Modularity in NEAT Reinforcement Learning Networks

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ABSTRACT

Modularity is essential to many well-performing structured systems, as it is a useful means of managing complexity [8]. An analysis of modularity in neural networks produced by machine learning algorithms can offer valuable insight into the workings of such algorithms and how modularity can be leveraged to improve performance. However, this property is often overlooked in the neuroevolutionary literature, so the modular nature of many learning algorithms is unknown. This property was assessed on the popular algorithm “NeuroEvolution of Augmenting Topologies” (NEAT) for standard simulation benchmark control problems due to NEAT’s ability to optimise network topology. This paper shows that NEAT networks seem to rapidly increase in modularity over time with the rate and convergence dependent on the problem. Interestingly, NEAT tends towards increasingly modular networks even when network fitness converges. It was shown that the ideal level of network modularity in the explored parameter space is highly dependent on other network variables, dispelling theories that modularity has a straightforward relationship to network performance. This is further proven in this paper by demonstrating that rewarding modularity directly did not improve fitness.

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1 INTRODUCTION

A long-standing interest in the field of neuroevolution has been studying the selective advantage of modularity in neural networks [6]. Neuroevolution seeks to find the optimal structure and connection weights of a network to best solve a given problem [9]. Most structured systems can be represented as a graph [10], such as social networks, road networks, organizations, and the human brain [13]. Where structure is important, modularity often determines the success of such systems. Road networks are denser within cities than between them, and communication within departments is typically greater than between departments. This heterogeneity of connections between network parts is what defines the modularity of the whole network. Despite obvious benefits, the amount of modularity and organisation optimal for a given problem is unclear and is an active area of research in many disciplines [18].

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The results of this paper show that the optimal modularity in an ANN is conditional on other network properties, and as such direct optimisation of modularity does not appear to offer performance benefits. MAP-Elites is used to show that NEAT-based networks can achieve superior performance when the conditional effect of another measure of network behaviour is optimised alongside modularity. The dynamics of modularity in NEAT are explored with NEAT inherently tending towards increasingly modular networks regardless of whether fitness has converged.

This paper will offer three main contributions. Firstly, it will explore how modularity evolves in NEAT for different problems over time. Multi-objective optimization is examined, where networks are rewarded to different degrees for exhibiting modular structure. Finally, a simple method using the MAP-Elites algorithm [16] is presented for analysing the effect of modularity on the fitness landscape of networks and for demonstrating the conditional relationship modularity has to other network measures.

The implementation for this project is available at humphreymunn/ModularityNEAT.
2 BACKGROUND

Artificial neural networks (ANNs) have become ubiquitous in science and technology as they provide a framework for automated learning and problem solving. They are graphical in nature, and optimization of ANN structure is an active area of research due to the large influence network structure and configuration has on performance [21].

One recent approach to optimizing network structure and learning is the field of neuroevolution (NE). It is inspired by biological evolution: by encoding parameters of the network such as structure and weights into an artificial genome, they can be mutated or used in network procreation by recombination of two parent networks. A population of solutions is stored, and artificial selection is applied at each generation to continually evolve only the highest performing networks found over successive generations [9].

An important feature of networks is their modular structure, as it can improve evolvability and learning [5]. Modularity has gained some attention in the neuroevolution community, and several ideas have been recently proposed to explain its evolutionary advantage [6] and how it can be leveraged to learn higher-performing networks. This suggests an analysis of the dynamics of modularity over training time in popular learning algorithms such as backpropagation and neuroevolution is beneficial. This has already led to improvements in fields such as deep learning [2].

Qiao and Gallagher [20] describe the three classes of modularity optimization: 1. Manually splitting tasks into modules using human knowledge. 2. Add evolutionary objectives to apply selective pressure towards modular structure and 3. Use a genome structure that explicitly encodes modularity so modular structures naturally form. Their paper re-explores the MENNAG algorithm [17] that explicitly encodes modularity in the genome and shows that this is beneficial for problems with a modular nature. An example of utilising human knowledge for modularity is presented by Togelius [24] called layer evolution, which outperforms related methods on robotics tasks. This technique involves users defining sub-behaviours of increasing complexity that the system tries to solve. The system learns automatically which of the learned modules to use for higher-level behaviours, eventually leading to a fully functioning system. Finally, [14] demonstrates that an additional objective towards modularity exceptionally improved performance for the HyperNEAT algorithm on some problems. They indirectly optimize modularity using the connection cost technique, which penalises networks by the number of connections they have. This technique has been shown to often increase performance and modularity of solutions [6, 7, 15].

This paper explores the technique of directly adding modularity as an evolutionary objective to NEAT networks. This is done for three reasons. 1. This is by far the easiest method, and if high-performing modular networks can be obtained this way there is no need for more complex methods. 2. To our knowledge, there is only one paper [15] that optimizes modularity directly for any neuroevolutionary algorithm, meaning there is potential for this to be an unexplored, effective strategy. 3. To test the assumption that the relationship between modularity and fitness can be disentangled via multi-objective optimisation. [15] does not successfully use single objectives due to the complexity of the robot locomotion tasks, and instead uses a combinatorial multi-objective evolutionary algorithm incorporating many objectives including modularity to obtain optimal solutions. The multi-objective technique is generally more flexible as it can be added onto existing algorithms and does not require domain knowledge from humans, which are inherently biased, difficult to obtain and are often outperformed by automated learning algorithms. Furthermore, exploring modular properties of existing algorithms can assist researchers in their choice of algorithm or help in the development of new, higher-performing algorithms that consider properties of network modularity.

2.1 Modularity Metric (Q-Score)

The modularity of networks is often defined by their Q-Score [12, 18], where:

\[ Q = \sum_{s=1}^{K} \left( 1 - \frac{l_s}{L} - \frac{d_s^2}{2L} \right) \] (1)

and K is the number of modules, L is the number of edges, \( l_s \) is the number of edges within module s, \( d_s \) is the sum of node degrees in s. A close approximation of the optimal Q-Score is used, as direct calculation is a NP-Hard problem [3]. Intuitively, maximising the Q-Score will calculate the optimal groupings of modules in the graph, and this maximal score determines the network modularity.

2.2 NeuroEvolution of Augmenting Topologies (NEAT)

NeuroEvolution of Augmenting Topologies is a popular neuroevolutionary algorithm to evolve network structure and weights [22]. It is recognizable for its similarities to natural evolution. NEAT proposes an innovative method of recombination of two parent networks of different structures or topologies, by crossing genes with the same historical markings - analogous to alleles in DNA recombination. A population can become divided into different species over time based on structural differences in genomes, resulting in selection of the fitness individuals to reproduce for the next generation to occur separately for each species. This protects newly created structures from immediately dying off before their weights are yet to be fine-tuned. This also allows for increasing complexity of structures if this provides selection advantage, enabling NEAT to find an optimal level of network complexity. NEAT also offers many types of possible mutations to the structure and weights, increasing the network search space.

2.3 Reinforcement Learning Benchmark Problems

Reinforcement Learning is an important paradigm in machine learning, concerned with sequential decision making in an environment [26]. Three benchmark reinforcement learning environments from OpenAI’s Gym were tested: Bipedal Walker, Acrobot, and Continuous Lunar Lander.

2.3.1 Bipedal Walker. The bipedal walker task requires the agent to walk to the end of the environment (Figure 1). Agent reward is simply the distance travelled in the time limit, with a penalty for falling over. The state space consists of 24 values: 10 lidar readings, each joint angle and speed, leg ground contacts, x
and y velocity, hull angle and hull angular velocity. The action space or output is the torque to be applied to each of the two hip joints and two knee joints. That is, $A \in [-1, 1]^4$.

![Figure 1: Bipedal Walker Environment](image1)

### 2.3.2 Continuous Lunar Lander

The continuous lunar lander task requires the agent to navigate a lunar lander to the landing pad at coordinates $(0,0)$ in a simulated physics environment (Figure 2). Agent rewards depend on how close the landing is to $(0,0)$, how much throttle is used (to maximise fuel efficiency), and whether the agent lands safely. The state space is given by the Lander’s coordinates $(x,y)$, velocities $(x,y)$, angle and angular velocity, and left leg and right leg contact with the ground (true / false). The action space or output is two values: 1. the main engine throttle, and 2. the left/right engine throttle (left is in $[-1,-0.5]$, right is in $[0.5, 1]$), where $A \in [-1, 1]^2$.

![Figure 2: Continuous Lunar Lander Environment](image2)

### 2.3.3 Acrobot

The Acrobot task requires the agent to control an actuated joint to swing a two-link pendulum above a specified height (Figure 3). The reward is simply how fast the agent can solve the task. The state space consists of the sine and cosine for each joint angle, and the angular velocity for each joint. The action at each time step is the torque to be applied on the joint. That is, $A \in \{-1, 0, 1\}$.

![Figure 3: Acrobot Environment](image3)

### 2.4 MAP-Elites

MAP-Elites is an evolutionary algorithm that creates a map or grid of high-performing solutions, where the dimensions of the grid are important features of the problem decided by the user. In this paper for example, network modularity is one of these important features. Each grid square represents the highest fitness individual whose features are within the ranges defined by the grid cell position, and the colour is the individual’s fitness. The algorithm generates an initial random population, which is added to the grid. Then at each generation, a set number of individuals are procreated and mutated to create offspring, which are then added to the grid. If two individuals overlap on the grid, the highest fitness individual is kept. This strategy has been shown to often outperform direct optimization of performance, as it typically explores more of the search space, biased by important features [16]. Furthermore, it provides information about the fitness landscape of individuals, revealing important features of the applied problem or genotype/phenotype mapping.

### 2.5 Deviation from Uniform Torque Output Distribution

For reinforcement learning tasks, the amount each network output node is activated largely impacts its behaviour. For example, a local optima to the bipedal walking task could involve only applying torque to one knee joint.

A simple method of approximating the deviation from an equal output neuron usage distribution is used to obtain a network feature in the range $[0,1]$. The range rule of thumb is a common approximation to the sample standard deviation, such that $S \approx \frac{b-a}{4}$, where $b-a$ is the sample range [25]. An array of the total absolute torque applied to each joint over the episode time is stored, $X = [x_1, x_2, \ldots, x_n]$ where $n =$ number of output neurons. The average over all episodes is taken. As the minimum range is 0, and maximum is $max\{X\}$, the normalized approximate deviation is then,

$$D = \frac{max\{X\} - min\{X\}}{max\{X\}}, \quad D \in [0, 1]$$

### 3 METHODS

Modularity and fitness from the NEAT algorithm were measured on three benchmark problems. 20 runs of the learning process were performed for each problem. NEAT hyperparameters were similar to the neat-openai-gym GitHub repository (Rojas, 2017) as these were found to work well and did not need further tuning. A 5-episode, 10-episode and 20-episode average was used during training for BipedalWalker, ContinuousLunarLander and Acrobot respectively to minimise noise when measuring fitness. The default feed-forward network configuration was used for the BipedalWalker and ContinuousLunarLander tasks, whereas Acrobot used a recurrent NEAT network.
Multi-objective optimization via adding an additional modularity reward to the fitness function was also assessed on BipedalWalker with varying levels of reward significance. This reward was scaled with the current fitness to bias increasingly modular networks as the population starts converging. An importance metric was defined, which was the maximum percentage of the current fitness that can be added to the fitness function. The new fitness function was defined as,

\[ F = R + Q \cdot I \cdot (\min \{ \max \{ R, a \}, b \} + a) \] (3)

where \( F \) = fitness, \( R \) = reward, \( Q \) = Q-Score, \( I \) = Q-Importance hyper-parameter, \((a,b)\) = lower and upper fitness bounds. This results in a fitness function where an increase in environment reward will increase modularity desirability and visa-versa.

Finally, the MAP-Elites algorithm was run on the BipedalWalker task, as this task was the most interesting due to its challenging nature. Two feature descriptors were applied: network Q-Score and torque output deviation (Equation 2). The grid was of size 20x20 to reduce the computational cost of a large grid. At each generation, 12 progeny were created with a mutation probability of 0.75 and crossover probability of 0.3 by random selection of solutions stored in the grid. Changing these probabilities had negligible effects on the map. The 12 progeny were tested in parallel at each generation. This was run for 30000 generations, where the grid had mostly converged by this time.

4 RESULTS

4.1 Original NEAT Modularity & Fitness

The modularity and fitness for the three reinforcement learning tasks using NEAT are displayed in Figure 4 and Figure 5. In all three tasks, modularity increased over each generation in the fittest individuals. The rate of increase and convergence differed between problems significantly. Both BipedalWalker and Acrobot experience a convergence of fitness but an increase in modularity that extends past this convergence. Modularity appears to have converged in ContinuousLunarLander and Acrobot at the end of training but not for the BipedalWalker. Modularity appears normally distributed over runs, as well as fitness except for BipedalWalker which has a bimodal distribution suggesting the algorithm often gets stuck in a locally optimal behaviour.

4.2 Rewarding Modularity on BipedalWalker

Figure 6 (top) shows the best fitness for importance values \( \{0, 0.1, 0.125, 0.15, 0.175, 0.2\} \) averaged over 20 runs (see Equation 3). There does not appear to be a linear relationship between increased modularity rewards and performance. While some particular values of \( I \) \((0.175, 0.125)\) had higher average performance, this was not found to be statistically significant. Figure 6 (bottom) shows the differences in how modularity evolves with these different reward amounts. There is a clear linear relationship to increased modularity rewards and a higher modularity indicating the reward function was effective.
4.3 MAP-Elites for BipedalWalker

The MAP-Elites algorithm was run on the BipedalWalker task for 30000 generations. Figure 7 clearly shows the importance of each feature, with the hot-spot of high-performing networks within the ranges $Q \in [0.25, 0.5]$, $D \in [0.55, 0.7]$. Modularity has reasonably performing solutions for all values, however $D$ (see Equation 2) is consistently poor past 0.8. This should correspond to the networks using predominantly a single output out of the 4 available. There are 2 main regions that are above 200 fitness, which correspond to different walking strategies. The highest-performing solution had a fitness of 254, which is higher than solutions obtained from standard NEAT (~248) in the previous experiments. Despite this, using $D$ did not lead to networks with an optimal gait that solved BipedalWalker as this requires an average fitness of at least 300.

5 DISCUSSION

These results show new insights about the workings of ANN modularity and its dynamics in neuroevolution, specifically with NEAT. One important observation is how the rate of change and convergence of the Q-Score depends on numerous factors. This paper supports the literature that claims the ideal range of modularity in networks is problem dependent. Qiao and Gallagher [20] show that Q-Score population averages for the MENNAG algorithm were distinct for the three tested problems, with BipedalWalker averaging $Q \approx 0.53$ after training. In comparison, our MAP-ELITES and NEAT experiments had optimal solutions, although with a lower fitness, for values $Q \approx [0.25, 0.7]$. Ethiraj and Levinthal [8] found intermediate levels of modularity resulted in the highest performance on a formal simulation model of organizational systems. The three tasks tested in this paper also exhibit different optimal Q-Score ranges, which seem to reflect the modular nature of each task. Furthermore, Suchorzewski and Chune [23] show that DSE (Developmental Symbolic Encoding) converged to a Q-score of 0.65 whereas Hyper-NEAT converged to 0.4 on the same retina problem. This suggests that the best level of modularity is influenced by multiple factors, including the algorithm and problem environment.

The MAP-Elites experiment in Figure 7 shows that the ideal modularity range can be conditionally dependent on other variables from a network. This algorithm and visualisation offers a unique way of understanding the effects of different network variables on an applied problem. The range of modularity which produced the best individuals from this experiment differs to the NEAT experiments in Figure 4, 5 and 6 despite sharing the same genotype-phenotype mapping. This suggests the selection criteria has an important influence on an optimal level of modularity, as all other aspects of the algorithm are identical to NEAT. This conditional dependence explains why a multi-objective approach optimising fitness and modularity directly does not lead to faster convergence.

Figure 6: Best fitness (top) and modularity (bottom) for each tested Q-Importance level (Equation 3). Each test is 10 runs, with 1 standard deviation confidence intervals.

Figure 7: MAP-Elites grid for BipedalWalker task.
or significantly higher performance (Figure 6). This may appear to be opposing findings that show rewarding modularity improves performance, such as the connection cost technique [14]. However, [14] does not provide a objective that is purely modularity-based, and may be due to the introduced pressure on the learning algorithm to produce sparse networks.

Interestingly, on both BipedalWalker and Acrobat tasks, modularity increases past the point where fitness converges as demonstrated in Figure 4. This property is not present in the literature. This effect may be due to an inherent bias in the NEAT algorithm towards more modular topologies. One hypothesis may be that NEAT has a bias for increased complexity, which is balanced out through increased modularity. This supports the popular idea that modularity can be a means of managing complexity [8]. This process may not escape local optima where fundamentally new networks are required for a different gait or strategy, instead of higher network complexity.

6 CONCLUSION

It is clear that modularity plays an important role in the success of neuroevolutionary learning algorithms. The speed, convergence point, and best values of modularity were shown to be influenced by the problem environment and the selection criteria of the evolutionary process. NEAT can be expected to increase modularity of solutions significantly throughout training which appears to imply a selectional advantage towards modularity. However, the modularity in the population can increase even after fitness has converged which indicates a bias for modular solutions in NEAT. This should be explored further as this property may benefit or hinder the algorithm significantly. Finally, it was shown that the ideal level of modularity found by the learning process is conditionally dependent on other network metrics so a direct optimisation approach to modularity is unlikely to help during network training.

REFERENCES

[1] Timo Aaltonen, J Adelman, T Akimoto, MG Albrow, B Alvarez Gonzalez, S Amerio, D Amidei, A Anastassov, A Annowi, J Antos, et al. 2009. Measurement of the top-quark mass with dilepton events selected using neuroevolution at CDF. Physical review letters 102, 15 (2009), 152001.
[2] Mohammed Amer and Tomás Maud. 2019. A review of modularization techniques in artificial neural networks. Artificial Intelligence Review 52, 1 (2019), 527–561.
[3] Ulrik Brandes, Daniel Delling, Marco Gaertler, Roberto Girke, Martin Hoefer, Zoran Nikoloski, and Dorothea Wagner. 2006. Maximizing modularity is hard. arXiv preprint physics/0608255 (2006).
[4] Greg Brockman, Vicki Cheung, Ludwig Pettersson, Jonas Schneider, John Schulman, Jie Tang, and Wojciech Zaremba. 2016. Openai gym. ArXiV preprint arXiv:1606.01540 (2016).
[5] Jeff Clune, Benjamin E Beckmann, Philip K McKinley, and Charles Ofria. 2010. Investigating whether HyperNEAT produces modular neural networks. In Proceedings of the 12th annual conference on Genetic and evolutionary computation. 635–642.
[6] Jeff Clune, Jean-Baptiste Mouret, and Hod Lipson. 2013. The evolutionary origins of modularity. Proceedings of the Royal Society b: Biological sciences 280, 1755 (2013), 20122863.
[7] Kai Olav Ellefsen, Jean-Baptiste Mouret, and Jeff Clune. 2015. Neural modularity helps organisms evolve to learn new skills without forgetting old skills. PloS computational biology 11, 4 (2015), e1004128.
[8] Sendil K Eshuraj and Daniel Levinthal. 2004. Modularity and innovation in complex systems. Management science 50, 2 (2004), 159–173.
[9] Dario Floreano, Peter Durr, and Claudio Mattiussi. 2008. Neuroevolution: from architectures to learning. Evolutionary intelligence 1, 1 (2008), 47–62.
[10] Michelle Girvan and Mark EJ Newman. 2002. Community structure in social and biological networks. Proceedings of the national academy of sciences 99, 12 (2002), 7821–7826.
[11] Bruno Grisci and Márcio Dorn. 2017. NEAT-FLEX: Predicting the conformational flexibility of amino acids using neuroevolution of augmenting topologies. Journal of Bioinformatics and Computational Biology 15, 03 (2017), 1750099.
[12] Roger Guimera and Lluís A Nunes Amaral. 2005. Functional cartography of complex metabolic networks. nature 433, 7028 (2005), 895–900.
[13] Boye Annfelt Høverstad. 2011. Noise and the evolution of neural network modularity. Artificial life 17, 1 (2011), 33–50.
[14] Joost Huijinga, Jeff Clune, and Jean-Baptiste Mouret. 2014. Evolving neural networks that are both modular and regular: Hyperneat plus the connection cost technique. In Proceedings of the 2014 Annual Conference on Genetic and Evolutionary Computation. 697–704.
[15] Joost Huijinga, Jean-Baptiste Mouret, and Jeff Clune. 2016. Does aligning phenotypic and genotypic modularity improve the evolution of neural networks?. In Proceedings of the Genetic and Evolutionary Computation Conference 2016. 125–132.
[16] Jean-Baptiste Mouret and Jeff Clune. 2015. Illuminating search spaces by mapping elites. ArXiv Preprint ArXiv:1504.04909 (2015).
[17] Jean-Baptiste Mouret and Stéphane Doncieux. 2008. MENNAC: a modular, regular and hierarchical encoding for neural-networks based on attribute grammars. Evolutionary Intelligence 1, 3 (2008), 187–207.
[18] Mark EJ Newman. 2006. Modularity and community structure in networks. Proceedings of the national academy of sciences 103, 23 (2006), 8577–8582.
[19] Evgenia Papavasileiou, Jan Cornelis, and Bart Jansen. 2021. A Systematic Literature Review of the Successors of “NeuroEvolution of Augmenting Topologies” - Evolutionary Computation 29, 1 (2021), 1–73.
[20] Yukai Qiao and Marcus Gallagher. 2020. An Implementation and Experimental Evaluation of a Modularity Explicit Encoding Method for Neuroevolution on Complex Learning Tasks. In Australasian Joint Conference on Artificial Intelligence. Springer, 138–149.
[21] Kenneth O Stanley, Jeff Clune, Joel Lehman, and Risto Miikkulainen. 2014. Designing neural networks through neuroevolution. Nature Machine Intelligence 1, 1 (2019), 24–35.
[22] Kenneth O Stanley and Risto Miikkulainen. 2002. Evolving neural networks through augmenting topologies. Evolutionary computation 10, 2 (2002), 99–127.
[23] Marcin Suchorzewski and Jeff Clune. 2011. A novel generative encoding for evolving modular, regular and scalable networks. In Proceedings of the 13th annual conference on Genetic and evolutionary computation. 1523–1530.
[24] Julian Togelius. 2004. Evolution of a subsumption architecture neurocontroller. Journal of Intelligent & Fuzzy Systems 15, 1 (2004), 15–20.
[25] Xiang Wan, Wenqian Wang, Jiming Liu, and Tiejun Tong. 2014. Estimating the top-quark mass with dilepton events selected using neuroevolution at CDF. Physics of the cosmic microwave background 20, 2 (2014), 1–11.
[26] Mark EJ Newman. 2006. Modularity and community structure in networks. Proceedings of the national academy of sciences 103, 23 (2006), 8577–8582.
[27] Mehmet Erkan Yuksel. 2018. Agent-based evacuation modeling with multiple exits using NeuroEvolution of Augmenting Topologies. Advanced Engineering Informatics 35 (2018), 30–55.