DARNELL KIKOO

Cross Health Insurance Prediction

FINAL PROJECT

Table of Contents

Business Background

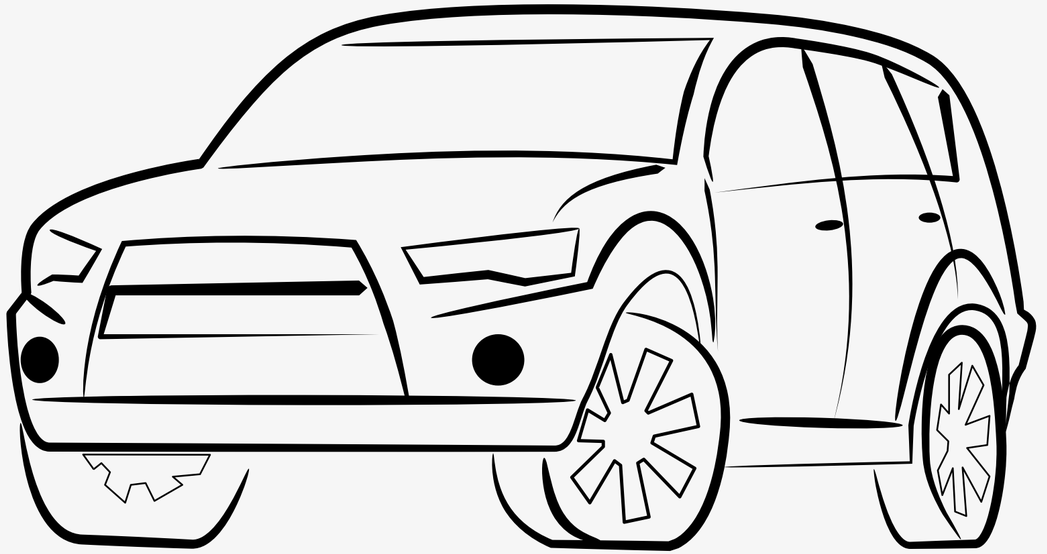
Background

I'm a freelance data scientist, recruited to work at one of the **bigest insurance company** in India

Our company wanted to increase the sales of vehicle insurance. Hence, I am asked to create a model to predict the possible reaction of policy holders if they are asked to buy one

Business Objectives

The objective of this project is to **predict** whether a policy holder would be **interested in insuring their vehicle.** Helping the company to increase their sales and minimizing the range of customers that should be contacted for sales



Output

The output of this project is a **model** to predict the **customer's response** given its feature

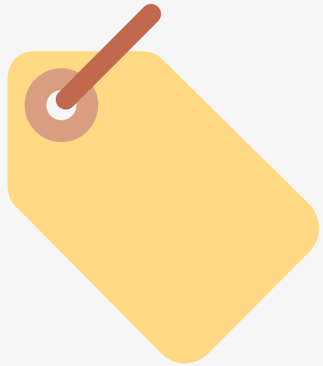
The feature includes Vehicle_Damage, Previously_Insured, Gender, etc.

Project Limitation

We have limited knowledge towards some features, such as region_code and anonimyzed policy_sales_channel

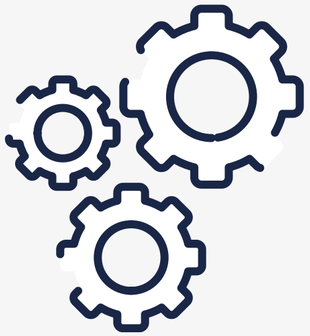
We also decided to remove customer rows who doesn't have Driving_License

Analytic Approach



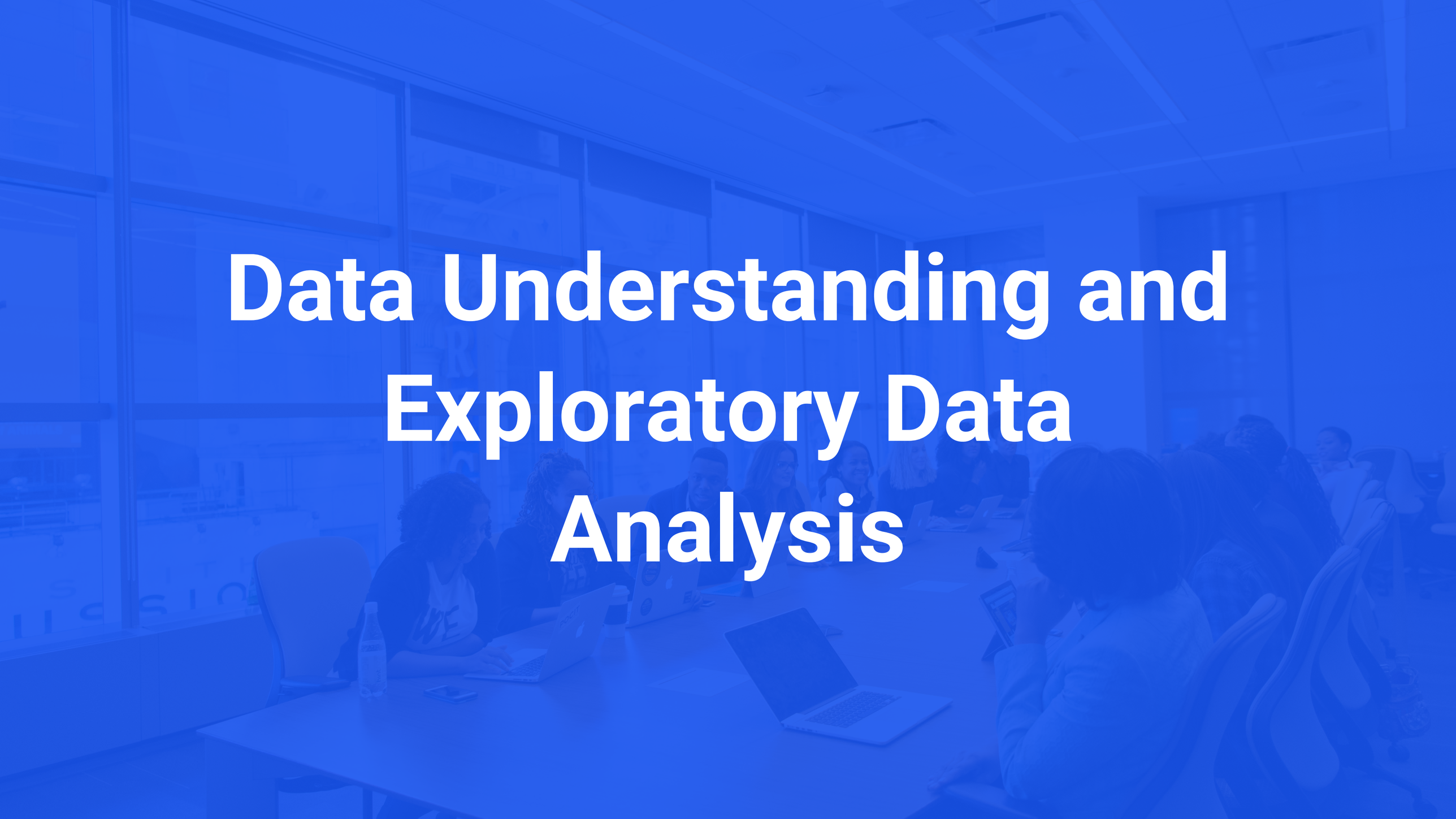
Machine Learning

Supervised Learning (Binary Classification)
Classify what response (label) the customer would give



Performance Measures

ROC_AUC
Precision, Recall, F1 and Accuracy to support our measurement



Data Understanding and Exploratory Data Analysis

Data Collection / Gathering

The dataset is provided by Kaggle, with 381109 Rows and 12 Columns

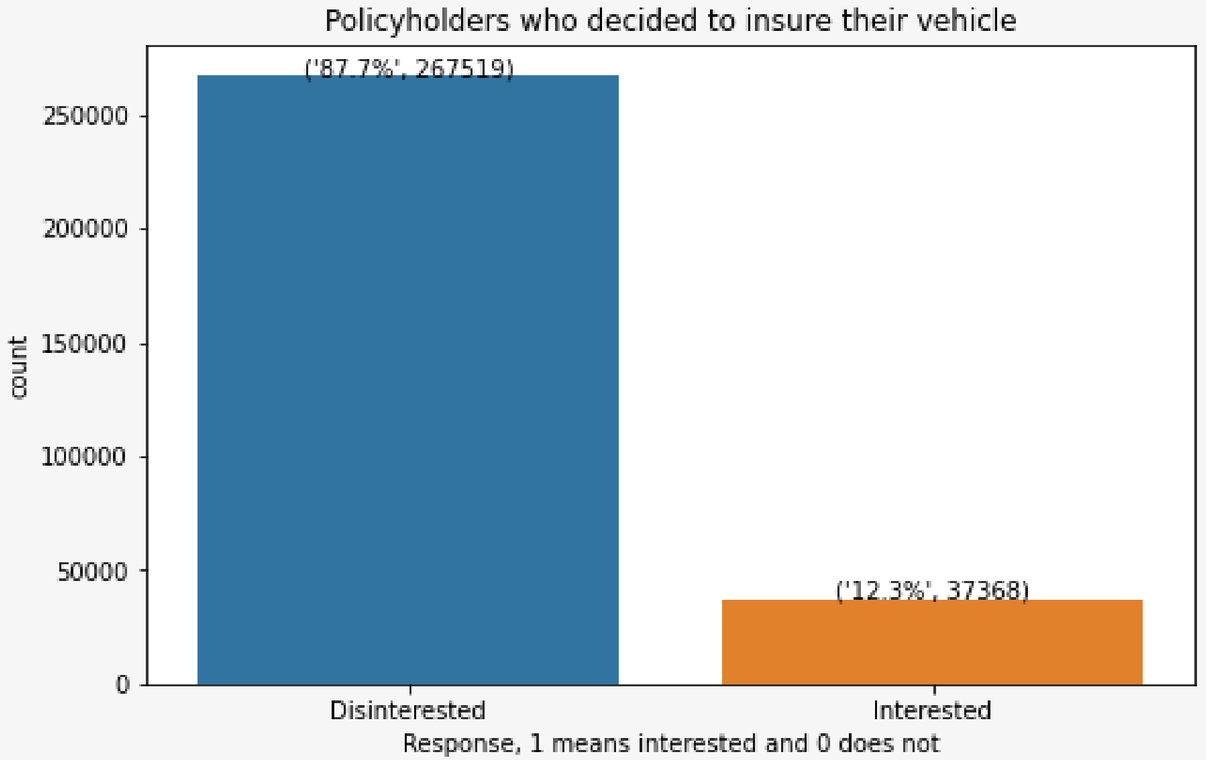
Column Explanation

No	Feature	Data Type	Distinct	Missing (%)	Description
1	id	int64	304887	0.0%	Unique ID for the customer
2	Gender	object	2	0.0%	Gender of the Customer
3	Age	int64	66	0.0%	Age of the customer
4	Driving_License	int64	2	0.0%	0:Customer does not have DL, 1:Customer already has DL
5	Region_Code	float64	53	0.0%	Unique code for the region of the customer
6	Previously_Insured	int64	2	0.0%	1:Customer already has Vehicle Insurance, 0:Customer doesn't have Vehicle Insurance
7	Vehicle_Age	object	3	0.0%	Age of the Vehicle
8	Vehicle_Damage	int64	2	0.0%	1:Customer got his/her vehicle damaged in the past. 0: Customer didn't get his/her vehicle damaged in the past
9	Annual_Premium	float64	46366	0.0%	The amount customer needs to pay as premium in the year
10	Policy_Sales_Channel	float64	152	0.0%	Anonymized Code for the channel of outreaching to the customer ie. Different Agents, Over Mail, Over Phone, In Person, etc.
11	Vintage	int64	290	0.0%	Number of Days, Customer has been associated with the company

Divided Dataset

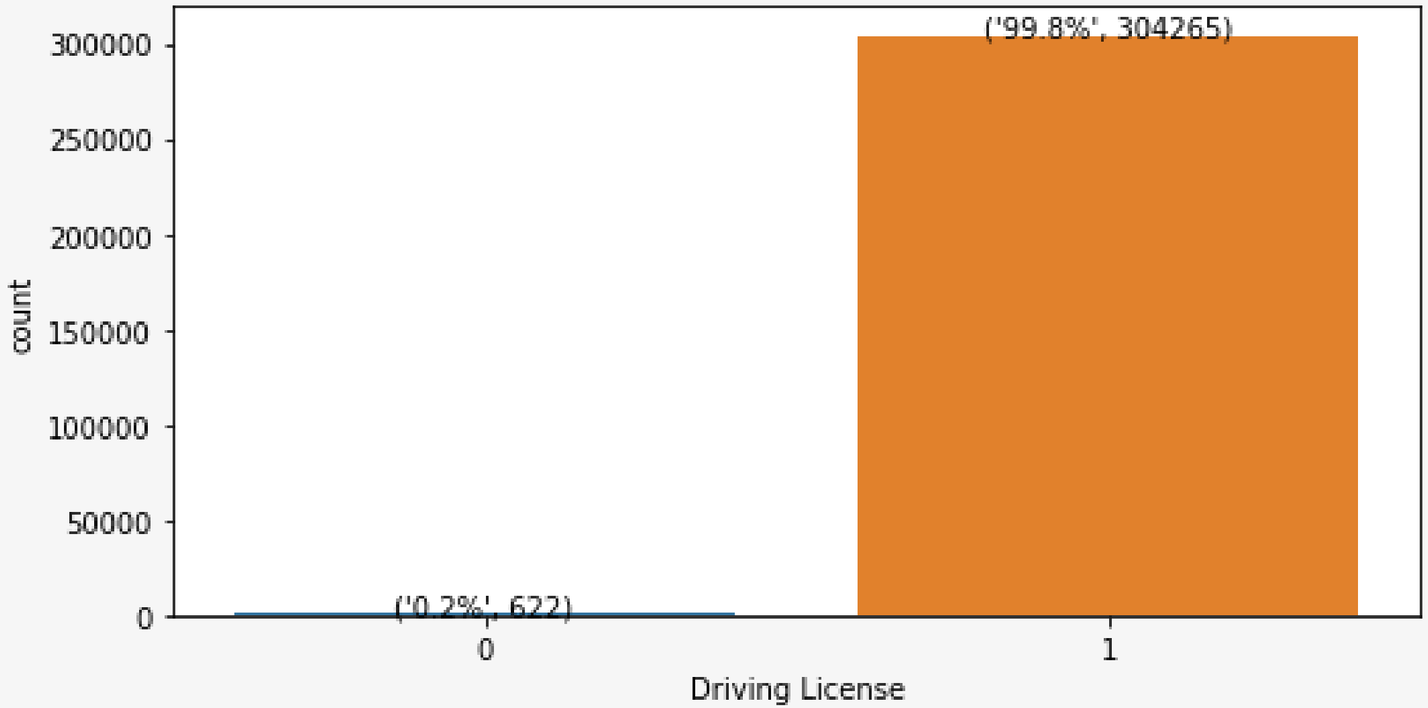
We split the data into the ratio of **80:20**, where the **80%** is used for **development**, and the **20%** is used for **final prediction**

Response Distribution



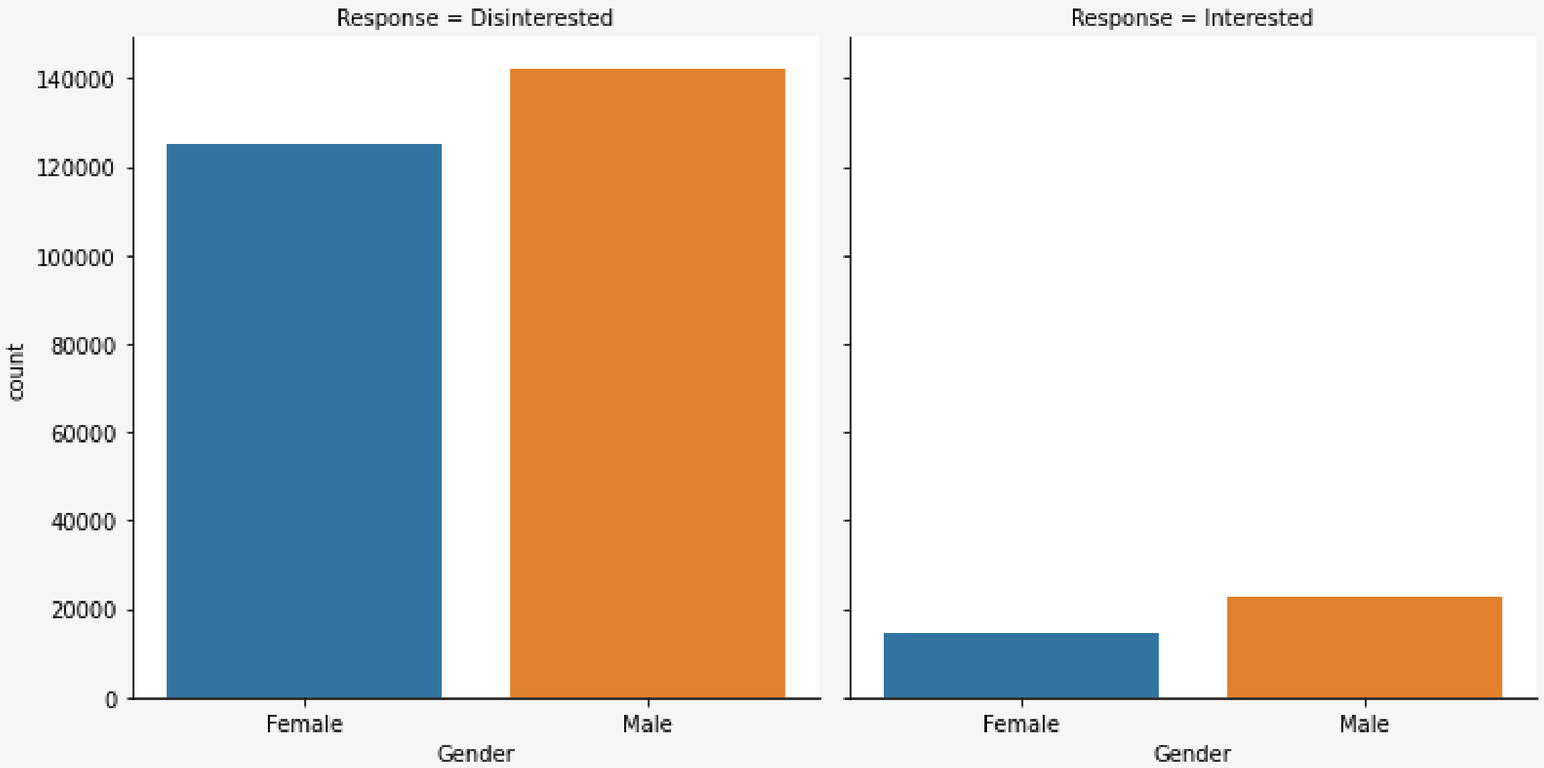
The chart shows the distribution of the response, which majority appeared to be disinterested. This explains that 87%++ policyholders don't seem to be interested in insuring their vehicle

Driving License



The chart shows majority (99.8%) of policyholders do have driving license. In fact, it is rare to see someone who buys vehicle license but doesn't have a driving license. Hence, we assume that this is caused by mistyping and will remove the rows without driving license

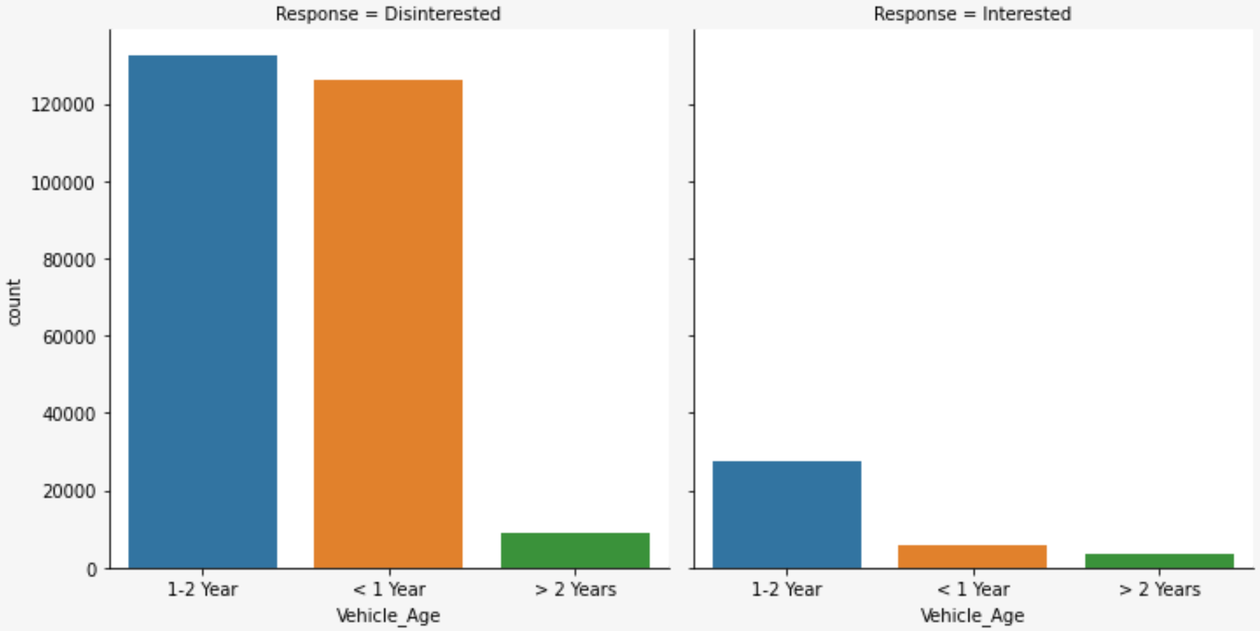
Gender on Response



Total male buy Insurance : 13.813196541395326%
Total female buy Insurance : 10.421891187082485%

From the given dataset, males are more likely to buy vehicle insurance regardless of their age, with a bigger margin of 3.4% compared to Female. We can say that male will give quite a big impact on the model

Vehicle Age on Response



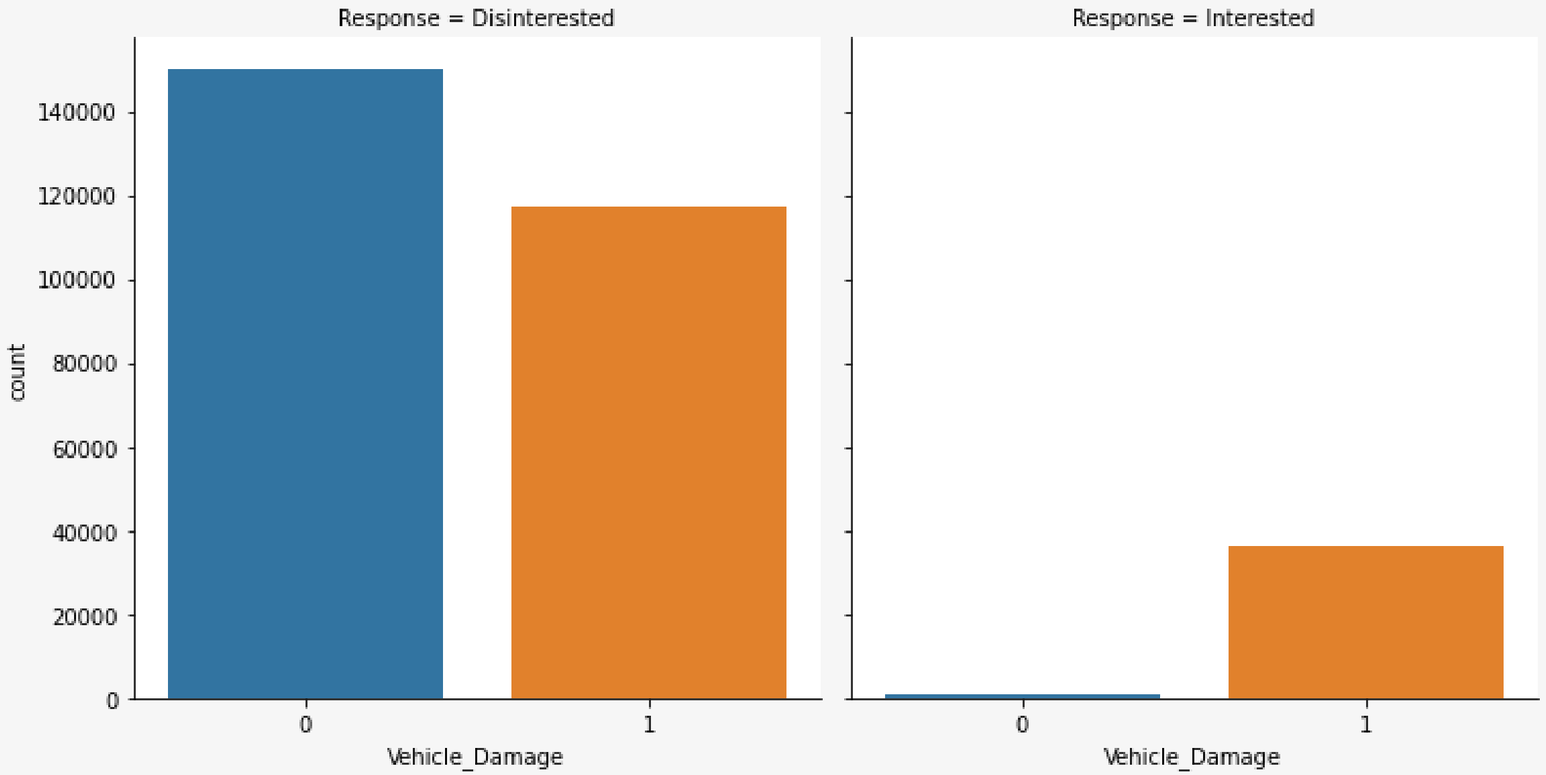
Customer's Vehicle Age 1-2 Year and buy Insurance : 17.32 %

Customer's Vehicle Age Less Than 1 Year and buy Insurance : 4.42 %

Customer's Vehicle Age More Than 2 Years and buy Insurance: 29.63 %

Based on the vehicle age, there are more customers who have a vehicle aged between 0-2 years. However, customer whose car age is above 2 years have a bigger number of purchase on vehicle insurance

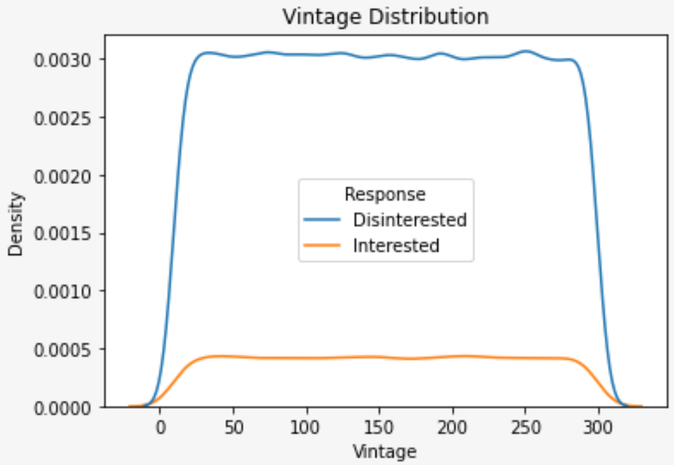
Vehicle Damage on Response

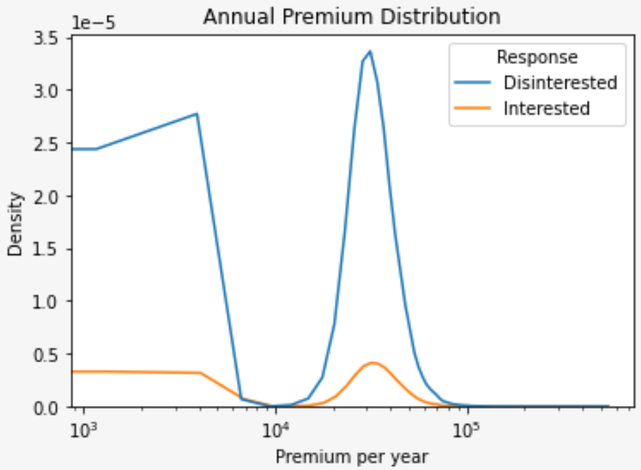


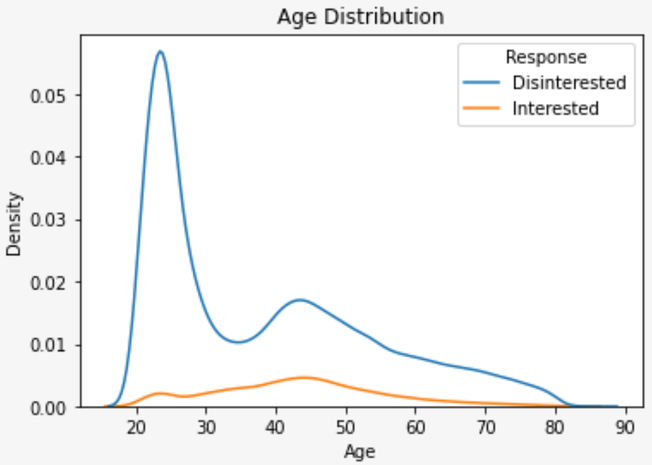
Customers who have ever had their vehicle damaged and buy Insurance: **23.74 %**
Customers who never had their vehicle damaged and buy Insurance : **0.52 %**

Majority of policyholders who buys vehicle insurance, are those who have ever had their vehicle damaged. This might be affected by the psychological trauma caused by unwanted accidents and damage their vehicle

Numerical Column Distribution

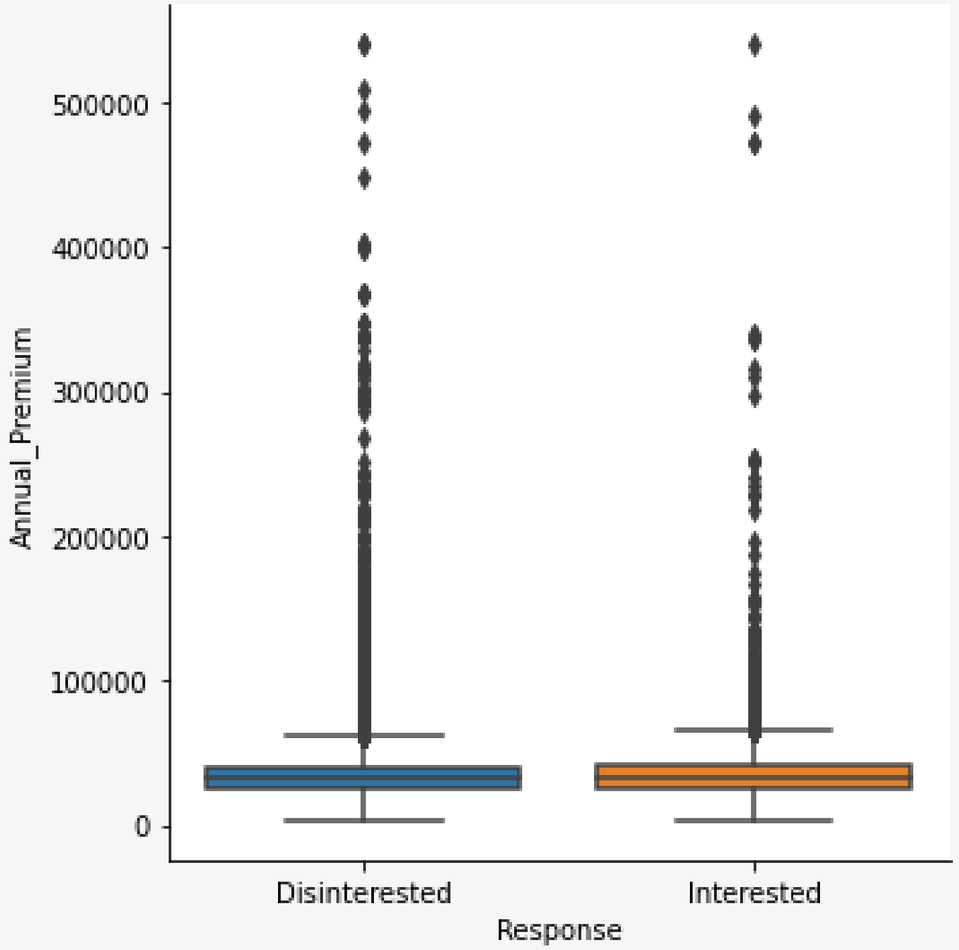






While the first 2 charts doesn't have any strong information, the third chart tells us that majority of customers who buy vehicle insurance were from the 40-50 Age range

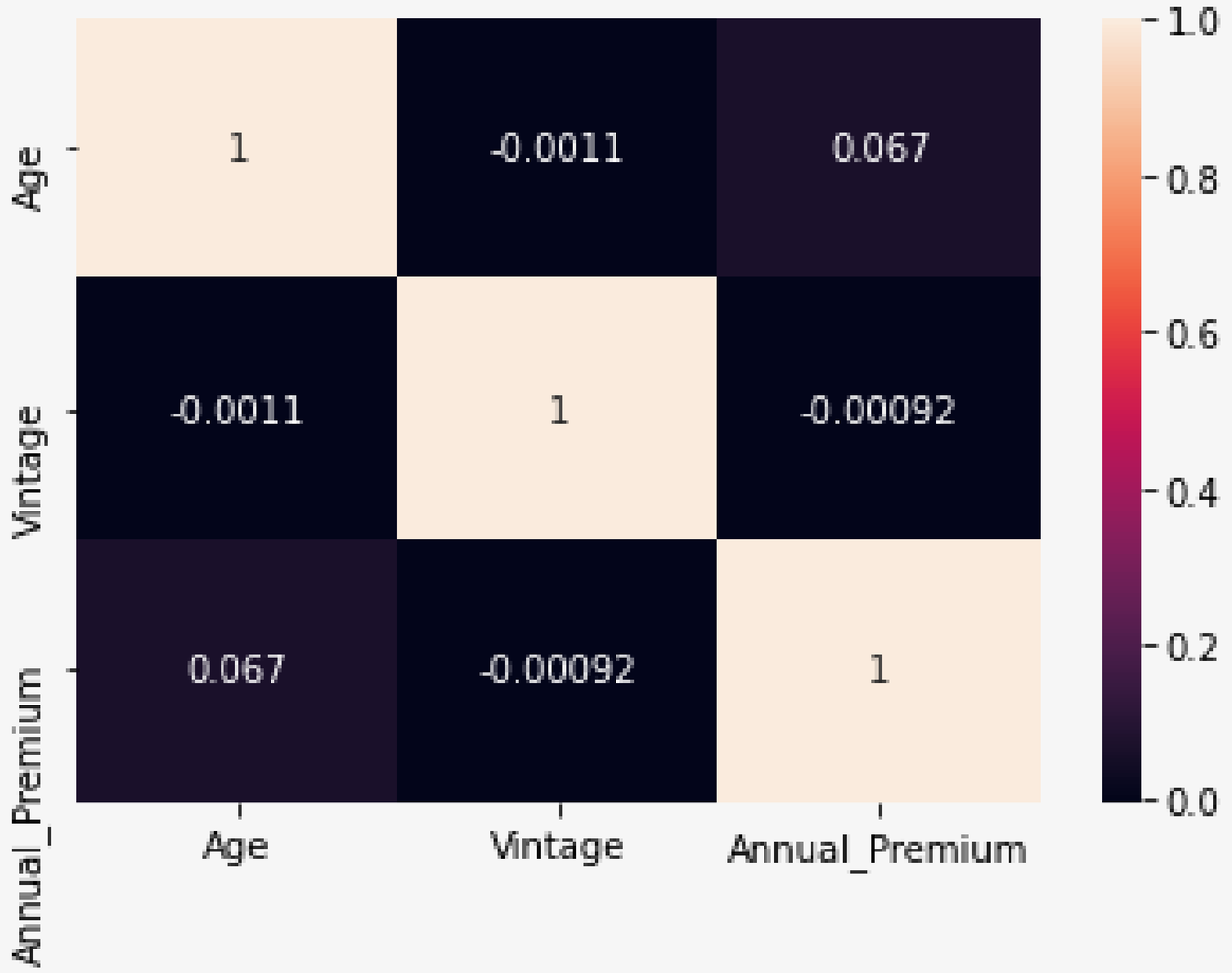
Customer's Annual Premium Distribution



The boxplot represents the outlier from the Annual_Premium feature. Most policyholders in India buys insurance below Rs 60,000.

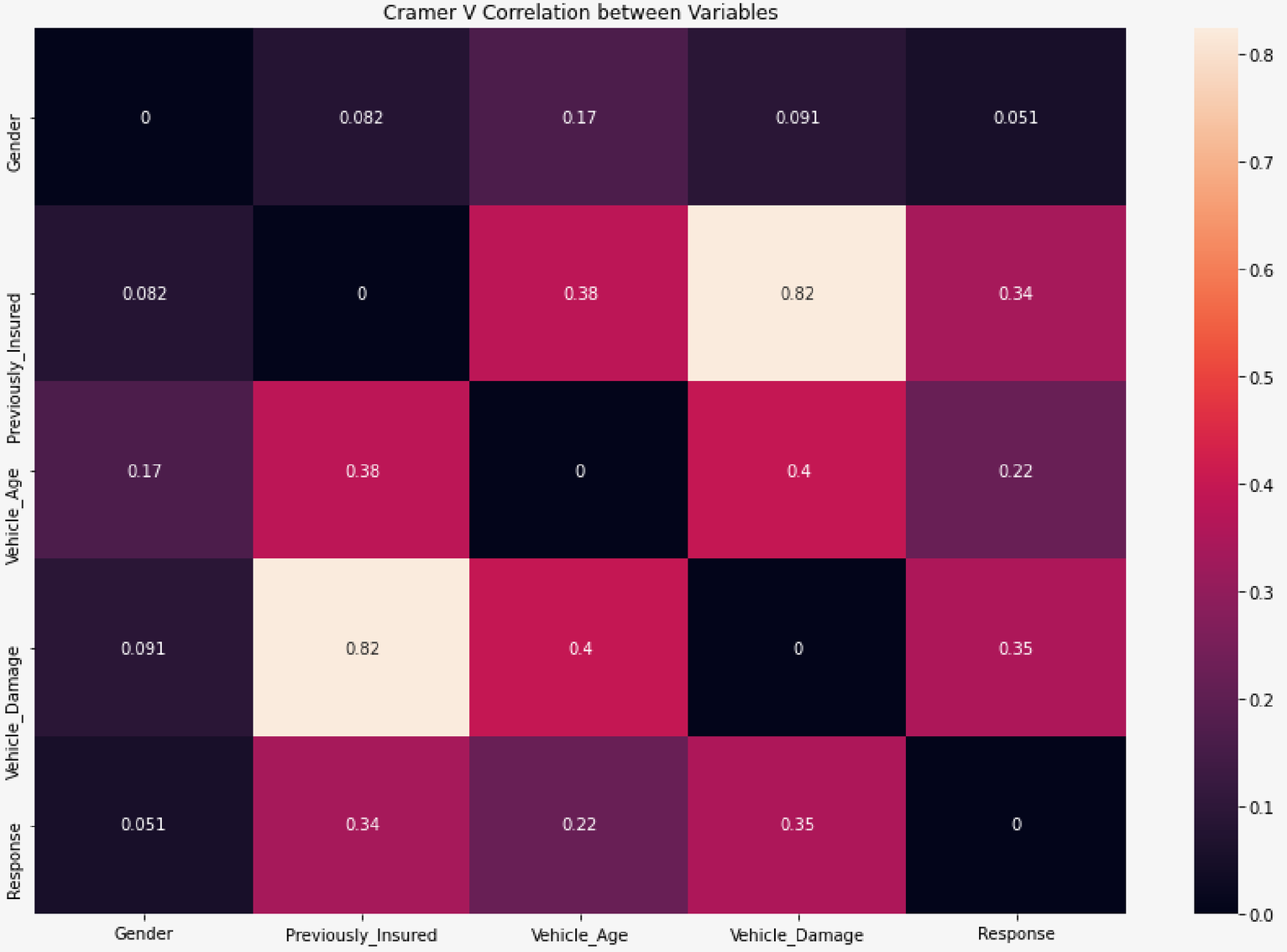
This shows the economic gap distribution between Indian citizens

Numerical Column Correlations



The heatmap doesn't show any strong correlation between features

Categorical Column Correlations With Response Using Cramers V Heatmap



The Previously_Insured feature seems to have a strong relation with Vehicle_Damage

This is supported by the fact that people who have had their vehicle damaged will buy a vehicle insurance

Categorical Column Correlations With Response Using Cramers V Heatmap

Kruskal-Wallis Test results of Gender
H Stat = 809.6826408737934
P = 4.2354192395808124e-178

Kruskal-Wallis Test results of Previously_Insured
H Stat = 35440.63114163706
P = 0.0

Kruskal-Wallis Test results of Vehicle_Age
H Stat = 14955.41399255504
P = 0.0

Kruskal-Wallis Test results of Vehicle_Damage
H Stat = 38204.02112771305
P = 0.0

Using the statistical Kruskal-Wallis Test, we can safely assume that the categorical columns could help distinguish the Response, as all the P-Values are below 0.05

Data Preprocessing

1

Casting Data Types

2

Remove Unwanted Feature

3

Remove Rows with no Driving License, then remove the column

4

Encode Categorical Columns

5

Remove Outlier on Annual_Premium column

6

Normalized Numerical Columns

Casting Data Types

Casting any categorical columns types to category

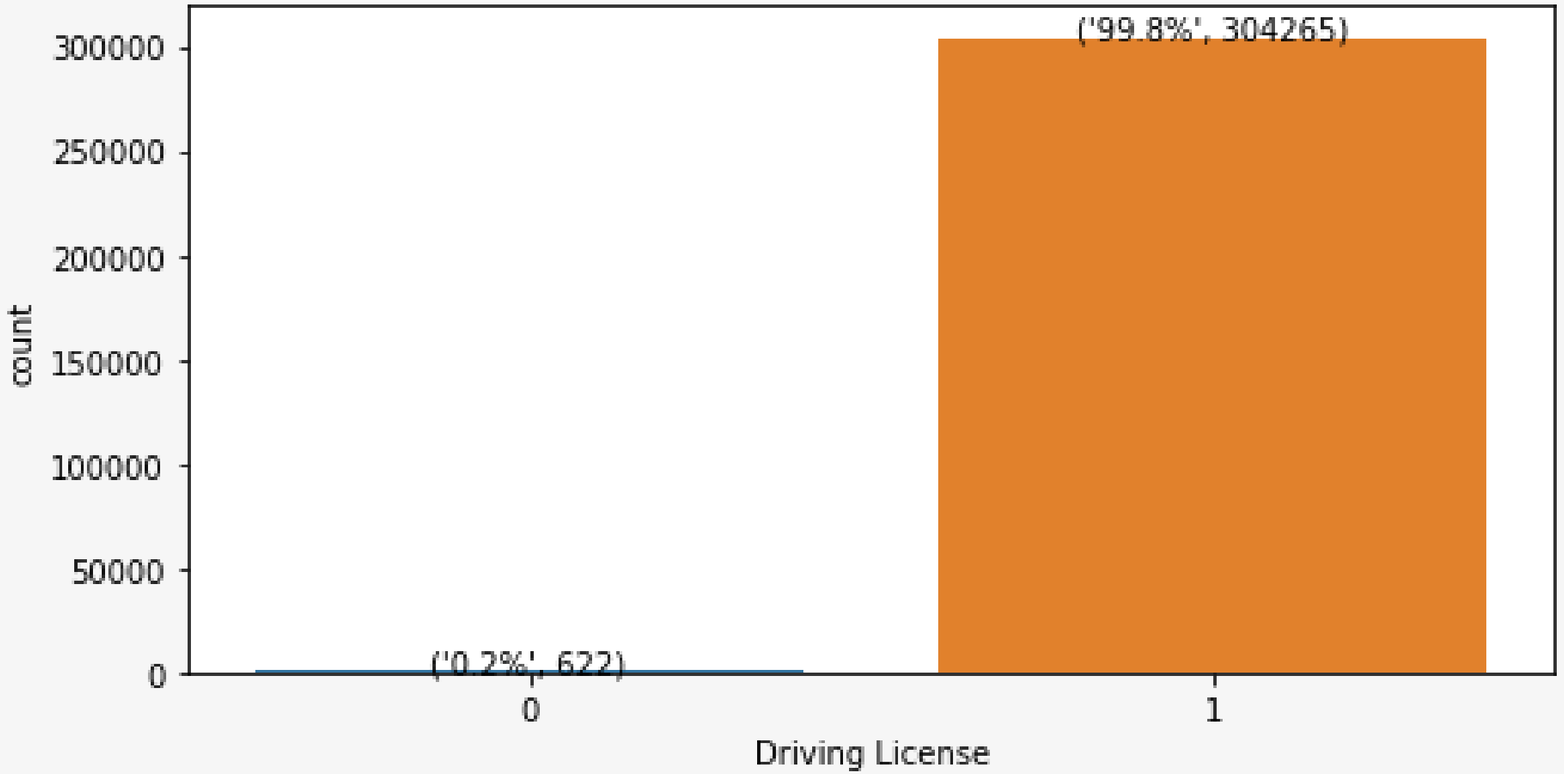
Remove Unwanted Feature

The feature Policy_Sales_Channel and Region_Code are not relevant to real world applications.

Policy_Sales_Channel are anonymized saling code of the insurance company. Hence, we can't use it as we don't know what was the meaning of the values behind the feature. On the other hand, Region_Code represents 53++ distinct values, whereas the Government India stated only 35 state codes in India

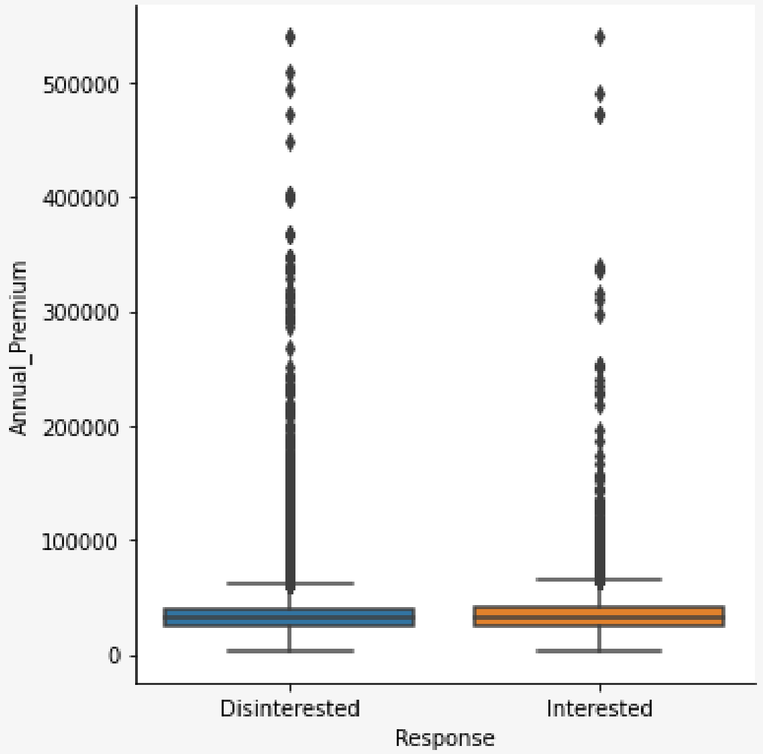
Encode Categorical Columns

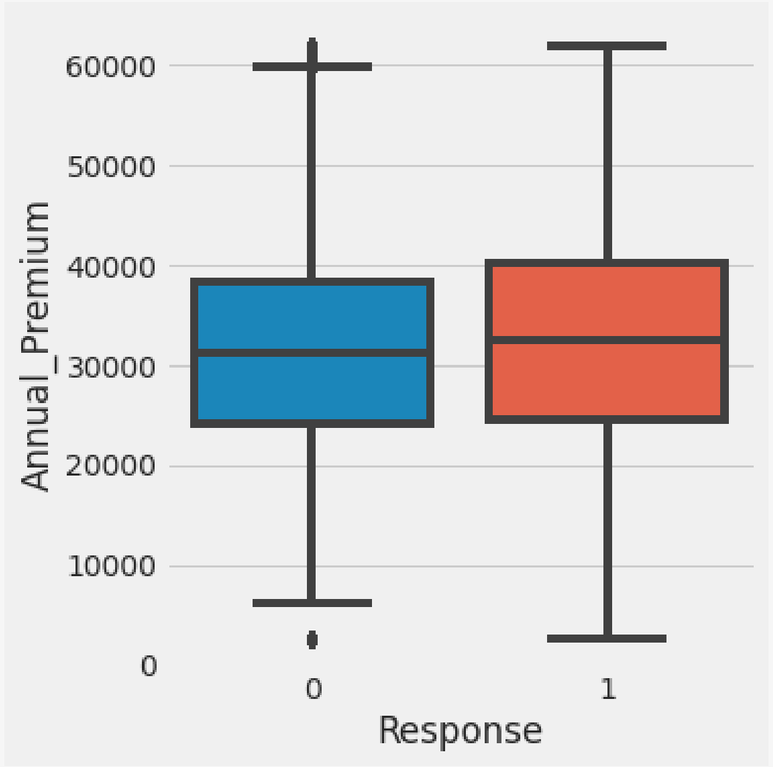
Remove Rows with no Driving License, then Remove the Column



The countplot shows that the number of people with no Driving License is really small, with a 6.2%. Hence, we decide to delete the row of customer without any Driving license, assuming that all of the customers who buy insurance vehicle must have a driving license.

Remove Outlier on Annual_Premium column





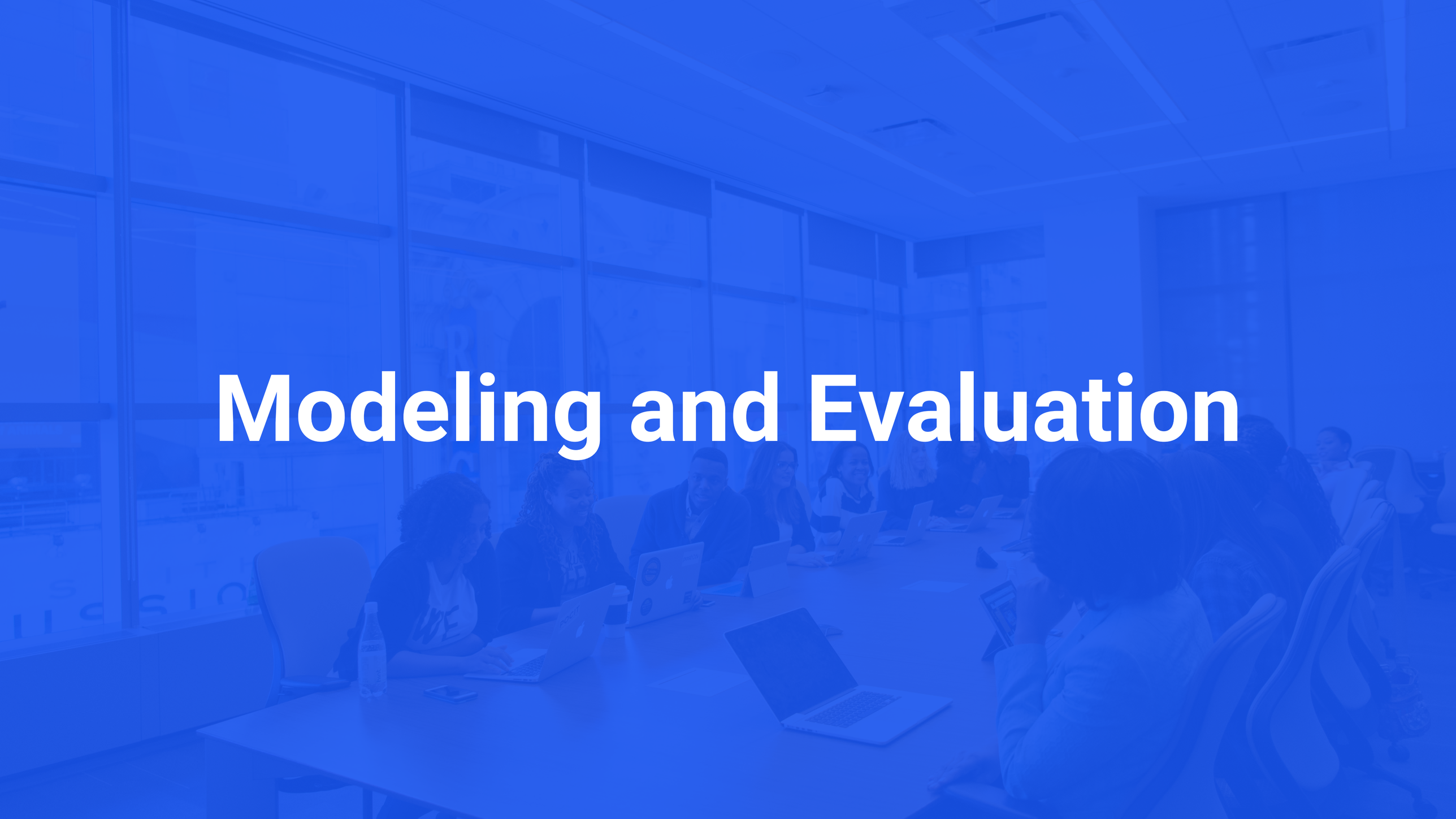
We will remove the outliers using the Inter Quartile Range(IQR) method.

Normalized Numerical Columns

	id	Age	Previously_Insured	Vehicle_Age	Vehicle_Damage	Annual_Premium	Vintage	Response	0	1
0	138389	0.415385	0	0.5	1.0	0.526802	0.560554	0	0.0	1.0
1	149691	0.384615	0	0.5	1.0	0.000000	0.024221	0	0.0	1.0
2	213565	0.046154	1	0.0	0.0	0.541090	0.401384	0	0.0	1.0
3	278877	0.046154	1	0.0	0.0	0.460329	0.197232	0	0.0	1.0
4	181394	0.292308	0	0.5	1.0	0.557421	0.020761	0	1.0	0.0

Normalizing numerical columns using MinMaxScaler, which has proven to improve our model by 23%

Modeling and Evaluation



Making Baseline Value

Making baseline value is important, so that we can use it as an measurement to improve and get our best model. In this case, we used LogisticRegression and DummyClassifier as our baseline model

Baseline Dummy Model ROC_AUC Score: 0.5

Baseline LogisticRegression Model without Normalization ROC-AUC Score: 0.6712248106072092

Baseline LogisticRegression After Normalization Model ROC-AUC Score: 0.8305344294005266

Split dataset and test over 10 models

	Model	Accuracy	F1	Precision	Recall	ROC
0	XGBoost	0.878081	0.821079	0.892945	0.878081	0.846362
1	Gradient Boosting	0.878081	0.821079	0.892945	0.878081	0.846156
2	LGBM	0.878115	0.821455	0.838209	0.878115	0.846132
3	CatBoost	0.877405	0.822915	0.818824	0.877405	0.842939
4	Logistic Regression	0.878013	0.821045	0.771019	0.878013	0.829902
5	LDA	0.875800	0.825152	0.816336	0.875800	0.828957
6	Gaussian	0.639716	0.700895	0.903455	0.639716	0.821410
7	Random Forest	0.854312	0.832645	0.818916	0.854312	0.810628
8	KNN	0.844852	0.831341	0.820965	0.844852	0.693938
9	Decision Tree	0.822046	0.822967	0.823902	0.822046	0.595975
10	SGD	0.878081	0.821079	0.892945	0.878081	0.000000

From the testing, we got XGBoostClassifier as our best model based on the ROC. We choose it to get the best threshold value.

Hence, we will use it for further evaluation

Parameter tuning using GridSearchCV

What we do next is parameter tuning. In this case, we will use a library called GridSearchCV from ScikitLearn to help us in finding the best tuning parameters. Parameter tuning is used to improve our model and get better score than non-tuned model

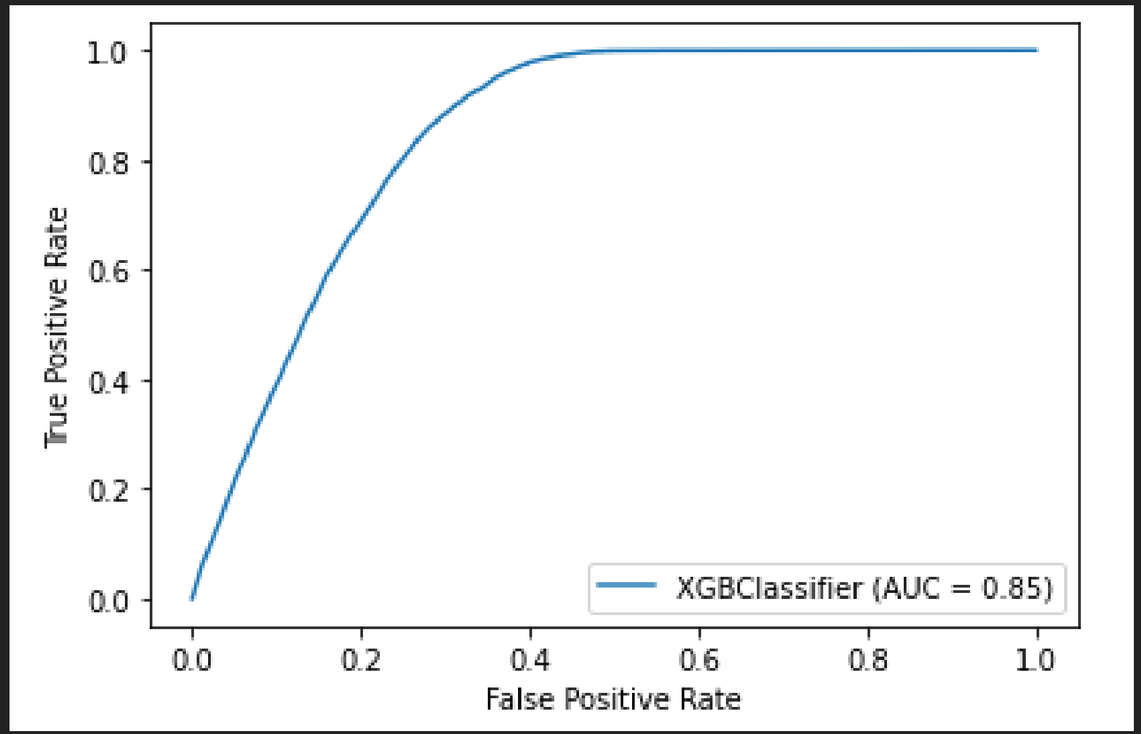
Evaluate the model

```
Accuracy score :  0.8780809189965368
F1 score :  0.8210786793124588
Precision score :  0.8929451813092658
Recall score :  0.8780809189965368
ROC score :  0.8467748807167663
              precision    recall  f1-score   support

           0       1.00      0.88      0.94     59195
           1       0.00      0.00      0.00         0

    accuracy                           0.88     59195
   macro avg       0.50      0.44      0.47     59195
weighted avg       1.00      0.88      0.94     59195
```

We then fit our model and test it with our test dataset. The precision and recall is still 0, it is because we still used the default threshold value, 0.5

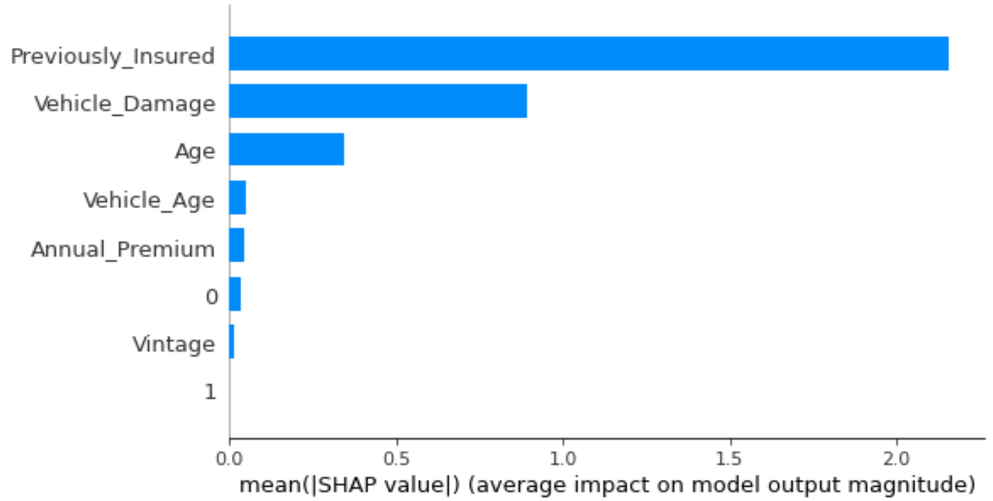
Changing Threshold Value

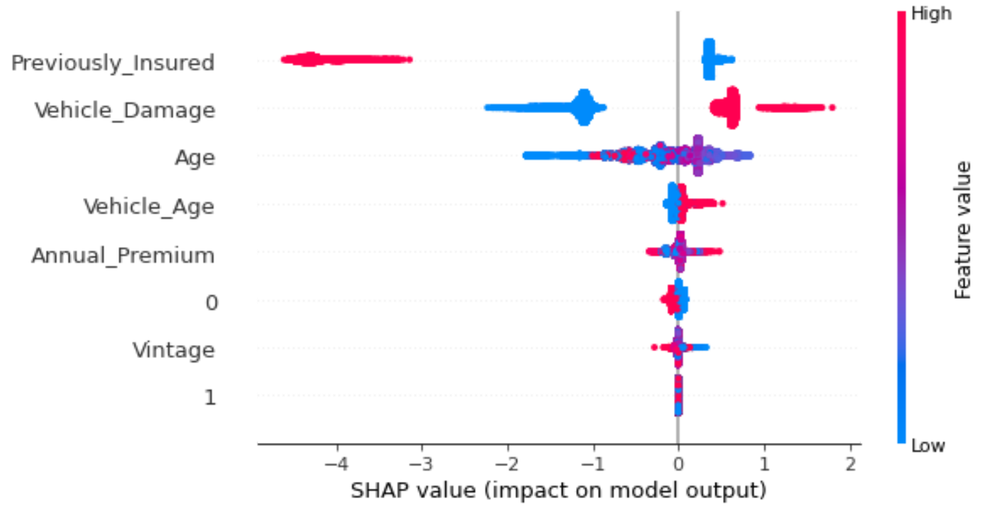
	precision	recall	f1-score	support
0	0.98	0.70	0.82	51978
1	0.29	0.89	0.44	7217
accuracy			0.72	59195
macro avg	0.63	0.79	0.63	59195
weighted avg	0.89	0.72	0.77	59195



We then change our threshold according to the ROC_AUC score 0.85, and achieved a different yet better recall and precision! We will still be using this threshold value for further prediction with unseen dataset

Feature Importance





Both SHAP value charts explained that Previously_Insured and Vehicle_Age was the most important feature, based on their feature importance

Prediction on Unseen Dataset

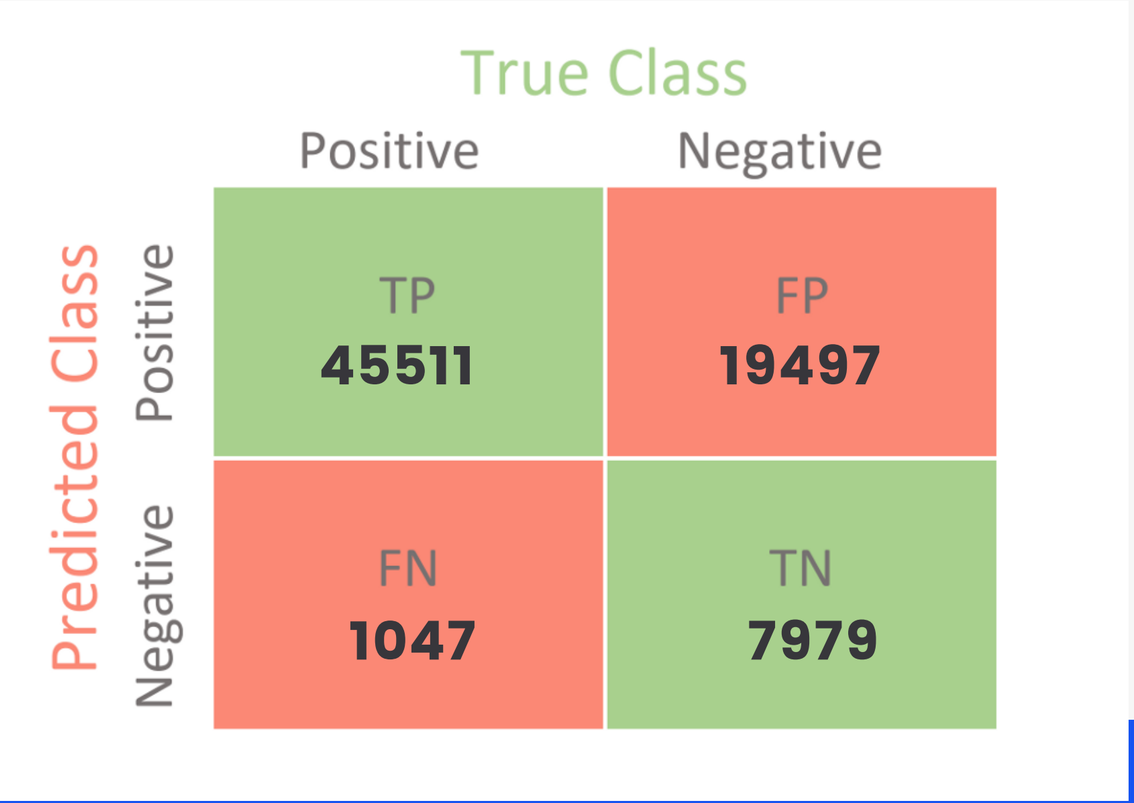
We then use the data than we have splitted for final prediction. The model has never seen this data yet. Hence, it is perfect for evaluation

```
Accuracy score :  0.8780830429262231
F1 score :  0.8210817228542153
Precision score :  0.8929467873483522
Recall score :  0.8780830429262231
ROC score :  0.8482817855576683
```

We still get a good score, despite our model facing unseen or new data

Using ROC_AUC as new threshold

We will still use our new threshold 0.85, to predict the new dataset. Then, we get the confusion matrix as below



If we want to target customers with any possibility to buy vehicle insurance, we can reduce the number of customers to be reached from 74034 to only 27476! This saves up to 62.9% in time and expenses

Model Improvement

Tuned XGBoost Model on Unseen Data **0.847**

↑ **69.4%**

Baseline Dummy Model ROC_AUC Score **0.5**
(Dummy Most_Frequent)

Using ROC_AUC score as the main metric, we managed to improve our metric score up to 69%!

Business Case Study

Business Case Study

By Using Machine Learning, the insurance company can save up to 62.89% in saling expenses(Reaching out customer, operation expenses, etc.

The insurance company can also save up time from contacting every single policyholders, assuming that they use the model prediction output to reach out customers

Conclusion and Reccomendation

Conclusion

Supervised Machine Learning has been proven to be able to predict the customer's response with 0.85 roc_auc score and 0.89 recall score

It also helps the company to reduce expenses up to **63%** from reaching out customers and sales

Reccomendation

Get a deeper domain knowledge regarding previous column that got dropped, which can be used to improve the model

Add more rows and features to the model, so to reduce underfitting and improve model variation

Focus to look reach out policyholders who have ever had their vehicle damaged

Contact Us

EMAIL ADDRESS

darnellkikoo@gmail.com

PHONE NUMBER

+6281218222211

CURRENT PROJECT GITHUB LINK:

https://github.com/darnellkikoo/AlgoBC_FProject

THANK YOU