OLA - Ensemble Learning

In [ ]:

Importing Libraries

In [3]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from scipy import stats
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
```

In [ ]:

Importing modules

In [71]:
```
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
```

In [ ]:

Downloading the Dataset

In [7]:
```
ola = pd.read_csv('ola_driver_scaler.csv')
ola.head()
```

Out[7]:

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

In [ ]:

Explorartory Data Analyss (EDA)

In [8]:
```
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
```

In [9]:
```
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
```

In [ ]:

In [10]:
```
ola.describe()
```

Out[10]:

	Unnamed: 0	Driver_ID	Age	Gender	Education_Level	Income	Joining Designation	
count	19104.000000	19104.000000	19043.000000	19052.000000	19104.000000	19104.000000	19104.000000	191
mean	9551.500000	1415.591133	34.668435	0.418749	1.021671	65652.025126	1.690536	
std	5514.994107	810.705321	6.257912	0.493367	0.800167	30914.515344	0.836984	
min	0.000000	1.000000	21.000000	0.000000	0.000000	10747.000000	1.000000	
25%	4775.750000	710.000000	30.000000	0.000000	0.000000	42383.000000	1.000000	
50%	9551.500000	1417.000000	34.000000	0.000000	1.000000	60087.000000	1.000000	
75%	14327.250000	2137.000000	39.000000	1.000000	2.000000	83969.000000	2.000000	
max	19103.000000	2788.000000	58.000000	1.000000	2.000000	188418.000000	5.000000	

In [ ]:

In [11]:
```
ola.describe(include='object')
```

Out[11]:

	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

In [ ]:

Dropping the Columns

In [12]:
```
# Unnamed and driver_id columns have the highest correlation and they are the same here,there

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

In [13]:
```
ola.nunique()
```

Out[13]:
```
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
```

In [14]:
```
ola.isna().sum()
```

Out[14]:
```
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 [ ]:

In [15]:
```
ola.head(5)
```

Out[15]:

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

In [ ]:

Data Processing an Feature Engineering

In [16]:
```
ola1 = ola.copy(deep=True)
```

In [ ]:

Target Variable Creation

In [ ]:
```
## Create a column called 'target' which tells whether the driver has left the company-
## and the driver whose last working day is present will have the value 1
```

In [17]:
```
first = (ola1.groupby('Driver_ID').agg({'LastWorkingDate':'last'})['LastWorkingDate'].isna())
first['LastWorkingDate'].replace({True:1,False:0},inplace=True)
first.rename(columns={'LastWorkingDate':'target'},inplace=True)
first.head()
```

Out[17]:

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

In [ ]:

In [18]:
```
## 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']).rese
QR2 = (ola1.groupby('Driver_ID').agg({'Quarterly Rating':'last'})['Quarterly Rating']).reset_
```

In [19]:
```
QR1.shape,QR2.shape
```

Out[19]:
```
((2381, 2), (2381, 2))
```

In [24]:
```
QR1.isna().sum(),QR2.isna().sum()
```

Out[24]:
```
(Driver_ID           0
 Quarterly Rating    0
 dtype: int64,
 Driver_ID           0
 Quarterly Rating    0
 dtype: int64)
```

In [25]:
```
first = first.merge(QR1,on='Driver_ID')
first = first.merge(QR2,on='Driver_ID')
```

In [26]:
```
first.head()
```

Out[26]:

	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 [27]:
```
first['Promotion'] = np.where(first['Quarterly Rating_x'] == first['Quarterly Rating_y'], 0,1
```

In [ ]:

In [ ]:
```
## Create a column which tells whether the monthly income has increased for that driver -
## and for those whose monthly income has increased we assign the value 1
```

In [28]:
```
incm1 =  (ola1.groupby('Driver_ID').agg({'Income':'first'})['Income']).reset_index()
incm2 = (ola1.groupby('Driver_ID').agg({'Income':'last'})['Income']).reset_index()
```

In [29]:
```
incm1.shape,incm2.shape
```

Out[29]:
```
((2381, 2), (2381, 2))
```

In [30]:
```
incm1.isna().sum(),incm2.isna().sum()
```

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

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

In [34]:
```
first.head()
```

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

In [35]:
```
first.tail()
```

Out[35]:

	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

In [36]:
```
first = first[['Driver_ID','target','Raise','Promotion']]
```

In [37]:
```
first.head()
```

Out[37]:

	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 [38]:
```
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)
```

In [39]:
```
ola1.reset_index(drop=True, inplace=True)
ola1 = ola1.merge(first,on='Driver_ID')
ola1.head()
```

Out[39]:

	Reportings	Driver_ID	Age	Gender	City	Education_Level	Dateofjoining	LastWorkingDate	Grade	Total Business Value	In
0	3	1	28.0	0.0	C23	2	24/12/18	03/11/19	1	1715580	1
1	2	2	31.0	0.0	C7	2	11/06/20	None	2	0	1
2	5	4	43.0	0.0	C13	2	12/07/19	27/04/20	2	350000	3
3	3	5	29.0	0.0	C9	0	01/09/19	03/07/19	1	120360	1
4	5	6	31.0	1.0	C11	1	31/07/20	None	3	1265000	3

In [ ]:

In [40]:
```
import regex

ola1['Age'] = ola1['Age'].astype('int64')
ola1['Cities'] =ola1['City'].astype('str').str.extractall('(\d+)').unstack().fillna('').sum(a
```

In [41]:
```
ola1.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 [ ]:

In [42]:
```
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')
```

In [43]:
```
ola1.head()
```

Out[43]:

	Reportings	Driver_ID	Age	Gender	Education_Level	Grade	Total Business Value	Income	Joining Designation	Quarterly Rating	month
0	3	1	28	0	2	1	1715580	172161	1	2	12
1	2	2	31	0	2	2	0	134032	2	1	12
2	5	4	43	0	2	2	350000	328015	2	1	11
3	3	5	29	0	0	1	120360	139104	1	1	12
4	5	6	31	1	1	3	1265000	393640	3	1	12

In [ ]:

In [44]:
```
sum(ola1.isna().sum())
```

Out[44]: 0

In [45]:
```
ola1.describe().T
```

Out[45]:

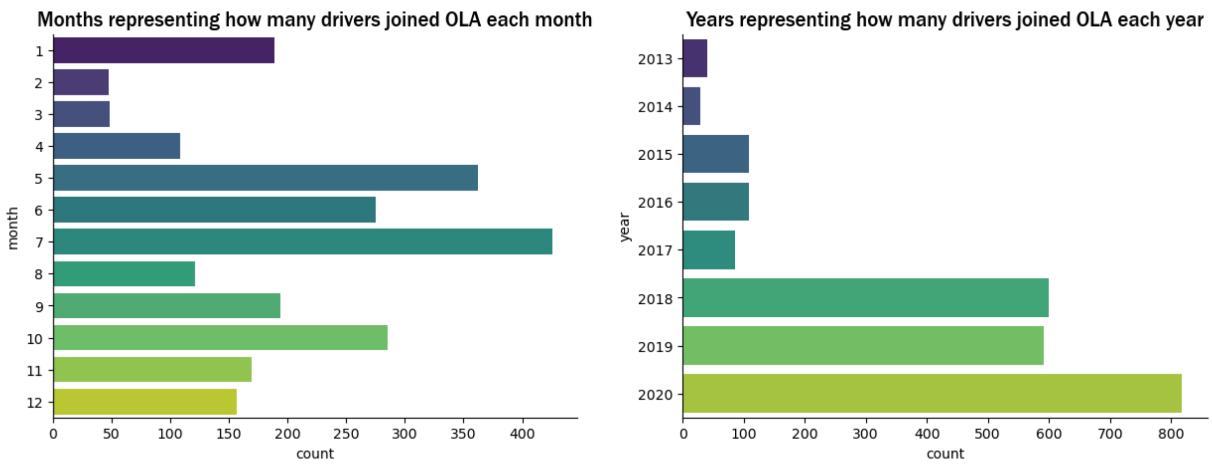
	count	mean	std	min	25%	50%	75%	max
Reportings	2381.0	8.023520e+00	6.783590e+00	1.0	3.0	5.0	10.0	24.0
Driver_ID	2381.0	1.397559e+03	8.061616e+02	1.0	695.0	1400.0	2100.0	2788.0
Age	2381.0	3.366317e+01	5.983375e+00	21.0	29.0	33.0	37.0	58.0
Gender	2381.0	4.103318e-01	4.919972e-01	0.0	0.0	0.0	1.0	1.0
Education_Level	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	3.427171e-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

In [ ]:
```

```

Data Visualization

Univariate

In [46]:
```
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 Got


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



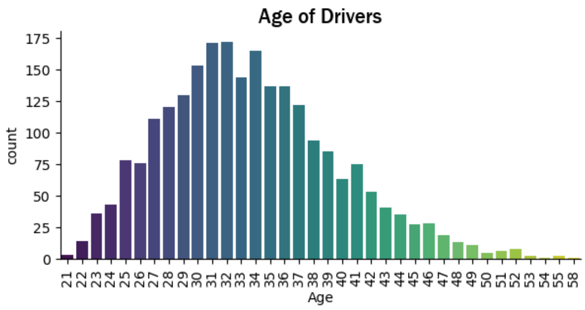
Observations:

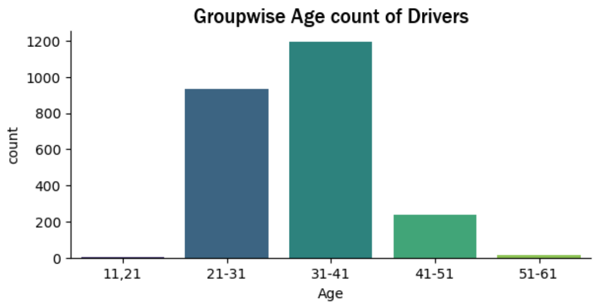
- July received the maximum number of drivers in 8 years.
- February and March receives the least number of Drivers joining OLA.
- Joining of Drivers receives a boost of about 500% after 2017.

In [ ]:

In [47]:

```
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()
```





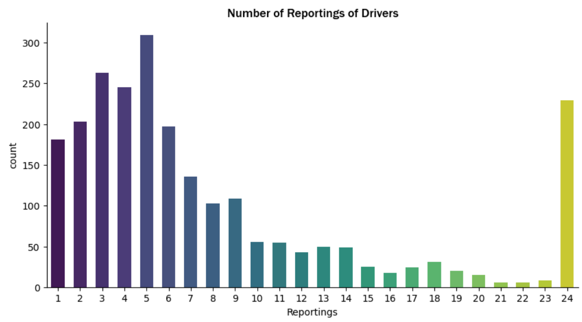
Observations:

- More number of drivers are between the age 31-41.

In [ ]:

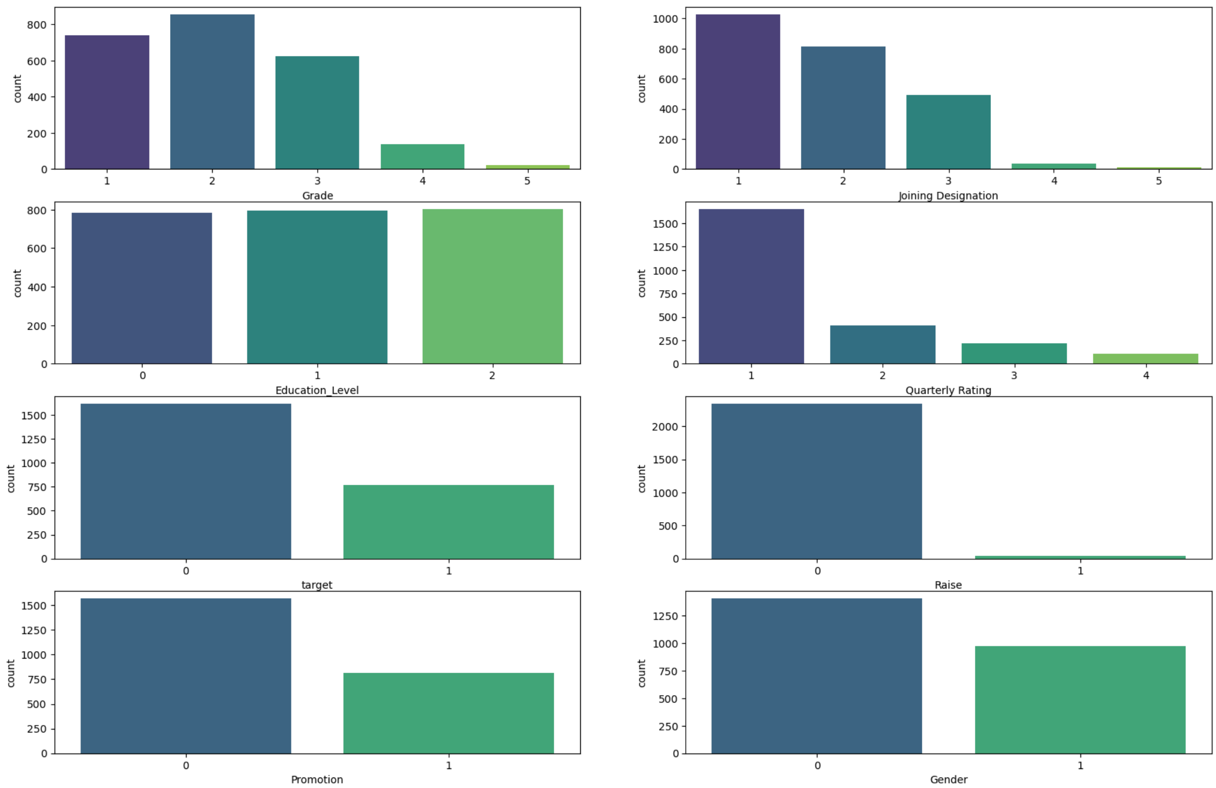
In [48]:

```
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)

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



In [ ]:

In [49]:
```
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()
```

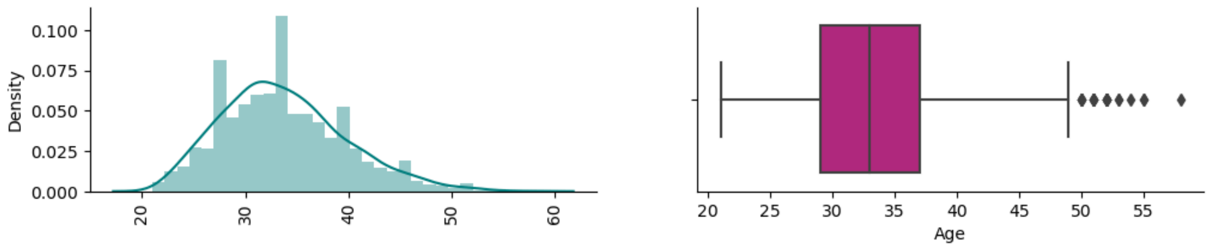


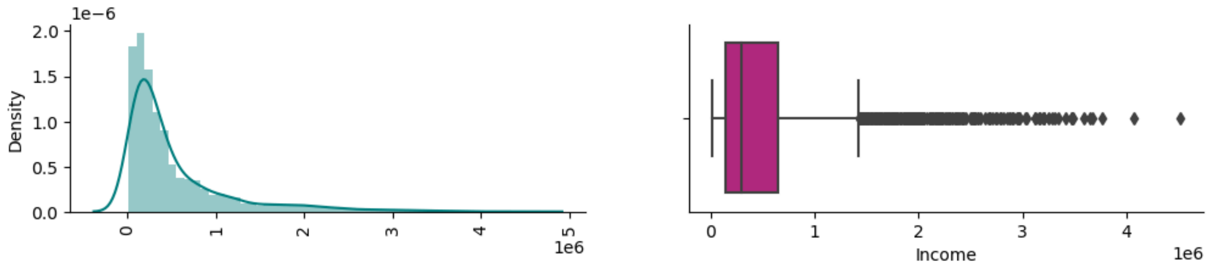
Observations:

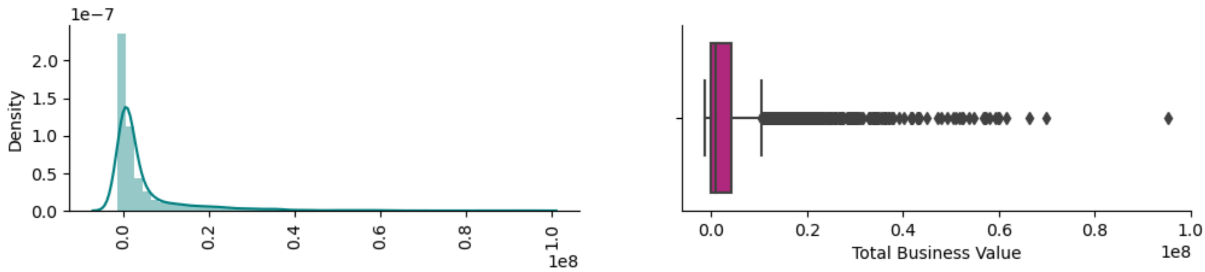
- Between 21 years(min age) to 58(max age) years of age, maximum number of drivers are 32 years, meanwhile the age group between 31-41 years of age receives the maximum number of drivers.
- 58.9% of the Drivers are male.
- City C20 has been used by the most of the drivers.
- There are 3 Education levels 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.

In [51]:
```python
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()
```



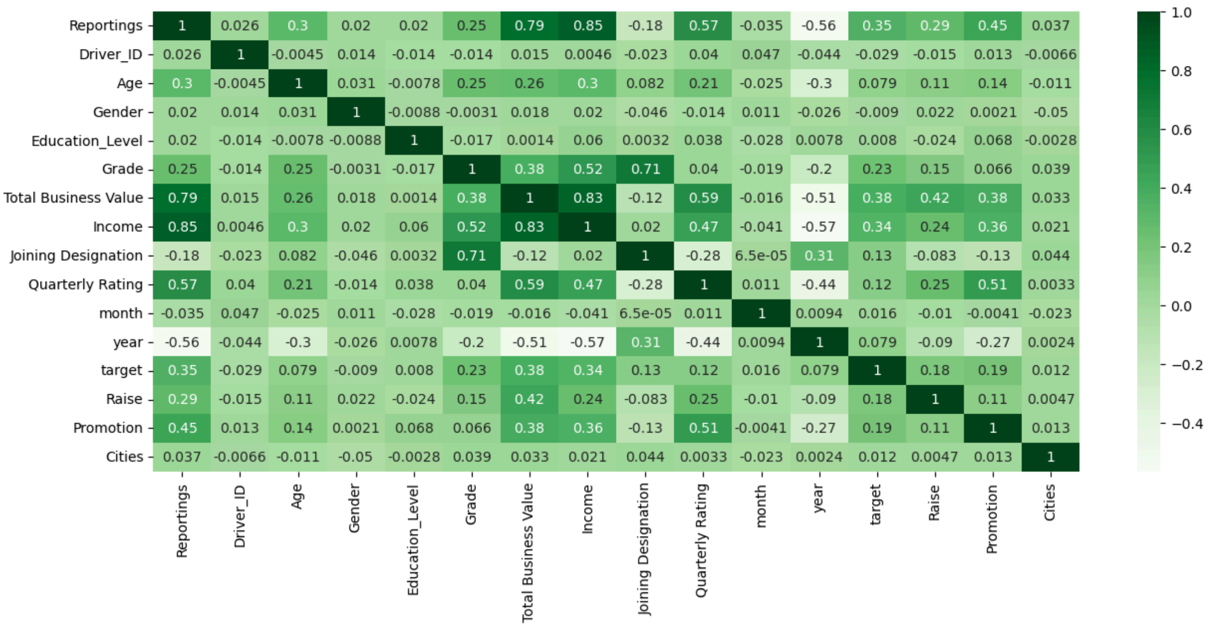




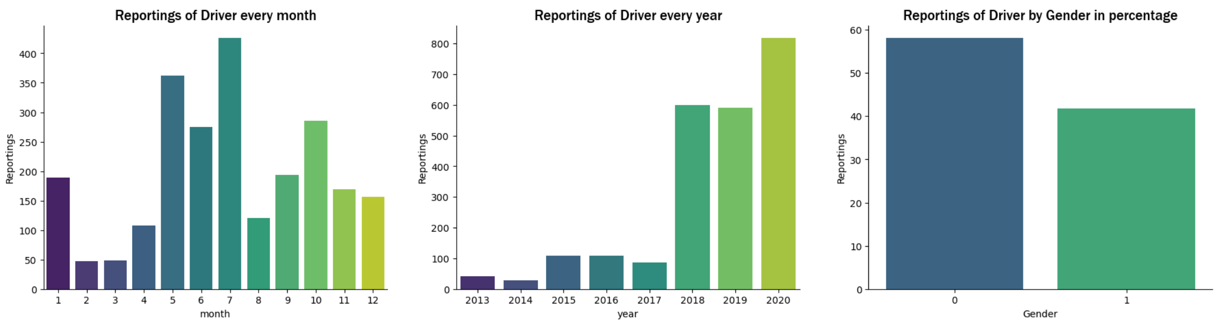
In [ ]:

Bivariate and multivariate

In [52]:
```
corr = ola1.corr()
plt.figure(figsize=(15,6))
sns.heatmap(corr,annot=True,cmap='Greens')
plt.show()
```



In [53]:
```
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', f
sns.despine()
sns.despine()
plt.show()
```

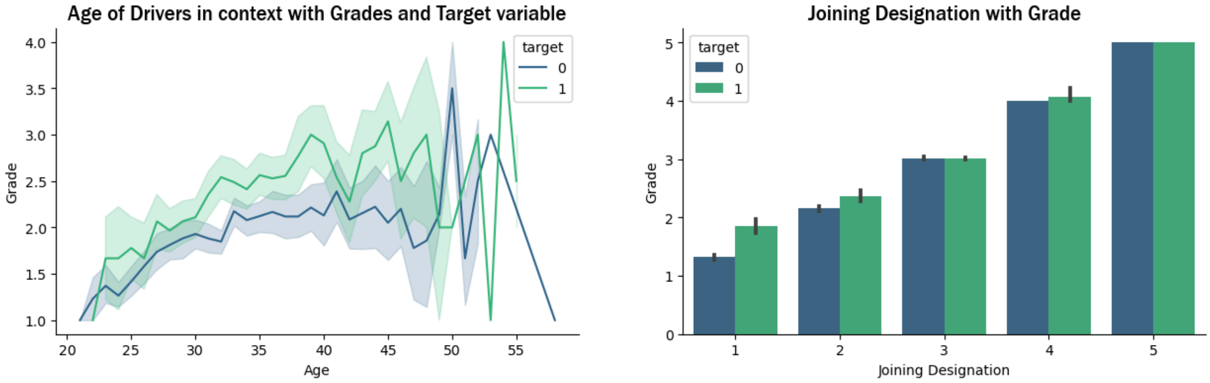


In [54]:
```
grouped_gender
```

Out[54]:

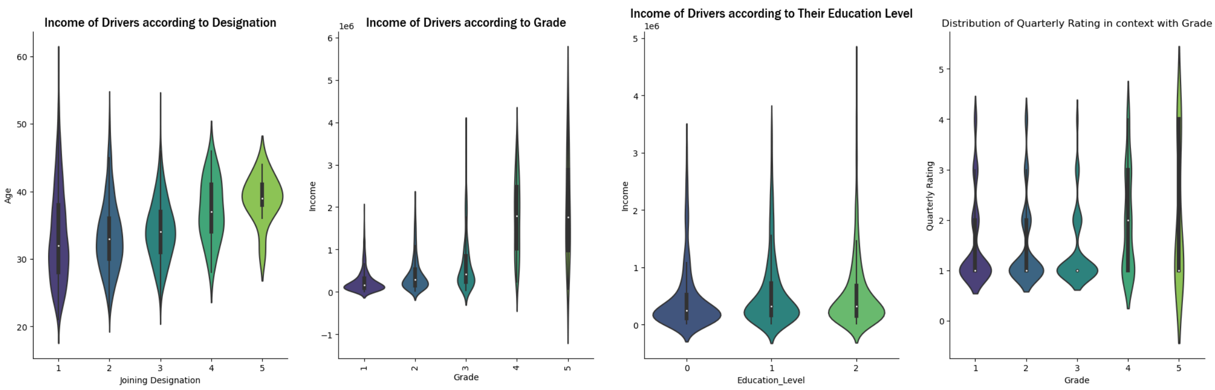
	Gender	Reportings
0	0	58.12
1	1	41.88

In [55]:
```
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 Goth

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()
```



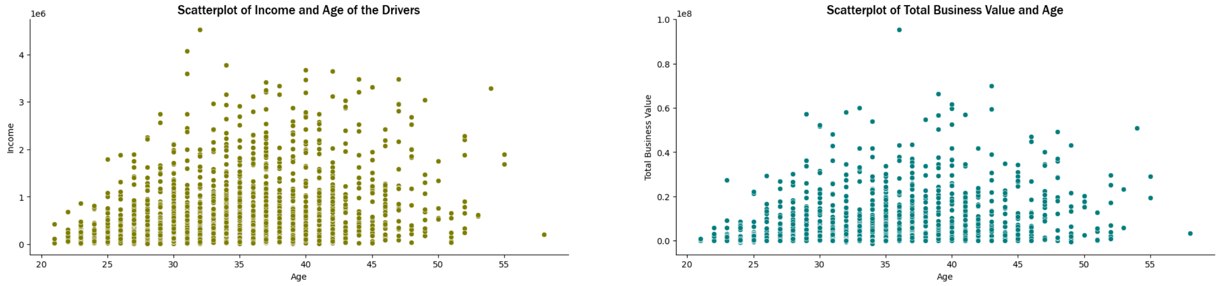
In [ ]:

In [56]:
```
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', fon
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=
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 Me
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()
```



In [ ]:

In [57]:
```
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', f
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', fo
sns.despine()
plt.show()
```



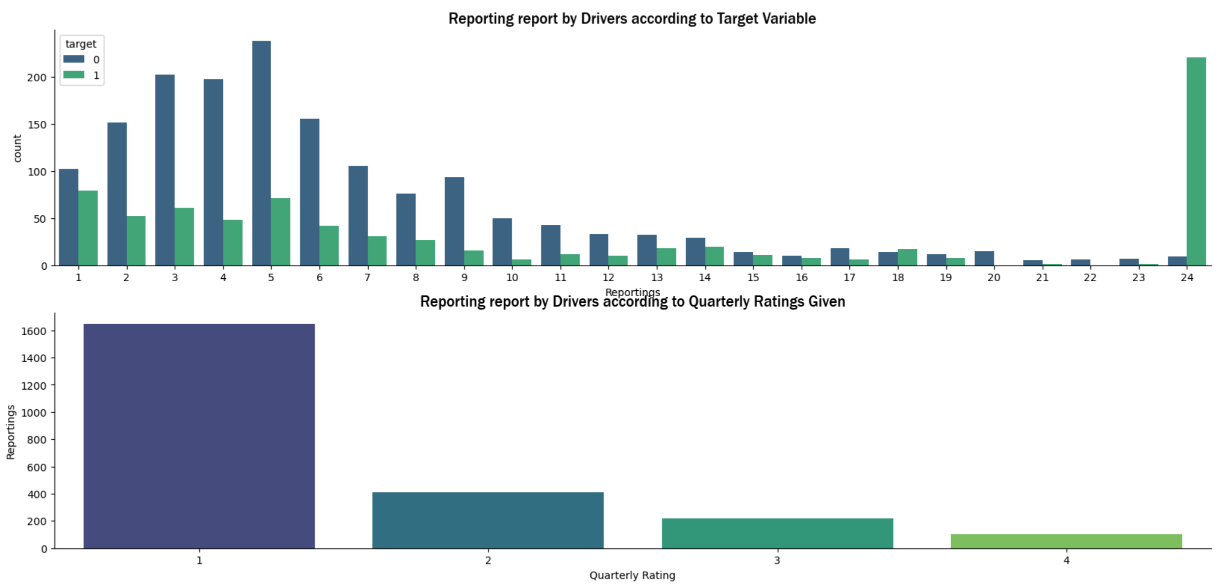
In [ ]:

In [58]:
```
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()
```

In [59]:
```
plt.figure(figsize=(15,8))
plt.subplot(3,3,1)
plt.pie(grouped_gender['Income'], labels=grouped_gender['Gender'], autopct='%1.1f%%', startan
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
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
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%
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%%', start
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%%', startan
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
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%%', st
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()
```

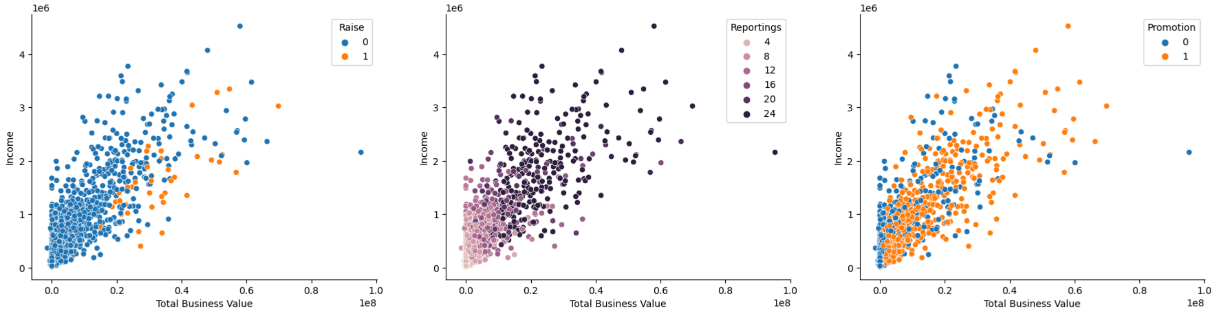
In [ ]:

In [60]:
```
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 Gothi

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='Frankl
sns.despine()
plt.show()
```



In [ ]:

In [61]:
```
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()
```

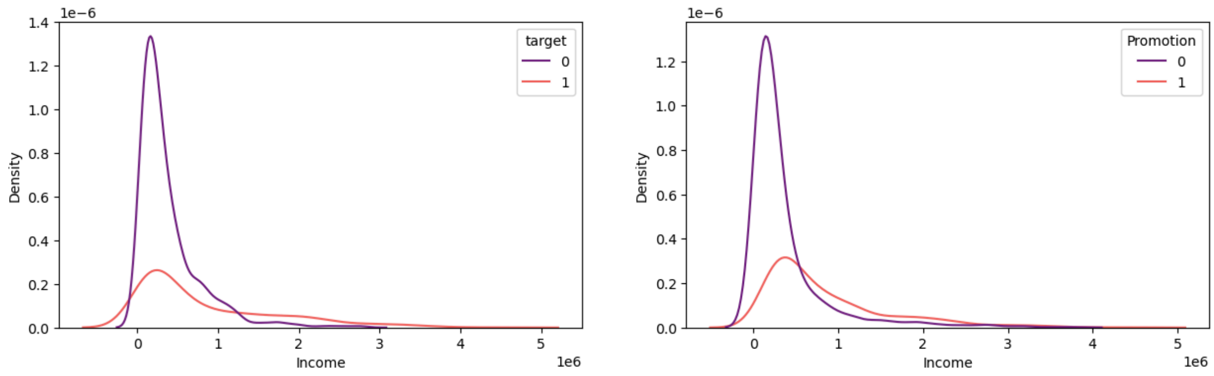


Observation:-

- 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 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 increases 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 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 enployees 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.

In [ ]:

In [62]:
```
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()
```



In [ ]:

Outlier Treatment

In [64]:
```
ola1.describe().T
```

Out[64]:

	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

In [ ]:

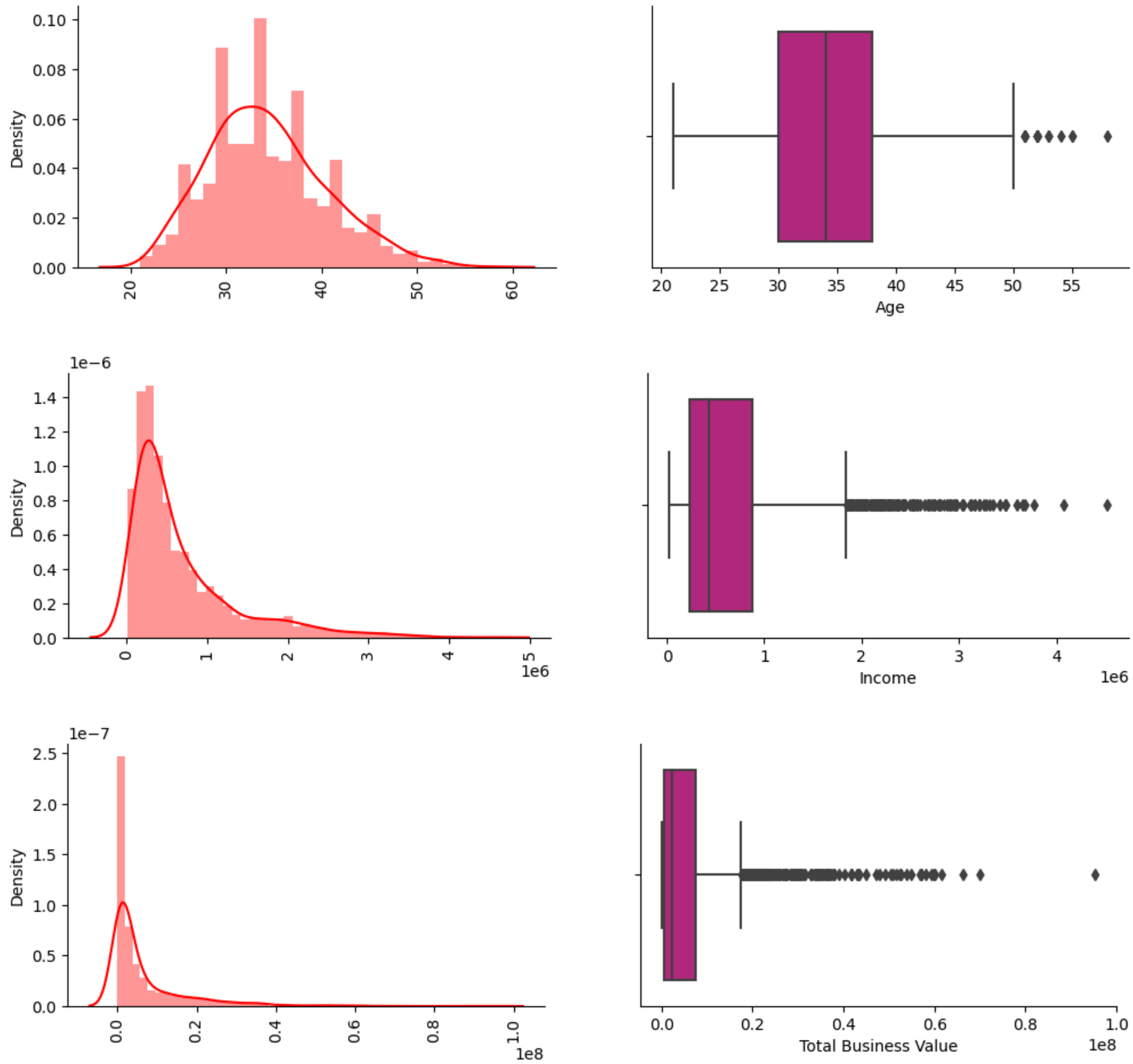
In [65]:
```
len(ola1[ola1['Total Business Value'] < 1])
```

Out[65]: 729

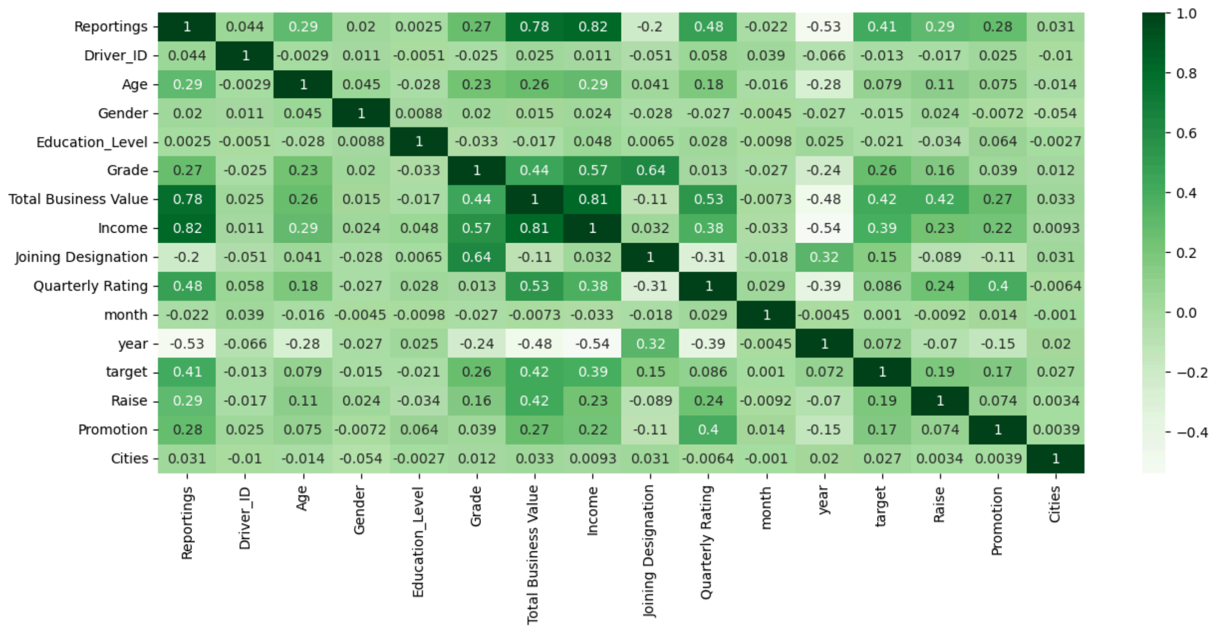
- Total Business Value column has some values in negative, which we can consider as outliers. There may affect the results of the our machine learning model.
- Considering the parts of datasets that has Total Business Value > 1. There are exactly 729 Driver having Total Business Value that less than 1.

In [67]:
```
ola1= ola1[ola1['Total Business Value'] > 1]
```

In [68]:
```
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()
```



In [69]:
```
corr = ola1.corr()
plt.figure(figsize=(15,6))
sns.heatmap(corr,annot=True,cmap='Greens')
plt.show()
```



In [70]:
```
ola1.describe().T
```

Out[70]:

	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

In [ ]:

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

In [ ]:

Data Preparation for Modelling

Importing packages

In [78]:
```
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 sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score
```

In [79]:
```
pip install xgboost
```

```
Requirement already satisfied: xgboost in c:\users\mateen\anaconda3\anoconda\lib\site-packag
es (2.0.3)
Requirement already satisfied: numpy in c:\users\mateen\anaconda3\anoconda\lib\site-packages
(from xgboost) (1.24.3)
Requirement already satisfied: scipy in c:\users\mateen\anaconda3\anoconda\lib\site-packages
(from xgboost) (1.10.1)
Note: you may need to restart the kernel to use updated packages.
```

In [80]:
```
from xgboost import XGBClassifier
```

In [81]:
```
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)
```

In [84]:
```
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=
    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()
```

In [85]:
```
X.head()
```

Out[85]:

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

In [86]:
```
ss= StandardScaler()
ss.fit_transform(X_train)
```

Out[86]:
```
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 [88]:
```
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: [0.843 0.876 0.876 0.867 0.858]
Mean: 0.8638066465256798
RandomForestClassifier(): [0.9  0.91 0.88 0.86 0.9 ]
Mean: 0.88981598461961
GradientBoostingClassifier: [0.891 0.918 0.882 0.879 0.848]
Mean: 0.8837517165613843
XGBoostClassifier: [0.7  0.75 0.75 0.75 0.76]
Mean: 0.879520278311819
```

In [ ]:

Machine Learning Model - Without the treatment of Class Imbalance.

Random Forest Classifier

In [ ]:
```
# 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']
# }
```

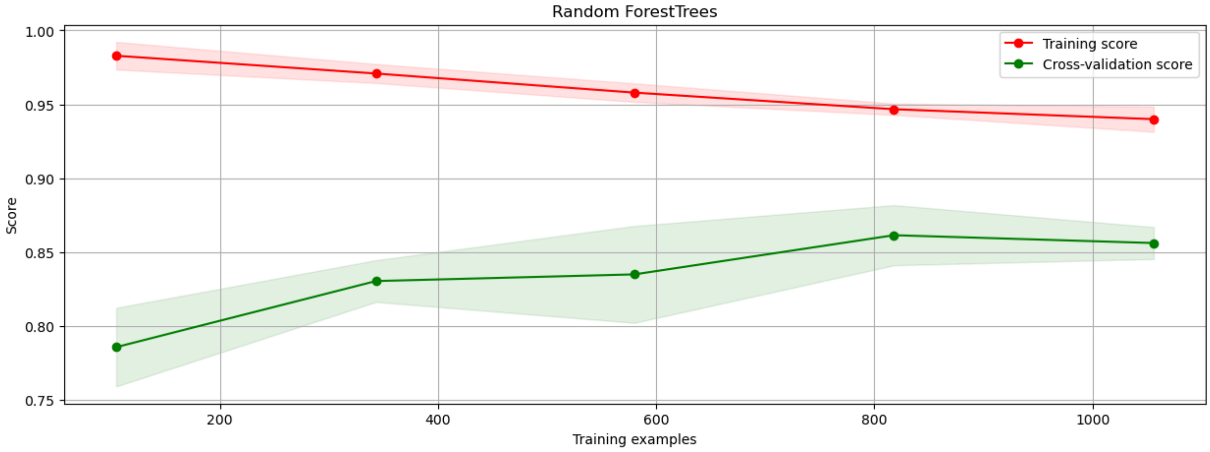
In [ ]:
```
# clf = GridSearchCV(model,param_grid,cv=10,scoring='recall')
# clf.fit(X_train,y_train)
```

In [91]:
```
# clf.best_params_
```

In [92]:
```
rf_clf1 = RandomForestClassifier(criterion='gini',max_depth=7,max_features='sqrt',n_estimator
rf_clf1.fit(X_train,y_train)
```

Out[92]:
```
RandomForestClassifier
RandomForestClassifier(max_depth=7, n_estimators=10)
```

In [93]:
```
plot_learning_curve(rf_clf1, X_train, y_train, "Random ForestTrees")
```



In [94]:
```
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: 0.9409538228614686
Test data accuracy: 0.8700906344410876
Accuracy of the model: 0.8700906344410876
ROC-AUC score test dataset:  0.9433146330060777
----------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.89      0.91      0.90       207
           1       0.84      0.81      0.82       124

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

----------------------------------------------------------------------
Confusion Metrix
[[188  19]
 [ 24 100]]
```

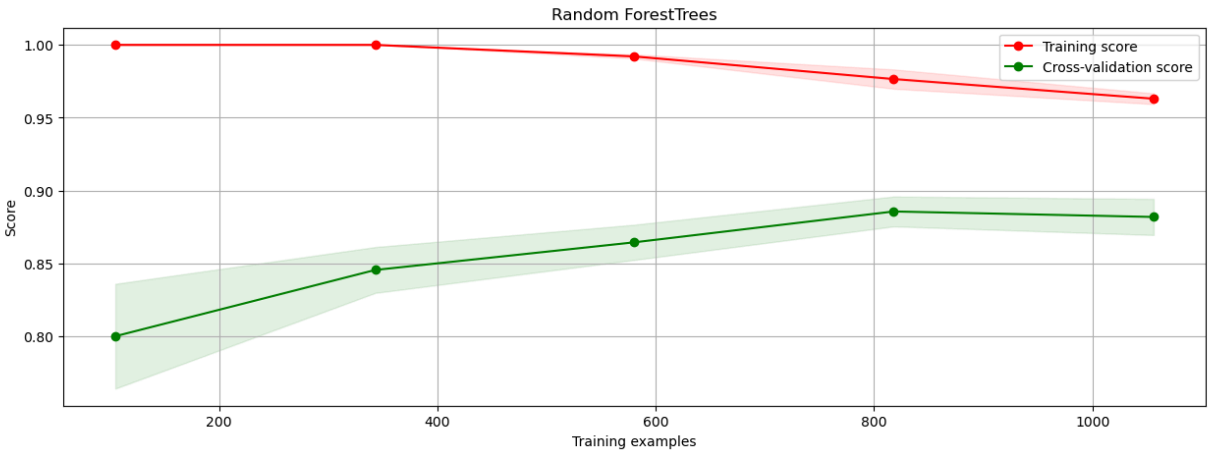
In [95]:
```
rf_clf_imp1 = rf_clf1.feature_importances_
```

In [ ]:

XG Boosting Classifier

In [96]:
```
gbc1 = GradientBoostingClassifier()
gbc1.fit(X_train, y_train)
y_pred = gbc1.predict(X_test)
proba =gbc1.predict_proba(X_test)[:, 1]
```

In [97]:
```
plot_learning_curve(gbc1, X_train, y_train, "Random ForestTrees")
```



In [98]:
```
gbc_clf_imp1 = gbc1.feature_importances_
```

In [99]:
```
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:  0.9492753623188406
------------------------------------------------------------
              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]]
------------------------------------------------------------
```

In [ ]:

Class Imbalance Treatment

In [100]:
```
plt.figure(figsize=(15,4))
sns.countplot(x=y_train,palette='Set2')
plt.title('Class Imbalance in the Data')
plt.show()
```

In [101]:
```
(y_train.value_counts()*100)/len(y_train)
```

Out[101]:
```
0    64.118092
1    35.881908
Name: target, dtype: float64
```

In [ ]:

In [102]:
```
from imblearn.over_sampling import SMOTE
```

In [103]:
```
smot = SMOTE(random_state=42)
X_train_smot,y_train_smot = smot.fit_resample(X_train,y_train.ravel())
```

In [104]:
```
X_train_smot.shape,y_train_smot.shape
```

Out[104]:
```
((1694, 15), (1694,))
```

In [105]:
```
X_test.shape,y_test.shape
```

Out[105]:
```
((331, 15), (331,))
```

In [106]:
```
from collections import Counter

c = Counter(y_train_smot)
print(c)
```

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

In [ ]:

Random Forest Classifier

In [107]:
```
clf = RandomForestClassifier()
clf.fit(X_train_smot,y_train_smot)
```

Out[107]:
```
▾ RandomForestClassifier

RandomForestClassifier()
```

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

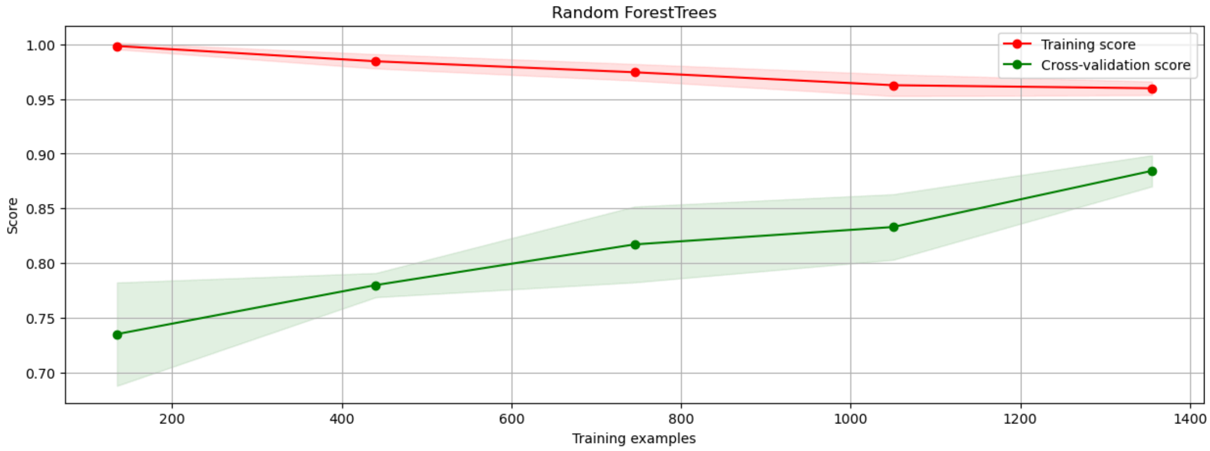
In [ ]:
```
# clf = GridSearchCV(clf,param_grid,cv=10,scoring='recall')
# clf.fit(X_train_smot,y_train_smot)
```

In [ ]:
```
# clf.best_params_
```

In [108]:
```
clf = RandomForestClassifier(criterion='gini',max_depth=8,
                             max_features='sqrt',n_estimators= 19)
clf.fit(X_train_smot,y_train_smot)
```

Out[108]:
```
RandomForestClassifier
RandomForestClassifier(max_depth=8, n_estimators=19)
```

In [109]:
```
plot_learning_curve(clf, X_train_smot, y_train_smot, "Random ForestTrees")
```



In [110]:
```
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       0.93      0.87      0.90       207
           1       0.80      0.90      0.85       124

    accuracy                           0.88       331
   macro avg       0.87      0.88      0.87       331
weighted avg       0.88      0.88      0.88       331

----------------------------------------------------------------------
Confusion Metrix
[[180  27]
 [ 13 111]]
```

In [111]:
```
rf_clf_imp2= clf.feature_importances_
```

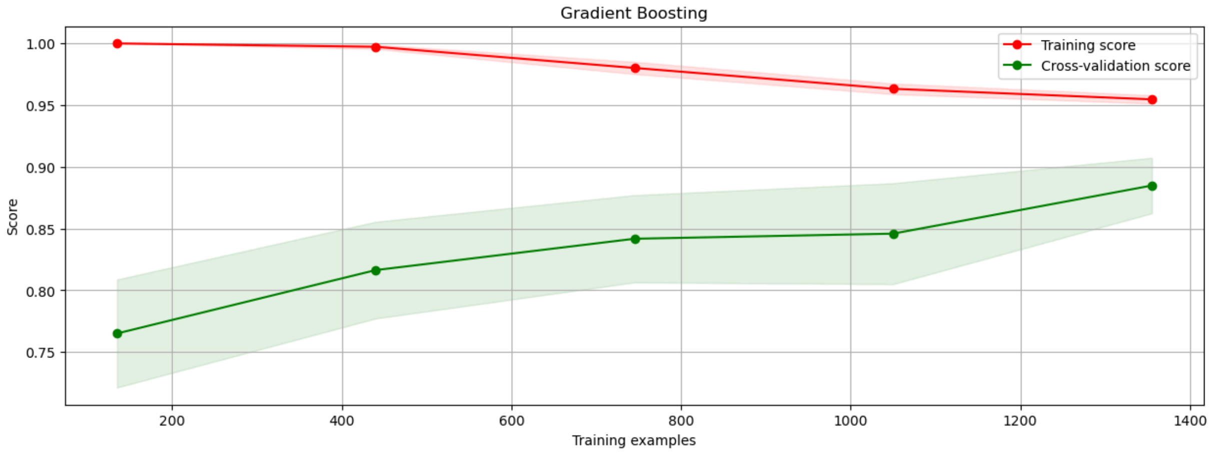
In [ ]:

Gradient Boosting Classifier

In [112]:
```
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]]
------------------------------------------------------------
```

In [113]:
```
plot_learning_curve(gbc2, X_train_smot, y_train_smot, "Gradient Boosting")
```



In [ ]:

In [115]:
```
data1 = pd.DataFrame({'Column_Name':X.columns,
                    'RandomForestClassifier':rf_clf_imp1,
                    'XGBClassifier':gbc_clf_imp1})
```

In [116]:
```
data2 = pd.DataFrame({'Column_Name':X.columns,
                    'RandomForestClassifier':rf_clf_imp2,
                    'XGBClassifier':gbc_clf_imp2})
```

In [117]:
```
data1
```

Out[117]:

	Column_Name	RandomForestClassifier	XGBClassifier
0	Reportings	0.212786	0.420886
1	Driver_ID	0.031960	0.011726
2	Age	0.029193	0.008050
3	Gender	0.005260	0.001376
4	Education_Level	0.009411	0.000841
5	Grade	0.054728	0.000934
6	Total Business Value	0.214938	0.125611
7	Income	0.100502	0.017364
8	Joining Designation	0.029194	0.006388
9	Quarterly Rating	0.064121	0.027930
10	month	0.017494	0.005265
11	year	0.183705	0.343869
12	Raise	0.005830	0.000000
13	Promotion	0.016444	0.018855
14	Cities	0.024433	0.010904

In [ ]:

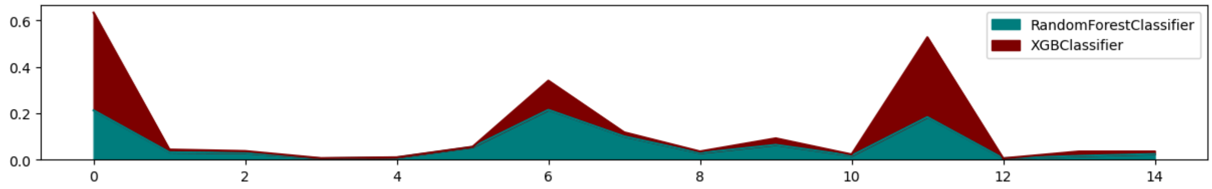
In [118]:
```
data2
```

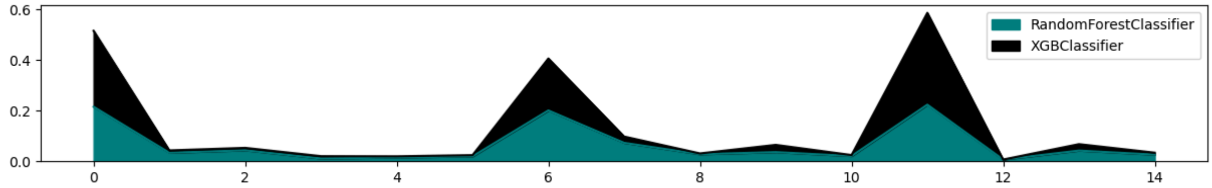
Out[118]:

	Column_Name	RandomForestClassifier	XGBClassifier
0	Reportings	0.215914	0.300373
1	Driver_ID	0.033918	0.009306
2	Age	0.043674	0.009607
3	Gender	0.011348	0.009140
4	Education_Level	0.015058	0.004877
5	Grade	0.019824	0.004796
6	Total Business Value	0.201281	0.205392
7	Income	0.073121	0.024849
8	Joining Designation	0.028162	0.003067
9	Quarterly Rating	0.036514	0.028597
10	month	0.021014	0.003862
11	year	0.224041	0.363063
12	Raise	0.007057	0.000000
13	Promotion	0.042500	0.025453
14	Cities	0.026575	0.007618

In [ ]:

In [119]:
```
data1.plot(kind="area", figsize = (15,2),color=['teal','maroon'])

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

plt.show()
```





In [ ]:

In [121]:
```
# calculating precision, reall and f1_score

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 [122]:
```
df = pd.DataFrame({'Model':['RandomForest','GradientBoosting','RandomForest','GradientBoostin
                  '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]})
```

In [123]:
```
df
```

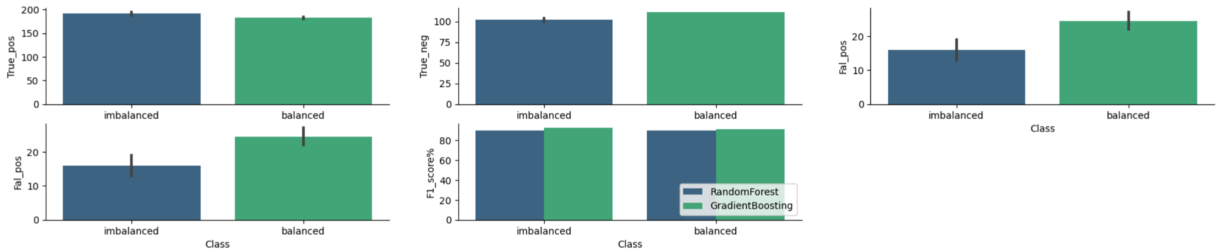
Out[123]:

	Model	Class	True_pos	Fal_pos	Fal_neg	True_neg	F1_score%	Precision%	Recall%
0	RandomForest	imbalanced	188	19	24	100	89.737470	90.821256	88.679245
1	GradientBoosting	imbalanced	194	13	20	104	92.161520	93.719807	90.654206
2	RandomForest	balanced	180	27	13	111	90.000000	86.956522	93.264249
3	GradientBoosting	balanced	185	22	13	111	91.358025	89.371981	93.434343

In [ ]:

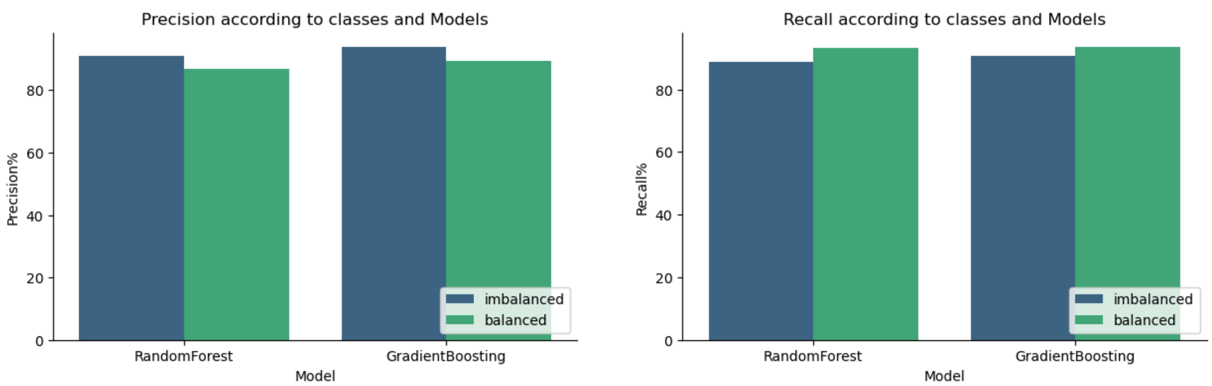
In [ ]:
```
# df.plot(kind="bar", figsize = (15,5),colormap='cividis')
# plt.title('Representation of True Positives, True Negatives,False Positives, False Negative:
# plt.show()
# ,color=['red','blue','olive','teal','maroon']
```

In [124]:
```
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()
```



In [ ]:

In [125]:
```
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()
```



In [ ]:

Insights:

- 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 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.
- Joining Designation Increases with increase in Grade.
- Top reporting days is 24 days.
- About 55% of the reportings of the employees has got Quarterly 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 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.

Recommendations:

- Out of 2381 drivers 1616 have left the company. Therefore we need to incentivize the drivers overtime or other perks to overcome churning
- The employees whose quarterly rating has increased are less likely to leave the organization.
- Company needs to implement the reward system for the customer who provide the feedback and rate drivers.
- The employees whose monthly salary has not increased are more likely to leave the organization.
- Company needs to get in touch with those drivers whose monthly salary has not increased and help them out to earn more by provider bonus and perks.
- Out of 2381 employees, 1744 employees had their last quarterly rating as 1.
- Out of 2381 employees, the quarterly rating has not increased for 2076 employees. This is red flag for the company which needs to regulate.
- Company needs to look why customers are not rating drivers.
- Last_Quarterly_Rating, Total_Business_Value & Quarterly_Rating_Increased are the most important features.
- Company needs to tracks these features as predicators
- We observe that we are not getting very high recall on target 0 which may be due to small unbalanced dataset. More data will overcome this issue.

In [ ]:

In [ ]:

In [ ]:

In [ ]: