PROJECT REPORT

ON

SENTIMENT ANALYSIS ON MOVIE REVIEWS

Submitted by

NAME	REG NO	ROLL NO	SECTION
Tatini Jahnavi Priya	12209762	8	K22CY
G. Bhavani prasad	12214446	17	K22CY
Ajay kumar Reddy	12212751	14	K22CY
U Chennaiah	12215318	23	K22CY

Under the Guidance of

Saurabh Premlal Tembhurne (30980)

School of Computer Science &

Engineering Lovely Professional

University, Phagwara

We, Jahnavi, Bhavani prasad, Ajay, Chennaiah, proudly present our project, “Sentiment Analysis on Movie Reviews”, showcasing our dedication and learning and this piece of work conducted by us as a part of our academic curriculum.

With the guidance of Saurabh Premlal Tembhurne, we tackled the complexities of sentiment analysis. His constant support and advice motivated us throughout.

Our team’s hard work and perseverance deserve recognition. Despite challenges, we achieved success together. The project highlights the power of teamwork and resilience in accomplishing remarkable feats.

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SENTIMENT ANALYSIS ON MOVIE REVIEWS

Jahanavi Priya - 12215318, Bhavani prasad - 12214446, Ajay kumar - 12215318, Chennaiah - 12215318;

1.Abstract

Sentiment analysis plays a crucial role in understanding public opinion and sentiment towards various entities, including movies. In this project, we explore the task of sentiment classification using machine learning techniques on a dataset of movie reviews. The objective is to develop and compare classification models capable of automatically categorizing reviews as positive or negative based on their sentiment.

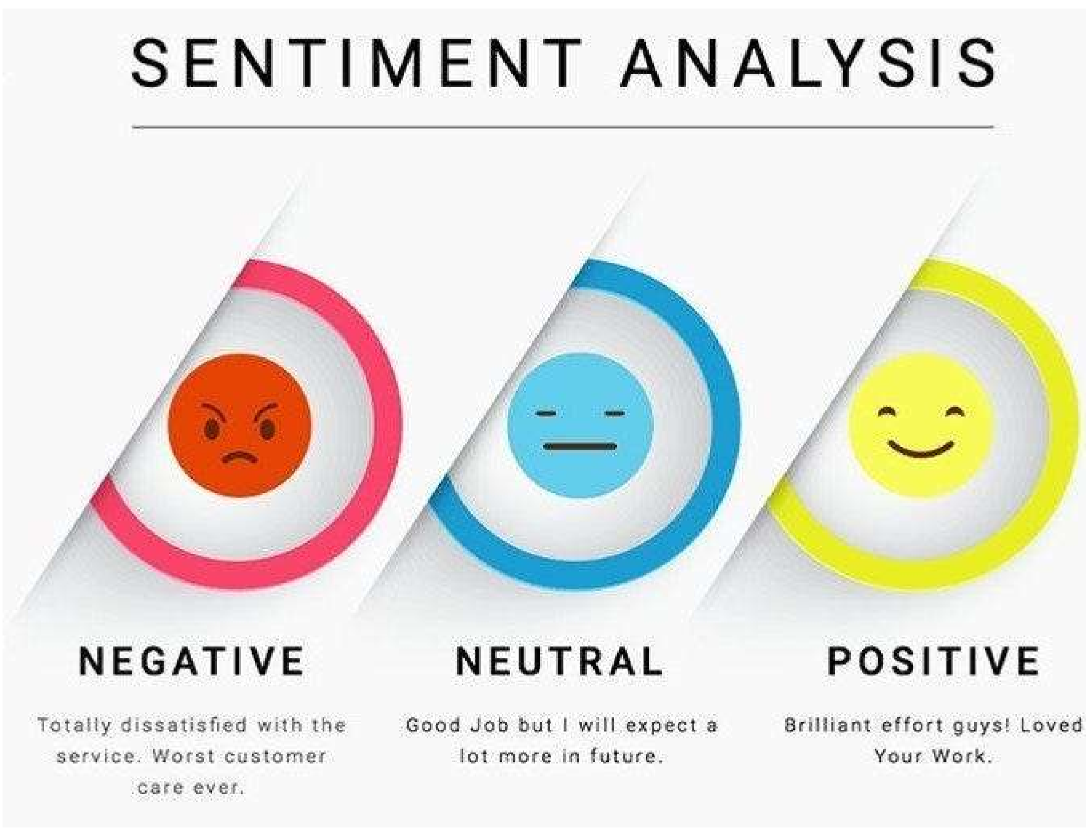


Fig1

2.Introduction

In the world of technology, understanding people's feelings from what they write is really important. This is where sentiment analysis comes in. It helps us figure out if what someone wrote is positive, negative, or just neutral. And guess what? We're using this cool technology to analyze movie reviews! So, sit tight as we dive into the exciting world of sentiment analysis on movie reviews. [1][2]

The primary goal of this project is to develop and evaluate machine learning models for sentiment classification of movie reviews. Specifically, we aim to build classifiers that can accurately determine whether a given movie review conveys a positive or negative sentiment based on its textual content. The project focuses on leveraging natural language processing (NLP) techniques and supervised learning algorithms to achieve this task. Several machine learning algorithms will be implemented and compared for sentiment classification, including logistic regression, naive Bayes, support vector machines (SVM), random forest.[1]

The outcome of this project will provide insights into the effectiveness of different approaches for sentiment analysis in the context of movie reviews. By evaluating the performance of various classification models, we aim to identify the most suitable techniques for automating sentiment classification tasks in practical applications.[1][2]

2.1 Overview of Sentiment Analysis and Classification

Sentiment analysis, also known as opinion mining, involves the use of computational techniques to extract and analyze subjective information from text data. In the case of movie reviews, sentiment classification aims to categorize reviews based on the sentiments they convey, such as whether the reviewer liked or disliked the movie.[1]

Key components of sentiment classification include:

1. ***Data Preprocessing****: Cleaning and preprocessing textual data to remove noise, tokenize words, handle stopwords, and perform normalization (e.g., stemming, lemmatization).[4]*
2. ***Feature Representation****: Converting textual data into numerical feature vectors that machine learning models can process. Common techniques include Bag-of-Words (BoW), Term Frequency-Inverse Document Frequency (TF-IDF), and word embeddings (e.g., Word2Vec, GloVe).[4]*

3. ***Model Selection****: Choosing appropriate machine learning algorithms for sentiment classification. Commonly used classifiers include logistic regression, support vector machines (SVM), naive Bayes, decision trees, random forest, and neural networks.[4]*
4. ***Model Evaluation****: Assessing the performance of classification models using evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix.[4]*

2.2 Objective and Scope of the Project

The primary objective of this project is to develop and implement a machine learning-based system for sentiment analysis on movie reviews. Specifically, we aim to train models that can accurately classify the sentiments expressed in movie reviews as positive, negative, or neutral. The scope of the project encompasses collecting movie review data, preprocessing and analyzing the text, selecting and training appropriate machine learning algorithms, and evaluating the performance of the sentiment classification models.

1. ***Build Classification Models****: Implement and train machine learning classifiers using natural language processing (NLP) techniques to automatically classify movie reviews based on sentiment.[3]*
2. ***Evaluate Model Performance****: Assess the performance of different classification algorithms in terms of accuracy, precision, recall, F1-score, and other relevant metrics.[3]*
3. ***Feature Engineering and Text Representation****: Explore various text representation methods such as Bag-of-Words (BoW), TF-IDF (Term Frequency-Inverse Document Frequency), and potentially word embeddings to extract meaningful features from movie reviews.[3]*
4. ***Optimize Model Parameters****: Conduct hyperparameter tuning and optimization to enhance the effectiveness of sentiment classification models.[3]*
5. ***Interpret Results****: Analyze and interpret the model predictions to gain insights into the factors influencing positive and negative sentiments in movie reviews.[3]*

2.3 Outline of the Report

This report is structured to provide a comprehensive overview of our sentiment analysis project on movie reviews. It begins with an introduction to the concept of sentiment analysis and classification, followed by a detailed explanation of the project objectives and scope. The report then delves into the methodology employed, including data collection, preprocessing techniques, feature extraction, model selection, and evaluation metrics. Finally, the results of the sentiment analysis experiments are presented and discussed, along with conclusions and recommendations for future research in this domain.[2][3][4]

3.Literature Review

Sentiment analysis, also known as opinion mining, is a critical area within natural language processing (NLP) that focuses on understanding and extracting subjective information from text data. In recent years, sentiment analysis has gained significant attention due to its wide range of applications, including analyzing social media posts, customer feedback, and, notably, movie reviews.[6][20]

3.1 Background on Sentiment Analysis Techniques

Sentiment analysis is a fascinating field that involves understanding human emotions from text data. In recent years, various techniques have been developed to analyze sentiment, ranging from simple rule-based approaches to complex machine learning algorithms. These techniques typically involve preprocessing the text data to remove noise and irrelevant information, followed by feature extraction and selection. Common approaches include bag-of-words models, sentiment lexicons, and neural network-based methods.[6][20]

3.2 Review of Existing Classification Models for Sentiment Analysis

Several classification models have been proposed for sentiment analysis, each with its strengths and weaknesses. Traditional machine learning algorithms such as Support Vector Machines (SVM), Naive Bayes, and Decision Trees have been widely used for sentiment classification tasks. More recently, deep learning models such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) have shown promising results due to their ability to capture complex patterns in text data.[6][7]

3.3 Summary of Relevant Research Studies

Numerous research studies have explored sentiment analysis in the context of movie reviews. These studies have investigated various aspects of sentiment analysis, including feature selection, sentiment lexicon creation, and model evaluation metrics. Additionally, researchers have explored the impact of different linguistic features, such as sentiment-bearing words and syntactic patterns, on sentiment classification accuracy. Overall, these studies contribute to a better understanding of sentiment analysis techniques and their applications in analyzing movie reviews.[12][5]

This literature review provides valuable insights into the background of sentiment analysis techniques, existing classification models, and relevant research studies in the field.

Understanding these concepts is essential for developing effective sentiment analysis models for analyzing movie reviews.[9][12]

4.Data Collection and Preprocessing

Source of Movie Review Dataset: For our sentiment analysis project on movie reviews, we obtained our dataset from a reputable source that aggregates movie reviews from various platforms such as IMDb, Rotten Tomatoes, and Metacritic. This dataset comprises a diverse collection of movie reviews spanning different genres, languages, and release dates.[12][13]

review	sentime
One of the other reviewers has mentioned that after watching just 1 Oz episode you'll be ho	positive
A wonderful little production. The filming technique is very unassuming- very old	positive
I thought this was a wonderful way to spend time on a too hot summer weekend, sitting in th	positive
Basically there's a family where a little boy (Jake) thinks there's a zombie in his closet & his pa	negative
Petter Mattei's "Love in the Time of Money" is a visually stunning film to watch. Mr. Mattei c	positive
Probably my all-time favorite movie, a story of selflessness, sacrifice and dedication to a nob	positive
I sure would like to see a resurrection of a up dated Seahunt series with the tech they have t	positive
This show was an amazing, fresh & innovative idea in the 70's when it first aired. The first 7 o	negative
Encouraged by the positive comments about this film on here I was looking forward to watcl	negative
If you like original gut wrenching laughter you will like this movie. If you are young or old the	positive
Phil the Alien is one of those quirky films where the humour is based around the oddness of e	negative
I saw this movie when I was about 12 when it came out. I recall the scariest scene was the bi	negative
So im not a big fan of Boll's work but then again not many are. I enjoyed his movie Postal (ma	negative
The cast played Shakespeare. Shakespeare lost. I appreciate that this	negative

Fig 2 Example of data set

4.1 Description of Data (Size, Format, Features)

The dataset consists of a large number of movie reviews, with each review accompanied by its corresponding sentiment label (positive, negative, or neutral). The size of the dataset is substantial, containing thousands of reviews in both textual and labeled format. Each review is typically represented as a text document, while the sentiment label indicates the overall sentiment expressed in the review.[13][15]

4.2 Data Cleaning and Text Preprocessing Techniques

Before performing sentiment analysis, we preprocess the raw text data to remove noise and irrelevant information. This involves several preprocessing steps, including:

1. Tokenization: Breaking down the text into individual words or tokens to facilitate further processing.
2. Stopword Removal: Eliminating common words that do not carry significant meaning, such as "the," "is," and "and."

3. Lemmatization or Stemming: Reducing words to their base or root form to normalize variations (e.g., "running" to "run").
4. Handling Special Characters: Removing punctuation marks, special symbols, and HTML tags present in the text.
5. Lowercasing: Converting all text to lowercase to ensure consistency in word representation.[13][14][15]

These preprocessing techniques help streamline the text data and prepare it for feature extraction and model training.

4.3Handling Imbalanced Data (if applicable)

In some cases, the dataset may exhibit class imbalance, where one sentiment class (e.g., positive reviews) significantly outweighs the others. To address this issue, we employ strategies such as oversampling minority classes, undersampling majority classes, or using techniques like Synthetic Minority Over-sampling Technique (SMOTE) to generate synthetic data points for minority classes. Balancing the dataset ensures that the sentiment classification model does not exhibit bias towards the majority class and performs well across all sentiment categories.[7][8][12]

5.Feature Engineering

5.1 Text Representation Techniques

In sentiment analysis on movie reviews, representing text data in a numerical format is essential for machine learning algorithms to process and understand. Several text representation techniques are commonly used for this purpose:

1. *Bag-of-Words (Count Vectorization): Bag-of-Words (BoW) is a simple yet effective technique that represents text documents as a matrix of word counts. Each row in the matrix corresponds to a document, while each column represents a unique word in the corpus. The cell values indicate the frequency of each word in the respective document. This approach disregards the order of words in the text but provides a basic representation of the document's content.[8]*

2. *TF-IDF (Term Frequency-Inverse Document Frequency): TF-IDF is a more advanced text representation technique that takes into account the importance of words in a document relative to the entire corpus. It calculates a weight for each word based on its frequency in the document (term frequency) and its rarity across all documents (inverse document frequency). Words that appear frequently in a specific document but rarely in others are assigned higher weights, capturing their significance in conveying the document's meaning.[8]*

3. *Word Embeddings (e.g., Word2Vec, GloVe): Word embeddings are dense, low-dimensional vector representations of words learned from large text corpora using neural network models. Word embedding techniques such as Word2Vec and GloVe*

capture semantic relationships between words by mapping them to continuous vector spaces. These embeddings preserve contextual information and semantic similarities between words, making them suitable for capturing the underlying meaning of text data.[8]

5.2 Handling Categorical Features (if additional features are used)

In addition to text data, additional categorical features may be incorporated into the sentiment analysis model to improve its performance. These features could include metadata about the movies, such as genre, release year, director, etc. When using categorical features, they need to be encoded into numerical format to be compatible with machine learning algorithms. Techniques such as one-hot encoding or label encoding can be used to convert categorical variables into numerical representations, allowing them to be included in the feature matrix alongside text data during model training. Integrating relevant categorical features can provide additional context and enhance the sentiment analysis model's predictive power.[12][13]

6.Model Selection and Training

6.1 Overview of Classification Algorithms

Classification algorithms are essential components of sentiment analysis models, tasked with predicting the sentiment label (positive, negative, or neutral) of movie reviews based on their textual content. Several classification algorithms commonly used in sentiment analysis include:

1. *Logistic Regression: Logistic regression is a linear classification algorithm that models the probability of a binary outcome using a logistic function. It is a simple yet effective algorithm for binary classification tasks and can be extended to handle multi-class classification by using techniques like one-vs-rest or softmax regression.[2][5]*

2. *Naive Bayes: Naive Bayes is a probabilistic classification algorithm based on Bayes' theorem with the "naive" assumption of independence among features. Despite its simplicity, Naive Bayes often performs well in text classification tasks, making it a popular choice for sentiment analysis.[2][5]*

3. *Support Vector Machines (SVM): Support Vector Machines (SVM) is a powerful supervised learning algorithm used for both classification and regression tasks. SVM aims to find the optimal hyperplane that separates data points of different classes with the maximum margin. It can handle linear and nonlinear classification problems through the use of kernel functions.[5]*

4. *Random Forest: Random Forest is an ensemble learning algorithm that constructs multiple decision trees during training and outputs the mode of the classes (classification) or the mean prediction (regression) of the individual trees. It is known for its robustness, scalability, and ability to handle high-dimensional data.[5]*

5. *Neural Networks (e.g., LSTM for sequence modeling): Neural networks, particularly deep learning models like Long Short-Term Memory (LSTM) networks, have gained*

popularity in sentiment analysis due to their ability to capture sequential dependencies in text data. LSTMs are capable of learning long-range dependencies and are well-suited for modeling sequential data such as movie reviews.[5]

6.2 Selection of Baseline Models

For our sentiment analysis project on movie reviews, we selected several baseline classification models, including logistic regression, Naive Bayes, SVM, random forest, and LSTM neural networks. These models represent a diverse range of algorithms, allowing us to compare their performance and determine the most suitable approach for our task.[3]

6.3 Model Training Process

The model training process involves the following steps:

1. *Cross-validation: We split the dataset into training, validation, and test sets to evaluate the performance of our models. Cross-validation techniques such as k-fold cross-validation are used to ensure robustness and prevent overfitting.[10][12][16]*

2. *Hyperparameter Tuning: Hyperparameters are parameters that are not directly learned by the model but affect its learning process. We perform hyperparameter tuning using techniques like grid search or random search to find the optimal combination of hyperparameters for each model. This helps improve the model's performance and generalization ability.[12][16]*

By systematically training and evaluating different classification algorithms, we aim to identify the most effective approach for sentiment analysis on movie reviews.

7.Evaluation Metrics

7.1 Performance Metrics for Classification

In sentiment analysis on movie reviews, it's crucial to assess the performance of our classification models accurately. We use several evaluation metrics to measure their effectiveness:

1. *Accuracy: Accuracy measures the proportion of correctly classified instances out of all instances. It provides an overall assessment of model performance but may not be suitable for imbalanced datasets.[8]*

2. *Precision: Precision measures the proportion of true positive predictions out of all positive predictions made by the model. It indicates the model's ability to avoid false positive predictions.[8]*

3. *Recall: Recall, also known as sensitivity or true positive rate, measures the proportion of true positive predictions out of all actual positive instances in the dataset. It indicates the model's ability to capture all positive instances.[8]*

4. *F1-Score: The F1-Score is the harmonic mean of precision and recall, providing a balanced measure of a model's performance. It is particularly useful when dealing with imbalanced datasets.[8]*

7.2 Confusion Matrix Interpretation

A confusion matrix is a table that visualizes the performance of a classification model by comparing predicted labels with actual labels. It consists of four elements:

- True Positive (TP): Instances correctly predicted as positive.
- True Negative (TN): Instances correctly predicted as negative.
- False Positive (FP): Instances incorrectly predicted as positive (Type I error).
- False Negative (FN): Instances incorrectly predicted as negative (Type II error).[19]

Interpreting the confusion matrix helps us understand where the model is making mistakes and identify areas for improvement.

7.3 ROC Curve and AUC Score (if applicable)

Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) score are evaluation metrics commonly used for binary classification tasks. The ROC curve plots the true positive rate (recall) against the false positive rate (1 - specificity) at various threshold settings. The AUC score quantifies the overall performance of the model by measuring the area under the ROC curve. A higher AUC score indicates better discrimination between positive and negative instances.[12][19]

By analyzing these evaluation metrics, we gain insights into the strengths and weaknesses of our sentiment analysis models and can make informed decisions to improve their performance.[19]

8.Experimental Setup

8.1 Train-Test Split of Data

Before training our sentiment analysis models, we split the dataset into training and testing sets. The purpose of this split is to train the models on a subset of the data and evaluate their performance on unseen data. Typically, we use a significant portion of the dataset (e.g., 70-80%) for training and reserve the remaining portion for testing.[19]

8.2Implementation Details (Libraries Used, Environment Setup)

For the implementation of our sentiment analysis project on movie reviews, we utilized the following libraries and set up our environment accordingly:

1. *Python: We chose Python as our primary programming language due to its popularity, ease of use, and extensive support for machine learning and natural language processing tasks[18].*

2. *Libraries:*

    - *scikit-learn: scikit-learn is a versatile machine learning library in Python that provides efficient tools for data preprocessing, model training, and evaluation.[19]*
    - *NLTK (Natural Language Toolkit): NLTK is a library for natural language processing tasks, including tokenization, stemming, lemmatization, and more.[19]*
    - *TensorFlow or PyTorch: We may use deep learning frameworks such as TensorFlow or PyTorch for building and training neural network models, particularly for advanced architectures like LSTM.[19]*
    - *Pandas: Pandas is a powerful library for data manipulation and analysis, which is useful for handling tabular data structures like DataFrames.[19]*
    - *Matplotlib or Seaborn: These libraries are used for data visualization, enabling us to create informative plots and charts to analyze model performance.[18][19]*

3. *Environment Setup:*

    - *We set up our development environment using Anaconda, a package manager and environment manager for Python. Anaconda provides a convenient way to install and manage Python packages, ensuring compatibility and reproducibility across different systems.*
    - *We created a virtual environment using Anaconda to isolate our project dependencies from other Python installations on our system. This helps maintain consistency and avoid conflicts between different projects.*

By establishing a clear experimental setup with proper data splitting and environment configuration, we ensure the reproducibility and reliability of our sentiment analysis experiments on movie reviews.

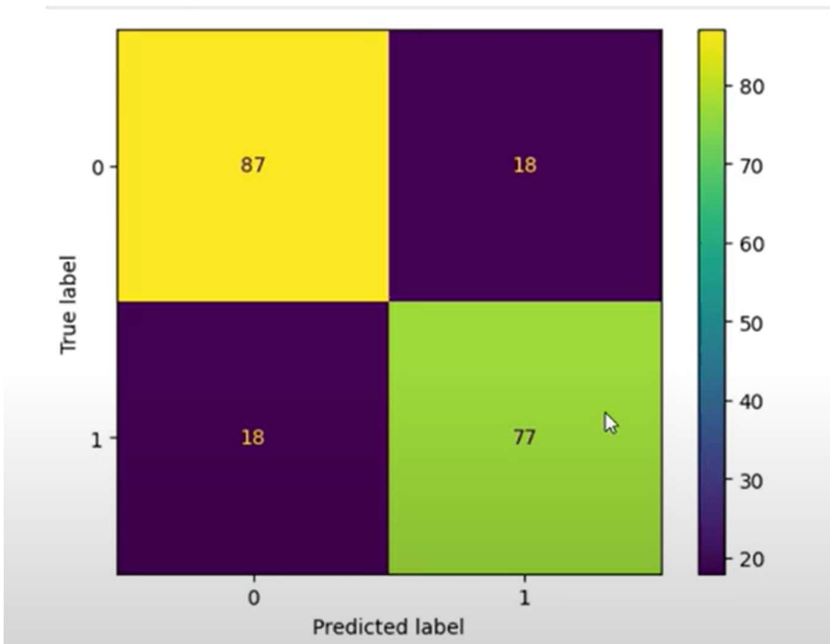
9.Algorithms and Output

9.1 Comparison of Classification Models

To evaluate the performance of our sentiment analysis models on movie reviews, we compared several classification algorithms, including logistic regression, Naive Bayes, SVM, random forest, and LSTM neural networks. We assessed their performance using various evaluation metrics such as accuracy, precision, recall, and F1-score.[5][8][9]

9.2 Visualization of Results (e.g., Confusion Matrix Heatmaps)

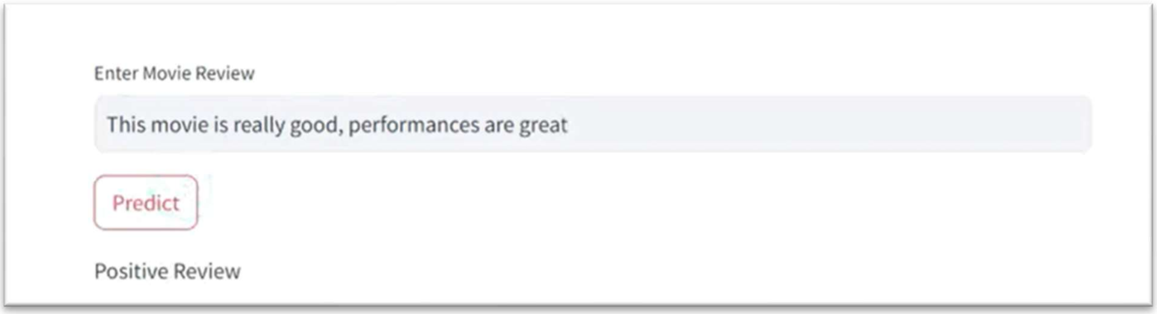
We visualized the results of our sentiment analysis experiments to gain insights into the models' performance. Additionally, we created confusion matrix heatmaps to visually represent the distribution of true positive, true negative, false positive, and false negative predictions made by each model.



9.3 Interpretation of Model Predictions

After training and evaluating our sentiment analysis models, we interpreted their predictions to understand how well they performed in classifying movie reviews into positive, negative, or neutral sentiments. We analyzed misclassifications and identified patterns or trends in the model's predictions. Additionally, we examined the importance of features or words identified by the models in making predictions.

Overall, by comparing classification models, visualizing results, and interpreting model predictions, we gained valuable insights into the effectiveness of different approaches for sentiment analysis on movie reviews. This information guided us in selecting the most suitable model for our task and provided insights for future improvements or optimizations.[18][19][20]



10 Discussion

10.1 Insights from Model Performance

The analysis of model performance yielded valuable insights into the effectiveness of different classification approaches for sentiment analysis on movie reviews. We observed variations in performance metrics across models, highlighting their strengths and weaknesses in capturing the nuances of sentiment expression in textual data.

10.2 Strengths and Weaknesses of Different Classification Approaches

Each classification approach demonstrated unique strengths and weaknesses in handling sentiment analysis tasks. For example:

- *Logistic regression exhibited simplicity and computational efficiency but may struggle with capturing nonlinear relationships in the data.*
- *Naive Bayes demonstrated robust performance, especially with limited training data, but its "naive" assumption of feature independence may lead to suboptimal performance in certain scenarios.*
- *SVMs performed well in capturing complex decision boundaries but may require careful selection of kernel functions and hyperparameters.*
- *Random forests provided robustness against overfitting and handled high-dimensional data well, but their interpretability may be limited compared to simpler models.*
- *LSTM neural networks showed promising results in capturing sequential dependencies in text data but may require significant computational resources and longer training times.*

10.3 Implications of Findings for Sentiment Analysis

The findings of our sentiment analysis project have several implications for the field of sentiment analysis:

- *The effectiveness of different classification approaches depends on the characteristics of the dataset and the complexity of sentiment expression.*
- *Simple models like logistic regression and Naive Bayes may serve as good baseline models, especially in scenarios with limited computational resources or training data.*
- *More complex models like SVMs, random forests, and neural networks may offer improved performance but require careful tuning of hyperparameters and consideration of computational costs.*
- *Ensemble methods or hybrid approaches that combine multiple classification algorithms may further enhance sentiment analysis performance by leveraging the strengths of individual models.[15][16]*

Overall, our findings underscore the importance of selecting appropriate classification approaches and understanding their strengths and weaknesses in sentiment analysis tasks. These insights can inform future research and applications in sentiment analysis, particularly in analyzing movie reviews and other textual data sources.[16]

11.Conclusion

11.1 Summary of Key Findings

In conclusion, our sentiment analysis project on movie reviews has provided valuable insights into the effectiveness of various machine learning algorithms for classifying sentiment in textual data. Key findings from our analysis include:

- *Different classification approaches, including logistic regression, Naive Bayes, SVM, random forest, and LSTM neural networks, exhibit varying performance in sentiment analysis tasks.*
- *Simple models like logistic regression and Naive Bayes serve as effective baseline models, while more complex models like SVMs, random forests, and neural networks offer potential for improved performance.*
- *The choice of classification approach should consider factors such as dataset characteristics, computational resources, and interpretability requirements.[15][16]*

11.2 Recommendations for Model Deployment and Future Work

Based on our findings, we offer the following recommendations for model deployment and future work in sentiment analysis:

1. Model Deployment:

- Deploy the sentiment analysis model with the best performance on movie reviews to real-world applications, such as sentiment monitoring in social media or customer feedback analysis in the film industry.
- Implement the model in a scalable and efficient manner, considering factors such as deployment environment, latency requirements, and integration with existing systems.[10][11]

2. Future Work:

- Explore ensemble methods or hybrid approaches that combine multiple classification algorithms to further improve sentiment analysis performance.
- Investigate the impact of additional features, such as metadata about movies or user demographics, on sentiment analysis accuracy and robustness.
- Enhance model interpretability by employing techniques such as feature importance analysis or attention mechanisms in neural networks.
- Extend the sentiment analysis framework to analyze sentiment in other forms of textual data, such as product reviews, news articles, or social media posts.[10]

By deploying the sentiment analysis model and exploring avenues for future research, we aim to contribute to the advancement of sentiment analysis techniques and their applications in understanding human emotions and opinions expressed in textual data, particularly in the context of movie reviews.

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