Term Deposit Customers

How to Identify, and target them

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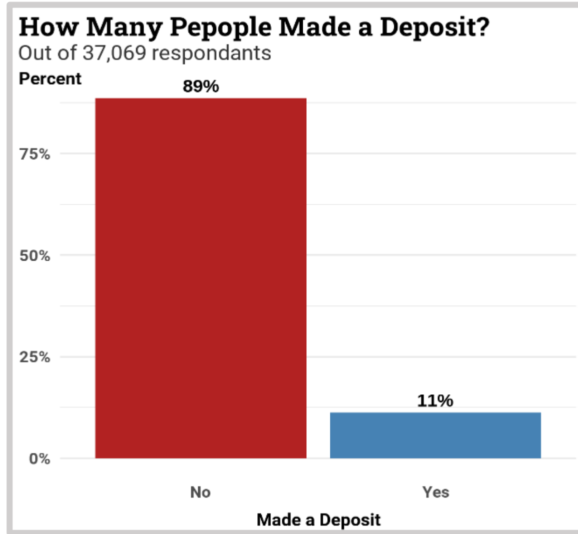
I. Amount of People That Deposited After our Marketing Campaigns

Given that we have a decent sized dataset with much of our previous marketing campaigns' data, we can use mathematics to model the different attributes that make a customer more likely to make term deposits into our bank.

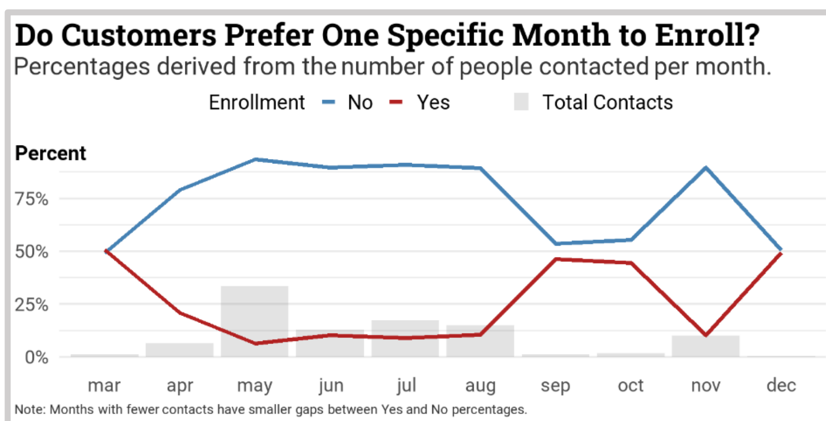
This dataset has around 37,000 rows, each representing a customer and many aspects of the time when we recorded his information, including on wether they made a term deposit or not. Around 11% of the people in our dataset made a deposit after our marketing campaigns. We can use their information to see what characteristics made them more prominent to deposit or not.



II. Success in Customer Reach per Month

We see some patterns when exploring the data. Take a look below at the percentage of respondents that deposited each month. Notice how some months have higher "Yes" counts than others. The fact that some months appear to have more succes than others is more related to the imbalance in the sampling methods month vs month.

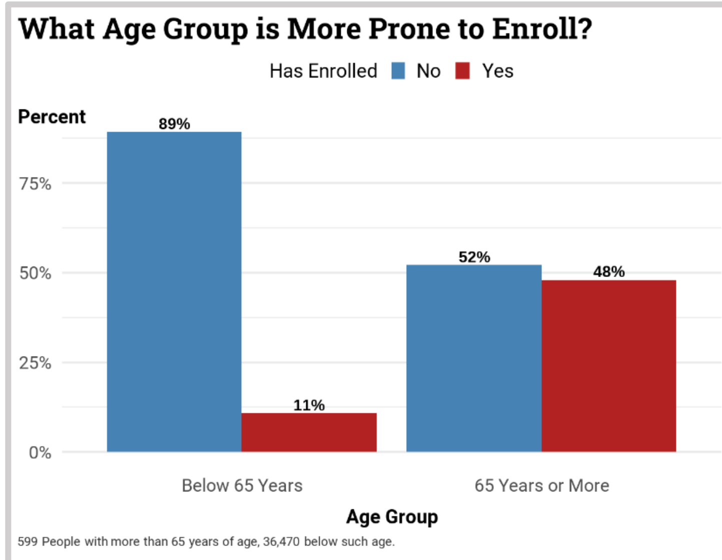
So the apparent success of March September October and December is not so much because those are the best months to get clients but that because we contacted less people in those months the percentages vary less.



III. Success in Customer Reach per Age

The same pattern is apparent when we checking age groups and comparing them. We see imbalance in the amount of people that deposit in our bank accounts vs those that don't for different age groups.

This is common in the data of our marketing campaigns for samples that are relatively smaller in size. For example we only have around 600 people that are 65 years or older, and almost 50% of them enrolled in the term deposits.



IV. How to Tackle the Imbalance Problem

The imbalance in our target group shows to be a problem, this because we are trying to know the characteristics of a client that succesfully deposits for a term but only few people have done that as per our records in this data set. So we have less people to get characteristics from. We can however make adjust for this situation by giving more weight to those observations that we are tragetting even when they are the minority class in this dataset.

After testing and moving we went forward with a XGBoost classifier model, what this means is that the algorithm we are using will consider facts such as the economic state of the time period, the sex, age, income and more features of the people in our marketing campaign to classify those who are more likely to deposit in our bank. We can check the results with a confusion matrix as seen below and get and F-1 score, where:

$$\textbf{F1-Score} = \frac{\text{Precission x Recall}}{\text{Presicion } + \text{ Recall}}$$

All an F-1 score is, is a metric that balances both precision (proportion of true positives of the classified positives) and recall (proportion of true positives out of all actual positives). It is often used in classification tasks to measure overall performance when class distributions are uneven.

$$\textbf{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$\textbf{Presicion} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

We trained our model in 80% of the dataset and tested it vs the remainder. The results of our table is seen below:

F1-Score	**True Positive**	**True Negative**
Predicted Positives	514	561
Predicted Negatives	372	5967

$$\text{F1-Score} = \mathbf{.52}$$

V. Final Conclusion

From this model we can trust that when the algorithm classifies one reccord as a possible customer for term deposits, 52% of the times it will be correct. This is significantly better than just guessing given the fact that if we planily guessed, we would only have a 11% chance of accurately guessing because we can assume that 11% of the people in our marketing campaigns are actually interested in making a deposit with us.

VI. Links to Work Notebooks and Predictions:

- Work Notebooks Link
- Predictions: