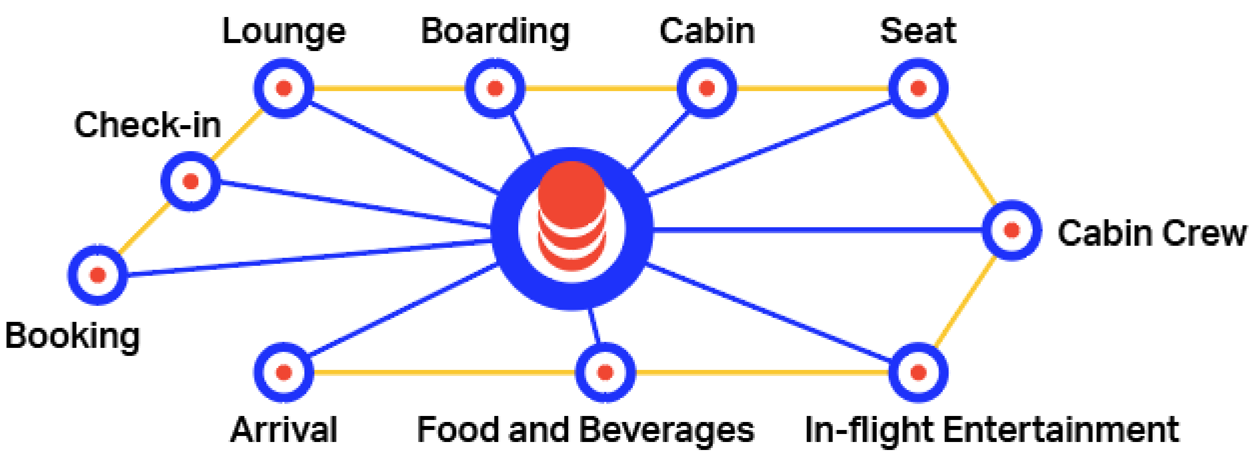
MSIN0097: Predictive Analytics

Individual Coursework

Airlines Customer Satisfaction

Predict Satisfaction Level



Word Count : 2078

(Excluding Table of Contents and References)

March 2021

Table of Contents

1. Problem Framing

Airlines industry is a fast-growing and customers' focused one. The sector has been facing dynamic changes due to *technological disruptions* which have shifted customers' preferences. This is in addition to the *pandemic* that has reduced international travel and added pressure on organizations to align with travel restrictions and accommodate individuals' safety. Infact, nowadays airlines' customers increasingly want **enjoyable and safe experience** that gives them diverse yet personalized offerings (PWC, 2021).

This project takes a Kaggle dataset of a survey conducted on more than 100k customers of an airlines company and which assesses feedback on travel attributes such as booking, arrival, checkin, and onboarding services, etc.

The *project* aims to:

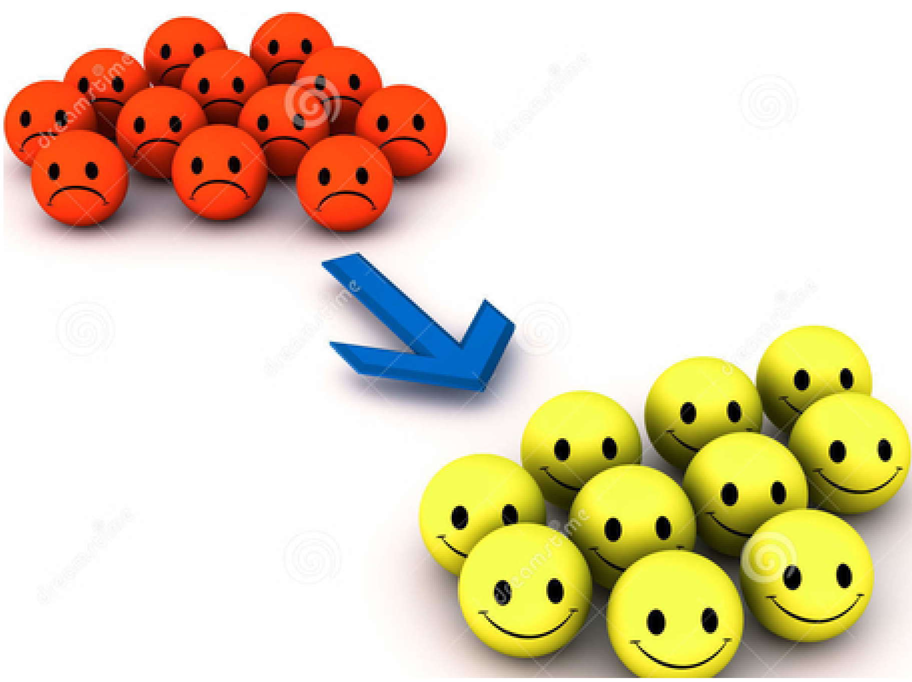
1- **explore and visualize** *customers' responses*,

2- **build** *machine learning models* that predict the satisfaction level of customers; the best model will be chosen based on high F-1 score and low Generalization error

3- **identify** the *features* that customers perceive as most important ones to feel satisfied so Airlines can improve these features to boost satisfaction level

4- **reccomend** *innovative data-driven strategies* which can implemented to turn unsatisfied customers to satisfied ones

The main assumption is that satisfaction will lock-in and retain customers. This will encourage them to book again with the same Airlines and consequently revenues will be increased.



In [17]:
```
#import needed packages
import pandas as pd
import os
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
from sklearn.svm import SVC
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix
from sklearn.linear_model import SGDClassifier
from sklearn.linear_model import RidgeClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import accuracy_score
import plotly.express as px
from sklearn.metrics import f1_score
from sklearn.ensemble import AdaBoostClassifier
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
from IPython.display import Image
from IPython.core.display import HTML
```

2. Data Cleaning and Transformation

This section includes basic data wrangling. The dataset doesn't require much needed cleaning. However, variables such as Customer Type, Class, Satisfaction, Gender, and Travel Type will be converted into categorical type. Unncessary columns will be dropped and missing values will be detected.

Two new variables will be created which will help in comprehensive data analysis:

1- over_all rating which will take the average of all numeric variables taken as a score of 5 from customers' feedback

2- total_delay which will sum up the arrival and departure delay

In [2]:
```
#Load the data
def load_data(data_path,filename):
    data_path = os.path.join(data_path, filename)
    return pd.read_csv(data_path)
Airlines = load_data('/project/',"Airlines.csv")
#inspect the data
Airlines.head()
```

Out[2]:

	Unnamed: 0	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/ time conv
0	0	70172	Male	Loyal Customer	13	Personal Travel	Eco Plus	460	3	
1	1	5047	Male	disloyal Customer	25	Business travel	Business	235	3	
2	2	110028	Female	Loyal Customer	26	Business travel	Business	1142	2	
3	3	24026	Female	Loyal Customer	25	Business travel	Business	562	2	
4	4	119299	Male	Loyal Customer	61	Business travel	Business	214	3	

5 rows × 25 columns

In [3]:
```
#get the data info
Airlines.info()
```

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

In [4]:
```
Airlines.shape #check the shape of the dataframe
#103904 datapoints and 25 columns
```

Out[4]:
```
(103904, 25)
```

In [5]:
```
Airlines.isna() #check for missing values
#no missing data
```

Out[5]:

	Unnamed: 0	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure time con
0	False	False	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	False	False	
...	...	...	...	...	...	...	...	...	...	
103899	False	False	False	False	False	False	False	False	False	
103900	False	False	False	False	False	False	False	False	False	
103901	False	False	False	False	False	False	False	False	False	
103902	False	False	False	False	False	False	False	False	False	
103903	False	False	False	False	False	False	False	False	False	

103904 rows × 25 columns

In [6]:
```
Airlines.duplicated() #check for duplicated values
#no duplicates
```

Out[6]:
```
0         False
1         False
2         False
3         False
4         False
          ...
103899    False
103900    False
103901    False
103902    False
103903    False
Length: 103904, dtype: bool
```

In [7]:
```python
#basic data transfromation
#change the variable type of gender, customer type, type of travel, class, &
#satsifaction into categorical
Airlines['Gender'] = Airlines['Gender'].astype('category')
Airlines['Type of Travel'] = Airlines['Type of Travel'].astype('category')
Airlines['Customer Type'] = Airlines['Customer Type'].astype('category')
Airlines['Class'] = Airlines['Class'].astype('category')
Airlines['satisfaction'] = Airlines['satisfaction'].astype('category')
#drop the unnamed column
Airlines.drop("Unnamed: 0", axis =1, inplace= True)
#check again
Airlines.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 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  category
 2   Customer Type                      103904 non-null  category
 3   Age                                103904 non-null  int64   
 4   Type of Travel                     103904 non-null  category
 5   Class                              103904 non-null  category
 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  category
dtypes: category(5), float64(1), int64(18)
memory usage: 15.6 MB
```

In [18]:
```
#create a new variable : over_all rating which is the average of all rated var
iables by customers
Airlines['overall_rating'] = round((Airlines['Inflight wifi service']+ Airline
s['Departure/Arrival time convenient'] +
Airlines['Ease of Online booking'] + Airlines['Gate location'] + Airlines['Foo
d and drink']+ Airlines['Online boarding'] +
Airlines['Seat comfort'] + Airlines['Inflight entertainment'] + Airlines['On-b
oard service'] + Airlines['Leg room service'] +
Airlines['Baggage handling'] + Airlines['Checkin service'] + Airlines['Infligh
t service'] + Airlines['Cleanliness'])/14,1)
#create a new variable: Total Delay which is the sum of departure and arrival
 delay times
Airlines['Total_Delay'] = (Airlines['Departure Delay in Minutes']+
                                    Airlines['Arrival Delay in Minutes'])
#inspect the dataframe again to see the new two columns
Airlines.head()
```

Out[18]:

	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ea O boo
0	70172	Male	Loyal Customer	13	Personal Travel	Eco Plus	460	3	4	
1	5047	Male	disloyal Customer	25	Business travel	Business	235	3	2	
2	110028	Female	Loyal Customer	26	Business travel	Business	1142	2	2	
3	24026	Female	Loyal Customer	25	Business travel	Business	562	2	5	
4	119299	Male	Loyal Customer	61	Business travel	Business	214	3	3	

5 rows × 26 columns

3. Data Exploratory Analysis and Visualisation

It is critical to explore the dataset and conduct data visualisations to pinpoint trends, correlations, and relationships between variables.

We will study the below:

1- Data distributions of variables through histograms and summary statistics

2- Data correlations among variables and by class through heatmaps

3- Relationship between satisfaction and gender, class, and customer type through bar graphs and count plots

4- Relationship between overall rating, satisfaction, and class through categorical plot

5- Relationship between satisfaction and age through stacked plot

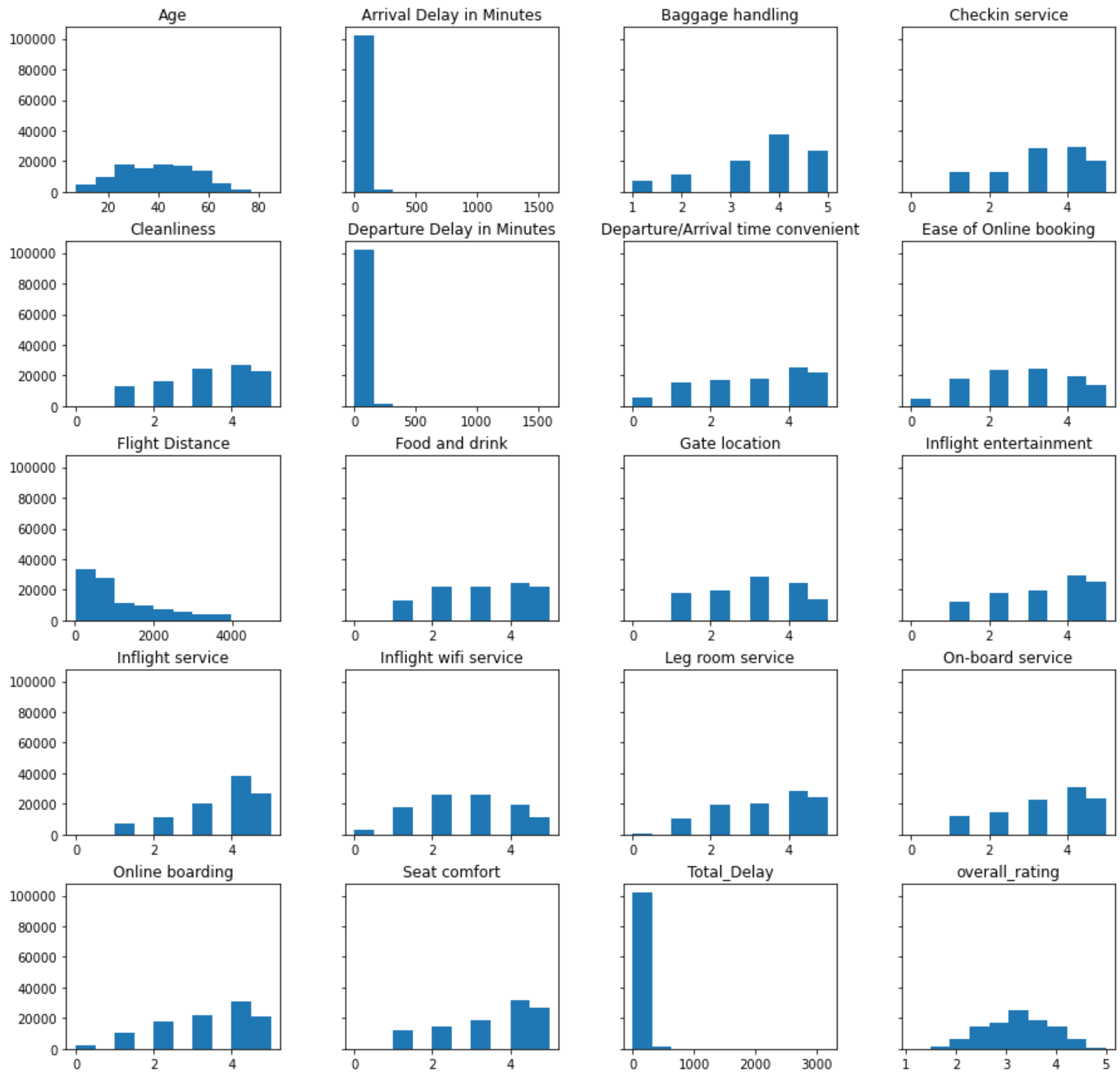
In [9]:
```
#Summary Statistics of numeric variables
#create a list of numeric variables
numeric_variables = ['Age', 'Flight Distance', 'Inflight wifi service', 'Depar
ture/Arrival time convenient','Ease of Online booking', 'Gate location', 'Food
and drink', 'Online boarding', 'Seat comfort',
'Inflight entertainment', 'On-board service', 'Leg room service', 'Baggage han
dling', 'Checkin service', 'Inflight service', 'Cleanliness', 'Departure Delay
in Minutes', 'Arrival Delay in Minutes', 'overall_rating', 'Total_Delay' ]
#apply the describe method and lambda function to round each number
Airlines[numeric_variables].describe().apply(lambda x:round(x,2)).T
```

Out[9]:

	count	mean	std	min	25%	50%	75%	max
Age	103904.0	39.38	15.11	7.0	27.0	40.0	51.0	85.0
Flight Distance	103904.0	1189.45	997.15	31.0	414.0	843.0	1743.0	4983.0
Inflight wifi service	103904.0	2.73	1.33	0.0	2.0	3.0	4.0	5.0
Departure/Arrival time convenient	103904.0	3.06	1.53	0.0	2.0	3.0	4.0	5.0
Ease of Online booking	103904.0	2.76	1.40	0.0	2.0	3.0	4.0	5.0
Gate location	103904.0	2.98	1.28	0.0	2.0	3.0	4.0	5.0
Food and drink	103904.0	3.20	1.33	0.0	2.0	3.0	4.0	5.0
Online boarding	103904.0	3.25	1.35	0.0	2.0	3.0	4.0	5.0
Seat comfort	103904.0	3.44	1.32	0.0	2.0	4.0	5.0	5.0
Inflight entertainment	103904.0	3.36	1.33	0.0	2.0	4.0	4.0	5.0
On-board service	103904.0	3.38	1.29	0.0	2.0	4.0	4.0	5.0
Leg room service	103904.0	3.35	1.32	0.0	2.0	4.0	4.0	5.0
Baggage handling	103904.0	3.63	1.18	1.0	3.0	4.0	5.0	5.0
Checkin service	103904.0	3.30	1.27	0.0	3.0	3.0	4.0	5.0
Inflight service	103904.0	3.64	1.18	0.0	3.0	4.0	5.0	5.0
Cleanliness	103904.0	3.29	1.31	0.0	2.0	3.0	4.0	5.0
Departure Delay in Minutes	103904.0	14.82	38.23	0.0	0.0	0.0	12.0	1592.0
Arrival Delay in Minutes	103594.0	15.18	38.70	0.0	0.0	0.0	13.0	1584.0
overall_rating	103904.0	3.24	0.66	1.1	2.8	3.3	3.7	5.0
Total_Delay	103594.0	29.93	76.15	0.0	0.0	2.0	24.0	3176.0

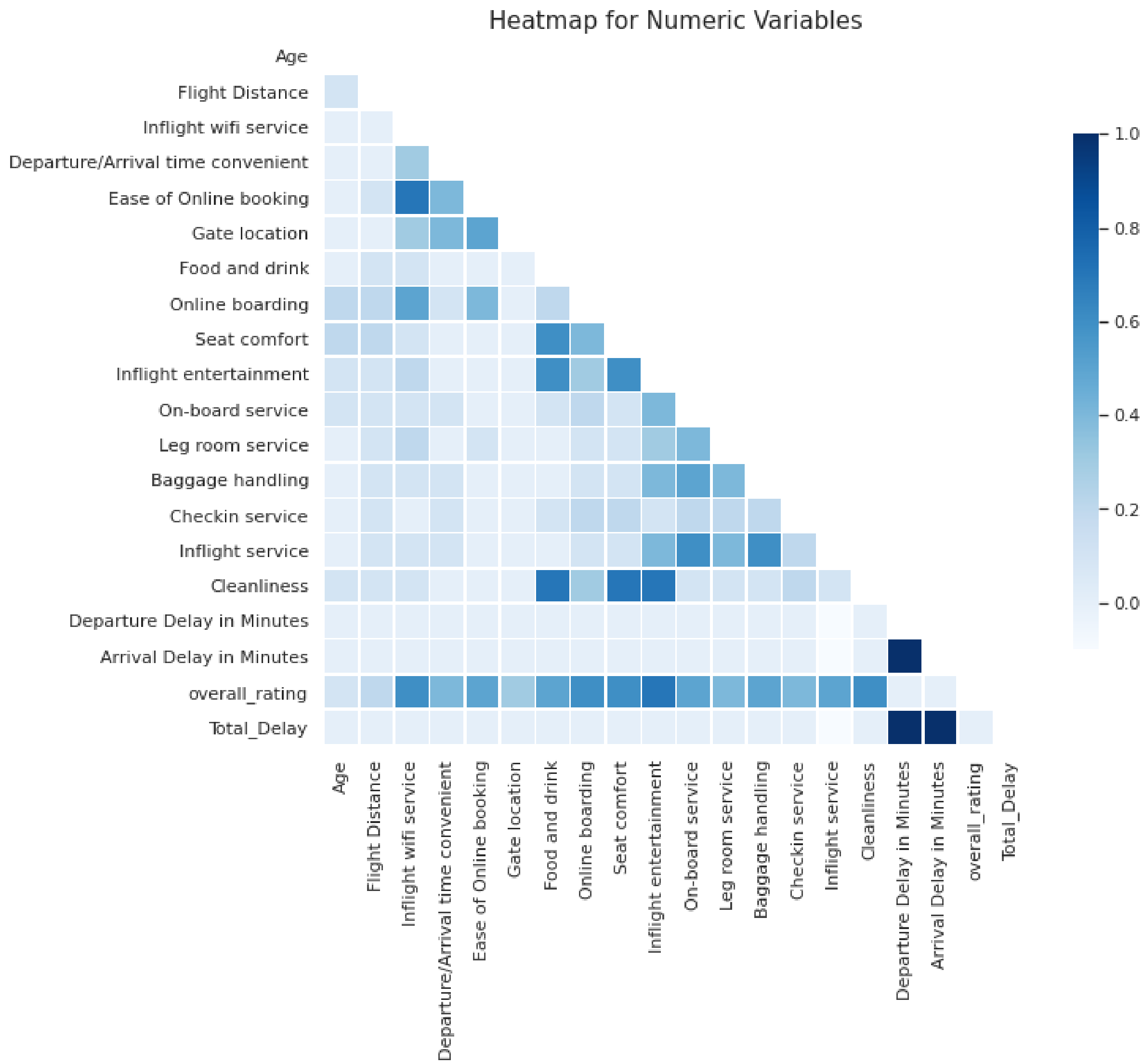
Satisfaction is affected by wifi and inflight service and older people constitute a big customer's base. The statistics show that wifi has the lowest average rating, inflight sercvce has the highest one, and the average age of customers is 40-years-old.

In [10]:
```
#create histograms for data distribution of numeric variables
hist = Airlines[numeric_variables].hist(bins =10, xlabelsize=10, ylabelsize=10
, grid=False, sharey= True, figsize = (15,15))
```



Types of distribution: Age and over_all rating have bell-shaped(normal pattern) whereas flight distance, departure, and arrival delays follow a right skewed one. Remaining variables have sort of unitary distribution.

In [11]:
```
#create a correlation heatmap for the numeric variables
sns.set(style='white') #set the style
corr = round(Airlines[numeric_variables].corr(),1) #define the correlation
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
f, ax = plt.subplots(figsize=(10,12)) #figure size
cmap = sns.diverging_palette(10,150, as_cmap=True) #figure colour
ax = sns.heatmap(corr, mask =mask, cmap="Blues", vmax= 1, annot = False,
annot_kws= {'size':12}, square=True, xticklabels=True, yticklabels=True,
linewidths=.6, linecolor='w', cbar_kws={'shrink': 0.5}, ax=ax) #input the ax v
aribales
ax.set_title('Heatmap for Numeric Variables', fontsize=15); #set the figure ti
tle
```

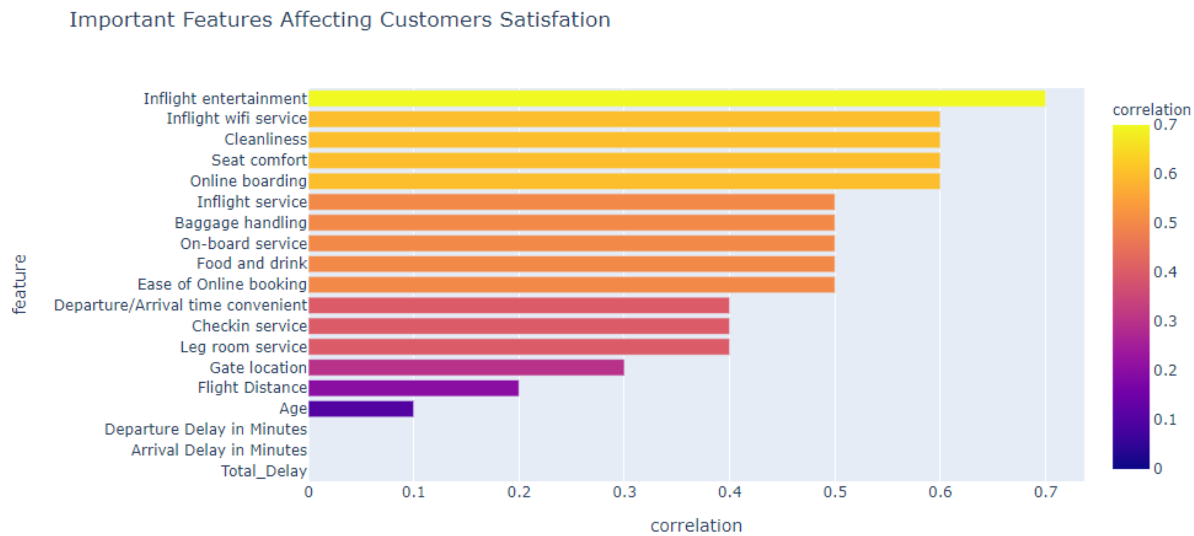


Overall rating is highly correlated with wifi service, online booking, boarding, seat comfort, and entertaiment. Additionally, other variables are still strongly correlated with each other (>0.3). So, we will consider using PCA to reduce dimensionality before building the models

In [65]:

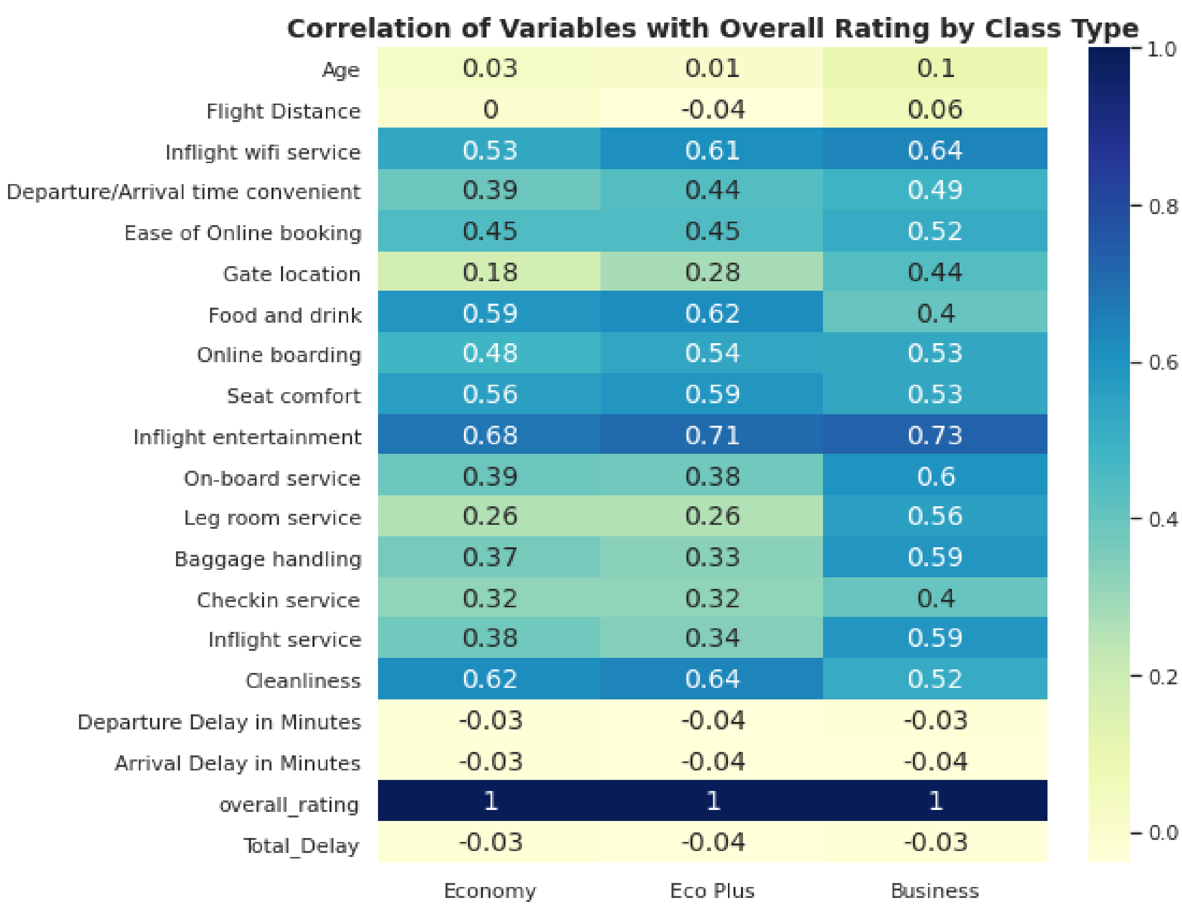
```
#Visualisize the correlations through a bar graph to identify the improtant fe
atures
corr1=corr.iloc[[-2]].T.sort_values(by="overall_rating").drop(index=["overall_
rating"]).reset_index() #take the correlation heatmap, sort by overall rating
 and reindex it
corr2 = corr1.rename({'index': 'feature', 'overall_rating': 'correlation'}, ax
is=1)  # rename the columns
fig = px.bar(corr2, y='feature', x='correlation',orientation="h",height=500, c
olor ='correlation', title="Important Features Affecting Customers Satisfatio
n");
#fig.show();
#save the figure and display it because it is an interactive one
Image(url= "https://user-images.githubusercontent.com/73695418/110239611-c9308
700-7f3f-11eb-938e-13596a2ad733.PNG")
```

Out[65]:



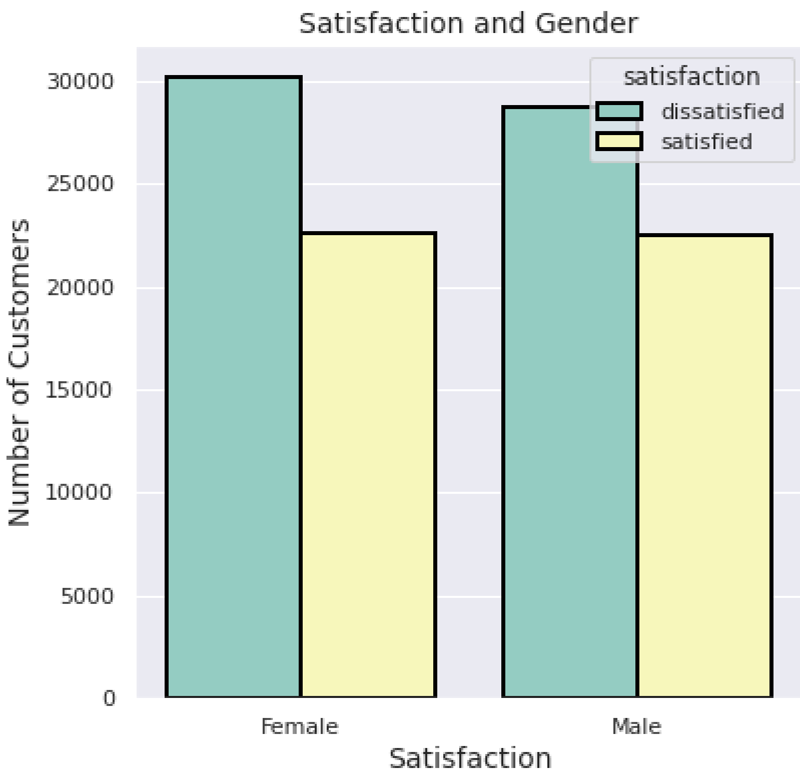
This graph further demonstrates that entertaiment, wifi, cleanliness, seat-comfort and online-boarding are the most important features for customer to provide high rating and feel satisfied.

In [136]:
```
#Study the correlaion of overall_rating by class type: eco, ecoplus, and busin
ess
#create 3 separate dataframes for each class type
economy_df = Airlines[Airlines['Class'] == "Eco"]
ecoplus_df = Airlines[Airlines['Class']== "Eco Plus"]
business_df = Airlines[Airlines['Class'] == "Business"]
#find the correlation matrix for each dataframe seperately
economy_df_corr = economy_df.corr()['overall_rating']
ecoplus_df_corr = ecoplus_df .corr()['overall_rating']
business_df_corr = business_df.corr()['overall_rating']

class_corr_df = pd.concat([economy_df_corr, ecoplus_df_corr, business_df_corr
], axis=1, keys = ['Economy', 'Eco Plus', 'Business']) #concateate the three c
orrelations
np.round(class_corr_df[1:], decimals=2) #apply the round function
f, ax = plt.subplots(figsize=(8, 8)) #set the figure size
heatmap = sns.heatmap(np.round(class_corr_df[1:], decimals=2), annot=True,
cmap="YlGnBu", xticklabels=True, yticklabels=True, annot_kws= {'size':14}, ax=
ax) #define the heatmap variables
heatmap.set_title('Correlation of Variables with Overall Rating by Class Type'
, fontweight="bold", fontsize=14); #set the title
```



Inflight Entertainment follOwed by wifi and cleanliness are the highest correlated variables with overall rating for the three classes. Business class cares more about on-board, leg-room, check-in and baggage handling.

In [40]:
```
#graph about satisfactiion and gender
plt.figure(figsize = (6,6))
sns.set(rc= {"font.size":14, "axes.titlesize":14, "axes.labelsize":14})
g = sns.countplot(x= 'Gender' , hue ='satisfaction', palette="Set3", saturatio
n=0.8, edgecolor=(0,0,0),linewidth=2, data=Airlines)#figure variables
g.set_title('Satisfaction and Gender') #set title
g.set_ylabel('Number of Customers') #y_label
g.set_xlabel('Satisfaction'); #x_label
```

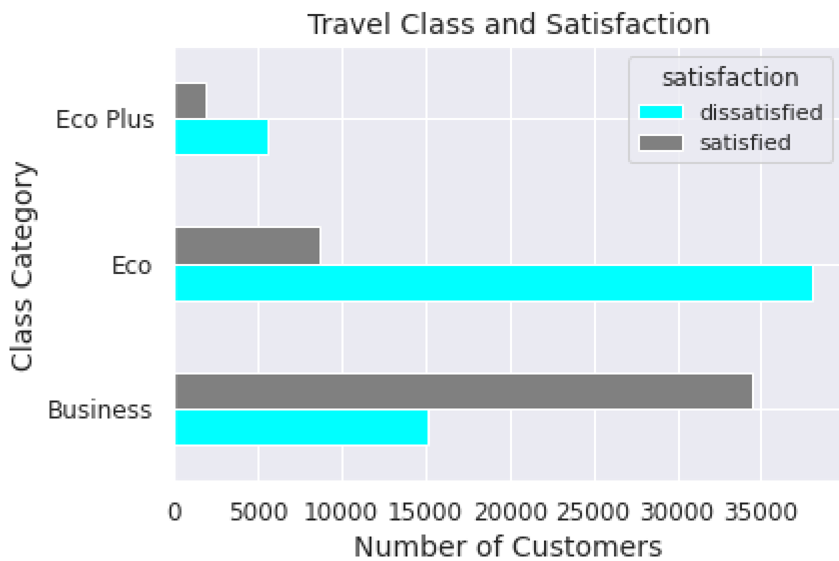


Overall, the number of dissatisfied customers is higher than the satisfied ones and specifically females are more dissatisifed than males.

In [46]:
```
#Number of Customers per Class Category
plt.figure(figsize=(6,4)) #figure size
ax=Airlines.groupby('Class')['id'].count().sort_values(ascending =False).plot(
kind='bar',color = 'teal') #figure variables
plt.ylabel('Class', fontsize = 14) #set y_label
plt.title('Number of Customers per Class', fontsize = 14); #set the figure tit
le
```

Business class captures the highest category of customers which shows that the service is mostly preferred by business customers

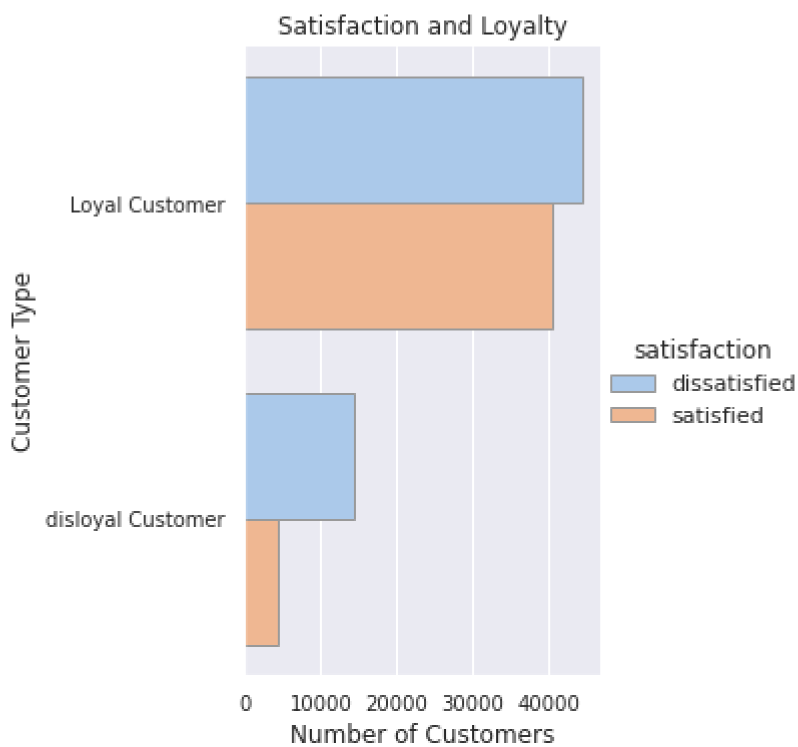
In [44]:
```
#Satisfaction and Class Category
by_cat_class = Airlines.groupby(['Class', 'satisfaction']) #group by Class and Category
by_cat_class.size() #get the size of the dataframe
ax = by_cat_class.size().unstack().plot(kind='barh', color = ['aqua', 'grey']) #unstack and plot
ax.set_title('Travel Class and Satisfaction', size =14) #title
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
ax.set_xlabel('Number of Customers', fontsize = 14) #set the x_label
ax.set_ylabel('Class Category', fontsize = 14); #set the y_label
```



Business customers are the most satisifed whereas eco-customers are the least satisfied. Most importantly, 80% of the total eco customers are dissatisfied. This indicates that the service is not delivered to match the preferences of different classes and a higher care was only given to business class

In [63]:
```
#Customer Satisfaction and Loyalty
plt.figure(figsize = (6,8)) #figure size
ax = sns.catplot(y="Customer Type", hue="satisfaction", kind="count",
            palette="pastel", edgecolor=".6",
            data=Airlines) #figure variables
sns.set(rc= {"font.size":12, "axes.titlesize":12, "axes.labelsize":12})
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.ylabel('Customer Type')
plt.xlabel('Number of Customers')
plt.title('Satisfaction and Loyalty');
```

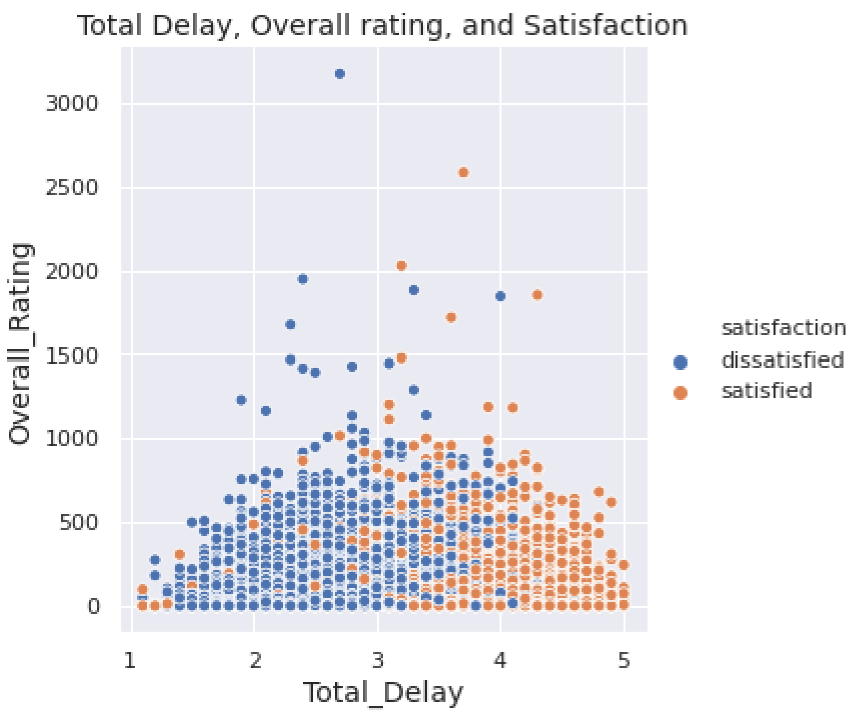
```
<Figure size 432x576 with 0 Axes>
```



Loyal customers tend to be dissatisfied which increases the risk of losing them

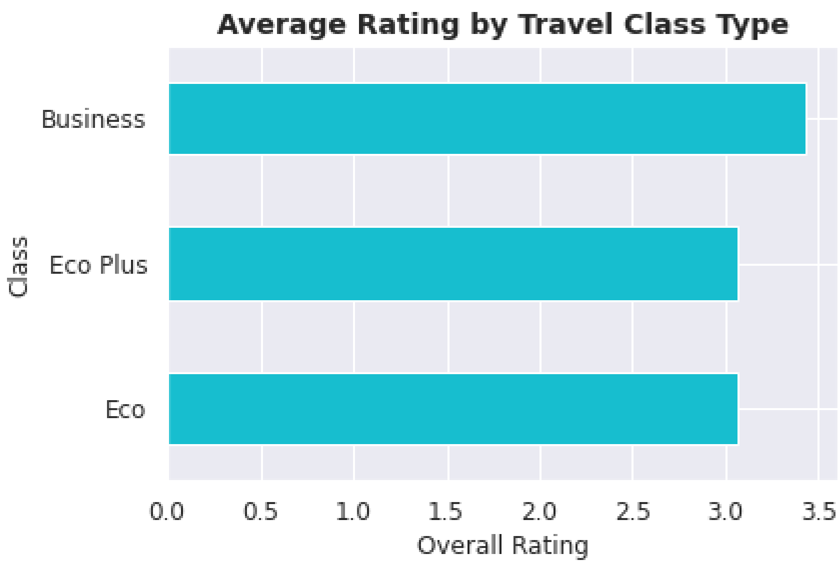
In [68]:
```
#Total Delay, over all rating and satisfaction
plt.figure(figsize = (8,6)) #figure size
sns.set(rc= {"font.size":14, "axes.titlesize":14, "axes.labelsize":14})
m = sns.relplot(x="overall_rating", y="Total_Delay",hue ='satisfaction',
            data=Airlines); #define variables
plt.title('Total Delay, Overall rating, and Satisfaction') #set title
plt.xlabel('Total_Delay') #x_label
plt.ylabel('Overall_Rating'); #set y_label
```

```
<Figure size 576x432 with 0 Axes>
```



Total Delay affects satisfaction whereby the lower delay time leads to a higher rating average and a satisfied customer

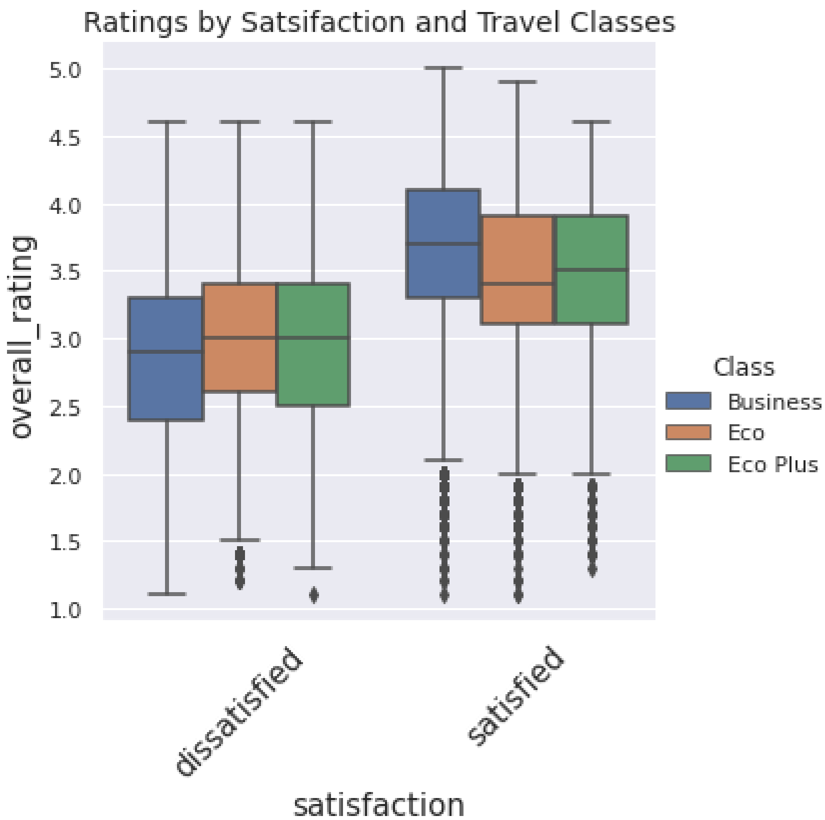
In [69]:
```
#Average Rating per Class Category
fig, ax = plt.subplots(figsize=(6,4)) #figure size
average_rating = Airlines.groupby(['Class']).mean()['overall_rating'].sort_values(ascending =True)
average_rating.plot(ax=ax, kind='barh', color ='tab:cyan') #plot the graph
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
ax.set_title('Average Rating by Travel Class Type', fontweight="bold", size =14) #set the title
ax.set_xlabel('Overall Rating', fontsize = 12)
ax.set_ylabel('Class', fontsize = 12);
```



Business Class provided higher rating average which affirms that they are genuily satisfied with the service

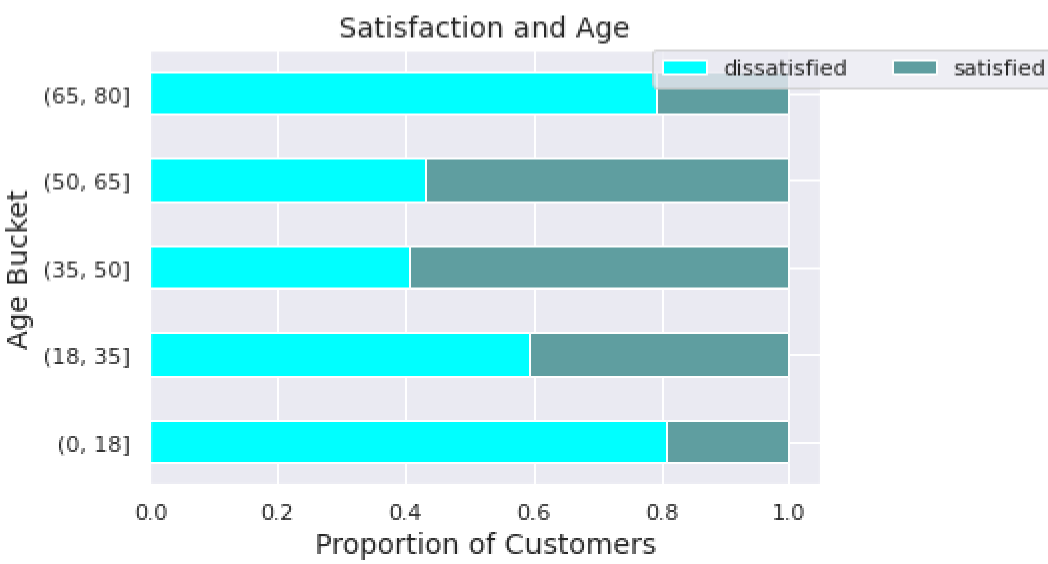
In [20]:
```
#Distribution of rating by Class Type and Satisfaction Level
plt.figure(figsize = (30,10)) #figure size
sns.set(rc= {"font.size":15, "axes.titlesize":15, "axes.labelsize":15 })
g= sns.catplot(x="satisfaction", y="overall_rating",  hue="Class", kind="box",
data=Airlines) #define variables
g.set_xticklabels(rotation = 45, fontsize = 15) #x_tick labels
plt.title('Ratings by Satsifaction and Travel Classes', size =14); #set title
```

```
<Figure size 2160x720 with 0 Axes>
```



As shown before, satisifed and specifically business customers give higher rating. However, this graph displays some outliers with very low ratings; this will be treated through standardization in the data preparation part.

In [23]:
```
#Discretize the overall_ratings into buckets
overall = Airlines['Age']
labels = pd.cut(overall, [0, 18, 35, 50, 65 , 80])
grouped = Airlines.groupby(['satisfaction', labels]) #group it by satisfaction
level
grouped.size().unstack(0) #unstack
#sum group amounts
bucket_sums = grouped.overall_rating.sum().unstack(0)
#normalize within buckets to visualize total ratings within each bucket by Sat
isfaction category
normed_sums = bucket_sums.div(bucket_sums.sum(axis=1), axis=0)
#plot the discretized ratings buckets and satisfaction
plot = normed_sums.plot(kind='barh', stacked=True, color= ['aqua','cadetblue']
)
plot.legend(loc="upper center",ncol=2,borderaxespad=0.,bbox_to_anchor=(1.05, 1
))
plot.set_title('Satisfaction and Age', size =14)
plot.set_xlabel('Proportion of Customers', fontsize = 14)
plot.set_ylabel('Age Bucket', fontsize =14);
```



Customers of age less than 18 and more than 65 are the least satisfied. The Airlines should consider implementing personalized services tailored for adults and old customers.

The **key takeaways** from the Visualisation part are that:

1- Satisfaction is stronlgy dependent on customers' experience on inflight entertainment, wifi service and cleanliness. Business class particularly cares about on-board, leg room, check-in services and baggage handling.

2- The Airlines are providing better consideration for business class while ignroing the interests of eco customers

3- Total delay is lowering overall rating and affecting satisfaction negatively

4- Age is a major criterion of customer's satisfaction. Adults and old people are not satisfied

4. Data Preparation

This section prepares the data for the machine learning models. Firstly, dataset will be splitted to train and test with a ratio of 80/20 respectively and the dependent variable: "satisfaction level" will be dropped out from the dataset and encoded as {0: 'unsatisfied', 1: 'satisfied'}. Then, a full pipeline will be built to impute and standarize the data and encode the categorical variables. To reduce dimensionality and number of features, PCA will be applied.

4.1 Train-test split

In [24]:
```
Airlines_1 = Airlines.copy() #make a copy of the data
train_set, test_set = train_test_split(Airlines_1, test_size=0.2, random_state
=42) #split the training (0.8) and test (0.2)
test_set.head() #inspect the test data
```

Out[24]:

	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient
80638	98687	Female	Loyal Customer	26	Personal Travel	Eco	861	2	4
43398	80734	Male	Loyal Customer	22	Business travel	Business	393	3	5
32751	5711	Female	Loyal Customer	59	Personal Travel	Eco	196	1	3
33571	23035	Female	Loyal Customer	32	Personal Travel	Eco	1020	2	3
71287	53962	Male	disloyal Customer	35	Business travel	Business	1117	2	2

5 rows × 26 columns

In [25]:
```
#drop the dependent variable from the train_set and keep it as separate predic
ted variable
x_train_set = train_set.drop("satisfaction", axis=1) #train set of independent
variables
y_train_set = train_set['satisfaction'] #train dependent variable
x_test_set = test_set.drop("satisfaction", axis=1) #test set of independent va
riables
y_test_set = test_set['satisfaction'] #test dependent variable
```

In [26]:
```
#define numeric and categorical variables
numeric_variables = ['Age', 'Flight Distance', 'Inflight wifi service', 'Depar
ture/Arrival time convenient', 'Ease of Online booking', 'Gate location', 'Foo
d and drink', 'Online boarding', 'Seat comfort',
'Inflight entertainment', 'On-board service', 'Leg room service', 'Baggage han
dling', 'Checkin service','Inflight service', 'Cleanliness', 'Departure Delay
 in Minutes', 'Arrival Delay in Minutes', 'overall_rating', 'Total_Delay' ]
categorical_variables = ['Gender', 'Customer Type', 'Type of Travel', 'Class']
```

4.2 Encoding Dependent Variable

In [27]:
```
#encode the dependent variable: satisfaction
labelencoder_y = LabelEncoder()
train_y = labelencoder_y.fit_transform(y_train_set)
print(train_y)
```

```
[0 0 0 ... 0 1 0]
```

4.3 Full Pipeline

In [28]:
```
#build a pipeline for numeric and categorical data
num_pipeline = Pipeline([('imputer', SimpleImputer(strategy="median")),
        ('std_scaler', StandardScaler()),]) #numeric pipeline
full_pipeline = ColumnTransformer([
        ("num", num_pipeline, numeric_variables  ),
        ("cat", OneHotEncoder(),categorical_variables),]) #full pipeline
x_train = full_pipeline.fit_transform(x_train_set) #apply the pipeline on the
 x_train set
x_train #print out
```

Out[28]:
```
array([[ 1.29986657, -0.14310337,  0.95637727, ...,  0.        ,
         1.        ,  0.        ],
       [ 0.04355119, -0.43800734,  0.95637727, ...,  1.        ,
         0.        ,  0.        ],
       [ 1.69659774, -0.80814191, -0.54993143, ...,  0.        ,
         1.        ,  0.        ],
       ...,
       [ 0.44028236,  0.00836091, -1.30308577, ...,  0.        ,
         1.        ,  0.        ],
       [-0.15481439, -0.87133562,  1.70953161, ...,  0.        ,
         1.        ,  0.        ],
       [-1.67561721, -0.8402403 ,  0.95637727, ...,  0.        ,
         1.        ,  0.        ]])
```

In [29]:
```
#Apply data pipeline transformation on test_set
test_y = labelencoder_y.fit_transform(y_test_set) #to encode the dependent var
iable (0,1)
x_test = full_pipeline.fit_transform(x_test_set ) #to apply full pipeline on t
est set
x_test #inspect
```

Out[29]:
```
array([[-0.89747814, -0.33225846, -0.54794265, ...,  0.        ,
         1.        ,  0.        ],
       [-1.16274657, -0.80121183,  0.20500295, ...,  1.        ,
         0.        ,  0.        ],
       [ 1.29098646, -0.99861314, -1.30088825, ...,  0.        ,
         1.        ,  0.        ],
       ...,
       [-2.02486899, -0.18796511, -0.54794265, ...,  0.        ,
         1.        ,  0.        ],
       [ 0.36254693,  2.04557563,  0.20500295, ...,  1.        ,
         0.        ,  0.        ],
       [-0.56589259, -1.10883723,  0.95794855, ...,  0.        ,
         0.        ,  1.        ]])
```

4.4 PCA

In [30]:
```
#Apply the Principal Component Analysis to reduce dimensionality and number of
features
pca = PCA(.95) #preserve the variance with 95%
pca.fit(x_train)
pca.n_components_
#number of variables have been reduced to 17
```

Out[30]:
```
PCA(n_components=0.95)
```

Out[30]:
```
17
```

In [31]:
```
1 - pca.explained_variance_ratio_.sum()
#only 0.04 of the dimensionality was lost
```

Out[31]:
```
0.041950205952189346
```

In [32]:
```
x_train_prepared = pca.transform(x_train) #apply the PCA on x_train
x_train_prepared
```

Out[32]:
```
array([[-0.8430599 , -0.19623251, -0.63466933, ...,  0.52269979,
         0.23432315, -0.84742384],
       [ 0.59735158,  0.35045008, -1.53814263, ..., -0.73766013,
         1.07875365, -1.87207963],
       [ 1.96572496, -0.9482699 ,  0.06138406, ...,  0.13199832,
         0.03029589, -0.11574157],
       ...,
       [ 5.08143228, 10.72571097,  1.00139477, ...,  0.96278747,
         0.53520084,  0.22644674],
       [-2.22157323, -0.32127893, -2.26179652, ...,  0.27396799,
        -0.05748409,  0.19271732],
       [-2.05663065, -0.47235299, -0.76711359, ...,  0.4197045 ,
        -0.07095604, -0.11693612]])
```

In [33]:
```
pca.fit(x_test)
x_test_prepared = pca.transform(x_test) #apply the PCA on x_test
x_test_prepared
```

Out[33]:
```
PCA(n_components=0.95)
```

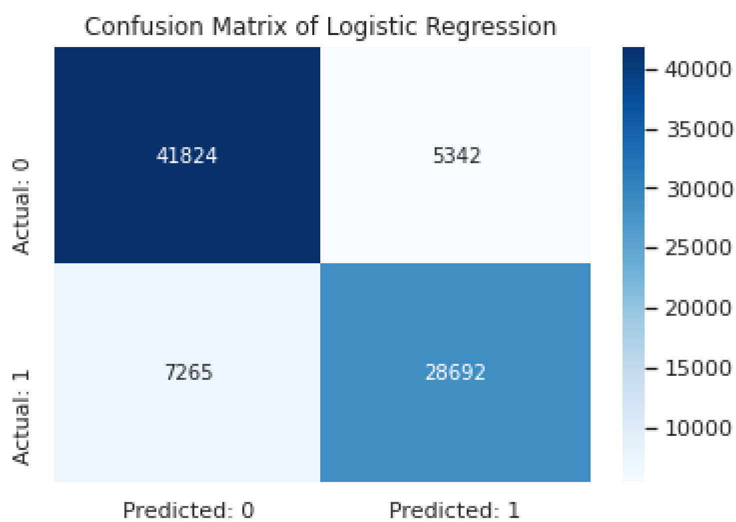
Out[33]:
```
array([[-2.2620847 , -0.58142659,  0.69285241, ..., -0.31985685,
        -0.49919723, -0.21334744],
       [ 1.07709261, -0.24786412, -2.67526151, ..., -0.38392716,
         0.05561265,  0.20007516],
       [ 1.16547757,  0.79448064,  1.16355854, ...,  0.10243261,
         0.1366903 ,  0.94597313],
       ...,
       [-1.38534877, -0.62041762,  0.93678142, ..., -1.56860761,
         0.0191605 , -0.23034488],
       [-2.24201044, -0.12744834,  0.45243588, ..., -0.05836203,
        -0.79859469, -0.91206511],
       [ 0.68788963, -0.80333664,  1.56116995, ...,  0.53517332,
         0.0222838 ,  0.02896342]])
```

5. Predictive Machine Learning (ML) Models

To predict the satisfaction level, we will try 7 ML models. Each model will be fitted on the trainset and the performance will be evaluated through investigating the confusion matrix, classification report, and cross-validation scores. In particular, the F-1 score which combines the precision and recall will be used as a *primary measure* of the model's performance. From a business perspective, the F-1 score will allow us to reduce the mis-classification error, or classifying dissatisfied customer as satisfied one and vise-versa. This will also minimize the risk of implementing wrong interventions for customers with incorrect category.

5.1 Logistic Regression

In [195]:
```
logmodel = LogisticRegression() #initiate the model
logmodel.fit(x_train_prepared , train_y ) #fit the model
y_predict_1 = logmodel.predict(x_train_prepared) #predict
confusion_1 = confusion_matrix(train_y, y_predict_1) #create the confusion mat
rix
confusion_1 = pd.DataFrame(data=confusion_1, columns=['Predicted: 0','Predicte
d: 1'],index=['Actual: 0 ','Actual: 1']) #transform it to dataframe
ax = plt.axes()
ax.set_title('Confusion Matrix of Logistic Regression')
sns.heatmap(confusion_1, annot=True, fmt ='d', cmap="Blues", linecolor='w') #p
lot confusion matrix as heatmap
plt.show()
print('Classification report: \n', classification_report(train_y ,y_predict_1
)) #classification report
scores_1 = cross_val_score(logmodel, x_train_prepared,  train_y, cv=3, scoring
="f1") #cross validation scores
print('Cross Validation Scores are: ', scores_1)
print("Average F1 score of Logistic Regression from Cross Validation is:  %0.2
f" % (scores_1.mean()));
```

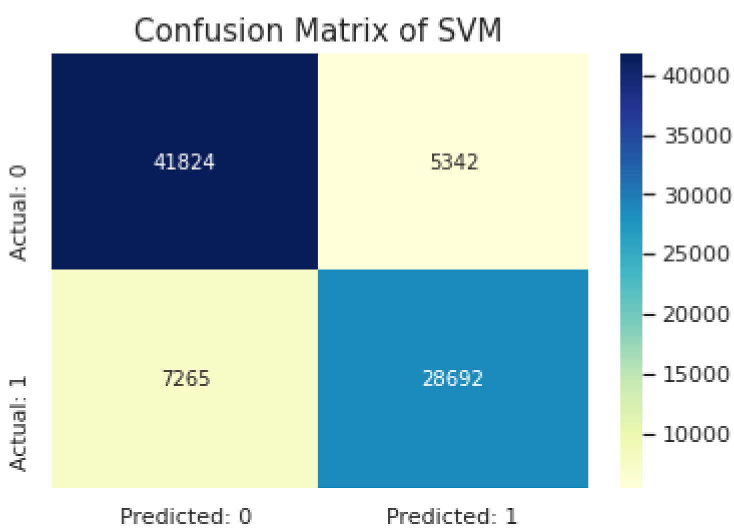



```
Classification report:
               precision    recall  f1-score   support

           0       0.85      0.89      0.87     47166
           1       0.84      0.80      0.82     35957

    accuracy                           0.85     83123
   macro avg       0.85      0.84      0.84     83123
weighted avg       0.85      0.85      0.85     83123

Cross Validation Scores are:  [0.81994697 0.81720615 0.82132899]
Average F1 score of Logistic Regression from Cross Validation is:  0.82
```

The logistic regression estimates the probability of customer belongs to either satisfied or unsatisfied class. The results present a F1-score of 82%. However, this model fails to account for non-linearity relationship between the dependent and independent variables. Additionally, since our dataset is still high dimensional, the model might over-fit on the training set, which overstates the accuracy of predictions and reduces generalizability.

5.2 Support Vector Machine (SVM) Classifier

In [86]:
```
svm_clf = SVC(gamma="auto", random_state=42) #initiate the model
svm_clf.fit(x_train_prepared , train_y) #fit the model
y_predict_2 = svm_clf.predict(x_train_prepared) #predict
confusion_2 = confusion_matrix(train_y, y_predict_2) #create the confusion mat
rix
confusion_2 = pd.DataFrame(data=confusion_2, columns=['Predicted: 0','Predicte
d: 1'],index=['Actual: 0 ','Actual: 1']) #transform it to dataframe
ax = plt.axes()
ax.set_title('Confusion Matrix of SVM')
sns.heatmap(confusion_1, annot=True, fmt ='d', cmap="YlGnBu", linecolor='w') #
plot confusion matrix as heatmap
plt.show()
print('Classification report: \n',classification_report(train_y ,y_predict_2))
#classification report
scores_2 = cross_val_score(svm_clf , x_train_prepared,  train_y, scoring="f1",
cv=3) #cross validation scores
print('Cross Validation Scores are: ',scores_2)
print("Average F-1 score of Support Vector Machine Classifier from Cross Valid
ation is %0.2f " % (scores_2.mean()))
```

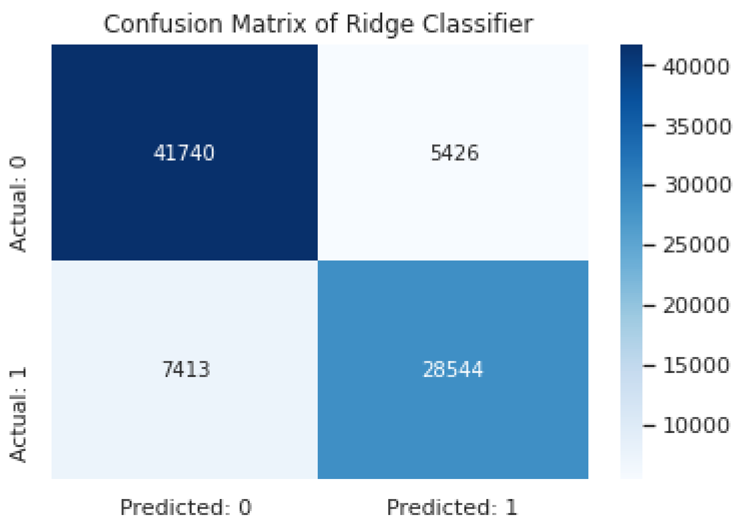



```
Classification report:
               precision    recall  f1-score   support

           0       0.94      0.97      0.95     47166
           1       0.95      0.92      0.94     35957

    accuracy                           0.95     83123
   macro avg       0.95      0.94      0.95     83123
weighted avg       0.95      0.95      0.95     83123

Cross Validation Scores are:  [0.92455232 0.92699864 0.92892042]
Average F-1 score of Support Vector Machine Classifier is 0.93
```

The SVM performs a clear margin of separation between classes (Satisfied vs Unsatisfied) and unlike logistic regression, it doesn't output probabilities. Infact, SVM is more effective in high dimensional spaces thus, it has a good prediction power on the Airlines dataset whereby the F-1 score is around 93%. However, this algorithm is not suitable for large datasets and it doesn't perform well when the target classes are overlapping. The model can be improved further through random search for hyperparameters to reduce overfitting.

5.3 Ridge Classifier

In [194]:
```
ridge_clf = RidgeClassifier() #initiate the model
ridge_clf.fit(x_train_prepared , train_y) #fit the model
y_predict_3 = ridge_clf.predict(x_train_prepared) #predict
confusion_3 = confusion_matrix(train_y, y_predict_3) #create the confusion matrix
confusion_3 = pd.DataFrame(data=confusion_3, columns=['Predicted: 0','Predicted: 1'],index=['Actual: 0 ','Actual: 1']) #transform it to dataframe
ax = plt.axes()
ax.set_title('Confusion Matrix of Ridge Classifier')
sns.heatmap(confusion_3, annot=True, fmt ='d', cmap="Blues", linecolor='w') #plot confusion matrix as heatmap
plt.show()
print('Classification report: \n', classification_report(train_y ,y_predict_3)) #classification report
scores_3 = cross_val_score(ridge_clf , x_train_prepared,  train_y, scoring="f1", cv=3) #cross validation scores
print('Cross Validation Scores are: ', scores_3)
print("Average F-1 score of Ridge Classifier from Cross Validation is: %0.2f" % (scores_3.mean()));
```



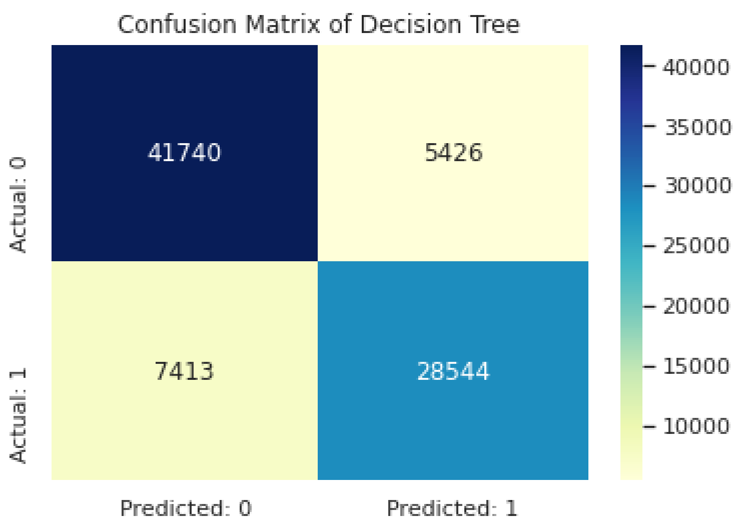

```
Classification report: 
               precision    recall  f1-score   support

           0       0.85      0.88      0.87     47166
           1       0.84      0.79      0.82     35957

    accuracy                           0.85     83123
   macro avg       0.84      0.84      0.84     83123
weighted avg       0.85      0.85      0.84     83123

Cross Validation Scores are:  [0.81701472 0.81358406 0.81812715]
Average F-1 score of Ridge Classifier from Cross Validation is: 0.82
```

The ridge classifier is a regularized model which improves the conditioning of the problem and reduces the variance of the estimates whereby it considers the highest value in prediction to accept target class. On the airlines dataset, the model has a F-1 score of 82%, this could be improved with an optimal choice of alpha (regularized hyperparameter).

5.4 DecisionTree Classifier

In [139]:

```
tree_clf = DecisionTreeClassifier(random_state=42) #initiate the model
tree_clf.fit(x_train_prepared , train_y)#fit the model
y_predict_4 = tree_clf.predict(x_train_prepared) #predict
confusion_4 = confusion_matrix(train_y, y_predict_4) #create the confusion matrix
confusion_4 = pd.DataFrame(data=confusion_4, columns=['Predicted: 0','Predicted: 1'],index=['Actual: 0 ','Actual: 1']) #transform it to dataframe
ax = plt.axes()
ax.set_title('Confusion Matrix of Decision Tree')
sns.heatmap(confusion_3, annot=True, fmt ='d', cmap="YlGnBu", linecolor='w') # plot confusion matrix as heatmap
plt.show()
print('Classification report: \n', classification_report(train_y ,y_predict_4)) #classification report
scores_4 = cross_val_score(tree_clf, x_train_prepared,  train_y, scoring="f1", cv=3) #cross validation scores
print('Cross Validation Scores are: ',scores_4)
print("Average F-1 score of Decision Tree Classifier from Cross Validation is %0.2f" % (scores_4.mean()))
```

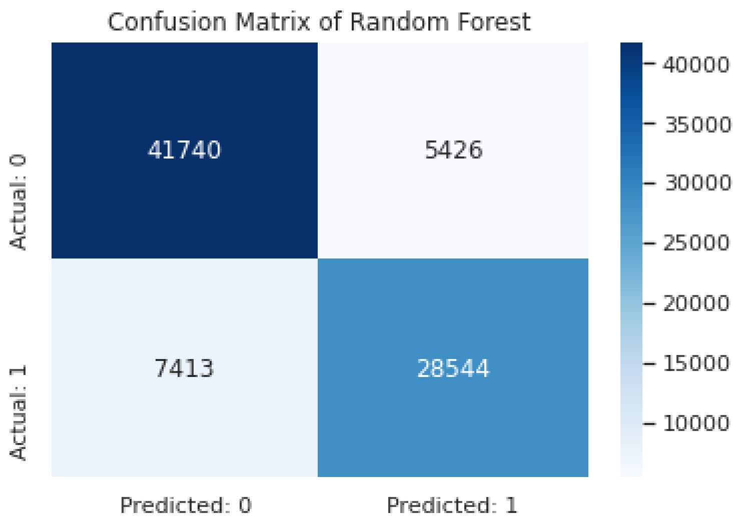



```
Classification report: 
               precision    recall  f1-score   support

           0       1.00      1.00      1.00     47166
           1       1.00      1.00      1.00     35957

    accuracy                           1.00     83123
   macro avg       1.00      1.00      1.00     83123
weighted avg       1.00      1.00      1.00     83123

Cross Validation Scores are:  [0.8446182  0.84302616 0.84761031]
Average F-1 score of Decision Tree Classifier from Cross Validation is 0.85
```

The Decision Tree is good at classifying unknown records and excluding unimportant features. However, it can be easily overfitted and it is sensitive for any change of data. It has a good performance in predicting the satisfaction level on the airlines dataset, but we will try next the random forest which uses an advanced approach of training individual trees.

5.5 Random Forest Classifier

In [140]:
```
rf_clf = RandomForestClassifier(random_state=42) #initiate the model
rf_clf.fit(x_train_prepared , train_y)#fit the model
y_predict_5 = rf_clf.predict(x_train_prepared) #predict
confusion_5 = confusion_matrix(train_y, y_predict_5) #create the confusion mat
rix
confusion_5 = pd.DataFrame(data=confusion_3, columns=['Predicted: 0','Predicte
d: 1'],index=['Actual: 0 ','Actual: 1']) #transform it to dataframe
ax = plt.axes()
ax.set_title('Confusion Matrix of Random Forest')
sns.heatmap(confusion_5, annot=True, fmt ='d', cmap="Blues", linecolor='w') #p
lot confusion matrix as heatmap
plt.show()
print('Classification report: \n', classification_report(train_y ,y_predict_5
)) #classification report
scores_5 = cross_val_score(rf_clf, x_train_prepared,  train_y, scoring="f1", c
v=3) #cross validation scores
print('Cross Validation Scores are: ', scores_5)
print("Average F-1 score of Random Forest Classifier from Cross Validation is
%0.2f" % (scores_5.mean()))
```

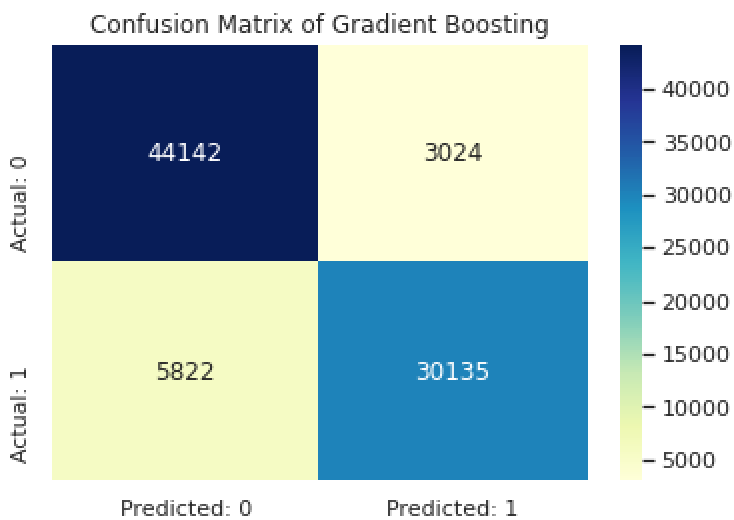



```
Classification report: 
               precision    recall  f1-score   support

           0       1.00      1.00      1.00     47166
           1       1.00      1.00      1.00     35957

    accuracy                           1.00     83123
   macro avg       1.00      1.00      1.00     83123
weighted avg       1.00      1.00      1.00     83123

Cross Validation Scores are:  [0.90206718 0.90136362 0.90432537]
Average F-1 score of Random Forest Classifier from Cross Validation is 0.90
```

The Random Forest model consists of many decisions trees. It uses bagging and feature randomness when building each tree. It has the power to predict the class and identify the relative feature importance. In our example, this model has higher performance than decision trees and this can be increased further through random search to find the optimal parameters.

5.6 Gradient Boosting Classifier

In [141]:
```
gb_clf = GradientBoostingClassifier(random_state=42) #initiate the model
gb_clf.fit(x_train_prepared , train_y) #fit the model
y_predict_6 = gb_clf.predict(x_train_prepared) #predict
confusion_6 = confusion_matrix(train_y, y_predict_6) #create the confusion mat
rix
confusion_6 = pd.DataFrame(data=confusion_6, columns=['Predicted: 0','Predicte
d: 1'],index=['Actual: 0 ','Actual: 1']) #transform it to dataframe
ax = plt.axes()
ax.set_title('Confusion Matrix of Gradient Boosting')
sns.heatmap(confusion_6, annot=True, fmt ='d', cmap="YlGnBu", linecolor='w') #
plot confusion matrix as heatmap
plt.show()
print('Classification report: \n', classification_report(train_y ,y_predict_6
)) #classification report
scores_6 = cross_val_score(gb_clf, x_train_prepared,  train_y, scoring="f1", c
v=3) #cross validation scores
print('Cross Validation Scores are: ', scores_6)
print("Average F-1 score of Gradient Boosting Classifier from Cross Validation
is %0.2f" % (scores_6.mean()))
```

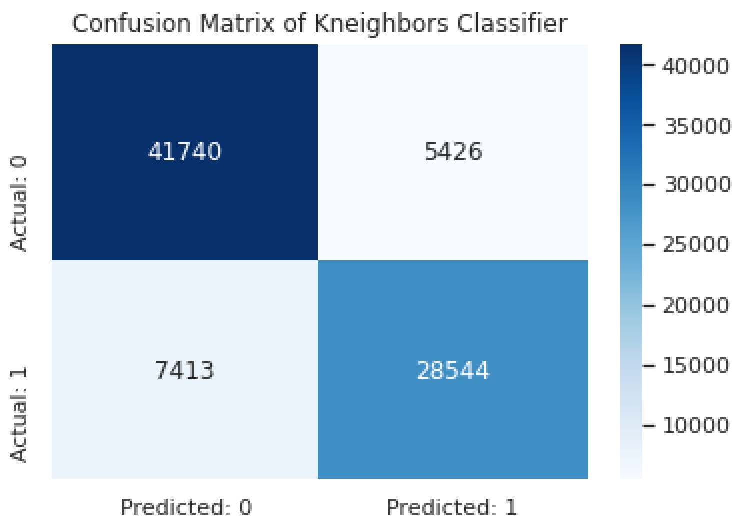



```
Classification report: 
               precision    recall  f1-score   support

           0       0.88      0.94      0.91     47166
           1       0.91      0.84      0.87     35957

    accuracy                           0.89     83123
   macro avg       0.90      0.89      0.89     83123
weighted avg       0.89      0.89      0.89     83123

Cross Validation Scores are:  [0.8691195  0.86644951 0.86871144]
Average F-1 score of Gradient Boosting Classifier from Cross Validation is 0.
87
```

The GradientBoosting Classifier is an algorithim which adds predictors to an ensemble, each one correcting its predecessor. It has a special learning_rate hyperparameter which scales the contribution of each tree and controls overfitting. Also, early stopping can be implemented to monitor generalization and stops when the error begins to degrade. The model has achieved a good F-1 score of 87% on the Airlines dataset.

5.7 K-nearest Neighbors Classifier

In [142]:
```
kne_classifier = KNeighborsClassifier() #initiate the model
kne_classifier.fit(x_train_prepared , train_y) #fit the model
y_predict_7 = kne_classifier.predict(x_train_prepared) #predict
confusion_7 = confusion_matrix(train_y, y_predict_7) #create the confusion mat
rix
confusion_7 = pd.DataFrame(data=confusion_7, columns=['Predicted: 0','Predicte
d: 1'],index=['Actual: 0 ','Actual: 1']) #transform it to dataframe
ax = plt.axes()
ax.set_title('Confusion Matrix of Kneighbors Classifier')
sns.heatmap(confusion_5, annot=True, fmt ='d', cmap="Blues", linecolor='w') #p
lot confusion matrix as heatmap
plt.show()
print('Classification report: \n', classification_report(train_y ,y_predict_7
)) #classification report
scores_7 = cross_val_score(kne_classifier, x_train_prepared,  train_y, scoring
="f1", cv=3) #cross validation scores
print('Cross Validation Scores are: ', scores_7)
print("Average F-1 score of Kneighbors Classifier from Cross Validation is %0.
2f" % (scores_7.mean()))
```




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

           0       0.93      0.97      0.95     47166
           1       0.96      0.91      0.93     35957

    accuracy                           0.94     83123
   macro avg       0.94      0.94      0.94     83123
weighted avg       0.94      0.94      0.94     83123

Cross Validation Scores are:  [0.89700568 0.90039155 0.90163371]
Average F-1 score of Kneighbors Classifier from Cross Validation is 0.90
```

K-neighbors is a classification model which classifies datapoints into separate clusters. Its limitation is that it gets slower as the data increases. It has a very good performance of F-1 score 90% on the Airlines dataset and it can be improved through finding the optimal number of clusters (k).

5.8 Shortlisted Models

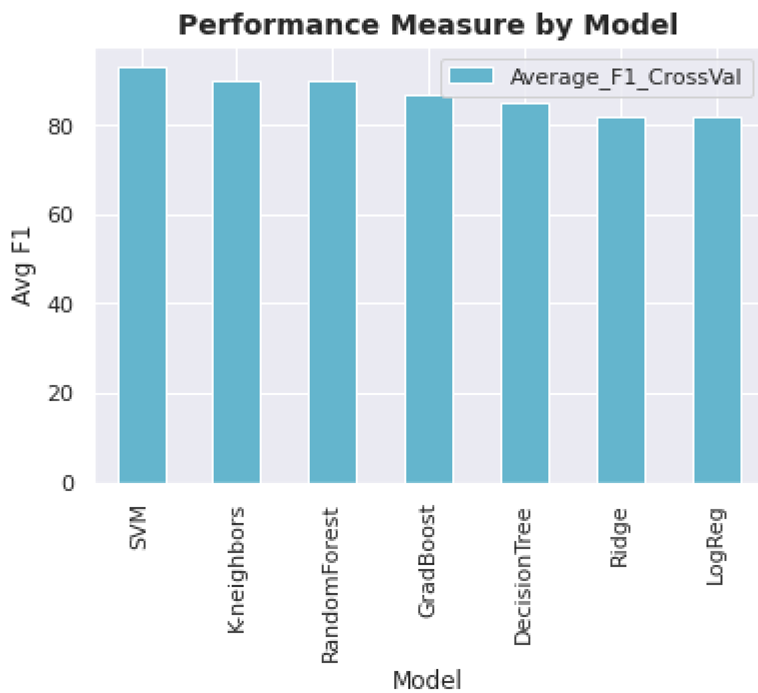
In [77]:
```
#create a dataframe for the avg f-1 scores of models
Models = ['SVM', 'K-neighbors', 'RandomForest', 'GradBoost', 'DecisionTree',
'Ridge', 'LogReg'] #define list of models
Average_F1_CrossVal = [93, 90, 90, 87, 85, 82, 82] #define list of F-1 scores
models_df = pd.DataFrame({'Average_F1_CrossVal': Average_F1_CrossVal}, index=M
odels) #build the dataframe
models_df
```

Out[77]:

	Average_F1_CrossVal
SVM	93
K-neighbors	90
RandomForest	90
GradBoost	87
DecisionTree	85
Ridge	82
LogReg	82

In [76]:
```
#visualize these scores in bar plot
plt.figure(figsize=(10,8)) #figure size
ax = models_df.plot.bar(color ='c')
ax.set_title('Performance Measure by Model', fontweight="bold", size =14) #set the title
ax.set_xlabel('Model', fontsize = 12) #set x_label
ax.set_ylabel('Avg F1', fontsize = 12); #set y_label
```

```
<Figure size 720x576 with 0 Axes>
```



The best four models with the highest F-1 score from Cross-alidation will be shortlised for fine-tuning:

1- Support Vector Machine : 93

2- K-nearest neighbors: 90

3- Random Forest: 90

4- Gradient Boosting : 87

6. Fine Tuning

We will be using the random search to tune the four selected models because our dataset is large. This search will enable us to set-up a grid of parameter values and find combinations to train the model and achieve better performance. After obtaining the optimal parameters of RandomForest and GradientBoosting algorithims specifically, the relative importance of features will be extracted to identify which variables are mostly affecting the predictor. Then, we will apply an ensemble method of a voting classifier to combine the predictions of the tuned estimators built in the four algorithims and obtain a better predictor so we can cross-check the models' perfromance on testset. If the voting ensemble won't work, we will try the Adaboost method. Lastly, we will select the final model and predict on the testset to measure the model's generalizability power.

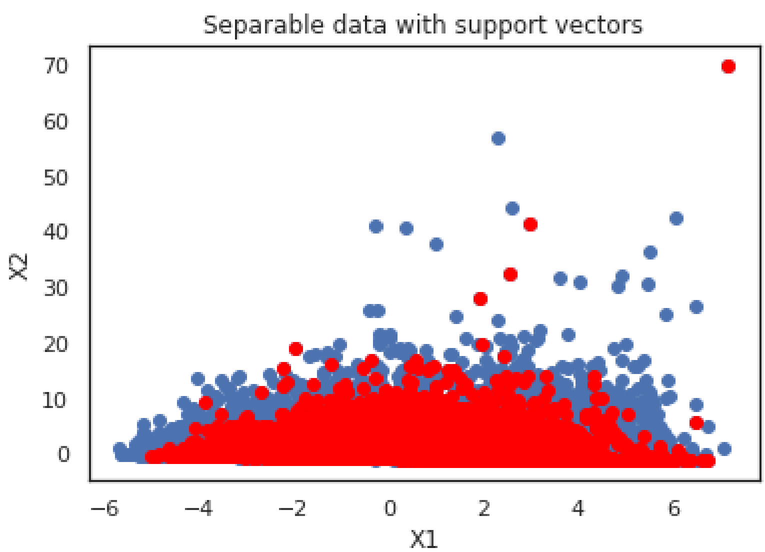
6.1 Random Search

In [25]:

```
# Use the random search for best hyperparameters of SVC
#initiate the model
model = SVC()
#define the hyperparameters
kernel = ['poly', 'rbf', 'sigmoid']
C = [50, 10, 1.0, 0.1, 0.01]
gamma = ['scale']
# define search
search_1 = dict(kernel=kernel,C=C,gamma=gamma)
# set up the SVC_random
random_search_1 = RandomizedSearchCV(estimator = model, param_distributions =
search_1, n_iter = 3, cv = 3, verbose=2, random_state=42, n_jobs = -1)
# Fit the random search model
SVC.random_result = random_search_1.fit(x_train_prepared , train_y)
# summarize results
print("Best: %f using %s" % (SVC.random_result.best_score_, SVC.random_result.
best_params_))
```

```
Fitting 3 folds for each of 3 candidates, totalling 9 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done   7 out of   9 | elapsed: 37.7min remaining: 10.8
min
[Parallel(n_jobs=-1)]: Done   9 out of   9 | elapsed: 41.4min finished

Best: 0.910037 using {'kernel': 'poly', 'gamma': 'scale', 'C': 50}
```

In [305]:
```
svm_clf = SVC(gamma="scale", kernel = 'poly', C = 50, random_state=42) #SVM be
st parameters model
svm_clf.fit(x_train_prepared , train_y) #fit the model
support_vectors = svm_clf.support_vectors_ # Get support vectors
# Visualize support vectors
plt.scatter(x_train_prepared[:,0], x_train_prepared[:,1])
plt.scatter(support_vectors[:,0], support_vectors[:,1], color='red')
plt.title('Separable data with support vectors')
plt.xlabel('X1')
plt.ylabel('X2')
plt.show()
#extracted from https://www.machinecurve.com/index.php/2020/05/05/how-to-visua
lize-support-vectors-of-your-svm-classifier/
```



Despite the SVM's computational complexity, we were able to find the best hyperparameters and visualized the data separation. The graph shows that the data is non-linear especially that the best kernel is obtained as "polynomial". It is also difficult to generate a clear decision boundary among the two classes (red and blue) as reflected in the figure.

In [20]:

```
#use random searching key for hyperparametres of KNeighborsClassifier
# define model
model = KNeighborsClassifier()
#define parameters
n_neighbors = range(1, 21, 2)
weights = ['uniform', 'distance']
metric = ['euclidean', 'manhattan', 'minkowski']
#define search
search_3 = dict(n_neighbors=n_neighbors,weights=weights,metric=metric)
#set up the search model
random_search_3 = RandomizedSearchCV(estimator=model, param_distributions=sear
ch_3, n_jobs=-1, cv=3, scoring='f1',error_score=0)
#fit the search
random_result_Knei = random_search_3.fit(x_train_prepared , train_y)
#summarize results
print("Best: %f using %s" % (random_result_Knei.best_score_,random_result_Knei
.best_params_))
```

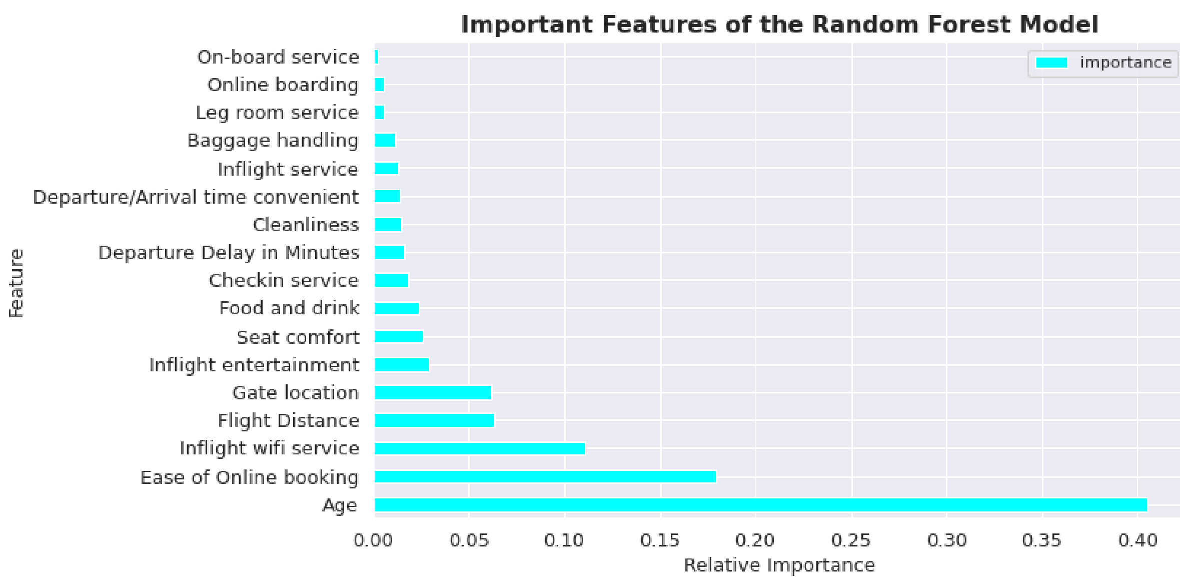
```
Best: 0.903675 using {'weights': 'uniform', 'n_neighbors': 11, 'metric': 'man
hattan'}
```

In [31]:

```
# use random search for RandomForestClassifier
#define the model
rnd_clf = RandomForestClassifier(random_state=42)
#define parameters
search_4 = [
    {'n_estimators': [3, 10, 30], 'max_features': [2, 4, 6, 8], 'bootstrap': [
False, True], 'max_depth': [2, 3, 4,8] }]
#set up the search search
random_search_4 = RandomizedSearchCV(rnd_clf , search_4, cv=3,
                           scoring='f1', return_train_score=True)
#fit the search
random_result_RF = random_search_4.fit(x_train_prepared , train_y)
#summarize results
print("Best: %f using %s" % (random_result_RF.best_score_,random_result_RF.bes
t_params_))
#extracted from: https://towardsdatascience.com/hyperparameter-tuning-the-rand
om-forest-in-python-using-scikit-learn-28d2aa77dd74
```

```
Best: 0.840864 using {'n_estimators': 30, 'max_features': 2, 'max_depth': 8,
'bootstrap': True}
```

In [88]:
```
#extract the important features from the new random forest model
new_rf_clf = RandomForestClassifier(n_estimators = 30, max_features = 4, max_d
epth = 8, bootstrap = True) #Random Classifier best parameters models
new_rf_clf.fit(x_train_prepared , train_y) #fit the model
feature_importances = new_rf_clf.feature_importances_ #find the feature import
ance
attributes = numeric_variables + categorical_variables #define the attributes
feat_importances = sorted(zip(feature_importances, attributes), reverse=True)
#create a sorted tuple
#visualise the feature importance of Random Forest
df_rf = pd.DataFrame(data = feat_importances) #create a dataframe
df_rf.columns = ['importance', 'feature'] #rename the columns
df_rf.set_index('feature', inplace=True)#set the index to be the features
fig, ax = plt.subplots(figsize=(10,6))
df_rf.plot(ax=ax, kind='barh', color ='aqua') #define the plot
plt.xticks(fontsize=13)
plt.yticks(fontsize=13)
ax.set_title('Important Features of the Random Forest Model', fontweight="bol
d", size =16) #set title
ax.set_xlabel('Relative Importance', fontsize = 13)
ax.set_ylabel('Feature', fontsize = 13);
```



The **best 4 features from RandomForest** are:

1- Age

2- Ease of Online Booking

3- Wifi Service

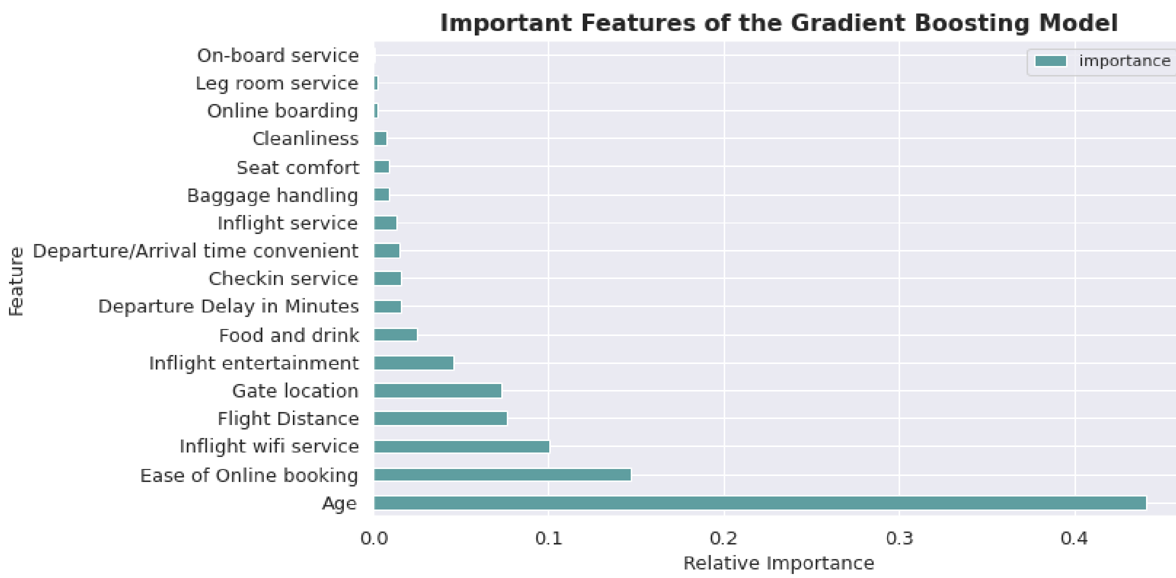
4- Gate Location

In [77]:
```
#use the results of the best parameters of Random Forest to find the best lear
ning rate of Gradient Boosting
#define learning rate list
lr_list = [0.1, 0.25, 0.5, 0.75, 1]
for learning_rate in lr_list:
    #set up the GB classifier to find learning rate with early stopping (warm_
start = True)
    new_gb_clf = GradientBoostingClassifier(n_estimators=30, warm_start=True,
learning_rate=learning_rate, max_features=4, random_state=42)
    #fit the model
    new_gb_clf.fit(x_train_prepared , train_y)
    #summarize the results
    print("Learning rate: ", learning_rate)
    print("score (training): {0:.3f}".format(new_gb_clf.score(x_train_prepared
, train_y)))
#extracted from: https://stackabuse.com/gradient-boosting-classifiers-in-pytho
n-with-scikit-learn/
```

```
Learning rate:  0.1
score (training): 0.867
Learning rate:  0.25
score (training): 0.885
Learning rate:  0.5
score (training): 0.895
Learning rate:  0.75
score (training): 0.898
Learning rate:  1
score (training): 0.897
```

The best score is at learning rate of 0.75

In [89]:
```
#get the important features of Grad Boosting Classifier
gb_clf = GradientBoostingClassifier(n_estimators=30, warm_start=True, learning
_rate=0.75, max_features=4, random_state=42) #Grad Boosting best parameters mo
dels
gb_clf.fit(x_train_prepared , train_y)
feature_importances_1 = gb_clf.feature_importances_ #find the feature importan
ce
attributes = numeric_variables + categorical_variables #define the attributes
feat_importances_1 = sorted(zip(feature_importances_1, attributes), reverse=Tr
ue) #create a sorted tuple
feat_importances_1;
#visualise the feature importance of Gradient Boosting Classifier
df_gb = pd.DataFrame(data = feat_importances_1) #create a dataframe
df_gb.columns = ['importance', 'feature'] #rename the columns
df_gb.set_index('feature', inplace=True) #set the index to be the features
fig, ax = plt.subplots(figsize=(10,6))
df_gb.plot(ax=ax, kind='barh', color ='cadetblue') #define the plot
plt.xticks(fontsize=13)
plt.yticks(fontsize=13)
ax.set_title('Important Features of the Gradient Boosting Model', fontweight=
"bold", size =16) #set title
ax.set_xlabel('Relative Importance', fontsize = 13)
ax.set_ylabel('Feature', fontsize = 13);
```



The **best 4 features from GradientBoosting** are:

1- Age

2- Ease of Online Booking

3- Wifi Service

4- Flight Distance

6.2 Ensemble Method: Voting Classifier

In [80]:

```
#set up an ensemble model using the best predictors (models with best paramete
rs)
svm_clf = SVC(gamma="scale", kernel = 'poly', C = 50, random_state=42) #SVM be
st parameters model
kn_classifier = KNeighborsClassifier(weights = 'uniform', n_neighbors = 7, met
ric = 'manhattan') #Kneighbors classifier best parameters model
rf_clf = RandomForestClassifier(n_estimators = 30, max_features = 4, max_depth
= 8, bootstrap = True) #Random Classifier best parameters models
gb_clf = GradientBoostingClassifier(n_estimators=30, warm_start=True, learning
_rate=0.75, max_features=4, random_state=42) #Grad Boosting best parameters mo
dels
#set up the voting classifier
voting_clf = VotingClassifier(
estimators=[('sv', svm_clf), ('kn', kn_classifier),('rf', rf_clf),('gb', gb_cl
f) ],
voting='hard')
voting_clf
```

Out[80]:

```
VotingClassifier(estimators=[('sv', SVC(C=50, kernel='poly', random_state=4
2)),
                             ('kn',
                              KNeighborsClassifier(metric='manhattan',
                                                   n_neighbors=7)),
                             ('rf',
                              RandomForestClassifier(max_depth=8,
                                                     max_features=4,
                                                     n_estimators=30)),
                             ('gb',
                              GradientBoostingClassifier(learning_rate=0.75,
                                                         max_features=4,
                                                         n_estimators=30,
                                                         random_state=42,
                                                         warm_start=True))])
```

In [82]:

```
#summarize the results of each predictor
for clf in (svm_clf, kn_classifier, rf_clf, gb_clf ,voting_clf):
    clf.fit(x_train_prepared, train_y) #fit on the train set
    y_predict = clf.predict(x_test_prepared) #predict on the test set
    print(clf.__class__.__name__, round(f1_score(y_predict, test_y),2)) #print
out the f-1 score of each model
#extracted from: https://github.com/ageron/handson-ml/blob/master/07_ensemble_
learning_and_random_forests.ipynb
```

```
SVC 0.57
KNeighborsClassifier 0.71
RandomForestClassifier 0.62
GradientBoostingClassifier 0.66
VotingClassifier 0.64
```

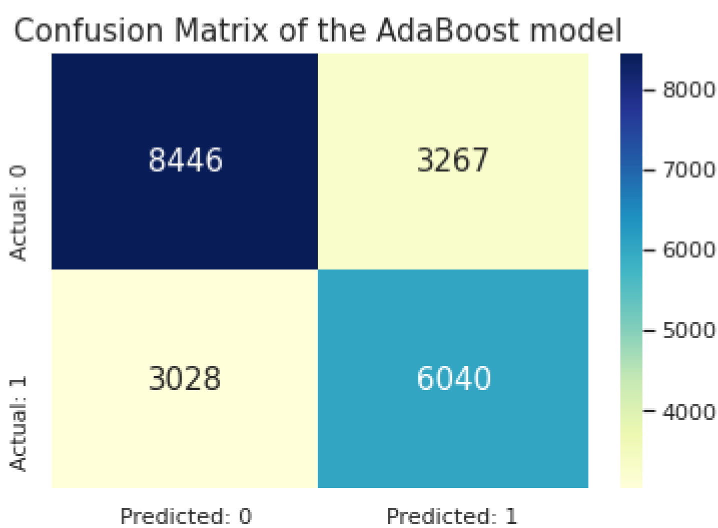
The voting classifier doesn't perform well because we don't have a good number of weak learners and they are not sufficiently diverse. We will try another ensemble.

6.3 Another Ensemble: Adaboost

In [84]:
```
# use random search for AdaboostClassifier
#define the model
adaboost_clf = AdaBoostClassifier(random_state=42)
#define parameters
search_5= [
    {'n_estimators': [3, 10, 15, 30], 'learning_rate': [0.1, 0.25, 0.5, 0.75,
1]}]

#set up the search search
random_search_5 = RandomizedSearchCV(adaboost_clf  , search_5, cv=3,
                           scoring='f1', return_train_score=True)
#fit the search
random_result_Adab = random_search_5.fit(x_train_prepared , train_y)
#summarize results
print("Best: %f using %s" % (random_result_Adab.best_score_,random_result_Adab
.best_params_))
```

```
Best: 0.809903 using {'n_estimators': 15, 'learning_rate': 0.75}
```

In [34]:
```
#Try to fit the model and predict on the testset
adaboost_clf = AdaBoostClassifier(n_estimators= 15, learning_rate = 0.75,  ran
dom_state=42)
adaboost_model = adaboost_clf.fit(x_train_prepared, train_y) #fit on the train
set
y_test_predict = adaboost_clf.predict(x_test_prepared) #predict on the test se
t
confusion_test = confusion_matrix(test_y, y_test_predict) #create the confusio
n matrix
confusion_test = pd.DataFrame(data=confusion_test, columns=['Predicted: 0','Pr
edicted: 1'],index=['Actual: 0 ','Actual: 1']) #transform it to dataframe
ax = plt.axes()
ax.set_title('Confusion Matrix of the AdaBoost model')
sns.heatmap(confusion_test, annot=True, fmt ='d', cmap="YlGnBu", linecolor='w'
) #plot confusion matrix as heatmap
plt.show()
print('Classification report: \n',classification_report(test_y, y_test_predict
)) #classification report
scores_test= cross_val_score(adaboost_model, x_test_prepared, test_y, scoring=
"f1", cv=3) #cross validation scores
print('Cross Validation Scores are: ',scores_test)
print("Average F-1 score of AdaBoosting Classifier is %0.2f " % (scores_test.m
ean()));
```



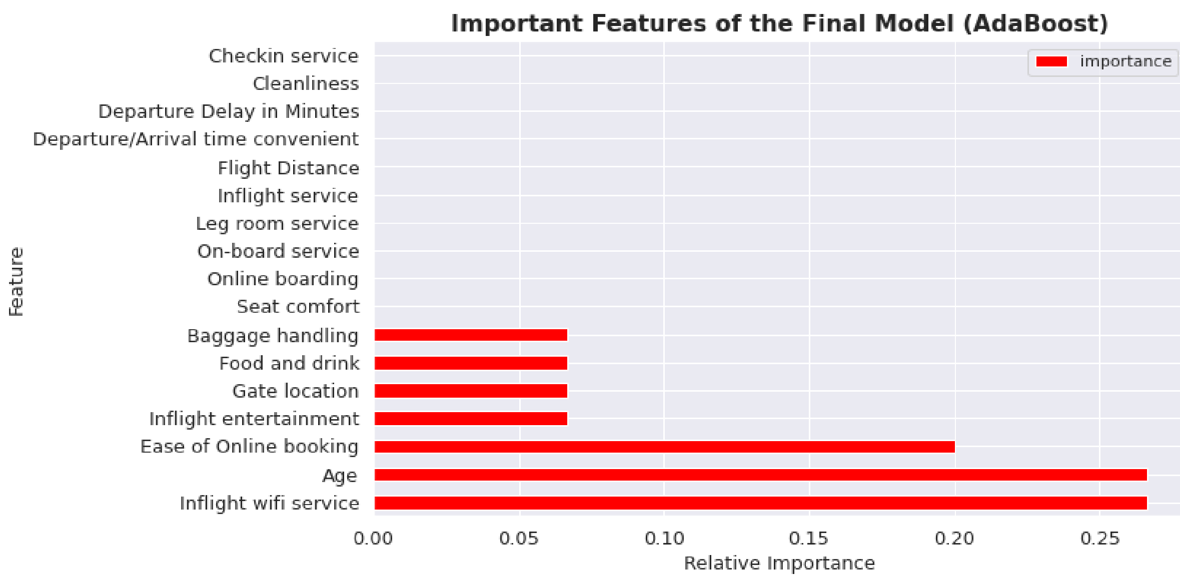

```
Classification report: 
               precision    recall  f1-score   support

           0       0.74      0.72      0.73     11713
           1       0.65      0.67      0.66      9068

    accuracy                           0.70     20781
   macro avg       0.69      0.69      0.69     20781
weighted avg       0.70      0.70      0.70     20781

Cross Validation Scores are:  [0.80626632 0.82206284 0.82432892]
Average F-1 score of AdaBoosting Classifier is 0.82
```

6.4 Final Model

Tuned Model (best parameters)	Performance on Trainset	Performance on Testset
SVMClassifier	0.91	0.57
KNeighborsClassifier	0.90	0.71
RandomForestClassifier	0.86	0.62
GradientBoostingClassifier	0.90	0.66
VotingClassifier	-	0.64
AdaBoostClassifier	0.81	0.82

If we compare the performance measure (F-1 score) of each of the models, we find that the SVM, Kneighbors, RF, and GB are somehow overfitted whereby they perform well on the train but less on the test. However, Adaboost algorithim is performing well on both datasets which indicates high generalizability power. Therefore, **Adaboost will be considered as our final proposed model**.

In [90]:
```
#extract the important features from the final model
feature_importances_3 = final_model.feature_importances_
attributes = numeric_variables + categorical_variables #define the attributes
feat_importances_3 = sorted(zip(feature_importances_3, attributes), reverse=True) #create a sorted tuple
feat_importances_3 #print out the results
#taken from: https://github.com/ageron/handson-ml/blob/master/02_end_to_end_machine_learning_project.ipynb
#visualise the feature importance of Ada Boosting Classifier
df_2 = pd.DataFrame(data = feat_importances_3) #create a dataframe
df_2.columns = ['importance', 'feature'] #rename the columns
df_2.set_index('feature', inplace=True) #set the index to be the features
fig, ax = plt.subplots(figsize=(10,6))
df_2.plot(ax=ax, kind='barh', color ='red') #define the plot
plt.xticks(fontsize=13)
plt.yticks(fontsize=13)
ax.set_title('Important Features of the Final Model (AdaBoost)', fontweight="bold", size =16) #set title
ax.set_xlabel('Relative Importance', fontsize = 13)
ax.set_ylabel('Feature', fontsize = 13);
```



The **best 4 features from Adaboost** are:

1- Wifi

2- Age

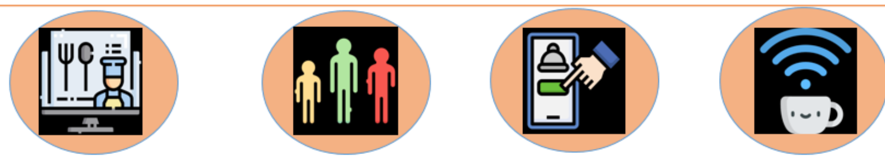
3- Online Booking

4- Entertaiment

7. Conclusion

Summarized Important Features

Exploratory Correlation Study	Random Forest	Gradient Boosting	AdaBoost
Inflight Entertainment	Age	Age	Inflight Wifi Service
Inflight Wifi Service	Ease of Online Booking	Ease of Online Booking	Age
Cleanliness	Inflight Wifi Service	Inflight Wifi Service	Ease of Online Booking
Seat Comfort	Flight Distance	Gate Location	Inflight Entertainment



Inflight Entertaiment, Age, Online Booking, and Wifi are the strongest features which determine customer's satisfaction. Our predictive system will be able to classify customers and support Airlines to continuosly monitor and assess their performance on the eyes of customers and improve accordingly.

8. Reccomendations

Based on the report's findings, we propose the below:

1- **Designing personalized packages for customers based on age categories** particularly targeting adults and old people who are the least satisfied.

2- **Surveying eco-customers** to identify their preferences and provide tailored services accordingly

3- **Improving the inflight wifi access and entertaiment**. For example, streaming Netflix or Spotify will give customers diverse and new-released options of music and films

4- **Implementing online booking assistance service** for customers navigating website and social media platforms

9. Limitations and Future Work

1- The report needs machine learning literature to identify proper algorithims that can fit our dataset and objective.

2- Fine tuning can be extended further; however, due to the time constraints, computational power and complexity, we weren't able to optimize all the scratched models and conduct grid search.

3- To have stronger predictive system, we should consider other hidden factors which affect customer's satisfaction such as seasonality, price flactuations, aircrew service. Also, qualitative data can be taken from open-ended customers' responses and studied through NLP such as sentiment analysis.

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2- MachineCurve. 2021. How to visualize support vectors of your SVM classifier? – MachineCurve. [online] Available at: https://www.machinecurve.com/index.php/2020/05/05/how-to-visualize-support-vectors-of-your-svm-classifier/ (https://www.machinecurve.com/index.php/2020/05/05/how-to-visualize-support-vectors-of-your-svm-classifier/) [Accessed 5 March 2021].

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