OLA - Ensemble Learning

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)

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)

In [1]:
```
# Analysis
#Importing Required Libraries

import numpy as np
```

```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import statsmodels.api as sm
from datetime import datetime
```

In [2]:
```python
df=pd.read_csv('ola_driver_scaler.csv')
df.head()
```

Out[2]:

	Unnamed: 0	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	La
0	0	01/01/19	1	28.0	0.0	C23	2	57387	24/12/18	
1	1	02/01/19	1	28.0	0.0	C23	2	57387	24/12/18	
2	2	03/01/19	1	28.0	0.0	C23	2	57387	24/12/18	
3	3	11/01/20	2	31.0	0.0	C7	2	67016	11/06/20	
4	4	12/01/20	2	31.0	0.0	C7	2	67016	11/06/20	

In [3]:
```python
df.shape
```

Out[3]:
```
(19104, 14)
```

In [4]:
```python
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 [5]:
```python
#calculating Total missing values
df.isnull().sum()
```

Out[5]:
```
Unnamed: 0                  0
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
```

Observations:

- There are some Missing Values
- Lets impute them with KNN Imputation

In [7]:
```
#Dropping Unnamed column which is not Required
df.drop(['Unnamed: 0'], axis=1, inplace=True)
```

In [8]:
```
#Converting series to numpy array to impute KNN IMputation
age=df['Age']
age=age.to_numpy(dtype ='float32').reshape(-1,1)
gender=df['Gender']
gender=gender.to_numpy(dtype ='float32').reshape(-1,1)
```

In [9]:
```
#Imputing Missing values with KNN Imoutation
from sklearn.impute import KNNImputer
imputer = KNNImputer(n_neighbors=5)

df['Age']=imputer.fit_transform(age)
df['Gender']=imputer.fit_transform(gender)
```

In [10]:
```
#After applying KNN imputaion it converted to numpy array so converted to Series
df['Age'] = pd.Series(df['Age'])
df['Gender'] = pd.Series(df['Gender'])
```

In [11]:
```
#converting float to INT type
df['Age'] = df['Age'].astype('int')
df['Gender'] = df['Gender'].astype('int')
```

In [12]:
```
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                   19104 non-null  int32 
 3   Gender                19104 non-null  int32 
 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: int32(2), int64(7), object(4)
memory usage: 1.7+ MB
```

In [13]:

```
#converting colums to datetime format to subtract them
df['MMM-YY']= pd.to_datetime(df['MMM-YY'])
df['Dateofjoining']= pd.to_datetime(df['Dateofjoining'])
df['LastWorkingDate']= pd.to_datetime(df['LastWorkingDate'])
```

In [14]:

```
df_new=df.groupby(['Driver_ID','Quarterly Rating']).agg({'MMM-YY':'last','Age':'la
                                                                   'Education_Level
                                                                        'LastWorkin
                                                                         'Grade':'f
                                                                   'Total Business \
df_new
```

Out[14]:

Driver_ID	Quarterly Rating	MMM-YY	Age	Gender	City	Education_Level	Dateofjoining	LastWorkingDate
1	2	2019-03-01	28	0	C23	2	2018-12-24	2019-03-11
2	1	2020-12-01	31	0	C7	2	2020-11-06	NaT
4	1	2020-04-01	43	0	C13	2	2019-12-07	2020-04-27
5	1	2019-03-01	29	0	C9	0	2019-01-09	2019-03-07
6	1	2020-09-01	31	1	C11	1	2020-07-31	NaT
...	...	...	...	...	...	...	...	...
2787	1	2019-06-01	28	1	C20	2	2018-07-21	2019-06-20
	2	2019-03-01	28	1	C20	2	2018-07-21	NaT
2788	1	2020-06-01	29	0	C27	2	2020-06-08	NaT
	2	2020-12-01	30	0	C27	2	2020-06-08	NaT
	3	2020-09-01	30	0	C27	2	2020-06-08	NaT

4023 rows × 11 columns

In [15]:

```
#Not all columns are present so applying reset index
df1=df_new.reset_index()
```

In [16]:

```
# sorted values to find diff in driver rating
df1.sort_values(by=['Driver_ID', 'MMM-YY'], inplace=True)
```

In [17]:

```
df1['Rating_Increased']=df1.groupby(['Driver_ID'])['Quarterly Rating'].diff()
df1['Rating_Decreased']=df1.groupby(['Driver_ID'])['Quarterly Rating'].diff()
```

In [18]:

```
# Created new Columns based on driver rating
df1['Rating_Increased']=df1['Rating_Increased'].apply(lambda x: 1 if x>0 else 0 )
df1['Rating_Decreased']=df1['Rating_Decreased'].apply(lambda x: 1 if x<0 else 0 )
```

In [19]:

```
df_new=df1.groupby(['Driver_ID']).agg({'MMM-YY':'last', 'Age':'last','Gender':'las
                                       'Dateofjoining':'first','LastWorkingDate':'
                                       'Grade':'last','Income':'last','Total Busin
                                       'Rating_Decreased':'last','Quarterly Rating

df_new
```

Out[19]:

	MMM-YY	Age	Gender	City	Education_Level	Dateofjoining	LastWorkingDate	Joini Designati
Driver_ID								
1	2019-03-01	28	0	C23	2	2018-12-24	2019-03-11	
2	2020-12-01	31	0	C7	2	2020-11-06	NaT	
4	2020-04-01	43	0	C13	2	2019-12-07	2020-04-27	
5	2019-03-01	29	0	C9	0	2019-01-09	2019-03-07	
6	2020-12-01	31	1	C11	1	2020-07-31	NaT	
...	...	...	...	...	...	...	...	
2784	2020-12-01	34	0	C24	0	2015-10-15	NaT	
2785	2020-10-01	34	1	C9	0	2020-08-28	2020-10-28	
2786	2019-09-01	45	0	C19	0	2018-07-31	2019-09-22	
2787	2019-06-01	28	1	C20	2	2018-07-21	2019-06-20	
2788	2020-12-01	30	0	C27	2	2020-06-08	NaT	

2381 rows × 14 columns

In [20]:

```
#Not all columns are present so applying reset index
df=df_new.reset_index()
df
```

Out[20]:

	Driver_ID	MMM-YY	Age	Gender	City	Education_Level	Dateofjoining	LastWorkingDate	D
0	1	2019-03-01	28	0	C23	2	2018-12-24	2019-03-11	
1	2	2020-12-01	31	0	C7	2	2020-11-06	NaT	
2	4	2020-04-01	43	0	C13	2	2019-12-07	2020-04-27	
3	5	2019-03-01	29	0	C9	0	2019-01-09	2019-03-07	
4	6	2020-12-01	31	1	C11	1	2020-07-31	NaT	
...	...	...	...	...	...	...	...	...	
2376	2784	2020-12-01	34	0	C24	0	2015-10-15	NaT	
2377	2785	2020-10-01	34	1	C9	0	2020-08-28	2020-10-28	
2378	2786	2019-09-01	45	0	C19	0	2018-07-31	2019-09-22	
2379	2787	2019-06-01	28	1	C20	2	2018-07-21	2019-06-20	
2380	2788	2020-12-01	30	0	C27	2	2020-06-08	NaT	

2381 rows × 15 columns

In [38]:

```
#creation of Target Variable
df['churn']=df['LastWorkingDate']
df['churn'].fillna(0, inplace = True)
df['churn']=df['churn'].apply(lambda x: 0 if x==0 else 1)
```

deriving basic insights from derived dataset

In [22]:

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

Out[22]:

```
0    2013
1     368
Name: Rating_Increased, dtype: int64
```

In [23]:

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

Out[23]:

```
0    1645
1     736
Name: Rating_Decreased, dtype: int64
```

In [24]:

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

Out[24]:
```
0    1408
1     973
Name: Gender, dtype: int64
```

In [25]:
```
df['Education_Level'].value_counts()
```

Out[25]:
```
2    802
1    795
0    784
Name: Education_Level, dtype: int64
```

In [39]:
```
df['churn'].value_counts()
```

Out[39]:
```
1    1616
0     765
Name: churn, dtype: int64
```

In [27]:
```
# Dupluicate value check
if df.shape[0] == df.drop_duplicates().shape[0] :
    print('No duplicates Found')
else:
    duplicates = df.shape[0] - df.drop_duplicates().shape[0]
    print('{} duplicates found'.format(duplicates))
```

```
No duplicates Found
```

In [28]:
```
df.describe().T
```

Out[28]:

	count	mean	std	min	25%	50%	75%
Driver_ID	2381.0	1.397559e+03	8.061616e+02	1.0	695.0	1400.0	2100.0
Age	2381.0	3.368459e+01	5.968409e+00	21.0	29.0	33.0	37.0
Gender	2381.0	4.086518e-01	4.916880e-01	0.0	0.0	0.0	1.0
Education_Level	2381.0	1.007560e+00	8.162900e-01	0.0	0.0	1.0	2.0
Joining Designation	2381.0	1.820244e+00	8.414334e-01	1.0	1.0	2.0	2.0
Grade	2381.0	2.082738e+00	9.359084e-01	1.0	1.0	2.0	3.0
Income	2381.0	5.933416e+04	2.838367e+04	10747.0	39104.0	55315.0	75986.0
Total Business Value	2381.0	4.586742e+06	9.127115e+06	-1385530.0	0.0	817680.0	4173650.0
Rating_Increased	2381.0	1.545569e-01	3.615577e-01	0.0	0.0	0.0	0.0
Rating_Decreased	2381.0	3.091138e-01	4.622253e-01	0.0	0.0	0.0	1.0
Quarterly Rating	2381.0	1.427971e+00	8.098389e-01	1.0	1.0	1.0	2.0
churn	2381.0	1.000000e+00	0.000000e+00	1.0	1.0	1.0	1.0

Observations:

- Some Missing Values are present in Given Dataset, Imputed with KNN Imputation.
- No Duplicates are found in Dataset after performing Feature engineering.
- No change in monthly income so not including that column for further analysis.
- Major Drivers are male according to Dataset.

- Total of 368 drivers rating has been increased.
- Total of 973 drivers rating has been Decreased.
- Major of Drivers are Graduated according to Dataset.
- There is a imabalance between churn and non churn data we need to use SMOTE techniques later to create Balance.

In [29]:
```
df_numerical=df.select_dtypes(exclude='object')
df_categorical=df.select_dtypes(include='object')
```

In [30]:
```
df_numerical.columns
```

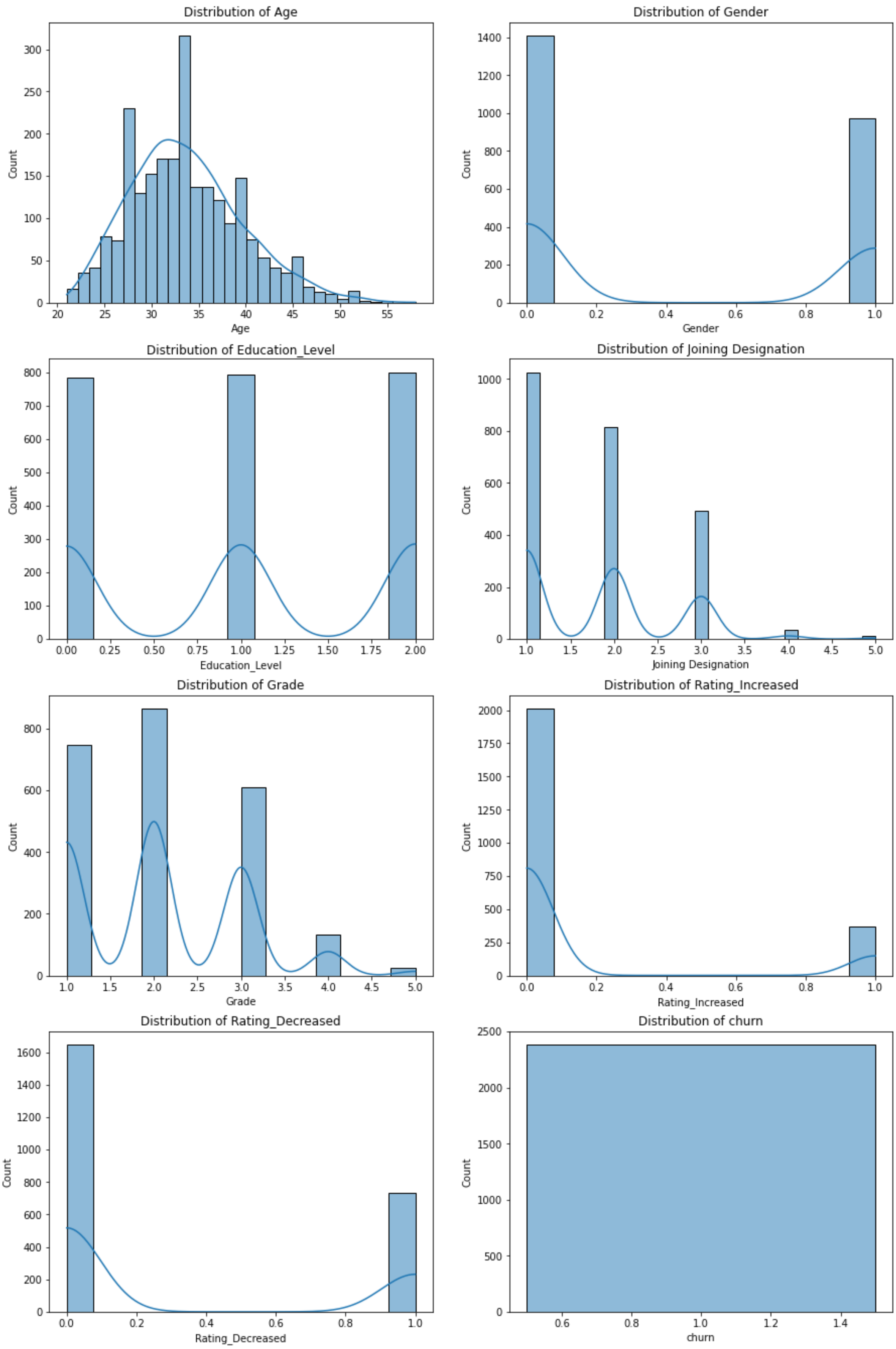
Out[30]:
```
Index(['Driver_ID', 'MMM-YY', 'Age', 'Gender', 'Education_Level',
       'Dateofjoining', 'Joining Designation', 'Grade', 'Income',
       'Total Business Value', 'Rating_Increased', 'Rating_Decreased',
       'Quarterly Rating', 'churn'],
      dtype='object')
```

In [31]:
```
df_categorical.columns
```

Out[31]:
```
Index(['City', 'LastWorkingDate'], dtype='object')
```

Univariate Analysis

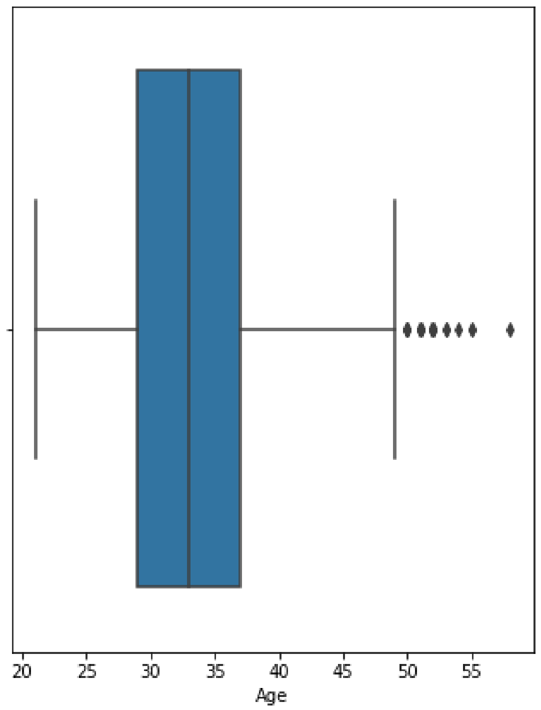
In [32]:
```
fig, axis = plt.subplots(nrows=4, ncols=2, figsize=(15, 10))
fig.subplots_adjust(top=1.9)

sns.histplot(data=df, x="Age", kde=True, ax=axis[0,0])
axis[0,0].set_title('Distribution of Age')
sns.histplot(data=df, x="Gender", kde=True, ax=axis[0,1])
axis[0,1].set_title('Distribution of Gender')
sns.histplot(data=df, x="Education_Level", kde=True, ax=axis[1,0])
axis[1,0].set_title('Distribution of Education_Level')
sns.histplot(data=df, x="Joining Designation", kde=True, ax=axis[1,1])
axis[1,1].set_title('Distribution of Joining Designation')
sns.histplot(data=df, x="Grade", kde=True, ax=axis[2,0])
axis[2,0].set_title('Distribution of Grade')
sns.histplot(data=df, x="Rating_Increased", kde=True, ax=axis[2,1])
axis[2,1].set_title('Distribution of Rating_Increased')
sns.histplot(data=df, x="Rating_Decreased", kde=True, ax=axis[3,0])
axis[3,0].set_title('Distribution of Rating_Decreased')
sns.histplot(data=df, x="churn", kde=True, ax=axis[3,1])
axis[3,1].set_title('Distribution of churn')
plt.show()
```

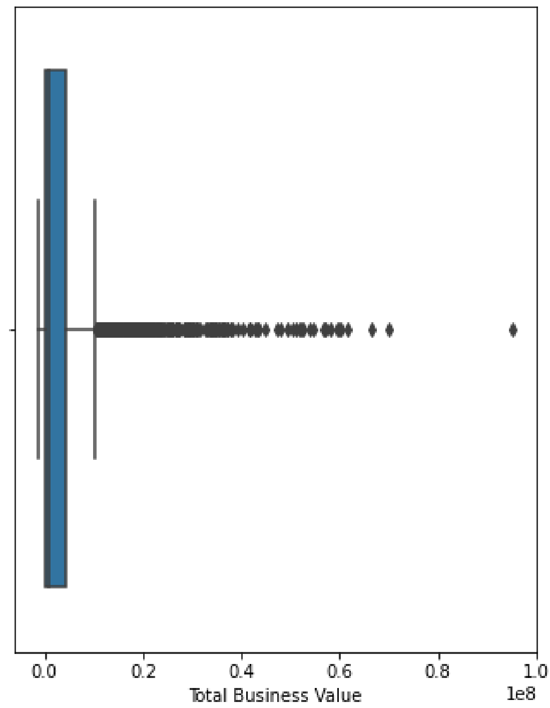


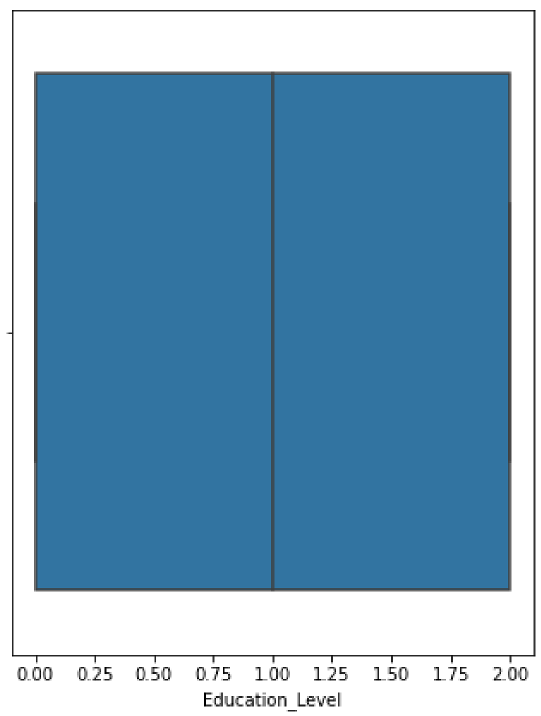
In [33]:

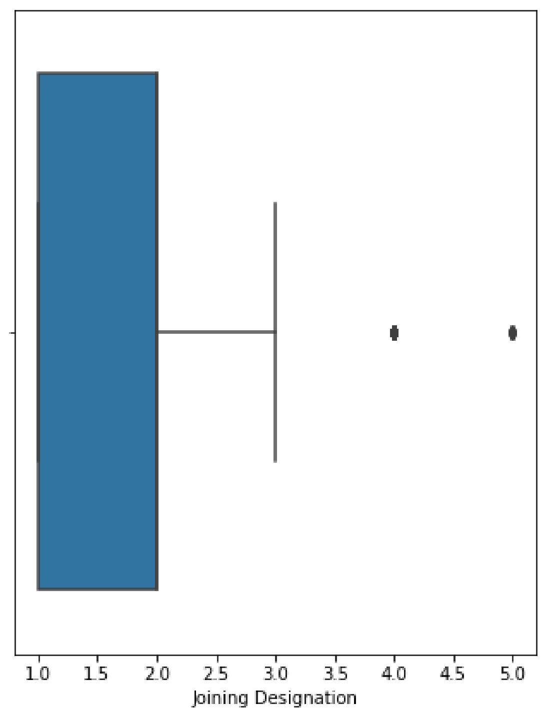
```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12, 10))
fig.subplots_adjust(top=1.9)

sns.boxplot(data=df, x="Age", ax=axis[0,0])
sns.boxplot(data=df, x="Total Business Value", ax=axis[0,1])
sns.boxplot(data=df, x="Education_Level", ax=axis[1,0])
sns.boxplot(data=df, x="Joining Designation", ax=axis[1,1])
sns.boxplot(data=df, x="Grade", ax=axis[2,0])
```

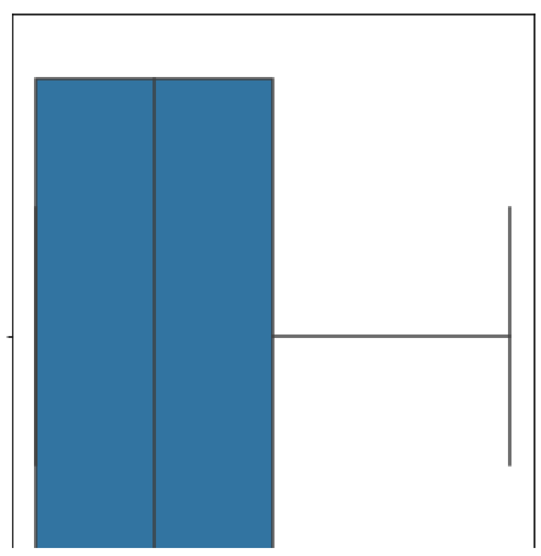
```
sns.boxplot(data=df, x="Income", ax=axis[2,1])
plt.show()
```

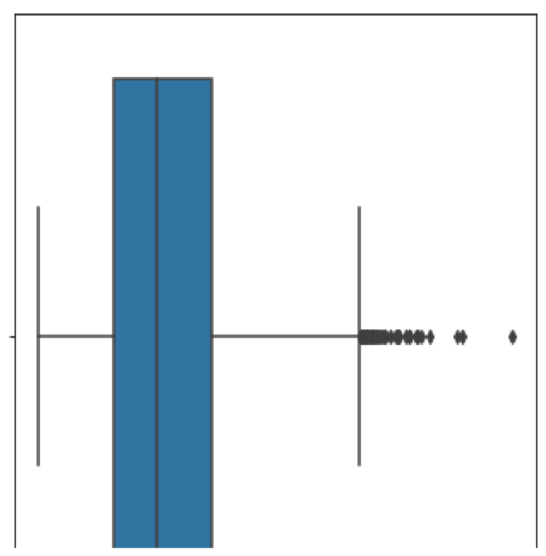

20 25 30 35 40 45 50 55
Age


0.0 0.2 0.4 0.6 0.8 1.0
1e8
Total Business Value


0.00 0.25 0.50 0.75 1.00 1.25 1.50 1.75 2.00
Education_Level

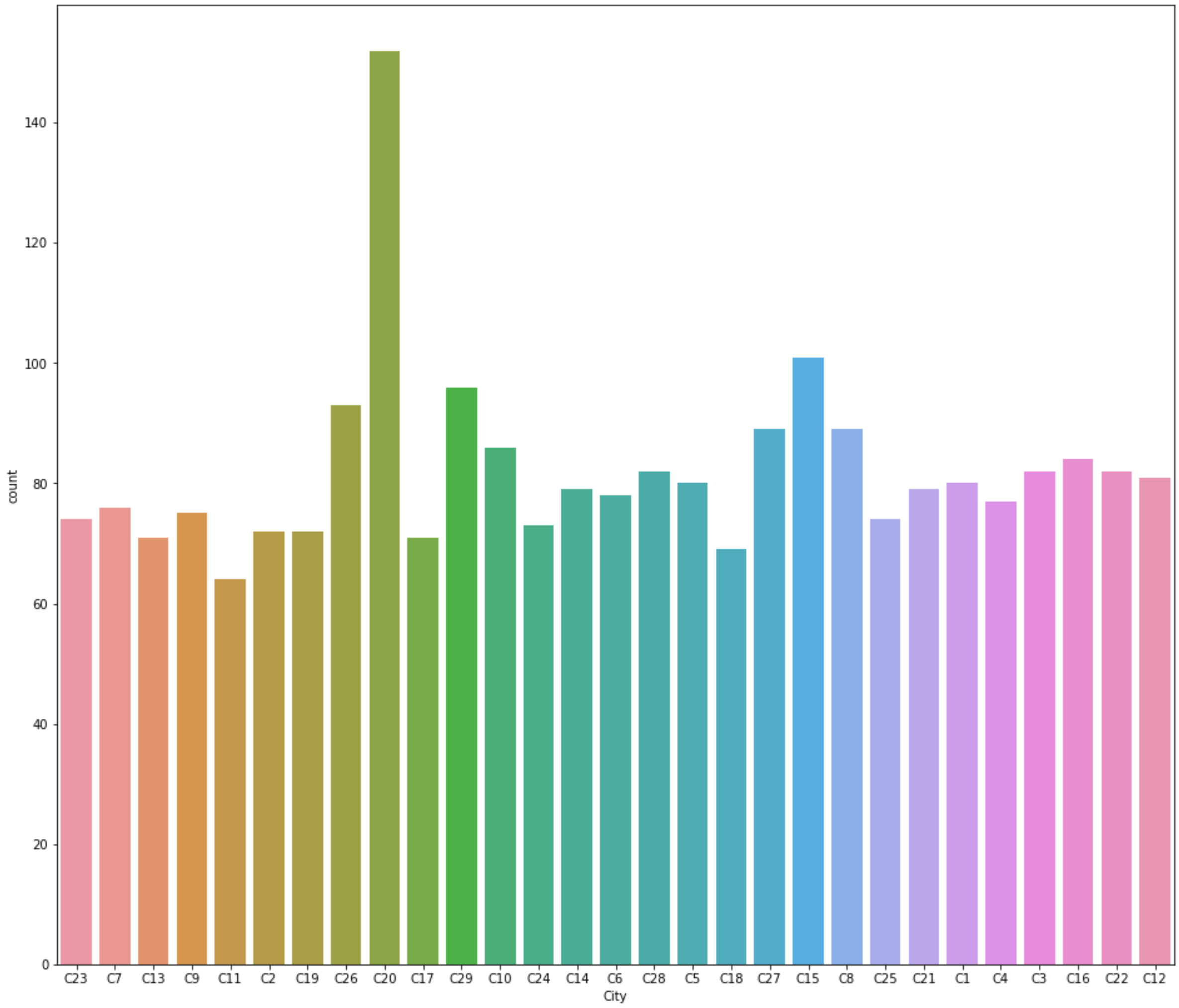

1.0 1.5 2.0 2.5 3.0 3.5 4.0 4.5 5.0
Joining Designation





In [34]:
```
fig, axis = plt.subplots(nrows=1, figsize=(16, 6))
fig.subplots_adjust(top=1.9)

sns.countplot(data=df, x="City")
```

Out[34]: <AxesSubplot:xlabel='City', ylabel='count'>



Observations:

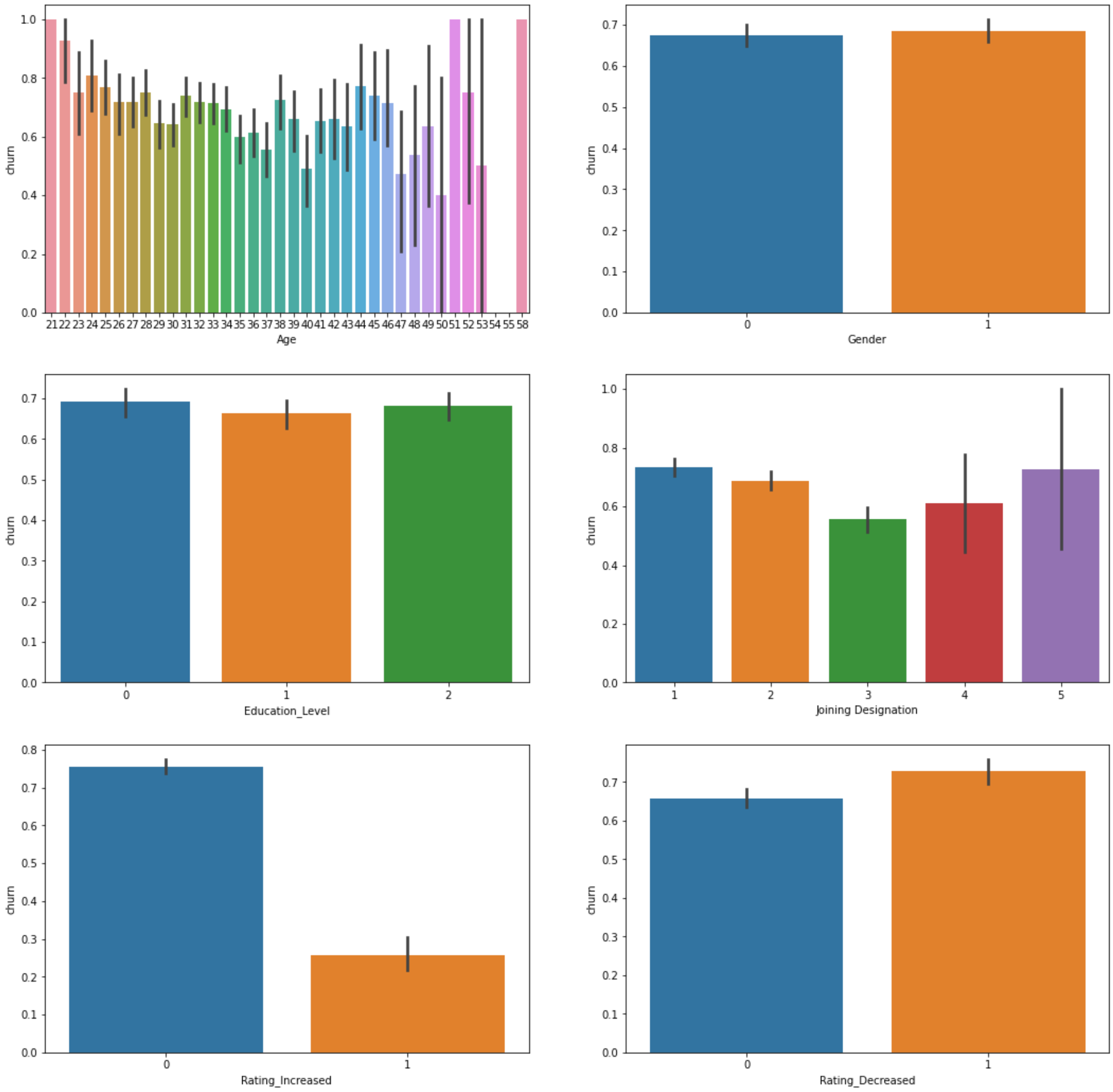
- More drivers are from city c20.
- The average age for Drivers are 30-35.
- Total of 368 drivers rating has been increased.
- Total of 973 drivers rating has been Decreased.
- More Male Drivers are present.

Bivariate and Multivariate Analysis

In [40]:
```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(18, 10))
fig.subplots_adjust(top=1.5)
```

```python
sns.barplot(x='Age', y='churn', data=df, ax=axis[0,0])
sns.barplot(x='Gender', y='churn', data=df, ax=axis[0,1])
sns.barplot(x='Education_Level', y='churn', data=df, ax=axis[1,0])
sns.barplot(x='Joining Designation', y='churn', data=df, ax=axis[1,1])
sns.barplot(x='Rating_Increased', y='churn', data=df, ax=axis[2,0])
sns.barplot(x='Rating_Decreased', y='churn', data=df, ax=axis[2,1])
```

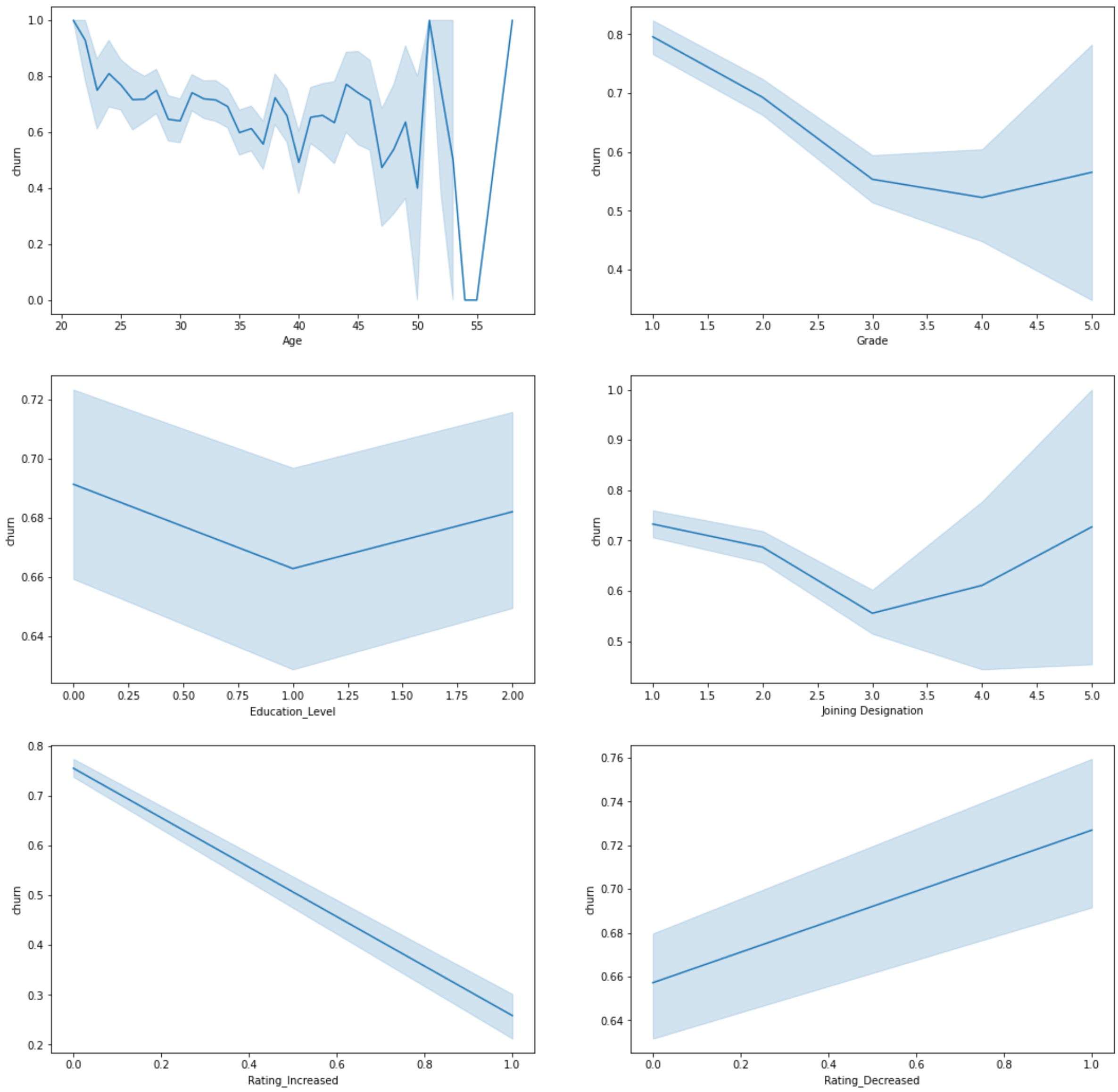
Out[40]: <AxesSubplot:xlabel='Rating_Decreased', ylabel='churn'>



In [41]:

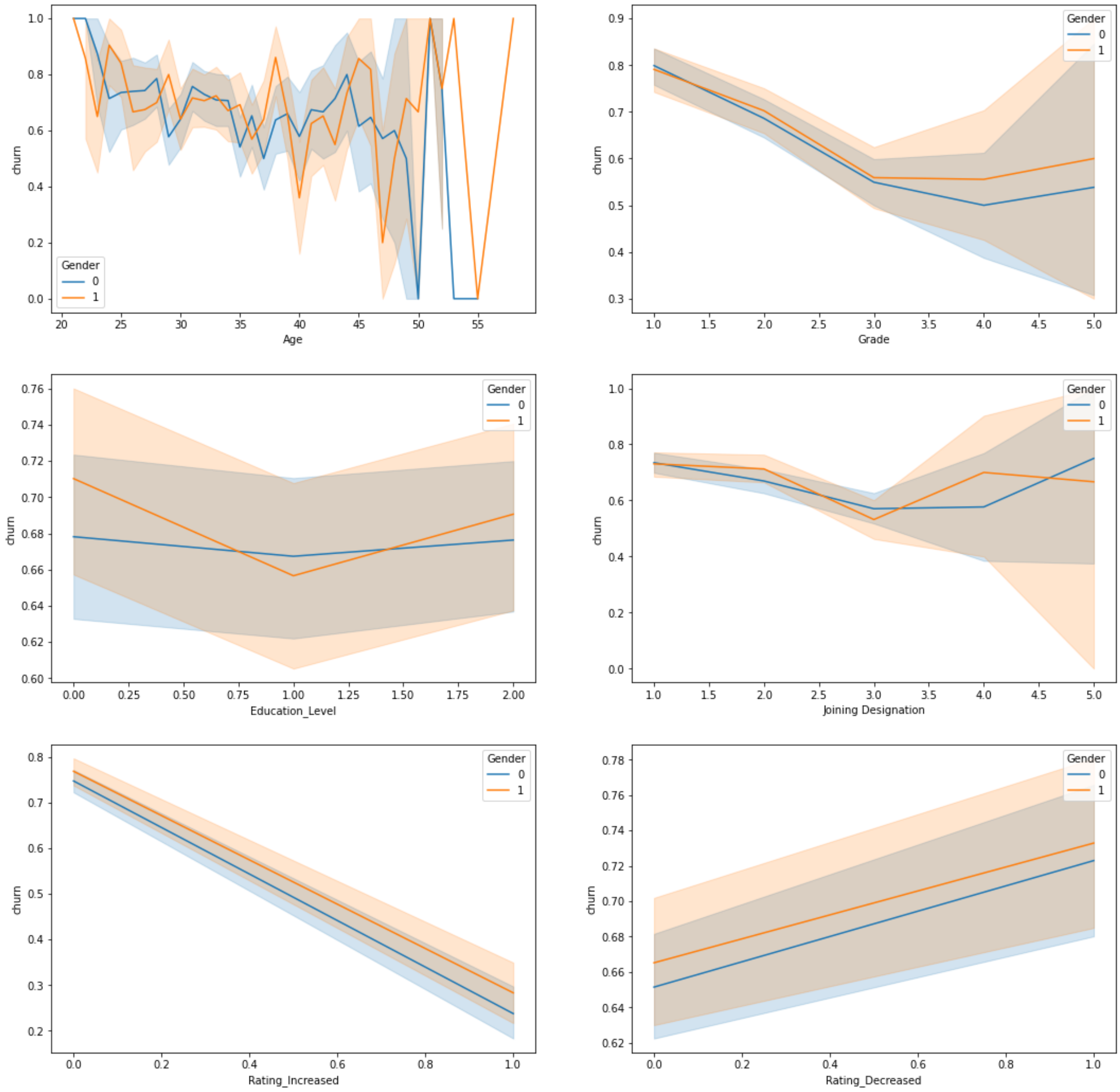
```python
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(18, 10))
fig.subplots_adjust(top=1.5)

sns.lineplot(x='Age', y='churn', data=df, ax=axis[0,0])
sns.lineplot(x='Grade',y='churn', data=df, ax=axis[0,1])
sns.lineplot(x='Education_Level',y='churn', data=df, ax=axis[1,0])
sns.lineplot(x='Joining Designation',y='churn', data=df, ax=axis[1,1])
sns.lineplot(x='Rating_Increased',y='churn', data=df, ax=axis[2,0])
sns.lineplot(x='Rating_Decreased',y='churn', data=df, ax=axis[2,1])
```

Out[41]: <AxesSubplot:xlabel='Rating_Decreased', ylabel='churn'>



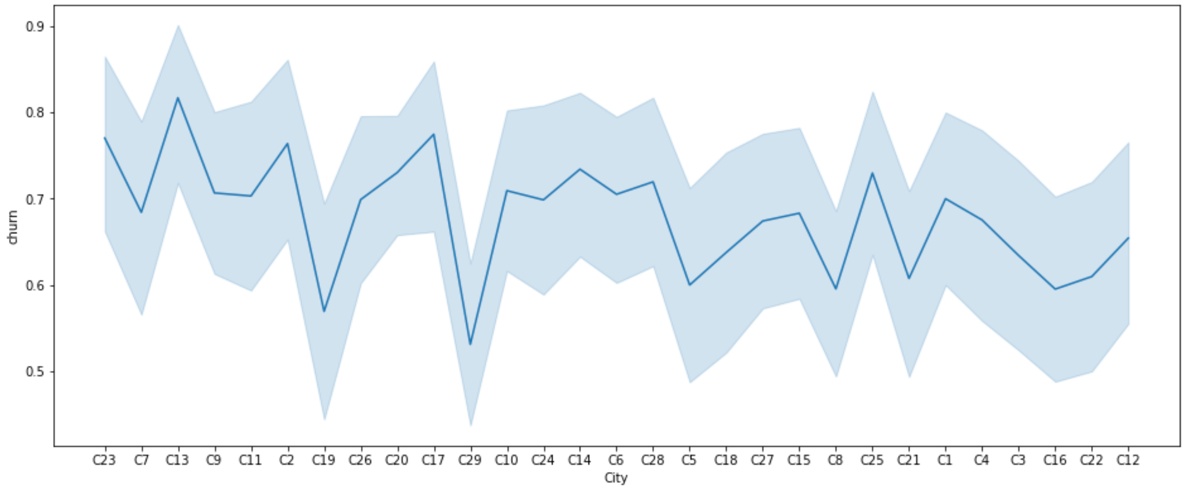
In [42]:
```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(18, 10))
fig.subplots_adjust(top=1.5)

sns.lineplot(x='Age',hue='Gender', y='churn', data=df, ax=axis[0,0])
sns.lineplot(x='Grade',hue='Gender', y='churn', data=df, ax=axis[0,1])
sns.lineplot(x='Education_Level',hue='Gender', y='churn', data=df, ax=axis[1,0])
sns.lineplot(x='Joining Designation',hue='Gender', y='churn', data=df, ax=axis[1,1
sns.lineplot(x='Rating_Increased',hue='Gender', y='churn', data=df, ax=axis[2,0])
sns.lineplot(x='Rating_Decreased',hue='Gender', y='churn', data=df, ax=axis[2,1])
```

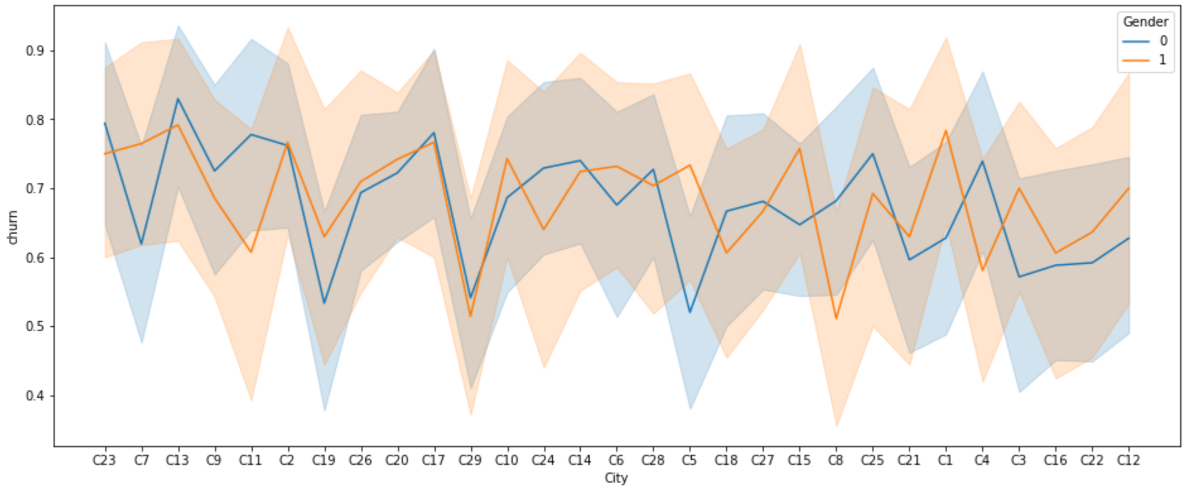
Out[42]:
```
<AxesSubplot:xlabel='Rating_Decreased', ylabel='churn'>
```



In [43]:
```python
fig, axis = plt.subplots(nrows=2, figsize=(16, 6))
fig.subplots_adjust(top=1.9)

sns.lineplot(x='City',y='churn',data=df,ax=axis[0])
sns.lineplot(x='City',hue='Gender',y='churn',data=df,ax=axis[1])
```

Out[43]: `<AxesSubplot:xlabel='City', ylabel='churn'>`





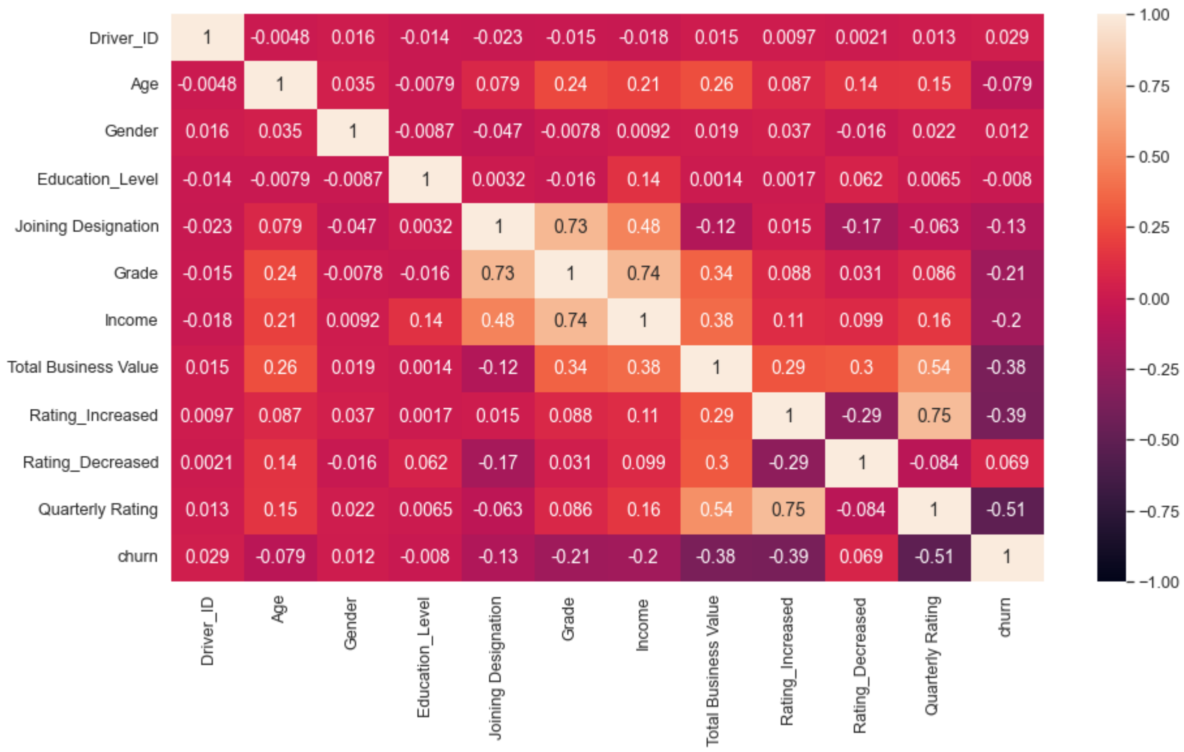
In [44]:
```
## correlation matrix for heat map
df.corr()
```

Out[44]:

	Driver_ID	Age	Gender	Education_Level	Joining Designation	Grade	Inco
Driver_ID	1.000000	-0.004829	0.015625	-0.014343	-0.023126	-0.014533	-0.0178
Age	-0.004829	1.000000	0.035064	-0.007876	0.079399	0.238908	0.2090
Gender	0.015625	0.035064	1.000000	-0.008747	-0.046815	-0.007765	0.0092
Education_Level	-0.014343	-0.007876	-0.008747	1.000000	0.003203	-0.016218	0.1401
Joining Designation	-0.023126	0.079399	-0.046815	0.003203	1.000000	0.726906	0.4805
Grade	-0.014533	0.238908	-0.007765	-0.016218	0.726906	1.000000	0.7372
Income	-0.017876	0.209025	0.009222	0.140189	0.480523	0.737210	1.0000
Total Business Value	0.015133	0.262775	0.018537	0.001392	-0.121368	0.340166	0.3794
Rating_Increased	0.009708	0.086854	0.036909	0.001734	0.015400	0.087604	0.1103
Rating_Decreased	0.002058	0.141208	-0.016209	0.061733	-0.172525	0.031182	0.0988
Quarterly Rating	0.012889	0.150336	0.021720	0.006544	-0.063404	0.085754	0.1634
churn	0.029269	-0.078571	0.012109	-0.007953	-0.127773	-0.205410	-0.2019

In [45]:
```
sns.set(font_scale=1.15)
plt.figure(figsize=(15,8))
sns.heatmap(df.corr(),annot=True, vmin=-1, vmax=1)
```

Out[45]: <AxesSubplot:>



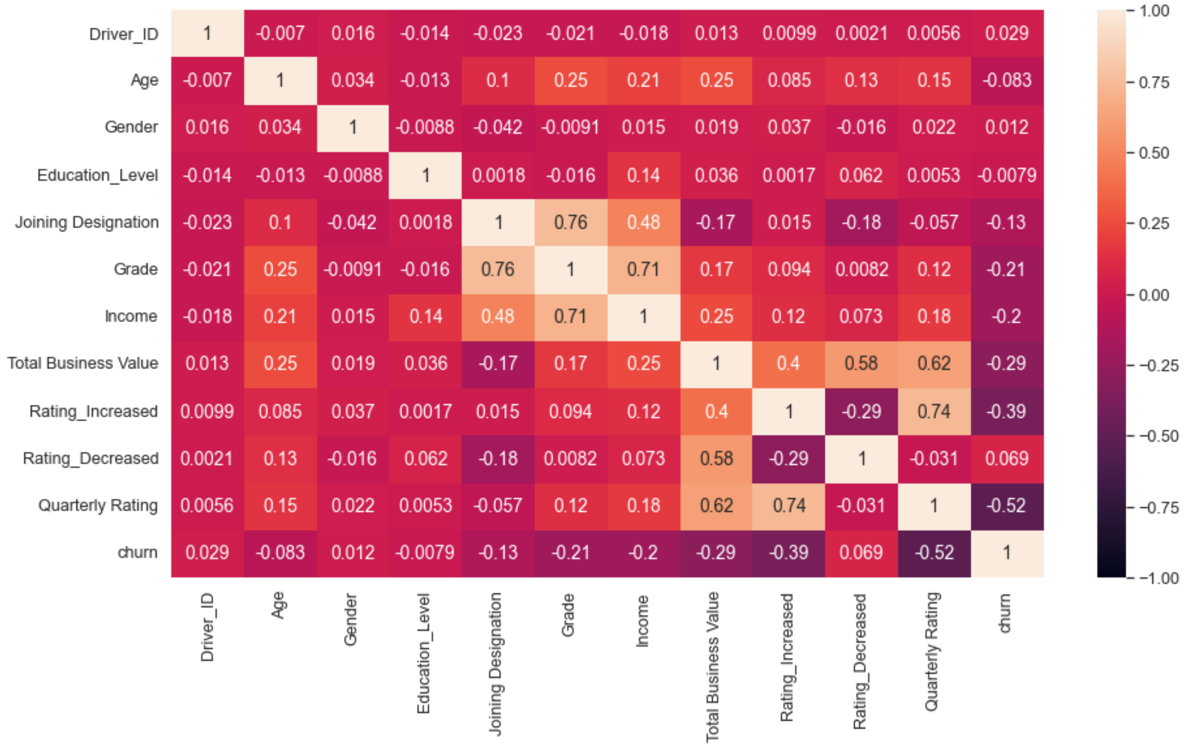
In [46]:
```
## spearman correlation matrix for heat map, used for better understanding
df.corr('spearman')
```

Out[46]:

	Driver_ID	Age	Gender	Education_Level	Joining Designation	Grade	Inco
Driver_ID	1.000000	-0.007009	0.015667	-0.014416	-0.023266	-0.021009	-0.0176
Age	-0.007009	1.000000	0.033503	-0.012812	0.104681	0.250074	0.2084
Gender	0.015667	0.033503	1.000000	-0.008789	-0.042323	-0.009093	0.0146
Education_Level	-0.014416	-0.012812	-0.008789	1.000000	0.001773	-0.015532	0.1440
Joining Designation	-0.023266	0.104681	-0.042323	0.001773	1.000000	0.756124	0.4823
Grade	-0.021009	0.250074	-0.009093	-0.015532	0.756124	1.000000	0.7066
Income	-0.017635	0.208455	0.014659	0.144004	0.482364	0.706632	1.0000
Total Business Value	0.012676	0.254588	0.019311	0.036434	-0.167053	0.170581	0.2475
Rating_Increased	0.009885	0.085197	0.036909	0.001693	0.015131	0.094179	0.1205
Rating_Decreased	0.002057	0.127446	-0.016209	0.061635	-0.184552	0.008236	0.0734
Quarterly Rating	0.005634	0.147853	0.021989	0.005278	-0.057107	0.117197	0.1786
churn	0.029218	-0.083440	0.012109	-0.007874	-0.129816	-0.211135	-0.2042

In [47]:
```
sns.set(font_scale=1.15)
plt.figure(figsize=(15,8))
sns.heatmap(df.corr('spearman'),annot=True,vmin=-1, vmax=1)
```

Out[47]: <AxesSubplot:>



Observations:

- Rating Decreased is positively correlated with churn data irrespective of Gender.
- If age of driver is high there is high chance of that driver churns according lineplot.
- No impact of Grade and Income of driver churns.
- Gender is slighlty impacting the churn data.
- Rating Increase is negatively correlated with churn irrespective of Gender.

Data Preparation for Modeling

In [48]:
```
df['City'].value_counts()
```

Out[48]:
```
C20    152
C15    101
C29     96
C26     93
C8      89
C27     89
C10     86
C16     84
C22     82
C3      82
C28     82
C12     81
C5      80
C1      80
C21     79
C14     79
C6      78
C4      77
C7      76
C9      75
C25     74
C23     74
C24     73
C19     72
C2      72
C17     71
C13     71
C18     69
C11     64
Name: City, dtype: int64
```

In [49]:
```
one_hot_encoded_data = pd.get_dummies(df, columns = ['City'])
one_hot_encoded_data
```

Out[49]:

	Driver_ID	MMM-YY	Age	Gender	Education_Level	Dateofjoining	LastWorkingDate	Joi Designa
0	1	2019-03-01	28	0	2	2018-12-24	2019-03-11 00:00:00	
1	2	2020-12-01	31	0	2	2020-11-06	0	
2	4	2020-04-01	43	0	2	2019-12-07	2020-04-27 00:00:00	
3	5	2019-03-01	29	0	0	2019-01-09	2019-03-07 00:00:00	
4	6	2020-12-01	31	1	1	2020-07-31	0	
...	...	...	...	...	...	...	...	
2376	2784	2020-12-01	34	0	0	2015-10-15	0	
2377	2785	2020-10-01	34	1	0	2020-08-28	2020-10-28 00:00:00	
2378	2786	2019-09-01	45	0	0	2018-07-31	2019-09-22 00:00:00	
2379	2787	2019-06-01	28	1	2	2018-07-21	2019-06-20 00:00:00	
2380	2788	2020-12-01	30	0	2	2020-06-08	0	

2381 rows × 44 columns

In [50]:

```
df_numerical=one_hot_encoded_data.select_dtypes(exclude='object')
df_categorical=one_hot_encoded_data.select_dtypes(include='object')
```

In [53]:

```
df_numerical['MMM-YY']=(df_numerical['MMM-YY'].astype(np.int64))
df_numerical['Dateofjoining']=(df_numerical['Dateofjoining'].astype(np.int64))
```

In [54]:

```
def detect_outliers(data):
    length_before=len(data)
    q1=np.percentile(data,25)
    q3=np.percentile(data,75)
    IQR=q3-q1
    upper_bound=q3+1.5*IQR
    lower_bound=q1-1.5*IQR
    if lower_bound<0:
        lower_bound=0
    length_after=len(data[(data>lower_bound)&(data<upper_bound)])
    data=data[(data<=upper_bound) & (data>=lower_bound)]
    print('After applying IQR Method')
    return f"{np.round((length_before-length_after)/length_before,3)}% outliers da
```

In [55]:

```
print("Before applying IQR Method:")
for col in df_numerical.columns:
    print(col,":", detect_outliers(df_numerical[col]))
```

```
Before applying IQR Method:
After applying IQR Method
Driver_ID : 0.0% outliers data found
After applying IQR Method
MMM-YY : 0.0% outliers data found
After applying IQR Method
Age : 0.015% outliers data found
After applying IQR Method
Gender : 0.591% outliers data found
After applying IQR Method
Education_Level : 0.329% outliers data found
After applying IQR Method
Dateofjoining : 0.06% outliers data found
After applying IQR Method
Joining Designation : 0.02% outliers data found
After applying IQR Method
Grade : 0.0% outliers data found
After applying IQR Method
Income : 0.02% outliers data found
After applying IQR Method
Total Business Value : 0.447% outliers data found
After applying IQR Method
Rating_Increased : 1.0% outliers data found
After applying IQR Method
Rating_Decreased : 0.691% outliers data found
After applying IQR Method
Quarterly Rating : 0.045% outliers data found
After applying IQR Method
churn : 0.321% outliers data found
After applying IQR Method
City_C1 : 1.0% outliers data found
After applying IQR Method
City_C10 : 1.0% outliers data found
After applying IQR Method
City_C11 : 1.0% outliers data found
After applying IQR Method
City_C12 : 1.0% outliers data found
After applying IQR Method
City_C13 : 1.0% outliers data found
After applying IQR Method
City_C14 : 1.0% outliers data found
After applying IQR Method
City_C15 : 1.0% outliers data found
After applying IQR Method
City_C16 : 1.0% outliers data found
After applying IQR Method
City_C17 : 1.0% outliers data found
After applying IQR Method
City_C18 : 1.0% outliers data found
After applying IQR Method
City_C19 : 1.0% outliers data found
After applying IQR Method
City_C2 : 1.0% outliers data found
After applying IQR Method
City_C20 : 1.0% outliers data found
After applying IQR Method
City_C21 : 1.0% outliers data found
After applying IQR Method
City_C22 : 1.0% outliers data found
After applying IQR Method
City_C23 : 1.0% outliers data found
After applying IQR Method
City_C24 : 1.0% outliers data found
After applying IQR Method
```

```
City_C25 : 1.0% outliers data found
After applying IQR Method
City_C26 : 1.0% outliers data found
After applying IQR Method
City_C27 : 1.0% outliers data found
After applying IQR Method
City_C28 : 1.0% outliers data found
After applying IQR Method
City_C29 : 1.0% outliers data found
After applying IQR Method
City_C3 : 1.0% outliers data found
After applying IQR Method
City_C4 : 1.0% outliers data found
After applying IQR Method
City_C5 : 1.0% outliers data found
After applying IQR Method
City_C6 : 1.0% outliers data found
After applying IQR Method
City_C7 : 1.0% outliers data found
After applying IQR Method
City_C8 : 1.0% outliers data found
After applying IQR Method
City_C9 : 1.0% outliers data found
```

Observations:

- Very less amount of data is present and outliers are too very less,
- lets not remove outliers and use this data to train the model.

Ensemble -Bagging Model

In [57]:

```python
targets = df_numerical['churn']
features = df_numerical.drop(columns = {'churn'})
```

In [59]:

```python
# splitting the data into train and test with some test size
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(features, targets, test_size=0
```

In [60]:

```python
# scaling the X_train and X_test
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)
X_test = scaler.fit_transform(X_test)
```

In [71]:

```python
#Building Ensemble Bagging Model
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier(random_state=7, max_depth=3, n_estimators=50)

#training the Model
model.fit(X_train,y_train)

#accuracy score
accuracy=model.score(X_test, y_test)

print(f'accuracy score: {accuracy}')
```

```
accuracy score: 0.9161425576519916
```

In [62]:

```python
# Handling Imbalance data with SMOTE Technique
from imblearn.over_sampling import SMOTE
from collections import Counter

smt = SMOTE()
X_sm, y_sm = smt.fit_resample(X_train, y_train)

print('Resampled dataset shape {}'.format(Counter(y_sm)))
```

```
Resampled dataset shape Counter({0: 1289, 1: 1289})
```

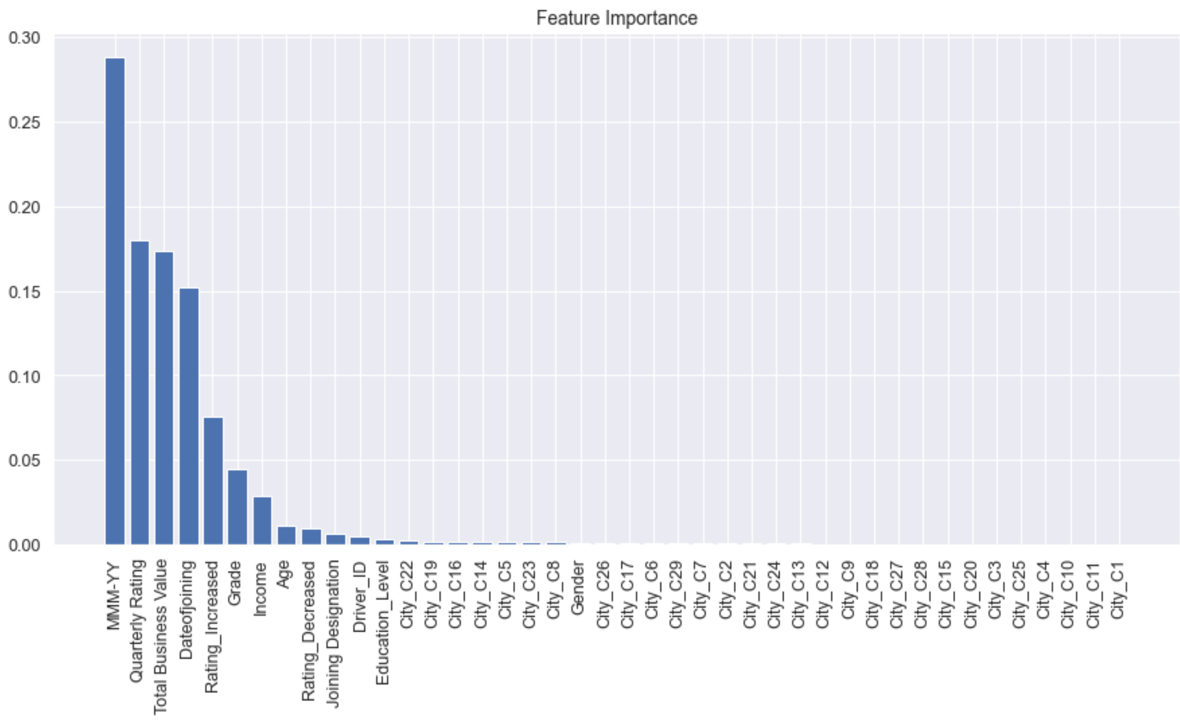
In [63]:

```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import KFold, cross_validate

tree_clf = RandomForestClassifier(random_state=7, max_depth=3, n_estimators=50)
kfold = KFold(n_splits=10)
cv_acc_results = cross_validate(tree_clf, X_sm, y_sm, cv = kfold, scoring = 'accura

print(f"K-Fold Accuracy Mean: Train: {cv_acc_results['train_score'].mean()*100} Va
print(f"K-Fold Accuracy Std: Train: {cv_acc_results['train_score'].std()*100} Vali
```

```
K-Fold Accuracy Mean: Train: 94.75474676491999 Validation: 93.9094501251772
K-Fold Accuracy Std: Train: 0.22269082954512817 Validation: 1.6124656378346365
```

In [64]:

```python
# Feature importance
import numpy as np
import matplotlib.pyplot as plt

clf = RandomForestClassifier(random_state=7, max_depth=3, n_estimators=50)
clf.fit(X_train, y_train)
importances = clf.feature_importances_
indices = np.argsort(importances)[::-1] # Sort feature importances in descending or
names = [features.columns[i] for i in indices] # Rearrange feature names so they ma
plt.figure(figsize=(15, 7)) # Create plot
plt.title("Feature Importance") # Create plot title
plt.bar(range(features.shape[1]), importances[indices]) # Add bars
plt.xticks(range(features.shape[1]), names, rotation=90) # Add feature names as x-a
plt.show() # Show plot
```



Observations:

- we got Accuracy of 92% using Random Forest Algorithm.
- Let's try Hyper parameter Tuning to get best Random Forest Parameters.

HyperParameter Tuning

In [65]:
```
# Defining Parametes
params = {
          'n_estimators' : [20,30,40,50],
          'max_depth' : [1,2,3],
          'criterion' : ['gini', 'entropy'],
          'bootstrap' : [True, False],
          'max_features' : [2,3,4,5,6,7],
         }
```

In [72]:
```
# Using GridSearchCV to get best Parameters for Model.
from sklearn.model_selection import GridSearchCV

# Tuning Function
tuning_function = GridSearchCV(estimator = RandomForestClassifier(),
                               param_grid = params,
                               scoring = 'accuracy',
                               cv = 3,
                               n_jobs=-1
                               )

# Fitting the Tuning Function
tuning_function.fit(X_train, y_train)

# Fetching best parameters and score
parameters = tuning_function.best_params_
score = tuning_function.best_score_
print(parameters)
print(score)
```

```
{'bootstrap': True, 'criterion': 'entropy', 'max_depth': 3, 'max_features': 7, 'n_
estimators': 20}
0.9574612715997252
```

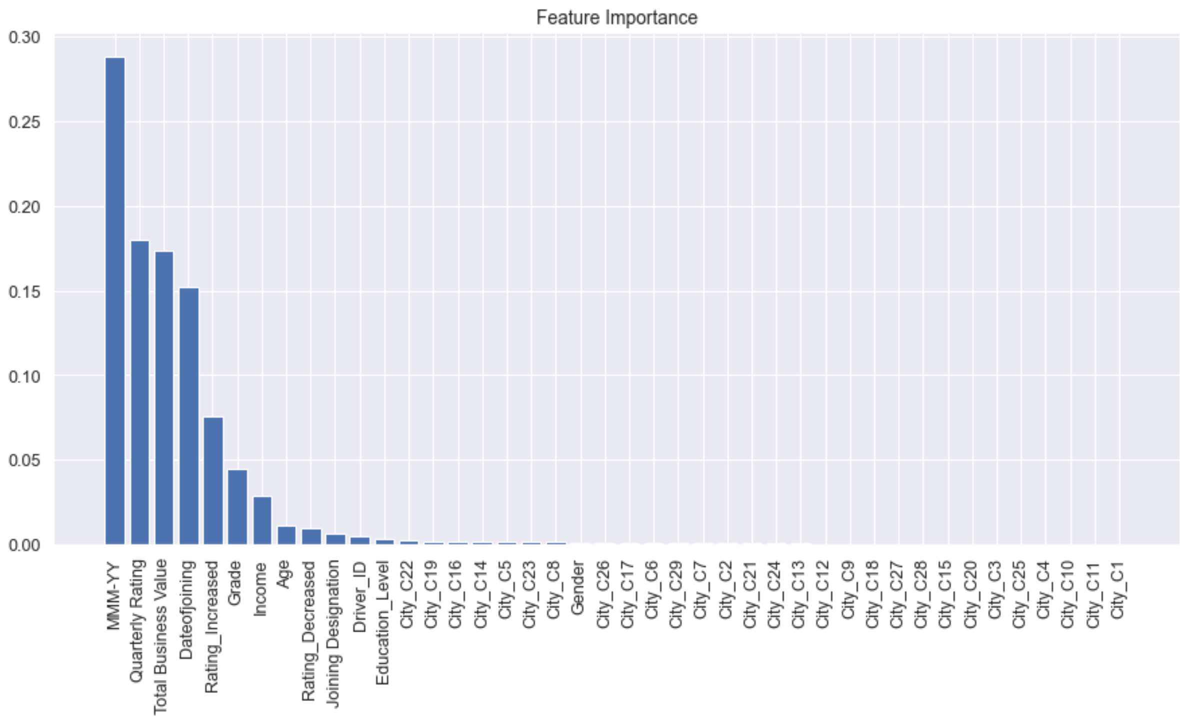
In [80]:
```
#Lets train the model with the best parameters.
#Building Ensemble Bagging Model
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier(random_state=7, max_depth=3, n_estimators=20, max_f

#training the Model
model.fit(X_train, y_train)

#Predicting the model
y_pred=model.predict(X_test)

#accuracy score
accuracy=model.score(X_test, y_test)

print(f'accuracy score: {accuracy}')
```

```
accuracy score: 0.9559748427672956
```

In [74]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import KFold, cross_validate

tree_clf = RandomForestClassifier(random_state=7, max_depth=3, n_estimators=20, ma
kfold = KFold(n_splits=10)
cv_acc_results = cross_validate(tree_clf, X_sm, y_sm, cv = kfold, scoring = 'accur

print(f"K-Fold Accuracy Mean: Train: {cv_acc_results['train_score'].mean()*100} Va
print(f"K-Fold Accuracy Std: Train: {cv_acc_results['train_score'].std()*100} Vali
```

```
K-Fold Accuracy Mean: Train: 94.98747381479447 Validation: 94.6852471872832
K-Fold Accuracy Std: Train: 0.258429506253071 Validation: 1.3008339018818098
```

In [75]:
```
# Feature importance
import numpy as np
import matplotlib.pyplot as plt

clf = RandomForestClassifier(random_state=7, max_depth=3, n_estimators=50)
clf.fit(X_train, y_train)
importances = clf.feature_importances_
indices = np.argsort(importances)[::-1] # Sort feature importances in descending o
names = [features.columns[i] for i in indices] # Rearrange feature names so they m
plt.figure(figsize=(15, 7)) # Create plot
plt.title("Feature Importance") # Create plot title
plt.bar(range(features.shape[1]), importances[indices]) # Add bars
plt.xticks(range(features.shape[1]), names, rotation=90) # Add feature names as x-
plt.show() # Show plot
```



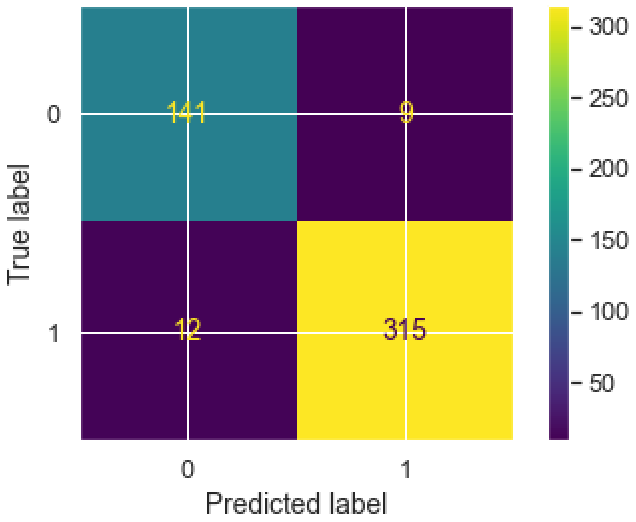
Observations:

- after applying Hyperparameter Tuning we got 95.5% Accuracy.

In [81]:
```
# Confusion Matrix
from sklearn.metrics import confusion_matrix,precision_score,recall_score,Confusio
cm = confusion_matrix(y_test, y_pred)
cm
```

Out[81]:
```
array([[141,   9],
       [ 12, 315]], dtype=int64)
```

In [82]:
```
disp=ConfusionMatrixDisplay(confusion_matrix=cm,
...                                   display_labels=model.classes_)
disp.plot()
plt.show()
```



- TN=True Negatives
- TP=True Positives
- FN=False Negatives
- FP=False Positives

In [83]:
```
TN=cm[0][0]
TP=cm[1][1]
FP=cm[0][1]
FN=cm[1][0]

print('True Negatives',TN)
print('True Positives',TP)
print('False Positives',FP)
print('False Negatives',FN)
```

```
True Negatives 141
True Positives 315
False Positives 9
False Negatives 12
```

In [84]:
```
# calculating Accuracy
def Accuracy(TN,TP,FP,FN):
    ans=(TN+TP)/(TN+TP+FP+FN)
    return ans
```

In [85]:
```
Accuracy(TN,TP,FP,FN)
```

Out[85]:
```
0.9559748427672956
```

In [86]:
```
Precision=precision_score(y_test,y_pred)
Precision
```

Out[86]:
```
0.9722222222222222
```

In [87]:
```
Recall=recall_score(y_test,y_pred)
Recall
```

Out[87]:
```
0.963302752293578
```

In [88]:
```
# Calculating F1 Score
def F1_score(Precision,Recall):
    ans=2*(Precision*Recall)/(Precision+Recall)
    return ans
```

In [89]:
```
F1_score=F1_score(Precision,Recall)
F1_score
```

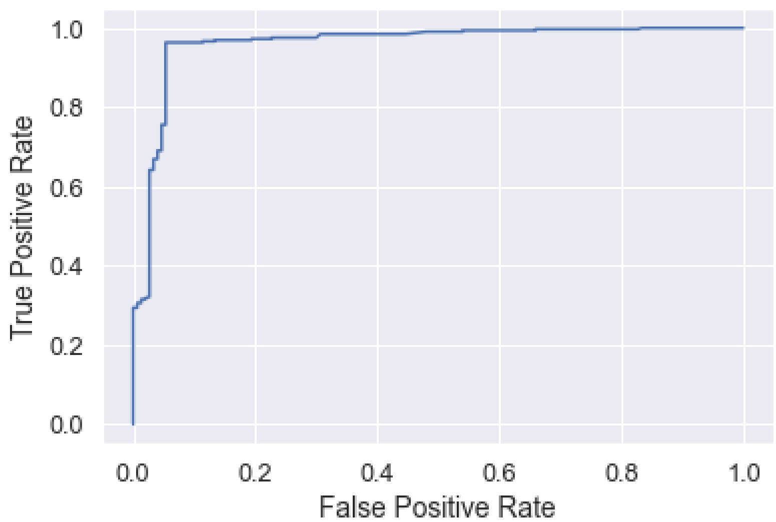
Out[89]:
```
0.9677419354838711
```

In [90]:
```
probs=model.predict_proba(X_test)[:,1]
```

In [91]:
```
# ROC AUC Curve
from sklearn.metrics import roc_auc_score,roc_curve
fpr,tpr,thres=roc_curve(y_test,probs)
plt.plot(fpr,tpr)
print('roc_auc_score:',roc_auc_score(y_test,probs))
# axis labels
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
```

```
roc_auc_score: 0.9613761467889909
```

Out[91]:
```
Text(0, 0.5, 'True Positive Rate')
```



Observations:

- Here, AUC score is greater than 0.50. it means our model can predict the positive & Negative class well.
- Max score can be 1 but we got 0.96.
- Our Model is doing Great according to this Area under curve

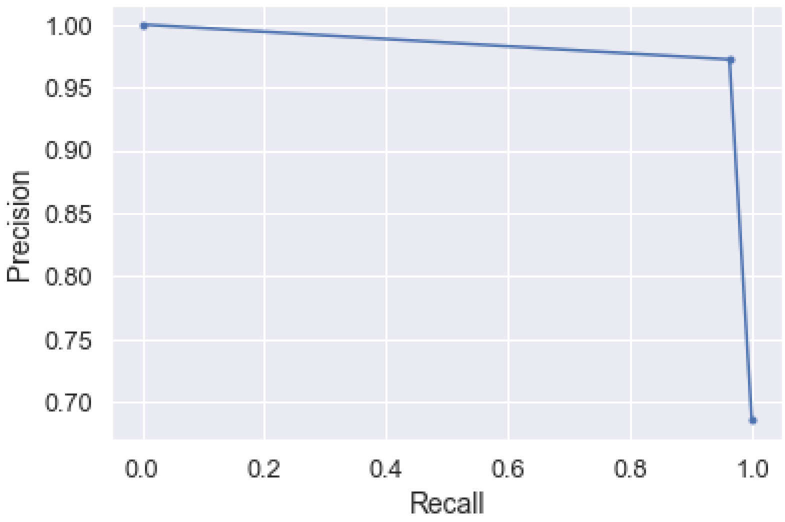
In [92]:
```
# Precision-Recall Curve
from sklearn.metrics import auc,precision_recall_curve,f1_score
lr_precision, lr_recall, _ = precision_recall_curve(y_test,y_pred)
lr_f1 = f1_score(y_test, y_pred)
```

```
auc(lr_recall,lr_precision)
print("f1 score",lr_f1)
plt.plot(lr_recall,lr_precision,marker='.')
# axis labels
plt.xlabel('Recall')
plt.ylabel('Precision')
```

```
f1 score 0.9677419354838711
```

Out[92]:

```
Text(0, 0.5, 'Precision')
```



Observations:

- F1 score is 0.967 which is very high
- According to this curve we get that There are high Precision and High Recall.
- This implies there are less false positives and false negatives.

Ensemble - Boosting Method

In [94]:

```
from xgboost import XGBClassifier
from sklearn.model_selection import RandomizedSearchCV,GridSearchCV
from sklearn.model_selection import StratifiedKFold
import datetime as dt
```

In [97]:

```
#Building Ensemble  Boosting Model
from sklearn.ensemble import RandomForestClassifier

xgb_model = XGBClassifier(n_estimators=40, objective='multi:softmax', num_class=15

#training the Model
xgb_model.fit(X_train,y_train)

#accuracy score
accuracy=xgb_model.score(X_test, y_test)

print(f'accuracy score: {accuracy}')
```

```
[20:00:56] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-gr
oup-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

accuracy score: 0.9538784067085954
```

In [98]:

```
# Handling Imbalance data with SMOTE Technique
from imblearn.over_sampling import SMOTE
from collections import Counter

smt = SMOTE()
X_sm, y_sm = smt.fit_resample(X_train, y_train)

print('Resampled dataset shape {}'.format(Counter(y_sm)))
```

```
Resampled dataset shape Counter({0: 1289, 1: 1289})
```

In [106…

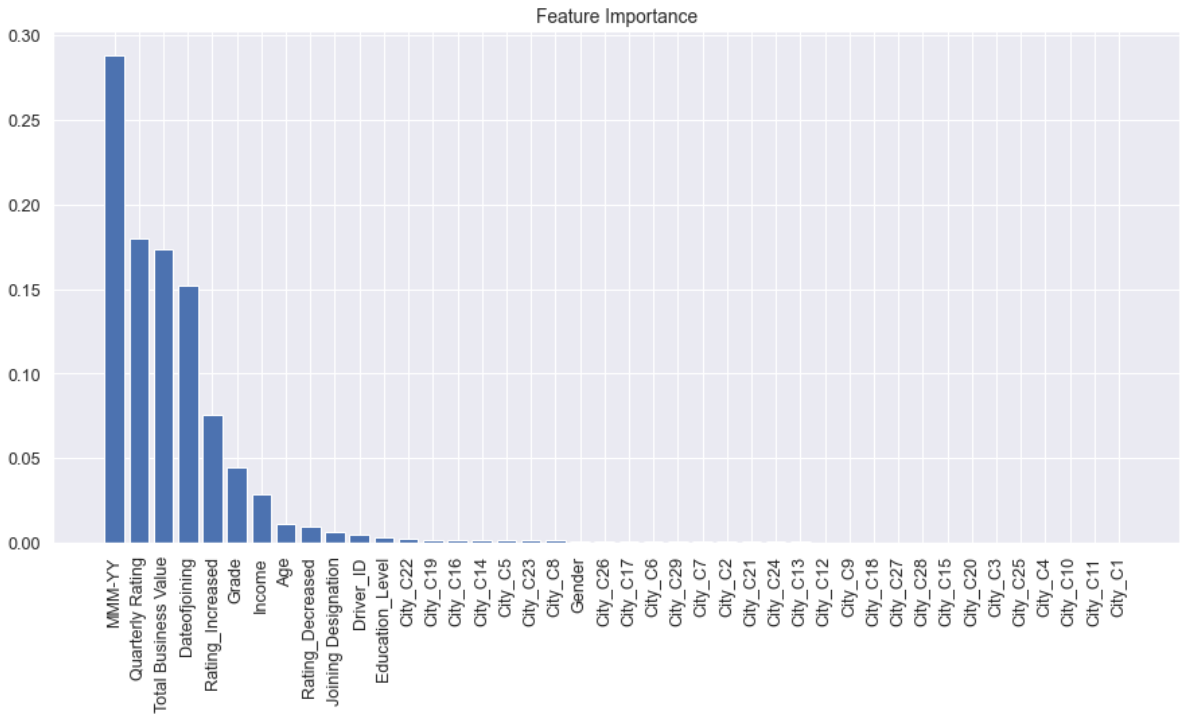
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import KFold, cross_validate

xgb_model = XGBClassifier(n_estimators=40, objective='multi:softmax', num_class=15
kfold = KFold(n_splits=10)
cv_acc_results = cross_validate(xgb_model, X_sm, y_sm, cv = kfold, scoring = 'accu

print(f"K-Fold Accuracy Mean: Train: {cv_acc_results['train_score'].mean()*100} Va
print(f"K-Fold Accuracy Std: Train: {cv_acc_results['train_score'].std()*100} Vali
```

```
[20:04:42] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-group-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:04:42] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-group-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:04:42] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-group-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:04:42] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-group-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:04:43] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-group-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:04:43] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-group-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:04:43] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-group-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:04:44] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-group-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:04:44] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-group-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:04:44] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-group-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

K-Fold Accuracy Mean: Train: 99.91380424608893 Validation: 95.73371942207342
K-Fold Accuracy Std: Train: 0.050988135452225684 Validation: 1.5000760375190425
```

In [107…

```python
# Feature importance
import numpy as np
import matplotlib.pyplot as plt

xgb_model = XGBClassifier(n_estimators=40, objective='multi:softmax', num_class=15
xgb_model.fit(X_train, y_train)
importances = clf.feature_importances_
indices = np.argsort(importances)[::-1] # Sort feature importances in descending o
names = [features.columns[i] for i in indices] # Rearrange feature names so they m
plt.figure(figsize=(15, 7)) # Create plot
plt.title("Feature Importance") # Create plot title
plt.bar(range(features.shape[1]), importances[indices]) # Add bars
plt.xticks(range(features.shape[1]), names, rotation=90) # Add feature names as x-
plt.show() # Show plot
```

```
[20:05:49] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-group-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.
```



Observations:

- we got Accuracy of 95.3% using XGBoost Algorithm.
- Let's try Hyper parameter Tuning to get best XGBoost Parameters.

HyperParameter Tuning

In [108…

```
# Defining Parametes
params = {
          'n_estimators' : [20,30,40,50],
          'max_depth' : [1,2,3],
          'learning_rate': [0.1, 0.5, 0.8],
          'subsample': [0.6, 0.8, 1.0],
          'colsample_bytree': [0.6, 0.8, 1.0],
         }
```

In [ ]:

```
folds = 3

skf = StratifiedKFold(n_splits=folds, shuffle = True, random_state = 1001)

random_search = RandomizedSearchCV(xgb, param_distributions=params, n_iter=10, scor

random_search.fit(X_sm, y_sm)
print(random_search.best_params_)
```

In [109…

```
# Using GridSearchCV to get best Parameters for Model.
from sklearn.model_selection import GridSearchCV

# Tuning Function
tuning_function = GridSearchCV(estimator = XGBClassifier(),
                               param_grid = params,
                               scoring = 'accuracy',
                               cv = 3,
                               n_jobs=-1
```

```python
                              )

# Fitting the Tuning Function
tuning_function.fit(X_train, y_train)

# Fetching best parameters and score
parameters = tuning_function.best_params_
score = tuning_function.best_score_
print(parameters)
print(score)
```

```
{'colsample_bytree': 1.0, 'learning_rate': 0.8, 'max_depth': 1, 'n_estimators': 3
0, 'subsample': 1.0}
0.9574629275441516
```

In [111…

```python
#Building Ensemble  Boosting Model
from sklearn.ensemble import RandomForestClassifier

xgb_model = XGBClassifier(n_estimators=40, objective='multi:softmax', num_class=15
                          max_depth=1,subsample=1.0,silent=True)

#training the Model
xgb_model.fit(X_train,y_train)

#accuracy score
accuracy=xgb_model.score(X_test, y_test)

print(f'accuracy score: {accuracy}')
```

```
[20:12:21] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-gr
oup-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

accuracy score: 0.9559748427672956
```

In [112…

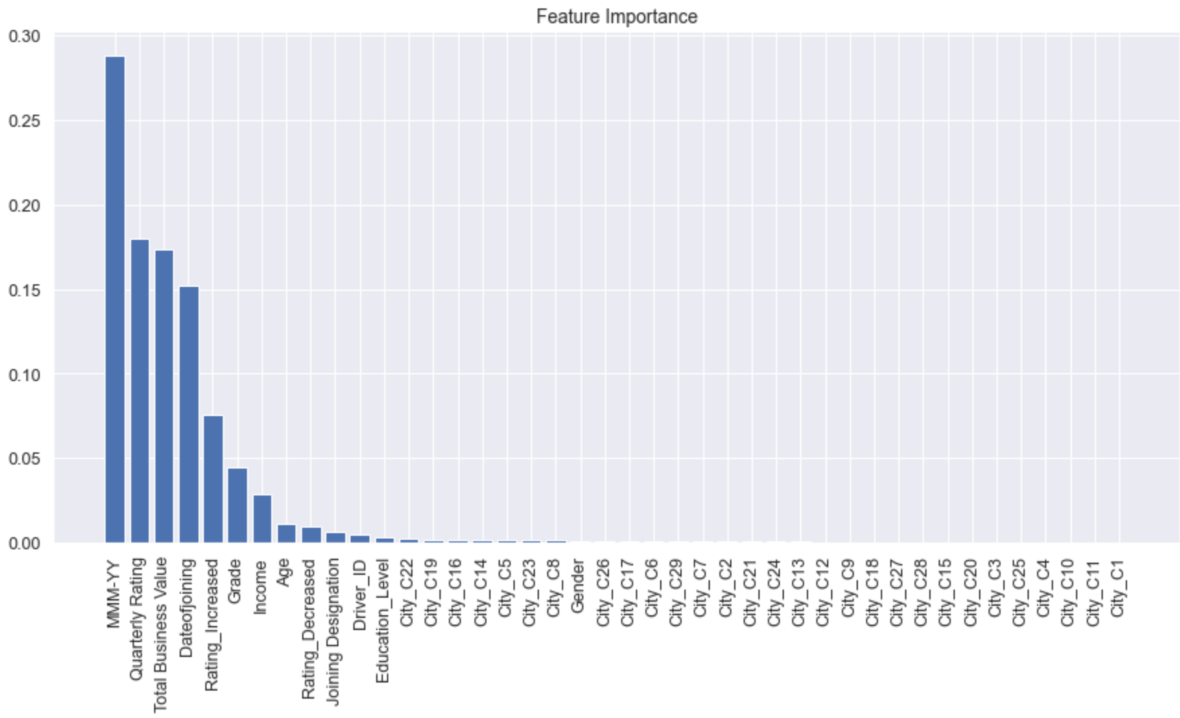
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import KFold, cross_validate

xgb_model = XGBClassifier(n_estimators=40, objective='multi:softmax', num_class=15
                          max_depth=1,subsample=1.0,silent=True)
kfold = KFold(n_splits=10)
cv_acc_results = cross_validate(xgb_model, X_sm, y_sm, cv = kfold, scoring = 'accu

print(f"K-Fold Accuracy Mean: Train: {cv_acc_results['train_score'].mean()*100} Va
print(f"K-Fold Accuracy Std: Train: {cv_acc_results['train_score'].std()*100} Vali
```

```
[20:13:28] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-gr
oup-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:13:29] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-gr
oup-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:13:29] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-gr
oup-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:13:29] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-gr
oup-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:13:29] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-gr
oup-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:13:29] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-gr
oup-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:13:29] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-gr
oup-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:13:30] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-gr
oup-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:13:30] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-gr
oup-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

[20:13:30] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-gr
oup-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.

K-Fold Accuracy Mean: Train: 96.21586452034646 Validation: 95.69465810032275
K-Fold Accuracy Std: Train: 0.2523114097029877 Validation: 1.1152665125941432
```

In [113…

```
# Feature importance
import numpy as np
import matplotlib.pyplot as plt

xgb_model = XGBClassifier(n_estimators=40, objective='multi:softmax', num_class=15
                          max_depth=1,subsample=1.0,silent=True)
xgb_model.fit(X_train, y_train)
importances = clf.feature_importances_
indices = np.argsort(importances)[::-1] # Sort feature importances in descending o
names = [features.columns[i] for i in indices] # Rearrange feature names so they m
plt.figure(figsize=(15, 7)) # Create plot
plt.title("Feature Importance") # Create plot title
plt.bar(range(features.shape[1]), importances[indices]) # Add bars
plt.xticks(range(features.shape[1]), names, rotation=90) # Add feature names as x-
plt.show() # Show plot
```

```
[20:14:05] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-gr
oup-i-0fc7796c793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.
```



Observations:

- After Applying Hyperparameter Tuning we got 95.5% Accuracy.

In [114…

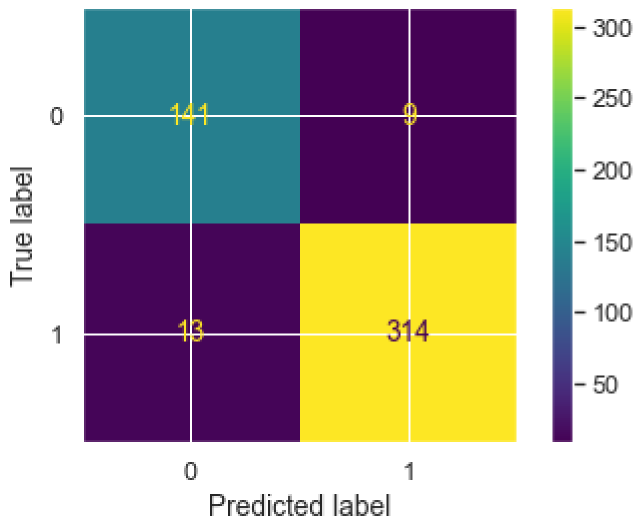
```
# Confusion Matrix
from sklearn.metrics import confusion_matrix,precision_score,recall_score,Confusio
cm = confusion_matrix(y_test, y_pred)
cm
```

Out[114]:

```
array([[141,   9],
       [ 13, 314]], dtype=int64)
```

In [115…

```
disp=ConfusionMatrixDisplay(confusion_matrix=cm,
...                                   display_labels=model.classes_)
disp.plot()
plt.show()
```



In [116…

```
TN=cm[0][0]
TP=cm[1][1]
FP=cm[0][1]
```

```
FN=cm[1][0]

print('True Negatives',TN)
print('True Positives',TP)
print('False Positives',FP)
print('False Negatives',FN)
```

```
True Negatives 141
True Positives 314
False Positives 9
False Negatives 13
```

In [117…

```
Accuracy(TN,TP,FP,FN)
```

Out[117]:

```
0.9538784067085954
```

In [118…

```
Precision=precision_score(y_test,y_pred)
Precision
```

Out[118]:

```
0.9721362229102167
```

In [119…

```
Recall=recall_score(y_test,y_pred)
Recall
```

Out[119]:

```
0.9602446483180428
```

In [126…

```
# Calculating F1 Score
def F1_score(Precision,Recall):
    ans=2*(Precision*Recall)/(Precision+Recall)
    return ans
```

In [127…

```
F1_score=F1_score(Precision,Recall)
F1_score
```

Out[127]:

```
0.9721362229102167
```

In [128…

```
probs=model.predict_proba(X_test)[:,1]
```

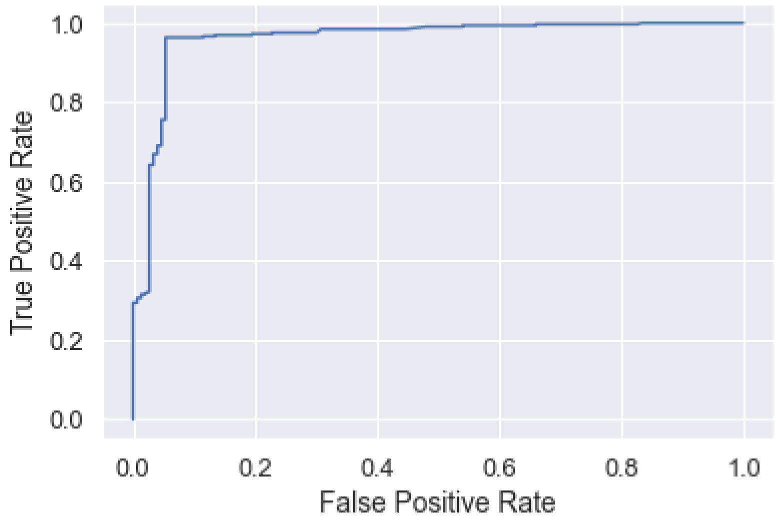
In [129…

```
# ROC AUC Curve
from sklearn.metrics import roc_auc_score,roc_curve
fpr,tpr,thres=roc_curve(y_test,probs)
plt.plot(fpr,tpr)
print('roc_auc_score:',roc_auc_score(y_test,probs))
# axis labels
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
```

```
roc_auc_score: 0.9613761467889909
```

Out[129]:

```
Text(0, 0.5, 'True Positive Rate')
```



Observations:

- Here, AUC score is greater than 0.50. it means our model can predict the positive & Negative class well.
- Max score can be 1 but we got 0.96.
- Our Model is doing Great according to this Area under curve

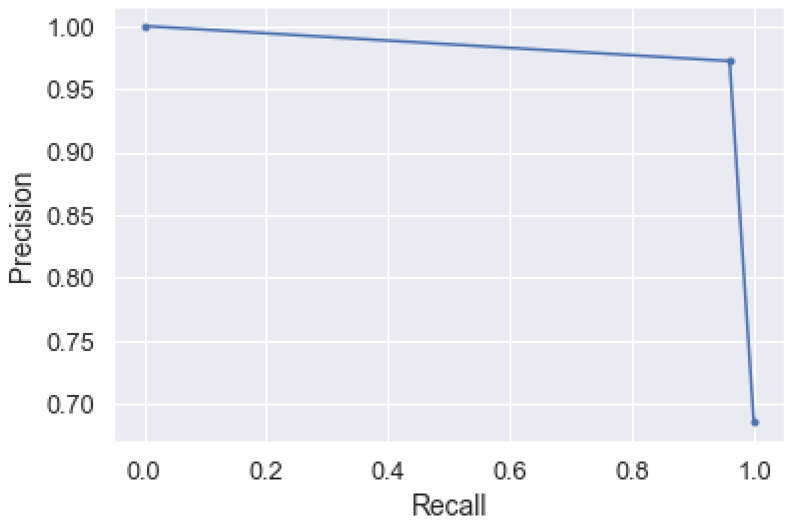
In [130…

```
# Precision-Recall Curve
from sklearn.metrics import auc,precision_recall_curve,f1_score
lr_precision, lr_recall, _ = precision_recall_curve(y_test,y_pred)
lr_f1 = f1_score(y_test, y_pred)
auc(lr_recall,lr_precision)
print("f1 score",lr_f1)
plt.plot(lr_recall,lr_precision,marker='.')
# axis labels
plt.xlabel('Recall')
plt.ylabel('Precision')
```

```
f1 score 0.9661538461538461
```

Out[130]:

```
Text(0, 0.5, 'Precision')
```



Observations:

- F1 score is 0.966 which is very high
- According to this curve we get that There are high Precision and High Recall.
- This implies there are less false positives and false negatives.

Actionable insights:

- No Duplicate Records Found
- some missing and outliers are present later imputed them.
- No change in monthly income so not including that column for further analysis.
- Major Drivers are male according to Dataset.
- Total of 368 drivers rating has been increased.
- Total of 973 drivers rating has been Decreased.
- Major of Drivers are Graduated according to Dataset.
- More drivers are from city c20.
- The average age for Drivers are 30-35.
- Rating Decreased is positively correlated with churn data irrespective of Gender.
- If age of driver is high there is high chance of that driver churns according lineplot.
- No impact of Grade and Income of driver churns.
- Gender is slighlty impacting the churn data.
- Rating Increase is negatively correlated with churn irrespective of Gender.
- F1-score for Bagging(Random Forest) is 96.77
- F1-score for Boosting(XGBoost) is 96.61

Recommendations:

- Drivers with Quarterly Rating Increased likely not to churn so provide some incentives or bonus to such Drivers.
- Drivers with Quarterly Rating Reduced likely to churn more, so try to connect with customers regarding the issues faced and try to clear that issues.
- Provide some paid leaves for Drivers to reduce churning of Drivers.
- Take Surveys in detailed manner to know the issues faced by Drivers.
- Payment might be the major reason try to monitor the payments paid to Driver.

```
In [ ]:
```