

# Health Insurance Owners Cross Sell Project Built Engine-checkpoint-checkpoint

October 21, 2020

## 1 Health Insurance Owners Cross Sell Project

- Data Source:Kaggle
  - Done by: Aravind R (J&J SD)
  - Client Name : Analytics Vidya Health insurance Company Indirect Data Engineer ###
- Agenda:
- Exploratory data analysis
  - Model development
  - Model Tuning
  - Model Deployment

```
In [1]: # Necessary Imports
import pandas as pd
import dtale as dt
import numpy as np
import plotly.express as pl
import matplotlib.pyplot as plt
import seaborn as sns
from bokeh.plotting import figure,show,output_notebook
output_notebook()
# Model Related
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier, BaggingClassifier, AdaBoostClassifier
from xgboost import XGBClassifier
from catboost import CatBoostClassifier
from sklearn.linear_model import SGDClassifier;
from sklearn.kernel_approximation import RBFSampler;
# Evaluation metrics
from sklearn.metrics import accuracy_score, balanced_accuracy_score, cohen_kappa_score, r
# if there is imbalance in classes
from imblearn.over_sampling import SMOTE
# Model Tuning Engines
# Model Tuning Engine's and Validation Engine(Final)
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV, cross_val_score, St
# Deploy Model to a file in binary format
```

```
import joblib as jb
plt.style.use('seaborn-whitegrid');
```

```
C:\Users\Aravind R\Anaconda3\lib\site-packages\dask\config.py:168: YAMLLoadWarning: calling yam
data = yaml.load(f.read()) or {}
C:\Users\Aravind R\Anaconda3\lib\site-packages\distributed\config.py:20: YAMLLoadWarning: call
defaults = yaml.load(f)
```

In [2]: *# Importing the dataset*

```
dataset_main = pd.read_csv('train.csv')
```

```
# Gathering information about the shape of the dataset
```

```
print(f"The No of rows is :{dataset_main.shape[0]} \nThe No Features is :{dataset_main
```

The No of rows is :381109

The No Features is :12

In [3]: *# Quite a big dataset lets gather the head of the dataset*

```
dataset_main.head(8)
```

```
Out[3]:
```

|   | id | Gender | Age | Driving_License | Region_Code | Previously_Insured | \ |
|---|----|--------|-----|-----------------|-------------|--------------------|---|
| 0 | 1  | Male   | 44  | 1               | 28.0        | 0                  |   |
| 1 | 2  | Male   | 76  | 1               | 3.0         | 0                  |   |
| 2 | 3  | Male   | 47  | 1               | 28.0        | 0                  |   |
| 3 | 4  | Male   | 21  | 1               | 11.0        | 1                  |   |
| 4 | 5  | Female | 29  | 1               | 41.0        | 1                  |   |
| 5 | 6  | Female | 24  | 1               | 33.0        | 0                  |   |
| 6 | 7  | Male   | 23  | 1               | 11.0        | 0                  |   |
| 7 | 8  | Female | 56  | 1               | 28.0        | 0                  |   |

|   | Vehicle_Age | Vehicle_Damage | Annual_Premium | Policy_Sales_Channel | Vintage | \ |
|---|-------------|----------------|----------------|----------------------|---------|---|
| 0 | > 2 Years   | Yes            | 40454.0        | 26.0                 | 217     |   |
| 1 | 1-2 Year    | No             | 33536.0        | 26.0                 | 183     |   |
| 2 | > 2 Years   | Yes            | 38294.0        | 26.0                 | 27      |   |
| 3 | < 1 Year    | No             | 28619.0        | 152.0                | 203     |   |
| 4 | < 1 Year    | No             | 27496.0        | 152.0                | 39      |   |
| 5 | < 1 Year    | Yes            | 2630.0         | 160.0                | 176     |   |
| 6 | < 1 Year    | Yes            | 23367.0        | 152.0                | 249     |   |
| 7 | 1-2 Year    | Yes            | 32031.0        | 26.0                 | 72      |   |

```
Response
0      1
1      0
```

```

2      1
3      0
4      0
5      0
6      0
7      1

```

```

In [4]: # Lets drop the id columns since its not necessary (we already have index)
dataset_main.drop('id',axis=1,inplace=True)
dataset_main.head(2)

```

```

Out[4]:  Gender  Age  Driving_License  Region_Code  Previously_Insured  Vehicle_Age \
0   Male    44             1           28.0                0    > 2 Years
1   Male    76             1           3.0                0    1-2 Year

      Vehicle_Damage  Annual_Premium  Policy_Sales_Channel  Vintage  Response
0             Yes      40454.0                26.0        217          1
1             No      33536.0                26.0        183          0

```

## 1.1 Exploritory Data Analysis

- Insights gathering

```

In [5]: # Features of the dataset
from termcolor import colored
print(colored("Feature Columns",color='blue'))
for i,j in enumerate(dataset_main.columns):
    print(i+1,j)

```

Feature Columns

```

1 Gender
2 Age
3 Driving_License
4 Region_Code
5 Previously_Insured
6 Vehicle_Age
7 Vehicle_Damage
8 Annual_Premium
9 Policy_Sales_Channel
10 Vintage
11 Response

```

```

In [6]: # Lets get the information of the dataset
dataset_main.info()

```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 381109 entries, 0 to 381108
Data columns (total 11 columns):

```

```

#      Column                Non-Null Count  Dtype
---  -
0      Gender                381109 non-null  object
1      Age                   381109 non-null  int64
2      Driving_License       381109 non-null  int64
3      Region_Code           381109 non-null  float64
4      Previously_Insured    381109 non-null  int64
5      Vehicle_Age           381109 non-null  object
6      Vehicle_Damage        381109 non-null  object
7      Annual_Premium        381109 non-null  float64
8      Policy_Sales_Channel  381109 non-null  float64
9      Vintage                381109 non-null  int64
10     Response              381109 non-null  int64
dtypes: float64(3), int64(5), object(3)
memory usage: 32.0+ MB

```

In [7]: # Summary Statistics of the dataset

```
dataset_main.describe()
```

```

Out[7]:
      count      Age  Driving_License  Region_Code  Previously_Insured  \
count  381109.000000    381109.000000    381109.000000    381109.000000
mean    38.822584         0.997869         26.388807         0.458210
std     15.511611         0.046110         13.229888         0.498251
min      20.000000         0.000000         0.000000         0.000000
25%      25.000000         1.000000         15.000000         0.000000
50%      36.000000         1.000000         28.000000         0.000000
75%      49.000000         1.000000         35.000000         1.000000
max      85.000000         1.000000         52.000000         1.000000

      Annual_Premium  Policy_Sales_Channel  Vintage  Response
count  381109.000000    381109.000000    381109.000000    381109.000000
mean    30564.389581         112.034295         154.347397         0.122563
std     17213.155057         54.203995         83.671304         0.327936
min      2630.000000         1.000000         10.000000         0.000000
25%     24405.000000         29.000000         82.000000         0.000000
50%     31669.000000        133.000000        154.000000         0.000000
75%     39400.000000        152.000000        227.000000         0.000000
max     540165.000000        163.000000        299.000000         1.000000

```

In [8]: # Checking for null values

```
dataset_main.isna().sum()
```

```

Out[8]: 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

```

- No Null values are present

```

In [9]: # Check of class imbalance
print("Class Distributions")
print()
print(dataset_main.Response.value_counts())
print()
print(f"Event Rate of Minority class(To be predicted): {(46710/381109)*100:.2f}%")

```

Class Distributions

```

0      334399
1       46710
Name: Response, dtype: int64

```

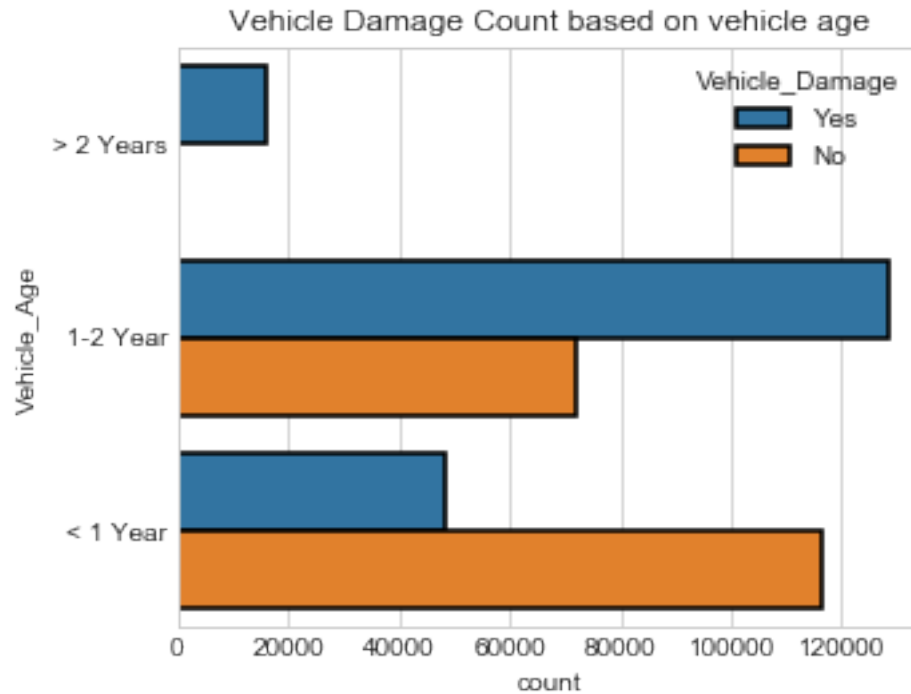
Event Rate of Minority class(To be predicted): 12.26%

- Eventhough we have greater than 5% event rate its best we go over Over sampling because it increases Accuracy and Balanced Accuracy
- Any how we try both with oversampling and without oversampling and compare the results

```

In [10]: # Lets check customers vechile damage based on vehicle age
plt.figure(figsize=(5,4))
sns.countplot(y=dataset_main.Vehicle_Age,linewidth=1.6,edgecolor='black',hue=dataset_main.Vehicle_Damage)
plt.title("Vehicle Damage Count based on vehicle age");

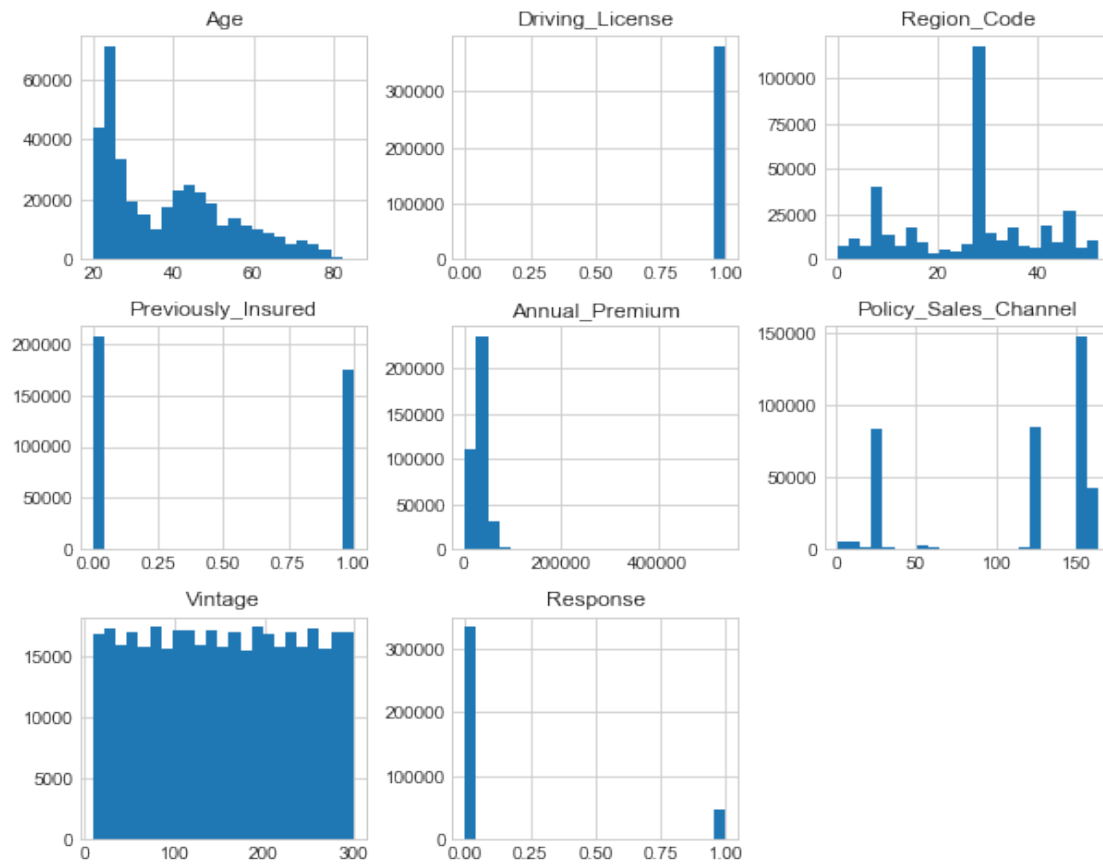
```



- From the above visualization vehicle age between 1-2 are prone to vehicle damage as expected and have high chance to respond for insurance

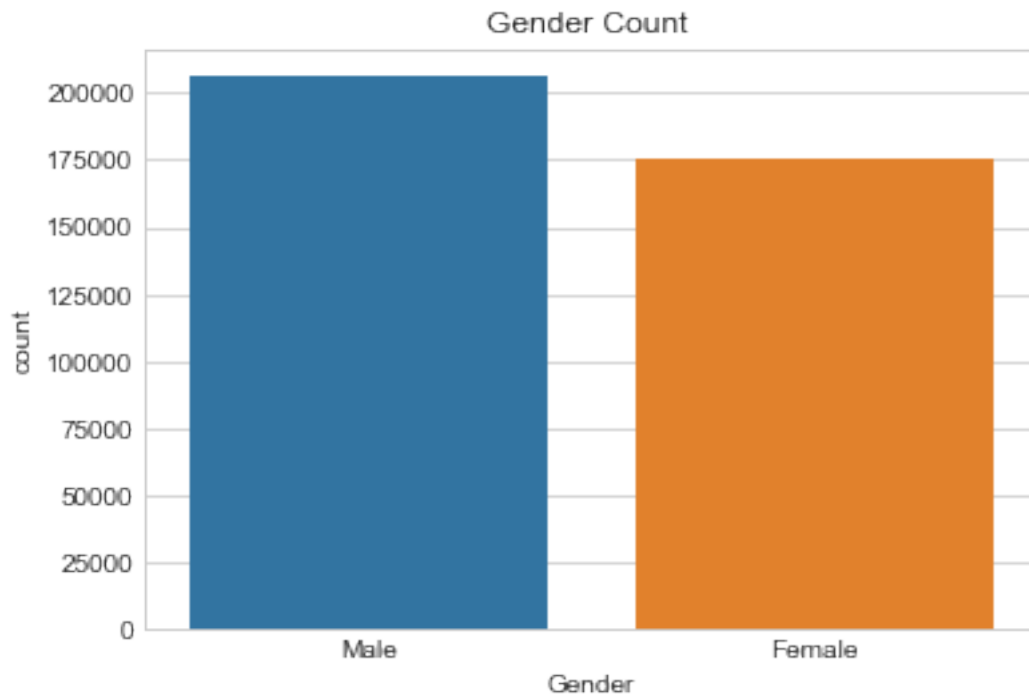
```
In [11]: # Histogram plot
ax = dataset_main.hist(figsize=(10,8),bins=23);
plt.suptitle("Summary Stats",fontsize=30);
```

# Summary Stats



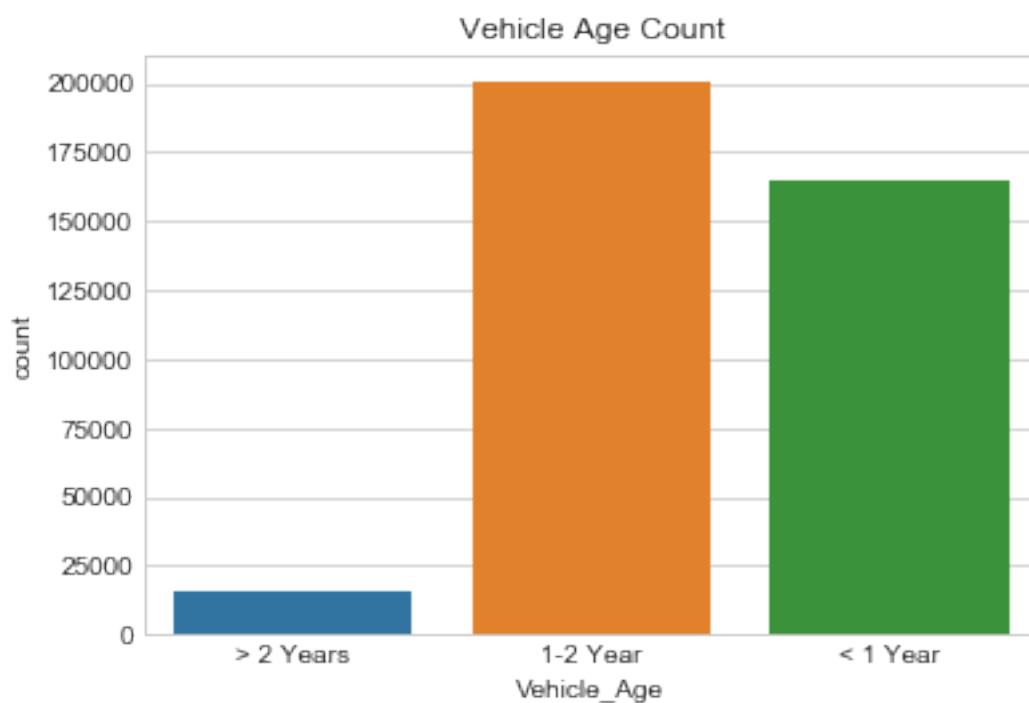
In [12]: # Seeing Category distribution

```
sns.countplot(dataset_main.Gender);  
plt.title("Gender Count ");
```



- More Male Samples compared to Female

```
In [13]: sns.countplot(dataset_main.Vehicle_Age)  
plt.title("Vehicle Age Count");
```



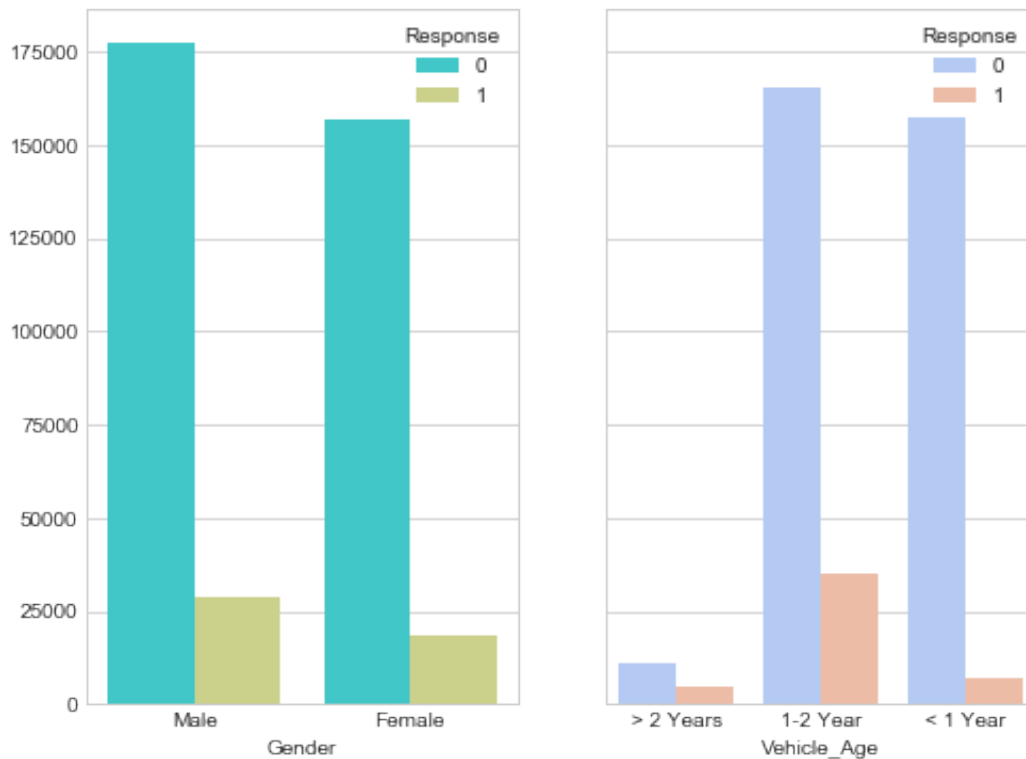


- There are more vehicles of the age 1-2

In [14]: # Seeing Distribution based on response

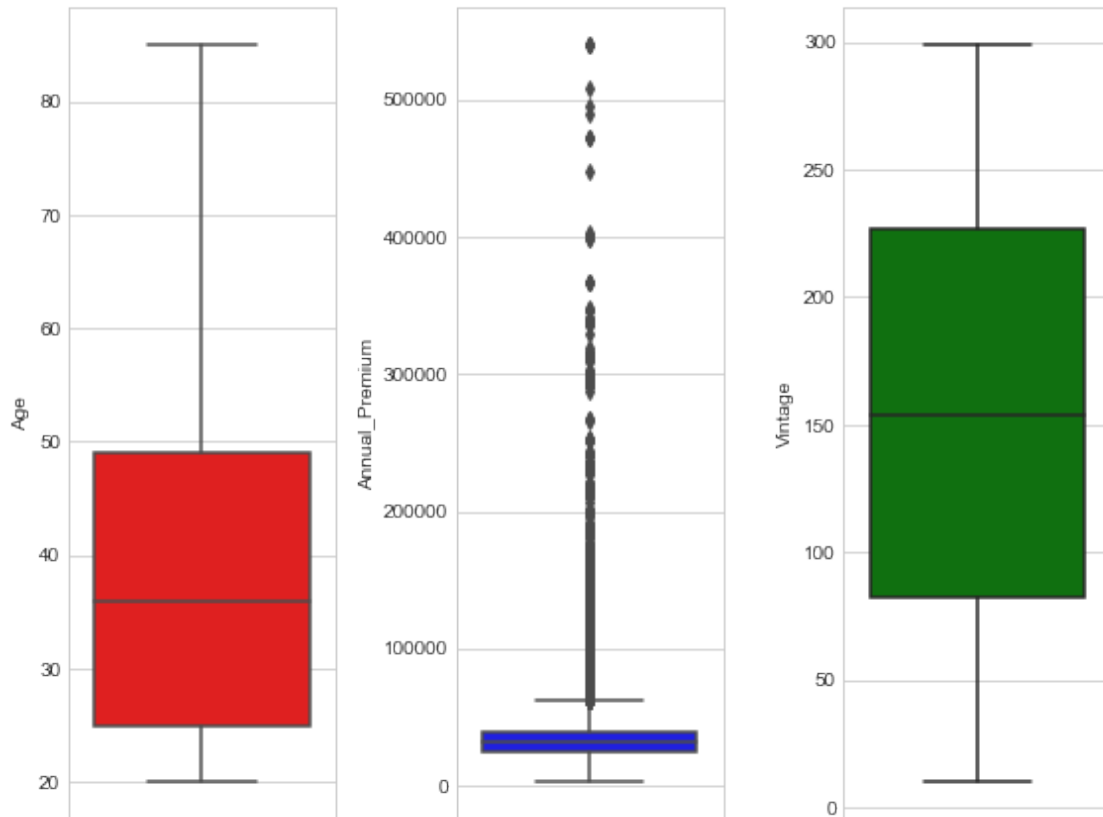
```
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(8,6), sharey=True)
sns.countplot(dataset_main.Gender, hue=dataset_main.Response, ax=ax[0], palette='rainbow')
sns.countplot(dataset_main.Vehicle_Age, hue=dataset_main.Response, ax=ax[1], palette='co
ax[0].set_ylabel("");
ax[1].set_ylabel("");
fig.suptitle("      Category Distribution Based On Response", fontsize=25, horizontalal
```

## Category Distribution Based On Response



```
In [15]: fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(8,6))
sns.boxplot(dataset_main.Age, ax=ax[0], orient='v', color='r')
sns.boxplot(dataset_main.Annual_Premium, ax=ax[1], orient='v', color='blue')
sns.boxplot(dataset_main.Vintage, ax=ax[2], orient='v', color='g')
plt.tight_layout()
plt.suptitle("Age -- Premium -- Vintage", y=1.08, fontsize=20);
```

## Age -- Premium -- Vintage



```
In [16]: # for plotting purposes
```

```
No_response = dataset_main[dataset_main['Response']==0]
```

```
response = dataset_main[dataset_main['Response']==1]
```

```
In [17]: m,c = np.polyfit(dataset_main['Age'],dataset_main['Vintage'],1)
```

```
q = m*dataset_main['Age']+c
```

In [18]: # Imbalance Determination

```
from bokeh.models import ColumnDataSource, CategoricalColorMapper
```

```
from bokeh.layouts import gridplot
```

```
source = ColumnDataSource(dict(x=[d for d in dataset_main.Age],y=[d for d in dataset_r
```

```
color_map = CategoricalColorMapper(factors=['0', '1'], palette=['red', 'blue'])
```

```
p = figure(plot_width=500,plot_height=500,title='Class imbalance',tools="")
```

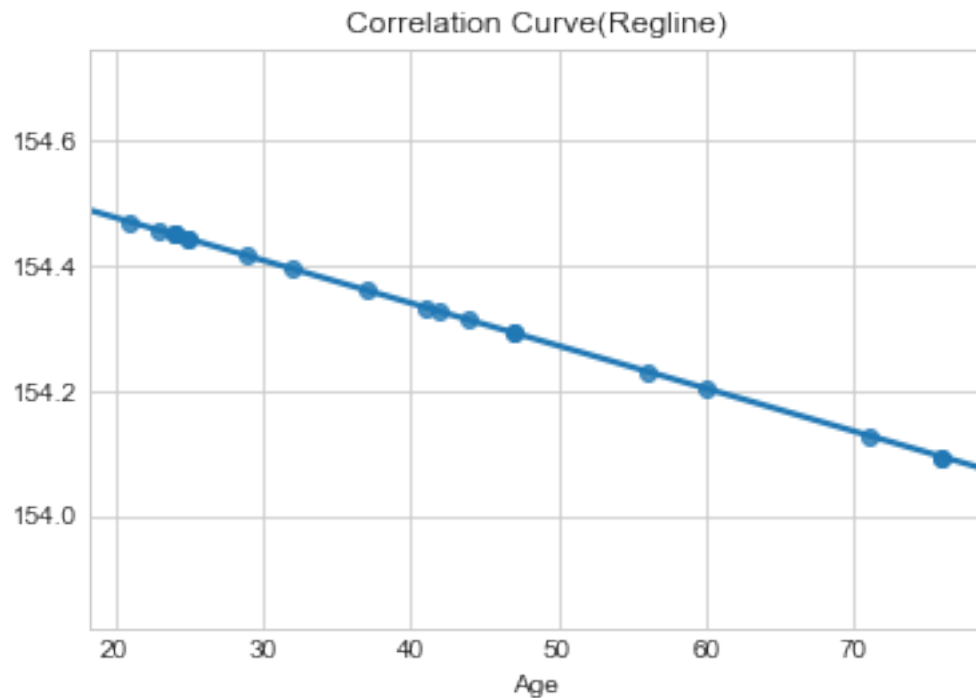
```
p.circle(x='x',y='y',source=source,color={'field':'label','transform':color_map},legender=legender)
```

```
d = figure(plot_width=200,plot_height=200,title='Regression Curve')
```

```
show(p)
```

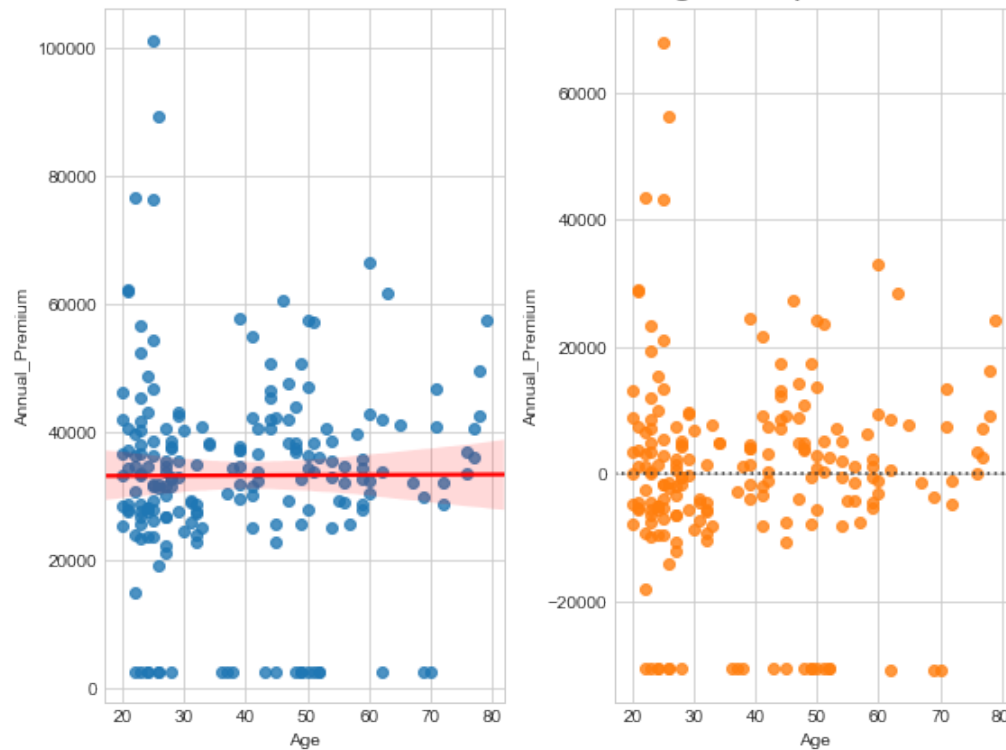
```
BokehDeprecationWarning: 'legend' keyword is deprecated, use explicit 'legend_label', 'legend_title', 'legend_location', 'legend_width', 'legend_height', 'legend_offset_x', 'legend_offset_y', 'legend_offset_align', 'legend_offset_val' instead.
```

```
In [19]: plt.title("Correlation Curve(Regline)")
sns.regplot(dataset_main['Age'][:20],q[:20]);
plt.ylabel("");
```



```
In [20]: # Correlation and residual variation between Age and premium amount
fig,ax = plt.subplots(nrows=1,ncols=2,figsize=(8,6),sharey=False)
sns.regplot(dataset_main['Age'][:200],dataset_main.Annual_Premium[:200],ax=ax[0],linecolor='red')
sns.residplot(dataset_main['Age'][:200],dataset_main.Annual_Premium[:200],ax=ax[1])
plt.suptitle("Correlation and residual variation between Age and premium amount",y=1.05)
plt.tight_layout()
```

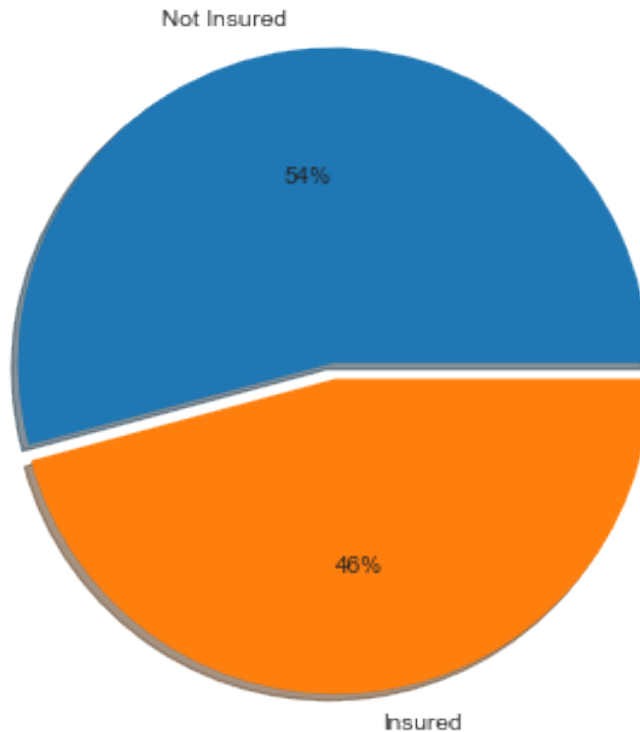
## Correlation and residual variation between Age and premium amount



In [21]: # Ratio of people Previously insured and who are not:

```
R1,R2 = dataset_main['Previously_Insured'].value_counts()[0]/len(dataset_main),dataset_main['Previously_Insured'].value_counts()[1]/len(dataset_main)
plt.figure(figsize=(6,6))
ax = plt.pie([R1,R2],labels=['Not Insured','Insured'],explode=[0.02,0.03],autopct="%.",
plt.title("Ratio of people Previously insured and who are not",fontsize=20);
```

## Ratio of people Previously insured and who are not



- From the above pie chart 46% of them have previously insured vehicle whereas the remaining part is the one where we must focus the 54% of customers

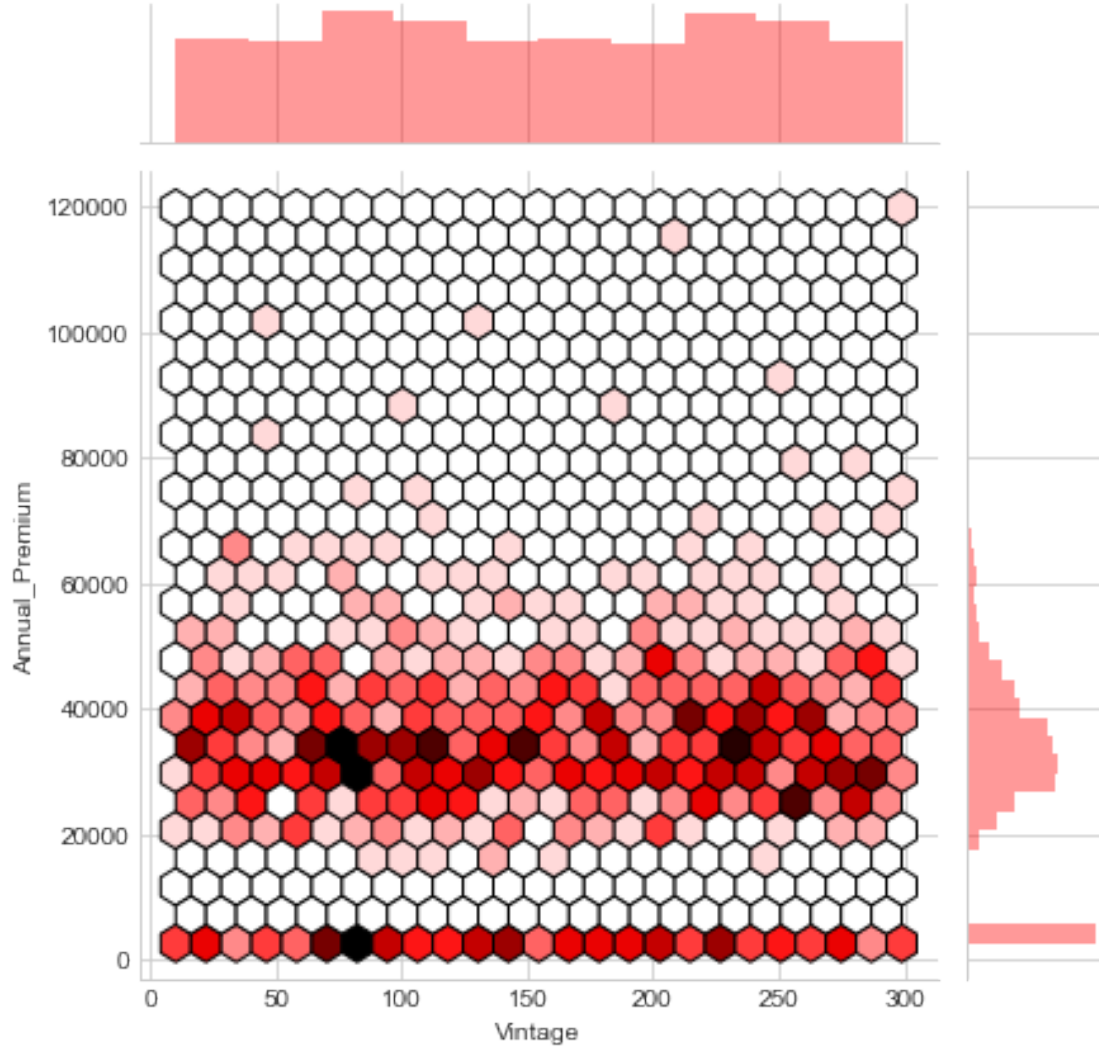
```
In [22]: # Lets go deep and consider how does vehicle damage in the past impact on annual premium
unique_values = ['No', 'Yes']
mean_1 = dataset_main[dataset_main['Vehicle_Damage']=='No']['Annual_Premium'].mean()
mean_2 = dataset_main[dataset_main['Vehicle_Damage']=='Yes']['Annual_Premium'].mean()

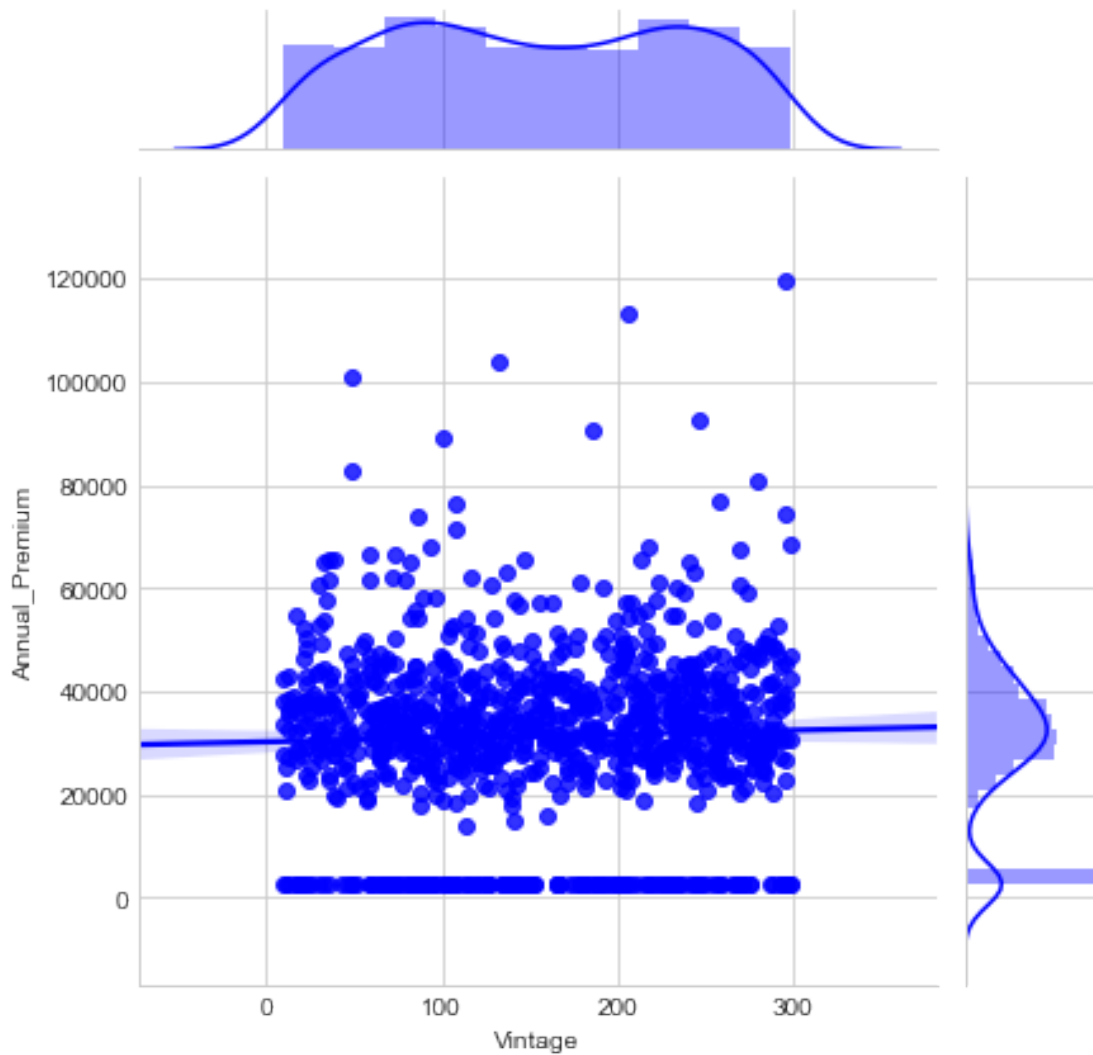
alfa = figure(x_range=unique_values, plot_width=452, plot_height=300, tools="", toolbar_location="bottom")
alfa.vbar(x=unique_values, top=[mean_1, mean_2], width=0.5)
show(alfa)
```

```
In [23]: # No of days with the company and Annual premium
p=sns.jointplot(x=dataset_main['Vintage'][:1000], y=dataset_main['Annual_Premium'][:1000])
p.fig.suptitle("Vintage Vs Premium", y=1.03, fontsize=20, horizontalalignment='left')

sns.jointplot(x=dataset_main['Vintage'][:1000], y=dataset_main['Annual_Premium'][:1000])
```

## Vintage Vs Premium

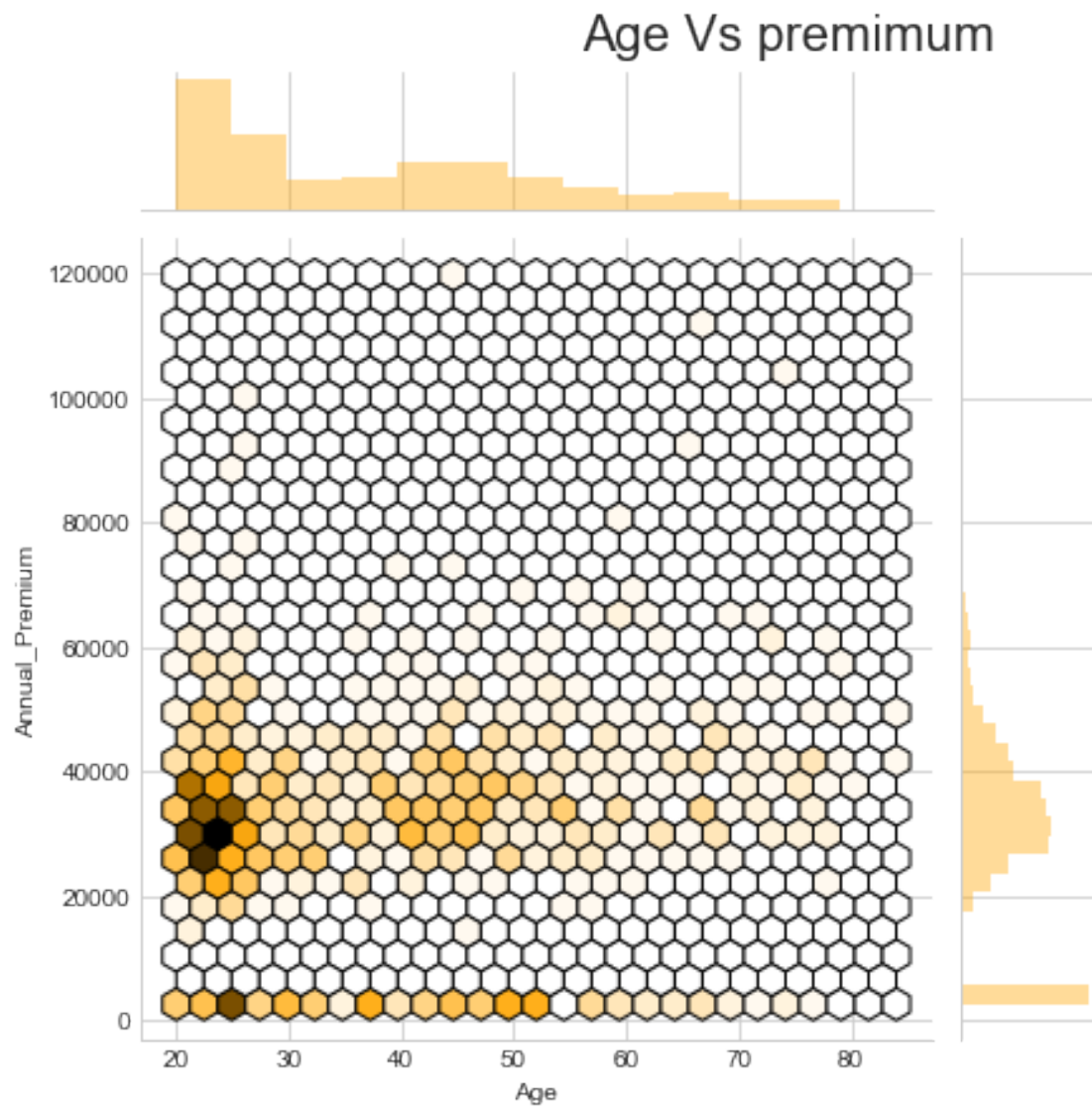




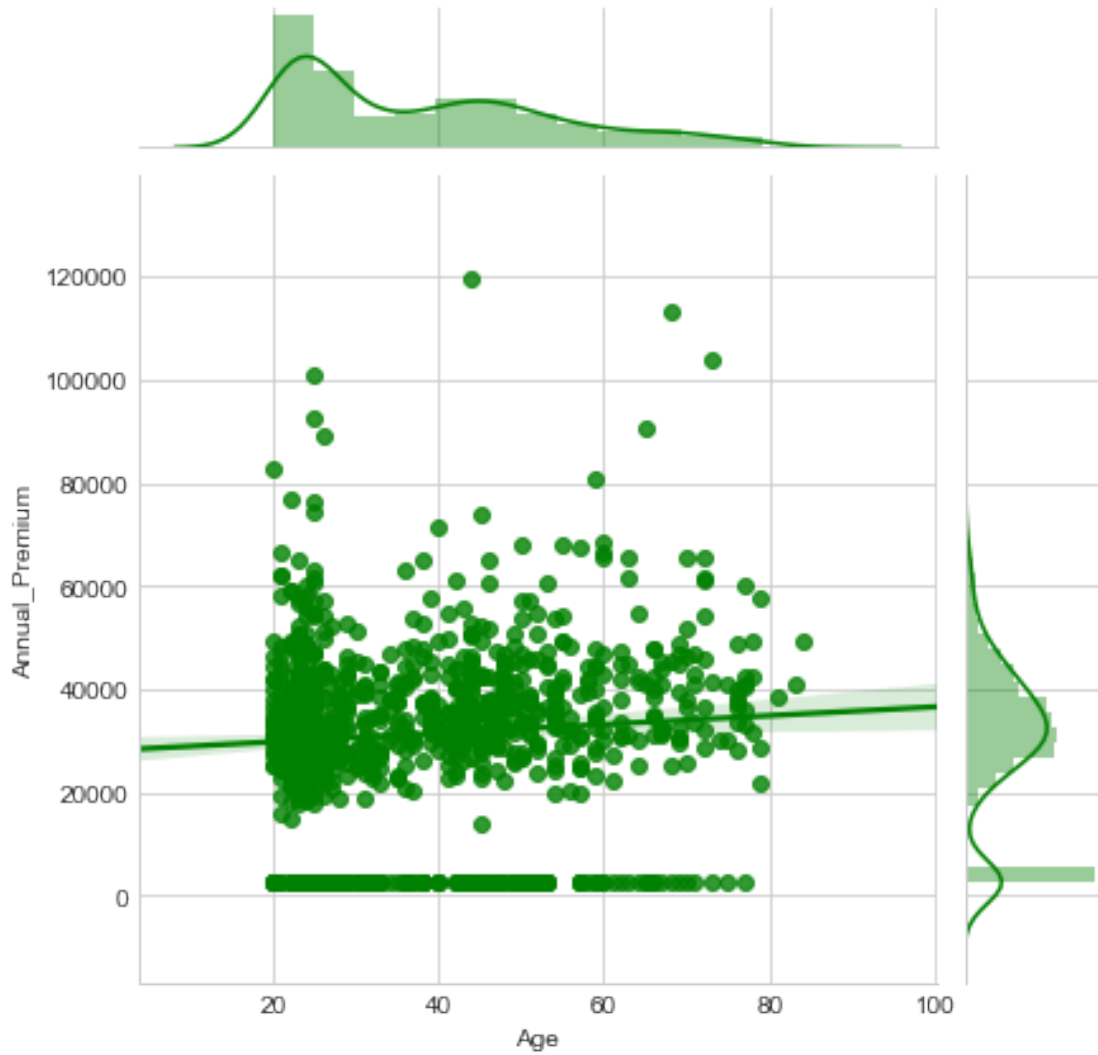
- Vintage days and Amount doesnot have any kind of correlation and Constant amount is maintained Below \$60,000

In [24]: # Check the same for age and Premium'

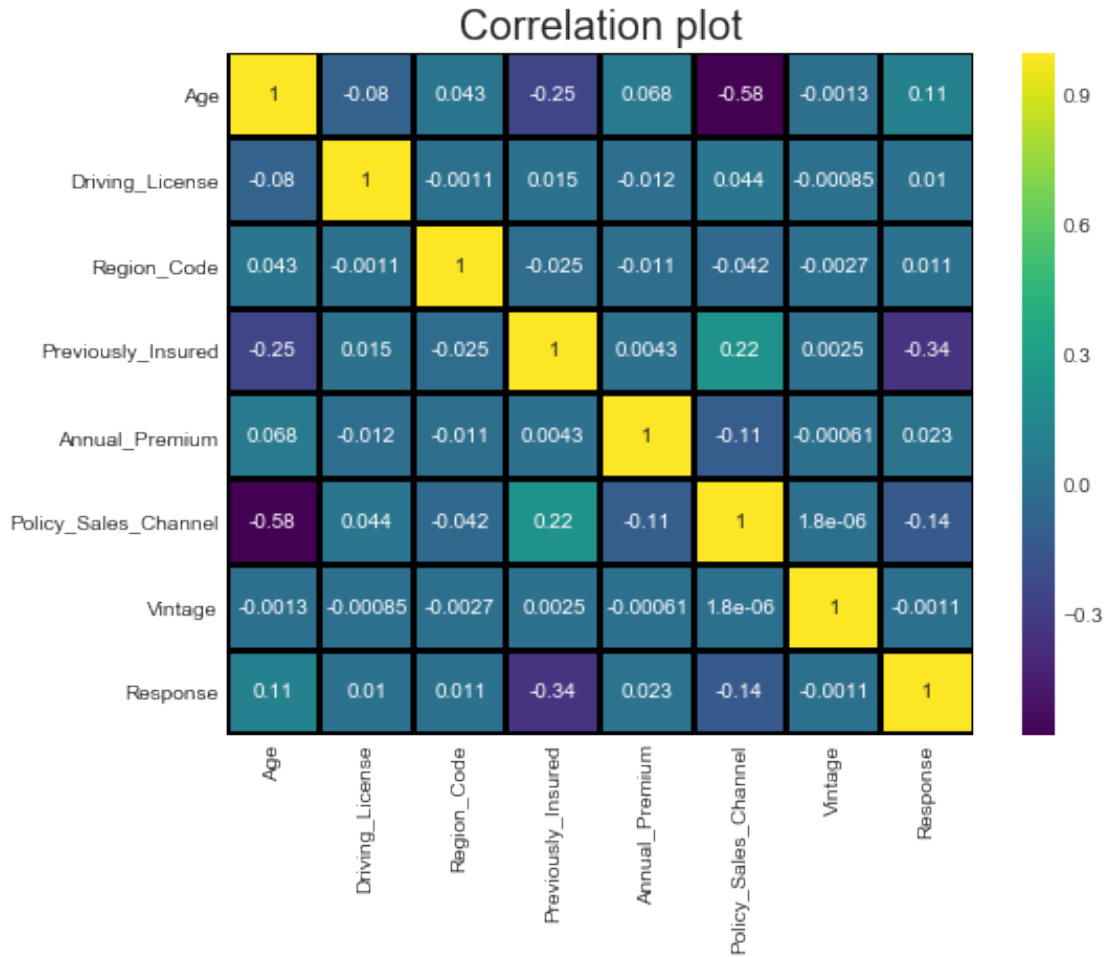
```
p=sns.jointplot(x=dataset_main['Age'][:1000],y=dataset_main['Annual_Premium'][:1000],kind='scatter')
p.fig.suptitle("Age Vs premium",y=1.03,fontsize=20,horizontalalignment='left')
sns.jointplot(x=dataset_main['Age'][:1000],y=dataset_main['Annual_Premium'][:1000],kind='scatter')
```







```
In [25]: # Correlation plot
plt.figure(figsize=(8,6))
ax = sns.heatmap(dataset_main.corr(),annot=True,cmap='viridis',linecolor='black',line
plt.title("Correlation plot",fontsize=20,y=1.01,)
bottom,top = ax.get_ylim()
ax.set_ylim(bottom+0.5,top-0.5);
```



```
In [26]: # Lets Check whether correlation is true for one entry as per heat map above
from scipy import stats
print(f"The Correlation value is:{stats.pearsonr(dataset_main.Age,dataset_main.Annual_Premium)}
```

The Correlation value is:0.06750700155668278  
The P-value is 0.0

**From the above the correlation matrix is correct and Age implies a +ve increase in the gradient of Premium**

#### Multidimensional Analysis

- We are going to gather the details of responses for Top 10 Regions

```
In [27]: # Taking the top22 responses region code from the dataframe
top22 = dataset_main.Region_Code.value_counts().index[:10]
```

```

indexs = []
for i in range(len(dataset_main)):
    for j in top22:
        if dataset_main.at[i, 'Region_Code']==j:
            indexs.append(i)

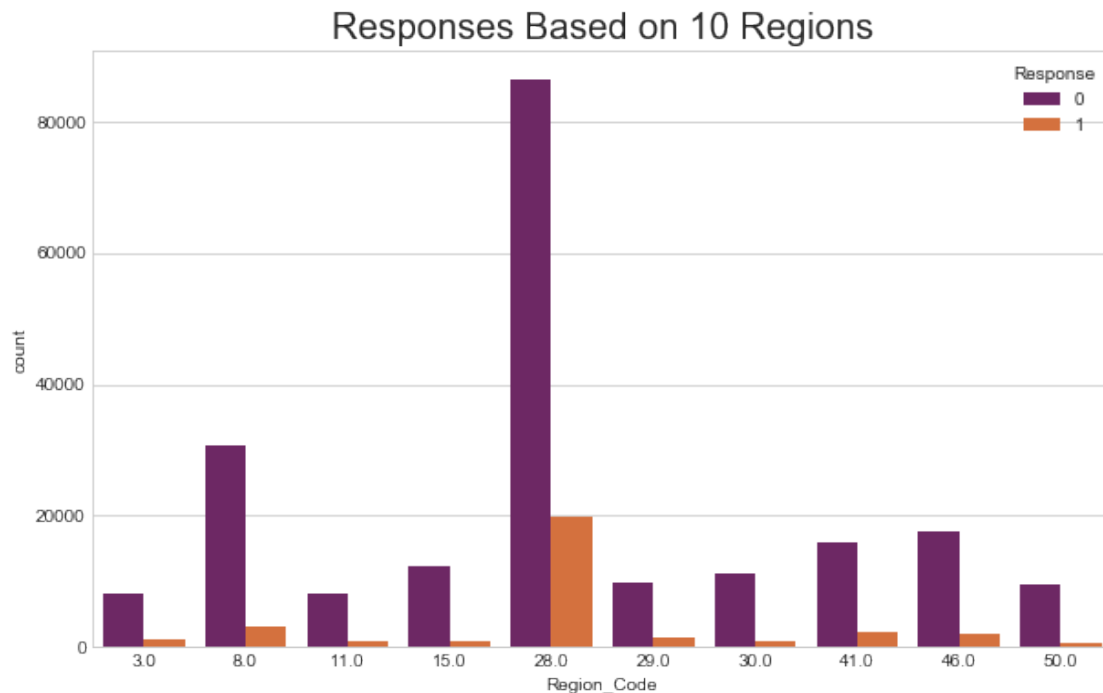
```

In [28]: *# Plotting the Required*

```

newFrame = dataset_main.iloc[indexs,:]
plt.figure(figsize=(10,6))
sns.countplot(newFrame['Region_Code'],hue=newFrame["Response"],palette='inferno');
plt.title("Responses Based on 10 Regions",fontsize=20);
sns.set_style("white");

```



- From the Above We can say Region code 28 has major responses and are in motive to apply for this Insurance(vehicle)
- Since we know that 46% of them have not previously insured lets consider them for the time being

In [29]: *# NOT insured customers data*

```

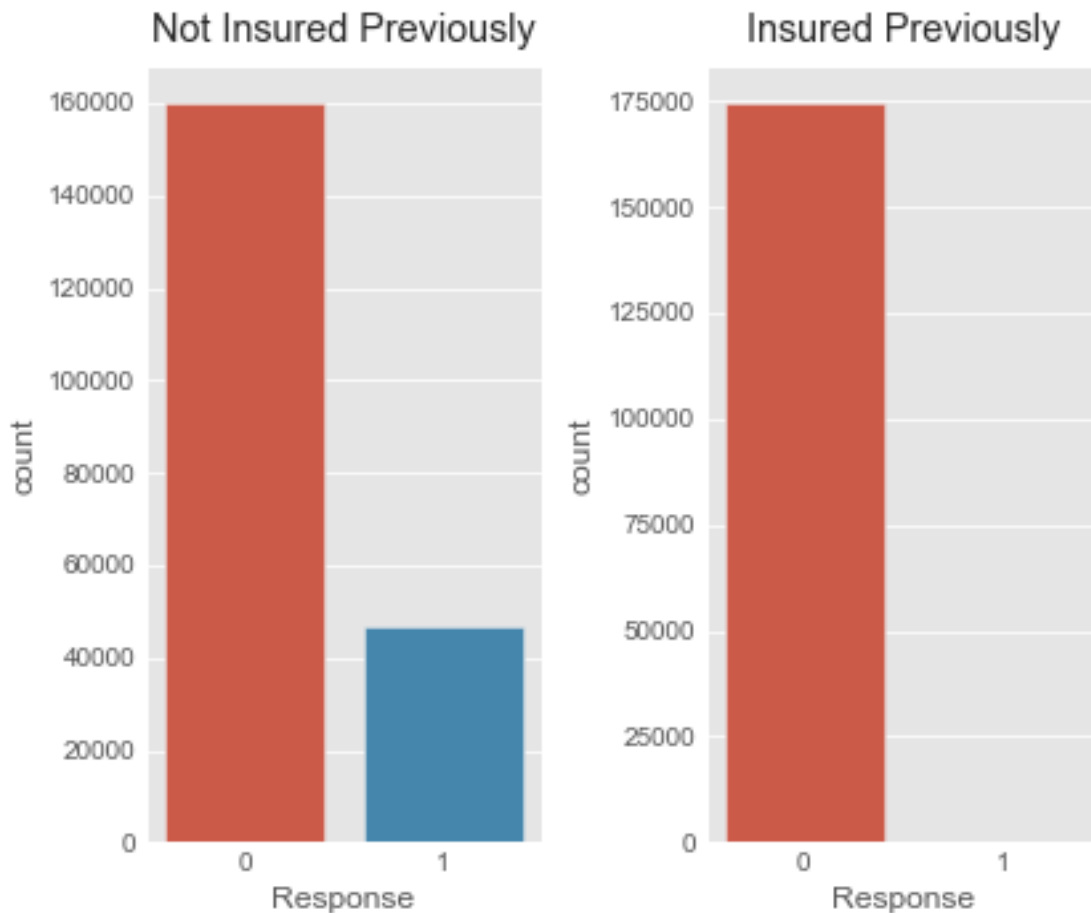
plt.style.use("ggplot")
not_insured = dataset_main[dataset_main["Previously_Insured"]==0]
# Insured customers data
fig,ax = plt.subplots(nrows=1,ncols=2,figsize=(6,5))
insured = dataset_main[dataset_main["Previously_Insured"]==1]

```

```

sns.countplot(not_insured['Response'],ax=ax[0])
sns.countplot(insured['Response'],ax=ax[1])
ax[0].set_title("Not Insured Previously",y=1.01)
ax[1].set_title("Insured Previously",y=1.01)
plt.tight_layout()

```



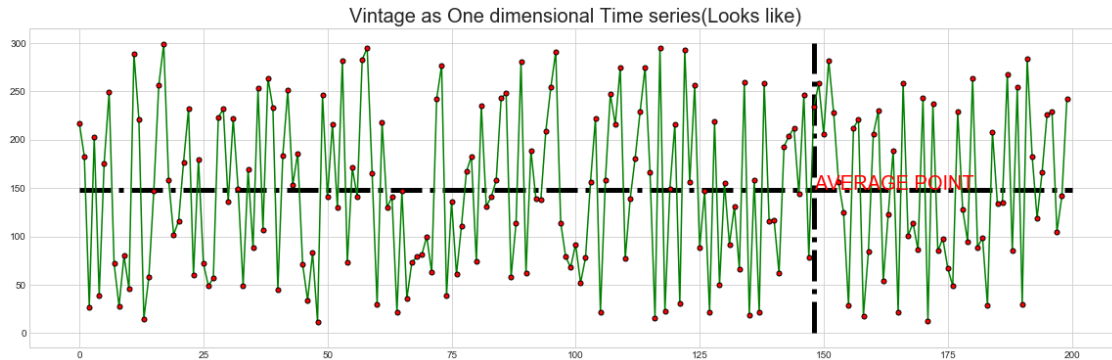
- Note a interesting thing 158 customers who have insured already have shown a postive re-  
sponse two things can be observed from this
- First and most it can be sampling error (error made during data gathering) possibility is high
- or May be because of any update in new insurance policy they might opt for it
- Let us consider the second scenario for the time being

```

In [30]: # just for fun time series but Vintage (doesnt make any sense anyhow lets see)
plt.style.use("seaborn-whitegrid")
plt.figure(figsize=(20,6))
plt.plot(dataset_main['Vintage'][:200],c='green',marker='.',markersize=10,markerfacecolor='white')

```

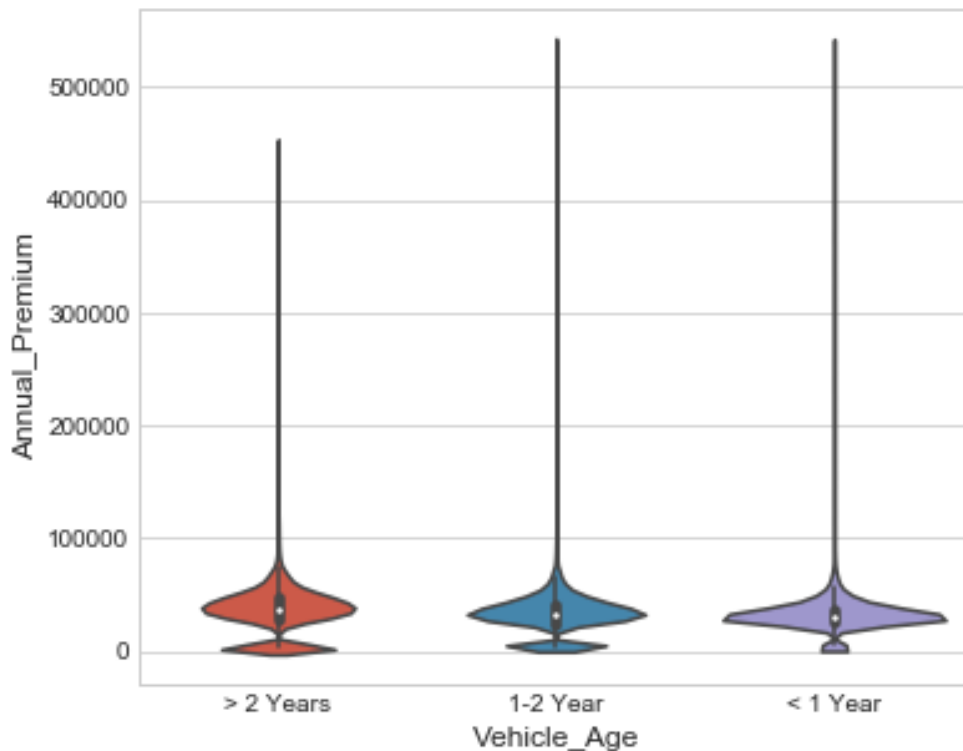
```
plt.hlines(y=148,xmin=0,xmax=200,linestyles='dashdot',linewidth=5)
plt.vlines(x=148,ymin=0,ymax=300,linestyles='dashdot',linewidth=5)
plt.annotate(s="AVERAGE POINT",xy=(148,148),c='red',fontsize=20)
plt.title("Vintage as One dimensional Time series(Looks like)",fontsize=20);
```



- Actually this analysis should not be undertaken but to show whether vintage point looks like time series signal just for some points we have emphasised this

```
In [31]: # Annual premium distributed based on vehicle age
plt.figure(figsize=(6,5))
sns.violinplot(dataset_main['Vehicle_Age'],dataset_main['Annual_Premium'])
plt.title("Annual premium distributed based on vehicle age",fontsize=20,y=1.02);
```

## Annual premium distributed based on vehicle age



```
In [32]: dataset_main.head()
```

```
Out[32]:
```

|   | Gender | Age | Driving_License | Region_Code | Previously_Insured | Vehicle_Age \ |
|---|--------|-----|-----------------|-------------|--------------------|---------------|
| 0 | Male   | 44  | 1               | 28.0        | 0                  | > 2 Years     |
| 1 | Male   | 76  | 1               | 3.0         | 0                  | 1-2 Year      |
| 2 | Male   | 47  | 1               | 28.0        | 0                  | > 2 Years     |
| 3 | Male   | 21  | 1               | 11.0        | 1                  | < 1 Year      |
| 4 | Female | 29  | 1               | 41.0        | 1                  | < 1 Year      |

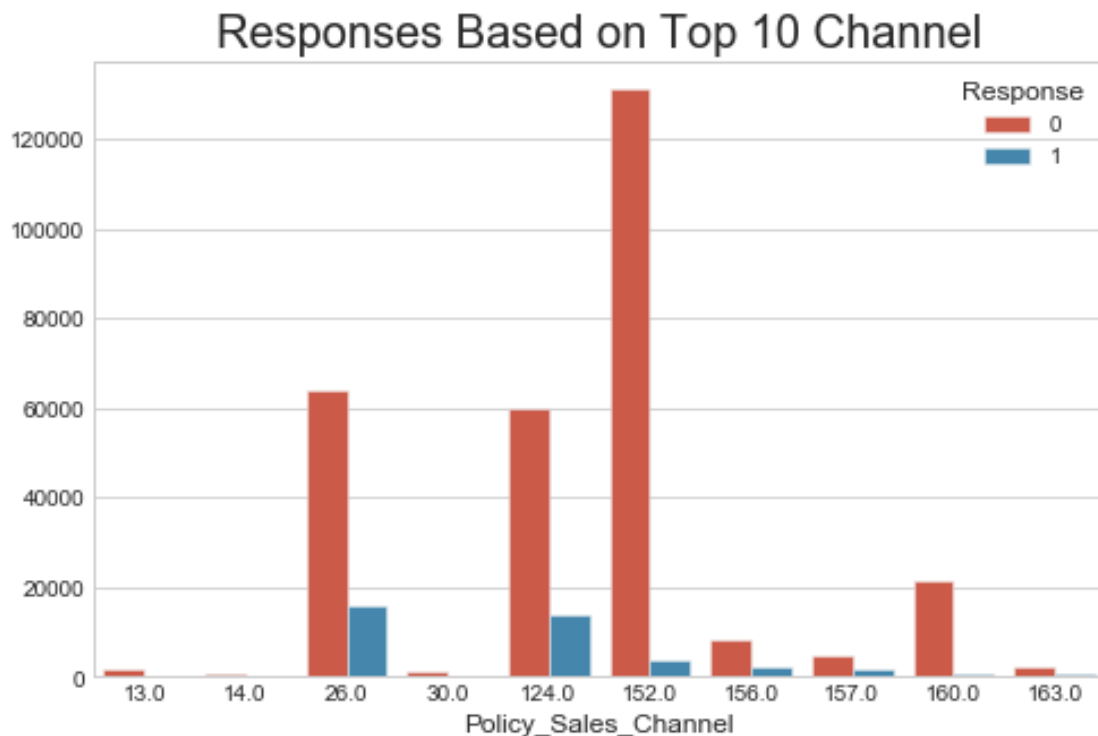
|   | Vehicle_Damage | Annual_Premium | Policy_Sales_Channel | Vintage | Response |
|---|----------------|----------------|----------------------|---------|----------|
| 0 | Yes            | 40454.0        | 26.0                 | 217     | 1        |
| 1 | No             | 33536.0        | 26.0                 | 183     | 0        |
| 2 | Yes            | 38294.0        | 26.0                 | 27      | 1        |
| 3 | No             | 28619.0        | 152.0                | 203     | 0        |
| 4 | No             | 27496.0        | 152.0                | 39      | 0        |

```
In [33]: # Top 10 Policy channel based on response
top_10_channel = dataset_main.Policy_Sales_Channel.unique()[:10]
index=[]
for i in range(len(dataset_main)):
    for j in top_10_channel:
```

```

if dataset_main.at[i,"Policy_Sales_Channel"]==j:
    index.append(i)
newframe2 = dataset_main.iloc[index,:]
plt.figure(figsize=(8,5))
sns.countplot(newframe2['Policy_Sales_Channel'],hue=dataset_main["Response"]);
plt.title("Responses Based on Top 10 Channel",fontsize=20);
plt.ylabel("");

```



In [5]: # Since we gave imbalancing in the dataset we can do smote oversampling technique to

```

# Storing backup
dataset_main2 = dataset_main.copy()
dataset_main2.head(5)

```

```

Out[5]:
  Gender  Age  Driving_License  Region_Code  Previously_Insured  Vehicle_Age \
0   Male   44                1          28.0                 0    > 2 Years
1   Male   76                1           3.0                 0    1-2 Year
2   Male   47                1          28.0                 0    > 2 Years
3   Male   21                1          11.0                 1    < 1 Year
4  Female   29                1          41.0                 1    < 1 Year

```

```

  Vehicle_Damage  Annual_Premium  Policy_Sales_Channel  Vintage  Response
0             Yes          40454.0                26.0      217         1

```

|   |     |         |       |     |   |
|---|-----|---------|-------|-----|---|
| 1 | No  | 33536.0 | 26.0  | 183 | 0 |
| 2 | Yes | 38294.0 | 26.0  | 27  | 1 |
| 3 | No  | 28619.0 | 152.0 | 203 | 0 |
| 4 | No  | 27496.0 | 152.0 | 39  | 0 |

```
In [6]: # Lets encode Gender Vehicle Age, Damage
for i in dataset_main2.columns:
    if pd.api.types.is_string_dtype(dataset_main2[i]) or pd.api.types.is_object_dtype(
        dataset_main2[i]):
        dataset_main2[i] = pd.Categorical(dataset_main2[i]).codes
```

```
In [7]: dataset_main2.head()
```

```
Out[7]:
```

|   | Gender | Age | Driving_License | Region_Code | Previously_Insured | Vehicle_Age | \ |
|---|--------|-----|-----------------|-------------|--------------------|-------------|---|
| 0 | 1      | 44  | 1               | 28.0        | 0                  | 2           |   |
| 1 | 1      | 76  | 1               | 3.0         | 0                  | 0           |   |
| 2 | 1      | 47  | 1               | 28.0        | 0                  | 2           |   |
| 3 | 1      | 21  | 1               | 11.0        | 1                  | 1           |   |
| 4 | 0      | 29  | 1               | 41.0        | 1                  | 1           |   |

|   | Vehicle_Damage | Annual_Premium | Policy_Sales_Channel | Vintage | Response |
|---|----------------|----------------|----------------------|---------|----------|
| 0 | 1              | 40454.0        | 26.0                 | 217     | 1        |
| 1 | 0              | 33536.0        | 26.0                 | 183     | 0        |
| 2 | 1              | 38294.0        | 26.0                 | 27      | 1        |
| 3 | 0              | 28619.0        | 152.0                | 203     | 0        |
| 4 | 0              | 27496.0        | 152.0                | 39      | 0        |

```
In [8]: # Encoded Dataset
dataset_main2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 381109 entries, 0 to 381108
Data columns (total 11 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Gender                381109 non-null  int8
1   Age                  381109 non-null  int64
2   Driving_License      381109 non-null  int64
3   Region_Code          381109 non-null  float64
4   Previously_Insured   381109 non-null  int64
5   Vehicle_Age          381109 non-null  int8
6   Vehicle_Damage       381109 non-null  int8
7   Annual_Premium       381109 non-null  float64
8   Policy_Sales_Channel 381109 non-null  float64
9   Vintage              381109 non-null  int64
10  Response             381109 non-null  int64
dtypes: float64(3), int64(5), int8(3)
memory usage: 24.4 MB
```



```
In [9]: # Creating Datastructures
X = dataset_main2.iloc[:, :-1].values
y = dataset_main2.iloc[:, -1].values

#Oversampling to reduce class imbalance
sm = SMOTE()
X,y = sm.fit_resample(X,y)
```

```
In [13]: # Before smote
pl.scatter(dataset_main,x='Age',y='Vintage',color='Response')
```

```
In [11]: # After smote
pl.scatter(x=X[:,1],y=X[:,9],color=y)
```

- From the above graph Nearest neighbours algorithm has been perfectly used by smote for oversampling and we have overcome class imbalances

## 1.2 Model Development

- Baseline Engine (Random Forest,catboost,....)

```
In [14]: # Creating a Custom Evaluator

# Model Performance Evaluator

def Model_Performance(model,name):

    """
    Custom Performance Engine (For classification Problems) by Aravind R
    1.accuracy_score
    2.balanced_accuracy_score
    3.plot_roc_curve and Score
    4.plot_precision_recall_curve
    5.cohen_kappa_score
    6.log_loss
    7.Confusion Matrix
    8.Classification Report
    Note: Dataset Must be splitted into X_train,X_test and y_train,y_test
    """

    print(f"\t\t {name} Performance Outline \t\t")
    pred_train = model.predict(X_train)
    pred_train_proba = model.predict_proba(X_train)

    pred_test = model.predict(X_test)
    pred_test_proba = model.predict_proba(X_test)

    print()
    print("\t Training Results\t")
```

```

print()
print("Accuracy Score: ",accuracy_score(y_train,pred_train))
print("Balanced Accuracy Score: ",balanced_accuracy_score(y_train,pred_train))
print("Cohen Kappa Score: ",cohen_kappa_score(y_train,pred_train))
print("Roc Score: ",roc_auc_score(y_train,pred_train_proba[:,1]))
print("Confusion Matrix:\n",confusion_matrix(y_train,pred_train))
print("Classification Report:\n",classification_report(y_train,pred_train))
plot_roc_curve(model,X_train,y_train)
print()

print("\t Testing Results\t")
print()
print("Accuracy Score: ",accuracy_score(y_test,pred_test))
print("Balanced Accuracy Score: ",balanced_accuracy_score(y_test,pred_test))
print("Cohen Kappa Score: ",cohen_kappa_score(y_test,pred_test))
print("Roc Score: ",roc_auc_score(y_test,pred_test_proba[:,1]))
print("Confusion Matrix: \n",confusion_matrix(y_test,pred_test))
print("Classification Report\n",classification_report(y_test,pred_test))
plot_roc_curve(model,X_test,y_test)

```

- Standardizing or normalizing the data did not provide better results
- Proceeding without Standardization

In [15]: `X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=0)`

In [49]: *# Creating Baseline Random forest Engine*  
`baseline_random_forest = RandomForestClassifier(n_estimators=100)`  
`baseline_random_forest.fit(X_train,y_train)`  
`Model_Performance(baseline_random_forest,"Random Forest")`

#### Random Forest Performance Outline

##### Training Results

```

Accuracy Score:  0.9999166947910748
Balanced Accuracy Score:  0.9999166963240207
Cohen Kappa Score:  0.9998333895824658
Roc Score:  0.9999999464164917
Confusion Matrix:
[[234062      9]
 [    30 234057]]
Classification Report:

```

|   | precision | recall | f1-score | support |
|---|-----------|--------|----------|---------|
| 0 | 1.00      | 1.00   | 1.00     | 234071  |
| 1 | 1.00      | 1.00   | 1.00     | 234087  |

|              |      |      |      |        |
|--------------|------|------|------|--------|
| accuracy     |      |      | 1.00 | 468158 |
| macro avg    | 1.00 | 1.00 | 1.00 | 468158 |
| weighted avg | 1.00 | 1.00 | 1.00 | 468158 |

### Testing Results

Accuracy Score: 0.9156100478468899  
 Balanced Accuracy Score: 0.9156086888184838  
 Cohen Kappa Score: 0.8312196360470046  
 Roc Score: 0.977506306082538

Confusion Matrix:

[[93571 6757]

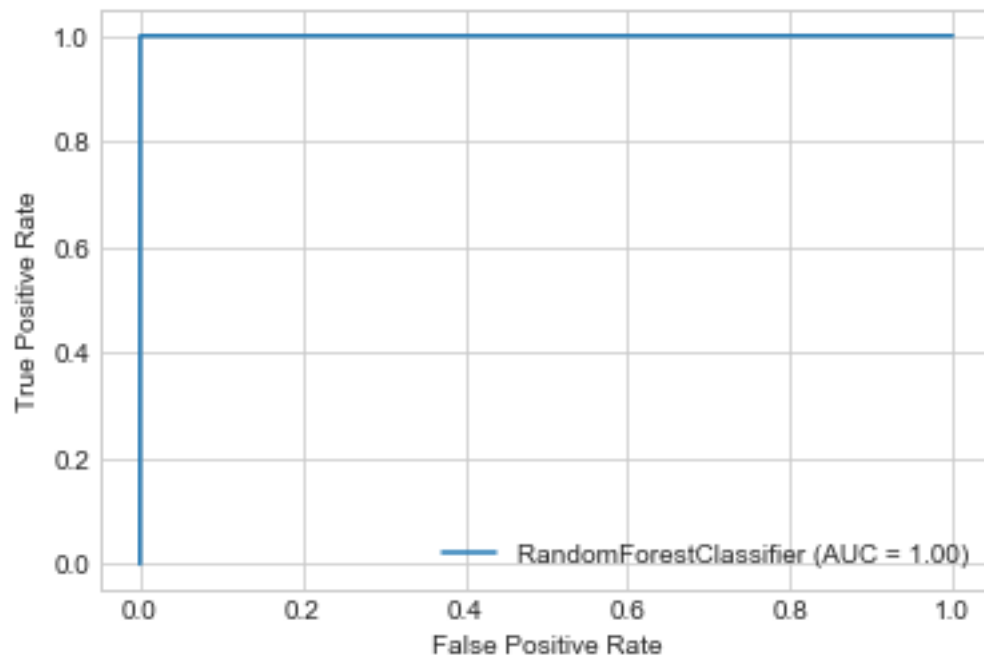
[10175 90137]]

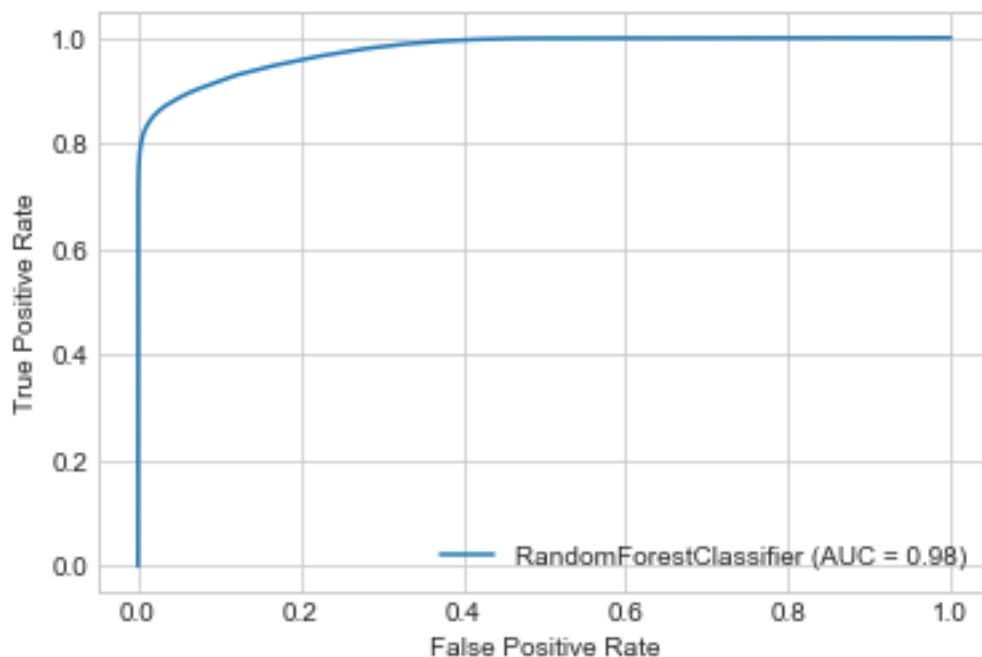
Classification Report

|   | precision | recall | f1-score | support |
|---|-----------|--------|----------|---------|
| 0 | 0.90      | 0.93   | 0.92     | 100328  |
| 1 | 0.93      | 0.90   | 0.91     | 100312  |

|              |      |      |      |        |
|--------------|------|------|------|--------|
| accuracy     |      |      | 0.92 | 200640 |
| macro avg    | 0.92 | 0.92 | 0.92 | 200640 |
| weighted avg | 0.92 | 0.92 | 0.92 | 200640 |





```
In [57]: # Creating Baseline Catboost Classifier (Based on previous Experience)
baseline_catboost = CatBoostClassifier()
baseline_catboost.fit(X_train,y_train)
```

Learning rate set to 0.142296

|     |                  |              |                   |
|-----|------------------|--------------|-------------------|
| 0:  | learn: 0.4827695 | total: 273ms | remaining: 4m 33s |
| 1:  | learn: 0.3960941 | total: 348ms | remaining: 2m 53s |
| 2:  | learn: 0.3477186 | total: 413ms | remaining: 2m 17s |
| 3:  | learn: 0.3276000 | total: 479ms | remaining: 1m 59s |
| 4:  | learn: 0.3195322 | total: 552ms | remaining: 1m 49s |
| 5:  | learn: 0.3112146 | total: 621ms | remaining: 1m 42s |
| 6:  | learn: 0.2957448 | total: 695ms | remaining: 1m 38s |
| 7:  | learn: 0.2925019 | total: 767ms | remaining: 1m 35s |
| 8:  | learn: 0.2898431 | total: 831ms | remaining: 1m 31s |
| 9:  | learn: 0.2870312 | total: 896ms | remaining: 1m 28s |
| 10: | learn: 0.2832157 | total: 976ms | remaining: 1m 27s |
| 11: | learn: 0.2776796 | total: 1.04s | remaining: 1m 26s |
| 12: | learn: 0.2763014 | total: 1.12s | remaining: 1m 24s |
| 13: | learn: 0.2717114 | total: 1.19s | remaining: 1m 23s |
| 14: | learn: 0.2675487 | total: 1.25s | remaining: 1m 21s |
| 15: | learn: 0.2611152 | total: 1.31s | remaining: 1m 20s |
| 16: | learn: 0.2569796 | total: 1.39s | remaining: 1m 20s |
| 17: | learn: 0.2543589 | total: 1.45s | remaining: 1m 19s |
| 18: | learn: 0.2518683 | total: 1.52s | remaining: 1m 18s |
| 19: | learn: 0.2498062 | total: 1.59s | remaining: 1m 17s |

|     |                  |              |                   |
|-----|------------------|--------------|-------------------|
| 20: | learn: 0.2486897 | total: 1.64s | remaining: 1m 16s |
| 21: | learn: 0.2479099 | total: 1.7s  | remaining: 1m 15s |
| 22: | learn: 0.2440608 | total: 1.78s | remaining: 1m 15s |
| 23: | learn: 0.2431318 | total: 1.85s | remaining: 1m 15s |
| 24: | learn: 0.2418041 | total: 1.91s | remaining: 1m 14s |
| 25: | learn: 0.2409767 | total: 1.97s | remaining: 1m 13s |
| 26: | learn: 0.2382270 | total: 2.04s | remaining: 1m 13s |
| 27: | learn: 0.2367039 | total: 2.11s | remaining: 1m 13s |
| 28: | learn: 0.2361702 | total: 2.17s | remaining: 1m 12s |
| 29: | learn: 0.2350157 | total: 2.23s | remaining: 1m 12s |
| 30: | learn: 0.2339778 | total: 2.29s | remaining: 1m 11s |
| 31: | learn: 0.2322143 | total: 2.36s | remaining: 1m 11s |
| 32: | learn: 0.2307163 | total: 2.43s | remaining: 1m 11s |
| 33: | learn: 0.2285193 | total: 2.5s  | remaining: 1m 11s |
| 34: | learn: 0.2268118 | total: 2.57s | remaining: 1m 10s |
| 35: | learn: 0.2259196 | total: 2.63s | remaining: 1m 10s |
| 36: | learn: 0.2257011 | total: 2.7s  | remaining: 1m 10s |
| 37: | learn: 0.2252429 | total: 2.76s | remaining: 1m 9s  |
| 38: | learn: 0.2240899 | total: 2.82s | remaining: 1m 9s  |
| 39: | learn: 0.2235541 | total: 2.89s | remaining: 1m 9s  |
| 40: | learn: 0.2232160 | total: 2.95s | remaining: 1m 9s  |
| 41: | learn: 0.2228721 | total: 3.01s | remaining: 1m 8s  |
| 42: | learn: 0.2225464 | total: 3.06s | remaining: 1m 8s  |
| 43: | learn: 0.2216330 | total: 3.14s | remaining: 1m 8s  |
| 44: | learn: 0.2205560 | total: 3.21s | remaining: 1m 8s  |
| 45: | learn: 0.2195217 | total: 3.27s | remaining: 1m 7s  |
| 46: | learn: 0.2188822 | total: 3.33s | remaining: 1m 7s  |
| 47: | learn: 0.2179138 | total: 3.41s | remaining: 1m 7s  |
| 48: | learn: 0.2175785 | total: 3.5s  | remaining: 1m 7s  |
| 49: | learn: 0.2167971 | total: 3.58s | remaining: 1m 7s  |
| 50: | learn: 0.2160070 | total: 3.64s | remaining: 1m 7s  |
| 51: | learn: 0.2144169 | total: 3.72s | remaining: 1m 7s  |
| 52: | learn: 0.2134352 | total: 3.83s | remaining: 1m 8s  |
| 53: | learn: 0.2124690 | total: 3.93s | remaining: 1m 8s  |
| 54: | learn: 0.2119436 | total: 4.04s | remaining: 1m 9s  |
| 55: | learn: 0.2111846 | total: 4.15s | remaining: 1m 9s  |
| 56: | learn: 0.2097505 | total: 4.25s | remaining: 1m 10s |
| 57: | learn: 0.2088536 | total: 4.34s | remaining: 1m 10s |
| 58: | learn: 0.2086160 | total: 4.42s | remaining: 1m 10s |
| 59: | learn: 0.2079391 | total: 4.52s | remaining: 1m 10s |
| 60: | learn: 0.2077142 | total: 4.58s | remaining: 1m 10s |
| 61: | learn: 0.2073102 | total: 4.67s | remaining: 1m 10s |
| 62: | learn: 0.2069401 | total: 4.75s | remaining: 1m 10s |
| 63: | learn: 0.2057845 | total: 4.81s | remaining: 1m 10s |
| 64: | learn: 0.2054172 | total: 4.88s | remaining: 1m 10s |
| 65: | learn: 0.2038755 | total: 4.95s | remaining: 1m 9s  |
| 66: | learn: 0.2033773 | total: 5.04s | remaining: 1m 10s |
| 67: | learn: 0.2017947 | total: 5.12s | remaining: 1m 10s |

|      |                  |              |                   |
|------|------------------|--------------|-------------------|
| 68:  | learn: 0.2003845 | total: 5.2s  | remaining: 1m 10s |
| 69:  | learn: 0.1999200 | total: 5.27s | remaining: 1m 10s |
| 70:  | learn: 0.1991886 | total: 5.34s | remaining: 1m 9s  |
| 71:  | learn: 0.1979457 | total: 5.42s | remaining: 1m 9s  |
| 72:  | learn: 0.1970520 | total: 5.49s | remaining: 1m 9s  |
| 73:  | learn: 0.1967020 | total: 5.56s | remaining: 1m 9s  |
| 74:  | learn: 0.1963212 | total: 5.62s | remaining: 1m 9s  |
| 75:  | learn: 0.1951749 | total: 5.7s  | remaining: 1m 9s  |
| 76:  | learn: 0.1945314 | total: 5.78s | remaining: 1m 9s  |
| 77:  | learn: 0.1944119 | total: 5.85s | remaining: 1m 9s  |
| 78:  | learn: 0.1942449 | total: 5.92s | remaining: 1m 8s  |
| 79:  | learn: 0.1938264 | total: 6s    | remaining: 1m 9s  |
| 80:  | learn: 0.1933242 | total: 6.09s | remaining: 1m 9s  |
| 81:  | learn: 0.1932490 | total: 6.15s | remaining: 1m 8s  |
| 82:  | learn: 0.1929290 | total: 6.23s | remaining: 1m 8s  |
| 83:  | learn: 0.1927395 | total: 6.32s | remaining: 1m 8s  |
| 84:  | learn: 0.1926635 | total: 6.41s | remaining: 1m 8s  |
| 85:  | learn: 0.1922030 | total: 6.5s  | remaining: 1m 9s  |
| 86:  | learn: 0.1921134 | total: 6.58s | remaining: 1m 9s  |
| 87:  | learn: 0.1914389 | total: 6.67s | remaining: 1m 9s  |
| 88:  | learn: 0.1911441 | total: 6.75s | remaining: 1m 9s  |
| 89:  | learn: 0.1909674 | total: 6.82s | remaining: 1m 8s  |
| 90:  | learn: 0.1905390 | total: 6.89s | remaining: 1m 8s  |
| 91:  | learn: 0.1901359 | total: 6.94s | remaining: 1m 8s  |
| 92:  | learn: 0.1897817 | total: 7.02s | remaining: 1m 8s  |
| 93:  | learn: 0.1897195 | total: 7.09s | remaining: 1m 8s  |
| 94:  | learn: 0.1892581 | total: 7.17s | remaining: 1m 8s  |
| 95:  | learn: 0.1890609 | total: 7.24s | remaining: 1m 8s  |
| 96:  | learn: 0.1888900 | total: 7.31s | remaining: 1m 8s  |
| 97:  | learn: 0.1887393 | total: 7.37s | remaining: 1m 7s  |
| 98:  | learn: 0.1885731 | total: 7.46s | remaining: 1m 7s  |
| 99:  | learn: 0.1881856 | total: 7.55s | remaining: 1m 7s  |
| 100: | learn: 0.1877934 | total: 7.61s | remaining: 1m 7s  |
| 101: | learn: 0.1873638 | total: 7.68s | remaining: 1m 7s  |
| 102: | learn: 0.1870651 | total: 7.75s | remaining: 1m 7s  |
| 103: | learn: 0.1868119 | total: 7.81s | remaining: 1m 7s  |
| 104: | learn: 0.1860680 | total: 7.9s  | remaining: 1m 7s  |
| 105: | learn: 0.1856807 | total: 7.97s | remaining: 1m 7s  |
| 106: | learn: 0.1847564 | total: 8.04s | remaining: 1m 7s  |
| 107: | learn: 0.1841205 | total: 8.12s | remaining: 1m 7s  |
| 108: | learn: 0.1835795 | total: 8.2s  | remaining: 1m 7s  |
| 109: | learn: 0.1829759 | total: 8.29s | remaining: 1m 7s  |
| 110: | learn: 0.1822266 | total: 8.36s | remaining: 1m 6s  |
| 111: | learn: 0.1817173 | total: 8.43s | remaining: 1m 6s  |
| 112: | learn: 0.1811733 | total: 8.51s | remaining: 1m 6s  |
| 113: | learn: 0.1809977 | total: 8.59s | remaining: 1m 6s  |
| 114: | learn: 0.1807972 | total: 8.65s | remaining: 1m 6s  |
| 115: | learn: 0.1806725 | total: 8.71s | remaining: 1m 6s  |

|      |                  |              |                  |
|------|------------------|--------------|------------------|
| 116: | learn: 0.1801931 | total: 8.77s | remaining: 1m 6s |
| 117: | learn: 0.1796655 | total: 8.86s | remaining: 1m 6s |
| 118: | learn: 0.1794828 | total: 8.93s | remaining: 1m 6s |
| 119: | learn: 0.1789826 | total: 9s    | remaining: 1m 5s |
| 120: | learn: 0.1787845 | total: 9.06s | remaining: 1m 5s |
| 121: | learn: 0.1785497 | total: 9.14s | remaining: 1m 5s |
| 122: | learn: 0.1784588 | total: 9.21s | remaining: 1m 5s |
| 123: | learn: 0.1782408 | total: 9.3s  | remaining: 1m 5s |
| 124: | learn: 0.1779094 | total: 9.39s | remaining: 1m 5s |
| 125: | learn: 0.1775000 | total: 9.47s | remaining: 1m 5s |
| 126: | learn: 0.1771318 | total: 9.54s | remaining: 1m 5s |
| 127: | learn: 0.1770402 | total: 9.61s | remaining: 1m 5s |
| 128: | learn: 0.1769605 | total: 9.67s | remaining: 1m 5s |
| 129: | learn: 0.1766468 | total: 9.74s | remaining: 1m 5s |
| 130: | learn: 0.1764522 | total: 9.83s | remaining: 1m 5s |
| 131: | learn: 0.1760739 | total: 9.93s | remaining: 1m 5s |
| 132: | learn: 0.1758491 | total: 10s   | remaining: 1m 5s |
| 133: | learn: 0.1755882 | total: 10.1s | remaining: 1m 5s |
| 134: | learn: 0.1754646 | total: 10.2s | remaining: 1m 5s |
| 135: | learn: 0.1753270 | total: 10.3s | remaining: 1m 5s |
| 136: | learn: 0.1750133 | total: 10.4s | remaining: 1m 5s |
| 137: | learn: 0.1748172 | total: 10.5s | remaining: 1m 5s |
| 138: | learn: 0.1747579 | total: 10.6s | remaining: 1m 5s |
| 139: | learn: 0.1746546 | total: 10.7s | remaining: 1m 5s |
| 140: | learn: 0.1740435 | total: 10.8s | remaining: 1m 5s |
| 141: | learn: 0.1738424 | total: 10.9s | remaining: 1m 5s |
| 142: | learn: 0.1736564 | total: 10.9s | remaining: 1m 5s |
| 143: | learn: 0.1735647 | total: 11s   | remaining: 1m 5s |
| 144: | learn: 0.1733860 | total: 11.1s | remaining: 1m 5s |
| 145: | learn: 0.1732356 | total: 11.2s | remaining: 1m 5s |
| 146: | learn: 0.1730022 | total: 11.3s | remaining: 1m 5s |
| 147: | learn: 0.1729019 | total: 11.4s | remaining: 1m 5s |
| 148: | learn: 0.1728344 | total: 11.4s | remaining: 1m 5s |
| 149: | learn: 0.1727153 | total: 11.5s | remaining: 1m 5s |
| 150: | learn: 0.1726798 | total: 11.6s | remaining: 1m 5s |
| 151: | learn: 0.1725136 | total: 11.7s | remaining: 1m 5s |
| 152: | learn: 0.1721646 | total: 11.8s | remaining: 1m 5s |
| 153: | learn: 0.1721289 | total: 11.9s | remaining: 1m 5s |
| 154: | learn: 0.1717666 | total: 12s   | remaining: 1m 5s |
| 155: | learn: 0.1716670 | total: 12.1s | remaining: 1m 5s |
| 156: | learn: 0.1713786 | total: 12.1s | remaining: 1m 5s |
| 157: | learn: 0.1713332 | total: 12.2s | remaining: 1m 5s |
| 158: | learn: 0.1712250 | total: 12.3s | remaining: 1m 5s |
| 159: | learn: 0.1710993 | total: 12.4s | remaining: 1m 4s |
| 160: | learn: 0.1710474 | total: 12.4s | remaining: 1m 4s |
| 161: | learn: 0.1709487 | total: 12.5s | remaining: 1m 4s |
| 162: | learn: 0.1707465 | total: 12.6s | remaining: 1m 4s |
| 163: | learn: 0.1706921 | total: 12.7s | remaining: 1m 4s |

|      |                  |              |                  |
|------|------------------|--------------|------------------|
| 164: | learn: 0.1705604 | total: 12.7s | remaining: 1m 4s |
| 165: | learn: 0.1705051 | total: 12.8s | remaining: 1m 4s |
| 166: | learn: 0.1704675 | total: 12.9s | remaining: 1m 4s |
| 167: | learn: 0.1704077 | total: 13s   | remaining: 1m 4s |
| 168: | learn: 0.1703769 | total: 13.1s | remaining: 1m 4s |
| 169: | learn: 0.1703213 | total: 13.2s | remaining: 1m 4s |
| 170: | learn: 0.1701658 | total: 13.3s | remaining: 1m 4s |
| 171: | learn: 0.1700015 | total: 13.3s | remaining: 1m 4s |
| 172: | learn: 0.1696796 | total: 13.4s | remaining: 1m 4s |
| 173: | learn: 0.1694866 | total: 13.5s | remaining: 1m 3s |
| 174: | learn: 0.1694613 | total: 13.6s | remaining: 1m 3s |
| 175: | learn: 0.1694150 | total: 13.6s | remaining: 1m 3s |
| 176: | learn: 0.1691478 | total: 13.7s | remaining: 1m 3s |
| 177: | learn: 0.1688773 | total: 13.8s | remaining: 1m 3s |
| 178: | learn: 0.1685706 | total: 13.8s | remaining: 1m 3s |
| 179: | learn: 0.1684061 | total: 13.9s | remaining: 1m 3s |
| 180: | learn: 0.1683270 | total: 14s   | remaining: 1m 3s |
| 181: | learn: 0.1682360 | total: 14.1s | remaining: 1m 3s |
| 182: | learn: 0.1681788 | total: 14.2s | remaining: 1m 3s |
| 183: | learn: 0.1680954 | total: 14.3s | remaining: 1m 3s |
| 184: | learn: 0.1680628 | total: 14.3s | remaining: 1m 3s |
| 185: | learn: 0.1680210 | total: 14.4s | remaining: 1m 3s |
| 186: | learn: 0.1679423 | total: 14.5s | remaining: 1m 3s |
| 187: | learn: 0.1679048 | total: 14.6s | remaining: 1m 3s |
| 188: | learn: 0.1678282 | total: 14.7s | remaining: 1m 2s |
| 189: | learn: 0.1678004 | total: 14.7s | remaining: 1m 2s |
| 190: | learn: 0.1677637 | total: 14.8s | remaining: 1m 2s |
| 191: | learn: 0.1677360 | total: 14.9s | remaining: 1m 2s |
| 192: | learn: 0.1677126 | total: 14.9s | remaining: 1m 2s |
| 193: | learn: 0.1676113 | total: 15s   | remaining: 1m 2s |
| 194: | learn: 0.1675874 | total: 15s   | remaining: 1m 2s |
| 195: | learn: 0.1675371 | total: 15.1s | remaining: 1m 1s |
| 196: | learn: 0.1674330 | total: 15.2s | remaining: 1m 1s |
| 197: | learn: 0.1673875 | total: 15.2s | remaining: 1m 1s |
| 198: | learn: 0.1673075 | total: 15.3s | remaining: 1m 1s |
| 199: | learn: 0.1672873 | total: 15.4s | remaining: 1m 1s |
| 200: | learn: 0.1671282 | total: 15.4s | remaining: 1m 1s |
| 201: | learn: 0.1670411 | total: 15.5s | remaining: 1m 1s |
| 202: | learn: 0.1670153 | total: 15.6s | remaining: 1m 1s |
| 203: | learn: 0.1669743 | total: 15.6s | remaining: 1m 1s |
| 204: | learn: 0.1668803 | total: 15.7s | remaining: 1m    |
| 205: | learn: 0.1668570 | total: 15.8s | remaining: 1m    |
| 206: | learn: 0.1667904 | total: 15.9s | remaining: 1m    |
| 207: | learn: 0.1667714 | total: 16s   | remaining: 1m    |
| 208: | learn: 0.1667484 | total: 16s   | remaining: 1m    |
| 209: | learn: 0.1664341 | total: 16.1s | remaining: 1m    |
| 210: | learn: 0.1663941 | total: 16.2s | remaining: 1m    |
| 211: | learn: 0.1663681 | total: 16.3s | remaining: 1m    |



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| 212: | learn: 0.1663152 | total: 16.4s | remaining: 1m    |
| 213: | learn: 0.1662922 | total: 16.4s | remaining: 1m    |
| 214: | learn: 0.1662696 | total: 16.5s | remaining: 1m    |
| 215: | learn: 0.1662468 | total: 16.6s | remaining: 1m    |
| 216: | learn: 0.1661362 | total: 16.7s | remaining: 1m    |
| 217: | learn: 0.1661126 | total: 16.7s | remaining: 60s   |
| 218: | learn: 0.1660901 | total: 16.8s | remaining: 59.9s |
| 219: | learn: 0.1658315 | total: 16.9s | remaining: 59.8s |
| 220: | learn: 0.1657441 | total: 17s   | remaining: 59.8s |
| 221: | learn: 0.1657141 | total: 17s   | remaining: 59.7s |
| 222: | learn: 0.1657004 | total: 17.1s | remaining: 59.6s |
| 223: | learn: 0.1656821 | total: 17.2s | remaining: 59.5s |
| 224: | learn: 0.1656645 | total: 17.3s | remaining: 59.5s |
| 225: | learn: 0.1656325 | total: 17.3s | remaining: 59.4s |
| 226: | learn: 0.1656130 | total: 17.4s | remaining: 59.2s |
| 227: | learn: 0.1655451 | total: 17.5s | remaining: 59.1s |
| 228: | learn: 0.1655016 | total: 17.5s | remaining: 59.1s |
| 229: | learn: 0.1653531 | total: 17.6s | remaining: 59s   |
| 230: | learn: 0.1652874 | total: 17.7s | remaining: 58.9s |
| 231: | learn: 0.1650995 | total: 17.8s | remaining: 58.9s |
| 232: | learn: 0.1650733 | total: 17.9s | remaining: 58.8s |
| 233: | learn: 0.1650202 | total: 18s   | remaining: 58.8s |
| 234: | learn: 0.1648768 | total: 18s   | remaining: 58.7s |
| 235: | learn: 0.1647725 | total: 18.1s | remaining: 58.6s |
| 236: | learn: 0.1647277 | total: 18.2s | remaining: 58.5s |
| 237: | learn: 0.1646506 | total: 18.2s | remaining: 58.3s |
| 238: | learn: 0.1646299 | total: 18.3s | remaining: 58.2s |
| 239: | learn: 0.1644372 | total: 18.4s | remaining: 58.2s |
| 240: | learn: 0.1644142 | total: 18.4s | remaining: 58.1s |
| 241: | learn: 0.1643974 | total: 18.5s | remaining: 58s   |
| 242: | learn: 0.1643555 | total: 18.6s | remaining: 57.9s |
| 243: | learn: 0.1643384 | total: 18.7s | remaining: 57.8s |
| 244: | learn: 0.1643094 | total: 18.7s | remaining: 57.7s |
| 245: | learn: 0.1642896 | total: 18.8s | remaining: 57.7s |
| 246: | learn: 0.1642597 | total: 18.9s | remaining: 57.5s |
| 247: | learn: 0.1642385 | total: 18.9s | remaining: 57.4s |
| 248: | learn: 0.1641993 | total: 19s   | remaining: 57.4s |
| 249: | learn: 0.1640431 | total: 19.1s | remaining: 57.3s |
| 250: | learn: 0.1640201 | total: 19.2s | remaining: 57.3s |
| 251: | learn: 0.1640008 | total: 19.3s | remaining: 57.2s |
| 252: | learn: 0.1639805 | total: 19.3s | remaining: 57.1s |
| 253: | learn: 0.1639319 | total: 19.4s | remaining: 57s   |
| 254: | learn: 0.1637783 | total: 19.5s | remaining: 56.9s |
| 255: | learn: 0.1637341 | total: 19.6s | remaining: 56.8s |
| 256: | learn: 0.1636830 | total: 19.6s | remaining: 56.7s |
| 257: | learn: 0.1636510 | total: 19.7s | remaining: 56.6s |
| 258: | learn: 0.1635435 | total: 19.8s | remaining: 56.6s |
| 259: | learn: 0.1635245 | total: 19.8s | remaining: 56.5s |

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| 260: | learn: 0.1635096 | total: 19.9s | remaining: 56.4s |
| 261: | learn: 0.1634959 | total: 20s   | remaining: 56.3s |
| 262: | learn: 0.1634431 | total: 20s   | remaining: 56.2s |
| 263: | learn: 0.1633914 | total: 20.1s | remaining: 56.1s |
| 264: | learn: 0.1633372 | total: 20.2s | remaining: 56s   |
| 265: | learn: 0.1632906 | total: 20.3s | remaining: 55.9s |
| 266: | learn: 0.1632698 | total: 20.3s | remaining: 55.8s |
| 267: | learn: 0.1632445 | total: 20.4s | remaining: 55.7s |
| 268: | learn: 0.1632253 | total: 20.5s | remaining: 55.6s |
| 269: | learn: 0.1631023 | total: 20.5s | remaining: 55.5s |
| 270: | learn: 0.1630423 | total: 20.6s | remaining: 55.4s |
| 271: | learn: 0.1630176 | total: 20.7s | remaining: 55.3s |
| 272: | learn: 0.1630003 | total: 20.8s | remaining: 55.3s |
| 273: | learn: 0.1629372 | total: 20.8s | remaining: 55.2s |
| 274: | learn: 0.1629093 | total: 20.9s | remaining: 55.1s |
| 275: | learn: 0.1628781 | total: 21s   | remaining: 55s   |
| 276: | learn: 0.1628593 | total: 21.1s | remaining: 55s   |
| 277: | learn: 0.1628444 | total: 21.1s | remaining: 54.9s |
| 278: | learn: 0.1627833 | total: 21.2s | remaining: 54.8s |
| 279: | learn: 0.1627327 | total: 21.3s | remaining: 54.7s |
| 280: | learn: 0.1624714 | total: 21.3s | remaining: 54.6s |
| 281: | learn: 0.1623149 | total: 21.4s | remaining: 54.5s |
| 282: | learn: 0.1622784 | total: 21.5s | remaining: 54.4s |
| 283: | learn: 0.1621955 | total: 21.6s | remaining: 54.4s |
| 284: | learn: 0.1620622 | total: 21.6s | remaining: 54.3s |
| 285: | learn: 0.1620414 | total: 21.7s | remaining: 54.2s |
| 286: | learn: 0.1619760 | total: 21.8s | remaining: 54.1s |
| 287: | learn: 0.1619505 | total: 21.9s | remaining: 54s   |
| 288: | learn: 0.1619053 | total: 21.9s | remaining: 54s   |
| 289: | learn: 0.1618913 | total: 22s   | remaining: 53.9s |
| 290: | learn: 0.1618771 | total: 22.1s | remaining: 53.9s |
| 291: | learn: 0.1618112 | total: 22.2s | remaining: 53.8s |
| 292: | learn: 0.1617375 | total: 22.3s | remaining: 53.7s |
| 293: | learn: 0.1616928 | total: 22.3s | remaining: 53.6s |
| 294: | learn: 0.1616755 | total: 22.4s | remaining: 53.5s |
| 295: | learn: 0.1616575 | total: 22.5s | remaining: 53.4s |
| 296: | learn: 0.1616404 | total: 22.6s | remaining: 53.4s |
| 297: | learn: 0.1615969 | total: 22.6s | remaining: 53.3s |
| 298: | learn: 0.1615786 | total: 22.7s | remaining: 53.2s |
| 299: | learn: 0.1615697 | total: 22.8s | remaining: 53.1s |
| 300: | learn: 0.1615471 | total: 22.8s | remaining: 53s   |
| 301: | learn: 0.1615268 | total: 22.9s | remaining: 52.9s |
| 302: | learn: 0.1615085 | total: 23s   | remaining: 52.9s |
| 303: | learn: 0.1613892 | total: 23.1s | remaining: 52.8s |
| 304: | learn: 0.1613576 | total: 23.1s | remaining: 52.7s |
| 305: | learn: 0.1612422 | total: 23.2s | remaining: 52.7s |
| 306: | learn: 0.1611822 | total: 23.3s | remaining: 52.6s |
| 307: | learn: 0.1611627 | total: 23.4s | remaining: 52.6s |

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| 308: | learn: 0.1611397 | total: 23.5s | remaining: 52.5s |
| 309: | learn: 0.1611226 | total: 23.5s | remaining: 52.4s |
| 310: | learn: 0.1610705 | total: 23.6s | remaining: 52.3s |
| 311: | learn: 0.1610536 | total: 23.7s | remaining: 52.2s |
| 312: | learn: 0.1610273 | total: 23.8s | remaining: 52.1s |
| 313: | learn: 0.1610111 | total: 23.9s | remaining: 52.1s |
| 314: | learn: 0.1609803 | total: 23.9s | remaining: 52s   |
| 315: | learn: 0.1609230 | total: 24s   | remaining: 52s   |
| 316: | learn: 0.1609025 | total: 24.1s | remaining: 51.9s |
| 317: | learn: 0.1608855 | total: 24.2s | remaining: 51.8s |
| 318: | learn: 0.1608654 | total: 24.2s | remaining: 51.7s |
| 319: | learn: 0.1608169 | total: 24.3s | remaining: 51.6s |
| 320: | learn: 0.1608010 | total: 24.4s | remaining: 51.5s |
| 321: | learn: 0.1607818 | total: 24.4s | remaining: 51.5s |
| 322: | learn: 0.1607174 | total: 24.6s | remaining: 51.5s |
| 323: | learn: 0.1606979 | total: 24.6s | remaining: 51.4s |
| 324: | learn: 0.1606876 | total: 24.7s | remaining: 51.3s |
| 325: | learn: 0.1606578 | total: 24.8s | remaining: 51.2s |
| 326: | learn: 0.1606396 | total: 24.8s | remaining: 51.1s |
| 327: | learn: 0.1606151 | total: 24.9s | remaining: 51s   |
| 328: | learn: 0.1605937 | total: 25s   | remaining: 50.9s |
| 329: | learn: 0.1605795 | total: 25s   | remaining: 50.8s |
| 330: | learn: 0.1605605 | total: 25.1s | remaining: 50.7s |
| 331: | learn: 0.1604871 | total: 25.2s | remaining: 50.6s |
| 332: | learn: 0.1604706 | total: 25.2s | remaining: 50.5s |
| 333: | learn: 0.1604543 | total: 25.3s | remaining: 50.4s |
| 334: | learn: 0.1604399 | total: 25.3s | remaining: 50.3s |
| 335: | learn: 0.1603698 | total: 25.4s | remaining: 50.2s |
| 336: | learn: 0.1603556 | total: 25.5s | remaining: 50.1s |
| 337: | learn: 0.1603000 | total: 25.5s | remaining: 50s   |
| 338: | learn: 0.1602803 | total: 25.6s | remaining: 49.9s |
| 339: | learn: 0.1602061 | total: 25.6s | remaining: 49.8s |
| 340: | learn: 0.1601843 | total: 25.7s | remaining: 49.7s |
| 341: | learn: 0.1601708 | total: 25.8s | remaining: 49.6s |
| 342: | learn: 0.1601593 | total: 25.8s | remaining: 49.5s |
| 343: | learn: 0.1601461 | total: 25.9s | remaining: 49.4s |
| 344: | learn: 0.1601297 | total: 26s   | remaining: 49.3s |
| 345: | learn: 0.1601141 | total: 26s   | remaining: 49.2s |
| 346: | learn: 0.1600960 | total: 26.1s | remaining: 49.1s |
| 347: | learn: 0.1600800 | total: 26.2s | remaining: 49s   |
| 348: | learn: 0.1600668 | total: 26.2s | remaining: 48.9s |
| 349: | learn: 0.1600534 | total: 26.3s | remaining: 48.8s |
| 350: | learn: 0.1600412 | total: 26.4s | remaining: 48.7s |
| 351: | learn: 0.1599013 | total: 26.4s | remaining: 48.7s |
| 352: | learn: 0.1598824 | total: 26.5s | remaining: 48.6s |
| 353: | learn: 0.1598257 | total: 26.6s | remaining: 48.5s |
| 354: | learn: 0.1598016 | total: 26.6s | remaining: 48.4s |
| 355: | learn: 0.1597835 | total: 26.7s | remaining: 48.3s |

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| 356: | learn: 0.1597707 | total: 26.7s | remaining: 48.2s |
| 357: | learn: 0.1597607 | total: 26.8s | remaining: 48.1s |
| 358: | learn: 0.1596866 | total: 26.9s | remaining: 48s   |
| 359: | learn: 0.1596656 | total: 26.9s | remaining: 47.9s |
| 360: | learn: 0.1596435 | total: 27s   | remaining: 47.8s |
| 361: | learn: 0.1596297 | total: 27.1s | remaining: 47.7s |
| 362: | learn: 0.1596127 | total: 27.1s | remaining: 47.6s |
| 363: | learn: 0.1595982 | total: 27.2s | remaining: 47.5s |
| 364: | learn: 0.1595831 | total: 27.3s | remaining: 47.4s |
| 365: | learn: 0.1595650 | total: 27.3s | remaining: 47.3s |
| 366: | learn: 0.1595441 | total: 27.4s | remaining: 47.2s |
| 367: | learn: 0.1595309 | total: 27.4s | remaining: 47.1s |
| 368: | learn: 0.1595048 | total: 27.5s | remaining: 47s   |
| 369: | learn: 0.1594456 | total: 27.6s | remaining: 46.9s |
| 370: | learn: 0.1594273 | total: 27.6s | remaining: 46.9s |
| 371: | learn: 0.1594120 | total: 27.7s | remaining: 46.8s |
| 372: | learn: 0.1593957 | total: 27.8s | remaining: 46.7s |
| 373: | learn: 0.1593780 | total: 27.8s | remaining: 46.6s |
| 374: | learn: 0.1593627 | total: 27.9s | remaining: 46.5s |
| 375: | learn: 0.1593436 | total: 28s   | remaining: 46.4s |
| 376: | learn: 0.1593206 | total: 28s   | remaining: 46.3s |
| 377: | learn: 0.1593069 | total: 28.1s | remaining: 46.2s |
| 378: | learn: 0.1592570 | total: 28.1s | remaining: 46.1s |
| 379: | learn: 0.1591960 | total: 28.2s | remaining: 46s   |
| 380: | learn: 0.1591313 | total: 28.3s | remaining: 45.9s |
| 381: | learn: 0.1591164 | total: 28.3s | remaining: 45.8s |
| 382: | learn: 0.1591021 | total: 28.4s | remaining: 45.8s |
| 383: | learn: 0.1590856 | total: 28.5s | remaining: 45.7s |
| 384: | learn: 0.1590704 | total: 28.5s | remaining: 45.6s |
| 385: | learn: 0.1590601 | total: 28.6s | remaining: 45.5s |
| 386: | learn: 0.1590483 | total: 28.7s | remaining: 45.4s |
| 387: | learn: 0.1590129 | total: 28.7s | remaining: 45.3s |
| 388: | learn: 0.1590038 | total: 28.8s | remaining: 45.2s |
| 389: | learn: 0.1589829 | total: 28.9s | remaining: 45.1s |
| 390: | learn: 0.1589288 | total: 28.9s | remaining: 45.1s |
| 391: | learn: 0.1589117 | total: 29s   | remaining: 45s   |
| 392: | learn: 0.1588885 | total: 29.1s | remaining: 44.9s |
| 393: | learn: 0.1588763 | total: 29.1s | remaining: 44.8s |
| 394: | learn: 0.1588555 | total: 29.2s | remaining: 44.7s |
| 395: | learn: 0.1588000 | total: 29.3s | remaining: 44.6s |
| 396: | learn: 0.1587844 | total: 29.4s | remaining: 44.6s |
| 397: | learn: 0.1587698 | total: 29.5s | remaining: 44.6s |
| 398: | learn: 0.1587601 | total: 29.6s | remaining: 44.5s |
| 399: | learn: 0.1586766 | total: 29.6s | remaining: 44.5s |
| 400: | learn: 0.1586609 | total: 29.7s | remaining: 44.4s |
| 401: | learn: 0.1586441 | total: 29.8s | remaining: 44.4s |
| 402: | learn: 0.1585904 | total: 29.9s | remaining: 44.3s |
| 403: | learn: 0.1585389 | total: 30s   | remaining: 44.2s |

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| 404: | learn: 0.1584998 | total: 30.1s | remaining: 44.2s |
| 405: | learn: 0.1584835 | total: 30.2s | remaining: 44.1s |
| 406: | learn: 0.1584494 | total: 30.3s | remaining: 44.1s |
| 407: | learn: 0.1584379 | total: 30.4s | remaining: 44.1s |
| 408: | learn: 0.1584235 | total: 30.5s | remaining: 44s   |
| 409: | learn: 0.1584041 | total: 30.5s | remaining: 43.9s |
| 410: | learn: 0.1583835 | total: 30.6s | remaining: 43.9s |
| 411: | learn: 0.1582989 | total: 30.7s | remaining: 43.8s |
| 412: | learn: 0.1582828 | total: 30.8s | remaining: 43.8s |
| 413: | learn: 0.1582698 | total: 30.9s | remaining: 43.7s |
| 414: | learn: 0.1582540 | total: 30.9s | remaining: 43.6s |
| 415: | learn: 0.1582430 | total: 31s   | remaining: 43.5s |
| 416: | learn: 0.1582240 | total: 31.1s | remaining: 43.4s |
| 417: | learn: 0.1582072 | total: 31.1s | remaining: 43.3s |
| 418: | learn: 0.1581918 | total: 31.2s | remaining: 43.2s |
| 419: | learn: 0.1581802 | total: 31.3s | remaining: 43.2s |
| 420: | learn: 0.1581684 | total: 31.3s | remaining: 43.1s |
| 421: | learn: 0.1581538 | total: 31.4s | remaining: 43s   |
| 422: | learn: 0.1581407 | total: 31.5s | remaining: 42.9s |
| 423: | learn: 0.1581245 | total: 31.5s | remaining: 42.8s |
| 424: | learn: 0.1581094 | total: 31.6s | remaining: 42.7s |
| 425: | learn: 0.1580895 | total: 31.7s | remaining: 42.7s |
| 426: | learn: 0.1580804 | total: 31.7s | remaining: 42.6s |
| 427: | learn: 0.1580683 | total: 31.8s | remaining: 42.6s |
| 428: | learn: 0.1580538 | total: 31.9s | remaining: 42.5s |
| 429: | learn: 0.1580421 | total: 32s   | remaining: 42.4s |
| 430: | learn: 0.1580283 | total: 32s   | remaining: 42.3s |
| 431: | learn: 0.1580195 | total: 32.1s | remaining: 42.2s |
| 432: | learn: 0.1579894 | total: 32.2s | remaining: 42.1s |
| 433: | learn: 0.1578945 | total: 32.2s | remaining: 42s   |
| 434: | learn: 0.1578856 | total: 32.3s | remaining: 42s   |
| 435: | learn: 0.1578713 | total: 32.4s | remaining: 41.9s |
| 436: | learn: 0.1578540 | total: 32.4s | remaining: 41.8s |
| 437: | learn: 0.1578326 | total: 32.5s | remaining: 41.7s |
| 438: | learn: 0.1578161 | total: 32.6s | remaining: 41.6s |
| 439: | learn: 0.1578020 | total: 32.6s | remaining: 41.5s |
| 440: | learn: 0.1577840 | total: 32.7s | remaining: 41.5s |
| 441: | learn: 0.1577738 | total: 32.8s | remaining: 41.4s |
| 442: | learn: 0.1577599 | total: 32.8s | remaining: 41.3s |
| 443: | learn: 0.1577367 | total: 32.9s | remaining: 41.2s |
| 444: | learn: 0.1577157 | total: 33s   | remaining: 41.1s |
| 445: | learn: 0.1577036 | total: 33s   | remaining: 41s   |
| 446: | learn: 0.1576957 | total: 33.1s | remaining: 40.9s |
| 447: | learn: 0.1576818 | total: 33.2s | remaining: 40.9s |
| 448: | learn: 0.1576551 | total: 33.2s | remaining: 40.8s |
| 449: | learn: 0.1576014 | total: 33.3s | remaining: 40.7s |
| 450: | learn: 0.1575844 | total: 33.4s | remaining: 40.6s |
| 451: | learn: 0.1575583 | total: 33.4s | remaining: 40.5s |

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| 452: | learn: 0.1575416 | total: 33.5s | remaining: 40.4s |
| 453: | learn: 0.1575284 | total: 33.5s | remaining: 40.3s |
| 454: | learn: 0.1575156 | total: 33.6s | remaining: 40.3s |
| 455: | learn: 0.1575030 | total: 33.7s | remaining: 40.2s |
| 456: | learn: 0.1574907 | total: 33.8s | remaining: 40.1s |
| 457: | learn: 0.1574553 | total: 33.8s | remaining: 40.1s |
| 458: | learn: 0.1574407 | total: 33.9s | remaining: 40s   |
| 459: | learn: 0.1574004 | total: 34s   | remaining: 39.9s |
| 460: | learn: 0.1573862 | total: 34.1s | remaining: 39.9s |
| 461: | learn: 0.1573725 | total: 34.2s | remaining: 39.8s |
| 462: | learn: 0.1573437 | total: 34.3s | remaining: 39.8s |
| 463: | learn: 0.1573258 | total: 34.3s | remaining: 39.7s |
| 464: | learn: 0.1572597 | total: 34.4s | remaining: 39.6s |
| 465: | learn: 0.1572452 | total: 34.5s | remaining: 39.6s |
| 466: | learn: 0.1571863 | total: 34.6s | remaining: 39.5s |
| 467: | learn: 0.1571658 | total: 34.7s | remaining: 39.4s |
| 468: | learn: 0.1571537 | total: 34.8s | remaining: 39.3s |
| 469: | learn: 0.1571455 | total: 34.8s | remaining: 39.3s |
| 470: | learn: 0.1571309 | total: 34.9s | remaining: 39.2s |
| 471: | learn: 0.1570679 | total: 35s   | remaining: 39.1s |
| 472: | learn: 0.1570517 | total: 35s   | remaining: 39s   |
| 473: | learn: 0.1570309 | total: 35.1s | remaining: 38.9s |
| 474: | learn: 0.1570160 | total: 35.2s | remaining: 38.9s |
| 475: | learn: 0.1570008 | total: 35.2s | remaining: 38.8s |
| 476: | learn: 0.1569884 | total: 35.3s | remaining: 38.7s |
| 477: | learn: 0.1569737 | total: 35.4s | remaining: 38.6s |
| 478: | learn: 0.1569585 | total: 35.4s | remaining: 38.5s |
| 479: | learn: 0.1569444 | total: 35.5s | remaining: 38.5s |
| 480: | learn: 0.1569290 | total: 35.6s | remaining: 38.4s |
| 481: | learn: 0.1569168 | total: 35.6s | remaining: 38.3s |
| 482: | learn: 0.1569078 | total: 35.7s | remaining: 38.3s |
| 483: | learn: 0.1568920 | total: 35.8s | remaining: 38.2s |
| 484: | learn: 0.1568801 | total: 35.9s | remaining: 38.1s |
| 485: | learn: 0.1568590 | total: 36s   | remaining: 38.1s |
| 486: | learn: 0.1568514 | total: 36.1s | remaining: 38s   |
| 487: | learn: 0.1568390 | total: 36.2s | remaining: 38s   |
| 488: | learn: 0.1568253 | total: 36.3s | remaining: 37.9s |
| 489: | learn: 0.1568133 | total: 36.4s | remaining: 37.9s |
| 490: | learn: 0.1568021 | total: 36.5s | remaining: 37.8s |
| 491: | learn: 0.1567884 | total: 36.6s | remaining: 37.8s |
| 492: | learn: 0.1567760 | total: 36.7s | remaining: 37.7s |
| 493: | learn: 0.1567664 | total: 36.8s | remaining: 37.7s |
| 494: | learn: 0.1567549 | total: 36.9s | remaining: 37.6s |
| 495: | learn: 0.1567389 | total: 37s   | remaining: 37.6s |
| 496: | learn: 0.1567248 | total: 37s   | remaining: 37.5s |
| 497: | learn: 0.1567091 | total: 37.1s | remaining: 37.4s |
| 498: | learn: 0.1566999 | total: 37.2s | remaining: 37.3s |
| 499: | learn: 0.1566812 | total: 37.2s | remaining: 37.2s |

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| 500: | learn: 0.1566680 | total: 37.3s | remaining: 37.2s |
| 501: | learn: 0.1566547 | total: 37.4s | remaining: 37.1s |
| 502: | learn: 0.1566469 | total: 37.4s | remaining: 37s   |
| 503: | learn: 0.1566352 | total: 37.5s | remaining: 36.9s |
| 504: | learn: 0.1566057 | total: 37.6s | remaining: 36.8s |
| 505: | learn: 0.1565949 | total: 37.6s | remaining: 36.7s |
| 506: | learn: 0.1565822 | total: 37.7s | remaining: 36.6s |
| 507: | learn: 0.1565192 | total: 37.7s | remaining: 36.6s |
| 508: | learn: 0.1565055 | total: 37.8s | remaining: 36.5s |
| 509: | learn: 0.1564918 | total: 37.9s | remaining: 36.4s |
| 510: | learn: 0.1564574 | total: 38s   | remaining: 36.4s |
| 511: | learn: 0.1564473 | total: 38.1s | remaining: 36.3s |
| 512: | learn: 0.1564368 | total: 38.1s | remaining: 36.2s |
| 513: | learn: 0.1563777 | total: 38.2s | remaining: 36.1s |
| 514: | learn: 0.1563011 | total: 38.3s | remaining: 36s   |
| 515: | learn: 0.1562697 | total: 38.3s | remaining: 36s   |
| 516: | learn: 0.1562408 | total: 38.4s | remaining: 35.9s |
| 517: | learn: 0.1562111 | total: 38.5s | remaining: 35.8s |
| 518: | learn: 0.1561927 | total: 38.6s | remaining: 35.8s |
| 519: | learn: 0.1561380 | total: 38.6s | remaining: 35.7s |
| 520: | learn: 0.1561229 | total: 38.7s | remaining: 35.6s |
| 521: | learn: 0.1561063 | total: 38.8s | remaining: 35.5s |
| 522: | learn: 0.1560398 | total: 38.9s | remaining: 35.5s |
| 523: | learn: 0.1560257 | total: 39s   | remaining: 35.4s |
| 524: | learn: 0.1560103 | total: 39s   | remaining: 35.3s |
| 525: | learn: 0.1559982 | total: 39.1s | remaining: 35.2s |
| 526: | learn: 0.1559839 | total: 39.2s | remaining: 35.1s |
| 527: | learn: 0.1559599 | total: 39.2s | remaining: 35.1s |
| 528: | learn: 0.1559449 | total: 39.3s | remaining: 35s   |
| 529: | learn: 0.1559332 | total: 39.4s | remaining: 34.9s |
| 530: | learn: 0.1559264 | total: 39.4s | remaining: 34.8s |
| 531: | learn: 0.1559136 | total: 39.5s | remaining: 34.7s |
| 532: | learn: 0.1558983 | total: 39.6s | remaining: 34.7s |
| 533: | learn: 0.1558878 | total: 39.7s | remaining: 34.6s |
| 534: | learn: 0.1558726 | total: 39.7s | remaining: 34.5s |
| 535: | learn: 0.1558615 | total: 39.8s | remaining: 34.4s |
| 536: | learn: 0.1558493 | total: 39.9s | remaining: 34.4s |
| 537: | learn: 0.1558380 | total: 39.9s | remaining: 34.3s |
| 538: | learn: 0.1558277 | total: 40s   | remaining: 34.2s |
| 539: | learn: 0.1558083 | total: 40.1s | remaining: 34.1s |
| 540: | learn: 0.1557956 | total: 40.2s | remaining: 34.1s |
| 541: | learn: 0.1557778 | total: 40.2s | remaining: 34s   |
| 542: | learn: 0.1557446 | total: 40.3s | remaining: 33.9s |
| 543: | learn: 0.1557361 | total: 40.3s | remaining: 33.8s |
| 544: | learn: 0.1557260 | total: 40.4s | remaining: 33.8s |
| 545: | learn: 0.1557062 | total: 40.5s | remaining: 33.7s |
| 546: | learn: 0.1556908 | total: 40.6s | remaining: 33.6s |
| 547: | learn: 0.1556795 | total: 40.6s | remaining: 33.5s |

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| 548: | learn: 0.1556631 | total: 40.7s | remaining: 33.5s |
| 549: | learn: 0.1556521 | total: 40.8s | remaining: 33.4s |
| 550: | learn: 0.1556175 | total: 40.9s | remaining: 33.3s |
| 551: | learn: 0.1555588 | total: 41s   | remaining: 33.2s |
| 552: | learn: 0.1555451 | total: 41s   | remaining: 33.2s |
| 553: | learn: 0.1555302 | total: 41.1s | remaining: 33.1s |
| 554: | learn: 0.1555137 | total: 41.2s | remaining: 33s   |
| 555: | learn: 0.1554978 | total: 41.3s | remaining: 33s   |
| 556: | learn: 0.1554808 | total: 41.4s | remaining: 32.9s |
| 557: | learn: 0.1553958 | total: 41.4s | remaining: 32.8s |
| 558: | learn: 0.1553836 | total: 41.5s | remaining: 32.7s |
| 559: | learn: 0.1553734 | total: 41.6s | remaining: 32.7s |
| 560: | learn: 0.1553586 | total: 41.7s | remaining: 32.6s |
| 561: | learn: 0.1553426 | total: 41.7s | remaining: 32.5s |
| 562: | learn: 0.1553304 | total: 41.8s | remaining: 32.5s |
| 563: | learn: 0.1553235 | total: 41.9s | remaining: 32.4s |
| 564: | learn: 0.1553123 | total: 42s   | remaining: 32.3s |
| 565: | learn: 0.1552952 | total: 42s   | remaining: 32.2s |
| 566: | learn: 0.1552829 | total: 42.1s | remaining: 32.2s |
| 567: | learn: 0.1552678 | total: 42.2s | remaining: 32.1s |
| 568: | learn: 0.1552547 | total: 42.3s | remaining: 32s   |
| 569: | learn: 0.1552450 | total: 42.4s | remaining: 32s   |
| 570: | learn: 0.1552303 | total: 42.5s | remaining: 31.9s |
| 571: | learn: 0.1552170 | total: 42.5s | remaining: 31.8s |
| 572: | learn: 0.1551840 | total: 42.6s | remaining: 31.7s |
| 573: | learn: 0.1551705 | total: 42.7s | remaining: 31.7s |
| 574: | learn: 0.1551560 | total: 42.7s | remaining: 31.6s |
| 575: | learn: 0.1551412 | total: 42.8s | remaining: 31.5s |
| 576: | learn: 0.1551286 | total: 42.9s | remaining: 31.4s |
| 577: | learn: 0.1551159 | total: 43s   | remaining: 31.4s |
| 578: | learn: 0.1551070 | total: 43s   | remaining: 31.3s |
| 579: | learn: 0.1550762 | total: 43.1s | remaining: 31.2s |
| 580: | learn: 0.1550646 | total: 43.2s | remaining: 31.2s |
| 581: | learn: 0.1550511 | total: 43.3s | remaining: 31.1s |
| 582: | learn: 0.1550384 | total: 43.4s | remaining: 31s   |
| 583: | learn: 0.1550246 | total: 43.5s | remaining: 31s   |
| 584: | learn: 0.1550118 | total: 43.5s | remaining: 30.9s |
| 585: | learn: 0.1550015 | total: 43.6s | remaining: 30.8s |
| 586: | learn: 0.1549893 | total: 43.7s | remaining: 30.8s |
| 587: | learn: 0.1549773 | total: 43.8s | remaining: 30.7s |
| 588: | learn: 0.1549640 | total: 43.9s | remaining: 30.7s |
| 589: | learn: 0.1549497 | total: 44s   | remaining: 30.6s |
| 590: | learn: 0.1549365 | total: 44.1s | remaining: 30.5s |
| 591: | learn: 0.1549256 | total: 44.2s | remaining: 30.4s |
| 592: | learn: 0.1549114 | total: 44.3s | remaining: 30.4s |
| 593: | learn: 0.1549019 | total: 44.4s | remaining: 30.3s |
| 594: | learn: 0.1548904 | total: 44.5s | remaining: 30.3s |
| 595: | learn: 0.1548801 | total: 44.5s | remaining: 30.2s |



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| 596: | learn: 0.1548669 | total: 44.6s | remaining: 30.1s |
| 597: | learn: 0.1548599 | total: 44.7s | remaining: 30s   |
| 598: | learn: 0.1548518 | total: 44.8s | remaining: 30s   |
| 599: | learn: 0.1548388 | total: 44.8s | remaining: 29.9s |
| 600: | learn: 0.1548250 | total: 44.9s | remaining: 29.8s |
| 601: | learn: 0.1548116 | total: 45s   | remaining: 29.7s |
| 602: | learn: 0.1547989 | total: 45s   | remaining: 29.6s |
| 603: | learn: 0.1547908 | total: 45.1s | remaining: 29.6s |
| 604: | learn: 0.1547769 | total: 45.2s | remaining: 29.5s |
| 605: | learn: 0.1547676 | total: 45.3s | remaining: 29.4s |
| 606: | learn: 0.1547540 | total: 45.4s | remaining: 29.4s |
| 607: | learn: 0.1547421 | total: 45.5s | remaining: 29.3s |
| 608: | learn: 0.1547336 | total: 45.6s | remaining: 29.2s |
| 609: | learn: 0.1546935 | total: 45.6s | remaining: 29.2s |
| 610: | learn: 0.1546806 | total: 45.8s | remaining: 29.1s |
| 611: | learn: 0.1546616 | total: 45.8s | remaining: 29.1s |
| 612: | learn: 0.1546507 | total: 45.9s | remaining: 29s   |
| 613: | learn: 0.1546315 | total: 46s   | remaining: 28.9s |
| 614: | learn: 0.1546205 | total: 46.1s | remaining: 28.8s |
| 615: | learn: 0.1546161 | total: 46.1s | remaining: 28.8s |
| 616: | learn: 0.1546027 | total: 46.2s | remaining: 28.7s |
| 617: | learn: 0.1545951 | total: 46.3s | remaining: 28.6s |
| 618: | learn: 0.1545760 | total: 46.3s | remaining: 28.5s |
| 619: | learn: 0.1545638 | total: 46.4s | remaining: 28.4s |
| 620: | learn: 0.1545525 | total: 46.5s | remaining: 28.4s |
| 621: | learn: 0.1545416 | total: 46.5s | remaining: 28.3s |
| 622: | learn: 0.1545315 | total: 46.6s | remaining: 28.2s |
| 623: | learn: 0.1545235 | total: 46.7s | remaining: 28.1s |
| 624: | learn: 0.1545153 | total: 46.7s | remaining: 28s   |
| 625: | learn: 0.1544946 | total: 46.8s | remaining: 28s   |
| 626: | learn: 0.1544820 | total: 46.9s | remaining: 27.9s |
| 627: | learn: 0.1544584 | total: 46.9s | remaining: 27.8s |
| 628: | learn: 0.1544468 | total: 47s   | remaining: 27.7s |
| 629: | learn: 0.1544392 | total: 47.1s | remaining: 27.7s |
| 630: | learn: 0.1544167 | total: 47.2s | remaining: 27.6s |
| 631: | learn: 0.1543790 | total: 47.3s | remaining: 27.5s |
| 632: | learn: 0.1543659 | total: 47.3s | remaining: 27.4s |
| 633: | learn: 0.1543579 | total: 47.4s | remaining: 27.4s |
| 634: | learn: 0.1543469 | total: 47.5s | remaining: 27.3s |
| 635: | learn: 0.1543359 | total: 47.5s | remaining: 27.2s |
| 636: | learn: 0.1542795 | total: 47.6s | remaining: 27.1s |
| 637: | learn: 0.1542571 | total: 47.7s | remaining: 27.1s |
| 638: | learn: 0.1542313 | total: 47.7s | remaining: 27s   |
| 639: | learn: 0.1542230 | total: 47.8s | remaining: 26.9s |
| 640: | learn: 0.1542150 | total: 47.9s | remaining: 26.8s |
| 641: | learn: 0.1542061 | total: 48s   | remaining: 26.7s |
| 642: | learn: 0.1541971 | total: 48s   | remaining: 26.7s |
| 643: | learn: 0.1541895 | total: 48.1s | remaining: 26.6s |

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| 644: | learn: 0.1541773 | total: 48.2s | remaining: 26.5s |
| 645: | learn: 0.1541649 | total: 48.3s | remaining: 26.4s |
| 646: | learn: 0.1541526 | total: 48.3s | remaining: 26.4s |
| 647: | learn: 0.1541286 | total: 48.4s | remaining: 26.3s |
| 648: | learn: 0.1541137 | total: 48.5s | remaining: 26.2s |
| 649: | learn: 0.1541048 | total: 48.5s | remaining: 26.1s |
| 650: | learn: 0.1540958 | total: 48.6s | remaining: 26.1s |
| 651: | learn: 0.1540530 | total: 48.7s | remaining: 26s   |
| 652: | learn: 0.1540482 | total: 48.8s | remaining: 25.9s |
| 653: | learn: 0.1540364 | total: 48.9s | remaining: 25.9s |
| 654: | learn: 0.1540235 | total: 49s   | remaining: 25.8s |
| 655: | learn: 0.1540108 | total: 49.1s | remaining: 25.8s |
| 656: | learn: 0.1540010 | total: 49.2s | remaining: 25.7s |
| 657: | learn: 0.1539920 | total: 49.3s | remaining: 25.6s |
| 658: | learn: 0.1539744 | total: 49.4s | remaining: 25.6s |
| 659: | learn: 0.1539668 | total: 49.5s | remaining: 25.5s |
| 660: | learn: 0.1539582 | total: 49.6s | remaining: 25.4s |
| 661: | learn: 0.1539469 | total: 49.6s | remaining: 25.3s |
| 662: | learn: 0.1539384 | total: 49.7s | remaining: 25.3s |
| 663: | learn: 0.1539315 | total: 49.8s | remaining: 25.2s |
| 664: | learn: 0.1539215 | total: 49.8s | remaining: 25.1s |
| 665: | learn: 0.1539075 | total: 49.9s | remaining: 25s   |
| 666: | learn: 0.1538893 | total: 50s   | remaining: 25s   |
| 667: | learn: 0.1538760 | total: 50.1s | remaining: 24.9s |
| 668: | learn: 0.1538693 | total: 50.2s | remaining: 24.8s |
| 669: | learn: 0.1538574 | total: 50.3s | remaining: 24.8s |
| 670: | learn: 0.1538472 | total: 50.4s | remaining: 24.7s |
| 671: | learn: 0.1538388 | total: 50.4s | remaining: 24.6s |
| 672: | learn: 0.1538320 | total: 50.5s | remaining: 24.5s |
| 673: | learn: 0.1538186 | total: 50.6s | remaining: 24.5s |
| 674: | learn: 0.1537906 | total: 50.6s | remaining: 24.4s |
| 675: | learn: 0.1537542 | total: 50.7s | remaining: 24.3s |
| 676: | learn: 0.1537438 | total: 50.8s | remaining: 24.3s |
| 677: | learn: 0.1537379 | total: 50.9s | remaining: 24.2s |
| 678: | learn: 0.1537293 | total: 51s   | remaining: 24.1s |
| 679: | learn: 0.1537208 | total: 51.1s | remaining: 24s   |
| 680: | learn: 0.1537081 | total: 51.2s | remaining: 24s   |
| 681: | learn: 0.1536954 | total: 51.3s | remaining: 23.9s |
| 682: | learn: 0.1536654 | total: 51.4s | remaining: 23.8s |
| 683: | learn: 0.1536555 | total: 51.5s | remaining: 23.8s |
| 684: | learn: 0.1536492 | total: 51.5s | remaining: 23.7s |
| 685: | learn: 0.1536399 | total: 51.6s | remaining: 23.6s |
| 686: | learn: 0.1536277 | total: 51.7s | remaining: 23.5s |
| 687: | learn: 0.1535964 | total: 51.8s | remaining: 23.5s |
| 688: | learn: 0.1535831 | total: 51.8s | remaining: 23.4s |
| 689: | learn: 0.1535603 | total: 51.9s | remaining: 23.3s |
| 690: | learn: 0.1535172 | total: 52s   | remaining: 23.2s |
| 691: | learn: 0.1535022 | total: 52s   | remaining: 23.2s |

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| 692: | learn: 0.1534905 | total: 52.1s | remaining: 23.1s |
| 693: | learn: 0.1534620 | total: 52.2s | remaining: 23s   |
| 694: | learn: 0.1534494 | total: 52.2s | remaining: 22.9s |
| 695: | learn: 0.1534370 | total: 52.3s | remaining: 22.8s |
| 696: | learn: 0.1534268 | total: 52.4s | remaining: 22.8s |
| 697: | learn: 0.1533782 | total: 52.4s | remaining: 22.7s |
| 698: | learn: 0.1533669 | total: 52.5s | remaining: 22.6s |
| 699: | learn: 0.1533556 | total: 52.6s | remaining: 22.5s |
| 700: | learn: 0.1533387 | total: 52.6s | remaining: 22.5s |
| 701: | learn: 0.1533276 | total: 52.7s | remaining: 22.4s |
| 702: | learn: 0.1533126 | total: 52.8s | remaining: 22.3s |
| 703: | learn: 0.1533032 | total: 52.8s | remaining: 22.2s |
| 704: | learn: 0.1532891 | total: 52.9s | remaining: 22.1s |
| 705: | learn: 0.1532768 | total: 53s   | remaining: 22.1s |
| 706: | learn: 0.1532624 | total: 53s   | remaining: 22s   |
| 707: | learn: 0.1532523 | total: 53.1s | remaining: 21.9s |
| 708: | learn: 0.1532420 | total: 53.2s | remaining: 21.8s |
| 709: | learn: 0.1532318 | total: 53.2s | remaining: 21.7s |
| 710: | learn: 0.1532145 | total: 53.3s | remaining: 21.7s |
| 711: | learn: 0.1532053 | total: 53.4s | remaining: 21.6s |
| 712: | learn: 0.1531916 | total: 53.4s | remaining: 21.5s |
| 713: | learn: 0.1531869 | total: 53.5s | remaining: 21.4s |
| 714: | learn: 0.1531779 | total: 53.6s | remaining: 21.4s |
| 715: | learn: 0.1531694 | total: 53.7s | remaining: 21.3s |
| 716: | learn: 0.1531566 | total: 53.8s | remaining: 21.2s |
| 717: | learn: 0.1531374 | total: 53.9s | remaining: 21.2s |
| 718: | learn: 0.1530928 | total: 53.9s | remaining: 21.1s |
| 719: | learn: 0.1530840 | total: 54s   | remaining: 21s   |
| 720: | learn: 0.1530696 | total: 54.1s | remaining: 20.9s |
| 721: | learn: 0.1530566 | total: 54.1s | remaining: 20.8s |
| 722: | learn: 0.1530493 | total: 54.2s | remaining: 20.8s |
| 723: | learn: 0.1530381 | total: 54.3s | remaining: 20.7s |
| 724: | learn: 0.1530277 | total: 54.3s | remaining: 20.6s |
| 725: | learn: 0.1530173 | total: 54.4s | remaining: 20.5s |
| 726: | learn: 0.1530072 | total: 54.5s | remaining: 20.5s |
| 727: | learn: 0.1529946 | total: 54.5s | remaining: 20.4s |
| 728: | learn: 0.1529817 | total: 54.6s | remaining: 20.3s |
| 729: | learn: 0.1529401 | total: 54.7s | remaining: 20.2s |
| 730: | learn: 0.1529296 | total: 54.8s | remaining: 20.1s |
| 731: | learn: 0.1529173 | total: 54.8s | remaining: 20.1s |
| 732: | learn: 0.1528702 | total: 54.9s | remaining: 20s   |
| 733: | learn: 0.1528603 | total: 55s   | remaining: 19.9s |
| 734: | learn: 0.1528424 | total: 55.1s | remaining: 19.9s |
| 735: | learn: 0.1528355 | total: 55.2s | remaining: 19.8s |
| 736: | learn: 0.1528244 | total: 55.3s | remaining: 19.7s |
| 737: | learn: 0.1528144 | total: 55.3s | remaining: 19.6s |
| 738: | learn: 0.1527997 | total: 55.4s | remaining: 19.6s |
| 739: | learn: 0.1527895 | total: 55.5s | remaining: 19.5s |

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| 740: | learn: 0.1527775 | total: 55.5s | remaining: 19.4s |
| 741: | learn: 0.1527577 | total: 55.6s | remaining: 19.3s |
| 742: | learn: 0.1527446 | total: 55.7s | remaining: 19.3s |
| 743: | learn: 0.1527335 | total: 55.8s | remaining: 19.2s |
| 744: | learn: 0.1527257 | total: 55.9s | remaining: 19.1s |
| 745: | learn: 0.1527154 | total: 55.9s | remaining: 19s   |
| 746: | learn: 0.1527052 | total: 56s   | remaining: 19s   |
| 747: | learn: 0.1526971 | total: 56.1s | remaining: 18.9s |
| 748: | learn: 0.1526890 | total: 56.1s | remaining: 18.8s |
| 749: | learn: 0.1526787 | total: 56.2s | remaining: 18.7s |
| 750: | learn: 0.1526659 | total: 56.3s | remaining: 18.7s |
| 751: | learn: 0.1526558 | total: 56.3s | remaining: 18.6s |
| 752: | learn: 0.1526312 | total: 56.4s | remaining: 18.5s |
| 753: | learn: 0.1526184 | total: 56.5s | remaining: 18.4s |
| 754: | learn: 0.1526072 | total: 56.5s | remaining: 18.3s |
| 755: | learn: 0.1525736 | total: 56.6s | remaining: 18.3s |
| 756: | learn: 0.1525577 | total: 56.7s | remaining: 18.2s |
| 757: | learn: 0.1525490 | total: 56.8s | remaining: 18.1s |
| 758: | learn: 0.1525387 | total: 56.8s | remaining: 18s   |
| 759: | learn: 0.1525256 | total: 56.9s | remaining: 18s   |
| 760: | learn: 0.1524989 | total: 57s   | remaining: 17.9s |
| 761: | learn: 0.1524930 | total: 57s   | remaining: 17.8s |
| 762: | learn: 0.1524811 | total: 57.1s | remaining: 17.7s |
| 763: | learn: 0.1524743 | total: 57.2s | remaining: 17.7s |
| 764: | learn: 0.1524669 | total: 57.3s | remaining: 17.6s |
| 765: | learn: 0.1524591 | total: 57.3s | remaining: 17.5s |
| 766: | learn: 0.1524500 | total: 57.4s | remaining: 17.4s |
| 767: | learn: 0.1524374 | total: 57.5s | remaining: 17.4s |
| 768: | learn: 0.1524244 | total: 57.5s | remaining: 17.3s |
| 769: | learn: 0.1524109 | total: 57.6s | remaining: 17.2s |
| 770: | learn: 0.1523855 | total: 57.7s | remaining: 17.1s |
| 771: | learn: 0.1523538 | total: 57.7s | remaining: 17.1s |
| 772: | learn: 0.1523398 | total: 57.8s | remaining: 17s   |
| 773: | learn: 0.1523042 | total: 57.9s | remaining: 16.9s |
| 774: | learn: 0.1522973 | total: 57.9s | remaining: 16.8s |
| 775: | learn: 0.1522895 | total: 58s   | remaining: 16.7s |
| 776: | learn: 0.1522828 | total: 58.1s | remaining: 16.7s |
| 777: | learn: 0.1522722 | total: 58.1s | remaining: 16.6s |
| 778: | learn: 0.1522338 | total: 58.2s | remaining: 16.5s |
| 779: | learn: 0.1522207 | total: 58.3s | remaining: 16.4s |
| 780: | learn: 0.1522105 | total: 58.3s | remaining: 16.4s |
| 781: | learn: 0.1521984 | total: 58.4s | remaining: 16.3s |
| 782: | learn: 0.1521874 | total: 58.5s | remaining: 16.2s |
| 783: | learn: 0.1521745 | total: 58.5s | remaining: 16.1s |
| 784: | learn: 0.1521637 | total: 58.6s | remaining: 16.1s |
| 785: | learn: 0.1521544 | total: 58.7s | remaining: 16s   |
| 786: | learn: 0.1521383 | total: 58.7s | remaining: 15.9s |
| 787: | learn: 0.1521286 | total: 58.8s | remaining: 15.8s |

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| 788: | learn: 0.1521243 | total: 58.9s | remaining: 15.7s |
| 789: | learn: 0.1521132 | total: 58.9s | remaining: 15.7s |
| 790: | learn: 0.1521004 | total: 59s   | remaining: 15.6s |
| 791: | learn: 0.1520907 | total: 59.1s | remaining: 15.5s |
| 792: | learn: 0.1520827 | total: 59.1s | remaining: 15.4s |
| 793: | learn: 0.1520723 | total: 59.2s | remaining: 15.4s |
| 794: | learn: 0.1520606 | total: 59.3s | remaining: 15.3s |
| 795: | learn: 0.1520526 | total: 59.3s | remaining: 15.2s |
| 796: | learn: 0.1520385 | total: 59.4s | remaining: 15.1s |
| 797: | learn: 0.1520220 | total: 59.5s | remaining: 15.1s |
| 798: | learn: 0.1520107 | total: 59.5s | remaining: 15s   |
| 799: | learn: 0.1520013 | total: 59.6s | remaining: 14.9s |
| 800: | learn: 0.1519933 | total: 59.6s | remaining: 14.8s |
| 801: | learn: 0.1519801 | total: 59.7s | remaining: 14.7s |
| 802: | learn: 0.1519724 | total: 59.8s | remaining: 14.7s |
| 803: | learn: 0.1519636 | total: 59.9s | remaining: 14.6s |
| 804: | learn: 0.1519544 | total: 59.9s | remaining: 14.5s |
| 805: | learn: 0.1519171 | total: 1m    | remaining: 14.4s |
| 806: | learn: 0.1519036 | total: 1m    | remaining: 14.4s |
| 807: | learn: 0.1518935 | total: 1m    | remaining: 14.3s |
| 808: | learn: 0.1518816 | total: 1m    | remaining: 14.2s |
| 809: | learn: 0.1518729 | total: 1m    | remaining: 14.1s |
| 810: | learn: 0.1518656 | total: 1m    | remaining: 14.1s |
| 811: | learn: 0.1518519 | total: 1m    | remaining: 14s   |
| 812: | learn: 0.1518444 | total: 1m    | remaining: 13.9s |
| 813: | learn: 0.1518347 | total: 1m    | remaining: 13.8s |
| 814: | learn: 0.1518251 | total: 1m    | remaining: 13.8s |
| 815: | learn: 0.1518189 | total: 1m    | remaining: 13.7s |
| 816: | learn: 0.1518054 | total: 1m    | remaining: 13.6s |
| 817: | learn: 0.1517977 | total: 1m    | remaining: 13.5s |
| 818: | learn: 0.1517845 | total: 1m    | remaining: 13.4s |
| 819: | learn: 0.1517731 | total: 1m    | remaining: 13.4s |
| 820: | learn: 0.1517651 | total: 1m    | remaining: 13.3s |
| 821: | learn: 0.1517610 | total: 1m 1s | remaining: 13.2s |
| 822: | learn: 0.1517499 | total: 1m 1s | remaining: 13.1s |
| 823: | learn: 0.1517359 | total: 1m 1s | remaining: 13.1s |
| 824: | learn: 0.1517248 | total: 1m 1s | remaining: 13s   |
| 825: | learn: 0.1517184 | total: 1m 1s | remaining: 12.9s |
| 826: | learn: 0.1517091 | total: 1m 1s | remaining: 12.8s |
| 827: | learn: 0.1517020 | total: 1m 1s | remaining: 12.8s |
| 828: | learn: 0.1516925 | total: 1m 1s | remaining: 12.7s |
| 829: | learn: 0.1516881 | total: 1m 1s | remaining: 12.6s |
| 830: | learn: 0.1516789 | total: 1m 1s | remaining: 12.5s |
| 831: | learn: 0.1516684 | total: 1m 1s | remaining: 12.4s |
| 832: | learn: 0.1516584 | total: 1m 1s | remaining: 12.4s |
| 833: | learn: 0.1516402 | total: 1m 1s | remaining: 12.3s |
| 834: | learn: 0.1516267 | total: 1m 1s | remaining: 12.2s |
| 835: | learn: 0.1516174 | total: 1m 1s | remaining: 12.1s |

|      |                  |              |                  |
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| 836: | learn: 0.1516073 | total: 1m 1s | remaining: 12.1s |
| 837: | learn: 0.1515934 | total: 1m 2s | remaining: 12s   |
| 838: | learn: 0.1515798 | total: 1m 2s | remaining: 11.9s |
| 839: | learn: 0.1515719 | total: 1m 2s | remaining: 11.8s |
| 840: | learn: 0.1515590 | total: 1m 2s | remaining: 11.8s |
| 841: | learn: 0.1515314 | total: 1m 2s | remaining: 11.7s |
| 842: | learn: 0.1515232 | total: 1m 2s | remaining: 11.6s |
| 843: | learn: 0.1515100 | total: 1m 2s | remaining: 11.5s |
| 844: | learn: 0.1515021 | total: 1m 2s | remaining: 11.5s |
| 845: | learn: 0.1514945 | total: 1m 2s | remaining: 11.4s |
| 846: | learn: 0.1514830 | total: 1m 2s | remaining: 11.3s |
| 847: | learn: 0.1514779 | total: 1m 2s | remaining: 11.3s |
| 848: | learn: 0.1514615 | total: 1m 2s | remaining: 11.2s |
| 849: | learn: 0.1514505 | total: 1m 3s | remaining: 11.1s |
| 850: | learn: 0.1514380 | total: 1m 3s | remaining: 11.1s |
| 851: | learn: 0.1514287 | total: 1m 3s | remaining: 11s   |
| 852: | learn: 0.1514187 | total: 1m 3s | remaining: 10.9s |
| 853: | learn: 0.1514119 | total: 1m 3s | remaining: 10.8s |
| 854: | learn: 0.1514033 | total: 1m 3s | remaining: 10.8s |
| 855: | learn: 0.1513925 | total: 1m 3s | remaining: 10.7s |
| 856: | learn: 0.1513766 | total: 1m 3s | remaining: 10.6s |
| 857: | learn: 0.1513722 | total: 1m 3s | remaining: 10.6s |
| 858: | learn: 0.1513611 | total: 1m 3s | remaining: 10.5s |
| 859: | learn: 0.1513542 | total: 1m 3s | remaining: 10.4s |
| 860: | learn: 0.1513432 | total: 1m 4s | remaining: 10.3s |
| 861: | learn: 0.1513323 | total: 1m 4s | remaining: 10.3s |
| 862: | learn: 0.1513192 | total: 1m 4s | remaining: 10.2s |
| 863: | learn: 0.1513091 | total: 1m 4s | remaining: 10.1s |
| 864: | learn: 0.1512990 | total: 1m 4s | remaining: 10s   |
| 865: | learn: 0.1512891 | total: 1m 4s | remaining: 9.95s |
| 866: | learn: 0.1512772 | total: 1m 4s | remaining: 9.88s |
| 867: | learn: 0.1512672 | total: 1m 4s | remaining: 9.8s  |
| 868: | learn: 0.1512625 | total: 1m 4s | remaining: 9.73s |
| 869: | learn: 0.1512509 | total: 1m 4s | remaining: 9.65s |
| 870: | learn: 0.1512452 | total: 1m 4s | remaining: 9.58s |
| 871: | learn: 0.1512350 | total: 1m 4s | remaining: 9.5s  |
| 872: | learn: 0.1512225 | total: 1m 4s | remaining: 9.43s |
| 873: | learn: 0.1512142 | total: 1m 4s | remaining: 9.35s |
| 874: | learn: 0.1511975 | total: 1m 4s | remaining: 9.27s |
| 875: | learn: 0.1511890 | total: 1m 4s | remaining: 9.2s  |
| 876: | learn: 0.1511372 | total: 1m 5s | remaining: 9.12s |
| 877: | learn: 0.1511117 | total: 1m 5s | remaining: 9.05s |
| 878: | learn: 0.1511009 | total: 1m 5s | remaining: 8.97s |
| 879: | learn: 0.1510925 | total: 1m 5s | remaining: 8.9s  |
| 880: | learn: 0.1510878 | total: 1m 5s | remaining: 8.83s |
| 881: | learn: 0.1510788 | total: 1m 5s | remaining: 8.75s |
| 882: | learn: 0.1510719 | total: 1m 5s | remaining: 8.68s |
| 883: | learn: 0.1510608 | total: 1m 5s | remaining: 8.6s  |

|      |                  |              |                  |
|------|------------------|--------------|------------------|
| 884: | learn: 0.1510498 | total: 1m 5s | remaining: 8.52s |
| 885: | learn: 0.1510402 | total: 1m 5s | remaining: 8.45s |
| 886: | learn: 0.1510285 | total: 1m 5s | remaining: 8.37s |
| 887: | learn: 0.1510205 | total: 1m 5s | remaining: 8.3s  |
| 888: | learn: 0.1510108 | total: 1m 5s | remaining: 8.22s |
| 889: | learn: 0.1510027 | total: 1m 5s | remaining: 8.15s |
| 890: | learn: 0.1509940 | total: 1m 5s | remaining: 8.07s |
| 891: | learn: 0.1509861 | total: 1m 6s | remaining: 8s    |
| 892: | learn: 0.1509691 | total: 1m 6s | remaining: 7.92s |
| 893: | learn: 0.1509635 | total: 1m 6s | remaining: 7.85s |
| 894: | learn: 0.1509526 | total: 1m 6s | remaining: 7.77s |
| 895: | learn: 0.1509413 | total: 1m 6s | remaining: 7.7s  |
| 896: | learn: 0.1509298 | total: 1m 6s | remaining: 7.62s |
| 897: | learn: 0.1509232 | total: 1m 6s | remaining: 7.55s |
| 898: | learn: 0.1509125 | total: 1m 6s | remaining: 7.47s |
| 899: | learn: 0.1509038 | total: 1m 6s | remaining: 7.4s  |
| 900: | learn: 0.1508922 | total: 1m 6s | remaining: 7.32s |
| 901: | learn: 0.1508803 | total: 1m 6s | remaining: 7.25s |
| 902: | learn: 0.1508690 | total: 1m 6s | remaining: 7.17s |
| 903: | learn: 0.1508558 | total: 1m 6s | remaining: 7.1s  |
| 904: | learn: 0.1508392 | total: 1m 6s | remaining: 7.03s |
| 905: | learn: 0.1508303 | total: 1m 6s | remaining: 6.95s |
| 906: | learn: 0.1508194 | total: 1m 7s | remaining: 6.88s |
| 907: | learn: 0.1508080 | total: 1m 7s | remaining: 6.8s  |
| 908: | learn: 0.1507921 | total: 1m 7s | remaining: 6.73s |
| 909: | learn: 0.1507840 | total: 1m 7s | remaining: 6.65s |
| 910: | learn: 0.1507718 | total: 1m 7s | remaining: 6.58s |
| 911: | learn: 0.1507503 | total: 1m 7s | remaining: 6.51s |
| 912: | learn: 0.1507399 | total: 1m 7s | remaining: 6.44s |
| 913: | learn: 0.1507317 | total: 1m 7s | remaining: 6.36s |
| 914: | learn: 0.1507227 | total: 1m 7s | remaining: 6.29s |
| 915: | learn: 0.1507116 | total: 1m 7s | remaining: 6.22s |
| 916: | learn: 0.1507028 | total: 1m 7s | remaining: 6.15s |
| 917: | learn: 0.1506914 | total: 1m 7s | remaining: 6.07s |
| 918: | learn: 0.1506774 | total: 1m 8s | remaining: 6s    |
| 919: | learn: 0.1506646 | total: 1m 8s | remaining: 5.92s |
| 920: | learn: 0.1506568 | total: 1m 8s | remaining: 5.85s |
| 921: | learn: 0.1506449 | total: 1m 8s | remaining: 5.77s |
| 922: | learn: 0.1506360 | total: 1m 8s | remaining: 5.7s  |
| 923: | learn: 0.1506260 | total: 1m 8s | remaining: 5.63s |
| 924: | learn: 0.1506098 | total: 1m 8s | remaining: 5.55s |
| 925: | learn: 0.1505792 | total: 1m 8s | remaining: 5.48s |
| 926: | learn: 0.1505674 | total: 1m 8s | remaining: 5.4s  |
| 927: | learn: 0.1505562 | total: 1m 8s | remaining: 5.33s |
| 928: | learn: 0.1505446 | total: 1m 8s | remaining: 5.26s |
| 929: | learn: 0.1505327 | total: 1m 8s | remaining: 5.18s |
| 930: | learn: 0.1505135 | total: 1m 8s | remaining: 5.11s |
| 931: | learn: 0.1505038 | total: 1m 9s | remaining: 5.04s |

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| 932: | learn: 0.1504902 | total: 1m 9s  | remaining: 4.96s |
| 933: | learn: 0.1504807 | total: 1m 9s  | remaining: 4.89s |
| 934: | learn: 0.1504716 | total: 1m 9s  | remaining: 4.81s |
| 935: | learn: 0.1504643 | total: 1m 9s  | remaining: 4.74s |
| 936: | learn: 0.1504529 | total: 1m 9s  | remaining: 4.67s |
| 937: | learn: 0.1504326 | total: 1m 9s  | remaining: 4.59s |
| 938: | learn: 0.1504210 | total: 1m 9s  | remaining: 4.52s |
| 939: | learn: 0.1504006 | total: 1m 9s  | remaining: 4.44s |
| 940: | learn: 0.1503610 | total: 1m 9s  | remaining: 4.37s |
| 941: | learn: 0.1503527 | total: 1m 9s  | remaining: 4.29s |
| 942: | learn: 0.1503418 | total: 1m 9s  | remaining: 4.22s |
| 943: | learn: 0.1503310 | total: 1m 9s  | remaining: 4.15s |
| 944: | learn: 0.1503223 | total: 1m 10s | remaining: 4.08s |
| 945: | learn: 0.1503183 | total: 1m 10s | remaining: 4s    |
| 946: | learn: 0.1503086 | total: 1m 10s | remaining: 3.93s |
| 947: | learn: 0.1502849 | total: 1m 10s | remaining: 3.86s |
| 948: | learn: 0.1502763 | total: 1m 10s | remaining: 3.79s |
| 949: | learn: 0.1502628 | total: 1m 10s | remaining: 3.71s |
| 950: | learn: 0.1502497 | total: 1m 10s | remaining: 3.64s |
| 951: | learn: 0.1502372 | total: 1m 10s | remaining: 3.57s |
| 952: | learn: 0.1502266 | total: 1m 10s | remaining: 3.49s |
| 953: | learn: 0.1502164 | total: 1m 10s | remaining: 3.42s |
| 954: | learn: 0.1502015 | total: 1m 11s | remaining: 3.35s |
| 955: | learn: 0.1501943 | total: 1m 11s | remaining: 3.27s |
| 956: | learn: 0.1501870 | total: 1m 11s | remaining: 3.2s  |
| 957: | learn: 0.1501802 | total: 1m 11s | remaining: 3.13s |
| 958: | learn: 0.1501532 | total: 1m 11s | remaining: 3.05s |
| 959: | learn: 0.1501396 | total: 1m 11s | remaining: 2.98s |
| 960: | learn: 0.1501290 | total: 1m 11s | remaining: 2.9s  |
| 961: | learn: 0.1501227 | total: 1m 11s | remaining: 2.83s |
| 962: | learn: 0.1501147 | total: 1m 11s | remaining: 2.76s |
| 963: | learn: 0.1501054 | total: 1m 11s | remaining: 2.68s |
| 964: | learn: 0.1500759 | total: 1m 11s | remaining: 2.61s |
| 965: | learn: 0.1500610 | total: 1m 11s | remaining: 2.53s |
| 966: | learn: 0.1500463 | total: 1m 12s | remaining: 2.46s |
| 967: | learn: 0.1500412 | total: 1m 12s | remaining: 2.38s |
| 968: | learn: 0.1500359 | total: 1m 12s | remaining: 2.31s |
| 969: | learn: 0.1500252 | total: 1m 12s | remaining: 2.23s |
| 970: | learn: 0.1500182 | total: 1m 12s | remaining: 2.16s |
| 971: | learn: 0.1499856 | total: 1m 12s | remaining: 2.09s |
| 972: | learn: 0.1499705 | total: 1m 12s | remaining: 2.01s |
| 973: | learn: 0.1499609 | total: 1m 12s | remaining: 1.94s |
| 974: | learn: 0.1499456 | total: 1m 12s | remaining: 1.86s |
| 975: | learn: 0.1499346 | total: 1m 12s | remaining: 1.79s |
| 976: | learn: 0.1499232 | total: 1m 12s | remaining: 1.72s |
| 977: | learn: 0.1499112 | total: 1m 13s | remaining: 1.64s |
| 978: | learn: 0.1498996 | total: 1m 13s | remaining: 1.57s |
| 979: | learn: 0.1498887 | total: 1m 13s | remaining: 1.49s |



|      |                  |               |                   |
|------|------------------|---------------|-------------------|
| 980: | learn: 0.1498834 | total: 1m 13s | remaining: 1.42s  |
| 981: | learn: 0.1498647 | total: 1m 13s | remaining: 1.34s  |
| 982: | learn: 0.1498589 | total: 1m 13s | remaining: 1.27s  |
| 983: | learn: 0.1498539 | total: 1m 13s | remaining: 1.2s   |
| 984: | learn: 0.1498494 | total: 1m 13s | remaining: 1.12s  |
| 985: | learn: 0.1498440 | total: 1m 13s | remaining: 1.05s  |
| 986: | learn: 0.1498383 | total: 1m 13s | remaining: 971ms  |
| 987: | learn: 0.1498307 | total: 1m 13s | remaining: 896ms  |
| 988: | learn: 0.1498205 | total: 1m 13s | remaining: 822ms  |
| 989: | learn: 0.1498128 | total: 1m 13s | remaining: 747ms  |
| 990: | learn: 0.1498045 | total: 1m 14s | remaining: 672ms  |
| 991: | learn: 0.1497923 | total: 1m 14s | remaining: 598ms  |
| 992: | learn: 0.1497797 | total: 1m 14s | remaining: 523ms  |
| 993: | learn: 0.1497748 | total: 1m 14s | remaining: 448ms  |
| 994: | learn: 0.1497670 | total: 1m 14s | remaining: 373ms  |
| 995: | learn: 0.1497595 | total: 1m 14s | remaining: 299ms  |
| 996: | learn: 0.1497481 | total: 1m 14s | remaining: 224ms  |
| 997: | learn: 0.1497324 | total: 1m 14s | remaining: 149ms  |
| 998: | learn: 0.1497226 | total: 1m 14s | remaining: 74.7ms |
| 999: | learn: 0.1497028 | total: 1m 14s | remaining: 0us    |

Out [57]: <catboost.core.CatBoostClassifier at 0x2ab8ce14860>

In [58]: Model\_Performance(baseline\_catboost,"Catboost Engine")

## Catboost Engine Performance Outline

### Training Results

Accuracy Score: 0.9303098526565817

Balanced Accuracy Score: 0.9303120626393908

Cohen Kappa Score: 0.8606203212264419

Roc Score: 0.9829784681444549

Confusion Matrix:

```
[[232895  1176]
```

```
[ 31450 202637]]
```

Classification Report:

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.88      | 0.99   | 0.93     | 234071  |
| 1            | 0.99      | 0.87   | 0.93     | 234087  |
| accuracy     |           |        | 0.93     | 468158  |
| macro avg    | 0.94      | 0.93   | 0.93     | 468158  |
| weighted avg | 0.94      | 0.93   | 0.93     | 468158  |

## Testing Results

Accuracy Score: 0.9266397527910686

Balanced Accuracy Score: 0.9266345969715704

Cohen Kappa Score: 0.853277991841622

Roc Score: 0.9792018529808397

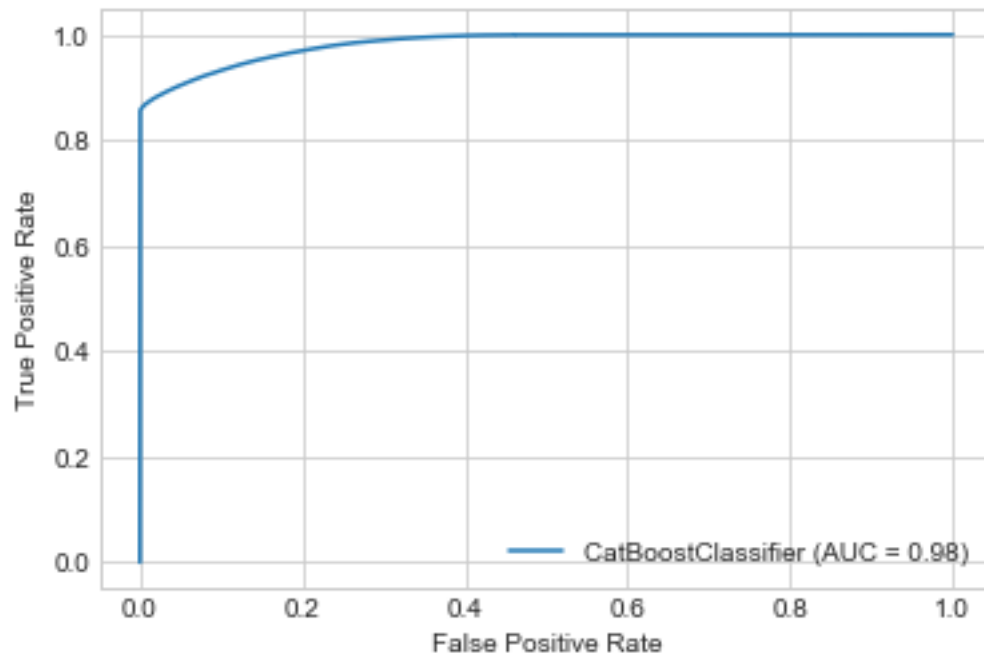
Confusion Matrix:

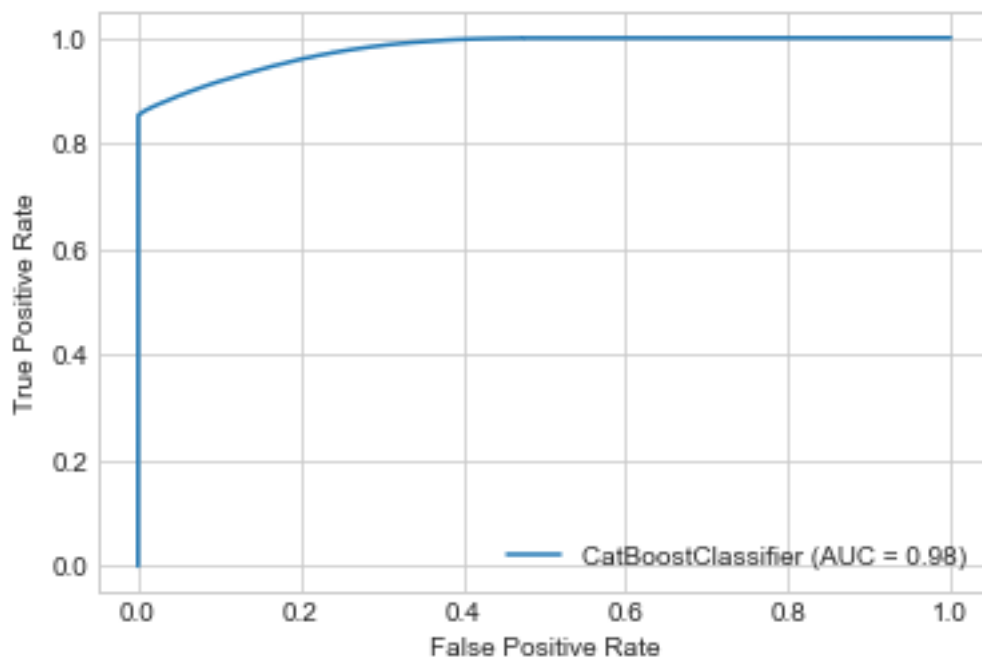
```
[[99454  874]
```

```
[13845 86467]]
```

Classification Report

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.88      | 0.99   | 0.93     | 100328  |
| 1            | 0.99      | 0.86   | 0.92     | 100312  |
| accuracy     |           |        | 0.93     | 200640  |
| macro avg    | 0.93      | 0.93   | 0.93     | 200640  |
| weighted avg | 0.93      | 0.93   | 0.93     | 200640  |





In [59]: # Lets Create Baseline Xgboost

```
baseline_Xgboost = XGBClassifier()
baseline_Xgboost.fit(X_train,y_train)
Model_Performance(baseline_Xgboost,"XGboost Engine")
```

XGboost Engine Performance Outline

Training Results

Accuracy Score: 0.8655005361437805

Balanced Accuracy Score: 0.8654983525682213

Cohen Kappa Score: 0.7309998972937818

Roc Score: 0.9588602471430142

Confusion Matrix:

```
[[187633  46438]
```

```
[ 16529 217558]]
```

Classification Report:

|           | precision | recall | f1-score | support |
|-----------|-----------|--------|----------|---------|
| 0         | 0.92      | 0.80   | 0.86     | 234071  |
| 1         | 0.82      | 0.93   | 0.87     | 234087  |
| accuracy  |           |        | 0.87     | 468158  |
| macro avg | 0.87      | 0.87   | 0.86     | 468158  |

|              |      |      |      |        |
|--------------|------|------|------|--------|
| weighted avg | 0.87 | 0.87 | 0.86 | 468158 |
|--------------|------|------|------|--------|

### Testing Results

Accuracy Score: 0.8649272328548644

Balanced Accuracy Score: 0.8649324143756401

Cohen Kappa Score: 0.7298572639562915

Roc Score: 0.9589183831606062

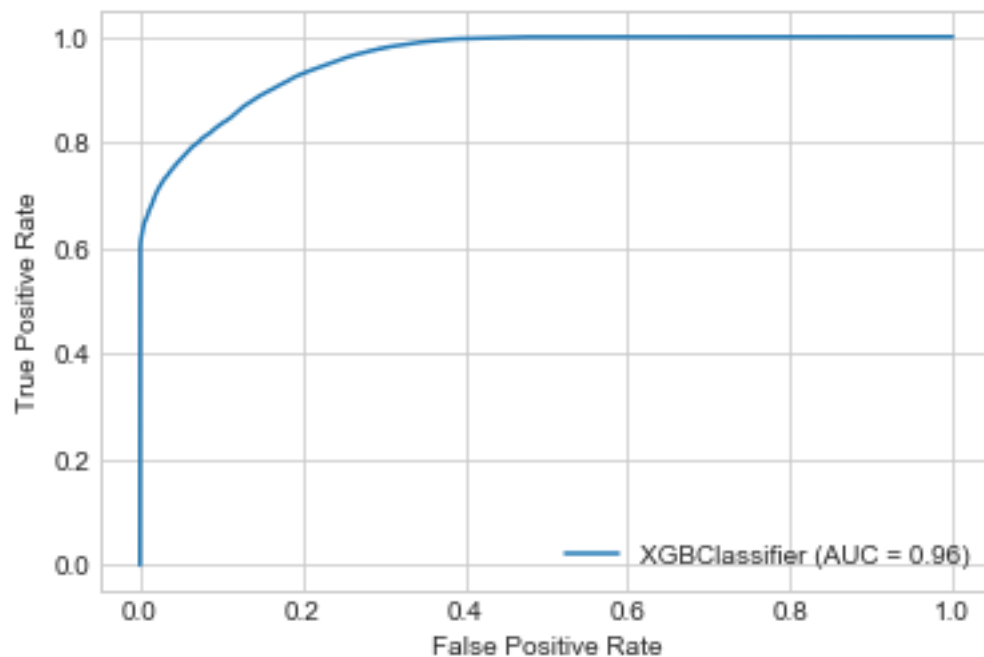
Confusion Matrix:

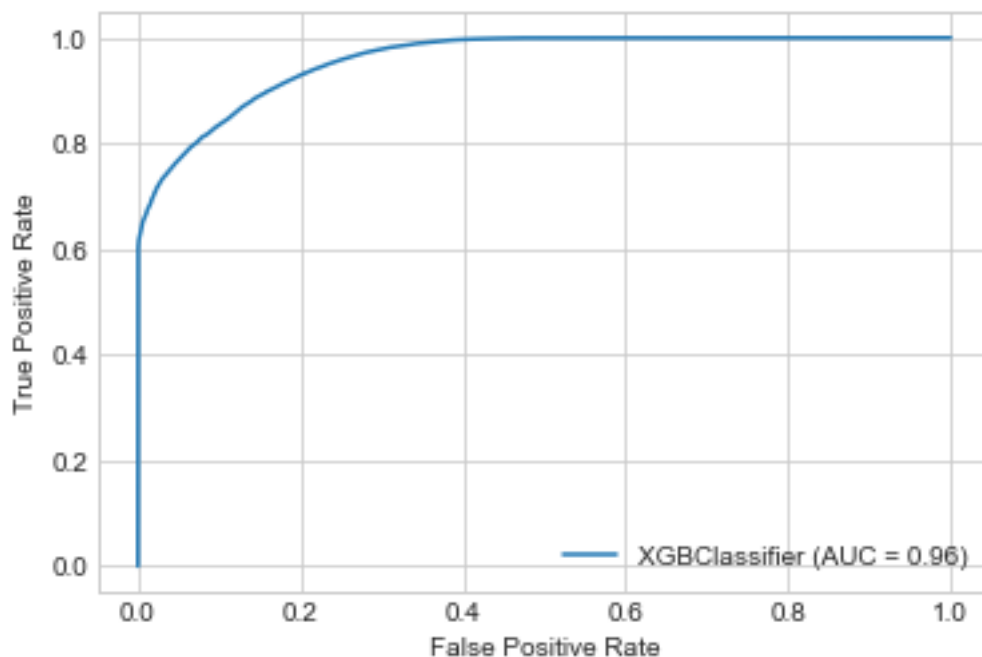
```
[[80258 20070]
```

```
[ 7031 93281]]
```

Classification Report

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.92      | 0.80   | 0.86     | 100328  |
| 1            | 0.82      | 0.93   | 0.87     | 100312  |
| accuracy     |           |        | 0.86     | 200640  |
| macro avg    | 0.87      | 0.86   | 0.86     | 200640  |
| weighted avg | 0.87      | 0.86   | 0.86     | 200640  |





In [14]: # Lets Create adaboost Engine

```
baseline_adaboost = AdaBoostClassifier()
baseline_adaboost.fit(X_train,y_train)
Model_Performance(baseline_adaboost,"AdaBoost Engine")
```

AdaBoost Engine Performance Outline

Training Results

Accuracy Score: 0.8754523045638438

Balanced Accuracy Score: 0.8754511407656131

Cohen Kappa Score: 0.7509040291143105

Roc Score: 0.9639459338362951

Confusion Matrix:

```
[[196947  37124]
```

```
[ 21184 212903]]
```

Classification Report:

|           | precision | recall | f1-score | support |
|-----------|-----------|--------|----------|---------|
| 0         | 0.90      | 0.84   | 0.87     | 234071  |
| 1         | 0.85      | 0.91   | 0.88     | 234087  |
| accuracy  |           |        | 0.88     | 468158  |
| macro avg | 0.88      | 0.88   | 0.88     | 468158  |

|              |      |      |      |        |
|--------------|------|------|------|--------|
| weighted avg | 0.88 | 0.88 | 0.88 | 468158 |
|--------------|------|------|------|--------|

### Testing Results

Accuracy Score: 0.8754734848484849

Balanced Accuracy Score: 0.8754762618502849

Cohen Kappa Score: 0.7509483517413785

Roc Score: 0.9643567189577512

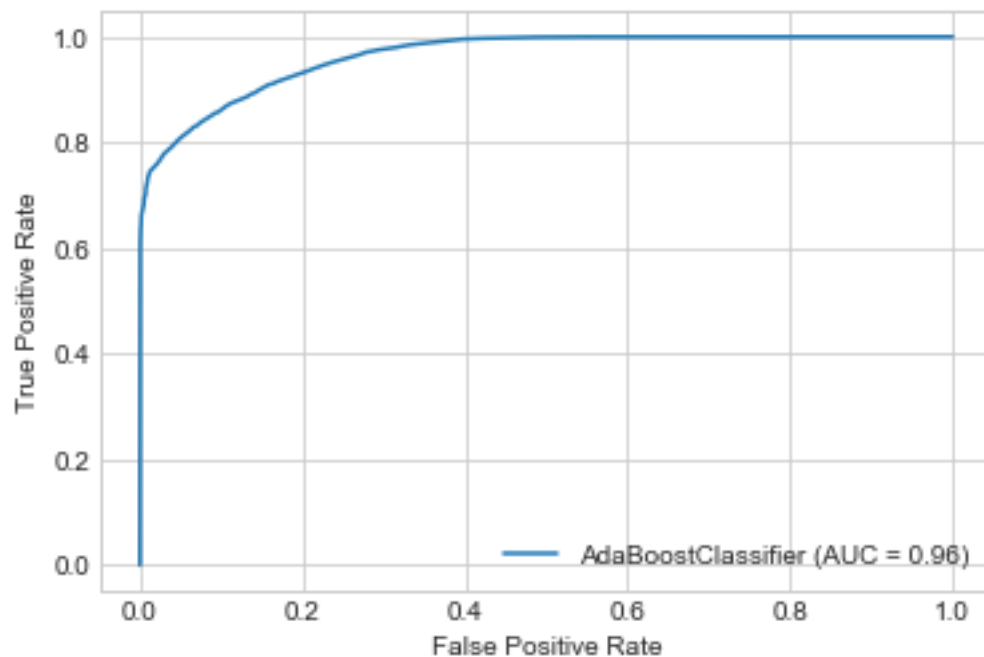
Confusion Matrix:

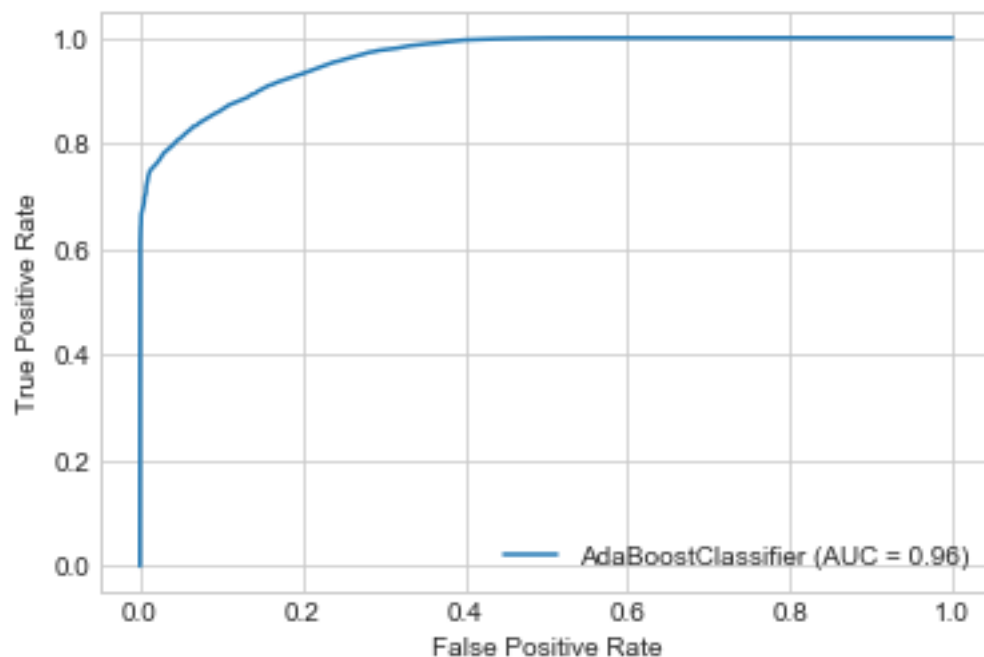
```
[[84341 15987]
```

```
[ 8998 91314]]
```

Classification Report

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.90      | 0.84   | 0.87     | 100328  |
| 1            | 0.85      | 0.91   | 0.88     | 100312  |
| accuracy     |           |        | 0.88     | 200640  |
| macro avg    | 0.88      | 0.88   | 0.88     | 200640  |
| weighted avg | 0.88      | 0.88   | 0.88     | 200640  |





```
In [60]: # lets create bagging classifier
baseline_bagging = BaggingClassifier(n_estimators=100)
baseline_bagging.fit(X_train,y_train)
Model_Performance(baseline_bagging,"Bagging Engine")
```

### Bagging Engine Performance Outline

#### Training Results

Accuracy Score: 0.9999081506670825  
 Balanced Accuracy Score: 0.9999081516160019  
 Cohen Kappa Score: 0.9998163013342991  
 Roc Score: 0.9999999582245741

Confusion Matrix:

```
[[234056    15]
 [    28 234059]]
```

Classification Report:

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 1.00      | 1.00   | 1.00     | 234071  |
| 1            | 1.00      | 1.00   | 1.00     | 234087  |
| accuracy     |           |        | 1.00     | 468158  |
| macro avg    | 1.00      | 1.00   | 1.00     | 468158  |
| weighted avg | 1.00      | 1.00   | 1.00     | 468158  |

## Testing Results

Accuracy Score: 0.9173245614035088

Balanced Accuracy Score: 0.9173224376878991

Cohen Kappa Score: 0.8346484196099156

Roc Score: 0.9759758738605895

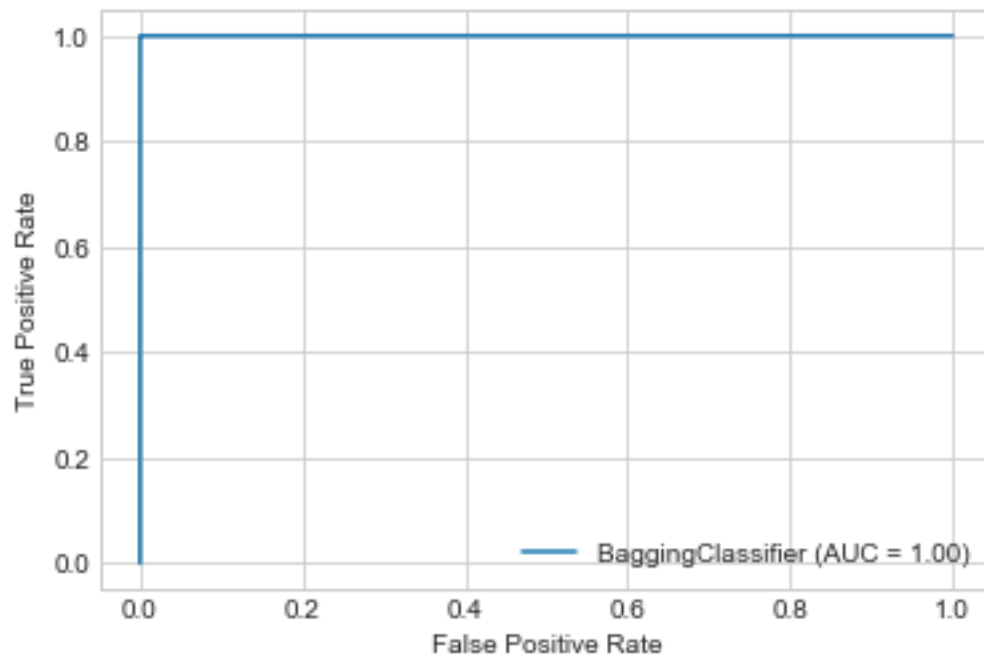
Confusion Matrix:

```
[[94705  5623]
```

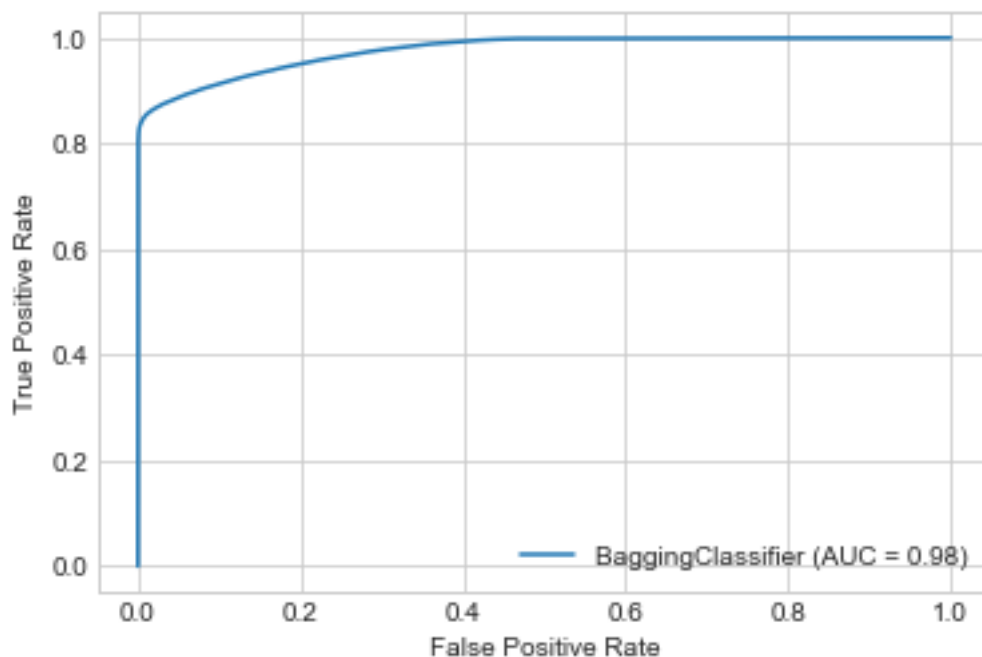
```
[10965 89347]]
```

Classification Report

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.90      | 0.94   | 0.92     | 100328  |
| 1            | 0.94      | 0.89   | 0.92     | 100312  |
| accuracy     |           |        | 0.92     | 200640  |
| macro avg    | 0.92      | 0.92   | 0.92     | 200640  |
| weighted avg | 0.92      | 0.92   | 0.92     | 200640  |







In [17]: # lets create baseline gradient boosting

```
baseline_gradient = GradientBoostingClassifier()
baseline_gradient.fit(X_train,y_train)
Model_Performance(baseline_gradient,"Gradient Boosting Engine")
```

Gradient Boosting Engine Performance Outline

Training Results

Accuracy Score: 0.8886871526279589

Balanced Accuracy Score: 0.8886869162632922

Cohen Kappa Score: 0.7773741998120279

Roc Score: 0.9689089957750263

Confusion Matrix:

```
[[206397 27674]
```

```
[ 24438 209649]]
```

Classification Report:

|           | precision | recall | f1-score | support |
|-----------|-----------|--------|----------|---------|
| 0         | 0.89      | 0.88   | 0.89     | 234071  |
| 1         | 0.88      | 0.90   | 0.89     | 234087  |
| accuracy  |           |        | 0.89     | 468158  |
| macro avg | 0.89      | 0.89   | 0.89     | 468158  |

|              |      |      |      |        |
|--------------|------|------|------|--------|
| weighted avg | 0.89 | 0.89 | 0.89 | 468158 |
|--------------|------|------|------|--------|

### Testing Results

Accuracy Score: 0.8883522727272727

Balanced Accuracy Score: 0.8883528646185659

Cohen Kappa Score: 0.7767048086845927

Roc Score: 0.9687916135474399

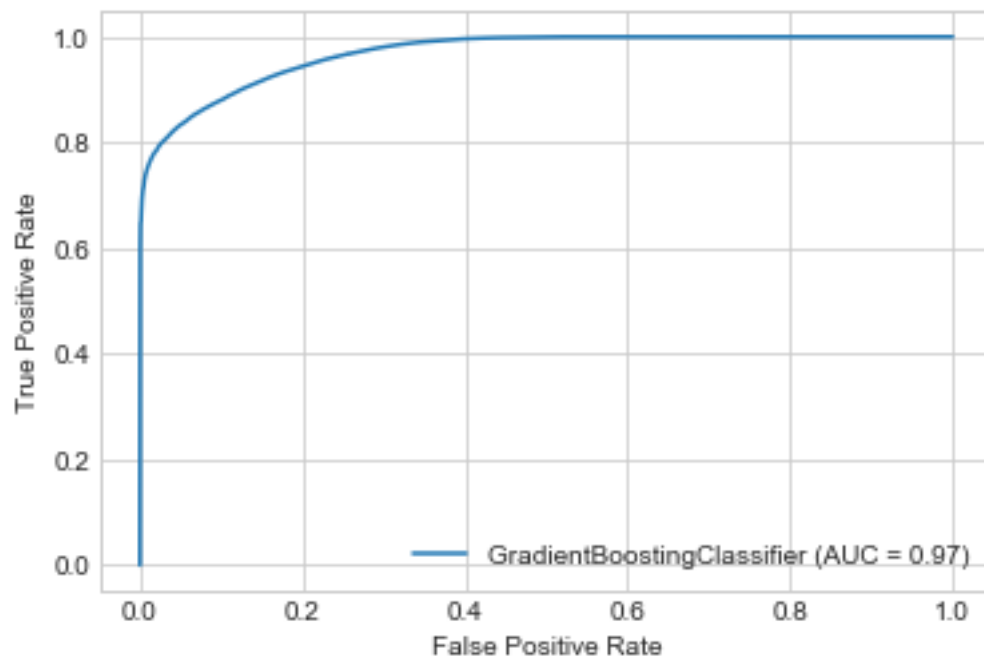
Confusion Matrix:

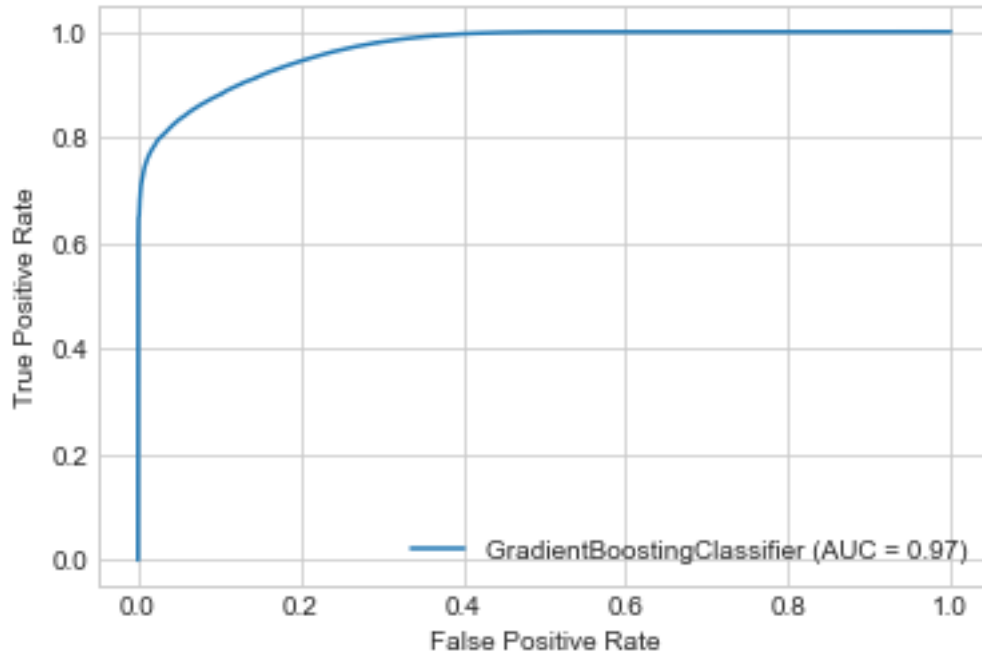
```
[[88382 11946]
```

```
[10455 89857]]
```

Classification Report

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.89      | 0.88   | 0.89     | 100328  |
| 1            | 0.88      | 0.90   | 0.89     | 100312  |
| accuracy     |           |        | 0.89     | 200640  |
| macro avg    | 0.89      | 0.89   | 0.89     | 200640  |
| weighted avg | 0.89      | 0.89   | 0.89     | 200640  |





```
In [21]: # Lets create a stochastic gradient descent engine with kernel approximation
Sampler =
baseline_sgd = SGDClassifier(loss='hinge',n_jobs=-1)
baseline_sgd.fit(X_train,y_train)
```

```
Out[21]: SGDClassifier(n_jobs=-1)
```

```
In [23]: print(baseline_sgd.score(X_train,y_train))
print(baseline_sgd.score(X_test,y_test))
```

```
0.540975482636204
0.5404954146730463
```

```
In [24]: baseline_sgd.coef_
```

```
Out[24]: array([[ -1.48345161e+00,  1.73247997e+02,  5.10255873e+03,
                  5.51444368e+01,  1.13874819e+03, -1.15700932e+03,
                 -2.53962057e+02,  1.25225847e+03,  2.60110169e+00,
                 -2.19695586e+03,  1.88504387e+01]])
```

```
In [25]: baseline_sgd.intercept_
```

```
Out[25]: array([40.45447831])
```

```
In [50]: # Deploying Random Forest Baseline
jb.dump(baseline_random_forest,"BaselineRandomForestEngine.sav")
```

```
Out[50]: ['BaselineRandomForestEngine.sav']
```

- Baseline Random Forest is Saved

```
In [56]: # Just for Check
baseline_random_forest.predict([[1, 44, 1, 28.0,
                                0, 2, 1, 40454.0, 26.0,
                                217]])
```

```
Out[56]: array([1], dtype=int64)
```

```
In [61]: # Deploying Baseline Bagging
jb.dump(baseline_bagging, "BaselineBaggingEngine.sav")
```

```
Out[61]: ['BaselineBaggingEngine.sav']
```

- Baseline Bagging Engine is Saved

```
In [62]: # Deploying catboost model also

jb.dump(baseline_catboost, "Catboost Engine.sav")
```

```
Out[62]: ['Catboost Engine.sav']
```

- Baseline catboost is deployed

### 1.3 Model Tuning

- Note: Model Tuning is not required because we have an optimal accuracy and the resulting Tuning can decrease the performance
- Lets jump to model evaluation

### 1.4 Model Evaluation

```
In [16]: model_evaluated = cross_val_score(RandomForestClassifier(n_estimators=100), X, y, cv=10)
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
```

```
[Parallel(n_jobs=-1)]: Done 7 out of 10 | elapsed: 6.6min remaining: 2.8min
```

```
[Parallel(n_jobs=-1)]: Done 10 out of 10 | elapsed: 8.9min finished
```

```
In [21]: print(f"The Average Cross validated Accuracy for a Random Forest model is: {model_evaluated.mean()}")
print(f"The Standard Deviation is:{model_evaluated.std()}")
```

```
The Average Cross validated Accuracy for a Random Forest model is: 90.98%
The Standard Deviation is:0.119055220858802
```

```
In [ ]:
```