

# History of Artificial Intelligence Before Computers



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## INTRODUCTION

The history of artificial intelligence (AI) is commonly supposed to begin with Turing's (1950) discussions of machine intelligence, and to have been defined as a field at the 1956 Dartmouth Summer Research Project on Artificial Intelligence. However, the ideas on which AI is based, and in particular those on which symbolic AI (see below) is based, have a very long history in the Western intellectual tradition, dating back to ancient Greece (see also McCorduck, 2004). It is important for modern researchers to understand this history for it reflects problematic assumptions about the nature of knowledge and cognition: assumptions that can impede the progress of AI if accepted uncritically.

## BACKGROUND

Symbolic AI is the approach to artificial intelligence that has dominated the field throughout most of its history and remains important. It is based on the physical symbol system hypothesis, enunciated by Newell and Simon (1976), which asserts, "A physical symbol system has the necessary and sufficient means for general intelligent action." In effect, it implies that knowledge is represented in the brain by language-like structures, and that thinking is a computational process that rearranges these structures according to formal rules. This view has also dominated cognitive science, which applies computational concepts to understanding human cognition (Gardner, 1985).

Many symbolic AI systems are based on formal logic, which represents propositions by symbolic structures, in which all meaning is conveyed in the structure's form, and which implements inference by the mechanical manipulation of those structures. Therefore, we will discuss the origins of formal logic and of the idea that knowledge and inference can be represented in this way. We will also consider the combinatorial methods used before the invention of computers as well as in modern AI for generating possible solutions to a problem, which leads to combinatorial explosion, a fundamental limitation of symbolic AI. Then we describe early modern attempts to design comprehensive knowledge representation languages (predecessors of those used in symbolic AI) and mechanical inference machines. We

conclude with a mention of alternative views of knowledge and cognition.

## THE HISTORICAL ROOTS OF SYMBOLIC AI

### Formal Logic

It is surprising, perhaps, that the original inspiration for symbolic knowledge representation can be found in ancient Greece, in particular in Pythagorean number theory (Burkert, 1972; Riedweg, 2005). In ancient Greece, as in many cultures, ancient and modern, pebbles were used for calculation by being moved in grooves in a similar way to the beads on an abacus. Indeed, the Latin word for *pebble* is *calculus*, and our word *calculate* comes from this manipulation of *calculi* (pebbles). In logic and mathematics, we use the word *calculus* for any system of notation in which we can accomplish some purpose by the manipulation of tokens according to formal, game-like, mechanical rules. (For example we have differential and integral calculi in mathematics and propositional and predicate calculi in logic.) To the extent that the rules are purely mechanical, they can, in principle, be carried out by a machine, which is why calculi are important in AI; if a process can be reduced to a calculus, it can be calculated by a machine.

The ancient Pythagoreans (Pythagoras, 572–497 B.C.E.) investigated number theory by means of arrangements of pebbles (Burkert, 1972; Riedweg, 2005). For example, they observed that certain numbers could be arranged into a square shape, and we still call these numbers *squares*. However, they also investigated triangular numbers as well as rectangles, pentagons, cubes, pyramids, and so forth. Although they did not prove theorems in the modern sense, they were able to demonstrate the truth of theorems in number theory by means of these arrangements. Thus, they discovered calculi could be used for reasoning as well as computation.

According to tradition, Pythagoras was the first to explain consonant musical intervals in terms of numerical ratios (Burkert, 1972). For example, a string one-half the length of another string sounds an octave higher; the shorter of two strings of lengths with the ratio 2:3 sounds a fifth higher, and so forth. Thus, a subtle perceptual distinction (the rela-

tive consonance of pitches) could be rendered logical and rational by reducing it to numerical ratios (Greek *logoi* and Latin *rationes*, terms that also refer to the articulation of thought in words or symbols; Maziarz & Greenwood, 1968). It is an example of the representation of expertise in terms of formal structures; judgments of consonance can be replaced by calculation.

The Pythagoreans believed that everything could be reduced to numbers and thus made intelligible, rational, and logical (Burkert, 1972; Burnet, 1930). Therefore, they were committed to the idea that all knowledge could be represented in terms of arrangements of otherwise meaningless tokens, that is, in formal structures (and hence, we may conclude, in computer data structures).

Aristotle (384-322 B.C.E.) is known as the originator of the science of logic, but two of his contributions in this area are especially relevant to AI. First, he began the development of formal logic by showing that valid inference could be distinguished from invalid inference on the basis of its form rather than on the meaning of its particular terms (words). In other words, Aristotle showed that valid inference is a matter of syntax (the grammatical form of an argument) rather than semantics (its meaning). This is important because it shows how inference can be carried out by the manipulation of symbols independently of their meaning, which means that, in principle, inference is a kind of computation. Stated differently, there is a calculus of valid inference.

Aristotle also began the study of modal logic, that is, logic in which propositions are not simply true or false, but in which the propositions may be possible, impossible, necessary, or contingent (Bocheński, 1970; Kneale & Kneale, 1962). Modal logic and its derivatives (such as tense logic, which deals with propositions whose truth values may change in time) are important in AI (Sowa, 1984).

Another contribution of Aristotle was the organization of knowledge into formal deductive structures, in which all the facts of a science were either stated as axioms or formally derivable from the axioms. The best-known example is Euclidean geometry, which was the exemplar of a systematic body of knowledge for over two millennia (Maziarz & Greenwood, 1968). Similar formal axiomatic structures are used in AI for representing a knowledge domain.

The investigation of logic continued over the following centuries. For example, the medieval scholastics (roughly 6<sup>th</sup> to 15<sup>th</sup> centuries) refined logic into a very precise instrument, although it was still based on a natural language (Latin) in contrast to modern symbolic logic. As a consequence, they became conscious of the limitations of natural language for exact knowledge representation and strove to compensate for its deficiencies. For example, they knew that the word *dogs* is used differently in the propositions “dogs are mammals” and “*dogs* is a plural noun.” AI knowledge representation languages have to deal with similar issues (Sowa, 1984). In the end, dissatisfaction with natural languages led to an

interest in developing artificial languages that were intended to be more rational (logical and precise). Behind this was the assumption that there is a universal grammar underlying all natural languages, and that it corresponds to the “language of thought”; therefore an artificial language, as an ideal vehicle for thought, ought to reflect this deep structure. Similar motivations underlie the development of AI knowledge representation languages (see below).

## Combinatorial Methods

The Middle Ages also saw the development of combinatorial approaches to solving problems (Bocheński, 1970). For example, the medieval scholastics used a combinatorial procedure to generate the 192 possible Aristotelian syllogisms, and then they crossed out the invalid ones. This is an example of a generate-and-test procedure, an approach still widely used in AI. The problem with generate-and-test procedures is combinatorial explosion: The number of combinations to be tested increases exponentially with their size.

These combinatorial procedures acquired an increased significance, which contributed to the eventual development of AI, from the kabbalah, a Jewish mystical tradition with Pythagorean affinities, which became popular in the Middle Ages (Eco, 1997; Scholem, 1960). According to this tradition, the text of the Torah reflects the logos (rational structure) of the universe. Therefore, since the Torah is written in the letters of the Hebrew alphabet, these letters correspond to the elementary categories and archetypal forms underlying the universe. As a consequence, the letters of the Hebrew words for things reveal their logical structure to one who knows how to interpret them. Combinatory processes figure prominently in kabbalah, and significant words, especially the names of God, were permuted in order to reveal hidden wisdom and discover new truths. For this purpose the kabbalists used rotating wheels and other devices to ensure that they did not omit any combinations of letters, an example of a mechanized generate-and-test procedure.

Similar in spirit to the kabbalah, and perhaps in part inspired by it, was the Great Art (*Ars Magna*) of Raymond Lull (also spelled Llull, 1232-1315; Bonner, 1985; Johnston, 1987; Yates, 1966). He intended it to be a “universal science of all sciences,” a systematic method by which knowledge could be discovered and proved. There were several versions of his system, but the most common one made use of nine “divine dignities,” or attributes of God, which took different forms in each domain of knowledge but provided the fundamental categories in each domain. These abstract qualities (Goodness, Magnitude, Duration, etc.) correspond closely to certain kabbalistic names of God. In Lull’s Art, as in kabbalah, we see an attempt to isolate the most basic categories that constitute all knowledge and to discover, therefore, an alphabet of thought. This remains an important goal in contemporary symbolic AI.

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