Statistical Science
2006, Vol. 21, No. 1, 19–23
DOI 10.1214/088342306000000051

Comment: Classifier Technology and the Illusion of Progress—Credit Scoring

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These comments support Hand's argument for the lack of practical progress in classifier technology by pursuing them a little deeper in the specific context of credit scoring. Academic development of modeling techniques tends to ignore the role of the practitioner and the impact of business objectives. In credit scoring it can be seen that the nature of the task forces practitioners to adopt modeling strategies that positively favor simple techniques or, at least, limit the possible advantage of sophisticated techniques. The strategies adopted by credit scorers can be viewed as a heuristic approach to inference of the unobserved (and unobservable) distribution of possible data sets. The technical progress examined by Hand has been aimed toward better goodness of fit. However, technical progress toward a more principled basis for inferring the distribution of future problem data would be more likely to be adopted in practice.

1. CREDIT SCORING

I am approaching this commentary as a domain-specific consumer of statistical technology. My concern is credit scoring (the use of predictive statistical models to control operational decision-making in consumer finance). Classical credit scoring is applied at the point of application for a loan to predict the risk of default (nonpayment) and to make the decision whether to approve that application for credit. The total value of the loans made under the control of credit scoring is immense, and the value added to the economy by better decision-making because of credit scoring is correspondingly large. Thus, credit scoring is a domain where improved decision-making due to better predictive modeling would be valuable and technical progress would be expected.

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Somewhat surprisingly, the statistical techniques currently used in credit scoring seem rather old-fashioned (often being simple regression models). This is not for lack of attempts to change the state of the art. New modeling techniques are regularly proposed for credit scoring (typically by academic researchers), but they are rarely adopted in practice. This lack of uptake cannot be blamed entirely on conservatism in the credit scoring community. The rewards of improvement are sufficiently high that once any lender adopts a better technique, there will be high competitive pressure for other lenders to do likewise. Rather, the continued use of simple predictive modeling techniques suggests that they have a practical advantage over more sophisticated techniques in credit scoring. Understanding the reasons for this advantage would be useful for the practice of applied predictive modeling in credit scoring and, more generally, might suggest productive avenues for the development of predictive modeling techniques to be applied in practical domains.

Professor Hand has worked extensively in credit scoring and it is likely that his experience in that domain motivated the writing of his paper, although his thesis, as stated, is not restricted to credit scoring. As a practitioner of credit scoring, I agree with the points he has raised. My aim here is to examine Hand's points a little further in the specific context of credit scoring, looking at the interaction of the technicalities of modeling with the demands imposed by the nature of the business task.

A brief description of the classical credit scoring problem is as follows. When credit is granted to consumers, some of the borrowers will default on their loans. The lender typically takes a loss on a defaulted loan. Ideally, a lender would predict which applicants would default and decline their applications for credit, thus avoiding the loss. The lender uses data available at the time of application to make that prediction and decision. The data may come from an application form, a credit bureau and the lender's own records if the applicant is an existing customer.

The potential predictors available at the time of application are not causally related to the outcome of