# Defining Functional Models of Artificial Intelligence Solutions to Create a Library that an Artificial General Intelligence can use to Increase General Problem Solving Ability

Andy E. Williams, Nobeah Foundation, Nairobi, Kenya

**Abstract**
The AI industry continues to enjoy robust growth. With the growing number of AI algorithms, the question becomes how to leverage all these models intelligently in a way that reliably converges on AGI. One approach is to gather all these models ingo a single library that a system of artificial intelligence might use to increase it's general problem solving ability. This paper explores the requirements for building such a library, the requirements for that library to be searchable for AI algorithms that might have the capacity to significantly increase impact on any given problem, and the requirements for the use of that library to reliably converge on AGI. This paper also explores the importance to such an effort of defining a common set of semantic functional building blocks that AI models can be represented in terms of. In particular, how that functional decomposition might be used to organize large scale cooperation to create such an AI library, where that cooperation has not yet proved possible otherwise. And how such collaboration, as well as how such a library, might significantly increase the impact of each AI and AGI researcher's work.

## Introduction

In complex systems design functional modeling provides a number of important benefits, such as permitting multidisciplinary cooperation in implementing large systems by defining functional components with well defined interfaces that remove the need to understand other disciplines [1] - [4].

The Functional Modeling Framework (FMF) discussed here [9] is also "human-centric" in choosing function definitions that can be validated within the innate conscious self-awareness common to all humans, rather than being defined in terms of some model of AGI and therefore requiring agreement with that model, even where inconsistent with some approaches. In the case of cognitive functions, the FMF defines them very simply as receiving sets of concepts as inputs, as producing sets of concepts as outputs, and as using other sets of concepts as the context within which the functions are executed.

## The Validity of a Functional Modeling Approach towards Representing AI Algorithms

Parts of the FMF, such as it's semantic modeling capability, are still under development. However, the FMF is of great potential importance to the study of AGI even without representing AI algorithms semantically in terms of a set of basic cognitive functions. Firstly, the principles of decentralization defined by this model are proposed to be critical in gaining the capacity to reliably maximize any collective (group) outcome, whether decentralization of AI, AI safety, or AI openness. Rather than maximizing collective outcomes, allowing processes to become centralized forces decision-making to align with the interests of a subset of decision-makers, often working against maximizing collective outcomes [11]. Secondly, while an AI maximizes impact on a problem, the adaptation processes defined by this model are proposed to be required to enable an AGI to maximize outcomes by choosing the optimal problem to solve[15].

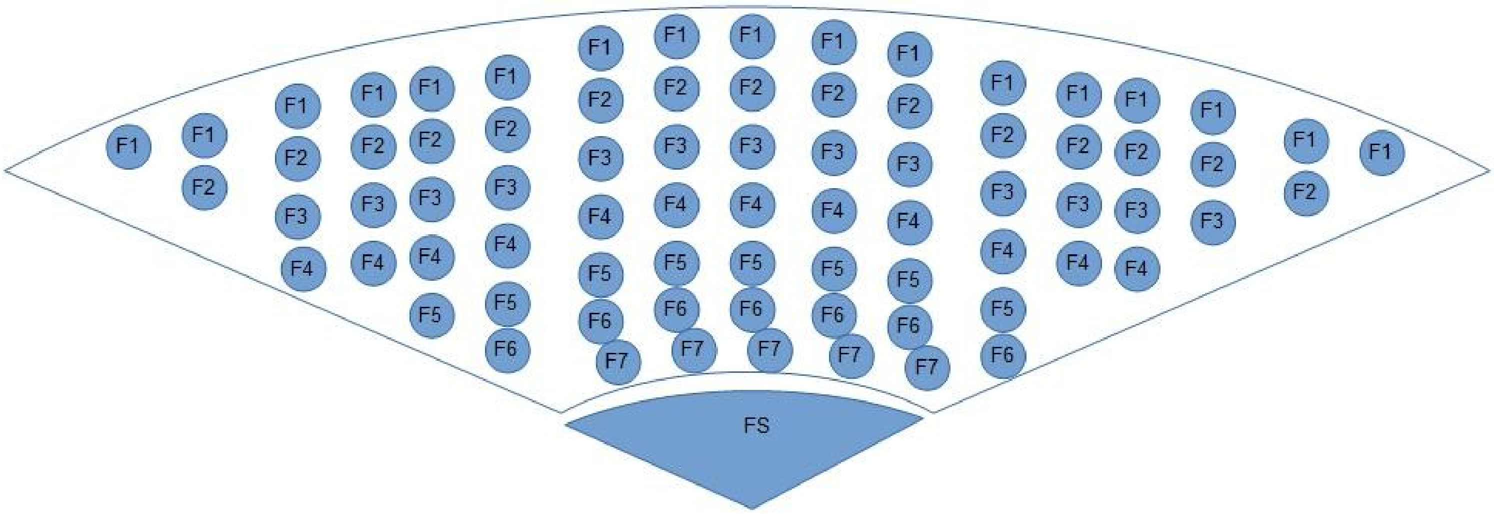
A library of AI algorithms can also be very useful without semantic modeling of the processes within the algorithms themselves. A useful library of AI algorithms might be constructed by creating functional models that simply define input, outputs, and context, essentially treating the AI algorithms themselves as black boxes that can be manually labeled (categorized) as different. Of course, in order to develop the capacity to automatically categorize AI algorithms in such a library, the capacity to represent any process in terms of the cognitive functions defined in a common framework like the FMF must be developed.

To gain the capacity to represent any process in terms of a common set of cognitive functions, this modeling approach proposes that cognition can be represented in terms of a discrete set of functions (functional units F1 to F7, and FS). On the input path (cognition of sensory or other input), the set of functional components implementing these 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 action or conclusions) these functional components are proposed to direct understanding through reasoning (reasoning meaning the process that enables answering the question "what fox jumped over what dog?").

**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 (Choose Problem to Solve and Reasoning Process to Solve it) | |

Multiple instances of each of these functions in a conceptual model of the brain that connects these functional units into paths, is proposed to have the capacity to represent any intuitive or rational methodical reasoning process.




This paper proposes that representation of reasoning processes in this way is possible because any intuitive reasoning can be represented in a functional model as a form of pattern detection. 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 reasoning process, can be represented in a functional model in terms of a function to detect patterns, and in terms of patterns representing a Turing complete set of logic functions, whether or not they are the functions AND, OR, and NOT.

As with all other components of this framework, the goal is not to design a static set of components that “solves” AGI, but to define a methodology for orchestrating cooperation that reliably converges on AGI. That is, to provide a methodology to improve or replace any component with ones that have greater fitness in achieving the targeted objective. For this reason, whether these are the correct cognitive functions into which reasoning can be decomposed, or whether the definitions of these functions are correct, are not critical.

Of course, reasoning requires semantic representation of both processes and information. Such representations define a multitude of relationships connecting any entity to other entities that define its potentially many properties. Each perspective defines a set of relevant relationships. For example, from the perspective of a comparison with a "mouse" a fox is "large". From the perspective of a comparison with a "horse" a fox is "small". In this framework the semantic representation (concept) of each entity are assumed together to form a space of concepts (a conceptual space).

In order to be able to retrieve all the relationships relevant to a given perspective, the conceptual space must store such perspectives. This is just one of the many requirements that a valid model of the conceptual space must fulfill. Many others have been observed. Again, the goal of this approach isn't for any one person or team to define all requirements, but instead to define a process of problem-solving that reliably orchestrates collectively intelligent cooperation across all teams in a way that converges on solving all problems necessary to achieve a given objective, in this case defining the cognitive space in a way that is consistent with achieving general problem solving ability in a system of cognition.

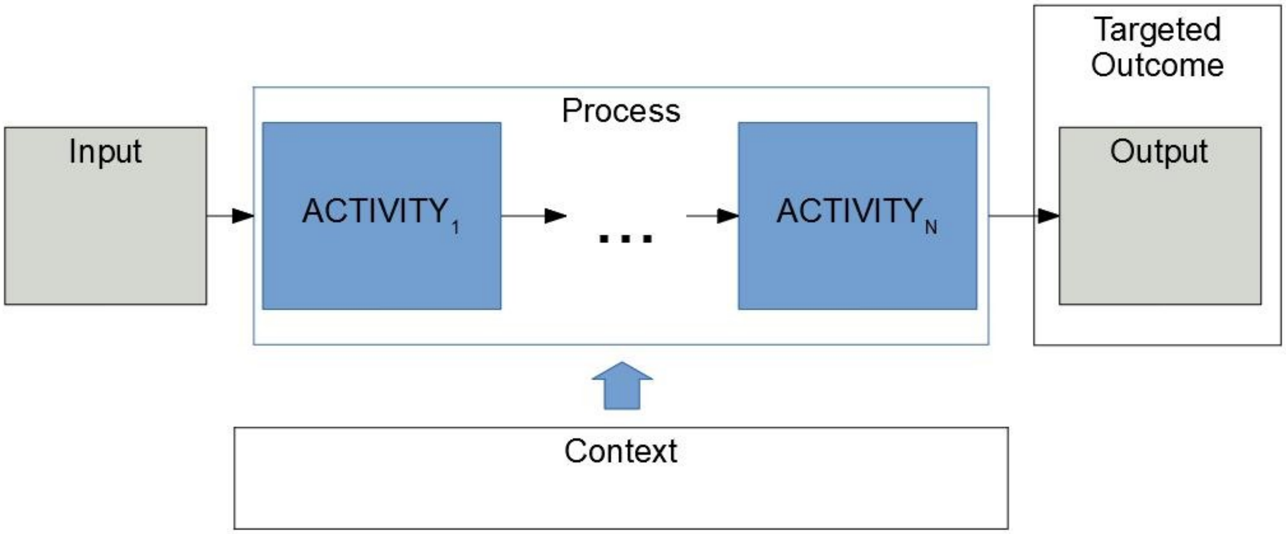
A library of AI algorithms will also benefit from the ability to include procedural programs. In addition to having the capacity to express AI functionality in terms basic cognitive functions, including procedural programs in a library that does not treat such programs as black boxes is proposed here to also require the ability to decompose procedures into a basic set of functions with semantic meaning. The proposed eXtensible Domain Modeling Framework (XDMF) [12] aims to do this, permitting a functional state space to potentially be constructed for each ontology defined within it. This functional state space in turn enables reasoning to be executed far more accurately. For example, the "manufacture" function of a business process defines set of functions that all operate on the same domain object ("product"). Each function in this domain might itself include a set of functions such as "assemble" that also operate on the same domain object (e.g. "part" that is either a component of, or a specific instance of a product). All these functions define the relationships connecting these concepts in the conceptual space. The space that the output of a reasoning process can occupy is then better defined.

Though within the business domain the XDMF already defines an extensive hierarchy of ontologies, like every other part of a human-centric functional model, every one of these components is meant to evolve to become more fit. However, the XDMF is also lacking many definitions. For this reason, an extensive library of such definitions will need to be built up within the XDMF before the XDMF can be used effectively to define a semantic data model capable of representing functional models of procedural reasoning processes and functions.

Whether procedural programs or AI, functional modeling of reasoning process or functions requires semantic modeling of the concepts input to and output from those processes or functions. Therefore in order to create a functional model of an AI solution a semantic definition of input and output concepts is required. This is intended to be provided by the implementation of conceptual space of the FMF, and by the XDMF. Since these is not yet available, each concept may be defined using a database of synonyms, this may allow that library of functions to be searched.

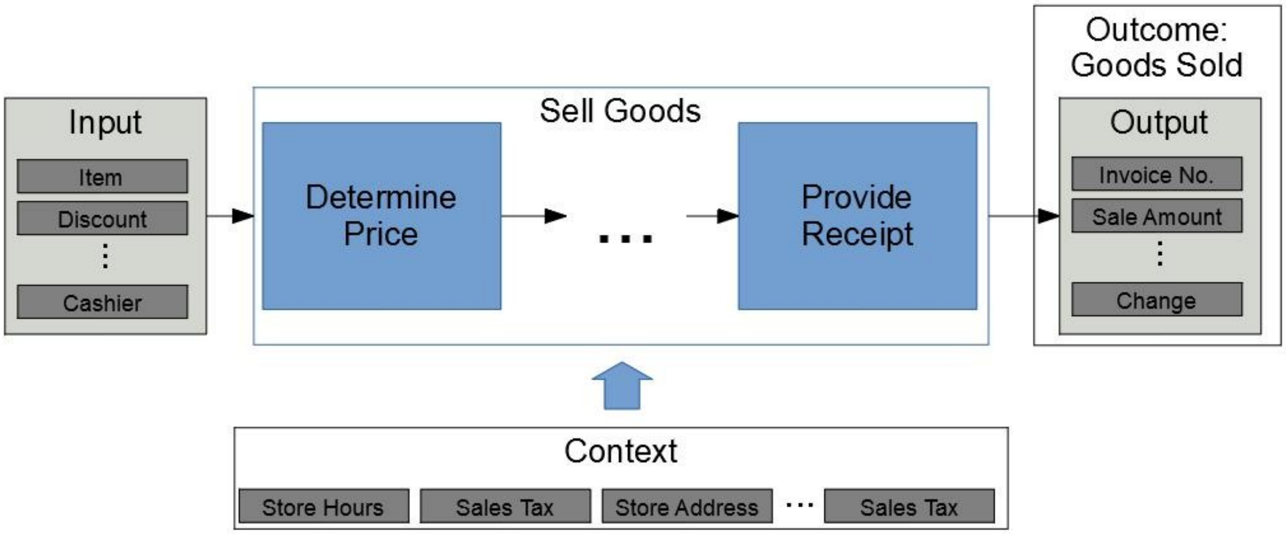
**Human-Centric Functional Modeling**

Functional modeling can be used to model both physical processes and virtual processes such as cognitive processes. In terms of virtual processes, each function a solution is required to have can be conceptually represented in terms of an input, an output, a context of execution, and an outcome related to that output. The context of execution represents all the information that the output is dependent on that is not part of the input, such as configuration parameters.




**Processes vs Functions**
Processes are defined here as functions that can receive input multiple times within the same instance of execution. An AI that plays chess is a process (Process: Play Chess) because each move of the opponent is a separate input within the instance of the game. However, the AI taking all the positions on the board as input and generating the next move is a function (Function: Move Chess Piece).

An example is the function "Sell Goods" that is involved in retail sales operations. In terms of its external interactions this function is described in terms of the concepts that form its inputs, its outputs, and the context in which it is executed. In terms of its implementation this function is executed through a number of specific activities.




The Functional Modeling Framework defines "human-centric" in terms of a set of precise principles by which functional components in any system must operate, as well as share data, and interact in other ways, in order for the system to have the capacity to maximize outcomes between all its functional components so that cooperation between those components is stable, rather than steadily accrueing resources in a way that is aligned with the interests of a subset of functional components, so that cooperation is unstable. For example, in operation, the FMF requires all processes to operate in a way that is: massively collaborative, peer-to-peer, node-centric (each node contains all the information required to participate in the cooperation, and therefore doesn't need to interpret information according to any "code" provided by any other source), and decentralized [11].

In essence, all of these considerations equate to the functional models of AI solutions and other reasoning processes being represented in the FMF as requiring semantically modeled (and therefore human-centric) inputs and outputs. In this way, inputs and outputs can be validated within the user's innate human awareness rather than requiring agreement with any private data or other source that can't be validated within the individual's experience of their awareness.

**Semantic Modeling and Natural Language Understanding (NLU)**

Semantic modeling has seen a great deal of success in recent years, having to some degree overcome its initial complexity so that it has become a core technology for the majority of today's NLP/NLU systems. Semantic data models are commonly expressed as ontologies in one or more domains. Part of the meaning stored in a semantic data model may be contained in the workflow that identifies the relationships which define meaning and which determines the context that in turn determines which relationships are valid. In current semantic models these relationships may be restricted to a basic set.

Rather than restricting the user to having to express meaning in terms of some basic set of relationships between concepts, where the user may not understand naturally concepts in terms of that set of relationships, a more human-centric approach would be to create the capacity to define any relationship as a concept, and to enable any relation to be used to define concepts.  Because any relationship between concepts in the FMF is a reasoning process or function that takes a set of concepts as input and produces another set of concepts as output in each context, and because any reasoning function may potentially be implemented as a logical operation, then this dependency of relationships on concepts, and concepts on relationships, has the potential to create circular logic. But in the FMF circular logic can always be broken by using a pattern estimation operation instead; the pattern matching that ML excels at.

**Implementation**

In general, there are two cases in which a functional model can be implemented. One is the case in which an equation to determine the outputs is known, that equation can be calculated, and the values for all the variables required to calculate the output of that equation are known. This is a representation of what in humans is the rational methodical reasoning process, and what in computing is represented using a procedural language. Rational methodical reasoning may occur at varying levels of abstraction. At the strategic level this outcome might be to determine the category of outcome to be targeted by subsequent parts of the reasoning process. At the tactical level it might be to determine the category of outcome to be targeted within that strategy. These reasoning processes can be combined in chains to problem solve, that is, to solve the problem of how to create a path to navigate the conceptual field from an initial concept to another targeted one. By creating a hierarchy of reasoning processes of differing levels of abstraction the mind is proposed to develop the capacity to reason methodically.

In the other case one or more of these is unknown, and the output must be estimated from past patterns. This is a representation of the intuitive reasoning process. Where the variables needed to evaluate the equation are missing, where the equation is missing, or where the equation does not adequately predict the solution, the solution must be predicted from past patterns. Intuitive reasoning is represented as this pattern based prediction. From this perspective, implementations such as Artificial intelligence or AI are essentially pattern based prediction. Functional models of the outcomes targeted by each AI solution as a combination of an AI implementation and set of training data, has the potential to represent each AI solution as a function with an input, output, and context. This modeling may allow a library of AI functions to be navigated by an artificial system of cognition such as the model of Artificial General Intelligence (AGI) recently defined [10].

**General Problem Solving Ability in the Functional Modeling Framework**

The FMF [9] represents the mind as navigating a functional state space in which each concept is considered to be localized in a field of concepts that exists at a point in some space. Because it is a space filled with concepts, the framework refers to it as a "conceptual space".

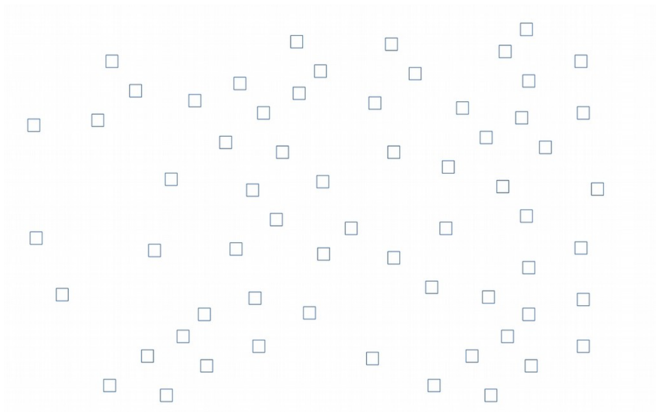


*Figure 1: The conceptual space as one of other perceptual spaces (visual and other sensory spaces, as well as emotional and awareness space).*

From this point of view any reasoning process requiring multiple concepts as inputs and producing multiple concepts as outputs is a path mapping one point in the conceptual space to another. A problem is then the lack of such a path.

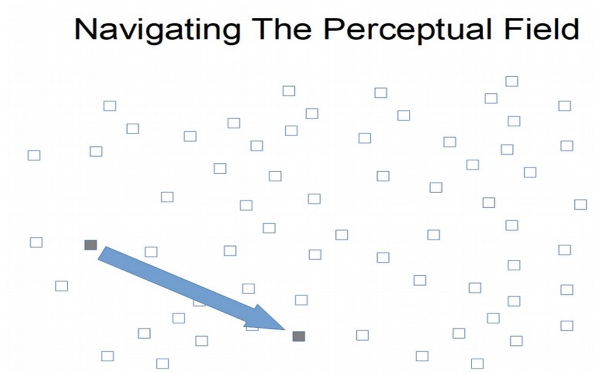



*Figure 2: Lack of a path (blue arrow) from one point in conceptual space to another defines a "problem".*

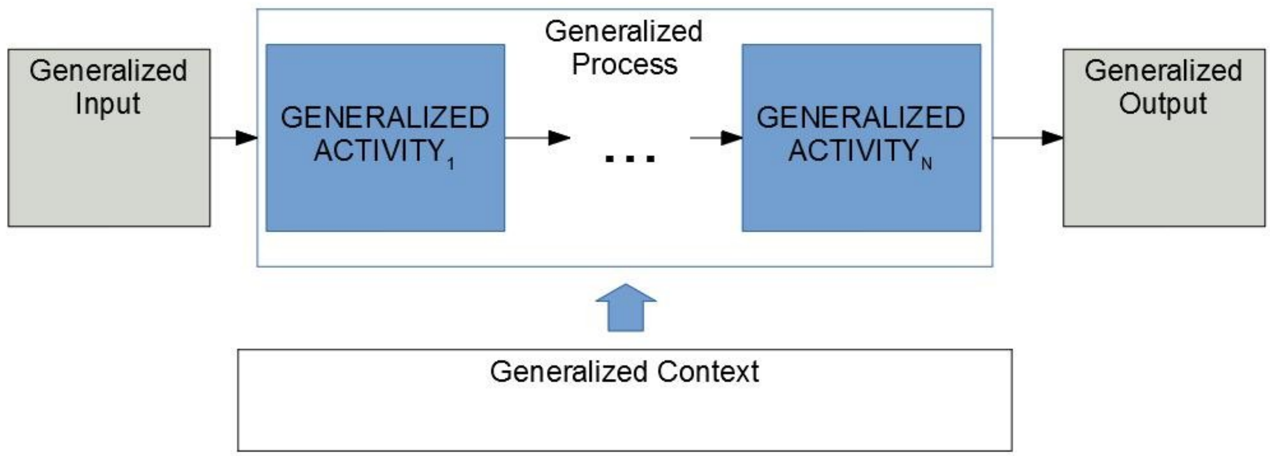
General problem solving ability from this perspective becomes a sequence of reasoning through which the mind can sustainably navigate the conceptual space in a way that potentially enables it to navigate from any concept to any other concept, that is, which gives the mind the ability to potentially solve any problem it can conceive of. In the model of AGI defined within the FMF, this stability is achieved by using the Lorentz equations to find the optimal problem to solve, so this library of problem solving functions can potentially be used to gain general problem solving ability [10],[14],[15].

**Defining a Library of Processes and Functions**

In order to be useful in this navigation, a library of cognitive processes and functions must define their input as a set of points representing a unique position in this cognitive space, and must define their output as a set of points representing a unique position in this cognitive space. For the AI algorithms in this library, the sets of input and output concepts belonging to each functional model of an AI algorithm must be sufficient to specify each AI algorithm as solving a specific problem, so the library forms a database of solutions. However, the usefulness of such a database is not just in being able to identify a specific AI algorithm as solving a specific problem. The usefulness also comes in being able to generalize other solutions so that they apply to the same problem, and being able to recognize sets of solutions that belong to the same problem so their problem solving fitness can be compared.

**Functional Modeling and Generalization**

Functional models can be generalized by modifying the activities so they apply to more general categories of inputs and outputs. This generalization itself is not a uniform, one-dimensional process. Some inputs, some outputs, some aspects of the context, or even some activities may be generalized in any given instance of a generalized process. Generalization along one of these dimensions may result in the function being more general in that more instances of that function are contained within that generalization group. Generalization is then from this perspective a multi-dimensional function with a specific input and a specific output that maps to a specific generalization group.




From the perspective of generalization, the sets of generalized input and output concepts belonging to each functional model of an AI solution can also specify that solution in such a database. A given AI solution may then potentially be represented by several sets of such “keys”.

**Further Thoughts**

Solutions currently on the market already provide access to a library of ML models, in one case through a marketplace that funds contests for the best ML model for a set of training data. However, a library of ML models that might be used by an AGI to increase it's general problem solving ability differs in some key ways. One is firstly not assuming the solution will be an ML model rather than some procedural process. Another is defining fitness in achieving outcomes in a way that is not dependent on specific training data, but is instead dependent on the meaning of data, and the domains formed by that meaning, so that relative fitness can be assessed for any training data within the given domain. For example, if an ML algorithm is intended to recognize faces, rather than comparing fitness of algorithms on data set X, in a human-centric approach algorithms might be compared by their performance on “rainy days” (i.e. using any "rainy day" data sets). A critical part of such a library is then a system for storing information about which function is optimal in each semantic domain [7]. Another difference is that human-centric functional models are semantic models. Defining a library of semantic models of AI solutions creates the possibility of algorithmically searching the library for AI algorithms targeting a given problem, using human-centric definitions that can’t be hijacked to serve the agenda of any service provider.

Many other potential advantages exist. For example, a number of companies are working to create open or decentralized solutions, not only in the field of AI, but in other areas as well. This functional model of cognition is proposed to be independent of implementation, and therefore may be equally applicable to both AGI, and to a General Collective Intelligence (GCI)  that improves general problem solving ability of groups, and therefore increases the probability of achieving impact on any problem targeted by the group, increases the potential magnitude of that impact, and helps make that impact reliably sustainable. For this reason, using this human-centric functional modeling approach to align research in AGI so that it reliably converges on implementing the functional components required for a working AGI, can potentially enable those components to be reused in a GCI that may in turn enable collective impact on goals such as decentralization of AI, or openness of AI, to be significantly increased.

As one example, decentralized AI solutions aim to combat the centralization that results in an ever-increasing accumulation of power and influence being concentrated in fewer and fewer hands. It also results in invisible bias that can't easily be combated. Decentralized AI providers aim to decentralize access to machine learning models, training data, and other aspects of the AI training and execution process. The decentralized data collection or distribution that might be targeted by such solutions is a fundamental part of GCI. Because this data collection is used for a much wider variety of purposes, the data collection functionality required in a GCI is again much more powerful.

As another example, open AI solutions aim to combat the safety risk that comes with closed and proprietary AI technology from a few big players being used in more and more critical applications in an ever increasing number of industries. This openness is also a fundamental part of GCI. In addition, game theory models [11] suggest that the principles of decentralized cooperation incorporated into GCI are critical to achieve AI safety. In terms of openness, rather than stick to a single model of technology sharing driven by a given ideology regarding what openness means, a GCI is ideology free. Instead it defines a functional objective for openness, namely that the benefits of sharing are maximized and are maximally sustainable in any given context. The GCI then incorporates any model of open sharing that maximizes the fitness of sharing in any given context, and uses this open sharing to create potentially unbeatable competitive advantage for participants in the group that cooperates in this way [11]. This competitive advantage potentially creates the capacity to reliably achieve pervasive openness where so far it has not yet proved achievable.

As a final example, decentralized applications aim to avoid any single point of failure by distributing execution over many users on a decentralized network with trustless protocols. Decentralized process execution is a fundamental part of GCI. The principles of decentralized cooperation in a GCI require all participating users to interact directly with the assistance of a private repository of applications, data, and identities belonging to the user, and within that user's sole control. Or alternatively users may interact via an agent within the users sole control, where the user has provided that agent with some access to their private repository. Because this functionality is used to achieve decentralization for a much wider variety of purposes, the decentralization functionality required in a GCI is much more powerful. The GCI can then use this decentralization to maximize outcomes for participants in the group that cooperates in this way. The value in cooperating to significantly increase collective outcomes can again potentially create an unbeatable competitive advantage for the cooperating group [11]. This competitive advantage creates the potential capacity to reliably achieve pervasive decentralization where so far it has not yet proved achievable. Since software merely automates processes, leveraging the decentralization functionality of this GCI model involves defining a functional model of the process by which decentralized execution of any process is achieved, identifying the functional components required to implement that model, and matching those functional components with those required by a GCI. Having determined where functionality already built or being built by service providers with similar goals, then providing that functionality to a funded project building a GCI for widespread deployment can not only potentially provide additional funding to those services providers, but also provide a larger market for deployment.

GCI defines several layers of decentralization this paper suggests are not found together otherwise, and therefore not present together in any current software products. Without all of these layers, game theory modeling [11] suggests that centralization will always tend to align solutions with the interests of a subset of decision-makers, rather than with maximizing impact on any collective problem. GCI requires a comprehensive set of decentralization features that for these reasons have the potential to achieve far greater impact on the goals of openness and decentralization. Rather than spending more effort to build a standalone openness or decentralization solution that is less functional, it makes sense to spend far less effort building a component of a far more functional solution, and then sharing any benefits arising from that solution.

A number of tasks remain in implementing these functional components. While they may not be initially required for a library of AI models that treats the models as black boxes, they will eventually be needed in order to have the capacity to represent all the constructs used in reasoning, and therefore that are used in all artifacts of reasoning such as any natural language text or speech. The requirements for these components, including the model for the conceptual space, and the requirements for other components of the FMF, must be elaborated and used to define implementations of those components that are validated through experimentation [8].

A set of Large Scale international Collaborative REsearch (LSCORE) initiatives are currently being conceptualized to do this, leveraging this human-centric functional modeling approach with the goal of permitting large scale collaboration to reliably converge on working models of human, artificial, and collective cognition (general collective intelligence), where such collaboration has not proved possible before. The FMF is intended to enable each LSCORE initiative to implement part of the total required set of components and to use them in either modeling the solutions (LSCORE-CI, and LSCORE-HACC),or modeling the problems (LSCORE-CI4SI&SD), so that together they form a semantic model of the problem space, and library of reasoning functions in a cognitive system capable of using general problem solving ability to navigate that problem space. Aligning cooperation between initiatives in this way may help ensure the research of any individual participant is relevant to a much larger set of problems, and therefore stakeholders.

- LSCORE-CI (Collective Intelligence)
- LSCORE-HACC (Human and Artificial Consciousness and Cognition)
- LSCORE-CI4SI&SD (Collective Intelligence for Social Impact and Sustainable Development)

The pre-planning phases of these proposed initiatives are intended to validate the framework and other assumptions on which the project is based. The planning phases of the proposed LSCORE initiatives are intended to elaborate those requirements. The implementation phases are intended to orchestrate large scale collaboration between the initiatives to implement them.

**Conclusions**

The term functional modeling has been taken to have different meanings in different contexts. In this context of defining reasoning functions in the conceptual space, functional modeling defines functions in terms of operations within a given context that act on input concepts to produce output concepts. Here the inputs, outputs, and contexts are also defined in terms of concepts. This simple approach to functional modeling is nevertheless extremely powerful in that it potentially enables all problem definitions to be combined into representation of the world as a single problem space that can be navigated by a cognitive system. And it is powerful in that it potentially enables all reasoning processes to be combined into a library of solutions that can be used to navigate that problem space.

**References**


[1] B. CHANDRASEKARAN, Representing function: Relating functional representation and functional modeling research streams, Artificial Intelligence for Engineering Design, Analysis and Manufacturing 2005, 19, 65–74, DOI: 10.10170S0890060405050079

[2] Eisenbart, B., Gericke, K., & Blessing, L. (2013). An analysis of functional modeling approaches across disciplines. Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 27(3), 281-289. doi:10.1017/S0890060413000280

[3] Zhengrong Cheng, Yongsheng Ma, A functional feature modeling method, Advanced Engineering Informatics, Volume 33, 2017, Pages 1-15, ISSN 1474-0346, https://doi.org/10.1016/j.aei.2017.04.003.

[4] Gabriel Axel Montes, Ben Goertzel, Distributed, decentralized, and democratized artificial intelligence, Technological Forecasting and Social Change, Volume 141, 2019, Pages 354-358, ISSN 0040-1625, https://doi.org/10.1016/j.techfore.2018.11.010. (http://www.sciencedirect.com/science/article/pii/S0040162518302920)

[5] Castelvecchi, D. Can we open the black box of AI?. Nature 538, 20–23 (2016) doi:10.1038/538020a

[6] S. Raval, Decentralized Applications: Harnessing Bitcoin's Blockchain Technology, Newton, MA, USA:O'Reilly Media, Aug. 2016.

[7] Andy E. Williams, Defining Optimal Domains for each Algorithm in a Library of Artificial Intelligence or Collective Intelligence Algorithms, working paper

[8] Andy E. Williams, Required Components for Implementing Models of Individual or Collective Cognition within the Functional Modeling Framework, working paper

[9] Williams, A. E. (2020, April 16). A Human-Centric Functional Modeling Framework for Defining and Comparing Models of Consciousness and Cognition. https://doi.org/10.31234/osf.io/94gw3

[10] Williams, A. E. (2020, April 20). A Model for Artificial General Intelligence. https://doi.org/10.31730/osf.io/xtq2v

[11] Andy E. Williams, The Principles Enabling Cooperation within Conscious Organisms and Collectives, working paper.

[12] Andy E. Williams, The eXtensible Domain Modeling Framework, working paper.

[13] Andy E. Williams, Model for Human, Artificial & Collective Consciousness (Part I), Journal of Consciousness Exploration & Research, Vol 10, No 4 (2019), pages 250-269

[14] Andy E. Williams, Model for Human, Artificial & Collective Consciousness (Part II), Journal of Consciousness Exploration & Research, Vol 10, No 4 (2019), pages 270-293

[15] Andy E. Williams, The Need for General Collective Intelligence in Addressing the Sustainable Development Goals, DOI:10.21203/rs.3.rs-18022/v1.