PRELIMINARY CONCEPT OF GENERAL INTELLIGENT NETWORK (GIN) FOR BRAIN-LIKE INTELLIGENCE

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ABSTRACT

Preliminary concept of AGI for brain-like intelligence is presented in this paper. The solution is mainly in two aspects: firstly, we combine information entropy and generative network (GAN like) model to propose a paradigm of General Intelligent Network (GIN). In the GIN network, the original multimodal information can be encoded as low information entropy hidden state representations (HPPs), which can be reverse parsed by the contextually relevant generative network into observable information. Secondly,we propose a generalized machine learning operating system (GML system), which includes an observable processor (AOP), an HPP storage system, and a multimodal implicit sensing/execution network. Our code will be released at `https://github.com/ggsonic/GIN`

1 Introduction

Learning from small data and completing reasoning is an important hallmark of human intelligence. Machine learning has evolved to the point where it still does not go beyond traditional software. Almost all algorithmic models are pre-defined for a particular single task, and once the problem goes beyond the pre-designed scope, the model stops working without surprise. If general intelligence (AGI) is to be achieved, machine learning systems must be able to be used to perform many different tasks, and preferably with some associative reasoning ability to learn from small samples of data and complete inference, which is considered to be the biggest dilemma in front of the AI field today.

Based on years of hands-on experience and insights in AI applications, we try to solve these two dilemmas mentioned above. The solution idea is mainly in two aspects: firstly, we combine information entropy and generative network (GAN like) model to propose a paradigm of General Intelligent Network (GIN). In the GIN network, the original multimodal information can be encoded as low information entropy hidden state representations (HPPs), and at the same time, these low entropy HPPs can be reverse parsed by the contextually relevant generative network into observable high entropy original information. The GIN network is mainly used to solve the problems related to small data learning to achieve spatial, temporal and logical/causal reasoning; secondly,we propose a generalized machine learning operating system (GML system), which includes an observable processor (AOP), an HPP storage system, and a multimodal implicit sensing/execution network. GML is mainly used to dynamically solve cross-domain, non-fixed structured non-specific tasks.

2 Conjecture 1: A hierarchical structured generative network paradigm that generates Human Level Intelligence.

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). We call this whole

[*]This work was performed while the author was an independent researcher

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).

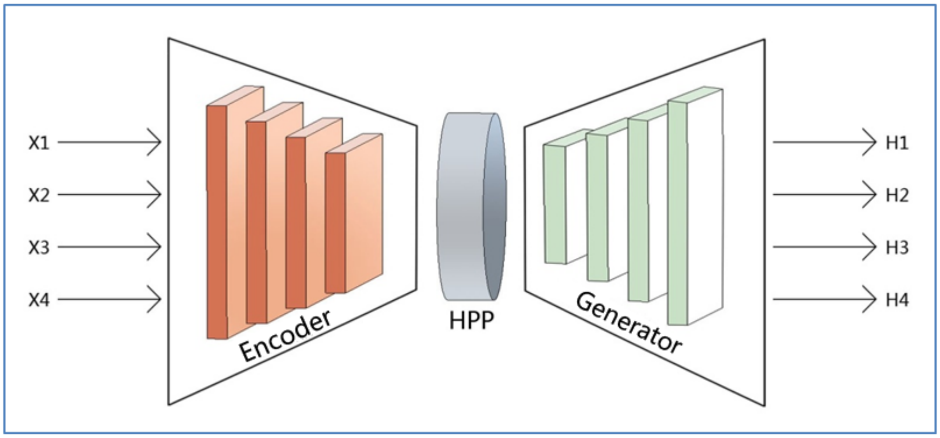

Figure 1: GIN

HPP When we recall someone or something, the image in our mind is often missing details, or missing colors, or only a few detailed fragments that we focus on, which is much smaller than the amount of information in the picture we have in existing deep learning models. This simplification is likely the result of hundreds of millions of years of evolution, which allows us to compute multiple dimensions in a short period of time with very little energy consumption.

In GIN, HPP itself is the "Knowledge" we can learn from the outside world. In the process of active thinking, HPPs can be used to reversely generate explicit images, and by analyzing these images, the correlations between different HPPs can be obtained, thus building up a new HPP with these existing HPPs hypper-connected.This new HPP can be saved and can be used as new "Knowledge" in GIN.

Neural Knowledge Compression (NKC) In GIN, as long as there are remaining computational resources, a special kind of process will be executed continuously. Series of HPPs can be continuously encoded as implicitly expressed information as long as the information entropy decreases. We call this process Neural Knowledge Compression (NKC). NKC will be kept performing and HPP storage space will be freed up. More importantly, new HPP which is more generalized can be obtained,and can be used to do deeper reasoning. Autonomous NKC is a novel method that diffs GIN from other networks.

Network Evolution In GIN, the network topology is huge complex hyper-connected structure in 3D space. Prior has played a large role in network evolutionary process. The function of most neurons in GIN is genetic. When new structure is required, a new neuron is branched out, trying to keep existing neurons unchanged.

3 Conjecture 2: The current deep learning approach is a special case of the GIN network in Conjecture 1.

In GIN, network structure is a complex topology consisting of multiple computational units hooked up to each other, while in the current deep learning model, this structure is reduced to the simplest layer of structure, and each layer is not subdividable,which can be seen as the projection of the GIN topology to a 2D plane.

While the network topology of the deep learning model is dedicated designed, the association relationships between intermediate layers of computational units are initially random and dynamic, and should be explored within large datasets. Then the model is highly domain specific.

4 Conjecture 3: Human neural networks are another special case of the GIN network in Conjecture 1.

Neural networks constructed based on neurons in humans and animals have extremely high real-time and processing efficiency, and are characterized by a lack of details and temporal discontinuities compared to deep learning models in computers. What is more, when the individual is sleeping or meditating, the whole neural system's computing resources are released and the NKC process is continuously performed, resulting in deeper knowledge and wisdom.

5 Conjecture 4: In GIN networks, information flow and information processing are subject to the principle of information entropy reduction.

For both humans and animals, the information received through vision, hearing, touch and smell is not only a large amount of data, but also chaotic and disorganized. It is conceivable that it would take a long time to process this data by current deep learning models, but both humans and animals can react to the surprise attack of natural enemies in milliseconds, and this real-time data processing capability is unimaginable for the existing deep learning models. Therefore, 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.

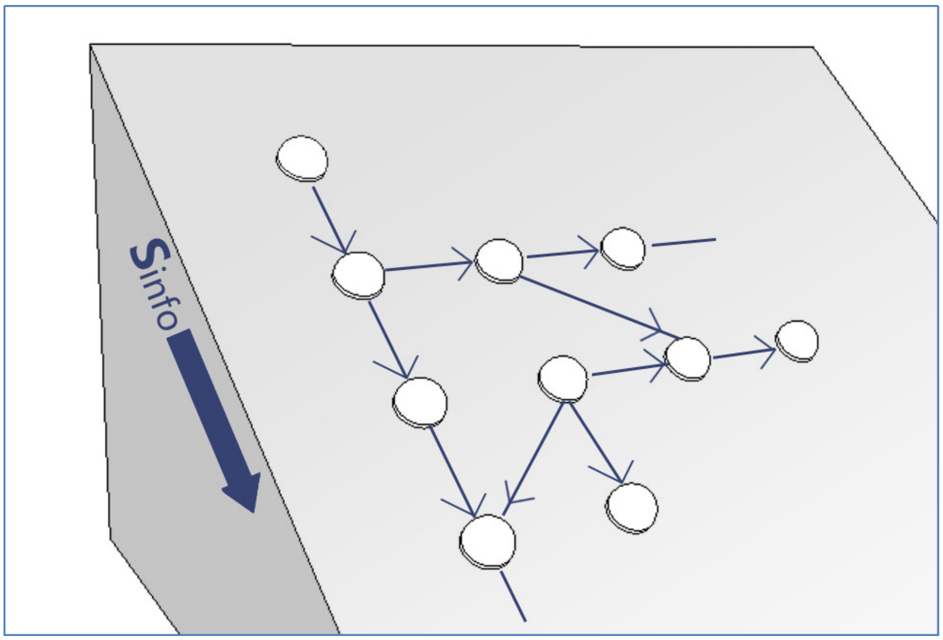

Figure 2: Information Flow

By observing human consciousness and computer deep learning models, we make the following kinetic conjecture: 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.

When the GIN network receives multimodal external information, there will be computing units to split this information into several unimodal information, multimodal to unimodal that is a process of entropy reduction; each unimodal computing unit then decomposes the complex and disordered information into images, which is another process of entropy reduction; each different image is then encoded into more abstract implicitly expressed images, and the implicitly expressed images are then encoded into Symbols, functions, key points,etc(lower entropy HPPs). And if these HPPs will have lower entropy after the next computation ,then this computation can continue.

An extreme example of such a reduced entropy calculation would be to drop all feature values after reducing the information entropy to a very low value; the information entropy is reduced, but the output becomes meaningless. Therefore, we add a condition to this conjecture: while the information entropy is reduced, the computation is valid only if it ensures that these computations can be reversed to generate the input content.We call this generative network Contextually Diverse Generative Network.These G-networks can generate diverse output results according to the contextual background, and these results and the relationship between the results trigger a new computation to reduce information entropy. Under this model, the GIN network continuously computes many different types of HPP results that are highly abstracted. Most of these results are useless, random, and dynamic, and only a few information bits are retained, after the generative network has verified the explicit results.

Like the evolutionary process of species selection, where organisms evolve in the same purposeless and random way, but the result of fitness for survival becomes the most effective sieve that eventually evolves millions of successful species. This makes us think that in the massive random entropy reduction computation, there will be many dimensions of knowledge and HPP will collide with each other and associate, which will surely produce a network topology that is favorable to the result, and also produce unexpected paths and knowledge association structures, and the process of corroboration and reinforcement of these structures may be the process that makes the machine generate the spark of association and reasoning.

This series of chained computations with high generalization ability has the potential to generate human-like associative and inferential thinking activities if they can be computed on their own.The implementation of generalized reasoning with STC (image reasoning, temporal reasoning and logical reasoning) is considered to be a sign of achieving human-like reasoning. In the GIN network model, we find dynamics that can bring such reasoning to completion.

6 Conjecture 5: HPP Dynamics - Spatial Reasoning.

The world objects change and so does the network inner representation. HPP can be implicitly transformed through one network and then through another, and the transformed HPP can be regenerated into a more realistic spatial image.

Aliaksandr Siarohin et al. released the First Order Motion Model (FOMM) deep learning model in 2019 [1] , a model that migrates and accomplishes a number of affine and transitive transformations based on the transformation of key points in an image.

Through this sequence of transformations, the prediction of the object's position, pose, relative scale, color, and other contents in a certain space is achieved. In GIN network, we borrow the idea of FOMM model and extend the application of affine and projective transformations to the hidden state representation result (HPP). A number of transformation functions are applied to the hidden state image patch, so that the elements of the graph within the hidden state image patch can be predicted for the purpose of spatial reasoning.

For example, when the camera observes a glass of water to determine whether there are enough other containers to hold this glass of water, the GIN network first does some vectorized abstraction of the water in the glass, such as simplifying it to a few key points, and then compare this vector contour with the vector contour of other containers such as bowls, water bottles, ladles, etc. in the space of projection transformation, and then generate a logical map of the hidden state of the container material permeability and other parameters, and associate these HPPs with the projection results and then calculate them to reason out which other containers can hold this glass of water.

7 Conjecture 6: HPP Dynamics - Temporal reasoning.

Temporal reasoning is concerned with the speed of change in the world and how HPP adapts. HPP algorithms are able to adapt themselves to the speed of motion of the target and can stealthily predict the location of the hidden point at the next moment.

The perception of time is significantly different between computers and humans. Computers perceive time continuously and uniformly through monolithic clocks and have millisecond granularity, while humans have evolved over tens of thousands of years, and most of the time their perception of time is discontinuous, uneven, and imprecise. When we analyze this process, we find that human temporal reasoning is actually a collection of spatial reasoning over a time series.

In the world model of Dreamver V2 [2] , the state and the generated image result of the next time step are obtained after extensive training, and then the inverse decoding is compared with the input image, and the decoder is rewarded if the result matches.

GIN borrows the temporal inference model from Dreamver V2, with the difference that instead of following a uniformly fine-grained timeline, we simulate human temporal inference for the purpose of inferring space at certain key points in time, which will have much higher timeliness. That is, by dynamically linking the implicit expressions of spatial inference for a series of time slices according to some association, temporal inference can be achieved in a very short time.

8 Conjecture 7: HPP dynamics-causal reasoning.

Logical reasoning can likewise be reduced to reasoning about images. Taking inspiration from the Horn clause, we translate all NLP cognition into observable images, which are then translated into causal reasoning through spatial and temporal reasoning. In Dreaver V2's world model, the logical reasoning of the game is likewise realized by reasoning about space and time in concert.

In GIN networks, logical relations can be disassembled into a number of HPPs expressed by implicit states, which in turn can be reverse encoded into abstract images by generative networks, and causal/logical inference can be accomplished by spatial inference and temporal inference on these images.

9 Conjecture 8: The structure of a generic machine learning operating system (GML system).

In the process of thinking about the structure of GIN networks, we constantly compare the human learning behavior with the process of software programming. We found that the existing software engineering paradigm is a proprietary form of structure and output for a specific purpose, taking machine production line as an example, each line is pre-coded, from state 1 to state 2 to state 3 to state N, and is written to death as a pipeLine. for solving specific problems the current software paradigm is undoubtedly effective, but it cannot support for dealing with generalized problems.

Combining the capabilities of the GIN network with reference to human problem solving, we designed a generalized machine learning operating system (GML system) with GIN as the core, which is multimodal in its input and is mainly used to dynamically solve cross-domain, non-fixed structured non-specific tasks.

The structure of GML consists of three main parts: an observable processor (AOP), an HPP storage system, and a multimodal implicit sensing/execution network (Figure 3).

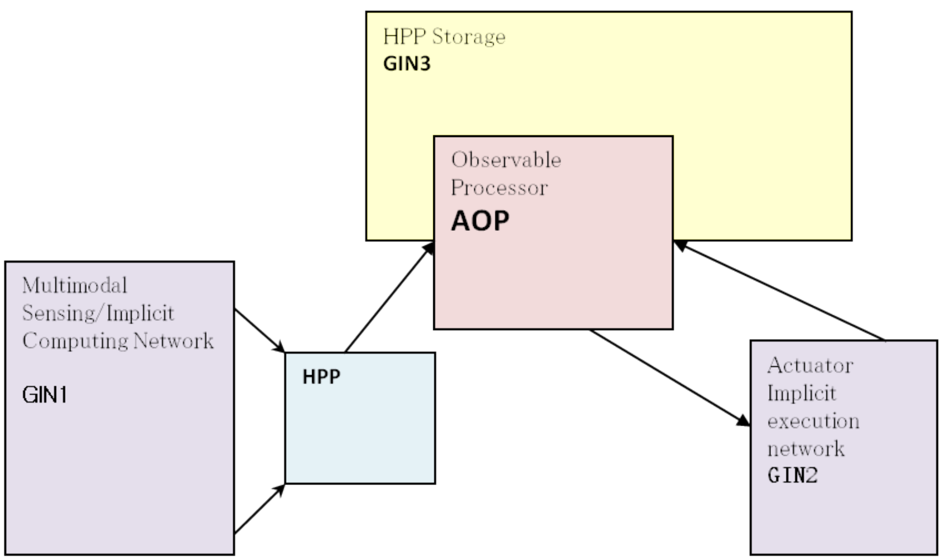

Figure 3: The structure of GML

First, multimodal information such as images, sounds, numbers, and texts are fed into a sensing implicit computational network, the first GIN network, which we denote as GIN1, and the output from GIN1 is a series of multimodal HPP implicit representations, which are fed to the explicit representation processor AOP, and combined with the HPP repository already inherent in the GIN network, GIN3 generates a series of visible images of possible relationships between these HPPs and performs spatial, temporal, and causal inference, in conjunction with the HPP repository already inherent in the GIN network. The inference results are fed to the implicit execution network GIN2, which executes the results of GIN3 and also feeds the computed HPPs back to the AOP as information input. If the AOP finds that combining the HPP repositories reduces the information entropy of the HPPs of GIN2 again, it proceeds to the next level of computation.

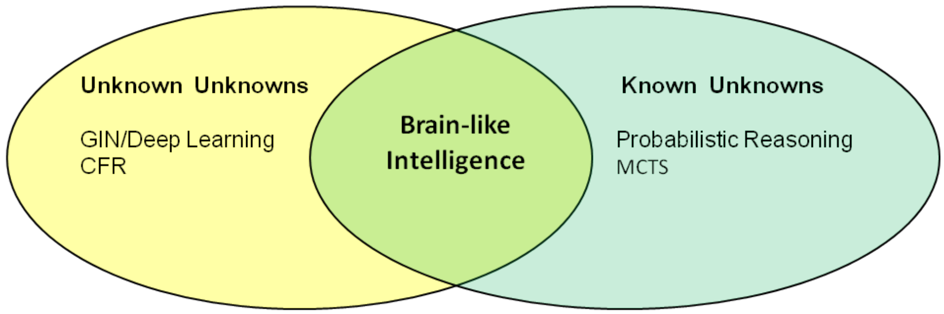

Figure 4: Predicting and Training with GML system

Predicting and Training In the GML system, information is input in parallel and output in parallel. Probabilistic inference provides a systematic way to quantify uncertainty, a.k.a. Known Unknowns. MCTS based probabilistic inference is effective to predict Known Unknowns. GIN, Neural System and modern Deep learning have the potential to identify and predict unknown patterns and behavior, a.k.a Unknown Unknowns. This prediction denoted as Unknown Unknown is because, in inner information sets, each inner state node does not know which of the nodes it is in. In this way, GIN or Deep Learning optimization process is essentially a variant of counterfactual regret minimization (CFR) (For further references see `https://github.com/ggsonic/GIN`).

In this article, GML system leverages all of the capabilities above in a systematic way. Unknown Unknowns information is parsed into Known Unknowns abstract images, and these abstract images can be used to calculate possible task topologies, task planning and acting can be further performed (Figure 4). This process would always keep running.

10 Conjecture 9: GML task decomposition and MCTS task tree for decision making.

In GML systems, there is only one AOP, and various computational tasks compete for computational resources in the AOP in a preemptive manner according to a weighting algorithm with favorable results. For simple deep learning networks, such as face recognition and helmet recognition models, the result can be predicted straightly. For more abstract and complex inference models, it is necessary to first decompose the task into multiple subtasks horizontally , and then decompose each subtask downward to do more computational tasks, which requires the introduction of MCTS state tree inference model to complete the most reasonable topology decision.

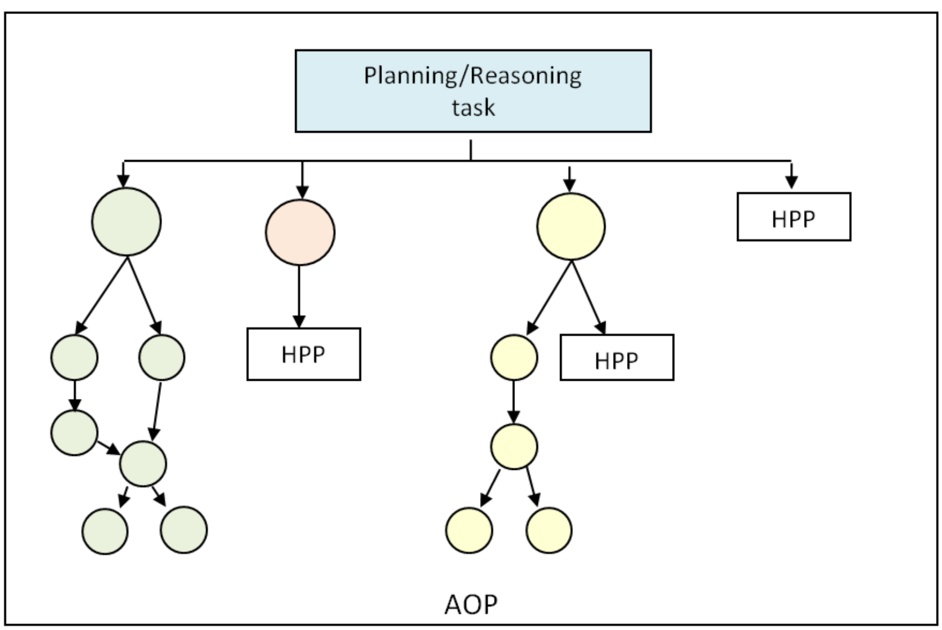

Figure 5: Rational Computing with GML system

Some topological fragments, which may be identified as optimal after several calculations, can be solidified by the GIN network as implicit output HPPs (Figure 5). these HPPs for decomposition of computational tasks, identification of topological relations of tasks, and resource allocation are somewhat different from the implicit HPPs for raw information processing, which are more like the process of human problem analysis and problem solving Accumulation.

These HPPs are the "knowledge structure" of GML, and the accumulated "knowledge structure" will be different for different GMLs due to different input information, different problem solving, and different computation time.

11 Conjecture 10: HPP Storage.

The process of collaborative computation of a large number of HPPs is the result-oriented observation-analysis-recall-experiment cycle of the GIN network. In the early stage of computation, a large number of HPPs are dynamic, random, and invalid, and only a small number of HPPs pass the AOP's test and are identified as HPPs favorable to the results, and the topologies associated with these HPPs are strengthened and given more computational resources. In the later stage of computation, the GIN network will evolve the topology that is most favorable to the results under this mechanism, and the HPPs generated under this structure will become "knowledge" that can be fixed and recorded in the HPP repository after repeated observation-analysis-recall-experiment cycles.

At the same time, after the GIN network optimization process is repeated many times, some topologies suitable for the results will be fixed gradually, forming a fixed paradigm for dealing with a specific problem, and this structure will be recorded as a fixed graph structure, which becomes the knowledge learned and precipitated by the machine.

HPP repository As the machine processes more and more problems, more and more a prior HPPs are stored down in GIN, and the comprehensive processing power keeps increasing.

Once the structure of the HPP is fixed, it will become a fixed paradigm. Most of the HPPs previously associated with it may no longer need to be repeatedly computed, they will be freed to do other things, and this fixed HPP tessellation will become a fixed, minimalist HPP topology.

12 Conjecture 11: Emotional Computing.

According to conjecture 4, except for purposeful GML-like computations, as long as there are remaining computational resources, the GIN network will connect various HPP patch to compute results with lower information entropy according to the principle of information entropy reduction, and some computations and connections may be initially purposeless and random. How can the GIN network develop a continuous self-motivation capability and self-evaluation system to produce HPPs that are more effective and valuable to it?

We have found that emotion is an inexhaustible and consistently effective system of positive motivation and evaluation for humans. For humans, different people have different emotions and interests in different things, which directly contributes to whether someone will enjoy doing something and whether they are good at it. For example, if a person likes to swim, it is mostly genetic, but also likely that he grew up in an environment where people gave positive evaluations of his swimming behavior, and in a subtle way, he got more positive signals from the activity of swimming, which made him more willing to spend time and experience on swimming, thus forming a virtuous circle, and he became better at the sport of swimming.

For tasks that are very purposeful, it is relatively easy to obtain an evaluation of whether they are valid or not. However, there are many tasks, especially HPPs with intermediate implicit states, where it is almost impossible to assess the rightness or wrongness of the results. If we ask a person whether he should wear a blue T-shirt or a plaid shirt today, it is difficult for him to give an answer by right or wrong, but he can make a quick decision by liking or disliking, and this emotional decision is not unconscious, it may be the result of many years of preference accumulation, and this decision may only be associated out right or wrong for some things in a few years.

There are three benefits of doing the design of Emotional Computing, one benefit is to make strategies for models that cannot be evaluated right or wrong in a short time; another benefit is to realize the personalized development of GIN networks through positive motivation and self-motivation, so that different GIN networks can obtain different preferences, and the collection of these personalizations together can obtain more complementary and creative learning networks; the third benefit is to strengthen the HPP computational pathway of more implicit state association through self-motivation, thus allowing GIN networks to achieve deeper reasoning.

13 Conjecture 12 : Enhanced GML combining Rational Computing + Emotional Computing.

The human mindset is rational accompanied by perceptual, so that the reasoning task can be carried on by perceptual computation when the rational computation encounters a bottleneck, and it will make the reasoning more personalized for different GMLs.

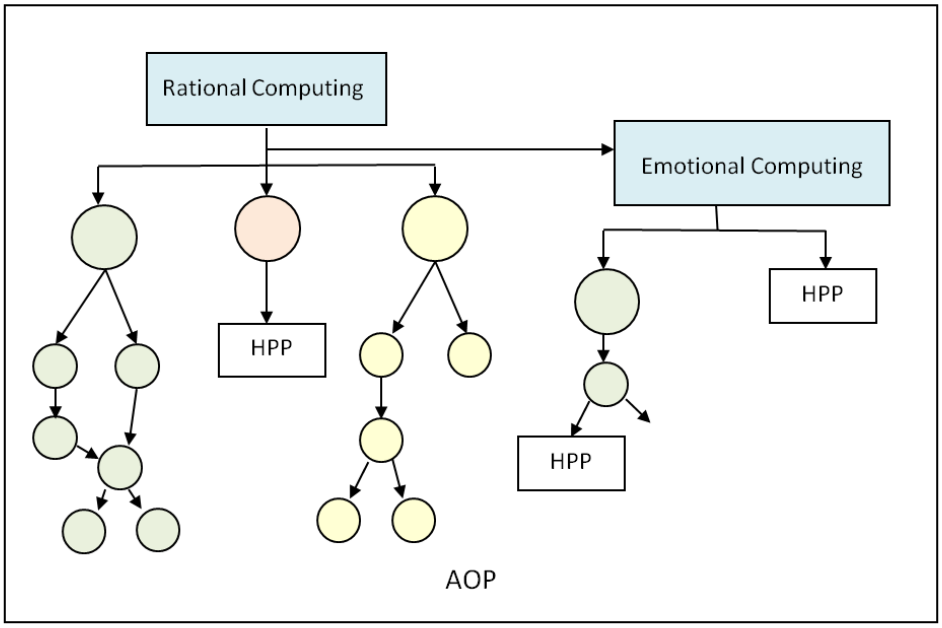

Figure 6: Enhanced GML system combining Rational Computing and Emotional Computing

Based on the above considerations, we take Rational Computing as the main line of reasoning and Emotional Computing as the auxiliary line of reasoning when performing a certain inference task (Figure 6). The Rational Computing process refers to Conjecture 9, first decomposing the task into several subtasks, then reasoning the task tree of each subtask with the topology of MCTS, and completing the reasoning by allocating resources according to the reasoned topology, and scoring this reasoning result according to the result; as a secondary line, the Emotional Computing is based on the a prior attitude as the judging HPP, as a way to Organize the decomposition of reasoning tasks and topology confirmation, and weight the reasoning process of Rational Computing according to the reasoning results, so as to image the reasoning topology and reasoning results of AOP from the side.

14 Conclusion

In summary,our main contributions are:

- A novel paradigm of General Intelligent Network (GIN) based on information entropy and generative network model.
- Brain-like GML system combining Rational Computing and Emotional Computing.
- Knowledge (HPP) Learning and Reasoning mechanism.

In this paper, More internal mathematical logic and working mechanism will be continuously updated to facilitate futher research effort in this area.

References

[1] Aliaksandr Siarohin, Stéphane Lathuilière, Sergey Tulyakov, Elisa Ricci, and Nicu Sebe. First order motion model for image animation. In *Conference on Neural Information Processing Systems (NeurIPS)*, December 2019.

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