Chapter XIV

Assessment of Evaluation Methods for Prediction and Classifications of Consumer Risk in the Credit Industry

Satish Nargundkar, Georgia State University, USA
Jennifer Lewis Priestley, Georgia State University, USA

ABSTRACT

In this chapter, we examine and compare the most prevalent modeling techniques in the credit industry. Linear Discriminant Analysis, Logistic Analysis and the emerging technique of Neural Network modeling. K-S Tests and Classification Rates are typically used in the industry to measure the success in predictive classification. We examine those two methods and a third, ROC Curves, to determine if the method of evaluation has an influence on the perceived performance of the modeling technique. We found that each modeling technique has its own strengths, and a determination of the “best” depends upon the evaluation method utilized and the costs associated with misclassification.
INTRODUCTION

The popularity of consumer credit products represents both a risk and an opportunity for credit lenders. The credit industry has experienced decades of rapid growth as characterized by the ubiquity of consumer financial products such as credit cards, mortgages, home equity loans, auto loans and interest-only loans, etc. In 1980, there was $55.1 billion in outstanding unsecured revolving consumer credit in the US. In 2000, that number had risen to $633.2 billion. However, the number of bankruptcies filed per 1,000 US households increased from one to five over the same period.

In an effort to maximize the opportunity to attract, manage, and retain profitable customers and minimize the risks associated with potentially unprofitable ones, lenders have increasingly turned to modeling to facilitate a holistic approach to Customer Relationship Management (CRM). In the consumer credit industry, the general framework for CRM includes product planning, customer acquisition, customer management and collections and recovery (Figure 1). Prediction models have been used extensively to support each stage of this general CRM strategy.

For example, customer acquisition in credit lending is often accomplished through model-driven target marketing. Data on potential customers, which can be accessed from credit bureau files and a firm’s own databases, is used to predict the likelihood of response to a solicitation. Risk models are also utilized to support customer acquisition efforts through the prediction of a potential customer’s likelihood of default. Once customers are acquired, customer management strategies require careful analysis of behavior patterns. Behavioral models are developed using a customer’s transaction history to predict which customers may default or attrite. Based upon some predicted value, firms can then efficiently allocate resources for customer incentive programs or credit line increases. Predictive accuracy in this stage of customer management is important because effectively retaining customers is significantly less expensive than acquiring new customers. Collections and recovery is a critical stage in a credit lender’s CRM strategy, where lenders develop models to predict a delinquent customer’s likelihood of repayment. Other models used by lenders to support the overall CRM strategy may involve bankruptcy prediction, fraud prediction and market segmentation.

Not surprisingly, the central concern of modeling applications in each stage of CRM is improving predictive accuracy. An improvement of even a fraction of a percent can translate into significant savings or increased revenue. As a result, many different modeling techniques have been developed, tested and
Related Content

Measuring Effectiveness: A DEA Approach Under Predetermined Targets
[www.igi-global.com/article/measuring-effectiveness/107067?camid=4v1a](www.igi-global.com/article/measuring-effectiveness/107067?camid=4v1a)

Decision Support as Knowledge Creation: A Business Intelligence Design Theory
[www.igi-global.com/article/decision-support-knowledge-creation/38938?camid=4v1a](www.igi-global.com/article/decision-support-knowledge-creation/38938?camid=4v1a)

Supply Chain Analytics in the Era of Big Data
Ching-Chung Kuo and Zhen Li (2014). *Encyclopedia of Business Analytics and Optimization* (pp. 2350-2363).
[www.igi-global.com/chapter/supply-chain-analytics-in-the-era-of-big-data/107419?camid=4v1a](www.igi-global.com/chapter/supply-chain-analytics-in-the-era-of-big-data/107419?camid=4v1a)
Information Quality Assessment for Asset Management Systems

Sang Hyun Lee and Abrar Haider (2014). *Information Quality and Governance for Business Intelligence* (pp. 128-147).

[www.igi-global.com/chapter/information-quality-assessment-for-asset-management-systems/96148?camid=4v1a](www.igi-global.com/chapter/information-quality-assessment-for-asset-management-systems/96148?camid=4v1a)