



## **X** Education

(Data Analysis to increase the lead conversion using marketing team)

Project by: Yogita Goswami Chandana Joshi





## X Education Case Study Analysis

#### **Problem Statement:**

The company markets its courses on several websites and captures the browsing history and application filled by the interested candidates. Observation is only around 30% of the interested candidates actually proceed to take the course. Analyze the data and provide insights to increase the conversion to 80% using targeted marketing to interested candidates

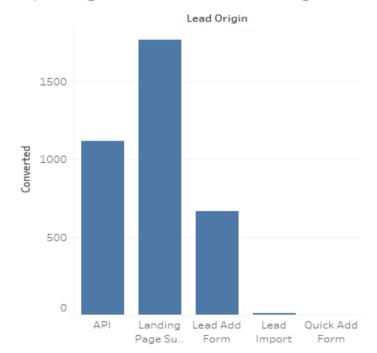
Available Data Source for analysis: Leads dataset having 9000 potential leads information like source and origin from which they learnt about the course, if they have subscribed to free magazine, newsletter, updates on different courses, time they spent on website, # of visits etc.



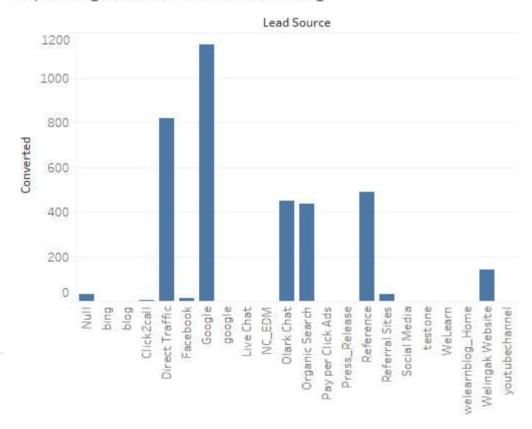


## **Step 1: Understanding the Data:**

Exploring Data for understanding



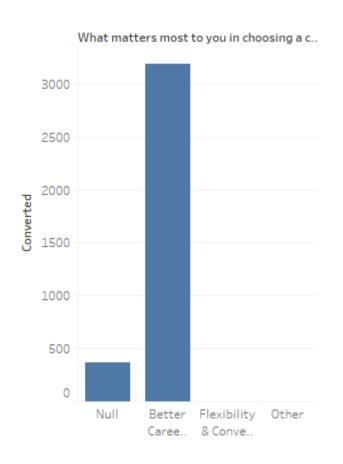
#### Exploring Data for understanding



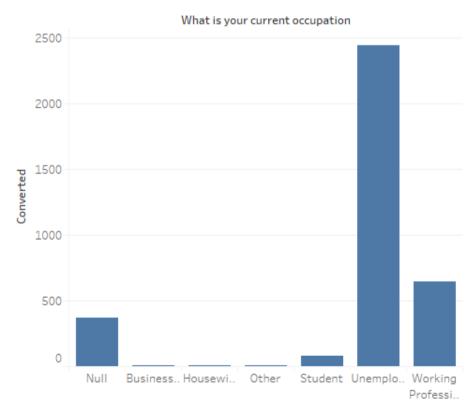




## **Step 1 : Understanding the Data:**



#### Exploring Data for understanding







## • Step 2: Handle Missing Values

Remove columns having more than 30% missing values

Remove missing values or impute them with relevant values.

Address all the missing values.

Out[574]:	Prospect ID	0.00
	Lead Number	0.00
	Lead Origin	0.00
	Lead Source	0.39
	Do Not Email	0.00
	Do Not Call	0.00
	Converted	0.00
	TotalVisits	1.48
	Total Time Spent on Website	0.00
	Page Views Per Visit	1.48
	Last Activity	1.11
	Country	26.63
	Specialization	15.56
	How did you hear about X Education	23.89
	What is your current occupation	29.11
	What matters most to you in choosing a course	29.32
	Search	0.00
	Magazine	0.00
	Newspaper Article	0.00
	X Education Forums	0.00
	Newspaper	0.00
	Digital Advertisement	0.00
	Through Recommendations	0.00
	Receive More Updates About Our Courses	0.00
	Tags	36.29
	Lead Quality	51.59
	Update me on Supply Chain Content	0.00
	Get updates on DM Content	0.00
	Lead Profile	29.32
	City	15.37
	Asymmetrique Activity Index	45.65
	Asymmetrique Profile Index	45.65
	Asymmetrique Activity Score	45.65
	Asymmetrique Profile Score	45.65
L	I agree to pay the amount through cheque	0.00
	A free copy of Mastering The Interview	0.00





**Step 3: Address categorical variables with Binary Mapping** 

Replace YES and NO with 1 and 0 using binary mapping function

**Step 4: Address other categorical variables with get dummies** for variables like Lead Origin, Lead source, Specialization, Last notable activity etc.

You will now have final Data frame where missing values and categorical variables are handled.

Step 5: Do the test and training split with the above data frame





1:

- Step 6 : Building a Model with GLM
- Step 7:Feature elimination with RFE
- Step 8: Check VIF and P values to eliminate features.

VIFs are less than 5, so we proceed to look at p values (to be less than 0.05)

	Features	VIF	
11	Country_unknown	2.65	
14	Specialization_dont know	2.18	
4	LeadOrigin_Lead Add Form	1.89	
3	LeadOrigin_Landing Page Submission	1.63	
18	MattersMost_dont know	1.61	
22	LastNotableActivity_SMS Sent	1.41	
7	LeadSource_Welingak Website	1.37	
1	Total Time Spent on Website	1.33	
0	Do Not Email	1.19	
17	CurrentOccupation_Working Professional	1.18	
24	LastNotableActivity_Unsubscribed	1.07	
6	LeadSource_Unknown	1.06	
20	LastNotableActivity_Olark Chat Conversation	1.06	
12	Specialization_Hospitality Management	1.02	
13	Specialization_Services Excellence	1.01	
15	HearAboutX_Email	1.01	
23	LastNotableActivity_Unreachable	1.01	
10	Country_Qatar	1.00	
9	Country_Nigeria	1.00	
8	Country_Italy	1.00	
16	CurrentOccupation_Housewife	1.00	
5	LeadSource_NC_EDM	1.00	





Iterate and remove features having higher p value, after final iteration we get below.

	coef	std err	Z	P> z	[0.025	0.975]
const	-0.3913	0.116	-3.369	0.001	-0.619	-0.164
Do Not Email	-1.5154	0.178	-8.532	0.000	-1.864	-1.167
Total Time Spent on Website	1.1025	0.041	27.151	0.000	1.023	1.182
LeadOrigin_Landing Page Submission	-0.8830	0.121	-7.278	0.000	-1.121	-0.645
LeadOrigin_Lead Add Form	2.4056	0.233	10.319	0.000	1.949	2.862
Lead Source_Welingak Website	2.3710	0.757	3.131	0.002	0.887	3.855
Country_unknown	1.0378	0.119	8.757	0.000	0.808	1.270
Specialization_dont know	-0.9764	0.122	-7.993	0.000	-1.216	-0.737
CurrentOccupation_Working Professional	2.3871	0.193	12.395	0.000	2.010	2.765
MattersMost_dont know	-1.1061	0.088	-12.580	0.000	-1.279	-0.933
LastNotableActivity_Had a Phone Conversation	3.1165	1.183	2.634	0.008	0.798	5.435
LastNotableActivity_SMS Sent	1.6237	0.080	20.390	0.000	1.468	1.780
LastNotableActivity_Unreachable	1.9850	0.524	3.788	0.000	0.958	3.012
LastNotableActivity_Unsubscribed	1.4439	0.519	2.780	0.005	0.426	2.462
					-	





• Step 9: List of features after removing features from RFE, look at top 3 co-efficients for getting significant 3 variables

Model Family:	Binomial	Df M	odel:	13				
Link Function:	logit	S	icale:	1.0000				
Method:	IRLS	Log-Likelih	nood:	-2607.3				
Date:	Mon, 10 Jun 2019	Devia	ance:	5214.5				
Time:	14:49:02	Pearson	chi2:	6.30e+03				
No. Iterations:	7	Covariance 1	Гуре: г	nonrobust				
			coef	f std err	z	P> z	[0.025	0.975]
		const	-0.3913	0.116	-3.369	0.001	-0.619	-0.164
		Do Not Email	-1.5154	0.178	-8.532	0.000	-1.864	-1.167
	Total Time Sper	nt on Website	1.1025	0.041	27.151	0.000	1.023	1.182
Lead0	rigin_Landing Pag	e Submission	-0.8830	0.121	-7.278	0.000	-1.121	-0.645
	LeadOrigin_Le	ad Add Form	2.4056	0.233	10.319	0.000	1.949	2.862
	LeadSource_Weli	ngak Website	2.3710	0.757	3.131	0.002	0.887	3.855
	Coun	try_unknown	1.0378	0.119	8.757	0.000	0.806	1.270
	Specialization	n_dont know	-0.9784	0.122	-7.993	0.000	-1.216	-0.737
CurrentOc	cupation_Working	Professional	2.3871	0.193	12.395	0.000	2.010	2.765
	MattersMo	st_dont know	-1.1061	0.088	-12.580	0.000	-1.279	-0.933
LastNotableAct	ivity_Had a Phone	Conversation	3.1165	1.183	2.634	0.008	0.798	5.435
	LastNotableActiv	ity_SMS Sent	1.6237	0.080	20.390	0.000	1.468	1.780
L	astNotableActivity	Unreachable	1.9850	0.524	3.788	0.000	0.958	3.012
Las	stNotableActivity_l	Jnsubscribed	1.4439	0.519	2.780	0.005	0.426	2.462





## Final list of variable

Do Not Email

**Total Time Spent on Website** 

LeadOrigin\_Landing Page Submission

LeadOrigin Lead Add Form

LeadSource\_Welingak Website

Country\_unknown

Specialization dont know

CurrentOccupation\_Working Professional

MattersMost dont know

LastNotableActivity Had a Phone Conversation

LastNotableActivity SMS Sent

LastNotableActivity\_Unreachable

LastNotableActivity\_Unsubscribed





# Important features

## Top 3 variables which are contributing for Lead conversion:

Check the co-efficient to find the most contributing 3 features

- 1.LastNotableActivity\_Had a Phone Conversation
- 2. LeadOrigin\_Lead Add Form
- 3. CurrentOccupation\_Working Professional

Model Family:	Binomial	Df M	odel:	13				
Link Function:	logit	S	icale:	1.0000				
Method:	IRLS	Log-Likelih	nood:	-2607.3				
Date:	Mon, 10 Jun 2019	Devi	ance:	5214.5				
Time:	14:49:02	Pearson	chi2:	6.30e+03				
No. Iterations:	7	Covariance 1	Гуре:	nonrobust				
			coe	f std err	Z	P> z	[0.025	0.975]
		const	-0.391	3 0.116	-3.369	0.001	-0.619	-0.164
		Do Not Email	-1.515	4 0.178	-8.532	0.000	-1.864	-1.167
	Total Time Sper	nt on Website	1.102	5 0.041	27.151	0.000	1.023	1.182
Lead0	rigin_Landing Page	Submission	-0.883	0.121	-7.278	0.000	-1.121	-0.845
	LeadOrigin_Le	ad Add Form	2.405	6 0.233	10.319	0.000	1.949	2.862
	Lead Source_Welin	ngak Website	2.371	0.757	3.131	0.002	0.887	3.855
	Coun	try_unknown	1.037	8 0.119	8.757	0.000	0.806	1.270
	Specializatio	n_dont know	-0.976	4 0.122	-7.993	0.000	-1.216	-0.737
CurrentOc	cupation_Working	Professional	2.387	1 0.193	12.395	0.000	2.010	2.765
	MattersMo	st_dont know	-1.106	1 0.088	-12.560	0.000	-1.279	-0.933
LastNotableAct	ivity_Had a Phone	Conversation	3.116	5 1.183	2.634	0.008	0.798	5.435
	LastNotableActiv	ity_SMS Sent	1.623	7 0.080	20.390	0.000	1.468	1.780
L	astNotableActivity_	Unreachable	1.985	0.524	3.788	0.000	0.958	3.012
Las	stNotableActivity_L	Insubscribed	1.443	9 0.519	2.780	0.005	0.426	2.462



# Top 3 variables which are contributing for Lead conversion: check co- efficients to find most contributing



- 1. LastNotableActivity
- 2. LeadOrigin
- 3. CurrentOccupation
  \_Working Professional

Model Family:	Binomial	Df M	lodel:	13				
Link Function:	logit	5	cale:	1.0000				
Method	: IRLS	Log-Likelih	nood:	-2607.3				
Date	: Mon, 10 Jun 2019	Devi	ance:	5214.5				
Time	14:49:02	Pearson	chi2:	6.30e+03				
No. Iterations	: 7	Covariance '	Туре:	nonrobust				
			coe	ef std err	z	P> z	[0.025	0.975]
		const	-0.391	3 0.116	-3.369	0.001	-0.619	-0.164
		Do Not Email	-1.515	4 0.178	-8.532	0.000	-1.864	-1.167
	Total Time Spe	nt on Website	1.102	5 0.041	27.151	0.000	1.023	1.182
Lead	Origin_Landing Pag	e Submission	-0.883	0.121	-7.278	0.000	-1.121	-0.645
	LeadOrigin_Le	ad Add Form	2.405	6 0.233	10.319	0.000	1.949	2.862
	Lead Source_Weli	ngak Website	2.371	0.757	3.131	0.002	0.887	3.855
	Coun	try_unknown	1.037	8 0.119	8.757	0.000	0.806	1.270
	Specialization	on_dont know	-0.976	4 0.122	-7.993	0.000	-1.216	-0.737
CurrentO	Occupation_Working	Professional	2.387	1 0.193	12.395	0.000	2.010	2.765
	MattersMo	st_dont know	-1.108	1 0.088	-12.560	0.000	-1.279	-0.933
LastNotableAd	ctivity_Had a Phone	Conversation	3.118	5 1.183	2.634	0.008	0.798	5.435
	LastNotableActiv	ity_SMS Sent	1.623	7 0.080	20.390	0.000	1.468	1.780
	LastNotableActivity	_Unreachable	1.985	0 0.524	3.788	0.000	0.958	3.012
L	astNotableActivity_l	Jnsubscribed	1.443	9 0.519	2.780	0.005	0.426	2.462





• Step 10: Predict the values , create confusion matrix and evaluate the accuracy of the model (accuracy= 0.81)

```
: # Confusion matrix
from sklearn import metrics
confusion = metrics.confusion_matrix(y_train_pred_final.Convert, y_train_pred_final.predicted)
print(confusion)

[[3506 447]
[ 741 1678]]

: # checking the accuracy.
print(metrics.accuracy_score(y_train_pred_final.Convert, y_train_pred_final.predicted))
0.8135593220338984
```

• Step 11: Find the cut off with specificity sensitivity and accuracy cut off=0.3

```
In [62]: 
# Let's plot accuracy sensitivity and specificity for various probabilities.
cutoff df.plot.line(x='prob', y=['accuracy','sensi','speci'])

10
08
06
04
02
04
06
08

In [63]: 
# Let's plot accuracy sensitivity and specificity for various probabilities.
cutoff df.plot.line(x='prob', y=['accuracy','sensi','speci'])

# Accuracy sensitivity and specificity for various probabilities.
cutoff df.plot.line(x='prob', y=['accuracy','sensi','speci'])

# Accuracy sensitivity and specificity for various probabilities.

# Accuracy sensitivity and sensitivity and specificity for various probabilities.

# Accuracy sensitivity and sensitivity and sensitivity and specificity for various probabilities.

# Accuracy sensitivity and sensitivity and
```





### Step 12: Assigning Lead score

Assigning lead score from 0 to 100

```
In [98]: y_pred_final['Score'] = y_pred_final.Convert_Prob.map(lambda x: round(x*100))
y_train_pred_final['Score'] = y_train_pred_final.Convert_Prob.map(lambda x: round(x*100))
```

We can see the equation is:

Logit(P) = - 0.3913 - 1.5154 x Do Not Email is Yes + 1.1025 x Total Time Spent on Website - 0.8830 x Lead Origin of 'Landing Page Submission' + 2.4056 x Lead Origin of 'Lead Add Form' + 2.3710 x Lead Source of 'Welingak Website' + 1.0378 x Country is Unknown - 0.9764 x Specialization dont know + 2.3871 x CurrentOccupation is Working Professional - 1.1061 x What MattersMost is dont know + 3.1165 x LastNotableActivity is 'Had a Phone Conversation' + 1.6237 x LastNotableActivity is 'SMS Sent' + 1.9850 x LastNotableActivity is 'Unreachable' + 1.4439 x LastNotableActivity is 'Unsubscribed'

Score = Logit(P) x 100 (score between 0 and 100)





# Suggestions/Recommendations

- 1. Marketing Teams can call the all the candidates who are unemployed or working professionals to explain about the course and try to give some special offers to attract the prospects.
- 2. Marketing Teams can call the candidates whose LeadOrigin is LeadAddform or Landingpage.
- 3. Marketing Teams can call candidates with LastNotableActivity as who had phone call, SMS sent or email opened.





# Thank You