Direct Marketing Campaign

Presented by:
Team Adelaide

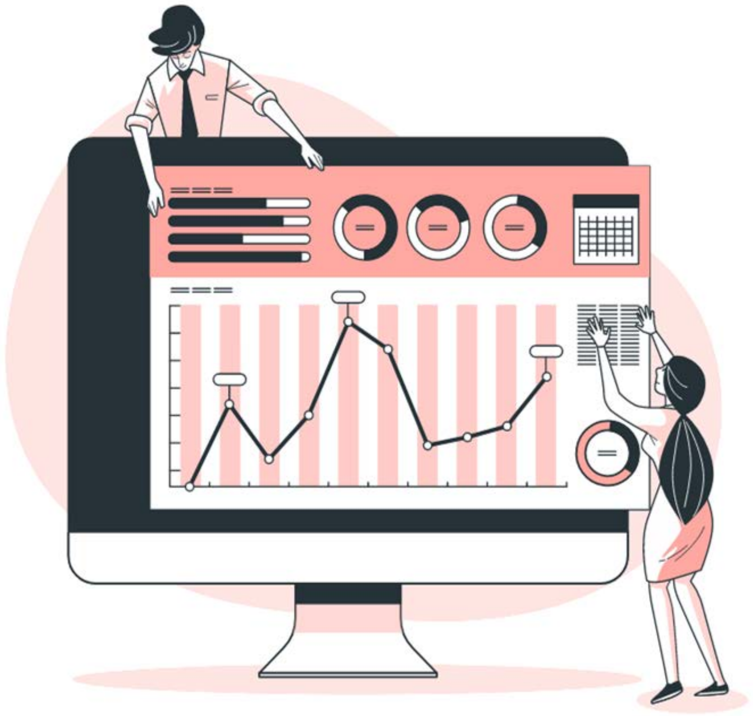


Table of contents

Executive Summary

Banking Sector

Competition to gain market share

Direct Marketing

Term deposit subscription through sales calls

Model Development

Achieved 0.91 accuracy and 0.90 F1 score with our best model

Recommendations

Provided recommendations to inform future marketing investments

Introduction

Client's Ask

ANZ Bank reached out to Team Adelaide to assist them in predicting the impact of direct marketing campaigns on their term deposit subscription.

Objective

Identify key characteristics of customers who subscribed and are most likely to subscribe to a term deposit subsequently and;

Present our findings and recommendations to the executive team at ANZ to inform their next marketing investment.

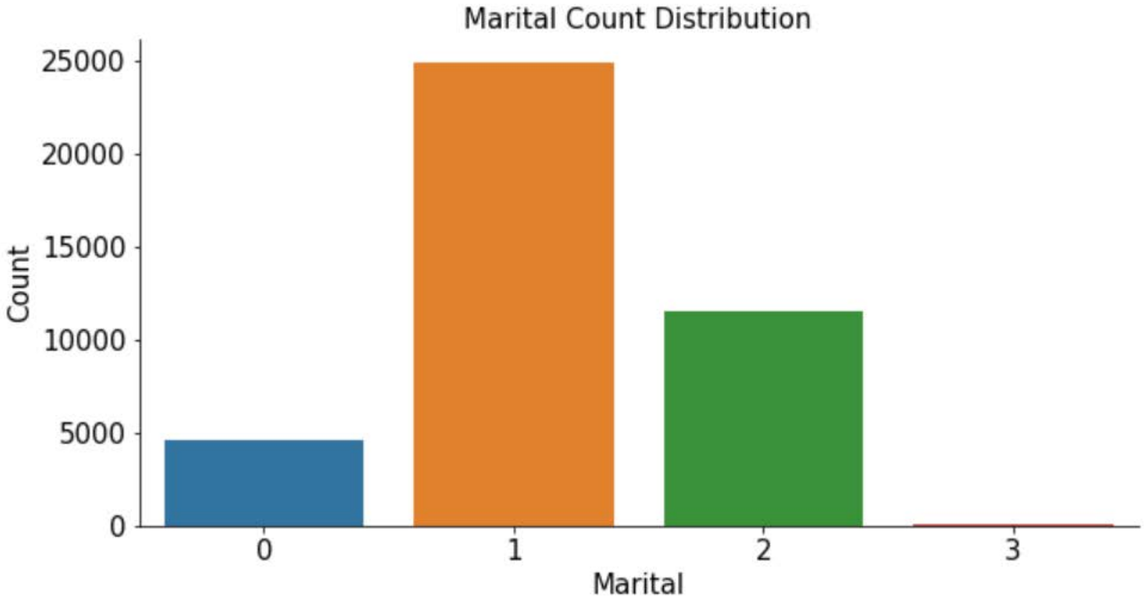
Data Description

Data Attributes

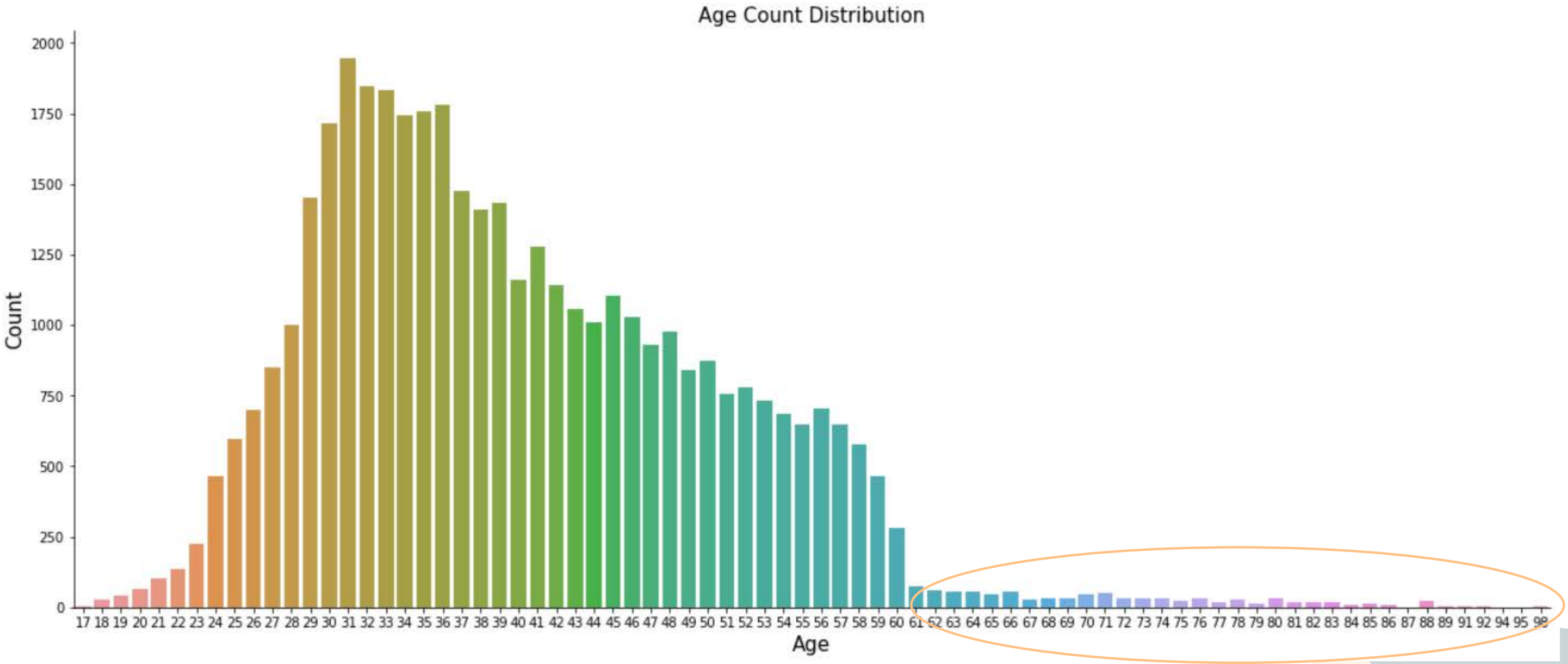
Data consists of 21 features and 41,188 entries

- Bank client data (Job, Education)
- Related with the last contact of the current campaign (Month, week)
- Social and economic context attributes (CPI, Employment Rate)
- Other attributes incl. (Campaign, previous)
- Output Variable: y - has the client subscribed a term deposit?

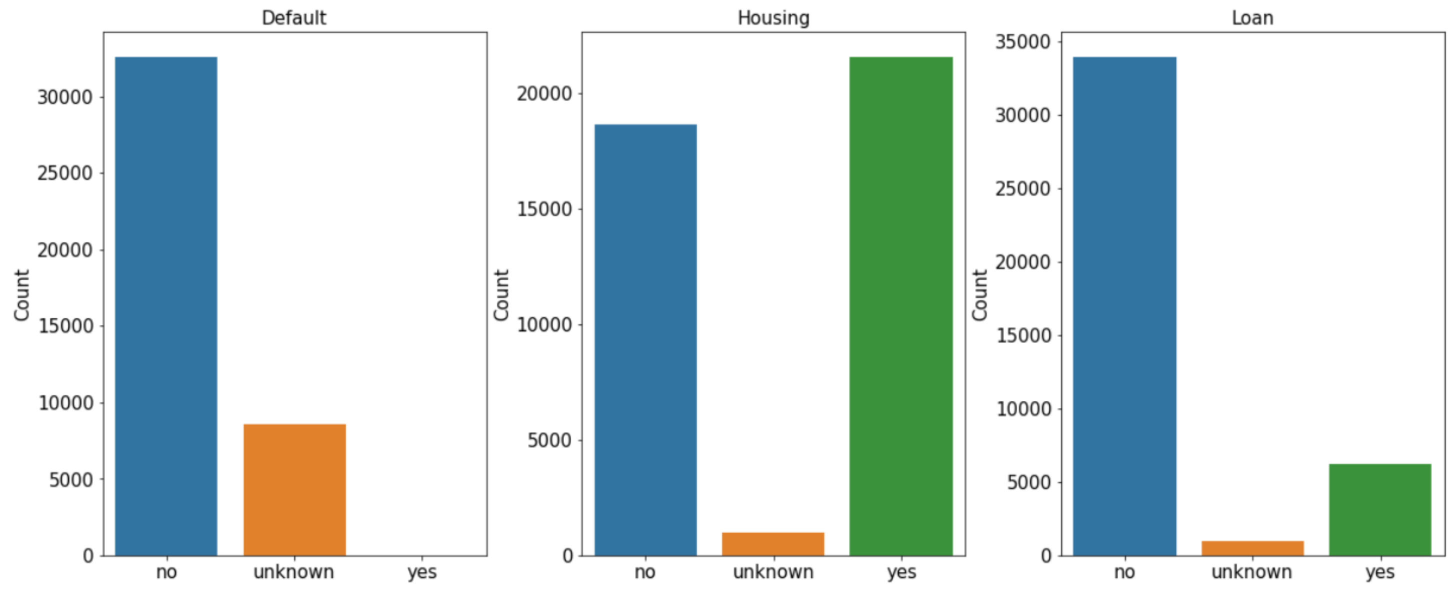
Exploratory Data Analysis – Marital Status



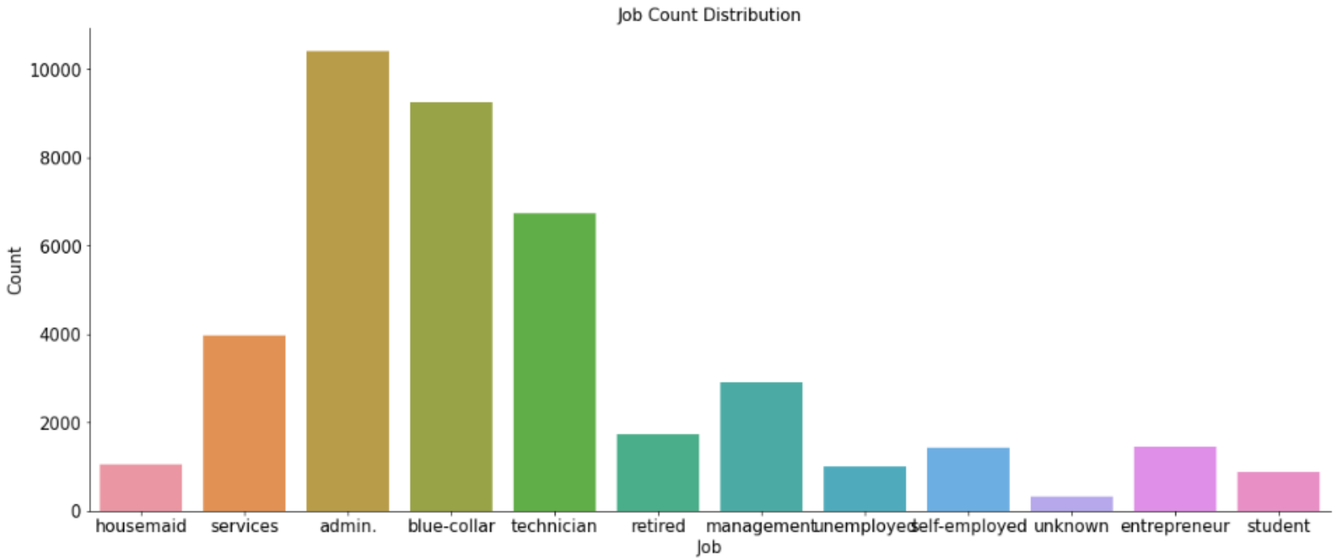
Exploratory Data Analysis – Age



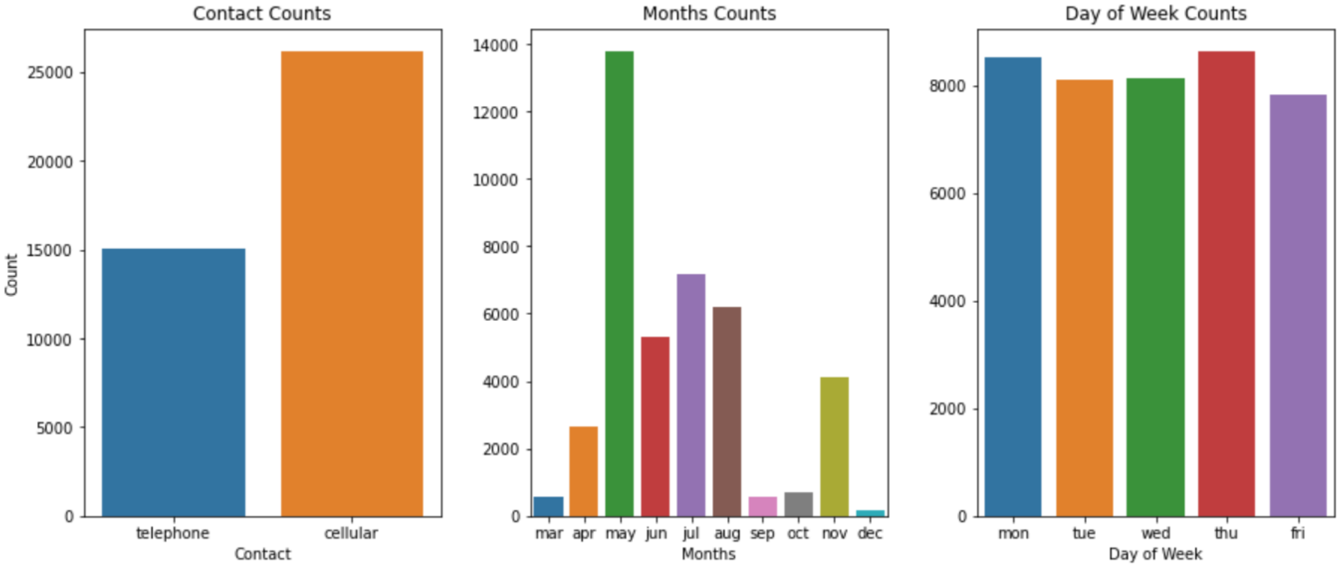
Exploratory Data Analysis – Financial Situation



Exploratory Data Analysis – Job Type

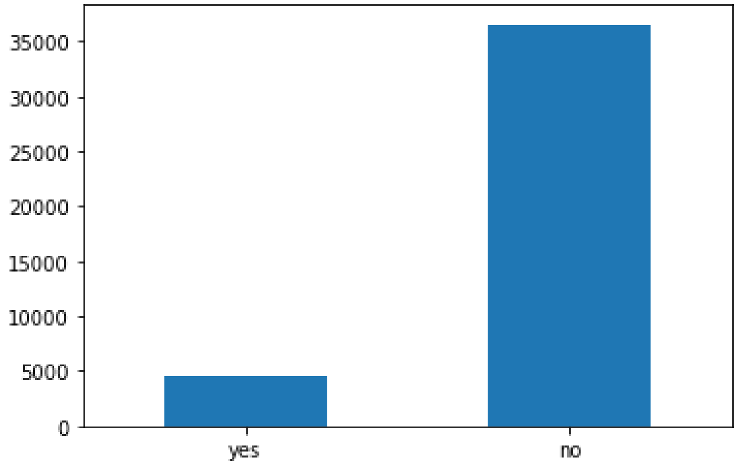


Exploratory Data Analysis– Last Contact



Data Cleaning & Feature Engineering

- Data has no duplicates and missing value
- There are outliers in some features such as ages (About 1.14 %)
- Converting some features to continuous Label Encoder is used since we'll apply feature scaling later
- Target variable is imbalanced
- After Splitting training and testing set, we apply standard scaler on both dataset

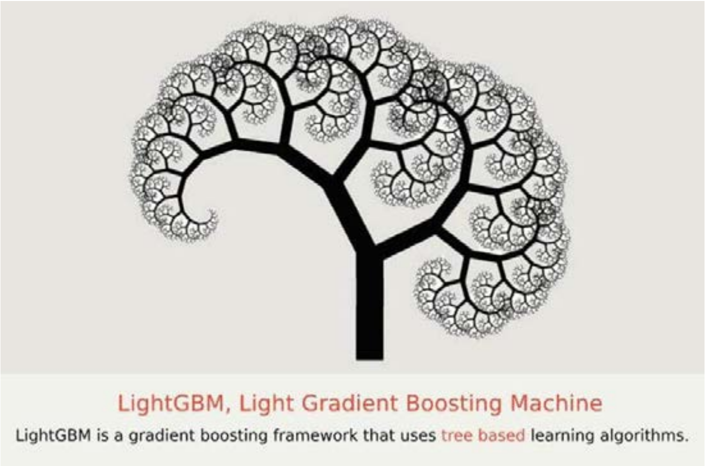


Model Analysis

Model Analysis : Cross Validation

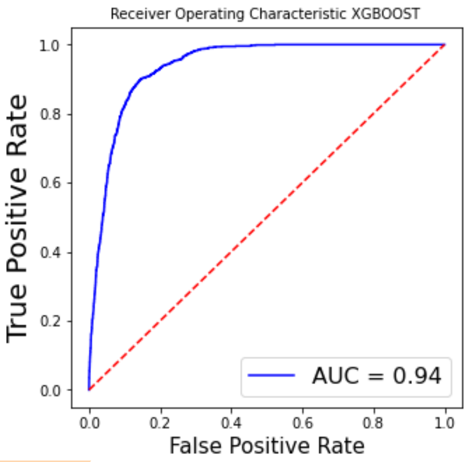
MODEL ACCURACY

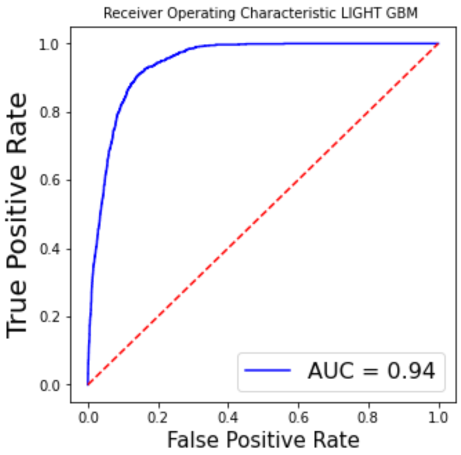
- LightGBM – 0.915
- XGBoost - 0.912
- Logistic Model – 0.910
- RadomForest - 0.908
- DecisionTree – 0.883



Model Analysis : Best Model

- AUC Score
- F1 Score
- Light GBM is the best model





F1 Score

XGBoost - 0.90

RadomForest - 0.90

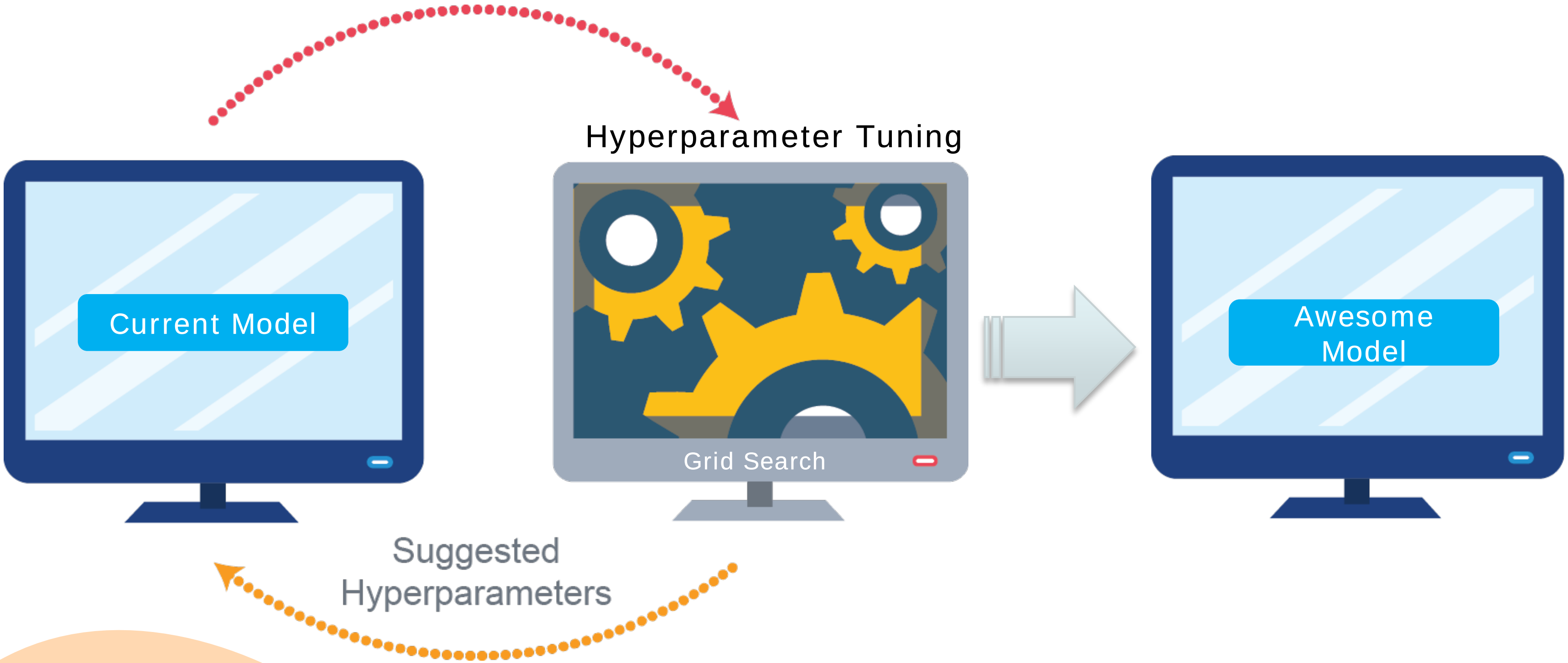
LightGBM - 0.90

DecisionTree – 0.88

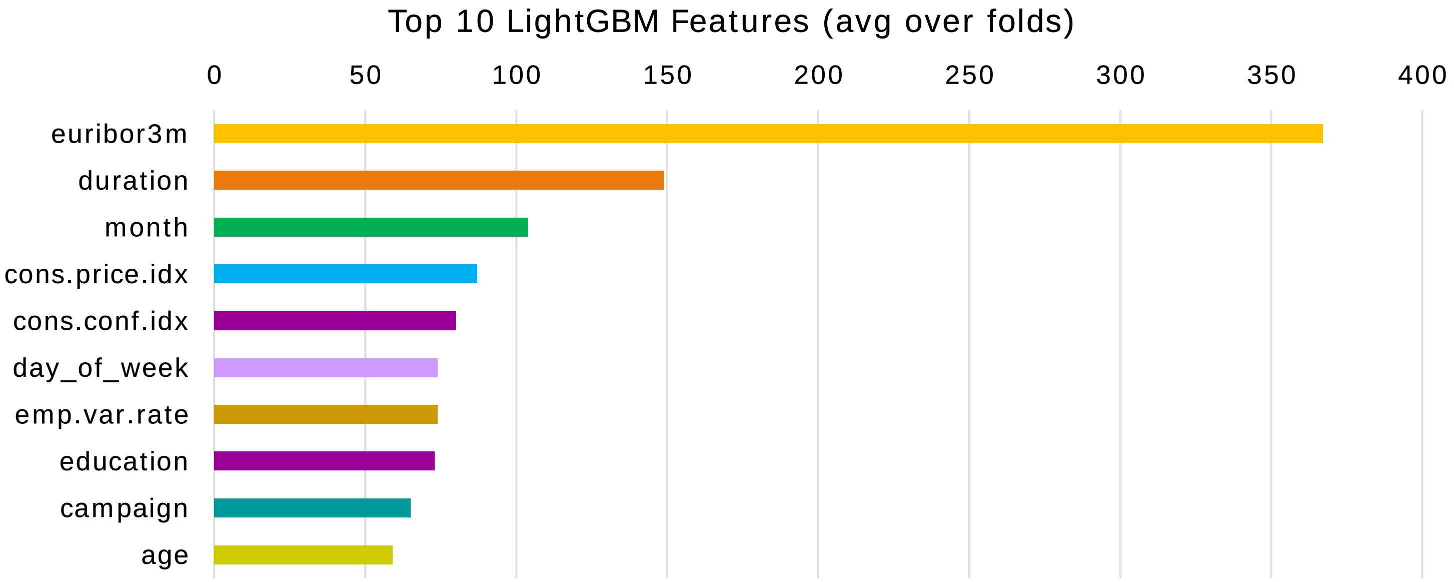
Logistic Model – 0.89

Model Enhancements

Model Tuning



Model Feature Importance



Re-trained Model Output

- We re-trained our model using the optimal parameters identified via Hyperparameter tuning and our model accuracy improved to 0.916 and weighted average F1 score to 0.90

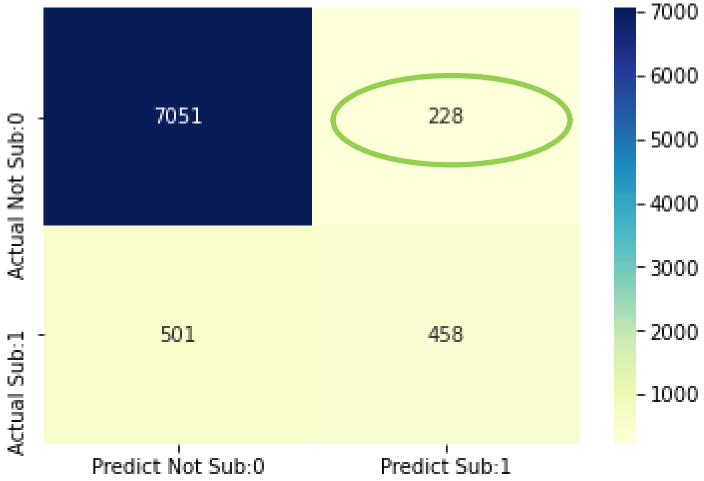
	Models	Score
5	LightGBM1	0.915599
4	LightGBM	0.914719
3	XGBoost	0.912200
2	Logistic Model	0.909681
0	Random Forest Classifier	0.909317
1	Decision Tree Classifier	0.884492

```
LGBM1 Reports
              precision    recall  f1-score   support

           0       0.93      0.97      0.95      7279
           1       0.67      0.48      0.56       959

    accuracy                           0.91      8238
   macro avg       0.80      0.72      0.75      8238
weighted avg       0.90      0.91      0.90      8238
```

Confusion Matrix




```
True Positives(TP) =  7051

True Negatives(TN) =  458

False Positives(FP) =  228

False Negatives(FN) =  501
```

Recommedations

Recommendations

Increase Revenue

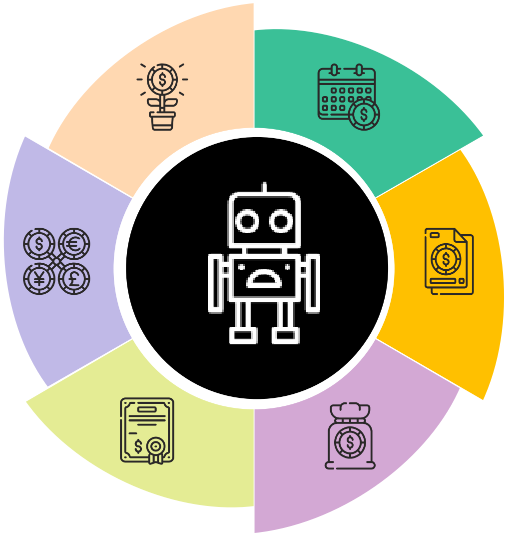
More Subscription = More Revenue = Increase Cross Opportunity

Campaign Effectiveness

Customize Campaigns, explore alternative marketing channels

Return on Investment

Campaign Investment vs. Revenue Generation



Demographics

Understand Customer Requirements to turn them into prospective clients

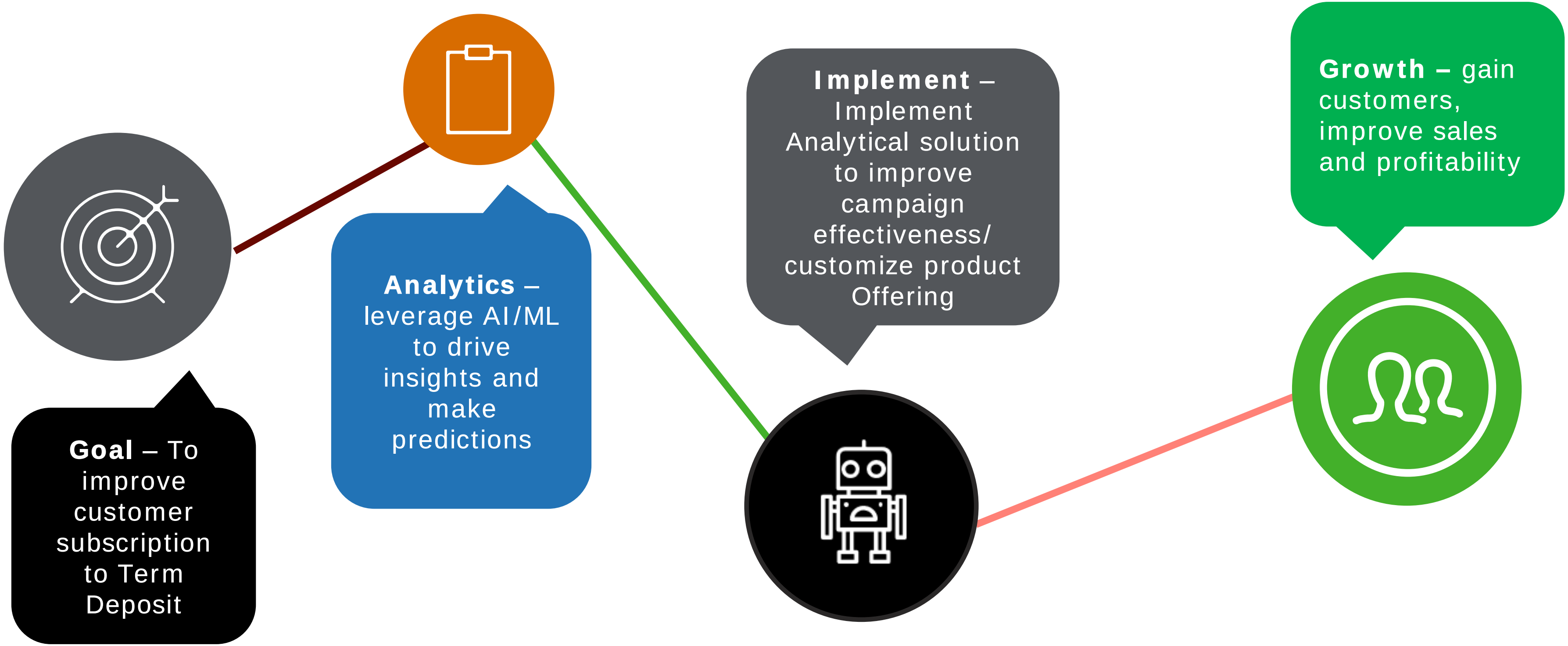
Product Features

Customize offering to match customer demand

Cost Effective

Time savings and cost effective implementation

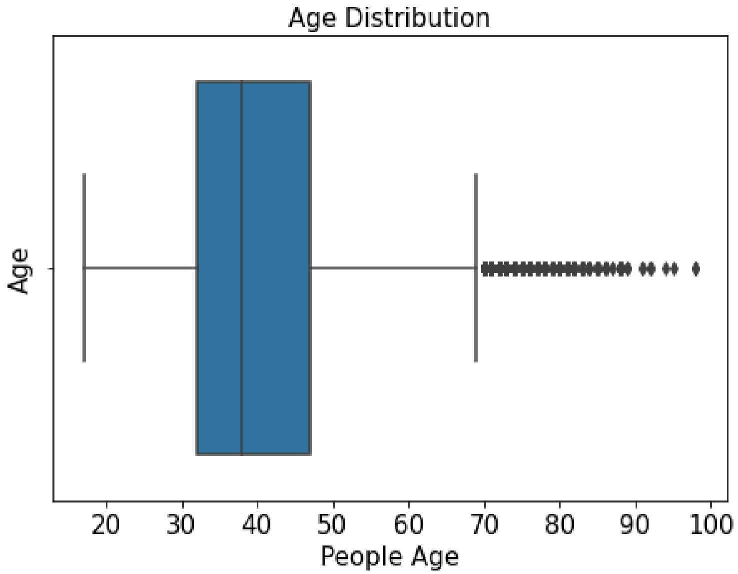
Conclusion

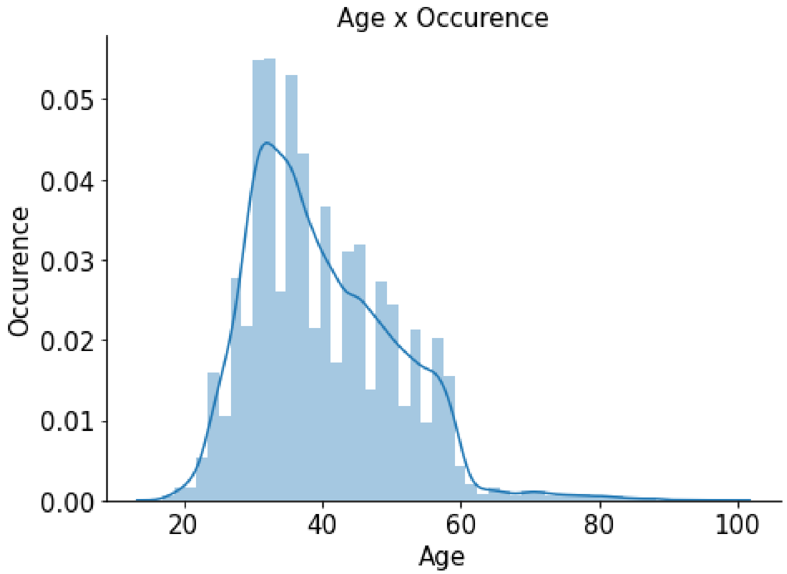

Goal – To improve customer subscription to Term Deposit
Analytics – leverage AI/ML to drive insights and make predictions
Implement – Implement Analytical solution to improve campaign effectiveness/ customize product Offering
Growth – gain customers, improve sales and profitability

Thank You

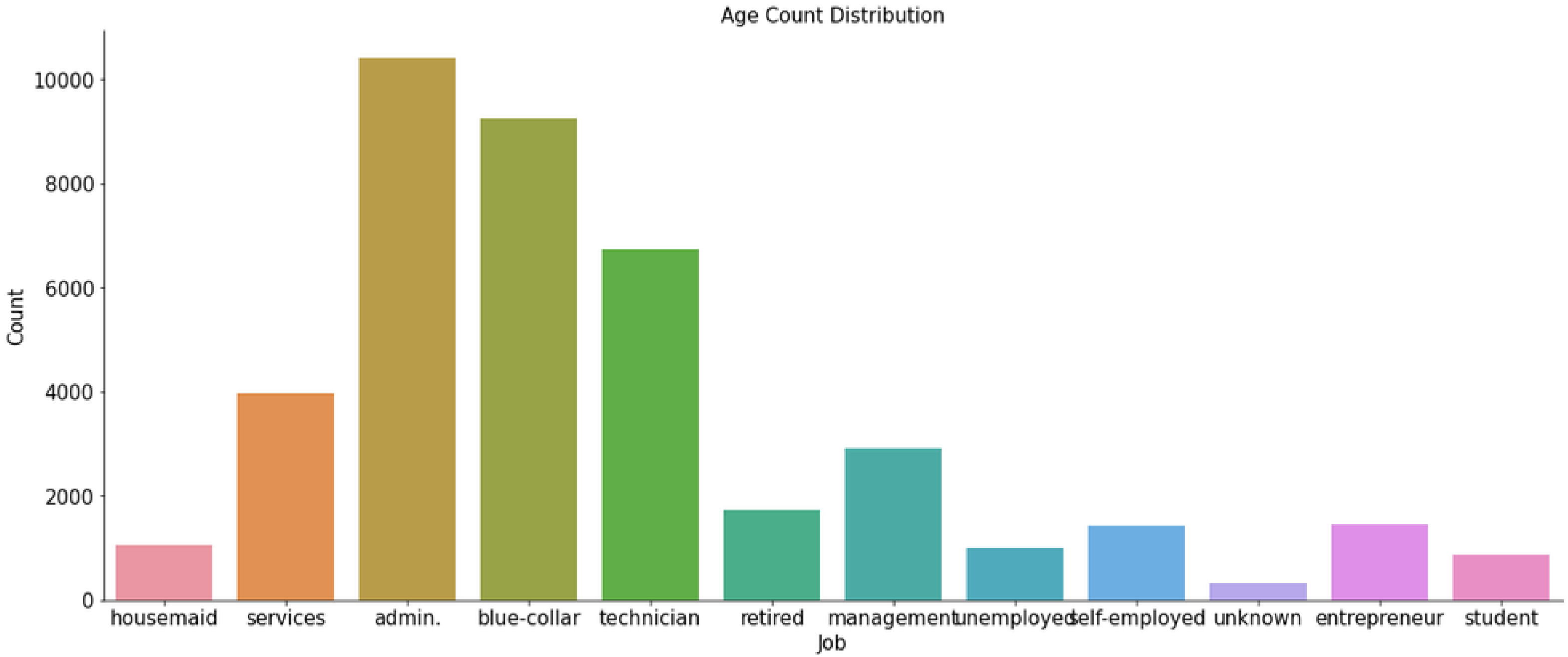
Appendix

Exploratory Data Analysis

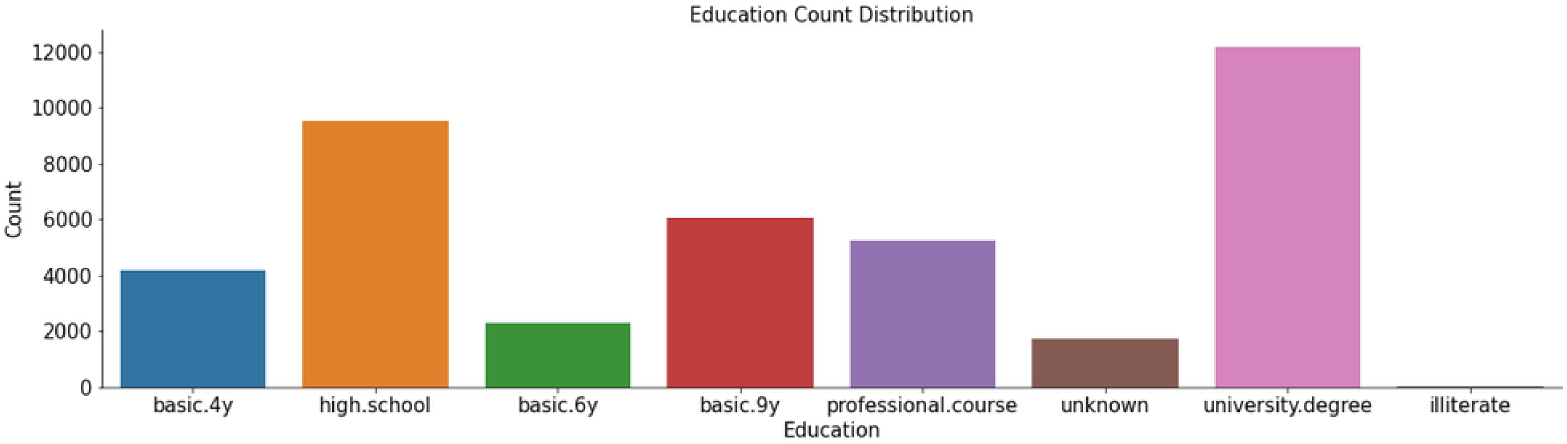




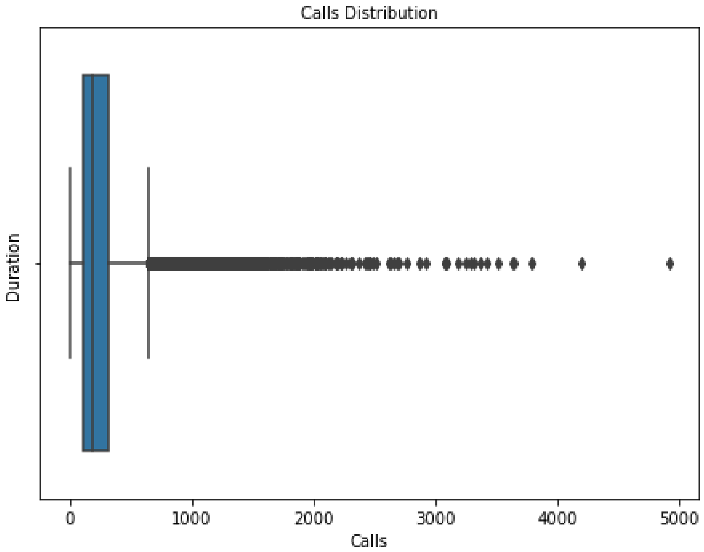
Exploratory Data Analysis

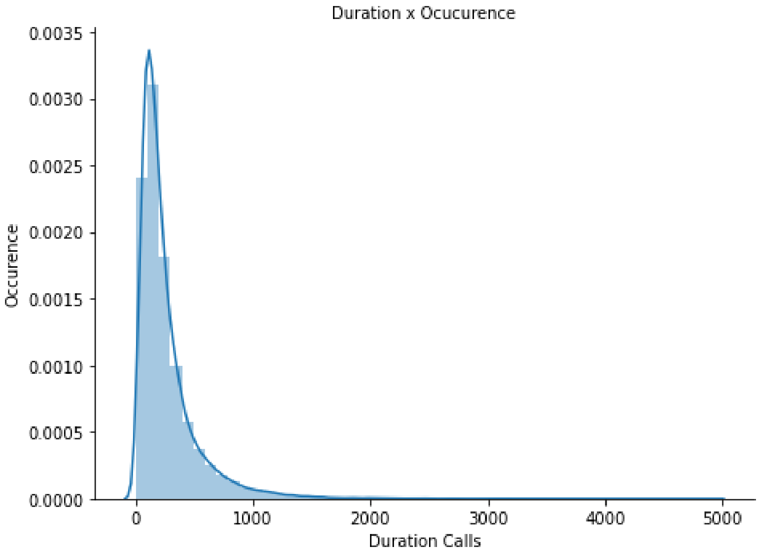


Exploratory Data Analysis

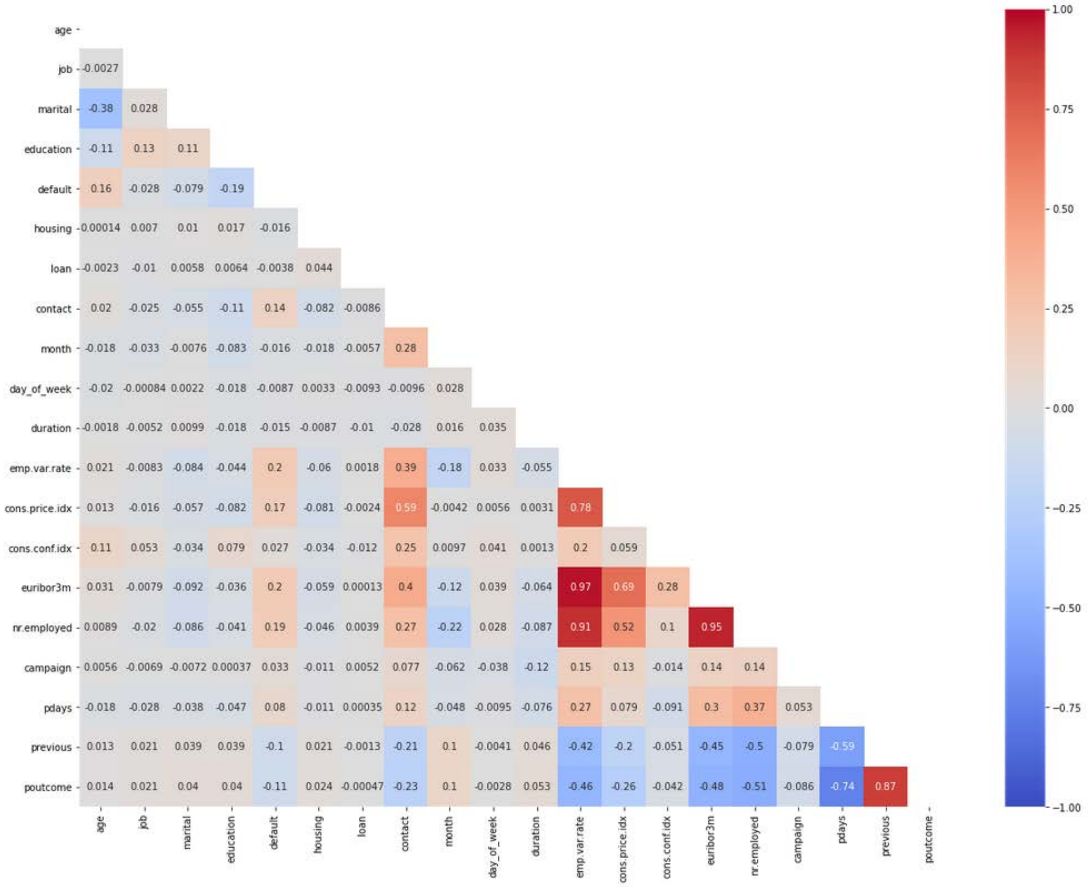


Exploratory Data Analysis





Correlation Heatmap



Model Reports

LOGR Reports

	precision	recall	f1-score	support
0	0.92	0.98	0.95	7279
1	0.66	0.36	0.46	959
accuracy			0.90	8238
macro avg	0.79	0.67	0.71	8238
weighted avg	0.89	0.90	0.89	8238

DTREE Reports

	precision	recall	f1-score	support
0	0.93	0.94	0.93	7279
1	0.50	0.49	0.50	959
accuracy			0.88	8238
macro avg	0.72	0.71	0.72	8238
weighted avg	0.88	0.88	0.88	8238

RFC Reports

	precision	recall	f1-score	support
0	0.93	0.96	0.95	7279
1	0.61	0.47	0.53	959
accuracy			0.90	8238
macro avg	0.77	0.72	0.74	8238
weighted avg	0.90	0.90	0.90	8238

Model Reports

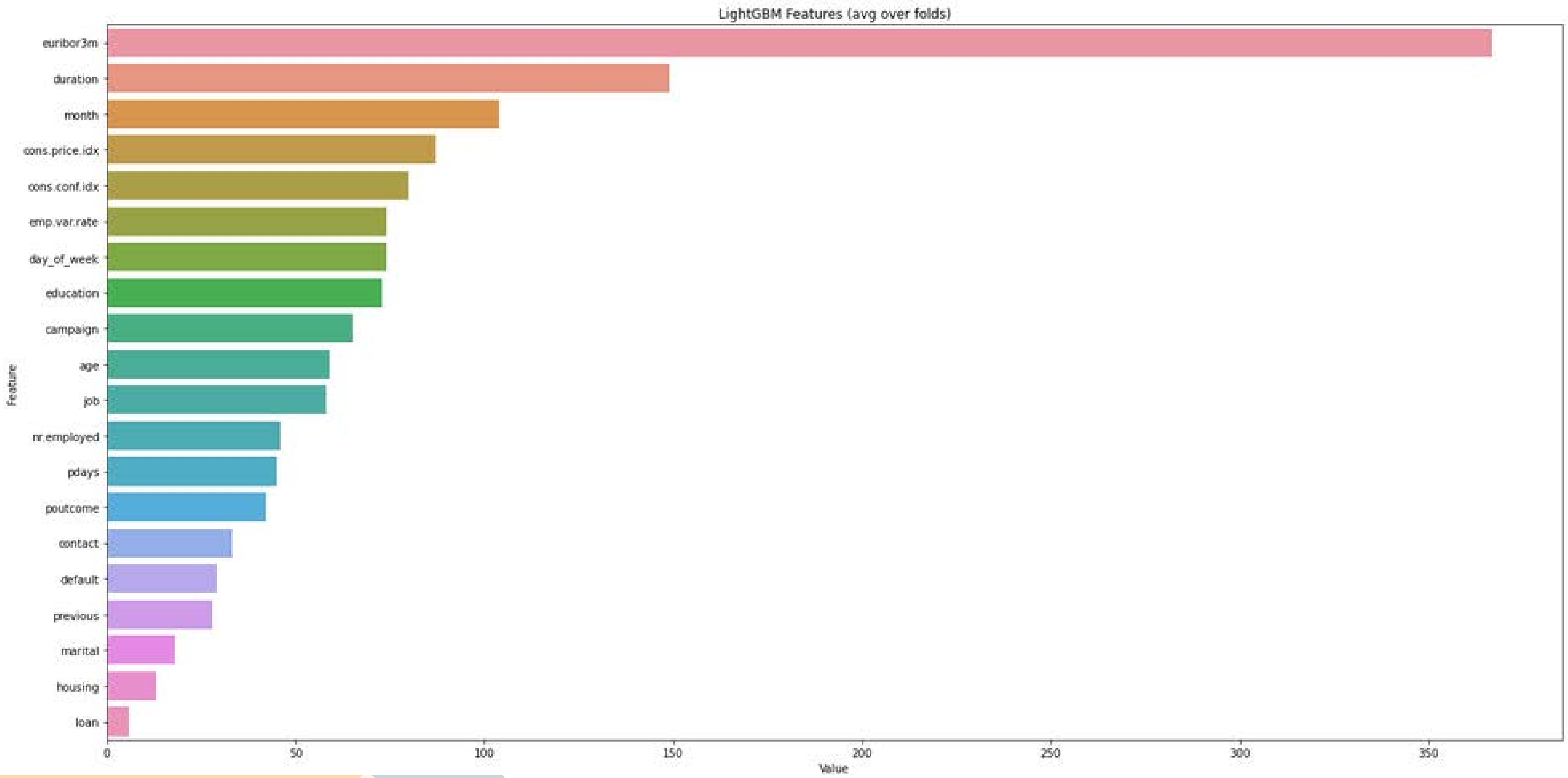
XGB Reports

	precision	recall	f1-score	support
0	0.94	0.96	0.95	7279
1	0.63	0.50	0.56	959
accuracy			0.91	8238
macro avg	0.78	0.73	0.75	8238
weighted avg	0.90	0.91	0.90	8238

LGBM Reports

	precision	recall	f1-score	support
0	0.94	0.96	0.95	7279
1	0.65	0.50	0.57	959
accuracy			0.91	8238
macro avg	0.79	0.73	0.76	8238
weighted avg	0.90	0.91	0.91	8238

Feature Importance : All Features



Hyperparameter Tuning : Optimal

Parameters	Optimal Value
boosting_type	gbdt
colsample_bytree	0.75
learning_rate	0.1
n_estimators	50
num_leaves	30
objective	binary
reg_alpha	1
reg_lambda	6
subsample	0.7