Evolving Neurocontrollers for the Control of Information Diffusion in Social Networks

Andrew Runka, Tony White School of Computer Science, Carleton University 1125 Colonel By Drive Ottawa, Ontario, Canada {arunka,arpwhite}@scs.carleton.ca

ABSTRACT

This paper presents a comparison of two Evolutionary Artificial Neural Network (EANN) variants acting as the autonomous control system for instances of the θ -Consensus Avoidance Problem (θ -CAP). A novel variant of EANN is proposed by adopting characteristics of a well-performing heuristic into the structural bias of the neurocontroller. Information theoretic landscape measures are used to analyze the problem space as well as variants of the EANN.

The results obtained indicate that the two neurocontroller variants learn distinctly different approaches to the θ -CAP, however, the newly proposed variant demonstrates improvements in both solution quality and execution time. A rampeddifficulty evolution scheme is demonstrated to be effective at creating higher quality results as compared to the standard scheme for EANNs. A correlation between the proposed instance difficulty and identifiable landscape characteristics is discovered as well.

Categories and Subject Descriptors

I.2.6 [Artificial Intelligence]: Learning—Connectionism and neural nets; I.2.8 [Artificial Intelligence]: Problem Solving, Control Methods, and Search

Keywords

Evolutionary algorithms, Neural networks, Influence, Control, Optimization

1. INTRODUCTION

Consensus in a social network is a terminal state relative to the diffusion of new information. Such a lack of diversity can leave a population susceptible to severe consequences. For example, a consensus of opinion in a financial market can lead to a bubble or a market run [2]. The imposition of external influence to prevent consensus in large-scale social networks is therefore an important problem. The automation of control in such cases can observe and inform human

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oversight, or where appropriate, take action with more speed and precision than human counterparts.

The Network Control Problem (NCP) formalization [4] describes a social network as a combination of structural and behavioural components, known as the network and the diffusion model respectively. The NCP then defines a pair of dependant optimization problems in terms of discovering both the structural and behavioural components of a control system. The objective of the control system is to direct the state of the social network via interactions at the node-state level. The amount of direct influence a control system has on the social network is constrained by a budget placed on the size of the set of controlled nodes. Thus the control system is required to determine both an optimal configuration of connections to the social network, and an optimal state-to-signal mapping for the control system's ongoing output.

The NCP formalizes a relation among a set of subproblems. In all subproblems the objective remains to control the state of a network, however the evaluation of specific states varies by problem. In the well-known case of the Influence Maximization Problem (IMP) [1], the goal is to select a controller configuration that maximizes the spread of a single selected node state, implying a static single state output as the fixed controller behaviour. Similarly, in [3], the problem of structural controllability is examined as a search for the minimum number of control sites and optimal placement thereof, without the associated search of an appropriate behavioural component for the control system. Solutions to these problems offer insight to the optimization of the *configuration* of the NCP, but not the behavioural component.

In [4], the θ -Consensus Avoidance Problem (θ -CAP) is defined as an NCP subproblem with both configuration and behavioural search requirements. In addition to considering the optimal configuration required to deliver appropriate control signals, the θ -CAP considers the dependent search for a state-to-signal mapping capable of maintaining an equilibrium of node states within the network. This paper extends the previous work to consider the optimization of the behavioural mapping for the θ -CAP.

To optimize the θ -CAP behavioural component, two variants of the Evolutionary Artificial Neural Network (EANN) metaheuristic are applied. In addition to establishing new benchmark results, this paper compares the implemented neurocontrollers in terms of their relative fitness, speed, and their evolved strategies of control. Landscape analysis is applied to distinguish characteristic differences in the search spaces explored by either variant.

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2. ALGORITHM DESIGN

Results from [4] demonstrate that an EANN control system is capable of consistently learning network balancing behaviour over a variety of random control system configurations and network types. Additionally, the Anti-Majority (AM) control system showed results competitive to the EANN over select problem instances of lower budget.

The AM heuristic can be modelled as a connectionist architecture with fixed weights as shown in Figure 1(c). This form of the AM is termed the Connectionist Anti-Majority (CAM) heuristic. The CAM control system requires no training, and computes an identical input-to-signal mapping as the standard AM control system. The number of input neurons is set to the number of unique observable nodes in the social network $(|N_{V_C}|)$. The number of hidden and output neurons are both set to the number of controlled nodes $(|V_C|)$. Axons between the input layer and hidden layer are added if and only if there exists an edge in the social network between the observed node and the controlled node. Inputs to the CAM control system are scaled and shifted to the range [-1,1]. Weights on axons between the input and hidden layer are fixed at 1, thus the hidden layer neurons encode an observed majority feature for each controlled node. The hidden layer connects in a 1-to-1 manner to the output layer. Weights on the hidden-to-output axons are fixed at -1 to produce an anti-majority value at each output.

The CAM control system performs identically to the AM: fast, competitive results for low-budget instances, but severe decrease in performance with high budgets. Alternatively, the EANN control system achieves consistently highquality results at the cost of a slow training phase. This paper proposes the Evolutionary Connectionist Anti-Majority (ECAM) control system as a middle ground between the prior two approaches. This is achieved by reducing the number of axons in the EANN scheme which require training based on the fixed weights in the CAM scheme, as seen in Figure 1(d). Axons between the input and hidden layers of the ECAM are configured and fixed as in the CAM structure. The hidden-to-output layer is fully-connected and adjustable. Initialization of the 'horizontal' axons (bold in Fig. 1(d)) is to -1 as in the CAM scheme, but are still ajustable through the EA training. All other axons are initialized randomly in the standard [-0.5,0.5) range.

In addition to the standard EA scheme, this paper presents a ramped difficulty evolution, in which the population begins by initially evolving to solve a problem instance with a high θ_G (=90%). Once the evolution is complete, or a single individual reaches the simulation step limit (500000 steps), the difficulty of the problem is increased by lowering the value of θ_G by 10% and the evolution is begun again. The population is evolved continuously through each level, so the population that reached the limit condition for one value of θ_G is the initial population for the next. This process is described in Algorithm 1.

3. CONCLUSION

This paper demonstrates the ability of an evolutionary neurocontroller to successfully act as the behavioural component for the θ -CAP. A ramped evolution scheme was observed to improve the quality of the evolved solutions. The novel, problem specific EANN variant, ECAM, achieves better quality results in less time on the more difficult small



Figure 1: Connectionist algorithms for control of a social network. a) A sample social network with 3 controlled nodes b) Standard EANN. c) CAM heuristic control system. d) ECAM control system.

Algorithm 1 Pseudo-code of the Ramped evolution EANN
for the θ -CAP.
Require: instance is a tuple (θ_G, B, G)
1: procedure RAMPEDEANN(<i>instance</i> , <i>maxGen</i>)

- 2: $instance.\theta_G \leftarrow 0.9$
- 3: $Pop \leftarrow InitPop(instance)$
- 4: while $instance.\theta_G \ge 0$ do
- 5: $Pop \leftarrow \text{TrainEANN}(instance, maxGen, Pop)$
- 6: $\operatorname{Report}(Pop)$
- 7: $instance.\theta_G \leftarrow instance.\theta_G 0.1$

budget instances. While the standard EANN attains consistently better results for instances with large budgets, the ECAM overcomes the weakness of the Anti-Majority heuristic to demonstrate extended durations of control for these instances as well. By limiting and biasing the search space of all possible EANN weights to only those available in the ECAM definition, the two algorithms converge to distinctly different control strategies.

The landscape analysis comparison of the two algorithms revealed unexpected similarity in the nature of the fitness landscapes traversed. Slight changes in the observed values, and increased average fitness over the majority of random walks, suggests that both networks search on the same fitness space, with the ECAM simply biased to a promising region thereof.

4. **REFERENCES**

- P. Domingos and M. Richardson. Mining the network value of customers. In Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining, pages 57–66, 2001.
- [2] D. Hirshleifer and S. Teoh. Thought and behavior contagion in capital markets. Handbook Of Financial Markets: Dynamics And Evolution, Handbooks in Finance, (9142), 2009.
- [3] Y. Liu, J. Slotine, and A. Barabási. Controllability of complex networks. *Nature*, pages 1–7, 2011.
- [4] A. Runka and T. White. Towards Intelligent Control of Influence Diffusion in Social Networks. *Social Network Analysis and Mining*, 5(1), 2015.