Lead scoring case study

PPT/PDF describing the analysis:

Group members: Sushmita, Vaibhavi, Taha

Problem statement

- An X Education need help to select the most promising leads, i.e. the leads that are most likely to convert into paying customers. The company requires us to build a model wherein you need to assign a lead score to each of the leads such that the customers with higher lead score have a higher conversion chance and the customers with lower lead score have a lower conversion chance. The CEO, in particular, has given a ballpark of the target lead conversion rate to be around 80%.

Goals and Objectives

- There are quite a few goals for this case study.
Build a logistic regression model to assign a lead score between O 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. These problems are provided in a separate doc file. Please fill it based on the logistic regression model you got in the first step. Also, make sure you include this in your final PPT where you'll make recommendations.

Solution steps:

- Data importing, cleaning and processing.
- EDA: Univariate, Bi-variate, multivariate analyses.
- Dummy variable and splitting data into train-test.
- Building the model (logistic regression)
- Manual feature selection using VIF
- Creating predictions after fine tuning
- Evaluating model, optimising cut-off, getting results (metrics) on test set and CONCLUSIONS.

Data processing

- Numpy, pandas, matplotlib, seaborn were used.
- Data cleaning -> replacing empty choices with nan, consistent casing, dropiing columns with high null %, imputing null values.

```
# Replace null values in Country by 'unknown'
df2['Country'] = df2['Country'].fillna('unknown')
# see unique value of the column after replacing value
df2['Country'].value_counts()
```
[27]

```
Country
india                   6491
unknown                 2301
united states             69
united arab emirates      53
singapore                 24
saudi arabia              21
united kingdom            15
australia                 13
qatar                     10
```

```
# Rechecking the percentage of missing values
round(100*(df2.isnull().sum()/len(df2.index)), 2)
```
[32]

```
Prospect ID                                      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                                  36.58
What is your current occupation                 29.11
What matters most to you in choosing a course   29.32
```

```
# Group values with a frequency of less than 10 into "others" to simplify the values in the Country column and avoid unnecessary complexity when build
contry_count = df2['Country'].value_counts()
top_country_count = contry_count[contry_count >= 10].index
# replace rare values by 'others'
df2['Country'] = df2['Country'].apply(lambda x: x if x in top_country_count else 'Other')
# see unique value in Tags column after replacing rare values by 'others' value
df2['Country'].value_counts()
```
Python

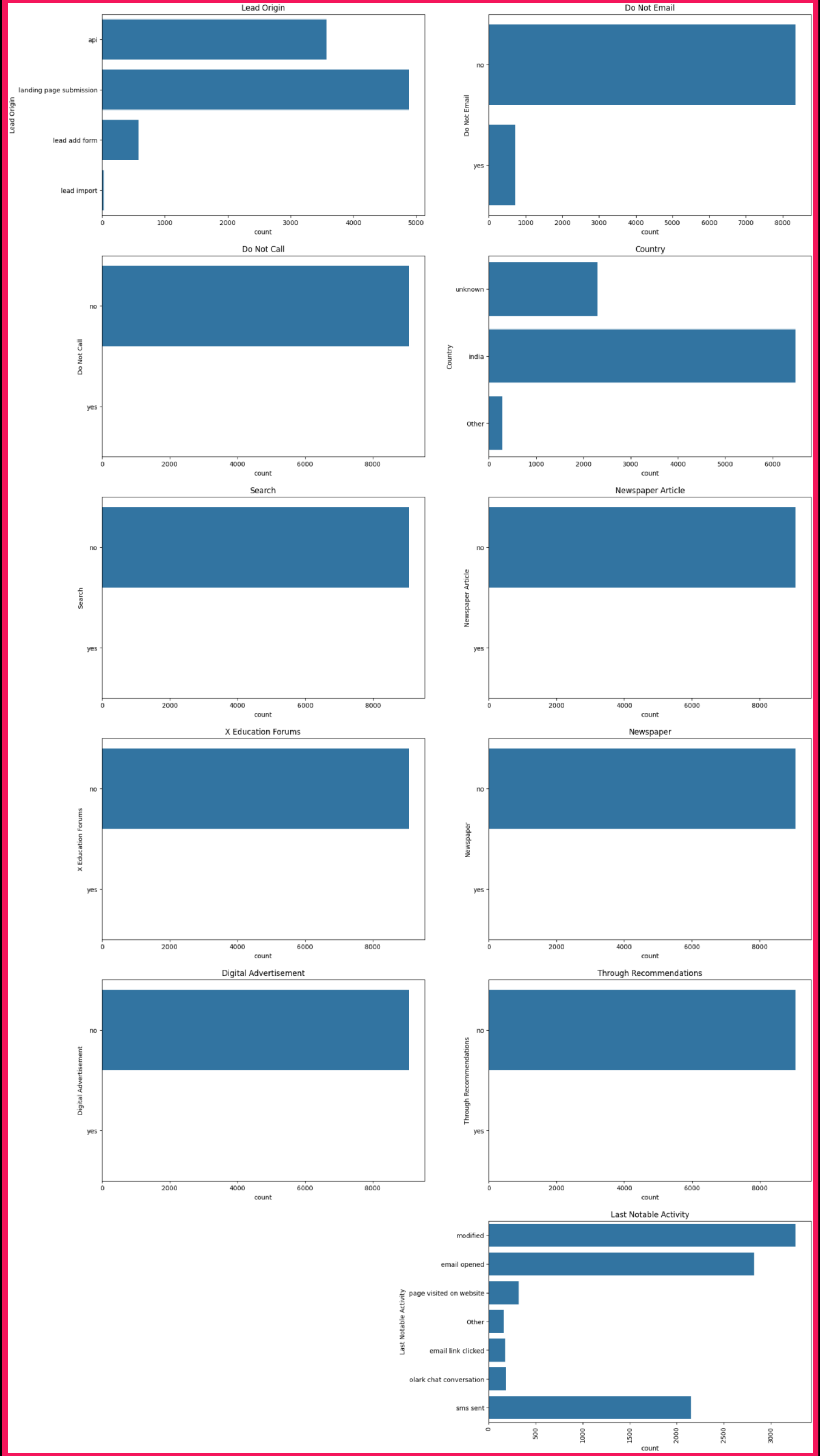
```
Country
india            6491
unknown          2301
Other              77
united states      69
```

EDA

Univariate analysis

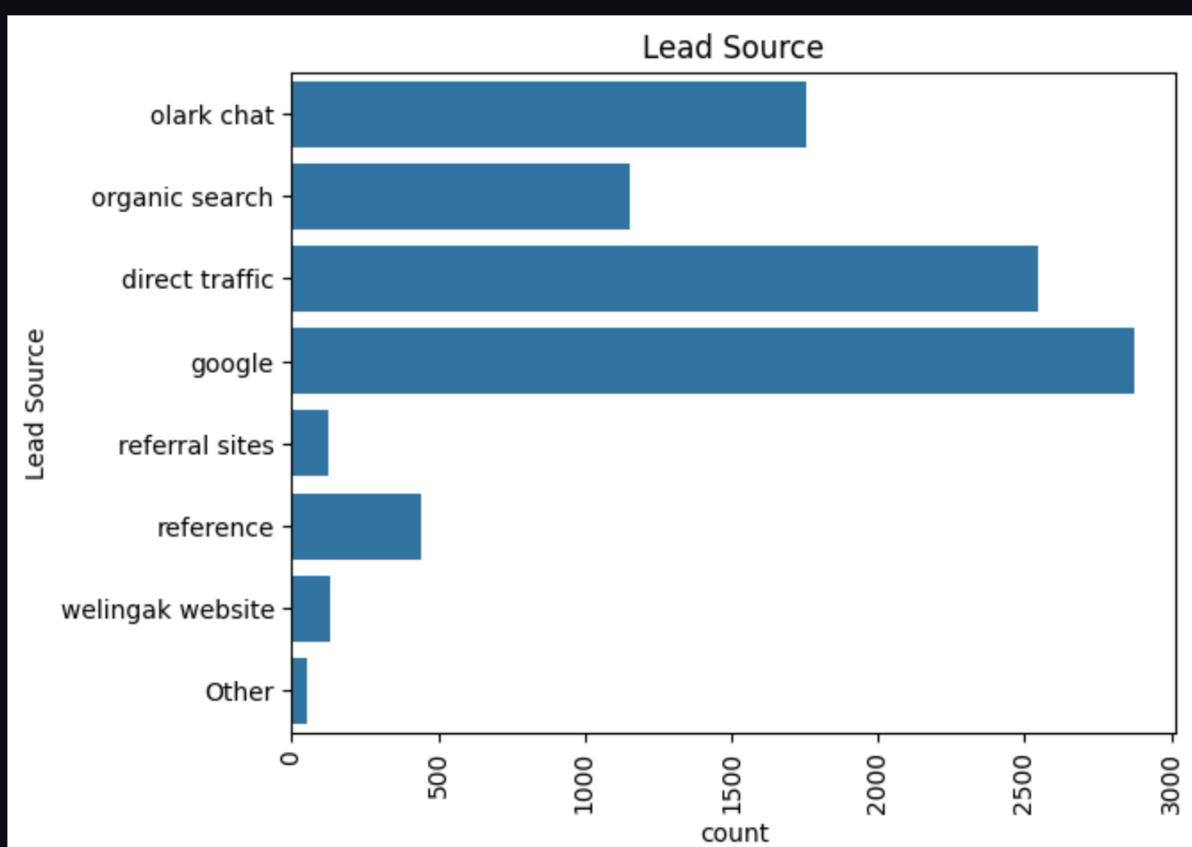
- Analysing counts of variables.
- Viewing histplots of variables.

```
plt.figure(figsize = (20,40))

plt.subplot(6,2,1)
sns.countplot(df_final['Lead Origin'])
plt.title('Lead Origin')

plt.subplot(6,2,2)
sns.countplot(df_final['Do Not Email'])
plt.title('Do Not Email')

plt.subplot(6,2,3)
sns.countplot(df_final['Do Not Call'])
plt.title('Do Not Call')

plt.subplot(6,2,4)
sns.countplot(df_final['Country'])
plt.title('Country')

plt.subplot(6,2,5)
sns.countplot(df_final['Search'])
plt.title('Search')
```



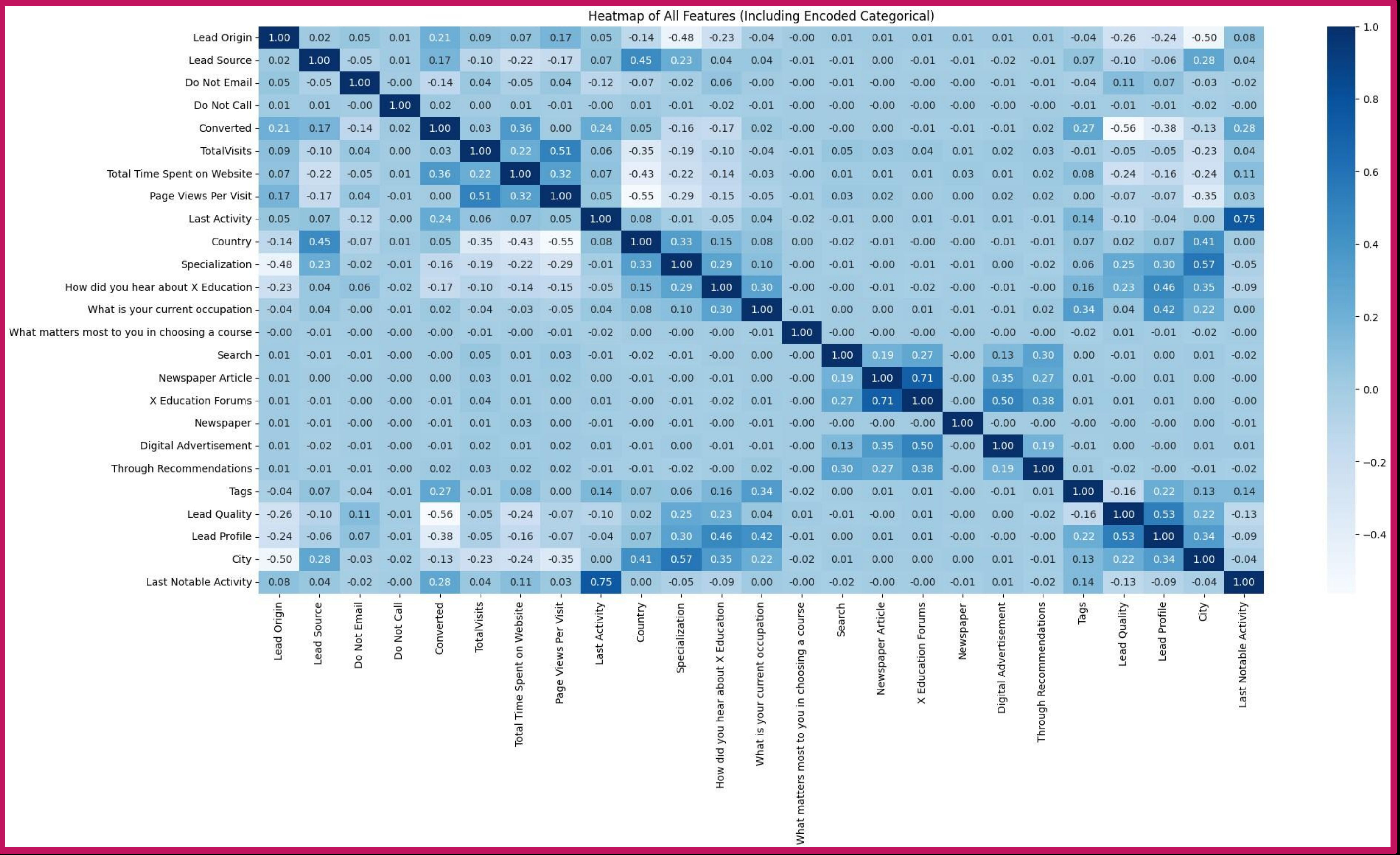
```python
import matplotlib.pyplot as plt
import seaborn as sns

categorical_columns = df_final.select_dtypes(include=['object', 'category']).columns.tolist()

plt.figure(figsize=(28, 30))

# Loop through categorical columns and plot
for idx, col in enumerate(categorical_columns, start=1):
    plt.subplot((len(categorical_columns) + 1) // 2, 2, idx)  # Adjust rows dynamically
    sns.countplot(x=col, hue='Converted', data=df_final)
    plt.yscale('log')
    plt.xticks(rotation=90)

plt.subplots_adjust(hspace=0.5)
plt.tight_layout()  # Prevent overlapping
plt.show()
```


```python
sns.countplot(df_final['Lead Source']).tick_params(axis='x', rotation = 90)
plt.title('Lead Source')
plt.show()
```

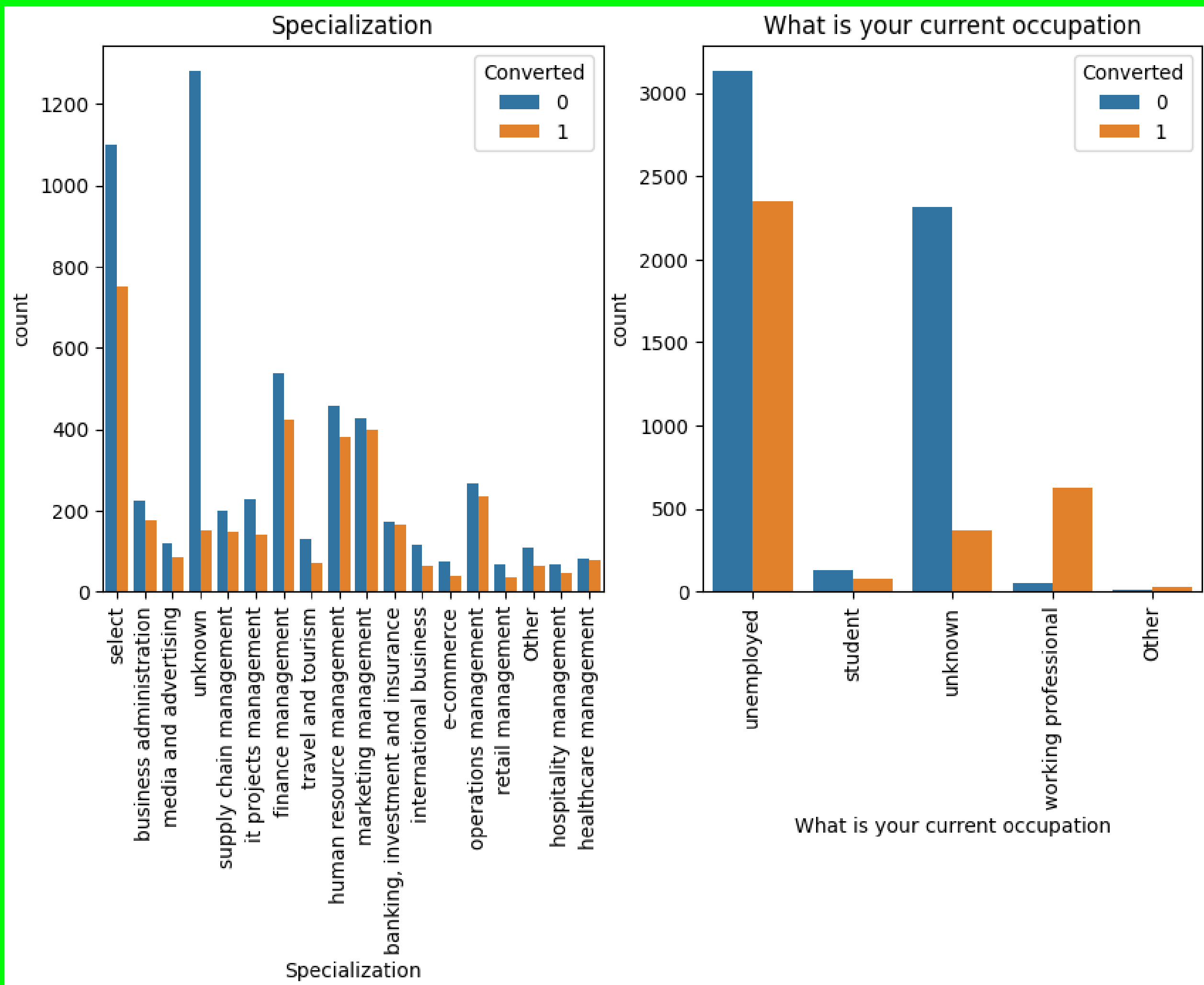


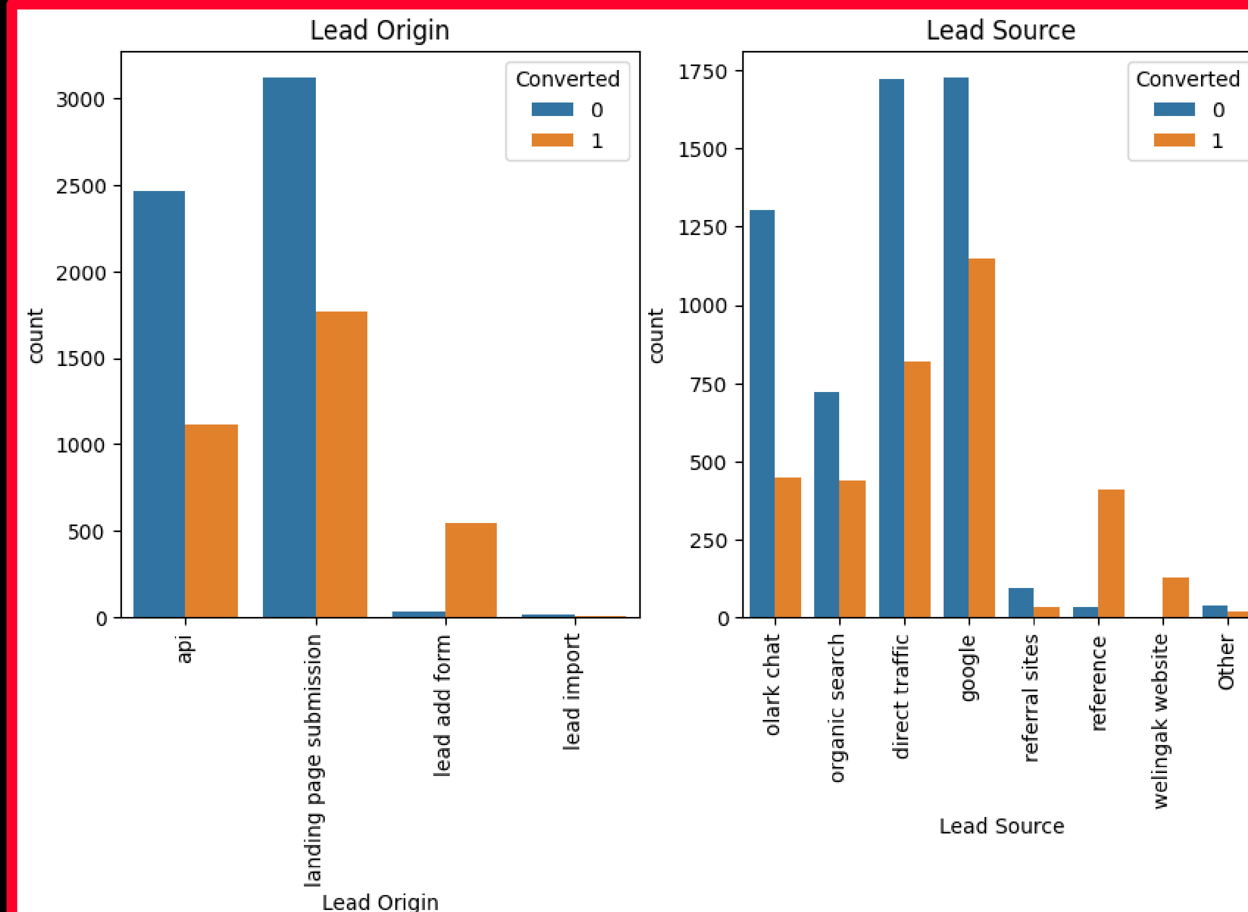
Multivariate analysis

- Checking the count of categorical columns.
- Using heatmap to study relationships between multiple variables.

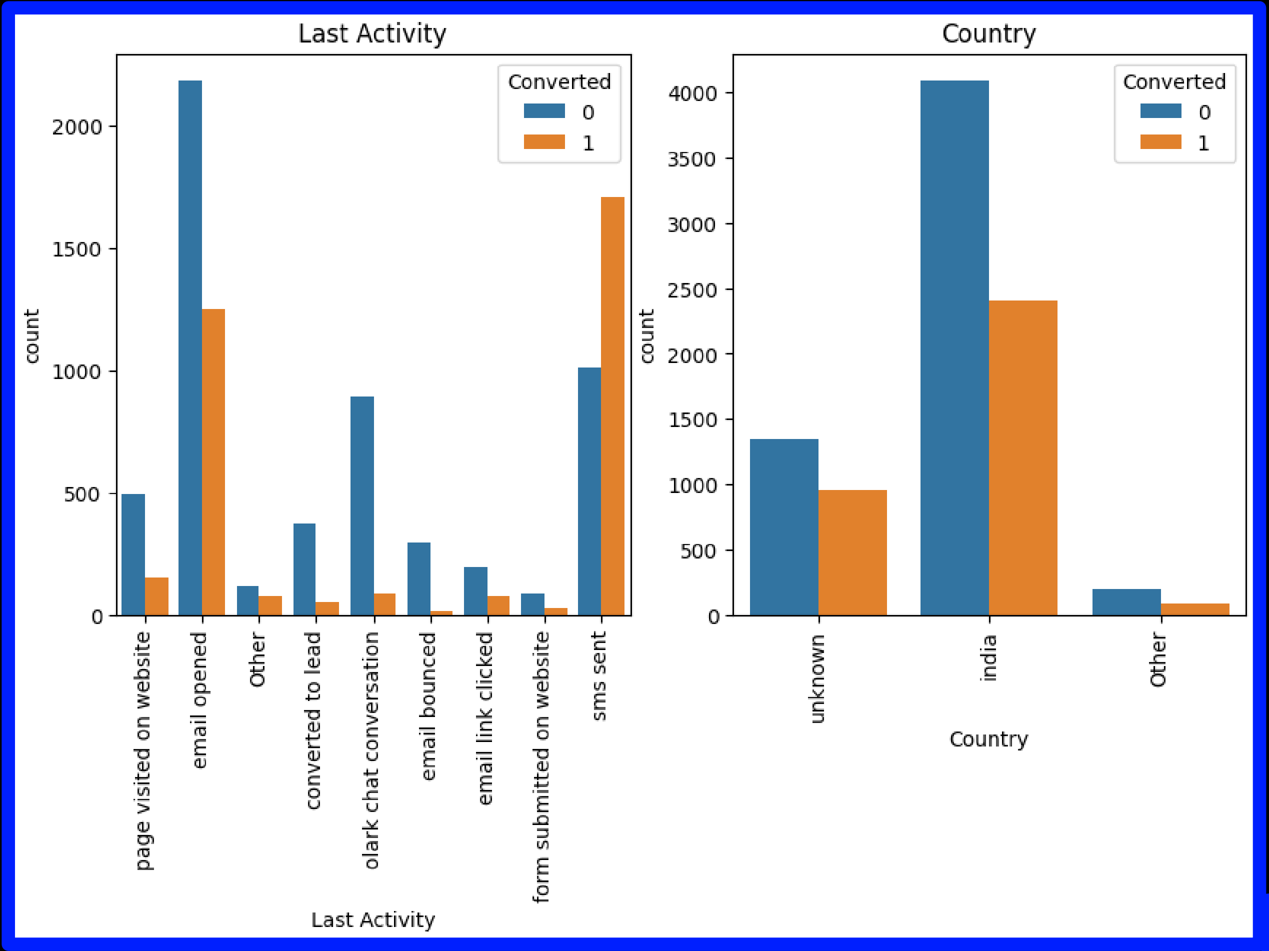


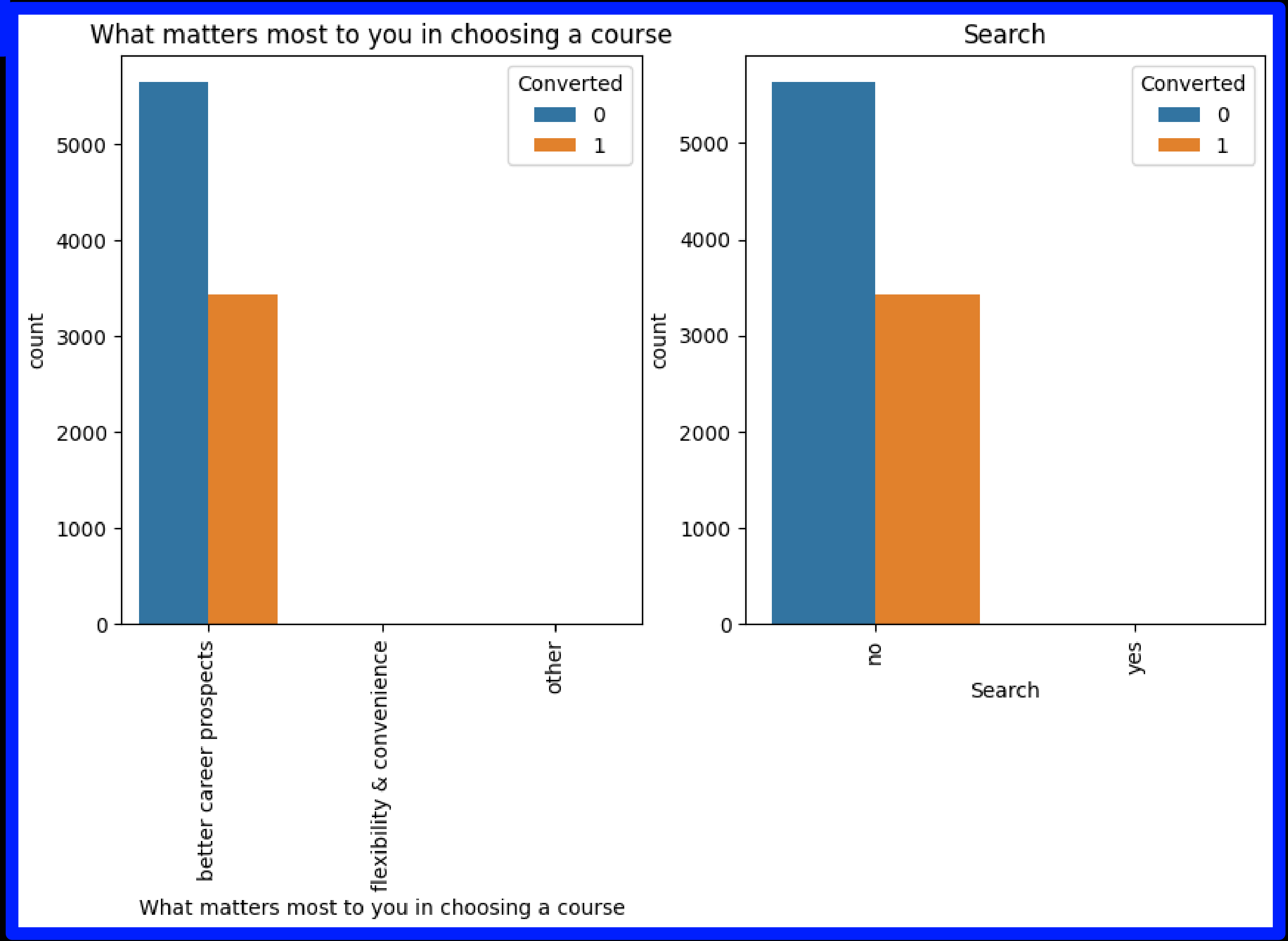
```
plt.figure(figsize = (10,5))

plt.subplot(1,2,1)
sns.countplot(x='Specialization', hue='Converted', data= df_final).tick_params(axis='x', rotation = 90)
plt.title('Specialization')

plt.subplot(1,2,2)
sns.countplot(x='What is your current occupation', hue='Converted', data= df_final).tick_params(axis='x', rotation = 90)
plt.title('What is your current occupation')
plt.show()
```






```
plt.figure(figsize = (10,5))

plt.subplot(1,2,1)
sns.countplot(x='Lead Origin', hue='Converted', data= df_final).tick_params(axis='x', rotation = 90)
plt.title('Lead Origin')

plt.subplot(1,2,2)
sns.countplot(x='Lead Source', hue='Converted', data= df_final).tick_params(axis='x', rotation = 90)
plt.title('Lead Source')
plt.show()
```


Last Activity
Country
Converted
0
1
count
page visited on website
email opened
Other
converted to lead
olark chat conversation
email bounced
email link clicked
form submitted on website
sms sent
unknown
india
Other


What matters most to you in choosing a course
Search
Converted
0
1
count
better career prospects
flexibility & convenience
other
no
yes

Creating Dummy vars, splitting into Train-Test data:

```python
df_final.loc[:, df_final.dtypes == 'object'].columns
```

Python

```
Index(['Lead Origin', 'Lead Source', 'Do Not Email', 'Do Not Call',
       'Last Activity', 'Country', 'Specialization',
       'What is your current occupation',
       'What matters most to you in choosing a course', 'Search',
       'Newspaper Article', 'X Education Forums', 'Newspaper',
       'Digital Advertisement', 'Through Recommendations',
       'A free copy of Mastering The Interview', 'Last Notable Activity'],
      dtype='object')
```

```python
# Create dummy variables using the 'get_dummies'
dummy = pd.get_dummies(df_final[['Lead Origin','Specialization' ,'Lead Source', 'Do Not Email', 'Last Activity', 'What is your current occupation','A
# Add the results to the master dataframe
df_final_dum = pd.concat([df_final, dummy], axis=1)
df_final_dum
```

Python

	Lead Origin	Lead Source	Do Not Email	Do Not Call	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Last Activity	Country	...	Last Notable Activity_form submitted on website	Last Notable Activity_had a phone conversation	Last Notable Activity_modified	Last Notable Activity_o... conversa
0	api	olark chat	no	no	0	0.0	0	0.00	page visited on website	not provided	...	False	False	True	F
1	api	organic search	no	no	0	5.0	674	2.50	email opened	india	...	False	False	False	F
2	landing page submission	direct traffic	no	no	1	2.0	1532	2.00	email opened	india	...	False	False	False	F

- The dataset is split into 70% training and 30% testing data while maintaining reproducibility using random_state as 10.

```python
# Split the dataset into 70% and 30% for train and test respectively
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, test_size=0.3, random_state=10)
```

Python

```python
# Import MinMax scaler
from sklearn.preprocessing import MinMaxScaler
# Scale the three numeric features
scaler = MinMaxScaler()
X_train[['TotalVisits', 'Page Views Per Visit', 'Total Time Spent on Website']] = scaler.fit_transform(X_train[['TotalVisits', 'Page Views Per Visit',
X_train.head()
```

Python

	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Lead Origin_landing page submission	Lead Origin_lead add form	Lead Origin_lead import	Specialization_business administration	Specialization_e-business	Specialization_e-commerce	Specialization_finance management
1289	0.014184	0.612676	0.083333	True	False	False	False	False	False	True
3604	0.000000	0.000000	0.000000	False	False	False	False	False	False	False
5584	0.042553	0.751761	0.250000	True	False	False	False	False	False	False
7679	0.000000	0.000000	0.000000	False	False	False	False	False	False	False
7563	0.014184	0.787852	0.083333	True	False	False	False	False	False	False

5 rows × 80 columns

Building the model

- Feature selection using RFE.
- Using statsmodels, view summary of logistic model.
- Examine p-values, accuracy.
- Calculate vif's to eliminate some features.

5. Model Building

```python
# Import 'LogisticRegression'
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
```

```python
# Import RFE
from sklearn.feature_selection import RFE
```

```python
from sklearn.linear_model import LogisticRegression

logreg = LogisticRegression()  # Ensure you define logreg first
rfe = RFE(estimator=logreg, n_features_to_select=15)  # Corrected syntax
rfe = rfe.fit(X_train, y_train)
```

```python
# Features that have been selected by RFE
list(zip(X_train.columns, rfe.support_, rfe.ranking_))
```

```
[('TotalVisits', True, 1),
 ('Total Time Spent on Website', True, 1),
 ('Lead Origin_lead add form', True, 1),
 ('Lead Source_direct traffic', True, 1),
 ('Lead Source_google', True, 1),
 ('Lead Source_organic search', True, 1),
 ('Lead Source_welingak website', True, 1),
 ('Do Not Email_yes', True, 1),
 ('Last Activity_olark chat conversation', True, 1),
```

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

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:	-3239.5
Date:	Wed, 12 Mar 2025	Deviance:	6478.9
Time:	15:49:53	Pearson chi2:	6.66e+03
No. Iterations:	21	Pseudo R-squ. (CS):	0.2697
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.0055	0.077	-13.139	0.000	-1.156	-0.856
TotalVisits	-19.8464	4.82e+04	-0.000	1.000	-9.45e+04	9.44e+04
Total Time Spent on Website	-22.6948	4.82e+04	-0.000	1.000	-9.45e+04	9.44e+04
Lead Origin_lead add form	2.5558	0.222	11.491	0.000	2.120	2.992
Lead Source_direct traffic	-0.2037	0.093	-2.201	0.028	-0.385	-0.022
Lead Source_google	0.1280	0.088	1.450	0.147	-0.045	0.301
Lead Source_organic search	0.0061	0.109	0.056	0.956	-0.207	0.219
Lead Source_welingak website	2.5529	1.033	2.472	0.013	0.529	4.577
Do Not Email_yes	-1.5104	0.154	-9.782	0.000	-1.813	-1.208
Last Activity_olark chat conversation	-1.4719	0.156	-9.461	0.000	-1.777	-1.167
Last Activity_sms sent	1.3379	0.065	20.623	0.000	1.211	1.465
What is your current occupation_housewife	23.2589	2.02e+04	0.001	0.999	-3.95e+04	3.96e+04
What is your current occupation_other	2.0102	0.725	2.773	0.006	0.589	3.431
What is your current occupation_working professional	2.8842	0.184	15.662	0.000	2.523	3.245
Last Notable Activity_had a phone conversation	23.2666	1.63e+04	0.001	0.999	-3.19e+04	3.19e+04
Last Notable Activity_unreachable	1.6314	0.547	2.981	0.003	0.559	2.704

```python
# Make a VIF dataframe for all the variables present
vif = pd.DataFrame()
vif['Features'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X_train.values, i) for i in range(X_train.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

	Features	VIF
2	Lead Origin_lead add form	1.47
9	Last Activity_sms sent	1.46
6	Lead Source_welingak website	1.31
3	Lead Source_direct traffic	1.21
4	Lead Source_google	1.19
12	What is your current occupation_working profes...	1.16
5	Lead Source_organic search	1.10
7	Do Not Email_yes	1.10
8	Last Activity_olark chat conversation	1.02
13	Last Notable Activity_unreachable	1.01
0	TotalVisits	1.00
1	Total Time Spent on Website	1.00
10	What is your current occupation_housewife	1.00
11	What is your current occupation_other	1.00

```python
X_train.drop('What is your current occupation_housewife', axis = 1, inplace = True)
```

```python
# Refit the model with the new set of features
X_train_sm = sm.add_constant(X_train)
logm3 = sm.GLM(y_train, X_train_sm, family = sm.families.Binomial())
res = logm3.fit()
res.summary()
```

Making predictions on the dataset:

```python
# Predicting the probabilities on the train set
y_train_pred = res.predict(X_train_sm)
y_train_pred[:10]
```

```
1289    0.298083
3604    0.269836
5584    0.076423
7679    0.269836
7563    0.076423
7978    0.586384
7780    0.274650
7863    0.983881
838     0.870389
708     0.298083
dtype: float64
```

```python
# Reshaping to an array
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]
```

```
array([0.2980832 , 0.26983639, 0.07642343, 0.26983639, 0.07642343,
       0.58638417, 0.2746502 , 0.9838813 , 0.87038897, 0.2980832 ])
```

```python
# Data frame with given convertion rate and probablity of predicted ones
y_train_pred_final = pd.DataFrame({'Converted':y_train.values, 'Conversion_Prob':y_train_pred})
y_train_pred_final.head()
```

	Converted	Conversion_Prob
0	1	0.298083
1	0	0.269836
2	0	0.076423
3	0	0.269836
4	0	0.076423

Evaluating the model and Optimising the cutoff

7. Model Evaluation

```python
# Importing metrics from sklearn for evaluation
from sklearn import metrics
```
[90] Python

```python
# Creating confusion matrix
confusion = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final.Predicted )
confusion
```
[91] Python

```
array([[3680,  215],
       [ 213, 2243]])
```

```python
# Predicted     not_churn    churn
# Actual
# not_churn        3403       492
# churn             729      1727
```
[92] Python

```python
# Check the overall accuracy
metrics.accuracy_score(y_train_pred_final.Converted, y_train_pred_final.Predicted)
```
[93] Python

```
0.9326090379467801
```

That's around 93% accuracy with is a very good value

```python
# Substituting the value of true positive
TP = confusion[1,1]
# Substituting the value of true negatives
TN = confusion[0,0]
# Substituting the value of false positives
FP = confusion[0,1]
# Substituting the value of false negatives
FN = confusion[1,0]
```

```python
# Calculating the sensitivity
TP/(TP+FN)
```

```
0.9132736156351792
```

```python
# Calculating the specificity
TN/(TN+FP)
```

```
0.944801026957638
```

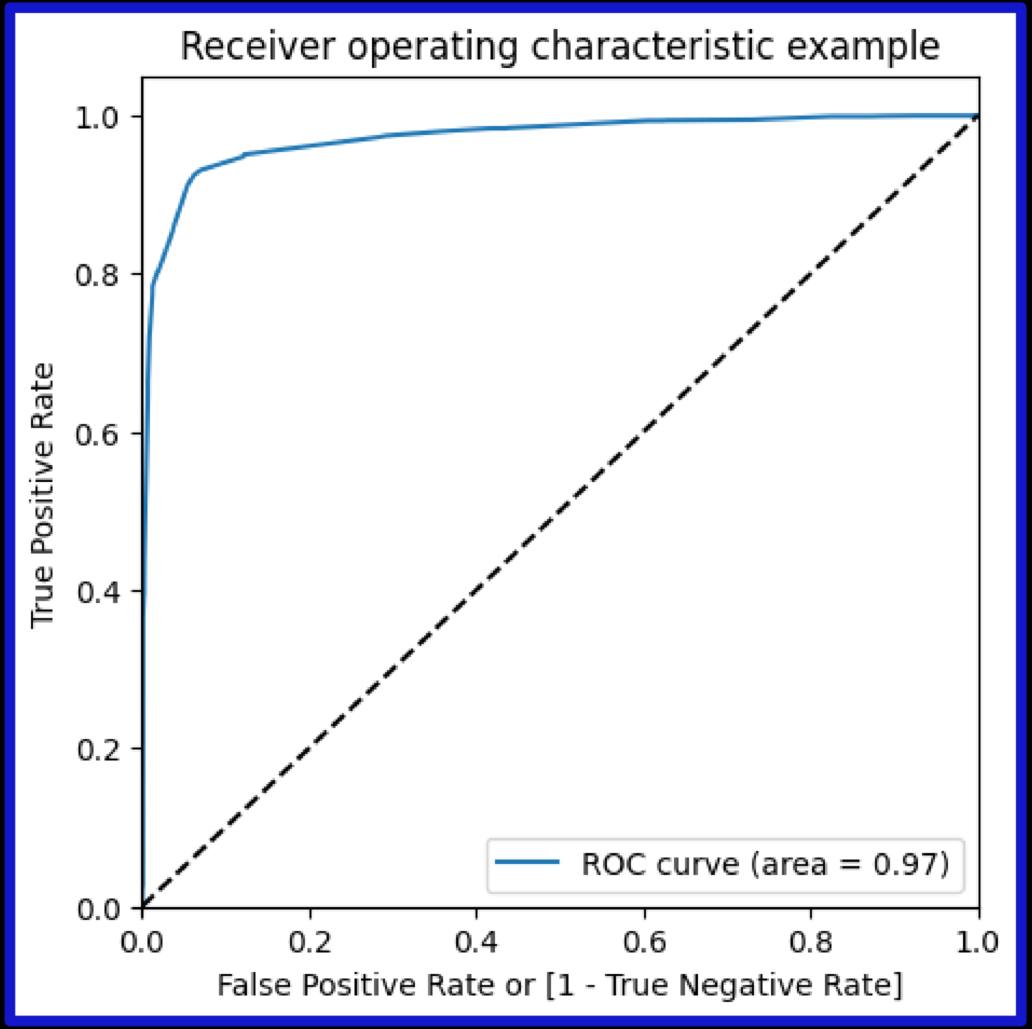
ROC curve

The previous cut off was randomely selected. Now to find the optimum one

```
# ROC function
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
                                              drop_intermediate = False )
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(5, 5))
    plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % auc_score )
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()

    return None
```

```
fpr, tpr, thresholds = metrics.roc_curve( y_train_pred_final.Converted, y_train_pred_final.Conversion_Prob, drop_intermediate = False )
```

```
# Call the ROC function
draw_roc(y_train_pred_final.Converted, y_train_pred_final.Conversion_Prob)
```



- **The area under ROC curve is 0.97 which is a very good value**

```python
# Check the overall accuracy
metrics.accuracy_score(y_train_pred_final.Converted, y_train_pred_final.final_predicted)
```

```
0.9324515824279641
```

```python
# Creating confusion matrix
confusion2 = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final.final_predicted )
confusion2
```

```
array([[3660,  235],
       [ 194, 2262]])
```

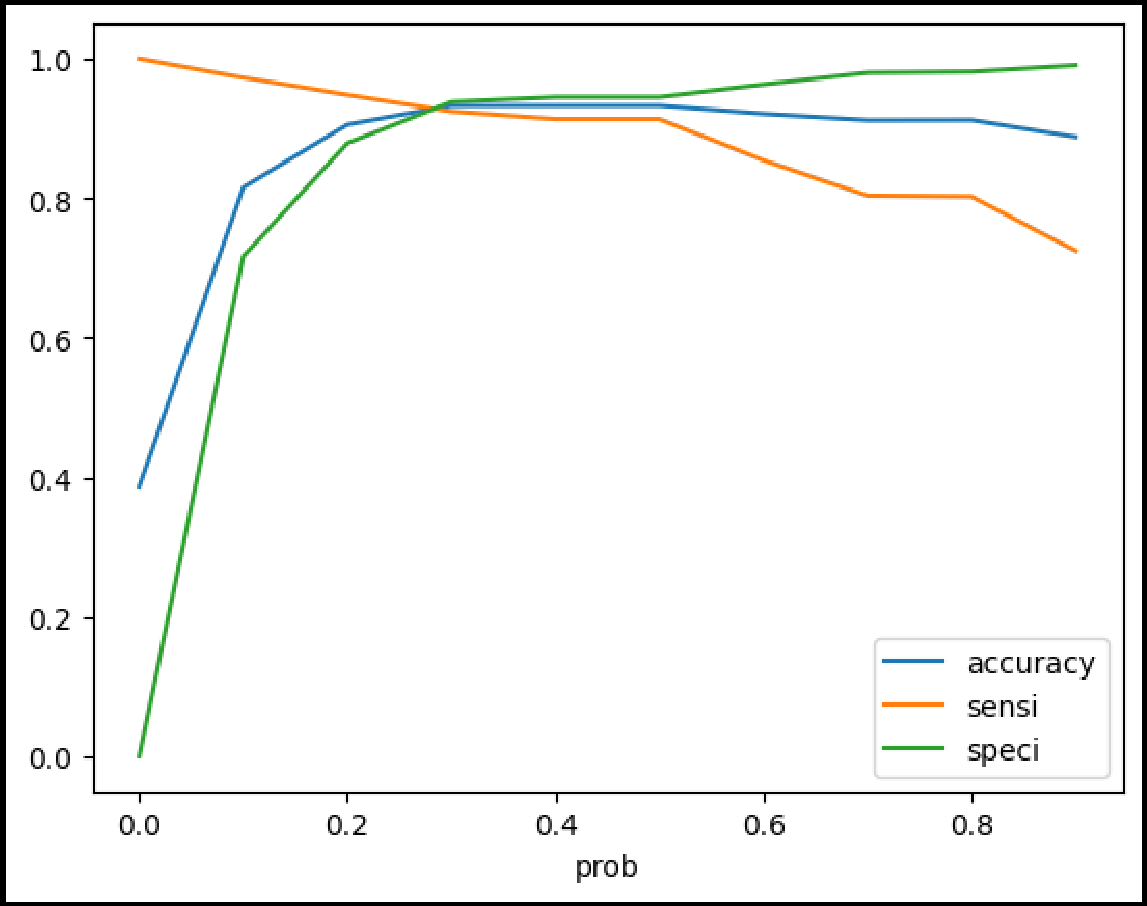
```python
# Substituting the value of true positive
TP = confusion2[1,1]
# Substituting the value of true negatives
TN = confusion2[0,0]
# Substituting the value of false positives
FP = confusion2[0,1]
# Substituting the value of false negatives
FN = confusion2[1,0]
```

```python
# Calculating the sensitivity
TP/(TP+FN)
```

```
0.9210097719869706
```

```python
# Calculating the specificity
TN/(TN+FP)
```

```
0.9396662387676509
```




```python
# Creating a dataframe to see the values of accuracy, sensitivity, and specificity at different values of probability cutoffs
cutoff_df = pd.DataFrame( columns = ['prob','accuracy','sensi','speci'])
# Making confusing matrix to find values of sensitivity, accurace and specificity for each level of probablity
from sklearn.metrics import confusion_matrix
num = [0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9]
for i in num:
    cm1 = metrics.confusion_matrix(y_train_pred_final.Converted, y_train_pred_final[i] )
    total1=sum(sum(cm1))
    accuracy = (cm1[0,0]+cm1[1,1])/total1

    speci = cm1[0,0]/(cm1[0,0]+cm1[0,1])
    sensi = cm1[1,1]/(cm1[1,0]+cm1[1,1])
    cutoff_df.loc[i] =[ i ,accuracy,sensi,speci]
cutoff_df
```

	prob	accuracy	sensi	speci
0.0	0.0	0.386711	1.000000	0.000000
0.1	0.1	0.518973	0.971498	0.233633
0.2	0.2	0.525114	0.970277	0.244416
0.3	0.3	0.750276	0.626221	0.828498
0.4	0.4	0.750276	0.626221	0.828498
0.5	0.5	0.750276	0.626221	0.828498
0.6	0.6	0.731696	0.416938	0.930167
0.7	0.7	0.714218	0.282980	0.986136
0.8	0.8	0.713274	0.279723	0.986650
0.9	0.9	0.679421	0.178339	0.995379

```python
# Plotting it
cutoff_df.plot.line(x='prob', y=['accuracy','sensi','speci'])
plt.show()
```

- **From the above graph it is visible that the optimal cut off is at 0.35**

Results and metrics on test set

- **Train Data:**
  Accuracy of around 92%, sensitivity of around 92% and specificity of around 93%, with current cut off 0.35.

- **Test Data:**
  Accuracy of around 92%, sensitivity of around 92% and specificity of around 93%, with current cut off 0.35.

- **Overall Accuracy: 93%**
  Current cut off :0.41
  Precision : 89%
  Recall : 91%

```python
# Check the overall accuracy
metrics.accuracy_score(y_pred_final['Converted'], y_pred_final.final_predicted)
```
[138] Python

```
0.9302240176276166
```

```python
# Creating confusion matrix
confusion2 = metrics.confusion_matrix(y_pred_final['Converted'], y_pred_final.final_predicted )
confusion2
```
[139] Python

```
array([[1635,  109],
       [  81,  898]])
```

```python
# Substituting the value of true positive
TP = confusion2[1,1]
# Substituting the value of true negatives
TN = confusion2[0,0]
# Substituting the value of false positives
FP = confusion2[0,1]
# Substituting the value of false negatives
FN = confusion2[1,0]
```
[140] Python

```python
# Precision = TP / TP + FP
TP / (TP + FP)
```
[141] Python

```
0.8917576961271102
```

```python
#Recall = TP / TP + FN
TP / (TP + FN)
```
[142] Python

```
0.9172625127681308
```

Conclusion

The key factors influencing potential buyers, ranked from most to least important, are:

1. The total duration spent on the website.
2. The overall number of visits.
3. The lead source, particularly when it comes from:
   - Google
   - Direct traffic
   - Organic search
   - Welingak website
4. The last recorded activity, specifically:
   - SMS interactions
   - Olark chat conversations
5. The lead origin being from a Lead Ad format.
6. The individual's current occupation being a working professional.

Considering these factors, X Education has a strong opportunity to convert nearly all potential buyers into actual customers, significantly boosting their course enrollments.