State-of-the-Art Survey

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Graham J. Williams
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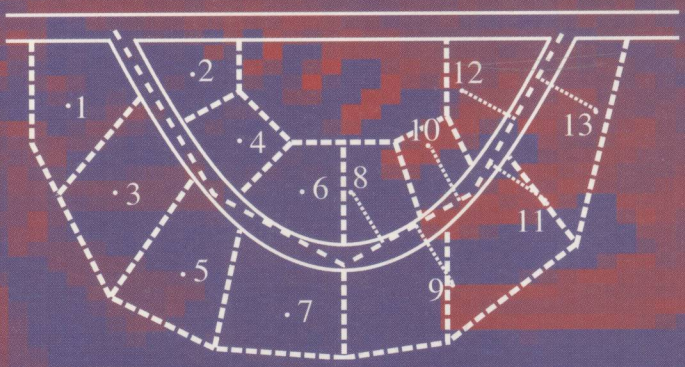
# Data Mining

## Theory, Methodology, Techniques, and Applications

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Graham J. Williams  Simeon J. Simoff (Eds.)

# Data Mining

## Theory, Methodology, Techniques, and Applications




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# Preface

Data mining has been an area of considerable research and application in Australia and the region for many years. This has resulted in the establishment of a strong tradition of academic and industry scholarship, blended with the pragmatics of practice in the field of data mining and analytics. ID3, See5, RuleQuest.com, MagnumOpus, and WEKA is but a short list of the data mining tools and technologies that have been developed in Australasia. Data mining conferences held in Australia have attracted considerable international interest and involvement.

This book brings together a unique collection of chapters that cover the breadth and depth of data mining today. This volume provides a snapshot of the current state of the art in data mining, presenting it both in terms of technical developments and industry applications. Authors include some of Australia's leading researchers and practitioners in data mining, together with chapters from regional and international authors.

The collection of chapters is based on works presented at the Australasian Data Mining conference series and industry forums. The original papers were initially reviewed for the workshops, conferences and forums. Presenting authors were provided with substantial feedback, both through this initial review process and through editorial feedback from their presentations. A final international peer review process was conducted to include input from potential users of the research, and in particular analytics experts from industry, looking at the impact of reviewed works.

Many people contribute to an effort such as this, starting with the authors! We thank all authors for their contributions, and particularly for making the effort to address two rounds of reviewer comments. Our workshop and conference reviewers provided the first round of helpful feedback for the presentation of the papers to their respective conferences. The authors from a selection of the best papers were then invited to update their contributions for inclusion in this volume. Each submission was then reviewed by at least another two reviewers from our international panel of experts in data mining.

A considerable amount of effort goes into reviewing papers, and reviewers perform an essential task. Reviewers receive no remuneration for all their efforts, but are happy to provide their time and expertise for the benefit of the whole community. We owe a considerable debt to them all and thank them for their enthusiasm and critical efforts.

Bringing this collection together has been quite an effort. We also acknowledge the support of our respective institutions and colleagues who have contributed in many different ways. In particular, Graham would like to thank Togaware (Data Mining and GNU/Linux consultancy) for their ongoing infrastructural support over the years, and the Australian Taxation Office for its

support of data mining and related local conferences through the participation of its staff. Simeon acknowledges the support of the University of Technology, Sydney. The Australian Research Council's Research Network on Data Mining and Knowledge Discovery, under the leadership of Professor John Roddick, Flinders University, has also provided support for the associated conferences, in particular providing financial support to assist student participation in the conferences. Professor Geoffrey Webb, Monash University, has played a supportive role in the development of data mining in Australia and the AusDM series of conferences, and continues to contribute extensively to the conference series.

The book is divided into two parts: (i) state-of-art research and (ii) state-of-art industry applications. The chapters are further grouped around common sub-themes. We are sure you will find that the book provides an interesting and broad update on current research and development in data mining.

November 2005 Graham Williams and Simeon Simoff

# Organization

Many colleagues have contributed to the success of the series of data mining workshops and conferences over the years. We list here the primary reviewers who now make up the International Panel of Expert Reviewers.

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# Generality Is Predictive of Prediction Accuracy

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**Abstract.** During knowledge acquisition it frequently occurs that multiple alternative potential rules all appear equally credible. This paper addresses the dearth of formal analysis about how to select between such alternatives. It presents two hypotheses about the expected impact of selecting between classification rules of differing levels of generality in the absence of other evidence about their likely relative performance on unseen data. We argue that the accuracy on unseen data of the more general rule will tend to be closer to that of a default rule for the class than will that of the more specific rule. We also argue that in comparison to the more general rule, the accuracy of the more specific rule on unseen cases will tend to be closer to the accuracy obtained on training data. Experimental evidence is provided in support of these hypotheses. These hypotheses can be useful for selecting between rules in order to achieve specific knowledge acquisition objectives.

## 1 Introduction

In many knowledge acquisition contexts there will be many classification rules that perform equally well on the training data. For example, as illustrated by the version space [1], there will often be alternative rules of differing degrees of generality all of which agree with the training data. However, even when we move away from a situation in which we are expecting to find rules that are strictly consistent with the training data, in other words, when we allow rules to misclassify some training cases, there will often be many rules all of which cover exactly the same training cases. If we are selecting rules to use for some decision making task, we must select between such rules with identical performance on the training data. To do so requires a learning bias [2], a means of selecting between competing hypotheses that utilizes criteria beyond those strictly encapsulated in the training data.

All learning algorithms confront this problem. This is starkly illustrated by the large numbers of rules with very high values for any given interestingness measure that are typically discovered during association rule discovery. Many systems that learn rule sets for the purpose of prediction mask this problem by making arbitrary choices between rules with equivalent performance on the

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training data. This masking of the problem is so successful that many researchers appear oblivious to the problem. Our previous work has clearly identified that it is frequently the case that there exist many variants of the rules typically derived in machine learning, all of which cover exactly the same training data. Indeed, one of our previous systems, The Knowledge Factory [3, 4] provides support for identification and selection between such rule variants.

This paper examines the implications of selecting between such rules on the basis of their relative generality. We contend that learning biases based on relative generality can usefully manipulate the expected performance of classifiers learned from data. The insight that we provide into this issue may assist knowledge engineers make more appropriate selections between alternative rules when those alternatives derive equal support from the available training data.

We present specific hypotheses relating to reasonable expectations about classification error for classification rules. We discuss classification rules of the form $Z \rightarrow y$, which should be interpreted as all cases that satisfy conditions $Z$ belong to class $y$. We are interested in learning rules from data. We allow that evidence about the likely classification performance of a rule might come from many sources, including prior knowledge, but, in the machine learning tradition, are particularly concerned with *empirical* evidence—evidence obtained from the performance of the rule on sample (training) data. We consider the learning context in which a rule $Z \rightarrow y$ is learned from a *training set* $D'=(x'_1, y'_1), (x'_2, y'_2), \ldots, (x'_n, y'_n)$ and is to be applied to a set of previously unseen data called a *test set* $D=(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)$. For this enterprise to be successful, $D'$ and $D$ should be drawn from the same or from related distributions. For the purposes of the current paper we assume that $D'$ and $D$ are drawn independently at random from the same distribution and acknowledge that violations of this assumption may affect the effects that we predict.

We utilize the following notation.

- $Z(I)$ represents the set of instances in instance set $I$ covered by condition $Z$.
- $E(Z \rightarrow y, I)$ represents the number of instances in instance set $I$ that $Z \rightarrow y$ misclassifies (the absolute error).
- $\varepsilon(Z \rightarrow y, I)$ represents the proportion of instance set $I$ that $Z \rightarrow y$ misclassifies (the error) $= \frac{E(Z \rightarrow y, I)}{|I|}$.
- $W \gg Z$ denotes that the condition $W$ is a proper generalization of condition $Z$. $W \gg Z$ if and only if the set of descriptions for which $W$ is true is a proper superset of the set of descriptions for which $Z$ is true.
- $NODE(W \rightarrow y, Z \rightarrow y)$ denotes that there is no other distinguishing evidence between $W \rightarrow y$ and $Z \rightarrow y$. This means that there is no available evidence, other than the relative generality of $W$ and $Z$, indicating the likely direction (negative, zero, or positive) of $\varepsilon(W \rightarrow y, D) - \varepsilon(Z \rightarrow y, D)$. In particular, we require that the empirical evidence be identical. In the current research the learning systems have access only to empirical evidence and we assume that $W(D')=Z(D') \rightarrow NODE(W \rightarrow y, Z \rightarrow y)$. Note that $W(D')=Z(D')$ does not preclude $W$ and $Z$ from covering different test cases at classification time and hence having different test set error. We utilize the

notion of *other distinguishing evidence* to allow for the real-world knowledge acquisition context in which evidence other than that contained in the data may be brought to bear upon the rule selection problem.

We present two hypotheses relating to classification rules $W \rightarrow y$ and $Z \rightarrow y$ learned from real-world data such that $W \gg Z$ and $NODE(W \rightarrow y, Z \rightarrow y)$.

1. $Pr(|\varepsilon(W \rightarrow y, D) - \varepsilon(true \rightarrow y, D)| < |\varepsilon(Z \rightarrow y, D) - \varepsilon(true \rightarrow y, D)|) > Pr(|\varepsilon(W \rightarrow y, D) - \varepsilon(true \rightarrow y, D)| > |\varepsilon(Z \rightarrow y, D) - \varepsilon(true \rightarrow y, D)|)$. That is, the error of the more general rule, $W \rightarrow y$, on unseen data will tend to be closer to the proportion of cases in the domain that do not belong to class $y$ than will the error of the more specific rule, $Z \rightarrow y$.
2. $Pr(|\varepsilon(W \rightarrow y, D) - \varepsilon(W \rightarrow y, D')| > |\varepsilon(Z \rightarrow y, D) - \varepsilon(Z \rightarrow y, D')|) > Pr(|\varepsilon(W \rightarrow y, D) - \varepsilon(W \rightarrow y, D')| < |\varepsilon(Z \rightarrow y, D) - \varepsilon(Z \rightarrow y, D')|)$. That is, the error of the more specific rule, $Z \rightarrow y$, on unseen data will tend to be closer to the proportion of negative training cases covered by the two rules[1] than will the error of the more general rule, $W \rightarrow y$.

Another way of stating these two hypotheses is that of two rules with identical empirical and other support,

1. the more general can be expected to exhibit classification error closer to that of a *default rule*, $true \rightarrow y$, or, in other words, of assuming all cases belong to the class, and
2. the more specific can be expected to exhibit classification error closer to that observed on the training data.

It is important to clarify at the outset that we are not claiming that the more general rule will invariably have closer generalization error to the default rule and the more specific rule will invariably have closer generalization error to the observed error on the training data. Rather, we are claiming that relative generality provides a source of evidence that, in the absence of alternative evidence, provides reasonable grounds for believing that each of these effects is more likely than the contrary.

*Observation.* With simple assumptions, hypotheses (1) and (2) can be shown to be trivially true given that $D'$ and $D$ are idd samples from a single finite distribution $\mathcal{D}$.

*Proof.*

1. For any rule $X \rightarrow y$ and test set $D$, $\varepsilon(X \rightarrow y, D) = \varepsilon(X \rightarrow y, X(D))$, as $X \rightarrow y$ only covers instances $X(D)$ of $D$.
2. $\varepsilon(Z \rightarrow y, D) = \frac{E(Z \rightarrow y, Z(D \cap D')) + E(Z \rightarrow y, Z(D - D'))}{|Z(D)|}$
3. $\varepsilon(W \rightarrow y, D) = \frac{E(W \rightarrow y, W(D \cap D')) + E(W \rightarrow y, W(D - D'))}{|W(D)|}$
4. $Z(D) \subseteq W(D)$ because $Z$ is a specialization of $W$.

[1] Recall that both rules have identical empirical support and hence cover the same training cases.

5. $Z(D \cap D') = W(D \cap D')$ because $Z(D') = W(D')$.
6. $Z(D - D') \subseteq W(D - D')$ because $Z(D) \subseteq W(D)$.
7. from 2-6, $E(Z \rightarrow y, Z(D \cap D'))$ is a larger proportion of the error of $Z \rightarrow y$ than is $E(W \rightarrow y, W(D \cap D'))$ of $W \rightarrow y$ and hence performance on $D'$ is a larger component of the performance of $Z \rightarrow y$ and performance on $D - D'$ is a larger component of the performance of $W \rightarrow y$. □

However, in most domains of interest the dimensionality of the instance space will be very high. In consequence, for realistic training and test sets the proportion of the training set that appears in the test set, $\frac{|D \cap D'|}{|D|}$, will be small. Hence this effect will be negligible, as performance on the training set will be a negligible portion of total performance. What we are more interested in is off-training-set error. We contend that the force of these hypotheses will be stronger than accounted for by the difference made by the overlap between training and test sets, and hence that they do apply to off-training-set error. We note, however, that it is trivial to construct no-free-lunch proofs, such as those of Wolpert [5] and Schaffer [6], that this is not, in general, true. Rather, we contend that the hypotheses will in general be true for 'real-world' learning tasks. We justify this contention by recourse to the similarity assumption [7], that in the absence of other information, the greater the similarity between two objects in other respects, the greater the probability of their both belonging to the same class. We believe that most machine learning algorithms depend upon this assumption, and that this assumption is reasonable for real-world knowledge acquisition tasks. Test set cases covered by a more general but not a more specific rule are likely to be less similar to training cases covered by both rules than are test set cases covered by the more specific rule. Hence satisfying the left-hand-side of the more specific rule provides stronger evidence of likely class membership.

A final point that should be noted is that these hypotheses apply to individual classification rules — structures that associate an identified region of an instance space with a single class. However, as will be discussed in more detail below, we believe that the principle is nonetheless highly relevant to 'complete classifiers,' such as decision trees, that assign different regions of the instance space to different classes. This is because each individual region within a 'complete classifier' (such as a decision tree leaf) satisfies our definition of a classification rule, and hence the hypotheses can cast light on the likely consequences of relabeling subregions of the instance space within such a classifier (for example, generalizing one leaf of a decision tree at the expense of another, as proposed elsewhere [8]).

## 2 Evaluation

To evaluate these hypotheses we sought to generate rules of varying generality but identical empirical evidence (no other evidence source being considered in the research), and to test the hypotheses' predictions with respect to these rules.

We wished to provide some evaluation both of whether the predicted effects are general (with respect to rules with the relevant properties selected at random)