# Predicting Response of Sales Phone Calls for a Bank's Sales Team

FINAL REPORT
Gabe Gibitz

Our current client is a bank with a sales team that is making thousands of cold calls. They have been keeping very good data, and they want to know whether or not a person will accept the offer being extended to them by their team.

## 1. Problem Statement

We are estimating that we can predict with at least **85% accuracy** whether or not a person will accept the offer of a loan over the phone.

## 2. Context

If you ask most sales professionals, they don't begin their sales career enjoying cold calls. Although these tactics have proven effective, time is wasted on the sea of "no's" these sales teams receive.

What if, from easily accessible information, we are able to accurately predict whether or not the prospect was going to say yes? This could **save time and money** by prioritizing these calls first. This information could also **increase the overall morale** of this organization's sales teams.

## 3. Our Approach

We have gathered nearly 40,000 interactions of sales personnel with potential clients. We will:

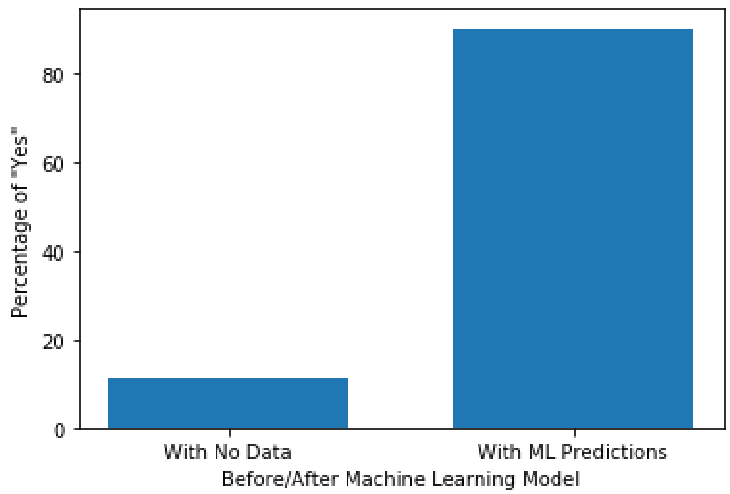
- Clean up any unfinished listings
- Delete the 'Duration' column because there is no way for us to know how long a call will be before our sales team makes the call.
- Split the list into a set (75%) to train our machine learning model and 25% to test
- Run this data through four classic classification models to predict if the potential client is more apt to say yes.

This will allow us to filter the next set of 40,000+ records through our model to give us our “A List” of people to call first. They have a much better chance of saying “Yes” to our team when offered a loan.

## 4. Our Findings

With nearly two dozen features (observable characteristics of the data) and 40,000 entries, it can be difficult to find commonalities across the potential clients who say “Yes” to our sales team. This, however, is simple for a machine learning algorithm.

**A DIRECT COMPARISON**
To the right is a chart of what predictions look like before and after running our data through machine learning algorithms.




Let’s look at this a bit more closely.

If we were to randomly call potential clients on this 40,000-name list, we have a 11.1% chance of someone saying “Yes.”

We pulled this number simply by dividing the number of people who said “Yes” by the total number of people in our list. The actual numbers turned out to be:

4,258 [Yes] / (4,258 [Yes] + 33,983 [No]) = 11.1%

From our modeling stage, our best machine learning model predicted whether a potential client on the other end of the phone would say “Yes” with an 89.5% accuracy. These would be the names where our team should invest the greatest effort first.

## 5. Recommendations & Further Research

With this shortened list, we are increasing our likelihood of a phone call being a “Yes” by more than 800%.

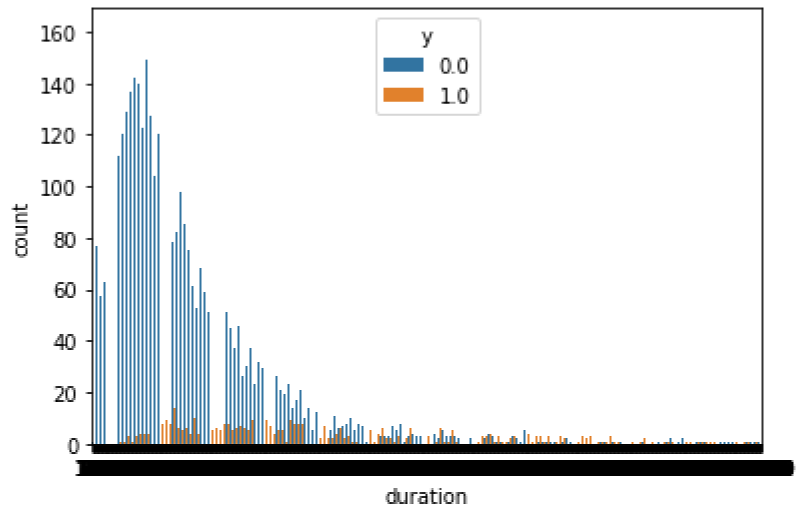
*This is a significant boost in effectiveness with our model.*

With this in mind, I also must remind all of us that no model is perfect. In fact, no model is even correct. This is simply a helpful way to prioritize our call list. I would recommend continuing to call the entire list with a prioritization on the predicted “Yes’s” from our current model.

Let’s turn our attention to points for further research.

We found a few intriguing pieces of data in our research that I want to bring to your attention. These peaked my interest, but they were outside the scope of this project.

**First, let’s look at duration**.



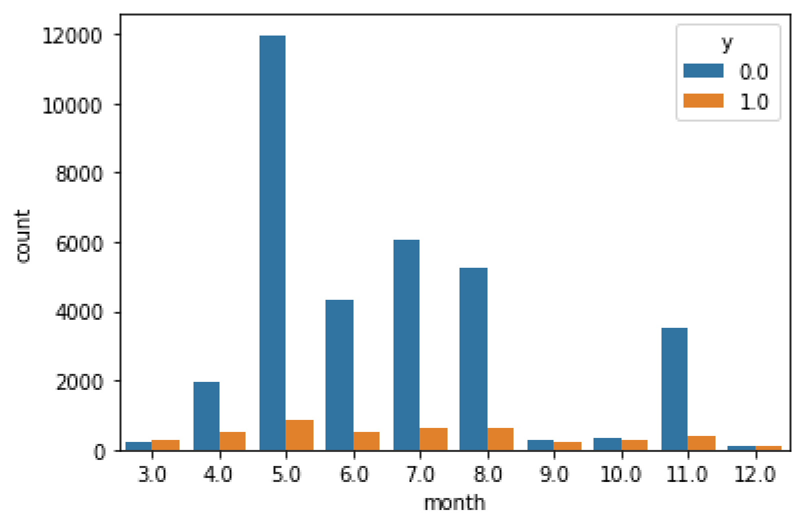

If you remember, we took this characteristic out of our final model because we don’t know the duration of a call before we place the call.

Therefore, we can’t predict a “Yes” before a call is placed.

However, the results to the right are intriguing. The “No’s” in blue follow an understandable curve. Many of them hang up quickly, resulting in a short duration.

However, the longer the potential client stayed on the phone, the more of a chance they had of saying “Yes.” Our sales team could include this in future sales training.

**Second, we found a significant spike in the ratio of “No” in blue and “Yes” in orange** in May (5.0), September (9.0), October (10.0) and December (12.0).

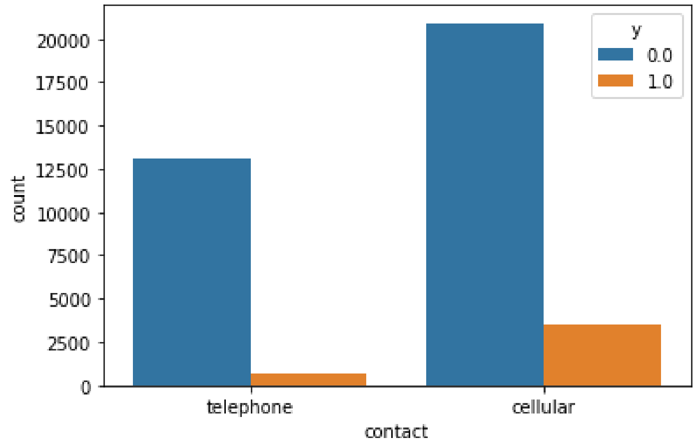



The month of May was skewed towards “No’s” and the remainder of the months above were skewed towards “Yes’s.”

I’d recommend these months be analyzed to see what could have gone wrong (May) or right (Sept., Oct. and Dec.)

**Finally, the amount of people who said “Yes” approved of a loan on a cell phone.**

Digging into this could shed light on living habits or some other characteristics that could be insightful moving forward with other sales campaigns in the coming years.




# 5. Conclusions

We went into this study with a goal of predicting a “Yes” from potential clients with an 85% confidence rate.

We came out of this study with a prediction rate of 89.4%. Applying our model to the next set of contacts should prove very useful for the sales team moving forward with an 800% increase in predicting that a potential client says “Yes” to a new loan.

We would love to work with you again on future projects in 2021!

Sincerely,
Gabe Gibitz