OLA Data Case Study

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Loading data into Pandas Dataframe

```
url="https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/002/492/original/ola_driver_scaler.csv"
data=pd.read_csv(url)
df=pd.DataFrame(data)
```

```
df.head()
```

	Unnamed: 0	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Tota Busines Valu
0	0	01/01/19	1	28.0	0.0	C23	2	57387	24/12/18	NaN	1	1	238106
1	1	02/01/19	1	28.0	0.0	C23	2	57387	24/12/18	NaN	1	1	-66548
2	2	03/01/19	1	28.0	0.0	C23	2	57387	24/12/18	03/11/19	1	1	
3	3	11/01/20	2	31.0	0.0	C7	2	67016	11/06/20	NaN	2	2	
4	4	12/01/20	2	31.0	0.0	C7	2	67016	11/06/20	NaN	2	2	

Next steps: Generate code with df | View recommended plots | New interactive sheet

- Shape of the data

```
df.shape
```

```
(19104, 14)
```

- 19104 rows and 14 columns

```
df.columns
```

```
Index(['Unnamed: 0', 'MMM-YY', 'Driver_ID', 'Age', 'Gender', 'City',
       'Education_Level', 'Income', 'Dateofjoining', 'LastWorkingDate',
       'Joining Designation', 'Grade', 'Total Business Value',
       'Quarterly Rating'],
      dtype='object')
```

```
df.describe()
```

	Unnamed: 0	Driver_ID	Age	Gender	Education_Level	Income	Joining Designation	Grade	Total Business Value	
count	19104.000000	19104.000000	19043.000000	19052.000000	19104.000000	19104.000000	19104.000000	19104.000000	1.910400e+04	1!
mean	9551.500000	1415.591133	34.668435	0.418749	1.021671	65652.025126	1.690536	2.252670	5.716621e+05	
std	5514.994107	810.705321	6.257912	0.493367	0.800167	30914.515344	0.836984	1.026512	1.128312e+06	
min	0.000000	1.000000	21.000000	0.000000	0.000000	10747.000000	1.000000	1.000000	-6.000000e+06	
25%	4775.750000	710.000000	30.000000	0.000000	0.000000	42383.000000	1.000000	1.000000	0.000000e+00	
50%	9551.500000	1417.000000	34.000000	0.000000	1.000000	60087.000000	1.000000	2.000000	2.500000e+05	
75%	14327.250000	2137.000000	39.000000	1.000000	2.000000	83969.000000	2.000000	3.000000	6.997000e+05	
max	19103.000000	2788.000000	58.000000	1.000000	2.000000	188418.000000	5.000000	5.000000	3.374772e+07	

- There are statistical information we can see in above table like Standard Deviation,mean of the column, max, etc..

- Data Types of the columns

- Convert date-like features to their respective data type

```
df['City']=df['City'].astype('category')
df['Dateofjoining']=df['Dateofjoining'].astype('datetime64[ns]')
df['LastWorkingDate']=df['LastWorkingDate'].astype('datetime64[ns]')
df['MMM-YY']=df['MMM-YY'].astype('datetime64[ns]')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19104 entries, 0 to 19103
Data columns (total 14 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Unnamed: 0            19104 non-null  int64
 1   MMM-YY                19104 non-null  datetime64[ns]
 2   Driver_ID             19104 non-null  int64
 3   Age                   19043 non-null  float64
 4   Gender                19052 non-null  float64
 5   City                  19104 non-null  category
 6   Education_Level       19104 non-null  int64
 7   Income                19104 non-null  int64
 8   Dateofjoining         19104 non-null  datetime64[ns]
 9   LastWorkingDate       1616 non-null   datetime64[ns]
 10  Joining Designation   19104 non-null  int64
 11  Grade                 19104 non-null  int64
 12  Total Business Value  19104 non-null  int64
 13  Quarterly Rating      19104 non-null  int64
dtypes: category(1), datetime64[ns](3), float64(2), int64(8)
memory usage: 1.9 MB
```

Encoding the Target Variable into 0 and 1

- Converting Target variable (LastWorkingDate) into 0 and 1, 0 for nott leaving and 1 for leaving.

```
#Creating another variable whether driver leave of not df['Is_Leaving']->  1: Leaving current compnay and 0: Not Leaving
df['Is_Leaving']=df['LastWorkingDate'].apply(lambda x: 0 if pd.isnull(x) else 1)
```

```
#Convert NaN values to 0
df['LastWorkingDate']=df['LastWorkingDate'].apply(lambda x: 0 if pd.isnull(x) else x)
```

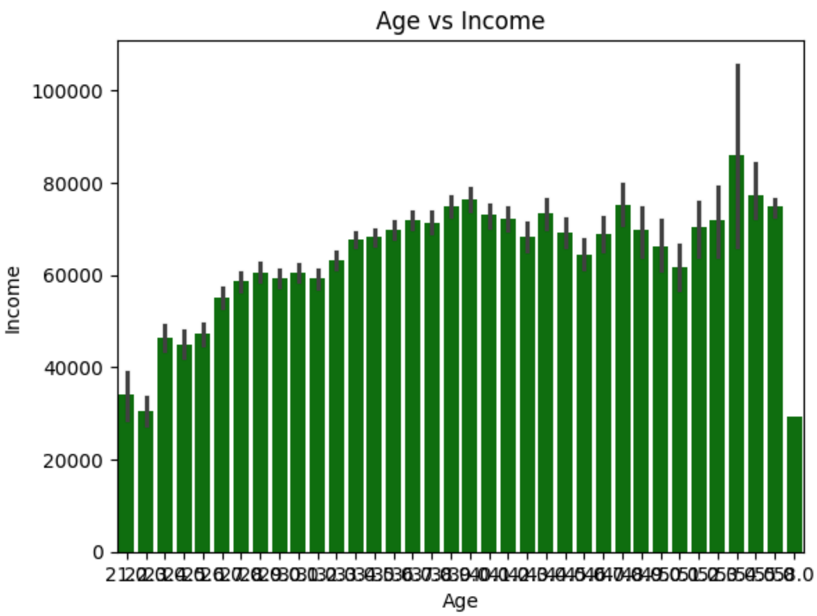
```
#df['LastWorkingDate'].value_counts()
```

- Currently 1615 driver are going to ressign

```
print("Total Number of Drivers : ",df['Driver_ID'].nunique())
```

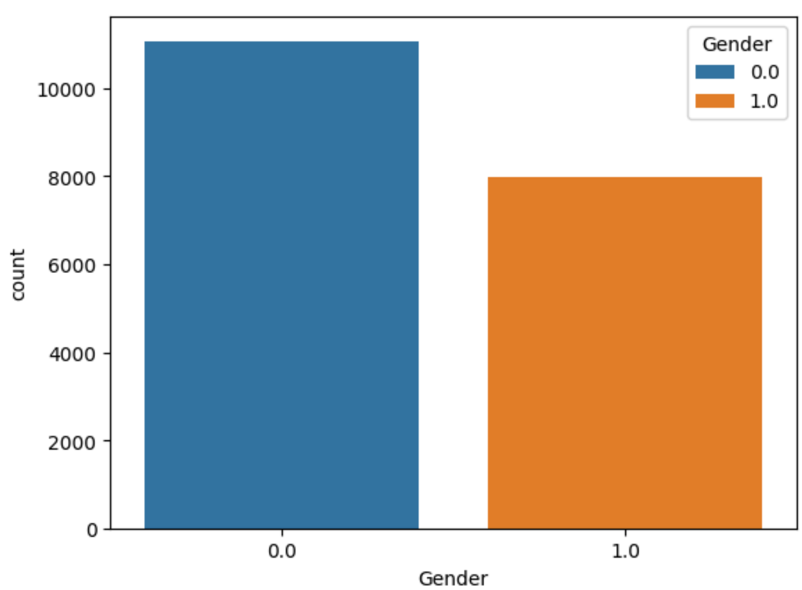
```
Total Number of Drivers :  2381
```

```
sns.barplot(x=df['Age'],y=df['Income'], color='green')
plt.xlabel('Age')
plt.ylabel('Income')
plt.title('Age vs Income')
plt.show()
```



- In the above plot it is clear that highest income category comes between 29 to 32 age category.

```
sns.countplot(data=df,x='Gender',hue=df['Gender'])
plt.show()
```



- In above plot 1 is Female and 0 is Male,
- In OLA drive Male member is higher than Female.

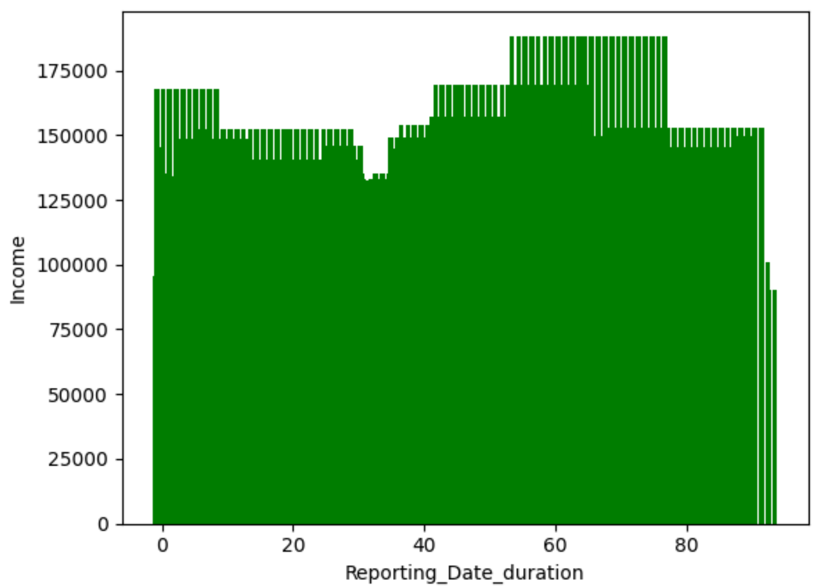
```
df.head(2)
```

	Unnamed: 0	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value
0	0	2019-01-01	1	28.0	0.0	C23	2	57387	2018-12-24	0	1	1	2381060
1	1	2019-02-01	1	28.0	0.0	C23	2	57387	2018-12-24	0	1	1	-665480

Next steps: Generate code with df View recommended plots New interactive sheet

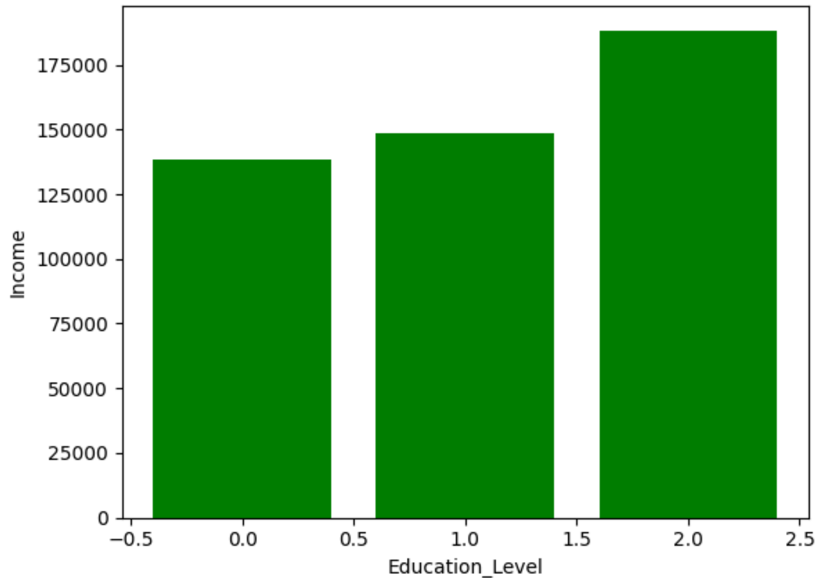
```
df['Reporting_Date_duration']=(df['MMM-YY']-df['Dateofjoining']).dt.days/30
```

```
plt.bar(x=df['Reporting_Date_duration'],height=df['Income'], color='green')
plt.xlabel('Reporting_Date_duration')
plt.ylabel('Income')
plt.show()
```



- According to above graph, the highest income holding by those people who has experiance between 60-80 months

```
plt.bar(x=df['Education_Level'],height=df['Income'], color='green')
plt.xlabel('Education_Level')
plt.ylabel('Income')
plt.show()
```



- Highest income holding by highest educated peoples

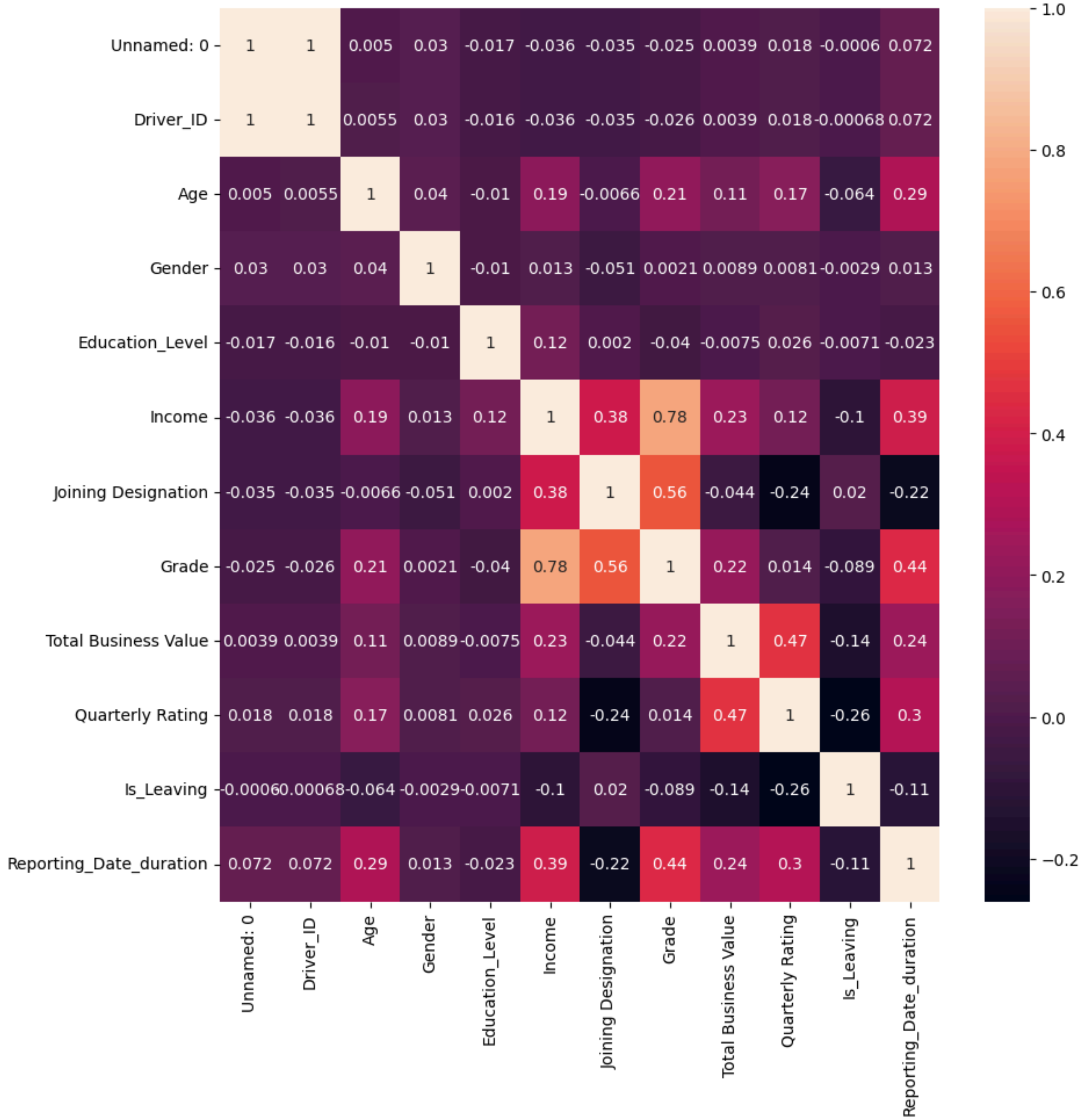
Finding Numerical columns

```
num_cal=df.select_dtypes(include=['int64','float64']).columns
num_cal
```

```
Index(['Unnamed: 0', 'Driver_ID', 'Age', 'Gender', 'Education_Level', 'Income',
       'Joining Designation', 'Grade', 'Total Business Value',
       'Quarterly Rating', 'Is_Leaving', 'Reporting_Date_duration'],
      dtype='object')
```

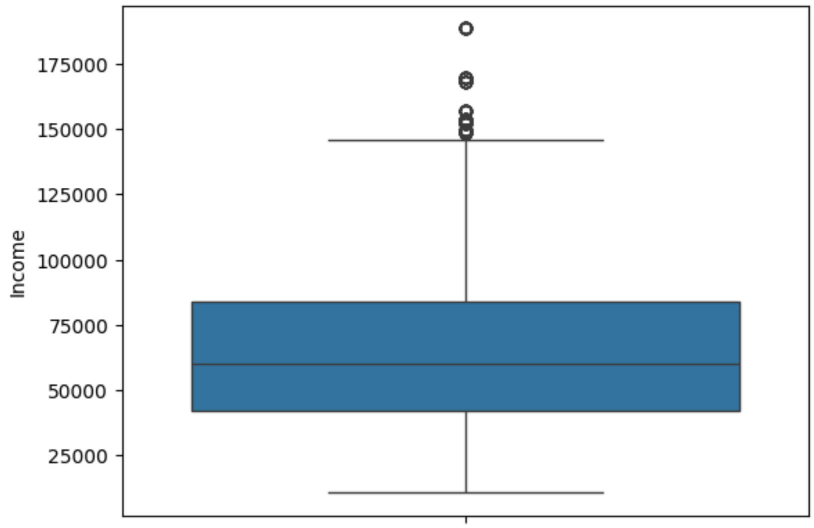
Co-relation map which indicate relationship between two features

```
plt.figure(figsize=(10,10))
sns.heatmap(df[num_cal].corr(),annot=True)
plt.show()
```



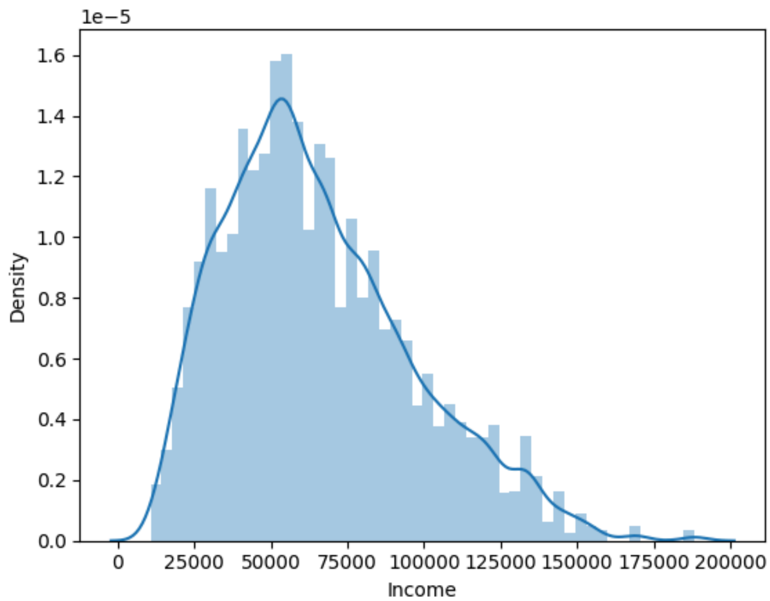
- Nearest to 1 indicate stronger relationship between two features
- Nearest to 0 is weak relationship.
- For e.g. Grade and Income has strong relationship

```
sns.boxplot(df['Income'])
plt.show()
```



- There are outliers in the Income feature

```
sns.distplot(df['Income'])
plt.show()
```



- The income column data is not normaly distributed, it is looking as right skewed distribution.

KNN Imputation : *Check for missing values and Prepare data for KNN Imputation*

```
df.isnull().sum()
```

	0
Unnamed: 0	0
Driver_ID	0
Age	0
Gender	0
City	0
Education_Level	0
Income	0
Joining Designation	0
Grade	0
Total Business Value	0
Quarterly Rating	0
Is_Leaving	0
Reporting_Date_duration	0
Quarter	0
Total_Months_Worked_In_OLA	0
Reporting_Year	0
Reporting_Month	0
MonthOfjoining	0
YearOfjoining	0

dtype: int64

- We have two featured with null values, Age and Gender
- Let's fill it by using KNNImputer library which is famous for filling null values by wornderfull strategies.

```
from sklearn.impute import KNNImputer
imputer=KNNImputer(n_neighbors=5)
df_imputed=pd.DataFrame(imputer.fit_transform(df[['Age','Gender']]),columns=['Age','Gender'])
df_imputed.head()
```

	Age	Gender
0	28.0	0.0
1	28.0	0.0
2	28.0	0.0
3	31.0	0.0
4	31.0	0.0

Next steps: Generate code with df_imputed View recommended plots New interactive sheet

```
df['Age']=df_imputed['Age']
df['Gender']=df_imputed['Gender']
```

```
df.isnull().sum()
```

	0
Unnamed: 0	0
MMM-YY	0
Driver_ID	0
Age	0
Gender	0
City	0
Education_Level	0
Income	0
Dateofjoining	0
LastWorkingDate	0
Joining Designation	0
Grade	0
Total Business Value	0
Quarterly Rating	0
Is_Leaving	0
Reporting_Date_duration	0

dtype: int64

What percentage of drivers have received a quarterly rating of 4 ?

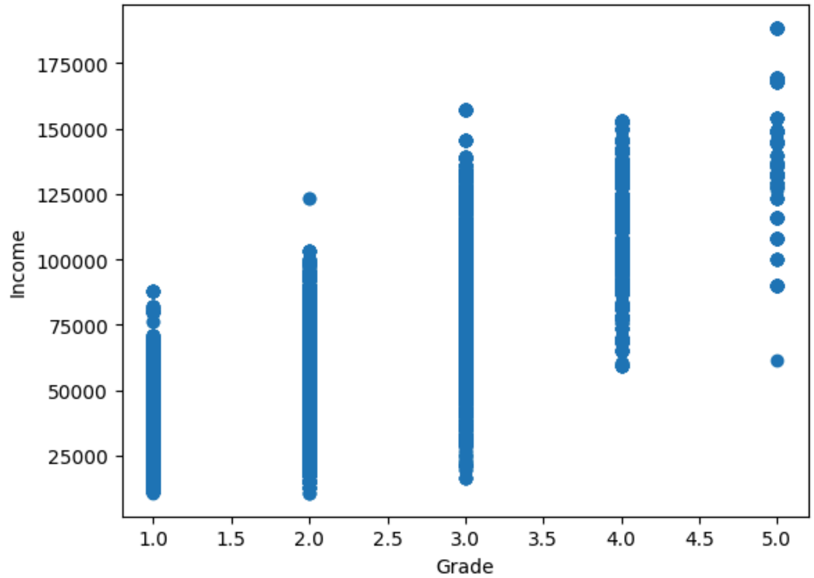
```
reting=df['Quarterly Rating'].value_counts()
print(round(reting/len(df)*100),2)
```

```
Quarterly Rating
1    40.0
2    29.0
3    20.0
4    10.0
Name: count, dtype: float64 2
```

- 10% drivers got 4 reting

Comment on the correlation between Age and Quarterly Rating.

```
plt.scatter(x=df['Grade'],y=df['Income'])
plt.xlabel('Grade')
plt.ylabel('Income')
plt.show()
print('Correaltion:',df['Grade'].corr(df['Income']))
```

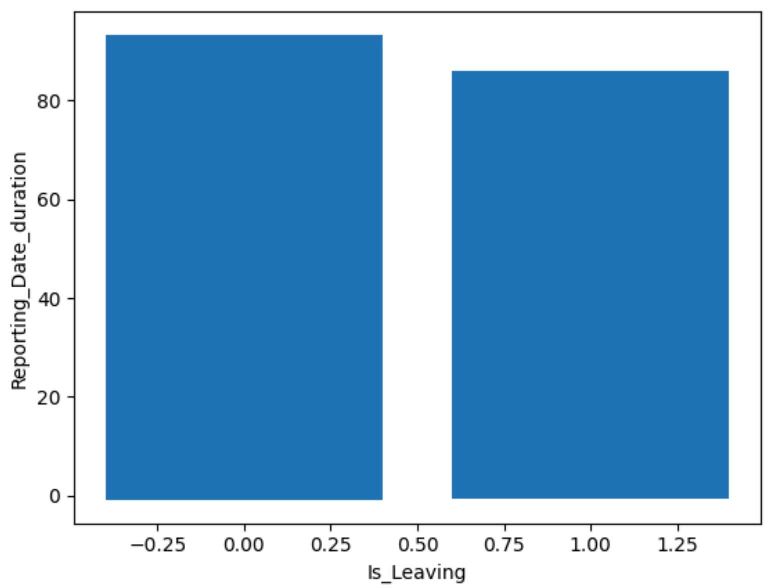



```
Correaltion: 0.7783833974539701
```

-Grade and Income has a very strong co-relation, that means salary is increased when grade increased

Checking whether the driver those are leaving how they are reporting as compare to those are not leaving

```
plt.bar(height=df['Reporting_Date_duration'],x=df['Is_Leaving'])
plt.xlabel('Is_Leaving')
plt.ylabel('Reporting_Date_duration')
plt.show()
```



- As per the bove plot I am trying to understand that those drive who are leaving those reporting time is less than those who are not leaving.

Name the city which showed the most improvement in Quarterly Rating over the past year

```
df['Quarter']=df['MMM-YY'].dt.quarter
df['Year']=df['MMM-YY'].dt.year
```

```
quaterly=df.groupby('City')['Quarter'].value_counts().reset_index()
quaterly.sort_values(by=['City','count'],ascending=False)
rating_2019=df.loc[(df['Year']==2019),('City','Quarterly Rating','Year')]
```

```
rating_2020=df.loc[(df['Year']==2020),('City','Quarterly Rating','Year')]
```

	City	Quarterly Rating	Year
3	C7	1	2020
4	C7	1	2020
6	C13	1	2020
7	C13	1	2020
8	C13	1	2020

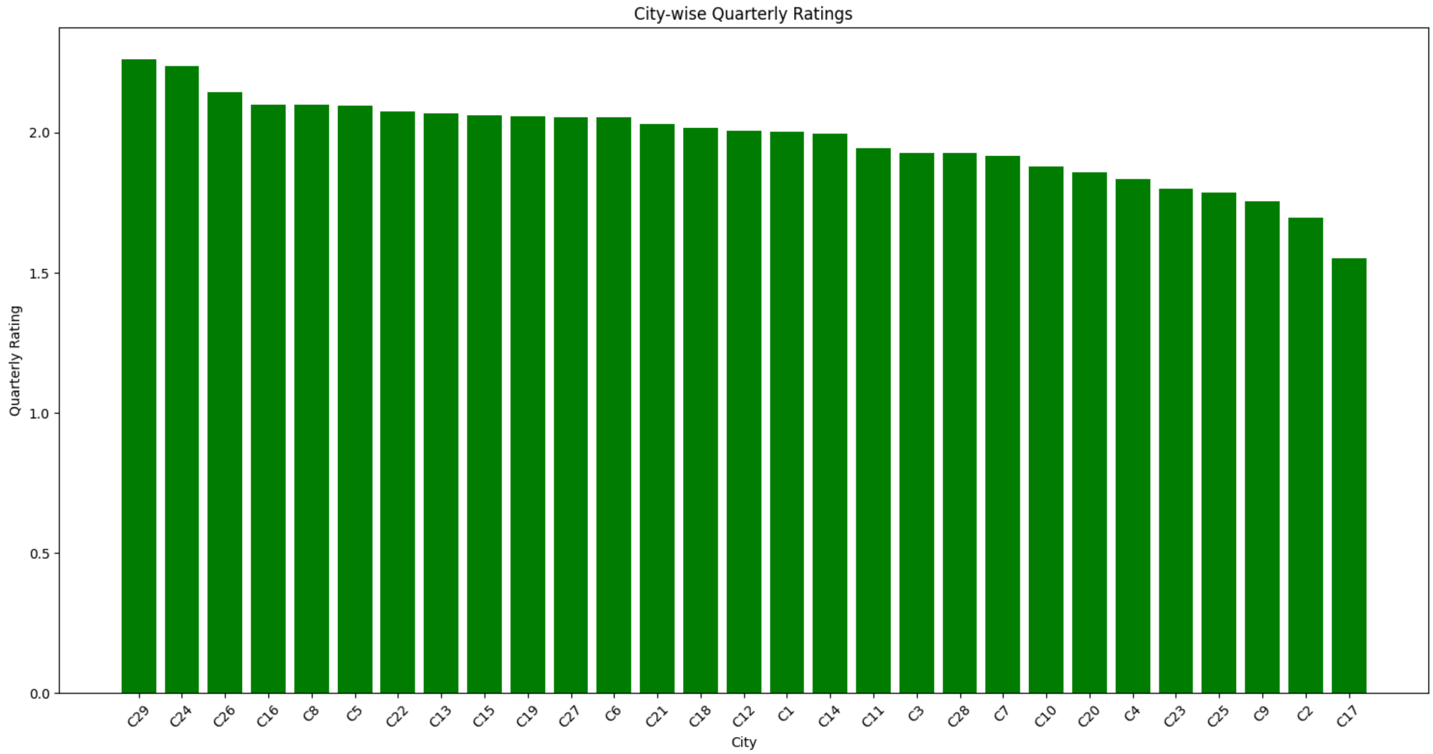
Next steps: Generate code with rating_2019 | View recommended plots | New interactive sheet

```
City_name=rating_2019.groupby('City')['Quarterly Rating'].mean().sort_values(ascending=False).reset_index()

City_name.head()
```

	City	Quarterly Rating
0	C29	2.261036
1	C24	2.236364
2	C26	2.142857
3	C16	2.100737
4	C8	2.097884

Next steps: Generate code with City_name | View recommended plots | New interactive sheet

```
import matplotlib.pyplot as plt

plt.figure(figsize=(15, 8))  # Ensure plt.figure is not overwritten

plt.bar(x=City_name['City'], height=City_name['Quarterly Rating'], color='green')
plt.xlabel('City')
plt.ylabel('Quarterly Rating')
plt.title('City-wise Quarterly Ratings')
plt.xticks(rotation=45)  # Optional: rotate x-axis labels for readability
plt.tight_layout()
plt.show()
```

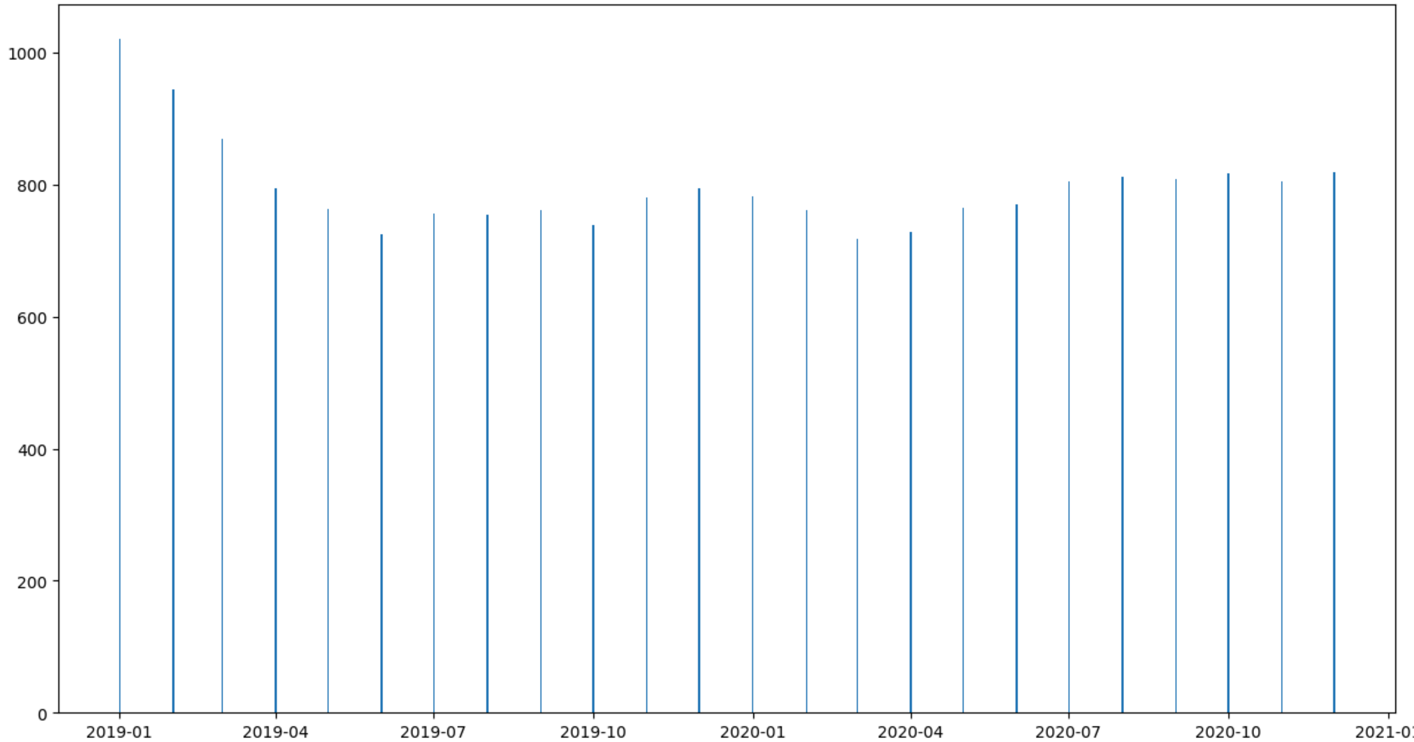


- The City C29 has the highest quterly rating average

Class Imbalance treatment

- Lets check imbalanced class in dataset

```
report=df['MMM-YY'].value_counts().reset_index()
plt.figure(figsize=(15,8))
plt.bar(x=report['MMM-YY'],height=report['count'])
plt.show()
```

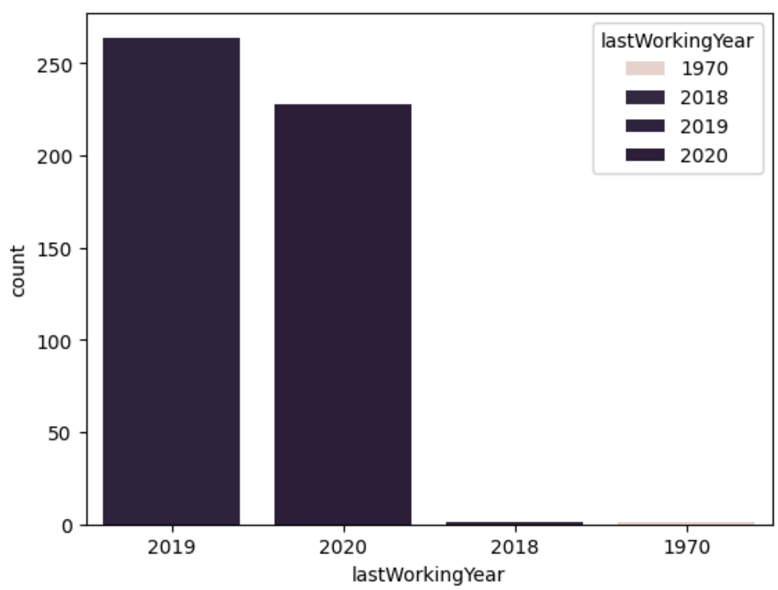


-As per the above plot we can see that the driver have reported the maximum time in Jan-2019.

-Converting df['LastWorkingDate'] column to datetime to fetch month and year

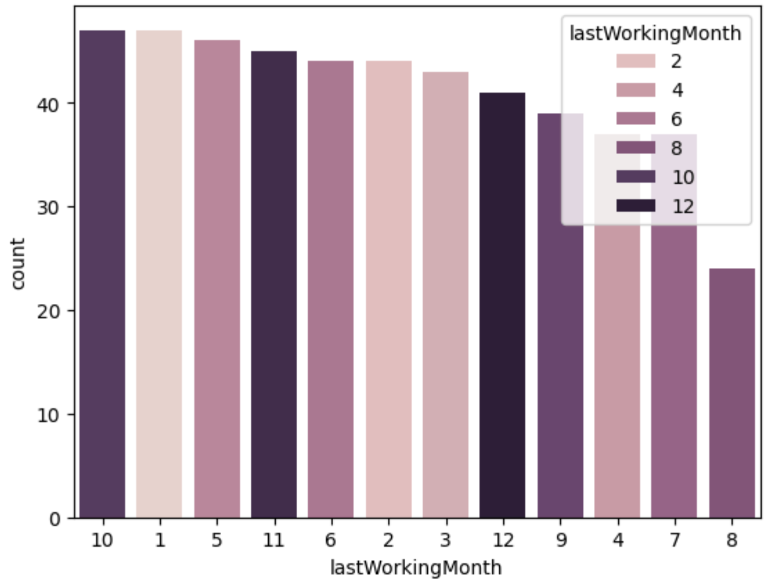
```
lastdate=df['LastWorkingDate'].value_counts().sort_values().reset_index()
lastdate['LastWorkingDate']=lastdate['LastWorkingDate'].astype('datetime64[ns]')
lastdate['lastdate']=lastdate['LastWorkingDate'].astype('datetime64[ns]')
lastdate['lastWorkingDay']=lastdate['LastWorkingDate'].dt.day
lastdate['lastWorkingMonth']=lastdate['LastWorkingDate'].dt.month
lastdate['lastWorkingYear']=lastdate['LastWorkingDate'].dt.year
```

```
sns.countplot(data=lastdate,x='lastWorkingYear',hue='lastWorkingYear',order=lastdate['lastWorkingYear'].value_counts().index)
plt.show()
```



- Highest number of drive leave the company in 2019
- It may be due to COVID19 period
- Next Year it get decreased the number of driver who left the OLA.

```
sns.countplot(data=lastdate,x='lastWorkingMonth',hue='lastWorkingMonth',order=lastdate['lastWorkingMonth'].value_counts().index)
plt.show()
```



- Most number of OLA driver left the company mostly in Jan and Oct month, near about 50 employees left.
- Less number of Drivers have left the company in AUG month, around 25 Employees.

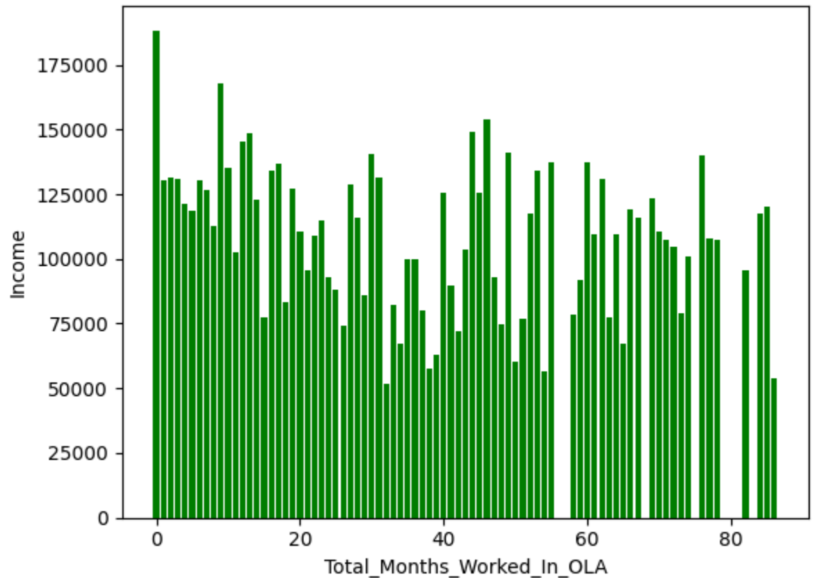
Count the total years of experiance of Drivers in OLA before letf the compnay.

- Converting column LastWorkingDate from Object to Datetime datatype.

```
df['LastWorkingDate']=df['LastWorkingDate'].astype('datetime64[ns]')
```

```
df['Total_Months_Worked_In_OLA']=(df['LastWorkingDate']-df['Dateofjoining'])
df['Total_Months_Worked_In_OLA']=df['Total_Months_Worked_In_OLA'].dt.days/30
df['Total_Months_Worked_In_OLA']=df['Total_Months_Worked_In_OLA'].apply(lambda x:0 if (x<0) else x)
df['Total_Months_Worked_In_OLA']=df['Total_Months_Worked_In_OLA'].astype('int')
```

```
plt.bar(x=df['Total_Months_Worked_In_OLA'],height=df['Income'], color='green')
plt.xlabel('Total_Months_Worked_In_OLA')
plt.ylabel('Income')
plt.show()
```



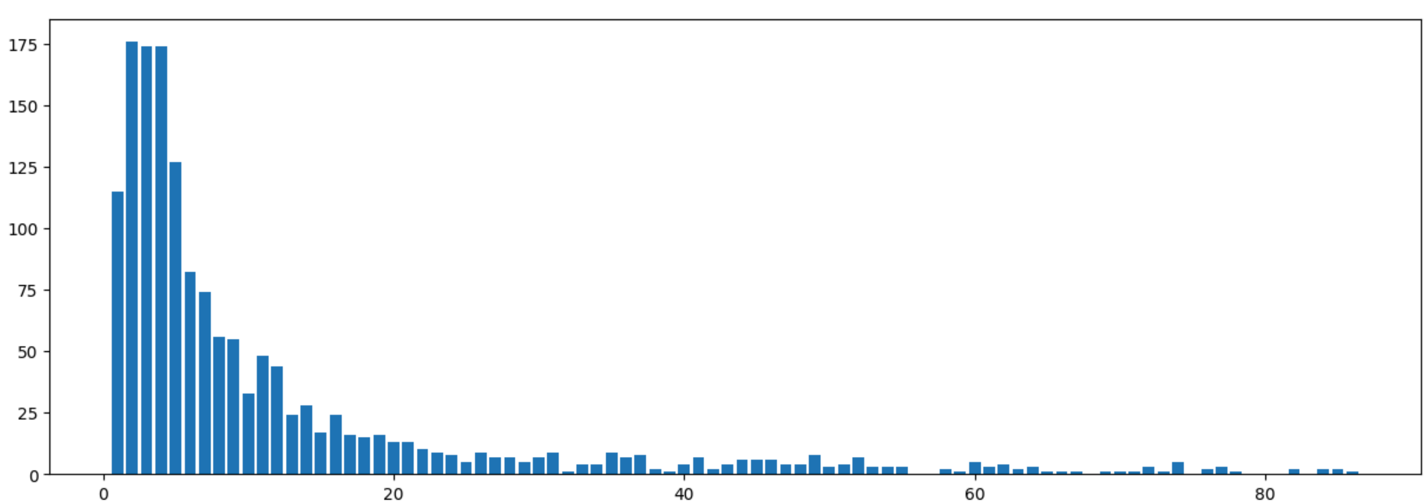
- According to the above plot the Drivers who left the OLA company within a month those are having highest number of income as compare to the other OLA drivers.
- `It mean who has the highest income as compare to other drivers those drivers can be left within a month of OLA join.`

```
a=df.loc[df['Total_Months_Worked_In_OLA']>0,'Total_Months_Worked_In_OLA'].value_counts().reset_index()
a.head()
```

	Total_Months_Worked_In_OLA	count
0	2	176
1	4	174
2	3	174
3	5	127
4	1	115

Next steps: Generate code witha View recommended plots New interactive sheet

```
plt.figure(figsize=(15,5))
plt.bar(x=a['Total_Months_Worked_In_OLA'],height=a['count'])
plt.show()
```



- Most of the OLA driver left the companies withing 10 m0nths
- It means there is high chances of left the company within 10 months from join date.

Encoding

- Encoding the Categorical value into number.

```
#df['City'].value_counts()
```

- Triying to encode by using LabelEncoder
- There are total 29 city

```
from sklearn.preprocessing import LabelEncoder,OrdinalEncoder
encoder=LabelEncoder()
df['City_le']=encoder.fit_transform(df['City'])
```

- Trying to encode by using Ordinal Encoding

```
oencoder=OrdinalEncoder()
df['City_oe']=oencoder.fit_transform(df[['City']])
```

- Trying to encode by using Target Encoding

```
from sklearn.preprocessing import TargetEncoder
tencoder=TargetEncoder()
df['City_te']=tencoder.fit_transform(df[['City']],df[['Is_Leaving']])
```

```
df['City_te'].value_counts()
```

City_te	count
0.102505	218
0.105628	213
0.115049	200
0.118462	198
0.053853	194
...	...
0.101570	87
0.115703	86
0.115873	84
0.094601	77
0.126556	77

145 rows × 1 columns

dtype: int64

- As we can see the above three encoding technique (Label,Ordinal and Target Encoding),
- We got the best encoding result from the target encoding.
- so we will keep the target encoding and delete the remaining columns.

```
df['City']=df['City_te']
df.drop(columns=['City_le','City_oe','City_te','Year'],inplace=True)
```

```
df.head(2)
```

	Unnamed: 0	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Tot Busine Val
0	0	2019-01-01	1	28.0	0.0	0.118097	2	57387	2018-12-24	1970-01-01	1	1	23810
1	1	2019-02-01	1	28.0	0.0	0.100644	2	57387	2018-12-24	1970-01-01	1	1	-6654

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
df['Reporting_Year']=df['MMM-YY'].dt.year
df['Reporting_Month']=df['MMM-YY'].dt.month
df['MonthOfjoining']=df['Dateofjoining'].dt.month
df['YearOfjoining']=df['Dateofjoining'].dt.year
```

- We are going to remove the LastWorkingDate colums as we already have created separate columns like, Is_Leaving,LastWorkingDay,LastWorkingMonth and LastWorkingYear for more analysis.

```
df.drop(columns=['LastWorkingDate','MMM-YY','Dateofjoining'],inplace=True)
```

Standardization :

- `We don't need to standardize features when using models like Naive Bayes, Decision Trees, Random Forest, XGBoost, or LightGBM because of the way these algorithms work internally.`

Class Imbalance treatment :

- Checking the number of positive and Negative classes

```
meaning=pd.DataFrame({'Is_Leaving':[0,1],'Meaning':['Continue with the OLA Company','Left the OLA Company']})

df['Is_Leaving'].value_counts().reset_index().merge(meaning,on='Is_Leaving',how='inner')
```

	Is_Leaving	count	Meaning
0	0	17488	Continue with the OLA Company
1	1	1616	Left the OLA Company

- `Here we can see the class is not balanced(Imbalanced)`
- `Number of employee left is very less as compare to Number of continue to work with OLA.`

First we will try to create model without changing the balanced class by using RandomForestClassifier

- Importing essential library

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
```

- `Partition the data into Train and Test`

```
X=df.drop(columns='Is_Leaving')
y=df['Is_Leaving']
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=42)
rf=RandomForestClassifier(n_estimators=100)
rf.fit(X_train,y_train)
```

```
▾ RandomForestClassifier
RandomForestClassifier()
```

- `Test the Model`

```
y_pred=rf.predict(X_test)
```

- `Check the accuracy of model`

```
rf1_acc_score=accuracy_score(y_test,y_pred)
rf1_acc_score
```

```
0.9971211724679403
```

- `Check the Confusion Matrix`

```
print(confusion_matrix(y_test,y_pred))
```

```
[[3490    0]
 [  11  320]]
```

```
(3490+320)/(3490+320+11+0)
```

```
0.9971211724679403
```

- `We will check classification report`

```
print(classification_report(y_test,y_pred))
```

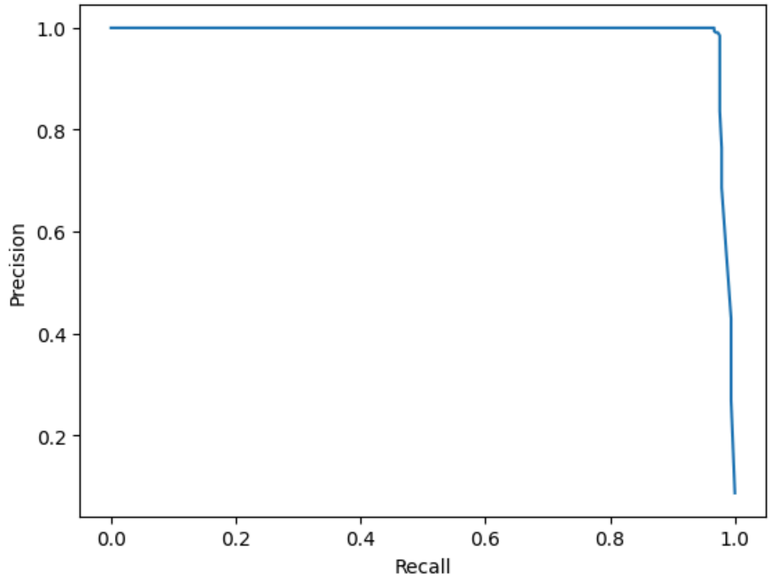
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      3490
           1       1.00      0.97      0.98       331

    accuracy                           1.00      3821
   macro avg       1.00      0.98      0.99      3821
weighted avg       1.00      1.00      1.00      3821
```

- `It is means the data is highly imbalanced`

`Les't Visually check the Precision-Recall Curve or ROC`

```
from sklearn.metrics import precision_recall_curve,roc_curve,auc
import matplotlib.pyplot as plt
y_scores=rf.predict_proba(X_test)[:,1]
print(y_scores)
precision,recall,thresholds=precision_recall_curve(y_test,y_scores)
fpr,tpr,thresholds=roc_curve(y_test,y_scores)
plt.plot(recall,precision)
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.show()
```

```
[0.98 0.   0.01 ... 0.98 0.95 0.91]
```



- `High precision can happen with very few positive predictions`

`Let's Try to balance the classes with the help of SMOTE`

`SMOTE :Systematic Minority Over-Sampling Technique`

- `We have less amount of positive classes, so we are using SMOTE to balance the class data.`

- Before Balancing the sample class

```
df['Is_Leaving'].value_counts()
```

	count
Is_Leaving	
0	17488
1	1616

dtype: int64

```
from imblearn.over_sampling import SMOTE
smote=SMOTE(random_state=42)
X_smote,y_smote=smote.fit_resample(X,y)
```

```
print('After Balacing the class data')
y_smote.value_counts()
```

```
After Balacing the class data
```

	count
Is_Leaving	
0	17488
1	17488

dtype: int64

`Let's try to train the model after balacing the class by using Bagging and Boosint algorithm`

Bagging: RandomForestClassifier Algorithm

```
X_train_smote,X_test_smote,y_train_smote,y_test_smote=train_test_split(X_smote,y_smote,test_size=0.2,random_state=42)
```