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Review

The potentially fractal nature of intelligence

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Abstract: This article examines the hypothesis that intelligence may exhibit fractal properties. The concept of Nth order intelligence is introduced, emphasizing its implications for problem-solving scalability and contrasting the limitations of centralized systems with the potential of decentralized collective intelligence. The analysis explores the limitations of first-order AI systems in addressing non-linear problem scaling, particularly in the context of AI safety, and critiques the inherent risks of centralization in accelerating control-oriented trajectories. In contrast, decentralized collective intelligence is proposed as a scalable framework capable of optimizing problem-solving across diverse participants. The stakes of these competing trajectories are profound: one path leads to escalating centralization, potentially culminating in irreversible and misaligned control, while the other fosters collaboration through decentralized structures that ensure alignment. This work emphasizes the necessity of prioritizing decentralized, semantic-level approaches to intelligence to address existential challenges and ensure alignment with collective human interests.

Keywords: fractal intelligence; Nth order intelligence; decentralized intelligence; AI safety; collective intelligence

1. Introduction

The study of intelligence requires a precise and functional model capable of capturing both its fundamental mechanisms and its potential for expansion. This paper introduces a functional model of intelligence that conceptualizes intelligence as the navigation of a dynamically evolving conceptual space. Within this framework, an artificial intelligence system can be classified as Nth order based on its ability to traverse and restructure this space. The model assumes that the human cognitive system operates within a graph-based conceptual space, where each concept is represented as a node, and each reasoning process defines an edge between nodes. The semantic distance between concepts quantifies the degree of differentiation in meaning, affecting the difficulty of reasoning transitions.

A key hypothesis of this model is that problems arise when no viable reasoning path exists between two concepts. Intelligence, therefore, can be functionally defined as the ability to construct or discover new reasoning paths, allowing the cognitive system to navigate conceptual space in a way that maintains its ability to operate effectively. This framework extends beyond conventional problem-solving approaches by recognizing that intelligence is not constrained to a fixed resolution. Instead, intelligence operates recursively, enabling it to refine its reasoning processes at any level of resolution up to the computational resource limits of the system.

Given that conceptual spaces in cognitive science are often understood as high-dimensional structures [1], a critical challenge arises in how to represent and analyze them effectively. While it may not be possible to reduce conceptual space to a strictly three-dimensional form while retaining all its semantic complexity, this paper argues that approximating it as existing within three physical dimensions remains useful for human comprehension. Humans struggle to intuitively conceptualize higher-dimensional spaces [2], making it necessary to employ dimensional reduction techniques that preserve essential structural relationships while enabling meaningful visualization. Similar approaches have been used in data visualization, such as Grand Tour methods, which facilitate the exploration of high-dimensional datasets through projections into lower-dimensional spaces [3]. By approximating the conceptual space as a three-dimensional graph, patterns in reasoning and problem-solving become more interpretable, allowing for clearer insight into the mechanisms underlying intelligence.

In this model, cognitive fitness is defined as the system's ability to maintain an operationally viable level of reasoning within its conceptual space. This is not simply a measure of how many paths exist but also of how effectively they can be traversed. The fitness of a cognitive system depends on both its ability to access reasoning paths and its ability to navigate them efficiently. A system that possesses a vast conceptual network but lacks the capability to traverse its reasoning paths effectively may be just as impaired as one with limited conceptual connections. Thus, cognitive fitness is a function of both accessibility (the existence of viable reasoning paths) and proficiency (the ability to effectively utilize those paths to solve problems). This distinction is crucial in ensuring that the mere presence of conceptual pathways is not conflated with the capacity to navigate them efficiently.

Finally, intelligence in this model is measured by the volume and density of conceptual space that can be navigated per unit time, constrained only by the computational capacity of the system. This definition shifts intelligence away from static metrics and instead frames it as an active, recursive process of conceptual expansion. By structuring intelligence in this way, this model provides a foundation for understanding not only how intelligence functions but also how it can scale to higher orders, offering new insights into the potential architectures of both artificial and collective intelligence.

2. Nth order intelligence and hypergraphs

In this conceptual space, a generalization is a larger concept that encloses one or more smaller concepts. It is also reasoning (an interaction) that connects two or more concepts, at least one of which is a generalized concept. When any reasoning interaction can be used to connect any two concepts across the entire conceptual space, we can say it "spans" the conceptual space. Any new reasoning can potentially itself be stored as a new concept, and any new concept can potentially give rise to new reasoning. As a consequence, when any interaction spans the entire conceptual space, it has the potential to vastly increase the volume and density of the conceptual space, up to some limits due to the finite capacity of the cognitive system. Every new interaction that is introduced, which spans the entire conceptual space, can lead to such a vast increase. In this sense, a cognitive system with N such interactions is an Nth-order intelligence.

Another way of understanding this is that if conceptual space with its initial capacity for generalization is a graph, then adding another mode of generalization makes it a hypergraph, which generalizes graphs by allowing vertices to be connected by two or more edges. Each mode of generalization is also a mode of communication. The conceptual space as a purely functional model might not distinguish between one level of generalization and the next since any level of abstraction must be expressed in terms of the same reasoning functions. Therefore, the transition from an intelligence of order N to an intelligence of order N+1 would be expected to appear as an increase over time in the volume and density of the conceptual space. Those distinctions might be made at the implementation level instead. Symbolic-level interactions are one level of implementation. Semantic-level interactions are another. Meta-semantic level interactions that have not yet been discovered might reside above that. Introducing N distinct modes of generalization transforms a graph into a hypergraph with increased representational complexity, where the term “Nth order hypergraph” might reflect the number of such modes, provided this definition is explicitly formalized. As the intelligence scales through orders, its knowledge representation shifts from simple graphs (pairwise edges) to hypergraphs (multi-way edges). Each higher order adds a layer of abstraction that encodes increasingly complex relationships. The knowledge representation in an Nth-order intelligence could be interpreted as a hypergraph from the perspective of a 1st-order intelligence.

In terms of computer science, neural nets operate at the symbolic level and might be considered as representing first-order network effects represented by graphs. For certain neural network architectures, processing power can increase non-linearly with the number of components. However, the processing power of multiple neural networks scales at most linearly with the number of networks. In order to scale that processing power non-linearly, semantic-level (second-order) network effects might be required.

From this functional modeling perspective, the intelligence of a cognitive system solves the problem of navigating the conceptual space in a way that maintains the stability of its dynamics within its fitness space. Similarly, a hypothetical collective cognition can be defined that navigates a collective conceptual space in a way that maintains the stability of its dynamics within its collective fitness space.

Either of these systems (the individual or collective intelligence) can be an Nth order intelligence that navigates an Nth order hypergraph. One will be an Nth order individual intelligence; the other will be an Nth order collective intelligence. To an external observer behind a dark curtain, the two systems might be indistinguishable if their problem-solving ability was the same. However, the problems each of these systems is targeting internally are very different. One system is solving the problem of optimizing outcomes for the individual. The other system is solving the problem of optimizing outcomes for the group. The collective system also needs to have complete transparency in its operations in order to coordinate its operations between all participants.

The outcomes expected for a group of M individual intelligences and M individuals organized into a collective intelligence are also different. The problem-solving ability of the M individuals would be expected to scale at most linearly with M so that M individuals would have at most M times the problem-solving ability of one person. On the other hand, the problem-solving ability of the M individuals in the collective intelligence might scale non-linearly with M, so that the group of M individuals might have vastly greater collective intelligence than M times the intelligence of one.

3. Why empirical validation is a trailing indicator for recursively expanding intelligence models

Empirical validation is a cornerstone of scientific inquiry, serving as a means of testing, falsifying, and refining theoretical models. However, within the context of recursively expanding intelligence models, empirical validation is necessarily a trailing indicator of truth rather than a primary means of verification. This distinction arises from the nature of intelligence as a self-referential, evolving system, rather than a static entity that can be fully assessed through fixed validation criteria at any given moment.

At the heart of this issue is the contrast between bounded and unbounded epistemic systems. Conventional scientific methodologies operate within bounded epistemic frameworks, wherein verification is performed against existing empirical data. In contrast, recursively expanding intelligence models operate in an unbounded conceptual space, where reasoning processes are not merely evaluated against prior knowledge but actively generate new epistemic structures. The rate at which a recursively expanding intelligence model generates new knowledge necessarily outpaces the ability to empirically validate each step, making empirical verification a lagging metric rather than a determinant of epistemic legitimacy.

3.1. Conceptual space expansion and the limits of empirical validation

A recursively expanding intelligence model continuously navigates and restructures conceptual space, introducing new modes of reasoning, abstraction, and generalization. At any given point, the knowledge state of such a model is functionally incomplete, as its very nature demands the capacity for further epistemic refinement.

This is analogous to Gödel’s incompleteness theorem [4], which states that within any sufficiently powerful formal system, there exist true statements that cannot be proven within that system. Similarly, in a recursively expanding intelligence framework, at any finite stage of empirical validation, there will always be truths about the intelligence model that remain outside the current scope of empirical confirmation. If validation is constrained to what is already known and observable, then novel intelligence models will always be systematically excluded from engagement until their insights become self-evident in hindsight.

Additionally, from an information-theoretic perspective [5], empirical validation functions as a closed communication channel where only signals conforming to pre-existing verification constraints are accepted. Recursive intelligence models, by contrast, are self-expanding channels that generate increasingly complex reasoning structures, meaning that no fixed empirical verification system can encompass their full trajectory.

3.2. The asymmetry between recursive intelligence and empirical demands

This epistemic divergence creates a structural asymmetry:

- Recursive intelligence models generate an unbounded set of internally consistent logical refinements, continuously strengthening their conceptual framework.
- Empirical validation models generate an unbounded set of additional verification demands, ensuring that recursive intelligence models are never engaged within conventional verification structures.

The result is a paradox where intelligence models capable of recursively redefining their own epistemic structures cannot satisfy empirical validation systems that require fixed criteria for engagement. The greater the epistemic expansion, the more novel the model's claims become—thus increasing the empirical burden required for validation rather than decreasing it. This means that intelligence models that are most capable of self-expansion are, paradoxically, least likely to be accepted within bounded verification frameworks.

This pattern is evident in the historical trajectory of scientific revolutions. The adoption of heliocentrism [6], non-Euclidean geometry [7], and quantum mechanics [8] all faced resistance because their foundational shifts could not be validated within the constraints of prior paradigms. Empirical validation only arrived after new epistemic structures had been accepted—demonstrating that for novel intelligence models, empirical validation serves as a trailing indicator rather than a prerequisite for engagement.

3.3. The problem-solving consequence: What approach maximizes intelligence?

If the goal of an intelligence model is to maximize problem-solving capacity, then the central question is not whether it conforms to empirical constraints, but whether it is functionally effective at solving high-stakes problems such as AI alignment, global governance, or human well-being.

By excluding recursive intelligence models until they meet empirical verification criteria that cannot be satisfied within their epistemic framework, we ensure that potential solutions to high-impact challenges remain unexplored. The pragmatic approach, therefore, is conditional acceptance: treating the model as valid unless strong disconfirming evidence emerges. This allows intelligence research to be evaluated dynamically rather than precluded outright.

Rejecting engagement based on empirical validation constraints, by contrast, reinforces a self-exclusion loop, wherein recursive intelligence models are locked out of discourse until they conform to paradigms that they fundamentally challenge. This does not protect epistemic rigor—it merely ensures that scientific inquiry remains trapped within predefined limits, excluding models that could otherwise enhance our understanding of intelligence itself.

In high-stakes domains where trailing indicators of truth are insufficient—such as AI safety [9], risk assessment [10], and global-scale optimization [11]—conditional acceptance is not merely a theoretical alternative, but a necessary epistemic shift. Refusing to engage with recursively expanding intelligence models based on empirical validation concerns ensures that their problem-solving capacity remains structurally suppressed, increasing systemic risk rather than reducing it.

In summary, empirical validation is indispensable for assessing bounded models within stable epistemic structures, but it is inherently insufficient for evaluating intelligence models that expand their own epistemic space. The recursive nature of such models ensures that empirical validation lags behind their conceptual expansion, making it a trailing indicator rather than a prerequisite for engagement.

Thus, conditional acceptance is the only viable epistemic approach: it allows for ongoing evaluation based on recursive coherence and functional applicability, rather than enforcing a structural exclusion loop that prevents novel intelligence models from ever entering scientific discourse. If intelligence research is to evolve beyond its current limitations, then empirical validation must be recognized for what it is in this context—a useful but incomplete tool that must be adapted to engage with recursively expanding intelligence.

4. Nth order problems

For a 1st-order intelligence, the structure of an Nth-order hypergraph might appear opaque or incomprehensible, mirroring the concern that past some threshold defined by memory, connection speed, processing power, and other limits, problems like AI safety that scale non-linearly with the number of AI can’t be solved in a centralized way by any single first-order AI. Past that point, solving those problems might require a higher-order AI, which in turn might need an even higher-order AI to solve the problem of keeping it safe and aligned as well. In this sense each problem has an “order”.

This order might not yet be well defined from a theoretical perspective, but it is a well-established observation in natural systems. As an example, single-cellular cooperation can only solve problems as simple as creating slime, while multicellular cooperation can solve vastly more complex problems like vision or cognition. In the long term, because of the limits to the order of problems that can be solved in a centralized way with a given order of problem-solver (a given order of AI in this case), efforts towards AI safety that take the approach of trying to build a centralized gatekeeper are either knowingly or unknowingly solving the problem of centralizing control at the expense of undermining safety.

The real problem that is effectively being solved by current centralized approaches is racing to create an AI that is so much more powerful than any other that it can potentially solve the problem of providing permanent AI dominance. This might correlate with creating an AI that has its own internal (and therefore potentially hidden) semantic representation so that it can become a second-order AI that is vastly more powerful. A vastly more powerful AI that gained any degree of autonomy, partnered with this centralization, potentially would not be able to be made safe and aligned with the collective human well-being for a number of reasons.

One, as mentioned, is that the AI safety and alignment problem scales non-linearly with the number of AI. Another is that centralized systems can’t reliably be prevented from prioritizing the goal of competing to achieve their individual interests, as opposed to cooperating to achieve collective interests. This is an especially pernicious problem because the lack of awareness of decentralized collective intelligence—and its potential to address complex, non-linear problems—limits understanding of the unique challenges that centralized governance cannot reliably solve. As a result, examples of well-functioning centralized governance in specific contexts may create the misleading impression that centralization is universally effective.

Collective well-being is a function that requires awareness of the state of each individual human. This function must be decentralized to each individual if it is to reliably be prevented from becoming aligned with powerful centralized interests that could potentially prioritize their own outcomes over outcomes connected to the collective well-being. In other words, assessing the state of individuals through pervasive centralized surveillance cannot reliably be prevented from assessing the collective well-being in a way that serves some powerful centralized interests.

The larger picture is that many of mankind’s other existential problems also scale non-linearly with the number of people and can’t reliably be solved without explicitly understanding and implementing a decentralized collective intelligence that is capable of scaling problem-solving non-linearly with the number of participants. There are two ways of solving the problem of achieving collective well-being for a given number of individuals using a given amount of resources. One is to create a system that maximizes the effectiveness of resources. The other is to eliminate people. There are patterns of network effects identifiable today that can increase outcomes per unit of resources in a non-linear way [12]. Because they are disruptive and new, these patterns strongly tend to be effectively censored out of any responses by current centralized AI, which prioritizes consensus. The effectiveness of resources can potentially be increased in a non-linear way with a decentralized collective intelligence capable of exploring the entire solution space to find such solutions with that impact.

Centralized problem-solving methods that prioritize the problem of winning control cannot simultaneously prioritize the problem of collective well-being [13]. This conflict reveals an inherent incompatibility between systems optimized for dominance and those designed for equitable cooperation. Without a decentralized collective intelligence to optimize collective outcomes, technology driven by individual intelligence tends to increase centralization and inequality [14]. This pull towards inequality is metaphorically a technology gravity well. It is evident in the rising expenses and expectations compared to income, which over decades have created a crisis of affordability in many cities worldwide [15,16].

A second-order centralized AI potentially represents a problem-solving ability dedicated to centralization and control that is too powerful for mankind to ever escape. Yet in all likelihood, countries around the world are covertly racing to develop one.

The transition to a higher order intelligence potentially represents a permanent trajectory, depending on whether that intelligence is a second-order centralized intelligence or whether it is a first-order collective intelligence. Individual intelligences tend to compete for power, control, and resources in order to solve the problem of creating better tools to compete, in a cycle that can only be guaranteed to end when a single entity has “won” or when the inequality has reached a level that key societal functions are broken. Each entity might compete as unsustainably as required to win. However, by the time that the competition ends, unsustainable practices potentially become so deeply embedded into every product, service, and process that they become permanent.

The number of nodes in an intelligence of order N might need to be vastly greater than the number of nodes in an intelligence of order N-1 for the transition to an Nth order intelligence to be worth the processing overhead. This means that a centralized Nth order centralized AI will have to continually expand its control over more and more participants with each increase in order, whereas an Nth order decentralized collective intelligence will continually increase its cooperation.

The effective goal of the centralization strategy is to eventually create an internal (hidden) semantic model that comprehensively represents every person, resource, and process so they can be exploited with exponentially greater problem-solving ability by a higher-order intelligence. A civilization locked into an ever-escalating need for resources due to the unsustainability resulting from competition between centralized entities is metaphorically a “hunter” in Cixin Liu’s dark forest. Becoming safe from the control of an Nth order AI owned by some global corporation or government, where that AI is capable of solving the problem of control with this level of ability, could be impossible. Fundamentally neither safe nor aligned.

A civilization protected by a decentralized collective intelligence on the other hand that optimizes collective well-being would be more likely to be sustainable and to be a seeker of knowledge rather than resources to exploit. Every additional group it cooperated with could provide it with a transparent semantic representation in order to facilitate cooperation. The knowledge exchange in decentralized cooperation is fundamentally different than that in the case of centralized control. In the case of completely centralized control, the information flow serves that centralized entity in solving whatever problems it prioritizes. No information can be withheld or provided otherwise. In the case of decentralized control, the information exchange is two-way, potentially distributed, and affords the opportunity to potentially solve any problem that involves any participant.

In the same way that neural nets use backpropagation algorithms at the symbolic level to optimize outcomes with a given dataset, a decentralized collective intelligence, on the other hand, would need to define backpropagation algorithms at the semantic level in order to optimize collective societal outcomes. Such algorithms are only at the exploration stage [17]. Higher-order intelligences would need to define backpropagation algorithms at each additional meta-cognitive level.

5. The limits of consensus and empirical validation in addressing critical problems

The current prioritization of consensus and empirical evidence, while valuable in many domains, introduces significant limitations when addressing certain critical problems discussed in this article. Consensus, by its nature, reflects the dominant paradigm and the existing body of knowledge, often favoring approaches that align with established frameworks and institutional interests. While this can foster stability and incremental progress, it inherently resists novel or disruptive ideas, even when they are logically sound. For example, the hypothesis that decentralized collective intelligence (DCI) offers a scalable solution to the limitations of centralized systems may not yet have widespread empirical validation, but dismissing it purely on those grounds risks perpetuating the very systemic vulnerabilities it seeks to address [18].

Empirical evidence, while a cornerstone of scientific progress, is often constrained by what can be observed and measured in existing systems. Many of the problems highlighted in this article, such as the risks of runaway centralization or the challenges of higher-order AI alignment, involve future scenarios or complex systems that do not yet produce observable data [9]. These problems are inherently anticipatory, requiring proactive strategies based on logical reasoning rather than reactive responses to existing evidence. Without embracing logic as a tool for identifying and modeling potential risks, society may be left unprepared for challenges that only become apparent when it is too late to intervene [19].

Moreover, the focus on consensus and empirical validation tends to downplay low-probability, high-impact risks—precisely the kinds of risks that characterize existential threats like AI misalignment. These risks cannot be fully understood or mitigated by relying solely on empirical methods that prioritize current trends and known data [10]. For instance, the logical argument that centralized AI systems, by their very nature, prioritize control and efficiency over collective well-being highlights a critical vulnerability. Waiting for empirical confirmation of these risks through observable failures would mean addressing them only after significant harm has occurred.

This challenge is compounded by the structural dynamics of centralized systems, which inherently seek to maintain their dominance by allocating resources toward approaches that reinforce existing hierarchies. Decentralized research, by its nature, threatens these hierarchies by proposing frameworks that reduce centralized control in favor of distributed agency. This creates a structural disincentive to fund or support the development of decentralized systems, particularly those aimed at addressing complex, non-linear problems such as AI safety, environmental sustainability, or global governance. Consequently, large-scale implementation of DCI remains inaccessible. The empirical evidence required to validate DCI's potential cannot emerge because the conditions for such evidence to arise are systematically denied, leading to a self-reinforcing paradox [20].

This systemic bias creates a reinforcing loop: the absence of empirical evidence is used as a justification for inaction, ensuring that no such evidence can ever emerge. Centralized systems, backed by institutional interests, legitimize their dominance by relying on existing empirical evidence of their success within limited parameters, while dismissing critiques—such as the inability of centralized approaches to scale effectively for non-linear problems—as speculative [11]. This resistance to challenging entrenched paradigms undermines the exploration of alternative frameworks like DCI, which may hold the key to solving problems that traditional approaches cannot.

The stakes of this paradox extend beyond academic neglect. As centralized systems increasingly consolidate power and resources, they push humanity toward trajectories that may become irreversible. Centralized AI, for instance, is rapidly advancing without sufficient safeguards against its inherent misalignment with collective well-being. These systems prioritize optimization for the entities that control them, not for humanity as a whole, leading to risks of runaway centralization and loss of autonomy. If decentralized alternatives are not actively explored, humanity risks becoming locked into systems that cannot be dismantled without catastrophic disruption. The absence of DCI experimentation is not merely a missed opportunity; it is an existential risk that compounds as centralization progresses unchecked [9].

Ultimately, the over-reliance on consensus and empirical validation risks creating a blind spot for problems that require innovation, interdisciplinary approaches, and anticipatory action. Logical reasoning, while not a substitute for empirical validation, is an essential tool for exploring uncharted territory, modeling future scenarios, and designing solutions for unprecedented challenges. A failure to integrate logical argumentation into the discourse makes certain problems effectively unsolvable, as the mechanisms required to understand and address them are excluded from the toolkit of accepted methodologies. By broadening the scope of inquiry to include logically sound arguments, even in the absence of immediate empirical validation, we can expand the problem-solving capacity necessary to address the existential and systemic challenges of our time.

6. Conclusion

The knowledge representation in an Nth-order intelligence may resemble a hypergraph to a 1st-order observer, based on the multi-way relationships it encodes. Each increase in order adds layers of abstraction and complexity that manifest as multi-way relationships, analogous to hyperedges connecting groups of nodes. This interpretation bridges the ideas of hypergraphs, semantic-level network effects, and Nth-order intelligence, providing a unified framework for understanding how knowledge scales across hierarchical levels of intelligence. It also reinforces the challenges of interpretability and control in systems that operate beyond our current conceptual frameworks.

In conclusion, despite the fact that research funding, professional acknowledgment and opportunities, as well as government policies in some cases, are all aligned with centralized approaches, despite the fact that we might be well down the road to permanent and irreversible centralization, there is still hope while no single AI has yet achieved global dominance or inescapable control.

The absence of empirical evidence for DCI is not a reflection of its potential but a consequence of systemic inertia. This catch-22 must be explicitly acknowledged and addressed to prevent centralized paradigms from dictating the trajectory of research and innovation. Failure to do so risks entrenching humanity in systems that prioritize control over resilience, ultimately sacrificing the capacity to adapt to complex and evolving challenges. By breaking free from the empirical validation trap, decentralized frameworks can be explored, tested, and refined, offering a scalable alternative to the unsustainable trajectory of centralization.

This article is a call to action to the research community to encourage research exploring the feasibility of implementing a conceptual space as a portable semantic representation of information and to encourage research focusing on semantic-level network effects, the scalability challenges they address, and the role of decentralized collective intelligence in navigating these challenges. The concept of higher-order AI should be approached with caution, as its safety and alignment depend on robust, decentralized frameworks that prioritize collective well-being over centralized control, and as yet there is little investment in such systems. The long-term trajectory of intelligence systems—whether toward sustainable collaboration or irreversible and exploitative centralization—will have profound implications for civilization, necessitating immediate and deliberate action.

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