Analyzing Airline Passenger Satisfaction: A Data-Driven Approach

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Abstract

This project delves into the multifaceted realm of airline passenger satisfaction analysis, employing a rich dataset encompassing diverse customer feedback. Beyond merely exploring the correlations between demographic attributes and satisfaction levels, our approach involves meticulous data preprocessing, encompassing the handling of missing values, categorical variable encoding, and outlier mitigation using the Interquartile Range (IQR) method. The ensuing exploratory data analysis illuminates crucial relationships, with a focus on factors such as departure delay, class, and their impact on overall satisfaction. Through a systematic progression, linear regression models identify pivotal features, while logistic regression emerges as a potent predictor of satisfaction, supported by commendable accuracy and F1 scores. The exploration extends to decision tree and random forest classifiers, providing nuanced insights into feature importance and hierarchical relationships. Hyperparameter tuning further refines the models, ultimately enhancing the accuracy of predictions. These findings contribute not only to a nuanced understanding of passenger satisfaction dynamics but also offer actionable insights for the airline industry in tailoring services to meet and exceed customer expectations.

About The Dataset

This dataset, sourced from Kaggle, comprises information from airline passengers, including demographic details, travel preferences, and satisfaction ratings. Key attributes include gender, age, flight distance, departure delay, and overall satisfaction. The goal is to understand the relationships between these factors and passenger satisfaction.

Mounting Google Drive and Importing Required Libraries

```
from google.colab import drive
drive.mount('/content/drive')
```

```
    Mounted at /content/drive
```

```
data_path = "/content/drive/MyDrive/DSC101/Data/"
```

```
import numpy as np
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

```
airplane_data = pd.read_csv(data_path+"airline_satisfaction.csv")
airplane_data.head()
```

	ID	Gender	Age	Customer Type	Type of Travel	Class	Flight Distance	Departure Delay	Arrival Delay	Depa and A Conve
0	1	Male	48	First-time	Business	Business	821	2	5.0	
1	2	Female	35	Returning	Business	Business	821	26	39.0	
2	3	Male	41	Returning	Business	Business	853	0	0.0	
3	4	Male	50	Returning	Business	Business	1905	0	0.0	
4	5	Female	49	Returning	Business	Business	3470	0	1.0	

5 rows × 24 columns

```
airplane_data.columns
```

```
Index(['ID', 'Gender', 'Age', 'Customer Type', 'Type of Travel', 'Class',
       'Flight Distance', 'Departure Delay', 'Arrival Delay',
       'Departure and Arrival Time Convenience', 'Ease of Online Booking',
       'Check-in Service', 'Online Boarding', 'Gate Location',
       'On-board Service', 'Seat Comfort', 'Leg Room Service', 'Cleanliness',
       'Food and Drink', 'In-flight Service', 'In-flight Wifi Service',
       'In-flight Entertainment', 'Baggage Handling', 'Satisfaction'],
      dtype='object')
```

```
airplane_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 129880 entries, 0 to 129879
Data columns (total 24 columns):
 #   Column                                  Non-Null Count   Dtype
---  ------                                  --------------   -----
 0   ID                                      129880 non-null  int64
 1   Gender                                  129880 non-null  object
 2   Age                                     129880 non-null  int64
 3   Customer Type                           129880 non-null  object
```

```
 4   Type of Travel                          129880 non-null  object
 5   Class                                   129880 non-null  object
 6   Flight Distance                         129880 non-null  int64
 7   Departure Delay                         129880 non-null  int64
 8   Arrival Delay                           129487 non-null  float64
 9   Departure and Arrival Time Convenience  129880 non-null  int64
 10  Ease of Online Booking                  129880 non-null  int64
 11  Check-in Service                        129880 non-null  int64
 12  Online Boarding                         129880 non-null  int64
 13  Gate Location                           129880 non-null  int64
 14  On-board Service                        129880 non-null  int64
 15  Seat Comfort                            129880 non-null  int64
 16  Leg Room Service                        129880 non-null  int64
 17  Cleanliness                             129880 non-null  int64
 18  Food and Drink                          129880 non-null  int64
 19  In-flight Service                       129880 non-null  int64
 20  In-flight Wifi Service                  129880 non-null  int64
 21  In-flight Entertainment                 129880 non-null  int64
 22  Baggage Handling                        129880 non-null  int64
 23  Satisfaction                            129880 non-null  object
dtypes: float64(1), int64(18), object(5)
memory usage: 23.8+ MB
```

```
airplane_data.shape
```

```
(129880, 24)
```

```
airplane_data.isnull()
airplane_data
```

	ID	Gender	Age	Customer Type	Type of Travel	Class	Flight Distance	Departure Delay	Arriva Dela
0	1	Male	48	First-time	Business	Business	821	2	5
1	2	Female	35	Returning	Business	Business	821	26	39

```
airplane_data.isnull().sum()
```

```
ID                                          0
Gender                                      0
Age                                         0
Customer Type                               0
Type of Travel                              0
Class                                       0
Flight Distance                             0
Departure Delay                             0
Arrival Delay                             393
Departure and Arrival Time Convenience      0
Ease of Online Booking                      0
Check-in Service                            0
Online Boarding                             0
Gate Location                               0
On-board Service                            0
Seat Comfort                                0
Leg Room Service                            0
Cleanliness                                 0
Food and Drink                              0
In-flight Service                           0
In-flight Wifi Service                      0
In-flight Entertainment                     0
Baggage Handling                            0
Satisfaction                                0
dtype: int64
```

```
airplane=airplane_data.drop(['Arrival Delay'],axis=1)
```

```
for col in airplane.columns:
    if airplane[col].dtype == 'object':
        airplane[col] = airplane[col].factorize()[0]
```

```
airplane.shape
```

```
(129880, 23)
```

```
int_cols=airplane.select_dtypes(include='int').columns
int_cols
```

```
Index(['ID', 'Gender', 'Age', 'Customer Type', 'Type of Travel', 'Class',
       'Flight Distance', 'Departure Delay',
       'Departure and Arrival Time Convenience', 'Ease of Online Booking',
       'Check-in Service', 'Online Boarding', 'Gate Location',
       'On-board Service', 'Seat Comfort', 'Leg Room Service', 'Cleanliness',
       'Food and Drink', 'In-flight Service', 'In-flight Wifi Service',
       'In-flight Entertainment', 'Baggage Handling', 'Satisfaction'],
      dtype='object')
```

```
selected_cols=['ID', 'Gender', 'Age', 'Customer Type', 'Type of Travel', 'Class',
       'Flight Distance', 'Departure Delay',
       'Departure and Arrival Time Convenience', 'Ease of Online Booking',
       'Check-in Service', 'Online Boarding', 'Gate Location',
       'On-board Service', 'Seat Comfort', 'Leg Room Service', 'Cleanliness',
       'Food and Drink', 'In-flight Service', 'In-flight Wifi Service',
       'In-flight Entertainment', 'Baggage Handling', 'Satisfaction']
```

```
for col in airplane.columns:
    if airplane[col].dtype == 'object':
        airplane[col] = airplane[col].factorize()[0]
```

```
Q1 = airplane[selected_cols].quantile(0.25)
Q3 = airplane[selected_cols].quantile(0.75)
IQR = Q3 - Q1
IQR
```

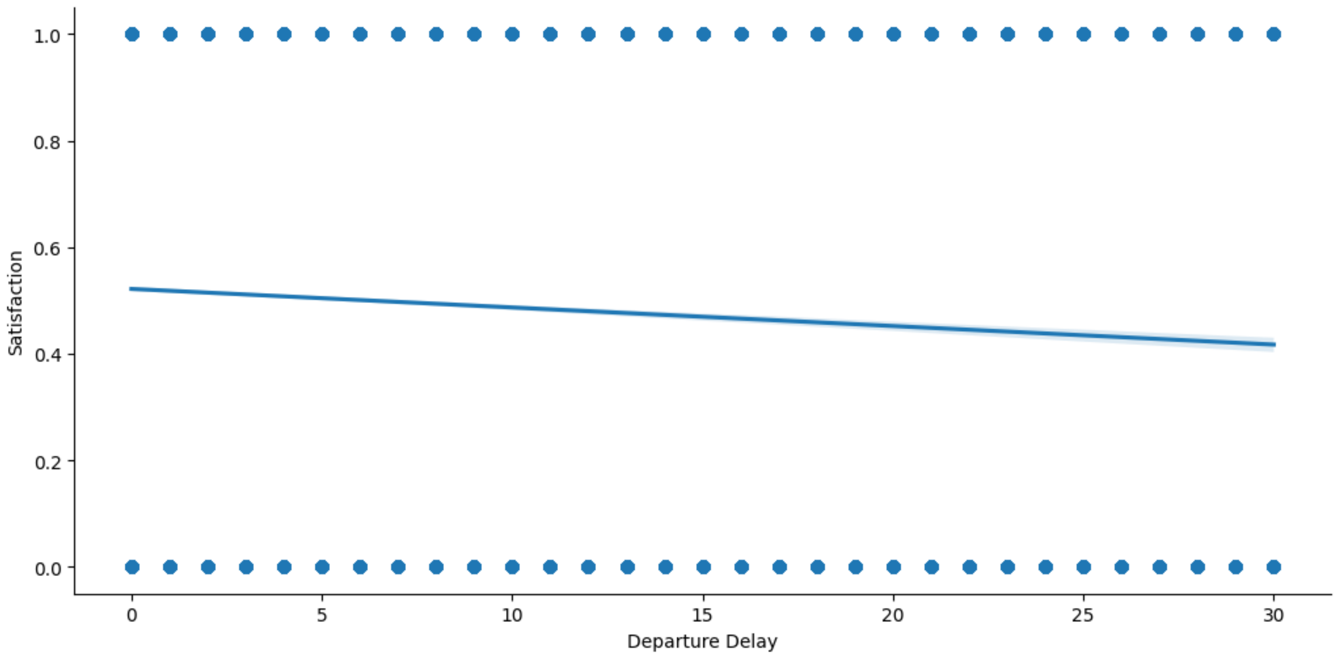
```
ID                                        64939.5
Gender                                        1.0
Age                                          24.0
Customer Type                                 0.0
Type of Travel                                1.0
Class                                         1.0
Flight Distance                            1330.0
Departure Delay                              12.0
Departure and Arrival Time Convenience        2.0
Ease of Online Booking                        2.0
Check-in Service                              1.0
Online Boarding                               2.0
Gate Location                                 2.0
On-board Service                              2.0
Seat Comfort                                  3.0
Leg Room Service                              2.0
Cleanliness                                   2.0
Food and Drink                                2.0
In-flight Service                             2.0
In-flight Wifi Service                        2.0
In-flight Entertainment                       2.0
Baggage Handling                              2.0
Satisfaction                                  1.0
dtype: float64
```

```
airplane_truncated = airplane[~((airplane[selected_cols] < (Q1 - 1.5 * IQR)) | (airp
```

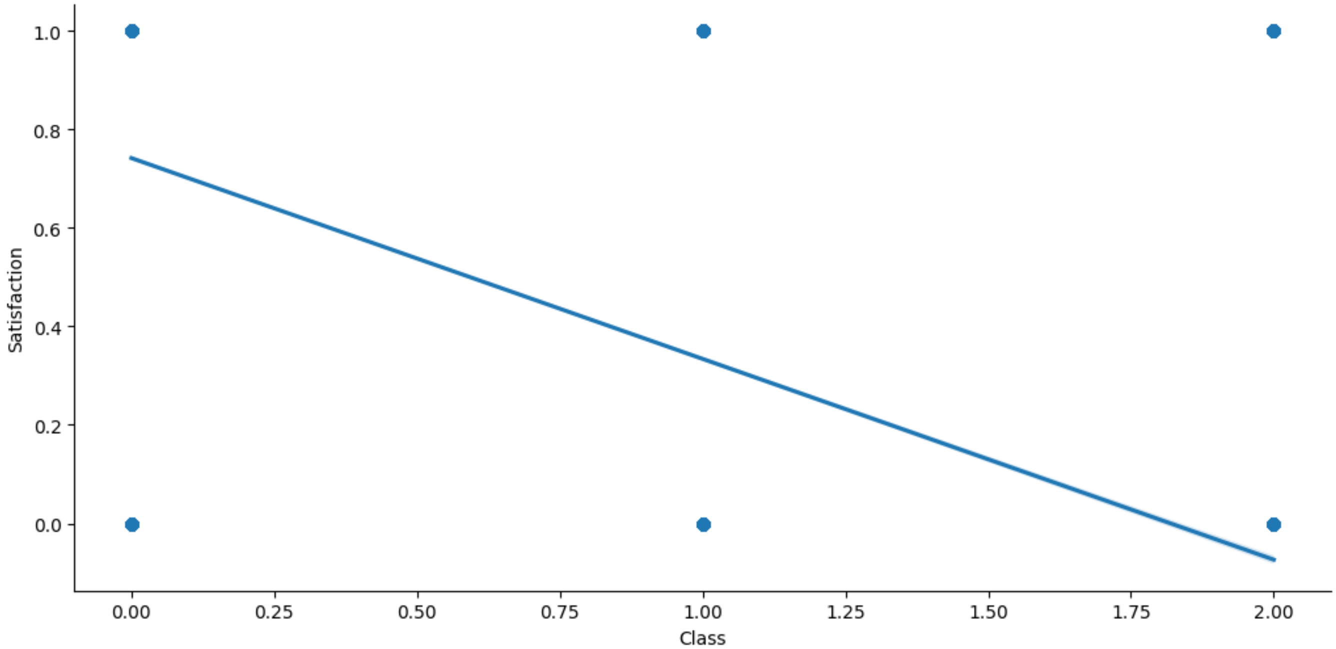
```
airplane_truncated.shape
```

```
(78316, 23)
```

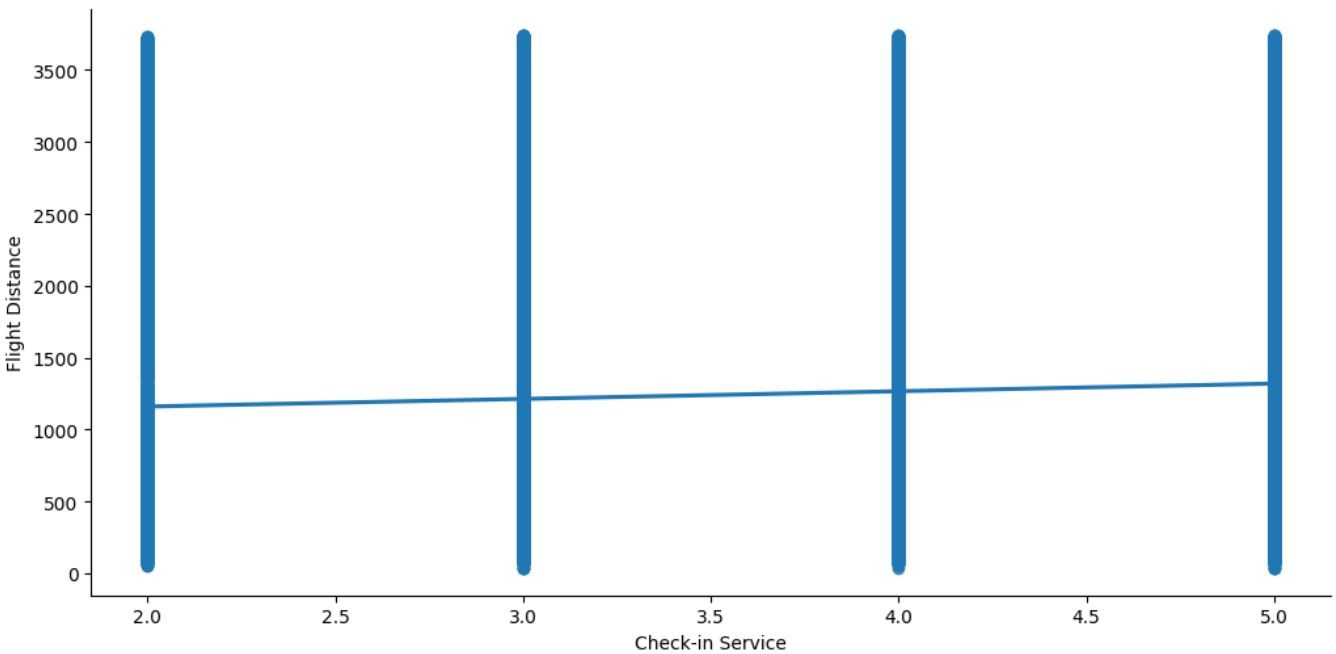
```
sns.lmplot(x="Departure Delay", y="Satisfaction", data = airplane_truncated, height
plt.show()
```



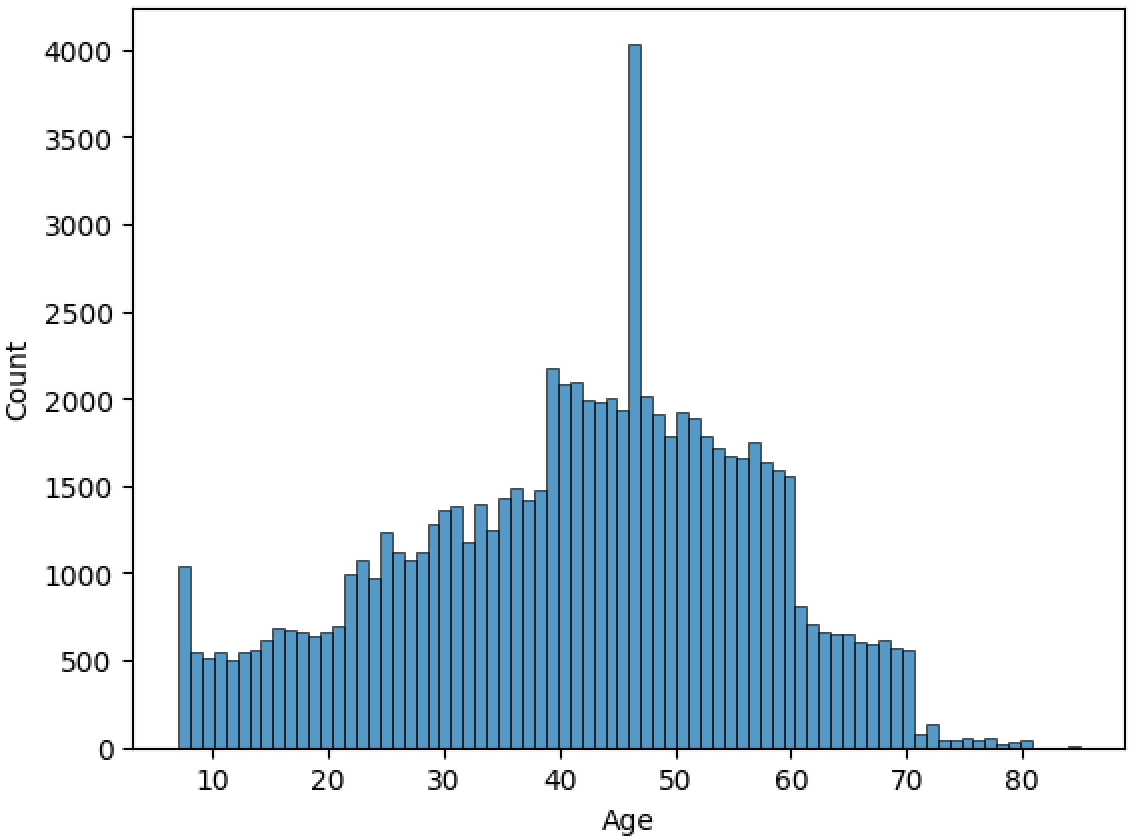

```
sns.lmplot(x="Class", y="Satisfaction", data = airplane_truncated, height = 5.2, asp
plt.show()
```



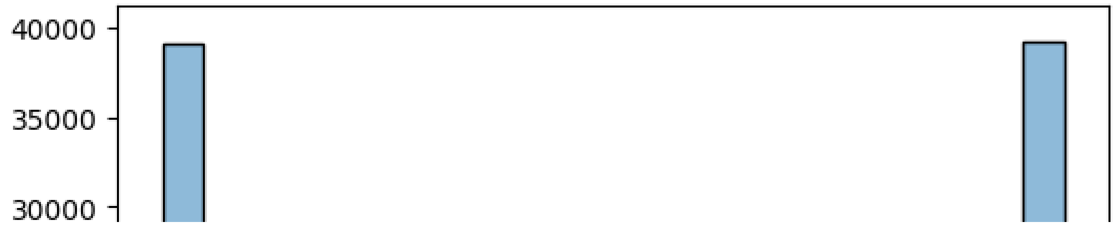

```
sns.lmplot(x="Check-in Service", y="Flight Distance", data = airplane_truncated, hei
plt.show()
```



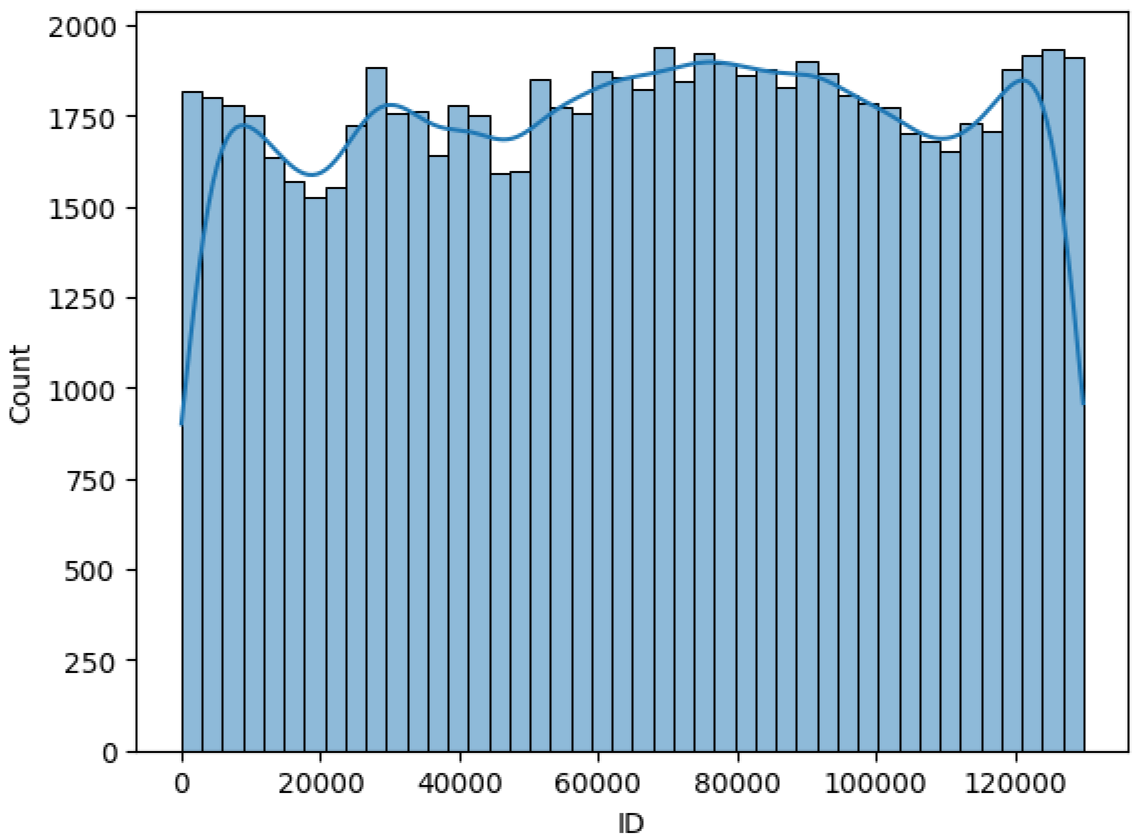
```
#Frequency table for age
sns.histplot(x="Age", data=airplane_truncated)
plt.show()
```



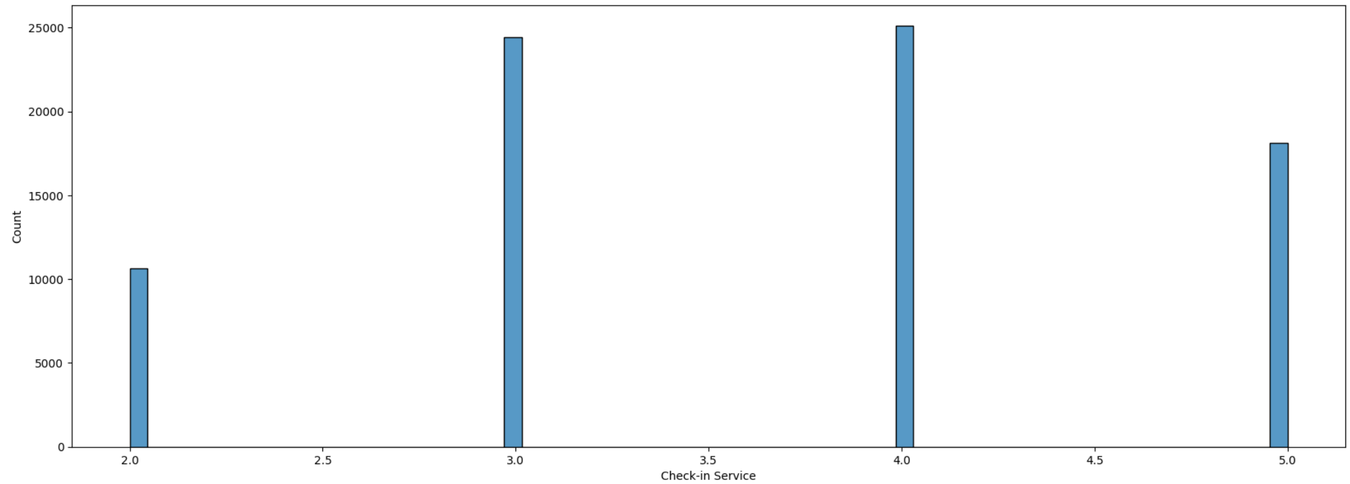

```
#Frequency table for gender
sns.histplot(x="Gender", data=airplane_truncated, kde=True)

# Show the plot
plt.show()
```



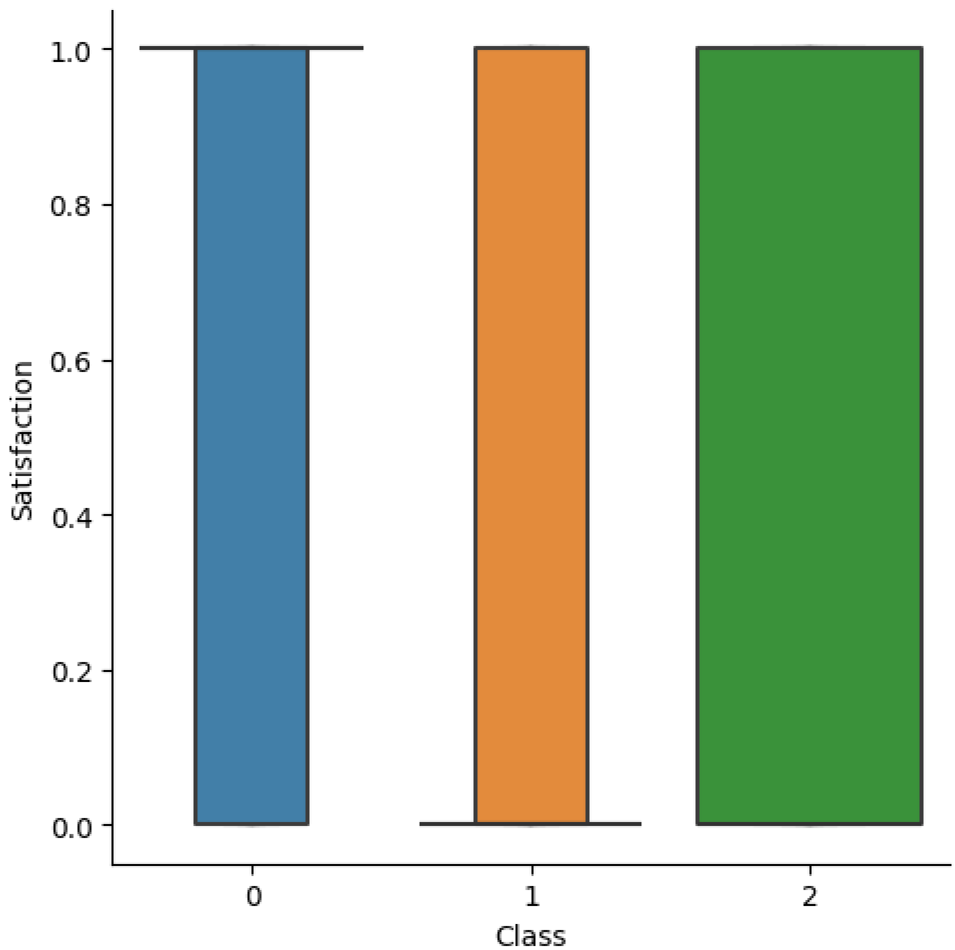

```
#Frequency table for ID
sns.histplot(x="ID", data=airplane_truncated, kde=True)

# Show the plot
plt.show()
```




```
# Plot a frequency histogram of the total crop land of Armenia
plt.figure(figsize=(20, 7))
sns.histplot(x="Check-in Service", data=airplane_truncated)

# Show the plot
plt.show()
```

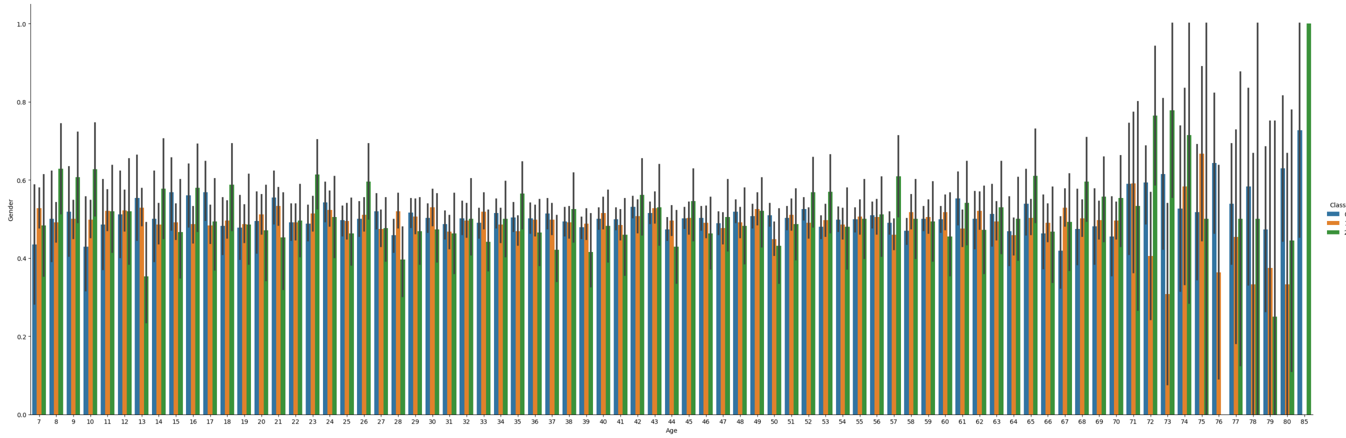



```
sns.catplot(data=airplane_truncated, kind="boxen", x="Class", y="Satisfaction")
plt.show()
```



```
plt.figure(figsize=(20, 10))
sns.catplot(data=airplane_truncated, kind="bar", x="Age", y="Gender", hue="Class", h
plt.show()
```

```
<Figure size 2000x1000 with 0 Axes>
```




```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
```

```
from sklearn.feature_selection import SelectKBest, f_regression
```

```
# Scale the data using StandardScaler
from sklearn.preprocessing import StandardScaler
```

```
from sklearn.feature_selection import RFE
```

```
X = airplane_truncated.drop('Satisfaction', axis=1)
y = airplane_truncated['Satisfaction']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_stat

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

lr = LinearRegression(fit_intercept = True)
lr.fit(X_train_scaled, y_train)

K= X.shape[1]

rmse=[]
r2=[]

for i in range(1,K+1):
  # Out of 14 x input features select k
  rfe = RFE(estimator=lr, n_features_to_select=i)
  # fit the RFE object to the data
  rfe.fit(X_train_scaled, y_train)

  # select only the selected features
  X_selected = X[X.columns[rfe.support_]]

  X_selected_train, X_selected_test, y_train, y_test = train_test_split(X_selected,


  lr = LinearRegression(fit_intercept = True)
  lr.fit(X_selected_train, y_train)

  y_pred = lr.predict(X_selected_test)
  rmse.append(np.sqrt(mean_squared_error(y_test, y_pred)))

  r2.append(r2_score(y_test, y_pred))


rmse
```

```
[0.39040990826736366,
 0.3598748902686404,
 0.34117766499817087,
 0.33962084527012243,
 0.3345452260049831,
 0.3291115005976038,
 0.3234634202091245,
 0.3206505716425819,
 0.3180340944602211,
 0.31734221093015913,
 0.31675563084636593,
 0.31643831671393075,
 0.3158215805814042,
 0.3154832177911638,
```

```
     0.3153044627615792,
     0.31511000519623955,
     0.31502928156935456,
     0.3150002142025347,
     0.3149083834172078,
     0.3148901275021143,
     0.3148876037661898,
     0.3148876037661898]
```

```
d={'k': range(1,K+1), 'rmse': rmse}
airline_rmse=pd.DataFrame(data=d)
```

```
airline_rmse
```

	k	rmse

```
airline_rmse.max()
```

```
k        22.00000
rmse      0.39041
dtype: float64
```

3 4 0.339621

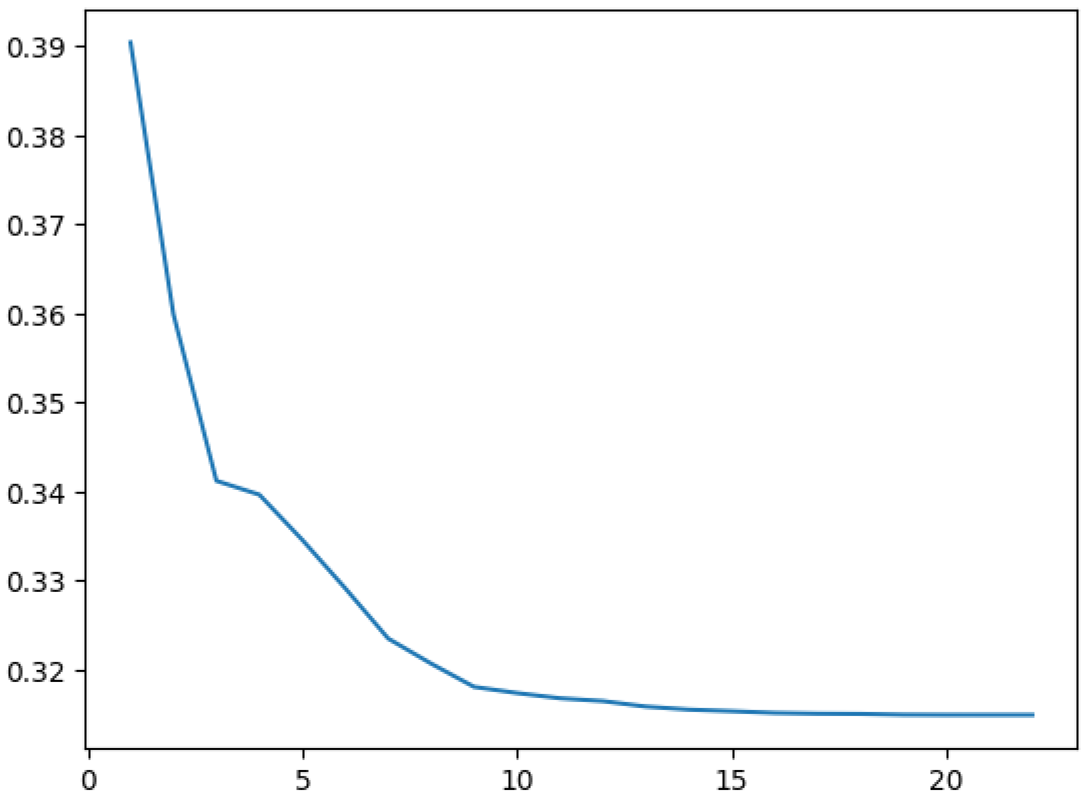
```
airline_rmse.min()
```

```
k        1.000000
rmse     0.314888
dtype: float64
```

7	8	0.320651

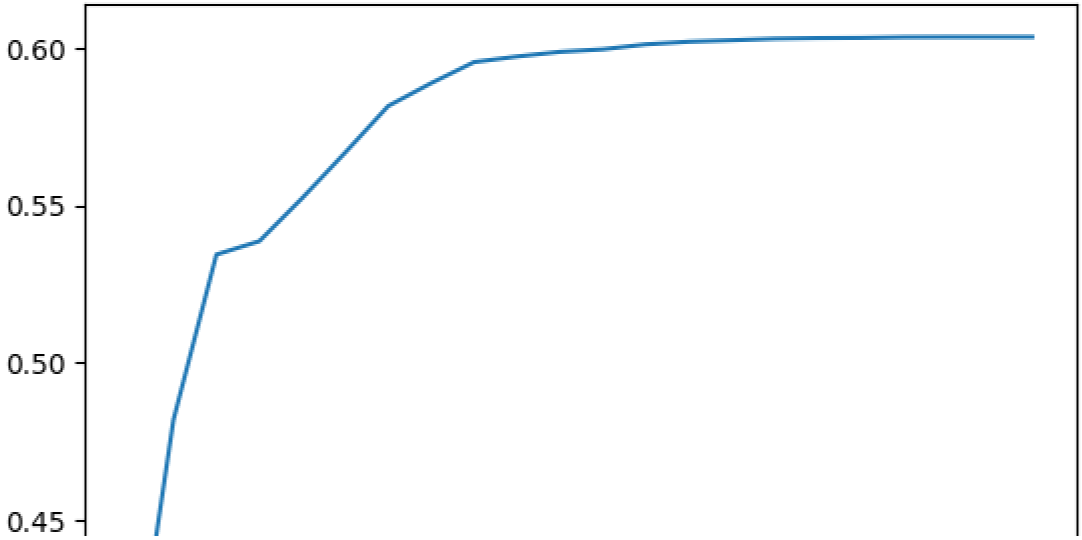
```
plt.plot(range(1,K+1),rmse)
```

```
[<matplotlib.lines.Line2D at 0x7fbb81ae40d0>]
```




```
plt.plot(range(1,K+1),r2)
```

```
[<matplotlib.lines.Line2D at 0x7fbb81919c90>]
```




```
# Out of 14 x input features select k
rfe = RFE(estimator=lr, n_features_to_select=50)
# fit the RFE object to the data
rfe.fit(X_train_scaled, y_train)

# select only the selected features
X_selected = X[X.columns[rfe.support_]]

X_selected_train, X_selected_test, y_train, y_test = train_test_split(X_selected, y,


scaler = StandardScaler()
X_selected_train_scaled= scaler.fit_transform(X_selected_train)
X_selected_test_scaled = scaler.transform(X_selected_test)

lr = LinearRegression(fit_intercept = True)
lr.fit(X_selected_train_scaled, y_train)

y_pred = lr.predict(X_selected_test_scaled)


rmse= np.sqrt(mean_squared_error(y_test, y_pred))

r2=r2_score(y_test, y_pred)


print("Root Mean Squared Error on train data:", rmse)
print("R-squared on train data:", r2)
```

```
Root Mean Squared Error on train data: 0.3114392936374533
R-squared on train data: 0.6118582455327233
```

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score,
```

```
from sklearn.feature_selection import RFE
from sklearn.feature_selection import SelectKBest, f_regression
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score,
```

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
from sklearn.linear_model import LogisticRegression

lr = LogisticRegression(max_iter=1000)
lr.fit(X_train_scaled, y_train)
```

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

```
K = X.shape[1]
```

```
accuracy=[]
f1=[]
```

```
for i in range(1,K+1):
  # Out of 14 x input features select k
  rfe = RFE(estimator=lr, n_features_to_select=i)
  # fit the RFE object to the data
  rfe.fit(X_train_scaled, y_train)

  # select only the selected features
  X_selected = X[X.columns[rfe.support_]]

  X_selected_train, X_selected_test, y_train, y_test = train_test_split(X_selected,


  logreg = LogisticRegression(max_iter=1000)
  logreg.fit(X_selected_train, y_train)

  y_pred = logreg.predict(X_selected_test)
  accuracy.append(accuracy_score(y_test, y_pred))

  f1.append(f1_score(y_test, y_pred))
```

```
accuracy
```

```
[0.6288304392236976,
 0.8221399387129724,
 0.8592951991828396,
 0.8648493360572013,
 0.8760214504596527,
 0.8790858018386108,
 0.880426455566905,
 0.8822139938712973,
 0.8837461695607763,
 0.8850229826353422,
 0.8844484167517875,
 0.8841292134831461,
 0.8845760980592441,
 0.8845122574055159,
 0.5072139938712973,
 0.5072139938712973,
 0.8341419816138917,
 0.8400791624106231,
 0.7981358529111338,
 0.8473569969356486,
 0.8430796731358529,
 0.8453779366700716]
```

```
f1
```

```
[0.6781800066423115,
 0.8271497704429829,
 0.8613662095861114,
 0.8668302195382777,
 0.877057482907065,
 0.8798223350253808,
 0.8812979276253249,
 0.8830576155162579,
 0.8848124486052249,
 0.8858754198086305,
 0.8853850050658563,
 0.8850028511689794,
 0.885395537525355,
 0.8852812480182636,
 0.6730484137405227,
 0.6730484137405227,
 0.8411980440097799,
 0.848448181983181,
 0.8073830409356726,
 0.8540916580216024,
 0.8503774044314584,
 0.8522810441571115]
```

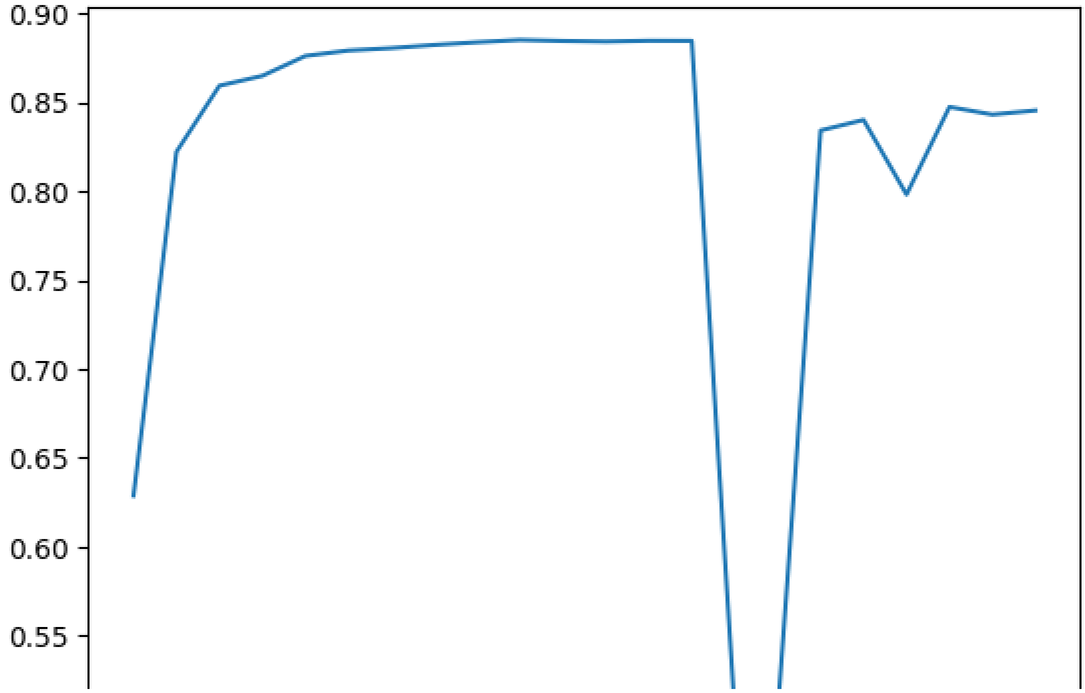
```
K1 = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22,
```

```
df = {'K': K1,
      'accuracy': accuracy,
      'f1': f1}
k_best = pd.DataFrame(data=df)
k_best
```

	K	accuracy	f1
0	1	0.628830	0.678180
1	2	0.822140	0.827150
2	3	0.859295	0.861366
3	4	0.864849	0.866830
4	5	0.876021	0.877057
5	6	0.879086	0.879822
6	7	0.880426	0.881298
7	8	0.882214	0.883058
8	9	0.883746	0.884812
9	10	0.885023	0.885875
10	11	0.884448	0.885385
11	12	0.884129	0.885003
12	13	0.884576	0.885396
13	14	0.884512	0.885281
14	15	0.507214	0.673048
15	16	0.507214	0.673048
16	17	0.834142	0.841198
17	18	0.840079	0.848448
18	19	0.798136	0.807383
19	20	0.847357	0.854092
20	21	0.843080	0.850377
21	22	0.845378	0.852281

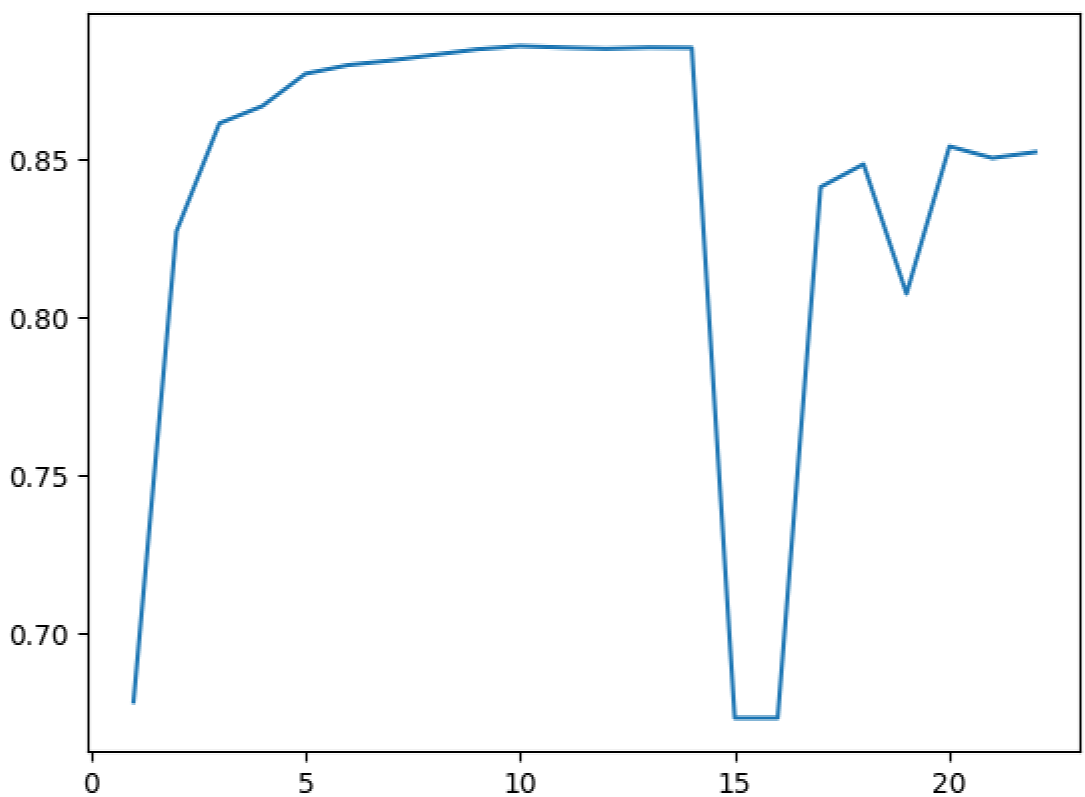
```
plt.plot(range(1,K+1),accuracy)
```

```
[<matplotlib.lines.Line2D at 0x7fbb80c21d50>]
```



```
plt.plot(range(1,K+1),f1)
```

```
[<matplotlib.lines.Line2D at 0x7fbb80c83d60>]
```



```
k_best[(k_best['accuracy'] == max(k_best['accuracy'])) & (k_best['f1'] == max(k_best
```

K accuracy f1

```
rfe = RFE(estimator=lr, n_features_to_select=10)
# fit the RFE object to the data
rfe.fit(X_train_scaled, y_train)

# select only the selected features
X_selected = X[X.columns[rfe.support_]]

X_selected_train, X_selected_test, y_train, y_test = train_test_split(X_selected, y,


logreg = LogisticRegression(max_iter=1000)
logreg.fit(X_selected_train, y_train)

y_pred = logreg.predict(X_selected_test)


y_pred = lr.predict(X_test_scaled)
cm=confusion_matrix(y_test, y_pred)
accuracy=accuracy_score(y_test, y_pred)
print(cm)
print(classification_report(y_test, y_pred))
print(accuracy)
```

```
[[1838 5881]
 [ 934 7011]]
              precision    recall  f1-score   support

           0       0.66      0.24      0.35      7719
           1       0.54      0.88      0.67      7945

    accuracy                           0.56     15664
   macro avg       0.60      0.56      0.51     15664
weighted avg       0.60      0.56      0.51     15664

0.5649259448416751
```

```
from sklearn.tree import DecisionTreeClassifier, export_graphviz
```

```
dtc = DecisionTreeClassifier(criterion='entropy',max_depth=2)
```

```
dtc.fit(X_train_scaled, y_train)
```

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', max_depth=2)
```

```
dtc.get_depth()
```

```
2
```

```
dtc.get_n_leaves()
```

```
4
```

```
dtc.get_params(['Age'])
```

```
{'ccp_alpha': 0.0,
 'class_weight': None,
 'criterion': 'entropy',
 'max_depth': 2,
 'max_features': None,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'random_state': None,
 'splitter': 'best'}
```

```
dot_data = export_graphviz(dtc, out_file=None, feature_names=X.columns, class_names=
```

```
y_pred = dtc.predict(X_test_scaled)
```

```
K = X.shape[1]
accuracy=[]
f1=[]

for i in range(1,K+1):
  # Out of 14 x input features select k
  rfe = RFE(estimator=dtc, n_features_to_select=i)
  # fit the RFE object to the data
  rfe.fit(X_train_scaled, y_train)

  # select only the selected features
  X_selected = X[X.columns[rfe.support_]]

  X_selected_train, X_selected_test, y_train, y_test = train_test_split(X_selected,


  dtc = DecisionTreeClassifier(criterion='entropy')
  dtc.fit(X_selected_train, y_train)

  y_pred = dtc.predict(X_selected_test)
  accuracy.append(accuracy_score(y_test, y_pred))

  f1.append(f1_score(y_test, y_pred))
```

```
accuracy
```

```
[0.8064989785495403,
 0.7466802860061287,
 0.8114785495403473,
 0.9034090909090909,
 0.9006001021450459,
 0.9160495403472931,
 0.9272854954034729,
 0.9353932584269663,
 0.9431818181818182,
 0.9459908069458631,
 0.9492466802860061,
 0.9546731358529111,
 0.9533963227783453,
 0.9546731358529111,
 0.9558222676200204,
 0.9579290091930541,
 0.9589504596527069,
 0.95920582226762,
 0.957035240040858,
 0.9576098059244127,
 0.9571629213483146,
 0.9575459652706844]
```

```
f1
```

```
[0.8265720661440751,
 0.7512225705329153,
 0.8148705410319101,
 0.9045486089205729,
 0.9019089019089019,
 0.9173007986919061,
 0.9283422459893048,
 0.9360545937065589,
 0.943834406159283,
 0.9467991447616653,
 0.949977977726043,
 0.9552614996849401,
 0.9541572469228837,
 0.9553964065837416,
 0.956510809451986,
 0.9586289158139243,
 0.9595877066180629,
 0.9598138481856487,
 0.957750015694645,
 0.9583019341873902,
 0.957822616129235,
 0.9581945055635884]
```

```
len(f1)
```

```
22
```

```
len(accuracy)
```

```
22
```

```
K1 = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22]
```

```
df = {'K': K1,
      'accuracy': accuracy,
      'f1': f1}
k_best = pd.DataFrame(data=df)
k_best
```

	K	accuracy	f1

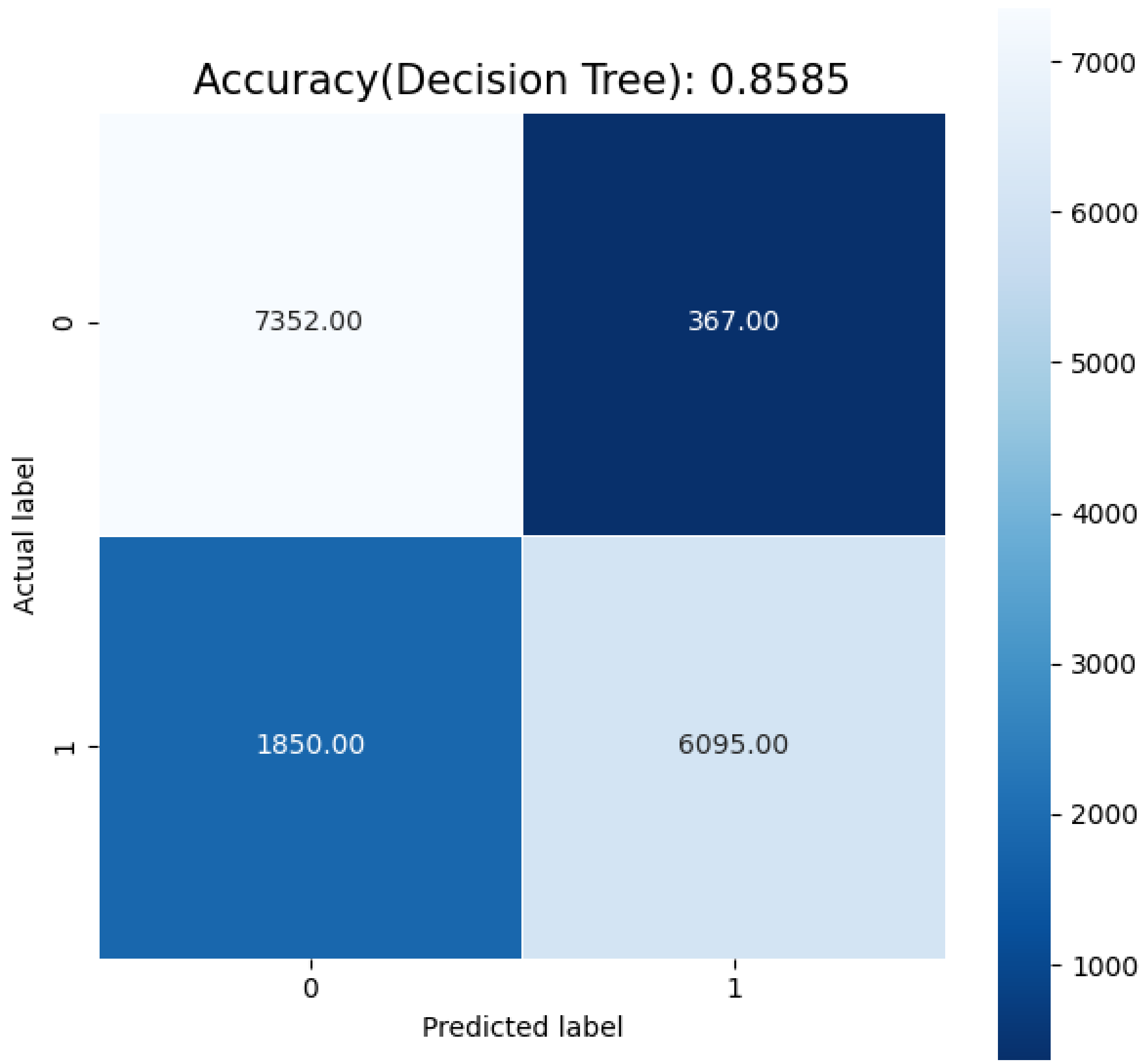
```
k_best[(k_best['accuracy'] == max(k_best['accuracy'])) & (k_best['f1'] == max(k_best
```

	K	accuracy	f1
17	18	0.959206	0.959814
3	4	0.903409	0.904349

```
# the best model so far is with k=9
rfe = RFE(estimator=dtc, n_features_to_select=18)
# fit the RFE object to the data
rfe.fit(X_train_scaled, y_train)

# select only the selected features
X_selected = X[X.columns[rfe.support_]]

X_selected_train, X_selected_test, y_train, y_test = train_test_split(X_selected, y,


dtc = DecisionTreeClassifier(criterion='entropy',max_depth=2)
dtc.fit(X_selected_train, y_train)

y_pred = dtc.predict(X_selected_test)

cm=confusion_matrix(y_test, y_pred)
scores=classification_report(y_test, y_pred, zero_division=1)
accuracy=accuracy_score(y_test, y_pred)
print(cm)
print(scores)
print(accuracy)
```

```
[[7352  367]
 [1850 6095]]
              precision    recall  f1-score   support

           0       0.80      0.95      0.87      7719
           1       0.94      0.77      0.85      7945

    accuracy                           0.86     15664
   macro avg       0.87      0.86      0.86     15664
weighted avg       0.87      0.86      0.86     15664

0.8584652706843718
```

```
plt.figure(figsize=(7,7))
sns.heatmap(cm, annot=True, fmt=".2f", linewidths=.5, square = True, cmap = 'Blues_r
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title = 'Accuracy(Decision Tree): {:.4f}'.format(accuracy)
plt.title(all_sample_title, size = 15);
```




```
import graphviz
```

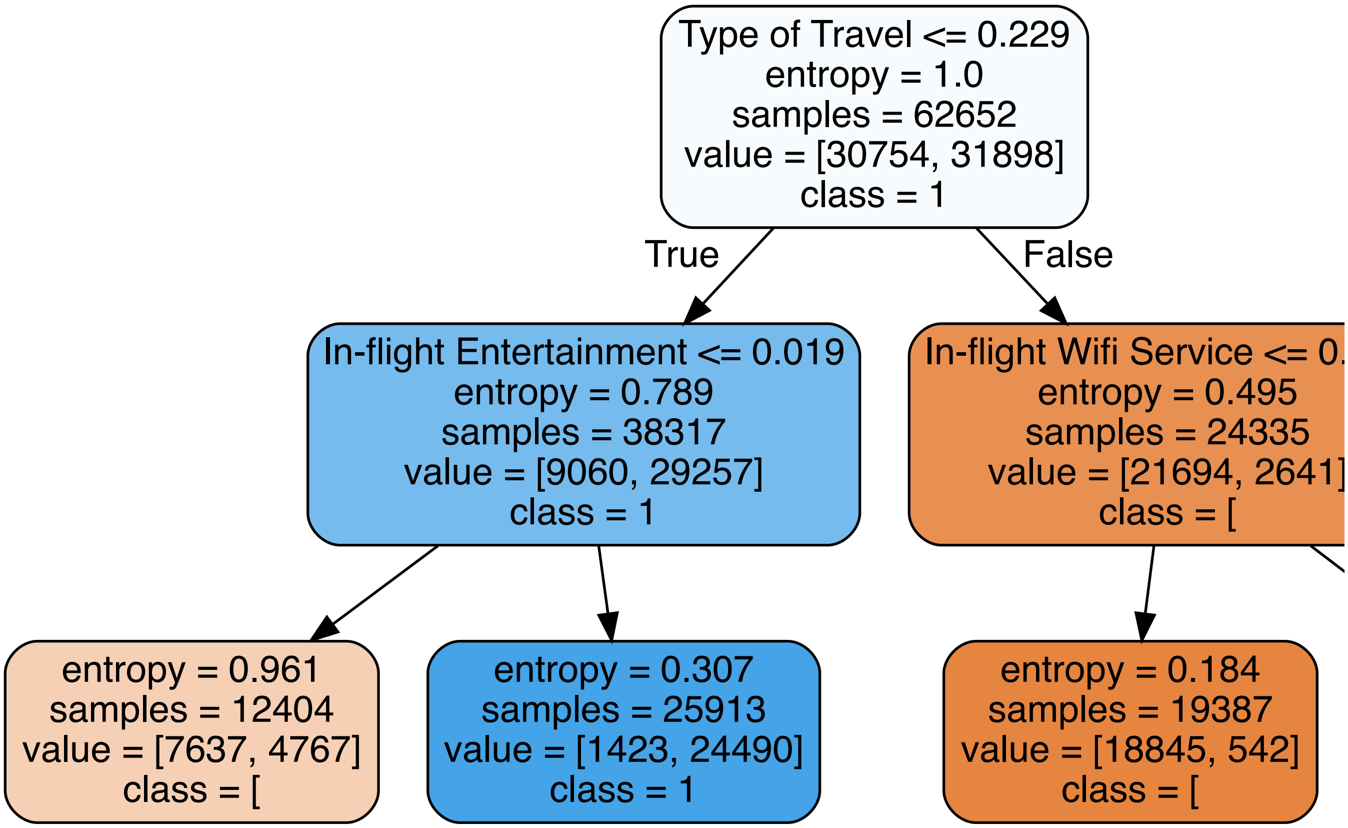
```
graph = graphviz.Source(dot_data)
graph.render("decision_tree", format='png')
graph.view()
```

```
'decision_tree.pdf'
```

```
graph = graphviz.Source(dot_data)
graph.format = 'png'
graph.render('decision_tree', view=True, format='png', cleanup=True)
graph.render('decision_tree', view=True, format='png', cleanup=True)
```

```
'decision_tree.png'
```

```
graph
```




```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, roc_curve, precision_recall_curve, auc
from sklearn.metrics import classification_report, confusion_matrix,accuracy_score,f
```

```
rfc = RandomForestClassifier(n_estimators=20, max_depth=7, min_samples_leaf=5)
```

```
rfc.fit(X_train_scaled, y_train)
```

```
▾ RandomForestClassifier
RandomForestClassifier(max_depth=7, min_samples_leaf=5, n_estimators=20)
```

```
K1 = X.shape[1]
accuracy=[]
f1=[]
y_pred = rfc.fit(X_train_scaled, y_train)

for i in range(1,K+1):
  # Out of 14 x input features select k
  rfe = RFE(estimator=rfc, n_features_to_select=i)
  # fit the RFE object to the data
  rfe.fit(X_train_scaled, y_train)

  # select only the selected features
  X_selected = X[X.columns[rfe.support_]]

  X_selected_train, X_selected_test, y_train, y_test = train_test_split(X_selected,


  rfc = RandomForestClassifier(n_estimators=20, max_depth=7, min_samples_leaf=5)
  rfc.fit(X_selected_train, y_train)

  y_pred = rfc.predict(X_selected_test)
  accuracy.append(accuracy_score(y_test, y_pred))

  f1.append(f1_score(y_test, y_pred))


accuracy
```

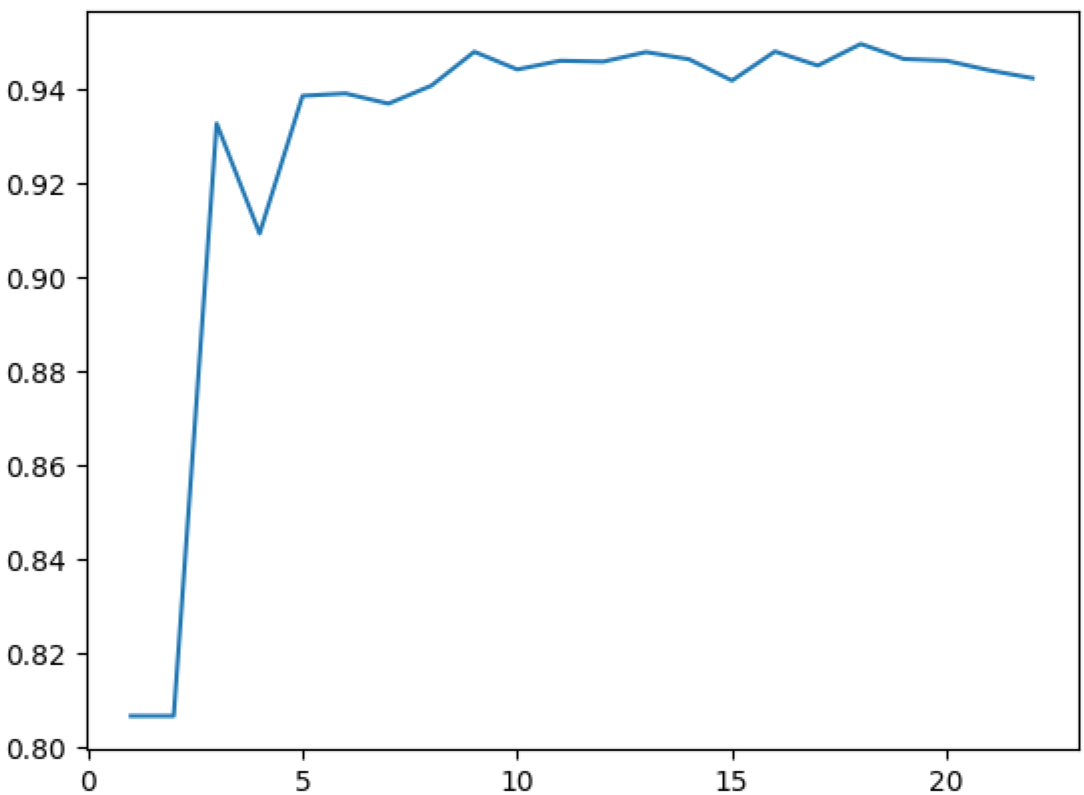
```
[0.8064989785495403,
 0.8064989785495403,
 0.9325842696629213,
 0.9091547497446374,
 0.9384576098059244,
 0.9389683350357507,
 0.9367977528089888,
 0.9406281920326864,
 0.9478421859039836,
 0.9440755873340143,
 0.9459269662921348,
 0.9457354443309499,
 0.9477783452502554,
 0.9462461695607763,
 0.9417134831460674,
 0.947906026557712,
 0.9449055158324822,
 0.9495020429009193,
 0.9463100102145046,
 0.9459269662921348,
 0.9438840653728294,
 0.9422242083758938]
```

```
f1
```

```
[0.8265720661440751,
 0.8265720661440751,
 0.9331899278754904,
 0.9089862488007676,
 0.9380781089414182,
 0.9389215435727064,
 0.9373893245636226,
 0.9408020369191599,
 0.9483532460964662,
 0.9444373969301026,
 0.9463890119627825,
 0.946311268317332,
 0.9482212938346625,
 0.9468098547062539,
 0.9419248139431333,
 0.9484262419416003,
 0.9451401690928739,
 0.9498637256766178,
 0.9465658555181397,
 0.9463006403347491,
 0.9439449014731203,
 0.9423530161156761]
```

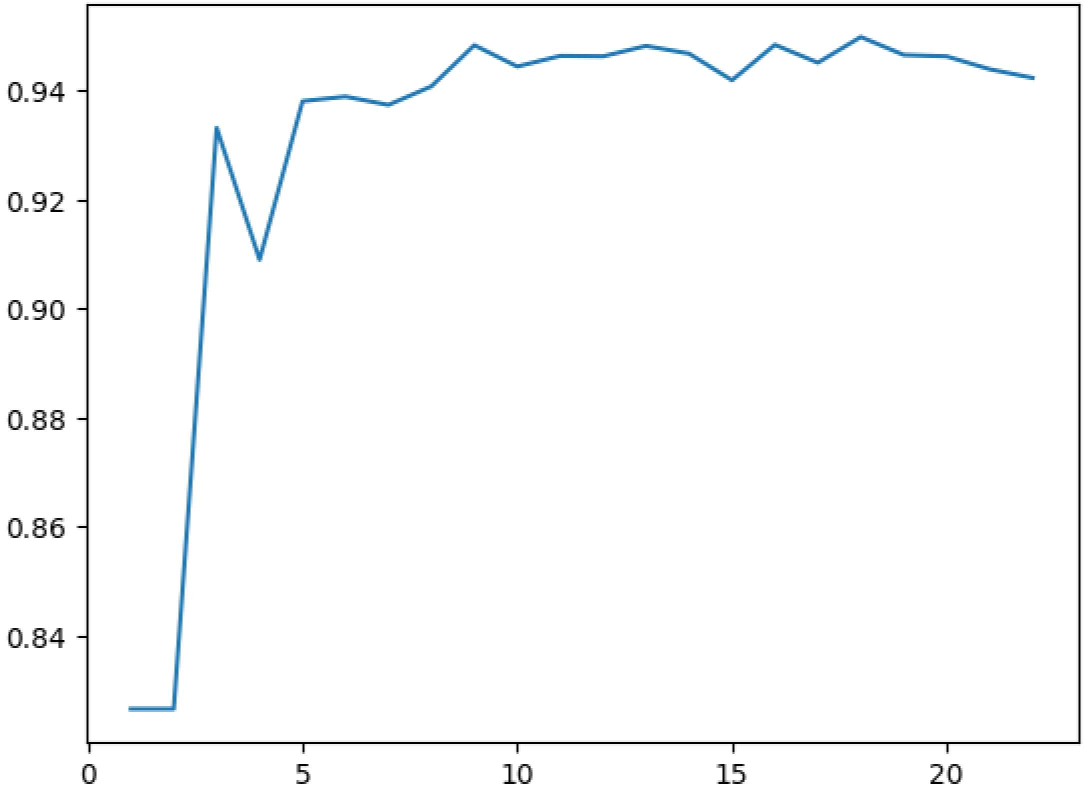
```
plt.plot(range(1,K+1),accuracy)
```

```
[<matplotlib.lines.Line2D at 0x7fbb808511b0>]
```




```
plt.plot(range(1,K+1),f1)
```

```
[<matplotlib.lines.Line2D at 0x7fbb8052ae30>]
```




```
K1 = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22]
```

```
df = {'K': K1,
      'accuracy': accuracy,
      'f1': f1}
k_best = pd.DataFrame(data=df)
k_best
```

	K	accuracy	f1
0	1	0.806499	0.826572
1	2	0.806499	0.826572
2	3	0.932584	0.933190
3	4	0.909155	0.908986
4	5	0.938458	0.938078
5	6	0.938968	0.938922
6	7	0.936798	0.937389
7	8	0.940628	0.940802
8	9	0.947842	0.948353
9	10	0.944076	0.944437
10	11	0.945927	0.946389

```
k_best[(k_best['accuracy'] == max(k_best['accuracy'])) | (k_best['f1'] == max(k_best
```

	K	accuracy	f1
17	18	0.949502	0.949864
15	16	0.947906	0.948426

```
from sklearn.metrics import classification_report, confusion_matrix,accuracy_score,f
# the best model so far is with k=9
rfe = RFE(estimator=rfc, n_features_to_select=18)
# fit the RFE object to the data
rfe.fit(X_train_scaled, y_train)

# select only the selected features
X_selected = X[X.columns[rfe.support_]]

X_selected_train, X_selected_test, y_train, y_test = train_test_split(X_selected, y,


rfc = RandomForestClassifier(n_estimators=20, max_depth=7, min_samples_leaf=5)
rfc.fit(X_selected_train, y_train)

y_pred = rfc.predict(X_selected_test)
```

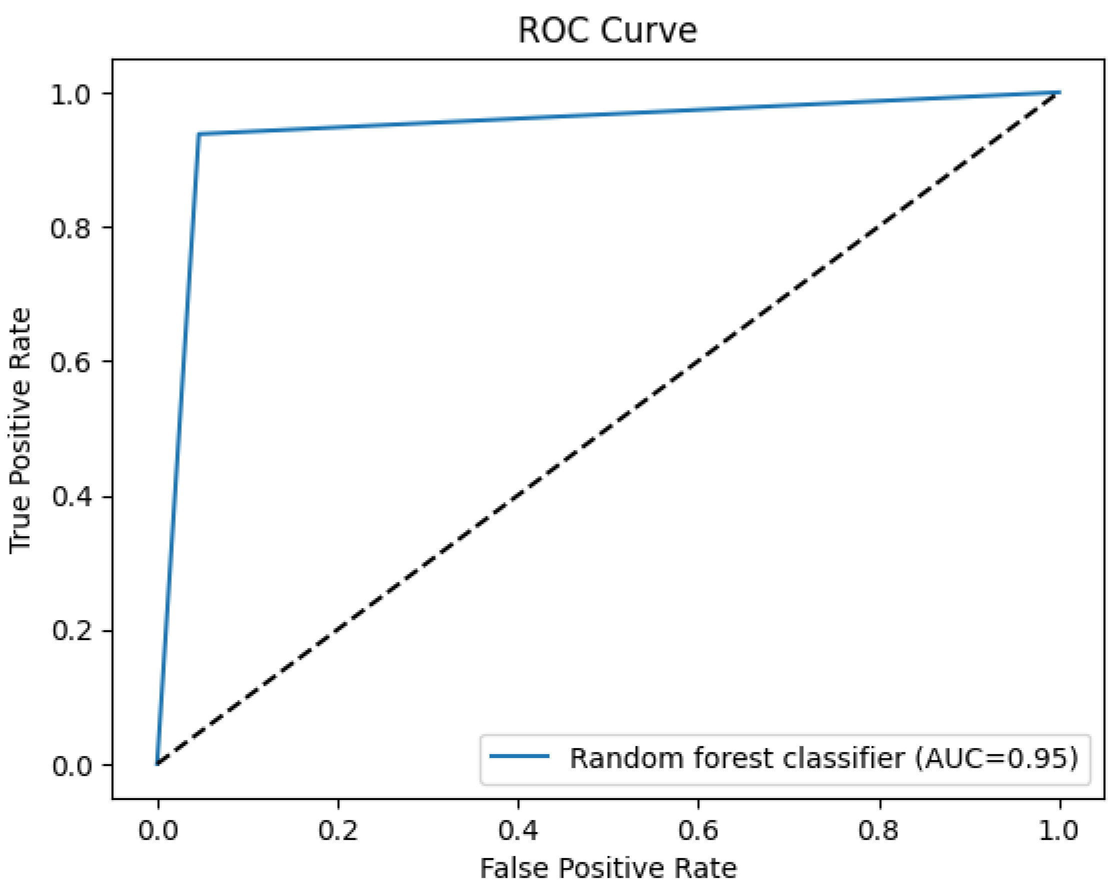
```
cm = confusion_matrix(y_test, y_pred)
accuracy = accuracy_score(y_test,y_pred)
report=classification_report(y_test, y_pred)
precision, recall, thresholds = precision_recall_curve(y_test, y_pred)
print(accuracy)
print(cm)
print(report)
```

```
0.9456716036772217
[[7362  357]
 [ 494 7451]]
              precision    recall  f1-score   support

           0       0.94      0.95      0.95      7719
           1       0.95      0.94      0.95      7945

    accuracy                           0.95     15664
   macro avg       0.95      0.95      0.95     15664
weighted avg       0.95      0.95      0.95     15664
```

```
plt.figure(figsize=(7,7))
sns.heatmap(cm, annot=True, fmt=".2f", linewidths=.5, square = True, cmap = 'Blues_r
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title = 'Accuracy(Random Forest): {:.4f}'.format(accuracy)
plt.title(all_sample_title, size = 15);
```


```
fpr, tpr, _ = roc_curve(y_test, y_pred)
```

```
plt.plot(fpr, tpr, label=f'Random forest classifier (AUC={accuracy:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.show()
```



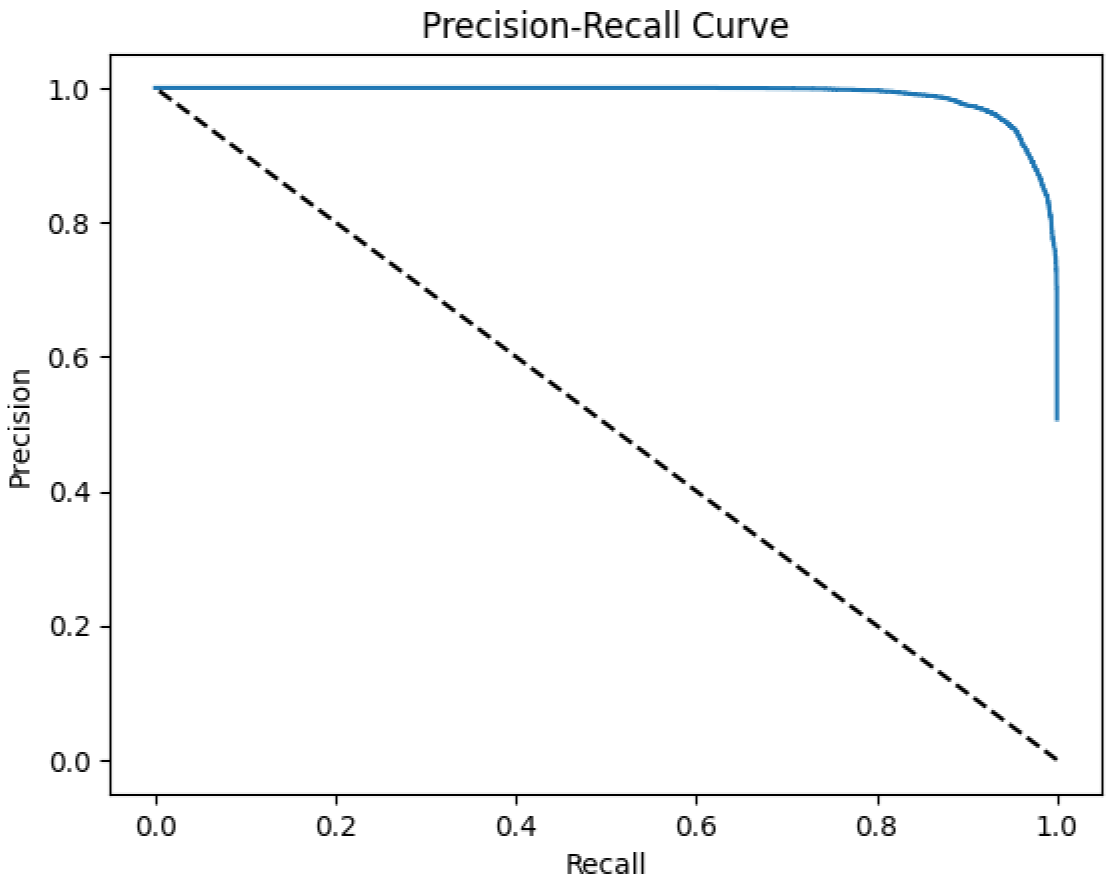

```
y_pred_prob = rfc.predict_proba(X_selected_test)[:, 1]
```

```
precision, recall, thresholds = precision_recall_curve(y_test, y_pred_prob)
```

```
auprc = auc(recall, precision)
print("Area under the PR curve (AUPRC):", auprc)
```

```
Area under the PR curve (AUPRC): 0.9903051391621421
```

```
plt.plot(recall, precision, label=f'(AUPRC={auprc:.2f})')
plt.plot([1, 0], [0, 1], 'k--')
plt.title('Precision-Recall Curve')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.show()
```




```
from sklearn.model_selection import RandomizedSearchCV
```

```
param_dist = {'n_estimators': [50, 100,150, 200],
              'max_depth': [5, 10, 15, 20],
              'min_samples_leaf': [1, 5, 10]}
```

```
rand_search = RandomizedSearchCV(estimator=rfc,
                                 param_distributions=param_dist,
                                 cv=5,
                                 n_iter=10,
                                 scoring='accuracy')
```

```
rand_search.fit(X_train_scaled, y_train)
```

```
▸ RandomizedSearchCV
▸ estimator: RandomForestClassifier
    ▸ RandomForestClassifier
```

```
print("Best Hyperparameters:", rand_search.best_params_)
```

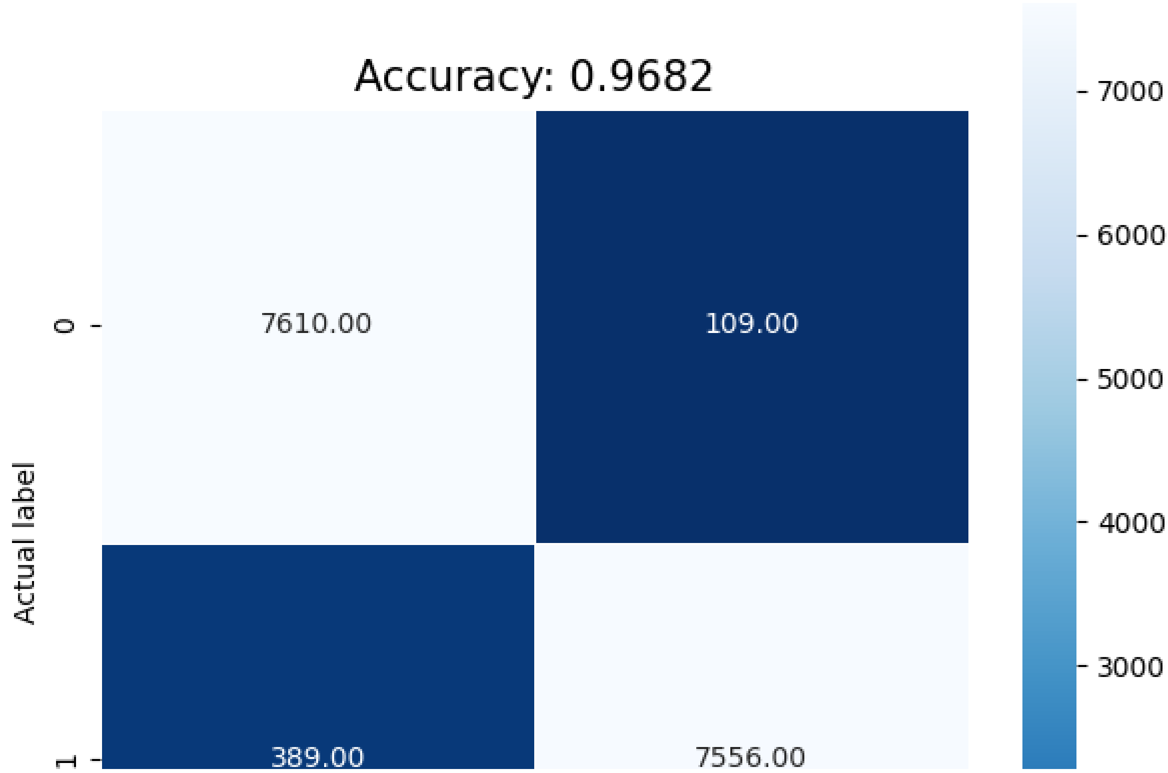
```
Best Hyperparameters: {'n_estimators': 200, 'min_samples_leaf': 1, 'max_depth':
```

```
y_pred = rand_search.predict(X_test_scaled)
```

```
cm=confusion_matrix(y_test, y_pred)
accuracy = rand_search.score(X_test_scaled, y_test)
report=classification_report(y_test, y_pred)
precision, recall, thresholds = precision_recall_curve(y_test, y_pred)
print(accuracy)
print(cm)
print(report)
```

```
0.9682073544433095
[[7610  109]
 [ 389 7556]]
              precision    recall  f1-score   support

           0       0.95      0.99      0.97      7719
           1       0.99      0.95      0.97      7945

    accuracy                           0.97     15664
   macro avg       0.97      0.97      0.97     15664
weighted avg       0.97      0.97      0.97     15664
```

```
plt.figure(figsize=(7,7))
sns.heatmap(cm, annot=True, fmt=".2f", linewidths=.5, square = True, cmap = 'Blues_r
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title = 'Accuracy: {:.4f}'.format(accuracy)
plt.title(all_sample_title, size = 15);
```



Results

Through robust data preprocessing, handling missing values, encoding categorical variables, and addressing outliers, the dataset was refined for analysis. Exploratory data analysis unveiled significant relationships, particularly in departure delay, class, and overall satisfaction. Employing linear regression, logistic regression, decision tree classifier, and random forest classifier models, the project achieved a notable accuracy of 97%. The predictive models, after rigorous evaluation