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.

Objective

we 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.

SO it's Binary Classification problem

DATA

```
!wget "https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/002/492/original/ola_driver_scaler.csv"
```

```
--2024-03-05 03:58:01--  https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/002/492/original/ola_driver_scaler.csv
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)... 18.172.139.61, 18.172.139.94, 18.172.139.46, ...
Connecting to d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)|18.172.139.61|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 1127673 (1.1M) [text/plain]
Saving to: 'ola_driver_scaler.csv'

ola_driver_scaler.c 100%[===================>]   1.08M  --.-KB/s    in 0.07s

2024-03-05 03:58:01 (16.3 MB/s) - 'ola_driver_scaler.csv' saved [1127673/1127673]
```

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

```
df = pd.read_csv("ola_driver_scaler.csv",index_col=0)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 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: 2.0+ MB
```

observation: this seems there are some null values in features

```
df.head()
```

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

```
df.isnull().sum()
```

```
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
```

```
# Considering people having lastworking date as churned and else are not churned.

df["IsChurn"] = np.where(df['LastWorkingDate'].isna(),0,1)
```

```
df.drop(['LastWorkingDate'],axis=1,inplace=True)
```

```
df.isnull().sum()
```

```
MMM-YY                   0
Driver_ID                0
Age                     61
Gender                  52
City                     0
Education_Level          0
Income                   0
Dateofjoining            0
Joining Designation      0
Grade                    0
Total Business Value     0
Quarterly Rating         0
IsChurn                  0
dtype: int64
```

```
df.describe()
```

	Driver_ID	Age	Gender	Education_Level	Income	Joining Designation	Grade	Total Business Value	Quarterly Rating
count	19104.000000	19043.000000	19052.000000	19104.000000	19104.000000	19104.000000	19104.000000	1.910400e+04	19104.000000
mean	1415.591133	34.668435	0.418749	1.021671	65652.025126	1.690536	2.252670	5.716621e+05	2.008899
std	810.705321	6.257912	0.493367	0.800167	30914.515344	0.836984	1.026512	1.128312e+06	1.009832
min	1.000000	21.000000	0.000000	0.000000	10747.000000	1.000000	1.000000	-6.000000e+06	1.000000
25%	710.000000	30.000000	0.000000	0.000000	42383.000000	1.000000	1.000000	0.000000e+00	1.000000
50%	1417.000000	34.000000	0.000000	1.000000	60087.000000	1.000000	2.000000	2.500000e+05	2.000000
75%	2137.000000	39.000000	1.000000	2.000000	83969.000000	2.000000	3.000000	6.997000e+05	3.000000
max	2788.000000	58.000000	1.000000	2.000000	188418.000000	5.000000	5.000000	3.374772e+07	4.000000

Start coding or generate with AI.

EDA

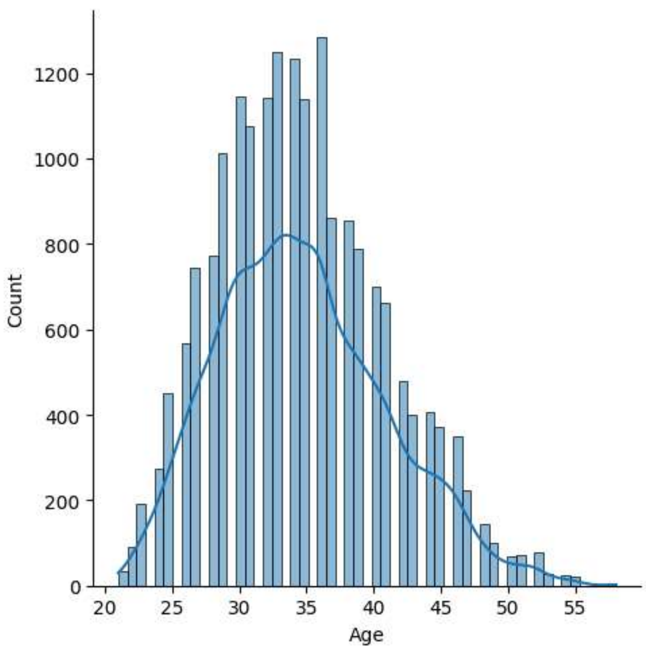
Univariate Analysis

```
df.dtypes
```

```
MMM-YY                   object
Driver_ID                 int64
Age                     float64
Gender                  float64
City                     object
Education_Level           int64
Income                    int64
Dateofjoining            object
Joining Designation       int64
Grade                     int64
Total Business Value      int64
Quarterly Rating          int64
IsChurn                   int64
dtype: object
```

```
sns.displot(df['Age'],kde=True)
```

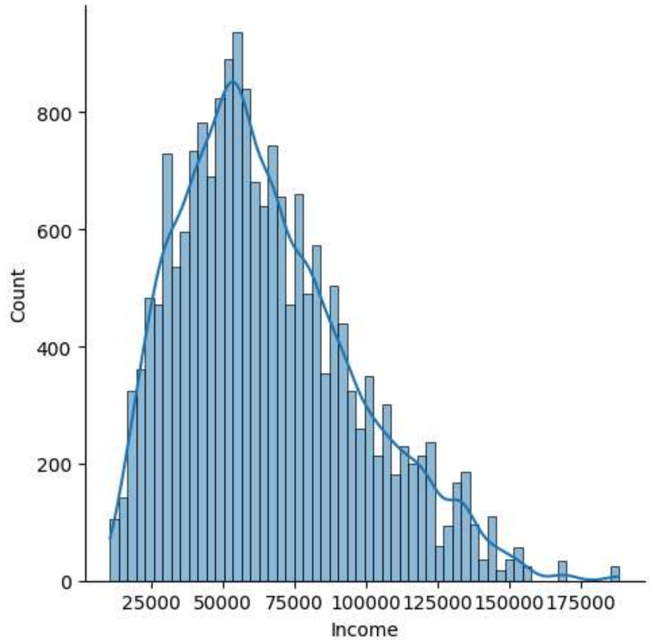
```
<seaborn.axisgrid.FacetGrid at 0x7a0a9ddb40d0>
```



Observation: Looks like Normal Distribution

```
sns.displot(df['Income'],kde=True)
```

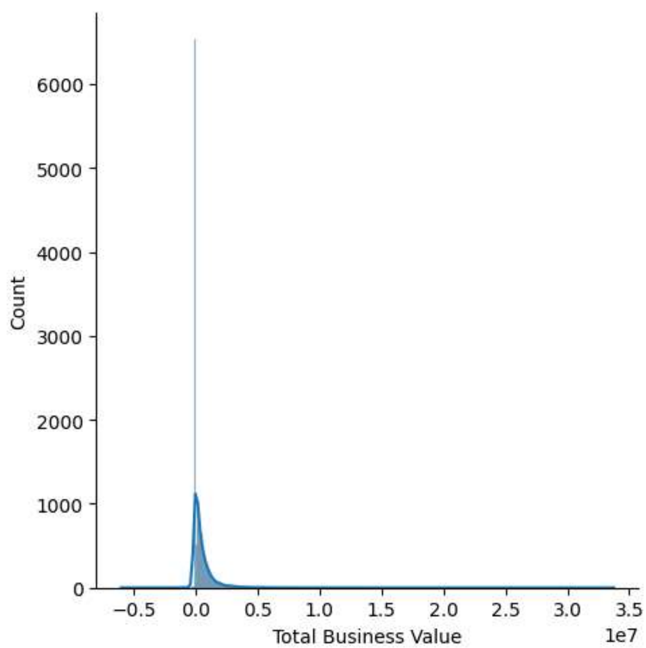
```
<seaborn.axisgrid.FacetGrid at 0x7a0a9f9b69b0>
```



Observation: Looks like right skewed normal Distribution

```
sns.displot(df['Total Business Value'],kde=True)
```

```
<seaborn.axisgrid.FacetGrid at 0x7a0a9def2ad0>
```

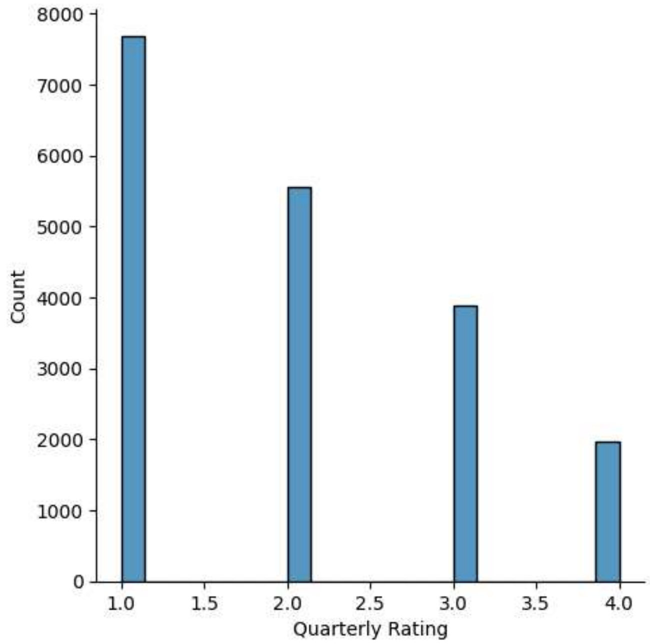


Observation

most of the times Bussiness value is Zero.

```
sns.displot(df['Quarterly Rating'])
```

```
<seaborn.axisgrid.FacetGrid at 0x7a0a9def34f0>
```



observation:

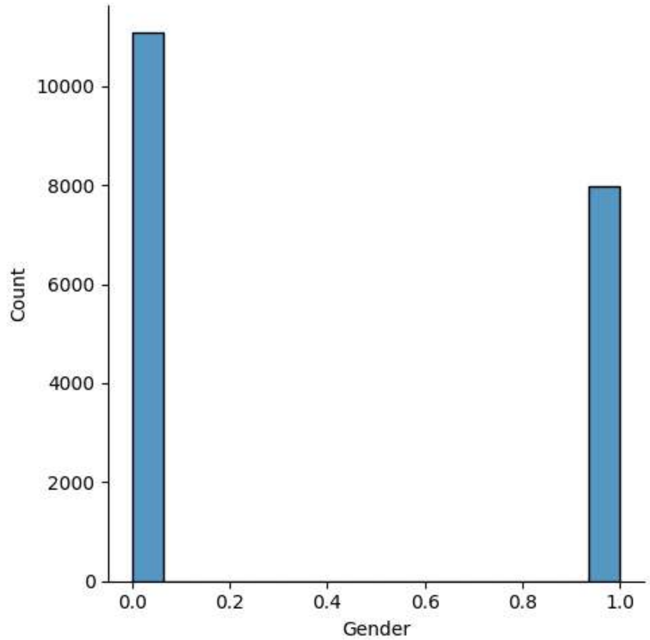
there are more low rated drivers than high rated

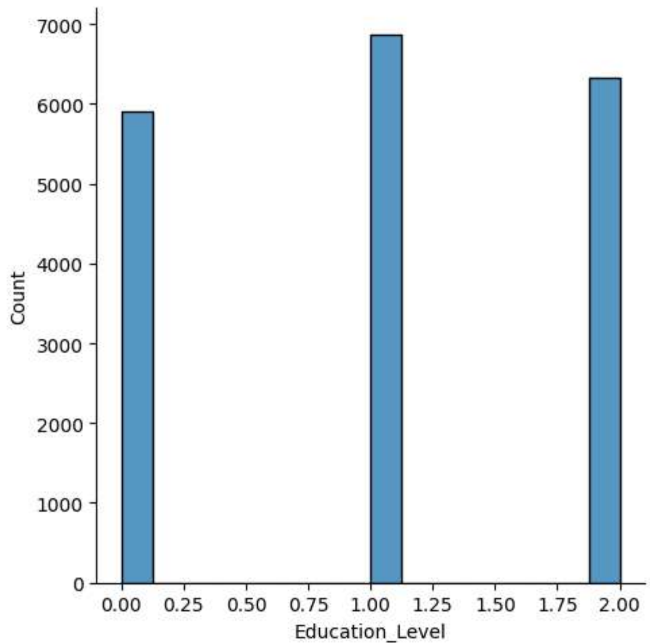
```
df['Education_Level'].value_counts()
```

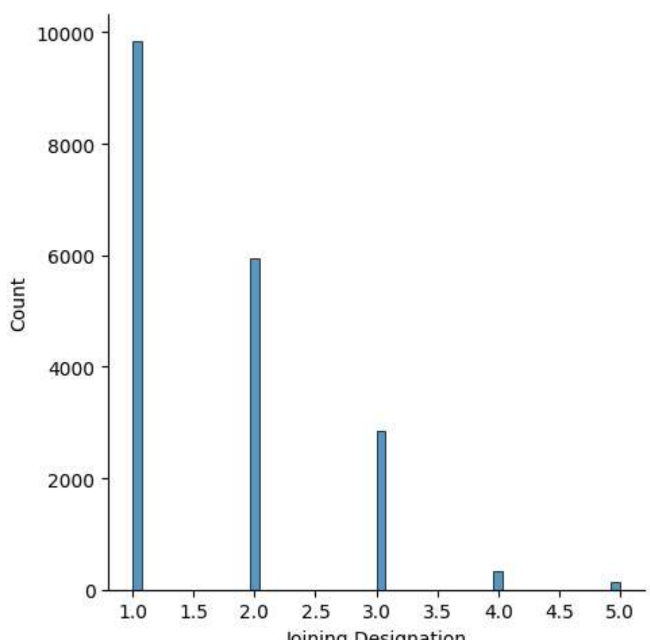
```
1    6864
2    6327
0    5913
Name: Education_Level, dtype: int64
```

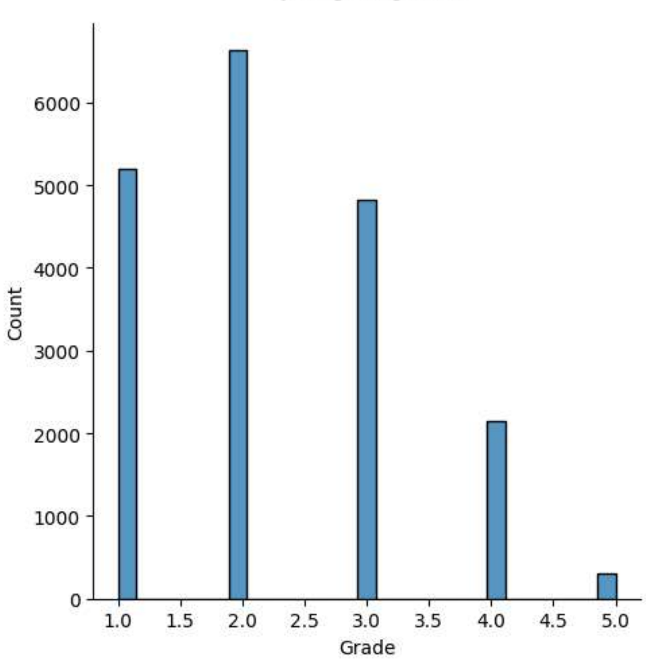
```
names = ['Gender',  'Education_Level'   ,   'Joining Designation'     , 'Grade']

for col in names:
  sns.displot(df[col])
```


Count
10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0
Gender

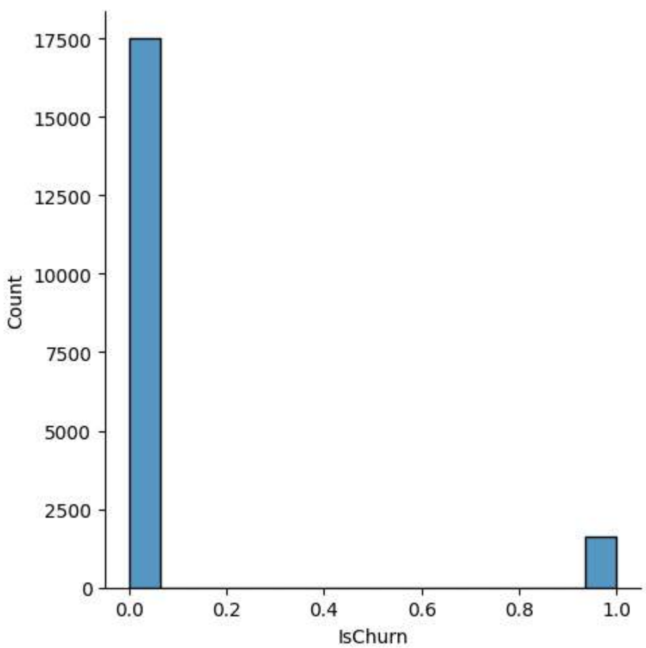

Count
7000
6000
5000
4000
3000
2000
1000
0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Education_Level


Count
10000
8000
6000
4000
2000
0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0




```
sns.displot(df['IsChurn'])
```

```
<seaborn.axisgrid.FacetGrid at 0x7a0a9cb4e560>
```



Observation:

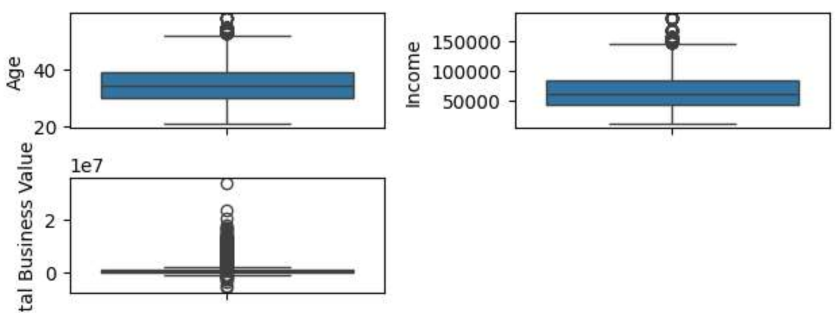
there is High imbalance in classes

```
df.select_dtypes(exclude='object')
```

	Driver_ID	Age	Gender	Education_Level	Income	Joining Designation	Grade	Total Business Value	Q
0	1	28.0	0.0	2	57387	1	1	2381060	
1	1	28.0	0.0	2	57387	1	1	-665480	
2	1	28.0	0.0	2	57387	1	1	0	
3	2	31.0	0.0	2	67016	2	2	0	
4	2	31.0	0.0	2	67016	2	2	0	
...	...	...	...	...	...	...	...	...	
19099	2788	30.0	0.0	2	70254	2	2	740280	
19100	2788	30.0	0.0	2	70254	2	2	448370	
19101	2788	30.0	0.0	2	70254	2	2	0	
19102	2788	30.0	0.0	2	70254	2	2	200420	
19103	2788	30.0	0.0	2	70254	2	2	411480	

Double-click (or enter) to edit

```
for i,col in enumerate(['Age',"Income","Total Business Value"]):
  plt.subplot(4,2,i+1)
  sns.boxplot(df[col])
  plt.tight_layout()
```




```
def calculate_outlier_percentage(data, feature, threshold=1.5):

  feature_data = data[feature]
  # Calculate the first and third quartiles (Q1 and Q3) for the feature
  Q1 = np.percentile(feature_data, 25)
  Q3 = np.percentile(feature_data, 75)
  # Calculate the IQR (Interquartile Range) for the feature
  IQR = Q3 - Q1
  # Define the lower and upper bounds for outlier detection for the feature
  lower_bound = Q1 - threshold * IQR
  upper_bound = Q3 + threshold * IQR
  # Identify outlier indices for the feature
  outlier_indices = np.where((feature_data < lower_bound) | (feature_data > upper_bound))
  # Calculate the percentage of outliers
  outlier_percentage = (len(outlier_indices[0]) / len(feature_data)) * 100
  return outlier_percentage


feature_index = 4 # Index of the feature (column) to analyze
threshold = 1.5

for feature in (['Age',"Income","Total Business Value"]):

    outlier_percentage = calculate_outlier_percentage(df, feature, threshold)
    print(f"Percentage of outliers in feature {feature}: {outlier_percentage:.2f}%")
```

```
Percentage of outliers in feature Age: 0.00%
Percentage of outliers in feature Income: 0.98%
Percentage of outliers in feature Total Business Value: 7.18%
```

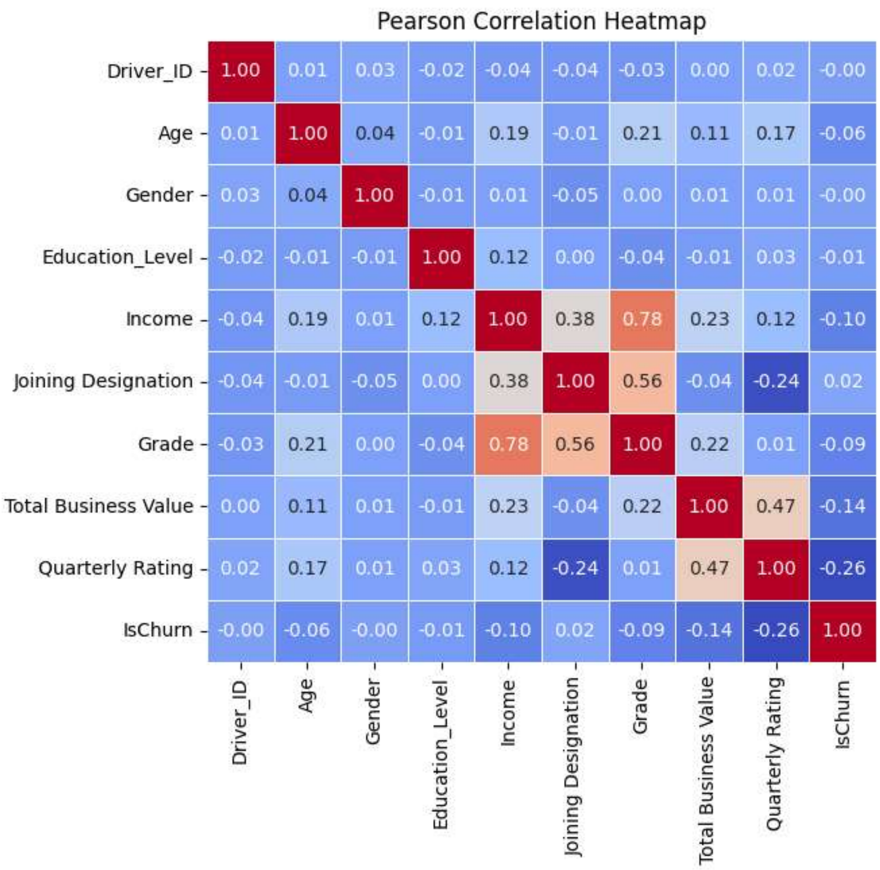
there is outliers which are in Age,Income are ignorable and Total Business value is having 7% of outliers

Bivariate Analysis

```
# Compute Pearson correlation coefficient
pearson_corr = df.corr()

# Create heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(pearson_corr, annot=True, cmap='coolwarm', fmt=".2f", linewidths=.5)
plt.title('Pearson Correlation Heatmap')
plt.show()
```

```
<ipython-input-21-dbb09d01d7b9>:2: FutureWarning: The default value of numeric_only in
  pearson_corr = df.corr()
```



Observation:

Income and Grade highly Correlated

```
df.isnull().sum()
```

```
MMM-YY           0
Driver_ID        0
Age             61
Gender          52
City             0
```

```
Education_Level          0
Income                   0
Dateofjoining            0
Joining Designation      0
Grade                    0
Total Business Value     0
Quarterly Rating         0
IsChurn                  0
dtype: int64
```

Feature Engineering

KNN Imputation

try to fill null values using knn imputation

```
df2 = df.dropna()    #  non null values df
```

```
df3 = df[df.isna().any(axis=1)]  # null values df
```

```
df2 = df2.drop(['MMM-YY',   'City', 'Dateofjoining'],axis=1)
```

```
X = df2.drop("IsChurn",axis=1)
y = df2['IsChurn'].apply(lambda x: 1 if x==1.0 else 0)
```

```
y.value_counts()
```

```
0    17385
1     1606
Name: IsChurn, dtype: int64
```

```
import numpy as np
from sklearn.datasets import load_iris
from sklearn.impute import KNNImputer
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

# Split data into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)

# Define a range of k values to test
k_values = [1, 3, 5, 7, 9]

# Evaluate performance for each k
best_k = None
best_score = float('inf')  # For MSE, lower is better
for k in k_values:
    # Create and fit the KNN imputer
    imputer = KNNImputer(n_neighbors=k)
    X_train_imputed = imputer.fit_transform(X_train)

    # Evaluate the imputer on validation set
    X_val_imputed = imputer.transform(X_val)
    score = mean_squared_error(X_val, X_val_imputed)

    # Update best_k if this 'k' performs better
    if score < best_score:
        best_score = score
        best_k = k

print("Best k:", best_k)
```

```
Best k: 1
```

```
imputer.transform(X_val)
```

```
array([[1.30000e+01, 3.00000e+01, 0.00000e+00, ..., 4.00000e+00,
        1.59359e+06, 1.00000e+00],
       [1.28500e+03, 3.10000e+01, 0.00000e+00, ..., 2.00000e+00,
        2.61940e+05, 2.00000e+00],
       [2.02800e+03, 4.00000e+01, 1.00000e+00, ..., 2.00000e+00,
        1.42930e+06, 4.00000e+00],
       ...,
       [2.58200e+03, 4.50000e+01, 0.00000e+00, ..., 1.00000e+00,
        3.00830e+05, 2.00000e+00],
       [3.12000e+02, 3.40000e+01, 0.00000e+00, ..., 2.00000e+00,
        0.00000e+00, 1.00000e+00],
       [2.40800e+03, 4.20000e+01, 0.00000e+00, ..., 4.00000e+00,
        9.12790e+05, 1.00000e+00]])
```

```
imputed_data = imputer.transform(df3.drop(['City' ,'Dateofjoining','MMM-YY',"IsChurn"],axis=1))
```

```
df2['Gender']
```

```
0        0
1        0
2        0
3        0
4        0
        ..
19099    0
19100    0
19101    0
19102    0
19103    0
Name: Gender, Length: 18991, dtype: int64
```

```
imputer.get_feature_names_out()
```

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

```
column_names = imputer.get_feature_names_out()

# Convert imputed data to DataFrame with column names
imputed_df = pd.DataFrame(imputed_data, columns=column_names)
```

```
imputed_df.head()
```

	Driver_ID	Age	Gender	Education_Level	Income	Joining Designation	Grade	Total Business Value
0	20.0	28.888889	1.000000	0.0	40342.0	3.0	3.0	0.C
1	22.0	34.555556	0.000000	2.0	31224.0	1.0	1.0	200000.C
2	24.0	38.444444	0.000000	2.0	76308.0	1.0	2.0	203240.C
3	40.0	31.111111	0.000000	0.0	59182.0	2.0	2.0	0.C

```
df3 = df3.reset_index()
```

```
df3
```

	index	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoini
0	72	02/01/20	20	NaN	1.0	C19	0	40342	25/10/
1	97	10/01/19	22	NaN	0.0	C10	2	31224	25/05/
2	110	07/01/19	24	NaN	0.0	C24	2	76308	25/05/
3	212	11/01/19	40	NaN	0.0	C15	0	59182	11/08/
4	240	02/01/19	43	27.0	NaN	C15	0	12906	13/07/
...	...	...	...	...	...	...	...	...	
108	18843	01/01/19	2751	NaN	0.0	C17	2	53115	11/05/
109	18928	12/01/19	2760	31.0	NaN	C20	0	51471	10/03/
110	18953	01/01/19	2765	26.0	NaN	C18	1	38809	10/02/
111	19024	02/01/19	2774	NaN	0.0	C15	1	42313	21/07/
112	19028	06/01/19	2774	40.0	NaN	C15	1	42313	21/07/

113 rows × 14 columns

```
threshold = 0.5

nan_indices = df3[df3['Gender'].isna()].index

imputed_values = imputed_df['Gender'][nan_indices]

# Replace NaN values with imputed values based on the condition
df3.loc[nan_indices, 'Gender'] = np.where(imputed_values < threshold, 0, 1)
```

```
# Identify NaN values in  DataFrame
nan_indices = df3[df3['Age'].isna()].index

imputed_values = imputed_df['Age'][nan_indices]

# Replace NaN values with imputed values based on the condition
df3.loc[nan_indices, 'Age'] = np.round(imputed_values,1)
```

```
df3 = df3.drop('index',axis=1)
```

```
merged_df = pd.concat([df.dropna(),df3],axis=0)  # merging df of imputed df and non nan df
```

```
merged_df
```

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	Des
0	01/01/19	1	28.0	0.0	C23	2	57387	24/12/18	
1	02/01/19	1	28.0	0.0	C23	2	57387	24/12/18	
2	03/01/19	1	28.0	0.0	C23	2	57387	24/12/18	
3	11/01/20	2	31.0	0.0	C7	2	67016	11/06/20	
4	12/01/20	2	31.0	0.0	C7	2	67016	11/06/20	
...	...	...	...	...	...	...	...	...	
108	01/01/19	2751	36.1	0.0	C17	2	53115	11/05/15	
109	12/01/19	2760	31.0	1.0	C20	0	51471	10/03/19	
110	01/01/19	2765	26.0	1.0	C18	1	38809	10/02/18	
111	02/01/19	2774	36.7	0.0	C15	1	42313	21/07/18	
112	06/01/19	2774	40.0	0.0	C15	1	42313	21/07/18	

19104 rows × 13 columns

```
merged_df['year']  = pd.to_datetime(merged_df['MMM-YY']).dt.year
merged_df['month'] = pd.to_datetime(merged_df['MMM-YY']).dt.month
merged_df['day']   = pd.to_datetime(merged_df['MMM-YY']).dt.day


merged_df['joining_year']  = pd.to_datetime(merged_df['Dateofjoining']).dt.year
merged_df['joining_month'] = pd.to_datetime(merged_df['Dateofjoining']).dt.month
merged_df['joing_day']     = pd.to_datetime(merged_df['Dateofjoining']).dt.day


reference_date = pd.to_datetime('1990-01-01')
# convertin these  object types to float values to fit models
# Calculate time difference
merged_df['MMM-YY'] = (pd.to_datetime(df['MMM-YY']) - reference_date).dt.days
merged_df['Dateofjoining'] = (pd.to_datetime(df['Dateofjoining']) - reference_date).dt.days


final_df = pd.get_dummies(merged_df,columns=['City'])


final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19104 entries, 0 to 112
Data columns (total 47 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   MMM-YY                19104 non-null  int64
 1   Driver_ID             19104 non-null  int64
 2   Age                   19104 non-null  float64
 3   Gender                19104 non-null  float64
 4   Education_Level       19104 non-null  int64
 5   Income                19104 non-null  int64
 6   Dateofjoining         19104 non-null  int64
 7   Joining Designation   19104 non-null  int64
 8   Grade                 19104 non-null  int64
 9   Total Business Value  19104 non-null  int64
 10  Quarterly Rating      19104 non-null  int64
 11  IsChurn               19104 non-null  int64
 12  year                  19104 non-null  int64
 13  month                 19104 non-null  int64
 14  day                   19104 non-null  int64
 15  joining_year          19104 non-null  int64
 16  joining_month         19104 non-null  int64
 17  joing_day             19104 non-null  int64
 18  City_C1               19104 non-null  uint8
 19  City_C10              19104 non-null  uint8
 20  City_C11              19104 non-null  uint8
 21  City_C12              19104 non-null  uint8
 22  City_C13              19104 non-null  uint8
 23  City_C14              19104 non-null  uint8
 24  City_C15              19104 non-null  uint8
 25  City_C16              19104 non-null  uint8
 26  City_C17              19104 non-null  uint8
 27  City_C18              19104 non-null  uint8
```

```
 28  City_C19             19104 non-null  uint8
 29  City_C2              19104 non-null  uint8
 30  City_C20             19104 non-null  uint8
 31  City_C21             19104 non-null  uint8
 32  City_C22             19104 non-null  uint8
 33  City_C23             19104 non-null  uint8
 34  City_C24             19104 non-null  uint8
 35  City_C25             19104 non-null  uint8
 36  City_C26             19104 non-null  uint8
 37  City_C27             19104 non-null  uint8
 38  City_C28             19104 non-null  uint8
 39  City_C29             19104 non-null  uint8
 40  City_C3              19104 non-null  uint8
 41  City_C4              19104 non-null  uint8
 42  City_C5              19104 non-null  uint8
 43  City_C6              19104 non-null  uint8
 44  City_C7              19104 non-null  uint8
 45  City_C8              19104 non-null  uint8
 46  City_C9              19104 non-null  uint8
dtypes: float64(2), int64(16), uint8(29)
memory usage: 3.3 MB
```

Modeling

```
X = final_df.drop(["IsChurn"],axis=1)
y = final_df['IsChurn']
```

```
# Split data into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Class imbalance handled here usign model instead of upsmapling and downsampling

# Calculate class weights
from sklearn.utils.class_weight import compute_class_weight

# Calculate class weights
class_weights = compute_class_weight(class_weight="balanced", classes=np.unique(y_train), y=y_train)
```

RandomForest

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV,RandomizedSearchCV
```

```
# Define the parameter grid
param_grid_rf = {
    'n_estimators': np.arange(50,200,50),
    'max_depth': np.arange(5,20,5),
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Initialize the Random Forest Classifier
rf_classifier = RandomForestClassifier(class_weight={0: class_weights[0], 1: class_weights[1]},random_state=42)

# Initialize GridSearchCV
grid_search_rf = RandomizedSearchCV(rf_classifier, param_grid_rf, cv=5, scoring='roc_auc')

# Fit the grid search to the data
grid_search_rf.fit(X_train, y_train)

# Get the best parameters
best_params_rf = grid_search_rf.best_params_
print("Best Parameters for Random Forest:", best_params_rf)

# Train the model with best parameters
best_rf_classifier = RandomForestClassifier(**best_params_rf, random_state=42)
best_rf_classifier.fit(X_train, y_train)
```

```
Best Parameters for Random Forest: {'n_estimators': 50, 'min_samples_split': 10, 'min_s
RandomForestClassifier
RandomForestClassifier(max_depth=15, min_samples_leaf=4, min_samples_split=10,
                       n_estimators=50, random_state=42)
```

```
class_weights
```

```
array([0.54726778, 5.78901515])
```

XGBoost

```
from xgboost import XGBClassifier

# Define the parameter grid
param_grid_xgb = {
    'learning_rate': [0.01, 0.1, 0.2],
    'n_estimators': [50, 100, 200],
    'max_depth': [3, 5, 7],
    'min_child_weight': [1, 3, 5],
    'gamma': [0, 0.1, 0.2],
    'subsample': [0.6, 0.8, 1.0],
    'colsample_bytree': [0.6, 0.8, 1.0],
    'reg_alpha': [0, 0.1, 0.5],
    'reg_lambda': [1, 2, 5]
}

ratio = (y_train.value_counts()[0]) / (y_train.value_counts()[1])
# Initialize the XGBoost Classifier
xgb_classifier = XGBClassifier(scale_pos_weight=ratio,random_state=42)

# Initialize GridSearchCV
grid_search_xgb = RandomizedSearchCV(xgb_classifier, param_grid_xgb, cv=5, scoring='roc_auc')

# Fit the grid search to the data
grid_search_xgb.fit(X_train, y_train)

# Get the best parameters
best_params_xgb = grid_search_xgb.best_params_
print("Best Parameters for XGBoost:", best_params_xgb)

# Train the model with best parameters
best_xgb_classifier = XGBClassifier(**best_params_xgb, random_state=42)
best_xgb_classifier.fit(X_train, y_train)
```

```
Best Parameters for XGBoost: {'subsample': 1.0, 'reg_lambda': 1, 'reg_alpha': 0, 'n_est
XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=1.0, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=0.2, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.2, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=3, max_leaves=None,
              min_child_weight=1, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=100, n_jobs=None,
              num_parallel_tree=None, random_state=42, ...)
```

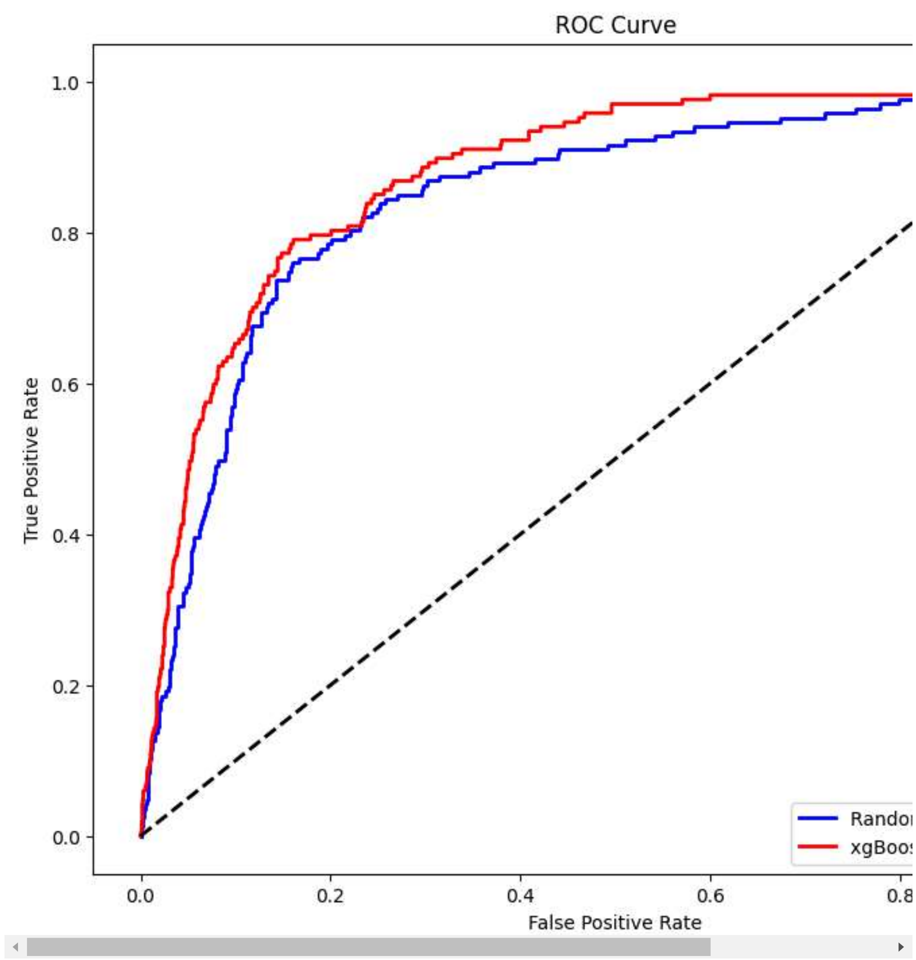
```
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

# Predict probabilities for each classifier
rf_probs = best_rf_classifier.predict_proba(X_test)[:, 1]
xgboost_probs = best_xgb_classifier.predict_proba(X_test)[:, 1]

# Compute ROC curve and ROC area for each classifier
rf_fpr, rf_tpr, _ = roc_curve(y_test, rf_probs)
xgboost_fpr, xgboost_tpr, _ = roc_curve(y_test, xgboost_probs)

# Compute AUC for each classifier
rf_auc = auc(rf_fpr, rf_tpr)
xgboost_auc = auc(xgboost_fpr, xgboost_tpr)

# Plot ROC curve for each classifier
plt.figure(figsize=(10, 8))
plt.plot(rf_fpr, rf_tpr, color='blue', lw=2, label=f'Random Forest (AUC = {rf_auc:.2f})')
plt.plot(xgboost_fpr, xgboost_tpr, color='red', lw=2, label=f'xgBoost (AUC = {xgboost_auc:.2f})')
plt.plot([0, 1], [0, 1], color='black', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



Observation:

seems Xgboost performing slightly better than Randomforest

```
from sklearn.metrics import classification_report, confusion_matrix

# Predictions
rf_predictions = best_rf_classifier.predict(X_test)
xgboost_predictions = best_xgb_classifier.predict(X_test)

# Confusion matrix
rf_conf_matrix = confusion_matrix(y_test, rf_predictions)
xgboost_conf_matrix = confusion_matrix(y_test, xgboost_predictions)
```