Course Number: CSDA 1050

Course Name: Advanced Analytics Capstone

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Assignment Title: A data-driven approach to predict term deposit subscriptions

Group Number: 1

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TABLE OF CONTENTS

EXECUTIVE SUMMARY

KEY BUSINESS OBJECTIVES & FINAL RECOMMENDATIONS

Marketers will agree that direct mail and telephone methods pack a powerful personal punch than more indirect methods of general brand creation and promotion. Our mission is to empower businesses with valuable insights and analytics from the processes and technologies of their current marketing strategies. Our approach is the use of a balanced assortment of techniques that include; filling gaps on useful data by information gathering and data structuring, finding overlooked and valuable insights from historical data, generating live insights on present campaigns, and influencing future initiatives by using advanced and holistic predictive models. Our product, specifically for financial institutions requiring an increase in customer term deposit subscriptions, is an analytical tool focused on improving direct marketing campaigns by telephone. The main objective of this client was to address the need for understanding which potential customer best responds to direct marketing efforts. Machine learning models were built to identify whether a customer would subscribe to a term deposit based on the parameters of a Portuguese banking dataset. The parameters of importance were job, education, duration of the last call and number of contacts performed before this campaign. Using a logistic regression and random forest classifier, we were able to predict with an accuracy of 90% and 91% respectively. Our final recommendations to the client are to improve data acquisition on potential customers for direct contact methods, improve incentives to purchase on the first contact, introduce campaigns to highlight advantages of term deposits to individuals who have a job in administration or have a university degree.

PROJECT PROPOSAL

One of the most personal decisions people make involve their finances. Direct-marketing methods via telephone give consumers time to digest the information and make educated choices. Once an advanced understanding of their current and potential customers is obtained, a personalized direct-telephone campaign can be used to introduce new products or encourage subscription to products previously denied by the customer. The scope of this project is set to make predictions on customer subscription, keeping in mind the limitations of economic stability at the time of data collection and other observations regarding the Portuguese bank dataset. By undergoing this challenge, we aim to:

- Pinpoint important factors that affect a customer's decision to subscribe to a term deposit
- Identify which group of customers is more likely to subscribe to a term deposit
- Reduce phone calls to our customers by our prediction

This will allow us to implement marketing strategies for our client.

METHODOLOGY

PRELIMINARY ANALYSIS, DATA MANIPULATION, DESCRIPTIVE ANALYSIS

The Bank Marketing dataset was obtained from the UCI Machine Learning Repository. This secondary dataset is a repository of 41,188 entries and is related with direct marketing campaigns of a Portuguese banking institution based on phone calls. Often, more than one contact to the same client was required, in order to assess if the bank term deposit would be ('yes') or not ('no') subscribed (Bank Marketing Data Set, n.d.). There are 21 attributes consisting of eleven categorical and ten numeric variables.

Average Customer:

- After duplicate rows were removed from the dataset, Table 1 in the appendix shows that age ranges from 17 to 98 years old. The duration of a call in the sample is anywhere from 0 to 4,918 seconds. An average individual in our sample is a 40-year-old and has a last contact duration of 258 seconds. This customer has been contacted three times during this campaign and the number of contacts performed before this campaign is zero with a consumer price index of $94 monthly.

y:

- Now, we will look at the dataset closely. Figure 1 in the appendix shows a distribution of 89% entries labeled with ‘no’ labeled (0) who did not subscribe, and 11% entries labeled with ‘yes’ labeled (1) who did subscribe.

job:

- In Table 2, a cross tabulation of the target variable ‘y’ with job shows that out of the 11% of the people who subscribed to a term deposit, 29% have an administration job, 16% are employed as a technician and 14% have a blue-collar job.

marital:

- A cross tabulation between ‘y’ and marital yielded that out of the 11% who subscribed to a term deposit 55% were married and 35% of them were single as seen in Table 3.

education:

- We did a cross tabulation of 'y' with education to understand the influence of education on the target variable (Table 4). Out of 11% of the people who did subscribe to a term deposit, 36% had a university degree and 22% had a high school diploma.

default:

- In Table 5, a cross tabulation of the target variable 'y' with default shows that out of the 11% who subscribed for a term deposit, 90% did not have a credit in default.

loan:

- A cross tabulation between 'y' and loan in Table 6 showed that 83% out of the 11% who subscribed to a term deposit did not have a personal loan.

contact:

- As seen in Table 7, 83% of the people who subscribed for a term deposit used a cellular phone.

duration:

- A correlation analysis was performed on the dataset as seen in Table 8 and a positive correlation of 0.4 was obtained with the target variable 'y' and the duration of the call with the client in seconds.
- The mean time of a call for people who subscribed to a term deposit is 553s whereas the mean time for a call for people who did not subscribe is 221s indicating the longer the call the likelier they were to subscribe.

campaign:

- Figure 2 in the appendix shows that about half of the people who subscribed for a term deposit did so after the first contact was made with them.

previous:

- A positive correlation of 0.2 can be seen in Table 8 between the 'y' variable and the variable 'previous' (the number of contacts performed before this campaign and for this client).
- The mean of the variable 'previous' of those who did not subscribed for a term deposit is 0.132 whereas the mean number for those who subscribed to a term deposit is 0.493. This leads us to believe the higher the number of contacts performed before this campaign and with a client, the likelier they will subscribe for a term deposit.

poutcome:

- It can be seen in Table 9 out of the 11% who subscribed to a term deposit, 68% are new clients and 19% were successful in the previous marketing campaign.

The variables emp.var.rate, cons.price.idx, cons.conf.idx, euribor3m and nr.employed had strong correlations with our target variable 'y' as seen in Table 8 and we deem them important for analysis. The variables housing, month, day_of_week and pdays were removed from the analysis. The remaining variables age, job, marital, education, default, loan, contact, duration, campaign, previous, poutcome, emp.var.rate, cons.price.idx, cons.conf.idx, euribor3m and nr.employed will be used in our Logistic Regression and Random Forest Classifier models to predict if people will subscribe to a term deposit.

MODEL BUILDING AND EVALUATION

Logistic Regression:

- To understand model performance, we divided the dataset into a 90% training set and a 10% test set while maintaining the ratio indicated in Figure 1 of if the client subscribed or did not subscribed to a term deposit.
- The bank marketing dataset contains attributes such as age, job, marital (inputs) which are independent variables in our modeling and y (the output) is the dependent variable that is separated into a binary class – 'no' or 'yes' if the client subscribed for a term deposit. In logistic regression we predict a category, if a client purchased a term deposit, 'no' or 'yes'. To implement the regression model, we ensure that the dataset is divided into 'no' or 'yes' setting the target variable in this dichotomous manner.
- To interpret the metrics using our prediction case on y for example, when our logistic regression model predicted 'y is going to be 'no' (0)', it is accurate 93% of the time, 'yes' (1) is predicted with 69% precision. In Recall, if the client didn't subscribe to a term deposit - 'no' (0) in the test set our logistic regression model can identify it 98% of the time; if the client did subscribe - 'yes' (1) is predicted 40% of the time. The final percentage (weighted average) of right prediction for if a client subscribed or did not subscribe as seen in Table 10 is 90%.

Random Forest Classifier:

- We next implement the Random Forest Algorithm which is great with a large dataset with higher dimensionality and handles unbalanced data. Random forest tries to minimize the overall error rate, so when we have an unbalanced dataset, the larger class will get a low error rate while the smaller class will have a larger error rate (Kho, 2019). In our random forest classifier, we again split the dataset into 90% training and 10% testing. For greater accuracy, the random_state parameter which controls the randomness of the bootstrapping of the samples used when building trees and the sampling of the features to consider when looking for the best split at each node was set to 0 (3.2.4.3.1. sklearn.ensemble.RandomForestClassifier, n.d.). The number of trees (n_estimators) was set to 200 since if there are more trees it will not allow overfitting trees in the model.
- The Random Forest Classifier generates a weighted average value as seen in Table 11 that tells us how the model performed. In our prediction case for 'y' for example, when our Random Forest model predicted 'y is going to be 'no' (0)', it is accurate 94% of the time, 'yes' (1) is predicted with 63% precision. In Recall, if there is 'y' that is 'no' in our test set our Random Forest model can identify it 96% of the time; 'yes' is predicted 52% of the time. The final percentage (weighted average) of right prediction for 'y' is 91%.

INSIGHTS AND SUMMARIZING RESULTS

Our data exploration has shown that job, marital, education, default and loan are the main factors influencing if someone subscribes to a term deposit. The group of customers who are married and have administrative or technician job with a university degree or a high school diploma with no credit in default and no personal loan are likely to subscribe to a term deposit. Additionally, about 50% of the customers did not purchase the deposit in the first contact and people have a higher chance of subscribing if the call lasts longer so it might be difficult to reduce phone calls. Obtaining customer's demographic information in advance before the phone call would help to target customers and improve subscriptions. These are the market strategies which should be of high priority.

Regarding the metric of accuracy, the two models are similar with 90-91% accuracy in identifying people who will subscribe no or yes to a term deposit. Since we are not interested particularly in identifying individuals who do not subscribe to a term deposit, this metric is not as valuable. The metrics of precision and especially recall are most useful since we could focus on the 'yes'

subscription predictions. Given that the Random Forest Classifier has the highest recall value of 52% and a precision of 63%, it is the favored model to employ going forward. In addition, we will work towards improving our Random Forest model so that it could predict 'yes' subscriptions with even more precision than 63%, and if there are 'yes' subscriptions we hope to identify them more than 52% of the time.

Our focus on this project was on people who subscribed to a term deposit, but useful information can also be gathered from those who did not subscribe to a term deposit. Marketers can use this to find reasons of decline and if they are other products, they would be interested in. A limitation of this project is the amount of deposit each customer subscribed is not known. This could result in bias in our conclusion. For example, the amount of deposit purchased by the recommended population could be lower than the amount of deposit purchased by the remaining group of customers. Acquiring relevant data would be a challenge for us.

CONCLUSION

The ability to predict individuals who will subscribe to a term deposit would be of interest to those companies which require this criterion to identify target recipients. This model can be employed by the financial institution bank, our primary stakeholder which will help to increase their net revenue. Market Executives may wish to utilize this model to carefully craft the marketing campaign to meet bank targets. Customer Service Team will play an important part in activating and delivering the marketing campaign. This model has proven successful in its ability to predict potential customers. The model of choice will be deployed with usage of a user-friendly application for the analysts and marketing team to stream static data into the app, conduct standard analysis on the client demographics, and make educated predictions of whether a future campaign will be successful on that individual. Maintenance of the model would be undertaken monthly to validate the performance of the model. After a new campaign has being completed, the data in the attributes will change therefore we will need to update our model.

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APPENDIX

	age	duration	campaign	pdays	previous	emp. var. rate	cons. price. idx	cons. conf. idx	euribor 3m	nr. employed
count	41164	41164	41164	41164	41164	41164	41164	41164	41164	41164
mean	40	258	3	962	0	0	94	-41	4	5167
std	10	259	3	187	0	2	1	5	2	72
min	17	0	1	0	0	-3	92	-51	1	4964
25%	32	102	1	999	0	-2	93	-43	1	5099
50%	38	180	2	999	0	1	94	-42	5	5191
75%	47	319	3	999	0	1	94	-36	5	5228
max	98	4918	56	999	7	1	95	-27	5	5228

Table 1: Statistical information on numerical attributes after duplicate entries were removed

job	admin.	blue-collar	entrepreneur	housemaid	management	retired	self-employed	services	student	technician	unemployed	unknown
y												
no	24.82	23.58	3.65	2.61	7.11	3.51	3.48	9.97	1.64	16.44	2.38	0.8
yes	29.11	13.76	2.67	2.29	7.07	9.36	3.21	6.96	5.93	15.74	3.10	0.8

Table 2: Cross tabulation of the 'y' target variable with job

marital	divorced	married	single	unknown
y				
no	11.32	61.28	27.21	0.19
yes	10.26	54.55	34.93	0.26

Table 3: Cross tabulation of the 'y' target variable with marital

education	basic. 4y	basic. 6y	basic. 9y	high. school	illiterate	professional. course	university. degree	unknown
y								
no	10.26	5.75	15.25	23.21	0.04	12.71	28.72	4.05
yes	9.23	4.05	10.20	22.23	0.09	12.83	35.96	5.41

Table 4: Cross tabulation of the 'y' target variable with education

default	no	unknown	yes
y			
no	77.67	22.32	0.01
yes	90.45	9.55	0.00

Table 5: Cross tabulation of the 'y' target variable with default

loan	no	unknown	yes
y			
no	82.35	2.42	15.24
yes	82.97	2.31	14.73

Table 6: Cross tabulation of the 'y' target variable with loan

contact	cellular	telephone
y		
no	60.98	39.02
yes	83.03	16.97

Table 7: Cross tabulation of the 'y' target variable with contact

	y
age	0.03
job	0.03
marital	0.05
education	0.06
default	-0.1
loan	-0.005
contact	-0.1
duration	0.4
campaign	-0.07
previous	0.2
poutcome	0.1
emp.var.rate	-0.3
cons.price.idx	-0.1
cons.conf.idx	0.05
euribor3m	-0.3
nr.employed	-0.4
y	1

Table 8: Correlation of all the variables with the target variable

poutcome	failure	nonexistent	success
y			
no	9.98	88.70	1.31
yes	13.04	67.68	19.28

Table 9: Cross tabulation of the 'y' target variable with poutcome

	precision	recall	f1-score	support
0	0.93	0.98	0.95	3644
1	0.69	0.40	0.50	473
accuracy			0.91	4117
macro avg	0.81	0.69	0.73	4117
weighted avg	0.90	0.91	0.90	4117

Table 10: Prediction table for if a client subscribed or did not subscribe to a term deposit using logistic regression

	precision	recall	f1-score	support
0	0.94	0.96	0.95	3665
1	0.63	0.52	0.57	452
accuracy			0.91	4117
macro avg	0.78	0.74	0.76	4117
weighted avg	0.91	0.91	0.91	4117

Table 11: Prediction table for if a client subscribed or did not subscribe to a term deposit using random forest classifier

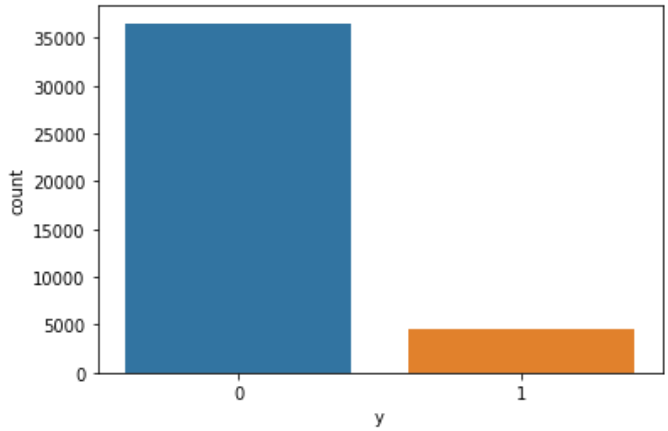

Figure 1: y categories, 0 & 1 for 'no' or 'yes' respectively

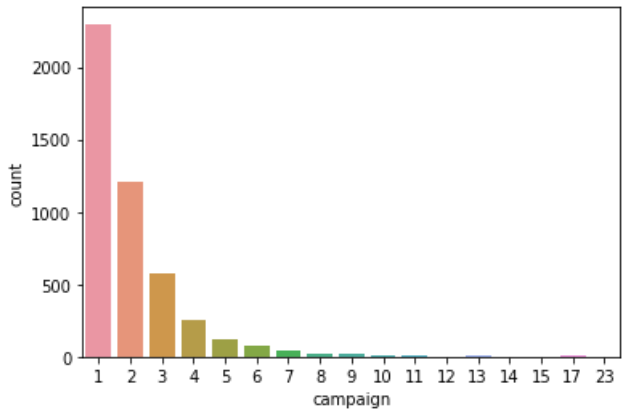

Figure 2: Count for the target variable 'y' when the outcome is 'yes' with campaign