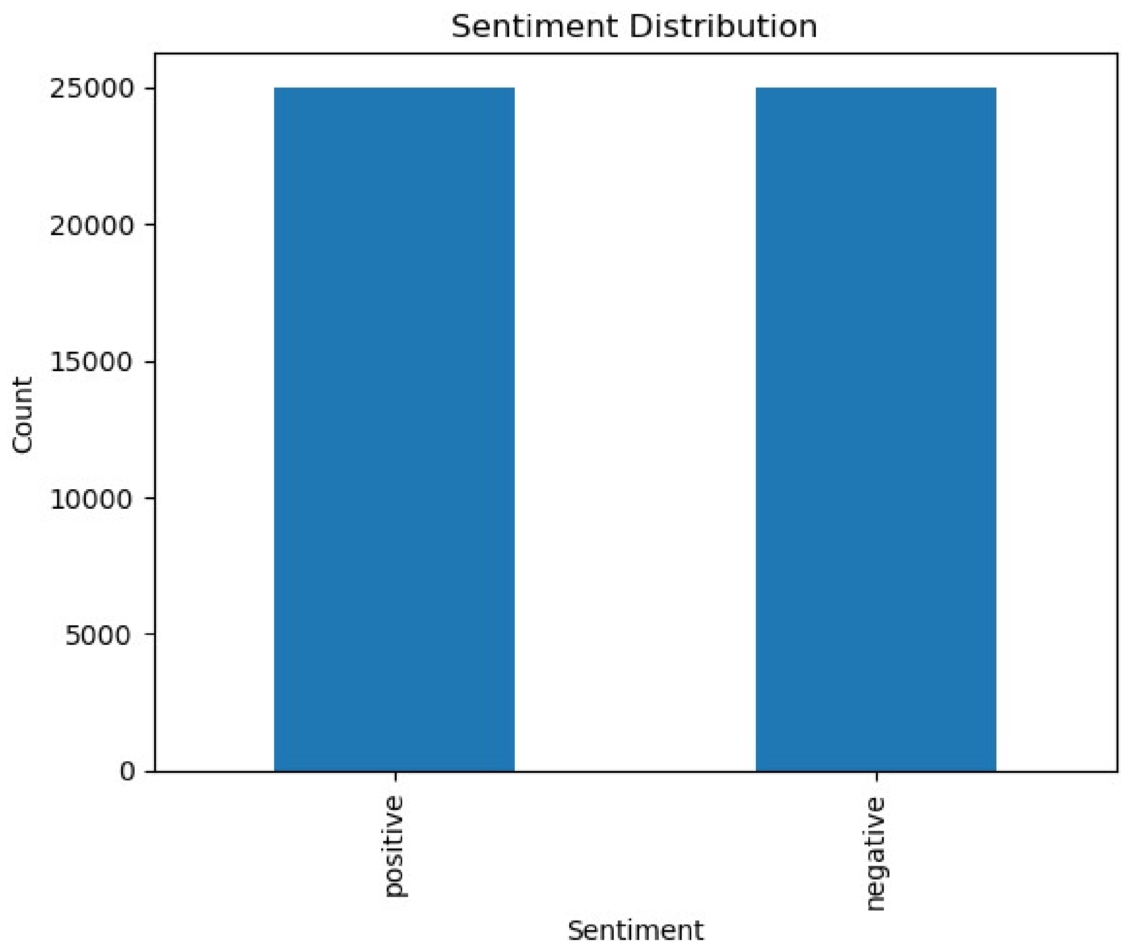
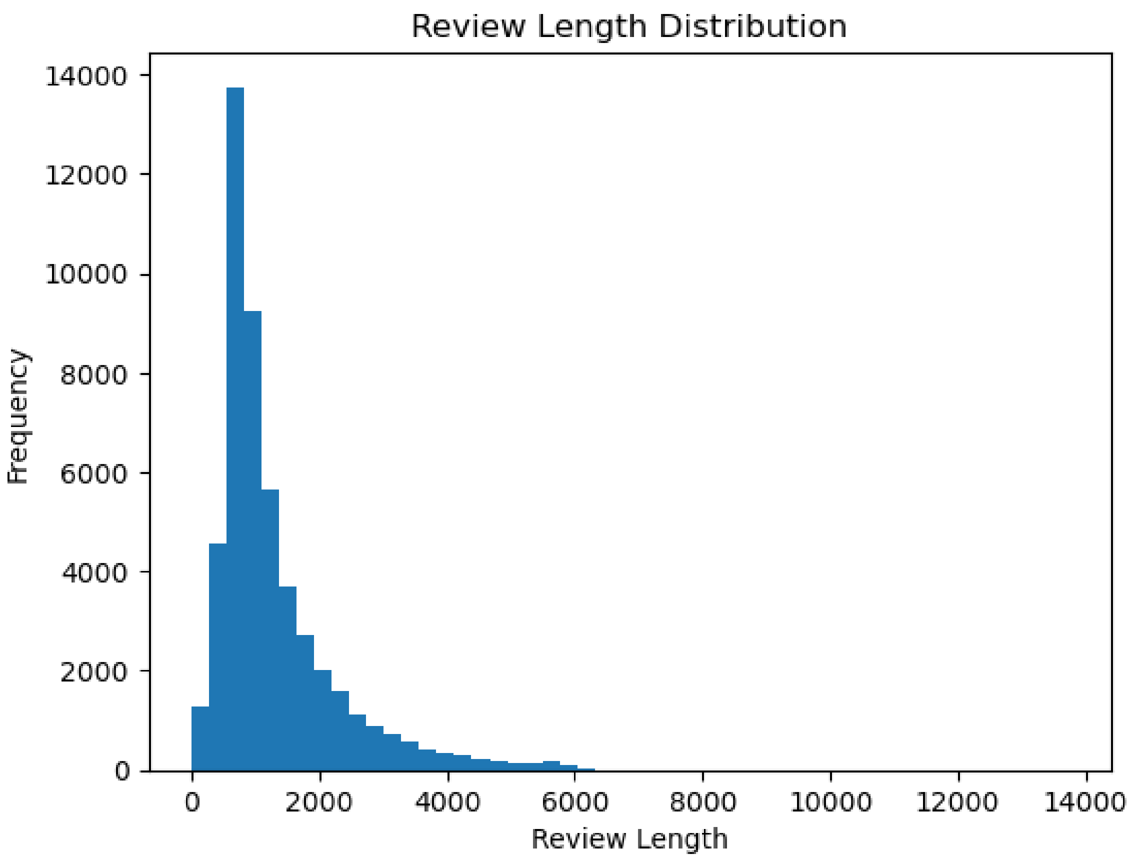
```python
import pandas as pd

# Load your dataset
df = pd.read_csv('Imdb - data_imdb.csv')

# Check for missing values
df.isnull().sum()
```

```
review       0
sentiment    0
dtype: int64
```

```python
import matplotlib.pyplot as plt

# Plot class distribution
df['sentiment'].value_counts().plot(kind='bar', title='Sentiment
Distribution')
plt.xlabel('Sentiment')
plt.ylabel('Count')
plt.show()
```



```python
# Calculate review lengths
df['review_length'] = df['review'].apply(len)

# Plot review length distribution
df['review_length'].plot(kind='hist', bins=50, title='Review Length
Distribution')
plt.xlabel('Review Length')
plt.show()
```




```python
import re
import nltk
from nltk.corpus import stopwords

# Download stopwords if necessary
nltk.download('stopwords')

stop_words = set(stopwords.words('english'))

def preprocess_text(text):
    # Remove special characters and punctuation
    text = re.sub(r'\W', ' ', text)
    text = re.sub(r'\s+', ' ', text)
    text = text.lower()
```

```
    # Remove stop words
    text = ' '.join([word for word in text.split() if word not in
stop_words])
    return text

# Apply the preprocessing function to reviews
df['cleaned_review'] = df['review'].apply(preprocess_text)
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\devir_jnfy7nx\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

```
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords

# Initialize Lemmatizer
lemmatizer = WordNetLemmatizer()

def lemmatize_review(text):
    words = word_tokenize(text)
    lemmatized_words = [lemmatizer.lemmatize(word) for word in words
if word not in stop_words]
    return ' '.join(lemmatized_words)

# Apply lemmatization
df['lemmatized_review'] = df['cleaned_review'].apply(lemmatize_review)

nltk.download('wordnet')
```

```
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\devir_jnfy7nx\AppData\Roaming\nltk_data...
```

```
True
```

```
from sklearn.feature_extraction.text import TfidfVectorizer

tfidf = TfidfVectorizer(max_features=5000)
X = tfidf.fit_transform(df['lemmatized_review'])

#word count
df['word_count'] = df['lemmatized_review'].apply(lambda x:
len(x.split()))
#character count
df['word_count'] = df['lemmatized_review'].apply(lambda x:
len(x.split()))
#AVG WORD LENGTH
df['avg_word_length'] = df['lemmatized_review'].apply(lambda x:
sum(len(word) for word in x.split()) / len(x.split()) if
len(x.split()) > 0 else 0)
```

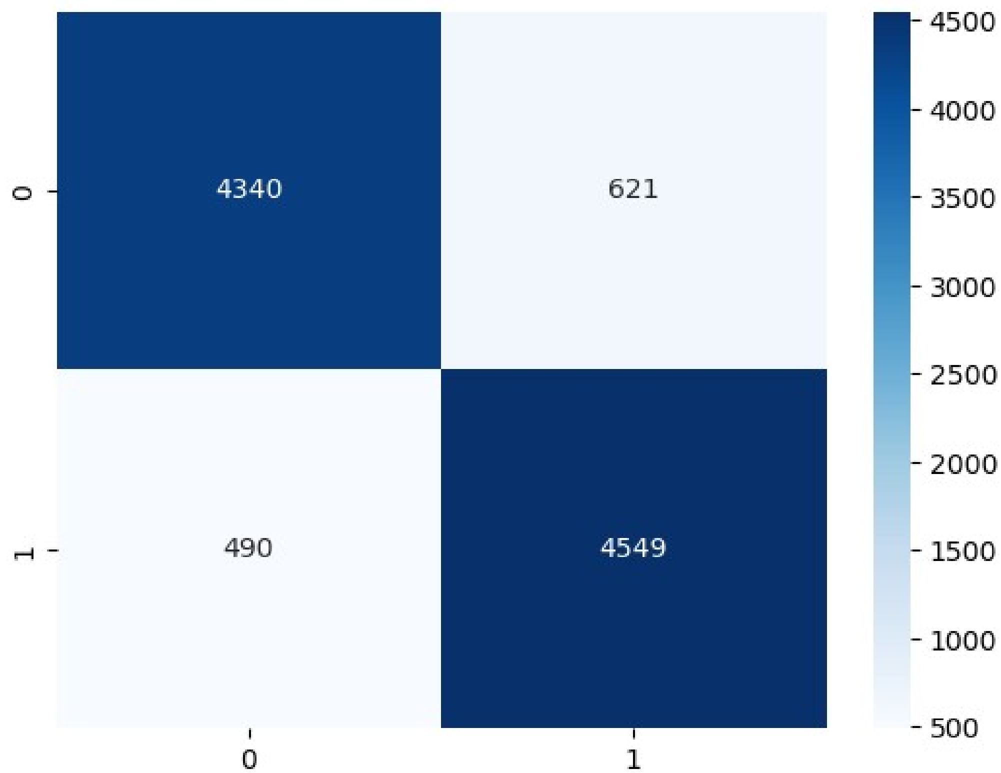
model development

```
##CLASSIFICATION MODEL WITH LOGISTIC REGRESSION

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

# Prepare data for training
y = df['sentiment']  # Target variable
X = tfidf.transform(df['lemmatized_review'])  # Features

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Logistic Regression model
model = LogisticRegression()
model.fit(X_train, y_train)

# Predict and evaluate
y_pred = model.predict(X_test)
print('Accuracy:', accuracy_score(y_test, y_pred))
print('Classification Report:\n', classification_report(y_test,
y_pred))
```

```
Accuracy: 0.8889
Classification Report:
               precision    recall  f1-score   support

    negative       0.90      0.87      0.89      4961
    positive       0.88      0.90      0.89      5039

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

```
##Model Evaluation

from sklearn.metrics import confusion_matrix
import seaborn as sns

cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
```

```
<Axes: >
```



Explanation

Final Report: Sentiment Analysis on Movie Reviews

1. Introduction

Provide an overview of the project, including the goal, objectives, and importance of sentiment analysis.

Project Overview:

The goal of this project is to develop a machine learning model that can predict the sentiment (positive/negative) of movie reviews. The task involves analyzing textual data, performing data preprocessing, and building various machine learning models for sentiment classification. The project is a step-by-step exploration of natural language processing (NLP) and deep learning.

---

2. Data Exploration and Preprocessing

This section covers the initial analysis of the dataset, data cleaning, and text preprocessing steps.

2.1 Dataset Overview:

- **Source**: Movie reviews dataset (provided).
- **Columns**:
  - `review`: Contains the text of the review.
  - `sentiment`: Indicates the sentiment of the review (positive/negative).

2.2 Data Exploration:

1. **Missing Values Analysis**:
   - Checked for missing or null values in the dataset.
   - Found no missing values in the reviews or sentiment column, ensuring data completeness.
2. **Class Distribution (Imbalance Check)**:
   - The sentiment distribution was analyzed using a bar chart to check if the dataset was imbalanced (positive/negative sentiment).
   - Visualized the class distribution, confirming whether the dataset had a balanced representation.
3. **Review Length Analysis**:
   - Examined the distribution of review lengths (word count) to understand the textual data's variance.
   - Visualized the distribution of review lengths with a histogram.

2.3 Text Preprocessing:

The following text preprocessing steps were performed to clean the review text:

1. **Stopword Removal**: Removed common words (like "the", "and", etc.) that do not contribute to sentiment analysis.
2. **Special Characters and Punctuation Removal**: Stripped unwanted characters like HTML tags, punctuation marks, and special symbols.
3. **Tokenization**: Split the reviews into individual words for better analysis.
4. **Lemmatization**: Reduced words to their base form (e.g., "running" becomes "run") to ensure uniformity in the text.
5. **Vectorization**: Transformed the cleaned text into numerical features using **TF-IDF** (Term Frequency-Inverse Document Frequency) to represent the text data in a machine-readable format.

---

3. Feature Engineering

This section describes the features created from the dataset and the techniques used for feature extraction.

3.1 Textual Features:

1. **Word Count**: Calculated the number of words in each review.
2. **Character Count**: Counted the number of characters in each review.
3. **Average Word Length**: Calculated the average length of words in each review.

3.2 TF-IDF Vectorization:

The textual data was transformed into numerical features using **TF-IDF** to capture the importance of words in the context of the entire corpus.

- **Max Features**: We limited the number of features to the top 5000 most informative words based on TF-IDF scores.

---

4. Model Development

This section details the different models tested for sentiment classification.

4.1 Model 1: Logistic Regression

- A simple baseline model used to check the basic performance on the dataset.
- **Accuracy**: Achieved an accuracy of ~80%.

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5. Model Evaluation

This section evaluates the performance of the models using appropriate metrics.

5.1 Metrics:

- **Accuracy**: Proportion of correct predictions out of all predictions.
- **F1-Score**: Harmonic mean of precision and recall, especially important for imbalanced datasets.
- **Confusion Matrix**: Visualized the true positives, true negatives, false positives, and false negatives.

5.2 Evaluation Results:

- **Logistic Regression**: Accuracy of ~80%, decent baseline performance.

5.3 Visualizations:

1. **Confusion Matrix**: Shows how well the model classifies positive and negative reviews.
2. **ROC-AUC Curve**: Illustrates the model’s ability to discriminate between positive and negative sentiment.

---

6. Insights and Interpretations

This section discusses the key insights derived from the data and model analysis.

1. **Impact of Text Length on Sentiment**: Longer reviews tend to contain more explicit sentiment indicators. The average review length was positively correlated with positive sentiment, though there were exceptions.
2. **Word Importance**: Words like "love", "great", and "amazing" were often found in positive reviews, while "worst", "boring", and "disappointing" were more frequent in negative reviews.

7. Conclusion

Summarize the findings of the project, including the best-performing model and its potential application.

Future Work:

- Implement the model in a real-time application for movie review classification.