LEAD SCORING CASE STUDY

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%.

BUSINESS GOAL

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.

SOLUTION FLOW

Data Sourcing, Cleaning and Preparing

Initially we have a dataset with 9240 datapoints with null values in some features and some irrelevant columns.
First these null values are treated and irrelevant columns are removed.

Data Analysis

Different graphs are plotted against target variable “converted” to see how different features behave and if they are significant enough to be included in the model or not. We removed quite a few columns at the end of this step and we finally have 18 features as opposed to 37 columns at the start.
From EDA, we infer the following points –
For Do Not Call, major conversion happened when calls were made, but 2 leads got converted when do not call was opted too.
For Last Activity, most conversions happened when sms was sent.
For Do Not Email, most conversions seen when email is sent.
Most Unemployeed had posiive conversion rate.
For Lead Origin, we see maximum conversion has happened from Landing Page.
From Google as Lead Source, most conversions happened.

Most conversions were found which were not Through Recommendations.
Positive conversion rate was seen when a free copy of mastering the interview was not asked.

Model Building

We first create dummy variables for categorical variables and drop the original columns. Then we convert the binary value columns to 0 or 1. The next step is scaling features. Post this our dataset is ready for model building.
We split the data into train and test data, a 70-30 split.
Now for the train set, we use RFE to select top 10 features to create a model. The model gives us these feature list –

- 'Lead Number'
- 'Total Time Spent on Website'
- 'LastNotableActivityD_Modified'
- 'LastNotableActivityD_SMS Sent'
- 'LeadOriginD_API'
- 'LeadOriginD_Lead Add Form'
- 'LastActivityD_Olark Chat Conversation'
- 'LastActivityD_SMS Sent'
- 'CurrentOccupationD_Unknown'
- 'CurrentOccupationD_Working Professional'

Now we see the model summary for p values and calculate VIF. We remove a few features based on high VIF and p values.
Finally, we get a model with these features –

- 'Total Time Spent on Website'
- 'LastNotableActivity - Modified'
- 'LeadOrigin - API'
- 'LeadOrigin - Lead Add Form'
- 'LastActivity - Olark Chat Conversation'
- 'LastActivity - SMS Sent'
- 'CurrentOccupation - Unknown'
- 'CurrentOccupation - Working Professional'

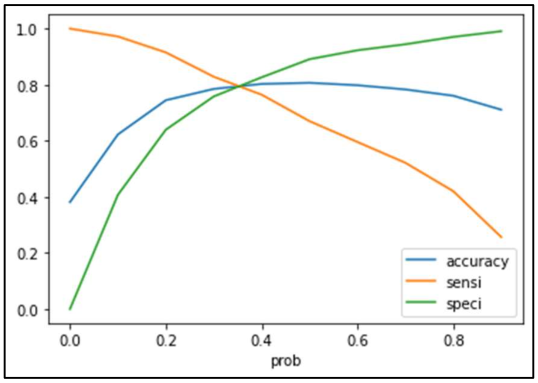
The final model summary is as follows –

Dep. Variable:	Converted	**No. Observations:**	6468
Model:	GLM	**Df Residuals:**	6459
Model Family:	Binomial	**Df Model:**	8
Link Function:	Logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2702.2
Date:	Mon, 17 Jul 2023	**Deviance:**	5404.3
Time:	18:26:24	**Pearson chi2:**	6.63e+03
No. Iterations:	6	**Pseudo R-squ. (CS):**	0.3897
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.9324	0.076	-25.435	0.000	-2.081	-1.783
Total Time Spent on Website	4.0544	0.150	26.983	0.000	3.760	4.349
LastNotableActivityD_Modified	-0.8949	0.079	-11.261	0.000	-1.051	-0.739
LeadOriginD_API	0.7522	0.077	9.831	0.000	0.602	0.902
LeadOriginD_Lead Add Form	3.6810	0.180	20.404	0.000	3.327	4.035
LastActivityD_Olark Chat Conversation	-0.5951	0.171	-3.482	0.000	-0.930	-0.260
LastActivityD_SMS Sent	1.1790	0.073	16.096	0.000	1.035	1.323
CurrentOccupationD_Unknown	-1.0617	0.086	-12.335	0.000	-1.230	-0.893
CurrentOccupationD_Working Professional	2.5578	0.186	13.757	0.000	2.193	2.922

We also calculate specificity, sensitivity, roc curve to get cut off, recall and precession and accuracy for the model.
Finally we test our said model on test set. We get following metrics for train and test set.

Train Set –




```
print("Sensitivity - ",TP/(TP+FN))
```

```
Sensitivity -  0.7789943227899432
```

```
print("Specificity - ",TN/(TN+FP))
```

```
Specificity -  0.8133433283358321
```

```
print(metrics.accuracy_score(y_train_pred_final.Converted, y_train_pred_final.Predicted_Values))
```

```
0.8002473716759431
```

accuracy of ~ 80% is pretty good

Test Set –

```
print('precision ',precision_score(y_predicted_final.Converted, y_predicted_final.predicted_final))

# recall
print('recall ',recall_score(y_predicted_final.Converted, y_predicted_final.predicted_final))
```

```
precision  0.7450302506482281
recall  0.7872146118721461
```

```
print("Specificity - ",TN/(TN+FP))
```

```
Specificity -  0.8240906380441264
```

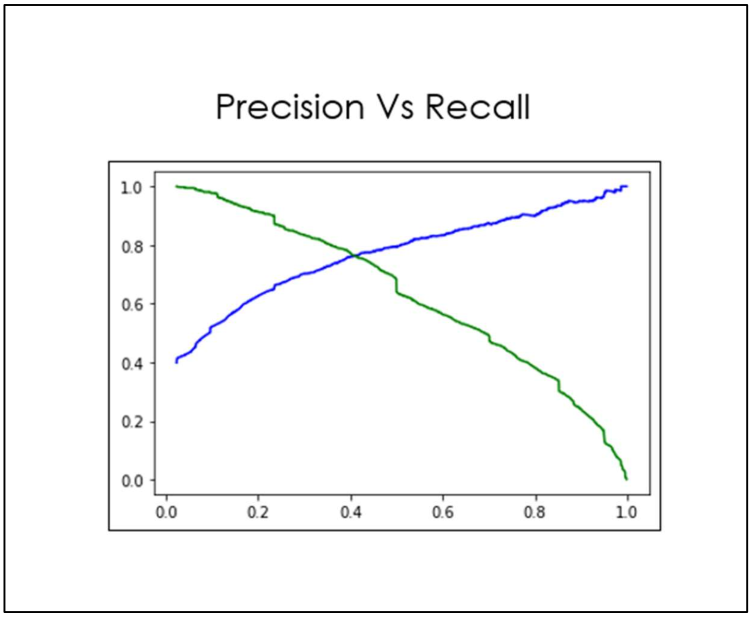
```
print("Sensitivity - ",TP/(TP+FN))
```

```
Sensitivity -  0.7872146118721461
```

```
metrics.accuracy_score(y_predicted_final.Converted, y_predicted_final.predicted_final)
```

```
0.8095238095238095
```

accuracy of ~ 80% on test data is good.



Deriving Results

- We see accuracy of about 80% on test data and about 80% on train data.
- Specificity, Sensitivity of test data is 0.82 and 0.78 respectively.
- Specificity, Sensitivity of train data is 0.81 and 0.77 respectively.
- Precision score on test data is 0.74 and Recall score is 0.78.
- model seems to perform good on train and test set.
- Company should focus more on Total Time Spent on Website, Lead Add Form (Lead Origin), Working Professional (Current Occupation) features.
- The conversion probability cut off is 0.38.