



Sentiment Analysis on Musical Instruments

Prof. Krupali Dhawale

Dept. of Artificial Intelligence, CHRCE, Nagpur

Abstract - Sentiment analysis, commonly referred to as opinion mining, is the systematic identification, extraction, quantification, and study of emotional states and subjective data through the use of natural language processing and text categorization. Sentiment analysis is frequently used in marketing, customer service, clinical medicine, reviews, survey answers, internet and social media, and healthcare materials. This project aims to do sentiment analysis on product evaluations for musical instruments. Online product reviews gathered from "kaggle.com" were the source of the data for this project. With positive results, we anticipate categorising review-level data.

Keywords – *sentimental analysis , logistic regression and NLP(TOC)*

I. INTRODUCTION

A sentiment is an attitude, belief, or conclusion brought on by a sensation. Sentiment analysis, commonly referred to as opinion mining, examines how individuals feel about particular things. Through different social media, including forums, microblogs, and online social networking sites, users may publish their own material. Many social media platforms disclose their application programming interfaces (APIs), which motivates academics and developers to gather and analyse data. However, there are a number of issues with those online data sources that can make sentiment analysis more difficult. The quality of people's opinions cannot be ensured because they are allowed to upload their own information, which is the first issue. The second problem is that such internet data's actual source is not always known. A ground truth is more akin to a label placed on an opinion, designating whether it is favourable, unfavourable, or neutral.

II. LITERATURE SURVEY

By taking into account a dataset with over 5.1 million product evaluations from Amazon.com with the products belonging to four categories, the most essential issue in sentiment analysis is the sentiment polarity categorization. The words in the sentence are categorised using a max-entropy POS tagger, which is accelerated using a second Python programme. Adverbs contain negation terms like no, not, and others, but phrases are specifically identified by the usage of negation of adjectives and negation of verbs. Various classification models, including Naive Bayesian, Random Forest, Logistic Regression, and Support Vector Machine, are chosen for categorization. Pang and Lee recommended removing objective sentences and isolating subjective ones for feature selection. They recommended a text-categorization method. It employs a minimal cut to detect subjective material Based on Twitter data, Gann et al. chose 6,799 tokens, each of which has a sentiment score, or TSI (Total Sentiment Index), indicating whether it is a positive or negative

$$TSI = \frac{p - \frac{tp}{tn} \times n}{p + \frac{tp}{tn} * n}$$

token. A TSI for a certain token is calculated as follows:

The ratio of the total number of positive tweets to the total number of negative tweets is given by where p is the number of times a token appears in positive tweets and n is the number of times a token appears in negative tweets.

III. RELATED WORK

In 2019, Saad and Yang [1] sought to provide a comprehensive ordinal regression-based machine learning algorithmic analysis of tweet sentiment. The proposed model includes pre-processing tweets as a first step, and an efficient feature was developed using the feature extraction model. For categorising the sentiment analysis, techniques including SVR, RF, Multinomial logistic regression (SoftMax),

and DTs were used. Furthermore, the suggested model was tested using the Twitter dataset. The test results demonstrated that the suggested model had the highest level of accuracy, and DTs performed well in comparison to alternative approaches. In order to address the problems, Fang et al. [2] suggested multi-strategy sentiment analysis models that make use of semantic fuzziness in 2018. The results have shown that the suggested High efficiency has been reached by the model. Afzaal et al. [3] suggested an aspect-based sentiment classification method, which recognised the characteristics precisely and achieved the highest classification accuracy, was suggested by them in 2019 [3]. Additionally, the plan was made into a mobile application that let travellers find the best hotel in the area, and the suggested model was examined using data from the actual world.

sets. The outcomes demonstrated that the proposed model was successful in both classification and recognition.

IV. MODULES AND IMPLEMENTATION

- **DATA COLLECTION:**

Amazon.com reviews on products were gathered between May 1996 and July 2014. Each review consists of the following information: 1) Reviewers ID, 2) Product Code, 3) Score, 4) Review Period, 5) Review Supportiveness, and 6) Review Text. There are no half-stars or quarter-stars because all ratings are based on a 5-star system, and all ratings.

- **SENTIMENT SENTENCE EXTRACTION & POS TAGGING:**

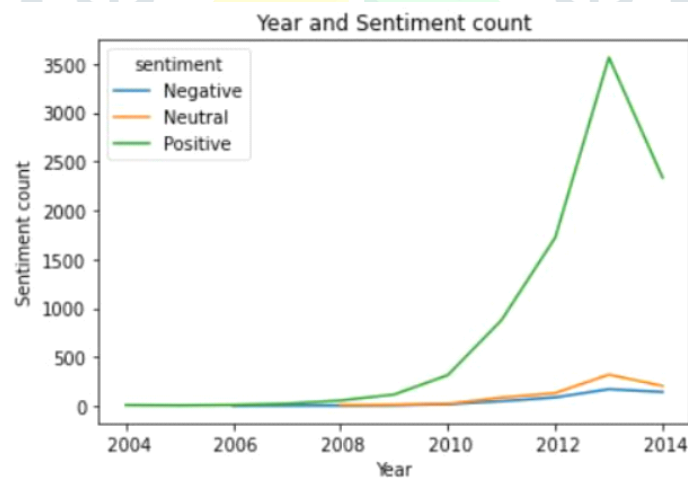
Tokenizing reviews after removing STOP phrases that have no bearing on emotion is essential for POS tagging. After the correct removal of STOP words like "am, is, are, the, but," and other similar words, the remaining phrases are converted to tokens. These tokens are used in the POS tagging procedure.

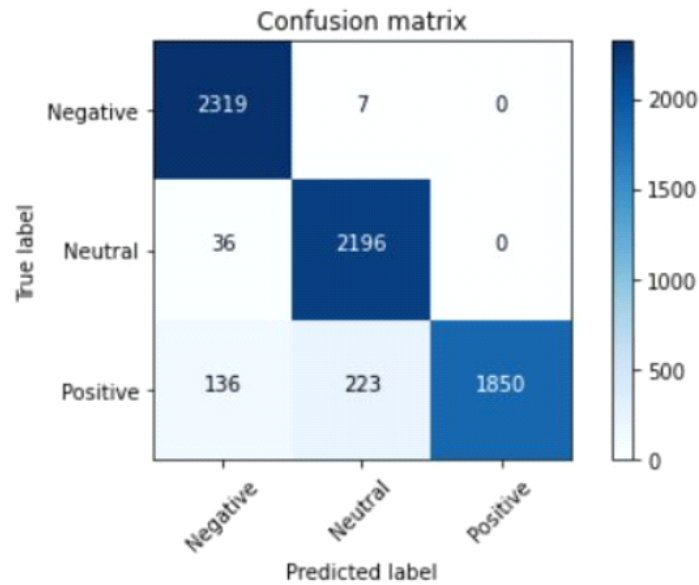
Natural language processing has developed part-of-speech (POS) taggers to classify words based on their parts of speech. For the following two reasons, a POS tagger is very beneficial for sentiment analysis: 1) Pronouns and nouns frequently lack emotional connotations. Such terms can be eliminated by a POS tagger. 2) A POS tagger can also be used to identify keywords that can be utilised in various sections of speech.

- **C. NEGATIVE PHRASE IDENTIFICATION:**

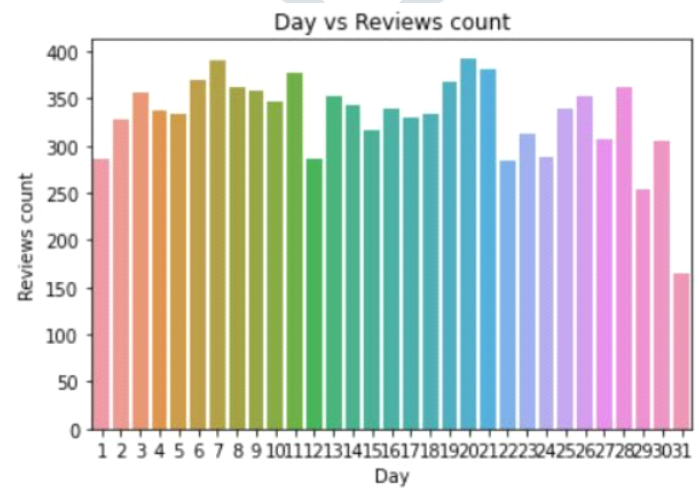
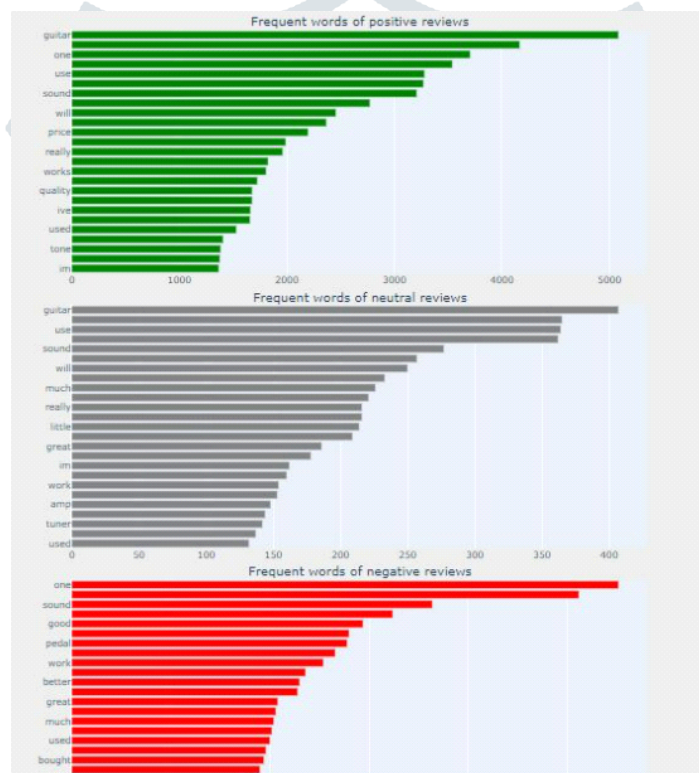
Words like adjectives and verbs can convey the opposite feeling by using negative prefixes. As an illustration, consider the following passage from a review of an electrical device: "The built-in speaker also has its uses but so far nothing new." The word "revolutionary" is a good one, according to the list. However, the statement "nothing revolutionary" typically evokes negative feelings. As a result, it is crucial to understand these terms. Negation-of-adjective (NOA) and negation-of-verb phrase types have been identified in this study (NOV).

V. RESULTS





Confusion Matrix



Days vs Reviews count

Classification Report:					
	precision	recall	f1-score	support	
0	0.93	1.00	0.96	2326	
1	0.91	0.98	0.94	2232	
2	1.00	0.84	0.91	2209	
accuracy			0.94	6767	
macro avg	0.95	0.94	0.94	6767	
weighted avg	0.94	0.94	0.94	6767	

Final Result

VI. FUTURE SCOPE

In the future, sentiment analysis will expand beyond the concepts of positive, negative, and neutral to understand and appreciate the value of understanding dialogues and what they reveal about consumers. Due to the growing volume and complexity of the data underlying those interactions, sentiment analysis is therefore becoming more and more important for these businesses.

Businesses and brands are still in charge of the majority of sentiment analysis for any project, employing data from social media, survey findings, and other sources of user-generated content. Marketers would be able to easily customise and personalise their services with the help of a thorough understanding and a lot larger and more comprehensive database. Based on criteria other than age, gender, income, and other superficial demographics, businesses can segment audiences even more. in the real

VII. CONCLUSION

Writings are categorised using the method of sentiment analysis based on the feelings they convey. The preparation of data, review analysis, and sentiment categorization—the three core elements of a typical sentiment analysis model—are covered in this article as exemplary methodologies.

Sentiment analysis, a growing area in text mining and computational linguistics, has experienced a considerable rise in academic interest in recent years. Future research should investigate novel classification models that can take into account the ordered labels property in rating inference, as well as sophisticated methods for collecting opinion and product attributes. Applications that exploit the findings of sentiment analysis are also expected to surface shortly.

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