Business Case: OLA - Ensemble Learning

Column Profiling:

1. MMMM-YY : Reporting Date (Monthly)
2. Driver_ID : Unique id for drivers
3. Age : Age of the driver
4. Gender : Gender of the driver – Male : 0, Female: 1
5. City : City Code of the driver
6. Education_Level : Education level – 0 for 10+ ,1 for 12+ ,2 for graduate
7. Income : Monthly average Income of the driver
8. Date Of Joining : Joining date for the driver
9. LastWorkingDate : Last date of working for the driver
10. Joining Designation : Designation of the driver at the time of joining
11. Grade : Grade of the driver at the time of reporting
12. Total Business Value : The total business value acquired by the driver in a month (negative business indicates cancellation/refund or car EMI adjustments)
13. Quarterly Rating : Quarterly rating of the driver: 1,2,3,4,5 (higher is better)

Problem Statement:

- Recruiting and retaining drivers is seen by industry watchers as a tough battle for Ola.
- Churn among drivers is high and it’s very easy for drivers to stop working for the service on the fly or jump to Uber depending on the rates.
- As the companies get bigger, the high churn could become a bigger problem. To find new drivers, Ola is casting a wide net, including people who don’t have cars for jobs. But this acquisition is really costly.
- Losing drivers frequently impacts the morale of the organization and acquiring new drivers is more expensive than retaining existing ones.
- You are working as a data scientist with the Analytics Department of Ola, focused on driver team attrition.
- You are provided with the monthly information for a segment of drivers for 2019 and 2020 and tasked to predict whether a driver will be leaving the company or not based on their attributes like
- Demographics (city, age, gender etc.)
- Tenure information (joining date, Last Date)
- Historical data regarding the performance of the driver (Quarterly rating, Monthly business acquired, grade, Income)

Analysing basic metrics

In [1]:
```
#importing different libaries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
from scipy import stats
import regex
import warnings
warnings.filterwarnings("ignore")
import statsmodels.api as sm
```

In [2]:
```
#Loading of dataset
df = pd.read_csv("../scaler/ola_driver_scaler.csv")
df.head()
```

Out[2]:

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

In [3]:
```
print('No. of Rows in the dataset: ',df.shape[0])
print('No. of Columns in the dataset: ',df.shape[1])
```

```
No. of Rows in the dataset:  19104
No. of Columns in the dataset:  14
```

In [4]:
```
df.info() #to observe the data type
```

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

Check for Duplicate Values

In [5]:
```
df.duplicated().sum()
```

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

- There are no duplicate instances in the data

In [6]:
```
# Check Missing Values
df.isna().sum()
```

Out[6]:
```
Unnamed: 0                  0
MMM-YY                      0
Driver_ID                   0
Age                        61
Gender                     52
City                        0
Education_Level             0
Income                      0
Dateofjoining               0
LastWorkingDate         17488
Joining Designation         0
Grade                       0
Total Business Value        0
Quarterly Rating            0
dtype: int64
```

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

Out[7]:

	Unnamed: 0	Driver_ID	Age	Gender	Education_Level	
count	19104.000000	19104.000000	19043.000000	19052.000000	19104.000000	19104
mean	9551.500000	1415.591133	34.668435	0.418749	1.021671	65652
std	5514.994107	810.705321	6.257912	0.493367	0.800167	30914
min	0.000000	1.000000	21.000000	0.000000	0.000000	10747
25%	4775.750000	710.000000	30.000000	0.000000	0.000000	42383
50%	9551.500000	1417.000000	34.000000	0.000000	1.000000	60087
75%	14327.250000	2137.000000	39.000000	1.000000	2.000000	83969
max	19103.000000	2788.000000	58.000000	1.000000	2.000000	188418

In [8]:

```
df.describe(include='object')
```

Out[8]:

	MMM-YY	City	Dateofjoining	LastWorkingDate
count	19104	19104	19104	1616
unique	24	29	869	493
top	01/01/19	C20	23/07/15	29/07/20
freq	1022	1008	192	70

Non-Graphical Analysis

In [9]:

```
# since  unnamed and driver_id columns have the highest correlation and they are
# here, dropping unnamed column
df.drop(columns='Unnamed: 0',axis=1,inplace=True)
```

In [10]:

```
# unique value Gender column(listed in %)
Gender = df['Gender'].value_counts(normalize=True).map(lambda calc: round(100*ca
Gender.columns = ['Gender', 'Count']
Gender
```

Out[10]:

	Gender	Count
0	0.0	58.13
1	1.0	41.87

In [11]:

```
# unique value City column(listed in %)
City = df['City'].value_counts(normalize=True).map(lambda calc: round(100*calc,2
City.columns = ['City', 'Count']
City
```

Out[11]:

	City	Count
0	C20	5.28
1	C29	4.71
2	C26	4.55
3	C22	4.23
4	C27	4.11
5	C15	3.98
6	C10	3.89
7	C12	3.81
8	C8	3.73
9	C16	3.71
10	C28	3.58
11	C1	3.54
12	C6	3.45
13	C5	3.43
14	C14	3.39
15	C3	3.33
16	C24	3.21
17	C7	3.19
18	C21	3.16
19	C25	3.06
20	C19	3.03
21	C4	3.03
22	C13	2.98
23	C18	2.85
24	C23	2.82
25	C9	2.72
26	C2	2.47
27	C11	2.45
28	C17	2.30

In [12]:

```
# unique value Education_Level column(listed in %)
Education_Level = df['Education_Level'].value_counts(normalize=True).map(lambda
Education_Level.columns = ['Education_Level', 'Count']
Education_Level
```

Out[12]:

	Education_Level	Count
0	1	35.93
1	2	33.12
2	0	30.95

In [13]:

```
# unique value Joining Designation column(listed in %)
JoiningDesignation = df['Joining Designation'].value_counts(normalize=True).map(
JoiningDesignation.columns = ['Joining Designation', 'Count']
JoiningDesignation
```

Out[13]:

	Joining Designation	Count
0	1	51.46
1	2	31.17
2	3	14.90
3	4	1.78
4	5	0.68

In [14]:

```
# unique value Grade column(listed in %)
Grade = df['Grade'].value_counts(normalize=True).map(lambda calc: round(100*calc
Grade.columns = ['Grade', 'Count']
Grade
```

Out[14]:

	Grade	Count
0	2	34.69
1	1	27.23
2	3	25.26
3	4	11.22
4	5	1.60

In [15]:

```
# unique value Quarterly Rating column(listed in %)
QuarterlyRating = df['Quarterly Rating'].value_counts(normalize=True).map(lambda
QuarterlyRating.columns = ['Quarterly Rating', 'Count']
QuarterlyRating
```

Out[15]:

	Quarterly Rating	Count
0	1	40.20
1	2	29.07
2	3	20.39
3	4	10.35

In [16]:

```
# Number of unique values in all columns
unique_num = ['MMM-YY','Driver_ID','Age','Gender','City','Education_Level','Inco
```

```
for col in unique_num:
  print(f"No. of unique values in {col}: {df[col].nunique()}")
```

```
No. of unique values in MMM-YY: 24
No. of unique values in Driver_ID: 2381
No. of unique values in Age: 36
No. of unique values in Gender: 2
No. of unique values in City: 29
No. of unique values in Education_Level: 3
No. of unique values in Income: 2383
No. of unique values in Dateofjoining: 869
No. of unique values in LastWorkingDate: 493
No. of unique values in Joining Designation: 5
No. of unique values in Grade: 5
No. of unique values in Total Business Value: 10181
No. of unique values in Quarterly Rating: 4
```

In [17]:
```
df.describe().loc[['min', 'max']]
```

Out[17]:

	Driver_ID	Age	Gender	Education_Level	Income	Joining Designation	Grade	Tot Busine Valu
min	1.0	21.0	0.0	0.0	10747.0	1.0	1.0	-6000000
max	2788.0	58.0	1.0	2.0	188418.0	5.0	5.0	33747720

Data Pre-Processing and Feature Engineering

In [18]:
```
# Target variable creation: Create a column called target which tells whether th
# driver whose last working day is present will have the value 1
first = (df.groupby('Driver_ID').agg({'LastWorkingDate':'last'})['LastWorkingDat
first['LastWorkingDate'].replace({True:1,False:0},inplace=True)
first.rename(columns={'LastWorkingDate':'target'},inplace=True)
first.head()
```

Out[18]:

	Driver_ID	target
0	1	0
1	2	1
2	4	0
3	5	0
4	6	1

In [19]:
```
# Create a column which tells whether the quarterly rating has increased for tha
# for those whose quarterly rating has increased we assign the value 1
QR1 =  (df.groupby('Driver_ID').agg({'Quarterly Rating':'first'})['Quarterly Rat
QR2 = (df.groupby('Driver_ID').agg({'Quarterly Rating':'last'})['Quarterly Ratin
```

In [20]:
```
QR1.shape,QR2.shape
```

Out[20]: ((2381, 2), (2381, 2))

In [21]:
```
QR1.isna().sum()
```

Out[21]:
```
Driver_ID            0
Quarterly Rating     0
dtype: int64
```

In [22]:
```
QR2.isna().sum()
```

Out[22]:
```
Driver_ID            0
Quarterly Rating     0
dtype: int64
```

In [23]:
```
first = first.merge(QR1,on='Driver_ID')
first = first.merge(QR2,on='Driver_ID')
```

In [24]:
```
first.head()
```

Out[24]:

	Driver_ID	target	Quarterly Rating_x	Quarterly Rating_y
0	1	0	2	2
1	2	1	1	1
2	4	0	1	1
3	5	0	1	1
4	6	1	1	2

In [25]:
```
first['Promotion'] = np.where(first['Quarterly Rating_x'] == first['Quarterly Ra
```

In [26]:
```
first
```

Out[26]:

	Driver_ID	target	Quarterly Rating_x	Quarterly Rating_y	Promotion
0	1	0	2	2	0
1	2	1	1	1	0
2	4	0	1	1	0
3	5	0	1	1	0
4	6	1	1	2	1
...	...	...	...	...	...
2376	2784	1	3	4	1
2377	2785	0	1	1	0
2378	2786	0	2	1	1
2379	2787	0	2	1	1
2380	2788	1	1	2	1

2381 rows × 5 columns

In [27]:
```
# Create a column which tells whether the monthly income has increased for that
# for those whose monthly income has increased we assign the value 1
incm1 =  (df.groupby('Driver_ID').agg({'Income':'first'})['Income']).reset_index
incm2 = (df.groupby('Driver_ID').agg({'Income':'last'})['Income']).reset_index()
```

In [28]:
```
incm1.shape,incm2.shape
```

Out[28]:
```
((2381, 2), (2381, 2))
```

In [29]:
```
incm1.isna().sum()
```

Out[29]:
```
Driver_ID    0
Income       0
dtype: int64
```

In [30]:
```
incm2.isna().sum()
```

Out[30]:
```
Driver_ID    0
Income       0
dtype: int64
```

In [31]:
```
first = first.merge(incm1,on='Driver_ID')
first = first.merge(incm2,on='Driver_ID')
```

In [32]:
```
first.head()
```

Out[32]:

	Driver_ID	target	Quarterly Rating_x	Quarterly Rating_y	Promotion	Income_x	Income_y
0	1	0	2	2	0	57387	57387
1	2	1	1	1	0	67016	67016
2	4	0	1	1	0	65603	65603
3	5	0	1	1	0	46368	46368
4	6	1	1	2	1	78728	78728

In [33]:
```
first['Raise'] = np.where(first['Income_x'] == first['Income_y'], 0,1)
```

In [34]:
```
first
```

Out[34]:

	Driver_ID	target	Quarterly Rating_x	Quarterly Rating_y	Promotion	Income_x	Income_y	Raise
0	1	0	2	2	0	57387	57387	0
1	2	1	1	1	0	67016	67016	0
2	4	0	1	1	0	65603	65603	0
3	5	0	1	1	0	46368	46368	0
4	6	1	1	2	1	78728	78728	0
...	...	...	...	...	...	...	...	...
2376	2784	1	3	4	1	82815	82815	0
2377	2785	0	1	1	0	12105	12105	0
2378	2786	0	2	1	1	35370	35370	0
2379	2787	0	2	1	1	69498	69498	0
2380	2788	1	1	2	1	70254	70254	0

2381 rows × 8 columns

In [35]:
```
first = first[['Driver_ID','target','Raise','Promotion']]
```

In [36]:
```
first.head()
```

Out[36]:

	Driver_ID	target	Raise	Promotion
0	1	0	0	0
1	2	1	0	0
2	4	0	0	0
3	5	0	0	0
4	6	1	0	1

In [37]:
```
functions = {'MMM-YY':'count',
             'Driver_ID':'first',
             'Age':'max',
             'Gender':'last',
            'City':'last',
             'Education_Level':'last',
             'Dateofjoining':'first',
            'LastWorkingDate':'last',
             'Grade':'last',
             'Total Business Value':'sum',
            'Income':'sum',
             'Dateofjoining':'first',
             'LastWorkingDate':'last',
            'Joining Designation':'last',
             'Grade':'last',
             'Quarterly Rating':'first'}
```

```
df = df.groupby([df[f'Driver_ID']]).aggregate(functions)
df['month'] = pd.to_datetime(df['Dateofjoining']).dt.month
df['year'] = pd.DatetimeIndex(df['Dateofjoining']).year
df.rename(columns={'MMM-YY':'Reportings'},inplace=True)
```

In [38]:

```
df.reset_index(drop=True, inplace=True)
df = df.merge(first,on='Driver_ID')
df.head()
```

Out[38]:

	Reportings	Driver_ID	Age	Gender	City	Education_Level	Dateofjoining	LastWorki
0	3	1	28.0	0.0	C23	2	24/12/18	0
1	2	2	31.0	0.0	C7	2	11/06/20	
2	5	4	43.0	0.0	C13	2	12/07/19	2
3	3	5	29.0	0.0	C9	0	01/09/19	0
4	5	6	31.0	1.0	C11	1	31/07/20	

In [39]:

```
df['Age'] = df['Age'].astype('int64')
df['Cities'] =df['City'].astype('str').str.extractall('(\d+)').unstack().fillna(
```

In [40]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2381 entries, 0 to 2380
Data columns (total 19 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Reportings            2381 non-null   int64  
 1   Driver_ID             2381 non-null   int64  
 2   Age                   2381 non-null   int64  
 3   Gender                2381 non-null   float64
 4   City                  2381 non-null   object 
 5   Education_Level       2381 non-null   int64  
 6   Dateofjoining         2381 non-null   object 
 7   LastWorkingDate       1616 non-null   object 
 8   Grade                 2381 non-null   int64  
 9   Total Business Value  2381 non-null   int64  
 10  Income                2381 non-null   int64  
 11  Joining Designation   2381 non-null   int64  
 12  Quarterly Rating      2381 non-null   int64  
 13  month                 2381 non-null   int64  
 14  year                  2381 non-null   int64  
 15  target                2381 non-null   int64  
 16  Raise                 2381 non-null   int32  
 17  Promotion             2381 non-null   int32  
 18  Cities                2381 non-null   int32  
dtypes: float64(1), int32(3), int64(12), object(3)
memory usage: 344.1+ KB
```

In [41]:

```
df.drop(columns=['Dateofjoining','LastWorkingDate','City'],axis=1,inplace=True)
df['Gender'].replace({'M':0,'F':1},inplace=True)
df['Gender'] = df['Gender'].astype('int64')
```

In [42]:
```
df.head()
```

Out[42]:

	Reportings	Driver_ID	Age	Gender	Education_Level	Grade	Total Business Value	Income	Des
0	3	1	28	0	2	1	1715580	172161	
1	2	2	31	0	2	2	0	134032	
2	5	4	43	0	2	2	350000	328015	
3	3	5	29	0	0	1	120360	139104	
4	5	6	31	1	1	3	1265000	393640	

In [43]:
```
df.isna().sum()
```

Out[43]:
```
Reportings            0
Driver_ID             0
Age                   0
Gender                0
Education_Level       0
Grade                 0
Total Business Value  0
Income                0
Joining Designation   0
Quarterly Rating      0
month                 0
year                  0
target                0
Raise                 0
Promotion             0
Cities                0
dtype: int64
```

In [44]:
```
df.describe().T
```

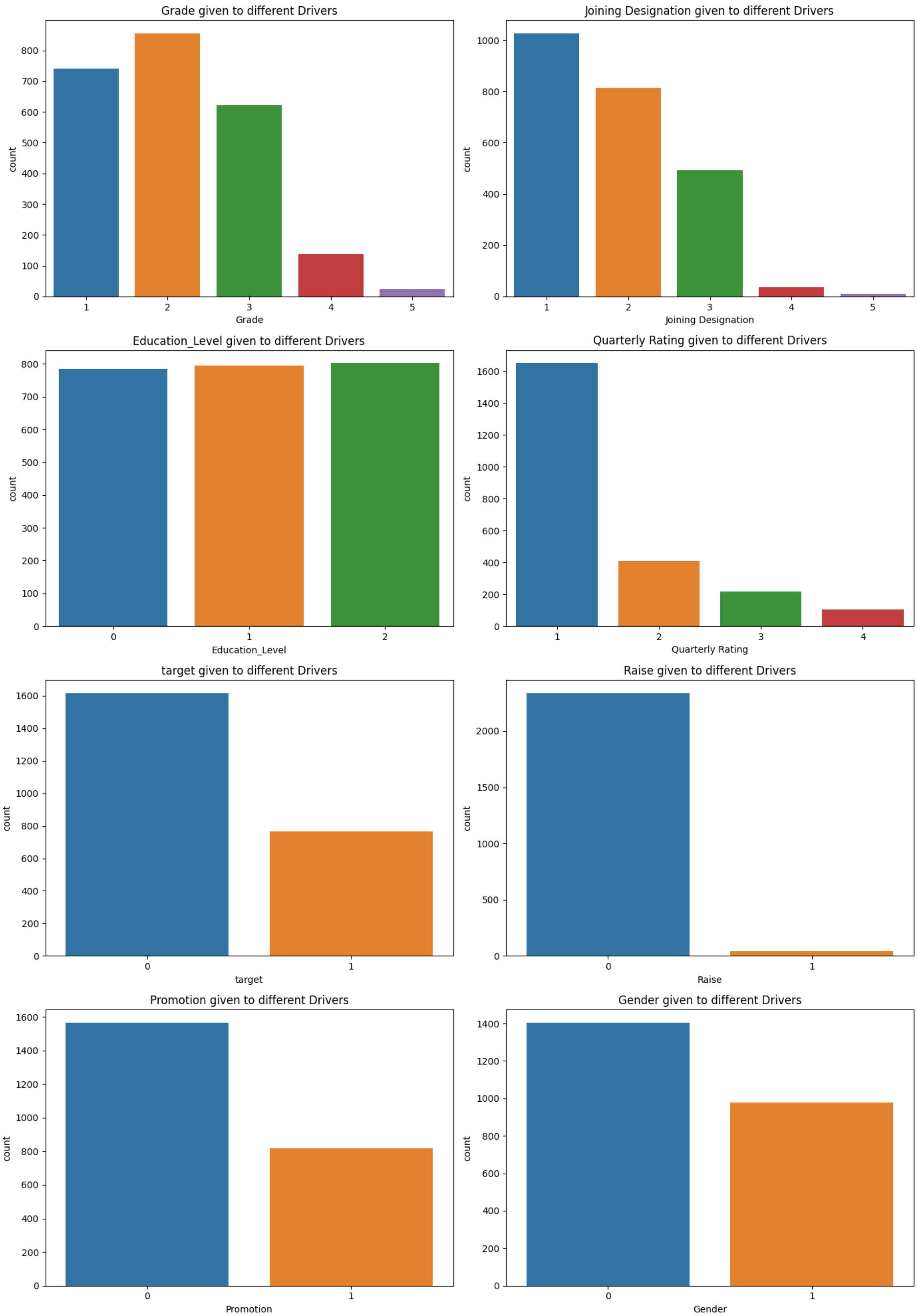
Out[44]:

	count	mean	std	min	25%	50%	
Reportings	2381.0	8.023520e+00	6.783590e+00	1.0	3.0	5.0	
Driver_ID	2381.0	1.397559e+03	8.061616e+02	1.0	695.0	1400.0	
Age	2381.0	3.366317e+01	5.983375e+00	21.0	29.0	33.0	
Gender	2381.0	4.103318e-01	4.919972e-01	0.0	0.0	0.0	
Education_Level	2381.0	1.007560e+00	8.162900e-01	0.0	0.0	1.0	
Grade	2381.0	2.096598e+00	9.415218e-01	1.0	1.0	2.0	
Total Business Value	2381.0	4.586742e+06	9.127115e+06	-1385530.0	0.0	817680.0	41
Income	2381.0	5.267603e+05	6.231633e+05	10883.0	139895.0	292980.0	6
Joining Designation	2381.0	1.820244e+00	8.414334e-01	1.0	1.0	2.0	
Quarterly Rating	2381.0	1.486350e+00	8.343483e-01	1.0	1.0	1.0	
month	2381.0	7.357413e+00	3.143143e+00	1.0	5.0	7.0	
year	2381.0	2.018536e+03	1.609597e+00	2013.0	2018.0	2019.0	
target	2381.0	3.212936e-01	4.670713e-01	0.0	0.0	0.0	
Raise	2381.0	1.805964e-02	1.331951e-01	0.0	0.0	0.0	
Promotion	2381.0	3.427131e-01	4.747162e-01	0.0	0.0	0.0	
Cities	2381.0	1.533557e+01	8.371843e+00	1.0	8.0	15.0	

Univariate Analysis

In [45]:

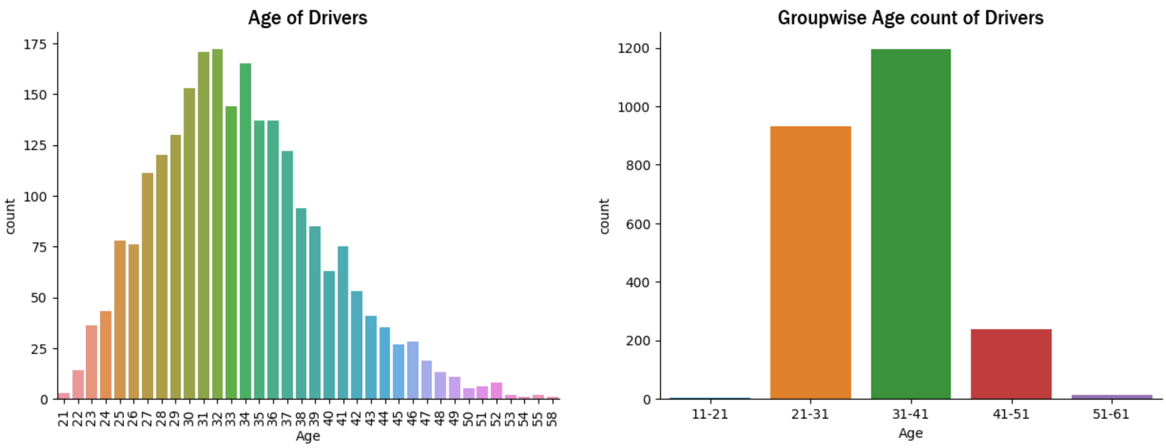
```
plot = ['Grade','Joining Designation', 'Education_Level' , 'Quarterly Rating', '

plt.figure(figsize=(14,20))
i=1
for col in plot:
  ax=plt.subplot(4,2,i)
  sns.countplot(x=df[col])
  plt.title(f'{col} given to different Drivers')
  i += 1

plt.tight_layout()
plt.show()
```



Conclusion:

- Male drivers constitute 58.9% of the total driver population.
- There are three education levels among drivers, all of which have nearly equal distributions within the driver community.
- The most frequent grade attained by drivers is Grade 2, with a declining count as the grade level increases.

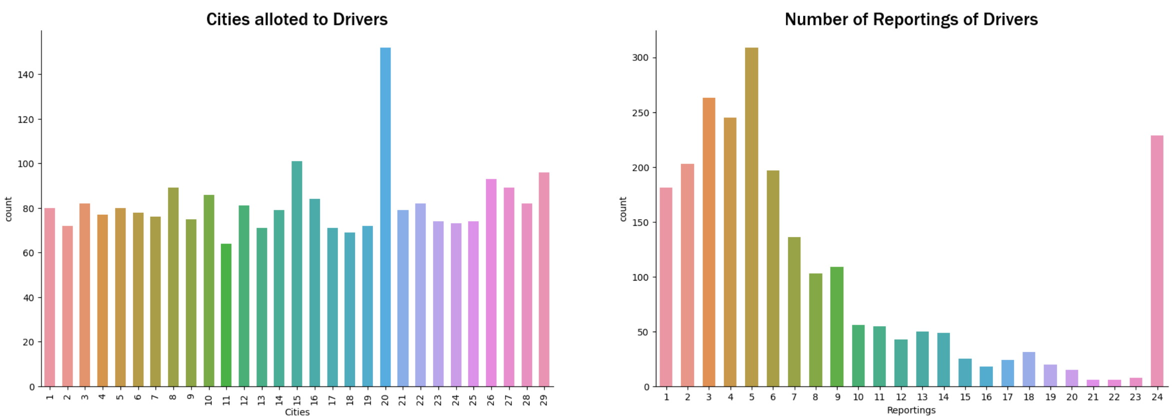
```
In [46]: fig = plt.figure(figsize=(15,5))
ax = fig.add_subplot(121)
sns.countplot(x=df.Age,width=0.8)
plt.title('Age of Drivers',fontname='Franklin Gothic Medium', fontsize=15)
plt.xticks(rotation=90)

ax = fig.add_subplot(122)
a = pd.cut(df.Age,bins=[11,21,31,41,51,61],labels=['11-21','21-31','31-41','41-5
sns.countplot(x=a)
plt.title('Groupwise Age count of Drivers',fontname='Franklin Gothic Medium', fc
sns.despine()
plt.show()
```



Conclusion:

- The majority of drivers fall between 21 and 58 years old, with 32 years being the most common age. Specifically, the peak number of drivers occurs within the age range of 31 to 41 years.

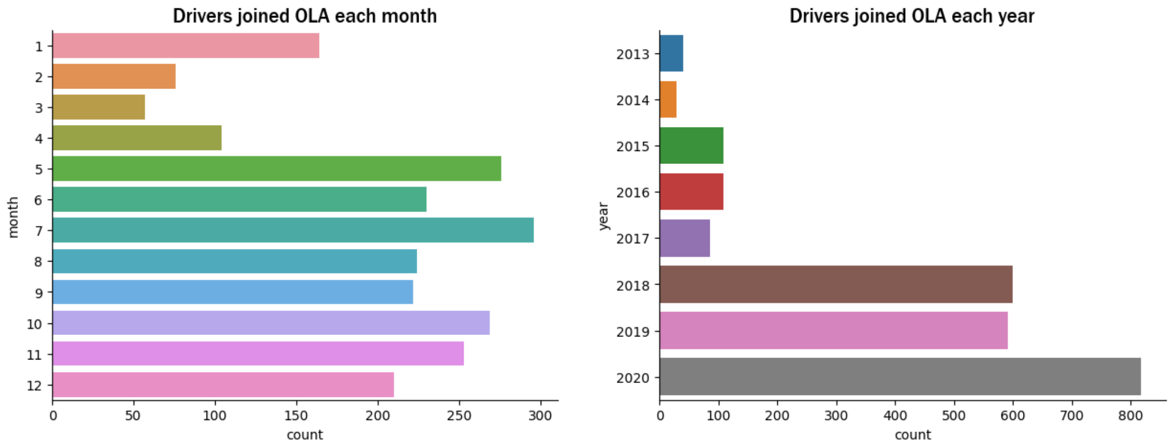
```
In [47]: fig = plt.figure(figsize=(22,7))
ax = fig.add_subplot(121)
sns.countplot(x=df.Cities,width=0.6)
plt.title('Cities alloted to Drivers',fontname='Franklin Gothic Medium', fontsiz
plt.xticks(rotation=90)

ax = fig.add_subplot(122)
sns.countplot(x=df.Reportings,width=0.6)
plt.title('Number of Reportings of Drivers',fontname='Franklin Gothic Medium', f
sns.despine()
plt.show()
```



Conclusion:

- The highest number of drivers prefer City C20 over other locations.
- Majority number of reportings of drivers prefer R6 over other number of reportings.

In [48]:
```
fig = plt.figure(figsize=(15,5))
ax = fig.add_subplot(1,2,1)
sns.countplot(y=df.month)
plt.title('Drivers joined OLA each month',fontname='Franklin Gothic Medium', for

ax = fig.add_subplot(1,2,2)
sns.countplot(y=df.year)
plt.title('Drivers joined OLA each year',fontname='Franklin Gothic Medium', font
sns.despine()
plt.show()
```

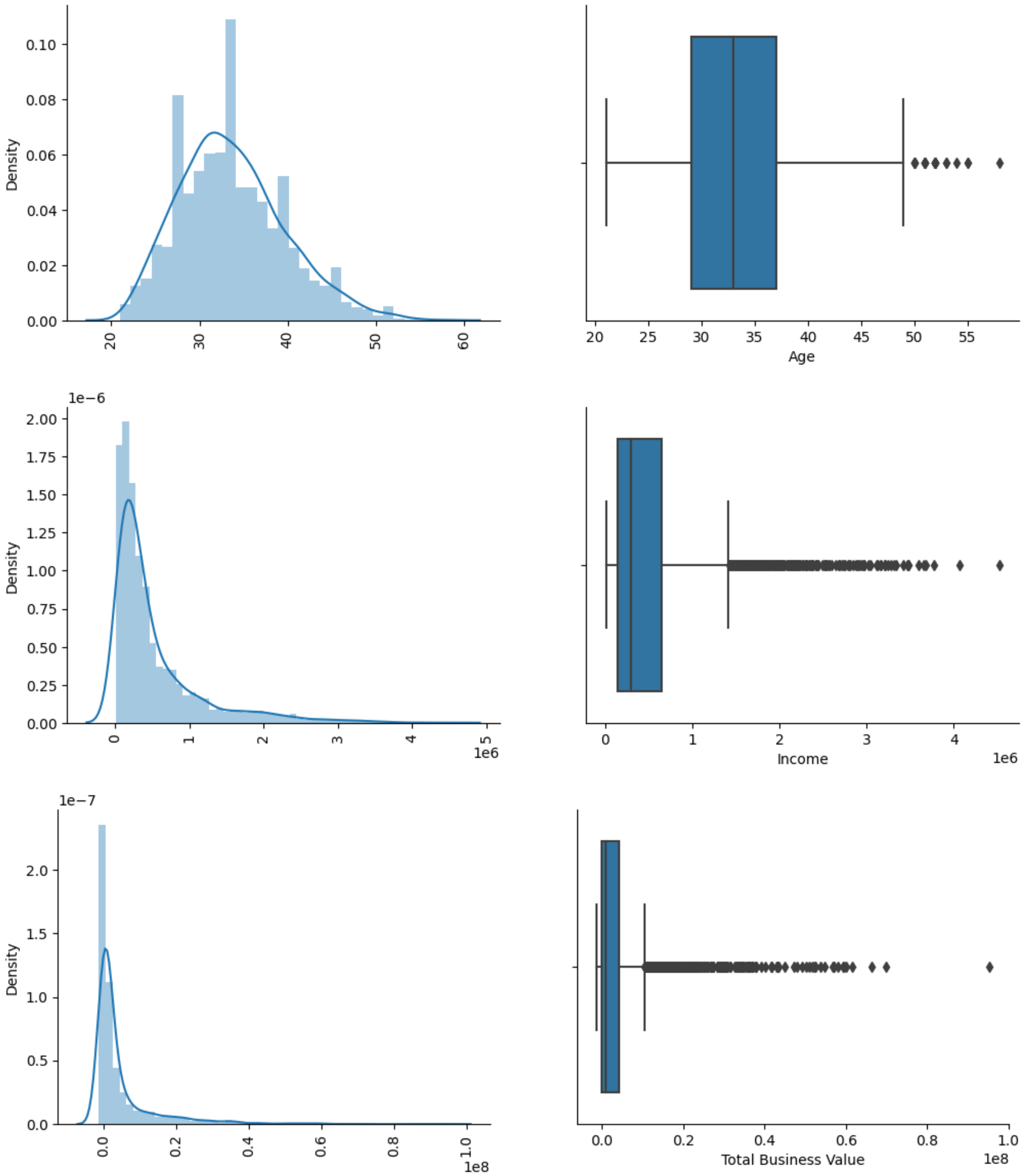


Conclusion:

- July received the maximum number of drivers in 8 years.
- February and March receives the least number of Drivers joining OLA.
- Joining of Drivers receives a boost of about 500% after 2017.

Outlier Detection

In [49]:
```
num_vars = df[['Age','Income','Total Business Value']]
for i in num_vars:
    plt.figure(figsize=(12,4))
    plt.subplot(121)
    sns.distplot(x=df[i])
    plt.title('')
    plt.xticks(rotation=90)

    plt.subplot(122)
    sns.boxplot(x=df[i])
    plt.title('')
    sns.despine()
    plt.show()
```



- Most of the distribution is highly skewed which tells us that they might contain outliers
- Almost all the continuous features have outliers present in the dataset.

Outlier Treatment

In [50]:
```
df.describe().T
```

Out[50]:

	count	mean	std	min	25%	50%	
Reportings	2381.0	8.023520e+00	6.783590e+00	1.0	3.0	5.0	
Driver_ID	2381.0	1.397559e+03	8.061616e+02	1.0	695.0	1400.0	
Age	2381.0	3.366317e+01	5.983375e+00	21.0	29.0	33.0	
Gender	2381.0	4.103318e-01	4.919972e-01	0.0	0.0	0.0	
Education_Level	2381.0	1.007560e+00	8.162900e-01	0.0	0.0	1.0	
Grade	2381.0	2.096598e+00	9.415218e-01	1.0	1.0	2.0	
Total Business Value	2381.0	4.586742e+06	9.127115e+06	-1385530.0	0.0	817680.0	41
Income	2381.0	5.267603e+05	6.231633e+05	10883.0	139895.0	292980.0	6
Joining Designation	2381.0	1.820244e+00	8.414334e-01	1.0	1.0	2.0	
Quarterly Rating	2381.0	1.486350e+00	8.343483e-01	1.0	1.0	1.0	
month	2381.0	7.357413e+00	3.143143e+00	1.0	5.0	7.0	
year	2381.0	2.018536e+03	1.609597e+00	2013.0	2018.0	2019.0	
target	2381.0	3.212936e-01	4.670713e-01	0.0	0.0	0.0	
Raise	2381.0	1.805964e-02	1.331951e-01	0.0	0.0	0.0	
Promotion	2381.0	3.427131e-01	4.747162e-01	0.0	0.0	0.0	
Cities	2381.0	1.533557e+01	8.371843e+00	1.0	8.0	15.0	

In [51]:
```
len(df[df['Total Business Value'] < 1])
```

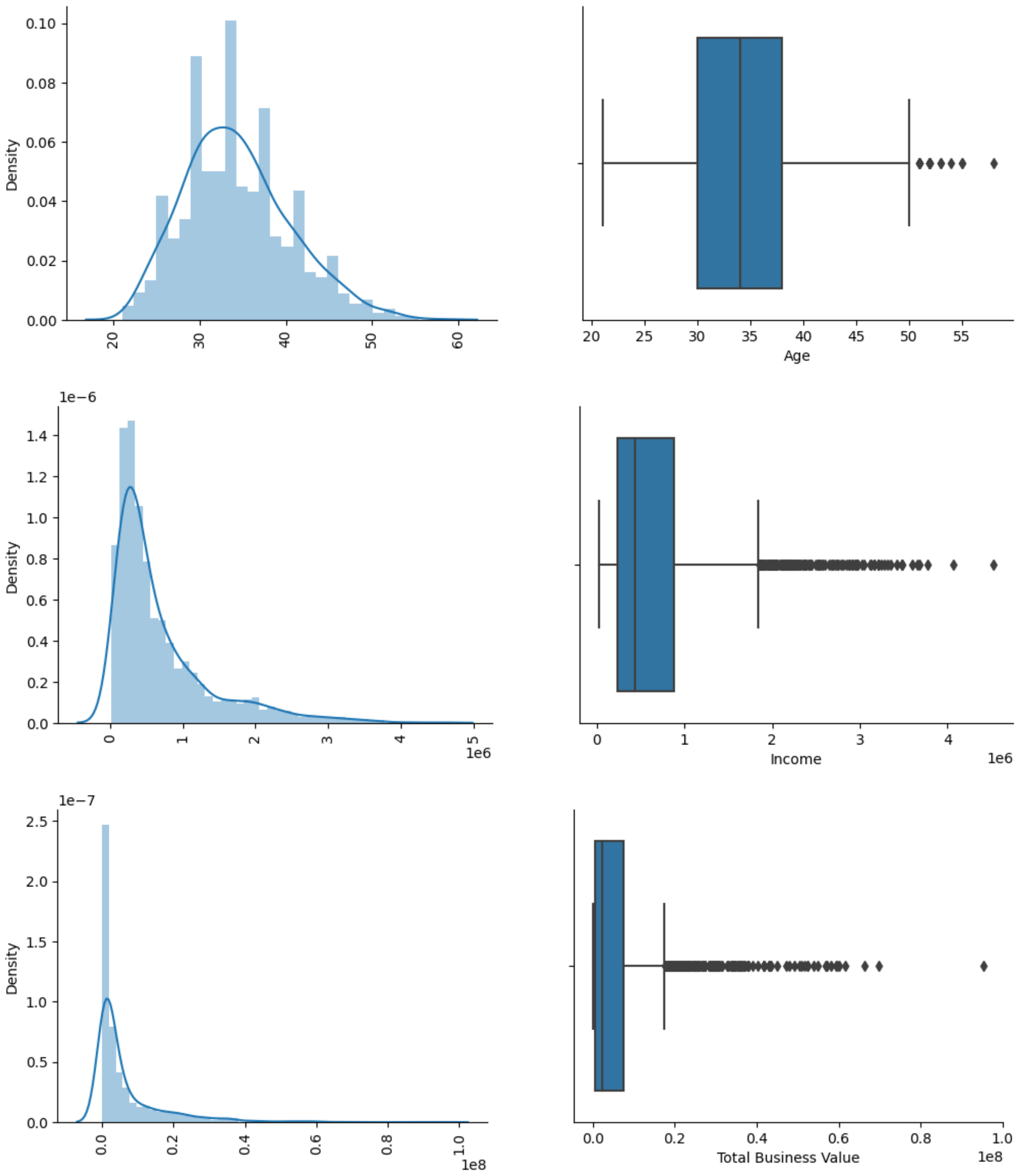
Out[51]: 729

- The Total Business Value column contains negative values, which we identify as outliers potentially influencing our machine learning model's outcomes.
- Focusing on segments of the dataset where Total Business Value exceeds 1, we observe outliers in the data that fall below this threshold, potentially affecting our model's accuracy.
- Specifically, among the dataset sections with Total Business Value greater than 1, we find precisely 729 drivers with values lower than 1, indicating a subset prone to outlier effects.

In [52]:
```
df= df[df['Total Business Value'] > 1]
```

In [53]:
```
num_vars = df[['Age','Income','Total Business Value']]
for i in num_vars:
    plt.figure(figsize=(12,4))
```

```
    plt.subplot(121)
    sns.distplot(x=df[i])
    plt.xticks(rotation=90)

    plt.subplot(122)
    sns.boxplot(x=df[i])
    sns.despine()
    plt.show()
```



In [54]:
```
df.describe().T
```

Out[54]:

	count	mean	std	min	25%	50%
Reportings	1652.0	1.026998e+01	6.967589e+00	1.0	5.0	8.0
Driver_ID	1652.0	1.390315e+03	8.082919e+02	1.0	679.5	1385.0
Age	1652.0	3.432385e+01	6.190776e+00	21.0	30.0	34.0
Gender	1652.0	4.158596e-01	4.930188e-01	0.0	0.0	0.0
Education_Level	1652.0	1.030872e+00	8.093284e-01	0.0	0.0	1.0
Grade	1652.0	2.144068e+00	9.719606e-01	1.0	1.0	2.0
Total Business Value	1652.0	6.613094e+06	1.032794e+07	19580.0	663022.5	2242080.0
Income	1652.0	6.864932e+05	6.814522e+05	20886.0	236652.5	428960.0
Joining Designation	1652.0	1.759685e+00	8.395129e-01	1.0	1.0	2.0
Quarterly Rating	1652.0	1.700363e+00	9.237035e-01	1.0	1.0	1.0
month	1652.0	7.136804e+00	3.067293e+00	1.0	5.0	7.0
year	1652.0	2.018208e+03	1.730439e+00	2013.0	2018.0	2018.0
target	1652.0	3.619855e-01	4.807202e-01	0.0	0.0	0.0
Raise	1652.0	2.602906e-02	1.592699e-01	0.0	0.0	0.0
Promotion	1652.0	4.933414e-01	5.001070e-01	0.0	0.0	0.0
Cities	1652.0	1.545278e+01	8.374318e+00	1.0	8.0	16.0

Bivariate Analysis & Multivariate Analysis

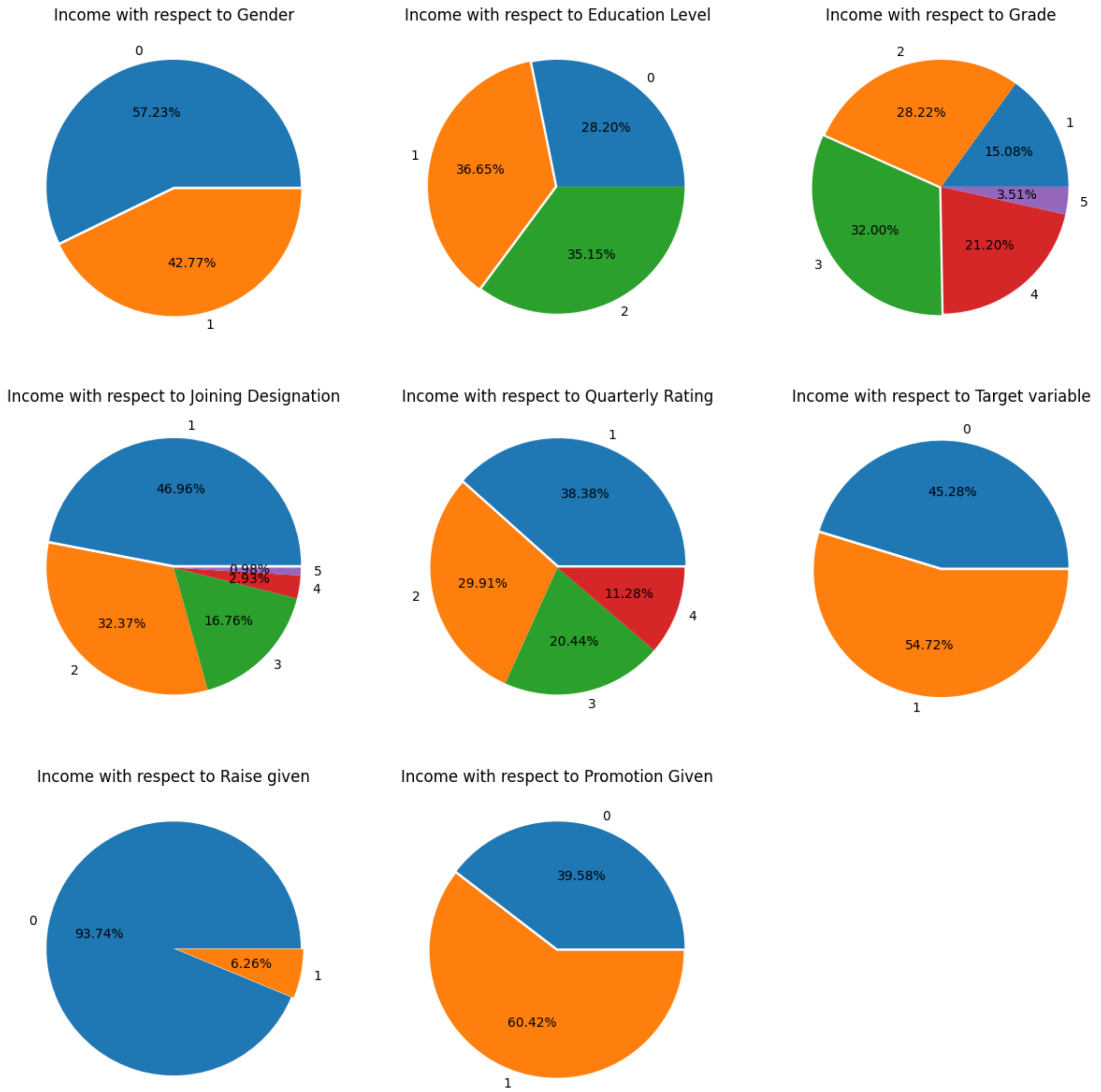
In [55]:

```
grouped_gender = df.groupby('Gender')['Income'].sum().reset_index()
grouped_education = df.groupby('Education_Level')['Income'].sum().reset_index()
grouped_grade = df.groupby('Grade')['Income'].sum().reset_index()
grouped_desig = df.groupby('Joining Designation')['Income'].sum().reset_index()
grouped_QR = df.groupby('Quarterly Rating')['Income'].sum().reset_index()
grouped_target = df.groupby('target')['Income'].sum().reset_index()
grouped_raise = df.groupby('Raise')['Income'].sum().reset_index()
grouped_promote = df.groupby('Promotion')['Income'].sum().reset_index()
```

In [56]:

```
plt.figure(figsize=(15,15))
plt.subplot(3,3,1)
plt.pie(grouped_gender['Income'], labels=grouped_gender['Gender'], explode = [0,
plt.title('Income with respect to Gender')

plt.subplot(3,3,2)
plt.pie(grouped_education['Income'], labels=grouped_education['Education_Level']
plt.title('Income with respect to Education Level')

plt.subplot(3,3,3)
plt.pie(grouped_grade['Income'], labels=grouped_grade['Grade'], explode = [0,0,0
```

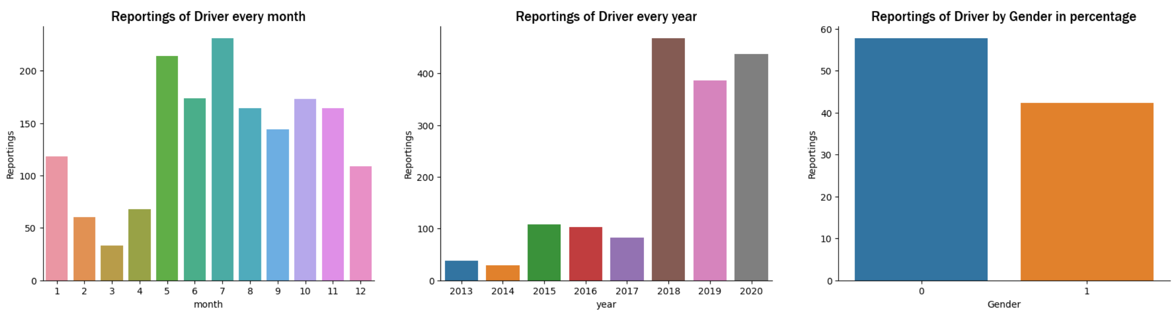
```
plt.title('Income with respect to Grade')

plt.subplot(3,3,4)
plt.pie(grouped_desig['Income'], labels=grouped_desig['Joining Designation'], ex
plt.title('Income with respect to Joining Designation')

plt.subplot(3,3,5)
plt.pie(grouped_QR['Income'], labels=grouped_QR['Quarterly Rating'], explode = [
plt.title('Income with respect to Quarterly Rating')

plt.subplot(3,3,6)
plt.pie(grouped_target['Income'], labels=grouped_target['target'], explode = [0,
plt.title('Income with respect to Target variable')

plt.subplot(3,3,7)
plt.pie(grouped_raise['Income'], labels=grouped_raise['Raise'], explode = [0,0.0
plt.title('Income with respect to Raise given')

plt.subplot(3,3,8)
plt.pie(grouped_promote['Income'], labels=grouped_promote['Promotion'], explode
plt.title('Income with respect to Promotion Given')

sns.despine()
plt.show()
```



Conclusion:

- So we see that there are 57% male employees and 43% female employees.
- The percentages of employees with different education levels are almost same for level 1 & 2.
- 97.3% of the employees who did not get a raise.
- Almost 43% of the employees joined at lowest designation 1. 34% joined at level 2, 20% at level 3 and below 2% joined at higher levels.
- Only 54.6% of the employees received a promotion, while 45.4% did not. However, only 5.7% received a raise in income.

In [57]:
```
fig = plt.figure(figsize=(22,5))
ax = fig.add_subplot(1,3,1)
grouped_months = df.groupby(['month'])['Reportings'].count().reset_index()
sns.barplot(data=grouped_months,x='month',y='Reportings')
plt.title('Reportings of Driver every month',fontname='Franklin Gothic Medium',

ax = fig.add_subplot(1,3,2)
grouped_years = df.groupby(['year'])['Reportings'].count().reset_index()
sns.barplot(x='year', y='Reportings', data=grouped_years)
plt.title('Reportings of Driver every year',fontname='Franklin Gothic Medium', f

ax = fig.add_subplot(1,3,3)
grouped_gender = df.groupby('Gender')['Reportings'].sum().reset_index()
grouped_gender['Reportings'] =(grouped_gender['Reportings']/sum(df.Reportings)*1
sns.barplot(x=grouped_gender['Gender'],y= grouped_gender['Reportings'])
plt.title('Reportings of Driver by Gender in percentage',fontname='Franklin Goth
sns.despine()
plt.show()
```



Conclusion:

- Number of employees has been increase with increase in year as well as number of reportings.
- The number of male employees found in reporting is more than women employees.

In [58]:
```
grouped_months
```

Out[58]:

	month	Reportings
0	1	118
1	2	60
2	3	33
3	4	68
4	5	214
5	6	174
6	7	231
7	8	164
8	9	144
9	10	173
10	11	164
11	12	109

In [59]:

```
grouped_years
```

Out[59]:

	year	Reportings
0	2013	38
1	2014	29
2	2015	108
3	2016	103
4	2017	82
5	2018	468
6	2019	387
7	2020	437

In [60]:

```
grouped_gender
```

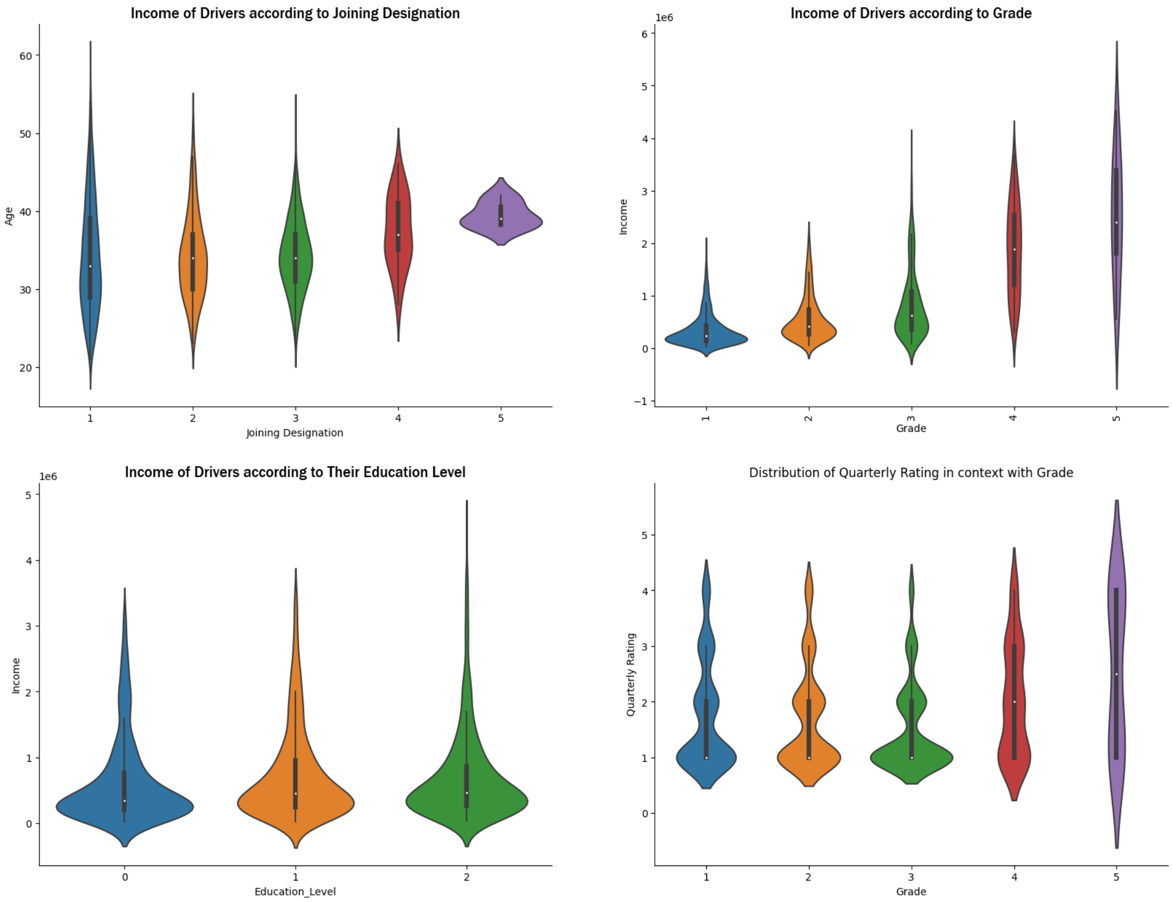
Out[60]:

	Gender	Reportings
0	0	57.74
1	1	42.26

In [61]:

```
plt.figure(figsize=(20,15))
plt.subplot(2,2,1)
sns.violinplot(y=df.Age,x=df['Joining Designation'])
plt.title('Income of Drivers according to Joining Designation',fontname='Frankli
plt.subplot(2,2,2)
sns.violinplot(x=df.Grade,y=df.Income)
plt.title('Income of Drivers according to Grade',fontname='Franklin Gothic Mediu
```

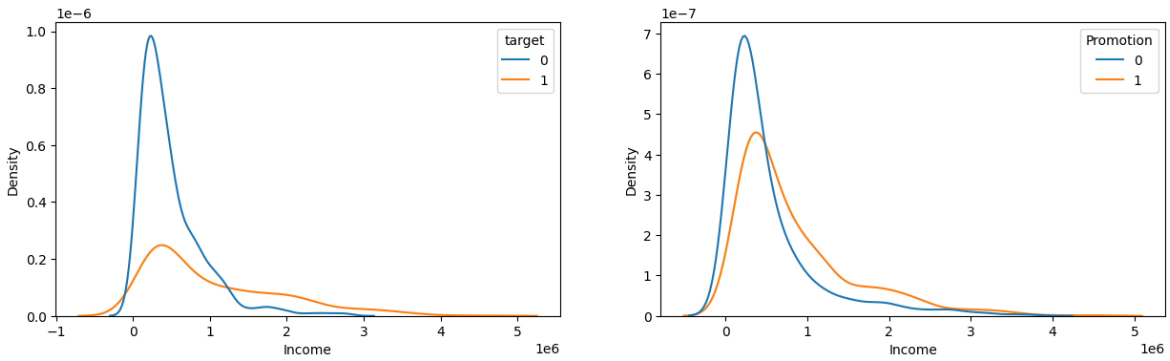
```
plt.xticks(rotation=90)
plt.subplot(2,2,3)
sns.violinplot(x=df.Education_Level,y=df.Income)
plt.title('Income of Drivers according to Their Education Level',fontname='Frank
plt.subplot(2,2,4)
sns.violinplot(x=df['Grade'],y=df["Quarterly Rating"])
plt.title('Distribution of Quarterly Rating in context with Grade')
sns.despine()
sns.despine()
plt.show()
```



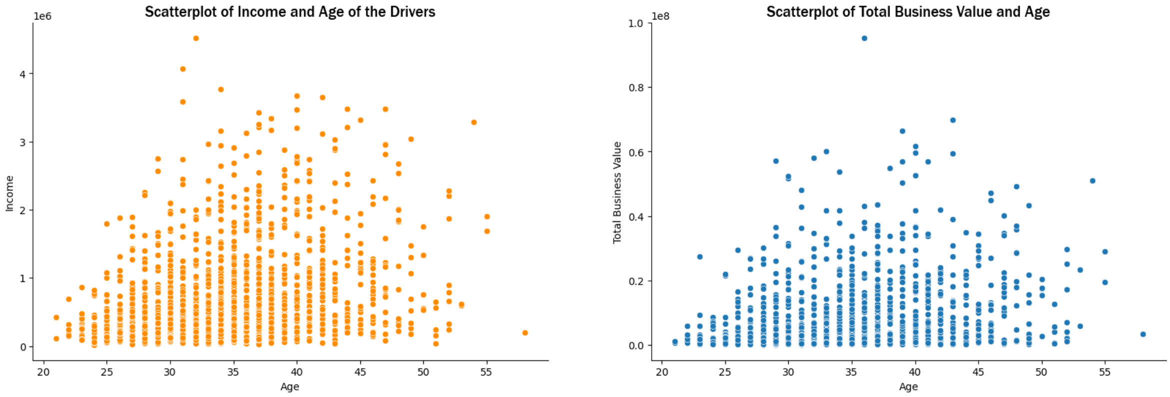
Conclusion:

- Income decreses with increase in Destination as about 4% of the employees hold higher designations.
- The median of the Income for employees having higher Grades is greater.
- Distribution of Income for employes at different Education level is about a change of 3-5% with level 0.
- Joining Designation Increases with increase in Grade.

In [62]:
```
plt.figure(figsize=(15,4))
plt.subplot(1,2,1)
sns.kdeplot(x=df.Income,hue=df['target'])
plt.subplot(1,2,2)
sns.kdeplot(x=df.Income,hue=df['Promotion'])
plt.show()
```



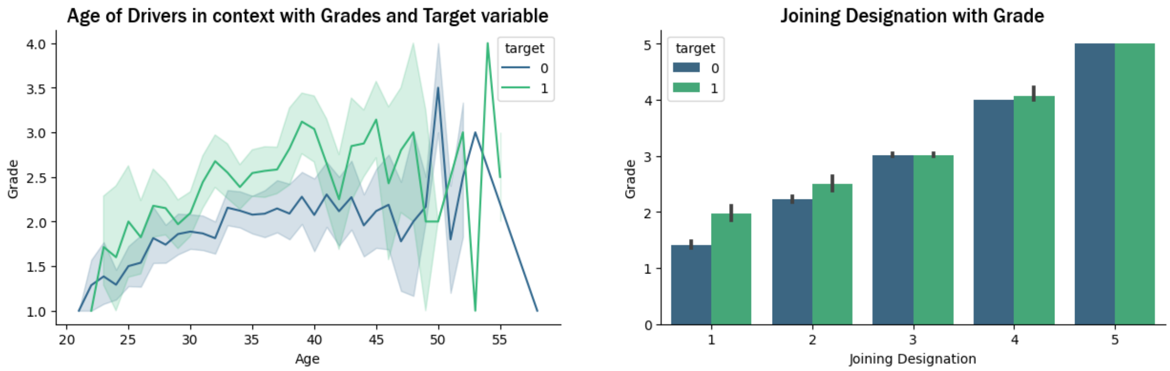
In [63]:
```
plt.figure(figsize=(20,6))
plt.subplot(1,2,1)
sns.scatterplot(x=df.Age,y=df.Income,color='darkorange')
plt.title('Scatterplot of Income and Age of the Drivers',fontname='Franklin Goth
plt.subplot(1,2,2)
sns.scatterplot(x=df.Age,y=df['Total Business Value'])
plt.title('Scatterplot of Total Business Value and Age',fontname='Franklin Gothi
sns.despine()
plt.show()
```



Conclusion:

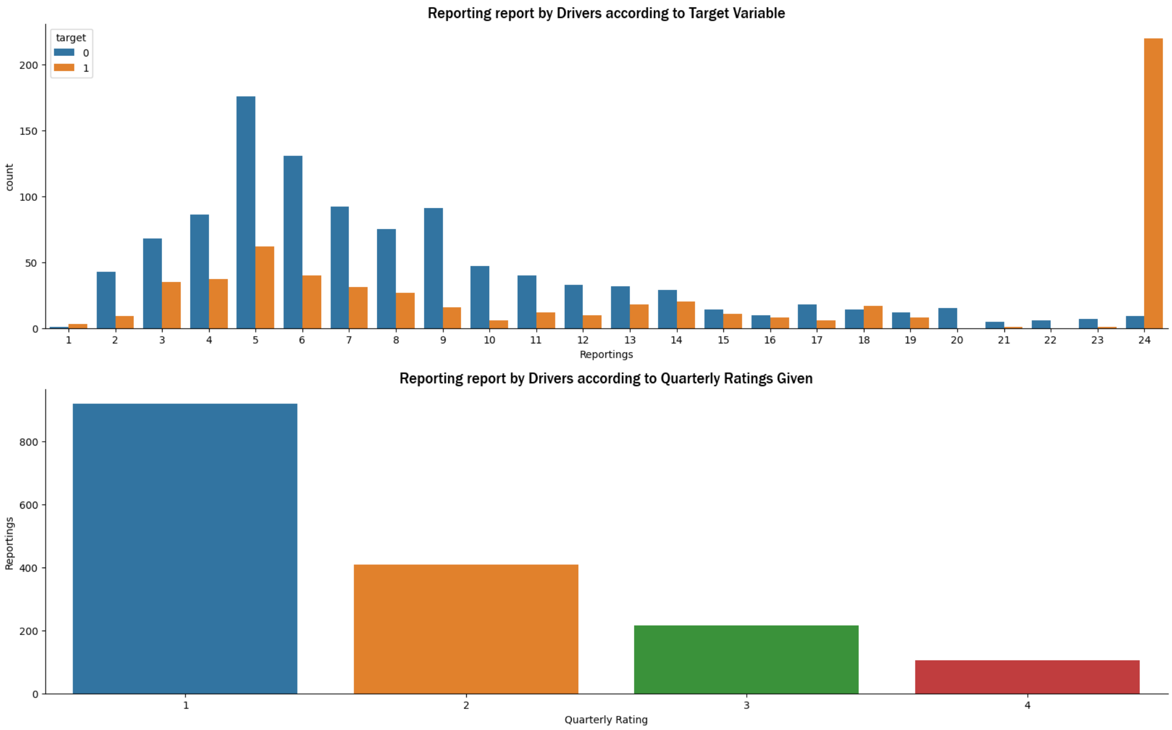
- Scatter plot of Income shows that Income increases with increase in age but after 45-50, we see a subtle decline.
- Scatter plot of Total Business Value shows an increase with increase in Age yet we notice a decline after 45.

In [64]:
```
fig = plt.figure(figsize=(15,4))
ax = fig.add_subplot(1,2,1)
sns.lineplot(x=df.Age,y=df.Grade,hue=df.target,palette='viridis')
plt.title('Age of Drivers in context with Grades and Target variable',fontname='

ax = fig.add_subplot(1,2,2)
sns.barplot(data=df, x="Joining Designation", y="Grade",palette='viridis',hue='t
plt.title('Joining Designation with Grade',fontname='Franklin Gothic Medium', fc
sns.despine()
plt.show()
```



- Joining Designation Increases with increase in Grade.

In [65]:
```
plt.figure(figsize=(20,12))
plt.subplot(2,1,1)
sns.countplot(x=df['Reportings'],hue=df.target)
plt.title('Reporting report by Drivers according to Target Variable',fontname='F

plt.subplot(2,1,2)
grouped_rating = df.groupby('Quarterly Rating')['Reportings'].count().reset_inde
sns.barplot(data = grouped_rating,y='Reportings',x='Quarterly Rating')
plt.title('Reporting report by Drivers according to Quarterly Ratings Given',fon
sns.despine()
plt.show()
```

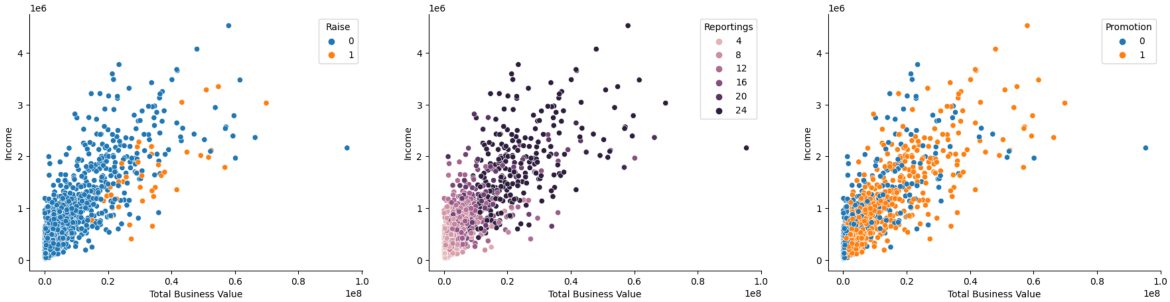


Conclusion:

- Max reporting days is 24 days.
- About 55% of the reportings of the employees has got Quarlerly Rating 1.

In [66]:
```
plt.figure(figsize=(22,5))
plt.subplot(1,3,1)
sns.scatterplot(x=df['Total Business Value'],y=df.Income,hue=df.Raise)
plt.subplot(1,3,2)
```

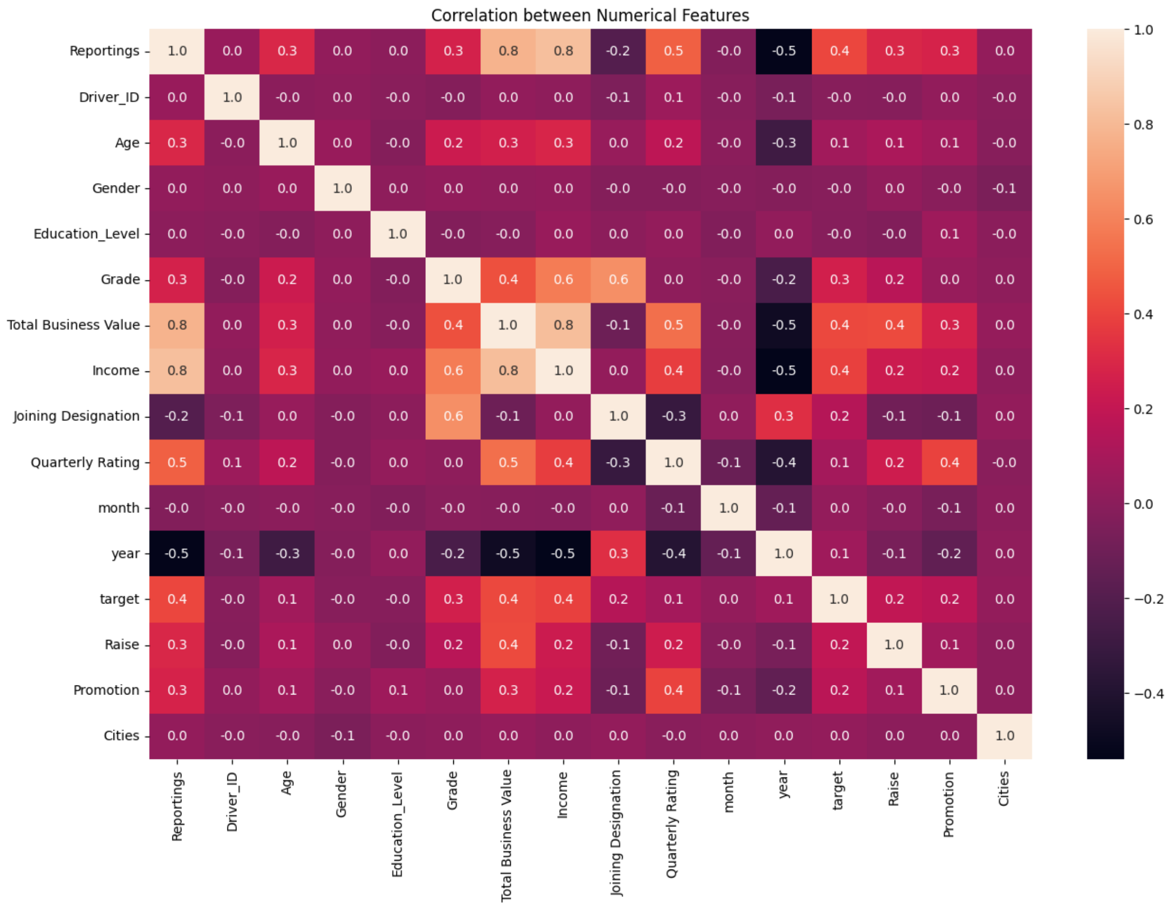
```
sns.scatterplot(x=df['Total Business Value'],y=df.Income,hue=df.Reportings)
plt.subplot(1,3,3)
sns.scatterplot(x=df['Total Business Value'],y=df.Income,hue=df.Promotion)
sns.despine()
plt.show()
```



Conclusion:

- Number of reportings increases with increase in Income as well as Total Business Value.

In [67]:
```
#Correlation between numerical features
plt.figure(figsize=(15,10))
sns.heatmap(df.corr(), annot=True, fmt=".1f")
plt.title('Correlation between Numerical Features')
plt.show()
```



Ensemble learning

```
In [68]: from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import (accuracy_score, confusion_matrix, classification_re
                             roc_auc_score, roc_curve, auc, ConfusionMatrixDispl
                             f1_score, recall_score, precision_recall_curve,
                             precision_score, RocCurveDisplay, average_precision
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
```

Train-Test Split

```
In [69]: X = df.drop('target',axis=1)
y = df['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, randc
```

```
In [70]: print(f'Shape of x_train: {X_train.shape}')
print(f'Shape of x_test: {X_test.shape}')
```

```
Shape of x_train: (1321, 15)
Shape of x_test: (331, 15)
```

```
In [71]: print(f'Shape of y_train: {y_train.shape}')
print(f'Shape of y_test: {y_test.shape}')
```

```
Shape of y_train: (1321,)
Shape of y_test: (331,)
```

Logistic Regression

```
In [72]: #Initialising object of Class LinearRegression()
model = LogisticRegression()    # training LinearRegression model
model.fit(X_train,y_train)
```

```
Out[72]: ▾ LogisticRegression
LogisticRegression()
```

```
In [73]: predictions = model.predict(X_test)
# Classification Report
print(classification_report(y_test, predictions))
```

```
              precision    recall  f1-score   support

           0       0.71      0.93      0.81       207
           1       0.77      0.37      0.50       124

    accuracy                           0.72       331
   macro avg       0.74      0.65      0.65       331
weighted avg       0.73      0.72      0.69       331
```

In [74]:
```python
# model.coef_[0]
pd.Series((zip(X.columns, model.coef_[0])))
```

Out[74]:
```
0                 (Reportings, 1.0134385160740076e-07)
1                   (Driver_ID, -8.54846070462366e-05)
2                       (Age, -1.2905703386145379e-05)
3                    (Gender, -2.1053824215102185e-07)
4            (Education_Level, -4.017845332616316e-07)
5                      (Grade, -8.489114635038955e-08)
6       (Total Business Value, 1.0711198496150669e-07)
7                     (Income, 2.5205592749856734e-07)
8         (Joining Designation, 6.335743681384692e-07)
9           (Quarterly Rating, -1.399853966974797e-06)
10                    (month, -1.6766034067654838e-06)
11                     (year, -0.0006508366149907002)
12                      (Raise, 3.681122397707675e-08)
13                 (Promotion, 2.2218742635693935e-08)
14                   (Cities, -3.2997198671441257e-06)
dtype: object
```

One Hot Encoding of Categorical Features

In [75]:
```python
from sklearn.preprocessing import OneHotEncoder
cat_cols = X.select_dtypes('category').columns
encoder = OneHotEncoder(sparse=False)
encoded_data = encoder.fit_transform(X[cat_cols])
encoded_df = pd.DataFrame(encoded_data, columns=encoder.get_feature_names_out(ca
x = pd.concat([X,encoded_df], axis=1)
x.drop(columns=cat_cols, inplace=True)
x.head()
```

Out[75]:

	Reportings	Driver_ID	Age	Gender	Education_Level	Grade	Total Business Value	Income	D
0	3.0	1.0	28.0	0.0	2.0	1.0	1715580.0	172161.0	
2	5.0	4.0	43.0	0.0	2.0	2.0	350000.0	328015.0	
3	3.0	5.0	29.0	0.0	0.0	1.0	120360.0	139104.0	
4	5.0	6.0	31.0	1.0	1.0	3.0	1265000.0	393640.0	
7	6.0	12.0	35.0	0.0	2.0	1.0	2607180.0	168696.0	

In [76]:
```python
scaler = StandardScaler()
scaler.fit_transform(X_train)
```

```
Out[76]: array([[-0.61446611, -1.09640018,  1.70794584, ..., -0.16737851,
                  1.023749  , -0.04979913],
                [ 1.93718866, -1.32951199,  1.54780698, ..., -0.16737851,
                 -0.97680193, -0.5247786 ],
                [-0.18919032, -1.0914666 ,  0.26669606, ..., -0.16737851,
                  1.023749  ,  1.25639439],
                ...,
                [-0.75622471,  0.03585718, -1.49483144, ..., -0.16737851,
                 -0.97680193, -0.88101319],
                [ 0.51960268,  1.32105562, -1.33469258, ..., -0.16737851,
                  1.023749  , -1.59348238],
                [-0.33094892,  0.60815284, -0.69413712, ..., -0.16737851,
                 -0.97680193, -0.28728886]])
```

In [77]:

```
from sklearn.model_selection import cross_validate
valid1 = cross_val_score(LogisticRegression(),X,y,cv=5)
print('Logistic Regression:',valid1.round(2))
print('Mean:',valid1.mean())
valid2 = cross_val_score( DecisionTreeClassifier(),X,y,cv=5)
print('Decision Tree:',valid2.round(3))
print('Mean:',valid2.mean())
valid3 = cross_val_score(RandomForestClassifier(),X,y,cv=5)
print('RandomForestClassifier():',valid3.round(2))
print('Mean:',valid3.mean())
valid4 = cross_val_score(GradientBoostingClassifier(),X,y,cv=5)
print('GradientBoostingClassifier:',valid4.round(3))
print('Mean:',valid4.mean())
valid5 =cross_val_score(XGBClassifier(),X,y,cv=5)
print('XGBoostClassifier:',valid1.round(2))
print('Mean:',valid5.mean())
```

```
Logistic Regression: [0.7  0.75 0.75 0.75 0.76]
Mean: 0.7415453629955141
Decision Tree: [0.894 0.879 0.873 0.885 0.861]
Mean: 0.878319143092557
RandomForestClassifier(): [0.93 0.94 0.91 0.91 0.92]
Mean: 0.9212926851597546
GradientBoostingClassifier: [0.931 0.937 0.909 0.909 0.909]
Mean: 0.9188684427355123
XGBoostClassifier: [0.7  0.75 0.75 0.75 0.76]
Mean: 0.9243138331960085
```

Machine Learning Model

In [78]:

```
# Random Forest Classifier
rf = RandomForestClassifier(criterion='gini',max_depth=7,max_features='sqrt',n_e
rf.fit(X_train,y_train)
```

Out[78]:

```
RandomForestClassifier
RandomForestClassifier(max_depth=7, n_estimators=10)
```

In [79]:

```
y_pred = rf.predict(X_test)
proba = rf.predict_proba(X_test)[:,1]
print("Train data accuracy:",rf.score(X_train, y_train))
print("Test data accuracy:",rf.score(X_test,y_test))
```

```
print('Accuracy of the model:', accuracy_score(y_test, y_pred))
print("ROC-AUC score test dataset: ", roc_auc_score(y_test, proba))
```

```
Train data accuracy: 0.9507948523845572
Test data accuracy: 0.8942598187311178
Accuracy of the model: 0.8942598187311178
ROC-AUC score test dataset:  0.9511259155368552
```

In [80]:
```
# Classification Report
print(classification_report(y_test, y_pred))
```

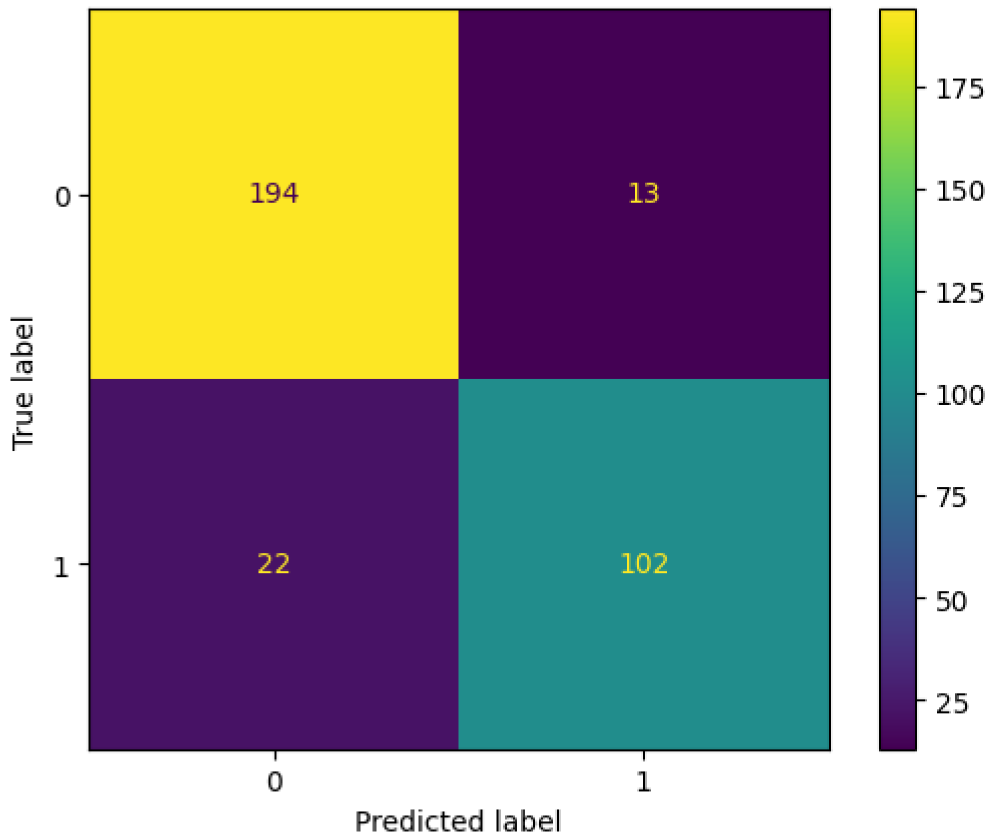
```
              precision    recall  f1-score   support

           0       0.90      0.94      0.92       207
           1       0.89      0.82      0.85       124

    accuracy                           0.89       331
   macro avg       0.89      0.88      0.89       331
weighted avg       0.89      0.89      0.89       331
```

Confusion Matrix

In [81]:
```
cm1=confusion_matrix(y_test,y_pred)
print(cm1)
ConfusionMatrixDisplay(confusion_matrix=cm1, display_labels=rf.classes_).plot()
```

```
[[194  13]
 [ 22 102]]
```

Out[81]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1f0563efbb0
>
```



In [82]:
```
rf_clf_imp1 = rf.feature_importances_
```

XG Boosting Classifier

In [83]:
```
gbc1 = GradientBoostingClassifier()
gbc1.fit(X_train, y_train)
y_pred = gbc1.predict(X_test)
proba =gbc1.predict_proba(X_test)[:, 1]
```

In [84]:
```
gbc_clf_imp1 = gbc1.feature_importances_
```

In [85]:
```
print('Train Score : ', gbc1.score(X_train, y_train))
print('Test Score : ', gbc1.score(X_test, y_test))
print('Accuracy Score : ', accuracy_score(y_test, y_pred))
print("ROC-AUC score test dataset: ", roc_auc_score(y_test, proba))
```

```
Train Score :  0.9704769114307343
Test Score :  0.918429003021148
Accuracy Score :  0.918429003021148
ROC-AUC score test dataset:  0.9589956365903071
```

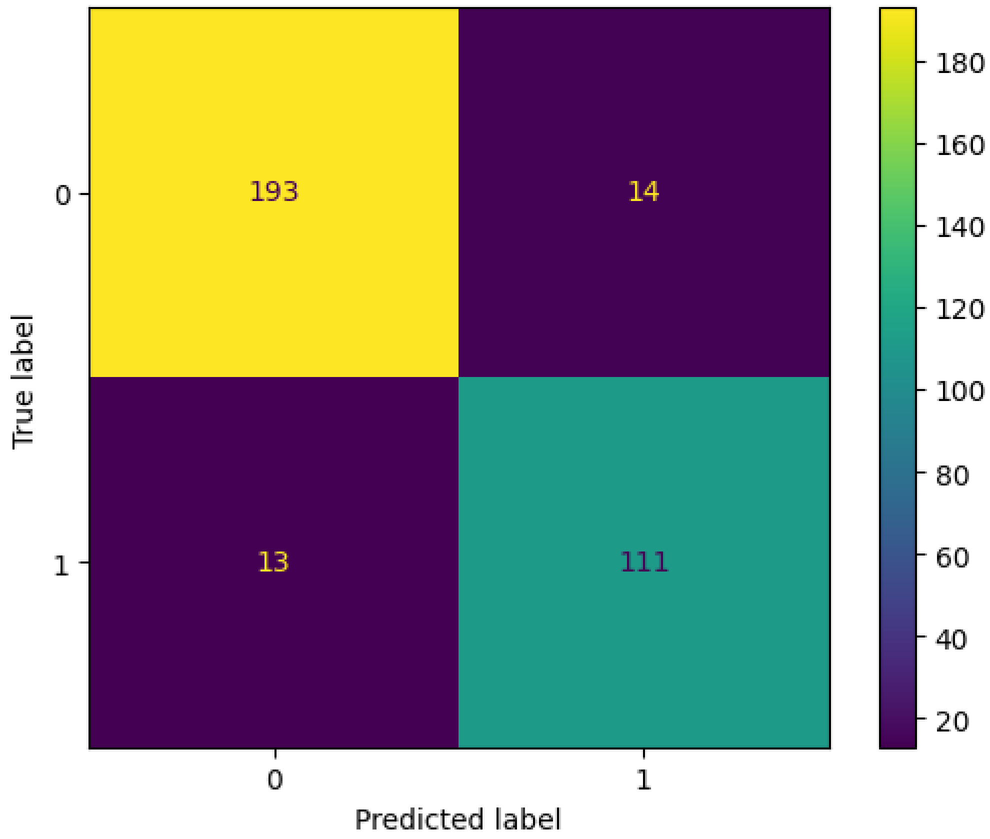
In [86]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.94      0.93      0.93       207
           1       0.89      0.90      0.89       124

    accuracy                           0.92       331
   macro avg       0.91      0.91      0.91       331
weighted avg       0.92      0.92      0.92       331
```

In [87]:
```
cm2=confusion_matrix(y_test,y_pred)
print(cm2)
ConfusionMatrixDisplay(confusion_matrix=cm2, display_labels=gbc1.classes_).plot(
```

```
[[193  14]
 [ 13 111]]
```

Out[87]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1f04086c5b0
>
```



Class Imbalance Treatment

In [88]:
```
plt.figure(figsize=(15,4))
sns.countplot(x=y_train,palette='Set2')
plt.title('Class Imbalance in the Data')
plt.show()
```

In [89]:
```
(y_train.value_counts()*100)/len(y_train)
```

Out[89]:
```
0    64.118092
1    35.881908
Name: target, dtype: float64
```

In [90]:
```
from imblearn.over_sampling import SMOTE
smot = SMOTE(random_state=42)
X_train_smot,y_train_smot = smot.fit_resample(X_train,y_train.ravel())
```

In [91]:
```
print(f'Shape of x_train: {X_train_smot.shape}')
print(f'Shape of x_test: {X_test.shape}')
```

```
Shape of x_train: (1694, 15)
Shape of x_test: (331, 15)
```

In [92]:
```
print(f'Shape of y_train: {y_train_smot.shape}')
print(f'Shape of y_test: {y_test.shape}')
```

```
Shape of y_train: (1694,)
Shape of y_test: (331,)
```

In [93]:
```
from collections import Counter
c = Counter(y_train_smot)
print(c)
```

```
Counter({0: 847, 1: 847})
```

Random Forest Classifier

In [94]:
```
rf_clf = RandomForestClassifier()
rf_clf.fit(X_train_smot,y_train_smot)
```

Out[94]:
```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [95]:
```
rf_clf = RandomForestClassifier(criterion='gini',max_depth=8,max_features='sqrt'
rf_clf.fit(X_train_smot,y_train_smot)
```

Out[95]:
```
▾ RandomForestClassifier
RandomForestClassifier(max_depth=8, n_estimators=19)
```

In [96]:
```
rf_clf_imp2=rf_clf.feature_importances_
```

In [97]:
```
y_pred = rf_clf.predict(X_test)
proba = rf_clf.predict_proba(X_test)[:,1]
print("Train data accuracy:",rf_clf.score(X_train, y_train))
print("Test data accuracy:",rf_clf.score(X_test,y_test))
print('Accuracy of the model:', accuracy_score(y_test, y_pred))
print("ROC-AUC score test dataset: ", roc_auc_score(y_test, proba))
```

```
Train data accuracy: 0.9651778955336866
Test data accuracy: 0.8821752265861027
Accuracy of the model: 0.8821752265861027
ROC-AUC score test dataset:  0.9395356085398162
```

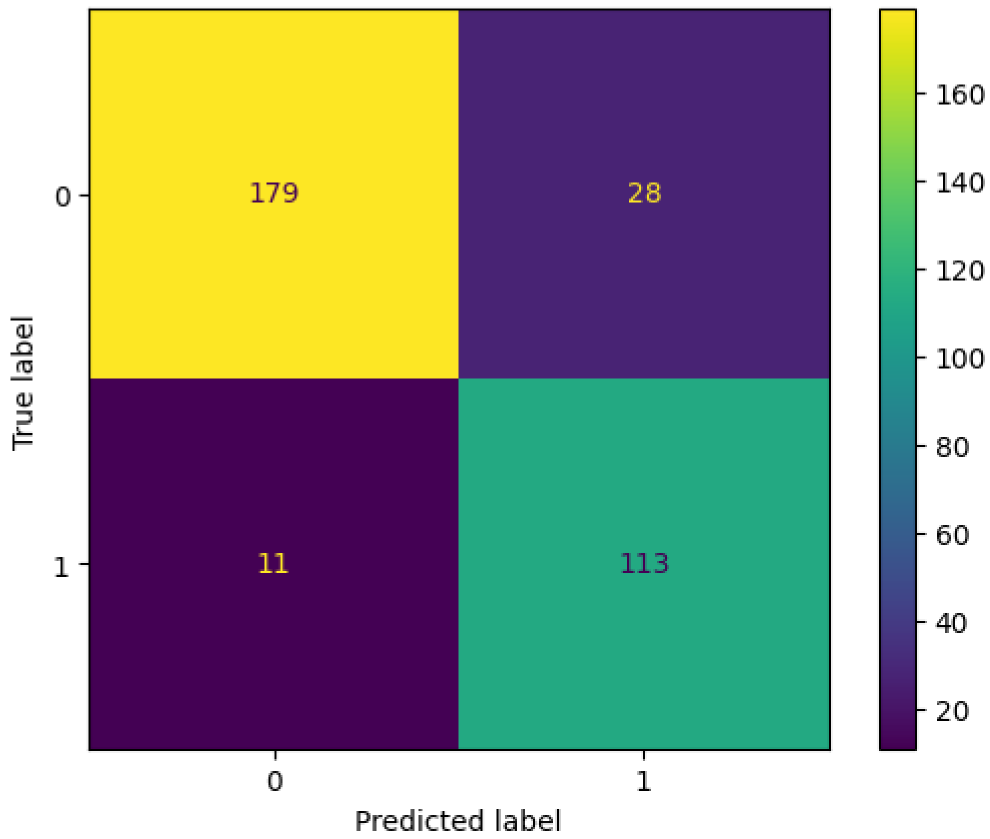
In [98]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.94      0.86      0.90       207
           1       0.80      0.91      0.85       124

    accuracy                           0.88       331
   macro avg       0.87      0.89      0.88       331
weighted avg       0.89      0.88      0.88       331
```

In [99]:
```
cm3=confusion_matrix(y_test,y_pred)
print(cm3)
ConfusionMatrixDisplay(confusion_matrix=cm3, display_labels=rf_clf.classes_).plo
```

```
[[179  28]
 [ 11 113]]
```

Out[99]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1f0592483d0
>
```



Gradient Boosting

In [100…
```
gbc2 = GradientBoostingClassifier()
gbc2.fit(X_train_smot, y_train_smot)
y_pred1 = gbc2.predict(X_test)
print(classification_report(y_test, y_pred1))
```

```
              precision    recall  f1-score   support

           0       0.94      0.90      0.92       207
           1       0.84      0.90      0.87       124

    accuracy                           0.90       331
   macro avg       0.89      0.90      0.90       331
weighted avg       0.90      0.90      0.90       331
```

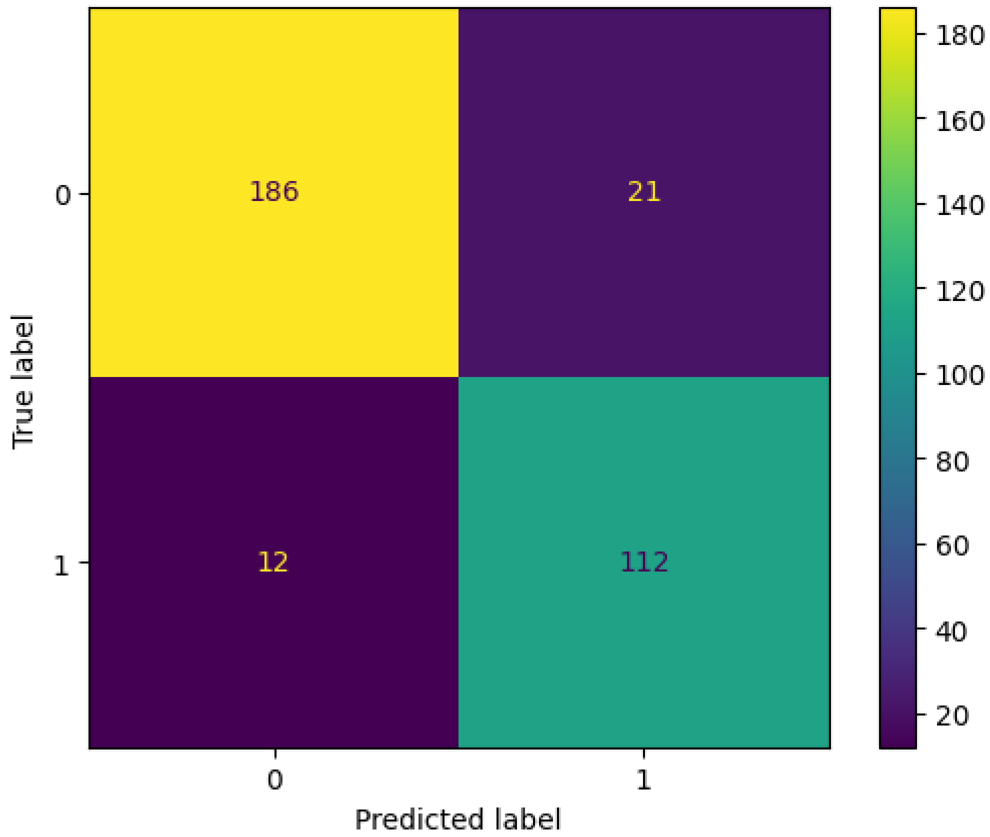
In [101…
```
gbc_clf_imp2 = gbc2.feature_importances_
```

In [102…
```
cm4=confusion_matrix(y_test,y_pred1)
print(cm4)
ConfusionMatrixDisplay(confusion_matrix=cm4, display_labels=gbc2.classes_).plot(
```

```
[[186  21]
 [ 12 112]]
```

Out[102]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1f055a0dd50
>
```



In [103…

```
data1 = pd.DataFrame({'Column_Name':X.columns,
                      'RandomForestClassifier':rf_clf_imp1,
                      'XGBClassifier':gbc_clf_imp1})
data1
```

Out[103]:

	Column_Name	RandomForestClassifier	XGBClassifier
0	Reportings	0.224529	0.391298
1	Driver_ID	0.025841	0.008175
2	Age	0.028662	0.005785
3	Gender	0.002997	0.000527
4	Education_Level	0.005954	0.000080
5	Grade	0.017067	0.002119
6	Total Business Value	0.123392	0.099514
7	Income	0.154728	0.023946
8	Joining Designation	0.041630	0.003108
9	Quarterly Rating	0.082160	0.008600
10	month	0.047856	0.086687
11	year	0.186714	0.345914
12	Raise	0.012125	0.000000
13	Promotion	0.025327	0.017654
14	Cities	0.021017	0.006594

In [104…

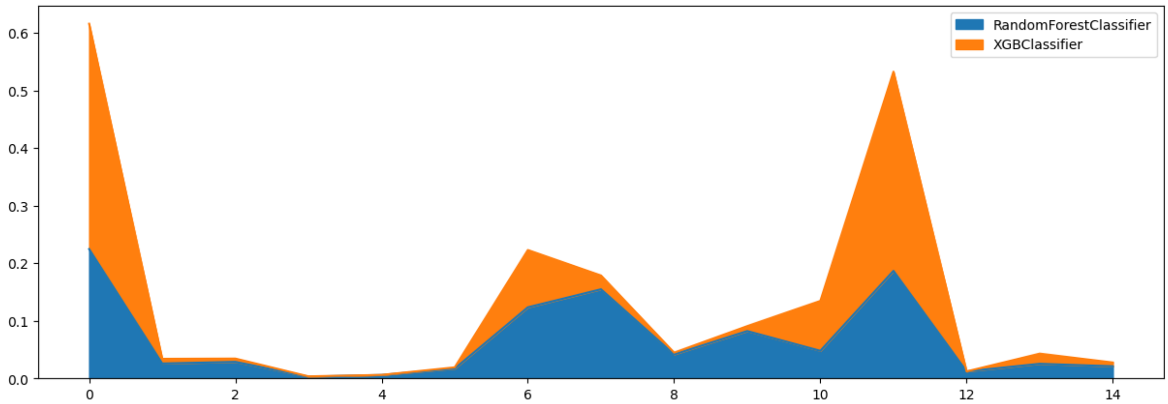
```
data2 = pd.DataFrame({'Column_Name':X.columns,
                      'RandomForestClassifier':rf_clf_imp2,
                      'XGBClassifier':gbc_clf_imp2})
data2
```

Out[104]:

	Column_Name	RandomForestClassifier	XGBClassifier
0	Reportings	0.179918	0.256746
1	Driver_ID	0.028432	0.007620
2	Age	0.041870	0.006710
3	Gender	0.012411	0.006807
4	Education_Level	0.014206	0.003721
5	Grade	0.024058	0.005191
6	Total Business Value	0.176874	0.196760
7	Income	0.134992	0.024653
8	Joining Designation	0.021441	0.003045
9	Quarterly Rating	0.048033	0.026927
10	month	0.058897	0.080916
11	year	0.203634	0.361113
12	Raise	0.006551	0.000000
13	Promotion	0.020975	0.013952
14	Cities	0.027709	0.005839

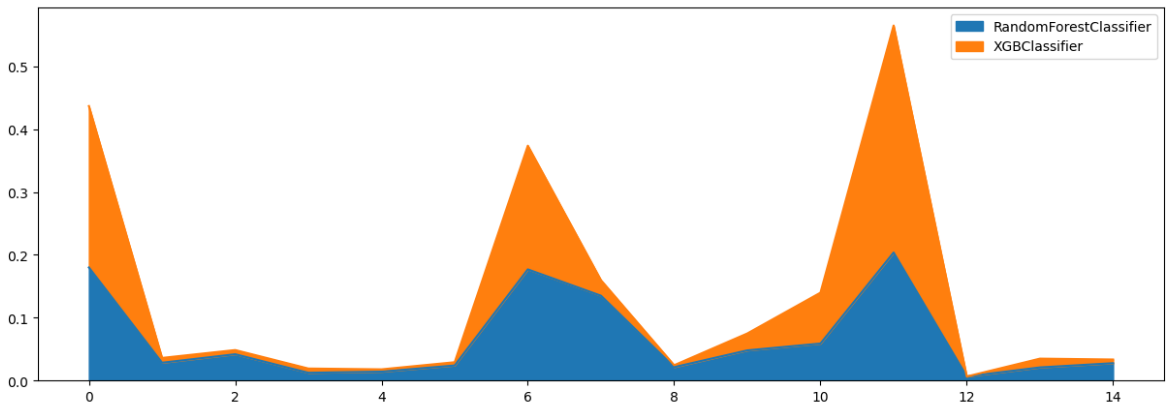
In [105…

```
data1.plot(kind="area", figsize = (15,5))
plt.show()
```



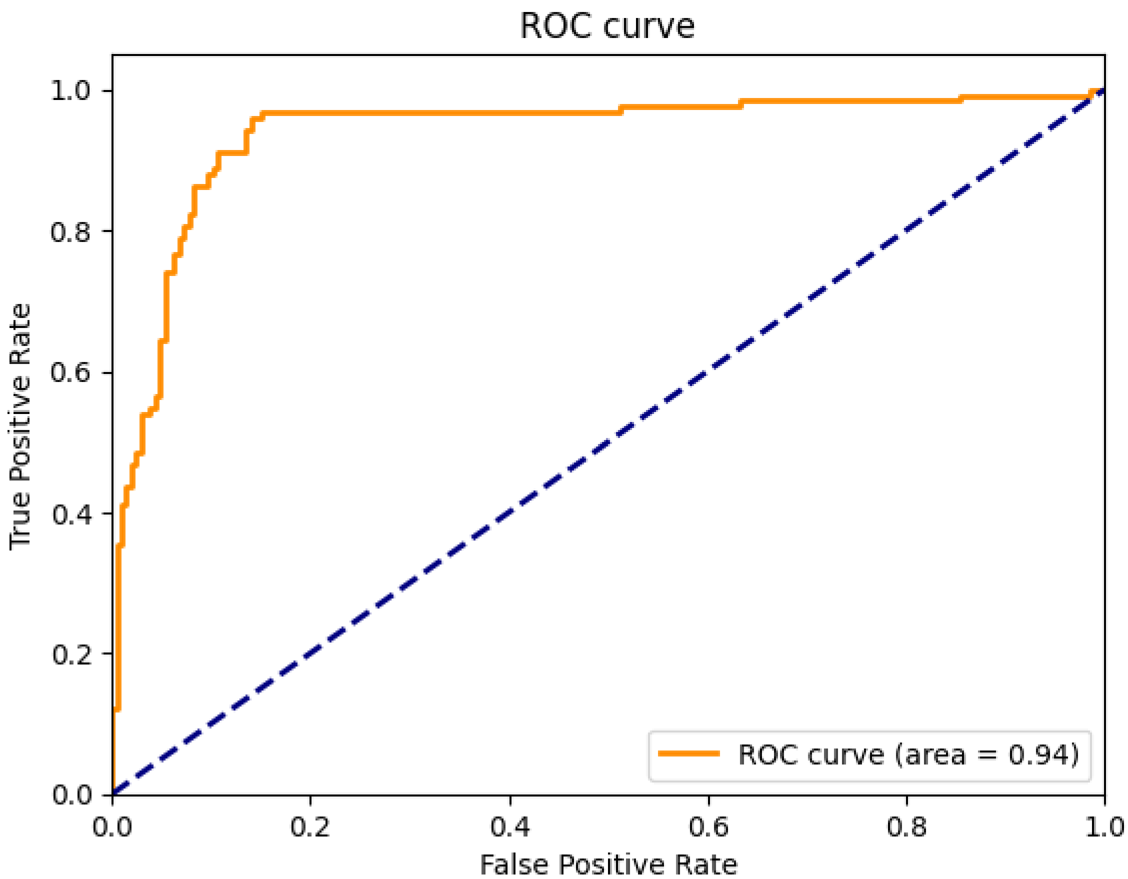
In [106…

```
data2.plot(kind="area", figsize = (15,5))
plt.show()
```



In [107…

```
# Compute the false positive rate, true positive rate, and thresholds
fpr, tpr, thresholds = roc_curve(y_test, proba)

# Compute the area under the ROC curve
roc_auc = auc(fpr, tpr)

# Plot the ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' %
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC curve')
plt.legend(loc="lower right")
plt.show()
```



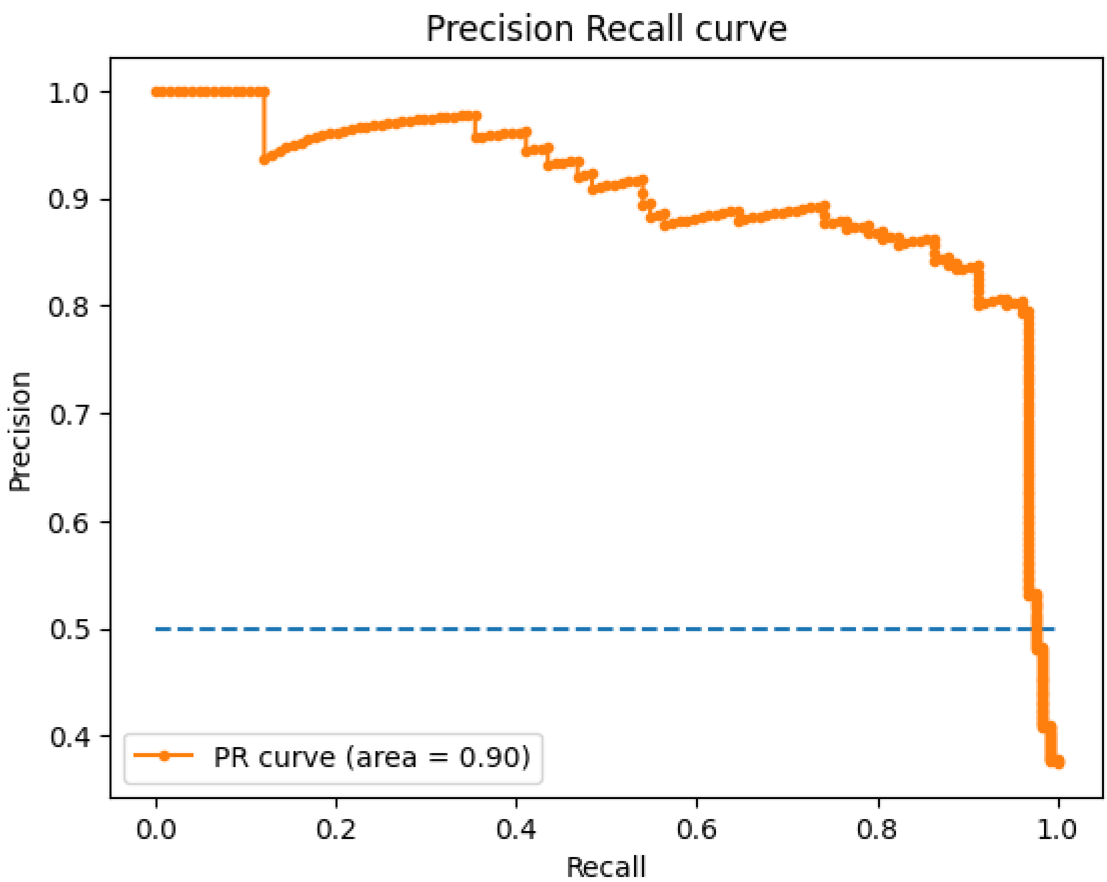
- The ROC AUC of 0.94 signifies that the model is able to discriminate well between the positive and the negative class.
- But it is not a good measure for an imbalanced target variable because it may be high even when the classifier has a poor score on the minority class.
- This can happen when the classifier performs well on the majority class instances, which dominate the dataset. As a result, the AUC may appear high, but the model may not effectively identify the minority class instances.

In [108…

```
def plot_pre_curve(y_test,proba):
    from sklearn.metrics import precision_recall_curve
    precision, recall, thresholds = precision_recall_curve(y_test, proba)
    # Area under Precision Recall Curve
    auprc = average_precision_score(y_test, proba)
    plt.plot([0, 1], [0.5, 0.5], linestyle='--')
    plt.plot(recall, precision, marker='.',label='PR curve (area = %0.2f)' % aup
    plt.title("Precision Recall curve")
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.legend(loc="lower left")
    plt.show()
```

In [109…

```
plot_pre_curve(y_test , proba)
```



In [110…

```
# calculating precision, reall and f1_score for every
tp1,fp1,fn1,tn1 =cm1[0][0],cm1[0][1],cm1[1][0],cm1[1][1]
tp2,fp2,fn2,tn2 =cm2[0][0],cm2[0][1],cm2[1][0],cm2[1][1]
tp3,fp3,fn3,tn3 =cm3[0][0],cm3[0][1],cm3[1][0],cm3[1][1]
tp4,fp4,fn4,tn4 =cm4[0][0],cm4[0][1],cm4[1][0],cm4[1][1]
```

```
precision1 = tp1/(tp1+fp1)
recall1 = tp1/(tp1+fn1)
precision2 = tp2/(tp2+fp2)
recall2 = tp2/(tp2+fn2)
precision3 = tp3/(tp3+fp3)
recall3 = tp3/(tp3+fn3)
precision4 = tp4/(tp4+fp4)
recall4 = tp4/(tp4+fn4)
f1_1 = (2*precision1*recall1)/(precision1+recall1)
f1_2 = (2*precision2*recall2)/(precision2+recall2)
f1_3 = (2*precision3*recall3)/(precision3+recall3)
f1_4 =(2*precision4*recall4)/(precision4+recall4)
```

In [111…

```
df = pd.DataFrame({'Model':['RandomForest','GradientBoosting','RandomForest','Gr
                  'Class':['Imbalanced','Imbalanced','Balanced','Balanced'],
                  'True_pos':[tp1,tp2,tp3,tp4],
                  'Fal_pos':[fp1,fp2,fp3,fp4],
                  'Fal_neg':[fn1,fn2,fn3,fn4],
                  'True_neg':[tn1,tn2,tn3,tn4],
                  'F1_score%':[f1_1*100,f1_2*100,f1_3*100,f1_4*100],
                  'Precision%':[precision1*100,precision2*100,precision3*100,pre
                  'Recall%':[recall1*100,recall2*100,recall3*100,recall4*100]})
```

In [112…

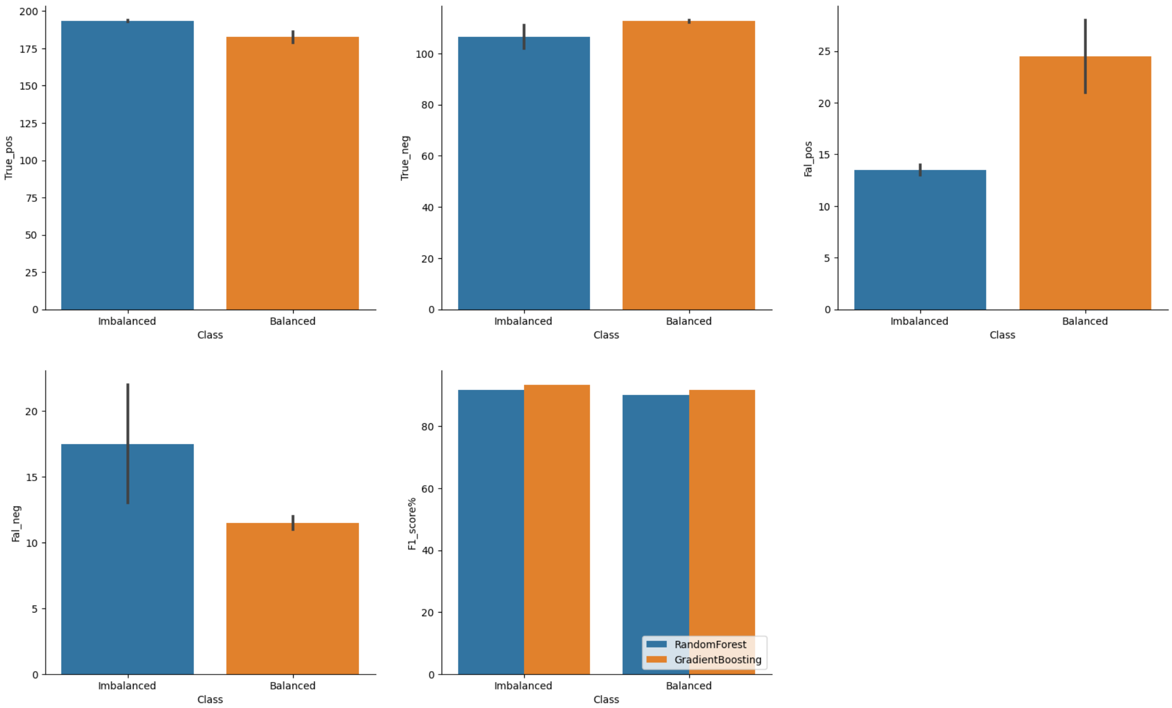
```
df
```

Out[112]:

	Model	Class	True_pos	Fal_pos	Fal_neg	True_neg	F1_score%	Preci
0	RandomForest	Imbalanced	194	13	22	102	91.725768	93.7
1	GradientBoosting	Imbalanced	193	14	13	111	93.462470	93.2
2	RandomForest	Balanced	179	28	11	113	90.176322	86.4
3	GradientBoosting	Balanced	186	21	12	112	91.851852	89.8

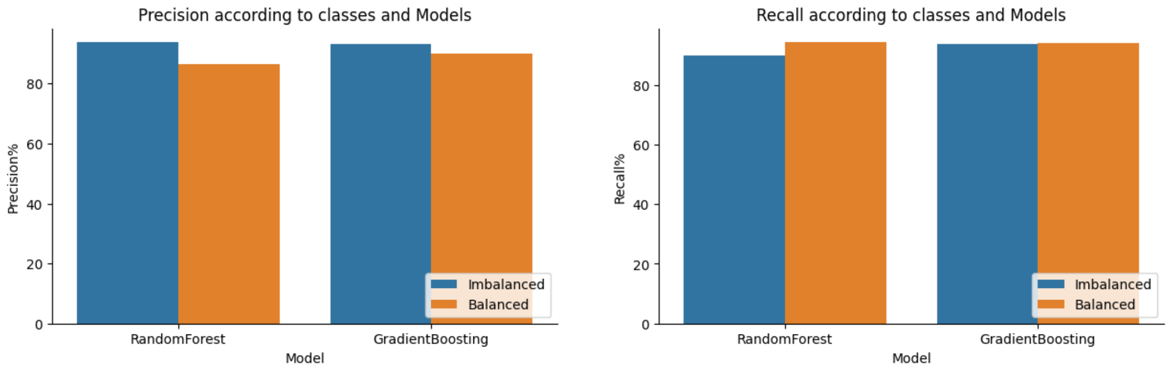
In [113…

```
# Representation of True Positives, True Negatives, False Positives, False Negat
plt.figure(figsize=(20,12))
plt.subplot(2,3,1)
sns.barplot(x=df.Class,y=df.True_pos)

plt.subplot(2,3,2)
sns.barplot(x=df.Class,y=df.True_neg)

plt.subplot(2,3,3)
sns.barplot(x=df.Class,y=df.Fal_pos)

plt.subplot(2,3,4)
sns.barplot(x=df.Class,y=df.Fal_neg)

plt.subplot(2,3,5)
sns.barplot(x=df.Class,y=df['F1_score%'],hue=df.Model)
plt.legend(loc='lower right')
sns.despine()
plt.show()
```



In [114...

```
plt.figure(figsize=(15,4))
plt.subplot(1,2,1)
sns.barplot(x=df.Model,y=df['Precision%'],hue=df.Class)
plt.title('Precision according to classes and Models')
plt.legend(loc='lower right')
plt.subplot(1,2,2)
sns.barplot(x=df.Model,y=df['Recall%'],hue=df.Class)
plt.title('Recall according to classes and Models')
plt.legend(loc='lower right')
sns.despine()
plt.show()
```



Insights

- Male drivers constitute 58.9% of the total driver population.
- There are three education levels among drivers, all of which have nearly equal distributions within the driver community.
- The most frequent grade attained by drivers is Grade 2, with a declining count as the grade level increases.
- The majority of drivers fall between 21 and 58 years old, with 32 years being the most common age. Specifically, the peak number of drivers occurs within the age range of 31 to 41 years.

- The highest number of drivers prefer City C20 over other locations.
- Majority number of reporting of drivers prefer R6 over other number of reporting.
- July received the maximum number of drivers in 8 years.
- February and March receives the least number of Drivers joining OLA.
- Joining of Drivers receives a boost of about 500% after 2017.
- So we see that there are 57% male employees and 43% female employees.
- The percentages of employees with different education levels are almost same for level 1 & 2.
- 97.3% of the employees who did not get a raise.
- Almost 43% of the employees joined at lowest designation 1. 34% joined at level 2, 20% at level 3 and below 2% joined at higher levels.
- Only 54.6% of the employees received a promotion, while 45.4% did not. However, only 2.6% received a raise in income.
- Number of employees has been increase with increase in year as well as number of reporting.
- The number of male employees found in reporting is more than women employees.
- Scatter plot of Income shows that Income increases with increase in age but after 45-50, we see a subtle decline.
- Scatter plot of Total Business Value shows an increase with increase in Age yet we notice a decline after 45.
- Income decreases with increase in Destination as about 4% of the employees hold higher designations.
- The median of the Income for employees having higher Grades is greater.
- Distribution of Income for employees at different Education level is about a change of 3-5% with level 0.
- The ROC AUC of 0.94 signifies that the model is able to discriminate well between the positive and the negative class.
- But it is not a good measure for an imbalanced target variable because it may be high even when the classifier has a poor score on the minority class.
- This can happen when the classifier performs well on the majority class instances, which dominate the dataset. As a result, the AUC may appear high, but the model may not effectively identify the minority class instances.
- Joining Designation Increases with increase in Grade.
- Top reporting days is 24 days.
- About 55% of the reporting of the employees has got quarterly Rating 1.
- Number of reporting increases with increase in Income as well as Total Business Value.
- Recall increased after treatment of data imbalance and is performing better in Gradient Boosting.
- Precision dropped after treatment of data imbalance and is performing better in Random Forest.
- F1_score increased after the treatment of imbalanced data and in Gradient Boosting.