OLA DRIVER CHURN PROJECT

```
import pandas as pd
import numpy as np
import seaborn as sns
from scipy import stats
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_curve
from sklearn.metrics import precision_recall_curve
from sklearn.model_selection import train_test_split, KFold, cross_val_score
from sklearn.preprocessing import MinMaxScaler
from datetime import datetime
from statsmodels.stats.outliers_influence import variance_inflation_factor
import warnings
warnings.filterwarnings("ignore")
```

```
ola = pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/002/492/original/ola_driver_scaler.csv')
```

```
ola.head()
```

	Unnamed: 0	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value	Quarterly Rating
0	0	01/01/19	1	28.0	0.0	C23	2	57387	24/12/18	NaN	1	1	2381060	2
1	1	02/01/19	1	28.0	0.0	C23	2	57387	24/12/18	NaN	1	1	-665480	2
2	2	03/01/19	1	28.0	0.0	C23	2	57387	24/12/18	03/11/19	1	1	0	2
3	3	11/01/20	2	31.0	0.0	C7	2	67016	11/06/20	NaN	2	2	0	1
4	4	12/01/20	2	31.0	0.0	C7	2	67016	11/06/20	NaN	2	2	0	1

EXPLORATORY DATA ANALYSIS

```
print('Rows in the ola dataset: ',ola.shape[0])
print('Columns in the ola dataset: ',ola.shape[1])
```

```
Rows in the ola dataset:  19104
Columns in the ola dataset:  14
```

```
ola.info()
```

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

`Column Profiling`: • MMMM-YY : Reporting Date (Monthly) (date-time)

• Age : Age of the employee (numerical)

• Gender : Gender of the employee – Male : 0, Female: 1 (categorical)

• City : City Code of the employee (categorical)

• Education_Level : Education level – 0 for 10+ ,1 for 12+ ,2 for graduate (categorical)

• Income : Monthly average Income of the employee (numerical)

• Date Of Joining : Joining date for the employee (date-time)

• LastWorkingDate : Last date of working for the employee - Target Feature (date-time, but will be converted to categorical)

• Joining Designation : Designation of the employee at the time of joining (categorical, ordinal)

• Grade : Grade of the employee at the time of reporting (categorical, ordinal)

• Total Business Value : The total business value acquired by the employee in a month (negative business indicates cancellation/refund or car EMI adjustments) (numerical)

• Quarterly Rating : Quarterly rating of the employee: 1,2,3,4,5 (categorical, ordinal - higher is better)

```
ola.describe()
```

	Unnamed: 0	Driver_ID	Age	Gender	Education_Level	Income	Joining Designation	Grade	Total Business Value	Quarterly Rating
count	19104.000000	19104.000000	19043.000000	19052.000000	19104.000000	19104.000000	19104.000000	19104.000000	1.910400e+04	19104.000000
mean	9551.500000	1415.591133	34.668435	0.418749	1.021671	65652.025126	1.690536	2.252670	5.716621e+05	2.008899
std	5514.994107	810.705321	6.257912	0.493367	0.800167	30914.515344	0.836984	1.026512	1.128312e+06	1.009832
min	0.000000	1.000000	21.000000	0.000000	0.000000	10747.000000	1.000000	1.000000	-6.000000e+06	1.000000
25%	4775.750000	710.000000	30.000000	0.000000	0.000000	42383.000000	1.000000	1.000000	0.000000e+00	1.000000
50%	9551.500000	1417.000000	34.000000	0.000000	1.000000	60087.000000	1.000000	2.000000	2.500000e+05	2.000000
75%	14327.250000	2137.000000	39.000000	1.000000	2.000000	83969.000000	2.000000	3.000000	6.997000e+05	3.000000
max	19103.000000	2788.000000	58.000000	1.000000	2.000000	188418.000000	5.000000	5.000000	3.374772e+07	4.000000

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

	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

```
# since  unnamed and driver_id columns have the highest correlation and they r the same
# here, dropping unnamed column
```

```
ola.drop(columns='Unnamed: 0',axis=1,inplace=True)
```

```
ola.nunique()
```

```
MMM-YY                     24
Driver_ID                2381
Age                        36
Gender                      2
City                       29
Education_Level             3
Income                   2383
Dateofjoining             869
LastWorkingDate           493
Joining Designation         5
Grade                       5
Total Business Value    10181
Quarterly Rating            4
dtype: int64
```

```
ola.isna().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
```

```
ola.head(3)
```

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value	Quarterly Rating
0	01/01/19	1	28.0	0.0	C23	2	57387	24/12/18	NaN	1	1	2381060	2
1	02/01/19	1	28.0	0.0	C23	2	57387	24/12/18	NaN	1	1	-665480	2
2	03/01/19	1	28.0	0.0	C23	2	57387	24/12/18	03/11/19	1	1	0	2

DATA PROCESSING AND FEATURE ENGINEERING

```
ola1 = ola.copy(deep=True)
```

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

first =  (ola1.groupby('Driver_ID').agg({'LastWorkingDate':'last'})['LastWorkingDate'].isna()).reset_index()
first['LastWorkingDate'].replace({True:1,False:0},inplace=True)
first.rename(columns={'LastWorkingDate':'target'},inplace=True)
first.head()
```

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

```
# Create a column which tells whether the quarterly rating has increased for that driver -
# for those whose quarterly rating has increased we assign the value 1
QR1 =  (ola1.groupby('Driver_ID').agg({'Quarterly Rating':'first'})['Quarterly Rating']).reset_index()
QR2 = (ola1.groupby('Driver_ID').agg({'Quarterly Rating':'last'})['Quarterly Rating']).reset_index()
```

```
QR1.shape,QR2.shape
```

```
((2381, 2), (2381, 2))
```

```
QR1.isna().sum(),QR2.isna().sum()
```

```
(Driver_ID           0
 Quarterly Rating    0
 dtype: int64,
 Driver_ID           0
 Quarterly Rating    0
 dtype: int64)
```

```
first = first.merge(QR1,on='Driver_ID')
first = first.merge(QR2,on='Driver_ID')
```

```
first.head()
```

	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

```
first['Promotion'] = np.where(first['Quarterly Rating_x'] == first['Quarterly Rating_y'], 0,1)
```

```
# Create a column which tells whether the monthly income has increased for that driver -
# for those whose monthly income has increased we assign the value 1
incm1 =  (ola1.groupby('Driver_ID').agg({'Income':'first'})['Income']).reset_index()
incm2 = (ola1.groupby('Driver_ID').agg({'Income':'last'})['Income']).reset_index()
```

```
incm1.shape,incm2.shape
```

```
((2381, 2), (2381, 2))
```

```
incm1.isna().sum(),incm2.isna().sum()
```

```
(Driver_ID    0
 Income       0
 dtype: int64,
 Driver_ID    0
 Income       0
 dtype: int64)
```

```
first = first.merge(incm1,on='Driver_ID')
first = first.merge(incm2,on='Driver_ID')
```

```
first.head()
```

	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

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

```
first.head()
```

	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

```
first.tail()
```

	Driver_ID	target	Quarterly Rating_x	Quarterly Rating_y	Promotion	Income_x	Income_y	Raise
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

```
first = first[['Driver_ID','target','Raise','Promotion']]
```

```
first.head()
```

	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

```
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'}
ola1 = ola1.groupby([ola1['Driver_ID']]).aggregate(functions)
ola1['month'] = pd.to_datetime(ola['Dateofjoining']).dt.month
ola1['year'] = pd.DatetimeIndex(ola1['Dateofjoining']).year
ola1.rename(columns={'MMM-YY':'Reportings'},inplace=True)
```

```
ola1.reset_index(drop=True, inplace=True)
ola1 = ola1.merge(first,on='Driver_ID')
ola1.head()
```

	Reportings	Driver_ID	Age	Gender	City	Education_Level	Dateofjoining	LastWorkingDate	Grade	Total Business Value	Income	Joining Designation	Quarterly Rating	month	year	target	Raise	Promotion
0	3	1	28.0	0.0	C23	2	24/12/18	03/11/19	1	1715580	172161	1	2	12	2018	0	0	0
1	2	2	31.0	0.0	C7	2	11/06/20	None	2	0	134032	2	1	12	2020	1	0	0
2	5	4	43.0	0.0	C13	2	12/07/19	27/04/20	2	350000	328015	2	1	11	2019	0	0	0
3	3	5	29.0	0.0	C9	0	01/09/19	03/07/19	1	120360	139104	1	1	12	2019	0	0	0
4	5	6	31.0	1.0	C11	1	31/07/20	None	3	1265000	393640	3	1	12	2020	1	0	1

```
import regex
ola1['Age'] = ola1['Age'].astype('int64')
ola1['Cities'] =ola1['City'].astype('str').str.extractall('(\d+)').unstack().fillna('').sum(axis=1).astype(int)
```

```
ola1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 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   int32  
 14  year                   2381 non-null   int32  
 15  target                 2381 non-null   int64  
 16  Raise                  2381 non-null   int64  
 17  Promotion              2381 non-null   int64  
 18  Cities                 2381 non-null   int64  
dtypes: float64(1), int32(2), int64(13), object(3)
memory usage: 335.0+ KB
```

```
ola1.drop(columns=['Dateofjoining','LastWorkingDate','City'],axis=1,inplace=True)
ola1['Gender'].replace({'M':0,'F':1},inplace=True)
ola1['Gender'] = ola1['Gender'].astype('int64')
```

```
ola1.head()
```

	Reportings	Driver_ID	Age	Gender	Education_Level	Grade	Total Business Value	Income	Joining Designation	Quarterly Rating	month	year	target	Raise	Promotion	Cities
0	3	1	28	0	2	1	1715580	172161	1	2	12	2018	0	0	0	23
1	2	2	31	0	2	2	0	134032	2	1	12	2020	1	0	0	7
2	5	4	43	0	2	2	350000	328015	2	1	11	2019	0	0	0	13
3	3	5	29	0	0	1	120360	139104	1	1	12	2019	0	0	0	9
4	5	6	31	1	1	3	1265000	393640	3	1	12	2020	1	0	1	11

```
sum(ola1.isna().sum())
```

```
0
```

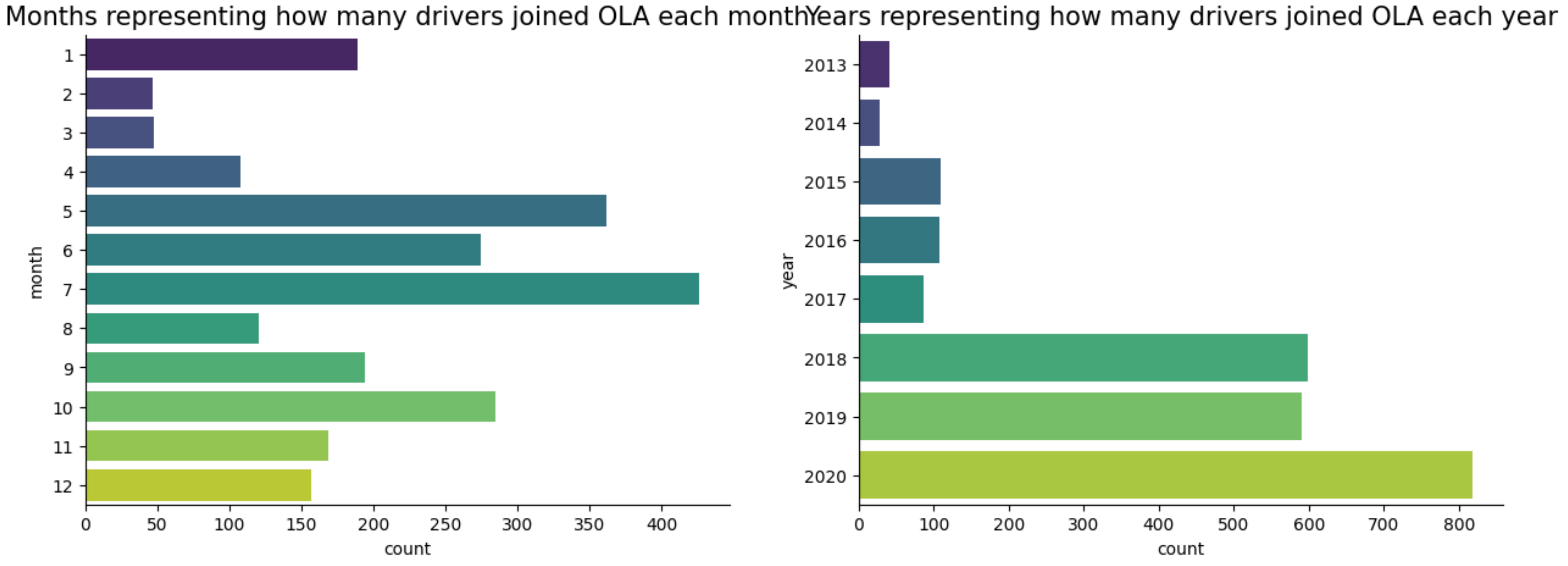
```
ola1.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Reportings	2381.0	8.023520e+00	6.783590e+00	1.0	3.0	5.0	10.0	24.0
Driver_ID	2381.0	1.397559e+03	8.061616e+02	1.0	695.0	1400.0	2100.0	2788.0
Age	2381.0	3.366317e+01	5.983375e+00	21.0	29.0	33.0	37.0	58.0
Gender	2381.0	4.103318e-01	4.919972e-01	0.0	0.0	0.0	1.0	1.0
Education_Level	2381.0	1.007560e+00	8.162900e-01	0.0	0.0	1.0	2.0	2.0
Grade	2381.0	2.096598e+00	9.415218e-01	1.0	1.0	2.0	3.0	5.0
Total Business Value	2381.0	4.586742e+06	9.127115e+06	-1385530.0	0.0	817680.0	4173650.0	95331060.0
Income	2381.0	5.267603e+05	6.231633e+05	10883.0	139895.0	292980.0	651456.0	4522032.0
Joining Designation	2381.0	1.820244e+00	8.414334e-01	1.0	1.0	2.0	2.0	5.0
Quarterly Rating	2381.0	1.486350e+00	8.343483e-01	1.0	1.0	1.0	2.0	4.0
month	2381.0	6.975220e+00	3.007801e+00	1.0	5.0	7.0	10.0	12.0
year	2381.0	2.018536e+03	1.609597e+00	2013.0	2018.0	2019.0	2020.0	2020.0
target	2381.0	3.212936e-01	4.670713e-01	0.0	0.0	0.0	1.0	1.0
Raise	2381.0	1.805964e-02	1.331951e-01	0.0	0.0	0.0	0.0	1.0
Promotion	2381.0	3.427131e-01	4.747162e-01	0.0	0.0	0.0	1.0	1.0
Cities	2381.0	1.533557e+01	8.371843e+00	1.0	8.0	15.0	22.0	29.0

DATA VISUALIZATION

Univariate

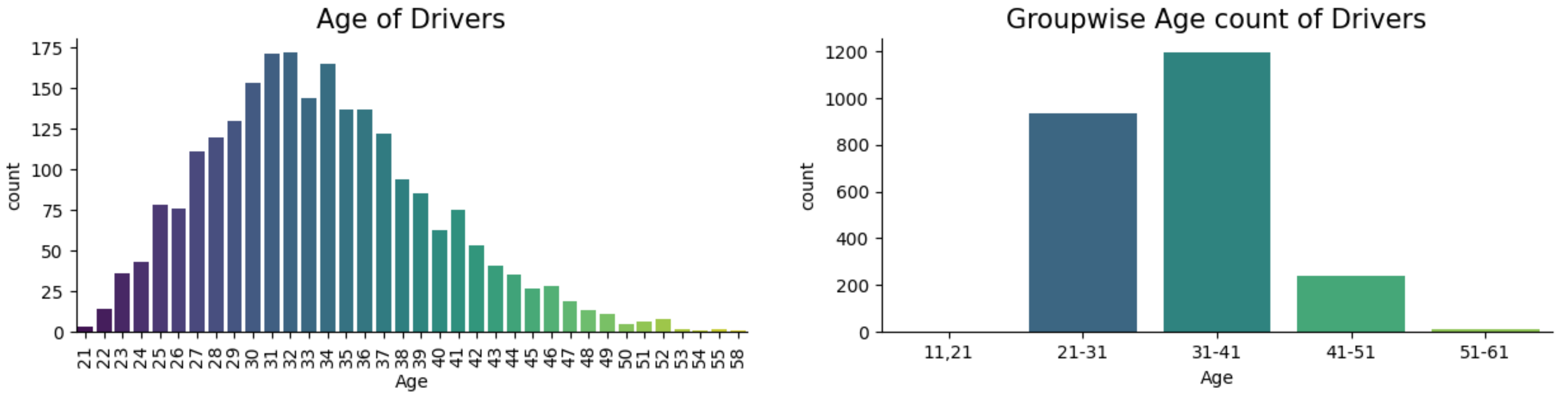
```
# figure1
fig = plt.figure(figsize=(15,5))
ax = fig.add_subplot(1,2,1)
sns.countplot(y=ola1.month,palette='viridis')
plt.title('Months representing how many drivers joined OLA each month',fontname='Franklin Gothic Medium', fontsize=15)


ax = fig.add_subplot(1,2,2)
sns.countplot(y=ola1.year,palette='viridis')
plt.title('Years representing how many drivers joined OLA each year',fontname='Franklin Gothic Medium', fontsize=15)
sns.despine()
plt.show()
```



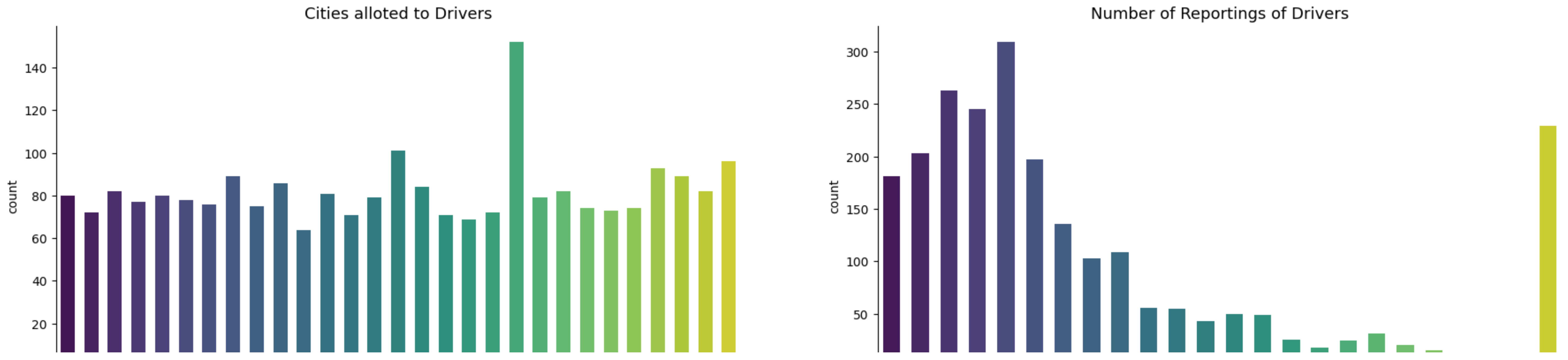
Observations:

```
- 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.
```

```
# figure2
fig = plt.figure(figsize=(15,3))
ax = fig.add_subplot(121)
sns.countplot(x=ola1.Age,palette='viridis',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(ola1.Age,bins=[11,21,31,41,51,61],labels=['11,21','21-31','31-41','41-51','51-61'])
sns.countplot(x=a,palette='viridis')
plt.title('Groupwise Age count of Drivers',fontname='Franklin Gothic Medium', fontsize=15)
sns.despine()
plt.show()
```

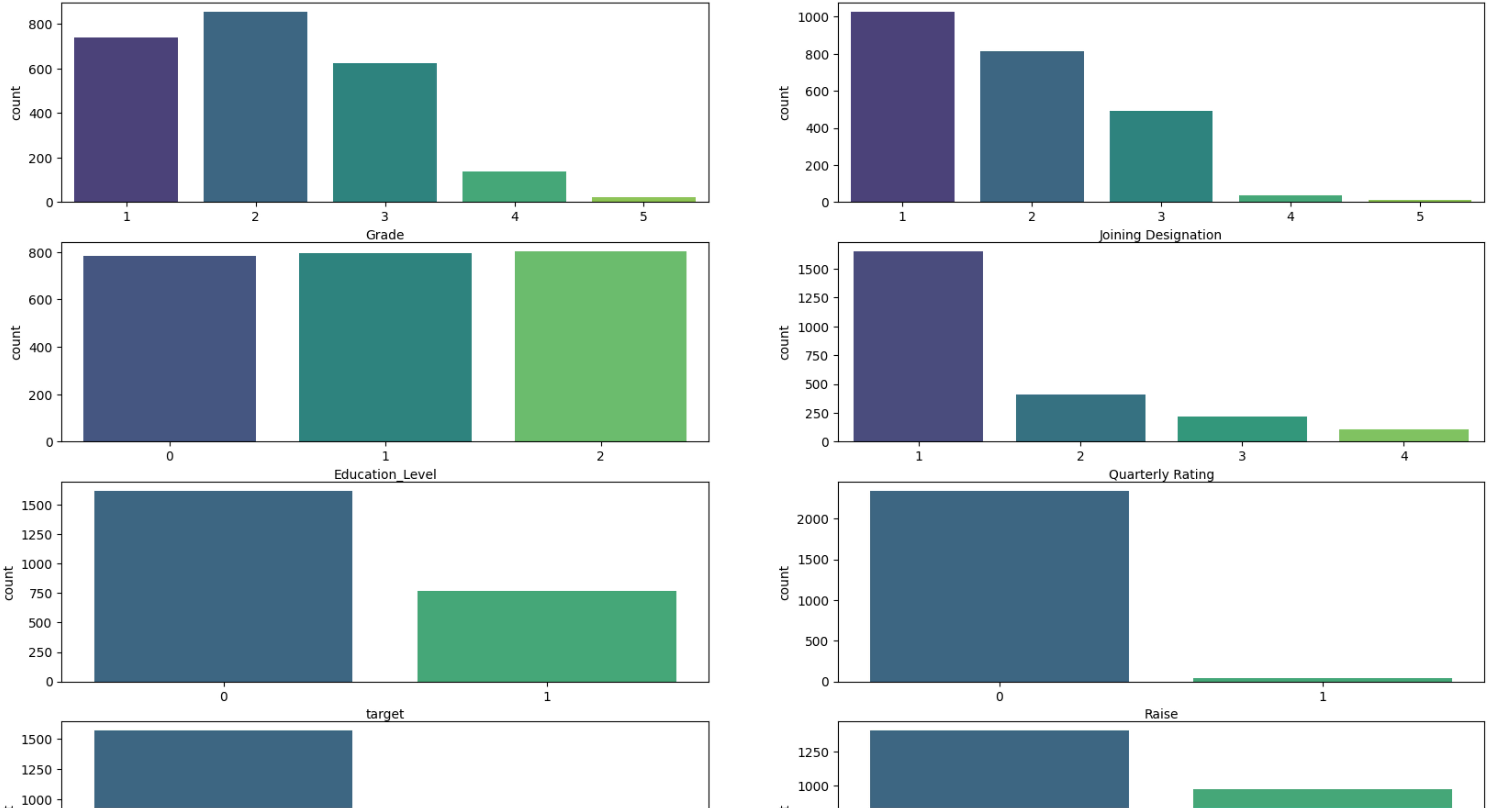


```python
# figure3
fig = plt.figure(figsize=(22,5))
ax = fig.add_subplot(121)
sns.countplot(x=ola1.Cities,palette='viridis',width=0.6)
plt.title('Cities alloted to Drivers',fontname='Franklin Gothic Medium', fontsize=13)
plt.xticks(rotation=90)

ax = fig.add_subplot(122)
sns.countplot(x=ola1.Reportings,palette='viridis',width=0.6)
plt.title('Number of Reportings of Drivers',fontname='Franklin Gothic Medium', fontsize=13)

# ax = fig.add_subplot(133)
# sns.countplot(x=ola1.Education_Level,palette='viridis')
# plt.title('Educational Level of Drivers',fontname='Franklin Gothic Medium', fontsize=13)
sns.despine()
plt.show()
```




```python
# figure4
plt.figure(figsize=(20,13))
plt.subplot(4,2,1)
sns.countplot(x=ola1.Grade,palette='viridis')
# plt.title('Grade given to different Drivers',fontname='Franklin Gothic Medium', fontsize=15)
plt.subplot(4,2,2)
sns.countplot(x=ola1['Joining Designation'],palette='viridis')
# plt.title('Grade given to different Drivers',fontname='Franklin Gothic Medium', fontsize=15)
plt.subplot(4,2,3)
sns.countplot(x=ola1.Education_Level,palette='viridis')
# plt.title('Grade given to different Drivers',fontname='Franklin Gothic Medium', fontsize=15)
plt.subplot(4,2,4)
sns.countplot(x=ola1['Quarterly Rating'],palette='viridis')
# plt.title('Grade given to different Drivers',fontname='Franklin Gothic Medium', fontsize=15)
plt.subplot(4,2,5)
sns.countplot(x=ola1.target,palette='viridis')
# plt.title('Grade given to different Drivers',fontname='Franklin Gothic Medium', fontsize=15)
plt.subplot(4,2,6)
sns.countplot(x=ola1.Raise,palette='viridis')
# plt.title('Grade given to different Drivers',fontname='Franklin Gothic Medium', fontsize=15)
```

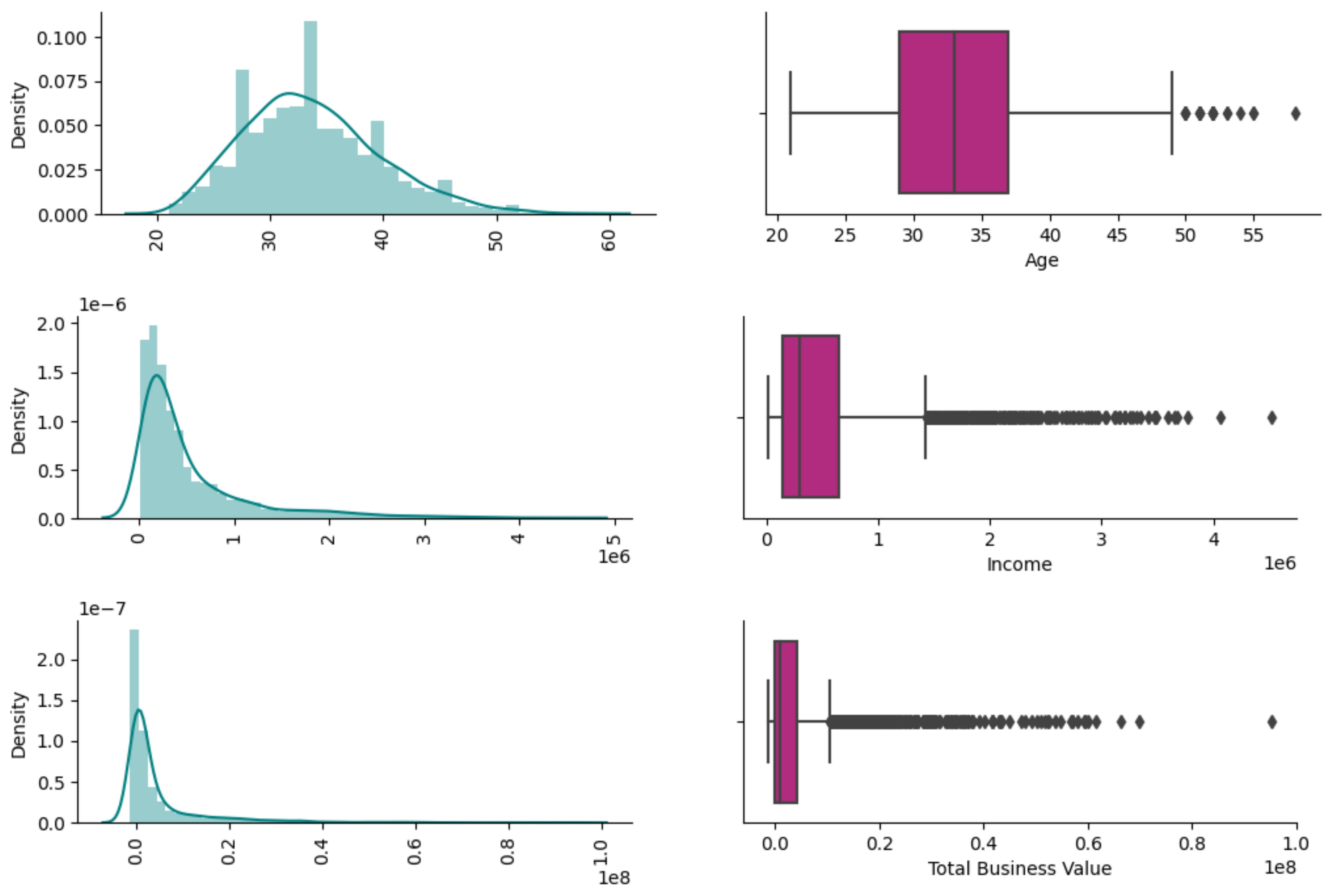
```
plt.subplot(4,2,7)
sns.countplot(x=ola1.Promotion,palette='viridis')
# plt.title('Grade given to different Drivers',fontname='Franklin Gothic Medium', fontsize=15)
plt.subplot(4,2,8)
sns.countplot(x=ola1.Gender,palette='viridis')
# plt.title('Grade given to different Drivers',fontname='Franklin Gothic Medium', fontsize=15)
plt.show()
```



Observations:

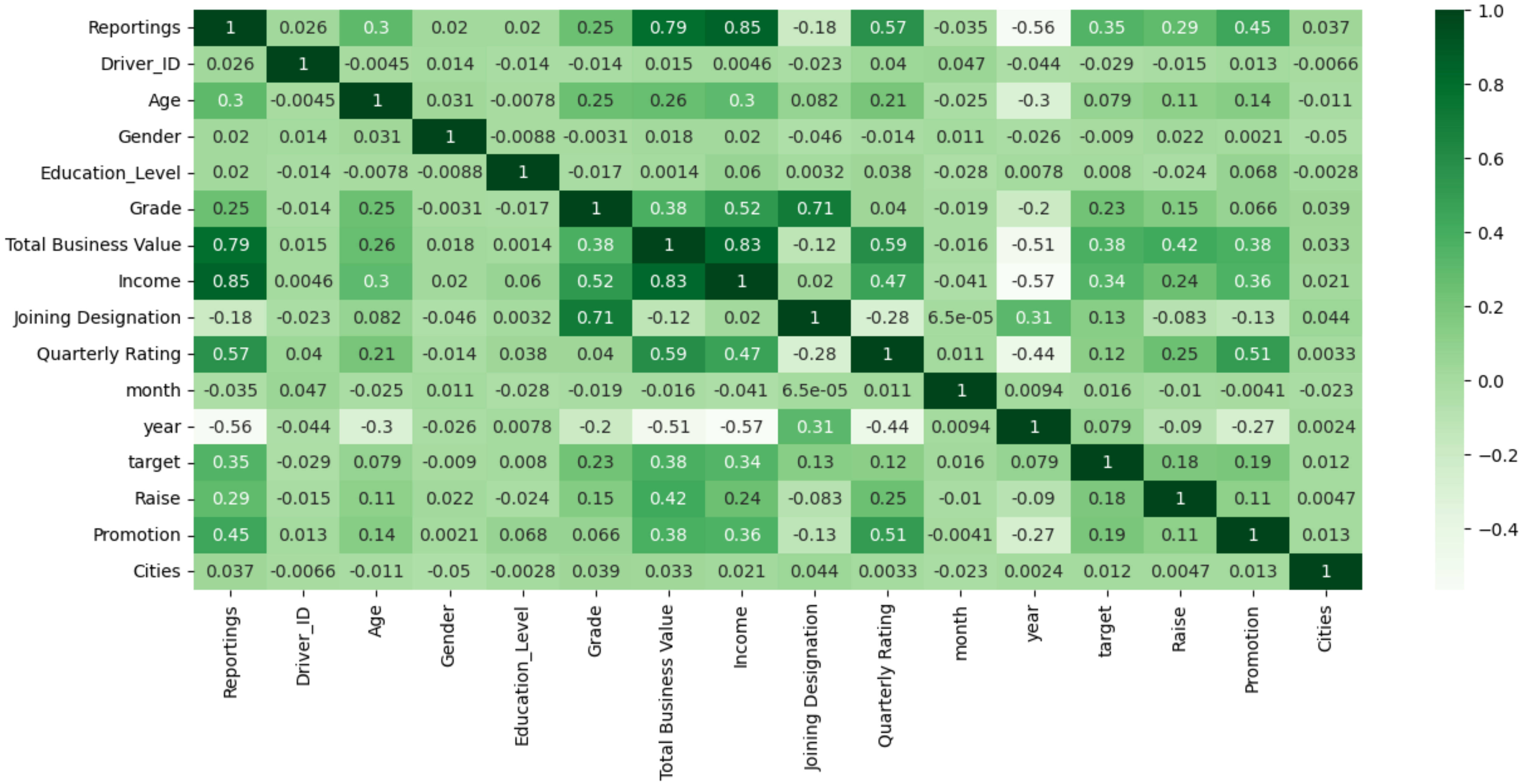
```
- Between 21 years(min age) to 58(max age) years of age, maximum number of drivers are 32 years o
meanwhile the age group between 31-41 years of age receives the maximum number of drivers.
- 58.9% of the Drivers are male.
- City C20 has been used by the most of the drivers.
- There are 3 Education levels and all of them alomst have the equal distribution of Drivers.
- Grade 2 has been received by most of the Drivers and then the count of grade keeps on falling.
```

```
a =ola1[['Age','Income','Total Business Value']]
for i in a:
    plt.figure(figsize=(12,2))
    plt.subplot(121)
    sns.distplot(x=ola1[i],color='teal')
    plt.title('')
    plt.xticks(rotation=90)

    plt.subplot(122)
    sns.boxplot(x=ola1[i],color='mediumvioletred')
    plt.title('')
    sns.despine()
    plt.show()
```

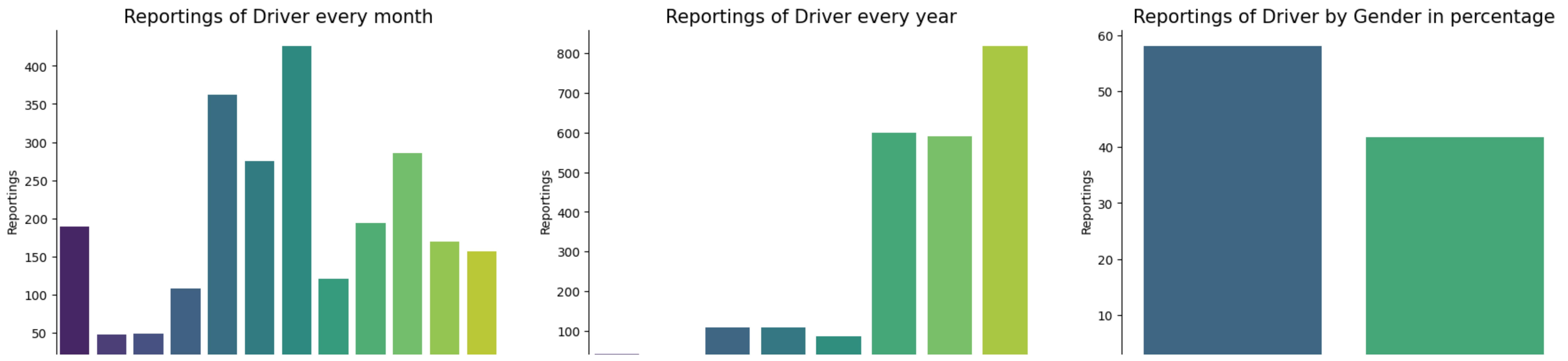


Bivariate and multivariate

```
corr = ola1.corr()
plt.figure(figsize=(15,6))
sns.heatmap(corr,annot=True,cmap='Greens')
plt.show()
```



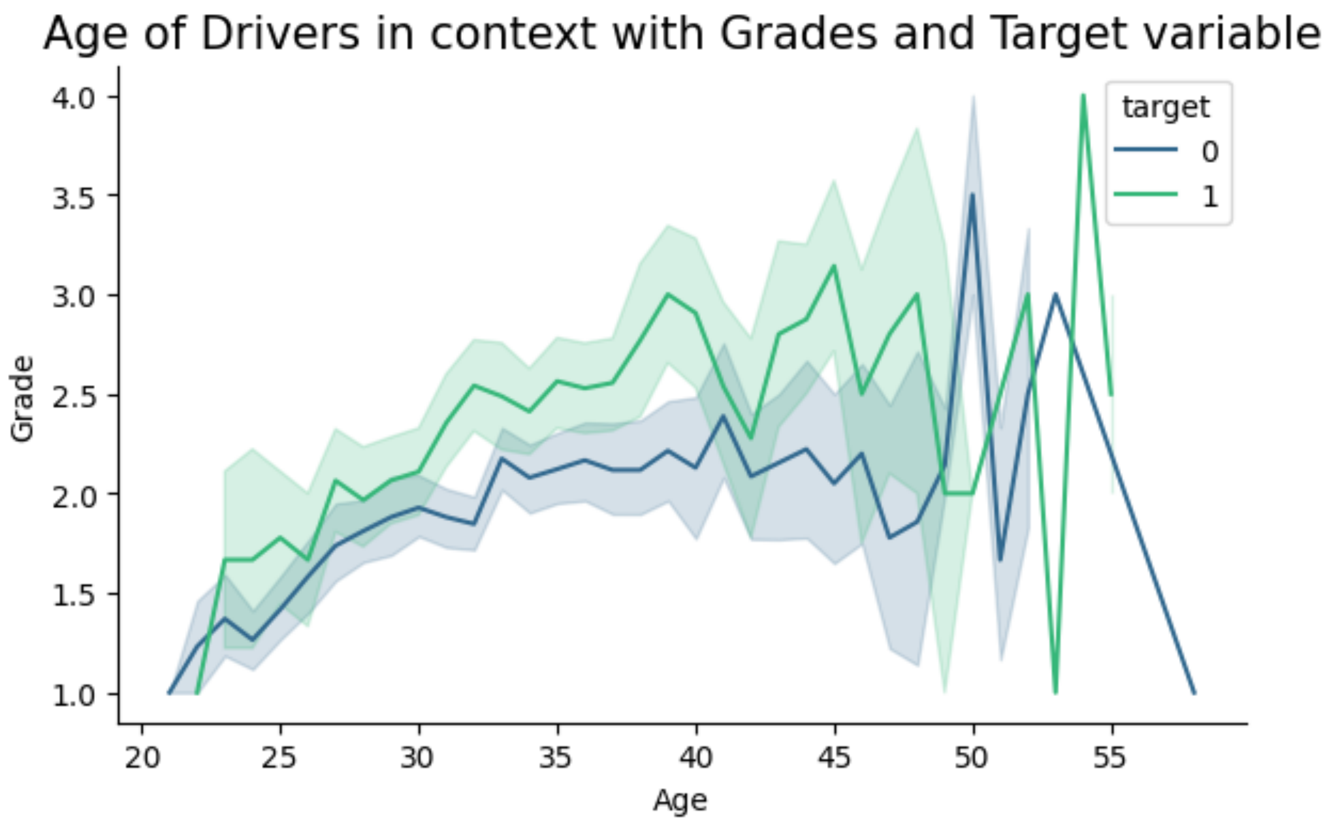
```
fig = plt.figure(figsize=(22,5))
ax = fig.add_subplot(1,3,1)
grouped_months = ola1.groupby(['month'])['Reportings'].count().reset_index()
sns.barplot(data=grouped_months,x='month',y='Reportings',palette='viridis')
plt.title('Reportings of Driver every month',fontname='Franklin Gothic Medium', fontsize=15)

ax = fig.add_subplot(1,3,2)
grouped_years = ola1.groupby(['year'])['Reportings'].count().reset_index()
sns.barplot(x='year', y='Reportings', data=grouped_years,palette='viridis')
plt.title('Reportings of Driver every year',fontname='Franklin Gothic Medium', fontsize=15)

ax = fig.add_subplot(1,3,3)
grouped_gender = ola1.groupby('Gender')['Reportings'].sum().reset_index()
grouped_gender['Reportings'] =(grouped_gender['Reportings']/sum(ola1.Reportings)*100).round(2)
sns.barplot(x=grouped_gender['Gender'],y= grouped_gender['Reportings'],palette='viridis')
plt.title('Reportings of Driver by Gender in percentage',fontname='Franklin Gothic Medium', fontsize=15)
sns.despine()
sns.despine()
plt.show()
```

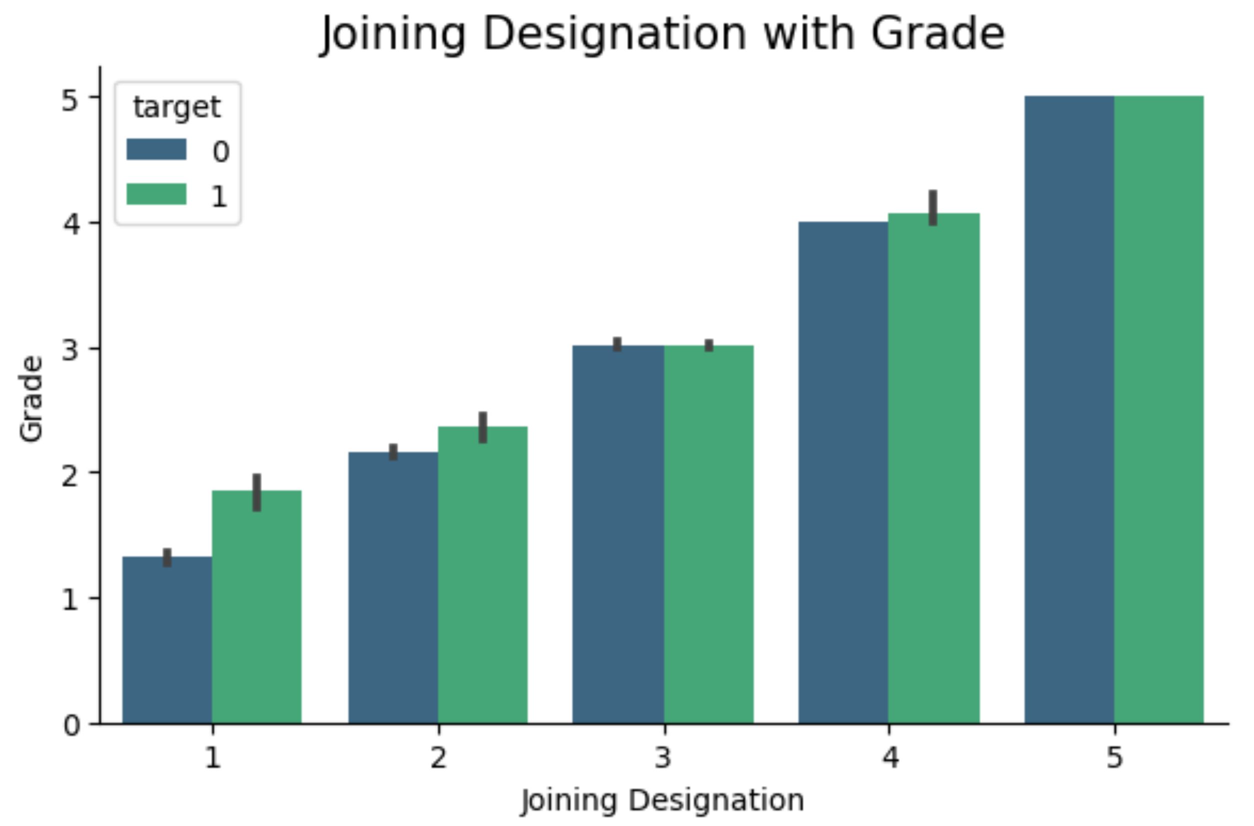



```
grouped_gender
```

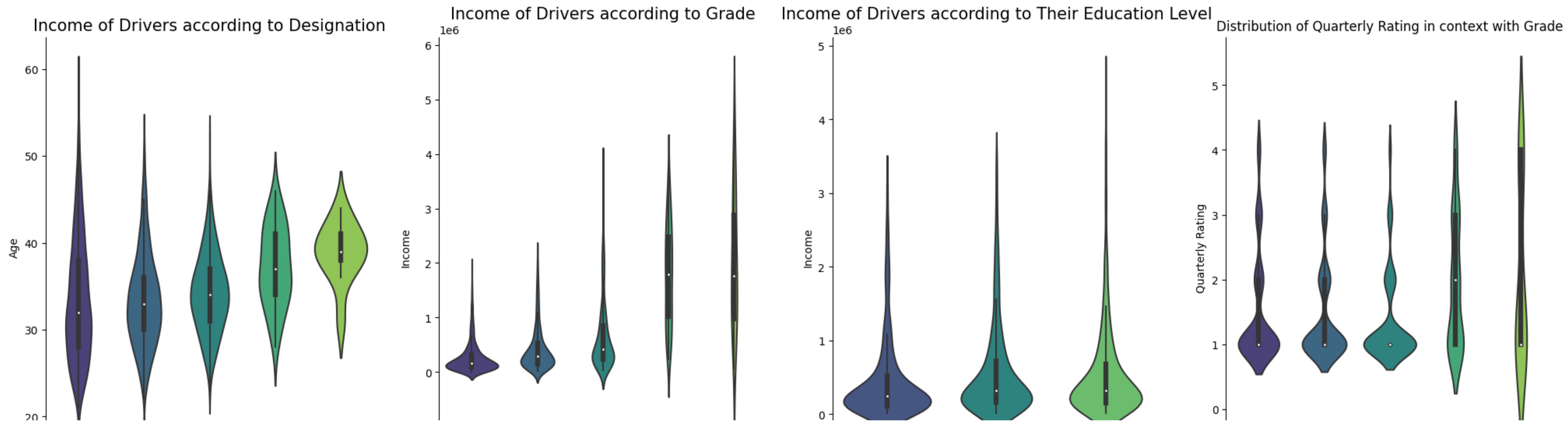
	Gender	Reportings
0	0	58.12
1	1	41.88

```
fig = plt.figure(figsize=(15,4))
ax = fig.add_subplot(1,2,1)
sns.lineplot(x=ola1.Age,y=ola1.Grade,hue=ola1.target,palette='viridis')
plt.title('Age of Drivers in context with Grades and Target variable',fontname='Franklin Gothic Medium', fontsize=15)

ax = fig.add_subplot(1,2,2)
sns.barplot(data=ola1, x="Joining Designation", y="Grade",palette='viridis',hue='target')
plt.title('Joining Designation with Grade',fontname='Franklin Gothic Medium', fontsize=15)
sns.despine()
plt.show()
```

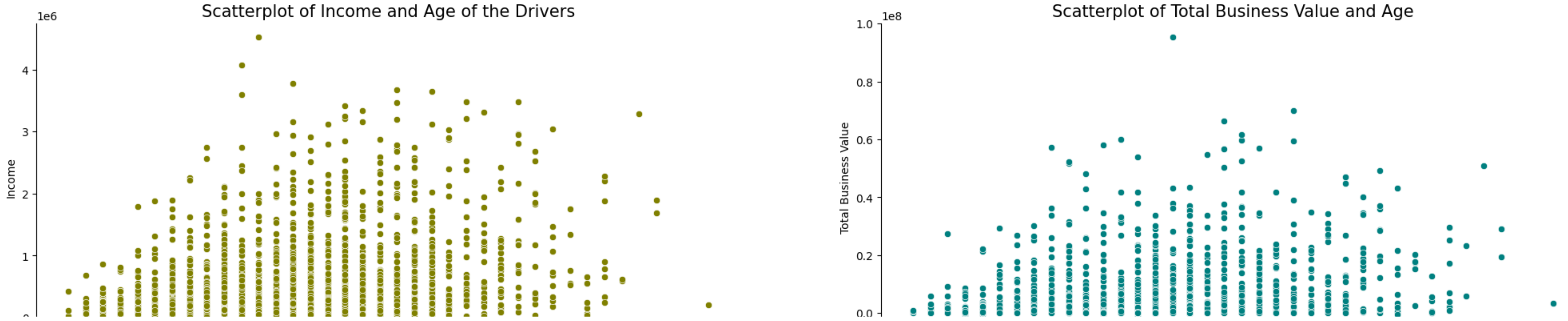




```
# figure7
plt.figure(figsize=(25,7))
plt.subplot(1,4,1)
sns.violinplot(y=ola1.Age,x=ola1['Joining Designation'],palette='viridis')
plt.title('Income of Drivers according to Designation',fontname='Franklin Gothic Medium', fontsize=15)
plt.subplot(1,4,2)
sns.violinplot(x=ola1.Grade,y=ola1.Income,palette='viridis')
plt.title('Income of Drivers according to Grade',fontname='Franklin Gothic Medium', fontsize=15)
plt.xticks(rotation=90)
plt.subplot(1,4,3)
sns.violinplot(x=ola1.Education_Level,y=ola1.Income,palette='viridis')
plt.title('Income of Drivers according to Their Education Level',fontname='Franklin Gothic Medium', fontsize=15)
plt.subplot(1,4,4)
sns.violinplot(x=ola1['Grade'],y=ola1["Quarterly Rating"],palette='viridis')
plt.title('Distribution of Quarterly Rating in context with Grade')
sns.despine()
sns.despine()
plt.show()
```



```
plt.figure(figsize=(25,5))
plt.subplot(1,2,1)
sns.scatterplot(x=ola1.Age,y=ola1.Income,color='olive')
plt.title('Scatterplot of Income and Age of the Drivers',fontname='Franklin Gothic Medium', fontsize=15)
plt.subplot(1,2,2)
sns.scatterplot(x=ola1.Age,y=ola1['Total Business Value'],color='teal')
plt.title('Scatterplot of Total Business Value and Age',fontname='Franklin Gothic Medium', fontsize=15)
sns.despine()
plt.show()
```



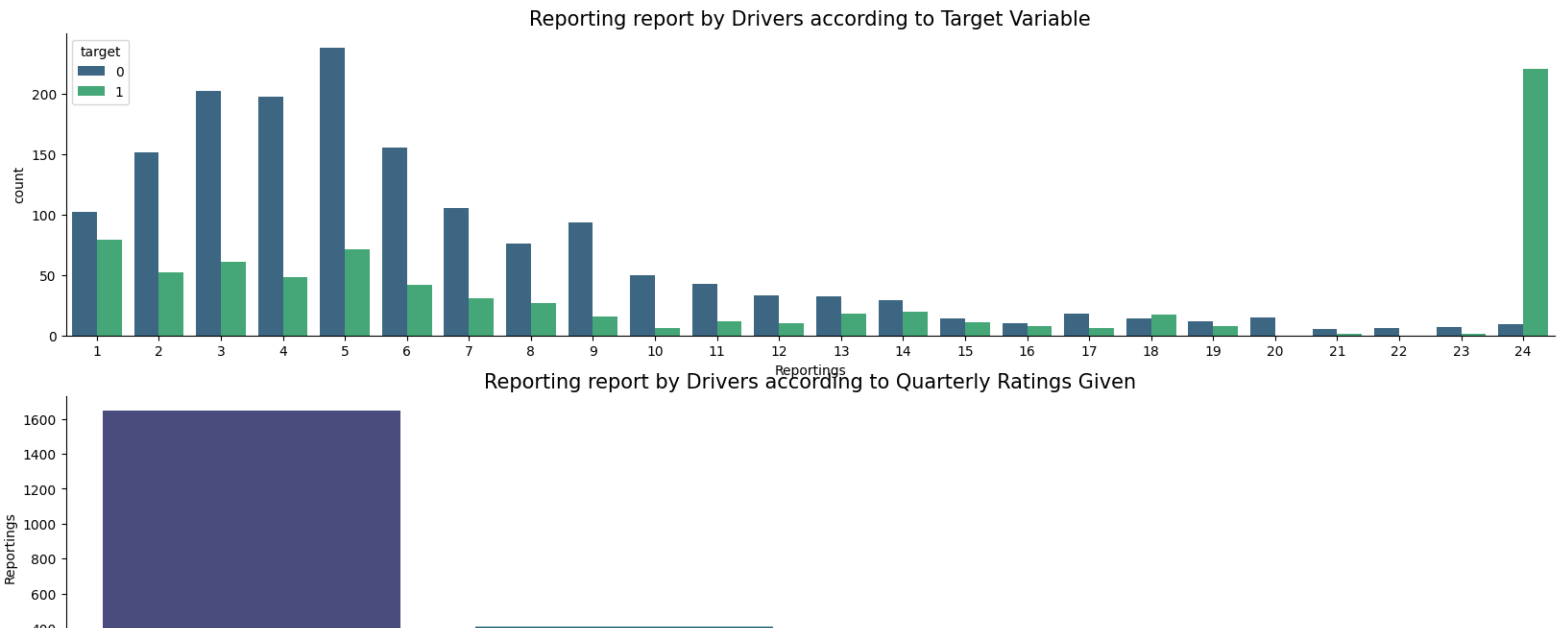

```
grouped_gender = ola1.groupby('Gender')['Income'].sum().reset_index()
grouped_education = ola1.groupby('Education_Level')['Income'].sum().reset_index()
grouped_grade = ola1.groupby('Grade')['Income'].sum().reset_index()
grouped_desig = ola1.groupby('Joining Designation')['Income'].sum().reset_index()
grouped_QR = ola1.groupby('Quarterly Rating')['Income'].sum().reset_index()
grouped_target = ola1.groupby('target')['Income'].sum().reset_index()
grouped_raise = ola1.groupby('Raise')['Income'].sum().reset_index()
grouped_promote = ola1.groupby('Promotion')['Income'].sum().reset_index()
```

```
plt.figure(figsize=(15,8))
plt.subplot(3,3,1)
plt.pie(grouped_gender['Income'], labels=grouped_gender['Gender'], autopct='%1.1f%%', startangle=90,colors=sns.color_palette('flare'))
hole = plt.Circle((0, 0), 0.5, facecolor='white')
plt.gcf().gca().add_artist(hole)
plt.title('Income with respect to Gender')
plt.subplot(3,3,2)
plt.pie(grouped_education['Income'], labels=grouped_education['Education_Level'], autopct='%1.1f%%', startangle=90,colors=sns.color_palette('flare'))
hole = plt.Circle((0, 0), 0.5, facecolor='white')
plt.gcf().gca().add_artist(hole)
plt.title('Income with respect to Education Level')
plt.subplot(3,3,3)
plt.pie(grouped_grade['Income'], labels=grouped_grade['Grade'], autopct='%1.1f%%', startangle=90,colors=sns.color_palette('flare'))
hole = plt.Circle((0, 0), 0.5, facecolor='white')
plt.gcf().gca().add_artist(hole)
plt.title('Income with respect to Grade')
plt.subplot(3,3,4)
plt.pie(grouped_desig['Income'], labels=grouped_desig['Joining Designation'], autopct='%1.1f%%', startangle=90,colors=sns.color_palette('flare'))
hole = plt.Circle((0, 0), 0.5, facecolor='white')
```

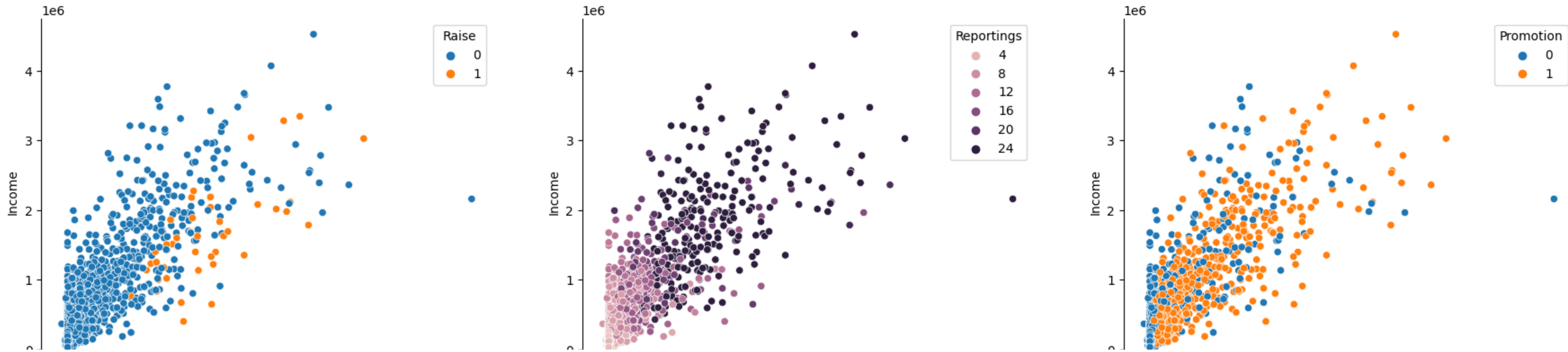
```
plt.gcf().gca().add_artist(hole)
plt.title('Income with respect to Joining Designation')
plt.subplot(3,3,5)
plt.pie(grouped_QR['Income'], labels=grouped_QR['Quarterly Rating'], autopct='%1.1f%%', startangle=90,colors=sns.color_palette('flare'))
hole = plt.Circle((0, 0), 0.5, facecolor='white')
plt.gcf().gca().add_artist(hole)
plt.title('Income with respect to Quarterly Rating')
plt.subplot(3,3,6)
plt.pie(grouped_target['Income'], labels=grouped_target['target'], autopct='%1.1f%%', startangle=90,colors=sns.color_palette('flare'))
hole = plt.Circle((0, 0), 0.5, facecolor='white')
plt.gcf().gca().add_artist(hole)
plt.title('Income with respect to Target variable')
plt.subplot(3,3,7)
plt.pie(grouped_raise['Income'], labels=grouped_raise['Raise'], autopct='%1.1f%%', startangle=90,colors=sns.color_palette('flare'))
hole = plt.Circle((0, 0), 0.5, facecolor='white')
plt.gcf().gca().add_artist(hole)
plt.title('Income with respect to Raise given')
plt.subplot(3,3,8)
plt.pie(grouped_promote['Income'], labels=grouped_promote['Promotion'], autopct='%1.1f%%', startangle=90,colors=sns.color_palette('flare'))
hole = plt.Circle((0, 0), 0.5, facecolor='white')
plt.gcf().gca().add_artist(hole)
plt.title('Income with respect to Promotion Given')
sns.despine()
plt.show()
```


Income with respect to Gender
1
42.2%
0
57.8%
Income with respect to Education Level
0
28.6%
2
35.1%
1
36.3%
Income with respect to Grade
1
15.5%
5
3.8%
4
19.5%
2
28.9%
3
32.3%
Income with respect to Joining Designation
5
4
3
18.6%
1
44.4%
2
32.7%
Income with respect to Quarterly Rating
4
10.2%
3
18.5%
1
44.3%
2
27.1%
Income with respect to Target variable
0
48.9%
1
51.1%
Income with respect to Raise given
1
5.7%
0
94.3%
Income with respect to Promotion Given
0
45.4%
1
54.6%

```
plt.figure(figsize=(20,9))
plt.subplot(2,1,1)
sns.countplot(x=ola1['Reportings'],hue=ola1.target,palette='viridis')
plt.title('Reporting report by Drivers according to Target Variable',fontname='Franklin Gothic Medium', fontsize=15)
plt.subplot(2,1,2)
grouped_rating = ola1.groupby('Quarterly Rating')['Reportings'].count().reset_index()
sns.barplot(data = grouped_rating,y='Reportings',x='Quarterly Rating',palette='viridis')
plt.title('Reporting report by Drivers according to Quarterly Ratings Given',fontname='Franklin Gothic Medium', fontsize=15)
sns.despine()
plt.show()
```



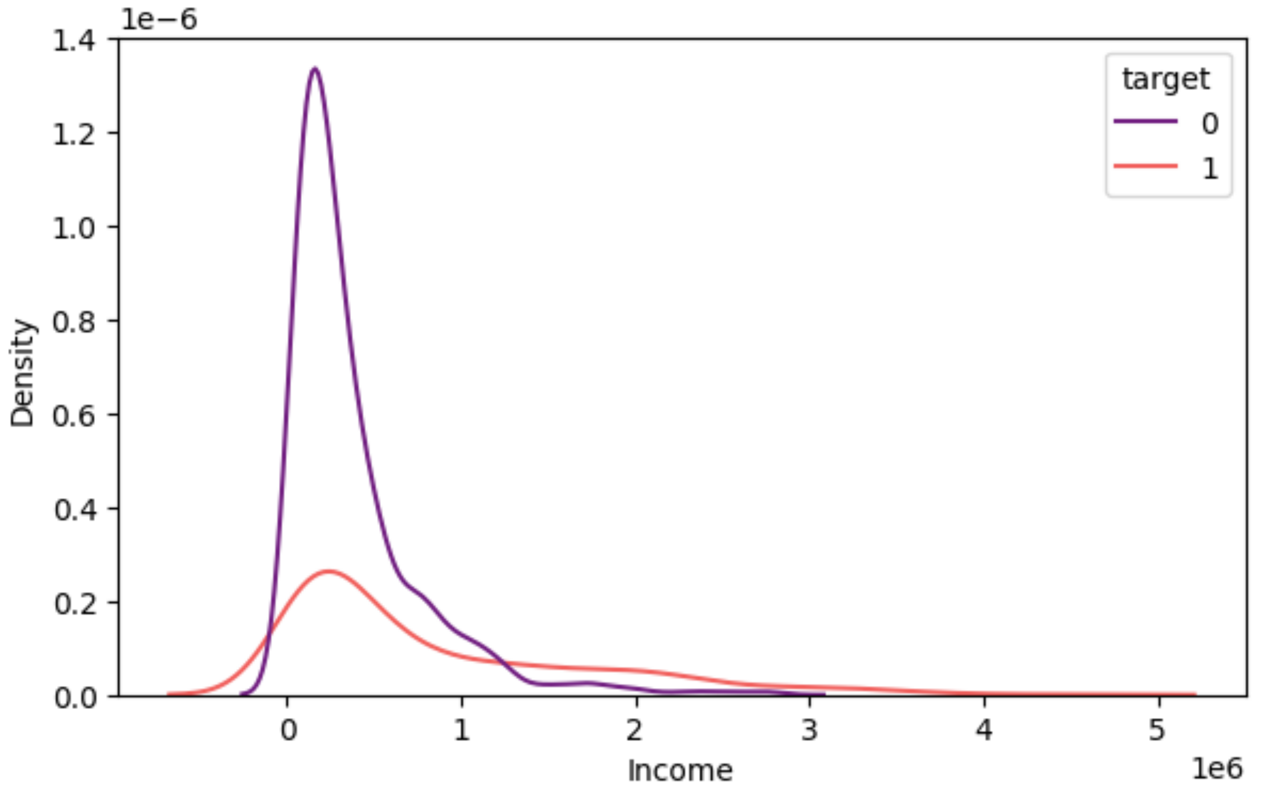
```
plt.figure(figsize=(22,5))
plt.subplot(1,3,1)
sns.scatterplot(x=ola1['Total Business Value'],y=ola1.Income,hue=ola1.Raise)
plt.subplot(1,3,2)
sns.scatterplot(x=ola1['Total Business Value'],y=ola1.Income,hue=ola1.Reportings)
plt.subplot(1,3,3)
sns.scatterplot(x=ola1['Total Business Value'],y=ola1.Income,hue=ola1.Promotion)
sns.despine()
plt.show()
```

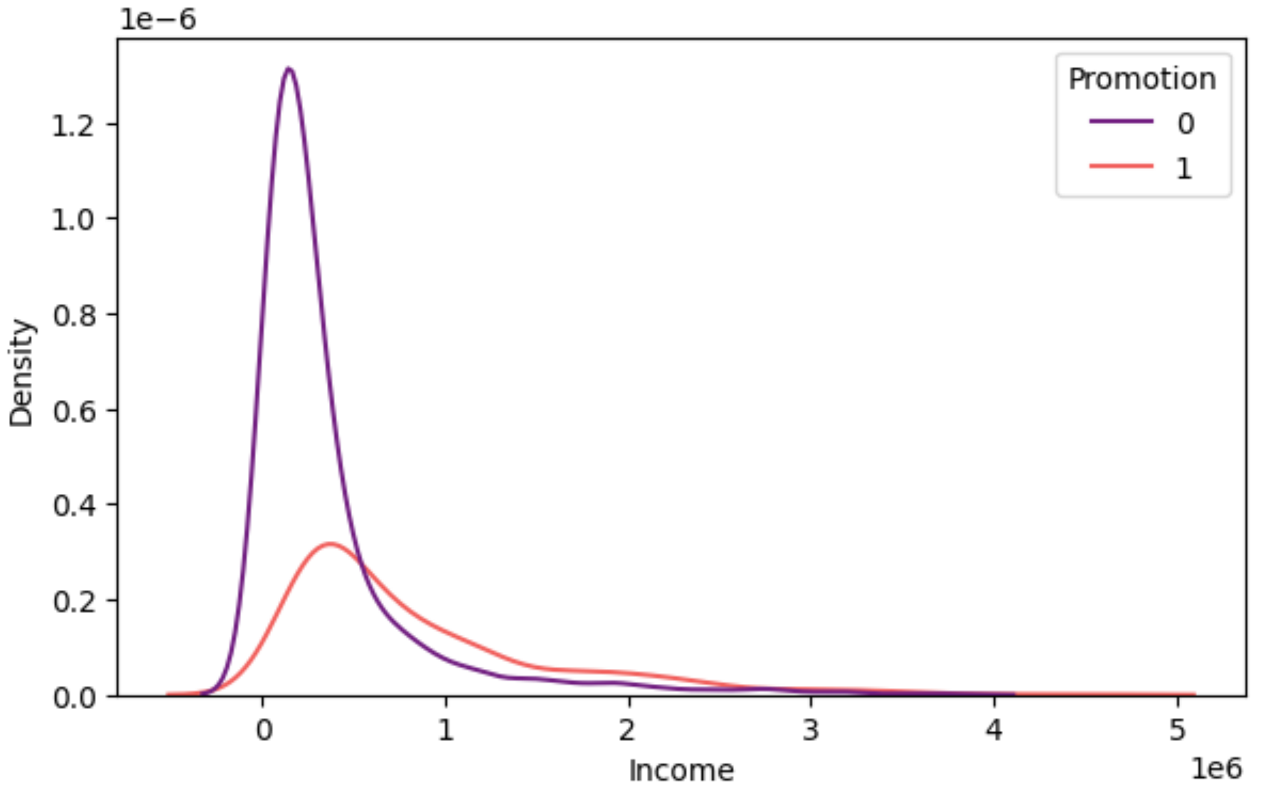


Observation:–

- 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.
- Majority (35%) of the employees currently are at designation level 2, followed by designation level 1 (31%) and 3 (26%). Less than 5% of the employees are currently in higher designations.
- 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 reportings.
- The majority of the employees seem to be associated with city C20.
- 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 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 enployes at different Education level is about a change of 3-5% with level 0.
- Joining Designation Increases with increase in Grade.
- Max reporting days is 24 days.
- About 55% of the reportings of the employees has got Quarlerly Rating 1.
- Number of reportings increases with increase in Income as well as Total Business Value.

```
plt.figure(figsize=(15,4))
plt.subplot(1,2,1)
sns.kdeplot(x=ola1.Income,hue=ola1['target'],palette='magma')
plt.subplot(1,2,2)
sns.kdeplot(x=ola1.Income,hue=ola1['Promotion'],palette='magma')
plt.show()
```





OUTLIER TREATMENT

```
ola1.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Reportings	2381.0	8.023520e+00	6.783590e+00	1.0	3.0	5.0	10.0	24.0
Driver_ID	2381.0	1.397559e+03	8.061616e+02	1.0	695.0	1400.0	2100.0	2788.0
Age	2381.0	3.366317e+01	5.983375e+00	21.0	29.0	33.0	37.0	58.0
Gender	2381.0	4.103318e-01	4.919972e-01	0.0	0.0	0.0	1.0	1.0
Education_Level	2381.0	1.007560e+00	8.162900e-01	0.0	0.0	1.0	2.0	2.0
Grade	2381.0	2.096598e+00	9.415218e-01	1.0	1.0	2.0	3.0	5.0
Total Business Value	2381.0	4.586742e+06	9.127115e+06	-1385530.0	0.0	817680.0	4173650.0	95331060.0
Income	2381.0	5.267603e+05	6.231633e+05	10883.0	139895.0	292980.0	651456.0	4522032.0
Joining Designation	2381.0	1.820244e+00	8.414334e-01	1.0	1.0	2.0	2.0	5.0
Quarterly Rating	2381.0	1.486350e+00	8.343483e-01	1.0	1.0	1.0	2.0	4.0
month	2381.0	6.975220e+00	3.007801e+00	1.0	5.0	7.0	10.0	12.0
year	2381.0	2.018536e+03	1.609597e+00	2013.0	2018.0	2019.0	2020.0	2020.0
target	2381.0	3.212936e-01	4.670713e-01	0.0	0.0	0.0	1.0	1.0
Raise	2381.0	1.805964e-02	1.331951e-01	0.0	0.0	0.0	0.0	1.0
Promotion	2381.0	3.427131e-01	4.747162e-01	0.0	0.0	0.0	1.0	1.0
Cities	2381.0	1.533557e+01	8.371843e+00	1.0	8.0	15.0	22.0	29.0

```
len(ola1[ola1['Total Business Value'] < 1])
```

```
729
```

As we can notice Total Business Value column has some values in negative.

We consider them as outlier which will affect the results of the our machine learning model.

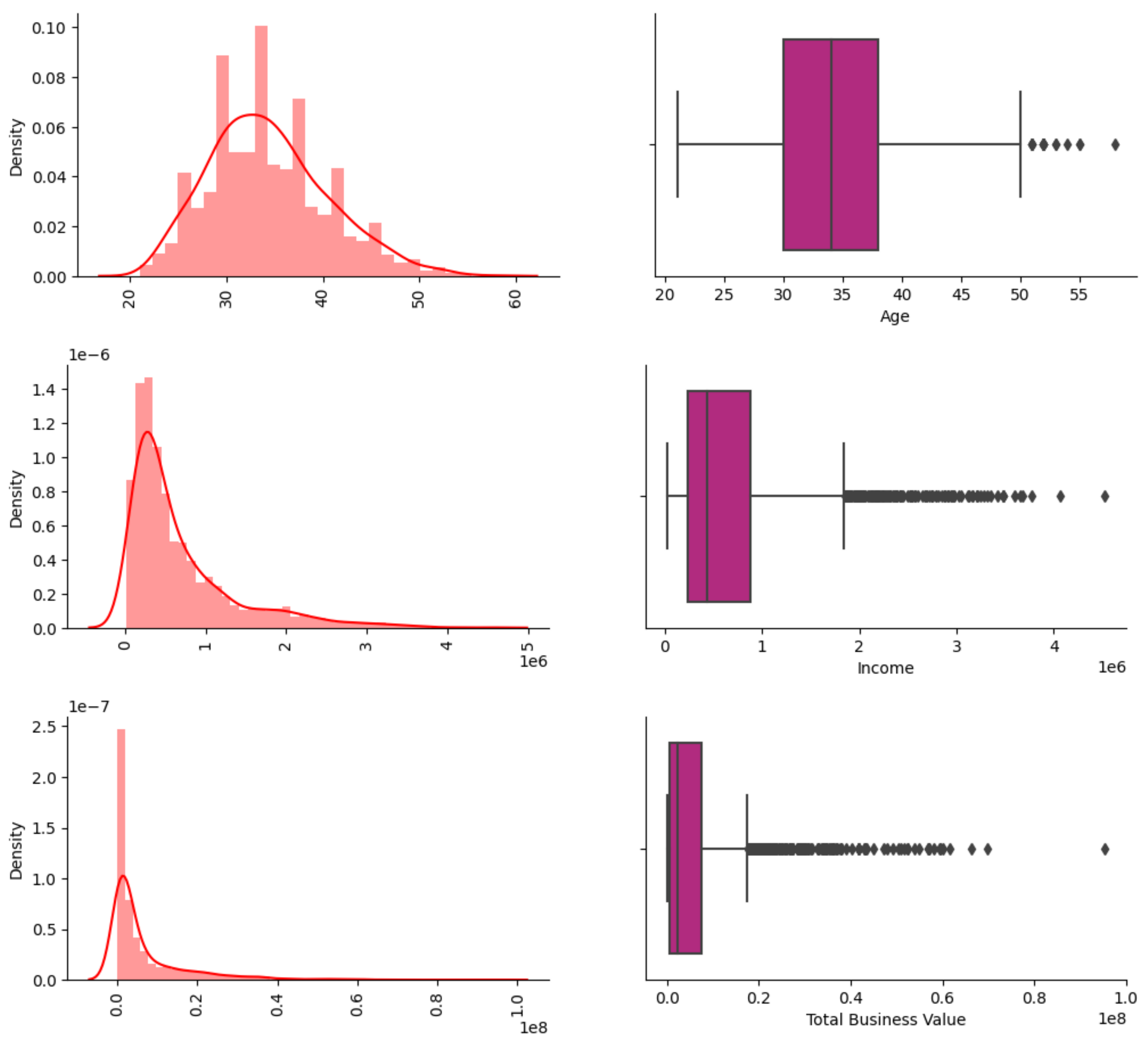
Considering the parts of datasets that has Total Business Value > 1.

There are exactly 729 Driver having Total Business Value that less than 1.

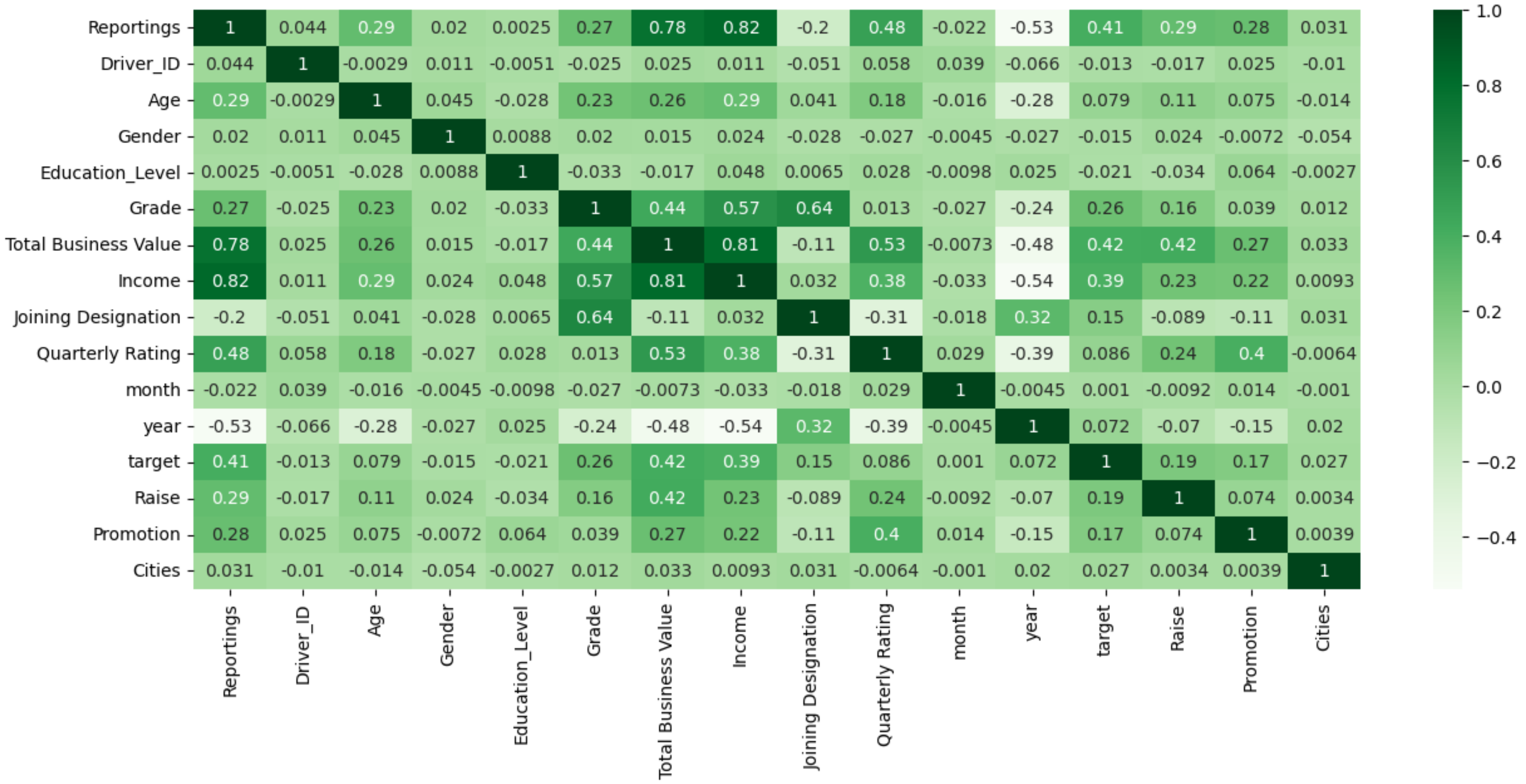
```
ola1= ola1[ola1['Total Business Value'] > 1]
```

```
a =ola1[['Age','Income','Total Business Value']]
for i in a:
    plt.figure(figsize=(12,3))
    plt.subplot(121)
    sns.distplot(x=ola1[i],color='red')
    plt.xticks(rotation=90)
```

```
#     plt.figure(figsize=(9,5))
    plt.subplot(122)
    sns.boxplot(x=ola1[i],color='mediumvioletred')
    sns.despine()
    plt.show()
```



```
corr = ola1.corr()
plt.figure(figsize=(15,6))
sns.heatmap(corr,annot=True,cmap='Greens')
plt.show()
```



```
ola1.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Reportings	1652.0	1.026998e+01	6.967589e+00	1.0	5.0	8.0	14.0	24.0
Driver_ID	1652.0	1.390315e+03	8.082919e+02	1.0	679.5	1385.0	2097.0	2788.0
Age	1652.0	3.432385e+01	6.190776e+00	21.0	30.0	34.0	38.0	58.0
Gender	1652.0	4.158596e-01	4.930188e-01	0.0	0.0	0.0	1.0	1.0
Education_Level	1652.0	1.030872e+00	8.093284e-01	0.0	0.0	1.0	2.0	2.0
Grade	1652.0	2.144068e+00	9.719606e-01	1.0	1.0	2.0	3.0	5.0
Total Business Value	1652.0	6.613094e+06	1.032794e+07	19580.0	663022.5	2242080.0	7418392.5	95331060.0
Income	1652.0	6.864932e+05	6.814522e+05	20886.0	236652.5	428960.0	877151.0	4522032.0
Joining Designation	1652.0	1.759685e+00	8.395129e-01	1.0	1.0	2.0	2.0	5.0
Quarterly Rating	1652.0	1.700363e+00	9.237035e-01	1.0	1.0	1.0	2.0	4.0
month	1652.0	6.914044e+00	3.021205e+00	1.0	5.0	7.0	9.0	12.0
year	1652.0	2.018208e+03	1.730439e+00	2013.0	2018.0	2018.0	2020.0	2020.0
target	1652.0	3.619855e-01	4.807202e-01	0.0	0.0	0.0	1.0	1.0
Raise	1652.0	2.602906e-02	1.592699e-01	0.0	0.0	0.0	0.0	1.0
Promotion	1652.0	4.933414e-01	5.001070e-01	0.0	0.0	0.0	1.0	1.0
Cities	1652.0	1.545278e+01	8.374318e+00	1.0	8.0	16.0	23.0	29.0

ENSEMBLE LEARNING:-

Data Prepration:-

The Trade-Off In general while choosing a model, we might choose to look at precision and recall scores and choose while keeping the follwing trade-off on mind : -

If we prioritize precision, we are going to reduce our false positives. This may be useful if our targeted retention strategies prove to be expensive. We don’t want to spend unnecessarily on somebody who is not even going to leave in the first place. Also, it might lead to uncomfortable situation for the employee themselves if they are put in a situation where it is assumed that they are going to be let go/ going to leave. • If we prioritize recall, we are going to reduce our false negatives. This is useful since usually the cost of hiring a new person is higher than retaining n experienced person. So, by reducing false negatives, we would be able to better identify those who are actually going to leave and try to retain them by appropriate measures (competitve remuneration, engagement program, etc).

```
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
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


X = ola1.drop('target',axis=1)
y = ola1['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state= 42)
```

```
from sklearn.model_selection import learning_curve
def plot_learning_curve(estimator, X, Y, title):
    train_sizes, train_scores, test_scores, _, _ = learning_curve(estimator,X,Y,return_times=True)
    fig, axes = plt.subplots(1, 1, figsize = (15, 5))
    axes.set_title(title)
    axes.plot
    axes.set_xlabel("Training examples")
    axes.set_ylabel("Score")
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    # Plot learning curve
#     32
    axes.grid()
    axes.fill_between(
    train_sizes,
    train_scores_mean - train_scores_std,
    train_scores_mean + train_scores_std,
    alpha=0.1,
    color="r",
    )
    axes.fill_between(
    train_sizes,
    test_scores_mean - test_scores_std,
    test_scores_mean + test_scores_std,
    alpha=0.1,
    color="g",
    )
    axes.plot(
    train_sizes, train_scores_mean, "o-", color="r", label="Training score"
    )
    axes.plot(
    train_sizes, test_scores_mean, "o-", color="g", label="Cross-validation score"
    )
    axes.legend(loc="best")
    plt.show()
```

```
X.head()
```

	Reportings	Driver_ID	Age	Gender	Education_Level	Grade	Total Business Value	Income	Joining Designation	Quarterly Rating	month	year	Raise	Promotion	Cities
0	3	1	28	0	2	1	1715580	172161	1	2	12	2018	0	0	23
2	5	4	43	0	2	2	350000	328015	2	1	11	2019	0	0	13
3	3	5	29	0	0	1	120360	139104	1	1	12	2019	0	0	9
4	5	6	31	1	1	3	1265000	393640	3	1	12	2020	0	1	11
7	6	12	35	0	2	1	2607180	168696	1	4	1	2019	0	1	23

```
ss= StandardScaler()
ss.fit_transform(X_train)
```

```
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]])
```

```
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: [0.84  0.852 0.864 0.839 0.848]
Mean: 0.8486716103634533
RandomForestClassifier(): [0.89 0.91 0.88 0.86 0.89]
Mean: 0.886183282980866
GradientBoostingClassifier: [0.891 0.918 0.885 0.879 0.845]
Mean: 0.8837517165613843
XGBoostClassifier: [0.7  0.75 0.75 0.75 0.76]
Mean: 0.8728645976380115
```

MACHINE LEARNING MODEL:-

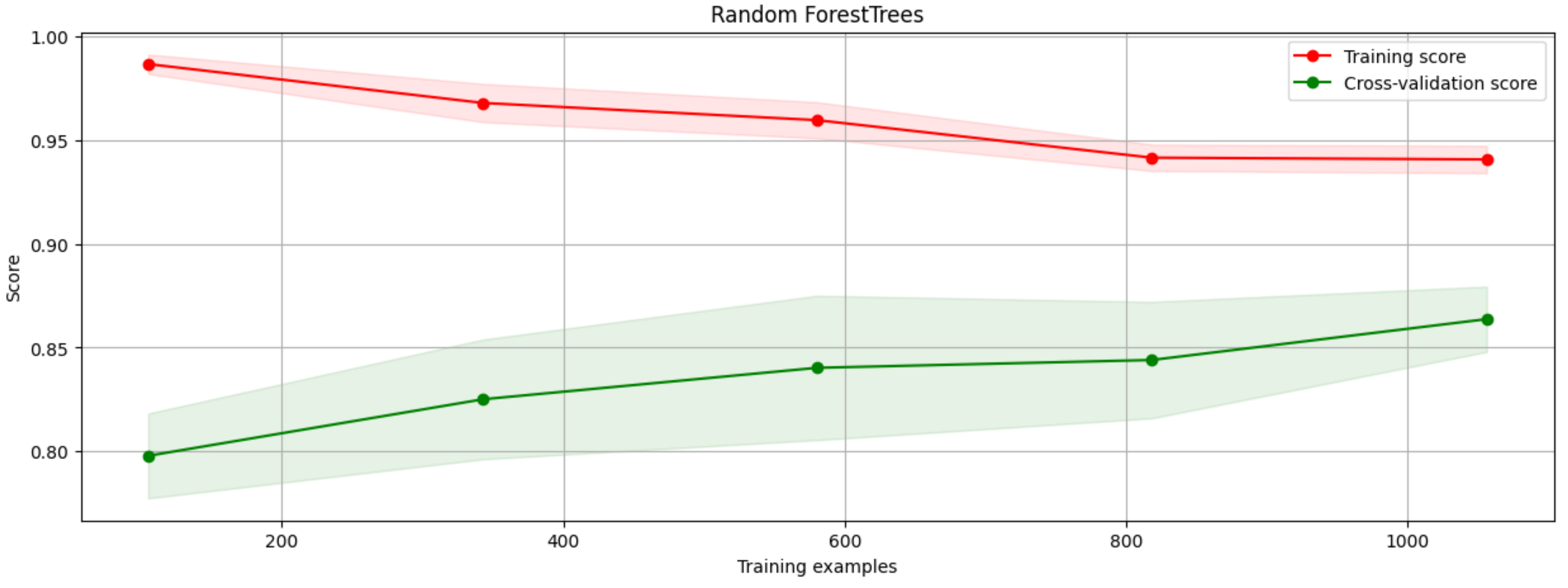
WITHOUT THE TREATMENT OF CLASS IMBALANCE

Random Forest Classifier

```
# model = RandomForestClassifier()
# param_grid = {
#     'n_estimators':list(range(10,20)),
#     'max_features': ['auto', 'sqrt', 'log2'],
#     'max_depth' : [4,5,6,7,8],
#     'criterion' :['gini', 'entropy']
# }


# clf = GridSearchCV(model,param_grid,cv=10,scoring='recall')
# clf.fit(X_train,y_train)


# clf.best_params_


rf_clf1 = RandomForestClassifier(criterion='gini',max_depth=7,max_features='sqrt',n_estimators=10)
rf_clf1.fit(X_train,y_train)
```

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

```
plot_learning_curve(rf_clf1, X_train, y_train, "Random ForestTrees")
```



```
y_pred = rf_clf1.predict(X_test)
proba = rf_clf1.predict_proba(X_test)[:,1]
print("Train data accuracy:",rf_clf1.score(X_train, y_train))
print("Test data accuracy:",rf_clf1.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))
print('-'*70)
print(classification_report(y_test, y_pred))
print('-'*70)
cm1 = (confusion_matrix(y_test, y_pred))
print('Confusion Metrix')
print(confusion_matrix(y_test, y_pred))
```

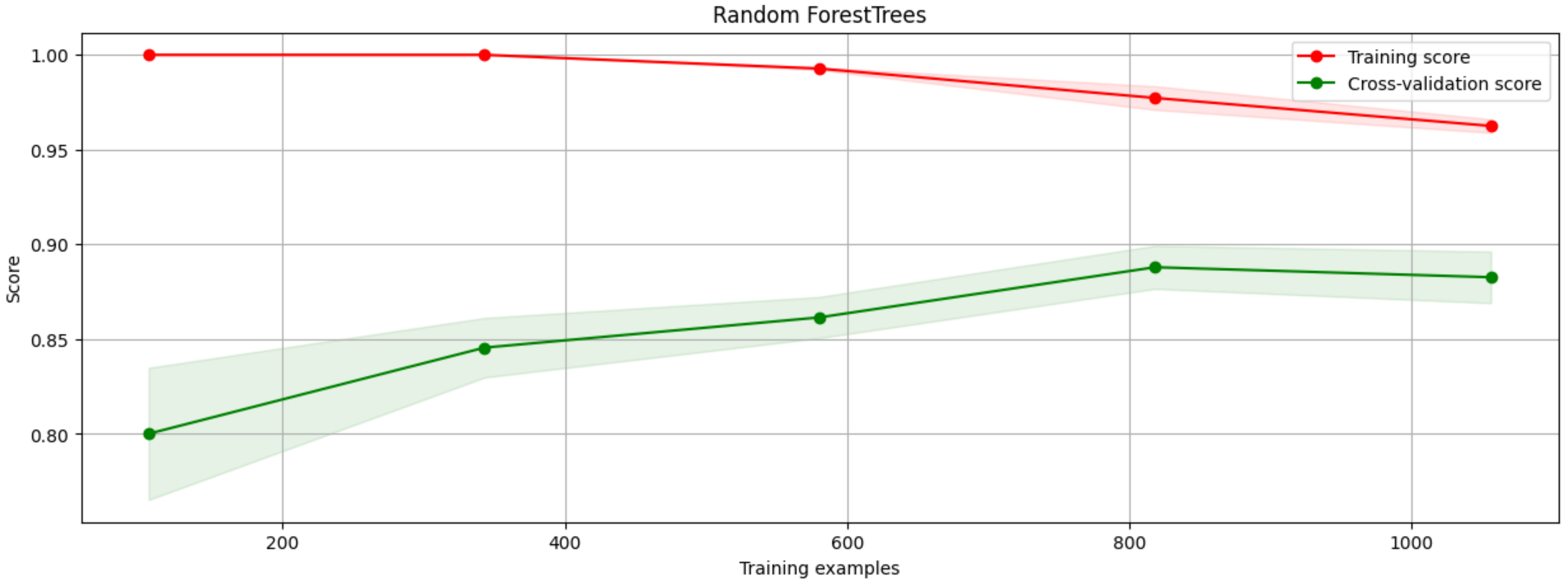
```
Train data accuracy: 0.9303557910673732
Test data accuracy: 0.8580060422960725
Accuracy of the model: 0.8580060422960725
ROC-AUC score test dataset:  0.9352501168770453
----------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.87      0.90      0.89       207
           1       0.83      0.78      0.80       124

    accuracy                           0.86       331
   macro avg       0.85      0.84      0.85       331
weighted avg       0.86      0.86      0.86       331

----------------------------------------------------------------------
Confusion Metrix
[[187  20]
 [ 27  97]]
```

```
rf_clf_imp1 = rf_clf1.feature_importances_
```

XG Boosting Classifier

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

```
plot_learning_curve(gbc1, X_train, y_train, "Random ForestTrees")
```




```
gbc_clf_imp1 = gbc1.feature_importances_
```

```
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))
print('-'*60)
print(classification_report(y_test, y_pred))
print('-'*60)
print('Confusion Matrix')
cm2 = (confusion_matrix(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print('-'*60)
```

```
Train Score :  0.9553368660105981
Test Score :  0.9003021148036254
Accuracy Score :  0.9003021148036254
ROC-AUC score test dataset:  0.9492364033037244
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.91      0.94      0.92       207
           1       0.89      0.84      0.86       124

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

------------------------------------------------------------
Confusion Matrix
[[194  13]
 [ 20 104]]
------------------------------------------------------------
```

CLASS IMBALANCE TREATMENT

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


```
(y_train.value_counts()*100)/len(y_train)
```

```
target
0    64.118092
1    35.881908
Name: count, dtype: float64
```

```
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())
```

```
X_train_smot.shape,y_train_smot.shape
```

```
((1694, 15), (1694,))
```

```
X_test.shape,y_test.shape
```

```
((331, 15), (331,))
```

```
from collections import Counter
c = Counter(y_train_smot)
print(c)
```

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

Randome Forest Classifier

```
clf = RandomForestClassifier()
clf.fit(X_train_smot,y_train_smot)
```

```
▾ RandomForestClassifier
RandomForestClassifier()
```

```
# param_grid = {
#     'n_estimators':list(range(10,20)),
#     'max_features': ['auto', 'sqrt', 'log2'],
#     'max_depth' : [4,5,6,7,8],
#     'criterion' :['gini', 'entropy']
# }
```

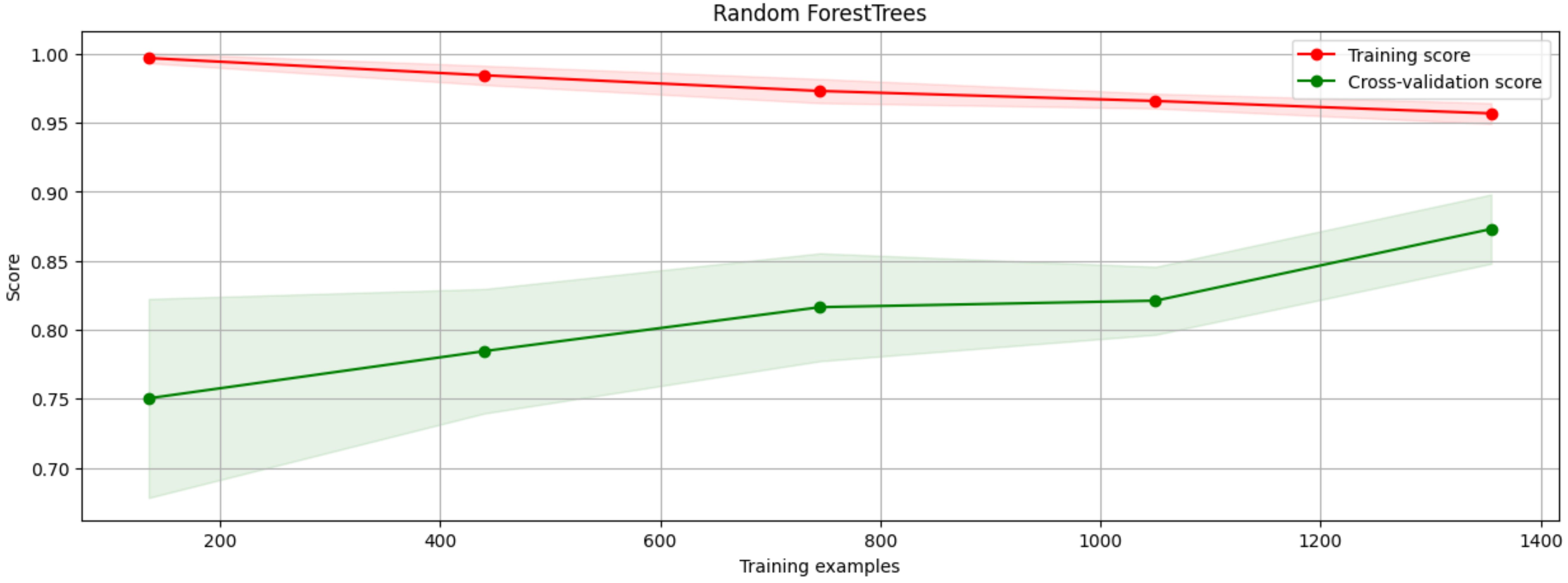
```
# clf = GridSearchCV(clf,param_grid,cv=10,scoring='recall')
# clf.fit(X_train_smot,y_train_smot)
```

```
# clf.best_params_
```

```
clf = RandomForestClassifier(criterion='gini',max_depth=8,
                             max_features='sqrt',n_estimators= 19)
clf.fit(X_train_smot,y_train_smot)
```

```
▾ RandomForestClassifier
RandomForestClassifier(max_depth=8, n_estimators=19)
```

```
plot_learning_curve(clf, X_train_smot, y_train_smot, "Random ForestTrees")
```




```
y_pred = clf.predict(X_test)
print('-'*70)
print(classification_report(y_test, y_pred))
print('-'*70)
print('Confusion Metrix')
cm3 = confusion_matrix(y_test, y_pred)
print(confusion_matrix(y_test, y_pred))
```

```
----------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.92      0.86      0.89       207
           1       0.79      0.88      0.83       124

    accuracy                           0.87       331
   macro avg       0.86      0.87      0.86       331
weighted avg       0.87      0.87      0.87       331

----------------------------------------------------------------------
Confusion Metrix
[[178  29]
 [ 15 109]]
```

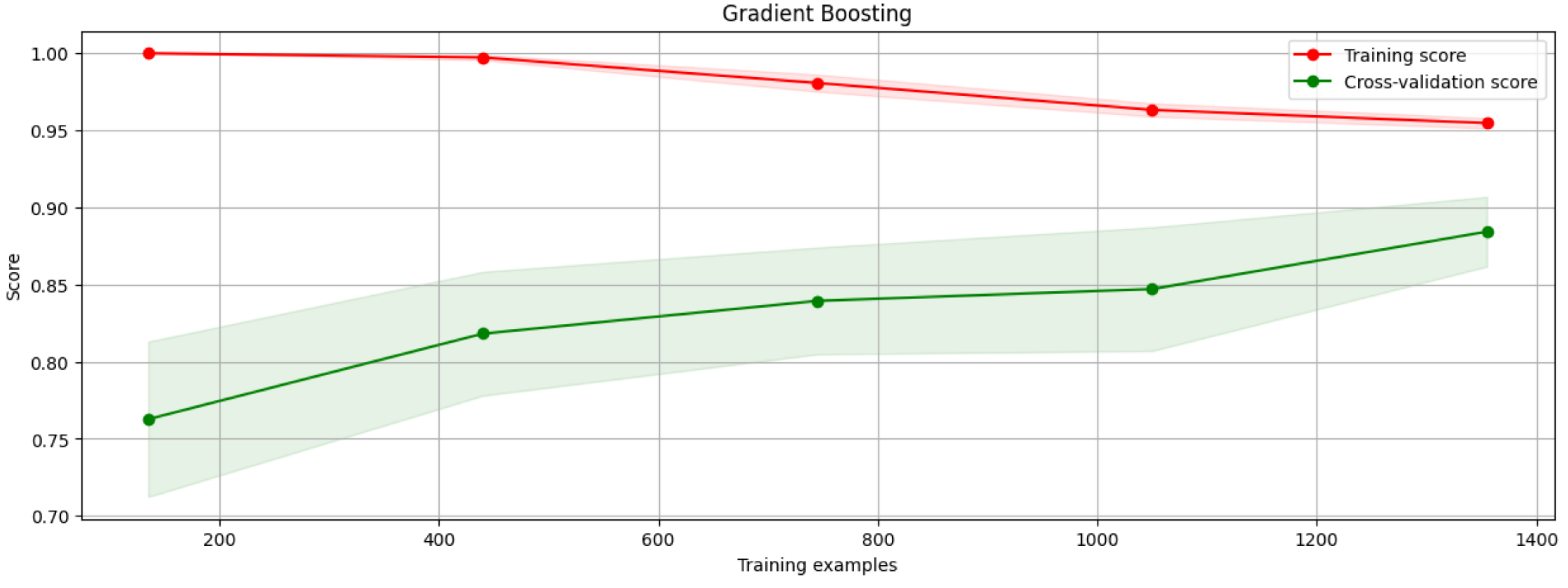
```
rf_clf_imp2= clf.feature_importances_
```

Gradient Boosting

```
gbc2 = GradientBoostingClassifier()
gbc2.fit(X_train_smot, y_train_smot)
y_pred1 = gbc2.predict(X_test)
gbc_clf_imp2 = gbc2.feature_importances_
print('-'*60)
print(classification_report(y_test, y_pred1))
print('-'*60)
cm4 = confusion_matrix(y_test, y_pred1)
print('Confusion Matrix')
print(cm4)
print('-'*60)
```

```
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.93      0.89      0.91       207
           1       0.83      0.90      0.86       124

    accuracy                           0.89       331
   macro avg       0.88      0.89      0.89       331
weighted avg       0.90      0.89      0.89       331

------------------------------------------------------------
Confusion Matrix
[[185  22]
 [ 13 111]]
------------------------------------------------------------
```

```
plot_learning_curve(gbc2, X_train_smot, y_train_smot, "Gradient Boosting")
```



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

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

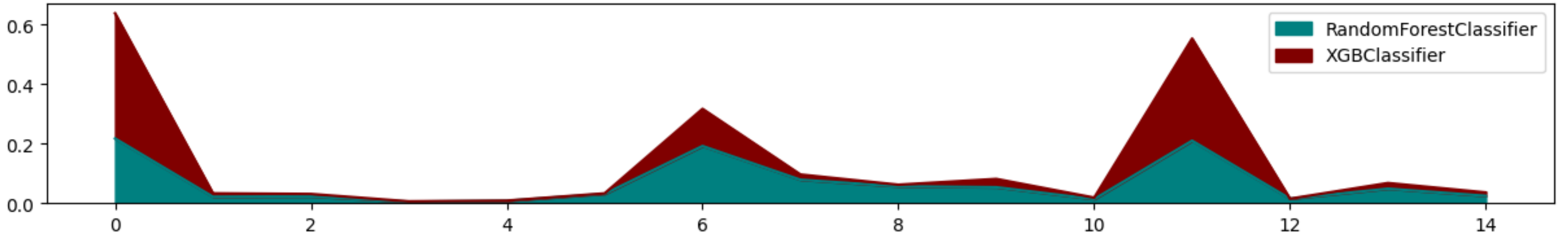
```
data1
```

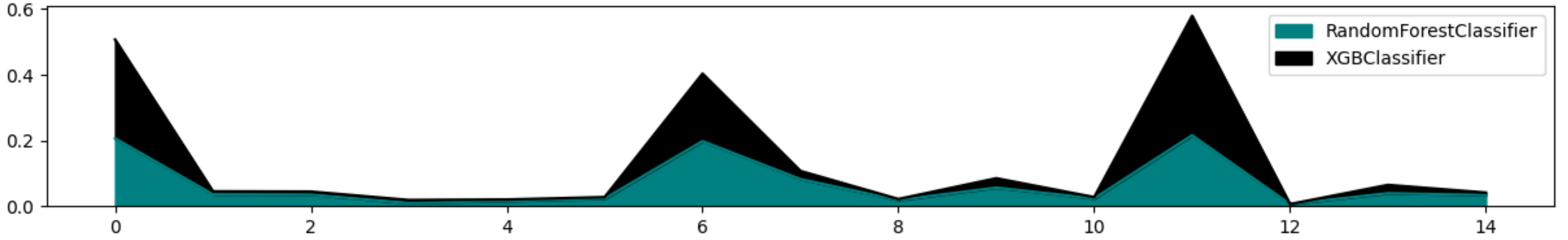
	Column_Name	RandomForestClassifier	XGBClassifier
0	Reportings	0.217610	0.420991
1	Driver_ID	0.021655	0.011572
2	Age	0.022748	0.008344
3	Gender	0.004886	0.001375
4	Education_Level	0.007877	0.000804
5	Grade	0.031205	0.001840
6	Total Business Value	0.192251	0.125029
7	Income	0.078846	0.017618
8	Joining Designation	0.056676	0.005482
9	Quarterly Rating	0.053705	0.027931
10	month	0.013754	0.004966
11	year	0.210138	0.343596
12	Raise	0.015083	0.000000
13	Promotion	0.048760	0.019118
14	Cities	0.024806	0.011333

```
data2
```

	Column_Name	RandomForestClassifier	XGBClassifier
0	Reportings	0.206026	0.300500
1	Driver_ID	0.036032	0.009306
2	Age	0.035114	0.009480
3	Gender	0.009850	0.009140
4	Education_Level	0.015698	0.004790
5	Grade	0.023011	0.004796
6	Total Business Value	0.197718	0.205370
7	Income	0.082312	0.024849
8	Joining Designation	0.018801	0.003067
9	Quarterly Rating	0.056434	0.028597
10	month	0.023761	0.003971
11	year	0.215539	0.363063
12	Raise	0.006485	0.000000
13	Promotion	0.039385	0.025453
14	Cities	0.033834	0.007618

```
data1.plot(kind="area", figsize = (15,2),color=['teal','maroon'])

data2.plot(kind="area", figsize = (15,2),color=['teal','black'])

plt.show()
```






```
# 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)
```

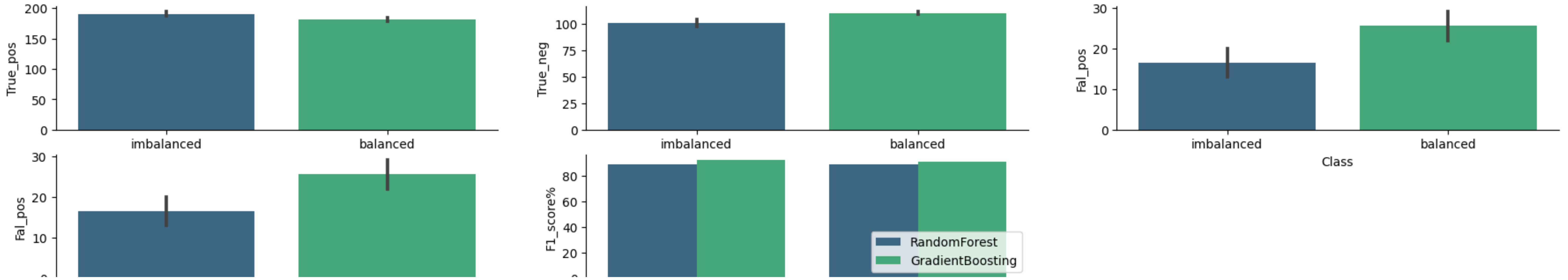
```
df = pd.DataFrame({'Model':['RandomForest','GradientBoosting','RandomForest','GradientBoosting'],
                  'Class':['imbalanced','imbalanced','balanced','balanced'],
                  'True_pos':[tp1,tp2,tp3,tp4],
                  'Fal_pos':[fp1,fp2,fp3,fp4],
                  'Fal_neg':[fn1,fn2,fn3,fn4],
                  '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,precision4*100],
                  'Recall%':[recall1*100,recall2*100,recall3*100,recall4*100]})
```

```
df
```

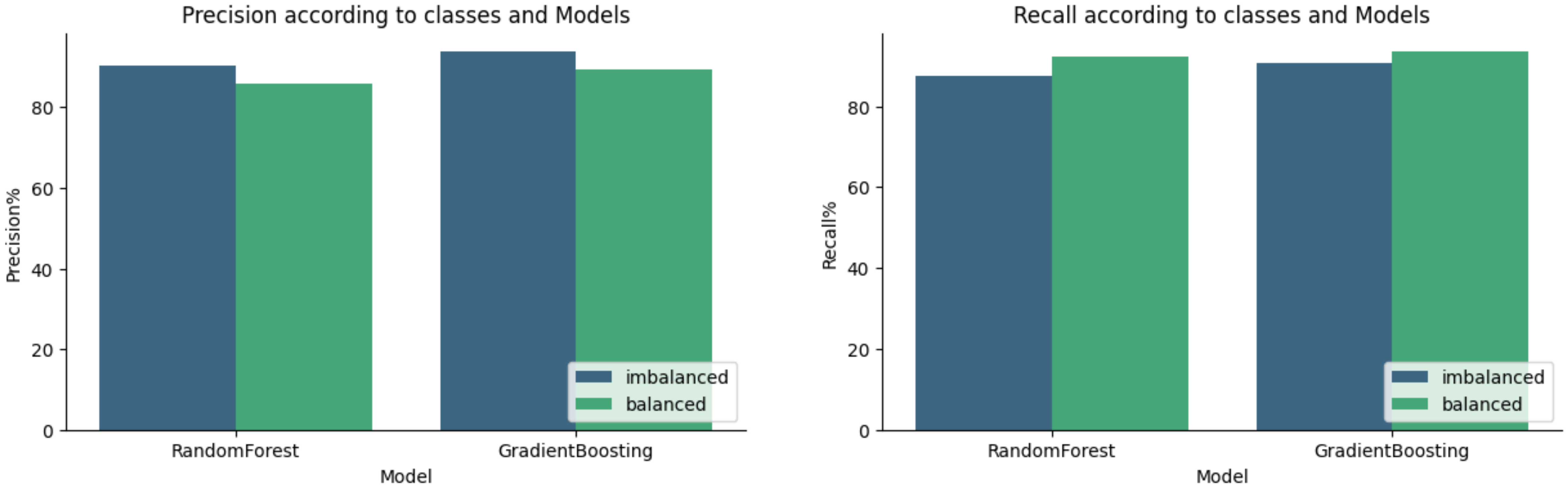
	Model	Class	True_pos	Fal_pos	Fal_neg	True_neg	F1_score%	Precision%	Recall%
0	RandomForest	imbalanced	187	20	27	97	88.836105	90.338164	87.383178
1	GradientBoosting	imbalanced	194	13	20	104	92.161520	93.719807	90.654206
2	RandomForest	balanced	178	29	15	109	89.000000	85.990338	92.227979
3	GradientBoosting	balanced	185	22	13	111	91.358025	89.371981	93.434343

```
# df.plot(kind="bar", figsize = (15,5),colormap='cividis')
# plt.title('Representation of True Positives, True Negatives,False Positives, False Negatives and F1_score of all the Models')
# plt.show()
# ,color=['red','blue','olive','teal','maroon']
```

```
plt.figure(figsize=(22,4))
plt.subplot(2,3,1)
sns.barplot(x=df.Class,y=df.True_pos,palette='viridis')
# plt.show()
plt.subplot(2,3,2)
sns.barplot(x=df.Class,y=df.True_neg,palette='viridis')
# plt.show()
plt.subplot(2,3,3)
sns.barplot(x=df.Class,y=df.Fal_pos,palette='viridis')
# plt.show()
plt.subplot(2,3,4)
sns.barplot(x=df.Class,y=df.Fal_pos,palette='viridis')
plt.subplot(2,3,5)
sns.barplot(x=df.Class,y=df['F1_score%'],palette='viridis',hue=df.Model)
plt.legend(loc='lower right')
sns.despine()
plt.show()
```



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



INSIGHTS

- 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.
- Majority (35%) of the employees currently are at designation level 2, followed by designation level 1 (31%) and 3 (26%). Less than 5% of the employees are currently in higher designations.
- 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 reportings.
- The majority of the employees seem to be associated with city C20.
- 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 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 enployes at different Education level is about a change of 3-5% with level 0.
- Joining Designation Increases with increase in Grade.
- Top reporting days is 24 days.
- About 55% of the reportings of the employees has got Quarlerly Rating 1.
- Number of reportings increases with increase in Income as well as Total Business Value.
- Recall increased after treatment of data imbalance and is performing bettee in Gradient Boosting.
- Precision dropped after treatment of data imbalance and is performing better in Random Forest.
- F1_score incresed after the treatment of imabalanced data and in Gradient Boosting.

SUBMITTED BY:

NOOHI NAAZ