Psychological Constructs for AI Systems: The Information Continuum

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Abstract - *Research for the development of credible solutions within the Information Continuum has been a 17 year journey that began in the mid 1990's when the we were designing new ways to perform data capture, processing, analysis, and dissemination of high volume, high data rate, streams of information (what today would be called a "big data" problem). Hence, data analysis and lack of quality user interaction within that process are not a new problem. Users have continued to be challenged with keeping up with the vast volumes and multiple streams of data that have had to be analyzed. By the time a user had grabbed a time-slice of data, plotted it, and analyzed it, 100's of Gigabytes of data had passed through the system. In order to provide some semblance of rational attack against the onslaught of data we created what could be likened to a virtual window into the system that allowed the analysts to "walk into the middle" of the data and look at it as it flowed through the system. Analysts could reach out and grab a set of data, rotate it through its axes, and perform automated analysis on the data while remaining within the system data flow. This way analysts could intelligently and rapidly hop between portions of data within multiple data streams to gain pattern and association awareness.*

Keywords: Information Continuum, Big Data, Artificial Intelligence, Knowledge Density, Knowledge Relativity.

1. Introduction

Our work in data representation and visualization resulted in a realization that each point in time within the rapid data flow was an independent and discrete information continuum with specific and qualitative state. Subsequently, analogous thoughts began to emerge from research in artificial intelligence and artificially cognitive system theory [6]. Envisioned was a virtual view within a portion of the human brain where one could view a given neural node, or a given neuron, and subsequently view data flow as data/information traveled in and out of the neuron [4]. Once gathered, a hypothesis emerged that the analysis of brain locale, data, and study of brain processes through this type of virtual environment, could lead to important understanding of learning, inferring, storing, and retrieving (reconstruction) and/or all aspects of human neural processing [1]. This led to the possibility of a theoretical Neural Information Continuum (NIC) [5].

2. Information Flow within a Synthetic Continuum

One of the first areas that must be investigated when considering an Artificially Intelligent System (AIS) is the flow of information. Humans take in ~200,000 pieces of sensory information each and every second of every day of our lives. Our senses (see, hear, smell , touch, etc.) are constantly receiving and processing information, correlating it, reasoning about it, assimilating it with what we already know, and finally leading to decision making based upon what was learned. For a system to become dynamic, self-evolving and ultimately autonomous, we propose to provide these same abilities; although the sensors and sensory perception systems may be synthetic and different, sensing a variety of information types that humans can't sense (e.g., infrared or RF information), the processes for autonomy, which correlate, learn, infer and make decisions, are the same. Besides receiving information from a variety of sources and types (e.g., auditory, visual, textual, etc.), another important aspect of information, is that the content is received at different times and at a variety of latencies (temporal differences between information). Additional characteristics include, a variety of associations between the information received and information the system may have already learned, or information about subjects never encountered. Therefore, these information characteristics and the challenging real-time processing required for proper humanistic assimilation, help us form the theory of the Autonomic Information Continuum (AIC). One of the first steps in developing our theory of synthetic autonomic hypotheses is observing/understanding the information continuum and the associated characteristics and operational relationships within the human brain. Hence, as we develop understanding of information flows into and out of neural nodes, types of information, processing mechanisms, distributions of information, enable us to establish foundational mathematical representations of these characteristics and relationships.

Processing, fusing, interpreting, and ultimately learning about and from received information requires taking into account a host of factors related to each piece or fragment of information. These include [7]:

- Information Types
- Information Latencies
- Information Associations e.g.:
    - Time, State, Strength, Relationship Type, Source, Format etc.
- Information Value
- Information Context

Mathematically modeling the information continuum field surrounding a node within our synthetic AIC, is accomplished via inclusion of each discrete association for any node *u*, takes the form shown in the following equation:

$$C\frac{du(x,y,t)}{dt} = -\frac{1}{R}u(x,y,t) + \int_x\int_y w(x,y)z(x,y,t)\,dxdy + I(x,y,t)$$

where:
u *represents the unit node of the system,*
x *represents the preprocessed input to node u,*
y *represents the output from node u,*
w represents the relative contextual information threads and association weight of *u* with its surrounding nodes, including a decay factor for each relative information thread that describes the relative contextual decay over time, where:

$$w = \sum_{j=1}^{M} \frac{1}{r_j} T_j KD_j W_j$$

where:

T *represents the Contextual Information Thread j derived from Fuzzy, Self-Organizing Contextual Topical Maps*
KD *represents Knowledge Density j of Information Thread T*
W *represents Weighting for Contextual Thread j, and:*

$$\sum_j W_j = 1$$

I represents the processing activity for node *u*,
z represents the learning functionality for node *u*,
1/R represents the decay rate for node u[1], and
C represents the capacity of node *u*.

This information field continuum equation allows us to analyze the equilibrium of nodal states within the AIC and to continuously assess the interactions and growth of independent information fragments within the system. Even in the most dense, most complex, cluttered information environments, each fragment of information and each action within the AIC is entropically captured explicitly and implicitly within Information Continuum Equation (ICE). This equation is the entropic engine which

[1] In this case, the decay represents the information's relative value over time.

provides the ongoing analysis and virtual view into a synthetic AIC. Equation 2-1 enables us to assess the performance and quality of processing and to understand the capacities, information flows, associations, and interactions of knowledge and memories within the system, as well as, supporting analysis and inherent understanding of real-time system behavior. The variables in ICE can be interpreted as the average values in a heterogeneous assembly of information nodes, where ICE describes the behaviors of the interactions among ***n*** node assemblies within a synthetic AIC processing system. The objective is to have the ability to measure, monitor, and assess multi-level states and behaviors, and how and what kinds of associative patterns are generated relative to the external inputs received by an AIC system. ICE provides the analysis needed to understand the AIS's ability for processing external content within an AIC. Hence, real-time assessment and monitoring, and subsequent appropriate control, are expected to allow us to avoid developing a rogue AIC, much to the chagrin of Hollywood script writers.

3. Information Processing Models

Establishing a hierarchy of information flow within an AIC is a key objective for development of synthetic autonomic characteristics (e.g. cognition, thinking, reasoning, and learning). An AIC will need to be able to ingest and process a variety of inputs from many diverse information sources, dissect the information into its individual information fragments, fuse the information, and then turn this information into a formation which can be used to determine action-actionable intelligence. An AIC system must be able to assess situations previously not encountered, and then decide on a course of actions, based on its goals, missions, and prior foundational collected knowledge pedigree.

The underlying issues and challenges facing Artificially Intelligent systems today are not new. Information processing and dissemination within these types of systems have generally been expensive to create, operate and maintain. Other artificially intelligent system challenges involve information flow throughout the system. If flow is not designed carefully and purposefully, the flood of information via messages within these systems and between their software and hardware components can cause delays in information transfer, delaying or stunting of the learning process which can result in incorrect or catastrophic decisions.

Therefore, real-time decision making processes must be supported by sensory information and knowledge continuously derived from all cognitive processes within the system simultaneously, in a collectively uniform and cooperative model. Additionally, transformation from information to knowledge within an AIC system requires new, revolutionary changes to the way information is represented, fused, refined, presented, and disseminated. Like the human brain, the cognitive processes within an AIC must form a cognitive ecosystem that allows self-learning, self-assessment, self-healing and sharing of information across its cognitive sub-processes, such that information is robustly learned and rapidly reusable.. This AIC ecosystem involves inductive, deductive, experimental, and abductive thinking in order to provide a complete Data-to-Information-to-Knowledge process explained in detail throughout the rest of the book. At a high-level, we are applying the theory of AIC and applying the constructs to the development of humanistic analogous AIS. The AIS human brain analogy provides two-main layers of processing, a ***Deductive Process*** and an ***Investigative Process***. The ***Deductive Process*** is utilized for assembling information that has been previously learned and stored in memories (deductive and inductive logic), whereas the ***Investigative Process*** looks for patterns and associations that have not been seen before (abductive and experimental logic) [2]. Figure 1 illustrates the differences between deductive, inductive, abductive, and experimental inferences [8].

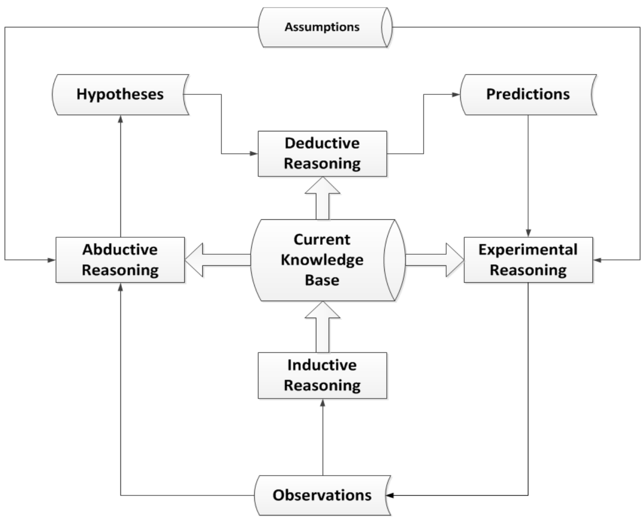

Figure 1 - Differences between Logical Inference Systems

Inductive Reasoning: Inductive reasoning involves concluding after evaluating facts; reasoning from specific facts to a general conclusion and allowing for inferencing. It also requires human experience to validate conclusions. An example might be: Zebras at the zoo have stripes; therefore all zebras have stripes [10].

Deductive Reasoning: Deductive reasoning is just the opposite. Deductive reasoning moves from general principle to specificity. This type of reasoning is based upon accepted truths. An example of deductive reasoning might be: I know that all zebras have stripes therefore when I go to the zoo, if I see a zebra, it will have stripes.

Abductive Reasoning: Abductive reasoning allows for explanatory hypothesis generation or generating ideas outside of the given facts to explain something that has no immediate satisfactory explanation.

There are a number of ways in which people reason, but most human reasoning follows one of these three reasoning systems. Other ways that humans' reason includes cause and effect reasoning where causes and after effects are considered. Analogical reasoning is a way of relating things to other novel situations. Comparative reasoning as it implies involves comparing things. Still another reasoning method is conditional or if/then reasoning. Many of us have used the pros and cons methods of reasoning as well. Systemic reasoning involves thinking that the whole is greater than the sum of its parts, and finally reasoning by using examples or analogies. Hence, there are numerous logical ways in which people reason about events and situations. An autonomous artificially intelligent system must be able to employ these same reasoning methods in order to interact with a random and often chaotic world.

4. Discussion

If we desire to create an Artificial Cognitive Architecture that encompasses the AIC discussed above, in order to create a system that can truly think, reason, learn, utilizing the inferences shown in Figure 1, we must consider the overall implications of such a system, including the psychological impacts and considerations both for humans and for the system itself [9]. Further research is needed to understand the psychological effects of not only real human-AI interaction, but also the effect of human interaction on AIC learning and self-evolving [3]. Sometimes learning from humans is a dangerous thing.

7. References

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