

Capstone Project Bank Marketing Effectiveness Prediction



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Problem Statement

The data is related with direct marketing campaigns (phone calls) of a Portuguese banking institution. The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, in order to access if the product (bank term deposit) would be ('yes') or not ('no') subscribed. The classification goal is to predict if the client will subscribe a term deposit (variable y).



Data Summary

- job: type of job (categorical: 'admin.', 'blue-collar', 'entrepreneur', 'housemaid', 'management', 'retired', 'self employed', 'services', 'student', 'technician', 'unemployed', 'unknown')
- marital: marital status (categorical: 'divorced', 'married', 'single')
- education: (categorical: 'primary', 'secondary', 'tertiary', 'unknown')
- default: has credit in default? (categorical: 'no', 'yes')
- housing: has housing loan? (categorical: 'no', 'yes')
- loan: has personal loan? (categorical: 'no', 'yes')
- contact: contact communication type (categorical: 'cellular', 'telephone', 'unknown')
- month: last contact month of year (categorical: 'jan', 'feb', 'mar', ..., 'nov', 'dec')
- poutcome: outcome of the previous marketing campaign (categorical: 'failure', 'success')

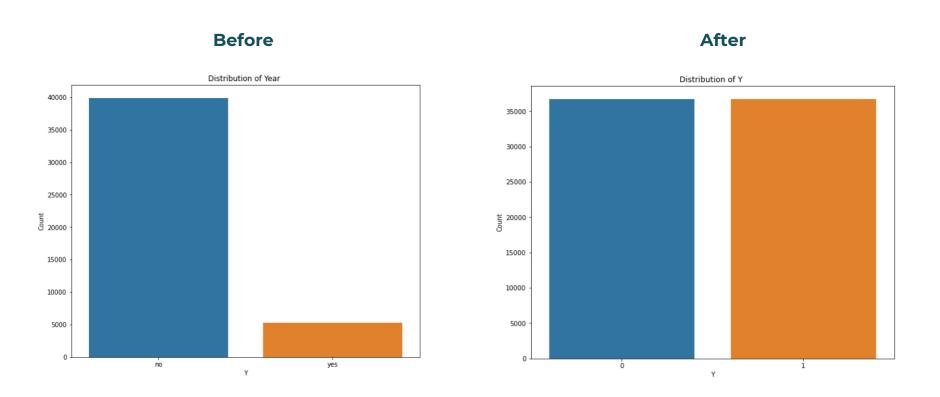


Contd ...

- day: last contact day of year(categorical: 1, 2, ..., 31)
- age : (numeric)
- duration: last contact duration, in seconds (numeric)
- campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)
- pdays: number of days that passed by after the client was last contacted from a previous campaign
- previous: number of contacts performed before this campaign and for this client (numeric)
- y has the client subscribed a term deposit? (binary: 'yes','no')

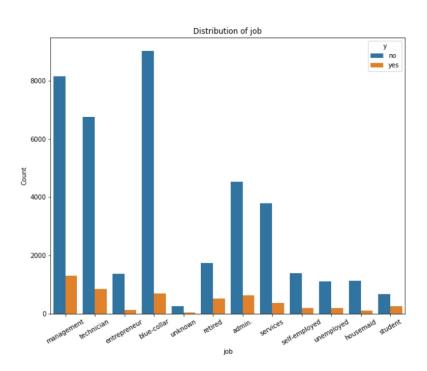


Count plot of Dependent Feature(Y)



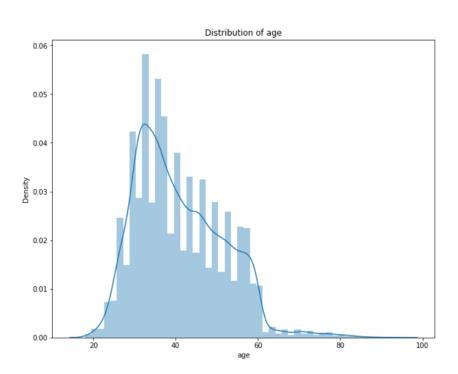


Count plot of Job



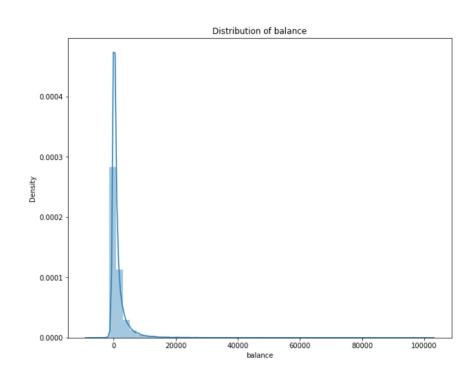


Distribution plot of Age



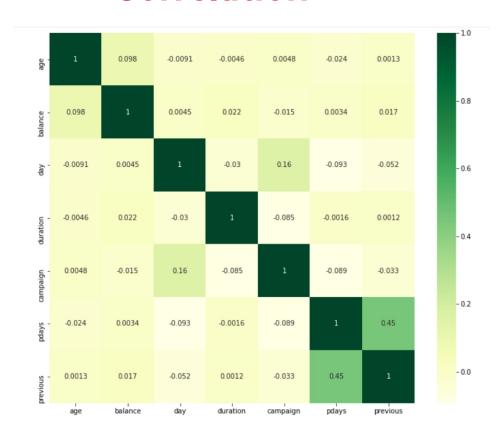


Distribution plot of Balance





Correlation





Logistic Regression

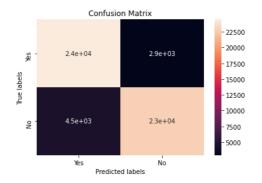
Best Parameters

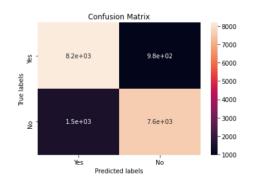
C: 0.1

ROC-AUC score

Train Data	0.93
Test Data	0.93

Confusion matrix of Train Data







K-Nearest Neighbors

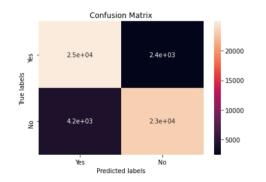
Best Parameters

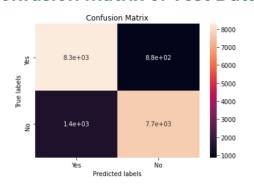
n_neighbors: 27

ROC-AUC score

Train Data	0.95
Test Data	0.93

Confusion matrix of Train Data







Decision Tree

Best Parameters

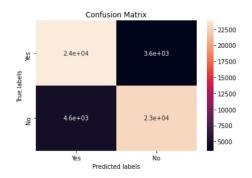
max_depth:10

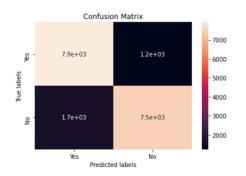
min_samples_leaf: 10 min_samples_split: 20

ROC-AUC score

Train Data	0.95
Test Data	0.93

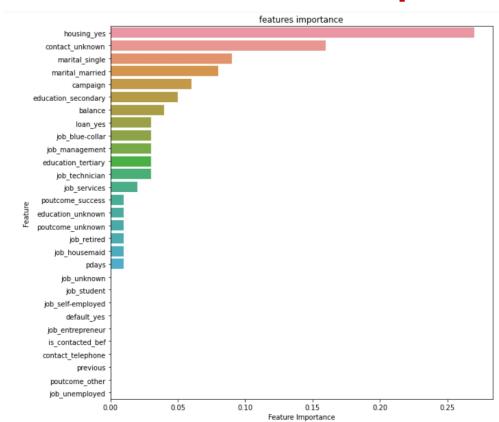
Confusion matrix of Train Data







Decision Tree Feature Importance





RandomForest

Best Parameters

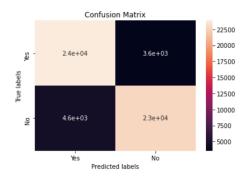
max_depth:10

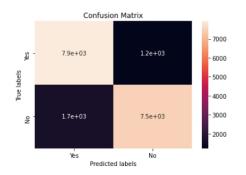
min_samples_leaf: 10 min_samples_split: 20

ROC-AUC score

Train Data	0.92
Test Data	0.92

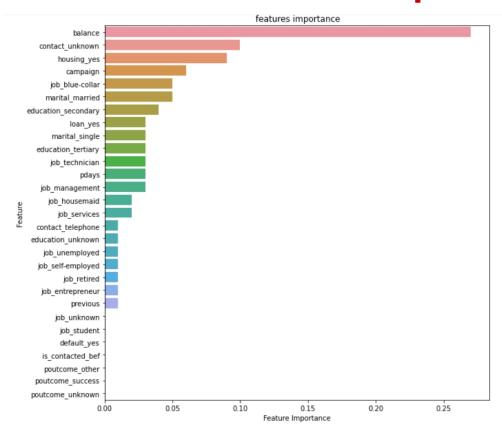
Confusion matrix of Train Data







RandomForest Feature Importance





XGBoost

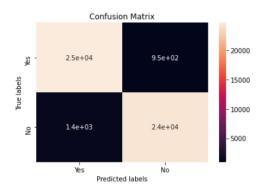
Best Parameters

learning_rate: 0.5

max_depth:9

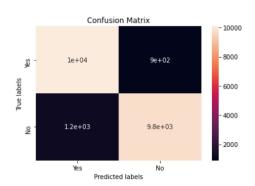
n_estimators: 125

Confusion matrix of Train Data



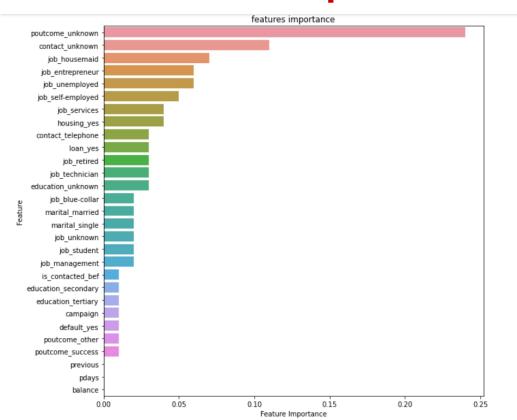
ROC-AUC score

Train Data	0.99
Test Data	0.95





XGBoost Feature Importance





Challenges

- Handling imbalanced datset
- Feature Engineering
- Optimising the Model



Conclusion

- For age, most of the customers are in the age range of 30-40.
- For balance, above 1000\$ is like to subscribe a term deposite.
- Comparing to all algorithms XGboost algorithm has best accuracy score and ROC-AUC score. So it is concluded as optimal model.



Q & A



Thank You