General Intelligent Network (GIN) and Generalized Machine Learning Operating System (GML) for Brain-Like Intelligence

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Abstract

This paper introduces a preliminary concept aimed at achieving Artificial General Intelligence (AGI) by leveraging a novel approach rooted in two key aspects. Firstly, we present the General Intelligent Network (GIN) paradigm, which integrates information entropy principles with a generative network, reminiscent of Generative Adversarial Networks (GANs). Within the GIN network, original multimodal information is encoded as low information entropy hidden state representations (HPPs). These HPPs serve as efficient carriers of contextual information, enabling reverse parsing by contextually relevant generative networks to reconstruct observable information.

Secondly, we propose a Generalized Machine Learning Operating System (GML System) to facilitate the seamless integration of the GIN paradigm into the AGI framework. The GML system comprises three fundamental components: an Observable Processor (AOP) responsible for real-time processing of observable information, an HPP Storage System for the efficient retention of low entropy hidden state representations, and a Multimodal Implicit Sensing/Execution Network designed to handle diverse sensory inputs and execute corresponding actions.

By combining the GIN paradigm and GML system, our approach aims to create a holistic AGI system capable of encoding, processing, and reconstructing information in a manner akin to human-like intelligence. The synergy of information entropy principles and generative networks, along with the orchestrated functioning of the GML system, presents a promising avenue towards achieving advanced cognitive capabilities in artificial systems. This preliminary concept lays the groundwork for further exploration and refinement in the pursuit of true brain-like intelligence in machines.

1 Introduction

In the ever-evolving landscape of artificial intelligence, the pursuit of General Artificial Intelligence (AGI) stands as a formidable challenge. One of the pivotal benchmarks of human intelligence lies in the capacity to learn from limited data and engage in intricate reasoning, a capability that existing machine learning models often struggle to emulate. The prevailing paradigm in machine learning tends to be task-specific, rendering models ineffective when confronted with challenges beyond their pre-defined scopes.

In response to this profound dilemma, drawn from years of hands-on experience and insights in AI applications, a groundbreaking approach emerges. This paradigmatic shift revolves around two interconnected pillars: the General Intelligent Network (GIN) and the Generalized Machine Learning Operating System (GML System). These concepts collectively strive to overcome the limitations associated with traditional machine learning, particularly in terms of adaptability to diverse tasks and the ability to reason from sparse datasets.

The GIN paradigm pioneers a fusion of information entropy principles and generative network models, reminiscent of the innovative Generative Adversarial Networks (GANs). Within the GIN framework, original multimodal information undergoes transformation into low information entropy hidden state representations (HPPs). This transformation allows for the encoding of contextual information efficiently. Remarkably, these low entropy HPPs become the foundation for reverse parsing, executed by contextually relevant generative networks, to reconstruct observable high entropy original information. In essence, GIN aims to tackle the challenges associated with small data learning, ushering in advancements in spatial, temporal, and logical/causal reasoning within AI systems.

Complementing the GIN paradigm, the GML System introduces a comprehensive infrastructure designed to seamlessly integrate the capabilities of GIN into the broader AGI framework. This system consists of three integral components: the Observable Processor (AOP), responsible for real-time processing of observable information; the HPP Storage System, ensuring efficient retention of low entropy hidden state representations; and the Multimodal Implicit Sensing/Execution Network, adept at handling diverse sensory inputs and executing corresponding actions.

Together, the GIN paradigm and GML System aspire to forge a holistic AGI system, mirroring the intricate processes of human intelligence. The strategic amalgamation of information entropy principles and generative networks, coupled with the orchestrated functionality of the GML System, charts a promising trajectory towards the realization of advanced cognitive capabilities in artificial systems. This preliminary concept serves as a foundation for ongoing exploration and refinement, propelling us closer to the elusive goal of instilling true brain-like intelligence in machines.[5][1][2][3][4]

2 Hypothesis 1: Unraveling the Potential of a Hierarchical Structured Generative Network Paradigm for Human-Level Cognitive Mastery

1. General Intelligent Network (GIN)

Upon receiving external information X, both living organisms and computers undergo a multi-layer calculation process. This involves multiple encoders with a lamellar structure, leading to the generation of a highly generalized abstract implicit expression result. Additionally, a generative network transforms these implicit expressions into visualized explicit results, forming what we term a General Intelligent Network (GIN). The fundamental processing information results, denoted as Hidden Point Patch (HPP), serve as the building blocks of knowledge within the GIN.

2. HPP as Cognitive Fragments

When recalling individuals or objects, our mental images often lack details, colors, or focus on specific fragments. This cognitive simplification, observed even in deep learning models, is attributed to millions of years of evolutionary adaptation. In the GIN framework, HPP itself constitutes the acquired "Knowledge" from the external world. During active thinking, HPPs can reverse-generate explicit images. Analyzing these images unveils correlations between different HPPs, facilitating the creation of hyper-connected HPPs. This new HPP, formed through these connections, is then stored and utilized as novel "Knowledge" in the GIN.

3. Neural Knowledge Compression (NKC)

Within GIN, Neural Knowledge Compression (NKC) is a continuous process that operates as long as computational resources permit. Series of HPPs undergo continuous encoding as implicitly expressed information, resulting in a decrease in information entropy. This NKC process not only frees up storage space but also yields more generalized HPPs, enabling deeper reasoning. The autonomous nature of NKC distinguishes GIN from other networks.

4. Network Evolution in 3D Space

The GIN's network topology is a vast, complex, hyper-connected structure in three-dimensional space. Prior structures play a crucial role in the network's evolutionary process. Most neurons in GIN function genetically, and when a new structure is needed, a new neuron branches out while attempting to maintain the stability of existing neurons. This ongoing evolutionary process contributes to the adaptability and dynamic nature of the GIN.

Whether it is a living organism or a computer, after receiving a series of external information X, it completes a multi-layer calculation with decreasing information entropy through multiple encoders with a lamellar structure, and finally outputs a highly generalized abstract implicit expression result; at the same time, these implicit expression results can also be native to a series of visualized explicit results H through a generative network (Figure 1).

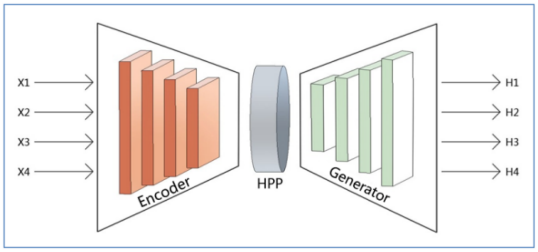

Figure 1: GIN

We call this whole network structure a General Intelligent Network (GIN), and the basic processing information results(the results of the hidden state expressions) are called Hiden Point Patch (HPP).

3 Hypothesis 2: Positioning Deep Learning as a Special Instance within the GIN Network Framework Proposed in Hypothesis 1

In the ever-evolving landscape of machine learning, Graph Isomorphism Networks (GIN) stand out for their intricate topology, characterized by a web of interconnected computational units. This complexity contrasts sharply with the streamlined structure of current deep learning models, where layers are singular and non-sub dividable, akin to a 2D projection of the GIN topology.

GIN: A Complex Topology Unveiled The GIN network structure is a marvel of complexity, featuring a sophisticated interplay of multiple computational units. These units, intricately connected, form a topology that defies simplicity, offering a nuanced representation of relationships within data. GIN's intricacies challenge the reductionist approach adopted by contemporary deep learning models.

Contemporary Deep Learning Models ,Simplified Structures In contrast, modern deep learning models present a simplified architecture, with each layer resembling a basic structural unit. This reductionist design, while efficient, entails a loss of the rich, multifaceted relationships embedded in the GIN topology. The layers are not subdividable, creating a 2D plane projection of the original intricate structure.

Random Dynamics vs Dedicated Design A notable distinction arises in the association relationships between intermediate layers of computational units. In GIN, these associations are initially random and dynamic, evolving organically within the vast expanse of large datasets. This dynamic nature contrasts sharply with the dedicated design inherent in contemporary deep learning models, underscoring the domain specificity of the latter.

Domain Specificity and Dataset Exploration The dynamism within GIN's association relationships emerges as a consequence of extensive exploration within large datasets. The random and dynamic nature of these associations speaks to the adaptability and versatility of GIN across diverse domains.

On the other hand, contemporary deep learning models, with their pre-defined associations, exhibit a higher degree of domain specificity.

Bridging the Gap As we navigate the realm of machine learning, the dichotomy between the complexity of GIN and the simplicity of current deep learning models becomes apparent. The challenge lies in striking a balance between intricacy and efficiency, as researchers seek to unravel the optimal design that harmonizes the dynamic exploration of associations with the domain specificity required for effective learning. The journey towards a unified model that encapsulates the best of both worlds continues, fueled by a quest for a more holistic understanding of the intricate relationships within data.

4 Hypothesis 3 within the Framework of Hypothesis 1 : Exploring the Relationship Between Human Neural Networks and Graph Isomorphism Networks

In the ever-evolving field of artificial intelligence, researchers continually seek inspiration from the intricacies of the human and animal brain to develop more efficient neural networks. One fascinating aspect is the remarkable real-time and processing efficiency observed in neural networks constructed based on biological neurons, setting them apart from conventional deep learning models in computers.

Efficiency and Simplicity Unlike their computer-based counterparts, neural networks inspired by the human and animal brain exhibit a remarkable lack of details and temporal discontinuities. This unique characteristic allows for streamlined processing and heightened efficiency, mimicking the brain's ability to swiftly handle complex tasks with minimal computational resources.

Unlocking Deeper Knowledge during Rest A noteworthy phenomenon arises when individuals enter states of rest such as sleep or meditation. During these periods, the entire neural system undergoes a fascinating process known as Neural Knowledge Consolidation (NKC). This process involves the release of computing resources within the neural network, enabling continuous and uninterrupted computation. As a result, the individual experiences a profound enhancement in the acquisition of deeper knowledge and wisdom.

Harnessing the Power of NKC Understanding and harnessing the power of NKC during periods of rest have significant implications for the development of advanced neural networks. This natural cognitive process not only contributes to the efficiency of information processing but also facilitates the integration of new insights, paving the way for more sophisticated artificial intelligence systems.

Exploring neural network construction inspired by the efficiency of human and animal neurons, coupled with the insights gained from NKC during restful states, holds promise for advancing the field of artificial intelligence. As researchers delve deeper into these phenomena, the potential for creating more effective and wisdom-driven neural networks becomes increasingly apparent, opening new avenues for the future of AI research and development.

5 Hypothesis 4: Decoding Information Dynamics, Exploring the Principle of Information Entropy Reduction in GIN Networks

In the exploration of information processing in both humans and animals, the astounding real-time capabilities of sensory perception raise questions about the efficiency of current deep learning models. This article delves into the concept of Contextually Diverse Generative Networks (CDGN) and the dynamics of information entropy reduction, drawing inspiration from observations of human consciousness and computer deep learning models.

Sensory Information Processing Examining the vast and disorganized data received through vision, hearing, touch, and smell, the article posits that animals exhibit strong neuronal coding abilities. The discussion centers on the rapid real-time responses to external stimuli, contrasting with the perceived limitations of existing deep learning models.

The GIN Network Structure The complexity of the Generative Information Network (GIN) is highlighted, consisting of hundreds of millions of neurons. Emphasis is placed on the need for universal dynamics to facilitate efficient information flow and processing within this intricate network.

Information Entropy Reduction Principle A key proposition is introduced—information flow and processing adhere to the principle of information entropy reduction. Analogous to water flowing from high to low, the article argues that as long as information entropy is reduced, computations can proceed downward or establish associations between computational units.

Multi modal Information Processing The GIN network's ability to handle multi modal external information is discussed. The process of entropy reduction involves splitting information into uni modal forms, further decomposing them into images, and encoding these images into abstract representations with lower entropy, such as symbols, functions, and key points.

Contextually Diverse Generative Network The article introduces the concept of a Contextually Diverse Generative Network (CDGN), emphasizing the generation of diverse output results based on contextual backgrounds. The validity of computations is tied to the condition that the entropy reduction should be reversible, ensuring meaningful output.

Evolutionary Analogy Drawing parallels with the evolutionary process of species selection, the article suggests that in the massive random entropy reduction computations, diverse dimensions of knowledge and High-Level Abstracted Patterns (HPP) collide and associate, leading to a network topology favorable to meaningful results.

Generalization and Reasoning Highlighting the potential for human-like associative and inferential thinking, the article explores how a series of chained computations with high generalization ability could mimic human reasoning. The GIN network's dynamics offer insights into achieving generalized reasoning, including image reasoning, temporal reasoning, and logical reasoning.

TTherefore, we can infer that animals have strong neuronal coding ability and each neuron processes very small data. Even so, the extraordinarily complex structure of the GIN network, composed of hundreds of millions of neurons, can complete the information flow and processing in a short time, and there must be some universal dynamics to ensure that each information flow will have an appropriate output result

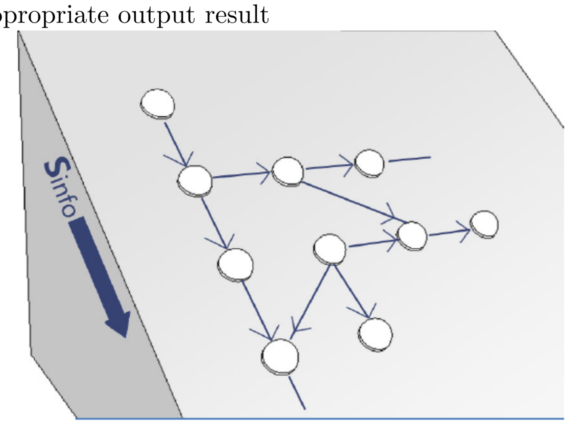

Figure 2: Information Flow

By observing human consciousness and computer deep learning models, we make the following kinetic Hypothesis : information flow and information processing are subject to the principle of information entropy reduction (Figure 2). Just like water flows from high to low, no matter how complex the intermediate path is, as long as the information entropy is reduced, then the computation of this computational unit can proceed downward or the association between these several computational units can be established.

6 Hypothesis 5: HPP Dynamics -Leveraging Affine and Projective Transformations for Object Interaction Prediction

In the realm of deep learning models, the concept of Hidden State Image Patch (HPP) plays a pivotal role in understanding and predicting transformations within a given space. Drawing inspiration from the First Order Motion Model (FOMM) introduced by Aliaksandr Siarohin et al. in 2019, the Graph Isomorphism Network (GIN) takes a step further by extending the application of affine and projective transformations to HPP.

The core idea involves a sequence of transformations applied to the hidden state image patch. This intricate process encompasses predicting object positions, poses, relative scales, colors, and other contents within a specific spatial context. The GIN network, borrowing from the FOMM model, accomplishes various affine and transitive transformations by manipulating key points in an image.

For instance, in a scenario where a camera observes a glass of water to determine the availability of other containers capable of holding it, the GIN network engages in vectorized abstraction of the water within the glass. This involves simplifying the representation to key points and subsequently comparing it with the vector contours of potential containers such as bowls, water bottles, and ladles. This comparison takes place in the space of projection transformation.

Following these transformations, a logical map of the hidden state emerges, capturing essential parameters like material permeability. These Hidden State Image Patches (HPPs) are then associated with the projection results. The GIN network employs sophisticated calculations to reason out which other containers in the observed space can effectively accommodate the glass of water.

In GIN network showcases the power of spatial reasoning through the integration of affine and protective transformations into the hidden state representation. This approach enables the model to predict and reason about object interactions within a given environment, opening up possibilities for advanced applications in computer vision and artificial intelligence.

7 Hypothesis 6:Temporal Reasoning in Heterogeneous Parallel Processing (HPP): Adapting to the Dynamic Speed of Change

In the realm of artificial intelligence, temporal reasoning plays a crucial role in addressing the dynamic nature of the world. Heterogeneous Parallel Processing (HPP) algorithms are at the forefront of this adaptation, particularly in their ability to adjust to the varying speeds of motion in a given environment. These algorithms excel in stealthily predicting the location of a hidden point in the immediate future.

Diverging from the continuous and uniform perception of time in computers, human temporal reasoning is characterized by its discontinuity, unevenness, and imprecision. Evolving over tens of thousands of years, human temporal cognition appears to be a composite of spatial reasoning over a time series. This distinction underscores the need for AI systems to emulate and synchronize with human-like temporal reasoning.

The World Model of Dreamver V2 provides a noteworthy approach to temporal reasoning. Through extensive training, it captures the state and generates images for the next time step. The inverse decoding process, which compares the decoded result with the input image, rewards the decoder for achieving a match. This methodology forms the foundation for GIN (Generic Inference Network), which adopts and refines the temporal inference model from Dreamver V2.

Unlike conventional approaches that follow a uniformly fine-grained timeline, GIN opts for simulating human temporal inference. This involves inferring space at specific key points in time, enhancing timeliness significantly. GIN dynamically links implicit expressions of spatial inference across various time slices, creating associations that enable rapid temporal inference. This innovative approach leverages the strengths of both spatial and temporal reasoning, promising efficient adaptability in the ever-changing landscape of artificial intelligence.

8 Hypothesis 7:Image-Based Logical Reasoning in Dreaver V2's World Model

In the realm of natural language processing (NLP) cognition, a novel approach inspired by Horn clauses has been introduced. This innovative method involves the transformation of logical reasoning into tangible images, subsequently facilitating the translation of these images into causal reasoning through spatial and temporal considerations. In the intricate world model of Dreaver V2, logical reasoning within the context of the game is achieved through a harmonious interplay of spatial and temporal reasoning

9 Hypothesis 8: Deconstructing Logical Relations in GIN Networks: HPPs and Generative Networks

Within GIN (Generative Image Network) networks, logical relations undergo disassembly into a series of High-Level Pictorial Representations (HPPs) expressed through implicit states. These implicit states can then undergo reverse encoding, transitioning into abstract images through the aid of generative networks. The convergence of causal and logical inference is subsequently realized through spatial inference and temporal inference applied to these abstract images. This innovative methodology offers a unique perspective on logical reasoning, blending image-based representations with advanced network architectures for nuanced cognitive processing.

10 Hypothesis 9:Architectural Blueprint for a Next-Generation Generic Machine Learning Operating System (GML System)

Generalized Machine Learning System (GML System) Overview

In our quest to conceptualize the structure of GIN networks, we draw parallels between human learning behavior and software programming processes.

Traditional software engineering operates within a proprietary structure, akin to a pre-coded machine production line. Each stage, from state 1 to state N, is rigidly defined, resembling a fixed pipeline. While effective for specific problem-solving scenarios, this paradigm falls short in addressing generalized problems.

Recognizing the limitations of the existing software paradigm, we propose a transformative approach. Leveraging the capabilities of the GIN network, we introduce a Generalized Machine Learning operating system (GML system). At its core, the GIN network facilitates a multimodal input, primarily designed for dynamically solving cross-domain, non-fixed structured, and non-specific tasks.

10.1 GML System Architecture

The GML system comprises three integral components:

Observable Processor (AOP)

The AOP acts as the first processing stage, receiving multimodal information such as images, sounds, numbers, and texts. The initial GIN network, denoted as GIN1, processes this input, generating a series of multimodal HPP implicit representations. These representations are then fed into the Explicit Representation Processor AOP.

HPP Storage System

The system includes a dedicated storage component for Hierarchical Planning Process (HPP) repositories. These repositories, combined with the output from GIN1, are processed by GIN3. This processor generates visible images, depicting potential relationships among the HPPs, facilitating spatial, temporal, and causal inference.

Multi modal Implicit Sensing/Execution Network

The final component incorporates the Implicit Execution Network GIN2. It executes the results from GIN3 and feeds the computed HPPs back to the AOP for further processing. If the AOP identifies a reduction in information entropy through the combination of HPP repositories, it proceeds to the next level of computation.

Predicting and Training in GML System

In the GML system, information is both input and output in parallel. Employing probabilistic inference, we systematically quantify uncertainty, categorizing it as Known Unknowns. Monte Carlo Tree Search (MCTS)-based probabilistic inference is employed for predicting Known Unknowns. Additionally, GIN, Neural Systems, and modern Deep Learning possess the potential to identify and predict unknown patterns and behaviors, termed Unknown Unknowns.

This predictive process aligns with the concept of Unknown Unknowns, where inner information sets lack awareness of their specific nodes. The GIN or Deep Learning optimization process essentially mirrors a variant of counterfactual regret minimization (CFR).

Continuous Operation and Multimodal Implicit Sensing/Execution Network

The GML system ensures continuous operation, seamlessly parsing Unknown Unknowns information into Known Unknowns abstract images. These abstract images, in turn, facilitate the calculation of possible task topologies, paving the way for effective task planning and execution (refer to Figure 4).

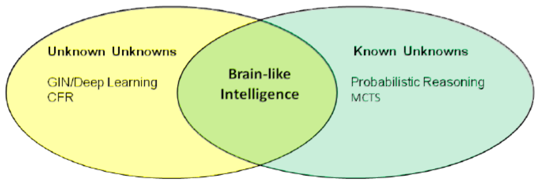

Figure 4: Predicting and Training with GML system

This perpetual process is encapsulated within the Multimodal Implicit Sensing/Execution Network, as illustrated in Figure 3.

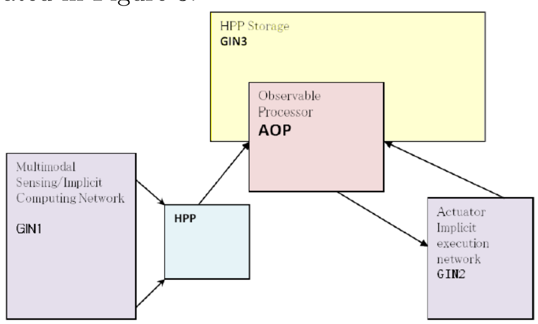

Figure 3: The structure of GML

11 Hypothesis 10: GML Task Decomposition and MCTS Task Tree Strategies

In GML (Generic Machine Learning) systems, the singular Allocation Optimization Processor (AOP) plays a pivotal role in managing computational resources. In a preemptive manner, various computational tasks vie for resources based on a weighting algorithm, yielding favorable outcomes. While straightforward for simple deep learning networks like face recognition and helmet detection models, the scenario becomes more intricate for abstract and complex inference models.

To address the complexity, a strategic approach involves horizontally decomposing tasks into multiple subtasks. Subsequently, each subtask undergoes further decomposition, expanding the scope of computational tasks. To facilitate this intricate process, the introduction of a Monte Carlo Tree Search (MCTS) state tree inference model becomes imperative. This model aids in making judicious decisions regarding the most reasonable topology, solidifying certain topological fragments as optimal through iterations.

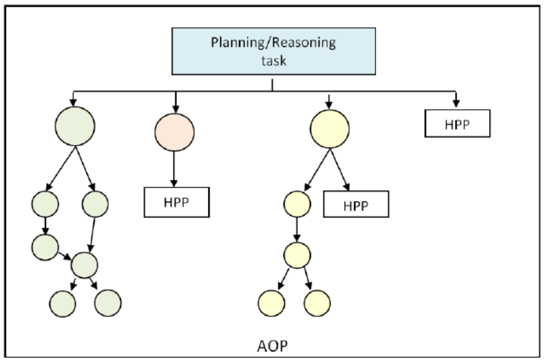

Figure 5: Rational Computing with GML system

Figure 5 illustrates the integration of these optimal fragments as implicit output Hierarchical Problem Patterns (HPPs). These HPPs, distinct from those involved in raw information processing, serve a multifaceted role in task decomposition, identification of topological relations, and resource allocation. Essentially, they resemble the human problem analysis and problem-solving processes, accumulating a unique "knowledge structure" for the GML.

The implicit HPPs shaped by GIN (Graph Isomorphism Network) networks form a dynamic foundation for GML. Unlike the fixed structure found in raw information processing, these HPPs evolve with different input information, varied problem-solving approaches, and diverse computation times. Therefore, the accumulated "knowledge structure" becomes a distinctive feature, reflecting the adaptability and intelligence of the GML system tailored to its specific context and objectives.

12 Hypothesis 11: Evolutionary Knowledge Precipitation in Collaborative Computation: The GIN Network's Dynamic HPP Paradigm

In the intricate landscape of collaborative computation, the GIN network orchestrates a result-oriented dance through the Observation-Analysis-Recall-Experiment (OARE) cycle, sculpting a dynamic tapestry of Highly Probable Pathways (HPPs). This intricate process unfolds in distinct stages, as the network sifts through a sea of dynamic, random, and invalid HPPs in the early computations, identifying only a select few that withstand the scrutiny of the Analysis of Probability (AOP) test.

These resilient HPPs, deemed favorable to the desired results, become the focal point for resource allocation, strengthening the associated topologies and enhancing their computational prowess. As the computation progresses, the GIN network evolves towards a topology most conducive to the intended outcomes. The HPPs generated within this refined structure transform into a repository of "knowledge" that solidifies through repeated OARE cycles.

The optimization journey of the GIN network involves the gradual fixation of topologies suitable for specific results, forming a paradigmatic framework. This fixed graph structure becomes ingrained knowledge, a product of the machine's learning and adaptation over numerous problem-solving instances. The HPP repository burgeons with a growing collection of a priori HPPs, amplifying the comprehensive processing power of the GIN network with each problem it encounters.

Once a HPP's structure solidifies, it transcends into a fixed paradigm, liberating associated HPPs from the need for repetitive computations. This liberation enables them to engage in diverse tasks, contributing to the formation of a streamlined, minimalist HPP topology. The culmination of this process unveils an evolutionary knowledge precipitation within the collaborative computation paradigm, illustrating the GIN network's capacity to adapt, learn, and optimize its problem-solving strategies over time.

13 Hypothesis 12:Emotional Computing in GIN Networks: Fostering Self-Motivation and Personalized Development for Enhanced High-Performance Patch Generation

In the realm of Graph Isomorphism Networks (GIN), addressing the challenge of continuous self-motivation and effective self-evaluation is crucial for the development of High-Performance Patches (HPPs). Conjecture 4 posits that, apart from purposeful computations, the GIN network can leverage remaining computational resources to connect various HPP patches. However, the assessment of intermediate implicit states in these computations poses a unique challenge. Inspired by the inexhaustible and consistently effective motivational system in humans, this discussion explores the integration of Emotional Computing into GIN networks as a solution.

Embracing Emotion as a Motivational Catalyst

Humans derive motivation from emotions and interests, influencing their engagement and proficiency in various activities. This emotional connection creates a positive feedback loop, driving individuals to invest time and effort into activities they enjoy. Translating this concept into GIN networks involves implementing emotional decision-making for tasks with ambiguous or intermediate states, promoting a continuous cycle of self-motivation.

Addressing the Challenge of Ambiguity in HPP Tasks

Many HPP tasks involve implicit states that defy easy evaluation of correctness. Through Emotional Computing, GIN networks can make decisions based on preferences, harnessing the benefits of accumulated emotional associations. This approach allows the model to navigate tasks that lack clear right or wrong answers, contributing to the development of strategies for evaluating results in the absence of immediate validation.

Personalized Development for Diverse GIN Networks

Emotional Computing introduces the concept of personalized development for GIN networks. By instilling positive motivations unique to each network, diverse preferences emerge. The aggregation of these personalized developments creates a collective intelligence that fosters complementary and creative learning networks, enhancing the overall adaptability and efficiency of GIN architectures.

Strengthening Implicit State Association for Deeper Reasoning: One of the key advantages of Emotional Computing in GIN networks is its ability to strengthen the computational pathway of more implicit state associations. By fostering self-motivation, GIN networks delve into deeper reasoning, enabling enhanced processing of complex tasks and facilitating a more nuanced understanding of intermediate states.

The integration of Emotional Computing into GIN networks introduces a paradigm shift in the development of self-motivation and personalized learning. By addressing the challenges posed by tasks with ambiguous or intermediate states, Emotional Computing empowers GIN networks to navigate complexities, fostering deeper reasoning and the generation of more effective and valuable High-Performance Patches.

14 Hypothesis 13: Integrating Rational and Emotional Computing for Personalized Inference Tasks

In this innovative approach to cognitive computing, the title "Harmonizing Human Cognition" emphasizes the synergy between rational and emotional elements in the human mindset. The proposal suggests that rational computation, often the primary mode of reasoning, can benefit from the involvement of perceptual, emotional aspects when faced with challenges or bottlenecks. This fusion of Rational Computing as the main reasoning line and Emotional Computing as the auxiliary line is illustrated in Figure 6.

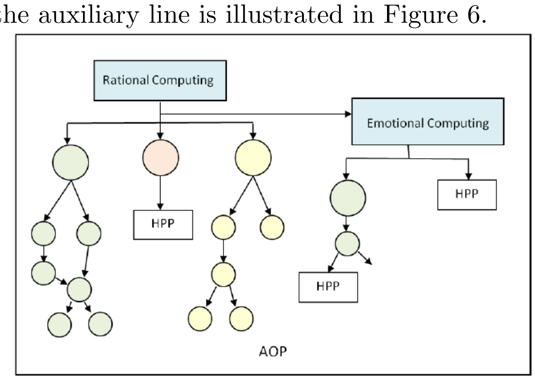

Figure 6: Enhanced GML system combining Rational Computing and Emotional Computing

The Rational Computing process, as outlined in hypothesis 9, involves breaking down a task into subtasks, applying a topology based on Monte Carlo Tree Search (MCTS), resource allocation, and scoring based on the result. This constitutes the primary reasoning pathway. Meanwhile, Emotional Computing serves as a secondary line by utilizing a prior attitude as the judging heuristic, guiding the decomposition of reasoning tasks, confirming topology, and influencing the weight of Rational Computing's reasoning process based on emotional responses. This approach aims to provide a more personalized and holistic perspective on reasoning, taking into account both rational and emotional dimensions for a comprehensive understanding of complex inference tasks.

15 Conclusion

In conclusion, this paper has introduced significant contributions to the field, centered around the innovative concept of the General Intelligent Network (GIN) based on information entropy and a generative network model. The integration of Rational Computing and Emotional Computing in a brain-like General Machine Learning (GML) system represents a noteworthy advancement, providing a comprehensive approach to artificial intelligence that mirrors the complexities of human cognition.

Furthermore, the incorporation of the Knowledge (HPP) Learning and Reasoning mechanism enhances the adaptability and decision-making capabilities of the proposed GIN model. By delving into the internal mathematical logic and working mechanisms, this paper lays the foundation for a deeper understanding of the GIN paradigm, offering valuable insights for future research endeavors in this domain.

It is important to note that the presented conclusions are just the beginning, as the commitment to ongoing updates of internal mathematical logic and working mechanisms underscores the dynamic nature of this research. These continuous developments aim to foster a collaborative and evolving environment, encouraging further exploration and refinement of the General Intelligent Network paradigm. Ultimately, the contributions presented herein contribute to the advancement of artificial intelligence, paving the way for future breakthroughs and innovations in this rapidly evolving field.

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