Airline Review Classification

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import spacy
from sklearn.feature_extraction.text import TfidfVectorizer
import tensorflow as tf
from tensorflow import keras
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.metrics import classification_report
import pickle
```

```
df=pd.read_csv(r"D:\MachineLearning\DataScienceCourse\
Airline_review.csv")
df.head(3)
```

```
   Unnamed: 0 Airline Name Overall_Rating
Review_Title  \
0           0  AB Aviation              9         "pretty decent
airline"
1           1  AB Aviation              1            "Not a good
airline"
2           2  AB Aviation              1  "flight was fortunately
short"

          Review Date  Verified  \
0  11th November 2019      True
1      25th June 2019      True
2      25th June 2019      True

                                              Review      Aircraft  \
0    Moroni to Moheli. Turned out to be a pretty ...           NaN
1   Moroni to Anjouan. It is a very small airline...          E120
2    Anjouan to Dzaoudzi. A very small airline an...  Embraer E120

  Type Of Traveller      Seat Type                Route Date Flown  \
0      Solo Leisure  Economy Class     Moroni to Moheli     Nov-19
1      Solo Leisure  Economy Class    Moroni to Anjouan     Jun-19
2      Solo Leisure  Economy Class  Anjouan to Dzaoudzi     Jun-19

   Seat Comfort  Cabin Staff Service  Food & Beverages  Ground Service
\
```

```
0           4.0                   5.0                4.0              4.0

1           2.0                   2.0                1.0              1.0

2           2.0                   1.0                1.0              1.0


   Inflight Entertainment  Wifi & Connectivity  Value For Money 
Recommended  
0                     NaN                  NaN              3.0 
yes  
1                     NaN                  NaN              2.0 
no  
2                     NaN                  NaN              2.0 
no  
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23171 entries, 0 to 23170
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Unnamed: 0              23171 non-null  int64  
 1   Airline Name            23171 non-null  object 
 2   Overall_Rating          23171 non-null  object 
 3   Review_Title            23171 non-null  object 
 4   Review Date             23171 non-null  object 
 5   Verified                23171 non-null  bool   
 6   Review                  23171 non-null  object 
 7   Aircraft                7129 non-null   object 
 8   Type Of Traveller       19433 non-null  object 
 9   Seat Type               22075 non-null  object 
 10  Route                   19343 non-null  object 
 11  Date Flown              19417 non-null  object 
 12  Seat Comfort            19016 non-null  float64
 13  Cabin Staff Service     18911 non-null  float64
 14  Food & Beverages        14500 non-null  float64
 15  Ground Service          18378 non-null  float64
 16  Inflight Entertainment  10829 non-null  float64
 17  Wifi & Connectivity     5920 non-null   float64
 18  Value For Money         22105 non-null  float64
 19  Recommended             23171 non-null  object 
dtypes: bool(1), float64(7), int64(1), object(11)
memory usage: 3.4+ MB
```

```
df.drop("Unnamed: 0",axis=1,inplace=True)
df.drop("Date Flown",axis=1,inplace=True)

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23171 entries, 0 to 23170
Data columns (total 18 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Airline Name            23171 non-null  object 
 1   Overall_Rating          23171 non-null  object 
 2   Review_Title            23171 non-null  object 
 3   Review Date             23171 non-null  object 
 4   Verified                23171 non-null  bool   
 5   Review                  23171 non-null  object 
 6   Aircraft                7129 non-null   object 
 7   Type Of Traveller       19433 non-null  object 
 8   Seat Type               22075 non-null  object 
 9   Route                   19343 non-null  object 
 10  Seat Comfort            19016 non-null  float64
 11  Cabin Staff Service     18911 non-null  float64
 12  Food & Beverages        14500 non-null  float64
 13  Ground Service          18378 non-null  float64
 14  Inflight Entertainment  10829 non-null  float64
 15  Wifi & Connectivity     5920 non-null   float64
 16  Value For Money         22105 non-null  float64
 17  Recommended             23171 non-null  object 
dtypes: bool(1), float64(7), object(10)
memory usage: 3.0+ MB
```

```
# Checking duplicate rows:
df.duplicated().value_counts()
```

```
False    23051
True       120
Name: count, dtype: int64
```

```
df = df.drop_duplicates().reset_index(drop=True)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23051 entries, 0 to 23050
Data columns (total 18 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Airline Name            23051 non-null  object 
 1   Overall_Rating          23051 non-null  object 
 2   Review_Title            23051 non-null  object 
 3   Review Date             23051 non-null  object 
 4   Verified                23051 non-null  bool   
 5   Review                  23051 non-null  object 
 6   Aircraft                7127 non-null   object 
 7   Type Of Traveller       19424 non-null  object 
```

```
 8   Seat Type                22062 non-null  object
 9   Route                    19335 non-null  object
 10  Seat Comfort             19007 non-null  float64
 11  Cabin Staff Service      18902 non-null  float64
 12  Food & Beverages         14496 non-null  float64
 13  Ground Service           18369 non-null  float64
 14  Inflight Entertainment  10827 non-null  float64
 15  Wifi & Connectivity     5918 non-null   float64
 16  Value For Money          22092 non-null  float64
 17  Recommended              23051 non-null  object
dtypes: bool(1), float64(7), object(10)
memory usage: 3.0+ MB
```

```
df.duplicated().value_counts()
```

```
False    23051
Name: count, dtype: int64
```

```
# For categorical columns
df['Aircraft']=df['Aircraft'].fillna(df['Aircraft'].mode().iloc[0])
df['Type Of Traveller']=df['Type Of Traveller'].fillna(df['Type Of
Traveller'].mode().iloc[0])
df['Seat Type']=df['Seat Type'].fillna(df['Seat Type'].mode().iloc[0])
df['Route']=df['Route'].fillna(df['Route'].mode().iloc[0])
```

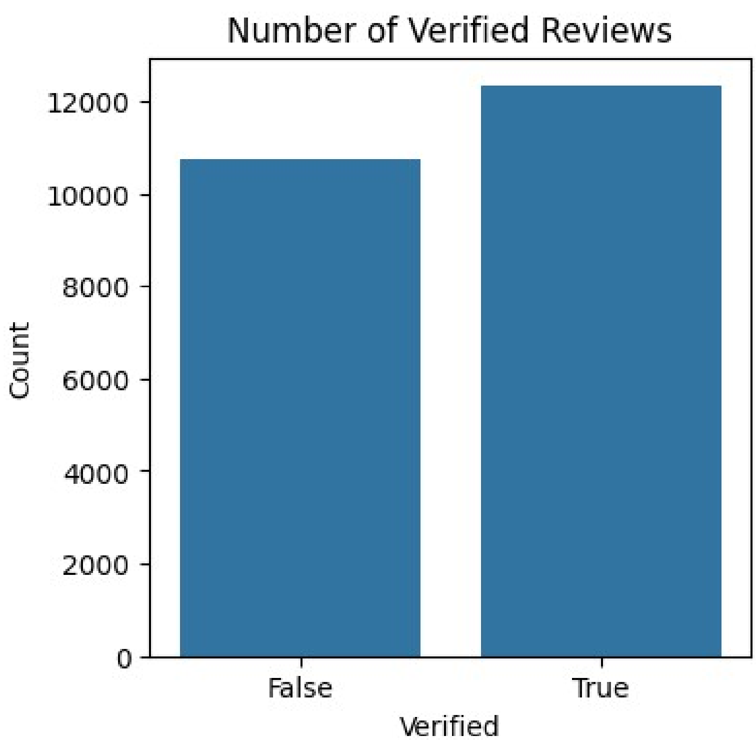
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23051 entries, 0 to 23050
Data columns (total 18 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Airline Name             23051 non-null  object
 1   Overall_Rating           23051 non-null  object
 2   Review_Title             23051 non-null  object
 3   Review Date              23051 non-null  object
 4   Verified                 23051 non-null  bool
 5   Review                   23051 non-null  object
 6   Aircraft                 23051 non-null  object
 7   Type Of Traveller        23051 non-null  object
 8   Seat Type                23051 non-null  object
 9   Route                    23051 non-null  object
 10  Seat Comfort             19007 non-null  float64
 11  Cabin Staff Service      18902 non-null  float64
 12  Food & Beverages         14496 non-null  float64
 13  Ground Service           18369 non-null  float64
 14  Inflight Entertainment  10827 non-null  float64
 15  Wifi & Connectivity     5918 non-null   float64
 16  Value For Money          22092 non-null  float64
 17  Recommended              23051 non-null  object
```

```
dtypes: bool(1), float64(7), object(10)
memory usage: 3.0+ MB

# For numerical columns
l=['Seat Comfort','Cabin Staff Service','Food & Beverages','Ground
Service','Inflight Entertainment','Wifi & Connectivity','Value For
Money']
for i in l:
    df[i]=df[i].fillna(df[i].median())
```

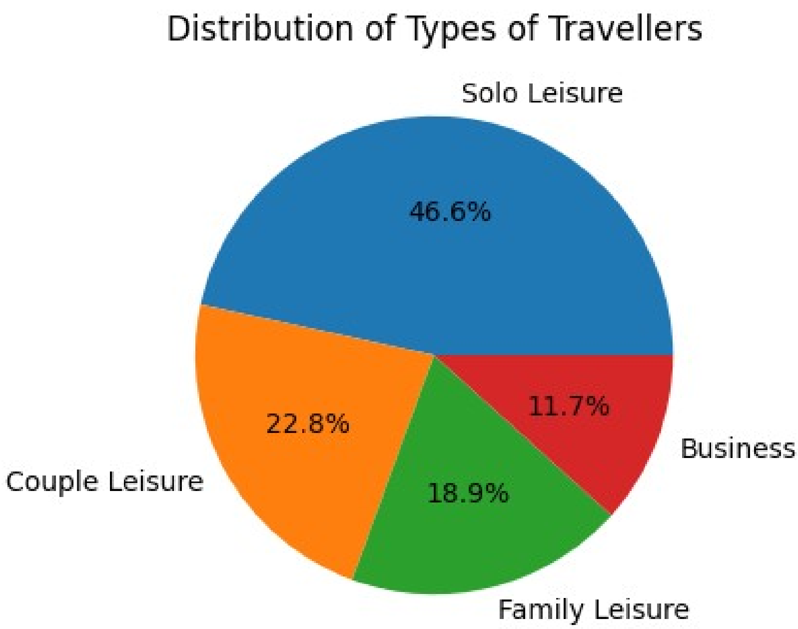
EDA (Data Visualization):

```
# Verified Reviews
plt.figure(figsize=(4, 4))
sns.countplot(x='Verified', data=df)
plt.title('Number of Verified Reviews')
plt.xlabel('Verified')
plt.ylabel('Count')
plt.show()
```

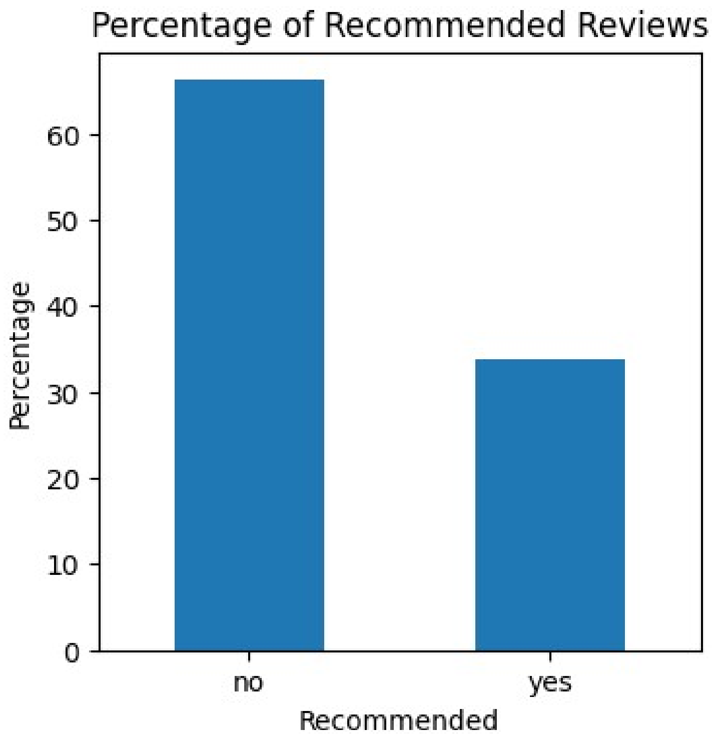



```
# Type of Traveller Distribution
traveler_distribution = df['Type Of Traveller'].value_counts()

# Distribution of types of Travellers
plt.figure(figsize=(6, 4))
traveler_distribution.plot(kind='pie', autopct='%1.1f%%')
```

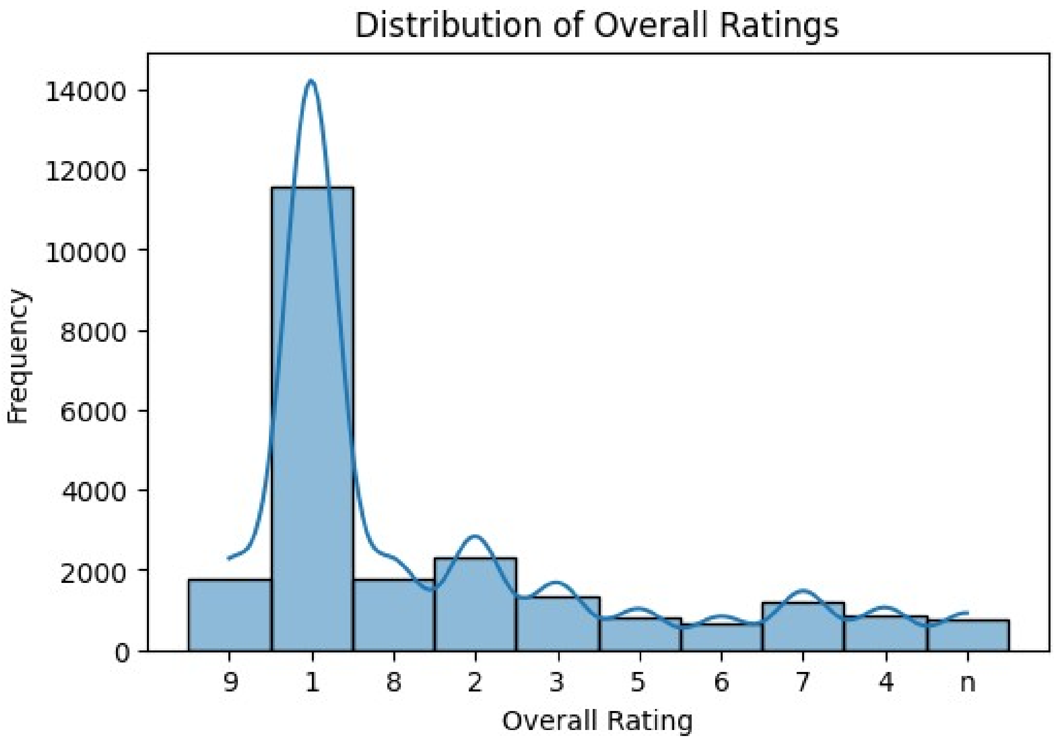
```
plt.title('Distribution of Types of Travellers')
plt.ylabel('')
plt.show()
```




```
# Percetage of recommened reviews
recommended_percentage =
df['Recommended'].value_counts(normalize=True) * 100
plt.figure(figsize=(4, 4))
recommended_percentage.plot(kind='bar', rot=0)
plt.title('Percentage of Recommended Reviews')
plt.xlabel('Recommended')
plt.ylabel('Percentage')
plt.show()
```



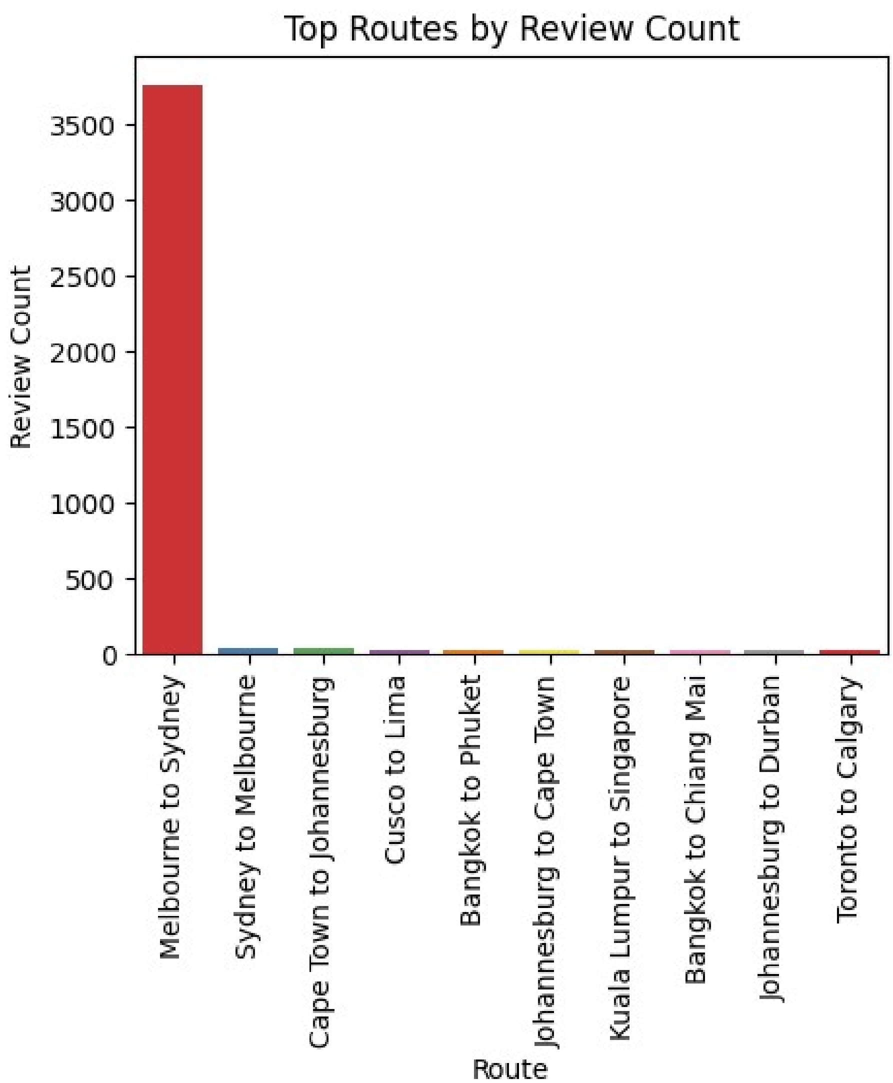

```
# Histogram of Overall Ratings:
plt.figure(figsize=(6, 4))
sns.histplot(df['Overall_Rating'], bins=10, kde=True)
plt.title('Distribution of Overall Ratings')
plt.xlabel('Overall Rating')
plt.ylabel('Frequency')
plt.show()
```



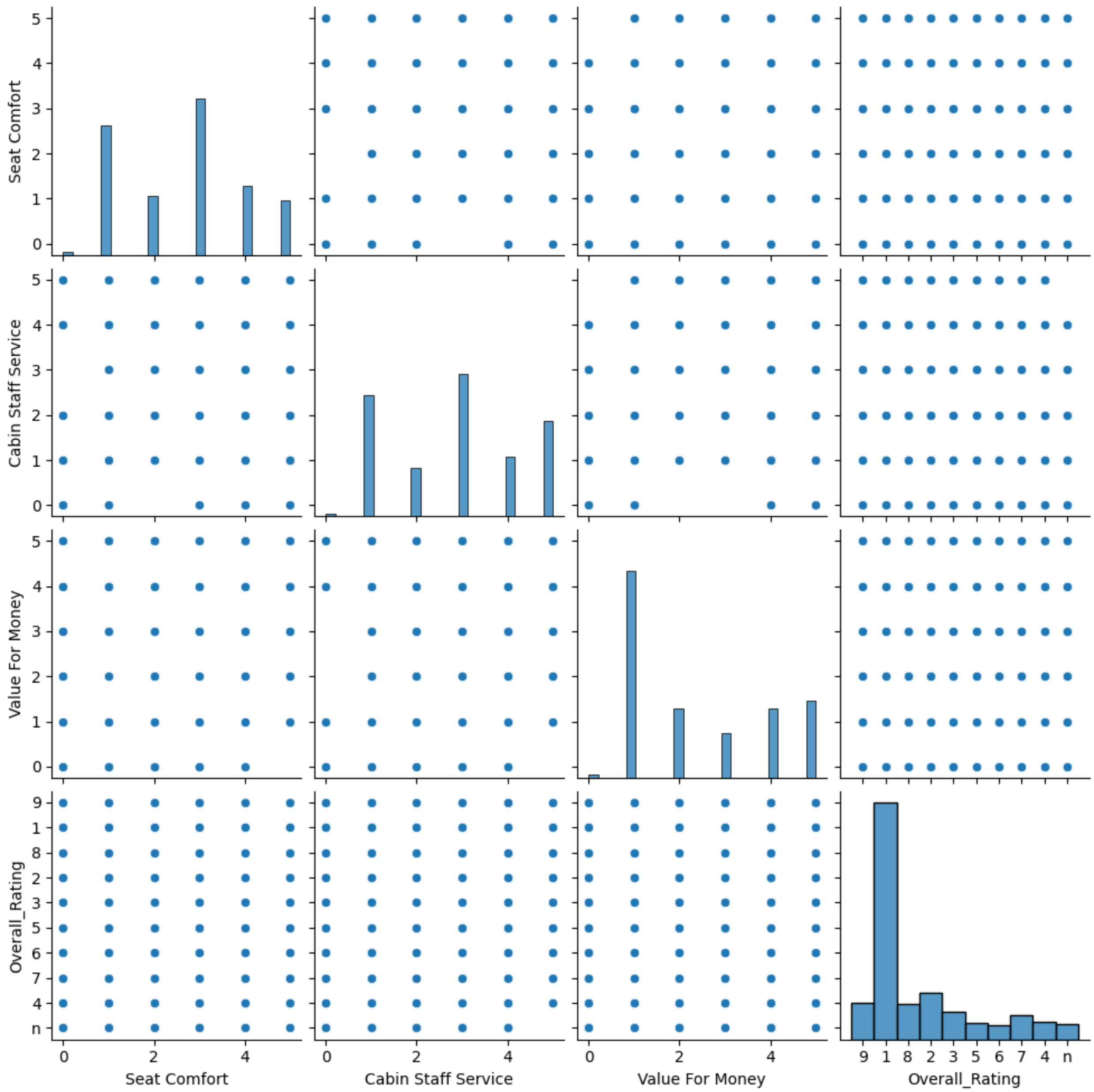

```
# Bar Plot for Top Routes:
top_routes = df['Route'].value_counts().head(10)
plt.figure(figsize=(5, 4))
colors = sns.color_palette("Set1", len(top_routes))
sns.barplot(x=top_routes.index, y=top_routes.values, palette=colors)
plt.title('Top Routes by Review Count')
plt.xlabel('Route')
plt.ylabel('Review Count')
plt.xticks(rotation=90)
```

```
C:\Users\Vidul\AppData\Local\Temp\ipykernel_34468\2586659521.py:5:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x=top_routes.index, y=top_routes.values, palette=colors)

([0, 1, 2, 3, 4, 5, 6, 7, 8, 9],
 [Text(0, 0, 'Melbourne to Sydney'),
  Text(1, 0, 'Sydney to Melbourne'),
  Text(2, 0, 'Cape Town to Johannesburg'),
  Text(3, 0, 'Cusco to Lima'),
  Text(4, 0, 'Bangkok to Phuket'),
  Text(5, 0, 'Johannesburg to Cape Town'),
  Text(6, 0, 'Kuala Lumpur to Singapore'),
```

```
  Text(7, 0, 'Bangkok to Chiang Mai'),
  Text(8, 0, 'Johannesburg to Durban'),
  Text(9, 0, 'Toronto to Calgary')])
```




```
# Pairwise Scatterplot for Correlation:
sns.pairplot(df, vars=['Seat Comfort', 'Cabin Staff Service', 'Value
For Money', 'Overall_Rating'])

<seaborn.axisgrid.PairGrid at 0x201094c2050>
```




```
## Removing unnecessary columns:
df.drop("Route",axis=1,inplace=True)
df.drop("Aircraft",axis=1,inplace=True)
df.drop("Review Date",axis=1,inplace=True)
df.drop("Airline Name",axis=1,inplace=True)
```

Encoding

```
df['Verified']=df['Verified'].replace({'True':1,'False':0})
df['Type Of Traveller']=df['Type Of Traveller'].replace({'Solo
Leisure':1,'Couple Leisure':2,'Family Leisure':3,'Business':4})
df['Seat Type']=df['Seat Type'].replace({'Economy Class':1,'Business
```

```
Class':2,'Premium Economy':3,'First Class':4})
df['Recommended']=df['Recommended'].replace({'yes':1,'no':0})

df['Overall_Rating']=df['Overall_Rating'].replace('n',10)

df['Overall_Rating']=df['Overall_Rating'].astype(int)

l=["Overall_Rating","Review_Title","Cabin Staff Service","Food &
Beverages","Recommended"]
df=df[l]

df.head(3)
```

```
   Overall_Rating                    Review_Title  Cabin Staff Service
\
0               9          "pretty decent airline"                  5.0

1               1             "Not a good airline"                  2.0

2               1  "flight was fortunately short"                  1.0


   Food & Beverages  Recommended
0               4.0            1
1               1.0            0
2               1.0            0
```

Preprocessing using spacy:

```
nlp=spacy.load("en_core_web_sm")
```

```
C:\Users\Vidul\AppData\Local\Programs\Python\Python311\Lib\site-
packages\spacy\util.py:910: UserWarning: [W095] Model 'en_core_web_sm'
(3.6.0) was trained with spaCy v3.6.0 and may not be 100% compatible
with the current version (3.7.2). If you see errors or degraded
performance, download a newer compatible model or retrain your custom
model with the current spaCy version. For more details and available
updates, run: python -m spacy validate
  warnings.warn(warn_msg)
```

```
# Important words (so that they are not lost)
exceptions = ["not", "never", "bad", "nice", "good", "great", "poor",
"excellent","no"]
def preprocess (text):
    text = text.lower() # to convert to lowercase (so that we can add
exceptions properly)
    doc=nlp(text)
    filtered_tokens=[]
    for token in doc:
        if token.text in exceptions:
            filtered_tokens.append(token.text)
```

```
        if token.is_stop or token.is_punct:
            continue
        filtered_tokens.append(token.lemma_)
    return " ".join(filtered_tokens)

df['Review']=df['Review_Title'].apply(lambda x: preprocess(x))
```

```
C:\Users\Vidul\AppData\Local\Temp\ipykernel_34468\4282974474.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df['Review']=df['Review_Title'].apply(lambda x: preprocess(x))
```

```
df.head(5)
```

```
   Overall_Rating                           Review_Title  Cabin Staff
Service  \
0               9                 "pretty decent airline"
5.0
1               1                    "Not a good airline"
2.0
2               1           "flight was fortunately short"
1.0
3               1    "I will never fly again with Adria"
1.0
4               1  "it ruined our last days of holidays"
1.0

   Food & Beverages  Recommended                     Review
0               4.0            1      pretty decent airline
1               1.0            0      not good good airline
2               1.0            0  flight fortunately short
3               2.0            0            never fly adria
4               1.0            0           ruin day holiday
```

```
df.columns
```

```
Index(['Overall_Rating', 'Review_Title', 'Cabin Staff Service',
       'Food & Beverages', 'Recommended', 'Review'],
      dtype='object')
```

```
df=df.rename(columns={'Cabin Staff Service': 'Cabin_Staff_Service',
'Food & Beverages': 'Food_Beverages'})
```

Text Vectorization

```
v1=TfidfVectorizer()
v1.fit(df["Review"])
rev_tfidf = v1.transform(df["Review"])

rev_tfidf

<23051x3892 sparse matrix of type '<class 'numpy.float64'>'
	with 68754 stored elements in Compressed Sparse Row format>

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23051 entries, 0 to 23050
Data columns (total 6 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   Overall_Rating       23051 non-null  int32  
 1   Review_Title         23051 non-null  object 
 2   Cabin_Staff_Service  23051 non-null  float64
 3   Food_Beverages       23051 non-null  float64
 4   Recommended          23051 non-null  int64  
 5   Review               23051 non-null  object 
dtypes: float64(2), int32(1), int64(1), object(2)
memory usage: 990.6+ KB
```

Splitting

```
# Combine TF-IDF vectors with the existing numerical columns:

# pd.DataFrame -- to convert into a dataframe
# .toarray() -- converts the sparse TF-IDF matrix into a dense matrix
# pd.concat([...], axis=1) -- concatenates the DataFrames created in
the first two parts (TF-IDF vectors for "rev" and "revTitle") and the
DataFrame from the third part (remaining numerical columns)

x = pd.concat([pd.DataFrame(rev_tfidf.toarray()),
               df.drop(columns=["Review_Title",
"Review","Recommended"])], axis=1)

y=df["Recommended"]

x

         0    1    2    3    4    5    6    7    8    9  ...  3885
3886  \
0      0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...   0.0
0.0
1      0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...   0.0
0.0
```

```
2      0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...   0.0
0.0
3      0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...   0.0
0.0
4      0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...   0.0
0.0
...    ...  ...  ...  ...  ...  ...  ...  ...  ...  ...  ...   ...   .
..
23046  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...   0.0
0.0
23047  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...   0.0
0.0
23048  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...   0.0
0.0
23049  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...   0.0
0.0
23050  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...   0.0
0.0

       3887  3888  3889  3890  3891  Overall_Rating
Cabin_Staff_Service  \
0       0.0   0.0   0.0   0.0   0.0               9
5.0
1       0.0   0.0   0.0   0.0   0.0               1
2.0
2       0.0   0.0   0.0   0.0   0.0               1
1.0
3       0.0   0.0   0.0   0.0   0.0               1
1.0
4       0.0   0.0   0.0   0.0   0.0               1
1.0
...     ...   ...   ...   ...   ...             ...                  .
..
23046   0.0   0.0   0.0   0.0   0.0               1
1.0
23047   0.0   0.0   0.0   0.0   0.0               1
3.0
23048   0.0   0.0   0.0   0.0   0.0               3
4.0
23049   0.0   0.0   0.0   0.0   0.0               6
4.0
23050   0.0   0.0   0.0   0.0   0.0               1
3.0

       Food_Beverages
0                 4.0
1                 1.0
2                 1.0
3                 2.0
```

```
4                  1.0
...                ...
23046              2.0
23047              2.0
23048              2.0
23049              3.0
23050              2.0

[23051 rows x 3895 columns]
```

```
x.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23051 entries, 0 to 23050
Columns: 3895 entries, 0 to Food_Beverages
dtypes: float64(3894), int32(1)
memory usage: 684.9 MB
```

```
y.info()
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 23051 entries, 0 to 23050
Series name: Recommended
Non-Null Count  Dtype
--------------  -----
23051 non-null  int64
dtypes: int64(1)
memory usage: 180.2 KB
```

```
x.columns = x.columns.astype(str)
```

```
# scaler = MinMaxScaler()
# scaler.fit(x)
# x = scaler.transform(x)
# x = pd.DataFrame(x)
# x.info()
```

TrainTestSplit

```
x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.2, random_state=42)
```

```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(18440, 3895)
(4611, 3895)
(18440,)
(4611,)
```

```
y_train
```

```
14149    0
3728     1
16249    1
450      0
17987    1
        ..
11964    0
21575    0
5390     0
860      0
15795    0
Name: Recommended, Length: 18440, dtype: int64
```

Model Training

1) Neural Networks

```
model1 = keras.Sequential([
    keras.layers.Input(shape=(x_train.shape[1],)),  # shape of the
input data
    keras.layers.Dense(64, activation='relu'),  # hidden layer
    keras.layers.Dense(1, activation='sigmoid')
])

model1.compile(
    optimizer='adam',
    loss='binary_crossentropy',
    metrics=['accuracy']
)

# Train the model
model1.fit(x_train, y_train, epochs=50)
```

```
Epoch 1/50
577/577 [==============================] - 7s 7ms/step - loss: 0.3107
- accuracy: 0.8885
Epoch 2/50
577/577 [==============================] - 4s 7ms/step - loss: 0.1759
- accuracy: 0.9310
Epoch 3/50
577/577 [==============================] - 4s 7ms/step - loss: 0.1486
- accuracy: 0.9427
Epoch 4/50
577/577 [==============================] - 5s 8ms/step - loss: 0.1335
- accuracy: 0.9494
Epoch 5/50
577/577 [==============================] - 5s 8ms/step - loss: 0.1220
```

```
- accuracy: 0.9530
Epoch 6/50
577/577 [==============================] - 4s 7ms/step - loss: 0.1120
- accuracy: 0.9584
Epoch 7/50
577/577 [==============================] - 4s 8ms/step - loss: 0.1053
- accuracy: 0.9617
Epoch 8/50
577/577 [==============================] - 4s 7ms/step - loss: 0.0997
- accuracy: 0.9653
Epoch 9/50
577/577 [==============================] - 4s 7ms/step - loss: 0.0943
- accuracy: 0.9670
Epoch 10/50
577/577 [==============================] - 4s 7ms/step - loss: 0.0901
- accuracy: 0.9685
Epoch 11/50
577/577 [==============================] - 4s 7ms/step - loss: 0.0864
- accuracy: 0.9695
Epoch 12/50
577/577 [==============================] - 4s 7ms/step - loss: 0.0829
- accuracy: 0.9716
Epoch 13/50
577/577 [==============================] - 4s 7ms/step - loss: 0.0803
- accuracy: 0.9729
Epoch 14/50
577/577 [==============================] - 4s 7ms/step - loss: 0.0790
- accuracy: 0.9734
Epoch 15/50
577/577 [==============================] - 4s 6ms/step - loss: 0.0757
- accuracy: 0.9739
Epoch 16/50
577/577 [==============================] - 5s 8ms/step - loss: 0.0740
- accuracy: 0.9751
Epoch 17/50
577/577 [==============================] - 5s 8ms/step - loss: 0.0715
- accuracy: 0.9755
Epoch 18/50
577/577 [==============================] - 4s 7ms/step - loss: 0.0704
- accuracy: 0.9765
Epoch 19/50
577/577 [==============================] - 5s 8ms/step - loss: 0.0688
- accuracy: 0.9768
Epoch 20/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0679
- accuracy: 0.9767
Epoch 21/50
577/577 [==============================] - 5s 8ms/step - loss: 0.0672
- accuracy: 0.9758
```

```
Epoch 22/50
577/577 [==============================] - 5s 8ms/step - loss: 0.0650
- accuracy: 0.9783
Epoch 23/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0637
- accuracy: 0.9786
Epoch 24/50
577/577 [==============================] - 5s 8ms/step - loss: 0.0623
- accuracy: 0.9798
Epoch 25/50
577/577 [==============================] - 5s 8ms/step - loss: 0.0616
- accuracy: 0.9793
Epoch 26/50
577/577 [==============================] - 4s 7ms/step - loss: 0.0596
- accuracy: 0.9805
Epoch 27/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0598
- accuracy: 0.9800
Epoch 28/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0593
- accuracy: 0.9804
Epoch 29/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0562
- accuracy: 0.9818
Epoch 30/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0553
- accuracy: 0.9818
Epoch 31/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0558
- accuracy: 0.9815
Epoch 32/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0558
- accuracy: 0.9813
Epoch 33/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0536
- accuracy: 0.9817
Epoch 34/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0534
- accuracy: 0.9822
Epoch 35/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0520
- accuracy: 0.9826
Epoch 36/50
577/577 [==============================] - 4s 7ms/step - loss: 0.0510
- accuracy: 0.9825
Epoch 37/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0513
- accuracy: 0.9827
Epoch 38/50
```

```
577/577 [==============================] - 4s 8ms/step - loss: 0.0511
- accuracy: 0.9828
Epoch 39/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0500
- accuracy: 0.9832
Epoch 40/50
577/577 [==============================] - 5s 8ms/step - loss: 0.0493
- accuracy: 0.9845
Epoch 41/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0493
- accuracy: 0.9826
Epoch 42/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0481
- accuracy: 0.9833
Epoch 43/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0470
- accuracy: 0.9847
Epoch 44/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0468
- accuracy: 0.9832
Epoch 45/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0466
- accuracy: 0.9844
Epoch 46/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0459
- accuracy: 0.9846
Epoch 47/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0460
- accuracy: 0.9844
Epoch 48/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0455
- accuracy: 0.9844
Epoch 49/50
577/577 [==============================] - 5s 8ms/step - loss: 0.0450
- accuracy: 0.9850
Epoch 50/50
577/577 [==============================] - 4s 8ms/step - loss: 0.0434
- accuracy: 0.9858

<keras.src.callbacks.History at 0x2010b3a69d0>
```

```python
# Evaluate the model
loss, accuracy = model1.evaluate(x_train, y_train)
print(f"Test accuracy: {accuracy}")
```

```
577/577 [==============================] - 5s 4ms/step - loss: 0.0396
- accuracy: 0.9867
Test accuracy: 0.9867136478424072
```

2) Random Forest Classifier

```
model2=RandomForestClassifier(n_estimators=100, random_state=42)
model2
```

```
RandomForestClassifier(random_state=42)
```

```
model2.fit(x_train, y_train)
y_pred2 = model2.predict(x_test)
print(classification_report(y_test, y_pred2))
```

```
              precision    recall  f1-score   support

           0       0.95      0.96      0.96      3051
           1       0.92      0.90      0.91      1560

    accuracy                           0.94      4611
   macro avg       0.94      0.93      0.93      4611
weighted avg       0.94      0.94      0.94      4611
```

3) KNeighbors Classifier

```
model3=KNeighborsClassifier()
model3
```

```
KNeighborsClassifier()
```

```
model3.fit(x_train, y_train)
y_pred3 = model3.predict(x_test)
print(classification_report(y_test, y_pred3))
```

```
              precision    recall  f1-score   support

           0       0.95      0.95      0.95      3051
           1       0.91      0.90      0.91      1560

    accuracy                           0.94      4611
   macro avg       0.93      0.93      0.93      4611
weighted avg       0.94      0.94      0.94      4611
```

4) Decision Tree Classifier

```
model4=DecisionTreeClassifier() # Increase the max_iter value
model4
```

```
DecisionTreeClassifier()
```

```
model4.fit(x_train, y_train)
y_pred4 = model4.predict(x_test)
print(classification_report(y_test, y_pred4))
```

```
              precision    recall  f1-score   support

           0       0.95      0.95      0.95      3051
           1       0.90      0.90      0.90      1560

    accuracy                           0.93      4611
   macro avg       0.93      0.93      0.93      4611
weighted avg       0.93      0.93      0.93      4611
```

5) Logistic Regression

```
model5=LogisticRegression(max_iter=1000) # Increase the max_iter value
model5
```

```
LogisticRegression(max_iter=1000)
```

```
model5.fit(x_train, y_train)
y_pred5 = model5.predict(x_test)
print(classification_report(y_test, y_pred5))
print(confusion_matrix(y_test,y_pred5))
```

```
              precision    recall  f1-score   support

           0       0.92      0.93      0.92      3051
           1       0.85      0.84      0.85      1560

    accuracy                           0.90      4611
   macro avg       0.89      0.88      0.88      4611
weighted avg       0.90      0.90      0.90      4611

[[2827  224]
 [ 254 1306]]
```

```
# Sample input data
input_data = [['This airline is great', 9, 5, 4], ['Not a good
experience', 2, 3, 2]]

# Create a DataFrame with the input data
input_df = pd.DataFrame(input_data, columns=['Review',
'Overall_Rating', 'Cabin Staff Service', 'Food & Beverages'])

# Preprocess the input data
# 1. Use the same TfidfVectorizer that you used for training data
rev_tfidf = v1.transform(input_df["Review"])

# 2. Concatenate the text features and numerical features
```

```python
x_input = pd.concat([pd.DataFrame(rev_tfidf.toarray()),
input_df.drop(columns=["Review"])], axis=1)
x_input.columns = x_input.columns.astype(str)

# Predict "Recommended" for the input data
y_pred_input = model1.predict(x_input)

# Selecting 0.5 as a threshold in model1
for i, review in enumerate(input_data):
    if(y_pred_input[i]<=0.5):
        print(f'Review: {review[0]}, Prediction: Not Recommended')
    if(y_pred_input[i]>0.5):
        print(f'Review: {review[0]}, Prediction: Recommended')
```

```
1/1 [==============================] - 2s 2s/step
Review: This airline is great, Prediction: Recommended
Review: Not a good experience, Prediction: Not Recommended
```

```python
columns=['Review', 'Overall_Rating', 'Cabin_Staff_Service',
'Food_Beverages']

# Save the trained TF-IDF vectorizer
with open('tfidf_vectorizer.pkl', 'wb') as f:
    pickle.dump(v1, f)

# Save the trained Random Forest classifier
with open('model.pkl', 'wb') as f:
    pickle.dump(model2, f)

# Save the column names of the feature matrix
with open('column_names.pkl', 'wb') as f:
    pickle.dump(columns, f)
```