# ANT: Artificial Neural Topology

Woody Hulse, Jonah Schwam, Pavani Nerella, Ilija Nikolov, Naishi Nishizawa

*CS2951X: Reintegrating AI*

## 1 Introduction

With the advancement in compute power and novel structures within Artificial Neural Networks (ANNs), research has accelerated in particular subfields to achieve marginal performance gains in particular subtasks. It is the current perception that an artificial general intelligence (AGI) capable of reasoning in multiple tasks (particularly in those on which it has not been trained) has been developed (McIntosh et al., 2023). A hypothetical AGI has become computationally attainable with modern hardware, which is able to effectively train models on the parameter level of sophisticated biological neural mechanisms, which brings into question the very efficacy of the ANN formulation in creating a model capable of general reasoning.

We will formalize our discussion on AGI within the reference frame of biological examples. An AGI is a continuously learning agent that, having some a priori experience, can perform broadly in inference tasks where it has not trained[2]. Conversely, conventional ANNs are only capable in domains adjacent to those in which they were explicitly trained.

The characteristic reasoning behavior in biological neural networks of comparable parameter magnitude to current ANNs suggests that there are key mechanisms present in biological neural networks, but not present in ANNs. There are models which aim to reconcile these differences such as Spiking Neural Networks (SNNs) and Radial Basis Function (RBF) networks, though these primarily control information flow between neurons rather than reforming the at-large network. State-of-the-art ANNs almost universally share two properties that significantly reduce their capability of replicating biological functions: they are layered in structure and non-stateful. Specifically, ANNs typically follow a formulaic approach to architecture assembly–create sequential or parallel-sequential layers to map input information to output information $f : \mathcal{X} \to \mathcal{Y}$, and construct such a mapping one-to-one and independent of previous input[1]. This structure, we believe, is highly restrictive on the flow of information through the graph and disallows continuous long-range interactions core to reasoning in biological networks.

Artificial Neural Topology (ANT) seeks to innovate with two primary mechanisms which we hypothesize are responsible for general intelligence.

## 2 Designing a Neural Topology

We reimagine artificial networks to be both non-layered and stateful. To do this, we define a directed, randomly locally connected graph $G = (V, E, X, \nabla X)$ initialized with a set of input vertices $V_{in}$ and $V_{out}$, each roughly colocated to reflect neural topology. Vertices in $V$ are instantiated with weight and bias vectors $w, b$ corresponding to their input and output and a non-linear activation function $\sigma$. We then define the following training routine for input data $\mathcal{X}$ and output data $\mathcal{Y}$:

**Algorithm.** ANT Training Routine

define $G = (V, E, X, \nabla X)$
**while not** done **do**
  **for** $v_i$ **in** V **do**
    **if** $v_i$ **in** $V_{in}$ **do** $y_i \leftarrow \sum_{x_k \in \mathcal{X}} (x_{ki} w_{ik})$
    **else do** $y_i \leftarrow \sum_{k \to i} (x_k w_{ik})$
    $a_i \leftarrow \sigma(y_i)$
    **if** $v_i$ **in** $V_{in}$ **do** $\hat{\mathcal{Y}} \leftarrow a_i$
    **else do** $x_{ji} \leftarrow a_{ij}$, $\forall j \in x$
  **for** $v_i$ **in** V **do**
    **if** $v_i$ **in** $V_{in}$ **do** $\nabla x_i \leftarrow \nabla L(\mathcal{Y}, \hat{\mathcal{Y}}) \cdot w_{ik} \cdot \nabla \sigma(y_i)$
    **else do** $\nabla x_i \leftarrow \sum_{i \to k} (\nabla x_i \cdot w_{ik} \cdot \nabla \sigma(y_i))$
    $\nabla w_i \leftarrow \sum_{i \to k} (\nabla x_i \cdot x_{ik} \cdot \nabla \sigma(y_i))$
    $w_i \leftarrow w_i - \alpha \cdot \nabla w_i$
    $x_{ji} \leftarrow \nabla x_{ij}$, $\forall j \in x$

Heuristically, this routine performs $\mathcal{O}(|V|)$ computations per timestep $t$ to perform a single set of output and gradient message passing to directly

[1] There exist network types which are recurrent and/or maintain internal states, though these networks are still largely restrictive in how they handle, store, and preserve information, and generally dissimilar to how biological neural circuitry maintains state.

upstream- and downstream-adjacent neurons, respectively. Note that in this computation, each vertex is disjointly computed, allowing for trivial parallelization on most hardware.

The relevance of this training regime as opposed to a conventional neural network cycle is the maintenance of the input and gradient state pair $(X, \nabla X)$ across time, enabling the type of long-range neurological circuit interactions that are prevalent in biological neural networks (Andrade et al., 2018). Other mechanisms emergent from neural graphs will be enabled by the existence of cycles and overall complexity of the topology, both of which not achievable with a conventional ANN.

Memory is an additional key component to ANT, and an important reason for maintaining the $(X, \nabla X)$ pair. Biological agents are posited to store memory through synapse potentiation - the process by which neurological connections store information by retaining energy and altering their excitability (Crystal & Glanzman, 2013). It may be feasible to emulate biological memory in an ANN by building a network with the ability to retain energy and continuously fire, rather than a traditional feed-forward network that maps from an input to an output space with a single pulse of energy. By building a network with the ability to retain energy and continuously fire, rather than a traditional feed-forward network that maps from an input to an output space with a single pulse of energy, we hope to demonstrate this capacity to emulate biological memory units.

ANT's formulation comes with several tradeoffs. ANNs are highly efficient on modern hardware due to the parallelizability of matrix and tensor composition on Graphics Processing Units (GPUs). ANT suffers from input/output latency due to information propagation taking multiple timesteps and performs fewer parameter updates due to an analogous latency in gradient backpropagation. ANT also cannot train on discrete input/output pairings due to its formulation. These issues, while important, each have concrete biological analogs (Olds et al., 1972) and are likely solvable through a combination of finer time resolution, proper parallelization, and hyperparameter tuning.

Preliminary evaluation of ANT's pure machine learning capabilities are positive. Simple fitting demonstrates that ANT can properly functionally approximate input/output relationships. Discrete reinforcement learning tasks such as CartPole show similarly positive outcomes, with both quick convergence (after $t \approx 100$ in CartPole) and great efficiency ($|V| \sim 8$). To drive ANT in an embedded system, we will design a modification of online actor-critic (A2C) to comply with our network formulation.

# 3 On the Conjoined Cognitive, Agent, and Embodied Models of General Intelligence

The goal of ANT is to achieve task generalizability through extraction of the abstract characteristics of biology from which general intelligence is emergent. We believe this requires two components. The first component, detailed in above sections, mandates a low-level abstraction of how cognition operates which we hope to topologically and functionally replicate. The second component is an interface with real-world phenomenon, or at least data that closely replicates the general complexity of reality.

We plan to demonstrate these features through robotics. Operating from the Reward is Enough hypothesis, which posits that all aspects of intelligence subserve reward maximization by an agent acting in its environment (Silver et al., 2021), through design of a policy optimization ANT can behave analogously to animals. Conversely, this also implies that our proposed agent can develop multiple aspects of intelligent behavior given a simple design of such a reward function. We aim to create a reward function that enables our agent to learn to navigate and traverse its environment. An example reward function will be to minimize distance relative to an infrared tag. This general distance-minimization reward is intended to incentivize the agent to efficiently navigate its environment to move toward the infrared tag. The reward function and agent will specifically omit any explicit program on how to use its limbs, take steps, or avoid obstacles.

In generalizing the environment to a small sensor-based observation space, the model forgoes assumptions about its environment and embraces continual learning. This further enables the agent to adapt to a non-stationary environment. At each timestep, the agent will make a partial observation of its state, currently formulated as an 18-dimensional feature vector encoding the orientation of each of its 11 joints, the 3-axis angular orientation of its body, its 3-dimensional physical orientation relative to the infrared tag, and a visual distance measurement from its 'eyes'. The joint orientation data will be read directly from each servo motor, the body orientation data will be read from an inertial measurement unit, the physical orientation data will be read from an infrared receiver, and the visual distance measurement will be observed from an ultrasonic sensor mounted on the agent's head. A sophisticated embodiment of ANT should exhibit sophisticated, animal-like behavior.

# 4 References


[1] McIntosh, Timothy R., et al. From Google Gemini to OpenAI Q* (Q-Star): A Survey of Reshaping the Generative Artificial Intelligence (AI) Research Landscape. ArXiv.org, 17 Dec. 2023, arxiv.org/abs/2312.10868. Accessed 3 Jan. 2024.

[2] Goertzel, Ben. "Artificial General Intelligence: Concept, State of the Art, and Future Prospects" Journal of Artificial General Intelligence, vol.5, no.1, 2014, pp.1-48. https://doi.org/10.2478/jagi-2014-0001

[3] G. P. Andrade, M. Ruszink and R. Kozma, "Graph Models of Neurodynamics to Support Oscillatory Associative Memories," 2018 International Joint Conference on Neural Networks (IJCNN), Rio de Janeiro, Brazil, 2018, pp. 1-8, doi: 10.1109/IJCNN.2018.8489419.

[4] Olds, J. L., Disterhoft, J. F., Segal, M., Kornblith, C. L., & Hirsh, R. F. (1972). Learning centers of rat brain mapped by measuring latencies of conditioned unit responses. Journal of Neurophysiology, 35(2), 202219. https://doi.org/10.1152/jn.1972.35.2.202

[5] Silver, David, et al. Reward is enough. Artificial Intelligence, vol. 299, Oct. 2021, p. 103535, https://doi.org/10.1016/j.artint.2021.103535.

[6] Crystal JD, Glanzman DL. A biological perspective on memory. Curr Biol. 2013 Sep 9;23(17):R728-31. doi: 10.1016/j.cub.2013.07.082. PMID: 24028954; PMCID: PMC5142816.