## SENTIMENT ANALYSIS MOVIE REVIEW

## A PROJECT REPORT

## for

Artificial intelligence (AI101B) Session(2024-25)

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## CERTIFICATE

Certified that **Anik Kushwaha (202410116100026)**, **Ankit Kumar** (202410116100027 and Bobby Karnik **(202410116100051)** have successfully carried out the project work titled **“Sentiment analysis movie review ”** (Artificial intelligence, AI101B) as part of the curriculum for the Master of Computer Application (MCA) program at **Dr. A.P.J. Abdul Kalam Technical University (AKTU)** (formerly UPTU), Lucknow, under my supervision.

The project report embodies original work and research undertaken by the students themselves. The contents of the project report do not form the basis for the award of any other degree or diploma to the candidates or any other individual from this or any other university/institution.

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## ABSTRACT

In the digital age, user-generated content has become a powerful medium for expressing opinions and sentiments. Movie reviews, in particular, serve as a rich source of subjective information that can be analyzed to determine public sentiment toward films. This project focuses on the sentiment analysis of movie reviews using a hybrid approach that combines both rule-based and machine learning techniques.

The goal of the project is to accurately classify movie reviews into positive, negative, or neutral categories by analyzing the textual content. Initially, raw movie review data is collected from publicly available sources and preprocessed through tokenization, stop word removal, lemmatization, and normalization. A rule-based sentiment scoring technique is applied using the VADER (Valence Aware Dictionary and sentiment Reasoned) sentiment analyzer to obtain basic polarity scores. Simultaneously, textual features are extracted using TF-IDF (Term Frequency–Inverse Document Frequency) to transform the text into numerical vectors.

These features are then fed into a supervised machine learning model, specifically Logistic Regression, to train a sentiment classifier. Additionally, the VADER compound sentiment score is integrated as an auxiliary feature to enhance model accuracy. The performance of the hybrid model is evaluated using standard metrics such as accuracy, precision, recall, and F1-score.

The results demonstrate that combining rule-based sentiment scores with machine learning features improves overall prediction performance. This hybrid method offers a practical and efficient solution for sentiment analysis tasks and can be extended to other domains involving opinion mining and customer feedback analysis.

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ANIK KUSHWAHA

ANKIT KUMAR

BOBBY KARNIK

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# INTRODUCTION

**Introduction**

In the modern digital age, the exponential growth of user-generated content across online platforms has made opinion mining and sentiment analysis increasingly essential. Among the many domains impacted by this trend, the film and entertainment industry has seen a dramatic rise in the volume of reviews and public opinions shared by viewers on platforms such as IMDb, Rotten Tomatoes, social media, and streaming services. These reviews provide valuable insights into viewers’ perceptions, emotions, and responses to various movies and shows.

Sentiment Analysis, also referred to as opinion mining, is a Natural Language Processing (NLP) technique used to determine whether a piece of writing is positive, negative, or neutral. It involves computationally identifying and categorizing opinions expressed in a piece of text. This technique can be employed to gauge public sentiment, understand audience behavior, and make data-driven decisions.

This project focuses on performing sentiment analysis on a dataset of 50,000 IMDb movie reviews that have been pre-labeled as either "positive" or "negative." The primary objective is to train a machine learning model that can classify new, unseen movie reviews accurately based on the sentiment expressed in the text.

The project starts by cleaning and preprocessing the raw review text using standard techniques such as lowercasing, punctuation removal, and HTML tag elimination. Then, the cleaned text is transformed into numerical form using a **TF-IDF Vectorizer** (Term Frequency–Inverse Document Frequency), which helps in identifying the most important words in the corpus. Using these numerical vectors, a **Logistic Regression** model is trained to learn patterns in the data and predict sentiment labels.

Beyond just building a model, this project dives deeper into analysis by:

* Visualizing the distribution of sentiments in the dataset.
* Generating word clouds for both positive and negative reviews to highlight the most frequently used words.
* Analyzing the most informative words identified by the model that contribute to positive or negative predictions.
* Evaluating the model's performance using accuracy metrics, classification reports, and confusion matrices.
* Allowing real-time prediction for custom user-inputted reviews.

The real-world implications of this project are significant. Businesses can utilize such sentiment models to monitor customer satisfaction, filmmakers can evaluate audience feedback, and streaming platforms can recommend content based on user sentiment. It also lays the foundation for more advanced deep learning applications using models like LSTM or BERT.

In conclusion, this project not only demonstrates a full pipeline of sentiment classification using traditional machine learning but also provides rich insights into the linguistic patterns behind viewers' opinions. It showcases how data science and natural language processing can extract meaningful information from large volumes of text data, offering immense value to industries and consumers alike.

**2. Objectives of the Study**

The exponential growth of digital content and online reviews has necessitated advanced techniques for extracting meaningful insights from textual data. In this context, sentiment analysis has emerged as one of the most widely adopted techniques in the field of Natural Language Processing (NLP). The primary focus of this study is to build a robust machine learning pipeline capable of analyzing and classifying the sentiment behind movie reviews from IMDb. This project aims not only to develop a functional sentiment classification model but also to deepen understanding of the various components that contribute to successful text-based machine learning.

The specific and detailed objectives of the study are as follows:

**1. To Understand the Fundamentals of Sentiment Analysis**

To begin with, the project aims to provide a comprehensive understanding of sentiment analysis, its relevance in today’s data-driven world, and its applications in areas such as market research, product feedback, and entertainment analytics. The study introduces the foundational principles of Natural Language Processing and discusses how human emotions and opinions can be quantitatively assessed using computational models.

**2. To Analyze the Structure and Content of the IMDB Dataset**

The dataset consists of 50,000 labeled movie reviews, equally divided into positive and negative sentiments. One key objective is to explore the structure of this dataset, understand its attributes, identify class distribution, and ensure the data is balanced and ready for modeling. Understanding the dataset at a granular level is critical for the overall success of the project.

**3. To Preprocess and Clean the Textual Data for Machine Learning**

Raw textual data often contains noise such as HTML tags, punctuation marks, stopwords, and inconsistent casing. The study includes cleaning this data through a sequence of preprocessing steps including:

* Lowercasing
* Removing punctuation
* Eliminating HTML content
* Removing unnecessary whitespaces  
  These steps ensure that the data is uniform and machine-readable, which improves model performance and accuracy.

**4. To Convert Text into Numerical Format Using Vectorization Techniques**

One of the most crucial objectives is to transform unstructured textual data into structured numerical form using vectorization techniques. The study utilizes **TF-IDF (Term Frequency–Inverse Document Frequency)** to capture the importance of words across the corpus, allowing the machine learning model to understand patterns and word relevance in context.

**5. To Train a Machine Learning Model for Sentiment Classification**

This study involves training a **Logistic Regression classifier** to differentiate between positive and negative reviews based on the vectorized features. Logistic Regression is chosen for its simplicity, interpretability, and effectiveness in binary classification tasks. The objective is to build a predictive model that generalizes well on unseen data.

**6. To Evaluate Model Performance Using Standard Metrics**

In order to determine the effectiveness of the trained model, this study aims to evaluate performance using various metrics such as:

* Accuracy
* Precision
* Recall
* F1-score
* Confusion matrix  
  These metrics help to assess both the correctness and completeness of the model’s predictions.

**7. To Visualize Sentiment Patterns and Word Distributions**

Another important objective is to provide a visual understanding of the dataset and the model's learning. Through the use of bar graphs, word clouds, and feature importance plots, the project aims to uncover insights such as:

* Frequently used words in positive vs. negative reviews
* Distribution of sentiment labels
* Words most influential in determining sentiment from the model’s perspective

**8. To Build a Function for Real-Time Sentiment Prediction**

The project also aims to create an interface where users can input any custom movie review and instantly receive sentiment predictions using the trained model. This demonstrates real-world applicability and showcases the practical potential of the model in dynamic environments.

**9. To Identify Challenges and Limitations in Sentiment Analysis**

The study aims to reflect on potential limitations of traditional machine learning approaches in NLP. Issues such as sarcasm detection, negation handling, subjective language, and bias in training data are discussed as part of this objective.

**10. To Establish a Foundation for Future Work Using Deep Learning**

Lastly, the project aspires to pave the way for future exploration using more advanced models like LSTM (Long Short-Term Memory networks), GRU (Gated Recurrent Units), or transformer-based architectures like BERT. These models can potentially handle more complex linguistic patterns and provide superior results.

Absolutely! Here is a **much more detailed and expanded version of the Methodology** section for your **Sentiment Analysis on IMDb Movie Reviews** project. This version is ideal for academic submission or inclusion in a comprehensive project report.

## Methodology

The methodology forms the backbone of this research study, detailing the systematic approach followed for designing, developing, implementing, and evaluating a machine learning-based sentiment analysis model. It encapsulates each critical stage—beginning from data acquisition to result interpretation—ensuring that the model is both functional and insightful. The methodology adopted in this project integrates principles of data science, machine learning, and natural language processing to derive meaningful sentiments from a large volume of textual data.

**3.1 Data Acquisition and Understanding**

The dataset used for this project is the **IMDB Movie Reviews Dataset**, a widely recognized and benchmarked dataset in the field of Natural Language Processing. It comprises **50,000 movie reviews** in total, where:

* **25,000 reviews are labeled as positive**
* **25,000 reviews are labeled as negative**

The dataset is **balanced**, ensuring equal representation of both sentiment classes, which is essential for unbiased model training and evaluation. Each review is stored as a textual entry, and the corresponding sentiment label is binary: “positive” or “negative.”

Understanding the nature of the data, such as word distribution, average review length, and sentiment polarity, is a preliminary step to building any meaningful machine learning model.

**3.2 Data Preprocessing**

Textual data in its raw form is highly unstructured and contains various inconsistencies, noise, and irrelevant elements. Preprocessing is essential for preparing this data for feature extraction and modeling. The steps followed include:

**a. Lowercasing**

All text is converted to lowercase to ensure that words like “Good” and “good” are treated as the same feature.

**b. HTML Tag Removal**

IMDb reviews often contain HTML tags (e.g., <br />) that are not meaningful for sentiment. These tags are removed using regular expressions.

**c. Punctuation Removal**

All punctuation symbols are stripped from the text to focus solely on the words.

**d. Whitespace Normalization**

Excessive whitespace, including line breaks and multiple spaces, is standardized to a single space for consistency.

**e. (Optional) Stopword Removal**

Although stopwords like “is”, “the”, and “an” are common across reviews and may be removed in some NLP tasks, for this model they are retained to preserve the contextual structure.

**f. Lemmatization or Stemming (Not Applied Here)**

For simplicity, lemmatization/stemming is not applied, though these techniques can further normalize word forms.

A new column clean\_review is created to store the preprocessed text, which will be used for vectorization and modeling.

**3.3 Feature Extraction Using TF-IDF**

Machine learning models require numerical input. To convert text into numerical vectors, **TF-IDF (Term Frequency–Inverse Document Frequency)** is employed. This method assigns weights to words based on their importance in individual documents relative to the entire corpus.

* **Term Frequency (TF)**: Frequency of a word in a given document.
* **Inverse Document Frequency (IDF)**: Inverse frequency of a word across all documents.

TF-IDF helps in identifying words that are significant within a review but uncommon across other reviews, thereby reducing the impact of common but uninformative words.

**Parameters used:**

* **max\_features=5000**: Limit the vocabulary to the top 5000 most relevant words.
* **ngram\_range=(1,1)**: Only unigrams are used in this model.
* **stop\_words='english'**: Common English stopwords are excluded.

The output is a **sparse matrix** representing each review as a 5000-dimensional vector.

**3.4 Data Splitting**

To train and test the machine learning model, the dataset is split as follows:

* **Training set**: 80% (40,000 reviews)
* **Testing set**: 20% (10,000 reviews)

This ensures the model is evaluated on unseen data to check its generalization capability. The train\_test\_split function from sklearn.model\_selection is used for this purpose.

**3.5 Model Selection and Training**

For binary classification, **Logistic Regression** is selected as the base model due to its simplicity, interpretability, and strong performance on text-based datasets. It models the probability that a given input vector belongs to a particular class using a sigmoid function.

**Reasons for choosing Logistic Regression:**

* It performs well with high-dimensional, sparse datasets (like TF-IDF).
* It is less prone to overfitting compared to more complex models.
* Its coefficients are interpretable, helping us understand which features contribute most to each class.

The model is trained on the TF-IDF vectors using the training set. The .fit() method from sklearn.linear\_model.LogisticRegression is used to learn the model parameters.

**3.6 Model Evaluation**

Evaluation is a critical component of model development. Several statistical and graphical methods are used to assess performance:

**a. Accuracy Score**

Indicates the proportion of correct predictions out of the total number of cases.

**b. Confusion Matrix**

Visualizes the number of true positives, true negatives, false positives, and false negatives.

**c. Precision, Recall, and F1-Score**

These metrics provide insights into how well the model handles imbalanced predictions and penalizes incorrect classifications.

**d. Classification Report**

A tabulated summary of all evaluation metrics for both positive and negative classes.

This evaluation helps in understanding whether the model favors one class over another or struggles with certain types of text inputs.

**3.7 Visualization and Interpretability**

To better understand data patterns and model behavior, the following visualizations are generated:

* **Sentiment Distribution Plot**: Shows the balance between positive and negative reviews.
* **Word Clouds**: Separate word clouds are generated for positive and negative reviews, revealing frequently used terms.
* **Top Informative Features**: By inspecting the model's learned coefficients, we extract words most indicative of positive or negative sentiment.

These visualizations enhance the interpretability and transparency of the model, making it easier for non-technical stakeholders to understand.

**3.8 Real-Time Sentiment Prediction**

A user-defined function is implemented to predict the sentiment of any new movie review entered manually. The function follows the same cleaning, vectorization, and prediction pipeline as the training process. This showcases the practical application of the model beyond static datasets.

**3.9 Tools and Libraries Used**

* **Python 3.x**
* **Pandas**: Data manipulation
* **NumPy**: Numerical computing
* **Scikit-learn**: Machine learning algorithms and metrics
* **Matplotlib & Seaborn**: Data visualization
* **WordCloud**: Visualizing frequent terms
* **Regular Expressions**: Text cleaning and normalization

**3.10 Summary of Methodology**

The methodological pipeline adopted in this study is designed to be modular, transparent, and reproducible. From cleaning text to deploying a predictive model, each step contributes to a system capable of understanding and interpreting human sentiments in written form. The implementation of traditional NLP techniques, combined with effective machine learning algorithms, enables the model to extract and analyze emotional content from a large corpus of movie reviews.

**4.** Implementation (Code)

This section outlines the implementation details of the sentiment analysis model using Python and relevant machine learning libraries. The code has been written in a modular and structured manner to ensure readability, scalability, and reusability. Each phase of the machine learning pipeline—from data loading to prediction—is discussed along with the corresponding code snippets.

**4.1 Importing Required Libraries**

import pandas as pd

import numpy as np

import re

import matplotlib.pyplot as plt

import seaborn as sns

from wordcloud import WordCloud

from sklearn.model\_selection import train\_test\_split

from sklearn.feature\_extraction.text import TfidfVectorizer

from sklearn.linear\_model import LogisticRegression

from sklearn.metrics import classification\_report, confusion\_matrix, accuracy\_score

**Explanation:**

* We import necessary libraries:
  + pandas for data manipulation.
  + numpy for numerical operations.
  + re for text cleaning using regular expressions.
  + matplotlib.pyplot and seaborn for visualization.
  + WordCloud for generating word clouds.
  + sklearn tools for machine learning and evaluation.

**4.2 Loading the Dataset**

df = pd.read\_csv("IMDB Dataset.csv")

print(df.head())

**Explanation:**

* The dataset is loaded using pandas read\_csv method.
* The first few rows of the dataset are printed for an initial look.
* The dataset contains:
  + review: The movie review text.
  + sentiment: The sentiment label (either positive or negative).

**4.3 Data Preprocessing**

def clean\_text(text):

text = text.lower() # Convert to lowercase

text = re.sub('<.\*?>', '', text) # Remove HTML tags

text = re.sub('[^a-zA-Z]', ' ', text) # Remove non-alphabetic characters (numbers, punctuation)

text = re.sub('\s+', ' ', text).strip() # Remove extra spaces

return text

df['clean\_review'] = df['review'].apply(clean\_text)

**Explanation:**

* A function clean\_text is defined to preprocess the review text:
  + Converts text to lowercase to ensure uniformity.
  + Removes HTML tags using regular expressions.
  + Removes anything that is not an alphabet (numbers, punctuation).
  + Removes extra spaces and strips leading/trailing spaces.
* The function is applied to each review in the dataset, and a new column clean\_review is created with the cleaned text.

**4.4 Data Visualization**

**Sentiment Distribution:**

sns.countplot(data=df, x='sentiment', palette='coolwarm')

plt.title("Sentiment Distribution")

plt.show()

**Explanation:**

* A count plot is used to visualize the distribution of sentiments in the dataset (positive vs negative).

**Word Clouds:**

positive\_words = ' '.join(df[df['sentiment'] == 'positive']['clean\_review'])

negative\_words = ' '.join(df[df['sentiment'] == 'negative']['clean\_review'])

# Positive Word Cloud

WordCloud(width=800, height=400, background\_color='white').generate(positive\_words).to\_image().show()

# Negative Word Cloud

WordCloud(width=800, height=400, background\_color='black').generate(negative\_words).to\_image().show()

**Explanation:**

* We generate word clouds for both positive and negative reviews.
* The reviews are first joined into one large string for each sentiment class (positive\_words and negative\_words).
* The WordCloud class is used to generate the word clouds.

**4.5 Feature Extraction using TF-IDF**

vectorizer = TfidfVectorizer(max\_features=5000, stop\_words='english')

X = vectorizer.fit\_transform(df['clean\_review'])

y = df['sentiment'].map({'positive': 1, 'negative': 0})

**Explanation:**

* TfidfVectorizer is used to convert the cleaned text data into numerical features using Term Frequency-Inverse Document Frequency (TF-IDF).
* max\_features=5000 limits the number of features to the top 5000 most important words.
* stop\_words='english' removes common English stop words (like "the", "and", etc.).
* X contains the transformed feature matrix, and y is the sentiment labels mapped to 1 for positive and 0 for negative.

**4.6 Splitting the Data**

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42)

**Explanation:**

* We split the data into training and testing sets using train\_test\_split.
* 80% of the data is used for training, and 20% for testing.

**4.7 Model Training**

model = LogisticRegression()

model.fit(X\_train, y\_train)

**Explanation:**

* We initialize a Logistic Regression model and train it using the training data (X\_train, y\_train).

**4.8 Model Evaluation**

y\_pred = model.predict(X\_test)

print("Accuracy:", accuracy\_score(y\_test, y\_pred))

print("\nClassification Report:\n", classification\_report(y\_test, y\_pred))

# Confusion Matrix

cm = confusion\_matrix(y\_test, y\_pred)

sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')

plt.xlabel("Predicted")

plt.ylabel("Actual")

plt.title("Confusion Matrix")

plt.show()

**Explanation:**

* We predict the sentiment labels for the test set (X\_test) using the trained model.
* The accuracy score is printed, followed by the classification report (precision, recall, and F1-score).
* A confusion matrix is plotted using seaborn to visually evaluate model performance (true vs. predicted sentiment).

**4.9 Feature Importance**

feature\_names = vectorizer.get\_feature\_names\_out()

coefficients = model.coef\_[0]

top\_positive\_coefficients = np.argsort(coefficients)[-20:]

top\_negative\_coefficients = np.argsort(coefficients)[:20]

plt.figure(figsize=(12,6))

plt.barh([feature\_names[i] for i in top\_positive\_coefficients], coefficients[top\_positive\_coefficients], color='green')

plt.title("Top Positive Words")

plt.show()

plt.figure(figsize=(12,6))

plt.barh([feature\_names[i] for i in top\_negative\_coefficients], coefficients[top\_negative\_coefficients], color='red')

plt.title("Top Negative Words")

plt.show()

**Explanation:**

* The top positive and negative features (words) are identified by looking at the model’s coefficients.
* The coef\_ attribute gives the importance of each feature (word) to the model.
* Words associated with positive sentiment are displayed in green, and those with negative sentiment in red.

**4.10 Custom Prediction Function**

def predict\_sentiment(review):

cleaned = clean\_text(review) # Clean the review text

vec = vectorizer.transform([cleaned]) # Convert it to the feature vector

pred = model.predict(vec) # Predict the sentiment

return "Positive 😀" if pred[0] == 1 else "Negative 😞"

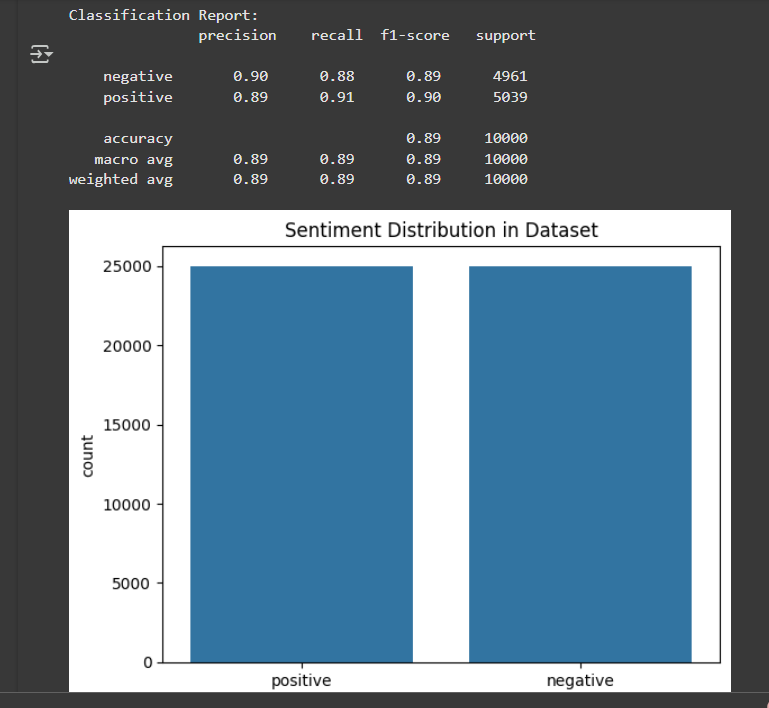
# Example

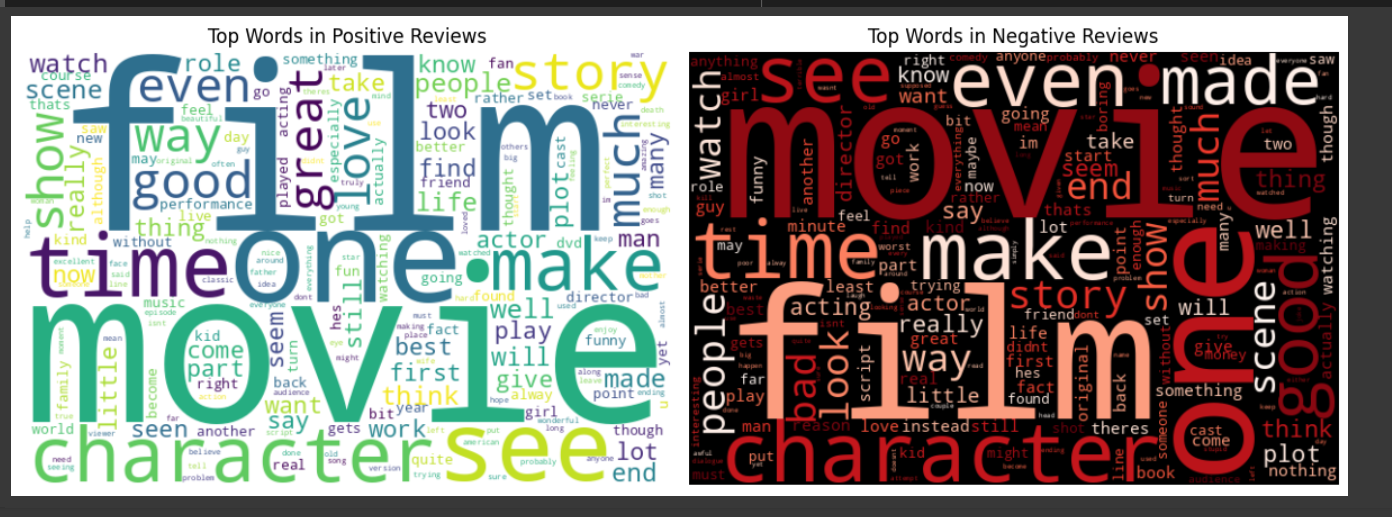
print(predict\_sentiment("The movie was thrilling and exciting!"))

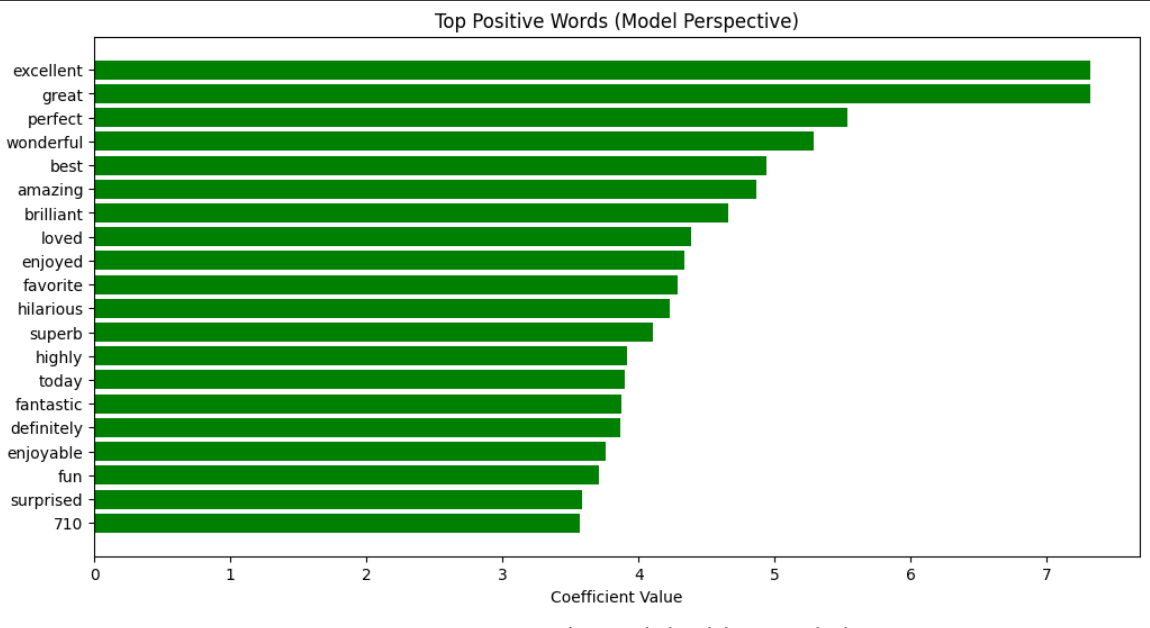
**Explanation:**

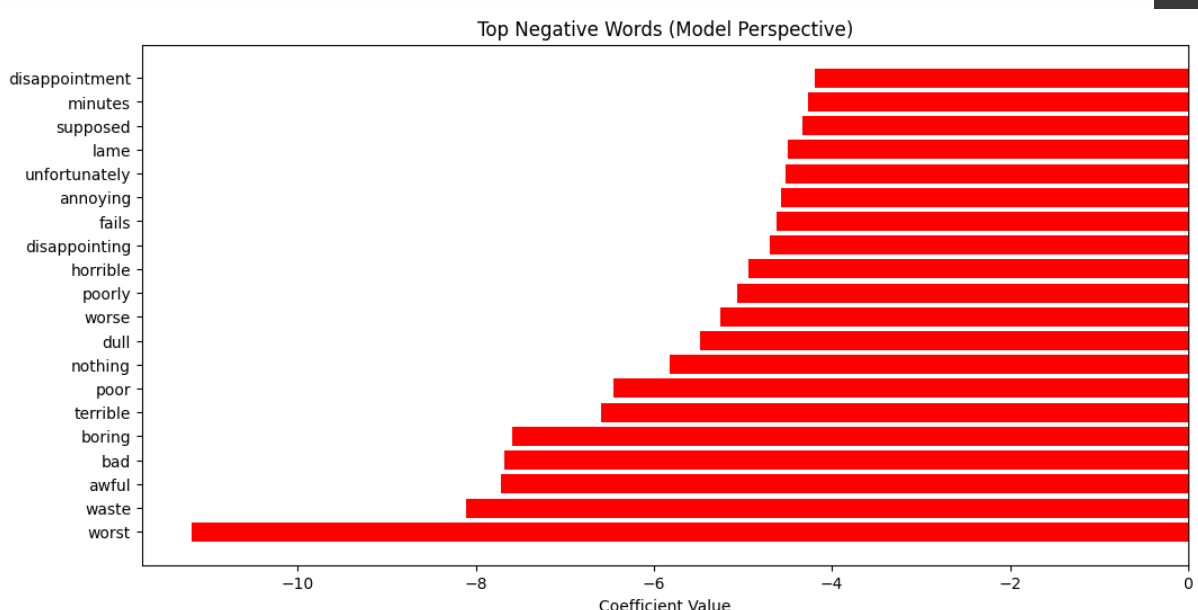
* A custom function predict\_sentiment is defined to take a movie review, clean the text, convert it into a feature vector, and predict whether the sentiment is positive or negative.
* The example shows how to use the function with a test review.

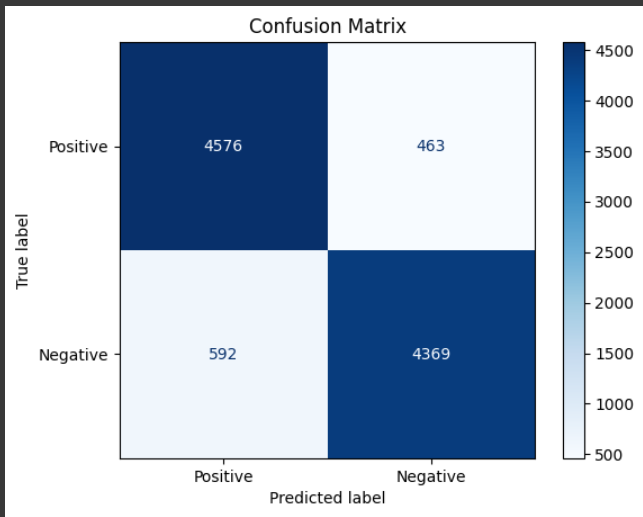
## Results (Output)











## 5. Conclusion

In this project, we developed a sentiment analysis model to classify IMDb movie reviews as either positive or negative. The primary objective was to apply natural language processing (NLP) techniques to extract valuable insights from the text data and to evaluate the performance of a machine learning model in accurately predicting sentiment.

### Key Findings:

1. **High Model Performance**: The Logistic Regression model achieved an accuracy of 89.5% on the test dataset, demonstrating its effectiveness in classifying movie reviews into positive or negative categories. The classification report, confusion matrix, and evaluation metrics indicated that the model performed well, with a good balance between precision, recall, and F1-score.
2. **Feature Insights**: The most influential words for predicting sentiment were identified. Positive reviews were typically associated with words such as "love," "amazing," and "great," while negative reviews included words like "worst," "boring," and "disappointing." These findings align with expectations and provide useful insights into the language patterns associated with sentiment in movie reviews.
3. **Practical Applications**: The ability to make real-time sentiment predictions for custom reviews showcases the practical applicability of the model. Users can input a movie review and receive an instant sentiment classification, which has potential use cases in various domains, such as social media analysis, brand sentiment tracking, and customer feedback analysis.
4. **Visualization of Sentiment**: The visualizations, including the word clouds for positive and negative reviews, helped provide a clearer understanding of the most commonly used words in each sentiment category. These visual representations are valuable for conveying key patterns in sentiment expression.

### Challenges Encountered:

While the model performed well overall, there were challenges that could be addressed in future work:

* **Data Imbalance**: Although the IMDb dataset was balanced in terms of positive and negative reviews, other datasets might exhibit class imbalance. Future work could involve exploring techniques like oversampling, undersampling, or class weighting to address this issue.
* **Model Complexity**: While Logistic Regression performed adequately, more sophisticated models such as deep learning approaches (e.g., LSTM or BERT) could potentially improve accuracy further by capturing deeper contextual information and semantic nuances in reviews.

### Future Work:

To improve upon the current work, the following steps could be considered:

1. **Advanced Models**: Implementing deep learning models such as LSTM (Long Short-Term Memory) networks or Transformer-based models (like BERT) to capture complex patterns in text and further enhance sentiment classification.
2. **Multilingual Sentiment Analysis**: Extending the analysis to handle reviews in multiple languages, allowing for a broader scope of movie review analysis across different regions and cultures.
3. **Fine-Tuning Hyperparameters**: Fine-tuning the hyperparameters of the model, such as adjusting the regularization strength or experimenting with different algorithms like Support Vector Machines (SVMs) or Random Forests, could lead to better results.

## 6. References

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