Business Case: OLA - Churn Prediction

As the companies get bigger, the high churn could become a bigger problem. To find new drivers, Ola is casting a wide net, including people who don't have cars for jobs. But this acquisition is really costly. Losing drivers frequently impacts the morale of the organization and acquiring new drivers is more expensive than retaining existing ones.

In [193]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style='whitegrid')

from sklearn.impute import KNNImputer
from sklearn.model_selection import KFold, cross_validate
from sklearn.model_selection import train_test_split, KFold, cross_val_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report,precision_recall_curve,accuracy_score

from sklearn.tree import DecisionTreeClassifier

from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from imblearn.over_sampling import SMOTE
```

In [21]:
```
df = pd.read_csv("ola_driver_scaler.csv")
df.drop(columns=['Unnamed: 0'],inplace=True)
```

In [22]:
```
df.head()
```

Out[22]:

	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
3	11/01/20	2	31.0	0.0	C7	2	67016	11/06/20	NaN	2	2	0	1
4	12/01/20	2	31.0	0.0	C7	2	67016	11/06/20	NaN	2	2	0	1

In [40]:
```
df.shape
```

Out[40]:
```
(19104, 13)
```

In [45]:
```
df.dtypes
```

Out[45]:
```
MMM-YY                  datetime64[ns]
Driver_ID                        int64
Age                            float64
Gender                         float64
City                            object
Education_Level                  int64
Income                           int64
Dateofjoining           datetime64[ns]
LastWorkingDate         datetime64[ns]
Joining Designation              int64
Grade                            int64
Total Business Value             int64
Quarterly Rating                 int64
dtype: object
```

In [44]:
```
df['MMM-YY'] = pd.to_datetime(df['MMM-YY'])
df['Dateofjoining'] = pd.to_datetime(df['Dateofjoining'])
df['LastWorkingDate'] = pd.to_datetime(df['LastWorkingDate'])   # converting all the date columns to date types
```

In [ ]:
```

```

In [25]:
```
df.head()
```

Out[25]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value	Quarterly Rating
0	2019-01-01	1	28.0	0.0	C23	2	57387	24/12/18	NaN	1	1	2381060	2
1	2019-02-01	1	28.0	0.0	C23	2	57387	24/12/18	NaN	1	1	-665480	2
2	2019-03-01	1	28.0	0.0	C23	2	57387	24/12/18	03/11/19	1	1	0	2
3	2020-11-01	2	31.0	0.0	C7	2	67016	11/06/20	NaN	2	2	0	1
4	2020-12-01	2	31.0	0.0	C7	2	67016	11/06/20	NaN	2	2	0	1

In [26]:
```
df.isna().sum()    # age and gender have nulls we need to fill, Lastworkingdate nulls can be ignored as they are part of targe
```

Out[26]:
```
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
```

After checking age and gender missing values we can back fill or forward fill based on the same driver ids , so using KNN imputation with 1 neighbour to fill with same driver_id with age and gender

In [27]:
```
gender_na = df.loc[df['Gender'].isna(),'Driver_ID'].values
age_na = df.loc[df['Age'].isna(),'Driver_ID'].values
```

In [28]:
```
df_na =  df.loc[df['Driver_ID'].isin(gender_na),['Driver_ID','Age','Gender']]
```

In [29]:
```
df_na.head()
```

Out[29]:

	Driver_ID	Age	Gender
239	43	27.0	1.0
240	43	27.0	NaN
257	49	21.0	0.0
258	49	21.0	NaN
259	49	21.0	0.0

In [30]:
```
df_na = df[['Driver_ID','Age','Gender']]
```

In [32]:
```
imputer = KNNImputer(n_neighbors=1)
imput = imputer.fit_transform(df_na)
df_na = pd.DataFrame(imput,columns=df_na.columns)
```

In [33]:
```
df_na.isna().sum()
```

Out[33]:
```
Driver_ID    0
Age          0
Gender       0
dtype: int64
```

In [34]:
```
df['Gender'] = df_na['Gender']
df['Age'] = df_na['Age']
```

In [38]:
```
df['Gender'].unique(),df['Age'].unique()
```

Out[38]:
```
(array([0., 1.]),
 array([28., 31., 43., 29., 34., 35., 30., 39., 42., 27., 26., 33., 40.,
        41., 32., 22., 44., 36., 21., 49., 37., 38., 46., 47., 48., 25.,
        24., 45., 51., 52., 23., 50., 53., 54., 55., 58.]))
```

In [202]:
```
df.isna().sum()  # we imputed this nulls of age and gender
```

Out[202]:
```
MMM-YY                      0
Driver_ID                   0
Age                         0
Gender                      0
City                        0
Education_Level             0
Income                      0
Dateofjoining               0
LastWorkingDate         17488
Joining Designation         0
Grade                       0
Total Business Value        0
Quarterly Rating            0
target                      0
income_sum                  0
income_mean                 0
income_min                  0
tbv_mean                    0
tbv_min                     0
grade_growth            16723
dtype: int64
```

In [ ]:

In [46]:
```
df.sort_values(by=['Driver_ID', 'MMM-YY'],inplace=True,ignore_index=True)
```

Getting unique driver rows and aggregating few columns based on the feature

In [47]:
```
df_u = df.drop_duplicates(subset=['Driver_ID'],keep="last",ignore_index=True)
```

In [48]:
```
df_u['target'] = df_u['LastWorkingDate'].notna().apply(int)
```

```
C:\Users\bharath.d.reddy\AppData\Local\Temp\ipykernel_28184\1014406890.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  df_u['target'] = df_u['LastWorkingDate'].notna().apply(int)
```

In [51]:
```
df_u['target'].value_counts(dropna=False)
```

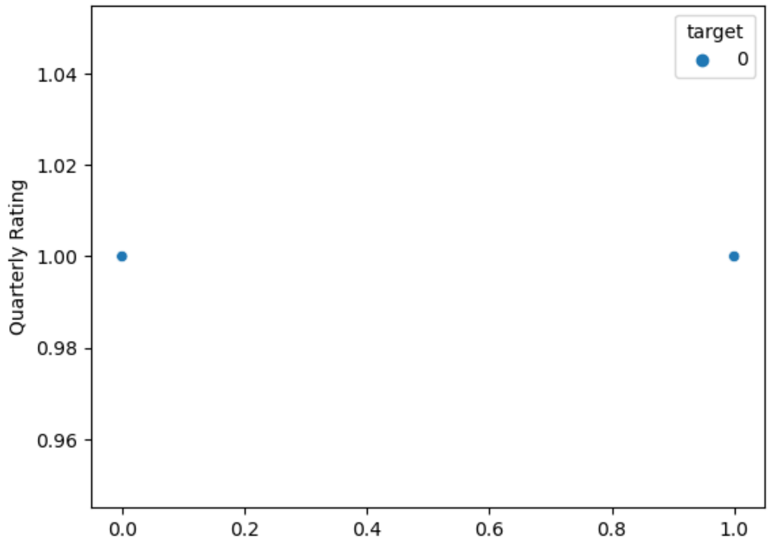
Out[51]:
```
1    1616
0     765
Name: target, dtype: int64
```

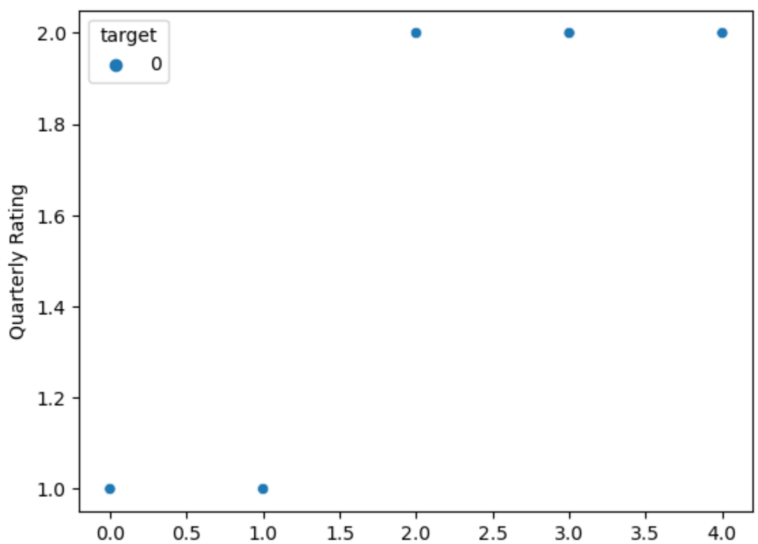
In [56]:
```
df = df.merge(df_u[['Driver_ID','target']],how='left' ,on='Driver_ID')
```

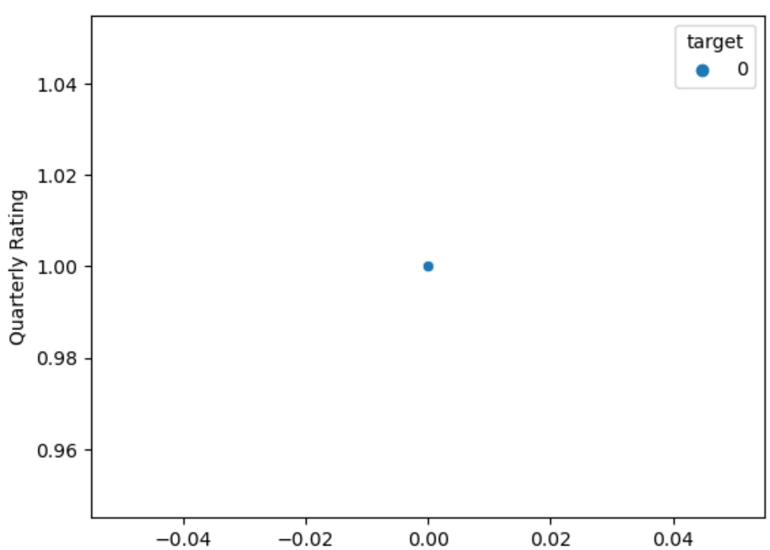
In [ ]:

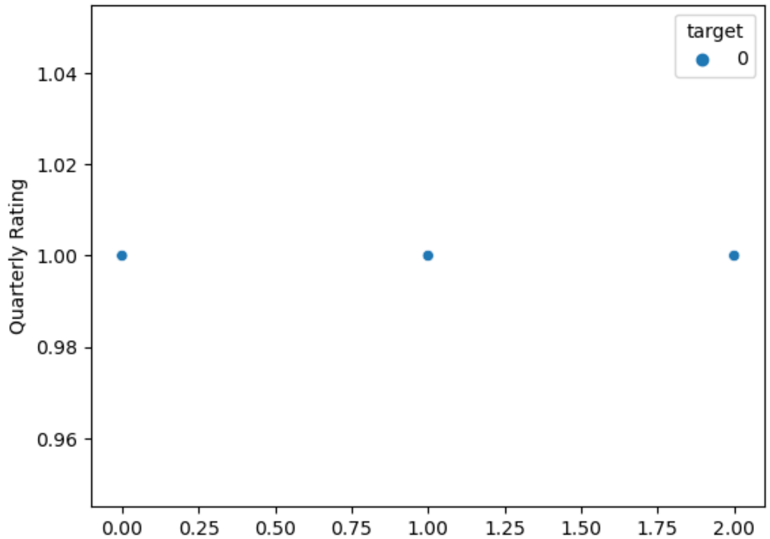
While aggregating few columns we are checking how do aggregate and what features needs to be created for the models

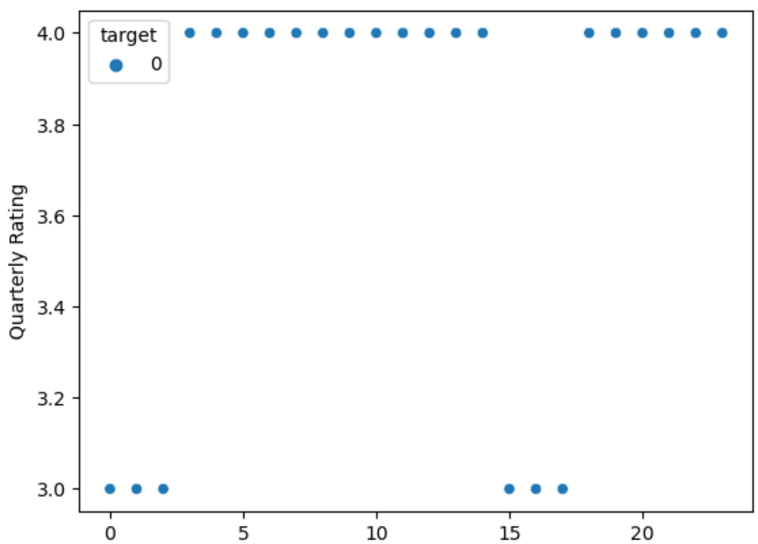
In [57]:
```
for i,d in enumerate(df['Driver_ID'].unique()):
    df_ = df[df['Driver_ID']==d]
    if sum(df_['target'])==0:
        sns.scatterplot(data=df_,y='Quarterly Rating',x=range(len(df_)),hue=df_['target'])
        plt.show()
        if i>10:
            break
```



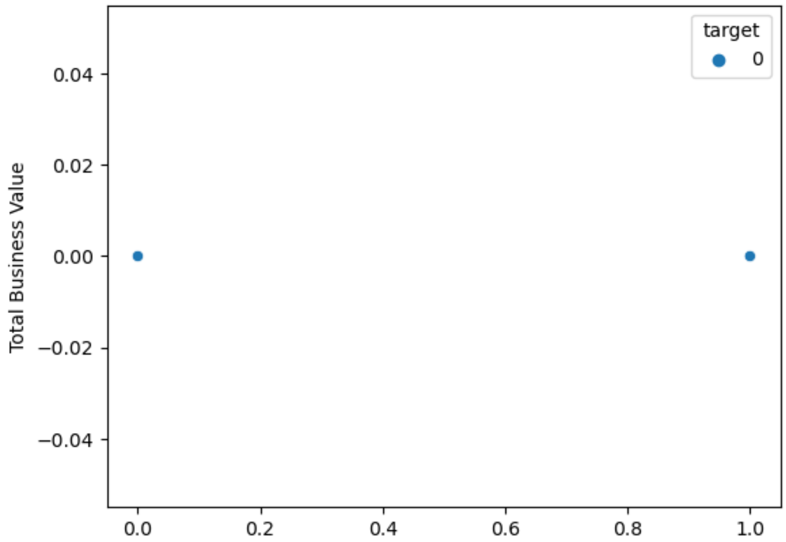


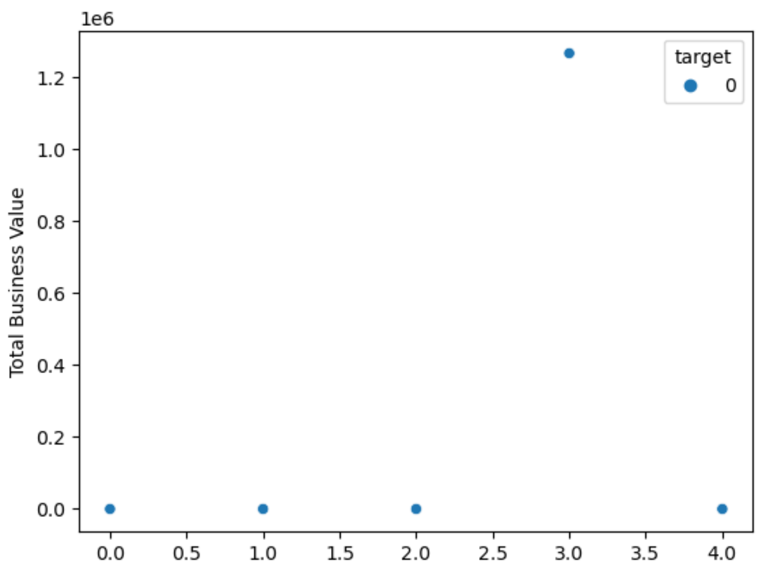


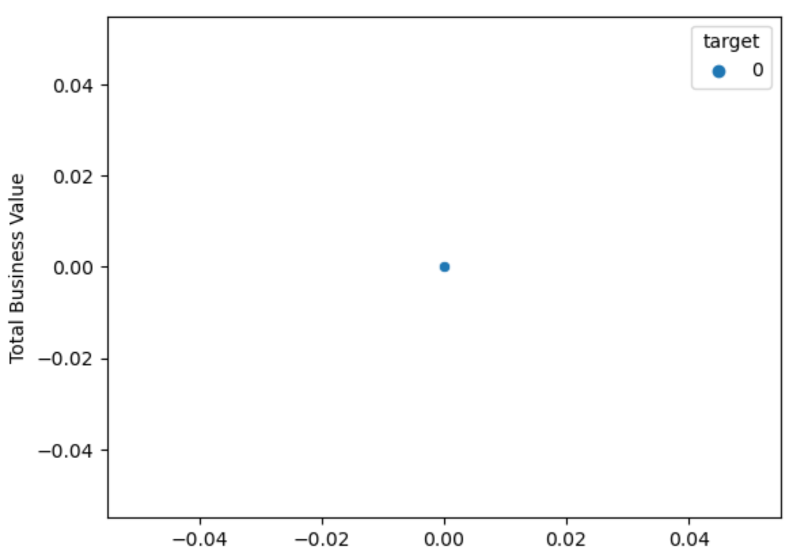

target
0
Quarterly Rating
1.04
1.02
1.00
0.98
0.96
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

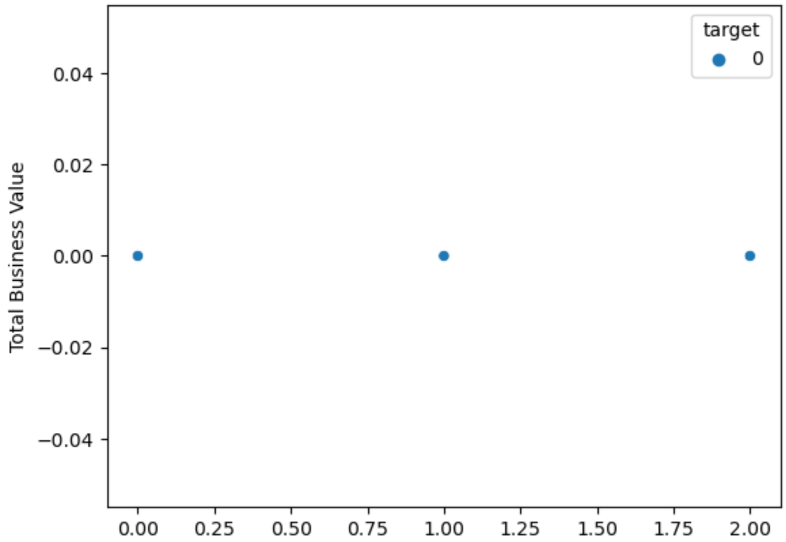

target
0
Quarterly Rating
4.0
3.8
3.6
3.4
3.2
3.0
0
5
10
15
20

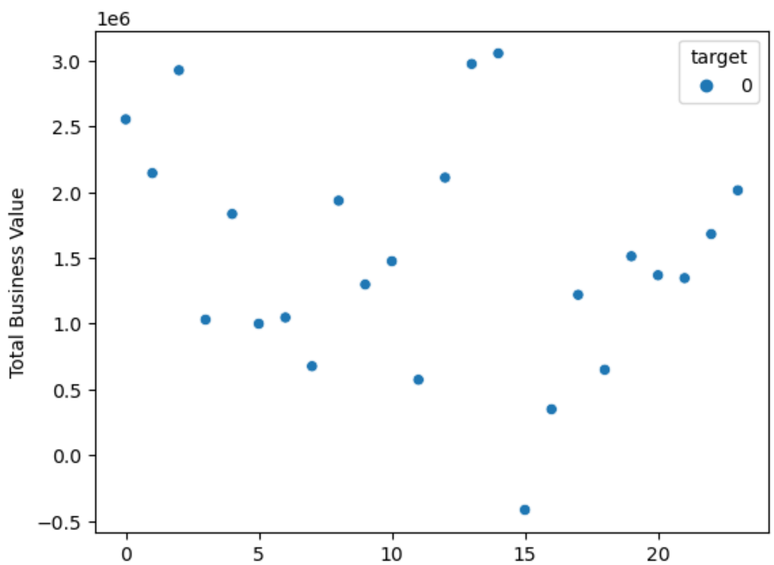
In [58]:
```
for i,d in enumerate(df['Driver_ID'].unique()):
    df_ = df[df['Driver_ID']==d]
    if sum(df_['target'])==0:
        sns.scatterplot(data=df_,y='Total Business Value',x=range(len(df_)),hue=df_['target'])
        plt.show()
        if i>10:
            break
```



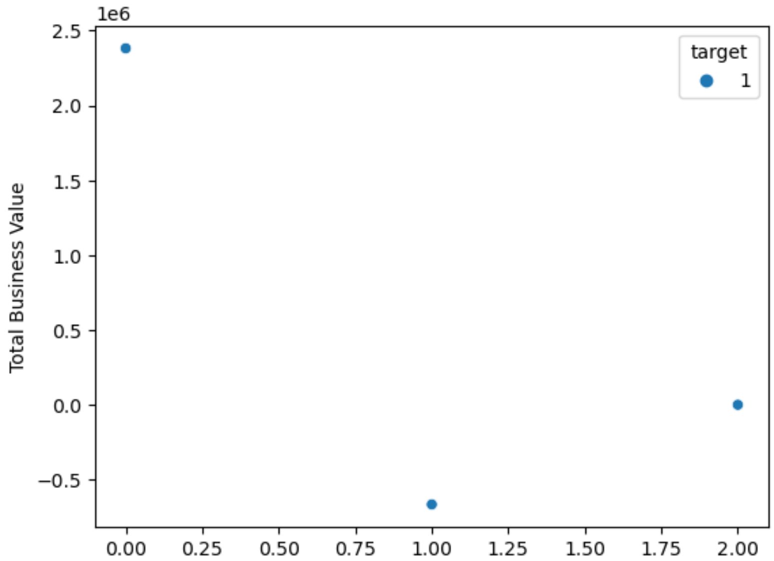


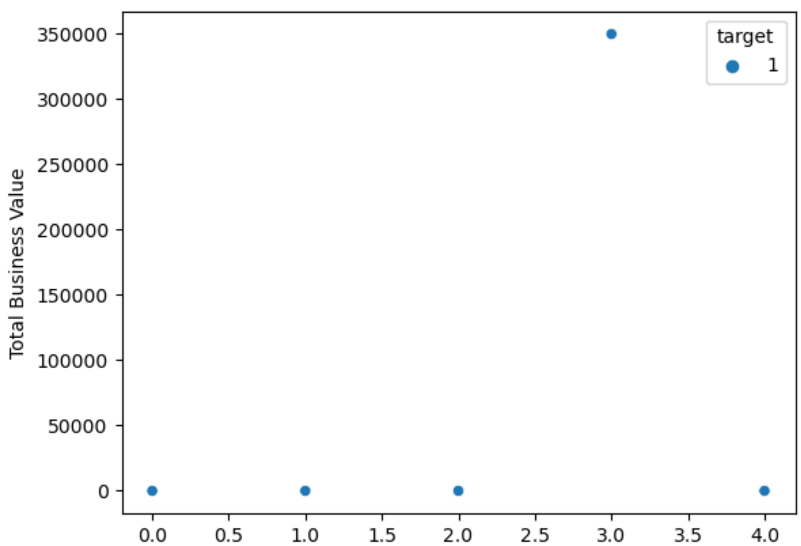


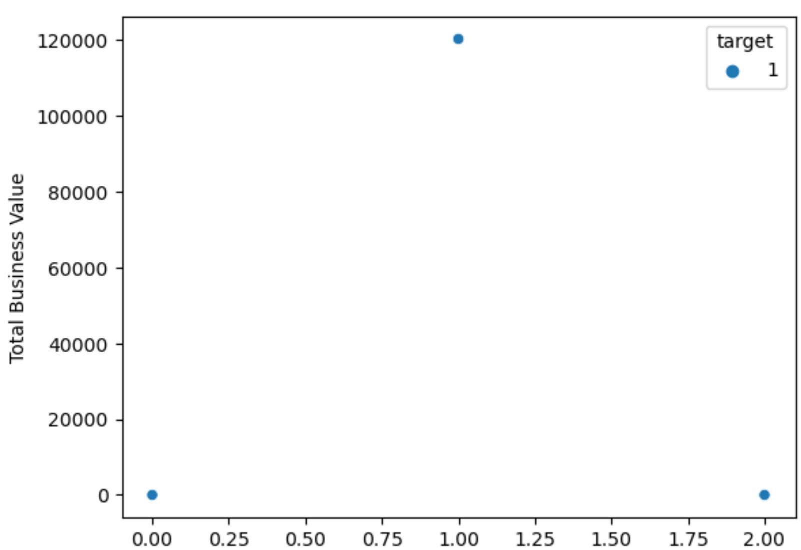

target
0
Total Business Value
0.04
0.02
0.00
−0.02
−0.04
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

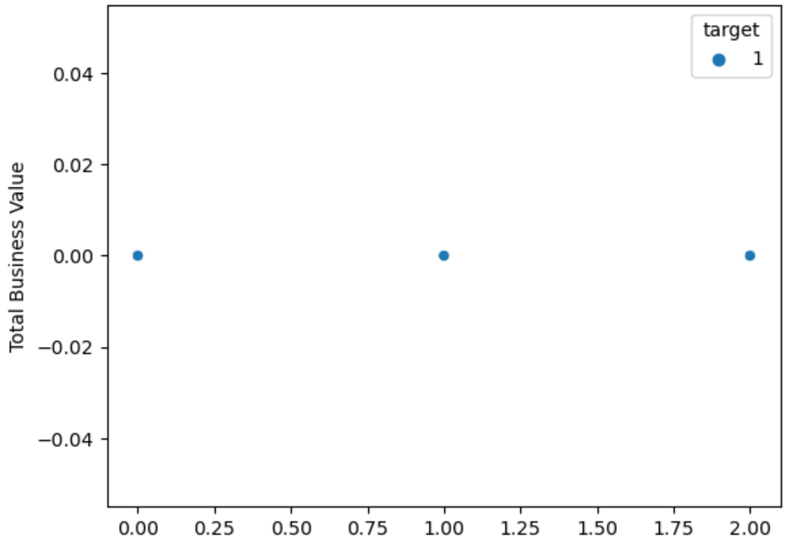

1e6
target
0
Total Business Value
3.0
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
0
5
10
15
20

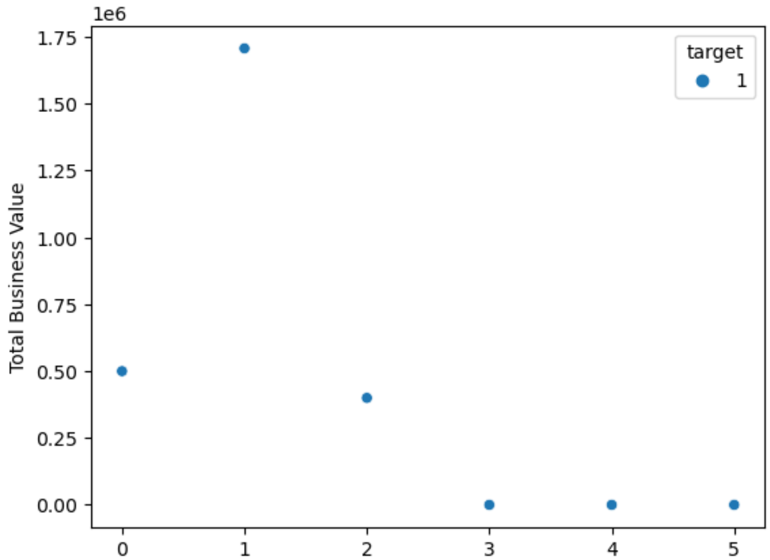
```
In [59]: for i,d in enumerate(df['Driver_ID'].unique()):
             df_ = df[df['Driver_ID']==d]
             if sum(df_['target'])>0:
                 sns.scatterplot(data=df_,y='Total Business Value',x=range(len(df_)),hue=df_['target'])
                 plt.show()
                 if i>10:
                     break
```

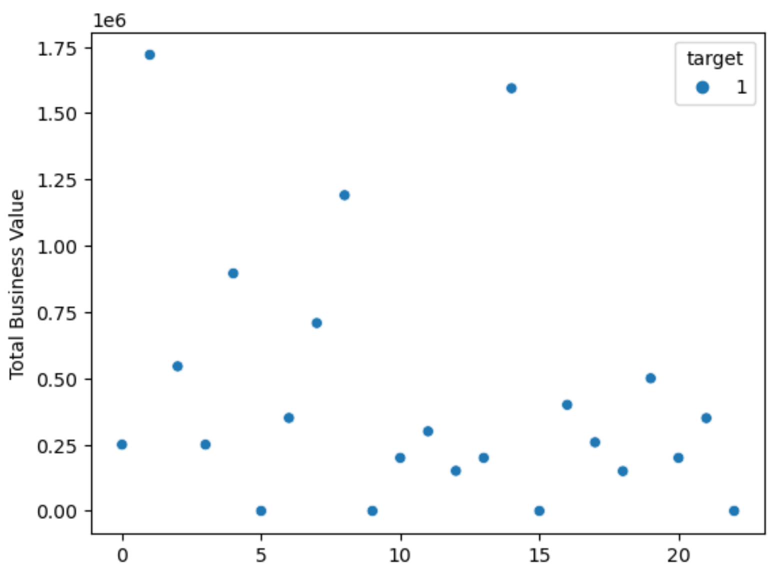


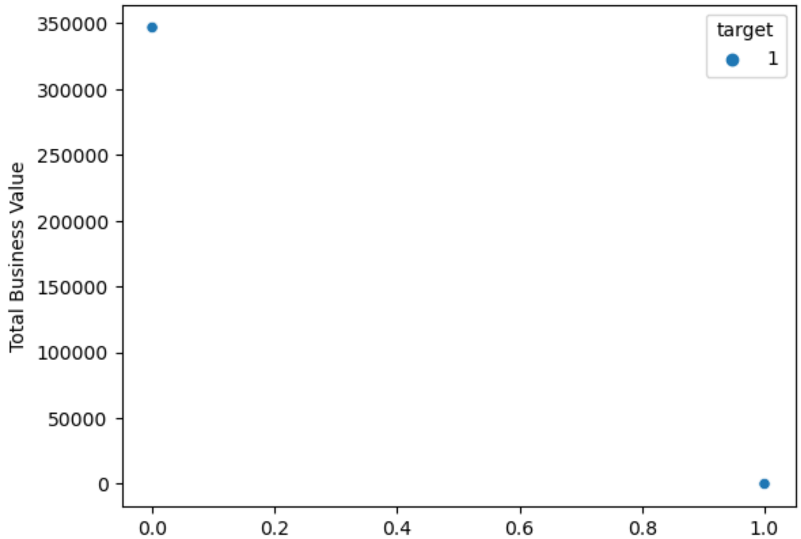


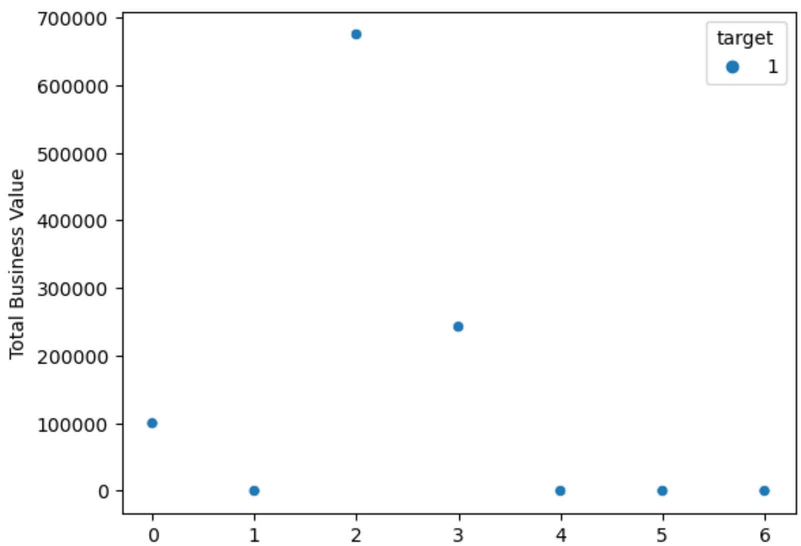



target
1
Total Business Value
0.04
0.02
0.00
−0.02
−0.04
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00


1e6
target
1
Total Business Value
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0
1
2
3
4
5


1e6
target
1
Total Business Value
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0
5
10
15
20





In [52]:
```
z_val_q = []
for i,d in enumerate(df_u['Driver_ID'].tolist()):
    df_= df[df['Driver_ID']==d]
    q_rate = df_['Quarterly Rating'].values
    z = 1.0*(q_rate[-1]-q_rate.mean())/q_rate.std()
    z_val_q.append(z)
```

```
C:\Users\bharath.d.reddy\AppData\Local\Temp\ipykernel_28184\3461315518.py:5: RuntimeWarning: invalid value encountered in dou
ble_scalars
  z = 1.0*(q_rate[-1]-q_rate.mean())/q_rate.std()
```

In [60]:
```
z_val_b = []
for i,d in enumerate(df_u['Driver_ID'].tolist()):
    df_= df[df['Driver_ID']==d]
    q_rate = df_['Total Business Value'].values
    z = 1.0*(q_rate[-1]-q_rate.mean())/q_rate.std()
    z_val_b.append(z)
```

```
C:\Users\bharath.d.reddy\AppData\Local\Temp\ipykernel_28184\1344979051.py:5: RuntimeWarning: invalid value encountered in dou
ble_scalars
  z = 1.0*(q_rate[-1]-q_rate.mean())/q_rate.std()
```

In [61]:
```
nag_val_b = []
for i,d in enumerate(df_u['Driver_ID'].tolist()):
    df_= df[df['Driver_ID']==d]
    q_rate = df_['Total Business Value'].values
    nag_val_b.append((q_rate<0).sum()>0)
```

In [62]:
```
df.shape,df_u.shape,len(z_val_q),len(z_val_b),len(nag_val_b)
```

Out[62]:
```
((19104, 14), (2381, 14), 2381, 2381, 2381)
```

So based on the chart analysis we created Z-score for last quarter so we will know while leaving do the drivers preform low, same for business value creating z score and last feature weather business have negative months for drivers

In [63]:
```
df_u['q_rate_z'] = z_val_q
df_u['buss_z'] = z_val_q
df_u['buss_neg'] = nag_val_b
```

```
C:\Users\bharath.d.reddy\AppData\Local\Temp\ipykernel_28184\2492878631.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  df_u['q_rate_z'] = z_val_q
C:\Users\bharath.d.reddy\AppData\Local\Temp\ipykernel_28184\2492878631.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  df_u['buss_z'] = z_val_q
C:\Users\bharath.d.reddy\AppData\Local\Temp\ipykernel_28184\2492878631.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  df_u['buss_neg'] = nag_val_b
```

In [64]:
```
df_u.head()
```

Out[64]:

ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value	Quarterly Rating	target	q_rate_z	buss_z	buss_n
1	28.0	0.0	C23	2	57387	2018-12-24	2019-03-11	1	1	0	2	1	NaN	NaN	Tr
2	31.0	0.0	C7	2	67016	2020-11-06	NaT	2	2	0	1	0	NaN	NaN	Fa
4	43.0	0.0	C13	2	65603	2019-12-07	2020-04-27	2	2	0	1	1	NaN	NaN	Fa
5	29.0	0.0	C9	0	46368	2019-01-09	2019-03-07	1	1	0	1	1	NaN	NaN	Fa
6	31.0	1.0	C11	1	78728	2020-07-31	NaT	3	3	0	2	0	0.816497	0.816497	Fa

In [66]:
```
df_u = df_u.fillna(0)     # filling nulls with 0 because nulls are
```

In [69]:
```
df_u['buss_neg'] = df_u.buss_neg.apply(int)
```

In [70]:
```
df_u.head()
```

Out[70]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value	Quarterly Rating	target	q_rate_z
0	2019-03-01	1	28.0	0.0	C23	2	57387	2018-12-24	2019-03-11 00:00:00	1	1	0	2	1	0.00000C
1	2020-12-01	2	31.0	0.0	C7	2	67016	2020-11-06	0	2	2	0	1	0	0.00000C
2	2020-04-01	4	43.0	0.0	C13	2	65603	2019-12-07	2020-04-27 00:00:00	2	2	0	1	1	0.00000C
3	2019-03-01	5	29.0	0.0	C9	0	46368	2019-01-09	2019-03-07 00:00:00	1	1	0	1	1	0.00000C
4	2020-12-01	6	31.0	1.0	C11	1	78728	2020-07-31	0	3	3	0	2	0	0.816497

In [87]:
```
df_u['experience'] = ((pd.to_datetime('2020-12-31')-df_u['Dateofjoining'])/np.timedelta64(1, 'M')).apply(int)
```

In [ ]:
```
Total Business Value
```

creating few additional columns as this columns makesense for the models

In [98]:
```
df_agg = df.groupby(['Driver_ID']).agg(income_sum=('Income', 'sum'),
                              income_mean=('Income', 'mean'),
                                income_min=('Income','min'),
                            tbv_mean=('Total Business Value', 'mean'),
                                tbv_min=('Total Business Value','min')).reset_index()
```

In [102]:
```
df_u = df_u.merge(df_agg,on='Driver_ID',how='left')
```

In [105]:
```
df['grade_growth'] = df_u['Grade']-df_u['Joining Designation']  # creating a feature if the grade decreased since joining
```

In [103]:
```
df_u.head()
```

Out[103]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	...	target	q_rate_z	buss_z	buss_neg	ex
0	2019-03-01	1	28.0	0.0	C23	2	57387	2018-12-24	2019-03-11 00:00:00	1	...	1	0.000000	0.000000	1	
1	2020-12-01	2	31.0	0.0	C7	2	67016	2020-11-06	0	2	...	0	0.000000	0.000000	0	
2	2020-04-01	4	43.0	0.0	C13	2	65603	2019-12-07	2020-04-27 00:00:00	2	...	1	0.000000	0.000000	0	
3	2019-03-01	5	29.0	0.0	C9	0	46368	2019-01-09	2019-03-07 00:00:00	1	...	1	0.000000	0.000000	0	
4	2020-12-01	6	31.0	1.0	C11	1	78728	2020-07-31	0	3	...	0	0.816497	0.816497	0	

5 rows × 23 columns

In [106]:
```
df.columns
```

Out[106]:
```
Index(['MMM-YY', 'Driver_ID', 'Age', 'Gender', 'City', 'Education_Level',
       'Income', 'Dateofjoining', 'LastWorkingDate', 'Joining Designation',
       'Grade', 'Total Business Value', 'Quarterly Rating', 'target',
       'income_sum', 'income_mean', 'income_min', 'tbv_mean', 'tbv_min',
       'grade_growth'],
      dtype='object')
```

In [120]:
```
df_ = df_u.drop(columns=['Dateofjoining','MMM-YY','LastWorkingDate','Driver_ID'])
```

In [110]:
```
df_.head()
```

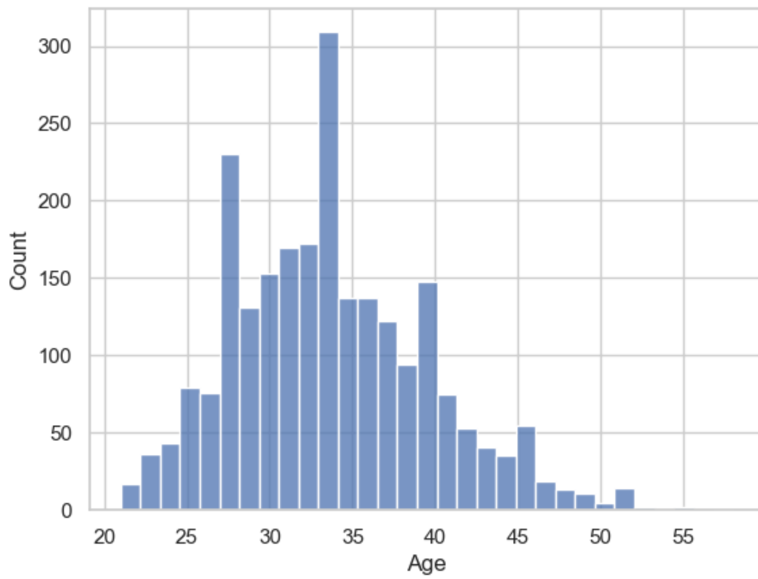
Out[110]:

Level	Income	Joining Designation	Total Business Value	Quarterly Rating	target	q_rate_z	buss_z	buss_neg	experience	income_sum	income_mean	income_min	tbv_mean	tbv_m
2	57387	1	0	2	1	0.000000	0.000000	1	24	172161	57387.0	57387	571860.0	-6654
2	67016	2	0	1	0	0.000000	0.000000	0	1	134032	67016.0	67016	0.0	
2	65603	2	0	1	1	0.000000	0.000000	0	12	328015	65603.0	65603	70000.0	
0	46368	1	0	1	1	0.000000	0.000000	0	23	139104	46368.0	46368	40120.0	
1	78728	3	0	2	0	0.816497	0.816497	0	5	393640	78728.0	78728	253000.0	

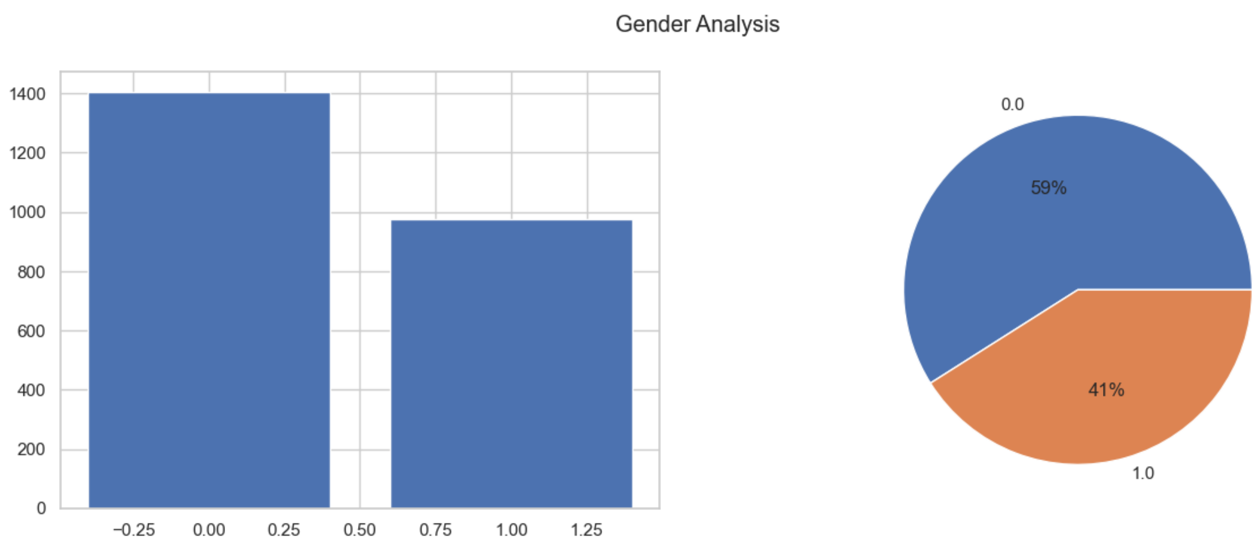
In [ ]:

In [122]:
```
sns.histplot(df_['Age'])
```

Out[122]: <AxesSubplot:xlabel='Age', ylabel='Count'>

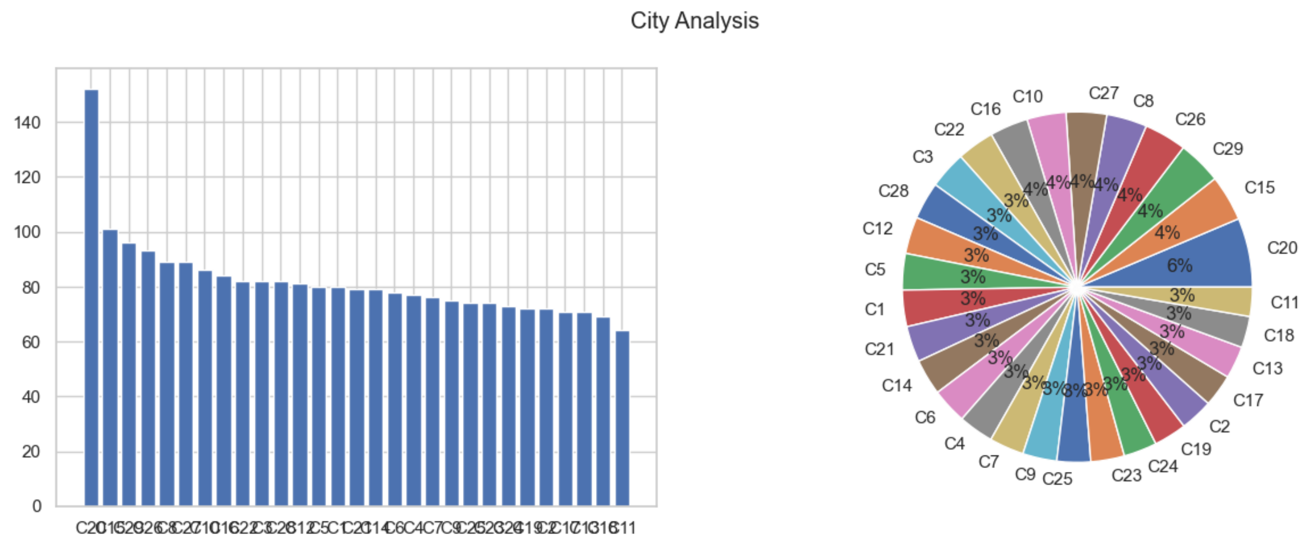


In [112]:
```
s_vc = df_['Gender'].value_counts()
fig, axs = plt.subplots(1, 2 , figsize =(15, 5))
fig.suptitle('Gender Analysis')
axs[0].bar(s_vc.index,s_vc.values)
axs[1].pie(s_vc.values,labels=s_vc.index, autopct='%1.0f%%')
plt.show()
```



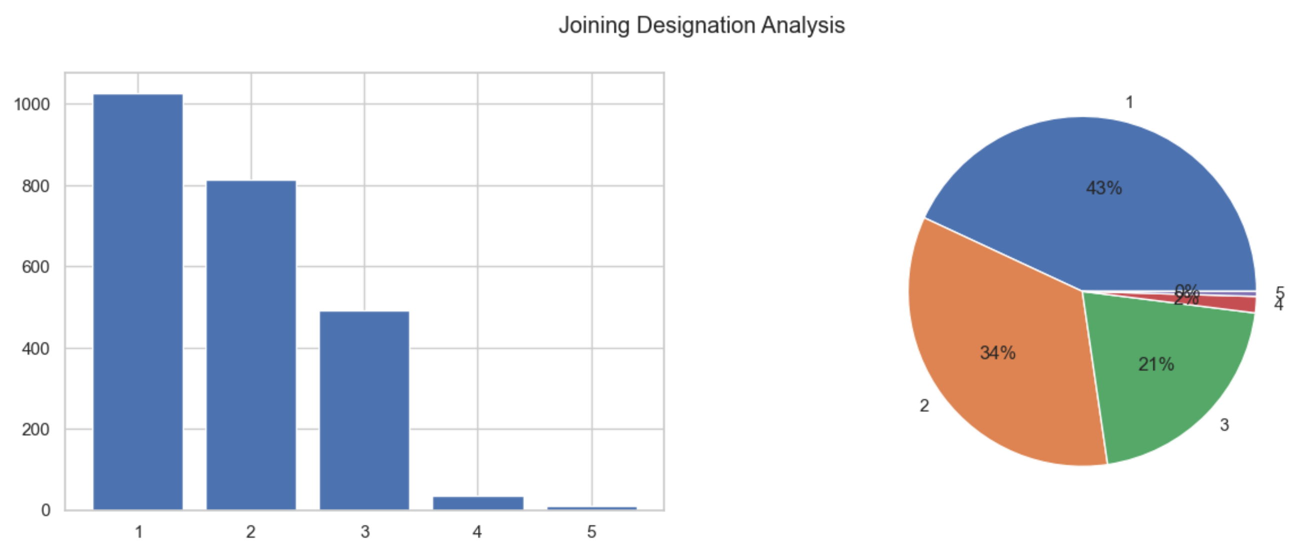
In [118]:

```
s_vc = df_['City'].value_counts()
fig, axs = plt.subplots(1, 2 , figsize =(15, 5))
fig.suptitle('City Analysis')
axs[0].bar(s_vc.index,s_vc.values)
axs[1].pie(s_vc.values,labels=s_vc.index, autopct='%1.0f%%')
plt.show()
```

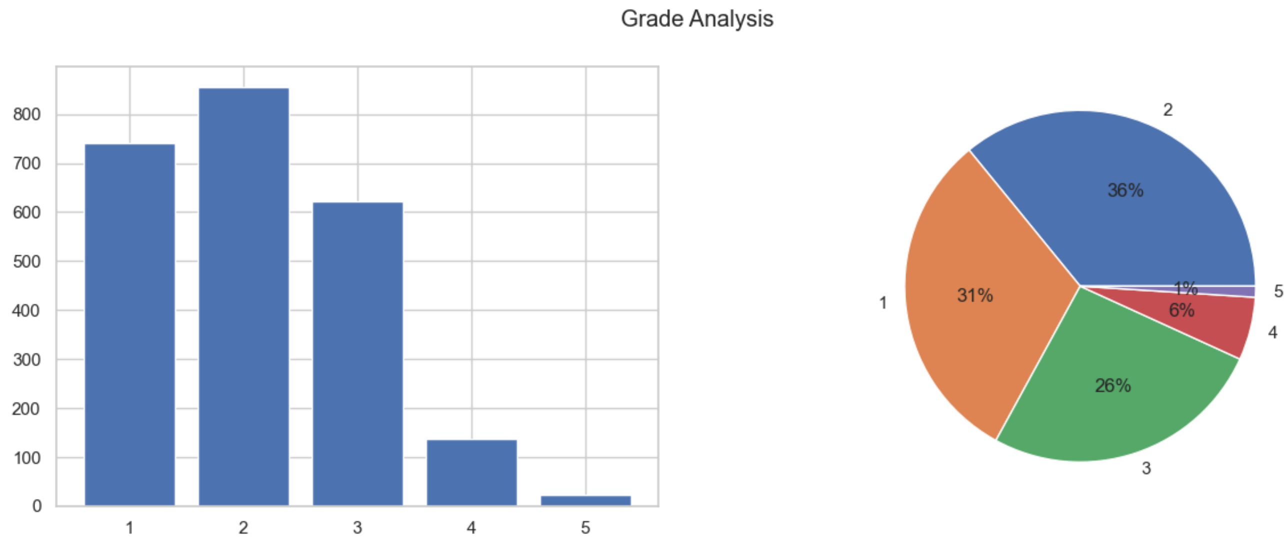


In [119]:

```
s_vc = df_['Joining Designation'].value_counts()
fig, axs = plt.subplots(1, 2 , figsize =(15, 5))
fig.suptitle('Joining Designation Analysis')
axs[0].bar(s_vc.index,s_vc.values)
axs[1].pie(s_vc.values,labels=s_vc.index, autopct='%1.0f%%')
plt.show()
```

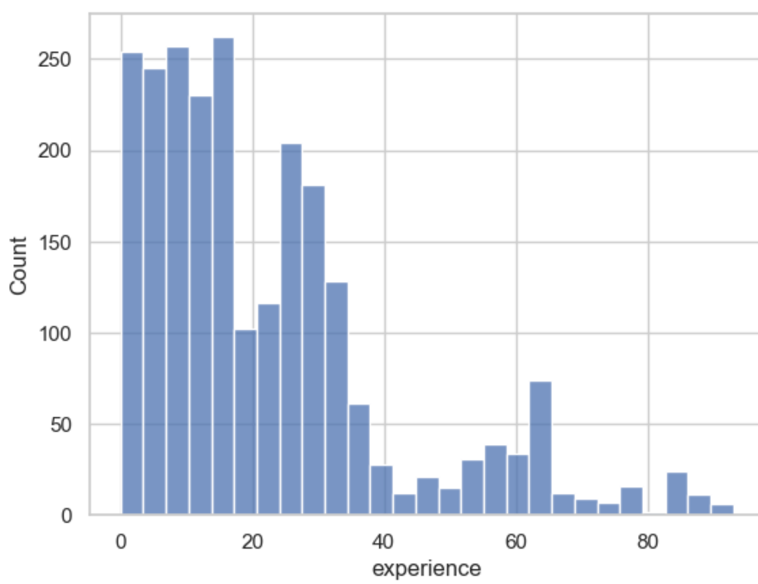


In [121]:
```
s_vc = df_['Grade'].value_counts()
fig, axs = plt.subplots(1, 2 , figsize =(15, 5))
fig.suptitle('Grade Analysis')
axs[0].bar(s_vc.index,s_vc.values)
axs[1].pie(s_vc.values,labels=s_vc.index, autopct='%1.0f%%')
plt.show()
```



In [123]:
```
sns.histplot(df_['experience'])
```

Out[123]: <AxesSubplot:xlabel='experience', ylabel='Count'>



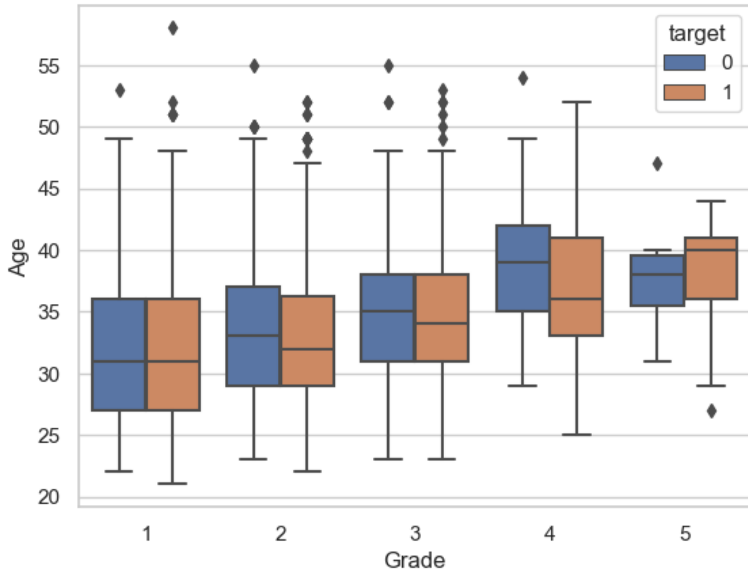
In [125]:
```
df_.head()
```

Out[125]:

	Age	Gender	City	Education_Level	Income	Joining Designation	Grade	Total Business Value	Quarterly Rating	target	q_rate_z	buss_z	buss_neg	experience	income_sum	i
0	28.0	0.0	C23	2	57387	1	1	0	2	1	0.000000	0.000000	1	24	172161	
1	31.0	0.0	C7	2	67016	2	2	0	1	0	0.000000	0.000000	0	1	134032	
2	43.0	0.0	C13	2	65603	2	2	0	1	1	0.000000	0.000000	0	12	328015	
3	29.0	0.0	C9	0	46368	1	1	0	1	1	0.000000	0.000000	0	23	139104	
4	31.0	1.0	C11	1	78728	3	3	0	2	0	0.816497	0.816497	0	5	393640	

In [130]:
```
sns.boxplot(x=df_['Grade'],y=df_['Age'],hue=df_['target'])
```

Out[130]: <AxesSubplot:xlabel='Grade', ylabel='Age'>

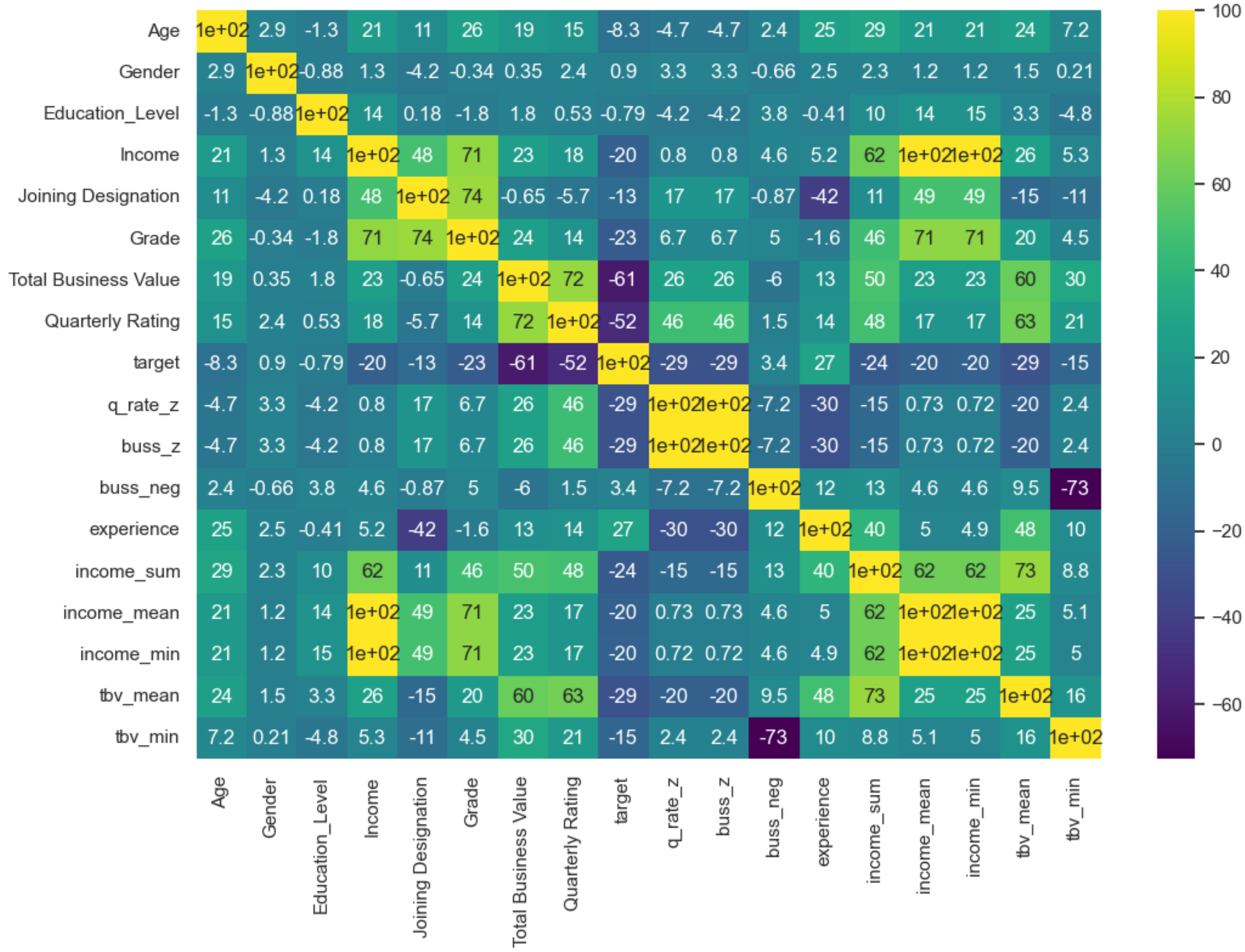


In [ ]:
```

```

In [133]:
```
spearman_corr = df_.corr(method='spearman')
pearson_corr = df_.corr()
```

In [134]:
```
spearman_corr = (100*spearman_corr).round(2)
pearson_corr = (100*pearson_corr).round(2)
```

In [138]:
```python
plt.figure(figsize=(12, 8))
sns.heatmap(spearman_corr, annot=True, cmap='viridis')
plt.show()
```



In [ ]:

In [139]:
```python
df_.head()
```

Out[139]:

	Age	Gender	City	Education_Level	Income	Joining Designation	Grade	Total Business Value	Quarterly Rating	target	q_rate_z	buss_z	buss_neg	experience	income_sum	i
0	28.0	0.0	C23	2	57387	1	1	0	2	1	0.000000	0.000000	1	24	172161	
1	31.0	0.0	C7	2	67016	2	2	0	1	0	0.000000	0.000000	0	1	134032	
2	43.0	0.0	C13	2	65603	2	2	0	1	1	0.000000	0.000000	0	12	328015	
3	29.0	0.0	C9	0	46368	1	1	0	1	1	0.000000	0.000000	0	23	139104	
4	31.0	1.0	C11	1	78728	3	3	0	2	0	0.816497	0.816497	0	5	393640	

In [141]:
```python
df_.City.nunique()
```

Out[141]: 29

In [142]:
```python
X = df_.drop(columns=['target'])
y = df_['target']
```

In [143]:
```python
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.25, stratify=y, random_state=42)
```

In [144]:
```
import category_encoders as ce

ce_target = ce.TargetEncoder(cols = ['City'])
X_train = ce_target.fit_transform(X_train, y_train)
X_test = ce_target.transform(X_test)
```

In [ ]:

In [147]:
```
tree_clf = DecisionTreeClassifier()
```

In [148]:
```
tree_clf.fit(X_train, y_train)
```

Out[148]:
```
DecisionTreeClassifier()
```

In [149]:
```
tree_clf.score(X_train, y_train)  #train accuracy
```

Out[149]:
```
1.0
```

In [150]:
```
tree_clf.score(X_test, y_test) # test accuracy
```

Out[150]:
```
0.8942953020134228
```

In [157]:
```
kfold = KFold(n_splits = 5)
```

In [158]:
```
cv_acc_results = cross_validate(tree_clf, X_train, y_train, scoring='accuracy',
                                cv = kfold, return_train_score = True  )
```

In [161]:
```
cv_acc_results['train_score'].mean()
```

Out[161]:
```
1.0
```

In [162]:
```
cv_acc_results['test_score'].mean()
```

Out[162]:
```
0.8879551820728292
```

In [ ]:

In [173]:
```
print(classification_report(y_test, tree_clf.predict(X_test)))
```

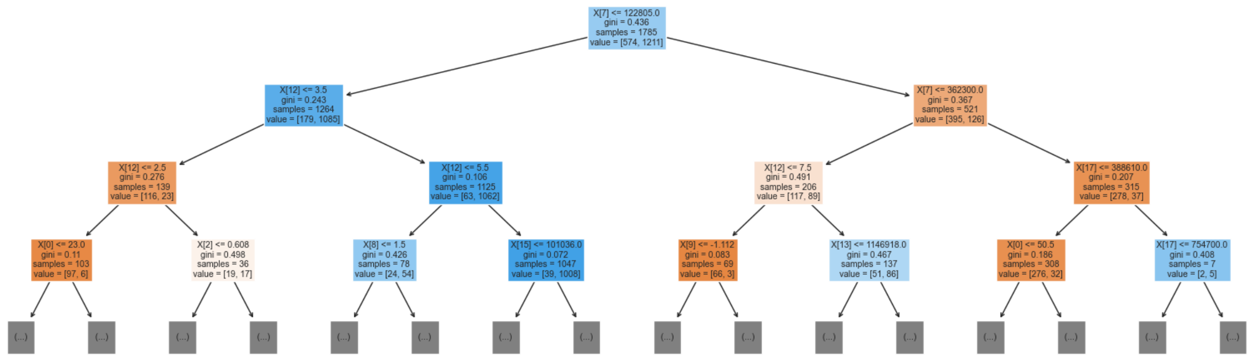
```
              precision    recall  f1-score   support

           0       0.83      0.84      0.84       191
           1       0.92      0.92      0.92       405

    accuracy                           0.89       596
   macro avg       0.88      0.88      0.88       596
weighted avg       0.89      0.89      0.89       596
```

In [ ]:

In [ ]:

In [163]:
```
from sklearn.tree import plot_tree
```

In [165]:
```python
plt.figure(figsize = (20, 6))
plot_tree(tree_clf, max_depth = 3, filled = True)
plt.show()
```



In [ ]:
```python

```

In [177]:
```python
rfc = RandomForestClassifier(random_state=42, n_estimators=100)

kfold = KFold(n_splits=10)
cv_acc_results = cross_validate(rfc, X_train, y_train, cv = kfold,
                                scoring = 'f1',
                                return_train_score = True)

print(f"K-Fold Accuracy Mean: Train: {cv_acc_results['train_score'].mean().round(3)*100} Validation: {cv_acc_results['test_sco
```

```
K-Fold Accuracy Mean: Train: 100.0 Validation: 93.60000000000001
```

In [169]:
```python
rfc = RandomForestClassifier(random_state=42, n_estimators=100)
rfc.fit(X_train, y_train)
```

Out[169]:
```
RandomForestClassifier(random_state=42)
```

In [172]:
```python
accuracy_score(y_test, rfc.predict(X_test))
```

Out[172]:
```
0.9261744966442953
```

In [174]:
```python
print(classification_report(y_test, rfc.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.90      0.87      0.88       191
           1       0.94      0.95      0.95       405

    accuracy                           0.93       596
   macro avg       0.92      0.91      0.91       596
weighted avg       0.93      0.93      0.93       596
```

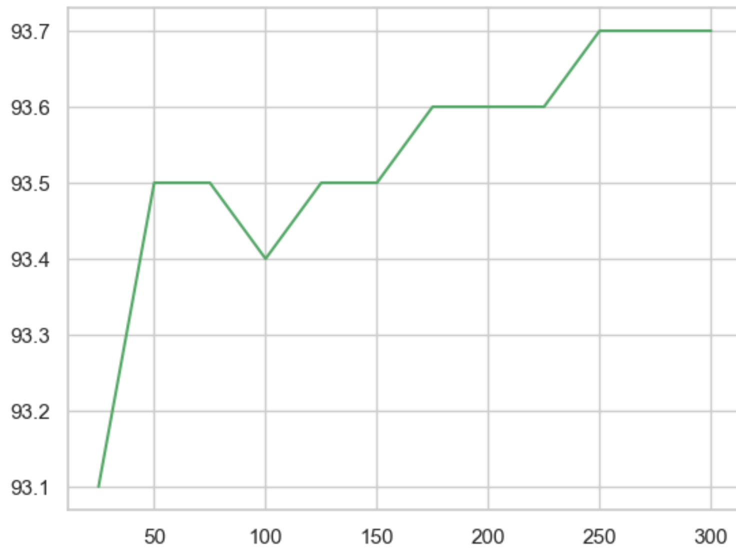
In [175]:
```python
from tqdm import tqdm
```

In [178]:

```python
x_values = []

y_values_valid_scores = []

for k in tqdm(range(25, 310, 25)):

    print(f"Traing with {k} Decision Trees")
    rfc = RandomForestClassifier(random_state=7, n_estimators=k,class_weight='balanced') ## i am letting each DT overfit

    kfold = KFold(n_splits=10)
    cv_acc_results = cross_validate(rfc, X_train, y_train, cv = kfold,
                                    scoring = 'f1',
                                    return_train_score = True)

    y_values_valid_scores.append(cv_acc_results['test_score'].mean().round(3)*100)
    x_values.append(k)
```

```
  0%|                                                                                  | 0/12 [00:00<?, ?it/s]

Traing with 25 Decision Trees

  8%|██████▌                                                                        | 1/12 [00:00<00:06,  1.75it/s]

Traing with 50 Decision Trees

 17%|█████████████▊                                                                 | 2/12 [00:01<00:08,  1.20it/s]

Traing with 75 Decision Trees

 25%|████████████████████▌                                                          | 3/12 [00:03<00:10,  1.15s/it]

Traing with 100 Decision Trees

 33%|███████████████████████████▎                                                   | 4/12 [00:05<00:12,  1.53s/it]

Traing with 125 Decision Trees

 42%|██████████████████████████████████                                            | 5/12 [00:07<00:13,  1.92s/it]

Traing with 150 Decision Trees

 50%|█████████████████████████████████████████                                     | 6/12 [00:10<00:13,  2.30s/it]

Traing with 175 Decision Trees

 58%|███████████████████████████████████████████████▊                               | 7/12 [00:14<00:13,  2.62s/it]

Traing with 200 Decision Trees

 67%|██████████████████████████████████████████████████████▋                        | 8/12 [00:18<00:12,  3.01s/it]

Traing with 225 Decision Trees

 75%|█████████████████████████████████████████████████████████████▌                 | 9/12 [00:22<00:10,  3.45s/it]

Traing with 250 Decision Trees

 83%|████████████████████████████████████████████████████████████████████▎         | 10/12 [00:27<00:07,  3.85s/it]

Traing with 275 Decision Trees

 92%|███████████████████████████████████████████████████████████████████████████▏  | 11/12 [00:32<00:04,  4.25s/it]

Traing with 300 Decision Trees

100%|██████████████████████████████████████████████████████████████████████████████████| 12/12 [00:38<00:00,  3.19s/it]
```

In [179]:
```
plt.plot(x_values, y_values_valid_scores, color = "g")

plt.show()
```



In [ ]:

In [182]:
```
rfc = RandomForestClassifier(random_state=42, n_estimators=175,class_weight='balanced')
rfc.fit(X_train, y_train)
```

Out[182]:
```
RandomForestClassifier(class_weight='balanced', n_estimators=175,
                       random_state=42)
```

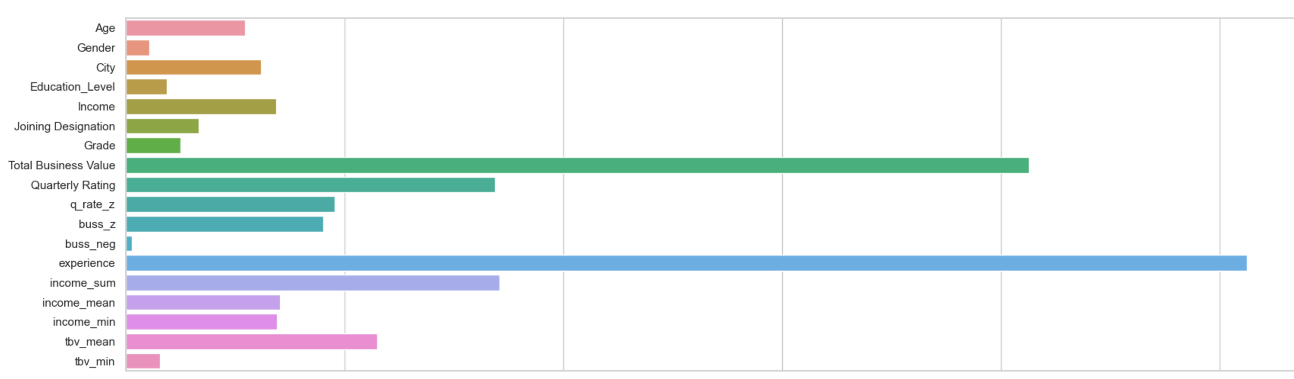
In [183]:
```
print(classification_report(y_test, rfc.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.90      0.86      0.88       191
           1       0.93      0.96      0.95       405

    accuracy                           0.92       596
   macro avg       0.92      0.91      0.91       596
weighted avg       0.92      0.92      0.92       596
```

In [188]:
```
plt.figure(figsize = (20, 6))
sns.barplot(rfc.feature_importances_,rfc.feature_names_in_ )
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variables as keyword
args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an expl
icit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[188]: <AxesSubplot:>



In [ ]:
```
Experience, Total Business Value, Income, Quarterly Rating,
```

In [191]:
```
sm = SMOTE(random_state=42)
X_train_res, y_train_res = sm.fit_resample(X_train, y_train)
```

In [194]:
```
gbc = GradientBoostingClassifier()
gbc.fit(X_train_res, y_train_res)
```

Out[194]:
```
GradientBoostingClassifier()
```

In [195]:
```
gbc.score(X_test,y_test)
```

Out[195]:
```
0.9328859060402684
```

In [198]:
```
print(classification_report(y_test,gbc.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.89      0.90      0.90       191
           1       0.95      0.95      0.95       405

    accuracy                           0.93       596
   macro avg       0.92      0.92      0.92       596
weighted avg       0.93      0.93      0.93       596
```

In [ ]:

Final Result Evaluation :

Decision Tree results :

```
Precision : 0.92 , Recall : 0.92
```

Random Forest results :

```
Precision : 0.93 , Recall : 0.96
```

Gredient Boosting results :

```
Precision : 0.95 , Recall : 0.95
```

We achieved best results with Gredient Boosting with 0.95 Precision and recall both, which is excellent in terms of the accuracy, we have build a very good model here.

In [ ]:

Insights and Recommendations

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.
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 employes at different Education level is about a change of 3-5% with level 0.
Joining Designation Increases with increase in Grade.
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.
Experience, Total Business Value, Income, Quarterly Rating are contributiong heavily for the classification

In [ ]:

```

```