Bank Marketing Project Proposal

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The Team

Chaitra Hegde

Masters Student at CDS,
Active learner of Data
Science methodologies and
Machine learning
techniques

Aakash Kaku

Masters Student at CDS,
Interested in using data
science techniques to make
informed business decisions

Neelang Parghi

Masters Student in Math/CS.
Studying scientific
computing but recently
interested in data science.

Agenda

- Business Understanding
- Data Exploration and Preparation
- Model Building
- Hyper-parameter Tuning and Model Evaluation
- Result / Outcomes

Business Understanding

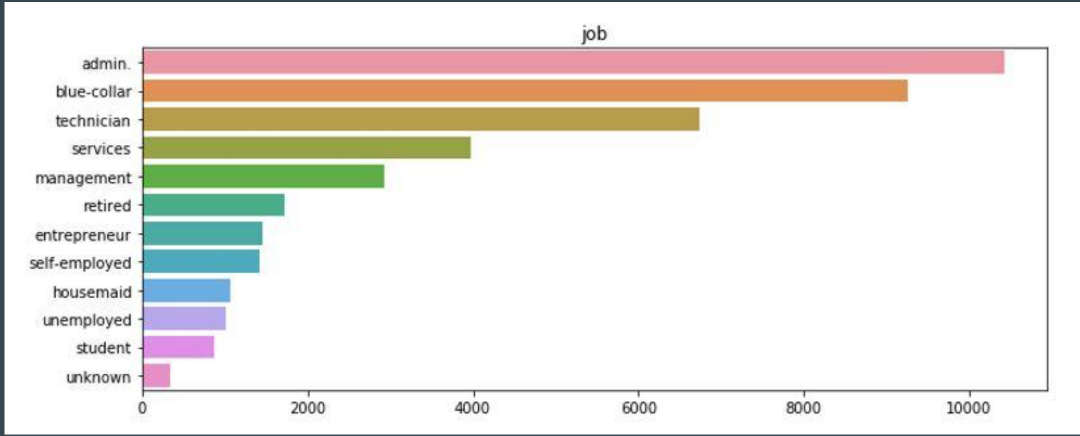
Business Understanding

- Problem Statement: Improve marketing campaign of a Portuguese bank by analyzing their past marketing campaign data and recommending which customer to target
- Problem Motivation: By devising such a prediction algorithm, the bank can better target its customers and better channelize its marketing efforts
- Banco de Portugal offered their clients fixed-term products such as CDs. Data was collected about each client, type of contact, and outcome.
- What can this data tell us about marketing success for this campaign?
- Can these data science techniques be applied to other areas?

Data Exploration and Preparation

Data Exploration and Preparation (1/2)

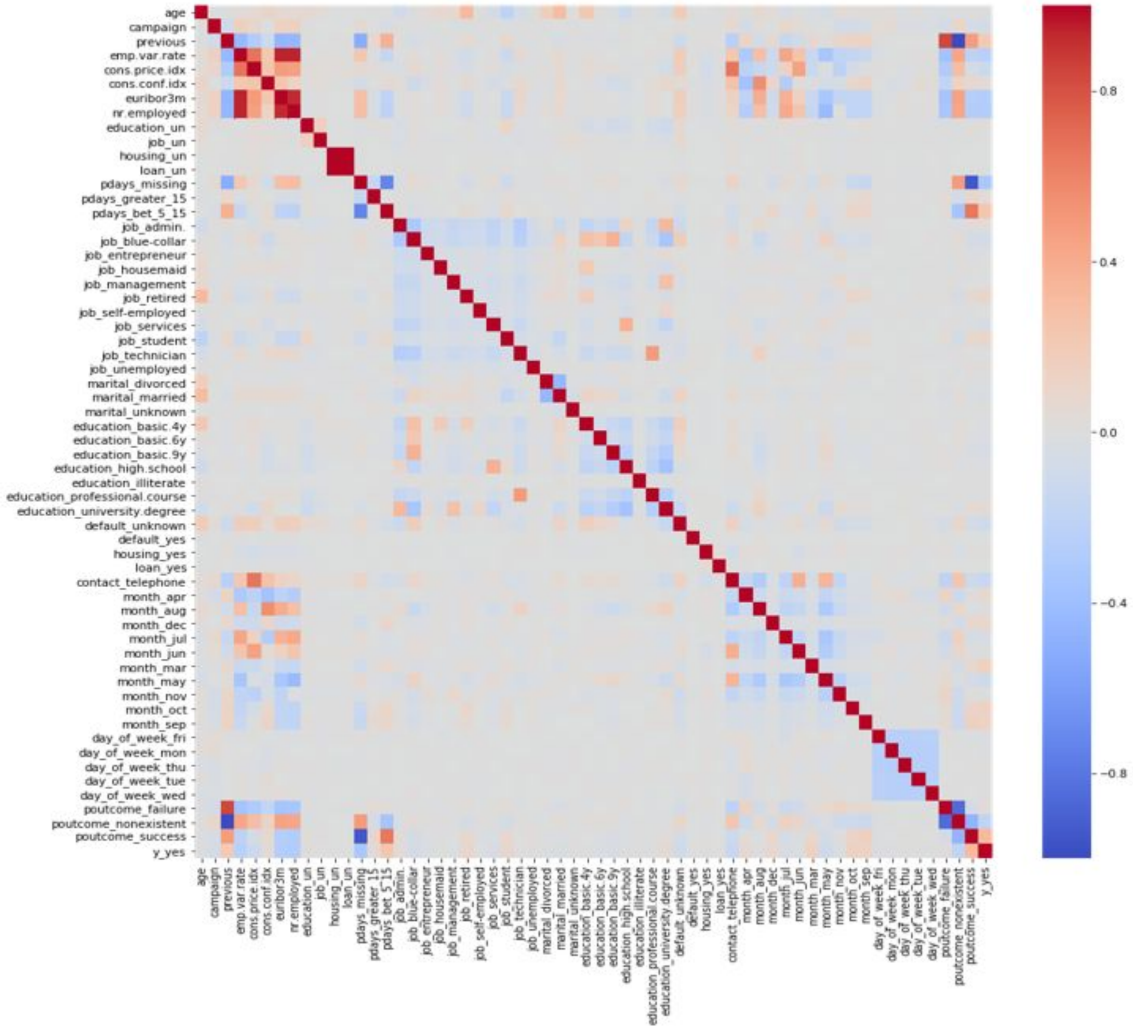
- All coding done in Python 3.
- Extensive use of pandas, numpy, matplotlib, as well as seaborn and sklearn packages.
- Dataset contained 20 different features on more than 41,000 clients.
- Features were both categorical and numerical. Target variable was binary (“Yes” or “No”).
- Pandas package was imported and a dataframe was created.
- Categorical variables were looked at first. Visualizations were created using the seaborn package.



Data Exploration and Preparation (2/2)

- Many features had missing values. How do we handle this?
- For categorical features, imputation using other independent variables. For example, cross-tabulation between 'job' and 'education'; 'age' and 'job'; 'home ownership' and 'loan status.'
- Among numerical features, fortunately only column (‘pdays’) had any missing values. Unfortunately, missing values made up the majority of the column.
- To handle this, ‘pdays’ was converted from a numerical feature to a categorical feature using buckets: < 5 days, 6-15 days, etc.
- Heatmap using seaborn package was created to show us any particularly strong correlations between the independent variables and the target variable outcome.

Correlation Heatmap :



Model Building

Model Building (1/2)

Logistic Regression

- sklearn.linear_model.LogisticRegression
- Its a classification model though name is Logistic regression
- Fits a sigmoid function to a data
- Outputs probability which is in [0,1] range unlike linear models.

Decision Tree

- sklearn.tree.DecisionTreeClassifier
- Simple to understand and effective
- Splits the data at every node based on one feature
- Uses information gain as measure for split

Model Building (2/2)

Random Forest

- Sklearn.ensemble.RandomForestClassifier
- Constructs multiple decision trees and takes the mode of those trees for an example to make the final decision
- Individual Trees are intentionally over fit and validation set is used to optimize the forest level parameters

AdaBoost and Gradient Boosting

- sklearn.ensemble.GradientBoostingClassifier
- sklearn.ensemble.AdaBoostClassifier
- Many decision trees with single split are constructed
- Instance which is hard to classify gets more attention by giving it a larger weight
- Gradient Boosting is generalized version of AdaBoost
- One weak learner is added at a time and existing weak learners remain unchanged

Hyper-Parameter Tuning and Model Evaluation

Hyper-parameter tuning and Model Evaluation

- Used mean AUC of 5 fold cross validation as the metric for evaluation
- Choose the model with highest mean AUC

Model	Hyper-parameters Tuned	Optimal hyper-parameters	Mean AUC
Logistic Regression	C: Regularization Coefficient Type: L1, L2	C = 0.1 L1 Logistic Regression	0.7903
Decisions Trees	Min. Split Value and Min. Leaf Value	Min. Split Value = 1110 Min. Leaf Value = 132	0.7919
Random Forests	Min. Split Value and Min. Leaf Value	Min. Split Value = 189 Min. Leaf Value = 7	0.7979
Gradient Boosted Trees	Min. Split Value and Min. Leaf Value	Min. Split Value = 85 Min. Leaf Value = 37	0.8006
AdaBoost	Number of Estimators	Number of Estimators = 1000	0.8157

Results / Outcome

Best Model and Feature Importance

- Best Model: AdaBoost with 1000 estimators.
- Obtained an AUC of 0.8036 on the test set.
- Below is the Feature Importance Chart for the AdaBoost Model:

Recommendations to the Marketing Team

Significant Variables	Recommendations
Libor Rate, Con.Price.Idx, Con.Conf.Idx	• Collaborate with the economic experts • Be a fast mover, capture customers before the competitors capture them
Age	• Target relatively Old Age people • Convey Peace of mind, Safe investment, steady income source as the value proposition
Duration, Mode of Contact: Telephone	• Try to engage customers and have longer calls • Preferably use Telephone as the mode of contact
Campaign	• Prioritize those customers to who were part of the previous marketing campaigns.

Thank You