Project Title - MOVIE REVIEW SENTIMENT ANALYSIS APPLICATION 😊 😳 😔

About the dataset ¶

IMDB dataset having 50K movie reviews for natural language processing or Text analytics.
This is a dataset for binary sentiment classification containing substantially more data than previous benchmark datasets. We provide a set of 25,000 highly polar movie reviews for training and 25,000 for testing. So, predict the number of positive and negative reviews using either classification or deep learning algorithms.

Data Loading and Exploration

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
data = pd.read_csv(r"C:\Users\vaish\Downloads\IMDB Dataset.csv")
```

In [3]:
```
data
```

Out[3]:

	review	sentiment
0	One of the other reviewers has mentioned that ...	positive
1	A wonderful little production. The...	positive
2	I thought this was a wonderful way to spend ti...	positive
3	Basically there's a family where a little boy ...	negative
4	Petter Mattei's "Love in the Time of Money" is...	positive
...	...	...
49995	I thought this movie did a down right good job...	positive
49996	Bad plot, bad dialogue, bad acting, idiotic di...	negative
49997	I am a Catholic taught in parochial elementary...	negative
49998	I'm going to have to disagree with the previou...	negative
49999	No one expects the Star Trek movies to be high...	negative

50000 rows × 2 columns

In [4]:
```
data.head()
```

Out[4]:

	review	sentiment
0	One of the other reviewers has mentioned that ...	positive
1	A wonderful little production. The...	positive
2	I thought this was a wonderful way to spend ti...	positive
3	Basically there's a family where a little boy ...	negative
4	Petter Mattei's "Love in the Time of Money" is...	positive

In [5]:
```
data.tail()
```

Out[5]:

	review	sentiment
49995	I thought this movie did a down right good job...	positive
49996	Bad plot, bad dialogue, bad acting, idiotic di...	negative
49997	I am a Catholic taught in parochial elementary...	negative
49998	I'm going to have to disagree with the previou...	negative
49999	No one expects the Star Trek movies to be high...	negative

In [6]:
```
data.shape
```

Out[6]:
```
(50000, 2)
```

In [7]:
```
data.info
```

Out[7]:
```
<bound method DataFrame.info of                                                    review sentiment
0      One of the other reviewers has mentioned that ...  positive
1      A wonderful little production. <br /><br />The...  positive
2      I thought this was a wonderful way to spend ti...  positive
3      Basically there's a family where a little boy ...  negative
4      Petter Mattei's "Love in the Time of Money" is...  positive
...                                                  ...       ...
49995  I thought this movie did a down right good job...  positive
49996  Bad plot, bad dialogue, bad acting, idiotic di...  negative
49997  I am a Catholic taught in parochial elementary...  negative
49998  I'm going to have to disagree with the previou...  negative
49999  No one expects the Star Trek movies to be high...  negative

[50000 rows x 2 columns]>
```

In [8]:
```
type(data)
```

Out[8]:
```
pandas.core.frame.DataFrame
```

In [65]:
```
print(f"Columns: {data.columns.tolist()}")
```

```
Columns: ['review', 'sentiment']
```

In [66]:
```
# Check for missing values
data.isnull().sum()
```

Out[66]:
```
review       0
sentiment    0
dtype: int64
```

Working With Sentiment

replaces the text labels "positive" and "negative" in the sentiment column with numeric values 1 and 0

In [9]:
```
data.replace({"sentiment":{"positive":1,"negative":0}},inplace=True)
```

In [10]:
```
data.head()
```

Out[10]:

	review	sentiment
0	One of the other reviewers has mentioned that ...	1
1	A wonderful little production. The...	1
2	I thought this was a wonderful way to spend ti...	1
3	Basically there's a family where a little boy ...	0
4	Petter Mattei's "Love in the Time of Money" is...	1

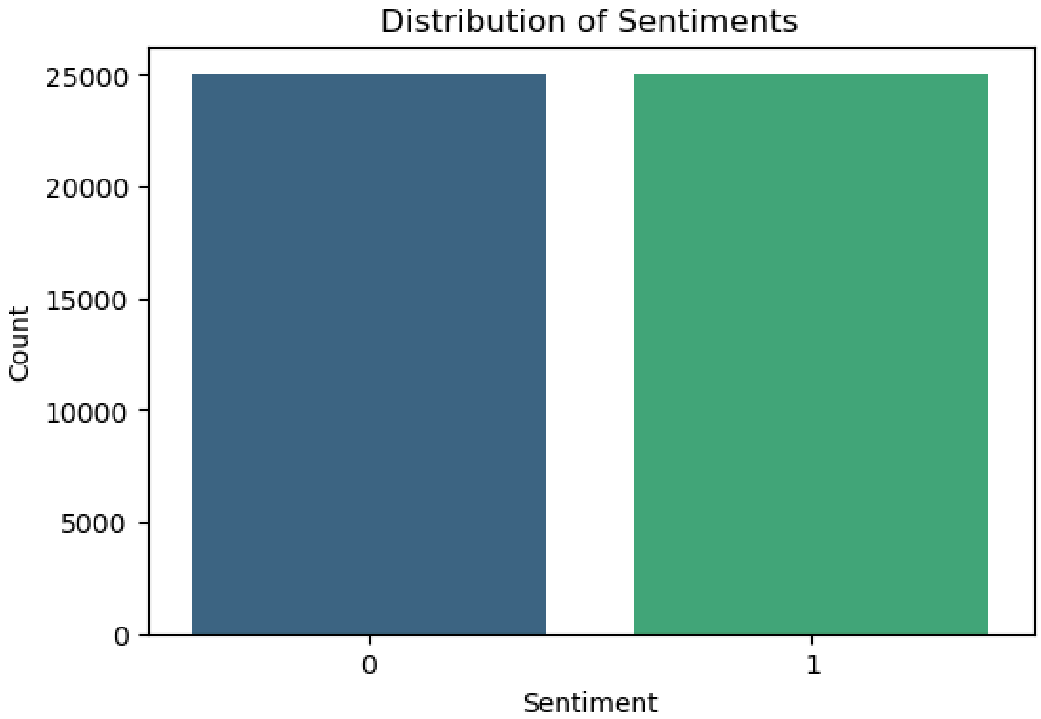
counts the number of occurrences of each sentiment (positive or negative) in the dataset.

In [68]:
```
sentiment_counts=data["sentiment"].value_counts()
```

In [72]:
```
sentiment_counts
```

Out[72]:
```
1    25000
0    25000
Name: sentiment, dtype: int64
```

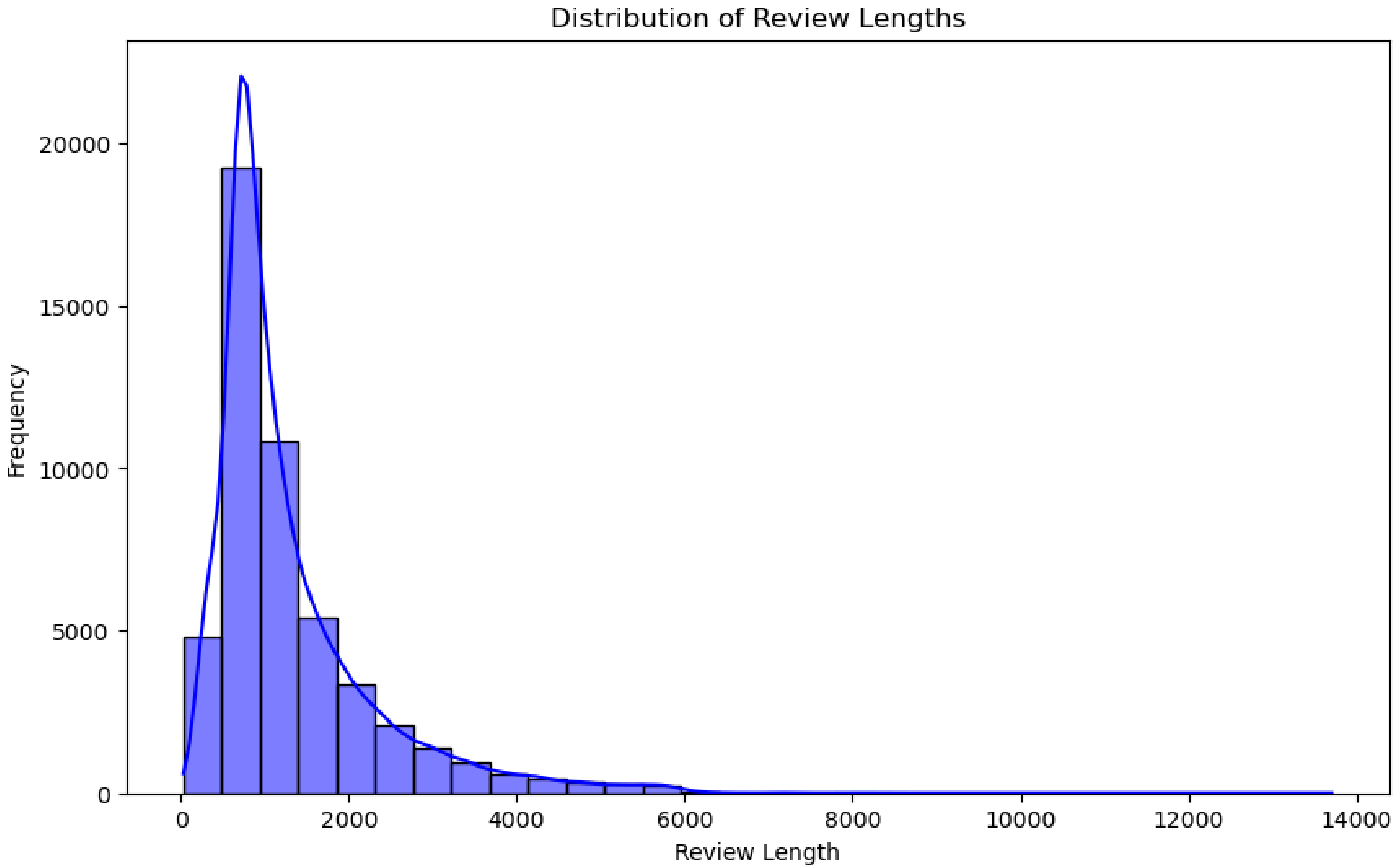
In [69]:
```
# sentiment distribution
plt.figure(figsize=(6, 4))
sns.barplot(x=sentiment_counts.index, y=sentiment_counts.values, palette="viridis")
plt.title("Distribution of Sentiments")
plt.xlabel("Sentiment")
plt.ylabel("Count")
plt.show()
```



understand the variation in review lengths and identify any patterns, like whether reviews tend to be short, lengthy, or varied.

In [70]:
```
# Length of Reviews
# Add a column for review length
data['review_length'] = data['review'].apply(len)

print(data['review_length'].describe())

plt.figure(figsize=(10, 6))
sns.histplot(data['review_length'], kde=True, bins=30, color="blue")
plt.title("Distribution of Review Lengths")
plt.xlabel("Review Length")
plt.ylabel("Frequency")
plt.show()
```

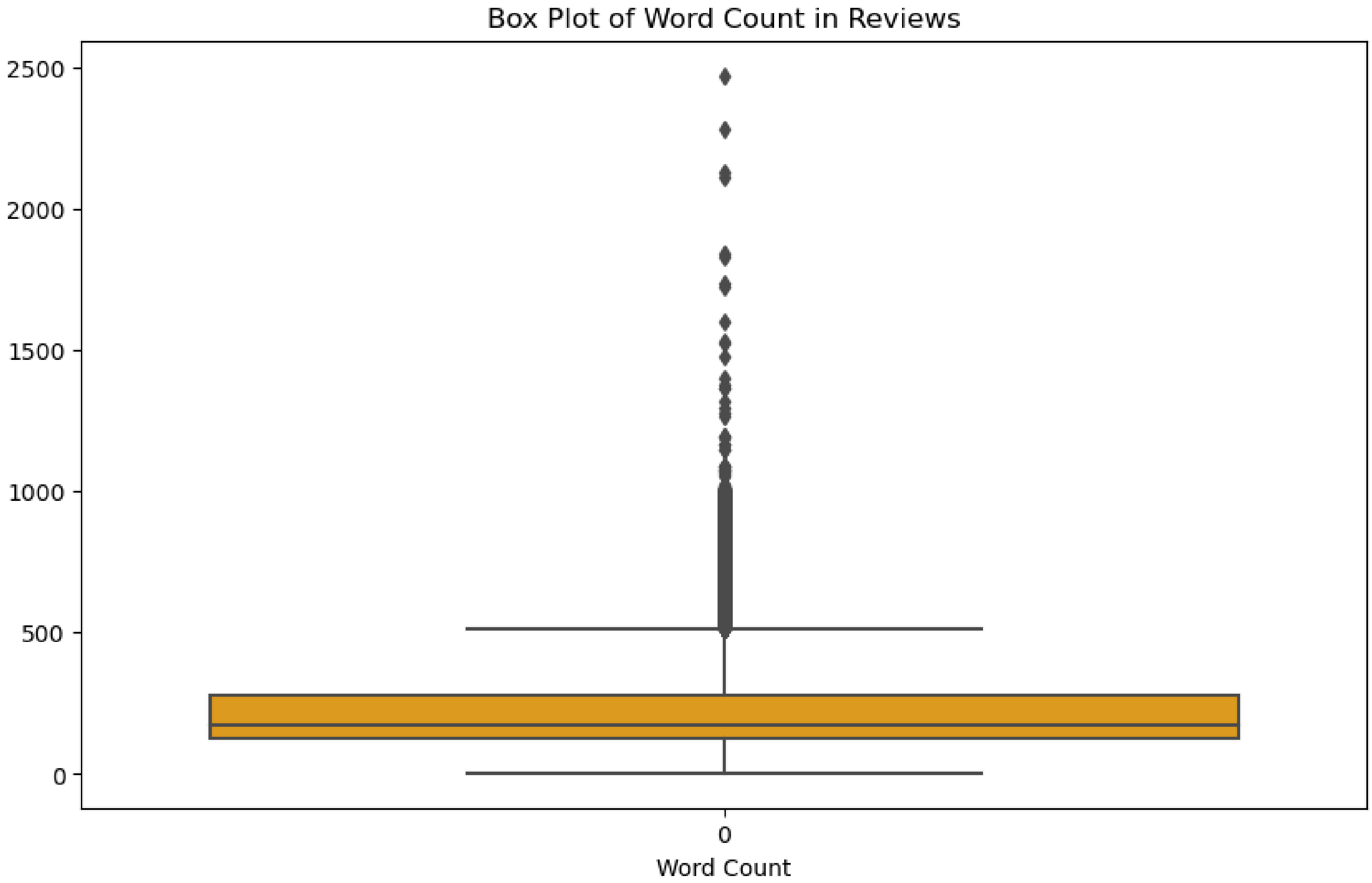
```
count    50000.000000
mean      1309.431020
std        989.728014
min         32.000000
25%        699.000000
50%        970.000000
75%       1590.250000
max      13704.000000
Name: review_length, dtype: float64
```



calculates the word count for each review, displays basic statistics about the word counts, and visualizes their distribution with a box plot.

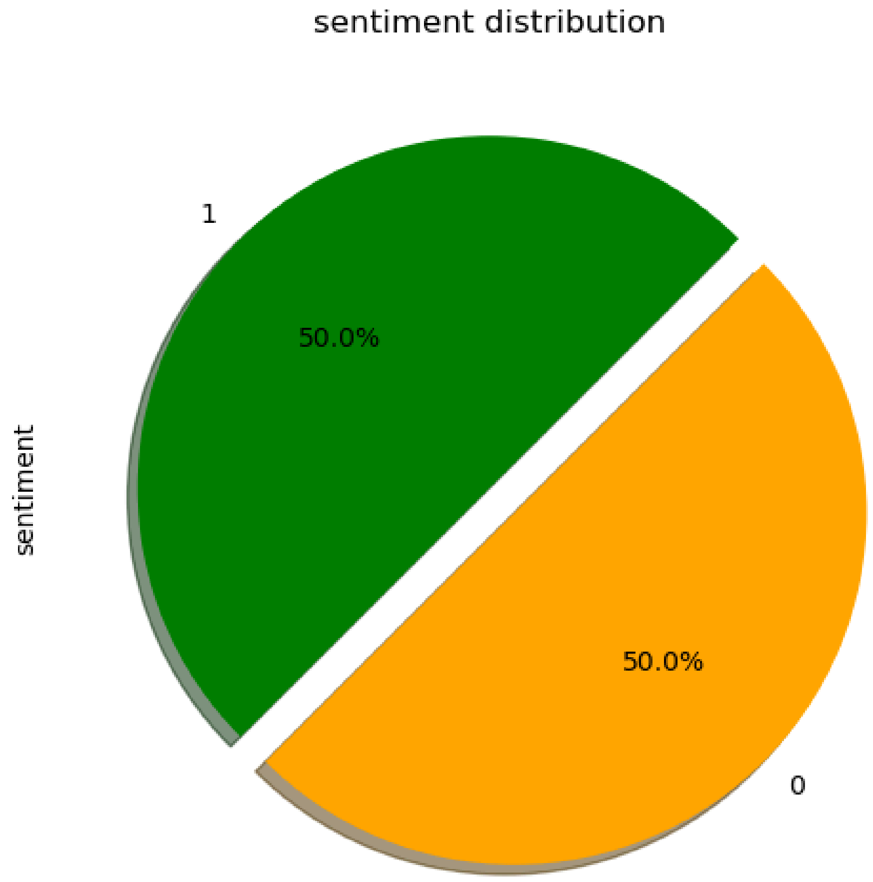
In [71]:
```
# Word Count Analysis
# Add a column for word count
data['word_count'] = data['review'].apply(lambda x: len(x.split()))
print(data['word_count'].describe())
plt.figure(figsize=(10, 6))
sns.boxplot(data['word_count'], color="orange")
plt.title("Box Plot of Word Count in Reviews")
plt.xlabel("Word Count")
plt.show()
```

```
count    50000.000000
mean       231.156940
std        171.343997
min          4.000000
25%        126.000000
50%        173.000000
75%        280.000000
max       2470.000000
Name: word_count, dtype: float64
```


Box Plot of Word Count in Reviews
2500
2000
1500
1000
500
0
0
Word Count

In [13]:
```
plt.figure(figsize=(10,6))
colors = ['green', 'orange']
data['sentiment'].value_counts().plot(kind='pie', autopct='%.1f%%',shadow = True,colors = colors,startangle = 45,
                 explode=(0, 0.1))
plt.title('sentiment distribution')
```

Out[13]: Text(0.5, 1.0, 'sentiment distribution')



Working With review

In [14]:
```
data['review'][999]
```

Out[14]:
```
"This is like a zoology textbook, given that its depiction of animals is so accurate. However, here are a few details that app
ear to have been slightly modified during the transition to film:<br /><br />- Handgun bullets never hit giant Komodo dragons.
It doesn't matter how many times you shoot at the Komodo, bullets just won't go near it.<br /><br />- The best way to avoid be
ing eaten by a giant Cobra, or a giant Komodo dragon, is just to stand there. The exception to this rule is if you've been tol
d to stay very still, in which case you should run off, until the Komodo is right next to you, and then you should stand ther
e, expecting defeat.<br /><br />- Minutes of choppy slow motion footage behind the credits really makes for enjoyable watchin
g.<br /><br />- $5,000 is a memory enhancement tool, and an ample substitute for losing your boating license/getting arrested.
<br /><br />- Members of elite army units don't see giant Komodo dragons coming until they are within one metre of the over-si
zed beings. Maybe the computer-generated nature of these dragons has something to do with it.<br /><br />- When filming a news
story aiming on exposing illegal animal testing, a reporter and a cameraman with one camera is all the gear and personnel you
will need; sound gear, a second camera, microphones etc are all superfluous.<br /><br />- When you hear a loud animal scream,
and one person has a gun, he should take it out and point it at the nearest person.<br /><br />- When you take a gun out, the
sound of the safety being taken off will be made, even if your finger is nowhere near the safety<br /><br />- Reporters agree
to go half-way around the world in order to expose something - without having the faintest idea what they're exposing. Backgro
und research and vague knowledge are out of fashion in modern journalism.<br /><br />- Handguns hold at least 52 bullets in on
e clip, and then more than that in the next clip. Despite that, those with guns claim that they will need more ammo.<br /><br
/>- Expensive cameras (also, remember that the reporter only has one camera) are regularly left behind without even a moment's
hesitation or regret. These cameras amazingly manage to make their way back to the reporter all by themselves.<br /><br />- Th
e blonde girl really is the stupid one.<br /><br />- The same girl that says not to go into a house because a Komodo dragon ca
n easily run right through it, thus making it unsafe, takes a team into a building made of the same material for protection -
and nobody says a word about it.<br /><br />- High-tech facilities look like simple offices with high school chemistry sets.<b
r /><br />- Genetically-modified snakes grow from normal size to 100 feet long in a matter of a day, but don't grow at all in
the weeks either side.<br /><br />- The military routinely destroys entire islands when people don't meet contact deadlines.<b
r /><br />- Men with guns don't necessarily change the direction they're shooting when their target is no longer right in fron
t of them. Instead, they just keep shooting into the air.<br /><br />- The better looking you are, the greater your chance of
surviving giant creatures.<br /><br />- Women's intuition is reliable enough to change even the most stubborn of minds.<br /><
br />- Any time you're being hunted by giant creatures is a great time to hit on girls half your age.<br /><br />- Animal nois
es are an appropriate masking noise for 'swearing' at the same volume.<br /><br />- Old Israeli and Russian planes are regular
ly used by the US Military."
```

Data Preprocessing

Cleaning steps

removing HTML Tags
extracting emojies -> The pattern re.compile('(?::|;|=)(?:-)?(?:)|(|D|P)') is a regular expression used to match and extract emojis from a given text. removing special chars,puntuation,sumbols
lower casing
removing stopwords
tokenization

In [73]:
```
import nltk
nltk.download('stopwords')
```

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

Out[73]:
```
True
```

import re: Imports the re module for regular expressions, which is used for text manipulation, such as finding or replacing patterns in text (e.g., removing punctuation or special characters).

import nltk: Imports the nltk (Natural Language Toolkit) library, which provides various NLP tools, including tokenization, stemming, and stopword removal.

from nltk.stem.porter import PorterStemmer: Imports the Porter Stemmer, a tool used for stemming (reducing words to their root form), which helps in normalizing words like "running" to "run".

from nltk.corpus import stopwords: Imports a list of stopwords (commonly used words like "the", "is", "in", etc.), which are often removed in NLP tasks since they don’t add much meaningful information.

In [16]:
```
import re
import nltk
from nltk.stem.porter import PorterStemmer
from nltk.corpus import stopwords
```

The preprocessing function cleans text by removing HTML tags, emojis, non-alphabetic characters, stopwords, and then stemming the remaining words.

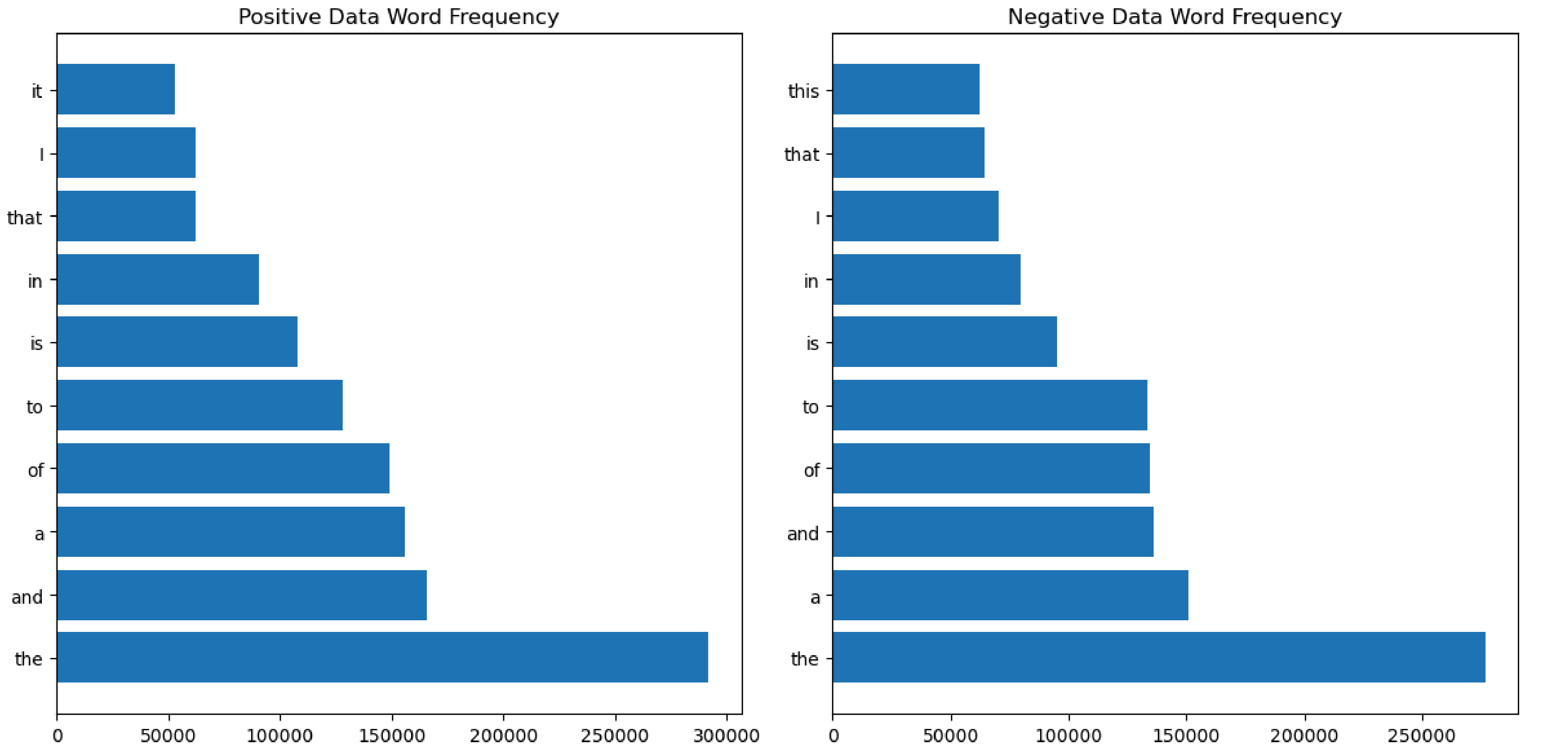
In [17]:
```
stopwords_set = set(stopwords.words('english'))
emoji_pattern = re.compile('(?::|;|=)(?:-)?(?:\)|\(|D|P)')

def preprocessing(text):
    text = re.sub('<[^>]*>', '', text)
    emojis = emoji_pattern.findall(text)
    text = re.sub('[\W+]', ' ', text.lower()) + ' '.join(emojis).replace('-', '')

    prter = PorterStemmer()
    text = [prter.stem(word) for word in text.split() if word not in stopwords_set]

    return " ".join(text)
```

In [18]:
```
preprocessing('this is my tags <h1> :) <p>helo world<p> <div> <div> </h2>')
```

Out[18]:
```
'tag helo world :)'
```

Visualizing Negative and Positive Words

In [19]:
```
positivedata = data[data['sentiment'] == 1]
positivedata = positivedata['review']
negdata = data[data['sentiment'] == 0]
negdata = negdata['review']

from collections import Counter

# Positive data
positivedata_words = ' '.join(positivedata).split()
positivedata_word_counts = Counter(positivedata_words)
positivedata_common_words = positivedata_word_counts.most_common(10)  # Display top 10 common words

# Negative data
negdata_words = ' '.join(negdata).split()
negdata_word_counts = Counter(negdata_words)
negdata_common_words = negdata_word_counts.most_common(10)  # Display top 10 common words


fig, axes = plt.subplots(1, 2, figsize=(12, 6))

# Positive data word frequency
axes[0].barh(range(len(positivedata_common_words)), [count for _, count in positivedata_common_words], align='center')
axes[0].set_yticks(range(len(positivedata_common_words)))
axes[0].set_yticklabels([word for word, _ in positivedata_common_words])
axes[0].set_title('Positive Data Word Frequency')

# Negative data word frequency
axes[1].barh(range(len(negdata_common_words)), [count for _, count in negdata_common_words], align='center')
axes[1].set_yticks(range(len(negdata_common_words)))
axes[1].set_yticklabels([word for word, _ in negdata_common_words])
axes[1].set_title('Negative Data Word Frequency')

plt.tight_layout()
plt.show()
```



TF-IDF Vertorizer to convert the raw documents into feature matrix

TfidfVectorizer(Term Frequency-Inverse Document Frequency) converts text reviews into numerical features (TF-IDF scores), where each review is represented as a vector. The sentiment labels (y) are stored separately, and these vectors can be used for machine learning models to predict sentiment.

In [20]:
```
from sklearn.feature_extraction.text import TfidfVectorizer

tfidf=TfidfVectorizer(strip_accents=None,lowercase=False,preprocessor=None,use_idf=True,norm='l2',smooth_idf=True)
y=data.sentiment.values
x=tfidf.fit_transform(data.review)
```

Train-Test Split

In [21]:
```
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Embedding, LSTM
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
```

splits the dataset into training (80%) and testing (20%) sets

In [22]:
```
train_data,test_data=train_test_split(data,test_size=0.2,random_state=42)
```

In [23]:
```
train_data.shape
```

Out[23]:
```
(40000, 2)
```

In [24]:
```
test_data.shape
```

Out[24]:
```
(10000, 2)
```

Tokenizer to process text data, limiting the vocabulary to the top 5000 most frequent words, and then fits the tokenizer on the training set reviews to build the word index.

In [25]:
```
tokenizer=Tokenizer(num_words=5000)
tokenizer.fit_on_texts(train_data["review"])
```

converts the text reviews into sequences of integers (where each word is replaced by its index in the tokenizer's word index) and then pads these sequences to ensure they all have a fixed length of 200 words

In [26]:
```
X_train=pad_sequences(tokenizer.texts_to_sequences(train_data["review"]),maxlen=200)
X_test=pad_sequences(tokenizer.texts_to_sequences(test_data["review"]),maxlen=200)
```

In [27]:
```
X_train
```

Out[27]:
```
array([[1935,    1, 1200, ...,  205,  351, 3856],
       [   3, 1651,  595, ...,   89,  103,    9],
       [   0,    0,    0, ...,    2,  710,   62],
       ...,
       [   0,    0,    0, ..., 1641,    2,  603],
       [   0,    0,    0, ...,  245,  103,  125],
       [   0,    0,    0, ...,   70,   73, 2062]])
```

In [28]:
```
X_test
```

Out[28]:
```
array([[   0,    0,    0, ...,  995,  719,  155],
       [  12,  162,   59, ...,  380,    7,    7],
       [   0,    0,    0, ...,   50, 1088,   96],
       ...,
       [   0,    0,    0, ...,  125,  200, 3241],
       [   0,    0,    0, ..., 1066,    1, 2305],
       [   0,    0,    0, ...,    1,  332,   27]])
```

In [29]:
```
Y_train=train_data["sentiment"]
Y_test=test_data["sentiment"]
```

In [30]:
```
Y_train
```

Out[30]:
```
39087    0
30893    0
45278    1
16398    0
13653    0
        ..
11284    1
44732    1
38158    0
860      1
15795    1
Name: sentiment, Length: 40000, dtype: int64
```

In [75]:
```
Y_test
```

Out[75]:
```
33553    1
9427     1
199      0
12447    1
39489    0
        ..
28567    0
25079    1
18707    1
15200    0
5857     1
Name: sentiment, Length: 10000, dtype: int64
```

Build LSTM(Long Short-Term Memory) Model

This model is a sequential neural network for binary sentiment classification, using an embedding layer for word representations, an LSTM layer to capture sequential dependencies, and a dense output layer with a sigmoid function to predict sentiment labels.

In [32]:
```
model = Sequential()
model.add(Embedding(input_dim=5000, output_dim=128, input_length=200))
model.add(LSTM(128, dropout=0.2, recurrent_dropout=0.2))
model.add(Dense(1, activation="sigmoid"))
model.build(input_shape=(None, 200))  # Build the model explicitly
```

```
C:\Users\vaish\AppData\Roaming\Python\Python311\site-packages\keras\src\layers\core\embedding.py:90: UserWarning: Argument `in
put_length` is deprecated. Just remove it.
  warnings.warn(
```

In [33]:
```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 200, 128)	640,000
lstm (LSTM)	(None, 128)	131,584
dense (Dense)	(None, 1)	129

Total params: 771,713 (2.94 MB)

Trainable params: 771,713 (2.94 MB)

Non-trainable params: 0 (0.00 B)

compiles the model for binary classification using the Adam optimizer, binary cross-entropy loss, and accuracy as the evaluation metric

In [34]:
```
model.compile(optimizer = "adam", loss="binary_crossentropy", metrics=["accuracy"])
```

The model will be trained for 5 epochs, processing 64 reviews at a time, and using 20% of the training data for validation.

In [35]:
```
model.fit(X_train, Y_train, epochs = 5, batch_size = 64, validation_split = 0.2)
```

```
Epoch 1/5
500/500 ━━━━━━━━━━━━━━━━━━━━ 234s 454ms/step - accuracy: 0.7306 - loss: 0.5259 - val_accuracy: 0.8236 - val_loss: 0.4002
Epoch 2/5
500/500 ━━━━━━━━━━━━━━━━━━━━ 230s 460ms/step - accuracy: 0.8269 - loss: 0.4097 - val_accuracy: 0.8460 - val_loss: 0.3624
Epoch 3/5
500/500 ━━━━━━━━━━━━━━━━━━━━ 239s 479ms/step - accuracy: 0.8598 - loss: 0.3432 - val_accuracy: 0.8735 - val_loss: 0.3147
Epoch 4/5
500/500 ━━━━━━━━━━━━━━━━━━━━ 236s 472ms/step - accuracy: 0.8919 - loss: 0.2752 - val_accuracy: 0.8569 - val_loss: 0.3507
Epoch 5/5
500/500 ━━━━━━━━━━━━━━━━━━━━ 234s 468ms/step - accuracy: 0.8911 - loss: 0.2752 - val_accuracy: 0.8712 - val_loss: 0.3286
```

Out[35]:
```
<keras.src.callbacks.history.History at 0x2ddbbd00510>
```

In [36]:
```
model.save('my_model.keras')
```

The model is evaluated on the test data, and it returns the loss and accuracy metrics to assess its performance.

In [37]:
```
loss,accuracy=model.evaluate(X_test,Y_test)
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 33s 99ms/step - accuracy: 0.8812 - loss: 0.3160
```

In [38]:
```
print(loss)
```

```
0.31189635396003723
```

In [39]:
```
print(accuracy)
```

```
0.8841999769210815
```

This saves the tokenizer to a file so it can be reused later without retraining.

In [40]:
```
import joblib
joblib.dump(tokenizer, "tokenizer.pkl")
```

Out[40]:
```
['tokenizer.pkl']
```

In [41]:
```
['tokenizer.pkl']
```

Out[41]:
```
['tokenizer.pkl']
```

Building Predictive System

This function takes a review, tokenizes and pads it, makes a prediction using the trained model, and returns whether the sentiment is "positive" or "negative".

In [58]:
```
def predictive_system(review):
    # Tokenize and pad the input review
    sequences = tokenizer.texts_to_sequences([review])
    print(f"Tokenized Sequence: {sequences}")  # Debugging: Check tokenization

    padded_sequence = pad_sequences(sequences, maxlen=200)

    prediction = model.predict(padded_sequence, verbose=0)
    print(f"Prediction Score: {prediction[0][0]}")

    sentiment = "positive" if prediction[0][0] > 0.5 else "negative"
    return sentiment
result = predictive_system("This movie was fantastic")
print(f"Predicted Sentiment: {result}")
```

```
Tokenized Sequence: [[11, 17, 13, 826]]
Prediction Score: 0.7628802061080933
Predicted Sentiment: positive
```

In [59]:
```
predictive_system("A trilling adventure with stunning visual")
```

```
Tokenized Sequence: [[3, 1170, 16, 1412, 1084]]
Prediction Score: 0.9632441997528076
```

Out[59]: 'positive'

In [60]:
```
predictive_system("Overall long and slow")
```

```
Tokenized Sequence: [[442, 190, 2, 561]]
Prediction Score: 0.4935157895088196
```

Out[60]: 'negative'

In [61]:
```
predictive_system("A visual masterpiece")
```

```
Tokenized Sequence: [[3, 1084, 932]]
Prediction Score: 0.9405654668807983
```

Out[61]: 'positive'

In [62]:
```
review_sentiment = predictive_system("Beautiful cinematography")
```

```
Tokenized Sequence: [[315, 625]]
Prediction Score: 0.8449392914772034
```

In [63]:
```
review_sentiment
```

Out[63]: 'positive'

In [64]:
```
predictive_system("I loved every minute of it. The characters were relatable, and the plot twists kept me on the edge of my sea
```

```
Tokenized Sequence: [[10, 427, 172, 791, 4, 9, 1, 102, 70, 2, 1, 110, 1267, 801, 68, 20, 1, 1248, 4, 56, 2033]]
Prediction Score: 0.9969888925552368
```

Out[64]: 'positive'

Deploy the Application Using Gradio

creates and launches an interactive web app where users can input a movie review, and it will return the predicted sentiment (positive or negative) using the predictive_system function. The app is shareable via a generated link.

In [54]:
```
import gradio as gr
title="MOVIE SENTIMENT ANALYSIS APPLICATION"
app=gr.Interface(fn=predictive_system,inputs="textbox",outputs="textbox",title=title)
app.launch(share=True)
```

```
Running on local URL:  http://127.0.0.1:7862 (http://127.0.0.1:7862)
Running on public URL: https://e2fbb3999856ab303a.gradio.live (https://e2fbb3999856ab303a.gradio.live)

This share link expires in 72 hours. For free permanent hosting and GPU upgrades, run `gradio deploy` from Terminal to deploy
to Spaces (https://huggingface.co/spaces)
```

MOVIE SENTIMENT ANALYSIS APPLICATION

review

This was an amazing movie .

output

Positive Sentiment 😊

Clear

Flag

Submit

Use via API · Built with Gradio

Out[54]:

Conclusion

In this project, we developed a Movie Sentiment Analysis Application using deep learning. After preprocessing the data by cleaning and tokenizing the reviews, we built an LSTM model to classify sentiments as positive or negative. The model was then evaluated for accuracy and deployed using a Gradio interface, allowing users to input movie reviews and receive real-time sentiment predictions. This project demonstrates the practical use of machine learning for sentiment analysis in text data.