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CREDIT CARD FRAUD PREVENTION METHODS FOR LATIN-AMERICA

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INTRODUCTION

One major concern on the credit card (CC) business rises from the dichotomous situation of trying to reduce fraud losses by preventing signing up "bad" card members or merchants without significantly affecting "good" affiliations.

Fraud can occur in many different ways, depending on whom is the one performing it. In this sense, fraud activities can come from two different sides: Card members and Merchants.

Fraud from a card member can be thought as a person, company or corporation committing default on the payments required for canceling past CC consumption. It can also be done through faked or stolen plastic cards. There are several different modalities of fraud, all of which require a creative way to detect them.

On the other hand, fraud losses can also come from the merchant side. A merchant is a service establishment (SE) affiliated by contract to a particular CC company. Once an establishment is affiliated, it is authorized to accept the card from a customer willing to buy on credit. At the end of the day, the establishment sends all sales vouchers to the CC company and gets a reimbursement net of a commission fee a few days later (commission and reimbursement period vary according to the CC company and the establishment).

Fraud from the merchant side can also take different shapes, ft can be done by submitting fake vouchers on fake sales, "stealing" information from the magnetic band of a customer's card and then utilizing that information to realize counterfeit transactions elsewhere, etc.

The present study presents a suggested methodology in order to prevent signing up merchants in Latin America who are expected to end up committing fraud activities.

Objective

The objective of this study is to show how to develop a service establishment (SE) default-scoring model as a tool for application's evaluation.

The following hypothesis should be considered:

Hypothesis 1: Establishment's credit history at the Commercial Credit Bureau by the time of signing can be predictive of a "Good / Bad" behavior as a CC affiliate. "Good" and "Bad" SE's can be defined as establishments presenting fraud losses above a certain percentage of their gross sales, for example.

Hypothesis 2: In small, independent businesses, owner's default behavior has a high positive correlation with the establishment's performance. In that sense, owner's personal credit history can also be predictive of establishment's "Good / Bad" behavior.

Methodology

The major sources of relevant information for developing a scoring-model (pre-affiliation equation which assigns each merchant a score, reflecting the likelihood of future fraud behavior) are a Setup form and a local Credit Bureau (CB).

A setup form is a form any establishment has to fifl in order to sign an affrfratiorr contract. Relevant information captured in this form can include:

- Owner's name
- Establishment address
- Other CC currently affiliated to the establishment
- Business category
- Business and Owner's official ID.

The setup form should be structured in such a way that it will allow us to do a first primary screening of the SE. Analysis of Credit Bureau data should only be required after an initial screening has been done using Setup form data. If this first data does not provide enough certainty of the establishment's behavior, then CB information can be obtained as a way of second screening.

In order to develop a model, a retrospective analysis should be done on a sample of affiliated merchants by utilizing data available at the time of their signing. The objective is to determine if by using Credit Bureau (CB) data the CC company could have obtained enough information in order to prevent signing up those establishments who eventually ended up having high a fraud loss ratio.

Steps:

1. Identify and assess local credit-information bureaus & companies.
2. Define and obtain sample to be used as "Modeling" data set.
3. Determine optimal variables from credit bureau report and Setup form to be considered in the model.

Each of these steps is detailed in the next few pages.

Stepl

Credit Bureau's databases and costs vary significantly across different markets. Some bureaus can prepare an 80-page thick company-investigative report costing $220 while others can provide on-line personal credit history information for just $ 0.65. Some Bureaus score establishments according to the quafity of their credit history; others, provide only negative information (Bank account cancellations, black lists, etc). Negative credit history information is the most relevant for helping prevent fraudulent SE affiliations.

Mexico, for example, has two important credit bureaus:

Personal Credit Bureau (in association with Trans Union Co.) - Provides individual's personal credit history. Inquiries and reports can be done and obtained on-line at a cost of US$3.3 each.

Commercial Credit Bureau (in association with Dun & Bradstreet) - Provides commercial and financial history of companies. Inquiries and reports can be done and obtained on-line at a cost of US$13.72 eactr. If no hit is obtained (no report found), the cost of the inquiry is only 25% of the cost of a report.

Of alt major markets in LA/C, Mexico has the most robust Credit Bureau data. If CB data is to be used, each country's particular legal restrictions for accessing CB information should be assessed.

For example, in Mexico you need the "express consent" of the person being inquired in order to access his/her report, unless you provide the CB with financial information regarding that person.

In Australia, personal credit bureau on owners can not be used for evaluating a merchant.

It is important to determine the key search field to pull CB data. In Mexico, the tax ID name and address are mandatory fields to process an inquiry. In this sense, in order to implement a successful Credit-Bureau-based scoring model, it is critical that these fields are accurately captured in each merchant's application form or else no Hits will be obtained.

Next is a list of different Latin American credit bureaus and their costs (as of July 1999).

Country

Argentina	Cost x report
Experian (Fidelitas) Business Report	$45:00
Experian (Fidelitas) Consumer Report	$ 3.00
Equifax	$ 6.72
Brazil	**Cost x report**
Serasa	$0.69
Mexico	**Cost x report**
Personal Credit Bureau (Transition)	$ 3.30
Commercial Credit Bureau (D&B)	$13.72
Chile	**Cost x report**
Dicom / Equifax	$5.52
Colombia	**Cost x report**
Datacredito	N/A

Step 2

The number of months of experience to realize if an establishment was fictitious or committed fraud activities shoufd be taken into account. For example, if it-takes the CC company 4 months to realize fraud losses, the sample should be delimited to merchants who were signed up at least more than 4 months ago. This is done in order to made sure that what will be considered to be Good merchants are not just "unripe" fraud merchants.

Step 3

The dependent variable chosen for the analyses was Good and Bad (which in the model takes a value of 1 if the establishment went Bad or 0 otherwise). Independent variables with potential predictive power over the dependent variable were analyzed. The sources of these variables are:

- **Merchant Application (Setup) form**

- Credit Bureau report
- Derived variables (i.e. age, gender or any transformation of other variables)

The variables from the Setup form to analyze at this early stage could be :

- Gender
- Age
- RFC type (personal or commercial tax ID)
- Industry Code (IC)
- ZIP code

Some variables drawn from a personal or commercial credit bureau report can be considered as likely determinants of probability of going bad. The relevant information that can be obtained will depend on how robust is a particular credit bureau. The Mexican Credit Bureau, for example offers the following information:

- Number of months since first registered in CB until date of signing
- Salary-based Annual Income
- Total outstanding debt in open accounts
- Total outstanding debt in closed accounts
- Total outstanding past-due debt in open accounts
- Total outstanding past-due debt in closed accounts
- Total revolving-credit line in open accounts
- Total revolving-credit line in closed accounts
- Total number of credits, open or closed, granted by any institution
- Total number of open credits / Total number of credits granted
- Total number (open or closed) of recently opened credits
- Total number of 30/60 day past-due credits
- Total number of 60/90 day past-due credits
- Total number of 90 day or more past-due credits
- Total number of forced-collected credits
- Total number of written-off credits

Some variables should further be transformed to better reveal their statistical association with the dependent variable. For example, an additional variable can be created by dividing each category of credit by the total number of credits.

This will tell us, not only how many forced collected credits did a SE have, but also what percentage of his total credits does that category represent. This is a variable that can be used to compare different SB's disregarding how many loans or credits each of them has.

Industry code and ZIP code variables can be grouped into categories, to consider their combined value and predictability.

Once CB data has been pulled for the sample, some initial analysis can be done such as sample's composition, broken down by different categories and correlation between independent variables and our Good / Bad dependent variable.

Setup from scoring model

Based on the results found with an initial analysis, some variables can be determined to have explanatory power on a merchant's behavior. These "best" variables could be, for example, Tax ID (personal or commercial), ZIP code and Industry Code (IC).

This model assigns each merchant a score between 0 to 100 (the higher the score, the higher the risk of being "Bad") based on the variables found on the application form.

With these procedure, we can establish lower-bound limit and upper-bound limit cut-off scores which should interpreted in the following way:

Lower cut-off: All applications scoring xx or less could had been approved without signing up any Bad SE. These applications represented xx% of total sign-ups between May 98 and April 99.

Upper cut-off: By declining applicants scoring xx or higher, the CC company would have prevented signing xx% Bad SEs without excluding any Good SE (Hit rate = 100%). These applications represented xx% of total sign-ups between May 98 and April 99.

Regression model

The regression model uses CB variables to develop an equation that predicts the likelihood of "Bad". Given the dichotomous nature of our dependent variable (Good or Bad), a Logistic regression should be used. This kind of regression forces the prediction equation to predict values between 0 and 1. A logistic regression predicts the natural log of the odds for a subject being in one category or another.

Credit Bureau Scoring Model

This second level screening method is applied selectively based on the Setup form model.

CONCLUSIONS

Credit Bureau report costs and information quality can vary widely from one country to another. Methodology in each particular country should be assessed accordingly. If the Credit Bureau Data is too expensive, a screening based only on Setup form can be the best alternative.

Domestic legal restrictions on personal information availability and management should be taken into account before establishing any model. In some countries it is illegal to use personal information regarding the establishment's owner to evaluate the establishment.

Setup forms are the best way to costlessly collect relevant information about a merchant that can be used as a first level screening before the affiliation.
Some CC companies require a lot of collaterals in order to affiliate a merchant. A balance should be sought between preventing signing up fraud establishments and neglecting potential businesses.

References:

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Faculty Comments

Some Latin American countries have started to present sustainable economic growth rates and historically low inflation rates. Foreign investment has grown significantly in most of those markets. This brings along several challenges for multinational corporations seeking overseas investments. In this sense, financial services will be playing a key role facilitating capital inflows in these emerging economies.

This research proposes an interesting methodology for Credit Card companies on their search for more efficient credit evaluation and fraud prevention.

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