

Airline_Passenger_Satisfaction

April 29, 2024

1 Flight Passenger Satisfaction Predictor

Dataset: <https://www.kaggle.com/datasets/teejmahal20/airline-passenger-satisfaction>

2 Import Libraries

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

from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import StandardScaler
warnings.filterwarnings('ignore')
```

3 Import Data and Quick Snapshot

```
[4]: #df_train = pd.read_csv('https://drive.google.com/uc?
→export=download&id=1Vcl5dxH7xKarsGRMQMFxDzDsi0TlPwA5', index_col=[0])
#df_test = pd.read_csv('https://drive.google.com/uc?
→export=download&id=1XqlCyshe7u0G29C0gjLQa88w6FhvXdG8', index_col=[0])
df_train = pd.read_csv('./train.csv', index_col=[0])
df_test = pd.read_csv('./test.csv', index_col=[0])
```

```
[5]: display(df_train)
```

```
[5]:
```

	id	Gender	Customer Type	Age	Type of Travel	Class	\
0	70172	Male	Loyal Customer	13	Personal Travel	Eco Plus	
1	5047	Male	disloyal Customer	25	Business travel	Business	
2	110028	Female	Loyal Customer	26	Business travel	Business	
3	24026	Female	Loyal Customer	25	Business travel	Business	

4	119299	Male	Loyal Customer	61	Business travel	Business
...
103899	94171	Female	disloyal Customer	23	Business travel	Eco
103900	73097	Male	Loyal Customer	49	Business travel	Business
103901	68825	Male	disloyal Customer	30	Business travel	Business
103902	54173	Female	disloyal Customer	22	Business travel	Eco
103903	62567	Male	Loyal Customer	27	Business travel	Business

	Flight Distance	Inflight wifi service	\
0	460	3	
1	235	3	
2	1142	2	
3	562	2	
4	214	3	
...	
103899	192	2	
103900	2347	4	
103901	1995	1	
103902	1000	1	
103903	1723	1	

	Departure/Arrival time convenient	Ease of Online booking	...	\
0	4	3	...	
1	2	3	...	
2	2	2	...	
3	5	5	...	
4	3	3	...	
...	
103899	1	2	...	
103900	4	4	...	
103901	1	1	...	
103902	1	1	...	
103903	3	3	...	

	Inflight entertainment	On-board service	Leg room service	\
0	5	4	3	
1	1	1	5	
2	5	4	3	
3	2	2	5	
4	3	3	4	
...	
103899	2	3	1	
103900	5	5	5	
103901	4	3	2	
103902	1	4	5	
103903	1	1	1	

	Baggage handling	Checkin service	Inflight service	Cleanliness	\
0	4	4	5	5	
1	3	1	4	1	
2	4	4	4	5	
3	3	1	4	2	
4	4	3	3	3	
...	
103899	4	2	3	2	
103900	5	5	5	4	
103901	4	5	5	4	
103902	1	5	4	1	
103903	4	4	3	1	

	Departure Delay in Minutes	Arrival Delay in Minutes	\
0	25	18.0	
1	1	6.0	
2	0	0.0	
3	11	9.0	
4	0	0.0	
...	
103899	3	0.0	
103900	0	0.0	
103901	7	14.0	
103902	0	0.0	
103903	0	0.0	

	satisfaction
0	neutral or dissatisfied
1	neutral or dissatisfied
2	satisfied
3	neutral or dissatisfied
4	satisfied
...	...
103899	neutral or dissatisfied
103900	satisfied
103901	neutral or dissatisfied
103902	neutral or dissatisfied
103903	neutral or dissatisfied

[103904 rows x 24 columns]

```
[6]: display(df_train.head())
```

```
[6]:
```

	id	Gender	Customer Type	Age	Type of Travel	Class	\
0	70172	Male	Loyal Customer	13	Personal Travel	Eco Plus	
1	5047	Male	disloyal Customer	25	Business travel	Business	
2	110028	Female	Loyal Customer	26	Business travel	Business	

3	24026	Female	Loyal Customer	25	Business travel	Business
4	119299	Male	Loyal Customer	61	Business travel	Business

	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	\
0	460	3		4
1	235	3		2
2	1142	2		2
3	562	2		5
4	214	3		3

	Ease of Online booking	...	Inflight entertainment	On-board service	\
0	3	...	5		4
1	3	...	1		1
2	2	...	5		4
3	5	...	2		2
4	3	...	3		3

	Leg room service	Baggage handling	Checkin service	Inflight service	\
0	3	4	4		5
1	5	3	1		4
2	3	4	4		4
3	5	3	1		4
4	4	4	3		3

	Cleanliness	Departure Delay in Minutes	Arrival Delay in Minutes	\
0	5	25		18.0
1	1	1		6.0
2	5	0		0.0
3	2	11		9.0
4	3	0		0.0

	satisfaction
0	neutral or dissatisfied
1	neutral or dissatisfied
2	satisfied
3	neutral or dissatisfied
4	satisfied

[5 rows x 24 columns]

3.1 Info and Shape

```
[7]: display(df_train.info())

print("\n\nShape of Training Data: ", df_train.shape)
print("Shape of Testing Data: ", df_test.shape)
```

```

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

```

[7]: None

```

Shape of Training Data: (103904, 24)
Shape of Testing Data: (25976, 24)

```

3.2 DF Describe

```
[8]: display(df_train.describe())
```

```

[8]:
count    id    Age  Flight Distance  Inflight wifi service \
count  103904.000000  103904.000000  103904.000000  103904.000000
mean    64924.210502   39.379706   1189.448375    2.729683
std     37463.812252   15.114964    997.147281    1.327829
min         1.000000    7.000000    31.000000    0.000000

```

25%	32533.750000	27.000000	414.000000	2.000000
50%	64856.500000	40.000000	843.000000	3.000000
75%	97368.250000	51.000000	1743.000000	4.000000
max	129880.000000	85.000000	4983.000000	5.000000

	Departure/Arrival time convenient	Ease of Online booking \
count	103904.000000	103904.000000
mean	3.060296	2.756901
std	1.525075	1.398929
min	0.000000	0.000000
25%	2.000000	2.000000
50%	3.000000	3.000000
75%	4.000000	4.000000
max	5.000000	5.000000

	Gate location	Food and drink	Online boarding	Seat comfort \
count	103904.000000	103904.000000	103904.000000	103904.000000
mean	2.976883	3.202129	3.250375	3.439396
std	1.277621	1.329533	1.349509	1.319088
min	0.000000	0.000000	0.000000	0.000000
25%	2.000000	2.000000	2.000000	2.000000
50%	3.000000	3.000000	3.000000	4.000000
75%	4.000000	4.000000	4.000000	5.000000
max	5.000000	5.000000	5.000000	5.000000

	Inflight entertainment	On-board service	Leg room service \
count	103904.000000	103904.000000	103904.000000
mean	3.358158	3.382363	3.351055
std	1.332991	1.288354	1.315605
min	0.000000	0.000000	0.000000
25%	2.000000	2.000000	2.000000
50%	4.000000	4.000000	4.000000
75%	4.000000	4.000000	4.000000
max	5.000000	5.000000	5.000000

	Baggage handling	Checkin service	Inflight service	Cleanliness \
count	103904.000000	103904.000000	103904.000000	103904.000000
mean	3.631833	3.304290	3.640428	3.286351
std	1.180903	1.265396	1.175663	1.312273
min	1.000000	0.000000	0.000000	0.000000
25%	3.000000	3.000000	3.000000	2.000000
50%	4.000000	3.000000	4.000000	3.000000
75%	5.000000	4.000000	5.000000	4.000000
max	5.000000	5.000000	5.000000	5.000000

	Departure Delay in Minutes	Arrival Delay in Minutes
count	103904.000000	103594.000000

mean	14.815618	15.178678
std	38.230901	38.698682
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	12.000000	13.000000
max	1592.000000	1584.000000

4 Data Cleaning and Preprocessing

```
[9]: # Replace spaces in column names with underscore

df_train.columns = df_train.columns.str.replace(' ', '_')
df_test.columns = df_test.columns.str.replace(' ', '_')
```

```
[10]: # Drop the unneeded ID Column

df_train.drop(columns=['id'], inplace=True)
df_test.drop(columns=['id'], inplace=True)
```

4.1 Handling Null Values

4.1.1 Display Null Values

```
[11]: # Display the Null Values

display(df_train.isnull().sum())
display(df_test.isnull().sum())
display(df_train[pd.isnull(df_train).any(axis=1)])
```

```
[11]: Gender                                0
Customer_Type                             0
Age                                         0
Type_of_Travel                             0
Class                                       0
Flight_Distance                           0
Inflight_wifi_service                      0
Departure/Arrival_time_convenient          0
Ease_of_Online_booking                    0
Gate_location                             0
Food_and_drink                             0
Online_boarding                            0
Seat_comfort                              0
Inflight_entertainment                     0
On-board_service                           0
```

```

Leg_room_service          0
Baggage_handling          0
Checkin_service           0
Inflight_service          0
Cleanliness               0
Departure_Delay_in_Minutes 0
Arrival_Delay_in_Minutes  310
satisfaction              0
dtype: int64

```

```

[11]: Gender          0
      Customer_Type   0
      Age             0
      Type_of_Travel  0
      Class           0
      Flight_Distance 0
      Inflight_wifi_service 0
      Departure/Arrival_time_convenient 0
      Ease_of_Online_booking 0
      Gate_location    0
      Food_and_drink    0
      Online_boarding   0
      Seat_comfort      0
      Inflight_entertainment 0
      On-board_service  0
      Leg_room_service  0
      Baggage_handling  0
      Checkin_service   0
      Inflight_service   0
      Cleanliness        0
      Departure_Delay_in_Minutes 0
      Arrival_Delay_in_Minutes 83
      satisfaction       0
      dtype: int64

```

```

[11]:
      Gender      Customer_Type  Age  Type_of_Travel  Class \
213      Female      Loyal Customer  38  Business travel  Eco
1124      Male      Loyal Customer  53  Personal Travel  Eco
1529      Male      Loyal Customer  39  Business travel  Business
2004      Female  disloyal Customer  26  Business travel  Business
2108      Female      Loyal Customer  24  Personal Travel  Eco
...      ...      ...      ...      ...      ...
102067      Male      Loyal Customer  49  Personal Travel  Eco Plus
102384      Male      Loyal Customer  58  Business travel  Eco
102552      Female  disloyal Customer  29  Business travel  Eco
102960      Male      Loyal Customer  58  Business travel  Eco
103540      Female      Loyal Customer  33  Personal Travel  Eco

```


	Flight_Distance	Inflight_wifi_service	\
213	109	5	
1124	1012	3	
1529	733	2	
2004	1035	3	
2108	417	2	
...	
102067	1249	2	
102384	733	3	
102552	1107	2	
102960	1088	4	
103540	359	4	

	Departure/Arrival_time_convenient	Ease_of_Online_booking	\
213	3	3	
1124	2	3	
1529	5	5	
2004	3	3	
2108	1	2	
...	
102067	5	2	
102384	3	3	
102552	1	1	
102960	4	1	
103540	4	4	

	Gate_location	...	Inflight_entertainment	On-board_service	\
213	3	...	5	5	
1124	4	...	4	4	
1529	5	...	2	2	
2004	1	...	2	3	
2108	2	...	5	1	
...	
102067	3	...	3	4	
102384	3	...	3	3	
102552	1	...	5	4	
102960	1	...	5	1	
103540	3	...	4	3	

	Leg_room_service	Baggage_handling	Checkin_service	Inflight_service	\
213	2	4	1	1	
1124	4	4	3	3	
1529	2	2	2	2	
2004	3	4	5	5	
2108	4	2	1	2	
...	

102067	5	4	3	4
102384	1	2	4	2
102552	1	5	5	3
102960	5	5	5	3
103540	2	5	3	5

	Cleanliness	Departure_Delay_in_Minutes	Arrival_Delay_in_Minutes	\
213	5	31	NaN	
1124	4	38	NaN	
1529	3	11	NaN	
2004	2	41	NaN	
2108	5	1	NaN	
...	
102067	3	230	NaN	
102384	3	55	NaN	
102552	5	0	NaN	
102960	5	0	NaN	
103540	4	42	NaN	

	satisfaction
213	satisfied
1124	neutral or dissatisfied
1529	neutral or dissatisfied
2004	neutral or dissatisfied
2108	neutral or dissatisfied
...	...
102067	neutral or dissatisfied
102384	neutral or dissatisfied
102552	neutral or dissatisfied
102960	satisfied
103540	neutral or dissatisfied

[310 rows x 23 columns]

4.1.2 Filling Null Values

```
[12]: # Set the null values of Arrival Delay to Departure Delay since if one departs a
      ↪ certain time late, they will most likely arrive that certain time late.
      ↪
      df_train['Arrival_Delay_in_Minutes'] = df_train['Arrival_Delay_in_Minutes'].
      ↪ fillna(df_train['Departure_Delay_in_Minutes'])
      df_test['Arrival_Delay_in_Minutes'] = df_test['Arrival_Delay_in_Minutes'].
      ↪ fillna(df_test['Departure_Delay_in_Minutes'])
```

```
[13]: # Null Values After fillna
      display(df_train.isnull().sum())
```

```
display(df_test.isnull().sum())
```

```
[13]: Gender                0
      Customer_Type         0
      Age                   0
      Type_of_Travel         0
      Class                  0
      Flight_Distance        0
      Inflight_wifi_service   0
      Departure/Arrival_time_convenient 0
      Ease_of_Online_booking  0
      Gate_location          0
      Food_and_drink          0
      Online_boarding         0
      Seat_comfort            0
      Inflight_entertainment  0
      On-board_service        0
      Leg_room_service        0
      Baggage_handling        0
      Checkin_service         0
      Inflight_service        0
      Cleanliness             0
      Departure_Delay_in_Minutes 0
      Arrival_Delay_in_Minutes 0
      satisfaction            0
      dtype: int64
```

```
[13]: Gender                0
      Customer_Type         0
      Age                   0
      Type_of_Travel         0
      Class                  0
      Flight_Distance        0
      Inflight_wifi_service   0
      Departure/Arrival_time_convenient 0
      Ease_of_Online_booking  0
      Gate_location          0
      Food_and_drink          0
      Online_boarding         0
      Seat_comfort            0
      Inflight_entertainment  0
      On-board_service        0
      Leg_room_service        0
      Baggage_handling        0
      Checkin_service         0
      Inflight_service        0
      Cleanliness             0
```

```

Departure_Delay_in_Minutes      0
Arrival_Delay_in_Minutes       0
satisfaction                    0
dtype: int64

```

4.2 Making Capitalization Consistent

```

[14]: # Adjust capitalization of columns
df_train['Customer_Type'].replace('disloyal Customer', 'Disloyal_Customer',
    ↪ inplace=True)
df_train['Customer_Type'].replace('Loyal Customer', 'Loyal_Customer',
    ↪ inplace=True)
df_train['Type_of_Travel'].replace('Business travel', 'Business_Travel',
    ↪ inplace=True)
df_train['Type_of_Travel'].replace('Personal travel', 'Personal_Travel',
    ↪ inplace=True)
df_train = df_train.rename(columns={'satisfaction': 'Satisfaction',
    ↪ 'Inflight_wifi_service':
    ↪ 'Inflight_Wifi_Service',
    ↪ 'Departure/Arrival_time_convenient':
    ↪ 'Departure/Arrival_Time_Convenient',
    ↪ 'Ease_of_Online_booking':
    ↪ 'Ease_of_Online_Booking',
    ↪ 'Gate_location': 'Gate_Location',
    ↪ 'Food_and_drink': 'Food_and_Drink',
    ↪ 'Online_boarding': 'Online_Boarding',
    ↪ 'Seat_comfort': 'Seat_Comfort',
    ↪ 'Inflight_entertainment':
    ↪ 'Inflight_Entertainment',
    ↪ 'On-board_service': 'On-board_Service',
    ↪ 'Leg_room_service': 'Leg_Room_Service',
    ↪ 'Baggage_handling': 'Baggage_Handling',
    ↪ 'Checkin_service': 'Checkin_Service',
    ↪ 'Inflight_service': 'Inflight_Service'})
df_train['Satisfaction'].replace('satisfied', 'Satisfied', inplace=True)
df_train['Satisfaction'].replace('neutral or dissatisfied',
    ↪ 'Neutral_Or_Dissatisfied', inplace=True)

df_test['Customer_Type'].replace('disloyal Customer', 'Disloyal_Customer',
    ↪ inplace=True)
df_test['Customer_Type'].replace('Loyal Customer', 'Loyal_Customer',
    ↪ inplace=True)
df_test['Type_of_Travel'].replace('Business travel', 'Business_Travel',
    ↪ inplace=True)
df_test['Type_of_Travel'].replace('Personal travel', 'Personal_Travel',
    ↪ inplace=True)

```

```

df_test = df_test.rename(columns={'satisfaction': 'Satisfaction',
                                  'Inflight_wifi_service': 'Inflight_Wifi_Service',
                                  'Departure/Arrival_time_convenient': 'Departure/Arrival_Time_Convenient',
                                  'Ease_of_Online_booking': 'Ease_of_Online_Booking',
                                  'Gate_location': 'Gate_Location',
                                  'Food_and_drink': 'Food_and_Drink',
                                  'Online_boarding': 'Online_Boarding',
                                  'Seat_comfort': 'Seat_Comfort',
                                  'Inflight_entertainment': 'Inflight_Entertainment',
                                  'On-board_service': 'On-board_Service',
                                  'Leg_room_service': 'Leg_Room_Service',
                                  'Baggage_handling': 'Baggage_Handling',
                                  'Checkin_service': 'Checkin_Service',
                                  'Inflight_service': 'Inflight_Service'})
df_test['Satisfaction'].replace('satisfied', 'Satisfied', inplace=True)
df_test['Satisfaction'].replace('neutral or dissatisfied', 'Neutral_Or_Dissatisfied', inplace=True)

display(df_train)
unstandardized_df_train = df_train.copy()

```

```

[14]:
      Gender  Customer_Type  Age  Type_of_Travel  Class \
0      Male  Loyal_Customer   13  Personal Travel  Eco Plus
1      Male  Disloyal_Customer  25  Business_Travel  Business
2      Female  Loyal_Customer   26  Business_Travel  Business
3      Female  Loyal_Customer   25  Business_Travel  Business
4      Male  Loyal_Customer   61  Business_Travel  Business
...      ...      ...      ...      ...      ...
103899  Female  Disloyal_Customer  23  Business_Travel  Eco
103900  Male  Loyal_Customer   49  Business_Travel  Business
103901  Male  Disloyal_Customer  30  Business_Travel  Business
103902  Female  Disloyal_Customer  22  Business_Travel  Eco
103903  Male  Loyal_Customer   27  Business_Travel  Business

      Flight_Distance  Inflight_Wifi_Service \
0          460          3
1          235          3
2         1142          2
3          562          2
4          214          3
...      ...      ...
103899         192          2
103900         2347         4

```

103901	1995	1
103902	1000	1
103903	1723	1

	Departure/Arrival_Time_Convenient	Ease_of_Online_Booking	\
0	4	3	
1	2	3	
2	2	2	
3	5	5	
4	3	3	
...	
103899	1	2	
103900	4	4	
103901	1	1	
103902	1	1	
103903	3	3	

	Gate_Location	...	Inflight_Entertainment	On-board_Service	\
0	1	...	5	4	
1	3	...	1	1	
2	2	...	5	4	
3	5	...	2	2	
4	3	...	3	3	
...	
103899	3	...	2	3	
103900	4	...	5	5	
103901	3	...	4	3	
103902	5	...	1	4	
103903	3	...	1	1	

	Leg_Room_Service	Baggage_Handling	Checkin_Service	Inflight_Service	\
0	3	4	4	5	
1	5	3	1	4	
2	3	4	4	4	
3	5	3	1	4	
4	4	4	3	3	
...	
103899	1	4	2	3	
103900	5	5	5	5	
103901	2	4	5	5	
103902	5	1	5	4	
103903	1	4	4	3	

	Cleanliness	Departure_Delay_in_Minutes	Arrival_Delay_in_Minutes	\
0	5	25	18.0	
1	1	1	6.0	
2	5	0	0.0	

3	2	11	9.0
4	3	0	0.0
...
103899	2	3	0.0
103900	4	0	0.0
103901	4	7	14.0
103902	1	0	0.0
103903	1	0	0.0

	Satisfaction
0	Neutral_Or_Dissatisfied
1	Neutral_Or_Dissatisfied
2	Satisfied
3	Neutral_Or_Dissatisfied
4	Satisfied
...	...
103899	Neutral_Or_Dissatisfied
103900	Satisfied
103901	Neutral_Or_Dissatisfied
103902	Neutral_Or_Dissatisfied
103903	Neutral_Or_Dissatisfied

[103904 rows x 23 columns]

4.3 Z-Score Standardization

```
[15]: # Data Standardization

scaler = StandardScaler()
numCols = df_train.select_dtypes(include=np.number).columns
df_train[numCols] = pd.DataFrame(scaler.fit_transform(df_train[numCols]),
    ↪ columns=df_train[numCols].columns)
display(df_train)

df_test[numCols] = pd.DataFrame(scaler.fit_transform(df_test[numCols]),
    ↪ columns=df_test[numCols].columns)
```

```
[15]:      Gender  Customer_Type  Age  Type_of_Travel  Class \
0      Male  Loyal_Customer -1.745279  Personal Travel  Eco Plus
1      Male  Disloyal_Customer -0.951360  Business_Travel  Business
2      Female  Loyal_Customer -0.885200  Business_Travel  Business
3      Female  Loyal_Customer -0.951360  Business_Travel  Business
4      Male  Loyal_Customer  1.430397  Business_Travel  Business
...      ...      ...      ...      ...      ...
103899  Female  Disloyal_Customer -1.083680  Business_Travel  Eco
103900  Male  Loyal_Customer  0.636478  Business_Travel  Business
103901  Male  Disloyal_Customer -0.620561  Business_Travel  Business
```

103902	Female	Disloyal_Customer	-1.149840	Business_Travel	Eco
103903	Male	Loyal_Customer	-0.819040	Business_Travel	Business

	Flight_Distance	Inflight_Wifi_Service \
0	-0.731539	0.203579
1	-0.957184	0.203579
2	-0.047584	-0.549533
3	-0.629246	-0.549533
4	-0.978244	0.203579
...
103899	-1.000307	-0.549533
103900	1.160869	0.956691
103901	0.807860	-1.302646
103902	-0.189991	-1.302646
103903	0.535081	-1.302646

	Departure/Arrival_Time_Convenient	Ease_of_Online_Booking \
0	0.616172	0.173776
1	-0.695245	0.173776
2	-0.695245	-0.541060
3	1.271880	1.603448
4	-0.039537	0.173776
...
103899	-1.350954	-0.541060
103900	0.616172	0.888612
103901	-1.350954	-1.255895
103902	-1.350954	-1.255895
103903	-0.039537	0.173776

	Gate_Location ...	Inflight_Entertainment	On-board_Service \
0	-1.547323 ...	1.231704	0.479403
1	0.018094 ...	-1.769081	-1.849161
2	-0.764614 ...	1.231704	0.479403
3	1.583511 ...	-1.018885	-1.072973
4	0.018094 ...	-0.268688	-0.296785
...
103899	0.018094 ...	-1.018885	-0.296785
103900	0.800803 ...	1.231704	1.255590
103901	0.018094 ...	0.481508	-0.296785
103902	1.583511 ...	-1.769081	0.479403
103903	0.018094 ...	-1.769081	-1.849161

	Leg_Room_Service	Baggage_Handling	Checkin_Service	Inflight_Service \
0	-0.266840	0.311769	0.549799	1.156436
1	1.253380	-0.535045	-1.821012	0.305848
2	-0.266840	0.311769	0.549799	0.305848
3	1.253380	-0.535045	-1.821012	0.305848

4	0.493270	0.311769	-0.240472	-0.544740
...
103899	-1.787061	0.311769	-1.030742	-0.544740
103900	1.253380	1.158582	1.340069	1.156436
103901	-1.026951	0.311769	1.340069	1.156436
103902	1.253380	-2.228672	1.340069	0.305848
103903	-1.787061	0.311769	0.549799	-0.544740

	Cleanliness	Departure_Delay_in_Minutes	Arrival_Delay_in_Minutes	\
0	1.305870	0.266393	0.070988	
1	-1.742292	-0.361375	-0.238223	
2	1.305870	-0.387532	-0.392828	
3	-0.980251	-0.099805	-0.160920	
4	-0.218211	-0.387532	-0.392828	
...	
103899	-0.980251	-0.309061	-0.392828	
103900	0.543829	-0.387532	-0.392828	
103901	0.543829	-0.204433	-0.032082	
103902	-1.742292	-0.387532	-0.392828	
103903	-1.742292	-0.387532	-0.392828	

	Satisfaction
0	Neutral_Or_Dissatisfied
1	Neutral_Or_Dissatisfied
2	Satisfied
3	Neutral_Or_Dissatisfied
4	Satisfied
...	...
103899	Neutral_Or_Dissatisfied
103900	Satisfied
103901	Neutral_Or_Dissatisfied
103902	Neutral_Or_Dissatisfied
103903	Neutral_Or_Dissatisfied

[103904 rows x 23 columns]

4.4 Encoding Categorical Data

4.4.1 Values in Categorical Columns

```
[16]: # All the different values for the Categorical Columns

print(df_train['Gender'].unique())
print(df_train['Customer_Type'].unique())
print(df_train['Type_of_Travel'].unique())
print(df_train['Class'].unique())
```

```
['Male' 'Female']
['Loyal_Customer' 'Disloyal_Customer']
['Personal_Travel' 'Business_Travel']
['Eco Plus' 'Business' 'Eco']
```

4.4.2 One-Hot Encoding

```
[17]: # One Hot Encoding for Categorical Features

categorical_columns = ['Gender', 'Customer_Type', 'Type_of_Travel']
ohe = OneHotEncoder(sparse_output=False)
one_hot_encoded = ohe.fit_transform(df_train[categorical_columns])
one_hot_df = pd.DataFrame(one_hot_encoded, columns=ohe.
    ↳get_feature_names_out(categorical_columns))

encoded_train = pd.concat([one_hot_df, df_train], axis=1)
encoded_train = encoded_train.drop(categorical_columns, axis=1)
display(encoded_train)

categorical_columns = ['Gender', 'Customer_Type', 'Type_of_Travel']
ohe = OneHotEncoder(sparse_output=False)
one_hot_encoded = ohe.fit_transform(df_test[categorical_columns])
one_hot_df = pd.DataFrame(one_hot_encoded, columns=ohe.
    ↳get_feature_names_out(categorical_columns))

encoded_test = pd.concat([one_hot_df, df_test], axis=1)
encoded_test = encoded_test.drop(categorical_columns, axis=1)
```

```
[17]:
```

	Gender_Female	Gender_Male	Customer_Type_Disloyal_Customer	\
0	0.0	1.0	0.0	
1	0.0	1.0	1.0	
2	1.0	0.0	0.0	
3	1.0	0.0	0.0	
4	0.0	1.0	0.0	
...	
103899	1.0	0.0	1.0	
103900	0.0	1.0	0.0	
103901	0.0	1.0	1.0	
103902	1.0	0.0	1.0	
103903	0.0	1.0	0.0	

	Customer_Type_Loyal_Customer	Type_of_Travel_Business_Travel	\
0	1.0	0.0	
1	0.0	1.0	
2	1.0	1.0	
3	1.0	1.0	
4	1.0	1.0	

...
103899	0.0	1.0
103900	1.0	1.0
103901	0.0	1.0
103902	0.0	1.0
103903	1.0	1.0

	Type_of_Travel	Personal Travel	Age	Class	Flight_Distance \
0		1.0	-1.745279	Eco Plus	-0.731539
1		0.0	-0.951360	Business	-0.957184
2		0.0	-0.885200	Business	-0.047584
3		0.0	-0.951360	Business	-0.629246
4		0.0	1.430397	Business	-0.978244
...	
103899		0.0	-1.083680	Eco	-1.000307
103900		0.0	0.636478	Business	1.160869
103901		0.0	-0.620561	Business	0.807860
103902		0.0	-1.149840	Eco	-0.189991
103903		0.0	-0.819040	Business	0.535081

	Inflight_Wifi_Service	...	Inflight_Entertainment	On-board_Service \
0	0.203579	...	1.231704	0.479403
1	0.203579	...	-1.769081	-1.849161
2	-0.549533	...	1.231704	0.479403
3	-0.549533	...	-1.018885	-1.072973
4	0.203579	...	-0.268688	-0.296785
...
103899	-0.549533	...	-1.018885	-0.296785
103900	0.956691	...	1.231704	1.255590
103901	-1.302646	...	0.481508	-0.296785
103902	-1.302646	...	-1.769081	0.479403
103903	-1.302646	...	-1.769081	-1.849161

	Leg_Room_Service	Baggage_Handling	Checkin_Service	Inflight_Service \
0	-0.266840	0.311769	0.549799	1.156436
1	1.253380	-0.535045	-1.821012	0.305848
2	-0.266840	0.311769	0.549799	0.305848
3	1.253380	-0.535045	-1.821012	0.305848
4	0.493270	0.311769	-0.240472	-0.544740
...
103899	-1.787061	0.311769	-1.030742	-0.544740
103900	1.253380	1.158582	1.340069	1.156436
103901	-1.026951	0.311769	1.340069	1.156436
103902	1.253380	-2.228672	1.340069	0.305848
103903	-1.787061	0.311769	0.549799	-0.544740

Cleanliness	Departure_Delay_in_Minutes	Arrival_Delay_in_Minutes \
-------------	----------------------------	----------------------------

0	1.305870	0.266393	0.070988
1	-1.742292	-0.361375	-0.238223
2	1.305870	-0.387532	-0.392828
3	-0.980251	-0.099805	-0.160920
4	-0.218211	-0.387532	-0.392828
...
103899	-0.980251	-0.309061	-0.392828
103900	0.543829	-0.387532	-0.392828
103901	0.543829	-0.204433	-0.032082
103902	-1.742292	-0.387532	-0.392828
103903	-1.742292	-0.387532	-0.392828

	Satisfaction
0	Neutral_Or_Dissatisfied
1	Neutral_Or_Dissatisfied
2	Satisfied
3	Neutral_Or_Dissatisfied
4	Satisfied
...	...
103899	Neutral_Or_Dissatisfied
103900	Satisfied
103901	Neutral_Or_Dissatisfied
103902	Neutral_Or_Dissatisfied
103903	Neutral_Or_Dissatisfied

[103904 rows x 26 columns]

4.4.3 Label Encoding (Ordinal Encoding)

```
[18]: # Ordinal Encoding for the Class where the order is Eco, Eco Plus, and then
      ↪ Business

enc = OrdinalEncoder(categories=[['Eco', 'Eco Plus', 'Business']])
encoded_train['Class'] = enc.fit_transform(encoded_train.loc[:, ['Class']])
enc = OrdinalEncoder(categories=[['Neutral_Or_Dissatisfied', 'Satisfied']])
encoded_train['Satisfaction'] = enc.fit_transform(encoded_train.loc[:,
      ↪, ['Satisfaction']])

display(encoded_train)

enc = OrdinalEncoder(categories=[['Eco', 'Eco Plus', 'Business']])
encoded_test['Class'] = enc.fit_transform(encoded_test.loc[:, ['Class']])
enc = OrdinalEncoder(categories=[['Neutral_Or_Dissatisfied', 'Satisfied']])
encoded_test['Satisfaction'] = enc.fit_transform(encoded_test.loc[:,
      ↪, ['Satisfaction']])
```

```

[18]:      Gender_Female  Gender_Male  Customer_Type_Disloyal_Customer  \
0              0.0          1.0                                0.0
1              0.0          1.0                                1.0
2              1.0          0.0                                0.0
3              1.0          0.0                                0.0
4              0.0          1.0                                0.0
...          ...          ...                                ...
103899         1.0          0.0                                1.0
103900         0.0          1.0                                0.0
103901         0.0          1.0                                1.0
103902         1.0          0.0                                1.0
103903         0.0          1.0                                0.0

      Customer_Type_Loyal_Customer  Type_of_Travel_Business_Travel  \
0              1.0                                0.0
1              0.0                                1.0
2              1.0                                1.0
3              1.0                                1.0
4              1.0                                1.0
...          ...                                ...
103899         0.0                                1.0
103900         1.0                                1.0
103901         0.0                                1.0
103902         0.0                                1.0
103903         1.0                                1.0

      Type_of_Travel_Personal_Travel      Age  Class  Flight_Distance  \
0              1.0 -1.745279      1.0      -0.731539
1              0.0 -0.951360      2.0      -0.957184
2              0.0 -0.885200      2.0      -0.047584
3              0.0 -0.951360      2.0      -0.629246
4              0.0  1.430397      2.0      -0.978244
...          ...          ...          ...
103899         0.0 -1.083680      0.0      -1.000307
103900         0.0  0.636478      2.0       1.160869
103901         0.0 -0.620561      2.0       0.807860
103902         0.0 -1.149840      0.0      -0.189991
103903         0.0 -0.819040      2.0       0.535081

      Inflight_Wifi_Service  ...  Inflight_Entertainment  On-board_Service  \
0              0.203579  ...              1.231704      0.479403
1              0.203579  ...             -1.769081     -1.849161
2             -0.549533  ...              1.231704      0.479403
3             -0.549533  ...             -1.018885     -1.072973
4              0.203579  ...             -0.268688     -0.296785
...          ...          ...          ...
103899         -0.549533  ...             -1.018885     -0.296785

```

103900	0.956691	...	1.231704	1.255590
103901	-1.302646	...	0.481508	-0.296785
103902	-1.302646	...	-1.769081	0.479403
103903	-1.302646	...	-1.769081	-1.849161

	Leg_Room_Service	Baggage_Handling	Checkin_Service	Inflight_Service	\
0	-0.266840	0.311769	0.549799	1.156436	
1	1.253380	-0.535045	-1.821012	0.305848	
2	-0.266840	0.311769	0.549799	0.305848	
3	1.253380	-0.535045	-1.821012	0.305848	
4	0.493270	0.311769	-0.240472	-0.544740	
...	
103899	-1.787061	0.311769	-1.030742	-0.544740	
103900	1.253380	1.158582	1.340069	1.156436	
103901	-1.026951	0.311769	1.340069	1.156436	
103902	1.253380	-2.228672	1.340069	0.305848	
103903	-1.787061	0.311769	0.549799	-0.544740	

	Cleanliness	Departure_Delay_in_Minutes	Arrival_Delay_in_Minutes	\
0	1.305870	0.266393	0.070988	
1	-1.742292	-0.361375	-0.238223	
2	1.305870	-0.387532	-0.392828	
3	-0.980251	-0.099805	-0.160920	
4	-0.218211	-0.387532	-0.392828	
...	
103899	-0.980251	-0.309061	-0.392828	
103900	0.543829	-0.387532	-0.392828	
103901	0.543829	-0.204433	-0.032082	
103902	-1.742292	-0.387532	-0.392828	
103903	-1.742292	-0.387532	-0.392828	

	Satisfaction
0	0.0
1	0.0
2	1.0
3	0.0
4	1.0
...	...
103899	0.0
103900	1.0
103901	0.0
103902	0.0
103903	0.0

[103904 rows x 26 columns]

4.4.4 Standardizing Encoded Data

```
[19]: # Standardized Encoded Data
std_encoded_train = encoded_train
std_encoded_train['Class'] = pd.Series(scaler.
    ↪fit_transform(encoded_train[['Class']]).flatten())
display(std_encoded_train)

std_encoded_test = encoded_test
std_encoded_test['Class'] = pd.Series(scaler.
    ↪fit_transform(encoded_test[['Class']]).flatten())
```

```
[19]:
```

	Gender_Female	Gender_Male	Customer_Type_Disloyal_Customer	\
0	0.0	1.0	0.0	
1	0.0	1.0	1.0	
2	1.0	0.0	0.0	
3	1.0	0.0	0.0	
4	0.0	1.0	0.0	
...	
103899	1.0	0.0	1.0	
103900	0.0	1.0	0.0	
103901	0.0	1.0	1.0	
103902	1.0	0.0	1.0	
103903	0.0	1.0	0.0	

	Customer_Type_Loyal_Customer	Type_of_Travel_Business_Travel	\
0	1.0	0.0	
1	0.0	1.0	
2	1.0	1.0	
3	1.0	1.0	
4	1.0	1.0	
...	
103899	0.0	1.0	
103900	1.0	1.0	
103901	0.0	1.0	
103902	0.0	1.0	
103903	1.0	1.0	

	Type_of_Travel_Personal_Travel	Age	Class	Flight_Distance	\
0	1.0	-1.745279	-0.029187	-0.731539	
1	0.0	-0.951360	1.009393	-0.957184	
2	0.0	-0.885200	1.009393	-0.047584	
3	0.0	-0.951360	1.009393	-0.629246	
4	0.0	1.430397	1.009393	-0.978244	
...	
103899	0.0	-1.083680	-1.067767	-1.000307	
103900	0.0	0.636478	1.009393	1.160869	

103901	0.0	-0.620561	1.009393	0.807860
103902	0.0	-1.149840	-1.067767	-0.189991
103903	0.0	-0.819040	1.009393	0.535081

	Inflight_Wifi_Service	...	Inflight_Entertainment	On-board_Service	\
0	0.203579	...	1.231704	0.479403	
1	0.203579	...	-1.769081	-1.849161	
2	-0.549533	...	1.231704	0.479403	
3	-0.549533	...	-1.018885	-1.072973	
4	0.203579	...	-0.268688	-0.296785	
...	
103899	-0.549533	...	-1.018885	-0.296785	
103900	0.956691	...	1.231704	1.255590	
103901	-1.302646	...	0.481508	-0.296785	
103902	-1.302646	...	-1.769081	0.479403	
103903	-1.302646	...	-1.769081	-1.849161	

	Leg_Room_Service	Baggage_Handling	Checkin_Service	Inflight_Service	\
0	-0.266840	0.311769	0.549799	1.156436	
1	1.253380	-0.535045	-1.821012	0.305848	
2	-0.266840	0.311769	0.549799	0.305848	
3	1.253380	-0.535045	-1.821012	0.305848	
4	0.493270	0.311769	-0.240472	-0.544740	
...	
103899	-1.787061	0.311769	-1.030742	-0.544740	
103900	1.253380	1.158582	1.340069	1.156436	
103901	-1.026951	0.311769	1.340069	1.156436	
103902	1.253380	-2.228672	1.340069	0.305848	
103903	-1.787061	0.311769	0.549799	-0.544740	

	Cleanliness	Departure_Delay_in_Minutes	Arrival_Delay_in_Minutes	\
0	1.305870	0.266393	0.070988	
1	-1.742292	-0.361375	-0.238223	
2	1.305870	-0.387532	-0.392828	
3	-0.980251	-0.099805	-0.160920	
4	-0.218211	-0.387532	-0.392828	
...	
103899	-0.980251	-0.309061	-0.392828	
103900	0.543829	-0.387532	-0.392828	
103901	0.543829	-0.204433	-0.032082	
103902	-1.742292	-0.387532	-0.392828	
103903	-1.742292	-0.387532	-0.392828	

	Satisfaction
0	0.0
1	0.0
2	1.0

3	0.0
4	1.0
...	...
103899	0.0
103900	1.0
103901	0.0
103902	0.0
103903	0.0

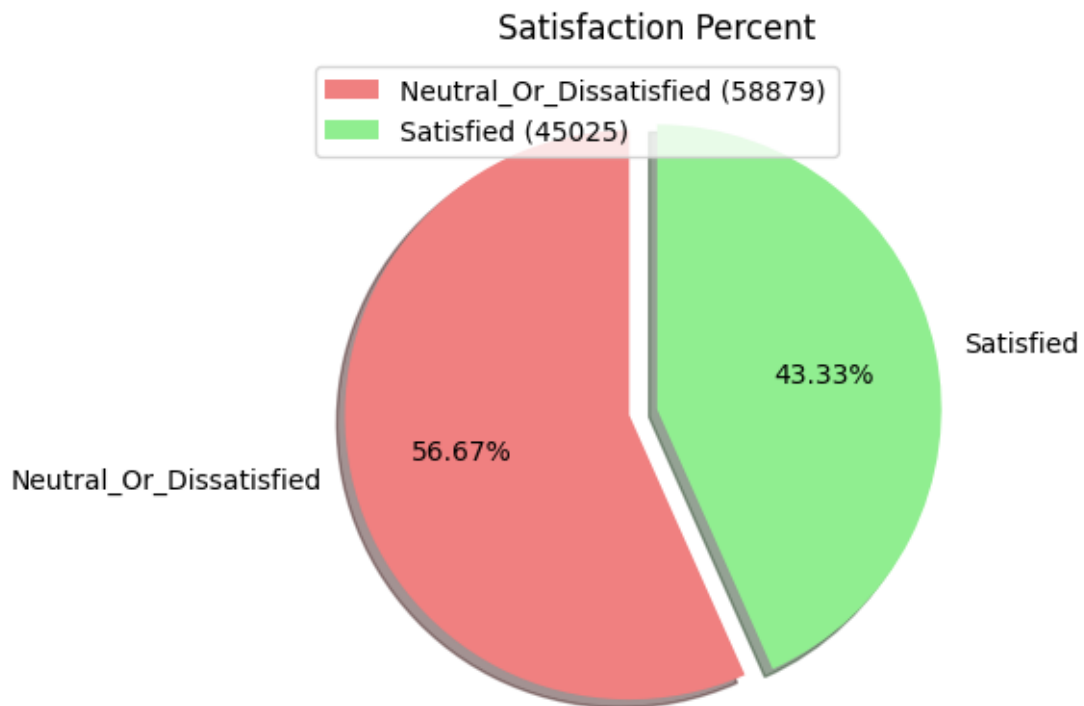
[103904 rows x 26 columns]

5 Exploratory Data Analysis

5.1 Satisfaction Percentage

```
[20]: fig, axes = plt.subplots(nrows=1, ncols=1)
axes.pie(df_train['Satisfaction'].value_counts(),
        labels=df_train['Satisfaction'].value_counts().index,
        explode=[0.1, 0],
        autopct='%1.2f%%',
        shadow=True,
        startangle=90,
        colors=["lightcoral", "lightgreen"])
axes.set_title('Satisfaction Percent')
legend_labels = [f'{label} ({count})' for label, count in
    ↪zip(df_train['Satisfaction'].value_counts().index, df_train['Satisfaction'].
    ↪value_counts())]
axes.legend(legend_labels, loc='upper left')
plt.show()
```

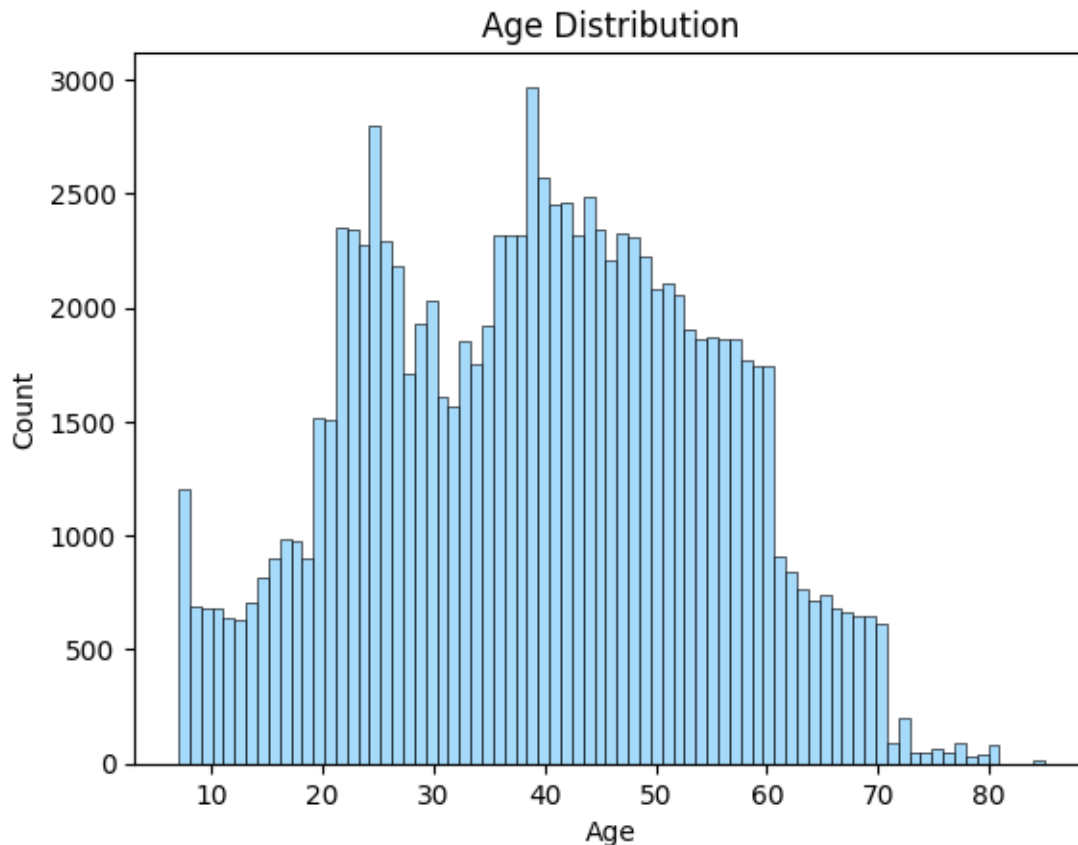
[20]:



5.2 Age Distribution

```
[21]: sns.histplot(data=unstandardized_df_train,x='Age', color="lightskyblue")  
plt.title("Age Distribution")  
plt.show()
```

[21]:



5.3 Average Satisfaction of Services

```
[22]: on_board_services = ['Inflight_Wifi_Service', 'Food_and_Drink', 'Seat_Comfort',
    ↳ 'Inflight_Entertainment',
    ↳ 'On-board_Service', 'Leg_Room_Service', 'Inflight_Service', 'Cleanliness']
average_on_ratings = unstandardized_df_train[on_board_services].mean()
average_on_ratings_df = pd.DataFrame({'On Board Service': average_on_ratings.
    ↳ index, 'Average Satisfaction Rating': average_on_ratings.values})
sns.barplot(x='On Board Service', y='Average Satisfaction Rating',
    ↳ data=average_on_ratings_df, palette='mako')
plt.xticks(rotation=45, ha='right')
plt.title('Average Satisfaction Ratings for On-board Services')
plt.show()

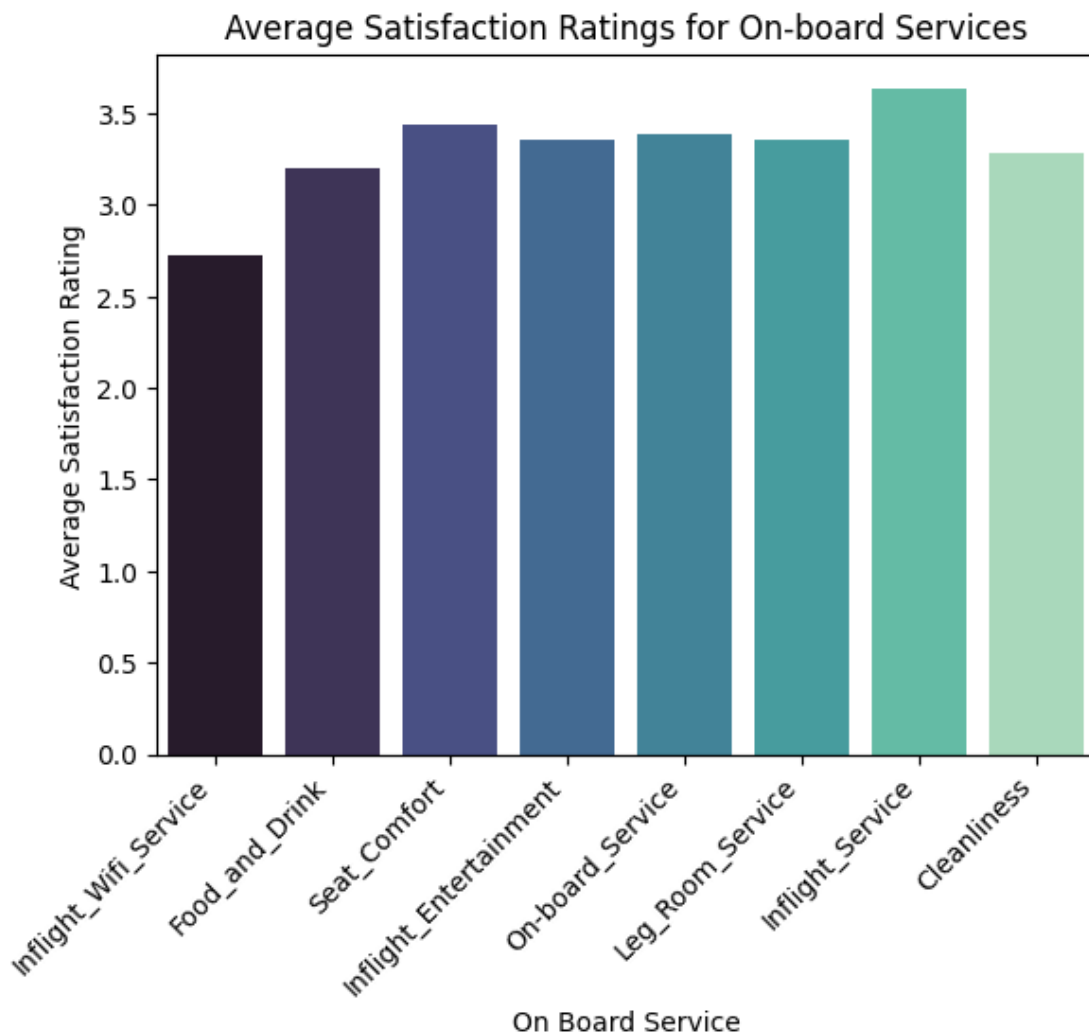
off_board_services = ['Departure/Arrival_Time_Convenient',
    ↳ 'Ease_of_Online_Booking', 'Gate_Location', 'Online_Boarding',
    ↳ 'Baggage_Handling', 'Checkin_Service']
average_off_ratings = unstandardized_df_train[off_board_services].mean()
```

```

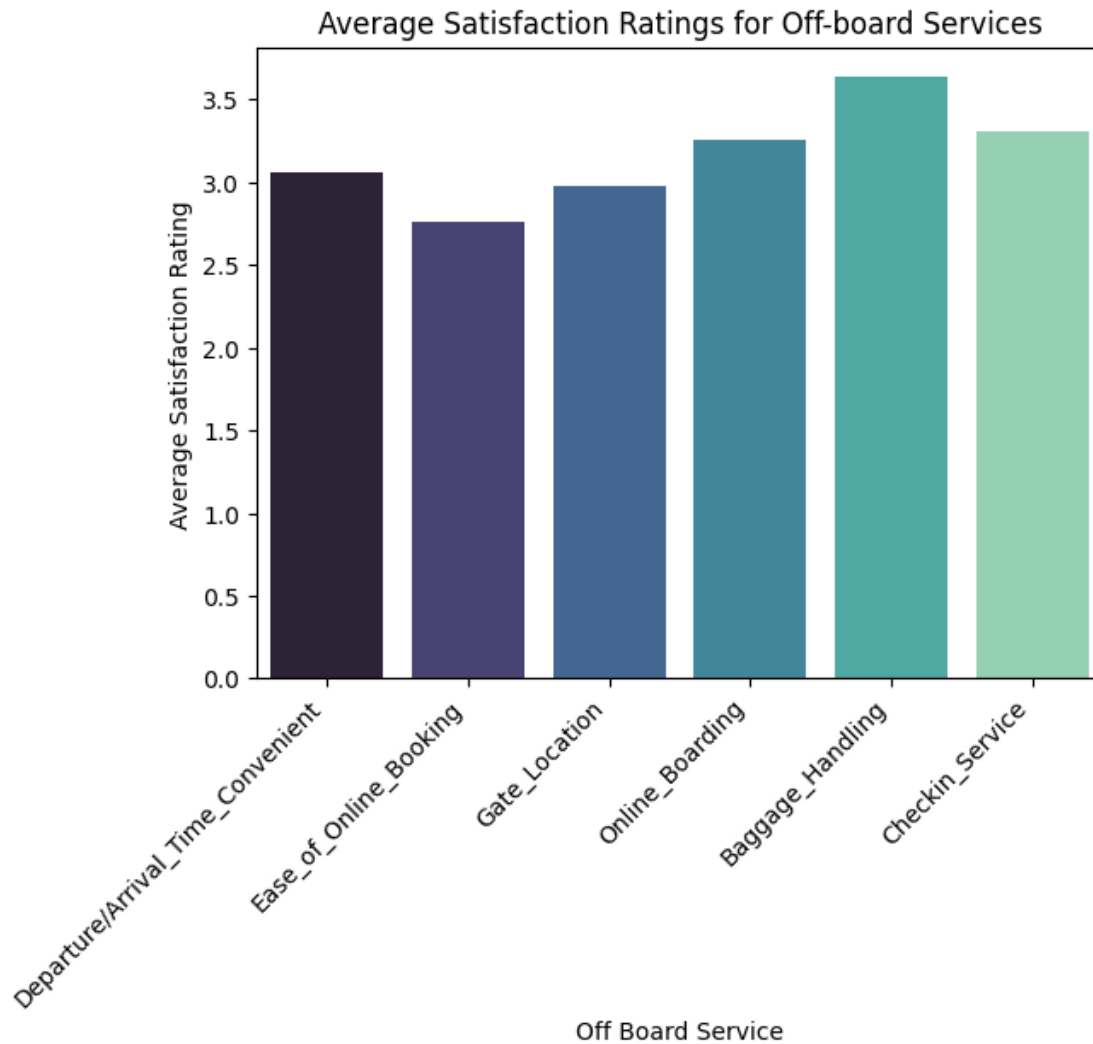
average_off_ratings_df = pd.DataFrame({'Off Board Service': average_off_ratings.
    ↳index, 'Average Satisfaction Rating': average_off_ratings.values})
sns.barplot(x='Off Board Service', y='Average Satisfaction Rating',
    ↳data=average_off_ratings_df, palette='mako')
plt.xticks(rotation=45, ha='right')
plt.title('Average Satisfaction Ratings for Off-board Services')
plt.show()

```

[22] :



[22] :



5.4 Satisfaction Distribution Based on Categorical Values

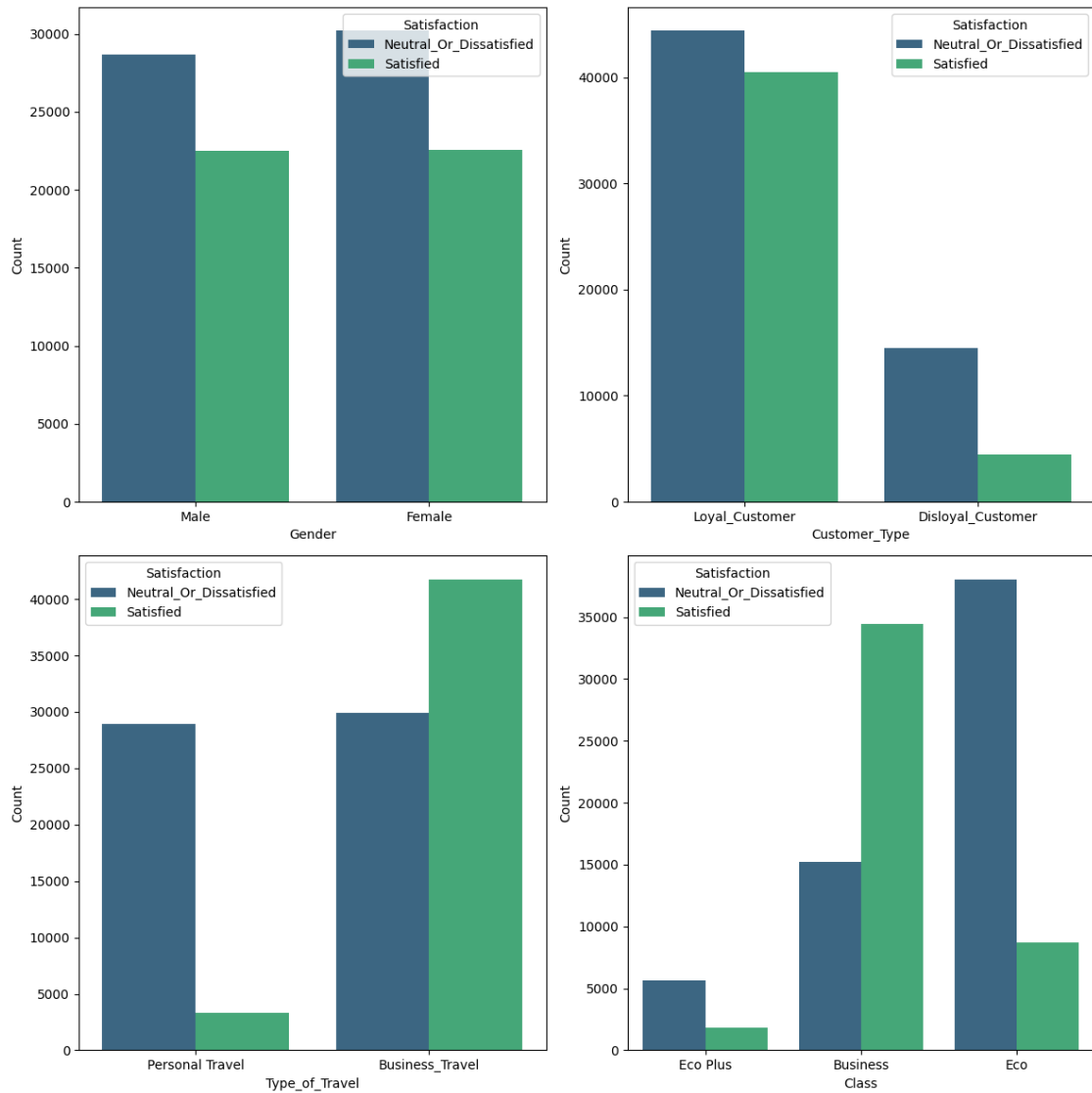
```
[23]: fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(12, 12))
data_cols = ['Gender', 'Customer_Type', 'Type_of_Travel', 'Class']

for i, col_name in enumerate(data_cols):
    row = i // 2
    col = i % 2
    sns.countplot(x=col_name, hue='Satisfaction', data=df_train, ax=axes[row, col],
                  palette='viridis')
    axes[row, col].set_xlabel(col_name)
    axes[row, col].set_ylabel('Count')

plt.tight_layout()
```

```
plt.show()
```

[23] :



5.5 Satisfaction Distribution Based on Numerical Values

```
[24]: fig, axes = plt.subplots(nrows=4, ncols=4, figsize=(25, 25))
data_cols = ['Inflight_Wifi_Service',
             'Departure/Arrival_Time_Convenient',
             'Ease_of_Online_Booking',
             'Gate_Location',
             'Food_and_Drink',
             'Online_Boarding',
             'Seat_Comfort',
             'Inflight_Entertainment',
```

```

        'On-board_Service',
        'Leg_Room_Service',
        'Baggage_Handling',
        'Checkin_Service',
        'Inflight_Service',
        'Cleanliness']

for i, col_name in enumerate(data_cols):
    row = i // 4
    col = i % 4
    sns.countplot(x=col_name, hue='Satisfaction', data=unstandardized_df_train,
→ax=axes[row, col], hue_order=["Satisfied", "Neutral_Or_Dissatisfied"],
→palette='mako')
    axes[row, col].set_xlabel(col_name)
    axes[row, col].set_ylabel('Count')
plt.tight_layout()
plt.show()

```

[24]:



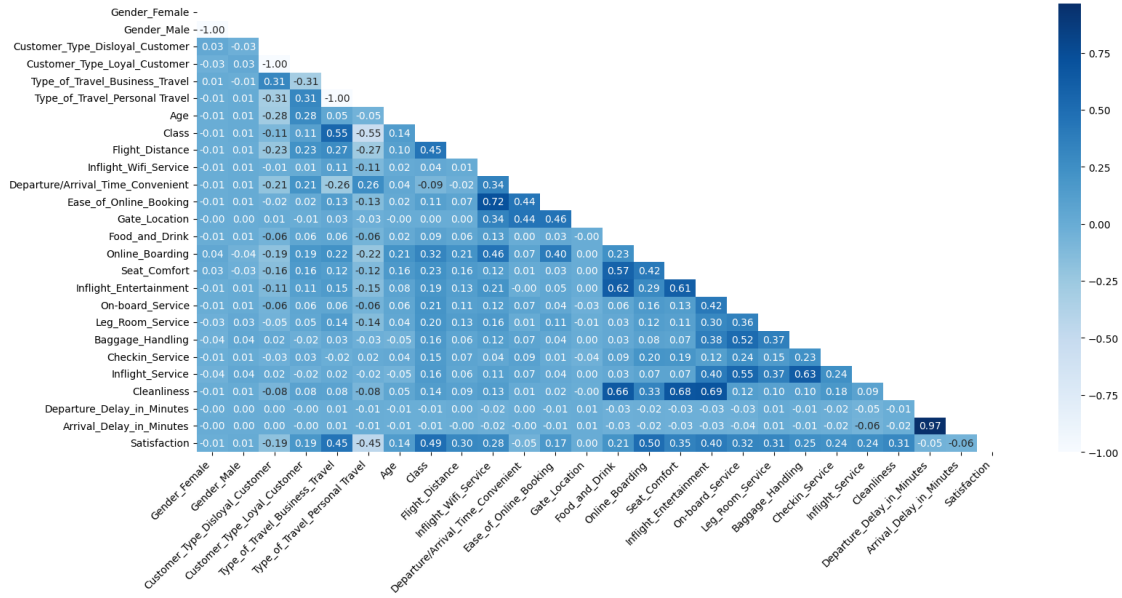
5.6 Correlation Matrix

```
[25]: plt.figure(figsize=(18,8))

corr = std_encoded_train.corr()
mask = np.triu(corr)

sns.heatmap(corr, annot=True, fmt='.2f', mask=mask, cmap="Blues")
plt.xticks(rotation=45, ha='right')
plt.show()
```

[25]:



6 Model Building

6.1 Splitting Data

```
[26]: X_train = std_encoded_train.drop('Satisfaction', axis=1)
X_test = std_encoded_test.drop('Satisfaction', axis=1)
Y_train = std_encoded_train['Satisfaction']
Y_test = std_encoded_test['Satisfaction']
```

6.2 Model Construction

```
[69]: from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import Perceptron, LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
classifiers = [("KNN", KNeighborsClassifier()),
                ("Gaussian Naive Bayes", GaussianNB()),
                ("Perceptron", Perceptron()),
                ("Logistic Regression", LogisticRegression()),
                ("Decision Trees", DecisionTreeClassifier()),
                ("Random Forest Classifier", RandomForestClassifier())]

for name, classifier in classifiers:
```

```
classifier.fit(X_train, Y_train)
```

7 Model Testing

```
[67]: from sklearn.metrics import accuracy_score, confusion_matrix

results = pd.DataFrame(columns=["Classifier", "Training Accuracy", "Testing_
→Accuracy"])

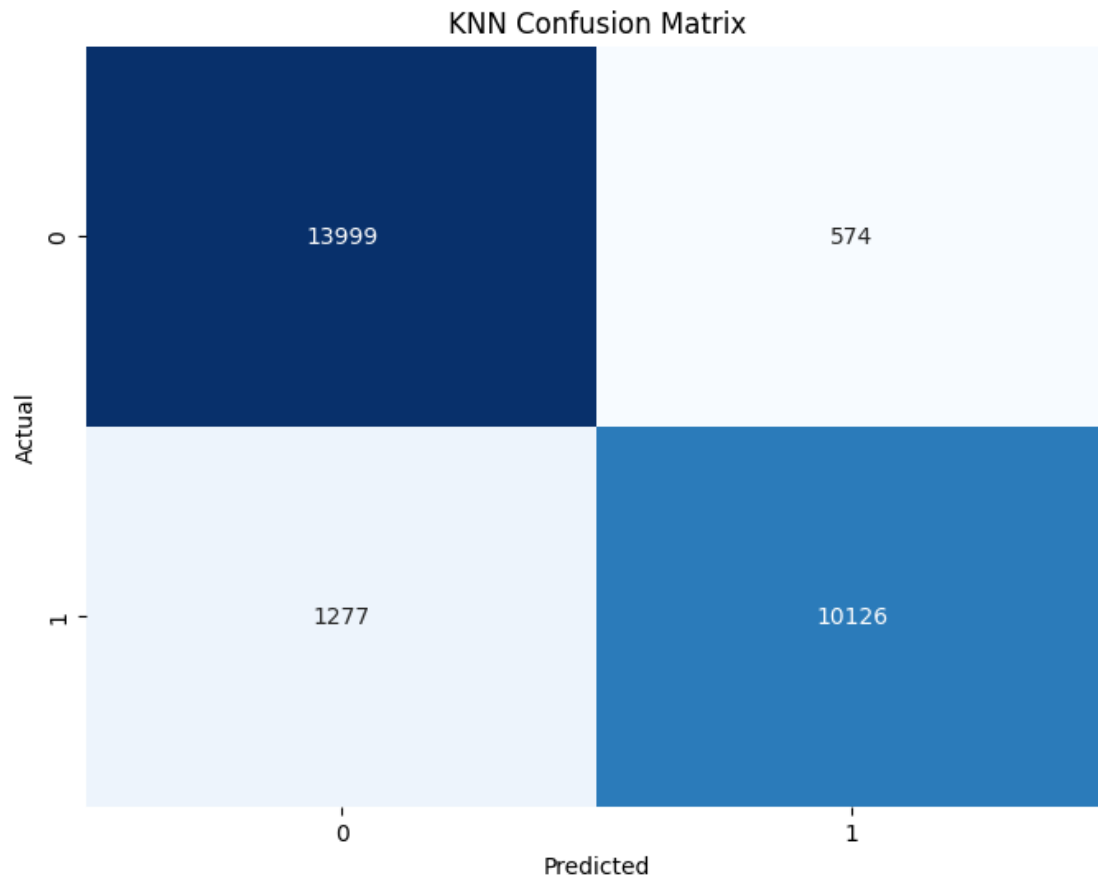
for name, classifier in classifiers:
    Y_pred_train = classifier.predict(X_train)
    Y_pred_test = classifier.predict(X_test)
    score = classifier.score(X_test, Y_test)
    train_accuracy_score = accuracy_score(Y_train, Y_pred_train)
    test_accuracy_score = accuracy_score(Y_test, Y_pred_test)
    print("Name: ", name)
    print("Training Accuracy Score: ", train_accuracy_score)
    print("Testing Accuracy Score: ", test_accuracy_score, "\n")
    data = pd.DataFrame([{"Classifier": name, "Training Accuracy":_
→train_accuracy_score, "Testing Accuracy": test_accuracy_score}])
    confusion = confusion_matrix(Y_test, Y_pred_test)
    plt.figure(figsize=(8, 6))
    sns.heatmap(confusion, annot=True, fmt="d", cmap="Blues", cbar=False)
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title(name + ' Confusion Matrix')
    plt.show()
    results = pd.concat([results, data], ignore_index=True)
```

Name: KNN

Training Accuracy Score: 0.9493763473975978

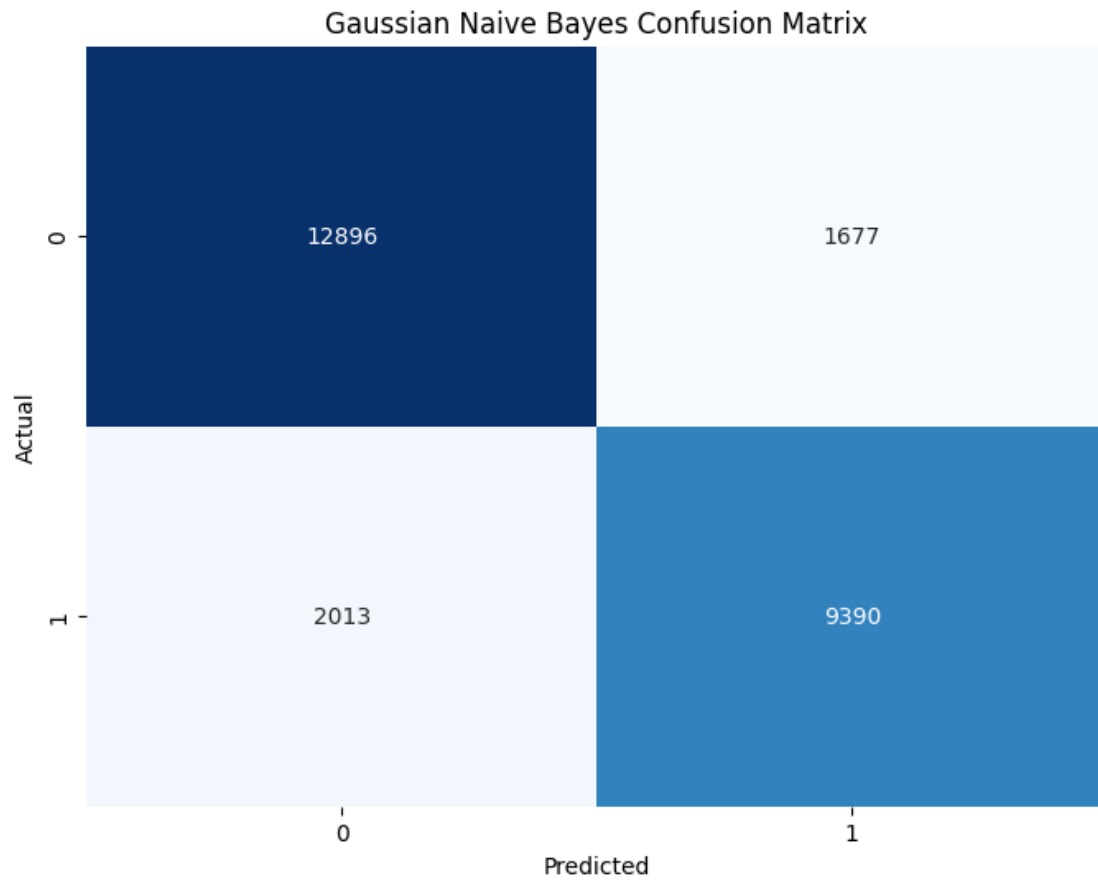
Testing Accuracy Score: 0.9287419156144133

[67]:



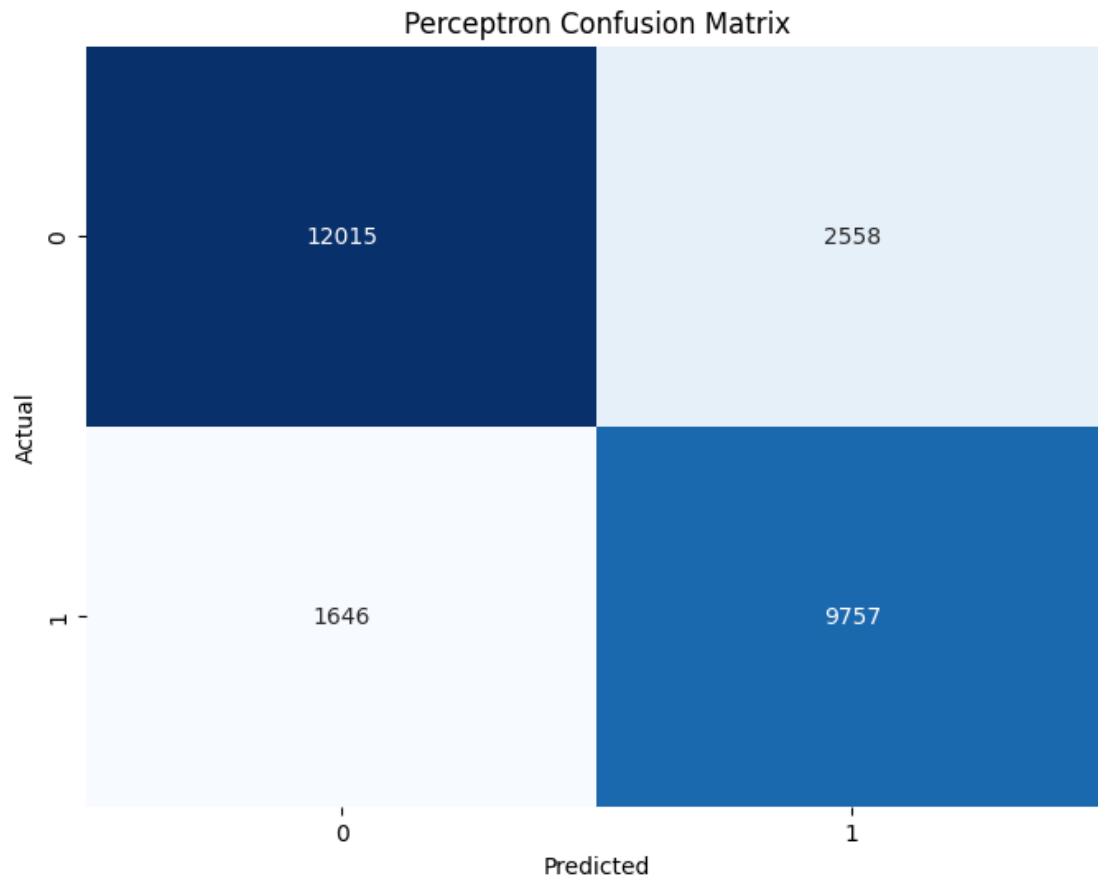
Name: Gaussian Naive Bayes
Training Accuracy Score: 0.8620072374499538
Testing Accuracy Score: 0.857945796119495

[67]:



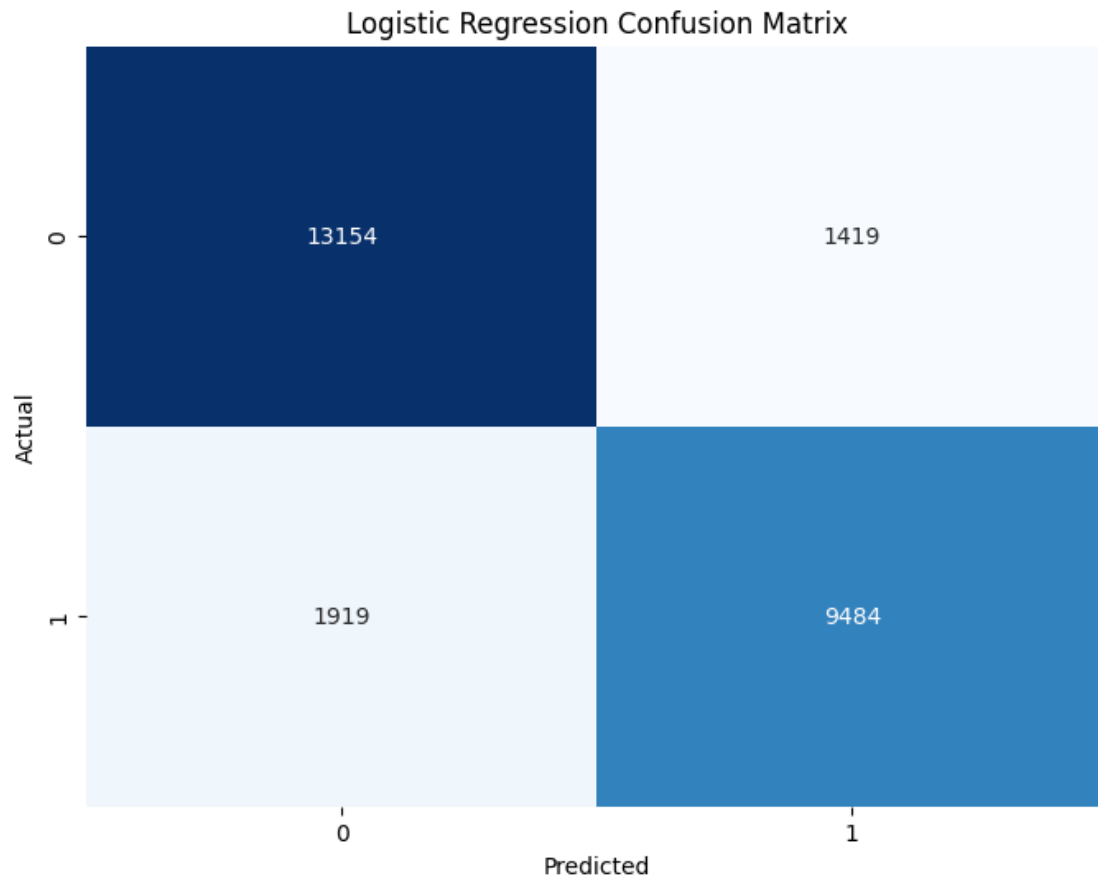
Name: Perceptron
Training Accuracy Score: 0.8347128118263012
Testing Accuracy Score: 0.8381582999692023

[67]:



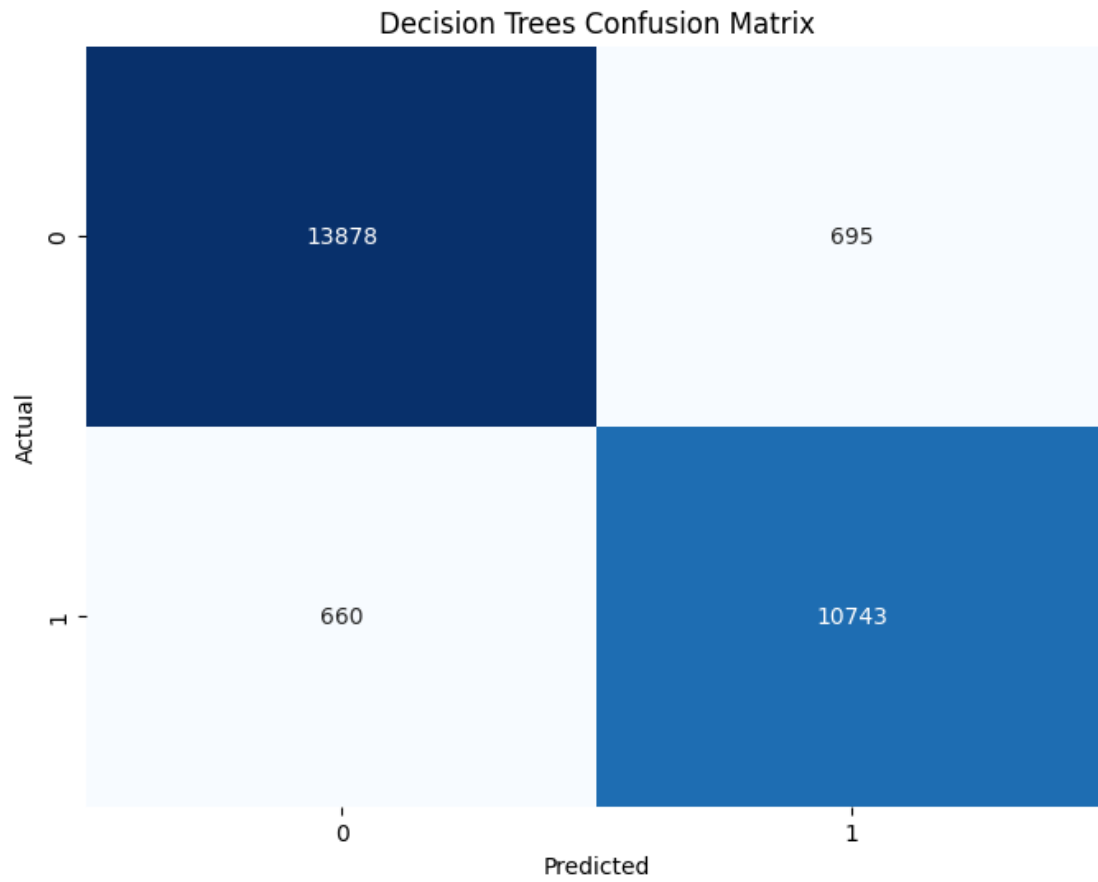
Name: Logistic Regression
Training Accuracy Score: 0.8748748845087774
Testing Accuracy Score: 0.8714967662457653

[67]:



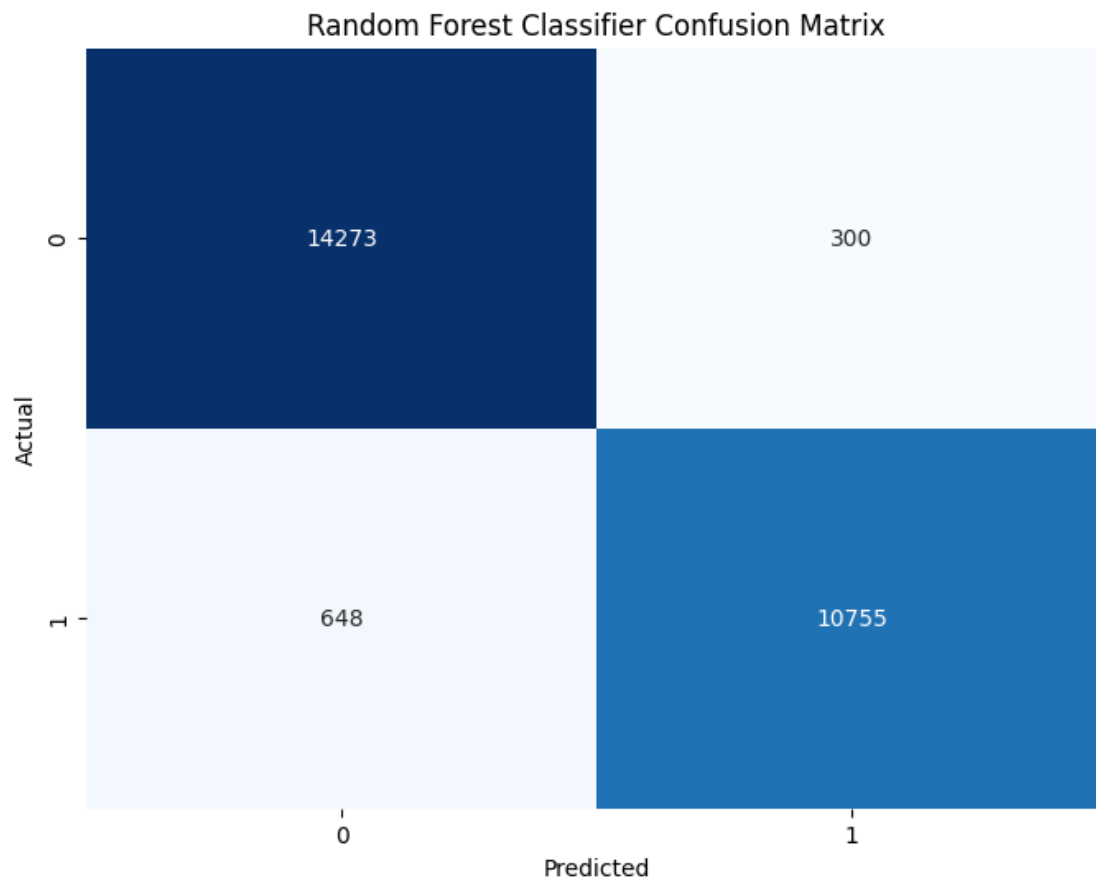
Name: Decision Trees
Training Accuracy Score: 1.0
Testing Accuracy Score: 0.9478364644287034

[67]:



Name: Random Forest Classifier
Training Accuracy Score: 1.0
Testing Accuracy Score: 0.9635047736372035

[67]:



```
[68]: %%latex
      $$Accuracy\ Score = \dfrac{TP + TN}{TP + TN + FP + FN}$$
```

[68]:

$$Accuracy\ Score = \frac{TP + TN}{TP + TN + FP + FN}$$

8 Model Comparison

```
[52]: styled_results = results.style.background_gradient(cmap='Blues',
      ↪subset=["Training Accuracy", "Testing Accuracy"])
      display(styled_results)
```

[52]: <pandas.io.formats.style.Styler at 0x7ff57d7a62f0>