## Data Preprocessing, Feature Selection, and Model Optimization

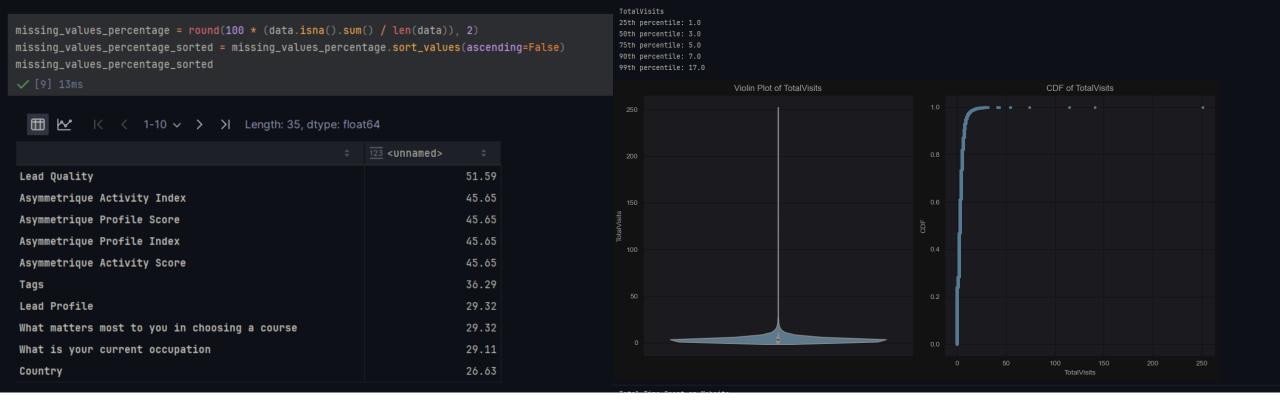
Steps for Data Exploration, Feature Selection, and Model Optimization

### Import Necessary Libraries

- Key Points:
  - pandas, numpy
  - seaborn, matplotlib
  - sklearn.metrics (accuracy\_score)
  - optbinning (BinningProcess)

## Data Exploration

- Key Points:
  - Check for duplicates and missing values
  - Identify and manage outliers
  - Example code for missing values, duplicates, and outliers visualization



The pictures demonstrate that their lot of nan value in each columns. The most interesting that there are outliers for Total Visit columns

# Feature Selection Using Correlation and Information Value (IV)

- Key Points:
  - Pearson correlation to check multicollinearity
  - Heatmap visualization
  - Remove highly correlated features with low IV values

|                                |          | Bin            | Count            | Count (%) | Non-event | Event |
|--------------------------------|----------|----------------|------------------|-----------|-----------|-------|
| Lead Origin                    |          | 0 [3 0]        | 2911             | 0.3938041 | 2020      |       |
| Lead Origin                    |          | 1 [1]          | 3903             | 0.5280032 | 2484      |       |
| Lead Origin                    |          | 2 [2 4]        | 578              | 0.0781926 | 39        |       |
| Lead Origin                    | Totals   |                | 7392             | 1         | 4543      |       |
| Lead Source                    |          | 0 [18 9 19 17  | 1554             | 0.2102273 | 1176      |       |
| Lead Source                    |          | 1 [1]          | 2049             | 0.2771916 | 1377      |       |
| Lead Source                    |          | 2 [7]          | 913              | 0.1235119 | 569       |       |
| Lead Source                    |          | 3 [3]          | 2295             | 0.3104708 | 1381      |       |
| Lead Source                    |          | 4 [21 10 14 13 | 581              | 0.0785985 | 40        |       |
| Lead Source                    | Totals   |                | 7392             | 1         | 4543      |       |
|                                |          | unique_bin     | ▼ top_bin        | ▼ freq_l  |           |       |
| 18 Tags                        | 4.82413  |                | 5 [16 26 20 5 18 | 15 1]     | 2842      |       |
| 19 Lead Quality                | 2.008334 |                | 5 [5 3]          |           | 4664      |       |
| 22 Lead Profile                | 1.088576 |                | 4 [4]            |           | 3314      | b     |
| 31 Total Time Spent on Website | 1.065929 |                | 5 [1.50, 416.50) |           | 2860      |       |
| 8 What is your current occupat | 1.007207 |                | 3 [3 4 0 2]      |           | 4694      | kı    |
| 4 Last Activity                | 0.845716 |                | 4 [3135]         |           | 3054      | to    |
| 28 Last Notable Activity       | 0.661166 |                | 4 [6918]         |           | 2931      |       |
| 1 Lead Source                  | 0.658413 |                | 5 [3]            |           | 2295      | tł    |
| 0 Lead Origin                  | 0.609527 |                | 3 [1]            |           | 3903      |       |
| 9 What matters most to you in  | 0.572587 |                | 2 [0 1]          |           | 5249      |       |
| 7 How did you hear about X Ec  | 0.478849 |                | 4 [610]          |           | 4122      |       |
| 6 Specialization               | 0.384737 |                | 5 [14 15 17 6 1  | 11]       | 2486      |       |
| 33 Asymmetrique Activity Score | 0.383068 |                | 5 Missing        |           | 3355      |       |
| 23 City                        | 0.356867 |                | 5 [60]           |           | 2645      |       |
| 34 Asymmetrique Profile Score  | 0.182607 |                | 5 Missing        |           | 3355      |       |
| 2 Do Not Email                 | 0.108354 |                | 2 [0]            |           | 6794      |       |
|                                |          |                |                  |           |           |       |

I exported the dataframe to binning\_table.csv and iv.csv to know which variables has the top IV and need to be input to the model

Event rate WoE

2849 0.3854167

2849 0.3854167

IV

0.932526 -3.0927735 0.55856897 0.05087976

0.60952684 0.05721954

0.65841257 0.06342542

2.06E-05

891 0.3060804 0.3518888 0.04641371 0.00577196

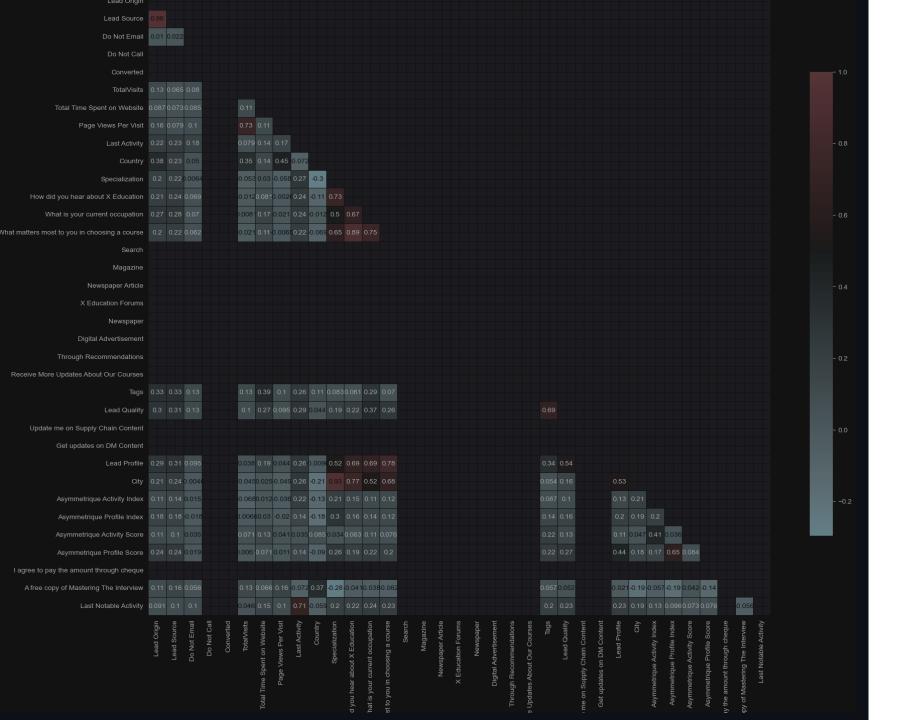
1419 0.3635665 0.0932982 0.00454416 0.00056781

378 0.2432432 0.6683604 0.08433482 0.01034992 672 0.3279649 0.2507846 0.01686061 0.00210207

914 0.3982571 -0.0538869 0.00090693 0.00011335

541 0.9311532 -3.0711594 0.5561453 0.05083947

344 0.3767798 0.0366192 0.00016492



After that, transfor the original input to dataframe, replaced it with WOE value. There are some conditions that need to filter for useful variables:

The correlation must be below 0.7, if it is greater than 0.7 -> eliminate the lower IV variable. Only choose the varibles which has the IV > 0.07

## Model Performance Summary

#### Key Points:

#### • Baseline Logistic Regression:

Accuracy: 0.81

• AUC: 0.88

#### Optimized Logistic Regression:

• Accuracy: 0.789

• AUC: 0.940

#### Optimized XGBoost:

• Accuracy: 0.904

• AUC: 0.966

## Threshold Optimization for XGBoost

#### Key Points:

- Adjust decision threshold to optimize accuracy
- Example code for finding the best threshold
- Best Threshold: 0.45
- Best Accuracy: 0.906

I choose the Xgboost for choosing the threshold because the performance of this model seems outstands the other 2 model (Baseline Logistic regression model and Optimzed Logistic regression model)