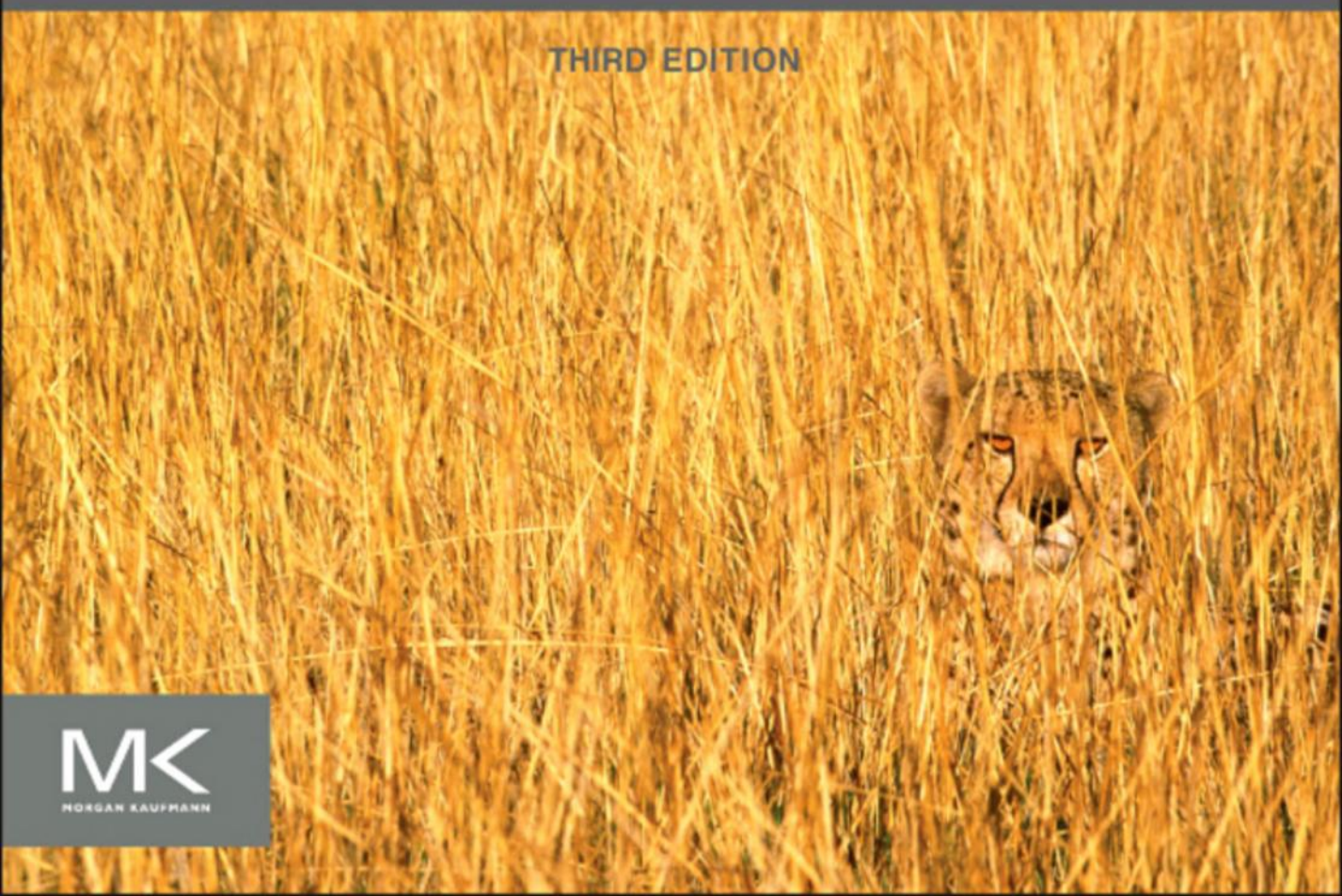
Ian H. Witten • Eibe Frank • Mark A. Hall

DATA MINING

Practical Machine Learning Tools and Techniques

THIRD EDITION



MK
MORGAN KAUFMANN

Data Mining

Third Edition

Data Mining
Practical Machine Learning Tools and Techniques

Third Edition

Ian H. Witten

Eibe Frank

Mark A. Hall

ELSEVIER

AMSTERDAM • BOSTON • HEIDELBERG • LONDON
NEW YORK • OXFORD • PARIS • SAN DIEGO
SAN FRANCISCO • SINGAPORE • SYDNEY • TOKYO

Morgan Kaufmann Publishers is an imprint of Elsevier

Morgan Kaufmann Publishers is an imprint of Elsevier
30 Corporate Drive, Suite 400, Burlington, MA 01803, USA

This book is printed on acid-free paper.

Copyright © 2011 Elsevier Inc. All rights reserved.

No part of this publication may be reproduced or transmitted in any form or by any means, electronic or mechanical, including photocopying, recording, or any information storage and retrieval system, without permission in writing from the publisher. Details on how to seek permission, further information about the Publisher's permissions policies and our arrangements with organizations such as the Copyright Clearance Center and the Copyright Licensing Agency, can be found at our website: *www.elsevier.com/permissions*.

This book and the individual contributions contained in it are protected under copyright by the Publisher (other than as may be noted herein).

Notices

Knowledge and best practice in this field are constantly changing. As new research and experience broaden our understanding, changes in research methods, professional practices, or medical treatment may become necessary.

Practitioners and researchers must always rely on their own experience and knowledge in evaluating and using any information, methods, compounds, or experiments described herein. In using such information or methods they should be mindful of their own safety and the safety of others, including parties for whom they have a professional responsibility.

To the fullest extent of the law, neither the Publisher nor the authors, contributors, or editors, assume any liability for any injury and/or damage to persons or property as a matter of products liability, negligence or otherwise, or from any use or operation of any methods, products, instructions, or ideas contained in the material herein.

Library of Congress Cataloging-in-Publication Data

Witten, I. H. (Ian H.)

Data mining : practical machine learning tools and techniques.—3rd ed. / Ian H. Witten, Frank Eibe, Mark A. Hall.

p. cm.—(The Morgan Kaufmann series in data management systems)

ISBN 978-0-12-374856-0 (pbk.)

1. Data mining. I. Hall, Mark A. II. Title.

QA76.9.D343W58 2011

006.3′12—dc22 2010039827

British Library Cataloguing-in-Publication Data

A catalogue record for this book is available from the British Library.

For information on all Morgan Kaufmann publications, visit our website at *www.mkp.com* or *www.elsevierdirect.com*

Printed in the United States

11 12 13 14 15 10 9 8 7 6 5 4 3 2 1

Working together to grow libraries in developing countries

www.elsevier.com | www.bookaid.org | www.sabre.org

ELSEVIER BOOK AID International Sabre Foundation

Contents

List of Figures

List of Tables

Preface

The convergence of computing and communication has produced a society that feeds on information. Yet most of the information is in its raw form: data. If *data* is characterized as recorded facts, then *information* is the set of patterns, or expectations, that underlie the data. There is a huge amount of information locked up in databases—information that is potentially important but has not yet been discovered or articulated. Our mission is to bring it forth.

Data mining is the extraction of implicit, previously unknown, and potentially useful information from data. The idea is to build computer programs that sift through databases automatically, seeking regularities or patterns. Strong patterns, if found, will likely generalize to make accurate predictions on future data. Of course, there will be problems. Many patterns will be banal and uninteresting. Others will be spurious, contingent on accidental coincidences in the particular dataset used. And real data is imperfect: Some parts will be garbled, some missing. Anything that is discovered will be inexact: There will be exceptions to every rule and cases not covered by any rule. Algorithms need to be robust enough to cope with imperfect data and to extract regularities that are inexact but useful.

Machine learning provides the technical basis of data mining. It is used to extract information from the raw data in databases—information that is expressed in a comprehensible form and can be used for a variety of purposes. The process is one of abstraction: taking the data, warts and all, and inferring whatever structure underlies it. This book is about the tools and techniques of machine learning that are used in practical data mining for finding, and describing, structural patterns in data.

As with any burgeoning new technology that enjoys intense commercial attention, the use of data mining is surrounded by a great deal of hype in the technical—and sometimes the popular—press. Exaggerated reports appear of the secrets that can be uncovered by setting learning algorithms loose on oceans of data. But there is no magic in machine learning, no hidden power, no alchemy. Instead, there is an identifiable body of simple and practical techniques that can often extract useful information from raw data. This book describes these techniques and shows how they work.

We interpret machine learning as the acquisition of structural descriptions from examples. The kind of descriptions that are found can be used for prediction, explanation, and understanding. Some data mining applications focus on prediction: They forecast what will happen in new situations from data that describe what happened in the past, often by guessing the classification of new examples. But we are equally—perhaps more—interested in applications where the result of "learning" is an actual description of a structure that can be used to classify examples. This structural description supports explanation and understanding as well as prediction. In our experience, insights gained by the user are of most interest in the majority of practical data mining applications; indeed, this is one of machine learning's major advantages over classical statistical modeling.

The book explains a wide variety of machine learning methods. Some are pedagogically motivated: simple schemes that are designed to explain clearly how the basic ideas work. Others are practical: real systems that are used in applications today. Many are contemporary and have been developed only in the last few years.

A comprehensive software resource has been created to illustrate the ideas in this book. Called the Waikato Environment for Knowledge Analysis, or Weka[1] for short, it is available as Java source code at *www.cs.waikato.ac.nz/ml/weka*. It is a full, industrial-strength implementation of essentially all the techniques that are covered in this book. It includes illustrative code and working implementations of machine learning methods. It offers clean, spare implementations of the simplest techniques, designed to aid understanding of the mechanisms involved. It also provides a workbench that includes full, working, state-of-the-art implementations of many popular learning schemes that can be used for practical data mining or for research. Finally, it contains a framework, in the form of a Java class library, that supports applications that use embedded machine learning and even the implementation of new learning schemes.

The objective of this book is to introduce the tools and techniques for machine learning that are used in data mining. After reading it, you will understand what these techniques are and appreciate their strengths and applicability. If you wish to experiment with your own data, you will be able to do this easily with the Weka software.

The book spans the gulf between the intensely practical approach taken by trade books that provide case studies on data mining and the more theoretical, principle-driven exposition found in current textbooks on machine learning. (A brief description of these books appears in the Further Reading section at the end of Chapter 1.) This gulf is rather wide. To apply machine learning techniques productively, you need to understand something about how they work; this is not a technology that you can apply blindly and expect to get good results. Different problems yield to different techniques, but it is rarely obvious which techniques are suitable for a given situation: You need to know something about the range of possible solutions. And we cover an extremely wide range of techniques. We can do this because, unlike many trade books, this volume does not promote any particular commercial software or approach. We include a large number of examples, but they use illustrative datasets that are small enough to allow you to follow what is going on. Real datasets are far too large to show this (and in any case are usually company confidential). Our datasets are chosen not to illustrate actual large-scale practical problems but to help you understand what the different techniques do, how they work, and what their range of application is.

The book is aimed at the technically aware general reader who is interested in the principles and ideas underlying the current practice of data mining. It will also

[1]Found only on the islands of New Zealand, the weka (pronounced to rhyme with "Mecca") is a flightless bird with an inquisitive nature.

be of interest to information professionals who need to become acquainted with this new technology, and to all those who wish to gain a detailed technical understanding of what machine learning involves. It is written for an eclectic audience of information systems practitioners, programmers, consultants, developers, information technology managers, specification writers, patent examiners, and curious lay people, as well as students and professors, who need an easy-to-read book with lots of illustrations that describes what the major machine learning techniques are, what they do, how they are used, and how they work. It is practically oriented, with a strong "how to" flavor, and includes algorithms, code, and implementations. All those involved in practical data mining will benefit directly from the techniques described. The book is aimed at people who want to cut through to the reality that underlies the hype about machine learning and who seek a practical, nonacademic, unpretentious approach. We have avoided requiring any specific theoretical or mathematical knowledge, except in some sections that are marked by a box around the text. These contain optional material, often for the more technically or theoretically inclined reader, and may be skipped without loss of continuity.

The book is organized in layers that make the ideas accessible to readers who are interested in grasping the basics, as well as accessible to those who would like more depth of treatment, along with full details on the techniques covered. We believe that consumers of machine learning need to have some idea of how the algorithms they use work. It is often observed that data models are only as good as the person who interprets them, and that person needs to know something about how the models are produced to appreciate the strengths, and limitations, of the technology. However, it is not necessary for all users to have a deep understanding of the finer details of the algorithms.

We address this situation by describing machine learning methods at successive levels of detail. The book is divided into three parts. Part I is an introduction to data mining. The reader will learn the basic ideas, the topmost level, by reading the first three chapters. Chapter 1 describes, through examples, what machine learning is and where it can be used; it also provides actual practical applications. Chapters 2 and 3 cover the different kinds of input and output, or *knowledge representation*, that are involved—different kinds of output dictate different styles of algorithm. Chapter 4 describes the basic methods of machine learning, simplified to make them easy to comprehend. Here, the principles involved are conveyed in a variety of algorithms without getting involved in intricate details or tricky implementation issues. To make progress in the application of machine learning techniques to particular data mining problems, it is essential to be able to measure how well you are doing. Chapter 5, which can be read out of sequence, equips the reader to evaluate the results that are obtained from machine learning, addressing the sometimes complex issues involved in performance evaluation.

Part II introduces advanced techniques of data mining. At the lowest and most detailed level, Chapter 6 exposes in naked detail the nitty-gritty issues of implementing a spectrum of machine learning algorithms, including the complexities that are necessary for them to work well in practice (but omitting the heavy mathematical

machinery that is required for a few of the algorithms). Although many readers may want to ignore such detailed information, it is at this level that the full, working, tested Java implementations of machine learning schemes are written. Chapter 7 describes practical topics involved with engineering the input and output to machine learning—for example, selecting and discretizing attributes—while Chapter 8 covers techniques of "ensemble learning," which combine the output from different learning techniques. Chapter 9 looks to the future.

The book describes most methods used in practical machine learning. However, it does not cover reinforcement learning because that is rarely applied in practical data mining; nor does it cover genetic algorithm approache, because these are really an optimization technique, or relational learning and inductive logic programming because they are not very commonly used in mainstream data mining applications.

Part III describes the Weka data mining workbench, which provides implementations of almost all of the ideas described in Parts I and II. We have done this in order to clearly separate conceptual material from the practical aspects of how to use Weka. At the end of each chapter in Parts I and II are pointers to related Weka algorithms in Part III. You can ignore these, or look at them as you go along, or skip directly to Part III if you are in a hurry to get on with analyzing your data and don't want to be bothered with the technical details of how the algorithms work.

Java has been chosen for the implementations of machine learning techniques that accompany this book because, as an object-oriented programming language, it allows a uniform interface to learning schemes and methods for pre- and postprocessing. We chose it over other object-oriented languages because programs written in Java can be run on almost any computer without having to be recompiled, having to go through complicated installation procedures, or—worst of all—having to change the code itself. A Java program is compiled into byte-code that can be executed on any computer equipped with an appropriate interpreter. This interpreter is called the *Java virtual machine*. Java virtual machines—and, for that matter, Java compilers—are freely available for all important platforms.

Of all programming languages that are widely supported, standardized, and extensively documented, Java seems to be the best choice for the purpose of this book. However, executing a Java program is slower than running a corresponding program written in languages like C or C++ because the virtual machine has to translate the byte-code into machine code before it can be executed. This penalty used to be quite severe, but Java implementations have improved enormously over the past two decades, and in our experience it is now less than a factor of two if the virtual machine uses a *just-in-time compiler*. Instead of translating each byte-code individually, a just-in-time compiler translates whole chunks of byte-code into machine code, thereby achieving significant speedup. However, if this is still too slow for your application, there are compilers that translate Java programs directly into machine code, bypassing the byte-code step. Of course, this code cannot be executed on other platforms, thereby sacrificing one of Java's most important advantages.

UPDATED AND REVISED CONTENT

We finished writing the first edition of this book in 1999, the second edition in early 2005, and now, in 2011, we are just polishing this third edition. How things have changed over the past decade! While the basic core of material remains the same, we have made the most opportunities to both update it and to add new material. As a result the book has close to doubled in size to reflect the changes that have taken place. Of course, there have also been errors to fix, errors that we had accumulated in our publicly available errata file (available through the book's home page at *http://www.cs.waikato.ac.nz/ml/weka/book.html*).

Second Edition

The major change in the second edition of the book was a separate part at the end that included all the material on the Weka machine learning workbench. This allowed the main part of the book to stand alone, independent of the workbench, which we have continued in this third edition. At that time, Weka, a widely used and popular feature of the first edition, had just acquired a radical new look in the form of an interactive graphical user interface—or, rather, three separate interactive interfaces—which made it far easier to use. The primary one is the Explorer interface, which gives access to all of Weka's facilities using menu selection and form filling. The others are the Knowledge Flow interface, which allows you to design configurations for streamed data processing, and the Experimenter interface, with which you set up automated experiments that run selected machine learning algorithms with different parameter settings on a corpus of datasets, collect performance statistics, and perform significance tests on the results. These interfaces lower the bar for becoming a practicing data miner, and the second edition included a full description of how to use them.

It also contained much new material that we briefly mention here. We extended the sections on rule learning and cost-sensitive evaluation. Bowing to popular demand, we added information on neural networks: the perceptron and the closely related Winnow algorithm, and the multilayer perceptron and the backpropagation algorithm. Logistic regression was also included. We described how to implement nonlinear decision boundaries using both the kernel perceptron and radial basis function networks, and also included support vector machines for regression. We incorporated a new section on Bayesian networks, again in response to readers' requests and Weka's new capabilities in this regard, with a description of how to learn classifiers based on these networks and how to implement them efficiently using AD-trees.

The previous five years (1999–2004) had seen great interest in data mining for text, and this was reflected in the introduction of string attributes in Weka, multinomial Bayes for document classification, and text transformations. We also described efficient data structures for searching the instance space: *k*D-trees and ball trees for finding nearest neighbors efficiently and for accelerating distance-based clustering. We described new attribute selection schemes, such as race search and the use of

support vector machines, and new methods for combining models such as additive regression, additive logistic regression, logistic model trees, and option trees. We also covered recent developments in using unlabeled data to improve classification, including the co-training and co-EM methods.

Third Edition

For this third edition, we thoroughly edited the second edition and brought it up to date, including a great many new methods and algorithms. Our basic philosophy has been to bring the book and the Weka software even closer together. Weka now includes implementations of almost all the ideas described in Parts I and II, and vice versa—pretty well everything currently in Weka is covered in this book. We have also included far more references to the literature: This third edition practically triples the number of references that were in the first edition.

As well as becoming far easier to use, Weka has grown beyond recognition over the last decade, and has matured enormously in its data mining capabilities. It now incorporates an unparalleled range of machine learning algorithms and related techniques. This growth has been partly stimulated by recent developments in the field and partly user-led and demand-driven. This puts us in a position where we know a lot about what actual users of data mining want, and we have capitalized on this experience when deciding what to include in this book.

As noted earlier, this new edition is split into three parts, which has involved a certain amount of reorganization. More important, a lot of new material has been added. Here are a few of the highlights.

Chapter 1 includes a section on web mining, and, under ethics, a discussion of how individuals can often be "reidentified" from supposedly anonymized data. A major addition describes techniques for multi-instance learning, in two new sections: basic methods in Section 4.9 and more advanced algorithms in Section 6.10. Chapter 5 contains new material on interactive cost–benefit analysis. There have been a great number of other additions to Chapter 6: cost-complexity pruning, advanced association-rule algorithms that use extended prefix trees to store a compressed version of the dataset in main memory, kernel ridge regression, stochastic gradient descent, and hierarchical clustering methods. The old chapter Engineering the Input and Output has been split into two: Chapter 7 on data transformations (which mostly concern the input) and Chapter 8 on ensemble learning (the output). To the former we have added information on partial least-squares regression, reservoir sampling, one-class learning, decomposing multiclass classification problems into ensembles of nested dichotomies, and calibrating class probabilities. To the latter we have added new material on randomization versus bagging and rotation forests. New sections on data stream learning and web mining have been added to the last chapter of Part II.

Part III, on the Weka data mining workbench, contains a lot of new information. Weka includes many new filters, machine learning algorithms, and attribute selection algorithms, and many new components such as converters for different file formats and parameter optimization algorithms. Indeed, within each of these categories Weka

contains around 50% more algorithms than in the version described in the second edition of this book. All these are documented here. In response to popular demand we have given substantially more detail about the output of the different classifiers and what it all means. One important change is the inclusion of a brand new Chapter 17 that gives several tutorial exercises for the Weka Explorer interface (some of them quite challenging), which we advise new users to work though to get an idea of what Weka can do.

Acknowledgments

Writing the acknowledgments is always the nicest part! A lot of people have helped us, and we relish this opportunity to thank them. This book has arisen out of the machine learning research project in the Computer Science Department at the University of Waikato, New Zealand. We received generous encouragement and assistance from the academic staff members early on in that project: John Cleary, Sally Jo Cunningham, Matt Humphrey, Lyn Hunt, Bob McQueen, Lloyd Smith, and Tony Smith. Special thanks go to Geoff Holmes, the project leader and source of inspiration, and Bernhard Pfahringer, both of whom also had significant input into many different aspects of the Weka software. All who have worked on the machine learning project here have contributed to our thinking: We would particularly like to mention early students Steve Garner, Stuart Inglis, and Craig Nevill-Manning for helping us to get the project off the ground in the beginning, when success was less certain and things were more difficult.

The Weka system that illustrates the ideas in this book forms a crucial component of it. It was conceived by the authors and designed and implemented principally by Eibe Frank, Mark Hall, Peter Reutemann, and Len Trigg, but many people in the machine learning laboratory at Waikato made significant early contributions. Since the first edition of this book, the Weka team has expanded considerably: So many people have contributed that it is impossible to acknowledge everyone properly. We are grateful to Remco Bouckaert for his Bayes net package and many other contributions, Lin Dong for her implementations of multi-instance learning methods, Dale Fletcher for many database-related aspects, James Foulds for his work on multi-instance filtering, Anna Huang for information bottleneck clustering, Martin Gütlein for his work on feature selection, Kathryn Hempstalk for her one-class classifier, Ashraf Kibriya and Richard Kirkby for contributions far too numerous to list, Niels Landwehr for logistic model trees, Chi-Chung Lau for creating all the icons for the Knowledge Flow interface, Abdelaziz Mahoui for the implementation of K*, Stefan Mutter for association-rule mining, Malcolm Ware for numerous miscellaneous contributions, Haijian Shi for his implementations of tree learners, Marc Sumner for his work on speeding up logistic model trees, Tony Voyle for least-median-of-squares regression, Yong Wang for Pace regression and the original implementation of M5′, and Xin Xu for his multi-instance learning package, *JRip*, logistic regression, and many other contributions. Our sincere thanks go to all these people for their dedicated work, and also to the many contributors to Weka from outside our group at Waikato.

Tucked away as we are in a remote (but very pretty) corner of the southern hemisphere, we greatly appreciate the visitors to our department who play a crucial role in acting as sounding boards and helping us to develop our thinking. We would like to mention in particular Rob Holte, Carl Gutwin, and Russell Beale, each of whom visited us for several months; David Aha, who although he only came for a few days did so at an early and fragile stage of the project and performed a great

service by his enthusiasm and encouragement; and Kai Ming Ting, who worked with us for two years on many of the topics described in Chapter 8 and helped to bring us into the mainstream of machine learning. More recent visitors include Arie Ben-David, Carla Brodley, and Stefan Kramer. We would particularly like to thank Albert Bifet, who gave us detailed feedback on a draft version of the third edition, most of which we have incorporated.

Students at Waikato have played a significant role in the development of the project. Many of them are in the above list of Weka contributors, but they have also contributed in other ways. In the early days, Jamie Littin worked on ripple-down rules and relational learning. Brent Martin explored instance-based learning and nested instance-based representations, Murray Fife slaved over relational learning, and Nadeeka Madapathage investigated the use of functional languages for expressing machine learning algorithms. More recently, Kathryn Hempstalk worked on one-class learning and her research informs part of Section 7.5; likewise, Richard Kirkby's research on data streams informs Section 9.3. Some of the exercises in Chapter 17 were devised by Gabi Schmidberger, Richard Kirkby, and Geoff Holmes. Other graduate students have influenced us in numerous ways, particularly Gordon Paynter, YingYing Wen, and Zane Bray, who have worked with us on text mining, and Quan Sun and Xiaofeng Yu. Colleagues Steve Jones and Malika Mahoui have also made far-reaching contributions to these and other machine learning projects. We have also learned much from our many visiting students from Freiburg, including Nils Weidmann.

Ian Witten would like to acknowledge the formative role of his former students at Calgary, particularly Brent Krawchuk, Dave Maulsby, Thong Phan, and Tanja Mitrovic, all of whom helped him develop his early ideas in machine learning, as did faculty members Bruce MacDonald, Brian Gaines, and David Hill at Calgary, and John Andreae at the University of Canterbury.

Eibe Frank is indebted to his former supervisor at the University of Karlsruhe, Klaus-Peter Huber, who infected him with the fascination of machines that learn. On his travels, Eibe has benefited from interactions with Peter Turney, Joel Martin, and Berry de Bruijn in Canada; Luc de Raedt, Christoph Helma, Kristian Kersting, Stefan Kramer, Ulrich Rückert, and Ashwin Srinivasan in Germany.

Mark Hall thanks his former supervisor Lloyd Smith, now at Missouri State University, who exhibited the patience of Job when his thesis drifted from its original topic into the realms of machine learning. The many and varied people who have been part of, or have visited, the machine learning group at the University of Waikato over the years deserve a special thanks for their valuable insights and stimulating discussions.

Rick Adams and David Bevans of Morgan Kaufmann have worked hard to shape this book, and Marilyn Rash, our project manager, has made the process go very smoothly. We would like to thank the librarians of the Repository of Machine Learning Databases at the University of California, Irvine, whose carefully collected datasets have been invaluable in our research.

Our research has been funded by the New Zealand Foundation for Research, Science, and Technology and the Royal Society of New Zealand Marsden Fund. The Department of Computer Science at the University of Waikato has generously supported us in all sorts of ways, and we owe a particular debt of gratitude to Mark Apperley for his enlightened leadership and warm encouragement. Part of the first edition was written while both authors were visiting the University of Calgary, Canada, and the support of the Computer Science department there is gratefully acknowledged, as well as the positive and helpful attitude of the long-suffering students in the machine learning course, on whom we experimented. Part of the second edition was written at the University of Lethbridge in Southern Alberta on a visit supported by Canada's Informatics Circle of Research Excellence.

Last, and most of all, we are grateful to our families and partners. Pam, Anna, and Nikki were all too well aware of the implications of having an author in the house ("Not again!"), but let Ian go ahead and write the book anyway. Julie was always supportive, even when Eibe had to burn the midnight oil in the machine learning lab, and Immo and Ollig provided exciting diversions. Bernadette too was very supportive, somehow managing to keep the combined noise output of Charlotte, Luke, Zach, and Kyle to a level that allowed Mark to concentrate. Among us, we hail from Canada, England, Germany, Ireland, New Zealand, and Samoa: New Zealand has brought us together and provided an ideal, even idyllic, place to do this work.