Project_9_Ola

September 29, 2022

0.1 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.

As the companies get bigger, the high churn could become a bigger problem. To find new drivers, Ola is casting a wide net, including people who don't have cars for jobs. But this acquisition is really costly. Losing drivers frequently impacts the morale of the organization and acquiring new drivers is more expensive than retaining existing ones.

You are working as a data scientist with the Analytics Department of Ola, focused on driver team attrition. You are provided with the monthly information for a segment of drivers for 2019 and 2020 and tasked to predict whether a driver will be leaving the company or not based on their attributes like

- Demographics (city, age, gender etc.)
- Tenure information (joining date, Last Date)
- Historical data regarding the performance of the driver (Quarterly rating, Monthly business acquired, grade, Income)

0.1.1 Column Profiling:

- MMMM-YY : Reporting Date (Monthly)
- Driver_ID : Unique id for drivers
- Age : Age of the driver
- Gender : Gender of the driver – Male : 0, Female: 1
- City : City Code of the driver
- Education_Level : Education level – 0 for 10+ ,1 for 12+ ,2 for graduate
- Income : Monthly average Income of the driver
- Date Of Joining : Joining date for the driver
- LastWorkingDate : Last date of working for the driver
- Joining Designation : Designation of the driver at the time of joining
- Grade : Grade of the driver at the time of reporting
- Total Business Value : The total business value acquired by the driver in a month (negative business indicates cancellation/refund or car EMI adjustments)
- Quarterly Rating : Quarterly rating of the driver: 1,2,3,4,5 (higher is better)

[1]:
```
#Importing the required libraries
import numpy as np
```

```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import ConfusionMatrixDisplay
from xgboost import XGBClassifier
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import PowerTransformer
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.pipeline import Pipeline
from sklearn.metrics import roc_auc_score,roc_curve
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```python
df=pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/
 ↪002/492/original/ola_driver_scaler.csv')
df.head()
```

[2]:
```
   Unnamed: 0    MMM-YY  Driver_ID   Age  Gender City  Education_Level  \
0           0  01/01/19          1  28.0     0.0  C23                2
1           1  02/01/19          1  28.0     0.0  C23                2
2           2  03/01/19          1  28.0     0.0  C23                2
3           3  11/01/20          2  31.0     0.0   C7                2
4           4  12/01/20          2  31.0     0.0   C7                2

   Income Dateofjoining LastWorkingDate  Joining Designation  Grade  \
0   57387      24/12/18             NaN                    1      1
1   57387      24/12/18             NaN                    1      1
2   57387      24/12/18        03/11/19                    1      1
3   67016      11/06/20             NaN                    2      2
4   67016      11/06/20             NaN                    2      2

   Total Business Value  Quarterly Rating
0               2381060                 2
1               -665480                 2
2                     0                 2
3                     0                 1
4                     0                 1
```

[3]:
```python
#Dropping the first column and checking the first 15 rows.
df=df.iloc[:,1:]
```

```python
df.head(15)
```

[3]:

```
       MMM-YY  Driver_ID   Age  Gender City  Education_Level  Income  \
0    01/01/19          1  28.0     0.0  C23                2   57387
1    02/01/19          1  28.0     0.0  C23                2   57387
2    03/01/19          1  28.0     0.0  C23                2   57387
3    11/01/20          2  31.0     0.0   C7                2   67016
4    12/01/20          2  31.0     0.0   C7                2   67016
5    12/01/19          4  43.0     0.0  C13                2   65603
6    01/01/20          4  43.0     0.0  C13                2   65603
7    02/01/20          4  43.0     0.0  C13                2   65603
8    03/01/20          4  43.0     0.0  C13                2   65603
9    04/01/20          4  43.0     0.0  C13                2   65603
10   01/01/19          5  29.0     0.0   C9                0   46368
11   02/01/19          5  29.0     0.0   C9                0   46368
12   03/01/19          5  29.0     0.0   C9                0   46368
13   08/01/20          6  31.0     1.0  C11                1   78728
14   09/01/20          6  31.0     1.0  C11                1   78728

   Dateofjoining LastWorkingDate  Joining Designation  Grade  \
0       24/12/18             NaN                    1      1
1       24/12/18             NaN                    1      1
2       24/12/18        03/11/19                    1      1
3       11/06/20             NaN                    2      2
4       11/06/20             NaN                    2      2
5       12/07/19             NaN                    2      2
6       12/07/19             NaN                    2      2
7       12/07/19             NaN                    2      2
8       12/07/19             NaN                    2      2
9       12/07/19        27/04/20                    2      2
10      01/09/19             NaN                    1      1
11      01/09/19             NaN                    1      1
12      01/09/19        03/07/19                    1      1
13      31/07/20             NaN                    3      3
14      31/07/20             NaN                    3      3

    Total Business Value  Quarterly Rating
0                2381060                 2
1                -665480                 2
2                      0                 2
3                      0                 1
4                      0                 1
5                      0                 1
6                      0                 1
7                      0                 1
8                 350000                 1
9                      0                 1
```

```
10                    0                  1
11               120360                  1
12                    0                  1
13                    0                  1
14                    0                  1
```

[4]:
```
#Checking the shape of the given dataset
df.shape
```

[4]:
```
(19104, 13)
```

[5]:
```
#Checking for percentage of missing values
np.round(df.isna().mean()*100,2)
```

[5]:
```
MMM-YY                   0.00
Driver_ID                0.00
Age                      0.32
Gender                   0.27
City                     0.00
Education_Level          0.00
Income                   0.00
Dateofjoining            0.00
LastWorkingDate         91.54
Joining Designation      0.00
Grade                    0.00
Total Business Value     0.00
Quarterly Rating         0.00
dtype: float64
```

[6]:
```
#Checking the data_type of each of the columns
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
```

[7]:
```
#Checking for duplicate observations.
df.duplicated().sum()
```

[7]:
```
0
```

0.1.2 Preliminary Observations

- There are a few missing values in columns - "Age" and "Gender". We will take care of missing values later.
- There are a lot of missing values in column - "LastWorkingDate". From this column, we can get our target variable. The drivers who have churned have a LastWorkingDate.
- "MMM-YY","Dateofjoining" and "LastWorkingDate" columns are in object data type. We might need to change to date_type format.
- Gender is a categorical variables as given in the problem statement, but is represented in float. We can convert to integer later.
- There are no duplicate observations.
- The report is generated on the 1st of every month.

[ ]:
```

```

[8]:
```
#Creating Another DataFrame to store Aggregate Level Information for each driver
dataset=pd.DataFrame(data=df['Driver_ID'].unique(),columns=['Driver_ID'])
print(dataset.shape) #There are total 2381 drivers.
dataset.head()
```

```
(2381, 1)
```

[8]:

	Driver_ID
0	1
1	2
2	4
3	5
4	6

[9]:
```
#Getting the list of drivers who have churned and who have not_churned
churned_drivers=set(df.loc[~df['LastWorkingDate'].isna(),'Driver_ID'])
not_churned_drivers=set(df['Driver_ID']).difference(churned_drivers)
```

[ ]:
```

```

0.1.3 Getting the Target Column - "Churn"

[10]:
```
def get_churn(x):
    if x in churned_drivers:
        return 1
    else:
        return 0
dataset['Churn']=dataset['Driver_ID'].apply(get_churn)
dataset.head()
```

[10]:
```
   Driver_ID  Churn
0          1      1
1          2      0
2          4      1
3          5      1
4          6      0
```

[11]:
```
print("Number Of Churned Drivers",(dataset['Churn']==1).sum())
print("Number Of Not_Churned Drivers",(dataset['Churn']==0).sum())
```

```
Number Of Churned Drivers 1616
Number Of Not_Churned Drivers 765
```

[12]:
```
df.loc[~df['LastWorkingDate'].isna(),'Churn']=1
df.loc[df['LastWorkingDate'].isna(),'Churn']=0
df.head()
```

[12]:
```
     MMM-YY  Driver_ID   Age  Gender City  Education_Level  Income  \
0  01/01/19          1  28.0     0.0  C23                2   57387
1  02/01/19          1  28.0     0.0  C23                2   57387
2  03/01/19          1  28.0     0.0  C23                2   57387
3  11/01/20          2  31.0     0.0   C7                2   67016
4  12/01/20          2  31.0     0.0   C7                2   67016

  Dateofjoining LastWorkingDate  Joining Designation  Grade  \
0      24/12/18             NaN                    1      1
1      24/12/18             NaN                    1      1
2      24/12/18        03/11/19                    1      1
3      11/06/20             NaN                    2      2
4      11/06/20             NaN                    2      2

   Total Business Value  Quarterly Rating  Churn
0               2381060                 2    0.0
1               -665480                 2    0.0
2                     0                 2    1.0
3                     0                 1    0.0
4                     0                 1    0.0
```

[ ]:

```

```

0.1.4 Getting The Duration For Which Each Driver Has Been Driving Vehicles

- For drivers who have churned, we can get the difference in no of days between DateOfJoining and LastWorkingDate
- For drivers who have not churned, we can get the difference in no of days between DateOfJoining and the Last_Monthly_Report_Date
- My expectation is that the last month report date is same for all not_churned drivers. Need to check.

[13]:

```
#Converting "MMM-YY","Dateofjoining" and "LastWorkingDate" columns to date_time␣
↪format
df[["MMM-YY","Dateofjoining","LastWorkingDate"]]=df[["MMM-YY","Dateofjoining","LastWorkingDate
↪astype('datetime64')
```

[14]:

```
#Finding out the last_Working_date for churned_drivers.
temp=df.loc[df['Churn']==1,['Driver_ID','LastWorkingDate']]

#Merging with the new Dataset.
dataset=pd.merge(left=dataset,right=temp,on='Driver_ID',how='left')
dataset.head()
```

[14]:

	Driver_ID	Churn	LastWorkingDate
0	1	1	2019-03-11
1	2	0	NaT
2	4	1	2020-04-27
3	5	1	2019-03-07
4	6	0	NaT

[15]:

```
#Finding out the latest date for monthly report for not_churned_drivers
last_report_dates=df[df['Driver_ID'].isin(not_churned_drivers)].
↪groupby(by='Driver_ID').max()['MMM-YY'].reset_index()

#Merging with the new Dataset.
dataset=pd.merge(left=dataset,right=last_report_dates,on='Driver_ID',how='left')
dataset.head()
```

[15]:

	Driver_ID	Churn	LastWorkingDate	MMM-YY
0	1	1	2019-03-11	NaT
1	2	0	NaT	2020-12-01
2	4	1	2020-04-27	NaT
3	5	1	2019-03-07	NaT
4	6	0	NaT	2020-12-01

[16]:

```
# Lets check if the last date for monthly report for all not_churned_drivers is␣
↪the same.
dataset['MMM-YY'].value_counts()
```

```
# This is strange. The last date should be the same for all drivers who have␣
↪not churned. Lets inspect further.
# There are few drivers for whom the last report date is not "2020-12-01",␣
↪which is the most occuring value.
```

[16]:
```
2020-12-01    741
2020-02-01      6
2020-05-01      6
2019-12-01      4
2020-01-01      3
2020-03-01      2
2020-06-01      2
2019-09-01      1
Name: MMM-YY, dtype: int64
```

[17]:
```
# Lets find out the report for the drivers whose last month report date is␣
↪"2020-02-01". Expecting 6 drivers.
temp_driver_ids=last_report_dates.
↪loc[last_report_dates['MMM-YY']=='2020-02-01','Driver_ID'].tolist()
print(len(temp_driver_ids))

df[df['Driver_ID'].isin(temp_driver_ids)]
# From the below table it is confirmed that the 6 drivers haven't churned␣
↪yet,but still don't have records till "2020-12-01"
# We can consider dropping such driver_ids.
```

6

[17]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	\
433	2020-01-01	66	27.0	1.0	C4	2	104286	
434	2020-02-01	66	27.0	1.0	C4	2	104286	
4209	2019-11-01	612	31.0	0.0	C17	0	29685	
4210	2019-12-01	612	31.0	0.0	C17	0	29685	
4211	2020-01-01	612	31.0	0.0	C17	0	29685	
4212	2020-02-01	612	31.0	0.0	C17	0	29685	
5054	2020-01-01	755	36.0	0.0	C8	1	25894	
5055	2020-02-01	755	36.0	0.0	C8	1	25894	
8226	2019-09-01	1224	33.0	0.0	C28	2	78442	
8227	2019-10-01	1224	33.0	0.0	C28	2	78442	
8228	2019-11-01	1224	33.0	0.0	C28	2	78442	
8229	2019-12-01	1224	33.0	0.0	C28	2	78442	
8230	2020-01-01	1224	33.0	0.0	C28	2	78442	
8231	2020-02-01	1224	33.0	0.0	C28	2	78442	
12788	2019-01-01	1893	38.0	0.0	C26	1	132819	
12789	2019-02-01	1893	38.0	0.0	C26	1	132819	
12790	2019-03-01	1893	38.0	0.0	C26	1	132819	

```
12791 2019-04-01       1893  38.0     0.0  C26              1  132819
12792 2019-05-01       1893  38.0     0.0  C26              1  132819
12793 2019-06-01       1893  38.0     0.0  C26              1  132819
12794 2019-07-01       1893  38.0     0.0  C26              1  132819
12795 2019-08-01       1893  38.0     0.0  C26              1  132819
12796 2019-09-01       1893  38.0     0.0  C26              1  132819
12797 2019-10-01       1893  38.0     0.0  C26              1  132819
12798 2019-11-01       1893  38.0     0.0  C26              1  132819
12799 2019-12-01       1893  38.0     0.0  C26              1  132819
12800 2020-01-01       1893  39.0     0.0  C26              1  132819
12801 2020-02-01       1893  39.0     0.0  C26              1  132819
12802 2020-02-01       1894  33.0     1.0   C7              2   51264

      Dateofjoining LastWorkingDate  Joining Designation  Grade  \
433      2020-01-21             NaT                    3      3
434      2020-01-21             NaT                    3      3
4209     2019-11-03             NaT                    1      1
4210     2019-11-03             NaT                    1      1
4211     2019-11-03             NaT                    1      1
4212     2019-11-03             NaT                    1      1
5054     2019-12-30             NaT                    3      3
5055     2019-12-30             NaT                    3      3
8226     2019-09-03             NaT                    3      3
8227     2019-09-03             NaT                    3      3
8228     2019-09-03             NaT                    3      3
8229     2019-09-03             NaT                    3      3
8230     2019-09-03             NaT                    3      3
8231     2019-09-03             NaT                    3      3
12788    2017-01-20             NaT                    5      5
12789    2017-01-20             NaT                    5      5
12790    2017-01-20             NaT                    5      5
12791    2017-01-20             NaT                    5      5
12792    2017-01-20             NaT                    5      5
12793    2017-01-20             NaT                    5      5
12794    2017-01-20             NaT                    5      5
12795    2017-01-20             NaT                    5      5
12796    2017-01-20             NaT                    5      5
12797    2017-01-20             NaT                    5      5
12798    2017-01-20             NaT                    5      5
12799    2017-01-20             NaT                    5      5
12800    2017-01-20             NaT                    5      5
12801    2017-01-20             NaT                    5      5
12802    2020-02-09             NaT                    3      3

       Total Business Value  Quarterly Rating  Churn
433                       0                 1    0.0
434                       0                 1    0.0
```

4209	0	1	0.0
4210	200000	1	0.0
4211	0	1	0.0
4212	0	1	0.0
5054	0	1	0.0
5055	0	1	0.0
8226	0	1	0.0
8227	0	2	0.0
8228	664800	2	0.0
8229	374910	2	0.0
8230	3318790	3	0.0
8231	0	3	0.0
12788	0	1	0.0
12789	0	1	0.0
12790	0	1	0.0
12791	0	1	0.0
12792	0	1	0.0
12793	0	1	0.0
12794	830060	2	0.0
12795	32730	2	0.0
12796	812880	2	0.0
12797	0	1	0.0
12798	0	1	0.0
12799	0	1	0.0
12800	0	1	0.0
12801	0	1	0.0
12802	0	1	0.0

[18]:
```
driver_ids_to_be_dropped=list(last_report_dates.loc[last_report_dates['MMM-YY'].
 ↪isin(last_report_dates['MMM-YY'].value_counts()[1:].index),'Driver_ID'])

#Total Drivers to be dropped
len(driver_ids_to_be_dropped)

print('As % of total drivers -',(100*len(driver_ids_to_be_dropped))/
 ↪len(dataset['Driver_ID']))
# There are about 1% not_churned drivers for whom we do not have complete␣
 ↪monthly date. We can remove these drivers.
```

```
As % of total drivers - 1.0079798404031919
```

[19]:
```
#Dropping observations of the 24 strange drivers from both df and dataset.
dataset=dataset[~dataset['Driver_ID'].isin(driver_ids_to_be_dropped)].
 ↪reset_index(drop=True)
df=df[~df['Driver_ID'].isin(driver_ids_to_be_dropped)].reset_index(drop=True)
```

[ ]:
```
```

[20]:
```python
#Combining columns "LastWorkingDate" and "MMM-YY" into 1 column.
def function(dataset):
    arr=[]
    Churn=dataset['Churn']
    LastWorkingDate=dataset['LastWorkingDate']
    MMM_YY=dataset['MMM-YY']
    for i,value in enumerate(Churn):
        if value==1:
            arr.append(LastWorkingDate[i])
        else:
            arr.append(MMM_YY[i])
    return arr
dataset['Last_Date']=function(dataset)
dataset.head(8)
```

[20]:

	Driver_ID	Churn	LastWorkingDate	MMM-YY	Last_Date
0	1	1	2019-03-11	NaT	2019-03-11
1	2	0	NaT	2020-12-01	2020-12-01
2	4	1	2020-04-27	NaT	2020-04-27
3	5	1	2019-03-07	NaT	2019-03-07
4	6	0	NaT	2020-12-01	2020-12-01
5	8	1	2020-11-15	NaT	2020-11-15
6	11	0	NaT	2020-12-01	2020-12-01
7	12	1	2019-12-21	NaT	2019-12-21

[ ]:

[21]:
```python
#Getting "DateOfJoining" column for every driver
temp=df.loc[~df[['Driver_ID','Dateofjoining']].
 ↪duplicated(),['Driver_ID','Dateofjoining']]
temp.head()

#Merging with the new Dataset.
dataset=pd.merge(left=dataset,right=temp,on='Driver_ID')
dataset.head()
```

[21]:

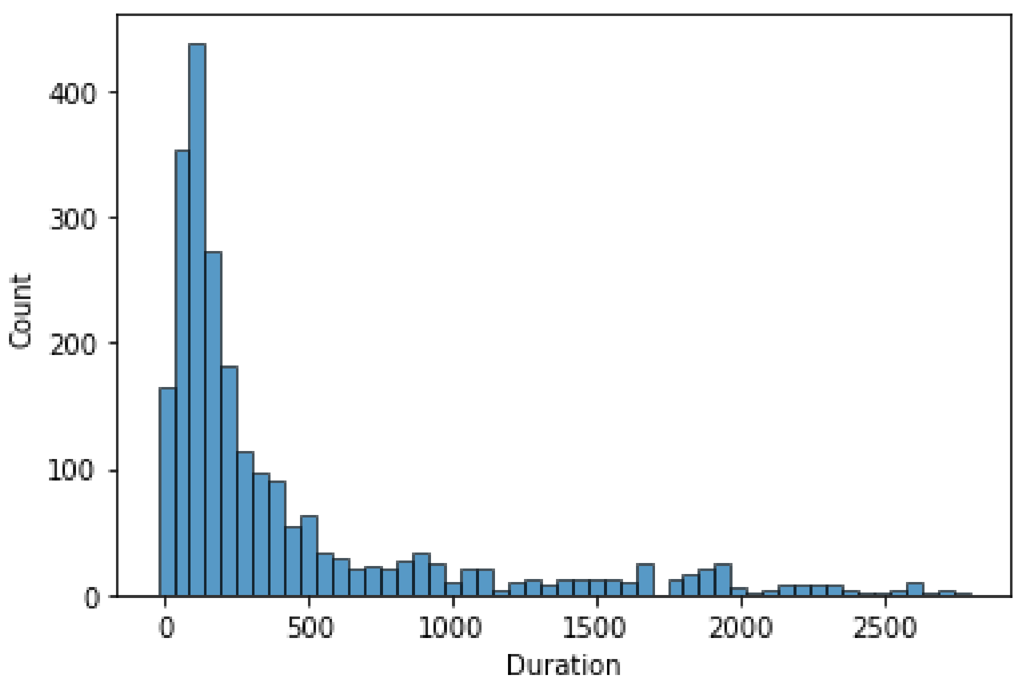
	Driver_ID	Churn	LastWorkingDate	MMM-YY	Last_Date	Dateofjoining
0	1	1	2019-03-11	NaT	2019-03-11	2018-12-24
1	2	0	NaT	2020-12-01	2020-12-01	2020-11-06
2	4	1	2020-04-27	NaT	2020-04-27	2019-12-07
3	5	1	2019-03-07	NaT	2019-03-07	2019-01-09
4	6	0	NaT	2020-12-01	2020-12-01	2020-07-31

[22]:
```python
#Calculating the total duration of driving for each driver in days by␣
 ↪subtracting "Dateofjoining" from "Last_Date"
dataset['Duration']=(dataset['Last_Date']-dataset['Dateofjoining']).dt.days
dataset.head()
```

[22]:
```
   Driver_ID  Churn LastWorkingDate     MMM-YY  Last_Date Dateofjoining  \
0          1      1      2019-03-11        NaT 2019-03-11    2018-12-24
1          2      0             NaT 2020-12-01 2020-12-01    2020-11-06
2          4      1      2020-04-27        NaT 2020-04-27    2019-12-07
3          5      1      2019-03-07        NaT 2019-03-07    2019-01-09
4          6      0             NaT 2020-12-01 2020-12-01    2020-07-31

   Duration
0        77
1        25
2       142
3        57
4       123
```

[23]:
```python
# Lets check if the "Duration" Column has correct data.
print(dataset[['Duration']].describe().T)
sns.histplot(dataset['Duration'])
plt.show()

# There are some very high values for "Duration" which can be dealt with later.
# But "Duration" feature also has negative values. But time can never be␣
↪negative. Lets inspect further.
```

```
           count        mean         std   min   25%    50%    75%     max
Duration  2357.0  425.196012  564.592189 -27.0  92.0  182.0  467.0  2801.0
```



[24]:
```
#Checking for observations which have negative values.
dataset[dataset['Duration']<0]
# The below records are of drivers who have not churned yet,but have joined OLA␣
↪in Dec_2020, but the last_monthly_report date is "2020-12-01"
# This is is strange,because the report would get generated on 1st of every␣
↪month,which is before their joining date.
# We can therefore drop these drivers because of this incorrect data
```

[24]:
```
      Driver_ID  Churn LastWorkingDate     MMM-YY  Last_Date Dateofjoining  \
6            11      0             NaT 2020-12-01 2020-12-01    2020-12-07
124         148      0             NaT 2020-12-01 2020-12-01    2020-12-11
175         205      0             NaT 2020-12-01 2020-12-01    2020-12-20
228         274      0             NaT 2020-12-01 2020-12-01    2020-12-20
240         288      0             NaT 2020-12-01 2020-12-01    2020-12-18
249         297      0             NaT 2020-12-01 2020-12-01    2020-12-19
257         309      0             NaT 2020-12-01 2020-12-01    2020-12-11
258         310      0             NaT 2020-12-01 2020-12-01    2020-12-11
319         378      0             NaT 2020-12-01 2020-12-01    2020-12-13
333         398      0             NaT 2020-12-01 2020-12-01    2020-12-07
431         508      0             NaT 2020-12-01 2020-12-01    2020-12-14
434         511      0             NaT 2020-12-01 2020-12-01    2020-12-15
461         540      0             NaT 2020-12-01 2020-12-01    2020-12-05
480         561      0             NaT 2020-12-01 2020-12-01    2020-12-21
493         575      0             NaT 2020-12-01 2020-12-01    2020-12-21
514         599      0             NaT 2020-12-01 2020-12-01    2020-12-14
535         622      0             NaT 2020-12-01 2020-12-01    2020-12-25
569         664      0             NaT 2020-12-01 2020-12-01    2020-12-11
607         711      0             NaT 2020-12-01 2020-12-01    2020-12-28
611         715      0             NaT 2020-12-01 2020-12-01    2020-12-19
623         733      0             NaT 2020-12-01 2020-12-01    2020-12-14
678         802      0             NaT 2020-12-01 2020-12-01    2020-12-12
685         810      0             NaT 2020-12-01 2020-12-01    2020-12-04
690         816      0             NaT 2020-12-01 2020-12-01    2020-12-12
696         824      0             NaT 2020-12-01 2020-12-01    2020-12-14
697         825      0             NaT 2020-12-01 2020-12-01    2020-12-11
705         834      0             NaT 2020-12-01 2020-12-01    2020-12-07
770         913      0             NaT 2020-12-01 2020-12-01    2020-12-15
868        1029      0             NaT 2020-12-01 2020-12-01    2020-12-18
975        1157      0             NaT 2020-12-01 2020-12-01    2020-12-07
980        1162      0             NaT 2020-12-01 2020-12-01    2020-12-14
1005       1194      0             NaT 2020-12-01 2020-12-01    2020-12-13
1006       1195      0             NaT 2020-12-01 2020-12-01    2020-12-18
1021       1210      0             NaT 2020-12-01 2020-12-01    2020-12-19
1073       1273      0             NaT 2020-12-01 2020-12-01    2020-12-07
1143       1358      0             NaT 2020-12-01 2020-12-01    2020-12-05
1281       1521      0             NaT 2020-12-01 2020-12-01    2020-12-07
1317       1568      0             NaT 2020-12-01 2020-12-01    2020-12-11
```

1363	1619	0	NaT	2020-12-01	2020-12-01	2020-12-08
1374	1632	0	NaT	2020-12-01	2020-12-01	2020-12-06
1389	1650	0	NaT	2020-12-01	2020-12-01	2020-12-11
1437	1708	0	NaT	2020-12-01	2020-12-01	2020-12-15
1467	1740	0	NaT	2020-12-01	2020-12-01	2020-12-05
1522	1812	0	NaT	2020-12-01	2020-12-01	2020-12-13
1584	1880	0	NaT	2020-12-01	2020-12-01	2020-12-11
1618	1925	0	NaT	2020-12-01	2020-12-01	2020-12-15
1642	1955	0	NaT	2020-12-01	2020-12-01	2020-12-11
1654	1971	0	NaT	2020-12-01	2020-12-01	2020-12-20
1706	2030	0	NaT	2020-12-01	2020-12-01	2020-12-05
1715	2039	0	NaT	2020-12-01	2020-12-01	2020-12-15
1732	2060	0	NaT	2020-12-01	2020-12-01	2020-12-18
1754	2088	0	NaT	2020-12-01	2020-12-01	2020-12-27
1883	2233	0	NaT	2020-12-01	2020-12-01	2020-12-19
1907	2261	0	NaT	2020-12-01	2020-12-01	2020-12-21
1937	2298	0	NaT	2020-12-01	2020-12-01	2020-12-08
1986	2360	0	NaT	2020-12-01	2020-12-01	2020-12-14
2130	2521	0	NaT	2020-12-01	2020-12-01	2020-12-18
2223	2631	0	NaT	2020-12-01	2020-12-01	2020-12-07

	Duration
6	-6
124	-10
175	-19
228	-19
240	-17
249	-18
257	-10
258	-10
319	-12
333	-6
431	-13
434	-14
461	-4
480	-20
493	-20
514	-13
535	-24
569	-10
607	-27
611	-18
623	-13
678	-11
685	-3
690	-11
696	-13

```
697         -10
705          -6
770         -14
868         -17
975          -6
980         -13
1005        -12
1006        -17
1021        -18
1073         -6
1143         -4
1281         -6
1317        -10
1363         -7
1374         -5
1389        -10
1437        -14
1467         -4
1522        -12
1584        -10
1618        -14
1642        -10
1654        -19
1706         -4
1715        -14
1732        -17
1754        -26
1883        -18
1907        -20
1937         -7
1986        -13
2130        -17
2223         -6
```

[25]:

```
# Getting the list of above Drivers.
drivers_to_drop=list(set(dataset.loc[dataset['Duration']<0,'Driver_ID']))

# Lets have a look at few of the records of these drivers.
df[df['Driver_ID'].isin(drivers_to_drop)][:10]
# The same issue can be seen from below records as well. The joining date is␣
↪after the date of report generation.
```

[25]:

```
         MMM-YY  Driver_ID   Age  Gender City  Education_Level  Income  \
21   2020-12-01         11  28.0     1.0  C19                2   42172
994  2020-12-01        148  41.0     0.0  C15                0   45288
1396 2020-12-01        205  39.0     0.0  C12                0   15826
1774 2020-12-01        274  39.0     0.0   C7                1   53224
```

```
1852 2020-12-01        288  41.0     1.0  C17              0   62901
1907 2020-12-01        297  38.0     0.0   C8              2  109473
1974 2020-12-01        309  30.0     1.0   C5              1   77597
1975 2020-12-01        310  27.0     1.0   C3              2   58439
2466 2020-12-01        378  33.0     0.0   C9              2   35057
2584 2020-12-01        398  30.0     0.0   C5              2   63280

     Dateofjoining LastWorkingDate  Joining Designation  Grade  \
21      2020-12-07             NaT                    1      1
994     2020-12-11             NaT                    2      2
1396    2020-12-20             NaT                    1      1
1774    2020-12-20             NaT                    2      2
1852    2020-12-18             NaT                    2      2
1907    2020-12-19             NaT                    3      3
1974    2020-12-11             NaT                    3      3
1975    2020-12-11             NaT                    1      1
2466    2020-12-13             NaT                    3      3
2584    2020-12-07             NaT                    2      2

      Total Business Value  Quarterly Rating  Churn
21                       0                 1    0.0
994                      0                 1    0.0
1396                     0                 1    0.0
1774                     0                 1    0.0
1852                     0                 1    0.0
1907                     0                 1    0.0
1974                     0                 1    0.0
1975                     0                 1    0.0
2466                     0                 1    0.0
2584                     0                 1    0.0
```

[26]:
```python
# Lets drop the above drivers from both our datasets.
dataset=dataset[~dataset['Driver_ID'].isin(drivers_to_drop)]
df=df[~df['Driver_ID'].isin(drivers_to_drop)]
dataset.reset_index(drop=True,inplace=True)
df.reset_index(drop=True,inplace=True)
```

[27]:
```python
# Dropping the columns - 'LastWorkingDate', 'MMM-YY', 'Last_Date'␣
↪and'Dateofjoining'
dataset.
↪drop(columns=['LastWorkingDate','MMM-YY','Last_Date','Dateofjoining'],inplace=True)
```

[28]:
```python
# A look at our updated dataset.
dataset.head(3)
```

[28]:
```
   Driver_ID  Churn  Duration
0          1      1        77
```

```
1            2       0         25
2            4       1        142
```

[ ]:

0.1.5 Inspecting and Aggregating “City” for each Driver in the new Dataset

[29]:
```
#Lets do a quick check if there there are multiple cities assigned to each␣
↪driver
df.groupby(by='Driver_ID').nunique()['City'].value_counts()

#We observe that all drivers have only 1 city mapped against them. Lets create␣
↪a new feature in our aggregated
# dataset and store the city for each driver
```

[29]:
```
1    2299
Name: City, dtype: int64
```

[30]:
```
#Getting the city for each driver
cities=df.loc[~df[['Driver_ID','City']].duplicated(),['Driver_ID','City']]
cities.head()
```

[30]:
```
    Driver_ID City
0           1  C23
3           2   C7
5           4  C13
10          5   C9
13          6  C11
```

[31]:
```
dataset = pd.merge(left=dataset,right=cities,on='Driver_ID')
dataset.head()
#Sucessfully created a new feature which stores the city for each driver.
```

[31]:
```
   Driver_ID  Churn  Duration City
0          1      1        77  C23
1          2      0        25   C7
2          4      1       142  C13
3          5      1        57   C9
4          6      0       123  C11
```

[ ]:

0.1.6 Inspecting and Aggregating "Education_Level" for each Driver in the new Dataset

[32]:
```
#Lets do a quick check if there there are multiple cities assigned to each␣
↪driver
df.groupby(by='Driver_ID').nunique()['Education_Level'].value_counts()

#We observe that all drivers have only 1 Education_Level against them. Lets␣
↪create a new feature in our aggregated
# dataset and store the Education_Level for each driver
```

[32]:
```
1    2299
Name: Education_Level, dtype: int64
```

[33]:
```
# Lets look at the different values of Education_Level
df['Education_Level'].unique()
```

[33]:
```
array([2, 0, 1], dtype=int64)
```

[34]:
```
#Getting the Education_Level for each driver
education_level=df.loc[~df[['Driver_ID','Education_Level']].
↪duplicated(),['Driver_ID','Education_Level']]
education_level.head()
```

[34]:

	Driver_ID	Education_Level
0	1	2
3	2	2
5	4	2
10	5	0
13	6	1

[35]:
```
dataset = pd.merge(left=dataset,right=education_level,on='Driver_ID')
dataset.head()
#Sucessfully created a new feature which stores the city for each driver.
```

[35]:

	Driver_ID	Churn	Duration	City	Education_Level
0	1	1	77	C23	2
1	2	0	25	C7	2
2	4	1	142	C13	2
3	5	1	57	C9	0
4	6	0	123	C11	1

[ ]:
```

```

0.1.7 Inspecting and Aggregating "Income" for each Driver in the new Dataset

[36]:
```python
# Lets have a look at few observation to understand how average income for each␣
↪driver is stored in the dataset.
df.head(15)

#It seems that the average income is repeated for every observation of each␣
↪driver.
```

[36]:
```
       MMM-YY  Driver_ID   Age  Gender City  Education_Level  Income  \
0  2019-01-01          1  28.0     0.0  C23                2   57387
1  2019-02-01          1  28.0     0.0  C23                2   57387
2  2019-03-01          1  28.0     0.0  C23                2   57387
3  2020-11-01          2  31.0     0.0   C7                2   67016
4  2020-12-01          2  31.0     0.0   C7                2   67016
5  2019-12-01          4  43.0     0.0  C13                2   65603
6  2020-01-01          4  43.0     0.0  C13                2   65603
7  2020-02-01          4  43.0     0.0  C13                2   65603
8  2020-03-01          4  43.0     0.0  C13                2   65603
9  2020-04-01          4  43.0     0.0  C13                2   65603
10 2019-01-01          5  29.0     0.0   C9                0   46368
11 2019-02-01          5  29.0     0.0   C9                0   46368
12 2019-03-01          5  29.0     0.0   C9                0   46368
13 2020-08-01          6  31.0     1.0  C11                1   78728
14 2020-09-01          6  31.0     1.0  C11                1   78728

   Dateofjoining LastWorkingDate  Joining Designation  Grade  \
0     2018-12-24             NaT                    1      1
1     2018-12-24             NaT                    1      1
2     2018-12-24      2019-03-11                    1      1
3     2020-11-06             NaT                    2      2
4     2020-11-06             NaT                    2      2
5     2019-12-07             NaT                    2      2
6     2019-12-07             NaT                    2      2
7     2019-12-07             NaT                    2      2
8     2019-12-07             NaT                    2      2
9     2019-12-07      2020-04-27                    2      2
10    2019-01-09             NaT                    1      1
11    2019-01-09             NaT                    1      1
12    2019-01-09      2019-03-07                    1      1
13    2020-07-31             NaT                    3      3
14    2020-07-31             NaT                    3      3

    Total Business Value  Quarterly Rating  Churn
0                2381060                 2    0.0
1                -665480                 2    0.0
2                      0                 2    1.0
```

```
3                    0                 1    0.0
4                    0                 1    0.0
5                    0                 1    0.0
6                    0                 1    0.0
7                    0                 1    0.0
8               350000                 1    0.0
9                    0                 1    1.0
10                   0                 1    0.0
11              120360                 1    0.0
12                   0                 1    1.0
13                   0                 1    0.0
14                   0                 1    0.0
```

[37]:
```
#Lets do a quick check if there there are multiple incomes assigned to each␣
↪driver
df.groupby(by='Driver_ID').nunique()['Income'].value_counts()

#We observe that most drivers have only 1 Income against them.
#However there are few drivers who have 2 different average incomes. Lets␣
↪inspect.
```

[37]:
```
1    2255
2      44
Name: Income, dtype: int64
```

[38]:
```
income_count=(df.groupby(by='Driver_ID').nunique()['Income'])
income_count[income_count==2].index

# These drivers have 2 average incomes in the dataset. Lets look at the␣
↪observations for driver_id 26.
```

[38]:
```
Int64Index([  26,   54,   60,   98,  275,  307,  320,  368,  434,  537,  568,
             580,  582,  638,  716,  789,  888, 1031, 1050, 1161, 1165, 1206,
            1249, 1274, 1316, 1327, 1770, 1783, 1817, 1840, 1852, 1877, 1918,
            2008, 2070, 2087, 2198, 2272, 2390, 2407, 2543, 2567, 2625, 2690],
           dtype='int64', name='Driver_ID')
```

[39]:
```
df[df['Driver_ID']==26]

# We can confirm from the below observations that certain drivers have 2␣
↪different incomes.
```

[39]:
```
        MMM-YY  Driver_ID   Age  Gender City  Education_Level  Income  \
137 2019-01-01         26  41.0     0.0  C14                2  121529
138 2019-02-01         26  41.0     0.0  C14                2  121529
139 2019-03-01         26  41.0     0.0  C14                2  121529
140 2019-04-01         26  41.0     0.0  C14                2  121529
```

```
141 2019-05-01          26  41.0     0.0  C14                2  121529
142 2019-06-01          26  41.0     0.0  C14                2  121529
143 2019-07-01          26  41.0     0.0  C14                2  121529
144 2019-08-01          26  41.0     0.0  C14                2  121529
145 2019-09-01          26  42.0     0.0  C14                2  121529
146 2019-10-01          26  42.0     0.0  C14                2  121529
147 2019-11-01          26  42.0     0.0  C14                2  121529
148 2019-12-01          26  42.0     0.0  C14                2  121529
149 2020-01-01          26  42.0     0.0  C14                2  121529
150 2020-02-01          26  42.0     0.0  C14                2  121529
151 2020-03-01          26  42.0     0.0  C14                2  132577
152 2020-04-01          26  42.0     0.0  C14                2  132577
153 2020-05-01          26  42.0     0.0  C14                2  132577
154 2020-06-01          26  42.0     0.0  C14                2  132577
155 2020-07-01          26  42.0     0.0  C14                2  132577
156 2020-08-01          26  42.0     0.0  C14                2  132577
157 2020-09-01          26  43.0     0.0  C14                2  132577
158 2020-10-01          26  43.0     0.0  C14                2  132577
159 2020-11-01          26  43.0     0.0  C14                2  132577
160 2020-12-01          26  43.0     0.0  C14                2  132577

    Dateofjoining LastWorkingDate  Joining Designation  Grade  \
137    2018-05-07             NaT                    1      3
138    2018-05-07             NaT                    1      3
139    2018-05-07             NaT                    1      3
140    2018-05-07             NaT                    1      3
141    2018-05-07             NaT                    1      3
142    2018-05-07             NaT                    1      3
143    2018-05-07             NaT                    1      3
144    2018-05-07             NaT                    1      3
145    2018-05-07             NaT                    1      3
146    2018-05-07             NaT                    1      3
147    2018-05-07             NaT                    1      3
148    2018-05-07             NaT                    1      3
149    2018-05-07             NaT                    1      3
150    2018-05-07             NaT                    1      3
151    2018-05-07             NaT                    1      4
152    2018-05-07             NaT                    1      4
153    2018-05-07             NaT                    1      4
154    2018-05-07             NaT                    1      4
155    2018-05-07             NaT                    1      4
156    2018-05-07             NaT                    1      4
157    2018-05-07             NaT                    1      4
158    2018-05-07             NaT                    1      4
159    2018-05-07             NaT                    1      4
160    2018-05-07             NaT                    1      4
```

```
     Total Business Value  Quarterly Rating  Churn
137                243110                 4    0.0
138                646330                 4    0.0
139              17651940                 4    0.0
140                242510                 4    0.0
141               1098080                 4    0.0
142               1212720                 4    0.0
143               2695910                 4    0.0
144                494710                 4    0.0
145                986540                 4    0.0
146               9950710                 4    0.0
147              13097320                 4    0.0
148               1086370                 4    0.0
149                732410                 2    0.0
150               1511840                 2    0.0
151               9226690                 4    0.0
152               1940050                 2    0.0
153                970030                 2    0.0
154                     0                 2    0.0
155                153590                 2    0.0
156               1710410                 2    0.0
157                440550                 2    0.0
158                744590                 2    0.0
159               1578270                 2    0.0
160               1453220                 2    0.0
```

[40]:
```
#Lets find out the average income of each driver and store it in the aggragated dataset.
income_avg=df.groupby(by='Driver_ID').mean()['Income'].reset_index()
income_avg[:5]
```

[40]:
```
   Driver_ID   Income
0          1  57387.0
1          2  67016.0
2          4  65603.0
3          5  46368.0
4          6  78728.0
```

[41]:
```
dataset=pd.merge(left=dataset,right=income_avg,on='Driver_ID')
dataset.head()
#Sucessfully created a new feature which stores the average_income for each driver.
```

[41]:
```
   Driver_ID  Churn  Duration City  Education_Level   Income
0          1      1        77  C23                2  57387.0
1          2      0        25   C7                2  67016.0
2          4      1       142  C13                2  65603.0
```

```
3           5      1        57   C9                 0  46368.0
4           6      0       123  C11                 1  78728.0
```

```
[ ]:
```

```
[42]: # Lets do another Feature Engineering step for Income
      # If the income has increased for a particular driver, then we can flag him as␣
       ↪1, or else 0.
      # To achieve this, we can compare the first month income and last month income␣
       ↪for every driver.

      # Getting the list of driver_ids
      all_driver_ids=dataset['Driver_ID']

      #Getting the indexes for every driver, and storing the key-value pair in a dict
      dict1={}
      for id in all_driver_ids:
          dict1[id]=list(df[df['Driver_ID']==id].index)
```

```
[43]: # Creating a Flag Column
      dataset['Income_Flag']=-1

      # Now lets compare the first and last month income for every driver and create␣
       ↪the flag feature in our dataset.
      for driver_id in all_driver_ids:
          first_index=min(dict1[driver_id])
          last_index=max(dict1[driver_id])
          first_income=df.iloc[first_index]['Income']
          last_income=df.iloc[last_index]['Income']
          if last_income>first_income:
              dataset.loc[dataset['Driver_ID']==driver_id,'Income_Flag']=1
          else:
              dataset.loc[dataset['Driver_ID']==driver_id,'Income_Flag']=0
```

```
[44]: # Lets have a look at the new feature that we created.
      dataset.head()
```

[44]:

	Driver_ID	Churn	Duration	City	Education_Level	Income	Income_Flag
0	1	1	77	C23	2	57387.0	0
1	2	0	25	C7	2	67016.0	0
2	4	1	142	C13	2	65603.0	0
3	5	1	57	C9	0	46368.0	0
4	6	0	123	C11	1	78728.0	0

```
[ ]:
```

0.1.8 Inspecting and Aggregating "Age" for each Driver in the new Dataset

[45]:
```
# From the inspection done earlier, we know "Age" feature has missing values.
df['Age'].isna().sum()
```

[45]:
```
61
```

[46]:
```
# Lets inspect the dataset for missing values in age feature
df[df['Age'].isna()]
```

[46]:
```
          MMM-YY  Driver_ID  Age  Gender City  Education_Level  Income  \
71    2020-02-01         20  NaN     1.0  C19                0   40342
96    2019-10-01         22  NaN     0.0  C10                2   31224
109   2019-07-01         24  NaN     0.0  C24                2   76308
211   2019-11-01         40  NaN     0.0  C15                0   59182
260   2019-05-01         49  NaN     0.0  C20                0   53039
…            …          …  …       …  …                  …       …
18180 2020-05-01       2690  NaN     0.0  C11                2   77662
18507 2020-08-01       2730  NaN     1.0  C16                2   69924
18565 2019-03-01       2738  NaN     0.0  C17                0   23068
18628 2019-01-01       2751  NaN     0.0  C17                2   53115
18809 2019-02-01       2774  NaN     0.0  C15                1   42313

      Dateofjoining LastWorkingDate  Joining Designation  Grade  \
71       2019-10-25             NaT                    3      3
96       2018-05-25             NaT                    1      1
109      2018-05-25             NaT                    1      2
211      2019-11-08             NaT                    2      2
260      2018-05-25             NaT                    1      2
…               …              …                    …      …
18180    2018-07-17             NaT                    1      2
18507    2019-07-08             NaT                    2      2
18565    2018-09-08             NaT                    1      1
18628    2015-11-05             NaT                    1      1
18809    2018-07-21             NaT                    1      1

       Total Business Value  Quarterly Rating  Churn
71                        0                 1    0.0
96                   200000                 3    0.0
109                  203240                 3    0.0
211                       0                 1    0.0
260                  124190                 1    0.0
…                       …                …      …
18180                692600                 4    0.0
18507                161860                 2    0.0
18565                639780                 3    0.0
18628                506550                 3    0.0
18809               1141280                 4    0.0
```

[61 rows x 14 columns]

[47]:
```python
# Lets get the list of driver_ids for whom there are missing values in Age.
missing_age_driver_ids=list(set(df.loc[df['Age'].isna(),'Driver_ID']))
len(missing_age_driver_ids)
#There are total 57 such drivers.
```

[47]: 57

[48]:
```python
# As this dataset has more than 1 observation for every driver,lets check for␣
↪valid values of "Age" for these drivers
# Since the records could be more than 12 months long, lets check for the␣
↪maximum age of each driver, since age may change.
missing_age_drivers_found=df[df['Driver_ID'].isin(missing_age_driver_ids)].
↪groupby('Driver_ID').max()['Age']
missing_age_drivers_found

#We found valid age for each of these drivers. Lets use these values in our␣
↪dataset.
```

[48]:
```
Driver_ID
20       26.0
22       41.0
24       31.0
40       32.0
49       22.0
63       28.0
69       32.0
103      26.0
120      27.0
167      26.0
179      26.0
183      26.0
204      31.0
215      26.0
305      24.0
313      31.0
325      26.0
369      32.0
422      27.0
458      31.0
541      27.0
560      42.0
607      27.0
617      22.0
718      27.0
```

```
778     31.0
901     32.0
954     31.0
1050    32.0
1072    28.0
1247    32.0
1378    28.0
1421    27.0
1430    31.0
1462    27.0
1588    42.0
1611    31.0
1669    22.0
1720    33.0
1852    55.0
1909    31.0
1932    28.0
1936    26.0
2073    21.0
2168    40.0
2273    32.0
2348    24.0
2351    31.0
2460    26.0
2507    26.0
2569    27.0
2618    28.0
2690    26.0
2730    32.0
2738    24.0
2751    32.0
2774    41.0
Name: Age, dtype: float64
```

[49]:

```
mapping=dict(zip(list(missing_age_drivers_found.
 ↪index),list(missing_age_drivers_found)))
mapping
#Now lets fill the missing age values.

for d_id in missing_age_driver_ids:
    df.loc[df['Driver_ID']==d_id,'Age']=mapping[d_id]
```

[50]:

```
#Checking if missing values have been removed
df['Age'].isna().sum()
```

[50]: 0

[51]:
```python
# Now lets store the max age of all drivers in the aggregate dataset
max_ages_of_drivers=df.groupby(by='Driver_ID').max()['Age']

dataset=pd.merge(left=dataset,right=max_ages_of_drivers,on='Driver_ID')
dataset.head()
#Sucessfully created a new feature which stores the max Age for each driver.
```

[51]:

	Driver_ID	Churn	Duration	City	Education_Level	Income	Income_Flag
0	1	1	77	C23	2	57387.0	0
1	2	0	25	C7	2	67016.0	0
2	4	1	142	C13	2	65603.0	0
3	5	1	57	C9	0	46368.0	0
4	6	0	123	C11	1	78728.0	0

	Age
0	28.0
1	31.0
2	43.0
3	29.0
4	31.0

[ ]:

0.1.9 Inspecting and Aggregating “Gender” for each Driver in the new Dataset

[52]:
```python
# There were few missing values in "Gender" Feature found in our preliminary␣
↪analysis
df['Gender'].isna().sum()
```

[52]: 52

[53]:
```python
# Lets check few the observation where there are missing values in the "Gender"␣
↪feature
df[df['Gender'].isna()][:20]
```

[53]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income
239	2019-02-01	43	27.0	NaN	C15	0	12906
257	2019-02-01	49	22.0	NaN	C20	0	53039
263	2019-08-01	49	22.0	NaN	C20	0	53039
463	2019-08-01	68	31.0	NaN	C29	0	79288
817	2019-02-01	116	21.0	NaN	C11	0	16477
856	2019-11-01	119	31.0	NaN	C29	1	71000
1509	2020-12-01	225	32.0	NaN	C14	0	44792
1885	2019-08-01	296	31.0	NaN	C20	1	65094
2267	2019-02-01	354	31.0	NaN	C11	0	60555
2349	2020-03-01	365	24.0	NaN	C22	0	44740
2656	2019-06-01	407	40.0	NaN	C13	1	58207

```
2905 2020-03-01       439  27.0     NaN   C3               1   60246
2969 2020-07-01       446  31.0     NaN  C22               0   50832
3262 2020-01-01       489  31.0     NaN  C12               2   49475
3407 2020-10-01       516  26.0     NaN  C29               0   41099
3597 2020-02-01       541  27.0     NaN   C1               2   71812
4173 2020-02-01       611  32.0     NaN  C10               1   39216
4340 2019-12-01       640  26.0     NaN   C8               1  105931
4727 2019-04-01       709  31.0     NaN  C13               1  135436
5310 2020-12-01       793  26.0     NaN   C7               2   92670

     Dateofjoining LastWorkingDate  Joining Designation  Grade  \
239     2018-07-13      2019-02-20                    1      1
257     2018-05-25             NaT                    1      2
263     2018-05-25             NaT                    1      2
463     2015-10-18             NaT                    1      3
817     2018-12-04             NaT                    1      1
856     2019-11-16             NaT                    3      3
1509    2020-07-13             NaT                    3      3
1885    2018-06-10             NaT                    1      2
2267    2018-11-30             NaT                    1      1
2349    2020-02-01             NaT                    2      2
2656    2016-05-17             NaT                    1      2
2905    2019-11-28             NaT                    1      1
2969    2020-02-01             NaT                    3      3
3262    2019-10-18             NaT                    1      1
3407    2019-07-04             NaT                    1      1
3597    2017-02-10             NaT                    1      2
4173    2020-01-13             NaT                    2      2
4340    2019-12-07             NaT                    3      3
4727    2018-08-04             NaT                    5      5
5310    2020-10-30             NaT                    3      3

      Total Business Value  Quarterly Rating  Churn
239                      0                 1    1.0
257                      0                 1    0.0
263                 300300                 2    0.0
463                 544930                 3    0.0
817                 129590                 1    0.0
856                      0                 1    0.0
1509                337020                 3    0.0
1885                145670                 2    0.0
2267                     0                 1    0.0
2349                     0                 1    0.0
2656                427570                 4    0.0
2905               1561820                 3    0.0
2969                890060                 2    0.0
3262                500510                 3    0.0
```

```
3407               422710               1    0.0
3597               200000               2    0.0
4173                    0               1    0.0
4340                    0               1    0.0
4727                    0               1    0.0
5310               127800               1    0.0
```

[54]:
```
# Lets get the driver_id for whom there are missing values in "Gender" column
gender_missing_driver_ids=list(set(df.loc[df['Gender'].isna(),'Driver_ID']))
len(gender_missing_driver_ids)
# There are total 51 driver_ids for whom there are missing values in Gender
```

[54]:
```
51
```

[55]:
```
# Lets check if we have values present for "Gender" in other observations for␣
↪the same driver_ids.
temp=df[df['Driver_ID'].isin(gender_missing_driver_ids)]
temp=temp.loc[~temp['Gender'].isna(),['Driver_ID','Gender']]
temp=temp[~temp.duplicated()]
temp.shape
# There are values present for all the 51 driver_ids
```

[55]:
```
(51, 2)
```

[56]:
```
mapping=dict(zip(temp['Driver_ID'],temp['Gender']))

# Lets replace the missing values in the dataset.
for d_id in gender_missing_driver_ids:
    df.loc[df['Driver_ID']==d_id,'Gender']=mapping[d_id]
```

[57]:
```
#Checking if missing values have been removed
df['Gender'].isna().sum()
```

[57]:
```
0
```

[58]:
```
# Now lets store the Gender of all drivers in the aggregate dataset
gender_drivers=df.loc[(~df[['Driver_ID','Gender']].
↪duplicated()),['Driver_ID','Gender']]

dataset=pd.merge(left=dataset,right=gender_drivers,on='Driver_ID')
dataset.head()
#Sucessfully created a new feature which stores the Gender for each driver.
```

[58]:
```
   Driver_ID  Churn  Duration City  Education_Level   Income  Income_Flag  \
0          1      1        77  C23                2  57387.0            0
1          2      0        25   C7                2  67016.0            0
2          4      1       142  C13                2  65603.0            0
3          5      1        57   C9                0  46368.0            0
```

```
4          6      0       123  C11                1  78728.0            0

    Age  Gender
0  28.0     0.0
1  31.0     0.0
2  43.0     0.0
3  29.0     0.0
4  31.0     1.0
```

Note : It was asked in the question to use KNN_Imputer to impute missing values. However during my exploration process, I found out that there are original values present in the dataset that can be directly used instead of using KNN, which would be an approximation missing value imputation technique.

[ ]:

```

```

0.1.10 Inspecting and Aggregating "Joining_Designation" for each Driver in the new Dataset

[59]:

```
# Lets check if there were multiple Joining_Designation for any of the drivers
df.groupby(by='Driver_ID').nunique()['Joining Designation'].value_counts()

# Observation - All the drivers have only 1 joining designation.
```

[59]:

```
1    2299
Name: Joining Designation, dtype: int64
```

[60]:

```
# We can store the Joining_Designation for each of the drivers in the␣
↪aggregated dataset.
joining_designation=df.loc[~df[['Driver_ID','Joining Designation']].
↪duplicated(),['Driver_ID','Joining Designation']]

dataset=pd.merge(left=dataset,right=joining_designation,on='Driver_ID')
dataset.head()
#Sucessfully created a new feature which stores the Joining_Designation for␣
↪each driver.
```

[60]:

```
   Driver_ID  Churn  Duration City  Education_Level   Income  Income_Flag  \
0          1      1        77  C23                2  57387.0            0
1          2      0        25   C7                2  67016.0            0
2          4      1       142  C13                2  65603.0            0
3          5      1        57   C9                0  46368.0            0
4          6      0       123  C11                1  78728.0            0

    Age  Gender  Joining Designation
0  28.0     0.0                    1
1  31.0     0.0                    2
```

```
2  43.0     0.0                    2
3  29.0     0.0                    1
4  31.0     1.0                    3
```

[ ]:

```

```

0.1.11 Inspecting and Aggregating "Grade" for each Driver in the new Dataset

[61]:

```python
# Lets check if there are multiple Grades for any of the drivers
df.groupby(by='Driver_ID').nunique()['Grade'].value_counts()

# Observation - Maximum drivers have 2 Grades,& few drivers have 1 Grade.Lets␣
↪check few records for drivers having 2 Grades.
```

[61]:

```
1    2255
2      44
Name: Grade, dtype: int64
```

[62]:

```python
temp=df.groupby(by='Driver_ID').nunique()['Grade']
multiple_grade_driver_ids=temp[temp==2].index
len(multiple_grade_driver_ids)

#There are 44 drivers who have 2 Grades. Lets have a look the observations for␣
↪one such driver.
```

[62]: 44

[63]:

```python
df[df['Driver_ID']==multiple_grade_driver_ids[0]]
# Perhaps with increase in time and performace, the Grade increases for drivers.
```

[63]:

```
         MMM-YY  Driver_ID   Age  Gender City  Education_Level  Income  \
137  2019-01-01         26  41.0     0.0  C14                2  121529
138  2019-02-01         26  41.0     0.0  C14                2  121529
139  2019-03-01         26  41.0     0.0  C14                2  121529
140  2019-04-01         26  41.0     0.0  C14                2  121529
141  2019-05-01         26  41.0     0.0  C14                2  121529
142  2019-06-01         26  41.0     0.0  C14                2  121529
143  2019-07-01         26  41.0     0.0  C14                2  121529
144  2019-08-01         26  41.0     0.0  C14                2  121529
145  2019-09-01         26  42.0     0.0  C14                2  121529
146  2019-10-01         26  42.0     0.0  C14                2  121529
147  2019-11-01         26  42.0     0.0  C14                2  121529
148  2019-12-01         26  42.0     0.0  C14                2  121529
149  2020-01-01         26  42.0     0.0  C14                2  121529
150  2020-02-01         26  42.0     0.0  C14                2  121529
151  2020-03-01         26  42.0     0.0  C14                2  132577
152  2020-04-01         26  42.0     0.0  C14                2  132577
```

153	2020-05-01	26	42.0	0.0	C14	2	132577
154	2020-06-01	26	42.0	0.0	C14	2	132577
155	2020-07-01	26	42.0	0.0	C14	2	132577
156	2020-08-01	26	42.0	0.0	C14	2	132577
157	2020-09-01	26	43.0	0.0	C14	2	132577
158	2020-10-01	26	43.0	0.0	C14	2	132577
159	2020-11-01	26	43.0	0.0	C14	2	132577
160	2020-12-01	26	43.0	0.0	C14	2	132577

	Dateofjoining	LastWorkingDate	Joining Designation	Grade	\
137	2018-05-07	NaT	1	3	
138	2018-05-07	NaT	1	3	
139	2018-05-07	NaT	1	3	
140	2018-05-07	NaT	1	3	
141	2018-05-07	NaT	1	3	
142	2018-05-07	NaT	1	3	
143	2018-05-07	NaT	1	3	
144	2018-05-07	NaT	1	3	
145	2018-05-07	NaT	1	3	
146	2018-05-07	NaT	1	3	
147	2018-05-07	NaT	1	3	
148	2018-05-07	NaT	1	3	
149	2018-05-07	NaT	1	3	
150	2018-05-07	NaT	1	3	
151	2018-05-07	NaT	1	4	
152	2018-05-07	NaT	1	4	
153	2018-05-07	NaT	1	4	
154	2018-05-07	NaT	1	4	
155	2018-05-07	NaT	1	4	
156	2018-05-07	NaT	1	4	
157	2018-05-07	NaT	1	4	
158	2018-05-07	NaT	1	4	
159	2018-05-07	NaT	1	4	
160	2018-05-07	NaT	1	4	

	Total Business Value	Quarterly Rating	Churn
137	243110	4	0.0
138	646330	4	0.0
139	17651940	4	0.0
140	242510	4	0.0
141	1098080	4	0.0
142	1212720	4	0.0
143	2695910	4	0.0
144	494710	4	0.0
145	986540	4	0.0
146	9950710	4	0.0
147	13097320	4	0.0

```
148         1086370           4    0.0
149          732410           2    0.0
150         1511840           2    0.0
151         9226690           4    0.0
152         1940050           2    0.0
153          970030           2    0.0
154               0           2    0.0
155          153590           2    0.0
156         1710410           2    0.0
157          440550           2    0.0
158          744590           2    0.0
159         1578270           2    0.0
160         1453220           2    0.0
```

[64]:
```
# Now lets store the Maximum Grade of all drivers in the aggregate dataset
grade_of_driver_ids=df.groupby(by='Driver_ID').max()['Grade']

dataset=pd.merge(left=dataset,right=grade_of_driver_ids,on='Driver_ID')
dataset.head()
#Sucessfully created a new feature which stores the Max Grade for each driver.
```

[64]:
```
   Driver_ID  Churn  Duration City  Education_Level   Income  Income_Flag  \
0          1      1        77  C23                2  57387.0            0
1          2      0        25   C7                2  67016.0            0
2          4      1       142  C13                2  65603.0            0
3          5      1        57   C9                0  46368.0            0
4          6      0       123  C11                1  78728.0            0

    Age  Gender  Joining Designation  Grade
0  28.0     0.0                    1      1
1  31.0     0.0                    2      2
2  43.0     0.0                    2      2
3  29.0     0.0                    1      1
4  31.0     1.0                    3      3
```

[ ]:
```

```

0.1.12 Inspecting and Aggregating "Total Business Value" for each Driver in the new Dataset

[65]:
```
# For "Total Business Value", we can take the summation of the all the␣
↪observations for this feature for each driver.
total_business_of_each_driver=df.groupby(by='Driver_ID').sum()['Total Business␣
↪Value']
```

```
dataset=pd.
 ↪merge(left=dataset,right=total_business_of_each_driver,on='Driver_ID')
dataset.head()
#Sucessfully created a new feature which stores the sum of total_business_value␣
 ↪for each driver in the aggregated dataset.
```

[65]:

```
   Driver_ID  Churn  Duration City  Education_Level   Income  Income_Flag  \
0          1      1        77  C23                2  57387.0            0
1          2      0        25   C7                2  67016.0            0
2          4      1       142  C13                2  65603.0            0
3          5      1        57   C9                0  46368.0            0
4          6      0       123  C11                1  78728.0            0

    Age  Gender  Joining Designation  Grade  Total Business Value
0  28.0     0.0                    1      1               1715580
1  31.0     0.0                    2      2                     0
2  43.0     0.0                    2      2                350000
3  29.0     0.0                    1      1                120360
4  31.0     1.0                    3      3               1265000
```

[ ]:

```

```

0.1.13 Inspecting and Aggregating "Quarterly Rating" for each Driver in the new Dataset

[66]:

```
# Lets check if there were multiple Quarterly Ratings for any of the drivers
df.groupby(by='Driver_ID').nunique()['Quarterly Rating'].value_counts()

#Observation-Drivers have got different ratings as per their quarter␣
 ↪performance.Most have got 1 kind of rating consitently.
```

[66]:

```
1    1203
2     654
3     352
4      90
Name: Quarterly Rating, dtype: int64
```

[67]:

```
# Now lets store the Average Quarterly Ratings of all drivers in the aggregate␣
 ↪dataset
ratings_drivers=df.groupby(by='Driver_ID').mean()['Quarterly Rating']

dataset=pd.merge(left=dataset,right=ratings_drivers,on='Driver_ID')
dataset.head()
#Sucessfully created a new feature which stores the Average Quarterly Ratings␣
 ↪for each driver.
```

[67]:

```
   Driver_ID  Churn  Duration City  Education_Level    Income  Income_Flag  \
0          1      1        77  C23                2  57387.0            0
1          2      0        25   C7                2  67016.0            0
2          4      1       142  C13                2  65603.0            0
3          5      1        57   C9                0  46368.0            0
4          6      0       123  C11                1  78728.0            0

    Age  Gender  Joining Designation  Grade  Total Business Value  \
0  28.0     0.0                    1      1               1715580
1  31.0     0.0                    2      2                     0
2  43.0     0.0                    2      2                350000
3  29.0     0.0                    1      1                120360
4  31.0     1.0                    3      3               1265000

   Quarterly Rating
0               2.0
1               1.0
2               1.0
3               1.0
4               1.6
```

[ ]:

[68]:

```
# Lets do another Feature Engineering step for Quarterly_Rating
# If the Quarterly_Rating has increased for a particular driver, then we can␣
↪flag him as 1, or else 0.
# To achieve this, we can compare the first month Quarterly_Rating and last␣
↪month Quarterly_Rating for every driver.

# Getting the list of driver_ids
all_driver_ids=dataset['Driver_ID']

#Getting the indexes for every driver, and storing the key-value pair in a dict
dict1={}
for id in all_driver_ids:
    dict1[id]=list(df[df['Driver_ID']==id].index)
```

[69]:

```
# Creating a Flag Column
dataset['Quarterly_Rating_Flag']=-1

# Now lets compare the first and last month Quarterly_Rating for every driver␣
↪and create the flag feature in our dataset.
for driver_id in all_driver_ids:
    first_index=min(dict1[driver_id])
    last_index=max(dict1[driver_id])
    first_income=df.iloc[first_index]['Quarterly Rating']
    last_income=df.iloc[last_index]['Quarterly Rating']
```

```
    if last_income>first_income:
        dataset.loc[dataset['Driver_ID']==driver_id,'Quarterly_Rating_Flag']=1
    else:
        dataset.loc[dataset['Driver_ID']==driver_id,'Quarterly_Rating_Flag']=0
```

[70]:
```
# Lets have a look at the new feature that we created.
dataset.head()
```

[70]:
```
   Driver_ID  Churn  Duration City  Education_Level   Income  Income_Flag  \
0          1      1        77  C23                2  57387.0            0
1          2      0        25   C7                2  67016.0            0
2          4      1       142  C13                2  65603.0            0
3          5      1        57   C9                0  46368.0            0
4          6      0       123  C11                1  78728.0            0

    Age  Gender  Joining Designation  Grade  Total Business Value  \
0  28.0     0.0                    1      1               1715580
1  31.0     0.0                    2      2                     0
2  43.0     0.0                    2      2                350000
3  29.0     0.0                    1      1                120360
4  31.0     1.0                    3      3               1265000

   Quarterly Rating  Quarterly_Rating_Flag
0               2.0                      0
1               1.0                      0
2               1.0                      0
3               1.0                      0
4               1.6                      1
```

[ ]:

0.2 Final Dataset

[71]:
```
# We have our final aggregated dataset, which can be used for analysis and␣
 ↪model building.
dataset.head()

# Taking a look at out Final_Dataset.
dataset.head()
```

[71]:
```
   Driver_ID  Churn  Duration City  Education_Level   Income  Income_Flag  \
0          1      1        77  C23                2  57387.0            0
1          2      0        25   C7                2  67016.0            0
2          4      1       142  C13                2  65603.0            0
3          5      1        57   C9                0  46368.0            0
4          6      0       123  C11                1  78728.0            0
```

```
    Age  Gender  Joining Designation  Grade  Total Business Value  \
0  28.0     0.0                    1      1               1715580
1  31.0     0.0                    2      2                     0
2  43.0     0.0                    2      2                350000
3  29.0     0.0                    1      1                120360
4  31.0     1.0                    3      3               1265000

   Quarterly Rating  Quarterly_Rating_Flag
0               2.0                      0
1               1.0                      0
2               1.0                      0
3               1.0                      0
4               1.6                      1
```

[72]:
```
#Checking the shape of the dataset
dataset.shape
```

[72]:
```
(2299, 14)
```

[73]:
```
# Final Check for NULL values
dataset.isna().sum()
#There are no null values.
```

[73]:
```
Driver_ID                0
Churn                    0
Duration                 0
City                     0
Education_Level          0
Income                   0
Income_Flag              0
Age                      0
Gender                   0
Joining Designation      0
Grade                    0
Total Business Value     0
Quarterly Rating         0
Quarterly_Rating_Flag    0
dtype: int64
```

[74]:
```
# Checking the Data Types of the columns
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2299 entries, 0 to 2298
Data columns (total 14 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Driver_ID              2299 non-null   int64
```

```
 1   Churn                   2299 non-null   int64
 2   Duration                2299 non-null   int64
 3   City                    2299 non-null   object
 4   Education_Level         2299 non-null   int64
 5   Income                  2299 non-null   float64
 6   Income_Flag             2299 non-null   int64
 7   Age                     2299 non-null   float64
 8   Gender                  2299 non-null   float64
 9   Joining Designation     2299 non-null   int64
 10  Grade                   2299 non-null   int64
 11  Total Business Value    2299 non-null   int64
 12  Quarterly Rating        2299 non-null   float64
 13  Quarterly_Rating_Flag   2299 non-null   int64
dtypes: float64(4), int64(9), object(1)
memory usage: 269.4+ KB
```

[75]:
```
#Checking for duplicate values.
dataset[dataset.duplicated()]
# There are not duplicate values.
```

[75]:
```
Empty DataFrame
Columns: [Driver_ID, Churn, Duration, City, Education_Level, Income,
Income_Flag, Age, Gender, Joining Designation, Grade, Total Business Value,
Quarterly Rating, Quarterly_Rating_Flag]
Index: []
```

[ ]:
```

```

0.2.1 Lets determine the categorical and continuous columns in our dataset.

[76]:
```
data_types=[]
categories=[]
for column in dataset.columns:
    categories.append(dataset[column].nunique())
    data_types.append(dataset[column].dtype)

pd.
 ↪DataFrame(data=[categories,data_types],index=['Categories','Data_Type'],columns=dataset.
 ↪columns).T
```

[76]:
```
                      Categories Data_Type
Driver_ID                   2299     int64
Churn                          2     int64
Duration                     879     int64
City                          29    object
Education_Level                3     int64
Income                      2260   float64
Income_Flag                    2     int64
```

```
Age                         36    float64
Gender                       2    float64
Joining Designation          5      int64
Grade                        5      int64
Total Business Value      1615      int64
Quarterly Rating           163    float64
Quarterly_Rating_Flag        2      int64
```

[77]:
```
continuous_columns=['Duration','Income','Age','Total Business Value','Quarterly␣
 ↪Rating']
categorical_columns=['City','Education_Level','Income_Flag','Gender','Joining␣
 ↪Designation','Grade','Quarterly_Rating_Flag']
```

[78]:
```
# Converting the data type of categorical columns to category
for column in categorical_columns:
    dataset[column]=dataset[column].astype('category')
```

[ ]:
```

```

0.2.2 Splitting The Data

[79]:
```
# Splitting the dataset into train and test datasets
dataset_train,dataset_test=train_test_split(dataset,test_size=0.
 ↪2,random_state=42,stratify=dataset['Churn'])
print("Train",dataset_train.shape)
print("Test",dataset_test.shape)
```

```
Train (1839, 14)
Test (460, 14)
```

Lets keep the Test_Data aside for now.

[ ]:
```

```

0.2.3 Descriptive Statistics

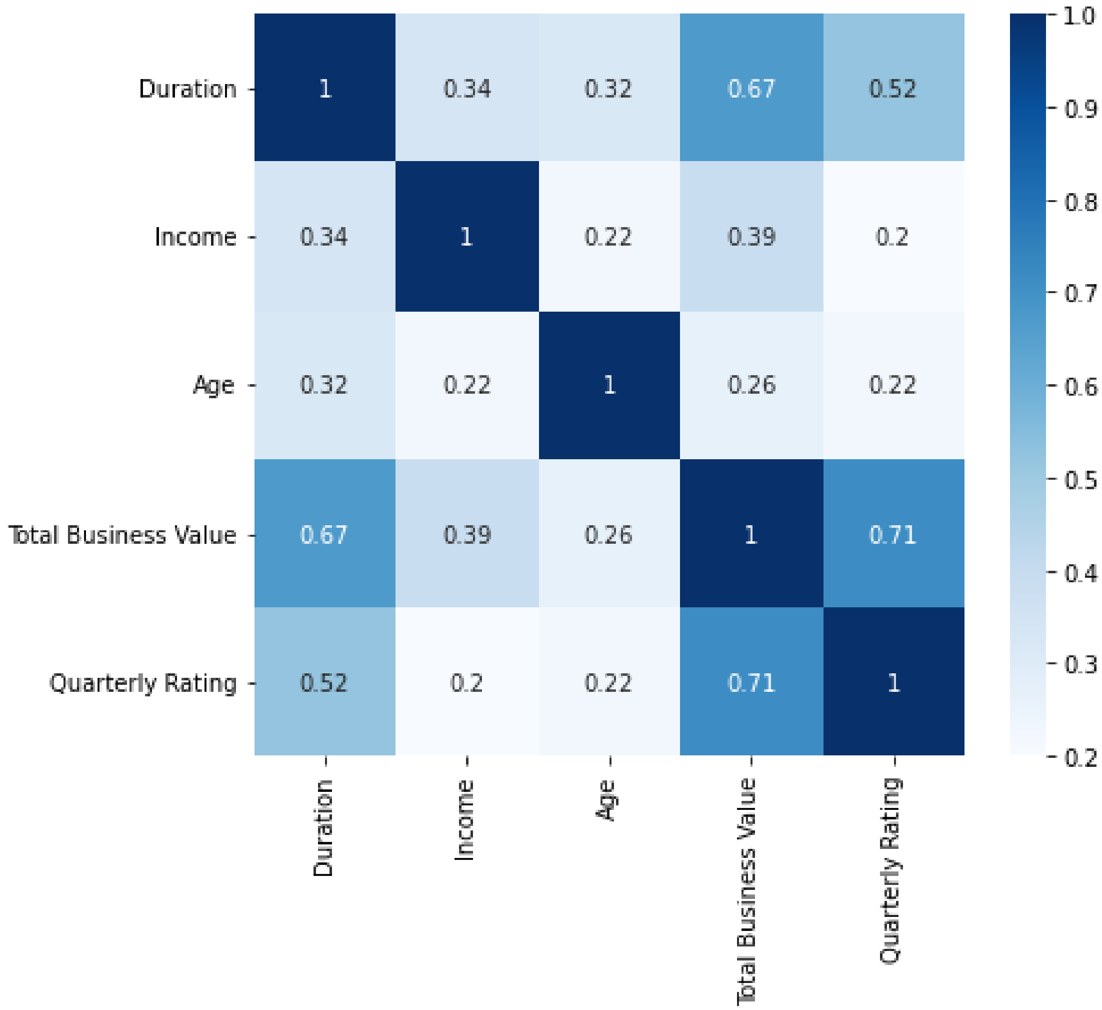
[80]:
```
# Continuous Variables
dataset_train[continuous_columns].describe()
```

[80]:

	Duration	Income	Age	Total Business Value \
count	1839.000000	1839.000000	1839.000000	1.839000e+03
mean	435.377379	59156.150565	33.764546	4.714062e+06
std	570.022273	28358.625209	6.007660	9.237594e+06
min	0.000000	10747.000000	21.000000	-1.385530e+06
25%	97.000000	39111.500000	29.000000	0.000000e+00
50%	185.000000	55108.000000	33.000000	8.643500e+05
75%	479.000000	75380.500000	37.000000	4.272055e+06
max	2801.000000	188418.000000	58.000000	9.533106e+07

```
       Quarterly Rating
count       1839.000000
mean           1.580203
std            0.725855
min            1.000000
25%            1.000000
50%            1.200000
75%            2.000000
max            4.000000
```

[81]:
```python
plt.figure(figsize=(7,6))
sns.heatmap(dataset_train[continuous_columns].corr(),annot=True,cmap='Blues')
plt.show()
```



There is strong correlation between :

- "Duration" and "Total_Business_Value"
- "Quarterly_Rating" and "Total_Business_Value"
- "Duration" and "Quarterly_Rating"

[82]:
```python
# Categorical Variables
dataset_train[categorical_columns].describe()
```

[82]:
```
        City  Education_Level  Income_Flag  Gender  Joining Designation  \
count   1839             1839         1839  1839.0                 1839
unique    29                3            2     2.0                    5
top      C20                1            0     0.0                    1
freq     115              622         1807  1074.0                  798

        Grade  Quarterly_Rating_Flag
count    1839                   1839
unique      5                      2
top         2                      0
freq      661                   1562
```

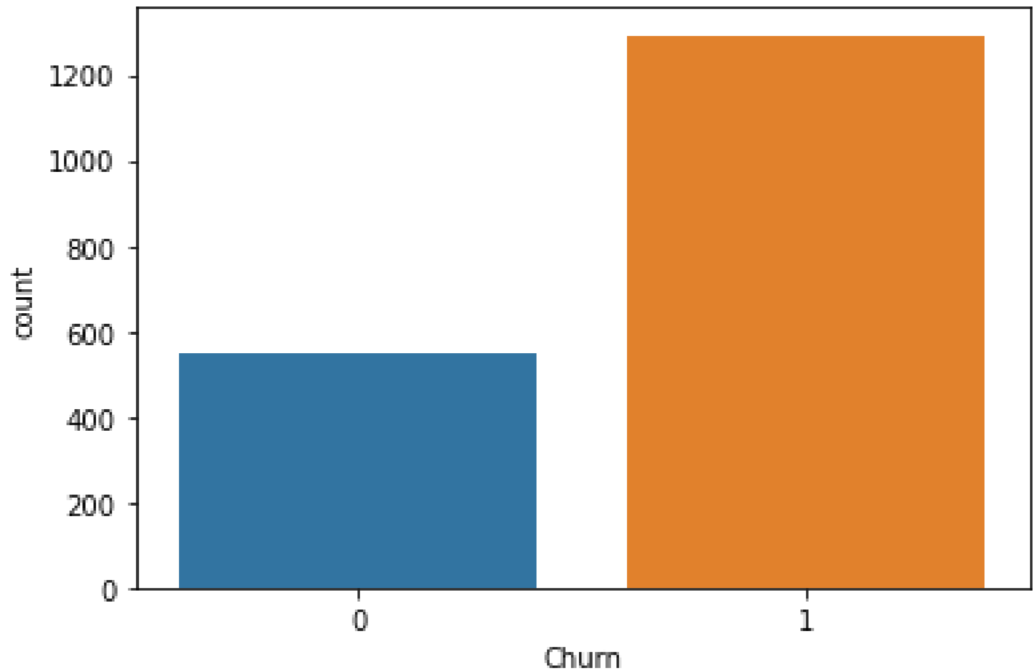
[ ]:

0.3 Analysis

0.3.1 Churn

[83]:
```python
#Target Column - Churn
print(np.round(100*dataset_train['Churn'].value_counts(normalize=True)))
sns.countplot(data=dataset_train,x='Churn')
plt.show()
# We have imbalanced data. Need to balance the data before building the model.
```

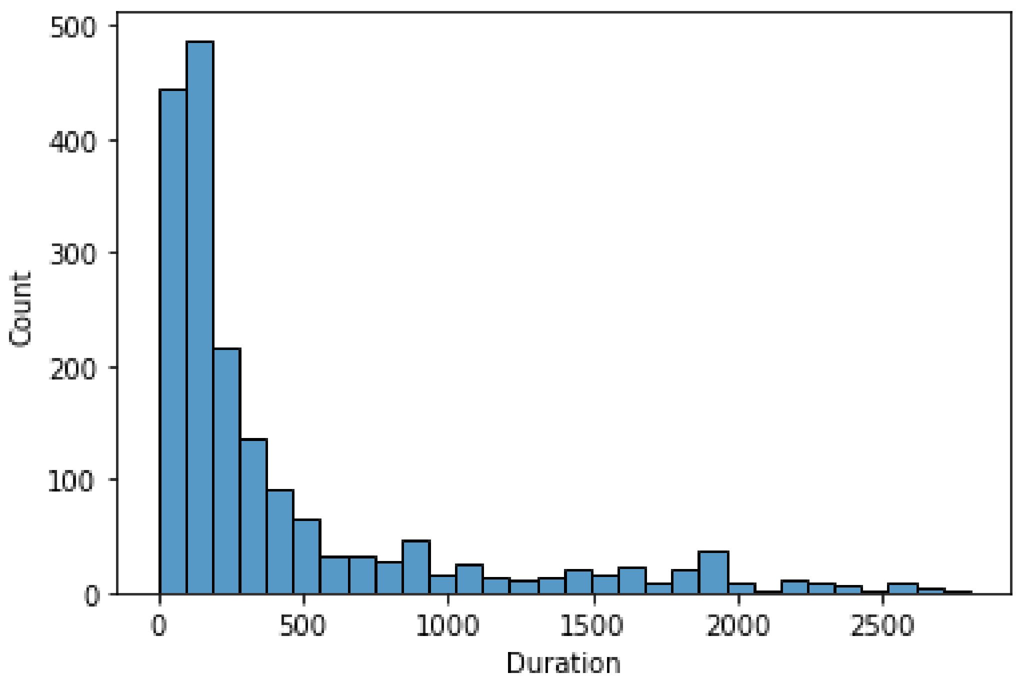
```
1    70.0
0    30.0
Name: Churn, dtype: float64
```

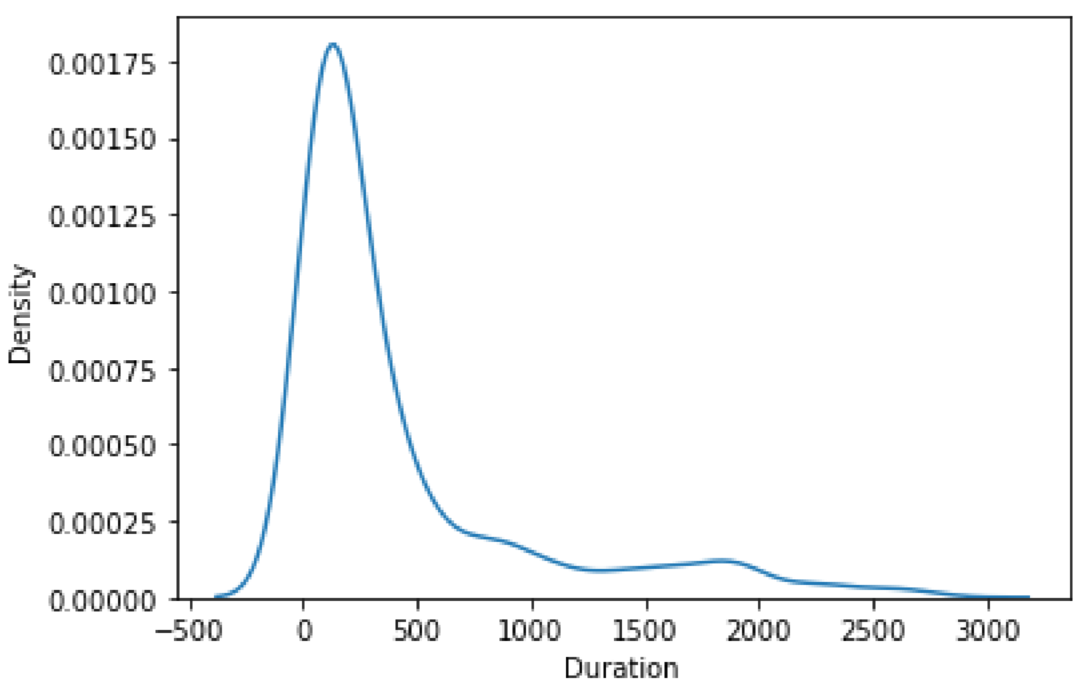


[ ]:

0.3.2 Duration

[84]:
```
# Lets look at the distribution of "Duration"
sns.histplot(data=dataset_train,x='Duration',bins=30)
plt.show()

sns.kdeplot(data=dataset_train,x='Duration')
plt.show()

# The distribution is highly right skewed.
# We can use Transformation to try to make it Normally Distributed.
```





[85]:

```
#Lets check the range of "Duration" feature.
dataset_train['Duration'].describe()
```

```
# The minimum value is 0, we cannot use Log_Transformation here, since log(0)␣
↪is -inf.
# Box-Cox tranformation also cannot be used, since Box-Cox transformation can␣
↪only be used for positive values.
# Lets try using Yeo-Johnson Transformation
```

[85]:

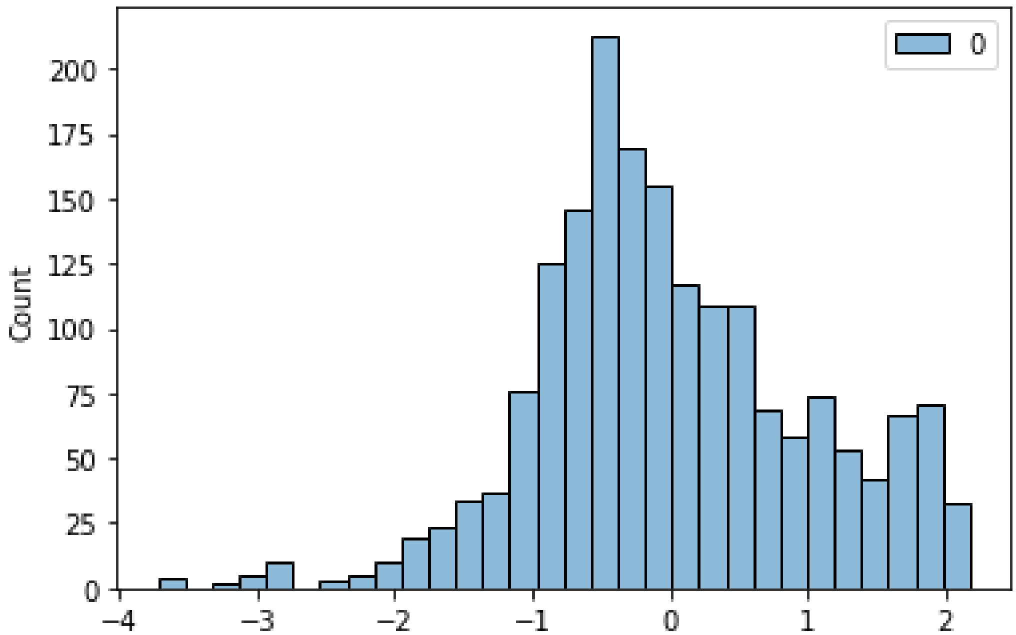
```
count    1839.000000
mean      435.377379
std       570.022273
min         0.000000
25%        97.000000
50%       185.000000
75%       479.000000
max      2801.000000
Name: Duration, dtype: float64
```

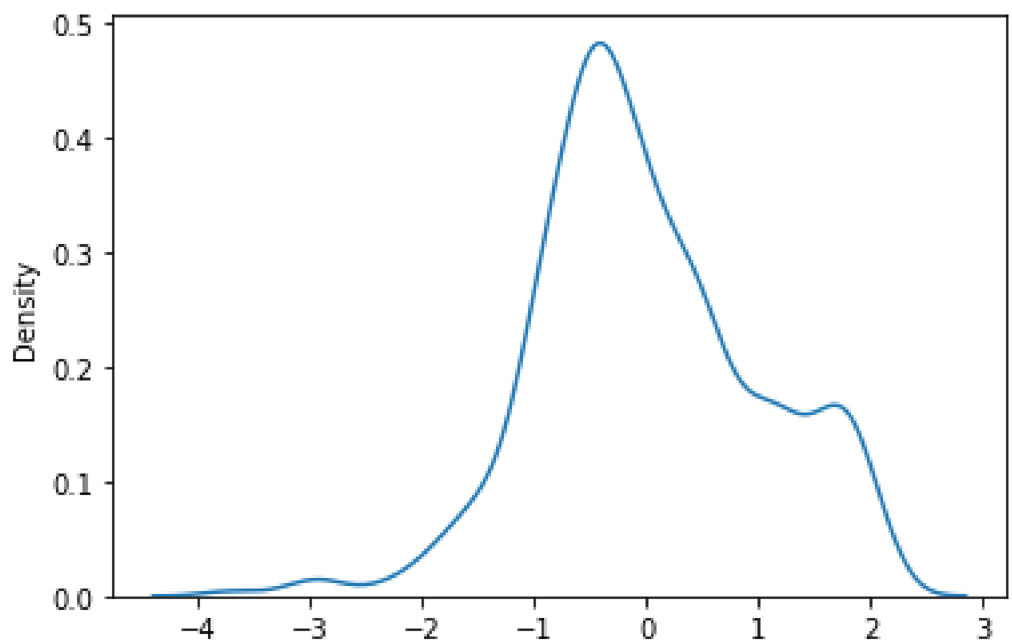
[86]:

```
yeo_johnson_transfomer=PowerTransformer(method='yeo-johnson')
Duration_transformed=yeo_johnson_transfomer.
↪fit_transform(dataset_train[['Duration']])
```

[87]:

```
# Lets look at the distribution of "Duration"
sns.histplot(Duration_transformed,bins=30)
plt.show()

sns.kdeplot(Duration_transformed.reshape(-1))
plt.show()

# The distribution is not exactly normal, but it is better than than the␣
↪original distribution.
# We can use Yeo-Johnson transformation on "Duration" feature.
```

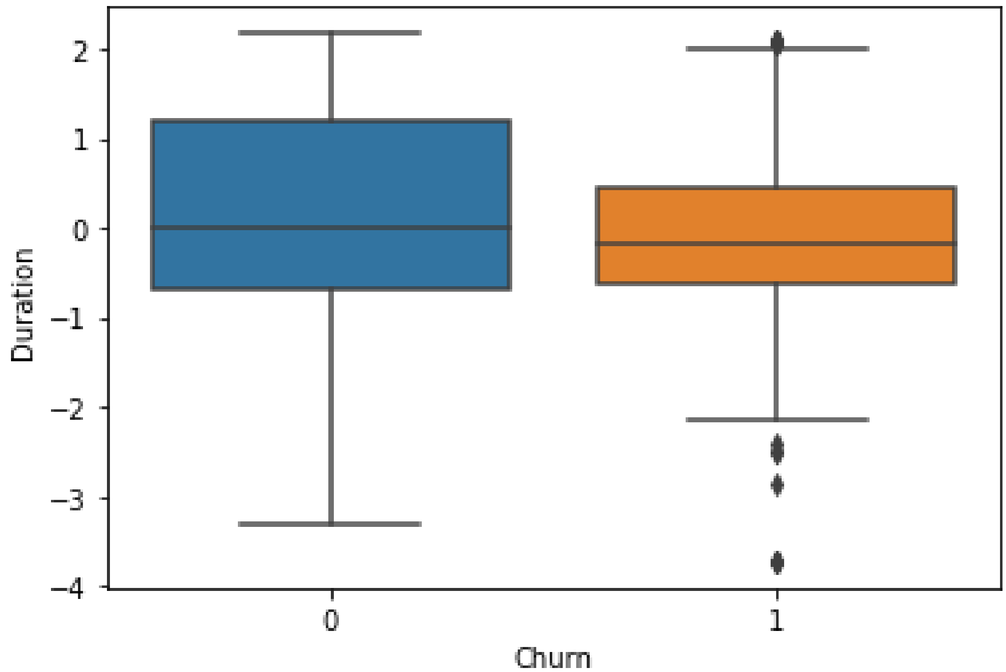




[88]:

```
# Transforming the "Duration" column
dataset_train['Duration']=Duration_transformed.reshape(-1)
dataset_test['Duration']=yeo_johnson_transfomer.
↪transform(dataset_test[['Duration']]).reshape(-1)
```

[89]:
```python
# Relationship of Duration with Churn
sns.boxplot(data=dataset_train,x='Churn',y='Duration')
plt.show()
# For people who Churn, the median Duration is lower.
```



[ ]:
```python

```

0.3.3 City

[90]:
```python
# Lets look at the unique number of categories for "City" Feature
print(dataset_train['City'].nunique(),"Categories") # There are 29 cities.
print(dataset_train['City'].unique())
```

```
29 Categories
['C4', 'C29', 'C6', 'C9', 'C7', …, 'C5', 'C12', 'C13', 'C11', 'C18']
Length: 29
Categories (29, object): ['C1', 'C10', 'C11', 'C12', …, 'C6', 'C7', 'C8',
'C9']
```

[91]:
```python
# Lets look at the frequecies of the difference categories.
round(dataset_train['City'].value_counts(normalize=True)*100,2)
```

[91]:
```
C20    6.25
C15    4.19
C26    4.19
```

```
C27    4.02
C29    3.92
C16    3.70
C1     3.64
C14    3.64
C10    3.59
C28    3.48
C3     3.43
C8     3.37
C4     3.37
C22    3.26
C21    3.26
C2     3.26
C18    3.26
C5     3.21
C9     3.21
C25    3.15
C12    3.10
C6     3.05
C23    2.99
C24    2.99
C7     2.99
C11    2.94
C19    2.88
C17    2.88
C13    2.77
Name: City, dtype: float64
```

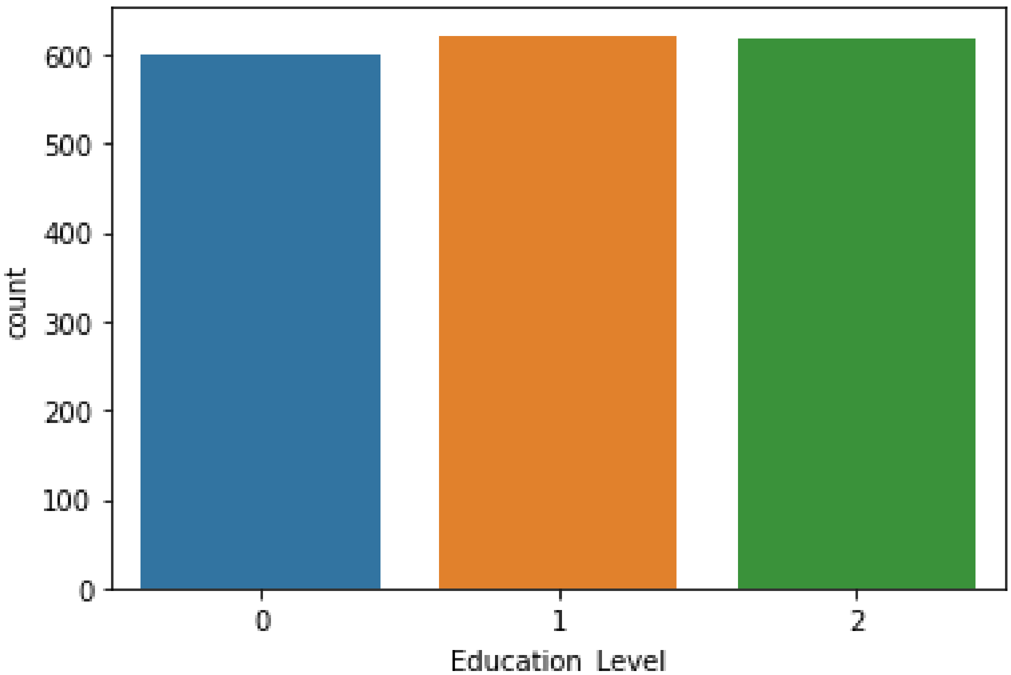
[92]:
```
# We can One-Hot-Encode this categorical column later.
```

[ ]:
```

```

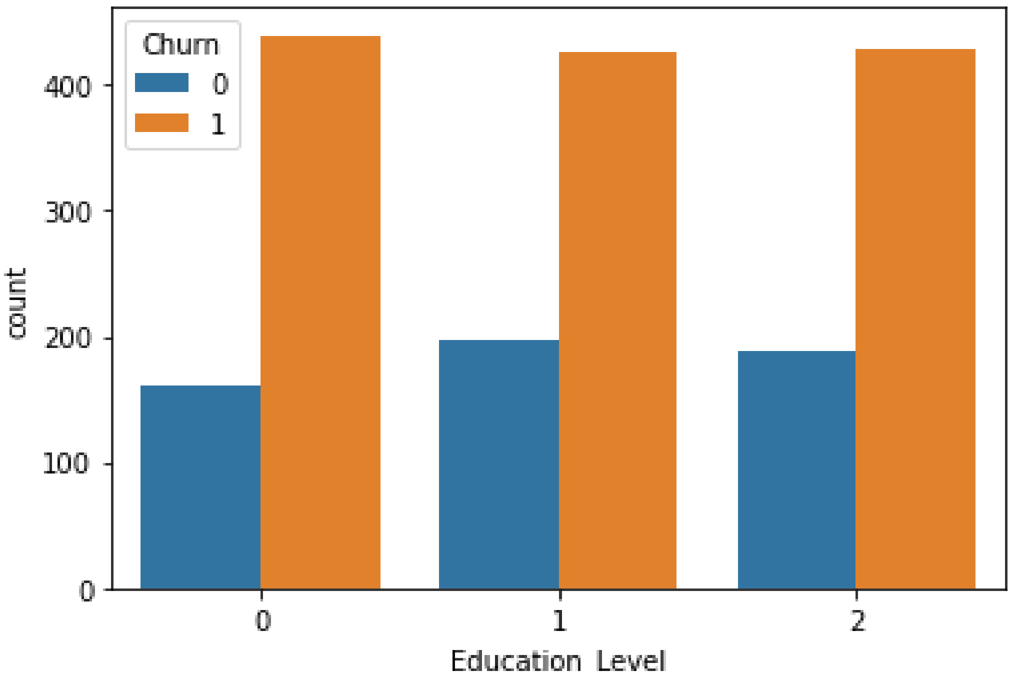
0.3.4 Education_Level

[93]:
```
# Lets check the frequency counts of the different categories of␣
↪"Education_Level" feature.
print(round(100*dataset_train['Education_Level'].
↪value_counts(normalize=True),2))
sns.countplot(dataset_train['Education_Level'])
plt.show()

# The percentages of the different categories appearing are almost same.
```

```
1    33.82
2    33.55
0    32.63
Name: Education_Level, dtype: float64
```



[94]:
```
# Relationship of Churn with Education_Level
sns.countplot(data=dataset_train,hue='Churn',x='Education_Level')
plt.show()

# The ratio of churn to non-churn is little different for Education_Level-0
```



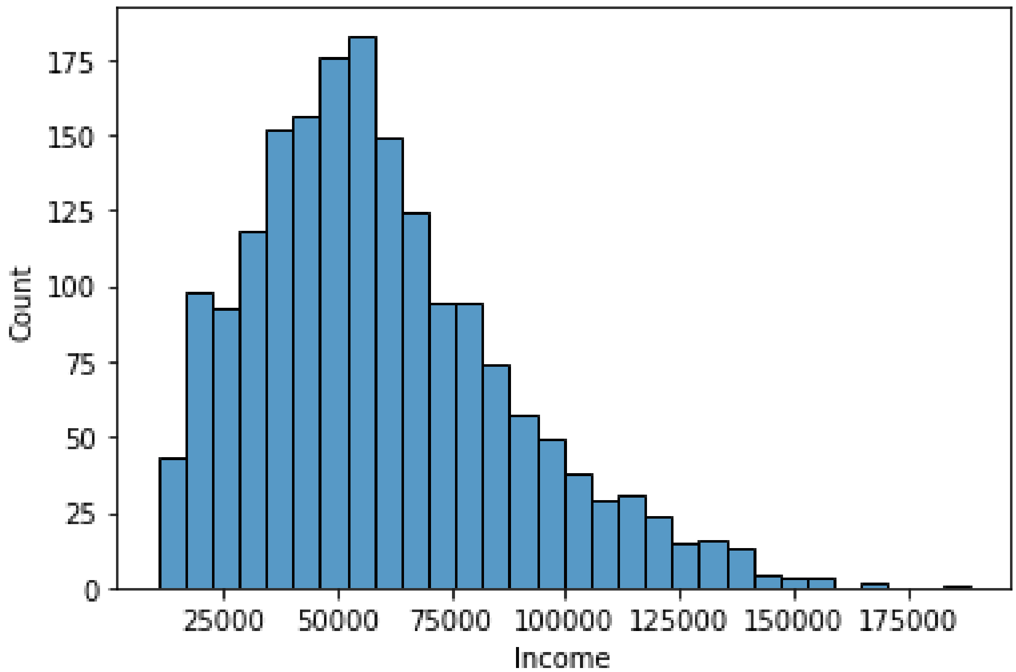
[ ]:

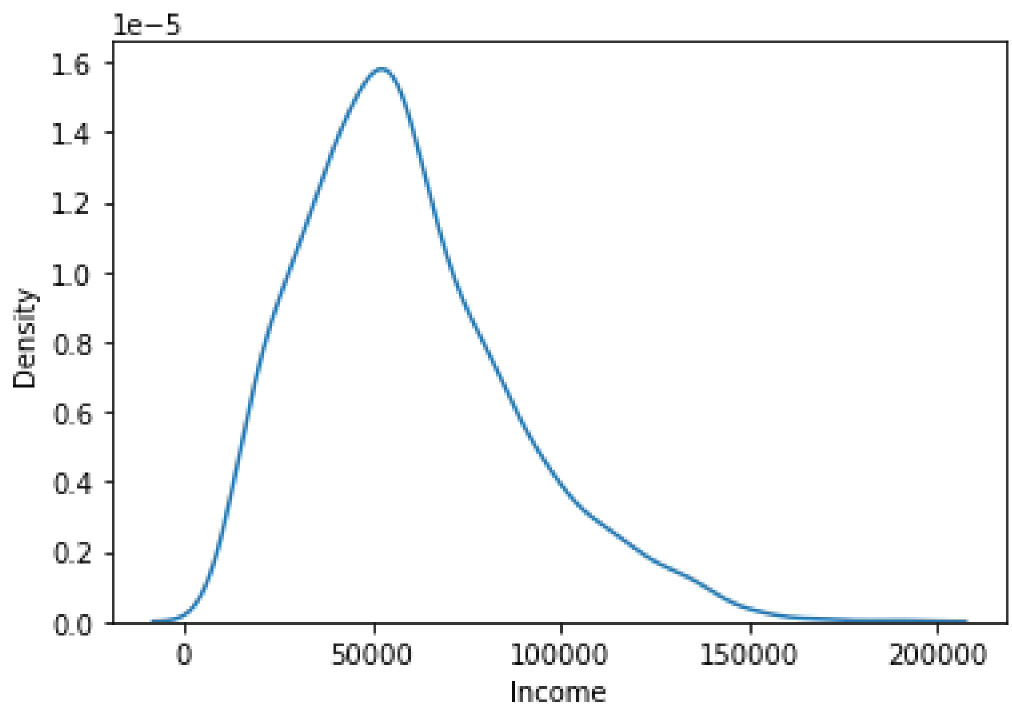
```

```

0.3.5 Income

[95]:

```
# Lets look at the distribution of "Income"
sns.histplot(data=dataset_train,x='Income',bins=30)
plt.show()

sns.kdeplot(data=dataset_train,x='Income')
plt.show()

# The distribution is right skewed.
# We can use Transformation to try to make it Normally Distributed.
```

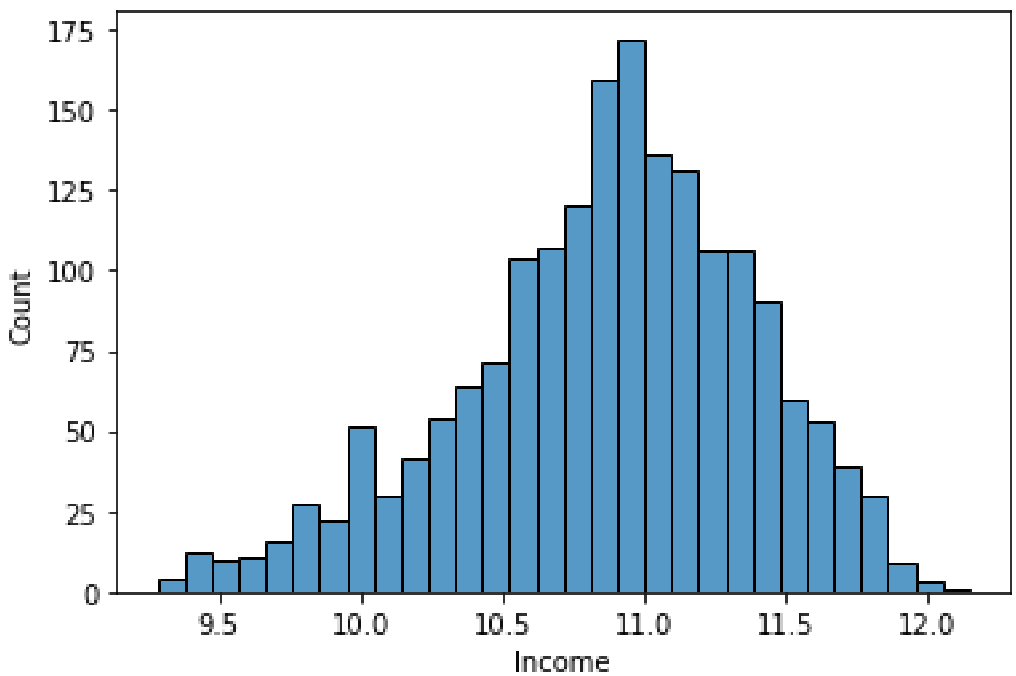

Count
0
25
50
75
100
125
150
175
25000
50000
75000
100000
125000
150000
175000
Income

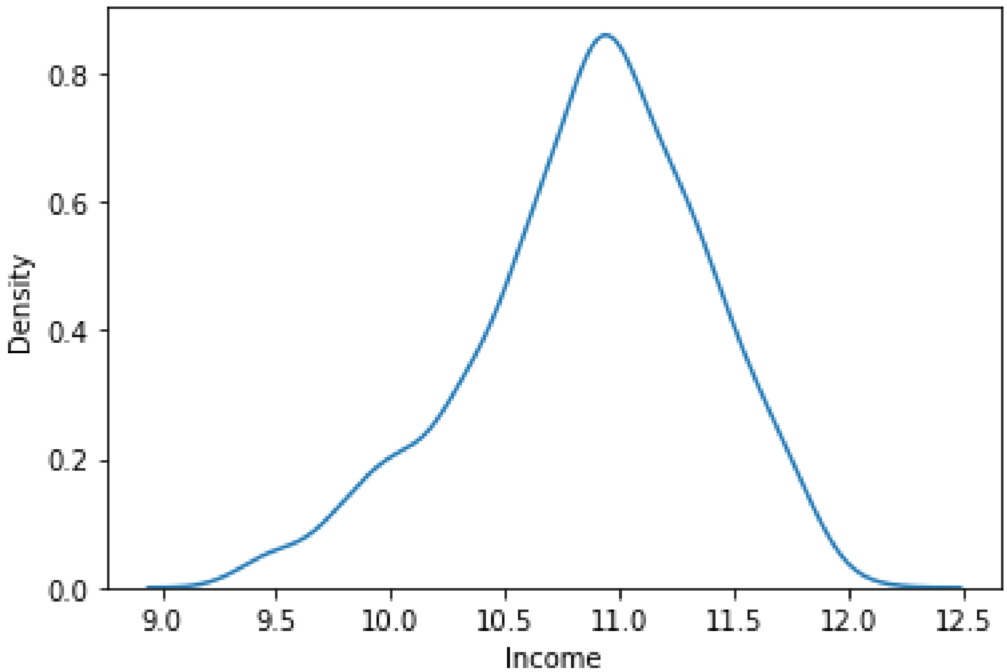

1e−5
Density
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
0
50000
100000
150000
200000
Income

[96]:
```
#Lets check the range of "Income" feature.
dataset_train['Income'].describe()

# We can use Log Transformation to try to make it Normally Distributed.
```

[96]:
```
count      1839.000000
mean      59156.150565
std       28358.625209
min       10747.000000
25%       39111.500000
50%       55108.000000
75%       75380.500000
max      188418.000000
Name: Income, dtype: float64
```

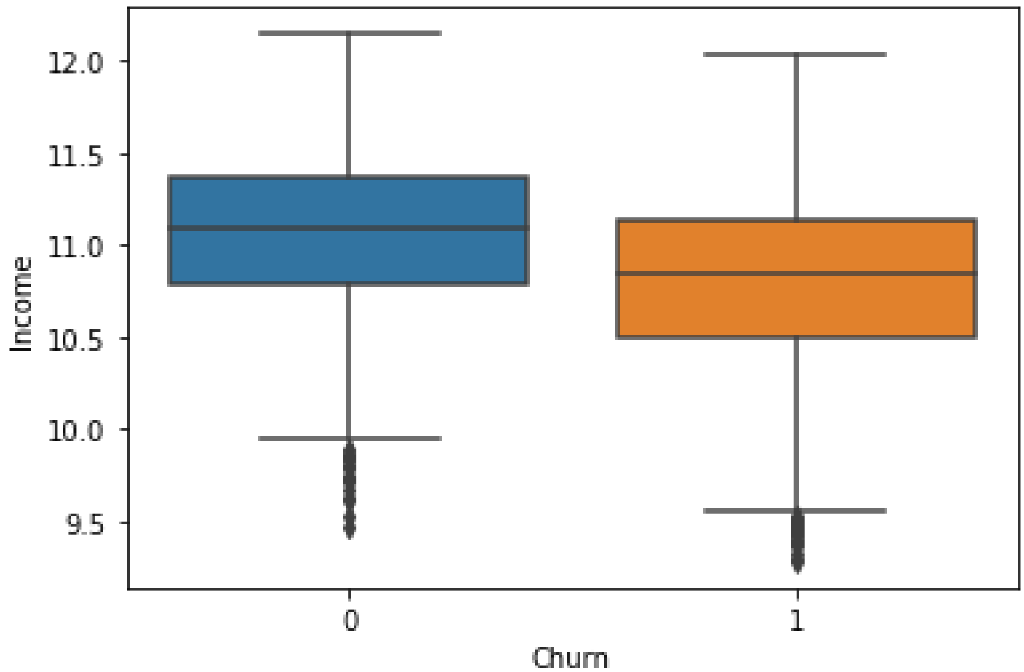
[97]:
```
sns.histplot(np.log(dataset_train['Income']),bins=30)
plt.show()

sns.kdeplot(np.log(dataset_train['Income']))
plt.show()

# After doing Log Transformation, we get a distribution which is almost␣
 ↪Normally Distributed.
# We can use Log transformation on "Income" feature.
```





[98]:
```
# Transforming the "Income" column
dataset_train['Income']=np.log(dataset_train['Income'])
dataset_test['Income']=np.log(dataset_test['Income'])
```

[99]:
```
# Relationship of Income with Churn
sns.boxplot(data=dataset_train,x='Churn',y='Income')
plt.show()
# For people who Churn, the median Income is lower.
```

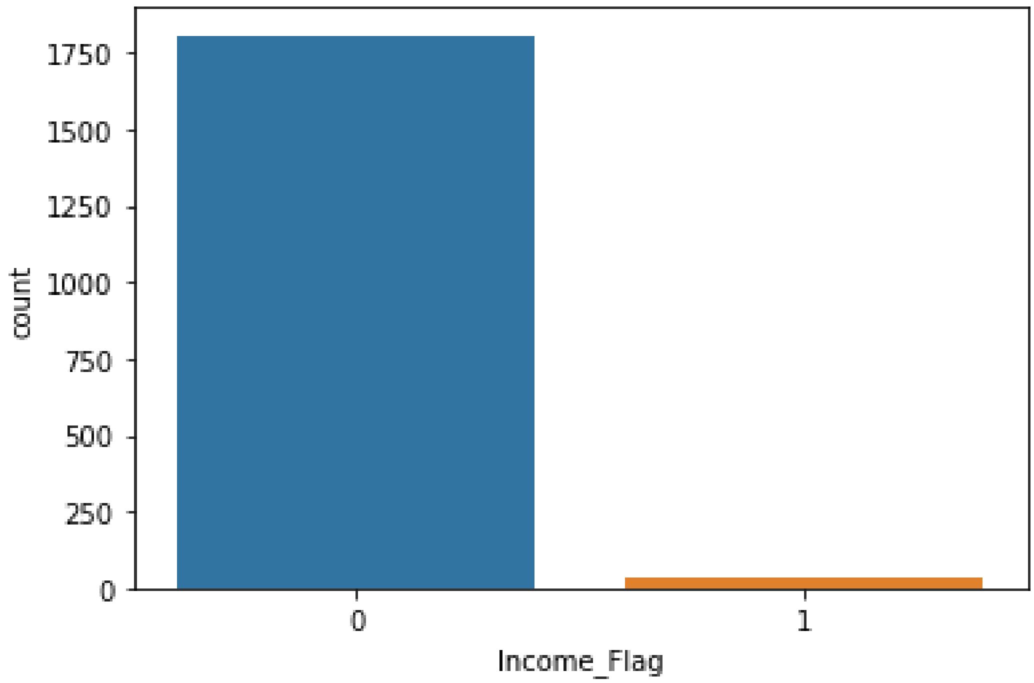


[ ]:

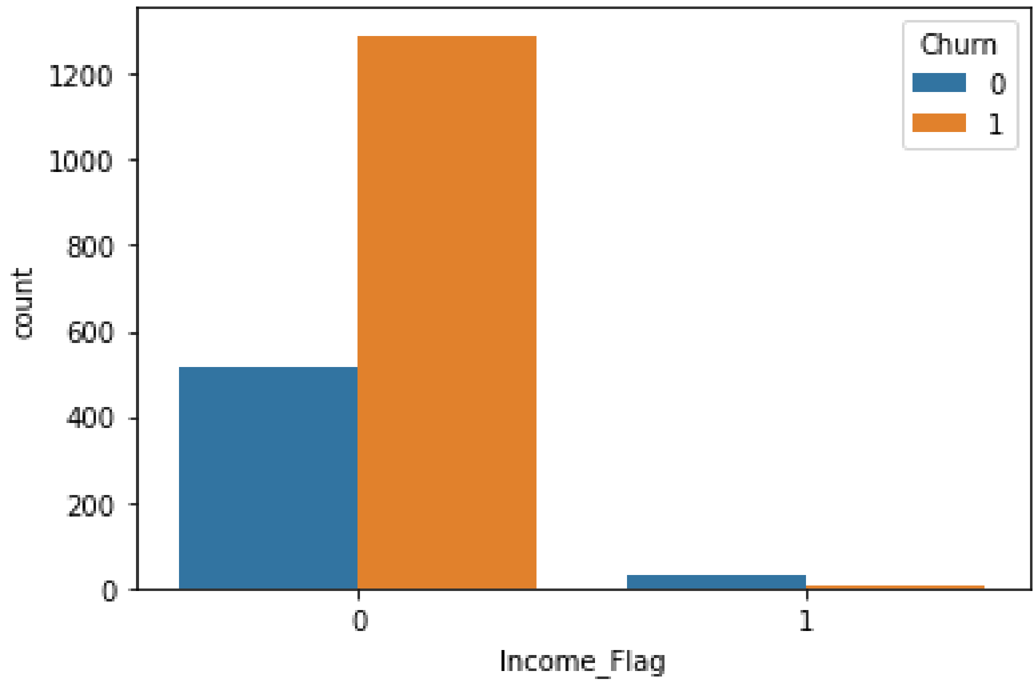
0.3.6 Income_Flag

[100]:
```
# Lets look at the frequecies of the difference categories of "Income_Flag".
print(round(dataset_train['Income_Flag'].value_counts(normalize=True)*100,2))
sns.countplot(dataset_train['Income_Flag'])
plt.show()

# Income Flag-1 signifies that the income of a particular driver has increased␣
↪over time.
# For very few people, the income has increased.
```

```
0    98.26
1     1.74
Name: Income_Flag, dtype: float64
```



[101]:
```
# Relationship of Churn with Income_Flag
sns.countplot(data=dataset_train,hue='Churn',x='Income_Flag')
plt.show()

# The ratio of churn to non-churn is different for different Income_Flag.

pd.
↪crosstab(dataset_train['Churn'],dataset_train['Income_Flag'],normalize='columns')
```



[101]:

Income_Flag	0	1
Churn		
0	0.28611	0.90625
1	0.71389	0.09375

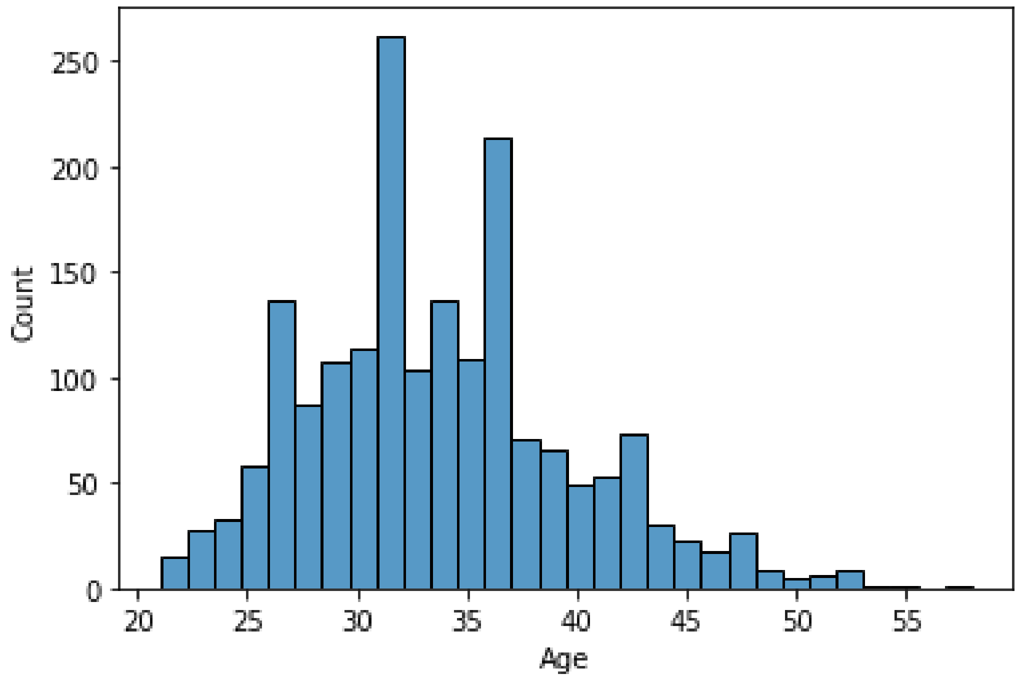
[ ]:

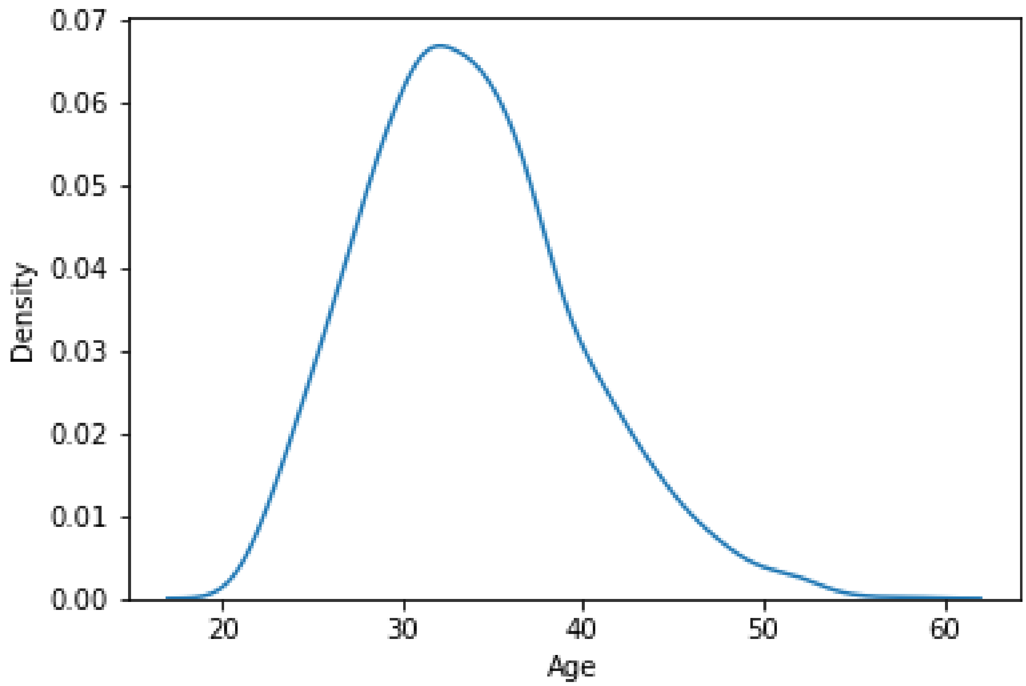
```

```

0.3.7 Age

[102]:

```
# Lets look at the distribution of "Age"
sns.histplot(data=dataset_train,x='Age',bins=30)
plt.show()

sns.kdeplot(data=dataset_train,x='Age')
plt.show()

# The distribution is little right skewed.
# We can use Transformation to try to make it Normally Distributed.
```

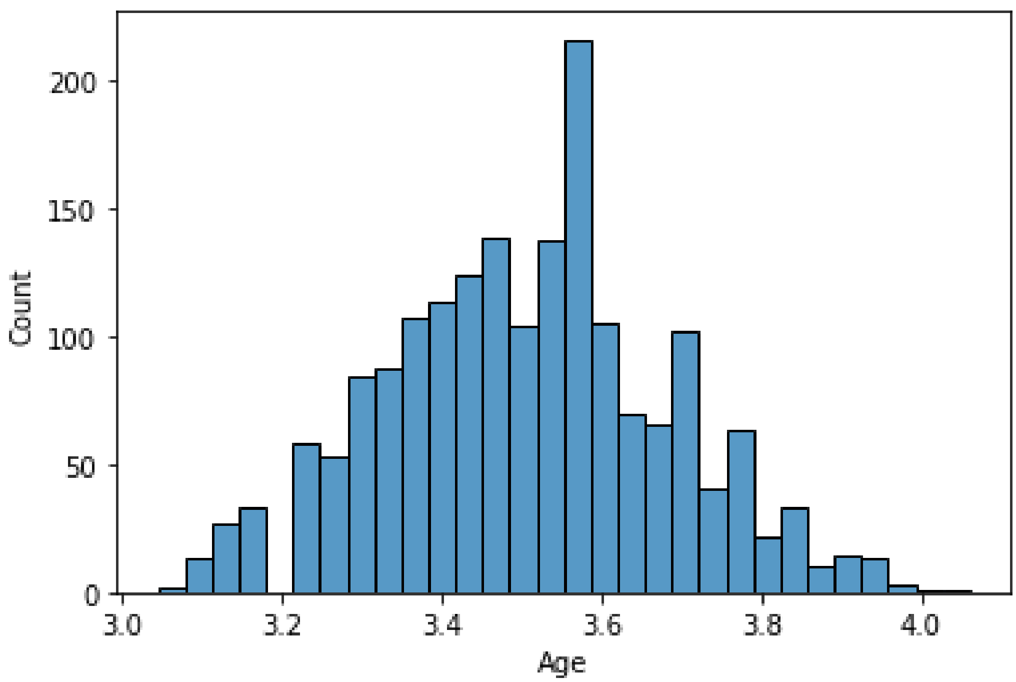

250
200
150
100
50
0
Count
20
25
30
35
40
45
50
55
Age

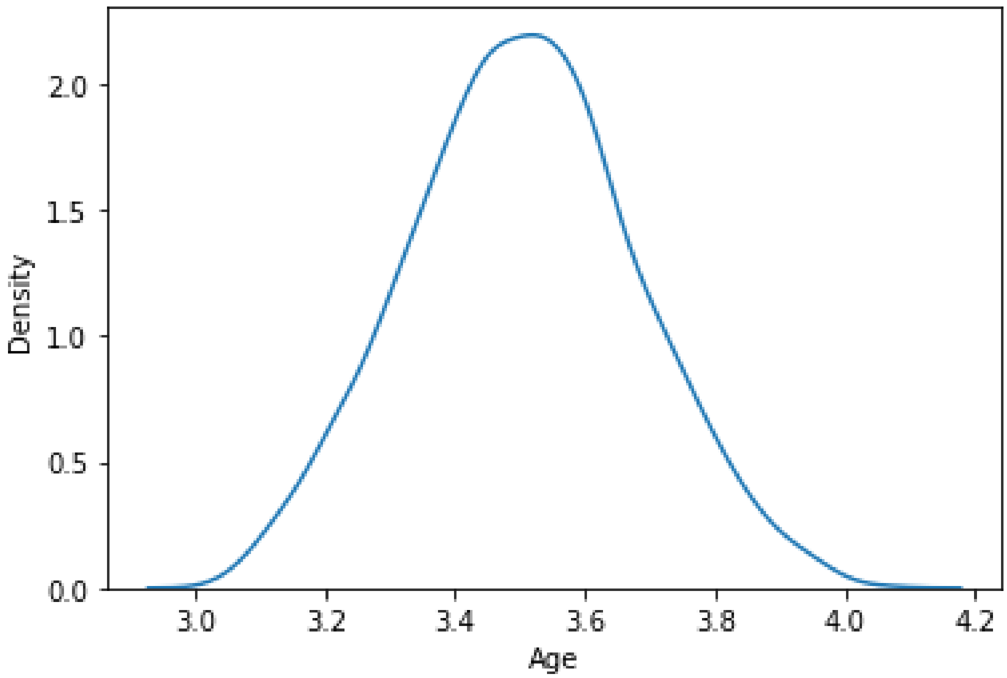

0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
Density
20
30
40
50
60
Age

[103]:
```
#Lets check the range of "Age" feature.
dataset_train['Age'].describe()

# We can use Log Transformation to try to make it Normally Distributed.
```

[103]:
```
count    1839.000000
mean       33.764546
std         6.007660
min        21.000000
25%        29.000000
50%        33.000000
75%        37.000000
max        58.000000
Name: Age, dtype: float64
```

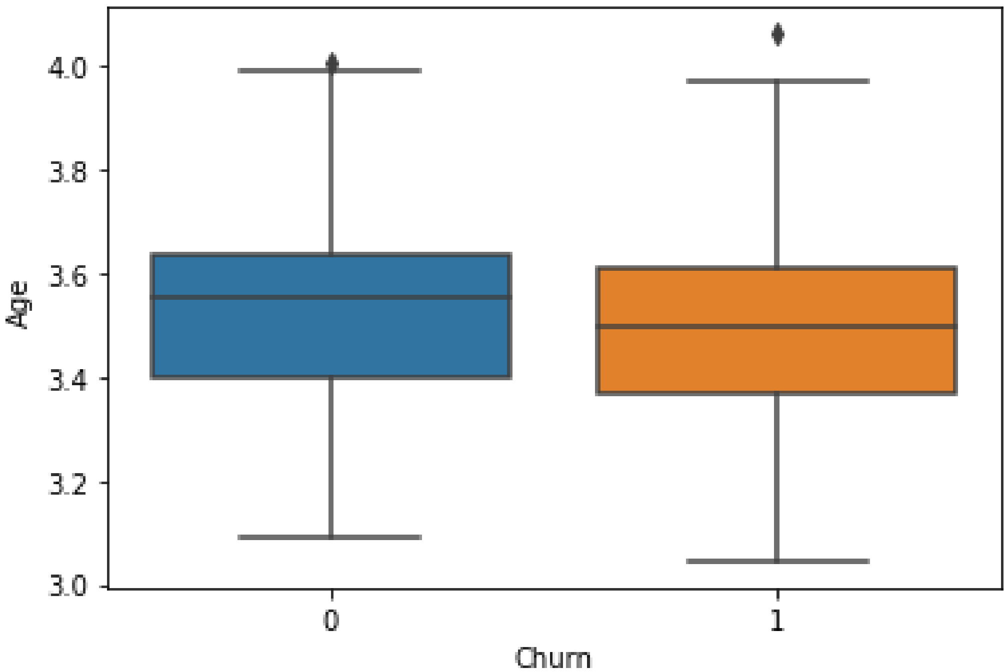
[104]:
```
sns.histplot(np.log(dataset_train['Age']),bins=30)
plt.show()

sns.kdeplot(np.log(dataset_train['Age']))
plt.show()

# After doing Log Transformation, we get a distribution which is almost␣
↪Normally Distributed.
# We can use Log transformation on "Age" feature.
```





[105]:
```
# Transforming the "Income" column
dataset_train['Age']=np.log(dataset_train['Age'])
dataset_test['Age']=np.log(dataset_test['Age'])
```

[106]:
```
# Relationship of Income with Churn
sns.boxplot(data=dataset_train,x='Churn',y='Age')
plt.show()
# For people who Churn, the median Age is lower.
```

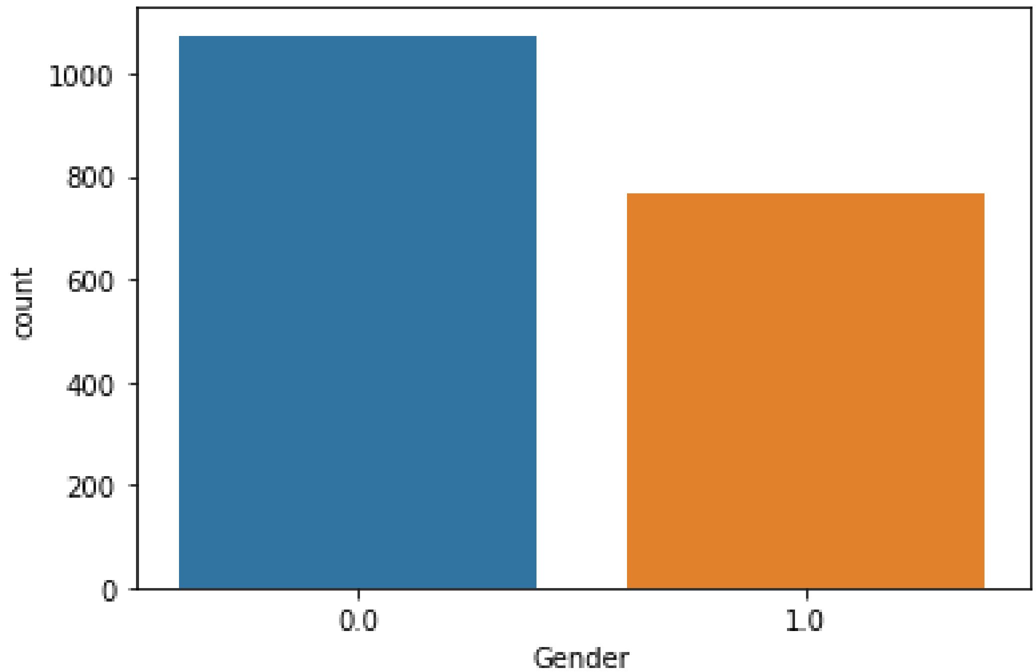



```
[ ]:
```

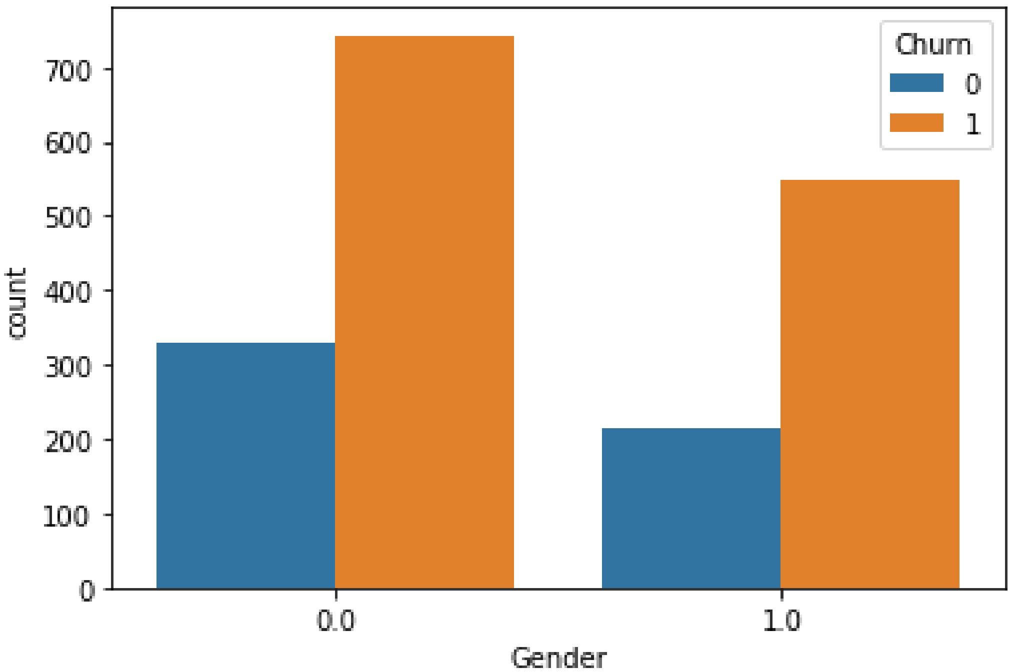
0.3.8 Gender

```
[107]: # Lets look at the frequecies of the difference categories of "Gender".
print(round(dataset_train['Gender'].value_counts(normalize=True)*100,2))
sns.countplot(dataset_train['Gender'])
plt.show()

# Gender-1 signifies that the driver is a female. Female:Male = 60:40
```

```
0.0    58.4
1.0    41.6
Name: Gender, dtype: float64
```



[108]:
```
# Relationship of Gender with Churn

sns.countplot(data=dataset_train,hue='Churn',x='Gender')
plt.show()

# The ratio of churn to non-churn is little different for different Genders.

pd.crosstab(dataset_train['Churn'],dataset_train['Gender'],normalize='columns')
```



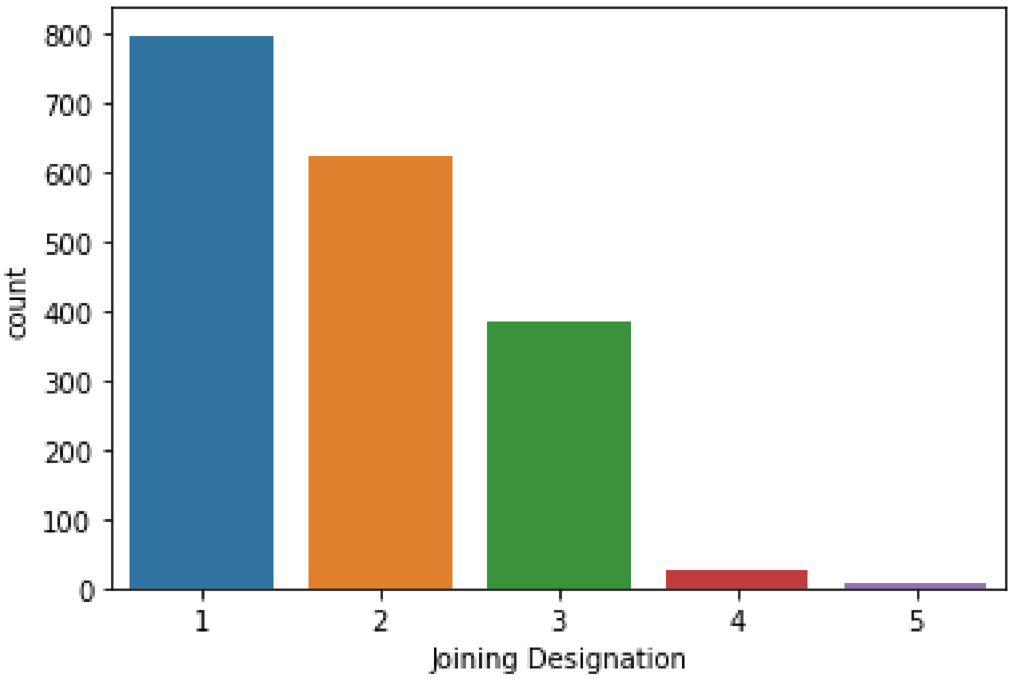

```
[108]: Gender       0.0       1.0
       Churn
       0       0.308194  0.281046
       1       0.691806  0.718954
```

```
[ ]:
```

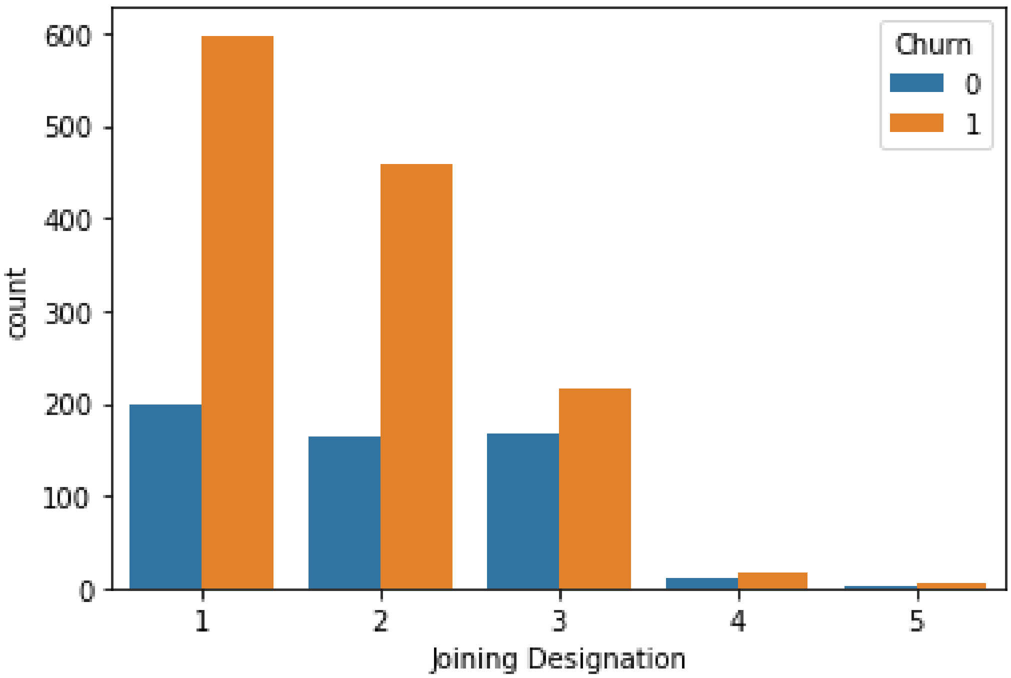
0.3.9 Joining Designation

```
[109]: # Lets check the frequency counts of the different categories of "Joining␣
        ↪Designation" feature.
       print(round(100*dataset_train['Joining Designation'].
        ↪value_counts(normalize=True),2))
       sns.countplot(dataset_train['Joining Designation'])
       plt.show()

       # Most drivers had joined at designations - 1 and 2.
```

```
1    43.39
2    33.82
3    20.83
4     1.52
5     0.44
Name: Joining Designation, dtype: float64
```



[110]:
```
# Relationship of Joining_Designation with Churn

sns.countplot(data=dataset_train,hue='Churn',x='Joining Designation')
plt.show()

# The ratio of churn to non-churn is different for different Joining␣
↪Designations.

pd.crosstab(dataset_train['Churn'],dataset_train['Joining␣
↪Designation'],normalize='columns')
```



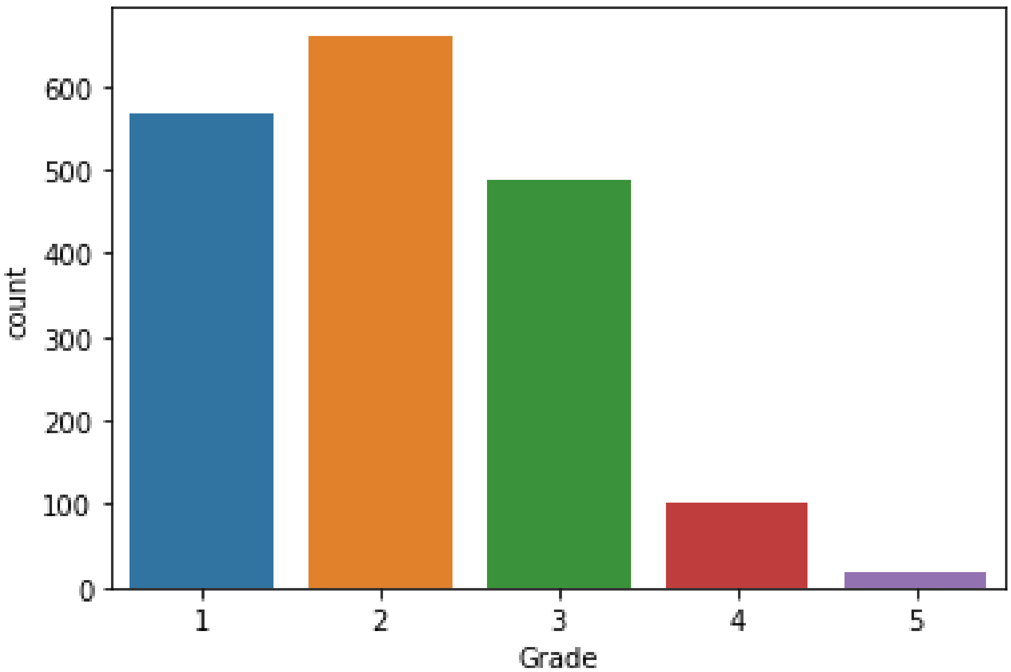
[110]:
```
Joining Designation         1         2         3         4     5
Churn
0                    0.250627  0.263666  0.438642  0.428571  0.25
1                    0.749373  0.736334  0.561358  0.571429  0.75
```

[ ]:

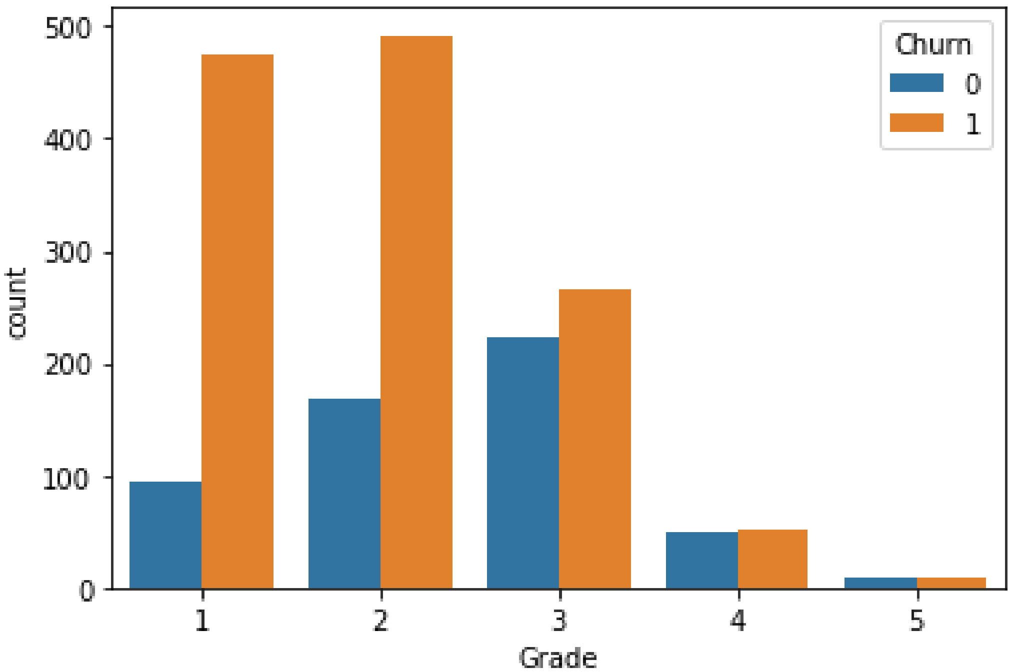
0.3.10 Grade

[111]:
```
# Lets check the frequency counts of the different categories of "Grade"␣
 ↪feature.
print(round(100*dataset_train['Grade'].value_counts(normalize=True),2))
sns.countplot(dataset_train['Grade'])
plt.show()

# Most drivers have current Grade as - 1,2 and 3.
```

```
2    35.94
1    30.94
3    26.54
4     5.49
5     1.09
Name: Grade, dtype: float64
```



[112]:
```
# Relationship of Grade with Churn

sns.countplot(data=dataset_train,hue='Churn',x='Grade')
plt.show()

# The ratio of churn to non-churn is different for different Grades.

pd.crosstab(dataset_train['Churn'],dataset_train['Grade'],normalize='columns')
```



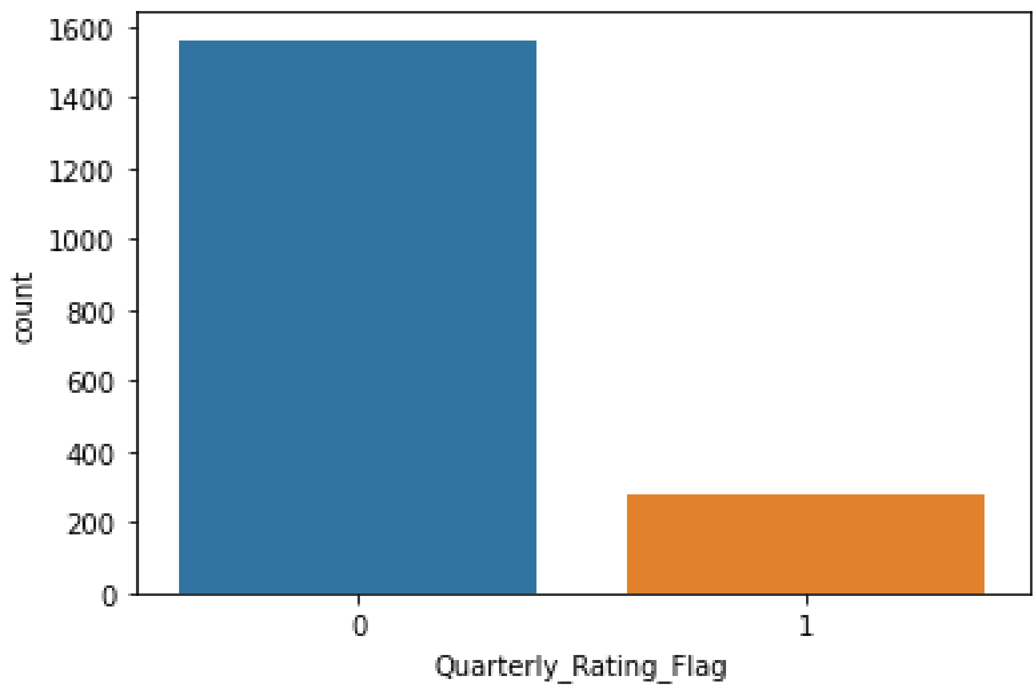

```
[112]: Grade          1         2         3        4    5
       Churn
       0       0.165202  0.255673  0.456967  0.49505  0.5
       1       0.834798  0.744327  0.543033  0.50495  0.5
```

```
[ ]:
```

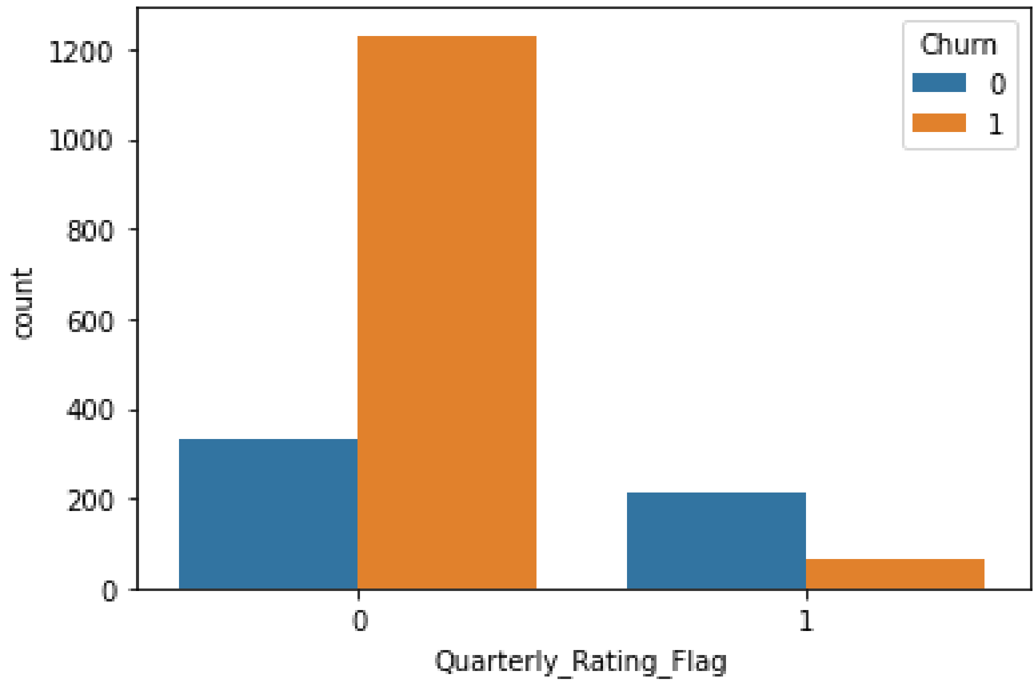
0.3.11 Quarterly_Rating_Flag

```
[113]: # Lets check the frequency counts of the different categories of "Quarterly␣
        ↪Rating" feature.
       print(round(100*dataset_train['Quarterly_Rating_Flag'].
        ↪value_counts(normalize=True),2))
       sns.countplot(dataset_train['Quarterly_Rating_Flag'])
       plt.show()

       # Most drivers have current Grade as - 1,2 and 3.
```

```
0    84.94
1    15.06
Name: Quarterly_Rating_Flag, dtype: float64
```



[114]:
```
# Relationship of Quarterly_Rating_Flag with Churn

sns.countplot(data=dataset_train,hue='Churn',x='Quarterly_Rating_Flag')
plt.show()

# The ratio of churn to non-churn is different for different␣
↪Quarterly_Rating_Flags.

pd.
↪crosstab(dataset_train['Churn'],dataset_train['Quarterly_Rating_Flag'],normalize='columns')
```



[114]:
```
Quarterly_Rating_Flag         0         1
Churn
0                      0.211908  0.776173
1                      0.788092  0.223827
```

[ ]:

0.4 Splitting into X and Y

[115]:
```
# Firstly lets drop the "Driver_ID" column
dataset_train.drop(columns=['Driver_ID'],inplace=True)
dataset_test.drop(columns=['Driver_ID'],inplace=True)
```

[116]:
```
# Splitting into X and Y
X_train=dataset_train.drop(columns=['Churn'])
Y_train=dataset_train['Churn']
X_test=dataset_test.drop(columns=['Churn'])
Y_test=dataset_test['Churn']
```

[ ]:

0.5 Encoding

[117]:
```
# Lets decide on which features to do Encoding.
X_train[categorical_columns].head()

# Only "City" feature need One Hot Encoding.
```

[117]:
```
      City Education_Level Income_Flag Gender Joining Designation Grade  \
731     C4               1           0    0.0                   1     1
1793   C29               2           0    0.0                   3     3
177     C6               2           0    1.0                   3     3
28     C29               2           0    0.0                   4     4
272     C9               0           0    1.0                   2     2

      Quarterly_Rating_Flag
731                       0
1793                      1
177                       0
28                        1
272                       0
```

[ ]:

0.6 Creating Transformer

[118]:
```
# Lets use a Transformer, for OneHotEncoding categorical columns and for␣
 ↪Scaling Numerical Columns.

transformer=ColumnTransformer(transformers=[
    ('scaling',StandardScaler(),continuous_columns),
   ␣
 ↪('one_hot_encoding',OneHotEncoder(drop='first',sparse=False,handle_unknown='ignore'),['City
    ],remainder="passthrough")
```

[119]:
```
# Transformed Data
X_train_transformed=transformer.fit_transform(X_train)
X_test_transformed=transformer.transform(X_test)
```

[ ]:

0.7 Handling Imabalanced Data using SMOTE

[120]:
```
# Getting Balanced Data using SMOTE.
smote_model=SMOTE(sampling_strategy='minority',random_state=42)
X_train_transformed_SMOTE,Y_train_SMOTE=smote_model.
 ↪fit_resample(X_train_transformed,Y_train)
```

[ ]:

1 Model 1 - Random Forests

[121]:
```
# Creating a Random_Forest Model.
rf_model=RandomForestClassifier()

# Creating a parameters_list to do Hyperparameter Tuning
parameters = {
    'n_estimators': [15,20,25,30,35,40,45,50],
    'max_depth':[9,10,11,12,13,14]}

# Creating a Grid_Search Object
model=GridSearchCV(rf_model,parameters,scoring='accuracy',cv=5)
model.fit(X_train_transformed_SMOTE,Y_train_SMOTE)

print(model.best_params_)
print(model.best_score_)
```

```
{'max_depth': 14, 'n_estimators': 45}
0.887490198128496
```

[122]:
```
# Using Grid_Search, the best accuracy that we are getting is 88.6 percent.
```

[ ]:

2 Model 2 - XGBoost

[123]:
```
# Creating a XGBoost Model.
xgb_model=XGBClassifier()

# Creating a parameters_list to do Hyperparameter Tuning
parameters = {
    'n_estimators': [15,20,25,30,35,40,45,50],
    'max_depth':[9,10,11,12,13,14],
    'learning_rate':[0.5,0.75,1]}

# Creating a Grid_Search Object
model=GridSearchCV(xgb_model,parameters,scoring='accuracy',cv=5)
model.fit(X_train_transformed_SMOTE,Y_train_SMOTE)

print(model.best_params_)
print(model.best_score_)
```

```
{'learning_rate': 0.5, 'max_depth': 14, 'n_estimators': 50}
0.8932891720125763
```

[124]:
```
# Using Grid_Search, the best accuracy that we are getting is 89.3 percent.
```

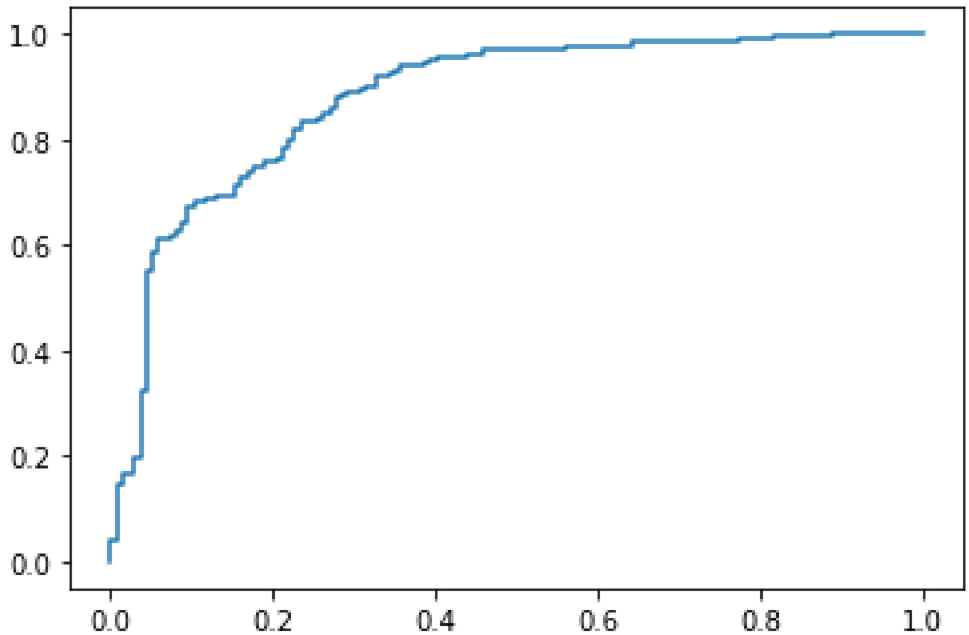
[125]:
```
#Since the XGBoost model has a better validation score, we can therefore use␣
↪this model for determining the test_set accuracy

# Creating the final XGBoost model to find test dataset accuracy.
model=XGBClassifier(learning_rate= 0.5, max_depth= 14, n_estimators= 50)

#Fitting the model
model.fit(X_train_transformed_SMOTE,Y_train_SMOTE)

# Predicting Test Dataset Accuracy
print("Accuracy:",model.score(X_test_transformed,Y_test))
# The test dataset accuracy is 84.3 percent, which is a good score.

# Getting the Predictions
Y_pred=model.predict(X_test_transformed)

# Getting the probabilities.
Y_pred_prob=model.predict_proba(X_test_transformed)
```

```
Accuracy: 0.8434782608695652
```

[126]:
```
# Getting the ROC_AUC Score.
roc_auc_score(Y_test,Y_pred_prob[:,1])

# A ROC_AUC score 0.88 is very good.
```

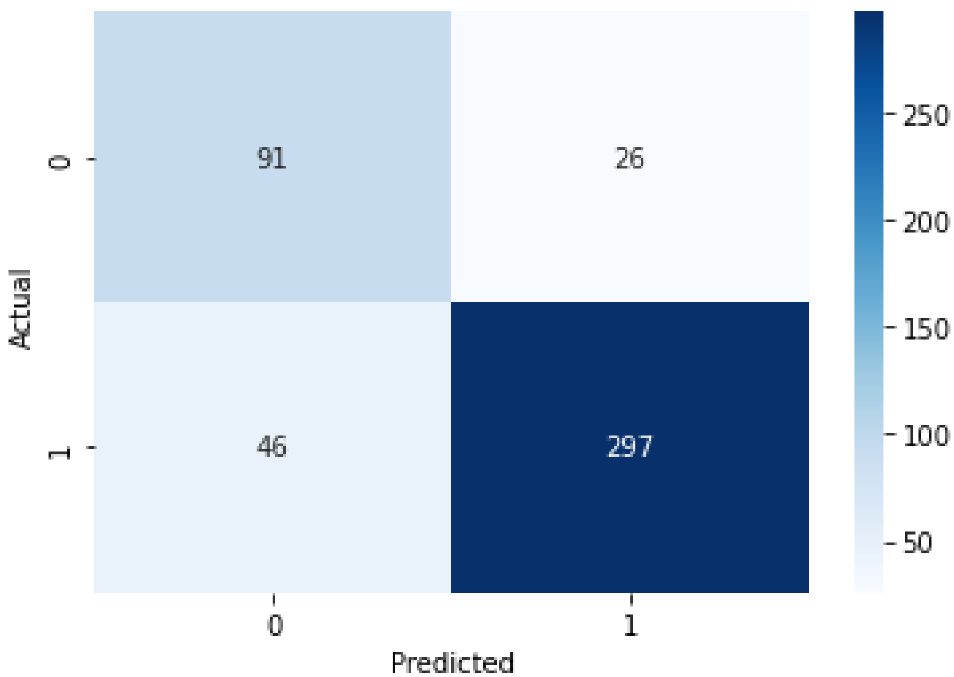
[126]: 0.8788049987570903

[127]:
```
# ROC_AUC_Curve.
fpr,tpr,thres=roc_curve(Y_test,Y_pred_prob[:,1])
plt.plot(fpr,tpr)
plt.show()

# The curve is close to the ideal model curve
```



[ ]:

[128]:
```
# Confusion Matrix
sns.heatmap(pd.crosstab(Y_pred,Y_test),annot=True,fmt='g',cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel("Actual")
plt.show()
```



[ ]:

2.1 Insights & Recommendations

- Our XGBoost model has an accuracy of almost 85% and ROC_AUC score of almost 88%. Doing better prepreocessing and feature transformation, engineering might help increase the model's performance even further.
- Duration is an important feature to determine Churn. Drivers who stay longer have a lower chance of leaving Ola. Ola can give more salary or other perks to make drivers stay longer. Income is a very important feature to determine Churn. Drivers who have a lower income are more probable to Churn.
- Almost 90 percent of drivers who had got a raise from Ola did not Churn. This can be an important point where Ola can give incentives and lucrative hikes to retain their drivers.
- Most drivers who Churn are relatively younger than those who don't. Ola can try to give certain goodies or hampers which can cater to the young drivers.
- Drivers who either join as Amateurs or as Highly Experienced have more chance of leaving. Ola can pay more to experienced drivers to earn their loyalty and can give lucrative incentives to young drivers to make them stay longer.
- Drivers with lower grades are more probable to Churn. Ola can increase their Grades after satisfactory performance to make drivers continue with Ola.
- Drivers whose Quarterly ratings had an increase had a 75 percent chance of not Churning. Therefore better hikes and ratings can also be an important factor to motivate drivers to continue with Ola.

[ ]: