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The problems addressed by artificial intelligence research vary widely, from designing autonomous vehicles for space exploration to developing 'intelligent' tools for engineering and design to modeling aspects of human behavior. Artificial intelligence approaches to these problems are characterized by the ability to explore alternative actions and, in many cases, to acquire new information during this exploration. This latter capability is called machine learning, and it enables an 'intelligent' system to improve its own performance, to concisely communicate its experience to a human analyst, and to model the adaptive nature of human intelligence.

Interest in machine learning has become widespread, but with growing interest comes greater impetus to question traditional assumptions that limit the power of the technology. For example, much of the early research on machine and natural concept learning was supervised in that the learner was told the category membership of environmental observations; the sole learning task was to summarize the commonality among members of the same categories and differences among competing ones. In contrast, unsupervised methods are not provided with this guidance; rather, they must discover 'useful' categories in the data using internalized heuristics. A second feature of many traditional concept learning models is that they assume that all environmental observations are available from the outset of learning. This nonincremental or 'batch' assumption can be contrasted with an incremental strategy that learns over a stream of observations.

We believe that unsupervised and incremental assumptions reflect many real-world situations in which humans find themselves, and that they are increasingly important in the construction of machine learn-
ing systems. Together, these two assumptions comprise the task that we call *concept formation*. Our interest in this area emanated from a common base of research by Mike Lebowitz, Janet Kolodner, and Roger Schank on the dynamic nature of memory. However, we took separate slants on a number of critical dimensions. Fisher's and Langley's work—individually, together, and with the help of others, notably Dennis Kibler—was concerned with inductive learning and took further inspiration from computational work by Robert Stepp and Ryszard Michalski on conceptual clustering, the framework for concept representation put forward by Edward Smith and Doug Medin, and psychological research on basic-level effects, most notably the work of Jim Corter and Mark Gluck. In contrast, Pazzani was more directly influenced by the psychological work of Tom Shultz and others on the development of causal reasoning, the knowledge-intensive approaches to machine learning developed by Gerald DeJong and Tom Mitchell, and the psychological findings of Greg Murphy and Doug Medin on the role of background knowledge in learning. These influences led to computational investigations of how knowledge acquired in one area can facilitate learning in related areas. Despite the differences in our work, it seemed clear that our research programs were not part of competing paradigms. Rather, we were addressing similar issues using similar mechanisms, though with somewhat different motivations and terminological conventions.

To promote interdisciplinary interaction between machine learning and cognitive psychology on unsupervised incremental methods, Langley suggested a symposium that would bring together researchers in both fields. The Symposium on Computational Approaches to Concept Formation was held at Stanford University in January, 1990. It was the second in a series of meetings in the area of machine learning administered through the Institute for the Study of Learning and Expertise (ISLE). The symposium was organized around 16 talks representing research in both machine learning and cognitive psychology. Our goal was to downplay surface distinctions between efforts in these communities, and to stress commonality in the research agendas. For example, both fields showed a recent interest in analytic and knowledge-intensive methods, as evident in explanation-based and case-based research, which can be contrasted with more traditional inductive, data-intensive learning. This dichotomy between knowledge-intensive and data-intensive methods has had a profound effect on how researchers in machine learning
and cognitive psychology view issues of similarity, memory, and problem solving, both in general and with respect to concept formation.

Our desire for cross-disciplinary interaction has also guided our organization of this book, which largely grew out of the presentations at the symposium. The chapters included in this volume are divided into three sections, the first being concerned with inductive, data-intensive methods for concept formation. In particular, Chapters 1 through 5 focus on measures of similarity, strategies for robust incremental learning, the representation and organization of discovered categories, and the psychological consistency of various approaches. In Chapter 1, Fisher and Pazzani give an overview of inductive concept learning in machine learning and psychology, with special emphasis on issues that distinguish concept formation from more prevalent supervised methods and from numeric and conceptual clustering. Chapter 2, by Anderson and Matessa, describes the cognitive consistency of two concept formation systems that are motivated by a rational analysis of human behavior relative to a variety of psychological phenomena. Martin and Billman’s discussion in Chapter 3 focuses on the merits of various schemes for representing and acquiring knowledge during concept formation. In Chapter 4, Richman reviews some of the earliest work in concept formation and offers some novel accounts of certain psychological data using these methods. In Chapter 5, Thompson and Langley describe a system that forms concepts with both complex componential structure and relations among their components.

In Chapters 6 through 10 we turn our attention from data-intensive approaches to those that exploit domain knowledge to bias the concept formation process. Fisher and Pazzani open that section with an overview of some psychological and computational motivations for bringing domain knowledge to bear in unsupervised models. However, the knowledge-intensive approach has the greatest number of adherents in an area of supervised learning, notably that of explanation-based learning. In Chapter 7, Mooney argues that, although explanation-based learning has traditionally been viewed as a supervised task, a number of systems in this paradigm are best cast as unsupervised.

Of course, the knowledge-intensive versus data-intensive dichotomy is somewhat misleading; it is more natural to think of these strategies as lying at far ends of a continuum. In many (if not most) situations, both background knowledge and data play a role in concept learning.
Chapter 8 by Ross and Spalding, and Chapter 9 by Wisniewski and Medin, address the relative role of knowledge and data in biasing human concept learning processes. Most of the experimental data that they describe were obtained in supervised settings, but their findings are nonetheless highly relevant to issues of similarity in concept formation. In fact, Yoo and Fisher describe an unsupervised system in Chapter 10 that embodies some of the principles introduced in these earlier chapters; their system exploits data and background knowledge to cluster and reuse past problem-solving experiences.

Finally, Chapters 11 through 15 extend the theoretical contributions of the first two sections, but they also focus on the utility of concept formation methods in particular contexts. Chapter 11 surveys the role of concept formation in scientific discovery, engineering, problem solving, natural language processing, and information retrieval. In Chapter 12, Reich and Fenves report on an application in engineering design, as well as addressing fundamental issues, such as dealing with numeric data. Iba and Gennari describe a system that learns to recognize physical movements in Chapter 13, using ideas from work on concept formation not only to acquire movement categories but also to determine their componential structure. In Chapter 14, Scott and Markovitch describe a learning system that is not passive, but that actively explores its environment through experimentation. In Chapter 15, Simon, Newell, and Klahr describe their Q-SOAR model of the development of number conservation in young children, which relies on a concept formation strategy to organize developmental experiences.

Collectively, these chapters represent the culmination of considerable effort. We are indebted to the many individuals and organizations who have contributed to this book. Most importantly, we thank participants of the Symposium on Computational Approaches to Concept Formation for their stimulating presentations and discussions, and to the authors of the chapters herein for their patience and dedication to quality. Funding for the symposium was provided by Grant No. 8921582 from the National Science Foundation, Grant No. N00014-90-J-1394 from the Office of Naval Research, a gift from the American Association for Artificial Intelligence, and Vanderbilt University. We thank the officials of these agencies and institutions for their support, which contributed to the smooth operation of the symposium. Mildred Tyler and Pam Wilson of Vanderbilt University, Caroline Ehrlich of the University of California, Irvine, and particularly Helen Stewart and Martha Del Alto of NASA
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We believe that the chapters collected here provide a representative cross-section of the work currently under way in the area of concept formation. In addition to cognitive scientists and AI researchers, the book should interest data analysts involved in clustering, philosophers concerned with the nature and origin of concepts, and researchers dealing with issues of similarity, memory organization, and problem solving. We hope that the book promotes interaction, and that researchers in related fields will help extend our understanding of the incremental and unsupervised acquisition of conceptual knowledge.
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