Problem Statement

- Recruiting and retaining drivers is seen by industry watchers as a tough battle for Ola. Churn among drivers is high and it's very easy for drivers to stop working for the service on the fly or jump to Uber depending on the rates.
- In this problem statement, we'll use bagging and boosting techniques to build a model that can predict what is the chance of a driver leaving based on his attributes

In [429]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder,StandardScaler
from sklearn.impute import KNNImputer
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report,f1_score,confusion_matrix,plot_confusion_matrix,auc,roc_curve
import xgboost as xgb
from category_encoders import *
```

In [430]:

```
df = pd.read_csv('ola_driver.csv')
```

In [431]:

```
df.drop('Unnamed: 0',axis=1,inplace=True)
```

In [432]:

```
df.info()
```

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

In [433]:

```
df.describe(include='all')
```

Out[433]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	(
count	19104	19104.000000	19043.000000	19052.000000	19104	19104.000000	19104.000000	19104	1616	19104.000000	19104.0
unique	24	NaN	NaN	NaN	29	NaN	NaN	869	493	NaN	
top	01/01/19	NaN	NaN	NaN	C20	NaN	NaN	23/07/15	29/07/20	NaN	
freq	1022	NaN	NaN	NaN	1008	NaN	NaN	192	70	NaN	
mean	NaN	1415.591133	34.668435	0.418749	NaN	1.021671	65652.025126	NaN	NaN	1.690536	2.2
std	NaN	810.705321	6.257912	0.493367	NaN	0.800167	30914.515344	NaN	NaN	0.836984	1.0
min	NaN	1.000000	21.000000	0.000000	NaN	0.000000	10747.000000	NaN	NaN	1.000000	1.0
25%	NaN	710.000000	30.000000	0.000000	NaN	0.000000	42383.000000	NaN	NaN	1.000000	1.0
50%	NaN	1417.000000	34.000000	0.000000	NaN	1.000000	60087.000000	NaN	NaN	1.000000	2.0
75%	NaN	2137.000000	39.000000	1.000000	NaN	2.000000	83969.000000	NaN	NaN	2.000000	3.0
max	NaN	2788.000000	58.000000	1.000000	NaN	2.000000	188418.000000	NaN	NaN	5.000000	5.0

Feature Engineering

In [434]:

```
def check_rating(group):
    selected = [False] * len(group)
    selected[0] = selected[-1] = True
    new_group = group[selected]

    first = new_group['Quarterly Rating'].values[0]
    last = new_group['Quarterly Rating'].values[-1]
    group['Increment Rating'] = 1 if last>first else 0
    return group
```

In [435]:

```
df = df.groupby('Driver_ID').apply(check_rating)
```

In [436]:

```
df.reset_index(drop=True,inplace=True)
```

In [437]:

```
df[df['Increment Rating']==0].tail(20)
```

Out[437]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value	Quarterly Rating	Increme Rati
19053	07/01/19	2782	26.0	0.0	C19	1	29582	16/05/19	NaN	1	1	0	1	
19054	08/01/19	2782	26.0	0.0	C19	1	29582	16/05/19	16/08/19	1	1	0	1	
19079	08/01/20	2785	34.0	1.0	C9	0	12105	28/08/20	NaN	1	1	0	1	
19080	09/01/20	2785	34.0	1.0	C9	0	12105	28/08/20	NaN	1	1	0	1	
19081	10/01/20	2785	34.0	1.0	C9	0	12105	28/08/20	28/10/20	1	1	0	1	
19082	01/01/19	2786	44.0	0.0	C19	0	35370	31/07/18	NaN	2	2	221080	2	
19083	02/01/19	2786	45.0	0.0	C19	0	35370	31/07/18	NaN	2	2	485270	2	
19084	03/01/19	2786	45.0	0.0	C19	0	35370	31/07/18	NaN	2	2	970380	2	
19085	04/01/19	2786	45.0	0.0	C19	0	35370	31/07/18	NaN	2	2	432240	2	
19086	05/01/19	2786	45.0	0.0	C19	0	35370	31/07/18	NaN	2	2	387660	2	
19087	06/01/19	2786	45.0	0.0	C19	0	35370	31/07/18	NaN	2	2	0	2	
19088	07/01/19	2786	45.0	0.0	C19	0	35370	31/07/18	NaN	2	2	318460	1	
19089	08/01/19	2786	45.0	0.0	C19	0	35370	31/07/18	NaN	2	2	0	1	
19090	09/01/19	2786	45.0	0.0	C19	0	35370	31/07/18	22/09/19	2	2	0	1	
19091	01/01/19	2787	28.0	1.0	C20	2	69498	21/07/18	NaN	1	1	408090	2	
19092	02/01/19	2787	28.0	1.0	C20	2	69498	21/07/18	NaN	1	1	250000	2	
19093	03/01/19	2787	28.0	1.0	C20	2	69498	21/07/18	NaN	1	1	319740	2	
19094	04/01/19	2787	28.0	1.0	C20	2	69498	21/07/18	NaN	1	1	0	1	
19095	05/01/19	2787	28.0	1.0	C20	2	69498	21/07/18	NaN	1	1	0	1	
19096	06/01/19	2787	28.0	1.0	C20	2	69498	21/07/18	20/06/19	1	1	0	1	

In [438]:

```
def create_target(group):
    group['Target'] = 1 if group['LastWorkingDate'].notnull().values.any() else 0
    return group
```

In [439]:

```
df = df.groupby('Driver_ID').apply(create_target)
```

In [440]:

```
df.reset_index(drop=True,inplace=True)
```

In [441]:

```
def check_income(group):
    selected = [False] * len(group)
    selected[0] = selected[-1] = True
    new_group = group[selected]

    first = new_group['Income'].values[0]
    last = new_group['Income'].values[-1]
    group['Increment Income'] = 1 if last>first else 0
    return group

df = df.groupby('Driver_ID').apply(check_income)
df.reset_index(drop=True,inplace=True)
```

In [442]:

```
df['Total Business Value'] = df.groupby('Driver_ID')['Total Business Value'].sum()
```

In [443]:

```
total_business_value = df.groupby(['Driver_ID'])['Total Business Value'].agg('sum')
```

In [444]:

```
df = df.drop_duplicates(subset=['Driver_ID'],keep='last')
```

In [445]:

```
df = pd.merge(df,total_business_value,on='Driver_ID')
```

In [ ]:

```

```

In [446]:

```
df['MMM-YY'] = pd.to_datetime(df['MMM-YY'],errors='ignore')
df['Dateofjoining'] = pd.to_datetime(df['Dateofjoining'],errors='ignore')
df['LastWorkingDate'] = pd.to_datetime(df['LastWorkingDate'],errors='ignore')
```

In [447]:

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

Out[447]:

```
MMM-YY                     0
Driver_ID                  0
Age                        7
Gender                    10
City                       0
Education_Level            0
Income                     0
Dateofjoining              0
LastWorkingDate          765
Joining Designation        0
Grade                      0
Total Business Value_x  2061
Quarterly Rating           0
Increment Rating           0
Target                     0
Increment Income           0
Total Business Value_y     0
dtype: int64
```

In [448]:

```
df[df['Target']==0]
```

Out[448]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value_x	Quarterly Rating	Increment Rating
1	2020-12-01	2	31.0	0.0	C7	2	67016	2020-11-06	NaT	2	2	350000.0	1	0
4	2020-12-01	6	31.0	1.0	C11	1	78728	2020-07-31	NaT	3	3	1017640.0	2	1
6	2020-12-01	11	28.0	1.0	C19	2	42172	2020-12-07	NaT	1	1	6962550.0	1	0
9	2020-12-01	14	39.0	1.0	C26	0	19734	2020-10-16	NaT	3	3	NaN	1	0
17	2020-12-01	25	31.0	0.0	C24	1	102077	2017-10-30	NaT	1	3	6570070.0	4	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2370	2020-12-01	2775	27.0	0.0	C9	0	85112	2020-10-02	NaT	3	3	NaN	1	0
2372	2020-12-01	2778	35.0	0.0	C13	2	50180	2020-11-29	NaT	2	2	NaN	1	0
2374	2020-12-01	2781	25.0	0.0	C23	2	46952	2020-02-17	NaT	2	2	NaN	4	1
2376	2020-12-01	2784	34.0	0.0	C24	0	82815	2015-10-15	NaT	2	3	NaN	4	1
2380	2020-12-01	2788	30.0	0.0	C27	2	70254	2020-06-08	NaT	2	2	NaN	2	1

765 rows × 17 columns

In [449]:

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

Out[449]:

```
1    1616
0     765
Name: Target, dtype: int64
```

In [450]:

```
df.drop(['Total Business Value_x'],axis=1,inplace=True)
```

In [451]:

```
df.rename(columns ={'Total Business Value_y':'Cumulative Business value'},inplace=True)
```

In [452]:

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

Out[452]:

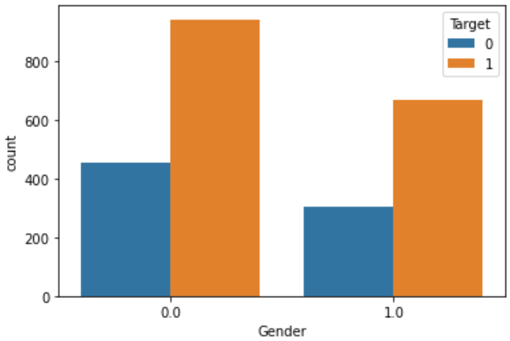
```
MMM-YY                         0
Driver_ID                      0
Age                            7
Gender                        10
City                           0
Education_Level                0
Income                         0
Dateofjoining                  0
LastWorkingDate              765
Joining Designation            0
Grade                          0
Quarterly Rating               0
Increment Rating               0
Target                         0
Increment Income               0
Cumulative Business value      0
dtype: int64
```

Univariate And Bivariate Analysis

In [453]:

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

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable
as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other argu
ments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

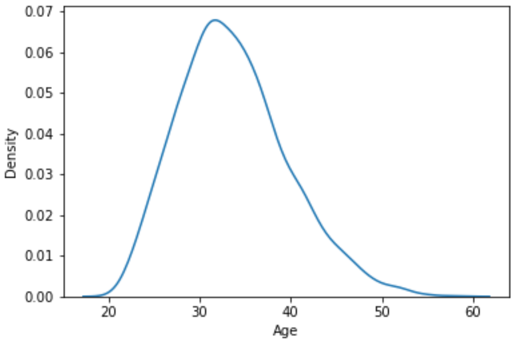


In [454]:

```
sns.kdeplot(df['Age'])
```

Out[454]:

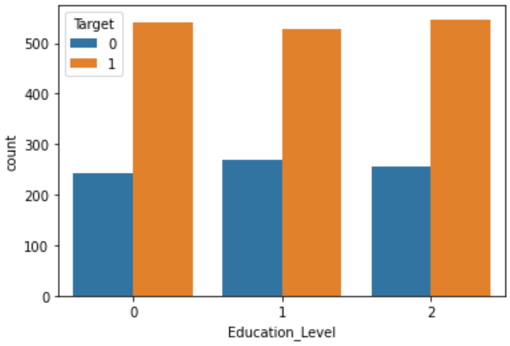
```
<AxesSubplot:xlabel='Age', ylabel='Density'>
```



In [455]:

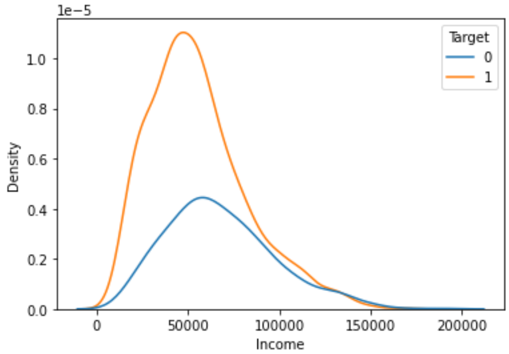
```
sns.countplot(df['Education_Level'],hue=df['Target'])
plt.show()
```

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable
as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other argu
ments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



In [456]:

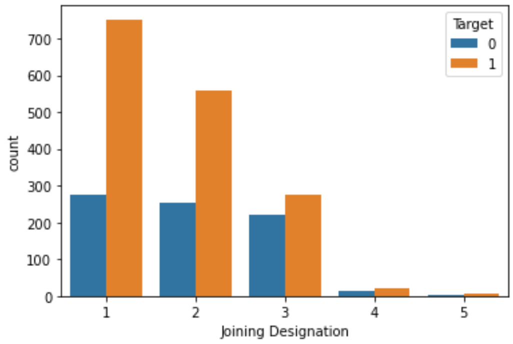
```
sns.kdeplot(df['Income'],hue=df['Target'])
plt.show()
```



In [457]:

```
sns.countplot(df['Joining Designation'],hue=df['Target'])
plt.show()
```

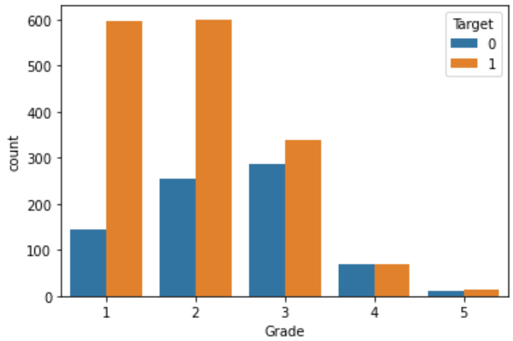
```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable
as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other argu
ments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



In [458]:

```
sns.countplot(df['Grade'],hue=df['Target'])
plt.show()
```

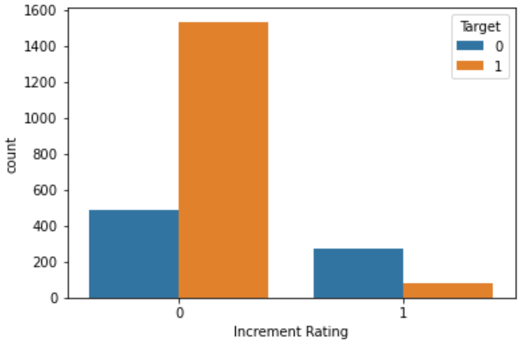
```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable
as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other argu
ments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



In [459]:

```
sns.countplot(df['Increment Rating'],hue=df['Target'])
plt.show()
```

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable
as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other argu
ments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

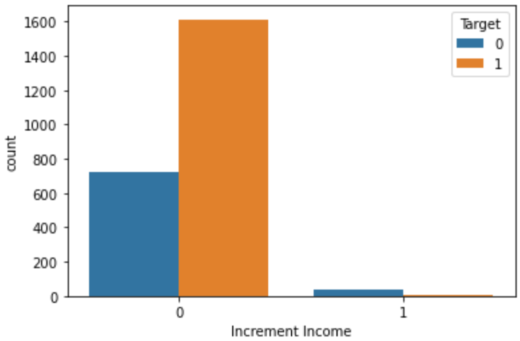


In [460]:

```


sns.countplot(df['Increment Income'],hue=df['Target'])
plt.show()
```

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable
as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other argu
ments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

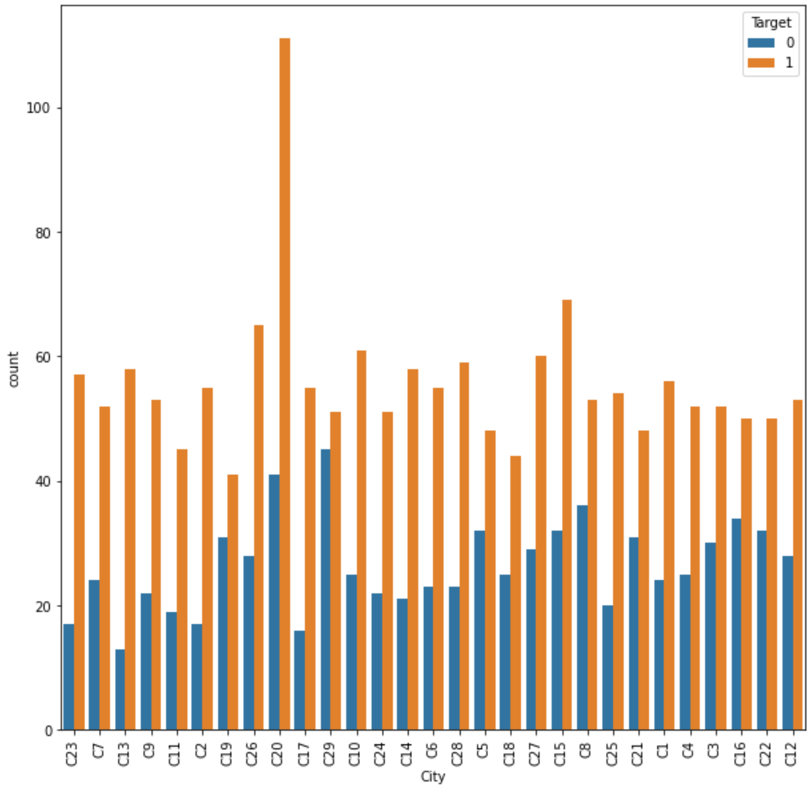


In [461]:

```
plt.figure(figsize=(10,10))
sns.countplot(df['City'],hue=df['Target'])
plt.xticks(rotation=90)

plt.show()
```

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable
as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other argu
ments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



In [462]:

```
df
```

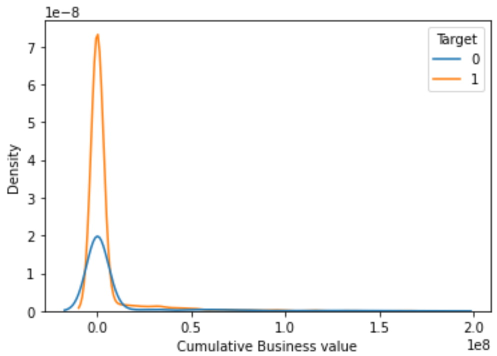
Out[462]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Quarterly Rating	Increment Rating	Target	Ir
0	2019-03-01	1	28.0	0.0	C23	2	57387	2018-12-24	2019-03-11	1	1	2	0	1	
1	2020-12-01	2	31.0	0.0	C7	2	67016	2020-11-06	NaT	2	2	1	0	0	
2	2020-04-01	4	43.0	0.0	C13	2	65603	2019-12-07	2020-04-27	2	2	1	0	1	
3	2019-03-01	5	29.0	0.0	C9	0	46368	2019-01-09	2019-03-07	1	1	1	0	1	
4	2020-12-01	6	31.0	1.0	C11	1	78728	2020-07-31	NaT	3	3	2	1	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
2376	2020-12-01	2784	34.0	0.0	C24	0	82815	2015-10-15	NaT	2	3	4	1	0	
2377	2020-10-01	2785	34.0	1.0	C9	0	12105	2020-08-28	2020-10-28	1	1	1	0	1	
2378	2019-09-01	2786	45.0	0.0	C19	0	35370	2018-07-31	2019-09-22	2	2	1	0	1	
2379	2019-06-01	2787	28.0	1.0	C20	2	69498	2018-07-21	2019-06-20	1	1	1	0	1	
2380	2020-12-01	2788	30.0	0.0	C27	2	70254	2020-06-08	NaT	2	2	2	1	0	

2381 rows × 16 columns

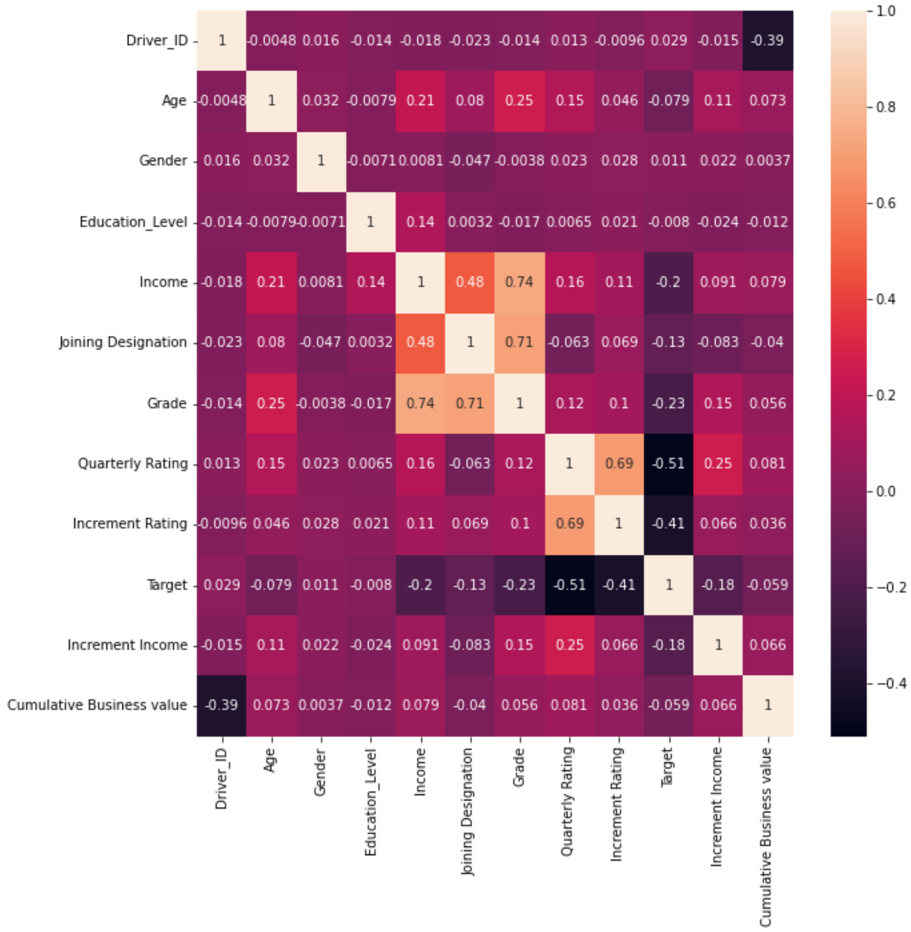
In [463]:

```python
sns.kdeplot(df['Cumulative Business value'],hue=df['Target'])
plt.show()
```



In [464]:

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



Comments:

- City C20 has the highest churn ratio. Most of the drivers are leaving from this city.
- People with no increment in income are more likely to leave in comparison to people to get an increment..
- Drivers with no increment in rating are more likely to leave..
- Riders with Grade 1 or 2 are more likely to leave..
- Riders with joining designation as 1 or 2 are more likely to leave..
- Riders with an average income of around 50,000 are more likely to leave..

In [465]:

```python
df.drop(['MMM-YY'],axis=1,inplace=True)
```

In [466]:

```
df.loc[241]
```

Out[466]:

```
Driver_ID                                   288
Age                                        41.0
Gender                                      1.0
City                                        C17
Education_Level                               0
Income                                    62901
Dateofjoining                 2020-12-18 00:00:00
LastWorkingDate                             NaT
Joining Designation                           2
Grade                                         2
Quarterly Rating                              1
Increment Rating                              0
Target                                        0
Increment Income                              0
Cumulative Business value             3980110.0
Name: 241, dtype: object
```

In [467]:

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

Out[467]:

```
1    1616
0     765
Name: Target, dtype: int64
```

In [468]:

```
df['tenure'] = (df['LastWorkingDate'] - df['Dateofjoining']).dt.days
```

In [469]:

```
bins = [0, 500, 3000]
labels = ['low','medium']
df['tenure'] = pd.cut(x = df['tenure'], bins = bins, labels = labels, include_lowest = True)
```

In [470]:

```
df['tenure'] = df['tenure'].astype('string')
df['tenure'] = df['tenure'].fillna('high')
```

In [471]:

```
df['tenure'] = df['tenure'].replace({'low':0,'medium':1,'high':2})
```

In [472]:

```
df.drop(['Dateofjoining','LastWorkingDate'],axis=1,inplace=True)
```

In [473]:

```
df.drop(['Driver_ID'],axis=1,inplace=True)
```

In [474]:

```
df['tenure']
```

Out[474]:

```
0       0
1       2
2       0
3       0
4       2
       ..
2376    2
2377    0
2378    0
2379    0
2380    2
Name: tenure, Length: 2381, dtype: int64
```

In [475]:

```
columns = df[['City','Income','Cumulative Business value']]
df.drop(['City','Income','Cumulative Business value'],axis=1,inplace=True)
df_columns = df.columns
```

In [476]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2381 entries, 0 to 2380
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Age                 2374 non-null   float64
 1   Gender              2371 non-null   float64
 2   Education_Level     2381 non-null   int64
 3   Joining Designation 2381 non-null   int64
 4   Grade               2381 non-null   int64
 5   Quarterly Rating    2381 non-null   int64
 6   Increment Rating    2381 non-null   int64
 7   Target              2381 non-null   int64
 8   Increment Income    2381 non-null   int64
 9   tenure              2381 non-null   int64
dtypes: float64(2), int64(8)
memory usage: 269.2 KB
```

Imputing age and gender Column

In [477]:

```
imputer = KNNImputer(n_neighbors=3)
df = imputer.fit_transform(df)
```

In [478]:

```
df = pd.DataFrame(df,columns=df_columns)
```

In [479]:

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

Out[479]:

```
Age                    0
Gender                 0
Education_Level        0
Joining Designation    0
Grade                  0
Quarterly Rating       0
Increment Rating       0
Target                 0
Increment Income       0
tenure                 0
dtype: int64
```

In [480]:

```
df = pd.merge(df,columns,left_index=True,right_index=True)
```

In [481]:

```
df.drop('tenure',axis=1,inplace=True)
```

In [482]:

```
y = df['Target']
X = df.drop('Target',axis=1)
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=42,stratify=y)
```

In [483]:

```
enc = TargetEncoder(cols=['City'], min_samples_leaf=20, smoothing=10).fit(X_train, y_train)
X_train = enc.transform(X_train)
X_test = enc.transform(X_test)
```

In [484]:

```
X_train
```

Out[484]:

	Age	Gender	Education_Level	Joining Designation	Grade	Quarterly Rating	Increment Rating	Increment Income	City	Income	Cumulative Business value
2242	34.0	1.0	0.0	3.0	3.0	1.0	0.0	0.0	0.661365	104058	0.0
1474	42.0	0.0	0.0	1.0	1.0	1.0	0.0	0.0	0.687392	51579	0.0
2132	27.0	0.0	1.0	2.0	2.0	1.0	0.0	0.0	0.800247	75458	0.0
1873	35.0	0.0	1.0	1.0	3.0	3.0	1.0	0.0	0.641139	69756	0.0
462	36.0	0.0	0.0	2.0	3.0	1.0	0.0	0.0	0.684972	109296	0.0
...	...	...	...	...	...	...	...	...	...	...	...
1883	39.0	0.0	1.0	1.0	4.0	4.0	1.0	0.0	0.708778	112513	0.0
1355	27.0	0.0	0.0	2.0	2.0	1.0	0.0	0.0	0.704070	49886	0.0
2229	39.0	0.0	1.0	1.0	1.0	2.0	0.0	0.0	0.487972	44154	0.0
2234	28.0	0.0	1.0	1.0	1.0	1.0	0.0	0.0	0.616747	53320	0.0
855	30.0	1.0	0.0	1.0	1.0	1.0	0.0	0.0	0.586336	58540	0.0

1904 rows × 11 columns

Bagging - Random Forest

In [485]:

```
parameters = {
    'n_estimators':[200,300,500,1000],
    'max_depth':[6,8,10],
    'class_weight':['balanced'],
    #'min_samples_split':[6,8,10],
    'random_state':[42],
    'oob_score':[True],

}
rf_model = RandomForestClassifier()
clf_rf = GridSearchCV(rf_model, parameters,scoring='f1',n_jobs=-1)
```

In [486]:

```
clf_rf.fit(X_train,y_train)
```

Out[486]:

```
▸        GridSearchCV
▸ estimator: RandomForestClassifier
     ▸ RandomForestClassifier
```

In [487]:

```
best_rf_model = clf_rf.best_estimator_
```

In [488]:

```
print("---------- Confusion Matrix for Train Data ----------")
rf_train_predictions = best_rf_model.predict(X_train)
print(classification_report(y_train, rf_train_predictions))
```

```
---------- Confusion Matrix for Train Data ----------
              precision    recall  f1-score   support

         0.0       0.90      0.83      0.86       612
         1.0       0.92      0.96      0.94      1292

    accuracy                           0.91      1904
   macro avg       0.91      0.89      0.90      1904
weighted avg       0.91      0.91      0.91      1904
```

In [489]:

```
print("---------- Confusion Matrix for Test Data ----------")
rf_test_predictions = best_rf_model.predict(X_test)

# print classification report
print(classification_report(y_test, rf_test_predictions))
```

```
---------- Confusion Matrix for Test Data ----------
              precision    recall  f1-score   support

         0.0       0.69      0.64      0.66       153
         1.0       0.84      0.86      0.85       324

    accuracy                           0.79       477
   macro avg       0.76      0.75      0.76       477
weighted avg       0.79      0.79      0.79       477
```

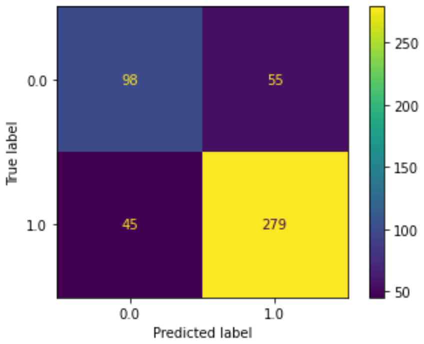
In [490]:

```
plot_confusion_matrix(best_rf_model,X_test,y_test)
```

```
/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function plot_confusio
n_matrix is deprecated; Function `plot_confusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one
of the class methods: ConfusionMatrixDisplay.from_predictions or ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
```

Out[490]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fe3c3bf0b50>
```



In [491]:

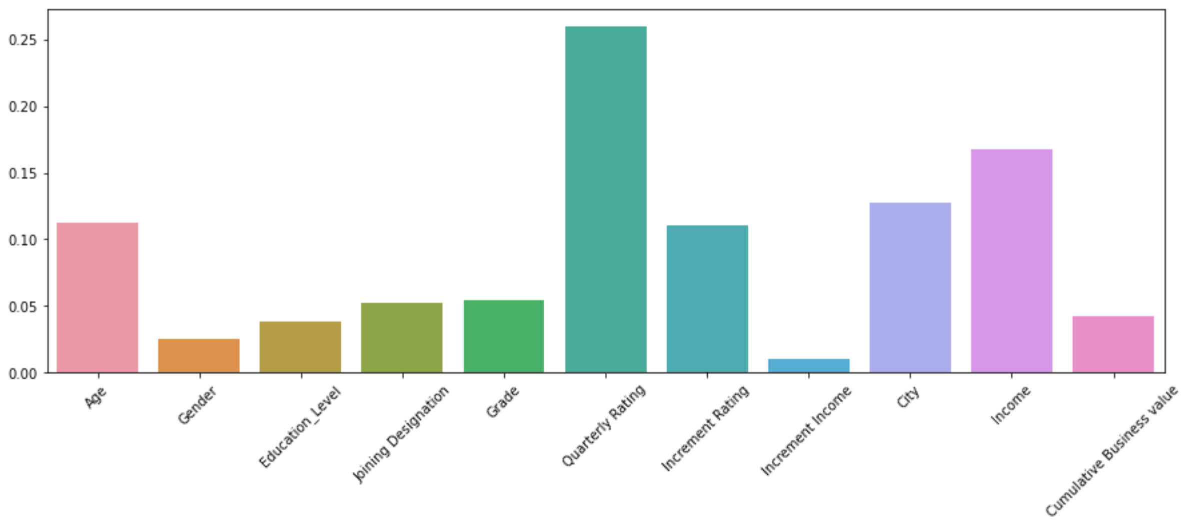
```
best_rf_model.feature_importances_
```

Out[491]:

```
array([0.11267364, 0.02502687, 0.03835819, 0.05214781, 0.05432243,
       0.25935888, 0.1103978 , 0.01067393, 0.12766773, 0.16712873,
       0.042244  ])
```

In [492]:

```
plt.figure(figsize=(15,5))
sns.barplot(x=X_train.columns, y=best_rf_model.feature_importances_)
plt.xticks(rotation=45)
plt.show()
```



In [493]:

```
print("f1-score for train data {}".format(f1_score(y_train,rf_train_predictions)))
print("f1-score for test data {}".format(f1_score(y_test,rf_test_predictions)))
```

```
f1-score for train data 0.9381404174573055
f1-score for test data 0.8480243161094225
```

In [494]:

```
print("Best Params for bagging",clf_rf.best_params_)
```

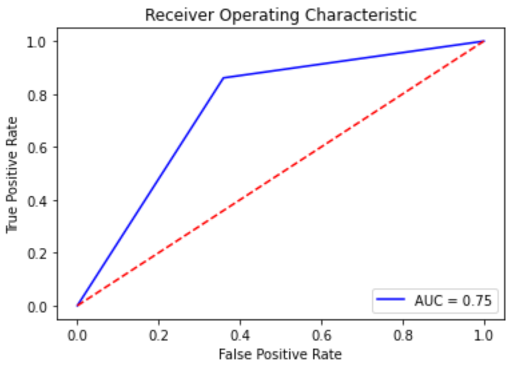
```
Best Params for bagging {'class_weight': 'balanced', 'max_depth': 10, 'n_estimators': 200, 'oob_score': True, 'ra
ndom_state': 42}
```

In [495]:

```
def buildROC(target_test,test_preds):
    fpr, tpr, threshold = roc_curve(target_test, test_preds)
    roc_auc = auc(fpr, tpr)
    plt.title('Receiver Operating Characteristic')
    plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
    plt.legend(loc = 'lower right')
    plt.plot([0, 1], [0, 1],'r--')
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
```

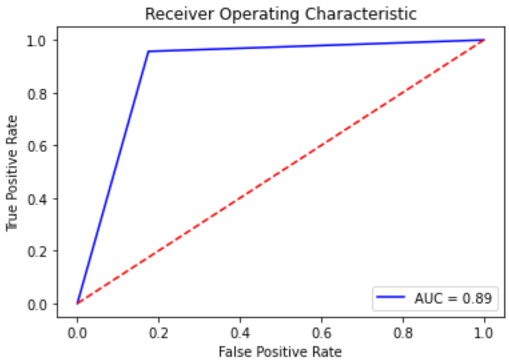
In [496]:

```
buildROC(y_test,rf_test_predictions)
```



In [497]:

```
buildROC(y_train,rf_train_predictions)
```



Comment On ROC and AUC: Since we are more focused on knowing who'll be leaving the company, we need a high TPR and thus a high threshold value will work for us.

Boosting - XGBoost

In [498]:

```
xgb_model = xgb.XGBClassifier()
parameters = {
              'objective':['binary:logistic'],
              'learning_rate': [0.05], #so called `eta` value
              'max_depth': [4,6,8],
              'subsample': [0.8,0.6,0.4],
              'colsample_bytree': [0.3,0.4,0.5,0.8],
              'scale_pos_weight':[1,10,20,50,100],
              'n_estimators': [1000,200,300], #number of trees, change it to 1000 for better results
              'seed':[42]
            }

clf_xg = GridSearchCV(xgb_model, parameters, n_jobs=-1,scoring='f1')
clf_xg.fit(X_train,y_train)
```

Out[498]:

```
▸ GridSearchCV
▸ estimator: XGBClassifier
    ▸ XGBClassifier
```

In [499]:

```
best_xg_model = clf_xg.best_estimator_
```

In [500]:

```
clf_xg.best_params_
```

Out[500]:

```
{'colsample_bytree': 0.3,
 'learning_rate': 0.05,
 'max_depth': 4,
 'n_estimators': 200,
 'objective': 'binary:logistic',
 'scale_pos_weight': 1,
 'seed': 42,
 'subsample': 0.4}
```

In [501]:

```
xg_train_predictions = best_xg_model.predict(X_train)

print(classification_report(y_train, xg_train_predictions))
```

```
              precision    recall  f1-score   support

         0.0       0.82      0.56      0.67       612
         1.0       0.82      0.94      0.88      1292

    accuracy                           0.82      1904
   macro avg       0.82      0.75      0.77      1904
weighted avg       0.82      0.82      0.81      1904
```

In [502]:

```
xg_test_predictions = best_xg_model.predict(X_test)

# print classification report
print(classification_report(y_test, xg_test_predictions))
```

```
              precision    recall  f1-score   support

         0.0       0.81      0.58      0.67       153
         1.0       0.82      0.94      0.88       324

    accuracy                           0.82       477
   macro avg       0.82      0.76      0.77       477
weighted avg       0.82      0.82      0.81       477
```

In [503]:

```
print("f1-score for train data {}".format(f1_score(y_train,xg_train_predictions)))
print("f1-score for test data {}".format(f1_score(y_test,xg_test_predictions)))
```

```
f1-score for train data 0.8765743073047858
f1-score for test data 0.8757225433526011
```

In [504]:

```
y_test.value_counts()
```

Out[504]:

```
1.0    324
0.0    153
Name: Target, dtype: int64
```

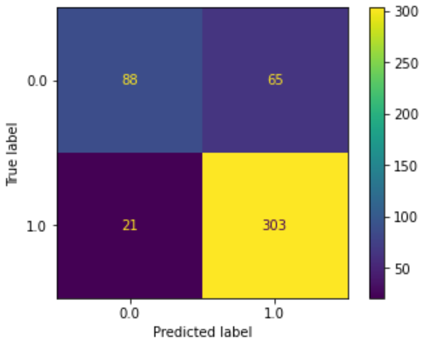
In [505]:

```
plot_confusion_matrix(best_xg_model,X_test,y_test)
```

```
/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function plot_confusio
n_matrix is deprecated; Function `plot_confusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one
of the class methods: ConfusionMatrixDisplay.from_predictions or ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
```

Out[505]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fe3c3ebea30>
```



In [506]:

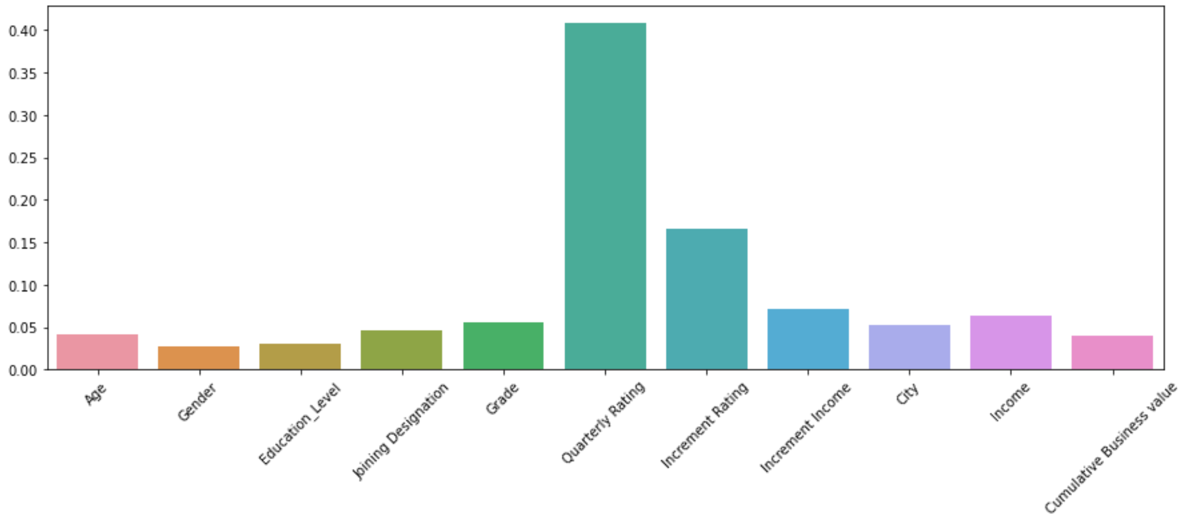
```
y_train.value_counts()
```

Out[506]:

```
1.0    1292
0.0     612
Name: Target, dtype: int64
```

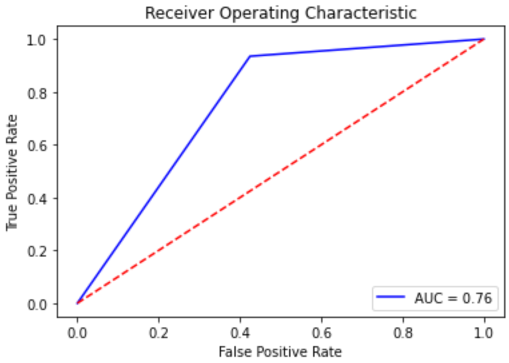
In [507]:

```
plt.figure(figsize=(15,5))
sns.barplot(x=X_train.columns, y=best_xg_model.feature_importances_)
plt.xticks(rotation=45)
plt.show()
```



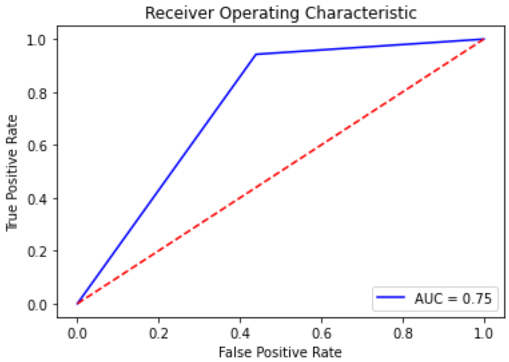
In [508]:

```
buildROC(y_test,xg_test_predictions)
```



In [509]:

```
buildROC(y_train,xg_train_predictions)
```



Comment On ROC and AUC: Since we are more focused on knowing who'll be leaving the company, we need a high TPR and thus a high threshold value will work for us.

Business Insights

- Qaurterly Rating matters a lot because if driver has a drop in rating, it will impact his income and thus will lead to attrition. Companies can work on developing a different metric to rate their performance and also help the drivers having a drop in rating.
- Company can bring in more driver friendly policies like life insurance, medical cover, incentives on increase in quarterly rating etc.
- The company can use the above model to detect if their is an employee having a high chance of leaving and then try to retain that employee.

In [ ]:

```
```