TOPOLOGY-AWARE APPROACH FOR THE EMERGENCE OF SOCIAL NORMS IN MULTIAGENT SYSTEMS

by

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ABSTRACT

MOHAMMAD RASHEDUL HASAN. Topology-aware approach for the emergence of social norms in multiagent systems. (Under the direction of DR. ANITA RAJA)

Social norms facilitate agent coordination and conflict resolution without explicit communication. Norms generally involve restrictions on a set of actions or behaviors of agents to a particular strategy and can significantly reduce the cost of coordination. There has been recent progress in multiagent systems (MAS) research to develop a deep understanding of the social norm formation process. This includes developing mechanisms to create social norms in an effective and efficient manner. The hypothesis of this dissertation is that equipping agents in networked MAS with "network thinking" capabilities and using this contextual knowledge to form social norms in an effective and efficient manner improves the performance of the MAS. This dissertation investigates the social norm emergence problem in conventional norms (where there is no conflict between individual and collective interests) and essential norms (where agents need to explicitly cooperate to achieve socially-efficient behavior) from a game-theoretic perspective. First, a comprehensive investigation of the social norm formation problem is performed in various types of networked MAS with an emphasis on the effect of the topological structures on the process. Based on the insights gained from these network-theoretic investigations, novel topology-aware decentralized mechanisms are developed that facilitate the emergence of social norms suitable for various environments. It addresses the convention emergence problem in both small and large conventional norm spaces and equip agents to predict the topological structure to use the suitable convention mechanisms. It addresses the cooperation emergence problem in the essential norm space by harnessing agent commitments and altruism where appropriate. Extensive simulation based experimentation has been conducted on different network topologies by varying the topological features and agent interaction models. Comparisons with state-of-the-art norm formation techniques show that proposed mechanisms facilitate significant improvement in performance in a variety of networks.

DEDICATION

To my father. I know he can see me...

And

To Rayeeda Abantika, my niece. She came into this world when I started this journey. She will continue after I stop.

ACKNOWLEDGMENTS

Most of the words and ideas that are presented in this dissertation are mine but these are the outcome of fruitful and enlightening interactions with many people over the past three years. First of all, I would like to acknowledge debt to my adviser Dr. Anita Raja, whose role in my life is more than an academic adviser. Without her, it wasn't possible for me to come up to this stage. The beauty and value of doctoral research is that it enables one to embark on a journey into a "road not taken" previously. This journey requires a great deal of internal courage as well as external support. Anita has been the source of incessant support for me throughout. She helped me to grasp the core issues in Multiagents systems as this course was not offered in past couple of years in UNC Charlotte. Although the primary premise of my research is Multiagent systems, I transgressed its boundary and strayed into other domains for a while before I could develop my own course. During this time Anita stood by my side and extended her unfaltering support. A PhD students need for intellectual guidance is most often met by the adviser, but seldom one gets the opportunity to pursue independent ideas no matter how quirky those may appear initially. I am fortunate that I received full cooperation from Anita to practice intellectual independence. I am particularly grateful to her for providing me the opportunity to attend the top-tier academic conferences in past two years. I can hardly underscore the significance of my experience gleaned from these conferences for shaping my thoughts that culminated into this dissertation. I worked mostly alone in the Distributed Artificial Research (DAIR) lab, but I don't regret because Anita was with me. We made a fruitful collaboration. It was worth.

My greatest intellectual experience in past three years is to learn about the disciplines of Network Science and Complex Systems. I will remain ever grateful to Dr. Mirsad Hadzikadic for introducing me to these fascinating and profound ventures of human thought. This dissertation builds on the knowledge and tools from these two disciplines. Our email conversations spanning more than two years would always remind me of this exciting intellectual journey. It is no exaggeration to state that without Dr. Mirsad my time at UNC Charlotte would have been a little more than ordinary.

I am indebted to Dr. Mohamed Shehab for giving me the opportunity to do research with him. Our joint venture resulted into a nice work on decentralized social networks, an area that is not addressed by many. We also collaborated writing a grant proposal on privacy conventions in online social network. I am enriched by the research skills that he taught me. He can germinate new ideas into one's mind and can inspire to pursue that.

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Jill Morgan, Office Manager of the Software and Information Systems Department at UNC Charlotte, made my life easier by patiently resolving the scholarship related issues in every semester. It helped me to solely concentrate on my research. I extend sincere gratitude to her. She is a wonderful person. Also I convey my gratitude to the Graduate Student Support Specialist ever-smiling Doralyn Bradely.

My mother maintained her online presence in my life almost every day since I left home. She offered a world full of happiness and color to me. I owe only one thing to her. My life.

My youngest sister, Charlene, took care of my mother during this time, otherwise I couldn't have peacefully concentrated on my research. The elder one, Anne, used to bring back the recollections of our collective childhood. She knows the secret of my happiness. These two sisters are the apple of my eye.

Suparna vowed to assist me in every possible way to successfully complete my dissertation; it was not part of her nuptial vow though! A new phase of our great friendship began since I started my doctoral research. During this time, she lived two lives: her own and mine. She experienced the agonies and ecstasies of my research as much as I did. This dissertation bears the sweet memories of her love and sacrifice.

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Working on doctoral research being far away from home country and dear ones is particularly a challenging task. I wish I could anticipate my debt to each person who contributed directly or indirectly towards the fulfillment of my dissertation. Also I wish I could thank the countless Maple and Dogwood trees, the restless squirrels, the geese and fire-flies during their nocturnal ritual around the UNC Charlotte campus that never failed to offer me the warmth of home and made my journey joyful. I wish I knew their names!

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CHAPTER 1: INTRODUCTION

Social norms are expectations of an agent about the behavior of other agents in society. They involve imposing restriction on a set of actions or behaviors of agents to a particular strategy. By adhering to a social norm, agents are able to achieve coordination and resolve conflicts without explicit communications. Social norms can reduce the uncertainty and complexity, and increase the reliability of the system [53, 68]. They help to reduce coordination overhead through simplifying agents' decision-making process by prescribing action choices in specific situations [78]. For example, by forming social norms, agent behavior can be regulated in an efficient manner in virtual societies such as electronic institutions [17] and agent-supported virtual enterprises [18]. Also, coordination and conflict resolution in the emerging field of social services computing [36] and ad-hoc sensor network applications [5] can be achieved efficiently by creating social norms. Therefore, establishing a social norm acts as a useful mechanism for deciding the dominant coordination strategy and facilitating consensus.

Open and dynamic Multiagent systems (MAS) require a social norm formulation approach that is distributed and evolves to adapt to changes in the environment. Unlike social systems in which the objective is to understand and predict the population level behavior based on empirically supported interaction rules (e.g., emergence and evolution of languages [46] or opinion formation [11]), artificial societies require participants to use mechanisms that give rise to fast and efficient convergence to a global norm. Therefore, designing mechanisms suitable for dynamic and large-scale MAS is the main concern of this dissertaion.

1.1 Motivation

With the increase of the number of users in online social networks (in March 2014 Facebook reported to have 802 million daily active users on average[1]) and growing interest in virtual communities for entertainment, business, commerce and socio-political reasons, the issue of norm emergence or global consensus formation in a decentralized fashion has become more topical [60, 38, 22]. We discuss three application scenarios below that underscore the importance of understanding and developing norm emergence mechanisms in virtual societies.

Motivating Application 1: Data on online social networks have great commercial value to marketing companies, competing networking sites and identity thieves. With the emergence of new web technologies, public developers are able to interface and extend the online websites services as applications (for example, in Facebook). Proposing a fine-grained access control model for controlling application access to the online social network user data does not solve the problem of extension vulnerabilities. This is because users might deny all the permissions or deny a subset of the permissions, thereby rendering the app non-usable. Moreover, it would be difficult for the app developers to design apps based on these diverse policy preferences. Therefore, it would be preferable for the users to reach a consensus on a preferred set of privacy

[1] http://newsroom.fb.com/company-info/

settings or *privacy conventions* so that the app developers could easily design their apps to target these small number of privacy conventions [27]. For example, users with conservative privacy inclinations [33] would align with a group of other users in their neighborhood that share the similar preferences. It would enable the users to select exactly one from the set of privacy profiles instead of specifying their preference for each of the requested permissions. This would ensure security with minimum user intervention as well as allow the users to enjoy the advanced app features.

Motivating Application 2: In *collaborative tagging systems*, such as Flickr, del.icio.us, CiteULike or Connotea, human web-users self-organize a system of tags to create and maintain social networks for sharing information [13]. This categorization system is useful for navigating through a large and heterogeneous body of resources. The existing works that are grounded in real tagging sites indicate the significance of developing deeper mechanisms for understanding the complex statistical behavior of the tagging dynamics. The key problem that requires deep investigation is: how does microscopic tagging activity of users result in the emergence of global categorization/convention in a decentralized fashion and how could such categorization formation be made faster?

Motivating Application 3: In the social networking and microblogging site Twitter[2], a common way of adding additional context and metadata to the short text messages or tweets is by using *hashtags*. It is a community-driven activity to create conventions. Hashtags are similar to tags used in Flickr. These are added inline to the tweet posts. It is a simple way for users to search for tweets that have a common topic.

[2] https://twitter.com/

Unlike traditional tagging systems used for information archival, Twitter hashtags can serve either as a label for identifying topically relevant streams of message or a prompt for commenting and sharing. Hashtags are more than labels for contextualizing statements, objects for bookmarking, or channels for sharing information. They are active virtual sites for constructing communities. Hashtags are used both as a topical identifier (e.g., #samsunggalaxy) and a symbol of a community membership (e.g., #worldforpeace) [39]. During the "Arab Spring" and other protests, activists used hashtags to coordinate their actions. There are several issues regarding hashtagging in Twitter that require deeper understanding, such as: how the use of novel hashtags co-evolve with the needs of their users in the presence of other hashtags? Why do some hashtags persist while others are just momentary blips? How do similar hashtags compete for attention? Why do users adopt some hashtags while reject others?

The issues and questions discussed in relation to the above three application scenarios motivate us to formulate the central research question in this dissertation which is to *understand the process of norm emergence in virtual societies and to develop agent-based mechanisms to make such emergence faster and effective.* The problem of norm emergence in these virtual societies characterized by large size, dynamic structure and complex network properties (e.g., degree-distribution in Facebook follows power-law form [12]), require an understanding of the structural properties of these systems and the effect of these properties on the process of norm formation. While the problem of norm emergence is not new in MAS, formulating the problem within the space of virtual societies enables this research to break novel ground in computer science research. Our initiative is inspired by John Hopcroft's remark on the importance of creating a scientific base for understanding the dynamics of the emerging large systems for which the existing tools in computer science are not sufficient[3]. The research goal of this dissertation is to perform a systematic and detailed investigation of the norm emergence problem in virtual societies. To do this, we develop a framework that captures the core research challenges of these real-world applications and uses a multiagent simulation based approach to investigate the various dimensions of the problem.

1.2 Problem Description

The study of the collective behavior of agents that includes social norm emergence in social and artificial systems has recently witnessed a burgeoning body of literature emphasizing the topological properties of these systems [21, 10]. These approaches consider the agents (social or artificial) to be situated on the nodes of connected graphs and their interactions are captured through the edges among the nodes. It has been observed that many of these agent networks exhibit complex network properties such as heterogeneity in the connectivity pattern, short path-length, high clustering and assortativity [42]. Therefore, it is our belief that *Network Science* is the natural framework for investigating the emergent global behavior of these systems. Advances in the understanding of complex networks have made it possible to investigate the potential implications of the topological properties of the networks on various dynamical processes including social norm formation in networked MAS.

[3] "Future Directions in Computer Science Research", WI-IAT keynote address, Atlanta, Georgia Nov. 19, 2013.

A rich stream of MAS research is devoted to the investigation of the influence of agent social network of interactions on the evolution of the norm emergence process [31, 19, 53, 76, 68, 56, 75, 1, 23]. Due to agent's partial observability of their neighborhood in networked MAS, norm propagation and adaptation becomes challenging. The existing mechanisms include various strategy update rules and social instruments to create norm in MAS organized as different types of networks (see Figure 1). Some researches make a strong claim that some networks are supposed to be better than others for promoting norms. For example, scale-free topologies are more efficient than small-world topologies for norm emergence [19, 23]. Many of these works use narrow investigations (with limited and fixed network parameters settings) to derive such generic conclusions. However, if we dig deeper into this issue, we observe that the performance of the scale-free networks significantly differs with the variation of topological properties of the network. For example, the algorithm [19] that claims the performance superiority of scale-free networks in general has been shown to fail in sparsely-connected scale-free networks [28]. Also, problems where an agent's preference over an action/norm is in conflict with the social welfare, highly-connected scale-free MAS networks are shown to be the most detrimental for cooperation (norm) formation [47]. Therefore, in many cases it is misleading or even false to claim that some topologies are in general better than other topologies. These observations motivate us to extensively investigate the role of network topology on the process of norm emergence. More specifically, we intend to investigate: which parameter configurations of a specific topology facilitate efficient norm formation and under what conditions?

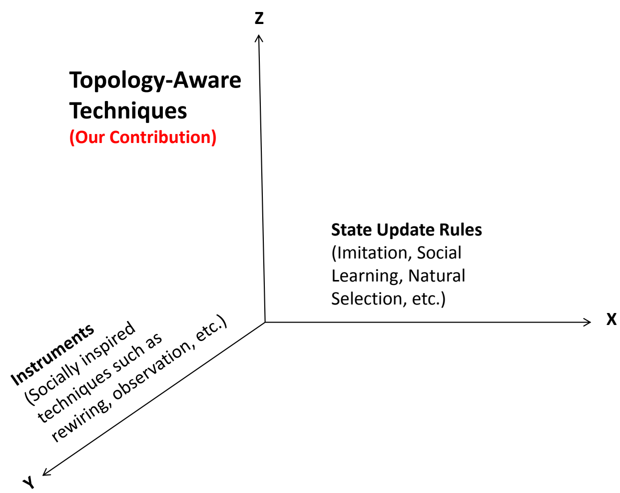


Figure 1: Mechanism design landscape.

While there have been some works that study the influence of network topology on norm creation, there is a lack of effort to harness the topological knowledge gained from these studies into the agent's decision-making process. To the best of our knowledge, *none of the existing mechanisms use topological insights to facilitate topologically-aware decision-making*. In open and dynamic MAS where the local neighborhood topology of the agents continuously changes, it is imperative for agents to adapt their norm emergence mechanisms and include topology-awareness in their decision-making process. Moreover, the knowledge that Network Science offers on the relationship between the topological properties and the dynamical processes can be used by the agents to make the norm emergence mechanisms more efficient.

To summarize, the central theme of this work that crosscuts a conglomerate body of research concerning norm emergence is the enhancement of this process by endowing the agents with topology-awareness (Figure 1). For informed decision making, agents are enabled to use the knowledge that is hidden in the topological structure of their neighborhood. Therefore, they are endowed with the capability of "network thinking". This includes the ability of agents to (i) predict of the global topological structure of the network based on local agent neighborhood data and use convention formation mechanisms suitable for that network topology, (ii) leverage social influence based on the degree-distribution of the agent neighborhood to augment norm formation, (iii) use the best possible network formation parameters to facilitate norm convergence. *The main hypothesis of this dissertation is that equipping agents in networked MAS with "network thinking" capability facilitates the emergence of social norms in an effective and efficient manner.*

1.3 Overview of the Approach

Previously we argued that sparsely-connected scale-free networks do not favor convention emergence [19] while the same network configurations are ideal for cooperation emergence [47]. This apparent contradiction leads us to identify another dimension of the norm emergence problem namely different types of agent interactions in MAS.

In his work [74], Villatoro used a taxonomy of social norms that is based on Coleman's categorization [16]. We use Villatoro's taxonomy that splits the general problem of social norm emergence into two categories from a game-theoretic perspective: conventional norms and essential norms (Figure 2). These two categories differentiate the inherent challenges present in each type of interaction and formulate suitable mechanisms.

In conventional norms[4], a group of agents tries to decide to adopt a behavioral

[4] Henceforth this is referred as conventions.

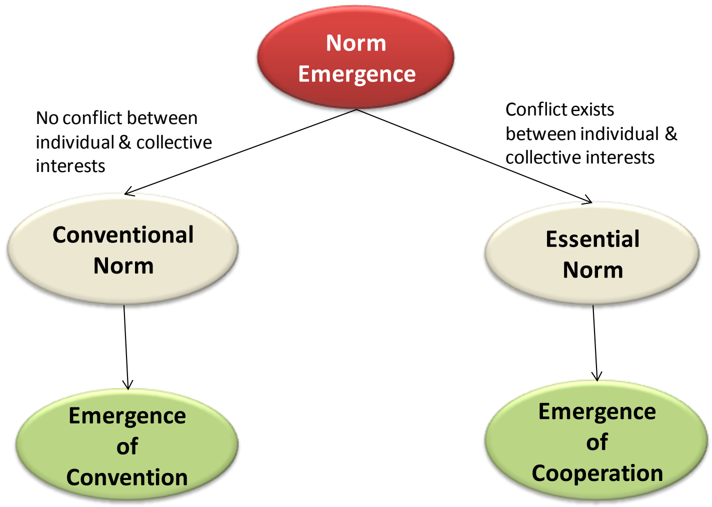


Figure 2: Villatoro's taxonomy for the norm emergence problem.

strategy from a given set [74]. There are no good reasons to prefer one strategy over the other and even the collective selection is arbitrary. It assumes no conflict in interest between the individual and the collective interests. Typically this type of problem is modeled using a pure-coordination game in which two equally beneficial convention alternatives exist [19], i.e., the available convention space is small. We also investigate convention emergence problems that involve large convention spaces. A special type of game, i.e., language game, is used to model these large convention space problems [23].

Essential norms, on the other hand, try to resolve conflicts between the individual and collective interests in applications where the individual and collective goals can be widely different [74]. It is applicable for scenarios in which individuals do not have incentives for cooperation. Formation of essential norms enables agents to cooperate and thereby achieve socially-efficient behavior. Similar to Villatoro's work, we approach the the problem of essential norm formation in the light of the *"Emergence* *of Cooperation"*. The Prisoner's Dilemma game captures the inherent social dilemma between the individual and the society and hence is used to model the emergence of cooperation problem.

In this dissertation, we investigate the problem of *convention emergence* within the space of conventional norms and *cooperation emergence* within the space of essential norms in the context of a MAS (Figure 2). Agents in the MAS can be organized as regular, random, small-world or scale-free networks. We consider both static and dynamic networks. In a dynamic network the links between the agents change over time while in static networks links remain unchanged.

We perform an especially detailed investigation of scale-free networks. In scale-free networks the node degree follows power-law distribution independent of the scale of the network, a feature suitable for large-scale MAS. Also the scale-free structure is robust against self mutation and environmental perturbation. Many real-world networks from biological to artificial domains, such as protein interaction networks, Internet, World Wide Web, etc., display similar scale-free property [8, 9]. Unlike many previous approaches, we distinguish the challenges inherent in different types of scale-free networks and perform an exhaustive investigation. For example, we address the challenges of norm emergence in sparse, moderate, and densely-connected scale-free networks. Also we investigate scale-free networks with various levels of clustering.

We adopt a network-theoretic approach towards the norm formation problem. This approach aims to develop a comprehensive understanding of the problem of social norm formation in various types of networked MAS with an emphasis on the effect of the topological structures on norm formation process (Figure 3). We investigate two

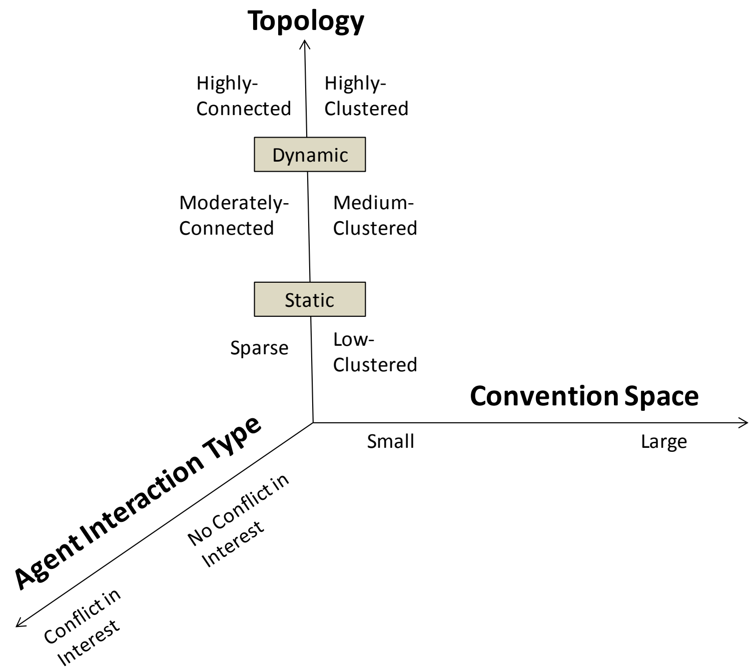


Figure 3: Norm emergence landscape.

types of agent interactions that include situations with no conflict in interest among the agents (conventional norm) and conflict in interest (essential norm). For conventional norm, both the small and large convention space is considered. In our work, small convention spaces have exactly two convention alternatives while large convention spaces have three or more alternatives. For example, in our language convention problem we considered a convention space of size 10^{10} (Chapter 3). Then, based on the insights gained from network-theoretic investigations, we develop novel topology-aware mechanisms that in conjunction with socially-inspired techniques facilitate the emergence of social norms suitable for various environments. We emphasize the ability of the agents in networked MAS to adopt *"network thinking"* capability to form social norms in an *effective* (a large majority of the society converges into a stable norm) and *efficient* (fast convergence) manner.

1.4 Research Goals

Since we address the problem of social norm emergence from two perspectives, we require different set of tools to solve the problems. Therefore, for the sake of clarity, we distinguish two sets of research goals for the two categories of norm.

Research Goals Set 1 - Emergence of Convention: We plan to explore the problem of emergence of convention both in small and large convention space (Figure 4). Following are our research goals with respect to these two convention spaces:

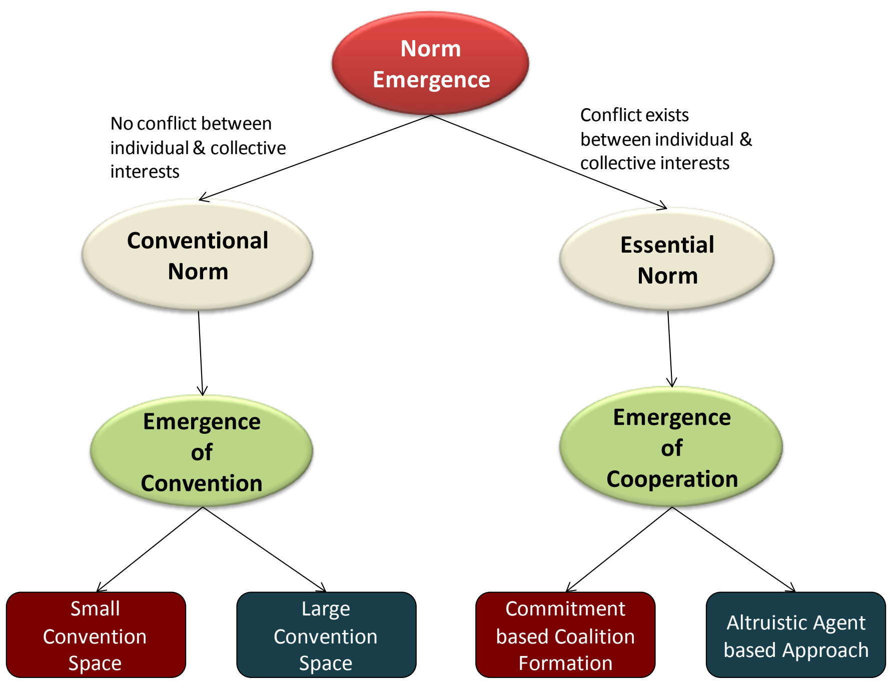


Figure 4: Research goals for convention and cooperation emergence.

Small Convention Space:

- RG1: We will investigate whether the existing simple distributed mechanisms are able to create a convention across various topologies. If not, then we need to figure out which mechanisms work across which networks or whether new mechanisms are needed to be designed for a particular topology. Due to the small size of convention space, we will not consider the time efficiency of the mechanism and will only focus on its solvability.

- RG2: We will identify the convention formation related challenges inherent in various types of scale-free networks (various average degree networks) and propose an efficient technique to resolve that.
- RG3: We plan to design a topology-aware meta reasoning process that enables agents to predict the topology of the network and automatically apply the suitable convention formation mechanism for that topology.

Large Convention Space:

- RG4: With the increase of the size of convention space, the problem becomes complex and requires more time and resource to converge into a single convention. Therefore, the key challenges of large convention space are to form conventions faster and to ensure that the quality of the emergent convention is high. We plan to design a topology-aware mechanism that is able to create a high-quality convention fast as compared to the state-of-the-art mechanisms.
- RG5: Unlike small convention space, existing approaches did not consider dynamic networks in large convention space. Therefore, we plan to implement a dynamic network model in large convention space that augments convention emergence process.
- RG6: We intend to identify the challenges of convention formation over different types of scale-free networks.

Research Goals Set 2 - Emergence of Cooperation: We address the emergence of cooperation problem for MAS that are organized as scale-free networks. Our literature review on this topic (in Chapter 2) indicates that the existing mechanisms are able to form cooperation in scale-free networks with only *limited success* when the networks are sparsely connected (average node degree is small) [29]. Moderate and highly-connected scale-free networks remain mostly unexplored domains for cooperation emergence. We plan to design two mechanisms to solve this problem (Figure 4). The first mechanism (discussed in Chapter 4.1) uses commitment based dynamic coalition formation technique and complex network dynamics to form cooperation in *moderately-connected* scale-free networks (where the average node degree is 20). The second mechanism (discussed in Chapter 4.2) considers *highly-connected* scale-free networks (where the average node degree is up to 50) and uses heterogeneous system design that includes a small fraction of altruistic agents. Following are our research goals with respect to these two mechanisms:

Dynamic Coalition Formation:

- RG7: We plan to build a dynamic coalition formation approach based on the topological features of the agent scale-free network. More specifically, we want to enable the agents to reason about the commitment based coalition formation using the topology of the network. Our goal is to both analytically and empirically establish the correlation between the coalition formation process and the scale-free network topology.
- RG8: We will investigate how the agents can self-organize the network of their neighborhood such that it augments the global coalition formation. We will

build a computational model to design an appropriate partner selection strategy for the agents that results in the emergence of a single coalition. This computational model will exhaustively investigate the process of coalition formation by varying the model parameters of scale-free networks such as minimum node-degree, degree-heterogeneity and clustering coefficient.

Altruistic Agent Based Approach:

- RG9: We plan to design a heterogeneous system design approach based on altruistic agents to establish cooperation.
- RG10: We will investigate exhaustively the efficacy of the altruistic agent based approach by varying the model parameters.

1.5 Contributions

The problem of social norm emergence in MAS spans across multiple dimensions and the existing works have covered only a fraction of this challenging terrain [63, 78, 31, 19, 53, 61, 20, 41, 76, 68, 56, 75, 1, 23]. Some of the relevant works are reviewed in Chapter 2. While these approaches offer useful mechanisms for creating norms, often times over-simplified assumptions limit the applicability of the solutions in real-world domains. For example, many works consider the MAS to be a static system [23] or consider fixed parameter settings for network investigation to arrive at a general conclusion [19]. This dissertation contributes to the existing gaps in the state-of-the-art approaches by exploring two dimensions of the norm emergence landscape (Figure 3). In the mechanism design landscape, our proposed novel topology-aware approach adds a new dimension to the space previously consists of strategy update rules and socially inspired instruments (see Figure 1). Our main contributions, C1 - C3, cover the two social norm categories: convention emergence and cooperation emergence. The first contribution involves convention emergence while the last two are on cooperation emergence:

C1: Topology-Aware Mechanisms to Facilitate Convention Emergence

We accomplish the research goals RG1-RG6 by proposing topology-aware (TA) mechanisms that enable agents to adopt "network thinking" to form conventions both in small and large convention space. For problems involving small convention space, we argue that no existing single simple distributed mechanism can create convention across various topologies. This hypothesis is both analytically and experimentally verified. We identify that while the existing state-of-the-art mechanism claims to form conventions across small-world, random and scale-free networks, it actually fails to resolve the stable sub-convention problem in sparse scale-free topologies. We propose a novel socially inspired technique to solve the convention emergence problem in sparse as well as in dense scale-free networks. The need for recognizing the neighborhood topology has been emphasized in order to use suitable convention mechanisms. A topology-aware convention selection mechanism is proposed that solves the convention emergence problem across both random and various types of scale-free networks.

In order to address the problem within a large convention space, we design a topology-aware mechanism that is able to create a social convention on various types of dynamic networks. We hypothesize that if agents are endowed with the capability of "network thinking" for decision-making, the convention formation process becomes faster and efficient. To validate this hypothesis, we use a language coordination problem for investigation. According to this problem, a society of agents construct a common lexicon in a decentralized fashion. Agents' interactions are modeled using a language game in which agents send their lexicons to their neighbors and update their lexicon based on the utility values of the received lexicons. A topology-aware utility computation mechanism is proposed that enables the agents to expedite the convention formation process. Moreover, to further augment this process, a socially-inspired technique, the *power of diversity*, is used. Agents are enabled to bring diversity in the population through a novel network reorganization technique that is based on the lexicon utility. 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). In addition to this, the efficacy of the topology-aware mechanism is tested by varying the topological features to develop an understanding about how the topology influences convention formation process. The conditions under which diversity brings benefit are also investigated.

C2: Emergence of Cooperation using Commitment based Dynamic Coalition Formation and Complex Network Dynamics

This contribution accomplishes research goals RG7-RG8. In order to achieve the emergence of cooperation in self-interested agent societies operating on moderately-connected scale-free networks, agents are enabled to control topological features during the network formation phase. Based on an extensive investigation of complex networks dynamics, agents are endowed with the "network thinking" capability for informed decision-making. A commitment-based dynamic coalition formation approach is proposed that results in a single coalition where agents mutually cooperate. Agents play an iterated Prisoner's Dilemma game with their immediate neighbors and offer commitments to their wealthiest neighbors in order to form coalitions. A commitment proposal, that includes a high breaching-penalty, incentivizes opponent agents to form coalitions within which they mutually cooperate and thereby increase their payoff. We argue analytically, and substantiate experimentally, how the value of the penalty should be set with respect to the minimum node degree and the payoff values such that convergence into optimal coalitions is possible. Using a computational model, we determine an appropriate partner selection strategy for the agents that results in a network facilitating the convergence into a single coalition and thereby maximizing average expected payoff.

C3: Emergence of Cooperation in Highly-Connected Networks Using Altruistic Agents

We achieve the research goals RG9-RG10 through this contribution. We investigate the importance and challenges of establishing cooperation among self-interested agents in MAS operating on highly-connected scale-free networks that are prevalent in society and nature. Existing imitation-based approaches for cooperation do not fare very well in these highly-connected networks. We proposed a stochastic influencer altruistic agent (StIAA) mechanism in which a small proportion of altruistic agents are introduced in the self-interested MAS. These altruistic agents, irrespective of their payoff, always cooperate with their neighbors while the self-interested agents try to maximize their payoff by imitating the wealthiest agents in their neighborhood. To determine optimality of their action choices, the self-interested agents imitate the cooperative action of their altruistic neighbors (should there be one) with a small exploration probability. We show, both analytically and experimentally, that StIAA performs significantly better in highly-connected networks than the existing imitation-based approaches. A comprehensive study of the performance of StIAA shows that it is both robust and scalable.

1.6 How to Read this Dissertation

This dissertation is structured in five chapters that includes:

Chapter 2 provides a background discussion and review of related literature on the convention emergence and cooperation emergence problems. It scans the existing body of works that tried to solve these problem in a decentralized fashion. While following the progress made in this line of research, it identifies some of the gaps and limitations that are addressed in the next two chapters.

Chapter 3 defines the convention emergence problem suitable for small convention space first. It presents an argument on why any single distributed mechanism is unable to create convention across various topologies and substantiates this with an analytical discussion. It hypothesizes the need for topology prediction by the agents. A socially inspired technique for convention formation in various types of scale-free networks is presented followed by a topology-aware convention selection mechanism. Results from extensive computational investigation supports the tenets of the proposed mechanism. Then follows the mechanism on large convention space. It hypothesizes that equiping agents with “network thinking” capability would augment the convention formation mechanism. It uses a lexicon convention problem to validate the proposed approach. A topology-aware mechanism is used to solve the problem and the comprehensive simulation results are compared with the existing state-of-the-art mechanisms. Detailed network-theoretic investigations are performed to understand how various degree-distribution and network reorganization approaches influence the convention formation process.

Chapter 4 identifies the importance of solving cooperation emergence problem in both moderately and highly-connected scale-free networks. It presents two mechanisms for solving the problem. First mechanism provides a commitment-based dynamic coalition formation technique. A theoretical analysis, substantiated by an extensive computational investigation, on the relationship between the commitment parameters and the network properties is discussed. It also equips agents with "network thinking" capability to control network formation and thereby to enhance a single coalition formation for better cooperation. Second mechanism solves the cooperation problem in highly-connected scale-free networks using a heterogeneous system design technique in which a small fraction of altruistic agents are used. A comprehensive simulation validates the robustness and scalability of this approach.

Chapter 5 draws conclusions of various research efforts implemented in this dissertation. It also identifies some of the directions in which this research could evolve in future.

CHAPTER 2: RELATED WORK

This chapter presents a discussion of related literature on the convention and co-operation emergence problems respectively. It also aims to clearly identify the goals of this dissertation with respect to the problem of convention emergence that are in the next two chapters.

2.1 Review of Related Literature on Convention Emergence

Coordination of agent activities in large multiagent systems (MAS) is central to cooperatively achieving goals. A social convention is considered to be a technique for increasing coordination [20, 68]. It helps to reduce the overhead of coordination by simplifying agents' decision-making process through the determination of action choices [78]. For example, in online social networks (such as in Facebook) creation of privacy-setting policy convention for third party applications could be useful for the both the users and app developers. It could help by tailoring apps based on the conventions and reduce users privacy risks [27]. Also the mechanism for predicting conventions in online communities (such as in Twitter) could be useful for understanding various socio-political phenomena [14, 32].

The distributed convention emergence mechanism has been used to understand, predict and create conventions in large structured systems including online social networks [14, 32, 27]. There exist copious amounts of literature that provide useful tools to solve this type of convention emergence problem [63, 78, 31, 19, 53, 61, 41, 76, 68, 56, 75, 1, 23]. The first MAS-based decentralized approach to the problem of the emergence of convention solely through local interaction was addressed by Shoham and Tennenholtz [62, 63, 64]. They undertook the challenge of designing an appropriate strategy update function as a representation of the agents decision-making process that when followed by the entire society would bring global coordination. They modeled the agent interactions using a 2-dimensional pure coordination (Pure-CG) and Prisoners Dilemma (PD) game. Their proposed strategy update function called Highest Cumulative Reward (HCR) rule that uses a reinforcement learning approach. According to HCR, agents choose the strategy that yielded the highest reward in the past m interactions. The approach is memory intensive since it stores information on the history of strategies and the associated rewards. The significance of this strategy update rule is that when it is followed by the entire society, it converges into a global convention. The authors have shown that the convention emergence is affected by the rate of strategy update and interval between memory flushes. The contribution of their work to the field lies in the fact that it demonstrated how agents strategy update rule that is based on local information can lead to self-coordination from initial disorder. However, the agents in their model are able to communicate with any other agents and their interactions are random. In other words, they did not consider a structured agent society.

Kittock [31] was the first researcher to investigate the impact of the agent society structures on convention emergence. He also used Pure-CG and PD to model agent interactions and a variation of the HCR strategy update function. He observed that the choice of the global structure affects the evolution of the convention. In particular, he conjectured that the diameter of a network is directly related to the rate of convergence. His experimentation was limited to regular and fully-connected networks.

In 1995, Walker and Woolridge [78] modeled the convention problem based on a Hunter-Gatherer society. According to this model, agents are enabled to move around the space and can choose a rule from a set of four rules. They proposed a simple intuitive strategy update function called the Simple Majority Rule that is based on the strategy of the majority in an agents neighborhood. They experimented with seven variations of this strategy with a small number of agents on a grid topology. The proposed simple majority rule brings 100% convergence at a faster rate due to the agent's ability to move around the grid

The realm of complex networks was first investigated by Delgado [19]. He used HCR as well as proposed the Generalized Simple Majority (GSM) strategy update function that is a stochastic version of Walker and Woolridges Simple Majority Rule. By modeling agent interactions using Pure-CG, he has shown that both GSM and HCR successfully converge into a 90% convergence state in complex networks (scale-free and small-world) as in fully-connected networks. In other words, he proved that a global convention can be reached at a lower cost (average degree in complex networks is smaller than that in fully-connected networks). Also he observed that convergence rate is slower in small-world networks than scale-free networks. He confirmed Kittocks conjecture that the rate of convergence is proportional to the diameter of the network. However, GMS fails to create a single convention in sparse scale-free networks.

The works discussed above that use Pure-CG to model agent interactions do not distinguish between the quality of the convention alternatives. Pujol et al. [53] varied the utility of the alternative conventions in a 2-dimensional CG. He experimented with two types of networks: low-clustered (random and SF) and high-clustered (SW and fully-connected). He observed that high-clustered system always converged to the most efficient convention (pareto-efficient) and that convention is stable.

Different types of multiagent learning algorithms were extensively studied by Sen and Airiau [61]. Instead of trying to select the appropriate strategy update function, agents use a social learning mechanism, that is similar to the one used by Shoham and Tannenholtz, in which they learn convention concurrently over repeated private interactions with randomly selected members from the society. They experimented with three reinforcement learning algorithms and studied the influence of the population size, the set of possible actions and the heterogeneity of the population on convention emergence. In addition to attempting to marry between convention emergence and multiagent learning, they contributed by investigating the impact of fixed-strategy and non-learning agents on the convention process. However, their agent society didn't have any structure and any agent potentially could interact with any other agent in the society. Mukherjee et al. [41] extended their work by investigating the impact of the neighborhood size on convention formation using a grid topology. Moreover, they investigated the effect of heterogeneous learning populations on the speed and nature of norms that emerge through social learning. They have shown that such distributed and individual learning is indeed a robust mechanism for evolving stable social norms.

None of the previous works investigated convention formation in *dynamic networks* except Walker and Woolridge. Another notable exception is the work done by Savarimuthu et al. [59] in which 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. In their work, the network of the agents dynamically changes as they move in a grid world. The authors show that this dynamic aspect facilitate 100% convergence into a single convention.

In the works discussed thus far, agents choose actions or strategy update functions based on its utility. Urbano et al. [73] used the *weight* of the agents to bias the decision-making process. The weight of the agents is defined based on a measure of *force*. The proposed strategy update function *Recruitment based on Force with Reinforcement* (RFR) enables agents to increase their force with successful interactions. However, in unsuccessful interactions, agents with lower force copies the force and strategy of the winner. According to RFR, agents first compare its force with its interaction partner. If the interaction partner's force is larger than the agent's force, it adopts both the convention and the force of its partner by increasing the force a factor of one. The force attribute should not be considered as the strength of an individual agent because as it diffuses through imitation it no more belongs to any agent. Instead it represents the force of the strategy the agent is adopting. The more the strategy is diffused, the more it will have stronger representatives. This approach performs well across random, regular, small-world and scale-free networks. However, Urbano et al. does not associate the force attribute of an agent with its position in the network (social status).

To expand the scope of the social learning, Villatoro et al. [75] use two social instruments, viz. rewiring and observation, to enhance the emergence of convention. Rewiring allows agents to control the links they share with other agents by replacing them intelligently. This direct control of the topology of the social network allows agents to control whom they interact with, resulting in increased reward without actually altering the reward function. On the other hand, observation allows agents to obtain partial information of the convention emergence process by observing other agents in the neighborhood. They used a *2-person m-action* game to model agent interaction and three strategy selection rules, such as Best Response Rule (BRR), Highest Cumulative Reward Rule (HCRR) and Memory Based Rule (MBR). They identify that the meta-stable convention states or sub-conventions prevent the formation of full convention because of the existence of stable barriers at frontiers. This phenomenon of sub-conventions is referred as *frontier effect*. In order to eliminate this frontier effect, agents are enabled to acquire partial global view (observation) and control over selecting interacting partners (rewiring). However, their work does not discuss the cost of using social instruments.

Abdallah [1] solves the problem of frontier effect by adopting an alternative technique to enable the agents to have a global view of the state of the system. It uses a hierarchical coordinator based scheme to overcome the frontier effect and establishes full convention without requiring topological reconfiguration. Agents are grouped into clusters being monitored by a coordinator and the clusters are organized hierarchically. Coordinators in each cluster recommend conventions for their clusters. Leveraging the hierarchical structure, the inconsistencies among the different coordinators are resolved. It uses a *2-person m-action* pure coordination game for agent interaction and Q-learning method to select actions. In this work, agents of a cluster acquire partial global view through the coordinators that observe the state of convergence of other clusters. The random hierarchical cluster formation scheme, however, does not take into account the effect of underlying topological constraints and the cost of communication between the coordinator and the cluster members.

The space of alternative conventions discussed in the above works is limited only to two dimensions and these works can be broadly categorized as searching in a small convention space for a global convention chosen from two possible convention alternatives. However, in large and open MAS, other challenging issues need to be considered. First, multiple convention alternatives may exist and hence the convention space could be complex. Second, it is possible that the existing convention seeds are not appropriate or of better quality. 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 provided in Salazar et al. [56] and Franks et al. [23]. They investigated a language coordination problem where a group of agents tries to create a lexicon convention through repeated interactions. This problem is inspired by Luc Steels' Naming Game model [65]. Luc Steels focused mainly 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. But agents are forced to align their vocabularies in order to obtain the benefit of cooperating through communication. Thus, a globally shared vocabulary emerges as a result of local adjustments of individual word-meaning association. The communication evolves through successive conversations, i.e., events that involve a certain number of agents (two, in practical implementations) and meanings. The agent society that plays the naming game is composed of a small number of agents and lacks any structural framework. Moreover, the scalability of this approach has not been investigated.

The significance of the Salazar et al. [56] and Franks et al. [23] approaches is that they consider large population of agents modeled using complex small-world and scale-free networks. In Salazar et al., a sophisticated agent architecture design is proposed to create high-quality language convention. On the other hand, in Franks et al., a set of privileged agents (influencer agents) equipped with high-quality lexicons are deployed to influence and expedite the convention formation process. However, these approaches do not reason about the costs associated with the sophisticated agent architecture design to those for the deployment and maintenance of the influencer agents. Moreover, the agent network is assumed to be static and requires a long time to converge into a large majority convention state.

The above discussion on related literature reveals lack of attention in the following areas: (1) although agents use smart strategy update functions and various instruments to expedite the speed of convergence, no work seems to leverage the topological knowledge for intelligent decision-making; (2) a rigorous and extensive study on all types of complex networks with variation of topological-parameters is missing; (3) there is no silver bullet to solve the convention problem; different mechanisms are needed for different environments with varying topologies, interactions etc.; therefore, there is a need for the agents' ability to predict the topology in which they are situated and then to use the most suitable mechanism; (4) there is a lack of extensive research on dynamic networks and finally (5) a deeper investigation on mechanisms for larger convention space is required.

2.2 Review of Related Literature on Cooperation Emergence

Essential norms cover the space of social norms that aims to resolve collective action problems in which there exists conflicts between individual and collective interests. In this type of problem, individuals are tempted not to contribute towards the common goal and their individual behavior may affect the welfare of the society. This conflict between the individual and the collective interests can be resolved by creating a social norm of cooperation. Therefore, formulating the problem as a *cooperation emergence* problem captures the characteristics of the essential norm problem. Here we present a discussion of related literature on the emergence of cooperation problem.

There has been a great deal of interest in the MAS community about the emergence and maintenance of cooperation among artificial agents. One of the challenging questions addressed is to design autonomous systems in which agents work together to achieve common shared goals. Traditionally the tension between personal and social goal is modeled by the Prisoner's Dilemma (PD) game. The PD game offers a powerful metaphor for understanding the challenges of the emergence of cooperation in the face of myopic selfish behavior. In PD, selfish and rational agents try to maximize their utility while interacting with each other. In a one-shot version of this PD game, the only dominant strategy equilibrium is defection which is not Pareto-efficient [45].

For cooperation to emerge, agents need to play the PD game repeatedly and use suitable strategy update functions. Axelord [7] has shown that the "tit-for-tat" strategy facilitates cooperation when PD game is played repeatedly among two agents. However, in unstructured MAS, repeated random interactions do not guarantee the evolution of cooperation [29]. Nowak [43] argues that in well-mixed populations solely natural selection based strategy update functions do not facilitate cooperation. He provided five rules or mechanisms that along with natural selection helped to emerge cooperation.

Unlike well-mixed populations, in structured societies where agents interact only with a sub-set of the population, socially inspired strategy update functions has been shown to emerge and sustain cooperation. Nowak and May [45] successfully used a simple deterministic imitation based strategy update function (imitate-best-neighbor or IB) on grid topology in which agents imitate the strategy of their best performing neighbors including itself (those who has the largest aggregate payoff from the PD game). Santos et al. [58] used a stochastic version of this imitation-based strategy update function (stochastic-imitate-random-neighbor or SA) to achieve cooperation on moderately-connected SF networks. According to this stochastic imitation rule, for each agent i one neighbor j is chosen randomly. Then if j's payoff is larger than i's payoff, i imitates j's strategy with a probability. SA increases the final fraction of cooperators with the heterogeneity of the degrees. However, these strategy update functions do not always guarantee cooperative behavior in structured MAS, nor do they establish full cooperation. Moreover, these imitation based approaches fail to facilitate cooperation in highly-connected scale-free networks [47, 29].

One significant approach towards solving the cooperation problem in highly-connected scale-free networks used the evolution of social network of interactions as well as the evolution of strategies [49]. These two evolutions follow different time-scales and it has been shown how this variation could affect the process of cooperation evolution. However, the cost of link rewiring is not included in the payoff calculation of the agents.

To solve the problem of evolution of cooperation with the goal of establishing full cooperation, several coalition formation mechanisms have been proposed. The dynamic coalition formation approach that is reviewed here differs from the existing coalition/team formation approaches in the MAS research community. Coalition/team formation mechanisms require the agents to consider all other agents in the network making the process computationally intractable for large networks [54, 24]. Moreover, their agents are constrained to stay in a coalition until the goals of the coalition are accomplished. While these works emphasize the design of negotiation protocols and efficient task distribution, the goal of the following works is to promote cooperation at the network level.

Salazar et al. [55] used a single coalition emergence approach for achieving full cooperation in MAS structured as complex networks. Using Axelrod's tribute/tax framework, they developed a centralized leader based coalition formulation model over complex networks where the agents pay an amount of tax to the leaders in order to join a coalition. They have shown that their distributed information sharing consensus mechanism effectively reduces the tax rate imposed by the leader. However, both the leader tax collection and information sharing require maintenance of network-wide multi-hop communication which would incur overhead cost. Moreover, they did not investigate the variation of topological features and its impact on their algorithms, and considered the underlying network as a pre-established, fixed configuration and static platform.

Peleteiro et al. [51] developed a similar coalition formation approach for enhancing cooperation over complex networks. Agents use learning automata techniques to adopt appropriate actions. After joining a coalition agents decide their actions towards the coalition members and the outsiders using a centralized voting method. However, no analysis of the voting method is given and hence it's not clear whether it is a centralized or decentralized scheme. Also the independent agents require to keep histories of their previous actions, but the impact of memory size is not analyzed.

Han et al. [4] used commitment to facilitate the emergence of cooperation in a population of agents that play non-iterated PD game. They have used a variant of the PD payoff matrix is defined to incorporate the penalty and commitment management cost and thereby to provide sufficient incentives for the agents to consider the advantage of mutual cooperation. Their work is based on an unstructured population with random interactions among the agents that use a social learning model and mutation for strategy adaptation. However, they did not consider the effect of their approach in iterated PD game and the role of network topology.

The impact of the topological features of complex networks on the emergence of cooperation has been studied by a band of physicists in the framework of evolutionary game theory. Santos et al. [57] has shown that the heterogeneous degree distribution in scale-free networks affects the cooperative behavior significantly. However in the context of social systems there are other topological features that need to be considered, e.g. impact of average degree, degree-degree correlation, clustering coefficient etc. The impact of average degree is tested on the scale-free, small-world and random networks by Tang et al. [71], and it has been shown that the outcome of the PD game is affected by the average degree of networks as the density of cooperators reaches its peak at specific values of average degree. The effect of high clustering over scale-free networks has been studied by Assenza et al. [6] where each node plays a PD game with its neighbors, and it is observed that cooperation can be significantly enhanced when clustering coefficient of the network is very high. Vukov et al. [77] has shown that if the players of the PD game over scale-free networks are endowed with basic cognitive abilities, such as the ability to distinguish their partners by remembering their last action, they could adopt reactive strategies by taking into account the past actions of the neighbors to establish high level of cooperation. This mechanism isolates the defectors and converts them into cooperators. But this approach requires memory-enabled agents and incurs extra cost.

The above topology-based works investigates only the domain of static complex networks. These networks are neither dynamic, nor they change/grow over time. Poncela et al. [52] studied the emergence of cooperation using a network growth model that is based on an evolutionary preferential attachment algorithm. The fitness of each node is defined as proportional to the accrued payoff from the PD game. New nodes are preferentially linked with the high fitness existing nodes and play the PD game with its neighbors accordingly. The resultant network is shown to be heterogeneous with the scale-free property. This work provides a useful understanding about how the microscopic dynamics could lead to the co-evolution of the structure and the macroscopic behavior of the SF network. However, the emergence of full cooperation seems to be impossible if the payoff for the temptation to defect is larger than the payoff for the reward.

The above research makes room for further investigation in the following directions: (1) both the coalition formation and commitment based approaches do not extensively study the impact of the variation of the topological features on cooperation emergence; for example, it needs to be investigated how the cost associated with the commitment based approach, such as penalty, is related to the topology of the network; (2) highly-connected complex networks pose challenge to emerge and sustain cooperation and the only existing approach relies on expensive rewiring mechanism; therefore, it is important to figure out a less-expensive solution for highly-connected networks (3) a more realistic system-design approach could be pursued to complement the strategy update functions for cooperation formation; for example, instead of using a homogeneous agent society, it would be interesting to investigate the impact of heterogeneous agents (that may include both self-interested and altruistic agents) on cooperation emergence.

CHAPTER 3: EMERGENCE OF CONVENTION

In a convention emergence problem, typically agents have to choose conventions from a set of convention alternatives or *convention seeds*. Hence, the size of the convention space could be small or large. In this chapter we present two mechanisms for convention emergence suitable for both small and large convention spaces respectively.

3.1 Topology-Aware Mechanism for Small Convention Space

3.1.1 Research Goals

Convention emergence problems for small convention space is typically modeled using pure-coordination game [63, 78, 31, 19, 53, 61, 41, 76, 68, 1]. In this type of problem, agents has two convention alternatives to choose from.

Previously we discussed (in Chapter 2) that although the state-of-the-art Generalized Simple Majority (GSM) mechanism [19] claims that it is able to form a single convention in scale-free and small-world networks, it fails to do so across all types of scale-free networks. This motivates us to propose a simple distributed mechanism that works across all types of scale-free networks. Our hypothesis is that no single distributed mechanism is able to form convention across all topologies. Therefore, it is important to design a mechanism that enables the agents to first recognize their global topological structure and then to choose a suitable mechanism for convention convergence for that particular topology.

To summarize, we emphasize the significance of employing "network thinking" by the agents to control their dynamics (choosing appropriate convention-selection mechanism) and the dynamical processes of the network (convention emergence).

We set the following sub-goals with regard to the emergence of convention in small convention space (EC-SCS) to achieve research goals RG1 - RG3 that we outlined in Chapter 1(page 12):

- EC-SCS1: Show that the existing state-of-the-art mechanism (that is the Generalized Simple Majority (GSM) mechanism) [73, 34] fails to form convention over sparse SF networks. This enables us to establish our hypothesis that no simple distributed mechanism, such as GSM, works across all types of networks.
- EC-SCS2: Design an efficient mechanism that forms convention in sparse as well as all types of scale-free networks.
- EC-SCS3: Design a topology-aware meta mechanism that enables the agents to predict the global topological structure of their network based on local neighborhood information and use suitable convention selection algorithms.

3.1.2 Problem Formulation

A formal definition of the *convention problem* includes the following components: (a) *the interaction model* that describes the interaction architecture, (b) a *coordination game model* that captures the agent interaction, and (c) *the information propagation model* that specifies the amount, type and direction of information exchange. A solution to this convention problem is the one in which a large majority of the agents converge into a single convention *in a reasonable amount of time.*

3.1.2.1 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), $E \subseteq V$ x V is the set of edges and n is the number of nodes. Once the graph or the network is formed by the agents, it becomes fixed. 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*.

Two types of graphs are used for investigation, (1) Barabasi-Albert (BA) model of scale-free network [8] and (2) random network. In future, other graph types can be considered.

3.1.2.2 The Coordination Game Model

The agent interactions are captured by a *2-person, 2-action* symmetric coordination game. This game is used to model a small convention space. Every agent is equipped to play this game with each one of its neighbors and their interactions are represented by the network links. The agents start playing the coordination game after the network is formed and the final network is considered as a closed system.

Every agent either chooses convention X or convention Y while playing the game with each one of its neighbors. Therefore, the *convention space* consists of two alternative conventions: X or Y. A social convention is reached when a large majority of the agents choose either X or Y convention consistently. The game is *perfect but incomplete information based* so that the agents do not know the payoff of their neighbors but are able to see the current conventions of their neighbors.

In a *2-person, 2-action* coordination game setting these two conventions intersect at four possible outcomes represented by designated payoffs: R_{XX} and R_{YY} for both adopting the same convention; and R_{XY} and R_{YX} for adopting different conventions. The payoff matrix is represented by Table 1. A *pure coordination game* is used that satisfies the following payoff conditions: $R_{XX} = R_{YY} = +1$ and $R_{XY} = R_{YX} =$ -1. Therefore, while reaching a convention is profitable, agents do not distinguish between the quality of the two conventions.

Table 1: Payoff matrix for the coordination Game

	X	Y
X	(R_{XX})	(R_{XY})
Y	(R_{YX})	(R_{YY})

3.1.2.3 Information Propagation Model

A spreading-based mechanism is used for the information propagation model because of its appealing speed of reaching a convention [19, 53]. In these spreading-based approaches, agents propagate some characteristics (conventions) over the members of the society to influence them to adopt it. Agents have access to the state of the current conventions of their neighbors. Neighbors provide this information when an agent makes such request. From real-world applications perspective, this assumption seems feasible. For example, in online social networks, participants are able to see their neighbors conventions [27]. The communication channel is assumed to be error-free. Since the agent communication is limited only within their local neighborhood, the cost associated with their communication is not considered.

3.1.2.4 GSM's Failure in Scale-free Networks

In this Subsection the previous theoretical argument that GSM leads to the convergence into a single convention in SF networks is disproved.

Theorem 1. *For any undirected random scale-free graph the Generalized Simple Majority (GSM) action update rule does not always lead the network towards a single convention.*

Proof. Theorem 1 is proved by using a counter example that negates the theoretical argument in [19] and establishes the claim made in Theorem 1.

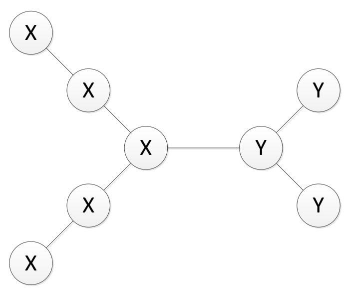


Figure 5: Small SF network.

Figure 5 shows a small SF network of 8 agents in which the minimum node degree is 1. Agents play a pure coordination game with their immediate neighbors and update their actions using the GSM rule. Figure 5 captures a snapshot of the convention evolution process where 5 agents adopted convention X and 3 agents adopted convention Y. As long as the network follows GSM, the two middle nodes would not change their current conventions in a reasonable amount of time. Therefore, it can be noticed that a stable barrier exists between the two middle nodes that is preventing the convergence into a single convention. In this type of setting, emergence of a single convention is not guaranteed as two sub-conventions may emerge concurrently and remain stable. The existence of stable barriers that prevents the emergence of a single convention is referred as *frontier effect* [75, 1]. Sparse SF networks such as this in Figure 5 where minimum node degree is 1 might occasionally experience the frontier effect and GSM is unable to resolve this problem. Therefore, in any undirected SF network the GSM does not always guarantee the emergence of a single convention.

It is also noted that the analytical evidence in [19] to prove GSM's effectiveness in SF networks relies on a strong assumption of the *homogeneity condition*. This assumption implies that the two conventions (X and Y) are uniformly distributed among the neighbors of each agent. Although it is generally true for complete and random networks, in sparse SF networks it does not hold because of the highly skewed degree-distribution and very low connectivity (as illustrated in Figure 5). This means the analysis of the mean-field equation in [19] does not guarantee convergence in sparse SF networks or in general SF networks that suffer from the frontier effect.

□

To address the limitation of the GSM, a convention selection algorithm for SF networks that includes sparse SF topologies is presented in the next section. However, this convention selection algorithm does not work as well in random networks as GSM does (this observation is experimentally verified this in Subsection 3.1.4). Therefore, in Subsection 3.1.3 a topology-aware convention selection algorithm (TACS) is proposed that works across both SF and random networks.

3.1.2.5 Accumulated Coupling Strength

In human society, people often prefer to join social cliques that is most beneficial to them. By joining the clique they inherit the status that the members of the clique maintain. The ACS convention selection algorithm is inspired by this social phenomenon. We assume 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 [76]. Therefore, initially agents with higher-degree have large CS and are in a position to induce greater influence over their neighbors to adopt its convention. Agents with lower CS value imitate their larger CS neighbors. When an agent adopts the convention of its largest CS neighbor, its own CS gets accumulated (that we refer as the Accumulated Coupling Strength or ACS) by adding the degree of all the agents that belong to the same convention in that subnetwork. This enables every new agent that adopts the convention of the subnetwork to inherit the social influence (with a large value of ACS) of that subnetwork. However, this ideal ACS requires every node to have global knowledge about the degree of every other node which is usually not feasible in distributed networks. Hence a fully distributed and approximately efficient variation of the ideal ACS is presented, as follows.

It requires that the CS of each agent gets accumulated by adding the degree of the its neighbor node from which it has adopted the convention. In other words, whenever a new node i adopts its neighbor j's convention, its coupling strength gets increased by the addition of the coupling strength of j with which it has coupled, i.e.,

$ACS_i = CS_i + CS_j$, where $CS_i <= CS_j$.

Therefore, even though initially only agents with large ACS could induce their conventions to their comparatively low ACS neighbors, as the game proceeds their coupling influence is propagated beyond their immediate neighborhood with the increase of their neighbors' ACS. This gradual accretion of the precedent builds up a social pressure that makes the emergence of a single convention possible.

We now provide a theoretical justification on why the Accumulated Coupling Strength (ACS) algorithm performs better in SF networks.

The ACS encodes the history of all previous influences and thereby acts as a social pressure to promote a specific convention. While a regular and homogeneous distribution may allow many equally strong social pressures to exist and sustain, the highly skewed degree-distribution of SF networks reduces the the chance of emerging multiple social pressures and aids convergence into a single convention.

In SF networks there are few high-degree nodes that influence their low-degree first-hop neighbors to adopt their conventions. As a consequence, the ACS values of these first-hop neighbors would be larger than that of their source-of-influence high-degree nodes. Therefore, these neighbors, with their accrued large ACS values, would propagate their influence (their conventions) in their respective neighborhoods. Due to the existing age-correlation among the high-degree nodes [8], a single convention gets propagated over the entire network.

Algorithm 1: Topology-Aware Convention Selection (TACS) 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**

3.1.3 Topology-Aware Convention Selection Algorithm

Algorithm 1 shows the 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. Due to partial observability, each individual agent is not aware of the overall network topology. The algorithm is executed from an agents perspective and we assume that the entire population simultaneously execute this algorithm. TACS first estimates the current network topology based on the available local information and using the maximum likelihood principle (Lines 1.2 - 1.9). Since the agents only use the degree-distribution information of their immediate neighbors, we assume that the cost associated with memory usage would be small and we ignore it. 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 neighbor with the current degrees under different topologies. Given that, identify the most likely topology and choose a convention selection algorithm that is most suitable for that particular topology.

We anticipate the possibility of making prediction error by the agents. However, the idea of this approach is to maximize the probability of identifying the right topology given the limited view an agent has. Increasing the agent view to more than one hop will decrease the chance of error at the expense of more overhead (cost of memory and processing would increase). Thus the agents are restricted to see the degree of their single-hop neighbors.

This work focuses on two types of topologies (random and scale-free) but the proposed algorithm can be extended to include other network types if needed. In what follows we provide the techniques for the calculation of the degree-distribution probabilities for both types of topologies.

Random Network: In random networks, the agent degrees are normally distributed and in SF networks degrees follow power-law distribution. Computation of the normal distribution function is trivial. For a given agent's degree x, the normal distribution is defined as following:

$$P_{random}(x) = \frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

The parameter μ in this formula is the mean of the degree-distribution. The parameter σ is its standard deviation; its variance is therefore σ^2.

Scale-Free Network: In scale-free (SF) networks, the degree-distribution of the nodes follow power-law form. The probability distribution for a quantity x that follows power-law can be represented as

$$P(x) \propto x^{-\alpha}$$

where α is a constant *scaling parameter*. Its value typically lies in the range of $2 < \alpha < 3$.

For distributions where the quantity of interest takes a discrete set of values (such as in our case), the following probability function is used [15]:

$$P_{scale-free}(x) = \frac{\alpha - 1}{x_{min}} \left(\frac{x}{x_{min}} \right)^{\alpha}$$

Typically power-law is applicable only for values greater than some minimum x_{min}. Determination of x_{min} is a non-trivial task because all values of x may not follow the power-law distribution. Since we generate the SF network in a controlled simulation environment by using the BA model, our SF network nodes follow power-law degree distribution starting from the minimum node degree to the maximum. Hence, the value of x_{min} is set to be equal to the minimum node degree of the SF network. In case of empirical data, there are standard estimation techniques for computing $x_(min)$ [15].

The scaling parameter α is calculated using the *method of maximum likelihood* (MLE) [15] which is a standard statistical approach for parameter estimation.

$$\alpha = 1 + n\left[\sum_{i=1}^{n} ln\frac{x_i}{x_{min}}\right]^{-1}$$

3.1.4 Simulation and Results Analysis

We conduct extensive simulations with the following goals: (a) to investigate whether the generalized simple majority (GSM) rule and the ACS algorithm converge into large majority convention states on both random and SF networks and then (b) to investigate how the proposed topology-aware convention selection algorithm (TACS) performs on these networks.

3.1.4.1 Setup

The agents are situated in a connected topology that limits the communications of each agent to their immediate neighbor set. An edge between two nodes of the network indicates that the agents interact and play the coordination game. Two types of networks of varying sizes are used: scale-free networks (SF) and random (RN) networks.

SF topologies are generated using the BA model [8][5]. Initially a small mesh network consisting of three nodes is formed and then each new node is added according to the preferential attachment rule of the BA model. We set the default minimum node degree as 1 in both models ($m = 1$). As a consequence, each new node gets connected to at most 1 existing node. Sparse SF topology (where minimum node-degree is 1) has been chosen for implementation because this type of topology generally experiences frontier effect [1] that the ACS algorithm tries to resolve.

[5] This model is described in Appendix A.

The random (RN) networks are generated first by adding a random node to every node in the network. This ensures that no node is isolated. Then edges are added between two randomly selected nodes. The number of these randomly added edges is double the network size.

The size of the RN and SF networks are varied starting from size 25 to 10000. Initially one of the two conventions, X or Y, is randomly assigned to every node in the network. Then the coordination game proceeds in rounds and each round has two phases: (i) the agents play the game with all the neighbors based on their current state of conventions and (ii) update the state based on the convention selection algorithm[6]. Three convention selection algorithms are used: the Generalized Simple Majority (GSM) [19] rule, Accumulated Coupling Strength (ACS) and Topology-Aware Convention Selection (TACS) algorithm.

Since state updates depend on the local neighborhood, *synchronous update* is considered in which the entire society updates their states simultaneously in discrete time-steps that gives rise to a discrete-time macro-level dynamics [69].

50 simulations are conducted by creating distinct instances of the networks. Each simulation consists of 1000 time-steps where a time-step refers to a single run of the program.

A converged single convention is considered as the one in which *90% or more agents have adopted the same convention* [31]. Two tailed t-tests are used to evaluate the statistical difference of the performance of the action update rules.

[6]The convention selection algorithm refers to the action or state update rules in literature [19]

3.1.4.2 Results

Comparison of GSM & ACS: Table 2 shows the performance of the GSM and the ACS for various size RN and SF networks. For each network size and type we created fifty network instances and used both the GSM and the ACS to observe the convergence process. The results indicate that in RN networks, GSM successfully leads the network to converge into a single convention. ACS performs extremely poorly in RN networks as the network size increases. Applying a two tailed t-test on this data shows that the difference in converging into a single convention between GSM and ACS is significant with p-values < 0.05. The reason for the poor performance of ACS in RN networks is following. Initially ACS enables nodes to cluster around the higher degree nodes in their neighborhood. Unlike SF networks, there aren't very high-degree nodes or hubs in RN networks. As a consequence, many clusters are formed. A cluster with comparatively very high ACS value could bias other clusters to converge into it. However, in RN networks, none of the clusters would have very high ACS value due to the absence of hub nodes. This results in poor performance of ACS in RN networks.

On the other hand, in SF networks ACS performs better than GSM, as expected. Only in the 25 agents SF network, GSM performs slightly better. But as the size of the network increases, GSM fails to lead the network towards the a single convention. The p-values (< 0.05) clearly indicate this performance difference between these two approaches. The reason for the poor performance of GSM in SF networks is that it fails to resolve frontier effect that we analytically explained in Subsection 3.1.2.4.

Table 2: Performance comparison between GSM & ACS in random (RN) & scale-free (SF) networks

Type	Size	GSM	ACS	t-test Values
RN	25	50	44	t=2.532183794 p=0.014590637
	100	50	20	t=8.034033595 p=1.69493E-10
	500	49	1	t=17.7044527 p=3.939E-28
	1000	50	4	t=18.29325883 p=1.53687E-23
	2000	50	2	t=20.19918638 p=2.08895E-25
	5000	49	1	t=15.96306336 p=1.37358E-26
	10000	49	1	t=18.95149434 p=1.64739E-31
SF	25	18	37	t=-3.091860652 p=0.002610898
	100	4	35	t=-10.39464223 p=1.88831E-17
	500	0	33	t=-15.63800236 p=1.54961E-24
	1000	0	27	t=-13.9046204 p=7.265E-21
	2000	0	34	t=-19.51279059 p=6.58889E-27
	5000	0	31	t=-20.75669196 p=4.08026E-27
	10000	0	27	t=-22.9619313 p=1.49407E-28

Performance of the TACS: Table 3 shows the performance of the TACS in comparison with the performance of GSM and ACS for various size RN and SF networks. For each network size and type, fifty network instances are generated and used TACS, GSM and ACS. For RN networks, it can be noticed that TACS performs as well as GSM. Overall the difference in the performance between TACS and GSM in RN networks is not significantly different with p-value greater than 0.05. The exceptions are the 100, 1000 and 2000 node networks where the p-values are less than 0.05. However, even in these networks both TACS and GSM always lead to a single convention. TACS performs well in RN networks, because it enables agents to recognize the RN topology and to use GSM. In contrast, the performance of ACS and TACS differs significantly in these RN networks with p-values always less than 0.05.

In contrast, the performance of TACS in SF networks is reasonably good. Agents are able to recognize the SF topology using TACS and correctly select ACS for con-

Table 3: Performance of the TACS in random (RN) & scale-free (SF) networks

Type	Size	TACS /GSM	t-test Values
RN	25	50 /50	t=1 p=0.322223406
	100	50 /50	t=4.149242849 p=0.000132341
	500	49 /49	t=0.362917143 p=0.717481569
	1 $x10^3$	50 /50	t=12.35106344 p=1.1612E-16
	2 $x10^3$	50 /50	t=17.07825128 p=2.84876E-22
	5 $x10^3$	50 /49	t=-0.710770264 p=0.480596257
	10 $x10^3$	50 /49	t=-0.689176472 p=0.493962921
SF	25	34 /18	t=-3.262565143 p=0.001555407
	100	31 /4	t=-9.6111065 p=8.45531E-16
	500	27 /0	t=-19.64977344 p=9.59525E-34
	1 $x10^3$	16 /0	t=-14.57863053 p=6.73781E-23
	2 $x10^3$	17 /0	t=-21.6798235 p=3.46767E-31
	5 $x10^3$	17 /0	t=-23.47521492 p=1.15992E-30
	10 $x10^3$	9 /0	t=-21.7111511 p=9.78724E-28

Type	Size	TACS /ACS	t-test Values
RN	25	50 /44	t=0.00825891 p=0.016517819
	100	50 /20	t=-7.90979507 p=2.6252E-10
	500	49 /1	t=-16.6143261 p=5.67608E-28
	1 $x10^3$	50 /4	t=-18.1241733 p=2.28718E-23
	2 $x10^3$	50 /2	t=-20.03074525 p=3.01478E-25
	5 $x10^3$	50 /1	t=-19.02586291 p=2.83241E-24
	10 $x10^3$	50 /1	t=-22.66426789 p=1.26534E-27
SF	25	34 /37	t=-0.056375585 p=0.955158569
	100	31 /35	t=1.380074681 p=0.170736207
	500	27 /33	t=0.789952988 p=0.431703075
	1 $x10^3$	16 /27	t=1.455369065 p=0.148898696
	2 $x10^3$	17 /34	t=2.5304794 p=0.013128434
	5 $x10^3$	17 /31	t=1.758085406 p=0.082023001
	10 $x10^3$	9 /27	t=2.629977583 p=0.009931446

The (TACS/GSM) columns show the number of times each algorithm succeeded to converge into a single convention (out of 50 simulations).

vention formation. The difference in the performance between TACS and ACS is not significant for smaller networks (size less than 2000) with p-values greater than 0.05. However, as the network size increases TACS appears to perform poorly as indicated by its performance difference with that of ACS with p-values less than 0.05. We explain this phenomenon in the following.

Table 4: Topology identification by the agents in TACS

Size	Type	#GSM Followers	#ACS Followers	Type	#GSM Followers	#ACS Followers
25	RN	24.9	0.1	SF	1.56	23.44
100		99.24	0.76		4.6	95.4
500		496.3	3.7		22.4	477.6
1 x10^3		991.7	8.3		47.36	952.64
2 x10^3		1985.8	14.2		90.08	1909.92
5 x10^3		4962.14	37.86		229.26	4770.74
10 x10^3		9920.72	79.28		450.22	9549.78

For each network type and size columns 3-4 and 6-7 show the average number of the agents that identified the topology as random (GSM followers) and as SF (ACS followers).

The number of times TACS is successful in leading the networks into a single convention in SF networks is smaller compared to RN networks. This is due to the comparatively smaller number of nodes in SF networks that correctly identify the topology compared to the number of nodes that correctly identify the topology in RN networks (see Table 4). This table shows the average number of agents that identified the local topology as RN and adopted the GSM rule (these nodes are denoted as the GSM followers); and the average number of agents that recognized the local neighborhood structure as SF and adopted the ACS rule (the ACS followers). We observe that when the network size becomes larger ($\geq$ 2000) the difference in numbers between the GSM followers (in RN networks) and the ACS followers (in SF networks) becomes significantly larger. As a consequence more nodes in RN networks use GSM than the nodes in SF networks that use ACS. This contributes to the comparatively poor performance of the TACS in SF networks. The majority of the agents in SF networks has smaller degree due to its power-law degree-distribution. Since the agents only use their single-hop neighbors' degree-distribution for computing the probability functions (both normal and power-law), for many agents it could represent a normal degree-distribution. Hence, these agents incorrectly identify their neighborhood topology as RN network use GSM instead of ACS resulting in poor performance.

3.1.5 Conclusions

The goal of this work is to design a mechanism that allows a population of agents to adapt towards forming a single convention in various types of complex networks. It is based on the need that emergence of a social convention can reduce the overhead of coordination in MAS. An evolutionary game theoretic approach is used here to solve the convention problem. Our hypothesis is that no single distributed mechanism is able to form convention across various topologies. Two types of MAS networks are chosen for investigation that are scale-free (SF) and random (RN) networks. First, we analytically show, and later experimentally substantiate, that the state-of-the-art Generalized Simple Majority (GSM) action update rule does not perform successfully across all different types of SF networks, particularly in sparse SF networks. Then an accumulated coupling strength (ACS) convention selection algorithm is presented that is able to create a single convention both in sparse and highly-connected SF networks. ACS encodes the history of all previous influences and thereby acts as a social pressure to promote a specific convention. However, ACS does not perform as well in RN 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 emergence algorithm. An extensive simulation study has been conducted on RN and SF networks. We show that a large majority of the agents correctly recognize their topology and use either GSM (for RN networks) or ACS (for SF networks) that leads to the convergence into a single convention.

We have accomplished the research goals EC-SCS1-3 by:

- Showing theoretically and experimentally that the GSM mechanism fails to converge in some SF networks and explain the flaw in the previous reported theoretical analysis [19].
- Proposing a simple mechanism (ACS) for SF networks that is based on a socially inspired technique. ACS only requires the agents' knowledge about their immediate local neighborhood and encodes all past interactions in the agents' state to create a social pressure that expedites the convention convergence.
- Proposing a topology-aware meta mechanism (TACS) that recognizes the underlying topology and select a suitable simple mechanism. Agents use their single-hop neighbors' degree-distribution to predict the global topology of the network.
- Experimentally verifying the hypothesis that no simple distributed mechanism are able to form convention across various topologies and that TACS performs significantly better than any single mechanism.

3.2 Topology-Aware Mechanism for Large Convention Space

3.2.1 Research Goals

Previously we discussed (in Chapter 2) two significant mechanisms by Salazar et al. [56] and Franks et al. [23][7] that addressed the convention emergence problem suitable for large convention space. We identified the following key limitations of these two mechanisms: agent networks are assumed to be static 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[8]. In real-world applications, speeding up the convention formation process is a major concern and challenge [40].

We propose a topology-aware convention formation mechanism for large convention space that is able to overcome the limitations of SRA and FGJ. To validate our approach, similar to FGJ, we investigate a *language coordination problem* that captures the challenges involved in creating high-quality convention in large and dynamic MAS. The topology-aware mechanism enables agents to use their social influence to expedite the convention formation process.

In real-world applications the structure of agent society could be of different types. Therefore, 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) networks. However, we emphasize scale-free topologies due to its

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

[8]Both in SRA and FGJ the time-period for investigating the emergence of 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.

omnipresence in social and artificial systems. Every agent starts off with an internal lexicon 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 has a high quality lexicon, they would increase the utility of their lexicons in proportion to their degree. As a consequence, these socially influential high-utility-lexicon agents bias their neighbors to accept their lexicons. This phenomenon expedites the convention formation process.

Moreover, to further augment this process, we use a socially-inspired technique which is the *power of diversity*. In [50], it has been shown from a social science perspective that diversity improves organizational productivity. It emphasizes that not all diversity is helpful and that the benefits rest on conditions. Being inspired by this approach, agents in our work are enabled to bring diversity in the population through a novel network reorganization technique that is based on the lexicon utility. According to this technique, 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 better-lexicon-utility-neighbor in the neighborhood and thereby improves the quality of lexicons. We show that the topology-aware mechanism along with the link diversity expedite the emergence of a stable and high-quality convention. In addition to this, we evaluate the efficacy of the topology-aware mechanism by varying the topological features to develop an understanding about how the topology influences convention formation process. We also investigate the conditions under which diversity brings benefit. For example, we implement both random reorganization and reorganization of links based on the lexicon utility and see which facilitates language coordination more efficiently.

We set the following sub-goals concerning the problem of emergence of convention in large convention space (EC-LCS) to achieve research goals RG4 - RG6 that we outlined in Chapter 1(page 13):

- EC-LCS1: Design a topology-aware mechanism that is both *(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).
- EC-LCS2: Model a *dynamic network* scenario that facilitates convention emergence.
- EC-LCS3: Investigate how the average degree of the SF topologies influence the convention formation process.
- EC-LCS4: Investigate various types of link diversity approaches in SF topologies and their influence on convention formation .

3.2.2 Problem Formulation

A formal definition of the *convention problem* includes the following components: (a) *the interaction model* that describes the interaction topology, (b) a *language game model* that captures the agent interaction, (c) *convention space* defines the number of alternative conventions and (d) *the information propagation model* that specifies the amount, type and direction of information exchange. A solution to this convention problem is the one in which the MAS converges to LMCS *in a reasonable amount of time.*

3.2.2.1 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. The numbers of nodes are 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).

Four types of graphs are used for investigation: (1) regular network in the form of ring topology, (2) Watts-Strogatz small-world network [79], (3) random network and (4) Barabasi-Albert (BA) model of scale-free network [8].

3.2.2.2 The Language Game Model

Agent interactions are based on the FGJ language game model which is a variation of Luc Steels original language game [67]. Steels designed a paradigm that enables artificial agents to play language games about situations they perceive and act upon in the real world; and self-organize communication systems from scratch. 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 and adapt high-quality convention and keep on creating 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.

3.2.2.3 Convention Space

The number of concepts and words are assumed to be equal ($|C| = |W|$). Therefore, the size of the convention space is bounded by ($|W|^{|C|}$). Similar to FGJ, 10 fixed concepts for 10 words are used; hence the possible size of the convention space is quite large (10^{10}).

3.2.2.4 Information Propagation Model

We use spreading-based mechanism for information propagation model because of its appealing speed of reaching a convention [19, 53]. In these spreading-based approaches, agents propagate some characteristics (conventions) over the members of the society to influence them to adopt it. Agents have access to the state of the current conventions (utility of the lexicons) of their neighbors. Neighbors provide this information when an agent makes such request. The communication channel is assumed to be error-free. Since the agent communication is limited only within their local neighborhood, the cost associated with their communication is ignored. Moreover, the information propagation is bidirectional. Even if the edge from agent A to B is removed, the edge from B to A remains.

3.2.3 Topology-Aware Convention Formation Mechanism

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. 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: $CE_i = \#succComm/20$.

(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 start 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 from the received mappings 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. Agents calculate lexicon specificity of a single concept (S_c) in a lexicon using the formula $S_c = \frac{1}{|W_c|}$ where W_c is the set of words associated with that concept. The specificity of a lexicon is the average of the specificity of all concepts:

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

The approach taken here augments the computation of lexicon utility by adding a *topological factor*. Therefore, 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 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 enabled to acquire 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.

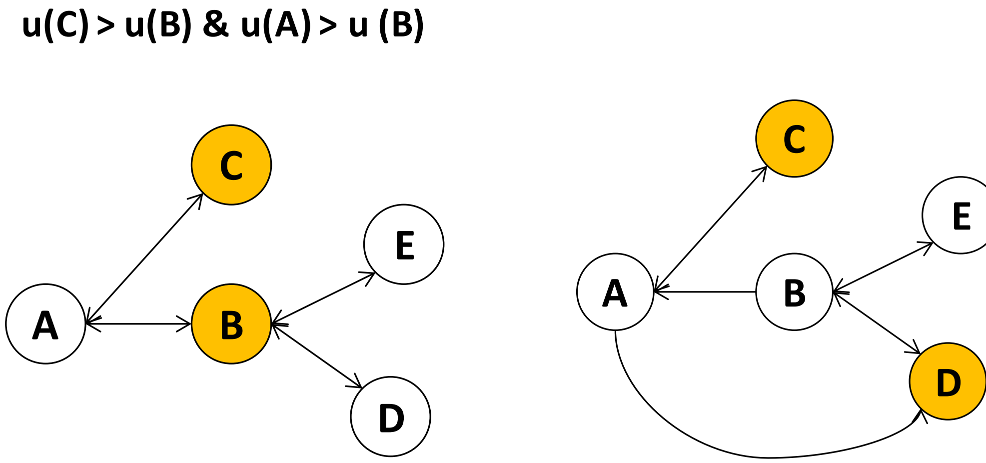
Algorithm 2: Topological Factor Computation

```
2.1 for each agent i:= 1 to n do
2.2     if LargestDegreeinNeighborhood(i) AND LexiconSpecificity(i) ≥ α then
2.3         TopologicalFactor(i) = Degree(i)
2.4     end
2.5     if LexiconSpecificity(i) ≥ λ then
2.6         TopologicalFactor(i) = μ
2.7     end
2.8 end
```

Algorithm 2 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 2.2 - 2.3). It increases the lexicon utility of these 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 lexicon specificity equal to or above a threshold value (λ) is enabled to set its topological factor as equal to a very large number (μ) as in lines 2.5 - 2.6. These agents then influence their neighbors, including the larger-degree agents, to adapt the high-quality lexicon mappings in fewer time-steps. Once a larger degree agent acquires high-quality lexicon, it begins to influence its larger neighbor base as in lines 2.2 - 2.3.

(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. 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 agents will not remove neighbors (including the lowest-lexicon-utility neighbor) that happen to have better lexicons than the agent. It then rewires with a randomly chosen neighbor of its removed neighbor. This way the diversity in the network is *conditioned*. Only a small number of agents would take part in network reorganization based on the assumption that the entire society may not get involved in reorganization. Another assumption is that 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.

Figure 6 shows how this reorganization works. At time t_1, agent A has two neighbors B and C. The lexicon utility of agent B is the lowest in A's neighborhood. Moreover, B's lexicon utility is smaller than that of A. Therefore, agent A stochastically removes its link with B and rewire with a randomly chosen neighbor of B (that could be D or E). Since the network is bi-directional, removing a link from agent A to B does not remove the link from B to A. At time t_2, agent A removes its link



(a) t_1 (b) t_2

Figure 6: Network reorganization ($t_1 < t_2$).

with B and rewire with one of B's neighbor with a probability given by the Fermi function [48] $p = [1 + e^{-\beta(u_A - u_B)}]^{-1}$. The parameter β controls the intensity of selection in that for larger values of it ($\beta \to \infty$) the edges of the lowest-lexicon-utility agents are *deterministically* removed and rewires to a randomly selected neighbor of the removed agent. It is assumed that only a small fraction of randomly selected agents take part in this network reorganization process.

3.2.3.1 Algorithm for Convention Formation Mechanism

Algorithm 3 describes the distributed convention formation mechanism. This algorithm is executed by each individual agent in the network. 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 communicative efficacy, lexicon specificity (Lines 3.2 - 3.5), topological factor and lexicon utilities (Lines 3.6

Algorithm 3: Topologically-Aware Algorithm

```
3.1  for each agent i:= 1 to n do
3.2      randomLexiconAssignment()
3.3      sendOneMappingToRandomNeighbor()
3.4      computeCommunicativeEfficacy(#succComm/20)
3.5      computeLexiconSpecificity(Equation 1)
3.6      computeTopologicalFactor(Algorithm 2)
3.7      computeLexiconUtility(Equation 2)
3.8      probabilisticLexiconSpreadingtoNeighbors()
3.9      probabilisticLexiconUpdate()
3.10     networkReorganization()
3.11 end
3.12 iterate (Lines 3.1 - 3.10)
```

- 3.7). They then probabilistically spread their partial lexicons and update their lexicons (Lines 3.8 - 3.10). This process repeats (Lines 3.1 - 3.10) over multiple rounds and a majority lexicon convention emerges.

3.2.4 Simulation and Results Analysis

We conduct simulations with the following goals: (i) compare the performance of two state-of-the-art lexicon convention formation mechanisms with the topology-aware (TA) mechanism on various types of networks including regular (ring), small-world (SW), random (RN) and scale-free (SF) networks, (ii) investigate how the TA mechanism performs across various degree SF networks and (iii) understand the amount of network reorganization required for emerging and sustaining convention across various topologies.

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.
- Average Network Reorganization: It provides a measure of the number of network reorganization, that includes link removal and rewiring, on average at each time-step. It helps to understand the required level of diversity for stable convention emergence.

3.2.4.1 Simulation Setup

We conduct experiments on four topologies: ring, SW, RN and SF.

We use Watts and Strogatz model to create small-world networks [79]. The rewiring probability is set to 0.1 (similar to SRA and FGJ). SF topologies are generated using the BA model [8][9].

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. Later average node degree is varied on SF topologies to see its effect on the performance.

Similar to FGJ, initially the internal lexicon of every agent is set with 10 fixed

[9]This model is described in Appendix A.

concepts and a randomized mapping of one or more words (from a set of 10 words) for each concept. The simulation proceeds according to Algorithm 3. For the computation of the lexicon utility, as in FGJ, the three weight constants are assumed to be equal to 1 (a = b = c = 1). 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.

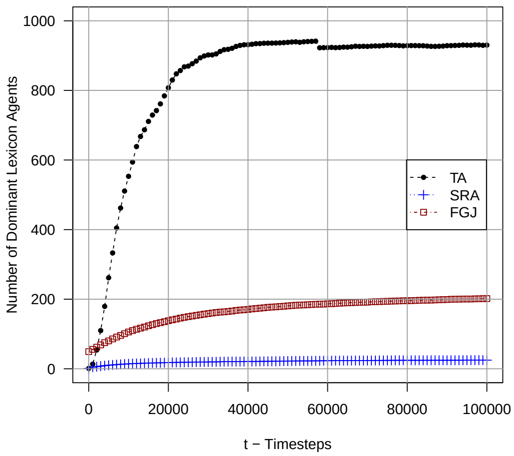
Table 5 provides the setting of the threshold levels of the parameters for the TA mechanism. α is set to be greater than or equal to 0.95 and λ is equal to 1.0. It enables the largest degree agents in any neighborhood to exert influence (by increasing their topological factor) only when their lexicon 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 maximum. 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).

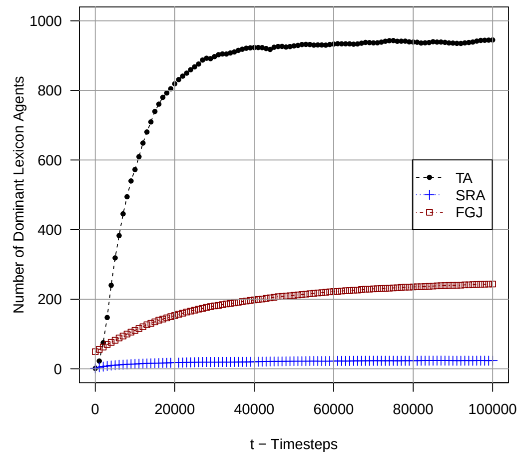
All the results reported are averages over 50 realizations for each network. Each simulation consists of 100,000 time-steps where a time-step refers to a single run of the program.

Table 5: Parameter Values for Simulation Configuration.

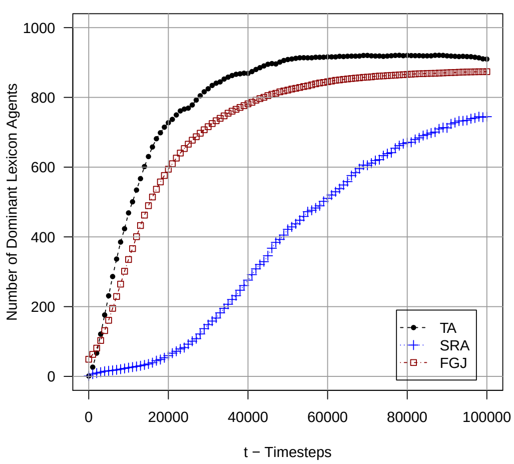
	α	λ	p_{send}	p_{update}
TA	≥ 0.95	$= 1.0$	0.01	0.01
SRA	N/A	N/A	0.01	0.01
FGJ	N/A	N/A	0.01	0.01



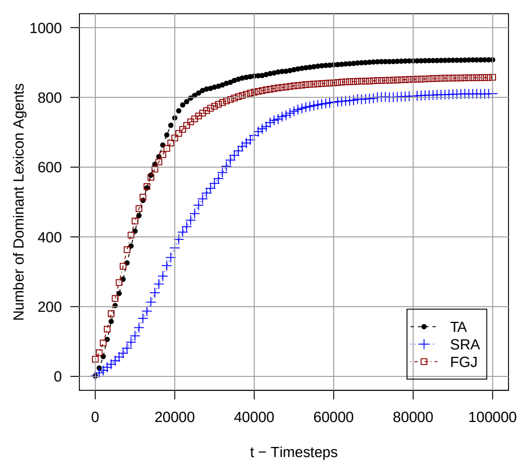
(a) Ring



(b) Small-World



(c) Random



(d) Scale-Free

Figure 7: Comparison of the number of dominant lexicon agents for the topology-aware (TA) approach with SRA and FGJ's approach.

3.2.4.2 Simulation Results

Convergence to LMCS & Speed of Convention Formation: Figure 7 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 6: Performance Comparison: %ACC refers to % of agents converged into a convention at timestep t. ACE & DLS are reported at 100,000 time-step.

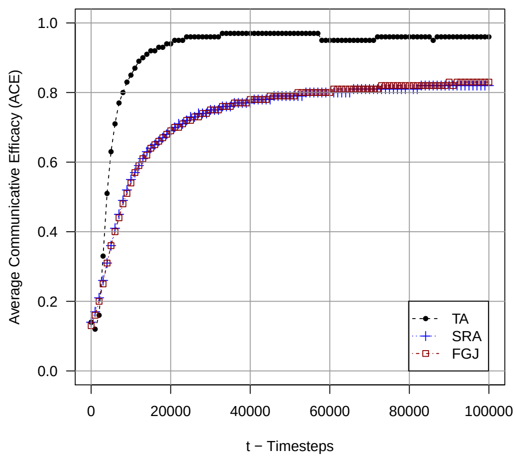
	Ring				Small-World			
	%ACC	t	ACE	DLS	%ACC	t	ACE	DLS
TA	80	18757	0.94	0.88	80	1837	0.94	0.87
	90	29323	0.96	0.88	90	30222	0.97	0.88
SRA	80	X			80	X		
	90	X			90	X		
FGJ	80	X			80	X		
	90	X			90	X		
	Random				**Scale-Free**			
	%ACC	t	ACE	DLS	%ACC	t	ACE	DLS
TA	80	27549	0.94	0.89	80	24375	0.94	0.94
	90	47595	0.97	0.90	90	68111	0.97	0.95
SRA	80	X			80	70660	0.96	0.98
	90	X			90	X		
FGJ	80	43961	0.92	1.0	80	35500	0.96	1.0
	90	X			90	X		

SRA and FGJ fail to converge into LMCS in RN and SF networks. Table 6 shows that SRA requires as many as 70,660 rounds to make 80% agents use the dominant lexicon in SF networks which it fails to do in RN topologies within 100,000 time-steps. On the other hand, TA requires 24,375 time-steps to have 80% agents to use a common lexicon in SF networks and 27549 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 4396 time-steps in RN networks.

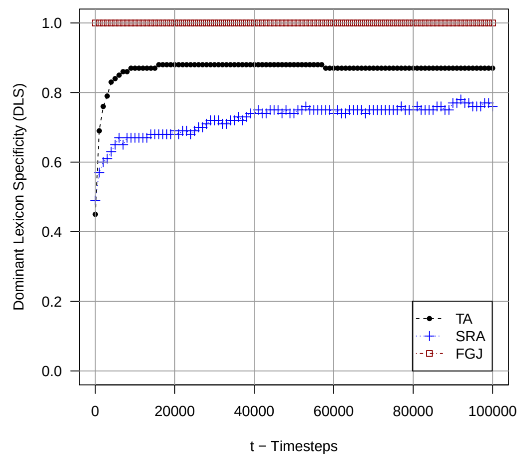
The performance of SRA and FGJ is worse in Ring and SW topologies. SRA enables less than 25 agents to form a single convention over these two topologies; and using FGJ less than 250 agents converge into a single convention within 100,000 time-steps. Both in Ring and SW networks, degree-heterogeneity is much less compared to RN and SF networks. As a consequence the spreading based approaches of SRA and FGJ require longer time for the convergence into a LMCS. However, 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. That's why spreading of high quality lexicon occurs faster in TA mechanism.

Average Communicative Efficacy (ACE) & Dominant Lexicon Specificity (DLS): Figures 8, 9, 10 and 11 show how ACE and DLS values change over time in four topologies for TA, SRA and FGJ.

In Ring networks, the ACE is significantly better in case of TA than SRA and FGJ (see Figure 8(a)). It indicates the level of coordination is high when agents use TA mechanism in Ring networks. 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) Ring: ACE



(b) Ring: DLS

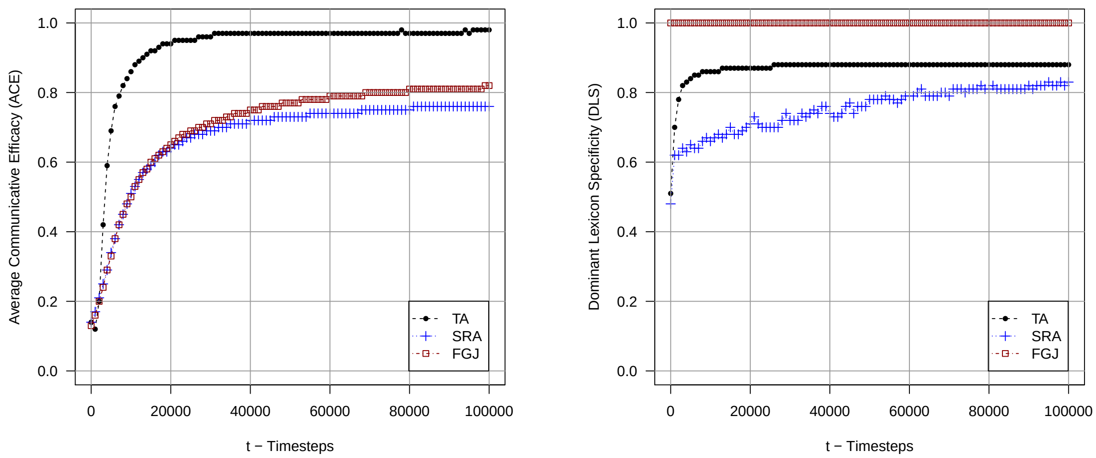
Figure 8: Comparison of the evolution of average communicative efficacy (ACE) & dominant lexicon specificity (DLS) in Ring networks. The values are averaged over 50 separate instances of simulation.

a fraction of the agents with the optimum quality lexicon that bias the rest of the network to adopt their lexicon.

We observe similar behavior of TA in SW networks. Figures 9(a) and 9(b) show that the ACE is significantly better in case of TA than SRA and FGJ. However, the DLS is not as good in TA as it is in FGJ.

Figures 10(a) and 10(b) show that, in RN networks, ACE is larger in TA than SRA and FGJ. The level of coordination for FGJ is better in RN networks than it is in SW networks, as can be seen from Figure 10(a). DLS for TA is not better than SRA and FGJ. In other words, although TA converges into LMCS (SRA and FGJ fail to do so), its DLS is only as high as 0.90 (Table 6).

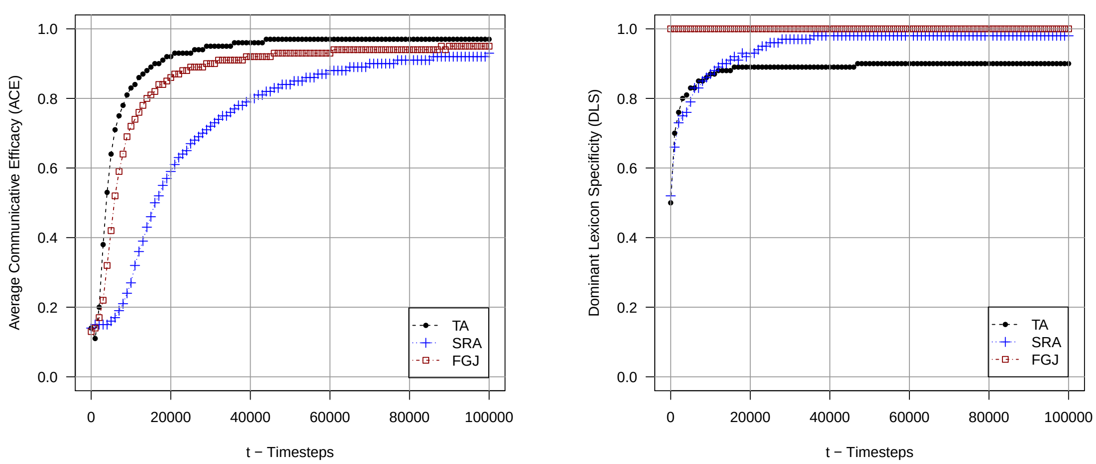
We follow similar behavior of ACE and DLS for TA in SF networks. Figures 11(a) and 11(b) indicate that while ACE is the largest using TA, DLS of TA is slightly



(a) Small-World: ACE

(b) Small-World: DLS

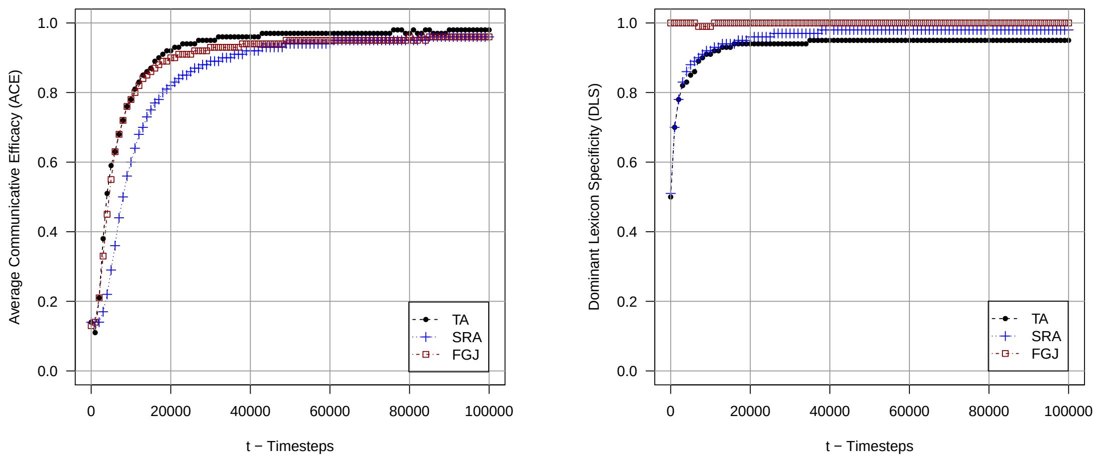
Figure 9: Comparison of the evolution of average communicative efficacy (ACE) & dominant lexicon specificity (DLS) in Small-World networks. The values are averaged over 50 separate instances of simulation.



(a) Random: ACE

(b) Random: DLS

Figure 10: Comparison of the evolution of average communicative efficacy (ACE) & dominant lexicon specificity (DLS) in Random networks. The values are averaged over 50 separate instances of simulation.



(a) Scale-Free: ACE (b) Scale-Free: DLS

Figure 11: Comparison of the evolution of average communicative efficacy (ACE) & dominant lexicon specificity (DLS) in Scale-Free networks. The values are averaged over 50 separate instances of simulation.

less than SRA and FGJ (Table 6). In other words, TA performs significantly better in SF topologies compared to other networks with respect to fast and guaranteed convergence to LMCS, and with respect to maintaining a large level of ACE and DLS.

Performance of TA Across Various Degree SF Networks: We try to understand the performance of TA across various degree SF networks. Figure 12 shows how dominant convention agents evolve over various degree SF topologies. We notice that MAS converges into LMCS only when the average node degree is 20 or above. SF networks with smaller average degree fail to create LMCS within 100,000 time-steps. As the network becomes more and more sparse, convention formation becomes slower. For example, in networks with average degree of 2, evolution of convention formation occurs very slowly. Smaller neighborhood slows down convention formation process because smaller average degree restrains information propagation. Moreover, the link diversity cannot reap much benefit due to slow improvement of the lexicon specificity.

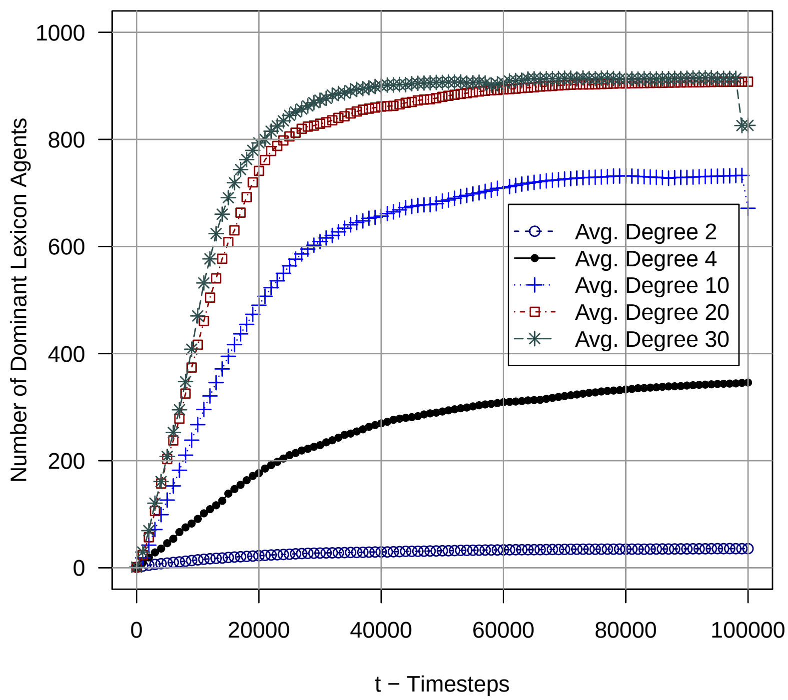


Figure 12: Comparison of the number of dominant lexicon agents for various average degree SF networks for the topology-aware (TA) approach.

Previous approaches (SRA and FGJ) claim to solve language convention problem in SF networks, however their investigation is only on networks with average degree 20. In other words, their results on SF networks are based on dense topologies and do not cover the range of all possible SF topologies. This dissertation points to the challenge of establishing fast convention in sparser SF networks.

Average Network Reorganization: Figure 13 shows the amount of average network reorganization that occurs in four topologies when agents use the TA mechanism. Although initially a lot of reorganization activities can be observed, as the MAS evolves towards converging into a dominant convention, the amount of reorganization decreases across all topologies. According to TA, agents stop reorganizing their network if the quality of their neighbors lexicons are better. We notice a sharp downward transition in SF networks which occurs faster, within 20,000 time-steps. Moreover, the average reorganization comes down to as small a value as 5 after the system converges into 80% convention state. It indicates that SF topologies require comparatively a smaller number of network reorganization to form convention.

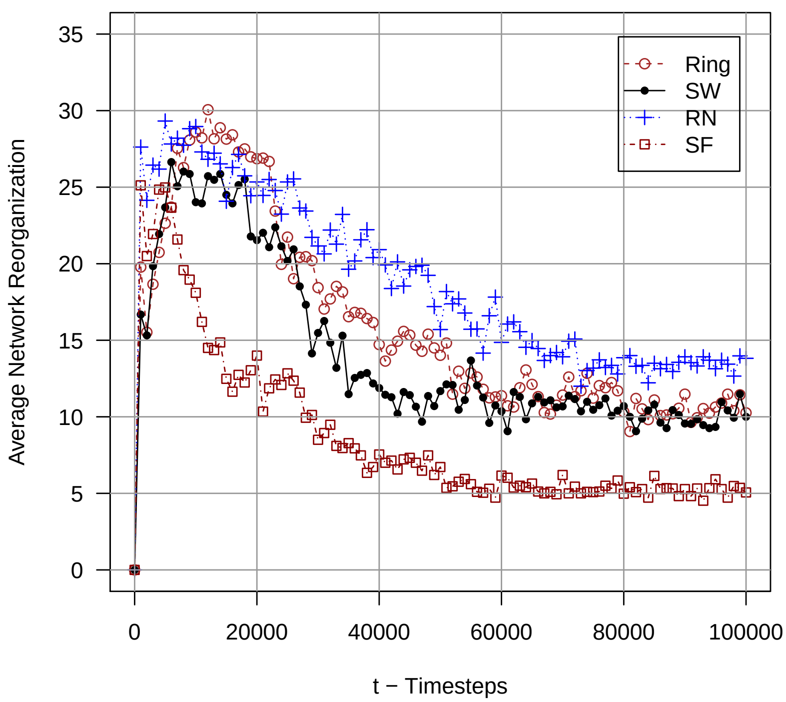
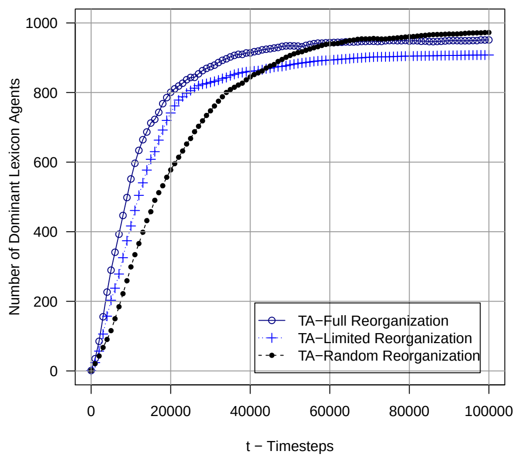


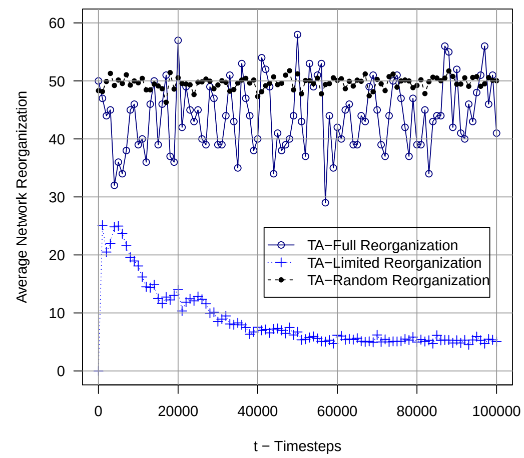
Figure 13: Average network reorganization in the topology-aware (TA) approach across four topologies.

In SF networks few hub nodes are connected to a large majority of the nodes. As a consequence, hubs are able to interact with a diverse set of nodes. In other words, due to the structure of the SF networks, hubs experience link diversity without explicit network reorganization. That's why it requires only a low level of network reorganization to form faster and high-quality convention.

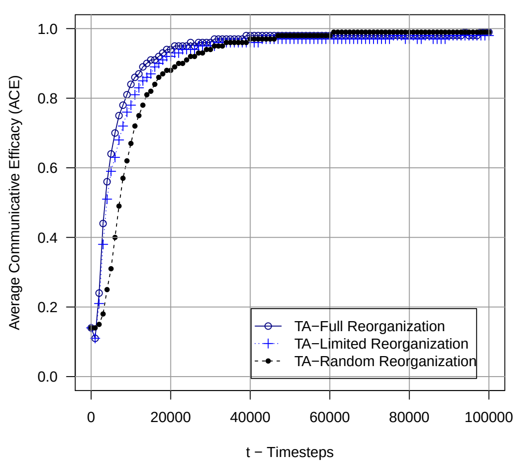
Reorganization decreases in SW and Ring topologies as well, although TA requires more reorganization in these topologies. Of the four, RN networks seem to be unruly and experience more reorganization activities for forming and sustaining a dominant convention. For example, unlike SF topologies, the decrease in the amount of reorganization in RN networks is not sharp and even after it converges into 90% convention state the amount of reorganization remains close to a comparatively large value of 15. Effect of Various Types of Link Diversity Techniques: In order to investigate the effect of link diversity over the process of convention formation in SF topologies, we perform a comparative investigation between the proposed link diversity technique and two of its variants. The proposed technique, that is based on Limited Reorganization, requires an agent to compare its lexicon utility with its lowest-lexicon-utility neighbor and *if the agent's lexicon quality is better than that of the lowest-lexicon-utility neighbor then this triggers a stochastic reorganization.* One variant of this technique, called "Full Reorganization", requires the agents to stochastically remove the lowest-lexicon-utility neighbor *irrespective of the value of its own lexicon utility* and subsequently rewire. Another variant, called "Random Reorganization", enables an agent to randomly choose a neighbor for reorganization. Figure 14(a) shows that although Full Reorganization mechanism is faster than Limited Reorganization, both mechanisms converge into LMCS. Random reorganization technique appears to be slower. The amount of network reorganization in Full Reorganization and Random Reorganization are significantly higher as can be seen in Figure 14(b). Agents, when



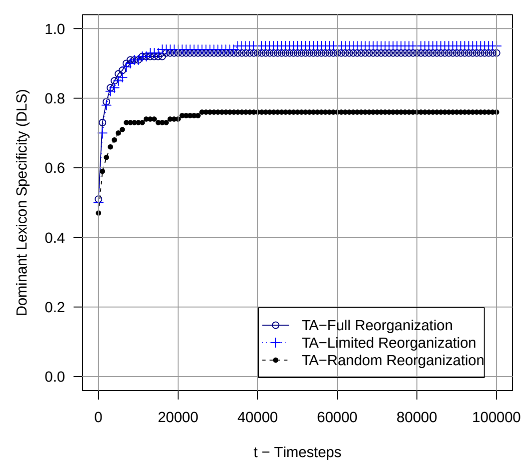
(a) Comparison of the Evolution of Dominant Lexicon Agents



(b) Comparison of the Average Network Reorganization



(c) Comparison of Average Communicative Efficacy (ACE)



(d) Comparison of Dominant Lexicon Specificity (DLS)

Figure 14: Comparison of the evolution of dominant lexicon agents, average network reorganization, average communicative efficacy and dominant lexicon specificity in Scale-Free networks among TA mechanism with full, limited and random network reorganization. The values are averaged over 50 separate instances of simulation.

using this two techniques, continuously reorganize their neighborhood even after the system converges into LMCS. This suggests that in situations where network reorganization is expensive, the Limited Reorganization approach pays off more. It also suggests that when a system experiences continuous reorganization (in highly dynamic scenario), Random Reorganization technique is able to create and sustain convention.

Figure 14(c) shows that the average communicative efficacy in Random Reorganization increases slowly. Moreover, the dominant lexicon specificity in Random Reorganization is much smaller than the other two being less than 0.8 (see Figure 14(d)). Therefore, we observe that although Random Reorganization technique enables agents to create a LMCS, the quality of the dominant lexicon is not good. The reason is that Random Reorganization process does not ensure the removal of lowest-lexicon-utility agents and does not increase the chance of having agents with better quality agents. It could remove agents with better quality lexicon as well. As a consequence, this "unconditional" reorganization technique does not enhance the convention formation process.

In contrast, the "conditional" reorganization in both Full and Limited Reorganization techniques improves both the effectiveness and efficiency of the convention process. According to these two techniques, agents are enabled to remove the lowest-lexicon-utility agents and could potentially bring agents with better lexicons in the neighborhood. This enhances the process of creating high quality lexicon convention. Therefore, we observe that *conditioned link diversity* facilitates better convention formation.

3.2.4.3 Discussion

TA mechanism is clearly better than SRA and FGJ as it enables MAS to converge into LMCS faster (within 100,000 time-steps) when the MAS is organized as RN and

SF networks. It is also able to create 80% agent convention state in Ring and SW networks within this time bound.

The DLS of FGJ is the largest because the influencer agents initialize their lexicon with the optimum specificity value and therefore are able to enforce their influence. This mechanism starts off with a best quality convention seed (perfect lexicon) carried by the influencer agents and hence does not require to improve this seed (or invent a new one). The speed of convention formation in FGJ is faster than SRA because of the existence of these influencer agents. However, FGJ does not provide cost estimate for deploying and maintaining these privileged agents.

Implementing dynamic network is a challenging task as it involves domain-specific knowledge and assumptions. In our work, we implement dynamic network topology through link diversity. The network reorganization approach is a result of a simple and realistic intuition that agents are more likely to disassociate with a neighbor that is not beneficial and would like to make acquaintance with better quality neighbors. However, this apparently simple intuition is difficult to implement because, again, it requires domain-specific assumptions, such as, how many neighbors should an agent remove from its neighborhood if they have poor quality lexicons? How many new connections this agent is supposed to create afterwards? Should the entire society engage into this type of network reorganization or only a fraction of the society would do so?

To keep the analysis simple and for the sake of a focused investigation, we adopt a *conditioned link diversity* mechanism that is based on a simple network reorganization approach. We intentionally choose a small value for this fraction (10%) based on the assumption that the entire society may not get involved in reorganization. The results from the investigation on two variants of reorganization approach indicate that *link diversity via network reorganization facilitates faster convention formation.*

3.2.5 Conclusions

The goal of this research 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 use a language coordination problem from FGJ for investigation. According to this problem, a society of agents construct a common lexicon in a decentralized fashion. Similar to FGJ, agents' interactions are modeled using a language game. In this game, agents send their lexicons to their neighbors and update their lexicon based on the utility values of the received lexicons. We propose a novel topology-aware utility computation mechanism that enables the agents to reorganize their neighborhood based on this utility estimate to expedite the convention formation process. 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.

We have accomplished the research goals EC-LCS1-4 by:

- Enabling the agents to use "network thinking" for controlling the dynamical process of convention formation suitable for a large convention space across various types of networks. This topology-aware mechanism facilitates the formation of a large majority convention much faster than the existing state-of-the-art approaches and ensures high-quality of the convention.

- Modeling dynamic topologies through a novel network reorganization technique.
- Analyzing the correlation between the degree-distribution and the convention formation process in SF topologies. Identifying the challenge of establishing convention in sparser SF topologies that slow down the process of convention formation.
- Investigating various types of link diversity approaches and how these influence convention formation in SF topologies. For example, the proposed *conditioned link diversity* improves the quality of lexicon than random link diversity approach.

CHAPTER 4: EMERGENCE OF COOPERATION

This chapter presents two mechanisms for the emergence of cooperation in moderate and highly-connected networks. The existing mechanisms are able to form cooperation in scale-free networks when the networks are sparsely connected (average node degree is small) that too only with limited success [29]. Moderate and highly-connected scale-free networks remain mostly unexplored domains for cooperation emergence.

The first mechanism (discussed in Subsection 4.1) uses commitment based dynamic coalition formation technique and complex network dynamics to form cooperation. Agents in the MAS are organized as scale-free networks and the proposed mechanism is able to form cooperation in *moderately-connected* scale-free networks (where average node degree is 20). The second mechanism (discussed in Subsection 4.2) considers *highly-connected* scale-free networks (where average node degree is up to 50) and uses a heterogeneous system design that includes a small fraction of altruistic agents. Highly-connected networks have been shown to be susceptible to defection and are the most challenging to sustain cooperation [29, 47]. We show that the altruistic agent based approach ensures cooperation in such networks.

4.1 Emergence of Cooperation using Commitment Based Dynamic Coalition Formation and Complex Networks Dynamics

Our aim here is to facilitate the emergence of cooperation in large MAS operating on scale-free (SF) networks where such cooperation helps maximize the global utility of the MAS. Agents organized as SF networks have moderate connectivity and play an iterated PD game with their immediate neighbors. We propose *a commitment-based dynamic coalition formation approach that leverages complex network dynamics.*

Dynamic Coalition Formation: Coalition formation provides a mechanism for promoting cooperation in complex networks [51, 55]. A coalition is defined as a group of agents who have decided to cooperate in order to perform a common task. By increasing the organizational level through coalitions, cooperation can be enhanced and maintained. The primary contribution in this research is a dynamic coalition formation approach that is based on commitment between agents. A commitment is a promise that an agent offers to another agent in order to influence that agent's strategy. An agent makes use of commitments to exploit the strength of its own strategic position [26]. It has been shown in [4] that commitments can be used to foster cooperation among self-interested agents in non-iterated PD game. Typically a commitment proposal includes a penalty to ensure that the breach of commitment would result in incurring a cost [4]. Self-interested and rational agents are enabled to offer commitments to their wealthy neighbors with whom they intend to form coalitions. Agents that offer commitments bear the cost of maintaining the coalition and promise to pay a penalty should they decide to leave the coalition. The penalty threshold is set such that it provides sufficient incentive to an otherwise non-cooperative neighbor agent to join the coalition and thereby cooperate. An agent moves into a different coalition with better social benefit if it is capable of paying the penalty.

Complex Network Dynamics: The secondary contribution in this work is that it investigates the effect of the complex network dynamics over the commitment-based dynamic coalition formation approach. It has been shown previously that although defection is the dominant strategy in the iterated PD game [29], the likelihood of cooperation is remarkably increased if the agent interaction is constrained by the underlying network topology [57, 71]. However, in these approaches, agents neither form the network nor use the network dynamics to enhance the emergence phenomenon. These works assume a pre-established static complex network platform and then employ agents on the nodes of the network for mutual interactions. In this work, instead of assuming a given network, agents are enabled *to form the desired network by choosing their interaction partners*. It determines the topological insights that, when embedded into agent partner selection strategy, result in a network always leading towards the emergence of a stable single coalition.

To summarize, we emphasize the significance of employing "network thinking" by the agents to control their dynamics and the dynamical processes of the network. *This work advances the state of the art by (i) developing a commitment-based dynamic coalition formation approach with an analytical study about how an effective commitment mechanism is related to the topology of the network and (ii) by determining the topological insights for the agents to choose their interaction partners to form a dynamically growing SF network that enhances the overall cooperation with* *maximized average expected utility.*

4.1.1 Research Goals

We address the following sub-goals for the emergence of cooperation using the dynamic coalition formation (EC-DCF) approach to achieve research goals RG7 and RG8 that we outlined in Chapter 1(page 14):

- EC-DCF1: In a networked interaction scenario, the challenge is to determine a penalty that facilitates the convergence into a single coalition and at the same time is high enough to incentivize the opponents to form coalitions. Our goal is to show both analytically and empirically how the penalty could be set based on the minimum number of immediate neighbors or minimum node degree of the SF network and the payoffs; and provide a sufficient condition that requires to be fulfilled in order for optimal coalitions to emerge.
- EC-DCF2: In order to gain the topological insights for network formation, our goal is to develop a computational model that investigates the performance of the dynamic coalition formation algorithm on various types of SF networks by varying the minimum node-degree, degree-heterogeneity and clustering coefficient. Specifically, we intend to investigate how a dynamical process of a network, namely the coalition formation, is influenced by its structural properties.

4.1.2 Problem Model

The agent interactions in the MAS are specified 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. The numbers of nodes are referred by n. Once the graph or the network is formed by the agents it becomes fixed. 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 graph follows scale-free property in which the distribution of node degree follows a power-law, $N_d \propto d^{-\gamma}$, where N_d is the number of nodes of degree d and γ is a constant.

The proposed decentralized coalition formation approach requires the agents to communicate only with their immediate neighborhood to form coalitions. We assume that agents are self-interested and rational. To initialize, agents are enabled to form the network by choosing their interaction partners dynamically. The adjacent agents (within single-hop distance) are defined as the *neighbors*. Every agent is equipped to play a *2-person* iterated PD game with each one of its neighbors and their interactions are represented by the network links. The agents start playing the PD game after the network is formed and the final network is considered as a closed system.

Agent i's payoff is denoted by $u(i, j)$ which agent i obtains by playing a PD game with its neighbor j. After every round of the game, the payoff received by playing the PD game with the neighbors gets accumulated and the accumulated payoff is defined as $\sum_{j=1}^{m} u(i, j)$, where j refers to the neighbors of i. Agents know the accumulated payoff of their neighbors. Every agent has a fixed strategy for each one of its neighbors, which is either to cooperate (C) or to defect (D). In a *2-person* PD game setting these two strategies intersect at four possible outcomes represented by designated payoffs: R (reward) and P (punishment) are the payoffs for mutual cooperation and defection, respectively, whereas S (sucker) and T (temptation) are the payoffs for cooperation by one player and defection by the other. The payoff matrix is represented by Table 7. For the PD game, the payoffs satisfy the condition $T > R > P > S$ and for iterated PD's we require $T + S < 2R$.

Table 7: Payoff Matrix for the Prisoner's Dilemma Game

	C	D
C	(R,R)	(S,T)
D	(T,S)	(P,P)

The iterated PD game proceeds in rounds and each round has three phases: (i) the agents play the game with all the neighbors using fixed strategies and compute the accumulated payoff, (ii) based on the payoff information of the neighborhood, the agents form/join coalition and (iii) update the strategies used in the coalition formation algorithm.

We define two types of agents: independent agents and coalition member agents. These two types are mutually exclusive. Initially all the agents are assumed to be independent. $Ind(v_i)$ refers to a set of independent agents $i : v_1, v_2, ..., v_n$. An agent v_i makes a commitment $Comm(v_i, v_j)$ to its neighbor agent v_j and forms a coalition $Coa(v_i, v_j)$. A coalition member agent is committed to the coalition; it always cooperates with its neighbors belonging to the same coalition and defects with others. In other words, it implements the strategy: *no cooperation without commitment*. However, an independent agent takes the interaction strategy that the majority of its neighbors adopted in the previous round. The next sub-section defines the coalition formation process and the algorithm.

4.1.3 Definitions, Algorithm and Theorem

Definition 1. *Commitment: An agent v_i makes a commitment $Comm(v_i, v_j)$ to its largest accumulated payoff neighbor v_i with whom it intends to form a coalition. The commitment proposal includes the following:*

1. *v_i would bear a small management cost β to maintain the coalition*

2. *v_i would pay a penalty α if it unilaterally breaks the coalition and vice versa*

Definition 2. *Coalition Formation: If the accumulated payoff of an independent agent $v_i \in Ind(v_i)$ is smaller than the accumulated payoff of its neighbor v_j whose payoff is the largest in v_i's neighborhood, i. e., if $\sum u(v_i) < \sum u(v_j)$ and $(v_i, v_j) \in E$, then v_i forms a coalition $Coa(v_i, v_j)$ with v_j by making a commitment $Comm(v_i, v_j)$ as defined in Definition 1. Agent v_i cooperates with the members of the same coalition and defects with others belonging to it's neighborhood.*

As in [4], the management cost is very small compared to the reward, i. e., $\beta << R$ and the penalty α is larger than the temptation payoff, i. e., $\alpha > T$ in order to offer enough incentive to an opponent to form a coalition.

Initially there would be multiple coalitions where agents may find it profitable to leave their existing coalitions and join new ones. The inter-coalition dynamics is defined as follows:

Definition 3. *Inter-Coalition Dynamics: If the accumulated payoff of a coalition agent v_i is smaller than the accumulated payoff of its neighbor v_j that belongs to another coalition, whose payoff is the largest in v_i's neighborhood, i. e., if $\sum u(v_i) <$*

$\sum u(v_j)$, $(v_i, v_j) \in E$ and $Coa(v_i) \neq Coa(v_j)$, then v_i leaves its existing coalition and joins the coalition of v_j if the following condition is fulfilled:

$$\frac{\sum u(v_i)}{2} > \alpha$$

Definition 4. *Coalition Convergence: After repeating the* Inter-Coalition Dynamics *phase multiple times the network converges into a single coalition where no agent either finds it beneficial to leave the existing coalition or to form a new one.*

In what follows, we describe the algorithms for the proposed coalition formation approach.

Algorithms: The Coalition Formation with Network Dynamics Algorithm (CFNDA) has 3 steps: network formation, initial coalition formation and decentralized coalition formation described below by procedures 1, 2 and 3 respectively (page 88, 89 and 90).

Procedure 1: NetworkFormation

Require: m_0 initial nodes
Require: number of edges (m) of the newly connected node: $m \leq m_0$
1. setInitialAttractiveness() = A;
2. setClusteringProbability() = p;
3. implementBAModel;
4. WHILE($m \leq m_0$)
5. {linkToNode(i): $\prod_{n \to i} = \frac{A+degree_i}{\sum_j (A+degree_j)}$;}
6. end;
7 implementExtendedBAModel;
8. linkToNode(i): $\prod_{n \to i} = \frac{A+degree_i}{\sum_j (A+degree_j)}$;
9. WHILE($m \leq m_0 - 1$)
10. {linkToNeighborOfNode(i)withProbability(p);
11. linkToNode(i)withProbability(p-1):
$\prod_{n \to i} = \frac{A+degree_i}{\sum_j (A+degree_j)}$;}
12. end;

```
Procedure 2: InitialCoalitionFormation
Require: Accumulated payoff is transparent
only to immediate neighbors
Require: All the agents are Independent
networkFormation();
randomStrategySelection();
playPDGamewithNeighbors();
FOR each agent i:= 1 to n
  IF maximumPayoffNeighbor(j) AND
payoff(i) < payoff(j)
    offerCommitmentTo(j);
    formCoalitionWith(j);
    payManagementCostBy(i);
  ELSE
    remainIndependentAgent(i)
END FOR
```

Network Formation: In the beginning agents choose their interaction partners and form the network as described in Procedure 1. Agents may either form the network according to the Barabasi-Albert (BA) SF model (lines 3-6) or may use an extended version of the BA model (lines 7-12). Since the BA model [8] suffers from low clustering, we also use the extended BA model [30]. According to these two models, agents are enabled to control the degree-heterogeneity of the network by a model parameter named initial attractiveness parameter (A). The clustering of the networks can be controlled using the clustering probability (p). These parameters are defined in the the description of the BA and extended BA model in Appendix A. In the BA model, all the links (m) of the new node are connected to the existing nodes using the preferential attachment rule (line 5). On the other hand, in the extended BA model only the first link of the new node is added using the preferential attachment rule (line 8). The remaining links of the new node ($m_0 - 1$) are added to the randomly chosen

Procedure 3: Decentralized Coalition Formation Algorithm

Require: Accumulated payoff is transparent only
to immediate neighbors

1. initialCoalitionFormation();
2. playPDGamewithNeighbors();
3. FOR each agent i:= 1 to n
4. IF coalitionAgent(i) AND
5. maximumPayoffNeighbor(j) AND
6. payoff(i) < payoff(j)
7. IF (notIndependentAgent(j))
8. IF $u(i)/2 > \alpha$
9. {offerCommitmentTo(j);
10. joinCoalitionOf(j);
11. payManagementCostBy(i)};
12. ELSE IF (independentAgent(j))
13. GOTO lines 9-11;
14. IF (coalitionAgent(i) AND
15. disconnectedFromCoalition(i))
16. {becomeIndependentAgent(i)};
17. IF (independentAgent(i))
18. GOTO lines 5-13;
19. mutation();
20. END FOR

neighbors of the first neighbor of the new node with the probability p (line 10) or using the preferential attachment rule with the probability *p-1* (line 11). By varying the value of A, the degree-heterogeneity of the resultant network can be controlled and p determines the clustering level of the extended BA model. A computational model, described in Subsection 4.1.4, determines how the agents should set these two topological parameters such that the resultant network enhances the emergence of a single coalition when agents form coalitions using algorithms 2 and 3.

Initial Coalition Formation: Procedure 2 depicts how initial coalitions are formed at the beginning of the game. Every agent starts out as an independent agent and there is no coalition. Agents choose their interaction strategy randomly and generate the payoff according to the payoff matrix in Table 7 by playing a *2-person* PD game with each one of its neighbors (lines 2-3). Then in lines 5-9, for every agent if the largest payoff neighbor j's accumulated payoff is larger than the agent i's payoff, it offers commitment to j and forms a coalition. It also bears the management cost of that coalition. An agent without any coalition members remains independent (line 11). After the first round, there would be multiple coalitions. The number of coalitions will depend on the size of the network.

Decentralized Coalition Formation: At the beginning of every round each agent plays the PD game and employs the coalition strategies to join/leave/switch or form a coalition according to Procedure 3. In lines 4-11 every coalition member agent i joins the coalition of it's largest payoff neighbor j if one-half of i's payoff is larger than the penalty. Agent i offers a commitment to j and bears the management cost of the coalition. If j is an independent agent, then i forms a coalition with it by offering a commitment and bearing the management cost (lines 12-13). If agent i is a coalition member agent but is disconnected from its coalition members (when an agent does not have any one-hop link to other members of its coalition, then it is considered to be disconnected from its coalition), it becomes an independent agent (lines 15-16). However, if i is an independent agent then it forms a new coalition according to lines 5-13.

Mutation: It is possible that some agents might become stable within sub-optimal coalitions where the majority of the neighbors do not belong to the agent's coalition. In order to allow these agents to move to optimal coalitions (which maximizes their payoff), they are enabled to explore the strategy space with a small probability. If the majority of a coalition-agent's neighbors are not its coalition members, that agent becomes independent if one-half of its payoff is larger than the penalty.

Proposition 1. *For any connected graph G with n nodes and (sufficiently) high penalty ($\alpha >$ temptation payoff), the agents increase their payoff through the coalition formation process.*

Proof. Let us consider three agents a_1, a_2 and a_3 are playing an iterated PD game with their immediate neighbors. Both a_2 and a_3 are the neighbors of a_1. Assume that after the first round of the game, the accumulated payoff of a_2 is the largest in a_1's neighborhood, i. e., $\sum u(a_2) > \sum u(a_3) > \sum u(a_1)$. Now according to the CFNDA, agent a_1 will form a coalition with a_2 by making a commitment and will start cooperating with the same coalition members in its neighborhood. This mutual cooperation may increase a_1's payoff. However, it is possible that a_1 was a defector with its other neighbors; in that case its payoff would not increase after joining a_2's coalition.

Now, in the next round of the game, after joining the coalition if the majority of a_1's neighbors belong to the same coalition, its payoff further increases through mutual cooperation. With this increased payoff a_1 will eventually attract its non-coalition neighbors to join a_1's coalition. This would result in a maximum payoff of a_1. On the other hand, if the majority of a_1's neighbor do not belong to its coalition and if one of the neighbors' payoff happens to be larger than that of a_1's payoff, then a_1 will leave its existing coalition and will form/join that neighbor's coalition if $\sum u(a_1)/2 > \alpha$ condition is satisfied. In the new coalition, a_1's payoff is expected to increase further because its coalition partner is the wealthiest in a_1's neighborhood and thereby it would attract more agents to join its coalition increasing the likelihood of mutual cooperation. However, this process may lead a_1 to a situation where it may get stuck in a sub-optimal coalition. The mutation strategy of the CFNDA could resolve this problem by allowing a_1 to move towards more beneficial coalitions and thereby increase its payoff.

□

Using Proposition 1 now it is proved that the coalition formation algorithm guarantees maximum average expected payoff in any scale-free random graph.

Theorem 2. *For any random scale-free graph G with n nodes and (sufficiently) high penalty ($\alpha >$ temptation payoff), the coalition formation process converges into a single coalition and maximizes the average expected payoff, if the minimum node-degree (min_d), penalty (α), reward (R) and punishment (P) payoffs fulfill the following condition:*

$$min_d \geq \frac{4\alpha}{R+P}$$

Proof. According to Proposition 1, it is sufficient to prove that in scale-free random graphs either a node has earned the maximum payoff (when all of its neighbors belong to the same coalition) or one-half of its payoff is larger than the penalty to move to another coalition leading towards the convergence into a single coalition that maximizes its payoff.

In any random scale-free graph, there are few high-degree nodes linked by many low-degree neighbors. Since initially the nodes interact based on randomly assigned strategies, the interaction partners of any node would be a uniform mixture of co-operators and defectors. This leads the high-degree nodes to generate high accumulated payoffs in their neighborhood. Therefore, most or all of the neighbors of the high-degree nodes form coalitions with them resulting all (or almost all)-cooperation sub-graphs around the high-degree nodes.

Let us assume that a_2 and a_3 are two high-degree nodes in a_1's neighborhood and that initially in the first round of the game a_1 has formed a coalition with a_2. Also assume that the degree of a_3 is larger than the degree of a_2, i.e., $d(a_3) > d(a_2)$. Therefore the number of cooperating coalition members of a_3 should be larger than that of a_2. This would increase the payoff of a_3. Hence, in the next round of the game a_1 finds it profitable to leave the coalition of a_2 and join the coalition of a_3 and thereby increase its payoff if $\sum u(a_1)/2 > \alpha$. Now we will prove that this condition is always satisfied until the entire network converges into a single coalition where no node has any motivation to leave the coalition.

Let us assume that in the first round of the game when a_1 belonged to a_2's coalition, x number of neighbors of a_1 cooperates with it (including the node a_2) and the remaining nodes of its neighborhood (which is at least, minimum degree of a_1 or $min_d(a_1) - x$) belong to different coalitions and hence are defectors. Therefore, after the end of the first round, the accumulated payoff of a_1 would be

$$\sum u(a_1) = x * R + (min_d(a_1) - x) * P$$

Now, in the next round, for a_1 to move to a_3's coalition for maximizing it's payoff,

a_1 needs to satisfy the following condition

$$\frac{x * R + (min_d(a_1) - x) * P}{2} > \alpha$$

We know that $\alpha > R > P$, hence for the above condition to be satisfied, both x and $min_d(a_1)$ have to be sufficiently large. Since initially there were equal number of cooperators and defectors, it is expected that at least half of a_1's neighbors would belong to the same coalition. Therefore,

$$\frac{\frac{min_d(a_1)}{2} * R + (min_d(a_1) - \frac{min_d(a_1)}{2}) * P}{2} \geq \alpha$$

$\implies \frac{min_d(a_1)}{4} * (R + P) \geq \alpha$

$\implies min_d(a_1) \geq \frac{4\alpha}{R+P}$

Therefore, if the minimum node-degree of G fulfills the above condition, the agents would tend towards beneficial coalitions, thereby increasing the number of cooperators in their neighborhood, until all the agents converge into a single coalition in which mutual cooperation guarantees the maximization of the average expected payoff of the agents.

□

4.1.4 Computational Model and Results Analysis

Our plan is threefold: (a) computationally validate the proposed approach by showing that if the penalty is set according to the condition provided in Theorem 2, convergence into optimal coalitions is possible, (b) show that the performance of the approach for the emergence of cooperation in moderately connected SF networks is better than two state-of-the-art approaches and (c) determine the topological insights that agents could use to choose their partners such that the resulting network facilitates cooperation.

For comparison, we specifically use two state-of-the-art action update rules, namely the *imitate-best-neighbor (IB)* [45] and the *stochastic imitate-random-neighbor (SA)* [58], that has been shown to facilitate the evolution of cooperation in SF networks [29]. The performance of these rules are studied over varying-degree SF networks. Although these two approaches do not use coalition formation for the evolution of cooperation, we investigate these to underscore the challenge of achieving cooperation in moderately connected networks. We use a computational model to conduct extensive simulations for the coalition formation approach by varying the node degree-heterogeneity and the clustering coefficient of the BA and the extended BA model[10]. The value of the initial attractiveness parameter (A) is increased in order to vary the degree-heterogeneity of the network and increase the value of the clustering probability p (used in the extended BA model) to generate medium ($p = 0.5$) and high-clustering ($p = 0.1$) networks respectively; and observe the state of convergence of the coalitions. Also we investigate how the average expected payoff increases in each type of network instantiation. Heterogeneity is measured by the standard deviation of the degree distribution.

[10]These models are described in Appendix A.

4.1.4.1 Simulation Setup

The network consists of 5000 agents represented as nodes in the SF network. A link between two nodes of the network indicates that the agents interact and play the PD game. The default minimum node degree is set to 10 in both models ($m = 10$).

The following values for the payoffs are considered: T = 5, R = 3, P = 1 and S = 0. According to Theorem 2, the value of the penalty (α) is set to 10. The value of the management cost (β) is chosen as 0.005.

All the results reported are averages over 100 realizations for each network for different values of the network parameters (e.g., degree-heterogeneity, clustering coefficient etc.). Each simulation consists of 500 time steps where a time step refers to a single run of the program. The mutation rate is set to 0.05 [55].

Table 8: IB & SA Rules: The average no. of cooperators (#Coop) and average expected payoff (ExPoff)

	IB		SA	
Min-Degree	#Coop	ExPoff	#Coop	ExPoff
1	1337.1	-75.49	1238.28	-78.37
2	2824.55	-31.43	2304.17	-47.41
3	400.81	-111.80	506.15	-108.04
5	0.0	-124.77	49.9	-123.53
10	0.0	-125.31	0.0	-124.92

The results are reported over 100 realizations of the network for various values of the minimum node degree. Both p and A are zero.

4.1.4.2 Simulation Results

Evolution of Cooperation vs. Minimum Node Degree: The effect of IB and SA action update rules are investigated over the final fraction of cooperators by varying the minimum node degree of the network. BA model ($p = 0.0$) is used with the initial attractiveness parameter A set to 0. Table 8 shows that the evolution of cooperation occurs only when the network is sparse, although extremely sparse networks (where minimum node degree is 1 or the average node degree is 2) do not facilitate cooperation. The average number of cooperators drops to zero for both update rules when the minimum node degree exceeds 5. This also results in very low average expected payoff of the network. However, from Tables 9 and 10 we observe that the proposed commitment-based dynamic coalition formation approach is able to increase mutual cooperation by converging into a single coalition and to maximize the average expected payoff of the agents in moderately connected networks (when minimum node degree is 10 or average node degree is 20).

Table 9: Commitment-based Coalition Formation in the BA Model: The average no. of coalitions (#Coa), average expected payoff (ExPoff), average Global Clustering Coefficient (GCC) and average Degree-Heterogeneity (DH)

	BA Model			
	p = 0.0			
A	#Coa	ExPoff	GCC	DH
0	1.44	20.21	0.02	52.58
50	1.18	21.76	0.01	27.54
100	1.14	21.74	0.01	25.57
500	1.01	21.98	0.01	23.96
1000	1.04	21.80	0.01	23.73
2000	1.03	21.93	0.01	23.58
5000	1.01	21.89	0.01	23.50
10000	1.00	21.97	0.01	23.48

The results are reported over 100 realizations of the network for various values of p and A.

Convergence of the Network: To observe the performance of the coalition formation approach over a low-clustering SF network, the initial attractiveness parameter is set

Table 10: Commitment-based Coalition Formation in the Extended BA Model: The average no. of coalitions (#Coa), average expected payoff (ExPoff), average Global Clustering Coefficient (GCC) and average Degree-Heterogeneity (DH)

	Extended BA Model							
	p = 0.5				p = 1.0			
A	#Coa	ExPoff	GCC	DH	#Coa	ExPoff	GCC	DH
0	1.51	20.74	0.13	52.25	1.96	16.46	0.31	52.35
50	2.93	19.60	0.12	34.25	3.66	14.64	0.41	50.65
100	1.08	21.73	0.12	31.43	1.87	20.83	0.42	52.07
500	1.01	22.08	0.12	29.54	3.61	15.85	0.45	49.21
1000	1.10	21.56	0.11	29.19	2.99	17.86	0.45	49.42
2000	1.15	20.62	0.12	29.14	3.11	15.96	0.44	50.07
5000	1.25	20.28	0.12	28.83	1.89	20.38	0.45	50.23
10000	1.19	21.09	0.11	28.99	1.93	20.45	0.46	50.53

The results are reported over 100 realizations of the network for various values of p and A.

to A = 0. Then it is gradually increased from 0 to 10,000. From Table 9 it can be observed that as A increases, the degree-heterogeneity of the network decreases and the likelihood of convergence into a single coalition increases. Therefore, *clearly the agents could benefit by selecting their partners by setting a large value of A during the network formation phase* (Procedure I in Subsection 4.1.3). It guarantees the convergence into a single coalition and maximizes the average expected payoff. The average global clustering coefficient of the network is very small, as expected from the standard BA model.

The extended BA model is used to investigate the effect of high clustering and degree-heterogeneity over the emergence of a single coalition. For both medium-clustering ($p = 0.5$) and high-clustering ($p = 1.0$) networks, the initial attractiveness parameter A is increased from 0 to 10,000. From Table 10 we observe that in the medium-clustered network, very large value of A (> 1000) does not necessarily improve the convergence.The best convergence can be achieved when A = 500. Hence, our expectations about improving the convergence by controlling the value of A are partially met by the results. On the other hand, in the high-clustered model, very large value of A (> 5000) is required to improve the convergence. In the high-clustered model we see that even a very large value of A does not decrease the degree-heterogeneity of the network significantly. The reason is that according to the extended model of the BA network with $p = 1.0$, only the selection of the first neighbor can be controlled by the parameter A.

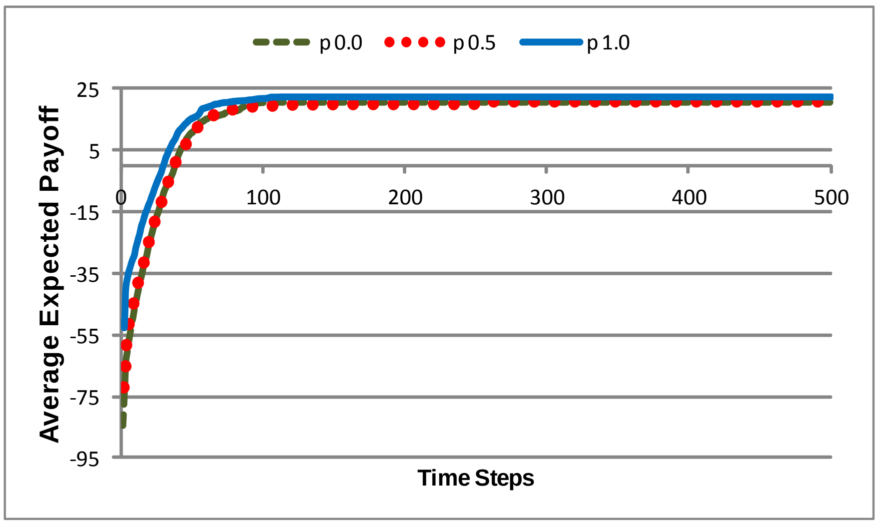


Figure 15: BA & Extended BA model: Increase of average expected payoff for various values of the clustering probability p.

Average Expected Payoff: Figure 15 shows how the average expected payoff varies over the iterations for 3 network types: low-clustering ($p = 0.0$), medium-clustering ($p = 0.5$) and high-clustering ($p = 1.0$). The value of A is set to 0 in these models. We notice that in all these three types of networks the average expected payoff increases and becomes stable at an optimum value. Also we observe that irrespective of the network clustering the commitment-based dynamic coalition formation approach improves the average expected payoff of the network and increases it in a similar fashion.

4.1.4.3 Discussion

The performance of the commitment-based approach depends on how the value of the penalty is set. The challenge is to determine an appropriate range of the penalty that is high enough to incentivize an opponent (larger than the temptation payoff) but not very high to obstruct the process of convergence into a single coalition. According to the required and sufficient condition in Theorem 2, for a moderately connected network with minimum node degree 10 (average node degree 20), this value should be no greater than 10. Using this value, the convergence can be guaranteed. Experimentation with different values of the node degree and the penalty (the result is not reported here) generates similar result. Therefore, unlike the existing approaches (IB and SA), the proposed approach is able to evolve cooperation and maximize the average expected payoff both in sparser and moderately connected networks.

We are able to fine-tune the performance of the proposed approach by enabling the agents to control the topological features (such as degree-heterogeneity and clustering) during the network formation phase. The agents in a MAS choose their interaction partners according to the preferential attachment rule of the BA model. In the extended BA model, a fraction of the nodes (depending on the clustering probability p) form the links according to this rule. In order to guarantee optimal convergence of the proposed approach, agents during the network formation phase need to choose their interaction partners using a large value of the parameter A. This decreases the node degree-heterogeneity and thereby reduces the number of large multiple coalitions that otherwise may lead towards converging into sub-optimal coalitions.

We observe that the average expected payoff in the highly-clustered network ($p = 1.0$) is not as high as in both the low and medium clustered networks. In highly-clustered network, a node is connected to its neighbor's neighbors. Therefore, the shared management costs across every agent's neighborhood are relatively high compared to low-clustered networks. This indicates that agent's partner selection strategy and the network formation affect the overall social benefit.

4.1.5 Conclusions

This research presents a commitment-based dynamic coalition formation approach to establish mutual cooperation in large MAS organized as moderately-connected SF networks. Interactions of the self-interested agents with their immediate neighbors are captured using an iterated PD game. Unlike many previous works that assume given pre-established networks, we enable agents to dynamically choose their interaction partners to form their network. Agents offer a commitment to their wealthiest neighbors in order to form coalitions. A commitment proposal, that includes a high penalty for breaching the commitment, incentivizes opponent agents to form coalitions inside which they mutually cooperate and thereby increase their payoff.

We have accomplished the research goals EC-DCF1-2 by:

- Determining analytically, and substantiating through experiments, how the value of the penalty should be set with respect to the minimum node degree and the payoff values such that convergence into profitable coalitions is possible.

- Contributing to the state-of-the-art by establishing cooperation in moderately-connected networks.
- Also this work is novel in that the agents are capable of controlling some topological features of the network that results in better convergence and increased average expected payoff.

4.2 Emergence of Cooperation in Highly-Connected Networks by Altruistic Agents

Many real-world SF networks, such as social networks, exhibit large average connectivity [2, 21, 25]. For instance, the average connectivity of a node in the Facebook network is reported to be 190 [72]. Previously it has been shown that imitation based rules (e.g., *imitate-best-neighbor (IB)* [45] and *stochastic imitate-random-neighbor (SA)* [58]) that facilitate cooperation in random networks and sparse SF networks are unable to establish cooperation in highly-connected SF networks [29]. Also, there exists a strong theoretical argument based on natural selection showing that high-connectivity among the nodes in SF networks results in diminished or no cooperation [47]. However there are many instances where it is critical to establish cooperation in highly-connected networks. For example, achieving consensus among the social network application users about acceptable privacy settings for individual applications is a key challenge [27]. Multi-agent based approach could offer a solution to this problem by establishing cooperation among the user community. Therefore, the central research question being addressed here is: *how to establish cooperation in*

MAS operating on highly-connected SF networks?

This work presents the design of a heterogeneous MAS composed of both the altruistic and self-interested agents and shows that it performs significantly better in *highly-connected* SF networks. We propose a stochastic influencer altruistic agent (StIAA) mechanism that is motivated by a novel definition of *cooperation* [44] in which the otherwise competing agents decide to aid each other within the space of their self-interested bounded rationality. The goal is to determine the conditions under which such cooperation thrives. In other words, the self-interested behavior of the agents is biased to make them cooperate with each other. To do this, we introduce a small proportion of altruistic agents in a self-interested society (similar to the influencer agents in [23, 41]). The altruistic agents are designed to always cooperate with their neighbors while the self-interested agents may cooperate or defect since their objective is to maximize their utility by imitating the strategy of the wealthiest agents in their neighborhood. However, since agents in SF networks typically only have partial-observability of their environment (have access only to the information about immediate neighborhood), it is possible that the self-interested agents may get stuck in a local maxima. Therefore, these agents are enabled to determine the optimality of their strategies by stochastically trying the strategy of the altruistic agents in their neighborhood with a small exploration probability [55]. By manipulating the self-interested behavior of the large majority of the population, the altruistic agents are able to facilitate cooperation. We analytically show that this probabilistic exploration creates a cluster of cooperators in SF networks that helps cooperation evolution. A comprehensive empirical study substantiates this claim.

In summary, this research hypothesizes that cooperation could emerge and be sustained in self-interested networked societies with the help of only handful of altruistic agents, and that it does not necessarily require the concerted effort of the entire society.

4.2.1 Research Goals

We set the following sub-goals for the emergence of cooperation using altruistic agents (EC-AA) based approach to achieve research goals RG9 and RG10 that we outlined in Chapter 1(on page 15):

- EC-AA1: Develop a heterogeneous system design approach that is composed of a large majority of self-interested agents and a small proportion of influencer altruistic agents to establish cooperation.
- EC-AA2: Determine an upper bound for the percentage of the altruistic agents to establish cooperation.
- EC-AA3: Investigate exhaustively the efficacy of the altruistic agent based approach by varying the model parameters such as initial number of cooperators, temptation level and size of the network.

4.2.2 Stochastic Influencer Altruistic Agent (StIAA) Mechanism

The large majority of the agents in the proposed MAS are self-interested, and therefore, they try to maximize their payoff by using the IB action update rule. According to this rule, each agent imitates the action of the wealthiest agent (including itself) in the next round. A small proportion of influencer altruistic agents are introduced at random locations that always cooperate with their neighbors. The idea of influencer agents is inspired by the influencer fixed strategy agents in [41, 23]. These IAAs broadcast their presence in their neighborhood to motivate the SIAs to reciprocate them. As mentioned earlier, the rational SIAs that increase their payoff by always adopting the action of their wealthiest neighbors may get stuck into local maxima due to partial observability of their network. Therefore, they are enabled to determine the optimality of their action choices (pareto-optimality) by trying the action of their neighbor IAAs with a small exploration probability $p_{explore}$.

In the following, we present an analytical argument in support of the better performance of the proposed StIAA mechanism in SF networks.

4.2.2.1 Analytical Discussion on StIAA's Performance in SF Networks

In SF networks, due to the degree-heterogeneity, some agents have high-degree connectivity while the majority of the agents have low-degree connectivity. As a consequence, the high-degree nodes or the hubs always reap higher accumulated payoffs as compared to their low-degree neighbors. If the majority of the neighbors of a hub node are cooperators, then it generates high payoff by cooperating but even higher payoff by defecting. Let us consider two hubs which are cooperator and defector (h_C & h_D) respectively. Since initially cooperators and defectors are distributed uniformly in the network, these hubs should have approximately equal number of cooperator (n_C) and defector (n_D) neighbors, i.e., $n_C \simeq n_D \simeq z/2$, where z is the average node degree of the hub. Therefore, the accumulated payoffs (ACP) of the two hubs should be: $ACP(h_C) = n_C * R + n_D * S \simeq z/2 * (R + S)$ and $ACP(h_D) = n_C * T + n_D * P \simeq z/2 * (T + P)$. Since $T + P > R + S$, the fitness of the defector hubs would be larger than that of the cooperator hubs. This is the reason why defection prevails when solely the imitation based strategies are pursued.

However, irrespective of the strategies adopted by the hubs, their accumulated payoffs are always greater than their low-degree neighbors. Let us consider a low-degree neighbor of a hub that may act as a cooperator (k_C) or a defector (k_D), and its accumulated payoff is $z_1/2*(R+S)$ (when it cooperates) or $z_1/2*(T+P)$ (when it defects), where z_1 is the average degree of this node. In SF networks, since the average degree of the hubs are much larger than the that of the low-degree nodes, i.e. $z >> z_1$, $ACP(h_C)$ or $ACP(h_D)$ is always larger than $ACP(k_C)$ or $ACP(k_D)$.

Previously it has been shown that when the agents follow the IB or SA state update rule, the behavior of the high-degree nodes or the hubs determine the asymptotic state of the network [29]. A defecting hub can lead its imitating neighbors towards defection. We find a remedy to this problem in a mechanism called "network reciprocity" that is able to resist or eliminate the invasion of the defectors [45]. According to this mechanism, if the cooperators are able to form clusters in which they mutually help each other, then cooperation evolves and sustains in the network. We now discuss how our StIAA based approach increases the likelihood of the hubs to form clusters of cooperators and thereby facilitates cooperation.

In StIAA, the influencer altruistic agents (IAAs) persuade their neighbors to cooperate. According to StIAA, the defector hubs that follow the IB state update rule may at some stage explore and reciprocate the strategy of its IAA neighbor. After becoming cooperators hubs would incur highest accumulated payoff as compared to their low-degree neighbors and thus would influence them to adopt its current action of cooperation. The hubs are interconnected due to the *age-correlation* among the nodes in the Barabasi-Albert model of SF networks. At one time-step of the iterative game it is possible that multiple interconnected hubs adopt (through exploration) the cooperative action of the IAAs in their neighborhood in the current round and thereby could lead the entire network towards evolving cooperation.

A small SF network is used as depicted in Figure 16 to illustrate this phenomenon. In (a) all agents are self-interested (SIAs) except one IAA. In the current round three SIA's act as defectors while one SIA cooperates. The accumulated payoff of the hub would be the largest (2T+2P) in its neighborhood and therefore its neighbors would adopt its defection strategy in the next round leading the network towards a defection state. The IAA alone is not able to resist this invasion of the defectors. However, since the SIAs try the action of their IAA neighbor with a small exploration probability, the hub may adopt the cooperative action of the IAA in one time-step as in (b). Again its accumulated payoff would be the largest and, as a consequence, its SIA neighbors would adopt its cooperation strategy. Thereby the entire network would evolve into a cooperation state in (c). However, it is important to note that if one of the neighbors of the hub (other than the IAA) is another hub that has adopted the action of defection, the cooperative hub may imitate its action and the network would turn into all-defectors. To resolve this problem both the hubs need to explore the action of the IAA in the current round. Simulation results indicate that this indeed happens in one of the time-steps as the network uses many iterations to finally converge into a majority cooperative state.

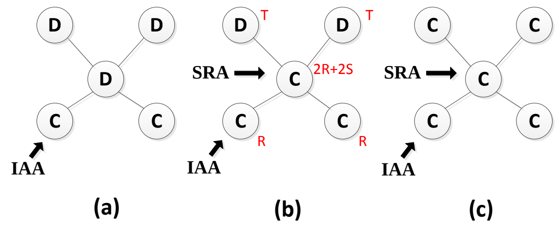


Figure 16: StIAA facilitating cooperation in a SF network: (a) One influencer altruistic agent (IAA) and four self-interested agents (SIA) of which three SIAs, including the hub, behave as defectors; (b) based on payoff differentials, the hub SIA might try IAA's cooperation strategy and act as a stochastic reciprocator agent (SRA) (c) all of the SIAs adopt the cooperation strategy of the hub SRA by following the imitate-best-neighbor (IB) state update rule.

Algorithm 4: Stochastic Influencer Altruistic Agent (StIAA) Mechanism

Require: Accumulated payoff is transparent only to the neighbors

```
4.1  begin
4.2      randomStrategySelection()
4.3      randomIAAselection()
4.4      playPDGamewithNeighbors()
4.5      computeAccumulatedPayoff()
4.6      for each agent i:= 1 to n do
4.7          r ← randomDouble()
4.8          if r < p_explore AND neighborOfSIA(i)==IAA then
4.9              i reciprocates the IAA
4.10         else
4.11             i follows the IB rule
4.12         end
4.13
4.14     end
4.15 end
4.16 iterate (Lines 4.4 - 4.13)
```

4.2.3 Algorithm for StIAA Mechanism

Algorithm 4 describes our StIAA mechanism. Initially the strategies (Cooperate or Defect) are randomly assigned among the agents and the IAAs are randomly selected; then agents play the PD game with their neighbors and compute the accumulated payoffs (Lines 4.4 - 4.13). Then (Lines 4.6 - 4.13) the SIAs try the action of their IAA neighbor with a small probability $p_{explore}$. Otherwise the SIAs update their strategies according to the IB action update rule. This process repeats (Lines 4.4 - 4.15) over multiple rounds and leads the network into a cooperation state. Since the updating of the actions depend on the local neighborhood, we implement *synchronous update* in which the entire society updates their states simultaneously in discrete time-steps that gives rise to a discrete-time macro-level dynamics.

4.2.4 Simulation and Results Analysis

We conduct simulations with the following goals: (i) compare the performance of our proposed StIAA mechanism with the two state-of-the-art imitation based approaches (IB and SA) and then (ii) perform a comprehensive empirical study on the performance of StIAA by varying the percentage of the initial number of cooperators, percentage of IAAs and the temptation payoff values.

4.2.4.1 Network Topology

The agents are situated on a connected topology that constrains the communications to the immediate neighbor set. An edge between two nodes of the network indicates that the agents interact and play the PD game.

The experiments are conducted on SF topologies of varying average degrees. In addition to this, the performance of StIAA is investigated in random (RN) networks as compared to the performance of the IB and SA action update rules over RN networks.

The SF topologies are generated using the Barabasi-Albert model. The minimum node degree is varied from 1 to 25 such that average node degree z lies between 2 to 50.

The random (RN) networks are generated first by adding a random node with every node in the network. This ensures that no node is isolated. Then we add links between two randomly selected nodes. The number of these randomly added links is varied to create networks with varying z in the range of 2 to 50.

4.2.4.2 Simulation Setup

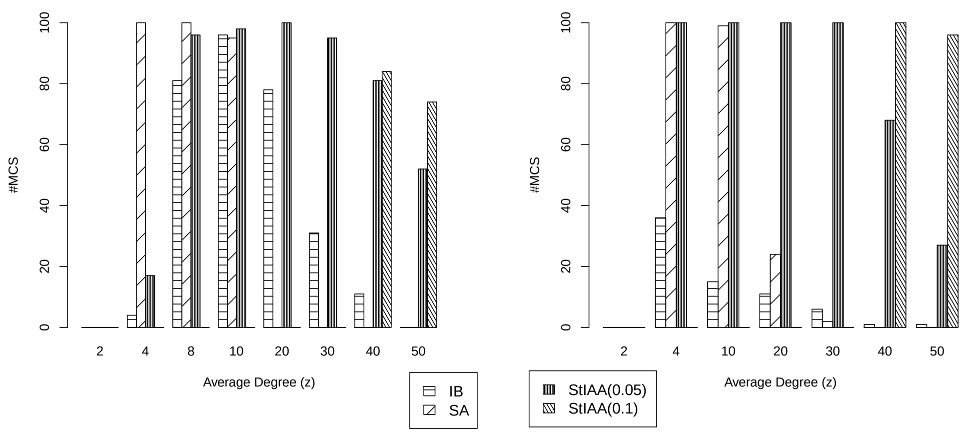
The network consists of 1000 agents represented as nodes in both the SF and RN networks. *A large majority cooperation state (LMCS) is defined as the one in which 90% or more agents cooperate with each other* [31]. In order to investigate the scalability of StIAA, experiments on 5000 agents SF networks are conducted as well.

The IAAs maintain their cooperation strategy during the course of the simulation. These agents not only behave altruistically (being always cooperative), but also try to influence their neighborhood agents to become altruistic (cooperative). Only 5% IAAs are considered to be the approximate upper bound (the same reported in [23]). For most of the experiments this value is maintained. However, this number is varied within the range of 1% to 7% to observe how it affects the performance of StIAA. Similar to [55], the exploration probability $p_{explore}$ is set to 0.05. However, for higher connectivity networks, this value is increased to 0.1 for getting better performance.

The following values for the PD payoff matrix are used in the simulations: R = 1, P = 0.1 and S = 0. Hence, the incentive to defect, T, is restricted to $1 < T < 2$. For most of our experiments we use the value 1.1 for the temptation payoff. However, this value is varied within the range 1.1 to 1.9 to investigate its effect on the performance of StIAA.

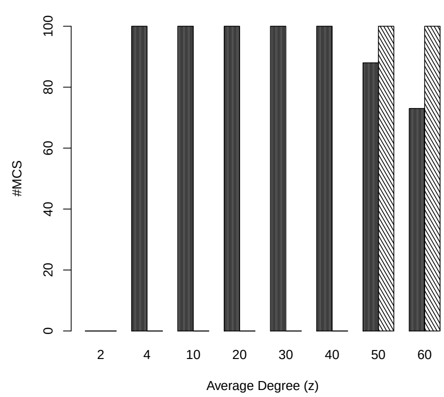
All the results reported are averages over 100 realizations for each network. Each simulation consists of 10,000 time-steps where a time-step refers to a single run of the program.

4.2.4.3 Simulation Results



(a) Random Network (1000 Agents)

(b) SF Network (1000 Agents)



(c) SF Network (5000 Agents)

Figure 17: Plot of average degree (z) vs. number of times each mechanism successfully converges into a large majority cooperation state (#LMCS) over 100 simulations; temptation payoff=1.1, initial cooperators=50%, IAA=5%.

Comparison of the Existing Imitation based Approaches with StIAA: Figure 17(a) and 17(b) show the performance of the IB, SA and StIAA for various average degree RN and SF networks respectively. The network size is limited to 1000 agents. For each average degree category, 100 network instances are created and three approaches are used to observe the process of evolution of cooperation. In SF networks, when the average degree is smaller (z in the range of 4 to 5), SA performs better than IB. However, as the average degree increases, both IB and SA fail to establish LMCS. We observe a similar pattern in RN networks in which larger average degree result in increasingly less or no cooperation.

In sparse SF and RN networks ($z \approx 2$), StIAA does not converge into LMCS (as also observed in case of IB and SA). However, for average degree between 4 to 30, StIAA converges to LMCS in almost all instances with $p_{explore}$ set to 0.05. However, when the average degree lies in the range of 40 to 50, this low value of $p_{explore}$ does not lead to LMCS. The results indicate that by increasing this value to 0.1, the likelihood of cooperation in these highly-connected SF networks can be significantly increased.

The performance of the StIAA in RN networks is not as good as in SF networks. The main reason for this relatively poor performance is that RN networks do not have the benefit of skewed degree-distribution. In SF networks, StIAA facilitates the formation of clusters of cooperators due to age-correlation among the hub nodes; and as a result cooperation evolves. On the other hand, unlike SF networks, in RN networks the degree of the nodes are neither very large nor are they intricately connected. As a consequence, clusters of cooperators are less likely to be formed. However, StIAA significantly outperforms IB and SA in RN networks.

Table 11: Effect of the variation of various parameters in 1000 agents SF networks. For each variation, the table shows the number of times the network successfully converges into a majority cooperation state (#LMCS) among 100 simulations.

		Variation of % of Cooperators & Temptation Payoff (T) (%IAA = 5)								
		%Coop=10			%Coop=30			%Coop=50		
		T=1.1	T=1.5	T=1.9	T=1.1	T=1.5	T=1.9	T=1.1	T=1.5	T=1.9
z	$p_{explore}$	#LMCS	#LMCS	#LMCS	#LMCS	#LMCS	#LMCS	#LMCS	#LMCS	#LMCS
2.054	0.05	0	0	0	0	0	0	0	0	0
4.035	0.05	100	27	0	100	27	1	100	28	100
9.981	0.05	100	100	100	100	100	100	100	100	100
19.889	0.05	100	100	100	100	100	100	100	100	100
29.759	0.05	99	62	6	100	73	14	100	78	12
39.579	0.05	20	0	0	56	1	0	68	5	0
	0.1	100	54	1	100	68	3	100	67	3
49.349	0.05	0	0	0	7	0	0	27	0	0
	0.1	72	0	0	90	1	0	96	0	0

Empirical Analysis of StIAA

In order to perform a comprehensive analysis of the performance of StIAA mechanism in SF networks, we vary the following parameters: (a) percentage of the initial number of cooperators (%Coopp), (b) temptation payoff values (T) and (c) percentage of the IAAs (%IAA).

Variation of % of Initial Cooperators: Table 11 shows the effect of the variation of the initial percentage of cooperators for various levels of the temptation payoff values. First, consider the situation when the temptation payoff value is set to 1.1 (columns 3, 6, and 9). The results indicate that when the initial percentage of cooperator is very low (10%), even in the most highly-connected networks ($40 < z < 50$) likelihood of cooperation is high. For example, in networks with $z \approx 50$, exploration probability of 1.1 establishes cooperation in 72% instances. With the increase in the percentage of initial cooperators, as in 30% and 50% cooperator networks, LMCS occurs 90% and 96% times respectively. Therefore, it appears that the variation in the percentage of initial cooperators does not affect the cooperation evolution process very much when temptation payoff is as low as 1.1. StIAA is able to evolve cooperation even if the initial fraction of cooperators is very small (e.g., 10%). Therefore, it is *robust* against the perturbation in the number of cooperators and can transform a majority defector society into a cooperative one.

Variation of Temptation Payoff: However, when the temptation payoff increases beyond 1.1, even with 50% initial cooperators the network does not evolve towards cooperation (columns 10 and 11) in very large neighborhoods (where z is approx. $40 \sim 50$). In other words, the performance of StIAA is sensitive to the payoff value of temptation. Both the IAAs and exploration probability need to be increased to facilitate cooperation where benefit of temptation is high.

Table 12: Effect of the variation of IAAs in 1000 agents SF networks. For each variation, the table shows the number of times the network successfully converges into a majority cooperation state (#LMCS) among 100 simulations.

		Variation of % of IAAs (%Coop=50, T=1.1)		
		%IAA=1	%IAA=3	%IAA=7
z	$p_{explore}$	#LMCS	#LMCS	#LMCS
2.054	0.05	0	0	0
4.035	0.05	99	100	100
9.981	0.05	97	100	100
19.889	0.05	68	100	100
29.759	0.05	29	89	100
39.579	0.05	19	29	92
	0.1	32	99	100
49.349	0.05	11	24	26
	0.1	21	52	100

Variation of % of IAAs: Table 12 shows the effect of various percentage of IAAs for a fixed 50% initial cooperators and 1.1 temptation payoff value. It can be seen that for smaller density of IAA (1% to 3%) StIAA does not always converge into LMCS beyond medium average connectivity networks (where $z > 20$). In case of 1% IAA the convergence scenario is not satisfactory when the average degree increases. Even with relatively large value of $p_{explore}$ ($= 0.1$), performance does not improve much. The improvement is not significant in case of 3% IAA. On the other hand, although 7% IAA provides better result, its difference with 5% IAA is not significant (columns 9 and 14). In other words, 5% IAA is a reasonably small number to maintain good performance. Therefore, this percentage is used as the *upper bound for the IAAs.*

Scalability of StIAA: In order to study the *scalability* of StIAA, its performance is investigated on 5000 agents SF networks with varying degrees within the range 2 to 60. Figure 17(c) shows that the performance of StIAA is even better than 1000 agents SF networks. For example, when the average neighborhood size becomes larger (such as when z is between 40 to 50), more than 80% times LMCS occurs. Further increasing the neighborhood size ($z \approx 60$) shows that more than 70% instances StIAA converges into LMCS. With an increased exploration rate ($p_{explore} = 0.1$), convergence rate is 100% even in very high average degree networks.

4.2.5 Conclusions

This research develops a stochastic influencer altruistic agent (StIAA) mechanism that is able to establish cooperation in MAS operating organized as *highly-connected* SF networks. A small proportion of influencer altruistic agents (IAAs) is introduced in the self-interested society. The IAAs, irrespective of their payoff, always cooperate with their neighbors while the self-interested agents (SIAs) try to maximize their payoff by imitating the wealthiest agent in their neighborhood. In order to check the optimality of their actions, the SIAs try the cooperative action of their IAAs (should there be one) with a small exploration probability. We conduct comprehensive simulations to evaluate the performance of StIAA.

We have accomplished the research goals EC-AA1-3 by:

- Proposing a heterogeneous system design approach that is composed of a large majority of self-interested agents and a small proportion of influencer altruistic agents.
- Showing that StIAA performs significantly better in highly-connected SF and RN networks than the existing state-of-the-art IB and SA action update rules.
- Determining a realistic upper bound for the percentage of the IAAs (only 5%) to ensure cooperation.
- Showing that StIAA is *robust* as it is able to evolve cooperation in societies that initially has very small fraction of cooperators.
- Showing that StIAA is *scalable* in that increasing the size of the network does not degrade its performance.

CHAPTER 5: CONCLUSIONS & FUTURE WORK

In this dissertation, we presented a topology-aware approach that facilitates the emergence of social norms in Multiagent Systems (MAS) organized as various types of networks. The motivation was to solve the norm emergence problem in virtual societies that are of large size and dynamic in nature. The type of MAS we study requires not only that a large majority of the population share norms but that such norms should emerge fast. Because of the dynamic nature of the MAS, norm emergence mechanisms have to be adaptive. We hypothesized that equipping agents in networked MAS with "network thinking" capabilities facilitate the emergence of social norms in an effective and efficient manner. Our topology-aware mechanisms solve the problem of *convention emergence* within the space of conventional norms and *cooperation emergence* within the space of essential norms. Therefore, our conclusions are separately drawn for these two types of norms.

5.1 Convention Emergence

We explored the challenges characteristic of various sizes of convention spaces within the domain of convention emergence. Since small convention space problems can be solved quickly, we emphasized the solvability of our mechanisms. Large convention space problems are complex and more difficult to solve. At times high-quality conventions may not exist in the system; this means agents need to create better conventions as well as search for one. Hence, we emphasized both solvability and efficiency of the solution approach.

For small convention space problems, we showed that no existing single simple distributed mechanism could create convention across various topologies. This claim is both analytically and experimentally verified. We focused our efforts especially in establishing norms in MAS organized as scale-free (SF) networks for two reasons: first, SF networks represent theoretical social networks and hence have many real-world applications; second, previous works don't address the importance of network topology and its influence on creating conventions [75]. Most existing works used specific configurations of SF networks (based on fixed parameter settings) and claimed to derive general conclusions about the norm emergence phenomenon in these networks [19]. We varied the SF model parameters and experimented with SF networks with low, medium and high connectivity. We explored the challenge of forming conventions in sparse SF topologies.

To summarize our approach, first we showed that the state-of-the-art Generalized Simple Majority (GSM) action update rule did not perform successfully across different types of SF networks, particularly in sparse SF networks. We, then, presented a novel socially inspired technique called accumulated coupling strength (ACS) convention selection algorithm that was able to create a single convention both in sparse and densely-connected SF networks. ACS encodes the history of all previous influences and thereby acts as a social pressure to promote a specific convention. However, ACS does not perform as well in random (RN) networks as GSM does. To address this problem, we developed a topology-aware convention selection (TACS) mechanism that enabled the agents to predict the global topology based on local information and then to select a suitable convention emergence algorithm. An extensive simulation on RN and SF networks showed that a large majority of the agents correctly recognized their topology and used either GSM (for RN networks) or ACS (for SF networks) that led to the convergence into a single convention.

For large convention space problems, we hypothesized that if agents were endowed with the capability of "network thinking", the convention formation process would become effective and efficient. To validate this hypothesis, we used a language coordination problem from [23] for our investigation where a society of agents constructed a common lexicon in a decentralized fashion. Similar to [23], agents' interactions were modeled using a language game. In this game, 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 use contextual knowledge to expedite the convention formation process. Moreover, a socially-inspired technique called the *power of diversity* was used. Agents were enabled to bring diversity in the population through network reorganization that was based on the lexicon utility. Extensive simulation results indicated that the mechanism was both effective (able to converge into a large majority convention state with more than 90% agents sharing a high-quality lexicon) and efficient (faster) when compared to two state-of-the-art mechanisms [56] and [23]. In addition to this, the efficacy of the topology-aware mechanism was tested by varying the topological features to develop an understanding of the influence of topology on the convention formation process. The conditions under which diversity was beneficial were also investigated.

Following are the contributions related to convention emergence problem. We relate them to research goals discussed in Chapter 1 in page 12 and put them in the context of Contribution C1 in page 15:

- For small convention spaces, ACS is able to create a convention in sparse as well as in dense SF networks. The TACS mechanism enables convention emergence in various topologies including RN and SF networks. This is a part of contribution C1 which is in response to research goals RG1 - RG3 outlined in Chapter 1(page 12).
- In large convention spaces, TA mechanism provides an effective and efficient solution that forms another part of contribution C1 which is in response to research goals RG4 - RG6 outlined in Chapter 1(page 13).

5.2 Cooperation Emergence

Moderately and highly-connected SF networks present the greatest challenge to evolve cooperation within the space of essential norms. We presented two mechanisms that solved the cooperation emergence problem across these SF networks. The first mechanism used a commitment based dynamic coalition formation technique and complex network dynamics to form cooperation. Agents in the MAS are organized as SF networks and the mechanism is able to form cooperation in *moderately-connected* SF networks (where the average node degree is 20). The second mechanism emphasized *highly-connected* SF networks (where the average node degree is up to 50) and used a heterogeneous system design approach that included a small fraction of altruistic agents. Highly-connected networks are claimed to be susceptible to defection and are the most challenging to sustain cooperation. We present our conclusions on these two mechanisms separately in the following two subsections.

5.2.1 Commitment Based Dynamic Coalition Formation Approach

We developed a commitment-based dynamic coalition formation approach to establish mutual cooperation in large MAS organized as moderately-connected SF networks. Interactions of the self-interested agents with their immediate neighbors were captured using an iterated Prisoner's Dilemma (PD) game. Unlike many previous works that assume being given pre-established networks, we enabled agents to dynamically choose their interaction partners to form their network. Agents offered a commitment to their wealthiest neighbors in order to form coalitions. A commitment proposal, that includes a high penalty for breaching the commitment, incentivizes opponent agents to form coalitions inside which they mutually cooperate and thereby increase their payoff. We enabled agents, to reason from a network-theoretic perspective, about determining the value of the penalty with respect to the minimum node degree and the payoff values such that convergence into optimal coalitions is possible.

5.2.2 Altruistic Agents Based Approach

We developed a stochastic influencer altruistic agent (StIAA) mechanism that is able to establish cooperation in MAS operating on *highly-connected* SF networks. A small proportion of influencer altruistic agents (IAAs) is introduced in the self-interested society. The IAAs, irrespective of their payoff, always cooperate with their neighbors while the self-interested agents (SIAs) try to maximize their payoff by imitating the wealthiest agent in their neighborhood. In order to check the optimality of their actions, the SIAs try the cooperative action of their IAAs (should there be one) with a small exploration probability. We conducted comprehensive simulations to show that StIAA performed significantly better in highly-connected SF and RN networks than the existing state-of-the-art action update rules. Moreover, we have determined a realistic lower bound for the percentage of the IAAs (only 5%) to ensure cooperation.

The following are the contributions related to cooperation emergence problem. We relate them to research goals discussed in Chapter 1 in page 12 and put them in the context of Contributions C2 - C3 mentioned in page 15:

- Our Commitment based Dynamic Coalition Formation approach evolves cooperation in moderately-connected SF networks. It fulfills contribution C2 which is in response to research goals RG7 and RG8 outlined in Chapter 1(page 14).
- Our altruistic agent based approach facilitates the emergence of cooperation in highly-connected SF and RN networks. It fulfills contribution C3 which is in response to research goals RG9 and RG10 outlined in Chapter 1(page 15):

5.2.3 Future Work

There are several directions in which this dissertation could evolve in future. For example, the TACS mechanism for small convention space can be extended to different types of networks. Also, the accuracy of the agents' prediction of the global network topology can be improved. The topology-aware approach for large convention space can be implemented on other topologies such as community networks [35], local-world evolving networks [37] and multiplex networks [70]. Additional future work include validating the mechanism on bigger convention space problems; considering malicious agents and error-prone communication; and extending the mechanism for solving convention problem to traffic assignment application and ontology sharing in biomedicine as follows.

- Traffic Assignment: The topology-aware convention formation mechanism can be used to solve the *traffic assignment* problem for modeling a transportation system [3]. Unlike centralized classical approaches in which trips are assigned to links or routes, a multi-agent approach can be used from the perspective of road users. These users are modeled as agents that autonomously select their routes in an adaptive way. This traffic convention problem is complex due to the large number of agents and the number of choices for alternative routes. Our topology-aware mechanism can be extended to expedite the process.
- Ontology Sharing in Biomedicine: In biomedicine research, shared ontology development is an important research problem [80]. An ontology represents the concepts and their interrelation within a knowledge domain. In biomedicine, several ontologies have been developed that provide standardized vocabularies to describe diseases, genes and gene products, physiological phenotypes, anatomical structures, and many other phenomena. Scientists use these ontologies to encode the results of their experiments and observations. Ontologies are used to perform integrative analysis to discover new knowledge. The challenge is to evaluate an ontology's representation of knowledge within its scientific domain. This requires developing a model for ontology sharing. Our language

convention formation approach can be extended to address the ontology sharing problem in biomedicine research. A multi-agent based system can be designed in which each agent represents an ontology [66]. Then the research question can be formulated as: how can agents develop a shared ontology in a decentralized fashion?

The commitment-based dynamic coalition formation approach and the altruistic agent based approach can be implemented on other types of networks such as small-world, regular, etc.

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APPENDIX A: NETWORK MODELS

In the context of social systems and in many real world applications we observe that the network exhibits both node degree-heterogeneity and high clustering. The standard Barabasi-Albert (BA) scale-free (SF) network model [8], however, suffers from low clustering. Moreover, the heterogeneous degree-distribution of the BA model is fixed by the constant power law scaling-exponent. Hence, to emulate more realistic scenarios, the following two SF network models are presented that is used to build the computational model in this dissertation.

A Barabasi-Albert Model

The BA SF model [8] is formed as follows:

(i) Growth: Starting from m_0 nodes, at every time step a new node is added with m ($m <= m_0$) edges which connect between the new node and m different previously existing nodes.

(ii) Preferential Attachment: A node i is chosen to be connected to the new node according to the probability $\prod_{n \to i} = \frac{A+k_i}{\sum_j (A+k_j)}$ where k_i is the degree of node i and **A** is a *tunable parameter* representing the initial attractiveness of each node. This parameter controls the degree-heterogeneity of the network.

B Extended Barabasi-Albert Model

The extended model [30] follows the growing process of the BA model that starts with m_0 nodes. At every time step a new node i is added to the network and gets connected with m ($m <= m_0$) of the previously existent nodes. The first link of node

i is added to node j of the network (with $j < i$) following the preferential attachment rule of the BA model. The remaining $m-1$ links are added in two different ways: (a) with clustering probability p the new node i is added to a randomly chosen neighbor of node j and (b) with probability $(1-p)$ node i gets connected to one of the previously existing node using the preferential attachment rule again. This procedure ensures a degree distribution of $p(k) \sim p^{-\gamma}$ with a tunable clustering coefficient.

With $p = 0$, the extended model transforms to the BA model with low clustering coefficient (at $\gamma = 3$). For values of $p > 0$, the clustering coefficient increases monotonously. Since this model partially follows the preferential attachment rule of the BA model (the first link of each new node is added through preferential attachment rule), the heterogeneity of the degree distribution of the extended BA model can also be controlled by A.