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MACHINE LEARNING

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1. SCOPE

Machine learning research seeks to develop computer systems that automatically improve their performance through experience. While specialized forms of learning programs exist today, the ultimate goal is to develop more broadly applicable systems with more robust learning capabilities. In the long run, such technology could lead to a fundamentally new

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type of computer software that, unlike present-day programs, continually improves through experience. If successful, machine learning research could produce computer systems such as robots that learn to operate in novel environments, speech understanding systems that automatically adapt to new speakers and new environmental conditions, knowledge-based consultant systems that collaborate with human experts to solve difficult problems and acquire new problem-solving tactics by observing the human's contribution to the eventual problem solution, or computer programs that acquire the ability to solve physics or calculus problems by reading a textbook chapter and working the practice problems at chapter's end.

The goal of machine learning research is to produce a domain-independent enabling technology for a broad range of computer applications. A breakthrough in machine learning could have a significant impact across a spectrum of computer applications as diverse as robotics, computer-aided design, intelligent databases, and knowledge-based consultant systems. Many applications of computers are increasingly knowledge based—that is, dependent on a large number of specific facts about the task domain. Machine learning offers the potential to remove the knowledge-acquisition bottleneck that limits performance and increases development costs for such systems.

To date, scores of computer programs have been developed that exhibit various forms of learning. For example, programs exist that learn rules for solving calculus problems (and improve problem-solving time by several orders of magnitude), that learn rules to diagnose soybean diseases (which perform as well as the best available human-provided rules), and that learn rules to interpret chemical mass spectrograms (which have been published in the *Journal of the American Chemical Society*). Programs exist that acquire the ability to produce or recognize correct pronunciation of English words. In fact, the most successful speech-recognition systems already rely heavily on (mostly statistical) learning techniques that allow them to adapt to variability and noise in their input. One commercially successful system for evaluating loan applications has been developed by a learning program that automatically formulates rules for assessing loan risk, given a large database of training cases. (Examples of additional learning programs are provided in the Appendix.)

These programs demonstrate the feasibility of machine-learning techniques in specific problem domains. Fundamental technical issues remain to be solved, however, before the potential impact of machine learning can be realized in a broad range of computer applications. We attempt here to characterize the current state of the field and to target specific areas for new research.

1.1 *Grand Challenges*

Below are several grand challenges that characterize the goals and potential capabilities of machine learning research within the coming decade, assuming sufficient levels of research support and corresponding levels of scientific progress. We have attempted to state these challenges in terms of concrete domain-specific tasks, but the underlying technical progress that they demand cuts across these tasks. Thus progress needed in the underlying science of machine learning to meet any one of these challenges would constitute progress toward them all.

1.1.1 A LEARNING HOUSEHOLD ROBOT TO ASSIST THE HANDICAPPED Robot systems will never operate robustly in complex, unknown, and changing worlds until they are provided with the ability to learn and adapt to changes in their environment. For example, consider the problems faced by a household robot aid to the handicapped that primarily performs fetching tasks (e.g. find and bring me my glasses, bring me the telephone). Such a system might be preprogrammed with general-purpose procedures for path planning, obstacle avoidance, low-level perception, and manipulation. However, it will have to learn by specializing these general weak methods to a particular set of tasks desired by a particular person in a particular household. It will have to learn to recognize specific objects (e.g. a specific pair of glasses) from multiple vantage points under multiple lighting conditions. It will have to learn to grasp and manipulate a specific set of objects (e.g. a specific telephone, or pair of glasses), which will change from day to day as its tasks change. It will have to learn a model of its changing environment and specific strategies for problem solving within this environment—a map of the house and objects within it, knowledge of which doors are typically locked, where the glasses are usually found, how these correlate with the previous whereabouts of the occupants, etc. Such knowledge might be learned via direct observation of the environment, advice from the human master, or active experimentation in the environment. While this is a large and open-ended problem, we believe a sustained funding effort could result in systems that pass the threshold of practical application for this task in a ten-year period. Such a breakthrough would have a dramatic impact in overcoming the brittleness of current robot systems, and would have a major influence on related applications of robotics such as hazardous cleanup and military reconnaissance.

1.1.2 A LEARNING ASSEMBLY ROBOT FOR FLEXIBLE MANUFACTURING In order to reduce costs and improve competitiveness in manufacturing, a great deal of attention is being given to flexible manufacturing systems that can be quickly reconfigured to manufacture and assemble a variety of parts. This challenge presents an opportunity to utilize machine-learning methods to extend substantially the flexibility and ease of reprogramming of such systems. Such a system must learn to perceive new types of parts, to adopt specialized strategies for efficiently manipulating them, and to assess the physical properties of such objects (e.g. their bending strength, coefficient of friction, etc) that affect assembly. One important subproblem here is to develop methods for efficiently training a robot to generalize from the specific actions performed during training. Teaching methods should formulate a general action schema that can be used by the learning machine as a program for assembling additional instances of the same part.

1.1.3 A LEARNING SPOKEN-DIALOG SYSTEM FOR ADVISING ON EQUIPMENT REPAIR We envision a system that learns to interact freely by way of speech with a human user to assist in troubleshooting and repairing a class of mechanical or electrical equipment (e.g. an automobile). The specific goal of this challenge is to develop a *generic* system, which can automatically acquire appropriate expertise for assisting with any of a broad class of equipment, given initial information concerning the schematics and the behavior of components of the system, along with an opportunity to assist and apprentice to humans performing such tasks. This task is a driver for extending the capability of speech-understanding systems, for extending the capability of human-machine collaborative problem solving, and for lowering the cost of developing knowledge-based consultants. Current expert systems are able to provide various kinds of advice for solving troubleshooting problems, and current speech systems can hold highly constrained dialogs for providing information. Research issues thus include learning problems associated with speech understanding, such as (*a*) learning to recognize new speakers, accents, and dialects, and previously known speakers under new environmental conditions; and (*b*) learning new vocabulary and grammar, and learning new ungrammatical constructs that occur in natural dialog. Issues related to collaborative problem solving include (*a*) learning a model of the user in order to determine the type and verbosity of advice to be provided (and to provide expectations to constrain the natural language–understanding system), and (*b*) learning new troubleshooting tactics by observing the user, so that the system acts both as an advisor and as an apprentice, gradually accumulating a body of expertise from the humans with which it collaborates.

1.1.4 A SYSTEM THAT LEARNS BY READING AND PRACTICING Such a system would learn by reading a chapter of a physics or calculus textbook and solving the problems at the end of the chapter. This goal pushes development of machine-learning approaches relevant to natural language and to acquisition of problem-solving strategies. The impact of success in this task would be to enable automatic development of knowledge-based problem-solving systems in many areas for which human-readable texts exist. A likely by-product would be better models of textbook learning and curriculum presentation. (A slightly different focus could be learning by reading an equipment manual. With this focus, the issue of learning by reading and practicing could be integrated with the above problem of developing a spoken-language system for advising on equipment repair.)

1.1.5 SELF-COMPILING EXPERT SYSTEMS: A LEARNING EXPERT SYSTEM FOR ENGINEERING DESIGN Experience suggests that expert systems for engineering design can only be developed after the application area has matured to the point that most design activity is routine (VT R1). The goal of this challenge would be to develop design-expert systems from first principles. A learning expert system would be given the basic knowledge of the task domain (e.g. physics, design requirements and constraints, manufacturing and assembly constraints), along with practice problems and a basis for critiquing designs. As with the equipment-repair advisor mentioned above, the goal here is to develop a generic system that can learn about a large class of design problems. After substantial practice on design problems, the system should have gained enough experience to reduce some portion of the design space to routine design rules. Other sources of information that could aid the learning process include examples of successful designs and interactive design sessions where the system can observe the design decisions of a human expert. This kind of learning expert system could be useful in emerging technologies such as molecular protein engineering, light-weight composite materials, or high-temperature superconductors.

1.1.6 AUTOMATED DISCOVERY OF IMPORTANT REGULARITIES IN SCIENTIFIC DATABASES Select two or three scientific problems where large databases exist (e.g. DNA sequences, protein folding, astronomical data) and employ machine-learning techniques to discover useful regularities in these databases. This task would provide the impetus for scaling-up existing learning methods and for developing new methods. It is likely that existing methods will not be able to solve this task without finding some way to incorporate domain knowledge into the learning process. This task would also provide an excellent testbed for comparing connectionist and non-connectionist learning methods.

1.2 *Missing Science*

The above grand challenges are plausible ten-year goals for a well-supported research effort. In order to achieve these goals, a number of technical issues must be addressed. The later section on research progress and opportunities considers these issues in greater detail. However, they can be summarized as follows:

1.2.1 IMPROVED METHODS FOR GENERALIZING FROM EXAMPLES The heart of any learning program is the ability to generalize; that is, to transfer knowledge learned in one situation to other situations. For example, in order to learn to recognize a new type of object, a learning vision system must have some mechanism that acquires a general recognition procedure from individual training images. Given a specific training example, issues include how information from that example should be stored, retrieved, and later applied so that it can be used effectively in a broad variety of situations. Much recent progress has been made on symbolic and connectionist mechanisms for generalizing from examples, and on data-intensive and knowledge-intensive mechanisms. Basic research is needed to extend and integrate this current body of methods.

1.2.2 INCREMENTAL LEARNING, MODULARITY, AND SCALING Current inductive learning techniques are limited in three related ways. First, some important learning algorithms (e.g. for connectionist networks) scale poorly. Learning usually becomes excruciatingly slow when task size and amount of training data increase. Second, many of the most popular inductive methods can only learn rules when the training data all describe the same, static environment. Third, existing methods focus primarily on "one-shot" situations where the task is to learn a rule from a collection of examples. This prevents them from being composed to learn complex sets of rules by building on the results of previous learning runs. All of these limitations must be overcome if we are to develop complex, adaptive systems for real-world environments. We must develop modular learning methods that can exploit previously learned knowledge to limit the size of each new learning task. Preliminary results have demonstrated success in particular domains, but much more work is required to establish a broad and general body of strategies for incremental learning in large systems.

1.2.3 METHODS FOR KNOWLEDGE COMPILATION The knowledge within a system, whether acquired by generalizing from examples or by interacting with a knowledge engineer, is often expressed in a form difficult to apply efficiently. For example, in many planning, scheduling, and design domains, it is relatively easy for an expert to specify a brute-force search-based program that is correct but very inefficient. Recent work in explanation-based generalization has begun to explore how this knowledge can be converted into efficient (compiled) forms such as macro operators and control rules. Much remains to be accomplished including exploring other forms of "compiled" knowledge and importing and extending methods from program optimization (e.g. partial evaluation, test incorporation, formal differentiation, and problem reformulation).

1.2.4 PROBLEM-SOLVING FRAMEWORKS THAT EMBED LEARNING MECHANISMS While the question of *how* to generalize from examples is a central research question, there are other critical questions as well. Research is needed on problem-solving frameworks that embed such generalization mechanisms and deal with questions such as *what* to learn, *when* to learn, *from what data* to learn, and *how to store and retrieve* what is learned. For example, an autonomous learning robot will have to make decisions about when to invoke its learning methods, which of its experiences to learn from, what types of knowledge to acquire, how to deal with redundant noisy data, and related issues. This research should focus both on frameworks specific to a particular class of problems (e.g. design, troubleshooting) and on general architectures for artificial agents that must deal with many types of problems.

1.2.5 STRONGER THEORETICAL UNDERSTANDING OF LEARNING In addition to the primary need for experimental research on learning, it is essential to develop a stronger theoretical understanding of the properties of proposed learning methods and of various learning tasks. Important research progress has been made along these lines over the past few years, deepening our understanding of the relationship among the number of training examples required for inductive learning, the size of the hypothesis space considered, the tolerance for error, and the probability of successful learning. Further research is needed to broaden such analyses to consider prior knowledge of the learner, and to understand the implications of these results for specific experimental learning mechanisms.

1.3 *Potential Breakthroughs*

Of course it is difficult to predict when or whether breakthroughs will occur. Nevertheless, we believe the potential exists for major advances that would have a broad impact on many computer applicatons:

1.3.1 NEW GENERATION OF KNOWLEDGE-BASED CONSULTANT SYSTEMS Learning systems that improve the knowledge bases of expert systems are still in the research stage, with a few notable successes in practice. If advances in machine learning push beyond the threshold of practical application, this could lead to a significant new generation of expert systems with an increased level of competence and dramatically lower costs for development and maintenance.

1.3.2 ORDER-OF-MAGNITUDE INCREASE IN FLEXIBILITY AND RELIABILITY OF REAL-TIME CONTROL SYSTEMS Most robot and other real-time control systems are notoriously inflexible once they are required to operate outside their preplanned range of operation. This is largely because of the difficulty of providing in advance for all possible error conditions and situations in which the system might have to operate. Progress on machine-learning applications to robot control could provide significantly greater flexibility and adaptability in such systems by allowing them to model their environment dynamically and adapt to unforeseen situations.

1.3.3 GENERAL-PURPOSE PROGRAMMING LANGUAGES FOR SELF-IMPROVING SOFTWARE Standard programming-systems technology assumes that a program is written, compiled, and then executed a number of times. Once compiled, the program remains unchanged until the programmer again intervenes. Recent research on the integration of learning mechanisms with general problem-solving systems has led to AI systems that continuously improve their own performance as they execute. Further improvements in the scope and robustness of such systems could revolutionize the software field by providing a new generation of programming languages that enable all programs written in the language to improve themselves automatically and continuously.

2. BACKGROUND

2.1 *Recent Growth of the Field*

As a field, machine learning has grown during the 1980s from a few dozen researchers to many hundreds. It has its own journals, several annual meetings, and constitutes the largest single component of the annual artificial intelligence meeting of the AAAI society. Sessions on machine learning are now regularly organized in conferences of related disciplines such as robotics, theoretical computer science, and expert systems. A major influx of connectionist research over the past five years has added substantially to the variety and numbers of researchers actively exploring machine learning.

The maturity of the field is also evidenced by significant methodological improvements over the past decade. Experimental work frequently makes use of carefully controlled comparisons between methods, and shared databases are now maintained informally by the community for such comparisons. Mathematical analyses of learning algorithms and of the complexity of various learning problems are common and have become the subject of an additional annual meeting.

2.2 *Relationship to Other Fields*

As pointed out above, progress in machine learning would impact a large number of fields simply by making available the technology for automated learning in applications in those fields. More fundamentally, the scientific goals of machine learning research overlap those of a number of other fields. Progress in machine learning may transfer to scientific progress in these fields, and vice versa:

2.2.1 ADAPTIVE CONTROL SYSTEMS Adaptive control systems form a model of the system they are controlling. Thus, they exhibit a specialized form of learning: modeling their environment using numerical representations. Machine-learning methods tend to employ different representations (e.g. symbolic, logical, neural network). The overlap with machine learning is especially important in robotics and other real-time control applications.

2.2.2 EDUCATION AND TEACHING Advances in our understanding of computer learning methods have been motivated by (and have motivated) advances in the psychology of human learning. In its initial stages, machine learning work was largely inspired by work on animal learning, and by theories of human concept formation. More recently, results from machine learning such as explanation-based learning have led a number of psychologists to search for evidence of similar learning strategies in humans. Advances in machine learning might have an important impact on our understanding of human learning and teaching strategies.

2.2.3 BIOLOGICAL NEURAL NETWORKS Connectionist learning methods are an important component of recent computer studies of simulated neural networks. Progress in understanding biological learning systems could provide important guidance to machine learning, and vice versa.

2.2.4 STATISTICS Statistical methods for data analysis and summarization overlap with machine learning methods for generalizing from training instances. This overlap is especially significant for providing insight on learning from noisy data.

2.2.5 THEORETICAL COMPUTER SCIENCE Over the past five years, machine learning has become an active area of study within theoretical computer science. The newer theoretical results in this area are beginning to make contact with experimental work in machine learning.

3. RECENT PROGRESS AND RESEARCH OPPORTUNITIES

This section briefly summarizes several of the most active areas of machine learning research. This summary is not intended to be exhaustive—for example, active areas of work such as genetic algorithms and case-based reasoning are not discussed explicitly. However, it is intended to summarize several major recent results and clear opportunities for further research.

3.1 *Inductive Generalization*

Forming general classes from specific examples is necessary for most any kind of learning, whether it is learning to recognize a telephone from training images from differing vantage points, or learning general strategies for problem solving from training instances of specific successful and failed attempts. Inductive generalization is the process of forming such general class descriptions from a collection of positive and negative training examples.

3.1.1 RECENT PROGRESS This is the most active area of recent research. Early inductive methods typically worked only for noise-free data and required that the concepts they acquired be described by a simple conjunction of instance features. Recent work on symbolic induction has led to approaches that remove such limitations, and these have been applied to acquiring decision rules for real-world tasks (e.g. medical diagnosis, plant diagnosis, predicting congressional voting records) with results that in some cases compare favorably with the best available human-provided decision rules. The research community is now regularly sharing sets of standard training data in order to obtain experimental comparisons of alternative induction mechanisms. This work has recently produced a small number of commercial ventures in this country and the United Kingdom, based on using such symbolic induction methods to develop expert systems automatically. In parallel with the work on symbolic induction, a burst of progress on connectionist (or neural network) induction methods has led to surprisingly strong results for problems such as learning of generation and recognition strategies for speech, and learning of low-level robot control strategies. These approaches are based on representing data via numeric feature vectors and representing decision rules via networks of neuron-like threshold elements. This work has gained a broad following and has led to its own conferences and journals. In addition to these two areas of experimental work on induction mechanisms, important progress has been made by theoreticians studying computational limits on the tractability of various learning tasks. One important thrust of this work has produced theorems that define the relationship among the number of examples needed to infer some general concept, the probability of an error in learning, and the size of the hypothesis space considered by the learner. This important development has led to the first significant theoretical predictions to impact experimental work in this area. This line of work has now also produced its own annual conference.

3.1.2 CURRENT ISSUES AND RESEARCH OPPORTUNITIES Although much progress has been made in this area, additional research is required in a number of areas, particularly dealing with issues of incremental learning and scaling to larger data sets and hypothesis spaces. One major limitation on all current induction methods is their strong dependence on the user-supplied representation, or vocabulary of instance features. A major technical challenge in this area is to develop methods for automatically refining this vocabulary as learning progresses. A second major challenge is to unify the various mechanisms in order to combine the advantageous properties of each (e.g. noise immunity, acceptance of incremental data, ability to handle disjunctive concepts, ability to learn within a changing environment, ability to take advantage of previous learning). It would be especially worthwhile to unify the connectionist and symbolic approaches to induction.

3.2 *Knowledge-Guided Learning*

Whereas inductive generalization is the process of forming descriptions of general concepts from many examples, knowledge-guided generalization acquires similar general descriptions from very few training examples. It utilizes considerable prior knowledge on the part of the learner. Such knowledge-guided methods can be viewed either as methods for utilizing prior knowledge to guide the generalization process or as methods for using examples to focus a process of compiling knowledge into more useful forms.

3.2.1 RECENT PROGRESS The notion of knowledge-guided, or explanation-based, generalization is a development of the 1980s. The importance of this development is that it provides practical methods for utilizing prior knowledge of the learner to replace the need for exponentially large numbers of training examples.[1] As an example from the domain of chess, consider the problem of learning the concept "the class of board positions in which my queen will be lost within two moves." Inductive generalization methods can acquire this concept from many examples of chess boards by determining which features are common to the positive instances. In contrast, knowledge-guided methods generalize from a single example by first constructing an explanation of *why* the queen will be lost (e.g. it is being attacked by a knight that is also attacking the king), and then extracting the *relevant* features of the example by retaining only the features mentioned in this explanation (e.g. the knight and king, but not the other

[1] Thus, the utilization of prior knowledge provides an answer to the (otherwise daunting) theoretical results which indicate that many important inductive inference problems are intractable *for learning agents that must begin with no prior knowledge*.

22 pieces on the board). Programs exist that can acquire reliable general strategy rules from a handful of training examples of successful or failed chess moves. Similar explanation-based learning methods have been successfully applied to acquiring strategies for robot planning, circuit design, computer configuration, algorithm design, and factory scheduling.

3.2.2 CURRENT ISSUES AND RESEARCH OPPORTUNITIES The main limitation of present approaches to explanation-based generalization is that they work best when the learner begins with a domain theory that is complete, consistent, and tractable. While such domain theories may be available in domains such as chess (where the known rules of the game constitute the needed domain theory), they are unavailable in many important domains (e.g. robotics, equipment diagnosis). Research has already begun to extend explanation-based methods to domains in which only incomplete theories are available to guide learning. However, much more remains to be done along these lines. A major challenge in this area is to unify inductive mechanisms with knowledge-guided mechanisms in order to develop approaches and representations that will be able to capitalize on whatever mix of data and prior knowledge is available for the learning task at hand. An additional aim of research is to extend the recent theoretical results on inductive inference to produce a new round of results that account for the role of prior knowledge.

3.3 *Problem-Solving Frameworks with Embedded Learning Mechanisms*

In order to build systems that improve with experience, one must confront issues beyond the issue of generalizing from examples. A major step forward in machine learning is the appearance over the past five years of general problem-solving architectures that embed mechanisms for generalization and that address issues such as *when* to learn, *from what data* to learn, and *in what representation* to learn.

3.3.1 RECENT PROGRESS A small number of general architectures have now been developed and partially tested. The most well-developed is Soar, a search-based architecture that learns by improving its search strategies. It is organized around the principle that all problems it faces can be cast as search problems (including the meta-problem of selecting an appropriate search move). This uniform organizing principle allows Soar to apply a single generalization mechanism to acquire knowledge to guide the many different types of search it must perform to solve a given task. The issues faced here extend to the impact on learning of choices of representation, memory indexing methods, problem-solving strategies, and so forth.

3.3.2 CURRENT ISSUES AND RESEARCH OPORTUNITIES Research should be funded to explore a range of alternative architectures that embed learning, and that make different choices regarding learning methods, memory storage and retrieval mechanisms, when to invoke learning, how to evolve appropriate representations, and so forth. New issues will no doubt be uncovered as this work proceeds—e.g. regarding scaling to larger knowledge bases and communication of results among several such architectures. One important milestone to reach in this area is to develop systems that can learn continuously and cumulatively, without needing to be reinitialized, and that continually adapt to a changing distribution of tasks.

3.4 *Knowledge Acquisition Aids for Export Systems*

In addition to the use of inductive inference methods to derive decision rules automatically in domains such as medical diagnosis and loan risk assessment, a number of approaches have been developed for interacting with human experts to collaborate in the development of expert rules. Such *semi-automated* methods for acquiring new knowledge are important, since they may be some of the earliest to cross the threshold into widespread practical application.

3.4.1 RECENT PROGRESS A number of approaches to semi-automated knowledge acquisition have been developed and tested over the past decade. In the area of medical diagnosis of rheumatism, the SEEK system uses a database of known correct diagnoses to pinpoint weak rules in a manually developed set, and to then interact with the user to determine useful refinements to these rules. A different mode of man-machine collaboration occurs in the LEAP system, which provides interactive aid in the design of digital circuits, and which acquires new circuit-design rules via explanation-based generalization of those portions of the design contributed by its users. A similar style is utilized in the ARMS system, which generalizes from user-supplied solutions to specific robot planning problems. Yet a third mode of collaboration is exemplified in the MOLE knowledge-acquisition aid system, which uses a model of the task being performed to drive its interaction with the user to request specific types of rules needed for the task.

3.4.2 CURRENT ISSUES AND RESEARCH OPPORTUNITIES Research is needed to expand the types of problems to which systems such as MOLE can successfully be applied, and to improve their methods of interaction with users. Research is also needed to integrate and extend generalization mechanisms in the context of such knowledge-based expert-system applications. Such studies will help bring these techniques to practical application.

4. POTENTIAL IMPACT

The potential impact of progress in machine learning extends to a number of areas:

- *On knowledge-based consultant systems*: Improve competence and adaptability, and lower development and maintenance cost.
- *On robotics and real-time control*: Dramatically improve flexibility and ability to operate in unanticipated situations.
- *On speech understanding*: Enable development of systems that can accommodate new users and new environments by adapting to their individual speech characteristics.
- *On technologies for software development/reuse*: Dramatically lower costs of initial development and maintenance.
- *On education and understanding of learning in humans*: Potential to provide computational models of learning that can help us understand similar processes in humans, possibly with significant ramifications for our educational system.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 *Conclusions*

For several reasons, we feel machine learning research is at an appropriate stage to benefit from a significant and sustained funding initiative.

5.1.1 RECENT TECHNICAL PROGRESS Recent progress—experimental, theoretical, and methodological—has led to the ability to build learning systems that acquire expertise comparable to the best human expert knowledge in narrow task domains. It has led to new learning mechanisms based on using prior knowledge of the learner to reduce the difficulty of inductive inference. It has led to new learning mechanisms based on simulated neural networks. It has led to a significantly improved theoretical understanding of the computational limits of specific learning mechanisms. We now understand enough of the problem of machine learning to identify specific research directions and appropriate task domains to serve as driving forces for the next round of progress.

5.1.2 GROWTH AND MATURATION OF FIELD As discussed earlier, the field has grown during the 1980s from a few dozen researchers to several hundreds. It has now grown to an appropriate size to sustain a significant research effort, and would benefit greatly from the focus that could be provided by a coordinated funding effort.

5.1.3 FUNDAMENTAL ENABLING TECHNOLOGY OF BROAD SIGNIFICANCE The goal of machine learning research is to develop a fundamental enabling technology that is application independent. A breakthrough in this area could affect a tremendous variety of applications of computers, including automated manufacturing, robotics, natural language, and computer-aided design. Its impact would be analogous to a breakthrough in compiler technology or hardware technology, in the sense that both of these are also application-independent technologies.

5.1.4 EVOLUTIONARY FORCES IN COMPUTER TECHNOLOGY The large recent increase in computer memory sizes (three orders of magnitude) in typical computers is exerting an important evolutionary force on computer software, forcing it to become more memory intensive. Machine learning researchers study ways to summarize and index large stores of previous experience; their efforts are therefore supported by this evolutionary trend toward large memory stores. A second evolutionary trend, in computer software, is the increasing complexity of software systems. This trend increases the need for self-documenting and self-monitoring programs. Machine learning research is the study of self-monitoring and self-refining systems, and will therefore be of increasing importance as the trend toward complexity continues.

5.2 *Recommendations*

A coordinated and sustained research effort might be expected to push machine-learning technology over the threshold of widespread practical application. We recommend such a research effort, emphasizing (*a*) basic research on significant technical issues, (*b*) selection of one or more grand-challenge problems to focus and measure new research progress, and (*c*) support for infrastructure to enable more effective comparison of systems and sharing of experimental data.

5.2.1 SCIENTIFIC ISSUES TO BE ADDRESSED The primary scientific issues to be addressed are:

- *Extension and integration of methods for generalizing from examples.* Funding agencies should support research on unifying and extending existing techniques to apply to domains with noisy data, incrementally provided training data, and disjunctive concepts. Research should focus on methods for automatically shifting or selecting representations and on combining data-intensive with knowledge-intensive approaches, connectionist with symbolic approaches.

- *Development of and experimentation with general problem-solving frameworks that embed learning mechanisms.* Funding agencies should support work on fundamental issues of organizing such architectures, as well as work on utilizing such frameworks across multiple task domains.
- *Development of a solid theoretical understanding of convergence properties and complexity of various classes of learning methods and problems.* Funding agencies should support especially those theoretical studies that guide ongoing experimental work, unify differing approaches, and uncover fundamental computational limits to various learning tasks.

5.2.2 GRAND CHALLENGES Several grand challenges might serve as focal points for a sustained research effort in machine learning. The benefits of such a focus include (*a*) greater synergy among different research groups and technical approaches, since they would be tested on comparable issues and applications; and (*b*) assurance that a sufficiently broad range of technical issues is addressed to produce a substantial practical impact. Several candidate challenges were described in the first section of this document. This list includes:

- A learning household robot to assist the handicapped
- A learning assembly robot for flexible manufacturing
- A learning spoken-dialog system for advising on equipment repair
- Machines that learn by reading and practicing
- Self-compiling expert systems: A learning expert system for engineering design
- Machines that can discover important regularities in scientific databases

5.2.3 SUPPORT FOR INFRASTRUCTURE A small level of funding should be allocated to efforts for sharing experimental data, programs, and testbeds. As noted earlier, informal efforts have already begun to share databases of training cases in order to allow more careful comparisons among different learning methods. Support should be provided to institutionalize this effort, at least by supporting one site to serve as a nationwide repository for datasets. Beyond this, it may also be important for the repository to accept, document, and maintain software implementing various proven learning methods, so that these may be utilized by many researchers.

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APPENDIX: EXAMPLES OF MACHINE LEARNING SYSTEMS

The following list contains examples of several types of machine-learning system and is intended to indicate the present state of the field:

- *Automatic induction of decision rules for medical diagnosis.* Symbolic inductive inference methods have been used by the ID3 system to form decision trees for diagnosing thyroid diseases (99% accuracy), which compared favorably with an expert system developed carefully by hand. Other researchers have produced similar results for lymphography and jaundice.
- *Explanation-based learning of search control knowledge.* Explanation-based methods have been used to acquire knowledge automatically that significantly reduces the number of search steps required by programs in many task domains. For example, for the task of computer configuration, such control knowledge has been acquired by the Soar system, reducing a search that originally required 1731 steps to a search of 7 steps. Control knowledge learned by the Prodigy system was found to be close in performance to the best hand-coded control rules.
- *Automatic acquisition of connectionist network for phoneme recognition.* Connectionist methods have automatically generated phoneme-recognition networks that outperform all previously developed approaches for the difficult task of distinguishing the voiced consonants "B," "D," and "G" (98%).
- *Discovery of new astronomical objects by finding statistical regularities in astronomical data.* Statistical methods for analyzing large volumes of astronomical data have been used in the Autoclass system to identify previously undetected regularities in a new class of astronomical objects. The classification of infrared astronomical sources produced by Autoclass is the basis of a new star catalog to appear shortly.
- *Connectionist learning of robot arm control.* Connectionist methods have been used to learn to control a direct-drive robot arm with high precision, mapping target arm configurations to robot joint commands.

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