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Fast Convention Formation in Dynamic Networks Using Topological Knowledge

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Abstract

In this paper, we design a distributed mechanism that is able to create a social convention within a large convention space for multiagent systems (MAS) operating on various topologies. Specifically, we investigate a language coordination problem in which agents in a dynamic MAS construct a common lexicon in a decentralized fashion. Agent interactions are modeled using a language game where every agent repeatedly plays with its neighbors. Each agent stochastically updates its lexicons based on the utility values of the received lexicons from its immediate neighbors. We present a novel topology-aware utility computation mechanism and equip the agents with the ability to reorganize their neighborhood based on this utility estimate to expedite the convention formation process. Extensive simulation results indicate that our proposed mechanism is both effective (able to converge into a large majority convention state with more than 90% agents sharing a high-quality lexicon) and efficient (faster) as compared to state-of-the-art approaches for social conventions in large convention spaces.

Introduction

Coordination of agent activities in large multiagent systems (MAS) is central to cooperative goal achievement. A social convention is a technique for increasing coordination (DeVylder 2007; Sugawara 2011). It helps to reduce the overhead of coordination by simplifying agents' decision-making process through the determination of action choices (Walker and Wooldridge 1995). Therefore, establishing a social convention acts as a useful mechanism for deciding the dominant coordination strategy for building consensus in MAS. For example, in online social networks (such as in Facebook) creation of privacy-setting policy convention for third party applications could be useful for both the users and the app developers. It could help by tailoring apps based on the conventions and reduce users privacy risks (Hasan 2013).

Online convention formation mechanisms are suitable for large and open MAS (Delgado 2002; Pujol et al. 2005; Villatoro, Sen, and Sabater-Mir 2009; Hasan and Raja 2013). However, these mechanisms deal with a relatively simple convention space in which a global convention is chosen from two possible convention alternatives or *convention seeds*. In large and open MAS, other challenging issues need to be considered. First, multiple convention seeds may exist and hence the convention space could be complex. Second, it is possible that the existing convention seeds are not appropriate or good enough. Therefore, agents may need to create new convention seeds as well as form a higher-quality convention. Two significant mechanisms for solving this type of convention problem are described in (Salazar, Rodriguez-Aguilar, and Arcos 2010) and in (Franks, Griffiths, and Jhumka 2013)[1]. They model the MAS using complex small-world and scale-free networks. SRA uses a spreading based mechanism while FGJ augments this process by using a set of privileged agents with high-quality convention seeds. However, both approaches assume a static agent network and are unable to form a Large Majority Convention State (henceforth referred as LMCS for short) in which 90% or more agents adopt a single convention in a reasonable amount of time[2].

In this paper, our goal is to design a convention formation mechanism in a dynamic MAS suitable for large convention space that is able to overcome the limitations of SRA and FGJ. Specifically, the intended mechanism should be **(i) effective** (able to converge into LMCS as well as the quality of the most common convention is high) and **(ii) efficient** (speed of reaching LMCS is fast). Similar to FGJ, in order to validate our approach, we investigate a **language coordination problem** that captures the challenges involved in creating high-quality conventions in large and open MAS.

To study the relevance of our contribution to practical applications, we consider a large number of agents in the MAS being organized as various types of networks that include regular, random (RN), small-world (SW) and scale-free (SF) topologies. However, we emphasize the scale-free topology that is ubiquitous in social and artificial systems.

In our approach, every agent starts off with an internal lex-

[1]Henceforth these two approaches are referred as SRA and FGJ respectively.

[2]In SRA as well as FGJ, the time-period for investigating the emergence of a lexicon convention is comprised of 100,000 time-steps of the simulation. We use this duration as a definition of *a reasonable amount of time* for convergence to occur.

icon that consists of a set of concepts and randomly assigned word mappings. These agents engage in repeated and pairwise interactions with their immediate neighbors. Agents' interactions are modeled using a language game in which they send lexicons to their neighbors and update their lexicons based on the utility values of the received lexicons. We propose a topology-aware utility computation mechanism that enables the agents to use contextual knowledge to expedite the convention formation process. According to this mechanism, if agents with the largest degree in their neighborhood have a high quality lexicon, they would increase the utility of their lexicons in proportion to their degree. We use the "mass media person" metaphor from social networks in which influential individuals have stronger influence than the average person (Kim et al. 2002). We enable the socially influential high-utility-lexicon agents to bias their neighbors towards accepting their lexicons. This "network thinking" phenomenon significantly expedites the convention formation process.

To further augment this process, we use a socially-inspired technique called the *power of diversity*. In (Page 2007), it has been shown that while diversity improves organizational productivity from a social science perspective, not all diversity is useful. In fact, the benefits of diversity rests on a certain set of criteria. Agents in our work are equipped to bring diversity in the population through a novel network reorganization technique that is based on the lexicon utility. An agent stochastically removes the smallest-lexicon-utility-neighbor from its neighborhood and rewires with a randomly chosen neighbor of the removed agent. This increases the chance of getting a better-lexicon-utility-neighbor in the neighborhood and thereby improves the quality of lexicons. We show that the topology-aware mechanism along with link diversity expedites the emergence of a stable and high-quality convention.

The main contributions of this paper are:

- Equipping agents to use "network thinking" to control the dynamical process of convention formation suitable for a large convention space.
- Modeling dynamic topologies through a novel network reorganization technique.
- Forming a large majority convention much faster than the existing state-of-the-art approaches and ensuring high quality of the convention.
- Extensive experimental analysis verifying our topology-aware mechanism.

The remainder of this paper is organized as follows. First, we discuss the relevant literature in the next section and formally frame the problem of convention emergence in the subsequent section. Then we present our proposed approach, followed by an extensive computational study. Finally we conclude with a summary of our observations and discussion of future work.

Related Works

A survey of existing approaches for convention formation in normative MAS (NorMAS) is provided in (Savarimuthu and Cranefield 2011). Most of the mechanisms presented here are limited to two-dimensional convention space and static topology. One exception is (Savarimuthu et al. 2009) where the role of dynamic network topologies over norm spreading and emergence is investigated. They used a dynamic network to model the agent society. Agent interactions are captured using Ultimatum Game and a role model based mechanism is used to solve the convention problem. However, their approach is limited to just a grid topology.

A topology-aware convention selection mechanism is presented in (Hasan, Abdallah, and Raja 2014). Although this approach is based on local information, it is implemented on a two-dimensional convention space. In (Gkantsidis et al. 2007), a centralized algorithm is used to generate topology awareness among the nodes. Unlike this approach, our goal in this paper is to augment nodes with topology-awareness based on solely local information.

Unlike the above approaches, SRA and FGJ solved the convention problem for **a larger convention space**. They have used a language coordination problem for investigation in which a group of agents tries to create a lexicon convention through repeated interactions. This problem was originally inspired by Luc Steels' *Naming Game* model. In (Steels 1995), Luc Steels focused on the formation of vocabularies, i.e., a set of mappings between words and meanings (for instance physical objects). In this context, each agent develops its own vocabulary in a random private fashion and then tries to align its vocabulary with others in order to obtain the benefit of cooperating through communication.

The significance of the SRA and FGJ approaches is that they considered a large population of agents modeled using complex small-world and scale-free networks. In SRA, a sophisticated agent architecture design is proposed to create high-quality language convention. On the other hand, in FGJ a set of privileged agents (influencer agents) equipped with high-quality lexicons is deployed to influence and expedite the convention formation process. However, these approaches do not consider the costs associated with the sophisticated agent architecture design or those for the deployment and maintenance of the influencer agents. Moreover, the agent network is assumed to be static and do not converge into LMCS within a reasonable amount of time.

In our approach, we address the above mentioned limitations of the large convention space problem.

Convention Problem

First we formally define the *convention problem* that includes the following components: (a) *the interaction model* that describes the interaction topology, (b) a *language game model* that captures the agent interaction, and (c) the *convention space* that defines the number of alternative conventions. A solution to this convention problem is the one in which the MAS converges to LMCS *in a reasonable amount of time*.

The Interaction Model

The agent interactions in the MAS are purely local and are constrained by an undirected graph $G(V, E)$ where V is the set of vertices (or nodes) and $E \subseteq V$ x V is the set of edges. Each node corresponds to an agent[3]. The numbers of nodes is referred by n. Two nodes v_i and v_j are neighbors if $(v_i, v_j) \in E$. The neighborhood $N(i)$ is the set of nodes adjacent to v_i. That is, $N(i) = \{v_j | (v_i, v_j)\} \in E \subset V$ and $|N(i)|$ is the degree of node v_i. The adjacent agents (within single-hop distance) are defined as the *neighbors*. The network is dynamic in that the nodes change their edges (social ties). Even if the edge from agent A to B is removed, the edge from B to A remains.

The Language Game Model

Agent interactions are based on the FGJ language game model which is a variation of Luc Steels' original language game (Steels 1999). Steels designed a paradigm that enables artificial agents to play language games about situations they perceive and act upon in the real world and also self-organize communication systems from scratch. In FGJ, initially the agents start off with randomized internal lexicons. Each lexicon has a set of *mappings* from concepts (C) to words (W). Because of the random allocation of the concept-word mapping, some concepts may have more than one word. In other words, *synonymy* may exist in the lexicon. The game is initialized with multiple convention alternatives or convention seeds (as defined previously). Agents spread their convention seeds through repeated interactions. We assume that agents are rational and hence accept conventions with high utility values. Agents adopt high-quality conventions and continuously create better convention seeds. Finally, one high-quality seed emerges as the dominant convention in the network. A high-quality lexicon is the one that has reduced or zero synonymy.

Convention Space

We assume that the number of concepts and words are equal ($|C| = |W|$). Therefore, the size of the convention space is bounded by ($|W|^{|C|}$). Similar to FGJ, we use 10 fixed concepts and 10 words; hence the possible size of the convention space is quite large (10^{10}).

Topology Aware Convention Formation

In each round of the language game, agents perform the following four tasks: (i) Communication, (ii) Lexicon Spreading, (iii) Lexicon Update, and (iv) Network Reorganization. The first three steps are based on FGJ. We augment their approach with a more informed lexicon utility computation mechanism as well as the ability for the network to reorganize. The lexicon update model is implemented as an asynchronous process in which agents spread and update their lexicons probabilistically.

(i) Communication: Every agent chooses a random neighbor and sends one word mapping for a randomly selected concept. The communication is successful if the receiving agent uses the same mapping. The sending agent i computes its *communicative efficacy* (CE_i) as the proportion of successful communications (succComm) over the last 20 time-steps: $CE_i = \#succComm/20$. Similar to FGJ, we use 20 time-steps to facilitate empirical comparison.

(ii) Lexicon Spreading: An agent sends its partial lexicon to its neighbors with a sending probability p_{send}. Every agent has a fixed lexicon transfer length. It sends a contiguous set of mappings from its lexicon equal to this transfer length starting from a randomly selected mapping. A receiving agent that updates its lexicon using this mappings starting from the same random point.

(iii) Lexicon Update: Each agent compares the utility of all the received mappings and choose the mapping with the largest utility. An agent updates its lexicon with the mappings received from its neighbors with an update probability p_{update}.

Utility Computation Mechanism: In FGJ, an agent computes its lexicon utility by adding its communicative efficacy with its lexicon specificity. Suppose W_c is the set of words associated with that concept. For every concept c in the lexicon with $W_c > 0$, agents calculate lexicon specificity (S_c) using the formula $S_c = \frac{1}{|W_c|}$. If a concept has no words associated with it, its S_c = 0. The specificity of a lexicon is the average of the specificity of all concepts:

$$S = \sum_{c \in C} S_c/|C|, |C| > 0 \tag{1}$$

In this paper, we augment the computation of lexicon utility by adding a *topological factor*. An agent i computes the utility of its lexicon (u_i) by summing up its communicative efficacy (CE_i), lexicon specificity (S_i) and a the topological factor (TF_i) as follows:

$$u_i = aCE_i + bS_i + cTF_i \tag{2}$$

where a, b and c are constants to adjust weights of these three parameters. The topological factor is introduced as an amplifying mechanism to expedite the convention formation process. Agents with the largest degrees (higher social status) in their neighborhood and better quality lexicons (high-quality seeds) are assigned large values for their topological parameter which increases their lexicon utility. As a consequence these high-degree nodes are able to influence a large number of agents to adopt their conventions quickly. *Our hypothesis is that within a local neighborhood, some agents would have larger connections (higher influence capability) and these agents could be empowered to strongly influence their neighbors to adopt the better quality lexicons that they have*. This would significantly enhance the speed of convention formation and improve the quality of the dominant lexicon.

Algorithm 1 describes the computation of the topological factor. Agents with the largest degree in their neighborhood and with lexicon specificity greater than or equal to a threshold value (α) set their topological factor to be the value of their degree (Lines 1.2 - 1.3). This increases the lexicon utility of the largest degree agents and thus these agents expedite the convention formation process. However, it is possible that initially the largest degree agents may not have lexicons with high specificity. Therefore, in order to facilitate these agents to adapt high-quality lexicons, any agent with

[3]Throughout the paper, we use agent and node interchangeably.

Algorithm 1: Topological Factor Computation

Require: Initially Topological Factor for all agents is zero.

1.1 **for** *each agent* i*:= 1 to* n **do**
1.2   **if** *LargestDegreeinNeighborhood(*i*) AND LexiconSpecificity(*i*)* $\geq \alpha$ **then**
1.3   TopologicalFactor(i) = Degree(i)
1.4   **end**
1.5   **if** *LexiconSpecificity(*i*)* $\geq \lambda$ **then**
1.6   TopologicalFactor(i) = μ
1.7   **end**
1.8 **end**

lexicon specificity equal to or above a threshold value (λ) is enabled to set its topological factor to be equal to a very large number (μ) as described in lines 1.5 - 1.6. These agents then influence their neighbors, including the larger-degree agents, to adapt the high-quality lexicon mappings in fewer time-steps. Once the larger degree agents acquire a high-quality lexicon, they start influencing their larger neighbor base as in lines 1.2 - 1.3.

(iv) Increased Diversity through Network Reorganization: Individual agents are capable of making rational choices to remove and rewire a link; and thereby increase the diversity in their neighborhood. Our assumption is that by removing the lowest-lexicon-utility neighbors and then by rewiring to randomly chosen neighbors beyond their neighborhood, agents can improve the chance of increasing their lexicon specificity by having neighbors with potentially better quality lexicons (Perc and Szolnoki 2008; Fu et al. 2008). In other words, this *link diversity* contributes to the creation of better convention seeds that results in facilitating high-quality convention formation. With a given probability, an agent removes an existing link with a neighbor with the lowest lexicon utility. However, it will do so only if its own lexicon utility is larger than its lowest-lexicon-utility neighbor. This is to ensure that an agent will not remove neighbors (including the lowest-lexicon-utility neighbor) that happen to have better lexicons than itself. The agent then rewires with a randomly chosen neighbor of its removed neighbor. This *conditions* the diversity in the network (unlike an unconditional random diversity). It is assumed that (a) only a small number of agents would take part in network reorganization and (b) only one neighbor would be removed to add a new neighbor. This way the total number of links can be maintained at a constant level and the degree-distribution of the nodes would remain unchanged. Since the network is bi-directional, removing an edge from agent A to B does not remove the edge from B to A.

If agent A is selected for rewiring, it chooses the edge with its lowest lexicon quality neighbor B for removal and to rewire with one of B's neighbor with a probability given by the Fermi function (Pacheco, Traulsen, and Nowak 2006) $p = [1 + e^{-\beta(u_A - u_B)}]^{-1}$. The parameter β controls the intensity of selection in that for larger values ($\beta \to \infty$) the edges of the lower lexicon-utility agents are *deterministically* removed and rewired to a randomly selected neighbor of the removed agent.

Algorithm 2: Topologically Aware Algorithm

2.1 **for** *each agent* i*:= 1 to* n **do**
2.2   randomLexiconAssignment()
2.3   sendOneMappingToRandomNeighbor()
2.4   computeCommunicativeEfficacy(#succComm/20)
2.5   computeLexiconSpecificity(Equation 1)
2.6   computeTopologicalFactor(Algorithm 1)
2.7   computeLexiconUtility(Equation 2)
2.8   probabilisticLexiconSpreadingtoNeighbors()
2.9   probabilisticLexiconUpdate()
2.10   networkReorganization()
2.11 **end**
2.12 iterate (Lines 2.1 - 2.10)

Algorithm for Convention Formation Mechanism

Algorithm 2 describes the distributed convention formation mechanism. This algorithm is executed by individual agents. Initially mappings for the lexicons are randomly assigned among the agents. Then each agent sends one random mapping to a randomly chosen neighbor and computes both its communicative efficacy and lexicon specificity (Lines 2.2 - 2.5). Each agent then computes its topological factor and lexicon utility (Lines 2.6 - 2.7). Then each agent probabilistically spreads its partial lexicon and updates its lexicon (Lines 2.8 - 2.10). This process repeats (Lines 2.1 - 2.10) over multiple rounds and a majority lexicon convention emerges.

Simulation and Results Analysis

We conduct simulations to compare the performance of two state-of-the-art lexicon convention formation mechanisms (SRA & FGJ) with our topology-aware (TA) mechanism on various types of networks including regular (Ring), small-world (SW), random (RN) and scale-free (SF) networks

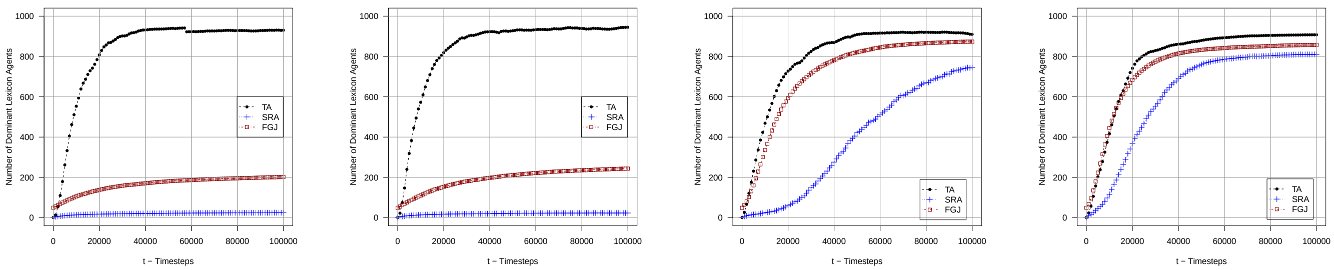
The dominant lexicon convention is defined as the one that is shared by the largest number of agents.

The following metrics are used for comparison:

- **Effectiveness:** A mechanism is defined to be effective if it is able to converge into a LMCS within a reasonable amount of time.
- **Efficiency:** This parameter measures how fast a network converges into a LMCS.
- **Dominant Lexicon Specificity (DLS):** It represents the lexicon specificity that belongs to the dominant convention. DLS helps to understand how lexicon specificity of the dominant convention evolves (improves) over time.
- **Average Communicative Efficacy (ACE):** It provides a measure of the average communicative efficacy of the system. ACE is used to understand the level of coordination of the system at each time-step.

Simulation Setup

We conduct experiments on four topologies: Ring, SW, RN and SF. Watts and Strogatz small-world model is used



(a) Ring (b) Small-World (c) Random (d) Scale-Free

Figure 1: Comparison of the number of dominant lexicon agents for the topology-aware (TA) approach with SRA and FGJ.

to create SW networks (Watts and Strogatz 1998). The rewiring probability is set to 0.1 (similar to SRA and FGJ). SF topologies are generated using the Barabasi-Albert model (Barabasi and Albert 1999).

Each type of network consists of 1000 agents represented as nodes in the network. An edge between two nodes of the network indicates that the agents can interact and play the language game. The average node degree in these networks are set to 20 for the purpose of comparison with the two baseline state-of-the-art approaches.

Similar to FGJ, initially the internal lexicon of every agent is set with 10 fixed concepts and a randomized mapping of one or more words (from a set of 10 words) for each concept. Due to random assignment of the words to the concepts, some concepts initially may not have any word associated with them. We ignore these concepts during the computation of the specificity for each concept. The simulation proceeds according to Algorithm 2. For the computation of the lexicon utility, similar to FGJ, the three parameters of equation 2 (CE, S & TF) are equally weighted (i.e., a = b = c = 1). We anticipate that for larger degree nodes, the value of TF would be very high so that having a larger weight for CE and S would not have much effect. For smaller degree nodes, TF is assumed to be zero; and only CE and S contribute towards utility computation. The spreading and updating probabilities are set to 0.01. Only 10% of the agents are randomly selected to take part in network reorganization using the Fermi function in which the value of β is set to 1.0.

Table 1 provides the setting of the threshold levels of the parameters for the TA mechanism. α is set to be greater than or equal to 0.95 and λ is equal to 1.0. It enables the largest degree agents in any neighborhood to exert influence (by increasing their topological factor) only when their lexicon specificity is equal to or above 0.95. However, any agent (including the smaller degree agents) can increase its topological factor when its lexicon specificity is optimum. For the calculation of the topological factor, μ is set to a large number 1000.

For implementing FGJ mechanism, 50 influencer agents are randomly deployed in the network, as in the original FGJ. These agents start off with a unique lexicon in which every concept has a single word mapping (lexicon specificity is optimum, i.e., equal to 1.0).

All the results reported are averages over 50 realizations for each network. Each simulation consists of 100,000 time-steps where a time-step refers to a single run of the program.

Table 1: Parameter Values for Simulation Configuration.

	α	λ	p_{send}	p_{update}
TA	≥ 0.95	$= 1.0$	0.01	0.01
SRA	N/A	N/A	0.01	0.01
FGJ	N/A	N/A	0.01	0.01

Table 2: Performance Comparison: %ACC refers to % of agents converged into a convention at timestep t. ACE & DLS are reported at 100,000 time-step.

	Ring				Small-World			
	%ACC	t	ACE	DLS	%ACC	t	ACE	DLS
TA	80	18757	0.94	0.88	80	1837	0.94	0.87
	90	29323	0.96	0.88	90	30222	0.97	0.88
SRA	80	X	N/A	N/A	80	X	N/A	N/A
	90	X	N/A	N/A	90	X	N/A	N/A
FGJ	80	X	N/A	N/A	80	X	N/A	N/A
	90	X	N/A	N/A	90	X	N/A	N/A

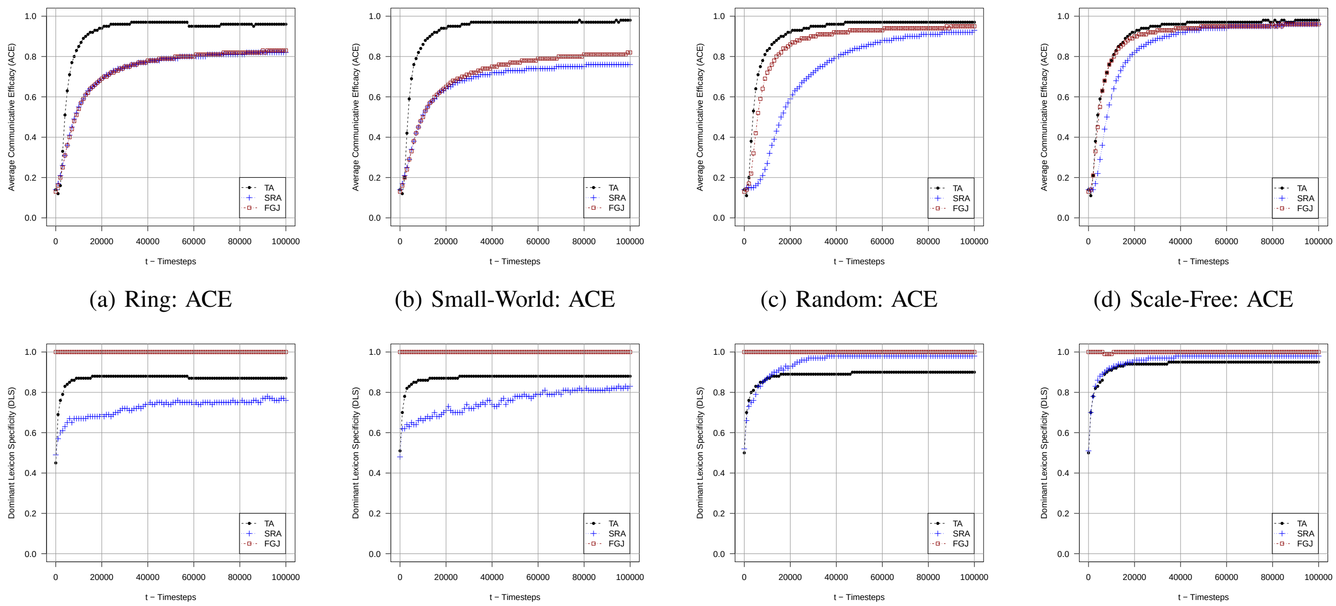
	Random				Scale-Free			
	%ACC	t	ACE	DLS	%ACC	t	ACE	DLS
TA	80	27549	0.94	0.89	80	24375	0.94	0.94
	90	47595	0.97	0.90	90	68111	0.97	0.95
SRA	80	X	N/A	N/A	80	70660	0.96	0.98
	90	X	N/A	N/A	90	X	N/A	N/A
FGJ	80	43961	0.92	1.0	80	35500	0.96	1.0
	90	X	N/A	N/A	90	X	N/A	N/A

Simulation Results

Convergence to LMCS & Speed of Convention Formation

Figure 1 shows how dominant convention agents evolve over time for TA, SRA and FGJ over Ring, SW, RN and SF topologies respectively. We observe that TA clearly outperforms the two state-of-the-art approaches in all four network types. A combination of the topology-aware lexicon-utility computation and link diversity enables 90% agents to converge into a single convention much faster than SRA and FGJ over these topologies.

Table 2 shows that SRA and FGJ fail to converge into LMCS in RN and SF networks within 100,000 time-steps. SRA requires as many as 70,660 rounds for 80% agents to use the dominant lexicon in SF networks which it fails to do in RN topologies . On the other hand, TA requires 24,375



(a) Ring: ACE (b) Small-World: ACE (c) Random: ACE (d) Scale-Free: ACE

(e) Ring: DLS (f) Small-World: DLS (g) Random: DLS (h) Scale-Free: DLS

Figure 2: Comparison of the evolution of average communicative efficacy (ACE) & dominant lexicon specificity (DLS) in four topologies. The values are averaged over 50 separate instances of simulation.

time-steps to have 80% agents to use a common lexicon in SF networks and 27,549 time-steps in RN networks. We observe similar poor performance in case of FGJ that requires 35,500 time-steps to have 80% agents to use a common lexicon in SF networks and 43,961 time-steps in RN networks.

The performance of SRA and FGJ is worse in Ring and SW topologies. SRA enables less than 25 agents to form a single convention over these two topologies; and using FGJ less than 250 agents converge into a single convention within 100,000 time-steps. Both in Ring and SW networks, degree-heterogeneity is much less compared to RN and SF networks. As a consequence the spreading based approaches of SRA and FGJ require longer convergence time to LMCS. On the other hand, TA mechanism enables agents to use their social influence to bias their neighbors to adopt conventions at a faster rate. Moreover, according to TA, if an agent has perfect lexicon, it increases the utility of its lexicon to strongly influence their neighbors. In addition to this, link diversity through network reorganization increases the chance of having better-lexicon-quality-neighbors. This explains the accelerated spreading of the high quality lexicon in the TA mechanism.

Average Communicative Efficacy (ACE) & Dominant Lexicon Specificity (DLS)

In all four topologies, the ACE is better for TA than SRA and FGJ (see Figure 2). It indicates the level of coordination is high when agents use TA mechanism. We discussed previously that the TA empowers the agents with perfect lexicons to expedite the convention formation process. Also link diversity helps to improve the chance of creating better lexicons. However, the DLS in FGJ is better than TA. The reason is that FGJ has the advantage of initializing a fraction of the agents with the optimum quality lexicon that bias the rest of the network to adopt their (perfect) lexicon.

Conclusion and Future Work

In this paper, our goal is to design a mechanism that is able to create a social convention within a large convention space for MAS operating on various types of dynamic networks. We hypothesize that if agents are endowed with the capability of "network thinking" and are enabled to use contextual knowledge for decision-making, the convention formation process becomes faster and efficient. To validate this hypothesis, we used a language coordination problem from FGJ for investigation. In this problem domain, a society of agents construct a common lexicon in a decentralized fashion. Similar to FGJ, agents' interactions were modeled using a language game where agents send their lexicons to their neighbors and update their lexicon based on the utility values of the received lexicons. We presented a novel topology-aware utility computation mechanism that enabled the agents to reorganize their neighborhood based on this utility estimate to expedite the convention formation process. A key idea here is that agents with the most influence (larger connections) in the network are harnessed to adopt the best lexicons in the neighborhood and to quickly influence the agents in their network to adopt the high-quality lexicons. Extensive simulation results indicate that the proposed mechanism is both effective (able to converge into a large majority convention state with more than 90% agents sharing a high-quality lexicon) and efficient (faster) as compared to SRA and FGJ.

As future work, we plan to vary the number of hub agents (zero to many) as well as the distance of the agents with the best lexicon to the hub agents and investigate the effectiveness of our approach.

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