In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.naive_bayes import MultinomialNB
from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.feature_extraction.text import TfidfVectorizer
from pandas.plotting import scatter_matrix
from matplotlib.gridspec import GridSpec
import nltk
nltk.download('stopwords')
nltk.download('punkt')
from nltk.corpus import stopwords
import string
from wordcloud import WordCloud
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
```

In [2]:

```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression, SGDClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import LinearSVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import VotingClassifier
from sklearn import tree # Import the tree module for DecisionTreeClassifier in GridSearc
hCV
from sklearn.metrics import accuracy_score
```

In [3]:

```
import os, re, time, zipfile, json, warnings
from pathlib import Path
import numpy as np
import pandas as pd

from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSearchCV
from sklearn.metrics import accuracy_score, precision_recall_fscore_support, confusion_ma
trix
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import LinearSVC
from sklearn.naive_bayes import MultinomialNB

import nltk
warnings.filterwarnings("ignore")
```

In [58]:

```
df =pd.read_csv('/content/Hotel_Reviews.csv')
df.head(5)
```

Out[58]:

	Hotel_Address	Additional_Number_of_Scoring	Review_Date	Average_Score	Hotel_Name	Reviewer_Nationality	Negative
0	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	8/3/2017	7.7	Hotel Arena	Russia	I am s that i m post av
1	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	8/3/2017	7.7	Hotel Arena	Ireland	No I
2	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	7/31/2017	7.7	Hotel Arena	Australia	Rooms but for bit
3	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	7/31/2017	7.7	Hotel Arena	United Kingdom	My rc dirty a afraic
4	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	7/24/2017	7.7	Hotel Arena	New Zealand	You bool your com

In [5]:

```
df.shape
```

Out[5]:

```
(515738, 17)
```

In [6]:

```
print(f"Feature names : {df.columns.values}")
```

```
Feature names : ['Hotel_Address' 'Additional_Number_of_Scoring' 'Review_Date'
 'Average_Score' 'Hotel_Name' 'Reviewer_Nationality' 'Negative_Review'
 'Review_Total_Negative_Word_Counts' 'Total_Number_of_Reviews'
 'Positive_Review' 'Review_Total_Positive_Word_Counts'
 'Total_Number_of_Reviews_Reviewer_Has_Given' 'Reviewer_Score' 'Tags'
 'days_since_review' 'lat' 'lng']
```

In [7]:

```
df.isnull().sum()
```

Out[7]:

	0
Hotel_Address	0
Additional_Number_of_Scoring	0
Review_Date	0
Average_Score	0
Hotel_Name	0
Reviewer_Nationality	0

Reviewer_Nationality	0
Negative_Review	0
Review_Total_Negative_Word_Counts	0
Total_Number_of_Reviews	0
Positive_Review	0
Review_Total_Positive_Word_Counts	0
Total_Number_of_Reviews_Reviewer_Has_Given	0
Reviewer_Score	0
Tags	0
days_since_review	0
lat	3268
lng	3268

dtype: int64

In [59]:

```
df = df.drop(['lat', 'lng'], axis=1)
display(df.head())
```

	Hotel_Address	Additional_Number_of_Scoring	Review_Date	Average_Score	Hotel_Name	Reviewer_Nationality	Negative
0	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	8/3/2017	7.7	Hotel Arena	Russia	I am that i m post av
1	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	8/3/2017	7.7	Hotel Arena	Ireland	No I
2	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	7/31/2017	7.7	Hotel Arena	Australia	Rooms but for bit
3	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	7/31/2017	7.7	Hotel Arena	United Kingdom	My rc dirty a afraic
4	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	7/24/2017	7.7	Hotel Arena	New Zealand	You bool your com

In [9]:

```
df.dropna(inplace=True)
```

In [10]:

```
print(f"Dataset shape after dropping null values : {df.shape}")
```

```
Dataset shape after dropping null values : (515738, 15)
```

In [60]:

```
df.columns.tolist(), df.head(2)
```

Out[60]:

```
(['Hotel_Address',
  'Additional_Number_of_Scoring',
  'Review_Date',
  'Average_Score',
  'Hotel_Name',
  'Reviewer_Nationality',
  'Negative_Review',
  'Review_Total_Negative_Word_Counts',
  'Total_Number_of_Reviews',
  'Positive_Review',
  'Review_Total_Positive_Word_Counts',
  'Total_Number_of_Reviews_Reviewer_Has_Given',
  'Reviewer_Score',
  'Tags',
  'days_since_review'],
                                        Hotel_Address  \
 0   s Gravesandestraat 55 Oost 1092 AA Amsterdam ...
 1   s Gravesandestraat 55 Oost 1092 AA Amsterdam ...

    Additional_Number_of_Scoring Review_Date  Average_Score   Hotel_Name  \
 0                           194    8/3/2017            7.7  Hotel Arena
 1                           194    8/3/2017            7.7  Hotel Arena

   Reviewer_Nationality                                    Negative_Review  \
 0             Russia     I am so angry that i made this post available...
 1            Ireland                                          No Negative

    Review_Total_Negative_Word_Counts  Total_Number_of_Reviews  \
 0                                397                     1403
 1                                  0                     1403

                                      Positive_Review  \
 0   Only the park outside of the hotel was beauti...
 1   No real complaints the hotel was great great ...

    Review_Total_Positive_Word_Counts  \
 0                                 11
 1                                105

    Total_Number_of_Reviews_Reviewer_Has_Given  Reviewer_Score  \
 0                                           7             2.9
 1                                           7             7.5

                                                Tags days_since_review
 0  [' Leisure trip ', ' Couple ', ' Duplex Double...           0 days
 1  [' Leisure trip ', ' Couple ', ' Duplex Double...           0 days   )
```

In [12]:

```
# Calculate the percentage of positive and negative reviews
total_reviews = len(df)
negative_percentage = (df['Negative_Review'].value_counts()['No Negative'] / total_revie
ws) * 100
positive_percentage = (df['Positive_Review'].value_counts()['No Positive'] / total_revie
ws) * 100

print(f"Percentage of Negative Reviews: {negative_percentage:.2f}%")
print(f"Percentage of Positive Reviews: {positive_percentage:.2f}%")
```

```
Percentage of Negative Reviews: 24.80%
Percentage of Positive Reviews: 6.97%
```

In [61]:

```
df["full_review"] = df["Positive_Review"].astype(str) + " " + df["Negative_Review"].asty
pe(str)

# Map reviewer score to sentiment
def score_to_sentiment(score):
    if score <= 4.0:
        return "negative"
    elif score < 7.0:
        return "neutral"
    else:
        return "positive"

df["sentiment"] = df["Reviewer_Score"].apply(score_to_sentiment)
```

In [62]:

```
df['sentiment']
```

Out[62]:

	sentiment
0	negative
1	positive
2	positive
3	negative
4	neutral
...	...
515733	positive
515734	neutral
515735	negative
515736	positive
515737	positive

515738 rows × 1 columns

dtype: object

In [69]:

```
df = df[df["full_review"].str.strip().astype(bool)]
```

In [70]:

```
df["review"] = df["Negative_Review"] + df["Positive_Review"]
df["review"] = df["review"].str.replace("No Negative", "")
df["review"] = df["review"].str.replace("No Positive", "")
df
```

Out[70]:

	Hotel_Address	Additional_Number_of_Scoring	Review_Date	Average_Score	Hotel_Name	Reviewer_Nationality	Ne
0	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	8/3/2017	7.7	Hotel Arena	Russia	tl p
1	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	8/3/2017	7.7	Hotel Arena	Ireland	

	Hotel_Address	Additional_Number_of_Scoring	Review_Date	Average_Score	Hotel_Name	Reviewer_Nationality	Ne
2	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	7/31/2017	7.7	Hotel Arena	Australia	R b
3	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	7/31/2017	7.7	Hotel Arena	United Kingdom	'
4	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	7/24/2017	7.7	Hotel Arena	New Zealand	you
...	...	...	...	...	...	...	
515733	Wurzbachgasse 21 15 Rudolfsheim F nfhaus 1150 ...	168	8/30/2015	8.1	Atlantis Hotel Vienna	Kuwait	n to
515734	Wurzbachgasse 21 15 Rudolfsheim F nfhaus 1150 ...	168	8/22/2015	8.1	Atlantis Hotel Vienna	Estonia	T li
515735	Wurzbachgasse 21 15 Rudolfsheim F nfhaus 1150 ...	168	8/19/2015	8.1	Atlantis Hotel Vienna	Egypt	u
515736	Wurzbachgasse 21 15 Rudolfsheim F nfhaus 1150 ...	168	8/17/2015	8.1	Atlantis Hotel Vienna	Mexico	
515737	Wurzbachgasse 21 15 Rudolfsheim F nfhaus 1150 ...	168	8/9/2015	8.1	Atlantis Hotel Vienna	Hungary	I w

515679 rows × 18 columns

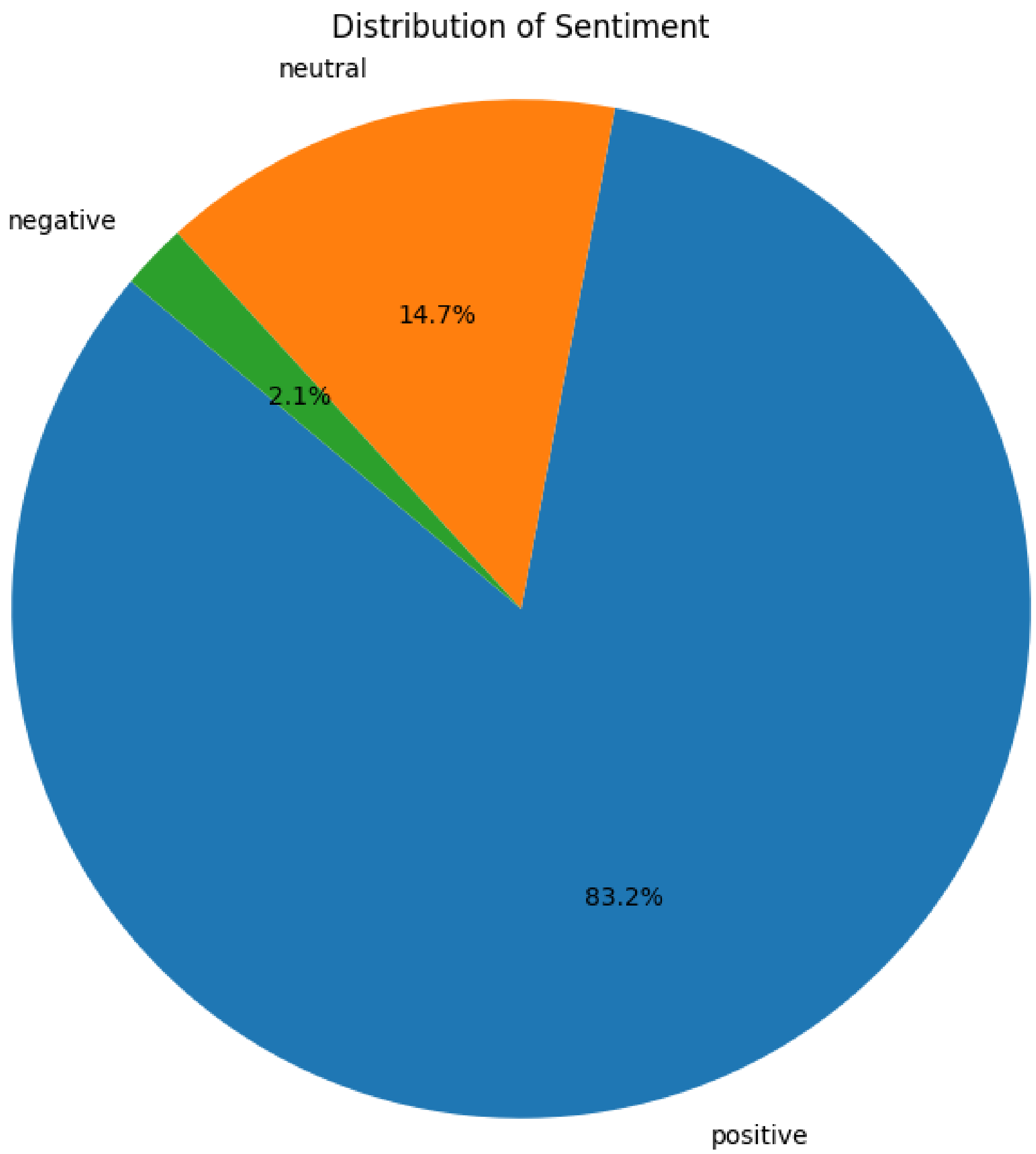
In [17]:

```
import matplotlib.pyplot as plt

# Calculate the value counts for the 'sentiment' column
sentiment_counts = df['sentiment'].value_counts()

# Create a pie chart
```

```
plt.figure(figsize=(8, 8))
plt.pie(sentiment_counts, labels=sentiment_counts.index, autopct='%1.1f%%', startangle=1
40)
plt.title('Distribution of Sentiment')
plt.axis('equal') # Equal aspect ratio ensures that pie is drawn as a circle.
plt.show()
```



In [71]:

```
df['Negative_Review'].dropna(inplace=True)
df['Positive_Review'].dropna(inplace=True)
df['review']
```

Out[71]:

	review
0	I am so angry that i made this post available...
1	No real complaints the hotel was great great ...
2	Rooms are nice but for elderly a bit difficul...
3	My room was dirty and I was afraid to walk ba...
4	You When I booked with your company on line y...
...	...
515733	no trolly or staff to help you take the lugga...
515734	The hotel looks like 3 but surely not 4 Brea...
515735	The ac was useless It was a hot week in vienn...

	review
515736	The rooms are enormous and really comfortable...
515737	I was in 3rd floor It didn t work Free Wife ...

515679 rows × 1 columns

dtype: object

In [72]:

```
df['review'] = df['review'].str.lower()
print(df['review'])
```

```
0          i am so angry that i made this post available...
1          no real complaints the hotel was great great ...
2          rooms are nice but for elderly a bit difficul...
3          my room was dirty and i was afraid to walk ba...
4          you when i booked with your company on line y...
                                ...
515733     no trolly or staff to help you take the lugga...
515734     the hotel looks like 3 but surely not 4  brea...
515735     the ac was useless it was a hot week in vienn...
515736     the rooms are enormous and really comfortable...
515737     i was in 3rd floor it didn t work free wife  ...
Name: review, Length: 515679, dtype: object
```

In [65]:

```
from nltk.stem import WordNetLemmatizer
from nltk.stem.porter import PorterStemmer
```

In [73]:

```
STOPWORDS = set(stopwords.words('english'))
LEMMATIZER = WordNetLemmatizer()
STEMMER = PorterStemmer()

def basic_clean(text):
    text = str(text).lower()
    text = re.sub(r"http\S+|www\S+", " ", text)
    text = re.sub(r"@\w+|#\w+", " ", text)
    text = text.translate(str.maketrans('', '', string.punctuation))
    text = re.sub(r"\d+", " ", text)
    return text

def tokenize(text):
    return text.split()

def remove_stopwords(tokens):
    return [t for t in tokens if t not in STOPWORDS and len(t) > 1]

def stem_tokens(tokens):
    return [STEMMER.stem(t) for t in tokens]

def lemmatize_tokens(tokens):
    return [LEMMATIZER.lemmatize(t) for t in tokens]

def clean_text_pipeline(text, use_stemming=True, use_lemmatization=False):
    text = basic_clean(text)
    tokens = tokenize(text)
    tokens = remove_stopwords(tokens)
    if use_lemmatization:
        tokens = lemmatize_tokens(tokens)
    if use_stemming:
        tokens = stem_tokens(tokens)
    return " ".join(tokens)

df["clean_text"] = df['review'].apply(lambda x: clean_text_pipeline(x, use_stemming=True
, use_lemmatization=False))
display(df.head())
```

	Hotel_Address	Additional_Number_of_Scoring	Review_Date	Average_Score	Hotel_Name	Reviewer_Nationality	Negative
0	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	8/3/2017	7.7	Hotel Arena	Russia	I am s that i m post av
1	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	8/3/2017	7.7	Hotel Arena	Ireland	No I
2	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	7/31/2017	7.7	Hotel Arena	Australia	Rooms but for bit
3	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	7/31/2017	7.7	Hotel Arena	United Kingdom	My ro dirty a afraid
4	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	7/24/2017	7.7	Hotel Arena	New Zealand	You bool your com

In [25]:

```
df['clean_text']
```

Out[25]:

	clean_text
0	angri made post avail via possibl site use pla...
1	real complaint hotel great great locat surroun...
2	room nice elderli bit difficult room two stori...
3	room dirti afraid walk barefoot floor look cle...
4	book compani line show pictur room thought get...
...	...
515733	trolli staff help take luggag room locat
515734	hotel look like sure breakfast ok got earlier ...
515735	ac useless hot week vienna gave hot air
515736	room enorm realli comfort believ famili member...
515737	rd floor work free wife staff kind

515679 rows × 1 columns

dtype: object

In [26]:

```
from collections import Counter
# Count the frequency of stopwords in the original reviews
stopword_counts = Counter()
for review in df['clean_text']:
    for word in review.split():
        if word.lower() in STOPWORDS:
            stopword_counts[word.lower()] += 1

print("Top 20 most frequent stopwords:")
for word, count in stopword_counts.most_common(20):
    print(f"{word}: {count}")
```

```
Top 20 most frequent stopwords:
other: 1923
will: 1314
that: 464
not: 236
up: 110
until: 103
own: 98
over: 98
can: 95
an: 94
in: 88
there: 83
what: 62
all: 59
am: 59
out: 55
with: 46
your: 26
down: 25
on: 22
```

In [27]:

```
# Create a word cloud from the cleaned text
all_clean_text = " ".join(df["clean_text"])

wordcloud = WordCloud(width=800, height=400, background_color='white').generate(all_clean
_text)

plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```

In [74]:

```
positive_reviews = df[df['sentiment'] == 'positive']['clean_text']
negative_reviews = df[df['sentiment'] == 'negative']['clean_text']

# word cloud for positive reviews
all_positive_text = " ".join(positive_reviews)
wordcloud_positive = WordCloud(width=800, height=400, background_color='white').generate(
all_positive_text)

plt.figure(figsize=(10, 5))
plt.imshow(wordcloud_positive, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Positive Reviews')
plt.show()

#  word cloud for negative reviews
all_negative_text = " ".join(negative_reviews)
wordcloud_negative = WordCloud(width=800, height=400, background_color='white').generate(
all_negative_text)

plt.figure(figsize=(10, 5))
plt.imshow(wordcloud_negative, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Negative Reviews')
plt.show()
```

Word Cloud for Positive Reviews

Word Cloud for Negative Reviews

In [30]:

```
sample_df = df.groupby("sentiment").apply(lambda x: x.sample(n=8000, random_state=42)).r
eset_index(drop=True)

# Split into train and test
X = sample_df["clean_text"].values
y = sample_df["sentiment"].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, ran
dom_state=42)
```

In [31]:

```
vectorizers = {
    "BoW": CountVectorizer(max_features=10000, ngram_range=(1,2), min_df=5),
    "TFIDF": TfidfVectorizer(max_features=10000, ngram_range=(1,2), min_df=5)
}
```

In [32]:

```
models = {
    "Multinomial Naive Bayes": MultinomialNB(),
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Decision Tree": DecisionTreeClassifier(max_depth=20, random_state=42),
    "Random Forest": RandomForestClassifier(n_estimators=100, max_depth=20, random_state
=42)
}
```

In [33]:

```
# Train and evaluate all combinations
results = []
for vec_name, vec in vectorizers.items():
    X_train_vec = vec.fit_transform(X_train)
    X_test_vec = vec.transform(X_test)

    for model_name, model in models.items():
        model.fit(X_train_vec, y_train)
        y_pred = model.predict(X_test_vec)
        acc = accuracy_score(y_test, y_pred)
        pr, rc, f1, _ = precision_recall_fscore_support(y_test, y_pred, average="macro")
        results.append({
            "Vectorizer": vec_name,
            "Model": model_name,
            "Accuracy": acc,
            "Precision": pr,
            "Recall": rc,
            "F1 Score": f1
        })

# Create a results table
results_df = pd.DataFrame(results).sort_values(by="F1 Score", ascending=False).reset_ind
ex(drop=True)
results_df
```

Out[33]:

	Vectorizer	Model	Accuracy	Precision	Recall	F1 Score
0	TFIDF	Logistic Regression	0.675417	0.675488	0.675417	0.675443
1	TFIDF	Multinomial Naive Bayes	0.674167	0.671482	0.674167	0.672589
2	BoW	Multinomial Naive Bayes	0.669375	0.665291	0.669375	0.666662

	Vectorizer	Model	Accuracy	Precision	Recall	F1 Score
2	BoW	Multinomial Naive Bayes	[illegible]	[illegible]	[illegible]	[illegible]
3	BoW	Logistic Regression	0.647917	0.647135	0.647917	0.647472
4	BoW	Random Forest	0.637083	0.626908	0.637083	0.627203
5	TFIDF	Random Forest	0.632708	0.625032	0.632708	0.626999
6	BoW	Decision Tree	0.561250	0.563954	0.561250	0.560739
7	TFIDF	Decision Tree	0.548125	0.575795	0.548125	0.553605

using different approach to improve accuracy

In [34]:

```
import re
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer

# Download necessary NLTK data
nltk.download('stopwords')
nltk.download('wordnet')

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

def preprocess_text(text):
    text = text.lower() # Convert to lowercase
    text = re.sub(r'\W', ' ', text) # Remove non-alphanumeric characters
    text = re.sub(r'\s+', ' ', text) # Remove multiple spaces
    tokens = text.split() # Tokenize
    tokens = [word for word in tokens if word not in stop_words] # Remove stop words
    tokens = [lemmatizer.lemmatize(word) for word in tokens] # Lemmatize
    return ' '.join(tokens)

# Apply preprocessing to the review columns
df['cleaned_negative_review'] = df['Negative_Review'].apply(preprocess_text)
df['cleaned_positive_review'] = df['Positive_Review'].apply(preprocess_text)

print("Text preprocessing complete.")
display(df[['Negative_Review', 'cleaned_negative_review', 'Positive_Review', 'cleaned_po
sitive_review']].head())
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
```

```
Text preprocessing complete.
```

	Negative_Review	cleaned_negative_review	Positive_Review	cleaned_positive_review
0	I am so angry that i made this post available...	angry made post available via possible site us...	Only the park outside of the hotel was beauti...	park outside hotel beautiful
1	No Negative	negative	No real complaints the hotel was great great ...	real complaint hotel great great location surr...
2	Rooms are nice but for elderly a bit difficul...	room nice elderly bit difficult room two story...	Location was good and staff were ok It is cut...	location good staff ok cute hotel breakfast ra...
3	My room was dirty and I was afraid to walk ba...	room dirty afraid walk barefoot floor looked c...	Great location in nice surroundings the bar a...	great location nice surroundings bar restauran...
4	You When I booked with your company on line y...	booked company line showed picture room though...	Amazing location and building Romantic setting	amazing location building romantic setting

In [35]:

```
from sklearn.model_selection import train_test_split

# Combine positive and negative reviews for a single text column
df['cleaned_reviews'] = df['cleaned_negative_review'] + " " + df['cleaned_positive_revie
```

```
w']

# based on the Reviewer_Score. We can set a threshold, e.g., score >= 7 is positive (1),
else negative (0).

df['sentiment'] = df['Reviewer_Score'].apply(lambda x: 1 if x >= 7 else 0)

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(df['cleaned_reviews'], df['sentiment
'], test_size=0.2, random_state=42)

print("Data split into training and testing sets.")
print(f"Training set size: {len(X_train)}")
print(f"Testing set size: {len(X_test)}")
```

```
Data split into training and testing sets.
Training set size: 412543
Testing set size: 103136
```

In [36]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
tfidf_vectorizer = TfidfVectorizer(max_features=5000 ,min_df=0,
                    max_df=1,
                    use_idf= True,
                    ngram_range= (1, 3))
# Fit and transform the training data
X_train_tfidf = tfidf_vectorizer.fit_transform(X_train)

# Transform the testing data
X_test_tfidf = tfidf_vectorizer.transform(X_test)

print("Text data converted to TF-IDF features.")
print(f"Shape of training features: {X_train_tfidf.shape}")
print(f"Shape of testing features: {X_test_tfidf.shape}")
```

```
Text data converted to TF-IDF features.
Shape of training features: (412543, 5000)
Shape of testing features: (103136, 5000)
```

In [37]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score

# Initialize and train a Logistic Regression model
# You can experiment with different parameters
log_reg_model = LogisticRegression(max_iter=1000) # Increased max_iter for convergence

log_reg_model.fit(X_train_tfidf, y_train)

print("Logistic Regression model trained.")

# Predict on the testing set
y_pred_log_reg = log_reg_model.predict(X_test_tfidf)

# Evaluate the model
print("Logistic Regression Model Evaluation:")
print(f"Accuracy: {accuracy_score(y_test, y_pred_log_reg)}")
print("Classification Report:")
print(classification_report(y_test, y_pred_log_reg))
```

```
Logistic Regression model trained.
Logistic Regression Model Evaluation:
Accuracy: 0.8802745888923363
Classification Report:
              precision    recall  f1-score   support

           0       0.72      0.48      0.58     17527
           1       0.90      0.96      0.93     85609

    accuracy                           0.88    103136
```

```
   macro avg       0.81      0.72      0.75    103136
weighted avg       0.87      0.88      0.87    103136
```

In [42]:

```python
# Train and evaluate all combinations
results = []
for vec_name, vec in vectorizers.items():
    # Assuming X_train and X_test contain the cleaned text data (e.g., from 'clean_text'
column)
    X_train_vec = vec.fit_transform(X_train)
    X_test_vec = vec.transform(X_test)

    for model_name, model in models.items():
        print(f"Training {model_name} with {vec_name}...")
        try:
            model.fit(X_train_vec, y_train)
            y_pred = model.predict(X_test_vec)
            acc = accuracy_score(y_test, y_pred)
            # Use 'weighted' average for precision, recall, f1 for multi-class
            pr, rc, f1, _ = precision_recall_fscore_support(y_test, y_pred, average="wei
ghted")
            results.append({
                "Vectorizer": vec_name,
                "Model": model_name,
                "Accuracy": acc,
                "Precision": pr,
                "Recall": rc,
                "F1 Score": f1
            })
            print(f"{model_name} with {vec_name} - Accuracy: {acc:.4f}, F1 Score: {f1:.4
f}")
        except Exception as e:
            print(f"Training {model_name} with {vec_name} failed: {e}")
```

```
Training Multinomial Naive Bayes with BoW...
Multinomial Naive Bayes with BoW - Accuracy: 0.8388, F1 Score: 0.8484
Training Logistic Regression with BoW...
Logistic Regression with BoW - Accuracy: 0.8837, F1 Score: 0.8746
Training Decision Tree with BoW...
Decision Tree with BoW - Accuracy: 0.8522, F1 Score: 0.8276
Training Random Forest with BoW...
Random Forest with BoW - Accuracy: 0.8332, F1 Score: 0.7606
Training Multinomial Naive Bayes with TFIDF...
Multinomial Naive Bayes with TFIDF - Accuracy: 0.8745, F1 Score: 0.8660
Training Logistic Regression with TFIDF...
Logistic Regression with TFIDF - Accuracy: 0.8854, F1 Score: 0.8769
Training Decision Tree with TFIDF...
Decision Tree with TFIDF - Accuracy: 0.8533, F1 Score: 0.8305
Training Random Forest with TFIDF...
Random Forest with TFIDF - Accuracy: 0.8329, F1 Score: 0.7598
```

In [44]:

```python
# Create a results table
results_df = pd.DataFrame(results).sort_values(by="F1 Score", ascending=False).reset_ind
ex(drop=True)
print("\n--- Model Comparison Table ---")
display(results_df)
```

```
--- Model Comparison Table ---
```

	Vectorizer	Model	Accuracy	Precision	Recall	F1 Score
0	TFIDF	Logistic Regression	0.885404	0.876536	0.885404	0.876888
1	BoW	Logistic Regression	0.883668	0.874362	0.883668	0.874553
2	TFIDF	Multinomial Naive Bayes	0.874467	0.864011	0.874467	0.866011
3	BoW	Multinomial Naive Bayes	0.838795	0.865653	0.838795	0.848364
4	TFIDF	Decision Tree	[illegible]	[illegible]	[illegible]	[illegible]

	Vectorizer	Model	Accuracy	Precision	Recall	F1 Score
4	TFIDF	Decision Tree	0.853252	0.832878	0.853252	0.830477
5	BoW	Decision Tree	0.852234	0.831254	0.852234	0.827600
6	BoW	Random Forest	0.833181	0.855722	0.833181	0.760591
7	TFIDF	Random Forest	0.832852	0.855919	0.832852	0.759783

In [46]:

```
# Save results
out_csv_ml = "/content/ml_model_results_summary.csv"
results_df.to_csv(out_csv_ml, index=False)
print(f"\nSaved results to {out_csv_ml}")
```

```
Saved results to /content/ml_model_results_summary.csv
```

Using NLP models

In [51]:

```
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, SimpleRNN, LSTM, GRU, Dense, Bidirectional
, Dropout
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_
auc_score
from sklearn.metrics import precision_recall_fscore_support
```

In [78]:

```
# Prepare data for deep learning models
max_words = 15000 # Reduced max_words to avoid memory issues
tokenizer = Tokenizer(num_words=max_words, oov_token="<OOV>")
tokenizer.fit_on_texts(df['clean_text'])
sequences = tokenizer.texts_to_sequences(df['clean_text'])
maxlen = 200
X = pad_sequences(sequences, maxlen=maxlen, padding='post', truncating='post')

# Map sentiment labels to numerical values (0, 1, 2)
sentiment_mapping = {"negative": 0, "neutral": 1, "positive": 2}
df["sentiment_numerical"] = df["sentiment"].map(sentiment_mapping)


# Check the shape of the DataFrame after dropping NaNs
print(f"Shape of DataFrame after dropping NaNs: {df.shape}")

# Re-map X and y to the cleaned dataframe
X = pad_sequences(tokenizer.texts_to_sequences(df['clean_text']), maxlen=maxlen, padding
='post', truncating='post')
y = df["sentiment_numerical"].values


# Split into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, ran
dom_state=42)

print("Train/Test shapes:", X_train.shape, X_test.shape, y_train.shape, y_test.shape)

# Define small models and train (SimpleRNN, LSTM, GRU, Bidirectional LSTM, Stacked LSTM)
vocab_size = min(max_words, len(tokenizer.word_index)+1)
embedding_dim = 64

def build_simple_rnn():
    model = Sequential([
        Embedding(vocab_size, embedding_dim, input_length=maxlen),
        SimpleRNN(64),
        Dense(len(sentiment_mapping), activation='softmax') # Changed to use the number
```

```
of sentiment classes
    ])
    model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['ac
curacy']) # Changed loss
    return model

def build_lstm():
    model = Sequential([
        Embedding(vocab_size, embedding_dim, input_length=maxlen),
        LSTM(64),
        Dense(len(sentiment_mapping), activation='softmax') # Changed to use the number
of sentiment classes
    ])
    model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['ac
curacy']) # Changed loss
    return model

def build_gru():
    model = Sequential([
        Embedding(vocab_size, embedding_dim, input_length=maxlen),
        GRU(64),
        Dense(len(sentiment_mapping), activation='softmax') # Changed to use the number
of sentiment classes
    ])
    model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['ac
curacy']) # Changed loss
    return model

def build_bidirectional_lstm():
    model = Sequential([
        Embedding(vocab_size, embedding_dim, input_length=maxlen),
        Bidirectional(LSTM(64)),
        Dense(len(sentiment_mapping), activation='softmax') # Changed to use the number
of sentiment classes
    ])
    model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['ac
curacy']) # Changed loss
    return model

def build_stacked_lstm():
    model = Sequential([
        Embedding(vocab_size, embedding_dim, input_length=maxlen),
        LSTM(64, return_sequences=True),
        LSTM(32),
        Dense(len(sentiment_mapping), activation='softmax') # Changed to use the number
of sentiment classes
    ])
    model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['ac
curacy']) # Changed loss
    return model

models_to_run = {
    'SimpleRNN': build_simple_rnn,
    'LSTM': build_lstm,
    'GRU': build_gru,
    'BiLSTM': build_bidirectional_lstm,
    'StackedLSTM': build_stacked_lstm
}

histories = {}
results = {}

# Train each model for a small number of epochs to demonstrate.
es = EarlyStopping(monitor='val_loss', patience=2, restore_best_weights=True)

for name, builder in models_to_run.items():
    print(f"\n\nTraining {name} ...")
    model = builder()
    try:
        history = model.fit(X_train, y_train, epochs=4, batch_size=128, validation_split
=0.15, callbacks=[es], verbose=2)
    except Exception as e:
```

```python
            print(f"Training {name} failed:", e)
            history = None
        histories[name] = history
        # evaluate
        try:
            preds_prob = model.predict(X_test, batch_size=256)
            preds = np.argmax(preds_prob, axis=1) # Changed to get the index of the max probability
            acc = accuracy_score(y_test, preds)
            # Precision, recall, f1 for multi-class
            from sklearn.metrics import classification_report
            report = classification_report(y_test, preds, target_names=sentiment_mapping.keys(), output_dict=True, zero_division=0) # Added zero_division=0
            prec = report['weighted avg']['precision']
            rec = report['weighted avg']['recall']
            f1 = report['weighted avg']['f1-score']
            # ROC AUC for multi-class (requires one-hot encoding or probability estimates)
            try:
                from sklearn.preprocessing import label_binarize
                y_test_bin = label_binarize(y_test, classes=[0, 1, 2])
                auc = roc_auc_score(y_test_bin, preds_prob, multi_class='ovr')
            except Exception as auc_e:
                print(f"AUC calculation failed for {name}: {auc_e}")
                auc = None

            results[name] = {'accuracy':acc, 'precision':prec, 'recall':rec, 'f1':f1, 'roc_auc':auc}
            print(name, "->", results[name])
        except Exception as e:
            print("Evaluation failed for", name, e)

# Prepare comparison table
results_df_nlp = pd.DataFrame.from_dict(results, orient='index')
results_df_nlp = results_df_nlp[['accuracy','precision','recall','f1','roc_auc']]
results_df_nlp = results_df_nlp.reset_index().rename(columns={'index':'model'})
print("\nNLP Model comparison:")
display(results_df_nlp)
```

```
Shape of DataFrame after dropping NaNs: (515679, 20)
Train/Test shapes: (412543, 200) (103136, 200) (412543,) (103136,)


Training SimpleRNN ...
Epoch 1/4
2740/2740 - 275s - 100ms/step - accuracy: 0.8317 - loss: 0.5183 - val_accuracy: 0.8298 - val_loss: 0.5208
Epoch 2/4
2740/2740 - 321s - 117ms/step - accuracy: 0.8318 - loss: 0.5176 - val_accuracy: 0.8298 - val_loss: 0.5205
Epoch 3/4
2740/2740 - 322s - 118ms/step - accuracy: 0.8319 - loss: 0.5172 - val_accuracy: 0.8298 - val_loss: 0.5205
Epoch 4/4
2740/2740 - 270s - 98ms/step - accuracy: 0.8319 - loss: 0.5170 - val_accuracy: 0.8298 - val_loss: 0.5223
403/403 ━━━━━━━━━━━━━━━━━━━━ 21s 52ms/step
SimpleRNN -> {'accuracy': 0.8316009928637915, 'precision': 0.6915602113320438, 'recall': 0.8316009928637915, 'f1': 0.7551428657512987, 'roc_auc': np.float64(0.5020994680960822)}


Training LSTM ...
Epoch 1/4
2740/2740 - 998s - 364ms/step - accuracy: 0.8316 - loss: 0.5177 - val_accuracy: 0.8298 - val_loss: 0.5205
Epoch 2/4
2740/2740 - 1015s - 370ms/step - accuracy: 0.8319 - loss: 0.5165 - val_accuracy: 0.8298 - val_loss: 0.5201
Epoch 3/4
2740/2740 - 989s - 361ms/step - accuracy: 0.8317 - loss: 0.5178 - val_accuracy: 0.8298 - val_loss: 0.5206
Epoch 4/4
2740/2740 - 978s - 357ms/step - accuracy: 0.8536 - loss: 0.3990 - val_accuracy: 0.8680 -
```

```
val_loss: 0.3228
403/403 ━━━━━━━━━━━━━━━━━━━━ 79s 195ms/step
LSTM -> {'accuracy': 0.8693181818181818, 'precision': 0.8425994113618389, 'recall': 0.869
3181818181818, 'f1': 0.8548167473430982, 'roc_auc': np.float64(0.908274869993957)}


Training GRU ...
Epoch 1/4
2740/2740 - 1148s - 419ms/step - accuracy: 0.8465 - loss: 0.4355 - val_accuracy: 0.8679 -
val_loss: 0.3298
Epoch 2/4
2740/2740 - 1108s - 405ms/step - accuracy: 0.8749 - loss: 0.3111 - val_accuracy: 0.8729 -
val_loss: 0.3160
Epoch 3/4
2740/2740 - 1166s - 425ms/step - accuracy: 0.8827 - loss: 0.2917 - val_accuracy: 0.8735 -
val_loss: 0.3101
Epoch 4/4
2740/2740 - 1184s - 432ms/step - accuracy: 0.8894 - loss: 0.2749 - val_accuracy: 0.8715 -
val_loss: 0.3148
403/403 ━━━━━━━━━━━━━━━━━━━━ 63s 156ms/step
GRU -> {'accuracy': 0.8742534129692833, 'precision': 0.8652212278613193, 'recall': 0.8742
534129692833, 'f1': 0.867396892848926, 'roc_auc': np.float64(0.9163167538212517)}


Training BiLSTM ...
Epoch 1/4
2740/2740 - 1752s - 639ms/step - accuracy: 0.8673 - loss: 0.3329 - val_accuracy: 0.8724 -
val_loss: 0.3135
Epoch 2/4
2740/2740 - 1780s - 650ms/step - accuracy: 0.8794 - loss: 0.2974 - val_accuracy: 0.8738 -
val_loss: 0.3100
Epoch 3/4
2740/2740 - 1723s - 629ms/step - accuracy: 0.8854 - loss: 0.2824 - val_accuracy: 0.8744 -
val_loss: 0.3110
Epoch 4/4
2740/2740 - 1757s - 641ms/step - accuracy: 0.8913 - loss: 0.2690 - val_accuracy: 0.8736 -
val_loss: 0.3167
403/403 ━━━━━━━━━━━━━━━━━━━━ 132s 327ms/step
BiLSTM -> {'accuracy': 0.8740304064536146, 'precision': 0.8584812986320292, 'recall': 0.8
740304064536146, 'f1': 0.8623998342292296, 'roc_auc': np.float64(0.9160871803479965)}


Training StackedLSTM ...
Epoch 1/4
2740/2740 - 1344s - 491ms/step - accuracy: 0.8319 - loss: 0.5172 - val_accuracy: 0.8298 -
val_loss: 0.5208
Epoch 2/4
2740/2740 - 1318s - 481ms/step - accuracy: 0.8319 - loss: 0.5163 - val_accuracy: 0.8297 -
val_loss: 0.5206
Epoch 3/4
2740/2740 - 1355s - 494ms/step - accuracy: 0.8317 - loss: 0.5134 - val_accuracy: 0.8298 -
val_loss: 0.4605
Epoch 4/4
2740/2740 - 1312s - 479ms/step - accuracy: 0.8657 - loss: 0.3379 - val_accuracy: 0.8710 -
val_loss: 0.3193
403/403 ━━━━━━━━━━━━━━━━━━━━ 110s 273ms/step
StackedLSTM -> {'accuracy': 0.87208152342538, 'precision': 0.8580547151973458, 'recall':
0.87208152342538, 'f1': 0.859741149281639, 'roc_auc': np.float64(0.9108849335163226)}

NLP Model comparison:
```

	model	accuracy	precision	recall	f1	roc_auc
0	SimpleRNN	0.831601	0.691560	0.831601	0.755143	0.502099
1	LSTM	0.869318	0.842599	0.869318	0.854817	0.908275
2	GRU	0.874253	0.865221	0.874253	0.867397	0.916317
3	BiLSTM	0.874030	0.858481	0.874030	0.862400	0.916087
4	StackedLSTM	0.872082	0.858055	0.872082	0.859741	0.910885

In [ ]:

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In [ ]:

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