AI

Artificial intelligence (AI) is firstly an academic discipline with various, often conflicting, views on what constitutes its area of research, as well as goals and approaches used, including logical, knowledge-based approach, on one hand, and machine learning approach, on the other. When probabilistic systems were plagued by theoretical and practical problems of data acquisition and representation[1], symbolic/knowledge-based approach prevailed and artificial neural networks research had been abandoned by AI and continued outside the AI, as "connectionism", by researchers from other disciplines including Hopfield, Rumelhart, and Hinton.By lay persons, however, the term is mostly used to mean AI applications, such as advanced web search engines (e.g., Google Search), recommendation systems (used by YouTube, Amazon, and Netflix), understanding human speech (such as Siri and Alexa), self-driving cars (e.g., Waymo), generative or creative tools (ChatGPT and AI art), and competing at the highest level in strategic game systems (such as chess and Go).[2]Artificial intelligence was founded as an academic discipline in 1956, and in the years since it has experienced several waves of optimism,[3][4] followed by disappointment and the loss of funding (known as an "AI winter"),[5][6] followed by new approaches, success, and renewed funding.[4][7] AI research has tried and discarded many different approaches, including simulating the brain, modeling human problem solving, formal logic, large databases of knowledge, and imitating animal behavior. In the first decades of the 21st century, highly mathematical and statistical machine learning has dominated the field, and this technique has proved highly successful, helping to solve many challenging problems throughout industry and academia.[7][8]The various sub-fields of AI research are centered around particular goals and the use of particular tools. The traditional goals of AI research include reasoning, knowledge representation, planning, learning, natural language processing, perception, and the ability to move and manipulate objects.[a] General intelligence (the ability to solve an arbitrary problem) is among the field's long-term goals.[9] To solve these problems, AI researchers have adapted and integrated a wide range of problem-solving techniques, including search and mathematical optimization, formal logic, artificial neural networks, and methods based on statistics, probability, and economics. AI also draws upon computer science, 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".[b] This raised philosophical arguments about the mind and the ethical consequences of creating artificial beings endowed with human-like intelligence; these issues have previously been explored by myth, fiction (science fiction), and philosophy since antiquity.[11] Computer scientists and philosophers have since suggested that AI may become an existential risk to humanity if its rational capacities are not steered towards goals beneficial to humankind.[c] Economists have frequently highlighted the risks of redundancies from AI, and speculated about unemployment if there is no adequate social policy for full employment.[12] The term artificial intelligence has also been criticized for overhyping AI's true technological capabilities.[13][14][15]HistoryMain articles: History of artificial intelligence and Timeline of artificial intelligenceSilver didrachma from Crete depicting Talos, a mythical intelligent automaton (c. 300 BC)Artificial beings with intelligence appeared as

storytelling devices in antiquity,[16] and have been common in fiction, as in Mary Shelley's Frankenstein or Karel Æ V²w2 "åP.R.[17] These characters and their fates raised many of the same issues now discussed in the ethics of artificial intelligence.[18]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.[19] This, along with concurrent discoveries in neurobiology, information theory and cybernetics, led researchers to consider the possibility of building an electronic brain.[20] The first work that is now generally recognized as AI was McCullouch and Pitts' 1943 formal design for Turing-complete "artificial neurons".[21]The field of AI research was born at a workshop at Dartmouth College in 1956.[d][23] The attendees became the founders and leaders of AI research.[e] They and their students produced programs that the press described as "astonishing":[f] computers were learning checkers strategies, solving word problems in algebra, proving logical theorems and speaking English.[g][26] By the middle of the 1960s, research in the U.S. was heavily funded by the Department of Defense[27] and laboratories had been established around the world.[28]Researchers in the 1960s and the 1970s were convinced that their methods would eventually succeed in creating a machine with artificial general intelligence and considered this the goal of their field.[29] Herbert Simon predicted, "machines will be capable, within twenty years, of doing any work a man can do".[30] Marvin Minsky agreed, writing, "within a generation ... the problem of creating 'artificial intelligence' will substantially be solved".[31]They had failed to recognize the difficulty of some of the remaining tasks.[h] Progress slowed and in 1974, in response to the criticism of Sir James Lighthill[33] 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. Early research into artificial neural networks was discredited by Minsky's and Papert's book Perceptrons, which was perceived as proving that this technology would never work.[34] The next few years would later be called an "AI winter", a period when obtaining funding for AI projects was difficult.[5]In the early 1980s, AI research was revived by the commercial success of expert systems,[35] 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.[4] However, beginning with the collapse of the Lisp Machine market in 1987, AI once again fell into disrepute, and a second, longer-lasting winter began.[6]Many researchers began to doubt that the current practices would be able to imitate all the processes of human cognition, especially perception, robotics, learning and pattern recognition.[36] A number of researchers began to look into "sub-symbolic" approaches to specific AI problems.[37] Robotics researchers, such as Rodney Brooks, rejected symbolic AI and focused on the basic engineering problems that would allow robots to move, survive, and learn their environment.[i] Tools were invented that could make reasonable guesses (known as "soft computing") and deal with uncertain

information.[42] Interest in neural networks and "connectionism" was revived by Geoffrey Hinton, David Rumelhart and others in the middle of the 1980s.[43] Connectionism began to succeed in the 90s when Yann LeCun successfully showed convolutional neural networks could recognize handwritten digits.[44]AI gradually restored its reputation in the late 1990s and early 21st century by exploiting formal mathematical methods and by finding specific solutions to specific problems. This "narrow" and "formal" focus allowed researchers to produce verifiable results and collaborate with other fields (such as statistics, economics and mathematics).[45] By 2000, solutions developed by AI researchers were being widely used, although in the 1990s they were rarely described as "artificial intelligence".[8]Several leading academic researchers became concerned that AI was no longer pursuing the original goal of creating versatile, fully intelligent machines. This concern has led to the founding of the subfield of artificial general intelligence (or "AGI"),[9] which had several well-funded institutions by the 2010s.Deep learning methods started to dominate accuracy benchmarks in 2012.[46] Deep learning's success depended on hardware improvements (faster computers,[47] graphics processing units, cloud computing[7]) and access to large amounts of data[48] (including curated datasets,[7] such as ImageNet). It soon proved to be highly successful at a wide range of tasks and was adopted throughout the field. For many specific tasks, other methods were abandoned.[j] The success of deep learning set off an explosion of interest and investment throughout the economy.[k] The number of software projects that use AI at Google increased from a "sporadic usage" in 2012 to more than 2,700 projects in 2015.[7] In a 2017 survey, one in five companies reported they had "incorporated AI in some offerings or processes".[50] The amount of research into AI (measured by total publications) increased by 50% in the years 2015–2019.[51] According to AI Impacts at Stanford, around 2022 about $50 billion annually is invested in artificial intelligence in the US, and about 20% of new US Computer Science PhD graduates have specialized in artificial intelligence;[52] about 800,000 AI-related US job openings existed in 2022.[53]In 2016, issues of fairness and the misuse of technology were catapulted into center stage at AI conferences, publications vastly increased, funding became available, and many researchers re-focussed their careers on these issues. The alignment problem became a serious field of academic study.[54]GoalsThe 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.[a]Reasoning, problem-solvingEarly researchers developed algorithms that imitated step-by-step reasoning that humans use when they solve puzzles or make logical deductions.[55] By the late 1980s and 1990s, AI research had developed methods for dealing with uncertain or incomplete information, employing concepts from probability and economics.[56]Many of 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.[57] 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.[58]Knowledge representationMain articles: Knowledge representation, Commonsense knowledge, Description logic, and Ontology

(information science)An ontology represents knowledge as a set of concepts within a domain and the relationships between those concepts.Knowledge representation and knowledge engineering[59] allow AI programs to answer questions intelligently and make deductions about real-world facts.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.[60] The most general ontologies are called upper ontologies, which attempt to provide a foundation for all other knowledge and act as mediators between domain ontologies that cover specific knowledge about a particular knowledge domain (field of interest or area of concern).AI research, building on the work of mathematics and philosophy, have developed tools to represent specific domains, such as objects, properties, categories and relations between objects;[61] situations, events, states and time;[62] causes and effects;[63] knowledge about knowledge (what we know about what other people know); and [64] default reasoning (things that humans assume are true until they are told differently and will remain true even when other facts are changing);.[65] Among the most difficult problems in AI are: the breadth of commonsense knowledge (the set of atomic facts that the average person knows) is enormous;[66] and the sub-symbolic form of most commonsense knowledge (much of what people know is not represented as "facts" or "statements" that they could express verbally).[58]Formal knowledge representations are used in content-based indexing and retrieval,[67] scene interpretation,[68] clinical decision support,[69] knowledge discovery (mining "interesting" and actionable inferences from large databases),[70] and other areas.[71]LearningMain article: Machine learningMachine learning (ML), a fundamental concept of AI research since the field's inception,[l] is the study of computer algorithms that improve automatically through experience.[m] [75]Unsupervised learning analyzes a stream of data and finds patterns and makes predictions without any other guidance.[76]Supervised learning requires a human to label the input data first, and comes in two main varieties: classification and regression.[77] Classification is used to determine what category something belongs in – the program sees a number of examples of things from several categories and will learn to classify new inputs. Regression is the attempt to produce a numeric function that describes the relationship between inputs and outputs and predicts how the outputs should change as the inputs change. 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".[78]In reinforcement learning the agent is rewarded for good responses and punished for bad ones. The agent classifies its responses to form a strategy for operating in its problem space.[79]Transfer learning is when the knowledge gained from one problem is applied to a new problem.[80]Computational learning theory can assess learners by computational complexity, by sample complexity (how much data is required), or by other notions of optimization.[81]Natural language processingMain article: Natural language processingA parse tree represents the syntactic structure of a sentence according to some formal grammar.Natural language processing (NLP)[82] 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 NLP include speech recognition, speech synthesis, machine translation, information extraction, information retrieval and question answering.[83]Starting in the 1960s, symbolic AI used formal syntax to translate the deep structure of sentences into logic. This failed to produce useful applications, due to the intractability of logic[57] and the breadth of commonsense knowledge.[66]Modern techniques include word embedding (how often one word appears near another),[84] "Keyword spotting" (searching for a particular word to retrieve information), and transformer-based deep learning (which finds patterns in text),[85] and others.[86] In 2019, generative pre-trained transformer (or "GPT") language models began to generate coherent text,[87][88] and by 2023 these models were able to get human-level scores on the bar exam, SAT, GRE, and many other real-world applications.[89]PerceptionFeature detection (pictured: edge detection) helps AI compose informative abstract structures out of raw data.Machine perception is the ability to use input from sensors (such as cameras, microphones, wireless signals,active lidar, sonar, radar, and tactile sensors to deduce aspects of the world. Computer vision is the ability to analyze visual input.[90] The field includes speech recognition,[91] image classification,[92] facial recognition, object recognition, [93] robotic perception,[94] among others.Social intelligenceMain article: Affective computingKismet, a robot with rudimentary social skills[95]Affective computing is an interdisciplinary umbrella that comprises systems that recognize, interpret, process or simulate human feeling, emotion and mood.[96] For example, some virtual assistants are programmed to speak conversationally or even to banter humorously; it makes them appear more sensitive to the emotional dynamics of human interaction, or to otherwise facilitate human–computer interaction. However, this tends to give naïve users an unrealistic conception of how intelligent existing computer agents actually are.[97] Moderate successes related to affective computing include textual sentiment analysis and, more recently, multimodal sentiment analysis, wherein AI classifies the affects displayed by a videotaped subject.[98]General intelligenceMain article: Artificial general intelligenceA machine with general intelligence can solve a wide variety of problems with breadth and versatility similar to human intelligence. [9]There have been several competing ideas about how to develop artificial general intelligence. In 1963, Herbert A. Simon predicted that symbolic AI would soon scale up to AGI, but these predictions failed to come true.[99] Hans Moravec and Marvin Minsky argue that work in different individual domains can be incorporated into an advanced multi-agent system or cognitive architecture with general intelligence.[100] Pedro Domingos hopes that there is a conceptually straightforward, but mathematically difficult, "master algorithm" that could lead to AGI.[101] Others believe that anthropomorphic features like an artificial brain[102] or simulated child development[n] will someday reach a critical point where general intelligence emerges. In 2023, many researchers felt that neuro-symbolic AI (such as Alpha Zero) showed the most promise.ToolsSearch and optimizationMain articles: Search algorithm, Mathematical optimization, and Evolutionary computationAI can solve many problems by intelligently searching through many possible solutions.[103] Reasoning can be reduced to performing a search. For example, logical proof can be viewed as searching for a path that leads from premises to conclusions, where each step is the application of an

inference rule.[104] Planning algorithms search through trees of goals and subgoals, attempting to find a path to a target goal, a process called means-ends analysis.[105] Robotics algorithms for moving limbs and grasping objects use local searches in configuration space.[106]Simple exhaustive searches[107] are rarely sufficient for most real-world problems: the search space (the number of places to search) quickly grows to astronomical numbers. The result is a search that is too slow or never completes. The solution, for many problems, is to use "heuristics" or "rules of thumb" that prioritize choices in favor of those more likely to reach a goal and to do so in a shorter number of steps. In some search methodologies, heuristics can also serve to eliminate some choices unlikely to lead to a goal (called "pruning the search tree"). Heuristics supply the program with a "best guess" for the path on which the solution lies.[108] Heuristics limit the search for solutions into a smaller sample size.[109]A particle swarm seeking the global minimumA very different kind of search came to prominence in the 1990s, based on the mathematical theory of optimization. For many problems, it is possible to begin the search with some form of a guess and then refine the guess incrementally until no more refinements can be made. These algorithms can be visualized as blind hill climbing: we begin the search at a random point on the landscape, and then, by jumps or steps, we keep moving our guess uphill, until we reach the top. Other related optimization algorithms include random optimization, beam search and metaheuristics like simulated annealing.[110] Evolutionary computation uses a form of optimization search. For example, they may begin with a population of organisms (the guesses) and then allow them to mutate and recombine, selecting only the fittest to survive each generation (refining the guesses). Classic evolutionary algorithms include genetic algorithms, gene expression programming, and genetic programming.[111] Alternatively, distributed search processes can coordinate via swarm intelligence algorithms. Two popular swarm algorithms used in search are particle swarm optimization (inspired by bird flocking) and ant colony optimization (inspired by ant trails).[112]LogicMain articles: Logic programming and Automated reasoningLogic[113] is used for knowledge representation and problem-solving, but it can be applied to other problems as well. For example, the satplan algorithm uses logic for planning[114] and inductive logic programming is a method for learning.[115]Several different forms of logic are used in AI research. Propositional logic[116] involves truth functions such as "or" and "not". First-order logic[117] adds quantifiers and predicates and can express facts about objects, their properties, and their relations with each other. Fuzzy logic assigns a "degree of truth" (between 0 and 1) to vague statements such as "Alice is old" (or rich, or tall, or hungry), that are too linguistically imprecise to be completely true or false.[118] Default logics, non-monotonic logics and circumscription are forms of logic designed to help with default reasoning and the qualification problem.[65] Several extensions of logic have been designed to handle specific domains of knowledge, such as description logics;[61] situation calculus, event calculus and fluent calculus (for representing events and time);[62] causal calculus;[63] belief calculus (belief revision); and modal logics.[64] Logics to model contradictory or inconsistent statements arising in multi-agent systems have also been designed, such as paraconsistent logics.[119]Probabilistic methods for uncertain reasoningMain articles: Bayesian network, Hidden Markov model, Kalman filter, Particle filter, Decision

theory, and Utility theoryExpectation-maximization clustering of Old Faithful eruption data starts from a random guess but then successfully converges on an accurate clustering of the two physically distinct modes of eruption.Many problems in AI (including in reasoning, planning, learning, perception, and robotics) require the agent to operate with incomplete or uncertain information. AI researchers have devised a number of tools to solve these problems using methods from probability theory and economics.[120] Bayesian networks[121] are a very general tool that can be used for various problems, including reasoning (using the Bayesian inference algorithm),[o][123] learning (using the expectation-maximization algorithm),[p][125] planning (using decision networks)[126] and perception (using dynamic Bayesian networks).[127] Probabilistic algorithms can also be used for filtering, prediction, smoothing and finding explanations for streams of data, helping perception systems to analyze processes that occur over time (e.g., hidden Markov models or Kalman filters).[127]A key concept from the science of economics is "utility", a measure of how valuable something is to an intelligent agent. Precise mathematical tools have been developed that analyze how an agent can make choices and plan, using decision theory, decision analysis, [128] and information value theory.[129] These tools include models such as Markov decision processes,[130] dynamic decision networks,[127] game theory and mechanism design.[131]Classifiers and statistical learning methodsMain articles: Statistical classification and Machine learningThe simplest AI applications can be divided into two types: classifiers ("if shiny then diamond") and controllers ("if diamond then pick up"). Controllers do, however, also classify conditions before inferring actions, and therefore classification forms a central part of many AI systems. Classifiers are functions that use pattern matching to determine the closest match. They can be tuned according to examples, making them very attractive for use in AI. These examples are known as observations or patterns. In supervised learning, each pattern belongs to a certain predefined class. A class is a decision that has to be made. All the observations combined with their class labels are known as a data set. When a new observation is received, that observation is classified based on previous experience.[132]A classifier can be trained in various ways; there are many statistical and machine learning approaches. The decision tree is the simplest and most widely used symbolic machine learning algorithm.[133] K-nearest neighbor algorithm was the most widely used analogical AI until the mid-1990s.[134] Kernel methods such as the support vector machine (SVM) displaced k-nearest neighbor in the 1990s.[135] The naive Bayes classifier is reportedly the "most widely used learner"[136] at Google, due in part to its scalability.[137] Neural networks are also used for classification.[138]Classifier performance depends greatly on the characteristics of the data to be classified, such as the dataset size, distribution of samples across classes, dimensionality, and the level of noise. Model-based classifiers perform well if the assumed model is an extremely good fit for the actual data. Otherwise, if no matching model is available, and if accuracy (rather than speed or scalability) is the sole concern, conventional wisdom is that discriminative classifiers (especially SVM) tend to be more accurate than model-based classifiers such as "naive Bayes" on most practical data sets.[139]Artificial neural networksMain articles: Artificial neural network and ConnectionismA neural network is an interconnected group of nodes, akin to the vast network of neurons in the human brain.Neural networks[138] were inspired by the

architecture of neurons in the human brain. A simple "neuron" N accepts input from other neurons, each of which, when activated (or "fired"), casts a weighted "vote" for or against whether neuron N should itself activate. Learning requires an algorithm to adjust these weights based on the training data; one simple algorithm (dubbed "fire together, wire together") is to increase the weight between two connected neurons when the activation of one triggers the successful activation of another. Neurons have a continuous spectrum of activation; in addition, neurons can process inputs in a nonlinear way rather than weighing straightforward votes.Modern neural networks model complex relationships between inputs and outputs and find patterns in data. They can learn continuous functions and even digital logical operations. Neural networks can be viewed as a type of mathematical optimization – they perform gradient descent on a multi-dimensional topology that was created by training the network. The most common training technique is the backpropagation algorithm.[140] Other learning techniques for neural networks are Hebbian learning ("fire together, wire together"), GMDH or competitive learning.[141]The main categories of networks are acyclic or feedforward neural networks (where the signal passes in only one direction) and recurrent neural networks (which allow feedback and short-term memories of previous input events). Among the most popular feedforward networks are perceptrons, multi-layer perceptrons and radial basis networks.[142]Deep learningRepresenting images on multiple layers of abstraction in deep learning[143]Deep learning[144] uses several layers of neurons between the network's inputs and outputs. The multiple layers can progressively extract higher-level features from the raw input. For example, in image processing, lower layers may identify edges, while higher layers may identify the concepts relevant to a human such as digits or letters or faces.[145] Deep learning has drastically improved the performance of programs in many important subfields of artificial intelligence, including computer vision, speech recognition, image classification[146] and others.Deep learning often uses convolutional neural networks for many or all of its layers. In a convolutional layer, each neuron receives input from only a restricted area of the previous layer called the neuron's receptive field. This can substantially reduce the number of weighted connections between neurons,[147] and creates a hierarchy similar to the organization of the animal visual cortex.[148]In a recurrent neural network (RNN) the signal will propagate through a layer more than once;[149] thus, an RNN is an example of deep learning.[150] RNNs can be trained by gradient descent,[151] however long-term gradients which are back-propagated can "vanish" (that is, they can tend to zero) or "explode" (that is, they can tend to infinity), known as the vanishing gradient problem.[152] The long short term memory (LSTM) technique can prevent this in most cases.[153]Specialized languages and hardwareMain articles: Programming languages for artificial intelligence and Hardware for artificial intelligenceSpecialized languages for artificial intelligence have been developed, such as Lisp, Prolog, TensorFlow and many others. Hardware developed for AI includes AI accelerators and neuromorphic computing. By 2019, graphics processing units (GPUs), often with AI-specific enhancements, had displaced central processing unit (CPUs) as the dominant means to train large-scale commercial cloud AI.[154]ApplicationsMain article: Applications of artificial intelligenceSee also: Embodied cognition and Legal informaticsFor this 2018 project of the artist Joseph Ayerle the AI had to learn 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.AI is relevant to any intellectual task.[155] Modern artificial intelligence techniques are pervasive and are too numerous to list here.[156] Frequently, when a technique reaches mainstream use, it is no longer considered artificial intelligence; this phenomenon is described as the AI effect.[157]In the 2010s, AI applications were at the heart of the most commercially successful areas of computing, and have become a ubiquitous feature of daily life. AI is used in search engines (such as Google Search), targeting online advertisements,[158] recommendation systems (offered by Netflix, YouTube or Amazon), driving internet traffic,[159][160] targeted advertising (AdSense, Facebook), virtual assistants (such as Siri or Alexa),[161] autonomous vehicles (including drones, ADAS and self-driving cars), automatic language translation (Microsoft Translator, Google Translate), facial recognition (Apple's Face ID or Microsoft's DeepFace), image labeling (used by Facebook, Apple's iPhoto and TikTok), spam filtering and chatbots (such as ChatGPT).There are also thousands of successful AI applications used to solve problems for specific industries or institutions. A few examples are energy storage,[162] deepfakes,[163] medical diagnosis, military logistics, foreign policy,[164] or supply chain management.Game playing has been a test of AI's strength since the 1950s. Deep Blue became the first computer chess-playing system to beat a reigning world chess champion, Garry Kasparov, on 11 May 1997.[165] 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.[166] 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.[167] Then it defeated Ke Jie in 2017, who at the time continuously held the world No. 1 ranking for two years.[168][169][170] Other programs handle imperfect-information games; such as for poker at a superhuman level, Pluribus[q] and Cepheus.[172] DeepMind in the 2010s developed a "generalized artificial intelligence" that could learn many diverse Atari games on its own.[173]DeepMind's AlphaFold 2 (2020) demonstrated the ability to approximate, in hours rather than months, the 3D structure of a protein.[174] Other applications predict the result of judicial decisions,[175] create art (such as poetry or painting) and prove mathematical theorems.Generative AI gained widespread prominence in the 2020s. "Large language model" systems such as GPT-3 (2020), with 175 billion parameters, matched human performance on pre-existing benchmarks, albeit without the system attaining a commonsense understanding of the contents of the benchmarks.[176] A Pew Research poll conducted in March 2023 found that 14% of Americans adults had tried ChatGPT, a large language model fine-tuned using reinforcement learning from human feedback.[177] While estimates varied wildly, Goldman Sachs suggested in 2023 that generative language AI could increase global GDP by 7% in the next ten years.[178][179]In 2023, the increasing realism and ease-of-use of AI-based text-to-image generators such as Midjourney, DALL-E, and Stable Diffusion[180][181] sparked a trend of viral AI-generated photos. Widespread attention was gained by a fake photo of Pope Francis wearing a white puffer coat,[182] the fictional arrest of Donald Trump,[183] and a hoax of an attack on the Pentagon,[184] as well as the usage in professional creative arts.

[185][186]AI interactive systems can improve the information exchange between physicians and patients in clinical settings, with a focus on patiens with long-term and chronic conditions, specifically migraine patients.[187]Intellectual propertyAI patent families for functional application categories and sub categories. Computer vision represents 49 percent of patent families related to a functional application in 2016.In 2019, WIPO reported that AI was the most prolific emerging technology in terms of the number of patent applications and granted patents, the Internet of things was estimated to be the largest in terms of market size. It was followed, again in market size, by big data technologies, robotics, AI, 3D printing and the fifth generation of mobile services (5G).[188] Since AI emerged in the 1950s, 340,000 AI-related patent applications were filed by innovators and 1.6 million scientific papers have been published by researchers, with the majority of all AI-related patent filings published since 2013. Companies represent 26 out of the top 30 AI patent applicants, with universities or public research organizations accounting for the remaining four.[189] The ratio of scientific papers to inventions has significantly decreased from 8:1 in 2010 to 3:1 in 2016, which is attributed to be indicative of a shift from theoretical research to the use of AI technologies in commercial products and services. Machine learning is the dominant AI technique disclosed in patents and is included in more than one-third of all identified inventions (134,777 machine learning patents filed for a total of 167,038 AI patents filed in 2016), with computer vision being the most popular functional application. AI-related patents not only disclose AI techniques and applications, they often also refer to an application field or industry. Twenty application fields were identified in 2016 and included, in order of magnitude: telecommunications (15 percent), transportation (15 percent), life and medical sciences (12 percent), and personal devices, computing and human–computer interaction (11 percent). Other sectors included banking, entertainment, security, industry and manufacturing, agriculture, and networks (including social networks, smart cities and the Internet of things). IBM has the largest portfolio of AI patents with 8,290 patent applications, followed by Microsoft with 5,930 patent applications.[189]PhilosophyMain article: Philosophy of artificial intelligenceDefining artificial intelligenceMain articles: Turing test, Intelligent agent, Dartmouth workshop, and Synthetic intelligenceAlan Turing wrote in 1950 "I propose to consider the question 'can machines think'?"[190] He advised changing the question from whether a machine "thinks", to "whether or not it is possible for machinery to show intelligent behaviour". [190] He devised the Turing test, which measures the ability of a machine to simulate human conversation.[191] Since we can only observe the behavior of the machine, it does not matter if it is "actually" thinking or literally has a "mind". Turing notes that we can not determine these things about other people[r] but "it is usual to have a polite convention that everyone thinks"[192]Russell and Norvig agree with Turing that AI must be defined in terms of "acting" and not "thinking".[193] However, they are critical that the test compares machines to people. "Aeronautical engineering texts," they wrote, "do not define the goal of their field as making 'machines that fly so exactly like pigeons that they can fool other pigeons.'"[194] AI founder John McCarthy agreed, writing that "Artificial intelligence is not, by definition, simulation of human intelligence". [195]McCarthy defines intelligence as "the computational part of the ability to

achieve goals in the world."[196] Another AI founder, Marvin Minsky similarly defines it as "the ability to solve hard problems".[197] These definitions view intelligence in terms of well-defined problems with well-defined solutions, where both the difficulty of the problem and the performance of the program are direct measures of the "intelligence" of the machine—and no other philosophical discussion is required, or may not even be possible.A definition that has also been adopted by Google[198][better source needed] – major practitionary in the field of AI. This definition stipulated the ability of systems to synthesize information as the manifestation of intelligence, similar to the way it is defined in biological intelligence.Evaluating approaches to AINo established unifying theory or paradigm has guided AI research for most of its history.[s] The unprecedented success of statistical machine learning in the 2010s eclipsed all other approaches (so much so that some sources, especially in the business world, use the term "artificial intelligence" to mean "machine learning with neural networks"). This approach is mostly sub-symbolic, neat, soft and narrow (see below). Critics argue that these questions may have to be revisited by future generations of AI researchers.Symbolic AI and its limitsSymbolic AI (or "GOFAI")[200] simulated the high-level conscious reasoning that people use when they solve puzzles, express legal reasoning and do mathematics. They were highly successful at "intelligent" tasks such as algebra or IQ tests. In the 1960s, Newell and Simon proposed the physical symbol systems hypothesis: "A physical symbol system has the necessary and sufficient means of general intelligent action."[201]However, the symbolic approach failed on many tasks that humans solve easily, such as learning, recognizing an object or commonsense reasoning. Moravec's paradox is the discovery that high-level "intelligent" tasks were easy for AI, but low level "instinctive" tasks were extremely difficult.[202] Philosopher Hubert Dreyfus had argued since the 1960s that human expertise depends on unconscious instinct rather than conscious symbol manipulation, and on having a "feel" for the situation, rather than explicit symbolic knowledge.[203] Although his arguments had been ridiculed and ignored when they were first presented, eventually, AI research came to agree.[t][58]The issue is not resolved: sub-symbolic reasoning can make many of the same inscrutable mistakes that human intuition does, such as algorithmic bias. Critics such as Noam Chomsky argue continuing research into symbolic AI will still be necessary to attain general intelligence,[205][206] in part because sub-symbolic AI is a move away from explainable AI: it can be difficult or impossible to understand why a modern statistical AI program made a particular decision. The emerging field of neuro-symbolic artificial intelligence attempts to bridge the two approaches.Neat vs. scruffyMain article: Neats and scruffies"Neats" hope that intelligent behavior is described using simple, elegant principles (such as logic, optimization, or neural networks). "Scruffies" expect that it necessarily requires solving a large number of unrelated problems. Neats defend their programs with theoretical rigor, scruffies rely only on incremental testing to see if they work. This issue was actively discussed in the 70s and 80s,[207] but eventually was seen as irrelevant. In the 1990s mathematical methods and solid scientific standards became the norm, a transition that Russell and Norvig termed in 2003 as "the victory of the neats".[208] However in 2020 they wrote "deep learning may represent

a resurgence of the scruffies".[36] Modern AI has elements of both.Soft vs. hard computingMain article: Soft computingFinding a provably correct or optimal solution is intractable for many important problems.[57] Soft computing is a set of techniques, including genetic algorithms, fuzzy logic and neural networks, that are tolerant of imprecision, uncertainty, partial truth and approximation. Soft computing was introduced in the late 80s and most successful AI programs in the 21st century are examples of soft computing with neural networks.Narrow vs. general AIMain article: Artificial general intelligenceAI researchers are divided as to whether to pursue the goals of artificial general intelligence and superintelligence (general AI) directly or to solve as many specific problems as possible (narrow AI) in hopes these solutions will lead indirectly to the field's long-term goals.[209][210] General intelligence is difficult to define and difficult to measure, and modern AI has had more verifiable successes by focusing on specific problems with specific solutions. The experimental sub-field of artificial general intelligence studies this area exclusively.Machine consciousness, sentience and mindMain articles: Philosophy of artificial intelligence and Artificial consciousnessThe philosophy of mind does not know whether a machine can have a mind, consciousness and mental states, in the same sense that human beings do. This issue considers the internal experiences of the machine, rather than its external behavior. Mainstream AI research considers this issue irrelevant because it does not affect the goals of the field. Stuart Russell and Peter Norvig observe that most AI researchers "don't care about the [philosophy of AI] – as long as the program works, they don't care whether you call it a simulation of intelligence or real intelligence."[211] However, the question has become central to the philosophy of mind. It is also typically the central question at issue in artificial intelligence in fiction.ConsciousnessMain articles: Hard problem of consciousness and Theory of mindDavid Chalmers identified two problems in understanding the mind, which he named the "hard" and "easy" problems of consciousness.[212] The easy problem is understanding how the brain processes signals, makes plans and controls behavior. The hard problem is explaining how this feels or why it should feel like anything at all, assuming we are right in thinking that it truly does feel like something (Dennett's consciousness illusionism says this is an illusion). Human information processing is easy to explain, however, human subjective experience is difficult to explain. For example, it is easy to imagine a color-blind person who has learned to identify which objects in their field of view are red, but it is not clear what would be required for the person to know what red looks like.[213]Computationalism and functionalismMain articles: Computational theory of mind, Functionalism (philosophy of mind), and Chinese roomComputationalism is the position in the philosophy of mind that the human mind is an information processing system and that thinking is a form of computing. Computationalism argues that the relationship between mind and body is similar or identical to the relationship between software and hardware and thus may be a solution to the mind–body problem. This philosophical position was inspired by the work of AI researchers and cognitive scientists in the 1960s and was originally proposed by philosophers Jerry Fodor and Hilary Putnam.[214]Philosopher John Searle characterized this position as "strong AI": "The appropriately programmed computer with the right inputs and outputs would thereby have a mind in exactly the same sense human beings have minds."[u] Searle counters this assertion with his Chinese room argument,

which attempts to show that, even if a machine perfectly simulates human behavior, there is still no reason to suppose it also has a mind.[217]Robot rightsMain article: Robot rightsIf a machine has a mind and subjective experience, then it may also have sentience (the ability to feel), and if so it could also suffer; it has been argued that this could entitle it to certain rights.[218] Any hypothetical robot rights would lie on a spectrum with animal rights and human rights.[219] This issue has been considered in fiction for centuries,[220] and is now being considered by, for example, California's Institute for the Future; however, critics argue that the discussion is premature.[221]FutureSuperintelligenceMain articles: Superintelligence, Technological singularity, and TranshumanismA superintelligence is a hypothetical agent that would possess intelligence far surpassing that of the brightest and most gifted human mind.[210]If research into artificial general intelligence produced sufficiently intelligent software, it might be able to reprogram and improve itself. The improved software would be even better at improving itself, leading to recursive self-improvement.[222] Its intelligence would increase exponentially in an intelligence explosion and could dramatically surpass humans. Science fiction writer Vernor Vinge named this scenario the "singularity".[223] Because it is difficult or impossible to know the limits of intelligence or the capabilities of superintelligent machines, the technological singularity is an occurrence beyond which events are unpredictable or even unfathomable.[224]Robot designer Hans Moravec, cyberneticist Kevin Warwick, and inventor Ray Kurzweil have predicted that humans and machines will merge in the future into cyborgs that are more capable and powerful than either. This idea, called transhumanism, has roots in Aldous Huxley and Robert Ettinger.[225]Edward Fredkin argues that "artificial intelligence is the next stage in evolution", an idea first proposed by Samuel Butler's "Darwin among the Machines" as far back as 1863, and expanded upon by George Dyson in his book of the same name in 1998.[226]RisksTechnological unemploymentMain articles: Workplace impact of artificial intelligence and Technological unemploymentIn the past, technology has tended to increase rather than reduce total employment, but economists acknowledge that "we're in uncharted territory" with AI.[227] A survey of economists showed disagreement about whether the increasing use of robots and AI will cause a substantial increase in long-term unemployment, but they generally agree that it could be a net benefit if productivity gains are redistributed.[228] Risk estimates vary; for example, in the 2010s Michael Osborne and Carl Benedikt Frey estimated 47% of U.S. jobs are at "high risk" of potential automation, while an OECD report classified only 9% of U.S. jobs as "high risk".[v][230] The methodology of speculating about future employment levels has been criticised as lacking evidential foundation, and for implying that technology (rather than social policy) creates unemployment (as opposed to redundancies).[12]Unlike previous waves of automation, many middle-class jobs may be eliminated by artificial intelligence; The Economist stated in 2015 that "the worry that AI could do to white-collar jobs what steam power did to blue-collar ones during the Industrial Revolution" is "worth taking seriously".[231] Jobs at extreme risk range from paralegals to fast food cooks, while job demand is likely to increase for care-related professions ranging from personal healthcare to the clergy.[232]Bad actors and weaponized AIMain articles: Lethal autonomous weapon, Artificial intelligence arms race, and AI safetyAI provides a

number of tools that are particularly useful for authoritarian governments: smart spyware, face recognition and voice recognition allow widespread surveillance; such surveillance allows machine learning to classify potential enemies of the state and can prevent them from hiding; recommendation systems can precisely target propaganda and misinformation for maximum effect; deepfakes aid in producing misinformation; advanced AI can make centralized decision making more competitive with liberal and decentralized systems such as markets.[233]Terrorists, criminals and rogue states may use other forms of weaponized AI such as advanced digital warfare and lethal autonomous weapons. By 2015, over fifty countries were reported to be researching battlefield robots.[234]Machine-learning AI is also able to design tens of thousands of toxic molecules in a matter of hours.[235]Algorithmic biasMain article: Algorithmic biasAI programs can become biased after learning from real-world data.[236] It may not be introduced by the system designers but learned by the program, and thus the programmers may not be aware that the bias exists.[237] Bias can be inadvertently introduced by the way training data is selected and by the way a model is deployed. [238] [236] It can also emerge from correlations: AI is used to classify individuals into groups and then make predictions assuming that the individual will resemble other members of the group. In some cases, this assumption may be unfair.[239] An example of this is COMPAS, a commercial program widely used by U.S. courts to assess the likelihood of a defendant becoming a recidivist. ProPublica claims that the COMPAS-assigned recidivism risk level of black defendants is far more likely to be overestimated than that of white defendants, despite the fact that the program was not told the races of the defendants.[240]Health equity issues may also be exacerbated when many-to-many mapping is done without taking steps to ensure equity for populations at risk for bias. At this time equity-focused tools and regulations are not in place to ensure equity application representation and usage.[241] Other examples where algorithmic bias can lead to unfair outcomes are when AI is used for credit rating, CV screening, hiring and applications for public housing.[236]At its 2022 Conference on Fairness, Accountability, and Transparency (ACM FAccT 2022) the Association for Computing Machinery, in Seoul, South Korea, presented and published findings recommending that until AI and robotics systems are demonstrated to be free of bias mistakes, they are unsafe and the use of self-learning neural networks trained on vast, unregulated sources of flawed internet data should be curtailed.[242]Existential riskMain articles: Existential risk from artificial general intelligence, AI alignment, and AI safetyIt has been argued AI will become so powerful that humanity may irreversibly lose control of it. This could, as the physicist Stephen Hawking puts it, "spell the end of the human race".[243] According to the philosopher Nick Bostrom, for almost any goals that a sufficiently intelligent AI may have, it is instrumentally incentivized to protect itself from being shut down and to acquire more resources, as intermediary steps to better achieve these goals. Sentience or emotions are then not required for an advanced AI to be dangerous. In order to be safe for humanity, a superintelligence would have to be genuinely aligned with humanity's morality and values so that it is "fundamentally on our side". [244] The political scientist Charles T. Rubin argued that "any sufficiently advanced benevolence may be indistinguishable from malevolence" and warned that we should not be confident that intelligent machines will by default treat us favorably.[245]The opinions amongst experts and industry insiders are mixed, with

sizable fractions both concerned and unconcerned by risk from eventual superintelligent AI.[246] Personalities such as Stephen Hawking, Bill Gates, Elon Musk have expressed concern about existential risk from AI.[247] In 2023, AI pioneers including Geoffrey Hinton, Yoshua Bengio, Demis Hassabis, and Sam Altman issued the joint statement that "Mitigating the risk of extinction from AI should be a global priority alongside other societal-scale risks such as pandemics and nuclear war"; some others such as Yann LeCun consider this to be unfounded.[248] Mark Zuckerberg stated that artificial intelligence is helpful in its current form and will continue to assist humans.[249] Some experts have argued that the risks are too distant in the future to warrant research, or that humans will be valuable from the perspective of a superintelligent machine.[250] Rodney Brooks, in particular, said in 2014 that "malevolent" AI is still centuries away.[w]CopyrightFurther information: Artificial intelligence and copyrightIn order to leverage as large a dataset as is feasible, generative AI is often trained on unlicensed copyrighted works, including in domains such as images or computer code; the output is then used under a rationale of "fair use". Experts disagree about how well, and under what circumstances, this rationale will hold up in courts of law; relevant factors may include "the purpose and character of the use of the copyrighted work" and "the effect upon the potential market for the copyrighted work".[252]Ethical machinesMain articles: Machine ethics, AI safety, Friendly artificial intelligence, Artificial moral agents, and Human CompatibleFriendly AI are machines that have been designed from the beginning to minimize risks and to make choices that benefit humans. Eliezer Yudkowsky, who coined the term, argues that developing friendly AI should be a higher research priority: it may require a large investment and it must be completed before AI becomes an existential risk.[253]Machines with intelligence have the potential to use their intelligence to make ethical decisions. The field of machine ethics provides machines with ethical principles and procedures for resolving ethical dilemmas.[254] The field of machine ethics is also called computational morality,[254] and was founded at an AAAI symposium in 2005.[255]Other approaches include Wendell Wallach's "artificial moral agents"[256] and Stuart J. Russell's three principles for developing provably beneficial machines.[257]RegulationMain articles: Regulation of artificial intelligence, Regulation of algorithms, and AI safetyOpenAI CEO Sam Altman testifies about AI regulation before a US Senate subcommittee, 2023The regulation of artificial intelligence is the development of public sector policies and laws for promoting and regulating artificial intelligence (AI); it is therefore related to the broader regulation of algorithms.[258] The regulatory and policy landscape for AI is an emerging issue in jurisdictions globally.[259] According to AI Index at Stanford, the annual number of AI-related laws passed in the 127 survey countries jumped from one passed in 2016 to 37 passed in 2022 alone.[260][261] Between 2016 and 2020, more than 30 countries adopted dedicated strategies for AI.[51] Most EU member states had released national AI strategies, as had Canada, China, India, Japan, Mauritius, the Russian Federation, Saudi Arabia, United Arab Emirates, US and Vietnam. Others were in the process of elaborating their own AI strategy, including Bangladesh, Malaysia and Tunisia.[51] The Global Partnership on Artificial Intelligence was launched in June 2020, stating a need for AI to be developed in accordance with human rights and democratic values, to ensure public confidence and trust in the technology.[51] Henry Kissinger, Eric Schmidt,

and Daniel Huttenlocher published a joint statement in November 2021 calling for a government commission to regulate AI.[262] In 2023, OpenAI leaders published recommendations for the governance of superintelligence, which they believe may happen in less than 10 years.[263]In a 2022 Ipsos survey, attitudes towards AI varied greatly by country; 78% of Chinese citizens, but only 35% of Americans, agreed that "products and services using AI have more benefits than drawbacks".[260] A 2023 Reuters/Ipsos poll found that 61% of Americans agree, and 22% disagree, that AI poses risks to humanity.[264] In a 2023 Fox News poll, 35% of Americans thought it "very important", and an additional 41% thought it "somewhat important", for the federal government to regulate AI, versus 13% responding "not very important" and 8% responding "not at all important". [265][266]In fictionMain article: Artificial intelligence in fictionThe word "robot" itself was coined by Karel Æ V² –â †—2 "# Æ y R.U.R., the title standing for "Rossum's Universal Robots".Thought-capable artificial beings have appeared as storytelling devices since antiquity,[16] and have been a persistent theme in science fiction.[18]A common trope in these works began with Mary Shelley's Frankenstein, where a human creation becomes a threat to its masters. This includes such works as Arthur C. Clarke's and Stanley Kubrick's 2001: A Space Odyssey (both 1968), with HAL 9000, the murderous computer in charge of the Discovery One spaceship, as well as The Terminator (1984) and The Matrix (1999). In contrast, the rare loyal robots such as Gort from The Day the Earth Stood Still (1951) and Bishop from Aliens (1986) are less prominent in popular culture.[267]Isaac Asimov introduced the Three Laws of Robotics in many books and stories, most notably the "Multivac" series about a super-intelligent computer of the same name. Asimov's laws are often brought up during lay discussions of machine ethics;[268] while almost all artificial intelligence researchers are familiar with Asimov's laws through popular culture, they generally consider the laws useless for many reasons, one of which is their ambiguity.[269]Several works use AI to force us to confront the fundamental question of what makes us human, showing us artificial beings that have the ability to feel, and thus to suffer. This appears in Karel Æ V²w2 "åP.R., the films A.I. Artificial Intelligence and Ex Machina, as well as the novel Do Androids Dream of Electric Sheep?, by Philip K. Dick. Dick considers the idea that our understanding of human subjectivity is altered by technology created with artificial intelligence.[270]See alsoAI safety – Research area on making AI safe and beneficialAI alignment – Conformance to the intended objectiveArtificial intelligence in healthcare – Machine-learning algorithms and software in the analysis, presentation, and comprehension of complex medical and health care dataArtificial intelligence arms race – Arms race for the most advanced AI-related technologiesArtificial intelligence detection softwareBehavior selection algorithm – Algorithm that selects actions for intelligent agentsBusiness process automation – Technology-enabled automation of complex business processesCase-based reasoning – Process of solving new problems based on the solutions of similar past problemsEmergent algorithm – Algorithm exhibiting emergent behaviorFemale gendering of AI technologiesGlossary of artificial intelligence – List of definitions of terms and concepts commonly used in the study of artificial intelligenceOperations research – Discipline concerning the application of advanced analytical methodsRobotic

process automation – Form of business process automation technologySynthetic intelligence – Alternate term for or form of artificial intelligenceUniversal basic income – Welfare system of unconditional incomeWeak artificial intelligence – Form of artificial intelligenceData sources – The list of data sources for study and researchExplanatory notes^ Jump up to:a b This list of intelligent traits is based on the topics covered by the major AI textbooks, including: Russell & Norvig (2021), Luger & Stubblefield (2004), Poole, Mackworth & Goebel (1998) and Nilsson (1998)^ This statement comes from the proposal for the Dartmouth workshop of 1956, which reads: "Every aspect of learning or any other feature of intelligence can be so precisely described that a machine can be made to simulate it."[10]^ Russel and Norvig note in the textbook Artificial Intelligence: A Modern Approach (4th ed.), section 1.5: "In the longer term, we face the difficult problem of controlling superintelligent AI systems that may evolve in unpredictable ways." while referring to computer scientists, philosophers, and technologists.^ Daniel Crevier wrote, "the conference is generally recognized as the official birthdate of the new science."[22] Russell and Norvig called the conference "the inception of artificial intelligence."[21]^ Russell and Norvig wrote "for the next 20 years the field would be dominated by these people and their students."[24]^ Russell and Norvig wrote "it was astonishing whenever a computer did anything kind of smartish".[25]^ The programs described are Arthur Samuel's checkers program for the IBM 701, Daniel Bobrow's STUDENT, Newell and Simon's Logic Theorist and Terry Winograd's SHRDLU.^ Russell and Norvig write: "in almost all cases, these early systems failed on more difficult problems"[32]^ Embodied approaches to AI[38] were championed by Hans Moravec[39] and Rodney Brooks[40] and went by many names: Nouvelle AI,[40] Developmental robotics,[41] situated AI, behavior-based AI as well as others. A similar movement in cognitive science was the embodied mind thesis.^ Matteo Wong wrote in The Atlantic: "Whereas for decades, computer-science fields such as natural-language processing, computer vision, and robotics used extremely different methods, now they all use a programming method called "deep learning." As a result, their code and approaches have become more similar, and their models are easier to integrate into one another."[49]^ Jack Clark wrote in Bloomberg: "After a half-decade of quiet breakthroughs in artificial intelligence, 2015 has been a landmark year. Computers are smarter and learning faster than ever."[7]^ Alan Turing discussed the centrality of learning as early as 1950, in his classic paper "Computing Machinery and Intelligence".[72] In 1956, at the original Dartmouth AI summer conference, Ray Solomonoff wrote a report on unsupervised probabilistic machine learning: "An Inductive Inference Machine".[73]^ This is a form of Tom Mitchell's widely quoted definition of machine learning: "A computer program is set to learn from an experience E with respect to some task T and some performance measure P if its performance on T as measured by P improves with experience E."[74]^ Alan Turing suggested in "Computing Machinery and Intelligence" that a "thinking machine" would need to be educated like a child.[72] Developmental robotics is a modern version of the idea.[41]^ Compared with symbolic logic, formal Bayesian inference is computationally expensive. For inference to be tractable, most observations must be conditionally independent of one

another. AdSense uses a Bayesian network with over 300 million edges to learn which ads to serve.[122]^ Expectation-maximization, one of the most popular algorithms in machine learning, allows clustering in the presence of unknown latent variables.[124]^ The Smithsonian reports: "Pluribus has bested poker pros in a series of six-player no-limit Texas Hold'em games, reaching a milestone in artificial intelligence research. It is the first bot to beat humans in a complex multiplayer competition."[171]^ See Problem of other minds^ Nils Nilsson wrote in 1983: "Simply put, there is wide disagreement in the field about what AI is all about."[199]^ Daniel Crevier wrote that "time has proven the accuracy and perceptiveness of some of Dreyfus's comments. Had he formulated them less aggressively, constructive actions they suggested might have been taken much earlier."[204]^ Searle presented this definition of "Strong AI" in 1999.[215] Searle's original formulation was "The appropriately programmed computer really is a mind, in the sense that computers given the right programs can be literally said to understand and have other cognitive states."[216] Strong AI is defined similarly by Russell and Norvig: "The assertion that machines could possibly act intelligently (or, perhaps better, act as if they were intelligent) is called the 'weak AI' hypothesis by philosophers, and the assertion that machines that do so are actually thinking (as opposed to simulating thinking) is called the 'strong AI' hypothesis."[211]^ See table 4; 9% is both the OECD average and the US average.[229]^ Rodney Brooks writes, "I think it is a mistake to be worrying about us developing malevolent AI anytime in the next few hundred years. I think the worry stems from a fundamental error in not distinguishing the difference between the very real recent advances in a particular aspect of AI and the enormity and complexity of building sentient volitional intelligence."[251]