Airline passenger satisfaction

Project Description

There is the following information about the passengers of some airline:

1. **Gender:** male or female
2. **Customer type:** regular or non-regular airline customer
3. **Age:** the actual age of the passenger

4. **Type of travel:** the purpose of the passenger's flight (personal or business travel)
5. **Class:** business, economy, economy plus
6. **Flight distance**
7. **Seat comfort:** seat satisfaction level (0: not rated; 1-5)
8. **Departure/Arrival time convenient:** departure/arrival time satisfaction level (0: not rated; 1-5)
9. **Food and drink:** food and drink satisfaction level (0: not rated; 1-5)
10. **Gate location:** level of satisfaction with the gate location (0: not rated; 1-5)
11. **Inflight wifi service:** satisfaction level with Wi-Fi service on board (0: not rated; 1-5)
12. **Inflight entertainment:** satisfaction with inflight entertainment (0: not rated; 1-5)
13. **Online Support**
14. **Ease of Online booking:** online booking satisfaction rate (0: not rated; 1-5)
15. **On-board service:** level of satisfaction with on-board service (0: not rated; 1-5)
16. **Leg room service**: level of satisfaction with leg room service (0: not rated; 1-5)
17. **Baggage handling:** level of satisfaction with baggage handling (0: not rated; 1-5)
18. **Checkin service:** level of satisfaction with checkin service (0: not rated; 1-5)
19. **Cleanliness:** level of satisfaction with cleanliness (0: not rated; 1-5)
20. **Online boarding:** satisfaction level with online boarding (0: not rated; 1-5)
21. **Departure delay in minutes**
22. **Arrival delay in minutes**

This data set contains a survey on **air passenger satisfaction**. The following **classification problem** is set:

It is necessary to predict which of the **two** levels of satisfaction with the airline the passenger belongs to:

1. *Satisfaction*
2. *dissatisfied*

Reading data

Import the main libiraries

In [5]:
```
import plotly.express as px
# ^^^ pyforest auto-imports - don't write above this line
import plotly.express as px
# Most important
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
import missingno as msno
import warnings
warnings.filterwarnings("ignore")
```

Load The DataSet

In [6]:
```
## Read the Csv file
```

In [7]:
```
# Take a copy from dataframe to "df_air"
```

Inspect The Data

In [8]:
```
# Show the head of the dataFrame
```

Out[8]:

	satisfaction	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Seat comfort	Departure/Arrival time convenient	Food and drink	...	Online support	Ease of Online booking	On-board service	s
0	satisfied	Female	Loyal Customer	65	Personal Travel	Eco	265	0	0	0	...	2	3	3	
1	satisfied	Male	Loyal Customer	47	Personal Travel	Business	2464	0	0	0	...	2	3	4	
2	satisfied	Female	Loyal Customer	15	Personal Travel	Eco	2138	0	0	0	...	2	2	3	
3	satisfied	Female	Loyal Customer	60	Personal Travel	Eco	623	0	0	0	...	3	1	1	
4	satisfied	Female	Loyal Customer	70	Personal Travel	Eco	354	0	0	0	...	4	2	2	

5 rows × 23 columns

Each row corresponds to one passenger, and each column to a specific feature.

In [5]:
```
# Show the Tail of the dataFrame
```

Out[5]:

	satisfaction	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Seat comfort	Departure/Arrival time convenient	Food and drink	...	Online support	Ease of Online booking	O boa servi
129875	satisfied	Female	disloyal Customer	29	Personal Travel	Eco	1731	5	5	5	...	2	2	
129876	dissatisfied	Male	disloyal Customer	63	Personal Travel	Business	2087	2	3	2	...	1	3	
129877	dissatisfied	Male	disloyal Customer	69	Personal Travel	Eco	2320	3	0	3	...	2	4	
129878	dissatisfied	Male	disloyal Customer	66	Personal Travel	Eco	2450	3	2	3	...	2	3	
129879	dissatisfied	Female	disloyal Customer	38	Personal Travel	Eco	4307	3	4	3	...	3	4	

5 rows × 23 columns

Explore The Data

In [6]:
```
# Number of rows and columns
```

Out[6]: (129880, 23)

In [7]:
```
# Summary to all columns
def check(df):
    l=[]
    columns=df.columns
    for col in columns:
        dtypes=df[col].dtypes
        nunique=df[col].nunique()
        sum_null=df[col].isnull().sum()
        l.append([col,dtypes,nunique,sum_null])
    df_check=pd.DataFrame(l)
    df_check.columns=['column','dtypes','nunique','sum_null']
```

Out[7]:

	column	dtypes	nunique	sum_null
0	satisfaction	object	2	0
1	Gender	object	2	0
2	Customer Type	object	2	0
3	Age	int64	75	0
4	Type of Travel	object	2	0
5	Class	object	3	0
6	Flight Distance	int64	5398	0
7	Seat comfort	int64	6	0
8	Departure/Arrival time convenient	int64	6	0
9	Food and drink	int64	6	0
10	Gate location	int64	6	0
11	Inflight wifi service	int64	6	0
12	Inflight entertainment	int64	6	0
13	Online support	int64	6	0
14	Ease of Online booking	int64	6	0
15	On-board service	int64	6	0
16	Leg room service	int64	6	0
17	Baggage handling	int64	5	0
18	Checkin service	int64	6	0

	column	dtypes	nunique	sum_null
19	Cleanliness	int64	6	0
20	Online boarding	int64	6	0
21	Departure Delay in Minutes	int64	466	0
22	Arrival Delay in Minutes	float64	472	393

We divide the features into Numerical_columns and Categorical_columns

In [9]:
```
Categorical_columns = df_air.select_dtypes(include=['object'])
```

In [10]:
```
## Some statistics on Numerical_columns
```

Out[10]:

	count	mean	std	min	25%	50%	75%	max
Age	129880.0	39.427957	15.119360	7.0	27.0	40.0	51.0	85.0
Flight Distance	129880.0	1981.409055	1027.115606	50.0	1359.0	1925.0	2544.0	6951.0
Seat comfort	129880.0	2.838597	1.392983	0.0	2.0	3.0	4.0	5.0
Departure/Arrival time convenient	129880.0	2.990645	1.527224	0.0	2.0	3.0	4.0	5.0
Food and drink	129880.0	2.851994	1.443729	0.0	2.0	3.0	4.0	5.0
Gate location	129880.0	2.990422	1.305970	0.0	2.0	3.0	4.0	5.0
Inflight wifi service	129880.0	3.249130	1.318818	0.0	2.0	3.0	4.0	5.0
Inflight entertainment	129880.0	3.383477	1.346059	0.0	2.0	4.0	4.0	5.0
Online support	129880.0	3.519703	1.306511	0.0	3.0	4.0	5.0	5.0
Ease of Online booking	129880.0	3.472105	1.305560	0.0	2.0	4.0	5.0	5.0
On-board service	129880.0	3.465075	1.270836	0.0	3.0	4.0	4.0	5.0
Leg room service	129880.0	3.485902	1.292226	0.0	2.0	4.0	5.0	5.0
Baggage handling	129880.0	3.695673	1.156483	1.0	3.0	4.0	5.0	5.0
Checkin service	129880.0	3.340807	1.260582	0.0	3.0	3.0	4.0	5.0
Cleanliness	129880.0	3.705759	1.151774	0.0	3.0	4.0	5.0	5.0
Online boarding	129880.0	3.352587	1.298715	0.0	2.0	4.0	4.0	5.0
Departure Delay in Minutes	129880.0	14.713713	38.071126	0.0	0.0	0.0	12.0	1592.0
Arrival Delay in Minutes	129487.0	15.091129	38.465650	0.0	0.0	0.0	13.0	1584.0

In [11]:
```
## Some statistics on Categorical_columns
```

Out[11]:

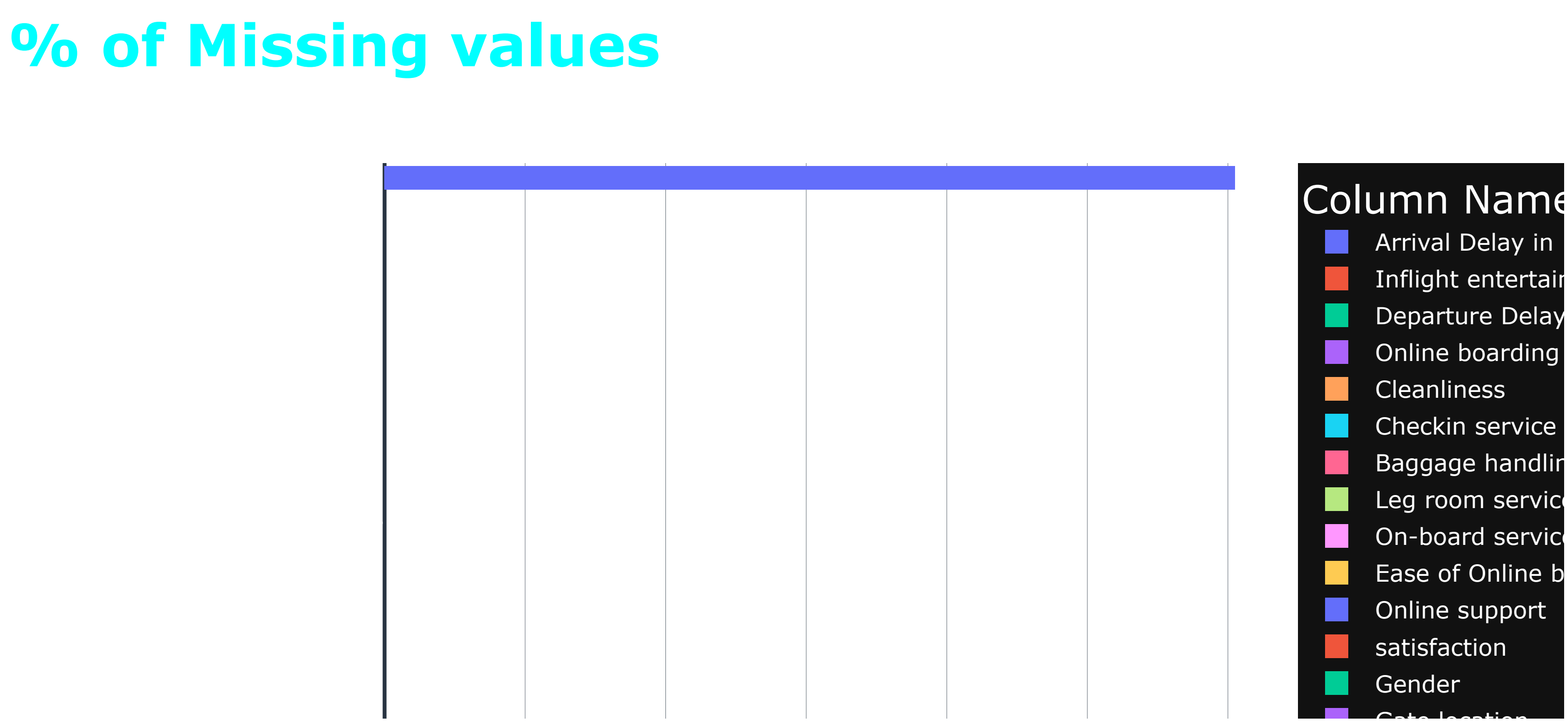
	count	unique	top	freq
satisfaction	129880	2	satisfied	71087
Gender	129880	2	Female	65899
Customer Type	129880	2	Loyal Customer	106100
Type of Travel	129880	2	Business travel	89693
Class	129880	3	Business	62160

Comment

> ***All columns is Numeric expcept [' satisfaction ' , ' Gender ' , ' Customer Type ' , ' Type of Travel ' , ' Class ']***

Discovering Missing Values

In [12]:
```
missing=(df_air.isnull().mean().sort_values(ascending=False)*100).reset_index()
missing.rename(columns={0:"Average"},inplace=True)
missing.head()

fig=px.histogram(missing,x="Average",y="index",title="<b>% of Missing values",color="index",labels={"Average":"%
fig.update_layout(
    font_color="white",
    font_size=12,
    title_font_color="cyan",
    legend_title_font_color="white",
    legend_title_font_size=20,
    template="plotly_dark",
    title_font_size=30

)

fig.show()
```



You may notice the following:

1. **The column** corresponding to the **Arrival Delay in Minutes feature has 393 missing values**.
2. **Many columns contain categorical values** but are of type 'object' or 'int64'. Let's replace this type with a special one designed for storing categorical values.

> **The first 22 features have been detailed above. The satisfaction feature is the target.**

In [13]:
```
df_air.columns
```

Out[13]:
```
Index(['satisfaction', 'Gender', 'Customer Type', 'Age', 'Type of Travel',
       'Class', 'Flight Distance', 'Seat comfort',
       'Departure/Arrival time convenient', 'Food and drink', 'Gate location',
       'Inflight wifi service', 'Inflight entertainment', 'Online support',
       'Ease of Online booking', 'On-board service', 'Leg room service',
       'Baggage handling', 'Checkin service', 'Cleanliness', 'Online boarding',
       'Departure Delay in Minutes', 'Arrival Delay in Minutes'],
      dtype='object')
```

Check the Duplicates in dataset

In [13]:
```
df_air.duplicated().sum()
```

Out[13]:
```
0
```

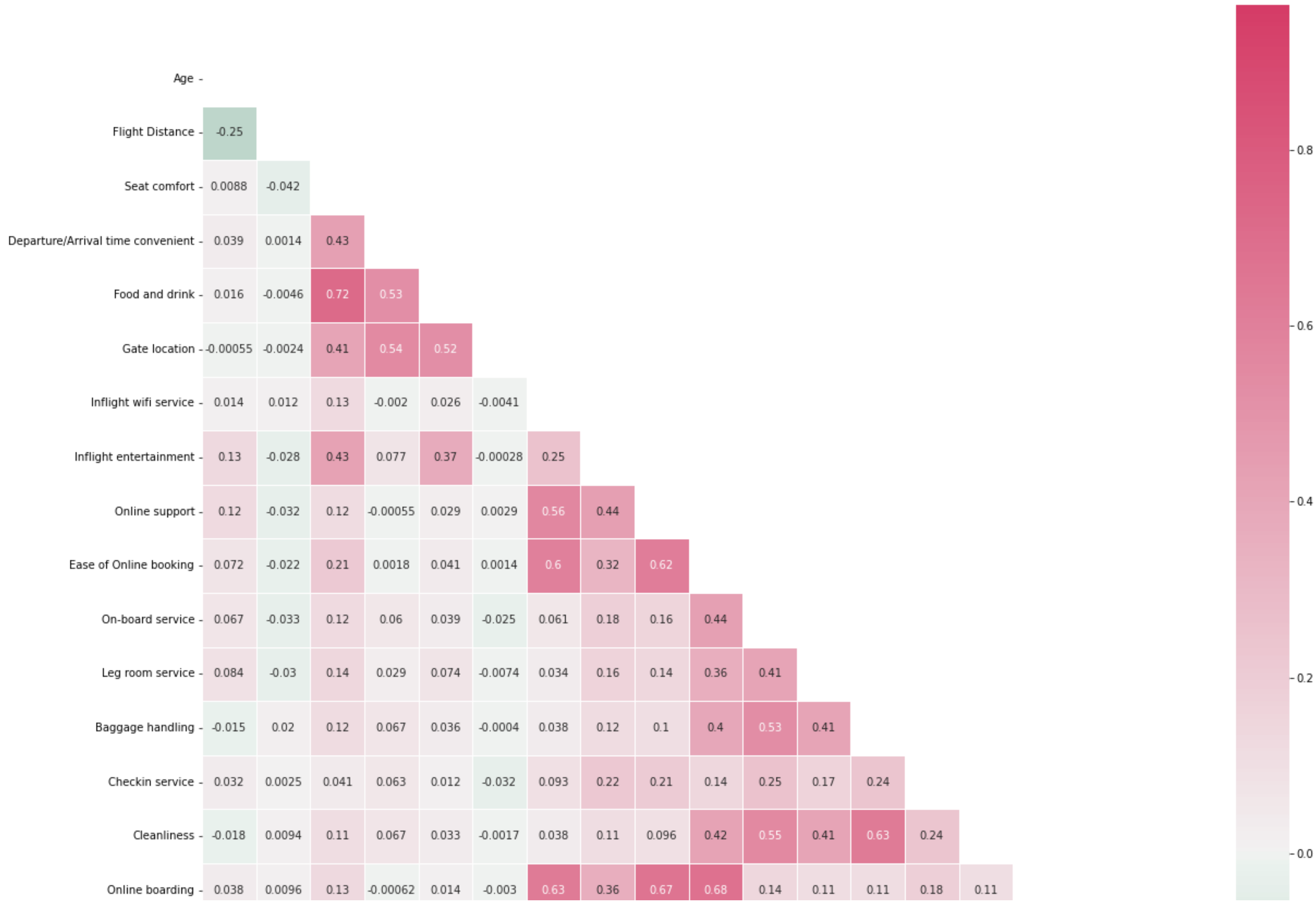
- **Thir is No duplicates in rows**

Data Visualization

Correlation among Features

In [14]:
```
corr = df_air.corr()
mask = np.triu(np.ones_like(corr, dtype=np.bool))
f, ax = plt.subplots(figsize=(20, 20))
cmap = sns.diverging_palette(150, 1, as_cmap=True)
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=None, center=0,square=True, annot=True, linewidths=.5, cbar_kws={"s
```

Out[14]: <AxesSubplot:>

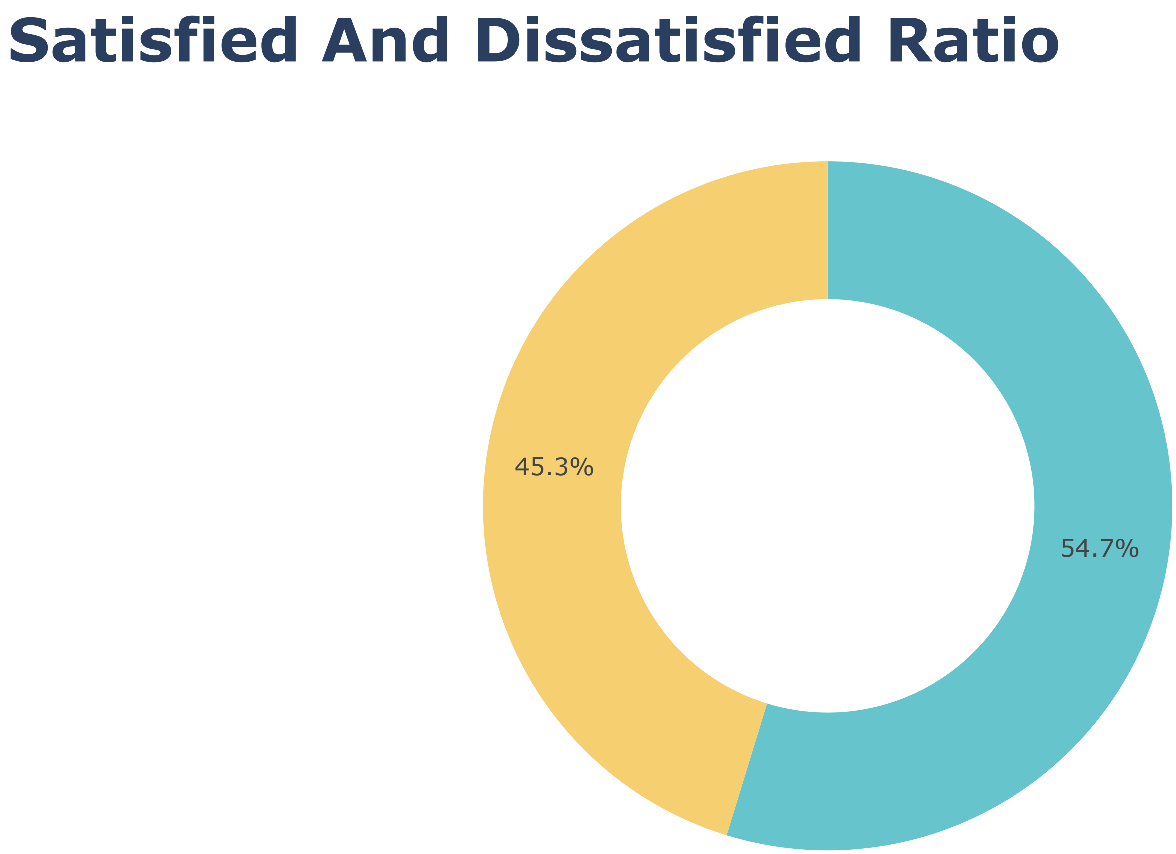


- There is a significat correlation between Departure Delay in Minutes and Arrival Delay in Minutes so we will drop one of 2 freatures to avoid multicolinearity problem.
- Encoding for categorical data, as our categorical columns not ordinal columns we will use getdummies function to encode them.

In [14]:
```
df_air = df_air.drop("Arrival Delay in Minutes",axis=1)
```

1) How Many People is Satisfied and Dissatisfied ?

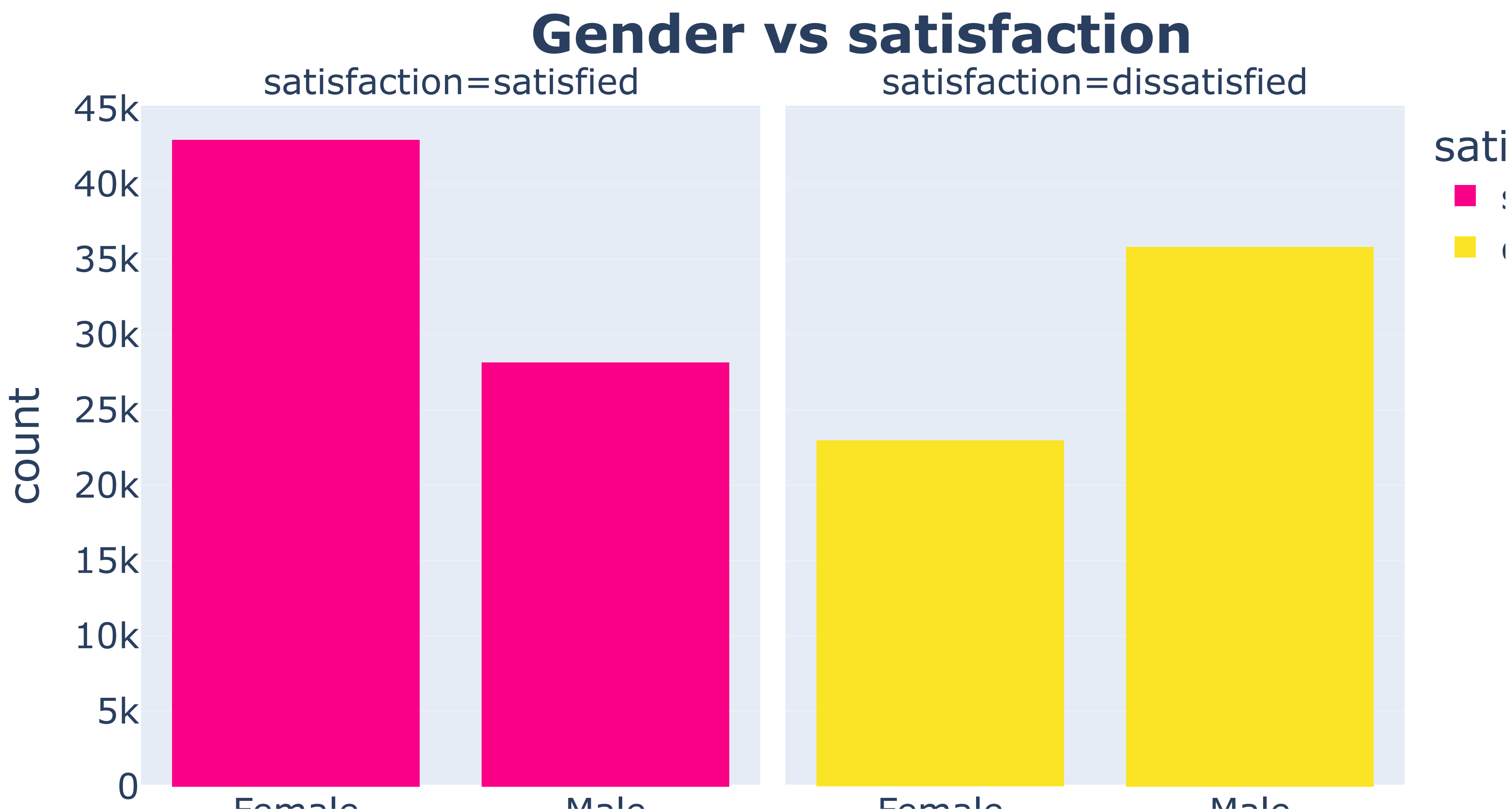
In [15]:
```
fig=px.pie(df_air,values=df_air["satisfaction"].value_counts(),
           names=["Satisfied","Dissatisfied"],title="<b>Satisfied And Dissatisfied Ratio",
           hole=.6,
       color_discrete_sequence=px.colors.qualitative.Pastel,template="plotly")
```



54.7% is Dissatisfied and 45.3% is Satisfied

2) How many women is dissatisfied and how many men is satisfied ?

In [16]:
```
fig=px.histogram(df_air,x="Gender",facet_col="satisfaction",color="satisfaction",color_discrete_sequence=px.colo
fig.update_layout(title="<b>"+"Gender"+" vs satisfaction", title_font_size=30,
                     font_size=20,
                     title_x=0.5,
                     hoverlabel_font_size=20,template="plotly")

fig.show()
```



- As we see the number of males and females almost the same there is a slightly differene.

- As we said before the count of males and females almost the same, that leads to it's correlation with satisfaction of the passenger is low
- From the plot we can see that the percentage of the man that is dissatisfied is more the percentage of women

3) What type of customer we have and which type that has the most satisfied people ?

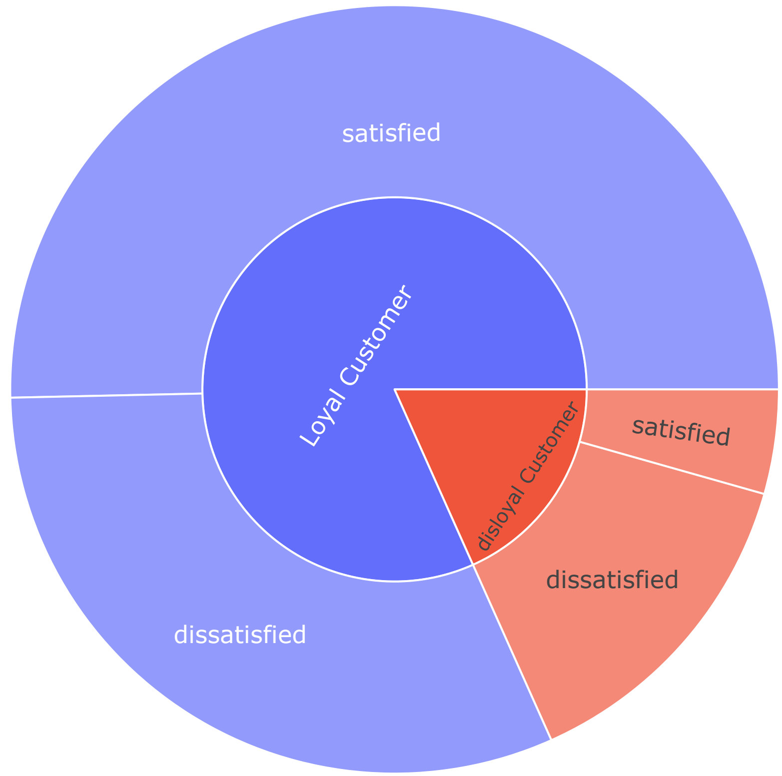
In [17]:
```
fig=px.violin(df_air,y="Age",x="Customer Type",color="satisfaction",title="<b>Age vs Customer Type vs satisfacti
```

- our Loyal Customers much more than Disloyal Customers that looks good for our services.
- As we see Disloyal Customers have less dissatisfaction than the loyel customers
- in Loyal Customers we have more dissatisfaction and that's a problem.

4) Which type of customers and which class has more dissatisfied

people ?

In [18]:
```
fig1 = px.sunburst(df_air,path=["Customer Type","satisfaction"],template="plotly")
```



loyal customer has more dissatisified customers

In [19]:
```
fig2 = px.sunburst(df_air,path=["Class","satisfaction"],template="plotly_white")
```

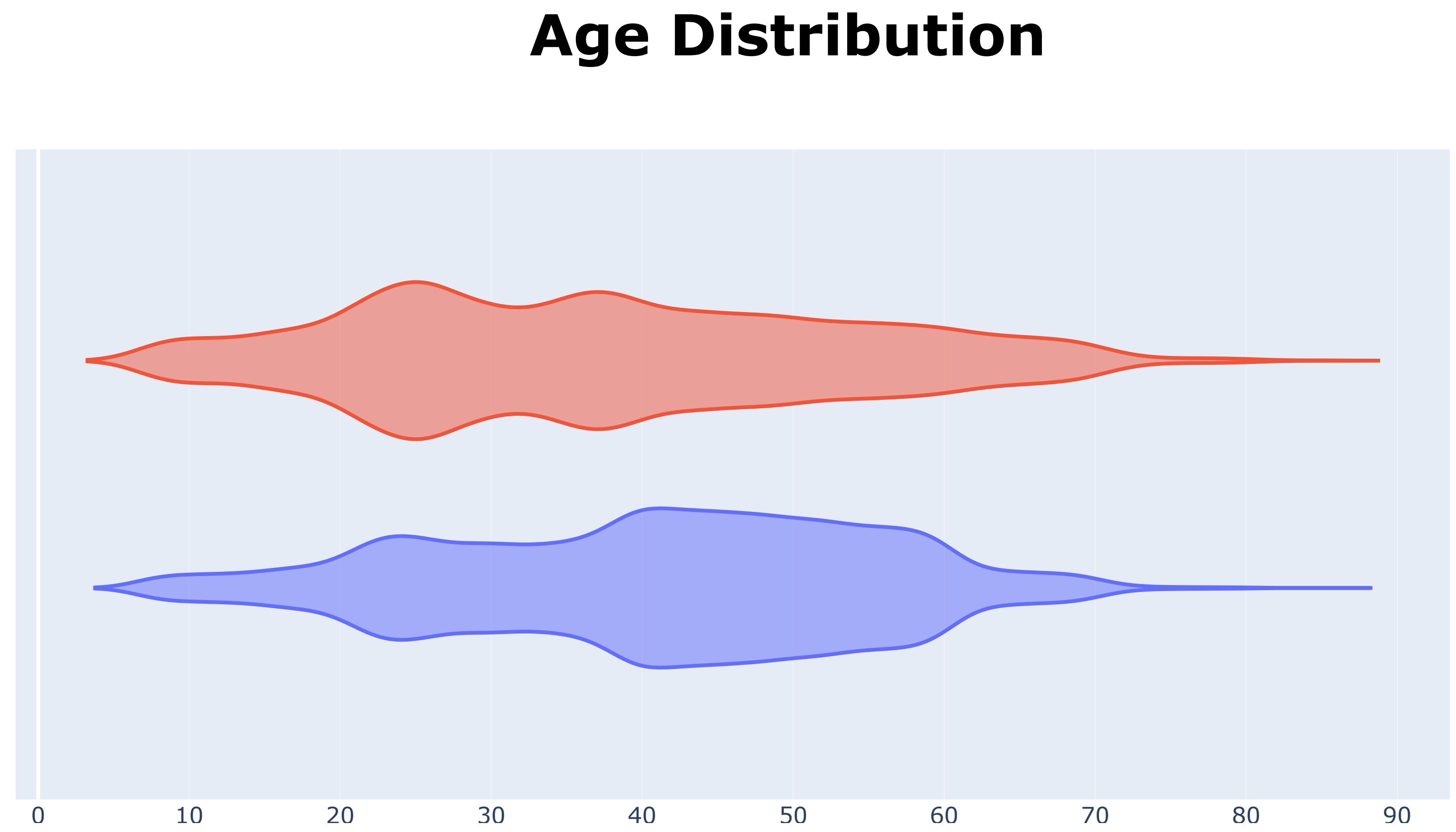
> ***Eco Class has more dissatisified customers***

- conclusion:

> Most dissatisfied customer is loyal customers and in Eco class

5) What is the ages of the customers who is satisfied and dissatisfied

In [20]:
```
feature = "Age"
fig=px.violin(df_air,x=featue,color="satisfaction",title="<b>"+featue+" Distribution",template="plotly_white
fig.update_layout(hovermode='x',title_font_size=30)
fig.update_layout(
title_font_color="black",
template="plotly",
title_font_size=30,
hoverlabel_font_size=20,
title_x=0.5
```



- the customers from 20-35 is the most dissatisfied

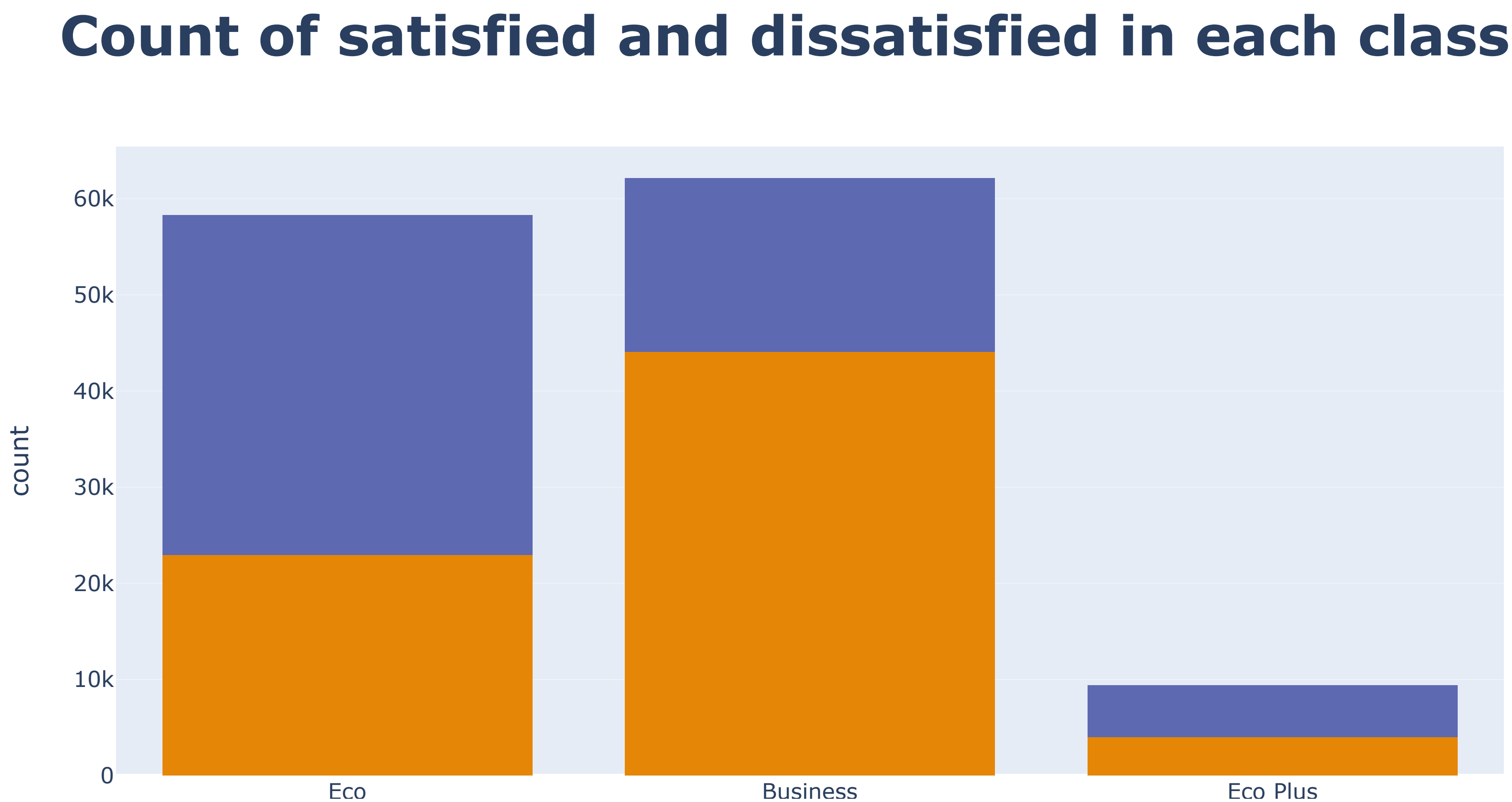
- the customers from 40-60 is the most satisfied

- We noticed from the graph that most of Young people is not satisfied with the service,Although The old people that their age range is between 40 to 60 is satisfied with the service.

> Our conclusion from that the company care more about old people

6) Which class has more dissatisfied people ?

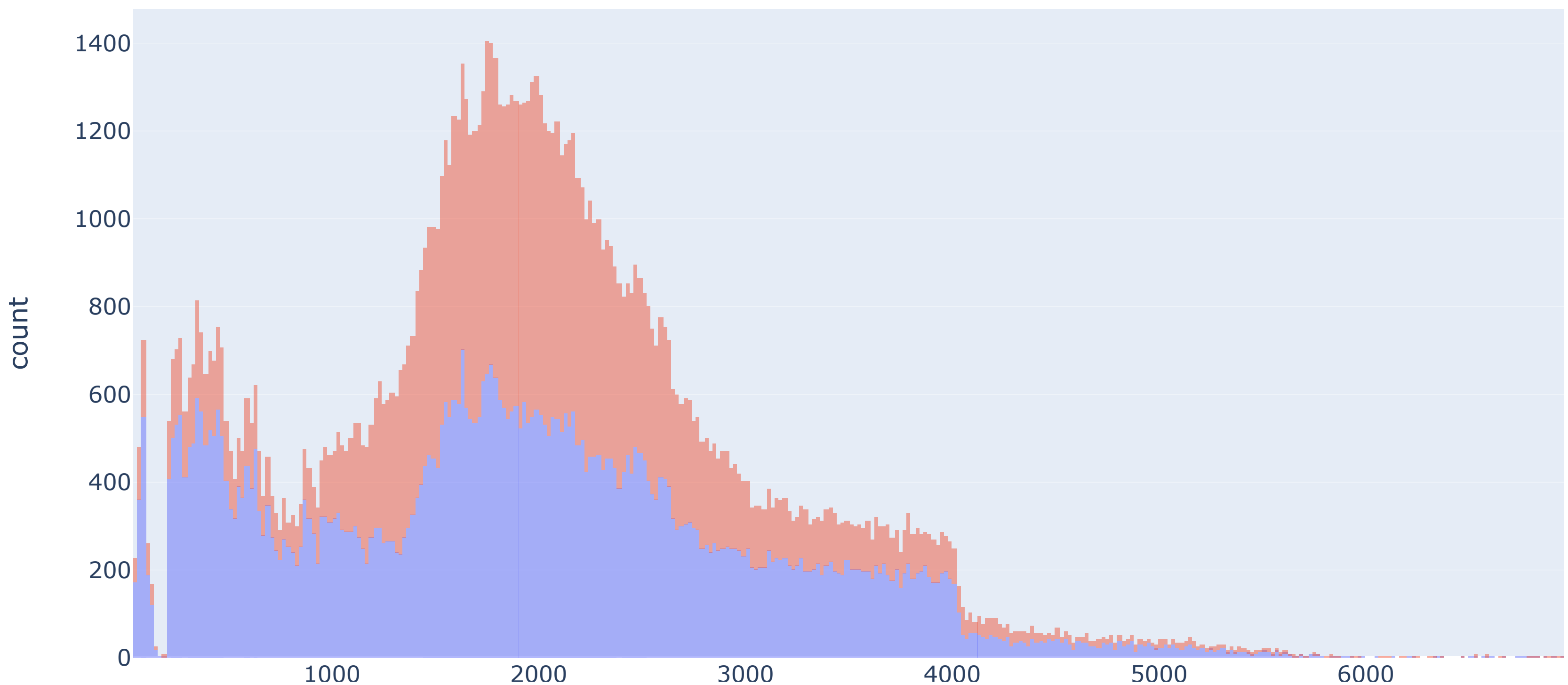
In [21]:
```
fig=px.histogram(df_air,x="Class",color="satisfaction",title="<b>Count of satisfied and dissatisfied in each cla
                 color_discrete_sequence=px.colors.qualitative.Vivid)
fig.update_layout(template="plotly")
```



We discoverd from the graph that the more dissatisfied people is in class Eco

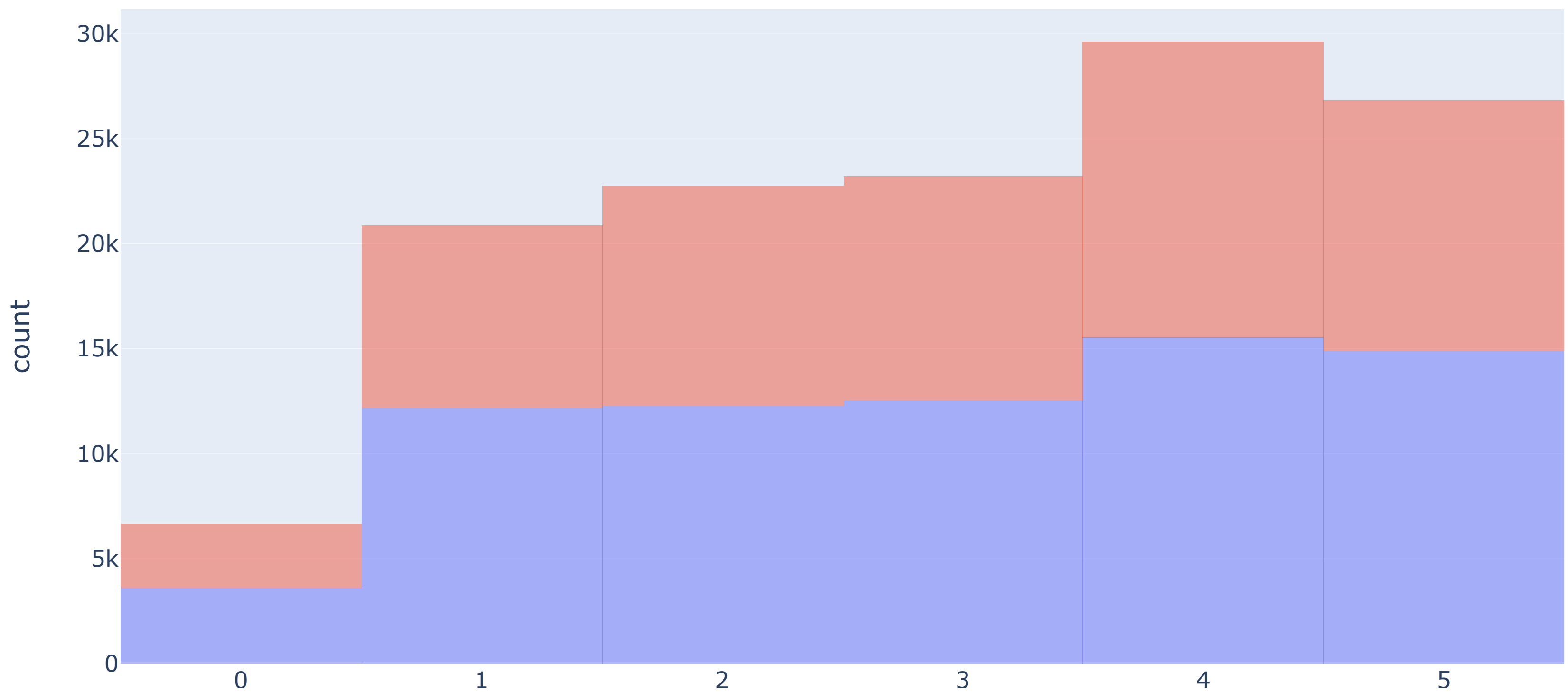
7) Is the flight distance is an important factor that affect the dissatisfaction process ?

In [22]:
```
x="Flight Distance"
fig=px.histogram(df_air,x="Flight Distance",color="satisfaction",title="<b>"+x+" Distribution",template="plotly_
fig.update_layout(hovermode='x',title_font_size=30)
fig.update_layout(
title_font_color="white",
template="plotly",
title_font_size=30,
hoverlabel_font_size=20,
title_x=0.5
)
fig.show()
```



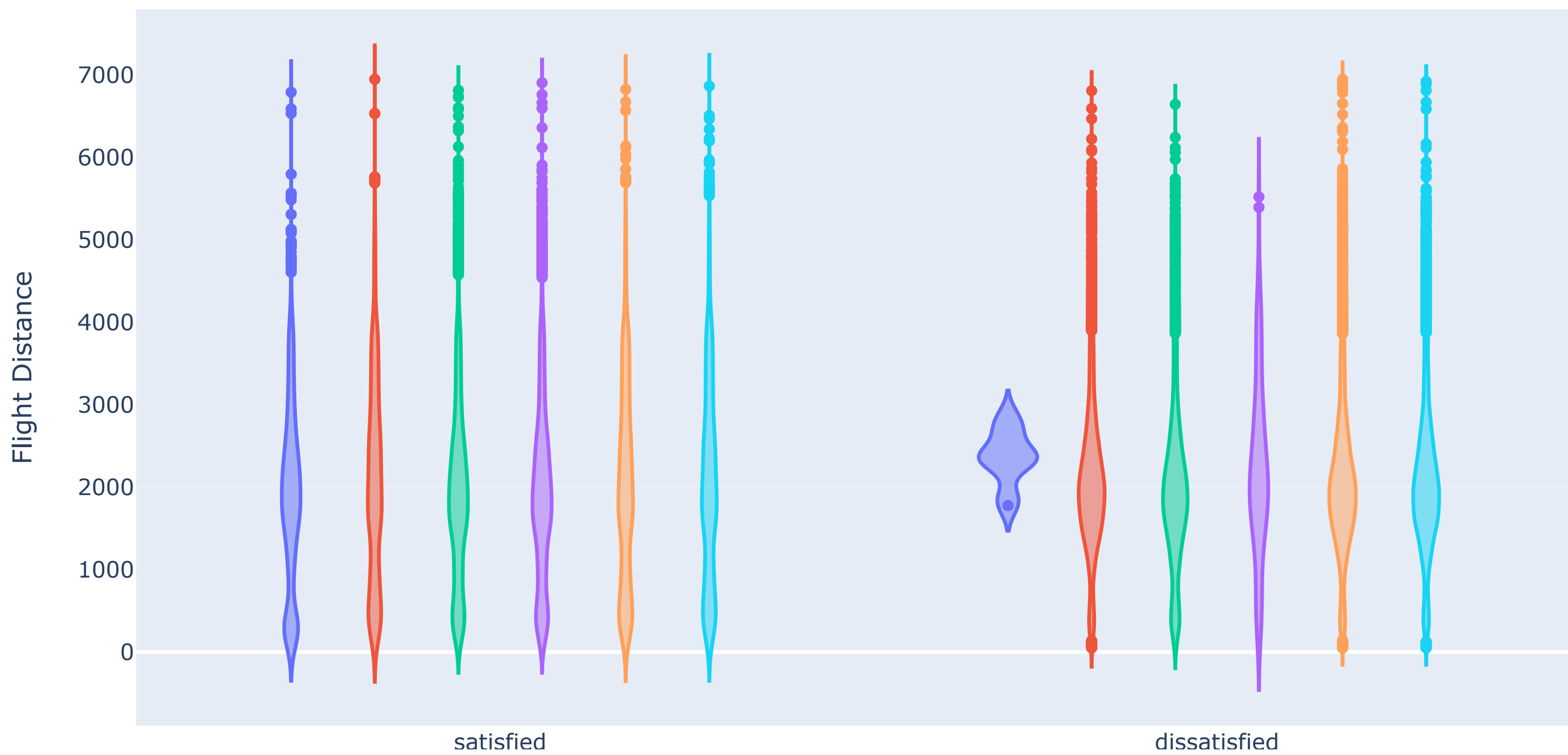
8) Is the Departure/Arrival time convenient with the passengers ?

In [23]:
```
x="Departure/Arrival time convenient"
fig=px.histogram(df_air,x=x,color="satisfaction",title="<b>"+x+" Distribution",template="plotly_white",opacity=0
fig.update_layout(hovermode='x',title_font_size=30)
fig.update_layout(
title_font_color="white",
template="plotly",
title_font_size=30,
hoverlabel_font_size=20,
title_x=0.5
```



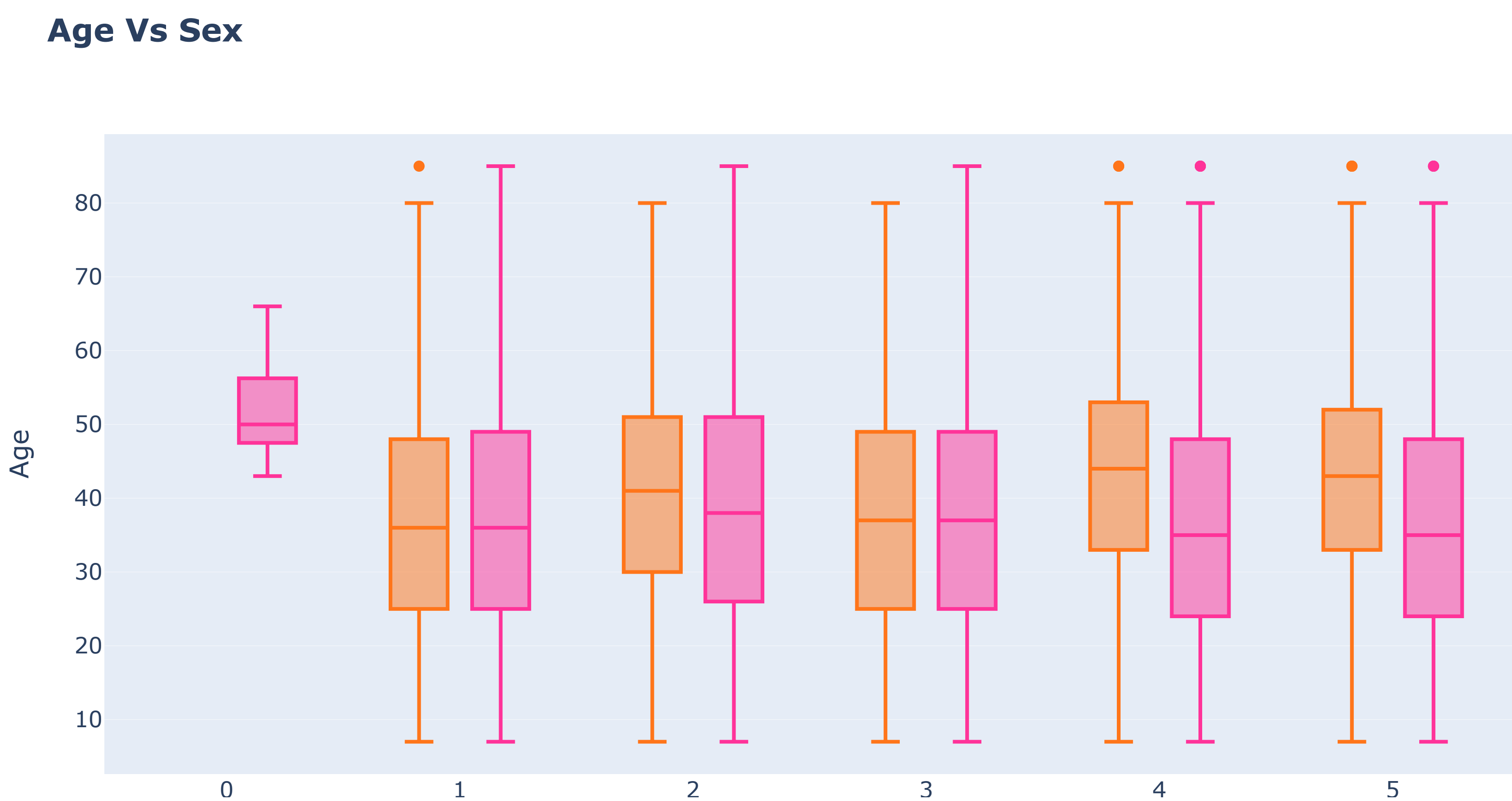
9) which factors that affect the dissatisfied people ?

In [24]:
```
fig=px.violin(df_air ,y="Flight Distance",x="satisfaction",color="Seat comfort",template="plotly_white")
fig.update_layout(hovermode='x',title_font_size=30)
fig.update_layout(
title_font_color="black",
template="plotly",
title_font_size=30,
hoverlabel_font_size=20,
title_x=0.5
```



10) What is the ages of people that dissatisified with On-board service ?

In [25]:
```
fig=px.box(data_frame=df_air,y="Age",x="On-board service",color="satisfaction",
           color_discrete_sequence=[" #ff751a","#ff3399"],title="<b>Age Vs Sex")
fig.update_layout(template="plotly")
```

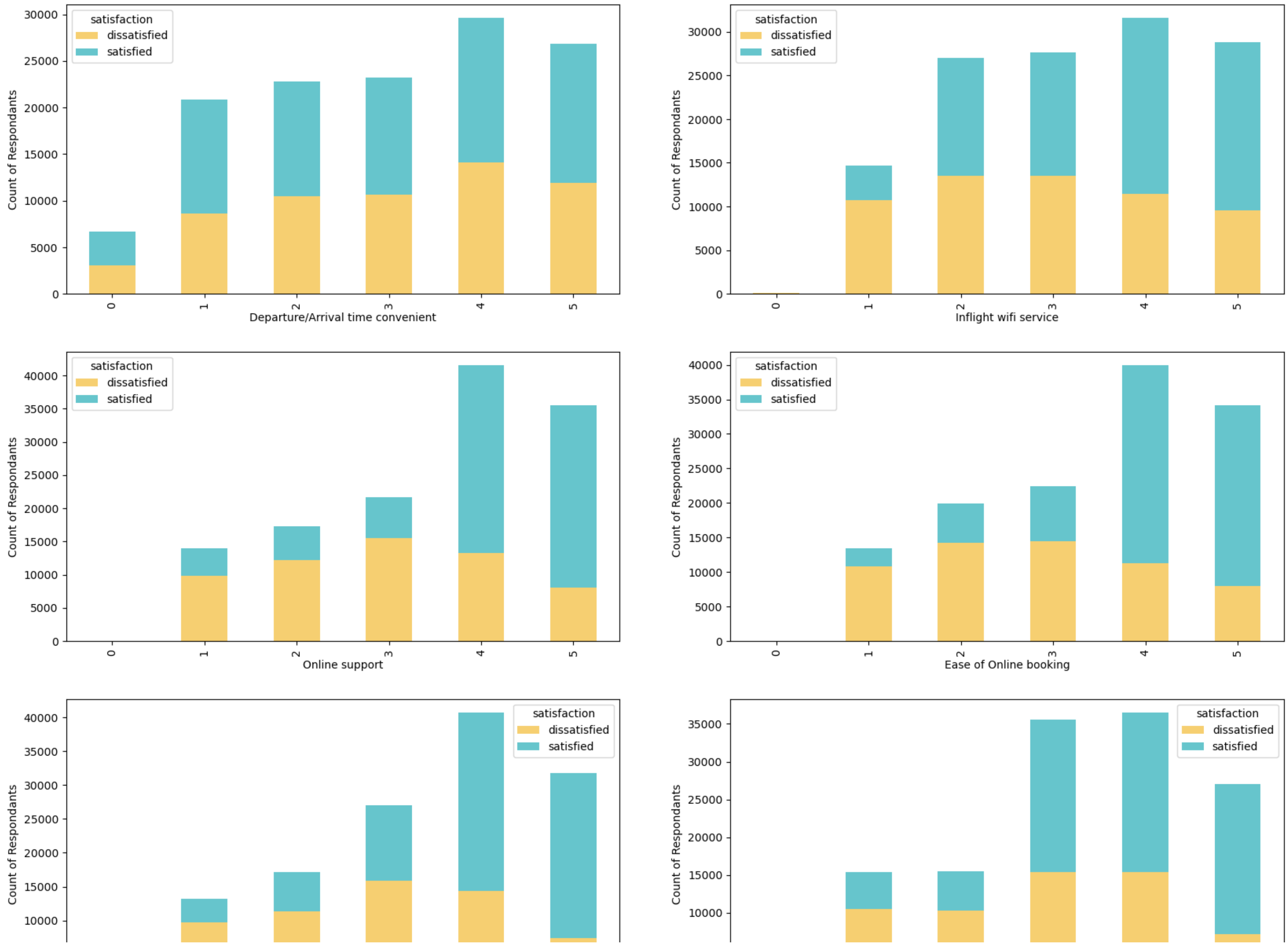


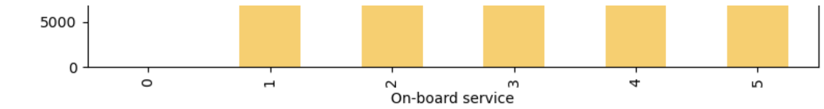
Their age concentrated between 43 to 66 years old

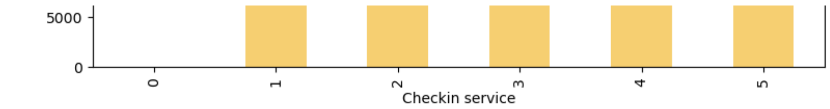
In [26]:
```
x_predictor_col = ['Departure/Arrival time convenient','Inflight wifi service', 'Online support',
```

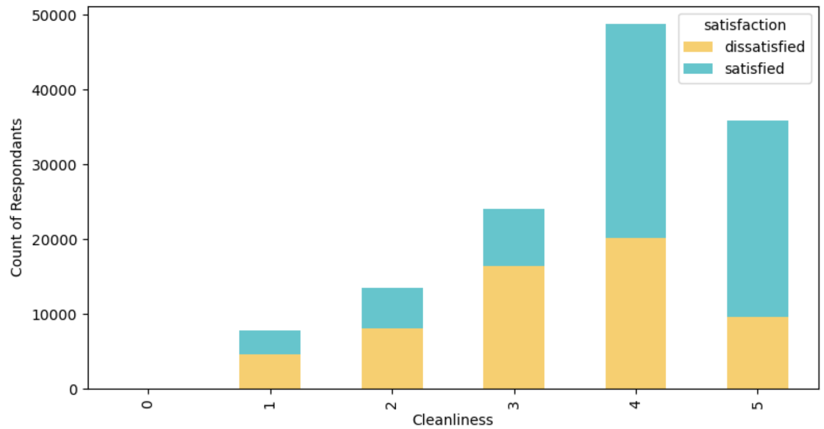
In [27]:
```
def create_plot_pivot(df, x_column):
    df_plot = df.groupby([x_column, 'satisfaction']).size() \
```

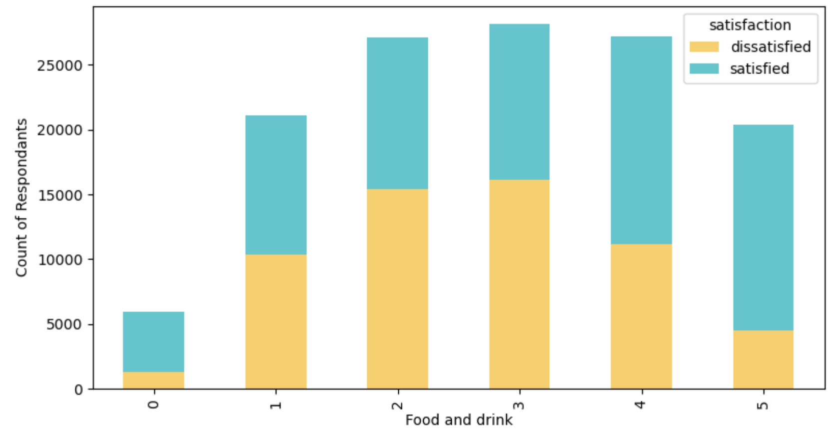
In [28]:
```
fig, ax = plt.subplots(4,2 , figsize=(20,22))
axe = ax.ravel()

for i in range(0,8):
    create_plot_pivot(data, x_predictor_col[i]).plot(kind='bar',stacked=True, ax=axe[i],color=["#F6CF71","#66C5C
    plt.xlabel(x_predictor_col[i])
```











insights

- Ease of online booking is an important factor affect the satisfaction
- online suuport is an important factor affect the satisfaction
- on board service is an important factor affect the satisfaction

In [30]:
```
fig=px.histogram(df_air,x="Type of Travel",facet_col="satisfaction",color="satisfaction")
fig.update_layout(title="<b>"+"Type of Travel"+" vs satisfaction", title_font_size=20,
                  font_size=20,
                  title_x=0.5,
                  hoverlabel_font_size=20,template="plotly")
```

Notes

- We have only 2 types of travel Personal Travel and Business Travel

- Out Business Travel much more than Personal Travel.
- That means we are working with Customers in Business Layer more

Encoding For object features

In [31]:
```
for i in df_air.select_dtypes(include=['object']):
```

Preprocessing

In [32]:
```
df_air.isnull().sum()
```

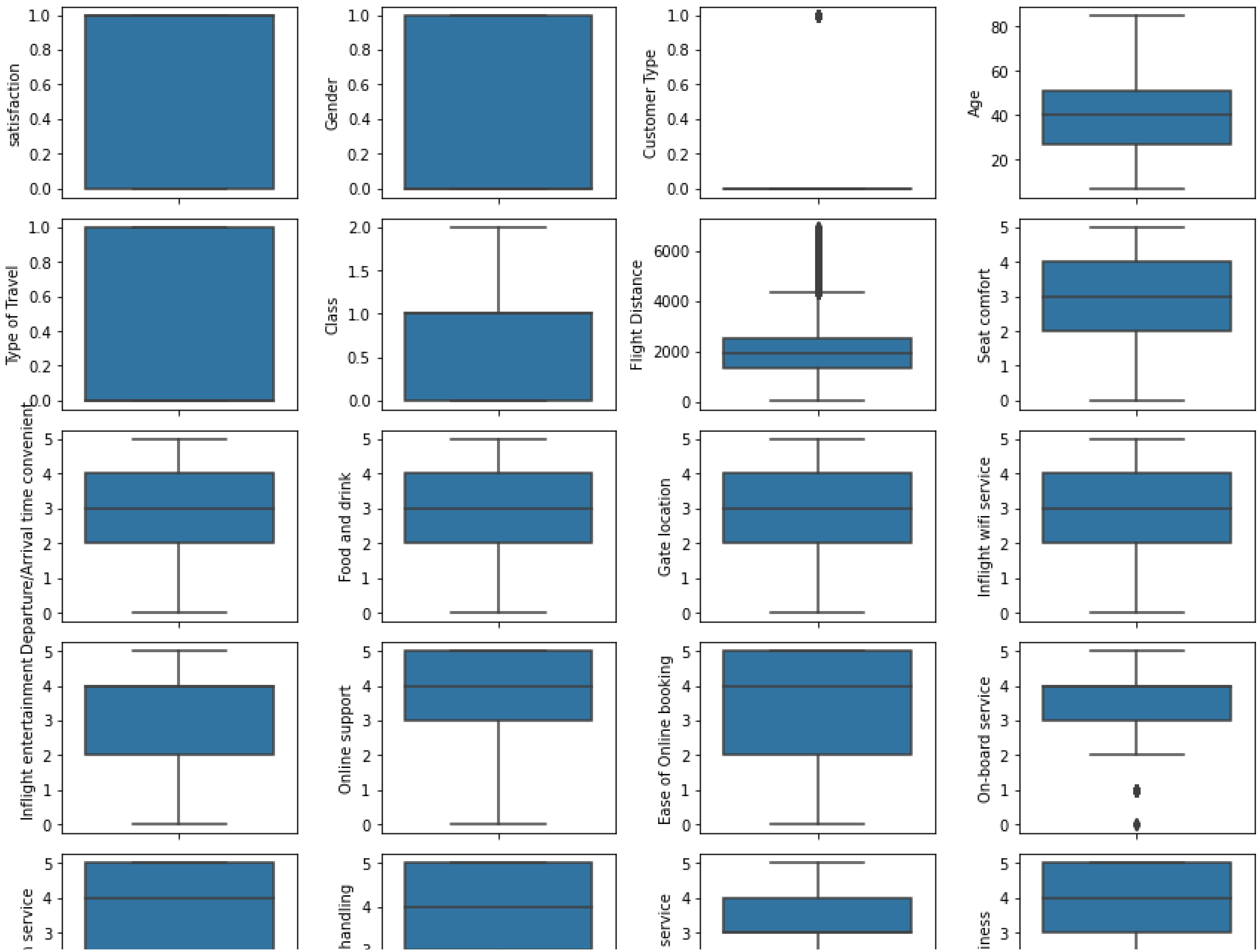
Out[32]:
```
satisfaction                          0
Gender                                0
Customer Type                         0
Age                                   0
Type of Travel                        0
Class                                 0
Flight Distance                       0
Seat comfort                          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
dtype: int64
```

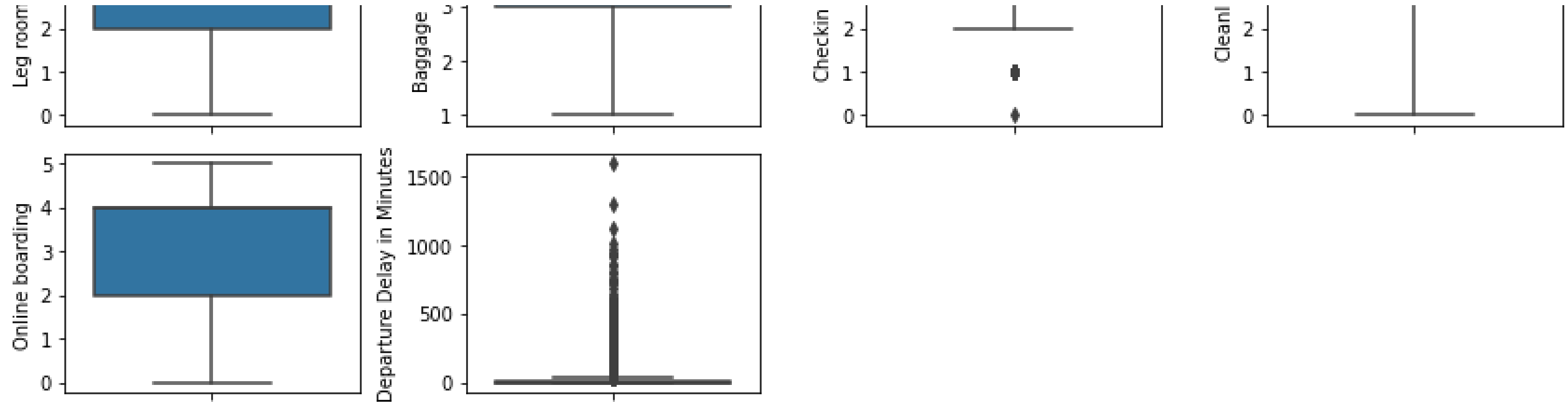
Discovering the Outliers

In [33]:
```
Q1 = df_air.quantile(0.25)
Q3 = df_air.quantile(0.75)
```

```
satisfaction                            1.0
Gender                                  1.0
Customer Type                           0.0
Age                                    24.0
Type of Travel                          1.0
Class                                   1.0
Flight Distance                      1185.0
Seat comfort                            2.0
Departure/Arrival time convenient       2.0
Food and drink                          2.0
Gate location                           2.0
Inflight wifi service                   2.0
Inflight entertainment                  2.0
Online support                          2.0
Ease of Online booking                  3.0
On-board service                        1.0
Leg room service                        3.0
Baggage handling                        2.0
Checkin service                         1.0
Cleanliness                             2.0
Online boarding                         2.0
Departure Delay in Minutes             12.0
dtype: float64
```

In [34]:
```
fig = plt.figure(figsize=(12,18))
for i in range(len(df_air.columns)):
    fig.add_subplot(9,4,i+1)
    sns.boxplot(y=df_air.iloc[:,i])
```





In [35]:
```
from collections import Counter
def detect_outliers(df,features):
    outlier_indices=[]

    for c in features:
        Q1=np.percentile(df[c],25)

        Q3=np.percentile(df[c],75)

        IQR= Q3-Q1

        outlier_step= IQR * 1.5

        outlier_list_col = df[(df[c]< Q1 - outlier_step)|( df[c] > Q3 + outlier_step)].index

        outlier_indices.extend(outlier_list_col)

    outliers_indices = Counter(outlier_indices)
```

In [36]:
```
df_air.loc[detect_outliers(df_air,['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',
```

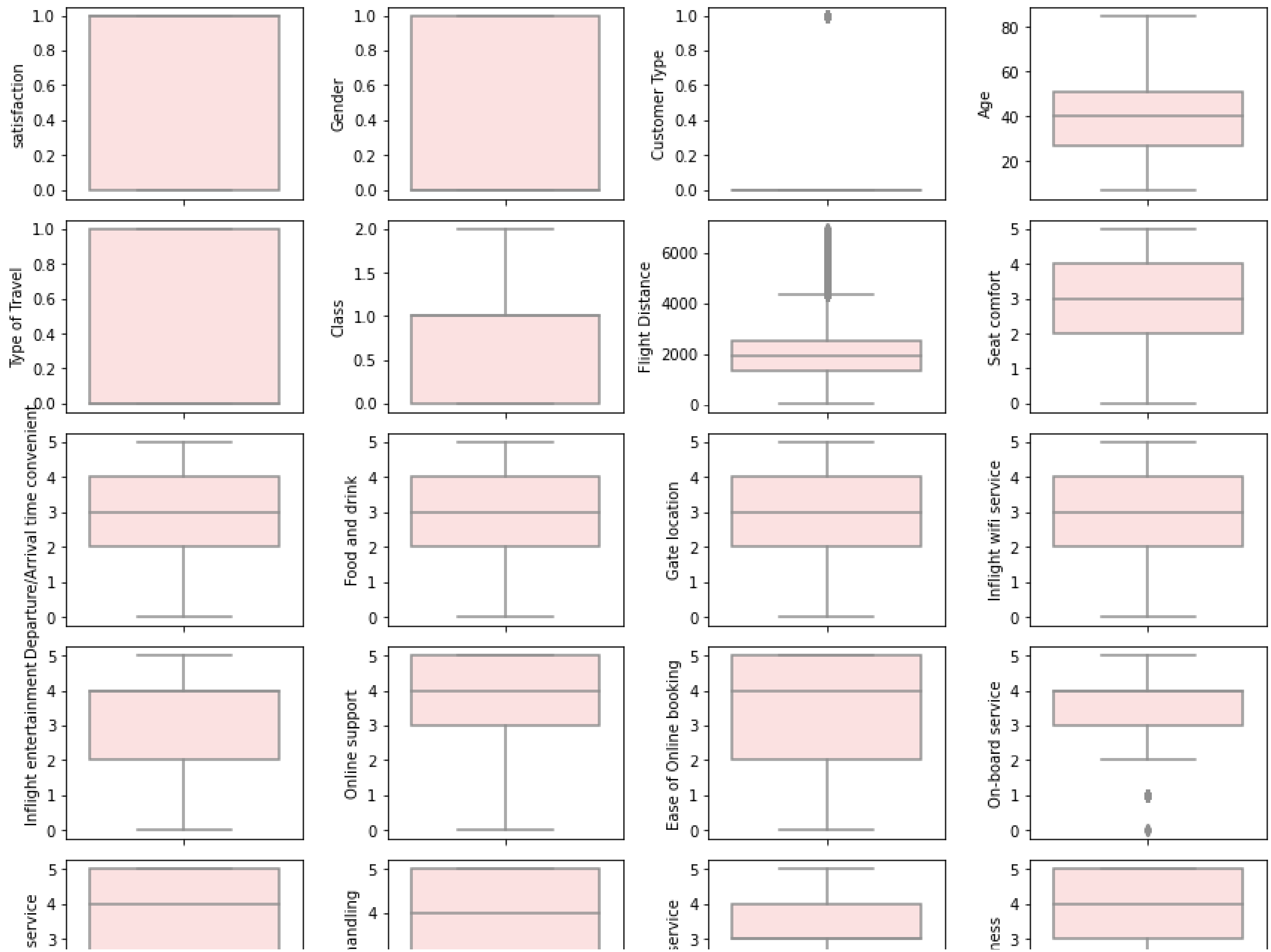
Out[36]:

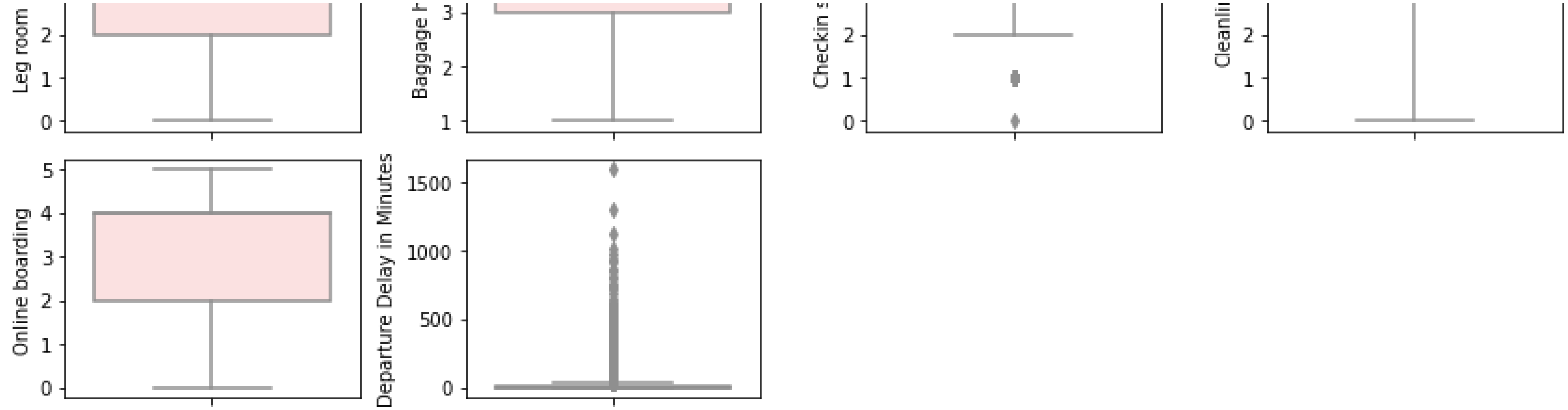
	satisfaction	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Seat comfort	Departure/Arrival time convenient	Food and drink	...	Inflight entertainment	Online support	Eas On book
7239	0	0	0	55	1	1	4338	1	5	1	...	5	4	
21607	0	1	0	36	1	1	4438	3	2	3	...	3	3	
22092	0	0	0	58	1	2	5945	3	2	3	...	1	5	
22692	0	0	0	64	1	1	5603	3	3	3	...	1	1	
23003	0	1	0	69	1	1	4692	3	3	3	...	3	3	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
123424	1	0	0	38	0	2	1456	5	1	1	...	5	5	
123567	1	1	0	36	0	1	1703	5	4	4	...	5	5	
127460	1	0	0	32	0	0	4041	4	1	4	...	5	5	
128995	1	1	0	40	0	1	1938	5	2	3	...	5	5	
129704	0	1	1	69	1	1	1780	2	4	2	...	2	2	

646 rows × 22 columns

In [37]:
```
df_air = df_air.drop(detect_outliers(df_air,[ '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',
```

In [38]:
```
fig = plt.figure(figsize=(12,18))
for i in range(len(df_air.columns)):
    fig.add_subplot(9,4,i+1)
    sns.boxplot(y=df_air.iloc[:,i],color="#FFDDDD")
```





Feature Selection

> **we have two methods that we will use to detect the best related features to our Target**
>
> **- Chi-Square**
>
> **- Feature Importance using Wrapper Method**
>
> **- Feature Permutation Importance**

In [39]:
```
from sklearn import preprocessing
r_scaler = preprocessing.MinMaxScaler()
r_scaler.fit(df_air)
```

Out[39]:

	satisfaction	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Seat comfort	Departure/Arrival time convenient	Food and drink	...	Inflight entertainment	Online support	Ease Onli booki
0	1.0	0.0	0.0	0.743590	1.0	0.5	0.031155	0.0	0.0	0.0	...	0.8	0.4	[illegible]
1	1.0	1.0	0.0	0.512821	1.0	0.0	0.349804	0.0	0.0	0.0	...	0.4	0.4	[illegible]
2	1.0	0.0	0.0	0.102564	1.0	0.5	0.302565	0.0	0.0	0.0	...	0.0	0.4	[illegible]
3	1.0	0.0	0.0	0.679487	1.0	0.5	0.083031	0.0	0.0	0.0	...	0.8	0.6	[illegible]
4	1.0	0.0	0.0	0.807692	1.0	0.5	0.044052	0.0	0.0	0.0	...	0.6	0.8	[illegible]

5 rows × 22 columns

Top 10 Feature Selection through Chi-Square¶

In [40]:
```
from sklearn.feature_selection import SelectKBest, chi2
X = modified_data.loc[:,modified_data.columns!='satisfaction']
y = modified_data[['satisfaction']]
selector = SelectKBest(chi2, k=10)
selector.fit(X, y)
```

```
Index(['Gender', 'Customer Type', 'Type of Travel', 'Class',
       'Inflight entertainment', 'Online support', 'Ease of Online booking',
       'On-board service', 'Leg room service', 'Online boarding'],
      dtype='object')
```

Feature Importance using Wrapper Method

In [41]:
```
from sklearn.feature_selection import SelectFromModel
from sklearn.ensemble import RandomForestClassifier as rf

X = df_air.drop('satisfaction', axis=1)
y = df_air['satisfaction']
selector = SelectFromModel(rf(n_estimators=100, random_state=0))
selector.fit(X, y)
support = selector.get_support()
features = X.loc[:, support].columns.tolist()
```

```
['Seat comfort', 'Inflight entertainment', 'Online support', 'Ease of Online booking']
[0.03312765 0.04548771 0.03242325 0.02964883 0.03816626 0.03771887
 0.14064488 0.02435838 0.0399856  0.02143006 0.01654909 0.18105274
 0.0671328  0.07533283 0.04306187 0.04162796 0.02441734 0.027383
 0.0284196  0.03433404 0.01769725]
```

the model told us that the top 5 features is Seat comfort,Inflight entertainment,Online support,Ease of Online booking,Leg room service

Feature Permutation Importance

In [42]:
```
import eli5
from eli5.sklearn import PermutationImportance
```

In [43]:
```
eli5.show_weights(perm, feature_names = X.columns.tolist())
```

Out[43]:

Weight	Feature
0.1485 ± 0.0005	Seat comfort
0.0708 ± 0.0007	Customer Type
0.0525 ± 0.0012	Inflight entertainment
0.0463 ± 0.0007	Gender
0.0333 ± 0.0009	Type of Travel
0.0326 ± 0.0005	Checkin service
0.0312 ± 0.0006	Online support
0.0277 ± 0.0005	Baggage handling
0.0252 ± 0.0006	Cleanliness
0.0223 ± 0.0006	Online boarding
0.0180 ± 0.0003	Class
0.0171 ± 0.0003	Leg room service
0.0160 ± 0.0008	On-board service
0.0137 ± 0.0004	Ease of Online booking
0.0126 ± 0.0001	Age
0.0094 ± 0.0005	Flight Distance
0.0086 ± 0.0002	Gate location
0.0077 ± 0.0003	Food and drink
0.0074 ± 0.0004	Departure/Arrival time convenient
0.0063 ± 0.0004	Departure Delay in Minutes
	… 1 more …

From all above results, finally we can combine and conclude the list of important features.

Really Important Features: Seat comfort,Customer Type,Inflight_entertainment,Gender,Checkin_service

Important Features: Type of Travel,Online support, Baggage handling,cleanliness,Online boarding,On_board service,Class

Modeling

Modling accoding to the best features

In [44]:
```
modified_data.columns
```

Out[44]:
```
Index(['satisfaction', 'Gender', 'Customer Type', 'Age', 'Type of Travel',
       'Class', 'Flight Distance', 'Seat comfort',
       'Departure/Arrival time convenient', 'Food and drink', 'Gate location',
       'Inflight wifi service', 'Inflight entertainment', 'Online support',
       'Ease of Online booking', 'On-board service', 'Leg room service',
       'Baggage handling', 'Checkin service', 'Cleanliness', 'Online boarding',
       'Departure Delay in Minutes'],
      dtype='object')
```

In [45]:
```
x = modified_data[['Seat comfort','Inflight entertainment','Ease of Online booking','Online support','Gender',
```

In [46]:
```
from sklearn.model_selection import train_test_split
```

In [47]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[47]:
```
((90463, 11), (38771, 11), (90463,), (38771,))
```

In [48]:
```
from sklearn.metrics import accuracy_score, roc_auc_score, classification_report, plot_confusion_matrix, plot_rc
```

In [49]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, plot_roc_curve
import warnings
```

In [50]:
```
logisreg_clf = LogisticRegression()
svm_clf = SVC()
dt_clf = DecisionTreeClassifier()
```

In [51]:
```
clf_list = [logisreg_clf, svm_clf, dt_clf, rf_clf, XGB_clf]
clf_name_list = ['Logistic Regression', 'Support Vector Machine', 'Decision Tree', 'Random Forest', 'XGBClassifi
```

In [52]:
```
train_acc_list = []
test_acc_list = []

for clf,name in zip(clf_list,clf_name_list):
    y_pred_train = clf.predict(X_train)
    y_pred_test = clf.predict(X_test)
    print(f'Using model: {name}')
    print(f'Trainning Score: {clf.score(X_train, y_train)}')
    print(f'Test Score: {clf.score(X_test, y_test)}')
    print(f'Acc Train: {accuracy_score(y_train, y_pred_train)}')
    print(f'Acc Test: {accuracy_score(y_test, y_pred_test)}')
    train_acc_list.append(accuracy_score(y_train, y_pred_train))
```

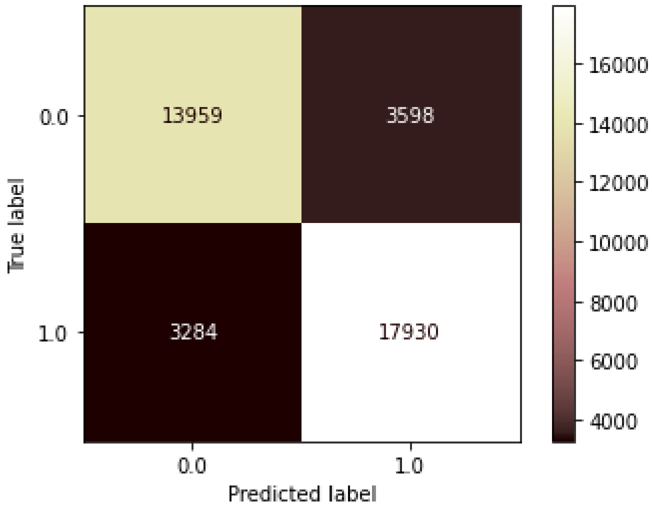
```
Using model: Logistic Regression
Trainning Score: 0.8237843096072427
Test Score: 0.822496195610121
Acc Train: 0.8237843096072427
Acc Test: 0.822496195610121
======================================================
Using model: Support Vector Machine
Trainning Score: 0.9236925593889215
Test Score: 0.9211008227799128
Acc Train: 0.9236925593889215
Acc Test: 0.9211008227799128
======================================================
Using model: Decision Tree
Trainning Score: 0.9620618374362999
Test Score: 0.9298186789094942
Acc Train: 0.9620618374362999
Acc Test: 0.9298186789094942
======================================================
Using model: Random Forest
Trainning Score: 0.9620618374362999
Test Score: 0.9347450413969204
Acc Train: 0.9620618374362999
Acc Test: 0.9347450413969204
======================================================
Using model: XGBClassifier
Trainning Score: 0.9445740247393962
Test Score: 0.9375822135100977
Acc Train: 0.9445740247393962
Acc Test: 0.9375822135100977
======================================================
```

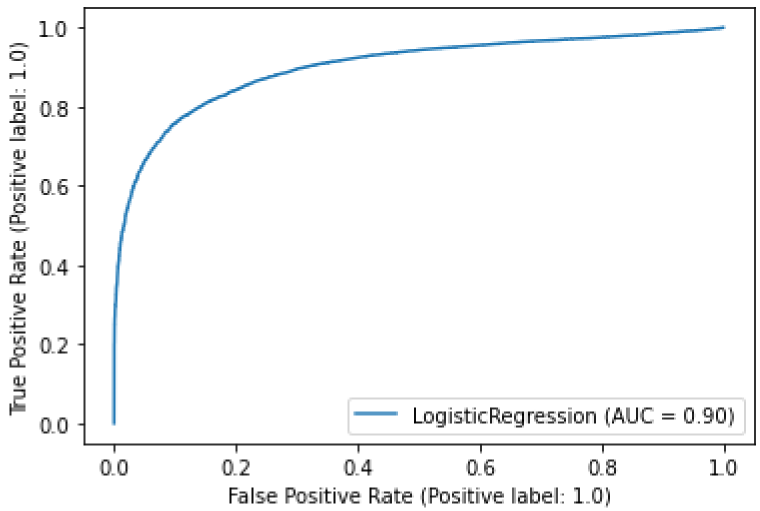
Model-1: Logistic Regression penalized with Elastic Net (L1 penalty = 50%, L2 penalty = 50%)

In [53]:
```
from sklearn.linear_model import LogisticRegression
import time
t0=time.time()
model= LogisticRegression()
model.fit(X_train,y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
roc_auc5 = roc_auc_score(y_test, y_pred)
time_taken5 = time.time()-t0
print("Accuracy = {}".format(accuracy))
print("ROC Area under Curve = {}".format(roc_auc5))
print("Time taken = {}".format(time_taken5))
print(classification_report(y_test,y_pred,digits=5))
```

```
Accuracy = 0.822496195610121
ROC Area under Curve = 0.8201320313753048
Time taken = 0.38945960998535156
              precision    recall  f1-score   support

         0.0    0.80955   0.79507   0.80224     17557
         1.0    0.83287   0.84520   0.83899     21214

    accuracy                        0.82250     38771
   macro avg    0.82121   0.82013   0.82061     38771
weighted avg    0.82231   0.82250   0.82235     38771
```

Out[53]:
```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x7fb9a5782cd0>
```



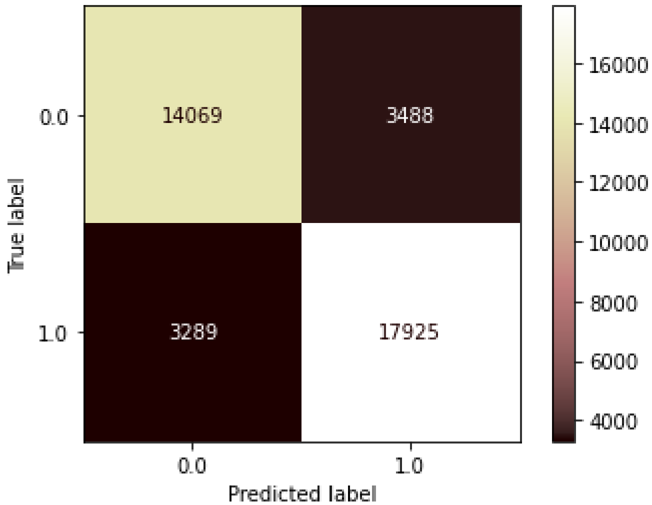


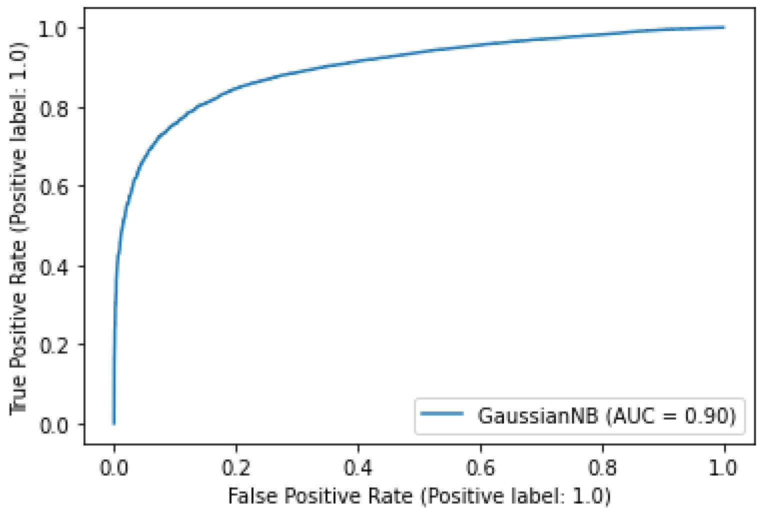
Model-2: Naive Bayes Classifier

In [54]:
```
from sklearn.naive_bayes import GaussianNB
import time
t0=time.time()
model= GaussianNB()
model.fit(X_train,y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
roc_auc4 = roc_auc_score(y_test, y_pred)
time_taken1 = time.time()-t0
print("Accuracy = {}".format(accuracy))
print("ROC Area under Curve = {}".format(roc_auc4))
print("Time taken = {}".format(time_taken1))
print(classification_report(y_test,y_pred,digits=5))
```

```
Accuracy = 0.8252044053545176
ROC Area under Curve = 0.8231468383127206
Time taken = 0.050367593765258 79
              precision    recall  f1-score   support

         0.0    0.81052   0.80133   0.80590     17557
         1.0    0.83711   0.84496   0.84102     21214

    accuracy                        0.82520     38771
   macro avg    0.82381   0.82315   0.82346     38771
weighted avg    0.82507   0.82520   0.82511     38771
```

Out[54]:
```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x7fba1b6772d0>
```





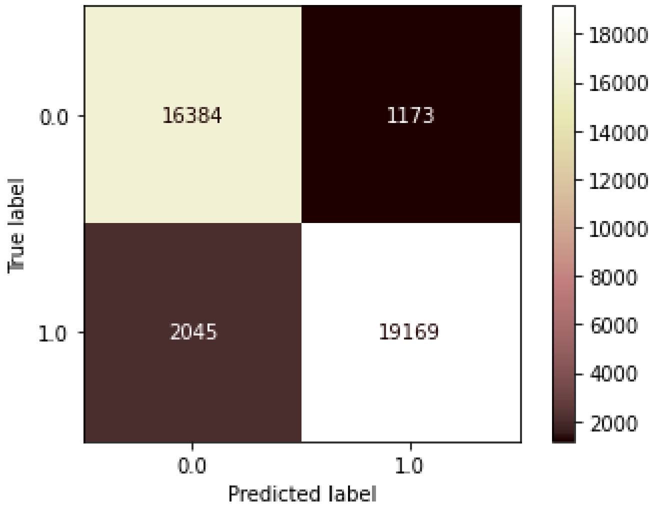
Model-3: K-Nearest Neighbor Classifier

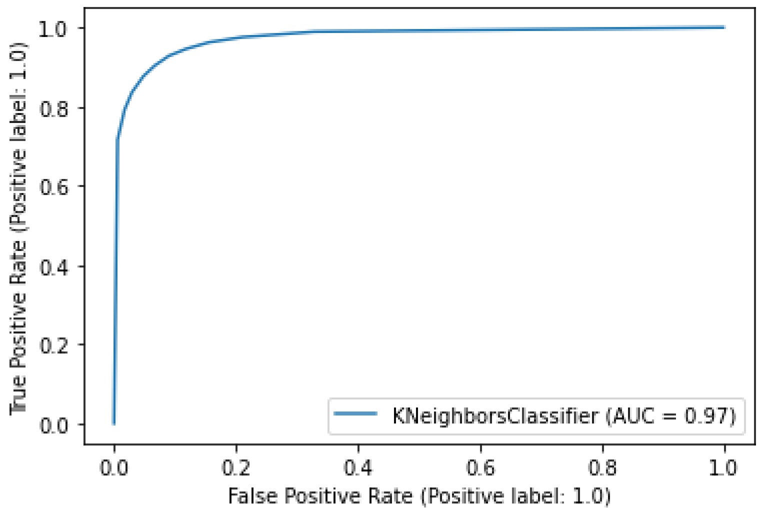
In [55]:

```
from sklearn.neighbors import KNeighborsClassifier
import time
t0=time.time()
model= KNeighborsClassifier(n_neighbors=10)
model.fit(X_train,y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
roc_auc1 = roc_auc_score(y_test, y_pred)
time_taken2 = time.time()-t0
print("Accuracy = {}".format(accuracy))
print("ROC Area under Curve = {}".format(roc_auc1))
print("Time taken = {}".format(time_taken2))
print(classification_report(y_test,y_pred,digits=5))
```

```
Accuracy = 0.9169998194526837
ROC Area under Curve = 0.9183952183564864
Time taken = 8.544821500778198
              precision    recall  f1-score   support

         0.0    0.88903   0.93319   0.91058     17557
         1.0    0.94234   0.90360   0.92256     21214

    accuracy                        0.91700     38771
   macro avg    0.91568   0.91840   0.91657     38771
weighted avg    0.91820   0.91700   0.91713     38771
```

Out[55]: <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x7fb9a3e61850>





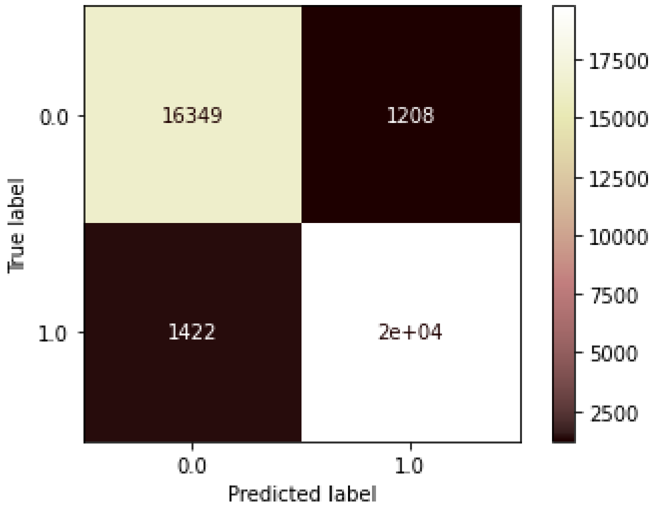
Model-4: Decision Tree Classifier

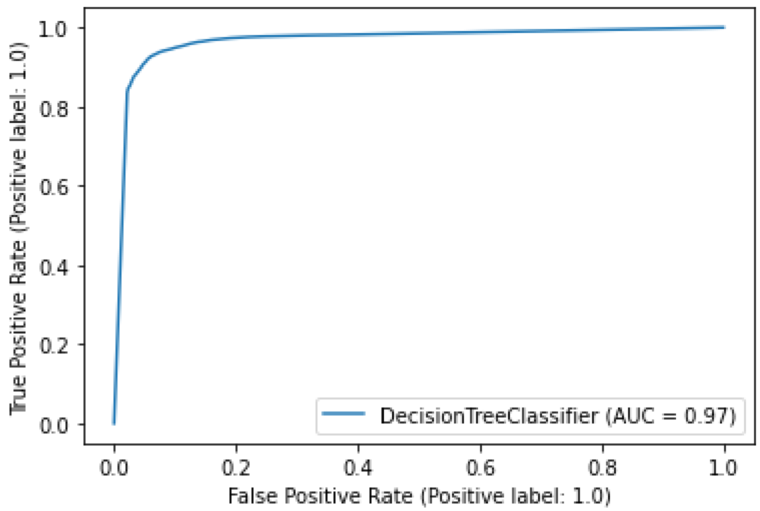
In [56]:

```python
from sklearn.tree import DecisionTreeClassifier
import time
t0=time.time()
model=DecisionTreeClassifier(max_depth=17)
model.fit(X_train,y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
roc_auc2 = roc_auc_score(y_test, y_pred)
time_taken3 = time.time()-t0
print("Accuracy = {}".format(accuracy))
print("ROC Area under Curve = {}".format(roc_auc2))
print("Time taken = {}".format(time_taken3))
print(classification_report(y_test,y_pred,digits=5))
```

```
Accuracy = 0.9321657940213046
ROC Area under Curve = 0.9320821643685702
Time taken = 0.30996680259704559
              precision    recall  f1-score   support

         0.0    0.91998   0.93120   0.92555     17557
         1.0    0.94248   0.93297   0.93770     21214

    accuracy                        0.93217     38771
   macro avg    0.93123   0.93208   0.93163     38771
weighted avg    0.93229   0.93217   0.93220     38771
```

Out[56]: <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x7fb9a5791850>



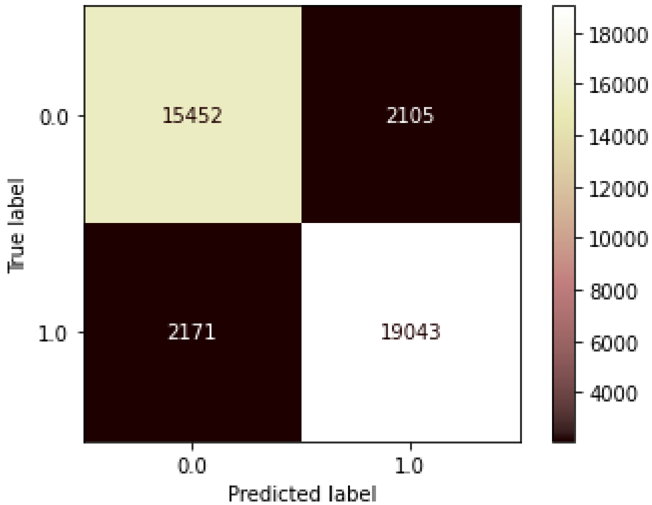


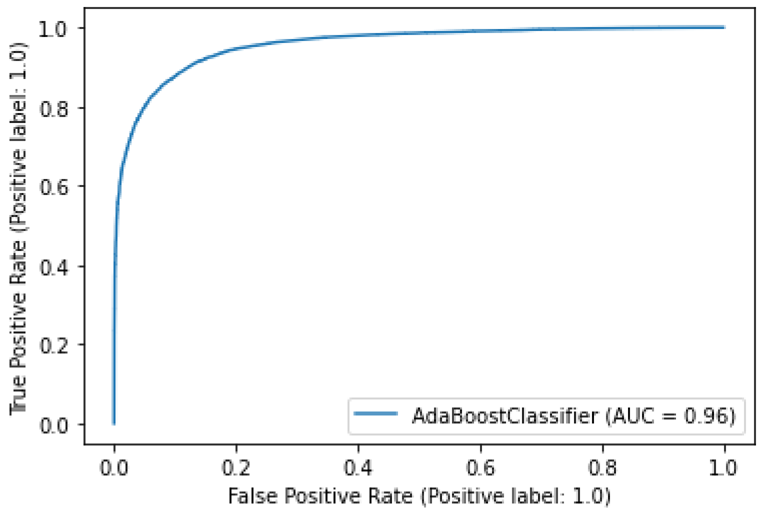
Model-5: Ada Boost Classifier

In [57]:
```
from sklearn.ensemble import AdaBoostClassifier as adab
import time
t0=time.time()
model=adab(n_estimators=500)
model.fit(X_train,y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
roc_auc3 = roc_auc_score(y_test, y_pred)
print("Accuracy = {}".format(accuracy))
time_taken4 = time.time()-t0
print("ROC Area under Curve = {}".format(roc_auc3))
print(classification_report(y_test,y_pred,digits=5))
print("Time taken = {}".format(time_taken4))
```

```
Accuracy = 0.8897113822186686
ROC Area under Curve = 0.8888833614381761
              precision    recall  f1-score   support

         0.0    0.87681   0.88010   0.87845     17557
         1.0    0.90046   0.89766   0.89906     21214

    accuracy                        0.88971     38771
   macro avg    0.88864   0.88888   0.88876     38771
weighted avg    0.88975   0.88971   0.88973     38771

Time taken = 30.294228315353394
```

Out[57]:
```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x7fb9a3bd8f90>
```


15452
2105
2171
19043
0.0
1.0
True label
Predicted label
18000
16000
14000
12000
10000
8000
6000
4000


AdaBoostClassifier (AUC = 0.96)
True Positive Rate (Positive label: 1.0)
False Positive Rate (Positive label: 1.0)
0.0
0.2
0.4
0.6
0.8
1.0

End