A Classification Problem: Health Insurance Cross Sell Prediction

University of San Diego

Master of Science, Applied Data Science

By: Minsu Kim, Connie Chow, and Abanather Negusu

October 2022

Author Note

We have no conflicts of interest to disclose.

Correspondence concerning this paper should be addressed to

Table of Contents

Introduction

The Vehicle Insurance market commands a value of $628B currently and is expected to increase to $1.2T by 2030 due to increase in global automobile production and sales. With the growing global population, a demand in growth for passenger and commercial vehicles is expected to increase over the next decade, in addition to self-driving cars as well. The number of traffic incidents is expected to grow proportionately as well. Having the ability to predict which customers are likely to signup for vehicle insurance within healthcare insurer businesses and other organizations is crucial to the ability to offer low-cost, affordable insurance to the masses.

Identification and Motivation

The purpose of this study is to assist our client company, a healthcare insurance company, with predicting which of its customers has a high probability of signing up for vehicle insurance well cross-sold to. The problem for this project can be framed as: Are there data mining prediction models that can be employed to accurately predict which customers are most likely to sign up for vehicle insurance when offered? Beyond predicting which customers would buy vehicle insurance, uncovering the characteristics of such customers will contribute to further product developments that can help the company to develop and offer low-cost and affordable future products to their customer base.

Method

The study followed a structured data research process, including exploratory data analysis, modeling, and evaluation, beginning with data acquisition, preparation, mining, and representation as described in this section.

Data Source and Collection

The values of the dataset represent each customer of the healthcare insurance company and whom were customers with the company since the past year. The dataset itself is hosted on Kaggle for the public. The training dataset contains 12 columns and 381,110 rows and the test dataset contains 13 columns and 127,038 rows. Each row represents a customer's information. Each column represents a different feature. These features can be divided into three categories: intrinsic characteristics (ie Age, Gender, Geographic Location), insurance plan (ie Sales Channel, Duration as Customer). The target column consists of the customer's "Response" to the cross-selling offer for vehicle insurance – 0 meaning rejected and 1 meaning accepted the offer and signed up. The dataset consists of both categorical and numerical variables.

Missing Values and Outliers

There were no missing values in this dataset. Boxplots were used to quickly detect any outliers and winsorize used to handle them. The top and bottom 3% and 1% respectively were replaced with the top and bottom values at the 3rd and 1st percentile. The extreme values should be kept but not treated so literally. Columns include 'Annual_Premium', 'Policy_Sales_Channel', and 'Vintage'.

Exploratory Data Analysis

Univariate Analysis

Overall, the study's exploratory data analysis process included univariate and multivariate feature exploration and selection to support the problem statement and our hypothesis. Throughout this process, interesting findings across prospective model features help

to inform best feature engineering and selection. For example, the following figure 1 visualizes the relationship between target “Response” and likely feature “Age”.

Figure 1

Age Predictor And Target Class

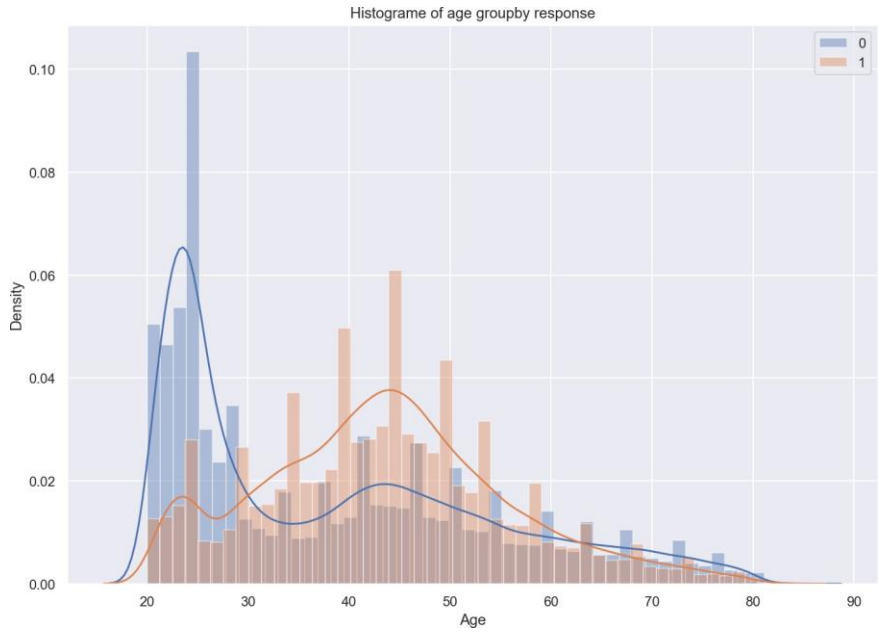


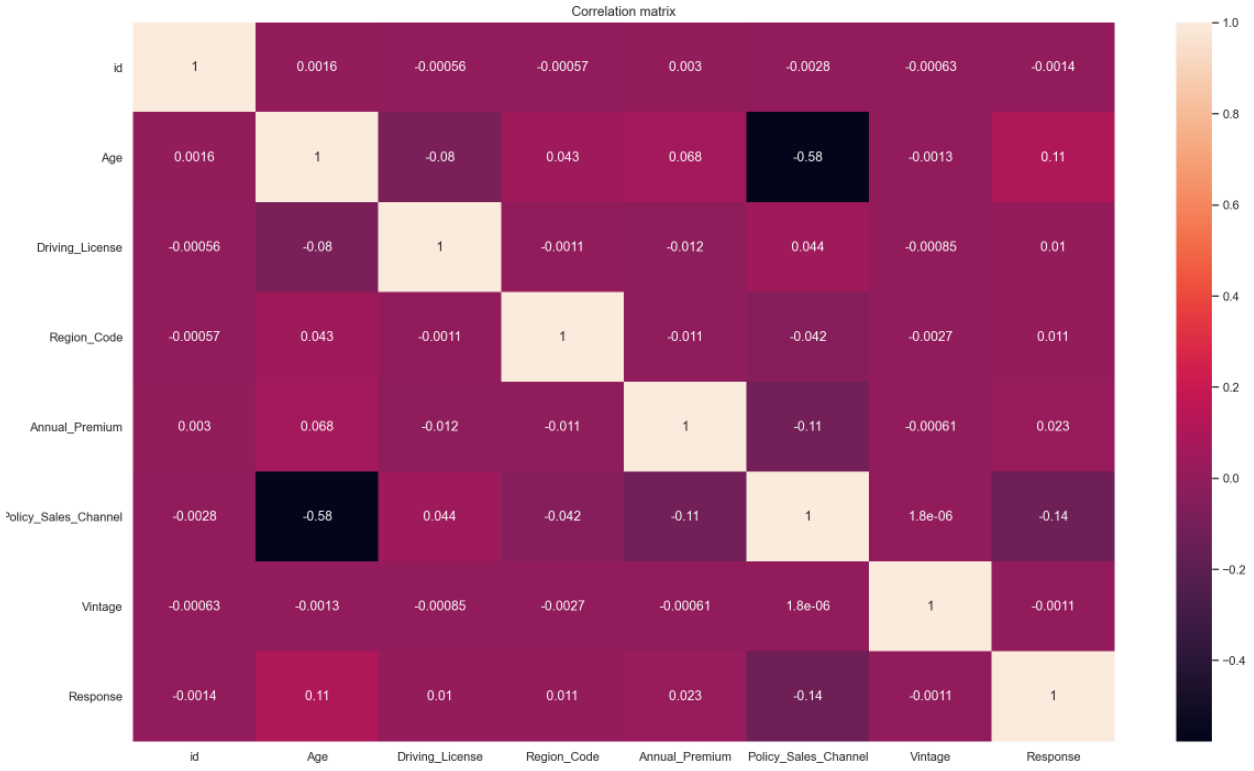
Figure 1 shows that customers among more middle age groups (35-55) are more likely to sign up for the vehicle insurance. Interestingly, the majority of customers fall within the age 20-30 range yet have the highest rate of rejecting the vehicle insurance offer. Despite this, the response rate among all the customers shows a normal distribution, maybe slightly skewed towards the younger age groups. Normal distributions are important in statistics data, normal distribution, also known as the Gaussian distribution, is a probability distribution that is symmetric about the mean, showing that data near the mean are more frequent in occurrence than data far from the mean.

Multivariate Analysis

Following univariate analysis , the study examined collinearity across all the variables as shown in the heatmap in Figure 2. It did not indicate any multicollinearity issues among predictors, as no high correlations (0.75+) were detected.

Figure 2

Correlation Matrix



Feature engineering

'Vehicle_Age', a categorical feature, was binned by numeric values 1, 2, and 3. Numeric features 'Age', 'Region_Code', 'Annual_Premium', 'Policy_Sales_Channel', and 'Vintage' are numeric values and were scaled. Features containing outliers had these data points eliminated, these include 'Annual_Premium' and 'Policy_Sales_Channel'.

Feature Selection

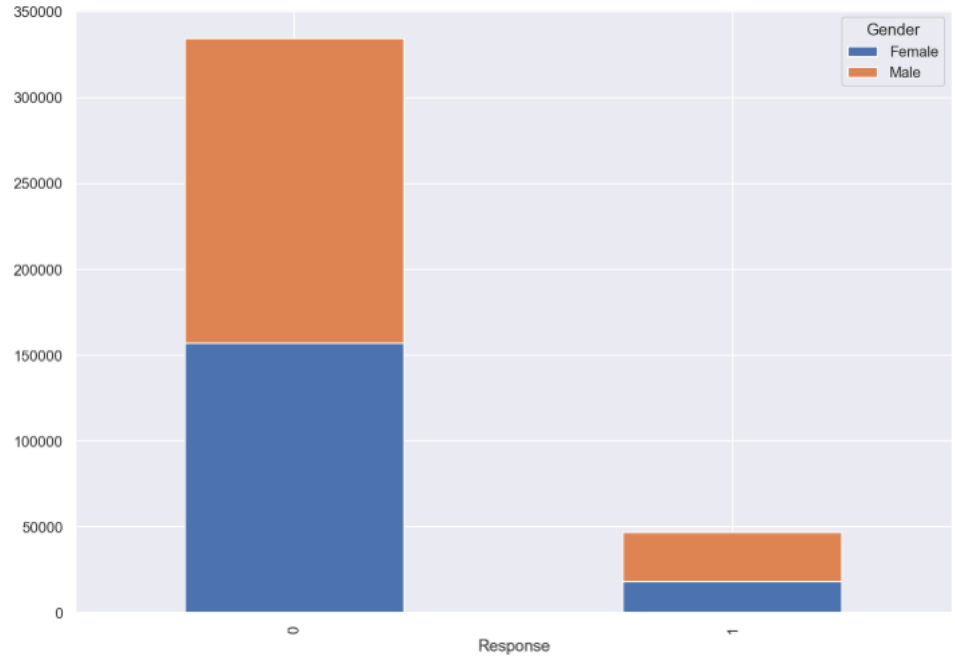
Correlation to the target showed high correlation of 'Vehicle_Damage', 'Age', 'Annual_Premium' and 'Region_Code' to 'Response'. With a cutoff of 0.4, no pairs of variables were found to be highly correlated to each other. 'Driving_License' column contained more than 95% value of 1, hence not containing useful information for model learning, this column and 'id' were dropped. Both Random Forest's feature importances and Recursive Feature Elimination (RFE) yielded the same set of features. RFE method starts with the full set of features and eliminates one by one until the set number is reached containing the highest performance measures. The only difference with correlation is that RFE and Random Forest found 'Previously_Insured' and 'Policy_Sales_Channel' to show strong predictive power for 'Response' variable. Hence we incorporated all of these into the feature selection set for Random Forest Classifier.

Modeling

We tried to use various types of models, i.e. tree-based, linear, non-linear, etc,.. Ultimately, the models chosen to be utilized were Stochastic Gradient Descent (SGD), Decision Tree, Ada Boost, Multi-Layer Perceptron (MLP), Random Forest and Logistic Regression. We started off by setting the 'Response' column as the target variable y, and the remaining columns except for member ID's as predictor variables X. As shown in Figure 3, there is a major class imbalance between the two response groups, with 0 representing no and 1 representing yes to insurance sale. The class imbalance issue was addressed using the Synthetic Minority Oversampling Technique, or SMOTE for short.

Figure 3

Check Imbalance in Response

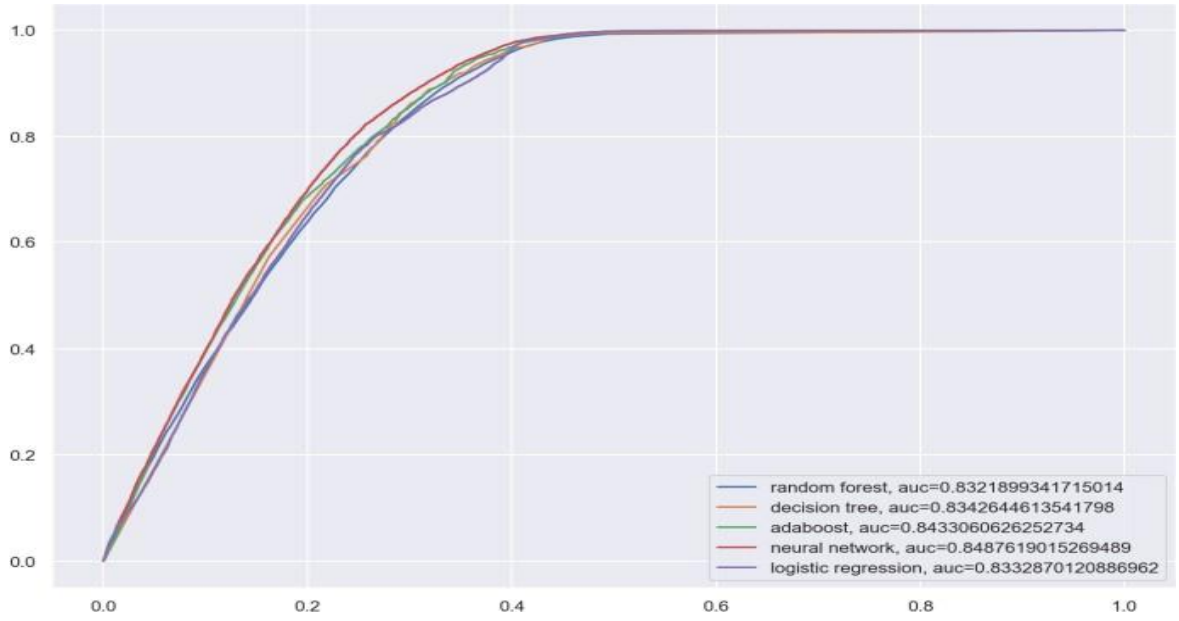


Each of the models was constructed using GridSearch which helped finding the best parameters. SGD's best parameters were maximum iteration of 1,000 with l2 penalty. Logistic regression model's best parameters were C value of 0.1, using liblinear solver with l2 penalty as well. Random forest had the best parameters of gini index and 100 estimators. Decision tree's best parameter was to use entropy index with maximum depth of 11, and ada boost's was 50 estimators. Lastly, MLP's best parameter was with tanh activation, 4 hidden layers, and 200 maximum iterations with adam solver.

The graph of ROC curves in Figure 4 represent AUC for all models. ROC curve illustrates performance measurement for the classification problems at various threshold settings. The 5 models demonstrate decent AUC values between 0.82 and 0.85.

Figure 4

Plot of Each Model's ROC Curve



Validation

After creating hyper tuning parameters within the models we can see in table 1 that random forest came out to have the highest score introducing at 91 percent. As the others came close to about the lower 80 percent range. Again this can be seen in table 1. In addition the Roc curve demonstrates how close in percentage all the models are. As close as they're we need to discuss that logistic regression had a very low score of 63 percent. From a modeling accuracy point Random Forest is the model that has produced the best results. However, now we will test just exactly how strong the models are running by inserting our models into the Fscore and confusion matrix to decide which model to go with.

We had used various methods to testing and validating model performance the first immediate metric we implemented is using e F1 score, which is calculated by :2*((precision*recall)/(precision+recall)). It is also called the F Score or the F Measure. Put another way, the F1 score conveys the balance between the precision and the recall (Brownlee, 2019), and is the best used in classification problems. As in table 1 we can see that the f1 high score percentage is the random forest coming in at 83 percent. This 83 percent represents the strength of the model of the random forest that has been previously. 83 percent is a very good score to have. Our two lowest scores came in at a tie were the linear model and logistic regression model at the percentage of 69 percent. Following the F1 score we wanted to test it again using a confusion matrix and see if there is some change there.

Table1

Accuracy of model on validation set

```
#Evaluate f1 score each model on validation dataset
from sklearn.metrics import f1_score

print("F1 score of random forest model is: ", f1_score(y_val, forest_pred, average='weighted'))
print("F1 score of linear model is: ", f1_score(y_val, linear_classifier_pred, average='weighted'))
print("F1 score of decision tree model is: ", f1_score(y_val, decisiontree_classifier_pred, average='weighted'))
print("F1 score of adaboost model is: ", f1_score(y_val, ada_pred, average='weighted'))
print("F1 score of Neural network model is: ", f1_score(y_val, nn_pred, average='weighted'))
print("F1 score of Logistic Regression model is: ", f1_score(y_val, log_pred, average='weighted'))
```

```
F1 score of random forest model is:  0.8384743930962543
F1 score of linear model is:  0.6990151795874153
F1 score of decision tree model is:  0.7827333454731527
F1 score of adaboost model is:  0.7640040282016075
F1 score of Neural network model is:  0.7477511390129322
F1 score of Logistic Regression model is:  0.6988456998788372
```

Confusion matrix

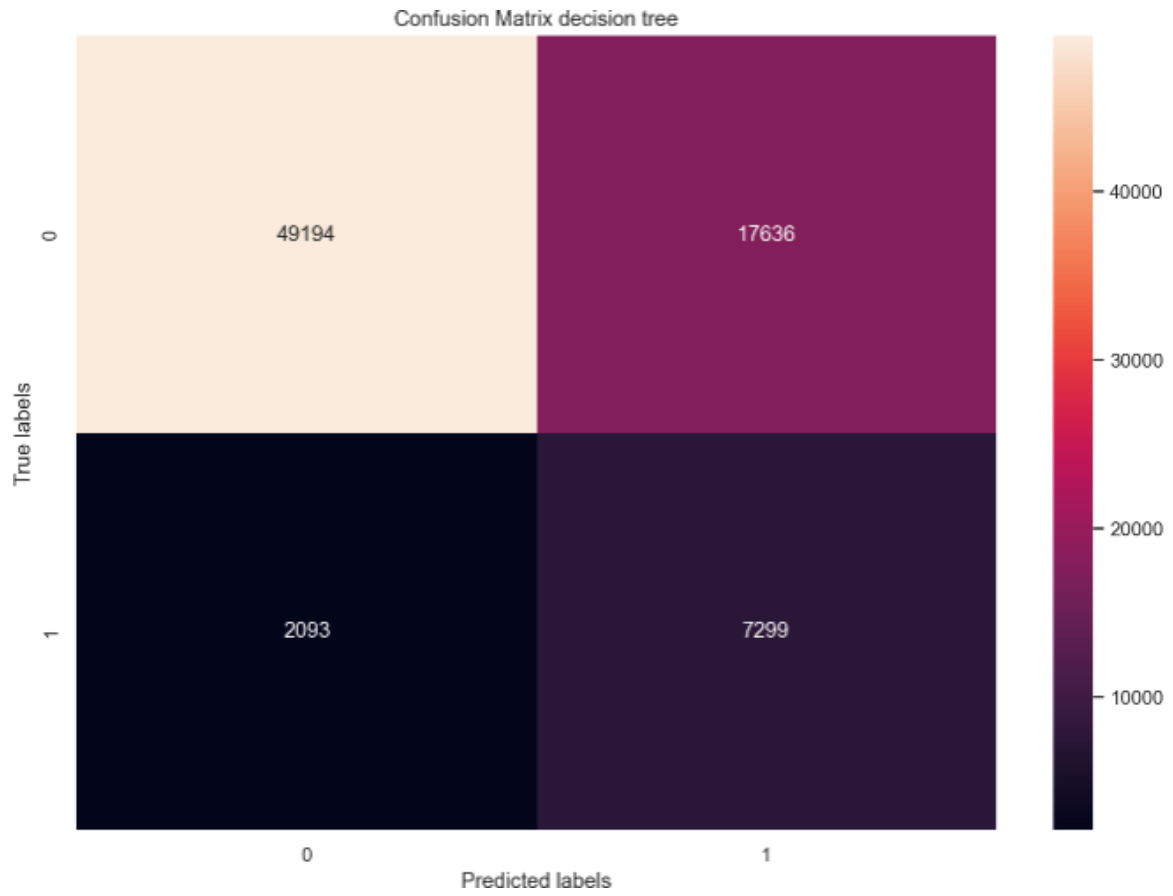
Following creating the six models we proceeded to evaluate the models by pushing them through the confusion matrix which consist of four basic characteristics that are used to define the measurement metrics of the classifiers. The four characteristics are: predicting or not predicting:

- TP (True Positive): TP represents the number of clients who will jump on board and purchase a vehicle insurance plan.

- TN (True Negative): TN represents the number of correctly classified clients who who are absent from purchasing vehicle insurance plan.
- FP (False Positive): FP represents the number of misclassified clients with the purchase of a vehicle insurance plan but actually they are absent. FP is also known as a Type I error.
- FN (False Negative): FN represents the number of clients misclassified as Presence but actually they are suffering from the Presence. FN is also known as a Type II error.

Figure 5

Confusion Matrix for Decision Tree



In Figure 5, we can see the visualization of the confusion matrix based on the four characteristics discussed earlier. The insight we were able to derive from the 5 matrix based models was that the decision tree model shows 49194 class 0 predicted true and 7299 class 1 predicted true, we have about 0.4% class 0 predicted wrong and 0.2% class 1 predicted wrong, this result is good.. Based on our confusion matrix we can agree that the decision tree algorithm has a good performance which will be considered as the best from the confusion matrix perspective. In 5 models, for the balancing result we should use a decision model to have better for both class 0 and 1.

Result

After creating hyper tuning parameters we can see in table 1 that random forest came out to have the highest score introducing at 91% percent. As the others came close to about the lower 80 percent range. Again this can be seen in table 1. In addition the Roc curve demonstrates how close in percentage all the models are. As close as they're we need to discuss that logistic regression had a very low score of 63%. From a modeling accuracy point Random Forest is the model that has produced the best results. We then wanted to validate the model by testing its F1 score which random forest succeeded with being the strongest model. However we wanted to take it a step further and use another metric called the confusion matrix which was interesting because that metric defined the decision tree to be the strongest model. In regards to which model we would recommend the random forest model .

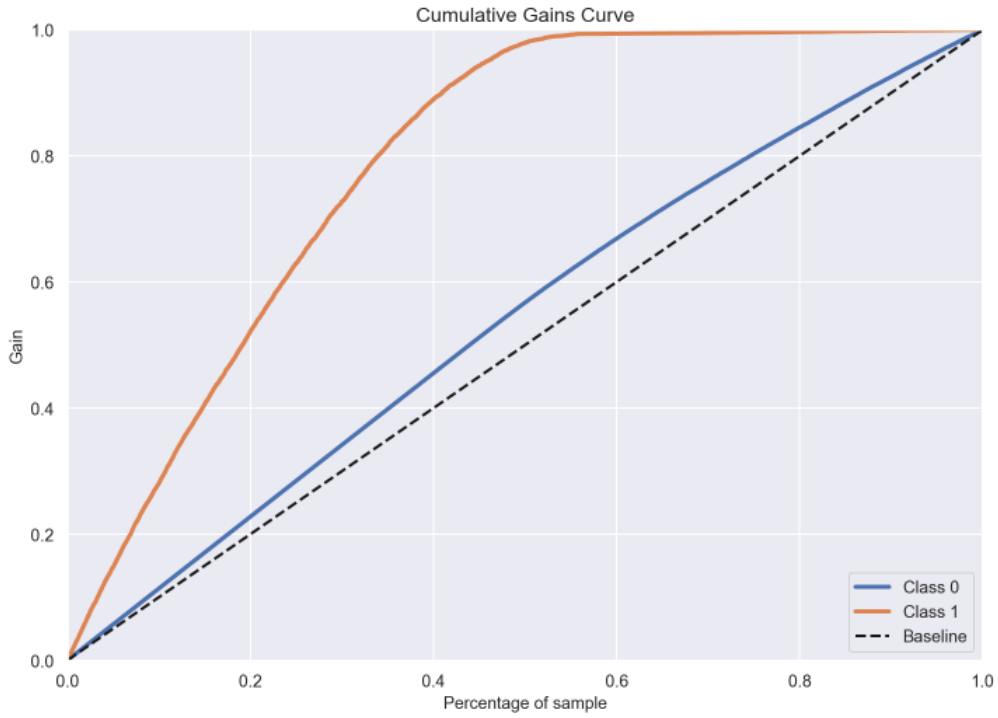
Reason being is that the model handles getting accurate number percentages better than the decision tree and it is most likely not to overfit the data. When it comes to selling products it is keen that high accuracy is very taken for account, therefore random forest is the best model for this choice of data.

Based on our model the percentage acceptance rate for the cross sell offer is 15% percent. As you can see in figure 6, the curve reaches 100% at about 50% of the sample. This means that if we send out cross-selling offers for vehicle insurance to the top 50% of our customers who have been predicted by our model to most likely buy, we can expect to achieve 100% of the gains or acceptances for cross-sells.

Figure 6

Cumulative Gain Curve

```
import scikitplot as skplt

forest_pred_proba = forest_classifier.predict_proba(X_val)
ax = skplt.metrics.plot_cumulative_gain(y_true = y_val, y_probas = forest_pred_proba)
```



Keep in mind that with RandomForestClassifier, the standard cutoff is at 0.5 for classification. So if a customer is predicted with 51% probability to purchase vehicle insurance in a cross-selling offer, they will be counted as likely to purchase with a value 1 instead of 0. With several more iterations, we can adjust this classification cutoff to more accurately reflect the reality, but for now we use the standard cutoff for initial modeling purposes.

In terms of the business implications, what this means is that for a given number of customers who receive the offer, 15% will end up accepting. To illustrate, given a set of 100,000 customers, the client's marketing department only needs to send out to 15,000 of those customers because those are the customers the model predicts are likely to purchase vehicle insurance. And of those

15,000, we only need to send out 7,500 to gain the full number of people who would sign up anyway. Given that the client customer base is 300,000, we can estimate to send out offers to 22,500 customers at a cost of $300 for the email marketing software costs. Additional costs needs to be factored in to calculate the ROI, see below:

Assuming the cost of developing and implementing this prediction model will be around the budget of: Duration: 3-4 months Salaries: 250k (USD) for a Team of 5 consisting of 2 Data Scientists, 1 Business Intelligence Expert, 2 Marketers Cost of Marketing Campaign: $300/month email marketing for 22,500 emails sent out Return: 22,500 customers at minimum annual coverage price of 561 USD = 12.6M USD additional revenue per 300,000 customers

==> ROI = 12.6M USD/((250k USD salaries/month * 4 months) + 1200 USD email marketing software) ~~ **12x on initial investment**

That is an ROI of 12x for this project. You risk approximately 1M USD, but you have a potential gain of 12.6M USD.

Next step is to understand how the client can reach these customers besides just sending emails.We recommend using some social media applications to reach the prospective audience. We need to tailor the method based on the age groups that are being reached out to. Lucky everyone uses social media so that is a safe route to go to cross sell to customers fast.

Discussion Future Plans

For future research below are some things we can consider to look further into the following below:.

- . we need to look into the cutoff threshold for classification to see if there would be improvements on accuracy of predictions.
- we could also add in more parameters to the modeling such as price of insurance, what price insurance people are predicted to sign up for and how that translates to projected revenue
- We can say we can sample from different groups more evenly spread out Stratified sampling vs random sampling.

References

Health Insurance Cross Sell Prediction. (2020, September 11). Kaggle. Retrieved October 14, 2022, from https://www.kaggle.com/datasets/anmolkumar/health-insurance-cross-sell-prediction?select=train.csv

Brownlee, J. (2020, January 16). *SMOTE for Imbalanced Classification with Python*. Machine Learning Mastery. https://machinelearningmastery.com/smote-oversampling-for-imbalanced-classification/

Brownlee, J. (2019, June 19). Classification accuracy is not enough: More performance measures you can use. Machine Learning Mastery. Retrieved October 15, 2022, from https://machinelearningmastery.com/classification-accuracy-is-not-enough-more-performance-measures-you-can-use/

Appendix A

Project Code

ADS_505_Final_Project_Team6

October 17, 2022

1 ADS 505: Final Project - Predicting Healthcare Cross-Selling

1.0.1 Project Team Members (Team 6):

Minsu Kim Abanather Negusu Connie Chow ### Table of Contents: 1. Problem Statement and Justification for Proposed Approach 2. Exploratory Data Analysis 3. Feature Engineering, Data Wrangling and Pre-Processing 4. Feature Selection 5. Dataset Splitting (Training, Testing, Validation Sets) 6. Model Selection, Performance Results, Final Model Selection 7. Next Steps/Recommendations

2 1. Problem Statement and Justification

2.0.1 Context:

Our client is an Insurance company that has provided Health Insurance to its customers. This client wants to build a model to predict whether the policyholders (customers) from past year will also be interested in Vehicle Insurance provided by the company. ### Purpose: Predict Health Insurance Owners' who will be interested in Vehicle Insurance

2.0.2 Data Setup

Import Required Libraries and Packages

[1]:
```
import numpy as np
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
import statistics
%matplotlib inline
%config InlineBackend.figure_format='retina'
from datetime import datetime
from scipy.stats.mstats import winsorize
import warnings
warnings.filterwarnings("ignore")
```

Load Training and Test Datasets

[2]:
```
train_df = pd.read_csv('https://raw.githubusercontent.com/connie-chow/datasets/
↪main/train.csv', sep=',')
test_df = pd.read_csv('https://raw.githubusercontent.com/connie-chow/datasets/
↪main/test.csv', sep=',')
```

Initial Data Summary

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

[3]:

	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	\
0	381110	Male	25	1	11.0	1	
1	381111	Male	40	1	28.0	0	
2	381112	Male	47	1	28.0	0	
3	381113	Male	24	1	27.0	1	
4	381114	Male	27	1	28.0	1	

	Vehicle_Age	Vehicle_Damage	Annual_Premium	Policy_Sales_Channel	Vintage
0	< 1 Year	No	35786.0	152.0	53
1	1-2 Year	Yes	33762.0	7.0	111
2	1-2 Year	Yes	40050.0	124.0	199
3	< 1 Year	Yes	37356.0	152.0	187
4	< 1 Year	No	59097.0	152.0	297

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

[4]:

	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	

	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	

	Response
0	1
1	0
2	1
3	0
4	0

[5]:
```
test_df_ori = test_df.copy()
```

[6]:
```
train_df.shape
```

[6]:
```
(381109, 12)
```

[7]:
```
print(train_df.dtypes)
```

```
id                        int64
Gender                   object
Age                       int64
Driving_License           int64
Region_Code             float64
Previously_Insured        int64
Vehicle_Age              object
Vehicle_Damage           object
Annual_Premium          float64
Policy_Sales_Channel    float64
Vintage                   int64
Response                  int64
dtype: object
```

[8]:
```
print(train_df.head(5))
```

```
   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

  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

   Response
0         1
1         0
2         1
3         0
4         0
```

Handle Missing Values

[9]:
```
# Checking for missing values
train_df.isna().sum()
```

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

Descriptive Statistics

[10]:
```
#Summary Statistic
train_df.describe()
```

[10]:

	id	Age	Driving_License	Region_Code	\
count	381109.000000	381109.000000	381109.000000	381109.000000	
mean	190555.000000	38.822584	0.997869	26.388807	
std	110016.836208	15.511611	0.046110	13.229888	
min	1.000000	20.000000	0.000000	0.000000	
25%	95278.000000	25.000000	1.000000	15.000000	
50%	190555.000000	36.000000	1.000000	28.000000	
75%	285832.000000	49.000000	1.000000	35.000000	
max	381109.000000	85.000000	1.000000	52.000000	

	Previously_Insured	Annual_Premium	Policy_Sales_Channel	\
count	381109.000000	381109.000000	381109.000000	
mean	0.458210	30564.389581	112.034295	
std	0.498251	17213.155057	54.203995	
min	0.000000	2630.000000	1.000000	
25%	0.000000	24405.000000	29.000000	
50%	0.000000	31669.000000	133.000000	
75%	1.000000	39400.000000	152.000000	
max	1.000000	540165.000000	163.000000	

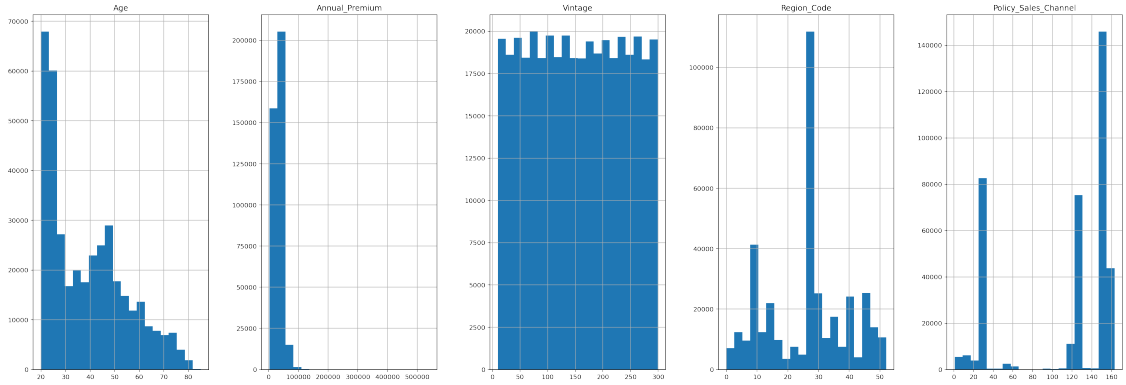
	Vintage	Response
count	381109.000000	381109.000000
mean	154.347397	0.122563
std	83.671304	0.327936
min	10.000000	0.000000
25%	82.000000	0.000000
50%	154.000000	0.000000
75%	227.000000	0.000000

```
max        299.000000        1.000000
```

3 2. Exploratory Data Analysis

Check distribution of data per column

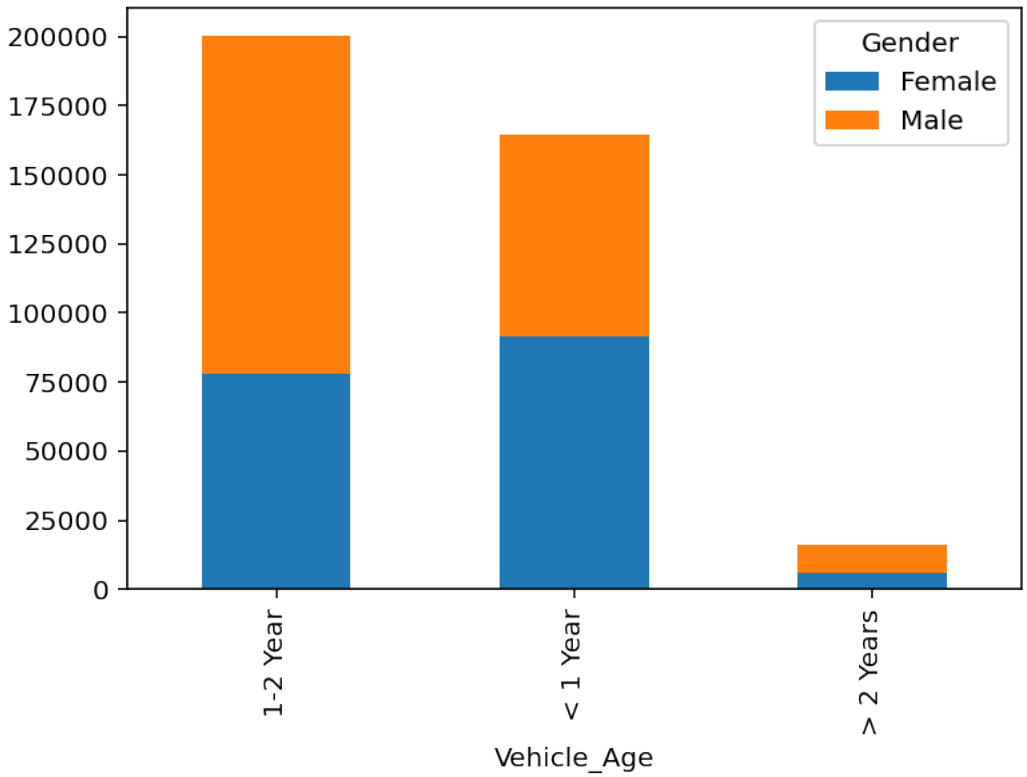
[11]:
```
# Histograms to check the distribution of values of numeric columns
num_cols = ['Age', 'Annual_Premium', 'Vintage', 'Region_Code',␣
 ↪'Policy_Sales_Channel']
fig, ax = plt.subplots(1, 5, figsize=(30, 10))
train_df[num_cols].hist(bins=20, figsize=(10, 7), ax=ax)
plt.show()
```



Vehicle Age by Gender

[12]:
```
train_df.groupby(['Vehicle_Age', 'Gender'])['Gender'].count().unstack().
 ↪plot(kind="bar", stacked=True)
```

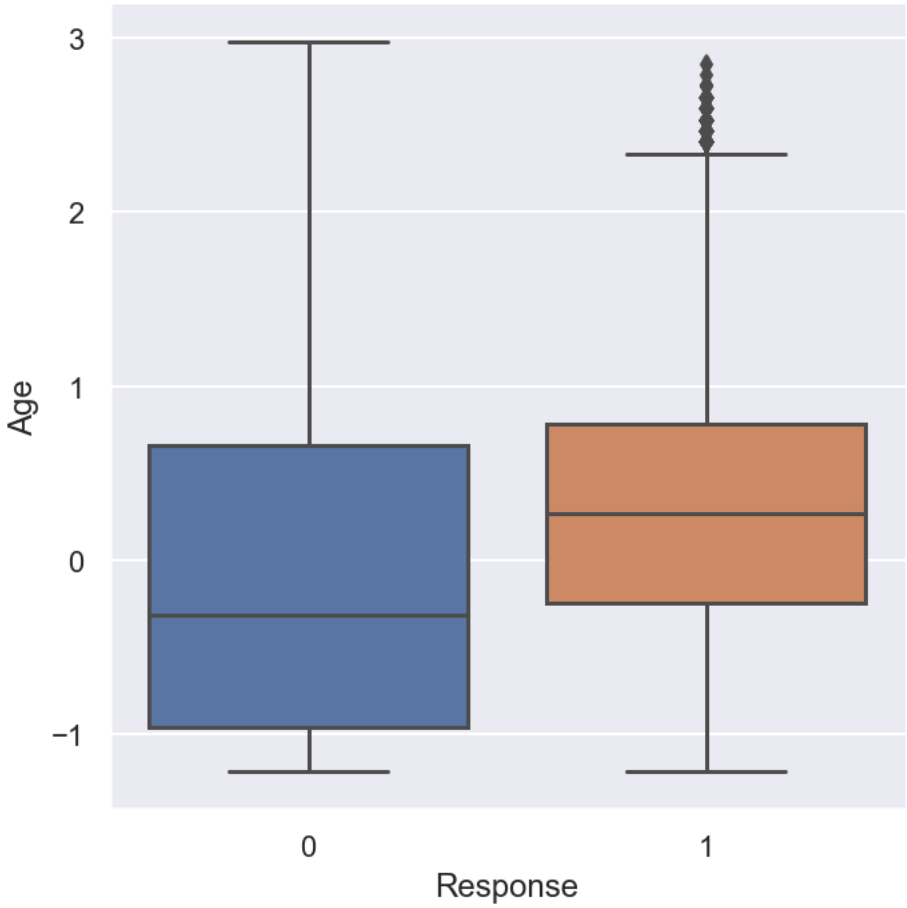
[12]:
```
<AxesSubplot:xlabel='Vehicle_Age'>
```



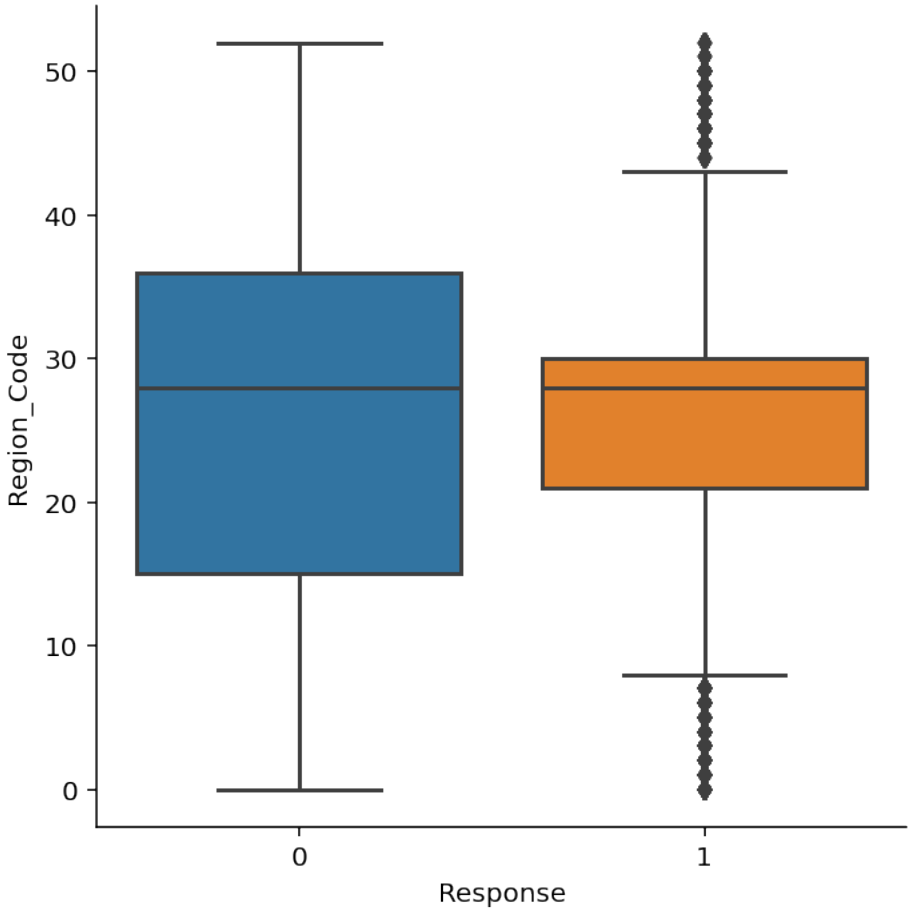
Check Outliers

[110]:
```
sns.catplot(x="Response", y="Age", data=train_df, kind="box");
```

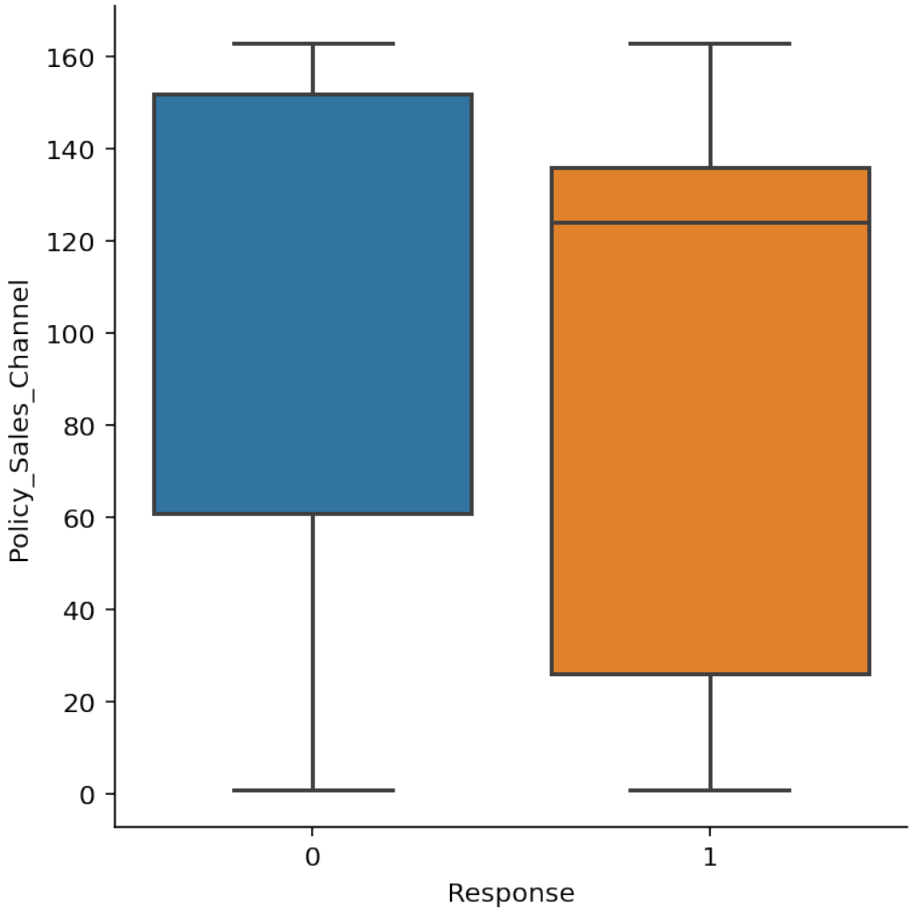
```
<Figure size 576x576 with 0 Axes>
```



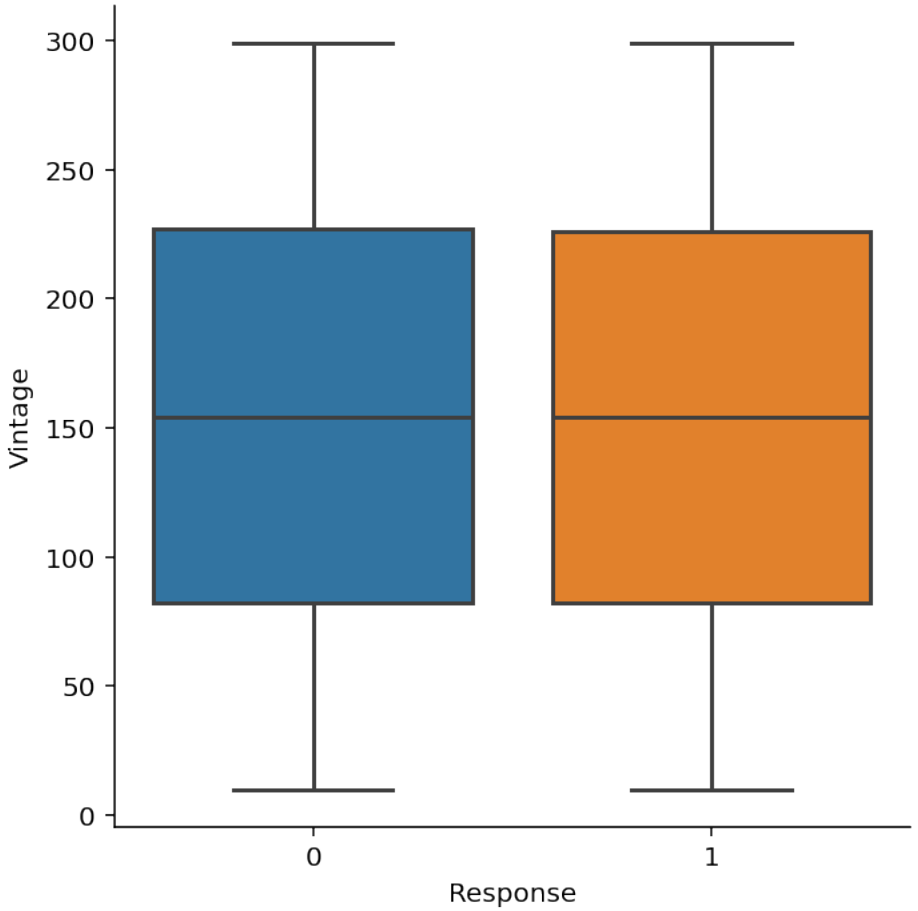
[14]:
```
sns.catplot(x="Response", y="Region_Code", data=train_df, kind="box");
```



[15]:
```
sns.catplot(x="Response", y="Policy_Sales_Channel", data=train_df, kind="box");
```

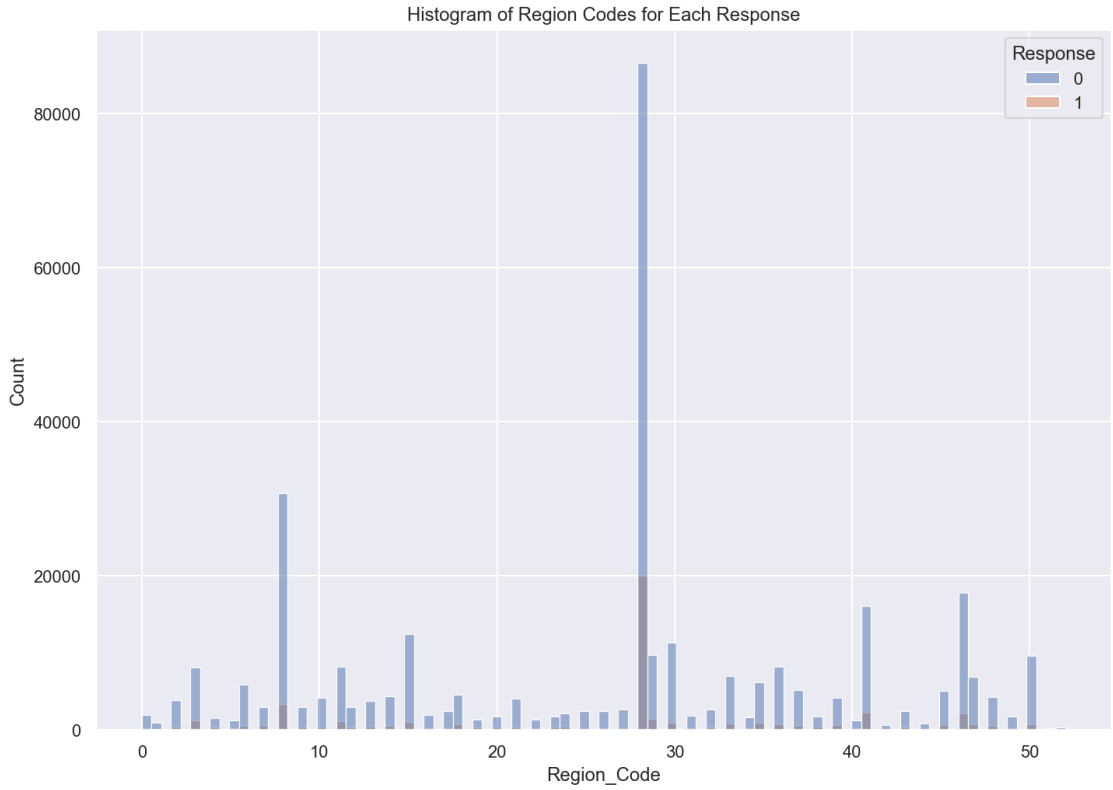


[16]:
```
sns.catplot(x="Response", y="Vintage", data=train_df, kind="box");
```



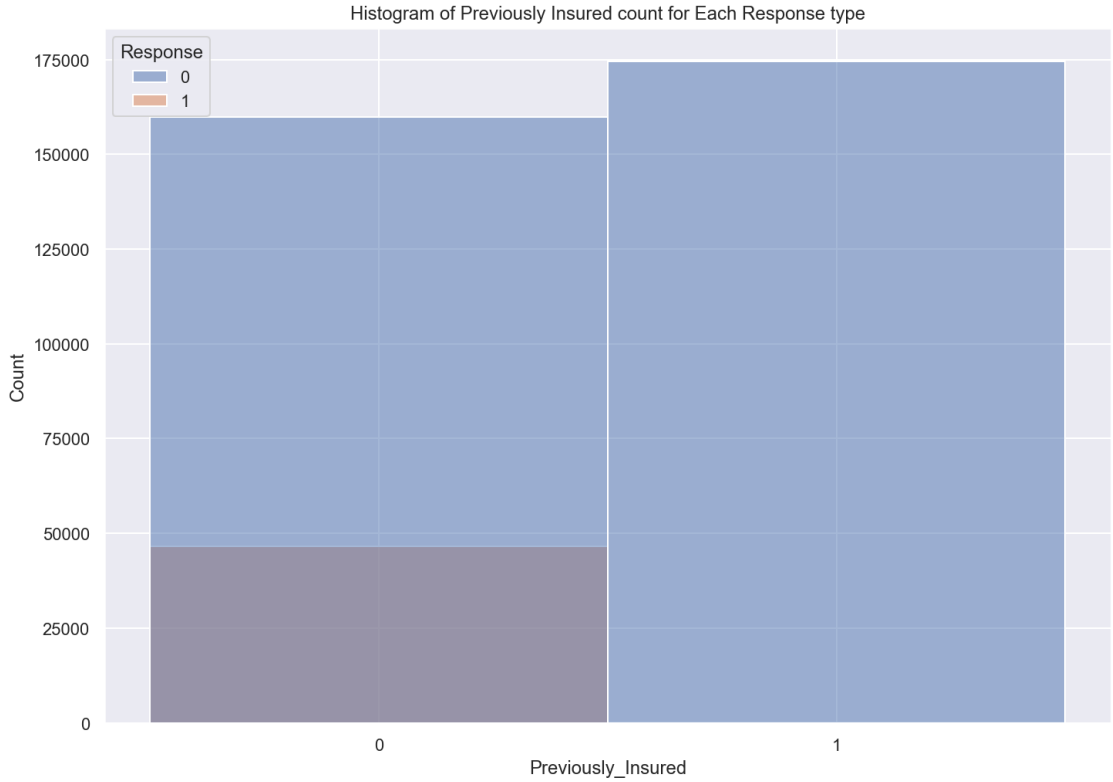
[17]:
```
sns.set(rc={'figure.figsize':(11.7,8.27)})
sns.histplot(data=train_df, x="Region_Code",
             hue = "Response").set(title = "Histogram of Region Codes for Each␣
↪Response")
```

[17]: [Text(0.5, 1.0, 'Histogram of Region Codes for Each Response')]



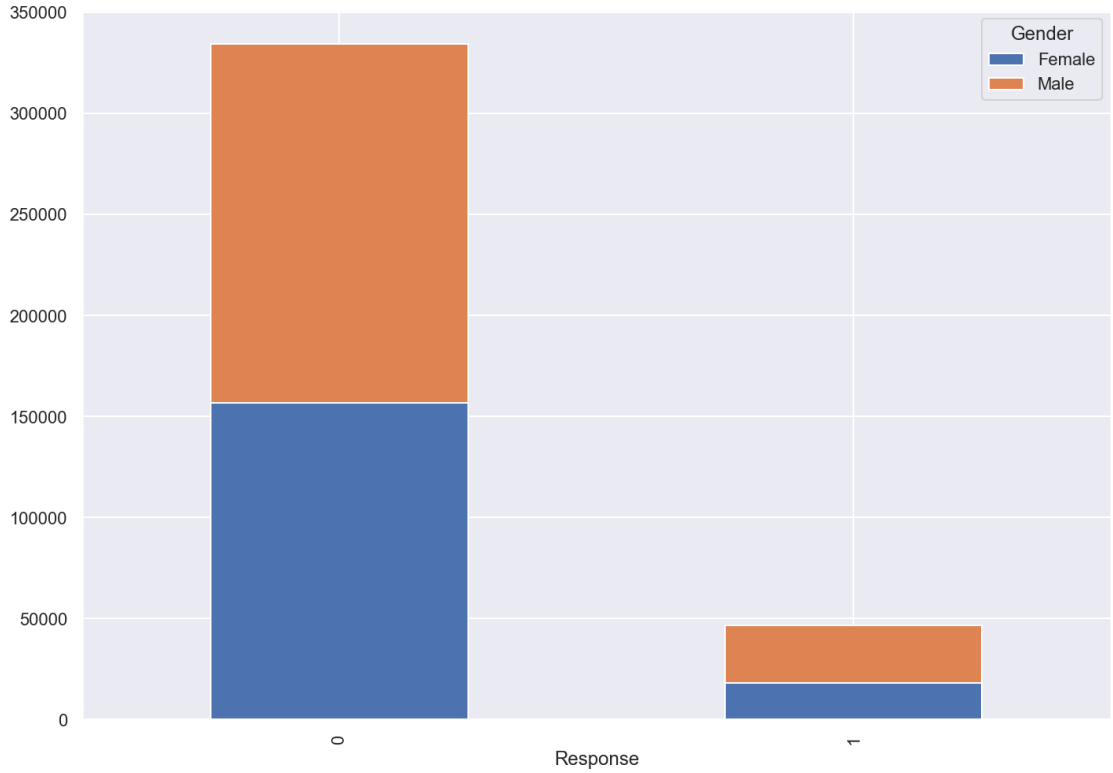
[18]:
```
train_df['Previously_Insured'] = train_df.Previously_Insured.astype(str)
sns.set(rc={'figure.figsize':(11.7,8.27)})
sns.histplot(data=train_df, x="Previously_Insured",
             hue = "Response").set(title = "Histogram of Previously Insured␣
 ↪count for Each Response type")
# none of the previously insured had a response 1, meaning previously insured␣
 ↪customers are NOT interested
```

[18]:
```
[Text(0.5, 1.0, 'Histogram of Previously Insured count for Each Response type')]
```



[19]:
```
train_df.groupby(['Response', 'Gender'])['Gender'].count().unstack().
↪plot(kind="bar", stacked=True)
```

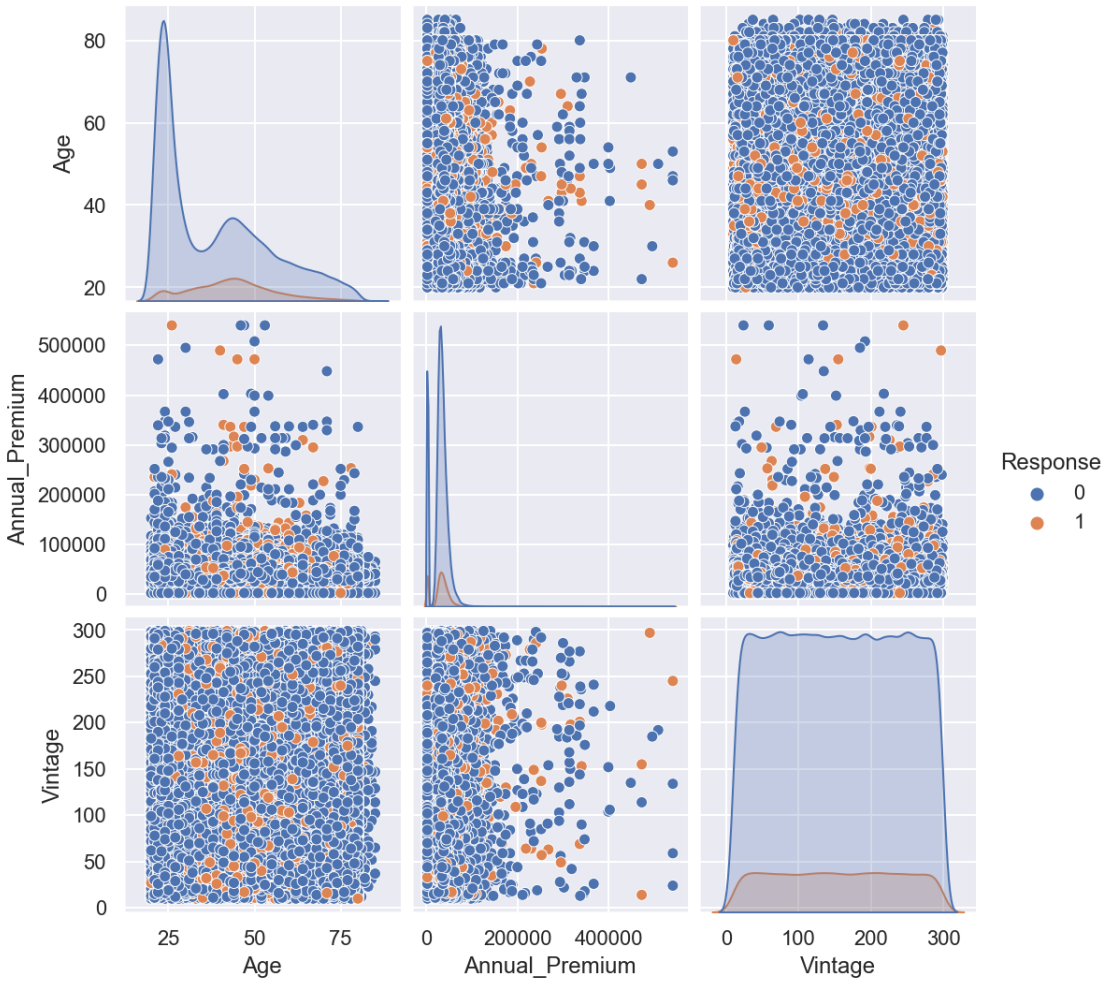
[19]: <AxesSubplot:xlabel='Response'>



[22]:
```
### We need to create some pair plot to see the relation between the features.
pairplot = train_df.drop(['id','Gender', 'Vehicle_Damage', 'Vehicle_Age',␣
↪'Driving_License', 'Region_Code','Policy_Sales_Channel','Previously_Insured'␣
↪], axis =1)
```

[23]:
```
sns.pairplot(pairplot, hue ='Response')
```

[23]:
```
<seaborn.axisgrid.PairGrid at 0x26aeec0b448>
```



#From the above graphs we can see that data is skewed, Before training the model we will correct the skewness using Preprocess

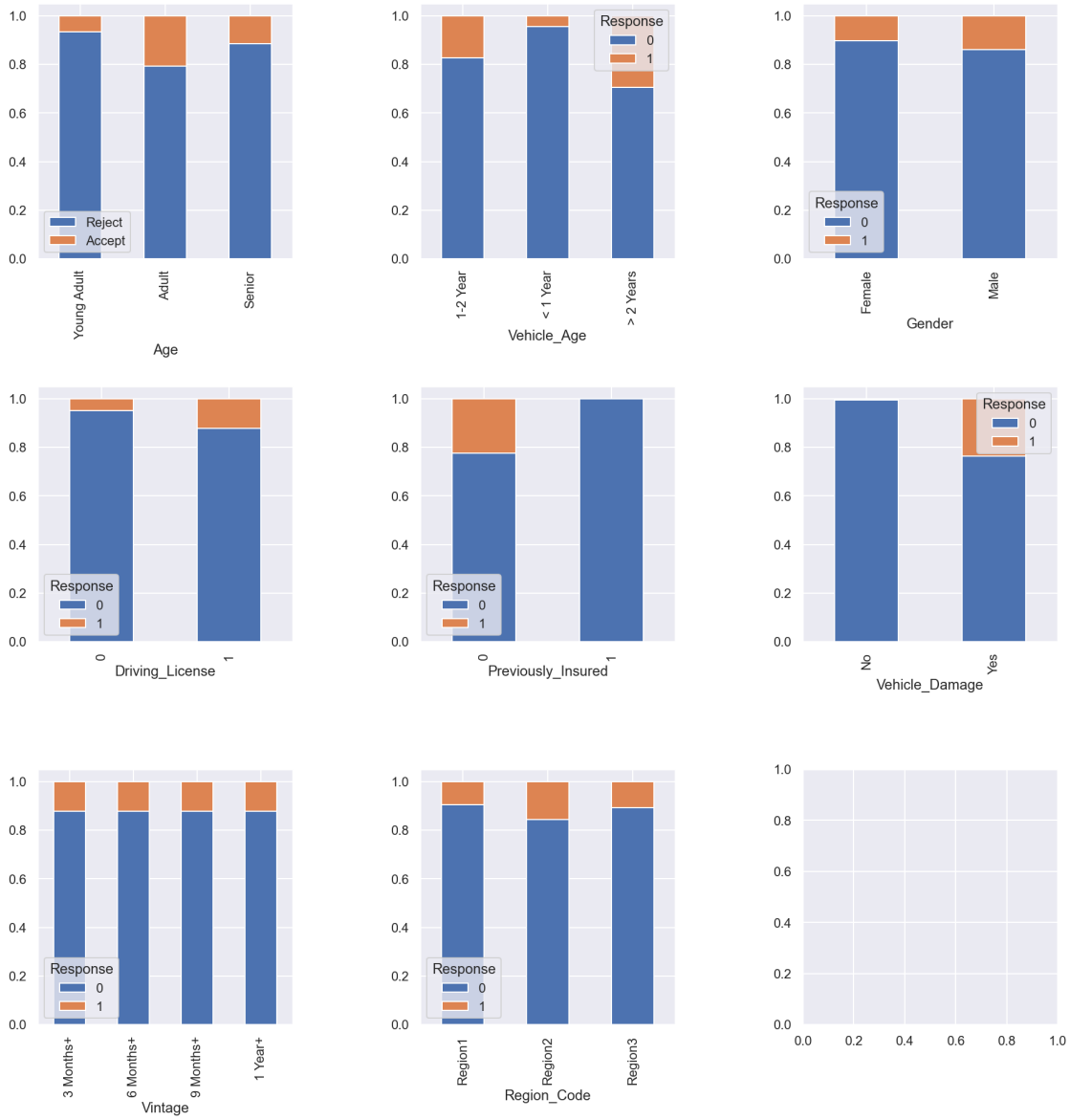
Normalized graphs showing response rate against categorical columns Normalizing the bar charts makes it easier to compare the Response within categories. For the first graph, Age column was plotted showing the positive response in orange (signs up for vehicle insurance) and negative response in blue (does not signup for vehicle insurance. Clearly, with the normalization, we can see that customers in the Adult (age 35-55) range had the highest positive response rate.

[24]:
```
# For better visualization, three columns will be temporarily binned: Age,␣
↪Region_Code, Vintage

# Bin 'Age' column categories: 0 to 35 = Young Adult, 36 to 55 = Adult, 56 to␣
↪99 = Senior
df_temp = train_df.copy()
df_temp['Age'] = pd.cut(df_temp['Age'], bins=[0,35,55,99],
```

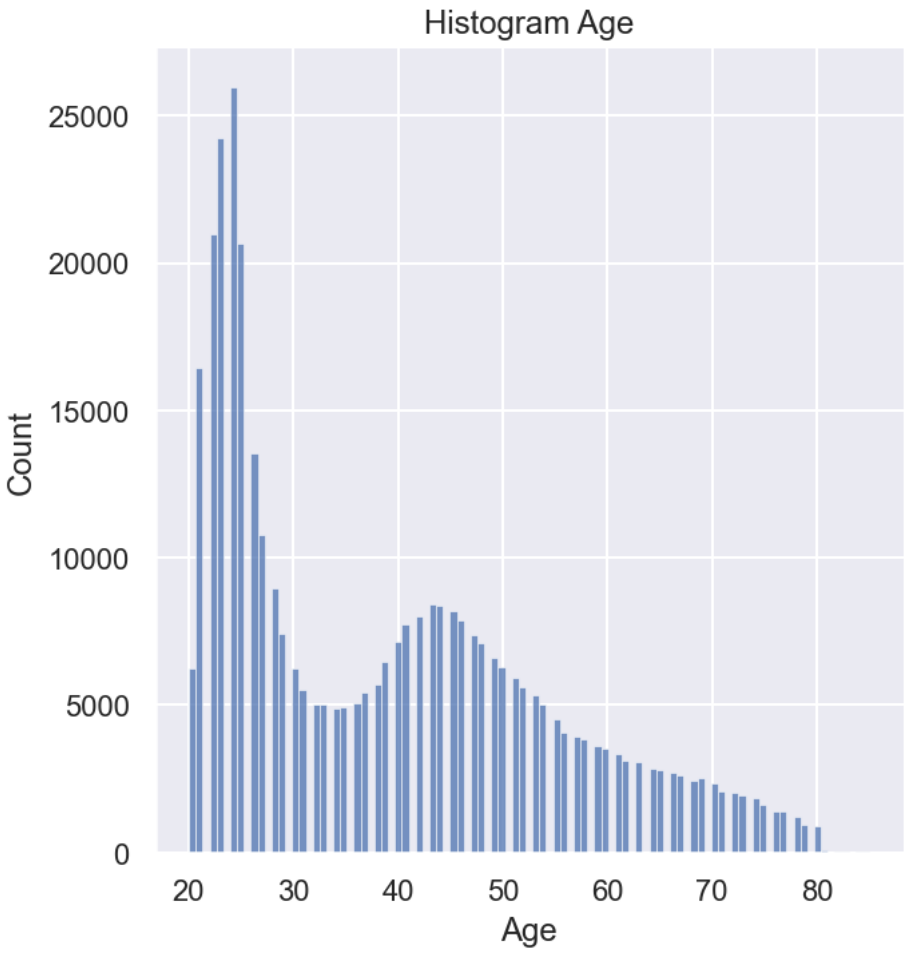
```
                        labels=['Young Adult', 'Adult', 'Senior'])

# Bin 'Vintage' column - so it's the number of days the customer has been with␣
 ↪the business
df_temp = df_temp.copy()
df_temp['Vintage'] = pd.cut(df_temp['Vintage'], bins=[0,91,183,274, 365],
                        labels=['3 Months+', '6 Months+', '9 Months+', '1␣
 ↪Year+'])

# Bin 'Region_Code' column - so it's the number of days the customer has been␣
 ↪with the business
df_temp = df_temp.copy()
df_temp['Region_Code'] = pd.cut(df_temp['Region_Code'], bins=[0,15,30,45],
                        labels=['Region1', 'Region2', 'Region3'])

# Define grid for dataframe plots
fig, axes = plt.subplots(nrows=3, ncols=3, figsize = (30, 30))
plt.subplots_adjust(left=0.1,
                    bottom=0.5,
                    right=0.5,
                    top=0.9,
                    wspace=0.5,
                    hspace=0.5)

crosstab_01 = pd.crosstab(df_temp['Age'], df_temp['Response'])
crosstab_norm = crosstab_01.div(crosstab_01.sum(1), axis = 0)
ax = crosstab_norm.plot(kind='bar', stacked = True, ax=axes[0,0])
ax.legend(["Reject", "Accept"])

crosstab_01 = pd.crosstab(df_temp['Vehicle_Age'], df_temp['Response'])
crosstab_norm = crosstab_01.div(crosstab_01.sum(1), axis = 0)
crosstab_norm.plot(kind='bar', stacked = True, ax=axes[0,1])
ax.legend(["Reject", "Accept"])

crosstab_01 = pd.crosstab(df_temp['Gender'], df_temp['Response'])
crosstab_norm = crosstab_01.div(crosstab_01.sum(1), axis = 0)
crosstab_norm.plot(kind='bar', stacked = True, ax=axes[0,2])
ax.legend(["Reject", "Accept"])

crosstab_01 = pd.crosstab(df_temp['Driving_License'], df_temp['Response'])
crosstab_norm = crosstab_01.div(crosstab_01.sum(1), axis = 0)
crosstab_norm.plot(kind='bar', stacked = True, ax=axes[1,0])
ax.legend(["Reject", "Accept"])

crosstab_01 = pd.crosstab(df_temp['Previously_Insured'], df_temp['Response'])
crosstab_norm = crosstab_01.div(crosstab_01.sum(1), axis = 0)
crosstab_norm.plot(kind='bar', stacked = True, ax=axes[1,1])
```

```
ax.legend(["Reject", "Accept"])

crosstab_01 = pd.crosstab(df_temp['Vehicle_Damage'], df_temp['Response'])
crosstab_norm = crosstab_01.div(crosstab_01.sum(1), axis = 0)
crosstab_norm.plot(kind='bar', stacked = True, ax=axes[1,2])
ax.legend(["Reject", "Accept"])

crosstab_01 = pd.crosstab(df_temp['Vintage'], df_temp['Response'])
crosstab_norm = crosstab_01.div(crosstab_01.sum(1), axis = 0)
crosstab_norm.plot(kind='bar', stacked = True, ax=axes[2,0])
ax.legend(["Reject", "Accept"])

crosstab_01 = pd.crosstab(df_temp['Region_Code'], df_temp['Response'])
crosstab_norm = crosstab_01.div(crosstab_01.sum(1), axis = 0)
crosstab_norm.plot(kind='bar', stacked = True, ax=axes[2,1])
ax.legend(["Reject", "Accept"])
```

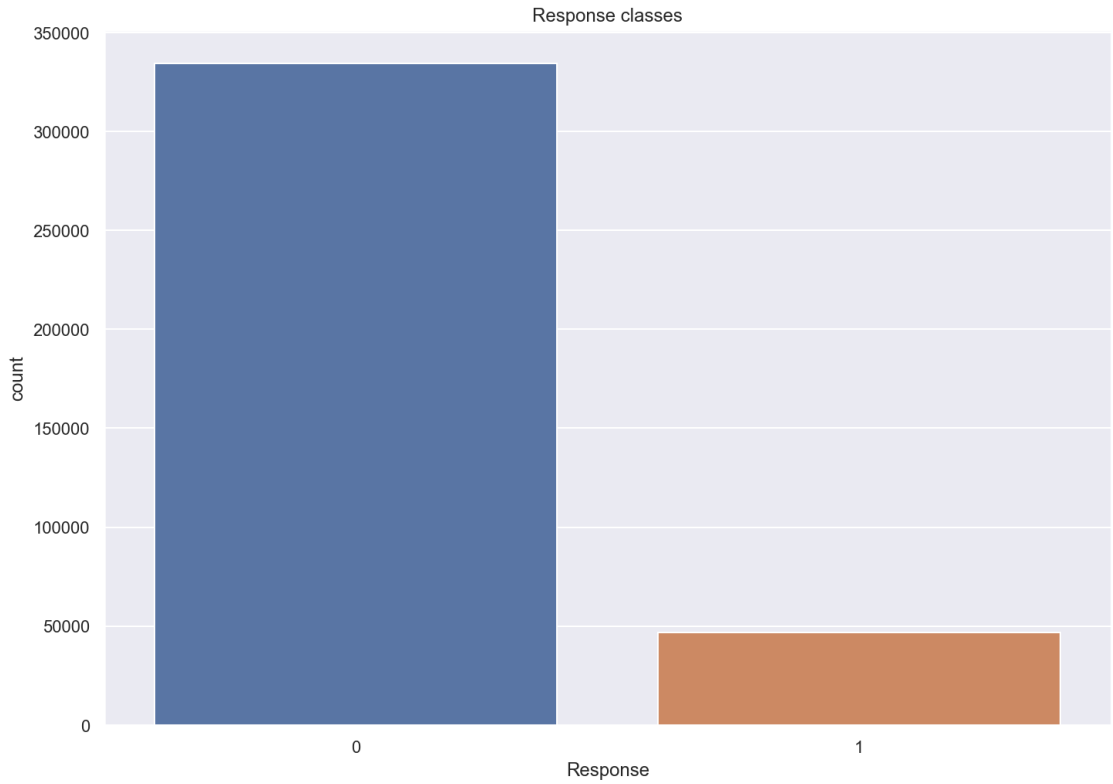
[24]: <matplotlib.legend.Legend at 0x26a84e50e48>



[25]:
```
sns.displot(train_df, x="Age")
plt.title("Histogram Age")#title of graph
plt.show()#show graph
```



[26]:
```
#Checking Target varaible
sns.countplot(train_df.Response)
plt.title("Response classes")#title of graph
plt.show()#show graph
```

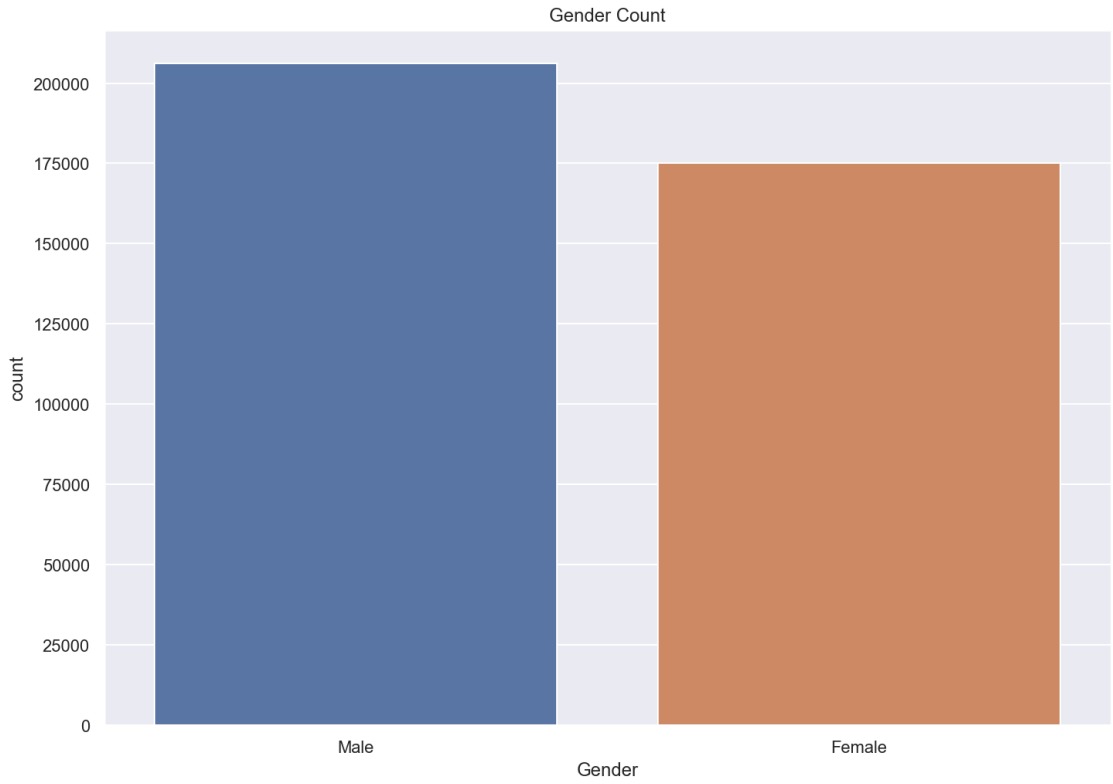


[27]:
```
#Checking the count of  values in response
train_df.Response.value_counts()
```

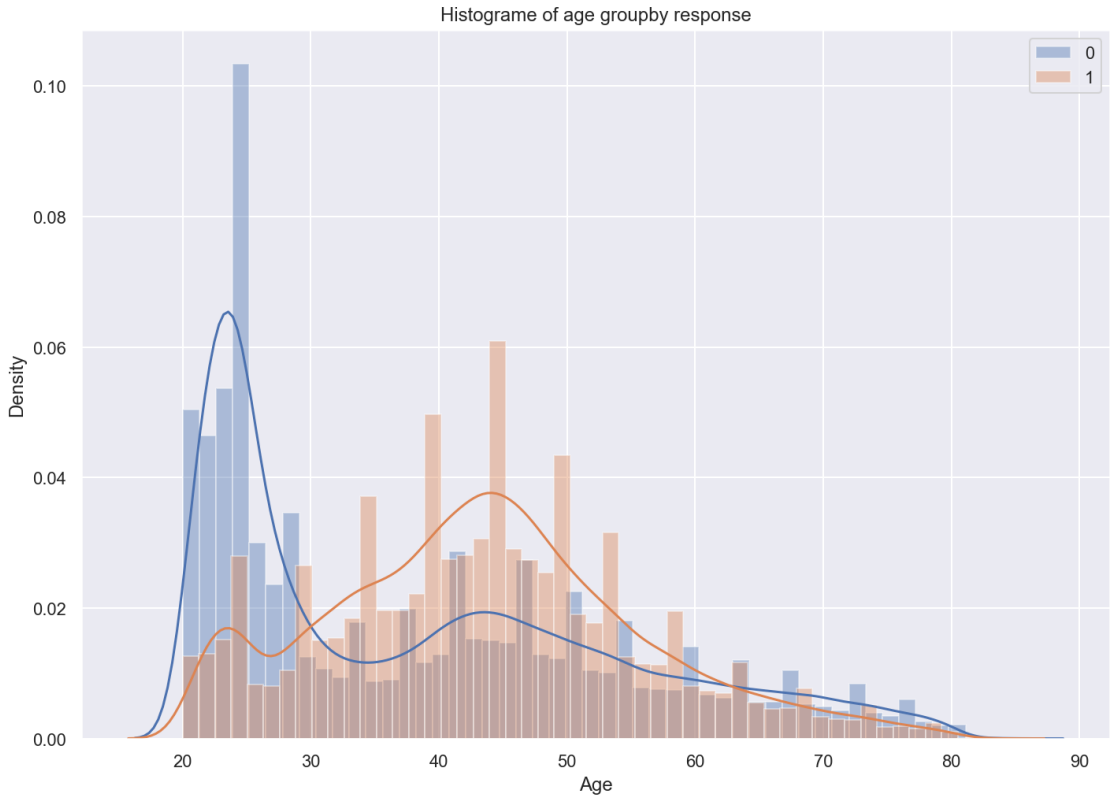
[27]:
```
0    334399
1     46710
Name: Response, dtype: int64
```

There are higher people who whould be not be intrested compared to people that would.

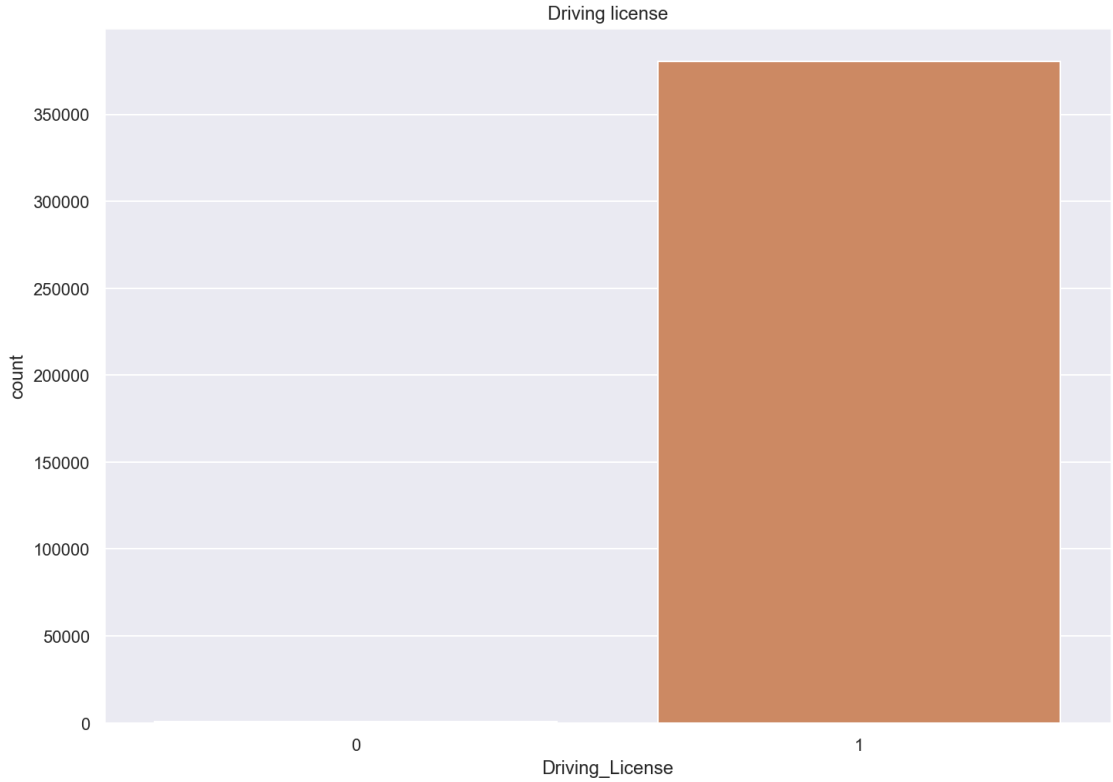
[28]:
```
#Checking gender count
sns.countplot(train_df.Gender)
train_df.Gender.value_counts()
plt.title("Gender Count")#title of graph
plt.show()#show graph
```



[29]:
```
sns.distplot(train_df[train_df.Response==0]['Age'], label='0')
sns.distplot(train_df[train_df.Response==1]['Age'], label='1')
plt.legend()
plt.title("Histograme of age groupby response")#title of graph
plt.show()#show graph
```

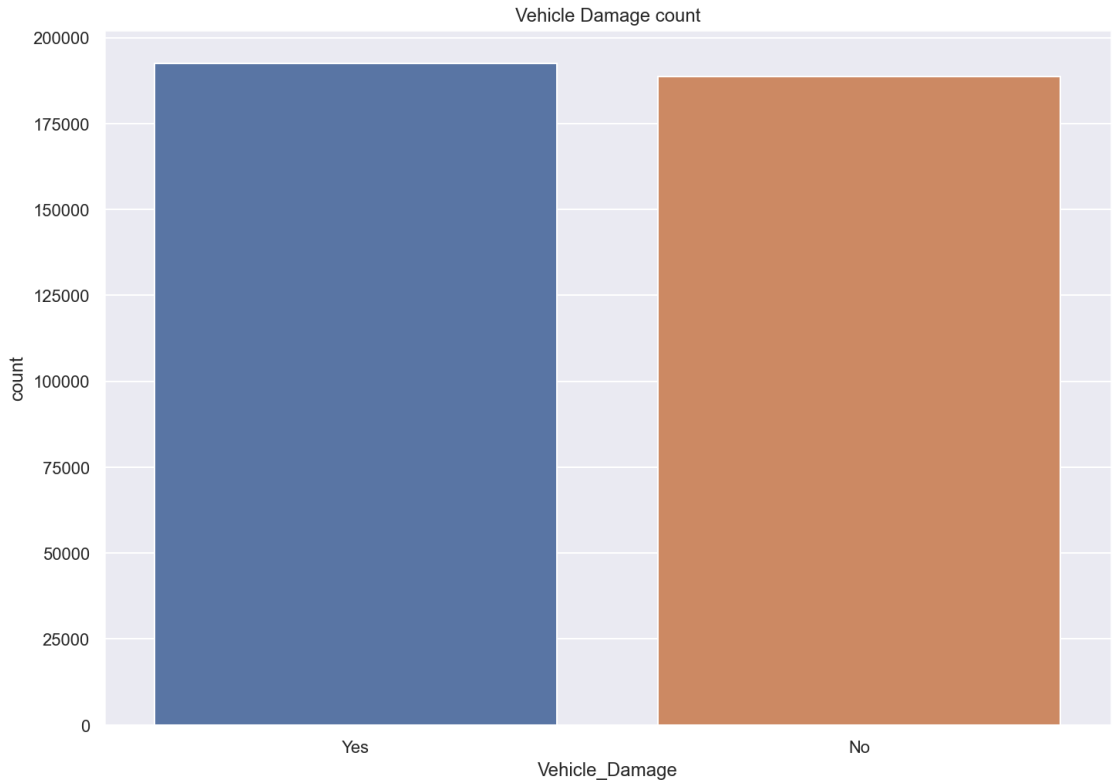


[30]:
```
#Checking  Driving_License count
sns.countplot(train_df.Driving_License)
train_df.Driving_License.value_counts()
plt.title("Driving license")#title of graph
plt.show()#show graph
```

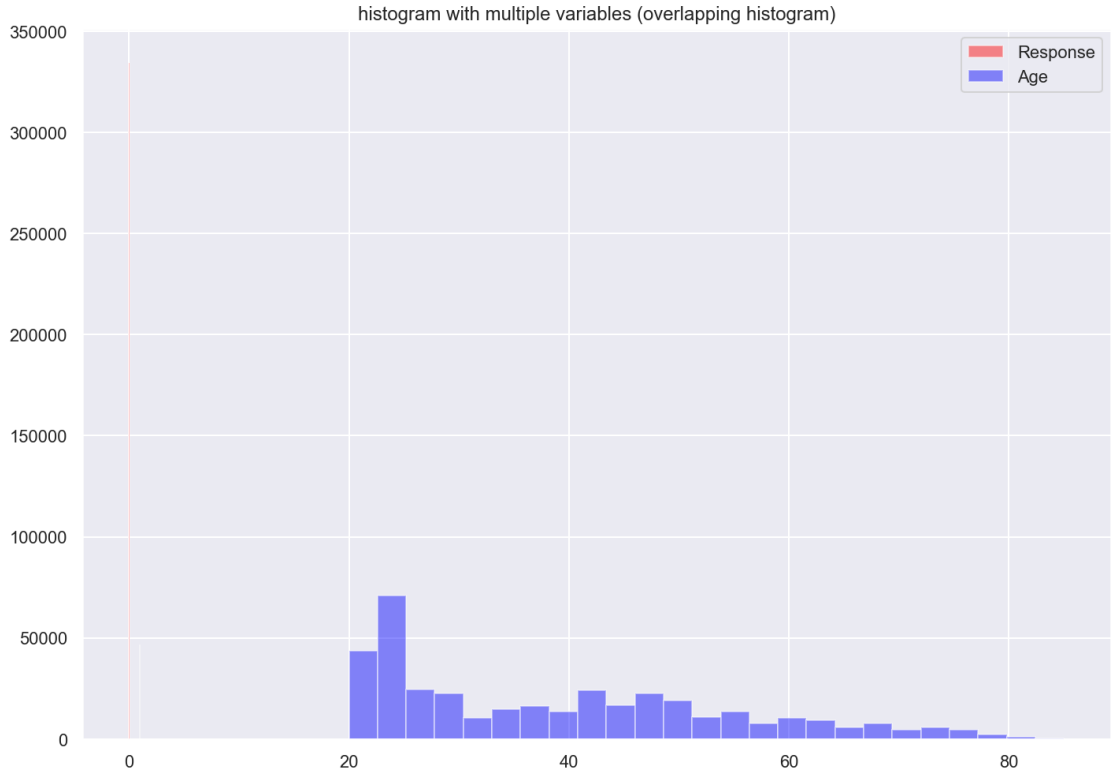


So when I ran this looks like everyone has a driver license BUT take a look at the count of numbers that do not have license its 812. I wonder if people will say yes or no based on having a license.

[31]:
```
#Checking  Vehicle_Damage count
sns.countplot(train_df.Vehicle_Damage)
train_df.Vehicle_Damage.value_counts()
plt.title("Vehicle Damage count")#title of graph
plt.show()#show graph
```

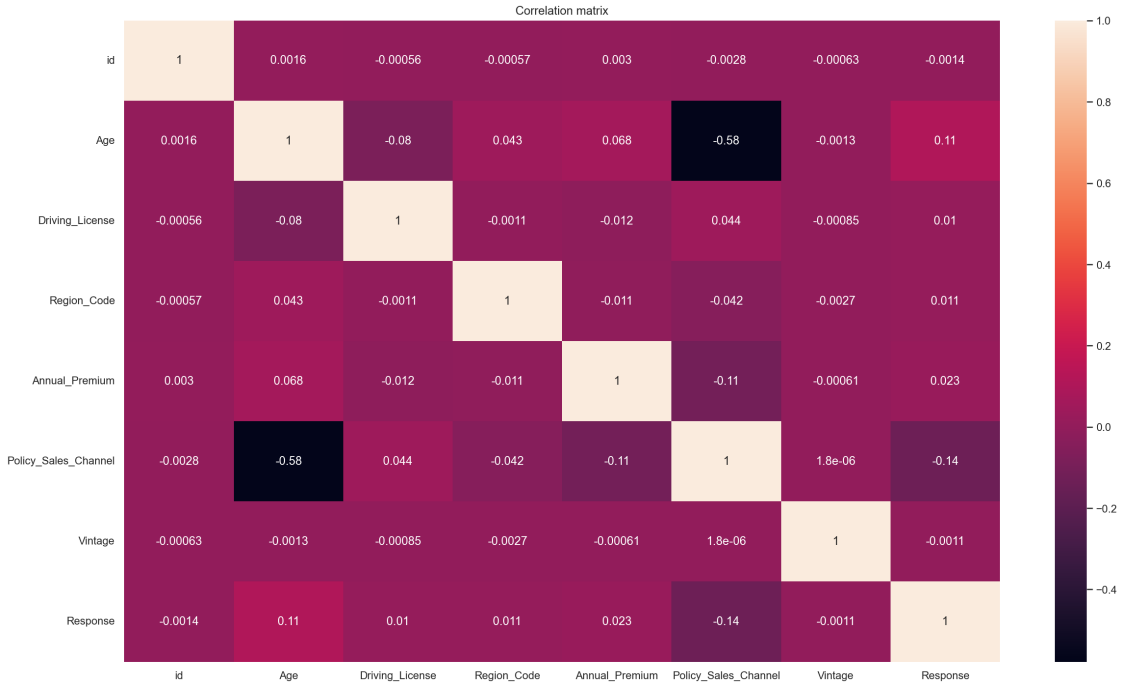


[32]:
```
# plotting two histograms on the same axis
plt.hist(train_df['Response'], bins=25, alpha=0.45, color='red')
plt.hist(train_df['Age'], bins=25, alpha=0.45, color='blue')

plt.title("histogram with multiple \
variables (overlapping histogram)")

plt.legend(['Response',
            'Age'])

plt.show()
```



No columns showed high correlation. Age and Policy Sales Channel showed high opposite correlation.

[33]:
```
plt.figure(figsize=(20, 12))
sns.heatmap(train_df.corr(), annot=True)
plt.title("Correlation matrix")#title of graph
plt.show()#show graph
```



Correlation of Variables to Target Age has the highest correlation which confirms the earliest chart when we plotted Age distribution against response distribution. Ages 35-55 had the highest correlation to a positive response. Next highest correlation is the Annual Premium and then Region Code. It could be the case that customers residing in a certain region preferred to buy their healthcare insurer's vehicle insurance, maybe they were happy with the company or did not want to bother looking elsewhere.

[34]:
```
print(train_df.corr()['Response'].sort_values(ascending=False))
```

```
Response                1.000000
Age                     0.111147
Annual_Premium          0.022575
Region_Code             0.010570
Driving_License         0.010155
Vintage                -0.001050
id                     -0.001368
Policy_Sales_Channel   -0.139042
Name: Response, dtype: float64
```

4 3. Feature Engineering, Data Wrangling and Pre-Processing

[35]:
```
train_df.dropna(inplace=True)
test_df.dropna(inplace=True)
```

[36]:
```
train_df
```

[36]:

```
             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
…           …      …  …                …           …                 …
381104   381105    Male   74                1         26.0                   1
381105   381106    Male   30                1         37.0                   1
381106   381107    Male   21                1         30.0                   1
381107   381108  Female   68                1         14.0                   0
381108   381109    Male   46                1         29.0                   0

       Vehicle_Age Vehicle_Damage  Annual_Premium  Policy_Sales_Channel  \
0        > 2 Years            Yes         40454.0                  26.0
1         1-2 Year             No         33536.0                  26.0
2        > 2 Years            Yes         38294.0                  26.0
3         < 1 Year             No         28619.0                 152.0
4         < 1 Year             No         27496.0                 152.0
…              …            …              …                   …
381104    1-2 Year             No         30170.0                  26.0
381105    < 1 Year             No         40016.0                 152.0
381106    < 1 Year             No         35118.0                 160.0
381107   > 2 Years            Yes         44617.0                 124.0
381108    1-2 Year             No         41777.0                  26.0

        Vintage  Response
0           217         1
1           183         0
2            27         1
3           203         0
4            39         0
…          …       …
381104       88         0
381105      131         0
381106      161         0
381107       74         0
381108      237         0

[381109 rows x 12 columns]
```

We have labeled the columns of vehicle damage to 1 and 0. 1 represents vehicle damage and 0 represents no damage.

[37]:
```
train_df['Vehicle_Damage'] = np.where(train_df['Vehicle_Damage']=='Yes', 1, 0)
test_df['Vehicle_Damage'] = np.where(test_df['Vehicle_Damage']=='Yes', 1, 0)
```

We have created buckets for vehicle age and labled it, if a vehicle age is less then 1 year = 1. And if the vehicle age is between 1 and 2 year = 2. And if the vehicle age is greather then 2 = 3.

[38]:
```
col         = 'Vehicle_Age'
conditions  = [train_df[col] == '< 1 Year', train_df[col] == '1-2 Year',␣
 ↪train_df[col] == '> 2 Years']
choices     = [1, 2, 3]
train_df['Vehicle_Age'] = np.select(conditions, choices, default=0)

conditions  = [test_df[col] == '< 1 Year', test_df[col] == '1-2 Year',␣
 ↪test_df[col] == '> 2 Years']
test_df['Vehicle_Age'] = np.select(conditions, choices, default=0)
```

[39]:
```
# Save temporary df before scaling, use this for RandomForestClassifier
df_rfc_temp = train_df
print(df_rfc_temp.head(5))
```

```
   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

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

   Response
0         1
1         0
2         1
3         0
4         0
```

Below we're resizeing the distribution of values for thesse columns 'Age', 'Region_Code', 'Annual_Premium', 'Policy_Sales_Channel', 'Vintage'. So that our mean of the observed values will be zero.

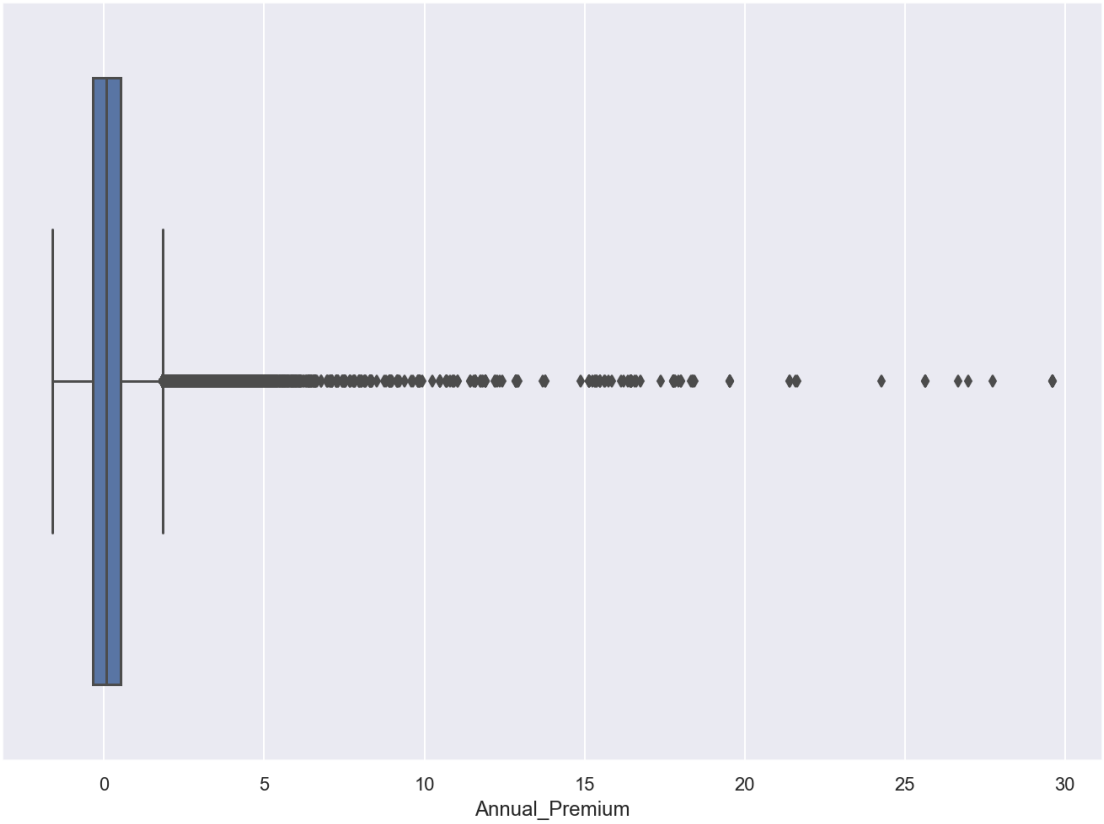
[40]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

```
for col in ['Age', 'Region_Code', 'Annual_Premium', 'Policy_Sales_Channel',␣
↪'Vintage']:
    train_df[col] =  scaler.fit_transform(np.array(train_df[col]).reshape(-1,␣
↪1))
    test_df[col] =  scaler.transform(np.array(test_df[col]).reshape(-1, 1))
```

Handling Skewnessand tranforming outliers & resampling

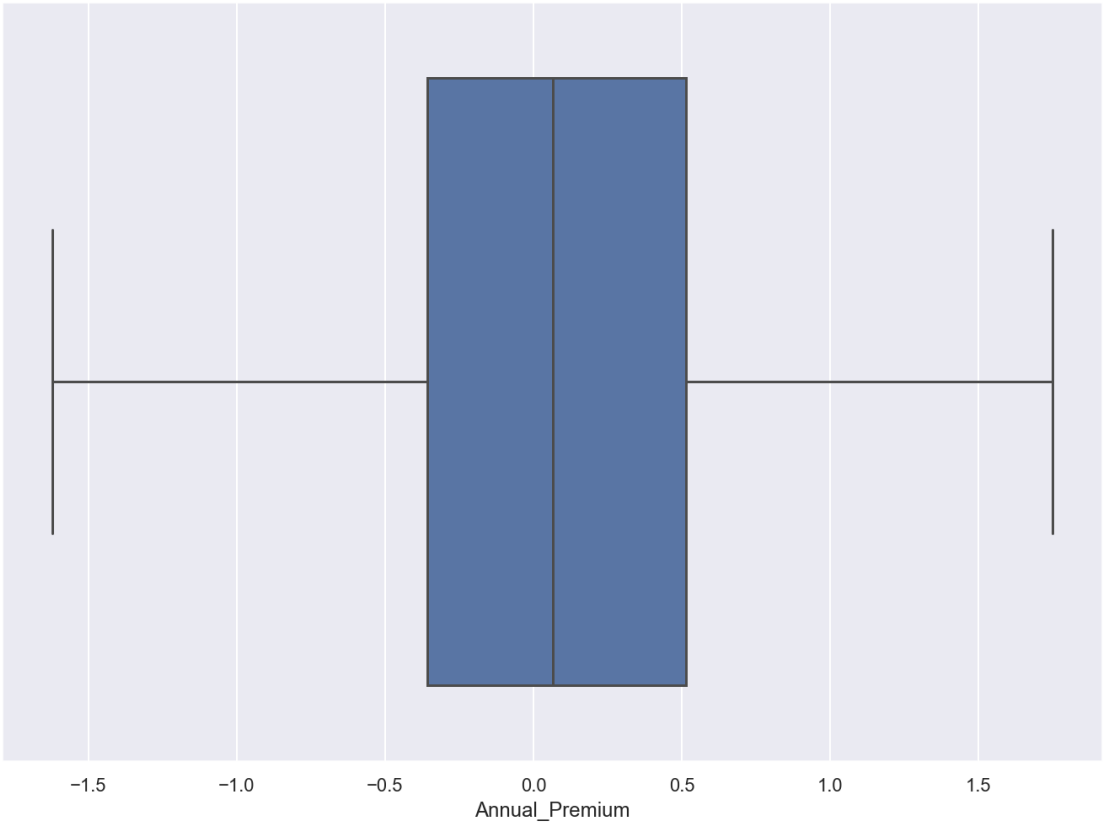
[41]:
```
sns.boxplot(train_df['Annual_Premium'])
```

[41]: <AxesSubplot:xlabel='Annual_Premium'>



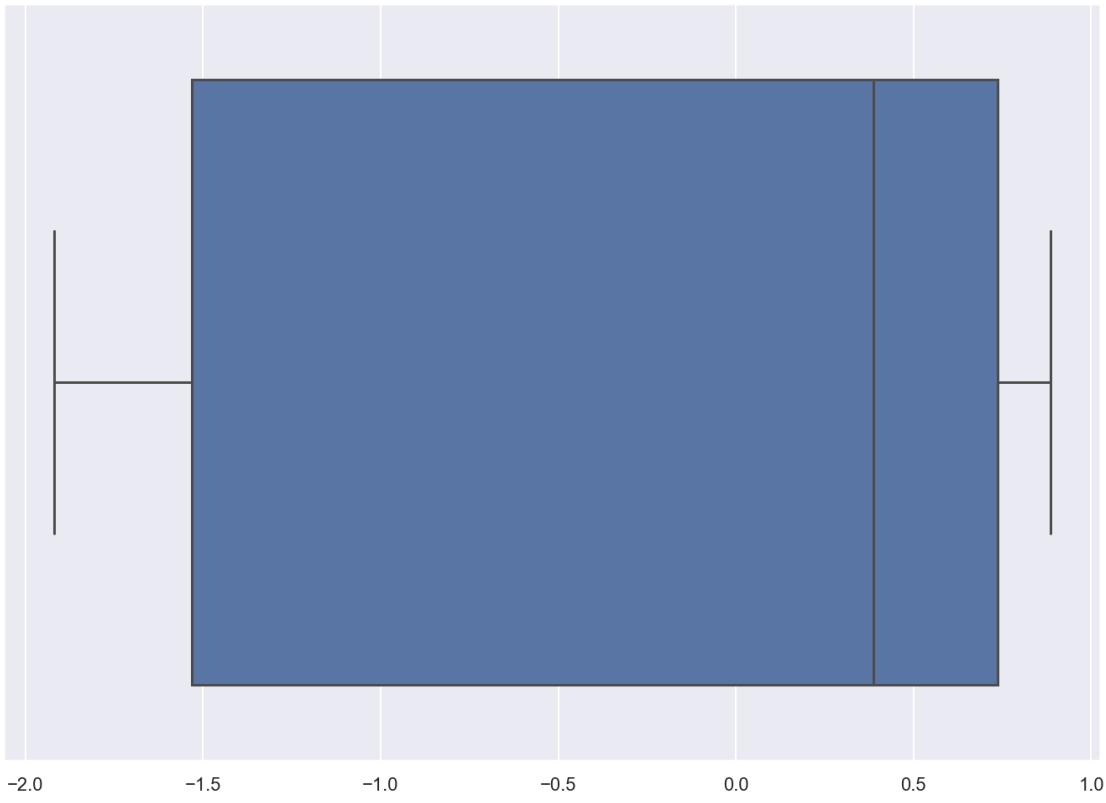
[42]:
```
train_df['Annual_Premium'] = winsorize(train_df['Annual_Premium'], (0.01, 0.03))
test_df['Annual_Premium'] = winsorize(test_df['Annual_Premium'], (0.01, 0.03))

sns.boxplot(train_df['Annual_Premium'])
```

[42]: <AxesSubplot:xlabel='Annual_Premium'>



[43]:
```
sns.boxplot(winsorize(train_df['Policy_Sales_Channel'], (0.01, 0.01)))
```

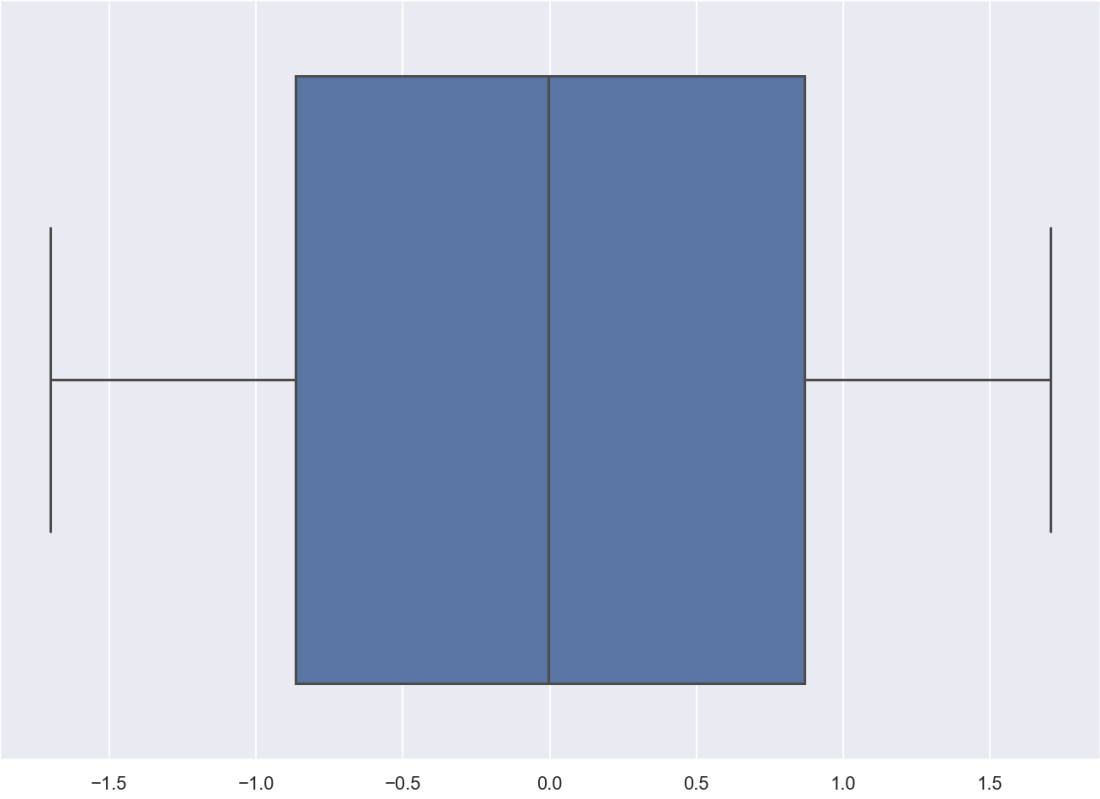
[43]: <AxesSubplot:>



[44]:
```
train_df['Policy_Sales_Channel'] = winsorize(train_df['Policy_Sales_Channel'],␣
↪(0.01, 0.01))
test_df['Policy_Sales_Channel'] = winsorize(test_df['Policy_Sales_Channel'], (0.
↪01, 0.01))
```

[45]:
```
sns.boxplot(winsorize(train_df['Vintage'], (0.01, 0.01)))
```

[45]: <AxesSubplot:>



[46]:
```
train_df['Vintage'] = winsorize(train_df['Vintage'], (0.01, 0.01))
test_df['Vintage'] = winsorize(test_df['Vintage'], (0.01, 0.01))
```

5 4. Feature Selection

We conduct feature selection to optimize the Random Forest Classifier. Features selection includes several separate, but comprehensive approach, see below.

Drop highly correlated features Conducted pairwise correlation to find features that are redundant. Ones that are highly correlated to each other do not provide the model with any extra information so we only keep one of those features. Vehicle_Age and Age are highly correlated to the probability that a customer will signup for vehicle insurance. Ages 35-55 were most likely to signup for the cross-selling offer, maybe because this age group is busy with families and are happy with the current healthcare insurance provider and don't have time to research or look around for vehicle insurance. With a cutoff of 0.3, there are no highly correlated pairs.

[47]:
```
# Use Label Encoder to encode the Vehicle_Age because there are 3 categorical␣
↪values which are ordinal in nature
from sklearn import preprocessing

le = preprocessing.LabelEncoder()
```

```
df_train_rfc = train_df
df_train_rfc['Vehicle_Age'] = le.fit_transform(df_train_rfc['Vehicle_Age'])

# one hot encode the Gender column because it contains Female or Male string␣
 ↪values
df_ohed = pd.get_dummies(df_train_rfc, columns = ['Gender'])
```

[48]:
```
corr_matrix = df_ohed.corr()
matrix = corr_matrix["Response"].sort_values(ascending=False)
matrix = matrix[abs(matrix) >= 0]

print("Features Correlated to Target - Ranked Highest to Lowest")
print(matrix)

print()
print("Pairwise Correlation - Determine Features That Are Highly Correlated -␣
 ↪Cutoff at 0.3")
# Indexing with numbers on a numpy matrix will probably be faster
corr = corr_matrix.values
rows, cols = corr.shape

for i in range(cols):
    for j in range(i + 1, cols):
        if corr[i, j] > 0.3:
            print(corr_matrix.columns[i] + ', ' + corr_matrix.index[j] + ': ' +␣
 ↪str(corr[i, j]))
```

```
Features Correlated to Target - Ranked Highest to Lowest
Response                1.000000
Vehicle_Damage          0.354400
Vehicle_Age             0.221874
Age                     0.111147
Gender_Male             0.052440
Annual_Premium          0.021957
Region_Code             0.010570
Driving_License         0.010155
Vintage                -0.001055
id                     -0.001368
Gender_Female          -0.052440
Policy_Sales_Channel   -0.139520
Name: Response, dtype: float64

Pairwise Correlation - Determine Features That Are Highly Correlated - Cutoff at
0.3
Age, Vehicle_Age: 0.7657901010871334
Vehicle_Age, Vehicle_Damage: 0.3968729148107117
Vehicle_Damage, Response: 0.35439954387975825
```

Drop Columns Low Information Features: Drop columns with low variance. The Driving_License column has more than 95% values of 1 and not 0. Thus feeding this column to the model will not provide it with any useful information as to making a prediction. Also, the id column is just an identifier for each customer, there is no learning to be made from this column so we drop it as well.

[49]:
```
df_ohed = df_ohed.drop(columns=['Driving_License'])
df_ohed = df_ohed.drop(columns=['id'])
```

Recursive Feature Elimination Method was employed to select features in addition to the correlation to target method. Age is the top feature to use which makes sense because our EDA chart showed that ages 35-55 had a high response rate. Region Code may also be top because most people are in a certain region code and maybe people in that geographic area are of a certain suburb/neighborhood with families and don't have time to research vehicle insurance companies. If they are happy with thier current healthcare insurance provider then when cross-selled to they just accept the offer and signup. Customers who were previously insured tended to accept the cross-selling offer. This would make sense because that means they can afford vehicle insurance and maybe the company made a better offer to them. Also, people who have experienced vehicle damage before (assuming they've been in an accident) probably are very likely to want to be insured to avoid out-of-pocket costs, so when approached with a better rate they are likely to signup especially if they have already established trust with their current healthcare insurance provider.

[50]:
```
# Select 10 features and print out in order of ranking
from sklearn.ensemble import RandomForestRegressor
from sklearn.feature_selection import RFE
from operator import itemgetter

regressor = RandomForestRegressor(n_estimators=100, max_depth=10)
n_features_to_select = 10
rfe = RFE(regressor, n_features_to_select=n_features_to_select)

X = df_ohed.drop(columns=['Response'])
y = df_ohed['Response']
rfe.fit(X, y)

# print out features selected in order of ranking
features = X.columns.to_list()
for x, y in (sorted(zip(rfe.ranking_ , features), key=itemgetter(0))):
    print(x, y)
```

```
1 Age
1 Region_Code
1 Previously_Insured
1 Vehicle_Age
1 Vehicle_Damage
1 Annual_Premium
1 Policy_Sales_Channel
```

```
1 Vintage
1 Gender_Female
1 Gender_Male
```

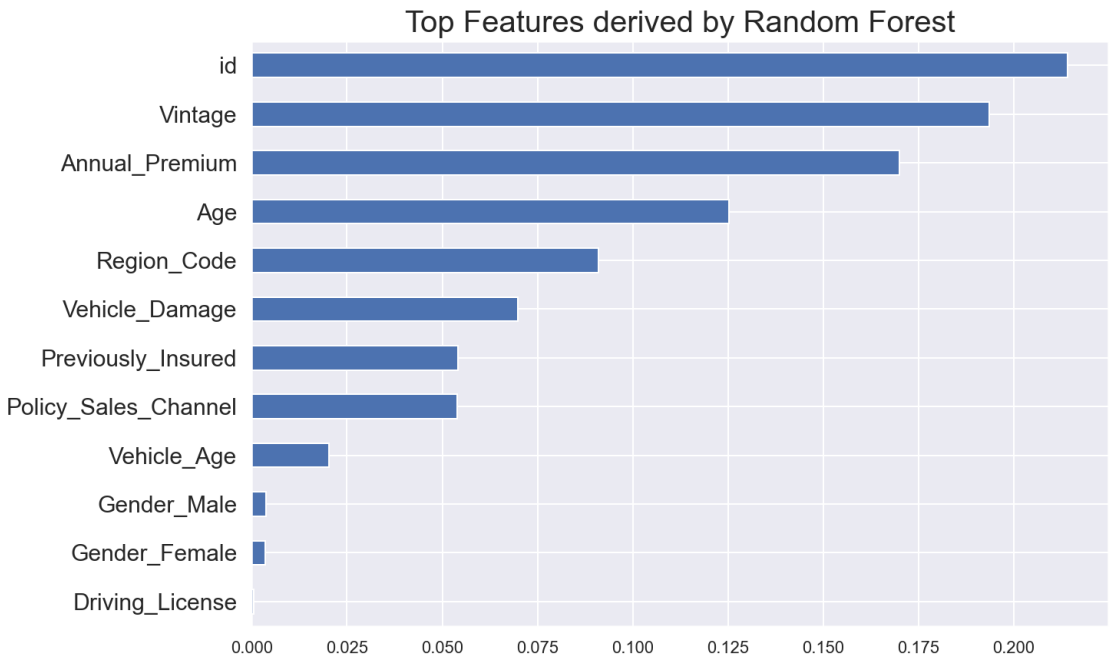
Vehicle Age, and both Genders were not listed as a top feature from RFE, so we drop them.

[51]:
```
df_ohed = df_ohed.drop(columns=['Gender_Male', 'Gender_Female'])
#print(df_ohed.head(5))
```

Random Forest Feature Importances The outcomes confirm what we see with Recursive Feature Elimination

[52]:
```
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(random_state = 0, n_estimators = 100)

df_rfc_temp = pd.get_dummies(df_rfc_temp, columns= ['Gender'])
X_rfc = df_rfc_temp.drop(columns=['Response'])
y_rfc = df_rfc_temp['Response']

model = rfc.fit(X_rfc, y_rfc)

# Plot the top features based on its importance and most important feature on␣
 ↪top
(pd.Series(model.feature_importances_, index = X_rfc.columns)
   .nlargest(47)
   .plot(kind='barh', figsize = [10,7])
   .invert_yaxis())

plt.yticks(size = 15)
plt.title('Top Features derived by Random Forest', size = 20)
```

[52]:
```
Text(0.5, 1.0, 'Top Features derived by Random Forest')
```



6 5. Dataset Splitting

Setup the dataset for train_test_split

[53]:
```
train_df = train_df.drop(columns=['id'])
test_df = test_df.drop(columns=['id'])
```

[54]:
```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
train_df['Gender'] = le.fit_transform(train_df['Gender'])
test_df['Gender'] = le.transform(test_df['Gender'])
```

[55]:
```
train_df
```

[55]:

	Gender	Age	Driving_License	Region_Code	Previously_Insured	\
0	1	0.333777	1	0.121784	0	
1	1	2.396751	1	-1.767879	0	
2	1	0.527181	1	0.121784	0	
3	1	-1.148985	1	-1.163187	1	
4	0	-0.633242	1	1.104409	1	
…	…	…	…	…	…	
381104	1	2.267815	1	-0.029389	1	
381105	1	-0.568774	1	0.802063	1	
381106	1	-1.148985	1	0.272958	1	

```
381107       0  1.881007                1    -0.936427                   0
381108       1  0.462713                1     0.197371                   0

        Vehicle_Age  Vehicle_Damage  Annual_Premium  Policy_Sales_Channel  \
0                 2               1        0.574539             -1.587234
1                 1               0        0.172636             -1.587234
2                 2               1        0.449053             -1.587234
3                 0               0       -0.113018              0.737321
4                 0               0       -0.178259              0.737321
…               …               …               …                     …
381104            1               0       -0.022912             -1.587234
381105            0               0        0.549093              0.737321
381106            0               0        0.264543              0.884912
381107            2               1        0.816389              0.220753
381108            1               0        0.651399             -1.587234

         Vintage  Response
0       0.748795         1
1       0.342443         0
2      -1.521998         1
3       0.581474         0
4      -1.378580         0
…            …       …
381104 -0.792954         0
381105 -0.279037         0
381106  0.079509         0
381107 -0.960275         0
381108  0.987826         0

[381109 rows x 11 columns]
```

[58]:
```
from sklearn.model_selection import train_test_split

from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from xgboost import XGBClassifier
from sklearn.metrics import confusion_matrix, classification_report, roc_curve,␣
 ↪roc_auc_score, plot_confusion_matrix
```

[59]:
```
y = train_df['Response']#get y
X = train_df.drop('Response', axis=1)#get x
```

[60]:
```
X_test = test_df
```

[61]:
```
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size = 0.2,␣
↪random_state = 19)#split dataset to train and val
```

6.0.1 Process imbalanced data with SMOTE

[62]:
```
# !pip install imbalanced-learn==0.6.0
# !pip install scikit-learn==0.22.1
```

We will use SMOTE to generate new data based on original data to solve imbalanced dataset problem. SMOTE first selects a minority class instance a at random and finds its k nearest minority class neighbors. The synthetic instance is then created by choosing one of the k nearest neighbors b at random and connecting a and b to form a line segment in the feature space. The synthetic instances are generated as a convex combination of the two chosen instances a and b

[63]:
```
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import GridSearchCV
#smote to process imbalance dataset

sm = SMOTE()
X_train_res, y_train_res = sm.fit_resample(X_train, y_train)
```

7 6. Model Selection

7.0.1 Hypertuning: Find best parameters

We will use GridSearchCV to find best parameters for each model.

Stochastic Gradient Descent

[64]:
```
parameters = {'penalty':('l1', 'l2'), 'max_iter':[500, 1000]}
linear_classifier = GridSearchCV(SGDClassifier(), parameters) #finetune to find␣
↪best parameters
linear_classifier.fit(X_train_res, y_train_res)
```

[64]:
```
GridSearchCV(estimator=SGDClassifier(),
             param_grid={'max_iter': [500, 1000], 'penalty': ('l1', 'l2')})
```

[65]:
```
linear_classifier.best_params_ #best parameters
```

[65]:
```
{'max_iter': 1000, 'penalty': 'l1'}
```

[66]:
```
linear_classifier.best_score_ #best score
```

[66]:
```
0.7847022650655233
```

Logistic Regression

[67]:
```
logit_reg = LogisticRegression(random_state=42)
```

[68]:
```
# defining gridesearch result viewer

def gridsearch_df_viewer(gridsearch__cv_results_):
  # search.cv_results_
  to_drop = ['mean_fit_time',
             'std_fit_time',
             'mean_score_time',
             'std_score_time',
             'split0_test_score',
             'split1_test_score',
             'split2_test_score',
             'split3_test_score',
             'split4_test_score']

  df = pd.DataFrame(gridsearch__cv_results_)
  df = df.drop(columns=to_drop)
  df = df.sort_values('rank_test_score')
  df = df.reset_index()
  return df.head(5)
```

[69]:
```
# Gridsearch to find best parameters for logistic regression using f1 weighted␣
 ↪score as measure
params={'penalty':['l2'],
        'C':[0.1,1,10],
        'solver':['newton-cg', 'lbfgs','liblinear']}

search = GridSearchCV(logit_reg, params, scoring='f1_weighted', n_jobs=-1)
search.fit(X_train_res, y_train_res)

gridsearch_df_viewer(search.cv_results_)
```

[69]:

	index	param_C	param_penalty	param_solver	params	mean_test_score	std_test_score	rank_test_score
0	2	0.1	l2	liblinear	{'C': 0.1, 'penalty': 'l2', 'solver': 'libline…	0.776121	0.000425	1
1	1	0.1	l2	lbfgs	{'C': 0.1, 'penalty': 'l2', 'solver': 'lbfgs'}	0.776074		
2	0	0.1	l2	newton-cg	{'C': 0.1, 'penalty': 'l2', 'solver': 'newton-…	0.776072		
3	5	1	l2	liblinear	{'C': 1, 'penalty': 'l2', 'solver': 'liblinear'}	0.776053		
4	3	1	l2	newton-cg	{'C': 1, 'penalty': 'l2', 'solver': 'newton-cg'}	0.776046		

```
1        0.000404                2
2        0.000407                3
3        0.000403                4
4        0.000420                5
```

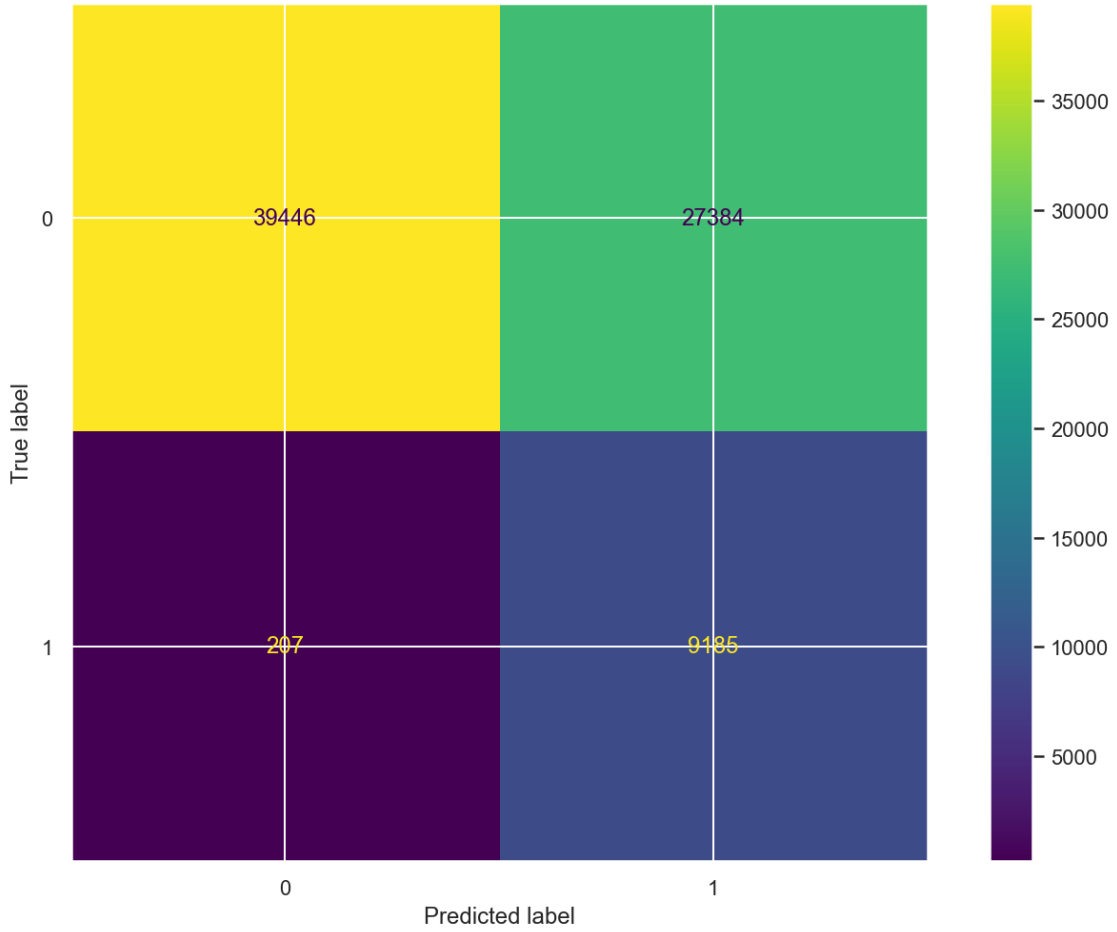
[70]:
```
logit_reg = LogisticRegression(random_state=42, penalty='l2',␣
↪solver='liblinear', C=0.1)
```

[71]:
```
logit_reg.fit(X_train_res, y_train_res)

logit_reg.score(X_val, y_val)
```

[71]:
```
0.6380178950959041
```

[72]:
```
plot_confusion_matrix(logit_reg, X=X_val, y_true=y_val)
```

[72]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x26a9124fa08>
```



[73]:
```
# F1 score for logistic regression

from sklearn.metrics import f1_score

lr_pred = logit_reg.predict(X_val)

f1_score(y_val, lr_pred, average='weighted')
```

[73]:
```
0.6988456998788372
```

[74]:
```
print(classification_report(lr_pred, y_val, target_names=['0','1']))
```

```
              precision    recall  f1-score   support

           0       0.59      0.99      0.74     39653
           1       0.98      0.25      0.40     36569

    accuracy                           0.64     76222
   macro avg       0.78      0.62      0.57     76222
weighted avg       0.78      0.64      0.58     76222
```

Random Forest

[75]:
```
parameters = {'criterion':('gini', 'entropy'), 'n_estimators':[50, 100]}
forest_classifier = GridSearchCV(RandomForestClassifier(), parameters)␣
 ↪#finetune to find best parameters
forest_classifier.fit(X_train_res, y_train_res)
```

[75]:
```
GridSearchCV(estimator=RandomForestClassifier(),
             param_grid={'criterion': ('gini', 'entropy'),
                         'n_estimators': [50, 100]})
```

[76]:
```
forest_classifier.best_params_ #best parameters
```

[76]:
```
{'criterion': 'entropy', 'n_estimators': 100}
```

[77]:
```
forest_classifier.best_score_ #best score
```

[77]:
```
0.9136859130103401
```

The best parameters of random forest are criterion: gini, n_estimators=100 if we train this model with these parameters we will have 0.83 on accuracy, this is highest accuracy with best parameter of random forest

Decision Tree

[78]:
```
parameters = {'criterion':('gini', 'entropy'), 'max_depth':[7, 11]}
```

```
decisiontree_classifier = GridSearchCV(DecisionTreeClassifier(), parameters)␣
↪#finetune to find best parameters
decisiontree_classifier.fit(X_train_res, y_train_res)
```

[78]:
```
GridSearchCV(estimator=DecisionTreeClassifier(),
             param_grid={'criterion': ('gini', 'entropy'),
                         'max_depth': [7, 11]})
```

[79]:
```
decisiontree_classifier.best_params_ #best parameters
```

[79]:
```
{'criterion': 'gini', 'max_depth': 11}
```

[80]:
```
decisiontree_classifier.best_score_ #best score
```

[80]:
```
0.8304942267291523
```

The best parameters of decision tree are criterion: entropy, max depth=11 if we train this model with these parameters we will have 0.83 on accuracy, this is highest accuracy with best parameter of decision tree model

AdaBoost

[81]:
```
parameters = {'n_estimators':[25, 50]}
ada_classifier = GridSearchCV(AdaBoostClassifier(), parameters) #finetune t␣
↪find best parameters
ada_classifier.fit(X_train_res, y_train_res)
```

[81]:
```
GridSearchCV(estimator=AdaBoostClassifier(),
             param_grid={'n_estimators': [25, 50]})
```

[82]:
```
ada_classifier.best_params_ #best parameters
```

[82]:
```
{'n_estimators': 50}
```

[83]:
```
ada_classifier.best_score_ #best score
```

[83]:
```
0.8128576448807318
```

The best parameters of adaboost is The maximum number of estimators is 50, if we train this model with this parameters we will have 0.81 on accuracy, this is highest accuracy with best parameter of adaboost model. => This accuracy is lower than random forest model.

Neural Network

[84]:
```
parameters = {'solver':('adam', 'sgd'), 'activation':('relu', 'tanh'),
              'hidden_layer_sizes':[2, 4], 'max_iter': [200, 400]}
nn = GridSearchCV(MLPClassifier(), parameters) #finetune t find best parameters
nn.fit(X_train_res, y_train_res)
```

[84]:
```
GridSearchCV(estimator=MLPClassifier(),
             param_grid={'activation': ('relu', 'tanh'),
                         'hidden_layer_sizes': [2, 4], 'max_iter': [200, 400],
                         'solver': ('adam', 'sgd')})
```

[85]:
```
nn.best_params_ #best parameters
```

[85]:
```
{'activation': 'tanh',
 'hidden_layer_sizes': 4,
 'max_iter': 200,
 'solver': 'adam'}
```

[86]:
```
nn.best_score_ #best score
```

[86]:
```
0.7954882686479061
```

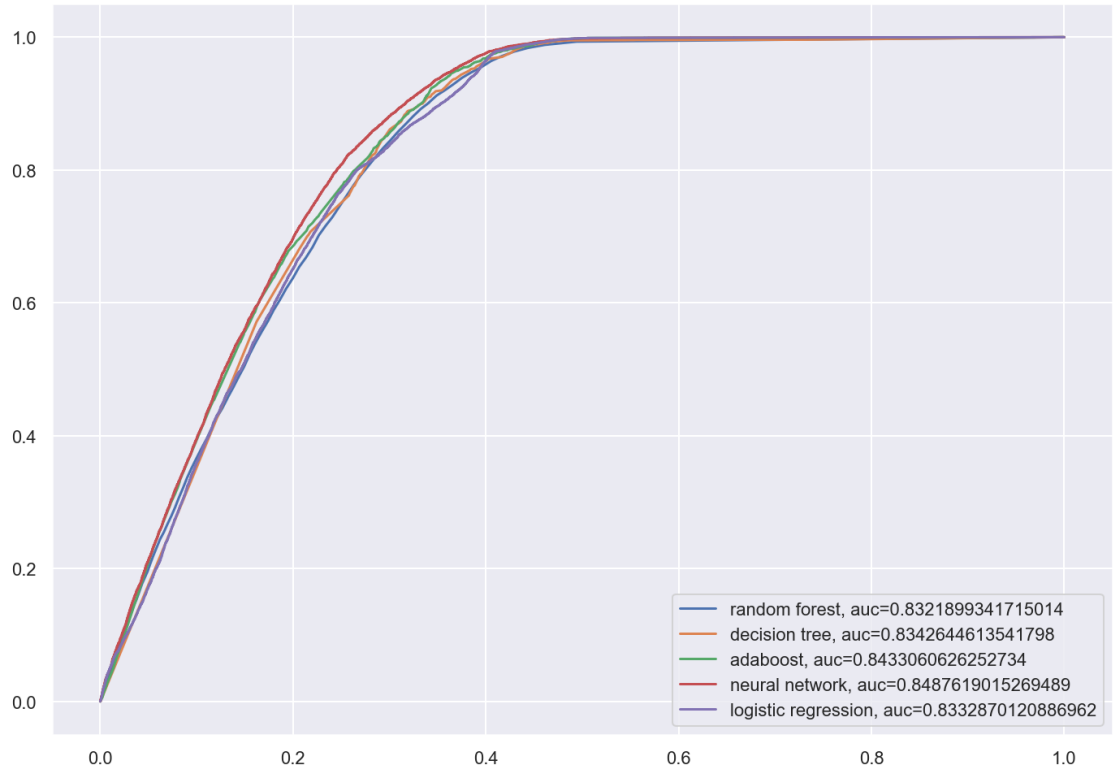
The best parameters of neural network are: activation: tanh, we use 4 hidden layers and adam as optimization. The accuracy is 0.79, this is lowest accuracy of 6 models we trained.

[112]:
```
forest_pred = forest_classifier.predict(X_val)#predict validation data
cm_forest = confusion_matrix(y_val, forest_pred) #traditional confusion matrix

linear_classifier_pred = linear_classifier.predict(X_val)#predict validation␣
↪data
cm_linear = confusion_matrix(y_val, linear_classifier_pred) #traditional␣
↪confusion matrix

decisiontree_classifier_pred = decisiontree_classifier.predict(X_val)#predict␣
↪validation data
cm_tree = confusion_matrix(y_val, decisiontree_classifier_pred) #traditional␣
↪confusion matrix

ada_pred = ada_classifier.predict(X_val)#predict validation data
cm_ada = confusion_matrix(y_val, ada_pred) #traditional confusion matrix

nn_pred = nn.predict(X_val)#predict validation data
cm_nn = confusion_matrix(y_val, nn_pred) #traditional confusion matrix

log_pred = logit_reg.predict(X_val)#predict validation data
cm_log = confusion_matrix(y_val, log_pred) #traditional confusion matrix
```

7.0.2 ROC Curve: Compare the Models

[113]:
```
forest_pred_proba = forest_classifier.predict_proba(X_val)[:,1] #predict␣
↪probabilities
fpr_forest, tpr_forest, _ = roc_curve(y_val,  forest_pred_proba) #calculate␣
↪false positive and true positive
```

```
auc_forest = roc_auc_score(y_val, forest_pred_proba) #auc score

decisiontree_classifier_pred_proba = decisiontree_classifier.
↪predict_proba(X_val)[::,1] #predict probabilities
fpr_tree, tpr_tree, _ = roc_curve(y_val,  decisiontree_classifier_pred_proba)␣
↪#calculate false positive and true positive
auc_tree = roc_auc_score(y_val, decisiontree_classifier_pred_proba) #auc score

ada_pred_proba = ada_classifier.predict_proba(X_val)[::,1] #predict␣
↪probabilities
fpr_ada, tpr_ada, _ = roc_curve(y_val,  ada_pred_proba) #calculate false␣
↪positive and true positive
auc_ada = roc_auc_score(y_val, ada_pred_proba) #auc score

nn_pred_proba = nn.predict_proba(X_val)[::,1] #predict probabilities
fpr_nn, tpr_nn, _ = roc_curve(y_val,  nn_pred_proba) #calculate false positive␣
↪and true positive
auc_nn = roc_auc_score(y_val, nn_pred_proba) #auc score

log_pred_proba = logit_reg.predict_proba(X_val)[::,1] #predict probabilities
fpr_log, tpr_log, _ = roc_curve(y_val,  log_pred_proba) #calculate false␣
↪positive and true positive
auc_log = roc_auc_score(y_val, log_pred_proba) #auc score

plt.plot(fpr_forest,tpr_forest,label="random forest, auc="+str(auc_forest))
plt.plot(fpr_tree,tpr_tree,label="decision tree, auc="+str(auc_tree))
plt.plot(fpr_ada, tpr_ada,label="adaboost, auc="+str(auc_ada))
plt.plot(fpr_nn,tpr_nn,label="neural network, auc="+str(auc_nn))
plt.plot(fpr_log,tpr_log,label="logistic regression, auc="+str(auc_log))

plt.legend(loc=4)
plt.show()
```



7.0.3 F1 score

[114]:
```
#Evaluate f1 score each model on validation dataset
from sklearn.metrics import f1_score

print("F1 score of random forest model is: ", f1_score(y_val, forest_pred,␣
 ↪average='weighted'))
print("F1 score of linear model is: ", f1_score(y_val, linear_classifier_pred,␣
 ↪average='weighted'))
print("F1 score of decision tree model is: ", f1_score(y_val,␣
 ↪decisiontree_classifier_pred, average='weighted'))
print("F1 score of adaboost model is: ", f1_score(y_val, ada_pred,␣
 ↪average='weighted'))
print("F1 score of Neural network model is: ", f1_score(y_val, nn_pred,␣
 ↪average='weighted'))
print("F1 score of Logistic Regression model is: ", f1_score(y_val, log_pred,␣
 ↪average='weighted'))
```

```
F1 score of random forest model is:  0.8384743930962543
F1 score of linear model is:  0.6990151795874153
F1 score of decision tree model is:  0.7827333454731527
F1 score of adaboost model is:  0.7640040282016075
```

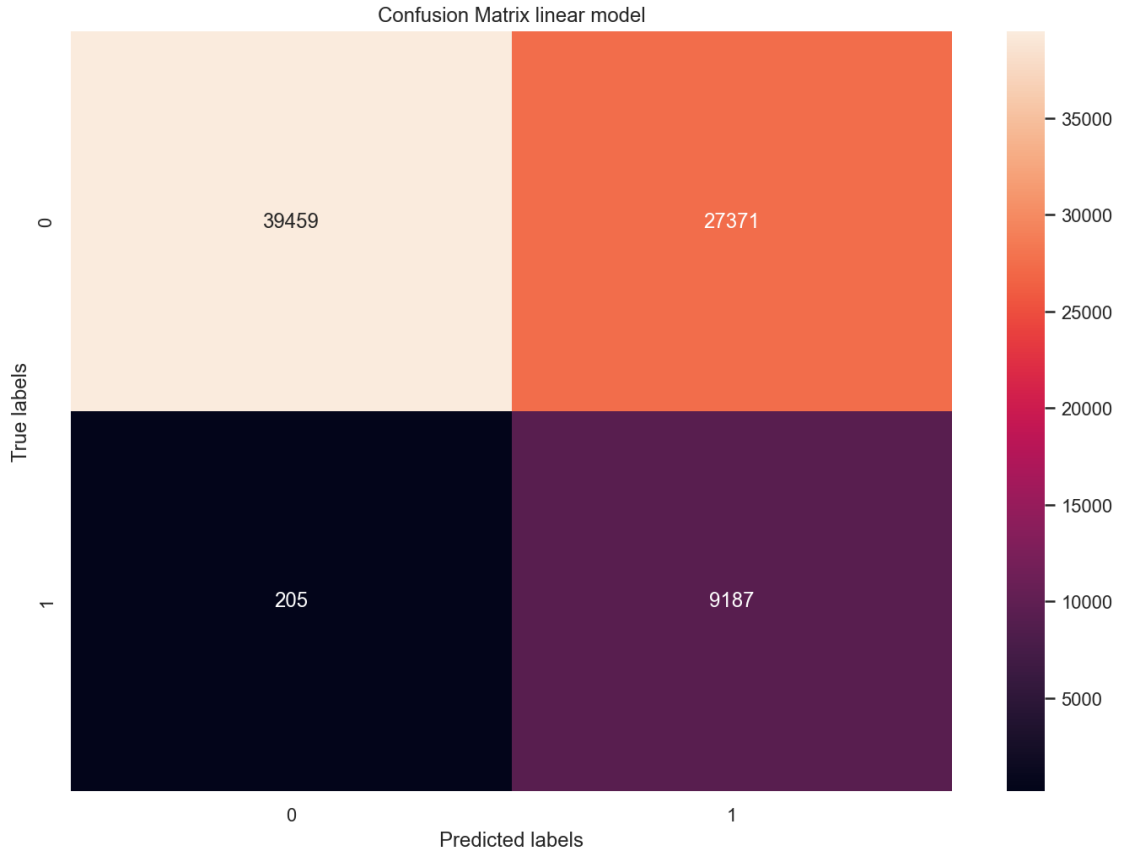
```
F1 score of Neural network model is:  0.7477511390129322
F1 score of Logistic Regression model is:  0.6988456998788372
```

=> Random forest has highest F1 score, this is best model

7.0.4 Confusion matrix

[93]:
```
target_names = ['0','1'] #class name
```

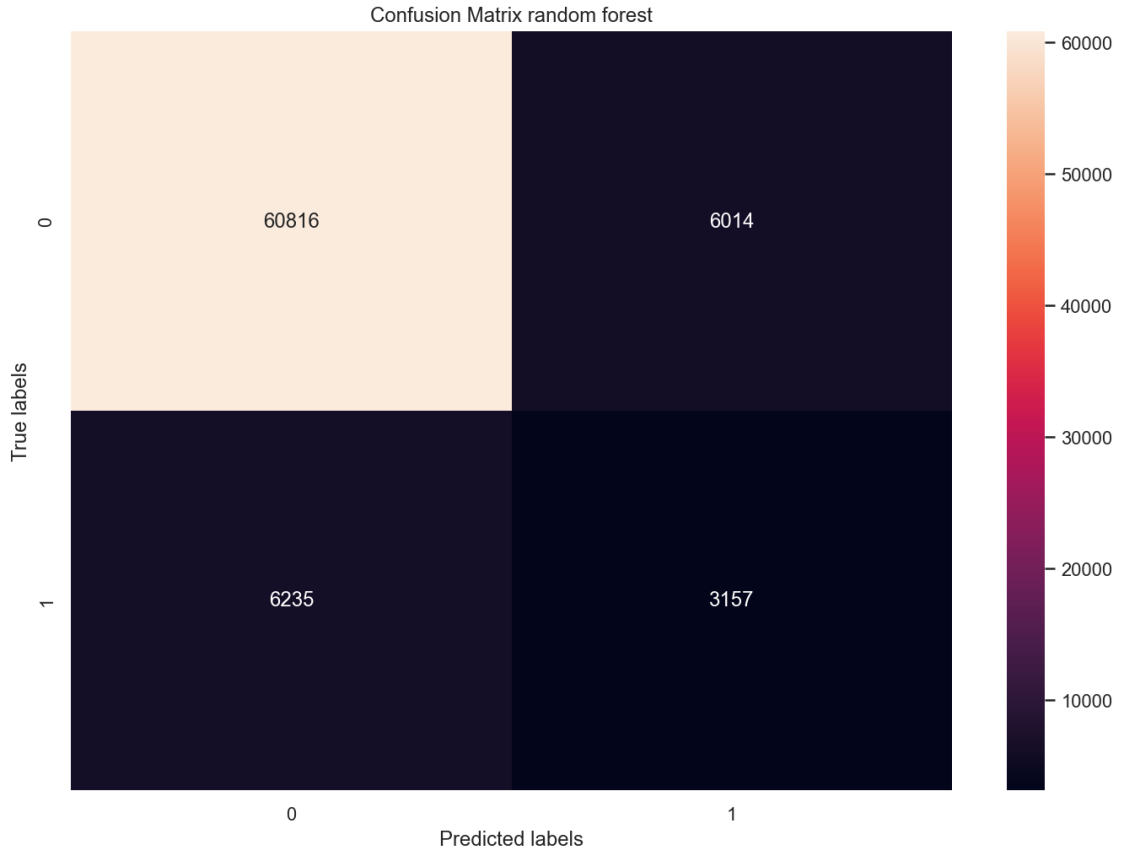
[94]:
```
ax = plt.subplot()
sns.heatmap(cm_linear, annot=True, fmt='g', ax=ax);
ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels');
ax.set_title('Confusion Matrix linear model');
ax.xaxis.set_ticklabels(target_names); ax.yaxis.set_ticklabels(target_names);
```



The graph show 39459 class 0 predict true and 9187 class 1 predict true, we have about 0.6% class 0 predict wrong and 0.1% class 1 predict wrong, this result isn't good for class 0.

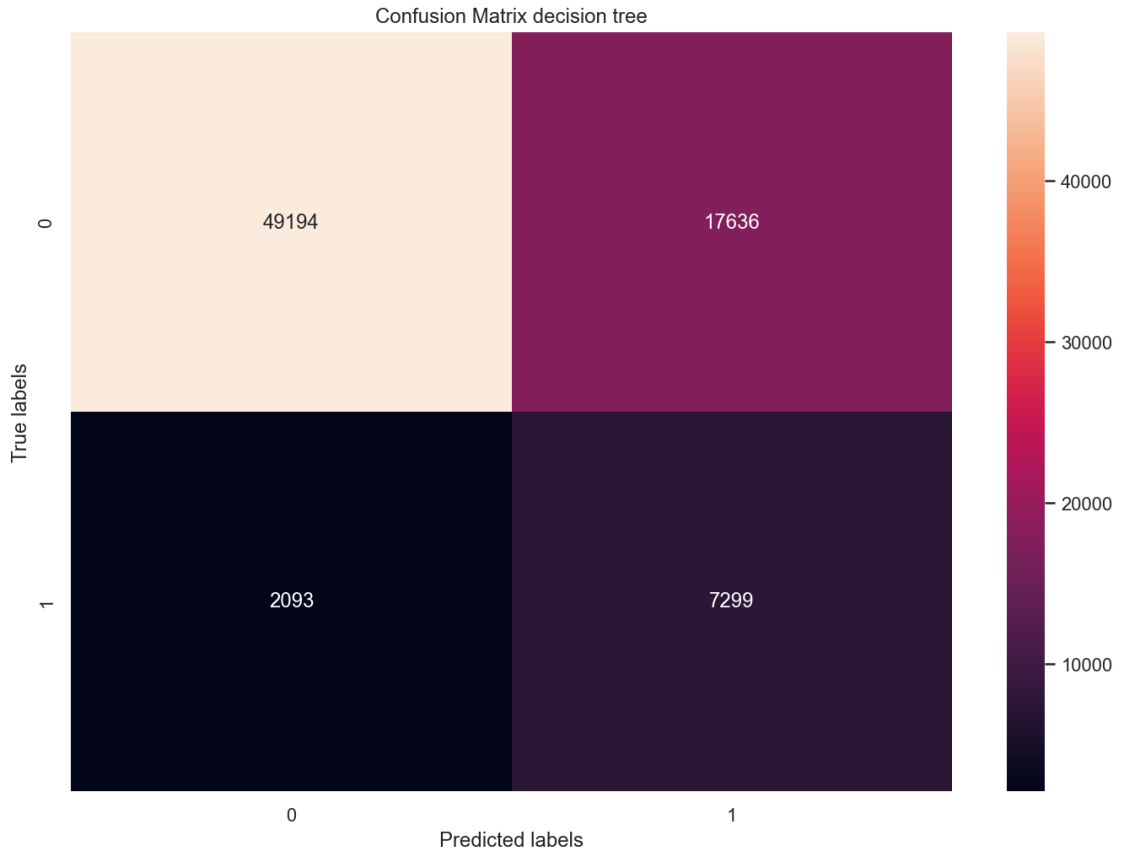
[95]:
```
ax = plt.subplot()
sns.heatmap(cm_forest, annot=True, fmt='g', ax=ax);
ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels');
```

```
ax.set_title('Confusion Matrix random forest');
ax.xaxis.set_ticklabels(target_names); ax.yaxis.set_ticklabels(target_names);
```



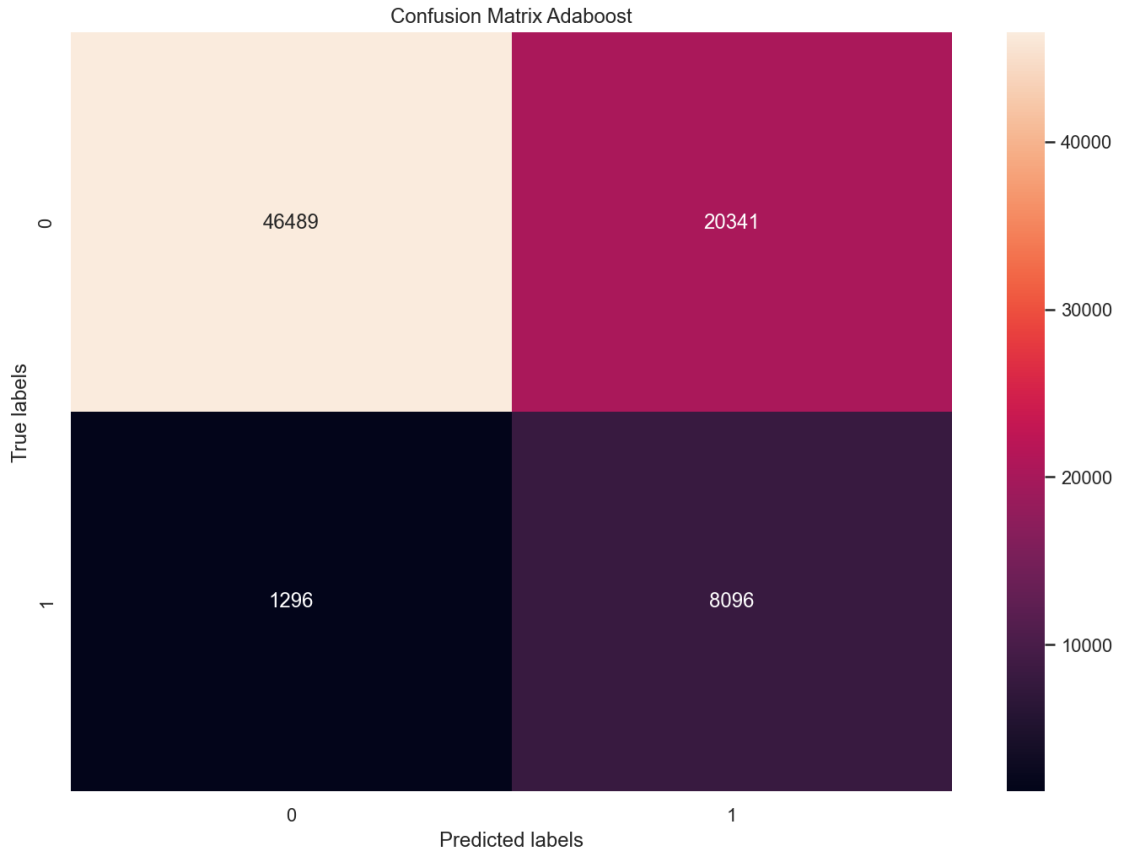
The graph show 60816 class 0 predict true and 3157 class 1 predict true, we have about 0.1% class 0 predict wrong and 0.3% class 1 predict wrong, this result isn't good for class 1 but it's very good when predict class 0.

[96]:
```
ax = plt.subplot()
sns.heatmap(cm_tree, annot=True, fmt='g', ax=ax);
ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels');
ax.set_title('Confusion Matrix decision tree');
ax.xaxis.set_ticklabels(target_names); ax.yaxis.set_ticklabels(target_names);
```



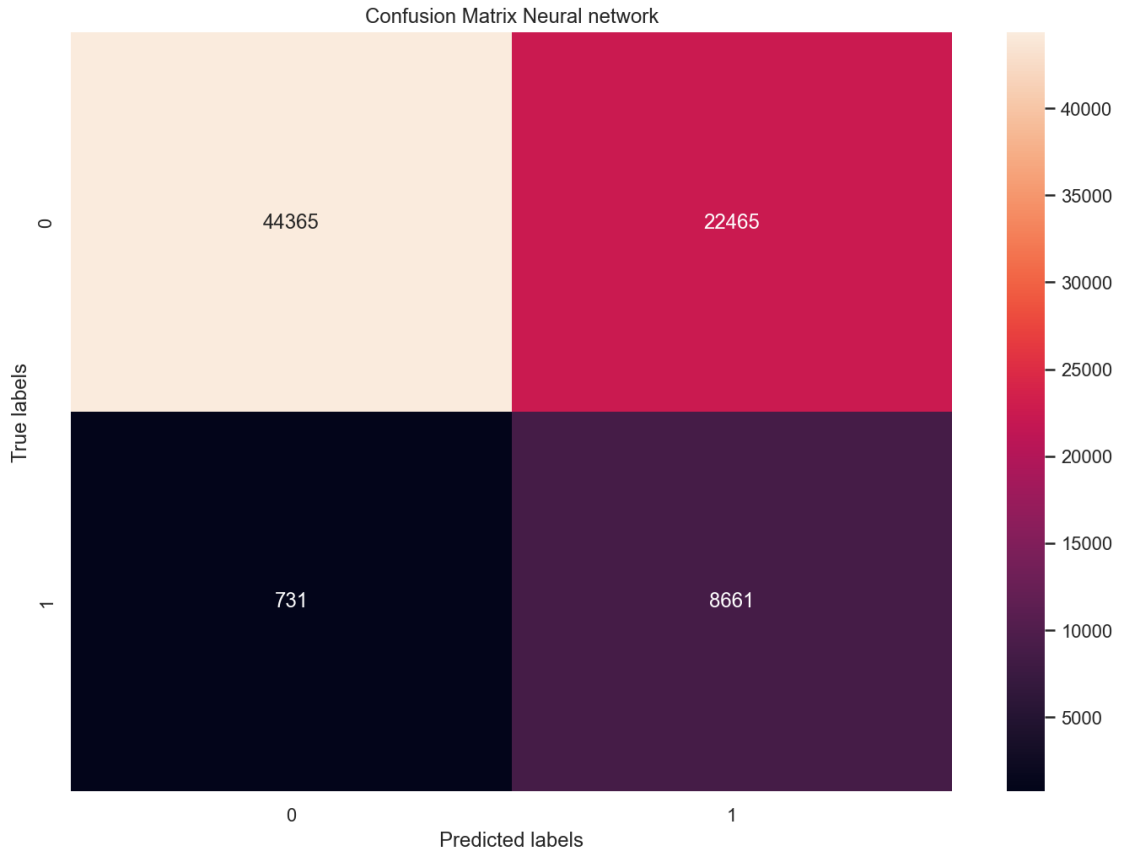
The graph show 49194 class 0 predict true and 7299 class 1 predict true, we have about 0.4% class 0 predict wrong and 0.2% class 1 predict wrong, this result is good.

[97]:
```
ax = plt.subplot()
sns.heatmap(cm_ada, annot=True, fmt='g', ax=ax);
ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels');
ax.set_title('Confusion Matrix Adaboost');
ax.xaxis.set_ticklabels(target_names); ax.yaxis.set_ticklabels(target_names);
```



The graph show 46489 class 0 predict true and 8096 class 1 predict true, we have about 0.45% class 0 predict wrong and 0.15% class 1 predict wrong, this model can predict class 1 better than decision tree but class 0 is not good.

[98]:
```
ax = plt.subplot()
sns.heatmap(cm_nn, annot=True, fmt='g', ax=ax);
ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels');
ax.set_title('Confusion Matrix Neural network');
ax.xaxis.set_ticklabels(target_names); ax.yaxis.set_ticklabels(target_names);
```



The graph show 44365 class 0 predict true and 8661 class 1 predict true, we have about 0.47% class 0 predict wrong and 0.12% class 1 predict wrong, we can see this model is best to classify class 1 but class 0 is not good.

=> In 5 models, for the balancing result we should use decision model to have better for both class 0 and 1.

7.0.5 Report

[99]:
```
print("Report model decision tree\n")
print(classification_report(linear_classifier_pred, y_val,␣
 ↪target_names=target_names))
```

```
Report model decision tree

              precision    recall  f1-score   support

           0       0.59      0.99      0.74     39664
           1       0.98      0.25      0.40     36558

    accuracy                           0.64     76222
```

```
   macro avg       0.78      0.62      0.57     76222
weighted avg       0.78      0.64      0.58     76222
```

[100]:
```
print("Report model random forest\n")
print(classification_report(forest_pred, y_val, target_names=target_names))
```

```
Report model random forest

              precision    recall  f1-score   support

           0       0.91      0.91      0.91     67051
           1       0.34      0.34      0.34      9171

    accuracy                           0.84     76222
   macro avg       0.62      0.63      0.62     76222
weighted avg       0.84      0.84      0.84     76222
```

[101]:
```
print("Report model decision tree\n")
print(classification_report(decisiontree_classifier_pred, y_val,␣
 ↪target_names=target_names))
```

```
Report model decision tree

              precision    recall  f1-score   support

           0       0.74      0.96      0.83     51287
           1       0.78      0.29      0.43     24935

    accuracy                           0.74     76222
   macro avg       0.76      0.63      0.63     76222
weighted avg       0.75      0.74      0.70     76222
```

[102]:
```
print("Report model Adaboost\n")
print(classification_report(ada_pred, y_val, target_names=target_names))
```

```
Report model Adaboost

              precision    recall  f1-score   support

           0       0.70      0.97      0.81     47785
           1       0.86      0.28      0.43     28437

    accuracy                           0.72     76222
   macro avg       0.78      0.63      0.62     76222
weighted avg       0.76      0.72      0.67     76222
```

[103]:
```
print("Report model Neural network\n")
print(classification_report(nn_pred, y_val, target_names=target_names))
```

```
Report model Neural network

              precision    recall  f1-score   support

           0       0.66      0.98      0.79     45096
           1       0.92      0.28      0.43     31126

    accuracy                           0.70     76222
   macro avg       0.79      0.63      0.61     76222
weighted avg       0.77      0.70      0.64     76222
```

[115]:
```
print("Report model Logistic Regression\n")
print(classification_report(log_pred, y_val, target_names=target_names))
```

```
Report model Logistic Regression

              precision    recall  f1-score   support

           0       0.59      0.99      0.74     39653
           1       0.98      0.25      0.40     36569

    accuracy                           0.64     76222
   macro avg       0.78      0.62      0.57     76222
weighted avg       0.78      0.64      0.58     76222
```

7.0.6 Make Prediction Using Test Dataset 'test_df'

This section to classify test dataframe

We use 5 models to predict result on test data, then create 4 new columns for each result.

[106]:
```
test_prediction_linear = linear_classifier.predict(X_test)
test_prediction_forest = forest_classifier.predict(X_test)
test_prediction_tree = decisiontree_classifier.predict(X_test)
test_prediction_ada = ada_classifier.predict(X_test)
test_prediction_nn = nn.predict(X_test)
```

[107]:
```
test_df_ori['Prediction_linear'] = test_prediction_linear
test_df_ori['Prediction_randomforest'] = test_prediction_forest
test_df_ori['Prediction_decisiontree'] = test_prediction_tree
test_df_ori['Prediction_adaboost'] = test_prediction_ada
test_df_ori['Prediction_neuralnetwork'] = test_prediction_nn
```

[108]:
```
test_df_ori #show final results
```

[108]:

	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	\
0	381110	Male	25	1	11.0	1	
1	381111	Male	40	1	28.0	0	
2	381112	Male	47	1	28.0	0	
3	381113	Male	24	1	27.0	1	
4	381114	Male	27	1	28.0	1	
…	…	…	…	…	…	…	
127032	508142	Female	26	1	37.0	1	
127033	508143	Female	38	1	28.0	0	
127034	508144	Male	21	1	46.0	1	
127035	508145	Male	71	1	28.0	1	
127036	508146	Male	41	1	29.0	1	

	Vehicle_Age	Vehicle_Damage	Annual_Premium	Policy_Sales_Channel	\
0	< 1 Year	No	35786.0	152.0	
1	1-2 Year	Yes	33762.0	7.0	
2	1-2 Year	Yes	40050.0	124.0	
3	< 1 Year	Yes	37356.0	152.0	
4	< 1 Year	No	59097.0	152.0	
…	…	…	…	…	
127032	< 1 Year	No	30867.0	152.0	
127033	1-2 Year	Yes	28700.0	122.0	
127034	< 1 Year	No	29802.0	152.0	
127035	1-2 Year	No	62875.0	26.0	
127036	1-2 Year	No	27927.0	124.0	

	Vintage	Prediction_linear	Prediction_randomforest	\
0	53	0	0	
1	111	1	0	
2	199	1	0	
3	187	0	0	
4	297	0	0	
…	…	…	…	
127032	56	0	0	
127033	165	1	0	
127034	74	0	0	
127035	265	0	0	
127036	231	0	0	

	Prediction_decisiontree	Prediction_adaboost	Prediction_neuralnetwork
0	0	0	0
1	1	1	1
2	1	1	1
3	0	0	0
4	0	0	0

```
...                    ...                    ...                    ...
127032                   0                      0                      0
127033                   1                      1                      1
127034                   0                      0                      0
127035                   0                      0                      0
127036                   0                      0                      0

[127037 rows x 16 columns]
```

[130]:
```
print("Percentage Acceptance Rate of Cross-Sell Offer:")
accept = len(test_df_ori[test_df_ori['Prediction_randomforest']==1])
total = len(test_df_ori)
print(accept/total)
```

```
Percentage Acceptance Rate of Cross-Sell Offer:
0.1536638931964703
```

7.1 Cumulative Gains Chart

This chart will enable us to predict how many offers need to be sent out to the current customers who are likely to purchase vehicle insurance when cross-sold to. We can then figure out the cost effectiveness of the model and communicate clearly to non-technical stakeholders the marketing campaign ROI on this project.

As you can see below, the curve reaches 100% at about 50% of the sample. This means, that if we send out cross-selling offers for vehicle insurance to the top 50% of our customers who have been predicted by our model to most likely buy, we can expect to achieve 100% of the gains or acceptances for cross-sells.

Keep in mind that with RandomForestClassifier, the standard cutoff is at 0.5 for classification. So if a customer is predicted with 51% probability to purchase vehicle insurance in a cross-selling offer, they will be counted as likely to purchase with a value 1 instead of 0. With several more iterations, we can adjust this classification cutoff to more accurately reflect the reality, but for now we use the standard cutoff for initial modeling purposes.

In terms of the business implications, what this means is that for a given number of customers who receive the offer, 15% will end up accepting. To illustrate, given a set of 100,000 customers, the client's marketing department only needs to send out to 15,000 of those customers because those are the customers the model predicts are likely to purchase vehicle insurance. And of those 15,000, we only need to send out to 7,500 to gain the full number of people who would signup anyway.

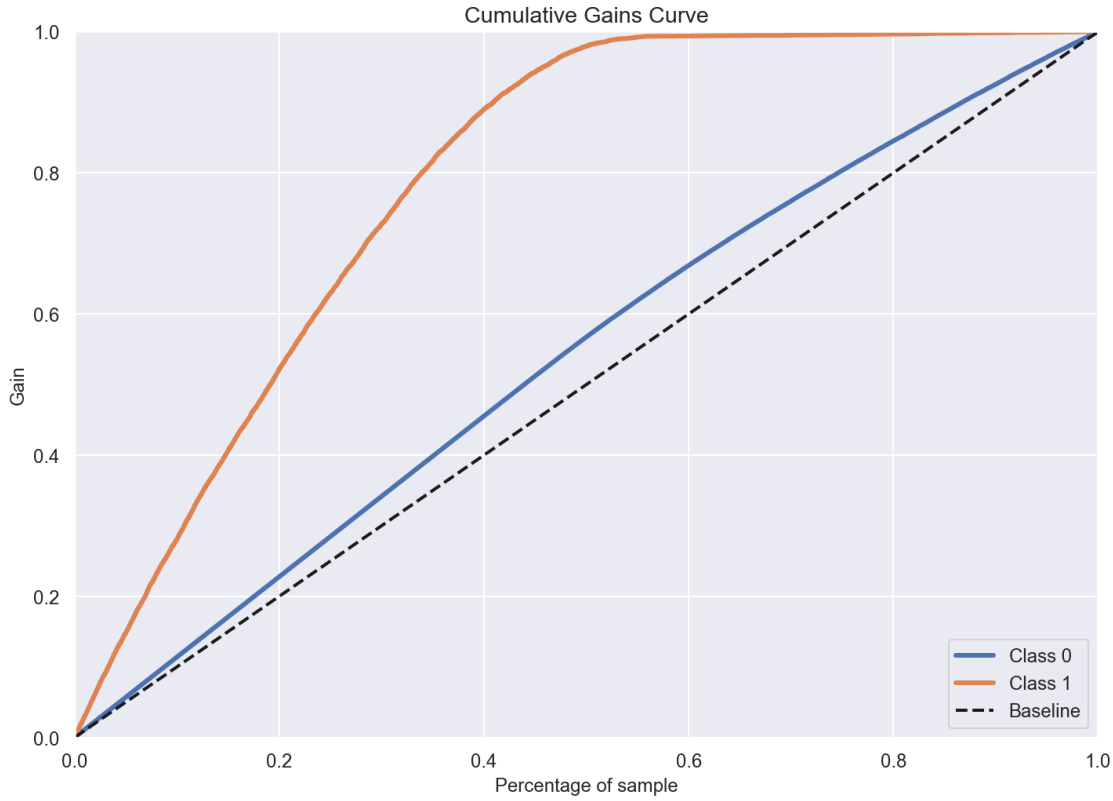
Give that the client customer base is 300,000, we can estimate to send out offers to 22,500 customers at a cost of $300 for the email marketing software costs. Additional costs needs to be factored in to calculate the ROI, see below:

Assuming the cost of developing and implementing this prediction model will be around the budget of: Duration: 3-4 months Salaries: 250k (USD) for a Team of 5 consisting of 2 Data Scientists, 1 Business Intelligence Expert, 2 Marketers Cost of Marketing Campaign: $300/month email marketing for 22,500 emails sent out Return: 22,500 customers at minimum annual coverage price of 561 USD = 12.6M USD additional revenue per 300,000 customers

==> ROI = 12.6M USD/((250k USD salaries/month * 4 months) + 1200 USD email marketing software) ~~ 12x on initial investment

That is an ROI of 12x for this project. You risk approximately 1M USD, but you have a potential gain of 12.6M USD.

[116]:
```
import scikitplot as skplt

forest_pred_proba = forest_classifier.predict_proba(X_val)
ax = skplt.metrics.plot_cumulative_gain(y_true = y_val, y_probas =␣
↪forest_pred_proba)
```



8 7. Next Steps/Recommendation

Refer to Written Report

Next steps is to understand how the client can reach these cusomters beisdes just sending emails.We recommend using some social media apllications to reach the perspective audience. We need to tailor the method based on the age groups that are being reached out to. Luckly everyone uses social media so that is a safe route to go to cross sell to customers fast.

ADS-505 Team Project Form & Business Brief Templates Team Project Form

Fill out this form and business brief and submit it by the end of Module 3 in Blackboard (2 pages max for each). Reference the file, "Final Project Business Brief Requirements.doc."

Team Number: 6

Team Leader/Representative: Abanather Negusu

Full Names of Team Members:

1. Abanather Negusu
2. Connie Chow
3. Minsu Kim

Title of Your Project: A Classification Problem: Health Insurance Cross Sell Prediction

Short Description of Your Project and Objectives: Our client, an insurance company who has provided health insurance to its customers wants to know whether those customers will also be interested in purchasing vehicle insurance coverage. The objective is to build a model to best predict whether each customer would be interested in purchasing vehicle insurance so the company can best strategize its communications and optimize revenue. We will be testing a few different models to find one with the best performance.

Name of Your Selected Dataset and Programming Language:
Health Insurance Cross Sell Prediction (https://www.kaggle.com/datasets/anmolkumar/health-insurance-cross-sell-prediction?select=train.csv)
Python

Description of Your Selected Dataset (source, number of variables, size of the dataset, etc.):
Source: Kaggle
Training set: 12 columns, 381,110 rows (20.4MB)
Test Set: 13 columns, 127,038 rows (6.60MB)

Provide your team GitHub link here: https://github.com/ADS-505-Applied-Data-Sci-for-Business

How many times have your team members met so far? We have not set aside a specific time to meet but have been very actively communicating over Slack.

What was the agreed-upon method of communication? Are you using any teamwork project management software, such as Deepnote, Trello, or Asana? If not, explain why? __We will communicate mostly through Slack and share codes via GitHub

Comments/ Roadblocks: None at the moment currently.

Team Project Business Brief

Purpose:
The purpose of this project is to determine which set of customers will be most likely to purchase vehicle insurance through the current healthcare insurance provider. By determining this set of customers to target, the health insurance company can adjust their marketing strategy to target these customers in upcoming marketing campaigns. This is important to achieve because if successful, it will result in an additional stream of revenue and profits, the expansion of the company's presence in the insurance sector, services and market share, all of which can be used to build out the company further to serve more customers in the future.

Background:
An insurance policy is an arrangement by which a company undertakes to provide a guarantee for specified loss and/or damage. Healthcare insurance companies are always looking to expand their businesses and serve more customers. Our client, an insurance company that currently offers health insurance plans, is looking to expand its services by possibly offering vehicle insurances to its existing customers. It is looking to do so with the optimal efficiency and budget for maximum profit and service to its customers.

The current average cost of vehicle insurance in the United States varies by credit and driver history. The rates can range from as low as $561 for minimum coverage to as high as $3139 full coverage for a driver with recent DUI and good credit. If even 10,000 of your customer base signs up for vehicle insurance, the outcome of your marketing campaign would result in a projected additional annual revenue for the company totalling anywhere from $5.6M to $31.4M.

Current Situation:
The client wants to predict which customers from the past year will be most likely to purchase vehicle insurance on top of their health insurance.

Key questions that this data science based project outcomes will address are:

1. Which of our client's current customers will be most likely to purchase the vehicle insurance when marketed to?
2. What are the attributes of such customers?
3. What is the estimate of revenue the client can expect to achieve through successful execution of this project?

Conclusion:

The very next course of action is to obtain a budget for the execution of a data science based project in which different prediction models are used to determine the best set of customers that will produce the maximum profit for the company, while also serving the most customers from its customer base.

Our project will unfold in three main parts. First EDA and random sampling of the customer base - we use KNN etc. Second part is the predictive modeling; we will build several model candidates in an attempt to best predict which customers are likely to purchase. Third and last part is to test and evaluate the said models and select the best one(s). The final model will be utilized to make the final prediction of the customers who will most likely purchase the vehicle insurance.