Knowledge Density Mapping for Derivation of Inference Potential

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Abstract - *Presented is a mathematical derivation and development of an information processing system's Inference Potential. This Inference Potential is determined from providing a measure of the Knowledge Density and Analytical Competency of the information processing systems, based on the contextual assessment of the question, or topic posed by the operator and analyst. The use of Knowledge Density and Analytical Competency to determine an AI systems Inference Potential will provide the methodologies to radically improve the performance and quality of Intelligence Processing Systems by allowing the system to "self analyze" their ability to answer questions and perform the analysis asked of them by operators and analysts.*

1 Introduction

The underlying issues and challenges posed by the introduction of Artificial Intelligence into system designs are not new. Information processing and dissemination systems are an expensive infrastructure to operate and more-often-than-not, these systems fail to provide analysts with tangible and useful situational information, typically overwhelming information analysts with system messages and other low-level data. Real-time human decision making processes must be supported by information derived from the fusion process and must operate in a uniform and cooperative model, fusing data into information and knowledge so information analysts can make informed decisions. One such construct that would aid the information analyst would be a measure of a system's ability to provide quality information and/or inference about a particular subject or question posted by the information analyst. Described here is the mathematical derivation and development of an information processing system's ***Inference Potential***. This *Inference Potential* is determined from providing a measure of the ***Knowledge Density*** and ***Analytical Competency*** of the information processing systems, based on the contextual assessment of the question, or topic posed by the operator and analyst. Such a measure would allow analysts to quickly understand the system's ability to provide quality knowledge about a subject, question, or topic, and could be used to discover knowledge holes or gaps in information processing systems. ***Knowledge Density Mapping*** facilitates information, intelligence, and memory integration, and allows faster accommodation of knowledge and knowledge characteristics. The *Analytical Competency* measure provides analysis, reasoning, and reporting capabilities of an Information Processing System's capabilities (provides cognitive intelligence).

2 Knowledge Density Mapping: A Pathway to AI Metacognition

As we push for "autonomous" systems, the need to provide a system with the ability to understand its own limitations and capabilities and to reason about them, in light of the duties or missions it is given, is becoming increasingly necessary. In humans, we call this ability "Metacognition." Metacognition in humans refers to higher order thinking which involves active control over the cognitive processes engaged in learning and performing. Activities such as planning how to approach a given task, monitoring comprehension, and evaluating progress toward the completion of a task are metacognitive in nature [1]. In an AI system, Metacognition, or ***Knowledge of Cognition***, refers to what a system knows about its own cognition or about cognition in general. In short, it describes the system's ability to think about how and what it thinks. It includes three different kinds of metacognitive awareness: declarative, procedural, and conditional knowledge.

- **Declarative Knowledge**: refers to knowing "about" things,
- **Procedural Knowledge**: refers to knowing "how" to do things, and
- **Conditional Knowledge**: refers to knowing the "why" and "when" aspects of cognition.

We can classify Knowledge of Cognition into three components [2]:

- **Metacognitive Knowledge**: (also called metacognitive awareness) is what the system knows about itself as a cognitive processor [13].
- **Metacognitive Regulation**: is the regulation of cognition and learning experiences through a set of activities that help the system control its learning [14]. This may be based on its understanding of its own "knowledge gaps."
- **Metacognitive Experiences**: are those experiences that have something to do with the current, on-going cognitive endeavors (current mission).

The push to define metacognition within an AI system drives us toward defining an overall Cognitive Ontology to allow metacognitive concepts to be defined within the context of an AI cognitive framework [3]. This need for metacognitive concepts within a system stems from the understanding that knowledge advances not by copying reality but by schematizing it within a formal framework. This allows emergent behavior to be recognized and captured [12]. An **emergent behavior** might be the formation of a new concept, 'bubbling up' from below the artificial conscious level of the system [4]. A simple way of stating this is that the systems would preserve their own **attention** and would, at every level, be concerned with avoiding *interruption and distraction* from their tasks or missions. Figure 1 illustrates the Artificial Cognitive Neural Framework created to accommodate Intelligent Information Agents that provide Metacognitive capabilities. Figure 2 provides the Metacognition Cognitive Lower Ontology for the Intelligent Information Agents [5].

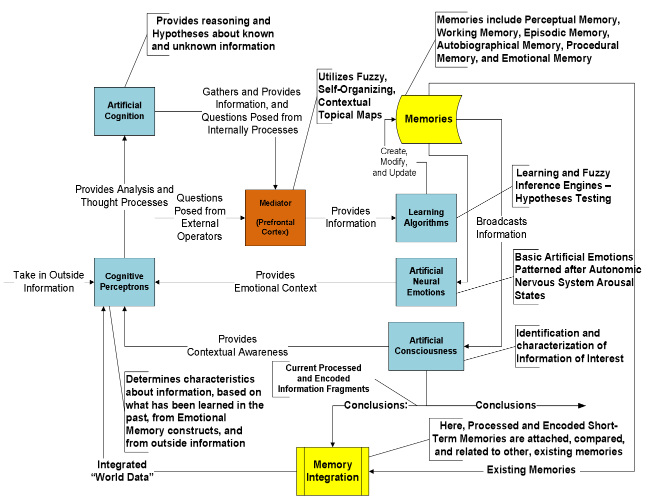

Figure 1 – Artificial Cognitive Neural Framework

In order to achieve metacognitive abilities within the overall AI system, the system must have the ability to measure its own knowledge about a particular topic or subject [6]. This measure of topical or subject knowledge involves measuring the "***density***" of knowledge the system possesses about this subject or topic in question. This ***Knowledge Density*** measure is based on the number of separate information fragments relative to the taxonomy of the topic or subject. Figure 3 provides the Knowledge Density Measure, based on separable topical information fragments [7]. In order to provide the parameters required to compute Knowledge Density, cognitive maps [15] track separable information fragments by topic, as illustrated in Figure 4.

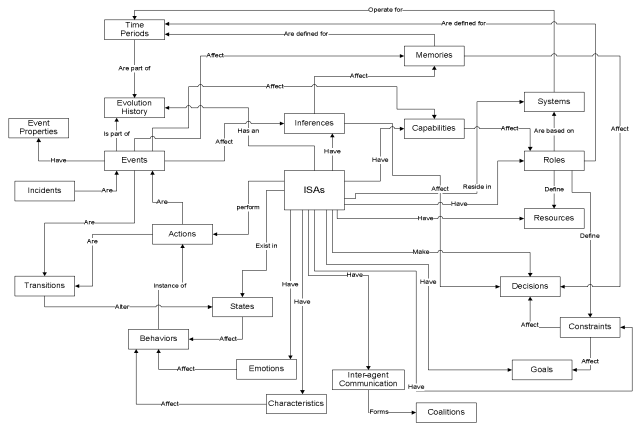

Figure 2 – The ACNF Cognitive Lower Ontology

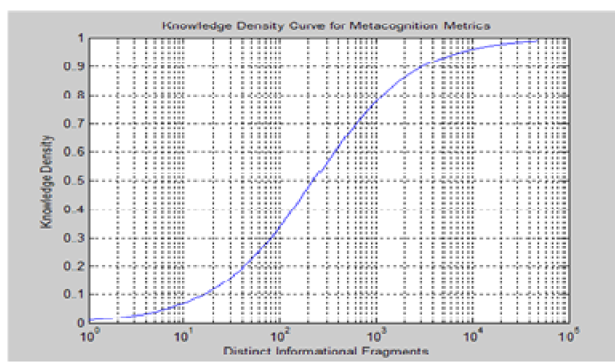

Figure 3 – Knowledge Density Computation

We use knowledge fragment measurements to ensure that we only store information relative to a topic or subject once. Information that is taken in is parsed and information fragments that have not been stored before are pulled out and stored in a cognitive map for that topic. Renyi's entropy measurement is utilized to separate information into topical information fragments. Renyi's entropy measurement is defined as [8]:

$$H_R(Y) = -\log \int_y p(y)^2 \, dy$$

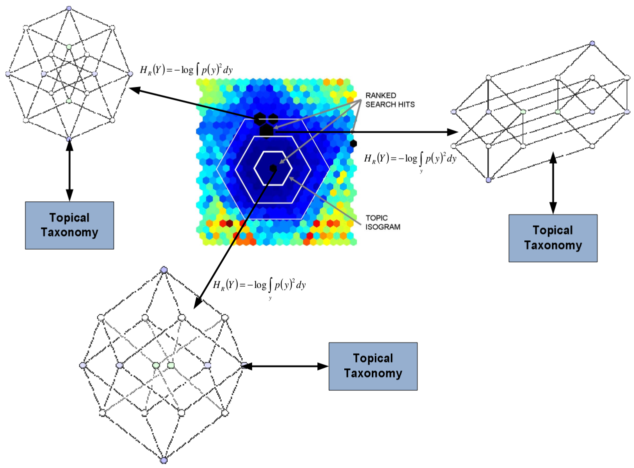

Figure 4 – Knowledge Density Mapping

Computationally, this is difficult, however, Renyi's measure, combined with the Parzen Density estimation method provides a computational model. We start by looking at the information densities, *p(y)*, as a sum of related topical cognitive maps, each centered at y_i, we get:

$$p(y) = \frac{1}{N}\sum_{i=1}^{N} G(y - y_i, \sigma I)$$

Therefore, Renyi's entropy can be computed as the sum of local information interactions (separate information fragments) over all pairs of informational entities. Informational associations are created within the Cognitive Topical Maps utilizing a ***Fuzzy Possibilistic Network*** and Inference Engine, based on Renyi's Theoretics. We use this possibilistic network because:

- It's robust in the presence of inexact information.
- It utilizes conditional possibilistics
  - Mutual Information measurement
  - Joint Informational membership rather than joint probabilities
- Excellent at showing qualitative relationships not attainable with Bayesian methods
  - Excellent at showing qualitative relationships not attainable with Bayesian methods
  - Creates decisions with conditional possibilistic attributes
- More useful with general questions about a subject domain

This methodology allows the Cognitive Topical Maps to be populated with separable information fragments, relative to a topic that maps to the topical taxonomy. This allows a measurement of the density of knowledge a system contains, relative to a topic or subject. Fuzzy, Self-Organizing Contextual Topical Maps are used to measure topics and how other topics relate. Knowledge Density is a measure of the density of knowledge a system has about a topic and the density of related topics that would be used to answer questions and/or analyze situations. The next piece of the Inference Potential computation is Analytical Competence, or, what is the competency of the system to provide the analysis being asked.

3 Analytical Competency

In order to quantifiably measure the a system's ***Inference Potential***, the system must be able to assess its ability to analyze information relative to a question or mission posed to it. We call this measure of analytical potential ***Analytical Competency***. The Analytical Competency measures relative to a topic or subject are based on the algorithms and software that is available:

- The algorithms actual technical skills - what is was designed to do
- The algorithms experiences – tied to emotional memory [16]
- The algorithms body of knowledge – what it has learned

Analytical Competency is tied to "***Areas of Expertise***" within the AI system. Figure 5 illustrates the information flow for the ***Analytical Competency*** measure.

One main element of the overall Analytical Competency measure is a measure of the algorithm's experiences, i.e., what have the algorithms processed before and what has been right and wrong with the analytical output. This is measured utilizing "Emotional Memories" within the AI system [17]. Within the ACNF framework, Drives, Priorities, and Constraints influence emotions. The behavioral subsystem receives situations and computes actions, while memories provide personality parameters and the various conscious agents' sensitivities to emotional computation [18]. If the cross-connectivity of the neural layers is considered as a matrix, we can compute emotional response from the column-wise fuzzy weightings (based on Dr. Levine's Autonomic Nervous System States) and the action response from the row-wise fuzzy weightings [7, 20]. This is analogous to the amygdale and hippocampus that involved in implicit and explicit emotional memories within the human brain [19].

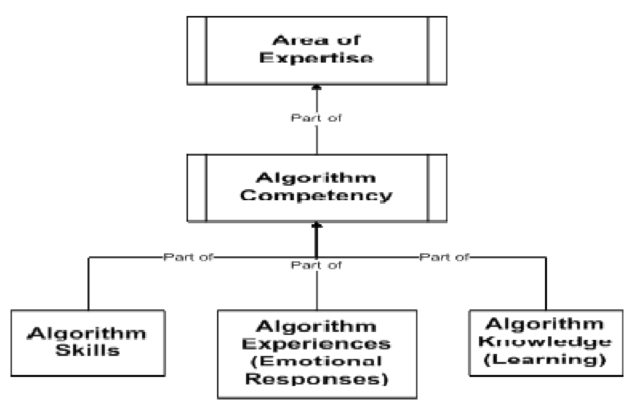

Figure 5 – Analytical Competency Measure Model

Respectively, the ACNF and the cognitive perceptron coalitions become emotionally aroused when they form semantic and episodic memories about situations that cause "stress" within an artificial neural system. Stress situations may involve a loss of resources, new data environments that are unfamiliar, new interfaces that are introduced into the environment or situations where the algorithms produced incorrect results. These cognitive representations of emotional situations better referred to as memories about emotions rather than emotional memories.

The effects of emotional arousal on explicit memory are due to processes that are secondary to the activation of emotional processing systems in the ACNF [9]. These emotional responses or emotional memories within the algorithmic long-term memories provide vital information that relates to how these algorithms have been able to respond or not respond to given assignments, topical analysis, or missions that have been assigned to the system.

Activity in these areas would be detected by the cognitive coalitions and would lead to increases in system emotional arousal (due to activation of modulation within the neural structure that leads to the release of cognitive problem, solution, search, and emotion agents [10]. These responses are stored and utilized, in part, as a measure of the analytical competency of a set of algorithms that make up an area of expertise within the system. The transmittal of informational content as well as emotional context allows information retrieval performance to be greatly enhanced, allowing for "cognitive economy" within the artificial neural system [11]. The ***Analytical Competency*** measure is based on inputs to the areas shown in Figure 5, illustrated in Figure 6 [18].

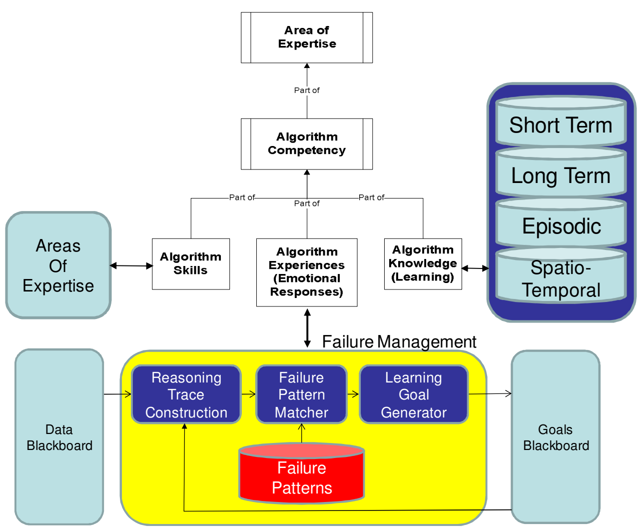

Figure 6 – Analytical Competency Measure Inputs

The actual Analytical Competency measurement is computed as:

$$AC_t = \frac{\sum_{i=1}^{n} w_i \sqrt{L_i^2 + A_i^2}}{n}, \text{ where}$$

$$w_i = \sqrt{\frac{\sum_{j=1}^{m} (\pm) E_j^2}{m}}, \text{ where } E_j = \text{emotional memory response}$$

$$L_i = \frac{\sum_{k=1}^{p} A_{E_k} C_k}{p}, \text{ where } A_{E_k} = \text{memories for area of expertise k and}$$

$$C_k = \text{completeness of memory}$$

$$A_i = \frac{\sum_{l=1}^{r} A_{R_l}}{r}, \text{ where } A_{R_l} = \text{Algorithm relevancy for lth algorithm}$$

The result is a rating from 0 to 1 of the Analytical Competency of the system for the question or mission posed.

4 Conclusions and Discussion

Once the Knowledge Density and Analytical Competency have been computed, the overall Inference Potential of the system for a given topic/subject/mission is:

$$IP = KD * AC$$

Producing a number between 0 and 1, where 0 means the system has no potential to produce a useful inference for the topic requested and 1 indicates that not only can the system produce useful inferences, but that the inferences will be useful and trustworthy.

Much more research is needed to validate this work and produce an automated way to compute Knowledge Density and Analytical competency. This work is also dependent on further research work on Artificial Neural Emotions, Metcognitive and Metamemory constructs, as well as further work on the ACNF. The purpose of this work is to provide a framework as research continues, for autonomous AI system to provide meaningful knowledge and self-assessments for operators of these systems.

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