Problem Statement

Help an Indian multinational ridesharing company, 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) and Historical data regarding the performance of the driver (Quarterly rating, Monthly business acquired, grade, Income). Also, provide actionable Insights & Recommendations to retain drivers since the high churn among drivers could become a bigger problem as the companies get bigger.

In [102…

```
#importing required libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [102…

```
#importing data set

data = pd.read_csv('driver.csv')
```

In [102…

```
data.head()
```

Out[1026]:

	Unnamed: 0	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining
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 [102…

```
data.tail()
```

Out[1027]:

	Unnamed: 0	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoi
19099	19099	08/01/20	2788	30.0	0.0	C27	2	70254	06/(
19100	19100	09/01/20	2788	30.0	0.0	C27	2	70254	06/(
19101	19101	10/01/20	2788	30.0	0.0	C27	2	70254	06/(
19102	19102	11/01/20	2788	30.0	0.0	C27	2	70254	06/(
19103	19103	12/01/20	2788	30.0	0.0	C27	2	70254	06/(

In [102…
```
data = data.drop(columns = 'Unnamed: 0')
```

In [102…
```
data.shape
```

Out[1029]:
```
(19104, 13)
```

In [103…
```
#data overiew - non-null counts and data types

data.info()
```

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

In [103…
```
#percentage of null values in each column

data.isnull().sum()*100/data.isnull().count()
```

Out[1031]:
```
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
```

Exploratory Data Analysis

In [103…
```
#converting date columns to date dtype

data['MMM-YY'] = data['MMM-YY'].astype('datetime64')
data['Dateofjoining'] = data['Dateofjoining'].astype('datetime64')
data['LastWorkingDate'] = data['LastWorkingDate'].astype('datetime64')
```

In [103…

```
#grouping by Driver_ID and storing the sum of Total Business value and last

df = data.groupby('Driver_ID').last()
df['Total Business Value'] = data.groupby('Driver_ID')['Total Business Valu
# df['Avg Quarterly Rating'] = data.groupby('Driver_ID')['Quarterly Rating'
df.reset_index(inplace = True)
```

In [103…

```
df.head()
```

Out[1034]:

	Driver_ID	MMM-YY	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorking
0	1	2019-03-01	28.0	0.0	C23	2	57387	2018-12-24	2019-(
1	2	2020-12-01	31.0	0.0	C7	2	67016	2020-11-06	
2	4	2020-04-01	43.0	0.0	C13	2	65603	2019-12-07	2020-(
3	5	2019-03-01	29.0	0.0	C9	0	46368	2019-01-09	2019-(
4	6	2020-12-01	31.0	1.0	C11	1	78728	2020-07-31	

In [103…

```
df.shape
```

Out[1035]:

```
(2381, 13)
```

In [103…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2381 entries, 0 to 2380
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Driver_ID             2381 non-null   int64
 1   MMM-YY                2381 non-null   datetime64[ns]
 2   Age                   2381 non-null   float64
 3   Gender                2381 non-null   float64
 4   City                  2381 non-null   object
 5   Education_Level       2381 non-null   int64
 6   Income                2381 non-null   int64
 7   Dateofjoining         2381 non-null   datetime64[ns]
 8   LastWorkingDate       1616 non-null   datetime64[ns]
 9   Joining Designation   2381 non-null   int64
 10  Grade                 2381 non-null   int64
 11  Total Business Value  2381 non-null   int64
 12  Quarterly Rating      2381 non-null   int64
dtypes: datetime64[ns](3), float64(2), int64(7), object(1)
memory usage: 241.9+ KB
```

In [103…

```
#percentage of null values in each column

df.isnull().sum()*100/df.isnull().count()
```

Out[1037]:
```
Driver_ID                0.000000
MMM-YY                   0.000000
Age                      0.000000
Gender                   0.000000
City                     0.000000
Education_Level          0.000000
Income                   0.000000
Dateofjoining            0.000000
LastWorkingDate         32.129357
Joining Designation      0.000000
Grade                    0.000000
Total Business Value     0.000000
Quarterly Rating         0.000000
dtype: float64
```

Data Overview

Before Cleaning

- 19104 rows and 13 columns

After Cleaning

- There are 2381 rows and 13 columns
- Each row represents the attributes of a driver (dependent variables) and their last working date (NaN if still working), independent variable.

Data Types

- Numerical(Continuous) variables - Age, Income, Total Business Value
- Numerical(Discrete) variables - Diver_ID, Gender, Education_Level, Joining Designation, Grade, Quarterly Rating
- Categorical variable - City
- Datetime variables - MMM-YY, Dateofjoining, LastWorkingDate

Non-Graphical Analysis

In [103…
```
#number of unique values

df.nunique()
```

Out[1038]:
```
Driver_ID               2381
MMM-YY                    24
Age                       36
Gender                     2
City                      29
Education_Level            3
Income                  2339
Dateofjoining            869
LastWorkingDate          493
Joining Designation        5
Grade                      5
Total Business Value    1629
Quarterly Rating           4
dtype: int64
```

In [103…
```
df.describe(datetime_is_numeric=True)
```

Out[1039]:

	Driver_ID	MMM-YY	Age	Gender	Education_Level	Inc
count	2381.000000	2381	2381.000000	2381.000000	2381.00000	2381.0C
mean	1397.559009	2020-03-31 15:04:09.475010560	33.663167	0.410332	1.00756	59334.15
min	1.000000	2019-01-01 00:00:00	21.000000	0.000000	0.00000	10747.0C
25%	695.000000	2019-09-01 00:00:00	29.000000	0.000000	0.00000	39104.0C
50%	1400.000000	2020-06-01 00:00:00	33.000000	0.000000	1.00000	55315.0C
75%	2100.000000	2020-12-01 00:00:00	37.000000	1.000000	2.00000	75986.0C
max	2788.000000	2020-12-01 00:00:00	58.000000	1.000000	2.00000	188418.0C
std	806.161628	NaN	5.983375	0.491997	0.81629	28383.6€

In [104…

```
#target variable churn
df['churn'] = df['LastWorkingDate'].isna().apply(lambda x: 0 if x else 1)
```

In [104…

```
#checking column churn
df['churn'].value_counts(normalize=True)
```

Out[1041]:

```
1    0.678706
0    0.321294
Name: churn, dtype: float64
```

In [104…

```
#checking column Gender
df['Gender'].value_counts(normalize=True)
```

Out[1042]:

```
0.0    0.589668
1.0    0.410332
Name: Gender, dtype: float64
```

In [104…

```
#checking column City
df['City'].value_counts()
```

Out[1043]:
```
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 [104…
```
#checking column Education_Level

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

Out[1044]:
```
2    802
1    795
0    784
Name: Education_Level, dtype: int64
```

In [104…
```
#checking column Joining Designation

df['Joining Designation'].value_counts()
```

Out[1045]:
```
1    1026
2     815
3     493
4      36
5      11
Name: Joining Designation, dtype: int64
```

In [104…
```
#checking column Grade

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

Out[1046]:
```
2    855
1    741
3    623
4    138
5     24
Name: Grade, dtype: int64
```

In [104…

```
#checking column Quarterly Rating

df['Quarterly Rating'].value_counts(normalize=True)
```

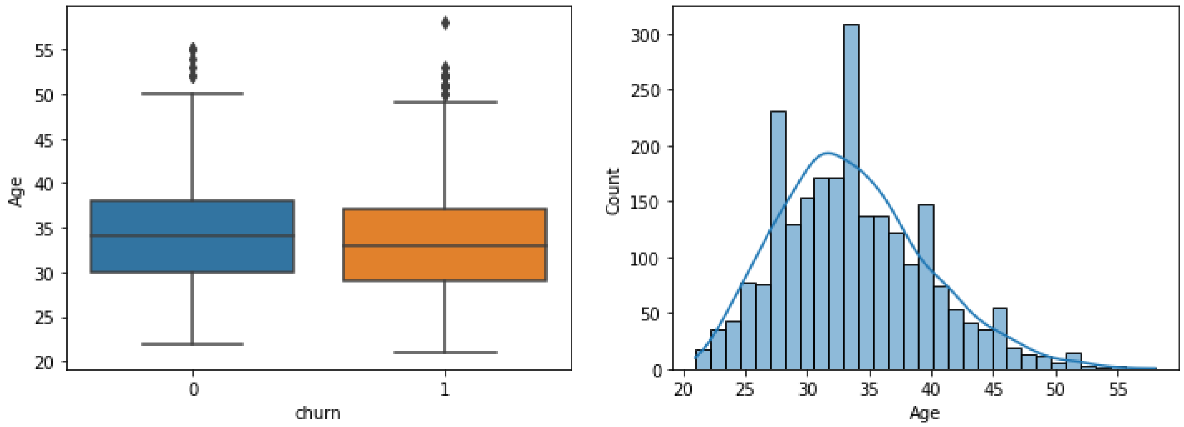
Out[1047]:

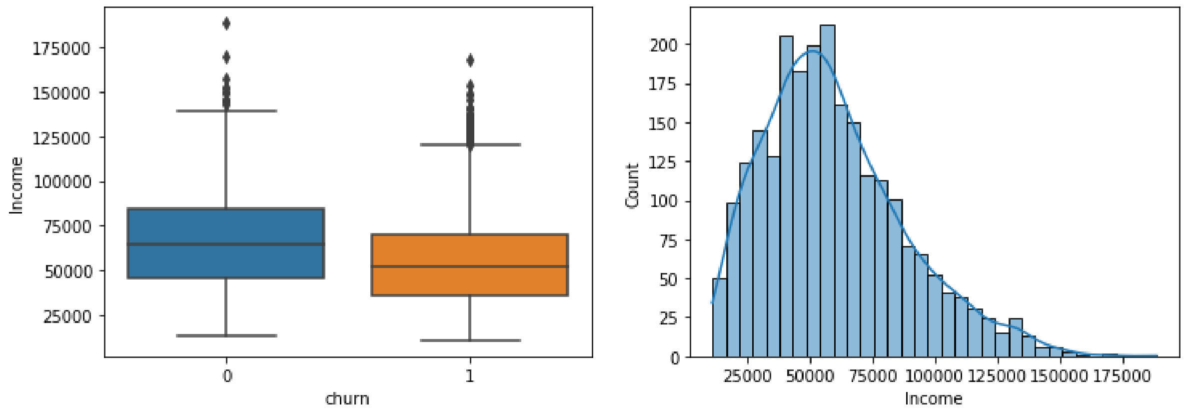
```
1    0.732465
2    0.152037
3    0.070559
4    0.044939
Name: Quarterly Rating, dtype: float64
```

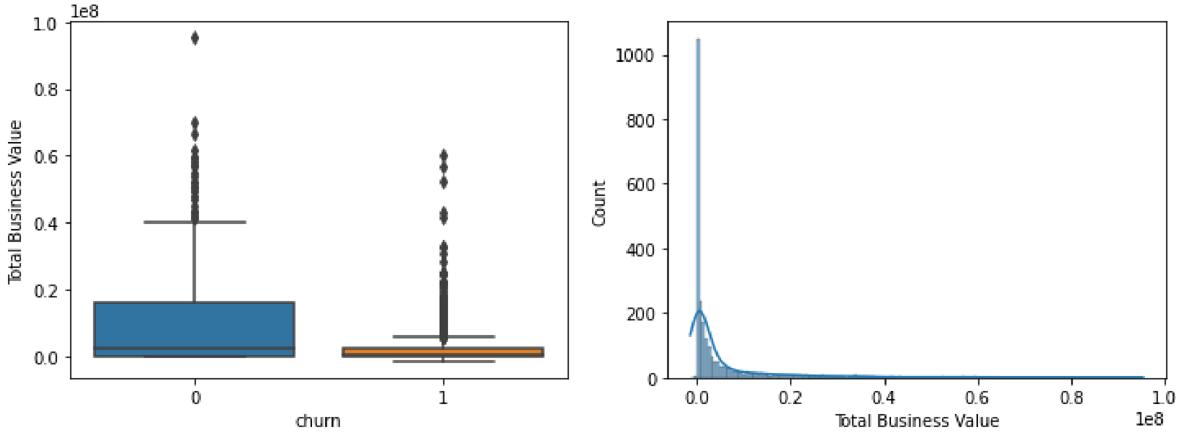
Visual Analysis

In [104…

```
#Distribution of numerical attributes

num_cols = ['Age', 'Income', 'Total Business Value']

for col in num_cols:
    plt.figure(figsize=(12,4))
    plt.subplot(121)
    sns.boxplot(data=df, y=col, x='churn')
    plt.subplot(122)
    sns.histplot(data=df, x=col, kde=True)
    plt.show()
```







In [104…

```
df[['Total Business Value', 'churn']]
```

Out[1049]:

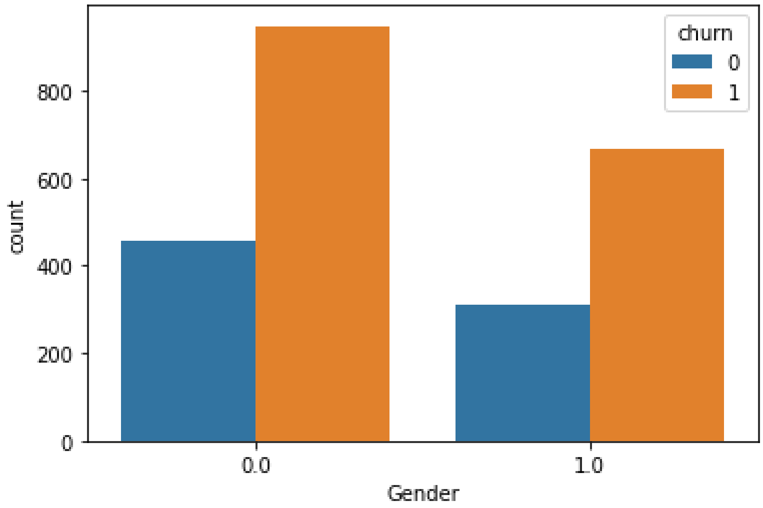
	Total Business Value	churn
0	1715580	1
1	0	0
2	350000	1
3	120360	1
4	1265000	0
...	...	...
2376	21748820	0
2377	0	1
2378	2815090	1
2379	977830	1
2380	2298240	0

2381 rows × 2 columns

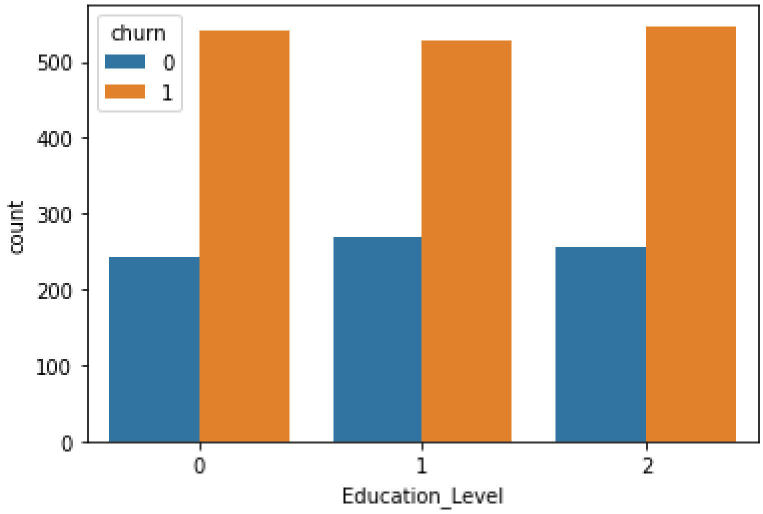
In [105…

```
#visualizing categorical attributes

cat_cols = ['Gender', 'Education_Level', 'Joining Designation', 'Grade', '(

for col in cat_cols:
    print(pd.crosstab(df[col], df['churn'], margins=True, normalize='index'
    sns.countplot(data=df, x=col, hue='churn')
    plt.show()
```

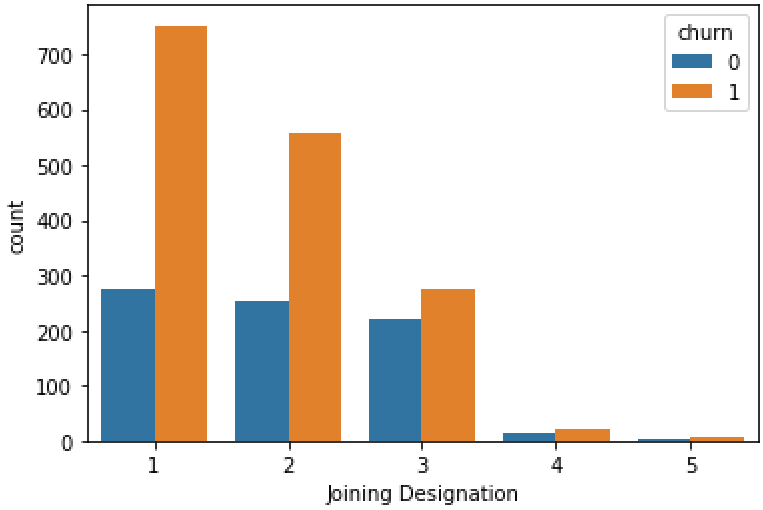
```
churn          0         1
Gender
0.0     0.324786  0.675214
1.0     0.316274  0.683726
All     0.321294  0.678706
```



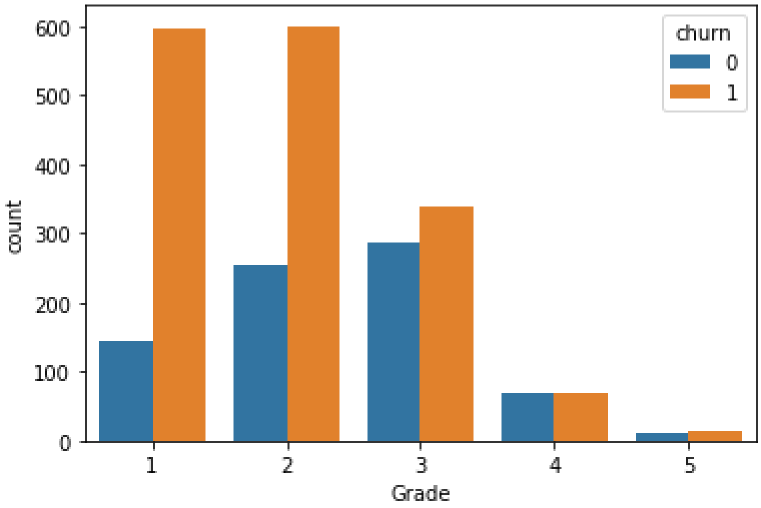

```
churn                  0         1
Education_Level
0               0.308673  0.691327
1               0.337107  0.662893
2               0.317955  0.682045
All             0.321294  0.678706
```



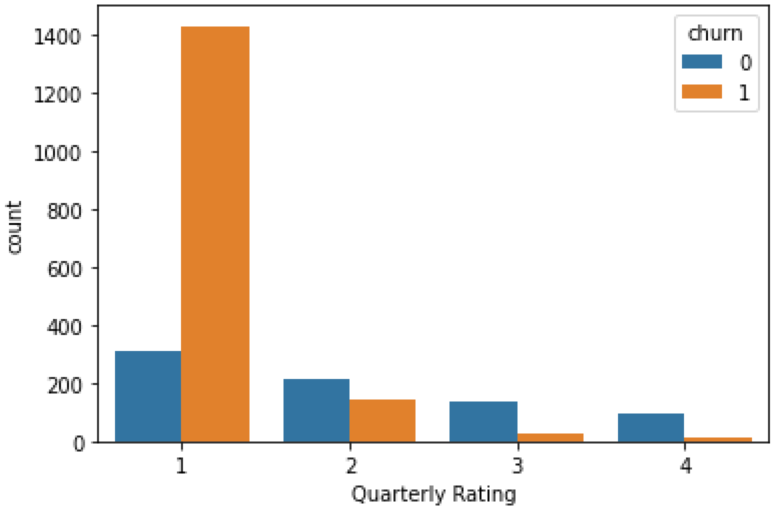

```
churn                      0         1
Joining Designation
1                   0.267057  0.732943
2                   0.312883  0.687117
3                   0.444219  0.555781
4                   0.388889  0.611111
5                   0.272727  0.727273
All                 0.321294  0.678706
```



```
churn         0         1
Grade
1      0.195682  0.804318
2      0.298246  0.701754
3      0.459069  0.540931
4      0.492754  0.507246
5      0.458333  0.541667
All    0.321294  0.678706
```

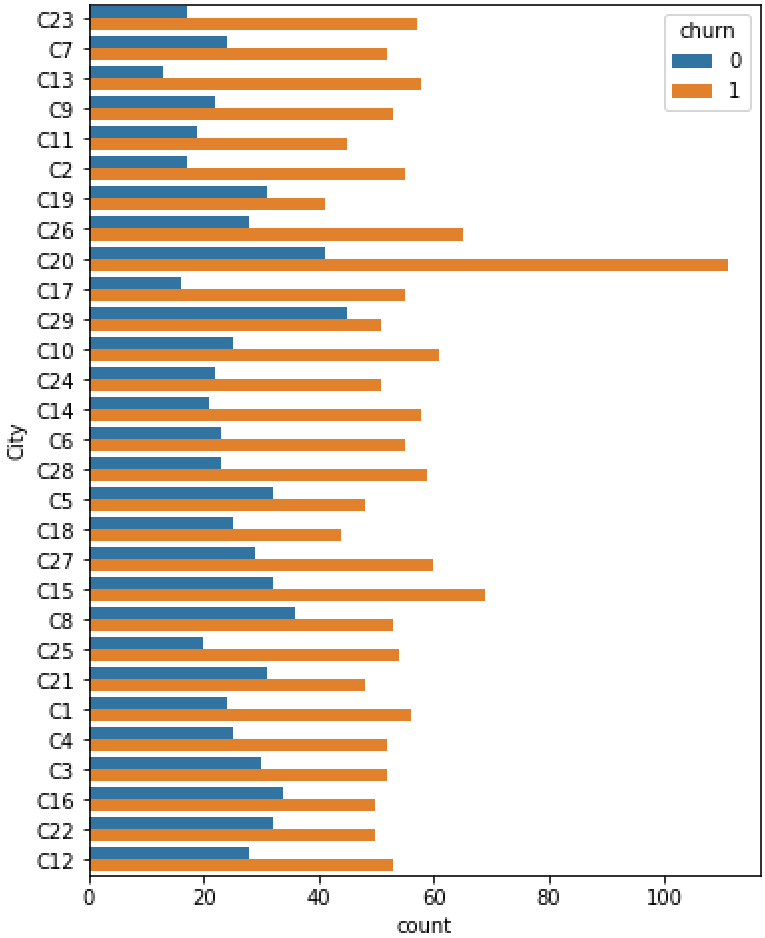



```
churn                     0         1
Quarterly Rating
1                  0.178899  0.821101
2                  0.596685  0.403315
3                  0.833333  0.166667
4                  0.906542  0.093458
All                0.321294  0.678706
```



In [105…

```
plt.figure(figsize=(6,8))
sns.countplot(data=df, y='City', hue='churn')
plt.show()
```



In [105…

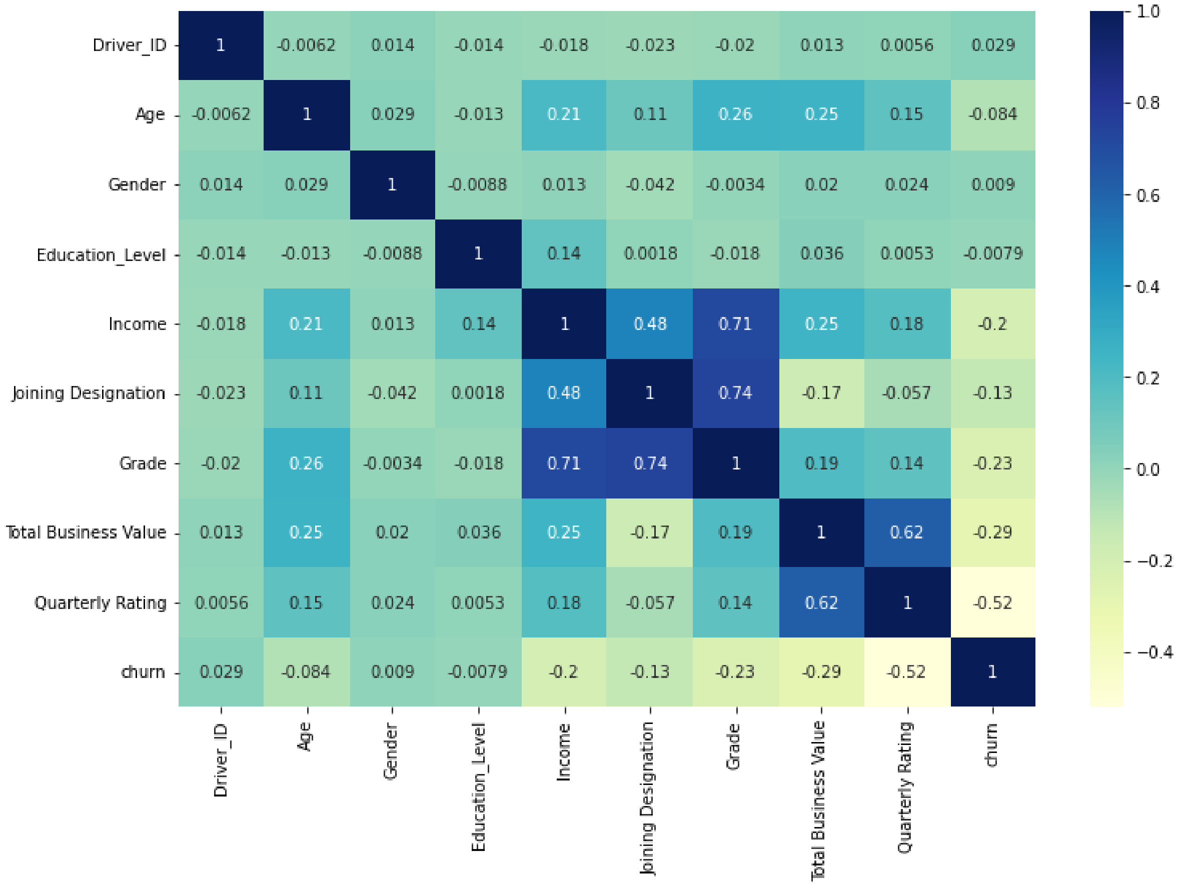
```
pd.crosstab(df['City'], df['churn'], margins=True, normalize='index')
```

Out[1052]:

churn	0	1
City		
C1	0.300000	0.700000
C10	0.290698	0.709302
C11	0.296875	0.703125
C12	0.345679	0.654321
C13	0.183099	0.816901
C14	0.265823	0.734177
C15	0.316832	0.683168
C16	0.404762	0.595238
C17	0.225352	0.774648
C18	0.362319	0.637681
C19	0.430556	0.569444
C2	0.236111	0.763889
C20	0.269737	0.730263
C21	0.392405	0.607595
C22	0.390244	0.609756
C23	0.229730	0.770270
C24	0.301370	0.698630
C25	0.270270	0.729730
C26	0.301075	0.698925
C27	0.325843	0.674157
C28	0.280488	0.719512
C29	0.468750	0.531250
C3	0.365854	0.634146
C4	0.324675	0.675325
C5	0.400000	0.600000
C6	0.294872	0.705128
C7	0.315789	0.684211
C8	0.404494	0.595506
C9	0.293333	0.706667
All	0.321294	0.678706

In [105…

```
plt.figure(figsize=(12,8))
sns.heatmap(df.corr(method='spearman'), cmap="YlGnBu", annot=True)
plt.show()
```



Observations Based on EDA

1. 68% of the drivers have churned over the period of two years from 2019 to 2020
2. Around 60% of the drivers are male and 40% are female drivers
3. City C20 has the highest number of drivers and C11 has the lowest
4. There is an equal representation of drivers from different levels of education
5. Majority of the drivers have a joining designation 1 and very few people have a designation 5
6. Most of the drivers have a grade of either 1 or 2 and people with grade 5 are very less in number
7. Over 70% have a last quarterly rating 1 and less than 2% have obtained a rating of 3 or 4
8. No significant difference is found in the churning behaviour based on gender and education level
9. Joining designation seem to have some impact on churning as people with a designation 3 tend to leave less

10. Grade has high impact on churning as over 80% of the drivers with a grade 1 leave the company where only 50-55% of the drivers with grade 3 or above leave

11. Quarterly rating has the highest impact on predicting churn as only 18% of the people with a rating 1 stay while 80-90% with a rating 3 or 4 stay

12. Churning is the highest in city C13 and the lowest in city C29

13. Grade is highly correlated with Income and Job Designation

14. Quarterly rating is the feature with the highest correlation with churn

15. Average income of those who stay is significantly higher than that of those drivers who leave the company

Data Preprocessing

In [105…

```
from sklearn.preprocessing import OneHotEncoder
from sklearn.impute import KNNImputer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from imblearn.over_sampling import SMOTE
```

KNN Imputation

In [105…

```
#percentage of null values in each column

df.isnull().sum()*100/df.isnull().count()
```

Out[1055]:

```
Driver_ID                 0.000000
MMM-YY                    0.000000
Age                       0.000000
Gender                    0.000000
City                      0.000000
Education_Level           0.000000
Income                    0.000000
Dateofjoining             0.000000
LastWorkingDate          32.129357
Joining Designation       0.000000
Grade                     0.000000
Total Business Value      0.000000
Quarterly Rating          0.000000
churn                     0.000000
dtype: float64
```

Column LastWorkingDate will be null if the driver hasn't left the company. So, a feature churn is derived from that and no imputation is required. No other feature has null values hence, no need of KNN imputation

Feature Engineering

In [105…

```
##Creating a column which tells whether the quarterly rating has increased
##for those whose quarterly rating has increased we assign the value 1
```

```
data_new = data.sort_values(by=['Driver_ID', 'MMM-YY'])
df['is_rating_increased'] = np.array((data_new.groupby(by='Driver_ID')['Qua
                            data_new.groupby(by='Driver_ID')['Quarterly Rat
df['is_rating_increased'] = df['is_rating_increased'].apply(lambda x: 0 if
```

In [105…

```
##Target variable creation: Create a column called target which tells wheth
##driver whose last working day is present will have the value 1

#Already created for EDA - Feature churn
df['target'] = df['churn']
```

In [105…

```
##Create a column which tells whether the monthly income has increased for
##for those whose monthly income has increased we assign the value 1

df['is_monthlyinc_increased'] = np.array((data_new.groupby(by='Driver_ID')[
                            data_new.groupby(by='Driver_ID')['Income'].firs
df['is_monthlyinc_increased'] = df['is_monthlyinc_increased'].apply(lambda
```

Encoding

In [105…

```
df['City'].unique()
```

Out[1059]:

```
array(['C23', 'C7', 'C13', 'C9', 'C11', 'C2', 'C19', 'C26', 'C20', 'C17',
       'C29', 'C10', 'C24', 'C14', 'C6', 'C28', 'C5', 'C18', 'C27', 'C1
5',
       'C8', 'C25', 'C21', 'C1', 'C4', 'C3', 'C16', 'C22', 'C12'],
      dtype=object)
```

In [106…

```
#One Hot Encoding categorical variable City
ohe = OneHotEncoder()

#fit and transform train data
feature_array = ohe.fit_transform(df[['City']]).toarray()
np.hstack(ohe.categories_)
```

Out[1060]:

```
array(['C1', 'C10', 'C11', 'C12', 'C13', 'C14', 'C15', 'C16', 'C17',
       'C18', 'C19', 'C2', 'C20', 'C21', 'C22', 'C23', 'C24', 'C25',
       'C26', 'C27', 'C28', 'C29', 'C3', 'C4', 'C5', 'C6', 'C7', 'C8',
       'C9'], dtype=object)
```

In [106…

```
feature_labels = np.hstack(ohe.categories_)
features = pd.DataFrame(feature_array, columns=feature_labels)
# features.head()
features.shape
```

Out[1061]:

```
(2381, 29)
```

In [106…

```
df = pd.concat([df, features], axis=1)
df.drop(columns=['City'], inplace=True)
df.head()
```

Out[1062]:

	Driver_ID	MMM-YY	Age	Gender	Education_Level	Income	Dateofjoining	LastWorkingDate
0	1	2019-03-01	28.0	0.0	2	57387	2018-12-24	2019-03-11
1	2	2020-12-01	31.0	0.0	2	67016	2020-11-06	NaT
2	4	2020-04-01	43.0	0.0	2	65603	2019-12-07	2020-04-27
3	5	2019-03-01	29.0	0.0	0	46368	2019-01-09	2019-03-07
4	6	2020-12-01	31.0	1.0	1	78728	2020-07-31	NaT

5 rows × 45 columns

Data preparation for modeling and testing

In [106…

```
df.columns
```

Out[1063]:

```
Index(['Driver_ID', 'MMM-YY', 'Age', 'Gender', 'Education_Level', 'Incom
e',
       'Dateofjoining', 'LastWorkingDate', 'Joining Designation', 'Grad
e',
       'Total Business Value', 'Quarterly Rating', 'churn',
       'is_rating_increased', 'target', 'is_monthlyinc_increased', 'C1',
'C10',
       'C11', 'C12', 'C13', 'C14', 'C15', 'C16', 'C17', 'C18', 'C19', 'C
2',
       'C20', 'C21', 'C22', 'C23', 'C24', 'C25', 'C26', 'C27', 'C28', 'C2
9',
       'C3', 'C4', 'C5', 'C6', 'C7', 'C8', 'C9'],
      dtype='object')
```

In [106…

```
df_final = df.drop(columns=['Driver_ID', 'MMM-YY', 'Dateofjoining', 'LastWo
df_final.shape
```

Out[1064]:

```
(2381, 40)
```

In [106…

```
df_final.columns
```

Out[1065]:

```
Index(['Age', 'Gender', 'Education_Level', 'Income', 'Joining Designatio
n',
       'Grade', 'Total Business Value', 'Quarterly Rating',
       'is_rating_increased', 'target', 'is_monthlyinc_increased', 'C1',
'C10',
       'C11', 'C12', 'C13', 'C14', 'C15', 'C16', 'C17', 'C18', 'C19', 'C
2',
       'C20', 'C21', 'C22', 'C23', 'C24', 'C25', 'C26', 'C27', 'C28', 'C2
9',
       'C3', 'C4', 'C5', 'C6', 'C7', 'C8', 'C9'],
      dtype='object')
```

In [106…

```
##target variable
y = df_final['target']
```

```
##input data
X = df_final.drop(columns=['target'])
```

In [106…

```
##splitting data into train, cv, test

X_train_cv, X_test, y_train_cv, y_test = train_test_split(X, y, test_size=0
X_train, X_val, y_train, y_val = train_test_split(X_train_cv, y_train_cv, t
```

In [106…

```
print(X_train.shape, X_val.shape, X_test.shape)
```

```
(1428, 39) (476, 39) (477, 39)
```

Standardization

In [106…

```
##scaling data
scaler = MinMaxScaler()
scaler.fit(X_train[X_train.columns])
df_train = X_train.copy()
X_train = scaler.transform(X_train[X_train.columns])  # returns numpy.ndarr

##transforming val and test data
X_test = scaler.transform(X_test[X_test.columns])

X_val = scaler.transform(X_val[X_val.columns])
```

Class Imbalance treatment

In [107…

```
#SMOTE over_sampling for imbalanced data
sm = SMOTE()
```

In [107…

```
X_sm, y_sm = sm.fit_resample(X_train, y_train)
```

In [107…

```
X_sm.shape
```

Out[1072]:

```
(1954, 39)
```

Model Building

DecisionTreeClassifier

In [107…

```
from sklearn.tree import DecisionTreeClassifier as DTC
from sklearn.model_selection import GridSearchCV
```

In [107…

```
params = {
    "max_depth" : [3, 5, 7],
    "max_leaf_nodes" : [15, 20, 25]
}

dtc_model = DTC()
clf = GridSearchCV(dtc_model, params, scoring = "accuracy", cv=5)
```

```
clf.fit(X_sm, y_sm)
```

Out[1074]:

```
▸ GridSearchCV
▸ estimator: DecisionTreeClassifier
  ▸ DecisionTreeClassifier
```

In [107…

```
res = clf.cv_results_

for i in range(len(res["params"])):
  print(f"Parameters:{res['params'][i]} Mean_score: {res['mean_test_score']
```

```
Parameters:{'max_depth': 3, 'max_leaf_nodes': 15} Mean_score: 0.77842612630
33642 Rank: 8
Parameters:{'max_depth': 3, 'max_leaf_nodes': 20} Mean_score: 0.77842612630
33642 Rank: 8
Parameters:{'max_depth': 3, 'max_leaf_nodes': 25} Mean_score: 0.78047740835
46463 Rank: 7
Parameters:{'max_depth': 5, 'max_leaf_nodes': 15} Mean_score: 0.80556757820
18493 Rank: 2
Parameters:{'max_depth': 5, 'max_leaf_nodes': 20} Mean_score: 0.80403042822
48016 Rank: 4
Parameters:{'max_depth': 5, 'max_leaf_nodes': 25} Mean_score: 0.80505738081
18564 Rank: 3
Parameters:{'max_depth': 7, 'max_leaf_nodes': 15} Mean_score: 0.81170699718
01432 Rank: 1
Parameters:{'max_depth': 7, 'max_leaf_nodes': 20} Mean_score: 0.80198963866
48305 Rank: 5
Parameters:{'max_depth': 7, 'max_leaf_nodes': 25} Mean_score: 0.79993442192
93069 Rank: 6
```

In [107…

```
print(clf.best_estimator_)
```

```
DecisionTreeClassifier(max_depth=7, max_leaf_nodes=15)
```

In [107…

```
dtc_model = clf.best_estimator_

dtc_model.fit(X_sm, y_sm)

print(dtc_model.score(X_test, y_test))
```

```
0.80083857442348
```

Ensemble - Bagging Algorithm

Random Forest

In [107…

```
from sklearn.ensemble import RandomForestClassifier as RFC
from sklearn.model_selection import RandomizedSearchCV
```

In [107…

```
params = {
    "n_estimators": [10,25,50,100,150,200],
    "max_depth" : [3, 5, 7],
    "max_leaf_nodes" : [15, 20, 25]
}
```

```
rfc = RFC(n_jobs = -1)
clf = RandomizedSearchCV(rfc, params, scoring = "accuracy", cv=3, n_jobs =

clf.fit(X_sm, y_sm)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
```

In [108…

```
print(clf.best_estimator_)
```

```
RandomForestClassifier(max_depth=7, max_leaf_nodes=20, n_estimators=200,
                       n_jobs=-1)
```

In [108…

```
rf = clf.best_estimator_

rf.fit(X_sm, y_sm)

print("Model acc",rf.score(X_test, y_test))
```

```
Model acc 0.8197064989517819
```

Ensemble - Boosting Algorithm

Gradient Boosting

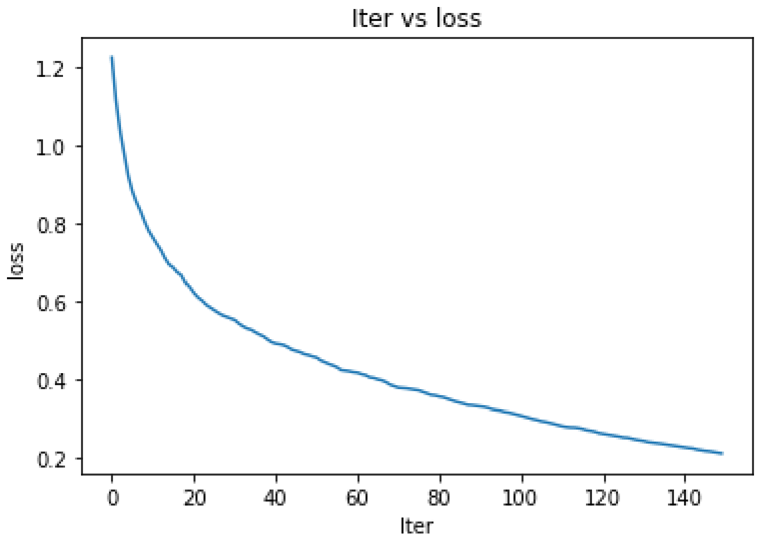
In [108…

```
from sklearn.ensemble import GradientBoostingClassifier as GBC
import datetime as dt

start = dt.datetime.now()
gbc = GBC(n_estimators=150, learning_rate=0.2, max_depth=4, random_state=0)
end = dt.datetime.now()

print(f"Time taken for training : {end - start}\nTraining accuracy:{gbc.sco
```

```
Time taken for training : 0:00:00.732172
Training accuracy:0.9872057318321392
Test Accuracy: 0.80083857442348
```

In [108…

```
plt.plot(gbc.train_score_)

plt.xlabel('Iter')
plt.ylabel('loss')
plt.title('Iter vs loss')
plt.show()
```



XGBoost

In [108…

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

In [108…

```
params = {
        'learning_rate': [0.06, 0.1, 0.2, 0.4, 0.6],
        'subsample': [0.3, 0.4, 0.6, 0.8],
        'colsample_bytree': [0.3, 0.4, 0.6, 0.8],
        'max_depth': [3, 4, 5],
        'n_estimators': [125, 150, 175]
        }
xgb = XGBClassifier(silent=True)
```

In [108…

```
folds = 3

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

grid_search = GridSearchCV(xgb, params, scoring='accuracy', n_jobs=-1, cv=s


start = dt.datetime.now()
grid_search.fit(X_sm, y_sm)
end = dt.datetime.now()
```

In [108…

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

```
 Best hyperparameters:
{'colsample_bytree': 0.8, 'learning_rate': 0.06, 'max_depth': 5, 'n_estimat
ors': 150, 'subsample': 0.8}
```

In [108…

```
best_xgb = XGBClassifier(n_estimators=175, subsample=0.6, max_depth=5, lea
best_xgb.fit(X_sm, y_sm)
```

Out[1088]:

```
▾ XGBClassifier
XGBClassifier(base_score=0.5, booster=None, colsample_bylevel=
1,
              colsample_bynode=1, colsample_bytree=0.6, gamma=
0, gpu_id=-1,
              importance_type='gain', interaction_constraints=N
one,
              learning_rate=0.06, max_delta_step=0, max_depth=
5,
              min_child_weight=1, missing=nan, monotone_constra
ints=None,
              n_estimators=175, n_jobs=0, num_parallel_tree=1,
```

In [108…

```
print(f"Time taken for training : {end - start}\nTraining accuracy:{best_xg
```

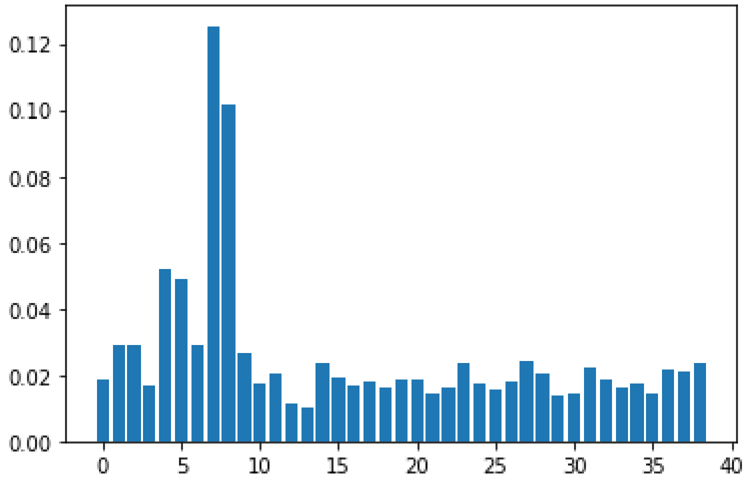
```
Time taken for training : 0:03:47.796244
Training accuracy:0.9196519959058342
Test Accuracy: 0.8218029350104822
```

Feature Importance

In [109…

```
print(best_xgb.feature_importances_)

plt.bar(range(len(best_xgb.feature_importances_)), best_xgb.feature_importa
plt.show()
```

```
[0.01843571 0.02875685 0.02912733 0.01698088 0.05219487 0.04907594
 0.02892354 0.1253906  0.10134501 0.02645308 0.01735362 0.02018533
 0.01142109 0.00992452 0.02367815 0.01952606 0.01674458 0.01810396
 0.0163741  0.01840518 0.01875165 0.01429379 0.01624138 0.02330503
 0.01723162 0.01551516 0.01789555 0.02391636 0.02046102 0.01392226
 0.01418739 0.02203643 0.01890856 0.0164425  0.01768811 0.01440419
 0.02186519 0.02108886 0.02344452]
```



In [109…

```
df_final.columns
```

Out[1091]:

```
Index(['Age', 'Gender', 'Education_Level', 'Income', 'Joining Designatio
n',
       'Grade', 'Total Business Value', 'Quarterly Rating',
       'is_rating_increased', 'target', 'is_monthlyinc_increased', 'C1',
'C10',
       'C11', 'C12', 'C13', 'C14', 'C15', 'C16', 'C17', 'C18', 'C19', 'C
2',
       'C20', 'C21', 'C22', 'C23', 'C24', 'C25', 'C26', 'C27', 'C28', 'C2
9',
       'C3', 'C4', 'C5', 'C6', 'C7', 'C8', 'C9'],
      dtype='object')
```

Important Features

1. Recent Quarterly Rating
2. Increase in Quareterly rating
3. Joining Designation
4. Grade

Summary of Models and Test Accuracies

1. Decision Tree

In [109…

```
dtc_model
```

Out[1092]:

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=7, max_leaf_nodes=15)
```

In [109…

```
dtc_model.score(X_test, y_test)
```

Out[1093]:

```
0.80083857442348
```

2. Random Forest

In [109…

```
rf
```

Out[1094]:

```
▾ RandomForestClassifier
RandomForestClassifier(max_depth=7, max_leaf_nodes=20, n_estimato
rs=200,
                       n_jobs=-1)
```

In [109…

```
rf.score(X_test, y_test)
```

Out[1095]:

```
0.8197064989517819
```

3. Gradient boost

In [109…

```
gbc
```

Out[1096]:

```
▾ GradientBoostingClassifier
GradientBoostingClassifier(learning_rate=0.2, max_depth=4, n_esti
mators=150,
                           random_state=0)
```

In [109…

```
gbc.score(X_test, y_test)
```

Out[1097]:

```
0.80083857442348
```

4. XGBoost

In [109…

```
best_xgb
```

Out[1098]:

```
XGBClassifier

XGBClassifier(base_score=0.5, booster=None, colsample_bylevel=
1,
              colsample_bynode=1, colsample_bytree=0.6, gamma=
0, gpu_id=-1,
              importance_type='gain', interaction_constraints=N
one,
              learning_rate=0.06, max_delta_step=0, max_depth=
5,
              min_child_weight=1, missing=nan, monotone_constra
ints=None,
              n_estimators=175, n_jobs=0, num_parallel_tree=1,
```

In [109…

```
best_xgb.score(X_test, y_test)
```

Out[1099]: 0.8218029350104822

Results Evaluation

In [110…

```
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.metrics import auc
```

In [110…

```
def results(model):

    #variable data will store y, probability and y_pred
    data = pd.DataFrame(y_test.copy())
    data.rename(columns={'target': 'y'}, inplace=True)
    data.reset_index(inplace=True)
    data.drop(columns=['index'], inplace=True)
    data['proba'] = model.predict_proba(X_test)[:, 1]
    data['y_pred'] = model.predict(X_test)
    print(data.head())
    print()

    #classification report
    print('Classification Report')
    cm = confusion_matrix(data['y'], data['y_pred'])
    print(cm)
    ConfusionMatrixDisplay(cm).plot()
    plt.show()
    print()

    # Accuracy
    acc = np.diag(cm).sum()/cm.sum()
    print('Accuracy = ', acc)

    #ROC AUC curve
    fpr, tpr, thres = roc_curve(data['y'], data['proba'])
    plt.xlabel('FPR')
    plt.ylabel('TPR')
    plt.plot(fpr, tpr)
    plt.title("ROC curve")
    plt.show()

    #ROC AUC Score
```

```
    score = roc_auc_score(data['y'], data['proba'])
    print('ROC AUC Score', score)

    return(data)
```

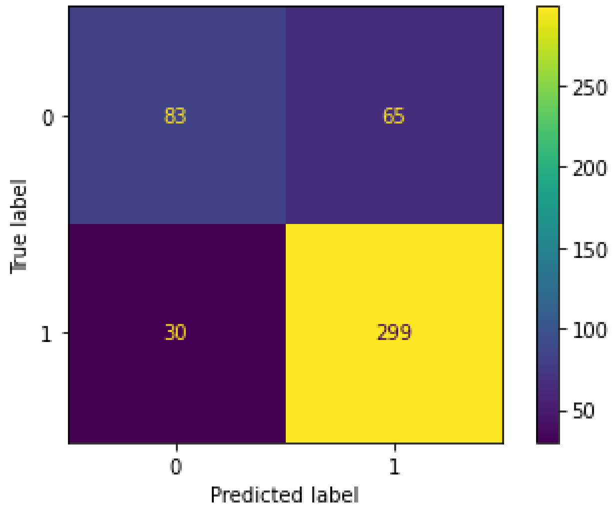
Classification Report and ROC AUC curve

1. Decision Tree

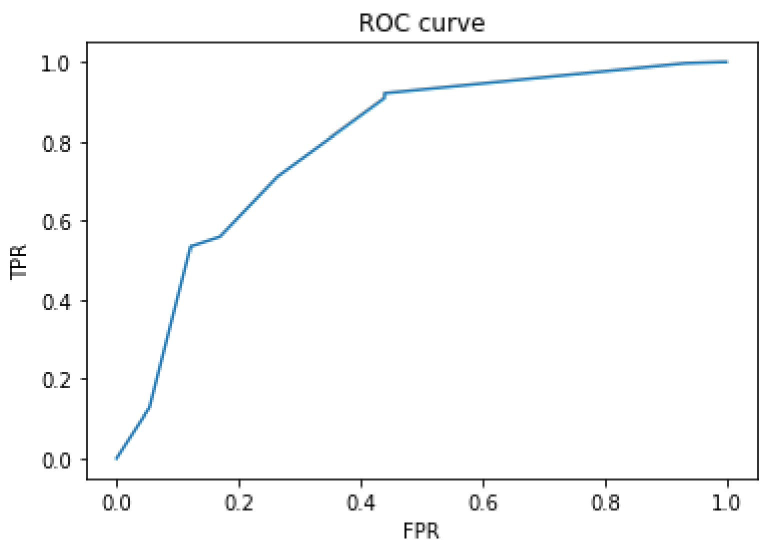
In [110…

```
## Decision Tree

dt_pred = results(dtc_model)
```

```
   y     proba  y_pred
0  0  0.687500       1
1  1  0.887133       1
2  1  0.887133       1
3  1  0.116473       0
4  0  0.895028       1

Classification Report
[[ 83  65]
 [ 30 299]]
```




```
Accuracy =  0.80083857442348
```



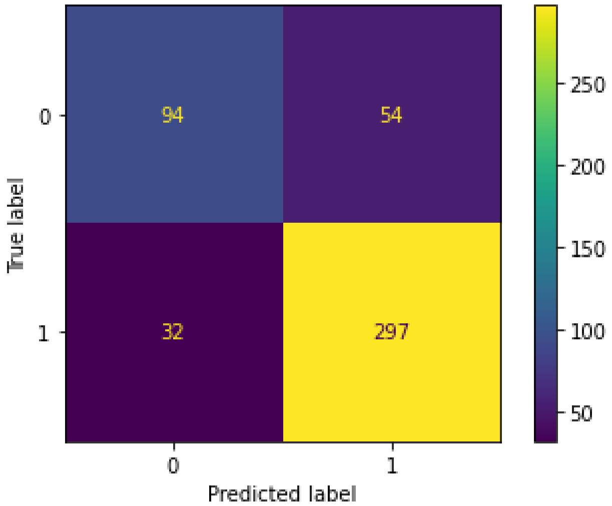

```
ROC AUC Score 0.7945863796927626
```

2. Random Forest

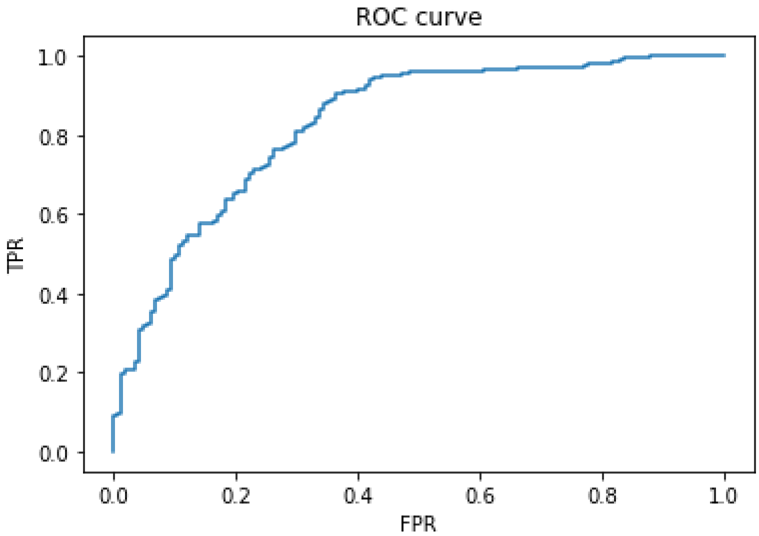
In [110…

```
## Random Forest

rf_pred = results(rf)
```

```
   y     proba  y_pred
0  0  0.714075       1
1  1  0.786600       1
2  1  0.801212       1
3  1  0.373270       0
4  0  0.684801       1

Classification Report
[[ 94  54]
 [ 32 297]]
```




```
Accuracy =  0.8197064989517819
```



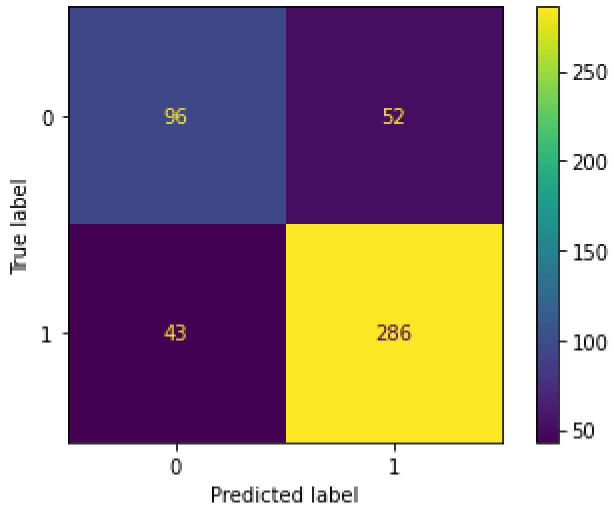

```
ROC AUC Score 0.829273802678058
```

3. Gradient Boost

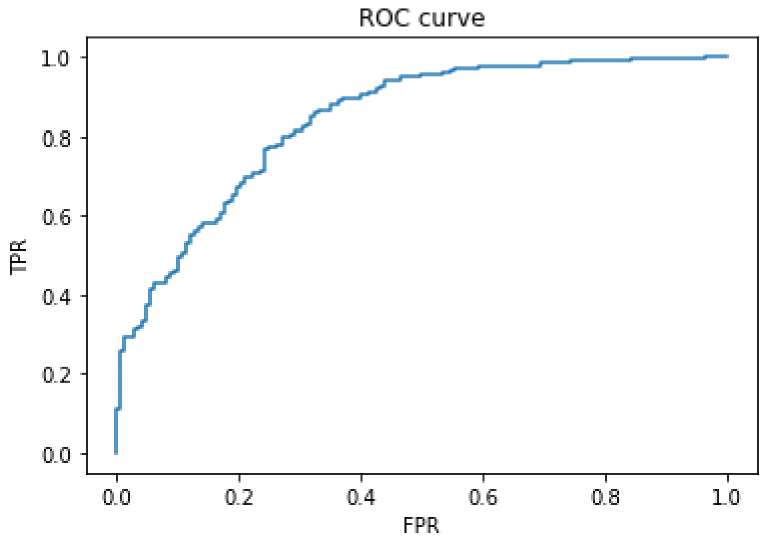
In [110…

```
## Gradient Boost

gbc_pred = results(gbc)
```

```
   y     proba  y_pred
0  0  0.955869       1
1  1  0.961343       1
2  1  0.967639       1
3  1  0.874478       1
4  0  0.929648       1

Classification Report
[[ 96  52]
 [ 43 286]]
```




```
Accuracy =  0.80083857442348
```



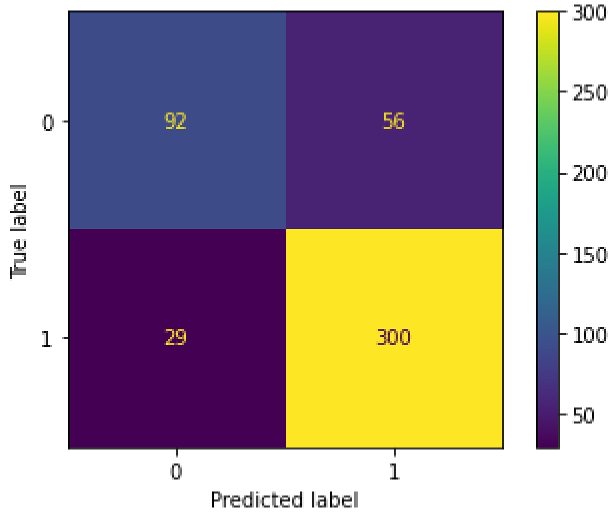

```
ROC AUC Score 0.8411443358251869
```

4. XGBoost

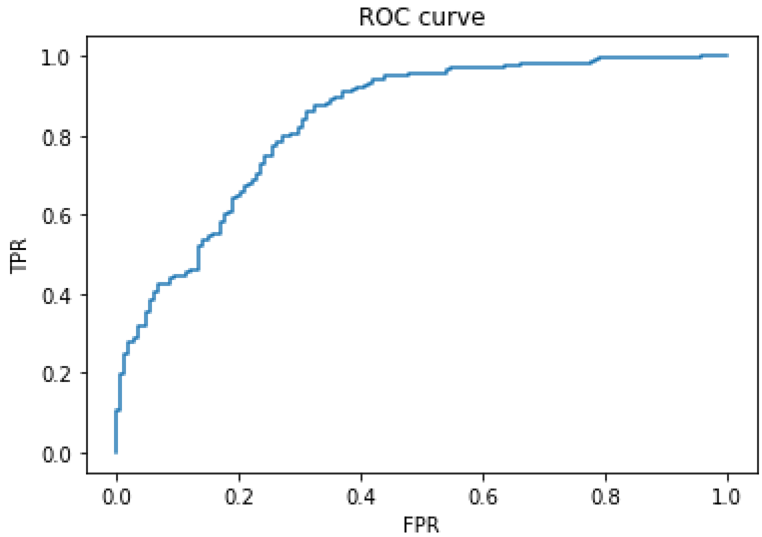
In [110…

```
## XGBoost

xgb_pred = results(best_xgb)
```

```
   y     proba  y_pred
0  0  0.842263       1
1  1  0.921066       1
2  1  0.778124       1
3  1  0.701307       1
4  0  0.915280       1

Classification Report
[[ 92  56]
 [ 29 300]]
```




```
Accuracy =  0.8218029350104822
```




```
ROC AUC Score 0.8355582025794792
```

Results

1. Decision Tree
   - Accuarcy: 80.08%
   - ROC AUC Score: 79.46%
2. Random Forest
   - Accuarcy: 81.97%
   - ROC AUC Score: 82.93%
3. Gradient Boost
   - Accuarcy: 80.08%
   - ROC AUC Score: 84.11
4. XGBoost
   - Accuarcy: 82.18%
   - ROC AUC Score: 83.56%

Actionable Insights

1. Joining designation has some impact on churning and people with a designation 3 tend to leave less compared to other designations

2. Grade has a high impact on churning as over 80% of the drivers with a grade of 1 leave the company whereas only 50-55% of the drivers with a grade of 3 or above left

3. The quarterly rating has the highest impact on predicting churn as only 18% of the people with a rating of 1 stay while 80-90% with a rating of 3 or 4 stay

4. Churning is the highest in cities C13, C17, and C23 and the lowest in city C29

5. Based on models, features having the highest impact on prediction are Quarterly Rating, Joining Designation, and Grade

6. The average income of those who stay is significantly higher than that of those drivers who leave the company

Recommendations

1. Providing a grade of 3 or above will help reduce the churn rate as the percentage of drivers leaving the company is highest among those who have a grade of 1 or 2

2. The majority of the drivers have a joining designation of 1, 2 or 3 so, going liberal with the designation could help retain more drivers as those who have a designation of 3 have the least churn rate

3. Incentives can be arranged based on the quarterly rating of a driver as it is the single most important feature determining whether a person is going to leave or stay

4. A greater percentage of commission or bonuses can be given to drivers who are based in cities C13, C17, and C29 as these are the cities having the highest churn rate

5. As expected, those who generate more income stay for a longer time hence, providing more commission or a good revenue sharing model will help retain drivers

In [ ]:

```

```