Backgroung Story

Invistico is one of the Airlines' company who wants to span their wings further in airline industries. Invistico is aware that Service quality will build a brand, which results in Customer Satisfaction and Customer Loyalty. Invistico needs a Business Recommendations and insights to Retain their Customers without excessive costs for the required Business Idea.

Problem Statement

The main purpose of this dataset is to predict whether a future customer would be satisfied with their service given the details of the other parameters values.

Also the airlines need to know on which aspect of the services offered by them have to be emphasized more to generate more satisfied customers.

In [1]:

```
import warnings
warnings.filterwarnings('ignore')
from sklearn.preprocessing import LabelEncoder
import pandas as pd, numpy as np, matplotlib.pyplot as plt, seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

In [2]:

```
flight=pd.read_csv('C:/Users/Dell/Downloads/Invistico_Airline.csv')
```

In [3]:

```
flight.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 129880 entries, 0 to 129879
Data columns (total 23 columns):
 #   Column                             Non-Null Count   Dtype  
---  ------                             --------------   -----  
 0   satisfaction                       129880 non-null  object 
 1   Gender                             129880 non-null  object 
 2   Customer Type                      129880 non-null  object 
 3   Age                                129880 non-null  int64  
 4   Type of Travel                     129880 non-null  object 
 5   Class                              129880 non-null  object 
 6   Flight Distance                    129880 non-null  int64  
 7   Seat comfort                       129880 non-null  int64  
 8   Departure/Arrival time convenient  129880 non-null  int64  
 9   Food and drink                     129880 non-null  int64  
 10  Gate location                      129880 non-null  int64  
 11  Inflight wifi service              129880 non-null  int64  
 12  Inflight entertainment             129880 non-null  int64  
 13  Online support                     129880 non-null  int64  
 14  Ease of Online booking             129880 non-null  int64  
 15  On-board service                   129880 non-null  int64  
 16  Leg room service                   129880 non-null  int64  
 17  Baggage handling                   129880 non-null  int64  
 18  Checkin service                    129880 non-null  int64  
 19  Cleanliness                        129880 non-null  int64  
 20  Online boarding                    129880 non-null  int64  
 21  Departure Delay in Minutes         129880 non-null  int64  
 22  Arrival Delay in Minutes           129487 non-null  float64
```

```
dtypes: float64(1), int64(17), object(5)
memory usage: 22.8+ MB
```

In [4]:

```
flight.head(n=20)
```

Out[4]:

	satisfaction	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Seat comfort	Departure/Arrival time convenient
0	satisfied	Female	Loyal Customer	65	Personal Travel	Eco	265	0	0
1	satisfied	Male	Loyal Customer	47	Personal Travel	Business	2464	0	0
2	satisfied	Female	Loyal Customer	15	Personal Travel	Eco	2138	0	0
3	satisfied	Female	Loyal Customer	60	Personal Travel	Eco	623	0	0
4	satisfied	Female	Loyal Customer	70	Personal Travel	Eco	354	0	0
5	satisfied	Male	Loyal Customer	30	Personal Travel	Eco	1894	0	0
6	satisfied	Female	Loyal Customer	66	Personal Travel	Eco	227	0	0
7	satisfied	Male	Loyal Customer	10	Personal Travel	Eco	1812	0	0
8	satisfied	Female	Loyal Customer	56	Personal Travel	Business	73	0	0
9	satisfied	Male	Loyal Customer	22	Personal Travel	Eco	1556	0	0
10	satisfied	Female	Loyal Customer	58	Personal Travel	Eco	104	0	0
11	satisfied	Female	Loyal Customer	34	Personal Travel	Eco	3633	0	0
12	satisfied	Male	Loyal Customer	62	Personal Travel	Eco	1695	0	0
13	satisfied	Male	Loyal Customer	35	Personal Travel	Eco	1766	0	1
14	satisfied	Female	Loyal Customer	47	Personal Travel	Eco	84	0	1
15	satisfied	Male	Loyal Customer	60	Personal Travel	Eco	1373	0	1
16	satisfied	Female	Loyal Customer	13	Personal Travel	Eco	3693	0	1
17	satisfied	Female	Loyal Customer	52	Personal Travel	Business	2610	0	1
18	satisfied	Female	Loyal Customer	55	Personal Travel	Eco	2554	0	1
19	satisfied	Female	Loyal Customer	28	Personal Travel	Eco	3095	0	1

20 rows × 23 columns

In [5]:
```
flight['Seat comfort'].value_counts()
```

Out[5]:
```
3    29183
2    28726
4    28398
1    20949
5    17827
0     4797
Name: Seat comfort, dtype: int64
```

In [6]:
```
flight.describe()
```

Out[6]:

	Age	Flight Distance	Seat comfort	Departure/Arrival time convenient	Food and drink	Gate locatio
count	129880.000000	129880.000000	129880.000000	129880.000000	129880.000000	129880.00000
mean	39.427957	1981.409055	2.838597	2.990645	2.851994	2.99042
std	15.119360	1027.115606	1.392983	1.527224	1.443729	1.30597
min	7.000000	50.000000	0.000000	0.000000	0.000000	0.00000
25%	27.000000	1359.000000	2.000000	2.000000	2.000000	2.00000
50%	40.000000	1925.000000	3.000000	3.000000	3.000000	3.00000
75%	51.000000	2544.000000	4.000000	4.000000	4.000000	4.00000
max	85.000000	6951.000000	5.000000	5.000000	5.000000	5.00000

In [7]:
```
flight.describe(include=object)
```

Out[7]:

	satisfaction	Gender	Customer Type	Type of Travel	Class
count	129880	129880	129880	129880	129880
unique	2	2	2	2	3
top	satisfied	Female	Loyal Customer	Business travel	Business
freq	71087	65899	106100	89693	62160

In [8]:
```
flight.isnull().sum()
```

Out[8]:
```
satisfaction                         0
Gender                               0
Customer Type                        0
Age                                  0
Type of Travel                       0
Class                                0
Flight Distance                      0
Seat comfort                         0
Departure/Arrival time convenient    0
Food and drink                       0
Gate location                        0
```

```
Inflight wifi service                0
Inflight entertainment               0
Online support                       0
Ease of Online booking               0
On-board service                     0
Leg room service                     0
Baggage handling                     0
Checkin service                      0
Cleanliness                          0
Online boarding                      0
Departure Delay in Minutes           0
Arrival Delay in Minutes           393
dtype: int64
```

In [9]:

```
#data cleaning and preprocessing
flight.fillna(flight['Arrival Delay in Minutes'].mean(), inplace=True)
flight.isnull().sum()
```

Out[9]:

```
satisfaction                         0
Gender                               0
Customer Type                        0
Age                                  0
Type of Travel                       0
Class                                0
Flight Distance                      0
Seat comfort                         0
Departure/Arrival time convenient    0
Food and drink                       0
Gate location                        0
Inflight wifi service                0
Inflight entertainment               0
Online support                       0
Ease of Online booking               0
On-board service                     0
Leg room service                     0
Baggage handling                     0
Checkin service                      0
Cleanliness                          0
Online boarding                      0
Departure Delay in Minutes           0
Arrival Delay in Minutes             0
dtype: int64
```

In [10]:

```
flight.shape
```

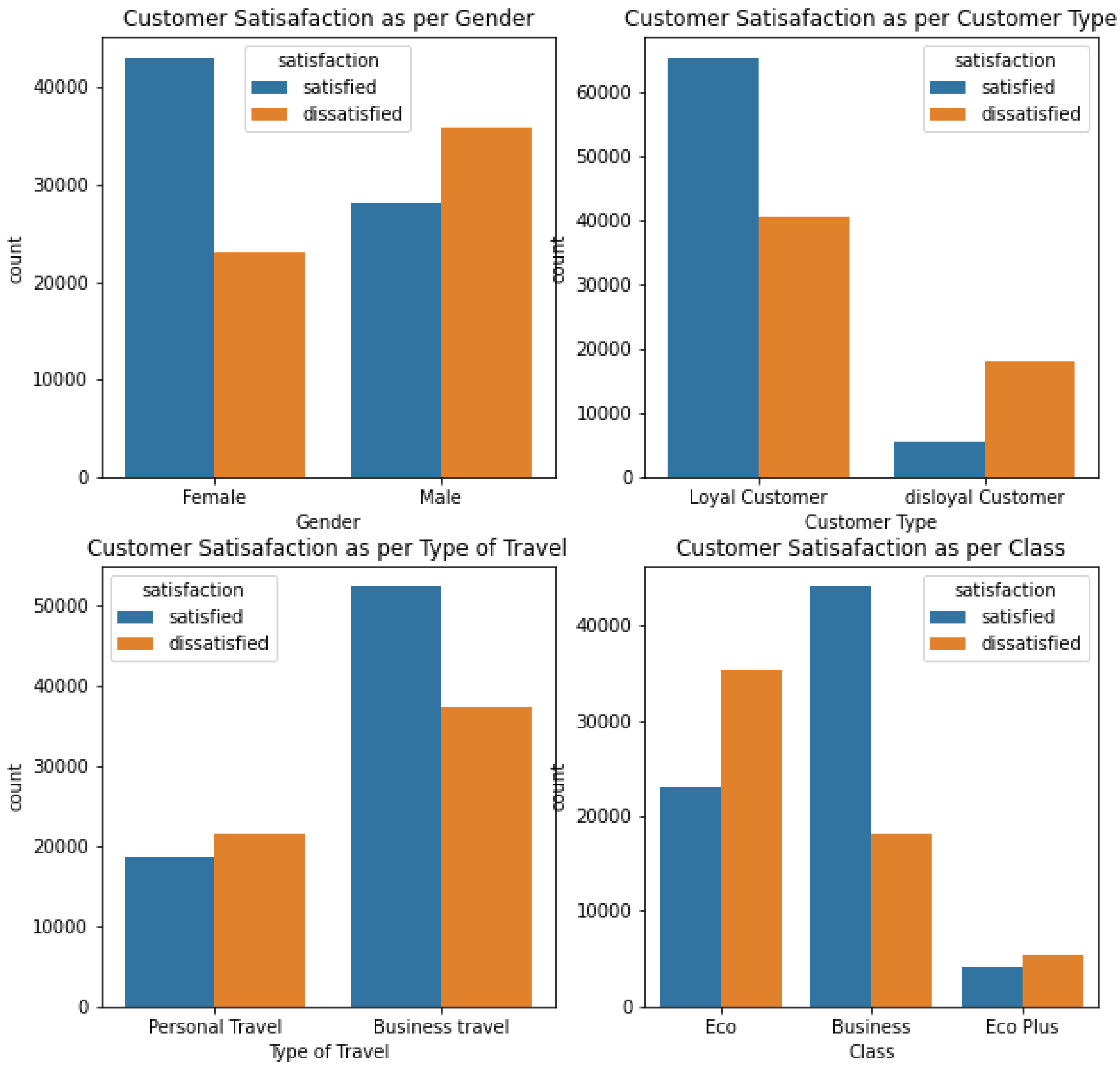
Out[10]:

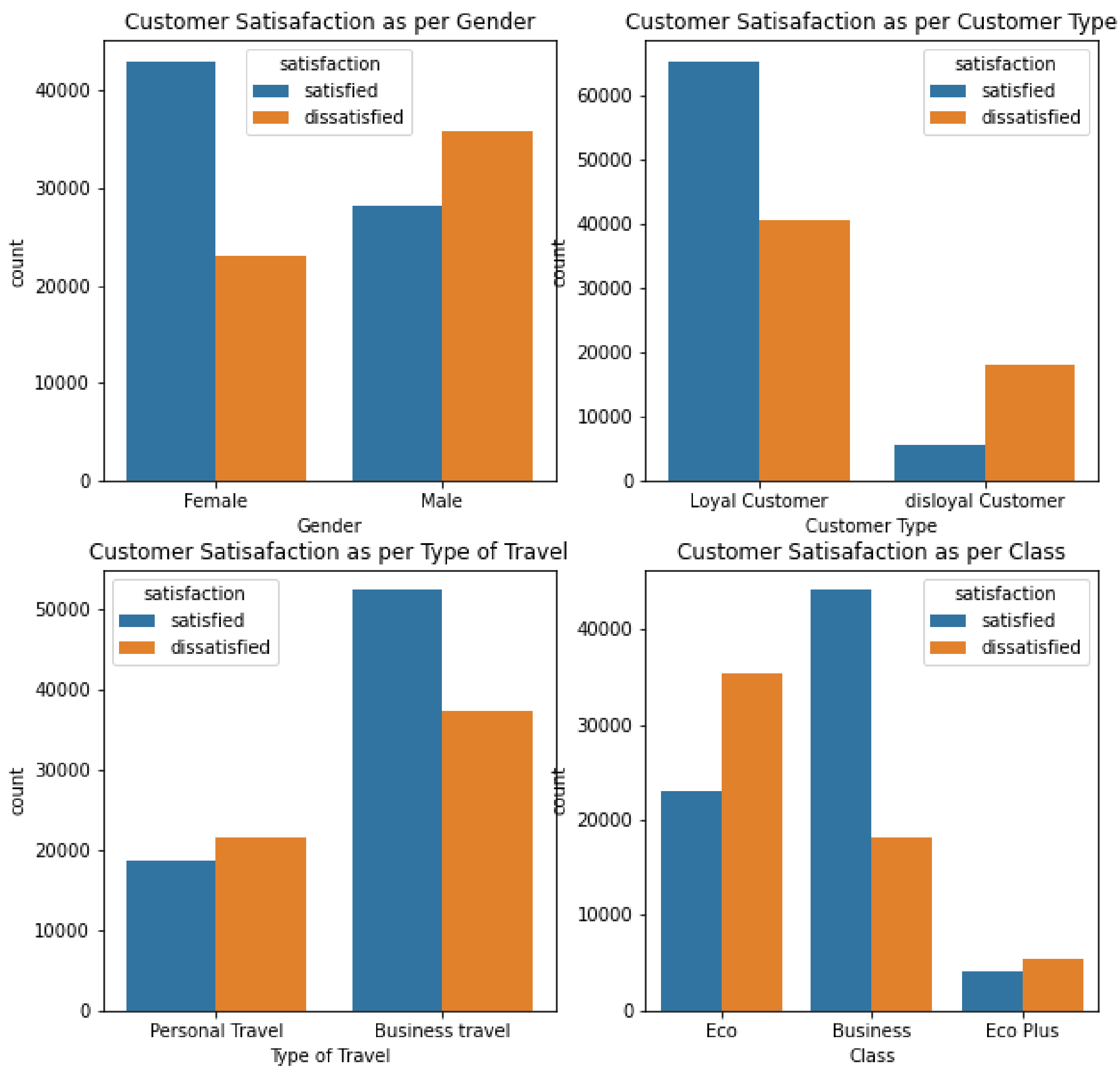
```
(129880, 23)
```

In [11]:

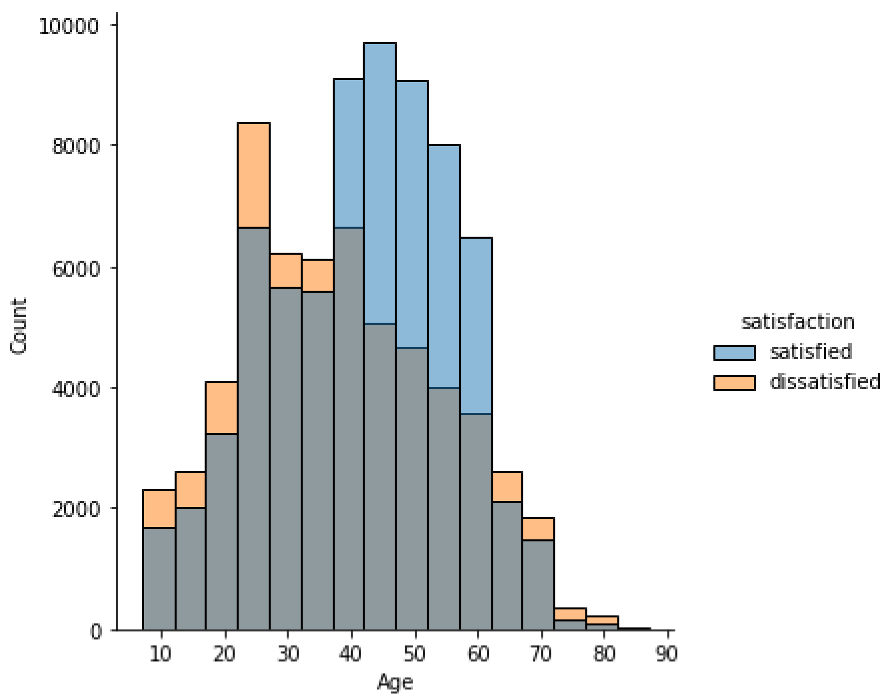
```
#EDA
fig,axs = plt.subplots(2,2,figsize=(10, 10))
cols=['Gender', 'Customer Type', 'Type of Travel', 'Class']
c=0
for i in range(2):
  for j in range(2):
    sns.countplot(data=flight,x=cols[c],hue='satisfaction',ax=axs[i][j])
    axs[i][j].set_title('\nCustomer Satisafaction as per {}'.format(cols[c]))
    c+=1
#EDA
fig,axs = plt.subplots(2,2,figsize=(10, 10))
cols=['Gender', 'Customer Type', 'Type of Travel', 'Class']
c=0
for i in range(2):
  for j in range(2):
    sns.countplot(data=flight,x=cols[c],hue='satisfaction',ax=axs[i][j])
```

```
    axs[i][j].set_title('\nCustomer Satisafaction as per {}'.format(cols[c]))
    c+=1
```





In [13]:
```
sns.displot(flight,x='Age',binwidth=5,hue='satisfaction')
plt.show()
```



Countplot and distributionplot conclusions :

```
Female Customers have higher satisfaction than Male Customers.
Loyal Customers have higher satisfaction than Disloyal Customers.
Business Travel has higher customer satisfaction than Personal Travel.
Business Class has the highest satisfaction between the 3 airlines
classes.
Customers of age group between 40 to 60 are more satisfied than
customers of other age group.
```

In [14]:

```
print("Gender:",flight['Gender'].unique())
print("Customer Type:",flight['Customer Type'].unique())
print("Type of Travel:",flight['Type of Travel'].unique())
print("class:",flight['Class'].unique())
print("satisfaction:",flight['satisfaction'].unique())

le=LabelEncoder()
flight['Gender']= le.fit_transform(flight['Gender'])
flight['Customer Type']= le.fit_transform(flight['Customer Type'])
flight['Type of Travel']= le.fit_transform(flight['Type of Travel'])
flight['Class']= le.fit_transform(flight['Class'])
flight['satisfaction']= le.fit_transform(flight['satisfaction'])

print("\nGender:",flight['Gender'].unique())
print("Customer Type:",flight['Customer Type'].unique())
print("Type of Travel:",flight['Type of Travel'].unique())
print("class:",flight['Class'].unique())
print("satisfaction:",flight['satisfaction'].unique())
```

```
Gender: ['Female' 'Male']
Customer Type: ['Loyal Customer' 'disloyal Customer']
Type of Travel: ['Personal Travel' 'Business travel']
class: ['Eco' 'Business' 'Eco Plus']
satisfaction: ['satisfied' 'dissatisfied']

Gender: [0 1]
Customer Type: [0 1]
Type of Travel: [1 0]
class: [1 0 2]
satisfaction: [1 0]
```

In [15]:

```
temp1 = flight.drop('satisfaction',axis=1)
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif_data = pd.DataFrame()
vif_data["feature"] = temp1.columns
vif_data["VIF"] = [variance_inflation_factor(temp1.values, i) for i in range(len(tem
vif_data
```

Out[15]:

	feature	VIF
0	Gender	2.036589
1	Customer Type	1.653533
2	Age	7.429683
3	Type of Travel	2.449458
4	Class	2.688083
5	Flight Distance	4.627909

	feature	VIF
6	Seat comfort	12.608373
7	Departure/Arrival time convenient	8.948996
8	Food and drink	13.520578
9	Gate location	10.201175
10	Inflight wifi service	13.895590
11	Inflight entertainment	13.717571
12	Online support	19.208906
13	Ease of Online booking	30.323385
14	On-board service	15.016947
15	Leg room service	11.260297
16	Baggage handling	21.324000
17	Checkin service	9.650491
18	Cleanliness	22.757016
19	Online boarding	20.723853
20	Departure Delay in Minutes	14.794080
21	Arrival Delay in Minutes	14.855233

In [16]:

```
flight=flight.drop(['Ease of Online booking','Cleanliness','Baggage handling'],axis=
```

In [17]:

```
temp1 = flight.drop('satisfaction',axis=1)
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif_data = pd.DataFrame()
vif_data["feature"] = temp1.columns
vif_data["VIF"] = [variance_inflation_factor(temp1.values, i) for i in range(len(tem
vif_data
```

Out[17]:

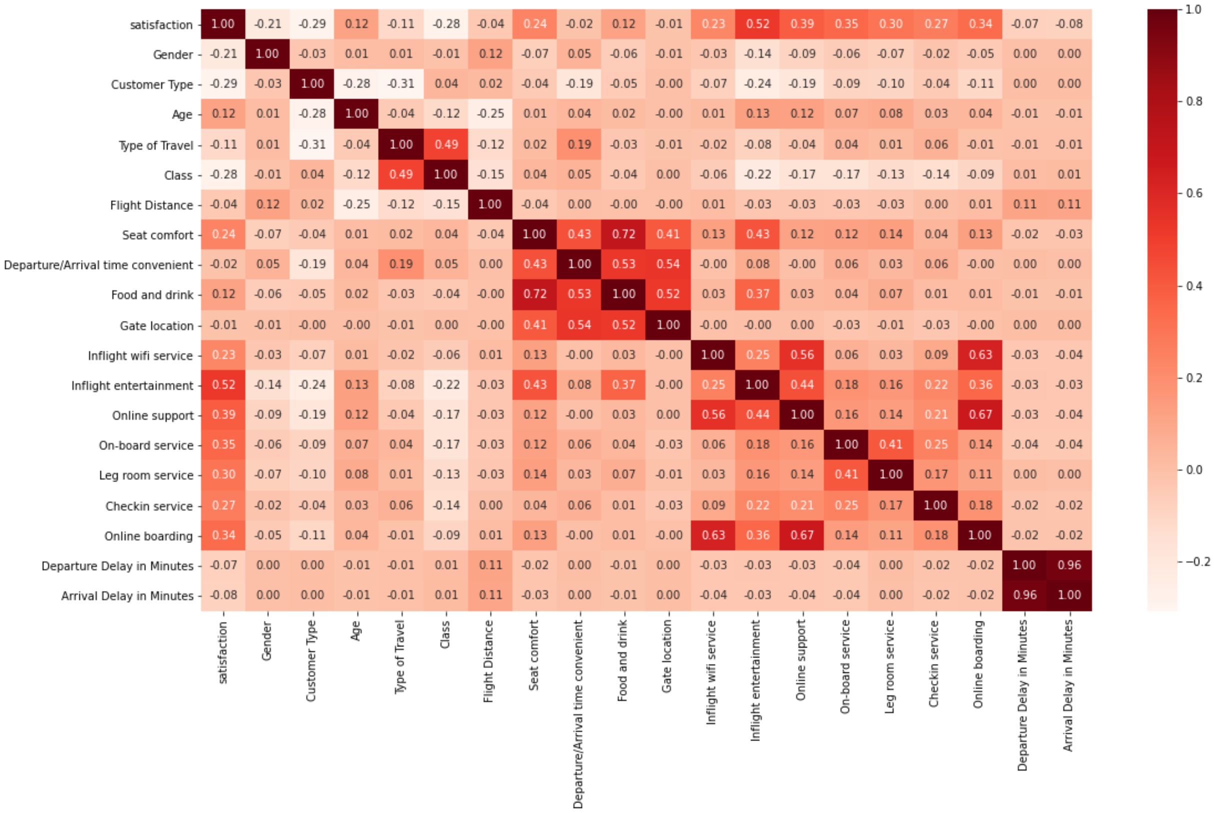
	feature	VIF
0	Gender	2.017812
1	Customer Type	1.544313
2	Age	7.352765
3	Type of Travel	2.390263
4	Class	2.687377
5	Flight Distance	4.494592
6	Seat comfort	12.261149
7	Departure/Arrival time convenient	8.861109
8	Food and drink	13.459679
9	Gate location	10.163144
10	Inflight wifi service	12.389819

	feature	VIF
11	Inflight entertainment	13.510408
12	Online support	18.136855
13	On-board service	10.564317
14	Leg room service	9.818189
15	Checkin service	8.996323
16	Online boarding	17.320791
17	Departure Delay in Minutes	14.793549
18	Arrival Delay in Minutes	14.852089

In [18]:

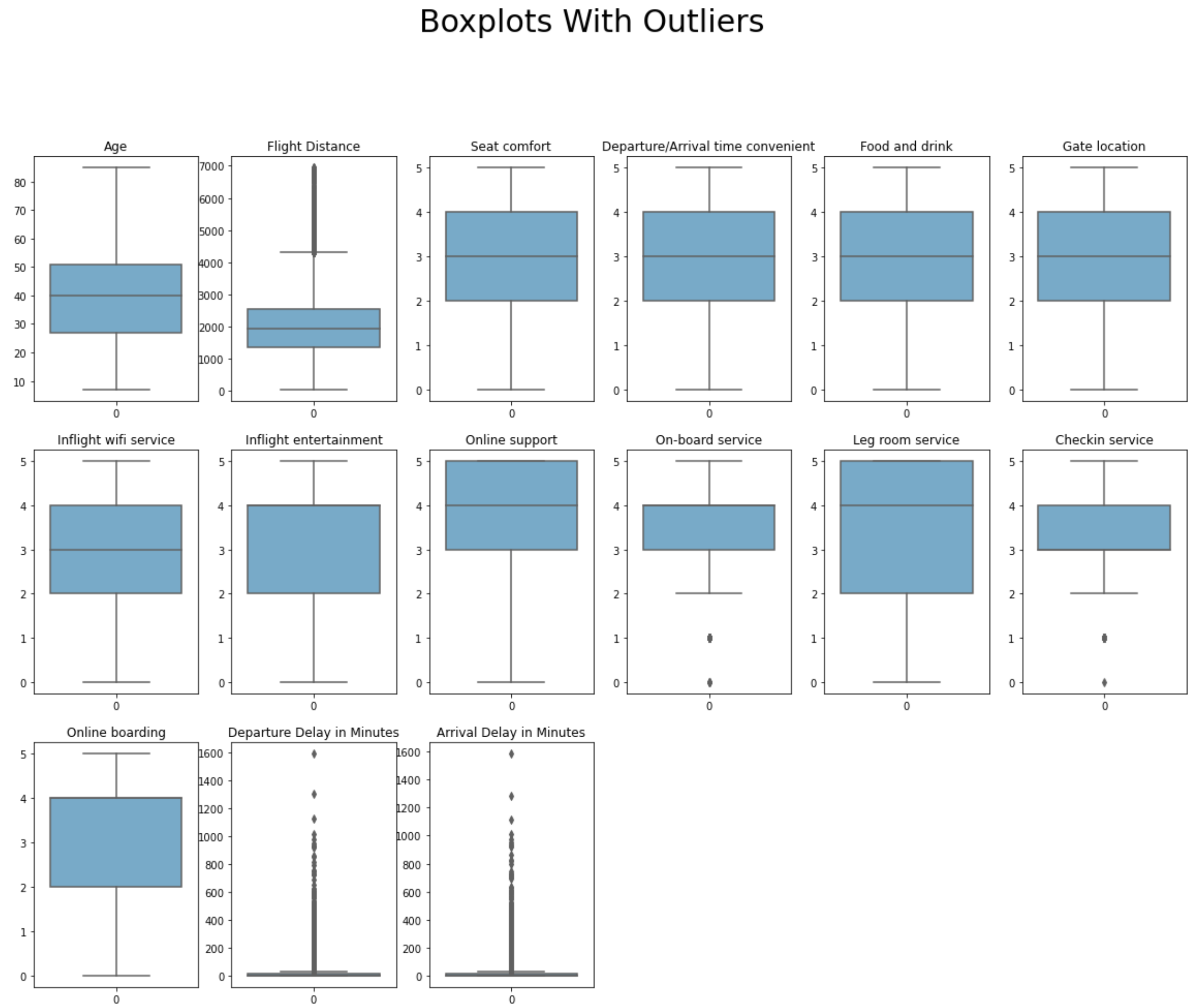
```
plt.figure(figsize=(18,10))
sns.heatmap(flight.corr(), cmap='Reds', annot=True, fmt='.2f')
```

Out[18]: <AxesSubplot:>



In [19]:

```
nonbinary_columns = [column for column in flight.columns if len(flight[column].uniqu
plt.figure(figsize=(20, 20))

for i, column in enumerate(nonbinary_columns):
    plt.subplot(4, 6, i + 1)
    sns.boxplot(data=flight[column], palette='Blues')
    plt.title(column)

plt.suptitle('Boxplots With Outliers', size=30)
plt.show()
```

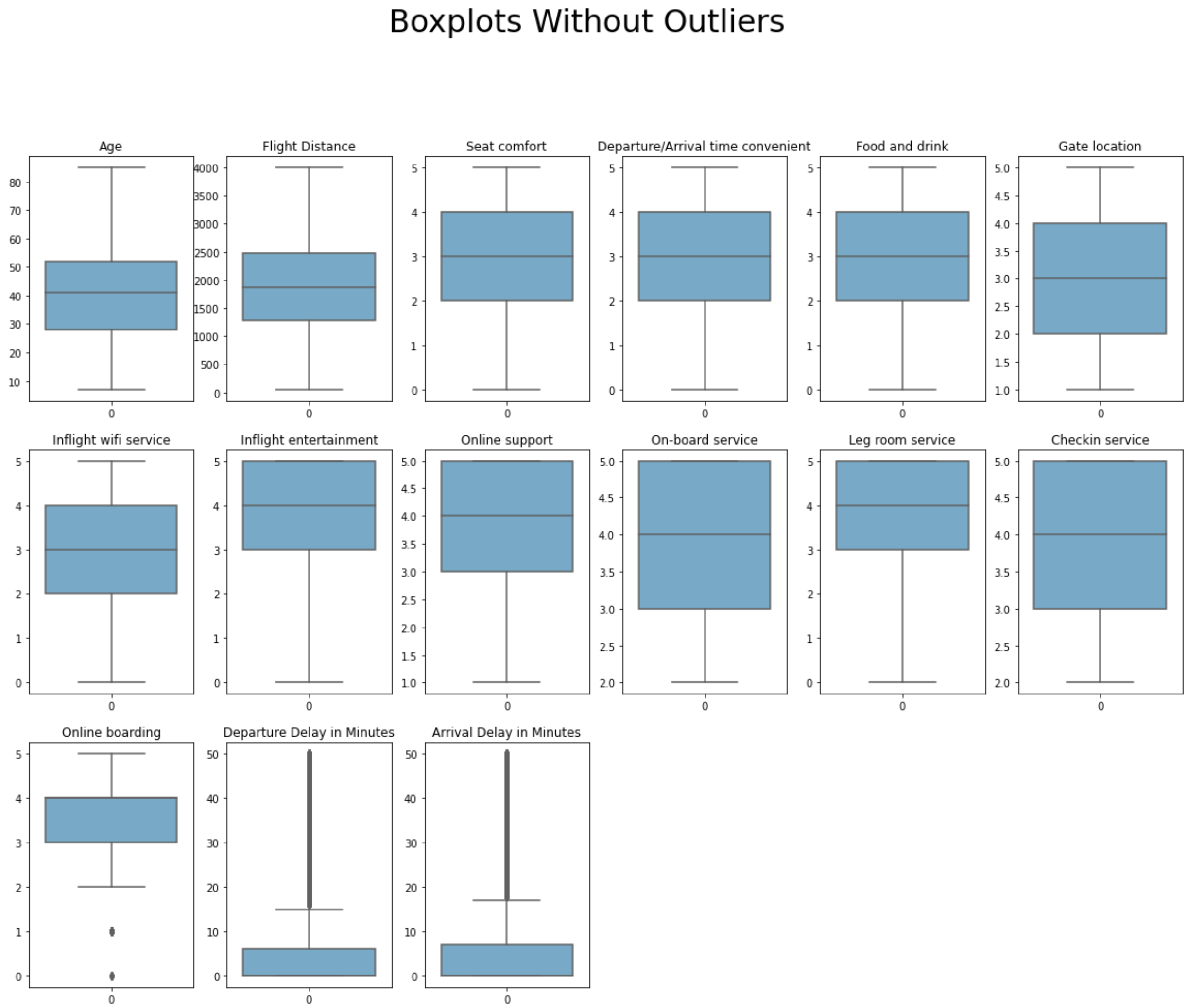


In [20]:

```python
#outlier Removal using IQR

flight = flight[flight['Flight Distance']<=4000]
flight = flight[flight['On-board service']>1]
flight = flight[flight['Checkin service']>1]
flight = flight[flight['Departure Delay in Minutes']<= 50]
flight = flight[flight['Arrival Delay in Minutes']<= 50]
```

In [21]:

```python
nonbinary_columns = [column for column in flight.columns if len(flight[column].uniqu
plt.figure(figsize=(20, 20))

for i, column in enumerate(nonbinary_columns):
    plt.subplot(4, 6, i + 1)
    sns.boxplot(data=flight[column], palette='Blues')
    plt.title(column)

plt.suptitle('Boxplots Without Outliers', size=30)
plt.show()
```



In [22]:

```
x=flight.drop('satisfaction',axis=1)
y=flight['satisfaction']
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3, random_st
x_train.shape,x_test.shape
```

Out[22]: ((64171, 19), (27503, 19))

In [23]:

```
#Implementing the model
import statsmodels.api as sm
logit_model=sm.Logit(y,x)
lr=logit_model.fit()
lr.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.390560
         Iterations 7
```

Out[23]:

Logit Regression Results

Dep. Variable:	satisfaction	**No. Observations:**	91674
Model:	Logit	**Df Residuals:**	91655
Method:	MLE	**Df Model:**	18
Date:	Thu, 16 Dec 2021	**Pseudo R-squ.:**	0.4144
Time:	13:32:57	**Log-Likelihood:**	-35804.
converged:	True	**LL-Null:**	-61141.

Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
Gender	-1.2074	0.019	-62.035	0.000	-1.246	-1.169
Customer Type	-2.5418	0.028	-92.159	0.000	-2.596	-2.488
Age	-0.0287	0.001	-46.016	0.000	-0.030	-0.027
Type of Travel	-1.1097	0.026	-42.318	0.000	-1.161	-1.058
Class	-0.8807	0.018	-49.269	0.000	-0.916	-0.846
Flight Distance	-0.0004	1.06e-05	-35.934	0.000	-0.000	-0.000
Seat comfort	0.3182	0.011	28.049	0.000	0.296	0.340
Departure/Arrival time convenient	-0.2175	0.008	-27.834	0.000	-0.233	-0.202
Food and drink	-0.2482	0.012	-21.565	0.000	-0.271	-0.226
Gate location	-0.0274	0.009	-3.198	0.001	-0.044	-0.011
Inflight wifi service	-0.1611	0.010	-16.478	0.000	-0.180	-0.142
Inflight entertainment	0.5930	0.009	62.846	0.000	0.575	0.611
Online support	0.1068	0.010	10.522	0.000	0.087	0.127
On-board service	0.3338	0.010	33.879	0.000	0.314	0.353
Leg room service	0.1981	0.008	24.374	0.000	0.182	0.214
Checkin service	0.1168	0.009	12.464	0.000	0.098	0.135
Online boarding	0.2610	0.011	24.151	0.000	0.240	0.282
Departure Delay in Minutes	0.0022	0.001	1.608	0.108	-0.000	0.005
Arrival Delay in Minutes	-0.0238	0.001	-17.675	0.000	-0.026	-0.021

Logistic Regression Model Fitting

In [24]:

```
from sklearn import metrics
logreg = LogisticRegression()
logreg.fit(x_train, y_train)
y_pred_test = logreg.predict(x_test)
y_pred_train = logreg.predict(x_train)
```

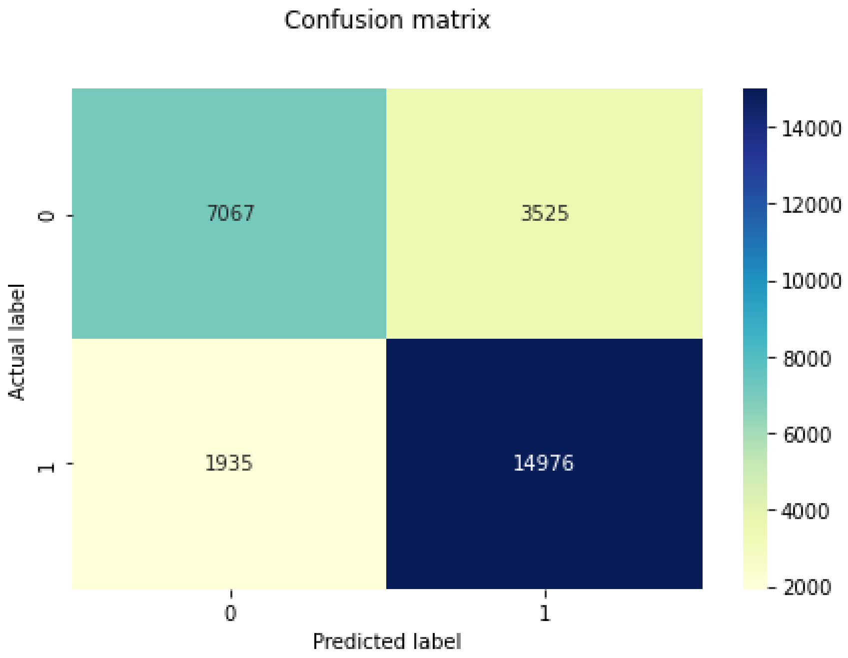
In [25]:

```
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_test, y_pred_test)
print(confusion_matrix)

sns.heatmap(pd.DataFrame(confusion_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

```
[[ 7067  3525]
 [ 1935 14976]]
```

Out[25]:

```
Text(0.5, 15.0, 'Predicted label')
```



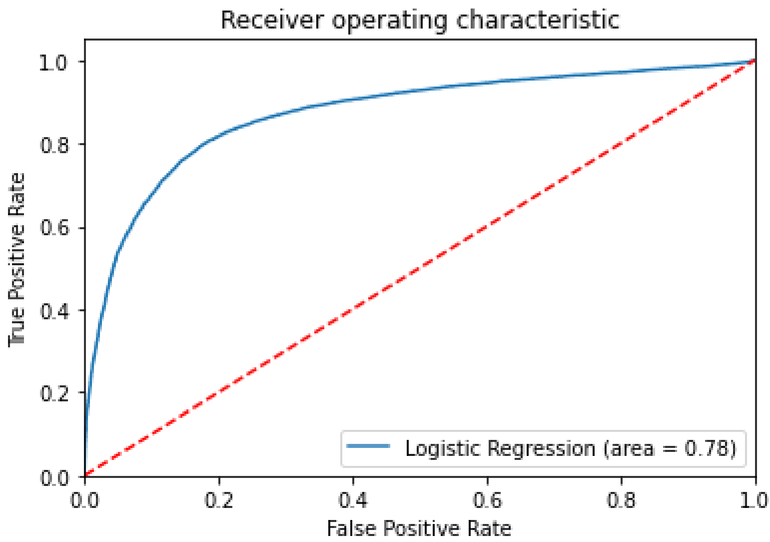
In [26]:

```
print(" Test Accuracy:",metrics.accuracy_score(y_test, y_pred_test))
print(" Train Accuracy:",metrics.accuracy_score(y_train, y_pred_train))

print("\nPrecision:",metrics.precision_score(y_test, y_pred_test))
print("Recall:",metrics.recall_score(y_test, y_pred_test))
```

```
 Test Accuracy: 0.8014762025960804
 Train Accuracy: 0.7990525315173521

Precision: 0.8094697583914383
Recall: 0.8855774348057477
```

In [27]:

```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
logit_roc_auc = roc_auc_score(y_test, logreg.predict(x_test))
fpr, tpr, thresholds = roc_curve(y_test, logreg.predict_proba(x_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
plt.show()
```



Decesion Tree

In [28]:

```
# Create Decision Tree classifer object
Dtc = DecisionTreeClassifier()

# Train Decision Tree Classifer
Dtc= Dtc.fit(x_train,y_train)

#Predict the response for test dataset
y_pred = Dtc.predict(x_test)
y_pred1 = Dtc.predict(x_train)
```

In [29]:

```
# Model Accuracy, how often is the classifier correct?
print("Test Accuracy:",metrics.accuracy_score(y_test, y_pred))
print("Train Accuracy:",metrics.accuracy_score(y_train, y_pred1))

print("\nPrecision:",metrics.precision_score(y_test, y_pred))
print("Recall:",metrics.recall_score(y_test, y_pred))
```

```
Test Accuracy: 0.9326618914300259
Train Accuracy: 1.0

Precision: 0.9458755255521999
Recall: 0.9445331441073858
```

RANDOM FOREST

In [30]:

```
classifier = RandomForestClassifier(n_estimators = 50)
classifier.fit(x_train, y_train)
y_pred_c1 = classifier.predict(x_test)
y_pred_c2 = classifier.predict(x_train)
```

In [31]:

```
# Model Accuracy, how often is the classifier correct?
print("Test Accuracy:",metrics.accuracy_score(y_test, y_pred_c1))
print("Train Accuracy:",metrics.accuracy_score(y_train, y_pred_c2))

print("\nPrecision:",metrics.precision_score(y_test, y_pred_c1))
print("Recall:",metrics.recall_score(y_test, y_pred_c1))
```

```
Test Accuracy: 0.9555321237683162
Train Accuracy: 0.9999064998207913

Precision: 0.9664050422166726
Recall: 0.9610904145230915
```

In [32]:

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

result = confusion_matrix(y_test, y_pred_c1)
print("Confusion Matrix:")
print(result)
result1 = classification_report(y_test, y_pred_c1)
print("Classification Report:",)
print (result1)
```

```
Confusion Matrix:
[[10027   565]
 [  658 16253]]
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.95      0.94     10592
           1       0.97      0.96      0.96     16911

    accuracy                           0.96     27503
   macro avg       0.95      0.95      0.95     27503
weighted avg       0.96      0.96      0.96     27503
```

Conclusion 1:

After using Machine Learning to analyze customer satisfaction, we find that Logistic regression is the best machine learning model to predict our customer satisfaction data.

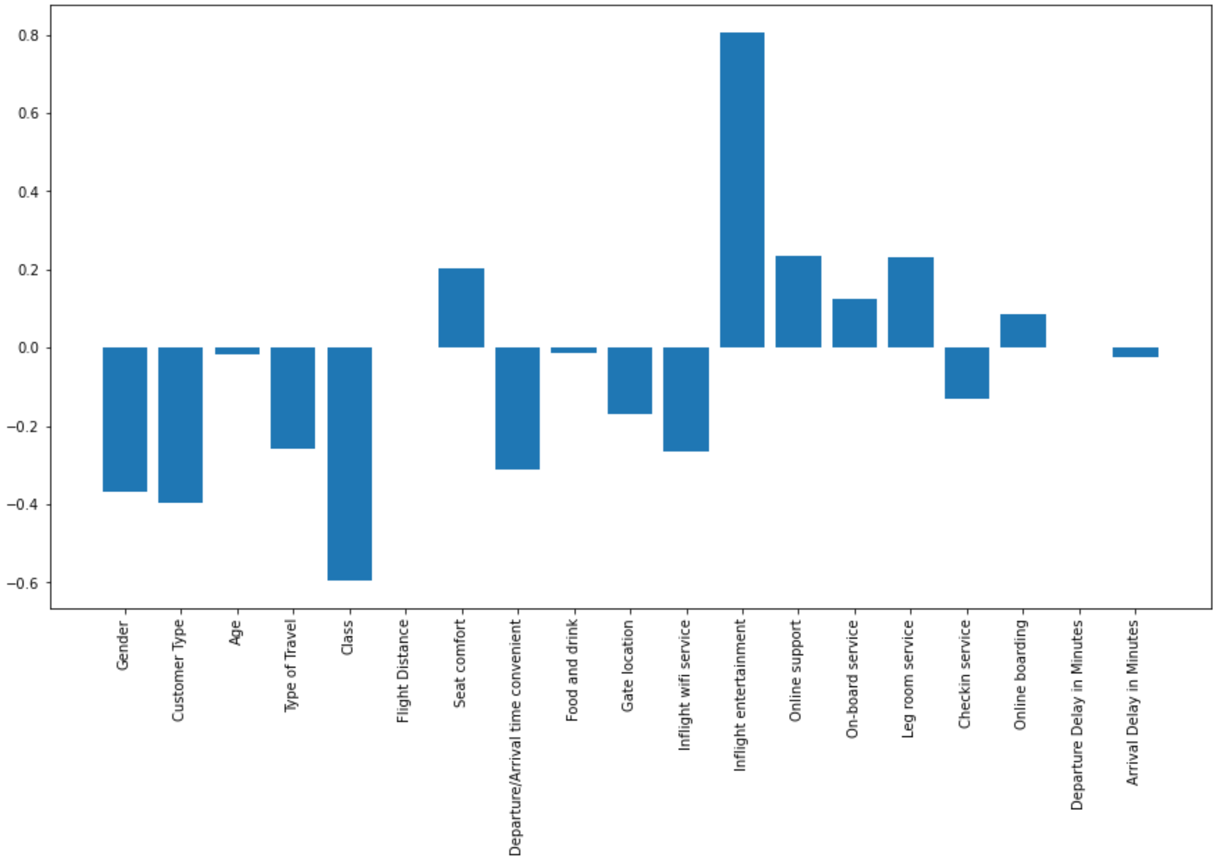
This model isn't Overfitting or Underfitting since the the accuracy differences between train and test data is almost equal.

In [33]:

```
# get importance
importance = logreg.coef_[0]

# summarize feature importance
for i,v in enumerate(importance):
    print('Feature: %0d, Score: %.5f' % (i,v))

    # plot feature importance
plt.figure(figsize=(15,8))
plt.bar(x.columns,importance)
plt.xticks(rotation=90)
plt.show()
```

```
Feature: 0, Score: -0.36874
Feature: 1, Score: -0.39738
Feature: 2, Score: -0.01655
Feature: 3, Score: -0.25712
Feature: 4, Score: -0.59506
Feature: 5, Score: -0.00038
Feature: 6, Score: 0.20318
Feature: 7, Score: -0.31199
Feature: 8, Score: -0.01198
Feature: 9, Score: -0.16916
Feature: 10, Score: -0.26451
Feature: 11, Score: 0.80657
```

```
Feature: 12, Score: 0.23405
Feature: 13, Score: 0.12554
Feature: 14, Score: 0.23114
Feature: 15, Score: -0.12970
Feature: 16, Score: 0.08528
Feature: 17, Score: 0.00243
Feature: 18, Score: -0.02279
```



Conclusion 2:

There are 4 services that are highly affects customer satisfaction in this Airlines data :

```
Inflight Entertainment
online support
leg room service
seat comfort
```

Invistico Airlines can choose to upgrade/investing more money and effort in those 4 services to improve their customer satisfactions.