VIDEO PESENTATION:
(https://drive.google.com/file/d/1LKkTFCaSmkD70sgprXiLqqaefCXs4gtc/view?usp=drive_link)

## The primary objective of this project is to build a machine learning classification model that ## can predict the sentiment of IMDb movie reviews. The dataset contains a collection of movie ## reviews, and each review is labeled as either positive or negative. ## Using text preprocessing, feature extraction techniques (such as TF-IDF), and various ## classification algorithms, the project will aim to develop a model that can effectively classify ## the sentiment of movie reviews. The model's performance will be evaluated using standard ## classification metrics, such as accuracy, precision, recall, and F1-score.

```
# Imported essential libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import re
import string

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 accuracy_score, classification_report,
confusion_matrix
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import LinearSVC
from sklearn.ensemble import RandomForestClassifier
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer

# Download NLTK resources
nltk.download('stopwords')
nltk.download('wordnet')
nltk.download('omw-1.4')
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\DELL\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\DELL\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package omw-1.4 to
[nltk_data]     C:\Users\DELL\AppData\Roaming\nltk_data...
[nltk_data]   Package omw-1.4 is already up-to-date!

True
```

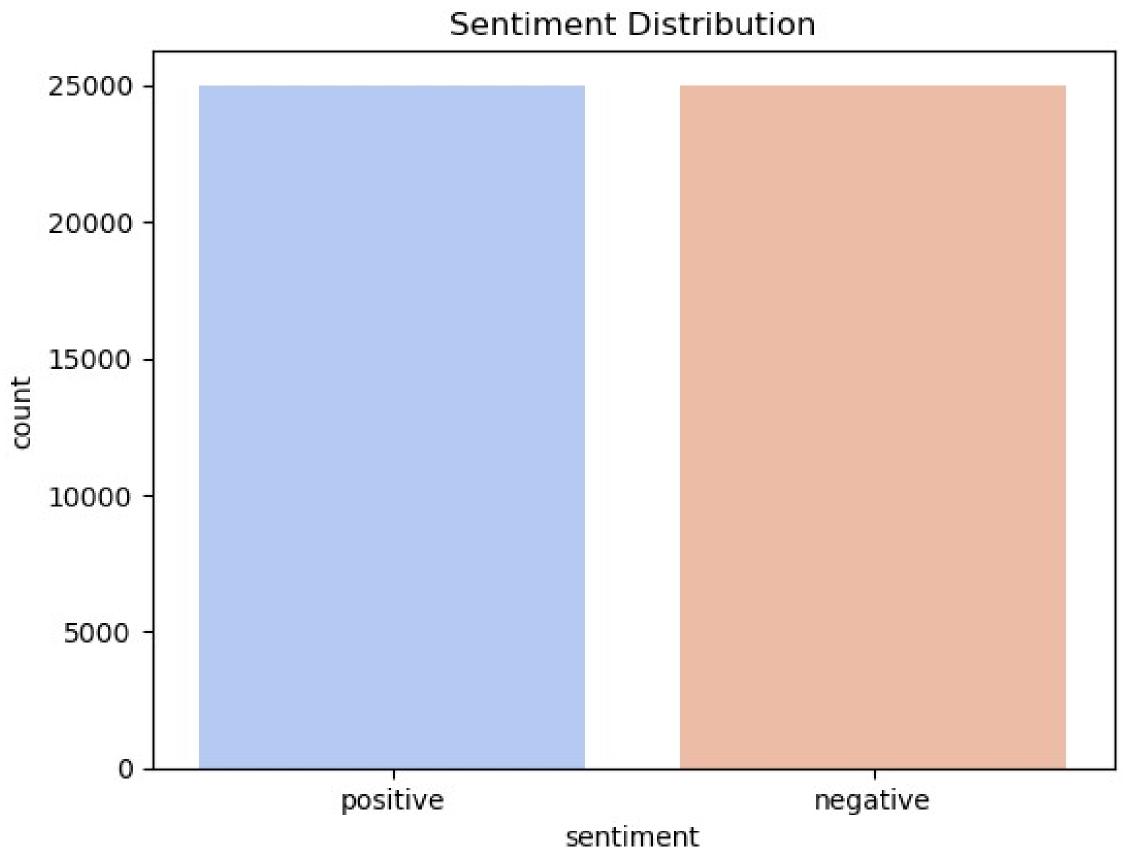
# 1. Data Exploration and Preprocessing

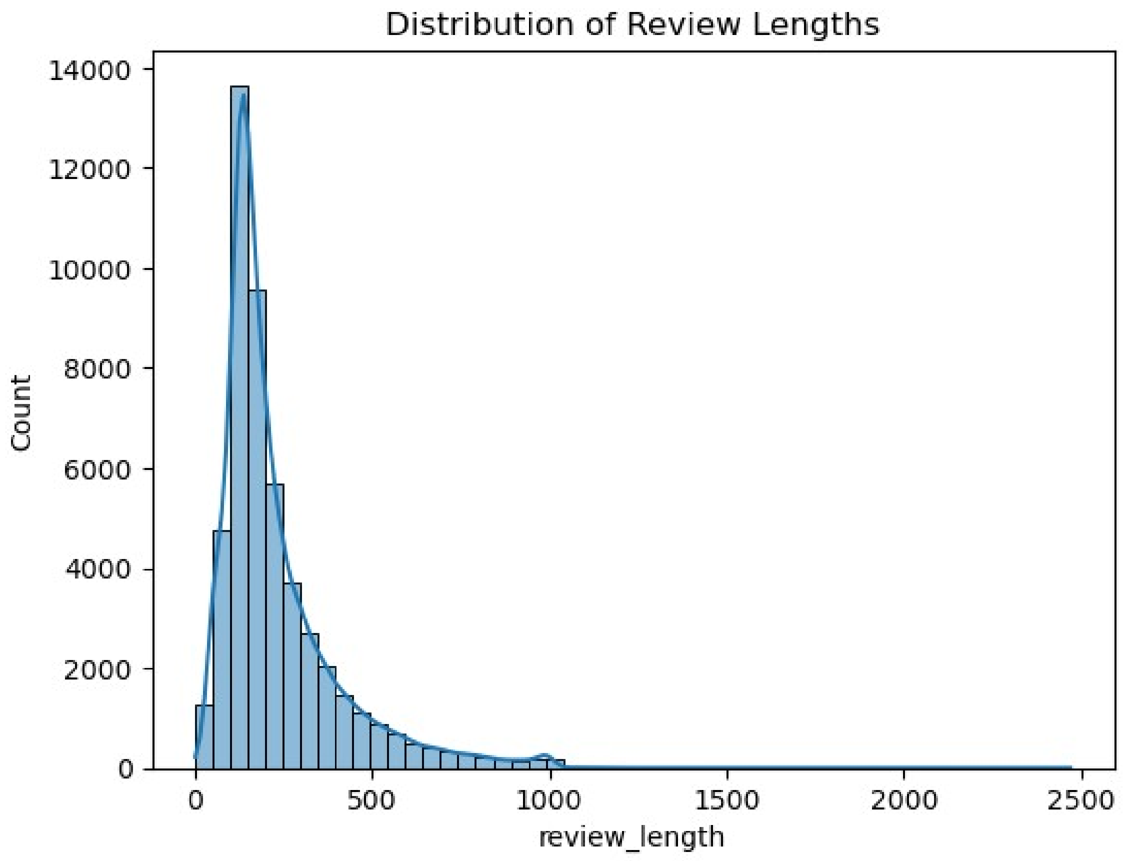
Analyzed the dataset for trends, missing values, and outliers.

```
# Loaded Dataset
df = pd.read_csv("Imdb - data_imdb.csv")
print("Shape of dataset:", df.shape)
df.head()

#  Basic Data Exploration
print("\nDataset Info:")
print(df.info())

print("\nClass Distribution:")
print(df['sentiment'].value_counts())
```

```
Shape of dataset: (50000, 2)

Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 2 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   review     50000 non-null  object
 1   sentiment  50000 non-null  object
dtypes: object(2)
memory usage: 781.4+ KB
None

Class Distribution:
sentiment
positive    25000
negative    25000
Name: count, dtype: int64
```

```
# Visualize sentiment distribution
sns.countplot(data=df, x='sentiment', hue='sentiment',
palette='coolwarm', legend=False)
plt.title("Sentiment Distribution")
plt.show()

# Review length analysis
df['review_length'] = df['review'].apply(lambda x:
len(str(x).split()))
sns.histplot(df['review_length'], bins=50, kde=True)
plt.title("Distribution of Review Lengths")
plt.show()
```


Sentiment Distribution
25000
20000
15000
10000
5000
0
count
positive
negative
sentiment



Performed data cleaning and text preprocessing

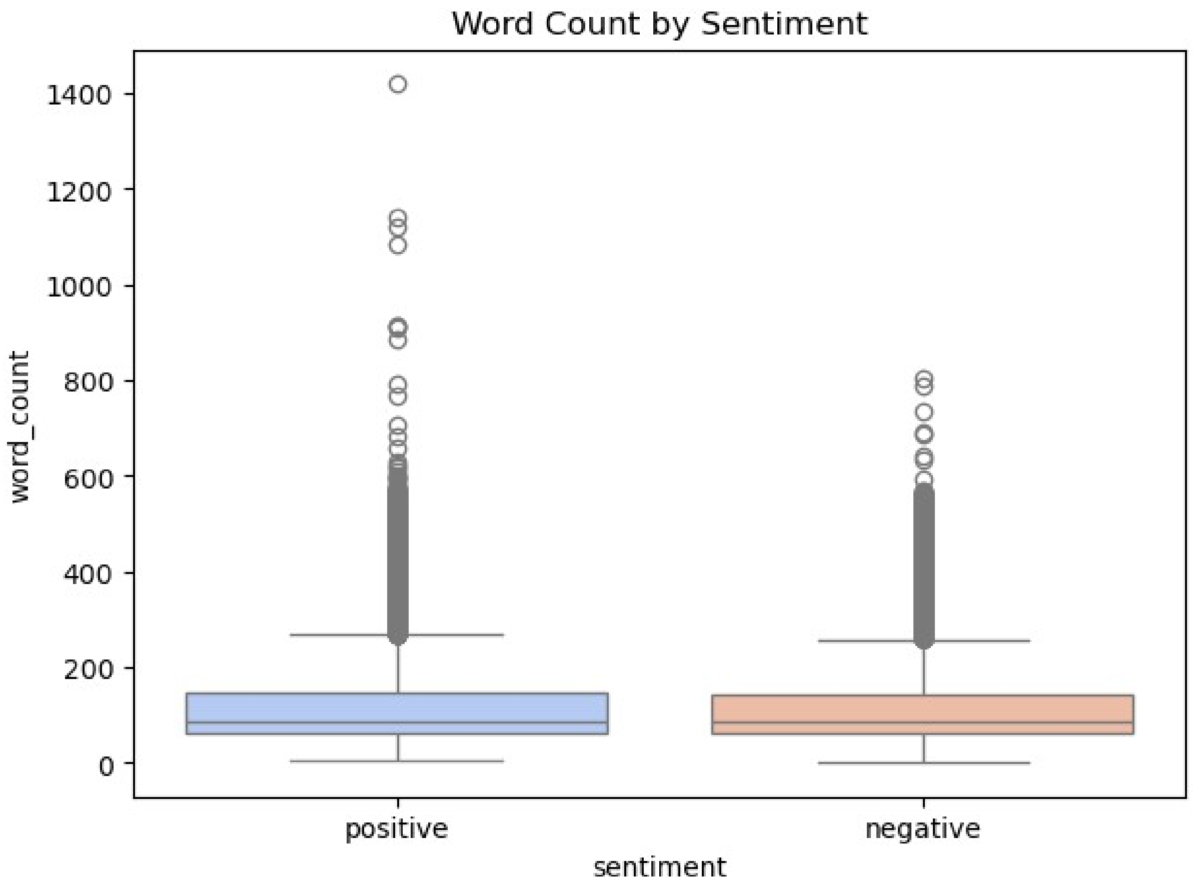
```
# Load English stopwords and initialize lemmatizer
stop_words = set(stopwords.words('english'))
lemmatizer = WordNetLemmatizer()

# Define text cleaning function
def clean_text(text):
    text = str(text).lower()  # Convert to lowercase
    text = re.sub(r'https?://\S+|www\.\S+', '', text)  # Remove URLs
    text = re.sub(r'<.*?>', '', text)  # Remove HTML tags
    text = re.sub(r'[^a-z\s]', '', text)  # Remove punctuation and
numbers
    words = [lemmatizer.lemmatize(w) for w in text.split() if w not in
stop_words]  # Remove stopwords and lemmatize
    return " ".join(words)

# Apply cleaning to review column
df['cleaned_review'] = df['review'].apply(clean_text)

# Preview cleaned data
df.head()
```

```
                                              review sentiment  
review_length  \
0  One of the other reviewers has mentioned that ...  positive  
307   
1  A wonderful little production. <br /><br />The...  positive  
162   
2  I thought this was a wonderful way to spend ti...  positive  
166   
3  Basically there's a family where a little boy ...  negative  
138   
4  Petter Mattei's "Love in the Time of Money" is...  positive  
230   

                                      cleaned_review  
0  one reviewer mentioned watching oz episode you...  
1  wonderful little production filming technique ...  
2  thought wonderful way spend time hot summer we...  
3  basically there family little boy jake think t...  
4  petter matteis love time money visually stunni...  
```

# 2. Feature Engineering

```
# Extract basic textual features from cleaned reviews
df['word_count'] = df['cleaned_review'].apply(lambda x: 
len(x.split()))  # Total number of words
df['char_count'] = df['cleaned_review'].apply(lambda x: len(x)) 
# Total number of characters
df['avg_word_length'] = df['char_count'] / df['word_count'] 
# Average word length

# Display sample features
print("\n Sample Textual Features:")
display(df[['cleaned_review', 'word_count', 'char_count', 
'avg_word_length']].head())

# Visualize word count distribution by sentiment
plt.figure(figsize=(7,5))
sns.boxplot(x='sentiment', y='word_count', data=df, hue='sentiment', 
palette='coolwarm', legend=False)
plt.title("Word Count by Sentiment")
plt.show()


 Sample Textual Features:

                                      cleaned_review  word_count  
char_count  \
0  one reviewer mentioned watching oz episode you...         167   
1125   
1  wonderful little production filming technique ...          84   
```

```
640
2  thought wonderful way spend time hot summer we...          85
580
3  basically there family little boy jake think t...          66
446
4  petter matteis love time money visually stunni...         125
851

   avg_word_length
0         6.736527
1         7.619048
2         6.823529
3         6.757576
4         6.808000
```

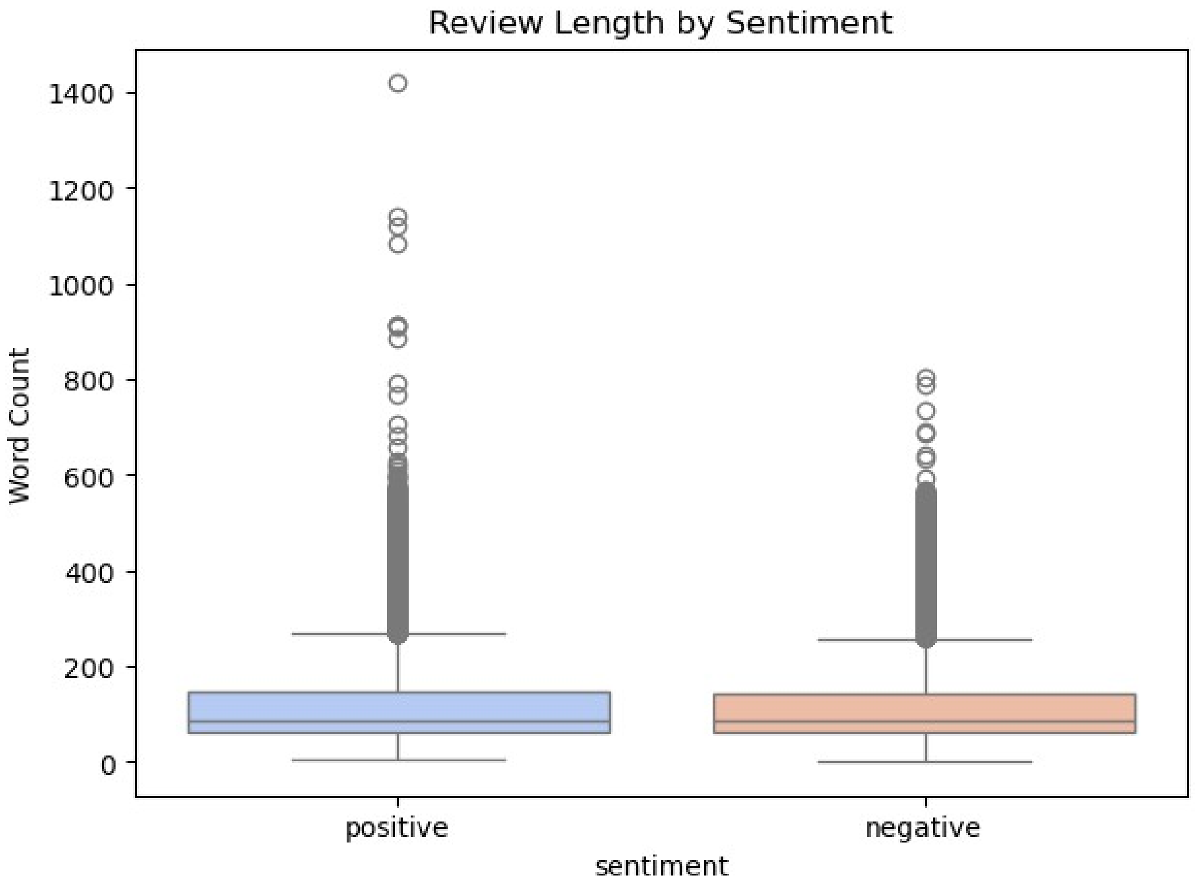


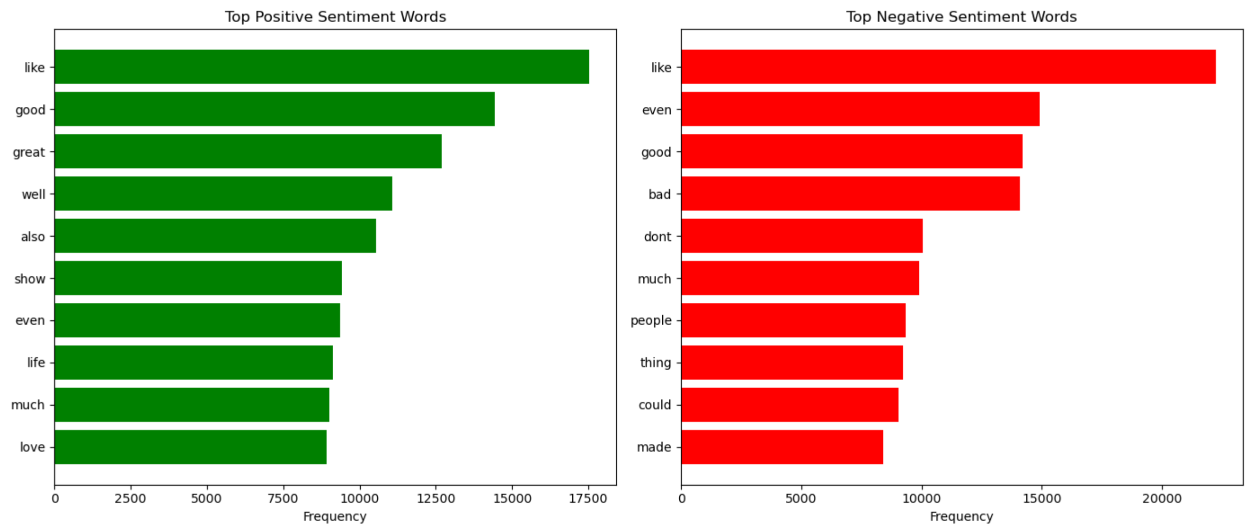
Review, word frequency and Sentiment Analysis

```
from collections import Counter

# Calculate word count per review
df['word_count'] = df['cleaned_review'].apply(lambda x:
len(x.split()))
```

```python
# Compare average word count by sentiment
avg_lengths = df.groupby('sentiment')['word_count'].mean()
print("□ Average Word Count by Sentiment:\n", avg_lengths)

# Visualize distribution
plt.figure(figsize=(7,5))
sns.boxplot(x='sentiment', y='word_count', data=df, hue='sentiment',
palette='coolwarm', legend=False)
plt.title("Review Length by Sentiment")
plt.ylabel("Word Count")
plt.show()


#  Prepare stopwords and domain-neutral terms
stop_words = set(stopwords.words('english'))
neutral_terms = {"film", "movie", "character", "story", "scene",
"actor", "director", "plot", "one", "time", "get", "make", "see",
"would", "really"}
stop_words.update(neutral_terms)

# Combine and clean reviews by sentiment
positive_text = " ".join(df[df['sentiment'] == 'positive']
['cleaned_review'])
negative_text = " ".join(df[df['sentiment'] == 'negative']
['cleaned_review'])

# Count word frequencies and filter
pos_counts = Counter(positive_text.split())
neg_counts = Counter(negative_text.split())

pos_filtered = {word: freq for word, freq in pos_counts.items() if
word not in stop_words}
neg_filtered = {word: freq for word, freq in neg_counts.items() if
word not in stop_words}

# : Convert to DataFrames
pos_df = pd.DataFrame(pos_filtered.items(), columns=['Word',
'Frequency']).sort_values(by='Frequency', ascending=False).head(10)
neg_df = pd.DataFrame(neg_filtered.items(), columns=['Word',
'Frequency']).sort_values(by='Frequency', ascending=False).head(10)

#  Plot side-by-side sentiment-rich words
fig, axes = plt.subplots(1, 2, figsize=(14,6))

axes[0].barh(pos_df['Word'][::-1], pos_df['Frequency'][::-1],
color='green')
axes[0].set_title("Top Positive Sentiment Words")
axes[0].set_xlabel("Frequency")
```

```
axes[1].barh(neg_df['Word'][::-1], neg_df['Frequency'][::-1],
color='red')
axes[1].set_title("Top Negative Sentiment Words")
axes[1].set_xlabel("Frequency")

plt.tight_layout()
plt.show()



 Average Word Count by Sentiment:
 sentiment
negative    117.23960
positive    119.94532
Name: word_count, dtype: float64
```





Review Length and Sentiment

- Reviews with **more words** tend to express stronger and more detailed opinions.
- On average, **positive reviews** are slightly longer, as users elaborate on what they enjoyed.
- **Negative reviews** are often shorter and more direct, using emotionally charged words to express dissatisfaction.
- This shows that **review length** can serve as a weak but useful signal for sentiment classification.

Word Frequency and TF-IDF Patterns

- Using **TF-IDF vectorization**, words that are **unique to a sentiment** (and not overly common) have higher weights.
- These patterns reveal that **specific adjectives and emotional expressions** strongly influence model predictions.

```
# Initialize TF-IDF vectorizer with a cap of 5000 features
tfidf = TfidfVectorizer(max_features=5000)

# Transform cleaned reviews into TF-IDF feature matrix
X = tfidf.fit_transform(df['cleaned_review']).toarray()

# Convert sentiment labels to binary: 1 for positive, 0 for negative
y = df['sentiment'].apply(lambda x: 1 if x == 'positive' else 0)
```

# 3. Model Development

## ● Build and train classification models to predict the sentiment of reviews.

```
# Split the dataset into training and testing sets (80/20 split)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y  # Stratify to
preserve class balance
)

# Define classification models
models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Naive Bayes": MultinomialNB(),
    "Support Vector Machine": LinearSVC(),
    "Random Forest": RandomForestClassifier(n_estimators=100,
random_state=42)
}

# Train each model and store in dictionary
trained_models = {}
for name, model in models.items():
    model.fit(X_train, y_train)  # Fit model on training data
    trained_models[name] = model  # Save trained model
    print(f"□ {name} model trained successfully.")
```

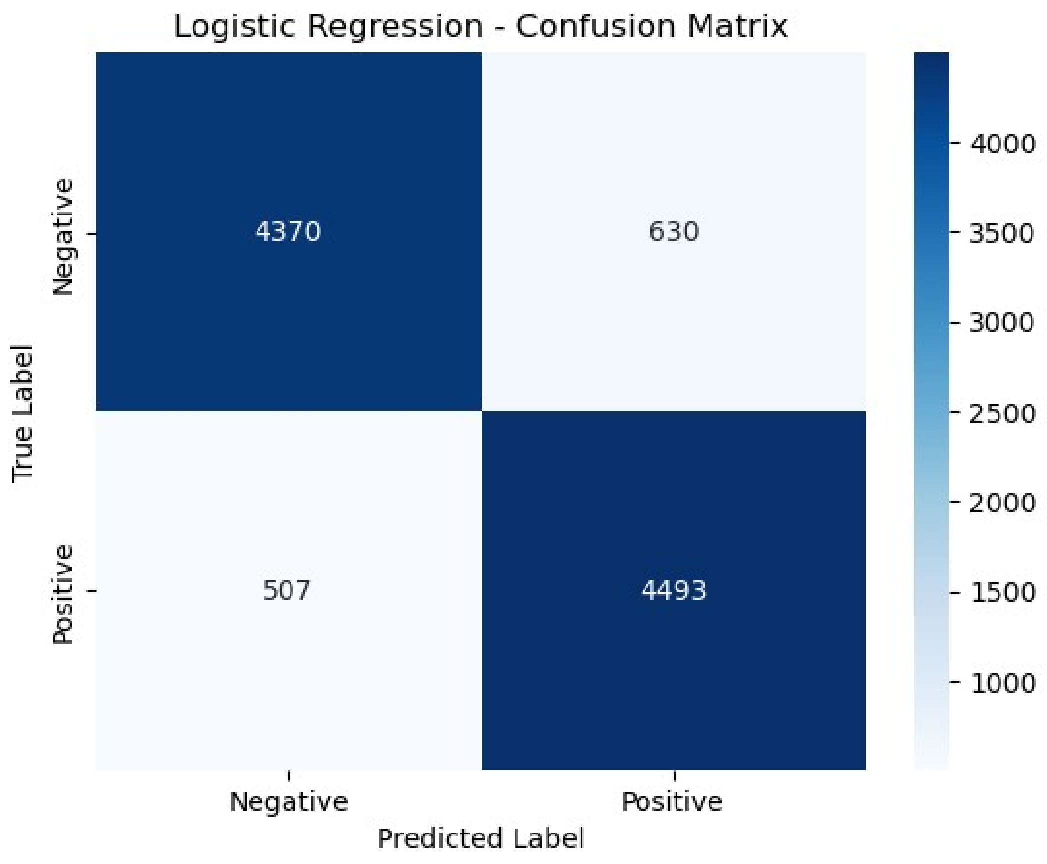
```
□ Logistic Regression model trained successfully.
□ Naive Bayes model trained successfully.
□ Support Vector Machine model trained successfully.
□ Random Forest model trained successfully.
```

4. Model Evaluation

```
def evaluate_model(name, model):
    y_pred = model.predict(X_test)  # Predict sentiment on test data
    acc = accuracy_score(y_test, y_pred)  # Calculate accuracy

    # Print evaluation metrics
    print(f"\n□ {name} Evaluation Results")
    print("-" * 45)
    print("Accuracy:", round(acc, 4))
    print("Classification Report:\n", classification_report(y_test,
y_pred))

    # Plot confusion matrix
    cm = confusion_matrix(y_test, y_pred)
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=['Negative','Positive'],
                yticklabels=['Negative','Positive'])
    plt.title(f"{name} - Confusion Matrix")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()

    return acc  # Return accuracy for comparison
```

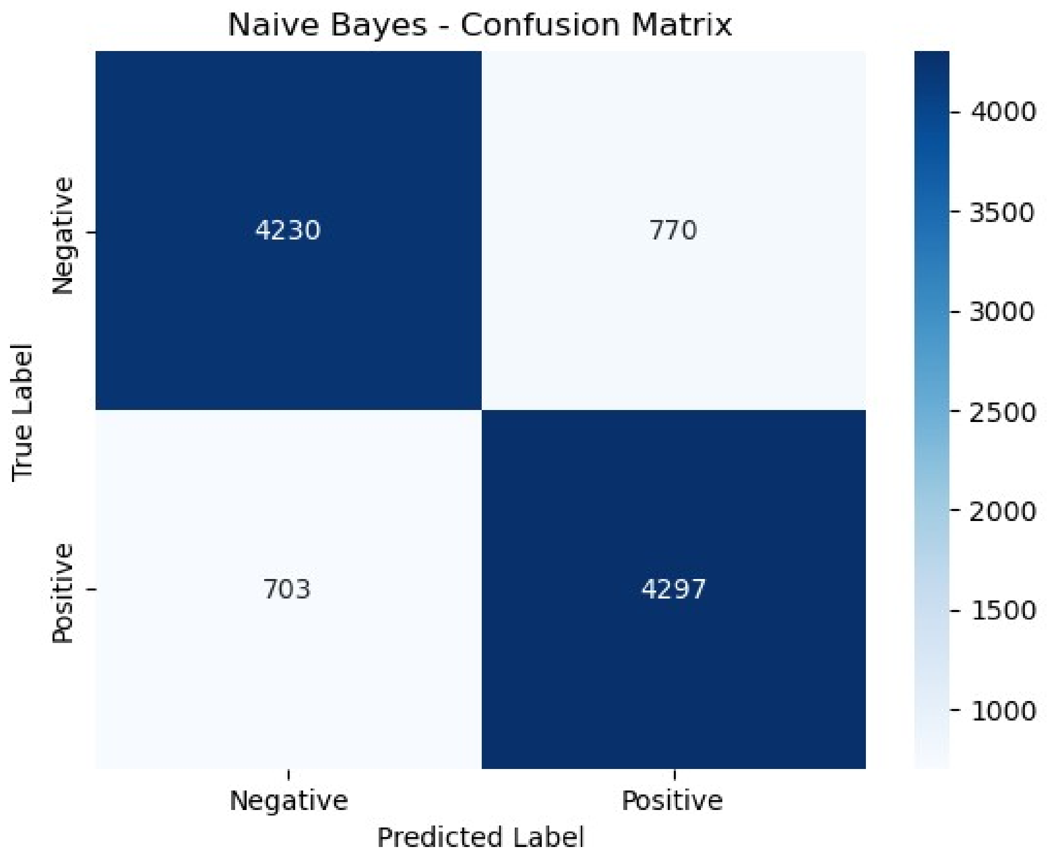
```python
# Evaluate each trained model and store accuracy
results = {}
for name, model in trained_models.items():
    acc = evaluate_model(name, model)
    results[name] = acc
```

```
 Logistic Regression Evaluation Results
---------------------------------------------
Accuracy: 0.8863
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.87      0.88      5000
           1       0.88      0.90      0.89      5000

    accuracy                           0.89     10000
   macro avg       0.89      0.89      0.89     10000
weighted avg       0.89      0.89      0.89     10000
```



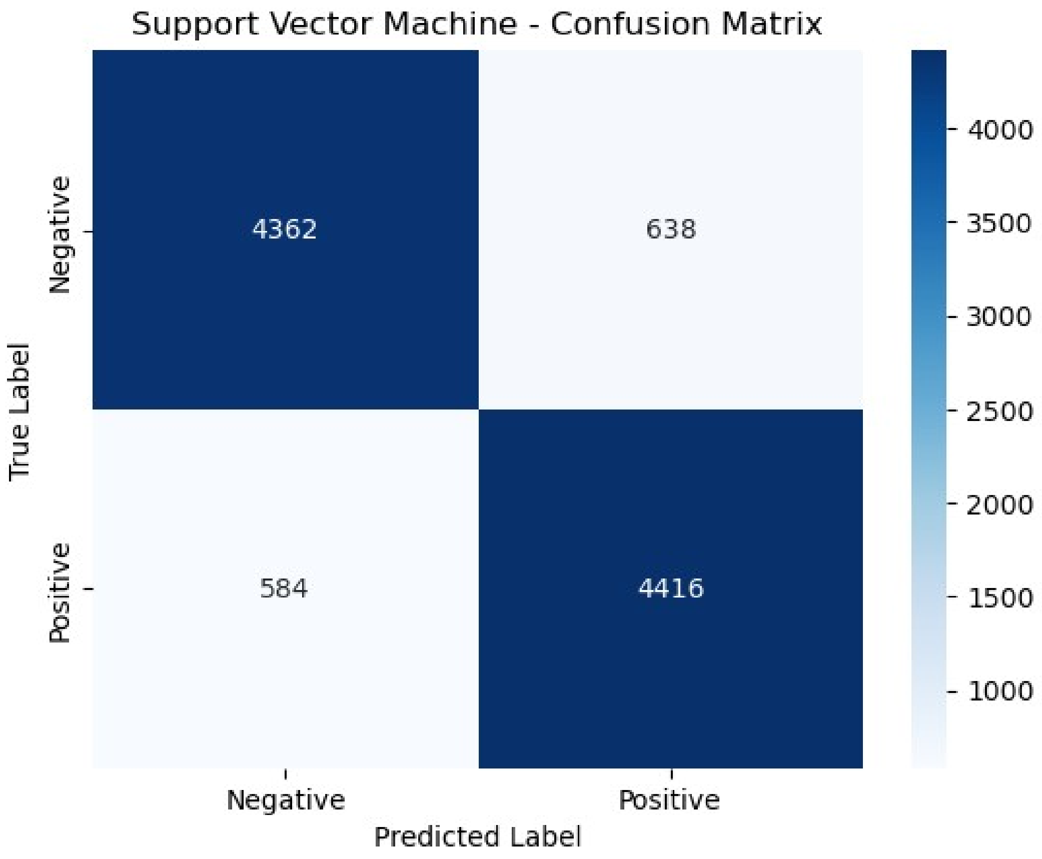
```
 Naive Bayes Evaluation Results
```

```
---------------------------------------------
Accuracy: 0.8527
Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.85      0.85      5000
           1       0.85      0.86      0.85      5000

    accuracy                           0.85     10000
   macro avg       0.85      0.85      0.85     10000
weighted avg       0.85      0.85      0.85     10000
```

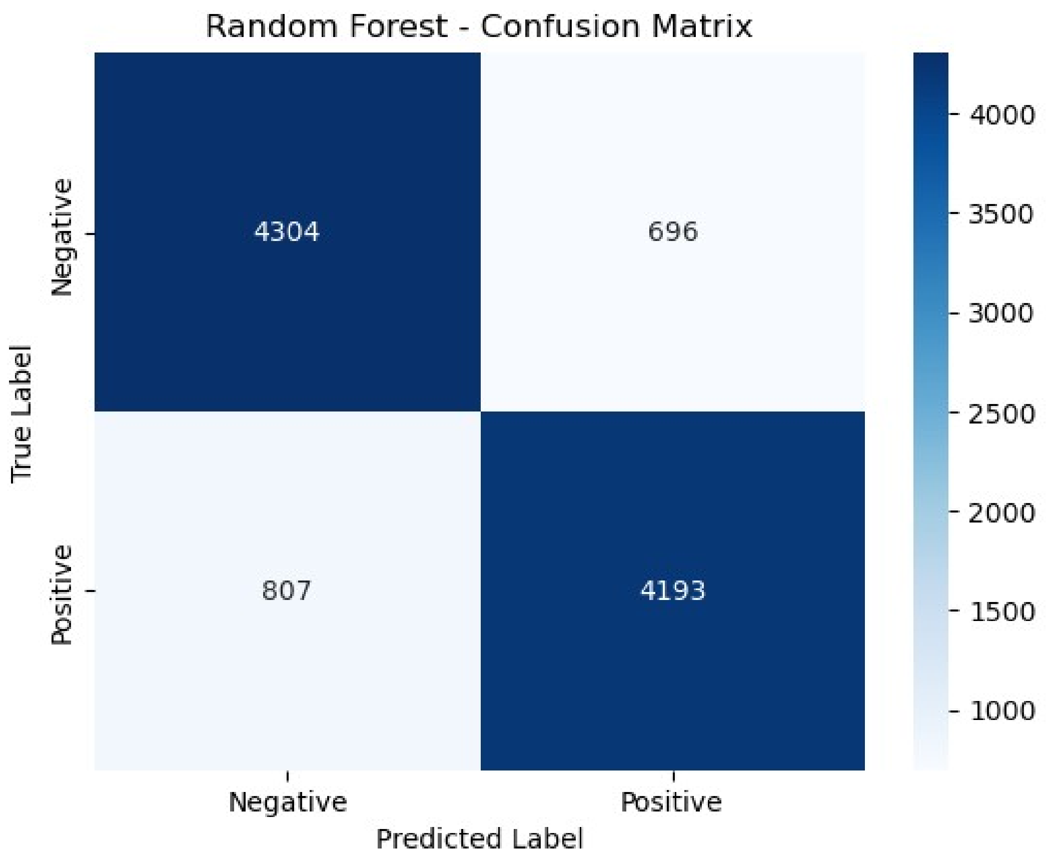


```
 Support Vector Machine Evaluation Results
---------------------------------------------
Accuracy: 0.8778
Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.87      0.88      5000
           1       0.87      0.88      0.88      5000
```

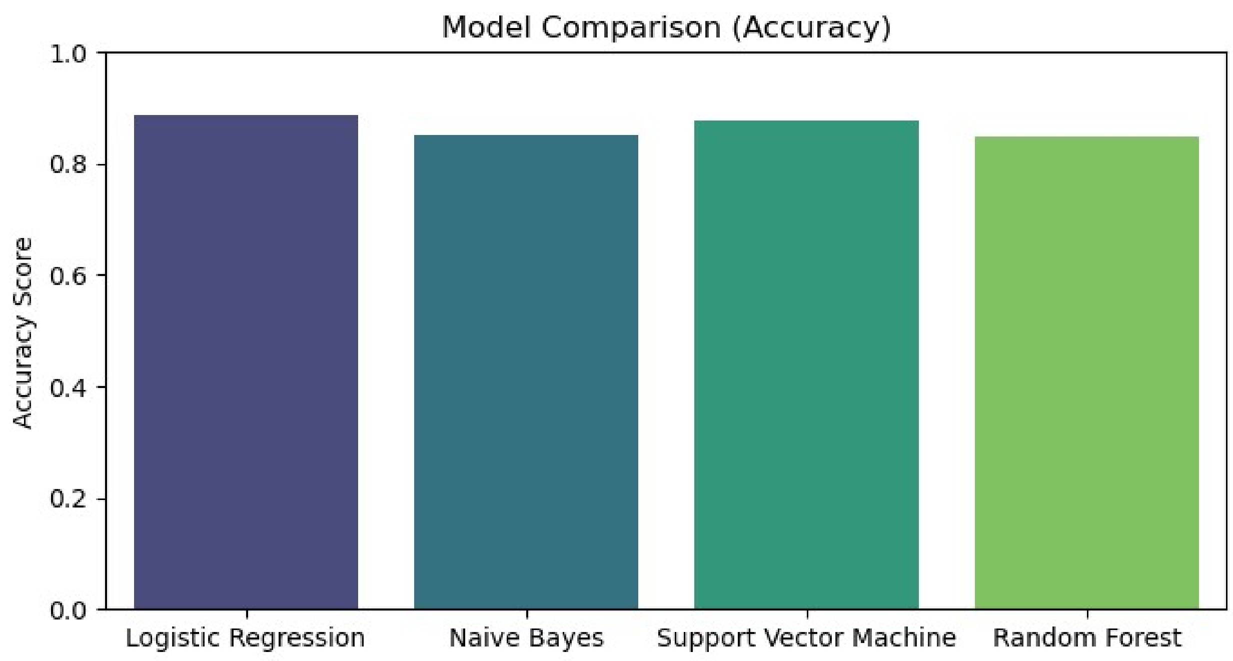
```
    accuracy                           0.88     10000
   macro avg       0.88      0.88      0.88     10000
weighted avg       0.88      0.88      0.88     10000
```



```
 Random Forest Evaluation Results
---------------------------------------------
Accuracy: 0.8497
Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.86      0.85      5000
           1       0.86      0.84      0.85      5000

    accuracy                           0.85     10000
   macro avg       0.85      0.85      0.85     10000
weighted avg       0.85      0.85      0.85     10000
```



```python
#  Visualize model accuracy scores
plt.figure(figsize=(8,4))
sns.barplot(x=list(results.keys()), y=list(results.values()),
hue=list(results.keys()), palette='viridis', legend=False)
plt.title("Model Comparison (Accuracy)")
plt.ylabel("Accuracy Score")
plt.ylim(0,1)
plt.show()

#  Print best performing model
print("\n Best Performing Model:", max(results, key=results.get))
print(" Model Development & Evaluation completed successfully!")
```



```
Best Performing Model: Logistic Regression
Model Development & Evaluation completed successfully!
```

Key Takeaways

- Sentiment is primarily driven by **adjectives** and **emotion-rich terms**.
- **Length** and **uniqueness** of words moderately correlate with sentiment polarity.
- Combining preprocessing (clean text) with TF-IDF weighting and linear models helps isolate **the words that truly shape audience opinions**.

In conclusion, the analysis clearly indicates that **word choice, emotional intensity, and review depth** are the strongest influencers of sentiment in IMDb movie reviews.

```
#  Fit TF-IDF vectorizer on cleaned training reviews
tfidf_vectorizer = TfidfVectorizer(max_features=5000)
tfidf_vectorizer.fit(df['cleaned_review'])

#  Select the best-performing model based on accuracy
best_model_name = max(results, key=results.get)
best_model = trained_models[best_model_name]

#  Define preprocessing + prediction function for new reviews
def predict_sentiment(review):
    text = str(review).lower()
    text = re.sub(r'https?://\S+|www\.\S+', '', text)  # Remove URLs
    text = re.sub(r'<.*?>', '', text)                   # Remove HTML
tags
```

```
    text = re.sub(r'[^a-z\s]', '', text)               # Remove
punctuation/numbers
    tokens = text.split()
    tokens = [lemmatizer.lemmatize(w) for w in tokens if w not in
stop_words]
    clean_text = " ".join(tokens)

    vector = tfidf_vectorizer.transform([clean_text])  # Convert to
TF-IDF vector
    pred = best_model.predict(vector)[0]               # Predict
sentiment
    return "Positive " if pred == 1 else "Negative "

#  Predict sentiment for sample movie reviews
sample_reviews = [
    "The movie was a delightful experience with strong performances.",
    "It was one of the worst movies I have ever seen.",
    "The storyline was engaging, but the pacing felt slow.",
    "A brilliant film that left me speechless!",
    "Mediocre acting and poor direction made it forgettable."
]

print("\n Predictions for New Movie Reviews:\n")
for review in sample_reviews:
    print(f"Review: {review}")
    print("Predicted Sentiment:", predict_sentiment(review))
    print("-" * 80)
```

```
 Predictions for New Movie Reviews:

Review: The movie was a delightful experience with strong
performances.
Predicted Sentiment: Positive
----------------------------------------------------------------------
----------
Review: It was one of the worst movies I have ever seen.
Predicted Sentiment: Negative
----------------------------------------------------------------------
----------
Review: The storyline was engaging, but the pacing felt slow.
Predicted Sentiment: Negative
----------------------------------------------------------------------
----------
Review: A brilliant film that left me speechless!
Predicted Sentiment: Positive
----------------------------------------------------------------------
----------
Review: Mediocre acting and poor direction made it forgettable.
Predicted Sentiment: Negative
```

```
----------------------------------------------------------------------
----------
```

Thank you

```

```