Vehicle Insurance Prediction

In [59]:

```
import pandas as pd
from hdfs import InsecureClient
import os
from pyspark.sql import SparkSession
import matplotlib.pyplot as plt
import seaborn as sns
```

In [4]:

```
sparkSession = SparkSession.builder.appName("EDA Vehicle Insurance").getOrCrea
te()
client_hdfs = InsecureClient('hdfs://localhost:9820')
```

In [5]:
```python
df = sparkSession.read.csv('hdfs://localhost:9820/test/Merge.csv', header=True
, inferSchema= True)
df.show()
```

```
+---+------+---+---------------+-----------+------------------+-----------+--
------------+--------------+--------------------+-------+--------+
| id|Gender|Age|Driving_License|Region_Code|Previously_Insured|Vehicle_Age|Ve
hicle_Damage|Annual_Premium|Policy_Sales_Channel|Vintage|Response|
+---+------+---+---------------+-----------+------------------+-----------+--
------------+--------------+--------------------+-------+--------+
|  1|  Male| 44|              1|         28|                 0|  > 2 Years|
Yes|         40454|                  26|    217|       1|
|  2|  Male| 76|              1|          3|                 0|   1-2 Year|
No|         33536|                  26|    183|       0|
|  3|  Male| 47|              1|         28|                 0|  > 2 Years|
Yes|         38294|                  26|     27|       1|
|  4|  Male| 21|              1|         11|                 1|   < 1 Year|
No|         28619|                 152|    203|       0|
|  5|Female| 29|              1|         41|                 1|   < 1 Year|
No|         27496|                 152|     39|       0|
|  6|Female| 24|              1|         33|                 0|   < 1 Year|
Yes|          2630|                 160|    176|       0|
|  7|  Male| 23|              1|         11|                 0|   < 1 Year|
Yes|         23367|                 152|    249|       0|
|  8|Female| 56|              1|         28|                 0|   1-2 Year|
Yes|         32031|                  26|     72|       1|
|  9|Female| 24|              1|          3|                 1|   < 1 Year|
No|         27619|                 152|     28|       0|
| 10|Female| 32|              1|          6|                 1|   < 1 Year|
No|         28771|                 152|     80|       0|
| 11|Female| 47|              1|         35|                 0|   1-2 Year|
Yes|         47576|                 124|     46|       1|
| 12|Female| 24|              1|         50|                 1|   < 1 Year|
No|         48699|                 152|    289|       0|
| 13|Female| 41|              1|         15|                 1|   1-2 Year|
No|         31409|                  14|    221|       0|
| 14|  Male| 76|              1|         28|                 0|   1-2 Year|
Yes|         36770|                  13|     15|       0|
| 15|  Male| 71|              1|         28|                 1|   1-2 Year|
No|         46818|                  30|     58|       0|
| 16|  Male| 37|              1|          6|                 0|   1-2 Year|
Yes|          2630|                 156|    147|       1|
| 17|Female| 25|              1|         45|                 0|   < 1 Year|
Yes|         26218|                 160|    256|       0|
| 18|Female| 25|              1|         35|                 1|   < 1 Year|
No|         46622|                 152|    299|       0|
| 19|  Male| 42|              1|         28|                 0|   1-2 Year|
Yes|         33667|                 124|    158|       0|
| 20|Female| 60|              1|         33|                 0|   1-2 Year|
Yes|         32363|                 124|    102|       1|
+---+------+---+---------------+-----------+------------------+-----------+--
------------+--------------+--------------------+-------+--------+
only showing top 20 rows
```

In [7]:
```
result_df = df.select("*").toPandas()
result_df.head()
```

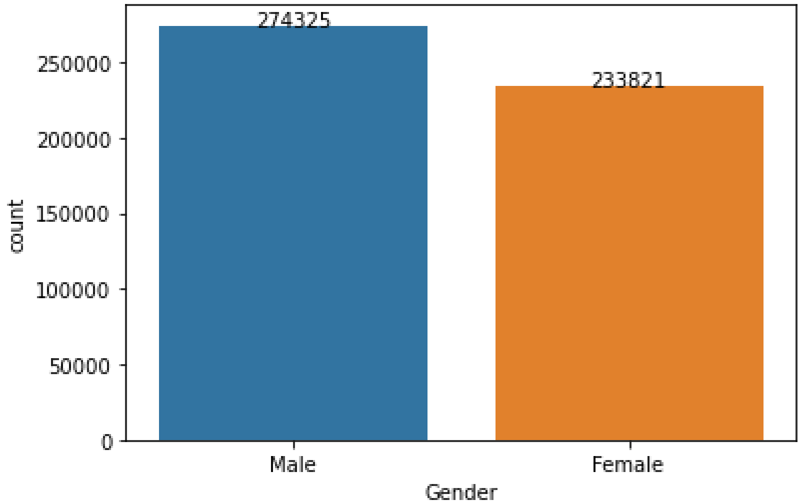
Out[7]:

	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	Vehicle_Age	Vehicle_Dai
0	1	Male	44	1	28	0	> 2 Years	
1	2	Male	76	1	3	0	1-2 Year	
2	3	Male	47	1	28	0	> 2 Years	
3	4	Male	21	1	11	1	< 1 Year	
4	5	Female	29	1	41	1	< 1 Year	

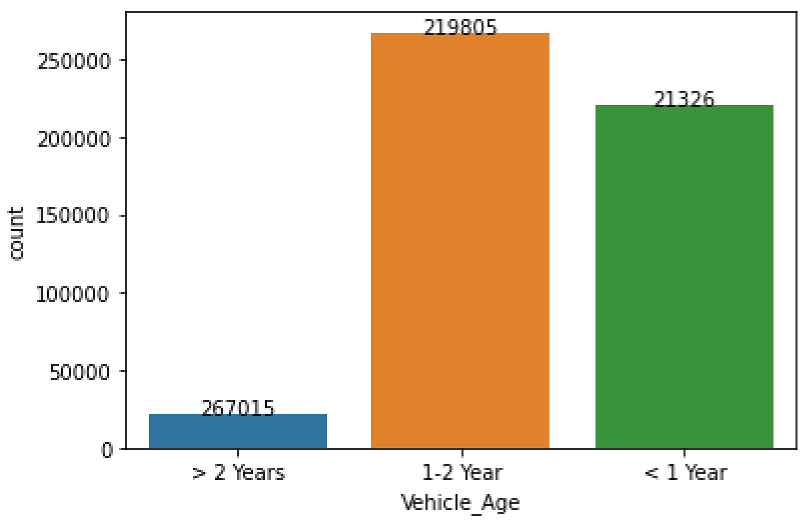
In [5]:
```
print(result_df.dtypes)
print(result_df.isnull().any())
print(result_df.isnull().sum())
```

```
id                        int32
Gender                   object
Age                       int32
Driving_License           int32
Region_Code               int32
Previously_Insured        int32
Vehicle_Age              object
Vehicle_Damage           object
Annual_Premium            int32
Policy_Sales_Channel      int32
Vintage                   int32
Response                  int32
dtype: object
id                       False
Gender                   False
Age                      False
Driving_License          False
Region_Code              False
Previously_Insured       False
Vehicle_Age              False
Vehicle_Damage           False
Annual_Premium           False
Policy_Sales_Channel     False
Vintage                  False
Response                 False
dtype: bool
id                       0
Gender                   0
Age                      0
Driving_License          0
Region_Code              0
Previously_Insured       0
Vehicle_Age              0
Vehicle_Damage           0
Annual_Premium           0
Policy_Sales_Channel     0
Vintage                  0
Response                 0
dtype: int64
```

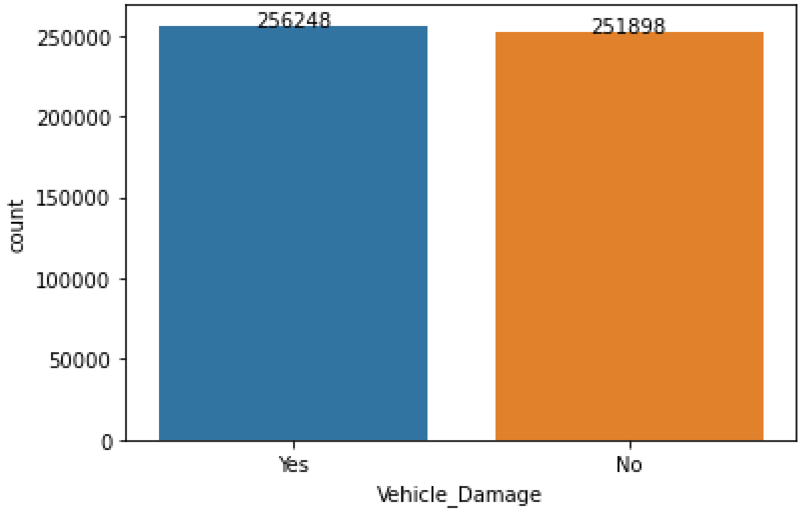
In [6]:
```
graph = sns.countplot(result_df.Gender)
graph.set_xticklabels(graph.get_xticklabels())
i=0
for p in graph.patches:
    height = p.get_height()
    graph.text(p.get_x()+p.get_width()/2., height + 0.1,
        result_df['Gender'].value_counts()[i],ha="center")
    i += 1
```



In [7]:
```
graph = sns.countplot(result_df.Vehicle_Age)
graph.set_xticklabels(graph.get_xticklabels())
i=0
for p in graph.patches:
    height = p.get_height()
    graph.text(p.get_x()+p.get_width()/2., height + 0.1,
        result_df['Vehicle_Age'].value_counts()[i],ha="center")
    i += 1
```

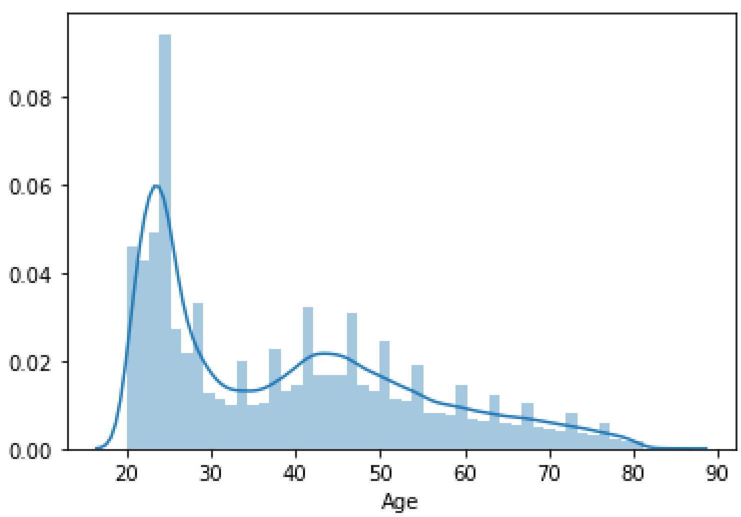


In [8]:
```
graph = sns.countplot(result_df.Vehicle_Damage)
graph.set_xticklabels(graph.get_xticklabels())
i=0
for p in graph.patches:
    height = p.get_height()
    graph.text(p.get_x()+p.get_width()/2., height + 0.1,
        result_df['Vehicle_Damage'].value_counts()[i],ha="center")
    i += 1
```



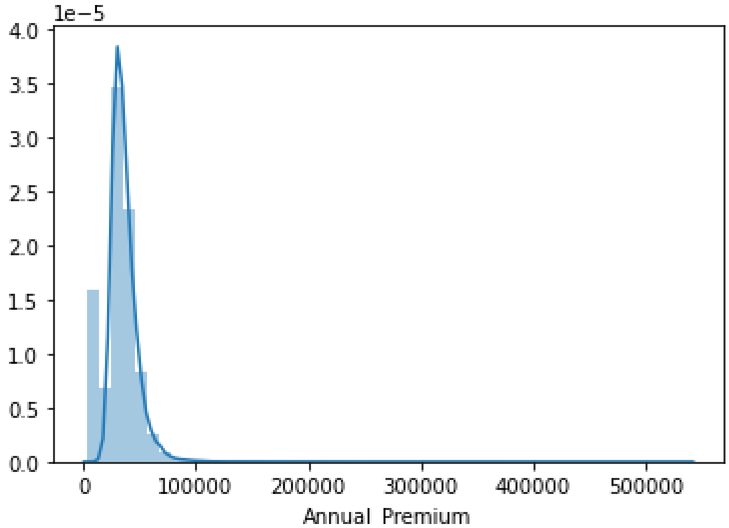
In [9]:
```
sns.distplot(result_df.Age)
```

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x1e61a0c7730>



In [10]:
```
sns.distplot(result_df.Annual_Premium)
```

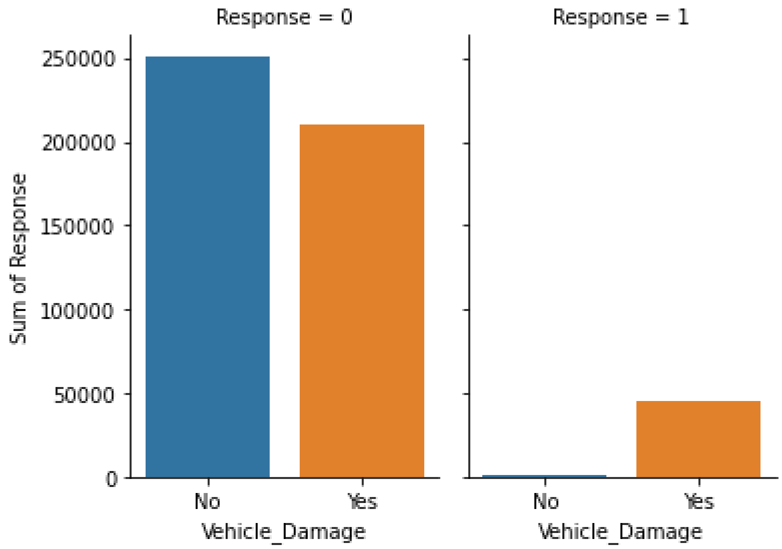
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x1e61465ce20>



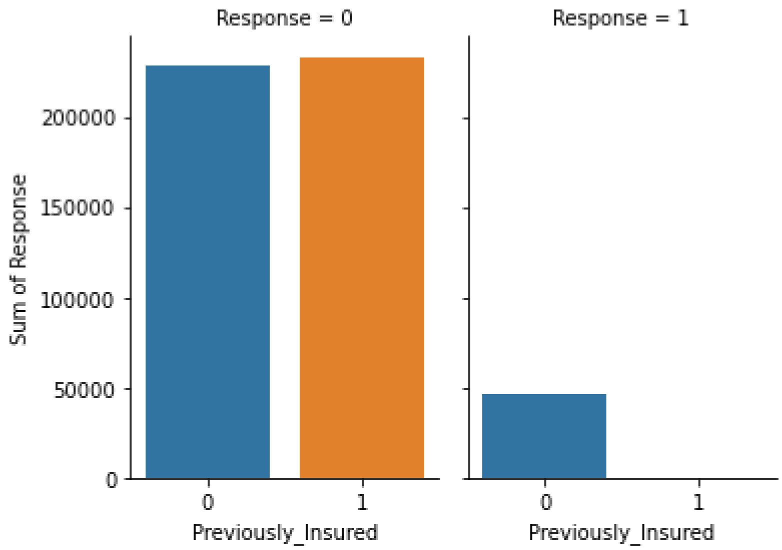
In [11]:
```
a=result_df.groupby(['Vehicle_Damage','Response']).size().sort_values(ascendin
g=False).reset_index(name='Sum of Response')
b=result_df.groupby(['Previously_Insured','Response']).size().sort_values(asce
nding=False).reset_index(name='Sum of Response')
c=result_df.groupby(['Gender','Response']).size().sort_values(ascending=False)
.reset_index(name='Sum of Response')
print(a)
print(b)
print(c)
```

```
  Vehicle_Damage  Response  Sum of Response
0             No         0           250916
1            Yes         0           210520
2            Yes         1            45728
3             No         1              982
   Previously_Insured  Response  Sum of Response
0                   1         0           232912
1                   0         0           228524
2                   0         1            46552
3                   1         1              158
   Gender  Response  Sum of Response
0    Male         0           245800
1  Female         0           215636
2    Male         1            28525
3  Female         1            18185
```

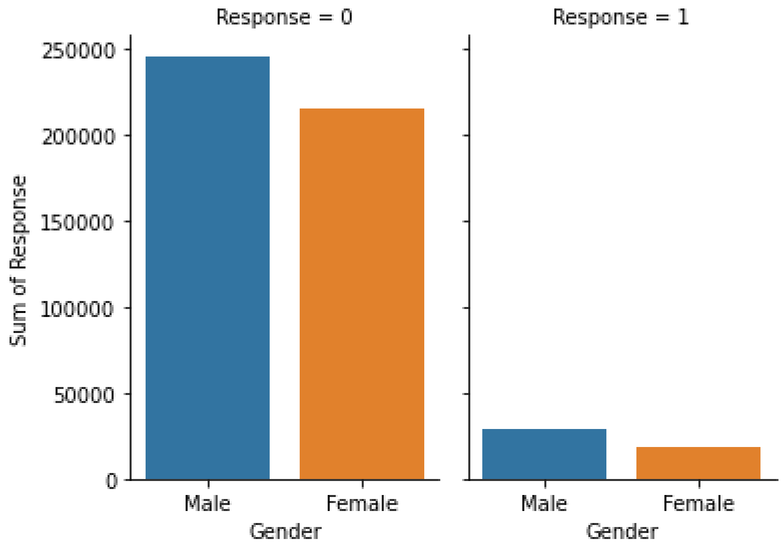
In [12]:
```
graph = sns.catplot(x="Vehicle_Damage", y="Sum of Response",col="Response",
                data=a, kind="bar",
                height=4, aspect=.7);
```



In [13]:
```
graph = sns.catplot(x="Previously_Insured", y="Sum of Response",col="Response"
,
                data=b, kind="bar",
                height=4, aspect=.7);
```



In [14]:
```
graph = sns.catplot(x="Gender", y="Sum of Response",col="Response",
                data=c, kind="bar",
                height=4, aspect=.7);
```



In [15]:
```
result_df.Vehicle_Age.unique()
```

Out[15]:
```
array(['> 2 Years', '1-2 Year', '< 1 Year'], dtype=object)
```

In [8]:
```
result_df.Gender[result_df.Gender == 'Male'] = 1
result_df.Gender[result_df.Gender == 'Female'] = 0

result_df.Vehicle_Damage[result_df.Vehicle_Damage == 'Yes'] = 1
result_df.Vehicle_Damage[result_df.Vehicle_Damage == 'No'] = 0

result_df['Gender'] = result_df['Gender'].astype(int)
result_df['Vehicle_Damage'] = result_df['Vehicle_Damage'].astype(int)
```

```
<ipython-input-8-8f978a608a47>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy
  result_df.Gender[result_df.Gender == 'Male'] = 1
<ipython-input-8-8f978a608a47>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy
  result_df.Gender[result_df.Gender == 'Female'] = 0
<ipython-input-8-8f978a608a47>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy
  result_df.Vehicle_Damage[result_df.Vehicle_Damage == 'Yes'] = 1
<ipython-input-8-8f978a608a47>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy
  result_df.Vehicle_Damage[result_df.Vehicle_Damage == 'No'] = 0
```

In [17]:
```
result_df.head()
```

Out[17]:

	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	Vehicle_Age	Vehicle_Da
0	1	1	44	1	28	0	> 2 Years	
1	2	1	76	1	3	0	1-2 Year	
2	3	1	47	1	28	0	> 2 Years	
3	4	1	21	1	11	1	< 1 Year	
4	5	0	29	1	41	1	< 1 Year	

In [9]:
```
from sklearn.preprocessing import LabelEncoder
labelencoder = LabelEncoder()
result_df['Vehicle_Age'] = labelencoder.fit_transform(result_df['Vehicle_Age'
])
```

In [19]:
```
result_df.head()
```

Out[19]:

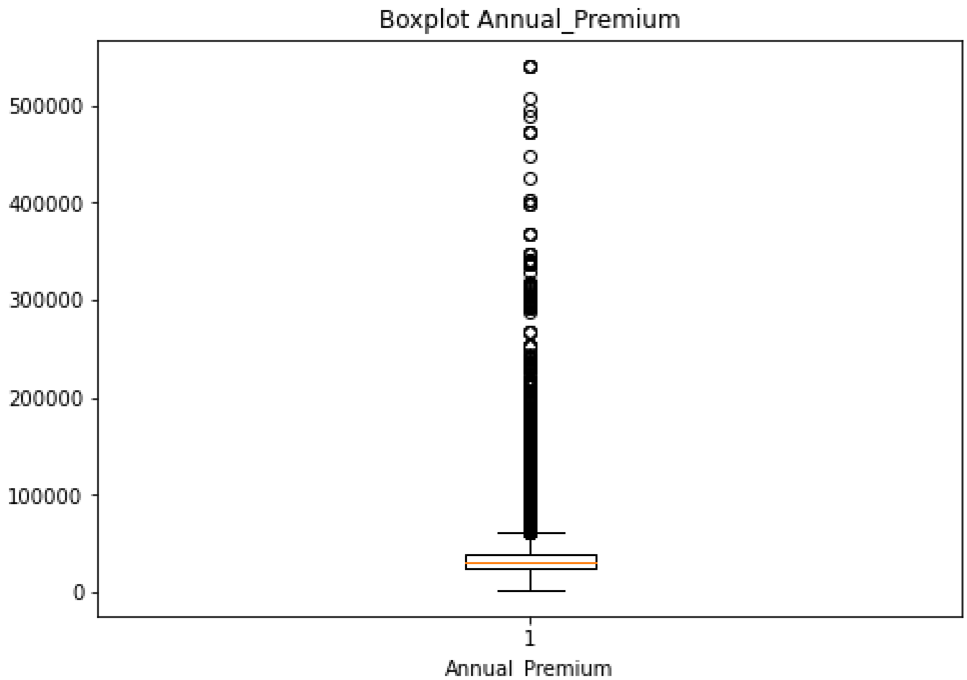
	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	Vehicle_Age	Vehicle_Dai
0	1	1	44	1	28	0	2	
1	2	1	76	1	3	0	0	
2	3	1	47	1	28	0	2	
3	4	1	21	1	11	1	1	
4	5	0	29	1	41	1	1	

In [20]:
```
numerical_columns=['Age', 'Region_Code','Annual_Premium','Vintage']
result_df[numerical_columns].describe()
```

Out[20]:

	Age	Region_Code	Annual_Premium	Vintage
count	508146.000000	508146.000000	508146.000000	508146.000000
mean	38.808413	26.406572	30554.453041	154.340123
std	15.500179	13.224921	17146.574625	83.668793
min	20.000000	0.000000	2630.000000	10.000000
25%	25.000000	15.000000	24381.000000	82.000000
50%	36.000000	28.000000	31661.000000	154.000000
75%	49.000000	35.000000	39403.750000	227.000000
max	85.000000	52.000000	540165.000000	299.000000

In [21]:
```
import matplotlib.pyplot as plt
fig = plt.figure()
# Create an axes instance
ax = fig.add_axes([0,0,1,1])
# Create the boxplot
bp = ax.boxplot(result_df['Annual_Premium'])
plt.xlabel("Annual_Premium")
plt.title("Boxplot Annual_Premium")
plt.show()
```



In [22]:
```
import numpy as np
outliers=[]
def detect_outlier(data_1):

    threshold=3
    mean_1 = np.mean(data_1)
    std_1 =np.std(data_1)


    for y in data_1:
        z_score= (y - mean_1)/std_1
        if np.abs(z_score) > threshold:
            outliers.append(y)
    return outliers
```

In [23]:
```
outlier_datapoints = detect_outlier(result_df["Annual_Premium"])
print(outlier_datapoints)
```

```
[89282, 101021, 82705, 90789, 119735, 104002, 92716, 112974, 139130, 98002, 2
67698, 125643, 85786, 95217, 101064, 86283, 136061, 117799, 84142, 91520, 872
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```

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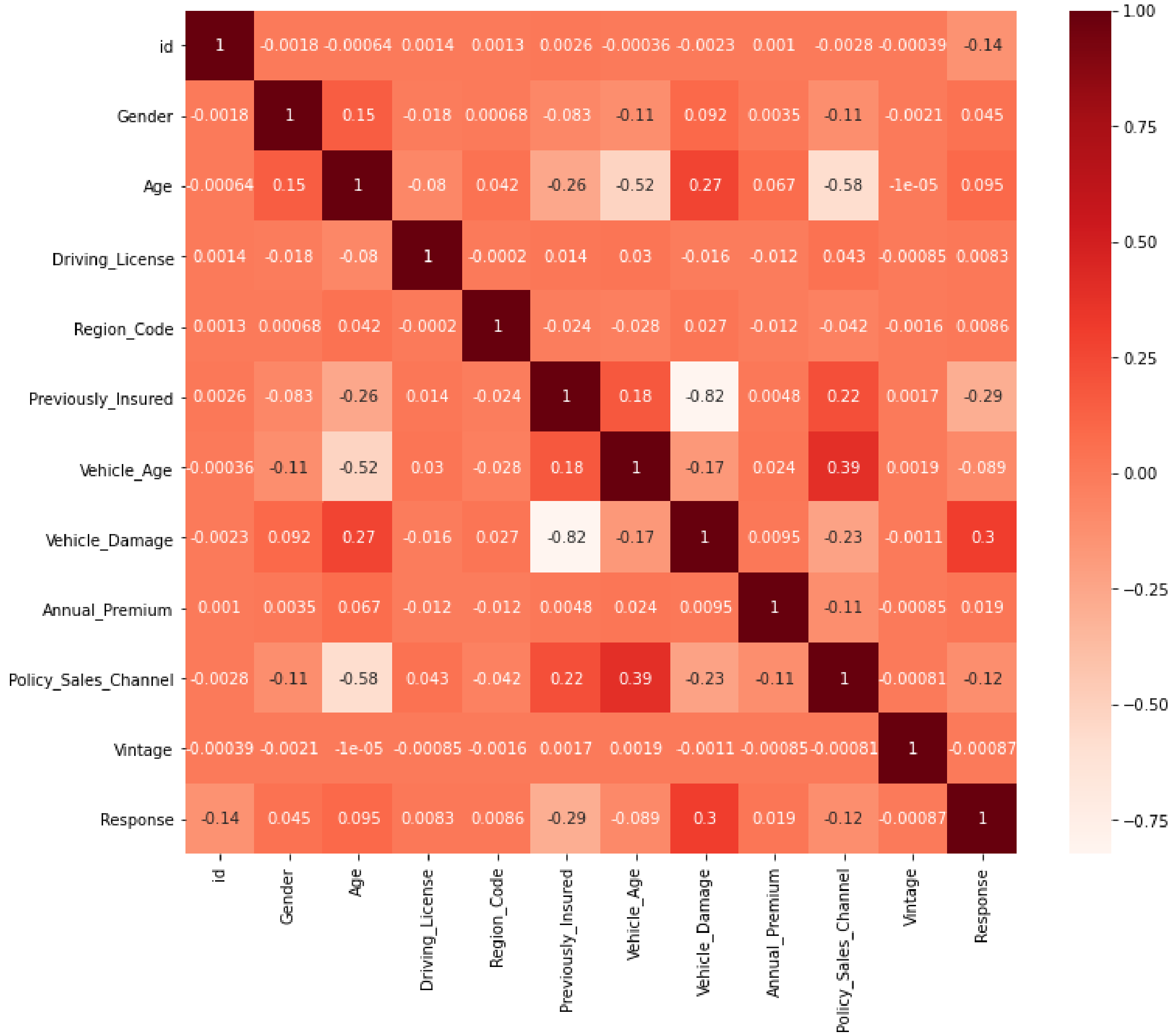
81]
```

In [24]:
```
#Using Pearson Correlation
plt.figure(figsize=(12,10))
cor = result_df.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
plt.show()
#Correlation with output variable
cor_target = abs(cor["Annual_Premium"])
#Selecting highly correlated features
relevant_features = cor_target[cor_target>0]
print("Correlation Coefficeint With Respect to Response")
print(relevant_features)
```




```
Correlation Coefficeint With Respect to Response
id                      0.001042
Gender                  0.003502
Age                     0.067392
Driving_License         0.012084
Region_Code             0.012012
Previously_Insured      0.004776
Vehicle_Age             0.023545
Vehicle_Damage          0.009504
Annual_Premium          1.000000
Policy_Sales_Channel    0.114035
Vintage                 0.000855
Response                0.019477
Name: Annual_Premium, dtype: float64
```

Linear Regression

In [25]:
```
x=result_df.drop(['Annual_Premium','id'], axis = 1)
y=result_df['Annual_Premium']
print(x.shape)
print(y.shape)
```

```
(508146, 10)
(508146,)
```

In [26]:
```
from sklearn.model_selection import train_test_split
train_features, test_features, train_labels, test_labels = train_test_split(x,
y, test_size = 0.3, random_state = 0)
```

In [27]:
```
print('Training Features Shape:', train_features.shape)
print('Training Labels Shape:', train_labels.shape)
print('Testing Features Shape:', test_features.shape)
print('Testing Labels Shape:', test_labels.shape)
```

```
Training Features Shape: (355702, 10)
Training Labels Shape: (355702,)
Testing Features Shape: (152444, 10)
Testing Labels Shape: (152444,)
```

In [28]:
```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(train_features, train_labels)
y_pred = model.predict(test_features)
```

In [29]:
```
print("Training set score: {:.4f}".format(model.score(train_features,train_lab
els)))

print("Test set score: {:.4f}".format(model.score(test_features,test_labels)))
```

```
Training set score: 0.0216
Test set score: 0.0202
```

In [30]:
```
print(model.coef_)
print(model.intercept_)
```

```
[-2.20296565e+02  5.68341300e+01 -2.40386630e+03 -2.20994504e+01
  1.84695901e+03  2.87446966e+03  7.89872640e+02 -4.05438669e+01
 -2.30672795e-01  9.38180788e+02]
33231.52629203656
```

In [31]:
```
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(test_labels, y_pred)
rmse = np.sqrt(mse)
print("RMSE value: {:.4f}".format(rmse))
```

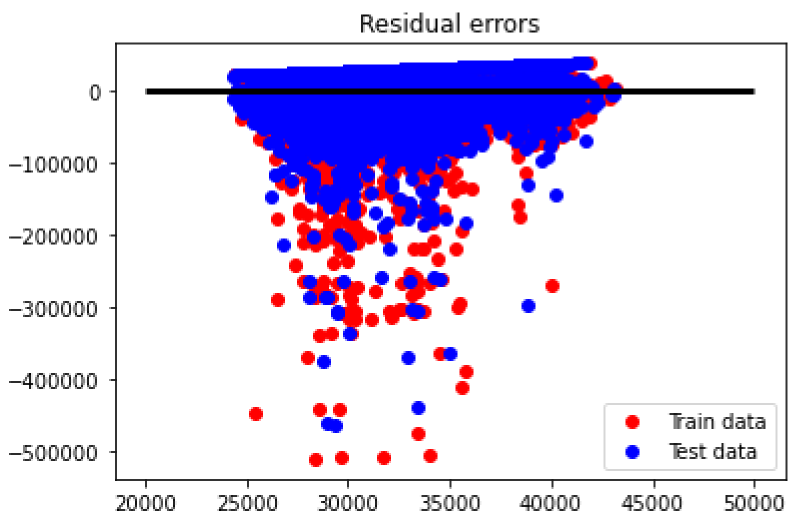
```
RMSE value: 16885.9328
```

In [32]:
```
# Calculate and print r2_score

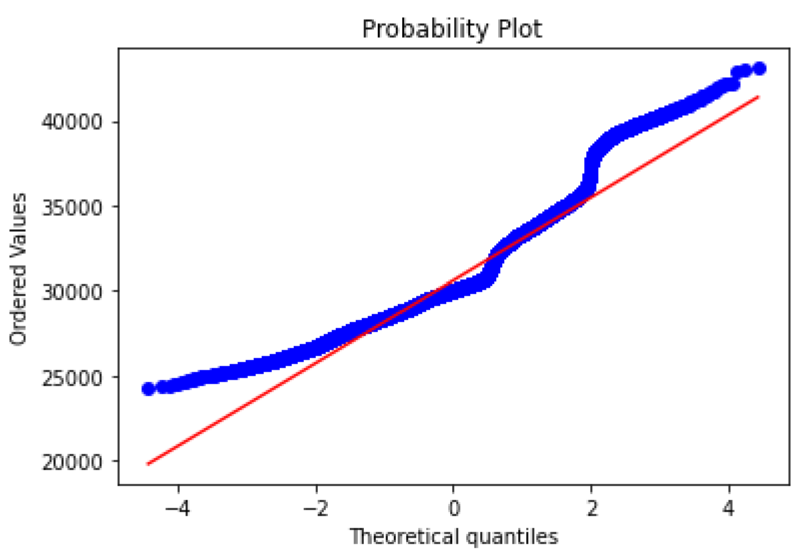
from sklearn.metrics import r2_score
print ("R2 Score value: {:.4f}".format(r2_score(test_labels, y_pred)))
```

```
R2 Score value: 0.0202
```

In [33]:
```
# Plotting residual errors
plt.scatter(model.predict(train_features), model.predict(train_features) - tra
in_labels, color = 'red', label = 'Train data')
plt.scatter(model.predict(test_features), model.predict(test_features) - test_
labels, color = 'blue', label = 'Test data')
plt.hlines(xmin = 20000, xmax = 50000, y = 0, linewidth = 3)
plt.title('Residual errors')
plt.legend(loc = 4)
plt.show()
```

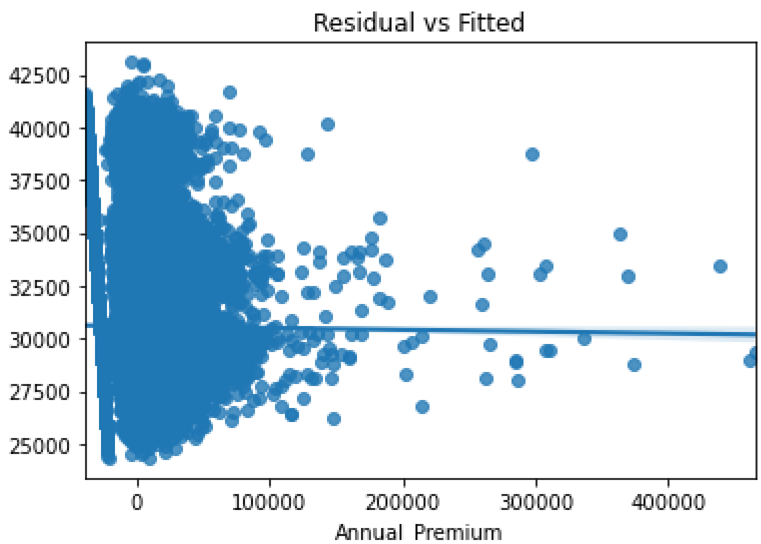


In [34]:
```
import statsmodels.api as sm
import pylab
import scipy.stats as stats
stats.probplot(y_pred.reshape(-1), dist="norm", plot=pylab)
pylab.show()
```



In [35]:
```
import seaborn as sns
residuals = test_labels - y_pred
ax = sns.regplot(x=residuals, y=y_pred)
ax.set_title('Residual vs Fitted')
```

Out[35]:
```
Text(0.5, 1.0, 'Residual vs Fitted')
```



Lasso, Ridge

In [36]:
```
from sklearn.linear_model import Lasso
```

In [37]:
```
lasso = Lasso()
lasso.fit(train_features,train_labels)
train_score=lasso.score(train_features,train_labels)
test_score=lasso.score(test_features,test_labels)
coeff_used = np.sum(lasso.coef_!=0)
print("training score:", train_score)
print("test score: ", test_score)
print("number of features used: ", coeff_used)
lasso001 = Lasso(alpha=0.01, max_iter=10e5)
lasso001.fit(train_features,train_labels)
train_score001=lasso001.score(train_features,train_labels)
test_score001=lasso001.score(test_features,test_labels)
coeff_used001 = np.sum(lasso001.coef_!=0)
print("training score for alpha=0.01:", train_score001)
print("test score for alpha =0.01: ", test_score001)
print("number of features used: for alpha =0.01:", coeff_used001)
lasso00001 = Lasso(alpha=0.0001, max_iter=10e5)
lasso00001.fit(train_features,train_labels)
train_score00001=lasso00001.score(train_features,train_labels)
test_score00001=lasso00001.score(test_features,test_labels)
coeff_used00001 = np.sum(lasso00001.coef_!=0)
print("training score for alpha=0.0001:", train_score00001)
print("test score for alpha =0.0001: ", test_score00001)
print("number of features used: for alpha =0.0001:", coeff_used00001)
```

```
training score: 0.021558759070389066
test score:  0.020205815285361806
number of features used:  10
training score for alpha=0.01: 0.02156062130858072
test score for alpha =0.01:  0.02020252115769039
number of features used: for alpha =0.01: 10
training score for alpha=0.0001: 0.02156062149479465
test score for alpha =0.0001:  0.020202470244255255
number of features used: for alpha =0.0001: 10
```

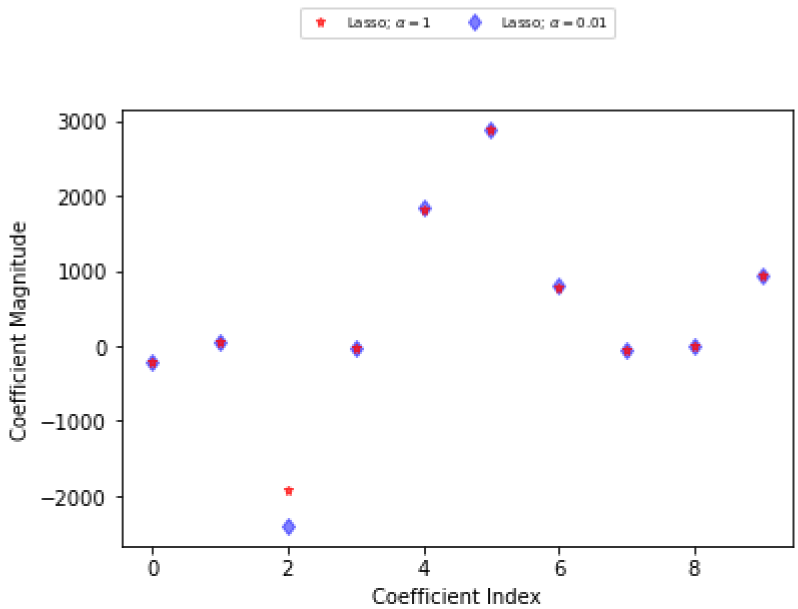
In [38]:
```
from sklearn.linear_model import Ridge
ridgereg = Ridge(alpha=0, normalize=True)
ridgereg.fit(train_features, train_labels)
y_pred = ridgereg.predict(test_features)
from sklearn import metrics
print("R-Square Value",r2_score(test_labels,y_pred))
print ("mean_absolute_error :",metrics.mean_absolute_error(test_labels, y_pred
))
print ("mean_squared_error : ",metrics.mean_squared_error(test_labels, y_pred
))
print ("root_mean_squared_error : ",np.sqrt(metrics.mean_squared_error(test_la
bels, y_pred)))
ridgereg = Ridge(alpha=0.1, normalize=True)
ridgereg.fit(train_features, train_labels)
y_pred = ridgereg.predict(test_features)
print("R-Square Value",r2_score(test_labels,y_pred))
print ("mean_absolute_error :",metrics.mean_absolute_error(test_labels, y_pred
))
print ("mean_squared_error : ",metrics.mean_squared_error(test_labels, y_pred
))
print ("root_mean_squared_error : ",np.sqrt(metrics.mean_squared_error(test_la
bels, y_pred)))
print(ridgereg.coef_)
```

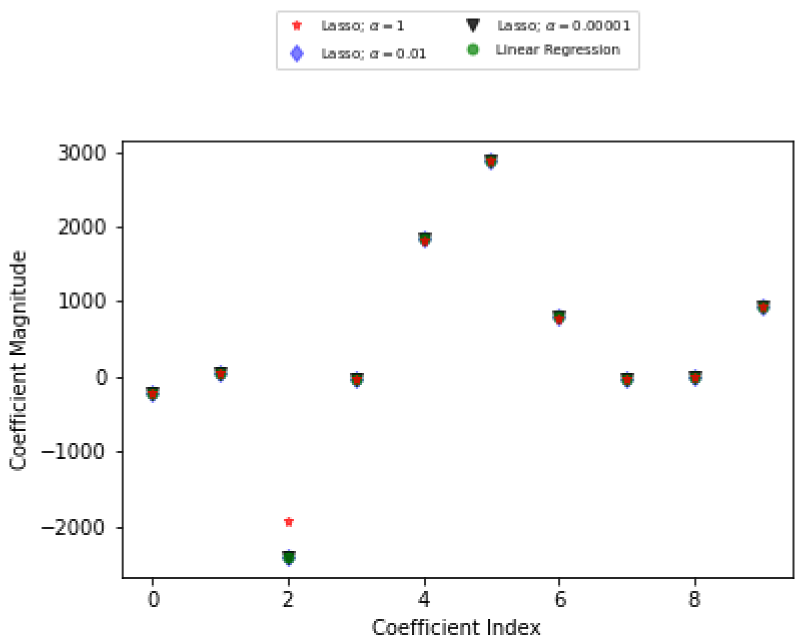
```
R-Square Value 0.02020246972837836
mean_absolute_error : 11950.144186561989
mean_squared_error :  285134727.5654296
root_mean_squared_error :  16885.932830774545
R-Square Value 0.020080346450857656
mean_absolute_error : 11939.191499945779
mean_squared_error :  285170267.1400758
root_mean_squared_error :  16886.985140636436
[-1.83744566e+02  5.12760030e+01 -2.35563745e+03 -1.96128702e+01
  1.30913268e+03  2.40050122e+03  3.91052677e+02 -3.56696578e+01
 -2.03058346e-01  8.41517289e+02]
```

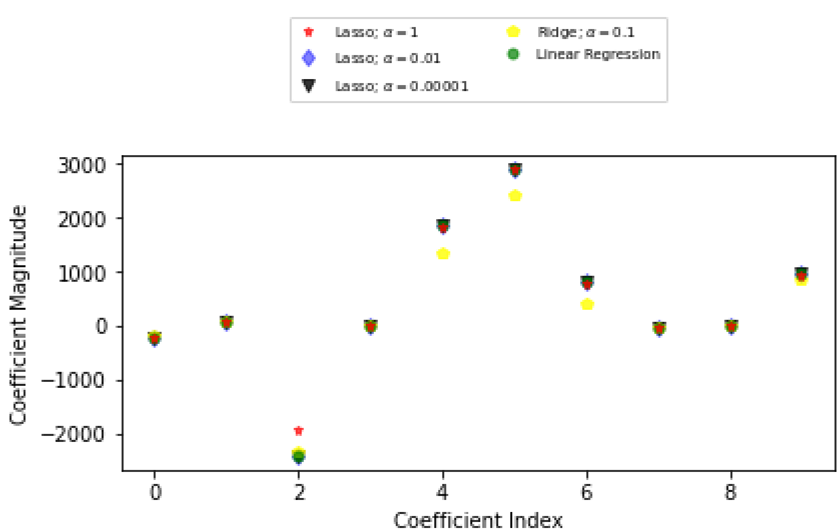
In [39]:
```
plt.plot(lasso.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color=
'red',label=r'Lasso; $\alpha = 1$',zorder=7)
plt.plot(lasso001.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,col
or='blue',label=r'Lasso; $\alpha = 0.01$')
plt.xlabel('Coefficient Index')
plt.ylabel('Coefficient Magnitude')
plt.legend(fontsize=7,loc="lower center", bbox_to_anchor=(0.5, 1.15), ncol=2)
plt.show()

plt.plot(lasso.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color=
'red',label=r'Lasso; $\alpha = 1$',zorder=7)
plt.plot(lasso001.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,col
or='blue',label=r'Lasso; $\alpha = 0.01$')
plt.plot(lasso00001.coef_,alpha=0.8,linestyle='none',marker='v',markersize=6,c
olor='black',label=r'Lasso; $\alpha = 0.00001$')
plt.plot(model.coef_,alpha=0.7,linestyle='none',marker='o',markersize=5,color=
'green',label='Linear Regression',zorder=2)
plt.xlabel('Coefficient Index')
plt.ylabel('Coefficient Magnitude')
plt.legend(fontsize=7,loc="lower center", bbox_to_anchor=(0.5, 1.15), ncol=2)
plt.show()

plt.plot(lasso.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color=
'red',label=r'Lasso; $\alpha = 1$',zorder=7)
plt.plot(lasso001.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,col
or='blue',label=r'Lasso; $\alpha = 0.01$')
plt.plot(lasso00001.coef_,alpha=0.8,linestyle='none',marker='v',markersize=6,c
olor='black',label=r'Lasso; $\alpha = 0.00001$')
plt.plot(ridgereg.coef_,alpha=0.8,linestyle='none',marker='p',markersize=6,col
or='yellow',label=r'Ridge; $\alpha = 0.1$')
plt.plot(model.coef_,alpha=0.7,linestyle='none',marker='o',markersize=5,color=
'green',label='Linear Regression',zorder=2)
plt.xlabel('Coefficient Index')
plt.ylabel('Coefficient Magnitude')
plt.legend(fontsize=7,loc="lower center", bbox_to_anchor=(0.5, 1.15), ncol=2)
plt.tight_layout()
plt.show()
```


Lasso; $\alpha = 1$
Lasso; $\alpha = 0.01$
Coefficient Magnitude
Coefficient Index


Lasso; $\alpha = 1$
Lasso; $\alpha = 0.01$
Lasso; $\alpha = 0.00001$
Linear Regression
Coefficient Magnitude
Coefficient Index


Lasso; $\alpha = 1$
Lasso; $\alpha = 0.01$
Lasso; $\alpha = 0.00001$
Ridge; $\alpha = 0.1$
Linear Regression
Coefficient Magnitude
Coefficient Index

Logistic Regression

In [34]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
```

In [35]:
```
x=result_df.drop('Response', axis = 1)
y=result_df['Response']
```

In [36]:
```
from sklearn.model_selection import train_test_split
train_features, test_features, train_labels, test_labels = train_test_split(x,
y, test_size = 0.3, random_state = 0)
```

In [37]:
```
from imblearn.under_sampling import NearMiss
nr = NearMiss()
train_features, train_labels = nr.fit_resample(train_features, train_labels)
```

In [38]:
```
print('Training Features Shape:', train_features.shape)
print('Training Labels Shape:', train_labels.shape)
print('Testing Features Shape:', test_features.shape)
print('Testing Labels Shape:', test_labels.shape)
```

```
Training Features Shape: (65378, 11)
Training Labels Shape: (65378,)
Testing Features Shape: (152444, 11)
Testing Labels Shape: (152444,)
```

In [39]:
```
from sklearn.linear_model import LogisticRegression

logreg = LogisticRegression(max_iter=1000)

logreg.fit(train_features, train_labels)

y_pred=logreg.predict(test_features)

print(classification_report(test_labels, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.94      0.30      0.46    138423
           1       0.11      0.82      0.19     14021

    accuracy                           0.35    152444
   macro avg       0.53      0.56      0.32    152444
weighted avg       0.87      0.35      0.43    152444
```

In [40]:
```
from sklearn import metrics
print("Accuracy:",metrics.accuracy_score(test_labels, y_pred)*100)
```

```
Accuracy: 35.086982760882684
```

In [41]:
```
print("Accuracy:",metrics.accuracy_score(test_labels, y_pred))
print("Precision:",metrics.precision_score(test_labels, y_pred))
print("Recall:",metrics.recall_score(test_labels, y_pred))
```

```
Accuracy: 0.35086982760882685
Precision: 0.1067787664700599
Recall: 0.8224805648669853
```

In [42]:
```
from sklearn import metrics
cnf_matrix = metrics.confusion_matrix(test_labels, y_pred)
cnf_matrix
```

Out[42]:
```
array([[41956, 96467],
       [ 2489, 11532]], dtype=int64)
```

In [43]:
```
import numpy as np
predictions = logreg.predict(test_features)
errors = abs(predictions - test_labels)
print('Mean Absolute Error:', round(np.mean(errors), 2), 'degrees.')
```

```
Mean Absolute Error: 0.65 degrees.
```

In [44]:
```
from sklearn.feature_selection import RFE
rfe = RFE(logreg, n_features_to_select=8)
fit = rfe.fit(train_features, train_labels)
print("Num Features: %d" % fit.n_features_)
print("Selected Features: %s" % fit.support_)
print("Feature Ranking: %s" % fit.ranking_)
print("Features:", train_features.columns)
```

```
Num Features: 8
Selected Features: [False  True  True  True  True  True  True  True False  Tr
ue False]
Feature Ranking: [4 1 1 1 1 1 1 1 3 1 2]
Features: Index(['id', 'Gender', 'Age', 'Driving_License', 'Region_Code',
       'Previously_Insured', 'Vehicle_Age', 'Vehicle_Damage', 'Annual_Premiu
m',
       'Policy_Sales_Channel', 'Vintage'],
      dtype='object')
```

In [45]:
```
logreg_imp = LogisticRegression(max_iter=1000)
train_important = train_features.drop(['id','Annual_Premium','Vintage'], axis=
1)
test_important = test_features.drop(['id','Annual_Premium','Vintage'], axis=1)
logreg_imp.fit(train_important, train_labels)
predictions = logreg_imp.predict(test_important)
errors = abs(predictions - test_labels)
print('Mean Absolute Error:', round(np.mean(errors), 2), 'degrees.')
print(classification_report(test_labels, predictions))
```

```
Mean Absolute Error: 0.38 degrees.
              precision    recall  f1-score   support

           0       0.99      0.58      0.73    138423
           1       0.19      0.97      0.32     14021

    accuracy                           0.62    152444
   macro avg       0.59      0.77      0.52    152444
weighted avg       0.92      0.62      0.69    152444
```

In [46]:
```
from sklearn import metrics
cnf_matrix = metrics.confusion_matrix(test_labels, predictions)
cnf_matrix
```

Out[46]:
```
array([[80271, 58152],
       [  488, 13533]], dtype=int64)
```

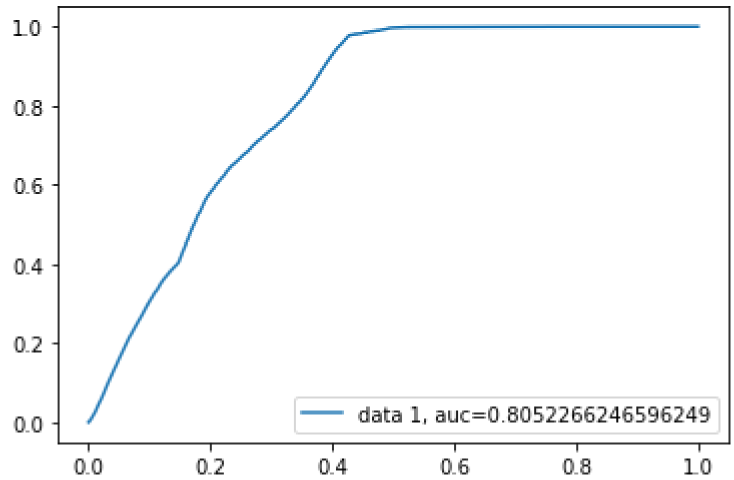
In [47]:
```
from sklearn import metrics
print("Accuracy:",metrics.accuracy_score(test_labels, predictions)*100)
```

```
Accuracy: 61.53341554931647
```

In [48]:
```
print("Accuracy:",metrics.accuracy_score(test_labels, predictions))
print("Precision:",metrics.precision_score(test_labels, predictions))
print("Recall:",metrics.recall_score(test_labels, predictions))
```

```
Accuracy: 0.6153341554931647
Precision: 0.1887842644904792
Recall: 0.9651950645460381
```

In [49]:
```
y_pred_proba = logreg_imp.predict_proba(test_important)[::,1]
fpr, tpr, _ = metrics.roc_curve(test_labels,  y_pred_proba)
auc = metrics.roc_auc_score(test_labels, y_pred_proba)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



Assignment 3

Decision Tree

In [56]:
```
import timeit
start = timeit.default_timer()
x=result_df.drop('Response', axis = 1)
y=result_df['Response']
from sklearn.model_selection import train_test_split
train_features, test_features, train_labels, test_labels = train_test_split(x,
y, test_size = 0.3, random_state = 0)
```

In [57]:
```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier()
dt.fit(train_features, train_labels)
dt_pred = dt.predict(test_features)
stop = timeit.default_timer()
print('Time: ', stop - start)
```

```
Time:  2.209480400000004
```

In [59]:
```
param_dict = {
    "criterion" : ['gini','entropy'],
    "max_depth":range(1,10),
    "min_samples_split":range(1,10),
    "min_samples_leaf":range(1,5)
}
from sklearn.model_selection import GridSearchCV
grid = GridSearchCV(dt,param_grid = param_dict,cv=10,verbose=1,n_jobs=-1)
grid.fit(train_features,train_labels)
```

```
Fitting 10 folds for each of 648 candidates, totalling 6480 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  52 tasks      | elapsed:    2.6s
[Parallel(n_jobs=-1)]: Done 352 tasks      | elapsed:   18.4s
[Parallel(n_jobs=-1)]: Done 634 tasks      | elapsed:   45.5s
[Parallel(n_jobs=-1)]: Done 984 tasks      | elapsed:  1.6min
[Parallel(n_jobs=-1)]: Done 1434 tasks      | elapsed:  2.8min
[Parallel(n_jobs=-1)]: Done 1984 tasks      | elapsed:  4.6min
[Parallel(n_jobs=-1)]: Done 2634 tasks      | elapsed:  7.5min
[Parallel(n_jobs=-1)]: Done 3384 tasks      | elapsed: 10.8min
[Parallel(n_jobs=-1)]: Done 4234 tasks      | elapsed: 12.4min
[Parallel(n_jobs=-1)]: Done 5184 tasks      | elapsed: 15.6min
[Parallel(n_jobs=-1)]: Done 6234 tasks      | elapsed: 20.8min
[Parallel(n_jobs=-1)]: Done 6480 out of 6480 | elapsed: 22.2min finished
```

Out[59]:
```
GridSearchCV(cv=10, estimator=DecisionTreeClassifier(), n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': range(1, 10),
                         'min_samples_leaf': range(1, 5),
                         'min_samples_split': range(1, 10)},
             verbose=1)
```

In [60]:
```
grid.best_params_
```

Out[60]:
```
{'criterion': 'entropy',
 'max_depth': 8,
 'min_samples_leaf': 3,
 'min_samples_split': 7}
```

In [61]:
```
start = timeit.default_timer()
dt = DecisionTreeClassifier(criterion='entropy', max_depth=8, min_samples_leaf
=3, min_samples_split=7)
dt.fit(train_features, train_labels)
dt_pred = dt.predict(test_features)
stop = timeit.default_timer()
print('Time: ', stop - start)
```

```
Time:  1.1883704000001671
```

In [62]:
```
errors = abs(dt_pred - test_labels)
print('Mean Absolute Error:', round(np.mean(errors), 2), 'degrees.')
print("Accuracy:",metrics.accuracy_score(test_labels, dt_pred)*100)
conf = confusion_matrix(test_labels,dt_pred)
print(conf)
```

```
Mean Absolute Error: 0.09 degrees.
Accuracy: 90.79596441972134
[[138412     11]
 [ 14020      1]]
```

In [63]:
```
print("Accuracy:",metrics.accuracy_score(test_labels, dt_pred))
print("Precision:",metrics.precision_score(test_labels, dt_pred))
print("Recall:",metrics.recall_score(test_labels, dt_pred))
```

```
Accuracy: 0.9079596441972134
Precision: 0.08333333333333333
Recall: 7.132158904500393e-05
```

In [64]:
```
importances = list(dt.feature_importances_)
feature_importances = [(feature, round(importance, 2)) for feature, importance
in zip(x.columns, importances)]
feature_importances = sorted(feature_importances, key = lambda x: x[1], revers
e = True)
[print('Variable: {:20} Importance: {}'.format(*pair)) for pair in feature_imp
ortances];
```

```
Variable: Previously_Insured   Importance: 0.55
Variable: id                   Importance: 0.28
Variable: Age                  Importance: 0.07
Variable: Vehicle_Damage       Importance: 0.07
Variable: Policy_Sales_Channel Importance: 0.02
Variable: Gender               Importance: 0.0
Variable: Driving_License      Importance: 0.0
Variable: Region_Code          Importance: 0.0
Variable: Vehicle_Age          Importance: 0.0
Variable: Annual_Premium       Importance: 0.0
Variable: Vintage              Importance: 0.0
```

In [66]:
```
rf_most_important = DecisionTreeClassifier(criterion='entropy', max_depth=8, m
in_samples_leaf=3, min_samples_split=7)
train_important = train_features.loc[:, ['Annual_Premium','Vintage','Age','Reg
ion_Code','Vehicle_Damage','Policy_Sales_Channel','Gender','Previously_Insure
d']]
test_important = test_features.loc[:, ['Annual_Premium','Vintage','Age','Regio
n_Code','Vehicle_Damage','Policy_Sales_Channel','Gender','Previously_Insured'
]]
rf_most_important.fit(train_important, train_labels)
predictions = rf_most_important.predict(test_important)
errors = abs(predictions - test_labels)
print('Mean Absolute Error:', round(np.mean(errors), 2), 'degrees.')
```

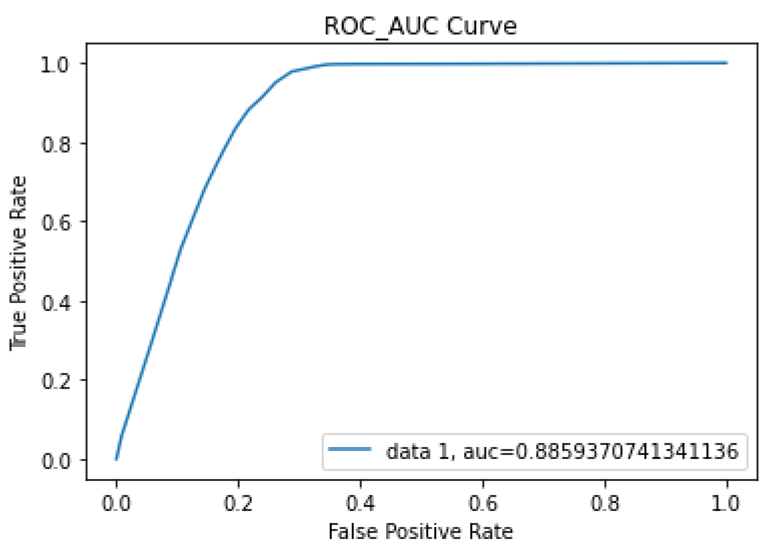
```
Mean Absolute Error: 0.09 degrees.
```

In [67]:
```
print("Accuracy:",metrics.accuracy_score(test_labels, predictions))
print("Precision:",metrics.precision_score(test_labels, predictions))
print("Recall:",metrics.recall_score(test_labels, predictions))
```

```
Accuracy: 0.9079137256959933
Precision: 0.13043478260869565
Recall: 0.00021396476713501176
```

In [68]:
```
y_pred_proba = dt.predict_proba(test_features)[::,1]
fpr, tpr, _ = metrics.roc_curve(test_labels,  y_pred_proba)
auc = metrics.roc_auc_score(test_labels, y_pred_proba)
print(auc)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.title("ROC_AUC Curve")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.show()
```

```
0.8859370741341136
```



Random Forest

In [50]:
```
import timeit
start = timeit.default_timer()
x=result_df.drop('Response', axis = 1)
y=result_df['Response']
from sklearn.model_selection import train_test_split
train_features, test_features, train_labels, test_labels = train_test_split(x,
y, test_size = 0.3, random_state = 0)
```

In [51]:
```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(n_estimators = 1000, random_state=42)
rf.fit(train_features, train_labels)
predictions = rf.predict(test_features)
stop = timeit.default_timer()
print('Time: ', stop - start)
```

```
Time:  1021.1808909000006
```

In [52]:
```
errors = abs(predictions - test_labels)
print('Mean Absolute Error:', round(np.mean(errors), 2), 'degrees.')
print("Accuracy:",metrics.accuracy_score(test_labels, predictions))
print("Precision:",metrics.precision_score(test_labels, predictions))
print("Recall:",metrics.recall_score(test_labels, predictions))
conf = confusion_matrix(test_labels,predictions)
print(conf)
```

```
Mean Absolute Error: 0.1 degrees.
Accuracy: 0.9047781480412479
Precision: 0.39983812221772563
Recall: 0.07046572997646387
[[136940   1483]
 [ 13033    988]]
```

In [53]:
```
importances = list(rf.feature_importances_)
feature_importances = [(feature, round(importance, 2)) for feature, importance
in zip(x.columns, importances)]
feature_importances = sorted(feature_importances, key = lambda x: x[1], revers
e = True)
[print('Variable: {:20} Importance: {}'.format(*pair)) for pair in feature_imp
ortances];
```

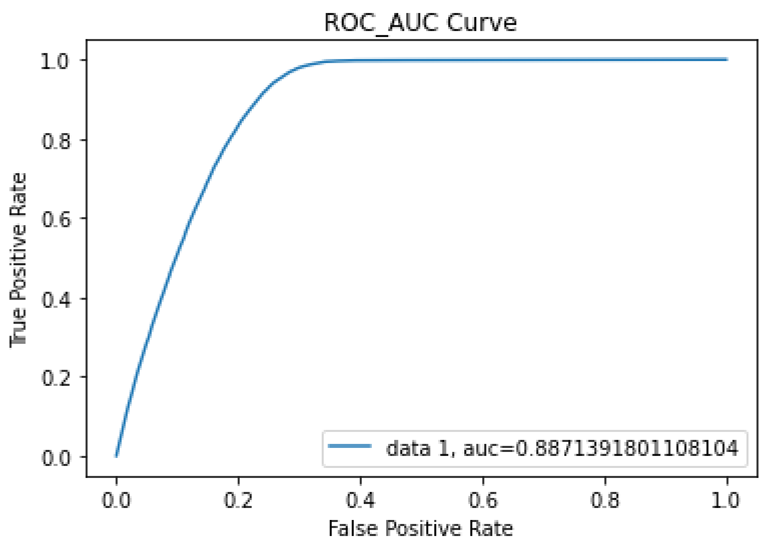
```
Variable: id                   Importance: 0.26
Variable: Vintage              Importance: 0.19
Variable: Annual_Premium       Importance: 0.17
Variable: Age                  Importance: 0.12
Variable: Region_Code          Importance: 0.08
Variable: Vehicle_Damage       Importance: 0.06
Variable: Policy_Sales_Channel Importance: 0.05
Variable: Previously_Insured   Importance: 0.04
Variable: Gender               Importance: 0.01
Variable: Vehicle_Age          Importance: 0.01
Variable: Driving_License      Importance: 0.0
```

In [54]:
```
print("Accuracy:",metrics.accuracy_score(test_labels, predictions))
print("Precision:",metrics.precision_score(test_labels, predictions))
print("Recall:",metrics.recall_score(test_labels, predictions))
```

```
Accuracy: 0.9047781480412479
Precision: 0.39983812221772563
Recall: 0.07046572997646387
```

In [55]:
```
y_pred_proba = rf.predict_proba(test_features)[::,1]
fpr, tpr, _ = metrics.roc_curve(test_labels,  y_pred_proba)
auc = metrics.roc_auc_score(test_labels, y_pred_proba)
print(auc)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.title("ROC_AUC Curve")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.show()
```

```
0.8871391801108104
```



GBM

In [87]:
```
import timeit
start = timeit.default_timer()
x=result_df.drop('Response', axis = 1)
y=result_df['Response']
from sklearn.model_selection import train_test_split
train_features, test_features, train_labels, test_labels = train_test_split(x,
y, test_size = 0.3, random_state = 0)
from imblearn.over_sampling import SMOTE
nr = SMOTE()
train_features, train_labels = nr.fit_sample(train_features, train_labels)
```

In [88]:
```
from sklearn.ensemble import GradientBoostingClassifier
gbm = GradientBoostingClassifier()
gbm.fit(train_features,train_labels)
predictions = gbm.predict(test_features)
stop = timeit.default_timer()
print('Time: ', stop - start)
```

```
Time:  97.52382639999996
```

In [ ]:
```
param ={
        "learning_rate" : [1, 0.5, 0.25, 0.1, 0.05, 0.01],
        "n_estimators" : [100, 200]}

grid_search = GridSearchCV(estimator = gbm, param_grid = param,
                          cv = 3, n_jobs = -1, verbose = 2)
grid_search.fit(train_features, train_labels)
grid_search.best_params_
```

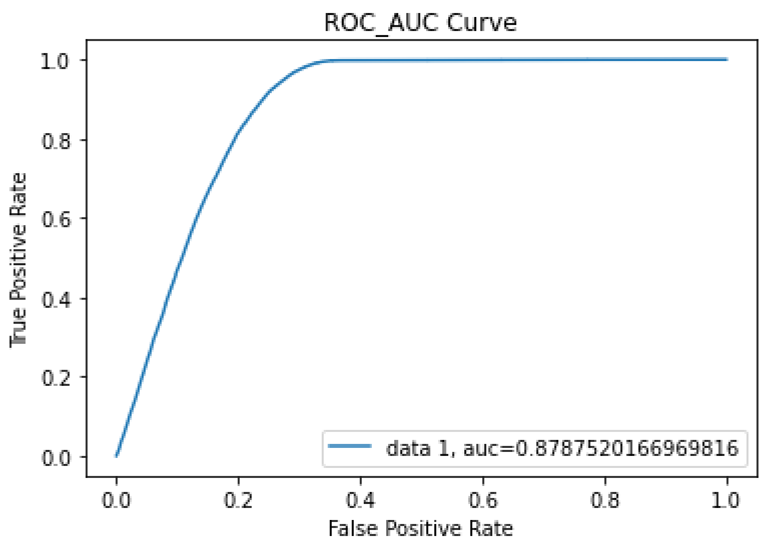
In [90]:
```
start = timeit.default_timer()
gbm = GradientBoostingClassifier(learning_rate=0.5, n_estimators=200)
gbm.fit(train_features,train_labels)
predictions = gbm.predict(test_features)
stop = timeit.default_timer()
print('Time: ', stop - start)
```

In [91]:
```
errors = abs(predictions - test_labels)
print('Mean Absolute Error:', round(np.mean(errors), 2), 'degrees.')
print("Accuracy:",metrics.accuracy_score(test_labels, predictions))
print("Precision:",metrics.precision_score(test_labels, predictions))
print("Recall:",metrics.recall_score(test_labels, predictions))
conf = confusion_matrix(test_labels,predictions)
print(conf)
```

```
Mean Absolute Error: 0.15 degrees.
Accuracy: 0.8491577234919052
Precision: 0.31757196292080014
Recall: 0.5570929320305257
[[121638  16785]
 [  6210   7811]]
```

In [92]:
```
y_pred_proba = gbm.predict_proba(test_features)[::,1]
fpr, tpr, _ = metrics.roc_curve(test_labels,  y_pred_proba)
auc = metrics.roc_auc_score(test_labels, y_pred_proba)
print(auc)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.title("ROC_AUC Curve")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.show()
```

```
0.8787520166969816
```



XGM

In [75]:
```
import timeit
start = timeit.default_timer()
x=result_df.drop('Response', axis = 1)
y=result_df['Response']
from sklearn.model_selection import train_test_split
train_features, test_features, train_labels, test_labels = train_test_split(x,
y, test_size = 0.3, random_state = 0)
from imblearn.over_sampling import SMOTE
nr = SMOTE()
train_features, train_labels = nr.fit_sample(train_features, train_labels)
```

In [84]:
```
from xgboost import XGBClassifier as xgb
model_xgb = xgb()
model_xgb.fit(train_features,train_labels)
best_preds = model_xgb.predict(test_features)
stop = timeit.default_timer()
print('Time: ', stop - start)
```

```
Time:  3162.954396
```

In [ ]:
```
from sklearn.model_selection import GridSearchCV
parameters = {
     "eta"    : [0.05, 0.10, 0.15, 0.20, 0.25, 0.30 ] ,
     "max_depth"        : [ 3, 4, 5, 6, 8, 10, 12, 15]}

grid = GridSearchCV(model_xgb,
                    parameters, n_jobs=-1,
                    scoring="neg_log_loss",
                    cv=3, verbose=2)
grid.fit(train_features, train_labels)
grid.best_params_
```

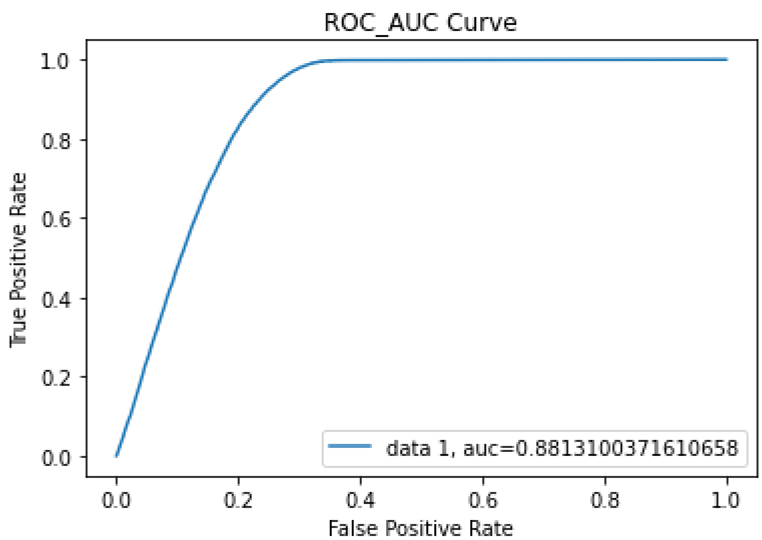
In [ ]:
```
start = timeit.default_timer()
model_xgb = xgb(eta=0.05, max_depth=12)
model_xgb.fit(train_features,train_labels)
best_preds = model_xgb.predict(test_features)
stop = timeit.default_timer()
print('Time: ', stop - start)
```

In [85]:
```
errors = abs(best_preds - test_labels)
print('Mean Absolute Error:', round(np.mean(errors), 2), 'degrees.')
print("Accuracy:",metrics.accuracy_score(test_labels, best_preds))
print("Precision:",metrics.precision_score(test_labels, best_preds))
print("Recall:",metrics.recall_score(test_labels, best_preds))
conf = confusion_matrix(test_labels,best_preds)
print(conf)
```

```
Mean Absolute Error: 0.15 degrees.
Accuracy: 0.8471897877253286
Precision: 0.3198943525207799
Recall: 0.5874046073746523
[[120913  17510]
 [  5785   8236]]
```

In [86]:
```
y_pred_proba = model_xgb.predict_proba(test_features)[::,1]
fpr, tpr, _ = metrics.roc_curve(test_labels,  y_pred_proba)
auc = metrics.roc_auc_score(test_labels, y_pred_proba)
print(auc)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.title("ROC_AUC Curve")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.show()
```

```
0.8813100371610658
```



Neural Network Classifier

In [1]:
```
from keras import Sequential
from keras.layers import Dense
```

In [28]:
```
x=result_df.drop('Response', axis = 1)
y=result_df['Response']
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x = sc.fit_transform(x)
```

In [29]:
```
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE
train_features, test_features, train_labels, test_labels = train_test_split(x,
y, test_size = 0.3)
nr = SMOTE()
train_features, train_labels = nr.fit_sample(train_features, train_labels)
```

In [12]:
```
print('Training Features Shape:', train_features.shape)
print('Training Labels Shape:', train_labels.shape)
print('Testing Features Shape:', test_features.shape)
print('Testing Labels Shape:', test_labels.shape)
```

```
Training Features Shape: (645800, 11)
Training Labels Shape: (645800,)
Testing Features Shape: (152444, 11)
Testing Labels Shape: (152444,)
```

In [13]:
```
def build_model():
    classifier = Sequential()
    classifier.add(Dense(6, activation='relu', kernel_initializer='random_norm
al', input_dim=11))
    classifier.add(Dense(6, activation='relu', kernel_initializer='random_norm
al'))
    classifier.add(Dense(1, activation='sigmoid', kernel_initializer='random_n
ormal'))
    classifier.compile(optimizer ='adam',loss='binary_crossentropy', metrics =
['accuracy'])
    return classifier
```

In [14]:
```
keras_model = build_model()
keras_model.fit(train_features,train_labels, batch_size=64, epochs=100)
```

```
Epoch 1/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3795 -
accuracy: 0.8377
Epoch 2/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3604 -
accuracy: 0.8446
Epoch 3/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3580 -
accuracy: 0.8448
Epoch 4/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3566 -
accuracy: 0.8451
Epoch 5/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3554 -
accuracy: 0.8454
Epoch 6/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3547 -
accuracy: 0.8454
Epoch 7/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3543 -
accuracy: 0.8453
Epoch 8/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3540 -
accuracy: 0.8453
Epoch 9/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3540 -
accuracy: 0.8453
Epoch 10/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3539 -
accuracy: 0.8454
Epoch 11/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3538 -
accuracy: 0.8455
Epoch 12/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3537 -
accuracy: 0.8454
Epoch 13/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3537 -
accuracy: 0.8453
Epoch 14/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3536 -
accuracy: 0.8454
Epoch 15/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3535 -
accuracy: 0.8455
Epoch 16/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3534 -
accuracy: 0.8457
Epoch 17/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3530 -
accuracy: 0.8456
Epoch 18/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3528 -
accuracy: 0.8458
Epoch 19/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3527 -
accuracy: 0.8459
```

```
Epoch 20/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3526 -
accuracy: 0.8459
Epoch 21/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3527 -
accuracy: 0.8460
Epoch 22/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3525 -
accuracy: 0.8460
Epoch 23/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3524 -
accuracy: 0.8460
Epoch 24/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3523 -
accuracy: 0.8462
Epoch 25/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3523 -
accuracy: 0.8461
Epoch 26/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3523 -
accuracy: 0.8461
Epoch 27/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3521 -
accuracy: 0.8461
Epoch 28/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3520 -
accuracy: 0.8462
Epoch 29/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3519 -
accuracy: 0.8464
Epoch 30/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3517 -
accuracy: 0.8464
Epoch 31/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3515 -
accuracy: 0.8467
Epoch 32/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3515 -
accuracy: 0.8464
Epoch 33/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3513 -
accuracy: 0.8465
Epoch 34/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3514 -
accuracy: 0.8466
Epoch 35/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3511 -
accuracy: 0.8465
Epoch 36/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3510 -
accuracy: 0.8468
Epoch 37/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3510 -
accuracy: 0.8467
Epoch 38/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3508 -
accuracy: 0.8469
```

```
Epoch 39/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3507 -
accuracy: 0.8472
Epoch 40/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3506 -
accuracy: 0.8471
Epoch 41/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3506 -
accuracy: 0.8471
Epoch 42/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3506 -
accuracy: 0.8471
Epoch 43/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3505 -
accuracy: 0.8470
Epoch 44/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3505 -
accuracy: 0.8472
Epoch 45/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3504 -
accuracy: 0.8471
Epoch 46/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3505 -
accuracy: 0.8471
Epoch 47/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3504 -
accuracy: 0.8471
Epoch 48/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3504 -
accuracy: 0.8473
Epoch 49/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3504 -
accuracy: 0.8472
Epoch 50/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3504 -
accuracy: 0.8471
Epoch 51/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3504 -
accuracy: 0.8472
Epoch 52/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3503 -
accuracy: 0.8472
Epoch 53/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3504 -
accuracy: 0.8472
Epoch 54/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3503 -
accuracy: 0.8472
Epoch 55/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3503 -
accuracy: 0.8472
Epoch 56/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3503 -
accuracy: 0.8473
Epoch 57/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3502 -
accuracy: 0.8474
```

```
Epoch 58/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3502 -
accuracy: 0.8472
Epoch 59/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3502 -
accuracy: 0.8473
Epoch 60/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3503 -
accuracy: 0.8471
Epoch 61/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3502 -
accuracy: 0.8473
Epoch 62/100
10091/10091 [==============================] - ETA: 0s - loss: 0.3502 - accur
acy: 0.84 - 17s 2ms/step - loss: 0.3502 - accuracy: 0.8473
Epoch 63/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3503 -
accuracy: 0.8473
Epoch 64/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3502 -
accuracy: 0.8474
Epoch 65/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3502 -
accuracy: 0.8472
Epoch 66/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3501 -
accuracy: 0.8473
Epoch 67/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3502 -
accuracy: 0.8473
Epoch 68/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3501 -
accuracy: 0.8474
Epoch 69/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3502 -
accuracy: 0.8474
Epoch 70/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3502 -
accuracy: 0.8473
Epoch 71/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3502 -
accuracy: 0.8471
Epoch 72/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3500 -
accuracy: 0.8474
Epoch 73/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3501 -
accuracy: 0.8473
Epoch 74/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3501 -
accuracy: 0.8473
Epoch 75/100
10091/10091 [==============================] - 16s 2ms/step - loss: 0.3501 -
accuracy: 0.8474
Epoch 76/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3501 -
accuracy: 0.8472
```

```
Epoch 77/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3500 -
accuracy: 0.8473
Epoch 78/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3501 -
accuracy: 0.8473
Epoch 79/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3501 -
accuracy: 0.8472
Epoch 80/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3501 -
accuracy: 0.8474
Epoch 81/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3500 -
accuracy: 0.8473
Epoch 82/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3500 -
accuracy: 0.8474
Epoch 83/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3501 -
accuracy: 0.8474
Epoch 84/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3500 -
accuracy: 0.8474
Epoch 85/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3500 -
accuracy: 0.8472
Epoch 86/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3500 -
accuracy: 0.8474
Epoch 87/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3499 -
accuracy: 0.8475
Epoch 88/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3499 -
accuracy: 0.8472
Epoch 89/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3499 -
accuracy: 0.8474
Epoch 90/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3499 -
accuracy: 0.8474
Epoch 91/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3499 -
accuracy: 0.8474
Epoch 92/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3499 -
accuracy: 0.8473
Epoch 93/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3499 -
accuracy: 0.8475
Epoch 94/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3499 -
accuracy: 0.8473
Epoch 95/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3499 -
accuracy: 0.8474
```

```
Epoch 96/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3499 -
accuracy: 0.8472
Epoch 97/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3499 -
accuracy: 0.8473
Epoch 98/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3499 -
accuracy: 0.8472
Epoch 99/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3499 -
accuracy: 0.8473
Epoch 100/100
10091/10091 [==============================] - 17s 2ms/step - loss: 0.3499 -
accuracy: 0.8474
```

Out[14]:

```
<tensorflow.python.keras.callbacks.History at 0x122c3422670>
```

In [30]:

```
eval_model=keras_model.evaluate(train_features, train_labels)
eval_model
```

```
20176/20176 [==============================] - 40s 2ms/step - loss: 0.3513 -
accuracy: 0.8465
```

Out[30]:

```
[0.35126250982284546, 0.8464527726173401]
```

In [31]:

```
y_pred=keras_model.predict(test_features)
y_pred =(y_pred>0.5)
```

In [32]:

```
print("Accuracy:",metrics.accuracy_score(test_labels, y_pred))
print("Precision:",metrics.precision_score(test_labels, y_pred))
print("Recall:",metrics.recall_score(test_labels, y_pred))
cm = confusion_matrix(test_labels, y_pred)
print(cm)
```

```
Accuracy: 0.7590918632415838
Precision: 0.26553637610827857
Recall: 0.9380787037037037
[[102751  35869]
 [   856  12968]]
```

In [33]:
```
from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.metrics import auc
from sklearn.metrics import roc_curve
y_pred_keras = keras_model.predict(test_features).ravel()
fpr_keras, tpr_keras, thresholds_keras = roc_curve(test_labels, y_pred_keras)
auc_keras = auc(fpr_keras, tpr_keras)
plt.plot(fpr_keras,tpr_keras,label="data 1, auc="+str(auc_keras))
plt.legend(loc=4)
plt.title("ROC_AUC Curve")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.show()
```