RISKS MANAGEMENT. A PROPENSITY SCORE APPLICATION

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Abstract Risk management is relatively unexplored in Romania. Although Romanian specialists dwell on theoretical aspects such as the risks classification and the important distinction between risks and uncertainty the practical relevance of the matter is outside existing studies. Present paper uses a dataset of consumer data to build a propensity scorecard based on relevant quantitative modeling.

Key Terms: Risks Management, propensity scorecard, business application

Introduction

Suppose that you work for a mail order enterprise that sends out a catalog of furnishings and housewares each month. As part of an upcoming sales campaign, you want to distribute a special catalog that is devoted to fine dining and contains kitchenware, dishes, and flatware. It's too expensive to send this catalog to all of your customers, so you need to target those most likely to buy. You do this by developing a propensity model and then using it to produce a new mailing list. Fortunately, you have an extensive record of customer purchases. The data includes variables that indicate whether customers bought kitchenware, dishes, or flatware in the past two years. This purchase history has been used to create a data set, which contains 65 variables and 1765 observations. A variable that is labeled TOTAL DINING (kitch+dish+flat) has been created. It contains the sum of the variables that are labeled Kitchen Product, Dishes Purchase, and Flatware Purchase. This variable will be the basis of the model you build, as its values indicate an interest in dining wares. Based on this variable the DINEBIN target varaible has been constructed. A profit matrix is computed based on costs and incomes associated with each action. Present analysis takes into consideration the prediction accuracy of different models and the probability thereshold is assigned based on maximizing the profits. Oversampling has been used to obtain the training dataset in order to boost the occurance of subjects interested in buying dining wares.

The Model

A summary of the statistical methods for assessing credit risk is offered by Hand and Henley (1997). Statistical scoring uses predictor variables to yields probabilities of default or to predict the repayment behavior of borrowers. Schreiner (2003) argues that Regression estimations, Discriminant analysis and Decisional trees are the most prevalent statistical methods that are used in assessing credit risk. However more sophisticated methods such as nonparametric smoothening, mathematical programming, Markov chains, recursive partitioning, genetic algorithms or neural networks are also available. Present analysis begins with considering Tree Analysis, Regressions and Neural Networks. Preliminary results allow us to drop Tree Analysis as comparatively inefficient.

A comparison between prediction accuracy of Regressions and Neural Networks is presented in Figure 1.

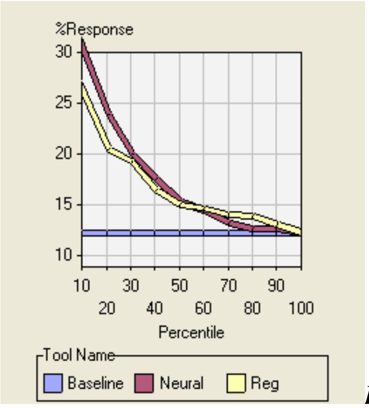

Figure 1 Prediction accuracy of Regression and Neural Networks

As one can see Neural Networks analysis leads to superior prediction accuracy. After training and validation of the model, you can see that it accurately predicts a purchase approximately 35 percent of the time for the top 10 percent of scores. This in turn has same implication about profits, as presented in Figure 2.

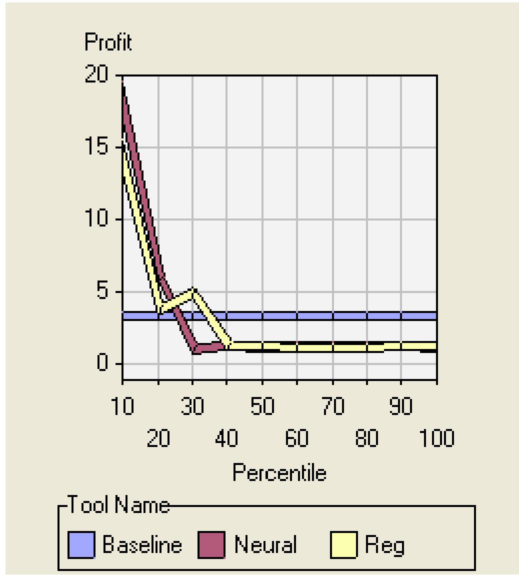

Figure 2. Non - Cumulative Estimated profits

The **Profit** chart calculates anticipated profits by combining response rates with the information that provided in the target profile. You can see that the neural networks model, if it's applied to the top ten percent of scores, should yield an average profit of about $20 per target. The decision tree model should bring in an average of $ 15, thus, combining the two strata yields a rough average of $ 17 per target. Profit chart confirms the superiority of Neural Network model.

Table 1. Models main results

	Neural Networks			Regression		
Average Profit	4.18	2.99	2.90	3.71	2.75	2.81
Misclassification Rate	0.48	0.49	0.53	0.48	0.50	0.52
Average Error	0.61	0.66	0.66	0.62	0.66	0.66

Taking into consideration average profit, misclassification rate and average error Table 1 confirms the superiority of Neural networks model. Propensity scores based on this model are presented in Table 2.

Table 2. Propensity score abstract

Obs	DINEBIN	P_DINEBIN1
1	1	0.52
2	1	0.52
3	1	0.52
4	1	0.52
5	1	0.52

6	1	0.52
7	1	0.52
8	1	0.52
9	1	0.51
10	1	0.49

We see that our model is accurate is accurate in predicting propensity scores. The propensity scorecard employs the top 30% of scores which maximizes profits.

Conclusion

Neural Networks analysis has proved superior to regression in modeling the propensity scores in present risk management application. The prediction accuracy of the model is very good for top scores. Analysis predicts an average profit of $ 4.18 with a maximum of $ 20 for the top 30 % scores.

Bibliography

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