Predictive Model on Campaign Impacts

Final Report for DSC148-WI24

Donald Taggart

dtaggart@ucsd.edu

Andrew Peng

apeng@ucsd.edu

**Introduction**

Direct marketing campaigns allow you to target the idea customer by understanding their needs and wants in order to gain customers in the most cost-effective way. However, while this method does result in a much higher customer-response rate, direct marketing and sale campaigns come with very high costs regarding management and administrative overhead. These costs can be reduced if the marketing campaign targets individuals and groups that are much more likely to purchase said product. In this project, we will build a model that will predict an individual’s response to a direct marketing campaign.

# Dataset

**1.1 Identify Dataset**

The dataset used will be data collected from a Portuguese banking institution based through phone calls (bank-full.csv). This **bank** [1] dataset was found on UCI’s machine learning repository and was obtained as a .csv file. The dataset contains 45,211 instances with 16 features as well as a corresponding variable for each instance to denote if the marketing campaign was successful in gaining a new term deposit subscriber. This data ranges from May 2008 to November 2010 and has no missing values.

Columns within the dataset focus on the basic features of each individual contacted (age, job category, marital status, education). It also included a few more in-depth measurements of each individual’s financial status (loan, housing, balance) as well as data summarizing if the individual had been contacted before for a similar campaign and the outcome of said campaign (last contacted, number of contacts, previous outcome).

**1.2 Basic Exploratory Data Analysis**

To gain a better understanding of the individuals who were contacted during the marketing campaign, we explored most of the columns within the dataset.

[INSERT IMAGES HERE AND ADD IN WHAT WAS USEFUL OR IMPACTFUL ABOUT THEM]

**1.3 Findings in EDA**

# Predictive Task

All material on each page should fit within a rectangle of 18 × 23.5 cm (7" × 9.25"), centered on the page, beginning 1.9 cm (0.75") from the top of the page and ending with 2.54 cm (1") from the bottom. The right and left margins should be 1.9 cm (.75"). The text should be in two 8.45 cm (3.33") columns with a .83 cm (.33") gutter.

# Model

## Normal or Body Text

Please use a 9-point Times Roman font, or other Roman font with serifs, as close as possible in appearance to Times Roman in which these guidelines have been set. The goal is to have a 9-point text, as you see here. Please use sans-serif or non-proportional fonts only for special purposes, such as distinguishing source code text. If Times Roman is not available, try the font named Computer Modern Roman. On a Macintosh, use the font named Times. Right margins should be justified, not ragged.

## Title and Authors

The title (Helvetica 18-point bold), authors' names (Helvetica 12-point) and affiliations (Helvetica 10-point) run across the full width of the page – one column wide. We also recommend phone number (Helvetica 10-point) and e-mail address (Helvetica 12-point). See the top of this page for three addresses. If only one address is needed, center all address text. For two addresses, use two centered tabs, and so on. For more than three authors, you may have to improvise.[[1]](#footnote-1)

## First Page Copyright Notice

Please leave 3.81 cm (1.5") of blank text box at the bottom of the left column of the first page for the copyright notice.

## Subsequent Pages

For pages other than the first page, start at the top of the page, and continue in double-column format. The two columns on the last page should be as close to equal length as possible.

Table 1. Table captions should be placed above the table

|  |  |  |  |
| --- | --- | --- | --- |
| **Graphics** | **Top** | **In-between** | **Bottom** |
| Tables | End | Last | First |
| Figures | Good | Similar | Very well |

## References and Citations

Footnotes should be Times New Roman 9-point, and justified to the full width of the column.

Use the “ACM Reference format” for references – that is, a numbered list at the end of the article, ordered alphabetically and formatted accordingly. See examples of some typical reference types, in the new “ACM Reference format”, at the end of this document. Within this template, use the style named *references* for the text. Acceptable abbreviations, for journal names, can be found here: <http://library.caltech.edu/reference/abbreviations/>. Word may try to automatically ‘underline’ hotlinks in your references, the correct style is NO underlining.

The references are also in 9 pt., but that section (see Section 7) is ragged right. References should be published materials accessible to the public. Internal technical reports may be cited only if they are easily accessible (i.e. you can give the address to obtain the report within your citation) and may be obtained by any reader. Proprietary information may not be cited. Private communications should be acknowledged, not referenced (e.g., “[Robertson, personal communication]”).

## Page Numbering, Headers and Footers

Do not include headers, footers or page numbers in your submission. These will be added when the publications are assembled.

# Literature

This dataset has been used by past studies, but mainly in the context of improving algorithmic fairness in machine learning, specifically in clustering algorithms. The following studies collectively highlight the versatility of the dataset and its ease of use by applying it to a range of challenges in machine learning.

However, the main difference between articles citing this dataset and the way we used this dataset lay in the way the dataset was used. Rather than a primary feature, the UCI bank dataset was more of a subsidiary to prove fairness in clustering algorithms. Thus, the state-of-the-art method was more akin to clustering over classification. This is likely due to its clean nature and lack of NaN values, leading to minimal work needed to prepare it for use. Thus, the main novelty of our work is more so regarding the fact that we are using recall as a evaluation metric rather than proving a hypothesis based on a new form of clustering or fairness.

**Clustering with Fairness Constraints: A Flexible and Scalable Approach** **[2]**

https://arxiv.org/pdf/1906.08207v1.pdf

The authors (Ziko, Granger, Yuan, and Ayed) do not intend to predict the outcome variable (term deposit subscription), but instead use the bank dataset as a control to contrast a synthetic dataset in order to demonstrate the effectiveness of their algorithm in handling real-world data with various demographic proportions. The main focus of the dataset is far different from our investigation. Instead of maximizing recall to correctly classify instances of data, the authors were more focused on comparing their method with existing fair-clustering methods to show the advantages of the method they had theorized regarding balancing fairness and clustering objectives.

While we focused on a more general overview (also focusing on past interactions with prior marketing campaigns, these authors constrained their dataset to create two initial clusters based on marital status to test fairness by dividing the data into three equal-sized groups, which was very different from the subset of data we used as we used every instance available.

Similar to one of our baselines, Ziko, Granger, Yuan, and Ayed proposed a clustering algorithm that involved K-means clustering.

**Fair Algorithms for Clustering [3]**

https://proceedings.neurips.cc/paper\_files/paper/2019/file/fc192b0c0d270dbf41870a63a8c76c2f-Paper.pdf

The authors (Bera, Chakrabarty, Flores, and Negahbani) in this article also do not intend to predict the outcome variable. Similar to the previous article, these authors used the UCI bank dataset as a way to focus on metrics to solve the problem of finding low-cost fair clustering methods. This dataset was one of several used to evaluate their algorithm. They focused on fair clustering, ensuring that each cluster had fair representation of different groups in the data. For clustering, the authors employed algorithms based on the lp-norm objective, which includes k-means, k-median, and k-center objectives.

While somewhat similar to the XGBoosting and k-nearest neighbors we tuned parameters for, these authors were less concerned about the performance of the model based on predicting the outcome variable and more concerned about how the model they had created stacked up against additional, state-of-the-art models that were normally used. While these authors ended up focusing more on the k-means objective, our project looked more in-depth into XGBoost. Additionally, we also focused on tuning hyper-parameters to increase the recall of our model while the authors of this article were more concerned with allowing groups to lie in multiple protected groups.

**ToPs: Ensemble Learning with Trees of Predictors [4]**

<https://arxiv.org/pdf/1706.01396.pdf>

This article (Jinsung Yoon, William R. Zame, and Mihaela van der Schaar, Fellow, IEEE) was the most similar to the model that we created. Here, the authors test the difference in two instantiations of ToPs (trees of predictors) that included adaboost, linear regression, logistic regression, logitboost, and random forests. Many of which we used in our baseline and final model. These instantiations allowed them to explore improvement of models, and also allowed them to compare the performance of their models to create a new approach to ensemble learning and prove that their method was better than other casual uses of state-of-the-art-methods in terms.

These authors employed a similar prediction model in predicting for the same y-variable (which allowed for a comprehensive evaluation of the ToPs algorithm’s effectiveness in comparison to other machine learning algorithms in predicting the acceptance of bank marketing offers based on clientele features. However, the main difference regarded on how they used their new approach. Unlike our project (which used recall), the authors here utilized area under the ROC curve as the loss function due to the unbalanced nature of the dataset that we also noticed.

# Result

.

# References

1. Bowman, M.,

1. <https://archive.ics.uci.edu/dataset/222/bank+marketing> [↑](#footnote-ref-1)