CSCI 6515 - Machine Learning for Big Data (Fall 2023)

Final Project

Group_ID: `7`

Group Members:

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1. Dataset Information

Dataset Name: `Airlines`

Link to the Dataset: `https://www.kaggle.com/datasets/teejmahal20/airline-passenger-satisfaction`

Dataset Description:

```
 This data set collects passenger information from an airline,
including personal information and information on flying habits.
```

2. Task Information

Task Goal: `Evaluate which factors are highly correlated with satisfaction.`

Task Description:

```
This task assesses passenger satisfaction levels based on the
information provided and in-flight preferences such as seat
position, in-flight beverages and entertainment. Additionally,
this task will build four ML models for comparison, which are
respectively logistic regression, random forest, KNN and naive
bayes.
```

3. Task Implementation: Coding

3.1 Preprocessing

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [ ]:
```
df=pd.read_csv('train.csv')
```

In [ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 103904 entries, 0 to 103903
Data columns (total 25 columns):
 #   Column                             Non-Null Count   Dtype  
---  ------                             --------------   -----  
 0   Unnamed: 0                         103904 non-null  int64  
 1   id                                 103904 non-null  int64  
 2   Gender                             103904 non-null  object 
 3   Customer Type                      103904 non-null  object 
 4   Age                                103904 non-null  int64  
 5   Type of Travel                     103904 non-null  object 
 6   Class                              103904 non-null  object 
 7   Flight Distance                    103904 non-null  int64  
 8   Inflight wifi service              103904 non-null  int64  
 9   Departure/Arrival time convenient  103904 non-null  int64  
 10  Ease of Online booking             103904 non-null  int64  
 11  Gate location                      103904 non-null  int64  
 12  Food and drink                     103904 non-null  int64  
 13  Online boarding                    103904 non-null  int64  
 14  Seat comfort                       103904 non-null  int64  
 15  Inflight entertainment             103904 non-null  int64  
 16  On-board service                   103904 non-null  int64  
 17  Leg room service                   103904 non-null  int64  
 18  Baggage handling                   103904 non-null  int64  
 19  Checkin service                    103904 non-null  int64  
 20  Inflight service                   103904 non-null  int64  
 21  Cleanliness                        103904 non-null  int64  
 22  Departure Delay in Minutes         103904 non-null  int64  
 23  Arrival Delay in Minutes           103594 non-null  float64
 24  satisfaction                       103904 non-null  object 
dtypes: float64(1), int64(19), object(5)
memory usage: 19.8+ MB
```

In [ ]:
```
df
```

Out[ ]:

	Unnamed: 0	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance
0	0	70172	Male	Loyal Customer	13	Personal Travel	Eco Plus	460
1	1	5047	Male	disloyal Customer	25	Business travel	Business	235
2	2	110028	Female	Loyal Customer	26	Business travel	Business	1142
3	3	24026	Female	Loyal Customer	25	Business travel	Business	562
4	4	119299	Male	Loyal Customer	61	Business travel	Business	214
...	...	...	...	...	...	...	...	..
103899	103899	94171	Female	disloyal Customer	23	Business travel	Eco	192
103900	103900	73097	Male	Loyal Customer	49	Business travel	Business	2347
103901	103901	68825	Male	disloyal Customer	30	Business travel	Business	1995
103902	103902	54173	Female	disloyal Customer	22	Business travel	Eco	1000
103903	103903	62567	Male	Loyal Customer	27	Business travel	Business	1723

103904 rows × 25 columns

In [ ]:

```
df.describe()
```

Out[ ]:

	Unnamed: 0	id	Age	Flight Distance	Inflight ser
count	103904.000000	103904.000000	103904.000000	103904.000000	103904.000
mean	51951.500000	64924.210502	39.379706	1189.448375	2.729
std	29994.645522	37463.812252	15.114964	997.147281	1.327
min	0.000000	1.000000	7.000000	31.000000	0.000
25%	25975.750000	32533.750000	27.000000	414.000000	2.000
50%	51951.500000	64856.500000	40.000000	843.000000	3.000
75%	77927.250000	97368.250000	51.000000	1743.000000	4.000
max	103903.000000	129880.000000	85.000000	4983.000000	5.000

In [ ]:

```
df['Unnamed: 0'].unique()
```

Out[ ]:

```
array([     0,      1,      2, ..., 103901, 103902, 103903], dtype=int6
4)
```

Finding and Processing:

1. The first column: Unnamed:0 is the number of index. We decided to delete it.
2. "id" is not relevant to our learning process. We decided to delete it.
3. Categorized features and label need to be changed to number:Gender/Customer Type/Type of Travel/Class/satisfaction
4. Other continuous feature need to be normalized: Age/Flight Distance/Departure Delay in Minutes/Arrival Delay in Minutes

In [ ]:
```
df=df.drop(['Unnamed: 0','id'],axis = 1)
```

In [ ]:
```
df.head()
```

Out[ ]:

	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arriv time convenier
0	Male	Loyal Customer	13	Personal Travel	Eco Plus	460	3	
1	Male	disloyal Customer	25	Business travel	Business	235	3	
2	Female	Loyal Customer	26	Business travel	Business	1142	2	
3	Female	Loyal Customer	25	Business travel	Business	562	2	
4	Male	Loyal Customer	61	Business travel	Business	214	3	

5 rows × 23 columns

In [ ]:
```
df = df.drop_duplicates()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 103904 entries, 0 to 103903
Data columns (total 23 columns):
 #   Column                             Non-Null Count   Dtype  
---  ------                             --------------   -----  
 0   Gender                             103904 non-null  object 
 1   Customer Type                      103904 non-null  object 
 2   Age                                103904 non-null  int64  
 3   Type of Travel                     103904 non-null  object 
 4   Class                              103904 non-null  object 
 5   Flight Distance                    103904 non-null  int64  
 6   Inflight wifi service              103904 non-null  int64  
 7   Departure/Arrival time convenient  103904 non-null  int64  
 8   Ease of Online booking             103904 non-null  int64  
 9   Gate location                      103904 non-null  int64  
 10  Food and drink                     103904 non-null  int64  
 11  Online boarding                    103904 non-null  int64  
 12  Seat comfort                       103904 non-null  int64  
 13  Inflight entertainment             103904 non-null  int64  
 14  On-board service                   103904 non-null  int64  
 15  Leg room service                   103904 non-null  int64  
 16  Baggage handling                   103904 non-null  int64  
 17  Checkin service                    103904 non-null  int64  
 18  Inflight service                   103904 non-null  int64  
 19  Cleanliness                        103904 non-null  int64  
 20  Departure Delay in Minutes         103904 non-null  int64  
 21  Arrival Delay in Minutes           103594 non-null  float64
 22  satisfaction                       103904 non-null  object 
dtypes: float64(1), int64(17), object(5)
memory usage: 18.2+ MB
```

In [ ]:
```
df['satisfaction'].unique()
```

Out[ ]:
```
array(['neutral or dissatisfied', 'satisfied'], dtype=object)
```

In [ ]:
```
from sklearn.preprocessing import LabelEncoder
```

In [ ]:
```
label_encoder = LabelEncoder()
df['Gender'] = label_encoder.fit_transform(df['Gender'])
df['Customer Type'] = label_encoder.fit_transform(df['Customer Type'])
df['Type of Travel'] = label_encoder.fit_transform(df['Type of Travel'])
df['Class'] = label_encoder.fit_transform(df['Class'])
df['satisfaction'] = label_encoder.fit_transform(df['satisfaction'])
```

In [ ]:
```
df.head()
```

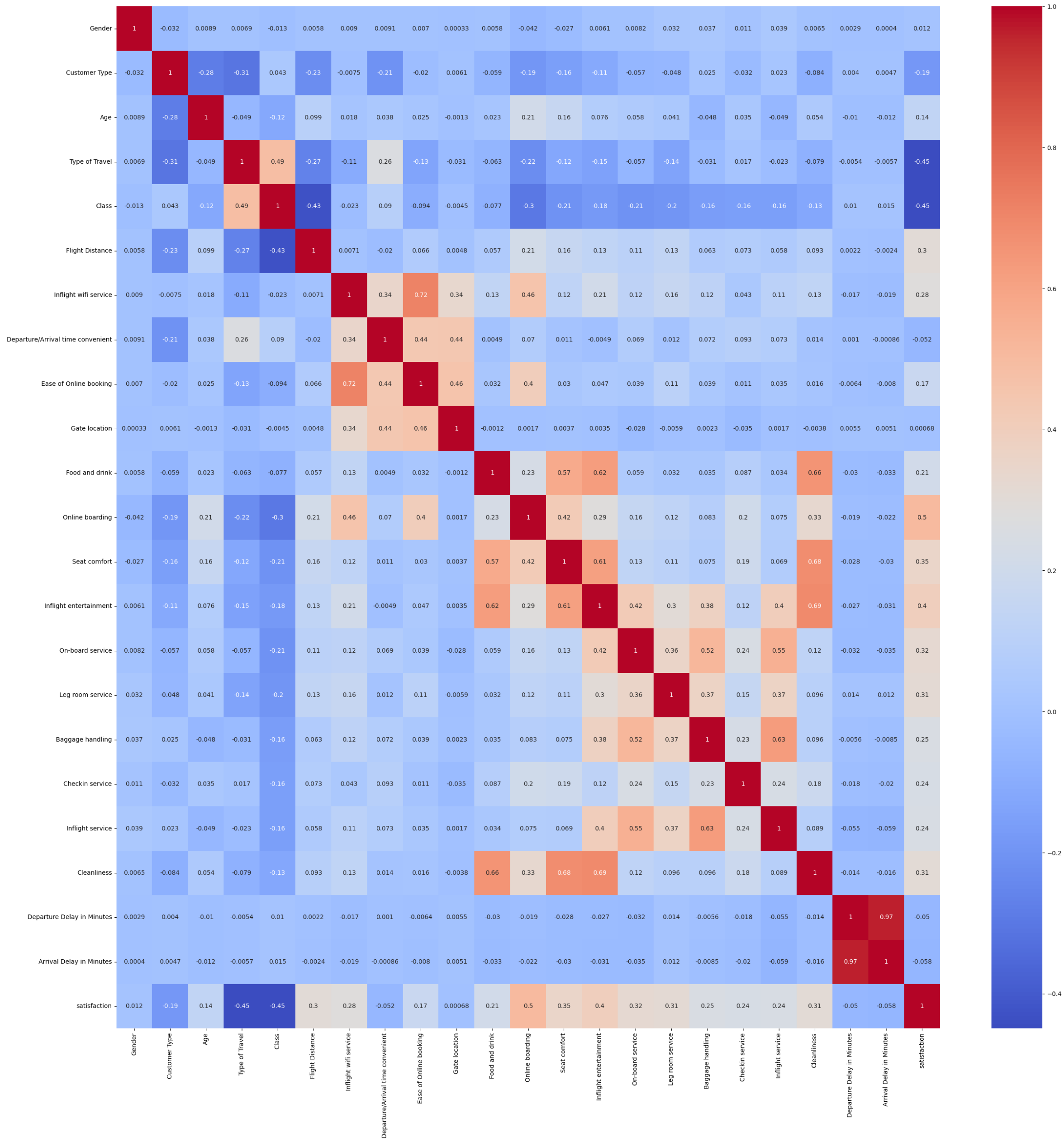
Out[ ]:

	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient
0	1	0	13	1	2	460	3	4
1	1	1	25	0	0	235	3	2
2	0	0	26	0	0	1142	2	2
3	0	0	25	0	0	562	2	5
4	1	0	61	0	0	214	3	3

5 rows × 23 columns

In [ ]:

```
heatmap=df.corr()
sns.heatmap(heatmap,annot=True,cmap='coolwarm')
plt.gcf().set_size_inches(30, 30)
```



From the above plot, we know that ease of online booking and inflight wifi service has a higher postive correlationship. Cleanliness and food and drink,

seat comfort and inflight entertainment have higher positive correlationship. Baggage handling and inflight service has a higher positive correlationship.Regarding to the final target:satisfaction, it has very little correlationship with Gender and Gate location

For those have low correlationship with the target(satisfaction), plot the pictures below to decide whether delete them：

Gender

Gate Location

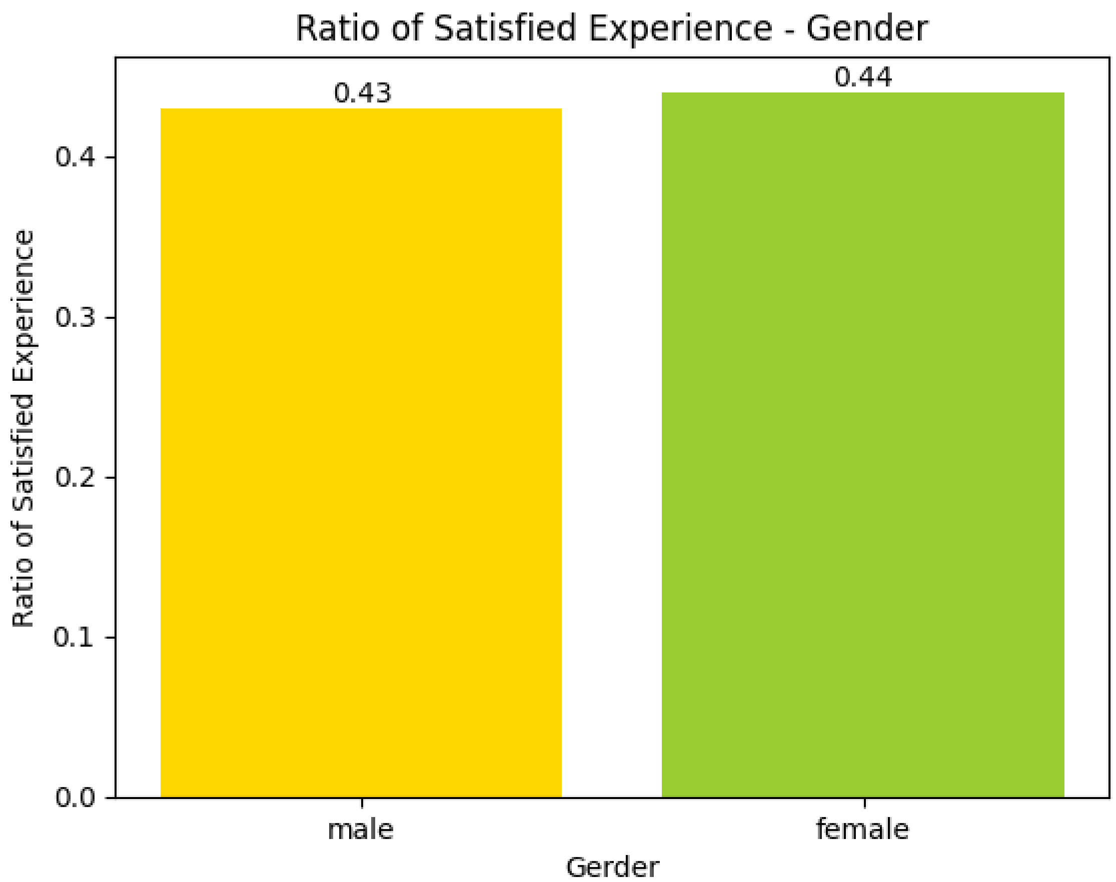
In [ ]:
```
ratio_male = round(len(df[(df['Gender'] == 0) & (df['satisfaction'] == 1)
ratio_female = round(len(df[(df['Gender'] == 1) & (df['satisfaction'] ==
print(ratio_male)
print(ratio_female)
```

```
0.43
0.44
```

In [ ]:
```
categories = ['male','female']
ratios = [ratio_male,ratio_female]
plt.bar(categories, ratios, color=['gold', 'yellowgreen'])
plt.xlabel('Gerder')
plt.ylabel('Ratio of Satisfied Experience')
plt.title('Ratio of Satisfied Experience - Gender')

for i in range(len(categories)):
    plt.text(categories[i], ratios[i], str(ratios[i]), ha='center', va='b

plt.show()
```



In [ ]:

```
ratio_gl0 = round(len(df[(df['Gate location'] == 0) & (df['satisfaction']
ratio_gl1 = round(len(df[(df['Gate location'] == 1) & (df['satisfaction']
ratio_gl2 = round(len(df[(df['Gate location'] == 2) & (df['satisfaction']
ratio_gl3 = round(len(df[(df['Gate location'] == 3) & (df['satisfaction']
ratio_gl4 = round(len(df[(df['Gate location'] == 4) & (df['satisfaction']
ratio_gl5 = round(len(df[(df['Gate location'] == 5) & (df['satisfaction']

print(ratio_gl0)
print(ratio_gl1)
print(ratio_gl2)
print(ratio_gl3)
print(ratio_gl4)
print(ratio_gl5)
```

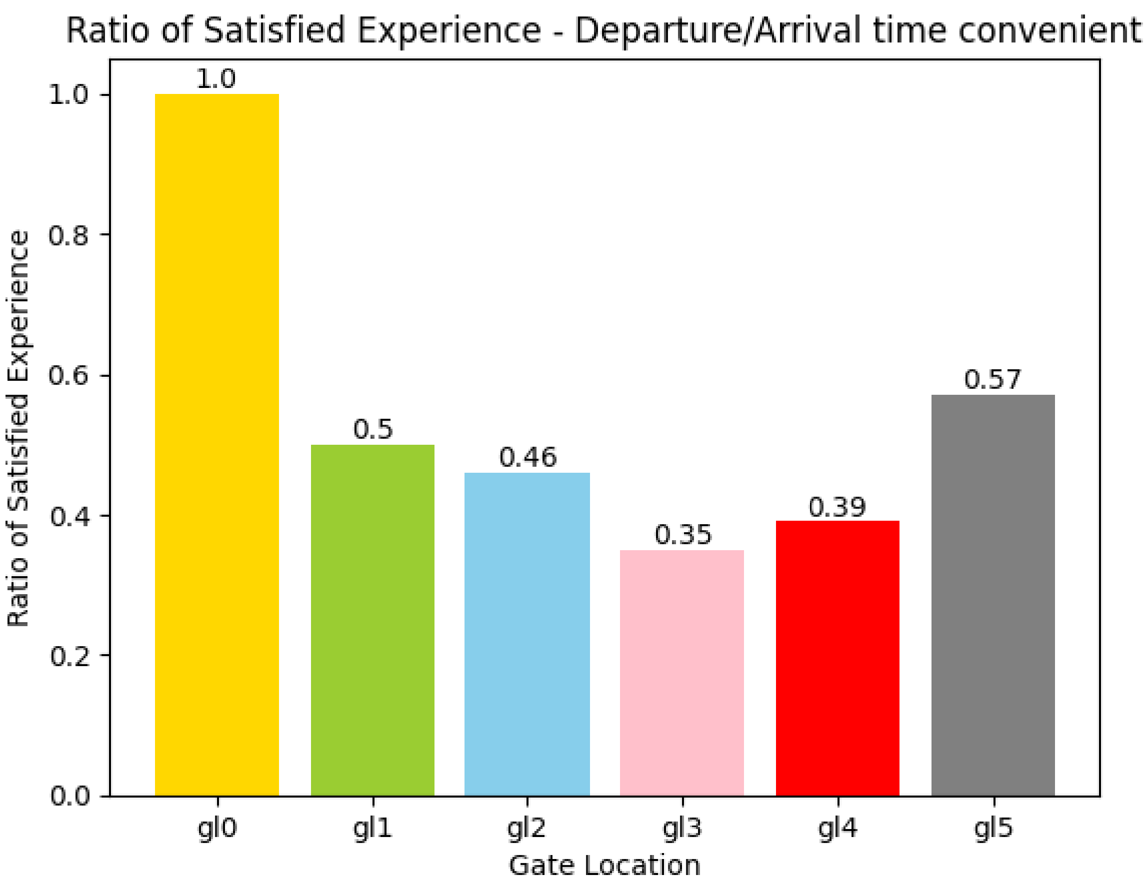
```
1.0
0.5
0.46
0.35
0.39
0.57
```

In [ ]:

```
categories = ['gl0','gl1','gl2','gl3','gl4','gl5']
ratios = [ratio_gl0,ratio_gl1,ratio_gl2,ratio_gl3,ratio_gl4,ratio_gl5]
plt.bar(categories, ratios, color=['gold', 'yellowgreen','skyblue','pink'
plt.xlabel('Gate Location')
plt.ylabel('Ratio of Satisfied Experience')
plt.title('Ratio of Satisfied Experience - Departure/Arrival time conveni

for i in range(len(categories)):
    plt.text(categories[i], ratios[i], str(ratios[i]), ha='center', va='b

plt.show()
```



Through the plots above, we decided to delete the gender column which has almost no effects on the final target results as no matter whether the customer is female or male, there is almost no difference on choosing the experience feeling

In [ ]:
```
df_train=df
df_train = df_train.dropna(axis=0)
df_train.head()
```

Out[ ]:

	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	E b
0	1	0	13	1	2	460	3	4	
1	1	1	25	0	0	235	3	2	
2	0	0	26	0	0	1142	2	2	
3	0	0	25	0	0	562	2	5	
4	1	0	61	0	0	214	3	3	

5 rows × 23 columns

In [ ]:
```
from sklearn.preprocessing import MinMaxScaler
columns_to_normalize = ['Age', 'Flight Distance', 'Departure Delay in Min
scaler = MinMaxScaler()
df_train[columns_to_normalize] = scaler.fit_transform(df_train[columns_to
df_train.head()
```

Out[ ]:

	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arriv time convenie
0	1	0	0.076923	1	2	0.086632	3	
1	1	1	0.230769	0	0	0.041195	3	
2	0	0	0.243590	0	0	0.224354	2	
3	0	0	0.230769	0	0	0.107229	2	
4	1	0	0.692308	0	0	0.036955	3	

5 rows × 23 columns

Processing the original test data csv:

In [ ]:
```
df_test=pd.read_csv('test.csv')
```

In [ ]:
```
df_test = df_test.dropna(axis=0)
```

In [ ]:
```
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 25893 entries, 0 to 25975
Data columns (total 25 columns):
 #   Column                             Non-Null Count  Dtype  
---  ------                             --------------  -----  
 0   Unnamed: 0                         25893 non-null  int64  
 1   id                                 25893 non-null  int64  
 2   Gender                             25893 non-null  object 
 3   Customer Type                      25893 non-null  object 
 4   Age                                25893 non-null  int64  
 5   Type of Travel                     25893 non-null  object 
 6   Class                              25893 non-null  object 
 7   Flight Distance                    25893 non-null  int64  
 8   Inflight wifi service              25893 non-null  int64  
 9   Departure/Arrival time convenient  25893 non-null  int64  
 10  Ease of Online booking             25893 non-null  int64  
 11  Gate location                      25893 non-null  int64  
 12  Food and drink                     25893 non-null  int64  
 13  Online boarding                    25893 non-null  int64  
 14  Seat comfort                       25893 non-null  int64  
 15  Inflight entertainment             25893 non-null  int64  
 16  On-board service                   25893 non-null  int64  
 17  Leg room service                   25893 non-null  int64  
 18  Baggage handling                   25893 non-null  int64  
 19  Checkin service                    25893 non-null  int64  
 20  Inflight service                   25893 non-null  int64  
 21  Cleanliness                        25893 non-null  int64  
 22  Departure Delay in Minutes         25893 non-null  int64  
 23  Arrival Delay in Minutes           25893 non-null  float64
 24  satisfaction                       25893 non-null  object 
dtypes: float64(1), int64(19), object(5)
memory usage: 5.1+ MB
```

In [ ]:

```
df_test.head()
```

Out[ ]:

	Unnamed: 0	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflig v serv
0	0	19556	Female	Loyal Customer	52	Business travel	Eco	160	
1	1	90035	Female	Loyal Customer	36	Business travel	Business	2863	
2	2	12360	Male	disloyal Customer	20	Business travel	Eco	192	
3	3	77959	Male	Loyal Customer	44	Business travel	Business	3377	
4	4	36875	Female	Loyal Customer	49	Business travel	Eco	1182	

5 rows × 25 columns

In [ ]:

```
df_test=df_test.drop(['Unnamed: 0','id'], axis=1)
df_test.head()
```

Out[ ]:

	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arriv time convenier
0	Female	Loyal Customer	52	Business travel	Eco	160	5	
1	Female	Loyal Customer	36	Business travel	Business	2863	1	
2	Male	disloyal Customer	20	Business travel	Eco	192	2	
3	Male	Loyal Customer	44	Business travel	Business	3377	0	
4	Female	Loyal Customer	49	Business travel	Eco	1182	2	

5 rows × 23 columns

In [ ]:

```
df_test['Gender'] = label_encoder.fit_transform(df_test['Gender'])
df_test['Customer Type'] = label_encoder.fit_transform(df_test['Customer
df_test['Type of Travel'] = label_encoder.fit_transform(df_test['Type of
df_test['Class'] = label_encoder.fit_transform(df_test['Class'])
df_test['satisfaction'] = label_encoder.fit_transform(df_test['satisfacti
```

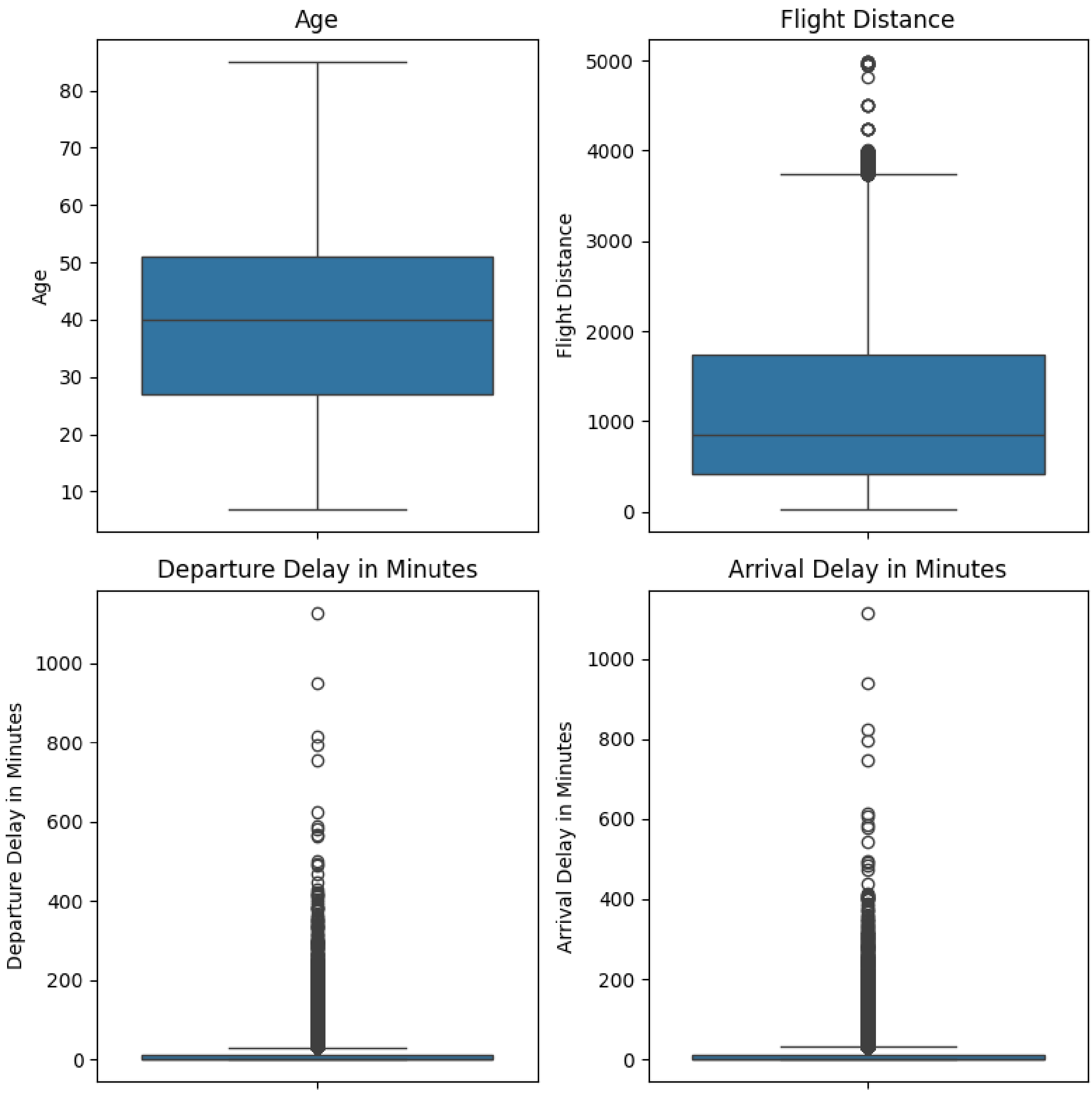
In [ ]:

```
continuous_columns = ['Age', 'Flight Distance', 'Departure Delay in Minut
import matplotlib.pyplot as plt
import seaborn as sns

# Plotting boxplots for continuous columns to identify outliers
plt.figure(figsize=(8, 8))

for i, col in enumerate(continuous_columns, 1):
    plt.subplot(2, 2, i)
    sns.boxplot(y=df_test[col])
    plt.title(col)

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



In [ ]:
```
columns_to_normalize = ['Gender','Age', 'Flight Distance', 'Departure Del
scaler = MinMaxScaler()
df_test[columns_to_normalize] = scaler.fit_transform(df_test[columns_to_n
df_test.head()
```

Out[ ]:

	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arriv time convenie
0	0.0	0	0.576923	0	1	0.026050	5	
1	0.0	0	0.371795	0	0	0.571890	1	
2	1.0	1	0.166667	0	1	0.032512	2	
3	1.0	0	0.474359	0	0	0.675687	0	
4	0.0	0	0.538462	0	1	0.232431	2	

5 rows × 23 columns

In [ ]:
```
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 25893 entries, 0 to 25975
Data columns (total 23 columns):
 #   Column                             Non-Null Count  Dtype  
---  ------                             --------------  -----  
 0   Gender                             25893 non-null  float64
 1   Customer Type                      25893 non-null  int32  
 2   Age                                25893 non-null  float64
 3   Type of Travel                     25893 non-null  int32  
 4   Class                              25893 non-null  int32  
 5   Flight Distance                    25893 non-null  float64
 6   Inflight wifi service              25893 non-null  int64  
 7   Departure/Arrival time convenient  25893 non-null  int64  
 8   Ease of Online booking             25893 non-null  int64  
 9   Gate location                      25893 non-null  int64  
 10  Food and drink                     25893 non-null  int64  
 11  Online boarding                    25893 non-null  int64  
 12  Seat comfort                       25893 non-null  int64  
 13  Inflight entertainment             25893 non-null  int64  
 14  On-board service                   25893 non-null  int64  
 15  Leg room service                   25893 non-null  int64  
 16  Baggage handling                   25893 non-null  int64  
 17  Checkin service                    25893 non-null  int64  
 18  Inflight service                   25893 non-null  int64  
 19  Cleanliness                        25893 non-null  int64  
 20  Departure Delay in Minutes         25893 non-null  float64
 21  Arrival Delay in Minutes           25893 non-null  float64
 22  satisfaction                       25893 non-null  int32  
dtypes: float64(5), int32(4), int64(14)
memory usage: 4.3 MB
```

3.2 Model development and training

3.2.1 Logistic Regression

In [ ]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score
X_train = df_train.iloc[:,0:22]
y_train = df_train.iloc[:,-1]
X_test = df_test.iloc[:,0:22]
y_test = df_test.iloc[:,-1]
```

In [ ]:

```
from sklearn.model_selection import GridSearchCV

# define param grid
param_grid = {
    'C': [0.001, 0.01, 0.1, 1, 10],
    'penalty': ['l1', 'l2','elasticnet'],
    'tol': [1e-4, 1e-3, 1e-2],
    'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']
}

# build model
logistic = LogisticRegression(max_iter=1000)

# GridSearchCV
grid_search = GridSearchCV(logistic, param_grid, cv=5, scoring='accuracy'
```

```
grid_search.fit(X_train, y_train)

# get best params and score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

# use best params
best_logistic = LogisticRegression(**best_params, max_iter=1000)
best_logistic.fit(X_train, y_train)
y_pred_best = best_logistic.predict(X_test)
accuracy_best = accuracy_score(y_test, y_pred_best)
class_report = classification_report(y_test, y_pred_best)

print("Classification Report:\n", class_report)
print("Best Parameters:", best_params)
print("Best Cross-Validation Score:", best_score)
print("Test Set Accuracy:", accuracy_best)
```

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

           0       0.87      0.90      0.89     14528
           1       0.87      0.83      0.85     11365

    accuracy                           0.87     25893
   macro avg       0.87      0.87      0.87     25893
weighted avg       0.87      0.87      0.87     25893

Best Parameters: {'C': 10, 'penalty': 'l1', 'solver': 'liblinear', 'tol':
0.001}
Best Cross-Validation Score: 0.8755719852758717
Test Set Accuracy: 0.8712393310933457
```

3.2.1.1 Model evaluation

In [ ]:

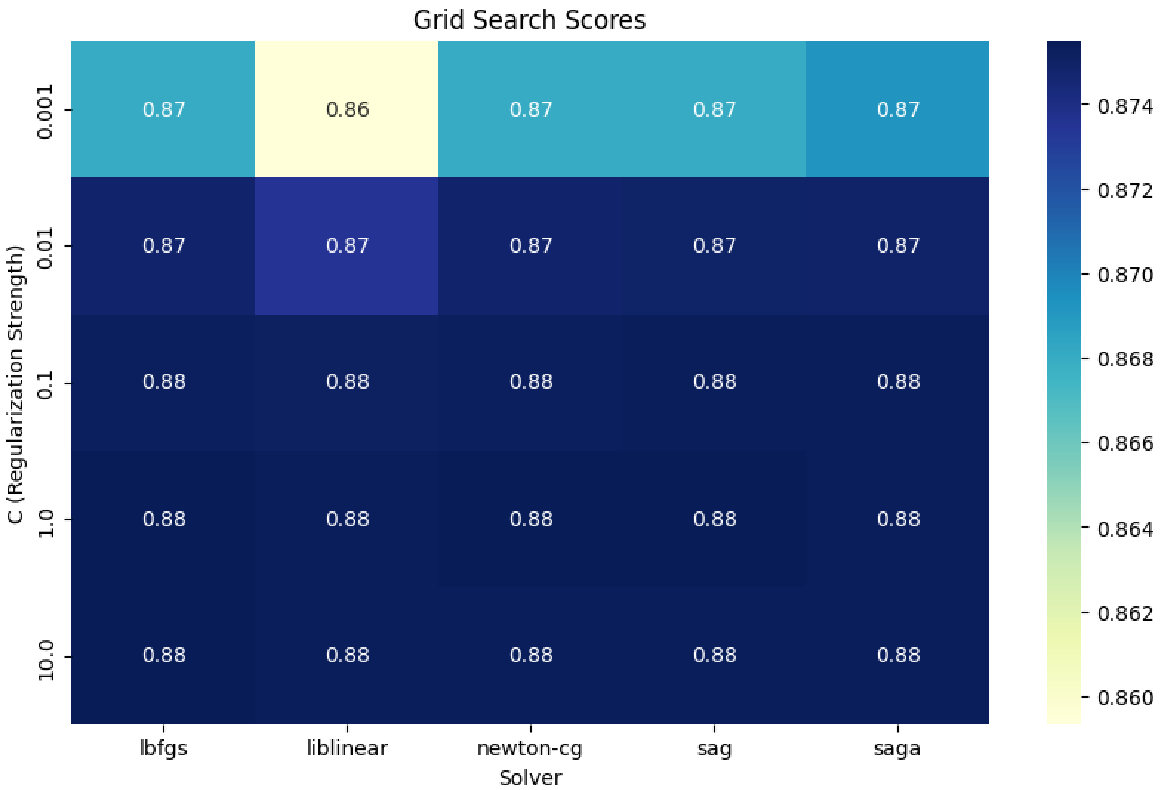
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# get result
results = pd.DataFrame(grid_search.cv_results_)

# choose parameters
param_1 = 'param_C'
param_2 = 'param_solver'

# plot
pivot_table = results.pivot_table(values='mean_test_score',
                                  index=[param_1],
                                  columns=[param_2])

plt.figure(figsize=(10, 6))
sns.heatmap(pivot_table, annot=True, cmap='YlGnBu')
plt.title('Grid Search Scores')
plt.xlabel('Solver')
plt.ylabel('C (Regularization Strength)')
plt.show()
```



3.2.2 KNN Classifier

In [ ]:
```
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report, accuracy_score
from sklearn.neighbors import KNeighborsClassifier

X_train = df_train.iloc[:,0:22]
y_train = df_train.iloc[:,-1]
X_test = df_test.iloc[:,0:22]
y_test = df_test.iloc[:,-1]


KNN = KNeighborsClassifier(n_neighbors=10)
KNN.fit(X_train.to_numpy(), y_train.to_numpy())
y_pred = KNN.predict(X_test.to_numpy())

cm = classification_report(y_test.to_numpy(),y_pred)
print(cm)
```

```
              precision    recall  f1-score   support

           0       0.91      0.97      0.94     14528
           1       0.96      0.88      0.92     11365

    accuracy                           0.93     25893
   macro avg       0.94      0.93      0.93     25893
weighted avg       0.93      0.93      0.93     25893
```

3.2.2.1 Hyperparameter tune

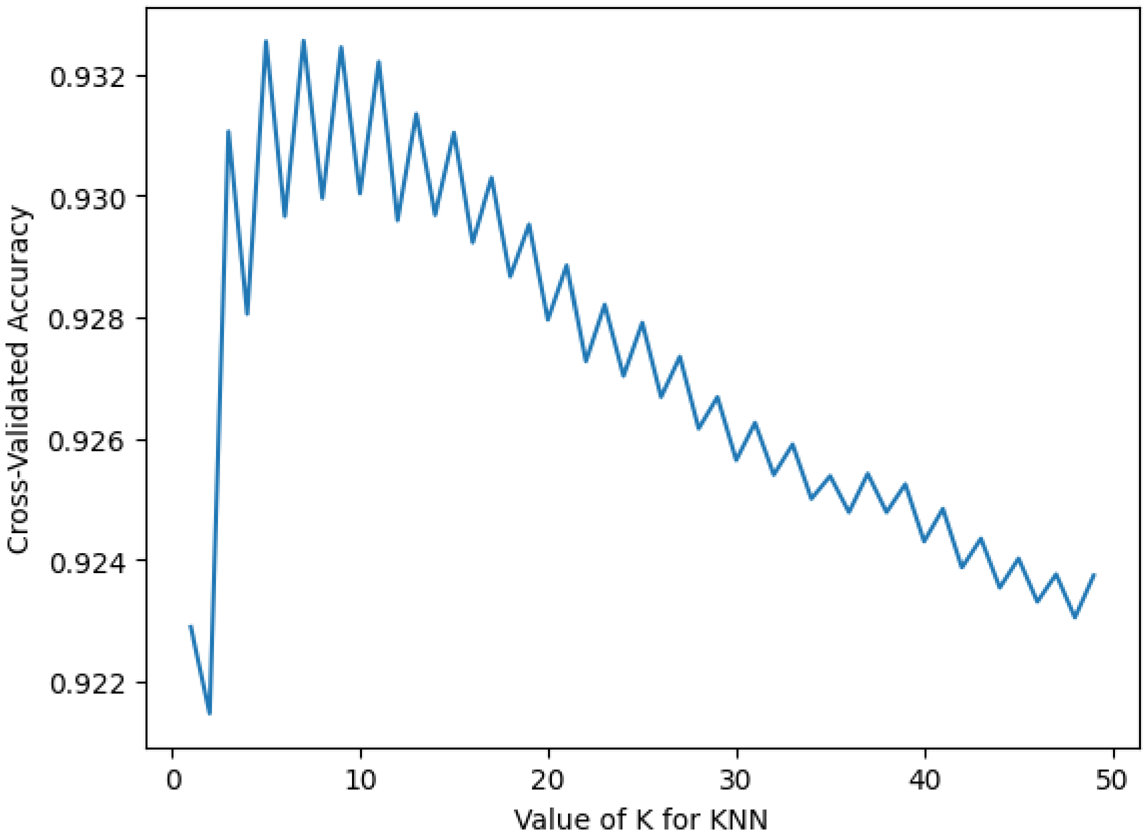
In [ ]:
```
k_range = range(1,50)
k_scores = []
```

```
#for i in cv_range:
for k in k_range:
    KNN = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(KNN, X_train.to_numpy(), y_train.to_numpy(),
    k_scores.append(scores.mean())
    #cv_scores[i,:] = k_scores
print(k_scores)
print(k_scores.index(max(k_scores)))
```

```
[0.9228912895767802, 0.9214723017047085, 0.9310578261642555, 0.92805575216
52222, 0.9325444132850735, 0.9296677976847395, 0.9325540685901244, 0.92995
73962692991, 0.9324478900521471, 0.9300346247327134, 0.9322065614702453,
0.9296002198673788, 0.9313474405894041, 0.929687112022038, 0.9310385202131
51, 0.9292333946830038, 0.930295236902535, 0.9286735248963746, 0.929532643
913617, 0.9279591935239198, 0.9288569337613646, 0.9272738196804224, 0.9282
101615702834, 0.9270324836441256, 0.927910922589463, 0.9266849905012371,
0.9273510518710346, 0.9261637437984094, 0.9266849942284348, 0.925642475664
1959, 0.9262602511907465, 0.9254011349689021, 0.9259030859704188, 0.925005
3597099643, 0.9253818178362053, 0.9247833380109661, 0.9254204343974111, 0.
924783339874565, 0.9252466854964684, 0.92430069855135, 0.9248412679776712,
0.9238759676270536, 0.924348959236014, 0.9235380962444385, 0.9240207534082
424, 0.9233064304219821, 0.9237601188752362, 0.9230458005479727, 0.9237408
082651349]
6
```

In [ ]:
```
plt.plot(k_range, k_scores)
plt.xlabel('Value of K for KNN')
plt.ylabel('Cross-Validated Accuracy')
```

Out[ ]:
```
Text(0, 0.5, 'Cross-Validated Accuracy')
```



3.2.2.2 Model evaluation

In [ ]:
```
KNN = KNeighborsClassifier(n_neighbors=k_range[k_scores.index(max(k_score
KNN.fit(X_train.to_numpy(), y_train.to_numpy())
y_pred = KNN.predict(X_test.to_numpy())

cm = classification_report(y_test.to_numpy(),y_pred)
print(cm)
```

```
              precision    recall  f1-score   support

           0       0.92      0.96      0.94     14528
           1       0.95      0.90      0.92     11365

    accuracy                           0.93     25893
   macro avg       0.94      0.93      0.93     25893
weighted avg       0.93      0.93      0.93     25893
```

3.2.3 Naive Bayers

In [ ]:
```
from sklearn.naive_bayes import GaussianNB
GaussNB = GaussianNB()
GaussNB.fit(X_train, y_train)
y_pred = GaussNB.predict(X_test)
cm = classification_report(y_test,y_pred)
print(cm)
```

```
              precision    recall  f1-score   support

           0       0.86      0.90      0.88     14528
           1       0.86      0.81      0.84     11365

    accuracy                           0.86     25893
   macro avg       0.86      0.86      0.86     25893
weighted avg       0.86      0.86      0.86     25893
```

In [ ]:
```
from sklearn.naive_bayes import BernoulliNB
BernoNB = BernoulliNB(force_alpha=True)
BernoNB.fit(X_train, y_train)
y_pred = BernoNB.predict(X_test)
cm = classification_report(y_test,y_pred)
print(cm)
```

```
              precision    recall  f1-score   support

           0       0.82      0.77      0.79     14528
           1       0.73      0.78      0.75     11365

    accuracy                           0.78     25893
   macro avg       0.77      0.78      0.77     25893
weighted avg       0.78      0.78      0.78     25893
```

In [ ]:
```
from sklearn.naive_bayes import MultinomialNB
MultiNomNB = MultinomialNB()
MultiNomNB.fit(X_train, y_train)
y_pred = MultiNomNB.predict(X_test)
cm = classification_report(y_test,y_pred)
print(cm)
```

```
              precision    recall  f1-score   support

           0       0.84      0.84      0.84     14528
           1       0.79      0.79      0.79     11365

    accuracy                           0.82     25893
   macro avg       0.82      0.81      0.81     25893
weighted avg       0.82      0.82      0.82     25893
```

3.2.4 Random Forest Classifier

In [ ]:
```
from sklearn.model_selection import train_test_split, RandomizedSearchCV,
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confus
```

In [ ]:
```
X_train = df_train.iloc[:,0:22]
y_train = df_train.iloc[:,-1]
X_test = df_test.iloc[:,0:22]
y_test = df_test.iloc[:,-1]

X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_
```

In [ ]:
```
rf_classifier = RandomForestClassifier(random_state=42)
```

3.2.4.1 Hyperparameter tune

In [ ]:
```
param_dist = {
    'n_estimators': [50, 100, 150],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
#     'max_features': ['auto', 'sqrt', 'log2']
}
```

In [ ]:
```
random_search = RandomizedSearchCV(rf_classifier, param_distributions=par
random_search.fit(X_train, y_train)
```

Out[ ]:
```
▸ RandomizedSearchCV
▸ estimator: RandomForestClassifier
    ▸ RandomForestClassifier
```

In [ ]:
```
print("Best Hyperparameters_RandomSearch:", random_search.best_params_)
```

```
Best Hyperparameters_RandomSearch: {'n_estimators': 100, 'min_samples_spli
t': 5, 'min_samples_leaf': 1, 'max_depth': None}
```

In [ ]:
```
best_rf_model_Random = random_search.best_estimator_
y_pred = best_rf_model_Random.predict(X_val)
```

In [ ]:
```
accuracy = accuracy_score(y_val, y_pred)
print("Random Search Validation Accuracy:", accuracy)
```

```
Random Search Validation Accuracy: 0.9622568656788455
```

In [ ]:
```
confusion_mat = confusion_matrix(y_val, y_pred)
print("Random Search Confusion Matrix:\n", confusion_mat)
```

```
Random Search Confusion Matrix:
 [[11427   228]
 [  554  8510]]
```

In [ ]:
```
class_report = classification_report(y_val, y_pred)
print("Random Search Classification Report:\n", class_report)
```

```
Random Search Classification Report:
               precision    recall  f1-score   support

           0       0.95      0.98      0.97     11655
           1       0.97      0.94      0.96      9064

    accuracy                           0.96     20719
   macro avg       0.96      0.96      0.96     20719
weighted avg       0.96      0.96      0.96     20719
```

In [ ]:
```
param_grid = {
    'n_estimators': [50, 100, 150],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
#     'max_features': ['auto', 'sqrt', 'log2']
}
```

In [ ]:
```
grid_search = GridSearchCV(rf_classifier, param_grid, cv=5, scoring='accu
grid_search.fit(X_train, y_train)
```

Out[ ]:
```
▸ GridSearchCV
▸ estimator: RandomForestClassifier
    ▸ RandomForestClassifier
```

In [ ]:
```
print("Best Hyperparameters_GridSearch:", grid_search.best_params_)
```

```
Best Hyperparameters_GridSearch: {'max_depth': None, 'min_samples_leaf':
1, 'min_samples_split': 2, 'n_estimators': 150}
```

**The processing time of Grid Search is much slower than Random Search.The different results of these two kinds of hyperparameter tuning methods are:

Random Search: "n_estimators": 100,

Grid Search: "n_estimators:: 150

Compare the performance for the validation set: (Random Search already done) **

In [ ]:
```
best_rf_model_Grid = grid_search.best_estimator_
y_pred = best_rf_model_Grid.predict(X_val)
```

In [ ]:
```
accuracy = accuracy_score(y_val, y_pred)
print("Grid Search Validation Accuracy:", accuracy)
```

```
Grid Search Validation Accuracy: 0.9619672764129543
```

In [ ]:
```
confusion_mat = confusion_matrix(y_val, y_pred)
```

```
print("Grid Search Confusion Matrix:\n", confusion_mat)
```

```
Grid Search Confusion Matrix:
 [[11416   239]
 [  549  8515]]
```

In [ ]:
```
class_report = classification_report(y_val, y_pred)
print("Grid Search Classification Report:\n", class_report)
```

```
Grid Search Classification Report:
               precision    recall  f1-score   support

           0       0.95      0.98      0.97     11655
           1       0.97      0.94      0.96      9064

    accuracy                           0.96     20719
   macro avg       0.96      0.96      0.96     20719
weighted avg       0.96      0.96      0.96     20719
```

3.2.4.2 Model evaluation

The performances from the two grids methods are almost the same, but random grid is better. Just use the hyperparameter from random grid to train the test dataset

In [ ]:
```
best_rf_model_Random = random_search.best_estimator_
y_test_pred = best_rf_model_Random.predict(X_test)
```

In [ ]:
```
accuracy = accuracy_score(y_test, y_test_pred)
print("Test Accuracy:", accuracy)
```

```
Test Accuracy: 0.9623836558143127
```

In [ ]:
```
confusion_mat = confusion_matrix(y_test, y_test_pred)
print("Confusion Matrix:\n", confusion_mat)
```

```
Confusion Matrix:
 [[14212   316]
 [  658 10707]]
```

In [ ]:
```
class_report = classification_report(y_test, y_test_pred)
print("Classification Report:\n", class_report)
```

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

           0       0.96      0.98      0.97     14528
           1       0.97      0.94      0.96     11365

    accuracy                           0.96     25893
   macro avg       0.96      0.96      0.96     25893
weighted avg       0.96      0.96      0.96     25893
```

In [ ]: