A Model for Artificial General Intelligence

Andy E. Williams(✉)

Nobeah Foundation, Nairobi, Kenya
awilliams@nobeahfoundation.org
http://www.nobeahfoundation.org

Abstract. A recently developed Functional Modeling Framework suggests that all models of cognition can be represented by a minimally reducible set of functions, and proposes to define the criteria for a model of cognition to have the potential for the general problem solving ability commonly recognized as true human intelligence. This human-centric functional modeling approach is intended to enable different models of AGI to be more easily compared so research can reliably converge on a single understanding, enabling the possibility of massively collaborative interdisciplinary projects to research and implement models of consciousness or cognition where difficulty in communicating very different ideas, particularly in the case of new models without a significant following, has prevented such massive collaboration from in practice having proved possible before. This paper summarizes a model of cognition developed within this framework.

Keywords: Adaptive problem solving · Functional Modeling Framework · Human-centric

1 Background – The Problem of Cognition

In common usage the term "general problem solving ability" functions to mean "a human-like level of ability to solve general problems through abstract reasoning" . Furthermore, taking a functional view of reasoning or understanding as processes with inputs, and outputs, and taking a functional view of problems as a set of input concepts and a set of output concepts that are bridged by such cognitive processes, it can be agreed that general human problem solving ability requires a general reasoning process that solves a general problem, that is, a general problem which all problems in the cognitive system can be defined as belonging to, and that all reasoning processes solve. And the one general problem that can be intuitively seen as being shared by all humans, is the problem of achieving "well-being" , where the exact meaning of that term will be specified.

While others such as Bach [17], or Strannegård [18] address the issue of goals or motivation in a cognitive system, those approaches focus on defining a system that targets achieving specific outcomes like securing sufficient food.

B. Goertzel et al. (Eds.): AGI 2020, LNAI 12177, pp. 357–369, 2020.
https://doi.org/10.1007/978-3-030-52152-3_38

However, any system constrained to solve a specific problem fails to meet the definition of adaptive problem solving because the system can't adapt to solve different problems. On the other hand, solving the most general possible definable problem of well-being, which is proposed here to be the fitness of the system to execute all its functions, enables the system to adapt to solve any problem that impacts fitness in performing any function, even functions that adaptive processes such as evolution may not have created yet. In the same way, solving such a general problem of well-being might also enable the system to eliminate functions that evolution or other adaptive processes no longer see as necessary.

The approach to AGI described in this paper represents the human organism in terms of a hierarchy of adaptive processes that each function to achieve a generalized property of fitness in their respective domains. Human functions are categorized as belonging to a number of functional components that include four functional systems (body, emotions, mind, and consciousness) with each system having its own metric for fitness that may be intuitively understood as well-being in that system. Formalization of the concept of well-being in terms of a functional model allows processes of observation to be confined to well-defined state spaces. Processes of self-observation then become processes for observing changes from one well-defined state in a well-defined space to another state in that same space. Any process of observation can then be seen as attempting to transmit a well-defined signal (truthful information), with the result that the ability of such processes to reliably transmit truth (as opposed to transmitting the noise of groundless speculation based on beliefs or other cognitive biases) is governed by well-understood information theory. Where before such self-observation had to be discarded as "anecdotal evidence" , this formalism makes external verification of self-observation reliably achievable [16].

In this approach, cognitive well-being is the goal of the mind in the domain of adaptation through cognition. Defining well-being as a measure of the fitness of that system to exercise all its functions matches the intuitive way that human-beings assess well-being. In comparison, current AI models from this perspective might lack a sufficiently general definition of well-being, and therefore lack a problem to solve that is sufficiently general to achieve human-like general problem-solving ability.

2 Introduction

In the FMF each functional system or functional component in a human is represented by the minimal set of functions (functions meaning behaviors or things the component can do) that can be used to compose all its behaviors. All the states then form a "functional state space" to which the system or component is confined and within which it navigates a path. Each function is essentially a vector in that space. The FMF can then be used to represent and compare models of living systems in terms of how they implement those functions, and in terms of how those implementations govern the dynamics of the system through that functional state space. This paper focuses on only one adaptive domain, the domain of adapting through reasoning that is implemented by the cognitive system, where the cognitive system is represented as moving through a conceptual space. The problem of AGI addressed in this paper is how to define a functional model of cognition that is simple (general) enough to apply to all problems of cognition in an intuitively understandable way that can be implemented, and can be intuitively validated to be complete enough to have general problem solving ability, and be intuitively validated as having the potential to be human-like. Other cognitive architectures, such as SOAR [19], or LIDA [16], also might define a list of functions. However, such functions differ where they do not form a minimally reduced set, as required to maximize generalizability in modeling the functions of any cognitive architectures. And they may differ in not separating the definition of functional models from any implementations. Defining a minimal functional model and defining a metric for the fitness of each implementation of that model is one potential way to compare all AGI research in a fashion that reliably converges on the observed functionality of cognition. Lacking this generalizability, and lacking this simple comparability, current research approaches may lack the capacity to reliably converge on a single understanding. Novel approaches to AGI, for example, may simply be ignored because of lack of popular following [4].

3 The Components of an AGI in the Functional Modeling Framework

The FMF proposes that the individual mind's cognitive functions consist of a number of functional units that process neural signals into concepts, and a number of functional units that process concepts according to the functions involved in cognition. Three lower order cognitive functions represented by the functional units F1 to F3 map to and from signal space to the conceptual space. And the higher order cognitive functions F4 to F7 and FS consisting of storage (memory), recollection, recognition of patterns, recognition of sequences of patterns, and the cognitive awareness FS, receive concepts from the functional state space of the cognitive system ("conceptual space") as input, and produce other concepts as output to that "conceptual space". By executing reasoning processes defined in terms of these functions, the cognitive system navigates this conceptual space.

Assuming that any concept in the human cognitive system can be represented by specifying the state of each of N neurons, then any concept can potentially be represented by a function F1 that detects the distribution of neural signals over the array of N neurons, a function F2 that detects the sequence of signals distributed over time, and a function F3 that detects a pattern in those distributions that represents a concept. Assuming that all concepts can be expressed in terms of their relationship with other concepts, and assuming that these relationships can be expressed in terms of reasoning, then if concepts are represented as points in a conceptual space, all concepts are separated from other concepts by paths that represent reasoning processes. All reasoning is then a path from one point in conceptual space to another.

A minimal set of functions potentially capable of spanning the entire conceptual space begins with a function F4 that stores concepts into the conceptual space, a function F5 that retrieves concepts from the conceptual space, a function F6 that detects patterns in the concepts, and a function F7 that detects sequences in the patterns. The function F4 is intuitively recognizable as memorizing, the function F5 is intuitively recognizable as remembering, F6 is intuitively recognizable as understanding a pattern or employing a pattern in reasoning, and F7 is intuitively recognizable as understanding a sequence of patterns or as employing a sequence of patterns in reasoning. These functions form a minimally reducible set not just within the cognitive system but across the entire human organism, since the same functions F1 to F3 are required for the body to perceive sensory signals as sensations, for the emotional system to perceive emotions, and for the consciousness to perceive awarenesses. In addition, the same function F4 is represented in the FMF as occurring in the body to process sensations, the same functions F4 to F5 are represented as occurring in the emotional system as an evolutionary adaptation to process emotions, and all the same functions F4 to F7 are represented as occurring in the consciousness system as an evolutionary adaptation to process all these awarenesses. The cognitive system must have the capacity to conceptualize all these sensations, emotions, and awarenesses. In the FMF conceptualization is represented as the three functions F1 to F3 being used to map each point in sensory space (each sensory perception), each point in emotional space (each emotion), or each point in awareness space (each self-awareness), to a point in conceptual space (to a concept). The consciousness system must also have the capacity to be aware of all concepts. As consciousness evolved functionality F3 to F7 to navigate awarenesses, the FMF represents this functionality as becoming incorporated in the cognition as well.

The set of these cognitive functions occurs on both the input processing path (cognition of sensory or other input) as well as the output path (cognition driving sensory or other output). The set of these input cognitive functions are proposed to act to receive understanding in terms of concepts (understanding meaning the process that enables comprehension of the sentence "the quick brown fox jumped over the lazy dog"). On the output path (using cognition to drive reason towards conclusions) these cognitive functions are proposed to direct reasoning (reasoning meaning the process that enables answering the question "what fox jumped over what dog?").

These functional units have an evolutionary order in that functional unit FN-1 must exist before its output can be available to be used in functional unit FN. This paper proposes that representation of any reasoning or understanding processes in this way is possible because any thought can be represented in a functional model as a form of pattern detection in concepts (F6), and in terms of a sequence of those patterns (F7). And since the set of functions AND, OR, as well as NOT can represent all logic and is therefore Turing complete, this paper proposes that any logic, and therefore the logic in any rational methodical thought process, can be represented in a functional model in terms of a function to detect patterns representing a Turing complete set of logical operations on concepts, whether or not those operations are the functions AND, OR, and NOT, and in terms of a sequence of those patterns (F7) (Table 1).

Table 1. Functional units in a system of human-like cognition as defined by the Functional Modeling Framework (FMF).

Functional Units in Systems of Cognition		
Functional Unit	Input Function	Output Function
F1 to F3	Create Concept	Create Signals from Concept
F4	STORE (Store Concept)	DECOMPOSE STORAGE (Determine Concept in Storage Function)
F5	RECALL (Recall Concept)	DECOMPOSE RECALL (Determine Concept in Recall Function)
F6	DETECT PATTERN (Detect Pattern in Concept)	DECOMPOSE PATTERN (Detect Concept in Pattern)
F7	DETECT SEQUENCE (Detect Sequence of Patterns in Concept)	DECOMPOSE SEQUENCE (Detect Concept in Sequence of Patterns)
FS	COGNITIVE AWARENESS	

As an example, consider how the following sentence might be represented with the set of cognitive functions and other functional components defined by the framework: "The quick brown fox jumped over the lazy dog". The words in the diagram represent concepts. The relationships between concepts from a given perspective are proposed to define the position of concepts in the conceptual space that is defined by the Functional Modeling Framework (Fig. 1).

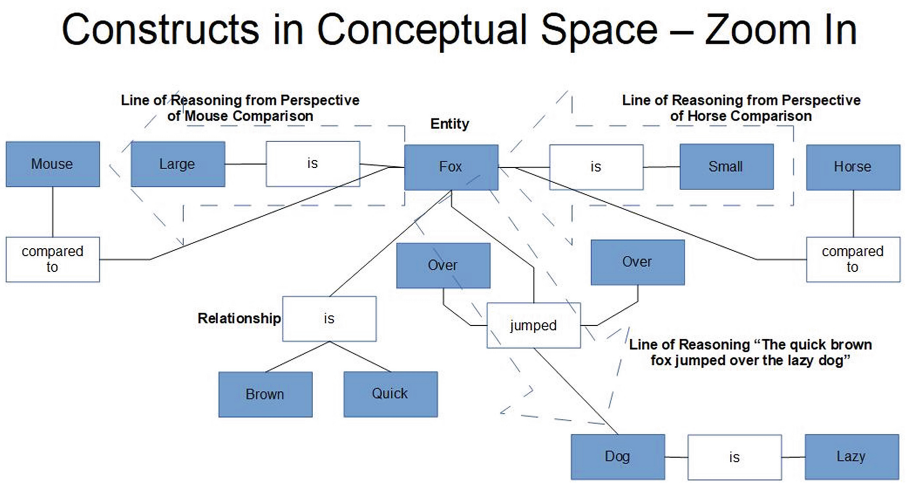

Fig. 1. Depiction of relationships in conceptual space.

The reasoning process that produces this natural language sequence can potentially be modeled in this case as beginning at a position on the diagram above representing a given perspective on the entity "fox", and then executing the RECALL function on the properties "quick" and "brown" and the DETECT PATTERN function to associate them with the "fox" to produce "the fox is quick" and "the fox is brown" . The process might then execute the DETECT SEQUENCE function to group "quick", "brown", and "fox" into "quick brown fox". The process might then execute the RECALL function on the relationship "jumped". And then might execute the RECALL function on the modifier "over". Finally, it might execute the RECALL function on "lazy dog", and then execute the DETECT SEQUENCE function to group "the quick brown fox", "jumped over", and "the lazy dog". Reasoning processes, such as those required to construct text or speech in natural language, then become a sequence of paths through the conceptual space. In this case, the first path P1 is "the fox is quick" (Fig. 2).

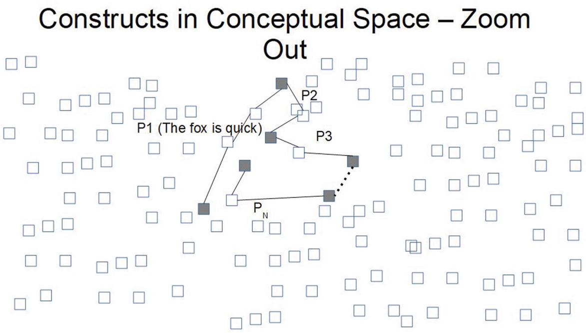

Fig. 2. High-level view of conceptual space.

As noted in the first diagram, there are a multitude of relationships connecting the fox to entities that define other of its properties. For example, from the perspective of a comparison with a "mouse" the fox is "large". From the perspective of a comparison with a "horse" the fox is "small". In order to be able to retrieve all the relationships relevant to a given perspective, the representation of the conceptual space must be complete enough to store such perspectives.

4 Adaptive Processes

As mentioned, the FMF also represents an intelligent entity as a hierarchy of adaptive processes with which it can adapt all of its processes to be more fit (the basic life processes L1 to L8). The FMF defines requirements for the basic life processes and the components that implement these processes, but leaves cognitive architectures to define their own implementations to ensure that the most fit component at executing any given required functionality can be taken from any other implementation suggested by any researchers, while ensuring the overall implementation model continues to become more fit at representing the functionality of cognition. The implementation model of AGI described in this paper serves as a reference implementation. The importance of representing intelligent entities in terms of a hierarchy of adaptive processes that together choose the optimal definition of any problem (optimum in terms of the choice that optimizes fitness), and that together choose the optimal solution to that problem, is that in order to increase problem solving fitness to the point that it is general enough to be human-like, nature's design process must remove the constraints against this optimization. And one of the constraints against optimization is whether and how functionality is segmented across components. The principles of intelligent cooperation between components (defined by the domain of adaptation through cooperation) dictate that systems must have the capacity to centralize decision-making where necessary to prioritize the function of a single component. And they must have the capacity to decentralize decision-making where necessary to maximize outcomes for all components. Centralization constrains the system from solving problems that are not aligned with the interests of the components in which decision-making is centralized. Functionality must be decentralized across all components to maximize impact on the problem as perceived by the entire system rather than becoming aligned with the interests of subset of components. To achieve this segmentation, nature must take a modular approach that separates adaptive processes into different domains and that chooses which adaptive functionality to put in each. This choice must be made according to the principles of intelligent cooperation between components if the set of domains is to have the capacity to maximize adaptive fitness across all domains. In other words, rather than defining an AGI as a single adaptive system, adaptive domains in an AGI must be limited in their functionality (modular and reuseable) so they can be adapted without having to change the entire system. As a result some of the constraints against problem definition and problem solving might exist in each adaptive domain. For example, each adaptive domain might lack the capacity to change its own adaptive functions. Therefore each adaptive domain must exist in a hierarchy of other adaptive domains if the constraints to its adaptability are to be removable.

5 An Algorithm for General Problem Solving Ability

General problem solving ability in the FMF is the ability to sustainably navigate the entire conceptual space so that it is potentially possible to navigate from any problem that can be defined within that conceptual space to any solution that can be formulated within that conceptual space. Where a non-intelligent system such as current computer programs solves the problem it's designers have chosen for it, a system with general human-like problem solving ability or true human intelligence, must have the ability to choose which problem to solve. The model of cognition described within this paper chooses which problem to solve through maintaining global stability in the dynamics with which it executes all reasoning processes, where that stability exists within a fitness space related to cognitive well-being.

The system of cognition is modeled as projecting the cognitive value minus cost of each activity being executed (its "fitness" in achieving its targeted outcome in terms of cognitive well-being) and either investing resources into the current reasoning activity until complete, or discontinuing the current reasoning activity to invest resources into the next (choosing to solve another problem) in a way that maintains stability in fitness to continue to execute these cognitive functions. In this way, investment of the cognitive system into each given reasoning process forms a kind of convection that is reflected in the motion of the cognitive system through fitness space. To implement this model, a system of equations capable of demonstrating this convection throughout a three dimensional fitness space (the Lorenz equations for convection) can then be used to define forces of selection of reasoning processes according to projected, targeted, and actual impact on cognitive well-being so that the path through fitness space might form this stable convection, despite the path through the conceptual space being potentially chaotic.

Having defined the equations governing this relationship, an algorithm for selecting the sequence of reasoning activities to be executed by the cognitive process in a way that approximates those dynamics has been defined. By executing reasoning activities in a sequence that keeps the state of cognitive well-being within a stable range, the cognitive system is proposed to gain the capacity to adaptively navigate the conceptual space as well as to gain the capacity to navigate the state space of the environment it conceptualizes. In this way, reasoning in the cognitive system is an adaptive process that enables the entity to find stability in greater regions of the external environment (to understand and reason about the external world). Where the parameters of the Lorenz equations can be chosen to form a globally stable dynamics (a strange attractor) in the cognitive well-being space, despite a chaotic path through the conceptual space. The same Lorenz equations can also be used to implement all the other functional components in the model so that their dynamics within their fitness spaces and state spaces obeys the same global stability despite local instability [2,3].

6 The Importance of an Intuitive Approach

From the standpoint that simple, ubiquitous patterns are intuitive, we would expect that human-beings should intuitively be able to describe their cognitive activities in terms of such a minimally reducible set of cognitive functions, that is, we would expect that such functions would then be consistent with the functions human beings could easily observe within their own self-awareness. In line with these expectations, while the majority of individuals might demonstrate the ability to reliably understand a cognitive process in terms of the FMF's functions (memorize, recall, recognize pattern, or recognize a sequence of patterns) through experiments that test the subject's consistency in using such labels in a wide range of circumstances, most individuals might fail to reliably label a thought in terms of the "perceptual associative memory" or other functions defined by other cognitive architectures. This is not a criticism of the usefulness of those cognitive architectures as potential implementations of AGI functionality, but instead is an illustration of the usefulness of defining simple and intuitive functional models of cognition, within which other cognitive architectures are implementations whose fitness in representing the observed functions of cognition can be measured and compared in order to reliably converge on the best working model of each element of functionality.

From this perspective of a minimal functional model, some functions that are commonly thought of as integral become mere details of some particular implementation of cognition. By analogy, a very simple functional model of computation might not make a distinction between long-term-storage on a hard drive and short-term storage in memory. But any effective implementation of the storage function would certainly identify the optimal implementation in each of those contexts. In the same way, this minimal functional model of the FMF identifies functions as having inputs, outputs, and separate information specifying the context of execution, and leaves other details to be a matter of choosing the optimal implementation of each function.

The approach to functional modeling used in this paper may be a radical departure in that it attempts to create a bridge between approaches for understanding the human system in terms of functions that can be observed in the individual's own self awareness, and approaches held to be "scientific" in restricting themselves to external measurements. Where the vast tradition of such observations has not before been readily accessible to the sciences, this human-centric approach formalizes the process of representing systems in terms of their functions that human beings already use intuitively, so that it is possible to leverage that vast understanding. Furthermore, rather than introducing jargon that forces researchers to adjust to an individual researcher's way of framing cognitive architectures, this human-centric formalization attempts to frame the general problem of cognition in a way that can be intuitively understood in natural language by anyone with a deep understanding of the problem.

The usefulness of the conceptual space defined for this domain of adaptation through cognition is that representing all cognitive processes as being confined to it (i.e. cognitive processes receive concepts as inputs and produce concepts as outputs) allows us to understand what the cognitive system can and cannot do. A cognitive process in the FMF cannot for example have an awareness as input or produce a physical movement as output. In discussions in which a researcher familiar with one cognitive architecture attempts to explain the implications of their model to a researcher versed in another cognitive architecture, any terms that can't be validated intuitively might easily be misinterpreted, making it too unclear what is being discussed for the discussion to be conclusive. This approach of confining behavior to an intuitively understandable functional state space means that a significant source of ambiguity is potentially removed. As a consequence, even when deducing the outcome of an unlimited number of reasoning operations resulting in very complicated patterns of behaviors of the cognitive system, like the patterns representing general problem solving ability, arriving at an answer becomes reliably achievable.

Breaking cognitive architectures down to a set of discrete, objectively defined functions that can be independently implemented by people from different disciplines might also facilitate massive interdisciplinary cooperation to do so, where such cooperation has not proven possible before. In fact, functional modeling approaches are commonly used in systems and software engineering to facilitate cooperation in the design of complex systems by removing the need for individuals in interdisciplinary teams to understand each other's approaches. A functional modeling approach that is also human-centric enables functional modeling to be extended to systems like consciousness or cognition for which functions can be observed within our innate human awareness, but for which the mechanisms of operation are unknown, and being unknown with no universally agreed upon models, researchers might propose models of those mechanisms from mathematics, neurology, physics, or a wide variety of other backgrounds that don't necessarily understand each other. Without this human-centric functional modeling to create the potential for massive interdisciplinary collaboration across disciplines, and between projects to implement poorly understood human functions like consciousness or cognition, the proliferation of models of cognition may tend to remain in silos, and their lessons remain unexplored wherever the complexity of translating between them remains too great to permit more than a tiny minority of models to be readily understood by people in different fields. With such a functional modeling approach, all work might be combined in a way that has the potential to reliably converge on the functions of a working model of AGI.

7 Conditions for an AGI to Be Valid in the FMF

In the FMF the ability to solve a specific problem, such as accomplished by narrow AI, is represented as the lack of a path from one concept to another concept, where that path is the solution. General problem solving ability is the ability to sustainably execute a library of reasoning processes, including reasoning processes that generate new reasoning, so that the cognitive system navigates the conceptual space in a sustainable way that creates the potential to navigate the entire cognitive space. That is, so it is potentially possible to navigate from any problem to any solution. In order to be a valid model of AGI, the FMF then requires this global stability in dynamics despite following a potentially locally chaotic path through the conceptual space. Models that don't explicitly define a maximally general fitness space and that don't explicitly constrain the dynamics in that fitness space to be globally stable, fail in this regard.

8 Implementation

Through defining every cognitive architecture as implementing one or more of these functions, the FMF aims to facilitate the use of best of breed implementations of each function to in turn facilitate convergence of all cognitive architectures into a single architecture that is more fit at representing cognition. Beginning by defining functional models of all rational methodical reasoning processes that can be catalogued (whether human deductive reasoning or reasoning defined in procedural software programs), and functional models of pattern based processes (whether human intuitive reasoning or AI pattern detection), the resulting library of reasoning might be used by all AGI implementations to increase their general problem-solving ability [14] where those implementations are compatible with such abstract functional models of reasoning. By defining the fitness of each reasoning process in achieving each of its outcomes, each implementation can gain the ability to reliably converge on the best reasoning process regardless of the number of such processes. By defining the domains (in terms of concepts) in which each implementation of each process is most fit in achieving those outcomes, each cognitive architecture can store or retrieve this information.

The FMF dictates that a number of functional components must be implemented in an AGI. However, having defined these functional components and their requirements, implementations of each component can proceed independently of each other, and in fact may have already existed for some time and might just need to be identified. Functional unit F3, for example, performs pattern detection, and since some form of pattern detection is general to all neural networks this has been demonstrated. In the case of position as in F1, sequence detection as in F2, storage as in F4, and the generalization involved in learning as in F7, we can show that each of these functions has been implemented as a neural network (position [5,6], sequence detection [7,8], storage [9–11], and the generalization [12,13]) and therefore that each mechanism has been explored in an actual implementation. The FMF suggests that nature follows precise principles of intelligent cooperation (the domain of adaptation through cooperation) that enable components of organisms to use decentralized cooperation to adapt any functions of the organism. Where AGI engineers experience the inability to coordinate and integrate the functions they create so those functions can cooperate, this may indicate that the interfaces defined by such efforts don't follow these specific principles by which the FMF suggests the implementation of such functions might be decoupled.

9 Conclusions

A model suggested to represent an AGI has been presented. Defining general human-like problem solving ability as a pattern of dynamical stability in cognitive well-being space (cognitive fitness space), and defining well-being or fitness more generally (the capacity to execute available cognitive functions) than might be the case with current cognitive architectures with more specific problem solving ability, this model is believed to be novel in identifying an equation which represents general human-like problem solving ability in satisfying those dynamics, and in identifying an algorithm for executing reasoning processes in a way that approximates that equation. As a result, this model is proposed to have the potential for general human-like problem solving ability. This model is also potentially new in defining a minimally reducible set of cognitive functions. While sophisticated AI implementations already exist, organization of all implementations by the same set of functional units enables problem solving reasoning to be constructed the same way for every implementation, so that the library of reasoning processes can steadily grow. Being able to compare the fitness of each implementation of a reasoning process or other element of functionality can also enable the fitness of all cognitive architectures to steadily improve in achieving the functionality required for cognition. Finally, to reiterate, human beings intuitively represent systems in terms of their functions. By formalizing this process of representation, this functional modeling approach enables AI researchers to access the vast traditions in which the functions of human cognition have been observed, where these observations have not been readily accessible to the sciences before. Since these traditions provide experientially verifiable definitions of terms that when defined intellectually are ambiguous, this in itself is a tremendous contribution to AGI research. In other words, intellectual reasoning has a capacity to arrive at truth that is finite (limited to problems in which adequate reasoning and the facts to plug into that reasoning exist) and potentially unreliable (reliable only where such reasoning is computationally reducible or simple enough to be accurately computed). Experiential reasoning has a capacity to arrive at truth that is infinite (the truth of an infinite number of observations can be experienced) and than can be reliable (experience can reliably be observed wherever awareness is practiced enough that an observation can be accurately identified as one's experience). The more experiential and less intellectual the discussion of cognition, potentially the more capable that discussion is of reliably converging on the truth.

References

1. Williams, A.E.: A Human-Centric Functional Modeling Framework for Defining and Comparing Models of Consciousness and Cognition, 16 April 2020. https://doi.org/10.31234/osf.io/94gw3
2. Williams, A.E.: Model for human: artificial l& collective consciousness (Part I). J. Consciousness Explor. l Res. **10**(4), 250–269 (2019)
3. Williams, A.E.: Model for human artificial l& collective consciousness (Part II). J. Consciousness Explor. l Res. **10**(4), 270–293 (2019)
4. Lucentini, D.F., Gudwin, R.R.: A comparison among cognitive architectures: a theoretical analysis. Procedia Comput. Sci. **71**, 56–61 (2015). https://doi.org/10.1016/j.procs.2015.12.198. ISSN 1877–0509
5. Bruyndonckx, P., Léonard, S., Tavernier, S.: Neural network-based position estimators for PET detectors using monolithic LSO blocks. IEEE Trans. Nuclear Sci. **51**, 2520–2525 (2004). ieeexplore.ieee.org

6. Ebong, I.E., Mazumder, P.: CMOS and Memristor-based neural network design for position detection. In: Proceedings of the IEEE (2012). ieeexplore.ieee.org
7. Sutskever, I., Vinyals, O.: Sequence to sequence learning with neural networks. In: QV Le - Advances in Neural Information Processing Systems 27 (NIPS 2014). papers.nips.cc
8. Houghton, G.: The problem of serial order: a neural network model of sequence learning and recall - Current research in natural language generation (1990). dl.acm.org
9. Nara, S., Davis, P., Totsuji, H.: Memory search using complex dynamics in a recurrent neural network model. Neural Netw. **6**, 963–973 (1993). Elsevier
10. Cohen, M.A., Grossberg, S.: Absolute stability of global pattern formation and parallel memory storage by competitive neural networks. IEEE Trans. Syst. Man Cybern. **42**, 288–308 (1983). ieeexplore.ieee.org
11. Yao, K., Peng, B., Zhang, Y., Yu, D.: Spoken language understanding using long short-term memory neural networks. In: 2014 IEEE Spoken Language Technology Workshop (SLT) (2014). ieeexplore.ieee.org
12. Aranson, I.S., Pikovsky, A., Rulkov, N.F.: Advances in Dynamics, Patterns, Cognition, LS Tsimring. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-53673-6
13. Sietsma, J., Dow, R.J.F.: Creating artificial neural networks that generalize. Neural Netw. **4**, 67–79 (1991). Elsevier
14. Williams, A.E.: Defining Functional Models of Artificial Intelligence Solutions to Create a Library that an Artificial General Intelligence can use to Increase General Problem Solving Ability, 27 April 2020. http://www.osf.io/preprints/africarxiv/hpzb7
15. Williams, A.E. (n.d.): A Mathematical Model for Identifying Truth in Observations Made within Individual Human Self-Awareness. Retrieved from osf.io/preprints/africarxiv/4nsgk
16. Franklin, S., Madl, T., D'Mello, S., Snaider, J.: LIDA: a systems-level architecture for cognition, emotion, and learning. IEEE Trans. Autonom. Mental Dev. **6**(1), 19–41 (2014)
17. Bach J.: A motivational system for cognitive AI. In: Schmidhuber J., Thórisson K.R., Looks M. (eds.) Artificial General Intelligence. AGI 2011. Lecture Notes in Computer Science, vol 6830. Springer, Heidelberg (2011) https://doi.org/10.1007/978-3-642-22887-2_24
18. Strannegård, C., Svangård, N., Bach, J., Steunebrink, B.: Generic Animats. In: Everitt T., Goertzel B., Potapov A. (eds.) Artificial General Intelligence. AGI 2017. Lecture Notes in Computer Science, vol 10414. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-63703-7_3
19. Laird, J.E.: The Soar Cognitive Architecture, MIT Press (2012) ISBN 0262300354, 9780262300353