UGBA 167: Marketing Analytics, Spring 2023
Cell2Cell Churn Management

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1 Introduction

This case required us to develop a model for predicting customer churn at "Cell2Cell," a fictitious wireless telecom company and use insights from the model to develop an incentive plan for enticing would-be churners to remain with Cell2Cell.

1.1 The Data

The data for the case is a scaled-down version of a full database generously donated by an anonymous wireless telephone company. There are 71,047 customers in the database, and over 65 potential predictors.

The data consists of 71,047 customers divided into calibration and validation sub-samples. The calibration data contain 40,000 customers, 20,000 of whom churn. The validation data contain 31,047 customers, 609 of whom churn.

The 50% churn rate in the calibration data is not realistic, but the "oversampling" of churners makes it easier to identify the profile of churners as distinct from the profile of non-churners by our models. The validation data contain roughly 2% churners, which is the current monthly churn rate at Cell2Cell.

In our calibration data, our labels are under the `churndep` variable. This is a binary label, indicating whether a customer churned or not. However, the dependent variable for the validation data is under the `churn` variable.

1.2 The Models

In this course, we used a specifically designed Python module called `mba263` for all of our models, which was designed for the graduate version of this course. This package is built off of the `statsmodel` module, inheriting all of the model properties with some alterations.

2 Churn Model Overview

2.1 Developing Our Model

For our predictive model, we chose Logistic Regression (logit) as this was a binary classification problem. Additionally, since we needed to see which features contributed the most to churn likelihood, we chose logistic regression as we could use odds ratios to determine the most important features we needed to address.

2.2 Cleaning the Data

We started by first partitioning our data into calibration and validation datasets. We then dropped rows with NaN values from both to ensure there would be no problems when developing our model.

2.3 Selecting Significant Variables

After we cleaned and partitioned our data, we created an initial logit model for the calibration data for feature selection. We used all variables to predict `churndep` and calculated each variable's odds ratio. Once we had all of our odds ratios, we filtered out variables that had p-values greater than

0.05. The remaining variables were used for our validation data logit model. The remaining variables are shown below:

	Odds ratios	std err	z	P>|z|	[0.025	0.975]
revenue	1.002028	0.000778	2.605858	0.009	1.000518	1.003539
mou	0.999794	0.000040	5.155842	0.000	0.999717	0.999872
recchrge	0.996746	0.000867	3.751430	0.000	0.995063	0.998429
overage	1.000748	0.000273	2.740770	0.006	1.000219	1.001278
roam	1.007515	0.002075	3.620837	0.000	1.003488	1.011541
changem	0.999488	0.000053	9.644100	0.000	0.999385	0.999591
changer	1.002328	0.000369	6.304969	0.000	1.001611	1.003044
unansvce	1.001212	0.000409	2.959440	0.003	1.000417	1.002006
custcare	0.994638	0.002489	2.154250	0.031	0.989808	0.999467
threeway	0.980656	0.010632	1.819508	0.069	0.960030	1.001281
incalls	0.998188	0.000845	2.143791	0.032	0.996548	0.999828
peakvce	0.999683	0.000196	1.612370	0.107	0.999302	1.000064
months	0.978629	0.001868	11.437477	0.000	0.975004	0.982254
uniqsubs	1.203820	0.023988	8.496779	0.000	1.157283	1.250356
actvsubs	0.811331	0.022568	8.359876	0.000	0.767548	0.855114
phones	1.056273	0.013462	4.180254	0.000	1.030158	1.082389
eqpdays	1.001433	0.000073	19.715186	0.000	1.001292	1.001574
age1	0.996107	0.000667	5.833665	0.000	0.994812	0.997401
children	1.083012	0.028021	2.962529	0.003	1.028652	1.137372
credita	0.845829	0.029850	5.164873	0.000	0.787920	0.903738
creditaa	0.702221	0.024116	12.347915	0.000	0.655436	0.749005
refurb	1.264295	0.040038	6.601080	0.000	1.186621	1.341969
webcap	0.852429	0.031900	4.625974	0.000	0.790542	0.914316
marryun	1.072678	0.030266	2.401329	0.016	1.013962	1.131394
newcelly	0.931861	0.024671	2.761958	0.006	0.884000	0.979722
income	0.993205	0.004573	1.485738	0.137	0.984333	1.002077
setprcm	0.899284	0.036136	2.787172	0.005	0.829181	0.969387
setprc	1.000585	0.000282	2.076106	0.038	1.000038	1.001132
retcall	2.097080	0.120985	9.067882	0.000	1.862368	2.331791

Figure 1: All of the variables that had a p-value less than 0.05

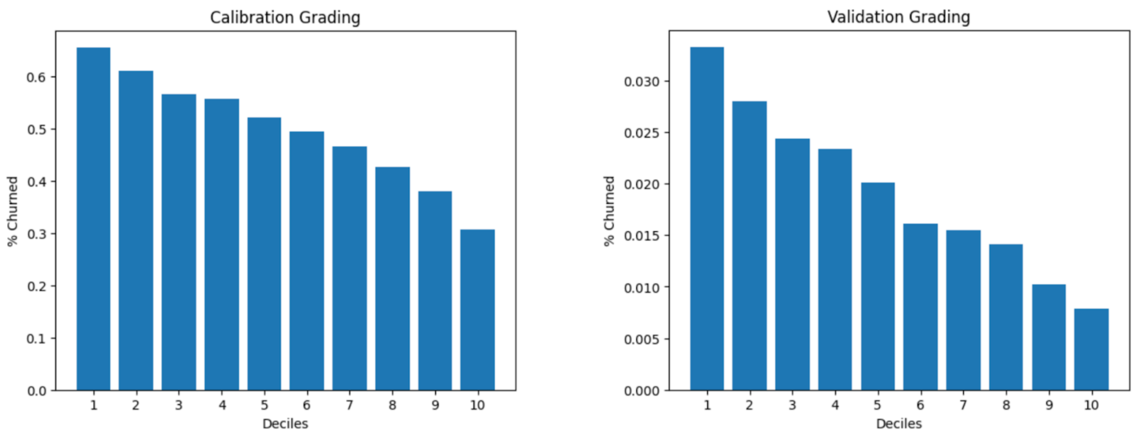
2.4 Developing the Model and using N-tile

Once we had all of our significant, we created another logit model based on our calibration data. This model would be used on the validation data to predict customer churn.

Once our model was built, we used it on our validation data and got the predicted probabilities of all 31,047 customers churning. From here, we used N-tile to sort the customers into 10 deciles based on churning probability. Customers in decile 1 had the highest probability of churning whereas customers in decile 10 had the lowest churn probability.

3 Predictive Performance

Once customers were sorted into their respective deciles based on the model's predicted churn rates, we evaluated our overall model's performance by looking at the actual churn rates per decile for our calibration and validation data:



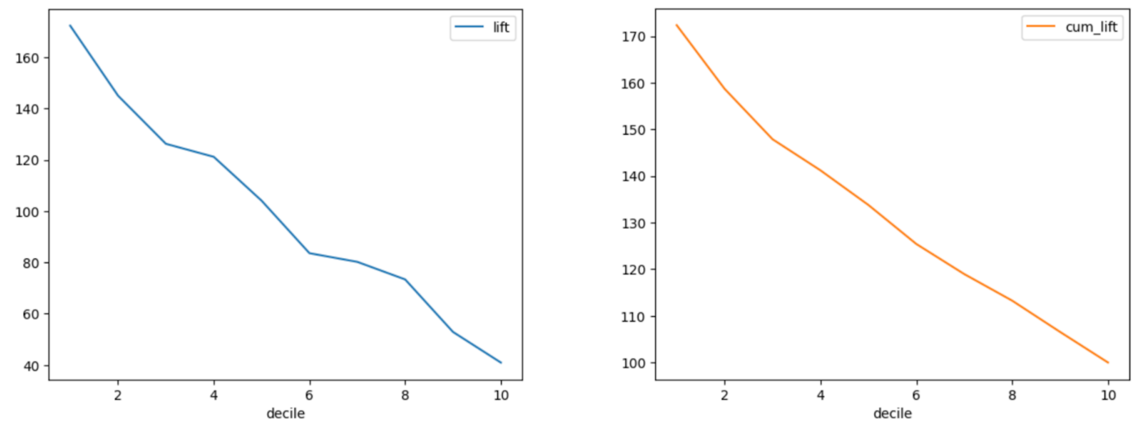
(a) Calibration Data (b) Validation Data

Figure 2: Percentage of Customers Churned by Decile

We can see that our churn percentages are decreasing for each decile, meaning that our model is performing relatively well, making correct predictions at which customers churn.

Next, we evaluated the lift of our model to quantify how much better our model performs in mitigating churn as opposed to random customer targeting:

From our lift charts, we can also see a decreasing trend, further suggesting that our model was performing relatively well. Overall, we attained a lift of 172.34, meaning that our model would mitigate churn 1.72 times better by targeting customers with higher likelihoods of churn as opposed to random targeting.



(a) Lift per Decile (b) Cumulative Lift

Figure 3: Percentage of Customers Churned by Decile

4 Developing a Retention Plan

4.1 Identifying Key Predictors

Once we identified that our predictive model was performing well, we used the model's variables and a normalized version of their odds ratio. We normalized the odds ratios as each ratio has a different scale and variability amount and some have different sign coefficients. The Normalized Odds Ratios were calculated as:

$$\text{Normalized Odds Ratio} = \text{Odds Ratio of Variable}^{\text{SD of Variable}}$$

If after normalization, the odds ratio were < 1, we calculated its inverse, doing $\frac{1}{\text{Normalized Odds Ratio}}$. Once we normalized our ratios, we ordered them in descending order and selected the top five variables.

4.2 Key Predictors

The variables selected were:

- `eqpdays`: This variable represents the number of days the current equipment has been owned by the customer. This variable may predict churn as customers with older phones are more likely to want a newer phone model. When upgrading phones, many customers consider switching cell phone providers while they're at it based on the current prices and benefits that competing companies provide at the time.
- `months` This variable represents the number of months a customer has had cell2cell services. This factor may predict churn as customers who have been with cell2cell for shorter periods are more likely to churn as they can change to another provider who offers them an enticing joining plan. As a result, this variable is important because we can contact clients and provide them with enticing offers to stay with us before a competitor does.

- `uniqsubs` uniqsubs is the "number of unique subscribers", which tells us the number of individuals listed with the account. This factor makes sense as the more subscribers an account has, the less likely they are to churn because the client has to go through the trouble of making everyone in the phone plan change providers. For example, we can see that the max value for uniqsubs is 196. If this account wanted to change providers, they would have to make all 196 users within those accounts change providers, which is a lot of friction for the customer. We would want to focus our attention on customers that have fewer unique subscribers by creating offers that incentivize them to include more unique subscribers in their plans.
- `actvsubs` actvsubs represents the number of active subscribers that are listed in one plan. This factor is an important measurement because inactive customers are more likely to churn if they are paying for a service that they no longer need. Therefore, it is important to develop marketing strategies to increase subscriber activities.
- `changem` changem represents the percent change in cell phone minutes used by the customer. This makes sense as an important factor as customers who are decreasing their usage may realize they have less of a need for cell phone services and therefore churn. Additionally, decreased usage may be a sign of a customer's dissatisfaction with cell2cell's services, as they are relying on it less. As a result, it will be important to target incentives toward customers who are beginning to decrease their minutes before there is too large of a decrease or they churn altogether.

4.3 Incentive Plans

After determining which variables contributed the most to the likelihood of churn, we devised three incentive plans to potentially mitigate churn:

- Providing an Upgrading Discount:
  - Near the end of a customer's contract, if they have stayed with cell2cell for over a year (`months > 12`) and they have had their equipment for over a year and a half (`eqpdays > 547`), we can provide discounts or promotions for upgrading to a new device. We would give a higher discount the more expensive the phone, up to a $200. By offering the upgrading incentive, customers with older devices are more likely to purchase newer devices and stay with Cell2Cell. This would target the `eqpdays` variable as it was one of our highest predictors of churn, which would help increase the length of stay for customers, and also target the `months` variable, which was also deemed a strong predictor of churn.
  - Additionally, while not a strong predictor for churn using variable ranking, the variable `refurb` showed a relatively monotonically decreasing relationship in decile grading, with the 1st decile having the highest probability of refurbished devices. Proposing an upgrading discount offer would also reduce the impact of the `refurb` variable towards churn. Although costs are associated with subsidizing upgraded equipment for customers, this would produce a net positive cash flow because the additional revenue from keeping a customer for longer would outweigh the costs. Especially if Cell2Cell were to keep customers in contracts, the revenue from extending a contract for another year or two would be higher than the costs for the incentive.
- Family or Group Discounts
  - We could offer discounted rates for adding additional lines to customers with only 1-2 individuals on their plan, discounting by $5 per additional line, with a cap at a $15

discount. This would get our yearly incentive cost per customer to be between \$60 and \$180. By offering group discounted rates, we can encourage long-term usage (increasing customer lifetime value) and loyalty among multiple customers.

  - This incentive would target `uniqsubs` and `actvsubs` variables as it would encourage existing accounts with lower unique and active subscribers to add additional people to their plans. Adding more people to their plans may make it harder for them to switch providers, hence the decrease in likelihood of churn. It would also encourage some `uniqsubs` who aren't `actvsubs` to be `actvsubs`, which had a smaller odds ratio than `uniqsubs`, meaning that `actvsubs` are less likely to churn than `uniqsubs`.

- Offering Lower Tiered Plans
  - We would suggest lowering a customer's plan to a lower tier if we observe they have a significant number of unused minutes or are decreasing their usage over time. We could then offer a rebate for the unused minutes the customer had left over, at a rate of \$1 per minute used, capping at \$200 off towards their next phone bill.
  - Offering to switch customers to a lower plan would reduce the likelihood that customers are unsatisfied with their plans, as they're less likely to be paying for more than they need. This would incentivize them to stay instead of canceling or switching to a new provider, even if they have less of a need for the services. This would target the `changem` variable as it would decrease the churn rate of customers with a negative percent change in minutes used. Furthermore, this would generate a net positive cash flow as it would provide additional revenue from customers staying for longer at no additional cost.

4.4 Evaluating Incentive Plans

One way that we can validate our implementations is that we could test our plan on different regions and see its effects. For instance, we would test our incentive plans in relatively similar counties in California, such as Alameda County (treatment group) and Orange County (control group). We would then track customer retention, churn, and revenue of each plan in Alameda County and compare them to Orange County. If we see an increase in customer retention and revenue and a decrease in churn rate in Alameda County compared to Orange County, we would know that our incentive plans are effective.

- Among our three plans, we would choose the offers that provide the largest increase in marginal revenue and the largest decrease in churn within the budget for incentive plans.

Another way we could measure our implementations is by measuring each offer group in one region, where we randomly select 20% of the qualified customers to be in our treatment group and the rest in the control group. We would then monitor their churn, revenue and retention rate. Like the first test plan, we then conclude the effectiveness of our plan based on our results. In addition, we could also calculate the lifetime value of a customer and we will set this to one year. If the lifetime value increases in our treatment group as compared to the control group, our plan is successful and we should implement it on all qualified customers.