Customer Centric Retention in Retail Banking

Retain your most valuable customers with AI Driven Data Science & Machine Learning

ABSTRACT

Learn how Retail Banks can Prevent Deposit Attrition and Stop Revenue Leakage, without huge investments in technology and resources.

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The easiest way to grow revenue is to keep your existing customers happy. It can cost up to five times as much to acquire a new customer, as it does to retain an existing one. Nurturing your existing customers, yields far better sales results with a success rate of 60-70% selling to existing customers compared to 5-20% selling to a new customer.

On average, US companies lose $136.8 billion per year due to churn - and it's avoidable. AMEX found that 33% of customers consider changing providers after even one instance of bad customer service. Getting something wrong not only hurts you, but it sends your customers to your opposition.

Financial Institution's must avoid losing existing customers while acquiring new ones. To make their portfolio profitable, banks should prioritize retaining their most valued customers. For these banks need to adopt a customer centric retention strategy based on data driven decisions and insights. The strategy should include proactive measures, next best actions in real time and early warning indicators required to protect potential churn and uplift customer experience.

This paper discusses how iTuring AutoML+ (Fully Automated Data Science Machine Learning Platform) and iTuring MLOps (Machine Learning Dev Ops) can help banks prevent deposit attrition and stop revenue leakage, without huge investments in technology and resources.

INTRODUCTION

To tackle the growing competition within retail banking, it is key that banks enhance customer experience and making banking simple, intuitive and easy. Financial institutions need to be on their toes to have an edge over competitors from new age digital banks and FinTech's. Improving customer experience and winning the trust and loyalty of customers is critical. But most banks fail to retain customers. Customer attrition can be identified based on their behaviors, movements and activities. There are typical patterns and trends that indicate customer churn, such as reducing transaction activities, raising complaints and finally closing their accounts, while some customer behaviors are hidden. There are two types of churn or attrition:

1. Soft attrition: Customer doesn't have any transaction activity for a period of time or steady decrease in level of activity or balance depletion over length of time are defined as inactivity or soft attrition.
2. Hard Attrition: Customer closes some or all account relationship with the bank. Further, we define hard attrition in two parts: Complete closure and partial closure. Customers end their entire relationship with bank and close all accounts is defined as complete hard attrition. When customer closes one account, but still maintains banking relationship along with other activities is defined as partial attrition.

There are many challenges that banks face in implementing effective retention strategies.

- First, banks need to build a single customer view and connects the dots between their client's account information, profiles, transaction data, product data, psychographic and life stage information, etc. They need to stitch the databases together and create features at customer level.
- Second, the bank needs to build an accurate predictive score and enable machine learning algorithms to self-learn and predict customer attrition behavior in real time.
- And last, the financial institutions need to intensify campaigns to deliver more efficient, customer focused, innovative offerings that are needed to reconnect with their customers.

To achieve this **iTuring** offers customer centric and personalized recommendations, early warning indicators and accurate predictive scores on likelihood of attrition.

ANALYTICAL OBJECTIVE

There are 4 top line analytical objectives for a bank to use CI's iTuring product to solve the problem of customer attrition:

1. Identify Causes of Attrition - Understand what the trigger event (inflection point) is, or which factors drives attrition for the single or multi service DDA customers.
2. Identifying Risky Customers - Develop an attrition machine learning algorithm that measures the propensity to attrite at customer level using above factors.
3. Contact Strategy formulation - Calculate and segment risky customers based on their relationship using attrition score thereby enabling development of contact strategies.

4. Best Next Action - The system would then enable the bank to use “event” based NBAs (Next Best Action) targeted at reducing customer attrition by applying timely and appropriate action.

iTuring enables banks to identify customers who are at risk of attrition for the identified product and undertake proactive retention measures in real time. The system also helps bank to write policies and business rule to build a sound retention strategy to identify and retain their high valued customers who are most likely to attrite in next few months on priority basis.

iTuring can process transaction, demographic, life stage, third party data and classify them into two windows- observation and performance window. It also allows users to keep latest data for external model evaluation.

MODELING POPULATION

Consider the entire list of customers that have one or more active accounts and have made at least one transaction at the observation point. The modeling population is grouped out of the customers who have opened their accounts before observation window. The system automatically splits the data into various sample modeling population, as well as into Training and Testing data sets. Additionally, it enables you to decide the split of the data into training and testing. It is recommended that you check the event rate/incidence rate if you are doing the split yourself vs. relying on iTuring’s automated capabilities. If you find incidence rate is low, it means your data is suffering from imbalance and fitting any model will not result in a good prediction and accuracy. To overcome imbalance problem, there are multiple sampling techniques like over-sampling, under-sampling, SMOTE etc to improve incidence rate and build a good model, these plus many more techniques are embedded and automated in iTuring.

Let us walk you through the analytical approach and steps that a leading retail bank in Canada used to predict attrition for their DDA product. They had a revenue leakage problem as a lot of high value customers were withdrawing their balances very soon after opening their accounts. The below content details their approach and the results they achieved with iTuring’s predictive models.

TARGET DEFINITION

As a primary step, you need to define attrition. In this case we defined customers who have made less than 3 transactions and have an average balance less than $200 in last 3 months, as attritors. In the performance window we defined attritors and non-attritors based on the above events and considered the previous three months data for creating features for regressing predictive models.

DATA MINING & DATA PREPARATION

Data mining and preparation are the most important tasks for building a machine learning model. In retail banking, data exists in multiple tables like customer, account, transaction, product, etc. You need to stitch and create a single view of the customer to measure behavior. Once you connect all the dots between multiple datasets and create a consolidated view of account and customer then you need to go about creating features which can help you identify behavioral pattern or early warning indicators of customer attrition. You need to create thousands of features to measure hidden behavior and pattern of customers who likely to churn. Some examples are:

- transaction activities
- channel utilization
- payment pattern
- payment preference
- customer credit and debit behavior
- discretionary and non-discretionary payment
- recurring debit and credit
- balance depletion
- increase and decrease in customer transaction behavior
- decline in POS transaction
- ATM withdrawal, ACH transaction, etc.

The data preparation tasks include table, record, and attribute selection as well as transformation and elimination of data for modelling which can be performed multiple times, in no prescribed order.

Below are the Model Results and Key Attrition Predictors for the DDA Attrition Model

- **Increase in ATM withdrawal Transaction Volume** - Customer's ATM transaction has increased in the last 3 months
- **Decline in ACH Credit Transactions Volume** - Accounts who's last 3-month average credit transactions made through ACH have decreased by >10% over that of prior 3 months average shows greater signs of attrition
- **Decline in Branch visit** - Customers who's last 3-month branch visit has drastically decreased are showing greater signs of attrition
- **Decline in POS (Point of Sale) Transactions Volume** - Accounts who's last 3-month average spend at POS has decreased by >10% over that of prior 3 months average
- **Decline in online transactions** - Accounts who's last 1-month average online transaction has decreased over 3 months have higher propensity to attrite

ATTRITION MODELING RESULTS AND PREDICTIVE SCORE EVALUATION

iTuring automatically develops thousands of machine learning models and performs champion vs challenger analysis and recommends the best-in-class model. The system has the ability to automatically measure model's performance using novel techniques like discrimination and calibration methods and evaluates against out-of-time datasets to make sure the model's predictive score holds effectively in real scenarios.

Discrimination measures how much the system can discriminate between cases with gold standard '1' and gold standard '0'. Calibration measures how close the estimates are to a "real" probability.

For the DDA Attrition case, iTuring recommended the Stochastic Gradient Boosting model has outperformed over other ML models to predict customers who are likely to attrite or become inactive.

Below are the key performance measures of attrition modeling results and predictive score evaluation:

The model correctly classified customers as attritors and non-attritors with 83% accuracy on development data set, 84% on validation dataset and 84% on an external dataset in out of time window.

The external dataset is untouched data for a data scientist, this is the window where a data scientist scores and evaluates the authenticity of his/her model in out of time. The model helps classify customers as attritor or non-attitor based on predictive score and cross classifies how much customers have been correctly classified into the right buckets.

There are multiple methods and key statistics to measure the accuracy of predictive models and scores. The predictive power of scores has been evaluated in three different steps:

- Overall model performance
- Discrimination based accuracy
- Calibration based accuracy.

The authenticity of predictive model depends on how well your model is classifying target as a target and non-target as non-target.

Figure 1: Performance measurement

Performance Measure	Development	Validation	External Validation
Overall			
True Negative Rate	82.74%	83.32%	83.73%
True Positive Rate	92.30%	92.03%	91.91%
Classification Accuracy	83.11%	83.68%	84.10%
Discrimination			
Discriminant Slope	0.2562	0.2555	0.2567
Area Under Curve	0.944	0.941	0.943
Gini Coefficient	0.889	0.883	0.886
Calibration			
Brier Score	2.72%	2.86%	3.11%

Discrimination Method to test Model Authenticity:

Area under the curve and Gini coefficient measure discrimination, i.e., the ability of the model to correctly classify attrition and non-attrition events. The accuracy of the model depends on how well the model separates the attritors and non-attritors. In this case, the model's area under the curve (Figure 1., 2.) is 94.46% on development, 94.15% on Validation and 94.32% on External dataset which shows the model performance is excellent. An area of 100% represents a perfect model; an area of 50% represents a worthless model.

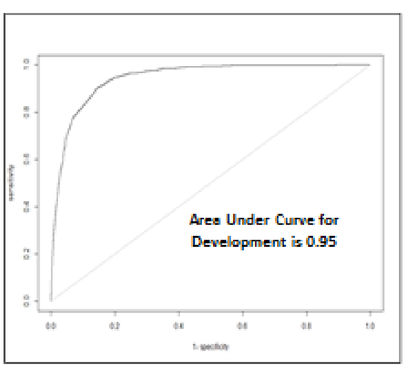
Similarly, another method Gini Coefficient (Figure 1.) has been also evaluated across development, validation and external validation and found >88% across all three data sets. The Gini coefficient is generally used in classification problems. Gini = 2*AUC - 1, where AUC is the area under the curve (see the ROC curve entry above). A Gini ratio above 60% corresponds to a good model.

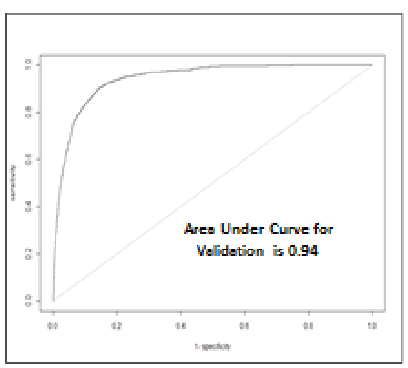
iTuring has other powerful discrimination methods to measure predictive power using Discrimination Slope (Figure 3.). The discrimination slope is calculated as the difference in means of model-based probabilities for attritor minus non-attritor. This is an alternative to see statistics (C is an area under curve) as measure of discrimination but influenced by model calibration. The attrition model has high calibration across all modeling datasets including external validation:

Figure 2: Discrimination Measures

Discrimination Measure	Mean Score Attrition = 1	Mean Score Attrition = 0	Discrimination Slope
Development	0.2853	0.0291	0.2562
Validation	0.2844	0.0289	0.2555
External Validation	0.2870	0.0303	0.2567

Figure 3: Area under curve





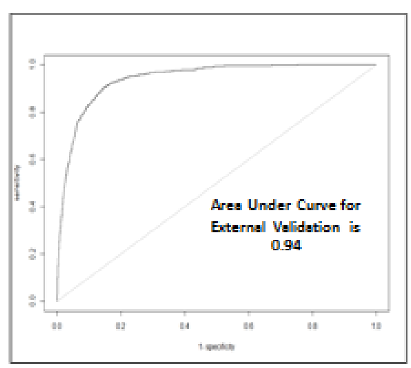
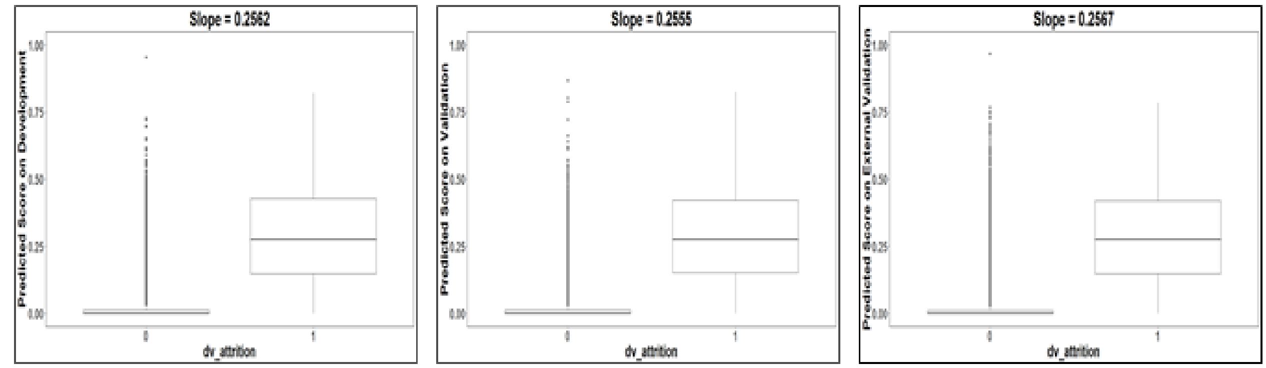


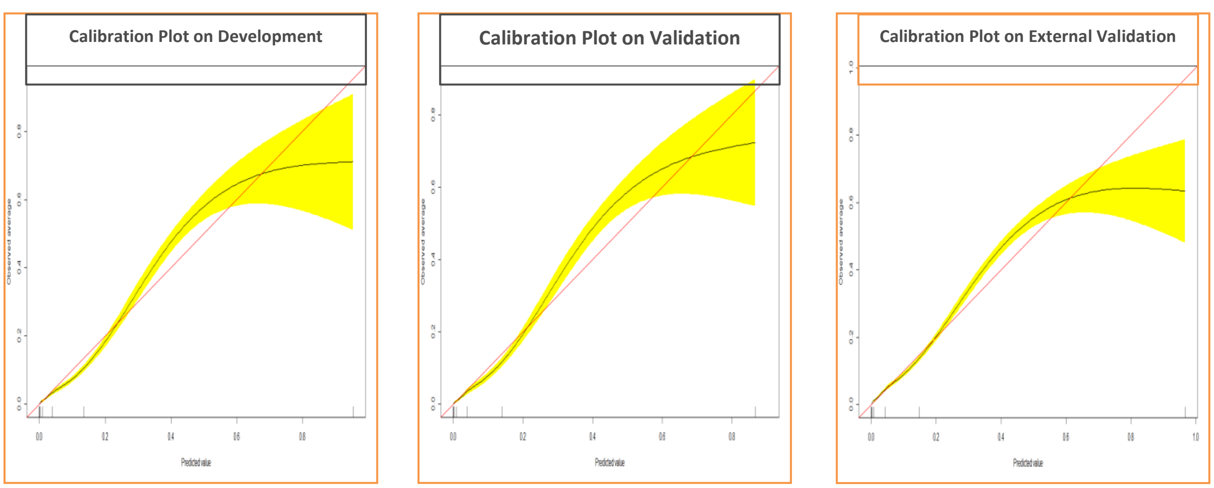
Figure 4: Discrimination Slope



Calibration method to test model authentication:

Calibration curve helps to understand how actual attritors and estimated probability closely fit each other. It also shows how much a model is classifying error discrepancy. The Brier score is a proper score function that measures the accuracy of probabilistic predictions for a model that predicts Pi for attritors out of N customers. The model estimates the expected squared difference between attritors status and predicted probability.

Figure 5: Calibration Plot



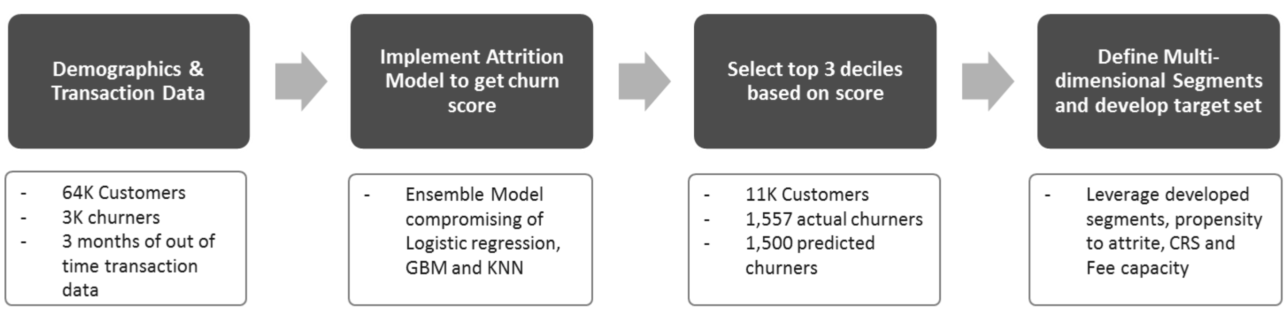
Brier Score of Development is only 1% on training and 2% on validation dataset which is best in class for predicting customer behavior.

CUSTOMER RETENTION STRATEGY

Proactive and Structured retention initiatives can be applied by identifying potential churners based on the relationship between their historical transactional activities and the engagement level.

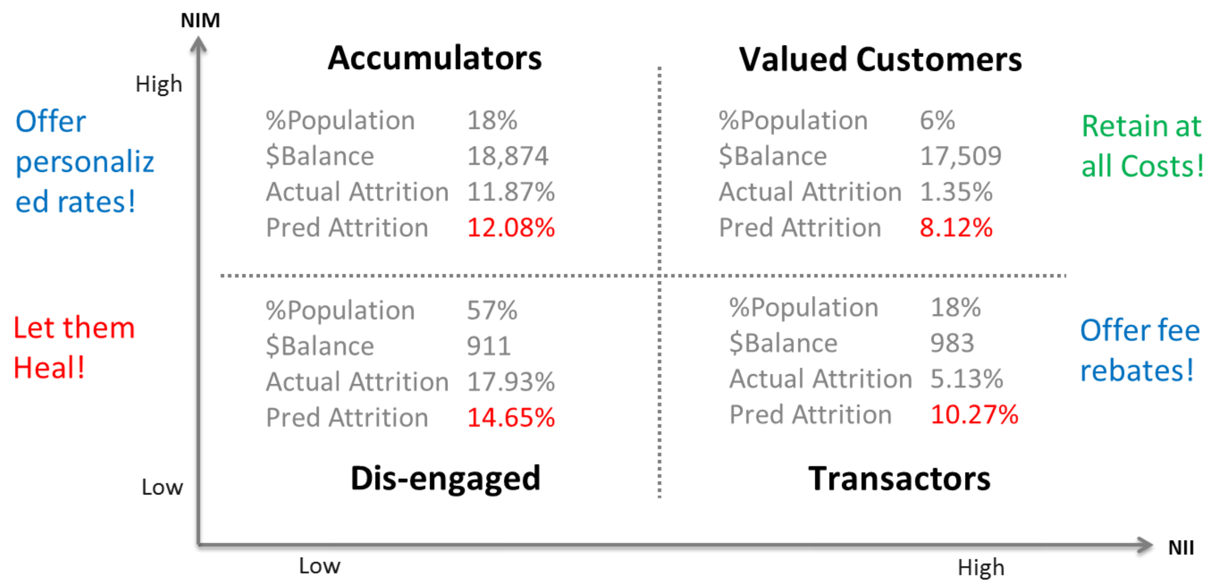
Sample data was used to conduct the analysis. A probability of attrition model was developed and validated on out of time data to calculate churn score. Also, fee capacity and Customer Value was calculated for each customer. After building and validating machine learning algorithms, we scored external data and identified customers from top 3 deciles based on high propensity.

Figure 6: Customer Segmentation Approach



Selected set of customers was further segmented based on Non-interest Income and Net Interest Margin to create targeted retention strategy.

Figure 7: Customer Priority Matrix



We further analyzed each segment using Customer Value and Fee Capacity. Fee capacity is defined as total fee generated from a customer out of total credit. You should also look at transaction activities and utilization of product and services for each segment to identify need based structured offer or rebate.

EARLY WARNING INDICATORS & BUSINESS IMPACT

Targeting strategy based on top 3 deciles will result in a lot of false positives. Hence, business rules were developed to identify risky customers using multi parameters like segment, attrition probability, Fee capacity and customer value to identify customer whose relationship is quite good but likely to attrite from the book.

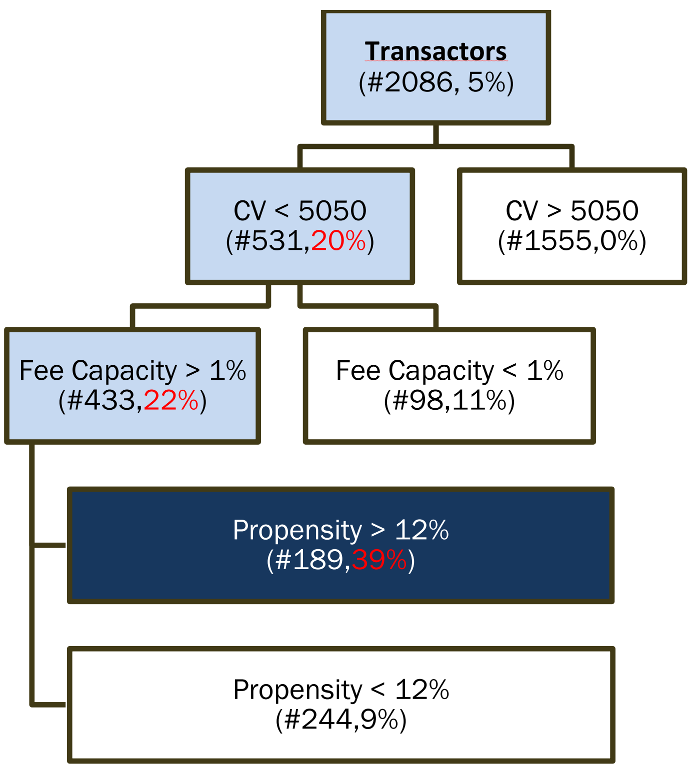
The opportunity set has a total of 11K customers but based on profitability segmentation we discarded the Dis-engaged population set as these customers result in minimal profitability. The focus should on retaining engaged profitable customers. Hence, Profitabily segments of Transactors, Accumulators and Valued customers were analyzed to develop a targeted business strategy.

Figure 8: Customer Segments

Segment	No. of Customers	% Churners
Dis-engaged	6,644	17.93%
Transactors	2,086	5.13%
Accumulators	2,098 #4,923	11.87% #366
Valued Customers	739	1.35%
TOTAL	**11,567**	**13.46%**

Business judgement and PRIM techniques were leveraged to identify the targeted and best performing rules leveraging multiple attributes like fee capacity, propensity to attrite, customer value and profitability segments.

Figure 9: Customer Segments



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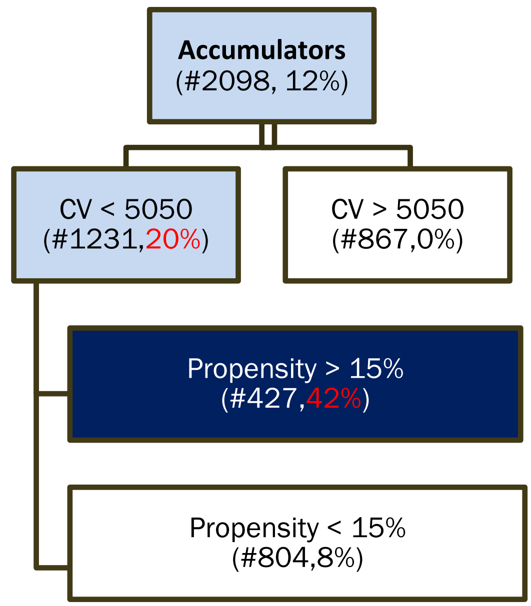

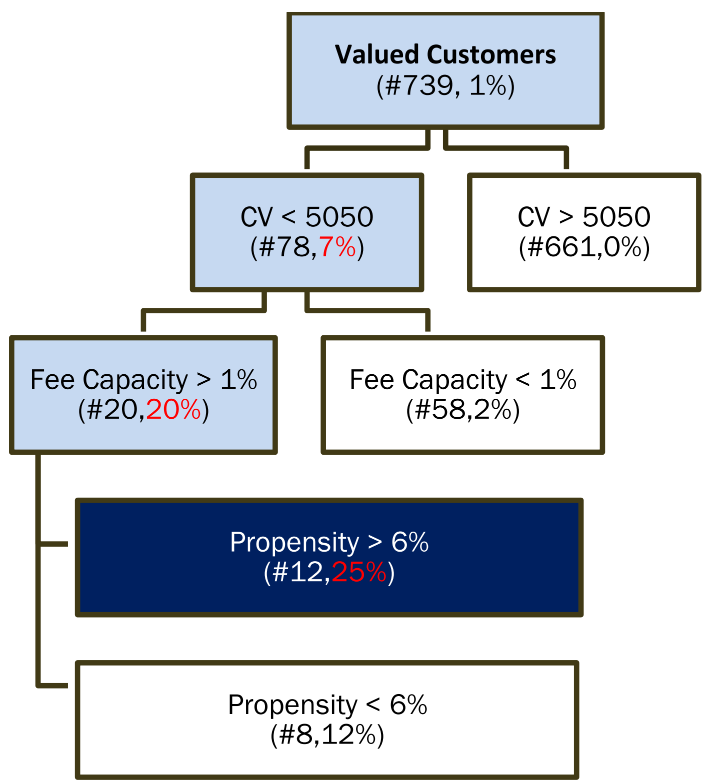

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BUSINESS RULES

Segment	Operator	Customer Value	Operator	Prob	Operator	Fee capacity
Transactors	&	**< 5050**	&	**> 12%**	&	**> 1%**
Accumulators	&	**< 5050**	&	**> 15%**	&	**> 0%**
Valued Customers	&	**< 5050**	&	**> 6%**	&	**> 1%**

The target set is defined based on above business rule, customers form segment valued Customer, accumulator and transactors were flagged and identified for retention measures.

Segment	No. of Customers	% Churners
Transactors	189	38.62%
Accumulators	427 #628	41.69% #254
Valued Customers	12	25.00%
TOTAL	**628**	**40.00%**

With the above retention strategy, the bank was able to save ~1.07M USD and reduce 33% false positives, thereby improving customer experience.

The next step was to define specific retention strategy for individual customers and recommend need based offers, rebates, etc. to retain valuable customers.

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CUSTOMER CENTRIC RETENTION STRATEGY

Finally, based on customer profile, engagement, transactional activites and competitor offering, we helped the bank design a focused retention strategy with need-based offers was designed and implemented to retain engaged and profitable customers.

Valued Customers	Population 1% Balance $26,256 Attrition 25% Fee Capacity > 1%	• Offer personalized services. • Best competitive rates • Offer concierge services • Offer dedicated RM • Enhance customer experience
Accumulators	% Population 5% Balance $20,221 %Attrition 41.69% Fee Capacity > 0%	• Offer higher deposit rates. • High Tenure CD's • Offer waived off fees for low cost channel usage • Offer Money Market account for higher returns
Transactors	% Population 3% Balance $328 %Attrition 38.62% Fee Capacity > 1%	• Lower ATM withdrawal charges • Waive off ACH transfer fees and Bill Pay • Offer competitive deposit rates • Offer Line of Credit/Personal