CREDIT CARD FRAUD DETECTION & LOSS PREVENTION

INITIAL SITUATION

During the customer onboarding stage, the bank identified customers as Prime (with good credit standing) or Sub-Prime (with poor credit history or bureau score). As a result, separate collections/recovery agencies were maintained for the two groups, (both internal and /or outsourced).

Sub-Prime customers were mostly rejected by credit card providers, generally as a result of origination characteristics when the customer applied for a credit card (e.g. income at the point of application)

The bank wanted to explore a credit card offering for the sub-prime segment with lower credit limits and harsher punishment for default, as it was expected that default / losses and frauds would be higher from this segment.

The combined effect these existing strategies lead to a gradual increase in roll forwards (accounts moving to higher delinquency stages) which eventually lead to losses including skip and fraud losses (where the Customer is untraceable). Furthermore, there was almost no improvement in recoveries from both agencies, whether focused on Prime or Sub-prime segments.

It was as though a saturation point had been reached.

APPROACH

Our task then was to maximize portfolio results by striking a balance between net losses and operational costs. We decided to focus on the mid stage delinquency window, defined as customer accounts which were 2-3 payments past due (PPD). The model identified that accounts slipping into early stage delinquency (1-2 PPD) was often self-corrected before reaching the 3 PPD barrier. This suggested that early lapses on part of the customer were generally rectified without any notable intervention from the bank.

A large volume of accounts was found in the 1-2 PPD bracket. The mid-stage delinquency window lay immediately before the late stage delinquency window (3+ PPD), so any strategy change for improved mid-stage activity would directly reduce Roll Forwards and Losses (including skip and fraud losses).

CHALLENGES FACED

After reviewing the model's findings, the theory proposed by the Data Scientist was that a customer may be high risk, regardless of the Prime / Sub-Prime categorisation. This was tested and validated using Baselining Analysis (checking a test on historical data and comparing results).

We expected that the proposed strategy would have higher operational costs as the bank would need to invest in testing the new strategy in the field. However, a significant reduction in losses (including Skip and Fraud Losses) was expected.

It would also mean the loss of Prime and Sub-Prime expertise across recovery agencies as the proposed model would distribute accounts based on risk rather than Prime/Sub-Prime categorization. At this juncture, it was agreed that model success would be measured by comparing total cost (operational cost + losses) between Test and Control.

SOLUTION

The new risk-based model did away with the Prime/Sub-Prime barrier and optimised recovery efforts. All high-risk accounts were treated with high intensity throughout the delinquency window.

We designed a high accuracy risk-based model using most recent customer attributes from the observation window (e.g. customer's current income as opposed to that recorded at the point of application). Based on the model outcome we grouped customers into risk bands: High, Medium and Low

- For High risk band accounts which were 31 - 60 Days Past Due (DPD) we proposed internal (agency) manual recovery, the most expensive option.
- For Medium risk band accounts we proposed a transition from an outsourced recovery agency to the internal manual recovery at 46 DPD
- For Low Risk (which was the majority of the population) the recovery was completely routed to the outsourced recovery option (thus saving operational costs)

Performance Window and Good Bad Definition as follows:

Base Population - 30 to 60 DPD Accounts in Observation with 6 Months Performance

Bad - Credit Losses or Fraud in Performance

Significant Variables:

The final model used a combination of the following variables

- Internal Behaviour Score (as of Observation Month)
- Utilization
- Number of delinquencies of 30+ and 60+ within the past 12 Months
- DPD

RESULT

Test Population had significantly lower gross losses (Fraud + Skip + Bankrupt) than the Control model

Declared Champion with $7 mm+ Cost Savings in 6 months of Implementation from 40% Test Population. Operationally it aided operational bandwidth by providing equal opportunity and competition across recovery agencies.

Chart showing Internal Behaviour Score effectively segregating High and Low Risk

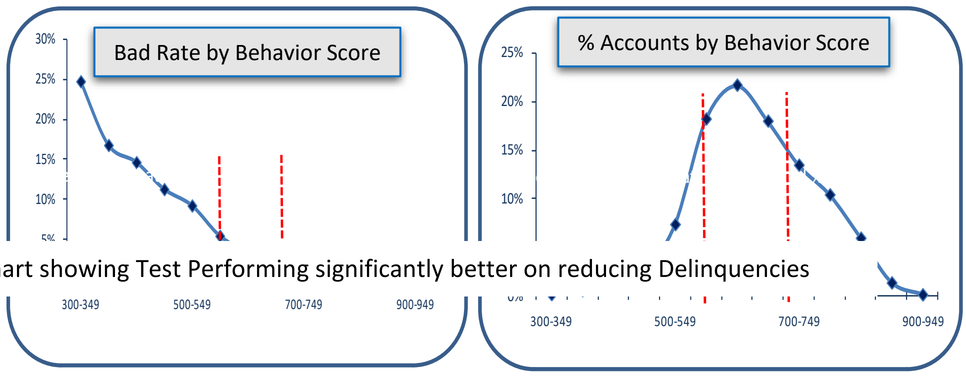

Chart showing Test Performing significantly better on reducing Delinquencies