BRSU

Advanced Scientific Working
-Essay-
Evolving neural networks through augmenting topologies

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1 REFERENCE

Stanley, K. O., & Miikkulainen, R. (2002). Evolving neural networks through augmenting topologies. Evolutionary computation, 10(2), 99-127.

2 ABSTRACT

An important question in neuroevolution is how to gain an advantage from evolving neural network topologies along with weights. We present a method, NeuroEvolution of Augmenting Topologies (NEAT), which outperforms the best fixed-topology method on a challenging benchmark reinforcement learning task. We claim that the increased efficiency is due to (1) employing a principled method of crossover of different topologies, (2) protecting structural innovation using speciation, and (3) incrementally growing from minimal structure. We test this claim through a series of ablation studies that demonstrate that each component is necessary to the system as a whole and to each other. What results is signicantly faster learning. NEAT is also an important contribution to GAs because it shows how it is possible for evolution to both optimize and complexify solutions simultaneously, offering the possibility of evolving increasingly complex solutions over generations, and strengthening the analogy with biological evolution.

3 ESSAY

3.1 WHAT IS THE PAPER ABOUT?

- A new algorithm called NEAT for neuroevolution (NE), i.e. the design of an artificial neural network using evolutionary techniques

3.2 WHY IS THIS RELEVANT?

- NE has shown to be faster and more efficient than reinforcement learning methods on tasks as single pole-balancing and robot arm control
- NE is effective in continuous and high dimensional state spaces
- Memory can easily be represented through recurrent neural networks, which makes NE a natural choice for non-Markovian tasks.

3.3 WHAT HAVE OTHERS DONE AND WHY IS THIS NOT SUFFICIENT?

- Topology of ANN chosen before the experiment
- Research on algorithms that evolved the topology/structure of an ANN provided inconclusive answers about why evolving the topology is superior to using fixed topologies
  - Evolving topology lead to solving the hardest pole-balancing task so far, but could be achieved with randomly initialized topologies afterwards five times faster.

- Evolving topology and weights significantly enhances the performance of NE

3.4 What have the author's done and why is this better?

- Introduction of NeuroEvolution of Augmented Topologies (NEAT)
  - Use of historical markings to keep track of the same genes in different solutions → Allows for an easy and meaningful application of the cross-over operator
  - Using speciation, i.e. compute the similarity of solutions and share their fitness if similar enough → Protection of new innovative solutions to give them time to develop their potential
  - Start with minimal solution and grew them more and more complex → Algorithm will search low dimensional search space first which enhances performance

3.5 How did they evaluate their solution?

- Comparison to SOA approaches in the creation of XOR gates → NEAT could outperform the other methods
- Comparison to SOA approaches in a double pole-balancing task → NEAT could outperform the other methods
- Tested necessity of cross-over → Significantly more evaluations needed to find a solution
- Tested necessity of speciation → Failure in about 25% and about seven times more runtime
- Tested necessity of complexification → Fixed ANN successful in about 20% and about 8.5 times slower

3.6 Scientific Deficit

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3.7 Scientific Contribution

- Method to optimize architecture and weights
  - Chen, Yuehui, et al. "Time-series forecasting using flexible neural tree model." Information sciences 174.3 (2005): 219-235.
  - Whiteson, Shimon, and Peter Stone. "Evolutionary function approximation for reinforcement learning." The Journal of Machine Learning Research 7 (2006): 877-917.
  - Clune, Jeff, et al. "Evolving coordinated quadruped gaits with the HyperNEAT generative encoding." Evolutionary Computation, 2009. CEC'09. IEEE Congress on. IEEE, 2009.

- Approach to overcome "course of dimensionality"
  - Togelius, Julian, et al. "Search-based procedural content generation: A taxonomy and survey." Computational Intelligence and AI in Games, IEEE Transactions on 3.3 (2011): 172-186.