advance_cross_prediction

August 23, 2021

0.1 Import Libraries

[1]:
```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
# %matplotlib inline
import seaborn as sns


# pd.set_option('display.max_columns',30)
# pd.set_option('display.max_rows',500)
```

0.2 Load the Dataset

[2]:
```
train_data=pd.read_csv('kowope/Train/train.csv')
test_data = pd.read_csv('kowope/Test/Test.csv')
```

[3]:
```
train_data.head()
```

[3]:
```
       id  Gender  Age  Driving_License  Region_Code  Previously_Insured  \
0  274711    Male   22                1         40.0                   0
1  216540  Female   26                1          8.0                   1
2   78984  Female   32                1         28.0                   0
3  218369    Male   32                1         37.0                   0
4  307216  Female   24                1         28.0                   0

  Vehicle_Age Vehicle_Damage  Policy_Sales_Channel  Vintage  Annual_Premium
0    < 1 Year            Yes                 152.0      203         25455.0
1    < 1 Year             No                  26.0       45         38393.0
2    < 1 Year            Yes                 122.0       35         32118.0
3    < 1 Year            Yes                 152.0      215         37711.0
4    < 1 Year            Yes                 156.0      222         48706.0
```

[4]:
```
test_data.head()
```

[4]:
```
      id  Gender  Age  Driving_License  Region_Code  Previously_Insured  \
0  16222    Male   54                1         28.0                   0
```

```
1  342481  Female   26                  1         3.0                   0
2   20916    Male   25                  1        28.0                   0
3   38704    Male   29                  1        24.0                   0
4  363809  Female   28                  1        28.0                   0

  Vehicle_Age Vehicle_Damage  Policy_Sales_Channel  Vintage
0   > 2 Years            Yes                  26.0       53
1    1-2 Year            Yes                 156.0      280
2    < 1 Year            Yes                 124.0      255
3    1-2 Year            Yes                 157.0      235
4    < 1 Year            Yes                  26.0      243
```

Observation * 'Annual_Premium' only is omitted in test_data

Description of each of the column headers in the data frame id: randomly generated numbers for customer

Gender: Gender of customer

Age: age of customer

Driving_licence: if customer has driving licence or not (yes=1, no=0)

Region_Code: region code of customer

Previously_Insured: if customer was previously insured or not (yes=1, no=0)

Vehicle_Age: age of customer's vehicle (< 1 year, 1-2 year, or >2 years)

Vehicle_Damage: if customer's vehicle has been damaged or not (yes=1, no=0)

Policy_sales_channel: No. of sales channel

vintage: vintage

Annual_Premium: Annual premium boutght by customer

0.3 Exploratory Data Analysis (EDA)

[5]:
```
#Get the shape of the datasets
print('train size', train_data.shape)
print('train size',test_data.shape)
```

```
train size (304887, 11)
train size (76222, 10)
```

[6]:
```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 304887 entries, 0 to 304886
Data columns (total 11 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
```

```
 0   id                    304887 non-null  int64
 1   Gender                304887 non-null  object
 2   Age                   304887 non-null  int64
 3   Driving_License       304887 non-null  int64
 4   Region_Code           304887 non-null  float64
 5   Previously_Insured    304887 non-null  int64
 6   Vehicle_Age           304887 non-null  object
 7   Vehicle_Damage        304887 non-null  object
 8   Policy_Sales_Channel  304887 non-null  float64
 9   Vintage               304887 non-null  int64
 10  Annual_Premium        304887 non-null  float64
dtypes: float64(3), int64(5), object(3)
memory usage: 25.6+ MB
```

[7]:
```python
#get a statistical summary of the dataset
train_data.describe()
```

[7]:
```
                  id            Age  Driving_License    Region_Code  \
count  304887.000000  304887.000000    304887.000000  304887.000000
mean   190738.657112      38.826897         0.997855      26.396239
std    110004.367239      15.515299         0.046265      13.228749
min         1.000000      20.000000         0.000000       0.000000
25%     95504.500000      25.000000         1.000000      15.000000
50%    190886.000000      36.000000         1.000000      28.000000
75%    285863.500000      49.000000         1.000000      35.000000
max    381109.000000      85.000000         1.000000      52.000000

       Previously_Insured  Policy_Sales_Channel        Vintage  Annual_Premium
count       304887.000000         304887.000000  304887.000000   304887.000000
mean             0.458127            112.053859     154.392214    30591.308311
std              0.498244             54.189288      83.670312    17239.285689
min              0.000000              1.000000      10.000000     2630.000000
25%              0.000000             29.000000      82.000000    24403.000000
50%              0.000000            134.000000     154.000000    31697.000000
75%              1.000000            152.000000     227.000000    39443.000000
max              1.000000            163.000000     299.000000   540165.000000
```

[8]:
```python
train_data.nunique()
```

[8]:
```
id                      304887
Gender                       2
Age                         66
Driving_License              2
Region_Code                 53
Previously_Insured           2
Vehicle_Age                  3
Vehicle_Damage               2
Policy_Sales_Channel       154
```

```
Vintage                        290
Annual_Premium               46479
dtype: int64
```

[9]:
```
# Finding count of null values in each of the columns in data
train_data.isnull().sum()
```

[9]:
```
id                      0
Gender                  0
Age                     0
Driving_License         0
Region_Code             0
Previously_Insured      0
Vehicle_Age             0
Vehicle_Damage          0
Policy_Sales_Channel    0
Vintage                 0
Annual_Premium          0
dtype: int64
```

[10]:
```
test_data.isnull().sum()
```

[10]:
```
id                      0
Gender                  0
Age                     0
Driving_License         0
Region_Code             0
Previously_Insured      0
Vehicle_Age             0
Vehicle_Damage          0
Policy_Sales_Channel    0
Vintage                 0
dtype: int64
```

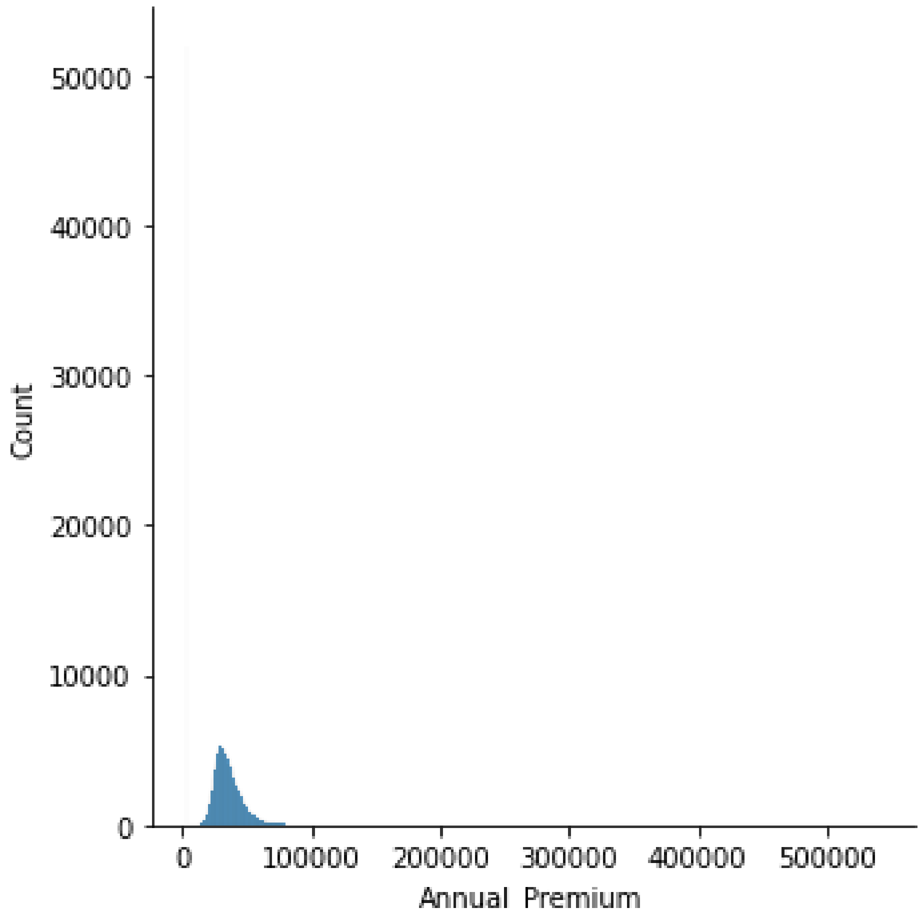
Observation * No Null Values in both train and test dataset * 'Gender', 'Vehicle_Age', and 'Vehicle_Damage' columns of 'object' dtype . so we need check the unique values of those columns, if any string values is present.

Observation

'Gender', 'Vehicle_Age', 'Vehicle_Damage' columns have few string values. We need to replace the string with corresponding int values.

[11]:
```
# sns.pairplot(train_data[1000:-1])
sns.displot(train_data['Annual_Premium'])
# dt = sns.load_dataset('kowope/Train/train.csv')
# dt.head()
```

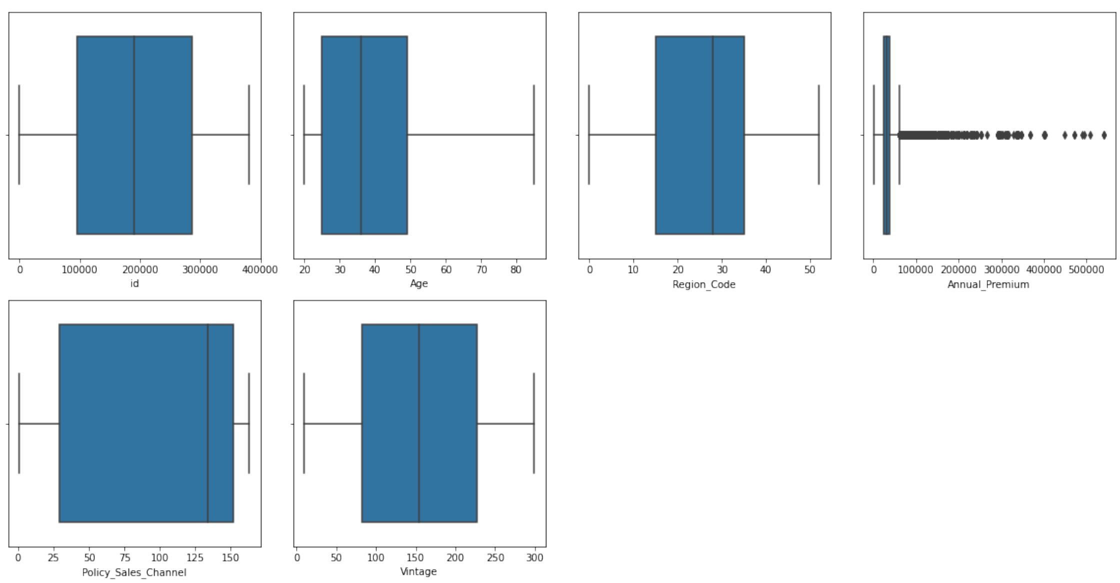
[11]:
```
<seaborn.axisgrid.FacetGrid at 0x1bf7a13d6a0>
```



[12]:
```
plt.figure(figsize=(16,16))
for i, col in enumerate(["id","Age",␣
↪"Region_Code","Annual_Premium","Policy_Sales_Channel", "Vintage"]):
    plt.subplot(4,4,i+1)
    sns.boxplot(train_data[col])
    plt.tight_layout()
```

```
C:\Users\hp\Anaconda3\envs\tf\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
C:\Users\hp\Anaconda3\envs\tf\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
```

```
  warnings.warn(
C:\Users\hp\Anaconda3\envs\tf\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
C:\Users\hp\Anaconda3\envs\tf\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
C:\Users\hp\Anaconda3\envs\tf\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
C:\Users\hp\Anaconda3\envs\tf\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
```



[13]:
```python
# check  if id values are unique or not
for i in train_data['id']:
```

```
    if i==test_data['id'][67]:
        print('yes')
```

[14]:
```
print("Unique Values in 'Gender' column are ",train_data['Gender'].unique())
print("Unique Values in 'Vehicle_Age' column are ",train_data['Vehicle_Age'].
 ↪unique())
print("Unique Values in 'Vehicle_Damage' column are␣
 ↪",train_data['Vehicle_Damage'].unique())
```

```
Unique Values in 'Gender' column are  ['Male' 'Female']
Unique Values in 'Vehicle_Age' column are  ['< 1 Year' '1-2 Year' '> 2 Years']
Unique Values in 'Vehicle_Damage' column are  ['Yes' 'No']
```

[15]:
```
# Checking frequency of each values in categorical columns␣
 ↪'job_type','marital_status,education_level','communication'
# & 'outcome' columns
train_data.Gender.value_counts()
```

[15]:
```
Male      164780
Female    140107
Name: Gender, dtype: int64
```

[16]:
```
train_data.Vehicle_Age.value_counts()
```

[16]:
```
1-2 Year     160195
< 1 Year     131852
> 2 Years     12840
Name: Vehicle_Age, dtype: int64
```

[17]:
```
train_data.Vehicle_Damage.value_counts()
```

[17]:
```
Yes    153959
No     150928
Name: Vehicle_Damage, dtype: int64
```

[18]:
```
train_data.Driving_License.value_counts()
```

[18]:
```
1    304233
0       654
Name: Driving_License, dtype: int64
```

0.4 Data Cleaning and Data Preprocessing

0.4.1 Converting Non Numeric Data Columns to Numeric Coulumns

As the model built for prediction understands numerical data columns better,we need to convert categorical data columns to numerical data columns by using dummy columns and one hot encoding methods

[19]:
```
mapping_dict = {
    "Gender": {
        "Male": 0,
        "Female": 1
    },
    "Vehicle_Damage": {
        "No": 0,
        "Yes": 1
    },
    # "Vehicle_Age": {
    #     "< 1 Year": 0,
    #     "1-2 Year": 1,
    #     "> 2 Years": 2,
    # }
}
```

[20]:
```
filtered_train_data = train_data.replace(mapping_dict)
filtered_train_data[['Gender', 'Vehicle_Damage']]
filtered_train_data = pd.get_dummies(filtered_train_data,␣
 ↪columns=['Vehicle_Age'])
```

[21]:
```
filtered_test_data = test_data.replace(mapping_dict)
filtered_test_data[['Gender', 'Vehicle_Damage']]
filtered_test_data = pd.get_dummies(filtered_test_data, columns=['Vehicle_Age'])
```

[22]:
```
filtered_train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 304887 entries, 0 to 304886
Data columns (total 13 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   id                   304887 non-null  int64
 1   Gender               304887 non-null  int64
 2   Age                  304887 non-null  int64
 3   Driving_License      304887 non-null  int64
 4   Region_Code          304887 non-null  float64
 5   Previously_Insured   304887 non-null  int64
 6   Vehicle_Damage       304887 non-null  int64
 7   Policy_Sales_Channel 304887 non-null  float64
 8   Vintage              304887 non-null  int64
 9   Annual_Premium       304887 non-null  float64
 10  Vehicle_Age_1-2 Year 304887 non-null  uint8
 11  Vehicle_Age_< 1 Year 304887 non-null  uint8
 12  Vehicle_Age_> 2 Years 304887 non-null  uint8
dtypes: float64(3), int64(7), uint8(3)
memory usage: 24.1 MB
```

[23]:
```
filtered_train_data = filtered_train_data.rename(columns={
    "Vehicle_Age_1-2 Year":"Vehicle_Age_1_2_Year",
    "Vehicle_Age_< 1 Year":"Vehicle_Age_lt_1_Year",
    "Vehicle_Age_> 2 Years":"Vehicle_Age_gt_2_Years"
})
filtered_train_data["Vehicle_Age_lt_1_Year"]=filtered_train_data["Vehicle_Age_lt_1_Year"].
 ↪astype('int')
filtered_train_data["Vehicle_Age_1_2_Year"]=filtered_train_data["Vehicle_Age_1_2_Year"].
 ↪astype('int')
filtered_train_data["Vehicle_Age_gt_2_Years"]=filtered_train_data["Vehicle_Age_gt_2_Years"].
 ↪astype('int')
filtered_train_data["Vehicle_Damage"]=filtered_train_data["Vehicle_Damage"].
 ↪astype('int')
```

[24]:
```
filtered_test_data = filtered_test_data.rename(columns={
    "Vehicle_Age_1-2 Year":"Vehicle_Age_1_2_Year",
    "Vehicle_Age_< 1 Year":"Vehicle_Age_lt_1_Year",
    "Vehicle_Age_> 2 Years":"Vehicle_Age_gt_2_Years"
})
filtered_test_data["Vehicle_Age_lt_1_Year"]=filtered_test_data["Vehicle_Age_lt_1_Year"].
 ↪astype('int')
filtered_test_data["Vehicle_Age_1_2_Year"]=filtered_test_data["Vehicle_Age_1_2_Year"].
 ↪astype('int')
filtered_test_data["Vehicle_Age_gt_2_Years"]=filtered_test_data["Vehicle_Age_gt_2_Years"].
 ↪astype('int')
filtered_test_data["Vehicle_Damage"]=filtered_test_data["Vehicle_Damage"].
 ↪astype('int')
```

0.4.2 removing outliers

[25]:
```
filtered_train_data.loc[filtered_train_data.Annual_Premium > 400000,␣
 ↪"Annual_Premium"] = 400000
```

[26]:
```
filtered_train_data = filtered_train_data.drop(['id'], axis=1)
# filtered_train_data.dropna()
```

[27]:
```
filtered_train_data.head()
```

[27]:
```
   Gender  Age  Driving_License  Region_Code  Previously_Insured  \
0       0   22                1         40.0                   0
1       1   26                1          8.0                   1
2       1   32                1         28.0                   0
3       0   32                1         37.0                   0
4       1   24                1         28.0                   0

   Vehicle_Damage  Policy_Sales_Channel  Vintage  Annual_Premium  \
0               1                 152.0      203         25455.0
```

```
1                0                    26.0       45           38393.0
2                1                   122.0       35           32118.0
3                1                   152.0      215           37711.0
4                1                   156.0      222           48706.0

   Vehicle_Age_1_2_Year  Vehicle_Age_lt_1_Year  Vehicle_Age_gt_2_Years
0                     0                      1                       0
1                     0                      1                       0
2                     0                      1                       0
3                     0                      1                       0
4                     0                      1                       0
```

[28]:
```
filtered_train_data.describe()
```

[28]:
```
              Gender            Age  Driving_License    Region_Code  \
count  304887.000000  304887.000000    304887.000000  304887.000000
mean        0.459537      38.826897         0.997855      26.396239
std         0.498361      15.515299         0.046265      13.228749
min         0.000000      20.000000         0.000000       0.000000
25%         0.000000      25.000000         1.000000      15.000000
50%         0.000000      36.000000         1.000000      28.000000
75%         1.000000      49.000000         1.000000      35.000000
max         1.000000      85.000000         1.000000      52.000000

       Previously_Insured  Vehicle_Damage  Policy_Sales_Channel  \
count       304887.000000   304887.000000         304887.000000
mean             0.458127        0.504971            112.053859
std              0.498244        0.499976             54.189288
min              0.000000        0.000000              1.000000
25%              0.000000        0.000000             29.000000
50%              0.000000        1.000000            134.000000
75%              1.000000        1.000000            152.000000
max              1.000000        1.000000            163.000000

             Vintage  Annual_Premium  Vehicle_Age_1_2_Year  \
count  304887.000000   304887.000000         304887.000000
mean      154.392214    30588.781565              0.525424
std        83.670312    17177.346735              0.499354
min        10.000000     2630.000000              0.000000
25%        82.000000    24403.000000              0.000000
50%       154.000000    31697.000000              1.000000
75%       227.000000    39443.000000              1.000000
max       299.000000   400000.000000              1.000000

       Vehicle_Age_lt_1_Year  Vehicle_Age_gt_2_Years
count          304887.000000           304887.000000
mean                0.432462                0.042114
```

```
std                     0.495418                0.200849
min                     0.000000                0.000000
25%                     0.000000                0.000000
50%                     0.000000                0.000000
75%                     1.000000                0.000000
max                     1.000000                1.000000
```

0.5 Build Machine Learning Model & Evaluate it

[29]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.linear_model import Lasso, LinearRegression
from sklearn.model_selection import␣
↪train_test_split,GridSearchCV,RandomizedSearchCV
from sklearn.metrics import classification_report,confusion_matrix,␣
↪mean_squared_error, mean_absolute_error
import xgboost as xgb
```

[30]:
```
#feature scaling
#normalize the "Age" and "Vintage" features with standardization
ss =StandardScaler()
num_feat = ['Age', 'Vintage']
filtered_train_data[num_feat] = ss.fit_transform(filtered_train_data[num_feat])
filtered_test_data[num_feat] = ss.fit_transform(filtered_test_data[num_feat])

#normalize "Annual_Premium" with min-max scaling
mm = MinMaxScaler()
filtered_train_data[['Annual_Premium']] = mm.
↪fit_transform(filtered_train_data[['Annual_Premium']])
filtered_train_data
```

[30]:
```
        Gender       Age  Driving_License  Region_Code  Previously_Insured  \
0            0 -1.084538                1         40.0                   0
1            1 -0.826727                1          8.0                   1
2            1 -0.440011                1         28.0                   0
3            0 -0.440011                1         37.0                   0
4            1 -0.955632                1         28.0                   0
…          …        …              …          …                 …
304882       0 -0.891180                1         47.0                   1
304883       0  1.944736                1         28.0                   0
304884       0 -0.955632                1         28.0                   0
304885       1  0.075610                1          8.0                   1
304886       0 -0.955632                1         15.0                   0

        Vehicle_Damage  Policy_Sales_Channel   Vintage  Annual_Premium  \
0                    1                 152.0  0.580945        0.057440
1                    0                  26.0 -1.307422        0.089999
```

```
2                      1                  122.0 -1.426939         0.074208
3                      1                  152.0  0.724365         0.088283
4                      1                  156.0  0.808027         0.115952
…                    …                    …        …          …
304882                 1                  160.0 -1.152050         0.051287
304883                 1                   26.0  1.620742         0.072980
304884                 0                  152.0 -1.104243         0.142094
304885                 0                   26.0  1.286095         0.066210
304886                 1                  152.0  1.214385         0.065058

        Vehicle_Age_1_2_Year  Vehicle_Age_lt_1_Year  Vehicle_Age_gt_2_Years
0                          0                      1                       0
1                          0                      1                       0
2                          0                      1                       0
3                          0                      1                       0
4                          0                      1                       0
…                        …                      …                       …
304882                     0                      1                       0
304883                     1                      0                       0
304884                     0                      1                       0
304885                     1                      0                       0
304886                     0                      1                       0

[304887 rows x 12 columns]
```

[31]:

```
filtered_train_data.describe()
```

[31]:

```
              Gender           Age  Driving_License    Region_Code  \
count  304887.000000  3.048870e+05    304887.000000  304887.000000
mean        0.459537  2.169590e-16         0.997855      26.396239
std         0.498361  1.000002e+00         0.046265      13.228749
min         0.000000 -1.213443e+00         0.000000       0.000000
25%         0.000000 -8.911797e-01         1.000000      15.000000
50%         0.000000 -1.822009e-01         1.000000      28.000000
75%         1.000000  6.556832e-01         1.000000      35.000000
max         1.000000  2.975977e+00         1.000000      52.000000

       Previously_Insured  Vehicle_Damage  Policy_Sales_Channel       Vintage  \
count       304887.000000   304887.000000         304887.000000  3.048870e+05
mean             0.458127        0.504971            112.053859 -6.448526e-17
std              0.498244        0.499976             54.189288  1.000002e+00
min              0.000000        0.000000              1.000000 -1.725731e+00
25%              0.000000        0.000000             29.000000 -8.652093e-01
50%              0.000000        1.000000            134.000000 -4.687622e-03
75%              1.000000        1.000000            152.000000  8.677858e-01
max              1.000000        1.000000            163.000000  1.728307e+00
```

```
       Annual_Premium  Vehicle_Age_1_2_Year  Vehicle_Age_lt_1_Year  \
count   304887.000000         304887.000000          304887.000000
mean         0.070360              0.525424               0.432462
std          0.043228              0.499354               0.495418
min          0.000000              0.000000               0.000000
25%          0.054793              0.000000               0.000000
50%          0.073148              1.000000               0.000000
75%          0.092642              1.000000               1.000000
max          1.000000              1.000000               1.000000

       Vehicle_Age_gt_2_Years
count           304887.000000
mean                 0.042114
std                  0.200849
min                  0.000000
25%                  0.000000
50%                  0.000000
75%                  0.000000
max                  1.000000
```

[32]:
```
X =filtered_train_data.drop(['Annual_Premium'], axis = 1)
y = filtered_train_data['Annual_Premium']
```

0.5.1 Train and Test Split

[33]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,␣
 ↪random_state = 3)
```

[34]:
```
print('xtrain', X_train.shape)
print('ytrain', y_train.shape)
print('xtest', X_test.shape)
print('ytest', y_test.shape)
```

```
xtrain (243909, 11)
ytrain (243909,)
xtest (60978, 11)
ytest (60978,)
```

[35]:
```
rf1 = RandomForestRegressor(random_state=1)
rf1.fit(X_train, y_train)
y_pred1 = rf1.predict(X_test)
print(np.sqrt(mean_squared_error(y_test, y_pred1)))
```

```
0.04100899619245232
```

[36]:
```
lm1 = LinearRegression()
lm1.fit(X_train, y_train)#lm1.fit(X_train, y_train)
y_pred = lm1.predict(X_test)
```

```
print(np.sqrt(mean_squared_error(y_test, y_pred)))
```

0.04289074001965307

[37]:
```
model=xgb.XGBRegressor(objective='reg:squarederror',learning_rate= 0.1,␣
↪max_depth=7, n_estimators=300)#objective='reg:squarederror',learning_rate= 0.
↪1, max_depth=7, n_estimators=300)
model.fit(X_train,y_train)
y_predict=model.predict(X_test)
# print('mean absolute', mean_absolute_error(y_test, y_predict))
mse = mean_squared_error(y_test, y_predict)
# print('mean squared error', mse)
print('root mean squared error', np.sqrt(mse))

print(y_predict)
```

```
root mean squared error 0.037306059685084846
[0.10049621 0.06478452 0.0703342  … 0.08173221 0.08770123 0.06526171]
```

0.5.2 Building ML Model

0.5.3 On full data for competition

[38]:
```
lm2 = LinearRegression()
lm2.fit(X, y)
```

[38]: LinearRegression()

[39]:
```
model2=xgb.XGBRegressor(objective='reg:squarederror',learning_rate= 0.1,␣
↪max_depth=7, n_estimators=300)#objective='reg:squarederror',learning_rate= 0.
↪1, max_depth=7, n_estimators=300)
model2.fit(X,y)
```

[39]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.1, max_delta_step=0, max_depth=7,
             min_child_weight=1, missing=nan, monotone_constraints='()',
             n_estimators=300, n_jobs=4, num_parallel_tree=1, random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
             tree_method='exact', validate_parameters=1, verbosity=None)
```

0.6 Prediction for Test Dataset

[40]:
```
#drop the "id" column
test_id = filtered_test_data['id'].to_numpy()
print(test_id)
filtered_test_data = filtered_test_data.drop(['id'], axis = 1)
filtered_test_data
```

```
[ 16222 342481  20916 … 303222 333830 245084]
```

[40]:
```
       Gender       Age  Driving_License  Region_Code  Previously_Insured  \
0           0  0.980501                1         28.0                   0
1           1 -0.826319                1          3.0                   0
2           0 -0.890848                1         28.0                   0
3           0 -0.632731                1         24.0                   0
4           1 -0.697260                1         28.0                   0
…         …       …              …            …                 …
76217       0  0.077091                1         28.0                   0
76218       1  0.012562                1         48.0                   0
76219       0  1.367677                1         28.0                   0
76220       0 -1.019907                1         15.0                   1
76221       0  1.238618                1          8.0                   1

       Vehicle_Damage  Policy_Sales_Channel   Vintage  Vehicle_Age_1_2_Year  \
0                   1                  26.0 -1.209060                     0
1                   1                 156.0  1.503816                     1
2                   1                 124.0  1.205041                     0
3                   1                 157.0  0.966021                     1
4                   1                  26.0  1.061629                     0
…                 …                   …       …                   …
76217               1                 124.0 -0.169323                     1
76218               0                 124.0  0.284815                     1
76219               1                  26.0  1.563571                     1
76220               0                 152.0 -0.671265                     0
76221               0                  26.0  0.966021                     1

       Vehicle_Age_lt_1_Year  Vehicle_Age_gt_2_Years
0                          0                       1
1                          0                       0
2                          1                       0
3                          0                       0
4                          1                       0
…                        …                     …
76217                      0                       0
76218                      0                       0
76219                      0                       0
76220                      1                       0
76221                      0                       0

[76222 rows x 11 columns]
```

[41]:
```python
predictions = model2.predict(filtered_test_data)
print(predictions)
```

```
[0.09831095 0.02479893 0.09748651 … 0.09714258 0.0757018  0.08505565]
```

[42]:
```
test_pred = lm2.predict(filtered_test_data)
```

0.7 Saving Prediction File

[43]:
```
data = {"id":test_id, "Annual_Premium":predictions}
res= pd.DataFrame(data)
res.index = filtered_test_data.index # for comparision
res.to_csv("prediction_result5.csv", index = False)
```