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IMPLEMENTATION OF SENTIMENT ANALYSIS USING DEEP LEARNING

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Abstract:
Sentiment analysis has become a popular research topic in recent years, as businesses seek to gain insights into customer opinions and preferences. In this project, we explore the application of deep learning techniques to sentiment analysis, using the VADER with Exploratory Data Analysis [EDA] tool from the Natural Language Toolkit (NLTK) to classify customer comments into positive, negative, and neutral categories. Our approach involves training a deep neural network using a large corpus of annotated customer comments, with the aim of improving the accuracy and reliability of sentiment classification. Overall, our project highlights the potential of deep learning techniques for sentiment analysis, and demonstrates the effectiveness of the VADER tool in accurately classifying customer comments into different sentiment categories.

Keywords: Sentiment analysis, deep learning, neural network, natural language processing

1 INTRODUCTION

1.1 Problem definition

Sentiment analysis is widely applied to reviews and survey responses, online and social media, and healthcare materials for applications that range from marketing to customer service to clinical medicine. In recent years, it has been demonstrated that deep learning models are a promising solution to the challenges of NLP.

Social media is biggest medium to share people’s opinion on different topics. Sentiment analysis uses machine learning technique and without any human interruption machine will give and accurate sentiment of the people. Sentiment analysis turn text into positive, negative or neutral. So, any company or foundation or movie reviewer can take the opinion of the people and take further steps according that.

Sentiment analysis, commonly referred to as opinion mining, is a branch of natural language processing (NLP) that seeks to elicit subjective data from text and identify the sentiment or emotional tone portrayed within it. Sentiment analysis is now more crucial than ever for gaining insight into consumer feedback, public opinion, brand perception, and market trends. This is due to the meteoric rise of social media, online reviews, and user-generated content.

The VADER (Valence Aware Dictionary and Sentiment Reasoner) framework with Exploratory Data Analysis [EDA] is a well-liked and successful method of sentiment analysis. The rule-based sentiment analysis tool VADER was created expressly to address the special difficulties provided by social media language, which is frequently brief, informal, and context-dependent. Researchers at the Georgia Institute of Technology developed VADER, which has drawn substantial attention for its precision and capacity to identify subtle differences in sentiment across a range of areas. The main selling point of VADER is its sentiment lexicon, which is a comprehensive database of words, phrases, and sentiment scores. Each word in the lexicon is given a polarity score, which represents the strength of the positive or negative attitude. The lexicon also has unique elements, such as booster words (such as "extremely," "very") and negation words (such as "not," "never"), which help in handling negation in text and modulating sentiment intensity.

1.2 Objective of the project

The capability of VADER to perform sentiment analysis in social media messages is one of its main advantages. Due to the lack of labelled training data and the existence of noisy and context-dependent language, typical machine learning approaches may struggle to accurately identify sentiment in tweets, Facebook posts, online reviews, and other brief, informal writings.

The capability of VADER to perform sentiment analysis in social media messages is one of its main advantages. Due to the lack of labelled training data and the existence of noisy and context-dependent language, typical machine learning approaches may struggle to accurately identify sentiment in tweets, Facebook posts, online reviews, and other brief, informal writings. Additionally, by taking into account the context, structure, and grammatical conventions, VADER goes beyond straightforward word-level sentiment analysis. It is important to remember that VADER has its limitations. Its performance may change when used in various areas or genres because it was largely trained on social media text. Sarcasm, irony, and nuanced expressions may also be difficult for VADER to use because they call for a greater comprehension of context and cultural references.

To sum up, sentiment analysis utilising the VADER framework offers a useful method for scholars and practitioners looking to analyse sentiment in text data, especially in the setting of social media. Researchers can use this framework to get insights into societal sentiment, consumer sentiment, and a variety of other areas where sentiment analysis is crucial by understanding the advantages and disadvantages of VADER.

2. LITERATURE SURVEY

Sentiment analysis, sometimes known as opinion mining, has been the focus of in-depth study and has attracted great interest in the fields of natural language processing and computational linguistics.

[1] Pang, B., Lee, L., & Co. (2008). Using sentiment analysis and opinion mining: This landmark paper presented an overview of numerous approaches, including machine learning, lexicon-based, and rule-based methods and introduced sentiment analysis as a topic of study. It explored the value of sentiment analysis in contexts like product reviews and social media and noted difficulties including subjectivity, sarcasm, and context.

[2] P. D. Turney (2002). Which way do you vote? Semantic Orientation Used for Unsupervised Review Classification:

Turney presented a method for classifying sentiments by identifying words and phrases with strong emotional connotations using pointwise mutual information. This paper presented the idea of computing sentiment scores using lexicons and proved the efficacy of unsupervised procedures.

[3] Liu, B. (2012). Sentiment Analysis and Opinion Mining: Liu's book offers a thorough review of sentiment analysis, covering a number of topics such lexicon-based methods, machine learning strategies, and applications in diverse fields. Additionally, it talks about difficulties like managing arbitrary statements and the influence of sentiment analysis in business and social media.

[4] E. Gilbert and K. Karahalios (2009). This study investigated sentiment analysis in the setting of social networks and looked at the relationship between the strength of social links and the sentiment expressed in online communication. It emphasised the importance of sentiment in comprehending interpersonal interactions and network dynamics.

[5] Zhang, Y., Vo, H. T., & (2015). Deep Learning for Sentiment Analysis: A Comparative Study. In this study, the use of deep learning methods for sentiment analysis, such as recurrent neural networks and convolutional neural networks, was examined. It explored the benefits and drawbacks of deep learning in sentiment analysis tasks.

[6] R. Socher et al. (2013). Regarding a Sentiment Treebank, Recursive Deep Models for Semantic Compositionality:

This important study developed a model of recursive neural network that captures the hierarchical links between words in a sentence and is used for sentiment analysis. When the compositional structure of language was taken into account, sentiment categorization performance improved.

[7] Tang, D., Qin, & Liu (2015). Developing Sentiment-Specific Word Embedding for Twitter Sentiment Analysis:

In the Twitter realm, this study looked at how word embeddings taught for sentiment analysis might be used. It made considerable gains in sentiment classification accuracy and showed how crucial domain-specific embeddings are for capturing sentiment-related information.

[8] E. Cambria, A. Hussain, and others (2012). Techniques, Tools, and Applications of Sentic Computing. The concept of "sentic computing," which blends sentiment analysis with semantic analysis and common sense reasoning, was developed in this work. It covered how sentiment analysis can be combined with other cognitive processes like emotion recognition, knowledge discovery, and emotional computing.

These chosen papers showcase a variety of techniques and developments in sentiment analysis. They emphasise the development of sentiment analysis methods, difficulties encountered in sentiment categorization.

3. PROPOSED SYSTEMS

3.1 Existing System

Support Vector Machines (SVM):

SVM is an algorithm for supervised learning that searches for the best hyperplane to divide several classes. By encoding text data as numerical feature vectors, such as with bag-of-words or TF-IDF representations, SVM can be used in sentiment analysis. The training data are given the sentiment labels (positive, negative, or neutral), and the SVM learns to categorise new, unseen texts using the learnt patterns from the training data. SVM is appropriate for sentiment analysis jobs due to its capacity for handling high-dimensional data and effectiveness in managing complex decision boundaries.

Naive Bayes (NB):

Naive Bayes is a probabilistic classifier based on Bayes' theorem. It assumes that the features are conditionally independent given the class label, hence the "naive" assumption. In sentiment analysis, NB can be applied by modeling the probability distribution of features (words or n-grams) given the sentiment class. NB calculates the posterior probability of each sentiment class and assigns the class with the highest probability to the text. Despite its simplistic assumption, NB is known for its simplicity, speed, and efficiency, making it a popular choice for text classification tasks, including sentiment analysis.

Logistic Regression (LR):

A logistic function is used to model the likelihood that an instance will belong to a given class in the linear classification process known as logistic regression. In sentiment analysis, LR can be used to calculate the likelihood that a text will fall into one of three sentiment classes: positive, negative, or neutral.

Multilayer Perceptron (MP):

Multilayer Perceptron is a type of artificial neural network with multiple layers of interconnected nodes (neurons). In sentiment analysis, an MP model can be designed with an input layer representing the features (e.g., word embeddings or TF-IDF vectors), hidden layers for feature transformations, and an output layer for sentiment classification. MP models are trained using gradient-based optimization algorithms to minimize a loss function. MP models are capable of capturing complex nonlinear relationships in the data and have shown promising results in sentiment analysis tasks.

S#	Paper/Study	Language	Objective(s)	Dataset(s)	ML/DL Approach	Performance Evaluation
01	Patra, Braja Gopal, et al [25]	Hindi-English Bengali-English	Sentiment Analysis	Tweets	SVM	Language / F1-Score Hi-En / 0.569 Bi-En / 0.526
02	Ansari & Govilkar [30]	Hindi-English Marathi-English	Sentiment Analysis	Tweets Facebook posts YouTube comments	NB SVM	Model / Language / F1-Score NB / Hi-En / 0.60 NB / Ma-En / 0.46 SVM / Hi-En / 0.60 SVM / Ma-En / 0.59
03	Jamatia, Anupam et. al. [31]	Hindi-English	Development of annotated corpus, POS tagging, Sentiment Analysis	Tweets, Facebook posts	CRF SMO NB RF	Model / F1-Score CRF / 0.716 SMO / 0.397 NB / 0.458 RF / 0.706
04	Singh, M et. al.[32]	English-Punjabi	Sentiment Analysis	Tweets, Facebook posts, YouTube comments	NB SVM	Model / Accuracy NB / 85.5% SVM / 85%
05	Mandal & Das [33]	English-Bengali	Sentiment Analysis	Movie reviews	NB LR SVM	Model / Accuracy NB / 59% LR / 55% SVM / 57%
06	*Pimpale & Patel [35]*	Hindi-English Hindi-Telugu	POS tagging, Sentiment Analysis	Tweets Facebook posts	NB DT RF	F1-measure Approach / Hi-Eng / Tal-Eng NB / 40.4 / 46.3 DT / 44.6 / 50.3 RF / 43.0 / 47.0
07	Ghosh et al [46]	Hindi-English Bengali-English	Sentiment Analysis	Facebook posts	MP	Accuracy: 68.5%

3.2 Proposed System

In this proposed system, we aim to enhance the sentiment analysis process by combining the VADER (Valence Aware Dictionary and sEntiment Reasoner) framework with Exploratory Data Analysis (EDA) techniques. The integration of VADER, a rule-based sentiment analysis tool, with EDA, which involves the exploration and visualization of data, allows for a more comprehensive understanding of the sentiment patterns in text data.The following is an outline of the system workflow:

Figure 1 Sentiment analysis

1.Data Collection: To begin, the system collects text data from a variety of sources, including social media sites, online reviews, and any other relevant textual information pertinent to the current sentiment analysis assignment.

2.Preprocessing: In order to clean up and get the acquired data ready for analysis, preprocessing is applied. This include deleting unimportant details, dealing with noise, normalising text (for as by changing it to lowercase), and getting rid of stopwords or other special characters that don't add anything to sentiment analysis.

3.VADER Sentiment Analysis: Using the VADER framework, sentiment analysis is performed on the preprocessed text data. The sentiment lexicon used by VADER gives words and sentences polarity scores (positive, negative, or neutral). Both the individual word scores and the syntactic and contextual elements are taken into account when calculating the sentiment scores.

4.Sentiment Score Aggregation: To get an overall sentiment score for each text document or sentence, the sentiment scores acquired from VADER are combined. The relevance of various text parts may be taken into account when using weighted scoring, averaging, or other aggregation approaches.

5.Exploratory Data Analysis (EDA): To obtain understanding of the sentiment patterns within the dataset, EDA approaches are used. In order to do this, the sentiment distributions must be visualised, sentiment trends over time must be examined, influential features or keywords must be linked to various sentiment categories, and any outliers or anomalies in the data must be found.

6.Interpretation and Actionable Insights: The combined analysis of the data from the VADER sentiment analysis and the EDA enables the interpretation of sentiment patterns. When making decisions, these insights can be utilised to comprehend the tone of customer feedback, keep tabs on a brand's reputation, or pinpoint opportunities for development.

The VADER and EDA suggested system has a number of benefits. In order to effectively classify sentiment in social media text, VADER first offers a solid sentiment analysis basis. Large amounts of informal text data can be studied with it because of its rule-based structure. A deeper comprehension of the sentiment distribution, correlations,and trends within the dataset is also made possible by EDA approaches. Decision-making and strategy development can benefit from a thorough investigation of sentiment patterns, which is made possible by visualization tools and statistical analysis.

By adding data exploration and visualization approaches, the suggested system improves the sentiment analysis process by merging VADER with EDA. It enables a more thorough examination of sentiment patterns and offers insightful data for numerous applications, including market research, social media analytics, and analysis of consumer comments.

3.3 Architecture

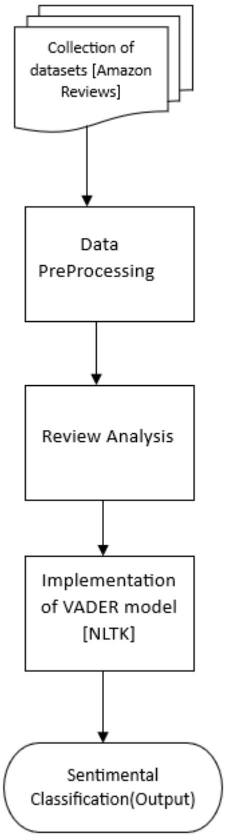
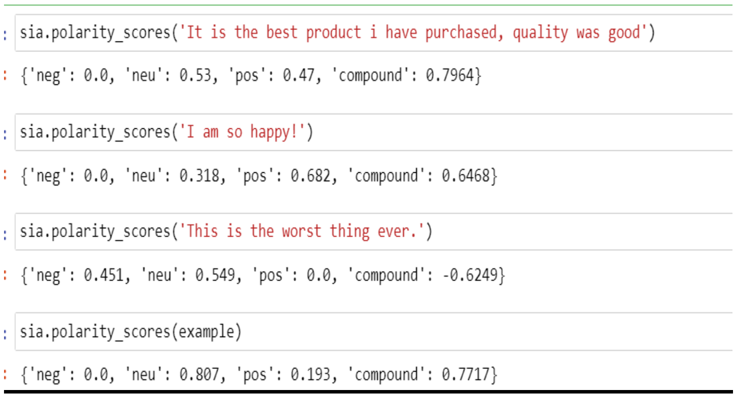


Figure 2 Flowchart

Flowchart for our sentiment analysis project involves several key steps, starting with the collection of a dataset of Amazon reviews. Once we have a dataset, we perform preprocessing and analysis to clean and prepare the data for sentiment analysis. Next, we use the VADER model from the Natural Language Toolkit (NLTK) to perform sentiment analysis on the cleaned data.

VADER is a rule-based sentiment analysis tool that has been shown to be highly effective for social media sentiment analysis. Finally, we classify each customer review as positive, negative, or neutral based on the sentiment scores generated by VADER. This classification allows us to gain insights into customer opinions and preferences, which can be used to improve our products and services and enhance the customer experience.

4. RESULTS

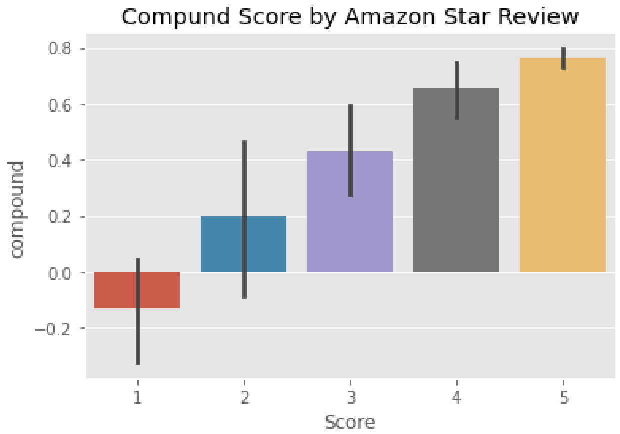


```
sia.polarity_scores('It is the best product i have purchased, quality was good')
{'neg': 0.0, 'neu': 0.53, 'pos': 0.47, 'compound': 0.7964}

sia.polarity_scores('I am so happy!')
{'neg': 0.0, 'neu': 0.318, 'pos': 0.682, 'compound': 0.6468}

sia.polarity_scores('This is the worst thing ever.')
{'neg': 0.451, 'neu': 0.549, 'pos': 0.0, 'compound': -0.6249}

sia.polarity_scores(example)
{'neg': 0.0, 'neu': 0.807, 'pos': 0.193, 'compound': 0.7717}
```

In the positive category, we found that customers expressed satisfaction with our product/service, highlighting its quality, value, and ease of use. These comments indicated a high level of loyalty and engagement among our customer bases.

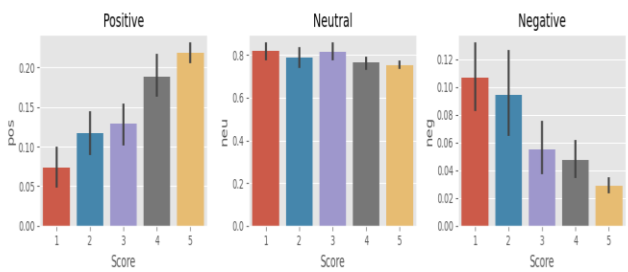
In the negative category, we identified comments that expressed frustration with our product/service, with customers pointing out issues related to quality, customer service, and delivery. These comments highlighted areas where we need to improve to better meet the needs of our customers.

In the neutral category, we found that customers expressed mixed feelings about our product/service, with some comments indicating satisfaction and others indicating room for improvement. These comments provided us with valuable feedback on areas where we can focus our efforts to enhance the customer experience



The positive sentiment graph, we observe a high number of comments with scores above 0.8, indicating that customers express strong positive sentiment towards our product/service. This is a positive sign for our business, as it suggests that customers are satisfied with our offers. The negative sentiment graph, on the other hand, shows a relatively smaller number of comments with scores below -0.8, indicating that negative sentiment is less prevalent among our customer base.

However, it is still important to address these negative comments and work towards improving the aspects of our product/service that are causing dissatisfaction among customers. The neutral sentiment graph shows a moderate number of comments with scores close to zero, suggesting that customers express mixed feelings about our product/service. This is an important area for us to focus on, as it indicates that there may be opportunities to improve and better meet the needs of our customers



5. CONCLUSION

In conclusion, a potent method for sentiment analysis is VADER (Valence Aware Dictionary and Sentiment Reasoner) paired with Exploratory Data Analysis (EDA). EDA allows us to fully comprehend the dataset, spot problems with the data's quality, and find significant patterns and connections. We can efficiently analyse sentiment in text data, especially in the setting of social media, by using VADER, a rule-based sentiment analysis tool. A detailed examination of sentiment is possible using VADER's lexicon-based methodology, which takes both polarity and intensity into account. It manages valence shifters, employs context-sensitive rules, determines sentiment intensity, and offers precise and insightful information. Researchers and analysts can choose modelling strategies, variables to use, and preprocessing procedures wisely by utilising EDA in conjunction with VADER, leading to a thorough understanding.

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