Estimating creditworthiness using profit modeling

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Abstract. The recent advancements in machine learning have enabled retail credit issuers to predict a customer’s net present value using behavioral and profit-based modeling approaches. The objective of this research is to curtail the risk associated with credit card underwriting which typically helps in deciding whether an applicant is creditworthy or not. It attempts to estimate the creditworthiness of a customer instead of evaluating the chances of them going delinquent on a debt. Credit issuers can utilize these models to identify potentially risky as well as profitable customers. Using a machine learning approach, profit-based models are constructed in this research using information acquired at the time of customer-acquisition.

Keywords—Profit Models, Credit Cards, Machine Learning, Underwriting, Retail Credit Risk

1. Introduction
An underwriter is empowered to place a customer into a particular risk category upon reviewing their application. Underwriters can decline the applicant altogether as well based on their evaluation. They also rely upon extensive medical knowledge and personal experience when underwriting cases [1]. The reliance upon their own experience and judgment causes inconsistency across the underwriters, resulting in inaccurate rate classifications [1]. Over time, this process has been automated to eliminate human errors and maintain transparency in the decision-making process. Automated underwriting has been a growing trend in the retail credit industry. In recent years, consumer credit portfolios have experienced extraordinary growth in developing countries [2]. This represents huge revenue opportunities in auto loans, home loans, and credit cards, and has created a tremendous need for more efficient and cost-effective credit analysis [2].

It is important to note that risk is not the only factor for approving a customer’s application. There is a possibility that a riskier customer can be more profitable than a safer customer based on the institution’s product line and business strategy. Profit-based modeling is relatively rarer because of the complications that it involves but institutions have turned to it as a result of the advances in machine learning methods in credit risk modeling.

Furthermore, the relationship between profit and risk in profit-based modeling typically depends on loan type, loan life, and expenses and incurred losses in a credit card. Some notable components of card profit include sub drivers of revenue that is composed of interchange income, interest income, and fees. Interchange income is the money that a financial institution earns
from swipe fees. Swipe fees are a percentage of the transaction that banks take from retailers each time a credit card is swiped to pay for a purchase [3].

For designing credit card portfolios, card issuers can rely on earn primarily on interchange income through transactors. A transactor is a consumer who pays their credit card balance in full and on time every month [4]. Transactors do not carry a balance from month to month; they always pay their credit card bills in full by the due date [4]. Card issuers can also design their portfolios based on revolvers. A revolver is a credit card issuer term for customers who carry balances, paying off those balances over time, thus “revolving” them [5].

This paper studies the empirical relationship between risk and profit pertinent to customers in order to estimate their creditworthiness. Using acquisition-level information, logistic regression model is applied to estimate the tendency of a customer to go delinquent or charge off. This estimation is used to organize accounts into interchange, neutral, and finance charge portfolios. An acquisition-level profit model is also constructed for the loans to predict credit worthiness of the customer.

**Related Works**

This builds on papers by Grodzicki and Koulayev [6] and Stavins [7] which study consumer credit card usage patterns generally. An influential study by Agarwal et al. [8] estimate the heterogeneous effect of credit line increases on components of marginal profit of customers across the FICO score spectrum. This component of our paper is closely related to this, but focuses on how empirical profitability relates to general measures of riskiness in cards at time of acquisition between different types of portfolios. Our paper can also be compared with the work on “Credit Risk Analysis Using Machine and Deep Learning Models” [9] that checks the decisional power of algorithms to provide loans to an enterprise. A wide variety of algorithms are studied in the research paper to single out the best one offering the highest accuracy and precision. Our paper differentiates from this work as we utilize information acquired during customer acquisition to rank customers based on risk and profitability by leveraging machine learning algorithms. The focus is directed on establishing a risk-profit relationship instead of studying numerous algorithms. Another paper that relates with our work is the study where machine learning algorithms are applied for consumer credit risk modeling [10]. A model to predict consumer delinquency is developed in the paper whereas, our paper stresses on studying customer behavior and their tendency to go delinquent taking the risk and profit landscape into account as well. Both profit and risk models are developed where the risk-model estimates the risk associated with individual loans before estimating the risk of accounts that can charge-off. For each account-level model for aspects like monthly balance, tendency to pay late fee and propensity to charge-off, hyperparameter searches and variable selection techniques are employed.

**2. Methodology**

2.1. Data Collection

Retail credit information is gathered from the records monitored by the Office of the Comptroller of the Currency. The data collected is composed of user credit card account activity beginning January 2008 to December 2015. It consists of actual payment information including outstanding balance, balance transfers, credit limits, among others. However, the figures acquired lack reward points that a user earns upon using a credit card. Such an inadequacy comprises the final output as it fails to account for this expenditure for an institution. It increases the likelihood of stating inaccurate profit margin for the company offering credit cards. A subset of this data set holds bureau attributes with variables relevant to trade lines. It is sourced from information gathered at the time of customer acquisition. These variables are utilized in constructing risk and ML-based profit models. Furthermore, over 100 thousand loans are analyzed by extracting data from multiple bank accounts across a window of 36 months since 2012.
2.2. Interchange, Finance Charge, and Neutral Portfolios
Information obtained from reputed banking institutions is blended with the existing data to create portfolios. These portfolios contain crucial information pertinent to a customer’s chances to go delinquent, and their spending behavior. Various card issuers categorize their customers’ accounts based on such premises. The factors considered while developing the portfolio algorithm that categorizes accounts on grounds of whether issuing institutions consider interchange earnings or rely on credit card finance charges are as follows: information gathered during customer acquisition, application details. Such groups are classified as ‘Interchange portfolio’ and ‘finance charge portfolio’. There is another ‘neutral portfolio’ for the accounts that do not fit in the either of the two portfolios.

2.3. Risk Model
A model for estimating the risk associated with individual loans is developed before estimating the risk of accounts that can charge-off. This system sorts the loans based on their vulnerability to risky behavior and assigns points to them accordingly. Based on such points, the riskiness of a customer is predicted. The risk score is computed by leveraging information acquired during customer acquisition. It designates a loan as ‘risky’ if the corresponding customer is reported delinquent based on the following criteria:

a. 60 days delinquent under a short duration (6 months)
b. 90 days delinquent under a relatively longer duration (1 year)
c. 120 days delinquent under 2 years
d. Charge-off in 2 years

Over 150 thousand loans are examined by extracting data from multiple bank accounts originating in 2012 till 2015. In order to enhance the estimation, the sample is divided into two distinct parts: 20% grouped as risky and 80% non-risky and an 80-20 training validation split is made.

Logistic regression is used for risk modeling which can be described as follows:

\[
\log \frac{p(y = 1)}{1 - p(y = 1)} = \alpha + \beta X + \epsilon
\]  

(1)

where \( y = 1 \) denotes the event that the customer is risky.

The predictors are first arranged in accordance with their univariate information value for variable selection. The variables are then segmented into decile bins and the Weight of Evidence (WOE) is computed in each of these bins which can be described as follows:

\[
WOE_i = \log \frac{P(i | y = 0)}{P(i | y = 1)} = \log \frac{\frac{N(y=0,i)}{N(y=0)}}{\frac{N(y=1,i)}{N(y=1)}} = \log \frac{P(y = 0 | i)}{P(y = 1 | i)}
\]  

(2)

IV is then calculated as a weighted sum of WOE values

\[
IV = \sum_{i=1}^{m} \left( \frac{N(y = 0, i)}{N(y = 0)} - \frac{N(y = 1, i)}{N(y = 1)} \right) WOE_i
\]  

(3)

A sample of variables are taken from interchange, finance charge, and neutral portfolios which are used to build the initial list. These are binned and after performing WOE transformations, they convert to log-odds of default in that portfolio. Now, regression is done to modify the model based on Akaike information criterion tests.
2.4. Profitability versus Risk - Empirical Relationship

In this section, a relationship is established to correlate profit and risk at the account level. It is presumed that the interchange income is 1% of total purchase volume.

The Net Profit Value (NPV) of each account for customer \(i\) can be described as follows:

\[
NPV(i) = \sum_{t=1}^{T(i)} \text{profit}(i; t)
\]  

(4)

Here, \(T(i)\) denotes the loan life of the customer \(i\).

2.5. E. Profit Model

If a card issuer acquires customers based on ranking of profitability, the portfolio would be restricted to the middle risk area as it would lead to the addition of both high and low risk customers in uncertain proportions. However, issuers are unaware of the most profitable customers at the time of booking. They still have to decide the most profitable customer based on credit bureau attributes and application-level information such as self-reported income. As a result, the shortcomings as well as benefits of predicting a customer’s profitability and risk based on information acquired during booking is observed. XGBoost is used to estimate a customer’s profitability and modeling revenue, probability of default and loss given default renders the best results at the account-level. This approach failed to differentiate between the various sources of revenue so it caused difficulty with interpretation. Therefore, the revenue drivers were modeled separately and full model estimation is started after driver structure selection. For each account-level model for aspects like monthly balance, tendency to pay late fee and propensity to charge-off, hyperparameter searches and variable selection techniques are employed.

3. Results and Discussion

XGBoost package is used to build the interchange, finance charge, and neutral portfolio models with 50 trees and a 0.1 learning rate for assorting the customers. XGBoost comes with a default variable importance measure that calculates how much each attribute split point improves the performance measure, weighted by the number of observations the node is responsible for. The findings show that the interchange portfolio consists of the highest number of creditworthy customers and finance charge portfolio contain the least of them.

In tables 1, 2, and 3, the most informative variables are listed per portfolio. One can see that certain significant risk drivers are common across portfolio, such as FICO of the primary borrower at origination, total borrower bankcard utilization, and total borrower bankcard credit limit. However, for some portfolios, number, balance, or credit limit of premium cards are highly predictive of borrower risk.

| Rank | Variable               | IV  |
|------|------------------------|-----|
| 1    | FICO                   | 1.06|
| 2    | Total Card Util.       | 0.72|
| 3    | Prem. Card CL          | 0.51|
| 4    | Prem. Card Bal.        | 0.48|
| 5    | Total Card Bal.        | 0.44|

Table 1. Top Predictor Information Value of Interchange Portfolio.
The maximum loan life is 36 months in this case because it accounts for data across 36 months from 2012 to 2015.

The above finance charges vs risk graphs across interchange, neutral, and finance charge portfolios are analyzed to estimate the total finance charges accumulated over the life of the loan. Low risk individuals tend to be lesser beneficial in terms of revenue generation because

**Figure 1.** Transactors vs Revolvers

| Rank | Variable              | IV  |
|------|-----------------------|-----|
| 1    | FICO                  | 1.02|
| 2    | Total Card Util.      | 0.71|
| 3    | Prem. Card CL         | 0.45|
| 4    | Prem. Card Bal.       | 0.44|
| 5    | Total Card Bal.       | 0.44|
they are generally transactors and do not accumulate interest. The high-risk individuals cannot accumulate large amount of interest because their credit limits are shorter and so is the duration of loan life. However, the graph indicates a point which contains enough revolvers that accumulate significant finance chargers owing to large credit limits and loan lives.

The next area of focus is interchange income. It is observed that low risk customers are less likely to use the credit card spite of having the tendency to spend more as a result of their higher income. The reason is that they have multiple cards competing with each other in their wallets. Also, the customers with minimal risk are seen to spend less and exercise control over their expenditure. Late fees and fees such as balance transfer fees, annual membership fees, and

Table 3. Top Predictor Information Value of Finance Portfolio

| Rank | Variable                  | IV   |
|------|---------------------------|------|
| 1    | FICO                      | 0.82 |
| 2    | Total Card Util.           | 0.46 |
| 3    | Prem. Card CL             | 0.41 |
| 4    | Prem. Card Bal.           | 0.36 |
| 5    | Total Card Bal.           | 0.36 |
Figure 3. Predicted versus Actual Finance Charges Over Risk Spectrum

Table 4. Values depicting Predicted vs Actual Finance Charges over Risk Spectrum

| Portfolio        | Somer’s D | R’S Score |
|------------------|-----------|-----------|
| Interchange      | 63.8      | 25.6      |
| Neutral          | 61.3      | 24.9      |
| Finance Charge   | 60.0      | 32.8      |

cash advance fee might be small but they also play a key role in computing the overall profit. Although the interchange portfolio would by itself have a lower optimal revenue” sweet spot,” as compared to finance charge portfolio it is also observable that an increase in risk is directly proportional to an increase in the other small fees. All such aspects combine to form the overall revenue strategy.

A grid search is performed to tune the tree depth and learning hyperparameters. The results of these searches can be summarized in the table below:
Figure 4. Predicted versus Actual Interchange Income Over Risk Spectrum

Table 5. Values depicting Predicted vs Actual Interchange Income over Risk Spectrum

| Portfolio        | Somer’s D | R² Score |
|------------------|-----------|----------|
| Interchange      | 57.5      | 26.4     |
| Neutral          | 63.3      | 29.0     |
| Finance Charge   | 59.6      | 26.8     |

Table 6. Values depicting Predicted vs Actual Revenue over Risk Spectrum

| Portfolio        | Somer’s D | R² Score |
|------------------|-----------|----------|
| Interchange      | 57.5      | 26.4     |
| Neutral          | 74.2      | 29.2     |
| Finance Charge   | 75.4      | 30.7     |
Figure 5. Predicted versus Actual Revenue Over Risk Spectrum

Table 7. Hyperparameters for Driver Submodels

| Submodel          | $\eta$ | Tree depth | Num Trees |
|-------------------|--------|------------|-----------|
| Finance Charge    | 0.009  | 6          | 2135      |
| Interchange Income| 0.001  | 2          | 6793      |
| Late Fees         | 0.005  | 8          | 2056      |
| Other Fees        | 0.014  | 7          | 928       |
| PD                | 0.005  | 9          | 455       |
| LGD               | 0.004  | 5          | 2696      |

Calculated on 20% holdout set.

The findings suggest that both the revenue model and aggregate profit model have poor predictive performance, but better rank-ordering performance. Profitable customers can be identified well enough with the data available at booking, as can be evidenced by the models’ Somer’s $D$ across driver, in the 40 – 50 range. In addition, the hump-shaped correlation between the elements of profit and risk is maintained between predicted and actual curves. It can be inferred that a ranking based on this score is a valid for estimating customer’s profitability.
4. Conclusion

Behavioral modeling and profit scores for underwriting is analyzed and a correlation is established between empirical profit and risk through a model developed using acquisition-level information. Financial institutions can potentially adopt these profit-based models for underwriting and loan management purposes to more precisely target profitable but potentially risky consumers. Hyperparameter searches and variable selection techniques are used for full model estimation and it is observed the results maintain the empirical profit-risk relationship. In the end, revolvers are found to be the most profitable customers with a higher income range and larger accumulated interest. The proportion of risk is higher than profit in portfolios that target low revolve rate spenders and those that are lower in the credit spectrum. Therefore, it is important to be mindful of risk-based guardrails when applying new modeling methodologies for risky customers. Portfolios that have a customer and product composition that targets low revolve-rate spenders have a minor increase in riskiness when switching to a profit score, while portfolios that are lower in the credit spectrum have a large increase in risk when using the profit score relative to a risk score. The increase in losses when using these scores is proportionally higher than the increase in profit, again concentrating in portfolios at the low end of the credit spectrum. This reinforces the well-known importance of risk-based guardrails when using new modeling methodologies in underwriting for issuers concentrating in higher risk customers.

Acknowledgments

I would like to express my appreciation to Mr. Suraj Kumar Jana for his valuable and constructive suggestions during the planning and development of this research work. His willingness to give his time so generously has been very much appreciated.

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