Lead Score Case Study

- Submitted by:-
- **Siddharth Khanna**
- **Deepak Kumar**

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 typical lead conversion rate at X education is around 30%.
- The Company wants to increase it to 80%.

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.

Methodology

1. Data Cleaning and making data set operational.
- Check Non values in all columns
- Check for duplicates data in all columns
- Drop the columns which is not useful
- Take care of outlier if its there.
- Impute values according to requirement

2.Use EDA for further classification analysis like univariate or Bivariate Analysis

3.Regression modelling- logistic regression build up

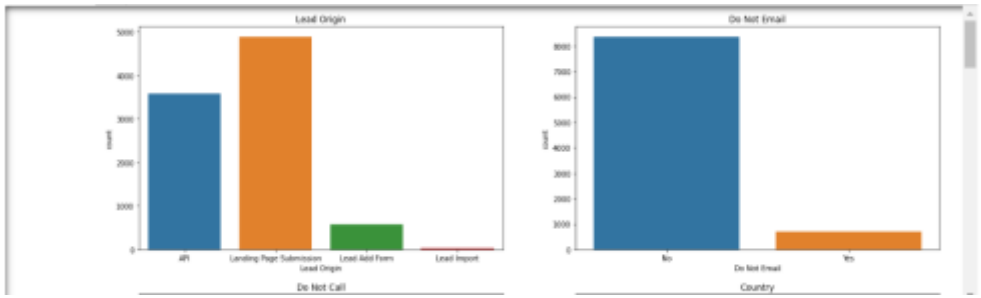
4. Model Analysis .

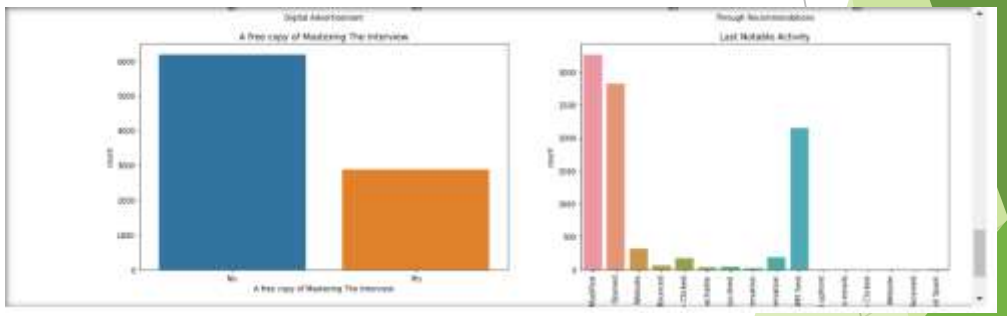
5.Conclusion and recommendation.

Data Knowledge(Impacting factors)

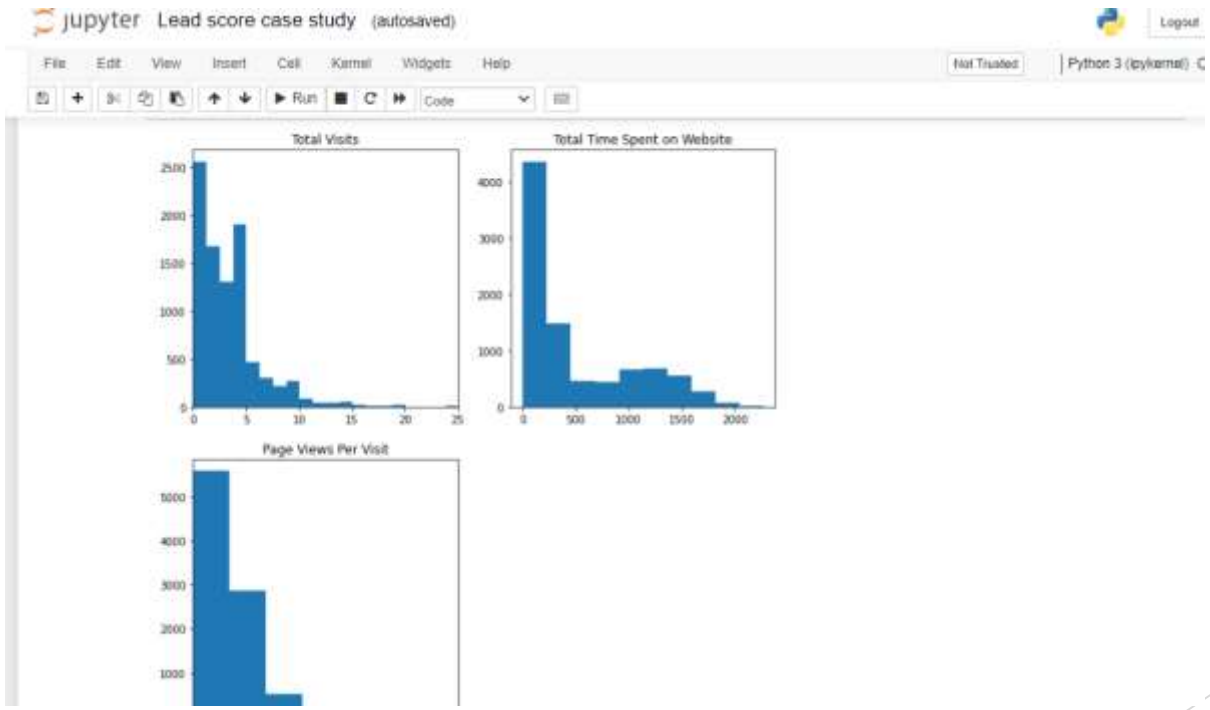
- Dropping of few columns where Null values are greater than 40% like Asymmetrique Activity Index, Asymmetrique Profile Index, Asymmetrique Activity Score, Asymmetrique Profile Score and etc….
- Tola number of rows- 97 and column- 9240
- Project Profile also dropped.

EDA- Univariate analysis



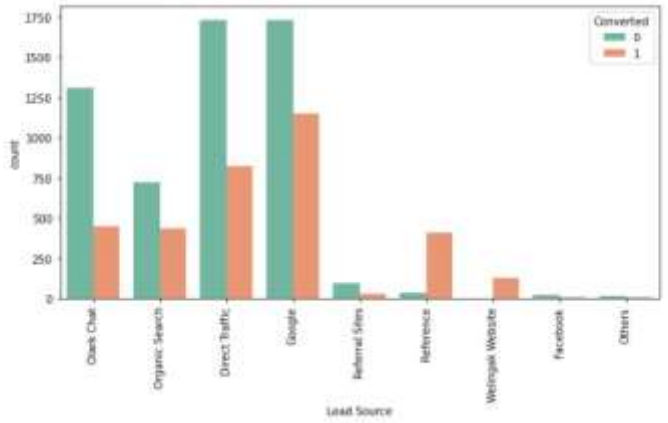


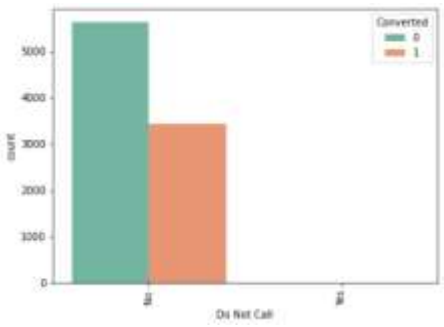
Numerical Variables

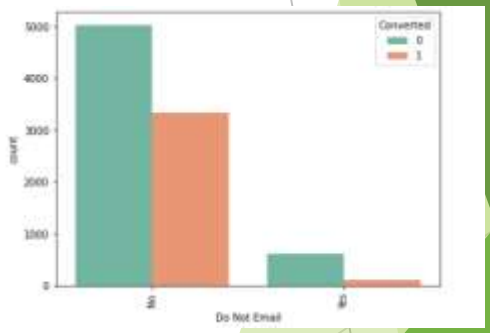


Lead Score Visualization

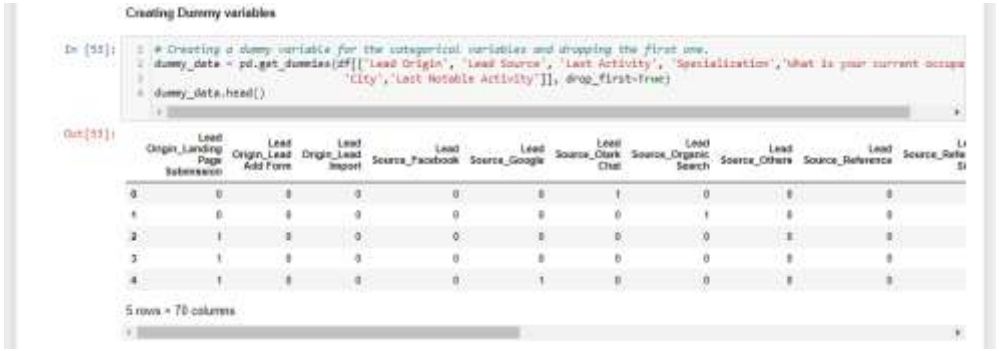
```
Out[46]: (array([0, 1, 2, 3, 4, 5, 6, 7, 8]),
          [Text(0, 0, 'Olark Chat'),
           Text(1, 0, 'Organic Search'),
           Text(2, 0, 'Direct Traffic'),
           Text(3, 0, 'Google'),
           Text(4, 0, 'Referral Sites'),
           Text(5, 0, 'Reference'),
           Text(6, 0, 'Welingak Website'),
           Text(7, 0, 'Facebook'),
           Text(8, 0, 'Others')])
```







Data Preparation(creating dummy variable)



Creating Dummy variables

```
In [53]:
# Creating a dummy variable for the categorical variables and dropping the first one.
dummy_data = pd.get_dummies(df[['Lead Origin', 'Lead Source', 'Last Activity', 'Specialization','What is your current occupa
                                'City','Last Notable Activity']], drop_first=True)
dummy_data.head()
```

Out[53]:

	Lead Origin_Landing Page Submission	Lead Origin_Lead Add Form	Lead Origin_Lead Import	Lead Source_Facebook	Lead Source_Google	Lead Source_Olark Chat	Lead Source_Organic Search	Lead Source_Others	Lead Source_Reference	Lead Source_Refe S
0	0	0	0	0	0	1	0	0	0	
1	0	0	0	0	0	0	1	0	0	
2	1	0	0	0	0	0	0	0	0	
3	1	0	0	0	0	0	0	0	0	
4	1	0	0	0	1	0	0	0	0	

5 rows × 70 columns

Splitting the data into train and test set

```
In [57]:
from sklearn.model_selection import train_test_split

# Putting feature variable to X
X = df.drop(['Prospect ID','Converted'], axis=1)
X.head()
```

Out[57]:

	Do Not Email	Do Not Call	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Lead Origin_Landing Page Submission	Lead Origin_Lead Add Form	Lead Origin_Lead Import	Lead Source_Facebook	Lead Source_Google	...	Last Notable Activity_Form Submitted on Website	Last Notable Activity_Had a Phone Conversation	Activ
0	0	0	0.0	0	0.0	0	0	0	0	0	...	0	0	
1	0	0	5.0	674	2.5	0	0	0	0	0	...	0	0	
2	0	0	2.0	1532	2.0	1	0	0	0	0	...	0	0	
3	0	0	1.0	305	1.0	1	0	0	0	0	...	0	0	
4	0	0	2.0	1428	1.0	1	0	0	0	1	...	0	0	

5 rows × 75 columns

Model Building

Model Building

```
In [44]: # Import 'LogisticRegression'
         from sklearn.linear_model import LogisticRegression
         # Import RFE
         from sklearn.feature_selection import RFE
         # Running RFE with 15 variables as output

         rfe = RFE(estimator=LogisticRegression(), n_features_to_select=15)
         rfe = rfe.fit(X_train, y_train)

In [45]: rfe.support_

Out[45]: array([False, False, False,  True, False,  True,  True, False, False,
                False,  True, False, False, False, False,  True, False,  True,
                False, False, False, False, False,  True,  True, False, False,
                False, False, False, False, False, False, False, False, False,
                False, False, False, False, False, False, False, False,  True,
                False, False, False, False, False,  True, False, False, False,
                 True, False, False, False, False, False,  True, False, False,
                False, False, False,  True, False, False, False, False,  True,
                 True, False, False])

In [46]: list(zip(X_train.columns, rfe.support_, rfe.ranking_))
```

Model Building

Model-1

```
In [68]: import statsmodels.api as sm

In [69]: #BUILDING MODEL #1

         X_train_sm = sm.add_constant(X_train[cols])
         logm1 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
         res = logm1.fit()
         res.summary()
```

Out[69]:

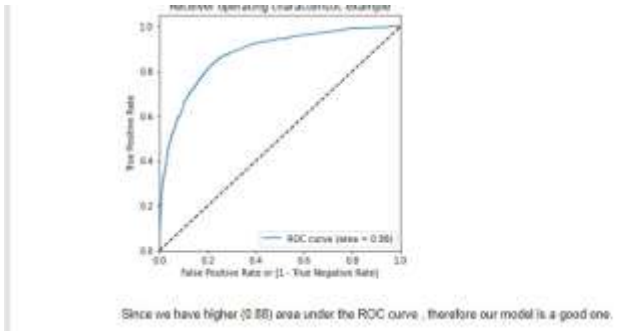
Generalized Linear Model Regression Results

Dep. Variable:	Converted	No. Observations:	6351
Model:	GLM	Df Residuals:	6335
Model Family:	Binomial	Df Model:	15
Link Function:	Logit	Scale:	1.0000
Method:	IRLS	Log-Likelihood:	-2648.0
Date:	Mon, 17 Oct 2022	Deviance:	5296.1
Time:	21:52:40	Pearson chi2:	6.48e+03
No. Iterations:	23	Pseudo R-squ. (CS):	0.3899
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.4346	0.123	-3.522	0.000	-0.677	-0.193
Total Time Spent on Website	1.0884	0.040	27.528	0.000	1.011	1.166

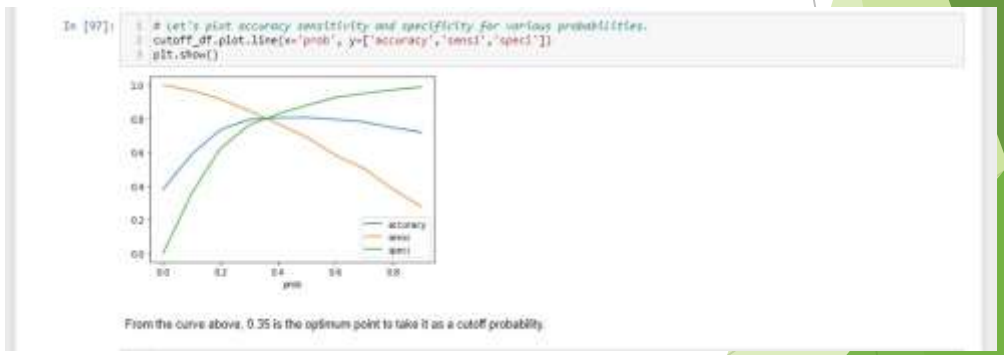
ROC Curve

optimise



Since we have higher (0.88) area under the ROC curve , therefore our model is a good one.

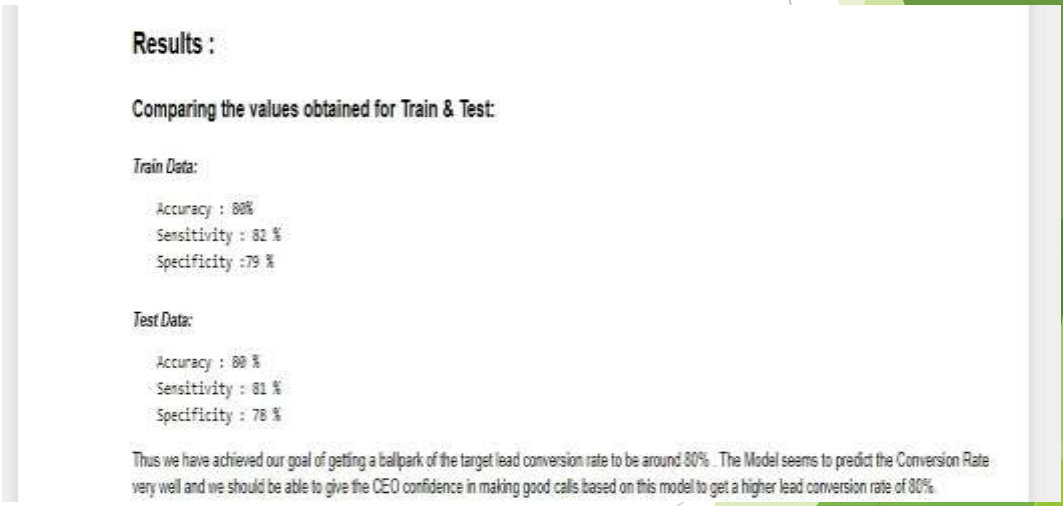
Final optimal



From the curve above, 0.35 is the optimum point to take it as a cutoff probability

Result evaluation

- Train Data:
- Accuracy : 80%
- Sensitivity : 82 %
- Specificity :79 %
- Test Data:
- Accuracy : 80 %
- Sensitivity : 81 %
- Specificity : 78 %



Results :

Comparing the values obtained for Train & Test:

Train Data:

```
Accuracy : 80%
Sensitivity : 82 %
Specificity :79 %
```

Test Data:

```
Accuracy : 80 %
Sensitivity : 81 %
Specificity : 78 %
```

Thus we have achieved our goal of getting a ballpark of the target lead conversion rate to be around 80% . The Model seems to predict the Conversion Rate very well and we should be able to give the CEO confidence in making good calls based on this model to get a higher lead conversion rate of 80%.

Conclusion Part

- Lead Origin Lead Add Form are the ones the to whom the calls should be made as conversion rate is high
- The company should make calls to the leads who are the "working professionals" as they are more likely to get converted.
- The company should make calls to the leads who spent "more time on the websites" as these are more likely to get converted.
- The company should make calls to the leads coming from the lead sources "Olark Chat" as these are more likely to get converted.
- The company should not make calls to the leads who chose the option of "Do not Email" as "yes" as they are not likely to get converted.

Thank You