LEAD SCORING CASE STUDY

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PROBLEM STATEMENT

An education company named X Education sells online courses to industry professionals. On any given day, many professionals who are interested in the courses land on their website and browse for courses.

The company markets its courses on several websites and search engines like Google. Once these people land on the website, they might browse the courses or fill up a form for the course or watch some videos. When these people fill up a form providing their email address or phone number, they are classified to be a lead. Moreover, the company also gets leads through past referrals. Once these leads are acquired, employees from the sales team start making calls, writing emails, etc. Through this process, some of the leads get converted while most do not. The typical lead conversion rate at X education is around 30%.

X Education has appointed you to help them select the most promising leads, i.e. the leads that are most likely to convert into paying customers. The company requires you to build a model wherein you need to assign a lead score to each of the leads such that the customers with higher lead score have a higher conversion chance and the customers with lower lead score have a lower conversion chance. The CEO, in particular, has given a ballpark of the target lead conversion rate to be around 80%.

STEPS AFTER READING THE DATA

Data Inspection:

- Data is read as a .csv file as the first step with proper encoding
- Data is inspected for its shape, describe and columns

Data Cleaning:

- Data is checked for any missing values, null values
- If there are null values in the data set, then they are being imputed with the median or mode based on the type of variable.
- In our Leads Dataset we have another value as “Select” which is also imputed with a value.
- This value corresponds that the user would not selected the field or the field value is not provided in the front end.

Few columns dropped from Dataset due to high variations:

Asymmetrique Activity Index

Asymmetrique Activity Score

Asymmetrique Profile Index

Asymmetrique Profile Score

Univariate Analysis with converted target variable:

- The current Lead conversion rate is 38% as per the dataset.

Lead Origin vs Converted

- When Lead Origin is compared with converted variable we observe that the conversion rate is around 30-35% via API and Landing page.
- But the count of the Leads are very less through Lead import and Lead Add Form which needs to be focused now.

Lead Source vs Converted

- The count of the leads is maximum from Google Ads, Direct Traffic, Organic search, Olark chat

Do Not Email vs Converted:

- Those customers who opt for the option of Do Not Email option as "No" get converted to Leads

Do Not Call vs Converted:

- Those customers who opt for the option of Do Not Call option as "No" get converted to Leads

City vs Converted:

- Most Leads who are converted are from the city of Mumbai than any other cities.

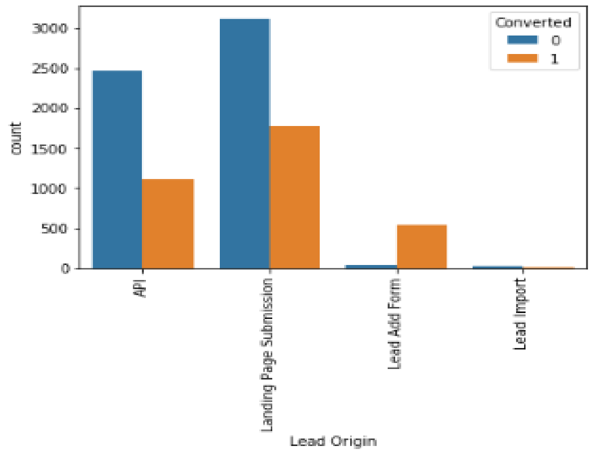
Last Activities vs Converted:

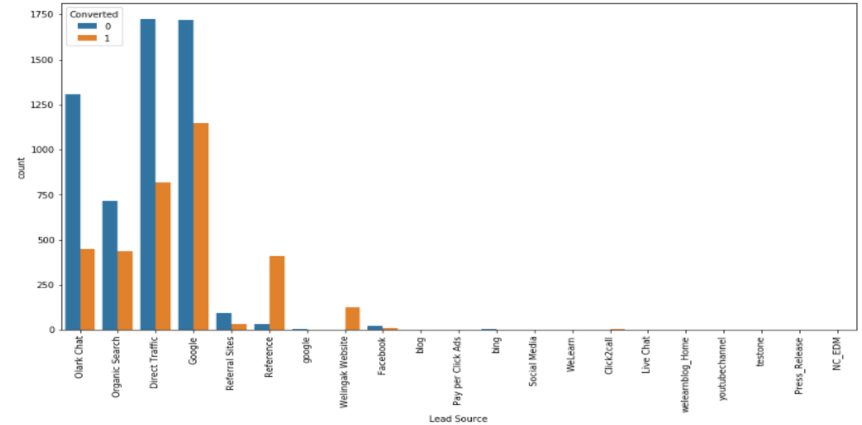
- Those customers whose last activity is reverting back to the email get mostly converted to Leads.

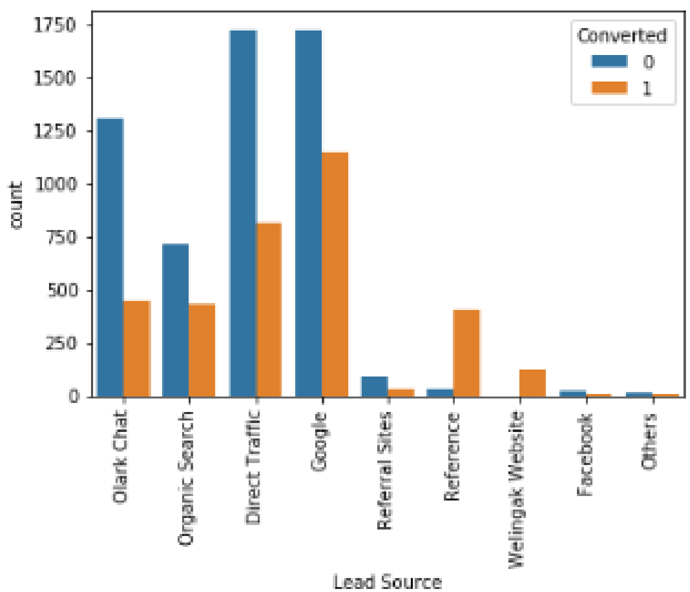
Last Notable Activity vs Converted:

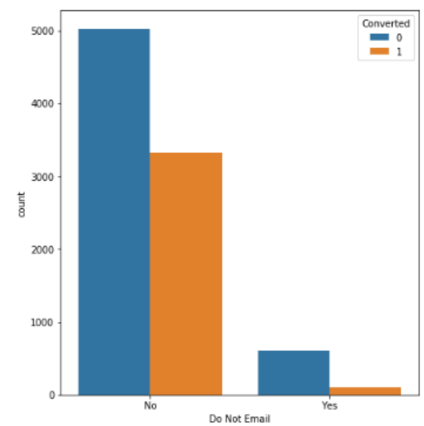
- Customers whose last notable activity as Email Opened and SMS Sent are mostly converted to Leads.

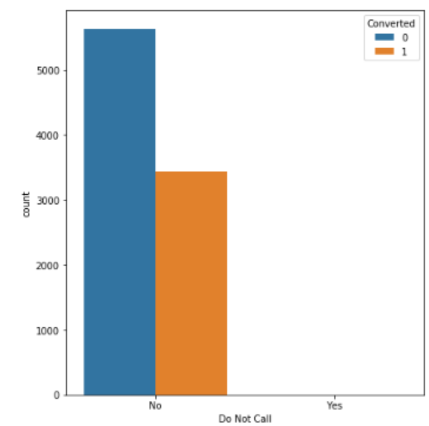
UNIVARIATE ANALAYSIS GRAPHS:











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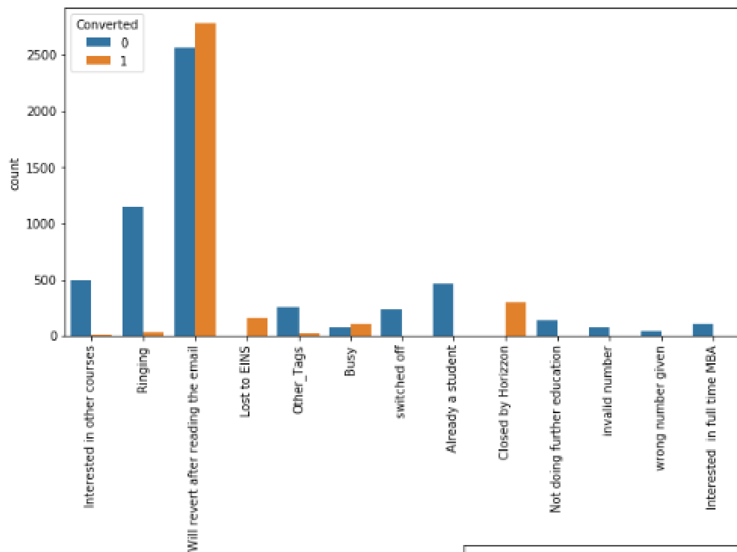
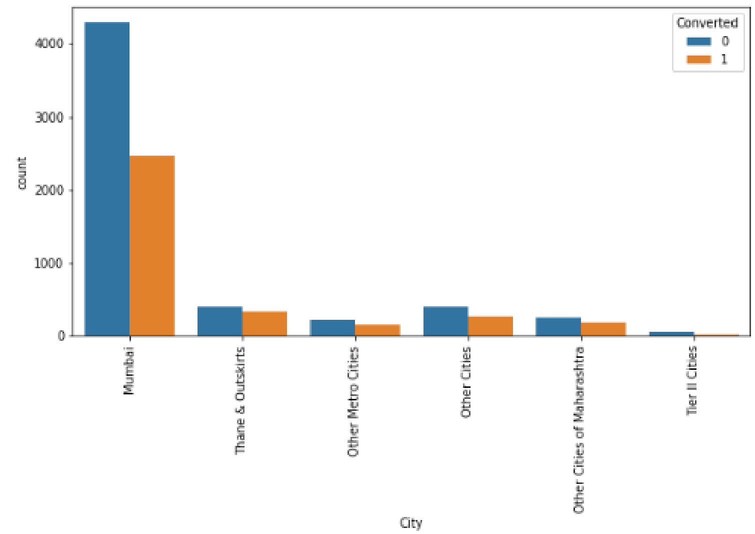
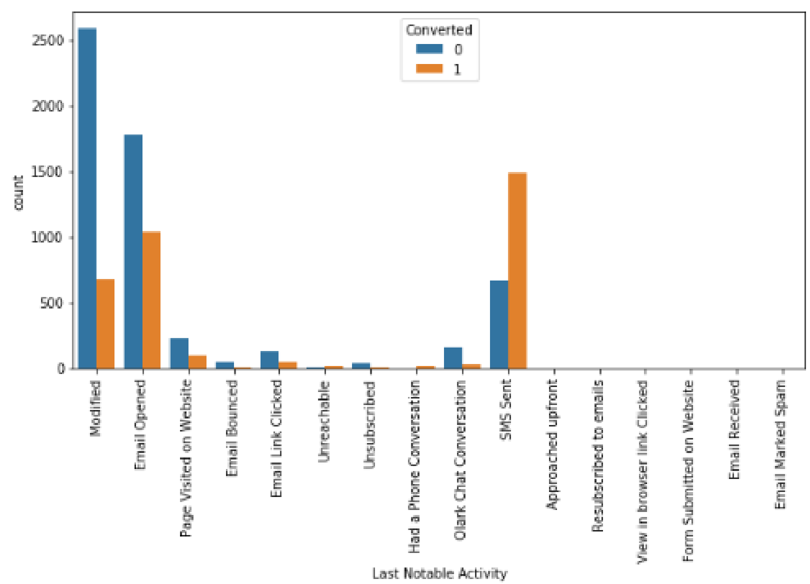






Decision to drop few columns:

- Few columns such as, What matters most to you in choosing course,Search,Magazine,NewspaperArticle,Through Recommendations etc. are the columns which does not give significant conclusions through univariate analysis.

Data Preparation:

- Converting columns which has the Yes and No as the values are converted to 1 and 0 for ease of dataset.
- Creating dummy variables for the categorical variables with multiple levels of values.

Train-Test Data Split:

- From skelearn use the train_test_split to split the data to test and training sets.
- Splitting the data set as 0.7 and 0.3 as the train and the test data sets.
- Using the Feature Scaling to scale and normalize the data in the split train and test data sets.

Note :

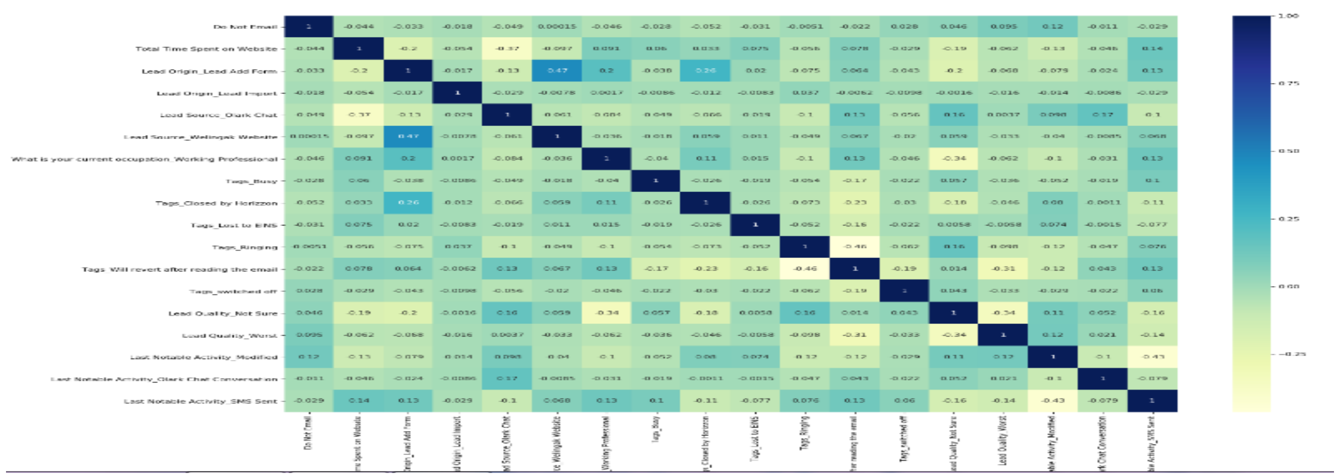
The current lead conversion rate is calculated for the entire dataset which when calculated comes to **38%**

Model Building:

- Using the Generalized Linear Model analyze the columns of the dataset using GLM()

Feature Selection using RFE:

- Running the RFE with 20 variables to get the significant and not significant columns
- Checking the VIF for all the columns selected through the RFE which should have VIF < 5
- Desirable value of VIF is VIF<5 and we also get all the variables VIF values < 5
- Visualizing the heatmap for the variables selected by RFE which can give an idea about multi-collinearity between variables.



Accuracy metrics and Beyond for train dataset:

- As calculated the accuracy metrics, we have observed that the overall accuracy is **92%**
- This means that we have correctly identified and predicted the significant variables.
- Sensitivity of the model is calculated by the below formula,

  TP / float(TP+FN) where,

  TP = true positive

  TN = true négatives

  FP = false positives

  FN = false négatives

  Sensitivity of the model is **88%**
- Specificity of the model built is calculated as,

  TN / float(TN+FP) where,

  TP = true positive

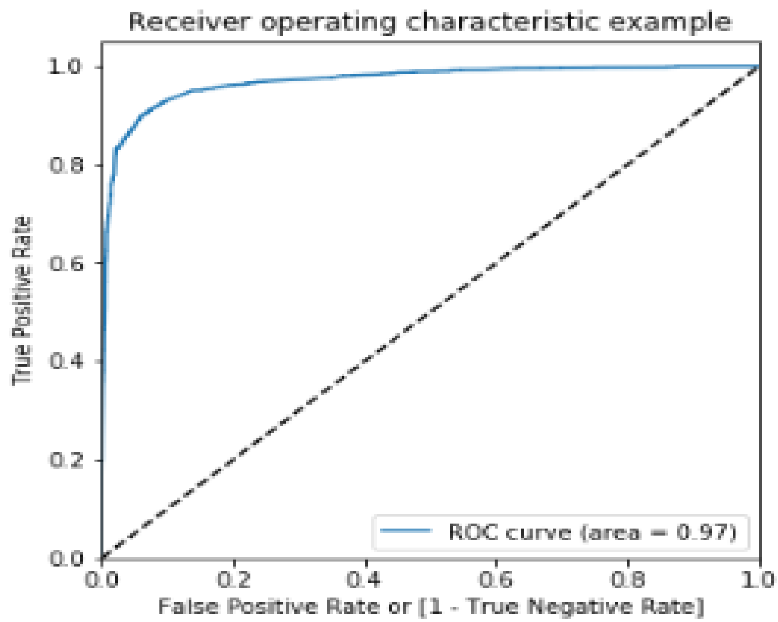
  TN = true négatives

  FP = false positives

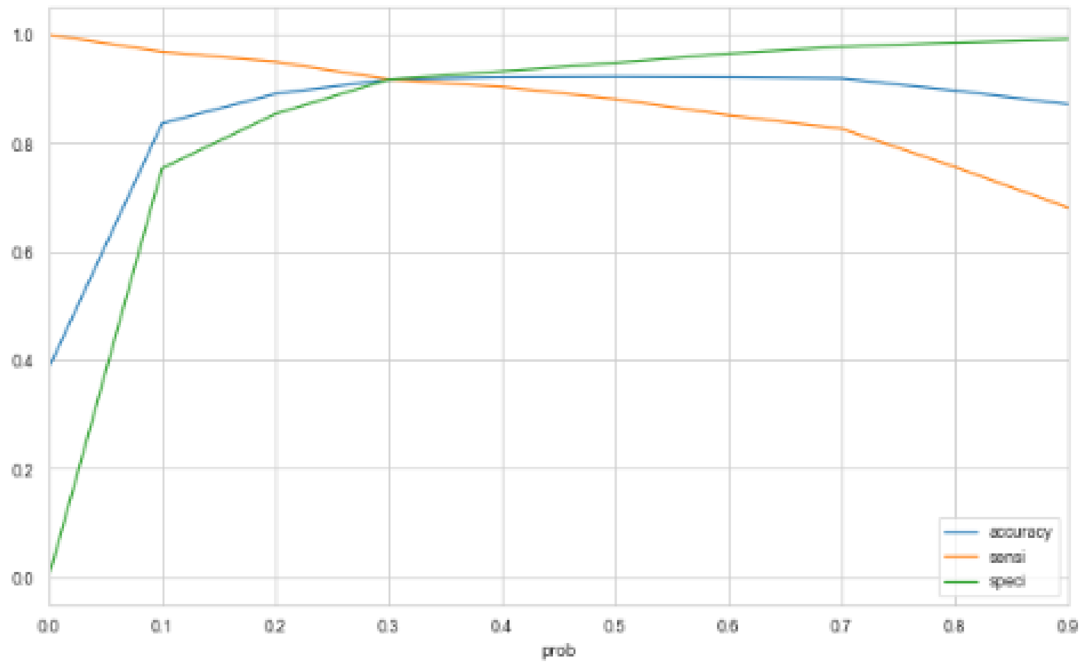
  FN = false négatives

  Specificity of the model is **94%**

- Plotting the ROC curve to find the **AreaUnderTheCurve(AUC)**, we get a perfect ROC curve which gives the AUC value as **97%**



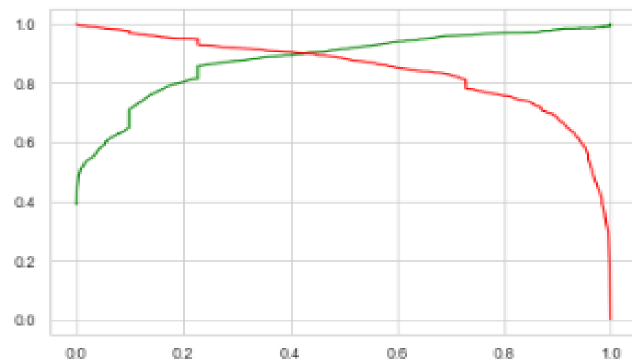
- Now we have to find the optimal cutoff point by taking multiple probabilities points to plot the sensitivity, specificity and accuracy



- From the above curve, we observe that the cutoff probability to be taken for optimum point is **0.3**

Precision and Recall metrics:

- Now we can calculate the precision and Recall values for the train data set which needs to be around the same range as expected between **70-90%**
- When calculated for precision we observed the resultant value is **91%** which is excellent but has to be consistent with the test data
- Recall value corresponds to around **88%** which is also optimum for a dataset to attain the requirement of 80% lead conversion rate.
- We now want to know the optimum threshold using the Precision and Recall thresholds in a graph. When we plot them we got the intersection at **0.42**



- But since we got the expected result in the previous metrics with sensitivity, specificity and accuracy we stick with the same metrics that gave the optimum cutoff as **0.3**

Accuracy metrics and Beyond for test dataset:

- As calculated the accuracy metrics, we have observed that the overall accuracy is **90.7%**
- This means that we have correctly identified and predicted the significant variables.
- Sensitivity of the model is calculated by the below formula,

  TP / float(TP+FN) where,

  TP = true positive

  TN = true négatives

  FP = false positives

  FN = false négatives

  Sensitivity of the model is **90.2%**
- Specificity of the model built is calculated as,

  TN / float(TN+FP) where,

  TP = true positive

  TN = true négatives

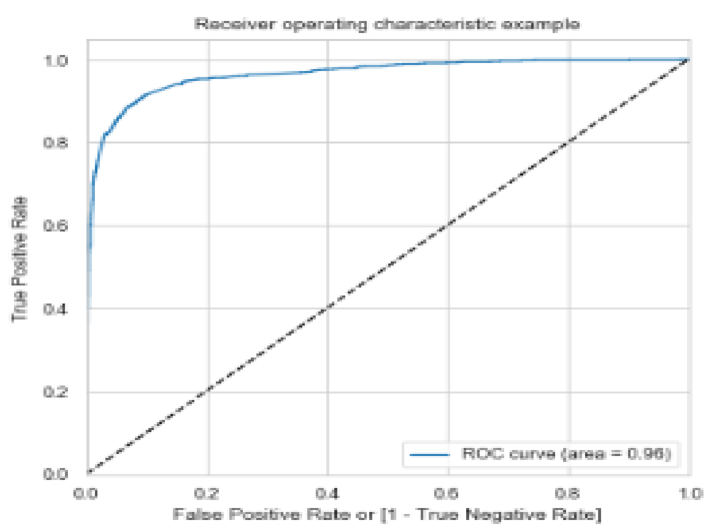
  FP = false positives

  FN = false négatives

  Specificity of the model is **91%**

Precision and Recall metrics for test dataset:

- Now we can calculate the precision and Recall values for the test data set which needs to be around the same range as train data set
- When calculated for precision we observed the resultant value is **85.2%** which is excellent but has to be consistent with the test data
- Recall value corresponds to around **90.2%** which is also optimum for a dataset to attain the requirement of 80% lead conversion rate.
- Plotting the ROC curve to find the **AreaUnderTheCurve(AUC)**, we get a perfect ROC curve which gives the AUC value as **96.3%** which is almost the same as train data set value of **97%**



Concatenating train and test data to find conversion probabilities:

- After concatenating those leads who have the **final_predict value as 1** and has a lead score more than **39** will be the leads identified as successful Leads in conversion of customers.

Features that are significant to the model evaluation:

- Using Feature importance technique, we identify the coefficients for the variables or features.
- Those features having a high and positive coefficients are strongly important for the lead conversion rates
- Some of the features which have strong positive coefficients are ,

Tags_Lost to EINS

Tags_Closed by Horizzon

Tags_Will revert after reading the email

- All metrics are close to each other both train and test datasets implying that the model is giving excellent results

- All metrics are in percentages **(%)**

Dataset	Auc	Sensitivity	Specificity	Accuracy	Precision	Recall
Train	97	88	94	92	91	88
Test	96.3	90.2	91	90.7	85.2	90.2

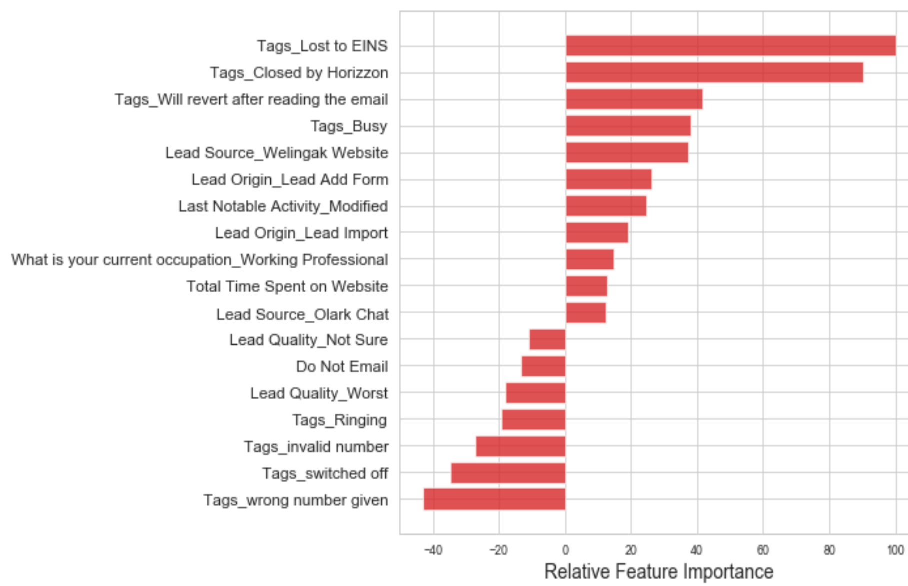
CONCLUSION AND PREDICTIONS

<u>Conclusion:</u>

The metrics and values such as accuracy,sensitivity,specificity,precision and recall values are very similar and identical for both test and train datasets implying that the model built is very effective in predicting the Lead conversion and in identifying the Leads with higher conversion rate.

The overall accuracy of <u>0.9174</u> at a probability threshold of <u>0.33</u> on the test dataset is also very acceptable.

Based on our model, some features are identified which contribute most to a Lead getting converted successfully.



The below mentioned features are those having the <u>positive</u> coefficients. So the <u>conversion probability of a lead increases with increase in values of the following features</u> in descending order:

Tags_Lost to EINS

Tags_Closed by Horizzon

Tags_Will revert after reading the email

Tags_Busy

Lead Source_Welingak Website

Lead Origin_Lead Add Form

Last Notable Activity_SMS Sent

Lead Origin_Lead Import

What is your current occupation_Working Profes

Total Time Spent on Website

Lead Source_Olark Chat

The below are the features with <u>negative</u> coefficients.

So the conversion <u>probability of a lead increases with decrease in values of the following features</u> in descending order

Last Notable Activity_Modified

Do Not Email

Last Notable Activity_Olark Chat Conversation

Tags_Ringing

Tags_switched off

Lead Quality_Not Sure

Lead Quality_Worst