Lead Scoring Case Study

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DSC 45 Batch

Repository Link: https://github.com/skynet451/Lead-Score-Case-Study-Upgrad

Problem Statement

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%.

Now, although X Education gets a lot of leads, its lead conversion rate is very poor. For example, if, say, they acquire 100 leads in a day, only about 30 of them are converted. To make this process more efficient, the company wishes to identify the most potential leads, also known as ‘Hot Leads’. If they successfully identify this set of leads, the lead conversion rate should go up as the sales team will now be focusing more on communicating with the potential leads rather than making calls to everyone.

Goals of the Case Study

- Build a logistic regression model to assign a lead score between 0 and 100 to each of the leads which can be used by the company to target potential leads. A higher score would mean that the lead is hot, i.e. is most likely to convert whereas a lower score would mean that the lead is cold and will mostly not get converted.

- There are some more problems presented by the company which your model should be able to adjust to if the company's requirement changes in the future so you will need to handle these as well. These problems are provided in a separate doc file. Please fill it based on the logistic regression model you got in the first step. Also, make sure you include this in your final PPT where you'll make recommendations.

Problem Solving Methods

Data Cleaning and Preparation

- Identify the data quality and clean based on requirement
- Handle null values based on converted rate without removing data points
- Data Imputation
- Outlier Analysis and treatment

Solve problem

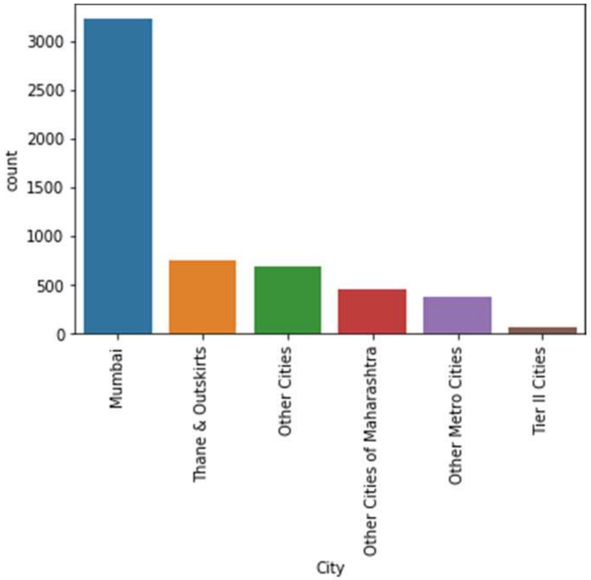
- Variable Processing
- Univariate Analysis (EDA)
- Train Test Split data
- Logistic fiegression Model Building

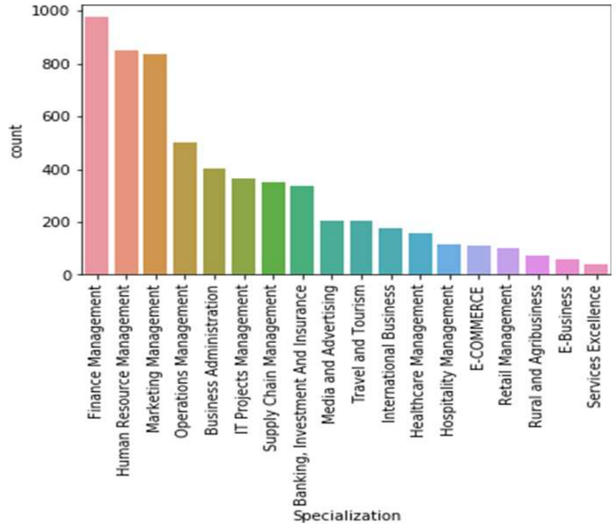
Identify influencing features

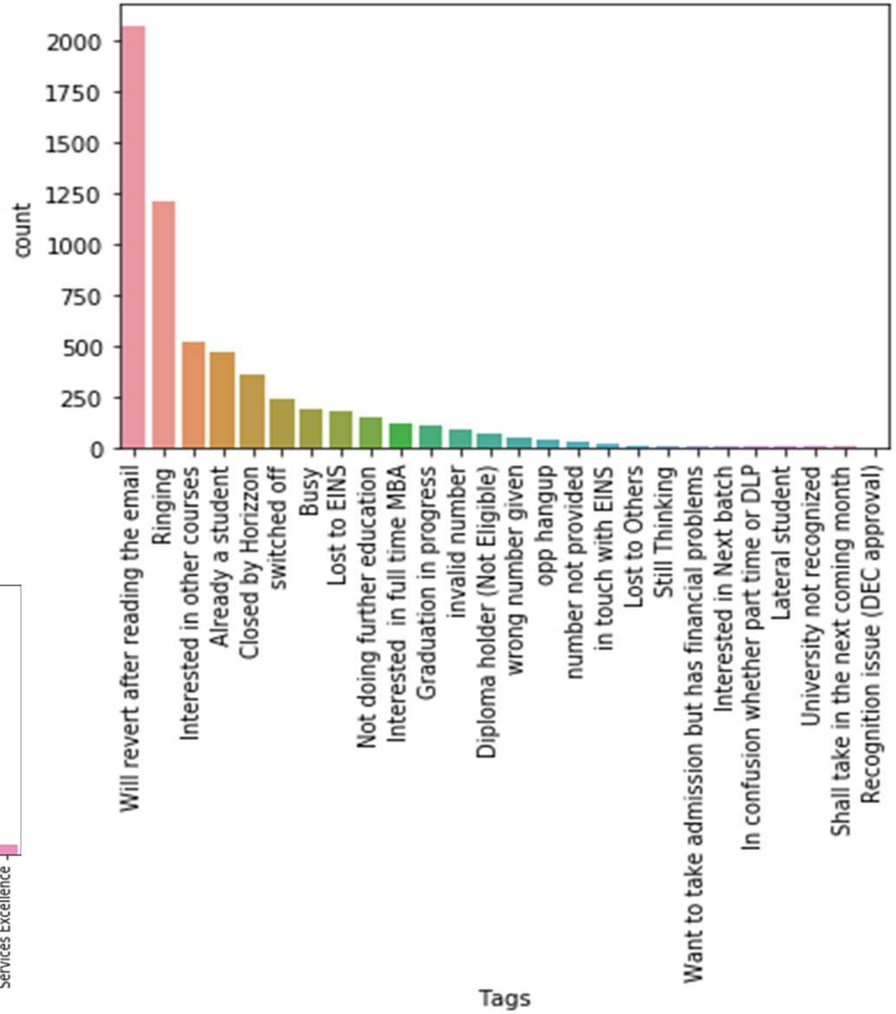
- Identify based on Logistic regression model
- Draw Conclusion and recommendations for model.

Data Cleaning

- Checked for duplicated values
- fieplaced Select with NaN
- Dropping unnecessary columns with only null values, single unique feature, rating columns.
- Imputed Values with highest count in particular columns
- Segregated all NA values into others as separate entity.
- Highly skewed columns were dropped.







Exploratory Data Analysis – Numerical Variable

<u>Following are observations</u>

Total visits

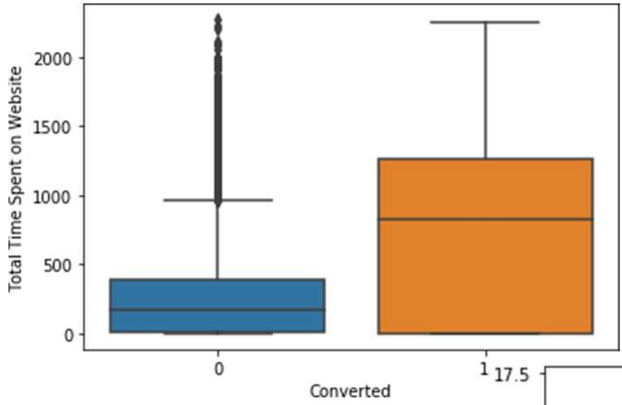
- Median for converted and non converted leads are same.
- Nothing conclusive based on Total Visits.

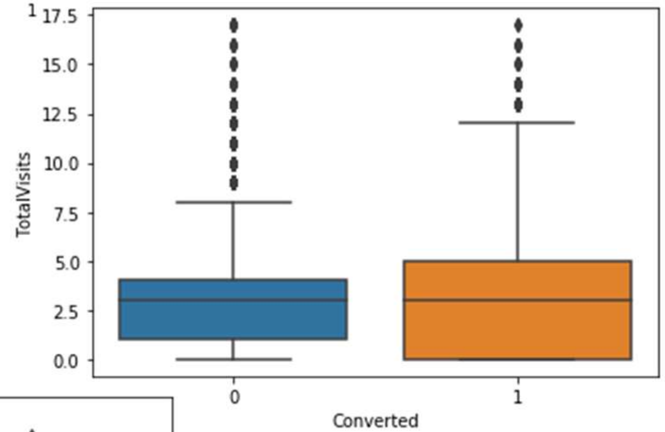
Total Time spent on website

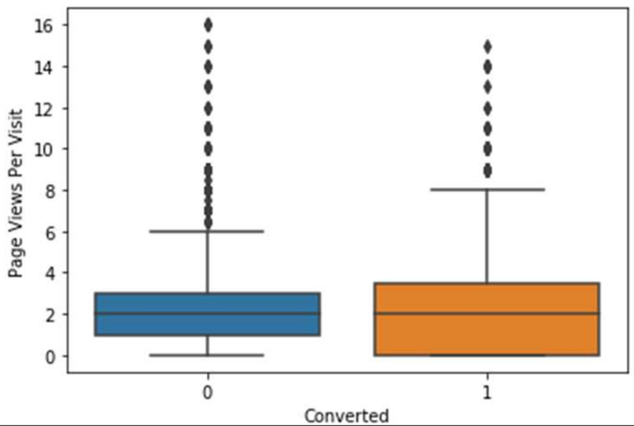
- Leads spending more time on the website are more likely to be converted
- Website should be made more engaging to make leads spend more time.

Page View Per Visit

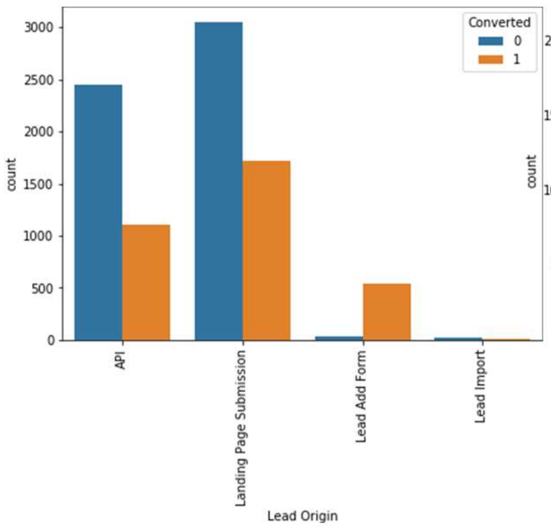
- No concrete reading from the page view per visit graphs.

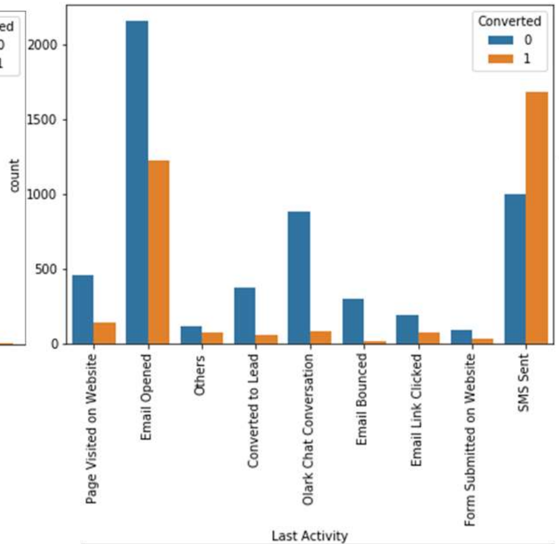


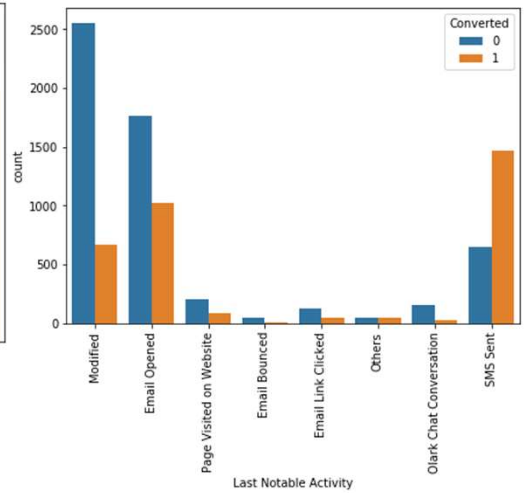


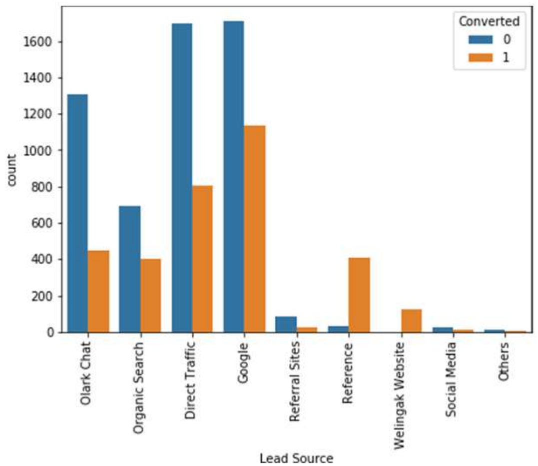


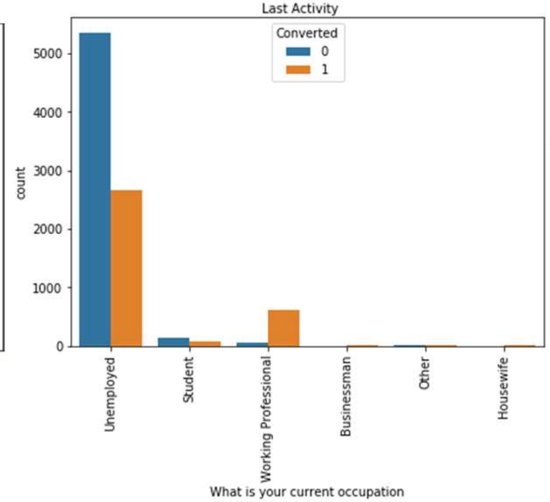
Exploratory Data Analysis – Univariate Analysis

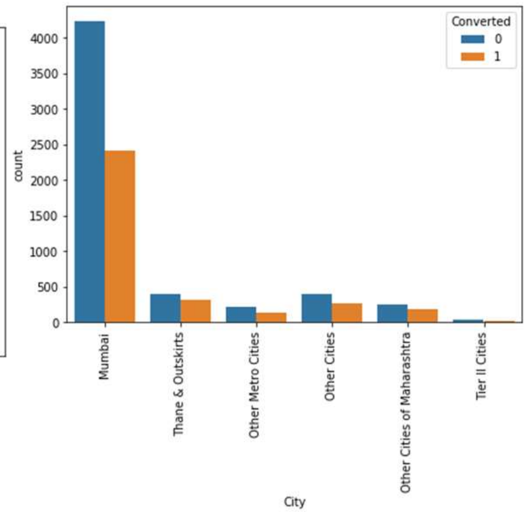












Distribution of Lead Origin

Landing page submission is comparatively high than the rest of the categories, lead form has high certainty in lead conversion.

Distribution of Lead Source

Google is the best lead source among all categories in the lead source, Direct traffic, Olark Chat and organic search are some of the best entities in lead source.

Distribution of occupation

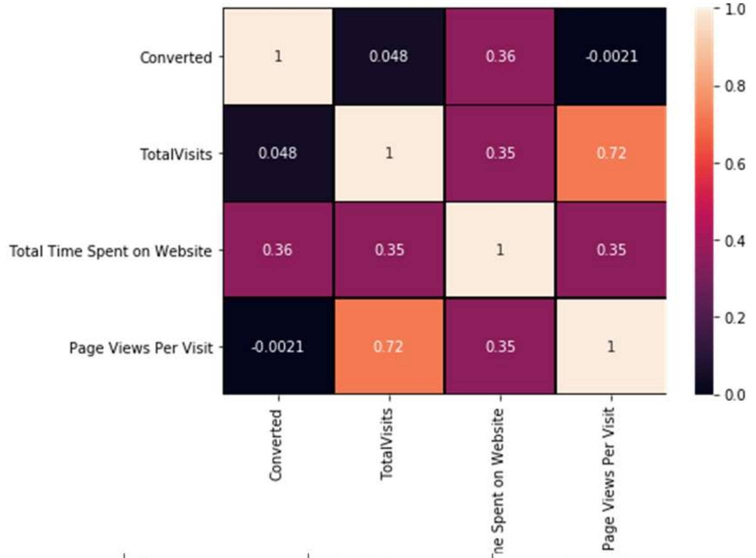
Working professionals and Unemployed going for the course have high chances of joining it

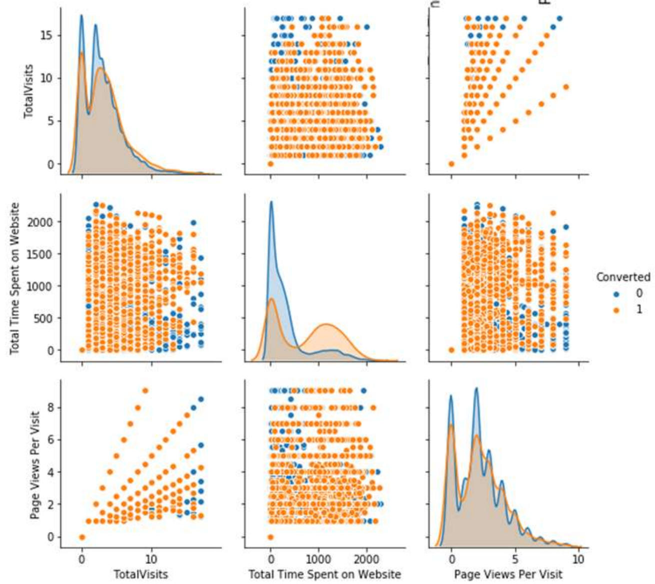
Distribution of the city

Most leads are from Mumbai city with maximum conversion count from the same

Exploratory Data Analysis – Bi variate Analysis

- From pair plot we can observe clearly that our dataset has highly skewed values with lot of random peaks.
- With heat map we can inference Total visits and Page view per visit has high correlation than other features.
- Total Visits and converted has very low correlation.
- Total Visits and Total time spent on website has a reasonable correlation.
- There is positive correlation between total time spent on website and conversion.
- There is almost no correlation in Page views per visit and total visits with conversion.





Model Building

- For Model building we need to scale and split data into train and test dataset.
- Wewill be using Logistic fiegression for building the model.
- Variable selection done through fiFE(recursive feature elimination) and further we remove features with high p value and VIF value.
- Analyzing various parameters for train dataset Specificity, Sensitivity, Accuracy, Precision and fiecall for train data.
- Plot the fiOC Curve which shows trade off between sensitivity and specificity.

```
col = X_train.columns[rfe.support_]

col

Index(['Total Time Spent on Website', 'LO_Lead Add Form', 'LS_Olark Chat',
       'LS_Welingak Website', 'LA_SMS Sent', 'Tags_Already a student',
       'Tags_Busy', 'Tags_Closed by Horizzon', 'Tags_Lost to EINS',
       'Tags_Not Specified', 'Tags_Ringing',
       'Tags_Will revert after reading the email', 'Tags_switched off',
       'LNA_Modified', 'LNA_Olark Chat Conversation'],
      dtype='object')
```

```
X_train.columns[~rfe.support_]

Index(['Do Not Email', 'TotalVisits', 'Page Views Per Visit',
       'A free copy of Mastering The Interview', 'LO_Landing Page Submission',
       'LO_Lead Import', 'LS_Direct Traffic', 'LS_Google', 'LS_Organic Search',
       'LS_Reference', 'LS_Referral Sites', 'LS_Social Media',
       'LA_Converted to Lead', 'LA_Email Bounced', 'LA_Email Link Clicked',
       'LA_Email Opened', 'LA_Form Submitted on Website',
       'LA_Olark Chat Conversation', 'LA_Page Visited on Website',
       'S_Banking, Investment And Insurance', 'S_Business Administration',
       'S_E-Business', 'S_E-COMMERCE', 'S_International Business',
       'S_Management Specialization', 'S_Media and Advertising',
       'S_Rural and Agribusiness', 'S_Services Excellence',
       'S_Travel and Tourism', 'CO_Businessman', 'CO_Housewife', 'CO_Student',
       'CO_Unemployed', 'CO_Working Professional',
       'Tags_Graduation in progress', 'Tags_Interested  in full time MBA',
       'Tags_Interested in other courses', 'Tags_Not doing further education',
       'City_Mumbai', 'City_Other Cities', 'City_Other Cities of Maharashtra',
       'City_Other Metro Cities', 'City_Thane & Outskirts',
       'LNA_Email Bounced', 'LNA_Email Link Clicked', 'LNA_Email Opened',
       'LNA_Page Visited on Website', 'LNA_SMS Sent'],
      dtype='object')
```

Logistic Regression Model

Using fiFE and Manual feature elimination for features having P-value more than 0.05and VIF more than 5. We reached a final model with P – Value less than 0.051 and VIF less than 5.

Generalized Linear Model Regression Results

Dep. Variable:	Converted	**No. Observations:**	6246
Model:	GLM	**Df Residuals:**	6230
Model Family:	Binomial	**Df Model:**	15
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1236.1
Date:	Fri, 04 Dec 2020	**Deviance:**	2472.3
Time:	21:51:25	**Pearson chi2:**	8.86e+03
No. Iterations:	8		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-3.5312	0.222	-15.925	0.000	-3.966	-3.097
Total Time Spent on Website	1.0779	0.061	17.634	0.000	0.958	1.198
LO_Lead Add Form	1.7357	0.421	4.127	0.000	0.911	2.560
LS_Olark Chat	1.3026	0.145	8.998	0.000	1.019	1.586
LS_Welingak Website	3.5853	0.849	4.223	0.000	1.921	5.249
LA_SMS Sent	1.9855	0.117	17.005	0.000	1.757	2.214
Tags_Already a student	-1.2401	0.635	-1.952	0.051	-2.485	0.005
Tags_Busy	2.6859	0.307	8.737	0.000	2.083	3.288
Tags_Closed by Horizzon	8.5865	0.765	11.220	0.000	7.087	10.086
Tags_Lost to EINS	7.4777	0.572	13.072	0.000	6.357	8.599
Tags_Not Specified	1.9071	0.219	8.697	0.000	1.477	2.337
Tags_Ringing	-1.6067	0.316	-5.078	0.000	-2.227	-0.987
Tags_Will revert after reading the email	6.4811	0.277	23.406	0.000	5.938	7.024
Tags_switched off	-2.2534	0.769	-2.929	0.003	-3.761	-0.746
LNA_Modified	-1.7770	0.127	-13.969	0.000	-2.026	-1.528
LNA_Olark Chat Conversation	-1.8176	0.422	-4.303	0.000	-2.646	-0.990

	Features	VIF
1	LO_Lead Add Form	1.77
9	Tags_Not Specified	1.69
11	Tags_Will revert after reading the email	1.66
4	LA_SMS Sent	1.65
2	LS_Olark Chat	1.64
13	LNA_Modified	1.49
0	Total Time Spent on Website	1.46
3	LS_Welingak Website	1.32
7	Tags_Closed by Horizzon	1.21
10	Tags_Ringing	1.12
5	Tags_Already a student	1.08
14	LNA_Olark Chat Conversation	1.08
8	Tags_Lost to EINS	1.07
6	Tags_Busy	1.05
12	Tags_switched off	1.03

Final Logistic Regression Model

Our final model has P-values tending to 0 and VIF values less than 2 which suggests that the mode is good to go and can be used to make predictions on the test data.

Generalized Linear Model Regression Results

Dep. Variable:	Converted	No. Observations:	6246
Model:	GLM	Df Residuals:	6231
Model Family:	Binomial	Df Model:	14
Link Function:	logit	Scale:	1.0000
Method:	IRLS	Log-Likelihood:	-1238.6
Date:	Sun, 06 Dec 2020	Deviance:	2477.3
Time:	05:54:27	Pearson chi2:	8.87e+03
No. Iterations:	8		
Covariance Type:	nonrobust		

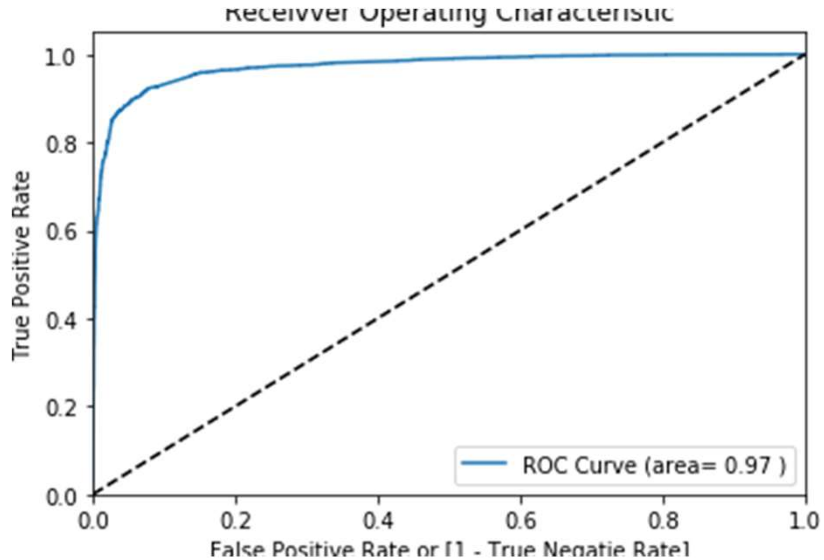
	coef	std err	z	P>|z|	[0.025	0.975]
const	-3.7490	0.208	-18.040	0.000	-4.156	-3.342
Total Time Spent on Website	1.0712	0.061	17.622	0.000	0.952	1.190
LO_Lead Add Form	1.7479	0.424	4.118	0.000	0.916	2.580
LS_Olark Chat	1.2885	0.144	8.927	0.000	1.006	1.571
LS_Welingak Website	3.5634	0.851	4.187	0.000	1.895	5.231
LA_SMS Sent	2.0096	0.117	17.214	0.000	1.781	2.238
Tags_Busy	2.8922	0.299	9.664	0.000	2.306	3.479
Tags_Closed by Horizzon	8.7931	0.762	11.538	0.000	7.299	10.287
Tags_Lost to EINS	7.6899	0.567	13.554	0.000	6.578	8.802
Tags_Not Specified	2.1195	0.206	10.277	0.000	1.715	2.524
Tags_Ringing	-1.4025	0.308	-4.548	0.000	-2.007	-0.798
Tags_Will revert after reading the email	6.6925	0.267	25.053	0.000	6.169	7.216
Tags_switched off	-2.0495	0.766	-2.676	0.007	-3.550	-0.549
LNA_Modified	-1.7700	0.127	-13.908	0.000	-2.019	-1.521
LNA_Olark Chat Conversation	-1.8100	0.421	-4.295	0.000	-2.636	-0.984

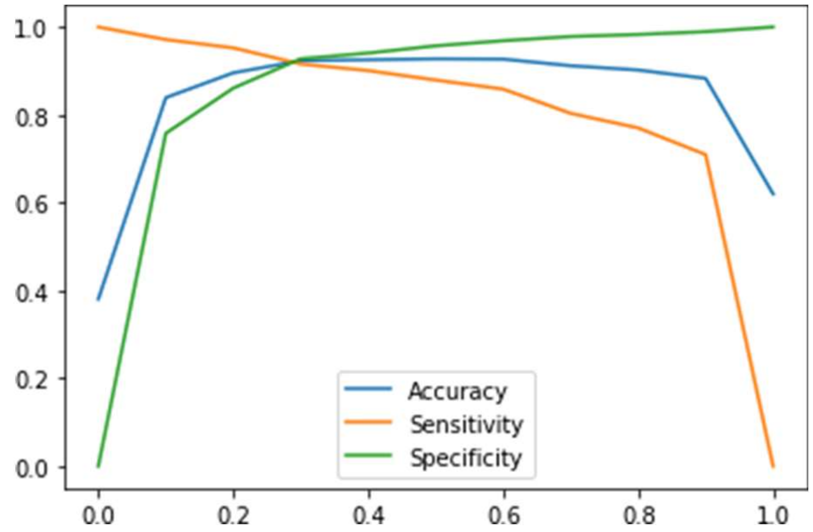
	Features	VIF
1	LO_Lead Add Form	1.77
10	Tags_Will revert after reading the email	1.66
4	LA_SMS Sent	1.65
8	Tags_Not Specified	1.65
2	LS_Olark Chat	1.62
0	Total Time Spent on Website	1.46
12	LNA_Modified	1.42
3	LS_Welingak Website	1.32
6	Tags_Closed by Horizzon	1.21
9	Tags_Ringing	1.12
7	Tags_Lost to EINS	1.07
13	LNA_Olark Chat Conversation	1.07
5	Tags_Busy	1.05
11	Tags_switched off	1.03

Plotting ROC Curve

ROC curve demonstrates several things

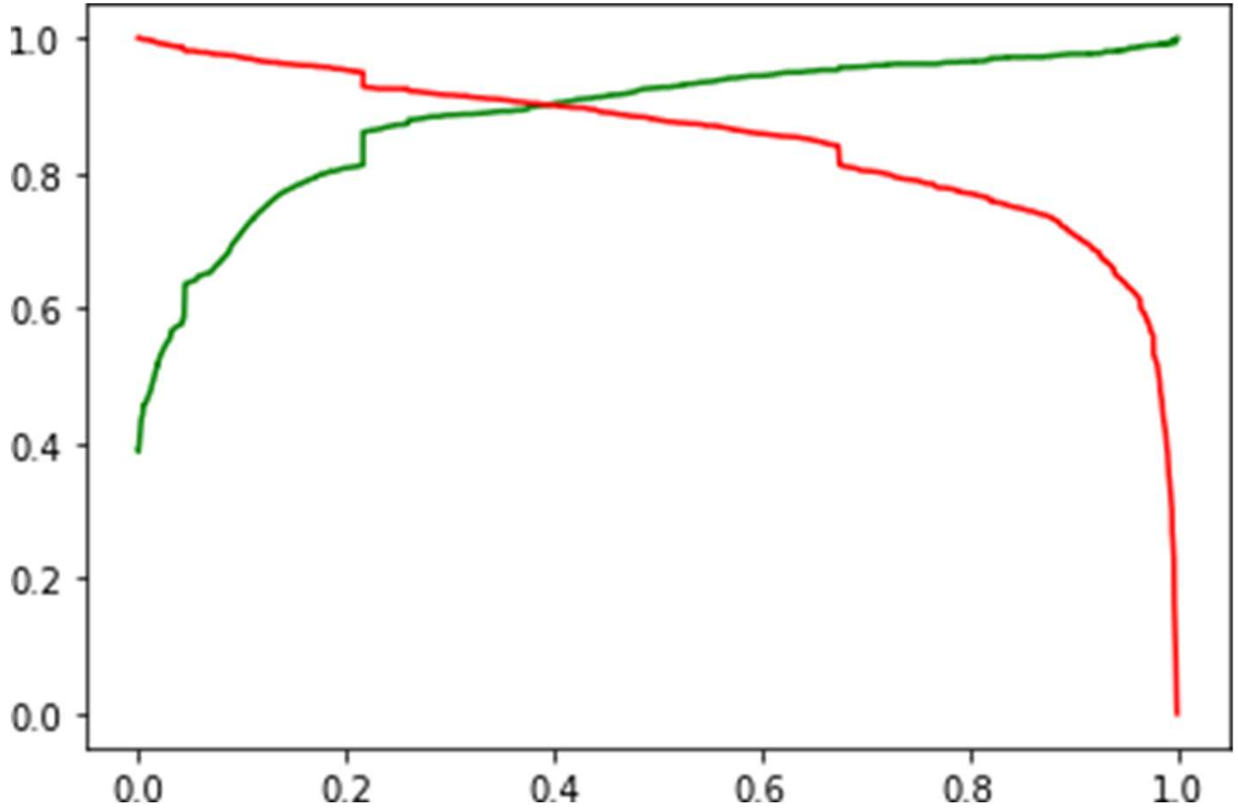
- It shows trade off between sensitivity and specificity.
- The closer the curve follows left hand border and then the top border of the fiOC space, this proves better accuracy of the test.
- The closer the curve comes to the 45-degree diagonal of the fiOC space, the less accurate the test.





Precision and recall trade off

As per Precision–fiecall trade off, the cut off is around 0.4.



Lead Score for varying cut off probability

Here we will examine the projected lead score for different cut off probability to estimate the lead. So, this will be a useful template to change the cut off based on business needs.

```
# Adding Lead Score Column as per buisness requirement

y_test_pred_final['Lead Score'] = y_test_pred_final['Conversion_prob']*100
y_test_pred_final.head()
```

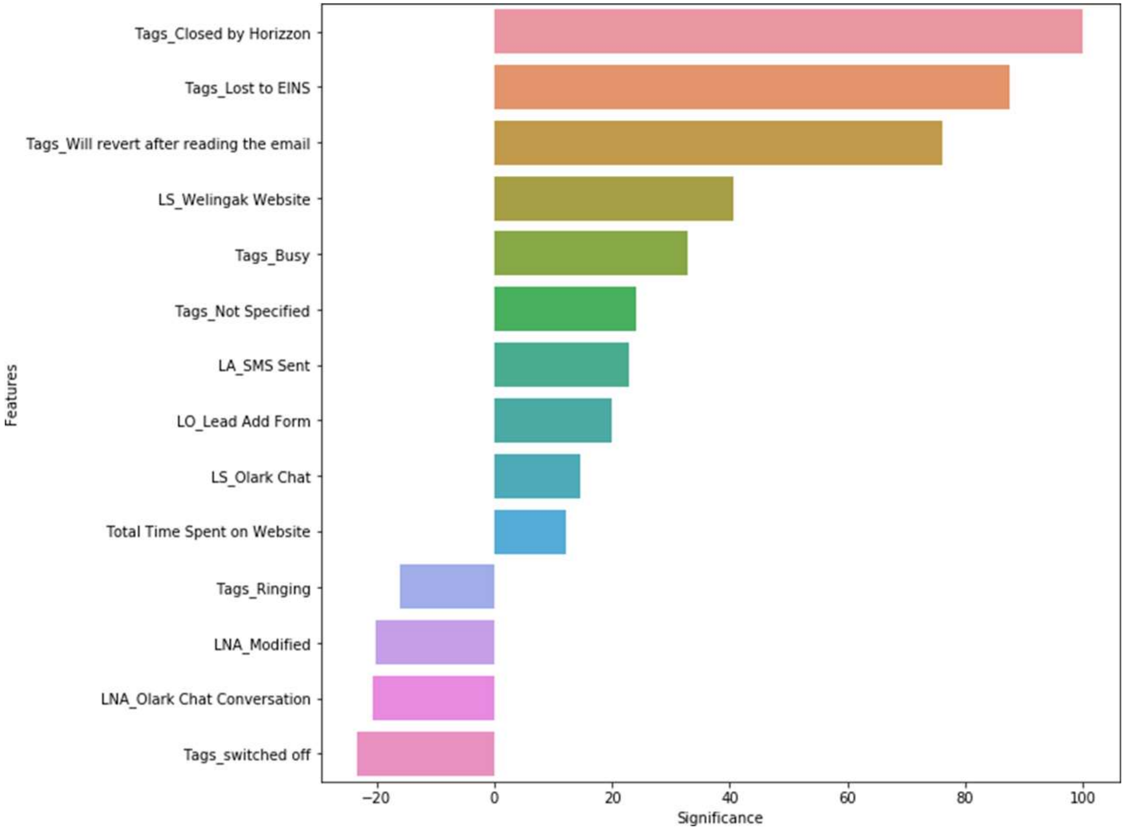
	StudentID	Converted	Conversion_prob	final_predicted	Lead Score
0	7625	0	0.178961	0	17.896082
1	5207	1	0.976689	1	97.668887
2	2390	1	0.996859	1	99.685870
3	4362	0	0.025840	0	2.583958
4	1023	0	0.016779	0	1.677865

```
# Let's also sort the leads by lead score to enable the team to close hot leads as per the lead score

y_test_pred_final.sort_values(by ='Lead Score',ascending = False, inplace = True)
y_test_pred_final.head()
```

	StudentID	Converted	Conversion_prob	final_predicted	Lead Score
779	4062	1	0.999974	1	99.997423
326	3339	1	0.999936	1	99.993584
2582	8103	1	0.999918	1	99.991847
218	6028	1	0.999860	1	99.986017
1936	2354	1	0.999807	1	99.980666

Recommendations to the Management



Top 3 variables that contribute the most towards the probability of a lead getting converted are:

- Tags_Closed by Horizzon
- Tags_lost to EINS
- Tags_will revert after reading the email

X education company needs to focus on following key aspects to improve overall conversion rate:

- Focus on the top 3 tags which are very positive for business.
- Focus on working professional who have high conversion rate.
- Increase user engagement on wellingak website since it helps higher conversion.
- Improving lead add form also improves lead conversion with high certainty