



# Analyzing Bank Marketing Campaigns

Miguel Santana

Flatiron School

Data Science | FT Cohort

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# Introduction

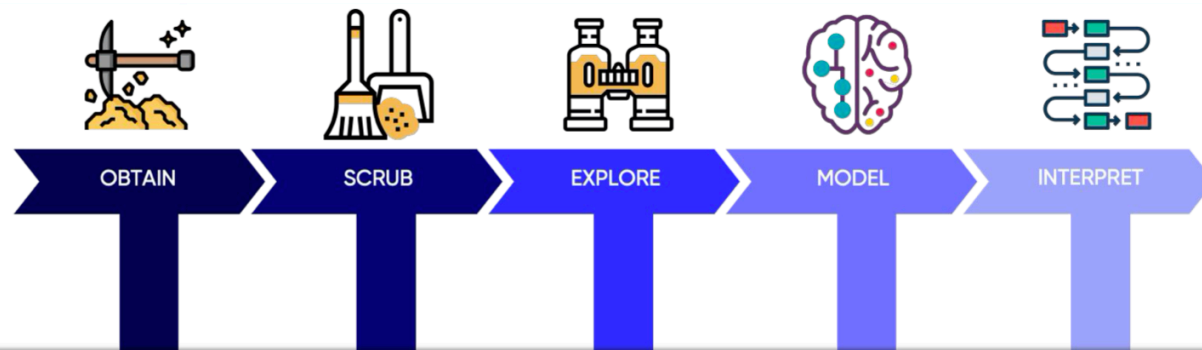
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- Methodology
- OSEMN Framework
- The Data | Cleaning
- Exploratory Data Analysis
- Modeling
- Interpret | Analyze
  - Features: Age & Number of Employees
  - Features: Campaign Contact & Days Since Last Contact
- Business Recommendations
- Conclusions & Limitations
- Future Work
- Thank you

# Methodology

- A Portuguese financial institution provided telemarketing data concerning marketing campaigns with the goal of predicting subscriber term deposits.
- Dataset included client, campaign, social and economic data
- Leveraged OSEMN framework to analyze the dataset and make key business recommendations

## Data Science Process



**O**  
Gather data from  
relevant sources

**S**  
Clean data to formats  
that machine  
understands

**E**  
Find significant patterns  
and trends using  
statistical methods

**M**  
Construct models to  
predict and forecast

**N**  
Put the results into  
good use

Originally by Hilary Mason and Chris Wiggins

## OSEMN Framework

# The Data | Cleaning

Available via UCI's Machine Learning Archive and Kaggle

- <http://archive.ics.uci.edu/ml/datasets/Bank+Marketing#>
- <https://www.kaggle.com/henriqueyamahata/bank-marketing>



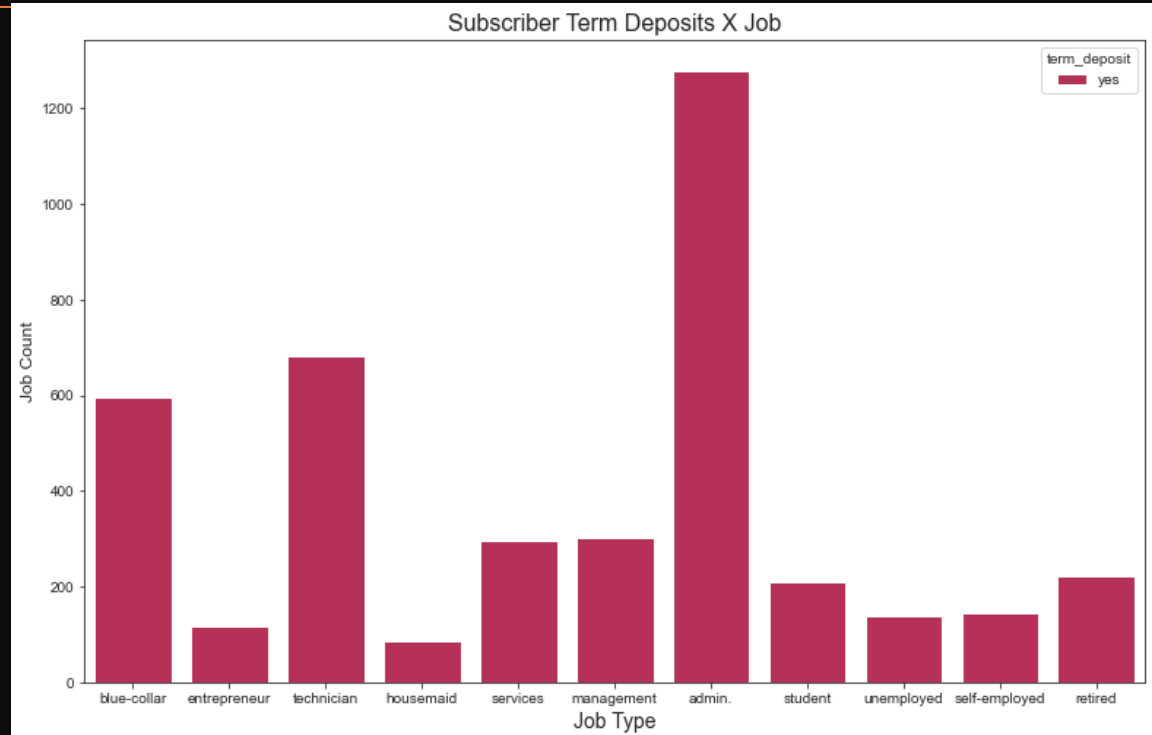
## Cleaning the data

- Addressing "unknown" values
- Focused on consumers who provided customer profile answers
- Removed Outliers
  - Age
- Feature Selection

## EXPLORATORY DATA ANALYSIS

### Most Common Client Features

- Job Type: admin
- Age: early thirties
- Education Level: university degree  
(see appendix for education)



## Modeling

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### Machine Learning Algorithms

- Gradient Boosting Classifier
- AdaBoost Classifier
- Logistic Regression
- Support Vector Machine
- K-Nearest Neighbors
- Random Forest
- Gaussian Naïve Bayes
- Decision Tree

### Accuracy Score

- 90.92%
- 90.70%
- 90.58%
- 90.30%
- 89.92%
- 89.73%
- 88.19%
- 84.47%

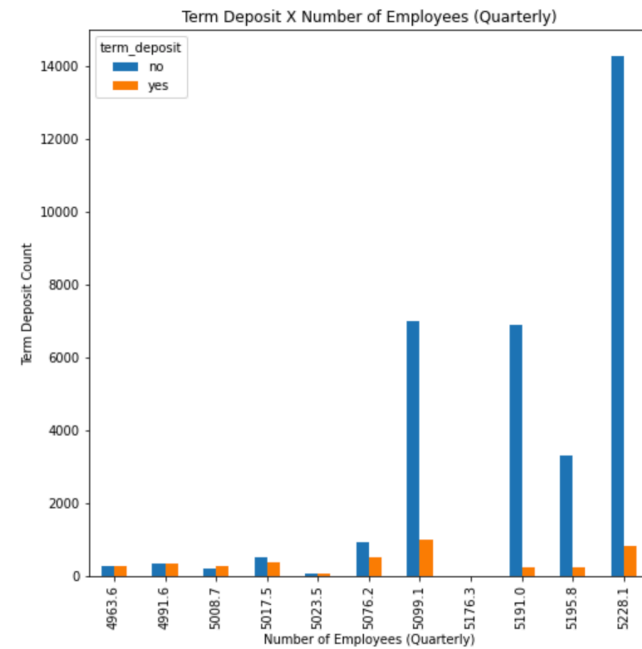
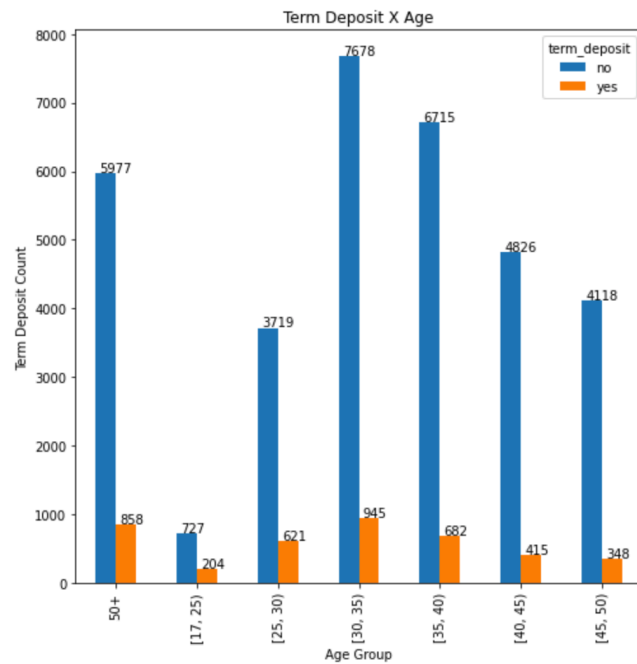
**The top models selected for feature evaluation were Gradient Boosting Classifier and Adaboost Classifier**

## Interpret | Analyze

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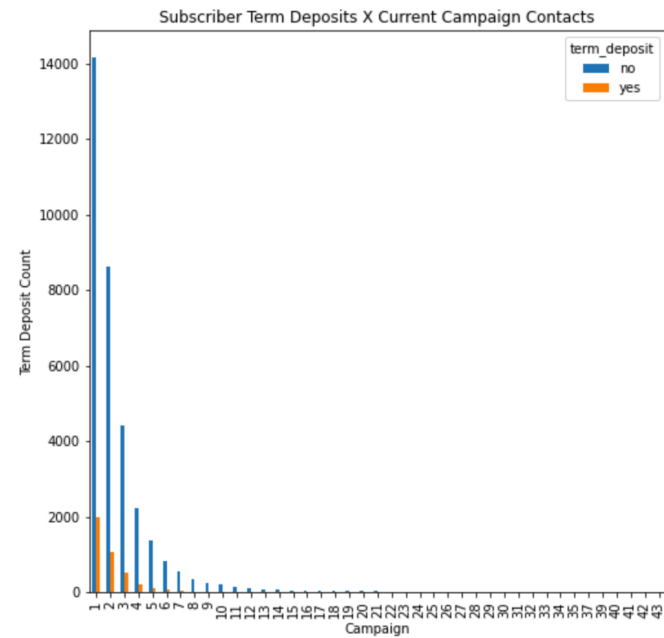
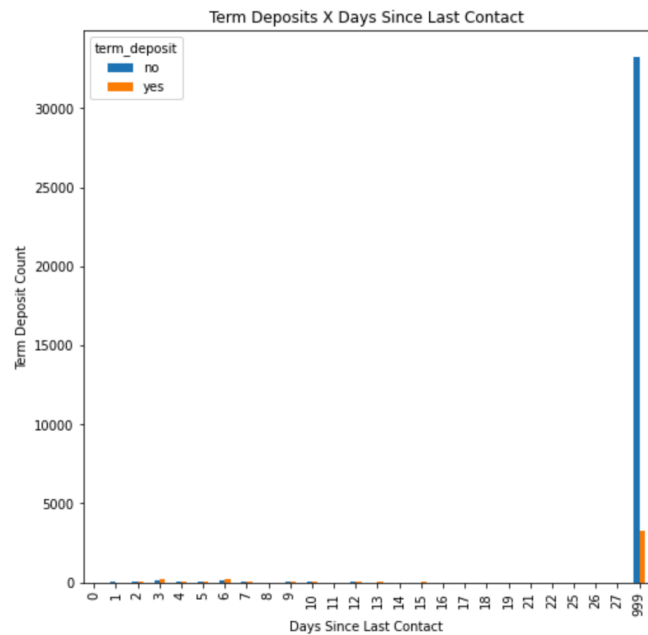
- Generated top 25 features (per model)
- Observed overlap | selected features
- Selected Top Features
  - Age
  - Number of Employees
  - Number of times contacted during the current campaign
  - Number of days since last contact (999 = no contact)





Features: Age & Number of Employees

# Features: Campaign Contact & Days Since Last Contact



# Business Recommendations

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- 1) Observe current marketing on consumers age 17-25. Use similarly structured marketing on consumers age 30-40.
- 2) Maintain an average employee level of 5076 or lower. Focus on productivity when employee levels go over 5076.
- 3) Deploy an A team to handle first 3 telemarketing contacts per customer.
- 4) Deploy B team to handle new callers and first-time bank clients.

# Conclusions & Limitations

## Conclusions

- Feature trends illustrate high subscriber counts but higher non-subscriber counts as volume increases.
- Employee effectiveness decreases as additional employees are hired (over 5076 quarterly) and volume increases.

## Limited to consumers that:

- Cite job type, marital status and education level
- Between the ages of 17 and 69

# Future Work

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- Observe Portuguese cultural customs that may influence the reception of marketing strategies
- Obtain and review additional marketing (non-telemarketing) to identify trends
  - Social Media
  - Internet
  - In office marketing
- Analyze employee performance metrics

# THANK YOU!

Questions? Miguel Santana | contact: [msantana269@gmail.com](mailto:msantana269@gmail.com)

Github Repo: <https://github.com/msantana269/Module-3-Project>



# Appendix

## Appendix: Educational Trends

