

```
[29]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.metrics import classification_report, confusion_matrix
```

```
[2]: # Read the dataset
df = pd.read_csv("train.csv")
```

```
[3]: # show the head of dataset
df.head()
```

```
[3]:
```

	Unnamed: 0	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	...	Inflight entertainment	On-board service	Leg room service	Baggage handling	Checkin service	Inflight service	Cleanliness	Departure Delay in Minutes	Arrival Delay in Minutes	satisfaction
0	0	70172	Male	Loyal Customer	13	Personal Travel	Eco Plus	460	3	4	...	5	4	3	4	4	5	5	25	18.0	neutral or dissatisfied
1	1	5047	Male	disloyal Customer	25	Business travel	Business	235	3	2	...	1	1	5	3	1	4	1	1	6.0	neutral or dissatisfied
2	2	110028	Female	Loyal Customer	26	Business travel	Business	1142	2	2	...	5	4	3	4	4	4	5	0	0.0	satisfied
3	3	24026	Female	Loyal Customer	25	Business travel	Business	562	2	5	...	2	2	5	3	1	4	2	11	9.0	neutral or dissatisfied
4	4	119299	Male	Loyal Customer	61	Business travel	Business	214	3	3	...	3	3	4	4	3	3	3	0	0.0	satisfied

5 rows x 25 columns

```
[5]: # Find Null values in variables
df.isnull().sum()
```

5 rows × 25 columns

```
[5]: # Find NULL values in variables  
df.isnull().sum()
```

```
[5]: Unnamed: 0      0  
id              0  
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
```

```
[7]: # Replace null value by most value  
df["Arrival Delay in Minutes"].fillna(df["Arrival Delay in Minutes"].value_counts().idxmax(), inplace=True)
```

```
[8]: df.isnull().sum()
```

```
[8]: Unnamed: 0      0
     id            0
     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
```

```
[9]: df.shape
```

```
[9]: (103904, 25)
```

```
[10]: df.info
```

```
[10]: <bound method DataFrame.info of      Unnamed: 0      id  Gender  Customer Type  Age  Type of Travel  \
0      0      70172  Male    Loyal Customer    13  Personal Travel
1      1      5047  Male  disloyal Customer    25  Business travel
2      2     11028  Female    Loyal Customer    26  Business travel
3      3     24026  Female    Loyal Customer    25  Business travel
4      4     119299  Male    Loyal Customer    61  Business travel
...    ...    ...    ...    ...    ...    ...
103899  103899  94171  Female  disloyal Customer    23  Business travel
103900  103900  73097  Male    Loyal Customer    49  Business travel
103901  103901  68825  Male  disloyal Customer    30  Business travel
103902  103902  54173  Female  disloyal Customer    22  Business travel
103903  103903  62567  Male    Loyal Customer    27  Business travel

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


[12]: df.corr()

[12]:

	Unnamed: 0	id	Age	Flight Distance	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	Departure Delay in Minutes	Arrival Delay in Minutes
Unnamed: 0	1.000000	0.002991	0.004786	0.002794	-0.002490	0.000739	0.001913	0.005073	-0.002162	0.001002	0.000044	0.001363	0.000813	0.004052	-0.000526	-0.004321	-0.000134	-0.001117	-0.000045	-0.000063
id	0.002991	1.000000	0.022857	0.095544	-0.021276	-0.002110	0.014163	-0.000606	0.001063	0.055477	0.052903	0.002300	0.055241	0.044634	0.074940	0.079273	0.079346	0.024965	-0.019546	-0.036997
Age	0.004786	0.022857	1.000000	0.099461	0.017859	0.038125	0.024842	-0.001330	0.023000	0.208939	0.160277	0.076444	0.057594	0.040583	-0.047529	0.035482	-0.049427	0.053611	-0.010152	-0.012105
Flight Distance	0.002794	0.095544	0.099461	1.000000	0.007131	-0.020043	0.065717	0.004793	0.056994	0.214869	0.157333	0.128740	0.109526	0.133916	0.063184	0.073072	0.057540	0.093149	0.002158	-0.002470
Inflight wifi service	-0.002490	-0.021276	0.017859	0.007131	1.000000	0.343845	0.715856	0.336248	0.134718	0.456970	0.122658	0.209321	0.121500	0.160473	0.120923	0.043193	0.110441	0.132698	-0.017402	-0.019042
Departure/Arrival time convenient	0.000739	-0.002110	0.038125	-0.020043	0.343845	1.000000	0.436961	0.444757	0.004906	0.070119	0.011344	-0.004861	0.068882	0.012441	0.072126	0.093333	0.073318	0.014292	0.001005	-0.000918
Ease of Online booking	0.001913	0.014163	0.024842	0.065717	0.715856	0.436961	1.000000	0.458655	0.031873	0.404074	0.030014	0.047032	0.038833	0.107601	0.038762	0.011081	0.035272	0.016179	-0.006371	-0.007947
Gate location	0.005073	-0.000606	-0.001330	0.004793	0.336248	0.444757	0.458655	1.000000	-0.001159	0.001688	0.003669	0.003517	-0.028373	-0.005873	0.002313	-0.035427	0.001681	-0.003830	0.005467	0.005178
Food and drink	-0.002162	0.001063	0.023000	0.056994	0.134718	0.004906	0.031873	-0.001159	1.000000	0.234468	0.574556	0.622512	0.059073	0.032498	0.034746	0.087299	0.033993	0.657760	-0.029926	-0.032466
Online boarding	0.001002	0.055477	0.208939	0.214869	0.456970	0.070119	0.404074	0.001688	0.234468	1.000000	0.420211	0.285066	0.155443	0.123950	0.083280	0.204462	0.074573	0.331517	-0.018982	-0.021874
Seat comfort	0.000044	0.052903	0.160277	0.157333	0.122658	0.011344	0.030014	0.003669	0.574556	0.420211	1.000000	0.610590	0.131971	0.105559	0.074542	0.191854	0.069218	0.678534	-0.027898	-0.029735
Inflight entertainment	0.001363	0.002300	0.076444	0.128740	0.209321	-0.004861	0.047032	0.003517	0.622512	0.285066	0.610590	1.000000	0.420153	0.299692	0.378210	0.120867	0.404855	0.691815	-0.027489	-0.030597
On-board service	0.000813	0.055241	0.057594	0.109526	0.121500	0.068882	0.038833	-0.028373	0.059073	0.155443	0.131971	0.420153	1.000000	0.355495	0.519134	0.243914	0.550782	0.123220	-0.031569	-0.035089
Leg room service	0.004052	0.044634	0.040583	0.133916	0.160473	0.012441	0.107601	-0.005873	0.032498	0.123950	0.105559	0.299692	0.355495	1.000000	0.369544	0.153137	0.368656	0.096370	0.014363	0.011924
Baggage handling	-0.000526	0.074940	-0.047529	0.063184	0.120923	0.072126	0.038762	0.002313	0.034746	0.083280	0.074542	0.378210	0.519134	0.369544	1.000000	0.233122	0.628561	0.095793	-0.005573	-0.008576
Checkin service	-0.004321	0.079273	0.035482	0.073072	0.043193	0.093333	0.011081	-0.035427	0.087299	0.204462	0.191854	0.120867	0.243914	0.153137	0.233122	1.000000	0.237197	0.179583	-0.018453	-0.020324
Inflight service	-0.000134	0.079346	-0.049427	0.057540	0.110441	0.073318	0.035272	0.001681	0.033993	0.074573	0.069218	0.404855	0.550782	0.368656	0.628561	0.237197	1.000000	0.088779	-0.054813	-0.058980
Cleanliness	-0.001117	0.024965	0.053611	0.093149	0.132698	0.014292	0.016179	-0.003830	0.657760	0.331517	0.678534	0.691815	0.123220	0.096370	0.095793	0.179583	0.088779	1.000000	-0.014093	-0.015732
Departure Delay in Minutes	-0.000045	-0.019546	-0.010152	0.002158	-0.017402	0.001005	-0.006371	0.005467	-0.029926	-0.018982	-0.027898	-0.027489	-0.031569	0.014363	-0.005573	-0.018453	-0.054813	-0.014093	1.000000	0.960247
Arrival Delay in Minutes	-0.000063	-0.036997	-0.012105	-0.002470	-0.019042	-0.000918	-0.007947	0.005178	-0.032466	-0.021874	-0.029735	-0.030597	-0.035089	0.011924	-0.008576	-0.020324	-0.058980	-0.015732	0.960247	1.000000

```
[16]: # Find null values in variables
df.isnull().sum()
```

```
[16]: Unnamed: 0      0
id              0
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
```

```
[18]: #Label_encoder
label_encoder = preprocessing.LabelEncoder()
df['Age'] = label_encoder.fit_transform(df['Age'])
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['Flight Distance'] = label_encoder.fit_transform(df['Flight Distance'])
df['Inflight wifi service'] = label_encoder.fit_transform(df['Inflight wifi service'])
df['Departure/Arrival time convenient'] = label_encoder.fit_transform(df['Departure/Arrival time convenient'])
df['Ease of Online booking'] = label_encoder.fit_transform(df['Ease of Online booking'])
df['Gate location'] = label_encoder.fit_transform(df['Gate location'])
df['Food and drink'] = label_encoder.fit_transform(df['Food and drink'])
df['Online boarding'] = label_encoder.fit_transform(df['Online boarding'])
df['Seat comfort'] = label_encoder.fit_transform(df['Seat comfort'])
df['Inflight entertainment'] = label_encoder.fit_transform(df['Inflight entertainment'])
df['On-board service'] = label_encoder.fit_transform(df['On-board service'])
df['Leg room service'] = label_encoder.fit_transform(df['Leg room service'])
df['Baggage handling'] = label_encoder.fit_transform(df['Baggage handling'])
df['Checkin service'] = label_encoder.fit_transform(df['Checkin service'])
df['Inflight service'] = label_encoder.fit_transform(df['Inflight service'])
df['Cleanliness'] = label_encoder.fit_transform(df['Cleanliness'])
df['Departure Delay in Minutes'] = label_encoder.fit_transform(df['Departure Delay in Minutes'])
df['Arrival Delay in Minutes'] = label_encoder.fit_transform(df['Arrival Delay in Minutes'])
df['satisfaction'] = label_encoder.fit_transform(df['satisfaction'])
```

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

```
[19]:
```

	Unnamed: 0	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	...	Inflight entertainment	On-board service	Leg room service	Baggage handling	Checkin service	Inflight service	Cleanliness	Departure Delay in Minutes	Arrival Delay in Minutes	satisfaction
0	0	70172	1	0	6	1	2	358	3	4	...	5	4	3	3	4	5	5	25	18	0
1	1	5047	1	1	18	0	0	144	3	2	...	1	1	5	2	1	4	1	1	6	0
2	2	110028	0	0	19	0	0	994	2	2	...	5	4	3	3	4	4	5	0	0	1
3	3	24026	0	0	18	0	0	446	2	5	...	2	2	5	2	1	4	2	11	9	0
4	4	119299	1	0	54	0	0	124	3	3	...	3	3	4	3	3	3	3	0	0	1

5 rows × 25 columns

```
[22]: X = df.drop('satisfaction', 1)
y = df.satisfaction
```

```
[23]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=2)
```

```
[25]: logicRegression_model = LogisticRegression()
logicRegression_model.fit(X_train, y_train)
```

```
[25]: LogisticRegression()
```

```
[26]: pred = logicRegression_model.predict(X_test)
```

```
[27]: pred
```

```
[27]: array([1, 0, 0, ..., 0, 0, 0])
```

```
[28]: #comparision
a = pd.DataFrame({'Actual value': y_test, 'Predicted value':pred})
a.head()
```

```
[28]:
```

	Actual value	Predicted value
18981	1	1
4555	0	0
44022	0	0
84411	0	0
91989	1	0

```
[30]: # Evaluation model
EvalMatrix = confusion_matrix(y_test, pred)
sns.heatmap(EvalMatrix, annot=True, fmt="d")
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
print(classification_report(y_test, pred))
```

	precision	recall	f1-score	support
0	0.65	0.78	0.71	11764
1	0.61	0.45	0.52	9017
accuracy			0.64	20781
macro avg	0.63	0.61	0.61	20781
weighted avg	0.63	0.64	0.63	20781

