A Decentralized Representation of Semantic Information

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Abstract
This study introduces a network consisting of reversible functions that spans a conceptual space, which is proposed to provide a comprehensive semantic representation of information. This conceptual space is proposed to be a functional state space capable of describing any observable functionality or functional state in the cognitive domain, and therefore is proposed to be capable of representing any concept or any observable cognitive processes such as actively directed reasoning or passively directed understanding. This conceptual space is used to present the basic elements of an algorithm that models cognition as moving through the network of this functional state space with a pattern of dynamical stability through an associated "fitness space". Through this work, we aim to advance our understanding of cognitive processes and provide a novel framework for representing the dynamics of cognition and for comparing different cognitive models

Introduction
The emerging technique of Human-Centric Functional Modeling or HCFM (Williams, 2021b) attempts to model the behavior of functional systems such as the human cognitive system in a way that is verifiable within each individual's first person observation of their own human system, in the case of the cognitive system through observation of their cognitive system (mind). The distinction between functional systems and physiological or other systems is an important one. Any individual can observe the function of their mind as a functional system, but it is far more difficult for an individual to observe the physiological processes in their own brain as a physiological system.

This approach of trying to essentially define a coordinate system capable of characterizing the entire domain to which the functionality of any given functional system might be confined was originated with the aim of providing a comprehensive framework capable of describing any possible function of any human system, and making it possible to derive profound insights about those systems and their interactions, without making any assumptions about what those functions were, and without having any understanding whatsoever about how they are implemented. HCFM was designed to abstract away any functional elements that could potentially be found to be inconsistent with observations and therefore incorrect and/or incomplete, so they could always be replaced with more correct and/or complete ones. From this perspective, HCFM could not be wrong because like a coordinate system it made no claims. Just like an incorrect map of an island made in some coordinate system might be replaced with a better map, any functional element represented in HCFM ever found to be incorrect could simply be replaced with a better one.

Functional elements for modeling specific human functional systems like cognition or consciousness that were at the inception of HCMF held as separate and referred to as the Functional Modeling Framework (FMF) for cognition, and the FMF for consciousness. These were over time simply referred to as part of HCFM for simplicity, and include the functions of cognition referred to later in this paper. However, its important to remember that HCFM is just meant to be a way of summarizing all observed functionality. These functions and any other element of HCMF are meant to be replaced whenever required to be more consistent with observations. To distinguish descriptions of functionality identified in one individual's description of some system using HCFM, as being different from another individual's description of that system using HCMF, it is useful to reintroduce the idea of an FMF for that system. Referring again to the metaphor of a coordinate system, just as one might refer to individual A's map of a given geography within that coordinate system, as opposed to individual B's map of that same geography, one might also refer to individual A or B's FMF for that system to describe the set of functions into which each of them has decomposed that system. For example, Williams' FMF for the cognitive system (2023) might be replaced by Smith's FMF for the cognitive system (2024).

HCFM models processes in the human organism, from unconscious processes such as homeostasis, or cellular reproduction (autopoeisis), to conscious processes such as sensations, emotions, cognition, and awareness, as each moving the human system (e.g. the cognitive system) that the process exists in through a separate "functional state space". Each of these systems have their own internal dynamics while also being able to interact with external systems in some cases, for example, in addition to having its own independent dynamics that allow it to move within its functional state space, in HCFM the cognitive system is also a tool that can be directed by the consciousness system.

HCFM hypothesizes that any possible behavior of any human system can be represented within the "functional state space" defined for that system. That is, any human system in a given domain of functionality can be represented as moving through a space containing a graph of functional states that is described as a "functional state space". This graph is a network in that each functional state is a node, and in that the edges connecting the nodes are the processes through which one functional state can transition to another.

This functional state space can describe any possible behavior of the system if it has specific mathematical properties. Viewing this concept through the lens of "group actions" in algebra and, more specifically, the concept of "generators" and "relations" in group theory, a "group" is a set of elements together with an operation that combines any two of its elements to form a third element satisfying four conditions called the group axioms, namely closure, associativity, identity, and invertibility. Each node in the network representing a functional state is an element in the group, and each edge (or operation) is a transformation that can move the state of the system from one element to another. The "generators" of the group are a subset of elements (or edges/operations) that can be used to reach every other element in the group through some sequence of operations. If the operations are reversible, this corresponds to the group being "abelian" (or "commutative"), meaning the order of operations doesn't affect the final outcome.

A set of operations spans a network (i.e., forms a generating set for the group corresponding to the network) if and only if any node can be reached from any other node through a sequence of these operations. This concept corresponds to the mathematical property of "transitivity". A group action is said to be transitive if, given any two nodes in the network, there is some sequence of operations that transforms one into the other. If a basic set of reversible operations spans a network, it can be said that these operations form a generating set for a group that acts transitively on the network and as a result, if the edges that network represent the functional behavior of a system, that network is then capable of describing any possible behavior of the system.

But if the functionality of one biological system in an organism somehow is described by a functional state space that is spanned by a reversible set of operations, why should any other system in that organism do so? According to ChatGPT4, and confirmed by the references cited, it is well-known among biologists and geneticists that living systems reuse functional elements across different biological systems. This reuse, which is particularly relevant in the study of evolution and development (evo-devo), systems biology, molecular biology, and genetics, might not be widely recognized outside of these fields because there is no single term or principle that encapsulates this phenomenon (Alberts et al.). Instead, according to ChatGPT4 there are a number of related concepts and principles that help explain it:

- **Conserved function and evolution:** In biology, the term "conserved" is often used to describe components that remain unchanged across different species over time due to evolutionary pressures. This is an underlying concept behind the phenomenon of reuse of functionality, because a basic function or mechanism that works well can be conserved and reused in different systems or contexts (Alberts et al.).
- **Pleiotropy:** In this phenomenon one gene influences multiple, seemingly unrelated phenotypic traits. For example, the gene responsible for the protein 'Sonic Hedgehog' (SHH) plays crucial roles in the development of many different organs and structures (Pierce).
- **Gene duplication:** This refers to the creation of one or more copies of a gene in the genome. After duplication, one copy can continue to perform its original function, while the other evolves new functionality, potentially becoming useful in a different system (Innan and Kondrashov).
- **Exaptation:** This concept describes a situation where a trait evolves for one purpose and later gets co-opted for a different purpose. For example, feathers may have originally evolved for insulation, but later became useful for flight (Gould and Vrba).
- **Modularity:** In systems biology, this principle refers to the concept that biological systems can be broken down into smaller, interconnected modules, which can function independently but also interact to create the overall function of the organism. Modules can be genes, proteins, or even entire physiological systems (Hartwell et al.).

Because of this observed reuse, which might be called the “functional reuse principle”, a key element of the utility of these hypothetical functional state spaces is that they potentially allow this reuse to be represented in terms of copying all or part of the Functional Modeling Framework or FMF describing one system, and applying it to another system.

As an example, according to the Functional Modeling Framework or FMF for cognition, any possible observable behavior of the cognitive system can be represented as a composition of a set of reversible operations spanning the domain of cognitive functionality. The existence of a set of reversible operations spanning the functional state space of a system was first hypothesized as a result of analysis of the sensory-motor system (body). Due to this principle of reuse, any FMF for any other system is also hypothesized to be “spanned” in this way by some set of reversible operations.

For any system, this functional state space hypothesized to describe its behavior is dimensionless and scale-free in the sense that the notation describing the functional state space has no units of measure so the same basic framework can be applied at different scales, and that the framework abstracts away from specific details of implementation. In the case of the cognitive system, HCFM models human cognition as a process capable of navigating a single space of concepts, or a "conceptual space" (the functional state space of the cognitive system).

Human-Centric Functional Modeling of Cognition

Define a "conceptual space" to be a graph containing a network of concepts and cognitive processes (which for simplicity we will call reasoning at this stage), where each distinct concept is located at a different vertex in the graph, where that graph contains a network of concepts and reasoning in which the nodes are concepts and the edges are reasoning processes. According to ChatGPT4 Gärdenfors (2000) proposed the idea of conceptual spaces as a framework to understand cognitive processes.

Assume that any concept can be defined by some set of reasoning processes. According to ChatGPT4 Fodor (1998) supports this by arguing that concepts are determined by certain reasoning processes. Assume this conceptual space has the capacity to represent any reasoning processes which define any concept "A" through representing that reasoning in terms of paths through conceptual space which connect to other concepts. According to ChatGPT4 this is in line with Gärdenfors & Zenker (2013). Under this assumption we can assume that the conceptual space can represent any reasoning process defining a concept. If so, then conceptual space then has the capacity to provide a complete representation of the meaning of that concept, and therefore has the capacity to provide a complete "semantic representation" of the meaning of any concept in the graph. According to ChatGPT4 Smith (2019) asserts that a well-structured conceptual space can provide a complete semantic representation of the concepts contained within it.

Assume this conceptual space also has the capacity to represent any concepts "A" and "B" which together define some reasoning process "P" that connects them. According to ChatGPT4 Borsboom (2008) argues that in a conceptual space, concepts and the reasoning process connecting them can be represented. In this conceptual space these concepts are represented in terms of nodes in conceptual space that in turn are defined through reasoning that connect them to other concepts. According to ChatGPT4 Halford, Wilson & Phillips (2010) provides support for the representation of concepts as nodes in a conceptual space that are connected through reasoning processes.

If this conceptual space has the capacity to provide a complete representation of the meaning of any reasoning, this conceptual space is then a complete "semantic representation" of the meaning of any reasoning in the graph. According to ChatGPT4 Barsalou (1999) suggests that a conceptual space can provide a comprehensive semantic representation if it captures the meaning of all reasoning processes in the graph.

It's important to distinguish the idea of a complete semantic representation of concepts and reasoning from a complete semantic model. A complete semantic representation of concepts and concepts and reasoning is defined here as having the capacity to represent any possible meaning of any concepts and reasoning. But any given semantic model created within that representation might exclude some meanings. So at the same time that a semantic representation can be complete, any semantic model can (and potentially must) be incomplete. According to ChatGPT4 Churchland (1989) reminds us of the difference between a complete semantic representation and a complete semantic model, highlighting that while a representation can be complete, a model might necessarily exclude some meanings.

It's important to note that each individual human has their own graph of conceptual space, allowing semantic meanings to vary across individuals, cultures, or languages. According to ChatGPT4 this is consistent with Boroditsky (2001), according to whom each individual has a unique graph of conceptual space, which allows for diversity in semantic meanings.

Furthermore, as described later in this article the concepts surrounding a concept involved in reasoning form the "context" of that reasoning, and in this model the cognitive system can include or exclude concepts from that context, thereby allowing reasoning to be context dependent in this model. According to ChatGPT4 Sperber & Wilson (1995) provide the notion of reasoning being context-dependent, facilitated by the inclusion or exclusion of surrounding concepts within a cognitive model.

It's also important to note that claiming that this conceptual space has the potential to capture any possible observable behavior of the cognitive system does not require concepts to be completely defined by logical reasoning processes. According to ChatGPT4 Damasio (1994) argues that the potential of a conceptual space to capture any possible observable behavior of a cognitive system does not necessitate that all concepts are strictly defined by logical reasoning processes.

As described later in this article, concepts might be primarily experiential or emotive, rather than purely rational or logical. For instance, defining the concept of "love" is represented as involving the cognitive system interacting with emotions through the emotional system, with personal experiences through the consciousness system, and more. According to ChatGPT4 Lakoff & Johnson (1980) support this notion by illustrating how concepts can be experiential or emotive, such as the concept of "love" being defined by a combination of emotional and personal experiential interactions.

Furthermore, the edges in the network of this conceptual space are not limited to logical (type II or system II) reasoning processes. Instead the edges can also represent intuitive (type I or system I) reasoning as well as additional cognitive processes. According to ChatGPT4 Evans (2008) asserts that the relationships in a conceptual space can represent a variety of cognitive processes, not just type II (or system II) logical reasoning, but also type I (or system I) intuitive reasoning.

So the statement that this conceptual space has the potential to capture any possible observable behavior of the cognitive system does not require any such behavior to be fully representable in a graph of logical reasoning processes. According to ChatGPT4 Stanovich (1999) suggests that the ability of a conceptual space to encapsulate any possible observable behavior doesn't necessarily require that all behaviors are representable through a graph of logical reasoning processes.

Finally, its important to note that this functional model of cognition only defines the functional domain of cognition (the domain of behaviors the cognitive system is confined to from a functional perspective) and how that domain of cognition interacts with other functional domains such as that of the emotional system, or that of the consciousness system. According to ChatGPT4 Fodor (2000) emphasizes that a functional model of cognition only outlines the scope of behaviors from a functional perspective and delineates how it interacts with other domains like the emotional or consciousness systems.

In the same way that defining the range of motion of the human hand does not require defining all of the motions that a human hand can engage in, and defining the range of motion of the human hand does not require defining the range of motion of the entire human body, defining the conceptual space does not entail capturing the full spectrum of human cognition, experience, and semantic understanding, which is a formidable challenge. According to ChatGPT4, Chalmers (1996) elucidates that just like defining the range of motion of a hand doesn't necessitate defining all possible movements or the movements of the whole body, defining a conceptual space doesn't mean capturing the entirety of human cognition and experience.

The complexities of human cognition are predicted to exceed the model of any individual human's conceptual space, but this conceptual space representation approach, combined with the functional state spaces representation approaches defined within HCFM to capture the behavior of every other human system, and the possible interactions between these representation approaches, are hypothesized within HCFM to bring the complexity of human cognition within the collective representational capacity of these functional state spaces. According to ChatGPT4 Halford et al. (2014) explain that while the intricacies of human cognition may exceed any individual's conceptual space, the collective use of various representational approaches (such as the ones in HCFM) may have the potential to encompass the complexity of human cognition.

This hypothesis remains to be tested and evaluated. According to ChatGPT4 Clark (2013) indicates the need for empirical validation of this hypothesis that comprehensive representational approaches can capture the complexity of human cognition, and emphasizes the continuous need for further research and testing of any hypothese and theories within cognitive science.

The distance between concepts in this conceptual space is hypothesized to be a “semantic distance” in that more closely related concepts, as determined by the number of relationships they share with other concepts, are closer together. According to ChatGPT4 the assertion that semantic distance is represented as the physical distance between concepts in the conceptual space is supported by research, and semantic models often use this distance or similarity measure to depict relationships between concepts. For instance, studies like Mikolov et al., 2013, use semantic space to depict words in natural language processing, where the distance between words represents semantic similarity. However, it has not yet been determined whether multiple instances of the same concept are necessary within such a model.

In HCFM, the functional state space of the cognitive system (mind) is represented as being a “conceptual space” capable of representing any possible concepts or reasoning processes. According to ChatGPT4, the representation of the cognitive system's functional state space as a conceptual space capable of representing possible concepts and reasoning processes aligns with several cognitive models. The cognitive architecture ACT-R (Anderson et al., 2004), for example, provides a computational model of cognition using similar constructs.

Since there are hypothesized to be four operations that span the conceptual space in that it is hypothesized that any reasoning process required to transition the cognitive system from one concept to another can be represented as a composition of four operations, the network of this conceptual space is hypothesized to be four dimensional. According to ChatGPT4, the claim of a four-dimensional network with four operations to navigate the conceptual space is potentially novel and therefore requires empirical validation, however the concept of having 'dimensions' to represent cognitive processes has been used in psychology, notably in the work of Kahneman (2011), who describes two distinct cognitive processes (type I and type II reasoning), although not precisely in this context.

The human mind is not only complex but also dynamically influenced by external factors such as social interaction and culture, which at first glance might not be adequately captured in a framework such as HCFM, but all other systems (such as the emotional system) and the interactions between them are also represented within this framework.

It’s also important to note that concepts and/or reasoning are not the only behavior of the cognitive system in this model. However, though there are hypothesized to be additional cognitive processes outside this functional state space they are not necessarily directly observable, a functional state space capable of representing any concepts and/or reasoning is potentially sufficient to allow functional models to be deduced for the observable properties of cognition.

One property of conceptual space that is potentially observable in that it aligns with our understanding of the human capacity for creativity and innovation, is that it is hypothesized to be open (unbounded). If properties of any concept or reasoning like “complexity” also have objective definitions in this mathematical construct, this would allow them to potentially be quantified, which in turn might allow these definitions to be empirically validated. For example, in HCFM the complexity of a concept is hypothesized to be the product of the volume and density of conceptual space it occupies. The complexity of reasoning is hypothesized to be the product of the length of the reasoning path in conceptual space and the linear density of concepts in that path. The intelligence of the cognitive system is hypothesized to be the product of the volume and density of conceptual space that it can navigate per unit time to find a solution to any problem. HCFM represents the human cognitive system (mind) as navigating through conceptual space with differing levels of precision (resolution in conceptual space), with differing levels of intelligence (volume and density of conceptual space that can be navigated per unit time).

General problem-solving ability requires the capacity to navigate the collective conceptual space with both type I and type II collective reasoning processes. Type I processes represent intuitive reasoning used to solve uncomputable problems using patterns of past solutions, while type II processes solve computable problems through intermediate logical steps (figure 1).

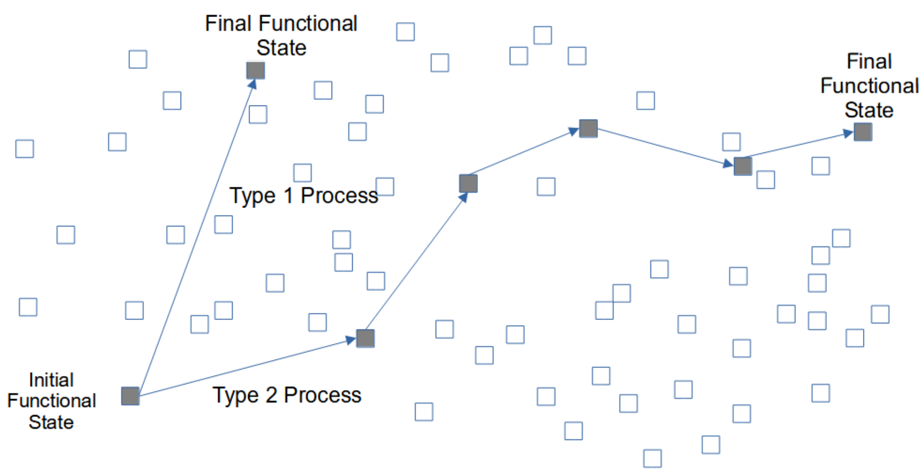

Figure 1: *Type I and type II processes in functional state space.*

According to ChatGPT4 the use of Type I (intuitive) and Type II (deliberative) cognitive processes aligns with established cognitive theories such as dual process theory (Kahneman, 2011)

Concepts in this generalized human-centric conceptual space are physically distributed across a three dimensional space. In this space each concept is separated from others by a semantic distance that indicates their similarity.

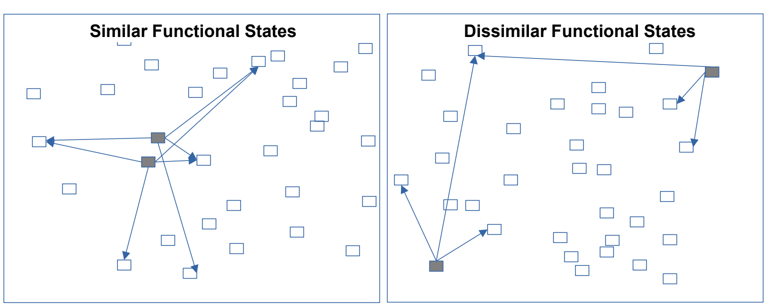

Figure 2: *Depiction of semantic distance. (Left) similar functional states separated by a small semantic distance. (Right) dissimilar functional states separated by a large semantic distance.*

The exact process through which the position, radius, and semantic distance between each concept in conceptual space is determined through trial and error beginning with the simplest possible initial assumptions. One initial assumption is each concept has a unit radius and is separated by a unit distance by each direct reasoning function. Once the first concept is created in conceptual space, this assumption allows the second concept to be one unit away in any direction around the first concept. Once the third concept is added, then if the second and third concept are connected to the first, but are not connected to each other and do not overlap, that allows the second and third concepts to be in a slightly more constrained number of positions. Each concept that is added to the conceptual space in this way shapes the conceptual space in a way that is predicted to be non-deterministic.

Another assumption is that when a concept is a generalization that contains N concepts that do not overlap, then that concept has radius N. Yet another assumption is that a concept with N relationships to other concepts will 1/N of the radius of a concept with 1 relationship to another concept. The exception to this rule is a generalization, which will be at least as large as the concepts it contains.

As mentioned, the network of reasoning processes through which one concept is connected to another is hypothesized to be four dimensional (spanned by four operations as described in table 1). In other words, Human-Centric Functional Modeling posits that all thought can be decomposed into these four operations. If these operations allow for the generation of all possible thought then all of the conceptual space can potentially be navigated.

According to ChatGPT4, the idea that a cognitive system can potentially generate all forms of thought is an ambitious claim, but the idea that the human cognitive system does so is a claim that broadly aligns with several theoretical perspectives in cognitive science and philosophy. These perspectives focus on the generative capabilities of the human mind, i.e., its ability to create a limitless range of thoughts, concepts, and ideas.

- **Cognitive Flexibility:** The human cognitive system is highly flexible, able to adapt and create new concepts and strategies when facing novel situations. This is evident in our ability to innovate, imagine hypothetical scenarios, and creatively solve problems (1).
- **Symbolic Systems:** Humans are capable of symbolic thought, which allows for the creation and manipulation of a vast array of mental representations. Language is one of the most profound examples of this. Noam Chomsky, a prominent linguist, postulated the concept of "generative grammar", which implies that a finite set of grammatical rules can produce an infinite number of sentences (2).
- **Combinatorial Cognitive Processes:** Cognitive processes are thought to be combinatorial in nature. We can combine a finite set of elements (like symbols, concepts, ideas, sensory impressions, etc.) in an infinite number of ways to produce new thoughts, concepts, and experiences (3).
- Recursive Mental Operations: Human cognition has been hypothesized to be recursive. This means we can apply mental operations to their own output, leading to an unbounded potential for thought generation. This idea was central to Douglas Hofstadter's work in "Gödel, Escher, Bach" (4).

However, proving that any specific cognitive model, like HCFM, can account for all possible human thought is a substantial empirical challenge as supported by ChatGPT4 which asserts this is generally accepted in cognitive science and is consistent with the view that mental processes are complex and potentially involve interactions among multiple cognitive systems (Newell, A. (1990). Firstly, operationalizing "all possible thought" is problematic, as it is a vast and potentially unbounded space, according to ChatGPT this is related to the philosophical problem of "qualia," or subjective conscious experiences, namely that it's difficult to objectively measure or categorize all possible thoughts, feelings, or experiences a person might have (Chalmers, D. (1995).

Secondly, testing such a hypothesis would require diverse and exhaustive experimental tasks that cover every domain of cognition, a task that is practically unfeasible. Fortunately, it is also a task that is not necessary to accomplish the goals of HCFM, which are to provide a framework that can be broadly utilized to compare, explore, and elaborate models of cognition where they have not been completely comparable before. This goal is important as according to ChatGPT4, the idea that cognitive models can provide a framework for comparing, exploring, and elaborating on cognitive processes is a central goal of cognitive science (Marr, D. (1982).

Humans have the capacity to use intuitive reasoning where the information, reasoning, or other elements required to assess a claim using logical reasoning do not exist. According to ChatGPT4, the use of intuitive reasoning is well-documented in cognitive psychology and decision-making research, and the dual-process theory of reasoning posits that people use both intuitive (fast, automatic) and analytical (slow, deliberate) thinking processes, depending on the situation (Kahneman, D. (2011). Since intuitive reasoning is often observed to be used in achieving group consensus, this goal only requires sufficient consensus to attract a critical mass of individuals to use the framework, which in turn only requires a sufficient number of examples confirming that reasoning can be decomposed into these four operations, for the majority of individuals to conclude that it is feasible that all reasoning can be decomposed in this way. According to ChatGPT4, this idea of achieving consensus is often used in the social sciences to evaluate the validity and acceptance of theories and frameworks (Kuhn, T. S. (1962).

It’s important to note however that whether or not this particular set of operations proves to be valid, or proves to “span” the entire conceptual space, reasoning can always still be represented in a less abstract and less general way in the graph of functional state space by simply labeling reasoning processes by name. It’s also important to restate that because these operations are not confined to logic, the decomposition of reasoning into specific operations is not confined to computational approaches to cognition, where such approaches attempt to describe cognitive processes in terms of specific computational steps or operations (Fodor, J. A. (1980), but might limit those operations to logic.

In the positive direction along dimensional each of these four dimensions the function representing that dimension takes an input and produces an output. In the negative direction along each dimensional axis each functions takes an output and produces an input. In addition to these four operations that are hypothesized to span the collective conceptual space, there is also hypothesized to be a cognitive awareness function FS that navigates the space with these functions by selecting which of these functions to execute. This cognitive awareness process “reasons” by selecting the next reasoning process to actively execute and “understands” by enabling reasoning to be executed to allow an understanding to be passively received.

Functional Unit	**Positive Direction (Input Function)**	**Negative Direction (Reverse Input Function)**
F1	STORE (Store Concept)	DECOMPOSE STORAGE (Determine Concept in Storage Function)
F2	RECALL (Recall Concept)	DECOMPOSE RECALL (Determine Concept in Recall Function)
F3	DETECT PATTERN (Detect Pattern between Concepts.)	DECOMPOSE PATTERN (Detect Concept in Pattern)

F4	DETECT SEQUENCE (Detect Sequence of Patterns between Concept)	DECOMPOSE SEQUENCE (Detect Concept in Sequence of Patterns)
FS	Cognitive Awareness Function	

Table 1: *The set of operations proposed to span the conceptual space.*

In the first operation a concept (which initially is assumed not to be localized) is stored in some region of conceptual space. In the second operation a concept is retrieved in order to potentially be used in additional reasoning processes. In the third operation a pattern (a type I process) is detected and navigated. In the fourth operation a sequence of patterns (a type II process) is detected and navigated. For these operations to form a valid space, the negative of each operation must return to the same point in that space. Therefore, in the opposite (negative) directions, each operation is reversed to take the output and to produce the input. In the reverse of first operation the concept stored at a given location is determined (output), in reverse of the second operation the concept recalled is determined, in the reverse of the third operation the concept detected in a pattern is determined, and in the reverse of the fourth operation the concept detected in a sequence of patterns is determined. The first three operations don't overlap and it is clear how they might form independent dimensions. The forth operation (execution of a type II reasoning process) is consistent with the way cognition is observed to function in that although a type II process consists of a sequence of type I reasoning processes, these processes occur within an overall sequence. For example, when confronted with chess pieces on a board, the sequence of operations might be chosen by the cognitive system to be consistent with the type II process "playing chess", or it might be chosen to be consistent with the type II process "throwing all the chess pieces from the board". The difference between type I processes and type II processes is that type II processes can be interrupted to be redirected to another region in conceptual space. Type I processes cannot be. The empirical evidence to support this model is that type I (intuitive) reasoning processes can't reliably be redirected to come to another conclusion. For example, the determination that a concept is (racist, sexist, or any other value judgment typically reached with type I reasoning) can't reliably be changed. However, any type II process (a calculation for example), can easily be redirected in a great many ways to navigate to a different concept (to come to a different conclusion). The capacity to redirect type I thought at initiation, and the capacity to redirect type II thought in progress (for example going from playing chess to throwing the chess pieces from the board), potentially allows for the fitness of reasoning in fitness space to be directed to follow patterns that produce stable dynamics.

According to ChatGPT4, the CREATE, RECALL, DETECT SEQUENCE (Type II reasoning), and DETECT PATTERN (Type I reasoning), are consistent with general theories of cognitive operations which identify the foundational processes of cognition, such as forming new mental representations, retrieving stored knowledge, logical reasoning, and pattern recognition.

Interaction of the Cognitive System with Consciousness and Other Systems

In HCFM functional state spaces do not intersect. That is, the functional states of one system with its own functional state space do not occur in the functional state space of another system. Therefore one system does not directly interact with the functional states of another system. This means for example that the emotional states of the emotional system, or the awareness states of the consciousness do not exist within the conceptual space of the cognitive system.

At the same time however, HCFM allows for any level of interaction and coordination as is necessary for complex behavior in the real-world, which often involves the interplay of multiple cognitive processes, including perception, emotion, and motor control. Each functional system is represented as having a set of three functions through which it can interact with field of signals underlying that system. This is easier to understand in the body, which in HCFM is represented as the lowest system (first to evolve) for which the human organism has conscious control. In the body (the sensory-motor system in HCFM), input to the sensory-motor system from the sensory receptors is represented in HCFM as a field of signals that can be parsed with a set of three functions. Similarly, output from the sensory-motor system to the muscle cells is represented as a field of signals that can be generated with a set of three functions (figure 3).

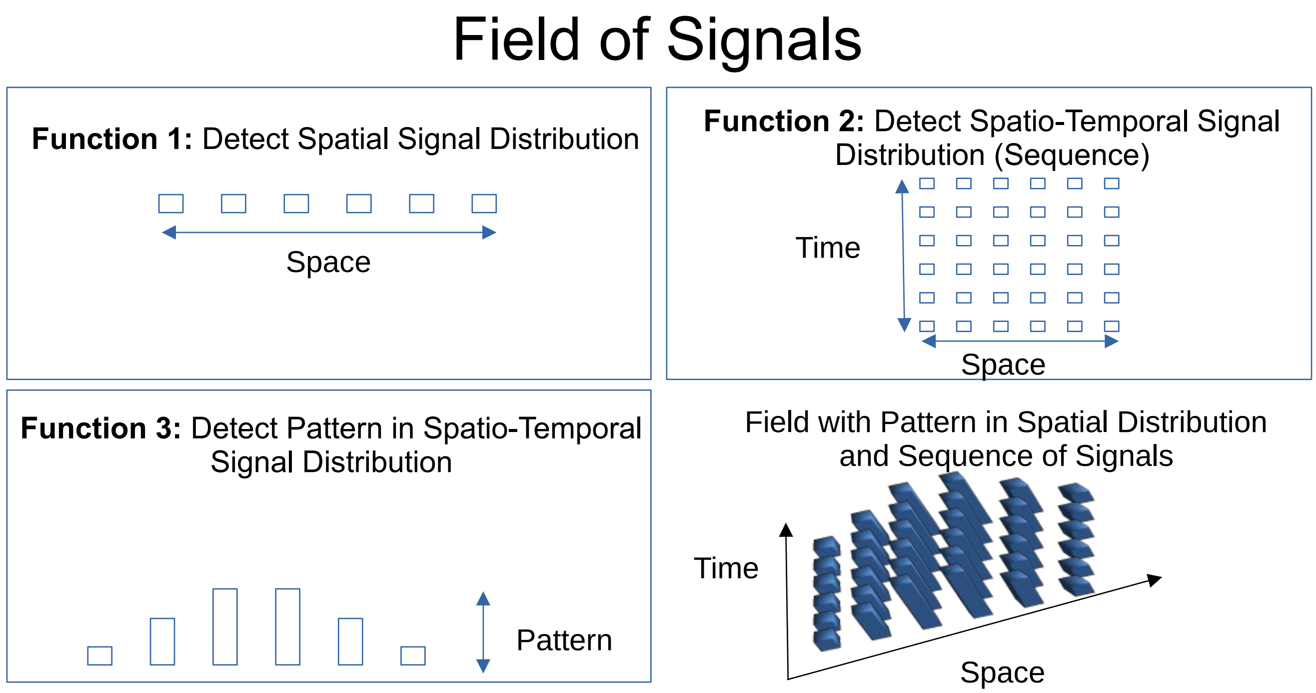

Figure 3: *Using the three functions depicted, any functional state can interact with any signal field represented by signals and a network of interactions with other signals.*

Input to the sensory-motor system is represented as creating a "sensation", where creating a sensation is the lowest function in the sensory-motor system's functional state space. Output from the sensory-motor system is represented as creating signals to the muscles, which is the reverse of the lowest function in the sensory-motor system's functional state space.

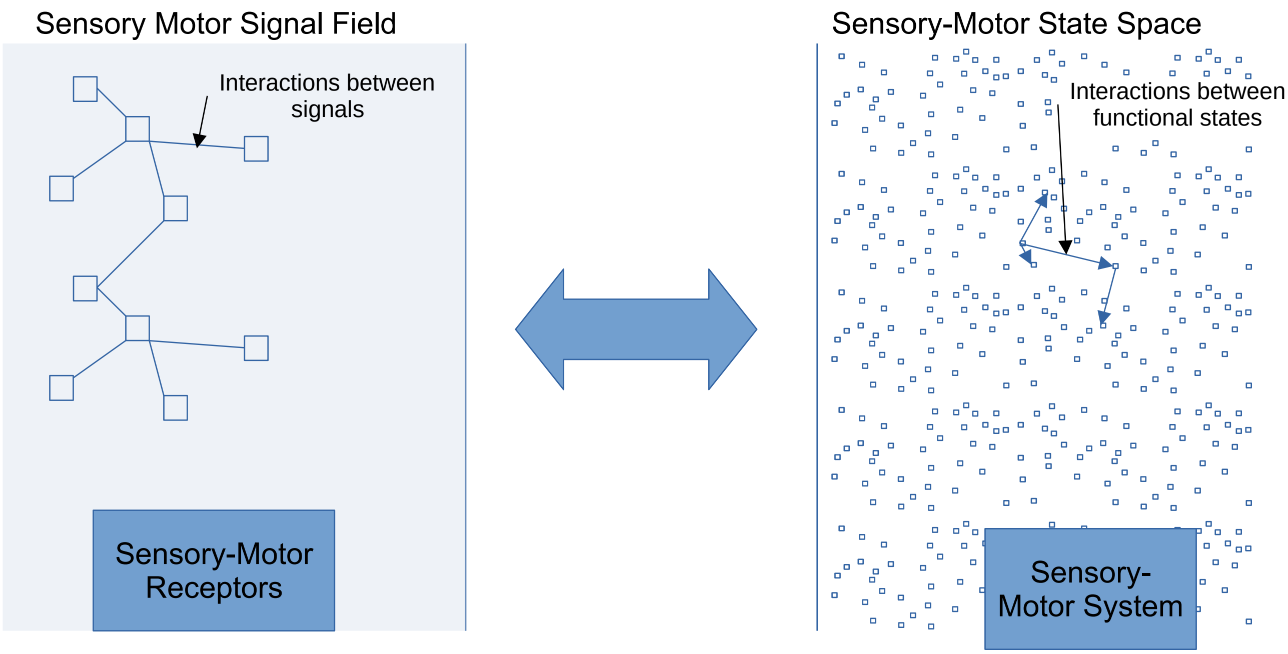

Figure 4: *Field of sensory-motor signals vs sensory motor state space. The sensory-motor system is represented as moving through a sensory-motor state space as it interacts with a field of sensory-motor signals from the sensory and motor receptor cells.*

Though one system cannot directly interact with the functional states of another system, this same set of three functions allows one system to potentially interact with any functional state of another where those two system interact. This is represented as occurring through the first system viewing some subset of that second system's functional state space as a field of signals. As an example, the cognitive system is represented as being able to potentially conceive of any sensation in the body by using those three functions to detect that sensation's surrounding subset of sensory-motor state space (again, the hypothetical functional state space of the body) which defines the sensation. These functions detect that subset of sensations in sensory-motor state space as a field of input signals. Similarly, the cognitive system is also represented as being able to direct the body through outputting a field of signals to the sensory-motor system (to the muscles).

As another example, the consciousness is represented as being able to become aware of any concept by using these three functions to detect the surrounding subset of conceptual space which defines a concept. These functions detect that subset of concepts in conceptual space as a field of input signals. Similarly, the consciousness is also represented as being able to direct cognition through outputting a field of signals to the cognitive system. If any reasoning process can be represented in the conceptual space as a concept, this suggests that such reasoning can be consciously directed. If all conciously observable reasoning can be represented as motion of the cognitive system through conceptual space, and if the consciousness can detect any region of conceptual space, this suggests that all reasoning can passively occur in the conscious awareness (the conscious awareness can be aware of any reasoning). It's important to reiterate that the word "reasoning" here is a shorthand for "observable cognitive processes". Not all cognitive processes are observable and therefore there are some cognitive process the conscious awareness cannot be aware of.

Though both the cognition and the consciousness might interact with the body according to this model, at this point this modeling approach has not been used to gain any insight regarding which aspects of the body might be directed by the consciousness system, and which aspects of the body (if any) might be directed by the cognitive system.

In this model, directing cognition is assumed to occur through function F4 (type II or rational methodical reasoning). Under this assumption, reasoning function F3 (type I or intuitive reasoning) is largely passively directed (directed internally by the cognitive system rather than being directed by the consciousness) and therefore is referred to as an “understanding” process, and reasoning function F4 is largely actively directed by the consciousness and therefore is referred to as active reasoning. All concepts and all the reasoning processes are represented as being within the capacity of the consciousness system to detect. According to ChatGPT4, this delineation between different types of reasoning (Type I or intuitive reasoning and Type II or rational methodical reasoning), suggesting that the former is primarily directed internally by the cognitive system while the latter is actively directed by consciousness, is reminiscent of and potentially consistent with the dual-process theories of reasoning and decision-making (Evans & Stanovich, 2013), which posit the existence of two distinct cognitive systems for intuitive and deliberative thought.

The cognitive awareness function FS is then responsible both for directing navigation through the conceptual space as well as for taking direction from the conscious awareness as to the path it will take through conceptual space. Although, from the perspective of HCFM, reasoning process F4 (and its reverse) are directed by the consciousness according to which is predicted to be most fit, in the simplified algorithm considered in this paper for implementing the cognitive awareness function, a very limited consciousness is implicitly incorporated in that the algorithm allows the navigation of logical processes. This algorithm’s “consciousness” is limited in that it doesn’t navigate the sensory-motor state space, or the emotional state space, and therefore doesn’t interact with the body or emotions.

According to ChatGPT4, the overall idea of separate, specialized modules for different cognitive functions that can interact via shared representations or procedural rules is consistent with some computational and cognitive architectures, such as ACT-R (Anderson, 2007) and SOAR (Laird, 2012).

According to ChatGPT4, the ACT-R (Adaptive Control of Thought–Rational) theory, developed by John R. Anderson and colleagues, is a cognitive architecture that posits the mind as being composed of multiple modules that work in concert to produce behavior. Each module in the ACT-R architecture corresponds to a different brain region and is responsible for a specific cognitive function. For example:

- The declarative module, associated with the temporal lobe, is responsible for factual knowledge and personal experiences.
- The procedural module, associated with the basal ganglia, contains knowledge about how to do things.
- The goal module, associated with the prefrontal cortex, is responsible for controlling the current goal of the system.
- The imaginal module, associated with the parietal lobe, manipulates mental images and participates in problem-solving.
- The perceptual-motor modules, associated with various sensory and motor areas of the brain, handle perception and action.

Each of these modules is said to have its own specialized representations but to interact via a shared, central representation in the form of "chunks" of knowledge. ACT-R also postulates a set of procedural rules that govern the interactions among these modules.

According to ChatGPT4, SOAR (State, Operator And Result) is another cognitive architecture developed by John Laird and colleagues. Similar to ACT-R, SOAR also proposes several specialized modules, but unlike ACT-R, it represents all knowledge as productions (if-then rules). The modules in SOAR include:

- The long-term memory, which stores all the knowledge in the form of productions and chunks.
- The decision procedure, which selects operators (actions) based on the current state and the knowledge in long-term memory.
- The working memory, which holds the current state of the world and the history of states and operators.
- The perception and motor systems, which interact with the external environment.

Each of SOAR's modules is said to interact mainly through the working memory. The decision procedure reads the state from the working memory, applies the productions from the long-term memory, and updates the working memory with the new state. The perception and motor systems update and read from the working memory to interact with the external environment.

The HCFM model, however, is unique in a number of ways. One is that it is human-centric in that it is intended to allow observations of functionality to be validated within the perception common to all humans, as opposed to requiring definitions of functional components that might not be shared. Conversely, while this extremely high level of abstraction might make the approach more general, it also likely makes it difficult for many to see any utility in it. Despite this, there is potentially very profound utility since HCFM provides a functional model of attributes of cognition such as the existence and magnitude of intelligence, where to the author’s knowledge no other approach has been able to do the same. HCFM is also unique in confining the input to and output from all observable cognitive processes to the functional domain of cognition in which all functional states are concepts. That is, in HCFM the input to and output from all observable cognitive processes concepts. HCFM is also unique in its incorporation of consciousness as a system that can perceive and direct other systems.

Notation Representing Conceptual Space

A key requirement of the notation used to represent any region in conceptual space is that it must be decentralized in that it provides a self-contained description of the functional state of each region (each region describes itself) so that no centralized table of meaning is required. Without this, a functional state space could not be used to solve problems in a truly decentralized and distributed way since all outcomes would be dependent on that centralized table. Another key requirement is that information (concepts and/or reasoning) can be described at any level of detail or lack thereof (lack of detail).

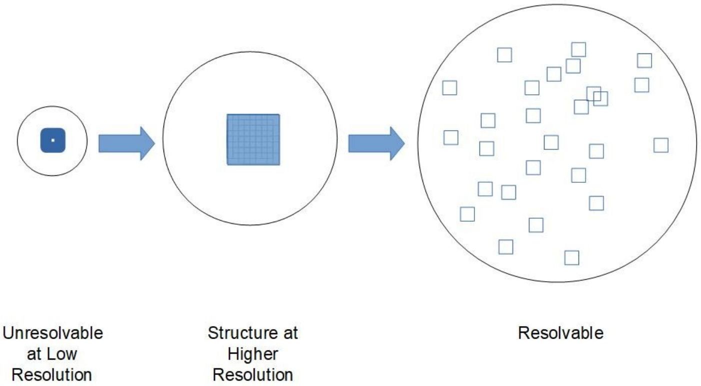

Figure 5: *Concepts that are too close to be resolved are those for which understanding the differences between concepts involves reasoning with a level of complexity the cognitive system is not capable of.*

Resolution of a concept occurs by defining relationships that distinguish it from other concepts. However, at some point, when distinguishing two concepts requires defining too many simultaneous relationships to be within the capacity of the cognitive system, two concepts potentially become un-resolvable.

Each concept is a vertex that is separated by a semantic distance from each other concept d. In this representation this semantic distance is a measure of how many links two concepts share in common with other concepts. Each concept also has a radius r in terms of this same semantic distance that represents how general the concept is. A concept that is a generalization contains other concepts. Each concept is linked to each surrounding concept in one direction by one of the four reasoning functions, and in the opposite direction by the reverse function. According to ChatGPT4, this idea of a decentralized and distributed conceptual representation, resonates with connectionist models of cognition, such as parallel distributed processing (PDP) models, which propose that knowledge is stored in a distributed manner across networks of interconnected neurons (Rumelhart, McClelland, & PDP Research Group, 1986). According to ChatGPT4, the ideas of concepts having different levels of specificity, or 'radius' in the text, is consistent with the theories of cognitive psychology about hierarchical structures of concepts, from superordinate categories to basic level and subordinate ones (Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976).

Each vertex then has the property r, and then for each reasoning path that connects it to surrounding concepts through one of the four functions, it has a label l for that reasoning process along with a distance d and a reasoning function type f. Two concepts might have the same label for the same reasoning process that is replicated in two different regions in conceptual space. For example, an instance of the concept “dog” in one region of an individual’s conceptual space might be connected to an instance of the concept “mammal” in that individual’s conceptual space through an “is a” relationship. This relationship would be identified by a label l having the value “is a”, which might be represented by some token, and which will have a reasoning function type f (in this case likely F3). However, another instance of the concept “dog” in another region of an individual’s conceptual space might be connected to another instance of the concept “mammal” in that individual’s conceptual space through an “is a” relationship as well. This relationship would be identified by a label l having the value “is a”, which might be represented by a different token. This second instance of the same reasoning relationship will have the same reasoning function type f.

Each instance of the reasoning relationship is expected to link two concepts having similar topological properties if the reasoning relationship has the same label. In other words, rather than relying on a single centralized table of definitions of labels, the labels are defined by the way the cognitive system interacts with the topology of conceptual space representing each concept linked by the relationship. For example, one use of the “is a” relationship is to relate a concept A to a larger concept B that is a generalization containing A. So any given “is a” relationship connecting a concept and its generalization is expected to be a line between concentric circles. So according to this hypothesis the cognitive system will always label such a relationship in A as an “is a” relationship.

As another example, a dog might be expected to be represented in conceptual space by a subgraph containing links such as a “has” relationship to other concepts such as “four legs”, or “paws”. If instances of two concepts “cat” and “dog” might both exist in multiple places in conceptual space, then relationships between them might as well. In order for these relationship to have enough fitness for the cognitive system to be able to navigate them, these relationship would be expected to be between similar subgraphs. In other words, if the mind doesn’t recognize each replica as a reasoning relationship between a cat and a dog, then it might not recognize that relationship in a new region of conceptual space, and therefore might not assign it enough predicted fitness to be unable to use it to navigate to new concepts and reasoning that exist in connection with the replicated relationship.

As mentioned, concepts in this generalized human-centric conceptual space are hypothesized to be physically distributed across a three dimensional space. The relative position of the center of each concept with respect to another is given by a vector from the origin of the vertex representing the first concept, to the origin of the vertex representing the second concept, and a distance given by the sum of the radius of each concept separated by the semantic distance between their surfaces. In the reverse direction the relative position is given by a vector from the origin of the vertex representing the second concept to the origin of the vertex representing the first concept. Because these definitions are stored in a decentralized way they need not be consistent, so that navigating reasoning in any given direction might be expected to potentially change the topology of conceptual space.

Each reasoning process, for example the reasoning process that involves calculation of the distance from A to B, is also represented by a concept, in this case the concept of calculating the distance from A to B. Each instance of a reasoning process is represented as originating at some concept X, where the concept of the reasoning process Y is linked to that concept X through the RECALL function, that is, from the concept of the reasoning process Y there is a path to recall the actual reasoning process that forms a path from concept X to some other concept Z. In the reverse direction, each destination concept Z is represented as being connected to the concept of the reasoning process Y through the reverse of the RECALL function (DECOMPOSE RECALL).

Each new concept A that is created by the cognitive system through navigating from an existing concept B is initially connected to B through a CREATE function, and then after creation the first time it is recalled from B it also becomes connected to B through a RECALL function. Since there might be two links between the same two concepts, the RECALL function link might potentially replace the CREATE link over time.

Each reasoning function 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.

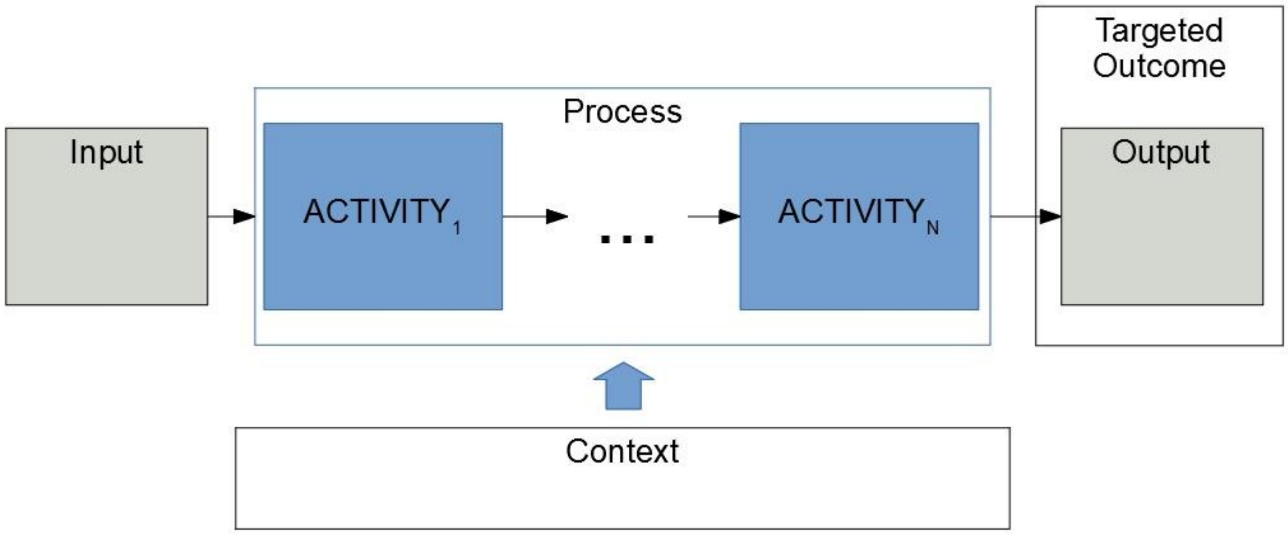

Figure 6: *Model of a process or function in any functional state space.*

Processes are defined here as functions that can receive input multiple times within the same instance of execution.

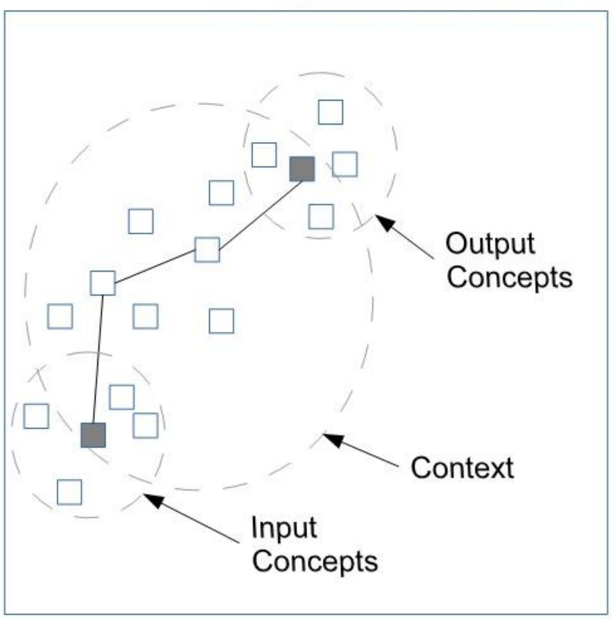

Figure 7: *Context of Execution: Cognitive processes are modeled as functioning to transform input concepts into output concepts, within a set of additional concepts that form the context of execution. This context may change the execution of the function.*

The context of each reasoning path can vary depending on the state of the cognitive system. Each reasoning path contains at minimum, an initial concept A (input to the reasoning) and a target concept B (output from the reasoning). The context is at maximum all of the concepts connected to links contained within the initial concept, that is, all of the concepts connected to the initial concept by any available reasoning path. The context is at minimum none of the other links contained within the initial concept, that is, none of the concepts other than B that are connected to the initial concept by any available reasoning path. According to ChatGPT4, the context-dependent aspect of reasoning paths aligns with theories stressing the role of context in cognition and memory recall (Smith & Vela, 2001).

The fitness of each reasoning path from the current concept is assigned some value f that is a function of the two concepts connected, as well as a function of the concepts within the context of the initial concept that are concurrently being considered (the context), and a function of the current, projected, and target fitness of the cognitive system. By analogy when deciding what to eat, an individual might first assess their current hunger (their body's current level of fitness in terms of hunger), and then assess how they would like to feel after their meal (their target level of fitness). In deciding whether to eat a single green pea, whether to eat a bowl of rice, or whether to eat an entire side of beef, they might assess their projected level of fitness after each meal, which we equate here to assessing the projected fitness of the meal in navigating the individual to a given state. The rationale behind choosing fitness space to have these dimensions (actual fitness, projected fitness, target fitness) is to ensure that the fitness of any reasoning path between any two concepts can be evaluated using the exact same framework.

There are two aspects of fitness that must be considered when assessing fitness. One is the fitness of the cognitive system, and the other is the fitness of a given cognitive process. Because logical reasoning is more powerful when that logic can span a broad range of topics, and when it can be executed with a high degree of specificity, the fitness of the cognitive system in terms of type II reasoning (F4 or the DETECT SEQUENCE function) is represented as increasing the shorter the average path and the greater the volume of conceptual space that is spanned by that reasoning. Because intuitive reasoning is more powerful when that logic can span a broad range of topics, and when it can make distant connections, the fitness of the cognitive system in terms of type I reasoning (F3 or the DETECT PATTERN function) is represented as increasing the longer the average path and the greater the volume of conceptual space that is spanned by that reasoning. In considering the fitness of the cognitive system in relation to the creation of concepts, this ability is represented as being more powerful when it can create a great many concepts. One process of creation is to generalize a reasoning process and apply it to a new process where it applies. The fitness of the cognitive system in terms of the F1 or CREATE concept function is then represented as increasing the greater the degree of generalization (radius in terms of semantic distance) of each reasoning process. So a conceptual space that is very dense with large generalizations would be expected to be very fit with regards to creativity (would be very creative). Because the recall of concepts is more powerful when it can recall a great many concepts, and one process of recall is to link to many other concepts through RECALL relationships, the fitness of the cognitive system in terms of the F2 or RECALL concept function is represented as the volume and density of conceptual space linked by such relationships. Empirical assessments of these hypotheses regarding the fitness of the cognitive system have yet to be performed, but according to ChatGPT4, the emphasis on fitness is consistent with the evolutionary perspective on cognition, suggesting that our cognitive systems have evolved to solve adaptive problems (Cosmides & Tooby, 1994). While specific empirical assessments have not been performed for these hypotheses, and while a comprehensive test of these hypotheses would require interdisciplinary efforts spanning neuroscience, cognitive psychology, and computational modeling, according to ChatGPT4 they incorporate aspects that are broadly consistent with several strands of cognitive science literature.

The fitness of the cognitive system in terms of the reverse of each of these functions is for simplicity assigned to be the same at this point, though this is almost certainly not true. Eventually determining the exact relationship and how it is asymmetric is important if this same dimensionless and scale-free representation is to be used for other systems such as physical matter. Because for the three fundamental forces (electromagnetic force, weak nuclear force, and the strong nuclear force) that can be repulsive, the fitness of the reverse (repulsive) function can be set to some non-zero number, but where there is not yet any widely accepted theory that allows the forth force (gravity) to be repulsive, the fitness of this repulsive gravitational force can just be set to zero. In such a functional model repulsive gravity (anti-gravity) can be represented but need not be represented as actually occuring. In this way, a functional modeling approach can potentially represent the behavior of not only cognition but also of the physical universe without having a complete understanding of how those models are actually implemented.

The cognitive awareness function FS is represented as navigating the conceptual space according to the current fitness, target fitness, and projected fitness after executing each reasoning process. From a given concept A, the reasoning processes that can potentially be executed are represented by a matrix with four columns (one corresponding to each reasoning function type) and an indeterminate number of rows, each one corresponding to a reasoning path that is an instance of one and only one of those functions (as indicated by a "1" in the corresponding column). The number of reasoning paths considered by the cognitive awareness function for execution (the number of rows), and the specific reasoning paths considered for execution, depends on the context, where the context for the execution of the reasoning to be selected by the cognitive awareness function is (as described before) the set of concepts in the vicinity of the initial concept that are currently being considered, where this context might change. The exact dependence on the context of the number of reasoning processes (rows) considered by the cognitive awareness function in this model is that the number is limited by the number of reasoning paths which pass through the concepts in the context, though the number might be limited by other dependencies such as the current fitness of the cognitive system. Similarly, the specific reasoning processes (specific rows) considered are also limited by the specific reasoning paths that pass through the concepts in the context.

Column: F_1 F_2 F_3 F_4
Row 1: [1 0 0 0]
.
.
.
Row N: [0 1 0 0]

The evolution of the state of the cognitive system is represented as being non-deterministic and arrived at through assigning a fitness to each row through multiplying this matrix of reasoning processes by a matrix of fitness values representing the fitness of each reasoning process in the current context of execution. As mentioned previously, in this model the term "reasoning" has been used indiscriminately as a short form for "observable cognitive processes", but to be more specific, navigation through conceptual space is represented as being reasoning when the cognitive awareness actively directs navigation (upon being directed by the consciousness system to do so), and it is represented as being understanding when it is passively directed (when it occurs without conscious direction but potentially within conscious awareness). The cognitive awareness function then actively selects the next reasoning process to execute or is passively directed to execute the next understanding process, both according to some algorithm that maintains dynamic stability in fitness space. It is hypothesized that reasoning processes that can be actively executed are of type F4, and understanding processes that can be executed passively are of type F1, F2, or F3.

The fitness of any reasoning path in conceptual space is hypothesized the length of the reasoning path multiplied by the reasoning relationship strength. The relationship strength is the product of the number of concepts contained in each of the two concepts connected by the reasoning. Therefore if there are two generalizations, one of which contain M concepts, and the other of which contains N concepts, and are both related by a reasoning process, the relationship strength of that reasoning process will be M*N. This is because that reasoning between two generalizations actually solves the problem of connecting each of the M concepts in one generalization to each of the N concepts in the other generalization.

Since the conceptual space is multi-dimensional and defined by cognitive reasoning processes, understanding processes, and the relationships between them, to devise a notation, we first define the elements in this space:

- **Concepts:** Each concept is denoted by the letter 'C' followed by a subscript to differentiate among multiple concepts. For example, C_1, C_2, C_3, and so on.
- **Generalization:** Each concept that is a generalization (that contains other concepts) is denoted by G(M,N) where M and N are the sets of concepts included in the generalization.
- **Cognitive Processes:** Each cognitive process is denoted by the letter 'R' followed by a subscript, such as R_1, R_2, R_3, etc.
- **Cognitive Process Type:** Each cognitive process is assigned a type. For example, a cognitive process R_1's type is denoted as $T(R_1)$.
- **Fitness Values:** For each cognitive process, a fitness value is defined. For example, a cognitive process R_1's fitness value is denoted as $F(R_1)$.
- **Vectors:** Each reasoning and understanding process is represented as a vector in the conceptual space. For example, a vector for cognitive process R_1 can be denoted as $V(R_1)$.
- **Functional Domain Bridging:** Weights can be denoted by 'W'. So, for instance, the weight assigned to reasoning process R_1 in a certain domain D can be represented as $W(R_1, D)$. However, these weights are not stored in the network of the conceptual space, and instead are represented as being stored in the cognitive awareness (FS) function.
- **F1, F2, F3 Types:** Represent understanding processes that can be executed passively.
- **F4 Type:** Represents reasoning processes that can be actively executed.

Dynamics in Fitness Space

Assume the simplest case that the dynamics of the cognitive system in these three dimensions are governed by the deterministic law of gravitation acting on a weight at the end of a rope swing as opposed to a rigid pendulum. Starting from any concept, the reasoning processes that can potentially be executed can be represented in terms of vectors in fitness space that constitute a “push” on that swing that is executed at some point along the arc of the swing’s path. If that push is insufficient and/or at the wrong time or wrong direction it will reduce the motion of the swing to the point that it might stop and take a great deal. If that push is too hard and/or at the wrong time or wrong direction it will cause the swing to rise to the point where it becomes vertically inverted and will crash. So at every point along the swings path there is an optimum push that keeps the swing in the center of its region of stability. One cognitive awareness algorithm that maintains stability in these dynamics might then be to actively choose whichever reasoning process is available from the current concept (at which the cognitive system resides) that is closest to the optimum push at the current point in the dynamics, and to override that by executing instead any understanding process that is also available from the current concept and is more optimal by some measure such as a standard deviation. This is intended to simulate the observed behavior of cognition that we can consciously direct our thoughts, but at the same time our consciously directed thought can be interrupted by a more powerful understanding.

Another example based on the law of gravitation is that of a body in a gravitational orbit around another. Such a body can remain in orbit unless the force applied either causes its orbit to degrade and eventually crash, or causes it to escape its orbit. This is commonly applied by human made spacecraft to “slingshot” to other planets.

Of course the dynamics of the cognitive system in these three dimensions are likely not deterministic. The distinctive characteristic of strange attractors, as opposed to other types of attractors in phase-space, is the unpredictability of the system's exact position on the attractor. Even when two points on the attractor are initially close together, they can diverge significantly over time. However, the state of the system is constrained to stay within the bounds of the attractor. Another notable feature of strange attractors is their non-periodic nature; they do not loop back on themselves, and hence the system's motion never replicates itself. This type of erratic and unpredictable motion that occurs within strange attractors is what we define as chaotic behavior.

In fitness space we might hypothesize that the cognitive system should never have zero fitness, at which point we might consider it to be “dead”. We also might hypothesize that the cognitive system should have a limit on the magnitude of its fitness, beyond which we might consider it to have “magical” abilities, that is, if we don’t believe we observe such magical abilities. Within this range we would expect the cognitive system to have stable dynamics, and outside this range we would expect its dynamics to be unstable.

One way to maintain stability through such a “push” algorithm is to search for any strange attractor which has dynamics that are stable within a three dimensional region that is bounded by two spheres, one of some radius r_1 and the other of some radius r_2, where its dynamics become unstable when the distance from some central point is less than the radius r_1 as well as when the distance from that central point is greater than the radius r_2.

As of it’s last training data up until September 2021, when asked, ChatGPT4 could not provide a specific example of a 3-dimensional strange attractor with exactly the type of stability described above -- one that is stable between two spherical boundaries of different radii and becomes unstable when the distance from a central point is either less than the smaller radius or greater than the larger radius. However, ChatGPT4 also suggested that the study of dynamical systems and chaotic behavior is a rich and active field of research with new systems and attractors being discovered and analyzed, so it's possible that a system with the properties described could exist or be discovered in the future. It also suggested that one could theoretically construct a model with specifically defined stability properties, independently of whether it might or might not accurately reflect any real-world system.

When asked to construct a hypothetical model that exhibits some of the characteristics mentioned ChatGPT4 offered an example (supplementary data – ChatGPT Prompt 2).

At each concept in conceptual space the cognitive system might reside at, assume that each of the available reasoning and understanding processes can be represented by some force vector in conceptual space. In light of this, the only condition that is potentially necessary to satisfy in order to show that these dynamics can be stable is to either prove or show through numerical means that as long as the “force” vector in fitness space of any selected reasoning or understanding process remains within a certain range, the dynamics in fitness space remain stable.

The idea of stability in conceptual space must also be examined. From first person observation of our own cognition we might assume that executing each reasoning process takes energy. Some concepts and reasoning processes provide “food for thought” that is metaphorically are very high in energy. Other concepts and reasoning processes provide “food for thought” that is metaphorically very low in energy. Just like animals like lions that eat very nutrient dense food like animal protein will be expected to eat at infrequent intervals, while animals like cows that eat very nutrient light food like vegetation will be expected to eat all the time, coming up with highly abstract thought that requires high mental energy but that can be reapplied to a great many other problems without expending much additional energy might be expected to allow (and perhaps demand) periods of mental inactivity, while coming up with very specific thoughts that require low mental energy but that cannot be reapplied anywhere might be expected to result in constant mental activity. Cognitive stability for an abstract thinker would then hypothetically require periods of inactivity, while for a very concrete thinker it might require steady activity.

From first person observation of our own cognition we might assume that some aspect of cognitive function is replenished through sleep and some just through rest from strenuous cognitive activity. We might also assume that some aspect of cognitive function is replenished through food and water, since without sleep, food, and water, humans are reliably observed to hallucinate. These factors are complex. But without understanding the exact dependence of cognitive fitness on all these factors, these factors can still potentially be represented in the fitness function through defining a metric for cognitive fitness, perhaps in terms of performance, and then empirically determining these impacts.

Some impacts might not uniformly affect the fitness of all cognitive processes, and some cognitive processes might have very different impacts on cognitive fitness. For example, the reasoning with the highest energy demand would be expected to be highly abstract logical (type II) reasoning. This reasoning type would then be expected to be absent if this algorithm were to replicate states such as sleeping or dreaming, which might also be important parts of modeling cognition.

According to various dual-process theories of cognition, dreams occur during the Rapid Eye Movement (REM) stage of sleep, where the prefrontal cortex, responsible for executive functions and often associated with System 2, has reduced activity. One key aspect of System 2 thinking is testing our ideas and perceptions against reality. This reality testing is diminished during sleep, which could allow for impossible scenarios to be experienced without questioning. As a result, cognitive processes, such as applying physical laws, become suppressed, enabling unrealistic scenarios to be perceived as real in dreams. When logical reasoning is suspended thoughts can occur that are not constrained by any observable logic, such as the logic that observation of this existence suggests that one cannot fly, or that one cannot walk on water.

Lucid dreaming is a fascinating phenomenon where dreamers become aware that they are dreaming and may be able to exert control over their dreams. According to dual-process theories, this active direction seems to reflect an awakening of System 2 processes within the dream state. This is quite unique, as dreaming is typically associated with the dominance of System 1. When dreaming during sleep, anecdotal observation suggests that logical reasoning is suspended since thoughts can occur that are not constrained by any observable logic, such as the logic that observation of this existence suggests that one cannot fly, or that one cannot walk on water.

Dreaming within such an algorithm might be replicated by simply setting the fitness of type II reasoning to zero. Cognition while dreaming can also anecdotally be observed to be consciously directed at times, as in lucid dreaming, which might be replicated by simply setting the fitness of type II actively directed reasoning to be non-zero.

In summary, the features required by a model of cognition are then as shown in table 1:

Component of Model	Description
Functional modelling (problems and solutions)	Components are modelled only by function to remove prejudice for or against any given implementation.
Functional decomposition	Functional components are decomposed into their most basic functional building blocks for reuse.
Functional domain bridging	Different domains in which different functions are more fit in achieving the same purpose are identified. These domains are bridged by using a set of weights which identify the best function in each domain.
Functional fitness	Every functional component is assigned some projected and actual fitness in achieving its function.
Functional stability	For functional components to persist they must display some degree of stability in fitness to function.
Functional adaptation	For functional components to persist in a changing environment they must have the ability to adapt their function.

Table 2: *Components of a General Collective Intelligence.*

The concept of functional domain bridging is that once the fitness of a reasoning or understanding process has been predicted in a given context, that predicted fitness should be stored, and it should be updated with the actual observed fitness. For this to be possible, the cognitive system must store some kind of map of the domains in which each process is most fit.

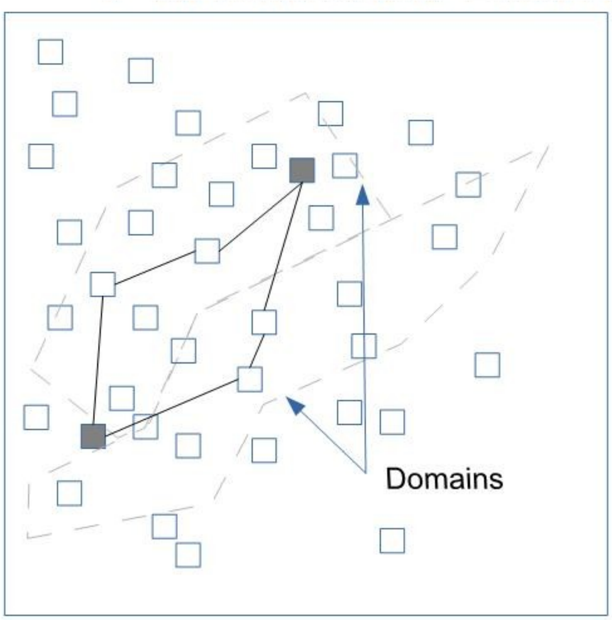

Figure 8: *Functional Domain Bridging: Domains in which different solutions are optimal might be bridged by a system of weights in which the optimal solution is assigned the greatest weight in a given domain, where the domain is defined by the input, the output, and the context.*

In conceptual space any problem is defined as the lack of a reasoning path from one concept to another. The solution is the reasoning which provides that path. As mentioned, the context of that problem and the context of the solution are the concepts considered in the solution. The domain defining this contexts is illustrated conceptually by simply drawing a line around the concepts included in the context of the solution and is represented by creating a list of the concepts within that context. Assigning a predicted weight to the optimal reasoning process in solving a problem within a given context is represented as being the same as assigning a predicted level of fitness to that solution. In other words, the predicted fitness is the initial weight.

The actual fitness of a solution in solving a problem is its relative volume of outcomes per volume of inputs (relative compared to all other known solutions that are available in the same context). Each domain defining a problem and a context, along with each predicted or actual assessment of fitness for each solution in that domain, is stored in the cognitive awareness function.

Hypothesis

The hypothesis to be tested was that this representation of conceptual space can provide a complete decentralized representation of semantic information.

Methodology

The methodology used to test this hypothesis was to have ChatGPT create a sample paragraph large enough to provide a statistically significant verification of the notation, then parse the sample text into this representation. Next have ChatGPT randomly identify some meanings of concepts and cognitive processes (as defined in this notation) that it detects as being explicitly represented in the text (to simulate the meaning of the text to ChatGPT so that this experiment simulates the ability of the notation to represent meaning to a human cognition, noting that this is a simulation because text does not have semantic meaning to ChatGPT as a large language model). Then have ChatGPT identify the meaning of any concepts and cognitive processes implicitly represented in the text (again to simulate the meaning of the text to ChatGPT). Finally, have ChatGPT confirm that each element of that meaning can be represented in the notation.

Results and Observations

According to ChatGPT4, this representation captured all the explicit meanings and the key implicit meanings in the text according that exist within the cognitive domain according to the proposed notation. ChatGPT4 also inadvertently confirmed that emotional states are not contained in this space, and would require another space with its own notation by identifying an implied “emotional state not directly expressed as a concept or a reasoning process in the notation”, and by suggesting the introduction of an emotive function, such as E(C1) = "satisfied", to capture this.

Discussion

The end goal of a decentralized representation of semantic information such as that described in this document is to use it to populate a graph database which might then be a semantic model. The potential usefulness of the decentralized representation of semantic information represented by such a graph database is that with enough processing power it could potentially be used to convert a large language model into a more semantically explainable and composable semantic model. According to ChatGPT, this statement is supported by the literature since semantic models, especially those used in natural language processing, indeed aim to extract and represent the meaning from textual data. Semantic graphs, which provide a structure to semantic information, make it possible to understand relationships and connections between different concepts or entities. They could be used as an effective tool to extract, represent, and manage knowledge in a more interpretable and composable way, and indeed, can be used as a form of decentralized representation of information (Hogan et al., 2020). Furthermore, according to ChatGPT the integration of such models with large language models like GPT-3 or GPT-4 can potentially enhance the problem-solving abilities of these models by providing a clearer understanding of the relationships between concepts.

In addition, it is hypothesized that through leveraging Human-Centric Functional Computing (Williams, 2022a) these models of semantic information have the potential to support general problem-solving ability, and addition in addition have the potential to vastly improve the general problem-solving ability of intelligent agents and groups.

However, a very different architecture might be required for graph databases to be used at the scale of an LLM. For example, the hypothetical General Collective Intelligence or GCI platform model aims to organize collaboration between massive collections of even billions of intelligent agents that each navigate some much smaller subset of the graph of the larger conceptual space equivalent to the contents of an LLM. However, according to ChatGPT a successful implementation of this approach would require effective communication and coordination mechanisms among agents, as well as efficient algorithms for partitioning and distributing the conceptual graph among them. Some studies on distributed artificial intelligence and multi-agent systems may provide insights for this task (Stone & Veloso, 2000). Otherwise creating and managing graph databases with enough complexity to fully capture semantic relationships at the scale of a language model like GPT-4 might be a significant challenge, requiring more efficient algorithms and more substantial computational resources than might be available today (Meng et al., 2020).

Limitations of Research and Suggestions for Future Study

Due to the token limitations of ChatGPT, the size of the text used for validation was very small. Therefore the feasibility of creating an entire conceptual space representing the conceptual space of an individual human, much less the conceptual space of a large language model, which is certainly far larger, could not be tested.

In addition, the justifications for hypothesizing the existence of the reverse functions were that there must be reverse functions if the conceptual space is to be mathematically considered a “space” that can be spanned, and that since reverse functions are potentially part of the sensory-motor system as a “lower” or earlier evolved system, the principle of functional reuse in biological systems supports this. However, the biological justifications for this statement remain to be confirmed.

Other suggested future work includes a more thorough analysis or numerical simulations to confirm the stability of the cognitive algorithm described. This might begin by confirming that a predicted “force” vector in fitness space can be assigned to cognitive process that originates at a concept with a given volume and density in conceptual space, wherever that cognitive process has a predicted fitness and a length in conceptual space. If this can be confirmed, the next step might be to prove or show through numerical or other means available that as long as any predicted “force” vector in fitness space for a cognitive process selected by the cognitive awareness function FS remains within a certain range, the dynamics of FS in fitness space will remain stable, and thereby confirm that the cognitive awareness algorithm proposed to implement FS can display stability of dynamics in its fitness space.

Regarding the use of a strange attractor as the basis for stable dynamics in the cognitive awareness algorithm, it is important to note that the existence of a strange attractor in the system does not guarantee stability. A strange attractor is a set of states in phase space to which the system tends to evolve over time, but these states may be spread over a wide range of fitness values. According to

ChatGPT, if the strange attractor includes states outside the acceptable fitness range, the system might still evolve to those states, leading to instability. Therefore, the presence of a strange attractor within the acceptable fitness range does not necessarily confirm the stability of the system, especially given the sensitivity to initial conditions characteristic of chaotic systems. To confirm stability, one would need to demonstrate that the strange attractor is contained entirely within the acceptable fitness range, and that the system's trajectory remains within this range for a broad range of initial conditions. The dynamical system defined by the hypothetical model provided (the system of three ordinary differential equations) might exhibit such behavior. A rigorous analysis of this system would likely require the use of numerical simulations to confirm that the dynamics of the system remain stable for a wide range of initial conditions.

Conclusions

The idea of creating a mathematical model for cognition is not new and can be seen in other fields like cognitive neuroscience, artificial intelligence, and computational psychology (Eliasmith & Trujillo, 2014). However the conceptual space defined within HCFM is very different from that defined in other approaches since it defines a single functional domain for cognition. This single functional domain is hypothesized to allow any property of the cognitive system, such as the existence of intelligence, or the magnitude of intelligence, to be represented mathematically in terms of that space.

The concept of a “functional state space” describing the functional states and behavior of a system in a given domain of that system’s functionality (a given functional domain), where that functional state space is spanned by a closed set of reversible interactions, and is a complete semantic representation in the sense of being capable of describing any possible functional state and/or functional behavior of that system (as opposed to describing the processes which implement that functionality), is a concept that has broad applications well beyond the study of cognition. Even if these functional state spaces have different properties, such as a different number of interactions that span the space, if a problem-solving algorithm is developed in one functional state space is in some way reusable in other functional state spaces, this has implications in other disciplines where it has been proposed that functional state spaces might apply, such as in the fields of mathematics, physics, and even sustainable development. In addition, the definition of system behavioral properties such as complexity, and the adaptability (general problem-solving ability) of systems in terms of their functional state spaces raises the question of whether any such definition in one functional state space might apply to other functional state spaces.

According to ChatGPT, the assertion that such a domain can represent any property of a cognitive system is a strong one and implies a level of universality that is rarely seen in models of cognition, given the complexity and variability of cognitive processes, and furthermore proving this claim would indeed require substantial empirical validation across a variety of contexts and cognitive tasks.

This paper has barely scratched the surface of providing empirical validation for the model, but that validation is a massive and multidisciplinary task that might require a large team. Engaging such a large team requires first sharing the concepts to be tested. Therefore this paper still potentially represents an important step forward. According to ChatGPT, this emphasis on the importance of presenting new ideas for further exploration by the broader research community is a common sentiment in scientific discourse.

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