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# Explainable AI in View of Ancient Philosophy How Homer and Aristotle Perceived Artificial Intelligence

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*Recursion is a difficult mathematical concept. It can lead to infinite loops in computers but on the other hand, if controlled, helps to train our natural neuronal network in our brain. Nevertheless, in the domain of τέχνη, recursion is difficult to handle. For Ancient Greek philosophers, such as Socrates, Plato, and Aristotle, τέχνη was a difficult term, most probably because they did not yet have the notion of mathematical recursion. The difference between γνώση resp. επιστήμη and τέχνη – observational knowledge (Gnosis) respectively science (Episteme), and technology (Techne) is reflected in today's discussion about explainable AI. This paper attempts to address today's problems with AI, whether AI becomes trustworthy, or authorities even can certify AI for safety purposes, by recurring to these antique philosophical notions. Combinatory Logic is explained, the graph model introduced, recursiveness discussed, and outlined how to make current AI explainable by defining Controlling Combinators.*

**Keywords:** *Explainable AI, Theoretical Computer Science, Graph Model of Combinatory Logic, Safe AI, Automated Decision Making, Controlling Combinators, Intelligent Systems.*

## Introduction

Since almost 3'000 years, robots are associated with female androids, because Homer in his Iliad, book 18, describes "golden handmaids" that "worked for him (Hephaistos), and were like real young women, with sense and reason (Nous, νόος), also voice, and strength, and all the learning of the immortals" (Homer, 2017, p. 18/419). The dream of artificial intelligence (AI) is quite old, so old, that it might be a condition for humanity. Today, that dream seems to have come true; however, its foundations are not so clear.

The Graph Model of Combinatory Logic models knowledge. It is an algebra that describes neural networks, *Natural Neural Networks* (NNN) and *Artificial Neural Networks* (ANN) alike. NNNs are a key element of nature, all living beings use some sort of neural network for survival. Humans have excelled in its use, not for survival only but for explaining physics and creating mathematics and logic, and even inventing gods that in turn create intelligent machines.

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However, it is apparent that not all NNN are alike. There exist huge differences. This paper explores some of these differences to explain the prospects of current AI.

## Literature Review and Motivation

Obviously, there are major systemic differences between NNN and ANN. While NNN have a very dynamic way of establishing and destroying connections between neuronal nodes that is not yet well understood by neuroscientists, the invention of transformers based on attention heads that establishes these connections is relatively new in ANNs (Vaswani, et al., 2017). NNNs contain physically unrestricted loops. By contrast, loop formation in ANNs has revealed major difficulties (Barceló, Pérez, & Marinković, 2019), since Turing-completeness means that loop formation could spiral out of control, as the halting problem is undecidable for Turing machines (Turing, 1937). The formation of loops is a key feature of all types of neural networks. In more precise mathematical terms, this is referred to as recursion.

The key to intelligence in its various forms is recursion. The ability to reflect effects of our actions distinguishes brains of higher animals and humans from more primitive neural networks, for instance in insects. Some insects keep trying to fly through solid glass windows despite continuous failures. Engeler (Engeler, Neural algebra on "how does the brain think?", 2019) calls that a *Controlling Combinator* what helps brains to reflect and learn.

Homer's short statement about the handmaids of Hephaistos reflects a continuous discussion between the notions related to Techne (τέχνη) and to reasoning. Techne by itself has no way of learning, much less of learning the wisdom of the immortals (νόος). Humans sometimes learned about the intentions of the gods, preferably by help of dreams, augurs, and priests. Homer, as a founder of some sort of religion, relates many ways how to learn from the gods. In the Iliad, Agamemnon's dream in book two was the key to telling the Greeks what Zeus wanted from them (Homer, 2017, p. 2/7). The dream raised false expectations, and Agamemnon was unable to discern the true intention of the gods; hence, he misunderstood the dream as divine advice to successfully fight the Trojans and conquer their citadel.

If not by dreams, leaders in antiquity often used the services of augurs, birdwatchers, or with the Latin word augurs, to learn from bird's flights the intention of the gods, or they went to an oracle, to a Pythia (πυθία, the high priestess of the Temple of Apollo at Delphi, serving as oracle). Compare with the comprehensive study of the knowledge and perception of the bird's world in ancient times by Lunczer (Lunczer, 2009).

What is the relationship between oracles and birdwatching on the one hand, and *Artificial Intelligence* (AI) on the other? Both can be explained by some kind of relationship between observations and resulting effect. In the first case it is learned by tradition, in the second by a specific "training set." Aristotle would both approaches call Gnosis (γνώση) (Aristoteles, 367-344 BCE).

Moreover, our ability to reflect recursively does not end with such relationships. There are relationships that have no apparent cause and effect, such as the incidental coincidence between the arrival of storks and the accumulation of children's births in rural societies. Both happen in spring. Children are born because the parents have been well fed back in the previous fall's harvest, and storks return because the spring's milder climate provides enough prey, but storks bring nothing. Our neural network recognizes such relationships. Humans describe such insights as "gut feeling" that often are better than any other formal, rational approach that bothers for cause and effect (Gigerenzer, 2007).

Predictions done with generative AI use the same mechanisms as the prophecies of the Pythia (πυθία) and the dreams received by some god. In both modern and ancient terms, these are hallucinations. The difficulty with hallucinations is that it is hard to assess whether they reflect reality properly. Not only a few of our ancient augurs and πυθία effectively relied on their gut feeling when talking to their sponsors; often, their hallucinations proved valuable and right. Today's generative AI quite often produces valuable responses to questions without doing anything else than producing hallucinations. ANNs are using Gnosis (γνώση), neither Episteme (επιστημη) nor Techne (τέχνη).

This paper explores this coincidence to explain what an AI does, and what an AI cannot provide. The *Graph Model of Combinatory Logic* (Engeler, Algebras and Combinators, 1981) explains the Gnosis (γνώση) approach, but also how an AI probably could go beyond statistical observations and start reasoning about causes and effects. This was called Episteme (επιστήμη). Finally, an approach combining Gnosis (γνώση) with Techne (τέχνη) is presented, creating intelligent systems that follow "the learning of the immortals."

## Methodology and Methods

The constituting elements of the graph model are *Combinators*, defined as sets of arrow terms of the form (1):

$$x_j \to y \tag{1}$$

The nodes of origin in the graph $x_j$ are a selection of *Observations*, selected by the choice function $j$, and the $y$ represent the target node, the node receiving a stimulus from the $x_j$, also interpreted as observed effect. Proper arrow terms are called *Concepts*. The claim is that these combinators, consisting of observations and concepts, represent knowledge (Fehlmann & Kranich, A General Model for Representing Knowledge - Intelligent Systems Using Concepts, 2024). This definition is highly recursive because you can observe concepts. Thus, arrow terms can contain other arrow terms including concepts. This model relies on Gnosis (γνώση), neither on επιστήμη nor τέχνη.

If this powerset is based on the null set, weights in nodes play no role in equation (1). If the powerset is based on some non-empty set of observations referring to some real-world items, or some imaginary items, then weights can describe the nodes' importance with respect to the target node. This powerset describes the behavior of both artificial and natural neural networks (Engeler, Neural algebra on "how does the brain think?", 2019). The choice function $j$ is not restricted to any "real" object observed, but to anything that impresses our neural network. A picture displaying a stork carrying a baby can as easily been selected as any modern deep fake AI-generated picture. This is the mechanism that augurs, dictators, and all kinds of populist parties use to gather their followers. In contrast, the era of enlightenment called for rational reasoning, something that neither an NNN nor an ANN provide for free. The era of enlightenment is long gone in history (Bristow, Fall 2023 Edition) but was already anticipated by Aristotle in his Organon (Aristoteles, 367-344 BCE). This is Techne (τέχνη). On the other hand, Plato's allegory of the gave reflects Gnosis (γνώση). It is not surprising that Engeler used the graph model also to investigate why Aristotle did not invent mathematical relations (Engeler, Aristotle' Relations: An Interpretation in Combinatory Logic, 2020).

Knowledge of all kinds is combined as follows. Let $M$ and $N$ be any combinators, then you can apply $M$ to $N$:

$$M \bullet N = \{b \mid \exists \mathrm{a_i} \rightarrow b \in M;\ a_i \in N\} \tag{2}$$

Equation (2) makes the graph model an algebra (Engeler, Algebras and Combinators, 1981). The algebra is Turing-complete because it is possible to define *Lambda Terms* that introduce a variable $x$ in $M$, allowing for an application of $M$ to some argument $N$ (Barendregt & Barendsen, 2000):

$$\lambda x. M \bullet N \tag{3}$$

In case of equation (3), $N$ replaces all occurrences of $x\ in\ M$. For formal definitions, consult (Fehlmann, Autonomous Real-time Testing – Testing Artificial Intelligence and Other Complex Systems, 2020, p. 5). In the graph model, Lambda terms contain no specific observations. It has the form of a complicated structural element whose application does not depend on its nodes' weights (Fehlmann, Managing Complexity – Uncover the Mysteries with Six Sigma Transfer Functions, 2016, p. 326ff). It is called *Lambda Concept*. For a proof of Barendregt's theorem for the graph model, see Fehlmann (Fehlmann, Theorie und Anwendung der Kombinatorischen Logik, 1981). Since Lambda concepts add programming capabilities to the graph model, it refers to Techne (τέχνη).

The graph model is versatile. It is possible to define models for explaining how the brain works (Engeler, Neural algebra on "how does the brain think?", 2019), give an algebraic description of *Quality Function Deploymen*t (QFD), see (Fehlmann, QFD as Algebra of Combinators, 2001) and (Fehlmann & Kranich, How to Explain Artificial Intelligence to Humans - Learning from Quality

Function Deployment, 2024), describe software and systems testing (Fehlmann & Kranich, Testing Artificial Intelligence by Customers' Needs, 2019), and requirements engineering (Fehlmann & Kranich, Requirements Engineering for Cyber-Physical Products, 2023). The latter works because the model includes both algorithms and cause-effect statements. Thus, it can be used for specifying requirements for intelligent systems that sometimes must adapt to the environment, based on γνώση, and sometimes implement strict rules, thus Techne (τέχνη), for instance when legal compliance, or safety, is a strict requirement (Fehlmann & Kranich, Requirements Engineering for Cyber-Physical Products, 2023). While generative AI can generate any idea, reasonable or not, lambda concepts can be used to ensure predictable behavior (Techne, τέχνη) from an *Intelligent System* (ISY)[1].

ISYs are a mix of lambda concepts and generative AI, of Techne (τέχνη) and Gnosis (γνώση). Thus, they behave partly like an ordinary program, executing rules, and partly they interpret their environment by observations made through the data received.

### *Cause and Effect*

Although arrow terms concepts often look like they are connecting cause and effect, they do not. They connect a selected set of observations with a specific effect. Concepts might as well describe storks bringing babies as weather conditions causing storks to fly. Humans, animals, and machines learn by connecting observations with effects, not by analyzing cause and effects. This is why antique augurs and πυθία often produced valuable prophecies. If there is a statistically significant relationship between selected observations $x_j$ and some observable effect $y$, there is often a cause-effect relationship behind it, although the exact relationship remains unknown. Many sciences rely on such concepts; for instance, medicine. You accept a new drug after some tests show a statistically relevant effect, without knowing the exact biomechanical mechanism. In contrary, having understood cause and effect in detail, often uncovers even better insights and results. The old called that επιστήμη.

While the graph model is rich enough to model cause and effect effectively, such as when applied to QFD, this does not mean that a trained ANN easily does understand cause and effect. There exist prompting techniques that provoke *Chain-of-Thought* (CoT) reasoning, it is by counting CoT relations that an ANN learns to apply this kind of reasoning (Jin & Lu, 2024). Therefore, the argumentation is still based on statistical occurrences and does not use strict logic, let alone physical evidence. CoT does not avoid hallucinations; it is more like augurs that can distinguish and explain positive and negative signs in birds' flights. This activity and the pertaining rules were called *auspicium* by Roman augurs.

[1]The reason adding the "Y" to "IS" unfortunately is of purely political nature.

*Explainable AI*

Humans actually have the same problem when using their brain to understand cause and effect. Most people must use various techniques, for instance, visual ideas, to produce logical evidence (Bessis, 2024).

Although logical thinking would be easy to implement with a graph model, there seem to be no examples of it in nature. The process is rather

a) The neural network hallucinates based on statistical observations;
b) An explanation is given based on undisputable cause and effect.

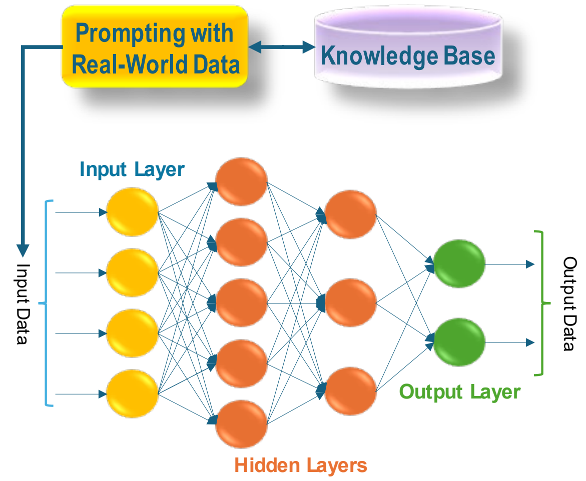
It is difficult to imagine how explainable AI could do better. This is an argument against using statistical techniques such as SHAP (SHapley Additive exPlanations), a game theoretical approach, or LIME (Local Interpretable Model-agnostic Explanations), a method that fits a surrogate glass-box model to the decision space of any black-box model prediction. For an overview, see Dallanoce (Dallanoce, 2022).

These techniques use some sort of sensitivity analysis to "prove" that an AI decision is robust and not dependent on some specific prejudices. This is still statistics and not reasoning. It might be valuable to assess the quality of a training set but does not explain AI.

Explainable AI must be defined as a combination of observation-based, statistical processing, typically by an ANN, and subsequent logical verification by a reasoning engine based on cause and effect and logic rules. This is the way most humans do it. People observe first and then explain on the basis of facts.

Getting logical deductions that reflect physical facts and carrying out the cause-effect reasoning is not easy and often incomplete. Medical research, for example, relies much more on statistical tests than on cause-and-effect relationships, such as those obtained through genetic engineering or a complete understanding of biochemical processes in the living body. Nevertheless, even only incomplete reasoning can uncover hallucinations. Often reasoning requires much less detail than full knowledge processing. For instance, when judging actions proposed by an ANN-based *Advanced Driving Assistance System* (ADAS), they can be checked against physical facts and traffic rules to guarantee safety. A quick and rough examination can already reveal false assumptions and false reactions proposed.

**Figure 1.** *The Resource-Augmented Generation (RAG) Approach*




There has been hope that *Resource-Augmented Generation* (RAG) is an approach that should provide explainability, by reducing hallucinations. This approach consists of prompting an ANN by facts, taken from some knowledge base. Thus, the arrow scheme chain of ANN starts with some initial observations that are facts. The hope is that the ANN then produces less hallucinations. That works, but unfortunately only partially. There is still no convincing evidence that the response of the ANN reflects truth.

The RAG approach uses a standard ANN, in Figure 1 represented by a multi-layer perceptron without loops. It transforms input data, a vector of tokens, through several (a few hundred) layers into an output vector. The attention heads of the transformer are not represented (Lewis, et al., 2020). Nevertheless, there is no guarantee that the ANN produces thanks to RAG anything else than hallucinations.

*Controlling Combinators*

The basic characteristic of ANN is that there are no loops allowed from the input layer to the output layer. There are hidden layers in between but they do not provide feedback. This holds for *Feedforward Neural Networks* (FNN). *Recurrent Neural Networks* (RNN) are bi-directional ANNs that allow the output from some nodes to affect subsequent input to the same nodes (Gerven & Bohte, 2017).

In contrast, the natural brain, as well as Engeler's graph model of combinatory logic, have feedback loops by dendrites that freely can stimulate or attenuate responses. As in every traditional computer program, such loops can loop forever and damage neuronal reactions. Thus, the brain has mechanisms that Engeler modelled as *Controlling Combinators*. These are crucial for further developing artificial intelligence and better approximate human intellectual capabilities (Engeler, Neural algebra on "how does the brain think?", 2019).

Let $X$ be some knowledge. The concept of *Control* involves a controlling operator $\mathbf{C}$ which acts on a controlled object $X$ by application $\mathbf{C} \bullet X$. Control means that the knowledge represented by $X$ is completely known and described. It is a similar approach to establishing a fixpoint.

Accomplishing control in the graph model algebra can be formulated by:

$$\mathbf{C} \bullet X = X \tag{4}$$

The equation (4) is a theoretical statement, usually resulting in an infinite loop process. Remember, ANNs do not normally allow for loops. For solving practical problems, an approximation is normally needed for stopping the loop processing in time. In order to approximate $X$, an ordering relation must exist on knowledge that allows to identify proximity to a solution. This ordering relation is for knowledge the inclusion of sets of arrow terms.

A *Control Sequence* solves the *Control Problem:*

$$X_0 \subseteq X_1 \subseteq X_2 \subseteq \cdots \subseteq X_n \subseteq \cdots \tag{5}$$

Equation (5) is an infinite series of finite sets of knowledge, determined by (6):

$$X_{i+1} = \mathbf{C} \bullet X_i, i \in \mathbb{N} \tag{6}$$

starting with an initial $X_0$. This is called *Focusing*. Focusing means that the knowledge represented by $X$ is approximatively known and described as needed. Some details can be found in Engeler (Engeler, Neural algebra on "how does the brain think?", 2019, p. 299). The controlling operator $\mathbf{C}$ gathers all knowledge that may help in the solution. Like a fixpoint combinator in combinatory logic, controlling operators are a structural element, not a single pair of observations and observed effect. The control problem is a repeated process of substitutions.

*Continuous Training for AI*

Controlling combinators can be used to build intelligent systems that learn continuously, because control sequences can provide continuous training based on empirical feedback received by some AI engine. The crucial point is to find a functional process for calculating the *Convergence Gap* that efficiently tells the intelligent systems how much it has learned. All computation must be executed on vectorized data using tokens. Such a system is suitable for implementing controlling combinators for a "mathematician," or a "violinist," as proposed by Engeler (Engeler, Neural algebra on "how does the brain think?", 2019).

While it is easy to calculate the convergence gap for the mathematician, once some reference is known – e.g., Wolfram|Alpha, see (Wolfram, 2023) – for the violinist, it is considerably more difficult. While for most violin pieces, reference recordings exist, it is currently not known how to measure the distance between a master recording and a student's attempt in music. Distance in AI (Sharma, 2024) always refers to Euclidean distance between two vectors, based on suitable tokens. But it is unknown which tokens to select, and how many. With today's methods, only decibels are measurable, such as for signal-to-noise. It is unclear how this helps the violinist to become better.

*Intelligent Systems (ISY)*

Euro Project Office has started a project to collect sample designs for ISY. It is freely available to interested parties against identification and authentication by a valid e-Mail (Fehlmann, Intelligent Systems, 2024). ISY can adapt to their environment.

**Figure 2.** *Implementation of a Controlling Combinator*

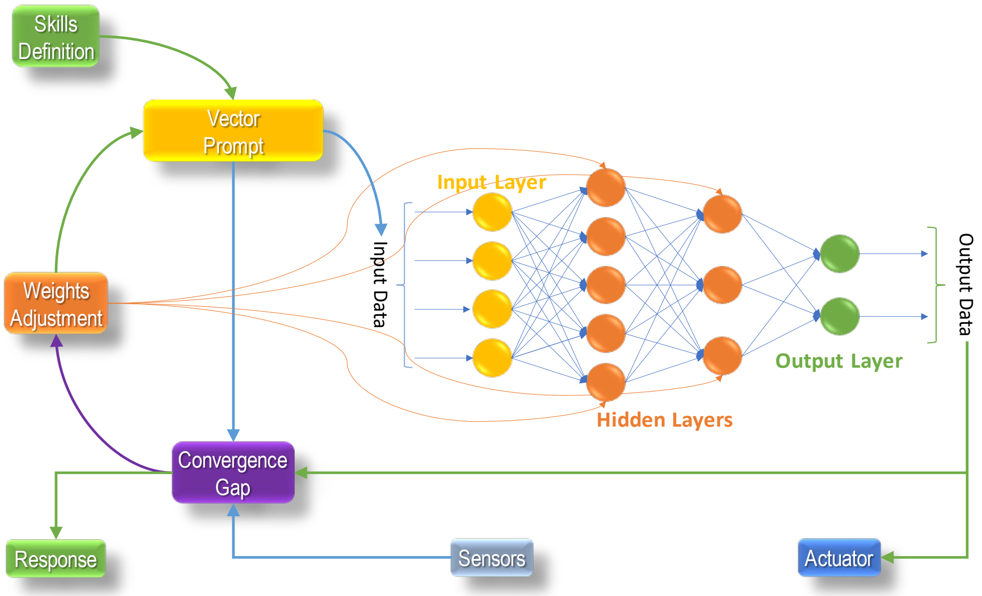



Figure 2 shows a design for continuous learning for an ANN. There are seven *Functional Processes* (FP) according to the ISO/IEC standard 19761 COSMIC (ISO/IEC 19761, 2019), needed to allow an ISY learning from empirical experiences gained by comparing the effects of output data with the reality influenced by the actuators and detected by sensors:

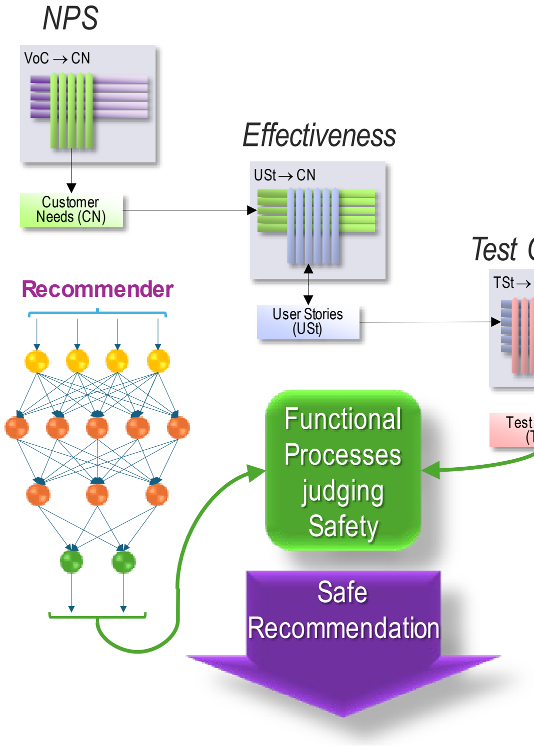
- The skills definition FP converts objects to token vectors;
- The vector prompt FP provides input data to some pretrained ANN;
- Output data FP triggers some action in the environment of the ISY;
- The sensors FP capture the effects of these actions;
- The convergence gap FP compares output data with action results;
- The weight adjustment FP trains the ANN accordingly;
- The response FP converts token vectors into objects.

All FPs use the same token vectors as the ANN as data. The track log from the convergence gap FP explains and controls all actions taken by such an ISY. This system could be used to train a computer implementation of Engeler's mathematician and violinist (Engeler, Neural algebra on "how does the brain think?", 2019).

*AI under Control*

A controlling combinator is not by itself a cause-effect control. It can explain how much an ANN has learned about reality and facts (Gnosis, γνώση) but not ascertain reasoning (Nous, νόος). The ANN still uses statistics when linking observations to concepts.

**Figure 3.** *Safe Recommendations by Autonomous Real-time Testing*




More stringent ISY compare their output data with knowledge gained from some strict knowledge-processing machine. An excellent candidate is testing. According to the principles of *Autonomous Real-time Testing* (ART) described in (Fehlmann, Autonomous Real-time Testing – Testing Artificial Intelligence and Other Complex Systems, 2020), tests can be described by arrow schemes; the same arrow schemes that an ANN processes. You can read equation (1) as a test case $x_j \rightarrow y$ with test data $x_j$, test data choice function $j$, and expected result $y$. Obviously, there is a huge gap in dimensions when comparing the few thousands of test cases, but an ANN is able to hallucinate about observations and concepts in some real world that can be tested.

The *Comprehensive QFD* shown in Figure 3 selects test cases to customer needs that were assessed with *Net Promoter Score* (NPS) (Fehlmann & Kranich, Requirements Engineering for Cyber-Physical Products, 2023). This is to avoid efforts spent on testing functionalities that are of no value for the customer. The effectiveness transfer function ensures that the choice of tests executed reflects customer needs, making this example of comprehensive QFD a strictly logical chain. The effectiveness matrix relies, like the test coverage matrix, on the number of data movements identified according to the ISO/IEC standard 19761 (ISO/IEC 19761, 2019); thus, on real, measurable data. It detects hallucinations produced by the Recommender, making recommended actions safe, testable, and explainable. It achieves this by looking whether the recommendation is covered by some existing test. To make this design work, test cases must be written using the Recommender's token vectors.

## Results

The referral to Homer and Aristotele in view of the graph model has shown that current AI raises wrong expectation if people believe an ANN does kind of reasoning. An ANN does Gnosis (γνώση) or hallucinate. Like the augurs of antiquity, but for similar reasons, explained by (Gigerenzer, 2007), these observations and hallucinations are more often hitting true points than not. If an ANN would be able to learn logic and reasoning, as is the goal of ARC Prize (Chollet, 2019), it would raise the problem of how to assure the quality of such reasoning. It would need exams like with humans.

The idea of testing potential hallucinations to ensure safety is more rewarding. There exist many such cases, where the combination of algorithmic rule-based programming with the power of generative AI can provide a whole class of innovative solutions called ISY.

## Discussion and Further Research

Working with arrow schemes can be cumbersome and resource intensive. It is not recommended using this model for actual computing; it is a theoretical construct that opens the way to better understanding the possibilities and limitations of generative AI but not an assembly language for AI. However, it might be possible to programmatically construct dedicated, specialized nodes in an ANN, for instance for reasoning about observations and concepts.

The big obstacle is how to generalize observations into intuitive ideal objects. For instance, it seems unknown how to recognize observations of circular objects and link them to the ideal, mathematical concept of a circle, something human brains can do easily. Current AI systems cannot address unfamiliar problems outside their training data, despite extensive training on large datasets. AI lacks the ability to learn new skills (Chollet, 2019).

The graph model is useful in devising innovative solutions to these problems (Fehlmann & Kranich, A General Model for Representing Knowledge - Intelligent Systems Using Concepts, 2024). The key to teaching an ANN mathematical intuition is the choice function in arrow schemes. The choice must be some ideal mathematical concept, not grounded as usual in an observation in some real world. These arrow schemes can do mathematical reasoning based on intuitive, immaterial objects. The details of their implementation in an ANN are yet open; nevertheless, by complementing Gnosis (γνώση) with Episteme (επιστήμη) a big step forward towards ISY can be expected.

David Bessis, a French mathematician and AI entrepreneur, published a book about how mathematicians do their reasoning, and how children learn by curiosity and develop mathematical intuition (Bessis, 2024). The book reads to a computer scientist like programming instructions for how to enhance ANNs with choice functions towards mathematical objects and provides innovative ideas how to reconcile Gnosis (γνώση) with Techne (τέχνη).

## Conclusions

It is recommended that AI engineers take courses in philosophy and in ancient cultures to better understand how today's AI is perceived and had been perceived over the centuries. Moreover, other disciplines than AI engineering often do have answers to the most pressing questions today: How to make AI intelligent?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