

Towards a “Master Algorithm” for Forming Faster Conventions On Various Networks

Extended Abstract

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ABSTRACT

In this paper, we argue the importance of developing a “Master Algorithm” that forms faster social convention among software agents on any network topology. We hypothesize that one possible approach towards building this “Master Algorithm” is to embed network awareness in agent’s decision-making process. As a first step towards this algorithm, we present a novel network aware convention formation (NACF) algorithm that equips agents with network awareness to select a suitable algorithm for creating faster conventions. The results obtained from an extensive set of simulations show that NACF successfully forms convention on various network scenarios. We also identify the limitations of NACF and provide insights for improvement.

KEYWORDS

Scale-free network; Random network; Planar network; Small-world network; Ring network; Scale-free community network; Convention; Network Awareness

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1 INTRODUCTION

In this paper, we investigate the problem of establishing coordination among software agents under various organizational structures. In many practical applications agents are faced with a number of plausible alternatives (e.g., possible directions, tasks, services, strategies, etc.) to choose from, and the goal is for all agents to agree on the same alternative [4–6, 11]. Coordination serves as a key requirement for designing this type of systems. The problem of creating coordination has been extensively addressed by the multiagent systems (MAS) community [2, 12–14, 14]. The most prevalent solution approach to this problem is modeled by forming social conventions in MAS [2, 14]. A social convention helps to reduce the overhead of coordination by simplifying agents’ decision-making process through the determination of action choices [17]. Therefore, establishing a social convention acts as an useful mechanism for deciding the dominant coordination strategy or building consensus in MAS. Given enough time and resource, agents in a MAS can create

a single convention. However, for many practical scenarios, such as swarm robots, wireless sensor networks, IoT service coordination, it is important to form conventions quickly. This paper investigates **mechanisms for forming faster conventions in a MAS**.

Various algorithms have been developed to form conventions in different type of agent networks [1, 7, 9, 10, 16]. These algorithms can be broadly divided into two categories: **collective learning** and **paired learning**. In collective learning algorithms, such as Simple Majority (SM) [1], Generalized Simple Majority (GSM) [1], social learning [16] and Accumulated Coupling Strength (ACS) [7], agents need to have knowledge of their entire neighborhood. On the other hand, in paired learning algorithms, such as Win-Stay Loose-Shift (WSLS) [10] and Win-Stay Loose-Probabilistic-Shift (WSLpS) [9], agents only need to have knowledge about one of their neighbors. However, none of these algorithms seem to work across all network types. For example, the SM algorithm fails in complex networks [1] while social learning fails in sparse Scale-Free networks [16]. Moreover, for a particular network type, an algorithm may not work for **all possible network configurations**. For example, while GSM is able to form conventions in larger average degree Scale-Free (SF) and Small-World (SW) networks [1, 8, 15], it fails on sparse network configurations. To address the challenge of forming conventions in sparse networks, ACS was developed. However, ACS does not work equally efficiently in Random (RN) networks [7]. A variation of WSLS has been proposed, which is called WSLpS, to form 100% convention in SF, SW, RN and regular networks [9]. However, this algorithm requires a very large number of iterations to reach a single convention, which makes it practically less useful.

A careful analysis of the existing convention algorithms suggests that neither the collective learning nor the paired learning algorithms can solely form conventions in all network types and configurations. Depending on the agent network type and network configuration, one algorithm performs better than other algorithms. However, in practical scenarios knowledge of the network topology and configuration may not be known a priori. Therefore, to solve the agent coordination problem in practical applications, it is important to design a “Master Algorithm” [3] that forms faster conventions on all networks types and configurations. In absence of such an algorithm, the applicability of convention algorithms are limited.

This paper draws on [7] with the goal of developing a “Master Algorithm” to form faster conventions on all network types and configurations. As a first step towards this goal, this paper presents a decentralized network aware convention formation (NACF) algorithm that works across various network types such as SF, RN,

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SW, Planar (PN), and scale-free community (SFC) networks and on various configurations of these topologies. NACF enables agents' to predict its global network topology solely based on local information. We show that when network awareness is embedded into agents' architecture, they are able to choose the most appropriate algorithm for establishing a convention much faster. We use a battery of convention algorithms that includes some existing algorithms as well as our proposed algorithms. In particular, we present a variation of the ACS algorithm called Adjusted Accumulated Clustering Coefficient (AACS), which forms convention in sparse SF topologies faster than ACS. Also we propose a variation of WSLpS, named as the Win-Stay Loose-Probabilistic-Shift Known-Neighbor (WSLpSKN), that expedites the convention formation process in SF and PN topologies by a great extent.

To summarize, in this paper we design a mechanism as a first step towards building the "Master Algorithm" by enabling agents to be **network aware** to select suitable convention algorithms. Our main contributions are as follows.

- Present a network-aware convention formation (NACF) algorithm that enables agents to predict their global topology and form conventions faster by choosing a suitable convention algorithm.
- Implementation of NACF on realistic agent societies including various static and dynamic networks such as SF, RN, SW, PN, and SFC.
- Present a variation of ACS that works better than ACS in sparse SF networks..
- Present a variation of WSLpS that works better than WSLpS in SF and PN networks.
- Identify the limitations of NACF and provide insights for improvement.

2 NETWORK AWARE CONVENTION FORMATION

Algorithm 1 is a pseudocode description of the network aware convention formation (NACF) algorithm. This algorithm is applied on a list of network topologies. The algorithm is executed by individual agents. Initially actions are randomly assigned among the agents. Then, for paired learning algorithms, each agent plays the 2-person pure coordination game with a randomly chosen neighbor. Each agent individually identifies their network topology (Lines 1.4 - 1.5). Then, based on their best estimate of the network topology, each agent selects a convention formation algorithm (Lines 1.5 - 1.6). The chosen algorithm enables them to update their actions. Then, they play the coordination game with one of their randomly selected neighbors (for paired learning algorithms). For dynamic scenarios, agents choose a random neighbor and probabilistically rewire with its chosen neighbor's neighbor [9]. This process repeats (Lines 1.4 - 1.10) until a stopping criterion, e.g., a majority convention emerges or a maximum number of iterations.

The list of convention formation algorithms that is used in Algorithm 1 includes five algorithms: Generalized Simple Majority (GSM) rule, Accumulated Coupling Strength (ACS), Adjusted Accumulated Coupling Strength (AACS), Win-Stay Loose-Probabilistic-Shift (WSLpS) and Win-Stay Loose-Probabilistic-Shift Known Neighbor (WSLpSKN).

Algorithm 1: Network Aware Convention Formation (NACF) Algorithm

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input :  $n \leftarrow$  number of agents
          $L \leftarrow$  list of topologies
          $CFA \leftarrow$  list of convention formation algorithms
         where  $CFA_l$  is suitable for topology  $l$ 
          $Iteration_{max} \leftarrow$  maximum number of iterations
output: Selected convention  $C$ .
1.1 createTopology( $n, l$ )
1.2 randomlyAssignActions( $n$ )
1.3 playGame( $n$ )
1.4 for each agent  $i := 1$  to  $n$  do
1.5   identifyNetworkTopology()
1.6   selectConventionFormationAlgorithm( $CFA_l \forall l \in L$ )
1.7   playGame()
1.8   networkReorganization()
1.9 end
1.10 Iteration = Iteration + 1
1.11 Repeat (Lines 1.4 - 1.10) until a majority convention
      emerges OR  $Iteration \geq Iteration_{max}$ 

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Both the GSM and WSLpS were given in [1] and [9], respectively. Our proposed WSLpSKN is based on WSLpS, and AACS is adapted from the ACS [7] for better performance.

These five algorithms are broadly divided into two categories. The algorithms in the first category is based on collective learning, in which agents need to have the knowledge of all agents in their neighborhood to determine their actions. GSM, ACS and AACS belong to this category. On the other hand, agents use paired learning for algorithms in the second category. In paired learning, they only need to have knowledge about one neighbor (randomly or deterministically chosen). WSLpS and WSLpSKN belong to this category.

3 CONCLUSIONS AND FUTURE WORK

In this paper, we argue the importance of developing a "Master Algorithm" that forms faster social conventions among software agents on any network topology. We provide evidence from literature that no single algorithm performs equally efficiently on various networks. We hypothesize that one possible approach for building this "Master Algorithm" is to embed network awareness in agent's decision-making process. As a first step towards building this algorithm, we present a novel network aware convention formation (NACF) algorithm that equips agents with network awareness to select a suitable algorithm for creating faster conventions.

In future, we plan to improve NACF to develop a complete version the "Master Algorithm" based on the observations obtained from the simulation results. In the modified NACF, agents should be able to choose an efficient algorithm based not only on the network topology, but also on the network configuration. Also, we will include more network scenarios (e.g., random community networks, hybrid networks) as well as investigate a larger convention space.

REFERENCES

- [1] J. Delgado. 2002. Emergence of social conventions in complex networks. In *Artificial Intelligence (141 (1-2))*. 171–185.
- [2] B. DeVylder. 2007. *The Evolution of Conventions in Multi-Agent Systems*. PhD Dissertation. Artificial Intelligence Lab Vrije Universiteit Brussel.
- [3] Pedro Domingos. 2015. *The Master Algorithm: How the Quest for the Ultimate Learning Machine Will Remake Our World* (1st ed.). Basic Books, New York, USA.
- [4] Niall Firth. 2017. Bitcoin tech to restore democracy. *New Scientist* 235, 3142 (2017), 8.
- [5] Alessandro Giusti, Jawad Nagi, Luca M. Gambardella, and Gianni A. Di Caro. 2012. Distributed Consensus for Interaction Between Humans and Mobile Robot Swarms (Demonstration). In *Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems - Volume 3 (AAMAS '12)*. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 1503–1504. <http://dl.acm.org/citation.cfm?id=2343896.2344082>
- [6] Mohammad Rashedul Hasan. 2013. Emergence of privacy conventions in online social networks. In *the Proceedings of the International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2013)*. 1433–1434.
- [7] Mohammad R. Hasan, Sherief Abdallah, and Anita Raja. 2014. Topology Aware Convention Emergence. In *the Proceedings of the International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2014)*. 1593–1594.
- [8] Kiran Lakkaraju and Les Gasser. 2009. Minimizing Information-Centric Convergence Cost in Multi-Agent Agreement Problems. In *Adaptive Learning Agents (ALA) workshop at the eighth International Conference on Autonomous Agents and Multi-Agent System (AAMAS)*. <http://teamcore.usc.edu/taylorm/ALA09/9.pdf>
- [9] Mihail Mihaylov, Karl Tuyls, and Ann Nowak. 2014. A decentralized approach for convention emergence in multi-agent systems. *Autonomous Agents and Multi-Agent Systems* 28, 5 (2014), 749–778. <https://doi.org/10.1007/s10458-013-9240-2>
- [10] Martin Nowak and Karl Sigmund. 1993. A strategy of win-stay, lose-shift that outperforms tit-for-tat in the Prisoner's Dilemma game. *Nature* 364, 6432 (1993), 56–58. <https://doi.org/10.1038/364056a0>
- [11] José N. Pereira, Porfirio Silva, Pedro U. Lima, and Alcherio Martinoli. 2014. Social-Aware Coordination of Multi-robot Systems Based on Institutions. In *Human Behavior Understanding in Networked Sensing - Theory and Applications of Networks of Sensors*. 407–430. https://doi.org/10.1007/978-3-319-10807-0_19
- [12] Josep M. Pujol, Jordi Delgado, Ramon SangEesa, and Andreas Flache. 2005. The Role of Clustering on the Emergence of Efficient Social Conventions.. In *the International Joint Conference on Artificial Intelligence (IJCAI) (2007-04-20)*, Leslie Pack Kaelbling and Alessandro Saffiotti (Eds.). 965–970.
- [13] S. Sen and S. Airiau. 2007. Emergence of norms through social learning. In *the International Joint Conference on Artificial Intelligence (IJCAI)*. 1507–1512.
- [14] Toshiharu Sugawara. 2011. Emergence and Stability of Social Conventions in Conflict Situations.. In *the International Joint Conference on Artificial Intelligence (IJCAI)*, Toby Walsh (Ed.). IJCAI/AAAI, 371–378.
- [15] Paulo Urbano, João Balsa, Luis Antunes, and Luís Moniz. 2008. Force Versus Majority: A Comparison in Convention Emergence Efficiency.. In *International Workshop on Coordination, Organisations, Institutions and Norms (COIN) at the Autonomous Agents and Multiagent Systems (AAMAS) Conference (2009-11-24) (Lecture Notes in Computer Science)*, Jomi Fred HEBner, Eric T. Matson, Olivier Boissier, and Virginia Dignum (Eds.), Vol. 5428. Springer, 48–63.
- [16] D. Villatoro, J. Sabater-Mir, and S. Sen. 2011. Social instruments for robust convention emergence. In *the International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2011)*. International Foundation for Autonomous Agents and Multiagent Systems.
- [17] Adam Walker and Michael Wooldridge. 1995. Understanding the Emergence of Conventions in Multi-Agent Systems.. In *Proceedings of the First International Conference on Multiagent Systems (ICMAS) (2004-11-16)*, Victor R. Lesser and Les Gasser (Eds.). The MIT Press, 384–389.