Problem Statement

Ola is trying to retain its drivers as churn rate amoung drivers is high and new driver acquisition is more expensive than retaining drivers. It needs data insights about which drivers are more likely to stop working based on their attributes such as their demographical data, performance ratings, tenure duration. The attributes are as outlined below:

MMM-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]:
```
# useful imports
import numpy as np, seaborn as sns, pandas as pd, matplotlib.pyplot as plt, scipy
```

In [2]:
```
df = pd.read_csv('ola_driver_scaler.csv')
df.head(10)
```

Out[2]:

	Unnamed: 0	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate
0	0	01/01/19	1	28.0	0.0	C23	2	57387	24/12/18	NaN
1	1	02/01/19	1	28.0	0.0	C23	2	57387	24/12/18	NaN
2	2	03/01/19	1	28.0	0.0	C23	2	57387	24/12/18	03/11/19
3	3	11/01/20	2	31.0	0.0	C7	2	67016	11/06/20	NaN
4	4	12/01/20	2	31.0	0.0	C7	2	67016	11/06/20	NaN
5	5	12/01/19	4	43.0	0.0	C13	2	65603	12/07/19	NaN
6	6	01/01/20	4	43.0	0.0	C13	2	65603	12/07/19	NaN
7	7	02/01/20	4	43.0	0.0	C13	2	65603	12/07/19	NaN
8	8	03/01/20	4	43.0	0.0	C13	2	65603	12/07/19	NaN
9	9	04/01/20	4	43.0	0.0	C13	2	65603	12/07/19	27/04/20

Since we can see that there are multiple rows for each Driver_ID, we would need to aggregate those rows later on in order to analyze each driver's data at once.

In [3]:
```
df.drop(['Unnamed: 0'],axis=1,inplace=True)
```

In [4]:
```
df.info() # some missing values are seen
```

```
<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
```

The numerical columns are:

In [5]:
```
df.columns[(df.dtypes == "float64") | (df.dtypes == "int64")]
```

Out[5]:
```
Index(['Driver_ID', 'Age', 'Gender', 'Education_Level', 'Income',
       'Joining Designation', 'Grade', 'Total Business Value',
       'Quarterly Rating'],
      dtype='object')
```

The categorical columns are:

In [6]:
```
df.columns[df.dtypes =="object"]
```

Out[6]:
```
Index(['MMM-YY', 'City', 'Dateofjoining', 'LastWorkingDate'], dtype='object')
```

In [7]:
```
df.shape
```

Out[7]:
```
(19104, 13)
```

Shape is 19104 rows and 13 columns

checking for null values

There are many missing values in Age, Gender, LastWorkingDate. Since they are less than 10% of the total entries in Age and Gender, we can impute them rather than removing the columns. But LastWorkingDate column has more than 90% missing entries. We would be checking it again after we aggregate the data for each driver.

In [8]:
```
df.isna().sum()*100/len(df)
```

Out[8]:
```
MMM-YY                   0.000000
Driver_ID                0.000000
Age                      0.319305
Gender                   0.272194
City                     0.000000
Education_Level          0.000000
Income                   0.000000
Dateofjoining            0.000000
LastWorkingDate         91.541039
Joining Designation      0.000000
Grade                    0.000000
Total Business Value     0.000000
Quarterly Rating         0.000000
dtype: float64
```

checking for duplicated values

There are no duplicate entries.

In [9]:
```
df.duplicated().sum()
```

Out[9]:
```
0
```

changing date columns to DateTime format

In [10]:
```
df['MMM-YY'] = pd.to_datetime(df['MMM-YY'])
df['Dateofjoining'] = pd.to_datetime(df['Dateofjoining'])
df['LastWorkingDate'] = pd.to_datetime(df['LastWorkingDate'])
```

Missing value treatment

In [15]:
```
cont = df[['Age', 'Gender']].values

# To calculate missing values for Age and Gender of drivers, use imputer class as rows for one dr
```

```
# and their other column values or attributes should be similar or closer than other drivers' att
from sklearn.impute import KNNImputer

imputer = KNNImputer(missing_values=np.nan, n_neighbors=3)
imputer = imputer.fit(cont)
cont = imputer.transform(cont).astype('int')
cont[:5]
```

Out[15]:

```
array([[28,  0],
       [28,  0],
       [28,  0],
       [31,  0],
       [31,  0]])
```

In [16]:

```
df[['Age', 'Gender']] = cont
```

Data aggregation

Feature Engineering Steps:

Create 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

Target variable creation: Create a column called target which tells whether the driver has left the company- driver whose last working day is present will have the value 1

Create 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 [109…

```
# grouping based on Driver ID
agg_df = df.groupby(['Driver_ID']).agg({'MMM-YY':'last','Age':'first','Gender':'first','City':'f
        'Education_Level':'first','Income':['first','last','mean'],'Dateofjoining':'first','LastW
         ,'Joining Designation':'first','Grade':'first','Total Business Value':'sum',
                                        'Quarterly Rating':['first','last','mean']})
df2 = agg_df.reset_index()
df2.head()
```

Out[109]:

	Driver_ID	MMM-YY	Age	Gender	City	Education_Level	Income			Dateofjoining	LastWorkingDate	
		last	first	first	first	first	first	last	mean	first	last	any
0	1	2019-03-01	28	0	C23	2	57387	57387	57387.0	2018-12-24	2019-03-11	True
1	2	2020-12-01	31	0	C7	2	67016	67016	67016.0	2020-11-06	NaT	False
2	4	2020-04-01	43	0	C13	2	65603	65603	65603.0	2019-12-07	2020-04-27	True
3	5	2019-03-01	29	0	C9	0	46368	46368	46368.0	2019-01-09	2019-03-07	True
4	6	2020-12-01	31	1	C11	1	78728	78728	78728.0	2020-07-31	NaT	False

In [110…

```
df2.columns = ['_'.join(col) for col in df2.columns.values]
```

In [111…

```
df2.columns
```

Out[111]:

```
Index(['Driver_ID_', 'MMM-YY_last', 'Age_first', 'Gender_first', 'City_first',
       'Education_Level_first', 'Income_first', 'Income_last', 'Income_mean',
       'Dateofjoining_first', 'LastWorkingDate_last', 'LastWorkingDate_any',
       'Joining Designation_first', 'Grade_first', 'Total Business Value_sum',
       'Quarterly Rating_first', 'Quarterly Rating_last',
       'Quarterly Rating_mean'],
      dtype='object')
```

In [112…

```
df2['Churn'] = df2['LastWorkingDate_any']
df2['Churn'] = df2['Churn'].astype('int')
```

In [113…

```
df2['RateIncrease'] = np.where((df2['Quarterly Rating_last'] > df2['Quarterly Rating_first']),1,(
```

In [114…

```
df2['Income_Increase'] = np.where((df2['Income_last'] > df2['Income_first']),1,0)
```

In [115…

```
df2['LastDate'] = np.where(df2['LastWorkingDate_last'].notnull(),
                      df2['LastWorkingDate_last'].dt.strftime('%Y-%m-%d'),
                      df2['MMM-YY_last'].dt.strftime('%Y-%m-%d'))
# replacing NaT values in last Working date column with Last reporting date 'MMM-YY'
```

In [116…

```
df2[['MMM-YY_last','LastWorkingDate_last','LastDate']].head()
```

Out[116]:

	MMM-YY_last	LastWorkingDate_last	LastDate
0	2019-03-01	2019-03-11	2019-03-11
1	2020-12-01	NaT	2020-12-01
2	2020-04-01	2020-04-27	2020-04-27
3	2019-03-01	2019-03-07	2019-03-07
4	2020-12-01	NaT	2020-12-01

In [117…

```
df2['tenure'] = pd.to_datetime(df2['LastDate']) - df2['Dateofjoining_first']
```

In [118…

```
df2 = df2.drop(['Income_first','Income_last','Quarterly Rating_first','Quarterly Rating_last','La
        ,'LastWorkingDate_any','MMM-YY_last','Dateofjoining_first'],axis=1)
```

In [119…

```
df2.rename(columns = {'Driver_ID_':'Driver_ID','Age_first':'Age','Gender_first':'Gender','City_fi
                      'Education_Level_first':'Education','Joining Designation_first':'Designati
                      'Total Business Value_sum':'Total_Biz_Value','Quarterly Rating_mean':'Quar
                     }, inplace=True)
```

In [120…

```
df2.head()
```

Out[120]:

	Driver_ID	Age	Gender	City	Education	Income_mean	Designation	Grade	Total_Biz_Value	Quarterly_Rating
0	1	28	0	C23	2	57387.0	1	1	1715580	2.0
1	2	31	0	C7	2	67016.0	2	2	0	1.0
2	4	43	0	C13	2	65603.0	2	2	350000	1.0
3	5	29	0	C9	0	46368.0	1	1	120360	1.0
4	6	31	1	C11	1	78728.0	3	3	1265000	1.6

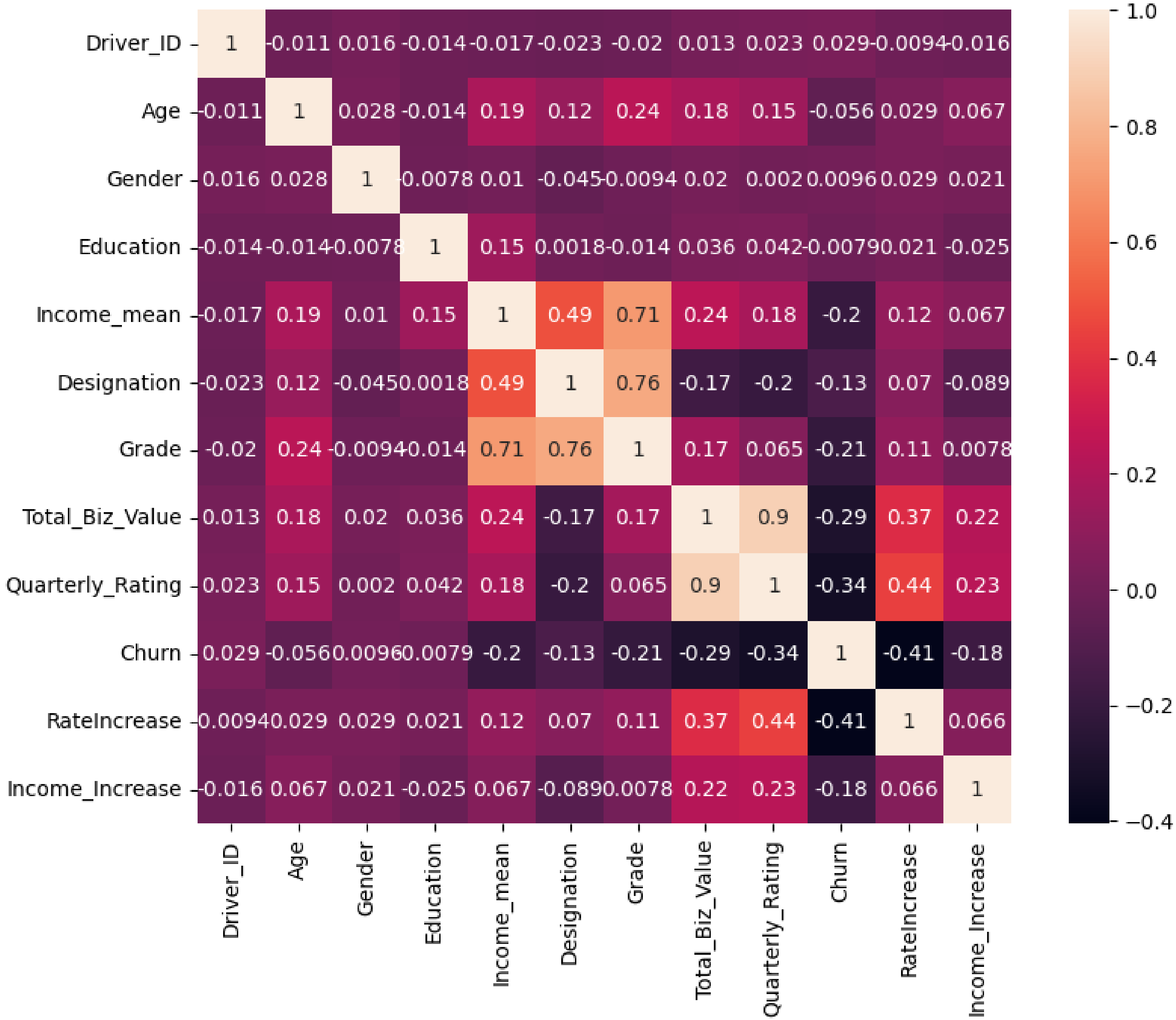
Multivariate analysis

In [80]:

```
# Spearman's Rank Correlation Coefficient
plt.figure(figsize=(10,7))
sns.heatmap(df2.corr(method='spearman'), square=True,annot=True)
```

```
C:\Users\Admin\AppData\Local\Temp\ipykernel_7664\1015870712.py:3: FutureWarning: The default val
ue of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to Fals
e. Select only valid columns or specify the value of numeric_only to silence this warning.
  sns.heatmap(df2.corr(method='spearman'), square=True,annot=True)
```

Out[80]: <AxesSubplot: >



The variables 'Quarterly Rating' and 'Total Business Value' are highly correlated (0.9), we will ignore one of them - Quarterly rating as we are also considering it in RateIncrease variable.

Grade and Designation are also correlated (0.76), and we would ignore Grade variable.

In [121…
```
df2.drop(['Grade','Quarterly_Rating','Driver_ID'],axis=1,inplace=True) # driver ID is not relatec
```

In [122…
```
df2['LastDate'] = pd.to_datetime(df2['LastDate']).dt.year
```

In [123…
```
df2.isna().sum()
```

```
Out[123]: Age                0
          Gender             0
          City               0
          Education          0
          Income_mean        0
          Designation        0
          Total_Biz_Value    0
          Churn              0
          RateIncrease       0
          Income_Increase    0
          LastDate           0
          tenure             0
          dtype: int64
```

```
In [124…  df2.head()
```

Out[124]:

	Age	Gender	City	Education	Income_mean	Designation	Total_Biz_Value	Churn	RateIncrease	Income_Increa
0	28	0	C23	2	57387.0	1	1715580	1	0	
1	31	0	C7	2	67016.0	2	0	0	0	
2	43	0	C13	2	65603.0	2	350000	1	0	
3	29	0	C9	0	46368.0	1	120360	1	0	
4	31	1	C11	1	78728.0	3	1265000	0	1	

Univariate analysis

```
In [125…  df2.describe() # numerical features
```

Out[125]:

	Age	Gender	Education	Income_mean	Designation	Total_Biz_Value	Churn	RateIncreas
count	2381.000000	2381.000000	2381.00000	2381.000000	2381.000000	2.381000e+03	2381.000000	2381.00000
mean	33.089038	0.410752	1.00756	59232.460484	1.820244	4.586742e+06	0.678706	0.15035
std	5.839201	0.492074	0.81629	28298.214012	0.841433	9.127115e+06	0.467071	0.35749
min	21.000000	0.000000	0.00000	10747.000000	1.000000	-1.385530e+06	0.000000	0.00000
25%	29.000000	0.000000	0.00000	39104.000000	1.000000	0.000000e+00	0.000000	0.00000
50%	33.000000	0.000000	1.00000	55285.000000	2.000000	8.176800e+05	1.000000	0.00000
75%	37.000000	1.000000	2.00000	75835.000000	2.000000	4.173650e+06	1.000000	0.00000
max	58.000000	1.000000	2.00000	188418.000000	5.000000	9.533106e+07	1.000000	1.00000

Age for drivers ranges from 21 to 58. Mean age is 33.09 which is close to median age 33 so there may not be many outliers.

Gender is a categorical data coded as 0 and 1.

Education_level is again a categorical data column, ranging from 0 to 2. Mean 1.01 and median 1, may be few outliers.

Income ranges from Rs. 10,747 to Rs. 1,88,418. Mean income is Rs. 59,232.46 and median is Rs. 55,285, which hints at the presence of outliers due to the large gap between mean and median.

Designation ranges from 1 to 5.

Total Business Value for their entire tenure ranges from loss of Rs. 13,85,530 to profit of above 9 Cr. (Rs. 9,53,31,060). Mean business value was Rs. 45,86,742 and median was Rs. 8,17,680, so there are outliers.

Churn, RateIncrease and Income_Increase are categorical values with 0 and 1 values.

tenure ranges from -27 days to 2801 days, mean 424 and median 180 so there would be many outliers. Negative tenure duration makes no sense so we would clip these values to keep minimum as 0.

In [126…
```
df2['tenure'] = df2['tenure'].dt.days
df2['tenure'].describe()
```

Out[126]:
```
count    2381.000000
mean      424.540109
std       564.404943
min       -27.000000
25%        91.000000
50%       180.000000
75%       467.000000
max      2801.000000
Name: tenure, dtype: float64
```

In [127…
```
df2['tenure'] = df2['tenure'].clip(lower=0)
df2['tenure'].describe()
```

Out[127]:
```
count    2381.000000
mean      424.852163
std       564.165833
min         0.000000
25%        91.000000
50%       180.000000
75%       467.000000
max      2801.000000
Name: tenure, dtype: float64
```

In [128…
```
df2['City'].describe()
```

Out[128]:
```
count      2381
unique       29
top         C20
freq        152
Name: City, dtype: object
```

City has 29 unique city codes, more common being C20.

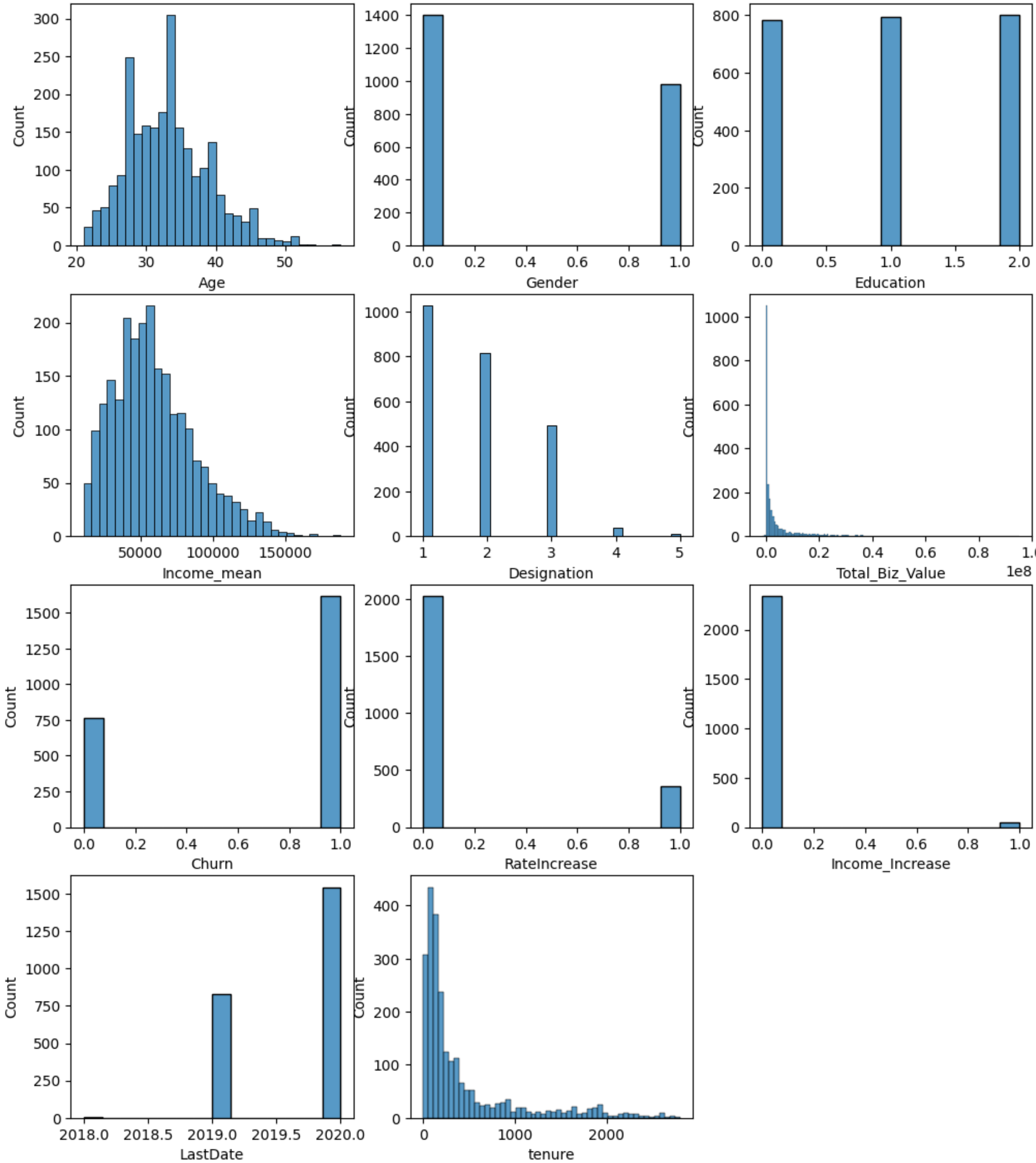
In [130…
```
df2.dtypes
```

```
Out[130]: Age                  int32
          Gender               int32
          City                object
          Education            int64
          Income_mean        float64
          Designation          int64
          Total_Biz_Value      int64
          Churn                int32
          RateIncrease         int32
          Income_Increase      int32
          LastDate             int64
          tenure               int64
          dtype: object
```

```
In [131…  continuous_cols = df2.columns[(df2.dtypes == 'int64')|(df2.dtypes == 'float64')|(df2.dtypes == ':
          continuous_cols
```

```
Out[131]: Index(['Age', 'Gender', 'Education', 'Income_mean', 'Designation',
                 'Total_Biz_Value', 'Churn', 'RateIncrease', 'Income_Increase',
                 'LastDate', 'tenure'],
                dtype='object')
```

```
In [133…  f = plt.figure()
          f.set_figwidth(12)
          f.set_figheight(14)
          n = len(continuous_cols)

          for i in range(n):
              plt.subplot(4,(n//4)+1,i+1)
              sns.histplot(data=df2, x=continuous_cols[i])
          plt.show()
```



The continuous variables look right skewed because of presence of outliers. If we remove the outliers, then we can get bell shaped curves. For the categorical variables:

There are more male drivers (0) than females drivers (1).

Education variable has uniform distribution across all 3 levels.

Most drivers join at the designation levels - 1,2 and 3. Very few join as 4 or 5.

Most drivers churn that means most drivers leave their jobs.

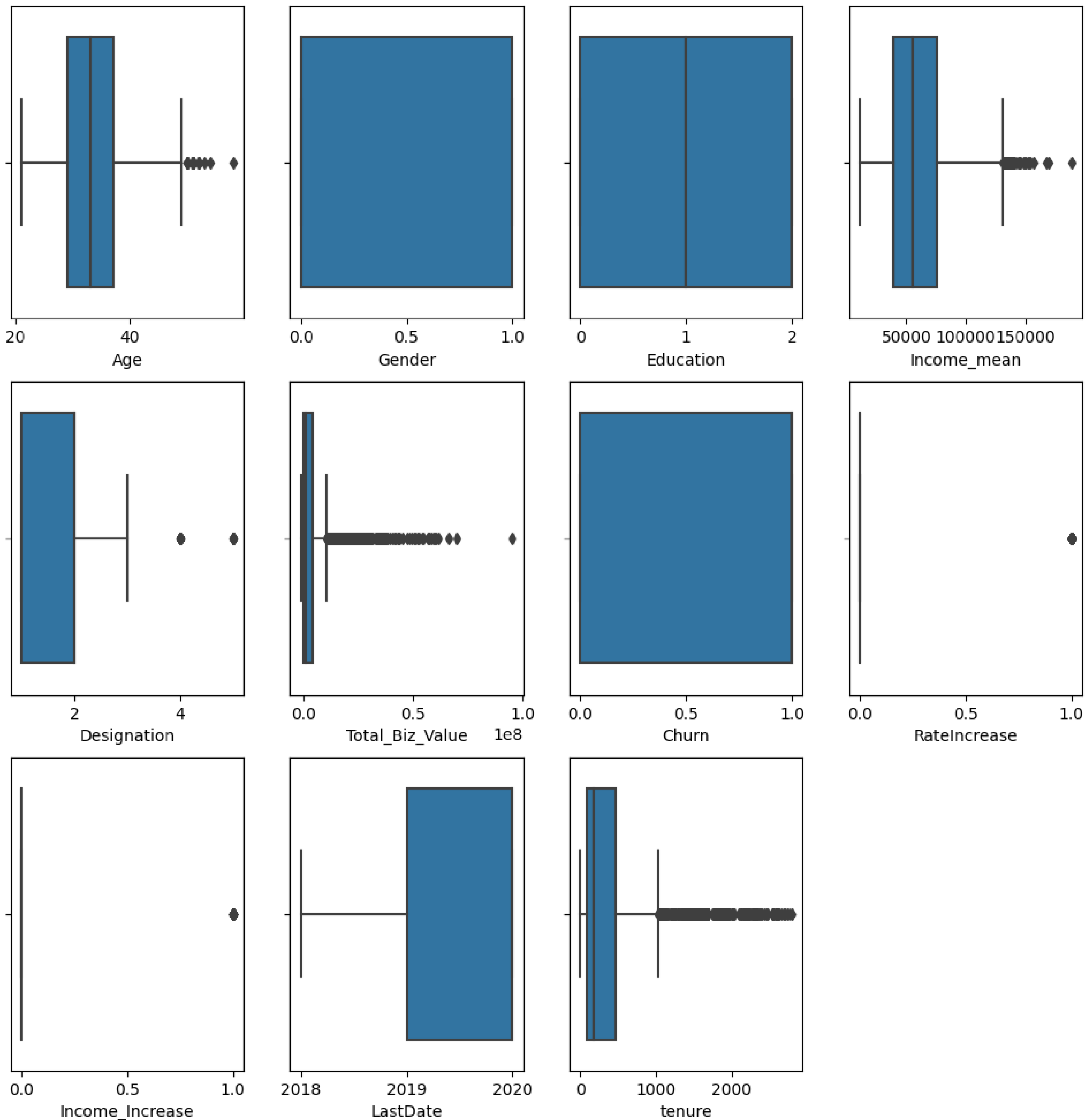
A few drivers had an increase in their quarterly ratings.

Very small number of drivers had an increase in their monthly income compared to when they started.

Most drivers left their jobs in the year 2020 maybe due to the pandemic. Some left in 2019, and very few in 2018.

In [135…

```
f = plt.figure()
f.set_figwidth(12)
f.set_figheight(12)
n = len(continuous_cols)

for i in range(n):
    plt.subplot(3,4,i+1)
    sns.boxplot(data=df2, x=continuous_cols[i])
plt.show()
```



There are many outliers but we need not worry as we are going to use non-parametric and non-linear models such Decision Trees, bagging and boosting algorithms which do not assume normality.

Now that we have checked the individual features, let's look at their relationship with each other.

Bivariate analysis

In [143…

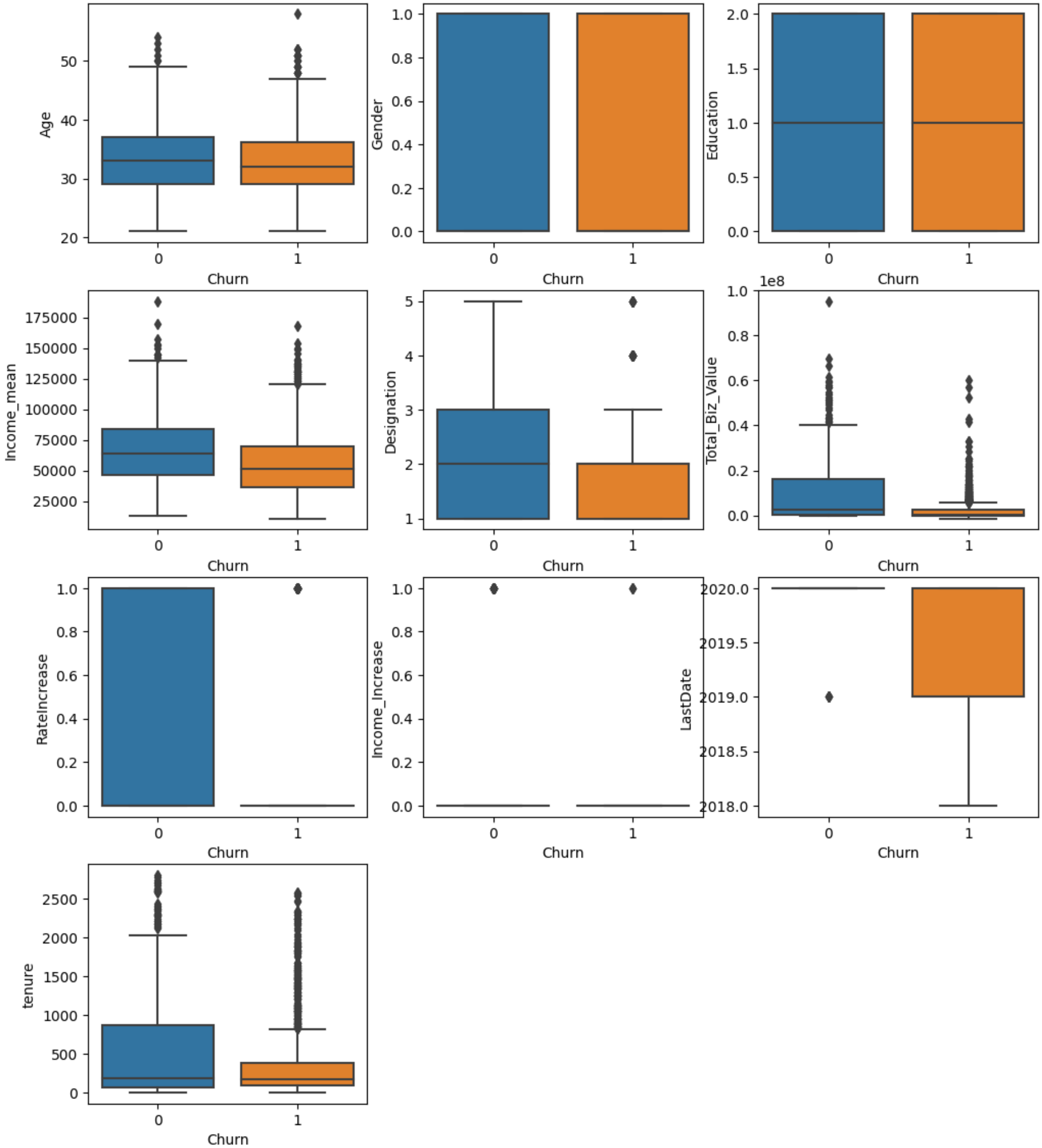
```
continuous_cols = continuous_cols.drop(labels = ['Churn'])
continuous_cols
```

Out[143]:

```
Index(['Age', 'Gender', 'Education', 'Income_mean', 'Designation',
       'Total_Biz_Value', 'RateIncrease', 'Income_Increase', 'LastDate',
       'tenure'],
      dtype='object')
```

In [146…

```
f = plt.figure()
f.set_figwidth(12)
f.set_figheight(14)
n = len(continuous_cols)

for i in range(n):
    plt.subplot(4,3,i+1)
    sns.boxplot(data=df2, y=continuous_cols[i],x='Churn')
plt.show()
```



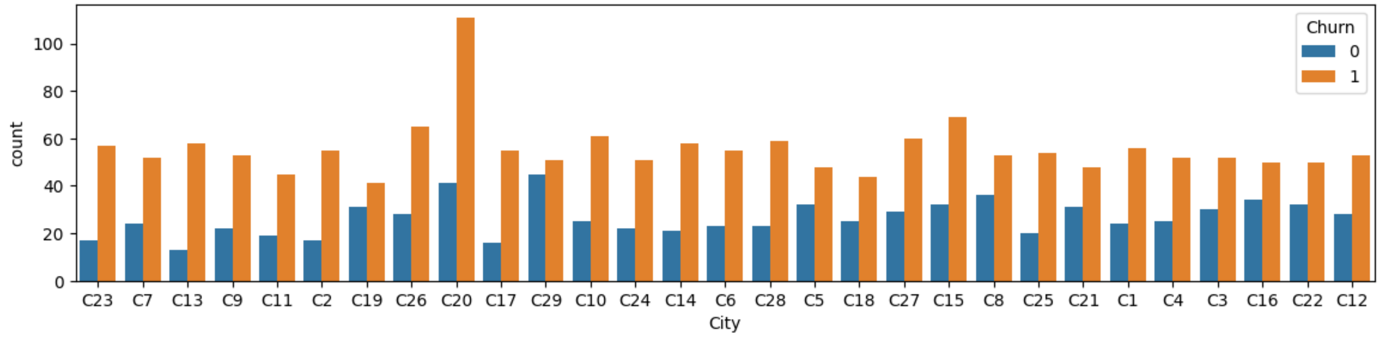
Mean income, designation while joining, and total business value are lower for drivers who churned than those who stayed.

There was no increase in quarterly ratings for those drivers who left, so they might have left due to lower customer evaluation and rating on their skills.

Tenure for those who churned also is lesser than those who stayed.

In [149…

```
f = plt.figure()
f.set_figwidth(14)
f.set_figheight(3)
sns.countplot(data=df2, x='City',hue='Churn')
plt.show()
```



Most common city for drivers to live or work at was C20. Maybe other cities can be targeted for marketing and calling more drivers to work for their business with enticing ads on job perks. In every city, there were more drivers who churned than those who stayed.

Encoding categorical variables

In [155…

```
X = df2.drop(['Churn'],axis=1)
Y = np.array(df2['Churn']).reshape(-1,1)
print(X.shape, Y.shape)
```

```
(2381, 11) (2381, 1)
```

In [156…

```
# from sklearn.preprocessing import LabelEncoder
# X['City'] = X['City'].apply(LabelEncoder().fit_transform)
# .join(df.select_dtypes(include=['number']))
X['City'] = X['City'].apply(lambda x:x[1:])
X.head()
```

Out[156]:

	Age	Gender	City	Education	Income_mean	Designation	Total_Biz_Value	RateIncrease	Income_Increase	LastI
0	28	0	23	2	57387.0	1	1715580	0	0	
1	31	0	7	2	67016.0	2	0	0	0	
2	43	0	13	2	65603.0	2	350000	0	0	
3	29	0	9	0	46368.0	1	120360	0	0	
4	31	1	11	1	78728.0	3	1265000	1	0	

Splitting data into training and testing dataset

In [177…

```
from sklearn.model_selection import train_test_split
# Create training and test split
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.05, random_state=4) #5% te
```

Class imbalance treatment as there are more drivers that churned(1) than those who stayed (0)

In [178…

```
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({1: 1533, 0: 1533})
```

Column Standarization

As the different churn predictor features are in different units, we cannot fairly compare them in terms of importance. We need to scale them to a standard range called standardization.

In [179…

```
# Mean centering and Variance scaling (Standard Scaling)
from sklearn.preprocessing import StandardScaler
X_columns = X_sm.columns
scaler = StandardScaler()
X_sm = scaler.fit_transform(X_sm)
X_test = scaler.transform(X_test)
X_sm = pd.DataFrame(X_sm, columns=X_columns)
X_sm.head()
```

Out[179]:

	Age	Gender	City	Education	Income_mean	Designation	Total_Biz_Value	RateIncrease	Income_In
0	0.337000	-0.730594	-1.678926	1.344522	-0.419114	-0.956998	-0.556362	-0.452455	-0.
1	-1.630738	1.368750	-1.428471	-1.169078	-0.974593	-0.956998	-0.499150	-0.452455	-0.
2	-0.378541	-0.730594	-1.052790	0.087722	-0.056401	0.277397	-0.556362	-0.452455	-0.
3	-0.736312	-0.730594	0.449934	1.344522	2.074695	-0.956998	0.416949	-0.452455	-0.
4	-0.378541	1.368750	0.950842	-1.169078	0.466384	1.511792	-0.556362	-0.452455	-0.

Decision tree

If we only use 1 Decision tree for simplicity, the results are shown below.

In [201…

```
from sklearn.tree import DecisionTreeClassifier
tree_clf = DecisionTreeClassifier(random_state=42, max_depth=7)
# Train on training data
print(tree_clf.fit(X_sm,y_sm))

# predict on test data
print(tree_clf.score(X_test,y_test))

from sklearn.model_selection import KFold, cross_validate

kfold = KFold(n_splits=10)
cv_acc_results = cross_validate(tree_clf, X_sm, y_sm, cv = kfold, scoring = 'accuracy', return_tr

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

```
DecisionTreeClassifier(max_depth=7, random_state=42)
0.8833333333333333
K-Fold Accuracy Mean: Train: 86.29413881315958 Validation: 79.45221519661068
K-Fold Accuracy Std: Train: 0.4916310407210009 Validation: 2.361663210966748
```

```
C:\Users\Admin\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but DecisionTreeClassifier was fitted with feature names
  warnings.warn(
```

In [211…

```
depths = [3,4,5,6,7,9,11,13,15]

for depth in depths:
    tree_clf = DecisionTreeClassifier(random_state=7, max_depth = depth, min_samples_leaf=10)

    cv_acc_results = cross_validate(tree_clf, X_sm, y_sm, cv = kfold, scoring = 'accuracy', retu

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

```
K-Fold for depth:3 Accuracy Mean: Train: 75.94051221036818 Validation: 64.60741734261566
K-Fold for depth: 3 Accuracy Std: Train: 0.8360330088883908 Validation: 11.994352323251272
***************
K-Fold for depth:4 Accuracy Mean: Train: 80.5970683559996 Validation: 79.57335377147602
K-Fold for depth: 4 Accuracy Std: Train: 1.3056612948613635 Validation: 8.190771601105276
***************
K-Fold for depth:5 Accuracy Mean: Train: 81.8257087476559 Validation: 72.92467692831747
K-Fold for depth: 5 Accuracy Std: Train: 0.33573411842263173 Validation: 5.0568736152981755
***************
K-Fold for depth:6 Accuracy Mean: Train: 83.93486008898414 Validation: 82.25319878222734
K-Fold for depth: 6 Accuracy Std: Train: 0.6911241522906072 Validation: 5.065702508255324
***************
K-Fold for depth:7 Accuracy Mean: Train: 85.14893812608013 Validation: 79.64744203870474
K-Fold for depth: 7 Accuracy Std: Train: 0.42376665417260606 Validation: 2.548332724510685
***************
K-Fold for depth:9 Accuracy Mean: Train: 87.45379811000625 Validation: 80.72289284877904
K-Fold for depth: 9 Accuracy Std: Train: 0.4698835221906135 Validation: 3.164794850387742
***************
K-Fold for depth:11 Accuracy Mean: Train: 89.18245688681573 Validation: 82.94351834110408
K-Fold for depth: 11 Accuracy Std: Train: 0.3620800506347022 Validation: 2.681578180778981
***************
K-Fold for depth:13 Accuracy Mean: Train: 89.92900704414014 Validation: 83.17195716505928
K-Fold for depth: 13 Accuracy Std: Train: 0.42125259443869956 Validation: 2.883785167361274
***************
K-Fold for depth:15 Accuracy Mean: Train: 90.0377329004943 Validation: 83.56400757914457
K-Fold for depth: 15 Accuracy Std: Train: 0.397351232208056 Validation: 2.6765807592278525
***************
```

The most similar training and validation scores were for max_depth=6.

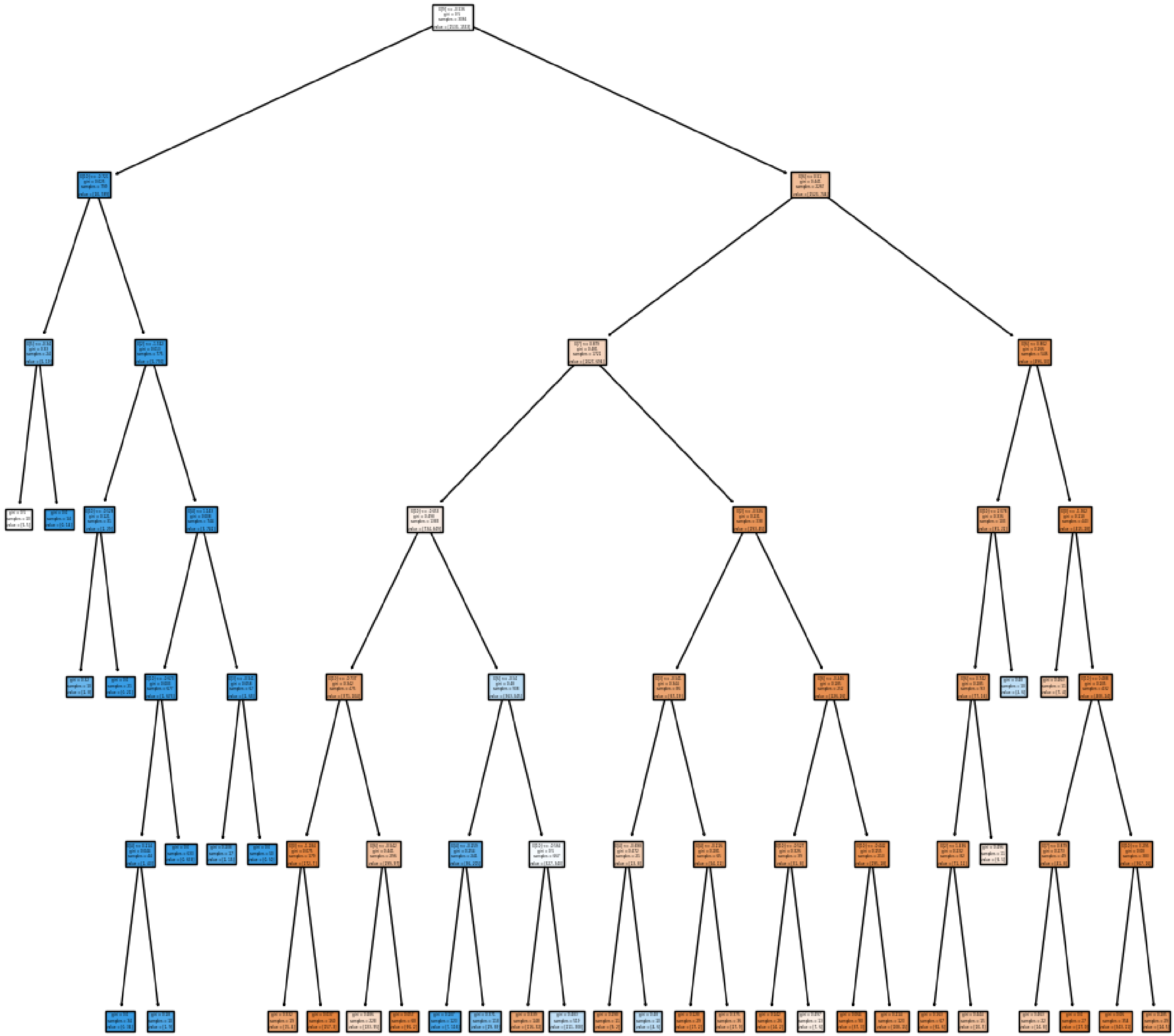
In [208…

```
tree_clf = DecisionTreeClassifier(random_state=7, max_depth = 6, min_samples_leaf=10)
tree_clf=tree_clf.fit(X_sm, y_sm)
pred = tree_clf.predict(X_test)
```

```
C:\Users\Admin\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but DecisionTreeClassifier was fitted with feature names
  warnings.warn(
```

In [209…

```
from sklearn.tree import plot_tree
plt.figure(figsize=(12,12))
plot_tree(tree_clf, filled=True);
```



Outliers impact a decision tree when the depth is high i.e. overfitted model. But we have kept the depth=6 low.

Ensemble technique - Random Forest Bagging algorithm

We need to use a non-parametric model like Decision Tree to fit a non-normal dataset. Bagging algorithms like Random Forest use an aggregation of decision trees with low bias and high variance, to reduce the variance and overfitting.

In [215…

```
tree_clf = RandomForestClassifier(random_state=7, max_depth=6, n_estimators=400, min_samples_lea
kfold = KFold(n_splits=10)
cv_acc_results = cross_validate(tree_clf, X_sm, y_sm, cv = kfold, scoring = 'accuracy', return_tr

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

```
K-Fold Accuracy Mean: Train: 86.34494749725536 Validation: 80.00585467628963
K-Fold Accuracy Std: Train: 0.7118091990246098 Validation: 3.5038702518691798
```

Now the train and validation scores are not very similar, but tolerable.

In [225…

```
tree_clf = RandomForestClassifier(random_state=7, max_depth=6, n_estimators=400)
kfold = KFold(n_splits=10)
cv_acc_results = cross_validate(tree_clf, X_sm, y_sm, cv = kfold, scoring = 'accuracy', return_tı

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

```
K-Fold Accuracy Mean: Train: 86.88856889967485 Validation: 80.1037874433161
K-Fold Accuracy Std: Train: 0.8492500288812925 Validation: 4.131991740310244
```

Now the train and validation scores are not very similar, but there is a slight increase in scores.

In [261…

```
# Defining Parametes
params = {
          'n_estimators' : [100,200,300,400],
          'max_depth' : [5,6,7,8],
          'criterion' : ['gini'],
          'bootstrap' : [True],
          'max_features' : [8,9,10]
         }
```

In [262…

```
from sklearn.model_selection import GridSearchCV

tuning_function = GridSearchCV(estimator = RandomForestClassifier(),
                               param_grid = params,
                               scoring = 'accuracy',
                               cv = 3,
                               n_jobs=-1
                               )
# Now we will fit all combinations, this will take some time to run. (5-6 mins)
tuning_function.fit(X_sm, y_sm)

parameters = tuning_function.best_params_
score = tuning_function.best_score_
print(parameters)
print(score)
```

```
{'bootstrap': True, 'criterion': 'gini', 'max_depth': 8, 'max_features': 8, 'n_estimators': 300}
0.8561643835616438
```

In [264…

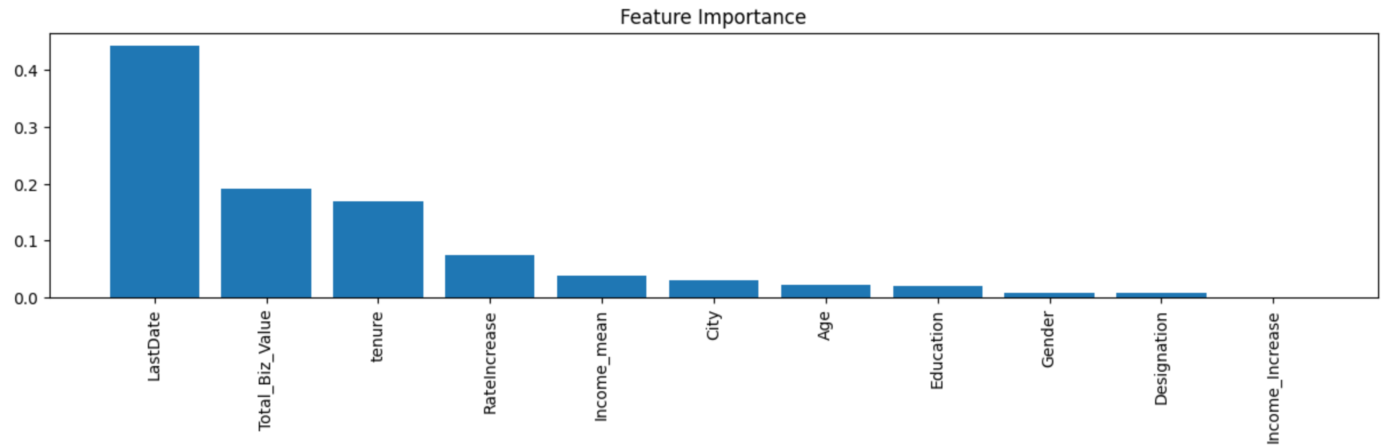
```
tree_clf = RandomForestClassifier(random_state=7, max_depth=8, n_estimators=300, max_features=8)
kfold = KFold(n_splits=3)
cv_acc_results = cross_validate(tree_clf, X_sm, y_sm, cv = kfold, scoring = 'accuracy', return_tı

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

```
K-Fold Accuracy Mean: Train: 92.31898238747553 Validation: 77.56033920417482
K-Fold Accuracy Std: Train: 0.4989255884141664 Validation: 4.551976698339208
```

In [265…

```
# Feature importance
tree_clf = RandomForestClassifier(random_state=7, max_depth=8, n_estimators=300, max_features=8)
tree_clf.fit(X_sm, y_sm)
importances = tree_clf.feature_importances_
indices = np.argsort(importances)[::-1] # Sort feature importances in descending order
names = [X_sm.columns[i] for i in indices] # Rearrange feature names so they match the sorted fe
plt.figure(figsize=(15, 3)) # Create plot
```

```
plt.title("Feature Importance") # Create plot title
plt.bar(range(X_sm.shape[1]), importances[indices]) # Add bars
plt.xticks(range(X_sm.shape[1]), names, rotation=90) # Add feature names as x-axis labels
plt.show() # Show plot
```



According to the RF bagging algorithm, the churn outcome was most affected by the Last working date, and then the other important features were Total Business value, tenure duration and increase in quarterly ratings.

In [266...

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

```
C:\Users\Admin\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
```

In [267...

```
from sklearn.metrics import confusion_matrix, precision_score, recall_score, plot_confusion_matr

testscore = accuracy_score(y_test,y_pred)
print('Test accuracy: ',testscore)

cm = confusion_matrix(y_test, y_pred)

cm_df = pd.DataFrame(cm,index = np.unique(y_test), columns = np.unique(y_test) )

cm_df.head()
```

```
Test accuracy:  0.8833333333333333
```

Out[267]:

	0	1
0	33	4
1	10	73

True negatives - 33 (drivers who stayed as predicted)

False positives - 4 (drivers who stayed but were predicted to churn)

False negatives - 10 (drivers who churned but were predicted to stay) - need the most attention as can cause huge financial losses

True positives - 73 (drivers who churned as predicted)

In [268...

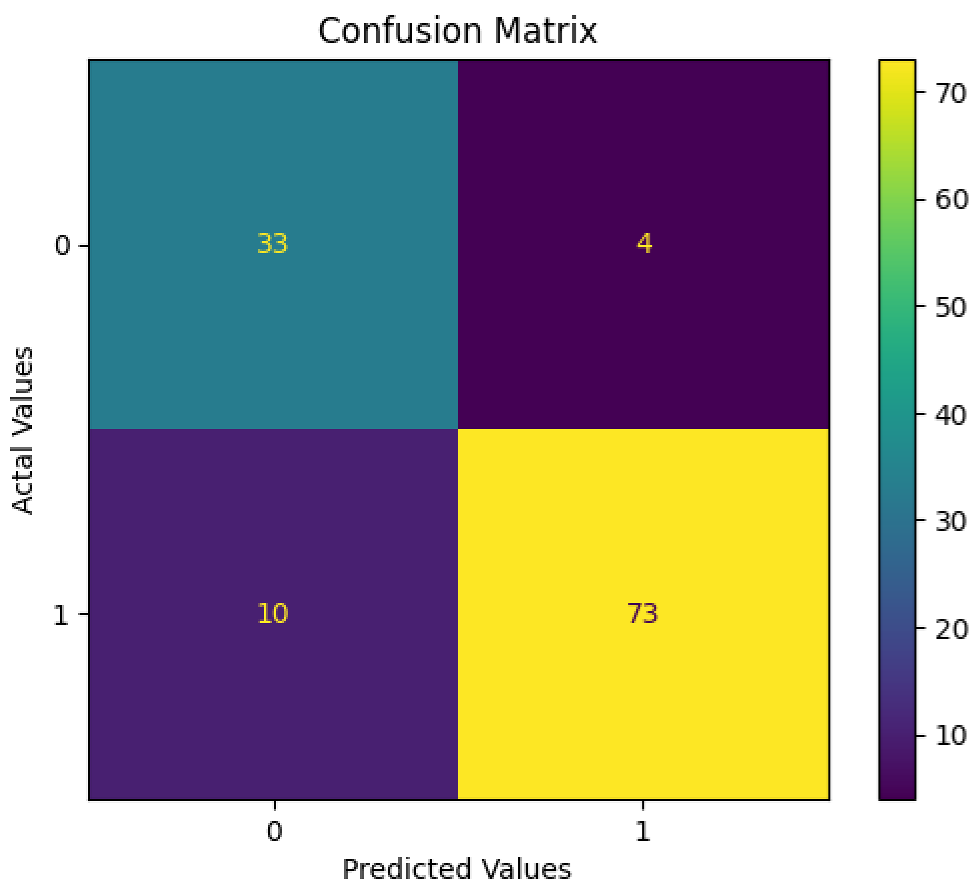
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.77      0.89      0.82        37
           1       0.95      0.88      0.91        83

    accuracy                           0.88       120
   macro avg       0.86      0.89      0.87       120
weighted avg       0.89      0.88      0.89       120
```

In [269…

```python
#Plotting the confusion matrix
plt.figure(figsize=(1,1))
plot_confusion_matrix(tree_clf,X_test,y_test)
#sns.heatmap(cm_df, annot=True,cmap='coolwarm')
plt.title('Confusion Matrix')
plt.ylabel('Actal Values')
plt.xlabel('Predicted Values')
plt.show()
```

```
C:\Users\Admin\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\utils\deprecati
on.py:87: FutureWarning: Function plot_confusion_matrix is deprecated; Function `plot_confusion_
matrix` is deprecated in 1.0 and will be removed in 1.2. Use one of the class methods: Confusion
MatrixDisplay.from_predictions or ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
C:\Users\Admin\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\base.py:450: Us
erWarning: X does not have valid feature names, but RandomForestClassifier was fitted with featu
re names
  warnings.warn(
<Figure size 100x100 with 0 Axes>
```



In [270…

```python
from sklearn.metrics import f1_score
print("Precision score is :",precision_score(y_test,y_pred))
print("Recall score is :",recall_score(y_test,y_pred))
print("F1 score is :",f1_score(y_test,y_pred))
```

```
Precision score is : 0.948051948051948
Recall score is : 0.8795180722891566
F1 score is : 0.9125
```

Precision score was 0.95 and there were very few false positives, drivers who stayed but were predicted to churn. They don't need much attention and can cause waste of resources but thankfully there were very few in number.

Recall score- 0.9 which means that there were few false negatives that caused financial losses as they churned but were predicted to stay, and this can be improved to decrease further losses.

ROC (Receiver Operating Characteristic curve) and AUC (Area Under Curve)

In [271…

```
y_proba = tree_clf.predict_proba(X_test)
y_proba.shape, y_test.shape
```

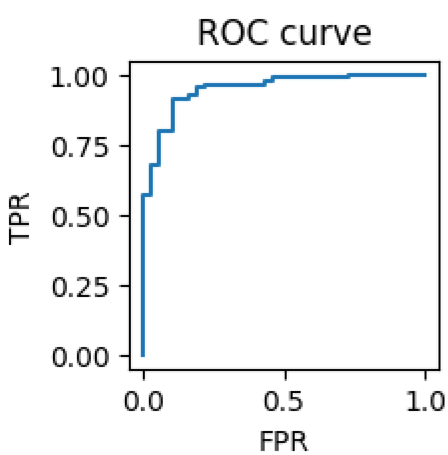
```
C:\Users\Admin\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
```

Out[271]:

```
((120, 2), (120, 1))
```

In [272…

```
from sklearn.metrics import roc_curve, roc_auc_score
fpr, tpr, thr = roc_curve(y_test, y_proba[:,1])
plt.figure(figsize=(2,2))
plt.plot(fpr,tpr)
plt.title('ROC curve')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.show()
```



There are more true positives than False positives, hence the ROC curve has more area under curve than 0.5.

In [273…

```
roc_auc_score(y_test,y_proba[:,1])
```

Out[273]:

```
0.9488765874308043
```

0.95 is very good area under curve score.

Ensemble Boosting algorithm - XGBoost

Boosting uses a series of decision stumps that have high bias and low variance (underfitted models), to add their contribution in a way that each reduces the error residual of the previous model and reduces bias and underfitting.

In [235…

```
from xgboost import XGBClassifier
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import StratifiedKFold

params = {
        'learning_rate': [0.1, 0.5, 0.8],
        'subsample': [0.6, 0.8, 1.0],
        'colsample_bytree': [0.6, 0.8, 1.0],
        'max_depth': [3, 4, 5]
        }
xgb = XGBClassifier(n_estimators=100, objective='multi:softmax', num_class=20, silent=True)

folds = 3

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

random_search = RandomizedSearchCV(xgb, param_distributions=params, n_iter=10, scoring='accuracy
                                   cv=skf.split(X_sm,y_sm), verbose=3, random_state=1001 )


# start = dt.datetime.now()
random_search.fit(X_sm, y_sm)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
[23:15:34] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-group-i-0fc7796c
793e6356f-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "silent" } are not used.
```

Out[235]:

```
▸ RandomizedSearchCV
▸ estimator: XGBClassifier
  ▸ XGBClassifier
```

In [236…

```
print('\n Best hyperparameters:')
print(random_search.best_params_)
```

```
 Best hyperparameters:
{'subsample': 1.0, 'max_depth': 4, 'learning_rate': 0.5, 'colsample_bytree': 0.8}
```

In [237…

```
best_xgb = XGBClassifier(n_estimators=100, objective='multi:softmax', num_class=20,
                         subsample=1.0, max_depth=4, learning_rate=0.5, colsample_bytree=0.8)
best_xgb.fit(X_sm, y_sm)
```

Out[237]:

XGBClassifier

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.8, 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=0.5, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=4, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
```

In [255…

```
y_pred = best_xgb.predict(X_test)
y_pred_train = best_xgb.predict(X_sm)

testscore = accuracy_score(y_test,y_pred)
trscore = accuracy_score(y_sm,y_pred_train)
print('Train accuracy: ',trscore)
print('Test accuracy: ',testscore)
cm = confusion_matrix(y_test, y_pred)

cm_df = pd.DataFrame(cm,index = np.unique(y_test), columns = np.unique(y_test) )

cm_df.head()
```

```
Train accuracy:  0.9960861056751468
Test accuracy:  0.8666666666666667
```

Out[255]:

	0	**1**
0	30	7
1	9	74

True negatives - 30 (drivers who stayed as predicted)

False positives - 7 (drivers who stayed but were predicted to churn)

False negatives - 9 (drivers who churned but were predicted to stay) - need the most attention as can cause huge financial losses

True positives - 74 (drivers who churned as predicted)

In [250…

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

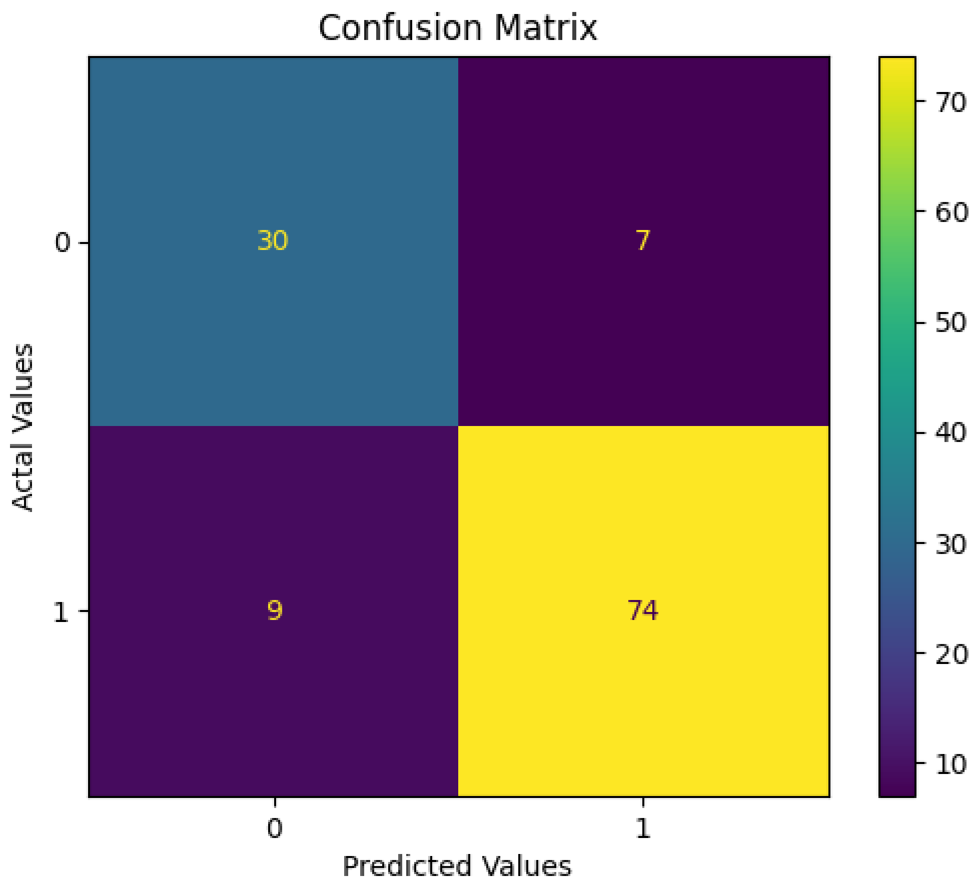
```
              precision    recall  f1-score   support

           0       0.77      0.81      0.79        37
           1       0.91      0.89      0.90        83

    accuracy                           0.87       120
   macro avg       0.84      0.85      0.85       120
weighted avg       0.87      0.87      0.87       120
```

In [239…

```
#Plotting the confusion matrix
plt.figure(figsize=(1,1))
plot_confusion_matrix(best_xgb,X_test,y_test)
```

```
#sns.heatmap(cm_df, annot=True,cmap='coolwarm')
plt.title('Confusion Matrix')
plt.ylabel('Actal Values')
plt.xlabel('Predicted Values')
plt.show()
```

```
C:\Users\Admin\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\utils\deprecati
on.py:87: FutureWarning: Function plot_confusion_matrix is deprecated; Function `plot_confusion_
matrix` is deprecated in 1.0 and will be removed in 1.2. Use one of the class methods: Confusion
MatrixDisplay.from_predictions or ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
<Figure size 100x100 with 0 Axes>
```



In [240…

```
from sklearn.metrics import f1_score
print("Precision score is :",precision_score(y_test,y_pred))
print("Recall score is :",recall_score(y_test,y_pred))
print("F1 score is :",f1_score(y_test,y_pred))
```

```
Precision score is : 0.9135802469135802
Recall score is : 0.891566265060241
F1 score is : 0.9024390243902438
```

Precision is 0.91 which is good as the number of false positives (7) are low, the drivers who stayed but were predicted to churn.

Recall-score: 0.89. Recall is high because of low number of False negatives. This is good as we are not losing too many drivers (9) to churn who were predicted to stay. But we can still improve recall score by encouraging drivers to stay and provide enticing perks and reduce financial losses.

ROC (Receiver Operating Characteristic curve) and AUC (Area Under Curve)

In [241…

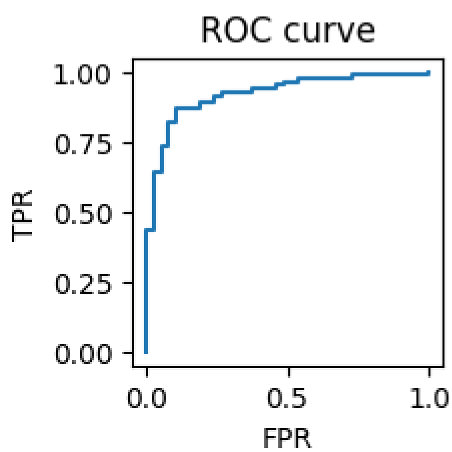
```
# from sklearn.linear_model import
y_proba = best_xgb.predict_proba(X_test)
```

```
y_proba.shape, y_test.shape
```

Out[241]: ((120, 20), (120, 1))

In [244…

```
from sklearn.metrics import roc_curve, roc_auc_score
fpr, tpr, thr = roc_curve(y_test, y_proba[:,1])
plt.figure(figsize=(2,2))
plt.plot(fpr,tpr)
plt.title('ROC curve')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.show()
```



There are more true positives than False positives, hence the ROC curve has more area under curve than 0.5.

In [243…

```
roc_auc_score(y_test,y_proba[:,1])
```

Out[243]: 0.9202214262455226

0.92 is a good area under curve.

Business Insights

There are more male drivers (0) than females drivers (1).

Education variable has uniform distribution across all 3 levels.

Most drivers join at the designation levels - 1,2 and 3. Very few join as 4 or 5.

Most drivers churn that means most drivers leave their jobs.

A few drivers had an increase in their quarterly ratings.

Very small number of drivers had an increase in their monthly income compared to when they started.

Most drivers left their jobs in the year 2020 maybe due to the pandemic. Some left in 2019, and very few in 2018.

Mean income, designation while joining, and total business value are lower for drivers who churned than those who stayed.

There was no increase in quarterly ratings for those drivers who left, so they might have left due to lower customer evaluation and rating on their skills.

Tenure for those who churned also is lesser than those who stayed.

Most common city for drivers to live or work at was C20. In every city, there were more drivers who churned than those who stayed.

According to the RF bagging algorithm, train accuracy:92.3% , test accuracy: 88.3%. The churn outcome was most affected by the Last working date, and then the other important features were Total Business value, tenure duration and increase in quarterly ratings. Precision score was 0.95 and there were very few false positives, drivers who stayed but were predicted to churn. They don't need much attention and can cause waste of resources but thankfully there were very few in number. Recall score- 0.9 which means that there were few false negatives that caused financial losses as they churned but were predicted to stay, and this can be improved to decrease further losses.

According to XGBoost algorithm: training accuracy:99.6% , test accuracy 86.67%. Precision is 0.91 which is good as the number of false positives (7) are low, the drivers who stayed but were predicted to churn. Recall-score: 0.89. Recall is high because of low number of False negatives. This is good as we are not losing too many drivers (9) to churn who were predicted to stay. But we can still improve recall score by encouraging drivers to stay and provide enticing perks and reduce financial losses.

Recommendations

Since there are more males than females, there is an opportunity for the business to increase the number of drivers by encouraging more female drivers to take up jobs.

Since we only have data from 2018, 2019 and 2020, out of which 2020 was the time of pandemic and cannot be used for general analysis, we need to collect more data from other years too in order to improve our analysis and reduce errors.

Drivers who left were those who did not have any increase in their ratings so maybe they can be encouraged to improve their driving skills and ratings by being given tips on customer satisfaction, communication with customers and safe driving tips to increase their ratings and therefore increase their sense of job satisfaction.

Most common city for drivers to live or work at was C20. Maybe other cities can be targeted for marketing and calling more drivers to work for their business with enticing ads on job perks.

It is important to retain drivers by offering them more job perks- such as designated resting areas especially for female drivers, reducing total business value loss by discouraging cancellation of rides and improve quarterly ratings for drivers. A survey can be conducted among drivers to understand their needs.

In [ ]: