## Vision and Arguments

It would do us some good to research what exactly a term deposit is and how a company makes money from it. We find that people are more likely to purchase term deposits during periods of high interest rates which is the opposite of what’s happening with the market right now. If people are less likely to purchase term deposits when interests rates are low, it is even more important for us to reach out to customers before interest rates have increased. It is equally important for us to consult with stakeholders to understand the impact of changing market conditions on term deposit sales and how fast we can expect to observe the impacts.

Since the bank is constrained by a $50K budget for this campaign (or 6,557 customers assuming a cost of $8 per customer call), a model that prioritizes leads based on their likelihood to convert would maximize campaign spend. Since we’re interested in identifying a bounded subset of the population that will maximize the conversion rate (better than random) and we’d ideally like to tune the model to accept more false positives if costs are marginal, we can use a ROC curve. Since we need a score to compare multiple models in the modelling process, we can use AUC which can be interpreted as the probability that a randomly chosen positive instance will be ranked ahead of a randomly chosen negative instance.

Model performance evaluation using an optimization objective like AUC is not enough, however - we need to measure the lift and a financial impact of a model to better determine if we should go through the effort of developing and deploying it. So we need to measure the net gain (profit) of the subset that the model chose to target which requires some estimation of costs and benefits.

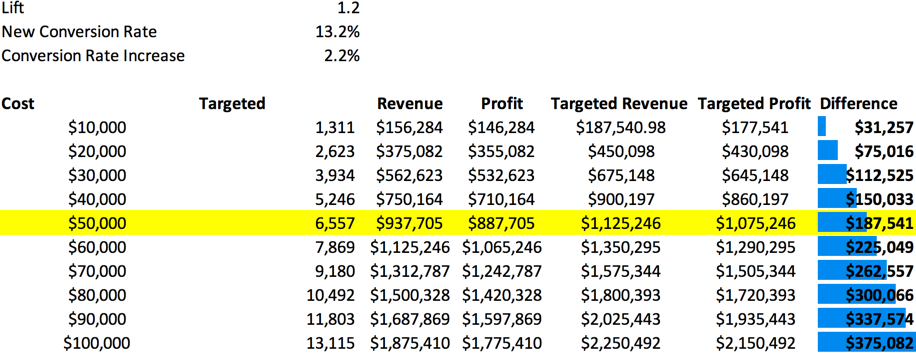
Using employee hourly costs and the estimated length of sales calls, we come up with an average call cost. Observing three different groups of deposit sizes, we calculate an unweighted average revenue. Finally, we perform a sensitivity analysis at various levels of model lift (improvement over baseline). Even at 1.2x lift (20% improvement) at the $50K budget, the bank is poised to earn over an additional $30K.

Luckily, the development and marketing team has already executed a pilot campaign and has created a dataset of the results which attributes of targeted customers which including customer, customer relationship, and socioeconomic attributes. Before we use the data to develop a machine learning model, we discuss with bank stakeholders what they feel is the best indicator to predict conversion. It turns out that a customer who has responded to a previous marketing bank campaign is likely to convert in the next one so that will be our baseline model. Ideally, we would use customer lifetime value estimates to build an additional baseline model but this data is not available. We’ll judge the success of additional modelling efforts to be the improvement over the existing conversion model.

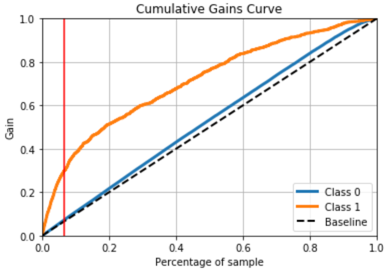
After performing a brief exploratory analysis of the pilot campaign dataset, we found that there were several attributes that are predictive of conversion in the current marketing campaign. Sticking with the idea of doing the simplest thing that could possibly work we’ll use the attributes as is, with some preprocessing so that they are compatible with machine learning models. If the initial model we produce is insufficient or we have time to experiment with additional features then we will do so in a controlled experiment.

A successful model will identify a subset of customers to target for which the conversion rate will be higher than the conversion rate of the entire population (11%) and will minimize the number of false positives so as to reduce campaign costs. Since our test set contains 8,238 customers and our target population contains 100,000 customers, we’ll keep the targeted group in the test set proportional to the 6,557 customers (6.6%) that we can afford to target in a full-scale deployment. With a test set size of 8,238, this works out to 543 targeted customers.

Using the bank’s pilot campaign dataset, we found that the last campaign prior to it achieved a 25% conversion rate which is more than double the current conversion rate of 11%. In a fuller treatment of the problem, we could construct a Bayesian model that uses the prior conversion rate and the pilot conversion rate (evidence) to compute a posterior estimation of the true conversion rate. Assuming we can achieve between an 11% and 25% conversion rate, the following chart shows that even with a moderate increase the current campaign conversion rate by 20% (to 13.2%), the bank is positioned to earn additional $187K in profit under the $50K marketing budget.



By simply choosing to target customers who converted in the last campaign and choosing customers at random when we run out of customers who previously converted, we found that we could improve the conversion rate by 250% (to 39%). While this is an impressive improvement, we found that a machine learning model performs even better at a lift of 354% (to 51%). As shown below, the model identifies 30% of campaign respondents in the top 6.6% of the population, ranked by probability to convert.



The classifier’s precision is fairly low at 51%, meaning that 49% of the targeted instances are false positives and won’t convert even though they were predicted to do so. Given the large profit margin of contacting a customer by phone, as estimated by our costs and benefits, we can accept the low precision.

