Topology Aware Convention Emergence

(Extended Abstract)

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ABSTRACT

Single convention convergence across different types of networks is a challenging multi-agent task. Our central hypothesis in this paper is that no simple distributed mechanism (such as the state-of-the-art Generalized Simple Majority (GSM) rule) can achieve this. We augment the agents with "network thinking" capability to solve this single convention convergence problem. Topological features such as node degree is used to design the accumulated coupling strength (ACS) convention selection algorithm. However, ACS does not perform as well in random networks as GSM does. Hence we propose a topology aware convention selection (TACS) algorithm that enables the agents to predict their local neighborhood topology and then to select a suitable convention selection algorithm. We have performed an extensive simulation study on random and SF networks showing that the majority of the agents correctly recognize their topology and use the appropriate convention mechanism leading to the convergence into a single convention.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: *Multiagent Systems*

General Terms

Algorithms, Design, Experimentation

Keywords

Multi-agent systems, Scale-free network, Random network, Convention Selection Algorithm, Network Thinking

1. INTRODUCTION

Reaching an agreement, a convention, or a consensus, is a fundamental coordination problem in multi-agent systems [3]. In such a problem, each agent is faced with a number of plausible alternatives to choose from, and the goal is for all the agents to agree on the same alternative.

Several simple mechanisms for reaching a convention were proposed, such as social learning [2] and Generalized Simple Majority (GSM) rule [1]. GSM used a non-deterministic approach where an agent chooses a convention with a probability proportional to dominance of the convention among the agent's neighbors. It was shown experimentally and argued theoretically that agents using GSM converge into a single convention in a variety of complex networks, including Scale-Free (SF) and Small-World (SW) networks [1].

The central hypothesis in this paper is that no simple distributed mechanism (such as GSM) works well across different types of complex networks. In Section 3, we empirically show that GSM does not work in sparse SF networks (a clear contradiction with the previous work [1]). In response, we propose another simple convention selection mechanism that works well for SF networks. Our proposed mechanism is called Accumulated Coupling Strength (ACS) that only requires the agents' knowledge about their immediate local neighborhood and encodes all past interactions in agents' state to create a social pressure that expedites the convergence. We empirically confirm, in congruence with our hypothesis, that ACS does not work as well in Random Networks as GSM does. We then propose a topology-aware convention selection (TACS) mechanism that enables agents to predict the underlying network topology and to choose a suitable mechanism accordingly. TACS is fully distributed and uses information only from immediate neighbors to predict the underlying topology based on the maximum likelihood principle.

2. PROPOSED SOLUTION

We propose a convention selection algorithm (ACS) that is best suited for SF networks. However, ACS does not work as well in random networks as GSM does (we experimentally verify this in Section 3). Therefore, we propose a topology aware convention selection algorithm (TACS) that works across both SF and random networks.

Accumulated Coupling Strength: The ACS convention selection algorithm is based on a simple intuition that agents might find it beneficial to adopt the conventions of their socially influential neighbors. During initialization of the game, this social influence of an agent is captured by its Coupling Strength (CS) that is represented by its degree [4]. Therefore, initially agents with higher-degree bear large CS and are in a position to induce greater influence over their neighbors to adopt its convention. We require that the CS of each agent gets accumulated by adding the degree of its neighbor node from which it has adopted the convention. In other words, whenever a new node i adopts its neigh-

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bor j's convention, its coupling strength gets incremented by coupling strength of j with which it has coupled, i.e., $ACS_i = CS_i + CS_j$, where $CS_i <= CS_j$.

Topology Aware Convention Selection Algorithm: Algorithm 1 shows our Topology Aware Convention Selection (TACS) algorithm. The purpose of the TACS algorithm is to dynamically choose the most suitable convention selection algorithm based on the network topology. In this work, we focus on two types of topologies (random and SF) but our proposed algorithm can be extended to include other network types as needed. In random networks, the agent degrees are normally distributed and in SF networks degrees follow power-law distribution. Due to partial observability, each individual agent is not aware of the overall network toplogy. TACS first estimates the current network topology using the available local information using the maximum likelihood principle (Lines 1.2-1.9). Then TACS selects a convention using the best-suited Convention-Selection algorithm for the estimated topology (Line 1.10). The maximum likelihood principle works as follows. For the node under consideration (that is choosing a convention), it computes the probability of having a neighbor with the current degrees under different topologies. Next, the algorithm identifies the most likely topology and choose a convention selection algorithm that is most suitable for that particular topology.

Algorithm 1: Topology Aware Selection (TAS) Algorithm

input : Node n for which to select a convention, list L of topologies to consider with corresponding degree probability distribution $P_l \forall l \in L$, and a list of corresponding convention selection algorithms $A_l \forall l \in L$ that is suitable for each topology

output: Selected convention C.

1.1 **begin**
1.2 $D_n \leftarrow$ the list of degrees of the local neighborhood for Node n (including node n itself).
1.3 **for** *every topology type* $l \in L$ **do**
1.4 $S_l \leftarrow 1$
1.5 **for** *every node degree* $d \in D_n$ **do**
1.6 $S_l \leftarrow S_l \times P_l(D_n(d))$
1.7 **end**
1.8 **end**
1.9 $l^* \leftarrow argmax_l S_l$
1.10 $C \leftarrow A_{l^*}(n)$
1.11 **end**

3. EXPERIMENTAL RESULTS

We conducted extensive simulations to evaluate the performance of our proposed topology aware convention selection algorithm (TACS) on random and SF networks.

Table 1 shows the performance of the TACS in comparison with the performance of the GSM and the ACS for various size random and SF networks. We conduct 50 simulations by creating distinct instances of the networks. Each simulation consists of 1000 time steps where a time step is a single run of the program. For random networks we notice that the TACS performs as well as the GSM. Overall the difference in the performance between the TACS and the GSM in random networks is not significantly different with p-value grater than 0.05. The exceptions are the 100, 1000 and 2000 size networks where the p-values are less than 0.05. However, even in these networks both the TACS and the GSM always lead to a single convention. In contrast, the performance of the ACS and the TACS differs significantly in these random networks with p-values always less than 0.05.

Table 1: Performance of the TACS in random (RN) & scale-free (SF) networks. The (TACS/GSM) columns show the number of times each algorithm succeeded to converge into a single convention (out of 50 simulations).

Type	Size	TACS /GSM	t-test Values	TACS /ACS	t-test Values
RN	25	50 /50	t=1 p=0.322223406	50 /44	t=0.00825891 p=0.016517819
	100	50 /50	t=4.149242849 p=0.000132341	50 /20	t=-7.90979507 p=2.6252E-10
	500	49 /49	t=0.362917143 p=0.717481569	49 /1	t=-16.6143261 p=5.67608E-28
	1 x10^3	50 /50	t=12.35106344 p=1.1612E-16	50 /4	t=-18.1241733 p=2.28718E-23
	2 x10^3	50 /50	t=17.07825128 p=2.84876E-22	50 /2	t=-20.03074525 p=3.01478E-25
	5 x10^3	50 /49	t=-0.710770264 p=0.480596257	50 /1	t=-19.02586291 p=2.83241E-24
	10 x10^3	50 /49	t=-0.689176472 p=0.493962921	50 /1	t=-22.66426789 p=1.26534E-27
SF	25	34 /18	t=-3.262565143 p=0.001555407	34 /37	t=-0.056375585 p=0.955158569
	100	31 /4	t=-9.6111065 p=8.45531E-16	31 /35	t=1.380074681 p=0.170736207
	500	27 /0	t=-19.64977344 p=9.59525E-34	27 /33	t=0.789952988 p=0.431703075
	1 x10^3	16 /0	t=-14.57863053 p=6.73781E-23	16 /27	t=1.455369065 p=0.148898696
	2 x10^3	17 /0	t=-21.6798235 p=3.46767E-31	17 /34	t=2.5304794 p=0.013128434
	5 x10^3	17 /0	t=-23.47521492 p=1.15992E-30	17 /31	t=1.758085406 p=0.082023001
	10 x10^3	9 /0	t=-21.7111511 p=9.78724E-28	9 /27	t=2.629977583 p=0.009931446

In SF networks the performance of the TACS is reasonably good. The difference in the performance between the TACS and the ACS is not significant for smaller networks (size less than 2000) with p-values greater than 0.05. However, GSM performs poorly in SF networks (p-values always less than 0.05). Therefore, TACS enables the large majority of the agents to correctly predict their topology and use either GSM (for random networks) or ACS (for SF networks) that leads to the convergence into a single convention.

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