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Quantitative credit risk assessment using support vector machines: Broad versus Narrow default definitions

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ABSTRACT

This paper compares support vector machine (SVM) based credit-scoring models built using Broad (less than 90 days past due) and Narrow (greater than 90 days past due) default definitions. When contrasting these two types of models, it was shown that models built using a Broad definition of default can outperform models developed using a Narrow default definition. In addition, this paper sought to create accurate credit-scoring models for a Barbados based credit union. Here, the results of empirical testing reveal that credit risk evaluation at the Barbados based institution can be improved if quantitative credit risk models are used as opposed to the current judgmental approach.

1. Introduction

Over the past decade, credit risk analysis has attracted significant attention from decision-makers at financial institutions around the world. This is in part due to the global economic crises and recent regulatory developments (e.g., Basel III). In addition, the increased competition within the financial services industry has led many firms to find innovative ways of leveraging risk in order to attain and/or maintain competitive advantage. As a result, in today's economic and business environment financial institutions face greater risk of losses associated with inappropriate credit approval decisions (Yu, Wang, & Lai, 2008).

To manage the increased risk of default (credit risk) facing financial institutions, evermore effective credit appraisal techniques are being developed. Traditional methods for evaluating customers' credit risks are based on the experience and judgement of staff. However, with increases in the number of applicants, these conventional approaches have become outdated, as they can no longer meet the demands for efficient and effective credit risk assessment.

In recent years, credit-scoring has emerged as a leading method used by financial institutions to assess credit risk (Huang, Chen, & Wang, 2007). The main idea behind credit-scoring involves the classification of potential customers into applicants with good credit and applicants with bad credit. This is done by evaluating the probability that the applicant will default based on a quantitative model built from historical data of past applicant/customer behaviour (Thomas, Oliver, & Hand, 2005).

When developing quantitative credit scorecards based on past customer behaviour, the criteria used to determine when a client is in default needs to be determined. Here, the Basle Committee on Bank Supervision has established two widely accepted criteria. According to the Basle Committee on Banking Supervision (Basel, 2006), a default is considered to have occurred when either or both of the two following events have taken place:

- The financial institution (Bank) considers that the obligor is unlikely to pay its obligations in full, and the financial institution is unable to realise (sell) security (if held) in order to satisfy the obligor's debts.
- The obligor is more than 90 days past due on any material credit obligation to the financial institution.

Possibly due to its ease of determination and less subjective nature, over the years many credit-scoring models have been developed using the 90 days past due rule as the default indicator. This practice raises two important questions. Firstly, can the performance of credit-scoring models be improved if more relaxed default definitions are used (e.g., 30 days past due, and 60 days past due)? In this paper, these more relaxed default definitions are referred to as "Broad" default definitions. The second question that emerges is whether the discriminatory properties of credit-scoring models can be improved if more severe default definitions are used to create quantitative credit scorecards (e.g., 120 days past due, and 150 days past due)? These more severe default definitions are referred to as "Narrow" definitions. To help shed light on these questions quantitative credit-scoring models are developed based on various default definitions, using data taken from a Barbados based credit union (the credit union).

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Preliminary investigation suggests that financial institutions in Barbados—a Small Island Developing State (SIDS)—have been slow to adopt quantitative credit-scoring as a means of credit risk assessment. The local credit unions are no different. Interviews with senior officials at one of the country's largest credit unions, suggest that most (if not all) credit unions in Barbados use the traditional judgmental approach when evaluating a potential client's credit risk. Accordingly, this paper also investigates whether credit risk assessment in a Barbados based credit union could be improved if a modern approach is adopted. While the impact of quantitative credit-scoring models in the credit union environment has been previously investigated, this study represents the first of its kind in the Barbados and SIDS context (Desai, Crook, & Overstreet, 1996).

The remainder of this paper is organised as follows. In Section 2, a brief-background regarding the credit union movement is presented. In addition, the current situation at the Barbados based credit union is outlined. Finally, this section presents a brief discussion on quantitative credit-scoring. In Section 3 the model evaluation metric and the model performance metrics used in this study are briefly discussed. Section 4 presents the Support Vector Machine algorithm, the classification technique used to develop the credit scoring models for the credit union. The details of the loan datasets provided by the credit union are presented in Section 5. Described in Section 6, is the methodology of the study. Section 7, discusses the results of the study, and Section 8 highlights the conclusions and directions for future research.

2. Credit unions and credit-scoring

2.1. What is a credit union?

Credit unions are co-operative financial institutions that share a common collectivist philosophy. Notwithstanding this similarity, credit unions differ according to many qualitative and quantitative characteristics. One major distinction between credit unions is often the common bond requirement for membership. The common bond is that characteristic that ties members together (e.g., profession, religion, vocation).

Once individuals have joined a credit union as members they enjoy equal rights to vote and participate in the governance and management of their institution. This democratic approach to corporate governance, in which all members are seen as key stakeholders without regard to deposit or loan size, has added to the popularity of credit unions as financial institutions of choice for many individuals across the globe.

Over the decades, there has been tremendous growth in the membership of credit unions. In addition to the democratic underpinnings of credit union philosophy, this trend has been attributed to the increased services on offer from credit unions, and to more relaxed interpretations of common bond requirements for membership.

2.2. Credit unions in Barbados and the situation at the study institution

In Barbados, the first credit union was formed in 1947. Since this time there has been an exponential growth in the number of credit unions and credit union members on the Island. At the time of the writing of this paper, the largest Barbados based credit union had over BB $ 791 billion in total assets reported in its 2012 annual report.

Credit union expansion in Barbados has not been without its challenges. The recent "Financial Stability Report" published by the Central Bank of Barbados (CBB) disclosed that local credit unions are experiencing increased delinquency rates since 2008. Loans' in arrears three months and over now stand at around 7.8% of gross credit union loans (CBB 2011, 2012).

In the case of the study institution, during the financial year 2011 to 2012 the percentage of nonperforming loans in the total loan portfolio moved from 4.8% to 6.9%. Further analysis of the position of the credit union reveals a critical situation with regard to the percentage increase in nonperforming loans when comparing closing 2011 and 2012 figures (Table 1). Impaired consumer loans has rinsed by 69.31% in 2012 when compared to 2011 closing balances. There has been a triple digit (160.81%) increase in non-performing Business loans. Moreover, impaired mortgage loans have increase by 27.27%. This situation is unsustainable and all efforts to arrest it, including the development of quantitative credit scorecards should be considered.

2.3. Credit-scoring

The literature has demonstrated that quantitative credit risk assessment using credit-scoring is an accurate means of credit risk evaluation (Crook, Edelman, & Thomas, 2007; Hand & Henley, 1997; Thomas, Edelman, & Crook, 1987; Thomas et al., 2005). Indeed since Fisher's (1936) seminal paper, there have been numerous quantitative studies outlining techniques aimed at differentiating between "good" and "bad" credit applicants. Many of these classification models are based on classical statistical methods such as Discriminant Analysis.

Discriminant analysis was first proposed by Fisher (1936) and is a parametric technique that has been widely applied in credit-scoring applications to discriminate between the two groups of applicants. For instance, Durand (1941) used discriminant analysis to evaluate car loan applicants. In addition, Altman (1986) used discriminant analysis to examine corporate bankruptcy.

Another popular statistical technique used to predict the likelihood of applicant delinquency is Linear Regression. When used for credit-scoring this technique establishes a threshold credit-score. This threshold score is derived from the linear (or polynomial) relationships between historic client features and their associated weights. Eq. (1) below depicts the classical hypothesis function used when training a linear regression classifier.

$$Z = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n \tag{1}$$

Here the variable n represents the number of features collected from potential clients. The features themselves are represented by the x's. The θ's represent the associated weights. The feature variables along with their weights are used to produce a credit-score, $Z \in \mathbb{R}$. When using linear regression, an applicant who scores below the threshold is rejected, while an applicant who scores above the predetermined threshold is granted credit. Orgler (1970) was one of the first researchers to use linear regression for credit-scoring. His work, on commercial loan analysis, demonstrated how this technique could be used in practical credit-scoring applications (Orgler, 1971).

Logistic Regression, as in (2), is another widely used classical statistical technique that has been applied to the field of credit-scoring. Logistic regression can be thought of as a special case of linear regression where $Z \in \{1,0\}$. To achieve this, the logistic/sigmoid function, $g(x) = \frac{1}{1+e^{-x}}$, is used to restrict the values assigned to Z.

$$Z = g(\theta^T x) = \frac{1}{1 + e^{-\theta^T x}} \tag{2}$$

Wiginton (1980) was one of the first researchers to use logistic regression for credit-scoring. Although his results were not very impressive the simplicity of logistic regression has led to it