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Credit Limit Management using Action-effect Models

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Abstract - **Management (i.e. initial allocation and subsequent increase / decrease) of credit limits is one of the most critical decisions related to credit card accounts. It affects a number of variables that have direct or indirect influence on the profitability of the portfolio. This paper proposes the use of a new type of model (termed action-effect model) to study the effect of credit limit increase / decrease actions. Complex interactions between conflicting variables like credit risk, probability of attrition, credit limit utilization and revenue generated are studied. The possibility of using simulation along with action-effect models to arrive at an 'optimum' credit limit for each credit card account in a portfolio is discussed.**

Keywords- Empirical modeling; Credit risk; Credit card portfolio; Basel (RWA) capital cost; Optimum credit limit

I. INTRODUCTION AND RELATED WORK

Traditional credit scoring is an application of techniques from areas of statistics, operations research, and related disciplines like machine learning and data mining, that attempts to forecast financial risk associated with lending. It is essentially a way of distinguishing groups with different credit risk in a population, based on observed characteristics.

Though the concept of recognizing groups in a population was introduced in statistics by [1], [2] was the first to propose that the technique could be used to distinguish between good and bad loans. The introduction of credit cards in the 1960s made automation of lending decisions a necessity and led to the realization of the usefulness of credit scoring. Since then there have been great advances in both techniques and applications of the concept of scoring. Much of the details of past research can be found in [3], [4], [5], [6] and [7].

Recently, the attention of researchers, as well as practitioners, has been drawn towards empirical modeling of various aspects of profitability as opposed to risk alone. This gradual maturing of the science of modeling within the practical world of credit operations is depicted in Fig. 1 below.

The move towards optimization of credit strategies and the focus on profitability is also evident from the discussions appearing in academic literature. For example, [8] stress the importance of customer behaviour (apart from credit risk) such as likelihood of responding to a marketing campaign, likelihood of attrition, and propensity to revolve account balance in assessing profitability of an account. Reference [9] studies the impact of score cut-offs of profitability and proposes a flexible pricing approach that is shown to be more profitable. Reference [10] derive a profit-maximizing score cut-off and a pricing curve from the ROC curve of a scoring model. Reference [11] describe a method of attracting profitable customers by offering them appropriate credit products. Reference [12] use quantile regression models to find distributions of profit and loss from a mortgage portfolio for various lending strategies. Reference [13] describe models to predict 'time to default' and discuss how it affects strategies related to profitability. Reference [14] stresses the importance of modeling continuous financial objectives of lenders like bad debt, revenue and profit. His results show that such approaches identify profitable accounts more accurately compared to traditional default risk classification models.

Reference [15] highlights another aspect of the problem domain. The work focuses on the modeling of the effects of certain account management actions like writing warning letters to customers who miss payments, on long-term objectives like profit. They also attempt to address the inherent 'selection bias' of that type of models.

This paper studies how action, related to credit limit management, taken on credit card accounts influences variables that are related to profitability, and proposes a 'composite action-effect' model to capture the complex interaction between the variables.

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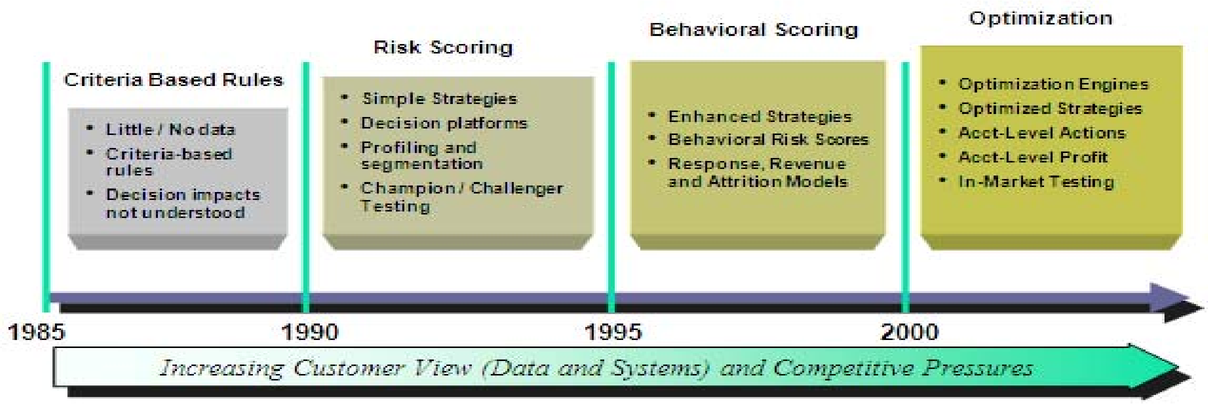

Figure 1. The move from Credit Scoring to Profit Optimization

II. CREDIT LIMIT INCREASE / DECREASE ACTIONS AND THEIR EFFECTS

Though, [15] outline the importance of customer reaction to specific actions taken, their work concentrates on the aspect of selection bias. There is very little research work reported in literature on the modeling of the customer reactions to credit limit management actions taken by lenders.

Lenders are motivated to take credit limit increase / decrease actions on credit card accounts due to a number of reasons. Credit limit decrease actions are taken primarily to reduce cost of Basel cost of RWA and potential losses. Excess unutilized credit limits increase RWA and blocks capital required. High unutilized credit limits in unused / infrequently used credit cards also increase the potential for fraud substantially. Behavioural models also indicate that sudden increase in balances in generally unused credit cards are closely linked to financial hardship of the card holder – as credit limits on other cards run out and payment difficulties make new credit hard to obtain, limits on the unused cards are utilized leading to further aggravation of the situation. To keep LGD under control, it is also appropriate to decrease credit limits on accounts with low behaviour scores. It is therefore in the interest of the lenders to decrease the credit limits on certain types card accounts to the extent possible without prompting adverse reactions from the customers, or where the decrease is justified in spite of adverse customer reaction. On the other hand, an increase in credit limit would normally lead to increase in revolving credit balances and therefore increased revenue. Increasing credit limits can also increase customer loyalty and therefore customer lifetime value. However, limit increases have to be provided only to those accounts that are found 'eligible' under some criteria, and likely to utilize the increased limit to increase the revolving credit balances.

Furthermore, the appropriate action should ideally be determined for each individual 'eligible' account because firstly, the 'quantum' of the action (i.e. the amount by which the credit limit should be increased / decreased) will depend on the parameters of each eligible account, and secondly, the reaction of each account holder is likely to be different. Thus, as shown in Fig. 1 above, profit optimizing credit limit management strategies are oriented towards account level actions and account level profits.

III. MODELING THE ACTION-EFFECTS

The interactions between the variables that affect the target variable (i.e. profit) are complex. The Influence Diagram shown in Fig. 2 below attempts to depict some of these. In this example three (input) variables: 'Behaviour Score', 'Utilization', and 'Propensity to Revolve' have been used to select the accounts eligible for the action. A simple cut-off value based criteria can be devised for the purpose.

Most of the possible actions produce opposing effects, and the overall effect on the target variable depends on the strength of each of those opposing effects. For example, increase in credit limit has the desirable effect of increasing revenue, but at the same time both probability of default (i.e. P(Default) in Fig. 2 below) and loss given default (LGD) are also increased. Similarly, decrease in credit limit, decreases expected loss but increases the probability of attrition (P(Attrition) in Fig. 2) and leads to decrease in expected revenue. The overall effect and the appropriate action will depend on which of these effects is stronger.

The quantum of effects can be expected to have non-linear relationships with the action variables (as shown in Fig. 3 below). Also, the direction of the overall effect may reverse beyond certain limits. For example, for a set of accounts with a particular set of characteristics, it might be profitable to increase credit limits up to a certain point beyond which the expected increase in revenue will not compensate the expected loss due to increased risk. The behaviour of each action-effect variable (viz.: 'Probability of Attrition', 'Probability of Default)', 'Change in Balance', and 'Loss Given Default') are modeled separately and then the combined effect is studied by calculating the 'Expected Revenue', 'Expected Loss', and then 'Profit'.

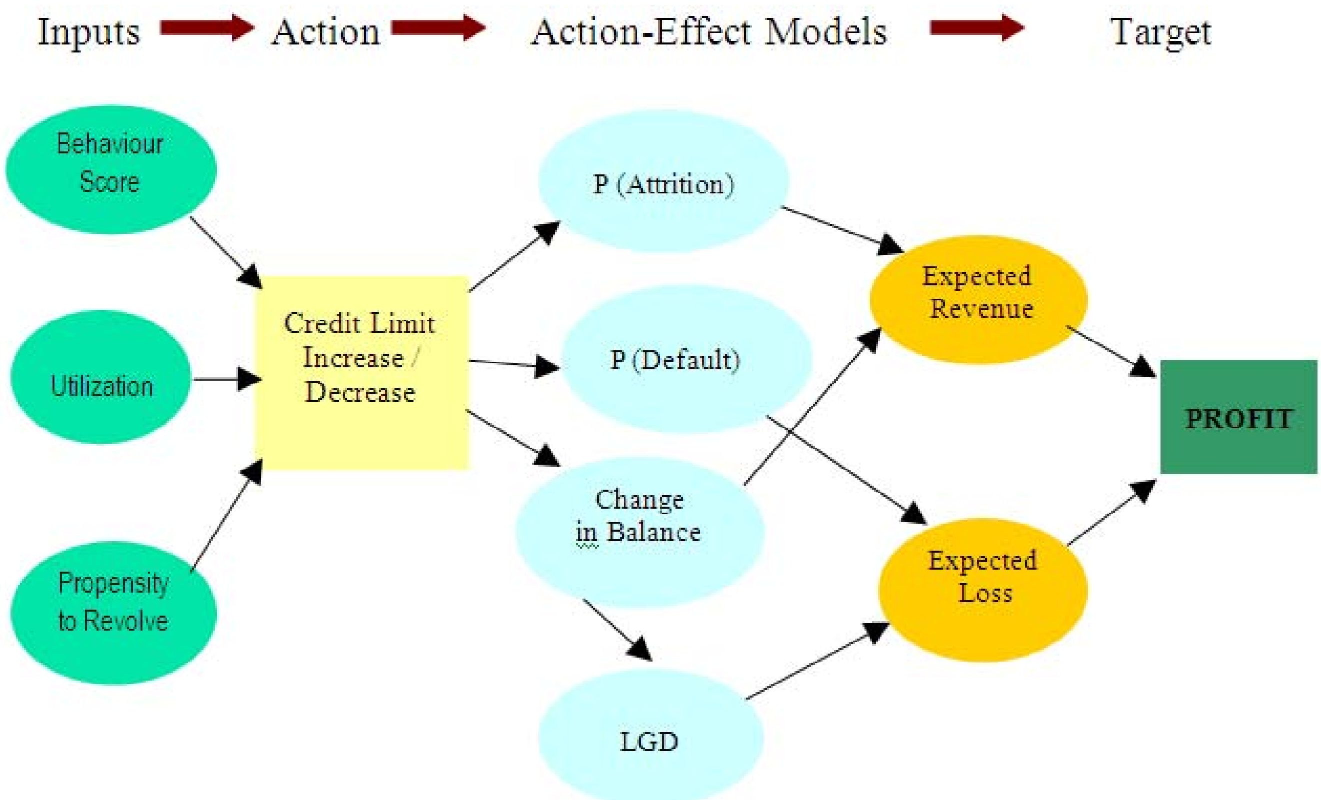

Figure-2. Influence Diagram showing Action-effect Models

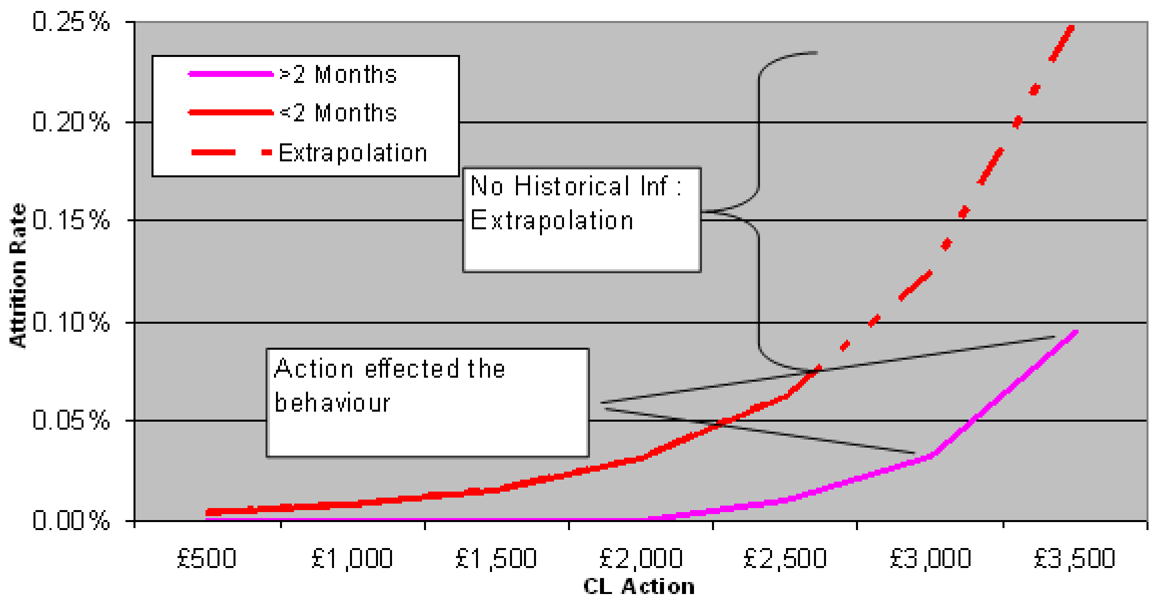

Figure-3. Hypothetical Action-effect Behaviour of Attrition

The possible behaviour of one of the action-effect variables (attrition) with respect to the action (credit limit decrease, in this case) is depicted in Fig. 3. The set of accounts for which these relationships are studied need to be similar to each other with respect to the other (control) variables. A series of such relationships (for different values of the control variables) constitute one 'action-effect model'. The relationships are derived from historical data of past champion / challenger testing of strategies, to the extent possible and then extrapolated (as shown in Fig. 3).

IV. USING THE MODEL

Ideally, an 'optimum' credit limit that leads to maximum profit could be derived for each account by 'simulating' the effect of increase / decrease actions over a range of action variable values. Since, millions of eligible accounts can be present in the lender's portfolio, it would be running simulations for each individual account would be unviable. In practice it is approximated by applying 'simulation' to sets of similar accounts. For example, narrow range of values of the input variables can be used to divide accounts into sets for simulation. Thus, accounts within a narrow range of Behaviour Scores, Utilization and Propensity to Revolve would define a set of accounts, and simulation would be used to find the (approximate) 'optimum' credit limit for each set of accounts. Increase / decrease action would then be taken to bring the credit limit of each account in a set to the optimum of that set.

V. CONCLUSIONS AND FURTHER WORK

In this work a method of modeling the effect of credit limit management actions has been examined, and a way of using the model to set credit limits of accounts consistent with the objective of maximizing profit has been discussed.

As shown by [15] there is an inherent selection bias in models of this type, and since unlike the situation with reject inference [16] the proportion of unselected cases are not small, the effect of the bias cannot be ignored. Also, where champion / challenger data is not available, the model building requires extensive extrapolation. The validity of this has not been established. Both these aspects need to be investigated further.

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