Methodologies for Continuous Life-long Machine Learning for AI Systems

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Abstract— Current machine learning architectures, strategies, and methods are typically static and non-interactive, making them incapable of adapting to changing and/or heterogeneous data environments, either in real-time, or in near-real-time. Typically, in real-time applications, large amounts of disparate data must be processed, learned from, and actionable intelligence provided in terms of recognition of evolving activities. Applications like Rapid Situational Awareness (RSA) used for support of critical systems (e.g., Battlefield Management and Control) require critical analytical assessment and decision support by automatically processing massive and increasingly amounts of data to provide recognition of evolving events, alerts, and providing actionable intelligence to operators and analysts [2 and 4].

Herein we prescribe potential methods and strategies for continuously adapting, life-long machine learning within a self-learning and self-evaluation environment to enhance real-time/near real-time support for mission critical systems. We describe the notion of continuous adaptation, which requires an augmented paradigm for enhancing traditional probabilistic machine learning. Specifically, systems which must more aptly operate in harsh/soft unknown environments without the need of a priori statistically trained neural networks nor fully developed learning rules for situations that have never been thought of yet. This leads to a hypothesis requiring new machine learning processes, in which abductive learning is applied. We utilize varying unsupervised/self-supervised learning techniques, statistical/fuzzy models for entities, relationships, and descriptor extraction. We also involve topic and group discovery and abductive inference algorithms. to expand system aperture in order to envision what outlying factors could have also caused current observations. Once extended plausible explanations are found, we will show how a system uses the afore mentioned implements to potentially learn about new or modified causal relationships and extend, reinterpret, or create new situational driven memories.

Keywords—Unsupervised Learning, Life-long Machine Learning, Abductive Learning

1. Introduction: Life-Long Machine Learning

A fully autonomous, artificially intelligent system has been the holy grail of AI for decades. However, current machine learning methodologies are too static and minimally adaptive enough to provide the necessary qualitative continuously self-adaptive learning required for possible decades of system performance. Therefore, we employ biologically inspired research and artificial human learning mechanisms for enabling AI neural pathways and memories to evolve and grow over time [5 & 8]. These mechanisms enable a paradigm shift providing continuous, or life-long, machine learning algorithm and method evolution. Our objective a new architecture and requires controls and mechanisms like artificial brain functions for enabling complete cognitive system management. In short, it requires Artificial Neurogenesis[1], a new machine learning architecture and methods enabling a continuously self-adapting neural fiber structure within an AI system as illustrated in Figure 1.

In this ANP, both explicit and implicit learning are required to adequately provide self-assessment throughout the AI system. Self-assessment is required for the system to understand how its self-adaptation is affecting all parts of the AI system [1]. Explicit learning, as defined here, requires cognitive and hierarchical associations, whereas implicit learning depends on non-cognitive, non-hierarchical associations, and, in general, occurs when a variable known to influence explicit learning has no effect in a comparable implicit learning condition [1]. Each

[1] Artificial Neurogenesis (literally the birth of artificial neurons) is the processes in which new neurons are generated within the artificial memory system.

type of learning has effects on the AI system's overall knowledge base and each type of learning may influence the other as more information is processed and stored within the various memory systems of the AI system. As illustrated in Figure 1, not only is the neural structure adaptive, but the learning rules themselves must be adaptable, driven by the continuous self-assessment functionality within the ANP. Figure 2 provides a high-level view of the coordination, interaction and influence Explicit Learning, Implicit Learning, and the AI systems Knowledge Base have on each other [6].

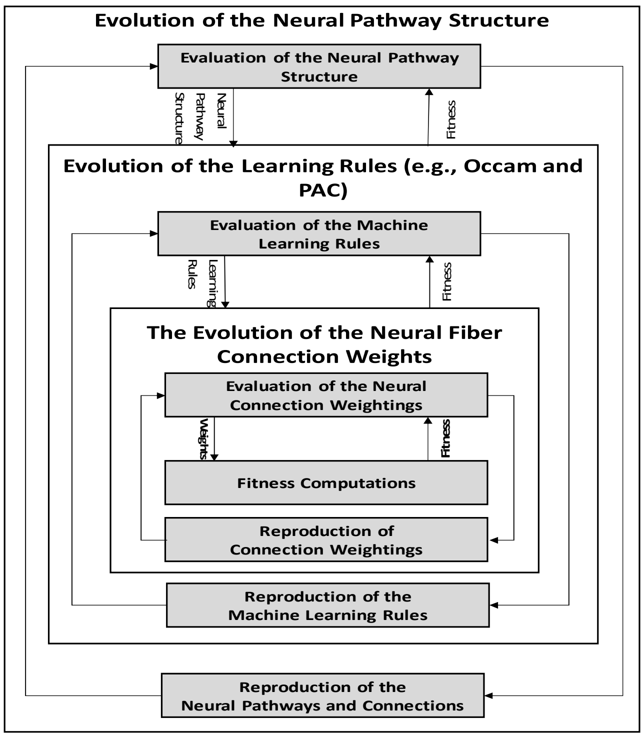

Figure 1 – The Artificial Neurogenesis Process (ANP)

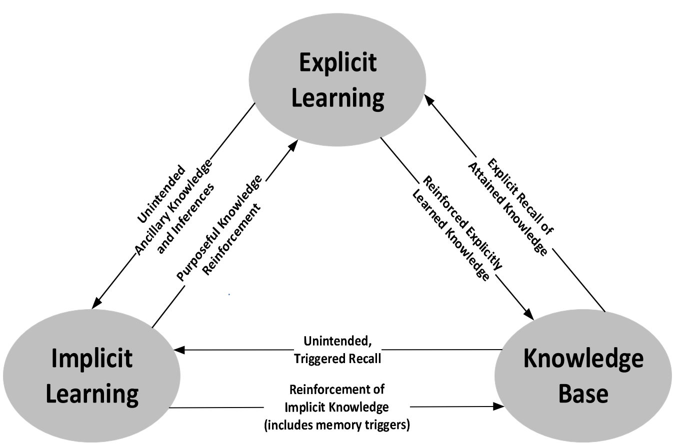

Figure 2 – The Implicit, Explicit, Knowledgebase Influence Triangle

A continuously adaptable, life-long machine learning architecture, from our studies, requires many types of learning to facilitate understanding how the entire system must adapt as it learns, reasons, as the environments the system is in change, and as the system ages. To provide continual real-time decision support over time, we feel the following memory systems must be in place, and each be self-adaptive:

1. **Perceptual Associative Memory**: the ability to interpret incoming stimuli by recognizing objects and by categorizing them.
2. **Procedural Memory**: memory for the performance of specific types of action. Procedural memory guides the processes the AI system performs and most frequently resides below the level of conscious awareness.
3. **Declarative Memory:** this is classical long-term memory and refers to memories that can be consciously recalled such as facts and knowledge (from the AI systems knowledge base).
4. **Transient Episodic Memory:** the memory of autobiographical events (times, places, associated emotions, and other contextual who, what, when, where, why knowledge) that can be explicitly stated or conjured. It is the collection of past system experiences that occurred at a particular time and place. Episodic memory stores unique events (or observations).
5. **Blackboard Memory:** a common knowledge base that is iteratively updated by the diverse set of components, software agents, etc. throughout the system. Blackboard memories typically start with a problem specification and end with a proposed solution.
6. **Sensory Memory:** this is the shortest-term type of memory. Sensory memory can retain impressions of the sensory information coming in through the various types of sensors the AI system has. These impressions are sent to the perceptual associative memory. These would be rudimentary at first, but then expand as the system learns.

Each type of memory is updated by life-long machine learning algorithms specifically created for that type of memory. In self-adaptive, continuous machine learning, there is no one learning algorithm or system that will suffice. Figure 3 illustrates the high-level architecture for a self-adaptive, continuous life-long learning structure for an AI system.

We employ Abductive Learning for finding the best explanation for a given set of observations or inferring cause from effect [10 and 11]. This accommodates adjustment of learning types for self-adaptation to environments, data, and experiences the system has not previously encountered. We define a simplified version of abductive learning, Occam Learning [9], which relates to finding the simplest explanation(s) when inferring cause from effect(s).

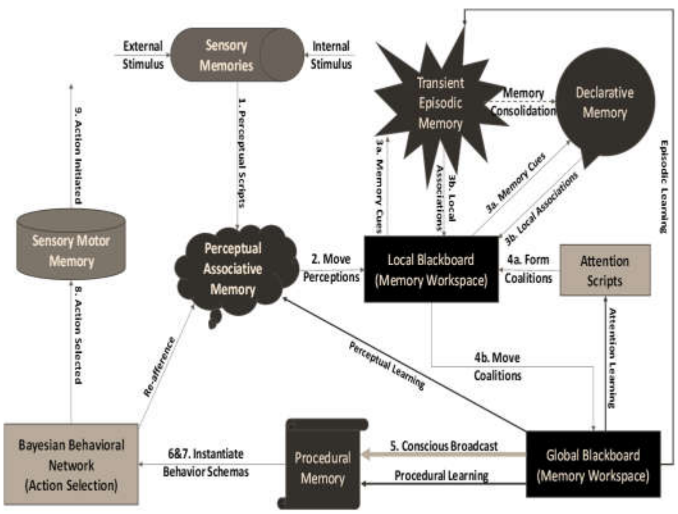

Figure 3. Life-long Machine Learning Process

The life-long learning architecture shown in Figure 3 is primarily used to describe support for procedural and perception learning. Our research shows that there are at least four types of learning required so a fully autonomous AI system can potentially learn, and reason. They are:

1. **Episodic Learning**: the process of storing/ retrieving experiences in the episodic memory and using it to improve behavior (responses to stimulus).
2. **Attention Learning**: also called concentration, attention learning stores triggers that allows the AI system to focus its efforts on objects or events of interest.
3. **Perceptual Learning**: the process of learning skills of perception. This allows continuous improvement in sensory processing (how to distinguish objects from sensory information – an example would be ATR), to complex categorizations of spatial and temporal patterns. Perceptual learning forms the foundation for an AI system to create complex cognitive processes (e.g., language). Perceptual learning drives adaptations (changes) in the AI systems neural circuitry or patterns.
4. **Procedural Learning**: learning by acquiring skill at performing a task. Procedural learning allows the AI system to perform a task "automatically" without consuming resources to determine how to accomplish the task [12].

2. Artificial Intelligence Machine Learning with Occam Abduction

Occam Abduction is used to find the simplest set of consistent assumptions and hypotheses, which, together with available background knowledge, entails adequate description/explanation for a given set of observations [2].

In formal logic notation, given $\boldsymbol{B_D}$, representing current background knowledge of domain $\boldsymbol{D}$, and a set of observations $\boldsymbol{O_D}$, on the problem domain $\boldsymbol{D}$, we look for a set of Occam Hypotheses, $\boldsymbol{H_D}$, such that:

- $\boldsymbol{H_D}$ is consistent[2] w.r.t. $\boldsymbol{B_D}$, and
- It holds that $\boldsymbol{B_D}, \models \boldsymbol{H_D}, \rightarrow \boldsymbol{O_D}$

Abduction consists of computing explanations (hypotheses) from observations. It is a form of non-monotonic reasoning and provides explanations that are consistent with a current state of knowledge and may become less consistent or inconsistent, when new information is gathered. The existence of multiple hypotheses (or explanations) is a general characteristic of abductive reasoning, and the selection of the preferred, or most simple, but possible, explanation is an important precept in Artificial Occam Abduction.

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[2] If $\boldsymbol{H_D}$ contains free variables, $\exists(\boldsymbol{H_D})$ should be consistent w.r.t. $\boldsymbol{B_D}$.

Abduction was originally embraced in Artificial Intelligence work as a non-monotonic reasoning paradigm to overcome inherent limitations in deductive reasoning. It is useful in Artificial Intelligence applications for natural language understanding, default reasoning, knowledge assimilation, belief revision, and very useful in multi-agent systems [8]. The Abduction form of inference, using hypotheses to explain observed phenomena, is a useful and flexible methodology of reasoning on incomplete or uncertain knowledge. Occam Abduction, defined herein, provides not only an answer, or cause, to the observations, it provides class properties of possible hypotheses within which observations are determined valid, and denotes the simplest set of hypotheses under which this is true.

2.1 Elementary Occam Abduction

There are several distinct types of interactions that are possible between two elementary Occam Abductive hypotheses $h_1, h_2 \in H_e$: [4]

- ***Associativity***: The inclusion of $h_1 \in H_e$ suggests the inclusion of h_2. Such an interaction may arise if there is knowledge of, for instance, mutual information (in a Renyi sense) between h_1 and h_2.
- ***Additivity***: h_1 and h_2 collaborate additively where their abductive and explanatory capabilities overlap. This may happen if h_1 and h_2 each partially explain dome datum $d \in D_0$ but collectively can explain more, if not all of D_0.
- ***Incompatibility***: h_1 and h_2 are mutually incompatible, in that if one of them is included in H_e then the other one should not be included.
- ***Cancellation***: h_1 and h_2 cancel the abductive explanatory capabilities of each other in relation to some $d \in D_0$. For example, h_1 implies an increase in a value, while h_2 implies a decrease in a value. In this case, one is used to support the hypothesis and the other is used to rebut the hypothesis.

The Occam Abductive Process is:

- Nonlinear in the presence of incompatibility relations
- Non-monotonic in the presence of cancellation relations
- The general case (nonlinear and non-monotonic) Occam Abduction hypothesis investigation is NP-complete.

Consider a special version of the general problem of synthesizing an Artificial Occam abductive composite hypothesis that is linear, and, therefore, monotonic. The synthesis is linear if:

$$\forall h_i, h_j \in H_e,\ \ q(h_i) \cup q(h_j) = q(\{h_i, h_j\})$$

The synthesis is monotonic if:

$$\forall h_i, h_j \in H_e,\ \ q(h_i) \cup q(h_j) \subseteq q(\{h_i, h_j\})$$

In this special version, we assume that the Occam hypotheses are non-interacting, i.e., each offers a mutually compatible explanation where their coverage provides mutual information (in a Renyi sense). We also assume that the Occam, abductive belief values found by the classification subtasks of abduction for all $h \in H_e$ are equal to 1 (i.e., true).

Under these conditions, the synthesis subtask of Artificial Occam Abduction can be represented by a bipartite graph, consisting of nodes in the set $D_0 \cup H_e$. This says there are not edges between the nodes in D_0, nor are there edges between the nodes in H_e. The edges between the nodes in D_0 and those nodes in H_e can be represented by a matrix $\boldsymbol{Q}$ where the rows correspond to $d \in D_0$ and the columns correspond to $h_t \in H_e$.

The entries in $\boldsymbol{Q}$ are denoted as $\boldsymbol{Q_{ij}}$ and indicate whether the given analyzed data are explained by a specific abductive Occam hypothesis. The entries are defined as:

$$Q_{i,j} = \begin{cases} 0 & \text{if datum } d_i \text{ is not explained by hypothesis } h_j \\ 1 & \text{if datum } d_i \text{ is explained by hypothesis } h_j \end{cases}$$

Given the matrix Q for the bipartite graph, the abductive, Occam synthesis subtask can be modeled as a set-covering problem, i.e., finding the minimum number of columns that cover all the rows. This ensures that the composite abductive, Occam hypothesis will explain all of D_0 and therefore be parsimonious[3].

Now we look at a special linear and monotonic version of the general abductive, Occam hypothesis synthesis subtask and look at a Possibilistic Abductive Neural Networks (PANNs) for solving it [1]. The first is based on an adapted Hopfield model of computation:

$$\forall i = 1,2,\ldots,n, \quad \sum_{j=1}^{m} Q_{ij} V_j \geq 1$$

For the Occam, abductive synthesis subtask, we associate variable $\boldsymbol{V_j}$ with each Occam hypothesis $h_t \in H_e$, to indicate if the Occam hypothesis is included in the composite Occam, abductive hypothesis $\boldsymbol{C}$. We then minimize the cardinality of $\boldsymbol{C}$ by:

$$\sum_{j=1}^{m} V_j$$

subject to the constraint that all data $d \in D_0$ are completely explained.

For the Occam, abductive network, the term in the energy function that represents the problem constraints must evaluate to zero when the constraint is satisfied and must evaluate to a large positive value when the constraint is not satisfied, forcing the evolving solution lattice to evolve accordingly [5]. For this energy term, we use a term expressed as a sum of expressions, one for each datum element, $\boldsymbol{d_i}$, such that the expression evaluates to zero, when hypothesis $\boldsymbol{h_j}$ that can explain the datum $\boldsymbol{d_i}$ is in the composite hypothesis, i.e., $\boldsymbol{V_j} = 1$. Given that $\boldsymbol{Q}$ is an incidence matrix (with elements either 0 or 1), the expression:

$$\sum_{i=1}^{n} \prod_{j=1}^{m} \{(1 - Q_{ij}) + (1 - V_j)\}$$

satisfies the following conditions:

- Each sum of the product terms can never evaluate to a negative number.
- The sum of the product terms, thus, can never evaluate to a negative number.
- Each product term evaluates to zero when a hypothesis that can explain the datum is in the composite; otherwise, it evaluates to a large value.
- The sum of the product term, thus, evaluates to zero when a composite set of hypotheses can explain all the data.

We derive our Occam abductive energy function as follows:

$$E = \alpha * \sum_{j=*1}^{m} V_j -$$
$$\beta * \sum_{i=1}^{n} \prod_{j=1}^{m} \{(1 - Q_{ij}) + (1 - V_j)\}$$

Where α and β are positive constants, and $\beta > \alpha$. The first term represents the cardinality of the Occam hypothesis and the second term represents the penalty for a lack of complete coverage; 0 indicates complete coverage.

3. Elementary Continuous Abduction

Continuous machine learning requires continuous abduction, which drives us to constantly look for ways to explain either the external environment, or things within the AI system (self-reflection). This requires an architecture and process for continuous abduction. Figure 4 illustrates this process.

Here, the assumptions are:

- The Occam causes are mutually exclusive and constitute exhaustive coverage of the effects.
- Each of the Occam causes is conditionally independent.
- Each of the Occam causes are not mutually incompatible.
- None of the Occam causes cancel the abductive explanatory capability of any other Occam cause.

[3] Note that the general set-covering problem is NP-complete.

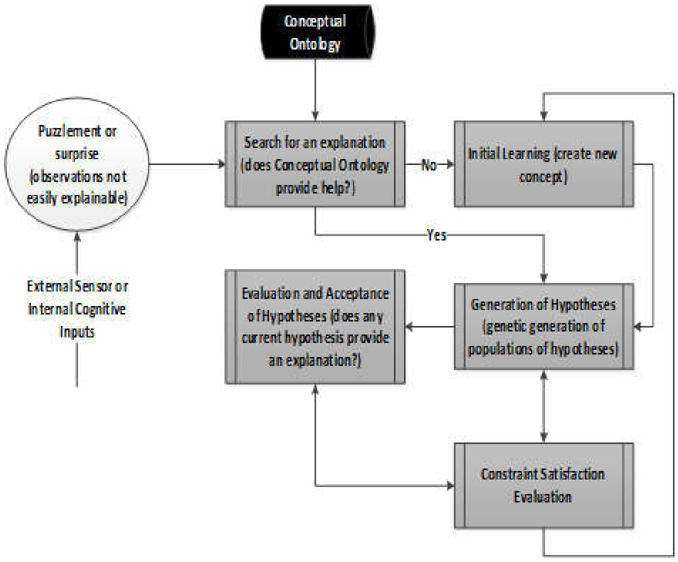

Figure 4 – Elementary Continuous Abduction

From Figure 4, we see that when observations are present for which there are no explanations, the Occam abduction system creates a set of hypotheses (possible explanations). Each of these hypotheses are tested to create a plausible set of explanations. The system expands to generalized hypotheses if needed. Figure 5 illustrates a high-level architecture for a generalized life-long machine learning abduction model. This architecture generalizes the observations into categories. If no concepts exist to explain the observations, new concepts must be created to accommodate the observations.

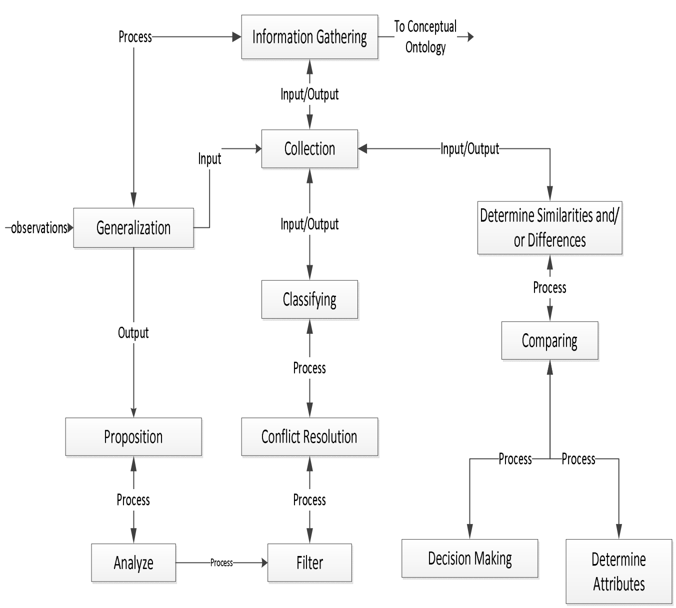

Figure 5 – Generalized Life-long Machine Learning Abduction

Hypotheses are generated by looking at similarities and differences between the observations and categories. Conflict between hypotheses must be adjudicated. Eventually, a set of non-interfering, non-overlapping hypotheses that explain the observations is created, learned from, and decisions made. Attributes of these hypotheses are categorized and learned, including any memory triggers that are needed.

4. Conclusions and Discussion

This is very preliminary work and much more research is required. Here we have presented a high-level view and discussion of the possibility of an AI system with continuously adapting, life-long machine learning. The architectures, structures, methods, and algorithms require a complete change from current thinking and development. We believe this is the future of autonomous and semi-autonomous AI systems. Research must be continued on the Occam Learning algorithms to determine what constitutes an acceptable Occam Abduction Energy level and to understand how to apply the weighting factors α and β in the Occam Energy Equation (i.e., is it domain specific?).

References

1. Stadler, M. (1997). Distinguishing Implicit and Explicit Learning. Psychonomic Bulletin & Review, V4(1):5-62
2. Crowder, J. A. 2002. Machine Learning: Intuition (Concept Learning) in Hybrid Neural Systems, NSA Technical Paper- CON-SP-0014-2002-06 Fort Meade, MD.
3. Crowder, J. 2004. Multi-Sensor Fusion Utilizing Dynamic Entropy and Fuzzy Systems. Proceedings of the Processing Systems Technology Conference, Tucson, AZ.
4. Crowder, J. 2005. Cognitive Systems for Data Fusion. Proceedings of the 2005 PSTN Processing Technology Conference, Ft. Wayne, Indiana.
5. Crowder, J. A. 2010a. The Continuously Recombinant Genetic, Neural Fiber Network. Proceedings of the AIAA Infotech@Aerospace-2010, Atlanta, GA.
6. Crowder, J. A., 2010c. Flexible Object Architectures for Hybrid Neural Processing

Systems. Proceedings of the 11th International Conference on Artificial Intelligence, Las Vegas, NV.

7. Franklin, S. (2005). Cognitive Robots: Perceptual Associative Memory and Learning. Proceedings of the 2005 IEEE International Workshop on Robot and Human Interaction.
8. Crowder, J. A. and Crowder, J. A., and Carbone, J. N. 2011a. Recombinant Knowledge Relativity Threads for Contextual Knowledge Storage. Proceedings of the 12th International Conference on Artificial Intelligence, Las Vegas, NV.
9. Carbone, J. N. and Crowder, J. 2011b. Transdisciplinary Synthesis and Cognition Frameworks. Proceedings of the Society for Design and Process Science Conference 2011, Jeju Island, South Korea.
10. Crowder, J. (2016). AI Inferences Utilizing Occam Abduction. Proceedings of the 2016 North American Fuzzy Information Processing Symposium, University of Texas, El Paso.
11. Crowder, J., and Carbone, J. (2017) Abductive Artificial Intelligence Learning Models. Proceedings of the 2017 International Conference on Artificial Intelligence, Las Vegas, NV.
12. Jahanshahi, W. (2007). The Striatum and probabilistic Implicit Sequence Learning. Brain Res. 1137,117-130.