LEAD SCORE CASE STUDY

Powering X Education's Sales Transformation

Submitted by:

- Sachin Kanchan
- Smita Gaikwad
- Megha Jain

Business Challenge - Lead Conversion

X Education - Online Professional Training Platform

- Current Situation:
  - Generates leads through websites, search engines, and referrals
  - Existing lead conversion rate: Only 30%
  - Significant resource wastage on low-potential leads
  - Inefficient sales process

- Key Pain Points:
  - Time and effort spent on unproductive leads
  - Missed opportunities with high-potential prospects
  - Lack of systematic lead prioritization

Our Strategic Solution - Lead Scoring Model

- **Objective: Develop a Predictive Lead Score**
- Model Highlights:
  - Scoring Range: 0-100
  - Purpose: Identify "Hot Leads" with high conversion potential
  - Goal: Improve conversion rate from 30% to 80%
- Key Deliverables:
  1. Logistic Regression Predictive Model
  2. Data-Driven Insights - Questionnaire
  3. Performance Visualization - PPT
  4. Actionable Recommendations - Summary
- Expected Outcomes:
  - Optimize sales team's efforts
  - Increase conversion efficiency
  - Reduce wasted resources
  - Systematic lead qualification process

Methodology

- Importing Libraries & Setting up Analytics Environment
- Dataset Inspection
- Data Pre-Processing
- Exploratory Data Analysis
- Model Building – Logistic Regression
- Model Evaluation
- Predictions on Test Set
- Lead Score Generation
- Findings & Recommendations

Dataset Inspection

- We start with 37 columns and over 9240 rows.
- Most of these columns are string, with only a handful of numerical features

	Lead Number	Converted	TotalVisits	Total Time Spent on Website	Page Views Per Visit	Asymmetrique Activity Score	Asymmetrique Profile Score
count	9240.000	9240.000	9103.000	9240.000	9103.000	5022.000	5022.000
mean	617188.436	0.385	3.445	487.698	2.363	14.306	16.345
std	23405.996	0.487	4.855	548.021	2.161	1.387	1.811
min	579533.000	0.000	0.000	0.000	0.000	7.000	11.000
25%	596484.500	0.000	1.000	12.000	1.000	14.000	15.000
50%	615479.000	0.000	3.000	248.000	2.000	14.000	16.000
75%	637387.250	1.000	5.000	936.000	3.000	15.000	18.000
max	660737.000	1.000	251.000	2272.000	55.000	18.000	20.000

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9240 entries, 0 to 9239
Data columns (total 37 columns):
 #   Column                                          Non-Null Count  Dtype
---  ------                                          --------------  -----
 0   Prospect ID                                     9240 non-null   object
 1   Lead Number                                     9240 non-null   int64
 2   Lead Origin                                     9240 non-null   object
 3   Lead Source                                     9204 non-null   object
 4   Do Not Email                                    9240 non-null   object
 5   Do Not Call                                     9240 non-null   object
 6   Converted                                       9240 non-null   int64
 7   TotalVisits                                     9103 non-null   float64
 8   Total Time Spent on Website                     9240 non-null   int64
 9   Page Views Per Visit                            9103 non-null   float64
 10  Last Activity                                   9137 non-null   object
 11  Country                                         6779 non-null   object
 12  Specialization                                  7802 non-null   object
 13  How did you hear about X Education              7033 non-null   object
 14  What is your current occupation                 6550 non-null   object
 15  What matters most to you in choosing a course   6531 non-null   object
 16  Search                                          9240 non-null   object
 17  Magazine                                        9240 non-null   object
 18  Newspaper Article                               9240 non-null   object
 19  X Education Forums                              9240 non-null   object
 20  Newspaper                                       9240 non-null   object
 21  Digital Advertisement                           9240 non-null   object
 22  Through Recommendations                         9240 non-null   object
 23  Receive More Updates About Our Courses          9240 non-null   object
 24  Tags                                            5887 non-null   object
 25  Lead Quality                                    4473 non-null   object
 26  Update me on Supply Chain Content               9240 non-null   object
 27  Get updates on DM Content                       9240 non-null   object
 28  Lead Profile                                    6531 non-null   object
 29  City                                            7820 non-null   object
 30  Asymmetrique Activity Index                     5022 non-null   object
 31  Asymmetrique Profile Index                      5022 non-null   object
 32  Asymmetrique Activity Score                     5022 non-null   float64
 33  Asymmetrique Profile Score                      5022 non-null   float64
 34  I agree to pay the amount through cheque        9240 non-null   object
 35  A free copy of Mastering The Interview          9240 non-null   object
 36  Last Notable Activity                           9240 non-null   object
dtypes: float64(4), int64(3), object(30)
memory usage: 2.6+ MB
```

Data PreProcessing

- `Select` seems to be erroneously captured in the data collection process despite not being a valid data point.
- We replaced this with 'Unknown’

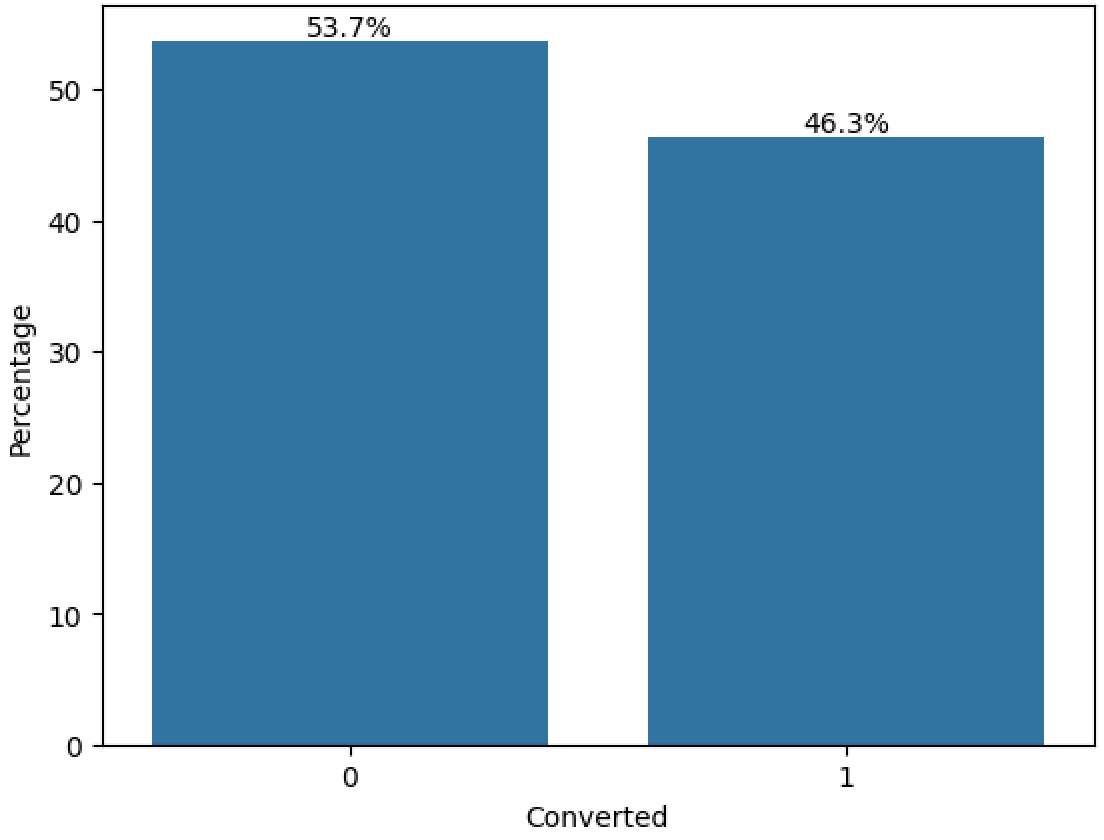
NULLS

- We dropped features with Null % over 30%
- Retained ‘TAGS’ column despite high null% owing to its importance
- Dropped rows where ‘TAGS’ was Null.
- In low null columns
    - for Numerical Features – Imputed nulls with median
    - For Categorical Features – imputed nulls with mode

- Capped Outliers in Numerical features
- Reduced sub-categories in ‘Lead Source’

Exploratory Data Analysis

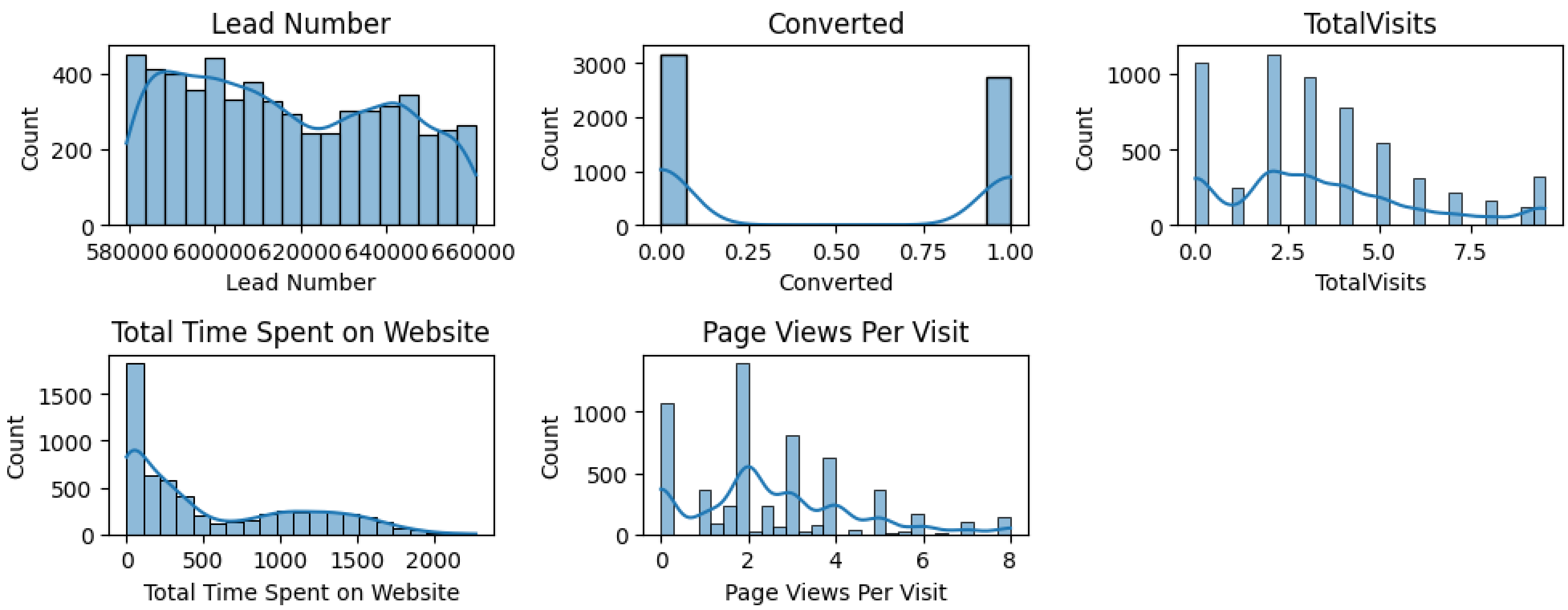
Target Imbalance



There is a slight imbalance in the Target variable in the given dataset.

Exploratory Data Analysis

Univariate Analysis - Numerical

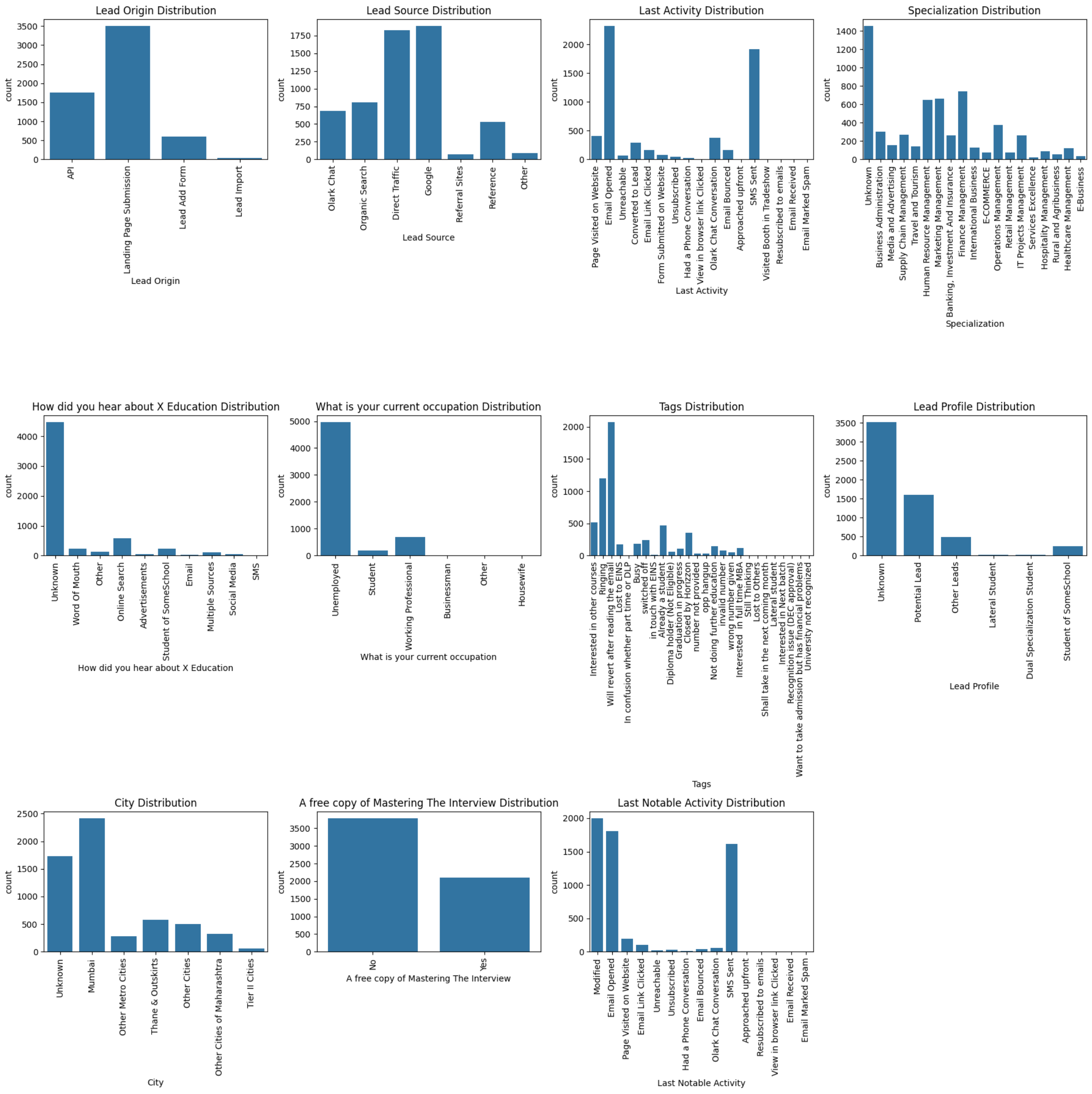


- We can see a slight skewness in the dataset
- It’s a right tailed distribution for most of the numerical features.

Exploratory Data Analysis

Univariate Analysis - Categorical

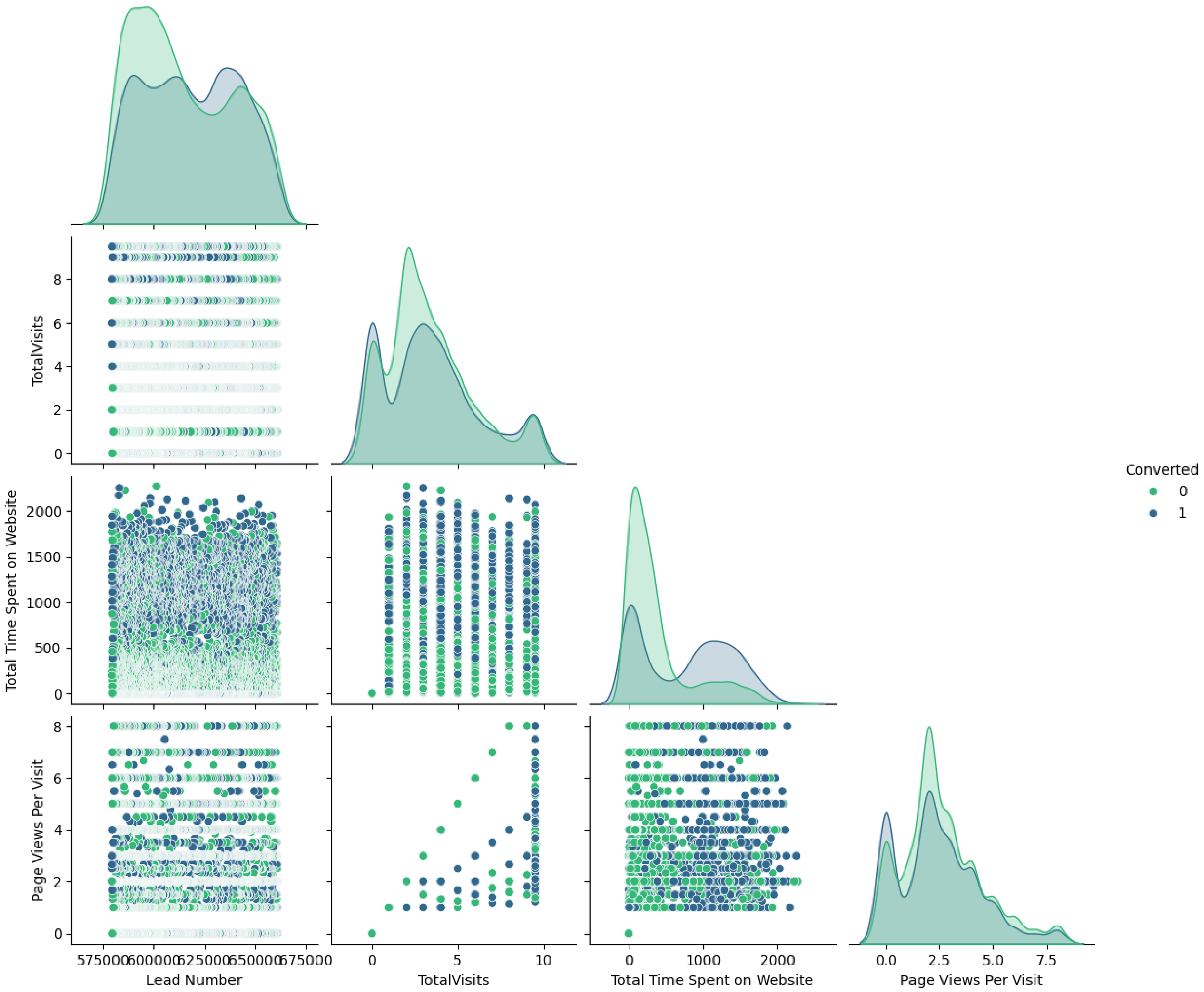
- We can see a huge imbalance in most of the categorical features
- Some of these seem moderately balanced



Exploratory Data Analysis

Bivariate Analysis - Numerical

- The only pair showing somewhat linear relationship is between - `TotalVisits` & `Page Views Per Visit`



Exploratory Data Analysis

Multivariate Analysis - Numerical

- A high correlation can be seen between `Page Views Per Visit` & `Total Time Spent on Website`
- A good Correlation can also be seen between `Total Time Spent on Website` & `Converted`
- This could imply that those who are highly interested to buy an education program visit the website often, or spend more time exploring the programs during their visits.

Model Building – Logistic Regression

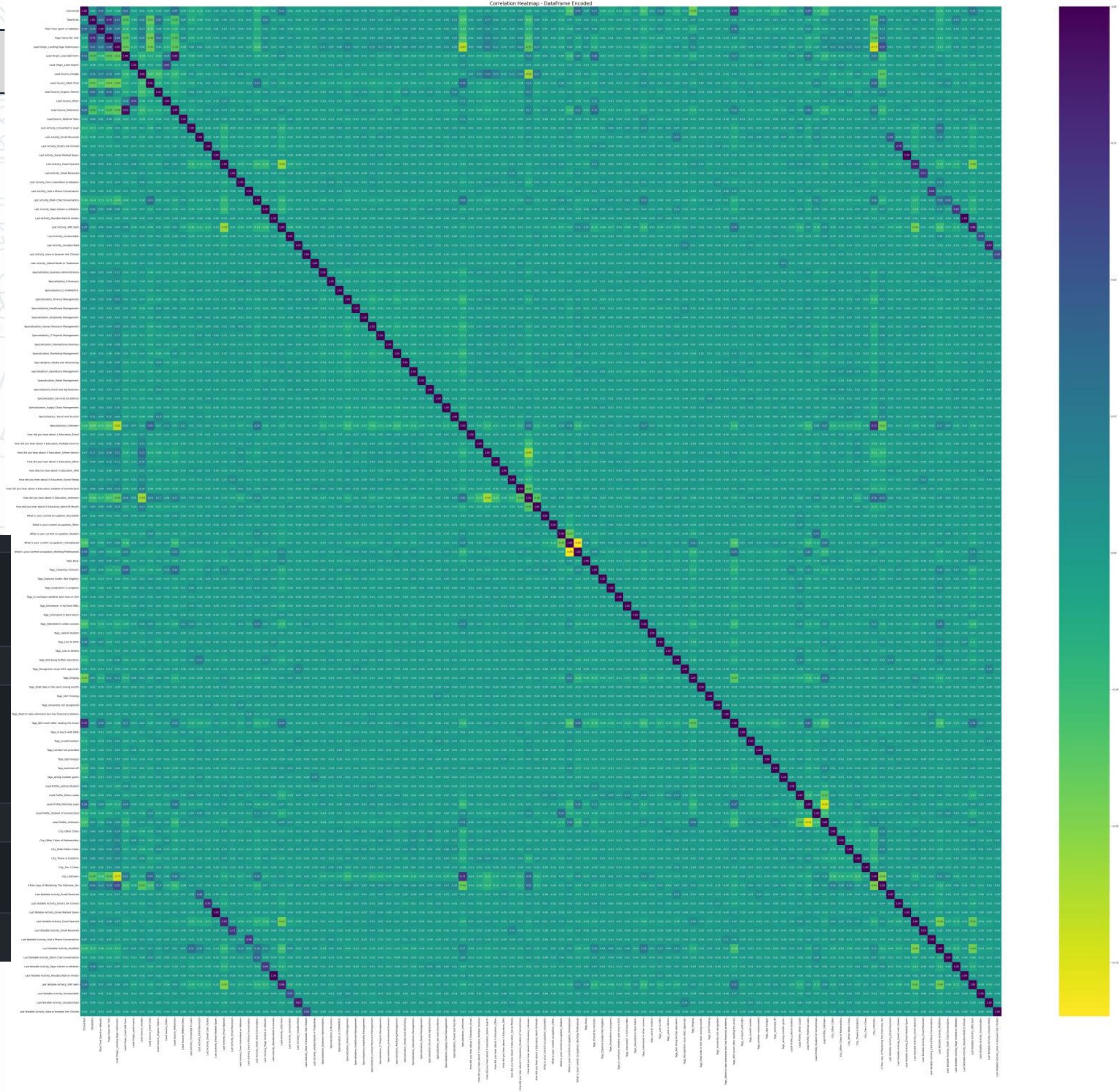
- We start with one-hot encoding the categorical columns
- We get 112 columns as a result
- Here we have a corr heatmap of all dummy features

```python
# Converting categorical variables into dummy variables (one-hot encoding)
df = pd.get_dummies(df, columns=categorical_cols, drop_first=True, dtype=int)
```
✓ 0.0s

```python
# Setting `Lead Number` as the DataFrame index
df = df.set_index('Lead Number',drop=True)
numerical_cols.remove('Lead Number')
```
✓ 0.0s

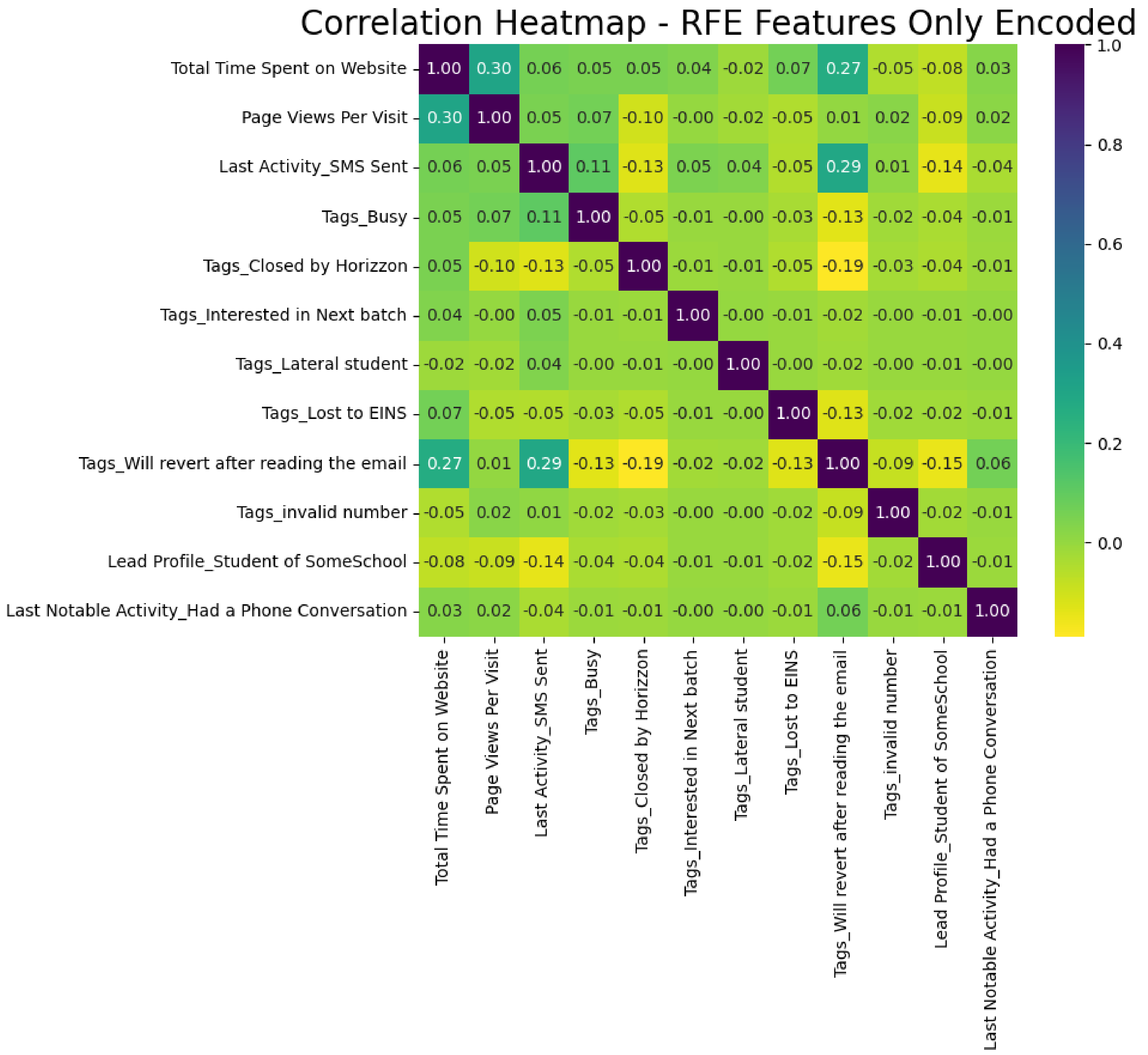
```python
df.shape
```
✓ 0.0s

```
(5887, 112)
```



Train-Test Split, Scaling & RFE

- We split the data into train & test sets
- Scale the Numerical features using MinMaxScaler
- Using RFE to quickly filter down 12 features for analysis
- We don't see extremely high correlation between features here, but we'll manually check using statsmodels



Final Model

- At the end of the 5th model, we have no longer any feature with high p-values or VIFs
- We stop dropping any more features and are left with 8 features

	feature	VIF
0	const	4.420
7	Tags_Will revert after reading the email	1.353
1	Total Time Spent on Website	1.261
2	Page Views Per Visit	1.158
3	Last Activity_SMS Sent	1.140
5	Tags_Closed by Horizzon	1.106
4	Tags_Busy	1.066
8	Lead Profile_Student of SomeSchool	1.056
6	Tags_Lost to EINS	1.055

Generalized Linear Model Regression Results

Dep. Variable:	Converted	No. Observations:	4709
Model:	GLM	Df Residuals:	4700
Model Family:	Binomial	Df Model:	8
Link Function:	Logit	Scale:	1.0000
Method:	IRLS	Log-Likelihood:	-580.59
Date:	Tue, 17 Dec 2024	Deviance:	1161.2
Time:	22:03:35	Pearson chi2:	4.05e+03
No. Iterations:	8	Pseudo R-squ. (CS):	0.6788
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-4.4580	0.215	-20.777	0.000	-4.879	-4.037
Total Time Spent on Website	3.4602	0.347	9.966	0.000	2.780	4.141
Page Views Per Visit	-1.1929	0.375	-3.177	0.001	-1.929	-0.457
Last Activity_SMS Sent	1.4433	0.179	8.076	0.000	1.093	1.794
Tags_Busy	3.3894	0.229	14.799	0.000	2.940	3.838
Tags_Closed by Horizzon	9.5875	1.017	9.423	0.000	7.593	11.582
Tags_Lost to EINS	7.7425	0.634	12.214	0.000	6.500	8.985
Tags_Will revert after reading the email	6.9136	0.207	33.392	0.000	6.508	7.319
Lead Profile_Student of SomeSchool	-2.3014	0.907	-2.537	0.011	-4.080	-0.523

Model Evaluation – Metrics – Train Set

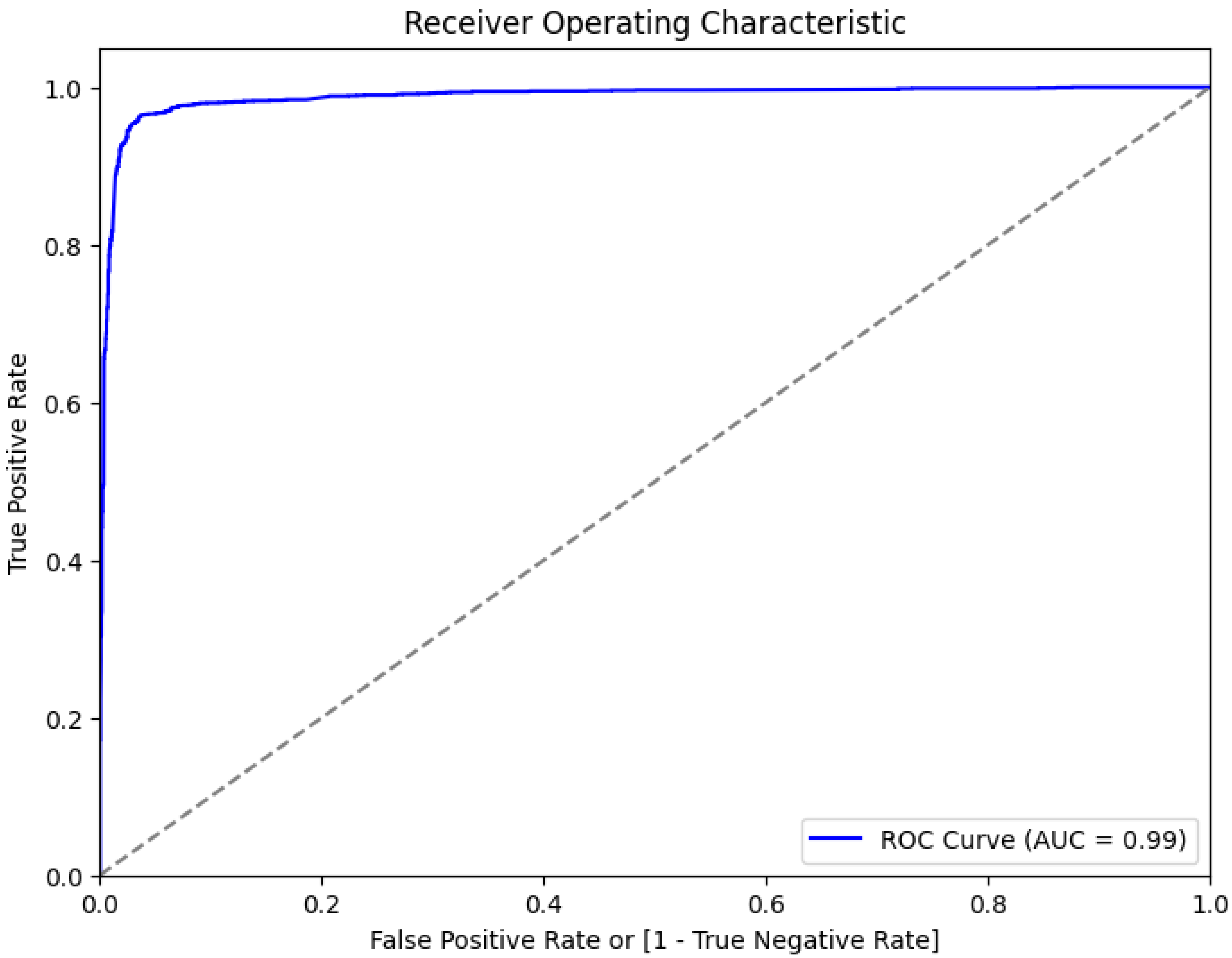
```
Training Performance:
              precision    recall  f1-score   support

           0       0.96      0.97      0.96      2502
           1       0.96      0.96      0.96      2207

    accuracy                           0.96      4709
   macro avg       0.96      0.96      0.96      4709
weighted avg       0.96      0.96      0.96      4709

Confusion Matrix (Training):
[[2416   86]
 [  90 2117]]
```

Accuracy	0.9626
Sensitivity (Recall)	0.9592
Specificity	0.9656

- We take a look at the Classification Report & Confusion Matrix of the Train Set
- Cross-Validation Scores: [0.96178344 0.96496815 0.95329087 0.96815287 0.95855473]
- Mean CV Accuracy: 96.14% (+/- 1.03%)

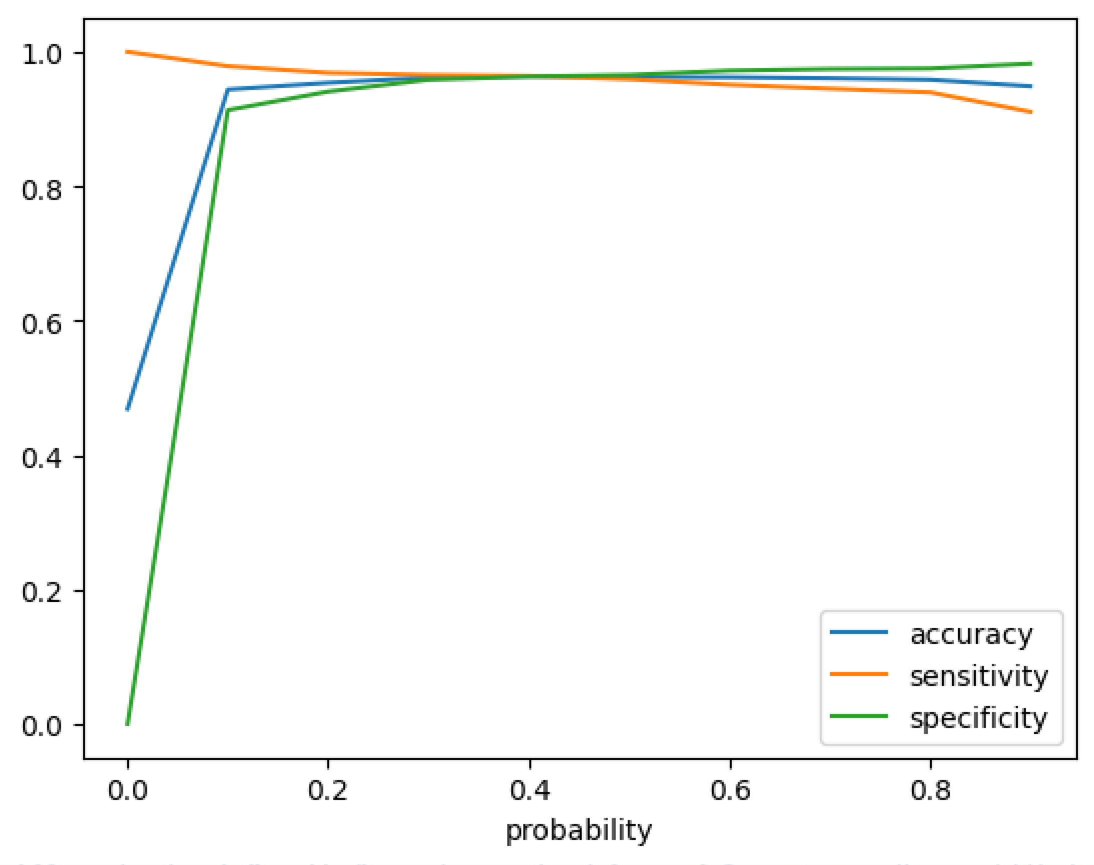
Model Evaluation – ROC AUC – Train Set

- The ROC curve with an AUC of 0.99 indicates that the logistic regression model is performing exceptionally well.
- This means the model is highly accurate in distinguishing between positive and negative classes. It has a strong ability to correctly classify instances into their respective categories.



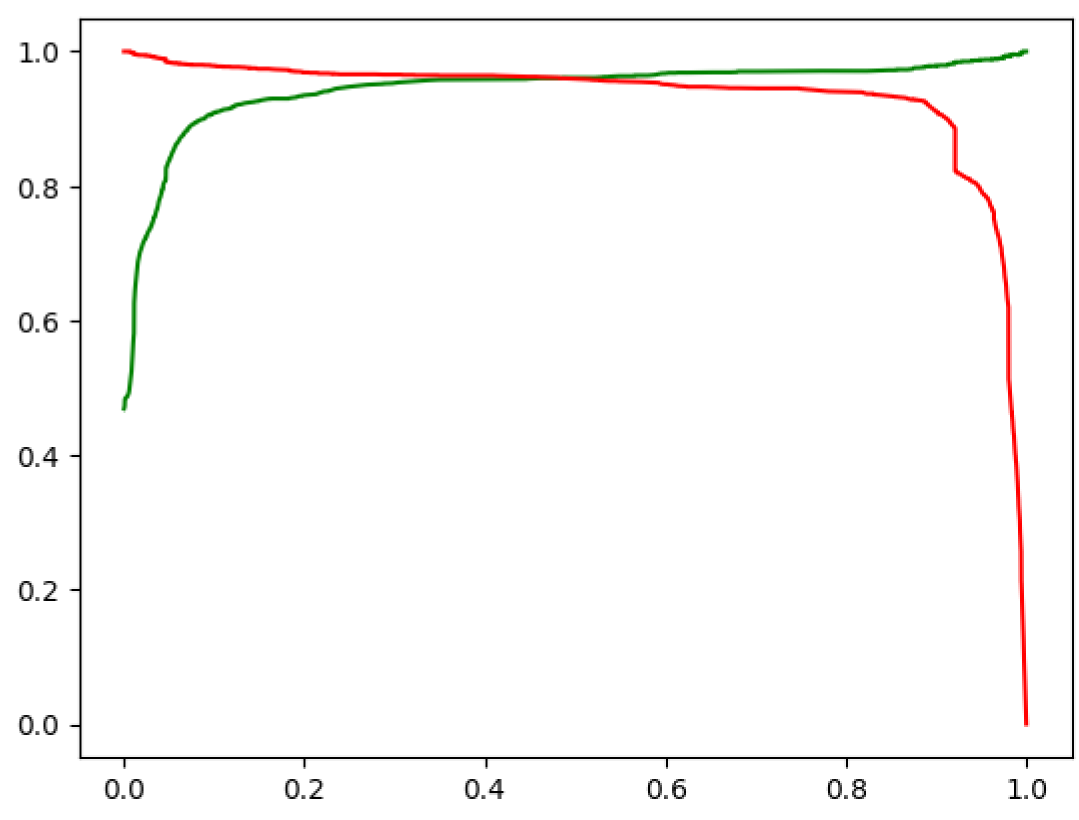
Optimal Cutoff – Accuracy-Sensitivity-Specificity

- We can see that all 3 curves intersect at about 0.4
- The accuracy at this threshold is 0.9637



Optimal Cutoff – Precision-Recall

- We can see that all Precision & Recall intersect at about 0.45
- The accuracy at this threshold is 0.9635



Predictions on Test Set – Evaluation Metrics

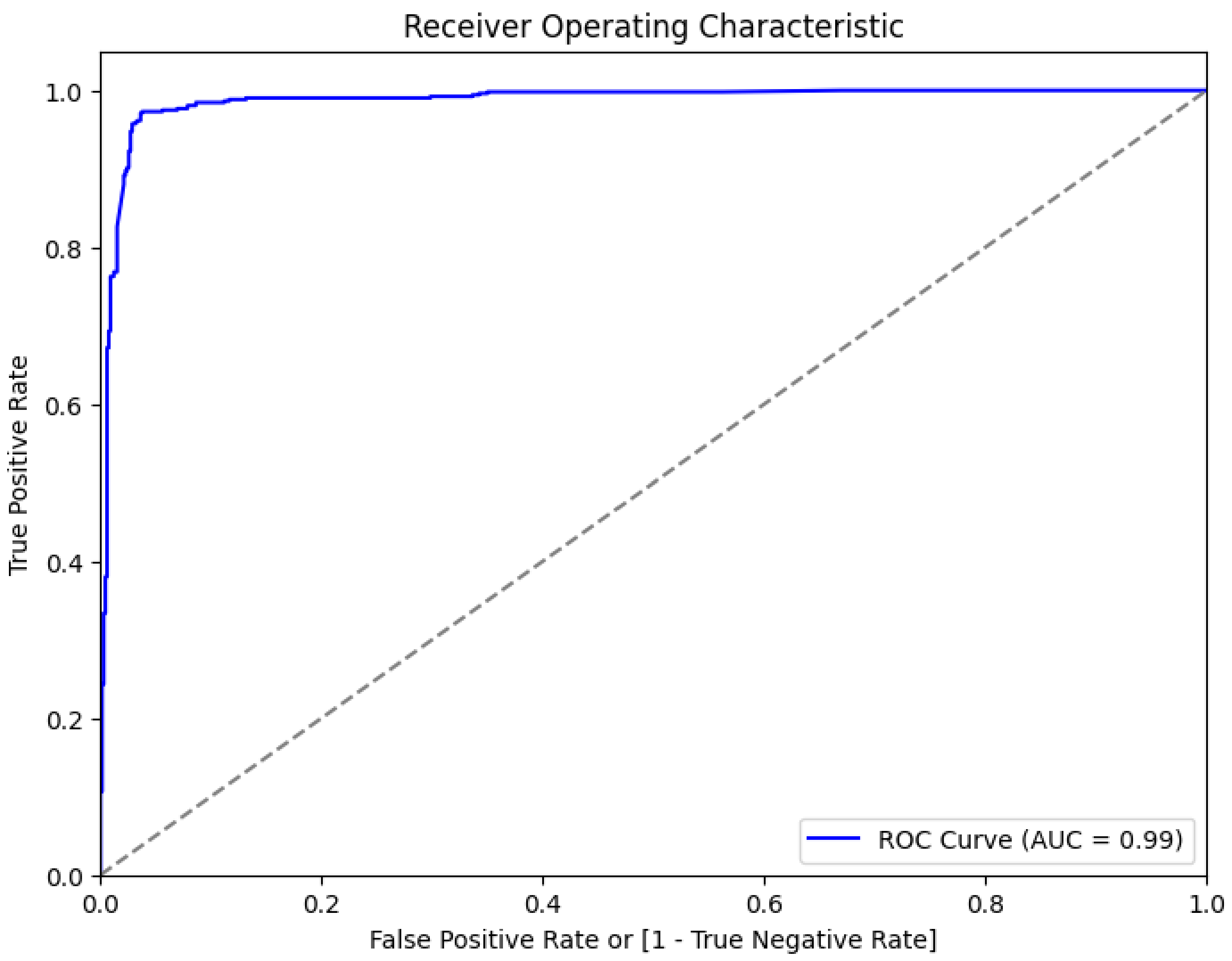
- We check for Accuracy on Test Set using both thresholds we found in the earlier sliders
- The 'Accuracy-Sensitivity-Specificity' threshold of 0.4 gives slightly higher accuracy in Test set, so we'll proceed with this value.

```
Testing Performance:
              precision    recall  f1-score   support

           0       0.98      0.96      0.97       660
           1       0.95      0.97      0.96       518

    accuracy                           0.97      1178
   macro avg       0.97      0.97      0.97      1178
weighted avg       0.97      0.97      0.97      1178

Confusion Matrix (Testing):
[[635  25]
 [ 14 504]]
```

Accuracy	0.9669
Sensitivity (Recall)	0.973
Specificity	0.9621

Model Evaluation – ROC AUC – Test Set

- In the Test Set we see an ROC curve with an AUC of 0.99.
- This means the model is highly accurate in distinguishing between positive and negative classes and can correctly classify instances into their respective categories.



Lead Score & Priority Labels

- Finally, we assign Lead Scores to each Lead
- Lead Score is basically the probability of the Lead to Convert multiplied by 100
- We also categorized the Leads as – Very High, High, Medium & Low Priority – based on their Lead Scores
- priority level based on a lead score:
    - Score > 80: Very High
    - Score > 60: High
    - Score > 40: Medium
    - Score ≤ 40: Low
- Higher scores indicate higher priority levels.

Key Findings

- **Overall Accuracy**: 96.14% (Mean CV Accuracy) on the training set, with consistent performance on the test set
- **ROC AUC Score**: 0.99, indicating excellent discrimination between converted and non-converted leads
- **High Sensitivity (Recall):** 95.92%, demonstrating strong ability to identify actual conversions
- **High Specificity:** 96.56%, showing robust performance in correctly identifying non-converting leads
- **Optimal Probability Threshold:** Identified at 0.4 using Accuracy-Sensitivity-Specificity curve analysis
- **Feature Significance:** Successfully reduced feature set while maintaining high predictive performance

Recommendations

1. Predictive Insights: Use the model's output to assign lead scores, enabling the sales and marketing teams to prioritize high-probability leads effectively.

2. Periodic Model Validation: Continuously retrain the model with updated data to ensure its performance remains aligned with evolving customer behaviors and market trends.

3. Optimize Campaign Strategies: Focus marketing and engagement efforts on activities or segments associated with high conversion probabilities as identified by the model.

4. Monitor Key Metrics: Conduct regular evaluations of the model’s sensitivity, specificity, and accuracy to ensure consistent performance.

5. Iterate and Enhance: Explore additional features, such as external data sources or behavioral metrics, to further refine the model’s predictive capabilities.

6. Strategic Use of Thresholds: Adjust the probability threshold based on specific business goals, such as increasing conversion rates or minimizing false negatives, to optimize resource allocation.