# ALANN: An event driven control mechanism for a non-axiomatic reasoning system (NARS)

Tony Lofthouse[1]

[1] Reasoning Systems Ltd, Andover, UK
Tony_lofthouse@btinternet.com

**Abstract.** Adaptive Logic and Neural network (ALANN): A neuro-symbolic approach to, event driven, attentional control of a NARS system. A spiking neural network (SNN) model is used as the control mechanism in conjunction with the Non-Axiomatic Logic (NAL). An inference engine is used to create and adjust links and associated link strengths and provide activation spreading under contextual control.

**Keywords:** Non-axiomatic logic, NARS, control, attention, neuro-symbolic

## 1 Introduction

The field of AGI research has often taken inspiration from the human brain, in particular, neural networks. The most plausible biological approach, it could be argued, is the spiking neural network (SNN) [5]. Despite the benefits of low energy requirements and implicit timing [1], SNNs have failed to match the achievements of the more typical artificial neural networks (ANN). This is, in part, due to a lack of an effective training regime for SNNs. Whilst ANNs have back propagation and gradient descent, there is no equally effective method for SNNs. The most fruitful area of research has been in Spike Timing Dependent Plasticity (STDP) [4]. There has been some recent progress in this area [10], but this does not yet match the results of back propagation and ANNs in general [10]. This paper presents an approach to combine the benefits of SNNs with a Non-Axiomatic Logic (NAL) [8] and a Non-Axiomatic Reasoning System philosophy (NARS). We will show that a symbolic logic (NAL) can assume the role of 'training' a SNN via an inference mechanism and form the framework of an attentional control mechanism for a reasoning system whilst operating under the Assumption of Insufficient Knowledge and Resources (AIKR).

### 1.1 Non-Axiomatic Reasoning System (NARS)

NARS was created as a concrete implementation of an adaptive reasoning system but now with multiple systems using the underlying principles it has become a methodology and underlying philosophy for developing AGI systems. ALANN is a concrete implementation of a NARS and adheres to the underlying requirements of; a unified principle of cognition which adapts to its environment, Finite – works with insufficient knowledge and resource (fixed), Real-time: responds in real time to new information and is Open to input from any domain (expressible in the input language).

NAL is a syllogistic logic and generally requires two premises to have a common term in order to apply an inference rule (there are exceptions to this such as temporal or structural inference) [8]. In principle a premise in NAL is a <*term copula term*> where *term* is a symbol or a premise and *copula* is a link, with a truth value, between terms. For the purpose of this discussion we will limit the range of NAL copulas and operators, but in NAL the number of copulas and operators is much larger [8]. In this paper we will assume a *term* is a symbol composed of letters and digits and a copula is an inheritance relation → [8]

Truth values in NAL are evidence based ($w_+$, $w_-$), where $w_+$ represents positive evidence and $w_-$ represents negative evidence, or alternatively as confidence *c* and frequency *f* tuple, where $f = \frac{w_+}{w_+ + w_-}$ and $c = \frac{w_+ + w_-}{k + w_+ + w_-}$, where *k* is a global personality parameter that indicates a global evidential horizon [8].

Inference under NAL is carried out by applying inference rules that, typically, match a pair of premises with a common term. For example, the deduction rule would be applied to the following premises*:* <*a* → *b*>, <*b* → *c*> |- <*a* → *c*> <*ded*>, where the premise <*a* → *c*> is derived from the two premises, which share a common term, *b*, where <ded> is a truth function that takes two truth values and returns a new derived truth value; ded : TV * TV -> TV. NAL has a range of truth functions to cover the semantically meaningful premise patterns, such as deduction, induction, abduction, and exemplification. There are additional truth functions that we will not cover here, for further details see [8].

Furthermore, two premises can be revised when they have matching content (assuming no overlapping evidence) using the revision truth function [8]. In this way evidence is accumulated over time.

NARS is a generative model and when provided with experience in the form of Narsese beliefs (premises), will generate derived beliefs. These derived beliefs form a belief network, interconnected by copulas. This network can be conceptualized as a node link graph.

Given that a NARS system must work with 'Finite' resource and knowledge it is necessary to limit the number of beliefs that the system retains at any one time. Additionally, only certain beliefs are relevant at a specific moment in time. The primary role of the control mechanism is to identify the contextually relevant subset of the belief network and remove the least useful beliefs when resource limits are reached. The control mechanism needs to respond in real-time.

### 1.2 Spiking Neural Networks

Spiking neural networks (SNN) are artificial neural networks that attempt to replicate the properties of biological neurons. A network is composed of nodes and links where nodes accumulate 'attention' and fire when a threshold is reached; links propagate the action potential through the network. Links have a weight which modifies the action potential. The network 'learns' by adjusting the link weights (typically using Spike

Timing Dependent Plasticity - STDP). Unlike ANNs, nodes do not necessarily fire each cycle but rather when sufficient activation has accumulated. Additionally, timing is an inherent property of SNNs.
The neuron model employed is effectively, accumulate action potential, which decays over time. If an activation threshold is exceeded, the neuron ‘fires’ propagating action potential to its ‘synapses’, with spikes, to connected nodes. A neuron is reset with its resting potential after firing and has a refractory period during which it cannot ‘fire’. Action potential is transported though the system by spikes. Spike strength is modulated by the synaptic strength. In this paper, we will assume the leaky integrator approach [4] to the neural model. although there are other approaches [4].

The SNN property of activation spreading, via contextual relevance, is precisely what is required for an AGI control mechanism.

## 2 Approach

The systems experience is defined as a stream of events E, which occur at a specific time and each event is weighted with an attention value (AV), semantics and some additional meta data (STAMP). An attention value is defined as [STI LTI] where STI is short term importance in the range (0, 1] and LTI is long term importance in the range (0 1). The attached semantics refer to the Narsese Term (premise) that the event represents, (for example <cat → animal>), as explained in the NARS overview. The semantic component may also contain a truth value (TV) containing (f, c).

The comparison to spiking neural networks is necessary, but not sufficient, to explain the way attention works in ALANN. In a traditional spiking network, a spike has strength and timing. In ALANN, a spike is also loaded with semantics, effectively smart spikes (similar to neuro-symbols) [7]. There are three primary components to the ALANN network model; nodes, links and events.

In ALANN, nodes have the properties of; leaky integrator approach to accumulate and lose action potential, activation threshold, action potential, resting potential and refractory period. Links between nodes have weight and semantics. Events have temporal significance, attention level and semantics.

Currently, ALANN belief-links are adjusted via an inference process (although STDP will be used to adjust the weights of the planned predictive-links - see future research). Evidence gathering is the basis of link weight adjustment in ALANN, where the revision truth function is used to accumulate evidence.

$$\text{rev: } w^+ = w_1^+ + w_2^+$$

$$w^- = w_1^- + w_2^-$$

Link strength is defined as the expectation value of the related belief truth, where expectation value is defined as:

$$\exp(f, c) = c(f - 0.5) + 0.5.$$

The node attention decay function is defined as:

$$e^{-\lambda\nabla}$$

Where $\boldsymbol{\lambda}$ is a scaling factor (typically 0.1) and determines the rate of decay and $\boldsymbol{\nabla}$ is the temporal distance between events (in milliseconds).

Node attention is accumulated as follows:

$$\text{attention}_{\text{node'}} = \_\text{or}(\text{attention}_{\text{node}}, \text{event}_{\text{sti}})$$

where:

$$\_\text{or}(x, y) = 1.0f - (1.0f - x) * (1.0f - y)$$

Belief-links, which exist between nodes, always have a related TV.

An events attention value is attenuated by belief-link strength (truth expectation of the related semantic term). The reduced event attention is then used to modify the node action potential. Events that have matching semantic content are revised with the matching belief-link (assuming no overlapping evidence). Events that do not have a matching belief-link generate a new link between the source node and the event destination node. Event destinations are determined by sending the event to each of the subterms contained within the semantic component.

At a high level the system can be considered as a feedback loop with input from external experience and inference results feeding back into the loop – effectively a cyclic system. One of the challenges with a cyclic system, where the system cycle contains a feedback loop with a gain function (from inference), is avoiding combinatorial explosion. Two aspects of the design enable the system to function without the expected combinatorial explosion from the feedback loop. Firstly, the node refractory period constrains the rate at which any one node can be cycled and contribute to the inference cycle, and secondly, an attention buffer is inserted into the event flow. The attention buffer is essentially a fixed length priority queue ordered by STI. In practice, the system is divided into multiple streams of activity with each stream having its own attention buffer which can be considered a form of winner-takes-all. The attention buffer also acts as a form of inhibition, where events are effectively competing for attention and the higher attention values inhibit the lower. Interestingly, the node latency period alone was able to eliminate the combinatorial explosion from the inference cycle, but the system performed better overall with the introduction of the attention buffer. Additionally, the node latency period inhibits short term cyclic inference where a node is repeatedly activated by its own output.

The system can be provided with input tasks such as 'find the answer to a question'. Given that knowledge is represented as a belief network, finding an answer to a question is a form of graph search. Tasks are potentially satisfied, by both forward and backward inference. Forward inference generates new knowledge and backward inference generates derived questions (tasks) that may help to satisfy the input task. Finding the balance between exploit and explore is critical to the effectiveness of the system. The approach taken is to partition search into shallow and deep search, where shallow determines the degree of exploration and deep the degree of exploitation. Essentially, when a derived task is satisfied (to a degree), it is exploited via deep search otherwise shallow search is the default. An important consideration is that an AGI system must be both finite and real-time therefore graph search, whether deep or shallow, is incremental as it must remain within the resource constraints provided and respond to new input at any time. To enforce this requirement the event attention (LTI) is used to specify deep or shallow search. Increasing the events attention value results in deeper search and reducing leads to shallow search.

Tasks, in ALANN, are represented by events (with a task type attribute), an implication of this is that tasks are not stored in the belief network but are transient. Tasks cycle around the system whilst they retain enough attention to compete with the other current events. Once the attention value drops too low the task event is forgotten. Due to this property, there is no guarantee that a specific task will be satisfied. It is dependent on the relative attention of the system at a specific moment. The attention of an event can increase or decrease based on the contextual relevance of the related sub terms within the semantic component.

## 3 Comparison

Three approaches are shown for comparison purposes: OpenCog, Neuro-symbolic principle and OpenNARS.
OpenCog initially used an activation spreading approach but then moved to ECAN. [2]. The approach used in ALANN is conceptually similar to the early activation spreading utilized by OpenCog. A key difference is that the semantics of the link types are managed differently: OpenCog explicitly defines link types between nodes whereas ALANN links contain link types within the semantics of the contained term. A further difference is that within OpenCog activation spreading was a separate process whereas in ALANN it is a step wise incremental unified process.

Neuro-symbolic principle [7]: Whilst there are some similarities: event driven and neuro-symbols, a key difference is the use of a logic with a formal grammar that defines the semantics and subsequently 'meaning' of both premises and the connecting belief-links. Furthermore, using a logic, NAL, as a basis for training the network weights, is a considerably different approach. A further difference is that no initial network configuration is required with the ALANN approach. It can boot-strap directly from experience and the generative NARS/NAL principles [9]. Finally, learning is unsupervised and does not require training and target data.

OpenNARS: link and bag approach with probabilistic selection mechanism. [3]. One of the significant differences between ALANN and OpenNARS is that ALANN is fully event driven. By this we mean that unlike in OpenNARS where concepts, task, beliefs and links are deterministically selected from 'bags', ALANN has no selection mechanism. Nodes and links in ALANN are activated purely by the flow of events within the system. The event flow is a form of activation spreading but rather than a cascade of activation throughout the system, activation spreading occurs one step at a time in conjunction with inference and the overall system cycle.

## 4 Discussion

Many, if not all, of the challenges of using ANN and DL for AGI [6] can be overcome with a neuro-symbolic approach and an inference engine. Transparency comes for free with a symbolic approach. The use of a reasoning engine to generate a network and its related link weights allows one shot learning and boot strapping, with no initial training period, directly from the systems experience. Given that NAL is an evidence-based logic, beliefs are derived from countable evidence and its conclusions can be fully audited by a competent human. NARS' are built upon a definition of intelligence that requires adaption to an environment under AIKR, therefore adaption to change is an intrinsic property of such a system. The generated belief network responds in real time to changes in the environment by adjusting link weights and forgetting less relevant nodes and links via a reasoning process.

Grammar and semantics constrain both the extent and search direction of the generated space (belief network). There are a limited, but still very large, number of meaningful combinations of premises. In this way the belief network is 'grown' into the possible search space by following the semantically meaningful pathways, under attentional control. The degree to which a search space can be explored is a factor of the environmental complexity and available resources. Any moderately complex environment will have a search space larger than can be explored in full. In NARS, attention and experience is the guide to explore and exploit the belief network. NARS is a so-called generative model as it builds its belief network in real time from experience.

The symbolic nature of knowledge representation allows for existing prior knowledge to be incorporated into the belief network with no training required. Finally, using the framework of a reasoning engine for inference, means that the system can use a single principle to support both open ended inference and link weight training.

## 5 Future research

The current scope of research on the ALANN control model is based on NAL 1-6. These NAL 'layers' are related to declarative knowledge and do not include temporal or procedural components.

The next steps in the research plan are three-fold:

- Incorporate 'predictive-links (for temporal beliefs) with a variant of STDP to adjust link weights. Predictive-links gain an additional property: link delay (similar to synaptic delay).
- Remove the need for separate truth values, by rationalizing eternal and event truth into a single principle.
- Add goal nodes to the belief network with supporting satisfying-links

In OpenNARS there is an anticipation process which is used to confirm or deny the correctness of predictive beliefs. The use of STDP to adjust link weights has the additional advantage that in can remove the need for the anticipation process. STDP is a form of evidence gathering in a similar way to the revision truth function. The addition of link delay enables precise timing in contextual mapping. OpenNARS also maintains multiple versions of truth for each node (concept), in particular, the need to separate eternal truth and event truth. By making nodes stateless from the perspective of truth value, the idea is to contextually generate truth value based on the link structure. Finally, adding goal nodes, which can be considered symmetrical to belief nodes, along with satisfying -links to support procedural reasoning.

Once the above steps are completed, implement the remaining NAL levels (7/8/9) to fully support episodic and procedural beliefs and events.

## 6 Conclusion

Using a symbolic reasoning engine as the framework for an AGI serves the dual purpose of providing an open-ended inference capability and a unified approach to adapting link weights in an unsupervised spiking neural network. The event driven design coupled with the SNN properties are shown to be an effective alternative to the more typical 'Bag' based approach to memory model and control.

A software implementation of the principles presented in this paper is available at the OpenNARS GitHub repository: https://github.com/opennars/ALANN2018.

### References


1. Ammar A., et al: A comparative study on spiking neural network encoding schema Cluster Computing (2019).
2. Ikle M., et al: Economic Attention Networks: Associative Memory and Resource Allocation for General Intelligence. Proceedings of the Second Conference on Artificial General Intelligence, Atlantis Press. (2009)
3. Hammer P., Lofthouse T., Wang P.: The OpenNARS Implementation of the Non-Axiomatic Reasoning System, Springer, Proceedings International Conference on Artificial General Intelligence (2016)
4. Izhekevich E., Dynamical System in Neuroscience, MIT Press (2007)
5. Maass, W., Networks of spiking neurons: The third generation of neural network models". *Neural Networks*. **10** (9): 1659–1671 (1997)
6. Marcus G.: Deep Learning: A Critical Appraisal, arXiv:801.00631 (2018)
7. Velik R., Bruckner D: Neuro-Symbolic Networks: Introduction to a New Information Processing Principle, Proceedings of the IEEE international conference on industrial Informatics (2008)
8. Wang P.: Non-Axiomatic Logic: A Model of Intelligent Reasoning, World Scientific, Singapore (2013)
9. Wang P.: Rigid Flexibility - The Logic of Intelligence, Springer (2006)
10. Yujie W., et al, Direct Training for Spiking Neural Networks: Faster, Larger, Better, arXiv:1809.05793v2 (2018)