## 1. Problem Statement & Analysis:

- An education company X sells online courses to various professionals and students through their website.
- They market these courses via different platforms. Based on the leads generated via these platforms, their marketing team pursues them individually.
- Our task at hand is to identify the specific factors that contributes significantly for a lead to get converted.
- We need to build a model and train it on the existing data to classify a lead as hot lead based on the conversion probability Their typical lead conversion has been around 30%.
- We need to build a logistic regression model wherein 80% of the leads that could get converted have to be classified as hot leads as per our model.

## 2. Approach:

- Our analysis and building of the model involved the following steps.
  - Data Cleaning
  - Data Preparation
  - Train Test Split
  - Correlation, Recursive feature Elimination, VIF

### a) Data Cleaning:

We have performed data cleaning after treating the missing values and finally obtained 9074 rows and 15 columns.

#### b) Data Preparation:

We removed the variables which are heavily skewed and modified the categories of few variables to suit the analysis

#### c) Train-test split:

- We have divided the dataset to dependent and independent variables by creating data sets X and y
- We have then divided th dataset to train and test with 70% of available data to be used for training the model.

### d) Correlation, Recursive feature Elimination, VIF:

- Using the RFE library from scikit learn, we have obtained the top 15 significant variables for building the model.
- After creating a logistic regression and making sure that all the varibales are significant without multi-collinearilty, we obtained the following final model.

# e) Final Model:

• Final model consists of following variables that are significant.

	Coefficient	Std err	z	P- value	2.5%'le	97.5%'le
const	-0.9347	0.124	-7.528	0.000	-1.178	-0.691
Do Not Email	-1.4107	0.169	-8.339	0.000	-1.742	-1.079
Total Time Spent on Website	1.1455	0.040	28.726	0.000	1.067	1.224
Lead Origin_Landing Page Submission	-0.2049	0.091	-2.241	0.025	-0.384	-0.026
Lead Origin_Lead Add Form	4.3319	0.226	19.204	0.000	3.890	4.774
Lead Origin_Lead Import	1.6907	0.448	3.777	0.000	0.813	2.568
Lead Source_Google	0.3644	0.080	4.539	0.000	0.207	0.522
Lead Source_Olark Chat	1.0229	0.127	8.082	0.000	0.775	1.271
Specialization_strong demand	-0.1785	0.083	-2.140	0.032	-0.342	-0.015
Tags_lost	1.0083	0.111	9.066	0.000	0.790	1.226
Tags_unresponsive	-1.1399	0.152	-7.509	0.000	-1.438	-0.842
Last Notable Activity_Modified	-0.8424	0.086	-9.792	0.000	-1.011	-0.674

Last Notable Activity_Other activity	-0.3013	0.129	-2.344	0.019	-0.553	-0.049
Last Notable Activity_SMS Sent	1.5179	0.088	17.245	0.000	1.345	1.690

# 3. Learnings from the assignment

- We evaluated the model initially by taking a cutoff value of conversion probability at 0.5.
- Although we obtained an accuracy of 80%, our sensitivity is only 68%.
- This meant that there is a 32% chance of us missing out on a prospective lead that has the potential to get converted.
- While sensitivity can be increased by increasing the cutoff for probability of conversion, this might cause a decrease in accuracy.
- Based on our plotting of accuracy, sensitivity and specificity against various cutoffs for probability of conversion, we found that optimal cutoff lies between 0.3-0.35
- On the training set we have evaluated the model by taking a cutoff at 0.35. This has improved the sensitivity to 81%
- This meant that model can now predict 81% of all the lead that could actually get converted.
- On the test set we reduced the reduced the cutoff to 0.3 and obtained a sensitivity of 80% which is also decent.
- While sensitivity could be further increased by increasing cutoff, this could lead to decrease in specificity which leads to lower predictability of leads that will not be converted. This leads us to chasing after leads that will not get converted.