Artificial Intelligence

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Abstract
Artificial intelligence (AI) is a multidisciplinary subject, typically studied as a research area within Computer Science. AI study aims at achieving a good understanding of the nature of intelligence and building intelligent agents that are computational systems demonstrating intelligent behavior. AI has been developed over more than 50 years. The topics studied in AI are quite broad, ranging from knowledge representation and reasoning, knowledge-based systems, machine learning and data mining, natural language processing, to search, image processing, robotics, and intelligent information systems. Numerous successful AI systems have been deployed in real-life applications in engineering, finance, science, health care, education, and service sectors. AI research has also significantly impacted the subject area of Library and Information Science (LIS), helping to develop smart Web search engines, personalized news filters, and knowledge-sharing and indexing systems. This entry briefly outlines the main topics studied in AI, samples some typical successful AI applications, and discusses the cross-fertilization between AI and LIS.

INTRODUCTION
This entry is about artificial intelligence (AI) [1–4] a multidisciplinary subject, typically studied within Computer Science. Ever since the dawn of civilization, humans have constantly asked questions regarding mechanisms of human intelligence. Human’s abilities to think, reason, learn, act to achieve goals, adapt to changing environment, etc., which are central to intelligence, fascinated philosophers, scientists for centuries. There is a long history of human endeavor in unveiling the mystery of human intelligence and building artificial systems capable of doing smart things like humans do. The early works in understanding human intelligence focused on studying how humans “know” the world around them and how the human thinking and reasoning are performed. As early as 2300 years ago, Aristotle, a great Greek philosopher, studied the laws of thought and proper ways of reasoning. In his work “Prior Analytics,” [5] Aristotle defines syllogism, a kind of logical argument, which allows deduction of a valid conclusion from two given premises. For example, from the premises that “All men are mortal” (major premise) and “Socrates is a man” (minor premise), one can infer by syllogism that “Socrates is mortal.” Over the long time after Aristotle, logicians such as Frege, Russell, Leibniz, Godel, Tarski, and others, have fully developed formal logic systems such as propositional logic and predicate logic, which formalize the thinking and reasoning process of humans. Moreover, such formal logic systems open up the possibility of being implemented on computational systems.

Endeavors of constructing mechanical/electronic artifacts to do calculation, concept manipulation, reasoning, and game playing can be found in many eras of human history. Such efforts contribute significantly to the foundations of AI. For more discussions on the foundations of AI, see section 1.1 in Russell and Norvig [1] and section 1.1 in Luger [2]. Around the twenty-sixth century B.C., the Chinese invented the abacus, the first mechanical tool in human history for performing arithmetic calculations (section 1.1.1 in Luger [2]). Similar calculating equipments were also discovered in Roman relics, in India, and in Egypt from ancient times. In 1623, Wilhelm Schickard, a German mathematician, created a calculating clock for addition and subtraction. Soon after in 1642, the famous calculating machine Pascaline was created by Blaise Pascal, a great French philosopher and mathematician. Pascaline is capable of addition and subtraction with carries and borrows. Pascal noted [6] “The arithmetical machine produces effects which approach nearer to thought than all the actions of animals.” Gottfried Wilhelm Leibniz, a great German philosopher and mathematician, believed that human reasoning could be reduced to mechanical calculations of some kind, and thus one could use the calculation results to find out who is right and who is wrong in cases of conflicting opinions. He wrote [7]

The only way to rectify our reasonings is to make them as tangible as those of the Mathematicians, so that we can find our error at a glance, and when there are disputes among persons, we can simply say: Let us calculate [calculamus], without further ado, to see who is right.
He envisioned that a machine could be devised for automatic derivation of scientific knowledge by deductive inference. In the late 1950s and early 1960s, amid the initial enthusiastic development of AI, Arthur Samuel developed a computer program that learns to play the game of Checkers, which could learn to improve its game-playing skills by playing against a copy of itself, playing with human players, and storing good moves from Master game books. In 1997, IBM’s Deep Blue Chess program, with a combination of parallel processing, fast search, and AI ideas, scored a historical win against world Chess champion Kasparov.

As can be seen from these brief descriptions, the philosophical roots of AI can be traced back to over 2300 years ago. The past 200–300 years have witnessed a rapid development in mathematics and science. The formalization of mathematics and science has laid the intellectual foundations of AI. AI as a multidisciplinary area draws on the development in diverse disciplines in addition to philosophy and mathematics, including economics, psychology, linguistics, control theory and cybernetics, and neurosciences. In particular, the birth of the electronic computer in the 1940s was instrumental and crucial to making AI a viable distinctive scientific discipline within Computer Science. The availability of digital computers in late 1940s made it possible for researchers at that time to write computer programs for playing games, performing logical reasoning, and problem-solving. Researchers could then empirically study the computer’s performance and analyze whether the computer demonstrated some kind of intelligence. In 1956, at Dartmouth College in Massachusetts, a two-month summer workshop was held and attended by 10 prominent researchers of AI, including John McCarthy, Marvin Minsky, Claude Shannon, Arthur Samuel, Allen Newell, and Herbert Simon. The workshop was a milestone that signified the birth of AI—a name suggested by McCarthy and agreed by all the attendees of the workshop.

In the early 1950s, researchers and the general public were all fascinated by the possibilities made prominent by the advent of the electronic computer era. People asked numerous questions about whether computers could be intelligent, e.g., do things that used to require human intelligence, what is intelligence, what would it take for us to consider a computer to be intelligent. Objecting views were raised by many to the idea that indeed a computer could be intelligent, given sufficient storage memory and processing power. Alan Turing, a great British mathematician and considered by many as the founding father of Computer Science/AI, proposed in 1950 the famous Turing test. Turing proposed to replace the question “Can machines think?” by the question of whether a digital computer can pass the Turing test. In the Turing test, a human interrogator converses in natural language with a computer and a human participant, which are located in rooms separated from the interrogator. The questions from the interrogator and the answers from the computer/human participant are transmitted via online typed messages (similar to today’s computer-relayed talk or instant messaging). After conversations for 5 min, the human interrogator needs to identify which one is the computer/human participant. According to Turing, a computer should be considered as “intelligent” if it passes the Turing test, i.e., if it fools the human interrogator over 30% of the time in many repeated trials. The central idea behind the Turing test is that a system is deemed intelligent if it can behave like humans. This conceptualization of intelligence (behaving like humans) makes it easier to discern intelligence because one does NOT need to know the inner workings of a system to judge whether the system is intelligent or not—it is sufficient to just look at the system’s behavior. Turing predicted that by the year 2000, man could program computers with large storage capacities (109 units) so well that the computers would easily pass the test with an average human interrogator. Although his prediction was not realized, the discipline of AI certainly has achieved great advancement over the 58 years from the proposal of the Turing test.

After over 50 years of development, AI has become an industry and a gradually maturing subject. Theories of AI—computational theories of intelligence—have advanced significantly, with many flourishing research topics areas developed and numerous successful AI systems deployed in real-world applications. Today, we enjoy the great benefits of modern computer and information technology in our daily lives, many with important AI components. We have smart online shopping tools that can recommend suitable products catering to the specific preferences of customers; personalized message filtering tools that help to sort out spam e-mails; robots that perform (or assist doctors to perform) medical procedures with great precision; intelligent online information tools that allow us to know what is going on in the world with the click of a mouse and to obtain, create, and share knowledge efficiently. We have seen the great miracle of electronic computers and AI that our great intellectual pioneers have envisioned, and much more. Today, AI is more exciting than ever as a research area, playing an increasingly important role in the age of information technology. See Buchanan for a brief account of AI history.

The rest of the entry is organized as follows. In the next section, the major topics of AI will be briefly described. Section on “Artificial Intelligence and Application” presents some sample applications of AI, along with a brief discussion of the impact of AI on LIS, and is followed by the conclusion. Readers interested to know more about the AI subject can consult leading text books and other online sources.
TOPICS OF STUDIES IN AI

In this section we survey some representative topics of AI study. Since AI is a very big and broad field, it is impossible to make a complete coverage of all topics of AI within the limited space of one entry. The omission of a topic in this entry is by no means an indication that the topic is not important.

Heuristic Search and Problem Solving

Heuristic search is a topic studied since the early days of AI. Researchers realized long ago that many AI problems could be viewed as a search problem. The concept of problem-solving as state space search was introduced in the 1950s. In problem-solving, each possible scenario related to the task at hand is formulated as a state, and the entire collection of all possible states is called the state space, which contains the initial state of the problem, and the desired solution state (often called goal state). A state S has a number of neighboring states N(S), which could be reached from state S in one step (by applying some state-transition operators). A state space could then be modeled as a (possibly weighted) graph with nodes representing states and edges connecting neighboring states. Given this view, solving a problem amounts to searching the state space (graph) to find a sequence of states that leads from the initial problem state to the goal state. For example, in computer checkers game-playing, each feasible board configuration constitutes a state in the search space. The initial state corresponds to the initial game board configuration and a board configuration in which the player (the computer) has won the game is one of the many goal states. A move of a piece in board configuration S transits it into a board configuration, which is a member of N(S). The problem of playing the checkers game successfully against an expert human player is reduced to finding a sequence of moves (states) in response to the human player’s moves such that the final state is a winning state for the computer.

For most search problems with real-world application, the search space is huge (or even infinite). Any blind exhaustive search method (such as breadth-first search and depth-first search) would suffer from combinatorial explosion that renders such search impractical. How to efficiently search the state space becomes a critical issue if we want to build useful AI applications. Heuristic search methods have been developed by AI researchers to efficiently search the state space and overcome combinatorial explosion. Typical heuristic search methods are based on using a heuristic evaluation function h to guide the search process. The best-known heuristic search algorithm is perhaps the A* algorithm for searching a weighted graph for shortest path from the starting node ns to the destination node nd. The algorithm maintains a list of open nodes and a list of closed nodes. Each open node n corresponds to an existing partial path ⟨ns, . . . , n⟩, which could be extended into a path from ns to nd via n. For each open node, a measure f(n) = g(n) + h(n) is used to estimate the length of the shortest path from ns to nd via n, where g(n) is the actual length of the path ⟨ns, . . . , n⟩ and h(n) is the heuristic estimate for the length of the shortest path ⟨n, . . . , nd⟩. The A* algorithm always selects from the open list the node n with the lowest f(n) value, considers the neighbors of node n for expanding the existing partial path in search for the shortest path from ns to nd. It has been shown that if the heuristic function h is admissible, namely, h(n) is always an underestimate of the actual length of the shortest path from node n to nd, then the A* algorithm is optimal in that it is guaranteed to find the shortest path from ns to nd. Various improvements of the A* algorithm have been proposed in the literature, including memory bounded A* (MA) and simple memory bounded A* (SMA), etc.

In using heuristic search for problem solving for specific applications, the design of the heuristic function h is a nontrivial task. One has to carefully analyze the specific problem at hand, formulate the search problem, and choose the h function by considering characteristics of the problem to be solved.

Knowledge Representation and Automated Reasoning

An intelligent agent must “know” the world around it, have knowledge about how to achieve goals (namely, what actions are needed to bring about a desired outcome), and can infer useful information from what it already knows in making intelligent decisions. Therefore, an intelligent agent should be a knowledge-based agent, with the ability to represent knowledge and perform automated reasoning from its knowledge.

Knowledge representation research (KR) studies and develops formal systems for representing knowledge in a knowledge base, whereas automated reasoning research focuses on finding efficient algorithms for inference from a given knowledge base represented in some formalization. These two areas of study are closely related.

Logic-based formalism is perhaps the most commonly used knowledge representation form in AI systems. See Genesereth and Nilsson for more discussions of logical foundations of AI. Under a logic-based knowledge representation scheme, an intelligent agent’s knowledge base is a set Δ of logical sentences in the representation logic language, and the inference problem faced by the agent becomes the problem of
deriving logical consequences of \( \Delta \) using valid inference rules of the logic. Propositional logic and first-order logic are most frequently used in practice for knowledge representation and reasoning.

When using logic as a tool for knowledge representation, one has to first define the syntax of the language for the logic, which specifies the basic symbols, logical connectives, and rules to formulate well-formed expressions (well-formed formulas) in that logic. For example, in propositional logic, the basic symbols are propositional symbols (typically represented by uppercase letters such as \( P, Q, R \)), each representing a proposition that can be true or false. The logical connectives in propositional logic include, \( \land, \lor, \text{ and } \neg \). So if \( P, Q \) are propositional symbols, then \( P \land Q, P \lor Q \) and \( \neg P \) are all well-formed formulas in the logic.

A logic must define the semantics of the language. Intuitively, semantics defines the “meaning” of well-formed formulas. The semantics of a logic defines the truth value of each formula for each possible world. The truth value for any well-formed formula in a possible world is obtained compositionally from the truth value of the basic proposition symbols in that possible world. For example, consider a propositional logic with two proposition symbols \( P \) and \( Q \), where \( P \) stands for the proposition “John is a professor at Harvard” and \( Q \) denotes the proposition “John lives in Boston.” Here we have totally four possible worlds: \( \{TT, TF, FT, FF\} \), where each possible world spells out the truth value assignment for \( P \) and \( Q \) in that world. For example, the possible world “TF” tells us that \( P \) is true and \( Q \) is false in this world. Thus, in this world, the well-formed formula \( P \land Q \) will be assigned the truth value “false (F)” because \( P \land Q \) is true in a possible world if and only if both \( P \) and \( Q \) are true in that world.

Once the semantics of a logic is defined, we can use logic for the purpose of reasoning, namely, we can ask the question, “can we derive conclusion \( \phi \) given our knowledge base \( \Delta \)?” This is the problem of checking whether \( \phi \) is a logical consequence of \( \Delta \)—whether \( \phi \) is true in all possible worlds in which \( \Delta \) is true. Automated reasoning is responsible for this task. Automated reasoning research aims at finding efficient, valid inference algorithms to support derivation of logical consequences. For automated reasoning in propositional logic and first-order logic, AI researchers pioneered by Alan Robinson have developed the resolution inference rule\(^{[19]} \) and many of its variants. Since the logical reasoning problem in propositional logic is essentially reduced to the satisfiability (SAT) problem, which is known to be computationally hard, many heuristic methods have been developed, which aim to find efficient solvers for the SAT problem.\(^{[20–22]} \) The development of resolution-based inference in first-order logic and the drive for a unified language for declarative knowledge representation and automated reasoning have led to the logic programming technique, hallmarked by the language PROLOG.\(^{[23]} \) In using PROLOG, one represents knowledge by a PROLOG program, and automated reasoning is carried out by the PROLOG interpreter that essentially performs resolution.

Researchers have developed a plethora of nonmonotonic logics for representing commonsense knowledge in the 1980s and 1990s. The idea is based on the observation that human commonsense knowledge is not well represented by propositional or first-order logic, so something new needs to be developed. Among the various frameworks proposed, we have Reiter’s Default Logic,\(^ {[24]} \) McCarthy’s circumscription,\(^ {[25]} \) etc. The studies on nonmonotonic logics and reasoning are closely related to the study of logic programming. Logics for dealing with time, events, knowledge, and belief have also been developed by AI researchers in order to more accurately model the real world. For example, situation calculus\(^ { [26]} \) and event calculus,\(^ { [27]} \) and temporal logic\(^ { [28]} \) as well as logic about actions\(^ { [29]} \) deal with time-, event-, action-related representation issues. Various logics on knowledge and beliefs\(^ { [30]} \) handle problems of representing (and reasoning about) beliefs and knowledge.

Knowledge representation studies involve not only developing formalisms (logic, etc.) for representing the real world, but also methodologies as to how to model the real world and represent the model within the chosen formalism. Generally speaking, decision on how to represent the world would require the identification of an ontology, which specifies the concepts (categories) for modeling the world and the taxonomy (inheritance hierarchy) relating the concepts. Other semantical relationships among concepts can also be included in an ontology. For example, when building an ontology for a university, we would identify concepts such as students, professors, courses, departments, employees, and staff. We can also organize the people in the university into a taxonomy (a tree) \( T \) with top node labeled as “person.” The two children nodes below the root would be labeled by “student” and “employee,” indicating a student is a person, and an employee is a person too. We could also identify other semantical relationships among concepts in this domain: for example, the relationship “enrolled-in” can be identified between “student” and “course,” indicating that students take courses. This kind of ontology specification bears close similarity with Semantic Networks,\(^ { [31]} \) a representation scheme developed in early years of AI research. Clearly, tools supporting the construction and maintenance of ontologies are highly desirable. Ongoing research on knowledge representation appears to focus on developing formal systems and tools for representing and processing ontologies with applications in the Semantic Web.\(^ { [32]} \) This includes the studies of a unified knowledge representation framework based on XML, RDF, OWL (Web Ontology Language),\(^ { [33]} \) etc., and development of tools for extracting/
Machine Learning

An intelligent system must have the ability to learn new knowledge so as to adapt in an ever-changing world around it. Machine Learning\[35,36\] study focuses on developing computational theories and algorithms that enable computers to learn. Since the early years of AI development, many researchers have pursued the ideas of a learning machine, and the field of Machine Learning is now a quite matured subfield within AI. Machine learning is closely related to the fields of data mining\[37\] and pattern classification.\[38\]

A typical intelligent agent with learning capability could be modeled as consisting of a learning element, a knowledge base, and a performance element. The agent interacts with the outside environment by performing some tasks (by the performance element) in the environment, and getting experience through observing the environment and its feedback to the agent. The learning element of the agent learns useful knowledge from the experiences, such that the learned knowledge will enable the performance element to do better on the task in the future. For example, consider a computer program that learns to play the game of checkers. The performance element here is a component that plays the game by using an evaluation function \( f \) on board configuration features to choose the next move. The outside environment is another copy of the program itself, and the experience gained by the computer will be a sequence of games between the computer and its opponent, as well as the game outcomes (win, loss, or draw). The learning element of the system could be a least-mean square-based linear function learning algorithm, if we define the evaluation function \( f \) to be a linear function of the game board features. Arthur Samuel’s Checkers program\[39\] has tested such set-ups.

Machine learning tasks can be classified as supervised, unsupervised, and reinforcement learning, depending on the kind of experience available to the learning agent. In supervised learning, the task is learning (an approximation of) a function \( f \) from a set of input–output pairs for \( f: \{ (x_1, f(x_1)), \ldots, (x_n, f(x_n)) \} \). Here the experience is encoded in the supervision: the function values at the points \( x_1, \ldots, x_n \). In the case of learning to classify Web pages as “interesting” or “uninteresting,” the function value \( f(x_i) \) for a Web page \( x_i \) will be just binary: 1 or 0 (denoting whether a Web page is interesting or uninteresting). In unsupervised learning, we do not have a beneficial teacher providing the labels \( (f(x_i)) \) for each observed \( x_i \), we can only identify the patterns present in the observed data \( \{ x_1, \ldots, x_n \} \). In some sense, unsupervised learning basically amounts to forming clusters from the data and thus identifying the inherent structures in the data. For reinforcement learning, the agent does get some feedback from the environment, but not in the form of direct supervision \( f(x) \) for each observed instance \( x \). Instead, the agent would perform a sequence of actions in the environment and then receive a “reinforcement” signal after performing the action sequence. For example, consider a robot exploring an open area with obstacles and trying to reach a specific goal location without bumping into the obstacles. Here we do not give specific supervisions as to what is the best move for each location—because such supervision may not be available anyway in practice. Instead, reinforcement signals could be assigned to reward or punish a sequence of actions. If the robot reached the target location through several moves without bumping into obstacles, it would get a positive reward. It would get a negative reward (punishment) when stumping into an obstacle.

Symbolic learning approaches represent the knowledge to be learned in symbolic forms such as decision trees, formulas in propositional logic, and logic programs, and learning often takes place in some form of symbolic manipulation/inference, loosely speaking. One popular learning algorithm is Quinlan’s Decision Tree learning algorithm,\[39\] which constructs a decision tree from a set of training examples, in a top-down fashion. Each example is represented by a vector of attribute-value pairs, together with a class label for the example. In each step of the tree construction, the algorithm checks to see if the examples associated with the existing node are of the same class. If so, the node is a leaf node, and marked by the class name. Otherwise, the algorithm chooses the “most discriminating attribute” to subdivide the examples associated with the node into disjoint subsets, and thus growing the tree. Then the tree construction process is applied recursively until the resulting subsets are “pure,” namely, consisting of examples from one class. Various works have been done on learning Boolean functions, learning decision lists, and learning logic programs. Artificial Neural Networks (ANNs)\[40,41\] follow a different approach to the learning task. ANN research was motivated by the desire to construct simplified mathematical, computational models that mimic the way human brain works, and hoping to achieve better performance on tasks requiring human intelligence. It is observed that human brains consist of large number of biological neurons, which are massively connected, each with relatively low switching speed in communications compared with the switching speed of electronic circuits. However, humans can perform, with amazing
speed, complex cognitive tasks such as recognizing a familiar face, which is still a difficult task for computers in spite of their speed advantages. This suggests that the processing power of the human brain may come from its highly parallel mode of information processing, and the connection patterns among the neurons are crucial in making such massively parallel processing possible. The study of ANN models represents efforts in trying to simulate this model of human brains. An ANN consists of a number of simple processing units, called neurons, each capable of computing simple functions such as linear functions and threshold functions, and sigmoid functions. The neurons are interconnected with real-valued weights. Neural networks can be used to do predictions, to perform classification tasks, to approximate functions, and to find clusters in input datasets. Learning in ANN amounts to adjusting the numerical-valued weights that connect the neurons. Such learning could be supervised, unsupervised, or a hybrid of supervised and unsupervised. In the supervised learning, perhaps the most well-known learning algorithms are perceptron training algorithm for a single linear threshold unit, and the backpropagation algorithm for training multilayer feedforward networks. Neural networks have been used widely in many successful applications.

Genetic Algorithms (GAs)\textsuperscript{[42]} are another distinctive family of methods for learning. GAs are search algorithms that are patterned after natural evolution. In using GA for learning, we are interested in searching for good solutions for a problem by selecting candidate solutions and recombining parts of candidate solutions guided by the mechanics of natural selection (survival of the fittest) and natural genetics (children inherit good traits from parents, with occasional mutations). GA maintains a current population of strings, each encoding a candidate solution to the problem. A fitness function $f$ is defined as that which measures the merit of a string as a solution to the problem. The objective of GA is to search for the best string that maximizes the fitness value. GA applies the genetic operators reproduction, crossover, mutation to the existing population in generating the next population of candidate solutions. In the reproduction process, strings from the existing population are sampled with probabilities proportional to their fitness values. Crossover operations will produce two new strings from two parent strings by exchanging segments of the parents. And finally mutations may be applied to randomly alter one bit in a string. Through evolutions of strings from one generation to the next, GAs perform structured yet randomized search of the space of all possible strings, often efficiently, in looking for the optimal or near optimal solutions. Koza’s genetic programming\textsuperscript{[43]} further extends the idea of GA by evolving computer programs for problem solving. GA research is closely related to studies of Artificial Life and evolutionary computing.

Another type of machine learning is statistical learning,\textsuperscript{[44]} utilizing probabilities and Bayesian theories for learning. In particular, graphical models aim at generating models represented as directed or undirected graphs with (conditional) probability tables attached to each node in the graph, and the entire graph captures joint distributions of a set of random variables. This includes learning Bayes Belief Networks\textsuperscript{[45]} and learning (conditional) Markov Networks. Probabilistic Relational Models (PRMs) and related learning models have also been developed.

**Natural Language and Speech Processing**

An intelligent system must have the capability to communicate and interact effectively with the outside world. Effective communications include receiving information (in various forms) from the world, understanding such information, and sending out information in suitable forms understandable to the outside world. Natural language processing and speech processing address the problems involved for an intelligent computer to communicate with humans using natural (written or spoken) language such as English.

Natural language processing\textsuperscript{[46]} research mainly handles the task of communicating with written natural language. The main topics studied include language understanding, language generation, and machine translation. The inputs to a natural language understanding system are written texts (articles, or paragraphs, or sentences) of some language, and the desired outputs are semantical structures represented in some form, which capture the semantic meanings of the inputs. Language generation handles the opposite side of the problem: Given semantic meanings to be communicated to the outside world, a natural language generator produces correct natural language sentences (paragraphs, articles) that convey the meanings accurately. Machine translation tackles the task of automated translating texts from the source language to the target language, say, from English to French.

In speech processing,\textsuperscript{[47]} the tasks are speech understanding and speech generation. Clearly, the apparatus of natural language processing techniques can be used as components of a speech processing system. For speech understanding, the main hurdle is speech recognition, which requires the capability of converting the spoken language inputs into written texts (so that natural language understanding tools can be utilized subsequently). Similarly, for speech generation, the major task is to map written texts to speech utterance. Converting continuous speech signals to written text requires multiple steps, from the initial step of signal sequence segmentation, to the step of phoneme recognition, followed by the step of mapping phonemes to
texts. Signal processing techniques are needed to handle speech signal noise removal and segmentation. Neural Networks and Hidden Markov Models are commonly used techniques for speech recognition and generation.\cite{48} Speech recognition and generation techniques\cite{49} are widely used in day-to-day applications, such as automated information systems in airlines and banks.

Natural language processing requires several important techniques. First, syntactical analysis tools such as parsers are necessary for analyzing the syntactical structures of sentences according to the language grammar—to find the subject, predicate, and the object in a sentence. Semantical analysis tools are needed to give semantic interpretation to the sentences. Contextual information and pragmatic background knowledge are also essential for semantic disambiguation (word meaning disambiguation, reference resolution, etc.). Thus, knowledge representation is also an important topic related to natural language processing.

Natural language processing is closely related to text-mining, which is an active area of study involving computer science and LIS. Text-mining aims to discover useful knowledge from large collections of textual documents, which can be seen as a generalization of natural language understanding. The studies in text-mining include text summarization, concept extraction, and ontology extraction.

### Signal, Image Processing, and Robotics

The communications between an intelligent agent and the outside world can take various forms, such as visual and audio signals, in addition to utterances in natural language. Moreover, an intelligent agent should be able to act in the world and thus effecting changes to the world around it as well. Signal and image processing research develops techniques that support computer perception and understanding of information in image, audio, and other sensory forms (such as radio signals, infrared, and GPS signals). Robotics put together the techniques of AI study and build robots that can act intelligently, change the world, and achieve desired goals.

Although signal processing has been mostly studied by researchers in Electrical Engineering (EE), it has close connection to building fully autonomous intelligent agents. Image processing\cite{50} and computer vision\cite{51} are important topics in AI and EE. In image processing, the main task is image understanding, namely, to build a semantic model of a given imagery; and in computer vision, the main task is visual scene understanding, i.e., to building a model of the world (the perceived visual scene). Further extension of visual scene understanding would include understanding video streams (sequence of scenes). The “understanding” of a visual scene/image involves recognition of the objects present, the relevant photometry/geometry features of the objects, and the (spatial or other) relationships among the objects. To achieve the objectives of image/scene understanding, several stages of image processing operations are needed. Initial processing of images includes low-level operations such as smoothing to filter out noise in the image signals, edge detection, and image segmentation to decompose the image into groups with similar characteristics. These low-level processing operations are local computations and require no prior knowledge about the images for the particular application. The next stage processing involves object recognition, which requires isolating each distinctive object, determining the object’s position and orientation (relative to the observer), and identifying the object shape. Objects are outlined by edges and described by a set of features, which are chosen by the designer of the image processing system. The feature could be shape-based (geometric features) or photometric features (such as textures, brightness, and shading). For this processing stage, the computations are not necessarily local; features for characterizing different objects could require computation involving the pixels of the entire image. Supervised learning or pattern classification\cite{38} methods are typically used for object recognition. The problem of object recognition from images is still highly challenging: a good object recognition system must perform well in spite of variations in the input image. The variations include changing illumination of the image, different pose and orientation of the objects, and translation, scaling of the objects. We humans are very good at recognizing, for example, familiar faces even if the faces are varied by wearing eye glasses, putting on a hat, having a different facial expression, or being illuminated differently. But such variations are still very hard to handle by computers.

Robotics\cite{52} studies the techniques for building robots, i.e., intelligent agents with capabilities to act in the physical world. The research in Robotics concerns with both the hardware and software aspects of robots. A robot possessed a set of sensors for perceiving its surrounding environment and a set of effectors (also called actuators) for effecting actions in the environment. For example, for a mobile robot such as the planetary rovers that explore the surface of Mars, it has range sensors for measuring distance to close-by obstacles and image sensors (cameras) for getting images of surrounding environment. It also has effectors such as wheels/legs, joints for moving around. Robots can be classified into three categories: 1) manipulators, which are robotic arms physically anchored at a fixed location, for example, garbage collection robot arms on the garbage van; 2) Mobile robots that move around using wheels, legs, etc.; and 3) hybrid—mobile robots with manipulators. In
particular, there has been an increasing interest in building
the so-called humanoid robots, which resemble
humans in physical design and physical appearance.

The research problems studied in robotics call for uti-
лизation of all major AI techniques. A robot must be
able to perceive its environment and represent the state
of its environment in some knowledge representation
form; it must be able to learn from its past experiences;
it must be able to perform inference in making decisions
about the correct move; it must be able to plan and act
intelligently; it must be able to handle uncertainty; and
it must be able to communicate effectively to teammates
and human users. Robotic perception addresses the
problem of constructing internal models/representations
of the environment from the sensory signals of the
robot. This includes the study on localization, i.e., locat-
ing the position of specific objects, on environment
mapping which allows the robot to construct a map of
its environment by observation and exploration. Robotic
motion research concerns with the planning and control
of robot moves by the effectors. Various control archi-
tectures have been proposed in the literature.

Robotics has found a wide range of successful appli-
cations in the real world. We will present some in the
next section on AI applications.

AI APPLICATIONS

AI has found many successful applications in various
sectors of the real world. Here we sample some of
them. The online resource from Wikipedia\[53\] gives
more samples.

Game playing. Since early days of AI, researchers
have studied the problem of computer game playing
using heuristic search methods and machine learning.
Arthur Samuel’s Checkers playing program pioneered
the studies in this aspect. Along with the advances in
computing power and AI research, many successful
computer game playing systems have been developed
that can compete at human master levels. TD-Gam-
mon\[54\] is a neural network-based program that plays
the game of Backgammon very well. The most well-
known computer game player is perhaps the Deep
Blue\[59\] Chess program from IBM. In a six-game match
against world Chess champion Kasparov, Deep Blue
achieved two wins, three draws, and one loss, thus over-
all it has won the match. Today there are many online
computer game playing programs (chess, go checkers,
backgammon, etc.) that people can play with and have
fun. Almost all such game programs utilize ideas from
AI in one way or the other.

Financial applications. Prominent financial firms in
Wall Street have employed proprietary software systems
for predicting stock-market trends and predicting stock
prices for assisting mutual fund managers to boost
investment returns. Although the details of such propri-
tary systems are held secret, it is known that at least a
number of them used neural networks.

Medicine and health care. In more than 100 hospitals
across the United States, nurses receive help from
robotic “tugs”\[55\] that tow carts that deliver everything
from meals to linens. Miniature robots have been used
in surgery procedures for a number of diseases\[56\] Data
mining and machine learning techniques have been
applied to find patterns of diseases and treatment effects
of various medications from huge amounts of medical
data. Intelligent medical imaging tools have been widely
used to identify tumors/nodules from X-ray/CT-scan
images for early detection and diagnosis of cancers.
Moreover, computational biology combined with micro-
array technology in biological sciences has enabled the
medical scientists to quickly identify or pin-point the
genes responsible for certain diseases.\[57\] The construc-
tion of large online medical knowledge bases and the
availability of such medical knowledge to ordinary peo-
ple contribute significantly to boost preventive care in
public health.

Engineering and manufacturing applications. The ideas
of heuristic search and GA have been widely used in solv-
ing optimization problems commonly seen in engineering
applications such as job-shop scheduling and air traffic
scheduling. In manufacturing, utilization of robotic arms
at assembly lines is quite common, and such application
enhances the productivity tremendously.

Environment protection. Remote-sensing techniques
have been widely used for gathering information about
the oceans, the atmosphere, the space, and the earth. It
is a difficult task to process the huge amount of environ-
ment data and find trends in environment change so as
to meet the challenge of climate change and global
warming. AI methods such as image processing, pattern
classification, and data clustering have been applied suc-
cessfully for analyzing environment data to assist
scientists in environment-related research.\[58\]

Space science explorations. Mobil robots have been
used to explore the unknown terrains on Mars. Accord-
ing to the Mars rover’s web page,\[59\]

NASA’s twin robot geologists, the Mars Exploration
Rovers, launched toward Mars on June 10 and July 7,
2003, in search of answers about the history of water on
Mars. They landed on Mars January 3 and January 24
PST, 2004 (January 4 and January 25 UTC, 2004). The
Mars Exploration Rover mission is part of NASA’s Mars
Exploration Program, a long-term effort of robotic explo-
ration of the red planet.

After more than 4 years of geological surveying, the
Mars Exploration Rover robots have ceased to commu-
nicate (November 11, 2008).
Intelligent information systems. AI research has significantly impacted the studies in LISs. Ideas in AI have been widely applied in information technology to build smart information systems. On the other hand, the explosive development of the Internet and the Web has fueled AI with many interesting and challenging research problems. Along with the challenges are the great opportunities to bring AI closer to ordinary people’s day-to-day lives. Nowadays we take it for granted that we can find information about anything by using online search engines such as Google, Yahoo, or Microsoft Live. Millions of consumers utilize online shopping tools to buy services and products. Digital libraries are a commonplace, accessible to a much larger audience than before. What people probably did not realize is that behind all these nice and fascinating online tools and services (such as search engine and online shopping tools) are there important contributions of AI. For example, association rule mining and other AI methods are routinely used in many major online shopping Web sites so that related products can be recommended to consumers.

Intelligent information systems studies have developed a number of AI-based approaches in information extraction, indexing, and smart information retrieval. In information extraction, text-mining and natural language processing methods are developed to obtain semantical information from texts in the form of concepts and their relationships. Such information is then used for indexing the source texts to facilitate retrieval. User profiles can be constructed by fuzzy clustering on user information-seeking behaviors (Web-click streams, etc.) to personalize the information service to individual users. User information-seeking behavior includes not only current session Web-click streams of the user, but also previously logged Web search activities that help to model the user. Fuzzy rule, Neural Networks, and GA have been applied to adapt user queries for better retrieval performance.

There are continuous efforts in building large-scale commonsense knowledge bases and making information/knowledge in the collection accessible to ordinary people. The Wikipedia is one of such knowledge bases. On the other hand, the studies in Semantic Web aims at building large knowledge bases in formats such that the semantics (contents) of the information can be interpreted and processed by computers across the Web. Clearly, Semantic Web would promote knowledge sharing and intelligent query-answering beyond what the existing Web search engines would support. Along this line, the CYC project is another notable example.

Many multimedia information retrieval systems have been constructed, resulting in various interesting applications such as music retrieval system and video-clip retrieval system. Image retrieval for security surveillance has been in practical use for quite some time.

Machine translation. Machine translation is one special type of intelligent information system service that supports automatic translation of texts from a source language to a target language. Today one can use machine translators at various online search engines, for example, Google. Although the performance is still not as good as that of human translators, machine translators are very useful in several ways. For one thing, human translators are highly specialized professionals and thus expensive to hire. Secondly, human translators would get tired and could not work as fast as computers. The common practice in using machine translation is to let the machines do the first (quick) cut of the translation and then let human translators polish the results produced by machines. This would greatly enhance the productivity of translation.

CONCLUSIONS

AI is an exciting research area. AI research is multidisciplinary in nature, drawing on advances in mathematics, philosophy, logic, computer science, information theory, control, cognitive science, and linguistics. The objective of AI is to understand the nature of intelligence and to build computer systems that behave intelligently. AI research covers a wide range of topics, many of which are briefly discussed in this entry. AI has found many successful applications that impact our daily life significantly. The entry samples some AI applications. AI and LISs have close connections, and cross-fertilization of research efforts between the two fields has been fruitful. Looking forward, we see great opportunities as well as challenges in realizing the dream of AI, which we embrace wholeheartedly.

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