Direct Mailing Marketing Predictive Analysis

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Executive Summary

Our company used to direct mail potential customers for new product promotion. Despite its relatively higher purchase rate, compared to digital promotion channels, direct mailing may cost much more for its delivery fees. Finding a way to maintain the high purchase rate while lowering the cost has always been an essential focus of the company.

To achieve this goal, our team has developed a predictive model which can predict whether a customer will respond to the mailings or not. We built a logistic regression to determine 1) the number of mailings being sent out 2) which customer should receive the mailings, according to specific requirements.

Based on the model's outcome, we have identified 1,679 target customers, which are more likely to respond to the mailings, out of 5,022 customers who we should send the mailings to. This strategy can save the company $1,194,300 in total.

Business Objective

Historically, direct mailing had been the dominant new customer acquisition channel. Despite digital marketing channels becoming popular over the past decade because of its lower cost and quicker access to the responses, the power of direct mailing in acquiring new customers is still very important. Compared to digital marketing, direct mailing has a stronger emotional impact, reaches people in all age groups, and creates greater awareness from a longer lifespan. Therefore, our company, a retail bank, keeps using direct mail as the first in a series of marketing impressions.

A key challenge of direct mailing campaigns is the cost. The price of sending mailings to the wrong audience is much higher than the price of using digital channels. To gain new customers of customer credit, one of a newly developed product, the sales team of our company has sent incentive mailings to people randomly selected from our customer database, encouraging them to apply for the new credit card. Two waves of mailings were sent, and each one is to 30,000 people. Even though the $900 average revenue generated by each responder is a satisfied result, the 5% response rate is far below the expectation. Therefore, the business objective of our project is to increase the effectiveness of direct mail campaigns by targeting the right people while generating additional revenue.

Key Actionable Business Initiative

One business initiative we've considered is A/B testing. Since the response rate from the two waves of incentive mailing did not meet the expectation, we would like to know if the offer we provided is a bad one and if we reached out to the right person at the right time. Without insights into the messaging, audience, and timing, it is difficult to increase the ROI of the campaign. However, we didn't go this way because running an experiment takes time. As far as we know, several competitors are planning to launch similar customer credit products, and therefore, we need to acquire new customers as soon as we can.

The other business initiative is to use big data analysis to ease the pain of targeting the wrong audience. With the right data, we will know precisely how customers engage with our bank and their spending behaviors, so the company can locate the right targets using the predictive model. We chose this plan over A/B testing because it is more impactful in terms of efficiency and cost-saving. Our execution plan includes: 1) evaluate all the model options, 2) select the relevant data and conduct feature engineering, 3) train the model on the 60,000 customers from the previous direct mail campaigns, 4) balance the model's number of positives predicted and True Positive by adjusting the threshold to meet the revenue target, and 5) apply the model on the rest customers referenced in the database and locate the targets for the next campaign.

Metrics of Success

The effectiveness of a direct mail campaign can be measured by revenue and cost - how much additional revenue will be generated by acquiring new customers and how much money needs to be paid for the unit price of the mailingl. Correspondingly, the success metric, in other words, the improvement of the direct mail effectiveness, can be measured by response rate and cost saved.

Role of Analytics

We as analysts leveraged statistics, data mining and programming techniques and utilized customer's past behaviors to predict their future activities. The most valuable thing we achieved via predictive analytics is precision. We saved our company time and budget to target the right people and generate additional revenue. Below is the summary table comparing our solution with the previous campaign. The success metrics are highlighted.

	Previous Campaign	Our Solution
# of Mails	60,000	5,022
# of Responders	2,994	1,679
Revenue/Responder	$900	$900
Total Revenue	$2,694,600	$1,500,300
Response Rate	5%	**33%**
Cost Saved		**85%**

Table 1. Metrics of Success

Note: The cost saved is standardized by assuming we apply the solution to the previous campaign to get the same revenue.

Thinking through the Analytics

Data Preparation

We are cooperating with several departments to gain available data that can be used for our analysis. In total, we have five datasets containing information regarding customer basic information, demographic information, mailings data indicating whether a customer has purchased the product, and transactions records of all customers. Our team decided to use the transaction record within three months prior to sending out the mails, since they can better represent customer’s loyalty and attitude towards the company.

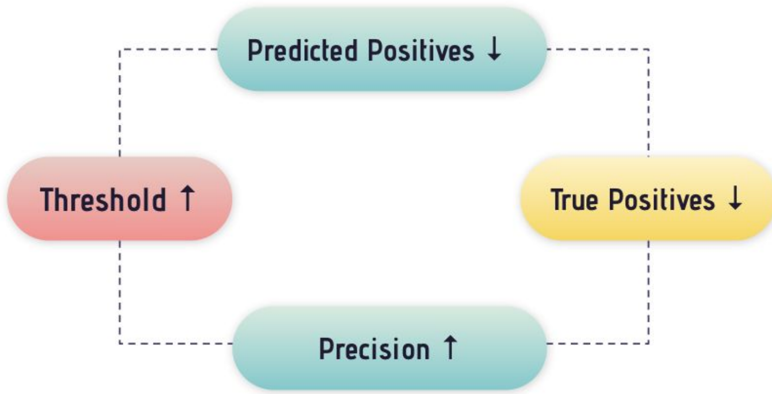
After data preprocessing, our final dataset contains 33 independent variables, which includes 27 numeric variables and 6 categorical variables. Our dependent variable is a binary variable which indicates whether a customer will purchase the product after receiving the mail.

Modeling

Considering the model will be used for various purposes, our team has constructed a pipeline to determine which customers should we target to send the mails based on specific demands, such as how much profit will be generated through this mailing campaign.

We chose logistic regression since it can return probability, so we can control the threshold, and therefore control the number of true positives. It is more suitable and flexible than the tree models in this case.

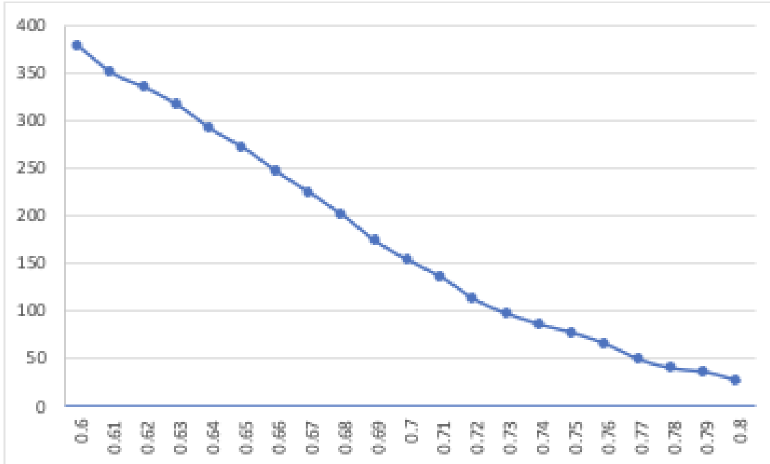
Threshold Selection



Pic 1. Threshold Selection

We selected the threshold according to how many true positives we are aiming at in the end. As we observed, when the threshold increases, both the number of positives predicted and the number of true positives decrease. What we want is an appropriate threshold that balances these two numbers. The best threshold can help us get at least 1,667 customers who will truly respond to the mail. At the same time, the number of positives predicted should be as small as possible so that the company would control the cost of sending those marketing mailings.

As our goal is to reach out to 1,667 positive responses from 300,000 customers in the targeted dataset, which is 0.56%. We assumed that true positives of the targeted dataset and the test dataset, whose size is 18,000, were similar. Thus we needed to reach out to 100 (18,000*0.56%) positive-response customers in the test dataset. We plotted the changes of the number of TP in the test dataset against the threshold of probability. It shows when the threshold is 0.73, the number of TP is the closest to 100. So 0.73 is the threshold we wanted.



Pic 2. True Positives vs. Thresholds

Model Results

We implemented the model in the targeted test dataset. The result showed that AUC is 0.68, the number of positives predicted is 5,022, and precision is 33.4%. Eventually we got 1,679 true positives.

In conclusion, instead of randomly sending the mailings to 33,400 customers to get 1,667 positive responses, by using our model, the company can get a similar positive response by only sending mailings to 5,022 customers in the test dataset.

Executing the Analytics

To successfully execute our analytics solution, we need to collaborate with many departments. First, we will frequently communicate with the marketing department to see what success metrics make the most sense for them. To involve these people, we need to show the detailed data of many metrics and explain how they changed before. What's more important, we will explain why defining a success metric can help them ease their work and prove they do a great job; Second, we need approval from the management / strategy team to implement and experiment; Third, data engineers from the IT department will help collect the data and ensure data quality; Last, we and the marketing department are going to be responsible for executing the analytics solution together; we need to make sure they understand our analytics and recommendations, and we can get a buy-in from them.

There are a lot of potential impediments: the data engineers might need to create a new data pipeline to collect the underlying data and the aggregated success metric we want, so we need to make sure it is easy for them; the leadership or the marketing department might not buy-in our model. We need an easy-to-follow and compelling story about how our predictive analysis will help the company to get support from the upper-level managers who can understand the importance of data-oriented strategies.

Implementing the Analytics

There are two recommendations for the company according to our analysis. One is that the company should test the marketing strategy on a sample of customers, use stats and machine learning models to find out the best way to implement it, and then roll out to all the customers.

The other one is that, based on our analysis, the model without transaction data has very little predictive power. So transaction data is very important for predicting customers behavior or response in the future. The company should leverage transaction data when doing other predictive analytics.

To implement these two recommendations, we need to show our mailings predictive results to the stakeholders, so they can trust us to do more testing on marketing strategies. Also, we need to communicate more with the sales department and build a bridge between us and sales, so we can have both access to the transaction data and a deeper knowledge of these data.

Scaling Up

We will keep improving the business initiative with predictive analytics. However, there are two organizational challenges that might limit our success of scaling up. One of them is that we need transaction data to build a model with great predictive power, but some customers might be new customers to all products from our bank and there is no transaction data of them, which might make the predictive analytics a little tricky. What we can do is to inform stakeholders in the company and make them understand we can only do high-quality predictive analytics on customers who have transactions, so we can lower their expectations a little bit, and they won't expect predictive analytics on new customers from outside.

The other challenge is that we need sample customers to collect the data of how they respond to the marketing strategies, but sometimes the company might not want to wait so long to settle the marketing strategies. There are two methods to address this challenge. We can cut the testing time from two months to one month or even two weeks, so we can change the marketing strategies very quickly. Besides, when we have many sample customers and different models to know what segments of customers will have what kinds of behaviors or responses. We can directly apply the results from the previous testing or models to know which customers have higher possibilities to respond to the marketing strategies.