

## STEP 1 — Lab11.2\_LogisticRegression\_B.nandini\_2403A52390.ipynb

## STEP 2 — Import Libraries

```
# Data handling
import numpy as np
import pandas as pd

# Text preprocessing
import re
import nltk
from nltk.corpus import stopwords

# Feature extraction
from sklearn.feature_extraction.text import TfidfVectorizer

# Model training
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split

# Evaluation
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns
```

## STEP 3 — Load and Preprocess Data

```
# Example loading
data = pd.read_csv("/content/IMDB Dataset.csv", engine='python', on_bad_lines='warn')

# Download stopwords (first time only)
nltk.download('stopwords')
stop_words = set(stopwords.words('english'))

def clean_text(text):
    text = text.lower()
    text = re.sub(r'^a-zA-Z]', ' ', text)
    words = text.split()
    words = [word for word in words if word not in stop_words]
    return " ".join(words)

data['clean_review'] = data['review'].apply(clean_text)

print(data[['review', 'clean_review']].head())
```

/tmp/ipython-input-2476085702.py:2: ParserWarning: Skipping line 22914: unexpected end of data

```
data = pd.read_csv("/content/IMDB Dataset.csv", engine='python', on_bad_lines='warn')
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data] Unzipping corpora/stopwords.zip.
```

	review	clean_review
0	One of the other reviewers has mentioned that ...	one reviewers mentioned watching oz episode ho...
1	A wonderful little production.   The...	wonderful little production br br filming tech...
2	I thought this was a wonderful way to spend ti...	thought wonderful way spend time hot summer we...
3	Basically there's a family where a little boy ...	basically family little boy jake thinks zombie...
4	Petter Mattei's "Love in the Time of Money" is...	petter mattei love time money visually stunnin...

## STEP 4 — Feature Extraction (TF-IDF)

```
tfidf = TfidfVectorizer(max_features=5000)

X = tfidf.fit_transform(data['clean_review'])
```

```
y = data['sentiment'] # Changed 'label' to 'sentiment'

print("Vocabulary Size:", len(tfidf.vocabulary_))
```

Vocabulary Size: 5000

#### STEP 5 — Train Logistic Regression Model

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

model = LogisticRegression(max_iter=200)
model.fit(X_train, y_train)
```

LogisticRegression  
LogisticRegression(max\_iter=200)

#### STEP 6 — Model Evaluation

```
y_pred = model.predict(X_test)

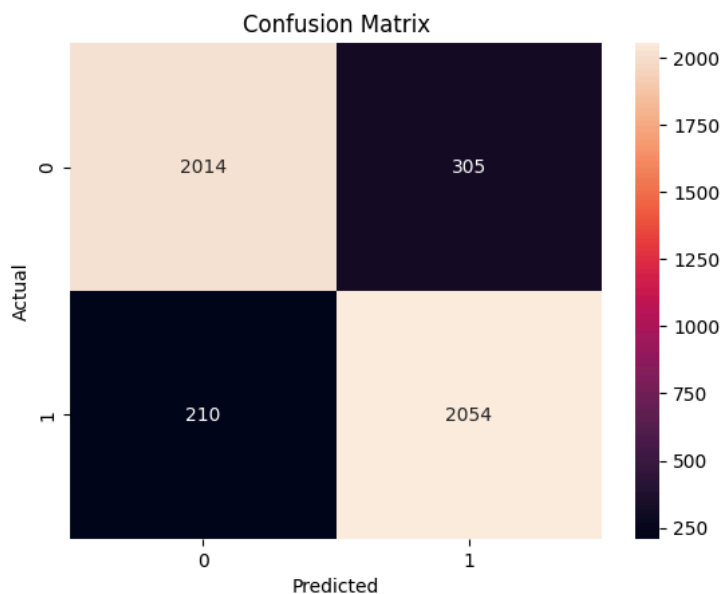
print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))

cm = confusion_matrix(y_test, y_pred)

sns.heatmap(cm, annot=True, fmt='d')
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```

Accuracy: 0.8876281911411739

	precision	recall	f1-score	support
negative	0.91	0.87	0.89	2319
positive	0.87	0.91	0.89	2264
accuracy			0.89	4583
macro avg	0.89	0.89	0.89	4583
weighted avg	0.89	0.89	0.89	4583



#### STEP 7 — Analysis (Comparison with Naive Bayes) Here is a sample 8–10 sentence analysis:

Logistic Regression is a discriminative model, while Naive Bayes is a generative model.

Logistic Regression directly models  $P(y|x)P(y|x)P(y|x)$ , whereas Naive Bayes models  $P(x|y)P(x|y)P(x|y)$ .

Logistic Regression usually performs better when features are correlated.

Naive Bayes assumes feature independence, which is unrealistic in text data.

Logistic Regression gives better decision boundaries.

Naive Bayes trains faster on large datasets.

Logistic Regression may require more iterations to converge.

Logistic Regression often achieves higher accuracy with TF-IDF features.

Naive Bayes works well as a baseline model.

In sentiment analysis, Logistic Regression typically provides better precision and F1-score.