# Artificial Intelligence Main Page

## Links:

* [Main Page](mainpage.html)
* [Artificial Intelligence History](artificialintelligencehistory.html)
* [Artificial Intelligence Basics](artificialintelligencebasics.html)
* [Artificial Intelligence Challenges](artificialintelligencechallenges.html)

[Artificial Intelligence](https://en.wikipedia.org/wiki/Artificial_intelligence)

Artificial intelligence (AI) is intelligence demonstrated by machines, unlike the natural intelligence displayed by humans and animals, which involves consciousness and emotionality. The distinction between the former and the latter categories is often revealed by the acronym chosen. 'Strong' AI is usually labelled as artificial general intelligence (AGI) while attempts to emulate 'natural' intelligence have been called artificial biological intelligence (ABI). Leading AI textbooks define the field as the study of "intelligent agents": any device that perceives its environment and takes actions that maximize its chance of achieving its goals.[3] Colloquially, the term "artificial intelligence" is often used to describe machines that mimic "cognitive" functions that humans associate with the human mind, such as "learning" and "problem solving".[4] As machines become increasingly capable, tasks considered to require "intelligence" are often removed from the definition of AI, a phenomenon known as the AI effect.[5] A quip in Tesler's Theorem says "AI is whatever hasn't been done yet."[6] For instance, optical character recognition is frequently excluded from things considered to be AI,[7] having become a routine technology.[8] Modern machine capabilities generally classified as AI include successfully understanding human speech,[9] competing at the highest level in strategic game systems (such as chess and Go),[10] and also imperfect-information games like poker,[11] self-driving cars, intelligent routing in content delivery networks, and military simulations.[12] Artificial intelligence was founded as an academic discipline in 1955, and in the years since has experienced several waves of optimism,[13][14] followed by disappointment and the loss of funding (known as an "AI winter"),[15][16] followed by new approaches, success and renewed funding.[14][17] After AlphaGo defeated a professional Go player in 2015, artificial intelligence once again attracted widespread global attention.[18] For most of its history, AI research has been divided into sub-fields that often fail to communicate with each other.[19] These sub-fields are based on technical considerations, such as particular goals (e.g. "robotics" or "machine learning"),[20] the use of particular tools ("logic" or artificial neural networks), or deep philosophical differences.[23][24][25] Sub-fields have also been based on social factors (particular institutions or the work of particular researchers).[19] The traditional problems (or goals) of AI research include reasoning, knowledge representation, planning, learning, natural language processing, perception and the ability to move and manipulate objects.[20] AGI is among the field's long-term goals.[26] Approaches include statistical methods, computational intelligence, and traditional symbolic AI. Many tools are used in AI, including versions of search and mathematical optimization, artificial neural networks, and methods based on statistics, probability and economics. The AI field draws upon computer science, information engineering, mathematics, psychology, linguistics, philosophy, and many other fields. The field was founded on the assumption that human intelligence "can be so precisely described that a machine can be made to simulate it".[27] This raises philosophical arguments about the mind and the ethics of creating artificial beings endowed with human-like intelligence. These issues have been explored by myth, fiction and philosophy since antiquity.[32] Some people also consider AI to be a danger to humanity if it progresses unabated.[33][34] Others believe that AI, unlike previous technological revolutions, will create a risk of mass unemployment.[35] In the twenty-first century, AI techniques have experienced a resurgence following concurrent advances in computer power, large amounts of data, and theoretical understanding; and AI techniques have become an essential part of the technology industry, helping to solve many challenging problems in computer science, software engineering and operations research.[36] https://en.m.wikipedia.org/wiki/File:Overfitted\_Data.

# Artificial Intelligence History Page

## Links:

* [Main Page](mainpage.html)
* [Artificial Intelligence History](artificialintelligencehistory.html)
* [Artificial Intelligence Basics](artificialintelligencebasics.html)
* [Artificial Intelligence Challenges](artificialintelligencechallenges.html)

Thought-capable artificial beings appeared as storytelling devices in antiquity,[37] and have been common in fiction, as in Mary Shelley's Frankenstein or Karel Čapek's R.U.R.[38] These characters and their fates raised many of the same issues now discussed in the ethics of artificial intelligence.[32] The study of mechanical or "formal" reasoning began with philosophers and mathematicians in antiquity. The study of mathematical logic led directly to Alan Turing's theory of computation, which suggested that a machine, by shuffling symbols as simple as "0" and "1", could simulate any conceivable act of mathematical deduction. This insight, that digital computers can simulate any process of formal reasoning, is known as the Church–Turing thesis.[39] Along with concurrent discoveries in neurobiology, information theory and cybernetics, this led researchers to consider the possibility of building an electronic brain. Turing proposed changing the question from whether a machine was intelligent, to "whether or not it is possible for machinery to show intelligent behaviour".[40] The first work that is now generally recognized as AI was McCullouch and Pitts' 1943 formal design for Turing-complete "artificial neurons".[41] The field of AI research was born at a workshop at Dartmouth College in 1956,[42] where the term "Artificial Intelligence" was coined by John McCarthy to distinguish the field from cybernetics and escape the influence of the cyberneticist Norbert Wiener.[43] Attendees Allen Newell (CMU), Herbert Simon (CMU), John McCarthy (MIT), Marvin Minsky (MIT) and Arthur Samuel (IBM) became the founders and leaders of AI research.[44] They and their students produced programs that the press described as "astonishing":[45] computers were learning checkers strategies (c. 1954)[46] (and by 1959 were reportedly playing better than the average human),[47] solving word problems in algebra, proving logical theorems (Logic Theorist, first run c. 1956) and speaking English.[48] By the middle of the 1960s, research in the U.S. was heavily funded by the Department of Defense[49] and laboratories had been established around the world.[50] AI's founders were optimistic about the future: Herbert Simon predicted, "machines will be capable, within twenty years, of doing any work a man can do". Marvin Minsky agreed, writing, "within a generation ... the problem of creating 'artificial intelligence' will substantially be solved".[13] They failed to recognize the difficulty of some of the remaining tasks. Progress slowed and in 1974, in response to the criticism of Sir James Lighthill[51] and ongoing pressure from the US Congress to fund more productive projects, both the U.S. and British governments cut off exploratory research in AI. The next few years would later be called an "AI winter",[15] a period when obtaining funding for AI projects was difficult. In the early 1980s, AI research was revived by the commercial success of expert systems,[52] a form of AI program that simulated the knowledge and analytical skills of human experts. By 1985, the market for AI had reached over a billion dollars. At the same time, Japan's fifth generation computer project inspired the U.S and British governments to restore funding for academic research.[14] However, beginning with the collapse of the Lisp Machine market in 1987, AI once again fell into disrepute, and a second, longer-lasting hiatus began.[16] The development of metal–oxide–semiconductor (MOS) very-large-scale integration (VLSI), in the form of complementary MOS (CMOS) transistor technology, enabled the development of practical artificial neural network (ANN) technology in the 1980s. A landmark publication in the field was the 1989 book Analog VLSI Implementation of Neural Systems by Carver A. Mead and Mohammed Ismail.[53] In the late 1990s and early 21st century, AI began to be used for logistics, data mining, medical diagnosis and other areas.[36] The success was due to increasing computational power (see Moore's law and transistor count), greater emphasis on solving specific problems, new ties between AI and other fields (such as statistics, economics and mathematics), and a commitment by researchers to mathematical methods and scientific standards.[54] Deep Blue became the first computer chess-playing system to beat a reigning world chess champion, Garry Kasparov, on 11 May 1997.[55] In 2011, in a Jeopardy! quiz show exhibition match, IBM's question answering system, Watson, defeated the two greatest Jeopardy! champions, Brad Rutter and Ken Jennings, by a significant margin.[56] Faster computers, algorithmic improvements, and access to large amounts of data enabled advances in machine learning and perception; data-hungry deep learning methods started to dominate accuracy benchmarks around 2012.[57] The Kinect, which provides a 3D body–motion interface for the Xbox 360 and the Xbox One, uses algorithms that emerged from lengthy AI research[58] as do intelligent personal assistants in smartphones.[59] In March 2016, AlphaGo won 4 out of 5 games of Go in a match with Go champion Lee Sedol, becoming the first computer Go-playing system to beat a professional Go player without handicaps.[10][60] In the 2017 Future of Go Summit, AlphaGo won a three-game match with Ke Jie,[61] who at the time continuously held the world No. 1 ranking for two years.[62][63] Deep Blue's Murray Campbell called AlphaGo's victory "the end of an era... board games are more or less done[64] and it's time to move on."[65] This marked the completion of a significant milestone in the development of Artificial Intelligence as Go is a relatively complex game, more so than Chess. AlphaGo was later improved, generalized to other games like chess, with AlphaZero;[66] and MuZero[67] to play many different video games, that were previously handled separately,[68] in addition to board games. Other programs handle imperfect-information games; such as for poker at a superhuman level, Pluribus (poker bot)[69] and Cepheus (poker bot).[11] See: General game playing. According to Bloomberg's Jack Clark, 2015 was a landmark year for artificial intelligence, with the number of software projects that use AI within Google increased from a "sporadic usage" in 2012 to more than 2,700 projects. Clark also presents factual data indicating the improvements of AI since 2012 supported by lower error rates in image processing tasks.[70] He attributes this to an increase in affordable neural networks, due to a rise in cloud computing infrastructure and to an increase in research tools and datasets.[17] Other cited examples include Microsoft's development of a Skype system that can automatically translate from one language to another and Facebook's system that can describe images to blind people.[70] In a 2017 survey, one in five companies reported they had "incorporated AI in some offerings or processes".[71][72] Around 2016, China greatly accelerated its government funding; given its large supply of data and its rapidly increasing research output, some observers believe it may be on track to becoming an "AI superpower".[73][74] By 2020, Natural Language Processing systems such as the enormous GPT-3 (then by far the largest artificial neural network) were matching human performance on pre-existing benchmarks, albeit without the system attaining commonsense understanding of the contents of the benchmarks.[75] DeepMind's AlphaFold 2 (2020) demonstrated the ability to determine, in hours rather than months, the 3D structure of a protein. Facial recognition advanced to where, under some circumstances, some systems claim to have a 99% accuracy rate.[76]

# Artificial Intelligence Basics Page

## Links:

* [Main Page](mainpage.html)
* [Artificial Intelligence History](artificialintelligencehistory.html)
* [Artificial Intelligence Basics](artificialintelligencebasics.html)
* [Artificial Intelligence Challenges](artificialintelligencechallenges.html)

Computer science defines AI research as the study of "intelligent agents": any device that perceives its environment and takes actions that maximize its chance of successfully achieving its goals.[3] A more elaborate definition characterizes AI as "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation."[77] A typical AI analyzes its environment and takes actions that maximize its chance of success.[3] An AI's intended utility function (or goal) can be simple ("1 if the AI wins a game of Go, 0 otherwise") or complex ("Perform actions mathematically similar to ones that succeeded in the past"). Goals can be explicitly defined or induced. If the AI is programmed for "reinforcement learning", goals can be implicitly induced by rewarding some types of behavior or punishing others.[a] Alternatively, an evolutionary system can induce goals by using a "fitness function" to mutate and preferentially replicate high-scoring AI systems, similar to how animals evolved to innately desire certain goals such as finding food.[78] Some AI systems, such as nearest-neighbor, instead of reason by analogy, these systems are not generally given goals, except to the degree that goals are implicit in their training data.[79] Such systems can still be benchmarked if the non-goal system is framed as a system whose "goal" is to accomplish its narrow classification task.[80] AI often revolves around the use of algorithms. An algorithm is a set of unambiguous instructions that a mechanical computer can execute.[b] A complex algorithm is often built on top of other, simpler, algorithms. A simple example of an algorithm is the following (optimal for first player) recipe for play at tic-tac-toe:[81] If someone has a "threat" (that is, two in a row), take the remaining square. Otherwise, if a move "forks" to create two threats at once, play that move. Otherwise, take the center square if it is free. Otherwise, if your opponent has played in a corner, take the opposite corner. Otherwise, take an empty corner if one exists. Otherwise, take any empty square. Many AI algorithms are capable of learning from data; they can enhance themselves by learning new heuristics (strategies, or "rules of thumb", that have worked well in the past), or can themselves write other algorithms. Some of the "learners" described below, including Bayesian networks, decision trees, and nearest-neighbor, could theoretically, (given infinite data, time, and memory) learn to approximate any function, including which combination of mathematical functions would best describe the world.[citation needed] These learners could therefore derive all possible knowledge, by considering every possible hypothesis and matching them against the data. In practice, it is seldom possible to consider every possibility, because of the phenomenon of "combinatorial explosion", where the time needed to solve a problem grows exponentially. Much of AI research involves figuring out how to identify and avoid considering a broad range of possibilities unlikely to be beneficial.[82][83] For example, when viewing a map and looking for the shortest driving route from Denver to New York in the East, one can in most cases skip looking at any path through San Francisco or other areas far to the West; thus, an AI wielding a pathfinding algorithm like A\* can avoid the combinatorial explosion that would ensue if every possible route had to be ponderously considered.[84] The earliest (and easiest to understand) approach to AI was symbolism (such as formal logic): "If an otherwise healthy adult has a fever, then they may have influenza". A second, more general, approach is Bayesian inference: "If the current patient has a fever, adjust the probability they have influenza in such-and-such way". The third major approach, extremely popular in routine business AI applications, are analogizers such as SVM and nearest-neighbor: "After examining the records of known past patients whose temperature, symptoms, age, and other factors mostly match the current patient, X% of those patients turned out to have influenza". A fourth approach is harder to intuitively understand, but is inspired by how the brain's machinery works: the artificial neural network approach uses artificial "neurons" that can learn by comparing itself to the desired output and altering the strengths of the connections between its internal neurons to "reinforce" connections that seemed to be useful. These four main approaches can overlap with each other and with evolutionary systems; for example, neural nets can learn to make inferences, to generalize, and to make analogies. Some systems implicitly or explicitly use multiple of these approaches, alongside many other AI and non-AI algorithms; the best approach is often different depending on the problem.[85][86] Learning algorithms work on the basis that strategies, algorithms, and inferences that worked well in the past are likely to continue working well in the future. These inferences can be obvious, such as "since the sun rose every morning for the last 10,000 days, it will probably rise tomorrow morning as well". They can be nuanced, such as "X% of families have geographically separate species with color variants, so there is a Y% chance that undiscovered black swans exist". Learners also work on the basis of "Occam's razor": The simplest theory that explains the data is the likeliest. Therefore, according to Occam's razor principle, a learner must be designed such that it prefers simpler theories to complex theories, except in cases where the complex theory is proven substantially better. The blue line could be an example of overfitting a linear function due to random noise. Settling on a bad, overly complex theory gerrymandered to fit all the past training data is known as overfitting. Many systems attempt to reduce overfitting by rewarding a theory in accordance with how well it fits the data, but penalizing the theory in accordance with how complex the theory is.[87] Besides classic overfitting, learners can also disappoint by "learning the wrong lesson". A toy example is that an image classifier trained only on pictures of brown horses and black cats might conclude that all brown patches are likely to be horses.[88] A real-world example is that, unlike humans, current image classifiers often don't primarily make judgments from the spatial relationship between components of the picture, and they learn relationships between pixels that humans are oblivious to, but that still correlate with images of certain types of real objects. Modifying these patterns on a legitimate image can result in "adversarial" images that the system misclassifies.[c][89][90] A self-driving car system may use a neural network to determine which parts of the picture seem to match previous training images of pedestrians, and then model those areas as slow-moving but somewhat unpredictable rectangular prisms that must be avoided. Compared with humans, existing AI lacks several features of human "commonsense reasoning"; most notably, humans have powerful mechanisms for reasoning about "naïve physics" such as space, time, and physical interactions. This enables even young children to easily make inferences like "If I roll this pen off a table, it will fall on the floor". Humans also have a powerful mechanism of "folk psychology" that helps them to interpret natural-language sentences such as "The city councilmen refused the demonstrators a permit because they advocated violence" (A generic AI has difficulty discerning whether the ones alleged to be advocating violence are the councilmen or the demonstrators[91][92][93]). This lack of "common knowledge" means that AI often makes different mistakes than humans make, in ways that can seem incomprehensible. For example, existing self-driving cars cannot reason about the location nor the intentions of pedestrians in the exact way that humans do, and instead must use non-human modes of reasoning to avoid accidents.[94][95]

# Artificial Intelligence Challenges Page

## Links:

* [Main Page](mainpage.html)
* [Artificial Intelligence History](artificialintelligencehistory.html)
* [Artificial Intelligence Basics](artificialintelligencebasics.html)
* [Artificial Intelligence Challenges](artificialintelligencechallenges.html)

The cognitive capabilities of current architectures are very limited, using only a simplified version of what intelligence is really capable of. For instance, the human mind has come up with ways to reason beyond measure and logical explanations to different occurrences in life. What would have been otherwise straightforward, an equivalently difficult problem may be challenging to solve computationally as opposed to using the human mind. This gives rise to two classes of models: structuralist and functionalist. The structural models aim to loosely mimic the basic intelligence operations of the mind such as reasoning and logic. The functional model refers to the correlating data to its computed counterpart.[97] The overall research goal of artificial intelligence is to create technology that allows computers and machines to function in an intelligent manner. The general problem of simulating (or creating) intelligence has been broken down into sub-problems. These consist of particular traits or capabilities that researchers expect an intelligent system to display. The traits described below have received the most attention.[20] Reasoning, problem solving Early researchers developed algorithms that imitated step-by-step reasoning that humans use when they solve puzzles or make logical deductions.[98] By the late 1980s and 1990s, AI research had developed methods for dealing with uncertain or incomplete information, employing concepts from probability and economics.[99] These algorithms proved to be insufficient for solving large reasoning problems because they experienced a "combinatorial explosion": they became exponentially slower as the problems grew larger.[82] Even humans rarely use the step-by-step deduction that early AI research could model. They solve most of their problems using fast, intuitive judgments.[100] Knowledge representation An ontology represents knowledge as a set of concepts within a domain and the relationships between those concepts. Main articles: Knowledge representation and Commonsense knowledge Knowledge representation[101] and knowledge engineering[102] are central to classical AI research. Some "expert systems" attempt to gather explicit knowledge possessed by experts in some narrow domain. In addition, some projects attempt to gather the "commonsense knowledge" known to the average person into a database containing extensive knowledge about the world. Among the things a comprehensive commonsense knowledge base would contain are: objects, properties, categories and relations between objects;[103] situations, events, states and time;[104] causes and effects;[105] knowledge about knowledge (what we know about what other people know);[106] and many other, less well researched domains. A representation of "what exists" is an ontology: the set of objects, relations, concepts, and properties formally described so that software agents can interpret them. The semantics of these are captured as description logic concepts, roles, and individuals, and typically implemented as classes, properties, and individuals in the Web Ontology Language.[107] The most general ontologies are called upper ontologies, which attempt to provide a foundation for all other knowledge[108] by acting as mediators between domain ontologies that cover specific knowledge about a particular knowledge domain (field of interest or area of concern). Such formal knowledge representations can be used in content-based indexing and retrieval,[109] scene interpretation,[110] clinical decision support,[111] knowledge discovery (mining "interesting" and actionable inferences from large databases),[112] and other areas.[113] Among the most difficult problems in knowledge representation are: Default reasoning and the qualification problem Many of the things people know take the form of "working assumptions". For example, if a bird comes up in conversation, people typically picture a fist-sized animal that sings and flies. None of these things are true about all birds. John McCarthy identified this problem in 1969[114] as the qualification problem: for any commonsense rule that AI researchers care to represent, there tend to be a huge number of exceptions. Almost nothing is simply true or false in the way that abstract logic requires. AI research has explored a number of solutions to this problem.[115] Breadth of commonsense knowledge The number of atomic facts that the average person knows is very large. Research projects that attempt to build a complete knowledge base of commonsense knowledge (e.g., Cyc) require enormous amounts of laborious ontological engineering—they must be built, by hand, one complicated concept at a time.[116] Subsymbolic form of some commonsense knowledge Much of what people know is not represented as "facts" or "statements" that they could express verbally. For example, a chess master will avoid a particular chess position because it "feels too exposed"[117] or an art critic can take one look at a statue and realize that it is a fake.[118] These are non-conscious and sub-symbolic intuitions or tendencies in the human brain.[119] Knowledge like this informs, supports and provides a context for symbolic, conscious knowledge. As with the related problem of sub-symbolic reasoning, it is hoped that situated AI, computational intelligence, or statistical AI will provide ways to represent this knowledge.[119] Planning A hierarchical control system is a form of control system in which a set of devices and governing software is arranged in a hierarchy. Main article: Automated planning and scheduling Intelligent agents must be able to set goals and achieve them.[120] They need a way to visualize the future—a representation of the state of the world and be able to make predictions about how their actions will change it—and be able to make choices that maximize the utility (or "value") of available choices.[121] In classical planning problems, the agent can assume that it is the only system acting in the world, allowing the agent to be certain of the consequences of its actions.[122] However, if the agent is not the only actor, then it requires that the agent can reason under uncertainty. This calls for an agent that can not only assess its environment and make predictions but also evaluate its predictions and adapt based on its assessment.[123] Multi-agent planning uses the cooperation and competition of many agents to achieve a given goal. Emergent behavior such as this is used by evolutionary algorithms and swarm intelligence.[124] Learning Main article: Machine learning For this project the AI had to find the typical patterns in the colors and brushstrokes of Renaissance painter Raphael. The portrait shows the face of the actress Ornella Muti, "painted" by AI in the style of Raphael. Machine learning (ML), a fundamental concept of AI research since the field's inception,[d] is the study of computer algorithms that improve automatically through experience.[e][127] Unsupervised learning is the ability to find patterns in a stream of input, without requiring a human to label the inputs first. Supervised learning includes both classification and numerical regression, which requires a human to label the input data first. Classification is used to determine what category something belongs in, and occurs after a program sees a number of examples of things from several categories. Regression is the attempt to produce a function that describes the relationship between inputs and outputs and predicts how the outputs should change as the inputs change.[127] Both classifiers and regression learners can be viewed as "function approximators" trying to learn an unknown (possibly implicit) function; for example, a spam classifier can be viewed as learning a function that maps from the text of an email to one of two categories, "spam" or "not spam". Computational learning theory can assess learners by computational complexity, by sample complexity (how much data is required), or by other notions of optimization.[128] In reinforcement learning[129] the agent is rewarded for good responses and punished for bad ones. The agent uses this sequence of rewards and punishments to form a strategy for operating in its problem space. Natural language processing A parse tree represents the syntactic structure of a sentence according to some formal grammar. Main article: Natural language processing Natural language processing[130] (NLP) allows machines to read and understand human language. A sufficiently powerful natural language processing system would enable natural-language user interfaces and the acquisition of knowledge directly from human-written sources, such as newswire texts. Some straightforward applications of natural language processing include information retrieval, text mining, question answering and machine translation.[131] Many current approaches use word co-occurrence frequencies to construct syntactic representations of text. "Keyword spotting" strategies for search are popular and scalable but dumb; a search query for "dog" might only match documents with the literal word "dog" and miss a document with the word "poodle". "Lexical affinity" strategies use the occurrence of words such as "accident" to assess the sentiment of a document. Modern statistical NLP approaches can combine all these strategies as well as others, and often achieve acceptable accuracy at the page or paragraph level. Beyond semantic NLP, the ultimate goal of "narrative" NLP is to embody a full understanding of commonsense reasoning.[132] By 2019, transformer-based deep learning architectures could generate coherent text.[133] Perception Main articles: Machine perception, Computer vision, and Speech recognition Feature detection (pictured: edge detection) helps AI compose informative abstract structures out of raw data. Machine perception[134] is the ability to use input from sensors (such as cameras (visible spectrum or infrared), microphones, wireless signals, and active lidar, sonar, radar, and tactile sensors) to deduce aspects of the world. Applications include speech recognition,[135] facial recognition, and object recognition.[136] Computer vision is the ability to analyze visual input. Such input is usually ambiguous; a giant, fifty-meter-tall pedestrian far away may produce the same pixels as a nearby normal-sized pedestrian, requiring the AI to judge the relative likelihood and reasonableness of different interpretations, for example by using its "object model" to assess that fifty-meter pedestrians do not exist.[137] Motion and manipulation Main article: Robotics AI is heavily used in robotics.[138] Advanced robotic arms and other industrial robots, widely used in modern factories, can learn from experience how to move efficiently despite the presence of friction and gear slippage.[139] A modern mobile robot, when given a small, static, and visible environment, can easily determine its location and map its environment; however, dynamic environments, such as (in endoscopy) the interior of a patient's breathing body, pose a greater challenge. Motion planning is the process of breaking down a movement task into "primitives" such as individual joint movements. Such movement often involves compliant motion, a process where movement requires maintaining physical contact with an object.[140][141][142] Moravec's paradox generalizes that low-level sensorimotor skills that humans take for granted are, counterintuitively, difficult to program into a robot; the paradox is named after Hans Moravec, who stated in 1988 that "it is comparatively easy to make computers exhibit adult level performance on intelligence tests or playing checkers, and difficult or impossible to give them the skills of a one-year-old when it comes to perception and mobility".[143][144] This is attributed to the fact that, unlike checkers, physical dexterity has been a direct target of natural selection for millions of years.[145] Social intelligence Main article: Affective computing Kismet, a robot with rudimentary social skills[146] Moravec's paradox can be extended to many forms of social intelligence.[147][148] Distributed multi-agent coordination of autonomous vehicles remains a difficult problem.[149] Affective computing is an interdisciplinary umbrella that comprises systems which recognize, interpret, process, or simulate human affects.[150][151][152] Moderate successes related to affective computing include textual sentiment analysis and, more recently, multimodal affect analysis (see multimodal sentiment analysis), wherein AI classifies the affects displayed by a videotaped subject.[153] In the long run, social skills and an understanding of human emotion and game theory would be valuable to a social agent. The ability to predict the actions of others by understanding their motives and emotional states would allow an agent to make better decisions. Some computer systems mimic human emotion and expressions to appear more sensitive to the emotional dynamics of human interaction, or to otherwise facilitate human–computer interaction.[154] Similarly, some virtual assistants are programmed to speak conversationally or even to banter humorously; this tends to give naïve users an unrealistic conception of how intelligent existing computer agents actually are.[155] General intelligence Main articles: Artificial general intelligence and AI-complete Historically, projects such as the Cyc knowledge base (1984–) and the massive Japanese Fifth Generation Computer Systems initiative (1982–1992) attempted to cover the breadth of human cognition. These early projects failed to escape the limitations of non-quantitative symbolic logic models and, in retrospect, greatly underestimated the difficulty of cross-domain AI. Nowadays, most current AI researchers work instead on tractable "narrow AI" applications (such as medical diagnosis or automobile navigation).[156] Many researchers predict that such "narrow AI" work in different individual domains will eventually be incorporated into a machine with artificial general intelligence (AGI), combining most of the narrow skills mentioned in this article and at some point even exceeding human ability in most or all these areas.[26][157] Many advances have general, cross-domain significance. One high-profile example is that DeepMind in the 2010s developed a "generalized artificial intelligence" that could learn many diverse Atari games on its own, and later developed a variant of the system which succeeds at sequential learning.[158][159][160] Besides transfer learning,[161] hypothetical AGI breakthroughs could include the development of reflective architectures that can engage in decision-theoretic metareasoning, and figuring out how to "slurp up" a comprehensive knowledge base from the entire unstructured Web.[162] Some argue that some kind of (currently-undiscovered) conceptually straightforward, but mathematically difficult, "Master Algorithm" could lead to AGI.[163] Finally, a few "emergent" approaches look to simulating human intelligence extremely closely, and believe that anthropomorphic features like an artificial brain or simulated child development may someday reach a critical point where general intelligence emerges.[164][165] Many of the problems in this article may also require general intelligence, if machines are to solve the problems as well as people do. For example, even specific straightforward tasks, like machine translation, require that a machine read and write in both languages (NLP), follow the author's argument (reason), know what is being talked about (knowledge), and faithfully reproduce the author's original intent (social intelligence). A problem like machine translation is considered "AI-complete", because all of these problems need to be solved simultaneously in order to reach human-level machine performance

Name: Mahmoud Walid Mahmoud Emam

B,N:882

Topic: Artificial Intelligence