Optimization of Initial Credit Limit Using Comprehensive Customer Features

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1 Introduction and Motivation

With a total of 36.24 million credit cards in operation with a spend of Rs. 41,437 crores in January'18 from a 28.85 million credit cards and usage of Rs. 32,691 crores in January'17, credit card market has shown an incredible growth in India. During the initial introduction of credit cards in the Indian market, the word credit did not go along with the Indian mentality, believing that credit cards would increase their liability and might lead to payment of huge interests, if not cleared on time. The tremendous growth in the recent times of this market can be accredited to the acceptance of 'spend now and pay later' strategy which was supported by the ease of digital payments, acceptance in almost every monetary transaction and the e-commerce boom along with the option to repay in easy instalments.

Traditionally, credit card issuers have relied upon the income and the score of an applicant to calculate his credit limit. In the current scenario, the average utilization on credit cards is only 30%. This highlights that a majority of customers have a huge unutilized limit, resulting in capital blockage for the institution. Additionally, post-issuance, 23.3% of the applicants do not activate the card. Hence, it is necessary to devise a dynamic and reliable method to determine credit limit which focuses on crucial factors like expected spending, odds of activation given the limit, behaviour on similar account, etc. This paper proposes a more granular methodology to determine the credit limit of a customer based on his expenditure potential and his credibility to payback based on his credit history, payment history and various demographic variables. The idea is to understand the role of the above factors and the methodologies adopted to address the problem of limit assignment.

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2 Literature Review

Businesses granting credit through credit cards faces numerous challenges with the growing demand and varied consumer behaviour. Researchers over the time have focused on credit limit increase and decrease post observing payment patterns on the account over a specified time period. Questions on usage of credit line, payment patterns in terms of revolving, profitability of the customer and how likely is the customer going to default in future have been raised and discussed. Various segmentation and prediction techniques have been devised and tested. Bierman and Hausman (1970) formulated a dynamic programming model in which the decision process focused on whether to grant credit or not and for what amount. In their formulation, the amount of credit offered was linked to the probability of non-payment or default. Haimowitz and Schwarz (1997) developed a framework of optimization based on clustering and prediction. Expected net present value is calculated at multiple credit lines combined with the probability of cluster memberships. This paper also highlights the future scope in terms of using multiple independent variables for optimization and studying their effects using other techniques such as neural networks. Research by Hand and Blunt (2001) highlighted the use of data mining techniques to predict spending patterns in a database of UK credit card transactions, specifically on the petrol stations. Dey (2010) highlighted the importance of understanding the action effect models and addressed the prominence of each component of revenue and risk. The research by Terblanche and Rey (2014) focused on the problem of determining optimal price to be quoted to the customer, such as income of the lender is maximized while taking price sensitivity into account. Using probability of default, loss given default and other factors, an equation describing the net present income is developed. Budd and Taylor (2015) presented a model to derive profitability from a credit card assuming that the card holder pays the full outstanding balance. Most of the research either focused on one constituent of optimal allocation or followed a single approach that is either from a pure risk or revenue perspective. Even though the elements described in this paper are discussed in multiple researches either one or more of the approaches, methodology and techniques are missing.

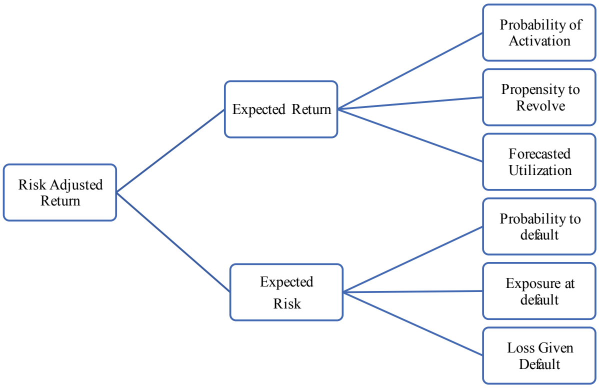
3 Methodology

The methodology to obtain an optimal initial credit limit for each customer is based on the information submitted during the application and bureau history of the customer (in case he/she has a previous line of credit). In this context, allocation and maintenance of pertinent credit limit will maximize revenue and minimize the risk associated.

Understanding the revenue and risk components, theoretically, a high credit limit has an advantageous effect of increased expected revenue, but at the same time both the probability of default and expected exposure at default also increase. Similarly, a low credit limit decreases expected loss but leads to a decrease in expected revenue. The overall effect and the appropriate action depend on which of these effects is stronger (Dey 2010).

Revenue generated from any credit card portfolio is influenced by complex interactions between several factors like probability of activation, probability of attrition, propensity to revolve and credit limit utilization, while the risk component comprises the probability of default at the time of acquisition, behavioural probability of default and exposure at default (Dey 2010).

The behaviour of each effect variable is modelled separately, and their combined effect defined as risk-adjusted return is studied.



Additionally, for modelling the above components monthly payment data, comprising statement data, balances, minimum amount due and the payment date of credit card customers were used.

- **Probability of Activation**: This model results in the probability of activation of the card given the limit assigned. The dependent variable was calculated using application data of customers. The value 1 was assigned to customers who activated the card, given a specific limit and 0 to others. Multiple (predictive) statistical techniques like logistic regression, gradient boosting and random forests were used to derive the predicted probability of activation. The models were then compared based on misclassification rate to obtain the final model.
- **Probability to Revolve**: One of the key constituents of the revenue component is interest, which is calculated on the deferred payments. For example, a customer pays a certain percentage of the current balance each month. The rest of the unpaid amount incurs an interest. For predicting this factor, customers are classified into 4 categories:

  – Transactor: A customer who pays the exact balance due each month and hence does not incur any interest charges
  – Accidental Revolver: A customer with deferred payment for less than or equal to two months

– Acute Revolver: Revolved less than or equal to 5 times
– Chronic regular revolver with more than 5 months of deferred payment.

Multinomial regression was used for calculating the odds of a customer belonging to a particular segment. Another model with a binary-dependent variable for revolver/non-revolver was developed, and the two models were compared using the Gini coefficient.

- **Forecasted Utilization**: Credit card customers fall into widely diverse categories; hence as a first step, the customers were clustered based on various behavioural variables like utilization of credit limit, delinquency on credit card, maximum delinquency on other accounts, payment patterns on credit card and additionally application variables like income, age, etc. A number of clusters were determined using the distance changes observed in the dendrogram, obtained through hierarchical clustering. This number was passed as an input to K-means clustering. As a next step, forecasted utilization was derived using unobserved component time series model, described by Famby (2008) as a multiple regression model with time-varying coefficients. This model was developed separately for each cluster. The added advantage of using a time series model is that incorporated the impact of seasonality in the data as credit card usage varied from season to season. Forecasted monthly average across all customers in a cluster formed the usage trajectory for that cluster. For example, when an application is received, using the results of the clustering procedure the customer is classified as a part of a specific cluster, whose forecasted usage trajectory is assigned to that customer.
- **Probability of Default**: This parameter is defined as risk for the institution at the time of acquiring the customer. If from the date of application, in the next 12 months, any customer with a delay past the due date of greater than or equal to 90 days was classified as a bad customer and good otherwise. Logistic regression was used to estimate the value of this parameter.
- **Exposure at Default**: This parameter is calculated based on the assumption that an account is likely to go bad, when utilization is maximum. The maximum forecasted utilization and the behavioural probability of default were used to calculate the value of this factor.
- **Behavioural Probability of Default**: Post acquiring, the likelihood of a customer falling in a particular default bucket in future based on the observed behaviour is the value for this factor. For this purpose, we have used the bureau score that comprehensively captures the performance of a customer over existing accounts.
- **Loss Given Default**: For this analysis, loss given default is assumed to be 100%. This implies that if the customer defaults on the portfolio, total outstanding balance is defined as the total loss.

The function of the above elements was used to optimize the initial credit limit of the customer.

RAR = ***f*** **(*Expected revenue, Expected risk*)** where:

f (*expected revenue*) = *f*(*expected utilization, probability of activation, probability to revolve, interest rate, interchange*) *f (expected* risk) = *f(probability of default at acquisition, exposure at default, loss given default, behavioural probability of default)*

The difference between the two, defined as the risk-adjusted returns, is maximized to obtain the optimal limit. The constraints for this optimization problem are linear combination of borrower's behavioural characteristics (affordability, etc.), lender's risk constraints (risk appetite, exposure, etc.) and operational requirements of the business (acquisition book size, costs, etc.). Initial convergence to the objective function maxima was attained through the most commonly used method known as the Lagrange multipliers. In addition, since the objective function and constraints combined lead to a convex optimization problem, Frank–Wolfe algorithm is used to attain the optimal limit corresponding to maximum RAR. The Frank–Wolfe method solves one subproblem at each iteration, produces a sequence of viable solutions over the region of interest and hence is computationally feasible (Freud and Grigas 2014).

4 Benefits to the Business

A method of modelling and determining the initial credit limit consistent with the objective of maximizing revenue and minimizing risk has been discussed. Each component being predicted can be applied separately to most customer decisions across the customer life cycle: customer acquisition and customer account management. Businesses based on their requirement can understand the trade-off between different scenarios, thereby enabling them to determine the best action for each customer. The approach enables improved customer decision-making process in terms of:

- Moving away from the traditional methodologies to taking a holistic view of the customer actions and decisions in terms of his spend and repayment behaviour
- Helping the business to understand optimal capital allocation through credit card
- Helping the business identify homogenous customer segment and design targeting strategies accordingly
- Using individual component models, to understand characteristics of customer segments, devise varied strategies and schemes to enhance customer experience and helping the business reduce churn and ensure adequate customer loyalty.

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