# LEAD SCORING CASE STUDY

LOGISTIC REGRESSION

### UNDERSTANDING THE DATASET

- We read the CSV file and have look at the data
- pandas's method : info, describe, shape, head, etc.,

Rawdata.describe()								
	Lead Number	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Asymmetrique Activity Score	Asymmetrique Profile Score	
count	9240.000000	9240.000000	9103.000000	9240.000000	9103.000000	5022.000000	5022.000000	
mean	617188.435606	0.385390	3.445238	487.698268	2.362820	14.306252	16.344883	
std	23405.995698	0.486714	4.854853	548.021466	2.161418	1.386694	1.811395	
min	579533.000000	0.000000	0.000000	0.000000	0.000000	7.000000	11.000000	
25%	596484.500000	0.000000	1.000000	12.000000	1.000000	14.000000	15.000000	
50%	615479.000000	0.000000	3.000000	248.000000	2.000000	14.000000	16.000000	
75%	637387.250000	1.000000	5.000000	936.000000	3.000000	15.000000	18.000000	
max	660737.000000	1.000000	251.000000	2272.000000	55.000000	18.000000	20.000000	
From A	bove description	looks like we h	nave missing val	ues oin the data				

#### PREPARING THE DATA

- Treating missing value
  - a) Considering `Select` as null
  - b) Deleted the columns which have more than 40% missing value
  - c) Putting the majority value for the columns

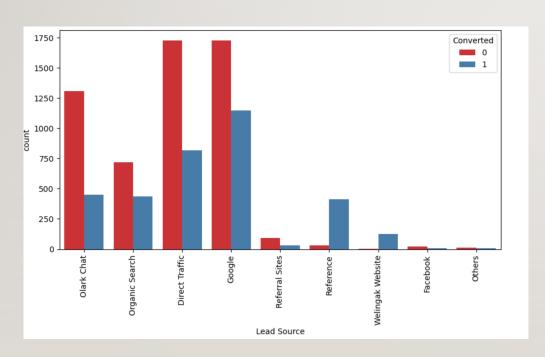
```
#### As most of the leads are from India we can change missing values to India only
Rawdata['Country']=Rawdata['Country'].replace(np.nan,'India')
```

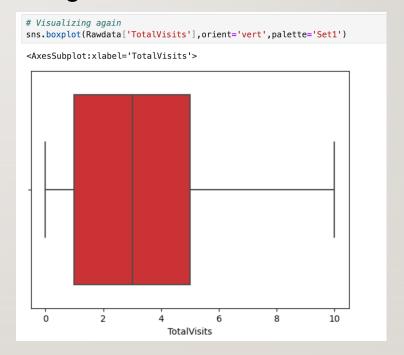
```
# converting the missing data in the 'What is your current occupation' column with 'Unemployed'

Rawdata['What is your current occupation']=Rawdata['What is your current occupation'].replace(np.nan,'Unemployed')
```

### DATA VISUALIZATION

• We have done the uni and bi variant analyziz for LeadOrigin, LeadSource, TotalVisits, etc





### BUILDING THE MODEL

- We built the model and analyzed the P-Value and VFI of each feature
- We removed the feature one by one based on the P-Value > 0.005 and VFI >= 5

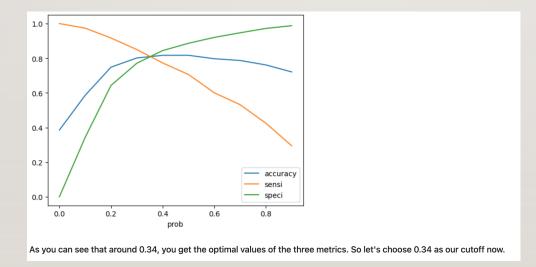
Generalized Linear Model Regression Results					
Dep. Variable:	Converted	No. Observations:	6351		
Model:	GLM	Df Residuals:	6338		
Model Family:	Binomial	Df Model:	12		
<b>Link Function:</b>	Logit	Scale:	1.0000		
Method:	IRLS	Log-Likelihood:	-2610.5		
Date:	Mon, 17 Jul 2023	Deviance:	5221.0		
Time:	18:43:07	Pearson chi2:	6.53e+03		
No. Iterations:	7	Pseudo R-squ. (CS):	0.4001		
Covariance Type:	nonrobust				

Сочагіапсе туре:	ποπισυμεί						
		coef	std err	z	P> z	[0.025	0.975]
	const	-0.0376	0.125	-0.300	0.764	-0.283	0.208
	Do Not Email	-1.5218	0.177	-8.611	0.000	-1.868	-1.175
	<b>Total Time Spent on Website</b>	1.0954	0.040	27.225	0.000	1.017	1.174
Lead	Origin_Landing Page Submission	-1.1940	0.128	-9.360	0.000	-1.444	-0.944
	Lead Source_Olark Chat	1.0819	0.122	8.847	0.000	0.842	1.322
	Lead Source_Reference	3.3166	0.241	13.747	0.000	2.844	3.789
	Lead Source_Welingak Website	5.8115	0.728	7.981	0.000	4.384	7.239
Last A	Activity_Olark Chat Conversation	-0.9613	0.171	-5.610	0.000	-1.297	-0.625
	Last Activity_Other_Activity	2.1751	0.463	4.699	0.000	1.268	3.082
	Last Activity_SMS Sent	1.2942	0.075	17.308	0.000	1.148	1.441
	Specialization_Others	-1.2025	0.125	-9.582	0.000	-1.448	-0.957
What is your current o	occupation_Working Professional	2.6083	0.194	13.454	0.000	2.228	2.988
	Last Notable Activity_Modified	-0.9004	0.081	-11.097	0.000	-1.059	-0.741

VIF	Features	
2.16	Specialization_Others	9
2.03	Lead Source_Olark Chat	3
1.78	Last Notable Activity_Modified	11
1.69	Lead Origin_Landing Page Submission	2
1.59	Last Activity_Olark Chat Conversation	6
1.56	Last Activity_SMS Sent	8
1.29	Total Time Spent on Website	1
1.24	Lead Source_Reference	4
1.18	What is your current occupation_Working Profes	10
1.13	Do Not Email	0
1.09	Lead Source_Welingak Website	5
1.01	Last Activity_Other_Activity	7

### CHOOSING THE OPTIMIZED PROBABILITY

- To get the y-pred we have to choose the optimum Probaility value
- We draw graph for variouse value of p b/w (0 to 1) for Sensitivity, Specificity and accruacy
- Optimized probability is 0.34



#### MODEL METRICS

• We calculated the accracy, specificity and senstivity with prob value 0.34

```
# Positive and Negative predictive value
print("Positive Predictive Value:",TP / float(TP+FP))
print("Negative Predictive Value: ",TN / float(TN+ FN))

Positive Predictive Value: 0.7261169633127498
Negative Predictive Value: 0.8757643135075042

Sensitivity: 0.8172526573998364 and Specificity: 0.8069142125480153 look good to go
```

#### MODEL INTERPRETATION

We have higher postive correlation with

- LeadSource\_WelingakWebsite
- LeadSource\_Reference

We have higher negative correlation with

- DoNotEmail
- SpecializationOthers

#### In other words:

- Sources WelingakWebiste and Reference have higher conversion
- Peoople who don't want to contact or others profession as have less conversion

	coef	std err	z	P> z	[0.025	0.975]
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## **THANK YOU**