Problem Statement

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, grad
e, Income)
```

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# metrics
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import roc_curve
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
```

In [3]:
```
df=pd.read_csv("")
```

In [4]:
```
df.head()
```

Out[4]:

	Unnamed: 0	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value
0	0	01/01/19	1	28.0	0.0	C23	2	57387	24/12/18	NaN	1	1	2381060
1	1	02/01/19	1	28.0	0.0	C23	2	57387	24/12/18	NaN	1	1	-665480
2	2	03/01/19	1	28.0	0.0	C23	2	57387	24/12/18	03/11/19	1	1	0
3	3	11/01/20	2	31.0	0.0	C7	2	67016	11/06/20	NaN	2	2	0
4	4	12/01/20	2	31.0	0.0	C7	2	67016	11/06/20	NaN	2	2	0

In [5]:
```
df.shape
```

Out[5]:
```
(19104, 14)
```

In [6]:
```
df.columns
```

Out[6]:
```
Index(['Unnamed: 0', 'MMM-YY', 'Driver_ID', 'Age', 'Gender', 'City',
       'Education_Level', 'Income', 'Dateofjoining', 'LastWorkingDate',
       'Joining Designation', 'Grade', 'Total Business Value',
       'Quarterly Rating'],
      dtype='object')
```

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19104 entries, 0 to 19103
Data columns (total 14 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Unnamed: 0            19104 non-null  int64  
 1   MMM-YY                19104 non-null  object 
 2   Driver_ID             19104 non-null  int64  
 3   Age                   19043 non-null  float64
 4   Gender                19052 non-null  float64
 5   City                  19104 non-null  object 
 6   Education_Level       19104 non-null  int64  
 7   Income                19104 non-null  int64  
 8   Dateofjoining         19104 non-null  object 
 9   LastWorkingDate       1616 non-null   object 
 10  Joining Designation   19104 non-null  int64  
 11  Grade                 19104 non-null  int64  
 12  Total Business Value  19104 non-null  int64  
 13  Quarterly Rating      19104 non-null  int64  
dtypes: float64(2), int64(8), object(4)
memory usage: 2.0+ MB
```

In [8]:
```
df.describe()
```

Out[8]:

	Unnamed: 0	Driver_ID	Age	Gender	Education_Level	Income	Joining Designation	Grade	Total Business Value	
count	19104.000000	19104.000000	19043.000000	19052.000000	19104.000000	19104.000000	19104.000000	19104.000000	1.910400e+04	191(
mean	9551.500000	1415.591133	34.668435	0.418749	1.021671	65652.025126	1.690536	2.252670	5.716621e+05	
std	5514.994107	810.705321	6.257912	0.493367	0.800167	30914.515344	0.836984	1.026512	1.128312e+06	
min	0.000000	1.000000	21.000000	0.000000	0.000000	10747.000000	1.000000	1.000000	-6.000000e+06	
25%	4775.750000	710.000000	30.000000	0.000000	0.000000	42383.000000	1.000000	1.000000	0.000000e+00	
50%	9551.500000	1417.000000	34.000000	0.000000	1.000000	60087.000000	1.000000	2.000000	2.500000e+05	
75%	14327.250000	2137.000000	39.000000	1.000000	2.000000	83969.000000	2.000000	3.000000	6.997000e+05	
max	19103.000000	2788.000000	58.000000	1.000000	2.000000	188418.000000	5.000000	5.000000	3.374772e+07	

In [9]:
```
lis=['City','Grade','Joining Designation','Education_Level','Gender','Quarterly Rating']

for i in lis:
    print(i, ': ',df[i].unique())
    print()
```

```
City :  ['C23' 'C7' 'C13' 'C9' 'C11' 'C2' 'C19' 'C26' 'C20' 'C17' 'C29' 'C10'
 'C24' 'C14' 'C6' 'C28' 'C5' 'C18' 'C27' 'C15' 'C8' 'C25' 'C21' 'C1' 'C4'
 'C3' 'C16' 'C22' 'C12']

Grade :  [1 2 3 4 5]

Joining Designation :  [1 2 3 4 5]

Education_Level :  [2 0 1]

Gender :  [ 0.  1. nan]

Quarterly Rating :  [2 1 4 3]
```

Data Preprocessing-1

Dropping unwanted column

In [10]:
```
df.drop(columns='Unnamed: 0',inplace=True)
```

KNN Imputing Data-Handling Missing Value

In [11]:
```
df.isnull().sum()
```

Out[11]:
```
MMM-YY                      0
Driver_ID                   0
Age                        61
Gender                     52
City                        0
Education_Level             0
Income                      0
Dateofjoining               0
LastWorkingDate         17488
Joining Designation         0
Grade                       0
Total Business Value        0
Quarterly Rating            0
dtype: int64
```

Presence of null value. To be handled

In [12]:
```
immuting_df=df.drop(columns=['MMM-YY','LastWorkingDate','Dateofjoining','City'])
```

In [13]:
```
from sklearn.impute import KNNImputer

imputer = KNNImputer(n_neighbors=3)
```

In [14]:
```
col=immuting_df.columns
immuting_df=imputer.fit_transform(immuting_df)
immuting_df=pd.DataFrame(immuting_df,columns=col)
```

In [15]:
```
df['Age']=immuting_df['Age']
```

In [16]:
```
df.isnull().sum()
```

Out[16]:
```
MMM-YY                      0
Driver_ID                   0
Age                         0
Gender                     52
City                        0
Education_Level             0
Income                      0
Dateofjoining               0
LastWorkingDate         17488
Joining Designation         0
Grade                       0
Total Business Value        0
Quarterly Rating            0
dtype: int64
```

Label Encoding of city

In [17]:
```
from sklearn.preprocessing import LabelEncoder
```

In [18]:
```
le = LabelEncoder()
df['City']=le.fit_transform(df['City'])
```

In [19]:
```
df.head()
```

Out[19]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value	Quarterly Rating
0	01/01/19	1	28.0	0.0	15	2	57387	24/12/18	NaN	1	1	2381060	2
1	02/01/19	1	28.0	0.0	15	2	57387	24/12/18	NaN	1	1	-665480	2
2	03/01/19	1	28.0	0.0	15	2	57387	24/12/18	03/11/19	1	1	0	2
3	11/01/20	2	31.0	0.0	26	2	67016	11/06/20	NaN	2	2	0	1
4	12/01/20	2	31.0	0.0	26	2	67016	11/06/20	NaN	2	2	0	1

Coverting to date time

In [20]:
```
df['MMM-YY']=pd.to_datetime(df['MMM-YY'])
```

In [21]:
```
df['Dateofjoining']=pd.to_datetime(df['Dateofjoining'])
```

In [22]:
```
df['LastWorkingDate']=pd.to_datetime(df['LastWorkingDate'])
```

Aggregating at drivers level

In [23]:
```
agg={
    'Age':['max'],
    'Gender':["first"],
    'City':["first"],
    'Education_Level':['last'],
    'Income':['mean'],
    'Dateofjoining':['min'],
    'LastWorkingDate':['max'],
    'Joining Designation':['min'],
    'Grade':['max'],
    'Total Business Value':['sum'],
    'Quarterly Rating':['mean']

}
```

In [24]:
```
groups = df.groupby('Driver_ID')
```

In [25]:
```
df_grp = df.groupby(by='Driver_ID', as_index=False).aggregate(agg)
df_grp.columns = df_grp.columns.droplevel(level=1)
```

In [26]:
```
#df.drop(columns='Driver_ID',inplace=True)
```

In [27]:
```python
df_grp.head(10)
```

Out[27]:

	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value	Quarterly Rating
0	1	28.0	0.0	15	2	57387.0	2018-12-24	2019-03-11	1	1	1715580	2.00000
1	2	31.0	0.0	26	2	67016.0	2020-11-06	NaT	2	2	0	1.00000
2	4	43.0	0.0	4	2	65603.0	2019-12-07	2020-04-27	2	2	350000	1.00000
3	5	29.0	0.0	28	0	46368.0	2019-01-09	2019-03-07	1	1	120360	1.00000
4	6	31.0	1.0	2	1	78728.0	2020-07-31	NaT	3	3	1265000	1.60000
5	8	34.0	0.0	11	0	70656.0	2020-09-19	2020-11-15	3	3	0	1.00000
6	11	28.0	1.0	10	2	42172.0	2020-12-07	NaT	1	1	0	1.00000
7	12	35.0	0.0	15	2	28116.0	2019-06-29	2019-12-21	1	1	2607180	2.50000
8	13	31.0	0.0	10	2	119227.0	2015-05-28	2020-11-25	1	4	10213040	1.26087
9	14	39.0	1.0	18	0	19734.0	2020-10-16	NaT	3	3	0	1.00000

Creating a column which tells whether the quarterly rating has increased for that driver - for those whose quarterly rating has increased we assign the value 1

In [28]:
```python
df_grp['Rating_Increase']=0
```

In [29]:
```python
groups = df.groupby('Driver_ID')
for name, group in groups:
    ratings = group['Quarterly Rating'].tolist()
    # check if the rating values are increasing or have at least one increase
    if any(x < y for x, y in zip(ratings, ratings[1:])):
        df_grp.loc[(df_grp['Driver_ID'] == name), 'Rating_Increase'] = 1
```

Creating a column which tells whether the quarterly rating has decreased for that driver - for those whose quarterly rating has decresed we assign the value 1

In [30]:
```
df_grp['Rating_Decrease']=0
```

In [31]:
```
groups = df.groupby('Driver_ID')
for name, group in groups:
    ratings = group['Quarterly Rating'].tolist()
    # check if the rating values are increasing or have at least one increase
    if any(x > y for x, y in zip(ratings, ratings[1:])):
        df_grp.loc[(df_grp['Driver_ID'] == name), 'Rating_Decrease'] = 1
```

Creating a column which tells whether the monthly income has increased for that driver - for those whose monthly income has increased we assign the value 1

In [32]:
```
df_grp['Monthly_Income_Increase']=0
```

In [33]:
```
groups = df.groupby('Driver_ID')
for name, group in groups:
    monthly_income = group['Income'].tolist()
    # check if the rating values are increasing or have at least one increase
    if any(x < y for x, y in zip( monthly_income,  monthly_income[1:])):
        df_grp.loc[(df_grp['Driver_ID'] == name), 'Monthly_Income_Increase'] = 1
```

In [34]:
```
df_grp.describe()
```

Out[34]:

	Driver_ID	Age	Gender	City	Education_Level	Income	Joining Designation	Grade	Total Business Value	Quarterl Ratin
count	2381.000000	2381.000000	2381.000000	2381.000000	2381.00000	2381.000000	2381.000000	2381.000000	2.381000e+03	2381.00000
mean	1397.559009	33.759765	0.410332	14.074339	1.00756	59232.460484	1.820244	2.097018	4.586742e+06	1.56630
std	806.161628	5.944614	0.491997	8.252167	0.81629	28298.214012	0.841433	0.941702	9.127115e+06	0.71965
min	1.000000	21.000000	0.000000	0.000000	0.00000	10747.000000	1.000000	1.000000	-1.385530e+06	1.00000
25%	695.000000	30.000000	0.000000	7.000000	0.00000	39104.000000	1.000000	1.000000	0.000000e+00	1.00000
50%	1400.000000	33.000000	0.000000	14.000000	1.00000	55285.000000	2.000000	2.000000	8.176800e+05	1.00000
75%	2100.000000	37.000000	1.000000	21.000000	2.00000	75835.000000	2.000000	3.000000	4.173650e+06	2.00000
max	2788.000000	58.000000	1.000000	28.000000	2.00000	188418.000000	5.000000	5.000000	9.533106e+07	4.00000

Duplicate value check

In [35]:
```
df.shape
```

Out[35]: (19104, 13)

In [36]:
```
df.drop_duplicates(inplace=True)
```

In [37]:
```
df.shape
```

Out[37]: (19104, 13)

In [ ]:

Adding feature of grade change

In [38]:
```
df_grp['Grade_Change']=df_grp['Grade']-df_grp['Joining Designation']
```

Adding Target feature of churning

In [39]:
```
df_grp['churn']=df_grp['LastWorkingDate'].isnull().astype(int)
# 1: not resigned
# 2: resigned
```

Adding feature of tenure

In [40]:
```
df_grp['tenure']=(df_grp['LastWorkingDate']-df_grp['Dateofjoining']).dt.days
```

In [41]:
```
df_grp.drop(columns='LastWorkingDate',inplace=True)
```

In [42]:
```
df_grp.drop(columns="Dateofjoining",inplace=True)
```

In [43]:
```
df_grp.head()
```

Out[43]:

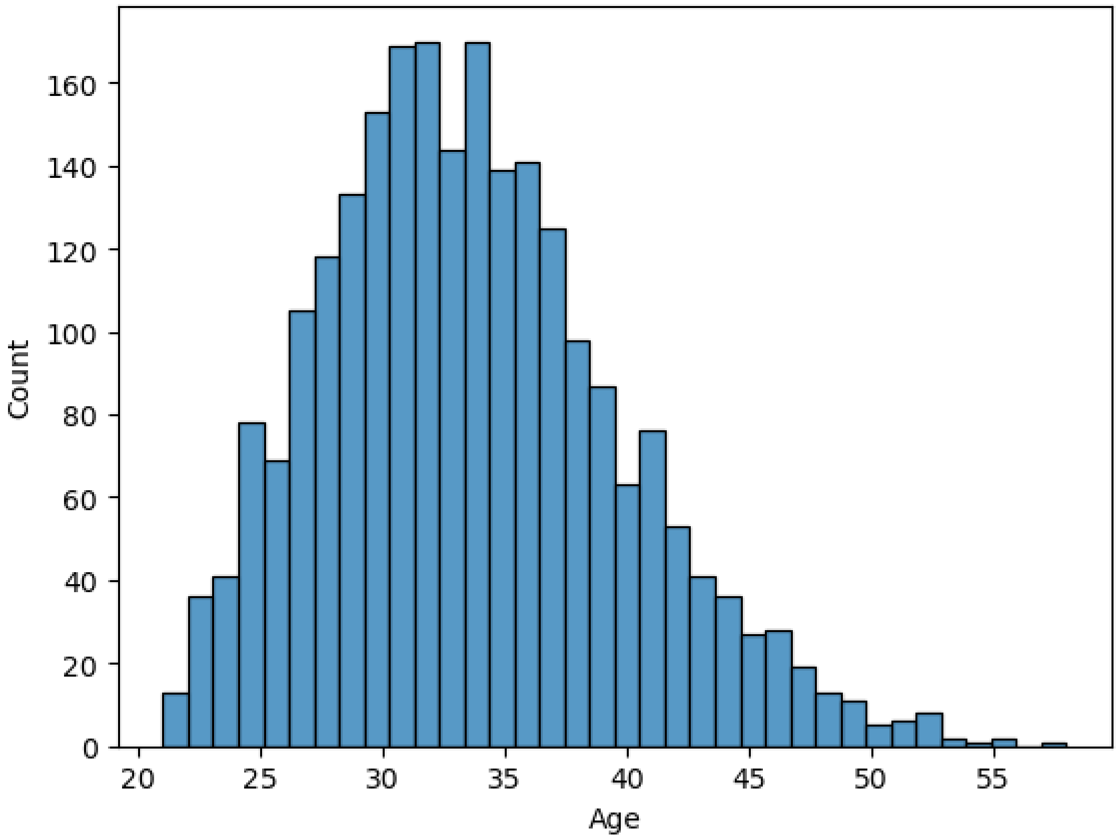
	Driver_ID	Age	Gender	City	Education_Level	Income	Joining Designation	Grade	Total Business Value	Quarterly Rating	Rating_Increase	Rating_Decrease	Monthly_
0	1	28.0	0.0	15	2	57387.0	1	1	1715580	2.0	0	0	
1	2	31.0	0.0	26	2	67016.0	2	2	0	1.0	0	0	
2	4	43.0	0.0	4	2	65603.0	2	2	350000	1.0	0	0	
3	5	29.0	0.0	28	0	46368.0	1	1	120360	1.0	0	0	
4	6	31.0	1.0	2	1	78728.0	3	3	1265000	1.6	1	0	

In [44]:
```python
df_grp['tenure'] = df_grp['tenure'].fillna(0)
```

Univariate Analysis

In [45]:
```python
sns.histplot(df_grp['Age'])
```

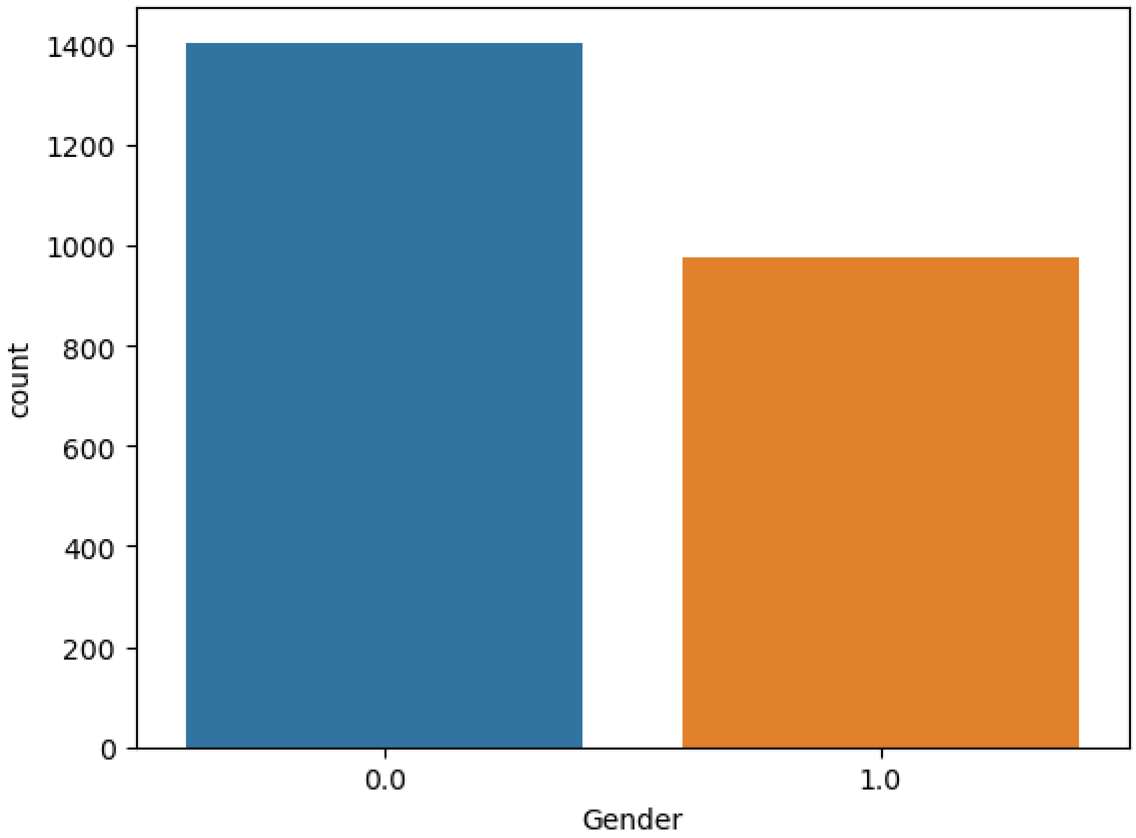
Out[45]: <AxesSubplot:xlabel='Age', ylabel='Count'>



In [46]:
```python
sns.countplot(df_grp['Gender'])
```

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

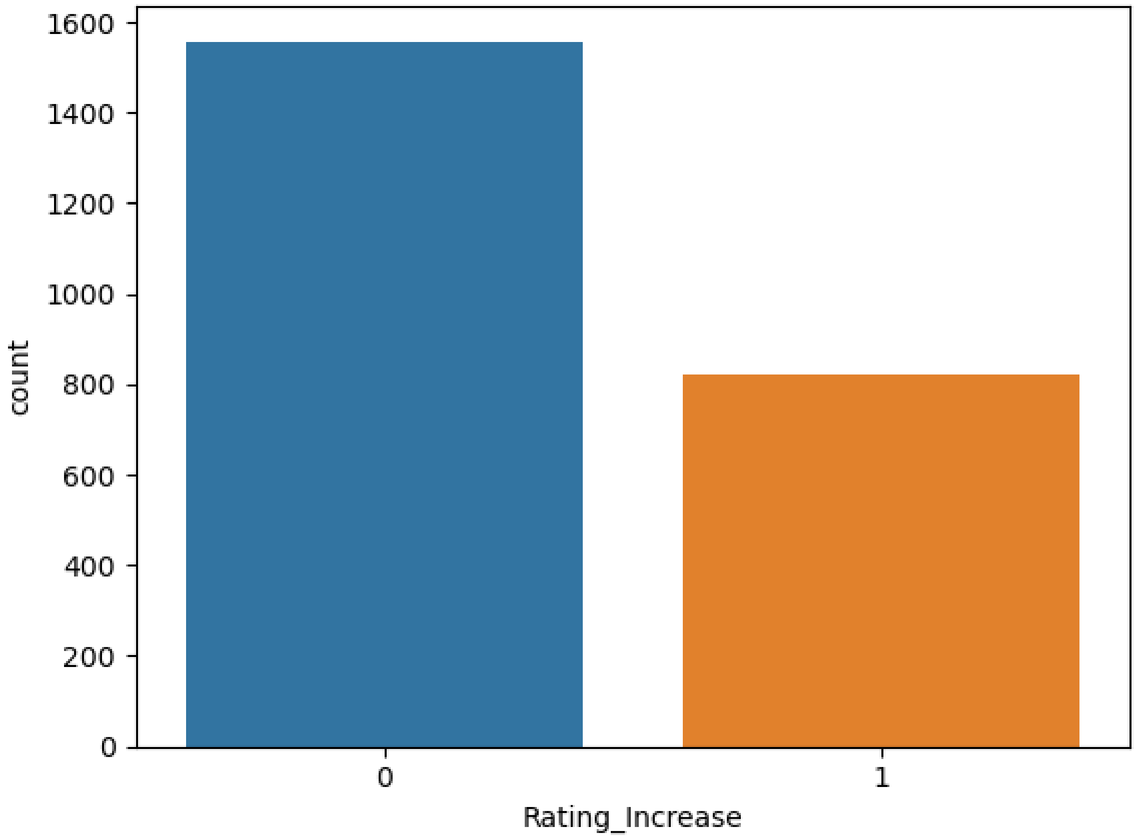
Out[46]:
```
<AxesSubplot:xlabel='Gender', ylabel='count'>
```



In [47]:
```
sns.countplot(df_grp['Rating_Increase'])
```

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

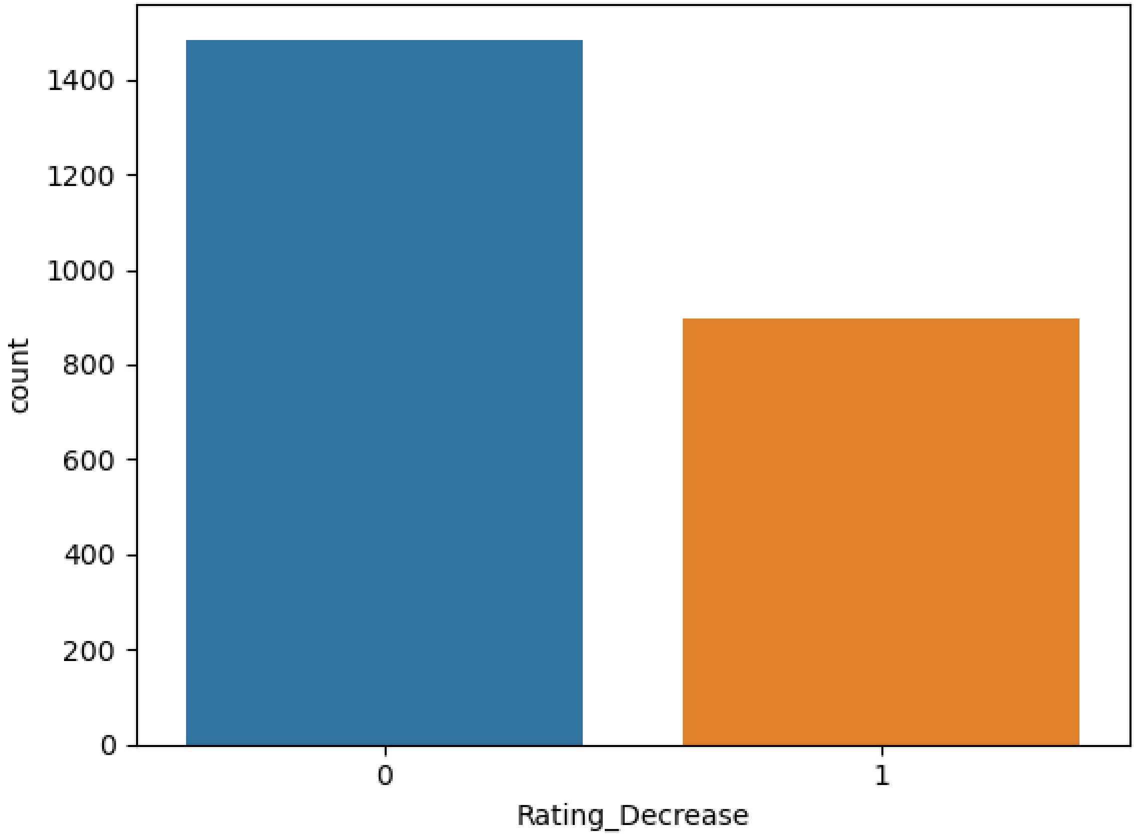
Out[47]: <AxesSubplot:xlabel='Rating_Increase', ylabel='count'>



In [48]:
```
sns.countplot(df_grp['Rating_Decrease'])
```

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

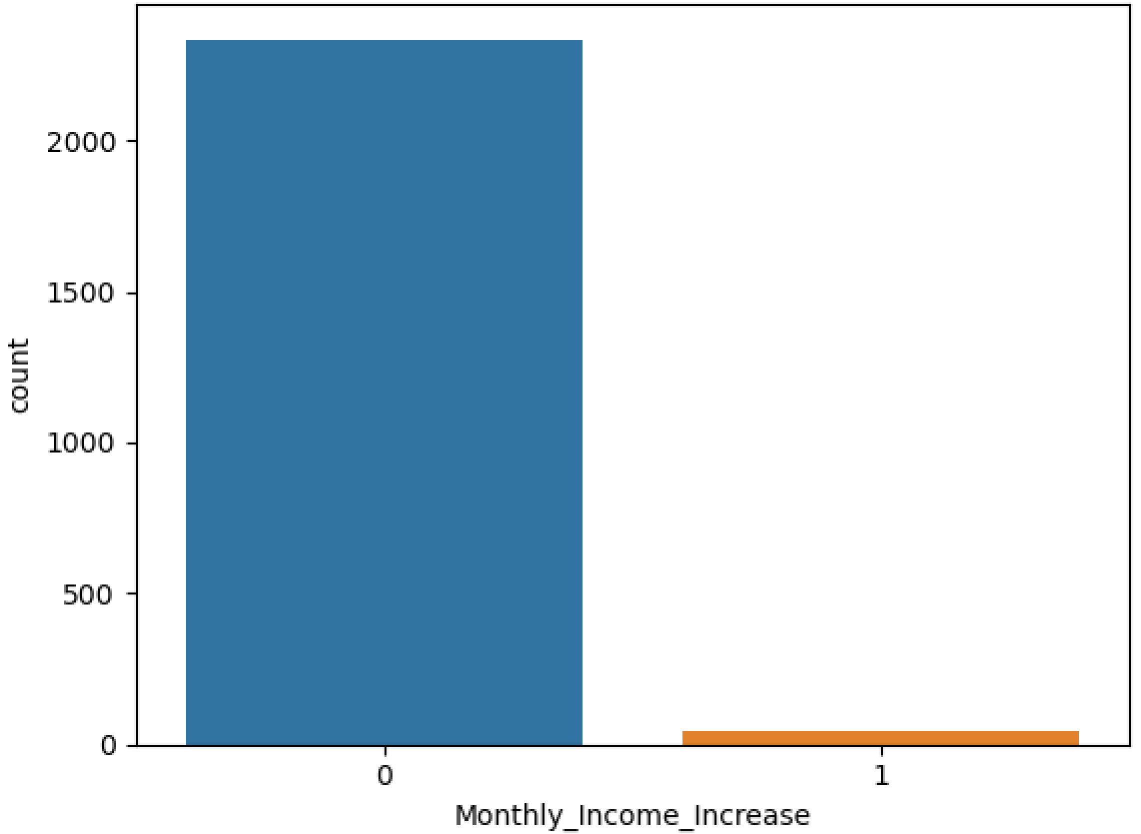
Out[48]:
```
<AxesSubplot:xlabel='Rating_Decrease', ylabel='count'>
```



In [49]:
```
sns.countplot(df_grp['Monthly_Income_Increase'])
```

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

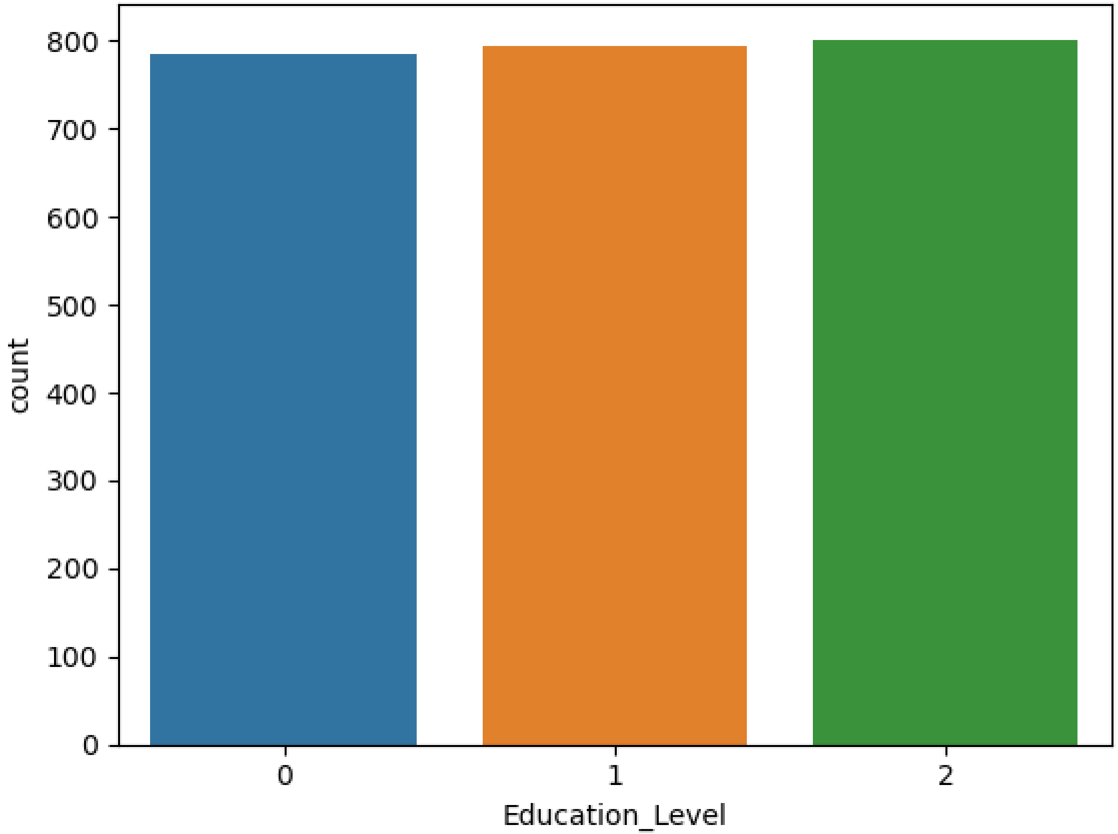
Out[49]:
```
<AxesSubplot:xlabel='Monthly_Income_Increase', ylabel='count'>
```



In [50]:
```
sns.countplot(df_grp['Education_Level'])
```

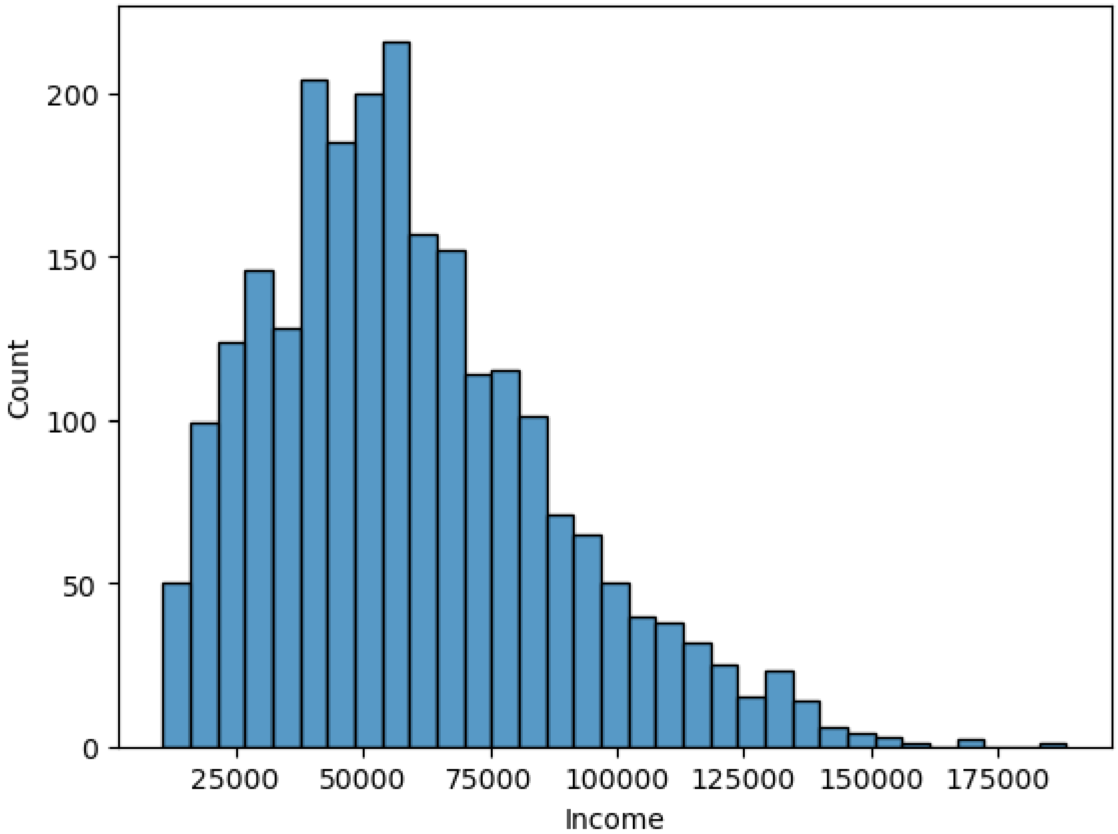
```
C:\Users\gokul\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as
a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments
without an explicit keyword will result in an error or misinterpretation.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

Out[50]: <AxesSubplot:xlabel='Education_Level', ylabel='count'>



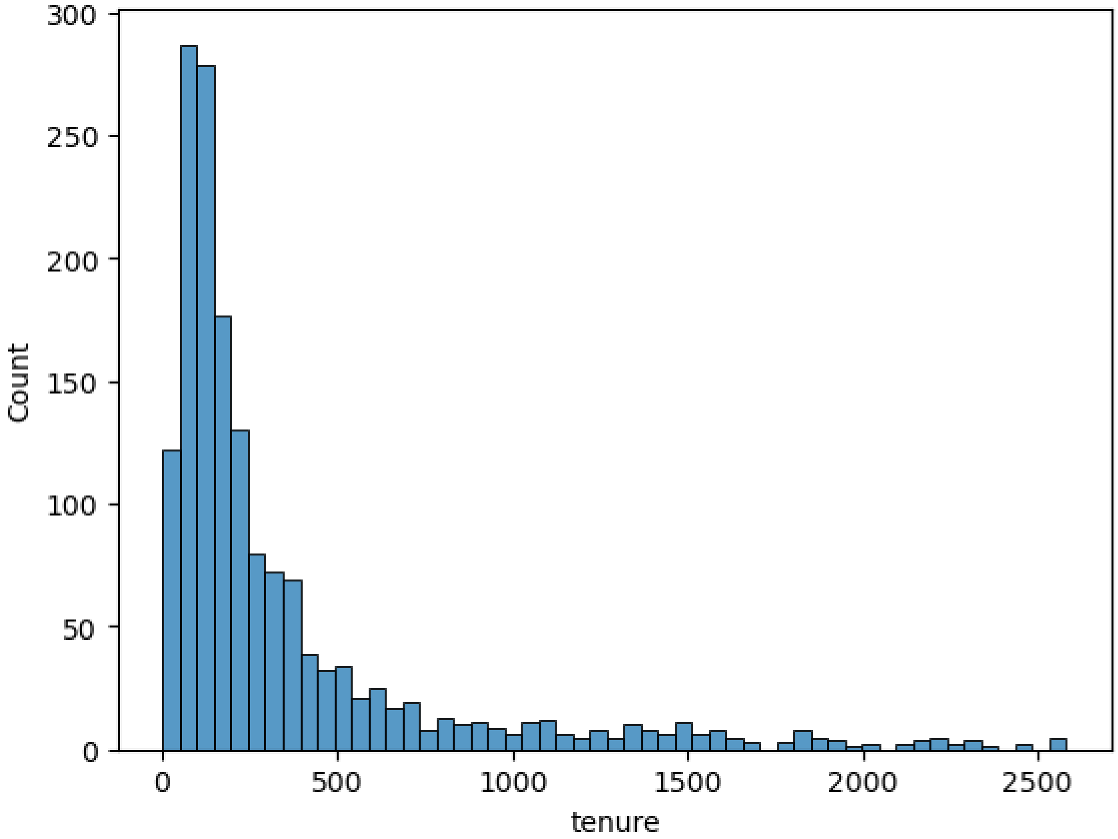
In [51]:
```
sns.histplot(df_grp['Income'])
```

Out[51]:
```
<AxesSubplot:xlabel='Income', ylabel='Count'>
```



In [52]:
```
sns.histplot(df_grp[df_grp['tenure']!=0]['tenure'])
# during of the service
```

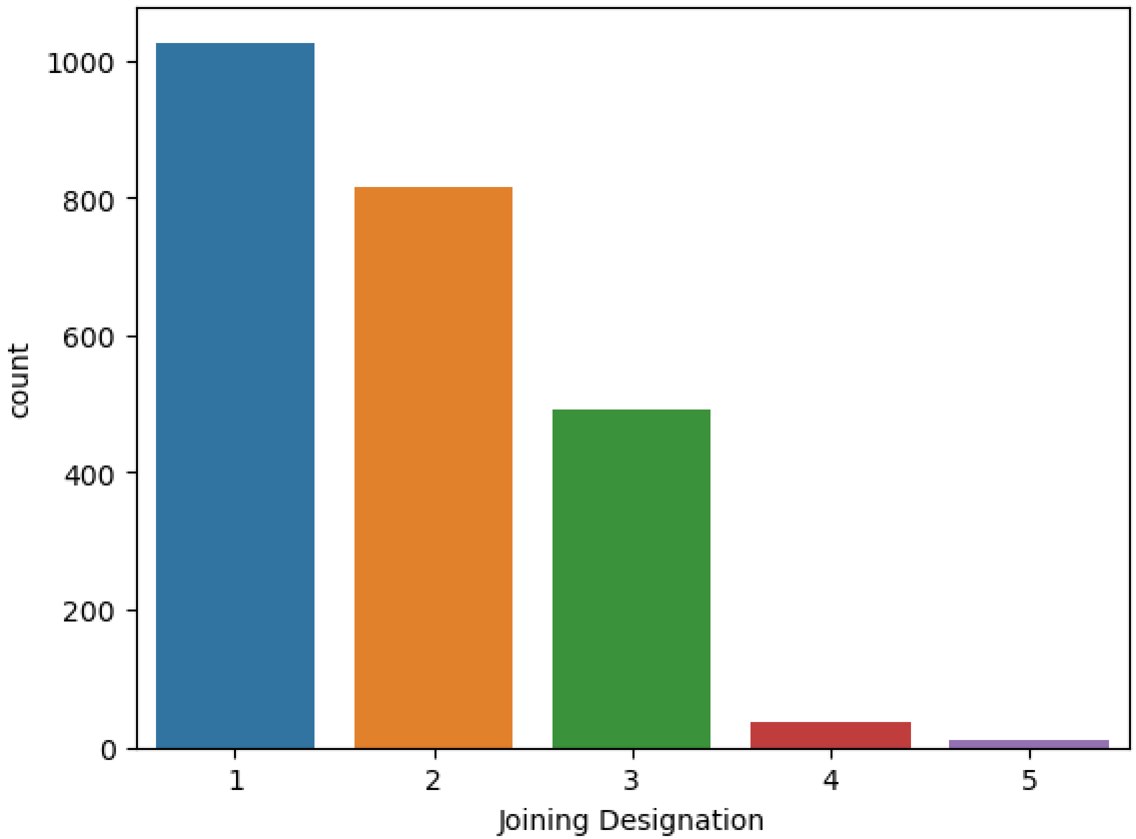
Out[52]: <AxesSubplot:xlabel='tenure', ylabel='Count'>



In [53]:
```
sns.countplot(df_grp['Joining Designation'])
```

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

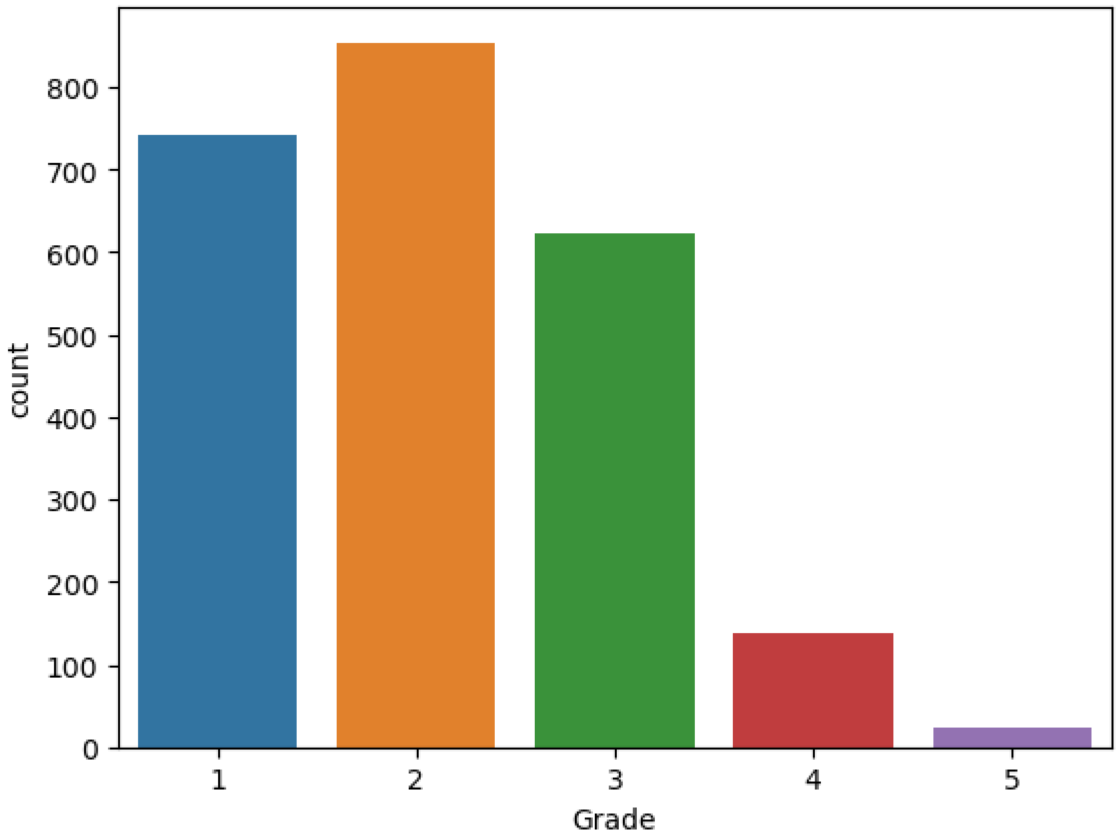
Out[53]:
```
<AxesSubplot:xlabel='Joining Designation', ylabel='count'>
```



In [54]:
```
sns.countplot(df_grp['Grade'])
```

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

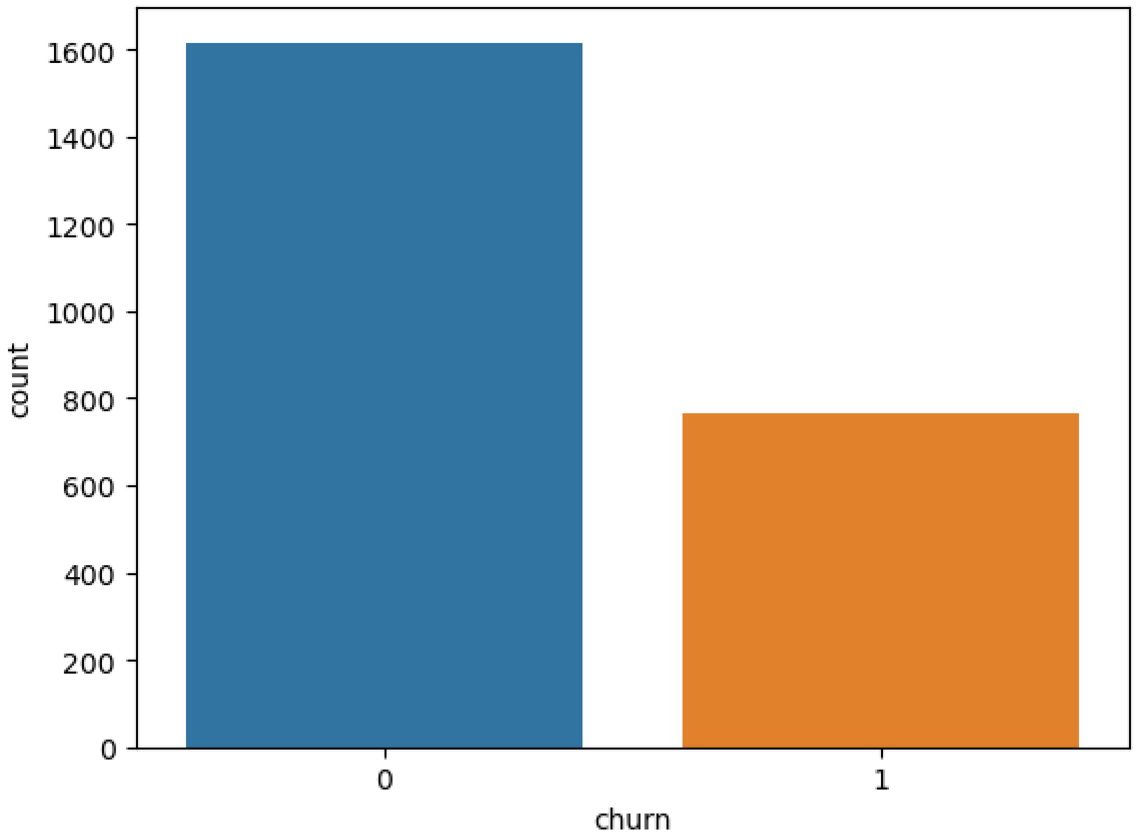
Out[54]:
```
<AxesSubplot:xlabel='Grade', ylabel='count'>
```



In [55]:
```
sns.countplot(df_grp['churn'])
```

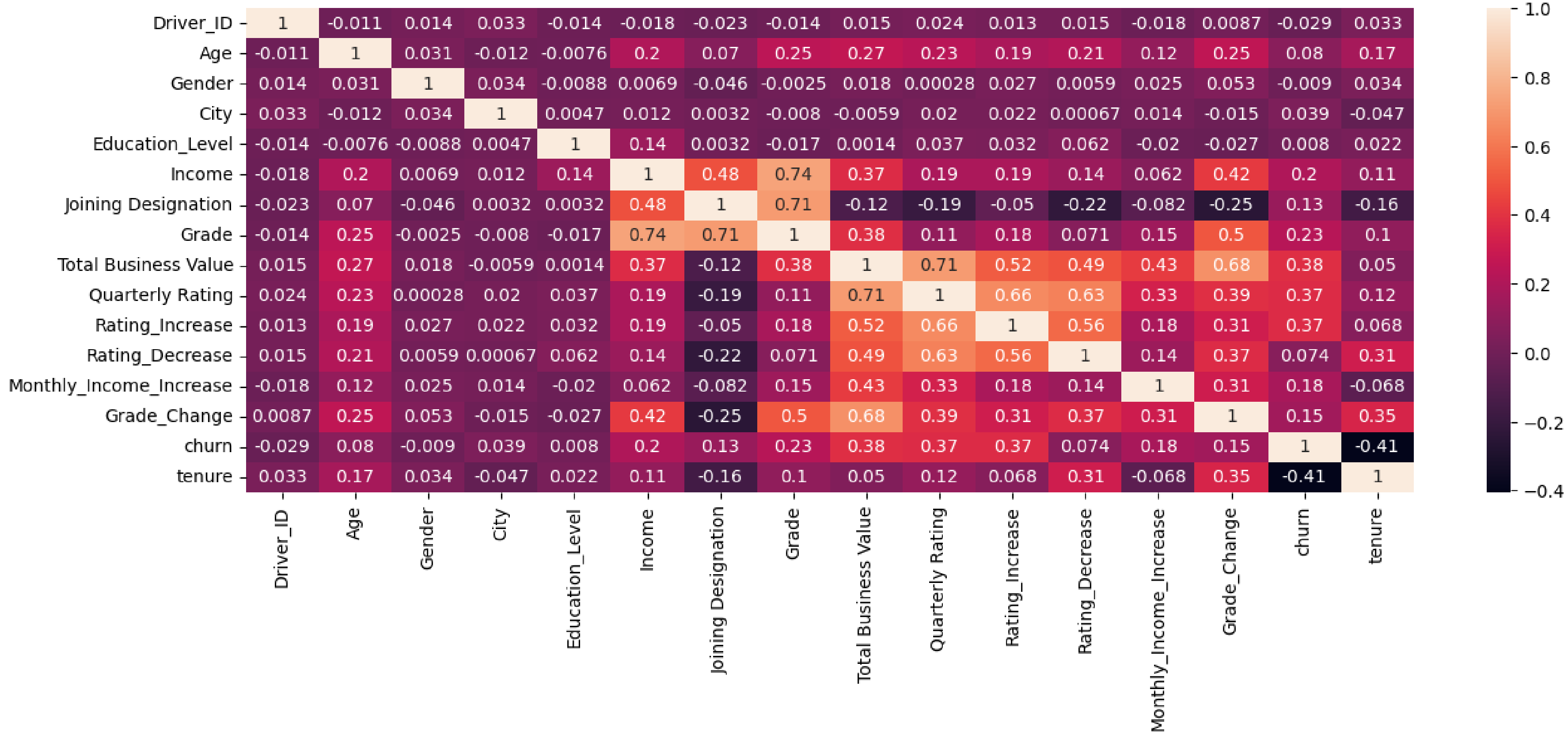
```
C:\Users\gokul\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as
a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments
without an explicit keyword will result in an error or misinterpretation.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

Out[55]:
```
<AxesSubplot:xlabel='churn', ylabel='count'>
```

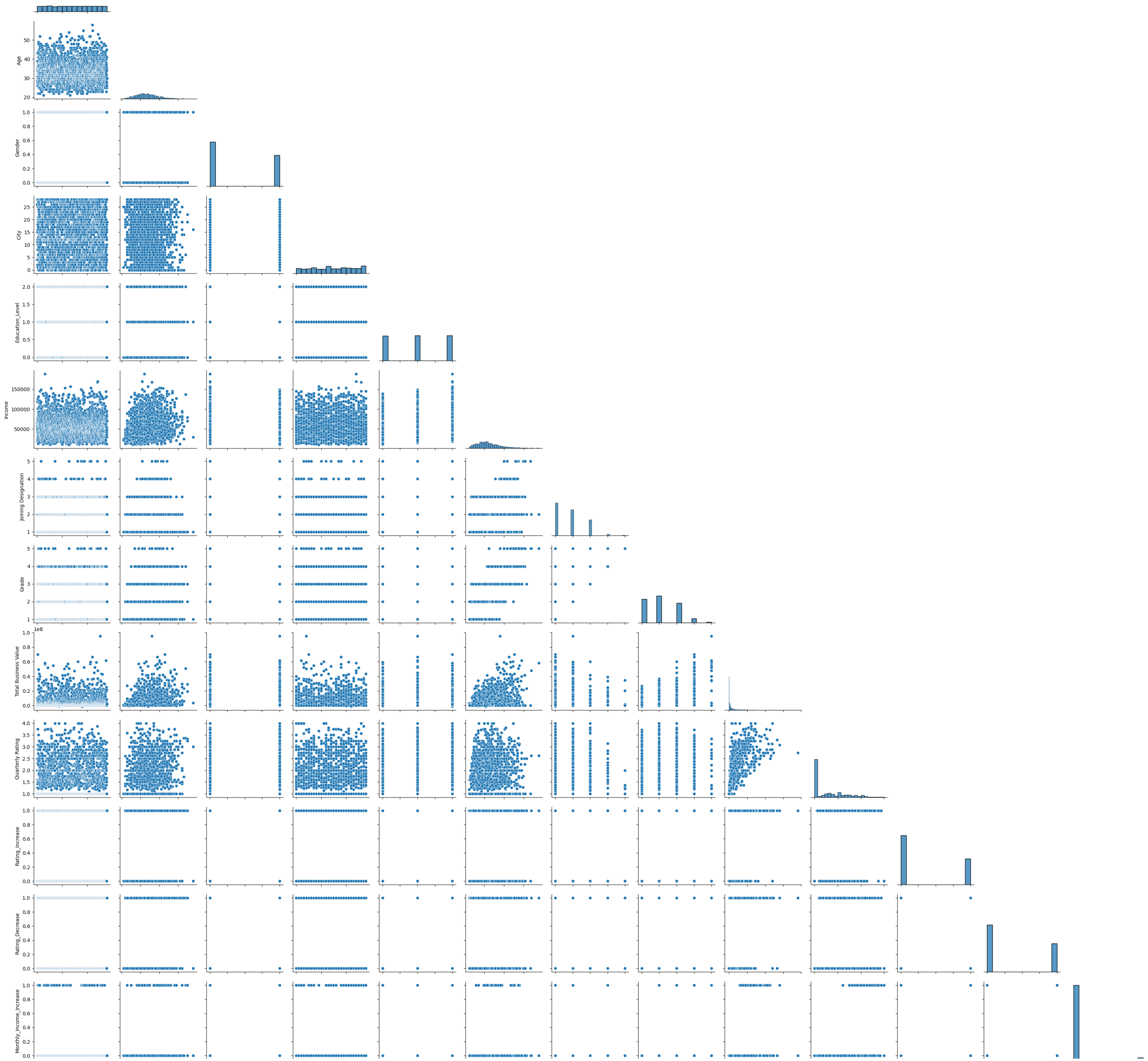


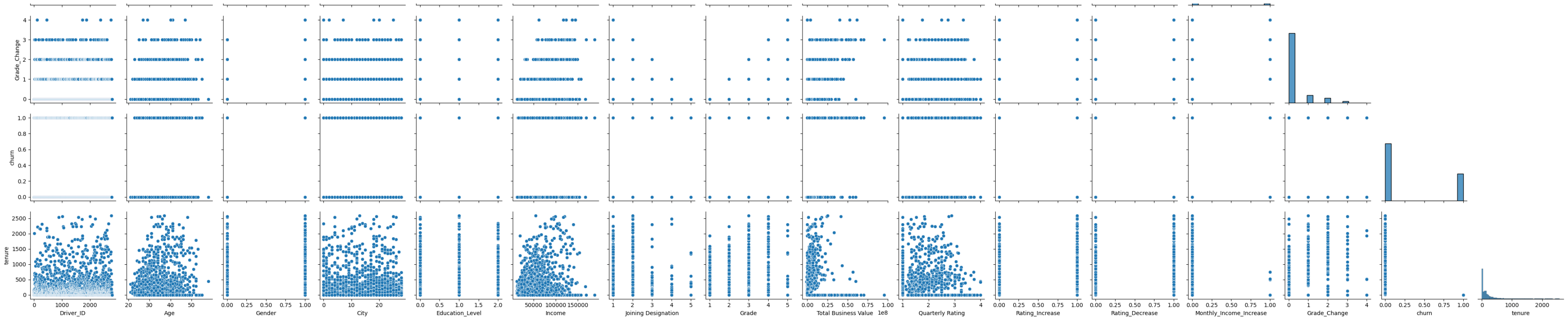
Bivariate Analysis

In [56]:
```
plt.figure(figsize=(15,5))
sns.heatmap(df_grp.corr(),annot=True)
plt.show()
```



In [57]:
```
sns.pairplot(df_grp,corner=True)
```
Out[57]:
```
<seaborn.axisgrid.PairGrid at 0x1c525795d60>
```


Age
Gender
City
Education_Level
Income
Joining Designation
Grade
Total Business Value
Quarterly Rating
Rating_Increase
Rating_Decrease
Monthly_Income_Increase
1e8



- There are almost same number of people for high and low educated people are working as drivers.
- Income is left skwed. May need transformation
- People leaving the job, mostly left the before completing 400 days of work
- More people join at lower designation. Try giving higher designation when people with experience is joining
- Most people are in grade 2 designation
- Quaterly rating and Business value generate have high correlation
- Joining desingation and Grade have high correlation. Which means people are stuck in there initial grade
- Income and grade have high correaltion. So people are stuck in there first grade there income is also not rising
- If busineess values generated is high grade increased rapidly
- If busineess values generated is low grade can decrease

Model Building

Data Processing

In [58]:
```
df_grp.columns
```

Out[58]:
```
Index(['Driver_ID', 'Age', 'Gender', 'City', 'Education_Level', 'Income',
       'Joining Designation', 'Grade', 'Total Business Value',
       'Quarterly Rating', 'Rating_Increase', 'Rating_Decrease',
       'Monthly_Income_Increase', 'Grade_Change', 'churn', 'tenure'],
      dtype='object')
```

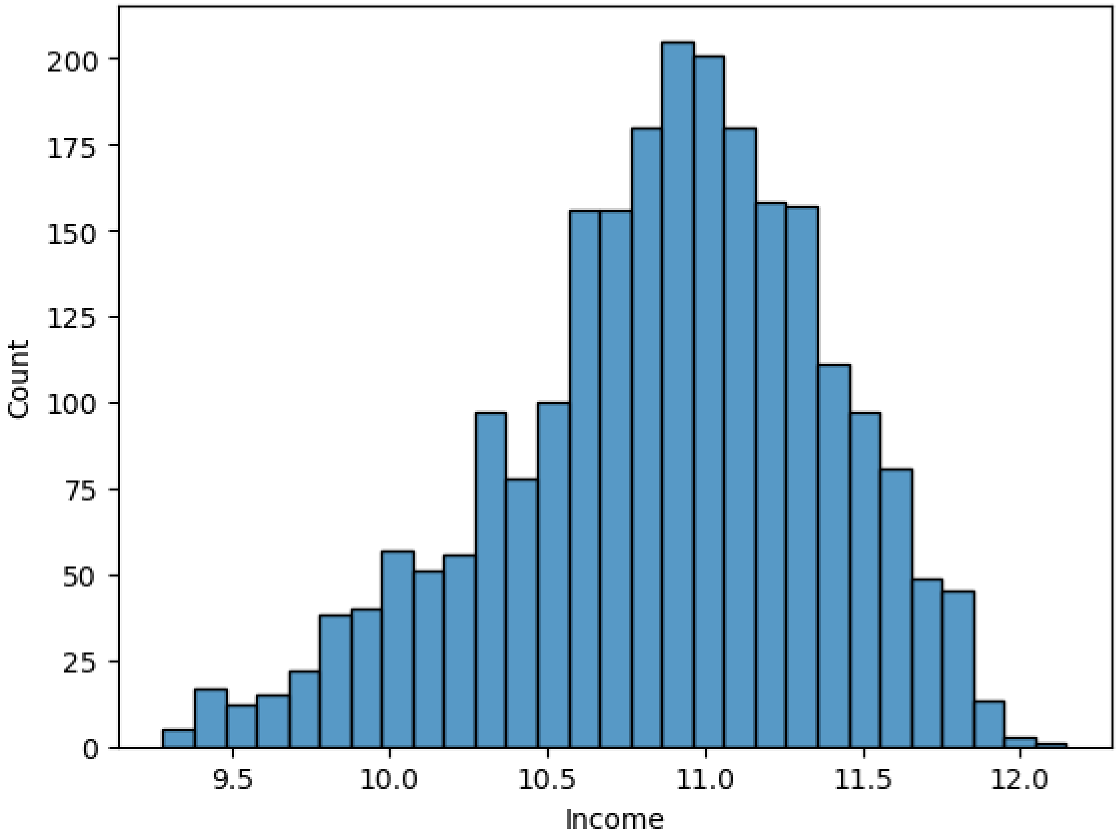
In [59]:
```
df_grp.drop(columns=['tenure'],inplace=True)
```

In [60]:
```
# Data Processing
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from statsmodels.tools.tools import add_constant
```

Log tranfomation of income

In [61]:
```
df_grp['Income']=np.log(df_grp['Income'])
```

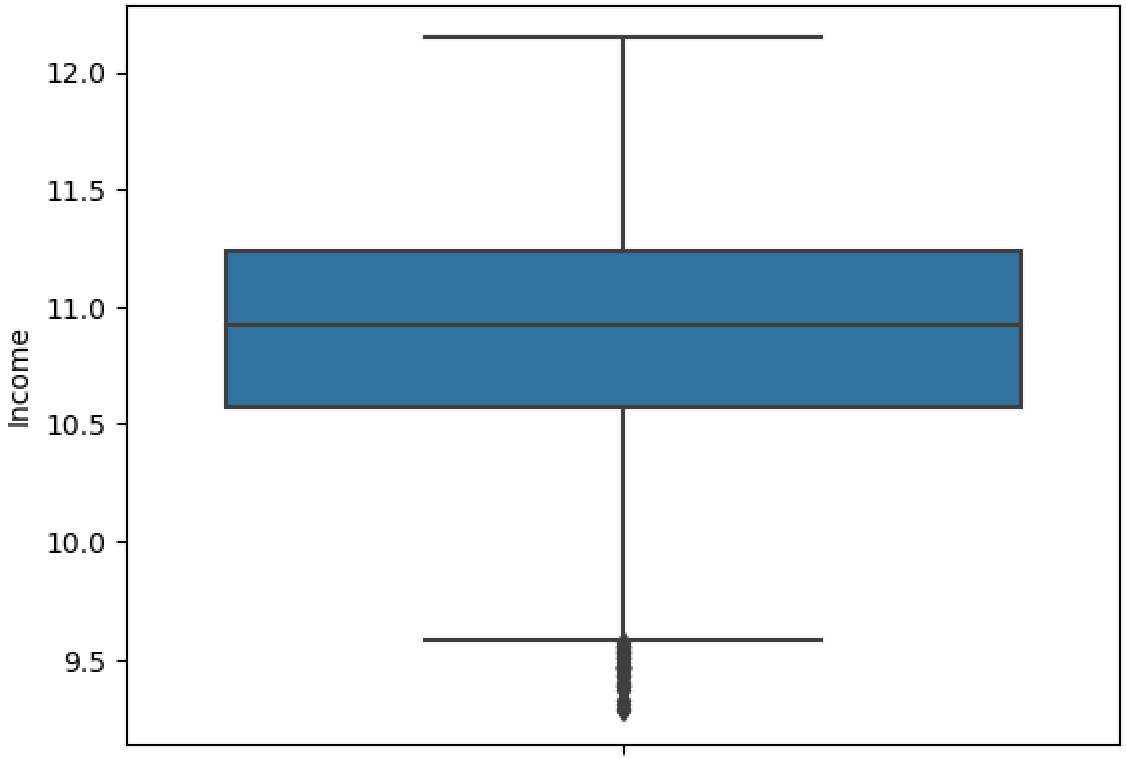
In [62]:
```
sns.histplot(df_grp['Income'])
```
Out[62]: <AxesSubplot:xlabel='Income', ylabel='Count'>



Outlier treatment

In [63]:
```
sns.boxplot(data=df_grp,y='Income')
```

Out[63]: <AxesSubplot:ylabel='Income'>



In [64]:
```
Q1 = np.percentile(df_grp['Income'], 25, interpolation = 'midpoint')
Q2 = np.percentile(df_grp['Income'], 50, interpolation = 'midpoint')
Q3 = np.percentile(df_grp['Income'], 75, interpolation = 'midpoint')
IQR = Q3 - Q1
low_lim = Q1 - 1.5 * IQR
up_lim = Q3 + 1.5 * IQR

df_grp=df_grp[(df_grp['Income']>low_lim) & (df_grp['Income']<up_lim)]
```

```
C:\Users\gokul\AppData\Local\Temp\ipykernel_4860\2903179881.py:1: DeprecationWarning: the `interpolation=` argument
to percentile was renamed to `method=`, which has additional options.
Users of the modes 'nearest', 'lower', 'higher', or 'midpoint' are encouraged to review the method they. (Deprecated
NumPy 1.22)
  Q1 = np.percentile(df_grp['Income'], 25, interpolation = 'midpoint')
C:\Users\gokul\AppData\Local\Temp\ipykernel_4860\2903179881.py:2: DeprecationWarning: the `interpolation=` argument
to percentile was renamed to `method=`, which has additional options.
Users of the modes 'nearest', 'lower', 'higher', or 'midpoint' are encouraged to review the method they. (Deprecated
NumPy 1.22)
  Q2 = np.percentile(df_grp['Income'], 50, interpolation = 'midpoint')
C:\Users\gokul\AppData\Local\Temp\ipykernel_4860\2903179881.py:3: DeprecationWarning: the `interpolation=` argument
to percentile was renamed to `method=`, which has additional options.
Users of the modes 'nearest', 'lower', 'higher', or 'midpoint' are encouraged to review the method they. (Deprecated
NumPy 1.22)
  Q3 = np.percentile(df_grp['Income'], 75, interpolation = 'midpoint')
```

Independent and target feature split

In [65]:
```
y=df_grp['churn']
X=df_grp.drop(['churn'], axis=1)
```

In [66]:
```
X.head()
```

Out[66]:

	Driver_ID	Age	Gender	City	Education_Level	Income	Joining Designation	Grade	Total Business Value	Quarterly Rating	Rating_Increase	Rating_Decrease	Monthl
0	1	28.0	0.0	15	2	10.957573	1	1	1715580	2.0	0	0	
1	2	31.0	0.0	26	2	11.112687	2	2	0	1.0	0	0	
2	4	43.0	0.0	4	2	11.091377	2	2	350000	1.0	0	0	
3	5	29.0	0.0	28	0	10.744365	1	1	120360	1.0	0	0	
4	6	31.0	1.0	2	1	11.273754	3	3	1265000	1.6	1	0	

VIF Check

In [67]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor

vif = pd.DataFrame()
vif['Features'] = X.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

```
C:\Users\gokul\anaconda3\lib\site-packages\statsmodels\stats\outliers_influence.py:193: RuntimeWarning: divide by ze
ro encountered in double_scalars
  vif = 1. / (1. - r_squared_i)
```

Out[67]:

	Features	VIF
6	Joining Designation	inf
7	Grade	inf
13	Grade_Change	inf
5	Income	62.57
1	Age	36.78
9	Quarterly Rating	18.86
8	Total Business Value	4.50
0	Driver_ID	4.02
3	City	3.93
11	Rating_Decrease	3.03
10	Rating_Increase	2.95
4	Education_Level	2.65
2	Gender	1.71
12	Monthly_Income_Increase	1.28

In [68]:
```python
X.drop(columns=['Joining Designation','Income','Grade','Quarterly Rating'],inplace=True)
```

In [69]:
```python
vif = pd.DataFrame()
vif['Features'] = X.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[69]:

	Features	VIF
1	Age	8.10
0	Driver_ID	3.73
3	City	3.67
5	Total Business Value	3.30
7	Rating_Decrease	2.59
6	Rating_Increase	2.55
4	Education_Level	2.49
9	Grade_Change	2.21
2	Gender	1.69
8	Monthly_Income_Increase	1.26

Test Train Split

In [70]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.6)
X_val, X_test, y_val, y_test = train_test_split(X_test, y_test, test_size=0.5)
```

Scaling - Using StandardScaler

In [71]:
```
sc = StandardScaler()
sc.fit(X_train)
X_train = sc.transform(X_train)
X_test = sc.transform(X_test)
```

Handiling Imbalance data

In [72]:
```
from imblearn.over_sampling import SMOTE
sm = SMOTE()
X_train, y_train = sm.fit_resample(X_train, y_train)
X_val, y_val = sm.fit_resample(X_val, y_val)
```

Model Building-1 (Bagging Algorithm)

In [73]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [74]:
```
model1=RandomForestClassifier()
```

In [75]:
```
model1.fit(X_train, y_train)
```

Out[75]:
```
RandomForestClassifier()
```

In [76]:
```
y_hat_train=model1.predict(X_train)
y_hat_val=model1.predict(X_val)
```

```
C:\Users\gokul\anaconda3\lib\site-packages\sklearn\base.py:443: UserWarning: X has feature names, but RandomForestCl
assifier was fitted without feature names
  warnings.warn(
```

In [77]:
```
train_score=f1_score(y_train,y_hat_train)
val_score=f1_score(y_val,y_hat_val)
print(train_score,val_score)
```

```
1.0 0.6736842105263158
```

Hyperparameter tuning

In [78]:
```
from sklearn.model_selection import GridSearchCV
```

In [79]:
```
model=RandomForestClassifier()
parameters = {'n_estimators':[50,100,150,200],
              'criterion':['gini', 'entropy', 'log_loss'],
              'max_depth':[5,6,7,8,9,10],
              'min_samples_split':[4,5,6,7]
             }
```

In [80]:
```
clf = GridSearchCV(model, parameters, scoring = 'accuracy',cv = 3,n_jobs=-1)
```

In [81]:
```
clf.fit(X_val, y_val)
```

```
C:\Users\gokul\anaconda3\lib\site-packages\sklearn\model_selection\_validation.py:372: FitFailedWarning:
288 fits failed out of a total of 864.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
288 fits failed with the following error:
Traceback (most recent call last):
  File "C:\Users\gokul\anaconda3\lib\site-packages\sklearn\model_selection\_validation.py", line 680, in _fit_and
_score
    estimator.fit(X_train, y_train, **fit_params)
  File "C:\Users\gokul\anaconda3\lib\site-packages\sklearn\ensemble\_forest.py", line 450, in fit
    trees = Parallel(
  File "C:\Users\gokul\anaconda3\lib\site-packages\joblib\parallel.py", line 1085, in __call__
    if self.dispatch_one_batch(iterator):
  File "C:\Users\gokul\anaconda3\lib\site-packages\joblib\parallel.py", line 901, in dispatch_one_batch
    self._dispatch(tasks)
  File "C:\Users\gokul\anaconda3\lib\site-packages\joblib\parallel.py", line 819, in _dispatch
```

In [82]:
```
clf.best_estimator_
```

Out[82]: RandomForestClassifier(max_depth=10, min_samples_split=4)

In [83]:
```
model1_val=clf.best_estimator_
```

In [84]:
```
model1_val.fit(X_train, y_train)
```

Out[84]: RandomForestClassifier(max_depth=10, min_samples_split=4)

In [85]:
```
y_hat_train=model1_val.predict(X_train)
y_hat_test=model1_val.predict(X_test)
```

In [86]:
```
train_score_f1=f1_score(y_train,y_hat_train)
test_score_f1=f1_score(y_test,y_hat_test)
print(train_score_f1,test_score_f1)
```

```
0.9238493723849373 0.6047619047619047
```

In [87]:
```
train_score=accuracy_score(y_train,y_hat_train)
test_score=accuracy_score(y_test,y_hat_test)
print(train_score,test_score)
```

```
0.927547770700637 0.7645390070921986
```

In [88]:
```
feature_improtance=pd.DataFrame(model1_val.feature_importances_,X.columns)
feature_improtance.sort_values(0)
```

Out[88]:

	0
Monthly_Income_Increase	0.013941
Gender	0.018851
Grade_Change	0.047569
Education_Level	0.060319
Rating_Decrease	0.061729
Age	0.118673
Driver_ID	0.125464
City	0.133173
Rating_Increase	0.145645
Total Business Value	0.274635

In [89]:
```
fpr, tpr, thresholds = roc_curve(y_test, y_hat_test)
precision, recall, thresholds = precision_recall_curve(y_test, y_hat_test)
```

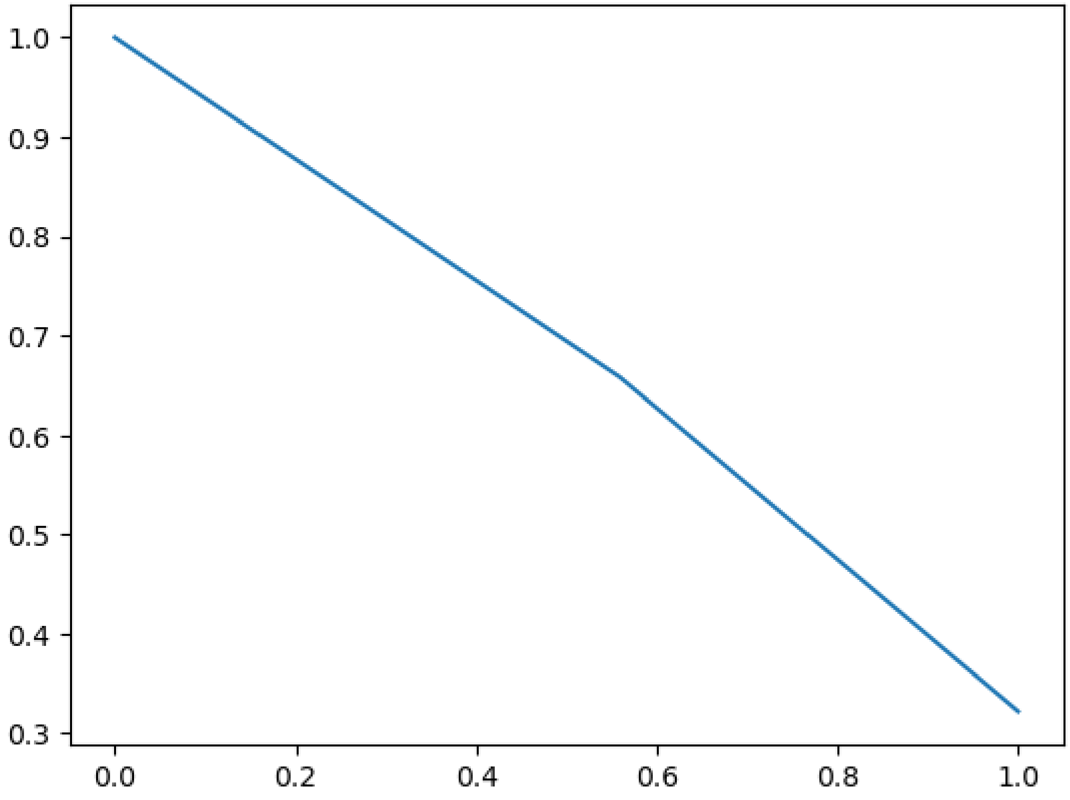
In [90]:
```
print('fpr, tpr, thresholds', fpr, tpr, thresholds)
print('precision, recall, thresholds',precision, recall, thresholds)
```

```
fpr, tpr, thresholds [0.         0.13807531 1.        ] [0.         0.55947137 1.        ] [0 1]
precision, recall, thresholds [0.32198582 0.65803109 1.        ] [1.         0.55947137 0.        ] [0 1]
```

Precision Recall Curve

In [91]:
```
sns.lineplot(y=precision,x=recall)
```

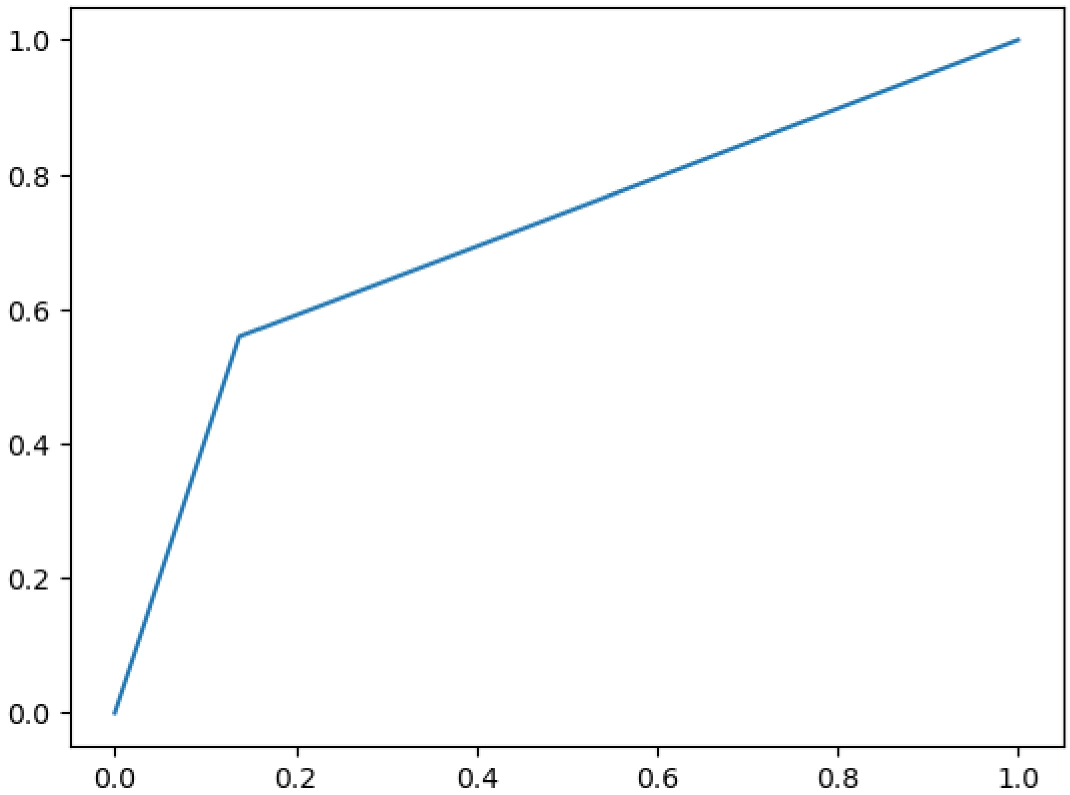
Out[91]: <AxesSubplot:>



ROC AUC Curve

In [92]:
```
sns.lineplot(x=fpr,y=tpr)
```

Out[92]: <AxesSubplot:>



Classification Report

In [93]:
```
target_names = ['class 0', 'class 1']
print(classification_report(y_test, y_hat_test, target_names=target_names))
```

```
              precision    recall  f1-score   support

     class 0       0.80      0.86      0.83       478
     class 1       0.66      0.56      0.60       227

    accuracy                           0.76       705
   macro avg       0.73      0.71      0.72       705
weighted avg       0.76      0.76      0.76       705
```

Confusion matrix

In [94]:
```
tn, fp, fn, tp = confusion_matrix(y_test, y_hat_test).ravel()

print((tn, fp, fn, tp))
```

```
(412, 66, 100, 127)
```

Comments on Metrics

- Area of precision recall curve is slightly above 0.5
- False negative are really large for this model
- Area under AUC Curve is largely 0.5
- After 0.5 trp for every increase in trp, there is a larger increade in fpr
- Accuracy of this model is aroung 76%
- F1 score of this model is around 0.60 which is really poor

Model Building-2 (Boosting Algorithm)

In [95]:
```
import xgboost as xgb
```

In [96]:
```
model2 = xgb.XGBClassifier()
model2.fit(X_train, y_train)
```

Out[96]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...)
```

In [97]:
```
y_hat_train2=model1.predict(X_train)
y_hat_test2=model1.predict(X_test)
```

In [98]:
```
train_score=f1_score(y_train,y_hat_train2)
test_score=f1_score(y_test,y_hat_test2)
print(train_score,test_score)
```

```
1.0 0.5741626794258374
```

Hyperparameter tuning

In [99]:
```
model=xgb.XGBClassifier()
parameters = {'subsample':[0.5,0.6,0.7,0.8,0.9,0.1],
              'lambda':[0.01, 0.1, 1],
              'alpha':[0.01, 0.1, 1],
              'eta':[0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1]
             }
```

In [100]:
```
clf = GridSearchCV(model, parameters, scoring = 'accuracy',cv = 3,n_jobs=-1)
```

In [101]:
```
clf.fit(X_val, y_val)
```

Out[101]:
```
GridSearchCV(cv=3,
             estimator=XGBClassifier(base_score=None, booster=None,
                                     callbacks=None, colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None,
                                     early_stopping_rounds=None,
                                     enable_categorical=False, eval_metric=None,
                                     feature_types=None, gamma=None,
                                     gpu_id=None, grow_policy=None,
                                     importance_type=None,
                                     interaction_constraints=None,
                                     learning_rate=None,...
                                     max_delta_step=None, max_depth=None,
                                     max_leaves=None, min_child_weight=None,
                                     missing=nan, monotone_constraints=None,
                                     n_estimators=100, n_jobs=None,
                                     num_parallel_tree=None, predictor=None,
                                     random_state=None, ...),
             n_jobs=-1,
```

In [102]:
```
clf.best_estimator_
```

Out[102]:
```
XGBClassifier(alpha=0.01, base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eta=0.1, eval_metric=None,
              feature_types=None, gamma=None, gpu_id=None, grow_policy=None,
              importance_type=None, interaction_constraints=None, lambda=0.1,
              learning_rate=None, max_bin=None, max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None, max_depth=None,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, n_estimators=100, n_jobs=None, ...)
```

In [103]:
```
model2_val=clf.best_estimator_
```

In [104]:
```
model2_val.fit(X_train, y_train)
```

Out[104]:
```
XGBClassifier(alpha=0.01, base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eta=0.1, eval_metric=None,
              feature_types=None, gamma=None, gpu_id=None, grow_policy=None,
              importance_type=None, interaction_constraints=None, lambda=0.1,
              learning_rate=None, max_bin=None, max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None, max_depth=None,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, n_estimators=100, n_jobs=None, ...)
```

In [105]:
```
feature_improtance=pd.DataFrame(model2_val.feature_importances_,X.columns)
feature_improtance.sort_values(0)
```

Out[105]:

	0
Monthly_Income_Increase	0.012569
Driver_ID	0.045479
Gender	0.052563
City	0.054053
Age	0.054864
Education_Level	0.065184
Total Business Value	0.082039
Grade_Change	0.114659
Rating_Decrease	0.172166
Rating_Increase	0.346423

In [106]:
```
y_hat_train=model2_val.predict(X_train)
y_hat_test=model2_val.predict(X_test)
```

In [107]:
```
train_score_f1=f1_score(y_train,y_hat_train)
test_score_f1=f1_score(y_test,y_hat_test)
print(train_score_f1,test_score_f1)
```

```
0.9830234438156832 0.580046403712297
```

In [108]:
```
train_score=accuracy_score(y_train,y_hat_train)
test_score=accuracy_score(y_test,y_hat_test)
print(train_score,test_score)
```

```
0.98328025477707 0.7432624113475177
```

In [109]:
```
fpr, tpr, thresholds = roc_curve(y_test, y_hat_test)
precision, recall, thresholds = precision_recall_curve(y_test, y_hat_test)
```

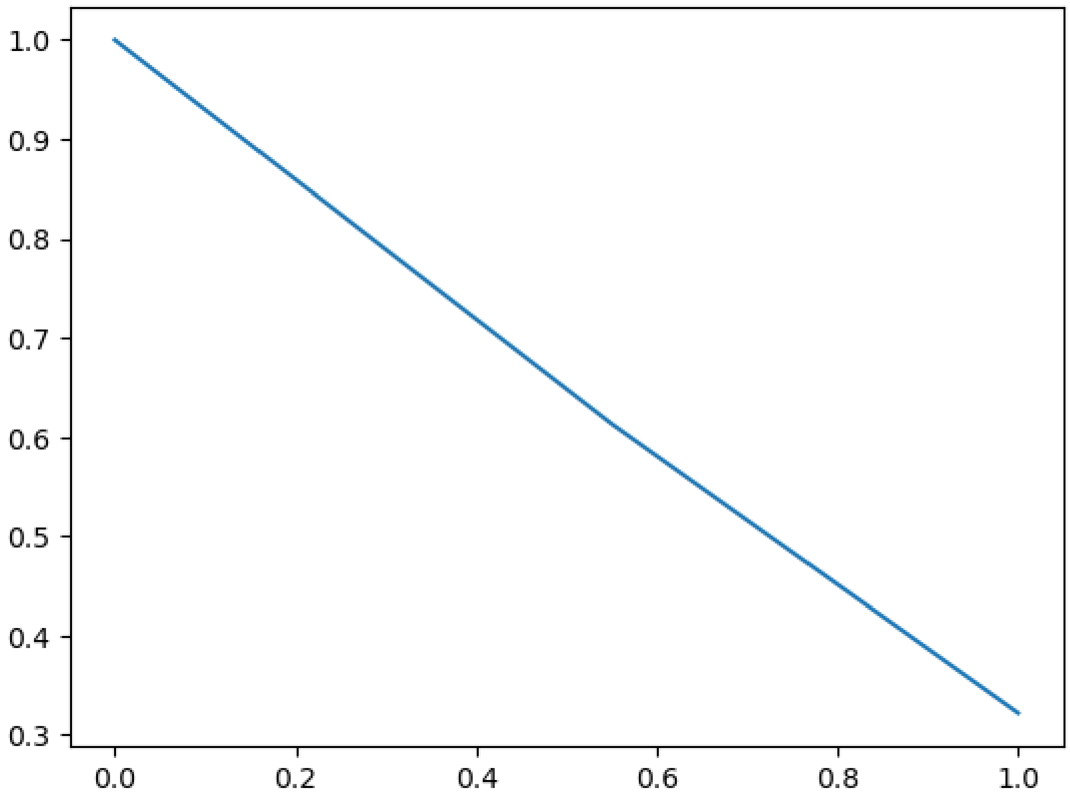
In [110]:
```
print('fpr, tpr, thresholds', fpr, tpr, thresholds)
print('precision, recall, thresholds',precision, recall, thresholds)
```

```
fpr, tpr, thresholds [0.         0.16527197 1.        ] [0.         0.55066079 1.        ] [0 1]
precision, recall, thresholds [0.32198582 0.6127451  1.        ] [1.         0.55066079 0.        ] [0 1]
```

Precision Recall Curve

In [111]:
```
sns.lineplot(y=precision,x=recall)
```

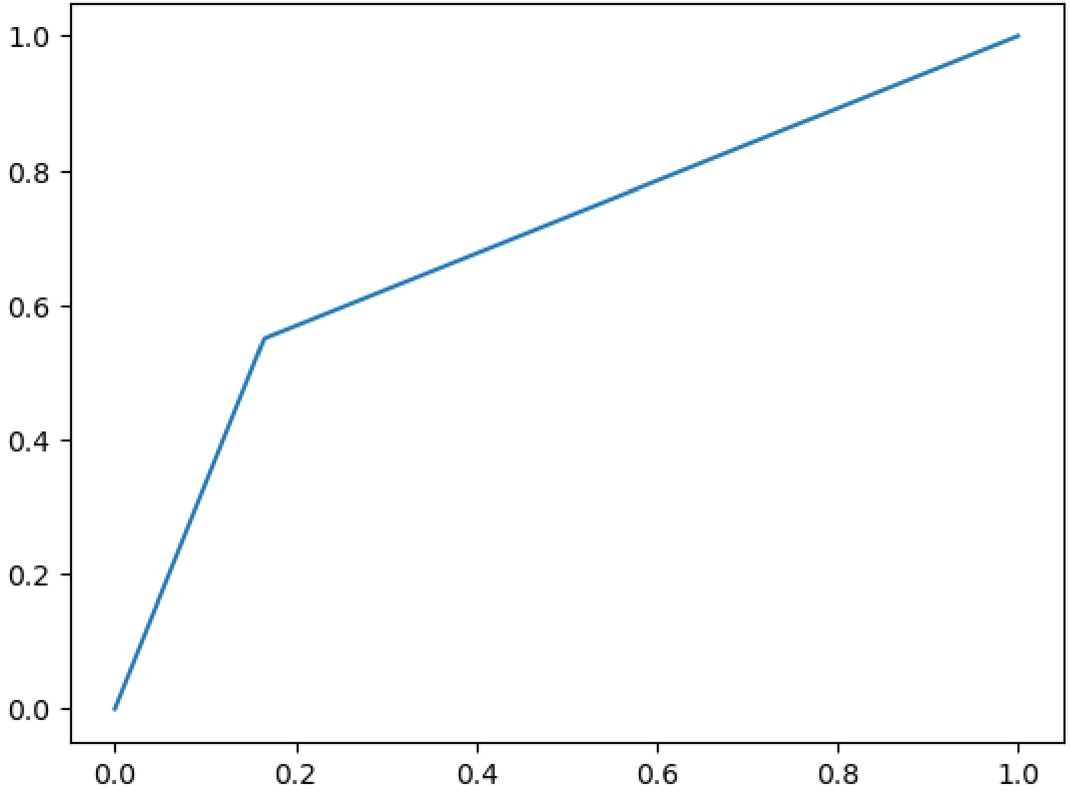
Out[111]: <AxesSubplot:>



ROC AUC Curve

In [112]:
```
sns.lineplot(x=fpr,y=tpr)
```

Out[112]:
```
<AxesSubplot:>
```



Classification Report

In [113]:
```
target_names = ['class 0', 'class 1']
print(classification_report(y_test, y_hat_test, target_names=target_names))
```

```
              precision    recall  f1-score   support

     class 0       0.80      0.83      0.82       478
     class 1       0.61      0.55      0.58       227

    accuracy                           0.74       705
   macro avg       0.70      0.69      0.70       705
weighted avg       0.74      0.74      0.74       705
```

Confusion matrix

In [114]:
```
tn, fp, fn, tp = confusion_matrix(y_test, y_hat_test).ravel()

print((tn, fp, fn, tp))
```

```
(399, 79, 102, 125)
```

Comments on Metrics

- Area of precision recall curve is 0.5
- False negative are really large for this model
- Area under AUC Curve is more than 0.5
- After 0.5 trp for every increase in trp, there is a larger increade in fpr
- Accuracy of this model is aroung 75%
- F1 score of this model is around 0.58 which is really poor

Actionable Insights

- Joining desingation and Grade have high correlation. Which means people are stuck in there initial grade
- Income and grade have high correaltion. So people are stuck in there first grade there income is also not rising
- Grade_Chang, Rating_Decrease, Rating_Increase, Total Business Value are the factors affecting the churn
- Accuracy of Bagging algorithm is coming as 80% whereas for boosting it is 68%
- After 500 days with the company churn rate decreases drastically
- City, age and gender contribute to less wrt to churing

Recommendations

- Grade promotion critiria to relaxed
- Rating_Decrease critiria to be made stringent
- Steps to be take to improve the
- Giving more incentives to the drivers during the initial stage with the company. Try to make them to stay for more than 650 days.
- Use random forest for prediction because it is computinally less expensive
- Use the random forest model to predict whether the person will chern or not and give incentives of grade change for those drivers
- Burden on driver for accuring business to be reduced.
- Training to improve the performace of the driver done inorder

In [ ]:

```

```