Comparative Sentiment analysis of product review using machine learning and deep learning algorithm

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Abstract—People today exchange ideas through online web discussion boards, blogs, and various social media platforms. We often give feedback and opinions on the various products, their brands and their services. Their feedback to a product not only increase the quality of the product but also affect buying decisions.

Keywords— Sentiment analysis, Python, Kaggle, Random Forest, XGBoost

Introduction

Now a days, various websites, blogs, forums and social media allow people to provide their views about the services and products. Sentiment Analysis, also called Opinion mining, is a study of sentiments which determine people's mindset, mood, reviews, evaluation and emotions regarding any product, activities, organization, events and their qualities. In General opinion cannot structure an issue but it can be subjective and if we collect opinions and reviews from multiple people or groups or people should be summarized. An approach for mining opinions and reviews is explained by [Jin.2006, Liu, 2010][1]. It was the most focused topic in their study and they described that the basic components are following.

Opinion holder: opinion holder is the person who expresses a particular opinion and review on a particular object or product.

Object: Object is the entity about which the users express their opinions and reviews.

Opinion: Opinion is a perspective, view, sentiment, or assessment about the object by user. There are two types of opinions regular and comparative. Regular opinions are opinions and reviews on specific entities which then can be classified into two categories direct and indirect opinion. Comparative opinions are the Comparisons of more than one entity.

Direct opinions: Direct Opinion are textual documents that directly gives the positive and negative opinions and views about the product. Example: "this laptop is too slow for gaming"

Enterprises use digital channels to support their items. Nowadays online reviews of
customers will affect purchasing decisions for a service. V arious e-
commerce firms, such as Amazon , eBay, Flipkart and Wa lmart evaluate feedback of its customers in various ways. Customers may post unstructured data, such as text, audio , images or videos .Websites, Web Forums , Blogs and various online review platforms. The encoding of natural languages (NLP) is an automated programming technique that analyze and consider vast numbers of views of consumers where they vary businesses build chat-bots to support customer interactions online. Grammar and product reviews dataset is taken from Kaggle .It consists of 71043 review comments. Review scale range consists of 1-5. Reviews of different products from multiple companies including walmart,amazon ,redsky,bestbuy,autopilicty,bazaarvoice are mention in dataset.

Related work

Xing Tooth clarified [2] that the subjective content are extricated, it comprises of sentences of feelings that must contain at least one positive or negative word. Such sentences are tokenized into English words which are unmistakable. The comparing labels are utilized agreeing to the parts of discourse within the expressions. Classification of opinions plays a major part in classifying unstructured data.Cui et al. partitioned online surveys of the products into positive and negative classes[3]. In their try, they utilized different machine learning calculations to test the different 100 K online item input trade-offs. Tooth et al. adapted with the feeling shaft categorization issue in Amazon.com’s online item surveys [4]. They are classified their comes about into two levels: (a) categorization at sentence level and (b)categorization at the review-level. The program was proposed by Bhatt et al. [5] that graded consumer evaluations they along side the input.

Patel proposed a method for machine learning, which classifies investigation sentiments term based, that's , positive or negative [6]. Sygkounas et al. had their inquire about checked on the ponder of semEval Twitter company and ESWC semantic discernment challenge they get an 88.05 percent precision result over the test set to distinguish the positive and feeling negative[7].Ray et al . Presented a assumption analytics framework utilizing R devices. Among them frame, they gotten a plain content from Twitter, pre-processed it and after that utilized a lexicon-based approach to assess client considerations [8].

Govindaraj[9] proposed a plan by which two sets of highlights are determined from the buyer audits: sound-related components reflecting the feelings and lexical characteristics. For a directed classifier these sets are utilized to gauge the customer conclusion. They utilized an sound conversation dataset in their tests arranged and downloaded from online store Amazon and YouTube, separately. Within the test [10], the creator utilized Python Information Investigation to construct a content classification Program, Characteristic Dialect Toolkit and Applications with Scikit-learn. Tried by McAuley et al.that open-ended inquiry did way better than twofold queries[11].For e-shopping websites Babu proposed a assumption examination technique[12].He utilized the lexicon SentiWordNet to discover scores for each word [13, 14]. Keith y al. displayed a blended approach to unmonitored machine learning and the NLP techniques [15].

The authors also have a study comparing classical machine learning methods such as supporting vector machine (SVM) and Bayesian Class (NB). Li also proposed a method for defining two stages: the extraction function and the learning of classifiers [16, 17].

Proposed Method

Our Purposed Method following all step to sentiment analysis through different algorithm.

Figure (2) World cloud of reviews

This world cloud is based on our data set which has been taken by ‘reviews.text’ attribute.

3.1 a) Statically data Analysis

We using different strategy like word (cloud, ratting, true and false analysis, matrices) for data analysis.

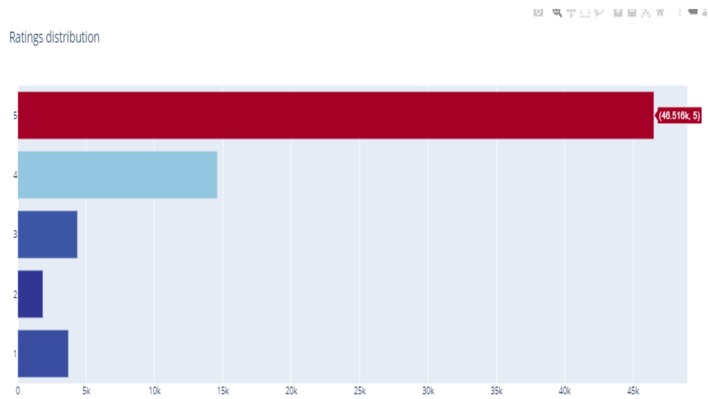


Figure (da1) Ratting under 5 number of range

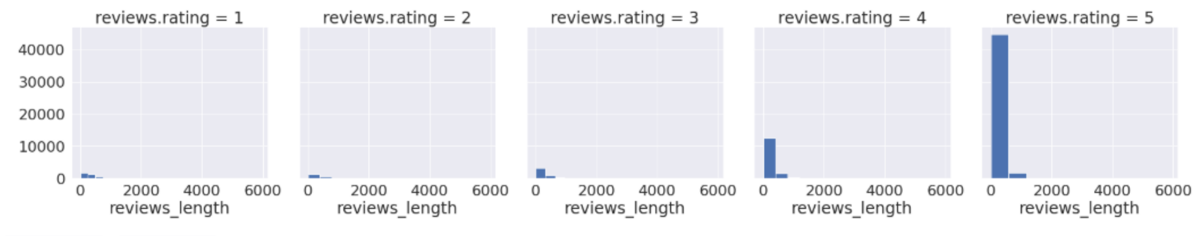


Figure (da2) Individual Ratting

3.2 Preprocessing

We use different method for preprocessing

- Tokenization
- Stop word Removal
- Punctuation marks removal
- Stemming

This is important part of preprocessing for sentiment analysis, it has converted in bag of words which is ready to implementation for molding.

3.5 Score Generation

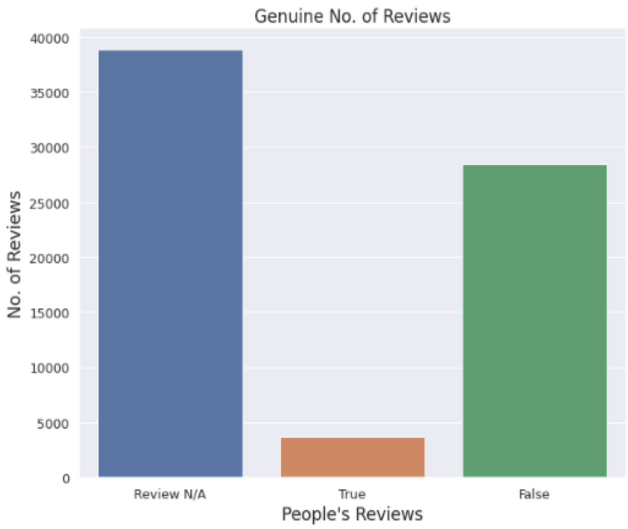


Figure (sg1) review judgment analysis

Under 40000 Review have nearest 5000 reviews are true and under 30000 are false which base on different category of product reviews as shown in Figure (sg1).

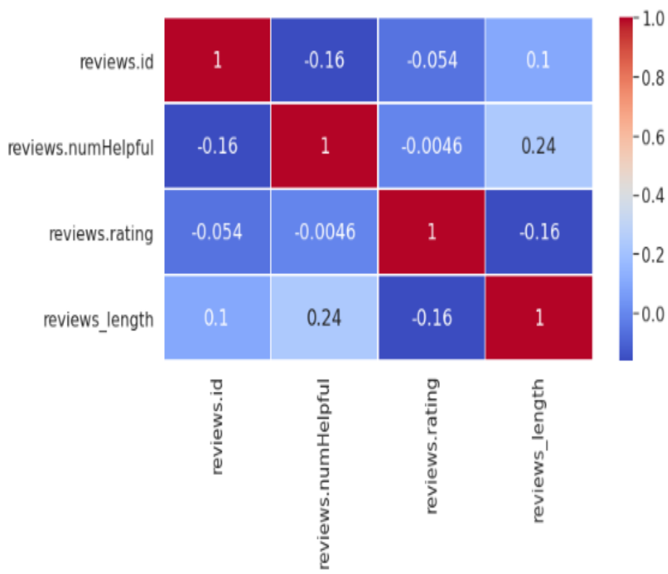


Figure (sg 2) Matrices analysis by Ratting

3.4 Sentiment Using Machine Learning Algorithms

Random Forest

1) Build multiple decision tree

2) Merges together

3) Get accurate prediction

Supervise machine learning algorithm and accuracy is 71 present which batter result is

XGBoost

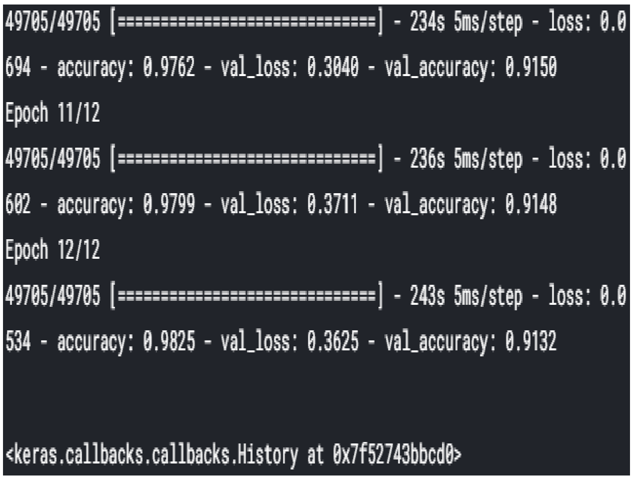
Extreme Gradient Boosting Supervised machine learning algorithms base on decision tree used a gradient boosting frame work.

Best result of sentiment analysis is 72%

3.4 Sentiment Using Deep Learning Algorithms

Using **LSTM** (Long Short-Term Memory network) Deep learning algorithm give best accuracy. For that purpose use 'keras' library which give 98% accuracy.

LSTM , a kind of recurrent neural network which is capable of predicting the future values while remembering the past information into account.



```
49705/49705 [==============================] - 234s 5ms/step - loss: 0.0
694 - accuracy: 0.9762 - val_loss: 0.3040 - val_accuracy: 0.9150
Epoch 11/12
49705/49705 [==============================] - 236s 5ms/step - loss: 0.0
602 - accuracy: 0.9799 - val_loss: 0.3711 - val_accuracy: 0.9148
Epoch 12/12
49705/49705 [==============================] - 243s 5ms/step - loss: 0.0
534 - accuracy: 0.9825 - val_loss: 0.3625 - val_accuracy: 0.9132


<keras.callbacks.callbacks.History at 0x7f52743bbcd0>
```

Figure (4) LSTM accuracy result

Loss= 'binary Crossentropy'

Optimizer = adam

Batch size=130

Epochs=12

These things use in our algorithms and give 98% accuracy as shown in Figure (4).

Results and Discussion

Random Forest	XGBoost
1)Build multiple decision tree 2) merges together 3) get accurate prediction	Extreme Gradient Boosting Supervised machine learning algorithms base on decision tree used a gradient boosting frame work.
`print("Random Forest Model accuracy",rf_accuracy)` `Random Forest Model accuracy 0.7151457541191382`	`print("XGBoost Model accuracy",xgb_accuracy)` `XGBoost Model accuracy 0.725496408956485`
Accuracy 71%	Accuracy 72%

The best result of deep learning algorithm if we set the Loss= 'binary Crossentropy' ,Optimizer = adam ,Batch size=130, and Epochs=12 then we achieved 98% accuracy which is greater than machine learning algorithm.

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