on this project shows that there have been several methods of implementing the system under different domain:

[1] This system aimed at sentiment classification of Amazon book reviews written in Italian language. The system has been implemented using NLP techniques, Lexicon-based approach. Classification of sentences is done through parsing. Here the dataset is collected from Amazon website. The system has been implemented using Python language. This system is able to classify both positive and negative reviews, with an average of about 82% accuracy.

[2] Twitter sentiment analysis offers organizations an ability to monitor public feeling towards the products and events related to them in real time. The first step of the sentiment analysis is the text pre- processing of Twitter data. This paper discussed the effects of text pre-processing method on sentiment classification performance in two types of classification tasks, and summed up the classification performances of six pre- processing methods using two feature models and four classifiers on five Twitter datasets. The Naive Bayes and Random Forest classifiers are more sensitive than Logistic Regression and Support Vector Machine classifiers when various pre-processing methods were applied.

[3] Online Social Networks generate a prodigious wealth of real-time information at an incessant rate. In this paper we study the empirical data that crawled from Twitter to

describe the topology and information spreading dynamics of Online Social Networks. We propose a measurement with three measures to state the efforts of users on Twitter to get their information spreading, based on the unique mechanisms for information retransmission on Twitter. It is noticed that small fraction of users with special performance on participation can gain great influence, while most other users play a role as middleware during the information propagation. Thus a community analysis is performed and four categories of users are found with different kinds of participation that cause the information dissemination dynamics.

[4] Hate speech detection on Twitter is critical for applications like controversial event extraction, building AI chatterbots, content recommendation, and sentiment analysis. We dene this task as being able to classify a tweet as racist, sexist or neither. The complexity of the natural language con- structs makes this task very challenging. We perform extensive experiments with multiple deep learning architectures to learn semantic word embeddings to handle this complexity. Our experiments on a benchmark dataset of 16K annotated tweets show that such deep learning methods outperform state-of-the-art char/word n- gram methods by ~18 F1 points.

[5] Motions play an important role in successful and effective human–human communication. In fact, in many situations, emotional intelligence is more important than IQ for successful interaction there is also significant evidence that rational learning in humans is dependent on emotions. Moreover, they find applications in various scenarios and companies, large and small that include the analysis of emotions and sentiments as part of their mission. Sentiment-mining techniques can be exploited for the creation and automated upkeep of review and opinion aggregation websites, in which opinionated text and videos are continuously gathered from the Web and not restricted to just product reviews, but also to wider topics such as political issues and brand perception.

3. PROPOSED SYSTEM

In proposed system, sentiment similarity analysis has been implemented using machine learning unsupervised and supervised algorithm. In this method modeled the sentiment classification problems as learning sentiment specific word embedded issue and designed three neural network to effectively incorporate the super vision from text data with sentiment labels. We propose an effective method to compute sentiment similarity from a connection between semantic space and emotional space. We show the effectiveness of our method in two NLP tasks namely, indirect question answer pair inference and sentiment orientation prediction. Our experiments show that sentiment similarity measure is an essential pre-requisite to obtain reasonable performances in the above tasks. We show that sentiment similarity significantly outperforms two popular semantic similarity measures, namely, PMI and LSA.

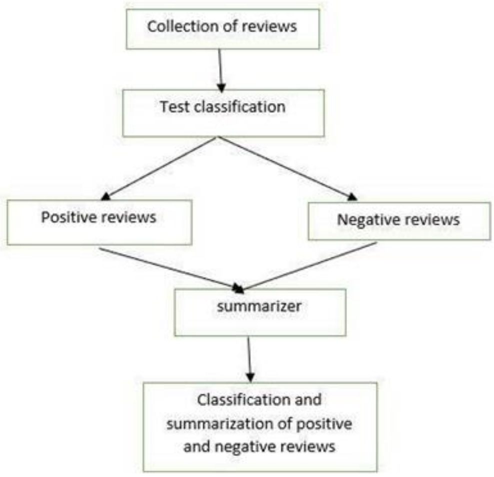

Fig -1: Block diagram

3.1 Collection of Dataset

The dataset used in this system has been fetched from Amazon. It is fetched as a .json file and it contains two columns namely Review text and Rating of the review. The dataset contains 10,00,000 data which are to be trained and analyzed.

3.2 Data Pre-processing

Pre-processing refers to the transformations applied to our data before feeding it to the algorithm. Whenever the data are collected from different sources it is collected in raw format, which is not feasible for analysis. The purpose of this step is to clean those raw data to make it feasible.

3.3 Text Summarization

Text summarization is a subdomain of Natural Language Processing (NLP) that deals with extracting summaries from huge chunks of texts. The steps involved in text summarization are (i) Fetching reviews from Amazon. (ii) Preprocessing. (iii) Convert text to sentences. (iv) Find weighted frequency of occurrence. (v) Calculating Sentence scores. (vi) Getting the summary.

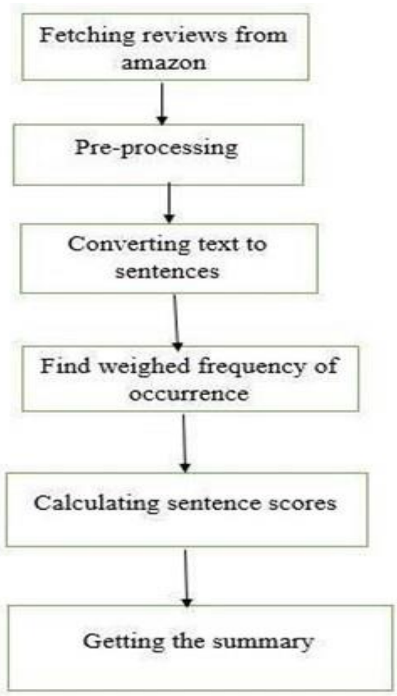

Fig -2: Block diagram – Summarization

3.3.1 Fetching reviews from Amazon

We first need to convert the whole paragraph into sentences. The most common way of converting paragraphs to sentences is to split the paragraph whenever a period is encountered. Text summarization is the technique for generating a concise and precise summary of voluminous texts while focusing on the sections that convey useful information, and without losing the overall meaning. Automatic text summarization aims to transform lengthy documents into shortened versions, something which could be difficult and costly to undertake if done manually. Machine learning algorithms can be trained to comprehend documents and identify the sections that convey important facts and information before producing the required summarized texts.

3.3.2 Pre-processing

After converting paragraph to sentences, we need to remove all the special characters, stop words and numbers from all the sentences. Performing the filtering assists in removing redundant and insignificant information which may not provide any added value to the text's meaning.

3.3.3 Convert text to sentences

We need to tokenize all the sentences to get all the words that exist in the sentences. Tokenization is the process of breaking up a given text into units called tokens. Tokens can be individual words, phrases or even whole sentences. In the process of tokenization, some characters like punctuation marks may be discarded. The tokens usually become the input for the processes like parsing and text mining.

3.3.4 Find weighted frequency of occurrence

Next we need to find the weighted frequency of occurrences of all the words. We can find the weighted frequency of each word by dividing its frequency by the frequency of the most occurring word. NLTK allows us to easily count the number of times that each word occurs in our text with nltk.FreqDist(); by dividing the number of times a given word occurs by the total number of words in our text, we can find the weighted frequency that each word occurs.

3.3.5 Calculating sentence scores

The final step is to plug the weighted frequency in place of the corresponding words in original sentences and finding their sum. It is important to mention that weighted frequency for the words removed during preprocessing (stop words, punctuation, digits etc.) will be zero and therefore is not required to be added.

3.3.6 Getting the summary

The final step is to sort the sentences in inverse order of their sum. The sentences with highest frequencies summarize the text.

3.4 Training the data

The data is trained to the algorithm or model so that it can accurately predict the outcome. The performance of the model is evaluated using some performance metric. The observations in the training set form the experience that the algorithm uses to learn.

3.5 Predicting and evaluating the model

This step involves partitioning the original observation dataset into a training set, used to train the model, and an independent set used to evaluate the analysis. The choice of evaluation metrics depends on a given machine learning task. The evaluation metric used here is classification.

4. CONCLUSIONS

This project was a good learning experience with fascinating challenges. Our passion for Machine learning drove us to choose this topic and complete it in a good way. Among the different tasks involved in the system implementation data collection and pre-processing was the most time consuming one. Major feature identification and Opinion mining are the technically difficult tasks. We are partially satisfied with the evaluation results, especially with performance which should be improved a lot with better cost-effective algorithms. Yet, we are highly satisfied with the accuracy of results in most of the products. Improving and enhancing this idea will be a very useful application. This system is used to extract feature-based feedback would be helpful to consumers of retail and e- commerce business. The industrialists, manufacturers and merchandisers can benefit from this system to improve the quality of their product and services.

In future, we would like to expand the project wherein the reviews of all other e- commerce websites would be analyzed. Also we would implement the project in such a way that it incorporates business analytics.

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