

MPRA

Munich Personal RePEc Archive

Applying CHAID for logistic regression diagnostics and classification accuracy improvement

Evgeny Antipov and Elena Pokryshevskaya

The State University Higher School of Economics

2009

Online at <https://mpra.ub.uni-muenchen.de/21499/>

MPRA Paper No. 21499, posted 29. March 2010 07:30 UTC

Evgeny Antipov

Affiliation: The State University Higher School of Economics and The Center for Business Analysis

E-mail address: eugene.antipov@gmail.com

Elena Pokryshevskaya

Affiliation: The State University Higher School of Economics and The Center for Business Analysis

Country: Russia

E-mail address: e.pokryshevskaya@gmail.com

Applying CHAID for logistic regression diagnostics and classification accuracy improvement

Abstract

In this study a CHAID-based approach to detecting classification accuracy heterogeneity across segments of observations is proposed. This helps to solve some important problems, facing a model-builder:

1. How to automatically detect segments in which the model significantly underperforms?
2. How to incorporate the knowledge about classification accuracy heterogeneity across segments to partition observations in order to achieve better predictive accuracy?

The approach was applied to churn data from the UCI Repository of Machine Learning Databases. By splitting the dataset into 4 parts, which are based on the decision tree, and building a separate logistic regression scoring model for each segment we increased the accuracy by more than 7 percentage points on the test sample. Significant increase in recall and precision was also observed. It was shown that different segments may have absolutely different churn

predictors. Therefore such a partitioning gives a better insight into factors influencing customer behavior.

Keywords: CHAID, logistic regression, churn prediction, performance improvement, segmentwise prediction, decision tree

1 Introduction

Classification problems are very common in business and include credit scoring, direct marketing optimization and customer churn prediction among others. Researchers develop and apply more and more complex techniques to maximize the prediction accuracy of their models. However, a common modeling problem is the presence of heterogeneity of classification accuracy across segments. Therefore building one model for all observations and considering only aggregate predictive accuracy measures may be misleading if a classifier performance varies significantly across different segments of observations. To cope with such an undesirable feature of classification models, analysts sometimes try to split the sample into several homogeneous groups and build a separate model for each segment or employ dummy variables. As far as we know, methods of automatic data partitioning in order to reduce such heterogeneity have not received much attention in papers on classification problems: researchers usually use some a priori considerations and make mainly univariate splits (e. g. by gender). Deodhar and Ghosh (2007)¹ stated that researchers most often do partitioning a priori based on domain knowledge or a separate segmentation routine.

Some researchers have proposed CHAID as an aid for better specifying and interpreting a logit model (Magidson, 1982², Ratner, 1997³). In this paper the CHAID-based approach is used for finding whether subgroups with significantly lower or higher than average levels of prediction accuracy can be found in data after applying the binary logistic regression. This approach is

employed for diagnostic purposes as well as for improving the initial model. We demonstrate that the proposed method can be used for splitting the dataset into several segments, followed by building separate models for each segment, which leads to a significant increase in classification accuracy both on training and test datasets and therefore, enhances logistic regression.

2 Models employed in the study

Logistic regression

In the logit (logistic) regression model, the predicted values for the dependent variable will always be greater than (or equal to) 0, or less than (or equal to) 1. This is accomplished by applying the following regression equation⁴:

$$y = \frac{e^{b_0 + b_1 \cdot x_1 + \dots + b_n \cdot x_n}}{1 + e^{b_0 + b_1 \cdot x_1 + \dots + b_n \cdot x_n}}$$

The name *logit* stems from the fact that one can easily linearize this model via the *logit* transformation. Suppose we think of the binary dependent variable y in terms of an underlying continuous probability p , ranging from 0 to 1. We can then transform that probability p as:

$$p' = \log_e \left(\frac{p}{1 - p} \right)$$

This transformation is referred to as the *logit* or *logistic* transformation. Note that p' can theoretically assume any value between minus and plus infinity. Since the logit transform solves the issue of the 0/1 boundaries for the original dependent variable (probability), we could use those (logit transformed) values in an ordinary linear regression equation. In fact, if we perform the logit transform on both sides of the logit regression equation stated earlier, we obtain the standard linear regression model:

$$p' = b_0 + b_1 \cdot x_1 + b_2 \cdot x_2 + \dots + b_n \cdot x_n$$

For a comprehensive but accessible discussion of logistic regression we suggest reading Hosmer et al. (2000⁵) and Kleinbaum (1994⁶).

Logistic regression is very appealing for several reasons: (1) logit modeling is well known, and conceptually simple; (2) the ease of interpretation of logit is an important advantage over other methods (e.g. neural networks); (3) logit modeling has been shown to provide good and robust results in comparison studies⁷. As for database marketing applications, it has been shown by several authors⁸ that logit modeling may outperform more sophisticated methods. Perhaps, the most serious problem with logistic regression, failure to incorporate nonmonotonic relationships, can be partly solved by numeric variables quantization (using classification trees, for example).

CHAID

CHAID is a type of decision tree technique, based upon adjusted significance testing (Bonferroni testing). The acronym CHAID stands for *Chi*-squared Automatic Interaction Detector. It is one of the oldest tree classification methods originally proposed by Kass (1980⁹; according to Ripley, 1996¹⁰, the CHAID algorithm is a descendent of THAID developed by Morgan and Messenger, 1973¹¹). CHAID will "build" non-binary trees (i.e., trees where more than two branches can attach to a single root or node), based on a relatively simple algorithm that is particularly well suited for the analysis of larger datasets. Also, because the CHAID algorithm will often effectively yield many multi-way frequency tables (e.g., when classifying a categorical response variable with many categories, based on categorical predictors with many classes), it has been particularly popular in marketing research, in the context of market segmentation studies.⁴ CHAID output is visual and easy to interpret. Because it uses multiway splits, it needs rather large sample sizes to work effectively as with small sample sizes the respondent groups can quickly become too small for reliable analysis. In this study we use CHAID as a diagnostic technique, which can be helpful in partitioning the dataset into several segments, which differ by the misclassification error of logistic regression model.

CART

CART algorithm was introduced in Breiman et al. (1986¹²). A CART tree is a binary decision tree that is constructed by splitting a node into two child nodes repeatedly, beginning with the root node that contains the whole learning sample. The CART growing method attempts to maximize within-node homogeneity. The extent to which a node does not represent a homogenous subset of cases is an indication of impurity. For example, a terminal node in which all cases have the same value for the dependent variable is a homogenous node that requires no further splitting because it is "pure." For categorical (nominal, ordinal) dependent variables the common measure of impurity is Gini, which is based on squared probabilities of membership for each category. Splits are found that maximize the homogeneity of child nodes with respect to the value of the dependent variable.

3 Methodology

CHAID-based diagnostics and classification accuracy improvement

Binary classifiers, such as logistic regression, use a set of explanatory variables in order to predict the class to which every observation belongs. Let X_1, \dots, X_n be the explanatory variables included into the classification model; Y_i - the observed class to which observation i belongs, \hat{Y}_i - the predicted class for this observation. Then variable C_i indicates whether the observation i is misclassified ($C_i=0$) or not ($C_i=1$).

1. On the training sample build the decision tree, using the CHAID algorithm with C_i as a dependent variable and with X_1, \dots, X_n as the explanatory variables. Choose the significance level you think is appropriate (in this study we will always use 5% significance level). Nodes of the tree represent the segments which differ by the correct classification rate. If no splits are made then classification accuracy is most likely to be homogenous across segments of observations.

2. If the revealed segments significantly differ in classification accuracy rate (both from the statistical and practical point of view) split the dataset into several non-overlapping subsets according to the information you have from the above mentioned decision tree. The number of segments primarily depends on the number of observations in different nodes of the tree.

Although CHAID has been chosen, there are hardly any arguments against the idea of trying other decision trees algorithms and choosing the best segmentation (from the point of view of an analyst). The attractive features of the proposed approach are its simplicity and interpretability. It can be easily implemented using widespread statistical packages such as PASW Statistics, Statistica or SAS. Due to its data mining nature this method works best on rather large datasets (over 1000 observations). However, as a purely diagnostic approach it may be applied to smaller ones as well.

Data

To illustrate the introduced approach we use the churn dataset from the UCI Repository of Machine Learning Databases¹³. The case study associated with this dataset is as follows. The early detection of potential churners enables companies to target these customers using specific retention actions, and should subsequently increase profits. A telecommunication company wants to determine whether a customer will churn or not in the next period, given billing data.

The dependent variable is whether the client churned or not. The explanatory variables are listed in Table 1. As we use this dataset mainly to illustrate a rather general approach, we do not set any specific misclassification costs or prior probabilities.

Table 1. Explanatory variables

Variable Name	Variable Description	Variable type
AccountLength	Account Length (months)	integer
IntlPlan	International plan	Dichotomous
VMailPlan	Voice mail plan	Dichotomous
VMail Message	Number of voice mail messages	integer
Day Mins	Total day minutes	continuous
Eve Mins	Total evening minutes	continuous
Night Mins	Total night minutes	continuous
Intl Mins	Total international minutes	continuous
CustServ Calls	Number of calls to customer service	integer

Before building the initial logit model we randomly divide our sample into training (2000 cases) and test (1333 cases) sets.

Logistic regression modeling and diagnostics

The parameter estimates of Model 1 are presented in Table 2. We use backward stepwise variable selection method with entry probability equal to 0.05 and removal probability equal to 0.1.

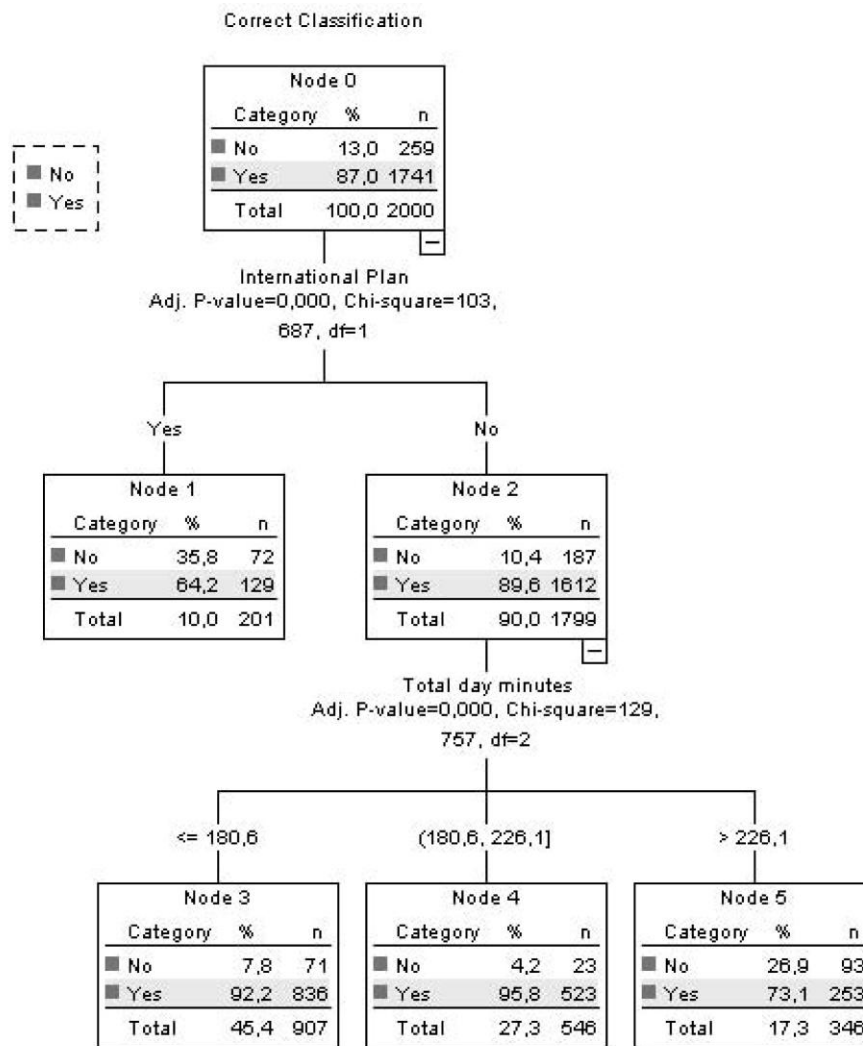
Table 2. Parameter Estimates of Model 1

Variable	B	Wald	Sig.	Exp(B)
Intercept	-8,347	115,246	0,000	
VMailPlan	1,990	11,921	0,001	7,318
IntlPlan	-2,020	195,416	0,000	0,133
VMailMessage	0,035	3,663	0,056	1,035

DayMins	0,013	142,833	0,000	1,013
EveMins	0,007	39,328	0,000	1,007
NightMins	0,004	11,005	0,001	1,004
IntlMins	0,085	17,269	0,000	1,088
CustServCalls	0,511	170,799	0,000	1,666

Then we generate variable C (the indicator of correct classification). After that we build a diagnostic CHAID decision tree (Fig. 1) using PASW Statistics 18 (SPSS Inc.), taking C as the dependent variable and all the predictors listed in Table 1 as the explanatory variables. To obtain segments large enough for the subsequent analysis we have set the minimum size of nodes to 200 observations.

Fig. 1. CHAID decision tree: accuracy of Model 1 (training sample)



From the diagnostic decision tree it is obvious that there is a significant difference between the accuracy in 4 groups automatically formed on the basis of total day minutes and international plan variables. The first segment has the lowest percentage of correctly classified customers (64.2%) and consists of those who have chosen the international plan, the other three segments include those who do not use the international plan: these segments are based on the number of total day minutes. The highest classification accuracy is within the segment of customers who use 180.6 – 226.1 total day minutes (95.8%).

We quantify the heterogeneity of classification accuracy using the following normalized measure of dispersion:

$$CV = \frac{\sqrt{\frac{\sum_{i=1}^N \left((PCC_i - \overline{PCC})^2 n_i \right)}{\sum_{i=1}^N n_i}}}{\overline{PCC}} = 0.125$$

Here PCC_i stands for the percentage correctly classified in segment i , \overline{PCC} is the percentage correctly classified in the whole training sample, n_i is the size of each segment, N is the number of segments.

Some possible ways of improving the model are listed below:

1. Override the model in the least predictable segments.
2. Split the dataset and build a separate model for each of the revealed segments.
3. Use some sort of ensembling with weights proportional to the probability that the classifier works best for this segment.

Although the third approach may be rather promising, its development requires some further research. We use the second alternative and build separate models for 4 large segments of data, revealed with the help of the CHAID decision tree (we set minimum node size to 300 to make our results robust by operating with rather large segments). The parameter estimates for Model 2 (the logistic regressions built on three segments separately) are presented in Table 3.

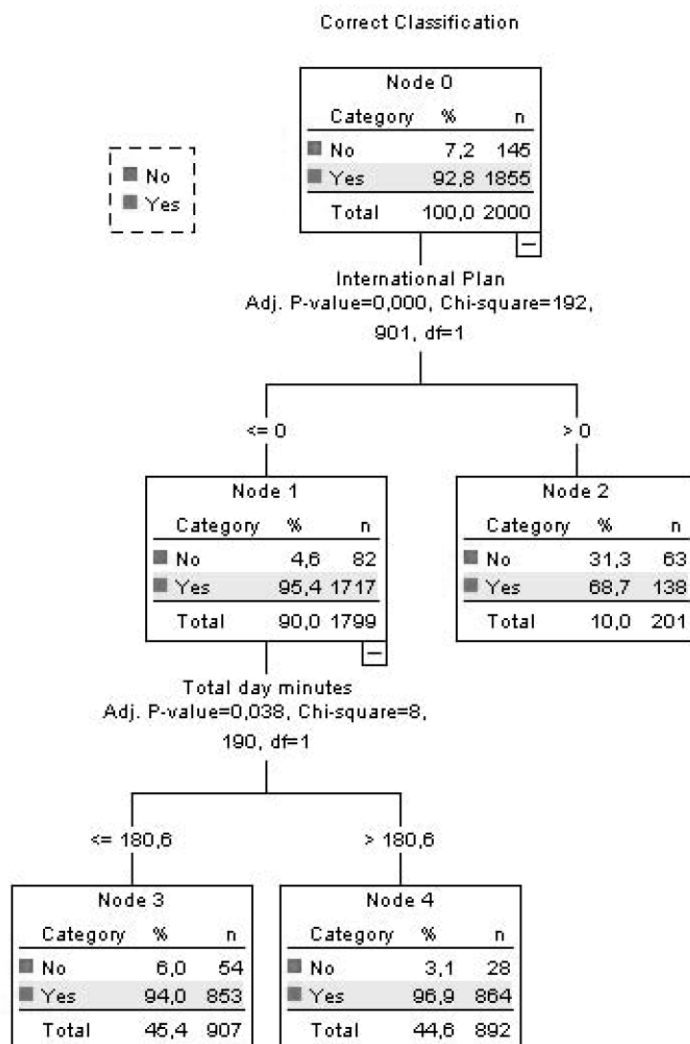
Table 3. Parameter Estimates of Model 2

Segment	Variable	B	Wald	Sig.	Exp(B)
International Plan	Intercept	-5,113	36,162	0,000	
	EveMins	0,004	3,090	0,079	1,004
	IntlMins	0,343	37,477	0,000	1,410
	CustServCalls	0,167	3,092	0,079	1,182
No International plan, Total day minutes<=180.6	Intercept	-4,272	71,615	0,000	
	EveMins	-0,005	4,172	0,041	0,995
	CustServCalls	1,174	199,041	0,000	3,235
No International plan, 180.6<=Total day minutes<=226.1	Intercept	-13,115	19,664	0,000	
	EveMins	0,006	3,242	0,072	1,006
	CustServCalls	0,271	5,128	0,024	1,312
	AccountLength	0,010	5,687	0,017	1,010
	VMailPlan	-3,197	4,633	0,031	0,041
	VMailMessage	0,099	5,482	0,019	1,104
	DayMins	0,029	4,785	0,029	1,029
	NightMins	0,007	3,750	0,053	1,007
No International plan, Total day minutes>=226.1	Intercept	-44,114	94,019	0,000	
	EveMins	0,052	84,346	0,000	1,053
	IntlMins	0,165	8,164	0,004	1,180
	VMailPlan	-15,162	14,828	0,000	0,000
	VMailMessage	0,237	4,790	0,029	1,267
	DayMins	0,101	77,305	0,000	1,106
	NightMins	0,027	42,572	0,000	1,027

The reference category is: Did not churn

From Table 3 it is obvious that the sets of automatically selected predictors are different for each of the four segments, which means the idea of building separate models for each segment is most likely to be a reasonable one. Not only this can lead to increased accuracy, but also can give managers some ideas on how to increase loyalty. For example, customers with more than 226.1 total day minutes may be extremely unsatisfied with the voice mail plan they are offered. The most appropriate interpretation may be provided only by an expert from the telecommunication company, who will probably find plenty of insights in such regression analysis output.

Fig. 2. CHAID decision tree: accuracy of Model 2 (training sample)



Although we observe some classification accuracy heterogeneity (Fig. 2), it became lower than in Model 1:

$$CV = \frac{\sqrt{\frac{\sum_{i=1}^N ((PCC_i - \overline{PCC})^2 n_i)}{\sum_{i=1}^N n_i}}{\overline{PCC}}} = 0.088$$

Another important improvement is the increase in Percentage Correctly Classified which reached 92.8% for the training sample and 92.1% for the test sample, compared to 87% and 85% correspondingly for Model 1 (see Tables 4 and 5).

Table 4. Classification table for Model 1

		Training sample		Test sample	
		Predicted Category		Predicted Category	
		Did not churn	Churned	Did not churn	Churned
Observed category	Did not churn	1681	36	1101	32
	Churned	223	60	168	32

Table 5. Classification table for Model 2

		Training sample		Test sample	
		Predicted Category		Predicted Category	
		Did not churn	Churned	Did not churn	Churned
Observed category	Did not churn	1687	30	1108	25
	Churned	115	168	80	120

When dealing with class imbalance it is often useful to look at recall and precision measures:

$$Recall = \frac{TP}{TP + FN}, \quad Precision = \frac{TP}{TP + FP},$$

where TP is the number of true positive, FN – the number of false negative and FP is the number of false positive predictions.

Recall (true positive rate) has increased (from 16% on test sample for Model 1 up to 60% for Model 2), as well as

precision (from 50% on test sample for Model 1 up to 82.8% for Model 2). This means that Model 2 allows targeting a larger share of potential churners than Model 1 and that a greater percent of customers indicated by the model as potential churners are worth targeting. From economic point of view the loyalty program based on Model 2 is most likely to be more efficient than the one based on Model 1.

Logistic Regression vs. CHAID and CART

To show that Model 2 is based on a competitive modeling approach, we have compared test sample AUC (Area under the ROC Curve) for Model 2, Model 1 and two data mining classification techniques: CHAID and CART. To avoid overfitting, the minimum size of a classification tree node was set at 100.

Table 6. Area under the curve comparison

Model	AUC
Logistic Regression (Model 1)	0.812
Logistic Regression (Model 2)	0.890
CHAID	0.691
CART	0.835

Standard logistic regression performed worse than CART, but better than CHAID. Model 2 has the highest AUC.

Although logistic regression tends to become an old-fashioned instrument, we believe it will still complement new data mining methods in managerial applications due to the following reasons:

1. Unlike classification trees, it gives a continuous predicted probability, which is helpful when direct marketers have to sort prospects by their propensity to churn, buy, etc. and do not want to

obtain too many tied ranks (even an ensemble of 2-3 decision trees may sometimes lead to insufficient number of different predicted probabilities).

2. It may be preferred by experienced analyst who are not satisfied with automatic model-building procedures and want to develop a tailor-made model with interactions and test some particular hypotheses.

3. It generally requires smaller samples than classification trees.

4. It often performs better than some state of the art techniques in terms of AUC, accuracy and other performance measures.

5. The standard logistic regression can be enhanced using bagging or approaches like the one described in this paper, leading to at least as high performance as of well-established machine learning algorithms.

6. Logistic regression failure to incorporate nonmonotonic relationships can be partly solved by numeric variables quantization (using classification trees, for example).

4 Conclusions and future work

In some applications, due to the heterogeneity of the data it is advantageous to learn segmentwise prediction models rather than a global model. In this study we have proposed a CHAID-based approach to detecting classification accuracy heterogeneity across segments of observations. This helps to solve 2 important problems, facing a model-builder:

1. How to automatically detect and visualize segments in which the model significantly underperforms?

2. How to incorporate the knowledge about classification accuracy heterogeneity across segments of observations to split cases into several segments in order to achieve better predictive accuracy?

We applied our approach to churn data from the UCI Repository of Machine Learning Databases. By splitting the dataset into 4 parts, which are based on the decision tree, and building a separate logistic regression scoring model for each segment we increased the accuracy by more than 7 percentage points on the test sample. From economic point of view the loyalty program based on Model 2 is most likely to be much more efficient than the one based on Model 1 thanks to an increase in recall (from 16% to 60%) and precision (from 50% to 82.8%). We have revealed that different segments may have absolutely different churn predictors. Therefore such a partitioning may give both prediction accuracy improvement and a better insight into factors influencing customer behavior. By calculating the AUC it was shown that Model 2 has outperformed CHAID and CART.

In our further research we plan to study, whether better performance may be achieved by using classification tree algorithms other than CHAID together with logistic regression. Applying decision trees to improve other classifiers such as Support Vector Machines, Random Forests etc. may also be a direction for future work.

References

1. Deodhar, M., Ghosh, J. (2007) A framework for simultaneous co-clustering and learning from complex data. *Proceedings of the 13th ACM SIGKDD international conference on Knowledge discovery and data mining*; 12-15 August 2007, San Jose, California, USA.
2. Magidson, J. (1982) Some Common Pitfalls in Causal Analysis of Categorical Data. *Journal of Marketing Research*, Vol. 19, No. 4, Special Issue on Causal Modeling (Nov., 1982), pp. 461-471.
3. Ratner, B. (2003) Statistical modeling and analysis for database marketing: effective techniques for mining big data. Chapman & Hall/CRC.

4. Hill, T. and Lewicki, P. (2007) *STATISTICS Methods and Applications*. StatSoft, Tulsa, OK.
5. Hosmer, David W.; Stanley Lemeshow (2000). *Applied Logistic Regression*, 2nd ed. New York; Chichester, Wiley.
6. Kleinbaum, D. G. 1994. *Logistic Regression: A Self-Learning Text*. New York: Springer-Verlag.
7. Neslin, S., Gupta, S., Kamakura, W., Lu, J. and Mason, C. (2006) Detection defection: Measuring and understanding the predictive accuracy of customer churn models. *Journal of Marketing Research* 43(2): 204–211.
8. Levin, N. and Zahavi, J. (1998) Continuous predictive modeling, a comparative analysis. *Journal of Interactive Marketing* 12: 5–22.
9. Kass, G.V. (1980) An Exploratory Technique for Investigating Large Quantities of Categorical Data. *Journal of Applied Statistics* 29(2): 119-127.
10. Ripley, B.D. (1996) *Pattern recognition and neural networks*. Cambridge: Cambridge University Press.
11. Morgan, J.N. and Messenger, R.C. (1973) THAID: A sequential analysis program for the analysis of nominal scale dependent variables. Institute of Social Research, University of Michigan, Ann Arbor. Technical report.
12. Breiman, L., J. H. Friedman, R. A. Olshen, and C. J. Stone. (1984) *Classification and Regression Trees*. New York: Chapman & Hall/CRC.
13. Blake, C. L. and Merz, C. J., Churn Data Set, UCI Repository of Machine Learning Databases, <http://www.sgi.com/tech/mlc/db/>. University of California, Department of Information and Computer Science, Irvine, CA, 1998.