# The Evolution of AI: Turing's Test and On

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**Abstract**

This paper follows the evolution of AI starting from Turing's pivotal question "Can Machines Think?", to present-day ramifications of the field. From symbolic systems to deep learning, the evolution of AI can be presented in chronological order, touching on the major issues that split the community over time: problem-solving verus pattern recognition, linguistics (competence versus performance), heuristics versus expertise, memory versus processing, and whether Machine Learning is really "learning". With a huge push in Machine Learning in the past decades, this paper examines the details of neural networks and why we are still a ways from Strong AI. With the advent of open-source neural net and dataflow libraries, anyone can become a programmer, both advancing the field of AI, while obfuscating the true problems with deep learning. Can we make machines understand their learned thoughts and learning behavior? Do we understand enough of neuroscience and physics to model the human brain? How can we bridge the gaps in AI to bring our world closer to Strong AI, intelligence that can explain its own logical representations?

# Introduction

AI has evolved much since Alan Turing proposed his Turing Test in *Mind*, expanding slowly at first, then increasingly rapidly over the years. AI progressed due to various issues within myriad fields including psychology, philosophy, and computer science. While these issues all advanced the field of Artificial Intelligence, many camps were split, contrasting theories about how to achieve true "Artificial Intelligence" and what the term exactly meant. From Alan Newell's and Herbert Simon's Symbolic Systems to Frank Rosenblatt's Perceptron, intelligence was outlined in different ways throughout the 1950s, leaving experts pointed in different directions. The main early issues of AI stemmed from methods of performing Artificial Intelligence, whether algorithmic versus heuristic, problem-solving versus recognition, psychology versus neuroscience, performance versus learning, and heuristic search versus expertise.[1] These issues presented the beginning of a foray into Artificial Intelligence that would be carried by further decades of research and work. Paradigm shifts continued in AI, progressing the field as a whole, yet also broadening it, slowing the pace of research as adherents divided on how to progress the science. From the 1970s to the 1980s, AI progressed through the previous issues, as well as common sense questions, natural language processing, size, storage, and power issues. Since research was ongoing in all of these branches, progress was slow, but increasingly steady as each subject brought additions to artificial intelligence. With the advances in power, researchers were able to create more advanced systems, yet there remained some questions in AI. Were symbolic systems correct, with their connection to pure math and logic or were learning systems correct? Do we really understand how learning systems work theoretically? Artificial intelligence progresses and the understanding of AI rises exponentially as we make advancements in research. Furthermore, with easy-to-use languages such as Python, and open source libraries such as Keras and TensorFlow, anyone can engage in deep learning. Learning systems can now be used and understood by experts in any field, allowing the combinatorial nature of AI to speed up evolution. On the other hand, while AI is constantly expanding and evolving, we are yet to progress past

Weak AI, with our most complex learning systems not proven to "understand." Even so, with advances in understanding our own intelligence and low barriers to entry for Machine Learning, we can bring all the shifts together increasingly easily, creating jumps forward as we connect the missing pieces.

## 1950s - 1960s

In the 1950s various issues and theories proposed by brilliant minds in different fields allowed for a broader discussion and a sharper introduction to the field of Artificial Intelligence as a whole. With Turing's Imitation Game and his pivotal question in "Can Machines Think?", the steady rise in understanding and progressing AI began.[2] Furthermore, with the first Artificial Intelligence conference put together by John McCarthy, the experts in this field began to merge their findings and experiments and present issues with each other's work as well as collaborate on defining the myriad terms in this expanding field.

### Problem-solving versus Learning

One of the first main issues in the 1950s was whether machines were to be systems for manipulating symbols as a "formal representation of the world," or whether they were models of the brain made to "simulate the interactions of neurons".[3]

Allen Newell and Herbert Simon concluded in 1955 that bits could be used as symbols. In 1956, they, along with computer scientist J.C. Shaw, developed the "first artificial intelligence program," designed to imitate the human problem-solving process. Their Logic Theorist made use of search, heuristics, and symbolic list processing, symbolizing the advent of artificial intelligence programming: programming machines to solve problems as humans do.[4] They later formally coined the Physical Symbol System Hypothesis, which boosted the problem-solving approach by approximating the mind and a machine as devices that "generated intelligent behaviour by manipulating symbols by means of formal rules."[3] The

Hypothesis asserted that "A physical symbol system has the necessary and sufficient means for general intelligent action."[5] This way of thinking stretched back to Descartes and even Plato as a classic idea of symbols and representations to simplify all phenomena to representative forms. If symbol systems is the way to go, machines must be able to solve problems using representations of intelligence in regular life. Increasingly complex instructions could be encoded into numbers and now symbols representing features of the real world. Ergo, this area of study jumped into proving theorems, playing games, and solving puzzles, marking the base camp for the study of artificial intelligence.

Many others saw artificial intelligence as continuous systems rather than symbolic and focused on pattern recognition as the goal. This recognition included learning meant to simulate the way our brains learn and recognize information. From this view arose the perceptron, an idea coined by Frank Rosenblatt. A perceptron is a system that recognizes similarities between patterns that "depends on probablistic rather than deterministic principles for its operation, and gains its reliability from the properties of statistical measurements obtained from large populations of elements."[6] Due to the need for training, a large amount of data was necessary, as well as the performance to search it. Since these perceptrons could create good results using neural networks, the previous symbolic, problem-solving methods became an add-on to this method of learning. Whereas before, computers were simply fed rules and instructions, these computers with perceptrons could "learn," becoming better with more training. This field became the dominant track of AI as "engineers came to accept the nervous system as too complex to be modeled by logic-level systems."[1]

## Heuristic Search versus Knowledge

As AI research flourished in the 1950s, most programs tended to use heuristic search methods, e.g. heuristics guiding search. In the 1960s, heuristic search methods began to narrow in scope, suggesting to some in the community that intelligence came from knowledge or expertise rather than search. However, heuristic search never fully diminished, as searches through the system's memory tended to guide heuristic searches in problem-solving AI. In this progress, the paradigm shifting did not leave the other side in the dust, but rather merged its process into the expert systems, creating better artificial intelligence and laying the groundwork for how to proceed in AI. Expertise required the use of data structures meant exclusively for searching, which called on power and size and time complexity optimization. With increases in processing power, as well as data structure usage, AI could use both heuristic search and memory search to create an intelligent system. Combining these ideas led the field of AI to the next step in evolution.

## 1960s - 1970s

As different AI research surfaced and expanded, the field found new issues to tackle. While early AI programs solved well-defined difficult tasks, these machines could not perform general "common-sense" tasks. Although John McCarthy called for programs with common in 1959, the shift did not occur until the mid 1960s with constructed puzzles designed to emulate everyday reasoning, such as the bananas-and-monkeys task.[7].[4] This shift did not unlock the same potentials as were hypothesized and powerful programs designed to handle large-scale problems were still created, with highly successful expert systems such as chess programs achieving excellent results with heuristic search and large knowledge bases. Therefore, research was shifted towards common sense rationality for a time, yet expert systems came back into the limelight in the mid 1970s, performing difficult tasks successfully combining heuristic search and expertise. However, these splits caused the evolution of AI to move more slowly through various fields and further problems.

### Memory versus Processing

Psychology always played a large role in the field of AI, with artificial intelligence systems attempting to simulate the way humans behave or the way our brains work. It stands to reason that the focus in psychology on how we process information would affect the evolution of AI. As psychology focused on memory as the information processor in humans, the field branched away from the 50s and 60s psychological research in artificial intelligence, which focused on problem-solving and concept formation.[8] This divide essentially left memory structure and architecture concerns as a psychological issue, moving memory research out of AI. Artificial Intelligence research was content to focus on the symbolic level, whereas psychology continued on the architectural level.

## Problem-solving versus Learning

Furthermore, the issues of problem-solving AI versus the learning neural networks continued through this decade and still continues to effect today. A major step in bringing the problem-solving AI and learning neural networks together was made by Lawrence Roberts, who, drawing upon the pattern recognition research conducted by Neisser and Selfridge, developed a method for recognizing three-dimensional object by modeling symbols as opposed to solely numbers.[9] By recognizing an object through reduction of its description to a scene rather than identifying an object, this pattern recognition problem fell squarely back into the problem-solving AI camp: describing a symbolic structure. This method was successful due to having a model of a situation from which to draw large amounts of information, which brought the topic squarely aside from pattern recognition. These differing approaches went their own ways by the late 1960s and from this brand of recognition arose many labs combining 3D recognition of polyhedra with robotics and computer vision. Unlike the other issues, these never merged together and continued advancing in their own rights, evolving AI separately.[1]

### Rigor in Neural Nets

A further controversy stemmed from the problem-solving versus learning debate, which diminished the use of neural networks. Seymour Papert and Marvin Minsky published a book titled *Perceptrons: An Introduction to Computational Geometry*, wherein they lambasted perceptrons as not being founded on a basic theory and not being able to explain its own knowledge. Their view was that neural nets "could never fill their promise of building models of mind: only computer programs could do this."[10] At the time of writing *Perceptrons*, the processing power and tools needed to make neural nets what we know today were not available, giving Minsky and Papert's views impactful credence. Their view that neural nets must stand up to a rigorous mathematical analysis holds a certain degree of importance to this day. Without understanding the performance of the perceptron in general, or the ability to measure such a performance, we cannot continue to use perceptrons to help with specific tasks without a degree of rigor in the field. "Without adequate basic theory, [Minsky and Papert] believed that attempting to use connectionist learning machines in practical applications was futile."[11] Whether one sees it as unfortunate or not, the release of this book in 1969 served to make neural networks less used up until the 1980s. While we now use deep learning and machine learning most in our modern idea of Artificial Intelligence, Minsky and Papert would still argue that our use of neural nets is still backed by vague and shallow theory. Whether or not Minsky and Papert could foresee the progress made through neural networks, the doubts they proposed continue to find purchase as we fail to find theoretical guidance in deep neural nets. The main issue is an inability to mathematically describe the set of images representing a dog, for example, the same way we would for a set of images representing a connected shape. "Absent a mathematical definition of what makes a cat look like a cat, the logical gap remains. Almost a proof is no proof."[11]

## Linguistics and Natural Language

Linguistics also offered a road bump in evolution, as there was a divide between the need for competence as stressed by Chomsky over performance.[12] Competence implied the general knowledge a speaker has of a language, the grammar in particular, while performance was the actual utterance of the language, which was affected by a variety of factors. This distinction further separated the fields at the time devoted to performance, one being artificial intelligence.[1] Since linguistics was not interested in performance, work in AI was essentially irrelevant to linguistics, splitting scientists on both sides of the spectrum.

### Understanding Natural Language

A large step forward in merging linguistics and AI came about in 1972 with Terry Winograd's *Understanding Natural Language*. Winograd combined heuristic search methods with expertise to develop a natural language processor called SHRDLU. In this pivotal paper, Winograd created a system that contained a parser, recognition grammar of English, semantic analysis, and a general problem solving system.[13] This system, SHRDLU, had been given an extensive model of its domain, along with its own mentality. SHRDLU could remember and discuss plans and actions. It could enter into dialogue with a human, responding correctly to English sentences, as well as asking for help when the heuristic systems could not understand using the aforementioned pieces. An interesting aspect of SHRDLU was that it was developed using procedural representations, meaning each piece of knowledge could call directly on another piece of knowledge.[13] While SHRDLU could only handle this task in a very specific domain and setup, the system was a catalyst for further development in natural language processing and how we build systems combining heuristics and expertise.

## 1980s - 1990s

As AI progressed into the 1980s, most of the fields were plugging away solidly, with the minor exception of neural nets, as Minsky and Papert had played their role in causing healthy skepticism of "learning" processes and perceptrons as a whole. That is not to say the field did not advance at all, as by the later 1980s, great improvements had been made in power, allowing for advances in speech recognition and other interesting tasks.

## Searle's Chinese Room

In 1980, John Searle published a paper, *Minds, Brains, and Programs* detailing an argument that has come to be known as the Chinese Room Argument. In it, Searle questioned whether a system that had been programmed to respond in Chinese was actually understanding the language versus just repeating back rules. He makes this assertion by stating that a person playing the Imitation Game could follow the instructions in a program and send responses back to the other in Chinese, essentially fooling the others and passing the Turing Test without having any proper understanding of the language whatsoever.[14] This argument provides a pivotal change in thinking in AI. Terry Winograd's SHRDLU was incredibly interesting and "knew" how to process language, but was it truly understanding the language? What makes up the basis of our understanding? Is it solely a grammar, semantics, syntax, and parser? Does our understanding stem from something more? Searle essentially invalidates the Turing Test by showing that a computer has the same features as a man being fed instructions without understanding, meaning the computer, even if it fools a human, is not truly understanding the relevant information. Searle's assertions explained that we are still at a state of Weak AI, without creating a mind that truly understands and can think the way we do. Furthermore, Searle attests that for AI to be Strong "it must be able to distinguish the principles on which the mind works from those on which nonmental systems work; otherwise it will offer us no explanations of what is specifically mental about the mental."[14] He goes on to attest something Turing talks about in his essay in *Mind*, namely "the Extent to which we regard something as behaving in an intelligent manner is determined as much by our own state of mind and training as by the properties of the object under consideration."[2] Technically, I could look at a system and say it has beliefs and mentality by creating my own distinction for mental versus non-mental. The mentality of the system lies in the beholder.

### Emperor's New Mind

A further pivotal book in AI was writen by Roger Penrose, *The Emperor's New Mind.* In it, Penrose argues "the *conscious* mind cannot work like a computer, even though much of what is actually involved in mental activity might do so.[15] He argues not only that our knowledge of psychology and physics is too incomplete, but primarily that conscious thought requires intuiting mathematical truths, which are not formalizable and therefore cannot be determined by computers. His secondary argument is that of physics and neuroscience: we cannot confirm if the act of thinking as physical brains in the study of physics is computable.[15] While Penrose's examples provided some problems and questions, in modern day our AI exhibits many of the cognitive processes he states are reasonable. The reason this book is suggested as pivotal in AI is that it forces us to ask the difficult question of whether or not our brain functions are computable. Where is our memory stored and how do we access it? Does memory exist everywhere or in a specific place? How do we compute the specific states and functions of neurons as they interact with context and our biochemical functions? Penrose's assertions helped us move forward with difficult questions on AI, even outright debunking some of his claims.

## 1990s - Present

As AI progressed through the late 1980s with machine learning coming back to the forefront (see Donald Michie's MENACE) and more powerful programming languages, both interpreted and compiled, we begin to see the exponential evolution of AI blast off. Our societal ideas of what Artificial Intelligence is changed over time, with predictive texting into deep learning and chess-playing all portraying steps of evolution on the way to Strong AI. In the 1990s to the present day, we see AI take on vast steps as we begin to recharacterize what a step of evolution means for AI in the scope of its growth. Steve Moyle, Oxford Machine Learning researcher, deems that "progress in science is humanity's greatest achievement," following up this assertion with the question, "Can AI be used as a tool to make discoveries?"[16]

## Scientific Progress with AI

In the mid 1990s, we begin seeing some exciting crossovers in biology and artificial intelligence, an especially important one being King et al's AI "tool builder" built to discover what makes certain chemicals cause cancer in rodents. While existing models could only explain about a third of examples, a new structural alert made by the AI "using atoms and their bond connectivities in chemicals was able to predict mutagenicity."[16] What is most important was that the AI generated alert was published in a scientific journal, following Turing's methodology in which background knowledge was used along with a logical input representation to generate a discovery that could be understood and vetted by a chemist.

King's lab did not stop in 1996 with this discovery, but published a further leap in AI scientists with the Robotic Scientist, a system made to apply artificial intelligence to carry out scientific experimentation.[17] In this experiment, the researchers attempted determining gene expressions in yeast. The AI performed "Closed Loop Learning," a method of learning wherein the AI created and tested its hypotheses, then would need to consider new hypotheses and experiments after the hypotheses failed or succeeded, all fully autonomously.[16] This research is pivotal to the advancement of AI as a tool for making scientific breakthroughs, something that progresses all of our understanding.

## Modern Day Programming

The last huge jump in AI in the modern era stems from the ease-of-use and low barriers to entry in Machine Learning specifically. With the introduction of Python in 1991 and much more recently, open source packages made to be used with Python, anyone can sit down and create their own neural net. Keras and TensorFlow, both open-source packages created in 2015 help create neural networks with simple Pythonic programming. This massive reduction in the barriers to entry of Machine Learning mean that not only computer scientists, but artists, medical professionals, construction works, or whomever can develop neural nets, launching the exponential expansion of Machine Learning.

## Conclusion

Whether or not neural networks are the future of AI, with further advancements into AI learning, pattern recognition, and problem-solving, we want to move even closer to Strong AI. Donald Michie defined Strong AI as a system that improves its performance and can communicate its updates and model in symbols. However, what we see today is usually complex models using deep neural networks of layers of artificial neurons, with large amounts of training samples.[16] This progress in deep learning allows us to do seemingly miraculous feats in pattern recognition, yet Machine Learning is not Artificial Intelligence. Until we can provide a basic theory for deep learning and provide mathematical rigor and a method for understanding what is happening in neural networks, we cannot proceed to truly Strong AI. Leon Bottou proclaims that the "current status of deep learning systems can be compared to the age of steam that marked the beginning of the industrial age."[11] As the steam engine changed the world before the laws of thermodynamics, so does deep learning without complete grasp of its theory. Without further understanding of deep learning, we need advances in neuroscience, psychology, computer performance, and physics to further evolve the field of AI, creating a machine that can not only "think," but understand its own thoughts.

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