Human Intelligence and General Collective Intelligence as Phase Changes in Animal Intelligence

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Abstract

The hypothesis that human intelligence represents a phase transition in animal intelligence is explored, as is the hypothesis that General Collective Intelligence (GCI), which has been defined as a system that organizes groups into a single collective cognition with the potential for vastly greater general problem-solving ability than that of any individual in the group, represents a phase transition in human intelligence. At these phase transitions, cognition can be demonstrated to gain the capacity for exponentially greater general problem-solving ability. When generalized as an Nth order pattern, these N phase transitions represent successively more powerful intelligences, where each of these super-intelligences can potentially be implemented as an Artificial General Intelligence (AGI), or as a General Collective Intelligence (GCI).

Keywords

General collective intelligence; artificial general intelligence, human cognition; animal cognition; phase change

Introduction

Many studies have attempted to differentiate between human and animal cognition. But such studies have only revealed that some animals have advanced cognitive abilities which further blurs the distinction between human and animal cognition. As a result, not only is there no consensus on what human intelligence entails, but the precise difference between animal and human intelligence has not been clarified, and it may still be true that “there is no consensus on the nature of animal intelligence despite a century of research” [1]. Language was thought to be the difference between human and animal intelligence, but some work has suggested that some animals have demonstrated some capacity for language as well [2]. In any case, other work suggests “the body of evidence from comparative studies lends increasing support to the notion that general intelligence is not unique to humans but also present in nonhuman animals and thus was not as tied up with language” as some had suggested [5]. Others argue on philosophical grounds that there is no animal action, only behavior, because animals lack agency [3]. Still others sidestep the question entirely with statements like “intelligence is a fundamental ability that sets humans apart from other animal species” [4], that assume the matter of differentiating, or even defining, human intelligence through some properties has been settled.

Because modular systems may readily evolve [6], [7]; [8], the evolution of the animal and human cognition as a massive set of domain-specific adaptations or modules has been proposed, though an inadequate explanation of plasticity and inadequate consideration of neural connectivity have been

suggested as potential weaknesses of such approaches [9], [10]. This paper proposes an evolutionary pathway leading from that modularity to the emergence of domain-general cognitive processes, in a way that both accounts for neural connectivity and plasticity, and does not require disproportionate amounts of energetically costly brain tissue compared to domain-specific specializations [11].

A Functional Model of Cognition

Functional modeling has long been used by teams to decouple large complex projects into simpler components that each require expertise in fewer domains, and that have well-defined interfaces that remove the need to understand disciplines related to other components, so that such projects can be reliably completed by large multidisciplinary teams.

Human-Centric Functional Modeling (HCFM) [12],[13] is a recently defined methodology that models a system as consisting of a minimal set of functions that can be used to compose all processes of the system that are observable directly within innate human awareness or through deduction by first principles. Executing each of these functions or processes puts the system in a different functional state, so that the system navigates a “functional state space”. The HCFM has been used to define a Functional Modeling Framework (FMF) [12], [13] that applies this approach to defining models of the human system. In the case of the cognitive system, this functional state space consists of concepts, or in other words is a “conceptual space”. Each cognitive process (reasoning or understanding) is then a path with which the cognitive system navigates through this conceptual space. Each concept is defined through its relationship to other concepts, which in turn are expressed in terms of reasoning or understanding, and therefore in terms of paths through the conceptual space. Concepts that are more specifically defined occupy a more highly localized (smaller) position in conceptual space.

Human Centric Functional Modeling has been used to define what is believed to be the first model of human cognition complete enough to have the potential capacity for human-like general problem-solving ability. Being a functional model independent of implementation, this model has been used to define a model for Artificial General Intelligence or AGI [14]. HCMF has also been used to define a model for General Collective Intelligence or GCI [16] a system that combines groups into a single entity with the potential capacity for general problem-solving ability that is vastly greater than that of any individual in the group.

A Functional Model of General Problem-Solving Ability

Navigating Conceptual Space

Figure 1: The squares represent concepts, and spatial distribution of the squares represents conceptual space. Reasoning traces a path between concepts.

From a functional perspective, in any system of cognition, whether human cognition, animal cognition, or general collective intelligence, reasoning processes are represented in the FMF as tracing a path or general collective intelligence, reasoning processes are represented in the FMF as tracing a path from one concept in the conceptual space to another from one concept in the conceptual space to another.

Problems are represented as the gap between one concept in the conceptual space and another. Solutions are represented as the set of reasoning process which bridge that gap.

The conceptual space of one organism or individual might also have different resolution than the conceptual space of another organism.

Unresolvable Concepts in the Conceptual Field

Figure 3: 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.

General problem solving ability is then the ability to sustainably navigate the conceptual space so that it is potentially possible to navigate from any problem that can be defined within that conceptual space to any solution that can be formulated within that conceptual space. And IQ then becomes proportional to the volume in conceptual space that can be navigated within the time of the typical IQ test.

General Problem Solving Ability

Figure 4: Larger volume of conceptual space navigated per unit time (left) results in higher general problem solving ability. A smaller volume of conceptual space navigated per unit time results in lower general problem-solving ability.

From this perspective, animals must clearly have some degree of general problem-solving ability. Where a non-intelligent system such as current computer programs solves the problem it's designers have chosen for it, a system with general human-like problem solving ability, must have the ability to choose which problem to solve. The model of cognition described within this paper chooses which problem to solve through maintaining global stability in the dynamics with which it executes all reasoning processes, where that stability exists within a fitness space related to cognitive well-being. Because this stability can be achieved through functions that are potentially chaotic in conceptual space (that is the reasoning executed is non-deterministic) this functional perspective cannot be called "mechanistic" as earlier functional approaches have been criticized as being. This functional representation of intelligence appears to be consistent with animal intelligence as well.

A Functional Model of Complexity

As mentioned, in the HCFM approach systems are defined in terms of a minimal set of functions from which all processes of the system can be composed. These functions might have first order interactions, or interactions between their interactions (second order interactions), up to some order N , where N is an integer that might be arbitrarily high. The level of complexity in any system that a cognitive system is capable of understanding (the level of complexity the cognitive system is capable of navigating) is the order N of simultaneous interactions in that system, which the cognitive system is capable of conceptualizing.

However, if all conceptual problems can be defined as the lack of a path through conceptual space, then a more general problem is the lack of a path between two larger regions in conceptual space.

Visual Representation of Generalizing a Problem Definition within Conceptual Space

Figure 5: A problem definition is a gap (left) between two specific concepts in conceptual space. Generalization defines the problem to be a gap (right) between two larger categories of concepts.

If we know the solution to any problem, then by generalizing any other problem sufficiently, that solution also comes to solve our more general problem. In other words, all problems can be solved by a sufficient level of generalization.

Since all problems can reliably be solved by generalizing the problem sufficiently, a higher order problem is one that is too complex to be defined in specific enough terms for the problem definition to be within the capacity of the cognitive system to conceive. A higher order solution is one that is too complex to be specified with a sufficient level of detail for the implementation of that solution to be within the capacity of the cognitive system to conceive.

Human Cognition as a Phase Transition in Capacity to Navigate Complexity

Human cognition, whether individual or in groups, faces a limit to the complexity of problems it can reliably define or solve, and a limit to the degree that it can reliably scale cooperation to increase that capacity. Firstly, concepts have a finite resolution in conceptual space that determines the capacity of the cognitive system to distinguish one concept from a similar one (one located nearby in conceptual space)

Resolution of Concepts in Conceptual Space

Figure 6: The resolution of a concept is defined by the degree to which its position is localized (its extent) in conceptual space. This in turn is dependent on the number of relationships which fix that position, and therefore is dependent on the complexity (number of simultaneous interactions) the cognitive system is able to navigate.

The cognitive system also faces a limit to its degree to generalize. This ability to generalize has a visual representation in conceptual space.

Visual Representation of Generalization within Conceptual Space

Figure 7: A problem is a gap between two points in conceptual space. A specific solution S₁ (left) is a single path between those points. Generalization of either the initial concept or final concept to occupy a larger conceptual space enables all the N relationships between those generalizations to be identified as solutions S_N.

This limit in ability to generalize arises because although a generalization occupies a larger and larger area in conceptual space, the concept of the generalization must become smaller as the generalization becomes larger. A generalization that applies to N entities must have relationships to those N entities. The number of relationships between one concept and other defines the resolution in conceptual space. Because a cognitive system has a finite capacity to navigate complexity, it has a finite resolution in its conceptual space. Because it has a finite resolution in its conceptual space, and because the capacity for generalization depends on this resolution, humans have a finite ability to generalize in precise terms. However, of course, it is always possible to generalize in arbitrarily imprecise terms.

From this perspective, human intelligence is a phase change in cognition. Because any relationships between generalizations are potential solutions to the problem of finding reasoning or understanding processes with which to navigate the conceptual space from some initial set of concepts to some final one. And this navigation is problem solving. So once the level of generalization increases to the point at which reasoning (the path from the initial set of concepts to the final one) can still be contained within the same generalization, then all N relationships between all M generalizations, where N and M are integers, become potential solutions. In other words, once reasoning becomes isomorphic and maps to the same generalization, the number of potential solutions to any problem which that reasoning might find, and hence the problem-solving ability of that system, increases exponentially. As the number of relationships defining concepts gains the potential to increase exponentially, concepts become more precisely defined points in conceptual space (smaller and more densely spaced).

Phase Change in Level of Generalization

Figure 8: As the capacity for generalization (represented by the enclosed area in conceptual space) increases, any reasoning process from the initial generalization to the final generalization is eventually enclosed within the same generalization. At this point, where reasoning processes become isomorphic, all N reasoning paths between all M generalizations potentially become solutions for each problem i .

Since general problem solving ability in this functional modeling approach is defined by the volume in conceptual space that can be navigated per unit time, and since level of problem-solving ability increases with capacity for generalization, this suggests that at some threshold of general problem-solving ability intelligence undergoes a phase change in which there is a sudden increase in density of concepts within the conceptual space, and a sudden increase in the size of the conceptual space, and a sudden increase the ability to navigate that conceptual space. Visually, this would appear as a phase change in the conceptual space as compared to the conceptual space of an animal.

Phase Change in Problem-Solving Ability

Figure 9: Before the phase change the cognitive system resolve concepts less precisely in conceptual space, and solve all problems with a smaller range of reasoning. At the phase change the cognitive system gains the ability to increase problem solving ability by abstracting solutions (both reasoning and physical tools) so they might be reused, including by storing and exchanging value in terms of impact on a problem, leading to a potentially exponential increase in the size of the conceptual space the problem-solving process might navigate, and a similar increase in the resolution with which the conceptual space might be navigated, which corresponds to a phase change in general problem-solving ability. This phase change is represented visually as the c

Generalizing the Pattern of Phase Transition to an Nth-Order Intelligence

Anecdotally, individual human intelligence appears unique in having sufficient general problem-solving ability to abstract the concept of value so that it's possible to see the value in creating any tool to achieve any purpose, and so it's possible to exchange and accumulate enough of that value for tools requiring great effort to design and build to be possible, and for today's automation through computing and other tools to be possible. The level of problem-solving ability allowing this abstraction defines a phase change in problem-solving ability.

General Collective Intelligence or GCI is predicted to create the additional problem-solving ability required to see the value in abstracting the concept of abstracting any concept, and the ability to reliably exchange and accumulate that value, so that designing, manufacturing, and funding products and services of higher order complexity become possible where they are not possible within human cognition today. GCI is predicted to make it possible to reliably see the value in cooperating to define abstractions (like patterns of cooperation) to create tools to achieve any purpose, where that cooperation, and therefore those tools, are not possible today. And it's predicted to create the additional problem-solving ability required to exchange and accumulate enough of that value for the computing processes of the future to be possible.

In this way intelligence can be seen as an Nth order pattern, in which successively higher orders of abstraction are implemented. Individual intelligence is first order, collective intelligence is second order, and a collective intelligence consisting of collective intelligences is second order, and so forth to the Nth order. Any Nth order intelligence will also have limits to the complexity it is able to reliably navigate. These limits will be defined both by the order N of the intelligence, and the capacity to store

and navigate reasoning processes with that higher order system. For example, if a general collective intelligence requires definition of a certain volume of conceptual space before it can navigate a greater volume of collective conceptual space than any individual can navigate their own conceptual space, then this requires defining whatever number of human-centric functional models (semantic models) for whatever number of concepts and for whatever number of collective reasoning processes, that are required to span this space. Since these modeling processes cannot currently be automated, this might require a minimum number of people.

Experimental Validation

Assuming that intelligence is related to the capacity of the cognitive system to navigate within a conceptual space a simulation of the movement of a system of cognition in a conceptual space was conducted to confirm that ability of the cognitive system to navigate that conceptual space might be interpreted as intelligence.

Artificial neural networks attempt to replicate certain capabilities of the brain, including generating and discovering new information through learning, without any assistance. These networks have emerged through mathematical modeling of the process by which the human brain is assumed to learn [21]. By defining a model of a network of concepts such a cognitive system might navigate, any act of perceiving, inferring, or other operations become an act of navigating that network [22]. This is consistent with the functional model of cognition referred to in this paper, which represents intelligence as the capacity to navigate the conceptual space per unit time. In networks, navigability corresponds to connectivity.

The conceptual space, as the functional state space of the cognitive system, is assumed to consist of concepts. These concepts are the nodes of the network of concepts navigated by the cognitive system. Edges in any network are the connections between nodes. In the case of the cognitive space edges are the processes (reasoning or understanding as the basis of problem solving, planning, etc.) providing the connections between concepts. There are some requirements in the structure of a such a network. First of all, the network must be undirected, where an undirected graph is graph, i.e., a set of objects (called vertices or nodes) that are connected together, where all the edges are bidirectional. Since the concepts are complementary (have meaning with respect to each other), reasoning can be defined to connect any concept A to some concept B, and that reasoning can be reversed to connect concept B to concept A. There can be no one-way interaction between nodes. In addition, the structure of the network must be dynamical. Because intelligence is an evolving phenomenon, it cannot be expressed in a fixed network topology.

Dynamic networks demonstrate a time-dependent change in topology [23]. Such changes in topology might be used to detect the changes in a network of concepts as they are navigated by a cognitive system, in order to relate those changes to intelligence. Some basic properties through which a change in topology might be detected are average degree, Global Clustering Coefficient (GCC) and Largest Connected Component (LCC) of the network. The average degree of an undirected graph measures the number of edges compared to the number of nodes. The Global Clustering Coefficient measures which nodes in a graph tend to cluster together. And the Largest Connected Component indicates the largest cluster, which is an induced subgraph of a network [24, 25].

The five-step algorithm below was implemented to model the navigation of a cognitive system through its conceptual space during the process of reasoning:

- 1) A series of experiments were conducted. Each experiment began with a random network (Erdős-Renyi graph) composed of 100 nodes representing unconnected concepts (concepts that have not yet been connected by any reasoning).
- 2) Edges representing reasoning processes were added based on a fixed reasoning probability in each timestep (max. 100).
- 3) Every edge representing a reasoning process was assumed to increase the probability to create a new edge between related nodes in the next timestep (the linking of A and B nodes and the binding of A to C, increase the likelihood that B would link to C).
- 4) The average degree, clustering coefficient and largest connected component were measured in every time step.
- 5) The overall experiment was averaged over ten thousand networks.

The topological change of a growing network as a result of one of these simulations is shown in figure 9.

Figure 10: Topological change of a dynamic network with increasing number of connections as the cognitive system continues to reason, showing the increase in ties between concepts.

Assuming that the cause-effect process be reversible, the growing network is undirected. The graphs of the average topological measurements of the growing networks in each experiment are shown in figure 10.

Figure 11: Top-left: Average degree. Top-right: global clustering coefficient. Bottom-left: the largest connected component versus time.

As can be seen, it is observed that topological measurements in a dynamic network modeled with the connections between the concepts develop with the growth of the network. If intelligence can be defined by the navigability of the cognitive system in conceptual space, the topological quantities of the network of concepts would be expected to increase. The increase in these quantities that was observed in the simulation supports this conclusion. Pearson's correlation coefficient is a statistic that measures linear correlation between two variables X and Y. This coefficient is expected to show correlations between the average degree, global clustering coefficient, and largest connected component versus time, if the network of concepts is growing as a result of the navigation of the cognitive system. Actual measurements of these correlation coefficients is presented below.

Metric	Correlation coefficients
GCC-Av. degree	0.7827
GCC-LCC	0.5943
LCC-Av. degree	0.7369

Table 1: Pearson's correlation coefficients between the topological properties of the network, showing growth in the network of concepts as would be expected if ability to navigate that network (intelligence) was related to growth in that network.

In conclusion, the correlations between the topological measurements are an expected result of a growing network of concepts. And the growth in the network of concepts with navigation of the conceptual space supports the conclusion that intelligence might be represented by the capacity of the cognitive system to navigate conceptual space. The behavior of all these topological properties individually is also consistent with this conclusion. Further work related to this model might define

network of concepts representing the conceptual spaces of various animal species, so the traffic flow within the network could be generated, and the evolutionary footsteps separating various species, including the phase shift described in this paper, might be modeled for further analysis.

Implications

Human intelligence has enabled mankind to not only generate a surplus of resources, which other animals can do, but has also given mankind sufficient capacity for abstraction to enable that surplus to be represented in abstract terms that remove the barriers to accumulation. Whether accumulation of knowledge of where fruits or vegetables can be gathered, whether accumulation of reasoning processes enabling prey animals to be outwitted or predator animals to be escaped, with such abstraction any accumulation can potentially be represented as, for example, abstract economic value that can be stored and exchanged, so that economic value can be potentially be accumulated at levels orders of magnitude greater. But value in the abstract is impact on any targeted problem in the world, so capacity to accumulate value is the capacity for humans to achieve impact on the entire world itself. And this removal of barriers to accumulating value has enabled human-beings to accumulate orders of magnitude greater value, and to have the potential for orders of magnitude greater impact on the world around us, than any other organism.

If it's true that no other animal has had the intelligence to have been able to abstract value into a form that can be accumulated in this way, then we would expect that the inability of any other animal to any general medium of exchange of value (i.e., money), should constitute experimental validation of this concept. While it is true that other animals have the capacity to exchange tokens for specific items [20], [19] no other animal has demonstrated the capacity to accumulate an exponentially greater value of tokens than others of their species. If problem-solving ability is impact on a particular outcome, one would expect this exponential increase in accumulation by some specific animal of a species if the species has a level of generalization past the point of this phase change, given the exponential increase in problem-solving ability predicted to come with this level of generalization. No such animal exists.

In summary, this analysis based on Human-Centric Functional Modeling suggests that adaptive problem-solving systems (systems that continually interact with their environments according to patterns of stable dynamics in some "fitness space") can undergo a "big bang" in which their functional state spaces increase exponentially in size and density when the distances at which their functional states might interact increases to span the entire functional state space. At this critical point the entire functional state space can be involved in a single interaction. Since the cognitive system can be represented as an adaptive problem-solving system that navigates a functional state space (the space of concepts or the "conceptual space"), this exponential increase ("big bang") has been hypothesized to occur in cognition, in particular it has been hypothesized as being linked to the difference between human and animal intelligence. Since physical matter, and hence the entire physical universe, can also be represented as an adaptive problem-solving system that navigates a functional state space, this exponential increase has been hypothesized to represent the cosmological big bang as well, an analogy that permits a new perspective on the cosmological big bang. Because all the contents in a system (such as the cognitive system or the observable universe) might interact when that system contracts to a single point and the interaction distances are zero. Or all the contents in the system might interact when the interaction distance of all the contents in the system increases to span the entire system. In addition, there might be some intermediate point at which a critical proportion of the contents of the system interact within some critical interaction distance, and as a result a "big bang" can occur. If human cognition can be used as an example of the dynamics of functional state spaces, this third option likely represents the truth. It is significant that all open functional state spaces potentially have the same representation as graphs containing networks of nodes representing functional states connected by

edges representing interaction processes, and therefore that this big bang appears to be a property of functional state spaces in general rather than a property of the interactions defining the physics of any particular functional state space. As a result, this perspective of the big bang appears to be completely independent of the laws governing the observable universe, which is significant because using Human-Centric Functional Modeling it is possible to construct functional state spaces for a hierarchy of simpler universes that contain contents that are not yet matter, but that add up to form our current universe and all its matter. Each of these universes might have their own “big bang”. Defining human cognition in terms of this more general problem of a “big bang” is in turn beneficial because it enables a much wider assortment of physicists, mathematicians, computer scientists, and others, to dedicate their efforts towards elaborating a solution.

Conclusions

In this paper, a functional modeling approach has been used to represent intelligence in terms of capacity to navigate a conceptual space per unit time. Defining this conceptual space as containing a network of concepts, this representation of intelligence appears to be confirmed by a simulation of how the topology of such a network would be expected to evolve through such navigation. Assuming this functional model, human intelligence has been represented as a phase change in this network topology as compared to animal intelligence. When this phase change model is generalized it suggests the possibility of defining a General Collective Intelligence or GCI with the capacity to vastly increase the problem-solving ability of groups. Since general problem-solving ability is relevant to every problem, it is relevant to every discipline of study, from fundamental physics, to curing cancer, as well as to all the existential challenges of today, from climate change, to poverty.

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