International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 10 Issue 7 ǁ July 2022 ǁ PP. 581-584

An Efficient Approach to Improve Aspect Based Classifier in Customers Review

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Abstract
In the business arena, the feedback of customers plays a pivotal role. Inappropriate reviews against a product may mislead both the consumer as well as the service provider. Review is a tool to sway consumer decisions and also can strengthen a company's credibility. Reviews have the power for clutching customer trust, and also create a healthy forum for the customers to interact with the company. As reviews are the lifeblood of certain service providers like the restaurant industry, do the restaurants get the correct reviews? Is a multi-dollar question. Customer review is the only keystone to making a restaurant stand out from the competition, raising engagement and ultimately increasing profits. In this paper, different types of reviews are analyzed and the reviews are classified according to the type. An Efficient Approach to Improve Aspect Based Classifiers in Customers Review is proposed to find, what the reviews are actually about, which in turn helps the service provider improve the business and also it helps the customer to make the decision about the service.

Keywords
Natural language process, Machine learning, Neural network, Classification, Transfer learning

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Date of Submission: 05-07-2022 Date of acceptance: 19-07-2022

I. INTRODUCTION

Due to the benefits of sharing previous customers' open experiences and opinions, online reviews have grown in importance among future customers with the development in online activities related with the purchase of restaurant services[1]. Customers now have more control in their decision-making thanks to reviews. User evaluations may steer customers to better restaurants, forcing lower-quality eateries to close or raise their standards in response to shifting customer preferences.

The reviews that classify the customers give to a restaurant are based on service or the quality of food. Everything is now available at our fingertips thanks to the internet, from grocery shopping to researching our next new car purchase. The internet is changing from a place to post a lovely website to advertise your business to a forum where customers may rate products and services based on opinions and comments from other customers [2]. Although it is simple to believe that customer evaluation and customer evaluations are significant, nothing illustrates this point more clearly than objective statistics on how reviews are used and how they affect businesses.This analyze how customers behave before and after using services or buying products, which can help develop plans to improve business.

These Reviews are of so much importance to the organization. Because based on the reviews the organization can improve their services and the quality of the product they deliver or which they provide. There are so many pseudo ratings coming in the current scenario, like one of the common problems which the companies are facing currently is the mixed type of reviews being put on the product. These kinds of diverse reviews kind of hinder the analysis and the decision made by both customers and the organization. Currently, they have to go through each of the reviews separately manually and then classify the review whether it has a review for a product or that was a review for a service [3]. For example, in-door delivery type restaurants or some online service providers of food, if the food leakage or packing was too bad when it was delivered. That was the mistake cost by the delivery person then the review should be classified as a service-based review and in the case where was not high quality or the quantity was less than the rating should be given for the food rather than for service [4]. Having wrong reviews against a product might be misleading for both the consumer as well as the organization itself. For example, if a person orders food online and the delivery was late, the consumer rate the product to 1-STAR. The next consumer browsing through the product might assume that the review isthe review for the quality of food.

The reviews based problems exist in present-day to day life, when we are browsing through online e-commerce sites [5]. So this is an important thing in the industry and also it has practical applications. Following are the consequences:

- People misjudge a particular food item based on the reviews given which might be actually given to the service that the restaurant or the delivery partner provided.
- If the reviews are properly grouped then the restaurants can take initiative to improve the quality of a particular product that the customer finds not up to the mark.
- The restaurants or the delivery partner can improve the quality of the service they provided to the particular employee.

So, in the review of literature, the existing solutions to the above said problems are analyzed.

II. REVIEW OF LITERATURE

As discussed in the introduction section collecting feedback from the user and predicting the views of the users are taken into account as parameters for doing this survey. It was analyzed how the said parameters are handled in decision making. In paper [6], using a Machine Learning algorithm the authors proposed a decision-making system and find the polarity of different entities. Restaurant reviews are taken as data to implement this proposed algorithm.Hadoop framework was used to classify product reviews in order to get the availability, price, and also suggestion to buy the product online, [7]. Aspect-based sentiment analysis is used from the reviews of the customers to analyze the challenges and to generate a report proposed in [8], here the reviews about the government applications are considered as data for implementation. In paper [10], aspect-based sentiment analysis was used to classify the given text into positive text and negative text. The proposed work considers only words in the document as input not as a whole sentence. The authors in [11] find the polarity of the opinion target in the given feedback like positive, negative, and neutral. In the work [12], the classification result for aspect category and aspect sentiment prediction was done with Twitter Corpus, here sentiment-based learning model was used. Aspect-based sentiment analysis on Economic and financial lexicons is focused on [13]. This proposed system extracts the sentiments from social media and the polarity score lies between -1 and +1.

III. PROPOSED SYSTEM

A. Problem Statement

In implementing the proposed system, the data from an online source are collected and loaded into a python environment using pandas. The collected data is split into training data set and a testing data set, which is a 90% and 10% split. After splitting the data we keep the test data aside so that later we can use this test data for model validation of the trained model. In-text pre-processing, the removal of Html content (Html tags) and Removal of non-alphabetic characters, URLs other HTTP requests available in the reviews they have marked are removed. Then tokenizing the review sentence is done and then each word will be converted into the specific word to their lemmatize form. As we know, Tokenization is a process of splitting a text object into smaller units which are also called tokens. Lemmatization is converting the words into their root form. So once we get the lemmatized word for each review we concatenate back all the words to reconstruct back the review. After text pre-processing, encoding of our target class was done using the label encoder which gives 0&1 for product and service. So here we are using a Neural Network based model. The first layer is converting text into Numerical Vector, for text encoding Universal Sentence Encoder which is a pre-trained model from Tensorflow is used.

It builds a classification model to predict whether the review belongs to a service-based review or is related to the quality of the food. After the classification of the review, every type of review can be analyzed separately and derive meaningful insight from them. This can be used to improve services or the quality of the product which they deliver also this gives proper ideas to customers without misleading them with improper reviews. Hear targeted clients are Online Food Delivery Giants.

The only mandatory required thing is that they should have a platform where they take customer review and record it properly. So that they plan to improve their services or improve their food based on these reviews. The present Scenario is that every restaurant tries to build an online presence and accept reviews and tries to better themselves.

B. Proposed Methodology

Here, at the very first, Load the data and Split the entire data into a train test set. Then work on the train data set and clean the text reviews. After that encode the target class and later build a Neural Network layer. Should keep the first layers as text encoders to covert the text reviews into numerical vectors, and add then and drop out layer as necessary for the neural network. Next, train the neural network using the training data and use the test data on the trained model and analyze the result. At last plot, the confusion matrix and calculate evaluation matrix-like precision, recall, and F1 score. Further time tune the model to improve the result.

We can better comprehend model evaluation by using precision and recall metrics, which take classification accuracy one step further. Depending on the task and our goals, we should choose one over the other.

Precision = TP/ TP+FP --------------(1)
Recall = TP/TP+FN ---------------(2)

Precision and recall are weighted averaged to produce the F1 score. Because it accounts for both false positives and false negatives, the F1 score is a more helpful metric than accuracy when it comes to issues with unequal class distribution. The ideal f1 score value is 1, and the unfavourable value is 0.

F1 score = 2 (Precision*Recall / Precision + Recall) --------------(3)

C. Mathematical Methodology

When measuring the effectiveness of a classification model, N, the number of target classes, is utilised to create a N x N matrix called a confusion matrix. The machine learning model's predictions are put up against the actual target values in a matrix.

By displaying the accurate and inaccurate (i.e., true or false) predictions for each class, the confusion matrix goes beyond classification accuracy. A confusion matrix is a 2 by 2 matrix when it comes to binary classification tasks. A 3x3 matrix is used when there are three different classes, and so on.

Consider the scenario where class A is positive and class B is negative. The following are the confusion matrix's key terms:

- **Predicting favourable results as positive is known as a true positive (TP) (ok)**
- **False positive (FP): Assuming negative information as positive (not ok)**
- **False negative (FN): Predicting positively and seeing it as a negative (not ok)**
- **Predicting negative class as negative (true negative, TN) (ok)**

D. Results & Discussion

Figure 1 displays a confusion matrix, which is a summary of the outcomes of a classification issue. With count values, the number of accurate and inaccurate predictions is tallied and separated by each class. The confusion matrix's secret lies in this. The confusion matrix demonstrates the various ways in which your classification model generates incorrect predictions. It provides insight into the types of errors being made, which is more relevant than just the errors your classifier is making. The drawback of relying solely on classification accuracy is mitigated by this breakdown. Here, based on the training data I have a plot confusion matrix, So here we can clearly see that we have a good amount of True Positives and True Negatives. 105 and 107 we can also see that False Negatives and False Positives are kindly low which is only 23 and 16, which is improve by Fine Tuning the model increasing the epochs and all.Model Evaluation is done on Test data which is not seen by the model. Since we have 82% Precision and 86% Recall which is fairly good, So the F1 Score also given a good result.

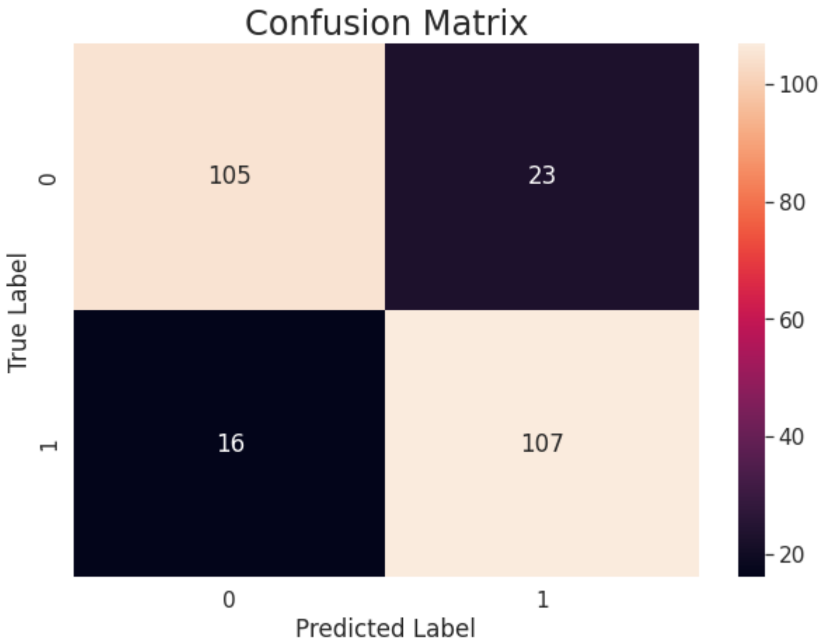

Fig 1 Results of Proposed System

Precision = TP/TP+FP
= 107/(107+23)=0.82

Recall = TP/TP+FN= 107/(107+16) = 0.86

By using (3),

$$\text{F1 score} = 2\left(\frac{precision\ *recall}{precision\ +recall}\right)$$

= 2(0.7052/1.68) = 2*0.4197
= 0.8394

IV. CONCLUSION

Customer review is a game changing parameter in business world especially in restaurants. Classifying the reviews posted by customers on restaurants' mostly based on service or the quality of food. Considering both the types of reviews as same and analysing will mislead the restaurant's decision making. In this paper, the reviews are divided into service based reviews and product based reviews. The confusion matrix and calculate evaluation matrix-like precision, recall and F1 score are calculated with the test data on the trained model and results are analysed. Here the model runs 50 epochs. Despite the fact that this is a reasonably excellent model, it aims to increase model efficiency by lowering the number of false negatives and false positives by fine tuning the model. In future, further training the model with other reviews from platforms like e-commerce websites to get a broader domain range.

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