General Problem-Solving Ability in Natural Systems as a Model for Computation

Andy E. Williams[1*]

[1] Nobeah Foundation, Nairobi, Kenya
[*] awilliams@nobeahfoundation.org

Abstract
Natural systems have demonstrated the ability to solve a wide range of adaptive problems as well as the ability to self-assemble in a self-sustaining way that enables them to exponentially increase impact on outcomes related to those problems. In the case of photosynthesis nature solved the problem of harnessing the energy in sunlight and then leveraged self-assembling and self-sustaining processes so that exponentially increasing impact on that problem is reliably achievable. Rather than having to budget a given amount of resources to create a mature tree, where those resources might not be reliably available, tree seedlings self-assemble in a self-sustaining way from very few resources to grow from having the capability of photosynthesis accompanying a single leaf, to the capability of photosynthesis accompanying what might be millions of leaves. If the patterns underlying this adaptive problem-solving could be abstracted so that they are generally applicable, they might be applied to social and other problems occurring at scales that currently are not reliably solvable. One is the Sustainable Development Goals (SDGs) funding gap. The funding believed to be required to address the SDGs is difficult to estimate, and may be anywhere between $2 trillion and $6 trillion USD per year. However, bridging the gap between the funding required to meet these goals and the funding available to do so is universally acknowledged to be a difficult and unsolved problem. This paper explores how abstracting the pattern for general problem-solving ability that nature has used to solve the problem of exponentially increasing impact on collective problems, and that nature has proven to be effective for billions of years, might be reused to solve "wicked problems" from implementing an Artificial General Intelligence (AGI) to funding sustainable development at the scale required to transform Africa and the world.

Keywords
general collective intelligence factor, General Collective Intelligence (GCI), Artificial General Intelligence (AGI), individual optimization, collective optimization

Introduction

Wicked problems by definition are problems that have not proven to be reliably solvable, and for which it might be difficult to know whether one has defined the correct problem in the first place. If solutions to wicked problems such as poverty exist, the challenge is to define a system of problem-solving able to increase problem-solving ability to the point that defining the optimal problems and discovering the optimal solutions is reliably achievable. In adapting organisms to fit different ecological niches, nature has proved to have the ability to explore a very wide range of ways of defining the problem of fitness, and has also proved to have the ability to discover a very wide range of solutions in order to achieve that fitness. What isn't clear however is exactly what general problem-solving ability in any given problem domain means, as well as whether natural systems have general problem-solving ability, and what kinds of problems can't reliably be solved without that ability. This paper attempts to abstract the concept of general problem-solving ability so that it can potentially be reapplied to solving wicked problems such as increasing the funding for sustainable development in Africa to the point that such development is reliably achievable [1], or implementing an Artificial General Intelligence [2].

The basic argument of this paper is that living organisms can be seen as systems of computation, and that this model of computation can be replicated to increase the problem-solving ability of human groups to the point that problems like artificial general intelligence (computers with human-like intelligence), or problems like ensuring African countries can generate the funding to support their own sustainable development at the scale required to radically transform the continent, are reliably solvable. Both of these are problems that haven't yet been solved, so by definition any solution must be new. Without understanding this it might be easy to come to the conclusion that the approach described in this paper is not new and adds nothing to the existing body of knowledge. This approach bears some relationship to collective intelligence and to artificial intelligence [4]. However, exponentially greater general problem-solving ability within individual or collective systems is fundamentally different. As described in a review of the literature which argues why this approach is fundamentally new [5], part of the challenge in communicating an understanding of this model is therefore that the extent to which it is too new and too disruptive to the existing body of knowledge to be easily understood and recognized.

An easy way to understand this model is viewing an organism as a system of computation able to optimize its outcomes as an individual, while a crowd or an ecosystem is a collection of organisms. As an analogy, consider a petri dish full of one million single-celled organisms dumped onto the floor. Those organisms might be able to travel one meter or so before they either die or need to find more food and other resources. However, if those one million single cells are organized into the form of an insect, they might be able to travel tens of kilometers to find food. In this way, nature has demonstrated the general problem-solving ability required for groups of cells to optimize themselves into a very different form. Through cooperation, nature has also demonstrated it can exponentially increase the ability of each of those one million cells to solve the problem of finding resources.

Assume a bird contains five hundred million cells. A set of single-celled organisms can easily number five hundred million, but they have never been observed to have the ability to spontaneously organize themselves to fly. To those five hundred million single-celled organisms, flight is not a reliably solvable problem. They don't collectively have an adaptive problem-solving process powerful enough to come up with a solution like flight. If finding food requires flight, then achieving that outcome becomes a "wicked problem. Furthermore, even if presented with the exact solution for how they can work together to achieve flight, those five hundred million single-celled organisms can’t even reliably evaluate that solution to be correct. This paper describes this adaptive problem-solving process. The model of Artificial General Intelligence referred to in this paper introduces this problem-solving ability to AI. The model of General Collective Intelligence referred to introduces this collective problem-solving ability to human groups so that far more complex problems like ensuring African countries can generate the funding to support their own sustainable development at the scale required to radically transform the continent are reliably solvable. A group of people organized by General Collective Intelligence is not merely a crowd but effectively behaves as a single organism. Furthermore, GCI creates the potential to incorporate intelligent agents representing each individual and interacting with collective reasoning processes on each individual's sole behalf. In a GCI those intelligent agents might be replicated an unlimited number of times, so that each individual might simultaneously interact with billions of reasoning processes. Where the effectiveness of current problem-solving processes is limited by the number of problem definitions or solutions that can be considered, GCI radically increases the scope and scale at which collective reasoning is possible. Other work explores in detail why despite the importance and the novelty of this model of problem-solving ability, groups can't reliably determine this model to be important or new, as well as how this problem of seeing the value in this model can reliably be solved in the same way nature has [5].

Human-Centric Functional Modeling

In Human-Centric Functional Modeling living systems are modeled as having a set of human-observable behaviours (functions). All the states accessible through these functions within a given domain of behaviour form a "functional state space" which the system acting in that domain moves through. Any collection of such systems then moves through a collective functional state space. As an example, the cognitive system executes reasoning and understanding processes, as it does so it moves from one concept to another, thereby moving through a space of concepts or a “conceptual space” (the functional state space of the cognitive system). Using this same approach a collective cognition can be represented as navigating through a collective conceptual space in order to solve group problems. Similarly, other living processes such as homeostasis, reproduction, and evolution can be represented as adaptive problem-solving systems which move through their own functional state spaces.

In each functional domain problems are defined as the lack of a path from an initial point in functional state space to a final target point in that space. Solutions are defined as paths which accomplish that navigation. In any adaptive domain there are two ways that problems can be solved. One is through recalling patterns of solutions (i.e. paths which solve the required problem of navigation) observed in the past when such solutions can’t be computed (i.e. when solutions are non-computable). Another is through using known path segments to compute the unknown path (i.e. using those path segments to compute the solution to the problem of navigation when solutions are computable). In the domain of cognition cognitive psychologists have confirmed the existence of these two problem-solving methods, namely type 1 (fast or intuitive) reasoning, and type 2 (slow or rational methodical) reasoning. Type 1 reasoning solves non-computable problems by recalling patterns of solutions observed in the past. Type 2 reasoning solves computable problems through some methodical process such as evaluating an equation.

Assume that any system can be described in terms of whatever behaviors it has that can be observed within the awareness that is innate to human beings. Define a domain of behavior as containing all processes in which any change in the state of the system remains in the same category. For example, the domain of cognition can be defined as including all reasoning or understanding processes that change the state of the cognitive system from one concept to another concept, with the result that all states in that domain are concepts. The domain object that describes the state in a given domain then restricts the behavior possible in that domain. Consider this network of functional states to be a graph containing a network of nodes, with each node representing a functional state, and with the connections between functional states representing the behavior through which the system can transition from one functional state to another. This graph of the network of states accessible through these behaviors is representation of a “functional state space” as in figure 1.

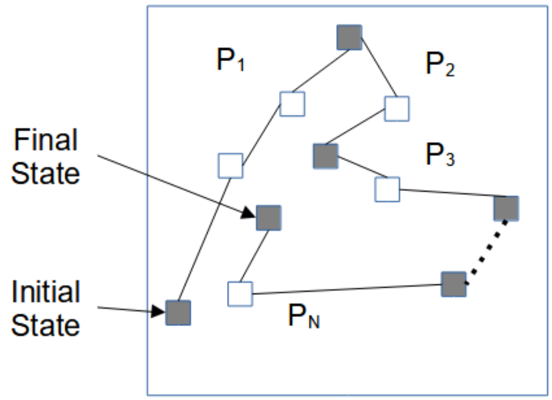

Figure 1. In Human-Centric Functional Modeling systems are represented as moving through a functional state space.

Assume that all the potentially complex behaviors in a given domain can be represented as some combination of a very simple set of behaviors (functions or operations). In other words, assume that any network of functional states can be constructed with some sequence of only a few different types of operations. In mathematical terms a set of operations is said to “span” a space when any point in that space can be represented as some combination of those operations. It has been hypothesized that a set of four operations can “span” any such network of functional states [2]. Representing the mind as moving through its own functional state space (again, a space of concepts or a “conceptual space”), then if a set of four operations spans this space, those four operations can potentially represent any reasoning or understanding process connecting concepts, and can therefore define any concept. The importance of having potentially created the capacity to represent all reasoning or understanding processes that might be used to navigate between concepts is that cognition can then be represented as some process of navigation between those concepts.

As with any functional state space, this conceptual space is a graph defined by a network of nodes. In conceptual space each node represent a concept, where those nodes are connected by edges representing the reasoning relationships that define those concepts. Therefore any section of the graph is potentially a complete semantic model providing a fully self-contained representation of meaning so that by exchanging sections of this graph it might be possible to exchange and accumulate meaning at exponentially greater rates, rather than just exchanging information. Conceptual space is potentially the first complete semantic representation in existence. No other complete semantic representation is believed to exist, since before this Human-Centric Functional Modeling approach it is believed there were no cognitive models suggested by any researcher to have the capacity to represent all of the functions of cognition, and as one researcher has stated “it is hard to imagine that one could give a complete theory of semantic representation outside of a complete theory of cognition in general” [3].

Cognition as an Optimization Function

Any system with a stable set of repeatable functions also must stay within a bounded region of a “fitness space” that describes the fitness of the system to execute its functions. A change in fitness of the system occurs as a result of some action, that is, some path, in functional state space. Defining this “fitness space” as having three dimensions given by the target value of fitness, the actual value of fitness, and the predicted value of fitness, then the path through this fitness space must stay within a bounded region of fitness space as in figure 2. In this sense the motion in fitness space must be stable globally throughout the fitness space, despite potentially being chaotic in functional state space due to random interactions with the environment.

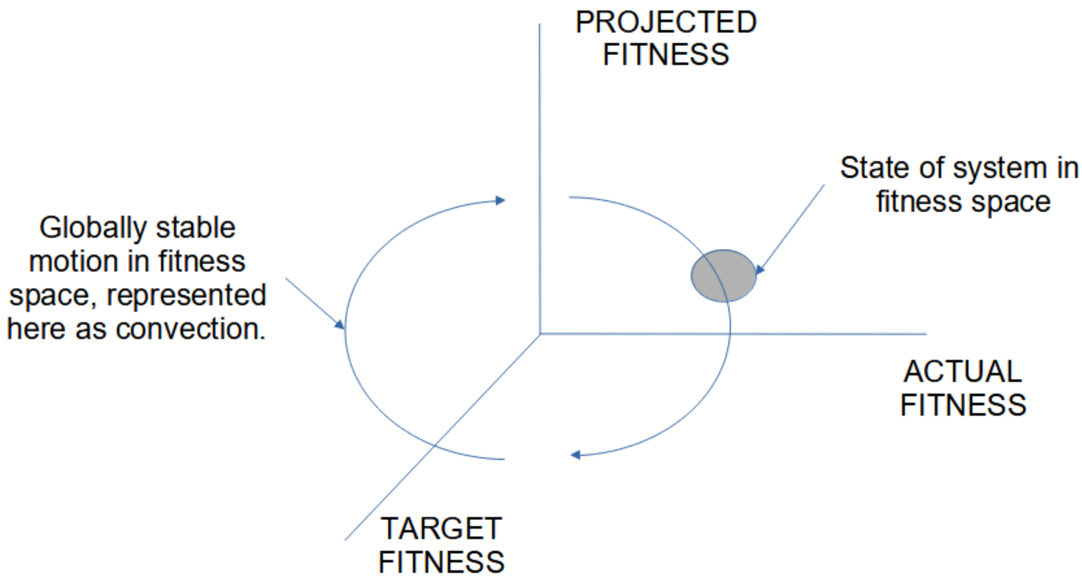

Figure 2. In Human-Centric Functional Modeling systems are represented as also moving through a fitness space as they move through functional state space.

In terms of the cognitive system we can intuitively understand its position in this fitness space as "cognitive well-being". In conceptual space a specific problem is represented as the cognitive system having to find reasoning or understanding processes that allow it to navigate a path from a specific initial concept to a specific final concept. General problem-solving ability is represented as the potential ability to find reasoning or understanding processes that allow it to potentially navigate a path from any initial concept in general to any final concept in general. Magnitude of general problem-solving ability is represented as being related to the total volume of conceptual space that can be navigated per unit time. If our cognition is to have the ability to continue to function it must tend to navigate our space of concepts (conceptual space) in a way that solves the problem of maintaining our cognitive well-being (fitness of the cognitive system) within a stable range. From the perspective of Human-Centric Functional Modeling this dynamically stable navigation of the conceptual space is general problem-solving ability in the cognitive domain, and the in performing this navigation through selection of reasoning processes the cognitive system acts as an optimization function.

From the functional modeling perspective cognition all reasoning or understanding can then potentially be navigated with a set of four operations, and all reasoning or understanding are selected by some process within the cognitive system (which we will call the "cognitive awareness process") that maintains fitness of the cognitive system within a stable range. This cognitive awareness process is itself hypothesized to contain six functional components [4]. An argument can potentially be constructed that six is the required number due to the number of degrees of freedom of the problem of achieving dynamic stability in fitness space. This argument is still being elaborated. For now six components have been chosen because that number appears to account for all of the immediately obvious problems. However, because any component of an adaptive functional model can be replaced by a component that is more fit, the number of these components can be changed in the future. In addition to the cognitive domain functions, the cooperation domain is used to scale processing over a vastly greater number of components. Other adaptive domains might be incorporated as well, such as the homeostasis and other domains described later in this paper and illustrated in figure 3.

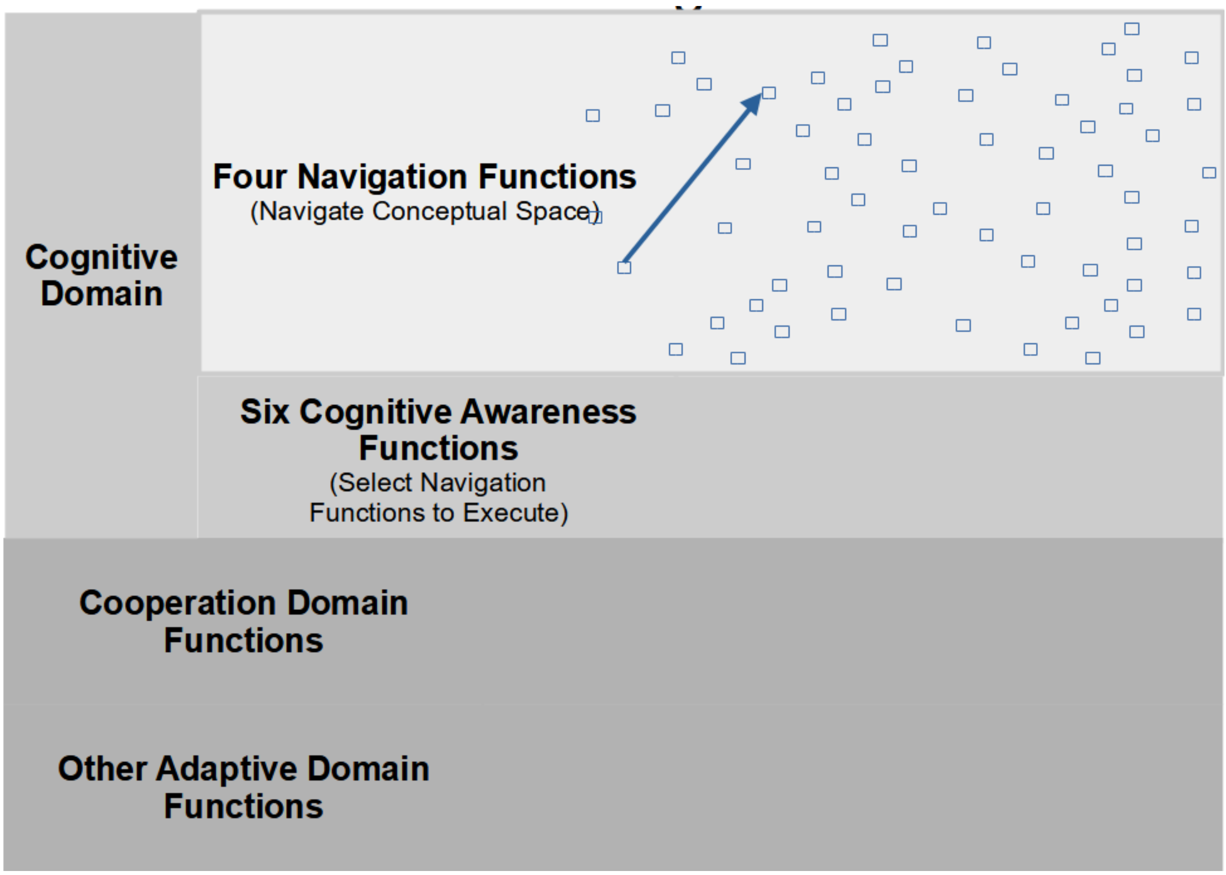

Figure 3. Components of a Human-Centric Functional Model of intelligence.

All the processes of life, beginning with homeostasis, and ending with consciousness, and cognition, can potentially be modeled as adaptive processes which navigate their own functional state spaces in a manner that is dynamically stable within their respective fitness spaces in this same way [6], [7]. Because all processes modeled this way might have dynamics that are confined to a bounded region of a fitness space represented in terms of these same three dimensions, the same mathematical equations describing motion that is globally stable in three dimensions might potentially be used to describe processes in all these different adaptive domains and therefore might be used to define an algorithm with general problem-solving ability. One example of a set of equations with such globally stable, locally unstable dynamics is the Lorenz equations for convection, which for certain parameters form a strange attractor.

Representing each adaptive process as operating within it's own adaptive domain, from the perspective of Human-Centric Functional Modeling the ability to potentially navigate to every region of the corresponding functional state space in a dynamically stable way is general problem-solving ability in that respective domain. Representing each process as being implemented by a functional component, these functional components have a natural order defined by their dependencies. For example, the capacity for homeostasis must come before the capacity for reproduction, which must in turn come before the capacity for evolution as in figure 4.

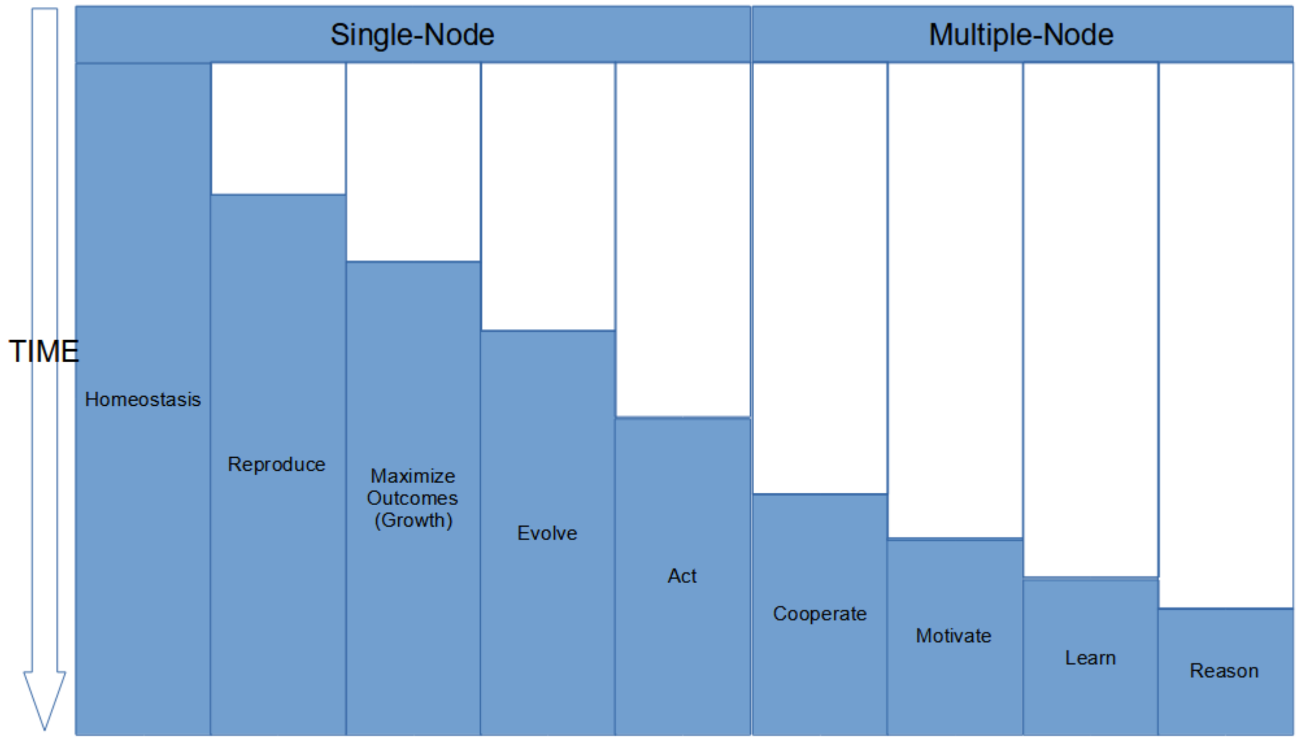

Figure 4. Adaptive processes and order of evolution.

Life can then be represented by a hierarchy of adaptive processes implemented by a hierarchy of functional components at the single cell or multiple cellular level. This hierarchy includes functional components corresponding to processes that occur at multiple levels within other functional components, such as reproduction which occurs at the cellular level as well as at the level of the entire organism. It also includes functional components that act as stand alone systems, like the emotions, cognition, and consciousness, which occur only once. This hierarchy can be generalized to represent artificial organisms or even collective organisms in which the basic components might be called "nodes" rather than cells as in figure 5.

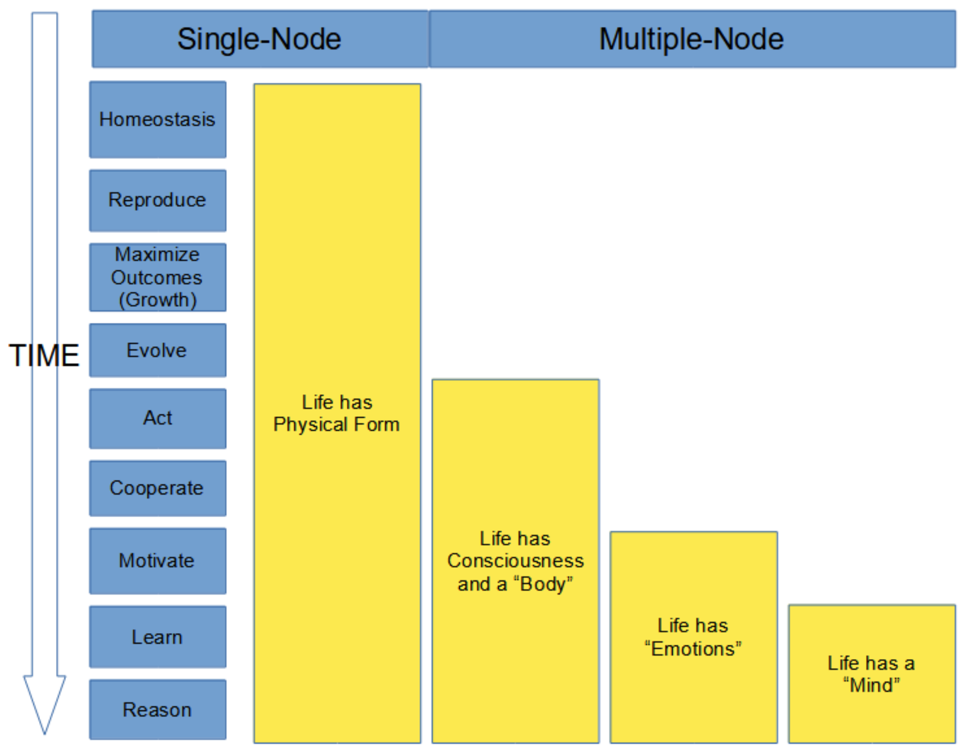

Figure 5. Functional systems and capacity for life processes.

In the hierarchy of functional components, lower level components might be contained within higher level ones. As additional adaptive processes are implemented life gains more functionality, and life develops the capacity to navigate greater and greater levels of complexity in its environment. At first life might just have the ability to tell whether there is a higher or lower concentration of some resource in the environment so that it might change its internal state to compensate. Then life might be able to detect gradients of that resource so it might move to different, more suitable, environments. Then life might be able to detect patterns in the locations of that resource. Each adaptive domain might add a new level of problem-solving ability.

As mentioned, any such adaptive process implemented by such a functional component operates within its own functional state space. Each function required to navigate that functional state space is implemented by a child functional component. Any such functional model must define an algorithm to select which function will be executed next, and which functional component will execute that function, based on the state of the collection of child functional components in fitness space and based on the dynamics required to maintains the fitness of that collection to execute the functions of the parent as in figure 6.

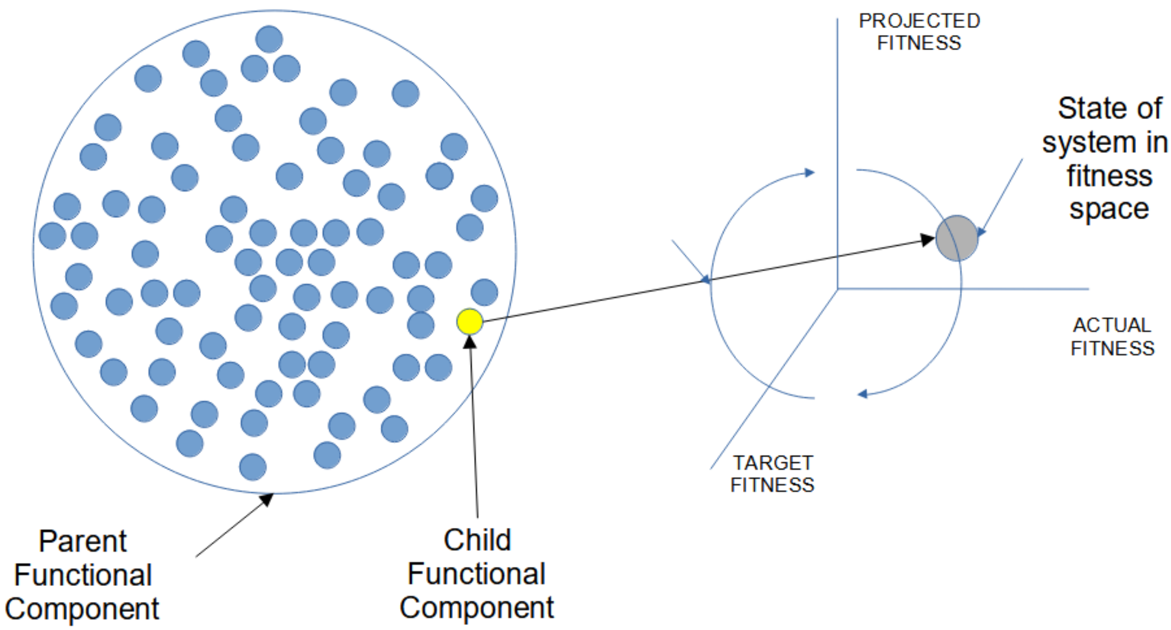

Figure 6. Some algorithm based on state in fitness space, and based on the dynamics required for stability in fitness space is used to select which functional component to execute next..

In functional state space any problem can be represented as the problem of navigating from a point representing one state, to a point representing another state. The required algorithm must navigate the functional state space in a way that can potentially solve any general problem of navigating from one functional state to another, or in other words, in a way that creates general problem-solving ability. In selecting which function is executed in order to find the optimal (most fit) solution for that problem, this algorithm can be seen as an outcome optimization function for the parent as an individual entity, or it can be seen as a collective outcome optimization function for all the child components. In other words, from the perspective of Human-Centric Functional Modeling, all living systems have the general problem-solving ability within their domain (the ability to solve both computable and noncomputable problems), and therefore have capacity to optimize any targeted collective outcomes for the functional components within their functional domain. And all living systems have the capacity to optimize any targeted outcomes for individual organism. This is general problem-solving ability in each domain that non-living systems of computation might not have.

In the same way that the individual cognition can be represented as navigating a conceptual space with general problem-solving ability, the collective cognition [8] can be represented as navigating a collective conceptual space with general problem-solving ability, which addresses the gap some researchers have noted between research in individual decision making and research in collective decision making [9]. The individual cognition can be represented as a system of optimization for the individual (a system of individual optimization), or it can be represented as a system of collective optimization for the functional components of cognition. Similarly, the collective cognition can be represented as a system of individual optimization for the collective as an entity, or it can be represented as a system of collective optimization for the individuals in the group. Like other group processes [10], this collective optimization is an emergent property of the group.

Other functional modeling approaches have long been used in the study of cognition [14] or in the study of other systems. Other functional modeling approaches have also been used to study processes such as self-organization [15]. The usefulness of potentially being able to use Human-Centric Functional Modeling to represent any system is that defining models universally understandable to all humans creates the opportunity to gain a single coherent understanding across widely different theoretical models or models for implementations. While such functional models ignore all details of implementation, such an approach is still potentially invaluable in solving the problem of converging on a single best understanding of any such adaptive system in a given domain. If all theories for how each function of the system is implemented can be decoupled into functional components, or if all actual implementations of those functions can be decoupled into functional components, and those functional components added to a library of functional components belonging to single common functional model, then if the fitness of each theory or implementation at achieving that function can be compared, the best component of every model created by any and all researchers can potentially be combined into a single most accurate picture. In the implementation of artificial cognition this implies the ability to more reliably and perhaps to far more quickly converge on a workable implementation. But this capacity for convergence also applies to homeostasis, evolution, and other living processes, as well as to processes in non-living systems such as the future Internet [11], or virtually any other technology [12]. As explained in a review of the existing literature on collective intelligence [5], these works exploring this capacity for convergence cite the same author because no other writings on this topic are believed to exist.

Centralized Processes Solve Problems for Different Parties than Decentralized Processes

A General Collective Intelligence platform is a hypothetical platform that organizes individuals into a single collective cognition [4] that might have general problem-solving ability that is exponentially higher than that of any individual in the group [16]. Many people approach the biggest problems in the world from the perspective that what's needed is to come up with a better solution. That is, to build a better mousetrap so to speak. But what isn't always considered is the need for decision systems able to reliably recognize a better mousetrap. A system able to solve the general problem of recognizing any better mousetrap is a system with general problem-solving ability. A system that increases the general problem-solving ability of groups is a General Collective Intelligence. Looking at the research on the impact of collective cognition of teams on team success [17] it seems reasonable to assume that without such a system, and therefore without sufficient collective general problem-solving ability, that is, without sufficient ability to collectively solve any general problem, that there might be patterns in the problems that can't be solved. What are these patterns?

One pattern might be systematically identifying the wrong problem. Imagine there's a famine that has left you and your family starving in South Sudan. Somewhere in Brussels, a program manager at a large humanitarian organization is deciding on what aid to send in response. Before deciding to send that aid, the program manager might go over the organization's long list of policies and procedures, perhaps making sure that any food aid meets the recommended minimum daily allowances of nutrients, perhaps making sure it comes from an approved supplier, perhaps making sure it comes from factories that meet its labor standards, and so forth, before finally sending three days worth of food aid after that process is concluded.

You in South Sudan on the other hand might have preferred to just take the money for that three days worth of aid and simply buy a month's worth of yams from a local trader that same day. Or you might have preferred to take that money and simply travel with your family to stay with relatives in neighboring Kenya, where instead of eating for three days, you and your family might be fed and sheltered for the next six months. But the possibility of an exponentially greater impact on food security in famine might not help whatsoever in ensuring those solutions get selected. Because you and the program manager are solving two different problems. You are solving the problem of the famine. The program manager in Brussels is solving the problem of satisfying his organization's policies.

Where our system of collective optimization (such as presumably described by the general collective intelligence factor (c) [18] that is innate to groups or the exponentially increased general collective intelligence factor that might be created by GCI) is absent or insufficient it is reasonable to assume that we can only reliably optimize individual outcomes. Assume that a general collective intelligence factor is present in any group and acts as a system of collective optimization, but that this general collective intelligence factor is insufficient to outweigh the influence of individual intelligence. If so, there might be reasoning to support the anecdotal observation that the stable balance that currently exists is for our collective efforts towards solving our most complex problems to be directed in ways that cannot reliably solve those problems. This is consistent with the hypothesis that wherever manipulating the variables of any group problem in a way that serves the collective well-being requires too great a level of this general collective intelligence factor, that manipulation can only be reliably be manipulated by individual entities in ways that serve their interests rather than serving the collective well-being. Applied to the previous example, enabling donors to provide funding directly to victims of famine might maximize collective well-being in some cases, but centralizing the execution of famine interventions might maximize collective well-being in some other cases. However, retaining the position to influence choices at all might constrain donor entities to always opting for centralization, thereby preventing maximization of outcomes.

More generally, as the patterns of cooperation required to solve the problem of maximizing collective outcomes become more complex, the general collective intelligence factor required to discover and execute those patterns increases. Where the general collective intelligence factor is limited, it might be true that any properties of societies involved in problem-solving that requires too great a level of general collective intelligence factor can only be reliably manipulated by entities in ways that serve their individual interests rather than serving the collective well-being. In other words, using groups with elected or appointed advocates as an example, the only stable pattern might be for advocates of groups to consciously or unconsciously manipulate their constituents in ways that allow them to successfully compete for the power to advocate, rather than to maximize the well-being of those they advocate for. However, having a sufficiently powerful system of collective optimization, societies might behave like organisms and reliably maximize collective outcomes using those same properties. In other words the stable pattern might be for groups to cooperate in ways that optimize collective outcomes.

Alignment of problem-solving with individual interests is a barrier to the deployment of General Collective Intelligence. Preventing alignment of collective problem-solving with the interests of a subset of individuals is a critical issue in the design of a GCI. It requires virtualization of all properties of the GCI platform so they can be changed by the group within the processes of the platform itself. For example, a GCI should be able to adopt any user interface that is best suited to manage a given collaboration so that the collaboration isn't restricted to the process envisioned by a single UI designer or single application owner [19]. Furthermore, the reasoning or understanding processes of any system of cognition might be based on intuition or on rational methodical reasoning. The purpose of a decentralized approach like General Collective Intelligence is to self-organize in a way that can be sustained in order to find solutions that can't reliably be intuited or reasoned by any individual so that non-intuitive and potentially far more complex solutions can also reliably be explored. If groups are unable to reliably explore such solutions without GCI this inability means that wicked problems can't reliably be solved. The potential inability of centralized approaches to address various issues, namely the SDGs funding gap, has been observed by others [21]. While quantifying the financial resources needed to implement the Sustainable Development Goals (SDGs) is complex and estimates vary widely; from USD 2.5 trillion to over USD 5 trillion a year, there is universal agreement that official development assistance (ODA) will not be enough to achieve the SDGs and that alternative methods of financing must be found. As observed by various sustainability researchers [21], there have been numerous claims of new blended finance and other instruments with the potential to unlock the trillions of dollars of private finance that is available for investment, but that investment simply hasn't materialized. In line with the hypothesis that without GCI the stable balance is for donor organizations to compete for funding and for sufficiently complex cooperation not to exist, the suggestion has often been made that cooperation to encourage investments in sustainable initiatives is lacking, and far more coordinated efforts are required. In line with the hypothesized existence of barriers to the implementation of a system of cooperation like GCI, the suggestion has also often been made that current efforts at building the knowledge base about ways to improve outcomes through cooperation remain fragmented. Because GCI has the potential to exponentially increase cooperation, in order to exponentially increase impact on the SDGs per program dollar, as well as having the potential to make those impacts sustainably self-funding [1], GCI might be the only known intervention with the potential capacity to reliably close the SDGs funding gap.

The inability of centralized approaches to reliably overcome ineffectiveness has also been observed. As noted by economist Tomi Ovaska [22], over the last 50 years developed countries have spent increasing amounts towards development aid with disappointing results. In line with the hypothesis that without GCI the stable balance is for processes to optimize outcomes for the decision-maker (the donor countries in this case), Ovaska notes that part of any aid constantly flows back to the wealthy donor countries through procurement contracts, and that aid benefits the donor countries in other ways such as buying preferential treatment for businesses from that country, buying increased international and regional clout, as well as advancing the ideological values of the donors. Because GCI is potentially a system of collective optimization, GCI might be the only known intervention with the potential capacity to reliably increase effectiveness in achieving the SDGs.

Wicked Problems and Decentralized Problem-Solving

As a conceptual example, consider a fictitious project to improve livelihoods in South Sudan. Assume that NGOs are currently trying to create jobs by running tailor training programs. But unfortunately, there's no clothing industry to hire the people they train, so this training doesn't reliably create jobs. Virtually all clothing is imported, and though cotton is a big crop, virtually all of it is exported. The value chain is broken, as in many cases elsewhere. But assume that with the uniforms needed for school children each year in South Sudan, there is the potential to create as many as 10,000 - 12,000 tailoring jobs if all the uniforms weren't imported. This might be about a thousand-fold increase over the few dozen tailors that are currently trained and that for the most part don't get jobs. To fix this broken value chain, we can define a series of projects. The first project will distribute school uniforms. To guarantee demand the project might offer stores that sell school uniforms a 50% discount for the first year in return for signing up to buy those uniforms for the next 5 years. We can then define a project on the to train tailors, a project to manufacture the uniforms and hire the tailors, a project to weave the cloth from local cotton, and a project to source the cotton from local growers for the same 5-year period. Each of these businesses cooperate though agreeing to buy key products or services from another business in the value chain, in return for another business in the chain agreeing to buy from them.

Each of these projects will be for-profit, and so can potentially be funded through private investment. An additional opportunity for cooperation comes in finding donors or government programs who are already committed to funding such job creation. Rather than these donors or governments having to pay

100% of the cost of funding new businesses in order to create jobs, they could be offered the opportunity to cooperate with this program by providing a much smaller amount of funding merely to incentivize private investment. Having only to incentize private investment rather than funding an entire business might allow donors or governments to fund only perhaps 20% of a program while still creating the same number of jobs, thereby multiplying job creation impact per dollar by 5 times.

Furthermore, new businesses are at best only likely to succeed 10% of the time. So funding new businesses as a way of creating jobs is only likely to be successful 10% of the time. However using a "pay for success" approach in which the donor or sponsoring government is allowed to pay that 20% through impact bonds that commit it to reimbursing each project only AFTER it creates the jobs, the probability of project success for the donor might increase from that 10% to near 100% per donor dollar. The businesses still won't be successful in creating jobs 100% of the time, but because the donor or government only pays when they are, that government will be 100% successful in its job creation per dollar spent. In going from 10% success in creating jobs to 100% success per dollar spent, the donor or government will multiply the impact of their funding by a further 10X. The total increase in impact per dollar for the donor in cooperating with this program is then up to 5 times multiplied by 10 times, or 50 times.

Once successfully piloted, a value chain can potentially be replicated with private investment in a number of other locations. Assume that pilot was replicated in 15 different places. Then in this example of deploying just a few of the many potential patterns of cooperation, the result is a total increase in impact per donor dollar of up to 5X, multiplied by 10X, multiplied by 15X, or 750X. This is an amazing multiplication of impact. And it doesn't require any more funding. All it requires is systematically leveraging cooperation. In addition, rather than just allowing the donor or government to fund these impact bonds through grants of cash, the program might also enable governments to fund these impact bonds through grants of tax credits. And where the number of jobs that can be created with a given amount of cash grants is finite, the number of jobs that can be created with tax credits is as great as the capacity of the market to absorb jobs.

Representing the cooperation in any such value chain as a collective reasoning process, a specific example of a General Collective Intelligence based algorithm for selecting collective reasoning and orchestrating participation in that collective reasoning can be seen in a "Social Impact Marketplace" software platform proposed to orchestrate participation in such value chains. In this platform, N potential participants in cooperation must select between M processes of cooperation (M potential value chains), where M is greater than N. An algorithm with the complete set of General Collective Intelligence functionality required for general problem-solving ability must implement all the forces in collective well-being space in order to move through that space in a way that maximizes collective well-being (fitness). However, key elements of those forces might be approximated while a more complete algorithm is being developed. One key element is that decentralizing the decision of which chain of cooperation will be used so that it isn't made by any single individual and aligned with that individual's interests, rather than with maximizing collective well-being. Such centralized processes might then represent the reasoning of some individual within a group, rather than representing collective reasoning. One potential collective reasoning algorithm is for the first individual to select the top N-1 chains of cooperation (i.e. collectively intelligent value chains) from their perspective, the second individual to select the top N-2 chains of cooperation from their perspective, and so forth until the Nth individual selects the final chain of cooperation that all N actors will participate to execute. In this way, the decision cannot so easily be centralized so that it eliminates all possibility of selecting optimal solutions where they don't align with the most powerful decision-makers.

What makes this cooperation intelligent is that it defines patterns of cooperation that significantly improve outcomes for all participants (donor, government, investor, entrepreneurs, and others) and then generalizes those patterns so they can be replicated in solving many different problems. Every problem solved then potentially increases the collective ability to solve every other problem. These patterns of cooperation have adjustable incentives so that participation in the cooperation can reliably be incentivized. For example, the impact bonds based on these tax credits or grants of cash can be increased until the projected returns for investors are sufficiently above market averages for the industry and geography, that investors might reliably be incentivized to invest. A General Collective Intelligence based platform (in this case a proposed "Social Impact Marketplace") might orchestrate this cooperation.

The creation of school uniforms in South Sudan is a fictitious example that might or might not define a valid value chain. But the point is not that this value chain is a potential solution. The point that some pattern of collectively intelligent cooperation, including across the value chain, might significantly improve collective outcomes and make those outcomes self-sustaining. By creating chains of cooperation that create enough value to incentivize parties to come together to create impact on collective challenges like the job creation above, collectively intelligent cooperation can make achievement of the Sustainable Development Goals essentially self-funding. And by identifying these patterns of cooperation we can create platforms to orchestrate it, thereby splitting the cost over many projects.

Measured in terms of outcomes per unit of resources for some set of decision-makers restricted to a minority and potentially one individual, all problems of achieving social, economic, environmental, or other collective impact can also be seen as individual or minority optimization problems. Measured in terms of collective outcomes per person per unit of resources for some set of decision-makers that includes the majority and potentially all individuals, all problems can be seen as collective optimization problems. All such collective optimization problems can potentially be addressed, and impact on those problems can potentially be exponentially increased through a network of self-sustaining cooperation self-assembled with the assistance of a General Collective Intelligence platform. The fictional example of the school uniform value chain in South Sudan defined a network of cooperation containing only five participants. However, networks can be defined containing any number of participants, up to the total population of billions [20]. When networks become this complex, it is no longer advantageous to simply create them. Rather than developing new networks of cooperation, in its "genome" a GCI might store optimized networks of cooperation between potentially billions or more individuals or organizations [13]. In order to maximize outcomes and to maximize sustainability of outcomes those networks of cooperation must then be adapted through homeostasis, evolution, reproduction, and other algorithms developed using this functional modeling approach.

Nature targets outcomes through self-assembling processes that grow, evolve, or become more fit in other adaptive domains, so life can find the resources to feed its own increase in ability to target those outcomes from resources that are already there in the environment. Processes that nature spent billions of years researching and perfecting are modeled and replicated within GCI. For example, rather than nonprofits competing for donor funding, a GCI might organize cooperation between thousands of NGOs to radically increase social, economic, or other impacts per dollar of program funds so programs are self-funding once launched. The conceptual case study of a network of only five organizations described here suggests that by reusing these natural patterns, increasing social impact per dollar by close to a thousand fold might be reliably achievable. Rather than being limited to the social impact possible with any finite amount of funding, making social impact sustainably self-funding might enable impact to be achieved at the scale required to transform communities globally. If so, then poverty, and other human suffering might already have reliably achievable solutions.

Next Steps

Because GCI is potentially so important while also being virtually unknown, it is critically important to mobilize collective effort and funding to validate or refute this potential of GCI to radically increase impact on collective problem-solving regarding wicked problems such as sustainable development in Africa. However, in validating this model of general problem-solving ability in natural systems its important to recognize that it is not general problem-solving ability itself that needs to be proven. Nature has demonstrated this ability for billions of years. The proposed Social Impact Marketplace software platform is a limited approximation of nature's method of general problem-solving ability that provides a concrete example in a very limited domain. This platform is part of a proposed ten phase Collective Intelligence based Program to Accelerate Achievement of the Sustainable Development Goals (CIPAA-SDGs) [1] that has also been designed to implement more and more GCI functionality with each phase, in order to steadily increase capacity to self-fund achievement of the SDGs in Africa until the entire SDGs funding gap can reliably be closed. It is hoped that this paper will inspire a study of the feasibility of this program.

Conclusion

GCI has the potential to exponentially increase general problem-solving ability, where an analysis of conceptual space suggests that ability has never been possible before and cannot be again until the implementation of an AGI or until the transition to a second order GCI [16]. If so, GCI might be the most important innovation in the history and immediate future of human civilization. In addition to reducing wicked problems and other complex problems so that they fit within human cognition and can reliably be navigated, and in addition to creating the potential to exponentially increase ability to solve those problems whether in physics, math, medicine, sustainable development, or any other problem domain, the fact that GCI is a collective virtual cognition that might be capable of collective optimization gives all of this further significance.

Without the specific set of features required to optimize collective outcomes, processes might be centralized and benefit potentially hidden actors in invisible ways. This suggests there are conditions under which, at one end of the spectrum, AI and other centralized problem-solving tools might optimize outcomes for a decreasing number of individuals. At the same time that Internet, social media, and other individual connectivity increases, products and services might be aligned with the interests of that decreasing few in ways that are too complex to be discerned. In this scenario the theoretical limit to centralization is when decision-making power rests in the hands of a single big tech company or single global government controlled by a single human. At the other end of the spectrum, problem-solving can optimize outcomes for an increasing number until decision-making power is fully distributed and optimizes outcomes for all.

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