

ANT: Artificial Neural Topology

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Abstract

As the parameter size of artificial neural networks (ANNs), particularly in computer vision (CV) and large language modeling (LLM), approaches the size of sensorimotor cortices in sophisticated biological organisms, AI research has been forced to reconcile with a gap in resulting generalized reasoning capabilities. The inability for ANNs to reason beyond observed data, we hypothesize, is the result of a lack of two key characteristics: the structure of the neural graph and the temporal statefulness of information travel. To address these shortcomings of the ANN formulation, we propose ANT, a time-state preserving topological analogy to biological neural networks. In this paper, we show the performance and task-generalizable capabilities of ANT in reinforcement learning (RL) settings compared to conventional artificial neural networks.

1 Introduction

The past several years have seen monumental research gains in Deep Learning. Recent advancements in Artificial Neural Network (ANN) architectures such as attention-based models [1], large-scale multi-modal models [2], and generative models have pushed toward and sometimes past human abilities in certain tasks [3]. Paired with the availability of modern compute resources like Graphics Processing Units (GPUs), the scale of some of the largest ANNs nears the order of magnitude of sophisticated biological agents known to possess complex reasoning behavior. While often designed to be performant within their training scope, these models have invigorated discussion on the bridge between task-specific intelligence and general intelligence in AI agents [4] [5]. These discussions, while in part predicated on more philosophical ideas of self awareness, autonomy, and consciousness, have yet to empirically conclude a human-like ability to reason—that is, the ability for an agent to com-

plete a task within an area it has not yet experienced [6]. To investigate the reason behind an inability for ANNs to reason given comparable computational complexity requires a consideration of how biological circuits function—specifically, characteristics important in neurological circuits not present in artificial networks.

Parameter count¹ of a selection of neural networks.

| Name | Type | Parameters |
|-------------------------------------|------------|--------------------------|
| Human (<i>Homo sapiens</i>) | Biological | $1.5 \cdot 10^{14}$ [7] |
| Cat (<i>Felis catus</i>) | Biological | $1.0 \cdot 10^{13}$ [8] |
| Gemini 1.5 (Google) | Artificial | $*2.4 \cdot 10^{12}$ |
| Claude 3 Opus (Anthropic) | Artificial | $*2.0 \cdot 10^{12}$ [9] |
| GPT-4 (OpenAI) | Artificial | $1.0 \cdot 10^{12}$ [10] |
| Rat (<i>Rattus norvegicus</i>) | Biological | $4.5 \cdot 10^{11}$ [11] |
| GPT-3 (OpenAI) | Artificial | $1.7 \cdot 10^{11}$ [10] |
| Mouse (<i>Mus musculus</i>) | Biological | $1.0 \cdot 10^{12}$ [12] |
| Honey Bee (<i>Apis mellifera</i>) | Biological | $1.0 \cdot 10^9$ [13] |

* denotes unpublished estimates

There are several viable explanations for the gap in generalized cognitive ability between artificial networks and animals, including the constrained training regimes of ANNs, a lack of real-world exploration, insufficiently sophisticated artificial neural network architectures, or insufficient search of the parameter space, among others. While each may contribute in part to the observed disparity, we argue the importance of two fundamental characteristics of biological neural networks not present in ANNs.

The first fundamental characteristic, statefulness, broadly pertains to the capacity of a system to retain information about its previous states. In neural circuits, this ability allows for the retention of data from earlier sensory inputs or cognitive activities, which in turn influences subsequent neural responses and behavioral outputs. The dynamics of neural statefulness are complex and involve various physical mechanisms, including short-term synaptic plasticity, signal potentiation, and presynaptic excitability. For instance, tetanic activation can temporarily enhance synaptic strength in a phenomenon known as augmentation. The synapse exhibits statefulness by amplifying signals that follow an initial activation signal [8].

¹A one-to-one comparison between biological and artificial neural network parameters is impossible due to the complex quantum-chemical nature of neural circuits, so we consider the estimated synaptic count to be the number of “parameters” in biological neural networks. This is by no means rigorous, it is purely illustrative of scale.

Moreover, the graph-like network topology of biological neural circuits facilitates multiple communication pathways among neurons, enhancing redundancy and robustness in neural processing. This structural complexity allows neural circuits to explore a broader hypothesis space compared to layered ANNs, thus enabling the circuits to support and adapt to more diverse logical functions. Basset & Bullmore indicate that specific graph structures, such as small-world networks, are particularly efficient in balancing global and local connectivity, which improves both the speed and accuracy of neural communication [9]. The combined attributes of statefulness and graph-like architecture contribute to the ability of neural circuits to undertake complex decision-making processes, adapt to new environments, and learn from prior experiences.

ANT does not aim to reconstruct the exact function and behavior of these biological neural networks. We make no aim to reconstruct the complex electrochemical interactions key in neuron-to-neuron interactions. Rather, our goal is to construct a network with a hypothesis class and hyperparameter space analogous to—and in some sense more powerful than—biological networks, particularly with respect to these characteristics absent in conventional ANNs.

2 Related Works

As Artificial Neural Networks evolve, despite the advancements, current ANNs still exhibit substantial deficiencies in generalized reasoning and cognitive flexibility when compared to biological systems. These deficiencies, we hypothesize, stem not from the scale of neural parameters but from fundamental differences in network architecture and dynamic information processing capabilities.

Biological Neural Complexity and Scaling Rules: Foundational research by Azevedo et al. [7] provides a detailed comparison of neuronal and nonneuronal cell counts across different species, illustrating that human brains are an isometrically scaled-up version of smaller primate brains. This scaling is not purely in terms of size but also involves complex interconnections and synaptic densities [7]. Further, Herculano-Houzel et al. delve into the isotropic fractionator method and the cellular scaling rules for rodent brains, establishing a quantitative baseline that directly informs the structural complexity needed in ANNs to approach biological realism [17], [18]. These studies suggest that the quest for artificial general intelligence (AGI) may be less about size and more about the intricate connectivity and stateful processing found in natural neural networks.

Temporal Dynamics and Statefulness in Biological Systems: Menzel and Giurfa (2001) explore the cognitive architectures of honeybees, demonstrating how even with a relatively small number of neurons, complex behaviors and decision-making capabilities can arise from highly optimized

neural circuitry [13]. This underscores the importance of stateful, dynamic interaction patterns in neural networks, which are often absent in traditional ANNs.

Drawing from Ananthanarayanan et al., who performed cortical simulations with a scale of 10^9 neurons and 10^{13} synapses, it becomes evident that simulating complex neural interactions requires not only computational power but also an innovative approach to neural connectivity and architecture [?]. Their work highlights the potential and the significant challenges in mimicking the structure and function of large-scale neural networks, which directly influences the design philosophy of ANT.

Moving Toward Generalized Cognitive Abilities: The discussion of task-specific intelligence versus general intelligence in AI has been a focal point of recent philosophical and empirical debates. Mijwil et al. critically examine the implications of large-scale language models like GPT-3 on academic integrity, which indirectly reflects on their capabilities and limitations in generalized settings [26]. These discussions provide a backdrop against which ANT is positioned, aiming to transcend the typical task-specific optimizations of current ANNs by embracing a more holistic, biologically inspired framework.

Our approach with ANT integrates these insights by developing a non-layered, stateful architecture that more closely replicates the interconnected and ongoing processing capabilities found in biological brains. By incorporating a graph-based structure and dynamic information flow, ANT seeks to foster a level of adaptability and cognitive flexibility that conventional ANNs have yet to achieve. Our idea is deeply rooted in a comprehensive understanding of biological neural networks, drawing from seminal works in neuroscience and recent advancements in computational models. By addressing the structural and operational limitations of traditional ANNs, ANT aims to bridge the gap between artificial and biological cognitive systems, paving the way for more sophisticated and versatile AI agents.

3 Methodology

ANT seeks to improve on existing neural structures primarily through a fundamental expansion in the hypothesis space of ANNs, in particular lifting those restrictions which mediate the unidirectional flow of information and gradients through the network and disallow the storage of a dynamic state as a prior to the model output.

3.1 Graph initialization

ANT is constructed with a randomly locally connected directed graph G of size $|G| = n$. Each vertex v_i has weight w_i , bias b_i , and activation σ_i properties with learnable w_i, b_i , similar to an ANN, performing an analogous mapping from the inputs of a neuron to its outputs. There are two sets of

vertices designated as input and outputs to the network, respectively, representing the sensory and motor components to the network.

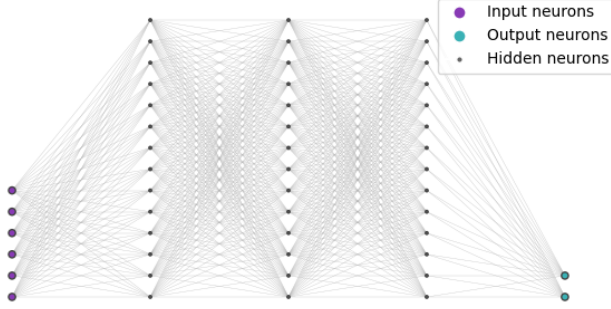


Figure 1. Example ANN architecture (baseline)

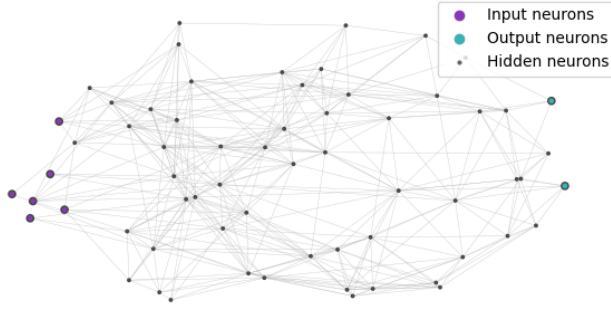


Figure 2. Example ANT architecture (initialization)

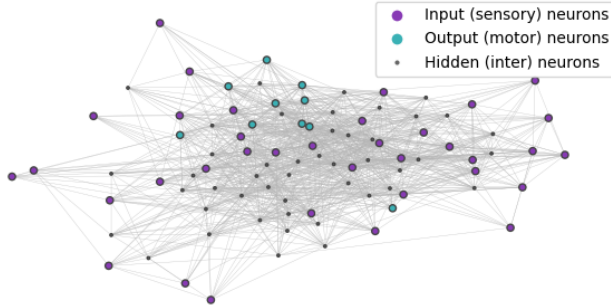


Figure 3. Subgraph of *C. elegans* neural topology [15]

This structure, while not an exact replica of neural topology, when combined with the genetic algorithm (see **3.3**) provides a superset of the hypothesis class which can mimic the neural circuit structures found in biological networks by forming recurrent, potentially cyclic dynamic relationships between neurons.

3.2 Update and Learning Mechanism

Unlike conventional artificial neural networks, ANT, like its biological counterpart, behaves dynamically across time. At

each timestep t a set of inputs \mathcal{X} of length ℓ are distributed to each of ℓ input neurons (where ℓ is defined at initialization). Then, simultaneously each neuron v_i computes $y_i = x_i w_i + b_i$ and applies σ_i on y_i , where x_i at time t is the outputs of inbound neurons at $t-1$, and distributes each vector component of y_i through corresponding outbound edges. The output $\hat{\mathcal{Y}}$ of the network is then the concatenated single-dimensional outputs of each output neuron.

Recent advances in the study of biological neurons reveal a complex learning mechanism within individual dendritic connections and synaptic clefts, as well as the known properties of the soma [22] [23] [24] [25]. With this, we model individual neurons as multiple perceptron relationships between inputs and outputs, rather than a more conventional single perceptron approach. Practically, weight matrix then becomes two-dimensional with a corresponding 1-dimensional bias vector.

Because ANT is designed to behave dynamically and learn continually, the gradient computation must be compatible with online updates as well. Typically, for a loss function L , proceeds by passing backward the product of an upstream jacobian with locally computed input gradients to compute a local partial derivative with respect to loss

$$\frac{\partial L}{\partial w_i} = \frac{\partial L}{\partial x_m} \cdot \frac{\partial x_m}{\partial x_l} \cdots \frac{\partial x_k}{\partial x_j} \cdot \frac{\partial x_j}{\partial w_i},$$

in a network where $v_i \rightarrow v_j \rightarrow \cdots \rightarrow v_l \rightarrow v_m$. However, a conventional backpropagation approach from ANNs mandates an acyclic graph to eliminate a circular dependency causing infinite gradient chains, preventing precomputing backpropagation chains. Therefore, gradients must be dynamically passed backward in a similar manner to forward propagation, where only one gradient passing “step” occurs at each t . This links the dependence of each partial gradient component of the chain to the timestep at which it was computed, barring cancellation in the expansion for an arbitrary L, w_i :

$$\frac{\partial L}{\partial w_{i_{t+k}}} \neq \frac{\partial L}{\partial x_{m_t}} \cdot \frac{\partial x_{m_{t+1}}}{\partial x_{l_{t+1}}} \cdots \frac{\partial x_{k_{t+k-1}}}{\partial x_{j_{t+k-1}}} \cdot \frac{\partial x_{j_{t+k}}}{\partial w_{i_{t+k}}}$$

To mathematically satisfy this approach, we can closely approximate the gradient chain by instead only episodically updating network weights at relatively distant time intervals, removing the weight parameter’s dependence on time. Then, for any adjacent neurons $i \rightarrow j$ passing gradients backward at $t, t+1$, respectively,

$$\begin{aligned}
\frac{\partial x_{k_t}}{\partial x_{j_t}} \cdot \frac{\partial x_{j_{t+1}}}{\partial x_{i_{t+1}}} &= \frac{\partial \sigma_j(y_{j_t})}{\partial y_{j_t}} \cdot \frac{\partial y_{j_t}}{\partial x_{j_t}} \cdot \frac{\partial \sigma_i(y_{i_{t+1}})}{\partial y_{i_{t+1}}} \cdot \frac{\partial y_{i_{t+1}}}{\partial x_{i_{t+1}}} \\
&= \frac{\partial \sigma_j(y_{j_t})}{\partial y_{j_t}} \cdot w_{j_t} \cdot \frac{\partial \sigma_i(y_{i_{t+1}})}{\partial y_{i_{t+1}}} \cdot w_{i_{t+1}} \\
&= \frac{\partial \sigma_j(y_{j_t})}{\partial y_{j_t}} \cdot w_j \cdot \frac{\partial \sigma_i(y_{i_{t+1}})}{\partial y_{i_{t+1}}} \cdot w_i
\end{aligned}$$

which, with an activation function that's near linear² across most of \mathbb{R} , approximates

$$\begin{aligned}
\frac{\partial \sigma_j(y_{j_t})}{\partial y_{j_t}} \cdot w_j \cdot \frac{\partial \sigma_i(y_{i_{t+1}})}{\partial y_{i_{t+1}}} \cdot w_i &\approx 1 \cdot w_j \cdot 1 \cdot w_i \\
&= \frac{\partial x_k}{\partial x_j} \cdot \frac{\partial x_j}{\partial x_i} \\
&= \frac{\partial x_k}{\partial x_i},
\end{aligned}$$

as desired. Applying this principle to the full gradient computation, ANT achieves an approximation of a dynamically learning network, similar to biological networks.

3.3 Evolution

To further emulate its biological counterpart, ANT also performs a genetic search over the hyperparameter space. Specifically, ANT modifies the connectivity and neuron count of the network. Specifically, for each mutation and with uniform $E \sim \text{Unif}(0, 1)$, edges are added with probability $E \leq p \cdot \frac{2e}{n(n-1)}$ and removed with probability $E \leq p_e \cdot \frac{n(n-1)-2e}{n(n-1)}$, where e, n are the current number of edges and neurons, respectively, and p_e is a parameter. The number of new neurons is defined by $N \sim \text{Pois}(p_n)$ with hyperparameter p_n .³ The evolution of ANT thus allows for larger and more complex networks to form. The ability of the genetic algorithm to change the topology of ANT enables selectively faster information travel between areas of the network where a locally connected network would otherwise require several timesteps to propagate information. This selective minimization of the degrees of separation between distal vertices is important for the learning speed of the at-large network, quick reactionary mechanisms, and other properties of biological circuits [CITE]

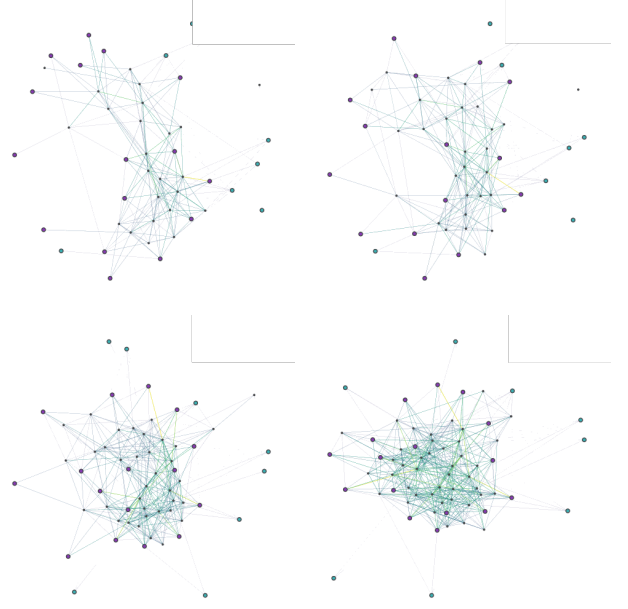


Figure 4. Evolution of a small ANT

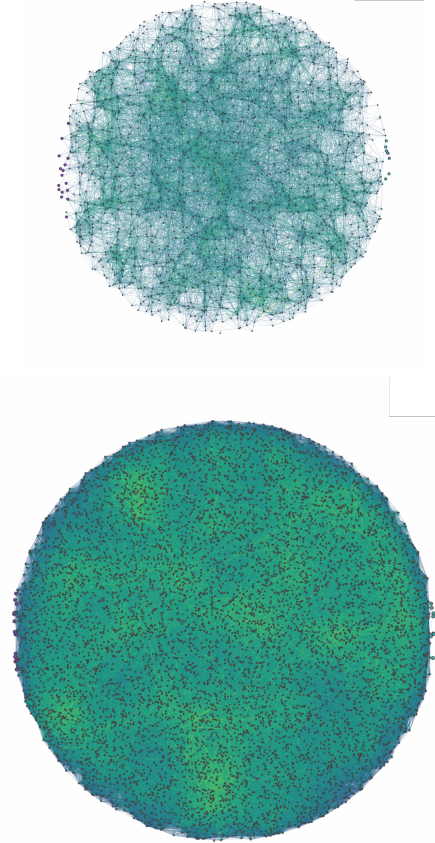


Figure 5. Evolution of a large ANT⁴

²An example of such an activation is $a_n(x) = n \tanh(\frac{x}{n})$, where $a_n(x) = x$ as $n \rightarrow \infty$

³We have not implemented neuron pruning, but this could also be included as a random variable or based on activity

⁴Activity is depicted on the "viridis" color gradient—purple is low, green/yellow is high

3.4 Reinforcement Learning

Due to the dynamic nature of ANT coupled with the objective of pursuing generalized intelligence, we use reinforcement learning (RL) as a medium through which to compare our results to ANNs.

ANT computes actions unconventionally compared to most other DQN or deep policy methods. Instead of mandating exploration with a user- or agent-controlled hyperparameter, we found exploration emergent from the dynamic structure of ANT. Intuitively, due to the variability of the input space, ANT cannot overfit in a traditional sense by forming explicit input-output mappings. In other machine learning settings this is a challenge, but in RL this leads to implicit exploration during the continual evolution of the internal state. Therefore, actions are simply determined as an argmax over the logit outputs of the network.

We also use the REINFORCE (REward Increment = Nonnegative Factor Offset Reinforcement Characteristic Eligibility) [20] policy gradient method used widely across reinforcement learning. We apply REINFORCE in a semi-online setting. As described before, gradient computation must occur in real time. To comply with this constraint, we accumulate gradient-reward pairs for T timesteps before applying REINFORCE to compute a gradient for the policy:

$$\sum_{t=0}^T \left[\nabla_{\theta} \log \pi_{\theta}(a_t | s_t) \cdot \sum_{k=t}^T \gamma^{k-t} \cdot r_k \right]$$

with discount factor γ at each T interval where $T \gg 1$.

3.5 Experimental Setup

Our experiments are predicated on assessing ANT’s ability to converge both more quickly and adaptively compared to its ANN counterpart. To assess this in a fundamental sense, we use

For comparison, we design an analogous ANN with similar mutation parameters, but only within its layered structure. For reinforcement learning, we use three discrete action-space Gym⁵ environments: Cartpole, Acrobot, and Lunar Lander. Cartpole is a balancing game where an agent must slide a cart to maintain the upright position of a pole. Acrobot requires an agent to apply appropriate force to a double pendulum to swing the bottom node over a certain height, and Lunar Lander requires an agent to land a lunar module with 3 thrusters on terrain.

⁵an open-source Python library originally developed by OpenAI and now maintained by the Farama Foundation.

⁶We maintain the same graph properties for the ANN. We only add vertices and edges to layers, as opposed to randomly connecting each to the existing graph as done in ANT evolution.

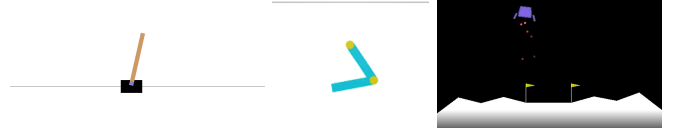


Figure 6. Cartpole (left), Acrobot (middle), Lunar Lander (right)

We complement these environments with the Context Adaptive Reinforcement Library (CARL) [19], a suite of analogously designed environments which float different physics properties to evaluate the generalizability of RL models, positing that if RL models are able to more quickly and reliably converge to high-reward solutions in environments which have object properties that vary, then they are more adaptable. While imperfect for investigating the capacity for ANT to achieve a general intelligence, at the scale of only a few dozen neurons we rationalize that a positive result in adaptability could translate to more complex reasoning behavior for larger-scale, more sophisticated topologies.

To train parameter efficiency, we create a “small” version of each model with 36 neurons and roughly ~ 450 trainable parameters and a “large” version of each with 66 neurons and ~ 1170 trainable parameters. In both cases, the ANN is structured as an MLP with 2 hidden layers while the ANT has a connectivity parameter p_e of 1.4, each with input and output sizes equal to the observation and action spaces of each respective environment.

We first compare the efficacy of an isolated gradient descent approach for training in each environment. For each experiment, we run 1000 epochs of the environment with reporting the best result across a search of 20 unique learning rate parameters.

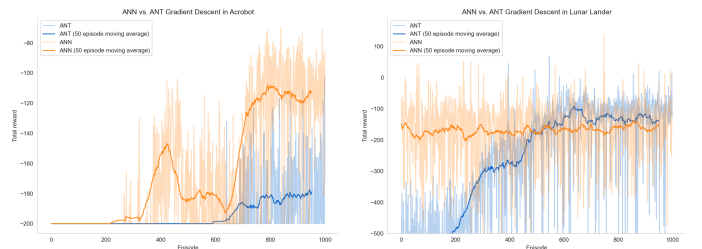


Figure 7. Sample ANN and ANT performance in Acrobot (left) and Lunar Lander (right) with only gradient descent

We run a similar experiment to test a joint gradient descent-evolutionary learning algorithm. For these experiments, we fix the two initial network structures as in SGD. For 20 evolutionary episodes, we first collect the top $k = 5$ networks from the previous episode, perform perturbations with a neuron addition rate regulated by $N \sim \text{Pois}(0.5)$, an

edge mutation rate with $p_e = 0.05$, and a weight perturbation with $W \sim \{\mathcal{N}(0, 1 \times 10^{-4})\}_{i=1}^e$ for a network with e edges.⁶ Each network is then trained for 100 episodes, after which an average reward is computed to determine the top- k . Below is an illustration of the best performing evolutionary path for the ANN and ANT in each environment, as well as close-performing neighbors.

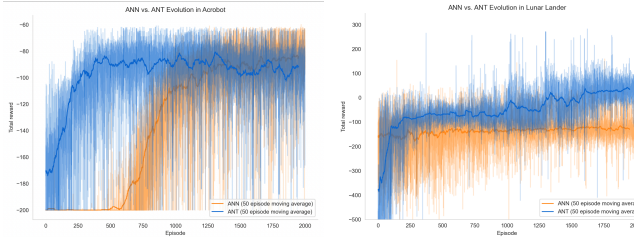


Figure 8. Sample ANN and ANT performance in Acrobot (left) and Lunar Lander (right) with evolution and gradient descent

3.6 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, ANT can behave analogously to animals through policy optimization [10]. Conversely, this implies that our proposed agent can develop multiple aspects of intelligent behavior given a simple design of such a reward function.

We developed both a virtual and physical agent with analogous environmental setups, where an agent navigates a 2D environment populated with obstacles and food. Upon reaching a food object, the agent receives a reward. The food-finding reward is intended to incentivize the agent to efficiently navigate its environment to move toward the food object. 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 makes a partial observation of its state, formulated as a 2-dimensional feature vector encoding the distance to the nearest object or obstacle in front of the agent as well as a boolean value indicating if food is present in the agent's field of vision. The agent can take 5 possible actions at each timestep: wait, rotate right, rotate left, move forward, or move backward.

For the physical agent, the observation space is observed using an ultrasonic sensor and Pixy2 camera. The ultrasonic sensor tracks the distance measurement to objects in front of the agent, and the Pixy2 has built-in object detection functionality to determine if food is present in its field of vision. The agent executes actions using two DC motors controlled with an L298N motor controller (Figure XB). After training ANT on the virtual environment, the trained network can be uploaded onto the physical agent to operate the agent and continue to learn. We hypothesize that a sophisticated

embodiment of ANT should exhibit sophisticated, animal-like behavior.

4 Results

We aim to demonstrate that, while conventional artificial neural networks are unable to converge quickly for small parameter counts, ANT can converge both quickly and robustly with high sample and parameter efficiency. We will first represent a sample learning trajectory for each experiment, then establish the rate of convergence.

4.1 Baseline Reinforcement Learning

With ANN-small and ANT-small as networks defined with 36 neurons and 66 neurons, respectively, we take the mean final reward over 100 different training runs with each

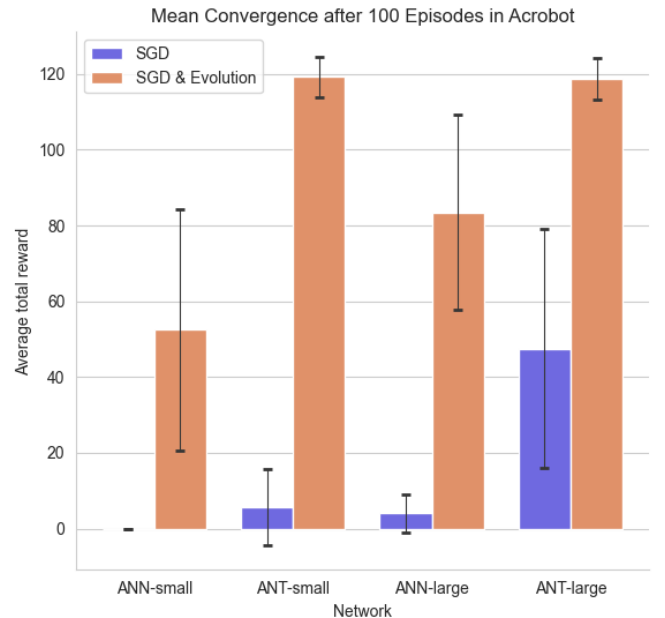


Figure 9. ANN and ANT 100 episode convergence

4.2 CARL

4.3 Robot Performance

Despite some successes in simulation, the translation to a physical agent failed due to the narrow observation space and discrepancies between the simulated and real-world environments.

For the physical agent, the ultrasonic sensor was prone to inconsistent distance measurements, and the computer vision algorithm frequently failed to detect the food or misidentified other objects as food. These inaccuracies led

to suboptimal decision-making and performance failures. Our attempts to rectify these issues through a hard-coded algorithm to locate food were unsuccessful, with a success rate of 20%. The failure of a hard-coded algorithm underscores that the performance failures are, in large part, due to limitations of the physical agent itself rather than the underlying network. This highlights the need for an expanded observation space, which could include integrating multiple sensors to take distance measurements at various angles.

Similarly, the ANT network was first trained in a controlled virtual environment, which does not adequately capture the complex dynamics of the physical world. Sensor inconsistencies, variations in motor functions, and dynamic environment elements were not modeled in the simulation and warrant a more intricate simulation environment. Incorporating Partially Observable Markov Decision Processes (POMDPs) could be beneficial in modeling the uncertainties and variabilities inherent in real-world interactions, leading to a more robust and adaptable agent.

4.4 Performance and Scalability

Due to the dynamic nature of ANT, the complexity of the update procedure runs linearly with respect to the number of neurons while suboperations within neurons require a linear compute time with respect to the number of connections, leading to a generally quadratic overall compute time. However, ANT is highly parallelizable, with each neuron operation occurring independently of other neurons and with genetic iterations that also run independently of other trials.

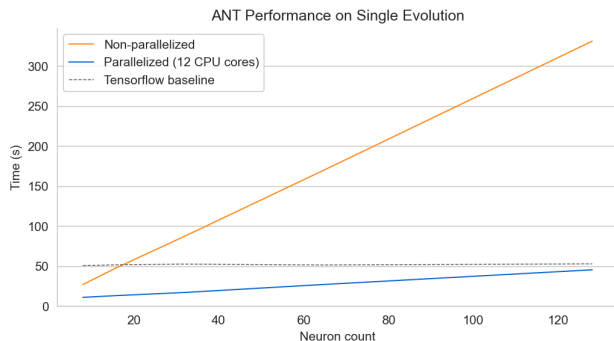


Figure 12. Speed of ANT with connectivity $\frac{1}{\sqrt{n}}$

ANT is currently constructed with Python which has a Global Interpreter Lock (GIL) preventing process threading, so we anticipate that a raw C/C++ implementation with threaded neuron operations would be even more computationally advantageous.

As opposed to the few large matrix compositions involved in ANN forward and backward propagation, most of the computations in ANT, while parallelizable, involve

many relatively small matrix operations. This imposes a necessary bound on the compute speed of ANT relative to conventional networks—where ANNs can use inbuilt matrix composition optimizations common in today’s Graphics Processing Units (GPUs), these improvements aren’t reflected to nearly the same degree on smaller compositions.

However, ANT’s computation is invariant of a notion of network “depth.” Where ANNs require the sequential computation of outputs and gradient depthwise, ANT can compute all gradients in parallel. When shifting the baseline to instead make deeper instead of wider networks, reducing the optimizability of its gradient calculation, ANT becomes distinctly more advantageous:

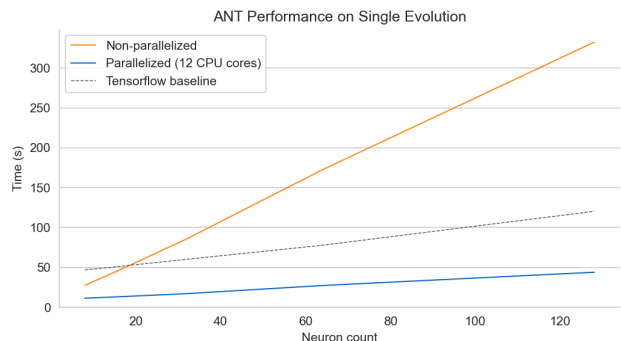


Figure 13. Speed of ANT with connectivity $\frac{1}{\sqrt{n}}$ (depthwise-expanded baseline network)

More experimentation with a more optimized code and better hardware is required to be conclusive on the speed of ANN compared to ANT, though it is likely that the computational tradeoff is problem-specific.

5 Summary and Conclusion

5.1 Limitations

There are several limitations of the ANT formulation which make it far from plug-in-play in conventional ANN settings. Because it is a dynamic network, ANT is not known to be capable of making distinct input-output functional pairings as in the context of supervised learning. In fact, in all settings which involve sharp discontinuities or heavy discretization of input, or non-temporal input, ANT’s formulation precludes it from use.

Further, not studied heavily in this paper is the sensitivity of ANT to initial conditions. As desired network complexity increases, the hyperparameter space grows exponentially as the total number of possible graph structures itself increases at a rate of 2^n where, as we have seen anecdotally, different graph constructions can yield dramatically different convergence times. In most cases for particular RL settings, ANT would fail to converge completely given

some graph initialization only with stochastic gradient descent. This requires the use of a genetic algorithm that, though optimizable, is a much more brute-force approach toward searching for viable network structures and may not be computationally feasible for large parameter spaces.

5.2 Future Work

The properties of ANT remain largely unstudied. Although we have investigated small-scale applications of ANT in RL studies in this paper, scaled RL applications and alternative machine learning applications are unknown. It is possible that scaling ANT is computationally difficult, however if the results at small scales indicate a similar convergence speeds for higher parameter counts then it would be worthwhile, especially if transfer learning were possible. Alternatively, like many dynamic networks, the convergence properties of ANT may be revealing in studying how biological neural networks may retain information, such as the memory-retention properties of Hopfield networks [21]. We also haven't investigated the graphs created by ANT's evolutionary algorithm. It is likely that they have emergent characteristics that could inform future development of ANT or other learning dynamic networks.

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