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RESEARCH ARTICLE

Human-Centric Functional Computing as an Approach to Human-Like Computation

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Abstract: This paper makes the argument that the hypothetical "functional state space"-based computing model described in this paper is a fundamentally new and different approach of disruptive importance. This paper argues that all functional states in any given functional state space can be reached in terms of a set of basic operations like in the case of other state spaces. The difference is that the functional states are separated in this space by a "semantic distance" that reflects their similarity, and that separating functional states according to similarity in this way introduces the possibility of generalizing between one functional state and another. Assuming all problems in understanding any system modeled in terms of functional state space can be represented as the lack of a path from one functional state to another, and that all solutions are represented by the processes within the system that allow the system to transition between the two functional states, then general problem-solving ability with respect to any system is potentially represented by the volume of its functional state space that can be navigated per unit time to find a solution, multiplied by the density of functional state space that has to be navigated through to find it. Simple geometric arguments in functional state space suggest that this separation of functional states by semantic distance in turn creates the possibility of exponentially increasing ability to solve problems in understanding the system when the ability to generalize can be increased until it spans the entire functional state space. Assuming the human cognitive system can be represented as operating within a functional state space (the so-called "conceptual space"), and assuming that this conceptual space is a complete semantic model of concepts and reasoning, then by computing in terms of paths providing a complete representation of the meaning of reasoning, where those navigate through that space between functional states providing a complete representation of the meaning of their underlying concepts, any individual or collective artificial cognition might potentially transfer meaning rather than just information at vastly greater speed and scale. The ability to transfer meaning suggests that one of the problems that computing based on functional state spaces deduced through Human-Centric Functional Modeling (or so-called "Human-Centric Functional Computing") might exponentially increase the capacity to solve is the problem of automatically generalizing computing solutions in order to reuse them in solving other problems where they apply, and doing so at vastly greater speed and scale without the need for human reprogramming.

Keywords: Human-Centric Functional Modeling, Human-Centric Functional Computing, General Collective Intelligence, functional state space

Human-Centric Functional Computing (HCFC) consists of using Human-Centric Functional Modeling to define functional state spaces and then computing in terms of known paths through these functional state spaces to discover new paths to potentially new functional states where doing so is useful in increasing fitness to solve a targeted problem. There is an argument that HCFC might be the most important concept in computing today, and perhaps in all history to date, since measuring importance by the potential increase in volume and density of conceptual space that a tool or concept might facilitate, then one particular model of HCFC (so-called "General Collective Intelligence" or GCI platforms) is predicted to facilitate the greatest expansion in conceptual space in human history to date and therefore predicted to be most important concept in history and in the immediate future until a second-order "GCI" might make it possible to achieve another exponential increase in the size and density of conceptual space.

1. Introduction

Human-Centric Functional Computing (HCFC) is an approach motivated by the fact that the functions of the mind currently cannot all be measured through any external tool, and therefore any theory about the mind must be validated through first-person observation or self-reflection (looking inwards). To enable these observations to be objectively useful, observations are made in terms of constructs called "functional state spaces" that are defined using a functional model of the human organism and the way it perceives its environment, thus the name "Human-Centric Functional Modeling" (HCFM) (Williams, 2022). The advantage of using this approach is that a human-centric approach to modeling that focuses on function rather than implementation is a modeling

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approach that is universal to all humans in not requiring any specialized tools or expertise to understand. This is critically important because use of any such tools or application of any such expert knowledge generally entails making assumptions that cannot be proven to be true within each individual's experience. A universal model that is also a complete semantic model, which in addition allows all problem-solving approaches (all approaches to artificial intelligence (AI) or AGI) to be represented in common terms, is a model that vastly multiplies the problem-solving approaches available and therefore is a model that can vastly increase our problem-solving ability, as outlined in this paper. The significance of representing cognition in terms of motion through such a functional state space is that doing so paints a very clear and simple picture of what general problem-solving ability (intelligence) actually is, how it might be exponentially increased, and what an exponential increase means. The significance of an exponential increase in general problem-solving ability is that it implies an exponential increase in ability to solve any problem in general. Since this exponential increase applies to every product or service, and every process along the entire business life cycle from research and development to recycling, and since this exponential increase is not predicted to be achievable by any other known method, HCFM and therefore HCFC are potentially the most significant innovation in the world today with respect to the impact of AI on EVERY technology.

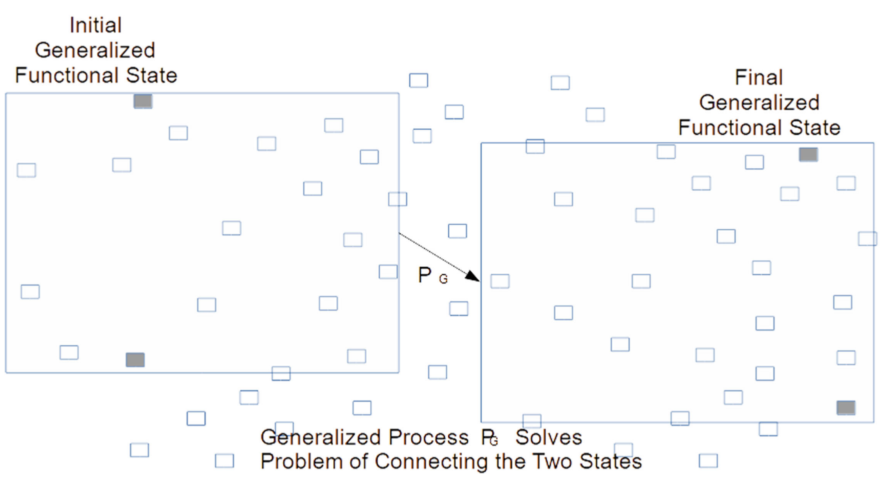
There is a growing amount of work in the area of human-like computing (Bundy & Mareschal, 2022; Dix, 2016) which is generally motivated by the sentiment that "if we can understand human perception and cognition, then we may be able to design more effective algorithms." This work is by nature cross-disciplinary, seeking to incorporate approaches such as neural-symbolic computing in order to improve on the "limited progress has been made towards understanding the principles underlying language and vision" (Besold et al., 2017).

HCFM (Williams, 2022) posits that the behavior of any system that can be perceived by a human can be represented in terms of constructs called functional state spaces, and that for any system whose behavior can be represented in terms of a functional state space, an implementation of HCFC (such as a General Collective Intelligence or GCI platform (Williams, 2022)), can be used to exponentially increase the general problem-solving ability of groups and therefore to exponentially increase their ability to solve any problem that concerns understanding the behavior of that system (Williams, 2022). Functional state spaces differ from state spaces (Nykamp, 2019) in that they define only one domain of a system's behavior, in that all functional states belong to a single category and can in turn contain other functional states of that category, in that it is hypothesized that all processes by which the system might transition between states can be expressed as a composition of some basic set of operations which can be used to uniquely identify or differentiate each process, and in that functional states are separated by degree of similarity (semantic distance). As an example, in the hypothetical conceptual space (the functional state space of the cognitive system) all functional states are concepts, all concepts can contain other concepts, and it is hypothesized that all reasoning processes with which the cognitive system might transition from one concept to another can be represented in terms of a path through this conceptual space that can be composed with a basic set of four operations (Williams, 2020). Assuming that computing is an automation of human reasoning, then all computing processes can also be uniquely represented in terms of a set of paths through this conceptual space.

Assuming that a problem can be defined in the collective conceptual space as the lack of a path between two concepts, and assuming that concepts can be any size, and that generalizations are concepts of larger size that smaller more specific concepts might fit into, then any problem solved by a reasoning process P_1 between two concepts can also be solved in a more general way by a reasoning process P_G between generalizations of those two concepts (Figure 1). For any problem involving the concepts C_i within the first generalization, or involving the concepts C_j within the second generalization, P_G is a generalized solution, and conversely all collective reasoning processes P_{ij} from any C_i to any C_j are specific solutions to P_G. If there are N concepts in the first generalization G_1 and M concepts in the second generalization G_2, then the number of reasoning solutions there will be is $M * N$. Therefore, when the ability to generalize is increased to the point that a generalization can span the entire collective conceptual space, the number of potential solutions in a conceptual space of N concepts will be N^2.

Figure 1 provides a representation in conceptual space of reasoning between two generalizations. In addition, each of these new reasoning paths is identified by a new concept. Therefore,

Figure 1
Problem-solving through generalization



increasing the ability to generalize until it spans the entire conceptual space involves the possibility of creating $(N^2)^2$ new concepts, which in turn creates the possibility for $((N^2)^2)^2$ new reasoning processes and so forth iteratively with unknown limits.

Since the density of conceptual space is determined by the number of concepts that a given concept is related to through reasoning processes (where an increase in that number makes concepts more specific and therefore smaller in conceptual space), this is also expected to exponentially increase the density of conceptual space. Assuming that general problem-solving ability is represented in conceptual space by the volume that can be navigated by the cognitive system per unit time multiplied by the density of concepts that must be navigated through, an exponential increase in the volume and density of conceptual space implies the possibility of an exponential increase in general problem-solving ability.

Assuming that the importance of a concept is a measure of the aggregate impact of that concept on all other concepts. All solutions (reasoning processes) to the question “how is this concept important to any other concept?” are represented by paths through conceptual space. If one concept solves the problem of impacting another concept, then the solution is represented by such a path. Since the same distance in conceptual space might contain a small number of large (poorly defined) concepts, or a very high number of small (precisely defined) concepts, the number of paths in any given volume of conceptual space is determined not just by the volume but also by the density of concepts in that volume. All existing impacts of that first concept on all other concepts are then predicted to be represented by the volume of conceptual space that first concept allows to be navigated, that might not otherwise be navigable, and multiplied by the density of conceptual space that must be navigated. Therefore, the importance of any tool or other concept is predicted to be the increase in the volume of conceptual space that the concept or tool allows to be navigated, multiplied by the density of that conceptual space. We will call this “effective intelligence.”

Processes in functional state space have input functional states, a set of functional states that define the context of execution for the process, output functional states, and outcomes associated with those outputs. Assuming that performance in achieving outcomes can potentially be measured in terms of volume of outcomes per unit of inputs. Assuming that in conceptual space an exponential increase in performance in terms of outcomes might be achieved through an exponential increase in narrow-problem-solving ability. The meaning of an exponential increase in narrow problem-solving ability in conceptual space might be interpreted in a number of ways (Figure 2).

In Figure 2, the ways of exponentially increasing narrow problem-solving ability in conceptual space are illustrated. Reasoning through an exponentially longer sequence of concepts at the same level of difficulty represented by R_{12}' traversing an exponentially greater distance per unit time than R_{12} at the same density of conceptual space is illustrated in the top left of Figure 2. Reasoning through exponentially more difficult concepts represented by R_{12}' traversing through an exponentially greater density of conceptual space per unit time than R_{12} is illustrated in the top right of Figure 2. Reasoning through more concepts that are more difficult represented by R_{12}' traversing through a combination of a greater density of conceptual space and greater distance per unit time than R_{12} is illustrated in the bottom left of Figure 2. Solving an exponentially more abstract problem represented by R_{12}' traversing between exponentially broader concepts C_1' and C_2' is illustrated in the bottom right of Figure 2.

While general problem-solving ability in conceptual space is hypothesized to be represented by the volume that can be navigated per unit of time, multiplied by the density of concepts that must be navigated through, narrow problem-solving ability is hypothesized to be approximated by the general problem-solving ability in the narrow rod-shaped volume of conceptual space enclosing an initial set of input concepts and a set of output concepts that is being targeted, where that set of input concepts together with that set of output concepts define a specific problem (Figure 3).

In Figure 3 (top left), a problem is defined by the lack of a path between an initial concept represented by a gray square at the bottom and a target concept represented by a gray square at

Figure 2
Interpretations of narrow problem-solving ability

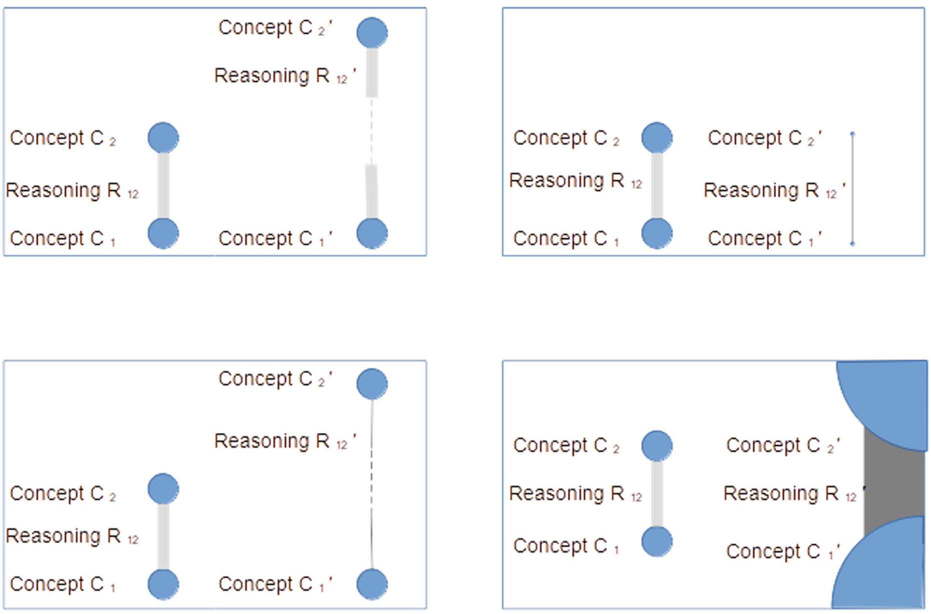
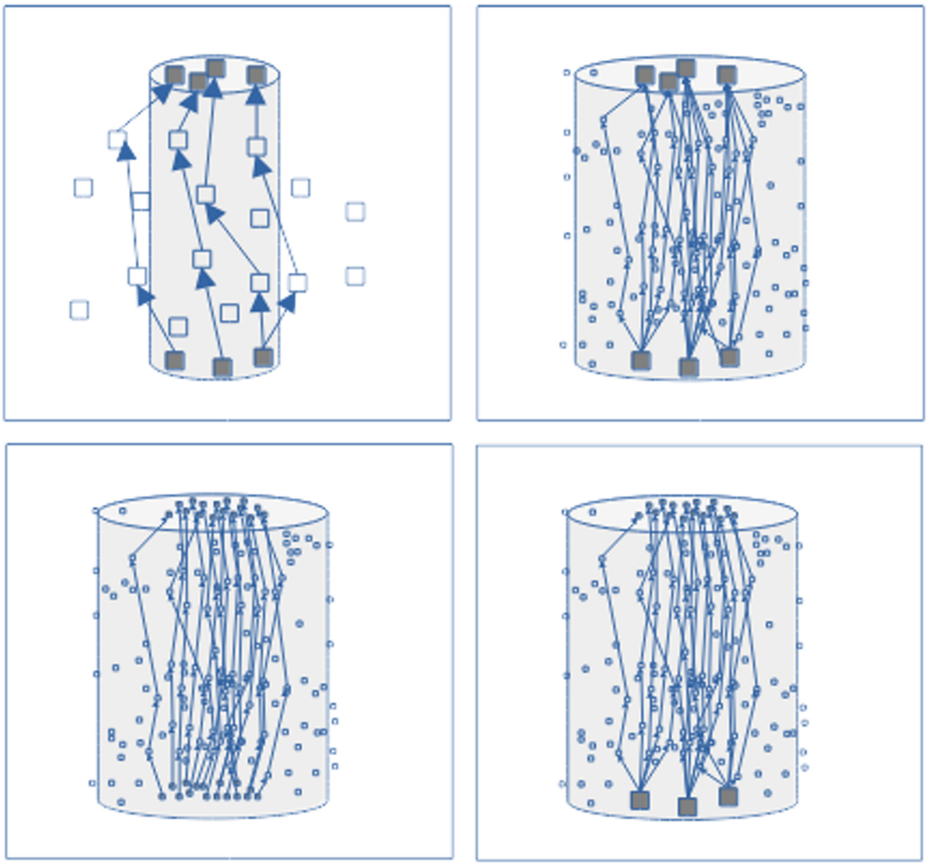


Figure 3
Narrow problem-solving ability



the top. A solution is defined by each path between them. Assuming that most solutions are nearby in conceptual space, when measuring increase in narrow problem-solving ability the initial problem-solving ability is approximated by the volume of the cylinder that most solutions are confined to, multiplied by the density of concepts in that volume. In Figure 3 (top right), an increase in ability to solve this same set of narrowly defined problems is represented by a larger number of paths representing more solutions for the same problem. These solutions might occupy a larger volume of conceptual space and might be specified with a greater level of detail, which means concepts that are more precisely located and of therefore of a higher density. In Figure 3 (bottom left), an increase in problem-solving ability can also be directed at redefining the problem in a number of more specific ways, which means decreasing the size of the input and output concepts (gray squares at bottom and top of cylinder). In Figure 3 (bottom right), if in general only the initial concepts in the problem are assumed to be fixed, then the output concepts might be redefined. In this case, the increase in narrow problem-solving ability between the top left diagram and the bottom right diagram might be approximated by the change in volume of outcomes per volume of inputs. If so, then the volume of outcomes per volume of inputs is a reasonable proxy for narrow problem-solving ability.

1.1. Advantages of the model

The advantage of the HCFC approach is that since the underlying HCFM approach is hypothesized to have the capacity to represent any AI algorithm or any procedural program, and since HCFC can potentially use any available optimization method to optimize any AI algorithm or any procedural program it can represent, as well as do so without reprogramming, it is hypothesized that HCFC can optimize any AI algorithm or any procedural program with any optimization process without reprogramming. As opposed to disconnected interventions related to AI and AGI that have no known path to reliably succeed in achieving the objective of AGI, it is predicted that HCFC might be used to deploy networks of interventions that reliably succeed. HCFC might also be used to massively scale collaboration to achieve AGI through these interventions.

2. Literature Review

The idea of "conceptual spaces" was published nearly three decades ago (Gärdenfors, 1993, 2004, 2014) in the attempt to "model conceptual reasoning in a way which is formal and yet reflects the fluidity of concept use in human cognition" (Tull, 2021). What is new is the idea of a single more general "conceptual space" that is in addition a member of the category "functional state spaces," where each functional state space is hypothesized to be capable of providing a complete representation of the meaning of any functional state or of any possible behaviors (i.e., a complete semantic model) of any conscious human perceptual system (sensory–motor system, emotional system, cognitive system, conscious awareness system). What is also new is the concept of viewing the human organism as a hierarchy of functional systems each described by such functional state spaces, and that such spaces can be used to represent other domains normally not within an individual's conscious awareness, such as any possible intercellular or other cooperation processes by which outcomes of processes might be scaled through cooperation. Only two of these domains are required to massively increase the problem-solving ability of groups through HCFM. In particular, assuming any possible reasoning or concepts can be represented within the conceptual space that has been defined as the functional state space of the cognitive system, and assuming that any possible cooperation process through which functional components of the cognitive system might cooperate to scale the resources of the cognitive system can be represented within the cooperation state space that also represents all possible modes of cooperation with which cells or other functional components of the human organism can cooperate to scale outcomes, then based on HCFC a GCI (Williams, 2022) can be defined to create the possibility of massively increasing that problem-solving ability. However, all of these additional domains can potentially contribute to group problem-solving.

The use of such state spaces to represent meaning (i.e., using state spaces as semantic representations) is not new and appears to have originated within philosophy in the study of logic (Boucher, 2015), specifically from the tradition of defining state spaces as semantic representations (Niiniluoto, 1987). Functionalism as an approach that defines systems according to their functions is also well established (Block, 1982). The functional state spaces described in this paper are represented by graphs containing a network of nodes representing the functional states of the system, where those nodes are connected by edges representing the processes through which the system might transition from each functional state to another. These states are called functional states because each one is defined by all the functions or processes by which the system might transition to another state. Since any biological system with repeatable behavior can potentially be modeled as a network (Yurkan et al., 2007), then since the cognitive system is biological, it stands to reason that all the above approaches might be combined to represent the behavior of the human cognitive system in terms of a graph specifying interactions between a network of functional states (the so-called "conceptual space").

Because semantic distance appears to be one of the key differences between functional state spaces and other state spaces, a literature search was conducted to assess any potential views on this topic by researchers whose key interests include semantic distance. However, opinions on the validity of this key property of conceptual space differ. For example, although this paper has portrayed semantic distance as pertaining to concepts, in the opinion one expert on the subject (Budanitsky & Hirst, 2001; Mohammad et al., 2007) in practice semantic distance relates to words as it is only through words that concepts can be represented (language-independent ontologies supposedly notwithstanding). Hirst suggests that embeddings of meaning derived by methods of deep learning can represent complex concepts insofar as they can represent sentences and whole paragraphs and hence can represent a concept described by that text. However, he argues, this is still tied to some specific language, such as English. Only by replicating the assessment of semantic distance in multiple languages and looking for some kind of a centroid he suggests (assuming that the results do in fact cluster at all), might it be possible to represent concepts in a truly language-independent way. In other words, in his opinion as it applies to cognition, the functional state space construct presented in this paper describes a "word space" rather than a "conceptual space." In order to justify the term conceptual space, the construct would not only have to be demonstrated to be valid for one language but would have to be demonstrated to be valid across all languages. This opinion that current assessments of semantic distance apply to only one language appears to be supported by other work in progress that explores techniques for assessing semantic distance (Xiao et al., 2022).

3. Hypothesis

The question asked here is whether it feasible that an exponential increase in general problem-solving ability is the most important innovation in the history of human civilization. The hypothesis is that given the definition of importance in conceptual space, this claim is feasible.

4. Research Methodology

Using simplifying assumptions, the potential importance of any possible computing method was analyzed in terms of volume and density in conceptual space in order to test the hypothesis.

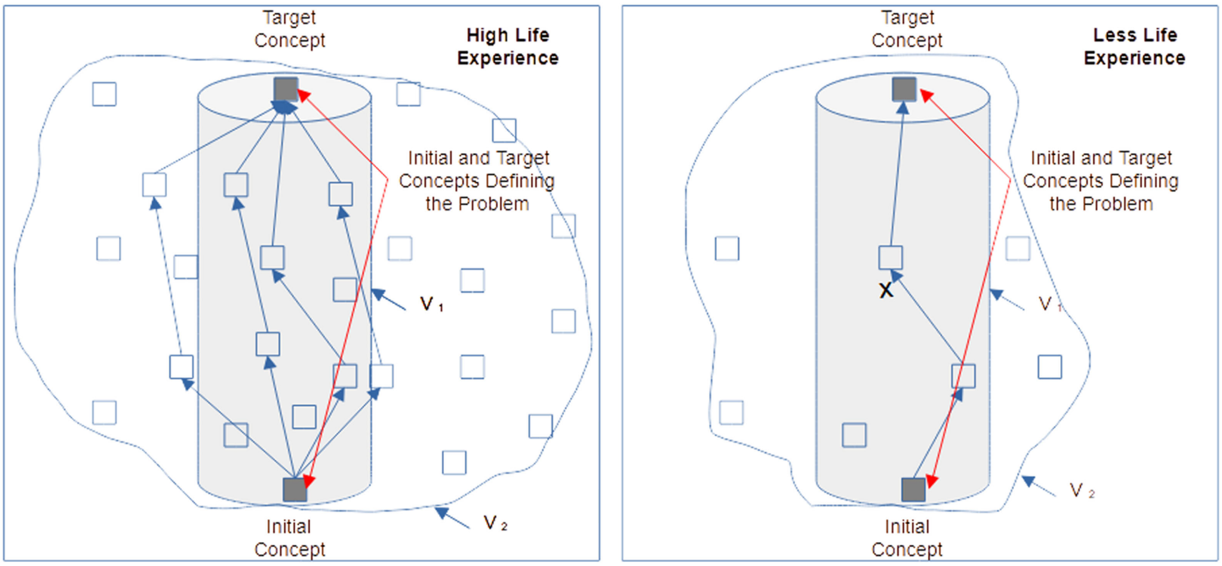
Before assessing whether the increase in intelligence predicted with HCFC justifies HCFC being seen as the most important innovation in the history of human civilization, it is important to analyze how the performance of any intelligence is assessed. In the case of a human, performance in any test of problem-solving would be expected to be determined by the probability of correctly answering the test questions, which, according to a simple analysis based on the functional model of cognition proposed within this HCFM approach, is predicted to be dependent on the following factors:

- The probability of the tester has identified the correct answer so that the problem-solving ability of the subject is accurately tested (P_{TC} = probability of test correctness). This is a deceptively important factor assuming it is true as predicted that humans have two different and incompatible ways of determining correctness in certain categories of problems (Williams, 2022)
- The reasoning and concepts available for problem-solving in the conceptual space depend on life experience. The density and volume of the region of the conceptual space of the subject that contains reasoning paths which lead to the correct answer might differ from the density and volume of the conceptual space of subjects with more life experience that have accumulated a greater density and volume of conceptual space. This is a measure of the probability that the problem is within their life experience (L = life experience of subject).
- The capacity of the subject to navigate the conceptual space in order to find those correct reasoning paths (IQ).
- The probability of the subject putting in the effort required during the test in order to be able to correctly execute those reasoning paths (P_E = motivation/effort).
- The dependence of performance in the test on the subject's effort (D_E = dependence on effort. That is, does a much higher level of effort affect performance a lot more or just a little more?).

Representing these factors visually in conceptual space (Figure 4), all reasoning that solves a given problem would be expected to be close to each other in conceptual space in terms of semantic distance. Solution attempts that wander far outside this region of conceptual space would be expected to be inefficient at best, and both incorrect and wasteful of time at worst.

In Figure 4A (left) in the case of high life experience, there might be many more concepts in the conceptual space. Assume problem-solving is more effective if confined to a narrow region

Figure 4
Functional model of human performance in IQ tests



V_1 that is represented here as a cylinder; however, the larger volume of conceptual space contains any concept that is related, and therefore that is in the context differentiating this particular instance of the problem, but that might not be directly useful in the solution is V_2. In figure 4A (right) in the case of less life experience, there will be fewer concepts in the conceptual space.

In other words, performance would be expected to be determined by this estimate:

$$\text{Performance} = CP_{TC}LP_E D_E(IQ)$$

Assuming C is some constant, assuming that P_{TC} is fixed since all subjects take the same test, and assuming L can be approximately fixed in the case of humans by choosing subjects of the same chronological age, then:

$$\text{Human performance} = C'P_E D_E(IQ), \text{where } C' = P_{TC}L$$

To the degree that $C'P_E D_E$ are fixed, it would be expected that human performance would vary approximately linearly with IQ. Consistent with this prediction and investigations of the relationship between IQ and one set of test scores (the Measurement and Treatment Research to Improve Cognition in Schizophrenia or MATRICS within the Consensus Cognitive Battery or MCCB), the statistically significant correlation between the full IQ score and the composite score was 0.70 (Mohn et al., 2014). This is consistent with other results showing a strong correlation (Song & Su, 2022).

In the case of machines, it is assumed that rather than having general problem-solving ability, machines instead might have narrow problem-solving ability for a number of different problems (each represented by a cylindrical problem-solving volume in Figure 5).

Machines are not known to yet have general problem-solving ability but instead might have narrow problem-solving ability in a number of problem domains. From this perspective, current measures of machine IQ might be expected to be somehow related to narrow problem-solving ability in a particular problem domain.

In Figure 5 (left), the case of high training might be viewed conceptually as there being many more concepts in the conceptual space. Whether this is correct requires further study. Problem-solving is expected to be confined to each narrow region V_i. In Figure 5 (right), if this conceptual model is correct, then in the case of less training there will be fewer concepts in the conceptual space to use for problem-solving.

On reviewing various measures of AI performance in the literature to determine whether they are consistent with this prediction of being correlated with narrow problem-solving ability, all such assessments that were reviewed were found to be too deeply entangled with the specifics of their own methodology to be easily comparable to the more abstract prediction presented here (Iantovics, 2021; Safari, 2021).

Returning to the question of whether the increase in intelligence predicted with HCFC justifies HCFC being seen as the most important innovation in the history of human civilization, perhaps the most important takeaway from this analysis on how the performance of any intelligence is assessed is that by these estimates, the performance of an average human IQ of 100 might not even be detectable on a single test capable of measuring the performance of an AGI or a GCI having an IQ of 10^9. Any test would have to adapt to ask the human far fewer questions of far lesser difficulty, or the human simply would not be able to complete it in order to provide any assessment of their IQ at all. In summary, without a functional model of IQ that is the same for humans and machines, and that is valid for an exponentially higher IQ, the importance of an exponentially greater IQ cannot be objectively predicted, the impact of an exponentially greater IQ cannot be objectively observed, and the question of whether an exponentially greater IQ is the most important innovation in human history cannot be answered.

5. Results and Analysis

Assuming that some computing method or technology like quantum computing might exponentially increase narrow problem-solving ability (Figure 4).

Figure 6 shows narrow vs general problem-solving ability in the functional state space of the collective cognition. Technology like quantum computing might exponentially increase capacity to

Figure 5
Functional model of performance in machine IQ tests

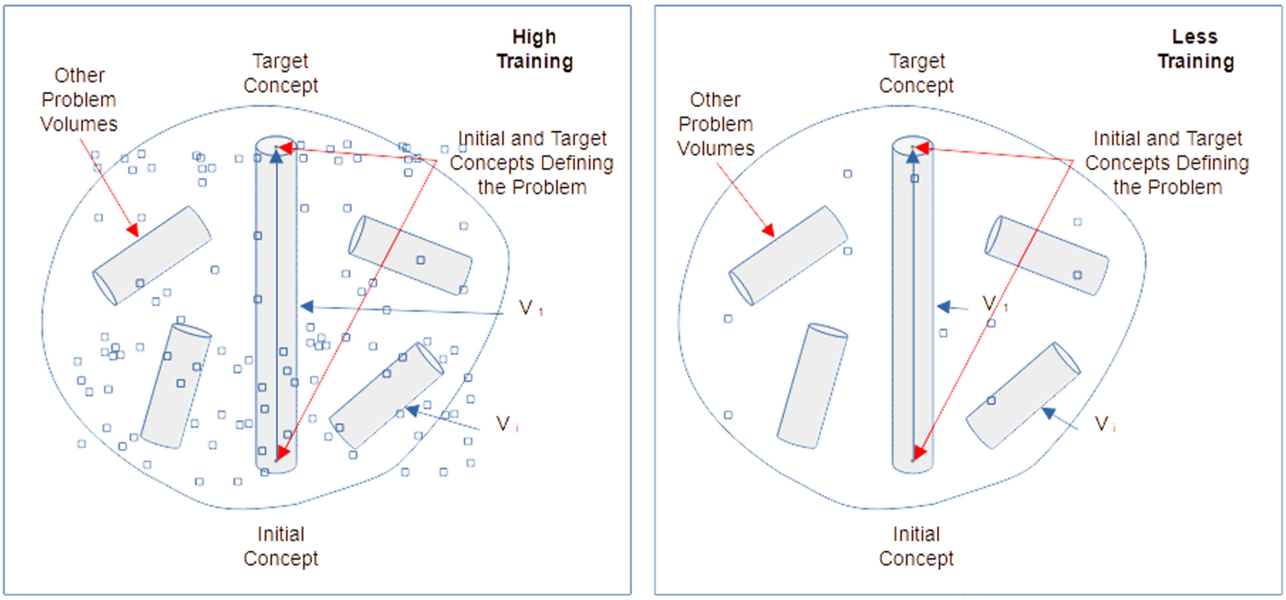
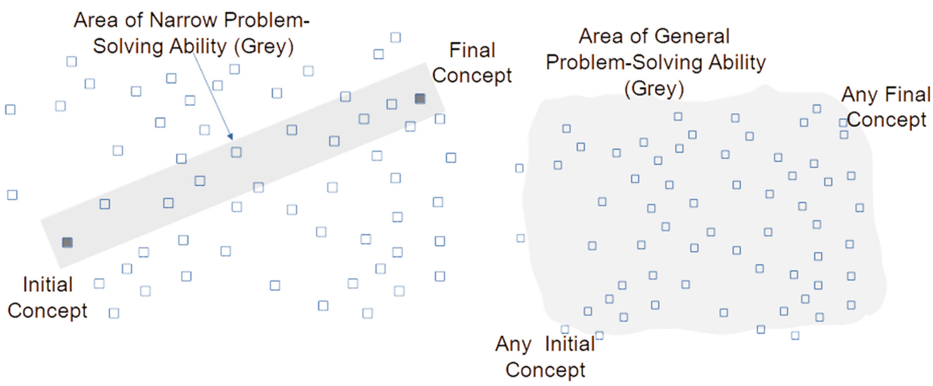


Figure 6
Narrow vs general problem-solving ability



solve specific problems. If a specific (i.e., narrow) problem is a rod-shaped region in conceptual space, this corresponds to an exponentially longer rod. But any technology that exponentially increases our general problem-solving ability implies an exponential increase in capacity to solve *EVERY* problem, including the problem of implementing quantum computing. This corresponds to the increase in volume resulting from extending that exponentially longer rod in every direction in conceptual space. However, since automating the process of extending that rod in every direction requires communicating meaning rather than just communicating information (i.e., it requires a semantic model of the existing solutions and a semantic model of the new problem to which those solutions are being applied), and since to this author's knowledge a semantic model has never existed before these functional state spaces, this exponential increase in general problem-solving ability cannot have been possible.

In summary, it is predicted that an exponential increase in general problem-solving ability requires the ability to communicate understanding, rather than information, so understanding can be transferred at this exponentially greater speed and scale. The transfer of meaning requires the capacity for complete semantic modeling, which is provided by functional state spaces. The potential capacity to generalize between any possible concepts or reasoning at the group level requires general problem-solving ability at the group level, which in turn requires GCI. Assuming it is true that without semantic modeling an exponential increase in effective intelligence is not possible, assuming as argued in this paper that an exponential increase in effective intelligence is possible through HCFC and has never been possible at any time before in human history, and assuming as argued in this paper that the importance of a technology is the increase in effective intelligence, then HCFC must be the most important technological innovation in human history.

6. Discussion

If it is correct that all concepts in the human cognitive system can be represented in terms of a basic set of operations (believed to be four in number) then all concepts can be uniquely identified and differentiated.

Assuming that all computing can be represented as the automation of human reasoning, then all computing processes can be represented as set of paths in conceptual space. Based again on simple geometrical arguments in this conceptual space, it is argued here that representing problems digitally might exponentially increase our ability to solve specific problems, but representing problems in terms of conceptual space might exponentially increase our general problem-solving ability, which means exponentially increasing our ability to solve any problem in general. Assuming conceptual space is a complete semantic model as believed, then meaning, including the meaning of computing solutions, rather than just information, can potentially be transferred at vastly greater speed and scale. This means that one of the problems this might exponentially increase capacity to solve is the problem of reusing computing solutions without reprogramming. Because of this, the analysis presented in this paper suggests that HCFC (using HCFM to define functional state spaces and then computing in terms of known paths through these functional state spaces) might be the most important concept in computing today and in addition suggests that by the potential increase in volume and density of conceptual space it might facilitate, one particular model of HCFC (the so-called a GCI platform) is the most important concept in human history to date and the most important concept in the immediate future until perhaps a second-order General Collective Intelligence (a GCI of GCI's) introduces another category of generalization capable of expanding to include a critical volume of the collective conceptual space, and in doing so makes it possible to achieve another exponential increase in the size and density of that collective conceptual space. However, functional state spaces are still hypothetical constructs because so far they have only been approximated. A number of problems like determining semantic distance still remain.

The importance of this paper is not in providing concrete algorithms that might be copied. Instead its importance is in directing the collective attention of the AI and applications community toward a new strategic path in which there might be far greater potential for research progress than has ever existed before, so that researchers might discover their own innovations. Even if complete implementations of functional state spaces have not yet been developed and are therefore not yet available for experimentation, the concept of functional state spaces has already enabled objective definitions to be proposed for properties such as complexity, general problem-solving ability, and narrow problem-solving ability, where to the knowledge of this author no objective definitions have existed in the past. These definitions have in turn enabled objective predictions of the relationships between these properties to be made, as well as predictions of how these properties (such as GCI) might be exponentially increased. Similarly, even if a complete GCI has not yet been developed, the concept of GCI as the most general possible model of collective reasoning among individuals and/or of distributed computation among intelligent agents is useful since (if correct) it facilitates modeling and optimizing all possible collective adaptive systems.

7. Future Research Directions

The most critical direction of research in the future has nothing to do with HCFC but instead has to do with the dynamics of group decision-making related to research. The result of no one knowing about HCFM and HCFC is that in comparison to the zero dollars currently spent deploying networks of HCFC-based interventions that might reliably succeed in achieving AGI and/or GCI, there are billions per year spent on disconnected interventions in all areas of AI that according to the HCFC model cannot reliably succeed in achieving this objective. Assuming that ensuring that AI reliably serves the collective well-being is a "collective optimization problem" in that such problems involve optimizing the collective well-being, then many and perhaps all of the existential challenges facing civilizations today are also collective optimization problems. If a model of computation based on HCFC (such as GCI) is a solution to this problem, then failing to investigate this path potentially equates to ignoring and failing to allocate resources to solutions to same collective optimization problem. If so, the human cost of this miss-allocation of funds is both staggering and tragic. If HCFM is a solution, it is one that no one has heard of. Perhaps this is because even contemplating such a radically different approach, much less letting the world know about it requires standing against this massive current of money, billions of dollars that is flowing in the exact opposite direction than it needs to. Or perhaps it is because whether intentional or unintentional, the funding system appears to restrict researchers (particularly unestablished ones) from straying in any direction radically different enough to result in the necessity of proving very strong claims.

In any case, if HCFM suggests the necessity of an entirely new approach for ensuring that AI reliably serves the collective well-being, then there is a larger importance in communicating this approach to a critical mass of people because the same approach is also essential in solving a great many other important problems. However, the greater the number of academic disciplines with something to contribute to this discussion, the smaller the likelihood that any individual has the formal background to tie these arguments in all these areas to the literature in each field. All of these factors together result in the unfortunate situation that what might be the most important contribution to ensuring that AI serves the public good is also one that goes unacknowledged and unexplored. To solve this problem, the most important future direction is to build a multidisciplinary network who might be interested in collaborating to publish on this topic, and discovering sufficient motivation for them to do so.

8. Summary

The approach described in this paper is based on a "conceptual space" that is far more general and "human-centric" than the conceptual spaces defined by others in very technical disciplines such as mathematics and physics. Those more technical definitions might make assumptions that break the capacity of the conceptual space to model all problems and solutions, and therefore all AI-related problem definitions and all AI solutions, as well as all methods by which they might be optimized. The benefit of a single human-centric and therefore universal approach to modeling cognition and other systems is a predicted exponential increase in general problem-solving ability stemming from the ability to more easily reuse problem-solving approaches. The challenge however with communicating the value proposition of this approach is communicating what is human-centric and therefore universal in every individual's experience, and what is intellectual, and therefore dependent on a specific set of concepts that might or might not exist in any given individual's understanding. The exponential increase in collective impact that HCFC predicts to be possible with a single universal approach to modeling cognition is only one of two predictions. The other is an exponential increase in ability to prevent collective impact. These possibilities are mutually exclusive. Without cracking the problem of building massive mind share for this human-centric approach, that massive increase in impact can only be driven in a centralized way that is aligned with the interests of some individual entity, rather than being driven in a decentralized way that is aligned with collective well-being.

9. Conclusion

The conclusions of this paper rest only on the assumptions that functional state spaces and models of HCFC like GCI can be implemented. However, far more important than the question of whether it is feasible that HCFC might exponentially increase general problem-solving ability is the issue of what to do if this question cannot be resolved within the available forum, namely within the N peer-reviewed pages allotted by the submission process of any given journal. In other words, what can be done if the question that must be addressed by a paper is too complex (occupies too great of a volume and density in conceptual space) for the answer to be proved feasible within the number of pages allowed by any submission process? Perhaps the problem needs to be redefined to a series of N much narrower questions that can more reliably be answered. But if so, how might assessment of those answers be coordinated so that this does not result in the necessity of N publication in sequence, which could stretch the process out beyond the lifetime of the investigator? What if those N questions span multiple disciplines? Perhaps the collective problem-solving ability needs to be increased by breaking the problem down into questions that can be given to experts of different specializations so that the collective ability to discover solutions does not rely on any limitations that cannot reliably be met, such as being able to communicate in minutes through X pages concepts that might take months and many more pages to learn. Perhaps the collective problem-solving ability needs to be increased by funding the efforts of reviewers so that efforts can be sustained beyond what is reliably achievable from reviewers who are generally forced to volunteer their time.

In any case, digital technology created through the use of computational methods has been heralded by many as one of the most important developments in recorded history (Oden, 2002). Simple geometrical arguments in functional state space (Williams, 2022) suggest that functional state space-based computing (HCFC) has the potential to be exponentially more powerful than digital computing or even than the qubit-based computing of quantum computers. Using state spaces to model the human cognitive system and other living processes as self-organizing adaptive problem-solving systems, and using those state space models to understand properties such as general problem-solving ability, ability to self-organize, and when problems are not reliably solvable without these properties at the group level, is consistent with the idea of an emerging "global brain" (Heylighen & Lenartowicz, 2017), which has in turn been associated with a technological singularity (Cadell, 2020), and which by definition is the most important technological event in human history. If as suggested by these arguments HCFC (which includes GCI) is predicted to be the trigger for that singularity, then HCFC is potentially the most important technological innovation in the world today. If so, it is important for the computing community to collaborate to test the claims made in this paper.

Recommendations

Anecdotally, representing cognition in terms of functional state spaces using HCFM seems to enable mathematical relationships to be defined for many if not all properties of cognition like general problem-solving ability (intelligence), or importance of a concept, or complexity. These properties also seem to be generalizable to other functional state spaces. For example, general problem-solving ability also appears to be a valid property in the "awareness space" navigated by the consciousness, where the ability to solve any problem of awareness appears to describe degree of "enlightenment." Whether or not creating functional definitions of properties in terms of functional state space is a fundamentally new contribution to each discipline focused on the study of some individual system (e.g., cognitive science with its focus on human cognition), or whether it is a fundamentally new contribution to the study of all systems (e.g., systems science) remains to be determined. Answering this question might require a broad multidisciplinary literature review.

Other questions that might require a broad interdisciplinary review are whether any existing work in the literature has explored the mechanisms through which it might be possible to increase the computing ability of a state space model; whether functional state space is unique in that it describes only one domain of behavior, or whether it is the case that any state space spanned by some set of vectors is a state space that describes only one domain of behavior; and whether there state space models with states that are not spanned by some set of vectors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

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