In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
from sklearn.impute import KNNImputer
```

In [3]:
```
data = pd.read_csv("/content/drive/MyDrive/Python_Note_Book/Business Case/Ola/ola_driver_scaler.csv")
```

Understanding the give Ola Drivers Data set

```
Dataframe shape
head and tail
dtypes
describe
```

In [4]:
```
data.shape
```

Out[4]:
```
(19104, 14)
```

In [5]:
```
data.head()
```

Out[5]:

	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

In [6]:
```
data.columns
```

Out[6]:
```
Index(['Unnamed: 0', 'MMM-YY', 'Driver_ID', 'Age', 'Gender', 'City',
       'Education_Level', 'Income', 'Dateofjoining', 'LastWorkingDate',
       'Joining Designation', 'Grade', 'Total Business Value',
       'Quarterly Rating'],
      dtype='object')
```

In [7]:
```
data.dtypes
```

Out[7]:
```
Unnamed: 0                 int64
MMM-YY                    object
Driver_ID                  int64
Age                      float64
Gender                   float64
City                      object
Education_Level            int64
Income                     int64
Dateofjoining             object
LastWorkingDate           object
Joining Designation        int64
Grade                      int64
Total Business Value       int64
Quarterly Rating           int64
dtype: object
```

In [8]:
```
data.describe()
```

Out[8]:

	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

Preparing the data

- Checking if there is null
- Dropping the irrelavant rows
- Renaming Columns
- Feature Creation

In [9]:
```
data.isnull().sum()
```

Out[9]:
```
Unnamed: 0                0
MMM-YY                    0
Driver_ID                 0
Age                      61
Gender                   52
City                      0
Education_Level           0
Income                    0
Dateofjoining             0
LastWorkingDate       17488
Joining Designation       0
Grade                     0
Total Business Value      0
Quarterly Rating          0
dtype: int64
```

In [10]:
```
# @title Dropping Irrelavent column.
data.drop(["Unnamed: 0"], axis=1, inplace=True)
data.head()
```

Out[10]:

	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 [11]:
```
# @title Checking any duplicate data entry
data.loc[data.duplicated()]
```

Out[11]:

MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value	Quarterly Rating

In [12]:
```
# @title Converting date related object fields to data type

data['MMM-YY'] = pd.to_datetime(data['MMM-YY'])
data['Dateofjoining'] = pd.to_datetime(data['Dateofjoining'])
data['LastWorkingDate'] = pd.to_datetime(data['LastWorkingDate'])
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19104 entries, 0 to 19103
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   MMM-YY                19104 non-null  datetime64[ns]
 1   Driver_ID             19104 non-null  int64
 2   Age                   19043 non-null  float64
 3   Gender                19052 non-null  float64
 4   City                  19104 non-null  object
 5   Education_Level       19104 non-null  int64
 6   Income                19104 non-null  int64
 7   Dateofjoining         19104 non-null  datetime64[ns]
 8   LastWorkingDate       1616 non-null   datetime64[ns]
 9   Joining Designation   19104 non-null  int64
 10  Grade                 19104 non-null  int64
 11  Total Business Value  19104 non-null  int64
 12  Quarterly Rating      19104 non-null  int64
dtypes: datetime64[ns](3), float64(2), int64(7), object(1)
memory usage: 1.9+ MB
```

In [13]:
```
data.head()
```

Out[13]:

	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	2018-12-24	NaT	1	1	2381060	2
1	2019-02-01	1	28.0	0.0	C23	2	57387	2018-12-24	NaT	1	1	-665480	2
2	2019-03-01	1	28.0	0.0	C23	2	57387	2018-12-24	2019-03-11	1	1	0	2
3	2020-11-01	2	31.0	0.0	C7	2	67016	2020-11-06	NaT	2	2	0	1
4	2020-12-01	2	31.0	0.0	C7	2	67016	2020-11-06	NaT	2	2	0	1

In [14]:
```python
# @title Looking into the data of a particular driver.

data[data["Driver_ID"] == 22]
```

Out[14]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value	Quarterly Rating
88	2019-01-01	22	40.0	0.0	C10	2	31224	2018-05-25	NaT	1	1	216170	2
89	2019-02-01	22	40.0	0.0	C10	2	31224	2018-05-25	NaT	1	1	404600	2
90	2019-03-01	22	40.0	0.0	C10	2	31224	2018-05-25	NaT	1	1	819960	2
91	2019-04-01	22	40.0	0.0	C10	2	31224	2018-05-25	NaT	1	1	601680	4
92	2019-05-01	22	40.0	0.0	C10	2	31224	2018-05-25	NaT	1	1	635700	4
93	2019-06-01	22	40.0	0.0	C10	2	31224	2018-05-25	NaT	1	1	121590	4
94	2019-07-01	22	40.0	0.0	C10	2	31224	2018-05-25	NaT	1	1	653680	4
95	2019-08-01	22	40.0	0.0	C10	2	31224	2018-05-25	NaT	1	1	1120560	4
96	2019-09-01	22	40.0	0.0	C10	2	31224	2018-05-25	NaT	1	1	696920	4
97	2019-10-01	22	NaN	0.0	C10	2	31224	2018-05-25	NaT	1	1	200000	3
98	2019-11-01	22	41.0	0.0	C10	2	31224	2018-05-25	NaT	1	1	306410	3
99	2019-12-01	22	41.0	0.0	C10	2	31224	2018-05-25	NaT	1	1	499480	3
100	2020-01-01	22	41.0	0.0	C10	2	31224	2018-05-25	NaT	1	1	500510	2
101	2020-02-01	22	41.0	0.0	C10	2	31224	2018-05-25	NaT	1	1	658430	2
102	2020-03-01	22	41.0	0.0	C10	2	31224	2018-05-25	NaT	1	1	103800	2
103	2020-04-01	22	41.0	0.0	C10	2	31224	2018-05-25	2020-04-26	1	1	0	1

In [15]:
```python
# @title Check for missing values and Prepare data for KNN Imputation
def update_Age_Gender(data):
    # create an object for KNNImputer
    imputer = KNNImputer(n_neighbors=2)
    data[["Gender","Age"]] = imputer.fit_transform(data[["Gender","Age"]])
    return data
```

In [16]:
```python
## Updating the age gender NAN value using KNN Imputer.
data = data.groupby(['Driver_ID']).apply(update_Age_Gender).reset_index(drop=True)
```

```
<ipython-input-16-0ec09a0692e5>:2: FutureWarning: Not prepending group keys to the result index of transform-like apply. In the future, the group keys will be included in the in
dex, regardless of whether the applied function returns a like-indexed object.
To preserve the previous behavior, use

        >>> .groupby(..., group_keys=False)

To adopt the future behavior and silence this warning, use

        >>> .groupby(..., group_keys=True)
  data = data.groupby(['Driver_ID']).apply(update_Age_Gender).reset_index(drop=True)
```

In [17]:
```
##check data
data.isnull().sum()
```

Out[17]:
```
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
dtype: int64
```

Now we have only Lastworking day left with NAN. So Assuming that a will have only one last working day with the company we can duplicate the value and later we can group by and aggregate it.

In [18]:
```
# @title Update the last working date of the drivers with NAN values.
def udpate_lwd(data):

    non_nan_values = data["LastWorkingDate"].dropna().unique()
    if len(non_nan_values) > 0:
       non_nan_value = non_nan_values[0]
       data["LastWorkingDate"].fillna(non_nan_value, inplace=True)

    return data
```

In [19]:
```
data = data.groupby(['Driver_ID']).apply(udpate_lwd).reset_index(drop=True)
data.head(15)
```

```
<ipython-input-19-689d2ddea429>:1: FutureWarning: Not prepending group keys to the result index of transform-like apply. In the future, the group keys will be included in the in
dex, regardless of whether the applied function returns a like-indexed object.
To preserve the previous behavior, use

        >>> .groupby(..., group_keys=False)

To adopt the future behavior and silence this warning, use

        >>> .groupby(..., group_keys=True)
  data = data.groupby(['Driver_ID']).apply(udpate_lwd).reset_index(drop=True)
```

Out[19]:

	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	2018-12-24	2019-03-11	1	1	2381060	2
1	2019-02-01	1	28.0	0.0	C23	2	57387	2018-12-24	2019-03-11	1	1	-665480	2
2	2019-03-01	1	28.0	0.0	C23	2	57387	2018-12-24	2019-03-11	1	1	0	2
3	2020-11-01	2	31.0	0.0	C7	2	67016	2020-11-06	NaT	2	2	0	1
4	2020-12-01	2	31.0	0.0	C7	2	67016	2020-11-06	NaT	2	2	0	1
5	2019-12-01	4	43.0	0.0	C13	2	65603	2019-12-07	2020-04-27	2	2	0	1
6	2020-01-01	4	43.0	0.0	C13	2	65603	2019-12-07	2020-04-27	2	2	0	1
7	2020-02-01	4	43.0	0.0	C13	2	65603	2019-12-07	2020-04-27	2	2	0	1
8	2020-03-01	4	43.0	0.0	C13	2	65603	2019-12-07	2020-04-27	2	2	350000	1
9	2020-04-01	4	43.0	0.0	C13	2	65603	2019-12-07	2020-04-27	2	2	0	1
10	2019-01-01	5	29.0	0.0	C9	0	46368	2019-01-09	2019-03-07	1	1	0	1
11	2019-02-01	5	29.0	0.0	C9	0	46368	2019-01-09	2019-03-07	1	1	120360	1
12	2019-03-01	5	29.0	0.0	C9	0	46368	2019-01-09	2019-03-07	1	1	0	1
13	2020-08-01	6	31.0	1.0	C11	1	78728	2020-07-31	NaT	3	3	0	1
14	2020-09-01	6	31.0	1.0	C11	1	78728	2020-07-31	NaT	3	3	0	1

Creating new feature columns.

In [20]:
```
# @title 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

data['Increased_Rating'] = (data['Quarterly Rating'] > data.groupby('Driver_ID')['Quarterly Rating'].shift(1)) * 1
```

In [21]:
```
# @title 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

data['target'] = np.where(data['LastWorkingDate'].isna(), 0, 1)
```

In [22]:
```
# @title 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

data['Increased_Income'] = (data['Income'] > data.groupby('Driver_ID')['Income'].shift(1)) * 1
```

In [23]:
```
# @title Create a column ride taken. count the number of times driver reported using the column "MMMM-YY"

data['ride_taken'] = data.groupby('Driver_ID')['MMM-YY'].transform('count')
```

In [24]:
```
# @title Create a column which tells whether driver grade were increase or not. if increased then assign 1 else 0

data['Grade_Increased'] = (data['Grade'] > data['Joining Designation']).astype(int)
```

In [25]:
```
# @title Create a column which have details if driver's grade increased.

data['Grade_Increased_diff'] = (data['Grade'] - data['Joining Designation']).astype(int)
```

Type *Markdown* and LaTeX: α^2

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

Out[26]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value	Quarterly Rating	Increased_Rating	target	Increased_Income	ride_taken	Grade_Increased	Grade_
0	2019-01-01	1	28.0	0.0	C23	2	57387	2018-12-24	2019-03-11	1	1	2381060	2	0	1	0	3	0	
1	2019-02-01	1	28.0	0.0	C23	2	57387	2018-12-24	2019-03-11	1	1	-665480	2	0	1	0	3	0	
2	2019-03-01	1	28.0	0.0	C23	2	57387	2018-12-24	2019-03-11	1	1	0	2	0	1	0	3	0	
3	2020-11-01	2	31.0	0.0	C7	2	67016	2020-11-06	NaT	2	2	0	1	0	0	0	2	0	
4	2020-12-01	2	31.0	0.0	C7	2	67016	2020-11-06	NaT	2	2	0	1	0	0	0	2	0	

In [27]:
```
# @title Aggregating Data set.
# Aggregate data in order to remove multiple occurrences of same driver data by storing unique Driver IDs in an empty dataframe and then bring all the features at same level

driver_data= data.groupby('Driver_ID').agg(
    {'Gender': 'first',
     'Age': 'max',
     'City': 'first',
     'ride_taken' : 'first',
     'Education_Level': 'max',
     'Grade': 'max',
     'Total Business Value':'sum',
     'Quarterly Rating': 'mean',
     'Income': 'mean',
     'Increased_Rating': 'max',
     'target': 'max',
     'Grade_Increased': 'max',
     'Grade_Increased_diff': 'max',
     'Increased_Income': 'max'}).reset_index()

driver_data.head()
```

Out[27]:

	Driver_ID	Gender	Age	City	ride_taken	Education_Level	Grade	Total Business Value	Quarterly Rating	Income	Increased_Rating	target	Grade_Increased	Grade_Increased_diff	Increased_Income
0	1	0.0	28.0	C23	3	2	1	1715580	2.0	57387.0	0	1	0	0	0
1	2	0.0	31.0	C7	2	2	2	0	1.0	67016.0	0	0	0	0	0
2	4	0.0	43.0	C13	5	2	2	350000	1.0	65603.0	0	1	0	0	0
3	5	0.0	29.0	C9	3	0	1	120360	1.0	46368.0	0	1	0	0	0
4	6	1.0	31.0	C11	5	1	3	1265000	1.6	78728.0	1	0	0	0	0

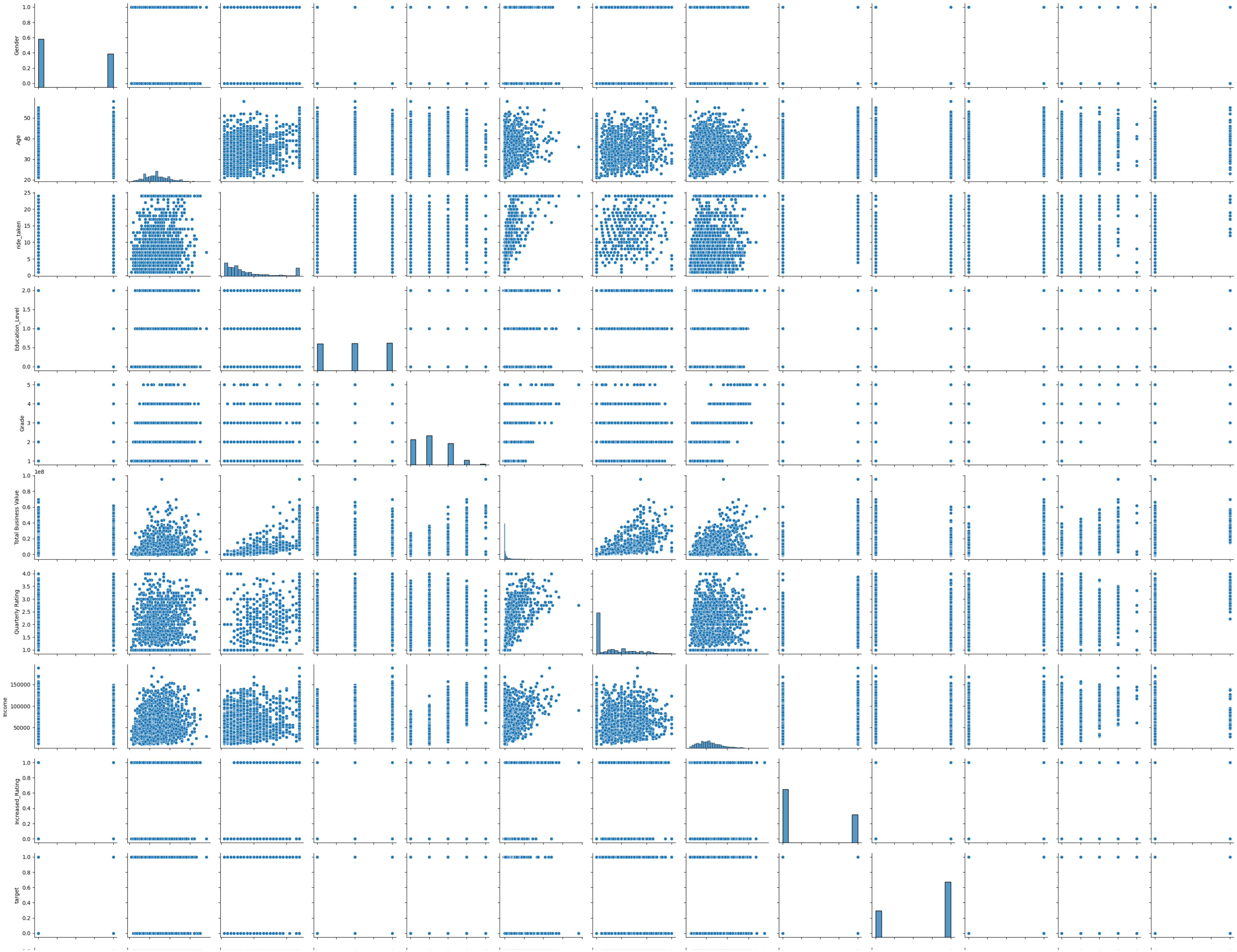
In [28]:
```
# @title Dropping Driver_ID column as its not relevant any more.
driver_data.drop(["Driver_ID"], axis=1, inplace=True)
```

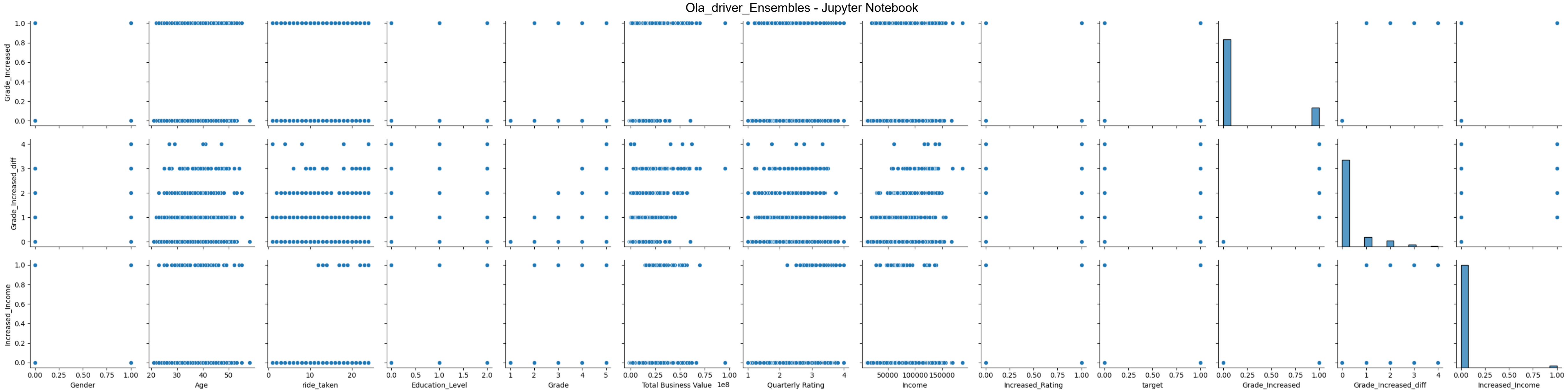
Analysing the aggregated data. ¶

- Checking Corelation
- Ploting different graphs

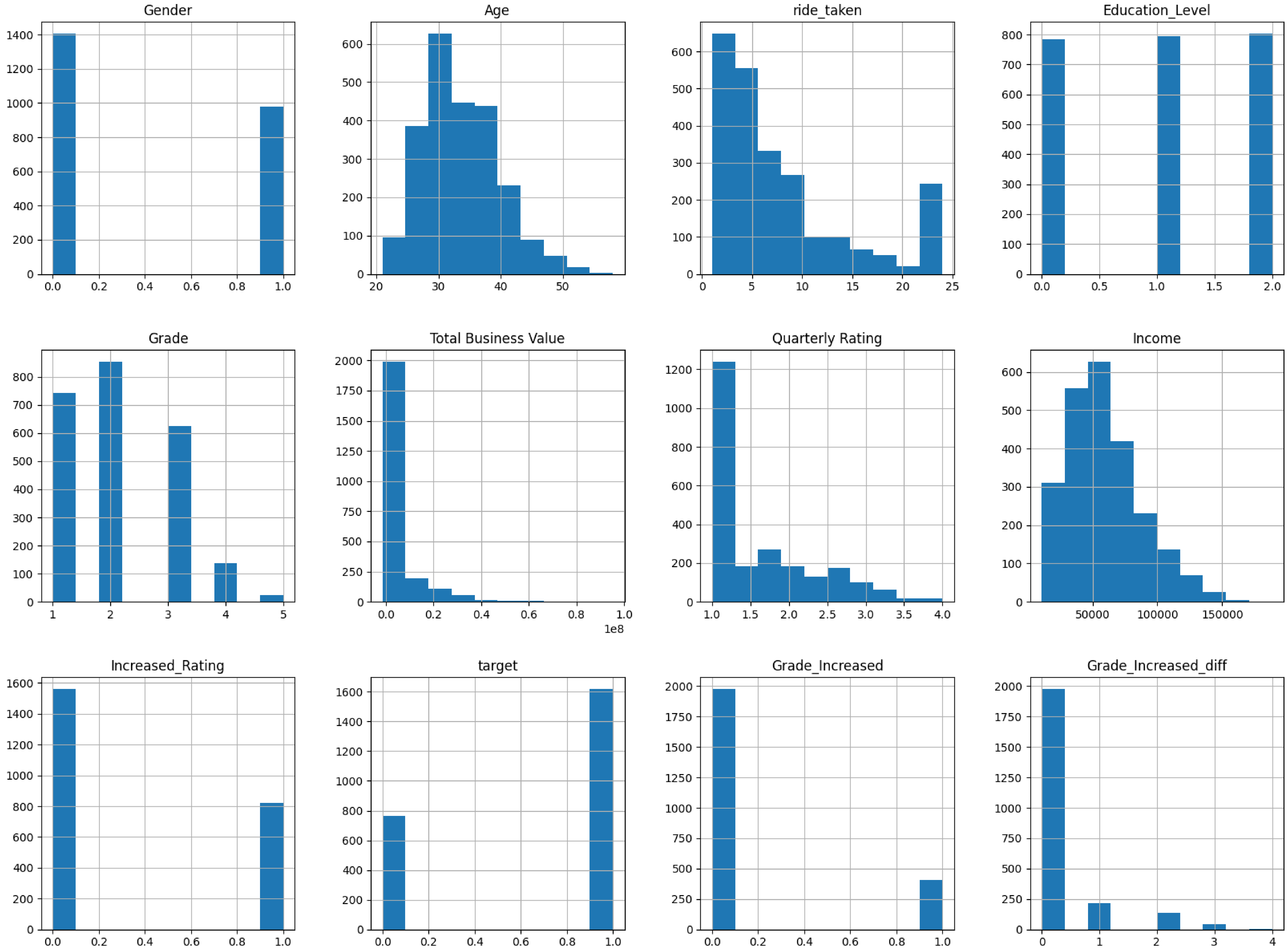
In [29]:
```
# @title Pair plot for the driver data
sns.pairplot(driver_data)
```

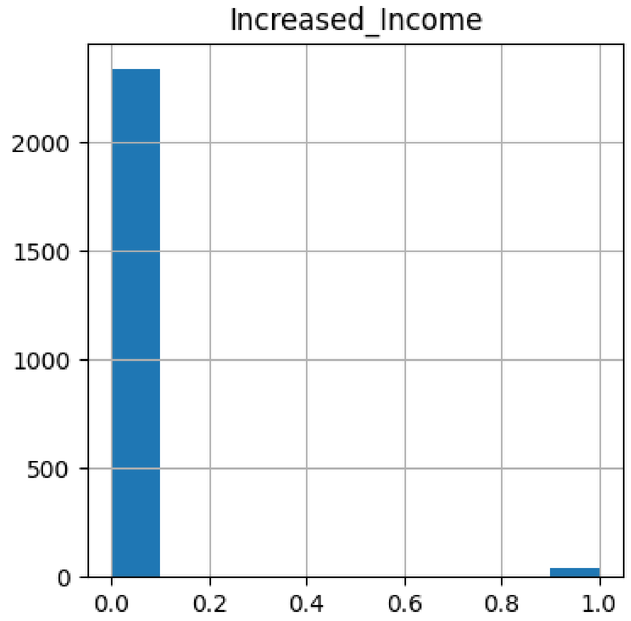
Out[29]:
```
<seaborn.axisgrid.PairGrid at 0x788a048baad0>
```


Gender
Age
ride_taken
Education_Level
Grade
Total Business Value
1e8
Quarterly Rating
Income
Increased_Rating
target


Grade_Increased
Grade_Increased_diff
Increased_Income
Gender
Age
ride_taken
Education_Level
Grade
Total Business Value
1e8
Quarterly Rating
Income
Increased_Rating
target
Grade_Increased
Grade_Increased_diff
Increased_Income

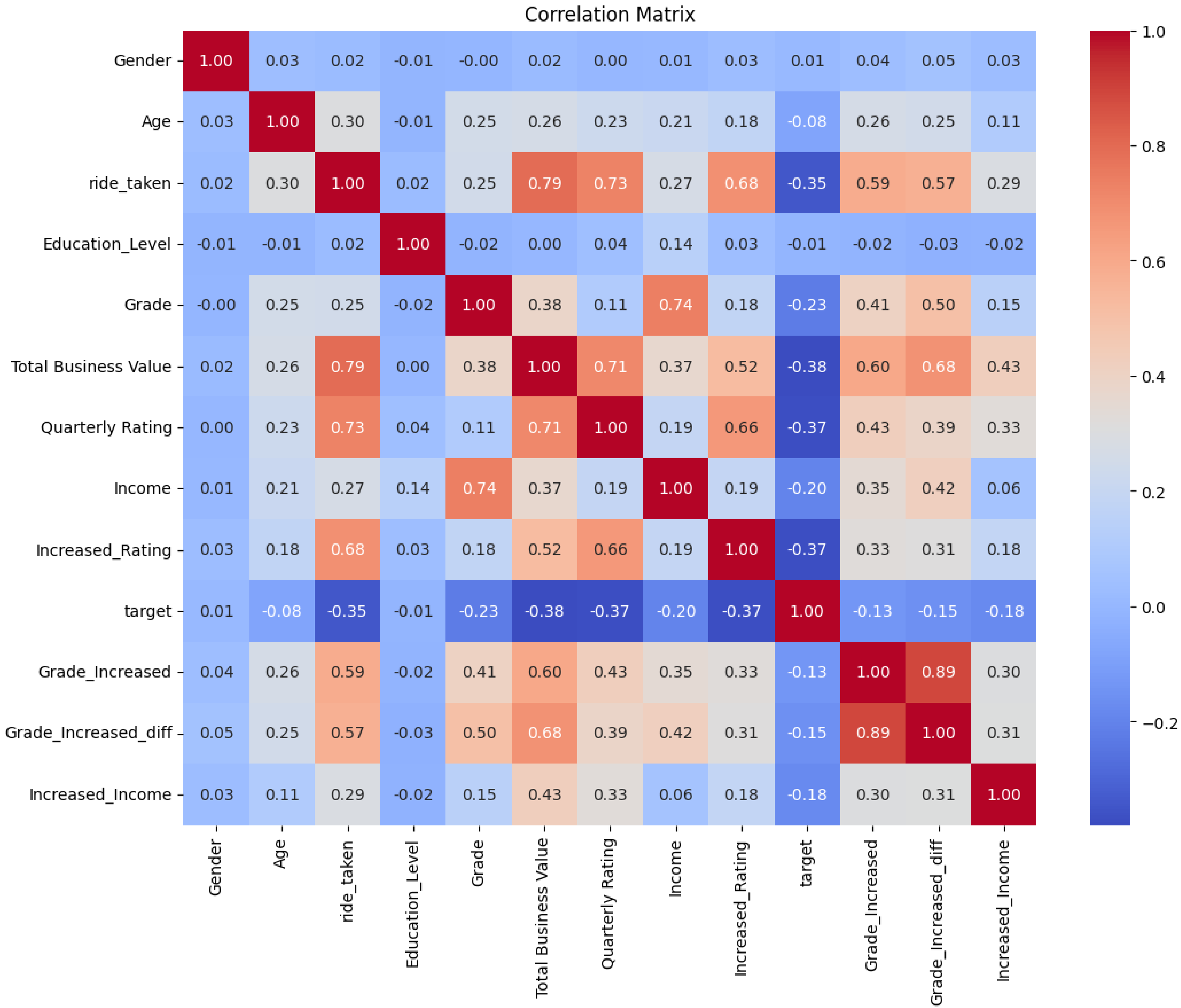
In [30]:
```
driver_data.hist(figsize = (20,20))
plt.show()
```


Gender
Age
ride_taken
Education_Level
Grade
Total Business Value
1e8
Quarterly Rating
Income
Increased_Rating
target
Grade_Increased
Grade_Increased_diff


Increased_Income
2000
1500
1000
500
0
0.0
0.2
0.4
0.6
0.8
1.0

In [31]:
```
# @title Heat map of driver data.
# Explore the correlation matrix and capture the correlation.
num_df = driver_data
correlation_matrix = num_df.corr()
plt.figure(figsize=(12, 9))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```

```
<ipython-input-31-9873b6aed278>:4: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only v
alid columns or specify the value of numeric_only to silence this warning.
  correlation_matrix = num_df.corr()
```


Correlation Matrix
Gender
Age
ride_taken
Education_Level
Grade
Total Business Value
Quarterly Rating
Income
Increased_Rating
target
Grade_Increased
Grade_Increased_diff
Increased_Income
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
1.00 0.03 0.02 -0.01 -0.00 0.02 0.00 0.01 0.03 0.01 0.04 0.05 0.03
0.03 1.00 0.30 -0.01 0.25 0.26 0.23 0.21 0.18 -0.08 0.26 0.25 0.11
0.02 0.30 1.00 0.02 0.25 0.79 0.73 0.27 0.68 -0.35 0.59 0.57 0.29
-0.01 -0.01 0.02 1.00 -0.02 0.00 0.04 0.14 0.03 -0.01 -0.02 -0.03 -0.02
-0.00 0.25 0.25 -0.02 1.00 0.38 0.11 0.74 0.18 -0.23 0.41 0.50 0.15
0.02 0.26 0.79 0.00 0.38 1.00 0.71 0.37 0.52 -0.38 0.60 0.68 0.43
0.00 0.23 0.73 0.04 0.11 0.71 1.00 0.19 0.66 -0.37 0.43 0.39 0.33
0.01 0.21 0.27 0.14 0.74 0.37 0.19 1.00 0.19 -0.20 0.35 0.42 0.06
0.03 0.18 0.68 0.03 0.18 0.52 0.66 0.19 1.00 -0.37 0.33 0.31 0.18
0.01 -0.08 -0.35 -0.01 -0.23 -0.38 -0.37 -0.20 -0.37 1.00 -0.13 -0.15 -0.18
0.04 0.26 0.59 -0.02 0.41 0.60 0.43 0.35 0.33 -0.13 1.00 0.89 0.30
0.05 0.25 0.57 -0.03 0.50 0.68 0.39 0.42 0.31 -0.15 0.89 1.00 0.31
0.03 0.11 0.29 -0.02 0.15 0.43 0.33 0.06 0.18 -0.18 0.30 0.31 1.00

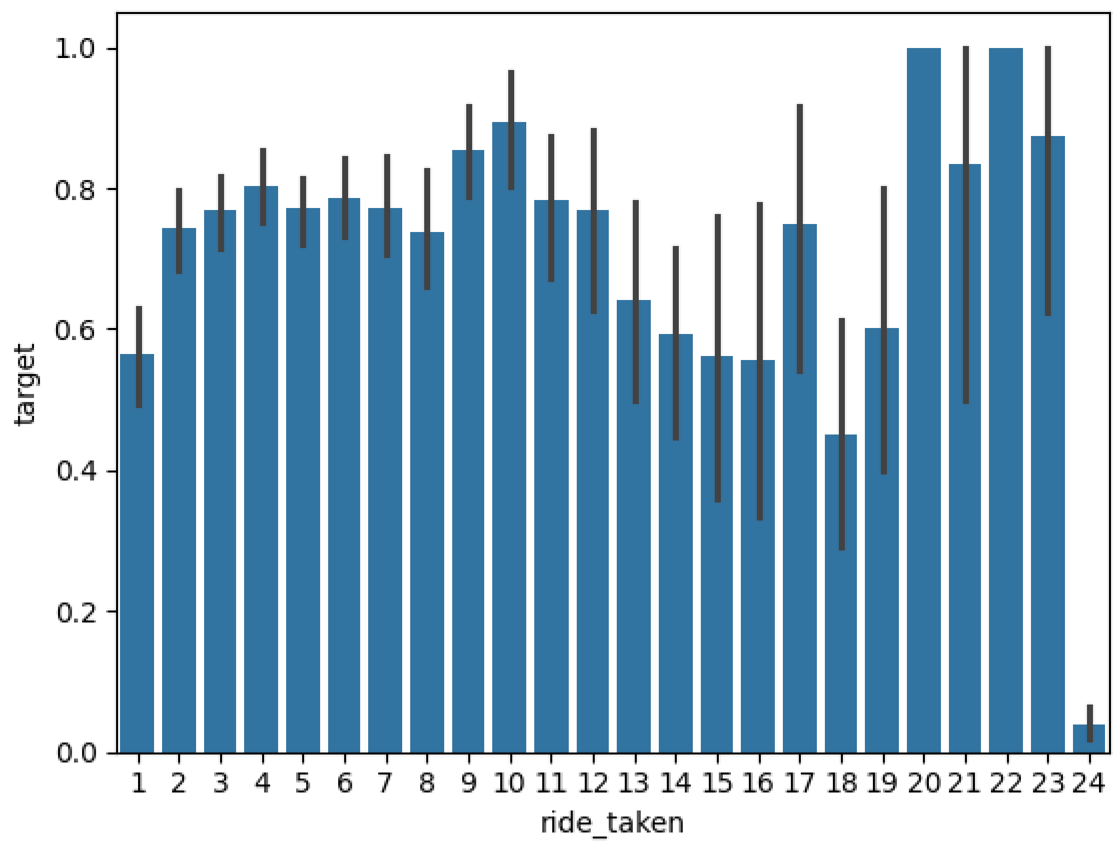
In [32]:
```
driver_data.head(15)
```

Out[32]:

	Gender	Age	City	ride_taken	Education_Level	Grade	Total Business Value	Quarterly Rating	Income	Increased_Rating	target	Grade_Increased	Grade_Increased_diff	Increased_Income
0	0.0	28.0	C23	3	2	1	1715580	2.000000	57387.0	0	1	0	0	0
1	0.0	31.0	C7	2	2	2	0	1.000000	67016.0	0	0	0	0	0
2	0.0	43.0	C13	5	2	2	350000	1.000000	65603.0	0	1	0	0	0
3	0.0	29.0	C9	3	0	1	120360	1.000000	46368.0	0	1	0	0	0
4	1.0	31.0	C11	5	1	3	1265000	1.600000	78728.0	1	0	0	0	0
5	0.0	34.0	C2	3	0	3	0	1.000000	70656.0	0	1	0	0	0
6	1.0	28.0	C19	1	2	1	0	1.000000	42172.0	0	0	0	0	0
7	0.0	35.0	C23	6	2	1	2607180	2.500000	28116.0	0	1	0	0	0
8	0.0	31.0	C19	23	2	4	10213040	1.260870	119227.0	1	1	1	3	0
9	1.0	39.0	C26	3	0	3	0	1.000000	19734.0	0	0	0	0	0
10	1.0	30.0	C23	2	0	2	346800	1.000000	52963.0	0	1	0	0	0
11	0.0	43.0	C20	7	2	1	1017640	1.428571	51099.0	0	1	0	0	0
12	1.0	27.0	C17	5	1	1	0	1.000000	31631.0	0	1	0	0	0
13	1.0	26.0	C19	6	0	3	0	1.000000	40342.0	0	1	0	0	0
14	1.0	34.0	C29	14	1	1	6962550	2.285714	22755.0	0	1	0	0	0

In [33]:
```
# @title Ride taken by Driver churn

sns.barplot(x = 'ride_taken', y = 'target', data = driver_data)
```

Out[33]: <Axes: xlabel='ride_taken', ylabel='target'>



Start applying ML Agrothim on the final data.

Checking the data Imbalance

In [34]:
```
driver_data["target"].value_counts()
```

Out[34]:
```
1    1616
0     765
Name: target, dtype: int64
```

In [35]:
```
driver_data["Increased_Rating"].value_counts()
```

Out[35]:
```
0    1558
1     823
Name: Increased_Rating, dtype: int64
```

In [36]:
```
driver_data["Increased_Income"].value_counts()
```

Out[36]:
```
0    2337
1      44
Name: Increased_Income, dtype: int64
```

In [37]:
```
driver_data["Grade_Increased"].value_counts()
```

Out[37]:
```
0    1973
1     408
Name: Grade_Increased, dtype: int64
```

Clearly we can see there is huge imbalance in the data.

The traget column contains the value count of the driver who left vs who are still working with OLA.

Clearly the is a data imbalance is observed.

In [38]:
```
final_data = driver_data
target = final_data['target'].copy()
final_data = final_data.drop(["target"], axis = 1)
```

In [39]:
```
final_data.head()
```

Out[39]:

	Gender	Age	City	ride_taken	Education_Level	Grade	Total Business Value	Quarterly Rating	Income	Increased_Rating	Grade_Increased	Grade_Increased_diff	Increased_Income
0	0.0	28.0	C23	3	2	1	1715580	2.0	57387.0	0	0	0	0
1	0.0	31.0	C7	2	2	2	0	1.0	67016.0	0	0	0	0
2	0.0	43.0	C13	5	2	2	350000	1.0	65603.0	0	0	0	0
3	0.0	29.0	C9	3	0	1	120360	1.0	46368.0	0	0	0	0
4	1.0	31.0	C11	5	1	3	1265000	1.6	78728.0	1	0	0	0

In [40]:
```
# @title Spliting the data in train and test with 80 / 20
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(final_data,
                                                    target,
                                                    test_size=0.25,
                                                    random_state=7,
                                                    stratify=target)
print("Number transactions X_train dataset: ", X_train.shape)
print("Number transactions y_train dataset: ", y_train.shape)
print("Number transactions X_test dataset: ", X_test.shape)
print("Number transactions y_test dataset: ", y_test.shape)
```

```
Number transactions X_train dataset:  (1785, 13)
Number transactions y_train dataset:  (1785,)
Number transactions X_test dataset:  (596, 13)
Number transactions y_test dataset:  (596,)
```

In [41]:
```
X_train.head()
```

Out[41]:

	Gender	Age	City	ride_taken	Education_Level	Grade	Total Business Value	Quarterly Rating	Income	Increased_Rating	Grade_Increased	Grade_Increased_diff	Increased_Income
72	1.0	45.0	C3	6	0	2	3248870	2.000000	62298.0	0	0	0	0
2019	1.0	43.0	C29	19	1	2	13233930	2.736842	35133.0	0	1	1	0
1488	0.0	23.0	C22	1	0	1	0	1.000000	47072.0	0	0	0	0
2047	0.0	26.0	C17	8	1	1	1368970	1.000000	23711.0	0	0	0	0
897	1.0	37.0	C7	6	0	2	754590	1.000000	47696.0	0	0	0	0

In [42]:
```
y_train
```

Out[42]:
```
72      1
2019    1
1488    1
2047    1
897     1
       ..
2173    1
743     1
1969    1
2343    1
297     0
Name: target, Length: 1785, dtype: int64
```

In [43]:
```
!pip install category_encoders
```

```
Collecting category_encoders
  Downloading category_encoders-2.6.3-py2.py3-none-any.whl (81 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 81.9/81.9 kB 1.2 MB/s eta 0:00:00a 0:00:01
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (1.25.2)
Requirement already satisfied: scikit-learn>=0.20.0 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (1.2.2)
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (1.11.4)
Requirement already satisfied: statsmodels>=0.9.0 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (0.14.1)
Requirement already satisfied: pandas>=1.0.5 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (1.5.3)
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (0.5.6)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.0.5->category_encoders) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.0.5->category_encoders) (2023.4)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from patsy>=0.5.1->category_encoders) (1.16.0)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.20.0->category_encoders) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.20.0->category_encoders) (3.3.0)
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.10/dist-packages (from statsmodels>=0.9.0->category_encoders) (23.2)
Installing collected packages: category_encoders
Successfully installed category_encoders-2.6.3
```

In [44]:
```
# @title Encoding the city column
### Hyper parameter tu
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)
```

Upsampling using SMOTE

In [45]:
```
from imblearn.over_sampling import SMOTE

smt = SMOTE()
X_sm, y_sm = smt.fit_resample(X_train, y_train)
print('Resampled dataset shape {}'.format(y_sm.value_counts()))
```

```
Resampled dataset shape 1    1211
0    1211
Name: target, dtype: int64
```

In [46]:
```
X_sm.head()
```

Out[46]:

	Gender	Age	City	ride_taken	Education_Level	Grade	Total Business Value	Quarterly Rating	Income	Increased_Rating	Grade_Increased	Grade_Increased_diff	Increased_Income
0	1.0	45.0	0.661544	6	0	2	3248870	2.000000	62298.0	0	0	0	0
1	1.0	43.0	0.592076	19	1	2	13233930	2.736842	35133.0	0	1	1	0
2	0.0	23.0	0.607729	1	0	1	0	1.000000	47072.0	0	0	0	0
3	0.0	26.0	0.748713	8	1	1	1368970	1.000000	23711.0	0	0	0	0
4	1.0	37.0	0.713332	6	0	2	754590	1.000000	47696.0	0	0	0	0

Hyper parameter tuning

In [47]:
```
# @title Tuning the **max_depth** hyperparameter to improve the model performance.

from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import KFold, cross_validate, cross_val_score

kfold = KFold(n_splits=10)

depths = [3,4,5,67,9,11,13,15]

for depth in depths:
    tree_clf = DecisionTreeClassifier(random_state=7, max_depth=depth)

    cv_acc_results = cross_validate(tree_clf, X_sm, y_sm, cv = kfold, scoring = 'accuracy', return_train_score = True)

    print(f"K-Fold for depth: {depth} Accuracy Mean: Train: {cv_acc_results['train_score'].mean()*100} Validation: {cv_acc_results['test_score'].mean()*100}")
    print(f"K-Fold for depth: {depth} Accuracy Std: Train: {cv_acc_results['train_score'].std()*100} Validation: {cv_acc_results['test_score'].std()*100}")
    print('***************')
```

```
K-Fold for depth: 3 Accuracy Mean: Train: 71.91493867652446 Validation: 70.3151039009625
K-Fold for depth: 3 Accuracy Std: Train: 1.1406978175549383 Validation: 6.822389862296324
***************
K-Fold for depth: 4 Accuracy Mean: Train: 74.1214827944811 Validation: 67.95803149338504
K-Fold for depth: 4 Accuracy Std: Train: 0.9414352371860604 Validation: 8.031836942692731
***************
K-Fold for depth: 5 Accuracy Mean: Train: 75.98854789883416 Validation: 69.19770091487263
K-Fold for depth: 5 Accuracy Std: Train: 1.0203739854366334 Validation: 4.161740344951361
***************
K-Fold for depth: 67 Accuracy Mean: Train: 100.0 Validation: 74.48729721456994
K-Fold for depth: 67 Accuracy Std: Train: 0.0 Validation: 4.5891750579224375
***************
K-Fold for depth: 9 Accuracy Mean: Train: 86.33357402393995 Validation: 73.45389926198007
K-Fold for depth: 9 Accuracy Std: Train: 0.8075867604613148 Validation: 3.6965767396956464
***************
K-Fold for depth: 11 Accuracy Mean: Train: 91.85700662285115 Validation: 74.11437608407306
K-Fold for depth: 11 Accuracy Std: Train: 1.0429293476942265 Validation: 4.720385966867157
***************
K-Fold for depth: 13 Accuracy Mean: Train: 96.36205270492735 Validation: 74.56824133591809
K-Fold for depth: 13 Accuracy Std: Train: 0.6915989503256034 Validation: 4.744874851389125
***************
K-Fold for depth: 15 Accuracy Mean: Train: 98.8530973302289 Validation: 74.8998401523654
K-Fold for depth: 15 Accuracy Std: Train: 0.45926794244206015 Validation: 4.441201029101075
***************
```

In [48]:
```
# @title Training with the best parameters - for depth: 3
max_depth = 3
tree_clf = DecisionTreeClassifier(random_state=7, max_depth=max_depth)
tree_clf=tree_clf.fit(X_sm, y_sm)
pred = tree_clf.predict(X_test)
```

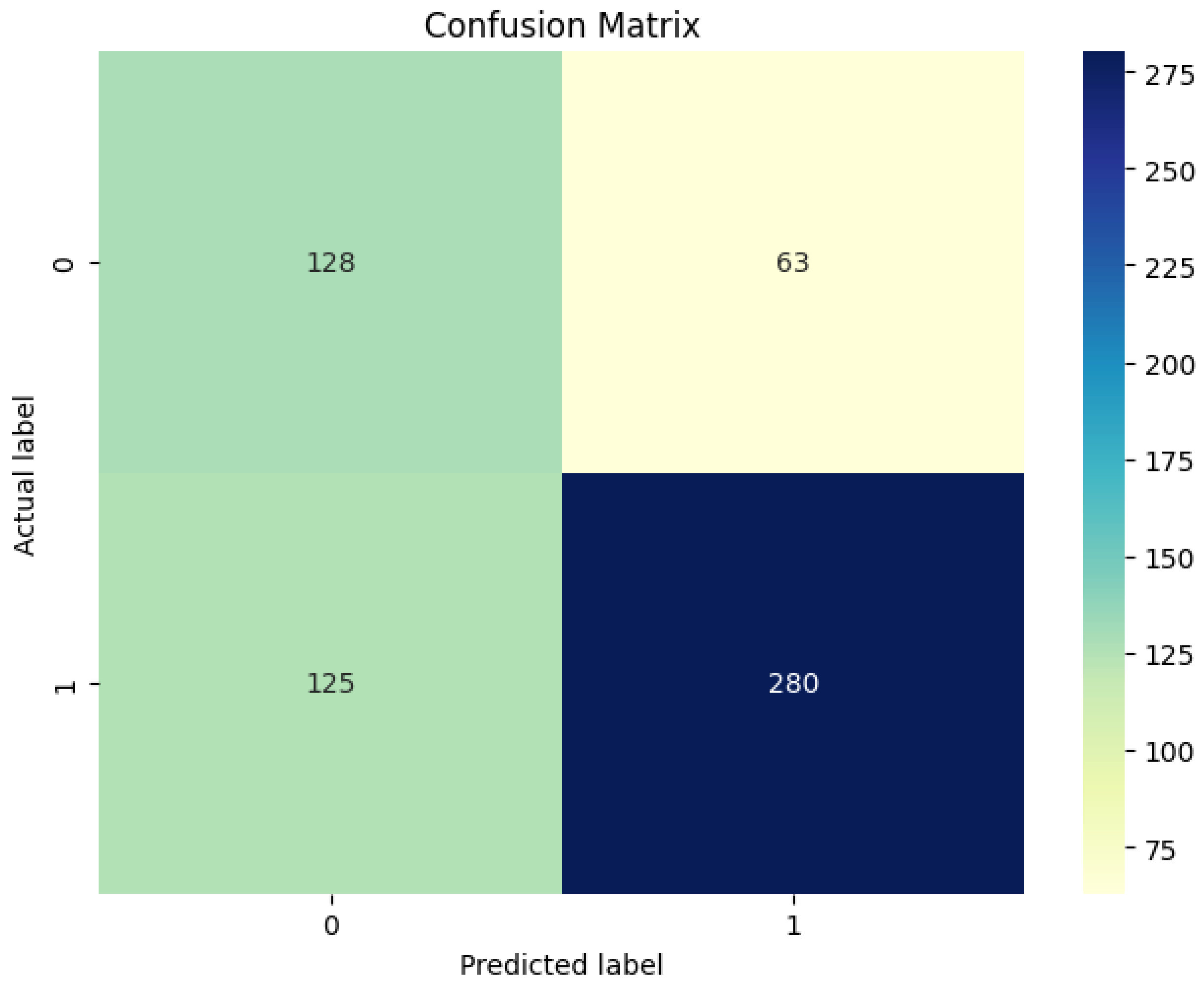
In [49]:
```
print("Train accuracy: {:.2f}".format(tree_clf.score(X_sm, y_sm)*100))
print("Test accuracy: {:.2f}".format(tree_clf.score(X_test, y_test)*100))
```

```
Train accuracy: 72.58
Test accuracy: 68.46
```

Ploting Confusion Matrix

In [50]:
```
# @title Plotting the confusion matrix for test data to visiulize  **TP**, **TN**, **FN**, **FP**.

from sklearn.metrics import confusion_matrix

cnf_matrix = confusion_matrix(y_test, pred)
fig, ax = plt.subplots()

# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')

plt.tight_layout()
plt.title('Confusion Matrix')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

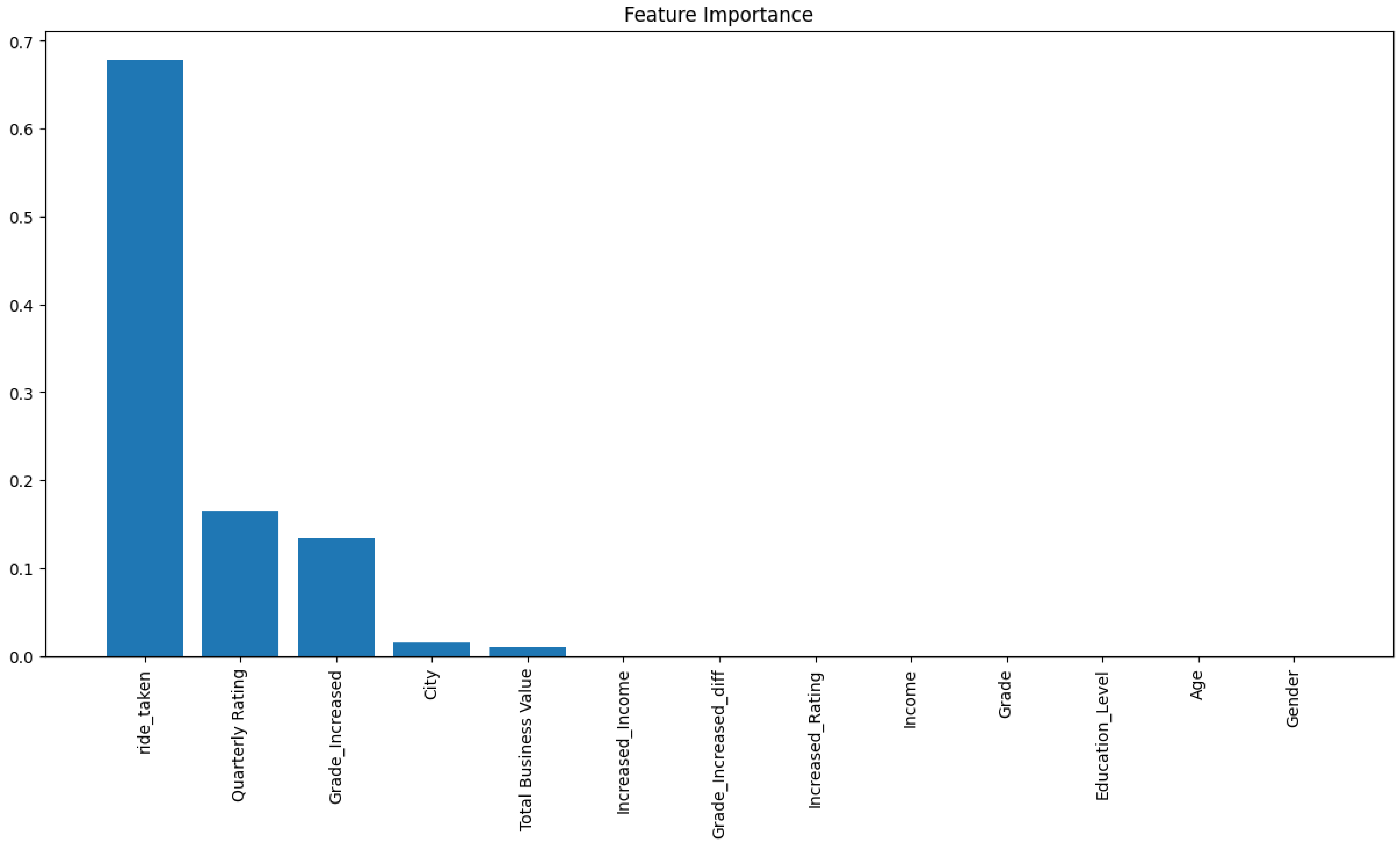
Out[50]:
```
Text(0.5, 23.52222222222222, 'Predicted label')
```



In [51]:
```
importances = tree_clf.feature_importances_
importances
```

Out[51]:
```
array([0.        , 0.        , 0.01460418, 0.67761368, 0.        ,
       0.        , 0.0098656 , 0.16433286, 0.        , 0.        ,
       0.13358367, 0.        , 0.        ])
```

In [52]:
```
indices = np.argsort(importances)[::-1] # Sort feature importances in descending order
names = [X_sm.columns[i] for i in indices] # Rearrange feature names so they match the sorted feature importances

plt.figure(figsize=(15, 7)) # Create plot
plt.title("Feature Importance") # Create plot title
plt.bar(range(X_sm.shape[1]), importances[indices]) # Add bars
plt.xticks(range(X_sm.shape[1]), names, rotation=90) # Add feature names as x-axis labels
plt.show() # Show plot
```



Using Bagging Method(Random Forest Alogrithm)

In [53]:
```
# @title Randomly apply RF classifier.
from sklearn.ensemble import RandomForestClassifier

rf_clf = RandomForestClassifier(random_state=7, max_depth=4, n_estimators=100)
```

In [54]:
```
kfold = KFold(n_splits=10)
cv_acc_results = cross_validate(rf_clf, X_sm, y_sm, cv=kfold, scoring='accuracy', return_train_score=True)

print(f"K-Fold Accuracy Mean: \"Train: {cv_acc_results['train_score'].mean()*100:.2f},  Validation: {cv_acc_results['test_score'].mean()*100:.2f}\"")
print(f"K-Fold Accuracy Std: \"Train: {cv_acc_results['train_score'].std()*100:.2f},  Validation: {cv_acc_results['test_score'].std()*100:.2f}\"")
```

```
K-Fold Accuracy Mean: "Train: 77.14,  Validation: 71.26"
K-Fold Accuracy Std: "Train: 1.53,  Validation: 11.81"
```

We can see that there is not much impact here. Now we need further optimize and hyper tune the RF parameters.

In [55]:
```
# @title Using Grid searchCV for parameter tuning.
params = {
          'n_estimators' : [100,200,300,400],
          'max_depth' : [3,5,10],
          'criterion' : ['gini', 'entropy'],
          'bootstrap' : [True, False],
          'max_features' : [8,9,10]
         }
```

In [56]:
```
from sklearn.model_selection import GridSearchCV

grid = GridSearchCV(estimator = RandomForestClassifier(),
                    param_grid = params,
                    scoring = 'accuracy',
                    cv = 3,
                    n_jobs=-1
                    )
```

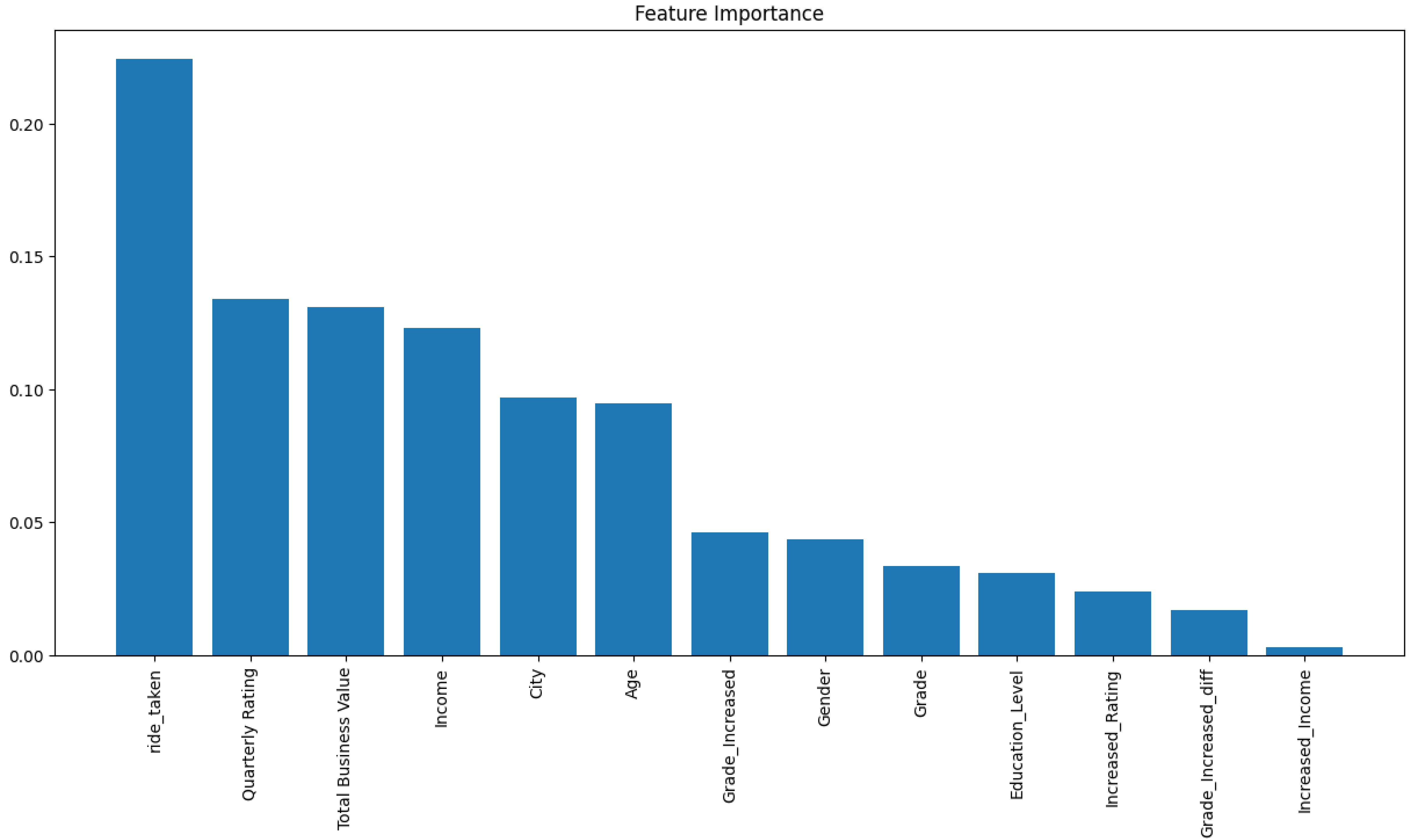
In [57]:
```
grid.fit(X_sm, y_sm)

print("Best params: ", grid.best_params_)
print("Best score: ", grid.best_score_)
```

```
Best params:  {'bootstrap': True, 'criterion': 'gini', 'max_depth': 10, 'max_features': 9, 'n_estimators': 300}
Best score:  0.8150470716216603
```

In [58]:
```
clf2 = RandomForestClassifier(random_state=7, bootstrap=True, criterion='gini',
                              max_depth=10, max_features=8, n_estimators=300)

kfold = KFold(n_splits=10)
cv_acc_results = cross_validate(clf2,  X_sm, y_sm, cv=kfold, scoring='accuracy', return_train_score=True)

print(f"K-Fold Accuracy Mean: \"Train: {cv_acc_results['train_score'].mean()*100:.3f}, Validation: {cv_acc_results['test_score'].mean()*100:.3f}\"")
print(f"K-Fold Accuracy Std: \"Train: {cv_acc_results['train_score'].std()*100:.3f},  Validation: {cv_acc_results['test_score'].std()*100:.3f}\"")
```

```
K-Fold Accuracy Mean: "Train: 95.091, Validation: 80.925"
K-Fold Accuracy Std: "Train: 0.563,  Validation: 3.134"
```

In [59]:
```
# @title Checking Feature importance.
clf2.fit(X_sm, y_sm)
importances = clf2.feature_importances_

indices = np.argsort(importances)[::-1] # Sort feature importances in descending order
names = [X_sm.columns[i] for i in indices] # Rearrange feature names so they match the sorted feature importances

plt.figure(figsize=(15, 7)) # Create plot
plt.title("Feature Importance") # Create plot title
plt.bar(range(X_sm.shape[1]), importances[indices]) # Add bars
plt.xticks(range(X_sm.shape[1]), names, rotation=90) # Add feature names as x-axis labels
plt.show() # Show plot
```



Using Gradient Booting Classifier

In [60]:
```
from sklearn.ensemble import GradientBoostingClassifier
```

In [61]:
```
gbc = GradientBoostingClassifier(n_estimators=150, max_depth=2, loss = 'log_loss')
```

In [62]:
```
gbc.fit(X_sm, y_sm)
```

Out[62]:
```
GradientBoostingClassifier(max_depth=2, n_estimators=150)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [63]:
```
# @title Train score
gbc.score(X_sm, y_sm)
```

Out[63]:
```
0.8550784475639966
```

In [64]:
```
# @title Test score
gbc.score(X_test, y_test)
```

Out[64]:
```
0.7734899328859061
```

Observe that train score is higher than the test score. Clearly case of overfitting.

Hyper typing of the parameters.

In [67]:
```
# @title Using Ramdonized Search cv.

from sklearn import tree
from sklearn.model_selection import RandomizedSearchCV
import datetime as dt

params = {
    "n_estimators": [10,25,50,100,150,200],
    "max_depth" : [3, 5, 10, 15, 20],
    "max_leaf_nodes" : [20, 40, 80]
}

rfc = RandomForestClassifier(n_jobs = -1)
clf_new = RandomizedSearchCV(rfc, params, scoring = "accuracy", cv=3, n_jobs = -1, verbose = 1)

start = dt.datetime.now()
clf_new.fit(X_sm, y_sm)
end = dt.datetime.now()
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
```

In [68]:
```
print(f"Time taken for fits : {end - start}")
```

```
Time taken for fits : 0:00:11.340031
```

Clearly there is an increase in performance.

In [69]:
```
res = clf_new.cv_results_

for i in range(len(res["params"])):
  print(f"Parameters:{res['params'][i]} Mean_score: {res['mean_test_score'][i]} Rank: {res['rank_test_score'][i]}")
```

```
Parameters:{'n_estimators': 50, 'max_leaf_nodes': 40, 'max_depth': 3} Mean_score: 0.7126356222982894 Rank: 10
Parameters:{'n_estimators': 50, 'max_leaf_nodes': 20, 'max_depth': 5} Mean_score: 0.7625996335693048 Rank: 9
Parameters:{'n_estimators': 100, 'max_leaf_nodes': 20, 'max_depth': 15} Mean_score: 0.7766449507404273 Rank: 7
Parameters:{'n_estimators': 100, 'max_leaf_nodes': 40, 'max_depth': 15} Mean_score: 0.7939895755374794 Rank: 4
Parameters:{'n_estimators': 10, 'max_leaf_nodes': 40, 'max_depth': 10} Mean_score: 0.7733389974685201 Rank: 8
Parameters:{'n_estimators': 100, 'max_leaf_nodes': 40, 'max_depth': 10} Mean_score: 0.7906825998584989 Rank: 5
Parameters:{'n_estimators': 200, 'max_leaf_nodes': 80, 'max_depth': 15} Mean_score: 0.7997712875376757 Rank: 3
Parameters:{'n_estimators': 200, 'max_leaf_nodes': 20, 'max_depth': 10} Mean_score: 0.7782971605710757 Rank: 6
Parameters:{'n_estimators': 50, 'max_leaf_nodes': 80, 'max_depth': 10} Mean_score: 0.8121551932144887 Rank: 1
Parameters:{'n_estimators': 50, 'max_leaf_nodes': 80, 'max_depth': 15} Mean_score: 0.8100909533332515 Rank: 2
```

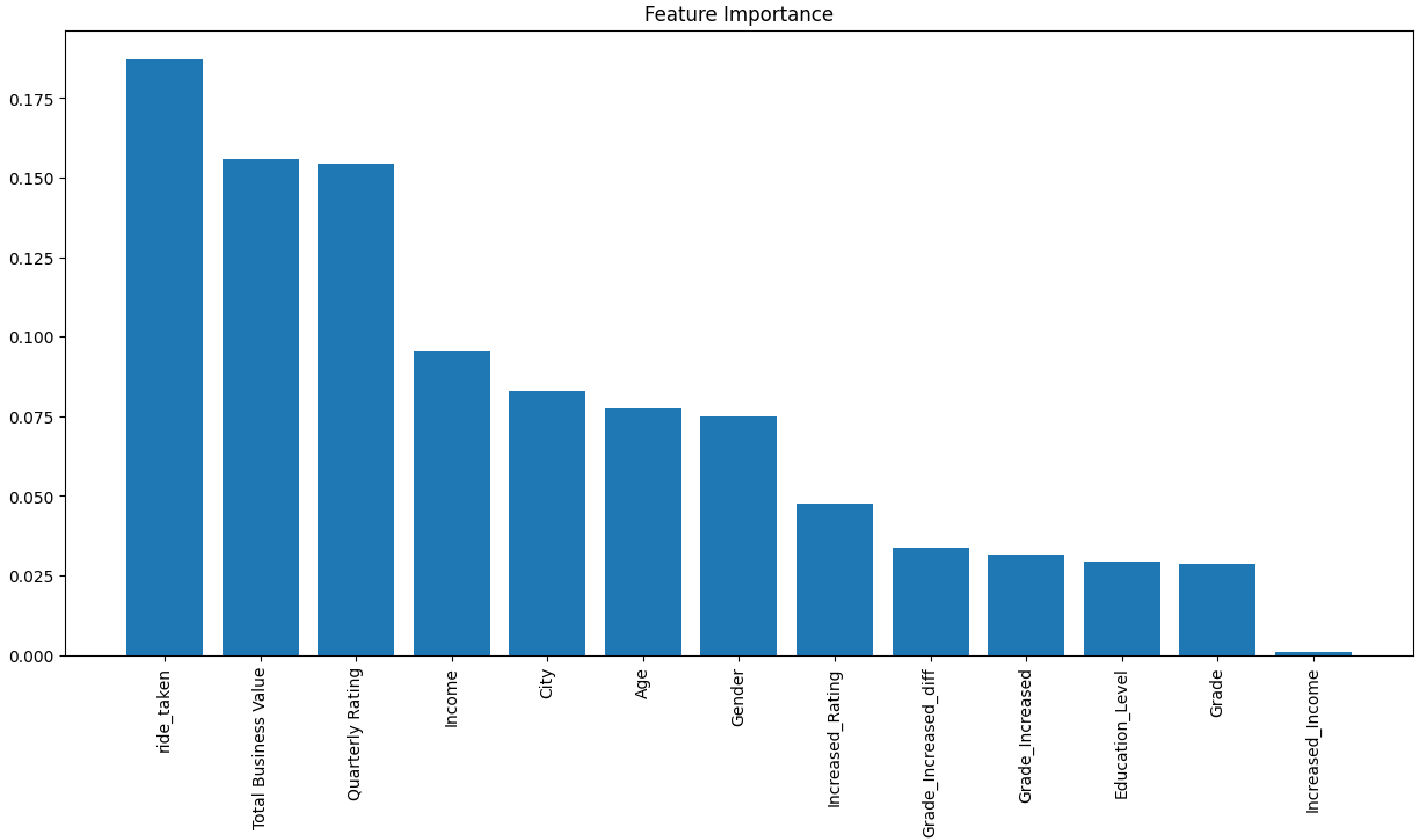
In [71]:
```
print(clf_new.best_estimator_)
```

```
RandomForestClassifier(max_depth=10, max_leaf_nodes=80, n_estimators=50,
                       n_jobs=-1)
```

In [73]:
```
rf = clf_new.best_estimator_

rf.fit(X_sm, y_sm)

print("Model acc",rf.score(X_test, y_test))
```

```
Model acc 0.7684563758389261
```

In [88]:
```
importances = rf.feature_importances_

indices = np.argsort(importances)[::-1] # Sort feature importances in descending order
names = [X_sm.columns[i] for i in indices] # Rearrange feature names so they match the sorted feature importances

plt.figure(figsize=(15, 7)) # Create plot
plt.title("Feature Importance") # Create plot title
plt.bar(range(X_sm.shape[1]), importances[indices]) # Add bars
plt.xticks(range(X_sm.shape[1]), names, rotation=90) # Add feature names as x-axis labels
plt.show() # Show plot
```



In [81]:
```
# @title Using GBDT.

params = {
    "n_estimators": [50,100,150,200],
    "max_depth" : [3, 4, 5, 7],
    "max_leaf_nodes" : [20, 40, 80],
    "learning_rate": [0.1, 0.2, 0.3]
}
```

In [82]:
```
gbc = GradientBoostingClassifier()
clf = RandomizedSearchCV(gbc, params, scoring = "accuracy", cv=3, n_jobs = -1, verbose = 1)

start_t = dt.datetime.now()

clf.fit(X_sm, y_sm)

end_t = dt.datetime.now()
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
```

In [83]:
```
print(f"Time taken for fits : {end_t - start_t}")
```

```
Time taken for fits : 0:00:17.230882
```

In [84]:
```
print(clf.best_estimator_)
```

```
GradientBoostingClassifier(learning_rate=0.2, max_depth=5, max_leaf_nodes=80,
                           n_estimators=150)
```

In [85]:
```
gbc = clf.best_estimator_

gbc.fit(X_sm, y_sm)

print("Model acc",gbc.score(X_test, y_test))
```

```
Model acc 0.7583892617449665
```

In [89]:
```
importances = gbc.feature_importances_

indices = np.argsort(importances)[::-1] # Sort feature importances in descending order
names = [X_sm.columns[i] for i in indices] # Rearrange feature names so they match the sorted feature importances

plt.figure(figsize=(15, 7)) # Create plot
plt.title("Feature Importance") # Create plot title
plt.bar(range(X_sm.shape[1]), importances[indices]) # Add bars
plt.xticks(range(X_sm.shape[1]), names, rotation=90) # Add feature names as x-axis labels
plt.show() # Show plot
```