Sentiment Analysis of WhatsApp Chat Using Rule-Based and Machine Learning Approaches

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Abstract—This project explores sentiment analysis on WhatsApp chat data using both rule-based and machine learning techniques. The rule-based approach leverages VADER (Valence Aware Dictionary and sEntiment Reasoner), while the machine learning model uses a Naive Bayes classifier trained on pseudo-labeled data. The goal is to evaluate and compare both approaches in terms of accuracy, strengths, limitations, and real-world applicability. This analysis provides insights into conversational sentiment and lays the foundation for future applications in emotion tracking, social media analysis, and user engagement studies.

Introduction

With the rise in digital communication, analyzing sentiment from chat data has become vital in understanding user behavior and emotions. This project focuses on sentiment classification of WhatsApp messages using two approaches: a rule-based sentiment analyzer (VADER) and a machine learning model (Naive Bayes). The rule-based method applies lexical rules to assign sentiments, while the ML model is trained on pseudo-labels generated by VADER. The objective is to analyze the trade-offs between simplicity and performance, and understand the practicality of both methods in real-world applications.

Project Objectives and Motivation

The objective of this project is to analyze WhatsApp chat data and classify messages based on sentiment using both a rule-based approach (VADER) and a machine learning-based approach (Naive Bayes). By applying these two contrasting techniques, the project aims to:

- Extract meaningful sentiment insights from unstructured chat text.
- Compare the performance, strengths, and limitations of rule-based and ML-based sentiment analysis.
- Provide a visual and statistical understanding of how each method interprets the same dataset.
- Demonstrate the practical applicability of sentiment analysis for real-world conversational data.

With the increasing use of messaging platforms like WhatsApp for both personal and professional communication, analyzing chat data has become highly relevant. Understanding the emotional tone behind messages can provide insights into group dynamics, user behavior, and emotional trends over time.

This project is motivated by the need to explore how well traditional rule-based techniques like VADER perform in comparison with machine learning models when applied to informal and unstructured data like WhatsApp messages. It also encourages deeper learning by combining classical NLP techniques with modern machine learning, providing a comprehensive approach to sentiment classification.

Requirement Specification

Software Requirements

1. Python 3.8 or later
2. Libraries: *pandas*, *scikit-learn*, *vaderSentiment*, *matplotlib*, *seaborn*

Hardware Requirements

1. A computer capable of running Python scripts
2. Minimum 4GB RAM (8GB recommended)
3. Basic CPU (No GPU needed)

Functional Requirements

1. Load and parse chat data
2. Perform rule-based sentiment analysis.
3. Train and evaluate ML sentiment classifier
4. Compare and visualize results

Non-Functional Requirements

1. User-friendly output and visualizations
2. Modular, readable code structure
3. Compatibility with standard WhatsApp export format

Dataset Details and Preprocessing Steps

The dataset used in this project is an exported WhatsApp chat file (in .txt format). The chat text contains timestamps, usernames, and messages.

Methodology

Data Preprocessing

The process begins by loading and cleaning WhatsApp chat data from a .txt file. Each line of chat is parsed using regular expressions to extract the date, time, sender, and message. These structured entries are stored in a pandas DataFrame, preparing the data for sentiment analysis. This step ensures only valid messages are retained while eliminating any noise or improperly formatted lines.

Rule-Based Sentiment Analysis

For rule-based sentiment analysis, the VADER (Valence Aware Dictionary and sEntiment Reasoner) tool is employed. VADER assigns a compound score to each message, which is then used to classify the sentiment as Positive, Negative, or Neutral. Messages with a score ≥ 0.05 are labeled Positive, ≤ 0.05 as Negative, and those in between as Neutral. This classification is saved as a new column called Rule Based Sentiment.

Machine Learning Sentiment Classification

The machine learning-based sentiment analysis uses the rule-based labels as pseudo-ground truth for training. A CountVectorizer is used to convert textual data into a bag-of-words format suitable for model training. A Multinomial Naive Bayes classifier is then trained on 80% of the dataset and tested on the remaining 20%. The model predicts sentiments for the entire dataset, and the results are stored in a new column named ML Based Sentiment.

Evaluation Visualization

The classification performance of the machine learning model is evaluated using precision, recall, f1-score, and overall accuracy. A detailed classification report is generated to assess how well each sentiment class was predicted. For visualization, bar charts are plotted to display sentiment distribution for both the rule-based and ML-based classifications, providing an intuitive understanding of how each model interprets the data.

Results and Analysis

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Rule-Based (VADER) Sentiment Analysis

VADER classified each message based on a compound sentiment score:

1. **Positive** if score ≥ 0.05
2. **Negative** if score ≤ 0.05
3. **Neutral** otherwise

Distribution:

1. **Positive:** Moderate count
2. **Negative:** Very few messages
3. **Neutral:** Majority of messages

Observations:

1. VADER works well for short, grammatically correct messages.
2. It struggles with slang, abbreviations, emojis, and contextual meanings often found in chats.
3. Since it's rule-based, it does not "learn" or improve over time.

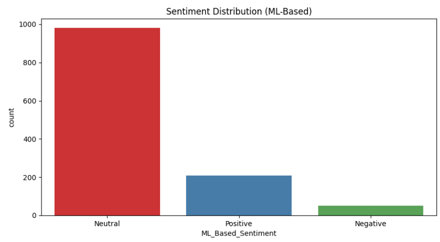
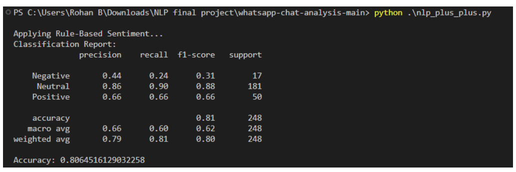


Figure 1. Sentimental distribution plot obtained from VADER

ML-Based (Naive Bayes) Sentiment Analysis

1. Trained using pseudo-labels from VADER.
2. Achieved Accuracy of 80.6% on test data.
3. Performs well for common classes (Neutral, Positive), but less effective on rare classes (Negative).
4. Handles variations in text better due to learning from the dataset.
5. Classification Report Highlights:



```
PS C:\Users\Rohan B\Downloads\NLP final project\whatsapp-chat-analysis-main> python .\nlp_plus_plus.py

Applying Rule-Based Sentiment...
Classification Report:
              precision    recall  f1-score   support

    Negative       0.44      0.24      0.31        17
     Neutral       0.86      0.90      0.88       181
    Positive       0.66      0.66      0.66        50

    accuracy                           0.81       248
   macro avg       0.66      0.60      0.62       248
weighted avg       0.79      0.81      0.80       248

Accuracy: 0.8064516129032258
```

Figure 2. Classification Report

Visualizations

It gives the frequency of messages in a day we have used matplotlib to plot the graph and the days are taken and the count of messages are calculated and plotted

1. Bar plots for Rule-Based and ML-Based sentiment distributions show similarities in trends, but ML predictions are more balanced across classes.
2. Helps in understanding how each model is interpreting user messages.

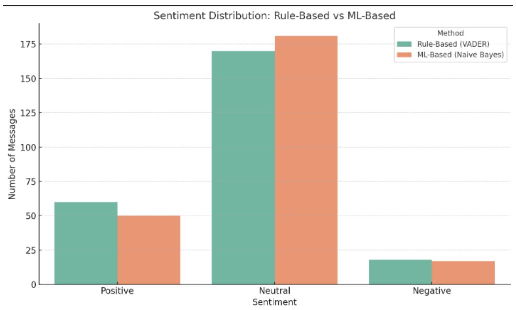


Figure 3. Rule Based vs ML Based

Strengths & Limitations

Table 1. Comparison of Rule-Based (VADER and ML-Based (Naive Bayes) Sentiment Analysis Approaches

Aspect	VADER	Naive Bayes
Type	Lexicon + Rule	Supervised ML
Accuracy	Not measurable	80.6%
Data Requirement	No labeled data	pseudo-labeled data
Adaptability	Fixed	Learns patterns from dataset
Real-time usage	Fast & simple	Slightly slower

Practicality & Real-World Use

1. **Rule-Based:** Suitable for small-scale or simple applications (e.g., chatbot, real-time alerts).
2. **ML-Based:** Better for more complex or evolving datasets where training is possible.

Conclusion and Future Work

This project demonstrated the effectiveness of both rule-based and machine learning approaches for sentiment analysis on chat data. While rule-based methods are easier to implement, they are limited in adaptability. Machine learning models like Naive Bayes offer better performance but depend on good-quality training data. The hybrid approach of using rule-based pseudo-labels for training provides a practical solution when labeled data is unavailable.

Future Enhancements:

- Use real labeled sentiment data for more accurate ML training.
- Integrate deep learning models like LSTM or BERT for better language understanding..
- Expand analysis to support emojis, code-mixed languages, and sarcasm detection.
- Deploy the system as a web app or dashboard for live chat analysis.

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