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

## 1 Exploring the Data:

```
[87]: raw_data = pd.read_csv('data/train.csv')
raw_data.head()
```

```
[87]: Unnamed: 0    id  Gender    Customer Type  Age  Type of Travel \
0          0   70172   Male    Loyal Customer   13  Personal Travel
1          1    5047   Male  disloyal Customer   25  Business travel
2          2  110028  Female    Loyal Customer   26  Business travel
3          3   24026  Female    Loyal Customer   25  Business travel
4          4  119299   Male    Loyal Customer   61  Business travel

      Class  Flight Distance  Inflight wifi service \
0  Eco Plus             460                3
1  Business             235                3
2  Business            1142                2
3  Business             562                2
4  Business             214                3

      Departure/Arrival time convenient  ...  Inflight entertainment \
0                                4  ...                5
1                                2  ...                1
2                                2  ...                5
3                                5  ...                2
4                                3  ...                3

      On-board service  Leg room service  Baggage handling  Checkin service \
0                   4                3                4                4
1                   1                5                3                1
2                   4                3                4                4
3                   2                5                3                1
```

```

4          3          4          4          3

Inflight service Cleanliness Departure Delay in Minutes \
0          5          5          25
1          4          1          1
2          4          5          0
3          4          2          11
4          3          3          0

Arrival Delay in Minutes      satisfaction
0          18.0 neutral or dissatisfied
1          6.0 neutral or dissatisfied
2          0.0      satisfied
3          9.0 neutral or dissatisfied
4          0.0      satisfied

[5 rows x 25 columns]

```

## 2 PreProcessing:

- drop unnamed column
- drop id column
- drop rows that have Nan

```
[88]: data = raw_data.drop(['id', 'Unnamed: 0'], axis=1)
data = data.dropna(axis=0)
```

```
[89]: data.describe()
```

```
[89]:
count      Age  Flight Distance  Inflight wifi service \
count  103594.000000    103594.000000    103594.000000
mean      39.380466    1189.325202      2.729753
std       15.113125     997.297235     1.327866
min        7.000000     31.000000     0.000000
25%       27.000000     414.000000     2.000000
50%       40.000000     842.000000     3.000000
75%       51.000000    1743.000000     4.000000
max       85.000000    4983.000000     5.000000

Departure/Arrival time convenient  Ease of Online booking \
count      103594.000000    103594.000000
mean           3.060081      2.756984
std           1.525233      1.398934
min            0.000000      0.000000
25%            2.000000      2.000000
50%            3.000000      3.000000

```

75%	4.000000	4.000000
max	5.000000	5.000000

	Gate location	Food and drink	Online boarding	Seat comfort \
count	103594.000000	103594.000000	103594.000000	103594.000000
mean	2.977026	3.202126	3.250497	3.439765
std	1.277723	1.329401	1.349433	1.318896
min	0.000000	0.000000	0.000000	0.000000
25%	2.000000	2.000000	2.000000	2.000000
50%	3.000000	3.000000	3.000000	4.000000
75%	4.000000	4.000000	4.000000	5.000000
max	5.000000	5.000000	5.000000	5.000000

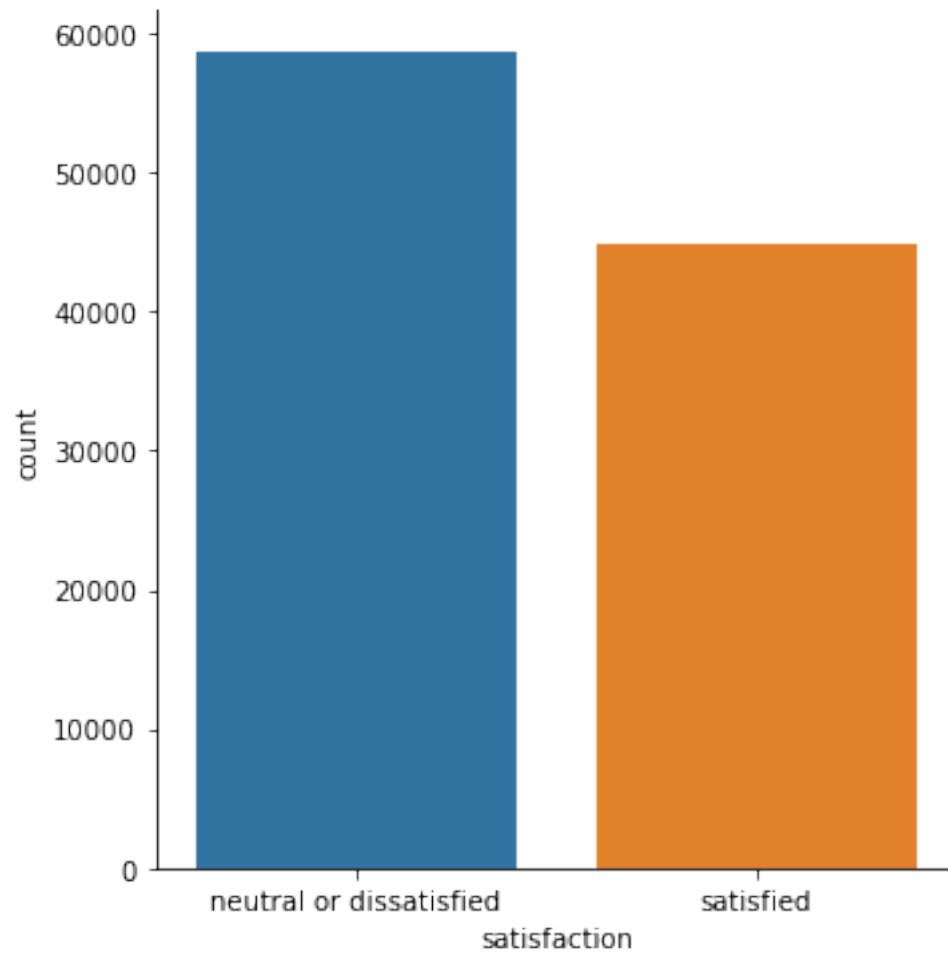
	Inflight entertainment	On-board service	Leg room service \
count	103594.000000	103594.000000	103594.000000
mean	3.358341	3.382609	3.351401
std	1.333030	1.288284	1.315409
min	0.000000	0.000000	0.000000
25%	2.000000	2.000000	2.000000
50%	4.000000	4.000000	4.000000
75%	4.000000	4.000000	4.000000
max	5.000000	5.000000	5.000000

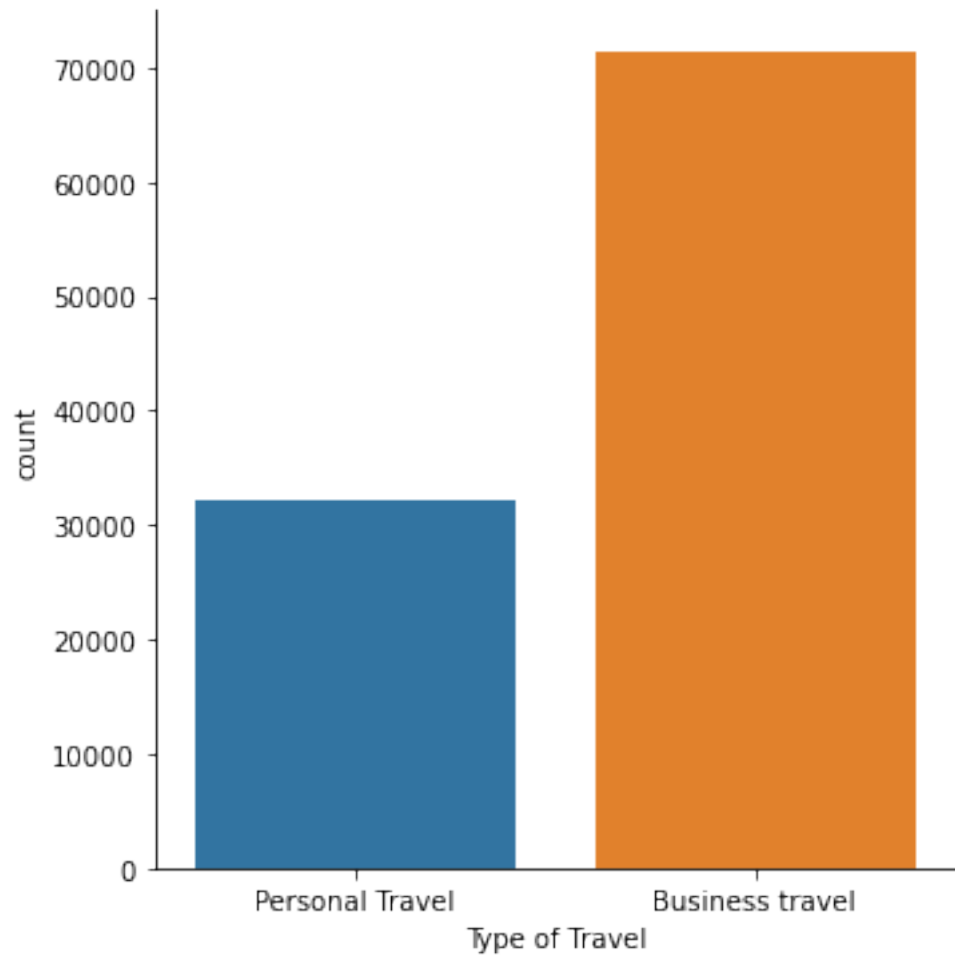
	Baggage handling	Checkin service	Inflight service	Cleanliness \
count	103594.000000	103594.000000	103594.000000	103594.000000
mean	3.631687	3.304323	3.640761	3.286397
std	1.181051	1.265396	1.175603	1.312194
min	1.000000	0.000000	0.000000	0.000000
25%	3.000000	3.000000	3.000000	2.000000
50%	4.000000	3.000000	4.000000	3.000000
75%	5.000000	4.000000	5.000000	4.000000
max	5.000000	5.000000	5.000000	5.000000

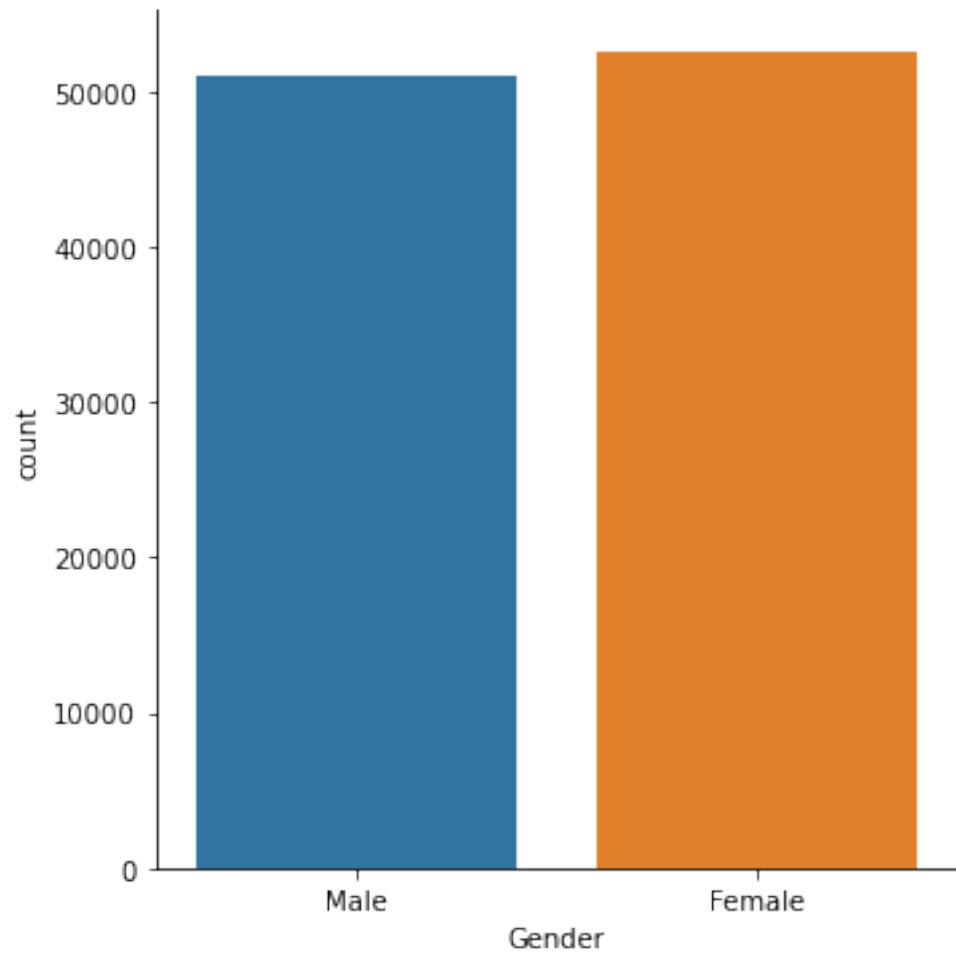
	Departure Delay in Minutes	Arrival Delay in Minutes
count	103594.000000	103594.000000
mean	14.747939	15.178678
std	38.116737	38.698682
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	12.000000	13.000000
max	1592.000000	1584.000000

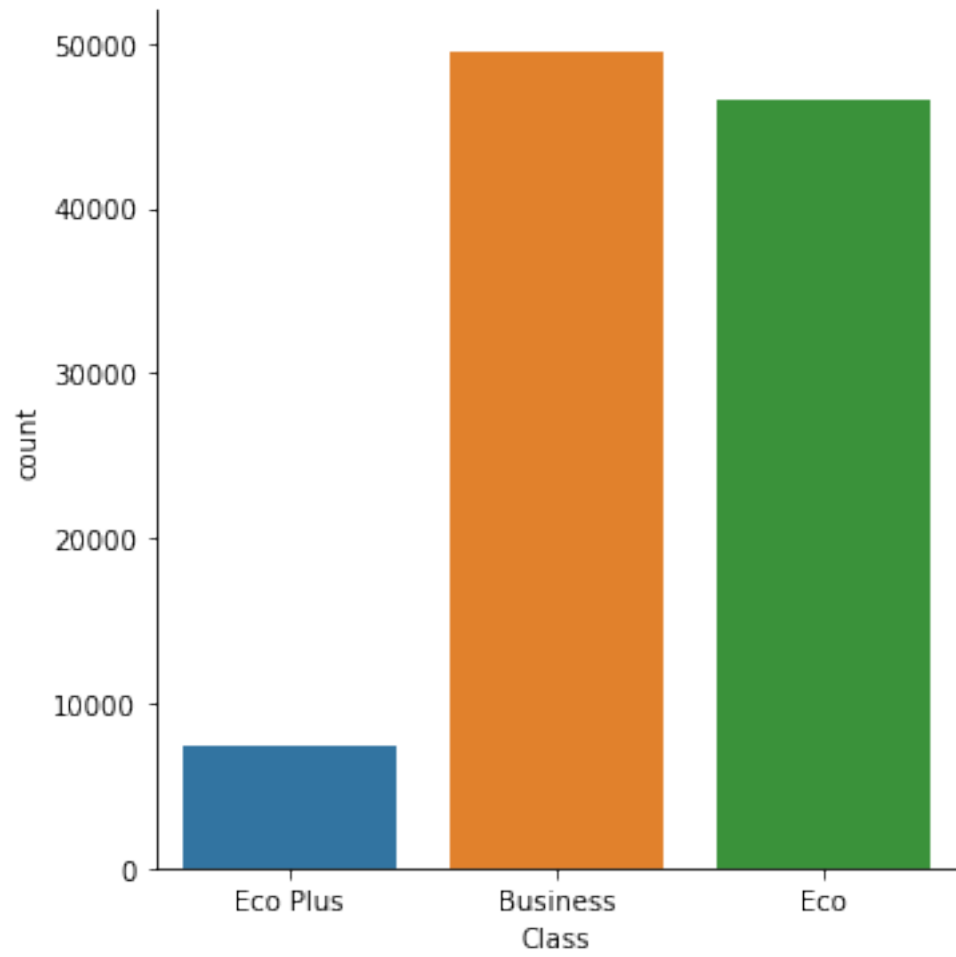
### 2.0.1 Change categorical data to numeric(using one hot encoding):

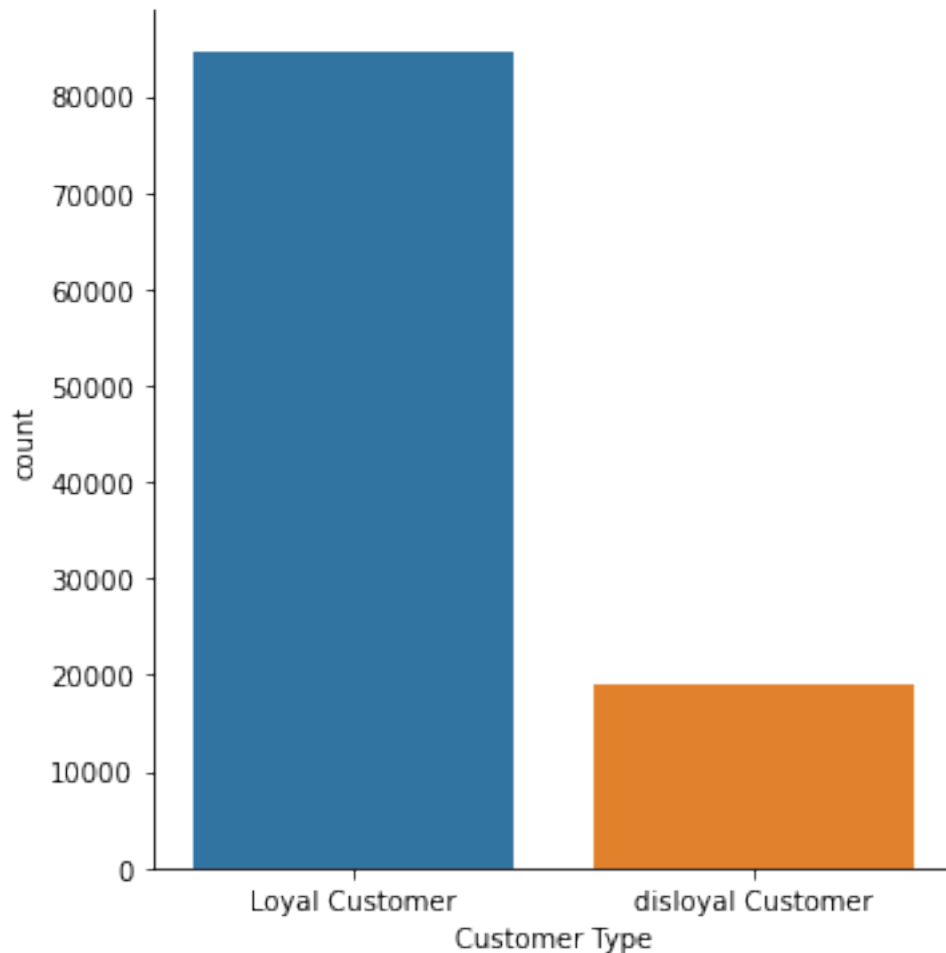
```
[90]: cat_cols = list(set(data.columns) - set(data._get_numeric_data().columns))
      for s in cat_cols:
          sns.catplot(x=s, kind="count", data=data)
```











```
[91]: encd_data = pd.get_dummies(data, columns =
      ↳ list(set(cat_cols)-set(['satisfaction'])))
encd_data['satisfaction'].replace(['neutral or dissatisfied', 'satisfied'], [0,
      ↳ 1], inplace=True)

print(encd_data.columns)
```

```
Index(['Age', 'Flight Distance', 'Inflight wifi service',
      'Departure/Arrival time convenient', 'Ease of Online booking',
      'Gate location', 'Food and drink', 'Online boarding', 'Seat comfort',
      'Inflight entertainment', 'On-board service', 'Leg room service',
      'Baggage handling', 'Checkin service', 'Inflight service',
      'Cleanliness', 'Departure Delay in Minutes', 'Arrival Delay in Minutes',
      'satisfaction', 'Gender_Female', 'Gender_Male',
      'Type of Travel_Business travel', 'Type of Travel_Personal Travel',
      'Class_Business', 'Class_Eco', 'Class_Eco Plus',
      'Customer Type_Loyal Customer', 'Customer Type_disloyal Customer'],
```



```
dtype='object')
```

```
[92]: encd_data.describe()
```

```
[92]:
```

	Age	Flight Distance	Inflight wifi service	\
count	103594.000000	103594.000000	103594.000000	
mean	39.380466	1189.325202	2.729753	
std	15.113125	997.297235	1.327866	
min	7.000000	31.000000	0.000000	
25%	27.000000	414.000000	2.000000	
50%	40.000000	842.000000	3.000000	
75%	51.000000	1743.000000	4.000000	
max	85.000000	4983.000000	5.000000	

	Departure/Arrival time convenient	Ease of Online booking	\
count	103594.000000	103594.000000	
mean	3.060081	2.756984	
std	1.525233	1.398934	
min	0.000000	0.000000	
25%	2.000000	2.000000	
50%	3.000000	3.000000	
75%	4.000000	4.000000	
max	5.000000	5.000000	

	Gate location	Food and drink	Online boarding	Seat comfort	\
count	103594.000000	103594.000000	103594.000000	103594.000000	
mean	2.977026	3.202126	3.250497	3.439765	
std	1.277723	1.329401	1.349433	1.318896	
min	0.000000	0.000000	0.000000	0.000000	
25%	2.000000	2.000000	2.000000	2.000000	
50%	3.000000	3.000000	3.000000	4.000000	
75%	4.000000	4.000000	4.000000	5.000000	
max	5.000000	5.000000	5.000000	5.000000	

	Inflight entertainment	... satisfaction	Gender_Female	\
count	103594.000000	... 103594.000000	103594.000000	
mean	3.358341	... 0.433394	0.507520	
std	1.333030	... 0.495546	0.499946	
min	0.000000	... 0.000000	0.000000	
25%	2.000000	... 0.000000	0.000000	
50%	4.000000	... 0.000000	1.000000	
75%	4.000000	... 1.000000	1.000000	
max	5.000000	... 1.000000	1.000000	

	Gender_Male	Type of Travel_Business travel	\
count	103594.000000	103594.000000	
mean	0.492480	0.689857	

std	0.499946	0.462554
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	1.000000
75%	1.000000	1.000000
max	1.000000	1.000000

	Type of Travel_Personal Travel	Class_Business	Class_Eco \
count	103594.000000	103594.000000	103594.000000
mean	0.310143	0.478145	0.449765
std	0.462554	0.499525	0.497472
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000
75%	1.000000	1.000000	1.000000
max	1.000000	1.000000	1.000000

	Class_Eco Plus	Customer Type_Loyal Customer \
count	103594.000000	103594.000000
mean	0.072089	0.817248
std	0.258637	0.386465
min	0.000000	0.000000
25%	0.000000	1.000000
50%	0.000000	1.000000
75%	0.000000	1.000000
max	1.000000	1.000000

	Customer Type_disloyal Customer
count	103594.000000
mean	0.182752
std	0.386465
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1.000000

[8 rows x 28 columns]

## 2.0.2 Normalize, using min max scaling:

```
[93]: def min_max_scaling(series):
        return (series - series.min()) / (series.max() - series.min())

for col in encd_data.drop(['satisfaction'], axis=1).columns:
    encd_data[col] = min_max_scaling(encd_data[col])
```

```
encd_data.describe()
```

[93]:

	Age	Flight Distance	Inflight wifi service	\
count	103594.000000	103594.000000	103594.000000	
mean	0.415134	0.233911	0.545951	
std	0.193758	0.201393	0.265573	
min	0.000000	0.000000	0.000000	
25%	0.256410	0.077342	0.400000	
50%	0.423077	0.163772	0.600000	
75%	0.564103	0.345719	0.800000	
max	1.000000	1.000000	1.000000	

	Departure/Arrival time convenient	Ease of Online booking	\
count	103594.000000	103594.000000	
mean	0.612016	0.551397	
std	0.305047	0.279787	
min	0.000000	0.000000	
25%	0.400000	0.400000	
50%	0.600000	0.600000	
75%	0.800000	0.800000	
max	1.000000	1.000000	

	Gate location	Food and drink	Online boarding	Seat comfort	\
count	103594.000000	103594.000000	103594.000000	103594.000000	
mean	0.595405	0.640425	0.650099	0.687953	
std	0.255545	0.265880	0.269887	0.263779	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.400000	0.400000	0.400000	0.400000	
50%	0.600000	0.600000	0.600000	0.800000	
75%	0.800000	0.800000	0.800000	1.000000	
max	1.000000	1.000000	1.000000	1.000000	

	Inflight entertainment	...	satisfaction	Gender_Female	\
count	103594.000000	...	103594.000000	103594.000000	
mean	0.671668	...	0.433394	0.507520	
std	0.266606	...	0.495546	0.499946	
min	0.000000	...	0.000000	0.000000	
25%	0.400000	...	0.000000	0.000000	
50%	0.800000	...	0.000000	1.000000	
75%	0.800000	...	1.000000	1.000000	
max	1.000000	...	1.000000	1.000000	

	Gender_Male	Type of Travel_Business travel	\
count	103594.000000	103594.000000	
mean	0.492480	0.689857	
std	0.499946	0.462554	
min	0.000000	0.000000	

25%	0.000000	0.000000
50%	0.000000	1.000000
75%	1.000000	1.000000
max	1.000000	1.000000

	Type of Travel_Personal Travel	Class_Business	Class_Eco \
count	103594.000000	103594.000000	103594.000000
mean	0.310143	0.478145	0.449765
std	0.462554	0.499525	0.497472
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000
75%	1.000000	1.000000	1.000000
max	1.000000	1.000000	1.000000

	Class_Eco Plus	Customer Type_Loyal Customer \
count	103594.000000	103594.000000
mean	0.072089	0.817248
std	0.258637	0.386465
min	0.000000	0.000000
25%	0.000000	1.000000
50%	0.000000	1.000000
75%	0.000000	1.000000
max	1.000000	1.000000

	Customer Type_disloyal Customer
count	103594.000000
mean	0.182752
std	0.386465
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1.000000

[8 rows x 28 columns]

```
[94]: # a function to do preprocessing
def preprocess(df):
    df = df.drop(['id', 'Unnamed: 0'], axis=1)
    df = df.dropna(axis=0)
    cat_cols = list(set(df.columns) - set(df._get_numeric_data().columns))
    encd_data = pd.get_dummies(df, columns =
    ↪list(set(cat_cols)-set(['satisfaction'])))
    encd_data['satisfaction'].replace(['neutral or dissatisfied', 'satisfied'],
    [0, 1], inplace=True)
```

```

for col in encd_data.drop(['satisfaction'], axis=1).columns:
    encd_data[col] = min_max_scaling(encd_data[col])

return encd_data

```

### 3 Perceptron

```
[95]: from sklearn.linear_model import Perceptron
```

```

[96]: X = encd_data.drop('satisfaction', axis=1)
      y = encd_data['satisfaction']

      perceptron = Perceptron(eta0=0.4, tol=None, max_iter= 1500)
      # eta0 -> learning rate
      # tol -> The stopping criterion. If it is not None, the iterations will stop
      # when (loss > previous_loss - tol).
      # max_iter -> The maximum number of passes over the training data (aka
      # epochs)
      perceptron.fit(X, y)

```

```
[96]: Perceptron(eta0=0.4, max_iter=1500, tol=None)
```

```

[97]: training_data_accuracy = perceptron.score(X, y)
      training_data_accuracy
      # Returns the mean accuracy on the given test data and labels.

```

```
[97]: 0.8305886441299689
```

#### 3.0.1 Test data:

```

[98]: test_data = pd.read_csv('data/test.csv')

      encd_test_data = preprocess(test_data)

      X_test = encd_test_data.drop('satisfaction', axis=1)
      y_test = encd_test_data['satisfaction']

      testing_data_accuracy = perceptron.score(X_test, y_test)
      testing_data_accuracy

```

```
[98]: 0.8335843664310818
```

## 4 Kernel trick using feature maps:

### 4.1 RBF feature mapping:

- [Feature mapping explained](#)
- [rbf feature mapping](#)
- [rbf sampler](#)
- [Kernel perceptron](#)

```
[99]: from sklearn.kernel_approximation import RBFSampler

rbf_feature = RBFSampler(n_components=3200, gamma=1/40, random_state=1)
X_rbf_mapping = rbf_feature.fit_transform(X)
```

```
[100]: X_rbf_mapping.shape
```

```
[100]: (103594, 3200)
```

```
[101]: clf = Perceptron(eta0=0.1, tol=1e-3)
clf.fit(X_rbf_mapping, y)
clf.score(X_rbf_mapping, y)
```

```
[101]: 0.9166457516844605
```

```
[102]: test_data = pd.read_csv('data/test.csv')

encd_test_data = preprocess(test_data)

X_test = encd_test_data.drop('satisfaction', axis=1)
y_test = encd_test_data['satisfaction']

X_test_rbf = rbf_feature.transform(X_test)
clf.score(X_test_rbf, y_test)
```

```
[102]: 0.9197852701502337
```