Supporting cooperation and coordination in open multi-agent systems

by

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Abstract

Cooperation and coordination between agents are fundamental processes for increasing aggregate and individual benefit in open Multi-Agent Systems (MAS). The increased ubiquity, size, and complexity of open MAS in the modern world has prompted significant research interest in the mechanisms that underlie cooperative and coordinated behaviour. In open MAS, in which agents join and leave freely, we can assume the following properties: (i) there are no centralised authorities, (ii) agent authority is uniform, (iii) agents may be heterogeneously owned and designed, and may consequently have conflicting intentions and inconsistent capabilities, and (iv) agents are constrained in interactions by a complex connecting network topology. Developing mechanisms to support cooperative and coordinated behaviour that remain effective under these assumptions remains an open research problem.

Two of the major mechanisms by which cooperative and coordinated behaviour can be achieved are (i) trust and reputation, and (ii) norms and conventions. Trust and reputation, which support cooperative and coordinated behaviour through notions of reciprocity, are effective in protecting agents from malicious or selfish individuals, but their capabilities can be affected by a lack of information about potential partners and the impact of the underlying network

structure. Regarding conventions and norms, there are still a wide variety of open research problems, including: (i) manipulating which convention or norm a population adopts, (ii) how to exploit knowledge of the underlying network structure to improve mechanism efficacy, and (iii) how conventions might be manipulated in the middle and latter stages of their lifecycle, when they have become established and stable.

In this thesis, we address these issues and propose a number of techniques and theoretical advancements that help ensure the robustness and efficiency of these mechanisms in the context of open MAS, and demonstrate new techniques for manipulating convention emergence in large, distributed populations. Specifically, we (i) show that gossiping of reputation information can mitigate the detrimental effects of incomplete information on trust and reputation and reduce the impact of network structure, (ii) propose a new model of conventions that accounts for limitations in existing theories, (iii) show how to manipulate convention emergence using small groups of agents inserted by interested parties, (iv) demonstrate how to learn which locations in a network have the greatest capacity to influence which convention a population adopts, and (v) show how conventions can be manipulated in the middle and latter stages of the convention lifecycle.

Dedicated to my father, Owain Franks, who gave me my first programming book. This thesis is a long delayed consequence of that initial inspiration.

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I reserve a special vote of thanks for Owain Franks and Ben Jones, for generously giving their time to proofread it.

Declarations

This thesis is presented in accordance with the regulations for the degree of Doctor of Philosophy. It has been composed by the author and has not been submitted in any previous application for any degree. The work described in this thesis has been undertaken by the author except where otherwise stated.

The work presented in this thesis is based on the following publications:

- Franks, H.P.W., Griffiths, N. and Jhumka, A. (2010) Image Scoring in Ad-Hoc Networks: An Investigation on Realistic Settings. In: 8th European Workshop on Multi-Agent Systems, Paris, France.
  The work presented in this publication appears in Chapter 3.

- Franks, H.P.W., Griffiths, N. and Jhumka, A. (2012) Robust reputation in decentralized markets. In: ACM EC 2012 Workshop on Incentives and Trust in E-Commerce, Valencia, Spain.
  The work presented in this publication appears in Chapter 3.

- Franks, H.P.W., Griffiths, N. and Jhumka, A. (2012) Manipulating convention emergence using influencer agents. Autonomous Agents and Multi-Agent Systems, Doi: 10.1007/s10458-012-9193-x
  The work presented in this publication appears in Chapter 5.

- Franks, H.P.W., Griffiths, N. and Anand, S. S. (2012) Learning vertex influence in complex social networks. In: Proceedings of the 12th International Conference on Autonomous Agents and Multiagent Systems, To Appear.

  The work presented in this publication appears in Chapter 6.

Abbreviations

Agents abbreviations

MAS	Multi-Agent System
P2P	Peer-to-Peer
T&R	Trust and Reputation
IS	Image Scoring
IA	Influencer Agent

Network abbreviations

LO	Lowest Overlap
HO	Highest Overlap
AO	Average Overlap
HEE	Highest Edge Embeddedness
LEE	Lowest Edge Embeddedness
AEE	Average Edge Embeddedness
ASPL	Average Shortest Path Length
AND	Average Neighbour Degree
LCC	Local Clustering Coefficient
BC	Betweenness Centrality

EC	Eigenvector Centrality
CC	Closeness Centrality
BFS	Breadth-First Search
SNS	Snowball Sampling
RW	Random Walk
MHRW	Metropolis-Hastings Random Walk
MHRW-DA	Metropolis-Hastings Random Walk with Delayed Acceptance

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CHAPTER 1

Introduction

Cooperative and coordinated behaviour are fundamental to increasing individual and aggregate welfare in Multi-Agent Systems (MAS)[1]. By cooperation, we mean the process by which agents select strategies while potentially incurring personal costs in order to attain mutual benefit; and by coordination the process by which agents act in such a way that they do not cause other agents to incur unnecessary costs. Both are key factors in allowing large populations of agents to interact in complex environments while reducing the ability of malicious agents to exploit individuals for personal gain. A wide variety of fields have significant interest in the mechanisms of cooperation and coordination, including biology, economics, sociology and computer science (Axelrod, 1986). The study of such behaviour serves two purposes (Lakkaraju & Gasser, 2008): (i) revealing how these processes have emerged in the natural world (e.g. Bolton *et al.* (2005); Fehr & Fischbacher (2004); Lotem *et al.* (1999); Riolo *et al.* (2001); Young (1993)) and (ii) increasing levels of coordinated and cooperative behaviour among agents

[1]We adopt the convention of MAS indicating both singular and plural usage throughout this thesis.

in artificial societies (e.g. Ebadi *et al.* (2008); Hales (1979); Shen *et al.* (2004); Walker & Wooldridge (1995)). In this thesis, we are primarily concerned with a specific kind of MAS, in which agents can join and leave freely. Such *open* systems embody particular properties that can reduce the efficacy of mechanisms for supporting coordinated and cooperative behaviour.

1.1 Open Multi-Agent Systems

MAS are an increasingly pervasive paradigm in real-world domains (Mamidi & Chang, 2012; Shieh *et al.*, 2012), and the need for scalable, distributed mechanisms for increasing coordinated and cooperative behaviour has seen a corresponding increase in research activity (Durfee, 2001; Purvis *et al.*, 2006). Open MAS characterise an enormous set of domains found in the real world, including Peer-to-Peer (P2P) networks, social networking and media, and many economic markets. In recent years, as computational capacity and connectivity have increased, these systems have become increasingly widespread and complex. Since agents join or leave freely, systems can be expected to contain large dynamic populations, complex connectivity structures, heterogeneous agent architectures, heterogeneous and potentially conflicting agent intentions, and homogeneous levels of authority (Sycara, 2008). Developing mechanisms for encouraging cooperative and coordinated behaviour that remain effective under these assumptions remains an open research problem.

Each of these features present specific challenges to mechanisms that promote desirable behaviour. Since populations are potentially large, any solution must be entirely decentralised, and agents joining and leaving freely may mean that many agent architectures and capabilities are present in the system. These agents may further be intermediaries for a variety of stakeholders (Ramchurn *et al.*, 2005). Accordingly, we cannot assume the ability to mandate behaviour conducive to cooperation or coordination across the population, and successful mechanisms should be robust to proportions of the population not adhering to behavioural assumptions beyond that of basic rationality. Since agents can join or leave freely, determining agent identity accurately may also be difficult.

In addition, the underlying network structures that constrain agent interactions and communications often exhibit complex properties (Albert & Barabási, 2002; Newman & Girvan, 2004) that significantly alter the dynamics of societies built upon them (Albert *et al.*, 2000; Delgado, 2002; Kittock, 1993; Pirzada & Mcdonald, 2006; Tomassini *et al.*, 2007). Consequently, while we assume uniform levels of agent authority, some agents may attain considerably more influence or power by virtue of their connectivity and the local network structure surrounding them.

1.2 Supporting cooperative and coordinated behaviour

Two established techniques for encouraging desirable behaviour in open MAS are (i) *norms and conventions*, which consider the interactions between agents in aggregate, and (ii) *trust and reputation*, which consider individual agents and ways to protect them from malicious or selfish agency. Many approaches for both (i) and (ii) are entirely decentralised and subsequently are suitable for application to open MAS. It should be noted that while we focus on norms, conventions, trust and reputation in this thesis, a large number of other mechanisms have been proposed for supporting coordinated or cooperative behaviour. For example, tags are a lightweight and effective mechanism in domains with low probabilities of repeat interaction (Griffiths, 2008), and organisational structures and patterns that specify agent authorities and roles are successful in closed systems (Zambonelli *et al.*, 2001). Contracts have also been proposed as ways of constraining agent behaviour in return for guarantees on system properties (Dellarocas, 2000). These techniques are successful in given domains but are not fully applicable to the challenges of open MAS domains that we consider.

1.2.1 Norms and conventions

Norms and conventions are socially adopted rules or standards of behaviour that reduce costs to agents associated with conflicting strategies and goals (Kittock, 1993), encourage cooperative behaviour between agents (Axelrod, 1986), reduce the ability of malicious agents to disrupt the system (Perreau de Pinninck *et al.*, 2009) and reduce the computational burden of action selection for individuals. Conventions are socially accepted standards of behaviour. There is no obligation to act according to the convention, but instead there exists an understanding that not to act in that way will potentially result in costs to the agent and the society through malcoordination. Norms incorporate an element of obligation, such that those who do not adhere to the norm might be punished. In many open MAS domains, considerations of time-variance and system complexity mean that conventions or norms cannot be designed *a priori* (Salazar *et al.*, 2010b). Open research problems include the generation, propagation, manipulation, and establishment of desirable norms and conventions in real time.

1.2.2 Trust and reputation

In trust and reputation mechanisms, agents assess the probability that another agent will carry out its obligations. Trust and reputation systems thus protect agents from selecting interaction partners which might reduce utility (Buchegger, 2005). Trust systems have been extensively investigated and have shown considerable success (e.g. Pirzada & Mcdonald (2006); Sabater *et al.* (2006)). The best-performing systems tend to incorporate a wide variety of information sources in calculating a trust assessment, limiting their applicability in domains with potentially anonymous agents and constrained resources (e.g. Huynh *et al.* (2006)). Reputation, often seen as a socially-accepted trust assessment of an individual, is an important component in systems where an individual's knowledge of a potential interaction partner is insufficient to calculate a reliable trust assessment. There are a number of open research questions relating to reputation systems, including the effects of incomplete information on system efficacy, and whether reputation can be used as a predictor of convention adherence.

1.3 Local interactions and information propagation

As illustrated in Figure 1.1, local interactions between agents underpin the operation of both of these mechanisms: trust and reputation mechanisms constrain action or partner selection towards those most likely to be beneficial to the agent, and conventions and norms restrict action selection towards those likely to result in behaviour that is beneficial for the society and, on average, the agent.

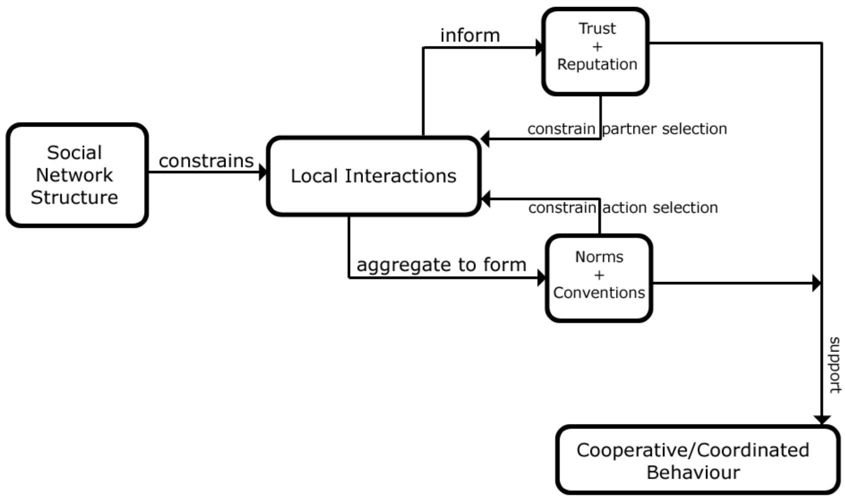


Figure 1.1: Illustration depicting conceptual organisation of research topics for cooperative and coordinated behaviour in open MAS.

Consequently, we require an understanding of factors that underlie partner and action selection choices in local interactions, such that we can (i) increase the efficacy and efficiency of mechanisms for convention and norm emergence, and trust and reputation systems, and (ii) exploit this knowledge to design new mechanisms more suited to the difficulties of open MAS domains.

Agent decision making processes are, for the most part, based on information gathered during interactions within the system. Consequently, the propagation of this information, whether explicitly by agents or through observation of agent behaviour, plays a major role in determining agent behaviour (e.g. Ghanem *et al.* (2012); Salazar *et al.* (2010b); Villatoro & Sabater-Mir (2011)). The transmission of information such as reputation and trust assessments, agent action selections, or agent identity, is fundamental to the effective operation of mechanisms that support cooperation or coordination. Agents only have access to local information about the system in which they are participating, and this can lead to partial or out-of-date information on which to base decisions.

Open MAS are also typically constrained by underlying network structures that limit communication and the potential interaction partners for an agent. The structural properties of these networks are highly complex and remain only partially understood. However, such network structures mediate information propagation and therefore have a significant impact on agent interaction decisions.

Understanding how information propagation and network structure alter the efficacy of typical mechanisms for establishing cooperative or coordinated behaviour is therefore fundamental, and forms a central theme in this thesis.

1.4 Problem definition

In this thesis, we investigate how mechanisms that support cooperative and coordinated behaviour, specifically trust, reputation, norms and conventions, can be made robust to the characteristic properties of open MAS discussed above, by exploiting knowledge regarding (i) information propagation through the system and (ii) the underlying network structure that mediates this propagation.

1.5 Objectives of the thesis

The overall objective of this thesis is to develop an understanding of how mechanisms for supporting trust, reputation, norms, and conventions can be effectively applied in open MAS in order to encourage cooperative and coordinated behaviour.

In detail, this thesis aims to do the following.

1. Explore how information propagation and network structure affect the emergence of cooperative and coordinated behaviour and develop strategies that support cooperative and coordinated behaviour robust to the challenges of open MAS, including decentralisation, homogeneous levels of agent authority, and complex network connectivity structures.

2. Identify modifications to simple trust and reputation mechanisms that (i) impart robustness in response to issues caused by insufficient information propagation and (ii) mitigate variance in efficacy caused by the underlying network structure.

3. Identify limitations in current research and models of convention emergence and develop a model of convention emergence that accounts for features of convention behaviour not typically described by current approaches.

4. Develop techniques for manipulating (i) which convention or norm a society adopts and (ii) levels of convention or norm adherence which are robust to the challenges of open MAS.

5. Identify methodologies for exploiting knowledge of the network structure to increase the efficacy of mechanisms that support cooperative and coordinated behaviour.

1.6 Contributions of the thesis

In this thesis we make 6 primary contributions, as follows.

1. We show that incomplete information and topological structure can significantly affect the operation of simple reputation mechanisms, and subsequently reduce levels of cooperative behaviour. We apply gossiping algorithms using simple aggregation rules to reduce the levels of incomplete information and show that this aids the establishment of cooperative behaviour. We characterise the configurations under which (i) incomplete information is a problem, and (ii) gossiping algorithms are applicable, and present an analysis of the effect of topological structure on gossiping efficacy. We show that uncertainty regarding agent strategies, for example in a highly varied population, can increase selfishness in a society, motivating the need for convention and norms.

2. We present a technique for manipulating convention adherence in populations of agents with uniform levels of authority, by inserting *Influencer Agents*, and show that (i) small numbers of Influencer Agents are sufficient to manipulate the emergent dominant convention, and (ii) Influencer Agents provide significant gains in both the number of agents adhering to a convention and the speed of convergence.

3. We analyse the impact of topological structure on Influencer Agent efficacy and show how different topological classes can significantly alter the quality and size of conventions that emerge. We develop a methodology for learning the specific metrics of a given network that predict Influencer Agent efficacy, and use this methodology to identify four specific metrics that are effective in predicting influence across a range of real-world networks. We build prediction models to identify particularly influential locations by exploiting knowledge of the underlying network structure. Applying these models allows significant gains in agent influence. We

demonstrate the insufficiency of typical synthetic network generation algorithms in modelling structures found in the real world, and show that the wide variety of structures found in such domains require adaptive mechanisms for efficient exploitation.

4. We identify several limitations in the descriptive power of the current theory of convention emergence and use aspects of convention emergence literature from several fields to synthesise a formalism for describing convention emergence in open MAS. We show how several established models for investigating convention emergence can be expressed in this formalism.

5. We use our convention formalism to (i) develop a general definition of conventions and norms, and (ii) define a wide variety of metrics of convention quality, support and stability, and show how these allow a more detailed analysis of conventions that enables us to characterise domains in which we either cannot attain or do not desire a single convention across the entire population.

6. We use our model of convention emergence to evaluate the effects of rewards, Influencer Agents, and incentives and sanctions on convention emergence at different stages in the convention lifecycle. We show that Influencer Agents are effective at manipulating conventions in the middle and late stages of emergence, provided there is a minimal level of population churn.

1.7 Structure of the thesis

The remainder of this thesis is structured as follows. For those unfamiliar with cooperation and coordination in open MAS, Chapter 2 introduces the key concepts and discusses relevant contributions in the literature. As discussed above, issues of network structure topology underpin much of the work presented in this thesis, and we provide a detailed introduction to the area in Appendix A.

Detailed literature reviews are contained within the relevant subsequent chapters as necessary, and readers familiar with open MAS and the study of network structures can omit these background discussions.

The remaining chapters present the main contributions of this thesis. Chapter 3 deals with trust and reputation mechanisms, while Chapters 4, 5, 6, and 7 deal with conventions.

In Chapter 3, we report on our investigations into the impact of incomplete information and network structure on cooperative behaviour supported by simple reputation mechanisms, and whether gossiping can mitigate negative effects.

We introduce our work on conventions and norms in Chapter 4, which reviews the current state of convention research and identifies several limitations. We define a formalism with which typical models of convention emergence can be described, and develop (i) a definition of conventions and (ii) a set of metrics defining convention support, stability and quality, which account for these limitations and facilitate future research. A detailed introduction to conventions is contained within this chapter, and we discuss concepts used throughout the remaining chapters of the thesis.

In the subsequent chapters, we address three areas for research identified in Chapter 4, namely, (i) how to manipulate which convention is adopted in distributed open MAS (Chapter 5), (ii) how to exploit knowledge of the underlying network structure when manipulating convention emergence (Chapter 6), and (iii) how to manipulate convention emergence in the middle and latter stages of the convention lifecycle (Chapter 7). Each of these chapters deals with largely independent work, although there is some overlap in concepts (for example, the usage of the Influencer Agent mechanism).

We discuss our conclusions, limitations of our work, and directions for future research in Chapter 8. Appendix B describes how typical models of convention emergence can be expressed in the formalism introduced in Chapter 4.

CHAPTER 2

Background and related work

This chapter reviews the essential related work that underpins this thesis and introduces motivating application domains. While this chapter includes only a high-level discussion of core concepts, detailed discussion of related work is introduced in subsequent chapters as necessary. In particular, Chapter 3 is primarily concerned with trust and reputation, and Chapter 4 discusses conventions in detail.

Within this chapter, Section 2.1 introduces coordination and cooperation, and discusses their desirability in open MAS. Sections 2.2 and 2.3 introduce trust, reputation, and conventions respectively, which are the key mechanisms investigated in this thesis. Finally, we include three case study scenarios in Section 2.4 to illustrate how the concepts included in this thesis might be applied in the real world.

2.1 Cooperative and coordinated behaviour

Cooperation and coordination are fundamental mechanisms for increasing aggregate welfare in open MAS (Jennings, 1993). We discuss typical characterizations in this section.

2.1.1 Coordination

Agents can be said to be *coordinated* when they select their decisions to reduce costs associated with unnecessary overlap or conflict. Without coordination agents can waste limited resources or fail to achieve goals that require collective effort (Durfee, 2001). Coordinated agents are likely to be more efficient (Salazar *et al.*, 2010b), even if not working on a shared objective.

Research into coordination between agents is often approached through the use of the *coordination game* (Shoham & Tennenholtz, 1997), where typical payoffs are shown in Table 2.1(a) (Sen & Airiau, 2007). Agents receive positive and equal payoff for selecting the same strategies, and negative and equal payoff for choosing differing strategies. The coordination game thus minimally encapsulates the fundamental tensions at the heart of a wide variety of interactions in open MAS. The quintessential social instruments for establishing coordinated behaviour are *conventions*, which we discuss in detail in Section 2.3.

	0	1
0	4,4	-1,-1
1	-1,-1	4,4

(a)

	C	D
C	3,3	0,5
D	5,0	1,1

(b)

Table 2.1: Payoff matrices for the (a) coordination game and (b) Prisoner's Dilemma.

2.1.2 Cooperation

Cooperation is typically considered a stronger form of coordination, in which agents interact to achieve mutual benefit, while potentially incurring a small personal cost. Cooperation has been studied in a wide variety of fields, including economics and evolutionary biology, and is typically investigated using the Prisoner's Dilemma (PD), a minimal representation of the dilemma at the heart of cooperation (Table 2.1(b)). Nowak (2006) considers cooperation from an evolutionary standpoint, in which selfish individuals forgo reproductive potential to aid each other, and thus increase the chances of any individual in the group as a whole reproducing. Nowak defined 5 mechanisms by which cooperation can arise in evolutionary systems: (i) kin selection, (ii) direct reciprocity, (iii) indirect reciprocity, (iv) network reciprocity, and (v) group selection. Kin selection does not translate easily to the computational domain, but the other mechanisms are rich sources for research in open MAS, and are introduced below. There are a number of limitations in this approach: it is not clear whether these rules are complete, in the sense that they describe all possible ways in which cooperation might be evolutionarily selected for. Furthermore, they are grounded in the evolutionary viewpoint, and this is clearly only an approximation of agent processes in typical open MAS. Nonetheless, they provide a useful starting point for developing mechanisms that encourage cooperative behaviour.

1. **Direct reciprocity**

   Direct reciprocity is the mechanism by which an agent that cooperates with another individual can expect cooperation back from that same individual in return, and is neatly encapsulated by the aphorism "you scratch my back, and I'll scratch yours". (Nowak & Sigmund, 2005) In repeated PDs, Axelrod (1987) has shown that the tit-for-tat strategy, in which agents reproduce the action their last partner selected, performs extremely effectively.

2. **Indirect reciprocity**

   Direct reciprocity, while effective at supporting cooperation, requires repeated interactions between the same two individuals. This cannot be guaranteed in many systems, particularly in open MAS domains with large populations. Indirect reciprocity is a mechanism by which agent a, after cooperating with agent b, can expect reciprocal cooperation in return from some other agent c[1], and is typically supported through notions of trust and reputation.

3. **Network reciprocity**

   While many early investigations focused on well-mixed populations (e.g. Axelrod (1986), Nowak & Sigmund (1998)), in real-world domains agent interactions are constrained by an underlying network structure that results in some agents interacting more than others, and precludes many agents from interacting with more than a small group at all (Nowak, 2006). Consequently, local communities can form that allow cooperative behaviour to flourish when it would not otherwise do so in a well-mixed group.

4. **Group selection**

   In a similar way to groups of agents that reciprocate due to their topological position, groups that form as a result of other processes may also facilitate cooperative behaviour. For example, agents forming groups based on tags, which represent observable markings or traits, have been shown to effectively support cooperative behaviour (Hales & Edmonds, 2005).

Nowak's rules provide a strong theoretical underpinning for designing mechanisms that support cooperative behaviour in open MAS. Trust and reputation mechanisms, which work via direct and indirect reciprocity, have seen considerable success in a wide variety of domains (e.g. Huynh *et al.* (2006), Pirzada & McDonald (2006), Sabater *et al.* (2006)). Chapter 3 investigates how inaccurate reputation assessments can undermine indirect reciprocity in open MAS. Conventions and norms, which are underpinned by a system of mutual expectations, can be used to support direct and indirect reciprocity and provide a mechanism

[1] In other words, "you scratch my back and someone else will scratch mine". (Nowak & Sigmund, 2005)

by which group selection can act (i.e. wherein a group is defined by convention adherence). These are investigated in Chapters 4, 5, 6, and 7. Chapter 4 introduces various concepts of convention membership and how to identify groups of agents. Network reciprocity clearly influences cooperative processes in all systems constrained by an underlying network structure, and the effect of network structure underpins much of the work presented in this thesis.

At the heart of research into cooperation and coordination is the dilemma: Why would agents act for mutual benefit when it is in their interest to act selfishly? Trust and reputation, and norms and conventions, are two key mechanisms by which cooperative and coordinated behaviour can be attained, and it is these we investigate in this thesis. Coordination and cooperation are intrinsically linked: if agents mutually cooperate, then they have coordinated as well, but the converse is not necessarily true.

2.1.3 The importance of local interactions

Agent-based systems operate under the assumption of a population of independent and autonomous entities making decisions in a distributed manner. These interactions can be described as *local* in the sense that they are based on a non-global view of information and cause non-global effects on the environment. In aggregate, local interactions can become system-wide trends, defining the behaviour of the system. While many MAS can be designed from a top-down perspective, as the complexity and size of the system increase this approach becomes increasingly difficult. Mataric (1993) notes that the top-down view limits exactly the type of interactions that result in complex behaviour in nature: "the global behaviour of complex systems [...] is determined by the local interactions of their constituent parts". As a result, much MAS research focuses on manipulating the choices of individuals with a view to changing the system-wide trends that result. In this thesis, we focus on manipulations designed to engender cooperative or coordinated behaviour. We are primarily concerned with two mechanisms for altering the choices of agents in local interactions:

trust and reputation (Chapter 3) and conventions and norms (Chapters 4, 5, 6, 7). Many other mechanisms exist, such as biasing partner-selection through tags (e.g. Griffiths (2008)), but we have chosen to investigate trust, reputation, norms and conventions since these are (i) major mechanisms for cooperative and coordinated behaviour and (ii) highly complementary: trust and reputation manipulate partner selection and norms and conventions manipulate action selection, meaning that the two classes of mechanism can be used in parallel.

2.2 Trust and reputation

Trust and reputation are highly successful mechanisms for supporting cooperative and coordinated behaviour (Josang *et al.*, 2007; Nowak & Sigmund, 1998; Pirzada & Mcdonald, 2006; Ramchurn *et al.*, 2005). Trust has been subject to many attempts at definition and we adopt the definition of Ramchurn *et al.* (2005): "Trust is a belief an agent has that the other party will do what it says it will (being honest and reliable) or reciprocate (being reciprocative for the common good of both), given an opportunity to defect to get higher payoff".

Trust encourages acts of direct reciprocity, and accordingly requires significant historical interaction data for accurate assessments (which can limit its accuracy and applicability). Instantiations of trust in MAS often make use of multiple dimensions of information (Huynh *et al.*, 2006; Sabater *et al.*, 2006) including that of reputation, typically defined as a socially known and accepted assessment of trustworthiness. The reputation component of trust and reputation systems thus allows societies to benefit from indirect reciprocity. Indirect reciprocity has been shown to be a greater force in encouraging cooperative behaviour than direct reciprocity in domains with a low probability of repeat interaction (Bravo & Tamburino, 2008). Given that many open MAS domains display this property, reputation is likely to be far more effective than simple trust mechanisms.

Trust and reputation systems that have exhibited the most promising results also tend to be the most architecturally complex (Huynh *et al.*, 2006; Sabater *et al.*, 2006). Given the properties of open MAS systems, such mechanisms may not be as suitable as those that have less complex requirements. However, while robust systems tend to incorporate more complex architectures, systems have been demonstrated that are remarkably simple and support cooperative behaviour in low-overhead environments. For example, *image scoring*, initially proposed by Nowak and Sigmund (1998), is a simplified model of reputation that exhibits low space and time complexity and promotes cooperation through indirect reciprocity. Similarly, Pirzada and Mcdonald (2006) exploit domain-specific insights to develop a low-overhead trust model applicable to communication routing in ad-hoc networks. The Pirzada and Mcdonald model is highly domain specific, and therefore not applicable to open MAS systems in general. Image scoring is perhaps the most applicable *lightweight* reputation mechanism available, but it is likely to be vulnerable to the challenges of open MAS. We investigate this further in Chapter 3.

Trust and reputation, while useful mechanisms for supporting cooperation, are not universally applicable as a solution to cooperative and coordinated behaviour in open MAS. They do not perform well in systems in which agents can be anonymous (since it is necessary to be able to link a single individual to an interaction history or reputation assessment), and they do not provide an account of how agents can coordinate their actions, or *what* action to select. Norms and conventions are a useful complementary mechanism that account for these limitations.

2.3 Norms and conventions

Conventions are generally thought of as *socially accepted expectations of behaviour*, and represent an aggregation of a population's choices in its individual interactions. System designers are typically concerned with reducing the cost associated with malcoordination between agents, and conventions are a useful abstraction for analysing the behaviour of large numbers of agents, to support this aim.

A wide variety of definitions have been proposed in the literature. Lewis (1969) defines a convention as a *regularity* in the behaviour of a population in repeated iterations of the same situation, subject to constraints such as the proportion of agents that conform to the regularity and the proportion of agents that expect others to conform. Goyal (1997) describes conventions as an arbitrary solution to a social problem, wherein individuals only conform because they expect others to conform. Shoham and Tennenholtz (1997) approach conventions from a game-theoretic perspective, defining a convention as a restriction of agents' decisions to a single choice in a given coordination game. Kittock (1993) considers a convention to exist when a high proportion of agents use the same given strategy. There is little universal agreement on what constitutes a convention, or conventional behaviour, and the theory of convention emergence is underdeveloped past the initial emergence phase. In Chapter 4, we propose a new formalism of conventions that unifies the above definitions into a cohesive framework that describes what conventional behaviour is and allows investigation into the entire convention lifecycle, which was previously not possible.

It is important to distinguish between conventions and *norms*, which also represent socially-accepted rules governing behaviour, but are generally considered to include an *obligation* to act according to the norm. Norms are thus a stronger form of convention, with mechanisms to encourage norm emergence typically including *incentives* or *sanctions* to motivate agent adherence (Agotnes *et al.*, 2009; Axelrod, 1986; Modgil *et al.*, 2009; Perreau de Pinninck *et al.*, 2009; Savarimuthu *et al.*, 2007; Sethi & Somanathan, 2002). Such mechanisms may require additional agent-level or society-level components, which may not always be practical. How sanctions and incentives can be practically applied remains an open research problem, with typical approaches including ostracism of defecting agents (e.g. Villatoro *et al.* (2011)). In this thesis, we focus on the behaviour of conventions without the additional element of obligation found in norms, although we do investigate lightweight sanctions and incentives in Chapter 7.

Conventions and norms can be viewed either as rules that are explicitly reasoned upon using some representative language, or as implicit phenomena that emerge from the choices of agents in repeated interactions. Each characterisation involves a number of areas for investigation: (i) using explicitly represented norms, fundamental concerns involve representation, reasoning and mechanisms for enforcement (e.g. Alechina *et al.* (2012), Boella & Torre (2004), Boella & Tosatto (2012), Modgil *et al.* (2009)), and (ii) considering implicit norms, research has focused on how norms emerge dynamically, the impact of network structure, and questions of enforcement (e.g. Axelrod (1986), Pujol *et al.* (2005), Salazar *et al.* (2010b), Sen & Airiau (2007), Villatoro *et al.* (2009a)). In this thesis we are concerned with the second characterisation, which sees social processes such as observation, imitation, and information propagation as key mechanisms by which agents coordinate strategy selection and shared and implicit norms and conventions subsequently emerge.

2.3.1 Online and offline generation

Conventions can be generated either online or offline. In this thesis, we are primarily concerned with conventions that emerge online. Offline generation is not, in general, suited to open MAS domains due to lack of knowledge of society characteristics, time-variance, and issues of computational tractability. Conventions generated offline tend to lack robustness to environmental change.

Relatively little research has considered the online generation of conventions. Recently, Morales *et al.* (2011) presented work on generating conventions using historical data on the success of a given convention. They situate agents in an abstract traffic model and use monitoring agents to determine the efficacy of imposed conventions. A machine-learning algorithm generates new conventions as necessary and these are communicated to the agents in the environment. Their approach is one of the few to address the generation of norms and conventions, and there are parallels between their monitoring agents and our proposed

Influencer Agents (see Chapter 5). However, their model requires a central authority to process convention data and generate new conventions, rendering it unsuitable to our domains of interest.

2.3.2 The El-farol bar problem and sub-conventions

Typical models of convention emergence, including those used by Walker and Wooldridge (1995), Sen and Airiau (2007), Salazar *et al.* (2010b) and Kittock (1993) all assume that the ideal goal is that of a single convention being agreed upon across the entire population. The El-farol bar problem, initially proposed by Arthur (1994) and extensively investigated since (e.g. De Cara *et al.* (1999)), provides a useful thought experiment for when multiple conventions might be ideal. The problem posits a population of individuals that wish to visit a bar on one day of a week, with the best night being when the number of other agents at the bar falls within a given range (i.e. not too empty, and not too full). The ideal situation occurs when exactly 1/7th of the population goes on each night of the week. Even in domains where a single convention is indeed the ideal situation, population size, network effects or other environmental conditions may render this goal unattainable.

The El-farol bar problem illustrates the major limitation with much of the current theory on conventions, in that they assume that the ideal or attainable goal in a system is to emerge a single convention. As a result, they provide a very limited account of how multiple conventions might co-exist, how to identify which convention might be better than another that is co-existing, or how to destabilise undesirable conventions. These are only a sub-set of the problems that may arise when dealing with conventions in open MAS, demonstrating the need for research in this area.

There is very little research currently addressing these problems. Goyal (1997) discusses a model in which conventions are non-exclusive, in that agents can hold more than one convention simultaneously. Agents are situated on a 1-dimensional lattice, and there are only two possible conventions, but Goyal analytically concludes that a medium cost of flexibility (i.e. the cost of simultaneously holding two conventions) can allow two conventions to co-exist. However, the use of a 1-dimensional lattice and a highly restricted convention space significantly reduce the applicability of these results, and we cannot therefore conclude how or if conventions might co-exist in general open MAS. There has also been some research into how sub-conventions can be destabilised in pursuit of a single dominant convention (e.g. Boyer & Orlean (1992), Villatoro (2011)), but little exploration beyond this.

The limitations in typical characterisations of conventions described above are analysed in detail in Chapter 4, where we propose a new definition of conventions which mitigates these flaws in traditional thinking.

2.3.3 Norms

Norms are generally considered to be a stronger form of conventions in that they embody an element of obligation. Norms may not be an arbitrary solution to an otherwise indistinguishable set of social choices (as conventions are), since the presence of the obligation means that norms can be used to support unique cooperative choices that would not otherwise be chosen (e.g. in the Prisoner's Dilemma). Norms are enforced using sanctions or incentives, and there has been significant research interest in their efficacy. Axelrod's seminal investigation of norms (Axelrod, 1986) modelled agent strategies as a combination of boldness and vengefulness, in which boldness indicated the agent's propensity to violate a norm, and vengefulness the agent's willingness to punish observed violations (at personal cost). Axelrod found that such sanctioning behaviour could create stable norm emergence, but subsequent investigations have cast doubt on the scalability of the results. Specifically, Galan (2005) has shown that Axelrod's norms may not be stable over long time periods, and Mahmoud (2011) has shown that the introduction of network topologies constraining agent interactions can also destabilise cooperative norms. How sanctions can be realistically applied remains an open research problem and is likely to be highly-domain specific, if possible at all. The most general form of sanctioning is likely to be ostracism, but it is unclear how this might be effectively implemented in open MAS.

Theoretical work has shown both sanctioning and incentives to be effective in enforcing norms, from Axelrod's original investigation (1986), to Villatoro's ostracism through reputation spreading (Villatoro *et al.*, 2011). Oliver (1980) concludes that incentives are effective at motivating small numbers of agents to cooperate, while sanctions are more effective (although they may be cyclical in efficacy) at motivating uniform cooperation at the expense of possibly generating hostilities that undermine the cooperation.

2.4 Case Study Scenarios

There are a variety of domains which can be characterised as open MAS, and are constrained by the properties discussed in Section 1.1. In this section, we introduce selected domains to which the research in this thesis is particularly applicable. It should be noted that while these scenarios are intended to motivate the research described in this thesis, our work is not targeted to a particular domain. Instead, we aim to address specific open issues that are typical of scenarios such as these, including how to exploit knowledge of the underlying network structure or how to manipulate convention emergence (see Section 1.6 for more details).

2.4.1 Scenario 1: distributed resource-limited domains

Many real-world open MAS domains are characterised by a large number of resource-limited (e.g. computational or bandwidth) agents interacting. These represent additional constraints on top of those we discussed in Section 1.1, such as large, heterogeneous populations and complex connecting network topologies.

Quintessential examples include Mobile Ad-hoc Networks (MANETs), Vehicular Ad-hoc Networks (VANETs), and wireless sensor networks. It has been shown that ad-hoc networks often exhibit a scale-free degree distribution (Sen,

2008) (see Appendix A for details), and network connectivity analysis has been shown to be successful in improving mechanism efficacy (Daly & Haahr, 2007). Trust and reputation mechanisms are highly applicable (Buchegger, 2005; Griffiths *et al.*, 2008), but may be limited by issues of anonymity, malicious manipulation of trust assessments, and resource constraints.

The connection properties of these domains make it challenging to achieve cooperation. MANETs exhibit scale-free properties in their connections (Sen, 2008), and VANETs exhibit extremes of sparse connectivity (e.g. a free-flowing motorway) and high levels of clustering (e.g. a traffic jam). Many typical applications, such as data sharing, imply that the number of interactions between agents is significantly higher than the population size, but dynamic or large populations may also result in situations with a very low probability of repeat interactions between pairs of agents.

2.4.2 Scenario 2: social networking and media

Social networking and media have seen explosive growth in recent years and are a rich source of data for research into social processes such as norm and convention emergence, language evolution, and innovation or idea diffusion. Research into social media usage is useful in that deeper understanding of natural social processes can inform artificial society design (for example, trust, reputation, norms, and conventions are all biologically-inspired mechanisms), and also provide insight into how to support desirable behaviour in human societies (Singh *et al.*, 2009). For example, applications in human society include (i) incentivising contributions to crowd-sourced datasets (such as Wikipedia), (ii) encouraging the emergence of mutually beneficial conventions, (iii) influencing groups to adopt a given convention, or (iv) encouraging users to switch to a preferred brand or propagating marketing information. Regarding the emergence of conventions, social media have enabled a variety of innovations, including notification of an individual's safety after emergencies, gathering data on ongoing situations, and propagating health and safety information (Merchant *et al.*, 2011).

Agent-based systems have been proposed as a feasible methodology for modelling marketing phenonema too complex for traditional approaches (Rand & Rust, 2011), and much research has focused on the *influence maximisation problem*, which is concerned with determining how best to target limited resources at k individuals to maximise diffusion through the population (e.g. Chen *et al.* (2009), Hartline *et al.* (2008), Kempe *et al.* (2005), Goyal & Bonchi (2011)).

Finally, as we discuss further in Appendix A, research into real-world network structures and how they influence agent interaction processes may require realistic datasets, and social media have afforded researchers access to much more accurate and complete datasets than previously available (Gjoka *et al.*, 2010).

2.4.3 Scenario 3: Peer-to-Peer (P2P) systems

P2P systems are characterised by large numbers of decentralised entities interacting directly with each other and exist in a wide variety of domains, including file sharing, instant messaging, collaboration in the workplace, and distributed computation (Shue *et al.*, 2003). As such, they encompass both computational and natural MAS domains. Typical challenges inherent in P2P systems include a lack of centralised authority, complex connectivity networks, and anonymity of individuals. Shue *et al.* (2003) provide a detailed overview of P2P systems, noting that ensuring the security and anonymity of peers remains a central research question. The structure and typical application of P2P systems render them highly applicable to open MAS research. For example, BitTorrent, a popular filesharing protocol, has been shown to have the structure of n-person cooperative dilemmas (Ruberry & Seuken, 2012), and many file-sharing networks have uniform levels of authority and are entirely decentralised.

2.5 Conclusions

In this chapter we have introduced the essential concepts that underpin the work presented in this thesis. Cooperation and coordination are key processes for increasing the aggregate welfare of agent societies, and in this thesis we focus on two major mechanisms for encouraging such behaviour: trust and reputation (Chapter 3) and norms and conventions (Chapters 4, 5, 6, 7).

Nowak's rules for cooperation (discussed in Section 2.1.2) provide a useful analytical starting point for describing the mechanisms behind the promotion of cooperative behaviour, and underpin the processes for both major mechanisms investigated in this thesis. A number of research questions remain open for both trust and reputation, and norms and conventions. Firstly, in Section 2.2 we discuss the need for supporting cooperation through indirect reciprocity. This raises questions regarding the accuracy of reputation assessments, particularly in the context of open MAS domains, and we investigate this in Chapter 3. Secondly, we discuss in Section 2.3.2 limitations with current theories of convention. Effectively applying mechanisms for norm and convention emergence requires resolution of these limitations, since it is highly likely that a single convention will not be an attainable goal in large open MAS. We discuss this in Chapter 4, and subsequently identify further directions for research which underpin the rest of the thesis.

This chapter should be seen as a broad introduction. Where relevant, we include further detailed background discussion of these concepts throughout this thesis. For example, Chapter 3 discusses trust and reputation in more detail and Chapter 4 provides a detailed analysis of research into convention emergence. We have provided an overview of network concepts and background literature in Appendix A for those unfamiliar with the field.

CHAPTER 3

Trust, Reputation and Gossiping

As discussed in Chapter 1, trust and reputation are fundamental mechanisms for protecting individuals from selfish or malicious behaviour in open MAS. In such systems, we can expect complex network structures and extremes of information availability (i.e. there may exist systems in which agents have insufficient information and systems in which agents have incomplete information, since they cannot feasibly observe all occurring interactions). In this chapter, we use a simple model of reputation to investigate the effects of incomplete information and underlying network structure on levels of cooperation in a population. We show that insufficient or incomplete information can undermine the efficacy of reputation and allow selfishness to dominate. We apply a simple gossiping algorithm to supplement observation of agent behaviour and show significant drops in levels of selfishness in the population.

3.1 Introduction

Many typical approaches to increasing levels of cooperative behaviour in highly decentralised open MAS domains have involved biasing interactions towards cooperative individuals. Such mechanisms serve two purposes: (i) protecting agents from individuals likely to engage in selfish behaviour and (ii) increasing the aggregate welfare of the population. The structure of many MAS domains implicitly creates incentives for selfish behaviour, such as free-riding in BitTorrent and other P2P networks (Ruberry & Seuken, 2012), or energy conservation in wireless sensor networks (Galstyan *et al.*, 2004).

Trust and reputation mechanisms, which incorporate observations and individual experience to aid decision making, introduce this bias into agent partner selection through direct (trust) and indirect (reputation) reciprocity (Nowak & Sigmund, 2005). An agent who has cooperated in the past is more likely to receive reciprocal cooperation from others. In domains in which the identity of interaction partners is known, trust and reputation can facilitate significant increases in aggregate welfare, but their efficacy is directly related to the quality and quantity of information available about individuals in the population (Sommerfeld *et al.*, 2008). Trust, which is based on direct observations of behaviour, can only be effective once historical interaction data are available. Reputation, which relies on observation or propagation of third-party agent behaviour, may be undermined by *incomplete information*, in which agents make decisions based on unrepresentative sets of observations. Direct and indirect reciprocity involve feedback effects: a cooperative action can cause many subsequent cooperative actions, and vice versa. Consequently, decisions made on incomplete information may be incorrect, in the sense that given full information the agent would have acted otherwise, and these mistakes will be amplified by the feedback of reciprocity.

Network topology also plays a significant role in the dynamics of trust and reputation mechanisms. By definition, agents are constrained to interact only with their direct neighbour set, and interaction behaviour can only be observed by those directly connected. Networks can support isolated communities of cooperators (Nowak & Sigmund, 2005) and the role of network structure in facilitating information propagation is well studied (e.g. Glinton *et al.* (2010), Newman (2003), Wang (2003)).

Trust and reputation mechanisms are highly suited to open MAS domains, and present a useful setting for investigating the impacts of incomplete information and network structure on levels of emergent cooperative behaviour. In this chapter, we empirically analyse the conditions under which mechanism efficacy is reduced and demonstrate a possible mechanism, namely *gossiping*, to mitigate the effects of incomplete information and exploit the ease of information transmission in typical network structures. Specifically, we show that incomplete information can result in inaccurate reputation assessments that subsequently reduce cooperation, and that the underlying network structure significantly influences emergent behaviour, both positively and negatively depending on the configuration. We supplement trust and reputation with gossiping, which can be used as a substitute for direct observation of interactions and has a low space and time complexity, using one of four aggregation rules. We show that gossiping can reduce selfishness in the population by up to 25%, and is particularly effective on real-world networks.

3.2 Background

In this section, we present background information and discussion relating to trust and reputation in general, image scoring, our adopted model of reputation, and gossiping.

3.2.1 Trust and reputation

Trust and reputation is an area that has seen significant research interest. As discussed in Chapter 2, we adopt the definition of trust as "a belief an agent has that the other party will do what it says it will (being honest and reliable) or reciprocate (being reciprocative for the common good of both), given an opportunity to defect to get higher payoff" (Ramchurn *et al.*, 2005). Other definitions are also commonly used, the most notable of which defines trust as the probability that an agent will fulfil its obligations (Teacy *et al.*, 2012). The incorporation of probability into the definition of trust has allowed mechanism designers to incorporate a range of statistical tools, such as Hidden Markov Models (Vogiatzis *et al.*, 2010) or Bayesian Networks (Regan *et al.*, 2006; Teacy *et al.*, 2012).

The latter definition has become dominant over recent years, and trust and reputation models have been designed that provide robust assessments in a wide variety of situations. Notably, HABIT (Teacy *et al.*, 2012) and BLADE (Regan *et al.*, 2006) can be used independent of the representation of behaviour that agents use. These models differ from the image scoring model adopted in this chapter in that they generate an assessment of the probability that an agent will fulfil their obligations (i.e. they adopt the second definition), whereas image scoring simply provides an indication of how selfish or cooperative a given potential interaction partner is (i.e. we adopt the former definition).

These systems are also robust to inaccurate or malicious assessments, since the statistical methods employed take into account the uncertainty of information regarding potential interaction partners. The robustness of trust and reputation systems to inaccurate assessments is a key concern (Josang, 2012), and the model of reputation that we adopt (namely, image scoring) does not incorporate any mechanisms to mitigate this effect. However, dealing with inaccurate assessments in this way does not increase the accuracy of assessments, but rather allows agents to identify and mitigate inaccuracies. The gossiping algorithm we propose as a mechanism to deal with inaccurate reputation assessments, on the other hand, increases the certainty and accuracy of assessments in the first place, before statistical measures would be needed.

Models for trust and reputation proposed in recent years, as discussed in

Chapter 2, are typically highly complex. Teacy *et al.* (2012) discuss the trade-off between accuracy and necessary time or computational resources. Their proposed model, HABIT, can scale depending on requirements and can be specified to individual domains. However, there remain constraints on the computational requirements of their model and the image scoring and gossiping mechanisms investigated in this chapter have far reduced computational and temporal complexities.

There are, to our knowledge, very few systems that have combined trust and reputation with gossiping mechanisms to increase the accuracy of assessments. Perhaps the closest to the work presented in this chapter is that of GossipTrust, introduced by Zhou and Hwang (2007). In GossipTrust, agents repeatedly gossip reputation values. The authors propose formal constraints on the accuracy of reputation assessments, and agents gossip until a given assessment has converged. Furthermore, all agents gossip, as opposed to the gossip mechanism proposed in this chapter, in which only observers to an interaction gossip. As a result, GossipTrust requires significant communications overheads compared to the system we investigate here. All nodes must reach consensus in GossipTrust, and while this is clearly good for guaranteeing robustness to incomplete information, our results with gossiping (Section 3.5.5) suggest that this is not necessary to gain significant improvements in mechanism efficacy. Finally, the authors do not test the effects of different aggregation rules for gossiping information, and only present results from one network. In this chapter, we propose and evaluate a number of aggregation rules for gossips and present results from a wide variety of network classes.

3.2.2 Image scoring

While many reputation mechanisms have been proposed, they rarely address fully the challenges posed by decentralised MAS domains. To investigate the challenges posed by incomplete information and the effect of underlying network structure, we require an implementation of reputation with low computational and bandwidth overheads.

Nowak and Sigmund introduced and extensively investigated *image scoring*, a simple instantiation of reputation modelling indirect reciprocity, in which cooperation emerges without requiring subsequent interactions between the same individuals (Nowak & Sigmund, 1998; Nowak & Sigmund, 2005). This property is key to its suitability in open decentralised systems. Each agent maintains an image score for each individual it interacts with or observes interacting. Cooperative actions increase the image score by one, and selfish actions decrease it by one. When deciding whether to cooperate or not, an agent compares its strategy, an integer, with the perceived image score of the potential partner (if no data is available, it is assumed to be zero). If the strategy is less than or equal to the image score, the agent cooperates. A population of n agents participate in m interactions each round, and the best performing strategies are reproduced using a genetic algorithm to provide the strategy set for the subsequent round. More detail of the model is given in Section 3.3.

Nowak and Sigmund found that cooperation emerges, but is often cyclical as non-cooperative agents invade populations of unconditionally cooperative agents and gain higher payoffs, causing the population to be subsequently dominated by conditionally cooperative agents, who are in turn superseded by unconditionally cooperative agents. Agents in the setup used by Nowak and Sigmund are randomly chosen and paired from the entire population for interactions, with the total number of interactions per round (m) being at most one order of magnitude larger than the number of agents in the population (n).

While image scoring is effective at supporting cooperation, we can identify situations in which it might be undermined by agents having incomplete or insufficient information regarding potential interaction partners. Firstly, if there are a large number of interactions per round compared to the number of agents (i.e. a high ratio of m/n), agents may have only observed a proportion of the interaction history of a potential interaction partner. If the observed subset of interactions is unrepresentative, this may result in a decision that the agent would not have taken given complete information. Similarly, if there are relatively few interactions (i.e. a low ratio of m/n), or agents have only recently entered a system, then agents may have insufficient information with which to make accurate decisions. In this chapter, we evaluate the extent to which these hypotheses are correct (i.e. that both low and high numbers of interactions cause increases in selfishness due to incomplete or insufficient information), and propose gossiping as a mitigating solution.

We note that an image score is not directly equivalent to reputation. Typical definitions of trust incorporate the notion that a trust value is the *probability* that an agent will fulfil its obligations (Teacy *et al.*, 2012), and reputation is typically defined as a socially-accepted trust value. An image score does not represent the socially-accepted probability that an agent will fulfil its obligations, but instead is a value that indicates, approximately, how cooperative or selfish an agent has been in the past. As such, image scores can be seen as a proxy for reputation.

3.2.3 Gossiping

Gossiping algorithms, initially introduced by Frieze and Grimmet (1985), perform data aggregation and spreading in distributed systems. Loosely modelled on the dynamics of human gossip, they are effective at spreading information through networks and have low space and time complexity and minimal bandwidth requirements when compared to traditional spreading mechanisms (Fernandess & Malkhi, 2007; Kempe & Kleinberg, 2003). They have previously been applied to constrained trust and reputation problems (Bachrach *et al.*, 2008; Ramchurn *et al.*, 2004; Zhou & Hwang, 2007), and can efficiently aggregate trust values without the need for complex data structures.

Typically, gossiping algorithms involve individual agents selecting a single partner and communicating a piece of information regarding a single topic or an individual (in our usage, an individual's image score). Agents therefore receive a number of *gossips* from different sources for a single topic or subject, and use an aggregation rule to incorporate this information into their knowledgebase. A wide variety of implementations of gossiping have been proposed, and we describe our instantiation in Section 3.3.5.

Gossiping is an attractive solution to the problems inherent in local perception of information by agents. Sommerfeld *et al.* (2007) have extensively investigated gossiping in humans and show that gossiping of information is an effective substitute for direct observation. Sommerfeld *et al.*'s subsequent work (2008) demonstrates that gossip is robust to propagation of inaccurate information, and concludes that humans use a majority rule: if the majority of gossips are positive, then the individual forms a positive opinion of the subject. The low overheads, high robustness when exposed to inaccurate information, and ability efficiently to spread and aggregate information in decentralised domains make gossiping highly applicable to our model.

3.3 Incorporating gossiping into image scoring

As discussed above, we adopt image scoring as a simplified model of reputation with which to investigate issues relating to incomplete information and the impact of network topology. These factors were identified in Section 1.5 as important areas for investigation. In this section, we introduce the image scoring model and describe how to incorporate a simplified gossiping mechanism with which to reduce the impact of incomplete information and mitigate any negative effects on cooperation as a result of the network structure.

3.3.1 Image scoring model

We reproduced the original setup used by Nowak and Sigmund (1998) as follows: each agent i is associated with a strategy k_i, chosen uniformly at random in the range $[-5, 6]$. Each agent maintains image scores I_a for each agent a it has observed interacting. Image scores are initialised at 0 and constrained to the range $[-5, 5]$. Each round, m pairs of agents are randomly chosen from a population of n agents, with one agent being designated as the donor and the other as the recipient. If the donor's strategy is less than or equal to its perception of the image score of the recipient, $k_{donor} \leq I_{recipient}$, then it confers a benefit b on the recipient at a cost c to itself. We adopt the values of $b = 1, c = 0.1$, as used by Nowak and Sigmund (1998). An agent assumes an image score of 0 if it has no data on the recipient. If the donor donates (cooperates), then the observers of that interaction increase their perception of the donor's image score by one (the recipient's image score remains the same). If the donor does not cooperate, the perceived image score of the donor, as held by the observers, is reduced by one. An agent's strategy k_i thus represents the degree of selfishness of potential interaction partners that that agent is willing to cooperate with.

Image scoring, as described above, provides a lightweight model of reputation. Originally, Nowak and Sigmund used it to investigate indirect reciprocity and demonstrate how cooperation can emerge in systems with a low probability of repeat interaction. In this chapter, we use it to investigate issues surrounding the application of reputation mechanisms in open MAS, and demonstrate that incomplete or insufficient information and the underlying network structure can all significantly alter the efficacy of indirect reciprocity in supporting cooperative behaviour. The lightweight nature of image scoring, and it's minimal representation of indirect reciprocity, render it highly applicable to open MAS and our investigation.

3.3.2 Observability of interactions

Nowak and Sigmund consider both *complete* and *partial* observability of interactions. In the partial observability settings, a number of agents (10 in Nowak and Sigmund's configuration) are chosen at random to observe each interaction. We model partial observability using an observability parameter, o, in the range $[0, 1]$, as the probability of each neighbour being selected to observe. If N_i denotes the set of neighbours for a given agent i, then, on average, $o \times |N_{donor} \cup N_{recipient}|$ observers are selected at random for each interaction.

Observations are assumed to be perfect, in that the interaction is observed fully without noise. Given $n = 100$, an observability of $o = 0.1$ is equivalent on a completely connected topology to the original setup of Nowak and Sigmund. Observability, in the static connection topologies investigated in this thesis, can be viewed as a simple abstract model of typical resource constraints, or intermittent hardware or communications failure.

3.3.3 Reproducing the population

After m interactions have been performed, offspring are generated in proportion to an agent's final aggregate payoff. If agent a_i has *fitness* f_i, where f_i is equal to its net benefit (i.e. the sum of the positive and negative payoffs incurred in individual interactions), then F is the net *population benefit* such that $F = \sum_{i=0}^{n} f_i$. An agent will produce $n \times f_i/F$ offspring. The strategy of the offspring is an exact copy of the parent strategy, with a small probability μ of mutation such that the strategy is set to a random value (we adopt the value of $\mu = 0.001$ used by Nowak and Sigmund). Nowak and Sigmund found that strategies do not converge to a single value except for when $o = 1$ and $\mu = 0$, but instead go through cycles as selfish agents become dominated by conditionally cooperative agents (called *discriminators* by Nowak and Sigmund), who only help other cooperative individuals. These agents are then superseded by unconditionally cooperative agents (also called *altruists* by Nowak and Sigmund), who are subsequently invaded by selfish agents (called *defectors* by Nowak and Sigmund).

Using reproduction in this model serves two purposes: (i) it allows us to replicate Nowak and Sigmund's original model and results, and (ii) it is an efficient way to determine which strategies gain the greatest aggregate payoff in response to a wide variety of population strategy distributions.

3.3.4 Strategy space delineation

Nowak and Sigmund characterise the strategy space as: $k \leq 0$ denotes cooperation, since agents will interact with most other agents, and $k > 0$ denotes defection (also called *selfish* by Nowak and Sigmund). We further divide the cooperative strategy space into *unconditionally cooperative* ($-5 \leq k \leq -2$) and *conditionally cooperative* ($-2 < k \leq 0$). We describe interaction choices as follows. We refer to interactions in which an agent cooperated based on its *perceived* image score of the recipient, when it should have defected based on the *actual* image score, or vice-versa, as *misclassified interactions*. An interaction is called *incorrect cooperation* if an agent cooperates when it should have defected. An *incorrect defection* is an interaction in which an agent defects (i.e. does not donate to the recipient) when it should have cooperated. The number of misclassified interactions is the sum of the incorrect cooperations and incorrect defections. Incorrect defections are undesirable since they reduce the donor's image score, leading to fewer subsequent donations to the donor. Incorrect cooperations are undesirable since they allow selfish agents to gain higher payoff, and become more likely to be reproduced.

The absolute value of an agent's image score that is maintained (to allow calculation of misclassified interactions) includes any incorrect cooperations or defections that that agent has made — it is the result of an agent's actual actions rather than how they should have acted given complete information. It should be noted that whether an interaction is labelled incorrect or not is based on a global view of the system (since it is determined by comparing an agent's decision with what they would do based on perfect knowledge of their interaction partner), and that an individual cannot know whether their choice is "correct" or not based on their local view of the system.

3.3.5 Gossiping mechanism

Gossiping is an appealing solution to the problem of incomplete information, and can supplement direct observation of interactions to increase the availability of information regarding potential interaction partners. In this section, we describe how our simple gossip mechanism is incorporated into image scoring in order to test its efficacy in supporting image scoring and promoting cooperative behaviour.

Our simple gossip mechanism spreads perceived image scores as follows: each agent maintains a queue of received gossips, which are processed in a separate gossip phase. After an interaction, each observer starts a gossip with probability *ogp* (observer gossip probability) by sending a gossip packet to a randomly chosen neighbour. The probability of any given agent starting a gossip thus depends both on o, the probability it is chosen as an observer, and on *ogp*, the probability that an observer starts a gossip. Each gossip packet contains the image score of the donor, as perceived by the gossip starter, the unique ID of the donor, the unique ID of the gossip starter, and a time to live (TTL).

Every *gossipRate* interactions, there is a gossip phase. Each agent in turn updates their image score values for each agent that they have received gossips about using some update rule, and propagates the gossip with $TTL_{t+1} = TTL_t - 1$ to a single randomly chosen neighbour that does not yet have the gossip. The process is repeated until $TTL = 0$. It is assumed that an agent can check if a neighbour has received a gossip already.

We propose four update rules that gossip receivers can use to incorporate received gossip information.

1. *Aggregate Average (AA):* The agent replaces its perceived image score for agent i with the average of its previous perceived score for i and the values contained in all the received gossips concerning i.

2. *Average Replace (AR):* The agent replaces its perceived image score for agent i with the average of the values contained in all received gossips

concerning i.

3. *Majority Replace (MR):* The agent replaces its perceived image score for agent i with the median value contained in all received gossips concerning i. As noted above, it is thought that this is approximately how humans process gossip (Sommerfeld *et al.*, 2008).

4. *Most Recent (MRec):* The agent replaces its perceived image score for i with the most recent value received, through gossips, concerning i.

Agents have incomplete information regarding interaction partners because they are unable to observe every interaction that a partner has engaged in. By introducing gossiping, we aim to increase the amount of information available so that individuals can make more accurate decisions without having to increase the number of observations they make. In this way, gossiping supplements (and, in some cases, substitutes) direct observation of agent behaviour. As such, levels of incomplete information should fall and, subsequently, cooperative behaviour will increase.

3.4 Experimental Setup

We model two primary situations in which incomplete information may undermine the efficacy of reputation: (i) when there is a very low probability of having observed any interactions, such as when first entering a system, and (ii) when there is a very low probability of observing a complete set of interactions. We model the first situation using a low ratio of interaction rate to population size, and the second situation using a very high ratio of interaction rate to population size. Nowak and Sigmund used parameters of $n = \{20, 50, 100\}$ and $m = \{125, 200, 300, 500, 1000\}$ (where n is the population size and m is the number of interactions per timestep), which is sufficient for modelling the first situation but limited for the second. To investigate the latter, we simulated $m = \{1000, 5000, 10000, 20000, 50000\}$ for $n = 100$ (i.e. a maximum ratio of

$m/n = 500$). We use $o = 0.1, \mu = 0.001, b = 1$, and $c = 0.1$, and unless otherwise stated, we use an observer gossip probability of $ogp = 1.0$ and $gossipRate = 1$. Since the diameter of the networks we generate in our simulations is typically less than 5 we use a TTL of 5. We performed a number of simulations scaling the population to $n = 1000$ to allow us to test the effects of group size.

We situate agents on a variety of network structures. We replicate Nowak and Sigmund's completely connected topology, and implement random (such that each pair of nodes is connected with probability p), scale-free and small-world synthetic networks[1]. Scale-free networks are generated using the Eppstein and Wang (2002) algorithm and small-world networks using Kleinberg's generation algorithm (2000). Additionally, we use 8 network samples created using Breadth-First Search (BFS) (see Appendix A and Chapter 6 for detailed discussion of BFS) from the Enron email dataset and the arXiv general relativity section collaboration network[2] to corroborate our results on networks that are structurally closer to those found in the real world. We use BFS, and not other network sampling algorithms, since (i) although it is known to be biased towards high degree nodes, it accurately retains the local network structures within the sample (Gjoka *et al.*, 2010), and (ii) it is intended only to be used as a check for generality of our results rather than a full investigation on real-world networks.

Our investigation focused on two main metrics: the strategy distribution for the population and the number of misclassified interactions. The results given are averaged over 20 runs for each parameter configuration, giving a standard deviation that ranges from 1–14%. We used $t = 10000$ generations of evolution. Due to the cyclic nature of strategies identified by Nowak and Sigmund, analysing results at an arbitrarily chosen generation (e.g. the final generation of $t = 10000$) is unlikely to provide a representative view of the simulation. Accordingly, we present results averaged over the course of the simulation.

[1] Generated using the Java Universal Network/Graph Framework http://jung.sourceforge.net/

[2] Both datasets are taken from http://snap.stanford.edu/data/

3.5 Results and discussion

In this section, we characterise the impact of incomplete information and network structure on image scoring, by investigating parameter settings that model the two vulnerable situations for reputation mechanisms identified above. We subsequently introduce gossiping and quantify the extent to which it can aid the emergence of cooperative behaviour.

3.5.1 Incomplete information due to high interaction rate

Initially, we evaluate the effect of high ratios of m/n. As discussed above, a high interaction rate relative to the number of agents increases the probability that agents will have incomplete information regarding potential interaction partners — although they will have observed a much higher number of interactions, the observability parameter keeps the *proportion* of unobserved interactions the same. Consequently, while the agent may have increased certainty regarding an interaction partner, the interactions that the agent has not observed may also be enough to cause incorrect decisions to be taken. In this section, we show that the latter is the case and that the increased number of observations does not necessarily increase the certainty of an image score assessment.

Figure 3.1(a) shows the effect on the population strategy distribution of varying m, the number of interactions each round, using $n = 100$ agents, $o = 0.1$ (i.e an average of 10 agents observing each interaction), $b = 1, c = 0.1, \mu = 0.001$, and a fully-connected network. This is equivalent to Nowak and Sigmund's original setup. The society is highly cooperative at $m = 1000$ (i.e. $m/n = 10$), with less than 10% of agents adopting selfish strategies (i.e. $k > 0$). Figure 3.2 shows the average strategy over time under this configuration, with the horizontal lines delineating selfish (above the top line), conditionally cooperative (between the two lines), and unconditionally cooperative (below the bottom line) strategies. We can clearly see the cyclic behaviour noted by Nowak and Sigmund. At $m = 1000$, 32 interactions were misclassified per round on average,

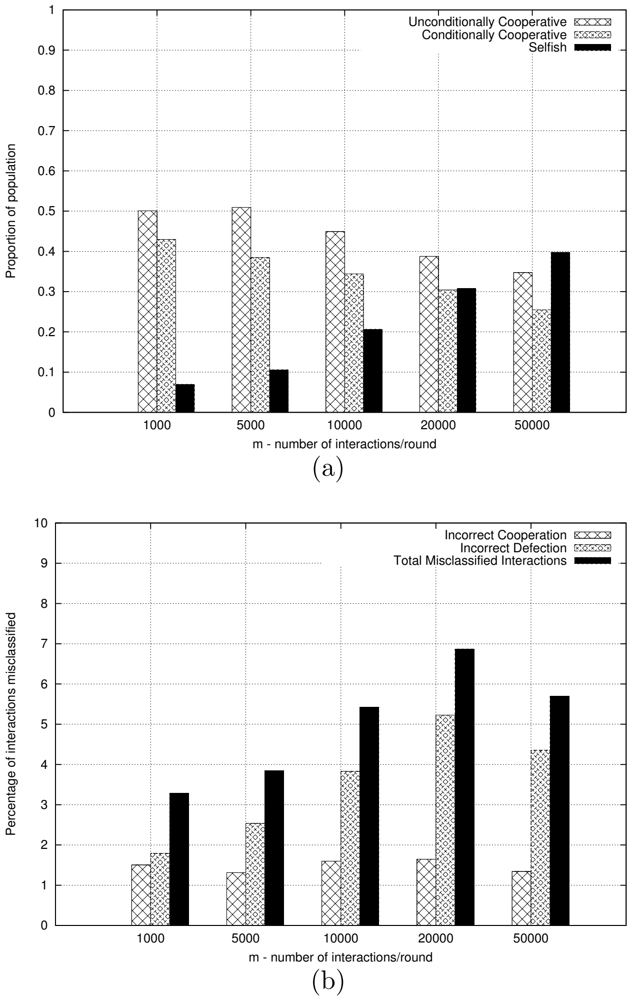


Figure 3.1: (a) Strategy classifications and (b) levels of misclassified interactions, using a completely connected topology, for $n = 100, o = 0.1, \mu = 0.001$, while varying m. Both the proportion of selfishness in the population and the levels of misclassified interactions rise with greater numbers of interactions.

i.e. a misclassification rate of 3.2%. As m increases, there are increases in (i) the levels of selfishness and (ii) the proportion of misclassified interactions.

Figure 3.1(b) plots the percentage of interactions that were misclassified over the entire simulation. When $m = 50000$ (i.e. $m/n = 500$), 40% of the population has adopted a selfish strategy and 5.7% of interactions are misclassified (i.e. an average of 2850 per round). The proportion of misclassified interactions falls slightly between $m = 20000$ and $m = 50000$, despite an increase in

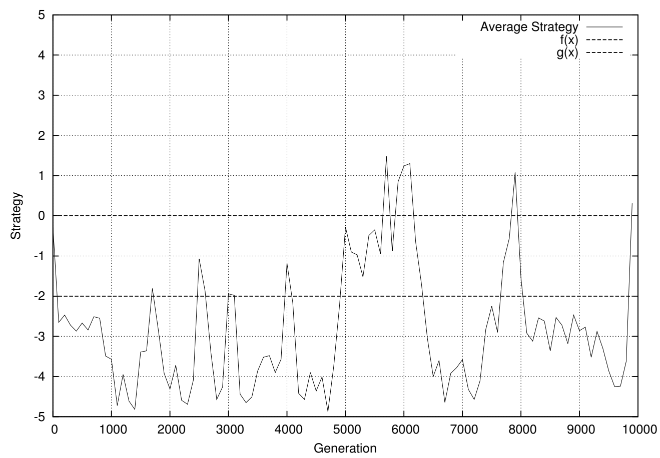


Figure 3.2: Average strategy over time, sampled every 100 generations, for $m = 1000$, for a representative run from Figure 3.1. In this run, the population is predominantly cooperative, and the cycles in agent strategy are clearly visible. The population does not converge on a steady-state.

selfishness. We believe that the strategy distribution of the population is an important determinant of levels of incomplete information. Recall that image scoring, through indirect reciprocity, induces a feedback effect in which cooperative actions cause subsequent cooperative actions, and vice-versa for defection. In a highly cooperative society, a choice by a donor to cooperate is likely to be correct (due to the high numbers of cooperators) even if made on the basis of highly incomplete information. The same is true, vice-versa, for defecting societies. However, when the strategy distribution is mixed, uncertainty regarding a recipient's strategy is higher, and subsequently choices made on the basis of incomplete information are more likely to be incorrect. This is evident in the results for $m = \{20000, 50000\}$, in which selfishness rises by 9%, while the proportion of misclassified interactions drops by 1%.

Figure 3.3 separates the misclassification of cooperative and defective actions for the results shown in Figure 3.1(b). At $m = 1000$, 0.24% of cooperative actions are incorrect — in all interactions in which a donor donated, only 0.24% would have been defections had the donor had complete information. Conversely, of all the interactions in which the donor defected, 26.4% would have

m	CC		SF		SW		Ran	
	S	IP	S	IP	S	IP	S	IP
1000	0.13	3.71	0.91	1.2	0.01	0.1	0.03	2.0
5000	0.10	3.76	0.005	1.8	0.02	0.3	0.01	0.4
10000	0.21	5.71	0.004	1.1	0.03	0.4	0.02	0.3
20000	0.30	6.94	0.006	1.1	0.06	0.6	0.02	0.2
50000	0.39	5.93	0.01	2.2	0.11	0.6	0.04	0.2

Table 3.1: Selfish proportion of population (S) and Percentage of Incorrect interactions (IP) for Completely Connected (CC), Scale Free (SF), Small World (SW) and Random (Ran) networks while varying m, when $n = 100$. All other parameters are as Figure 3.1.

been cooperative had the donor had complete information. This corroborates the discussion above, since the society is more than 90% cooperative. As m rises, the proportion of defections that are misclassified rises (to a peak of 58%) and then falls, as the rising proportion of selfish agents reduces the probability that an interaction partner is cooperative, and subsequently that the decision to defect is incorrect.

These results demonstrate two relationships: the proportion of (i) misclassified interactions and (ii) selfish strategies both increase as m/n increases. We believe that incomplete information is a key component of the mechanism by which the increasing interaction rate results in reduced support for cooperative behaviour.

3.5.2 Effect of network structure

It is also important to investigate the relationship between network structure and the impact of incomplete information. We initially investigate random, scale-free and small-world networks. Random networks are a useful middle ground between completely connected networks and scale-free or small-world networks, which are known to model features of networks found in the real world (Albert & Barabási, 2002). Instead of pairs of agents being chosen randomly, the donor is now selected at random from the population and the recipient is chosen at random from the donor's neighbour set.

In random networks, each pair of agents is connected with probability p.

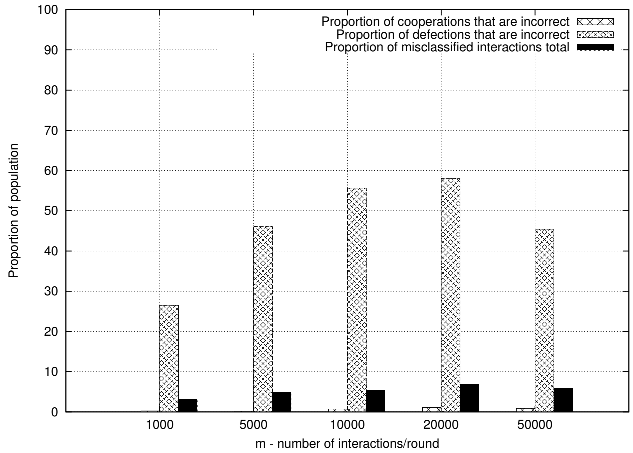
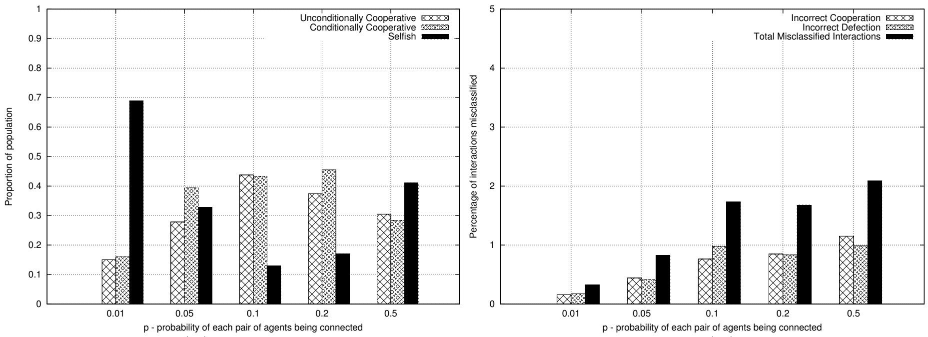


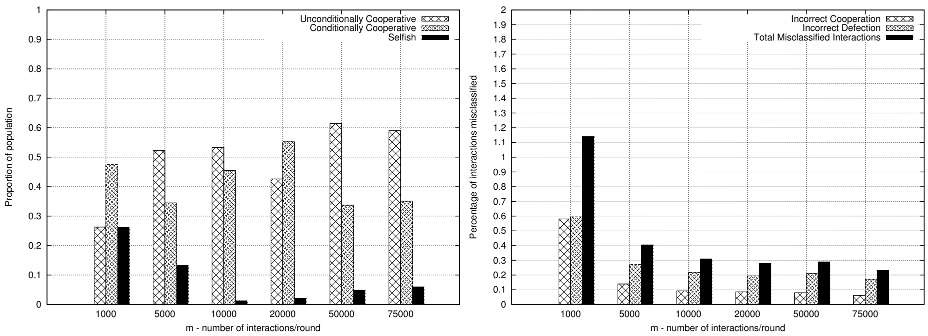
Figure 3.3: Interactions misclassified as proportion of interaction type for simulation runs in Figure 3.1. The proportion of cooperations that are incorrect is the number of interactions in which the donor donated incorrectly divided by the total number in which the donor donated (as opposed to divided by the total number of interactions for the donor).

Assuming an undirected graph, $p = 0.1$, and $n = 100$, each agent is connected to 4.95 neighbours on average. Given that sparse connectivity is a feature of many open MAS, it is useful to evaluate the effect of varying p. Figure 3.4(a) plots the strategy distribution for the same configuration as in Figure 3.1(a), but situated on a random network. Selfishness dominates at $p = 0.01$, since there are so few agents observing interactions that indirect reciprocity cannot take hold. Cooperation takes hold as p rises to 0.1, but selfishness again rises as p increases up to 0.5. For these values of p, there are sufficient neighbours that incomplete information, due to any given neighbour only observing a small subset of a potential recipient's history, becomes significant. Figure 3.4(b), which plots the levels of misclassified interactions, demonstrates this: at $p = 0.5$, 2.09% of interactions are misclassified, whereas there are negligible misclassified interactions at $p = 0.01$. Random networks show statistically significant differences in the levels of selfishness compared to completely connected networks. T-values for a two-tailed t-test range from 0.031 at $m = 1000$ to 6.37×10^{-20} at $m = 50000$, demonstrating that the introduction of network topology has significantly affected the operation of image scoring.



(a) (b)

Figure 3.4: (a) Strategy classifications and (b) levels of misclassified interactions, using a random topology, varying p, with $m = 1000$. Results are given for $n = 100, o = 0.1$, and $\mu = 0.001$.



(a) (b)

Figure 3.5: (a) Strategy classifications and (b) levels of misclassified interactions, for scale-free topology, varying m, using 1000 edges in total, and with all other settings as Figure 3.4.

Scale-free networks show strong support for cooperative behaviour, as illustrated by the results shown in Figure 3.5(a). Although a certain number of interactions are required to initially support cooperative behaviour (i.e. at $m = 1000$), as m rises we no longer see the characteristic rise in selfishness observed in completely-connected or random networks. Unconditional cooperators in particular are dominant, suggesting that the structure of scale-free networks allows groups of agents to cooperate with reduced vulnerability to selfish invaders. Figure 3.5(b), which shows the misclassified interactions for data in Figure 3.5(a), corroborates this: with a maximum total proportion of misclassified interactions of 1.13% at $m = 1000$.

Scale-free topologies are known to have beneficial properties regarding information propagation and robustness to untargeted malicious action. For example, Delgado (2002) used a model of social convention emergence to show that complex (i.e. scale-free and/or small-world) networks are more efficient than regular graphs with the same average node degrees, and that scale-free networks are as efficient at spreading information as fully-connected graphs. Barabási and Albert (2002) also noted the remarkable fault-tolerance of scale-free networks. The robustness of scale-free networks is partially derived from their clustering: there are highly-internally connected groups with relatively few links to the rest of the population. In the context of our investigation, we hypothesise that this grouping effect allows image scoring to act with a much smaller average connectivity, since there will be many such groups in which agents are highly visible to other agents within that group. As discussed previously, visibility of agents is important for the efficacy of image scoring. We use the term *visibility* to denote the combination of observability and topological connectivity, since both influence how many agents might observe an interaction. Sen (2008) demonstrated the existence of scale-free topological structure in mobile ad-hoc networks, and many other real-world networks are known to be scale-free (Albert & Barabási, 2002). The robustness of image scoring on scale-free networks is thus highly important, as it demonstrates the broad applicability of the technique.

3.5.3 Incomplete information due to low interaction rate

Scaling the ratio of m/n to high values means that agents are likely to have incomplete information regarding the set of interactions a potential recipient has participated in. This represents a vulnerable configuration, as our previous results show, but agents are also likely to be vulnerable when this ratio is very low. Under this configuration, while agents may have complete information regarding a potential recipient's history, there may be insufficient historical data to make accurate decisions. This is particularly true when agents first enter a system.

Figure 3.6 shows the strategy distribution with $n = 100$, and $m = \{125, 300\}$ (i.e. a ratio of $m/n = \{1.25, 3\}$), across a variety of synthetic networks. For the majority of network classes, selfishness dominates within the population. The proportion of selfish agents is particularly high for $m = 125$, and tends to decrease as m increases to 300. This supports our hypothesis that the interaction history is insufficient at low levels of m, reducing the ability of indirect reciprocity to support cooperation. Small-world networks appear to significantly support cooperative behaviour, and we believe this is because these networks make agent interactions highly visible to potential future donors. Our results suggest that both configurations that we examine, namely (i) a very high rate of interactions, and (ii) a very low rate of interactions, are vulnerable settings in which indirect reciprocity is less effective due to either incomplete information (as in configuration (i)) or insufficient information (as in configuration (ii)).

We learn three important lessons from the results from the previous sections:

1. **The level of incorrect interaction choices is dependent on the probability of having witnessed a recipient's interactions.**
   This probability is based on a number of factors, including the degree of a node, the observability in the population, and the number of interactions. We observe higher proportions of incorrect interaction choices in both vulnerable situations, namely, when the interaction rates are high and

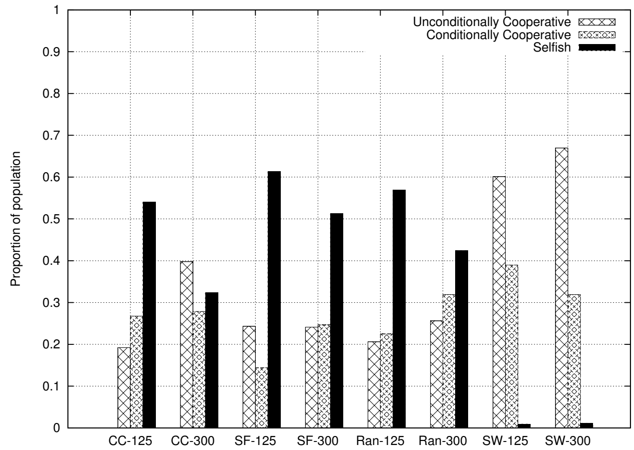


Figure 3.6: Comparison of population strategy distribution over 4 classes of topology: Completely Connected (CC), Scale-Free (SF), Random (Ran), and Small World (SW), using $m = \{125, 300\}$ and $n = 100$. There are clear differences in population behaviour between topological classes, with scale-free being particularly conducive to selfish behaviour. Small-world networks appear highly supportive of cooperative behaviour, which may be due to the effects of clustering.

when the interaction rates are low.

2. **Incomplete information has an observable effect on levels of emergent cooperation.**

   Nowak and Sigmund (1998) note that when moving from their initial model, equivalent to an observability of $o = 1$, to an observability of $o = 0.1$, a larger number of interactions are needed to establish cooperation. Our results corroborate this and establish that higher levels of incomplete information (whether caused by low node degree or high numbers of interactions) lead to more selfish societies.

3. **The levels of cooperation are highly dependent on the underlying topological structure of the social network.**

   Random graphs, and to a lesser extent, scale-free networks, significantly reduce the detrimental effects of incomplete information and aid the emergence of high levels of cooperation.

3.5.4 Larger population sizes

		Proportion of population		
Network	Parameter	UC	CC	S
Eppstein	1000 edges	0.33	0.20	0.46
Eppstein	5000 edges	0.36	0.23	0.39
Eppstein	10000 edges	0.41	0.25	0.32
Kleinberg	CE1	0.42	0.26	0.31
Kleinberg	CE5	0.43	0.20	0.36
Kleinberg	CE10	0.34	0.30	0.35

Table 3.2: Strategy distribution for various scale-free and small-world networks. UC is Unconditionally Cooperative, CC is Conditionally Cooperative, and S is Selfish. CE is the Clustering Exponent, $n = 1000$, and $m = 1000$. Results are given for $o = 0.1, \mu = 0.001$.

Our results so far are limited in the sense that we have only simulated 100 agents. In this section, we briefly describe the results from simulations involving a population size of 1000.

As Table 3.2 shows, scaling up the population to $n = 1000$ agents introduces a smoothing effect. Overall, the model behaviour is very similar to when $n = 100$. The influence of incomplete information appears slightly reduced, but the populations are more evenly distributed with selfishness remaining significant. Interestingly, the support that small-world networks displayed for cooperative behaviour is no longer present, and selfishness levels are similar to scale-free networks. Scaling the number of edges in scale-free networks slightly reduces the level of selfishness, corroborating our hypothesis regarding visibility of agent interactions.

Our results show significant levels of selfishness across a variety of configurations. We conclude that there are three primary influences on levels of selfishness:

1. *Underlying network topology*

   Selfishness is significant in scale-free networks (structurally closest to the real world), but small-world networks are particularly supportive of cooperative behaviour. Small-world networks have low shortest path lengths and high clustering, implying a higher probability of connection between observers of an interaction and potential interaction pairs[3].

2. *Interaction rate*

   At very low rates (i.e. $m = 125$), there is not time for indirect reciprocity to take hold and selfishness increases (i.e. image scoring suffers from a *cold start* problem). As m increases selfishness is slightly reduced (down to 1.07% at $m = 1000$), but again rises as we approach $m = 50000$ (up to 31.4%). At low and high values of m, there is a higher probability of an agent having insufficient information with which to make an accurate assessment of a potential partner. As a result, the efficacy of image scoring is drastically reduced, and selfishness rises. These represent vulnerable configurations for reputation mechanisms.

3. *Population strategy distribution*

   A population with an equal strategy distribution increases the effect of incomplete information, by increasing the uncertainty about a potential partner's strategy and making a decision based on incomplete information more likely to be incorrect. This has important implications for mechanisms that aid the emergence of social norms and conventions, which reduce the strategy choices available to agents. In systems with high levels of normative control, incomplete information is reduced due to lower uncertainty about agent strategies, and reputation mechanisms may subsequently become more effective. Accordingly, we focus on conventions and norms for the remaining chapters of this thesis.

3.5.5 Introducing gossiping

In this section, we present results from implementing gossiping and the effect of the aggregation rule adopted. Table 3.3 compares levels of selfishness in the population for the same configuration as Figure 3.1, except that agents gossip

[3] Recall that although observers may be connected with the recipient of an interaction, they only update the score of the donor. For the observation to be of use, the observer must then also interact with the donor.

		Selfishness		
Topology	m	$ogp = 0$	$ogp = 1$	Diff.
Completely-Connected	125	0.540	0.418	**0.122**
Completely-Connected	300	0.324	0.221	**0.103**
Scale-free	125	0.613	0.479	**0.134**
Scale-free	300	0.512	0.330	**0.182**
Random	125	0.569	0.527	**0.042**
Random	300	0.424	0.256	**0.168**

Table 3.3: Comparison of the average proportion of selfish agents in the population for the runs in Figure 3.6, when agents either do not gossip (i.e. when $ogp = 0$) or gossip using the Average Replace update rule (i.e. when $ogp = 1$).

	Selfishness					
Topology	$ogp = 0$	$ogp = 1$				max. Diff.
		AA	AR	MR	MRec	
Enron-1	0.29	0.33	0.20	0.33	0.04	**0.25**
Enron-2	0.31	0.35	0.22	0.33	0.19	**0.12**
Enron-3	0.33	0.38	0.25	0.18	0.21	**0.15**
Enron-4	0.39	0.20	0.25	0.21	0.16	**0.23**
arXiv-1	0.33	0.39	0.21	0.19	0.15	**0.18**
arXiv-2	0.34	0.50	0.10	0.30	0.15	**0.24**
arXiv-3	0.34	0.40	0.19	0.35	0.22	**0.15**
arXiv-4	0.27	0.21	0.16	0.33	0.19	**0.11**

Table 3.4: The effect of gossiping on selfishness in real-world network samples with the population using each individual update rule (i.e. Aggregate Average (AA), Average Replace (AR), Majority Replace (MR), or Most Recent (Mrec)). Results are shown for $ogp = 1, n = 1000$, and $m = 1000$.

and use our Average Replace update rule.

Figure 3.7 shows the strategy distribution using our update rules together with a control configuration with no gossiping, on a scale-free topology with $m = 1000$. Finally, Table 3.4 shows the results from using gossiping on the real-world network samples, with $n = 1000$.

On average over the 4 update rules, 331.7 million gossips were started, with 1.436 billion gossip packets sent over 10 million interactions, or 143 packets per interaction. Agents adopted a new image score for a given individual 496.4 million times. On average, a single gossip causes 1.50 image score changes. Aggregate Average is the only rule to incorporate the agent's current image score perception of the gossip subject, whereas the other three rules only take

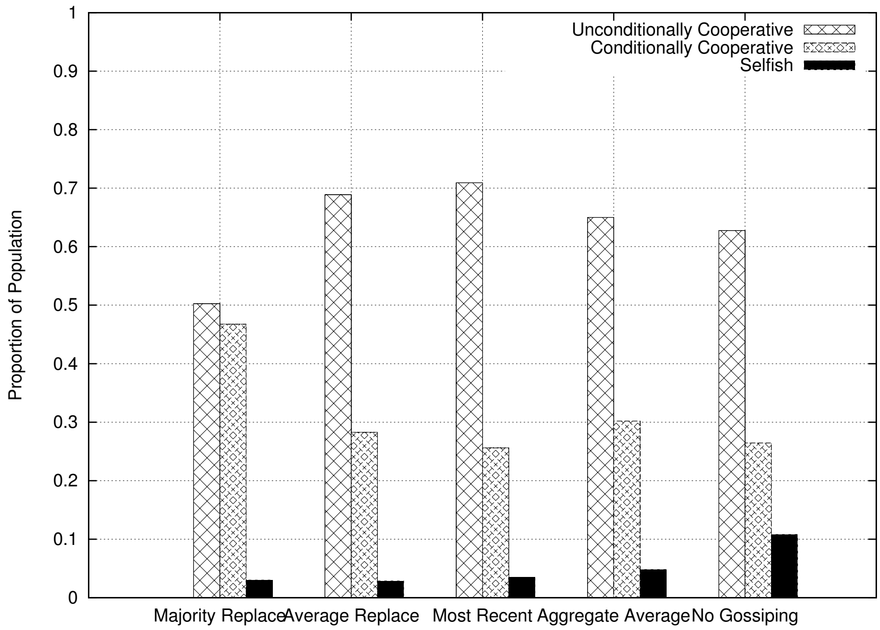


Figure 3.7: Strategy distribution using gossiping with $m = 1000$, on a scale-free network with 1000 edges, while varying the update rule that agents use to update their image score from received gossips. All of the aggregation rules support a drop in selfish behaviour.

into account the gossips received about a given gossip subject. A gossip using the Aggregate Average rule causes, on average, 1.09 image score changes, whereas the other rules cause 1.67 (Average Replace), 1.63 (Most Recent), and 1.60 (Majority Replace) changes in image score respectively. Clearly, update rules that do not incorporate the *current* perception of the subject's image score perform better. That Most Recent performs as well as the others suggests that many of the updates are for when agents have no information (i.e. they assume an image score of 0), and the gossip provides initial data to make a choice with. Aggregate Average incorporates the assumption of an image score of 0, biasing the resultant updated value. These results suggest that gossiping is a useful mechanism by which new entrants to a system can start interacting quickly without having to observe the population to gain sufficient information.

In the real-world network samples, Aggregate Average still performs poorly, but Most Recent gives the most consistently beneficial results. These results are given for $m = 1000$, and as such agents are likely to have very little or no information on potential interaction partners. The Most Recent rule is equivalent to allowing each of the gossip recipients to act as an observer of the interaction being gossiped about, and thus reduces the number of interactions necessary for indirect reciprocity to take hold. This corroborates our conclusion that gossiping is a particularly useful supplement to reputation for new entrants to a system, or in systems characterised by high levels of population churn. While the difference gossiping makes in the real-world networks is generally larger than in the synthetic networks, sometimes the introduction of gossiping results in an increase in selfishness (particularly with Aggregate Average, though never with Most Recent). Why this is the case requires further investigation, but these results imply careful consideration must be given to how agents incorporate information attained through gossiping.

From these results, we can conclude the following:

1. **Gossiping significantly reduces levels of selfishness in the society.**

   On average, the introduction of gossiping reduces levels of selfishness by around 10% in the synthetic networks and around 18% in the real-world network samples.

2. **There does not appear to be a relationship between the number of interactions and the reduction in selfishness, whereas there is one between network structure and gossip efficacy.**
   The real-world network samples and scale-free synthetic networks in particular show significant reductions in selfish behaviour. Given the ubiquity of scale-free degree distributions in real-world open MAS domains, these results suggest that gossiping can be practically applied. Random networks are not as conducive to gossiping as other network classes, which may be a consequence of their reduced clustering. As argued above, clustering increases the probability of observations being useful, and since gossips are a substitute for direct observation this property translates across.

3. **All update rules except Aggregate Average show a statistically significant decrease in selfishness ($\alpha = 0.05$).**
   In the synthetic networks, Aggregate Average performs worse than the other update rules, whereas the other update rules perform fairly equally. In the real-world network samples, Most Recent performs consistently and with the greatest reduction in selfish behaviour, but the other update rules occasionally result in an increase in selfish behaviour.

3.5.6 Gossiping without observation of interactions

A key feature of our model is the observation of interaction results by the neighbours of the participants. Observers underpin indirect reciprocity through two mechanisms: (i) updating their own perception of the donor's image score, for use in subsequent interactions with the donor, and (ii) gossiping information regarding the donor to other individuals who may also subsequently interact with the donor. In some domains, we may not be able to assume that interactions are observable. In such cases, we would like to know whether image scoring

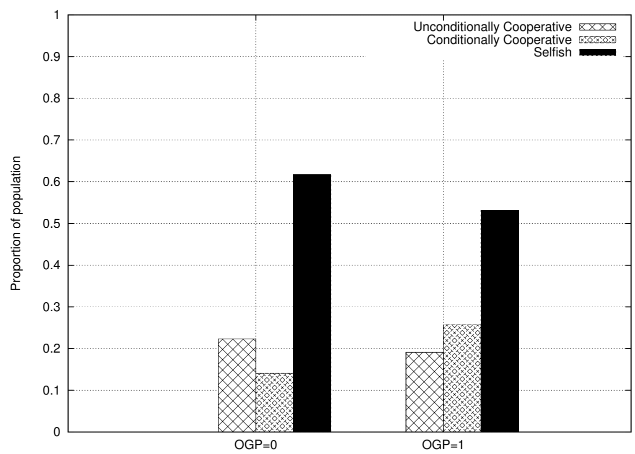


Figure 3.8: The population strategy distribution when neighbours cannot observe interactions with either gossiping ($ogp = 1$) or no gossiping ($ogp = 0$), for $n = 100$, and averaged over all networks and network samples.

is still effective at promoting indirect reciprocity, and if not, whether gossiping can recover that efficacy. Nowak and Sigmund note that reduced observability means that a larger number of interactions are required to sustain cooperation.

Accordingly, we performed simulations in which interactions were not observable. Only the recipient, therefore, updates their perceived image score for each interaction, and only recipients or donors start gossips. Figures 3.8 and 3.9 show the strategy distribution, averaged over all network topologies, for a no-observation configuration with $m = 1000$ and $n = \{100, 1000\}$ respectively. Selfishness dominates, and we witness a sharp increase in misclassified interactions: with 100 agents, 3% of interactions are misclassified, compared with 0.6% for the identical configuration with observation.

From these results, we can see that gossiping retains some efficacy but only produces around a 10% decrease in selfishness for $n = 100$, falling to less than 5% for $n = 1000$. Since gossips are now only started by interaction participants, fewer gossips regarding each agent are circulated. This reduces the efficacy of aggregation rules, and makes errors in perception more likely to be propagated (if agents receive any gossips at all). We see this in the misclassified interaction data where there is no statistically significant drop in misclassified

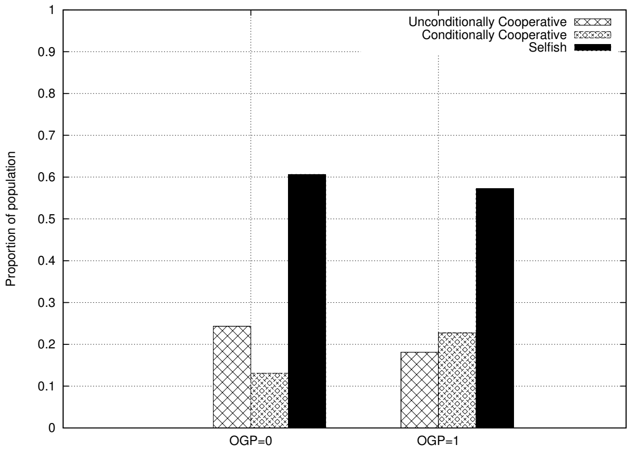


Figure 3.9: The population strategy distribution when neighbours cannot observe interactions with either gossiping ($ogp = 1$) or no gossiping ($ogp = 0$), for $n = 1000$, and averaged over all networks and network samples.

interactions when introducing gossiping, despite the fall in selfishness. The decrease in selfishness for $n = 1000$ is lower than for $n = 100$. We believe this to be a result of each agent having an increased neighbourhood size (due to the increase in population size), which combines with the sparser rate of gossips to mean that agents frequently do not benefit from gossiping. Interestingly, the number of unconditional cooperators falls with the introduction of gossiping, while the number of conditional cooperators rises. We believe that the presence of gossiping allows conditional cooperators to make more accurate choices, while unconditional cooperators are consistently exploited by the large proportion of selfish agents.

3.5.7 Gossiping with high cost of cooperation

Throughout our results, the cost of giving cooperation is kept at one tenth the benefit of receiving cooperation. The cost of cooperation has been the subject of much research (e.g. Ohstuki *et al.* (2009)), and it is important to investigate whether gossiping can help support cooperation in the face of a low benefit/cost ratio. Figure 3.10 shows the strategy distribution, averaged across all network topologies, for $c = \{0.1, 0.5, 0.9\}$, and $n = 1000$.

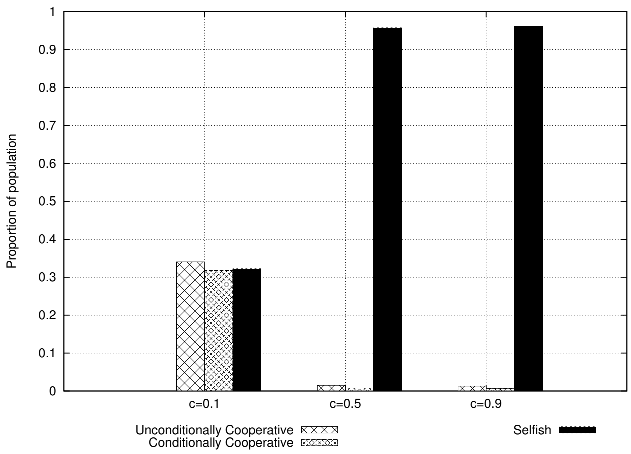


Figure 3.10: Population strategy distribution while increasing the cost of cooperation for populations with no gossiping, averaged across all network topologies. Results are given for $m = 1000, o = 0.1, \mu = 0.001$.

Image scoring appears to be ineffective at supporting cooperative behaviour as the cost of cooperation rises past half the benefit conferred. The high cost of cooperation means that it is evolutionarily advantageous for agents to defect consistently. The introduction of gossiping mitigates this effect partially at $c = 0.5$, but appears entirely ineffective at $c = 0.9$. At $c = 0.5$, the introduction of gossiping allows those agents that are cooperative to make accurate assessments regarding which (small) subset of agents they may cooperate with. However, at $c = 0.9$, this benefit is overcome by the cost of cooperation, and there is very little incentive for agents to cooperate at all. As such, in this case gossips will simply confirm the selfishness of potential recipients, rather than support cooperation in the face of selfishness.

3.6 Conclusions

Highly decentralised open MAS require robust, low-cost mechanisms for supporting cooperation and protecting individuals from selfish or malicious behaviour, particularly for new entrants to a system. We have investigated two issues that can influence the efficacy of image scoring as a simplified model

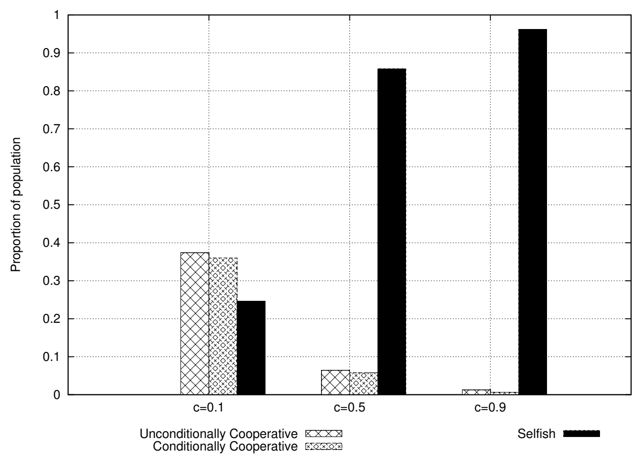


Figure 3.11: Population strategy distribution while increasing the cost of co-operation for populations which gossip, averaged across all update rules and network topologies. Results are given for $m = 1000, o = 0.1, \mu = 0.001$.

of reputation in settings that closely model those found in practical domains, namely (i) incomplete information and (ii) underlying network structure. Our results show that incomplete information can undermine the feedback effects that indirect reciprocity introduces into a system and subsequently increase the levels of selfishness in the population, whereas network structures found in the real world act to mitigate selfishness.

In detail, we have shown that (i) incomplete information can significantly undermine lightweight reputation mechanisms, with up to 62% of defection actions (using a completely connected network topology) taken incorrectly, and (ii) that the underlying network topology has a significant influence on levels of selfishness in the population. We applied gossiping algorithms and showed that (iii) they reduce levels of selfishness by up to 25%, with the biggest gains found on topologies sampled from real-world networks. We found that (iv) simply using the most recently gossiped information about a potential partner results in the most consistent benefits, suggesting that gossiping may be particularly useful for agents first entering a system. Gossiping is not effective in all situations: when the cost of cooperation is high, or there is no external observability of agent interactions, the efficacy of gossiping is drastically reduced.

Both extremes of the ratio m/n represent vulnerable situations for simple reputation mechanisms. Our results are corroborated on real-world network samples, but we note that our investigation in this area is limited. For future work, we plan to repeat the entire analysis on real-world networks, and determine the risks of incomplete information in such settings.

An effect to note from our results is that of the visibility of interactions on the levels of cooperation observed. Many open MAS domains are characterised by sparse topologies and our results appear to show that the efficacy of image scoring is reduced in such settings. Implementing gossiping with the Most Recent update rule shows significant reductions in selfishness, and is equivalent to increasing the visibility of interactions (for example by increasing network connectivity). Gossiping has been applied successfully within the specific topological challenges of VANETs (Bako *et al.*, 2007; Costa *et al.*, 2008) and MANETs (Buchegger, 2005), and also within the domain of reputation mechanisms (Bachrach *et al.*, 2008; Mundinger & Le Boudec, 2006). Our results with no observability demonstrate the challenges of supporting cooperation in systems with low interaction visibility. In future work, we aim to extend our gossiping mechanism to cope better in systems with low observability of interactions.

Our results suggest that a key component driving incomplete information is the strategy distribution of the population. In populations where there is significant uncertainty regarding the strategy of a potential interaction partner, there is a higher chance of decisions made on the basis of incomplete information being incorrect (when compared to the decision that would have been made with complete information). Conventions and norms, which reduce the population strategy distribution, may therefore be useful mechanisms in conjunction with trust and reputation. Furthermore, while trust and reputation are effective mechanisms for protecting individuals from malicious behaviour, their performance is limited in systems with anonymity and they do not provide an account of how agents can solve coordination problems (in which agents must agree on a solution from a potentially large set of indistinguishable options). We explore conventions and norms in detail in the remaining chapters of this thesis.

CHAPTER 4

Conventions

Trust and reputation are effective mechanisms for manipulating partner selection, but they do not perform well in systems with potentially anonymous agents, and they do not provide an account of which actions an agent should select to most effectively coordinate or cooperate with others. Conventions are a particularly effective mechanism for manipulating action selection, and they are the focus of the remainder of this thesis. In this chapter, we review the literature surrounding the emergence and establishment of conventions, and identify several limitations in typical models of conventions. To address these limitations, we define a formalism within which distinct models of convention emergence can be expressed and easily compared. We subsequently propose a new definition of convention that accounts for several of the limitations identified, and define metrics of a convention's support, stability and quality. Furthermore, we identify three areas for future research: (i) determining how populations might be manipulated to adopt a given convention, (ii) how to exploit topological information to refine mechanisms that support convention emergence, and (iii) how to manipulate established conventions that are in the middle and latter stages of the convention lifecycle. These research areas are considered in detail in Chapters 5, 6 and 7 respectively.

4.1 Introduction

While trust and reputation are effective mechanisms for protecting individuals from malicious behaviour, their performance is limited in systems with anonymity. Furthermore, they do not provide an account of how agents might *coordinate* their actions. The use of conventions has shown particular promise as a distributed mechanism for coordinating interactions (Boyer & Orlean, 1992; Delgado, 2002; Goyal, 1997; Pujol *et al.*, 2005; Vylder, 2007; Walker & Wooldridge, 1995). Conventions can promote desirable behaviour in large, heterogeneous populations with uniform levels of authority. In this chapter, we survey the current state of thought in research into conventions, and propose a formalisation which can describe a variety of open MAS models focusing on convention emergence. We identify a number of limitations in traditional characterisations used in the agents community and areas where research questions remain. The subsequent chapters of this thesis deal with three of these limitations in detail: specifically, (i) how to manipulate convention emergence in open MAS domains (Chapter 5), (ii) how to exploit knowledge of network structure to improve mechanism efficacy (Chapter 6), and (iii) the amenability of conventions to manipulation in the middle to latter stages of the convention lifecycle (Chapter 7). We use language and notation from our formalism to describe models used in experiments in the remainder of the thesis.

While significant understanding of conventions has been attained, limitations of current models of convention emergence reduce their applicability in large dynamic real-world MAS. Specifically, existing models are typically unable to describe the *quality*, *support* or *stability* of a convention, or account for how multiple conventions might co-exist. Furthermore, there has been limited research into the middle and latter stages of the convention life cycle. In this chapter, we begin by reviewing the conceptual foundations of conventions (Section 4.2) and the current state of the art (Section 4.3) and identify the limitations. We then propose a conceptual framework for conventions and show how common existing models can be expressed within it to allow direct comparison. Our framework comprises an interaction formalism (Section 4.4) and a rich definition of conventions and metrics (Section 4.5) that significantly extends existing approaches to address important limitations. Finally, Section 4.6 concludes the chapter and identifies future directions.

4.2 The foundations of conventions

Conventions are generally thought of as *socially accepted expectations of behaviour*, and represent an aggregation of a population's choices in its individual interactions. System designers are typically concerned with reducing the cost associated with malcoordination between agents, and conventions are a useful abstraction for analysing the behaviour of large numbers of agents, to support this aim.

There have been a wide variety of definitions proposed in the literature. Lewis (1969) defines a convention as a *regularity* in the behaviour of a population in repeated iterations in the same situation, subject to constraints such as the proportion of agents that conform to the regularity and the proportion of agents that expect others to conform. Goyal (1997) describes conventions as an arbitrary solution to a social problem, wherein individuals only conform because they expect others to conform. Shoham and Tennenholtz (1997) approach conventions from a game-theoretic perspective, defining a convention as a restriction of agents' decisions to a single choice in a given coordination game. Kittock (1993) considers a convention to exist when a high proportion of agents use the same given strategy.

4.2.1 The role of expectations

Uniting these definitions is the theme of mutual expectation in repeated iterations in similar situations: agents make choices based on the expected choices of others. As such, conventions are primarily necessary where agents' decisions involve *externalities*, in which the individual's choice (and utility) depends partially or wholly on the choice of others, and vice-versa (Schelling, 1973). In such systems, conventions provide a mechanism for (i) generating a set of mutual expectations that resolve coordination problems, and (ii) influencing agent strategy selection towards mutually and societally beneficial outcomes.

Consider the El Farol bar problem (Arthur, 1994; De Cara *et al.*, 1999), in which agents must decide on which day of the week to visit a bar. Each agent desires the number of other individuals present to be within a certain range, such that the bar is not too empty or too busy. There is no salient difference between any of the days, and an agent's decision is based purely on its expectation of what others will do. However, their decisions are in turn also based on such expectations. This loop of mutual expectations leads to infinite regress without resolution if there are no external factors to break it. Lewis (1969) called these expectations n^{th} *order expectations*, such that "I expect that you expect me to do x" is a second-order expectation.

Lewis (1969), and many subsequent works on convention emergence (e.g. Young (1993), Garrod (1994), and Boyer & Orlean (1992)), identify two principal mechanisms by which higher order expectations can be generated and subsequently resolved: *salience* and *precedence*.

- *Salience* is some feature of a potential choice that marks it out as more likely to be chosen by others. Lewis (1969) notes that this may not be an advantageous feature, but merely marked out as noticeable by some property.

- *Precedence* is a special form of salience: the choice is more expected because it has been previously observed. Young (1993) identifies precedence as the primary driver behind the emergence of conventions, through "gradual accretion".

Schelling (1973) was among the first to argue that either salience or precedence is necessary to break the infinite loop resulting from reasoning on higher-order expectations. Boyer and Orlean (1992) take this further, arguing that coordination problems cannot be solved using purely individual rationality, due to this regress. Shoham and Tennenholtz (1997) discuss the concept of *socially rational* choices, which embody the idea of an optimal choice for the society. Such a choice might manifest as the highest expected aggregate utility, or some other notion of *best* for the society, which may or may not be consistent with individual rationality. Conventions are a way of facilitating socially-rational decisions when agents are given a set of choices that are otherwise indistinguishable (and thus not amenable to decisions based on individual rationality).

Lewis (1969), Garrod (1994), and Boyer and Orlean (1992) all argue that conventions are self-reinforcing. Once a set of mutual expectations is created, subsequent choices based on those expectations serve to increase their strength. Lewis (1969) uses the analogy of a fire: "under favorable conditions, a sufficient concentration of heat spreads and perpetuates itself". Existing research into convention emergence has thus focused on two main questions: (i) what conditions are favourable for convention emergence, and (ii) how can an emerging convention become established throughout a population?

The above discussions indicate limitations in existing definitions of conventions, in that (i) they assume near-universal conformity is either an ideal or attainable goal, disregarding situations in which we desire or can only attain multiple (or partially adopted) conventions (i.e. Section 4.2 and typically held definitions of conventions), (ii) they provide no way to quantify the desirability of conventions (i.e. whether agents or designers prefer one convention over another) or their potential for establishment (Section 4.2, and the lack of quantifiable metrics in works discussed), and (iii) they provide no way to fully describe the evolution of a convention from uncoordinated individual choices to the emergence of an aggregate consensus (Section 4.2.1: the majority of work examines the processes of initial emergence), which is an important step towards developing effective mechanisms for managing conventions.

4.2.2 The convention life cycle

A complete theory of conventions must account for the evolution of a convention from a set of uncoordinated behaviours between interacting agents to the establishment of regular, expected choices. There have been a number of efforts investigating the mechanisms through which this occurs, but limited attempts to unify the results into a single cohesive framework. Hollander and Wu (2011) provide an overview of norms-related literature (norms being a form of convention in which adherence is motivated through sanctions or incentives), and outline a norm life cycle containing several processes: creation, transmission, recognition, enforcement, acceptance, modification, internalisation, emergence, forgetting, and evolution. Their view of the life cycle is focused on the agent perspective, while we consider the convention life cycle from the perspective of a convention as an entity in itself. Strictly speaking, in this thesis we focus on the *emergence* phase in the characterisation presented by Hollander and Wu (2011), and we do not discuss agent specific processes such as internalisation, forgetting, or the representation of conventions or norms.

At the beginning of the convention life cycle, salience or precedence causes a given strategy or choice to be selected with greater regularity than others. The expected utility of a strategy is a form of salience, since choices with a higher expected utility are more likely to be selected than those with lesser utility. Assuming that agents have different interaction partners over time, the mutual expectations that arise from salience and precedence will spread. At some point such a strategy is considered a convention, and typically system designers hope that it will spread throughout the population.

Research into how salience and precedence contribute to convention emergence has seen significant attention (e.g. Lewis (1969), Sen & Airiau (2007), Villatoro *et al.* (2009a)), but there has been little research on the process by which a convention grows or dissipates once a system of mutual expectation emerges, or on how it might become established across a whole population. Much work in the area adopts the convention definition proposed by Kittock (1993), in which a convention exists when a proportion of the population (typically 90–100%) adheres to it a proportion of the time (again, typically considered to be 90–100%). However, this offers little insight into the middle and latter stages of the convention life cycle, and is insufficient for domains in which such high levels of adherence to a single convention are either undesirable or unattainable.

We identify three possible states that a convention can attain: (i) *establishment* as dominant convention, (ii) *co-existence* with other conventions, or (iii) *destabilisation* and dissipation. The typical definitions, such as that of Kittock (1993), are concerned purely with establishment, and do not consider the conditions under which co-existence and destabilisation might occur (or whether they are desirable or not). We therefore consider the convention life cycle as only partially understood: the forces of precedence and salience that generate the initial set of mutual expectations that eventually form a convention are well documented (Lewis, 1969; Vylder, 2007; Young, 1993; Young, 1996), but the middle and latter stages of convention emergence have seen only limited research (notable examples include Villatoro (2011), Hollander & Wu (2011), and Boyer and Orlean (1992)). Moreover, the typically adopted definitions and models of conventions do not account for more than one convention existing in a population (with some exceptions, such as De Cara *et al.* (1999) and Villatoro (2011)), and do not support quantitative analysis of a convention's quality, support or stability. In the next section, we review the major research contributions relating to conventions, and describe how they fit within the convention life cycle.

4.3 Perspectives on conventions

In this thesis, we are concerned with the adoption and (online) adaption of conventions in the absence of a central authority. Various researchers have considered off-line design of conventions (Agotnes & Wooldridge, 2010; Shoham & Tennenholtz, 1995) and centralised imposition of conventions (Boman, 1999; Grizard *et al.*, 2007), but these tend not to be applicable to open MAS domains due to limited knowledge of society characteristics, time variance, and computational difficulty. It is important to distinguish between conventions and *norms*, which also represent socially-accepted rules governing behaviour, but are generally considered to include an *obligation* to act according to the norm (Agotnes *et al.*, 2009; Axelrod, 1986). Norms are a stronger form of convention, typically using incentives and sanctions to motivate adherence. In this chapter we focus on conventions, but believe that our conceptual framework could be generalised to norms in future work.

4.3.1 Conventions in agent systems

Walker and Wooldridge (1995) were among the first to investigate convention emergence in agent-based systems. Walker and Wooldridge developed an abstract model in which agents with a finite memory of past interactions select strategies in repeated interactions. The authors focused on designing a strategy update function that enables efficient conventions to emerge. They conclude that a simple majority rule, in which agents select the strategy that they have observed in others the most, performed best. it is important to note that their results are difficult to generalise: the model focuses on an idiosyncratic illustrative scenario (agents scavenging food in an open area) and uses a small convention space (4 possible conventions). Their formalism is also limited, particularly with respect to open MAS, by orienting metrics with respect to individual *runs* of a system (i.e. implying a clearly defined start- and end-point for a system). However, their contributions mark an important starting point in defining a unifying formalism for describing the emergence of conventions.

How agents select their strategy has a significant role in convention emergence, and has been further examined in detail by Vylder (2007) and Shoham and Tennenholtz (1997)[1], among others. Walker and Wooldridge (1995) also proposed metrics for the speed of convention convergence, and the number of strategy changes agents make. Their work was an important first step in determining quantitative descriptions, but was limited by its assumption that a single convention across the entire population was both the ideal outcome and possible to attain. As such, their work corroborates the power of precedence but offers no insight into the latter stages of the convention life cycle, or into the potential co-existence of multiple conventions.

Kittock (1993) demonstrated that conventions can emerge from pairwise interactions between agents, and identified the influence of the underlying network structure constraining interactions. More recent work has considered the interplay between network structure and convention emergence (Delgado, 2002; Griffiths & Anand, 2012; Mukherjee *et al.*, 2008; Pujol *et al.*, 2005; Savarimuthu *et al.*, 2007; Villatoro *et al.*, 2009a), and it is clear that a full understanding of conventions requires consideration of network effects. We discuss this further in Section 4.5.7. The link between network structure and convention emergence is only partially understood, and we investigate how to exploit knowledge of the network structure to manipulate convention emergence in Chapter 6.

Salazar *et al.* (2010a) consider convention emergence in the language coordination domain. Conventions can emerge from propagation of partial *convention seeds* (i.e. partial lexicons), with agents selecting which seeds to incorporate based on precedence in previous interactions (Salazar *et al.*, 2010b; Salazar *et al.*, 2010a). However, this requires that conventions be expressible in partial form, which is not possible in many domains. In Chapter 5, we show that with certain network topologies, the language coordination domain does not converge

[1]Shoham and Tennenholtz (1997) show that a Highest Cumulative Reward (HCR) update rule, in which agents select the strategy that has performed best overall in their memory, is highly effective at supporting convention emergence.

on a single shared lexicon, but instead agents form communities with high levels of internal coordination (Franks *et al.*, 2013). Such situations are not accounted for by the typical definitions of conventions.

Convention emergence is often illustrated by considering coordination games, such as the rules of the road (Sen & Airiau, 2007; Morales *et al.*, 2011). As with the language coordination scenario, the ideal is for every agent to adhere to the same convention, but this may be unrealistic. As the multitude of conventions in real-world traffic systems shows, it is not necessary for a single global convention to pervade for high levels of local coordination to emerge. However, the cost of inappropriate or inefficient sets of conventions is very high. Sen and Airiau (2007) model social learning through repeated coordination games, showing that: (i) a convention can emerge through anonymous private interactions, (ii) a very small proportion of agents can influence which convention emerges, and (iii) isolated sub-populations can maintain divergent conventions when they co-interact a small proportion of the time (up to 20%).

4.3.2 Lewis' analysis of convention

Lewis (1969) provided one of the first and most detailed examinations of conventions to date, which aimed to precisely define and analyse conventions in a general form, including tacit non-agreed conventions (as considered in this thesis). Lewis defines a convention as a regularity R in the behaviour of a population engaging in repeated interactions in which the following properties are satisfied in a proportion of at least d_0 of the interactions.

1. At a minimum, a proportion of d_1 individuals conform to R.
2. At a minimum, a proportion of d_2 expects a minimum proportion of d_1 individuals to conform to R.
3. At a minimum, a proportion of d_3 individuals have approximately the same preferences regarding the potential decisions that can be made.

4. At a minimum, a proportion of d_4 individuals would prefer that at least one additional individual conform to R, given that d_1 already conform.

5. At a minimum, a proportion of d_5 individuals would prefer that, if at least d'_1 individuals already conform to R' (where R' is a possible regularity such that an agent cannot conform to both R and R'), then at least one additional individual conform to R'.

The *degree of conventionality* of a regularity (i.e. a candidate convention) can thus be defined as a tuple $\langle d_0, d_1, d_2, d_3, d_4, d_5 \rangle$, indicating how strictly the definition holds. Lewis argues that the ideal convention has degree $\langle 1, 1, 1, 1, 1, 1 \rangle$, such that all members of the population adhere all the time, expect others to adhere all the time, have approximately the same preferences, and so on. Property 4 requires that the more individuals conform to R, the more desirable it is. Property 5 captures that R is a single arbitrary choice among many alternatives, and that there is no reason for R to be established beyond that of precedence. That is, an alternative regularity R' exists with the same properties as R (although with a different degree of conventionality), and that the context in which R and R' exist can therefore be considered a coordination problem.

As argued above, we might not desire a single convention as the ideal outcome. We must therefore handle Property 4 with care, as it logically results in only one convention. Similarly, Property 5 requires modification, since there are a number of situations in which a given regularity may be more or less intrinsically desirable beyond the number of agents conforming (e.g. in the Prisoner's Dilemma). Property 3 is limited in that *absent the social pressures of a convention* an agent's choice may be different; that is, there may be a difference between the action an agent prefers and that implied by convention.

The definition presented here omits a further property that Lewis (1969) identifies for a convention, namely that it must be *common knowledge*. Recent research, notably Sen and Airiau (2007), Walker and Wooldridge (1995), and Shoham and Tennenholtz (1997), has shown that private learning can result in conventions emerging, indicating that common knowledge is not necessarily a prerequisite of convention emergence. Young (1993) also demonstrates that *complete* knowledge of a convention is not required for a convention to emerge, since incomplete information may be a primary driver of convention change.

Lewis' definition identifies a number of important properties: (i) that a convention requires a regularity of behaviour across multiple instances of a given situation, and (ii) that a system of mutual expectation regarding behaviour is necessary for a convention to become established.

While Lewis' definition assumes the ideal of a single convention across the entire population, a small modification generalises the definition effectively to include situations in which multiple co-existing conventions are desirable, such as the El Farol bar problem. Rather than defining a convention with respect to the whole population, a convention can be defined with respect to those that currently conform to it. With this restriction Properties 1–5 hold within the convention (retaining the limitations identified above): of those that adopt a convention, we expect everyone to conform, we expect that everyone expects everyone else to conform, and so on. Note that this formulation implies that a single agent can be in a convention with itself. This modification is the basic inspiration underpinning our conceptual framework of conventions presented in this chapter.

Many subsequent definitions have included less formal constraints on what can and cannot be regarded a convention. Perhaps the most commonly used in the context of agent-based systems are those proposed by Shoham and Tennenholtz (1997) and Kittock (1993). The former describe conventions as a restriction on the choices available to individuals, and the latter describes a convention as existing when a significant proportion of the population chooses a given strategy a significant proportion of the time. Both of these definitions, with the caveats listed above, are implied by adopting a modified form of Lewis' definition. In the former, a behaviour that is a regularity among a group of individuals who have mutual expectations about members of the group conforming necessarily constrains which actions the agents will consider (especially in the absence of differentiation by salience). In the latter, the equivalence follows by definition.

4.3.3 Convention research in other fields

There is a variety of research in other fields relating to convention emergence, particularly in the psychological and economic domains. Human populations are particularly adept at efficiently emerging conventions without explicit agreement, and incorporating insights from these fields into the theory of conventions typically used in agents research may yield significant benefits. In this section, we focus on the work of Garrod (1994), whose experiments with humans provides significant insight into how convention emergence occurs in our society, and Boyer and Orlean (1992), who discuss convention behaviour and manipulation in the latter stages of the convention lifecycle. The latter is a particularly under-investigated area in open MAS. We use the results from these works in the development of our definition and metrics of convention, and in investigating how to manipulate convention emergence in the latter stages of the convention lifecycle (Chapter 7) respectively.

Garrod (1994) investigated human convention emergence, using an experiment in which people evolve coordinated description languages when solving problems. Volunteers are paired and play a maze game in which they must describe maze positions to the other player in order to prevail. The volunteers were divided into two groups: one in which individuals remained in the same pair for the duration of the experiment (9 iterations of the maze game), while the other group changed pairing each game (within the community represented by the group). Analysis of the language used to describe the maze shows three categories of representation used by pairs: (i) *line*, such as "first row and third column", (ii) *path*, such as "two along from you", and (iii) *matrix*, in which vertical and horizontal lines are named according to a scheme such as that from chess (e.g. "C4"). Within each category, there are a number of different instantiations of representation.

Pairs in the community group took longer to agree than the isolated pairs. However, their representation (a form of matrix) was agreed across the entire community, despite communication only being local between pairs. Conversely, isolated pairs quickly agreed on a representation, but the representations were wildly divergent between pairs. From the experiment results, Garrod (1994) concluded the following.

1. There is a local coordination process between individuals in a pair, by which local precedence and salience have a strong influence on the representation that is chosen.

2. When the community has agreed on a representation, players have a stronger preference to act according to convention than to the constraints of local precedence and salience.

3. When two players meet with conflicting chosen representations, the representation that tends to get chosen (mostly implicitly) is that which is represented most frequently in the *joint* history of the players.

4. The community group explores potential representations more widely at the beginning than the isolated pairs group, before settling on a single representation across the entire community.

5. The local coordination process between individuals, which incorporates precedence and salience, leads to a global coordination process as those individuals interact with others in the population and “infect” them with their preferences.

6. An important component of the community convention emergence is the ability of individuals to monitor their communicative success — typically modelled in the agents community through reinforcement learning and/or a personal interaction history.

7. High simulated population churn, achieved by pairing individuals with others in such a way that they do not form a community with repeated interactions, decreased the levels of coordination drastically. This has significant implications for open MAS with high levels of population churn.

Garrod (1994) argued that the results are a consequence of community effects rather than the influence of a given individual, since there is not sufficient time in the experiments for an individual to gain influence or standing within the group. However, the influence of an individual over a population is complex with respect to conventions, since precedence creates feedback effects, and any one action might propagate significant changes through a population. As such, it is not appropriate to entirely disregard the potential influence of individuals in convention emergence, although the results suggest that community effects can transcend individual actions. We use the influence of individuals as the basis of our *Influencer Agent* mechanism, which is explored in subsequent chapters. The setup used by Garrod is equivalent to a population connected by a fully-connected network, which also would not imbue any individual with special standing from network effects[2].

There are relatively few investigations into the latter stages of convention establishment. One of the most detailed was presented by Boyer and Orlean (1992), who attempt to account for how an established convention can be superseded by a preferable one. They identify four situations that can overcome the reinforcement feedback effects of an established convention.

1. *Convention collapse.* If the environment (including the population of agents) is drastically and suddenly altered, the previously established convention may lose its force of precedence and provide room for new conventions to become established.

2. *External invasion.* When a new group with an alternate convention joins a population, the force of precedence already present in the new group allows

[2]We investigate this type of special standing in Chapter 6.

the alternate convention to gradually undermine the currently established one.

3. *Translation.* If there is a possible new convention that is compatible with the previous convention, then the costs associated with adopting the new convention are removed and the new convention can become established more easily.

4. *Collective agreement.* If a sufficient proportion of the population explicitly agrees to collectively adopt a new convention it can easily become established. Boyer and Orlean (1992) note that this requires the existence of a central authority, and since this is impractical for open MAS we do not consider this route to convention change.

Boyer and Orlean (1992) also conclude that the best way for a new convention to become established is to begin in a localised space and progressively invade the rest of the population. This is a form of "gradual accretion of precedence" (Young, 1993).

There has been little research into co-existing sub-conventions, with the notable exception of Villatoro and Sabater-Mir (2011) who propose *social instruments* as a way of identifying and mitigating less desirable sub-conventions, that might be supported by self-reinforcing underlying network structures. However, they assume that sub-conventions are necessarily those that we want to destabilise, and do not consider the potential desire to support co-existing sub-conventions.

The contributions of Boyer and Orlean (1992) and Villatoro and Sabater-Mir (2011) are concerned with how conventions might be manipulated by interested parties in order to support the adoption of desirable behaviour across the population. However, research in this area is limited and there are, to our knowledge, no proposed mechanisms for manipulating which convention a population adopts in open MAS. Such a mechanism is the focus of Chapter 5.

4.3.4 The convention life cycle revisited

Based on the above discussion, we propose the following view of the life cycle of a typical convention. First, agents engaging in local interactions select strategies based on intrinsic salience or an assessment based on previous interactions (either observed or experienced). As precedence accumulates for one strategy over another, more agents choose it and its momentum increases. Under typical definitions, such as that of Kittock (1993), this continues until some proportion of the population choose that strategy some proportion of the time, at which point it is considered an established convention. However, based on the definition of Lewis (1969), we can consider it a convention with a given degree of conventionality at almost any point, with the degree of conventionality gradually strengthening. In practice, conventions will either become established, co-exist, or destabilise. Although the beginning of this process, by which the forces of salience and precedence combine to form regular behaviours, is well described in the literature, beyond that point there has been comparatively little work. The behaviour of conventions in the middle and latter stages of the convention lifecycle, and how they might be manipulated, is the focus of Chapter 7.

The preceding sections demonstrate the limitations in current approaches to convention emergence in open MAS. While there are a variety of useful contributions, they tend to be investigated with respect to disparate models, and it can be difficult to generalise or draw conclusions across multiple works. While there have been some attempts to propose a framework within which to place these contributions (most notably Walker and Wooldridge (1995)), unifying convention theory into a cohesive whole remains an open research question. Current definitions of conventions fail to take into account the possibility that a single convention may not be a desirable or attainable ideal, and there has been relatively little work that incorporates research from other fields (such as psychological research on convention emergence in human society) or investigates a convention's behaviour after its initial emergence. There is therefore a clear need for (i) a unifying formalism with which different models of convention emergence can be expressed and directly compared, (ii) a definition of conventions which takes into account these limitations and incorporates as much of the current thinking, across fields, as possible, and (iii) the definition of metrics that can be used to quantify convention behaviour throughout the convention lifecycle.

4.3.5 Illustrative examples

Throughout this chapter we will refer to a number of example scenarios to illustrate our approach: the coordination game domain; a coordination game which incorporates interaction history; the language domain; the donation game; and the El Farol bar problem (as introduced in Section 4.2). In particular, the language domain and the coordination game domain are used experimentally in the remainder of this thesis and are therefore described in more detail in subsequent chapters (specifically, Chapters 5 and 6 for the language domain and Chapters 6 and 7 for the coordination game domain).

	Go	Yield
Go	-1,-1	3,2
Yield	2,3	1,1

(a)

	0	1
0	4,4	-1,-1
1	-1,-1	4,4

(b)

Table 4.1: Payoff matrices for the social dilemma (a) and coordination game (b).

Sen and Airiau (2007) investigate social dilemma and coordination games, illustrated by two cars approaching an intersection, where each driver must decide whether to yield or go. In the social dilemma formulation (Table 4.1(a)) one driver yielding and the other going is the most preferable outcome. In the coordination game (Table 4.1(b)) the preferred outcome is both agents choosing the same strategy, such as driving on the same side of the road.

Villatoro *et al.* (2009b) propose a variation of the traditional coordination game, that we refer to as the historical coordination game. In this setting the payoff that agents receive is determined by the number of times a strategy has been selected by the interaction participants, i.e. it is dependent on the *joint histories* of the participants rather than solely on their instantaneous strategy selections.

Salazar *et al.* (2010b) consider convention emergence in the language coordination domain, in which agents are associated with a *lexicon* (see Figure 5.1 in Chapter 5, where we introduce the model in more detail), namely a set of mappings from words to concepts. There are 10 possible words, and 10 possible concepts, (i.e. 10^{10} possible lexicons), and agents share partial lexicons along with quality estimates based on interaction history, such that the population eventually agrees on a single shared lexicon. Language is a natural way of illustrating convention emergence, and incorporates realistic assumptions regarding convention space size. Clearly, a single lexicon in use by the entire population is the ideal outcome, but in large populations whose interactions are constrained by some underlying network structure this goal may be unreachable. This hypothesis is confirmed in Chapter 5, where we investigate manipulating conventions in the language coordination domain.

We also illustrate aspects of our approach with the donation game used by Nowak and Sigmund (1998), in which agents are selected for pairwise asymmetric interactions. One agent is denoted the *donor*, and the other the *recipient*, such that the donor must decide whether to confer a benefit b on the recipient at personal cost c (it is assumed that $b > c$). This model is introduced and investigated in greater detail in Chapter 3.

4.4 Interaction formalism

As described above, research on convention emergence in agent-based systems has been set in disparate domains with very different properties, making it difficult to directly compare results. This section outlines the interaction formalism that forms the base of our conceptual framework, within which we can describe and compare commonly used models of conventions. The formalism is loosely

Category	Notation and definition	Description
Population	$Ag = \{1, ..., N\}$	The population of agents.
	N	The size of the population.
Social network	$G = (Ag, E)$	The underlying social network constraining interactions between agents. Ag is the set of nodes (i.e. agents), and E is the set of connections between them.
Neighbourhood	$N(Ag_x)$	The set of agents with which an agent Ag_x can communicate.

Table 4.2: Basic notation used in our formalism for describing open MAS models concerned with convention emergence.

based on work by Walker and Wooldridge (1995), although we have incorporated significant modifications to allow description of different models in a single unified approach. We describe our formalism with reference to the example scenarios introduced above. For clarity, the notation introduced in this section is summarised in in Tables 4.2, 4.3, and 4.4. We use this formalism to describe the models used in the remainder of this thesis using consistent language and notation. The work in the remainder of this thesis also explores the behaviour of conventions that co-exist, and does not make the assumption that a single convention is the ideal or attainable goal.

We assume a population of agents, $Ag = \{1, ..., N\}$, situated on some underlying network structure $G = (Ag, E)$, where Ag is the set of nodes in the network, and E is the set of connections between agents (we assume a directed network for full generality). We assume that agents can only interact with others in their *neighbourhood*, defined as the set of agents with which an agent has a direct connection. We denote the neighbourhood of a given agent Ag_x as $N(Ag_x)$. The set of agents and the set of edges may both vary significantly over time. An edge connecting agent a to agent b represents that a may communicate with or interact with b.

Agents participate in a given MAS by interacting with zero or more other agents[3]. Every participant in an interaction engages by selecting an appropri-

[3] Walker and Wooldridge (1995) note the existence of agent actions that do not involve other individuals, but do not include them in their model. We define interactions as involving at least one agent (rather than at least two agents) since our definition of a convention as a

ate strategy. Each agent receives a (potentially different) payoff, dependent on the strategy chosen, joint interaction history, and environmental configuration. Agents update their internal strategy selection based on information gained during the interaction (e.g. payoff, knowledge of other agents' strategies if available, etc.). In a coordination game a strategy might represent driving on the left or right, driving through amber lights or stopping, or yielding to traffic from a given direction. In the language coordination domain, a strategy is a mapping of words to concepts. In both domains, an interaction involves two agents, with the payoff being determined by comparison of the strategies chosen, with payoff highest when the strategies *align*. Alignment, in this context, means strategies that complement each other. In the language coordination domain, strategies align when agents use the same mapping of words to concepts, and so can understand each other. In a coordination game, it may not be the *same* strategy that is needed, but complementary strategies that most efficiently coordinate the agents involved, such as one agent yielding to the driver on the right and the other driving onwards.

4.4.1 Dimensions

For many domains, there are multiple *dimensions* of strategies over which agents must reason. Considering the road traffic example, agents must decide whether to drive on the left or the right, *and* whether to consider amber lights passable or not. We make the modelling assumption that the interactions in which agents make these selections are independent, in that an agent's choice of whether to drive on the left or the right does not affect its decision of whether to stop at amber lights. There may exist situations in which this assumption does not hold, but we maintain that such situations can be abstractly represented in our model in a form that does not violate this assumption (i.e. as a single 'composite' dimension). To incorporate the notion of dimension into our formalism, we assume a set of dimensions D, and define a set of strategies that agents can

recurring standard of behaviour does not necessarily mandate multiple agents.

select with respect to a given dimension d as:

$$\Sigma_d = \{\sigma_1, ..., \sigma_{s_d}\}$$

where s_d is the number of strategies characterising dimension d. In the example above, we have $\Sigma_{side} = \{\text{left}, \text{right}\}$ and $\Sigma_{amber} = \{\text{go}, \text{stop}\}$. Note that different dimensions may have different numbers of possible strategies. For the purposes of discussion, we call each σ_i a *strategy*, but we also use the term to represent more conceptual notions, such as ideas or linguistic mappings. Interactions are defined with respect to a given dimension, with all participants constrained to the set of strategies available in that dimension.

4.4.2 Roles

Agent interactions are often asymmetric, in the sense that each agent plays a different *role* in the interaction. Commonly considered asymmetric interactions include the donation scenario introduced above (Nowak & Sigmund, 1998), and determining when a driver should yield at a junction (Sen & Airiau, 2007). Other real-world examples of asymmetric interactions abound, such as auctions, task allocations, etc. Each dimension is associated with a set of roles:

$$R_d = \{r_1, ..., r_{\rho_d}\}$$

where ρ_d is the number of roles for dimension d. The set of all roles is denoted $\mathbf{R}$.

The strategies an agent can select are constrained by the role it fulfils in an interaction. Similarly, the visibility of information regarding the agent and its choice is defined by the role. Agents use information from interactions to update their strategy selection algorithms and to inform future decisions. The information an agent might receive (depending on the domain) includes the identity of others in the interaction, their strategy selection, their individual payoff and their overall utility over some number of previous interactions (for example, lexicon quality estimates in the language coordination game). To describe the various observability constraints in different settings, we define a role as a tuple:

$$r = \langle ID, S, P, U, p \rangle$$

where the boolean properties ID, S, P, U specify whether an agent's identity (ID), strategy selection (S), payoff received (P), and overall utility (U) are observable, and p is the probability that the tuple of values will be observed. That is, for an agent a fulfilling role $r_{eg} = \langle true, true, true, true, 1 \rangle$ in an interaction, all other agents in the interaction will, with probability 1, know agent a's identity, the strategy it selected, the payoff it received, and its overall utility across all previous interactions (or the last m interactions depending on memory limitations and the domain).

The agents that receive this information may not be explicitly part of the interaction. For example, Axelrod (1986) and Nowak and Sigmund (1998) incorporate external observers into each interaction, such that each observer receives information on (in these cases) participants' strategy selections, without actually selecting a strategy themselves. In our formalism, external observers can be represented as participants in an interaction, fulfilling a role of $observer$. In most situations, information relating to observers is private, but situations exist in which observers also influence the outcome of an interaction directly. For example, in Axelrod's model of meta-norms (Axelrod, 1986), observer agents must decide whether to punish defections, and if they are subsequently observed to not punish, they themselves may be punished.

To illustrate our roles concept, consider the donation game (see Section 4.3.5 (Nowak & Sigmund, 1998)). In our formalism, the roles of donor, recipient and observer can be represented as:

$$r_{donor} = \langle ID = true, S = true, P = true, U = false, p = p \rangle$$

$$r_{recipient} = \langle ID = false, S = false, P = false, U = false, p = 0\rangle$$

$$r_{observer} = \langle ID = false, S = false, P = false, U = false, p = 0\rangle$$

where p is the probability of observation. Subsequent work has proposed that observers can use the recipient's identity in combination with the donor's choice to aid their strategy update (Milinski *et al.*, 2001). This can be incorporated by allowing the recipient's identity to be observed:

$$r_{recipient} = \langle ID = true, S = false, P = false, U = false, p = p\rangle$$

We assume that its role determines the set of strategies from which an agent may select, but there may also be strategies that can be selected in multiple roles (for example, consider the many road situations in which stopping is a valid strategy). As such, we define the set:

$$\Sigma_{d,Q} = \{\sigma_1, ..., \sigma_{s_{d,Q}}\} | Q \in \mathcal{P}(R_d)$$

as the strategies that can be selected in a given dimension d for a given combination of roles Q (i.e. $\mathcal{P}(R_d)$ denotes the power set of R_d), where $s_{d,Q}$ is the number of such strategies. A strategy can subsequently be specified as selectable in multiple roles (i.e. strategies can be selected in defined arbitrary sub-sets of the set of roles). We can now redefine the set of strategies for a dimension as the union of the strategies selectable in each role that comprises the given dimension:

$$\Sigma_d = \bigcup_{r \in R_d} \Sigma_{d,r}$$

In summary, agents engage in an interaction in a given dimension by selecting a strategy from the set of strategies available for the role which the agent is fulfilling in that interaction. The notion of dimension allows us to distinguish between independent situations in a given domain in which different strategy selections may be appropriate. The notion of a role allows us to describe in-

Dimensions	D	The set of dimensions in which interactions can occur.
	$\Sigma_d = \{\sigma_1, ..., \sigma_{s_d}\}$	The set of strategies that can be used in a given dimension d.
	s_d	The number of strategies that are available in a given dimension d.
Roles	$\mathbf{R}$	The set of roles that can be assigned to agents in interactions.
	$R_d = \{r_1, ..., r_{\rho_d}\}$	The set of roles that can be selected in a given dimension d.
	$r = \langle ID, S, P, U, p \rangle$	A role defining whether agent identity ID, strategy selection S, payoff received P, and utility U are observable, with p being the probability that the tuple of values is observed.
	ρ_d	The number of roles that exist in a given dimension d.
	$\Sigma_{d,Q} = \{\sigma_1, ..., \sigma_{s_{d,Q}} \| Q \in \mathcal{P}(R_d)\}$	The set of strategies that can be selected in dimension d for any role $r \in Q$, where Q is a subset of of the power set of R_d.
Interaction	$\mathbf{I}$	The set of all interactions.
	$I = \langle d, \langle Ag_1, \sigma_1, r_1 \rangle, ..., \langle Ag_n, \sigma_n, r_n, \rangle \rangle$	An interaction, defined by the dimension d in which it is set, and a set of tuples of agents, the strategies they selected (if the interaction has been performed), and the roles to which they are assigned.
	n	The number of participants in an interaction.
	$par_x(t) \mapsto \mathbf{I}$	The set of interactions that agent x participated in at time t.
	$obs_x(t) \mapsto \mathbf{I}$	The set of interactions that agent x observed at time t.
Interaction Regime	$IR : \mathbb{N} \times \mathcal{P}(Ag) \times \mathcal{P}(E) \times \mathbb{R} \mapsto \mathbf{I}$	A function which generates the set of interactions to occur in a given timestep.

Table 4.3: Model level concepts and notation used in our formalism for describing open MAS models concerned with convention emergence.

teractions in which agent choices are asymmetric, such that each agent has a different set of strategies from which to select.

4.4.3 Interactions

An interaction involves the strategy selections of one or more agents being *compared* and each agent receiving some *payoff*. The comparison of strategies and subsequent payoff may be either an internal agent process or an external process, defined by the environment. An interaction is a tuple containing the dimension in which it occurs, and further tuples defining each participating agent, the strategy they select, and the role they are assigned[4]:

$$I = \langle d, \langle Ag_1, \sigma_1, r_1\rangle, ..., \langle Ag_n, \sigma_n, r_n, \rangle\rangle$$

where n is the number of agents participating in the interaction. The set of all interactions is denoted $\mathbf{I}$. For simplicity, we use this representation to describe the interaction before the strategies are selected (such that each σ_i term is not bound) and after the participants have selected their strategies. In the language coordination domain, an example interaction before strategy selection might be denoted as:

$$I_a = \langle Communication, \langle Ag_1, \sigma_1, Speaker\rangle, \langle Ag_2, \sigma_2, Hearer\rangle\rangle$$

while after strategy selection, the interaction might become:

$$\begin{aligned} I_a \quad = \quad & \langle Communication, \langle Ag_1, Table \mapsto Concept1, Speaker\rangle, \\ & \langle Ag_2, Chair \mapsto Concept1, Hearer\rangle\rangle \end{aligned}$$

4.4.4 Interaction regime

We assume, as with most formalisms and models of MAS, that time can be modelled as discrete steps. In each timestep, a number of interactions are performed. To describe which interactions are performed in a given timestep and which agents are participants, we define an *interaction regime* function:

$$IR : \mathbb{N} \times \mathcal{P}(Ag) \times \mathcal{P}(E) \times \mathbb{R} \mapsto \mathcal{P}(\mathbf{I})$$

This function takes a timestep, the population of agents, the edges connecting those agents, and an interaction probability $ip \in [0, 1]$, and returns a set of interactions to be performed during the timestep. Note that although we

[4]For clarity of discussion, we say that a role is assigned to an agent, but in reality a role is likely to be defined by the situation in which an agent interacts. For example, we might say that an agent that wants to communicate with another is assigned the role of speaker.

define this function with respect to a given timestep, it allows for asynchronous interaction regimes since we do not assume that every agent interacts in any given timestep[5]. We use the interaction probability to allow our formalism to describe the various interaction regimes in common models of MAS. For example, Salazar *et al.* (2010b) assume that every agent interacts at least once in a timestep, whereas Nowak and Sigmund (1998) assume a given number of interactions happen each timestep, with agents chosen randomly each time (i.e. $|IR(t, Ag, E, p)| = m$, where m is constant).

4.4.5 Agent memory

In a similar manner to Walker and Wooldridge, we assume that agents maintain an internal *memory* in which all available details of the interactions the agent has observed or participated in are stored. An entry in the memory of agent x for a given interaction i is given by:

$$m_x(i) = \langle d, \langle Ag_1, \sigma_1, r_1, p_1, u_1 \rangle, ..., \langle Ag_n, \sigma_n, r_n, p_n, u_n \rangle \rangle$$

That is, an agent may record (if the situation allows) the dimension in which the interaction occured, the agents that participated, the role that each agent fulfilled, the strategies that were selected, the payoffs that the agents received, and their overall utilities. Recall that whether these data are observable is defined by the role assigned to each agent. We assume that observers to any interaction are selected from the union of the neighbour sets of the participants in the interaction (illustrated in Figure 4.1). We write $par_x(t, r)$ to denote the set of interactions in which agent x fulfilled role r at time t, and, for simplicity, $obs_x(t)$ to denote the set of interactions that agent x observes during timestep t[6]. The notation $obs_x(t)$ is thus equivalent to $par_x(t, observer)$. The set of all

[5]There is a significant body of research concluding that results from simulations with synchronised interaction regimes may not be generalisable to the real world, in which we would expect asynchronous interactions (Page, 1997).

[6]Note that this differs from Walker and Wooldridge, who use *obs*() to denote the number of times an agent has observed a given strategy.

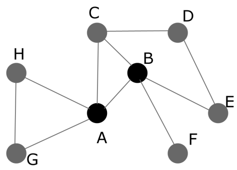


Figure 4.1: Example showing how the observation set is determined. Here, all agents except D are considered observers of the interaction between agents A and B, since they are connected to at least one of the participants.

agent memories is denoted $\mathbf{M}$, and the set of memories of agents that engaged in interaction i is denoted $\mathbf{M}_i$. We denote the number of times an agent x has observed strategy σ_i in dimension d as $obsHist_{x,d}(\sigma_i)$, and the number of times an agent x has used strategy σ_i in dimension d as $usedHist_{x,d}(\sigma_i)$.

4.4.6 Agent payoff

The payoff an agent receives is a function of the interaction in question and the memories of the agents involved, although different scenarios may ignore some aspects, dependent on the specific dimension and role in question (e.g. in the coordination game agents' memories do not affect the payoff). The payoff received by an agent x in dimension d when fulfilling role r is therefore given by:

$$P_{x,d,r} : \mathbf{I} \times \mathcal{P}(\mathbf{M}) \mapsto \mathbb{R}$$

The implementation of this function may be either a payoff matrix, or determined by how many times a given strategy has occurred in agent memories, or dependent on the identities of the participants, depending on the domain in question. Note that our formalism allows for different payoff functions in different dimensions or roles of the convention space. For example, in the image scoring scenario, the recipient receives a benefit b if the donor donates, the donor incurs a separate cost c, and observers receive no payoff (Nowak & Sigmund, 1998).

With respect to agents there are two important processes to consider: (i) the process by which an agent *selects* their strategy in a given interaction, and (ii) the process by which an agent *learns* from the interactions it engages in (including as an observer).

Strategies are chosen using a function, which maps an interaction and the agent's memory to a strategy. The agent's choice therefore depends (if the model allows) on the dimension in which the interaction occurs, the agent's role, its memory, and the other agents in the interaction:

$$ss_{x,d,r} : \mathbf{I} \times \mathbf{M} \mapsto \Sigma_{d,r}$$

After each interaction, the participants can update their internal strategy selection mechanisms based on their payoff, memory, and other interaction details (dependent on the domain). For example, Sen and Airiau (2007) use learning algorithms such as Q-learning (Waktins, 1989) or WoLF (Bowling, 2001) to update strategy selection choices. We assume that any other learning processes occur in this function, such as updating the memory with the available data from the most recent interaction. The strategy selection update function is defined as:

$$su_{x,d,r} : \mathbf{M} \times \mathbf{I} \times ss_{x,d,r} \mapsto ss_{x,d,r}$$

4.4.7 Expressing pre-existing models

In the previous section, we defined a formalism within which many common models of convention emergence can be expressed. The next section uses this formalism to define our model of convention emergence. To demonstrate the ability of this formalism to describe other models we include an account of how (i) Sen and Airiau's model of private learning (Sen & Airiau, 2007), (ii) Walker and Wooldridge's investigation into the effect of strategy update rules (Walker & Wooldridge, 1995), and (iii) Villatoro *et al.*'s convention emergence with history-based payoffs (Villatoro *et al.*, 2009b) can all be represented in this formalism in Appendix B. We also provide an example of the comparative analysis that

Memory	m_x $\mathbf{M}$ $m_x(i) = \langle I_i, \mathcal{P}(\mathbb{R})\rangle$ $\mathbf{M}_i$ $obsHist_{x,d}(\sigma_i)$ $usedHist_{x,d}(\sigma_i)$	The internal memory of an agent x. The set of memories of all agents. A single entry of a memory for a given interaction i. The set of memories of agents that engaged in interaction i. The number of times an agent x has observed strategy σ_i in dimension d. The number of times an agent x has used strategy σ_i in dimension. d
Payoff function	$P_{x,d,r} : \mathbf{I} \times \mathcal{P}(\mathbf{M}) \mapsto \mathbb{R}$	The payoff that agent x receives in an interaction in dimension d when fulfilling role r.
Strategy selection	$ss_{x,d,r} : \mathbf{I} \times \mathbf{M} \mapsto \Sigma_{d,r}$	An agent x's strategy selection function for an interaction in dimension d and role r.
Strategy update	$su_{x,d,r} : \mathbf{M} \times \mathbf{I} \times ss_{x,d,r} \mapsto ss_{x,d,r}$	The function an agent x uses in dimension d and role r to update its strategy selection function given participation in, or observation of, an interaction.

Table 4.4: Agent level concepts and notation used in our formalism for describing open MAS models concerned with convention emergence.

is possible when expressing models in our formalism.

4.5 Defining conventions

In this section we present our view of conventions using the interaction formalism defined above. Our model supports a more nuanced view than has typically been considered in the context of agent-based systems, and enables us to characterise conventions throughout their life cycle.

We view conventions as a standard of behaviour that adhering agents are likely to follow with significant probability. As such, an agent can be in a convention with itself, or with a very small number of other agents. However, such conventions are likely to be regarded as being of poor quality. We show how previous definitions of convention emergence can be expressed in our model. Using our definition of conventions, and the subsequently defined metrics of convention quality, support and stability, conventions can be fully analysed from the initial stage of mutual expectation through to one of the three possible end-states: establishment, co-existence, or destabilisation.

We adopt this definition of conventions for the remainder of this thesis, and investigate the entire lifecycle of conventions. Specifically, Chapter 7 explores convention behaviour in the middle and latter stages of the convention lifecycle.

4.5.1 Motivating arguments

A convention is generally thought of as a socially-accepted standard of behaviour, but precise definitions, in the context of agent-related research, tend to be limited. As noted above, conventions are typically accepted as *established* when some proportion of the population adheres to the convention some proportion of the time (with 90% or 100% being typical thresholds) (Kittock, 1993). In addition to the limitations of this definition noted above (e.g. assuming that a single convention is either desirable or attainable), it also leads to a binary view: conventions are either established or not, and we do not have any way of evaluating candidate conventions before they are accepted as established. In order to effectively reason about conventions and sub-conventions, we adopt a definition of convention that is purposefully broad and encompasses system states which would not traditionally be classed as containing conventions. Based on this definition we subsequently define a number of quality and support metrics. This leads to a more intuitive notion of convention with which we can determine (i) the desirability of a convention, (ii) the stability of a convention, (iii) the set of agents that are most influential on convention adoption, and (iv) the set of agents that should be targeted to most effectively aid the emergence of a given convention. Our aim is to provide a framework in which the process of how populations move from a set of agents acting disparately and independently to a set of agents with a desirable set of coordinated strategies can be effectively described. Such a description will enable the development of more effective approaches for manipulating (both encouraging and discouraging) convention emergence.

Note that all subsequent definitions in this section are assumed to be for a given *dimension*, and as such can be written with a subscript d in multidimensional convention spaces. The definitions can further be applied to each individual role r. For simplicity, we omit d and r, and define the given measures for domains with one dimension and one role. Generalisation to $|D| > 1$ and $|R| > 1$ is trivial.

4.5.2 Basic definitions

We begin by distinguishing between sets of agents that select a given strategy in a given timestep and those who do not. The set of agents that have chosen a given strategy $\sigma \in \Sigma$ at time t is given by:

$$chosen(\sigma, t) = \{x | x \in Ag \wedge self_x(i, t) = \sigma | i \in par_x(t)\}$$

where $self_x(i, t)$ is the strategy chosen by agent x in interaction i in timestep t, and $par_x(t)$ returns the set of interactions that x participated in during timestep t. Walker and Wooldridge (1995) use this to define a *convergence* measure (here slightly modified to fit our notation), namely the fraction of agents using the most popular strategy at time t:

$$conv(t) = \frac{max\{|chosen(\sigma, t)| \mid \sigma \in \Sigma\}}{|Ag|}$$

However, this metric is insufficient for our purposes, as the intuition behind it is that convergence increases until all agents use a given strategy. We derive a more flexible convergence measure below.

4.5.3 Agent adherence and membership

Before defining conventions and measures of convention quality and support, we require a way of defining whether we consider an agent to be a member of a convention or not, and of establishing the *existence* of a convention.

The exact strategy an agent will select at any given timestep is uncertain, since most learning algorithms incorporate some degree of exploration such that

100% adherence to a single strategy is unlikely to occur. It is useful to quantify an agent's *adherence* to a strategy ϕ as the probability of that agent choosing ϕ at time t:

$$adh(x, \phi, t) = P(x \in chosen(\phi, t))$$

We subsequently define the set of conventions Φ_t that exist in a population at time t as follows:

$$\phi \in \Phi_t \iff \exists x : x \in chosen(\phi, t) \wedge adh(x, \phi, t) > \gamma$$

That is, a given strategy σ is considered to be a convention at time t if there is at least one agent using that strategy with a probability greater than some threshold γ. We use ϕ to denote a strategy that is also a convention (i.e. it is used by at least one agent with probability greater than γ), and a strategy that may or may not be a convention as σ. This distinction allows us to separate strategies selected by chance, exploration or some other process and those selected with sufficient frequency to be considered conventions.

We define the average adherence to a strategy σ to be the mean adherence across the agents that chose σ in a timestep:

$$averageAdh(\sigma, t) = \frac{\displaystyle\sum_{x \in chosen(\sigma,t)} adh(x, \sigma, t)}{|chosen(\sigma, t)|}$$

We assume that the temporal variance of *adh* is low, such that an agent that satisfies $adh(x, \phi, t) > \gamma$ at time t is also likely to satisfy it at $t + 1$ (Walker and Wooldridge (1995) discussed that strategy change typically incurs a *cost* to the agent, and so expect the number of strategy changes needed before a convention was established to be minimised). Note that since strategy selection is likely to be relatively complex, we cannot easily establish the exact adherence of an agent. We can estimate adherence based on the agent's interaction history, by considering the proportion of the last n interactions in which the agent selected

ϕ.

Using adherence, we define a convention as *established* if the average adherence is greater than the *convention establishment threshold* β, a model-wide parameter:

$$estbl(\phi, t) \iff \phi \in \Phi_t \wedge averageAdh(\phi, t) > \beta$$

That is, a convention is established iff, considered over all the agents that selected the strategy in that timestep, the average adherence is greater than β. Given the definition of Kittock (1993) we might set $\beta = 0.9$ or $\beta = 1.0$. Note that unlike Kittock we might consequently consider a convention with only one or two adherents as established, but it would score particularly poorly in our metrics of convention quality, support and stability, which we define later in this section.

4.5.4 Convention membership sets

Now that we have defined adherence and the conditions under which we consider a convention to be established, we can usefully define the extent to which agents are part of a convention. We propose that agents can be either: (i) *members* of a convention, in that they currently adhere to it with probability greater than β, or (ii) *users* of a convention, in that they used the convention strategy in the current timestep but do not satisfy the adherence criteria. We can further split the set of members into those who are *active* and used the convention strategy in the current timestep, and those who are *passive* and did not use the convention strategy in the current timestep.

Let $activeMember(x, \phi)$ denote that agent x adheres to an established convention ϕ at time t:

$$activeMember(x, \phi, t) \iff estbl(\phi, t) \wedge x \in chosen(\phi, t) \wedge adh(x, \phi, t) \geq \beta$$

That is, agents that satisfy $activeMember(x, \phi, t)$ not only adhere to the established convention but also used that strategy in that timestep. Passive membership is defined as:

$$passiveMember(x, \phi, t) \iff estbl(\phi, t) \wedge x \notin chosen(\phi, t) \wedge adh(x, \phi, t) \geq \beta$$

A passive member is an agent whose adherence to the convention is greater than the threshold, but who has not selected that strategy in the current timestep. For example, an agent who has selected strategy a for the last 9 timesteps, but explores another strategy in the current timestep by choosing strategy b, will have an adherence of 0.9 to a. It therefore constitutes a passive member of a in the current timestep.

An agent is therefore a member of a convention if it is a passive or active member:

$$member(x, \phi, t) \iff (activeMember(x, \phi, t) \vee passiveMember(x, \phi, t))$$

Then the convention membership set for a given convention at time t is given by:

$$membership(\phi, t) = \{member(x, \phi, t) | x \in Ag, \phi \in \Phi_t\}$$

We can denote an agent that is not part of a convention, but used the strategy defining the convention, as:

$$user(x, \phi, t) \iff estbl(\phi, t) \wedge x \in chosen(\phi, t) \wedge adh(x, \phi, t) < \beta$$

The set of agents that are users of a convention is therefore defined as:

$$usership(\phi, t) = \{user(x, \phi, t) | x \in Ag, \phi \in \Phi_t\}$$

An agent that neither used the strategy nor adheres to the convention is considered a non-user:

$$nonuser(x, \phi, t) \iff estbl(\phi, t) \wedge x \notin chosen(\phi, t) \wedge adh(x, \phi, t) < \beta$$

Thus the set of non-users is given by:

$$nonUsership(\phi, t) = \{nonuser(x, \phi, t) | x \in Ag, \phi \in \Phi_t\}$$

and similarly for non-members:

$$nonMembership(\phi, t) = \{nonuser(x, \phi, t) \vee user(x, \phi, t) | x \in Ag, \phi \in \Phi_t\}$$

There are some practical advantages to being able to describe agents in these terms. It is clear that we need a way of describing which agents are members of a convention, but the ability to define *usership* may allow us to target mechanisms for encouraging convention adherence to those most likely to benefit, or to analyse the population state. This, in turn, suggests that designers might target such mechanisms at the set of (i) members, (ii) non-members, (iii) users, or (iv) non-users, or any combination thereof. There are hypotheses supporting the targeting of each, and in future work it will be useful to empirically evaluate the effectiveness of such targeting. In the rest of this thesis, we focus on supporting and manipulating convention emergence by targeting non-members, but we believe that our work may be refined by altering the targeted set. For example, in Chapter 5 we use small groups of agents to encourage non-members to adopt a given convention, and it may be possible to increase their efficacy by targeting (for example) users alone.

4.5.5 Support of conventions

Now that we have defined a convention, adherence, and membership, we can define various metrics that encompass a more nuanced view of convention quality, desirability, size, and stability than that provided by previous formalisations. We have already defined average adherence as the average adherence over all the agents that *chose* that strategy in a given timestep, but using the notions of *member* and *user* we can determine several other useful quantities. With a slight abuse of notation, we write $\chi(\phi, t)$ to denote any one of $membership(\phi, t)$, $usership(\phi, t)$, $nonMembership(\phi, t)$, $nonUsership(\phi, t)$, or any union or intersection thereof. We can thus generalise the definition of average adherence as:

$$averageAdh_{\chi}(\phi, t) = \frac{\sum\limits_{x \in \chi(\phi,t)} adh(x, \phi, t)}{|\chi(\phi, t)|}$$

For example, we might calculate $averageAdh_{membership}(\phi, t)$, and compare it with $averageAdh_{usership}(\phi, t)$.

While the number of conventions needed to establish an ideal coordinated system is variable and potentially unknown, it is useful to calculate how many agents are a member of some convention. With this in mind, we can define the convention membership ratio for the whole population:

$$cmr(t) = \frac{|\{x | member(x, \phi, t) \wedge \phi \in \Phi_t\}|}{N}$$

Thus a $cmr(t) = 1$ represents a population in which every agent is a member of an established convention, and $cmr(t) = 0$ indicates a population with no established conventions.

We now have a set of functions that allow us to describe:

1. To what degree agents support a convention. The adherence measure allows us to distinguish between a set of identical strategies being selected by chance, and a set of strategies being selected with high probability.

2. The number of established conventions in a population.

3. The fraction of agents currently adhering to a convention.

4. How many agents are becoming adherents: the average adherence measure does not assume that a convention is established. As such, it encapsulates those agents that have (say) 50% adherence — still high, and therefore perhaps worthy of targeted actions to encourage full adherence.

4.5.6 Quality and stability of conventions

When selecting a strategy, an agent has two sources of relevant information: its own personal experience, and its observations of how other agents act (assuming observability of interaction choices). We call the former *personal* preference and the latter *social* preference. In our conceptual framework, the social preference is that determined by information gained when fulfilling the *observer* role in an interaction. We denote the strategy selected by agent x's personal experience as $per_{x,d,r}$, and that selected by its social experience $soc_{x,d,r}$. These are defined with respect to a dimension d and a role r, such that agents can learn a different strategy for each role and dimension (i.e. $soc_{x,d,speaker}$ selects a strategy for an agent x based on information received on agents fulfilling the *speaker* role, when x is fulfilling the *observer* role). In many domains, system designers also expect agents to engage in some *exploration* of the strategy space. The process of strategy selection discussed here relates to selection *after* the agent has decided not to explore.

Intuition regarding conventions and norms illustrates the distinction between social and personal choice: typically, we imitate others (i.e. choose social precedence) on entering a new system, when we have relatively little experience, and subsequently place more weighting on personal preference as we gain more experience.

Ideally, we would like the strategy selected by each choice to be the same, implying that the choice suggested by convention is the best choice for the agent and vice-versa. If this is true for all agents in the convention, then the convention can be considered *stable*, as no agent is likely to act otherwise.

We define an agent's *dissonance* as an indication of whether there is a difference between that agent's personal and social strategy preferences:

$$diss(x) = \begin{cases} 0 & \text{if } per(x) = soc(x) \\ 1 & \text{otherwise} \end{cases}$$

We can then define average dissonance over the population:

$$averageDiss_{\chi}(\phi, t) = \frac{\sum\limits_{x \in \chi(\phi,t)} diss(x)}{|\chi(\phi, t)|}$$

An important measure of convention quality is the benefit an agent gains from adhering to it. In the investigation of convention emergence in humans performed by Garrod (1994), an individual gains the most benefit (i.e. any benefit at all) from selecting the strategy most represented in the joint history of the interaction participants. An agent can estimate this by inspecting its own interaction history. The *relative benefit* an agent x gets by selecting σ is:

$$relBen(\sigma, x) = P_x(\sigma) - histScore(\sigma, x)$$

where $histScore(\sigma, x)$ is the payoff x estimates it will gain based on its own interaction history and $P_x(\sigma)$ is the actual payoff x attains for selecting σ. Note that this benefit will change depending on which neighbour the agent interacts with, and that it is not always positive. For example, consider driving on the left or right. As a thought experiment, one can imagine a time when there was no convention on which side to drive. The relative benefit of people adhering to an emerging convention of driving on one side would be large, given the experience of not knowing which side people would drive on. However, once the convention is established, the additional benefit of adhering is low, and we do not notice the additional payoff we get by being part of the convention. Were we to defect, however, and drive on the "wrong side", we would incur significant negative payoff. If an agent that has a history of mixed choices is situated next to agents adhering strongly to one convention, then the relative benefit of selecting a strategy not defined by the convention is likely to be negative, as the payoff will be zero but the *histScore* will be positive. The relative benefit therefore encapsulates that conventions are *social* choices, in that an agent must consider not just its own choice of strategy but also that of those it interacts with. Finally, we can also define $\overline{relBen}_{\chi}(\sigma)$ as the average relative benefit the agent set χ attains by selecting strategy σ.

$$\overline{relBen}_{\chi}(\sigma) = \frac{\displaystyle\sum_{x \in \chi(\phi,t)} relBen(\sigma, x)}{|\chi(\phi, t)|}$$

While a number of these metrics are not fully computable in practical scenarios, estimates for each of them can be obtained. Given that the question of whether a convention exists or not, and determining its quality, support or stability, are inherently uncertain processes in the real world, we consider it reasonable to estimate these metrics. Our notion of conventions and related metrics is defined in a formalism within which a wide variety of models of convention emergence can be expressed. As such, our metrics can be calculated in these models for detailed analysis of their behaviour. We expect that analysis of such systems using our metrics will reveal additional details about the nature of conventions from which novel mechanisms for manipulating convention emergence can be designed.

4.5.7 Linking connection topology with conventions

As discussed in Section 4.3, topological influences on conventions are significant. By incorporating notions from social network analysis, we can further extend our framework for describing conventions.

While a set of agents that are entirely disconnected in the social network topology may be considered part of the same convention, it is intuitive to assert that a convention with all adherents as members of a single connected component of the network is in some way stronger or preferable. Certainly, it is more difficult for non-adherents to destabilise a convention in which the adherents are strongly connected and thus able to preferentially interact with other adherents. We can therefore define a measure $comp_{\chi}(\phi, t)$ to represent the number of connected components in the subgraph containing only agents from the given set, i.e. $\{v \in \chi(\phi, t) \cap V\}$. A useful example would be $comp_{membership}(\phi, t)$, the number of connected components in the network defined by agents that have an adherence greater than β to the convention. If $comp_{membership}(\phi, t) = 1$, then it is likely to be a convention highly resistant to external invasion. Indeed, it seems intuitive that the ideal situation is for all conventions that exist to have $comp_{membership} = 1$. For clarity of discussion, we will call a connected component in the sub-graph defined by the agents in $membership(\phi, t)$ a *convention component*.

Other notions from network analysis are also applicable. Costa and Da Rocha (2006) proposed extending notions of degree and clustering coefficient from single nodes to sub-graphs. These generalisations do not require the sub-graph to be connected. As such, we can directly apply these metrics to the connected components of the subgraphs defined by the membership sets. That is, we can directly define the degree and clustering coefficient of a convention, using the set of agents that are members, or the degree or clustering coefficient of the set of users of a convention.

The degree of a convention membership set corresponds to the number of non-member agents that can be directly interacted with; a useful indicator of a convention's ability to further spread. The clustering coefficient of a convention membership set corresponds to the extent to which members are likely to interact with other members, a key property for convention stability. Furthermore, Costa and Da Rocha (2006) introduce the neighbourhood of a sub-graph, as the set of nodes that are connected to the sub-graph, plus the set of nodes in the sub-graph itself. We might then further define the *fringe* of a sub-graph as the neighbourhood of the sub-graph with the nodes in the sub-graph removed. The fringe of a convention component therefore corresponds to the nodes that members of the convention component might interact with that use a different convention or strategy, and thus are likely to be good candidates for targeted mechanisms to aid convention emergence.

In many convention emergence scenarios, agents interact randomly with their neighbours. Given that the greatest payoff is attainable when an agent's neighbours use the same convention, we can expect that a connected component with a single convention will be most stable when its internal connectivity is greater than its connectivity to the rest of the network. This is similar to the typical definition of *community structure* in a social network (Newman & Girvan, 2004), such that a convention that is topologically mapped onto strong community structures is likely to be the most stable.

Clearly, the study of the underlying network structure should reveal significant insight into the nature of conventions. We make a first step in evaluating this hypothesis in Chapter 6, where we investigate to what extent knowledge of the network structure can improve the ability of individuals to manipulate which convention a population adopts.

4.6 Conclusions and further work

In this chapter, we have given an overview of the state of the art in research regarding convention emergence, and identified a number of limitations that impede a full quantitative understanding of convention emergence in large decentralised populations of individuals. In response, we have defined a conceptual framework for describing open MAS with conventions, and illustrated how existing convention emergence formulations can be easily expressed in it to enable comparison. We propose a new definition of conventions that allows for the coexistence of multiple conventions and facilitates analysis of conventions before they are traditionally accepted as being established. Our proposed set of metrics for describing convention quality, adherence and stability aims to support analysis of the middle to latter stages of the life cycle of conventions. Our future work will aim to analyse typical models of convention emergence within our conceptual framework. It is our expectation that such analysis will yield detailed insight into the nature of conventions, allowing us to design novel mechanisms for (i) determining which conventions are desirable, (ii) identifying those we wish to destabilise, (iii) supporting the emergence of desirable conventions, and (iv) determining a configuration of coordinated and co-existing conventions in populations where we may not be able to or may not wish to establish a single convention.

The conceptual framework presented in this chapter is a first step, in which we re-orient the traditional agent-based perspective regarding conventions to more closely fit the view of *regularities* as suggested by Lewis (1969), in which an agent has a significant probability of repeatedly choosing a given action. As such, we consider a wider variety of behaviour as conventional, and can use our metrics of quality, adherence and stability to determine how desirable each convention is. Our metrics also provide natural ways to quantify the conventions at which it might be useful to target supporting mechanisms, and it is our aim to evaluate this in future research. We envisage useful applications for our framework in a wide variety of domains, including social media and marketing, mechanisms for protecting conventions from external invasion, and mechanisms for destabilising undesirable conventions. In subsequent chapters in this thesis, we adopt the syntax of our formalism for describing the agent interaction models that we use. Appendix B also provides examples of how the formalism can describe common models of convention emergence.

There have been very few attempts to provide a unifying framework for convention emergence in open MAS. The most applicable proposal, that of Walker and Wooldridge (1995), oriented its formalism with respect to runs of a system, implying a well-defined start and end point for a system. This significantly reduces its applicability to open MAS. Walker and Wooldridge also defined very few metrics for quantifying properties of conventions, and focused on convention convergence and the number of strategy changes that agents make. These metrics assume that a single convention is the ideal or attainable goal, which may not be the case. The formalism described in this chapter does not rely on a notion of runs, does not assume a single convention is ideal or attainable, and defines many more metrics to quantify a wide variety of convention properties.

To our knowledge, there are no other convention frameworks that address these issues and are therefore suited to convention emergence in open MAS.

The work in this chapter suggests a wide variety of directions for future research, including evaluating targeting mechanisms for convention emergence at a specific group (i.e. users, non-users, and so on), extending the work on linking topological structure with convention behaviour, and examining the set of metrics described here in established models of convention emergence to determine whether or not they provide any insight into the behaviour of conventions. These extensions are outside the scope of this thesis, and in subsequent chapters we focus on investigating the *manipulation* of conventions. Specifically, Chapter 5 focuses on whether conventions can be manipulated in open MAS at all, Chapter 6 determines the extent to which knowledge of the underlying network structure can be exploited, and Chapter 7 determines the extent to which conventions can be manipulated in the middle and latter stages of the life cycle.

CHAPTER 5

Manipulating conventions using Influencer Agents

In the previous chapter, we discussed a number of limitations with the current theory of conventions and identified directions for future research. One area for investigation which has seen limited attention is the manipulation of conventions. In this chapter, we investigate how conventions might be manipulated in open MAS. We propose the Influencer Agent (IA) mechanism, in which a small proportion of agents with specific goals and strategies are inserted into the population in order to manipulate which convention the society adopts. We show that small proportions can be highly effective, and demonstrate that exploiting topological features can improve efficacy. IAs are a fundamental mechanism in the remaining chapters of this thesis: in Chapter 6, we investigate how exploiting knowledge of the underlying network structure can improve IA efficacy, and in Chapter 7 we show how IAs can be used to manipulate conventions in the middle and latter stages of the convention lifecycle, and empirically analyse the efficacy of equipping IAs with sanctions and incentives.

5.1 Introduction

Conventions are known to encourage high levels of coordination, but efficiently manipulating *which* convention emerges remains an open research problem. Considerations of limited knowledge of society characteristics, time variance, and computational difficulty often preclude the ability to generate and impose high quality conventions *a priori*. Mechanisms that encourage online generation and adoption of appropriate conventions often assume the ability to universally incorporate additional structures into agent or society architecture. In this thesis, we assume heterogeneous ownership of agents (Chapter 1) and that agents are able to join and leave freely at run-time. Subsequently, we cannot rely on adding additional structures into agent architectures, or make any guarantees that the proportion of agents adopting a particular mechanism will be sufficient to ensure feasibility. Similarly, we cannot assume that we can impose society-level structures on the system. As such, we require a model of how purely rational agents might be manipulated into adopting high quality conventions and otherwise aided in increasing levels of coordination within the system.

In this chapter, we propose inserting a small number of agents, with specific conventions and strategies, such that the population as a whole, through their normal rational selection of actions, is guided towards the adoption of high quality conventions. We call these inserted agents *Influencer Agents* (IAs), and show that a small proportion of IAs in an artificial society can efficiently aid the generation and propagation of high quality conventions. This mechanism of manipulating convention emergence does not require any assumptions of agent behaviour beyond rationality, and to our knowledge does not currently exist in this form in the literature.

To demonstrate the IA mechanism, we adopt a model of convention emergence in the language coordination domain, primarily defined by Salazar *et al.* (2010b). Agents are associated with individual lexicons, mappings from words to concepts, with which they attempt to emerge a single shared lexicon by communicating and sharing partial lexicons. The emergence of a shared lexicon constitutes the emergence of a convention. For a full description of the model, see Section 5.4. We rely extensively on Salazar *et al.*'s work to demonstrate our IA mechanism. The model that they present incorporates realistic assumptions, such as complex connecting topologies and very large convention spaces. Very few models of convention emergence use such large convention spaces, and by using this property the demonstration of IA efficacy is less likely to be due to chance. Furthermore, Salazar *et al.* have presented extensive results showing that simple agent strategies can lead to high-quality convention emergence, and the quasi-continuous nature of the convention space (as opposed to the discrete convention spaces of the majority of models) allows us to measure the *extent* of an IA's efficacy, as opposed to a binary observation of whether they were successful or not.

We discuss the IA concept, the research that inspired it, and possible strategies with which IAs can be equipped in Sections 5.2 and 5.3. Section 5.4 details our experimental setup, and Section 5.5 establishes baseline model behaviour and presents results demonstrating the efficacy of the IA concept. Finally, Section 5.6 discusses conclusions and directions for future work.

5.2 Influencer Agents

We define an Influencer Agent (IA) as an agent inserted by any interested party (typically the system designer or manager) with the specific goal of influencing and aiding the emergence of appropriate conventions, for example to increase the aggregate utility of an artificial society. Initially, we are concerned with facilitating the *emergence of a single, high quality convention*, but IAs might also be used to block the emergence of certain conventions or coordinate the emergence of multiple appropriate conventions (such as in the El-Farol Bar problem (Arthur, 1994)). This is further discussed in Section 5.5.6. IAs were inspired by a number of contributions in the literature that include the notion of a small proportion of unprivileged agents influencing the aggregate behaviour of an entire artificial society.

Our initial inspiration is based on the work of Garlick and Chli (2009), who created an agent-based model to investigate the effects of curfews in civil disturbances. While their domain of interest is very different to ours, they consider two important concepts: (i) a small proportion of policemen agents attempting to influence the society towards peaceful outcomes, and (ii) a notion of social influence based on communication between agents. They found that restricting communication, and thus influence, could significantly change the outcome of the model, and that free communication allowed agents to direct large populations towards their preferred outcome (i.e. rebellion or peace). Given that we expect few limitations on communication in our domains beyond the usual factors of noise and agents failing or leaving, this may translate to realistic open MAS domains.

While exploring how agents with fixed convention adherence (i.e. that use one strategy without possibility of changing) affect the conventions that emerge, Sen and Airiau (2007) found that four agents fixed on one strategy (of two alternatives) was sufficient to influence a population of 3000 agents to adopt that strategy. These results suggest that small numbers of agents can heavily influence large groups of self-interested individuals. However, Sen and Airiau's model is limited by three assumptions: (i) there are only two possible conventions, (ii) agents are randomly paired from the whole population rather than constrained by an underlying network structure, and (iii) interactions are private. With the intention of moving the model towards more realistic settings, we adopt a domain with many potential conventions (10^{10} with the parameter settings used in Section 5.5 where we discuss our results) and situate agents within a connecting topology.

Yu *et al.* (2010) show that small sets of informed individuals can guide large groups towards coordinated outcomes, with the aim of solving problems of distributed consensus. However, their approach requires significant additional components of agent architecture. Similarly, Oh and Smith (2008) discuss using a subset of agents in a population as *leaders* for other agents in multi-agent learning for resource allocation problems, such that the agents who follow them are saved the computational burden and other costs of convention generation. The authors argue that this approach aids convention emergence in highly dynamic societies since new agents can employ social learning rather than environmental exploration when entering the system. Our contribution has some similarities here, in that IAs are analogous to leader agents, and similarly bear costs associated with convention emergence (although in our current formulation IAs do not generate conventions, this being an area for future investigation).

Axelrod's model of norm emergence (Axelrod, 1986) requires observing agents to punish norm violators, and results in high levels of emergent cooperation. However, the model considers populations in which (i) the entire population is able to punish norm violators, (ii) agents are not situated on a network that constrains their interactions, and (iii) the convention space is limited to two dimensions.

Grizard *et al.* (2007) consider a system that links reputation assessments with cooperative social norms, where control agents are injected to monitor agents and sanction their behaviour (if necessary) by reducing their reputation, which leads to ostracism effects. They obtain encouraging results, but require the imposition of society-level components. Despite homogeneous authority and large populations, individual agents can clearly have a significant effect on emergent social dynamics.

Little work has been done on the generation of conventions themselves. Recently, Morales *et al.* (2011) have presented work on generating conventions using historical data on the success of a given convention. They situate agents in an abstract traffic model and use monitoring agents to determine the efficacy of imposed conventions. A machine-learning algorithm generates new conventions as necessary and these are communicated to the agents in the environment. Their work is one of few to address the generation of norms and conventions and there are parallels between their monitoring agents and our IAs. However, their model requires a central authority to process convention data and generate new conventions, whereas our IAs act independently and attempt to influence nearby agents to a given convention.

5.3 Strategies for IAs

We consider systems in which all agents have uniform levels of authority, and thus we cannot elevate the privileges or abilities of any inserted IAs above the rest of the population. However, there is still potential for significant influence. We can identify a number of potential strategies IAs might use: (i) lead-by-example, (ii) incentives and sanctions, and (iii) information propagation. We present an overview of these potential strategies below, but in the remainder of this chapter we are only concerned with leading-by-example as a means to explore the feasibility of the IA concept (we investigate agents with incentives and sanctions in Chapter 7).

Lead-by-Example: Sen and Airiau (2007) use a model of private interactions that introduced the notion of small sets of agents with fixed strategies being able to affect the norms adopted in a relatively large population. This implies that IAs may be able to choose strategies that enable them to *lead-by-example*, interacting with other agents using actions determined by high quality conventions. Agents observe these actions and incorporate them into their own strategies, allowing the convention to spread throughout the population. Additional targeting of where to insert high-influence agents (e.g. by using topological information such as node degree (Chen *et al.*, 2009; Kempe & Kleinberg, 2003)) might further increase the efficacy and robustness of this strategy, although this was not considered by Sen and Airiau.

Incentives and Sanctions: Both *incentives* and *sanctions* have been extensively studied in the literature over a wide variety of fields, and both are known to play a significant role in the emergence and enforcement of social norms. Oliver (1980) concludes that incentives are an effective way to motivate small groups, whereas sanctions are more effective at generating unanimous cooperation once a small group has been established (though at the expense of potentially generating hostilities that will disrupt such cooperation). The model of civil violence described by Garlick and Chli (2009) sanctions agents by restricting communications, and their results show that this significantly influences the normative outcome[1]. Axelrod (1986) showed that punishment for norm violation could create stable cooperative populations, although more recent investigations have cast doubt on the scalability of results from this model (Galan & Izquierdo, 2005; Mahmoud & Keppens, 2011). Despite this, sanctions and incentives remain powerful tools for aiding convention and norm emergence. Implementation of sanctions and incentives is likely to be domain-specific, and it is not intuitively clear how IAs might be able to effectively incorporate these notions into their strategies.

Information Propagation: It has long been accepted that *information propagation* plays a lead role in social dynamics. For example, Garlick and Chli's restriction of communications inherent in imposing a curfew had significant effects. Similarly, gossiping of information can replace the need for direct observation of interactions (Sommerfeld *et al.*, 2007), which is a core component of many of the convention emergence models discussed above (e.g. Shoham & Tennenholtz (1997), Walker & Wooldridge (1995)). IAs could be used to propagate trust and reputation assessments, high quality conventions, or other useful information, and could even block or otherwise disrupt communications from non-compliant agents.

In the remainder of this thesis we focus primarily on the strategy of lead-by-example as a demonstration of the feasibility of the notion of IAs (although

[1]Note that this influence is not always towards the preferred outcome, with the direction the population takes being dependent on its current state.

we investigate the use of IAs with sanctions and incentives in Chapter 7). We aim to confirm the hypothesis that small proportions of agents in a population can significantly influence convention emergence in an artificial society. As such, the agents that we consider are as simple as possible in terms of strategy. Specifically, the IAs we propose are identical to the other agents in the population, except that they do not adapt their behaviour in response to conventions proposed by others (instead, they adhere only to their own, fixed convention). Informally, we view such IAs as attempting to lead-by-example. This use of IAs relies on the rationality of agents: IAs attempt to propagate high quality conventions, and agents adopting these conventions avoid costs associated with malcoordination.

IAs represent a model in which a small proportion of inflexible agents spread a given convention for the duration of the simulation. We also present a second model, in Section 5.5, in which we give a specific initial convention to a (potentially larger) proportion of agents and then let them continue as normal. These alternatives apply to different potential real-world situations; the latter being a good fit for domains in which we can temporarily influence a large set of agents, and the former being more suited to situations in which we can insert a small number of agents explicitly under our ownership and control. In Section 5.5, we use the latter model in some of our simulations when validating certain aspects of our IA model. However, in this chapter we are primarily interested in characterising and quantifying the effects small groups of agents can have on populations many times their size, rather than the effects of groups of flexible agents adopting and adapting an initially implanted convention.

5.4 Experimental setup

Our experimental setup is based on that used by Salazar *et al.* (2010b), with some elaboration where details of the original configuration are unspecified. Agents are situated within a network structure that constrains the selection of neighbours with whom they can communicate, and the properties of this structure have a significant impact on population behaviour (see Appendix A for details). In this chapter, we focus on evaluating IAs using synthetic small-world and scale-free networks, which are intended to reflect features of realistic domains (Albert & Barabási, 2002). In subsequent chapters we validate IAs on real-world networks and examine the extent to which synthetic networks are useful models of real-world network structures. We describe many of the features of our experimental setup using the formalism introduced in Chapter 4. Summaries of the notation used can be found in Tables 4.2, 4.3, and 4.4.

The strategy of each agent is represented using a *lexicon*, a mapping from *words* to *concepts*. We denote the set of words as W and the set of concepts as C. We assume that $|W| = |C|$. We denote the set of mappings in a lexicon from elements of W to elements of C as M. We assume, for simplicity, that $|M| = |W|$. Each agent starts with a randomised lexicon, meaning that each element of W is mapped to a randomly selected element of C (such that multiple words may map to the same concept).

Agents attempt to communicate with each other using their lexicons, and track the success of their communications. Furthermore, they also exchange and update their lexicons in a manner analagous to a distributed genetic algorithm. Agreeing on a shared lexicon allows agents to communicate effectively with each other, and reduces costs associated with miscommunication. As such, a shared lexicon represents our notion of a convention. For simplicity, in this chapter we calculate convention adherence (see Chapter 4) using a history length of 1: agents either adhere to a convention or they do not. The membership set of a convention thus consists of all agents that currently use that lexicon. We refer to the (potentially partial) lexicons that agents communicate as *convention seeds*, since they have the potential to become established conventions. Figure 5.1 illustrates the lexicon structure and agent communications.

In this domain, there are many potential conventions[2] with an intrinsic qual-

[2] There are w^c possible conventions, where w is the number of words and c is the number of concepts (Salazar *et al.*, 2010b).

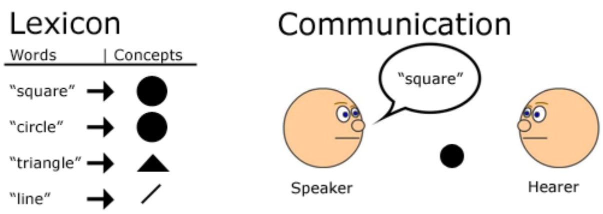


Figure 5.1: Illustration of a lexicon and a simple communication action.

ity metric called *lexicon specificity.* The specificity of a lexicon is the proportion of words that identify a single concept, such that a one-to-one mapping gives a specificity of 1, while a two-to-one mapping gives 0.5 specificity. To calculate specificity for a single concept in a lexicon, we use the formula $S_c = \frac{1}{|W_c|}$, where S_c is the specificity of concept c and W_c is the set of words that identify that concept. If no words identify a concept then $S_c = 0$. The specificity of a lexicon is defined as the average of the specificity of all concepts, or formally:

$$S = \frac{\sum_{c \in C} S_c}{|C|}$$

There may exist multiple conventions of the same quality, in which case it does not matter which one the agents choose as long as they agree. Adhering to a convention allows an agent to avoid the cost associated with being unable to communicate successfully with others. Given the potential size of lexicons, it is not practical for agents to propagate entire vocabularies. This means that agents have incomplete information about other agents' lexicons, and can thus only estimate their quality. We do not know *a priori* if an ideal lexicon exists in the population. Convention emergence is thus a highly challenging problem in the language domain, making it a useful setting for the investigation of convention emergence dynamics. We note that the results of Salazar *et al.* (2010b) show efficient and fast convergence to a high quality convention, but require extensive additional architecture (such as components for self-protection and internal noise generation to increase lexicon diversity) to be built into agents. In our investigation, we have replicated the core components of the convention spreading mechanism introduced by Salazar *et al.* (2010b) of information transfer and selection. We assert that these components will be universally adopted by agents that are rational: agents will choose the best convention they can based on the available information, and attempt to reduce costs associated with malcoordination by spreading their "way of doing things"[3]. We use this domain to investigate the ability of small numbers of unprivileged IAs to influence the behaviour of a population.

5.4.1 Interaction regime

Within each timestep of the simulation, there are three phases: (i) agent communication, (ii) lexicon spreading, and (iii) lexicon update. The communication, spreading, and updating actions are split into separate loops to prevent unforeseen synchronisation effects, such as agents updating their lexicons from out-of-date information. The full interaction regime for the simulation is shown in Algorithm 1.

Communication

In the first phase, every agent in turn fulfils the role of *speaker*. The speaker selects a random neighbour, fulfilling the role of *hearer*, and sends them a one-word communication about a concept. The payoff for the speaker is 1 if both agents choose the same strategy (i.e. have the same mapping) and 0 otherwise. For the hearer, the payoff is always 0. An agent's *communicative efficacy* is the average payoff over the last 20 timesteps (discussed in more detail in Section 5.4.4). Note that Salazar *et al.* (2010b) define communicative efficacy as the difference between successful (understood) and unsuccessful (not understood) communications, calculated every 20 timesteps. We use the normalised form for clarity of analysis.

[3]Spreading of conventions can also be interpreted observationally, such that agents receiving a convention from another can be said to be observing that agent's convention.

Spreading

After all agents have acted as a speaker in a timestep, each agent is in turn given a chance to send their lexicon (either partially or completely) to all their neighbours. We assume that agents update their lexicons based on information provided by others (i.e., there is no centralised authority). Consideration must be given to the synchronicity of the agent update processes. Given the literature concerning the limitations of synchronous strategy update (Page, 1997; Szabó & Fath, 2007), we use an asynchronous probabilistic update model: during each timestep, an agent sends lexicon information (see below) with probability p_{send}, and updates its lexicon based on received information with probability p_{update}. This differs from Salazar *et al.* (2010b) who combine both probabilities into a single value for spreading. They do not explicitly state when agents initiate their update processes, or whether they are synchronised, but the model presented in Salazar *et al.* (2008) suggests that agents update after a given number of timesteps with a given probability.

Salazar *et al.* (2010b) consider two potential mechanisms for lexicon spreading: *Complete* transfer (also called *Copy* transfer) and *Partial* transfer. In complete transfer, agents send their entire lexicons to their neighbours. This should only be seen as an idealised scenario — in practice, it is likely that resource constraints such as bandwidth will mean that only partial transfer is possible, and we therefore focus on partial transfer. Salazar *et al.* (2010b) state that their partial transfer mechanism is based on recombination techniques from evolutionary algorithms literature, but they give no further detail.

We define partial transfer using a two-point crossover mechanism that mirrors two-point crossover in genetic algorithms, in which two points are selected in the parent gene strings. Everything between those two points is swapped, generating two offspring. In our case, we generate a single offspring, in the form of a new lexicon, using the following mechanism:

1. Each agent is associated with an integer l, individually chosen uniformly

at random at the start of the simulation, that defines the lexicon transfer length. This represents the number of mappings an agent will try to spread from its lexicon to other agents (i.e. $l = |W|$ corresponds to complete transfer). For simplicity, we assume that all agents have the same number of words and concepts in their lexicons.

2. When an agent decides to initiate a partial transfer, it selects a random start point, a, in its lexicon such that $a + l \leq |W|$.

3. Then, l mappings are selected from the lexicon starting at mapping a, and are communicated to the neighbour set of the agent.

4. If a recipient chooses to incorporate these mappings in the update phase then it replaces l mappings in its own lexicon, starting at a, with the received mappings.

Updating

When selecting which of the incoming partial lexicons to incorporate into their own lexicon, agents can use either *random* or *elitist* strategy update functions (Salazar *et al.*, 2010b). Random strategy update selects between each incoming convention seed uniformly at random, whereas the elitist strategy update picks the seed with the highest quality. Salazar *et al.* (2010b) assume that agents send a quality valuation with the convention seeds, and that this is honest. In our investigation we adopt this assumption, but note that this is idealistic. The quality valuation for a lexicon (whether partial or complete) is the sum of the communicative efficacy and specificity for the full lexicon, and so the two components are evenly weighted.

An agent's strategy is encapsulated by the population-wide variables p_{send} and p_{update}, the agent-specific variable l, its individual lexicon, and the agent-specific update strategy of random or elitist.

IAs are modelled as agents with a fixed lexicon: they attempt to propagate their own lexicon as normal (which may or may not be shared with other IAs),

Algorithm 1 Interaction regime

```
//I is set of interactions
//Communication Phase
for all Agent ∈ Population do
    Partner ← getRandomNeighbour(Agent)
    I ← I ∪ ⟨LC, ⟨Agent, σ_1, Speaker⟩, ⟨Partner, σ_2, Hearer⟩⟩
end for

//Spreading
for all Agent ∈ Population do
    r ← randomDouble()
    if r < pSend then
        I_new ← ⟨LC, ⟨Agent, σ_1, Sender⟩⟩
        i ← 0
        for all Neighbour ∈ Agent.getNeighbours() do
            I_new ← I_new ∪ ⟨Neighbour, σ_i, Receiver⟩
            i ← i + 1
        end for
        I ← I ∪ I_new
    end if
end for

//Updating
for all Agent ∈ Population do
    r ← randomDouble()
    if r < pUpdate then
        I ← I ∪ ⟨LC, ⟨Agent, σ_1, Updater⟩⟩
    end if
end for
return I
```

but will discard any incoming partial lexicons, regardless of their quality. Unless otherwise specified, IAs are all given the same initial lexicon. In practice there is likely to be an upper bound on how many agents it might be practical to insert into a system. For example, there might be a limit of a proportion of 0.05 IAs in a population (e.g. 50 agents out of 1000) that it is realistic to insert. However, for evaluation purposes we performed simulations with proportions up to 0.4. While such proportions are likely to be impractical, they are useful in characterising the behaviour of the model.

5.4.2 Roles, dimensions and observability

There is one dimension in this domain, which we call LC (for language coordination), with each possible lexicon representing one strategy. There are five roles: in a communication interaction, there is a *speaker* and *hearer*, in a lexicon propagation interaction, there is a *sender* and several *receivers*, and in an update interaction, there is an *updater*. The interaction regime returns interactions that satisfy the following properties: the first N interactions consist of pairs of agents fulfilling speaker and hearer roles, such that every agent in the population is chosen as speaker once. Subsequently, each agent is chosen with a probability p_{send} to act as sender, with each of its neighbours designated as a receiver. Finally, each agent is chosen with probability p_{update} to perform strategy update. The full set of roles is therefore $R = \{$speaker, hearer, sender, receiver, updater$\}$.

An agent's broadcast of its mappings is equivalent to the neighbours of that agent observing their strategy, identity and payoff. Thus,

$$R_{speaker} = R_{hearer} = \langle ID = true, P = true, S = true, U = false, p = 1\rangle$$

For sender/updater interactions, the sender propagates their strategy (which is partially incorporated in the strategy update function):

$$R_{sender} = \langle ID = true, P = true, S = true, U = true, p = 1\rangle$$

The updater and receiver roles are anonymous:

$$R_{updater} = \langle ID = false, P = false, S = false, U = true, p = 0\rangle$$

$$R_{receiver} = \langle ID = false, P = false, S = false, U = true, p = 0\rangle$$

5.4.3 Network topology

Agents are situated on a connecting topology which constrains communications to the immediate neighbour set. We use the Java Universal Network/Graph library (version 2.0.1)[4] to generate connecting topologies.

Our scale-free topologies are generated using the Eppstein and Wang power-law generator (Eppstein & Wang, 2002). This differs from Barabási and Albert's (1999) model of incremental growth, by instead evolving a graph with constant size and density using a Markov process. The algorithm takes three parameters, the total number of vertices n, the total number of edges e, and the number of edge insertions/deletions r. We use a value of $r = 1000000$.

Small-world topologies are generated using the Kleinberg small-world generator (Kleinberg, 2000). In this model, an $m \times n$ lattice is augmented with a number of extra connections chosen with probability $p \propto d^{-\alpha}$, where α is the clustering exponent, a parameter to the model, and d is the lattice distance between the two nodes being considered for a new edge. Our implementation here differs from Salazar *et al.* (2010b), who generated small-world topologies using the Watts-Strogatz beta model and scale-free topologies using the Barabási-Albert model. More recent versions of JUNG do not include a generator for the Watts-Strogatz model. There are significant structural differences in networks generated by each model, most notable of which is that the Kleinberg generator

[4]http://jung.sourceforge.net/

tends to produce significantly lower clustering coefficients and networks with low numbers of edges. The two main parameters to this algorithm are lattice size and clustering exponent, and we use the default configuration in which each node is augmented with one extra connection. Unless otherwise stated, we use a 10×100 lattice with a clustering exponent $\alpha = 5$.

5.4.4 Metrics

There are a number of important metrics which help characterise the efficacy and efficiency of convention emergence:

1. *Communicative efficacy:* The average communicative efficacy of the system at each generation measures the ability of agents to communicate with each other effectively, and thus acts as a proxy for the level of coordination within the system.

2. *Dominant convention membership:* As our results show, it is rare that all agents agree upon a single lexicon. The number of agents sharing the most commonly used lexicon is one indication of the level of convention adherence in the population.

3. *Distance of the most common lexicon from the initial IA lexicons:* The distance between two lexicons is defined as the number of mappings which are different. We are interested in the ability of IAs to influence the convention that is adopted throughout the entire population. If the most commonly used lexicon in the population is that used by the IAs, then the distance is zero and we can consider the IAs to have been successful.

4. *Number of conventions with given membership:* Considering the number of conventions and their sizes allows us to explore their evolution over time. For example, if there are 1000 conventions of size 1, then each agent has its own unique lexicon. One group of 750 agents and many other groups of small size would indicate one dominant, commonly-used convention,

Parameter	Value
Number of mappings in lexicon	10
P_{send}	0.001
P_{update}	0.001
t (Timesteps)	100000
n (Population Size)	1000

Table 5.1: Default parameters used for the simulation configuration.

but with the rest of the population fragmented without strong convention emergence.

5.4.5 Simplifying assumptions

We make two main simplifying assumptions, namely that (i) the underlying connecting topology is static, and (ii) our agents are homogeneous (aside from the minor differences of IAs).

Static connecting topologies are known to induce different system dynamics than dynamic topologies (Brandt & Sigmund, 2005), and consequently there are limits to how far we can generalise our model to domains characterised by high levels of churn. However, there is relatively little work on modelling dynamic topologies, and defining how a topology is likely to change over time is likely to involve incorporating domain-specific assumptions about agent or environment behaviour. Such modifications are outside the scope of this thesis, although an investigation of the efficacy of IAs under population churn is presented in Chapter 7.

There has been significant work on dealing with agent heterogeneity, but it remains an open research area. Typical approaches involve specifying agent communication languages and protocols, although there is a risk of increasing barriers to participation, particularly for agent societies with disparate levels of agent complexity (Dellarocas & Klein, 2000). Singh (2000) argues that the majority of existing communication languages are insufficient for application in open MAS domains, which tend to exhibit high levels of agent autonomy and heterogeneity. Extending our contributions to populations of heterogeneous agents is discussed in Chapter 7 but is beyond the scope of the current work.

5.4.6 Configuration

Unless otherwise stated, we use $t = 10000$ with both elitist and random strategy update, on a variety of networks that reflect features of real-world domains. This is a basic implementation of the model of Salazar *et al.* (2010b), without the additional components of innovation, self-protection, or noise. Since we consider copy transfer to be impractical, we use partial lexicon transfer only. Results are averaged over 30 runs, using the parameter values specified in Table 5.1.

5.4.7 Differences from Salazar *et al.*

The model implemented here is very similar to that used by Salazar *et al.*. Specifically, we have implemented their model exactly except that agents do not incorporate the components of self-protection, or innovation. Agents therefore consist of the minimal set of components from Salazar *et al.* necessary for convention emergence to occur within the model. Our IA mechanism is entirely novel and we use different synthetic network generators and parameter settings for the network structures constraining agent interactions. In Sections 5.5.1 and 5.5.2, we evaluate the basic model as used by Salazar *et al.* without our IA mechanism or Salazar *et al.*'s components of self-protection or innovation, and corroborate a number of their results. All results presented after these sections are entirely novel and do not incorporate any further aspects of Salazar *et al.*'s work.

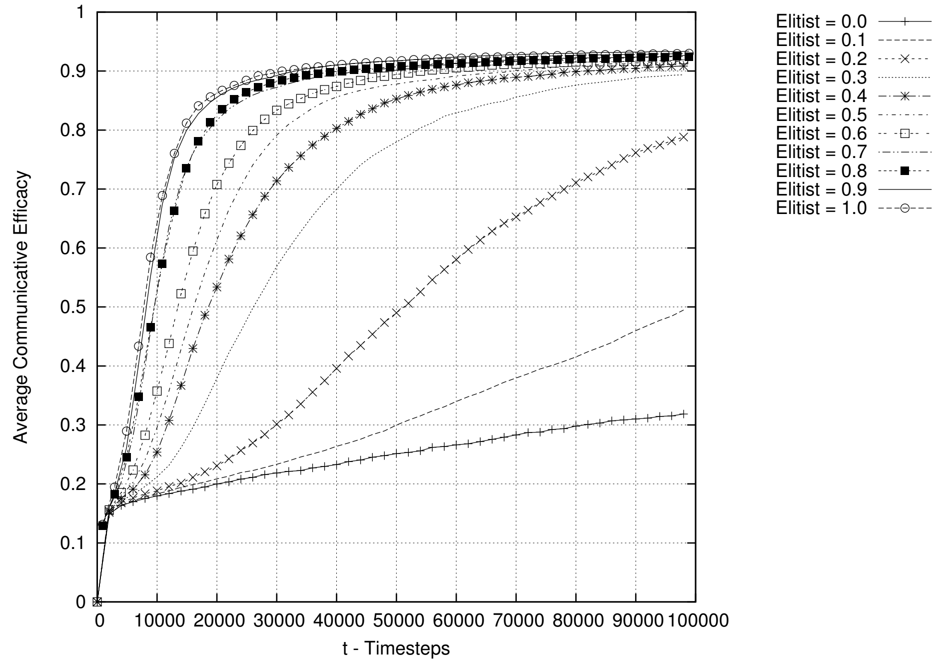
5.5 Results and discussion

We organise our results as follows. Initially, we report the baseline system behaviour without IAs and evaluate the impact of the underlying network topology. We subsequently introduce IAs and quantify the extent to which they can be used to manipulate convention emergence, and compare their efficacy with our second model discussed in Section 5.3. Finally, we evaluate the effect of targeting IA location by degree, and the impact on IA efficacy if IAs are given imperfect conventions to propagate.

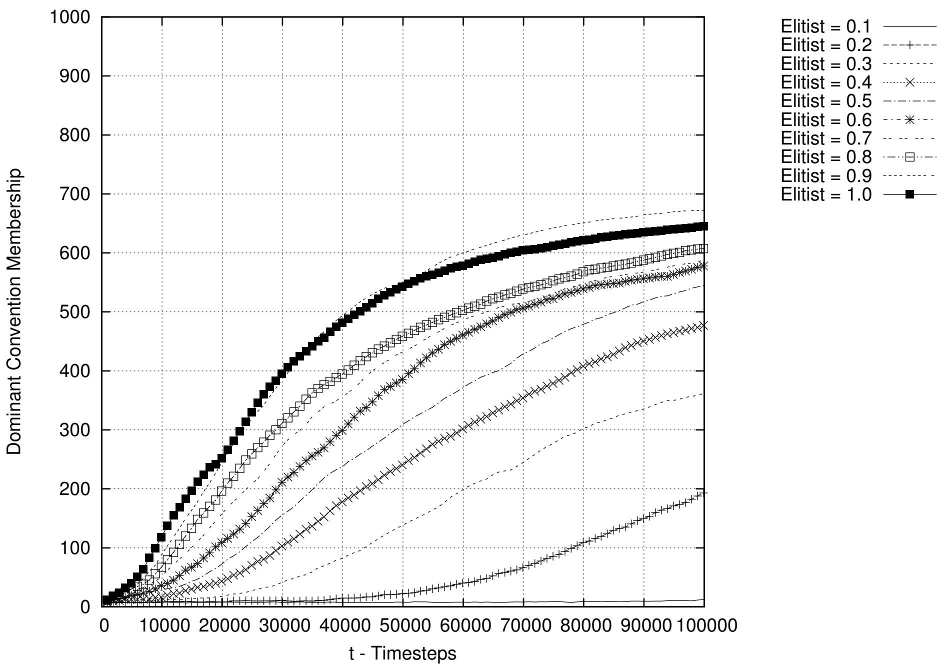
5.5.1 Convention emergence without Influencer Agents

Figure 5.2(a) plots average communicative efficacy over time for 1000 agents on a scale-free network with 10000 edges, while varying the proportion of elitist strategies. Recall that an agent using an elitist strategy will use the lexicon seed with the highest quality evaluation (out of all of those it has received) to update its own lexicon. Even proportions of elitist strategies are plotted with symbols, while odd proportions are plotted as dashed lines. Increasing the proportion of elitist agents significantly increases the rate of gains in communicative efficacy and its final value. Between elitist proportions of 0.8 and 0.9, the gains are significant ($\alpha = 0.05$) when using a two-tailed T-test ($p = 0.0316$). We see no further gains with elitist proportions of 1.0. This may be a result of the exploration effect that random lexicon selection agents introduce. There are a number of reasons why the population does not converge on a single, universal convention. When using 10000 edges, networks are rarely fully connected and the probability of 100% adherence to the same convention is negligible. Furthermore, we use low probabilities for lexicon spreading and update, and low-degree nodes are unlikely to receive many partial lexicons with which to update. Low-degree nodes are therefore unlikely to adhere to the dominant lexicon by $t = 10000$, resulting in less than 100% communicative efficacy.

This is illustrated in Figure 5.2(b), which plots the membership of the most common lexicon (i.e. the *dominant* lexicon) over time and shows that the dominant lexicon membership is larger with $Elitist = 0.9$ than $Elitist = 1.0$, although the difference is not significant ($p = 0.3528$). Interestingly, Salazar *et al.* (2010b) reported increased system performance when incorporating notions of controlled noise into agents' internal convention generation, which adds



(a)



(b)

Figure 5.2: (a) Average communicative efficacy, and (b) dominant convention membership using a scale-free topology with 1000 agents and 10000 edges, with varying proportions of elitist and random lexicon update strategies in the population. Elitist strategies result in significant gains in coordination levels and convergence time.

weight to the hypothesis that a small proportion of random agents aids system performance.

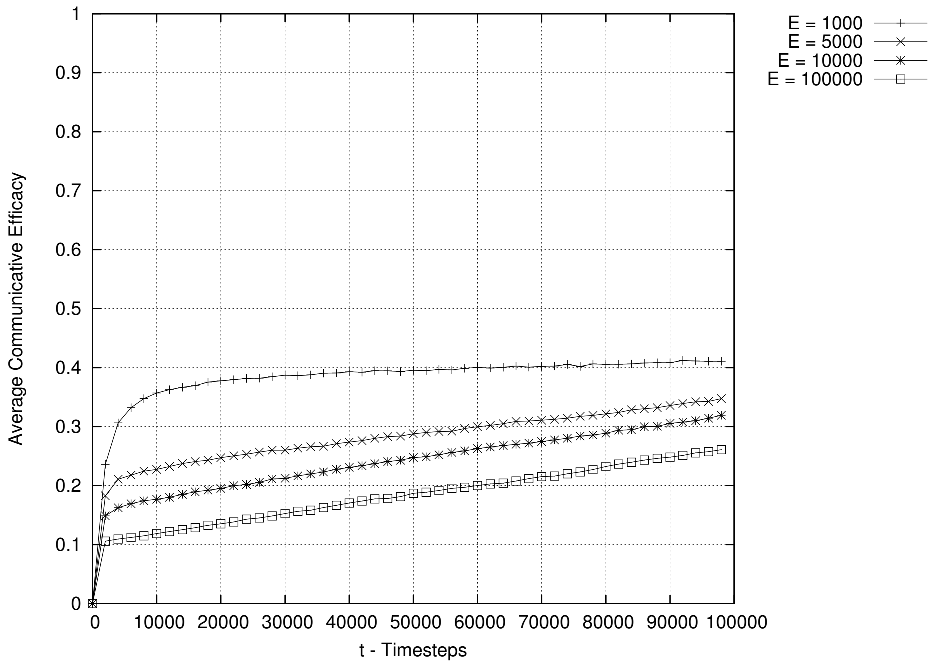
5.5.2 The effect of network topology without Influencer Agents

It is important to investigate the effects of network topology on the dynamics of our model. Figure 5.3(a) plots the results of simulations on scale-free networks with random lexicon selection agents and edge counts from 1000 (very low) to 100000 (very high)[5]. With 1000 edges, convergence is fast to a stable average communicative efficacy of around 0.4. As the number of edges increases, the rate of convergence slows as the higher edge count results in larger neighbour sets. With larger neighbour sets, the number of individuals with whom an agent has to agree on a convention is increased, hence the slower convergence.

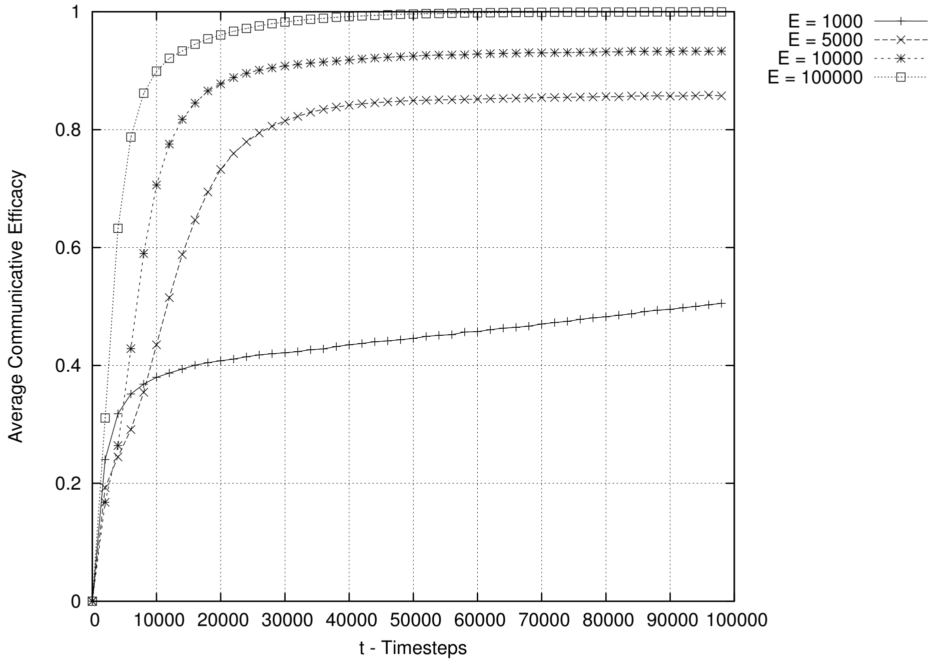
Figure 5.3(b) shows results using the same parameters as in Figure 5.3(a), but with fully elitist populations. The number of edges strongly influences both the speed of convergence and the final communicative efficacy reached, with agents in a network with 100000 edges reaching a perfect lexicon. This is significant, since it corroborates results presented by Salazar *et al.* (2010b), and also indicates the significant role that the underlying communication topology plays in convention emergence. A number of factors are influenced by the number of edges in a scale-free topology, including average node degree and average shortest path length. Given a larger number of edges, agents will not only have larger local neighbourhoods, but will also have shorter average path lengths to a larger cross-section of the society. Both factors allow high quality conventions to be spread to a larger subset of the population more efficiently.

Figure 5.4 shows the average communicative efficacy for populations situated on a small world topology while varying the clustering exponent (CE). We can clearly see that (i) elitist populations are significantly more efficient than random

[5]The total number of edges in a scale-free network is the main parameter for the Eppstein & Wang generating algorithm we use (Eppstein & Wang, 2002).



(a)



(b)

Figure 5.3: Average communicative efficacy for a population of 1000 (a) random selection and (b) elitist selection strategy agents while varying the total number of edges in a scale-free topology.

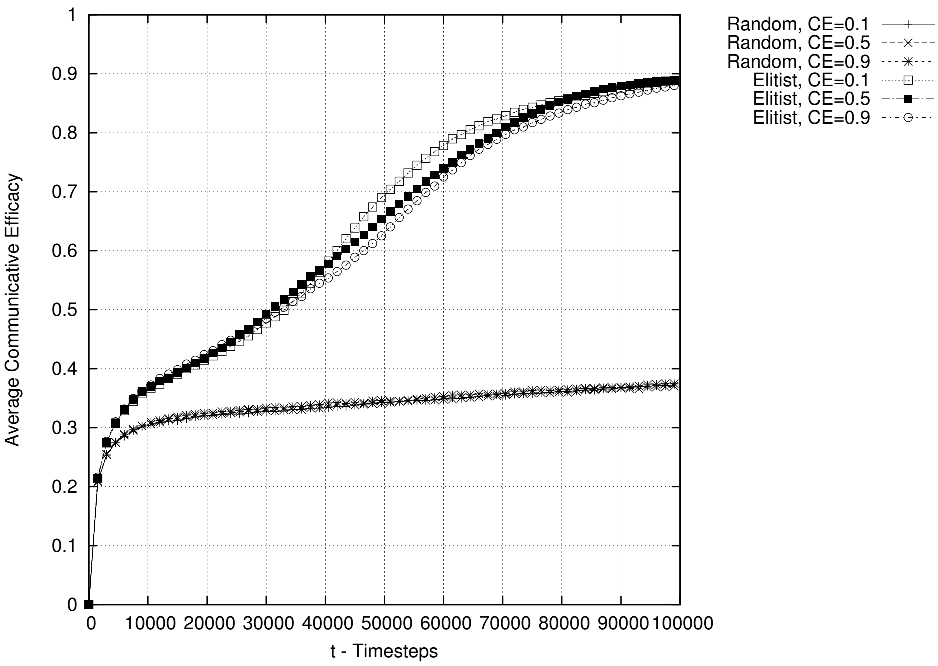
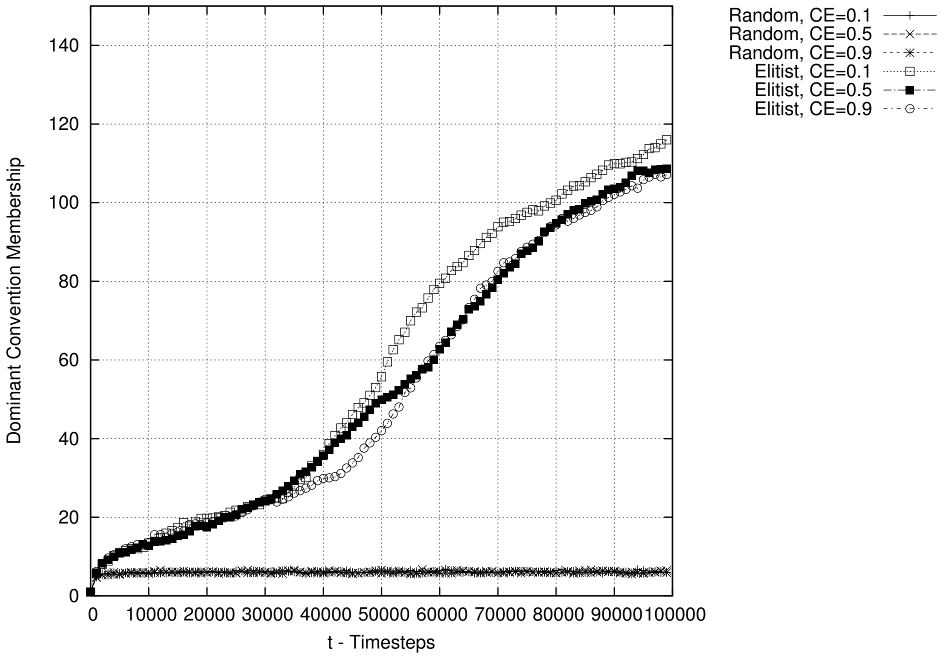


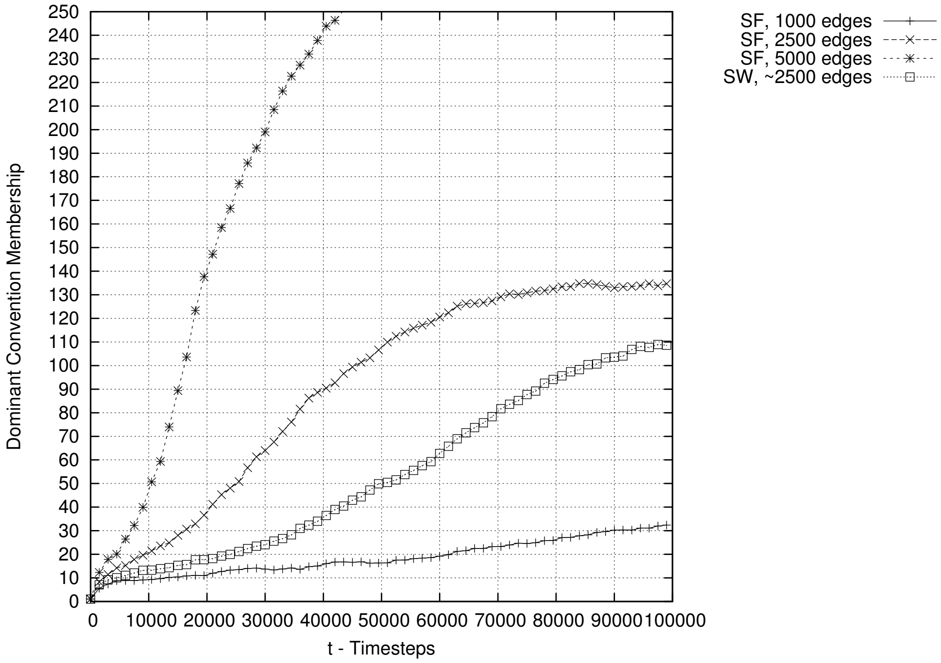
Figure 5.4: Average communicative efficacy for 100% elitist and 100% random lexicon selection populations on small-world networks while varying the Clustering Exponent (CE).

selection populations, (ii) the clustering exponent has a negligible effect, and (iii) convergence is slower on small-world networks than scale-free networks (shown in Figure 5.3), as reported by Salazar *et al.* (2010b). We believe that the faster convergence on scale-free networks is due to the presence of hub nodes, which connect disparate clusters and allow information to spread more effectively than on networks that lack these features (Albert & Barabási, 2002).

Figure 5.5 shows the membership over time for the dominant convention. Figure 5.5(a) shows results for 100% random and 100% elitist populations on a small-world network while varying the clustering exponent. On small-world networks we witness fragmented populations, with around 100 to 150 agents adhering to the dominant convention at $t = 10000$. As noted in Section 5.4, we use the default Kleinberg small-world network generator configuration, which results in networks with relatively few edges. We see the behaviour on small-world networks replicated in scale-free networks with similar edge numbers (Figure



(a)



(b)

Figure 5.5: Dominant convention membership for (a) 100% elitist and 100% random lexicon selection populations on small-world networks while varying the Clustering Exponent (CE) and (b) comparable scale-free and small-world networks.

Timestep	Number of groups of size	ACE
0	1000×1	0.0
1000	922×1, 25×2, 2×4, 4×5	0.135
10000	298×1, 28×2, 11×3, 5×4, 1×5, 1×6, 1×8, 2×9, 1×10, 1×12, 1×13, 1×14, 1×17, 1×18, 1×19, 1×23, 1×28, 1×31, 1×37, 1×40, 1×47, 1×66, 1×77, 1×104	0.706
50000	34×1, 1×2, 1×22, 1×23, 2×25, 1×27, 1×29, 1×31, 1×32, 1×106, 1×644	0.757
100000	33×1, 1×20, 1×22, 4×23, 1×28, 1×29, 1×41, 1×735	0.934

Table 5.2: Number of groups (n) of size (s), and average communicative efficacy (ACE), at various timesteps (presented as $n \times s$), for a fully elitist population of 1000 agents situated on a scale-free topology with 10000 edges.

5.5(b)). Due to the constrained y-axis, the plot for 5000 edges is only partially shown, and we note that results for this configuration are similar to other runs with higher numbers of edges. Simulations with $t = 500000$ show that populations with up to a 0.2 proportion of elitist agents have still not converged by the end of the simulation, but higher proportions do all converge.

To analyse the evolution of the population in more depth, we can evaluate the size of the membership groups for each convention. Initially we expect there to be 1000 lexicons, each with 1 adherent. For the purposes of this chapter, we assume that the ideal outcome is 1 convention with 1000 adherents. Table 5.2 details five snapshots of the system at $t = 0, 1000, 10000, 50000, 100000$, using fully elitist populations on a scale-free network with 10000 edges for a single representative run. Figure 5.6 plots the latter four snapshots, but due to the difficulty of clearly plotting the whole dataset these figures are for illustrative purposes and only show a subset of the data. The x-axis corresponds to group size and the y-axis shows the number of conventions with a given membership at that time. At $t = 1000$, a large number of co-existing conventions have emerged with a small number of adherents. The plots for $t = 50000$ and $t = 100000$ show the dominant evolutionary pattern: a single convention begins to dominate and grows steadily throughout the simulation, while the rest of the population remains fragmented. There is one secondary group of around 100 agents at $t = 50000$, but this has dissipated by $t = 100000$. The dominant convention converges at around 735 members.

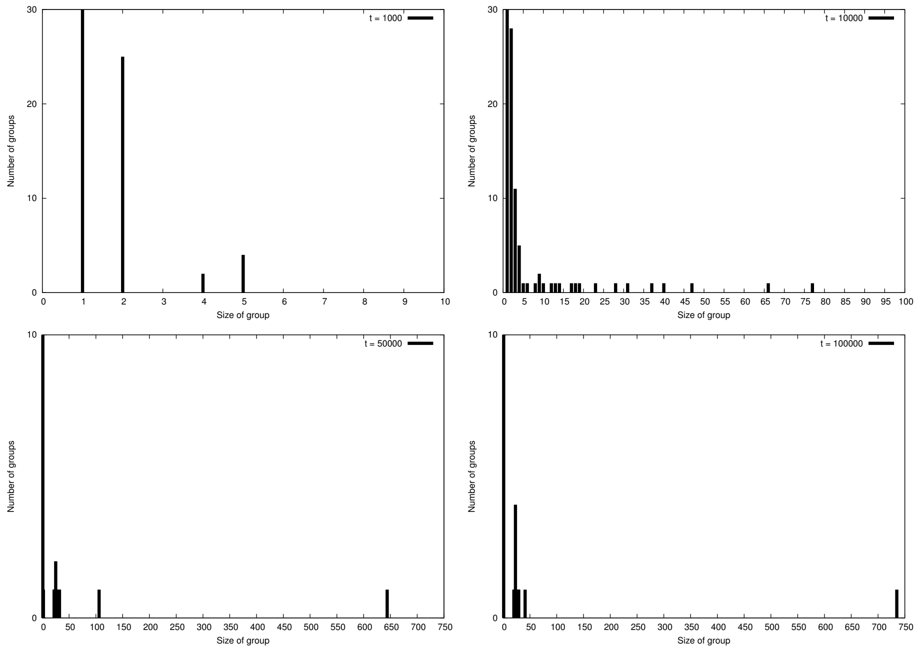


Figure 5.6: Distribution of agent lexicon groups at t = 1000, 10000, 50000, and 100000, using a fully elitist population of 1000 agents situated on a scale-free topology with 10000 edges. The scales of the axes change between graphs for clarity of illustration. Figures are ordered in time from left to right and top to bottom. A single lexicon quickly emerges with the majority of individuals adhering; the remaining agents are split between fragmented groups of largely homogeneous size.

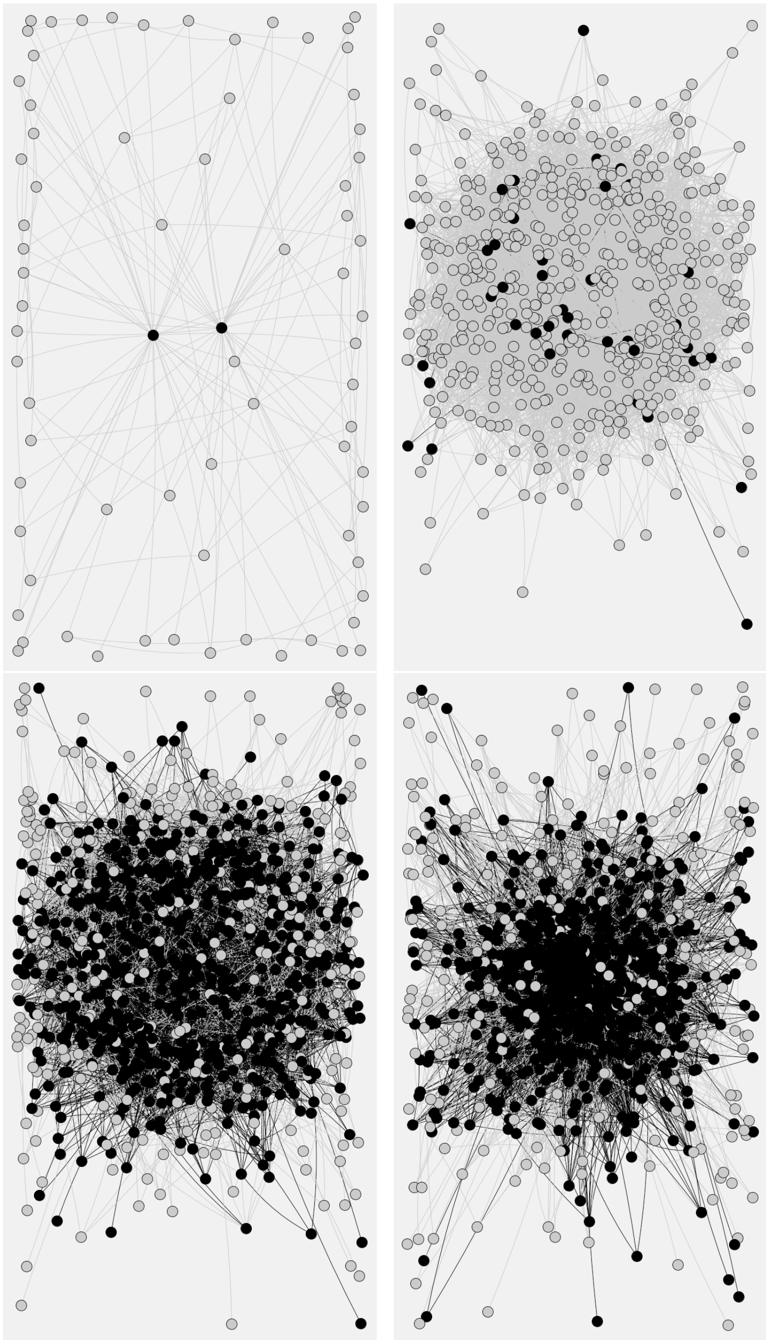


Figure 5.7: Visualisation of group growth of the most dominant lexicon (by the end of the simulation) for a typical run at t = 250, 10000, 50000 and 100000 on a scale-free network. Agents using the lexicon in question are plotted dark, and their direct neighbours are plotted light. No other agents are plotted. Edges between two directly connected agents using the dominant lexicon are plotted dark. Figures are ordered in time from left to right and top to bottom.

Figure 5.7 contains four visualisations of the evolution of groups during a typical run on a scale-free topology with 10000 edges. Each image shows only the agents using the lexicon that eventually becomes dominant (dark), or those that are directly connected to them (light). Edges are coloured dark if the agents connected by that edge are both using the dominant lexicon. Note that since the set of agents displayed in each image is different, the layout of the network is different between images and we therefore cannot use these images to infer results based on node position. While the large numbers of agents and edges between them mean that the images are cluttered, we can make the following observations by visualising the evolution of the groups in this way:

1. Initially, agents adhering to a lexicon are rarely directly connected but also are rarely more than 1 hop apart. We believe that the nature of partial lexicon spreading and update results in a correlation between topological and lexical distance. Lexicons are unlikely to have any mappings in common initially due to the large convention space, but since spreading of lexicons is solely between neighbours, agents at opposite ends of the network are unlikely to be exposed to the same convention unless agents along the path between them also adhere.

2. Lexicons that go on to become dominant usually gain one or more high-degree adherents early on in the simulation, such that a large subset of the population gets exposed to the lexicon early on.

3. The nodes that are not part of the dominant lexicon at the end of the simulation tend to be low-degree nodes on the fringe of the network.

4. The set of agents using a lexicon is rarely constant, and agents join and leave the lexicon convention constantly in the early stages. The lexicon that eventually dominates is distinguished therefore by having more agents join it each timestep than leave it.

5. The lexicon that eventually becomes dominant already exists in the pop-

ulation at $t = 250$. Although the use of partial transfer makes this seem surprising, we hypothesise that this is due to a combination of (i) low update and spreading rates and (ii) an agent a using a lexicon successfully implies that *other* agents will update using a's seeds, spreading a's lexicon throughout the population (even though a might subsequently alter its own lexicon).

Analysis of the previous data suggests that the behaviour of the model on scale-free and small-world networks is markedly different. Scale-free networks are characterised by a single dominant group and the existence of fragmented sets of agents that do not adhere to the dominant convention. These agents typically exhibit the low node degrees that characterise locations at the fringes of the network. Conversely, in small-world networks the population tends to split into a few smaller groups, each one achieving high average levels of internal coordination. We have included the group data for small-world networks in the first column of Table 5.5, and therefore do not reproduce it here.

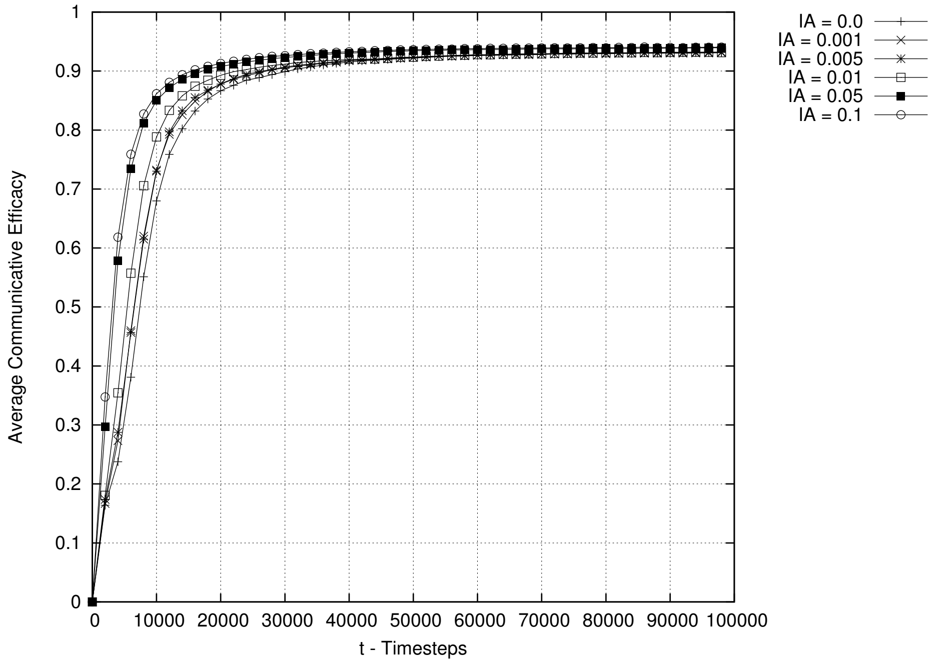
Convention emergence is faster and of higher quality in populations of elitist agents. Given that choosing the best convention is a rational decision, it is safe to assume that populations can be modelled as fully elitist. As such, in the remainder of this chapter we use an elitist proportion of 1.0. The results presented above suggest that an elitist proportion of 0.9 performs at least as well, but this would run contrary to our assumption of agent rationality and therefore is outside the scope of this investigation.

Our results corroborate those presented by Salazar *et al.* (2010b), who showed that populations converge to a high quality convention when using elitist lexicon update strategies. Small-world networks converge more slowly than scale-free networks, although the convergence speed on the small-world networks presented here is significantly slower than that presented by Salazar *et al.* (2010b). While these results validate our model and implementation with respect to Salazar *et al.* (2010b), we use different network topology generation algorithms. Our results on scale-free networks exhibit similar trends, suggesting that the Barabási-Albert and Eppstein & Wang algorithms generate networks with similar topological features. However, the behaviour we observe on small-world networks is markedly different. We believe this to be due to significant structural differences between networks generated by the Watts-Strogatz and Kleinberg models.

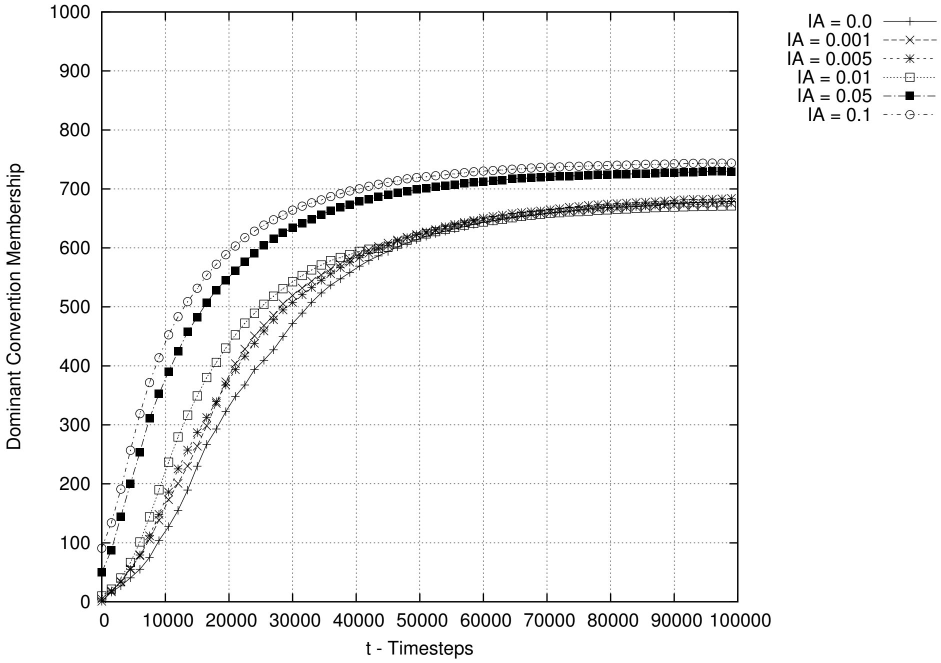
5.5.3 Introducing IAs

Having established the baseline behaviour of the system, we introduce a small proportion of IAs to determine (i) whether they can influence the dominant convention towards that proposed by the IAs and (ii) whether they provide any other benefits, in terms of speed of convergence and quality of convention, beyond being able to manipulate *which* convention the population agrees upon. To simplify analysis, we assume that IAs have a high quality lexicon (i.e. 1.0 specificity) and that all IAs share the same lexicon. IAs are randomly placed in the network. As discussed later in Section 5.5.5 and Chapter 6, the location of IAs does affect their ability to influence the population. However, initially we are only concerned with confirming their feasibility in general.

Figures 5.8(a) and 5.8(b) plot average communicative efficacy and dominant convention membership respectively, over time for varying proportions of IAs on a scale-free network with 10000 edges. Small proportions of IAs (up to proportions of 0.005, or 5 IAs in our population of 1000) result in significant increases in the rate of communicative efficacy gain, but not in final value reached. It may be that the increased speed is due to the presence of a high quality lexicon at the start of the simulation, which we discuss in Section 5.5.4. With 100 IAs (i.e. a proportion of 0.1) all runs end with the IA lexicon being accepted as the dominant convention. However, this is unlikely to be a practical proportion of IAs to use. In Section 5.5.5, we show that targeting IA placement by degree results in significant increases in influence, and we explore the impact of topological targeting in detail in Chapter 6. When placed randomly, five IAs (i.e. a proportion of 0.005) result in 43% of runs ending with the IA lexicon being



(a)



(b)

Figure 5.8: (a) Average communicative efficacy, and (b) dominant convention membership for varying proportions of IAs that are initialised with same high quality lexicon. Results are shown for a scale-free network topology with 10000 edges. The non-IA population is entirely elitist. IAs result in moderate increases in coordination and large increases in dominant convention membership.

accepted as the dominant convention.

This corroborates Sen and Airiau's (2007) results, in which four fixed-strategy agents was sufficient to influence a population of 3000 agents in a model with two possible conventions. In 46% of runs (i.e. an additional 3%) the dominant lexicon differs by at most 2 mappings from the IA lexicon (i.e. the lexicons have a *distance* of 2), and the majority of runs which do not end in convergence to the IA lexicon have a distance of 9 or 10. As such, either the IA lexicon is adopted or an entirely distinct lexicon becomes dominant. We believe this to be due to early group dynamics: if a large group initially adopts a non-IA lexicon, then IAs will be less able to influence this group. The additional 3% of runs that end with a close match to the IA lexicon being adopted are likely a result of the partial transfer mechanism.

Between IA proportions of 0.0 and 0.005 (i.e. between 0 and 5 IAs in 1000 agents), the change in average communicative efficacy is not significant ($p = 0.2564$) but the gain in dominant convention membership is significant ($p = 0.03730$). Between proportions of 0.0 and 0.01 (i.e. an addition of 10 IAs into a population of 1000), we find significance in both the gains in communicative efficacy and the dominant convention membership, ($p = 0.01254$ and $p = 0.00064$ respectively). These results suggest that IAs can give significant benefits to a population beyond simply manipulating the convention that emerges.

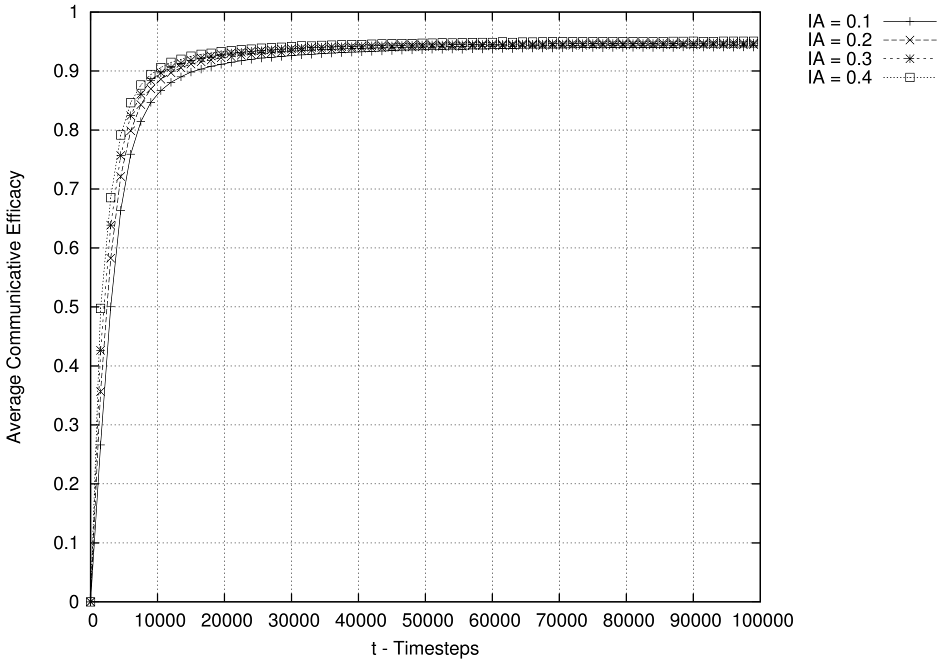
Figures 5.9(a) and 5.9(b) show the average communicative efficacy and dominant convention membership respectively, for the same configuration as Figure 5.8, but with very high proportions of IAs. As noted above, we consider these proportions to be impractical for real-world application, but they are useful for understanding the dynamics of the approach. There are further gains in the dominant convention membership and the speed of convergence to the upper bound of lexicon adherents, and a minor gain in the speed of convergence for average communicative efficacy, but we see significant diminishing returns (given that each dataset represents an additional 100 IAs).

Figures 5.10(a) and 5.10(b) show the average communicative efficacy and dominant convention membership, respectively, for the same configuration as Figure 5.8, but on small-world networks. While the trends are similar, the convergence rate and dominant convention membership are both lower. Controlling convention emergence on small-world networks requires more IAs than on scale-free networks, but costs may be reduced through more refined IA strategies or topological targeting. Our results suggest that the presence of hubs, a key feature of scale-free networks, reduces convergence time.

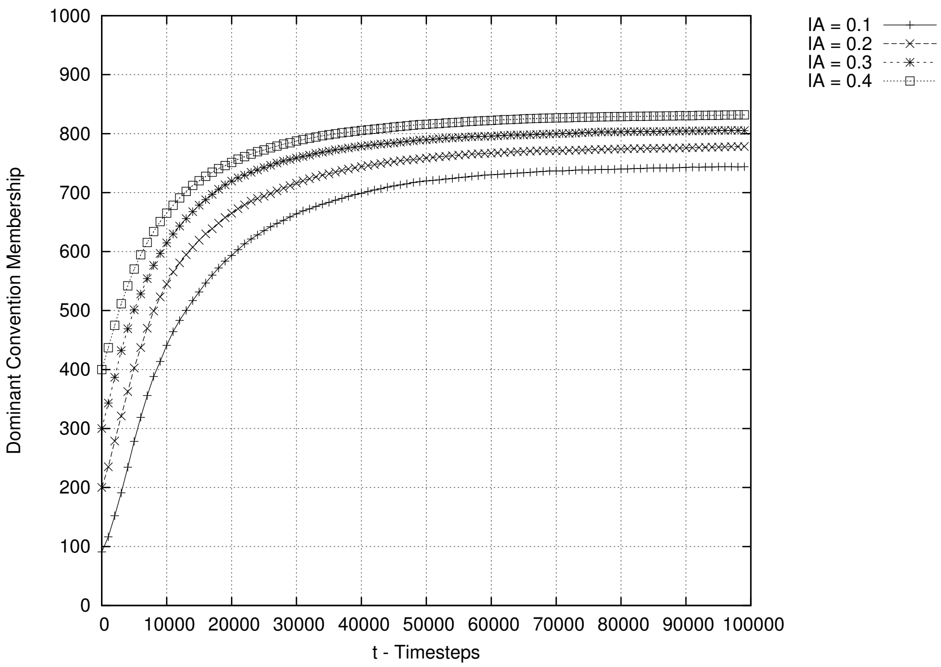
Since average communicative efficacy is a proxy for the level of coordination, we cannot say that IAs are increasing the levels of coordination in these systems. However, we are not just interested in increasing levels of coordination, but also in (i) determining the extent to which we can affect *which* convention is adopted by a society, (ii) increasing adherence to the dominant convention, and (iii) exploiting the impact small groups of agents can have on much larger populations. Our results suggest positive outcomes to all three objectives.

5.5.4 Inserting agents versus inserting conventions

The introduction of IAs into the population entails two major differences in the configuration of the model: (i) the existence of a small proportion of agents with a fixed strategy, and (ii) the existence of a high quality lexicon in the population at the start of the simulation. We are interested in manipulating convention emergence using the former, and thus we need to quantify the effects of the latter without the existence of fixed-strategy agents in the population. Accordingly, in this section we replace IAs with agents that are given the same high quality initial lexicon, but in all other respects are identical to regular agents (i.e. they propagate and update their lexicon as normal). For clarity of discussion, we call these agents HQ (high quality) agents. These simulations are an implementation of the second model defined in Section 5.3, in that rather than using a small proportion of inflexible agents to continuously propagate a convention, we instead imbue a certain proportion of standard agents with a high quality convention and determine how this affects convention emergence.

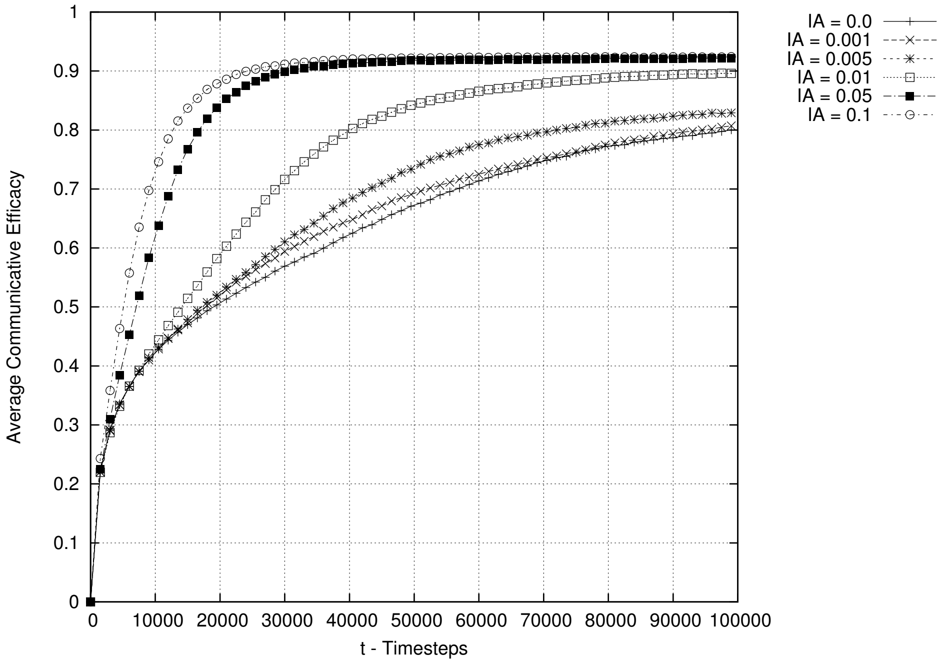


(a)

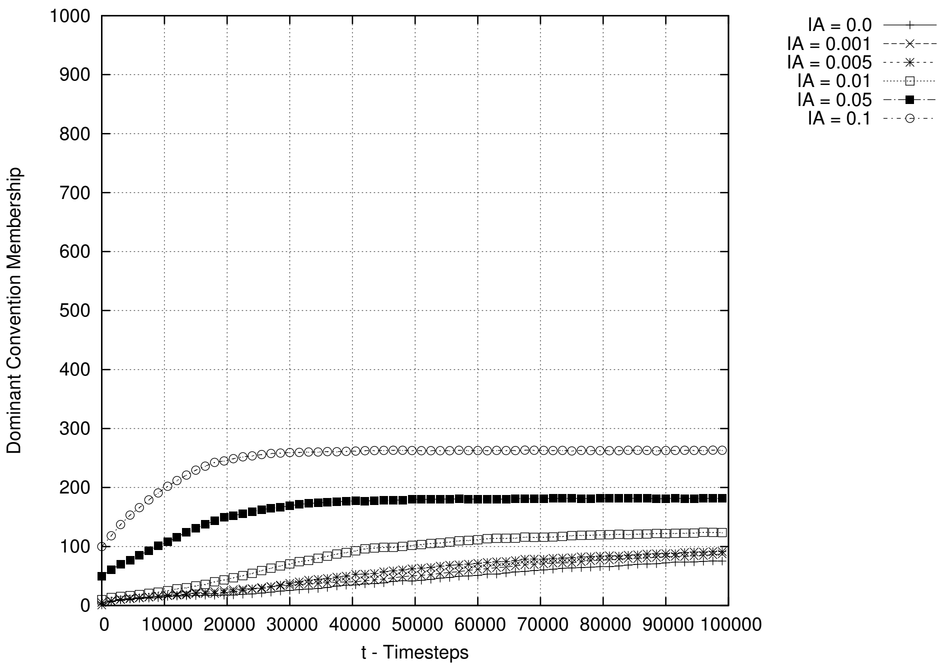


(b)

Figure 5.9: (a) Average communicative efficacy and (b) dominant convention membership for very high proportions of IAs that are initialised with same high quality lexicon. Results are shown for a scale-free network topology with 10000 edges. The non-IA population is entirely elitist.



(a)



(b)

Figure 5.10: (a) Average communicative efficacy and (b) dominant convention membership for varying proportions of IAs that are initialised with same high quality lexicon. Results are shown for a small-world network topology. The non-IA population is entirely elitist.

Figures 5.11(a) and 5.11(b) show average communicative efficacy and dominant convention membership, respectively, while varying the proportion of HQ agents on a scale-free network. Comparing with Figure 5.8, we observe similar behaviour for values between 0.01 and 0.1 (i.e. practical proportions). For proportions of 0.005, there is no significant difference in dominant convention membership ($p = 0.7798$). Comparing a proportion of 0.01 (i.e. 10 agents), the dominant convention membership is significantly different ($p = 0.01653$), with HQ agents performing better than IAs. Increasing the proportions, we observe IAs gaining slightly more adherents (743 with IAs compared to 726 with HQ agents) with high significance ($p = 2.642 \times 10^{-16}$). Even at high proportions of HQ agents (and comparing with Figure 5.9(b)), the differences are slight but in favour of IAs. However, with HQ agents we *cannot control which convention emerges*. With IAs, we can control the emergent convention and further see marginal gains in the metrics discussed above.

When inspecting communicative efficacy, the differences between IAs and HQ agents are only significant at proportions of 0.05 and above ($p = 1.057 \times 10^{-5}$). Gains in communicative efficacy do not scale linearly with the proportion of HQ agents inserted. As Figure 5.11(a) shows, we do not see any major improvements in average communicative efficacy on scale-free networks, even with very high proportions of HQ agents. On small-world networks (Figure 5.12), we observe the opposite: increasing the proportion of HQ agents results in increases of communicative efficacy. It is not clear whether HQ agents increase the upper bound of communicative efficacy that the society can attain due to the slower convergence rates on small-world networks, but there are significant increases in the speed of convergence. Seeding populations on small-world networks with high quality conventions might therefore reduce the additional costs associated with controlling conventions discussed above. Comparing Figures 5.11(a) and 5.9(a), we observe that IAs result in much faster convergence than HQ agents at high proportions.

Table 5.3 shows results for statistical significance tests comparing the domi-

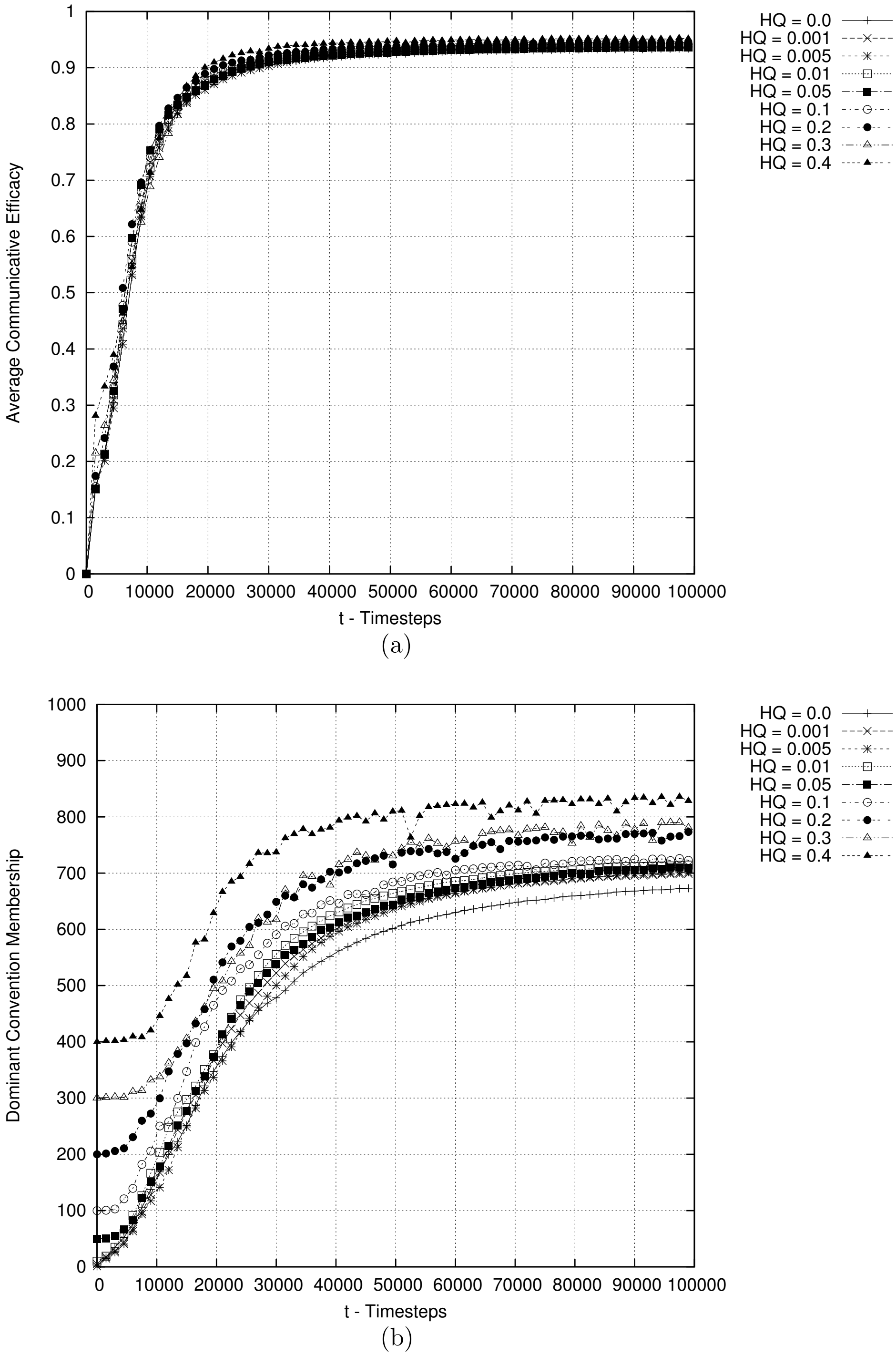


Figure 5.11: (a) Average communicative efficacy, and (b) dominant convention membership for varying proportions of agents initialised with the same high quality lexicon. Results are shown for a scale-free network topology with 10000 edges.

	IA proportion						
HQ proportion	0.4	0.3	0.2	0.1	0.05	0.01	0.005
0.4	∘	∘	∘	∘	∘	∘	∘
0.3	∘	∘	∘	•	∘	∘	∘
0.2	∘	∘	∘	•	•	∘	∘
0.1	∘	∘	∘	∘	∘	∘	∘
0.05	∘	∘	∘	∘	∘	•	∘
0.01	∘	∘	∘	∘	∘	∘	∘
0.005	∘	∘	∘	∘	∘	•	•

Table 5.3: Statistical significance resulting from a t-test of the levels of dominant convention membership exhibited with different proportions of IA or HQ agents, with $\alpha = 0.05$, where • represents non-significant differences, and ∘ significant differences.

	IA proportion						
HQ proportion	0.4	0.3	0.2	0.1	0.05	0.01	0.005
0.4	∘	∘	∘	∘	∘	•	•
0.3	∘	∘	∘	∘	∘	•	•
0.2	∘	∘	∘	∘	∘	•	•
0.1	∘	∘	∘	∘	∘	•	•
0.05	∘	∘	∘	∘	∘	•	•
0.01	∘	∘	∘	∘	∘	•	•
0.005	∘	∘	∘	∘	∘	•	•

Table 5.4: Statistical significance resulting from a t-test of the average communicative efficacy exhibited with different proportions of IA or HQ agents, with $\alpha = 0.05$, where • represents non-significant differences, and ∘ significant differences.

nant convention membership between HQ and IA agents on a scale-free network with 10000 edges. If the p-value is significant, with $\alpha = 0.05$, the entry is marked ∘, otherwise, the entry is marked •. We can see that 300 HQ agents (a proportion of 0.3) is statistically indistinguishable from 100 IAs (a proportion of 0.1), while 5 HQ agents are statistically indistinguishable from both 10 and 5 IAs. At very low proportions, the effects of HQ and IA agents are difficult to distinguish. Table 5.4 shows, in the same format as Table 5.3, statistical significance tests for average communicative efficacy for the same set of runs. Low proportions of IAs and HQs are still indistinguishable, but IAs see significant gains over HQ agents as the proportions increase.

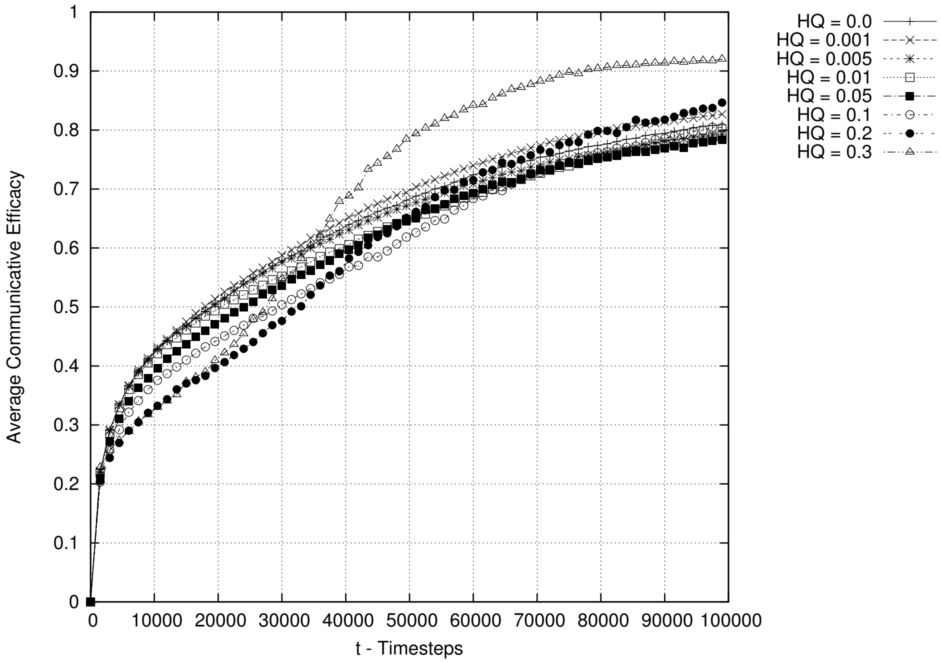


Figure 5.12: Average communicative efficacy for varying proportions of agents given a high quality lexicon at the start of the simulation, situated on a small-world network topology.

5.5.5 Effect of position of IAs in the network

Previous results are given for IAs placed randomly in the network. A great deal of research (e.g. Chen *et al.* (2009), Kempe & Kleinberg (2003)) has acknowledged that high-degree nodes are likely to be more influential than low-degree nodes. To confirm whether topological properties influence the effectiveness of IAs, we ran simulations in which IAs are (for simplicity) given a high quality lexicon initially and placed according to node degree.

When placing a 0.005 proportion of IAs at locations with the *highest* node degree in a scale-free topology, 66% of runs ended with the dominant lexicon being at most a distance of 2 from the initial IA lexicon (which we term a *win*). The average distance over 30 runs is 2. This represents a 20% increase in the average distance over random placement. Placing IAs by *lowest* node degree, we observe only 20% of runs ending in wins, and the average distance over 30 runs is 7.

On both scale-free and small-world topologies, a 0.01 proportion of IAs (i.e. 10 agents in 1000), placed by highest node degree, is enough to result in 100% of runs ending with a win, demonstrating the power of topologically-informed placement. Using knowledge of topological properties such as node degree, IAs may be able to incorporate re-wiring strategies to move themselves to more influential positions in the connecting topology of an artificial society, and we consider how to exploit topological knowledge in Chapter 6.

Figures 5.13(a) and 5.13(b) show the average communicative efficacy and dominant convention membership respectively for varying proportions of IAs when placed by node degree on a scale-free network. Figures 5.14(a) and 5.14(b) show the corresponding results for a small-world network. As before, IAs exhibit diminishing returns at high proportions (i.e. 0.1 to 0.4), implying that the gains we see at low proportions are close to the upper bound. At these high proportions, placement by node degree does not lead to significantly different values for our metrics than random placement, and so we have not included these data. It is interesting to note that the number of agents adhering to the dominant convention falls slightly when placing agents by node degree (as opposed to randomly), despite the ability of IAs to control which convention emerges increasing.

Table 5.5 shows group data for representative runs inserting IAs by node degree on small-world networks. For clarity, the group sizes between which we aggregate group numbers change between cells. As discussed above, agents form small groups rather than adhering to a single dominant convention. Inserting 5 IAs has a small effect, with larger dominant group size and more large groups. Between 5 and 10 IAs, there is a more profound impact on group formation, with more large groups and three groups with 100 or more agents. The data illustrate the slower emergence of conventions on small-world networks, but despite this IAs still have a visible and beneficial effect.

Timestep	Number of groups of size		
	$IA = 0.0$	$IA = 0.005$	$IA = 0.01$
0	1000×1	995×1, 1×5	990×1, 1×10
1000	902×1 $28 \times 2 \leq s \leq 4$ 2×5	897×1 $39 \times 2 \leq s \leq 4$ 2×5	909×1 $33 \times 2 \leq s \leq 4$ 1×12
10000	673×1 $76 \times 1 < s < 5$ $19 \times 5 \leq s < 15$ 1×22	681×1 $69 \times 1 < s < 5$ $21 \times 5 \leq s < 8$ 2×20	635×1 $65 \times 1 < s < 5$ $18 \times 5 \leq s < 15$ $1 \times 15, 2 \times 17$ 1×25
50000	368×1 $61 \times 1 < s < 5$ $41 \times 5 \leq s < 15$ $7 \times 15 \leq s < 25$ 1×27	320×1 $61 \times 1 < s < 5$ $14 \times 5 \leq s < 15$ $16 \times 15 \leq s < 35$ 1×42	47×1 $28 \times 1 < s < 15$ $2 \times 15 \leq s < 50$ $8 \times 50 \leq s < 100$ $1 \times 100, 1 \times 107$
100000	171×1 $28 \times 1 < s < 5$ $54 \times 5 \leq s < 25$ $10 \times 25 \leq s < 45$ 1×46	6×1 $5 \times 1 < s < 5$ $14 \times 5 \leq s < 50,$ $7 \times 50 \leq s < 85,$ 1×89	2×1 $5 \times 1 < s < 5$ $16 \times 5 \leq s < 50$ $7 \times 50 \leq s < 100$ $1 \times 100, 1 \times 114, 1 \times 115$

Table 5.5: Number of groups (n) of size (s) at various timesteps (presented as $n \times s$) for representative runs with a 0.0, 0.005, and 0.01 proportion of IAs inserted by highest node degree on a small-world network topology.

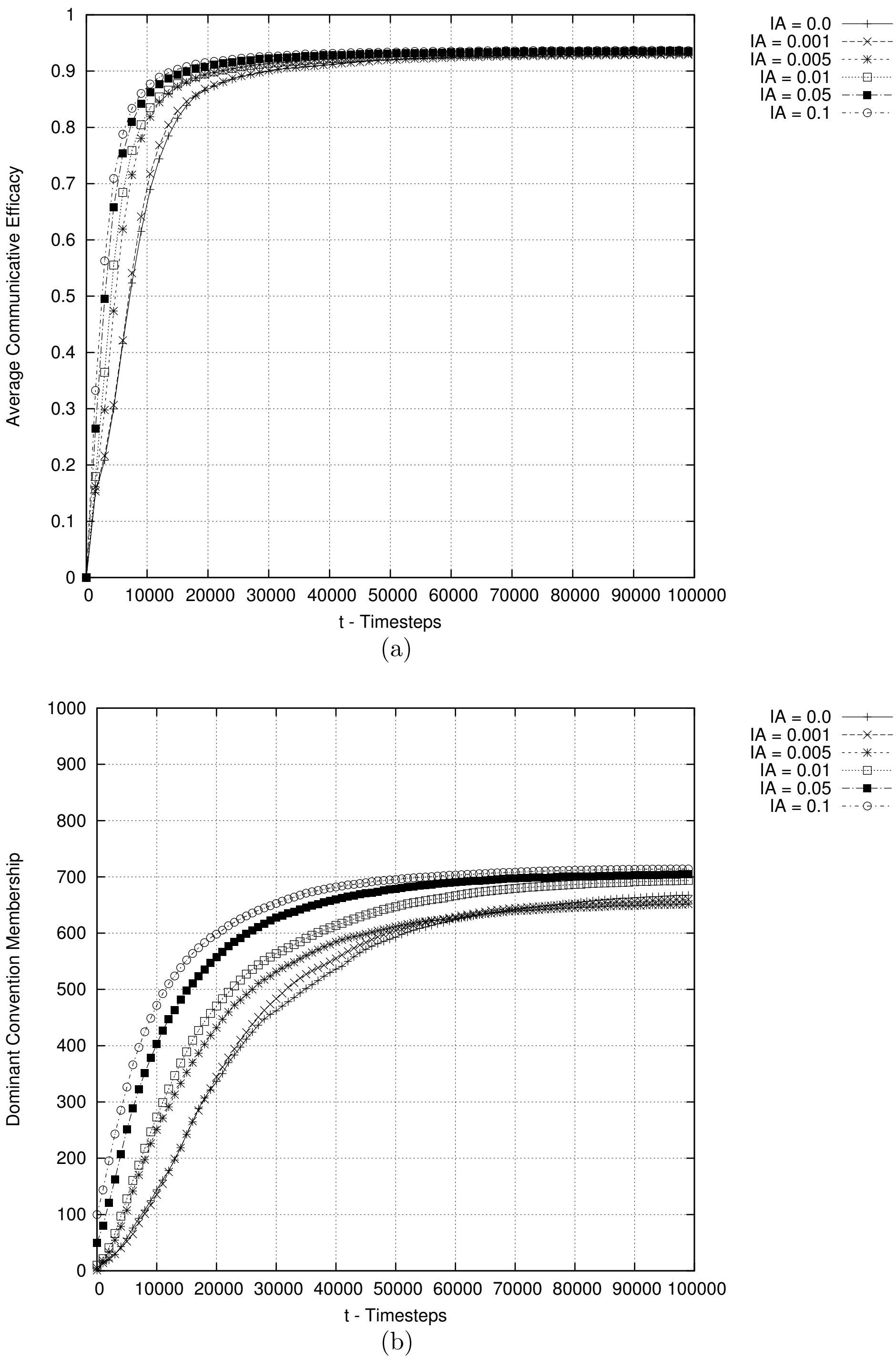


Figure 5.13: (a) Average communicative efficacy, and (b) dominant convention membership for varying proportions of IAs when placed in the network by node degree. Results are shown for a scale-free network topology with 10000 edges. The non-IA population is entirely elitist.

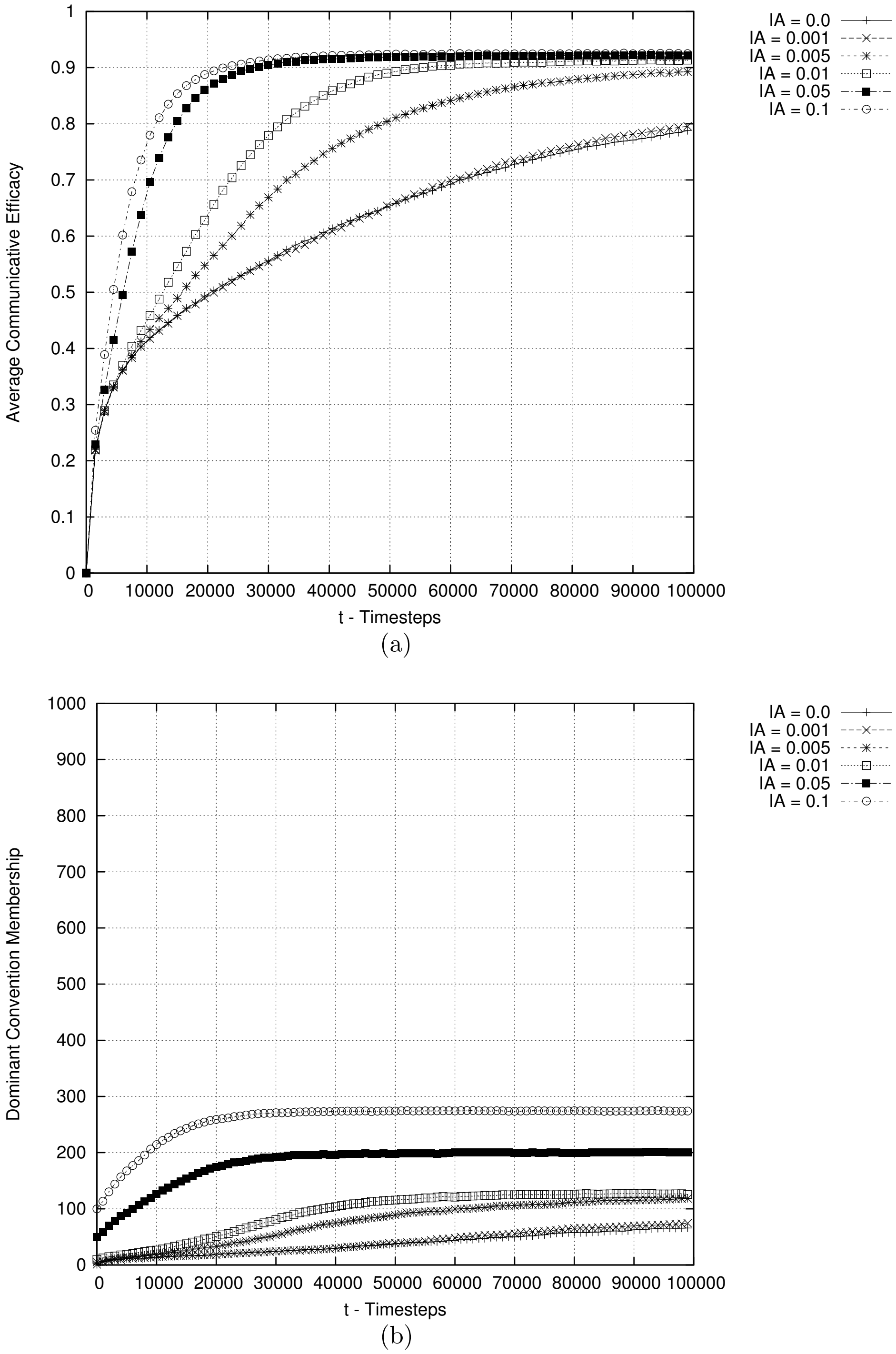


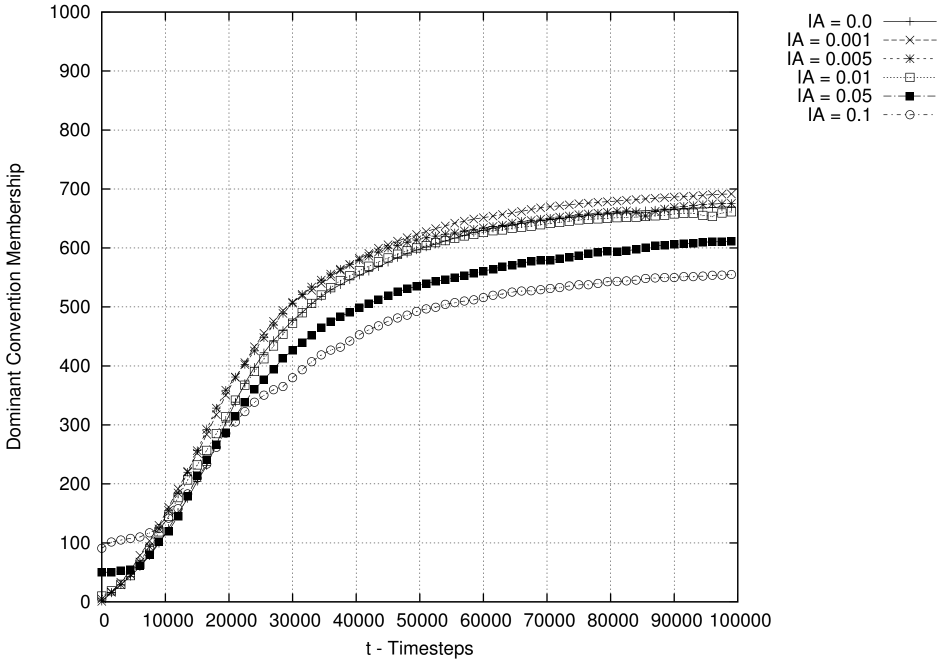
Figure 5.14: (a) Average communicative efficacy, and (b) dominant convention membership for varying proportions of IAs when placed in the network by node degree. Results are shown for a small-world network topology. The non-IA population is entirely elitist.

5.5.6 IAs with imperfect conventions

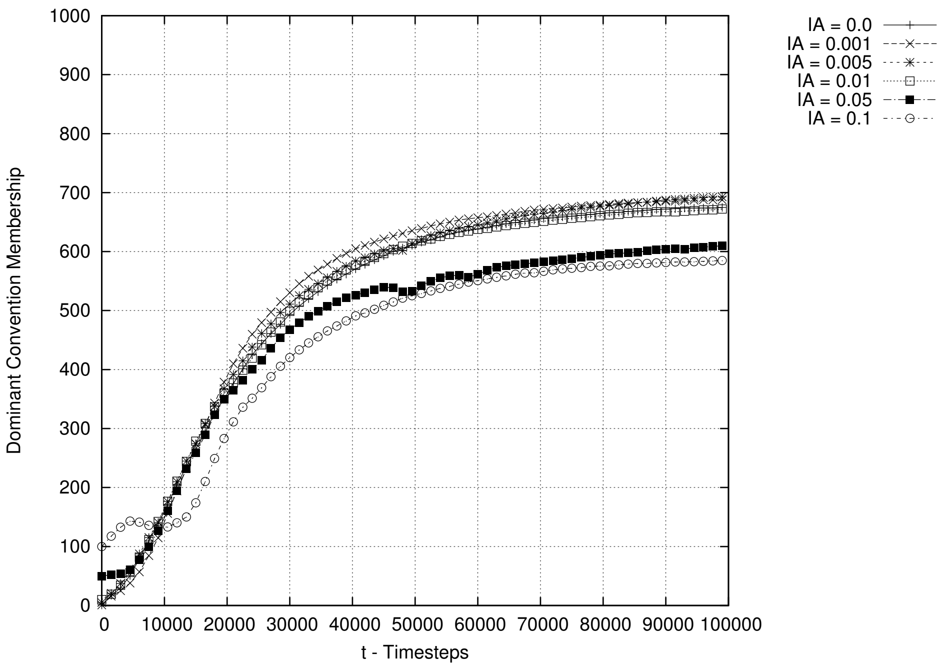
For simplicity, we have so far assumed that IAs use ideal lexicons. Realistically, it may not be possible to identify ideal conventions *a priori*. In this section, we investigate the effects of IAs using randomly generated lexicons. These are likely to be of poor quality: in a sample of 200 randomly generated lexicons, the average specificity was 0.521 (with standard deviation 0.129). Since the population is elitist, these lexicons are unlikely to be adopted, but it is important to explore whether they impede the emergence of high quality conventions. In the real world, we expect that IAs will be able to adapt and thus still aid the emergence of high quality conventions.

Figure 5.15(a) shows the dominant convention membership, on a scale-free topology, for IA proportions from 0.0 to 0.1. All IAs are given the same randomly generated lexicon. Initially, there is little difference between runs, as the average quality of lexicons in the whole population is also poor. As the system progresses the runs start to diverge, with higher proportions of IAs resulting in significantly fewer agents adopting the dominant lexicon. Interestingly, a proportion of 0.001 performs slightly better than a proportion of 0.0, but the difference is not statistically significant. Figure 5.15(b) shows results using the same configuration as Figure 5.15(a), but instead with each IA given a *different* randomly generated lexicon. As we increase the numbers of IAs with poor quality lexicons we see a decrease in the dominant convention membership, but the magnitude of the decrease is smaller when IAs propagate different poor quality lexicons. A small set of IAs propagating poor quality lexicons can be viewed as equivalent to a low level of noise in the model. When IAs have different poor quality lexicons, increasing the proportion of IAs increases the level of noise, with corresponding detrimental effects. Conversely, when the IAs use a single poor lexicon, increasing the proportion of IAs constitutes a coordinated malicious effort by the IAs to disrupt convention emergence, and the detrimental effects are larger.

Figures 5.16(a) and 5.16(b) show the average communicative efficacy for

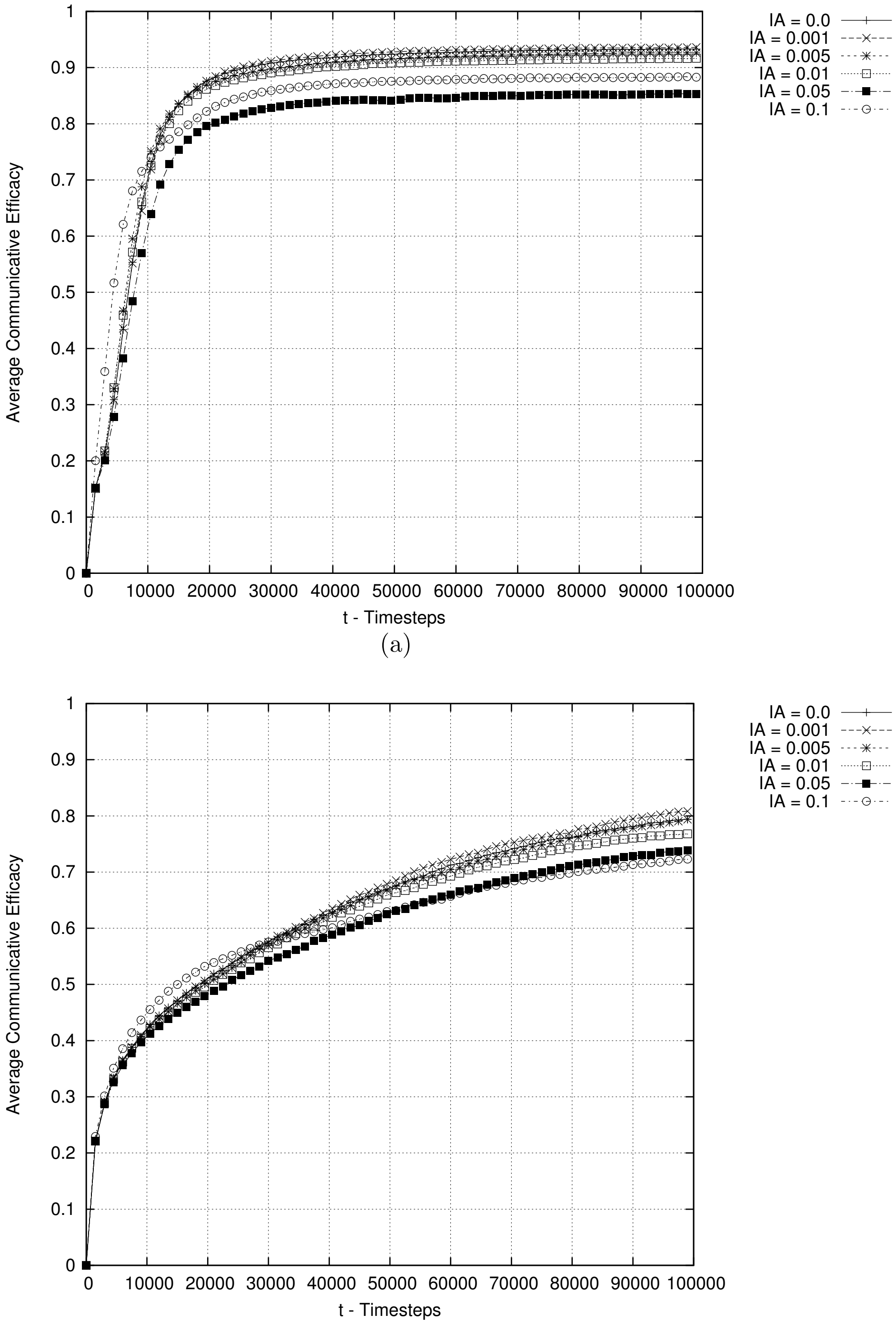


(a)



(b)

Figure 5.15: Number of agents using most common lexicon on scale-free topology with 1000 agents and 10000 edges, while varying proportion of IAs. In (a) IAs are given the same random (and therefore, on average, poor quality) lexicon, whereas in (b) IAs are given different, unique random lexicons.



(a)

(b)

Figure 5.16: Average communicative efficacy for (a) scale-free and (b) small-world networks while varying the proportion of IAs. IAs are given the same random lexicon.

scale-free and small-world topologies respectively, with IAs given the same poor quality lexicon. Increasing the number of IAs with poor lexicons significantly reduces the level of average communicative efficacy. On scale-free topologies the communicative efficacy actually increases from IA proportions of 0.05 to 0.1. This may be due to the effect of the communicative efficacy between IAs themselves, being given the same lexicon, beginning to have a significant impact on the overall average.

Analysis of the data shows significant differences in system dynamics between individual runs, where before (in configurations discussed in the previous sections) there had been no significant differences between runs. Table 5.6 shows the group evolution in three representative runs which we have classified as good, bad or average according to the number of agents adopting the dominant convention by the end of the simulation. For clarity of presentation, some groups have been aggregated between intervals instead of listing every individual value. We can see that while the fragmentation of the population into groups is roughly similar at the start of the simulation, as time progresses the bad run remains highly fragmented and with a much smaller dominant group than that attained in the good run.

There are only two differences between these individual runs, given that they all have the same parameter settings: (i) the set of lexicons given to agents at the beginning, and (ii) the connecting topology and location of IAs, which are random. One of these factors must account for the disparity in convention emergence between individual runs. Simulations without IAs do not show such a significant disparity between individual runs, so the differences in runs cannot be due to the set of lexicons given to regular agents, and we can focus our analysis on the lexicons given to IAs. We measured the average distance of IA lexicons from their neighbouring agents' lexicons, and the average specificity of these lexicons, reasoning that these are the two main properties that will affect convention emergence due to lexicon differences. However, we found no statistically significant difference between the runs. Therefore, the only remaining

Timestep	Number of groups of size		
	Bad run	Average run	Good run
0	950×1, 1×50	950×1, 1×50	950×1, 1×50
1000	886×1 $22 \times 1 < s < 20$ 1×52	864×1 $22 \times 1 < s < 20$ 1×50	862×1 $30 \times 1 < s < 20$ 1×52
10000	309×1 $70 \times 1 < s < 20$ $5 \times 20 < s < 50$, 1×50 1×64	331×1 $75 \times 1 < s < 20$ $8 \times 20 < s < 50$ 1×51 1×58	625×1 $72 \times 1 < s < 20$ $1 \times 20 < s < 50$ 1×51
50000	44×1 $4 \times 1 < s < 20$ $4 \times 20 < s < 50$, $6 \times 50 < s < 90$ 1×346	48×1 $4 \times 1 < s < 20$ $6 \times 20 < s < 50$ $3 \times 50 < s < 90$ 1×481	51×1 $0 \times 1 < s < 20$ $9 \times 20 < s < 50$ 1×52 1×593
100000	41×1 $3 \times 1 < s < 20$ $5 \times 20 < s < 50$, $6 \times 50 < s < 90$, 1×445	40×1 $2 \times 1 < s < 20$ $7 \times 20 < s < 50$, $3 \times 50 < s < 90$, 1×566	34×1 $0 \times 1 < s < 20$ $9 \times 20 < s < 50$ 1×51 1×640

Table 5.6: Number of groups (n) of size (s) at various timesteps (presented as $n \times s$) for representative bad, average, and good runs, for an IA proportion of 0.05 inserted randomly on a scale-free network topology with 10000 edges. IAs are given the same random, and therefore poor quality, lexicon.

explanation for the differences between the runs is the difference in connecting topology and the placement of IAs on that topology. These results therefore corroborate other work implicating network structure in convention emergence dynamics (e.g. Pujol *et al.* (2005), Villatoro *et al.* (2009a)).

5.6 Conclusions and future work

Our results show that small groups of unprivileged agents can effectively and significantly influence the emergence of conventions within open MAS. When agents are able to generate high quality conventions to spread to the population, we find that just 5 randomly placed IAs in a population of 1000 can influence the rest of the population to use their conventions 43% of the time. When we place each IA according to highest node degree, we can influence the rest of the population to use the IA convention 100% of the time with only 10 IAs in a population of 1000.

Our results with IAs with poor quality lexicons show that this influence goes both ways, such that convention emergence can be fragmented and almost entirely eliminated with the same small proportion of IAs who use poor quality conventions. We note that these results also imply that topological properties have a major influence on the emergence of conventions. Scale-free networks are particularly conducive to high quality convention emergence, but our results suggest that the cost of convention manipulation on small-world networks is higher, and convergence is much slower. It may be possible to place IAs at highly influential locations to increase the probability of convention emergence. In the next chapter (Chapter 6), we propose a methodology for learning the best locations at which to place IAs in any given network, and show that IAs can be significantly more effective when placed using topological knowledge.

The strategy investigated for IAs here is very simple, namely that of attempting to propagate a single high quality convention. In Chapter 7 we explore IAs in more depth by equipping them with incentives and sanctions, and determine the extent to which they can manipulate established conventions.

Our results imply that malicious or faulty agents can disrupt convention emergence with ease, and demonstrate the fragility of convention emergence in open MAS. That malicious agents could use dishonest quality valuations or attempt to block the propagation of high quality convention seeds in order to fragment convention emergence conflicts with our desire to minimise intrusive additions or impositions on agent behaviour. This is especially so as such action is typically dealt with either through self-protection (as with Salazar *et al.* (2010a)) or the use of social mechanisms such as sanctions or incentives. We will therefore likely be forced to compromise on non-intrusiveness to deal with the practicalities of malicious behaviour, but we still do not require assumptions about the form this self-protection will take for the above results to hold.

CHAPTER 6

Determining agent influence

In the previous chapter, we demonstrated how to manipulate conventions using the Influencer Agent (IA) mechanism. An interesting result of the investigation was that targeting IAs using node degree can significantly increase their efficacy. In this chapter, we explore whether this result can be generalised, and how topological information can be exploited to increase IA efficacy. We propose a methodology for learning the network value of an agent, in terms of the extent to which it can influence the rest of the population. We quantify its success and show that exploiting knowledge of the network structure using our methodology can significantly increase the efficacy of IAs. We evaluate our methodology in the context of two agent-interaction models: (i) the language coordination domain introduced in Chapter 5 and (ii) a coordination game domain based on work presented in Chapter 4. The latter model also forms the basis of the work presented in Chapter 7. A summary of the major network concepts used in this chapter can be found in Appendix A.

6.1 Introduction

Modern application domains for open Multi-Agent Systems (MAS) are typically constrained by an underlying network connecting individual agents. A wide variety of research has shown that these networks display rich structure that significantly influences the dynamics of agent interactions and the flow of information (e.g. Easley & Kleinberg (2010), Fagyal *et al.* (2010), Mossel & Roch (2010), Sen (2008), Villatoro *et al.* (2009a)). The structure of a network can mean that some individual locations are significantly more important than others, by virtue of being able to influence large proportions of a population, controlling the flow of information through a network, or connecting disparate communities of individuals (as with the vital *hub* nodes in scale-free networks (Li *et al.*, 2005)). Determining the importance of individual locations is thus a key research question in a variety of fields including computer science, biology, chemistry, sociology and economics (Chen *et al.*, 2009; Kempe & Kleinberg, 2003; McDonald, 2007). In this chapter, we focus on location importance in terms of *influence*: the extent to which an individual can manipulate the choices of the rest of a population due to its location. We propose a novel methodology for learning the network value of a node requiring only (i) a way of estimating the effective influence an agent exerts on a population and (ii) the ability to sample a portion of the network. Our methodology can be used online and can be used to predict influence across a wide variety of domains. By online, we mean that our methodology can be applied to active open MAS by learning from agent interactions as they occur. As such, it is more generally applicable than typical mechanisms formulated to solve the influence maximisation problem (see Section 6.2.1 for more details).

We apply three instantiations of our methodology: (i) determining which of fourteen metrics of location are effective heuristics for influence, (ii) unsupervised learning of influence using principal components analysis, and (iii) supervised learning of influence using linear regression models. We evaluate our methodology on a variety of synthetic and real-world networks, and show that four out of fourteen of our chosen metrics of location effectively predict node influence across a highly heterogeneous range of networks. To evaluate our approach we use two common domains concerned with convention emergence: (i) Salazar *et al.*'s (2010b) language emergence and (ii) a coordination game, such as that used by Sen and Airiau (2007). Conventions typically emerge through the "gradual accretion of precedence" (Young, 1996), due to the existence of feedback effects in which an agent's choice in an interaction influences the choices of agents in the future. Investigating influence using convention emergence thus has two advantages: (i) it provides a natural measure of influence, since the actions of a highly influential agent are more likely to be reproduced in the rest of the population than those of a less influential agent, facilitating research into the impact of network structure on influence, and (ii) it is a domain in which research into influence can be usefully applied to improve existing techniques. In this chapter we also provide an in-depth discussion of network sampling techniques and the overheads inherent in applying our methodology and calculating each topological metric.

6.2 Background

In this section, we review current approaches to determining influence. A variety of information from Chapter 2 and Appendix A is also relevant, but is not reproduced here.

6.2.1 Influence propagation

One of the earliest investigations into influence was contributed by Domingos *et al.* (2001), who attempted to define the *network value* of an individual by modelling a market as a Markov random field. More typically, influence has been investigated in the context of the Linear Threshold or Independent Cascade models (Kempe & Kleinberg, 2003), in which nodes in a network are considered to be either *active* or *inactive*, where active could represent believing an idea or adopting a convention. A node can switch from inactive to active either based on how many of its neighbours are currently active, or by an active node targeting it for activation. In such models, researchers have investigated how to find k individuals that maximise the number of nodes eventually made active in the network. This is known as the *influence maximisation problem*. While in general this problem is NP-hard, approximate solutions using degree and distance centrality heuristics have shown good results, and Watts (2002) has shown that high-degree nodes are more likely to cause cascade effects, corroborating the assumption that node degree is a useful metric of influence. Kempe *et al.* (2003) show that a greedy algorithm can achieve results within a known bound (63%) of the optimal while being computationally tractable (although the approach is still computationally expensive). Chen *et al.* (2009) propose a computationally cheap alternative using a degree-discount heuristic, in which the nominal degree of a node is discounted when one or more of its neighbours has already been chosen. The influence maximisation problem has been extensively investigated (e.g. Goyal & Bonchi (2011), Hajian & White (2012)), but the extent to which these results generalise to other open MAS domains is unknown. Khrabrov and Cybenko's (2010) recent study concluded that node in-degree did not in fact correlate with user influence in the Twitter social network, placing empirical data at odds with the success of node degree in the work on influence maximisation. Although this is an isolated disagreement with the idea of node degree indicating influence, we hypothesise that there are various facets of influence propagation that the influence maximisation problem does not capture. Our methodology mitigates this by learning a statistical model of influence from the available empirical data.

Fagyal *et al.* (2010) investigate the role of network structure in language change, and further validate the assumption of node degree being an important indicator of agent influence. They also conclude that peripheral nodes play an important role in keeping norms stable, demonstrating that network features other than node degree deserve investigation. Determining influential users in real-world social networks has been a popular research topic due to the potential applications for marketing and PR (Kempe *et al.*, 2005). Trusov *et al.* (2010) have attempted to tractably measure influence in real-world social networks using log-in activity, and Hartline *et al.* (2008) provide a useful example of how influence research can be applied in the real world.

We are aware of only a small number of contributions that explicitly investigate the role of agent influence in realistic open MAS domains other than social media. Sen and Airiau (2008) investigate convention emergence with private interactions, and show that 4 agents in a population of 3000 can influence the population to adopt a given convention (from two alternatives). Although they do not model an underlying connecting topology, their results demonstrate the significant influence that small proportions of agents can have in open MAS. Other investigations have also shown that a small number of individuals can influence a population of agents (Oh & Smith, 2008; Yu *et al.*, 2010).

6.3 Methodology for learning influence

In this section we present a general methodology for predicting the influence of an agent at a given location within a network. We assume the existence of a measure of influence, to be chosen depending on the domain, and a network $G < V, E >$, where V is a set of agents and E is a set of edges that constrain the permitted communications between agents. We also assume the ability to sample properties of locations within the network, and either global knowledge of the network or (more practically) the ability to sample smaller sub-networks around the nodes in question.

The offline instantiation of our methodology is as follows:

1. If necessary, sample a sub-graph $G_s \subset G$ from the network around selected locations to obtain a portion of the network of interest. In cases where the domain involves very large populations, this may be required to allow

practical application of the methodology.

2. Sample a representative set $S \subset V$ of n locations within the network[1], where $n << |V|$, where representative implies sampling nodes of both high and low influence.

3. Choose a measure of influence, and a model of influence propagation.

4. Compute the influence of an agent located at each of the locations in S, on the rest of the population (e.g. by running multiple simulations of the influence model).

5. Calculate topological location metrics for all nodes in V.

6. Build a prediction model using the topological metrics and the estimated influence of agents placed at locations in S to *predict* which network locations are highly influential, and use it to predict the influence of all nodes in V.

Algorithm 2 summarises the methodology.

Algorithm 2 Methodology for learning node influence

$G_s \leftarrow sampleSubGraph(G)$
$S_{G_s} \leftarrow sampleNodes(G_s, n)$
$I \leftarrow Array()$ *//Array of measured influence*
$L \leftarrow Array()$ *//Array of Location metric values*
for all $V_i \in S_{G_s}$ **do**
    $I[i] \leftarrow simulateInfluenceModel(G_s, V_i)$ *//Get influence of node* V_i
    $L[i] \leftarrow calculateMetricValues(G_s, V_i)$
end for
$M \leftarrow buildPredictionModel(I, L)$
for all $V_i \in G_s$ **do**
    $print(M.predictValue(V_i))$
end for

To perform this methodology online, we modify step 3 as follows. Rather than running multiple simulations for each sampled node, select a measure of influence that can be measured online (e.g. if investigating Twitter, one might

[1]If step 1 is performed, then $V \equiv V_s$ and $E \equiv E_S$. To simplify presentation, we omit the subscript.

choose the number of re-tweets) and measure sufficient data for building the prediction model.

The main computational expense in our methodology is the calculation of topological metrics for all nodes in V and, if used, the influence model simulations for each location in S, which is $O(|S||E|k)$, where k is the number of simulation cycles. Depending on the size of S this can be significantly less than using the full network, which is $O(|V||E|k)$. Additionally, step 1 allows us to use a sample of the network to estimate influence, reducing the computational expense of the methodology. We recognise that the expense of computing location metrics is varied and might be high, and while we do not explicitly account for this within the methodology, we discuss local and approximation algorithms for our selected metrics in Section 6.4.

6.3.1 Selecting representative node samples

In order to effectively predict influence our methodology requires a sample of nodes that reflect the range of influence and topological metrics in the network. If the influence distribution is highly skewed then a random sample will not be representative (we discuss this further in Section 6.7). Therefore, we propose selecting a sample by stratifying nodes using degree. Since degree is known to be indicative of influence (Chen *et al.*, 2009), our hypothesis is that this approach will give a more representative sample in terms of influence.

To obtain a stratified sample, we divide the network into bins, and sort the nodes by degree. In this chapter we use 10 bins, with a threshold of $|V|/10$ nodes per bin, where $|V|$ is the number of nodes in the network. We add all nodes of each degree into the current bin, starting with the lowest degree nodes, until the threshold is reached. If adding all nodes of a given degree pushes a bin over the threshold, we do not split the remainder but add all nodes of the same degree. We then sample an equal number of nodes from each bin, until we have reached our required sample size.

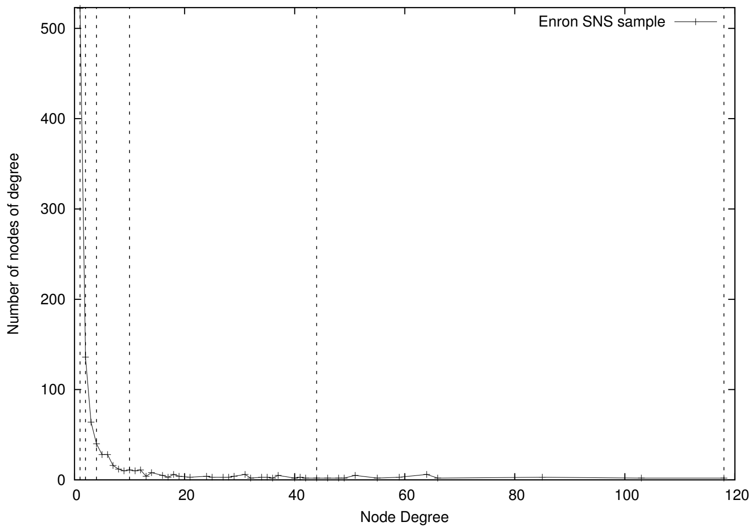


Figure 6.1: Degree distribution of an Enron-SNS network sample, where the dotted lines denote the boundaries of each bucket when applying our stratified sampling technique.

6.4 Topological metrics

In this section, we introduce the metrics which we hypothesise may aid in predicting node influence, and discuss their computational tractability. There are a huge number of possible metrics that can be calculated for any given node in a network. We have selected 14 metrics that are commonly found in the literature and have attractive hypotheses for being predictive of influence. For metrics where we have not provided an explicit reference, it is because the metric is either of a trivial nature (e.g. node degree) or very commonly used.

6.4.1 Metrics

There are a wide variety of metrics that quantify the structural properties of a given location in a network. Assuming a network, $G < V, E >$, and a given node $v_i \in V$, we hypothesise that the following metrics may be implicated in determining influence.

1. **Degree centrality**

   If $N(v_i)$ denotes the set of neighbours for v_i, then node degree centrality

$k_i = |N(v_i)|$. Intuitively, the more nodes that v_i can directly communicate with, the more of the population that node can directly influence[2]. Degree centrality is trivial to compute with local information.

2. **Local Clustering Coefficient (LCC)**

   The Local Clustering Coefficient measures the extent to which the neighbours of v_i are connected to each other. If $e_{ij} \in E$ denotes an edge between v_i and v_j, $v_i, v_j \in V$, then

   $$LCC(v_i) = \frac{2|e_{jk}|}{k_i(k_i - 1)} : v_j, v_k \in N(v_i), e_{jk} \in E$$

   Initially introduced by Watts and Strogatz (1998), LCC is a useful measure of community structure in a network. A node v_i with a high LCC is likely to be able to influence the local cluster in which it is embedded more effectively than nodes external to the cluster, and choices by neighbours of v_i are more likely to be reinforced by v_i in subsequent interactions.

3. **Average Neighbour Degree (AND)**

   Average Neighbour Degree measures the average degree centrality of the neighbours of a node. While a given node may not be intrinsically influential itself, communicating with a neighbouring influential neighbour may allow further opportunities for manipulating a population. We define AND as

   $$AND(v_i) = \frac{\sum_{v_j \in N(v_i)} |N(v_j)|}{|N(v_i)|}$$

4. **Edge Embeddedness and Overlap (EE/EO)**

   Edge embeddedness and overlap are two related measures that determine the extent to which the endpoints of an edge are embedded within a cluster of nodes. Edge embeddedness is defined as

   $$EE(e_{ij}) = |N(v_i) \bigcap N(v_j)|$$

[2] An intuition effectively encapsulated by the aphorism “It’s not what you know, but who you know”.

Edge overlap is subsequently defined as

$$EO(e_{ij}) = \frac{EE(e_{ij})}{|N(v_i) \bigcup N(v_j)|}$$

Since these metrics are defined on a per-edge basis, we use three measures of each metric for a given node:

(a) *Average (AEE/AEO)*: The average embeddedness or overlap will be highest when a node is highly embedded within a local cluster, providing opportunities to influence a small group of nodes simultaneously.

(b) *Highest (HEE/HEO)*: Taking the maximum embeddedness or overlap indicates whether a node has any edges highly embedded within a cluster, while allowing for the node itself to be connected to a wide variety of other nodes or clusters.

(c) *Lowest (LEE/LEO)*: An edge with low embeddedness or overlap may connect disparate clusters of nodes, allowing the nodes on each endpoint to influence across disparate communities in a network.

5. **Average Shortest Path Length (ASPL)**

Given a geodesic, or shortest, path between two nodes $v_i, v_j \in V$, defined by a set of edges $E_{spl}(v_i, v_j) \in E$, the average shortest path length for v_i is given by

$$ASPL(v_i) = \frac{\sum_{v_j \in V \setminus v_i} |E_{spl}(v_i, v_j)|}{|V| - 1}$$

Assuming a node's influence diminishes as the number of hops increases, a node with low ASPL may be able to indirectly influence a larger proportion of the population than a node with a correspondingly higher ASPL.

6. **Betweenness Centrality (BC)**

Node centralities are a class of metrics that attempt to measure various facets of importance of a node. The betweenness centrality of v_i specifically measures the number of shortest paths in a network that pass through

v_i. If σ_{jk} is the set of shortest paths that exist from v_j to v_k, and $\sigma_{jk}(v_i)$ is the set of shortest paths from v_j to v_k that pass through v_i, then

$$BC(v_i) = \sum_{v_i, v_j, v_k \in V, v_i \neq v_j \neq v_k} \frac{|\sigma_{jk}(v_i)|}{|\sigma_{jk}|}$$

Betweenness centrality is a useful measure of how much information is likely to flow through node v_i, given that communications are likely to be along shortest paths. As such, a node with high betweenness has the ability to manipulate the information flow in a network more effectively than a node with low betweenness.

7. **Closeness Centrality (CC)**

   Closeness Centrality is a measure of how quickly information can spread from a given node. If $SPL(v_i, v_j)$ indicates the shortest path between v_i and v_j, then CC is calculated as

$$CC(v_i) = \frac{1}{\sum_{v_j \in V \setminus v_i} |SPL(v_i, v_j)|}$$

   Since the assumption of information transfer following shortest paths may not hold in all domains, it may also be useful to calculate random walk centralities, which follow the identical definitions as above but use random walks instead of shortest paths. However, calculating these measures can be prohibitively expensive.

8. **Eigenvector Centrality (EC)**

   Initially proposed by Bonacich (1987), eigenvector centrality is calculated using the eigenvector of the largest eigenvalue given by the adjacency matrix representing the network in question. A node is central if it is connected to other nodes that are central, and the measure takes into account both direct and indirect connections between nodes. Google's PageRank algorithm is a variant of EC, and this supports our intuition that EC may effectively estimate influence.

Each entry a_{v_i,v_j} in the adjacency matrix A is 1 if $e_{ij} \in E$ and 0 otherwise. The eigenvector centrality of a node v_i is subsequently calculated as

$$EC(v_i) = \frac{1}{\lambda} \sum_{v_j \in N(v_i)} a_{v_i,v_j} \times EC(v_j)$$

where λ is a constant.

9. **Hyperlink-Induced Topic Search (HITS)**

   Initially introduced by Kleinberg (1999), HITS attempts to measure *hubs* and *authorities* in a network. The motivation behind Kleinberg's work is that in any given WWW search topic, there are a number of pages that contain authoritative information and a number of pages that link to many authorities. As such, HITS is a recursive measure in which hubs are nodes that connect to many authorities and authorities are nodes that are pointed to by many hubs. A page that ranks highly under this algorithm can be said to be more influential. We incorporate this metric into our work to test this hypothesis.

   The algorithm to calculate HITS is quite involved in comparison to the other metrics discussed, so we do not reproduce it here. It is fully described in Kleinberg (1999).

In total, we evaluate 14 metrics for the extent to which they determine node influence. Broadly, each metric can be linked to influence as follows. Eigenvector Centrality (EC), Betweenness Centrality (BC), Closeness Centrality (CC), Hyperlink-Induced Topic Search (HITS), and Average Shortest Path Length (ASPL) all measure the ability of a node to manipulate information flow in a network. Local Clustering Coefficient (LCC), embeddedness, and overlap measure the extent to which a node is part of a cluster of nodes. Highly clustered areas of networks have efficient internal information propagation, and a node that is very central to such a cluster is likely to be able to influence that cluster more effectively. Degree centrality is a measure of how many nodes a given individual is able to directly influence, and Average Neighbour Degree (AND) is a measure of how many nodes a given individual can indirectly influence to a depth of 2.

6.4.2 Computational tractability

While a number of these metrics are highly tractable, some of them require either, or both, of (i) global knowledge of the network, and (ii) significant computational resources. In typical on-line analysis of MAS networks these properties are unlikely to be attainable. The following discussion evaluates the computational costs and data requirements of each of our chosen metrics.

Node degree, local clustering coefficient, edge embeddedness, edge overlap, and neighbour degrees are all easily computable with local knowledge. The most significant concerns are the centrality measures, which have typically required both global knowledge of the network and significant computational resources.

Edge betweenness is used in the Girvan and Newman (GN) algorithm for finding community structure (Gregory, 2008). Edge betweenness is a measure of the number of shortest paths between all nodes that contain a given edge, computable in $O(mn)$ with global knowledge of a network with n nodes and m edges. Gregory (2008) proposed a local measure, *h-betweenness*, which only considers paths of maximum length h. Computation subsequently involves a breadth-first search (BFS) of depth h around the node in question, and then computing the betweenness on the BFS-sampled sub-graph. While Gregory provides strong results demonstrating the technique's efficacy when substituted into the GN algorithm, there are no results on the actual accuracy of the estimation. Marsden (2002) uses a similar technique, defining an egocentric betweenness centrality using the neighbours of a node, equivalent to 1-betweenness in Gregory's measure. Marsden found that the ranking of nodes given by egocentric betweenness and the traditional global betweenness is very similar, but only evaluated fairly simple networks.

Andersen *et al.* (2007) have demonstrated a technique for calculating the

Sampling mech.	BC		EC		CC	
	$h = 2$	$h = 3$	$h = 2$	$h = 3$	$h = 2$	$h = 3$
BFS	0.90	0.96	0.36	0.42	-0.37	0.41
SNS	0.75	0.93	0.14	0.36	-0.49	0.62
MHRW	0.02	0.02	0.50	0.61	-0.72	-0.74
MHRWDA	0.02	0.02	0.51	0.61	-0.73	-0.74

Table 6.1: Correlation between estimated centrality using Gregory's h-betweenness concept and actual centrality, for Betweenness Centrality (BC), and applying the technique to Eigenvector Centrality (EC) and Closeness Centrality (CC), averaged over 15 networks for each sampling technique (see Section 6.5 for more details).

PageRank of a node, which is a variant of Eigenvector Centrality (EC), using only local information. The technique requires examination of $O(e^{-1})$ nodes for a given error bound of e. Interestingly, the paper notes the potential of PageRank for approximating influence in a network.

Closeness centrality is computable in either $O(n^3)$ or $O(nm + n^2 logn)$ (depending on the algorithm used) given global knowledge, and faster for certain network classes. Eppstein and Wang (2004) have demonstrated a fast approximation algorithm for computing closeness centrality, but this still requires global knowledge.

To our knowledge, there are no known local algorithms for HITS, but Gollapudi *et al.* (2007) have demonstrated a highly effective approximation algorithm for HITS-like ranking algorithms that demonstrates considerable efficiency gains. The original proposal for HITS (Kleinberg, 1999) calls for determining an initial seed set of around 200 nodes (in the context of finding pages on the world wide web), and then performing a limited snowball sampling (see Section 6.5) around this set. HITS does not require global knowledge of the network, but still has highly non-local information requirements.

We performed a series of tests for determining the accuracy of centrality estimation using Gregory's h-betweenness technique (Gregory, 2008). For each node, we calculated the actual centrality measure and an estimation on the subgraph induced by BFS around the node depth-limited to $h = \{2, 3\}$. Table 6.1 presents the correlation between the estimation and actual value. Each sampling

	Local Data		Global Data
Metric	Computable	Approximatable	Fast approx.
Degree	✓		
Local Clustering Coefficient	✓		
Edge embeddedness	✓		
Edge overlap	✓		
Average Neighbour Degree	✓		
Betweenness Centrality	x	✓	
Closeness Centrality	x	x	✓
Eigenvector Centrality	x	✓	
HITS	x	x	✓

Table 6.2: Computational and information requirements for the calculation of each metric that we hypothesise might predict node influence.

technique was used to sample 15 networks of size 1000 from each of the three full networks we consider (see Section 6.5 for more details on the sampling mechanisms). Note that Gregory's method was proposed only for betweenness-centrality, which shows the best correlations. The other centrality measures are included for completeness, but show much poorer estimation accuracy. For closeness centrality, this is by definition, since CC measures the inverse of the sum of the shortest path length to all other nodes, and with $h = 2$ the path length is either 1 or 2 for all nodes. The technique used for sampling the network clearly has a significant impact on the efficacy of the estimation technique, implying that (i) estimating graph measures in this way is highly sensitive to the local topological structure, and (ii) that each sampling technique reproduces unique subsets of the structural properties of the full network.

Table 6.2 summarises the computational tractability of these metrics. For clarity, we have categorised HITS as requiring global information, but note that it requires sampling of a portion of the global network rather than the entire network itself.

6.5 Network sampling

In this section, we discuss common approaches to sampling networks from real-world datasets. We analyse their efficacy in reproducing properties of the network being sampled, and describe the properties of networks sampled using each technique from the datasets that we use in this chapter.

6.5.1 Network sampling techniques

A wide variety of synthetic network generators have been proposed, but tend to be poor models of real-world networks (Leskovec *et al.*, 2008; Newman, 2003). To demonstrate the applicability of our methodology, we require datasets representing networks found in real-world domains. Real-world networks typically exhibit two limiting properties: (i) they can be very large, beyond any size that is practically usable in a large number of simulations, and (ii) they contain a wide variety of rich structural properties that cannot be reproduced by current synthetic network generation algorithms (we demonstrate this in Section 6.7). We cannot typically expect to use global knowledge of the network to determine influential nodes in practical applications. As such, sampling a portion of the network is often a necessary step in our methodology.

Careful consideration must therefore be given to the sampling technique. Ideally, we would like the structural properties of the sampled sub-network to be as close as possible to the network that it is sampled from, for important metrics such as clustering coefficient or average degree, and other significant metrics such as degree distribution or edge embeddedness distribution.

There are a number of possible sampling techniques that can be used. Each starts at a random node, and progressively adds nodes to a seed set until a threshold is reached.

1. **Breadth-first search (BFS)**
   In each iteration of BFS, all the neighbours of seed-set nodes that are not already in the seed set are added, until the threshold is reached.

2. **Snowball-sampling (SNS)**
   SNS proceeds identically to BFS, except within each iteration, if adding all the new neighbours to the seed-set would push the seed set past the

threshold, then neighbours are chosen randomly from those available until the threshold is reached.

3. **Random-walk (RW)**

   A random walk adds one node at a time, by following a random traversal through the network from the start node. Each neighbour is chosen with uniform probability.

4. **Metropolis-Hastings Random Walk (MHRW)**

   MHRW is a random-walk with transition probabilities biased away from high-degree nodes, in an attempt to generate a uniform sampling (in terms of degree) of nodes from the network. It was initially investigated in this context by Gjoka *et al.* (2010), who demonstrated that MHRW produces a uniform sampling of nodes from the full network and effectively preserves the node degree distribution, known to be a key component in the study of complex networks (Gjoka *et al.*, 2010).

5. **Metropolis-Hastings Random Walk with Delayed Acceptance (MHRW-DA)**

   MHRW-DA is the same as MHRW but with a further modification of transition probabilities to reduce the likelihood of re-visiting nodes. Initially introduced by Lee *et al.* (2012), MHRW-DA covers more of the network when sampling, increasing the estimation accuracy.

6. **Albatross sampling**

   Introduced by Jin *et al.* (2011), Albatross sampling is a random walk with modified transition probabilities and a chance of randomly jumping to another node in the network, in order to gain greater coverage and avoid problems associated with sampling networks with multiple connected components.

BFS, SNS and RW are all known to be biased towards high-degree nodes, distorting the degree distribution and the structure of the sampled network away from that of the full network (Gjoka *et al.*, 2010). However, BFS and SNS produce good coverage of the local area around the start node, and so retain local structure. As such, they are subject to greater variation between samples, but may be useful for ensuring that a wide variety of structural properties are tested. MHRW, MHRW-DA and Albatross have all been shown to converge towards the node degree distribution exhibited in the full network being sampled. For all these sampling methods, there are no guarantees about the reproduction of any other metrics or structural properties.

6.5.2 Technique efficacy

In order to evaluate the efficacy of each sampling technique, we sampled 15 graphs of 1000 nodes per sampling technique for each of three networks (for a total of 225 networks). In this thesis, we use the following networks: (i) a peer connection network from Gnutella (a P2P file-sharing platform), (ii) the Enron email dataset, and (iii) the arXiv general relativity section collaboration network[3]. The Enron and arXiv networks are both based on human interactions, but are generated by very different processes: the Enron dataset represents email communications, while arXiv is based on more formal links made through research collaborations. Conversely, Gnutella is a computational network representing links in a P2P system. Since these networks are generated by very different processes they display varied structural properties, allowing us to evaluate our methodology on a range of structures. The Gnutella and Enron networks are directed, but MHRW, MHRW-DA and Albatross sampling all explicitly only consider undirected networks. Consequently, we treat each network as undirected.

The high-level metrics are summarised in Tables 6.3, 6.5 and 6.4. The global clustering coefficient (GCC) is the average of the clustering coefficients for each node. Diameter describes the longest shortest path-length between a pair of nodes in the network. Centralization is a measure of how much heterogeneity

[3]All taken from the Stanford large dataset collection, http://snap.stanford.edu/data/

exists in a graph (Dong & Horvath, 2007): if we define the *density* of a network as

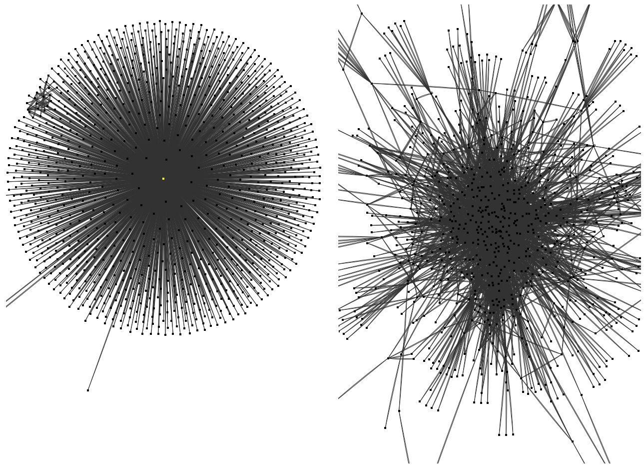
$$Density = \frac{mean(k)}{n-1}$$

where k denotes node degree, then we can define centralization as

$$Centralization = \frac{max(k)}{n} - Density$$

Centralization indicates the extent of variation of node degree in the network — a low centralization indicates that most nodes have a similar connectivity, whereas high centralization implies a higher degree of structural variation throughout the network. While this measure is mainly practically applied in biological studies, it is useful here as an indication of the extent to which a mechanism has generated a uniform sampling.

From examination of the data in Tables 6.3, 6.5 and 6.4, we can see that no single technique produces an ideal sample. As discussed above, BFS and SNS are known to be highly biased towards high-degree nodes, but produce good coverage of localised areas in a network. The standard deviation between samplings is highest using these techniques, indicating a large variation in structural properties between samples. The centralisation is also very high using BFS and SNS, indicating that a much higher level of internal hetereogeneity is introduced by using these sampling techniques. MHRW and MHRW-DA tend to have the lowest standard deviation between samples, and produce networks with metric values such as average degree, clustering coefficient and centralisation much closer to the full network than SNS and BFS. However, the diameter of MHRW and MHRW-DA is far higher than in the full graph, which we hypothesise is due to the random walk nature of these techniques covering large areas of the network. Given that these sampled networks clearly no longer display the small-world property, we cannot assert that many of the structural properties of the full network are reproduced, beyond the node degree distribution. Albatross sampling also displays low variance between samples, and produces networks



(a) (b)

Figure 6.2: Structure of an example network sample produced by (a) Snowball sampling (SNS) and (b) MHRW sampling.

with centralisation values closest to that of the full network.

However, Albatross sampled networks appear to be very sparse, with low edge numbers, average degrees, and clustering coefficients. There do not appear to be any consistent differences between SNS and BFS, beyond that SNS tends to produce network samples with lower average degrees — perhaps indicating that SNS is slightly less biased towards high degree nodes. However, SNS can often produce distorted network structures depending on the initial node chosen. Figure 6.2a shows a SNS network sample where the first node sampled has a very large degree, resulting in a star-shaped sample with unrepresentative node degree distribution and clustering coefficient. Figure 6.2b shows a MHRW sample of the same network, clearly showing a more homogeneous network structure.

If we are to claim that our methodology works in a general sense, we must be careful to analyse as many network structures as possible. We believe that the best approach is to use a portfolio of network samples derived using a variety of sampling techniques. Using BFS or SNS allows us to apply our methodology on samples which are more representative of localised areas of the full network, and the higher variance between samples indicates a wider variety of structural properties will be analysed. Using MHRW or MHRW-DA allows analysis of

Sampling tech.	Nodes	Edges	Avg.Degree	CC	Diameter	Centralization
None	62586	147892	4.726	0.005	Inf.	0.001
BFS	1009.2 (7.73)	1246 (95)	2.47 (0.18)	0.026 (0.005)	6.93 (0.80)	0.03 (0.004)
SNS	1000 (0)	1197.8 (54.5)	2.40 (0.11)	0.02 (0.008)	7.33 (0.98)	0.034 (0.008)
MHRW	1000 (0)	1122.3 (13.1)	2.24 (0.03)	0.008 (0.004)	36.4 (4.4)	0.005 (0.001)
MHRWDA	1000 (0)	1120.1 (10.8)	2.24 (0.02)	0.007 (0.003)	38.7 (3.22)	0.005 (0.001)
Albatross	1000 (0)	353.5 (22.8)	0.71 (0.05)	0.002 (0.003)	Inf.	0.004 (0.001)

Table 6.3: Important global metrics for network samples produced by applying each sampling technique to the Gnutella network, averaged over 15 repeats. Standard deviation is in brackets.

samples in which we can be sure that the node degree distribution is closer to that of the full network, but we cannot make any assertions about other properties. Given that the diameter is so much larger in network samples produced using these techniques, it is likely that there are other as-yet undocumented biases introduced. Albatross sampling appears to produce more homogeneous samples, but these are far sparser than the full network, and highly disconnected when $n = 1000$, and so we do not feel that analysis on these networks would be helpful in this context.

Therefore, in the remainder of this thesis, we sample, from each of the Gnutella, Enron, and arXiv datasets, 5 network samples using SNS, 5 network samples using MHRW, and 5 network samples using MHRW-DA, making a total of 45 networks with which to test our methodology. In this chapter, we also initially include a number of synthetic networks for comparison:

1. Scale-free networks generated using Eppstein's power-law generation algorithm (Eppstein & Wang, 2002). We use two Eppstein power-law networks, generated with 1000 nodes and 5000 and 10000 edges respectively.

2. Small-world networks generated using Kleinberg's algorithm (Kleinberg, 2000). We generate Kleinberg small-world networks of 1000 nodes, with a clustering exponent of 1, and a maximum of 1, 3 or 7 additional edges per node.

Comparing the properties of the real-world networks (Tables 6.5, 6.4, 6.3) with the synthetic network properties in Table 6.6 illustrates the significant

Sampling tech.	Nodes	Edges	Avg.Degree	CC	Diameter	Centralization
None	36692	183831	10.02	0.497	13	0.037
BFS	1255 (291)	16584 (6242)	26.2 (6.5)	0.55 (0.04)	3.8 (0.8)	0.66 (0.2)
SNS	1000 (0)	7751 (3760)	15.5 (7.5)	0.44 (0.13)	4.5 (0.92)	0.51 (0.31)
MHRW	1000 (0)	4480 (443)	8.96 (0.89)	0.52 (0.03)	11 (1.41)	0.10 (0.02)
MHRWDA	1000 (0)	4495 (255)	9.00 (0.51)	0.52 (0.02)	10.6 (1.04)	0.10 (0.02)
Albatross	1000 (0)	733.6 (41.2)	1.47 (0.08)	0.32 (0.02)	Inf.	0.07 (0.01)

Table 6.4: Important global metrics for network samples produced by applying each sampling technique to the Enron network, averaged over 15 repeats. Standard deviation is in brackets.

Sampling tech.	Nodes	Edges	Avg.Degree	CC	Diameter	Centralization
None	5242	14496	5.526	0.530	17	0.014
BFS	1006 (2.93)	4065 (512)	8.08 (1.02)	0.58 (0.01)	8.5 (0.79)	0.06 (0.01)
SNS	1000 (0)	3663 (405)	7.32 (0.81)	0.53 (0.04)	8.67 (1.18)	0.06 (0.01)
MHRW	1000 (0)	3561 (413)	7.12 (0.83)	0.57 (0.02)	14.3 (1.04)	0.05 (0.01)
MHRWDA	1000 (0)	3190 (394)	6.38 (0.79)	0.58 (0.02)	15.5 (1.41)	0.04 (0.01)
Albatross	1000 (0)	1851 (193)	3.70 (0.39)	0.45 (0.02)	Inf.	0.03 (0.00)

Table 6.5: Important global metrics for network samples produced by applying each sampling technique to the arXiv network, averaged over 15 repeats. Standard deviation is in brackets.

Generated graphs averaged over 15 repeats, standard dev. in brackets

Network	Nodes	Edges	Avg.Degree	CC	Diameter	Centralization
Eppstein-5000	1000 (0)	5000 (0)	10 (0)	0.02 (0.00)	6 (0)	0.026 (0.00)
Eppstein-10000	1000 (0)	10000 (0)	20 (0)	0.035 (0.00)	6 (0)	0.04 (0.00)
Kleinberg-1c	1000 (0)	2991 (2.66)	5.98 (0.01)	0.001 (0.00)	7 (0)	0.004 (0.00)
Kleinberg-3c	1000 (0)	4899 (12.3)	9.78 (0.02)	0.03 (0.00)	5.2 (0.41)	0.01 (0.00)
Kleinberg-7c	1000 (0)	8629 (15.8)	17.2 (0.03)	0.05 (0.00)	4 (0)	0.012 (0.00)

Table 6.6: Important global metrics for networks produced by the Eppstein and Kleinberg network generators, averaged over 15 repeats. Standard deviation is in brackets. For the Eppstein networks, the number annotation after Eppstein indicates the number of edges. For the Kleinberg networks, the "-c" annotation indicates the additional number of extra connections (a parameter to the algorithm) that was used to generate the network.

differences between the real world and synthetic networks. This is best demonstrated by inspecting the clustering coefficient, which is far higher in real-world networks. This is indicative of the structural differences between these networks and the insufficiency of common network generation algorithms in modelling real-world domains. The synthetic generation algorithms produce consistently structurally similar graphs. For example, over 200 generated Eppstein power-law networks, using identical configurations, the standard deviation for node degree is 0 and the standard deviation for clustering coefficient is 0.001.

We note that the usage of static network structure (and constant population sizes) is a limitation of our work, given our aspiration to study open systems in which we can expect the population and network structure to vary over time. However, the study of dynamic networks is underdeveloped and given the differences between synthetic static networks and real-world networks, we cannot assume that we could guarantee generality when introducing dynamism into our study. Further, in this chapter we are interested in demonstrating the feasibility and efficacy of the methodology. As such, adapting the methodology to work on dynamic networks is clearly a consideration for future work.

6.6 Experimental setup

To evaluate our methodology for learning influence, as described in Section 6.3, we use two major models of convention emergence in open MAS, namely, Salazar *et al.*'s language coordination (Salazar *et al.*, 2010b), and the coordination game (described, for example, in Sen & Airiau (2007)). In each experiment, we insert a single fixed-strategy Influencer Agent (IA) at a randomly chosen location, and measure the extent to which the population converges on the strategy of the IA.

We apply our methodology as follows. From each of the Gnutella, Enron and arXiv networks described above, we sample 45 sub-networks of 1000 nodes using SNS, MHRW and MHRW-DA. We sample 50 locations, using either random or stratified-by-degree sampling, and run our simulation 20 times for each location, giving a total of 1000 simulation runs per sub-network. After each simulation, we measure the extent to which the agent at this node influenced the rest of the population, and calculate each of the fourteen topological metrics for that location. We use Principal Components Analysis (PCA) for unsupervised learning and fit Linear Regressions (LR) for supervised learning. We then run new simulations using the location predicted as most influential by each model, and determine the extent to which influence has increased against random sampling.

We use the Java Universal Network/Graph Framework[4] in our simulations and Cytoscape[5] for off-line structural analysis of networks. Statistical analyses are performed using R[6] and Weka[7].

6.6.1 Language coordination domain

The first domain that we use to learn node influence is Salazar *et al.*'s (2010b) language coordination, as described in Chapter 5. Recall that in this domain agents attempt to establish a social convention in the form of a shared vocabulary. Over time a shared lexicon, a set of mappings from words to concepts, emerges. We run each simulation for 50000 timesteps, and each agent propagates their lexicon with a probability of 0.01 and updates their lexicon with a probability of 0.01. By the end of a typical simulation run 600–800 agents have adopted the dominant lexicon (see Section 5.5 for a more detailed analysis of the population's behaviour in this domain).

In this domain, we define an agent's *influence* as the similarity between its lexicon (L) and final dominant lexicon in the population (L') using Jaccard's similarity coefficient: $J(L, L') = |L \cap L'|/|L \cup L'|$, where a similarity of 1 implies that agents use an identical lexicon, and 0 implies there are no mappings in common.

[4]http://jung.sourceforge.net/
[5]http://www.cytoscape.org/
[6]http://www.r-project.org/
[7]http://www.cs.waikato.ac.nz/ml/weka/

6.6.2 Coordination game domain

To corroborate our results in the language coordination domain, we use a model of convention emergence loosely based on Sen and Airiau's private learning (Sen, 2008) and Walker and Wooldridge's model of convention emergence with local information (Walker & Wooldridge, 1995), with modifications based on the work described in Chapter 4. Each timestep, every agent in turn engages in an interaction with a randomly chosen neighbour, using a coordination game with ten possible choices (see Table 6.7 for the payoff function, $P_{x,d,r}$). Since social imitation and information propagation are fundamental processes in the emergence of conventions, we split strategy selection for each agent into two mechanisms: (i) *personal*, based on the individual's direct interaction history, and (ii) *social*, based on the interactions an individual has observed (see Section 4.5.6 for details). When selecting a strategy, agents choose uniformly at random between personal and social choices.

	0	1	...	9
0	4,4	-1,-1	...	-1,-1
1	-1,-1	4,4	...	-1,-1
⋮	⋮	⋮		⋮
9	-1,-1	-1,-1	...	4,4

Table 6.7: Payoff structure for the 10-action coordination game.

In typical real-world open MAS, we can assume that agents will have a wide variety of goals, architectures and internal algorithms. To model this heterogeneity, we use a variety of strategy selection mechanisms. For personal experience, agents' strategy selection ($ss_{x,d,r}$) and update ($su_{x,d,r}$) functions are implemented using either a Q-learning algorithm (Waktins, 1989) or WoLF-PHC (Bowling, 2001). When selecting a strategy based on social experience, an agent's $ss_{x,d,r}$ and $su_{x,d,r}$ functions are implemented using either Q-learning, WoLF-PHC, Highest Cumulative Reward (HCR) (Walker & Wooldridge, 1995), or Most Recently observed (MR). At the start of the simulation, each agent is initialised with a mechanism for personal and a mechanism for social choice chosen uniformly at random, giving a total of 8 possible agent configurations. Agents explore in 10% of interactions by selecting a strategy uniformly at random.

The ideal goal is for the population to converge to a state in which every agent selects the same strategy, resulting in population-wide coordination. In practice, we find that around 3 or 4 strategies persist as co-existing conventions, each having similar numbers of adherents. We define a “win” as a simulation run in which the dominant strategy (i.e. the strategy or lexicon with the highest number of adherents) is that used by the IA, and use the normalised number of wins over 20 simulation repeats as our metric of influence. Due to the co-existence of conventions with similar adherence numbers, the exploration of agents, and the higher possibility of a win being the result of chance, influence is harder to measure accurately in this domain.

6.7 Results

We structure the results of evaluating our methodology as follows: initially, we focus on the language coordination domain, and analyse the predictive power of each individual metric. Subsequently, we analyse the results of learning influence prediction models, and demonstrate that refining models learnt from the initial individual metrics can significantly improve accuracy. We corroborate our results in the coordination game domain, and finally use our results from both domains to derive the properties of an ideal measure of influence.

6.7.1 Targeting IAs using individual metrics

Inspecting the extent to which individual metrics predict influence may allow us to refine our models, and analysis of the correlations between each metric and influence reveals that Degree, EC, HEE, and HITS all robustly correlate with influence over all networks. These metrics are statistically significantly correlated in over 90% of the networks (with correlations ranging from 0.68 in the arXiv networks to 0.27 in the Enron networks), whereas the other metrics statistically significantly correlate only in isolated networks (on average, in 48% of networks). Correlating with influence in isolated networks is likely to be due to unique network structures, and these metrics are less likely to indicate influential nodes in the general case. This corroborates previous research on the link between node degree and influence (e.g. Chen *et al.* (2009)), but to our knowledge this is the first time that EC, HEE and HITS have been shown to predict influence.

Ranking nodes by each of the four identified metrics results in significant overlap over the top 5 nodes — with 7.8 unique nodes over the top 5 for each metric (a 0.39 proportion, standard deviation 0.15), where disjoint sets would give 20 unique nodes. While each metric selects roughly similar sets as being the most influential, their relative rankings are unique. Figure 6.3 plots normalised EC, HEE and HITS against degree, from which we can see the correlations. Interestingly, HEE and HITS clearly bisect the population, which may be useful for splitting a population into influential and non-influential nodes, while EC has an approximately linear relationship with degree.

Table 6.8 shows the average lexicon similarity and the number of wins for placing an IA at the location that maximises each heuristic, where a win is defined as a simulation run in which the dominant lexicon in the population has at most 2 different mappings from the IA lexicon. Results are averaged over each class of network sample. We see significant gains across all four metrics, particularly in the arXiv and Enron networks. With random placement, an agent is only able to successfully influence the population 2 times in 100, but placing by heuristic can increase this to 60 times in 100. There is no consistency in which metric performs best across network samples, and this is likely to be due to unique network structures in each class of network.

The synthetic networks show very few gains in influence using targeted placement, and very few of the metrics significantly correlate with influence for these networks. We believe that the networks generated by current synthetic genera-

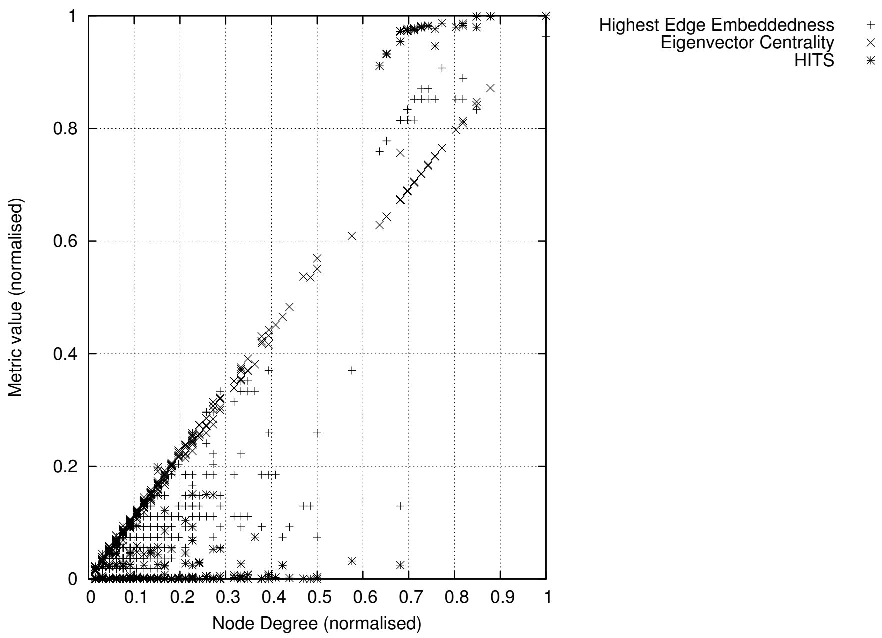


Figure 6.3: Correlation of HEE, EC, and HITS with node degree in an example arXiv-SNS network sample.

tion algorithms are too homogeneous for any given location to gain significant influence over others, and our results demonstrate that, since the potential for influence is so much lower, the synthetic networks used here are poor models of networks found in the real world. Accordingly, we focus only on the real-world network samples for the remainder of this thesis.

6.7.2 Targeting IAs using learnt models

We subsequently apply our methodology by learning three models: (i) the Principal Component (PC) that most correlates with influence, (ii) a Linear Regression (LR) model on all 14 metrics, and (iii) a linear regression model on Degree, EC, HEE and HITS (4LR), which are the best 4 heuristics as discussed above. We consider two sampling approaches for selecting a representative set of nodes: random and stratified (as described in Section 6.3).

We trained our model as follows. For each combination of sampling technique (i.e. SNS, MHRW and MHRW-DA) and network (i.e. arXiv, Enron, Gnutella),

Network	Average lexicon similarity					Number of wins (normalised)				
	Degree	HE	EC	HITS	Random	Degree	HE	EC	HITS	Random
arXiv-SNS	0.58	0.54	**0.6**	0.54	0.16	0.47	0.41	**0.5**	0.40	0.03
arXiv-MHRW	0.54	**0.6**	0.56	0.58	0.18	0.41	**0.50**	0.47	0.42	0.02
arXiv-MHRWDA	**0.6**	0.58	0.56	0.48	0.16	**0.5**	**0.5**	0.47	0.37	0.02
Enron-SNS	**0.58**	0.56	0.48	0.54	0.16	0.45	**0.47**	0.34	0.42	0.02
Enron-MHRW	0.62	0.48	0.55	**0.63**	0.16	0.55	0.41	0.44	**0.56**	0.02
Enron-MHRWDA	0.56	0.58	**0.6**	**0.6**	0.16	0.47	0.47	**0.6**	**0.6**	0.02
Gnutella-SNS	0.4	0.3	0.38	**0.5**	0.18	0.30	0.18	0.25	**0.41**	0.06
Gnutella-MHRW	0.22	0.18	0.2	**0.38**	0.16	0.08	0.05	0.06	**0.21**	0.02
Gnutella-MHRWDA	0.3	0.2	0.3	**0.34**	0.18	**0.2**	0.06	0.17	0.18	0.04
Eppstein-5000	0.35	**0.40**	0.17	0.265	0.19	**0.4**	0.33	0.05	0.1	0.1
Eppstein-10000	**0.46**	0.32	0.20	0.25	0.23	**0.25**	0.2	0.05	0.2	0.15
Kleinberg-CE1-1c	**0.31**	0.21	0.14	0.2	0.19	**0.25**	0.13	0.05	0.1	**0.25**
Kleinberg-CE1-3c	0.25	0.22	0.31	**0.29**	0.23	0.2	0.13	0.2	**0.23**	0.14
Kleinberg-CE1-7c	**0.37**	0.3	0.16	0.244	0.23	**0.3**	0.23	0.07	0.13	0.14
Kleinberg-CE10-1c	0.19	0.16	0.15	**0.28**	0.27	0.1	0.1	0.1	**0.2**	0.1
Kleinberg-CE10-3c	0.15	0.17	0.19	**0.28**	0.2	0.07	0.1	0.1	**0.17**	0.12
Kleinberg-CE10-7c	**0.44**	0.17	0.25	0.26	0.29	**0.37**	0.17	0.17	0.1	0.12

Table 6.8: Average lexicon similarity and number of wins for placing a single fixed-strategy agent (IA) either at a location maximising one of the chosen metrics or randomly. The best performing placement strategies are in bold. In the Kleinberg networks, the "CE" annotation indicates the clustering exponent (a parameter of the algorithm) used to generate the network.

there are five network samples, from which 50 nodes are selected for IA placement either randomly or using stratification. We divide the data on how influential each location is in each network sample into four network samples for training, and one network sample for testing, for each possible combination of the five networks into four and one. Once trained, we measured the correlation between the predicted influence and measured influence for the testing data (to gain an estimation of the accuracy of our technique). Finally, we train the model on all available data for a network sample, and use it to predict which locations might be most influential. We evaluate this prediction by running simulations with an IA at the location predicted as maximising influence.

Table 6.9 shows the average correlations between predicted influence and actual influence for the test data, demonstrating that models learnt on randomly sampled nodes are particularly poor at predicting influence. Learning on stratified data shows high correlations, indicating higher quality models. This corroborates our hypothesis that there are relatively few nodes of influence in a network, with the majority having similar and low influence. Consequently, a random node sample is unlikely to select many high influence nodes, which reduces the quality of learnt prediction models. A random node sample is therefore not representative in terms of influence, and so the stratified approach should be used. Figure 6.4 plots the predicted influence in an arXiv-SNS network sample using the LR model on a stratified node sample, and we can clearly see that less than 10% of the nodes account for almost all the influence. The Gnutella-MHRW network sample does not fit a linear regression model using randomly sampled data, since the majority of nodes are zero-valued for many of the metrics. This occurs for nodes of very low degree, and is an extreme example of the effect discussed above.

To evaluate the efficacy of each prediction model, we place an IA at the location predicted as most influential by each model, and repeat the simulations. Table 6.10 shows the average lexicon similarity and normalised number of wins using models learnt on stratified node sampling. We have omitted results for models learnt using random node sampling, since they are less effective: across all networks, the average lexicon distance is 0.35 (standard deviation 0.1) and the average proportion of wins is 0.2 (standard deviation 0.12). Nodes selected as influential by the models learnt from random node sampling exhibit less than half the influence of those selected by either individual heuristics or the models learnt from stratified sampling, indicating that random sampling of nodes does not give a sufficient range of influential nodes to learn accurate models.

Targeting IAs using locations predicted as influential by learnt models based on stratified data results in significant gains in influence. In the arXiv, Enron and Gnutella-SNS network samples, these increases are roughly equal to that gained by placing by single metric over random placement. In the arXiv and Enron network samples, the best performing model is 4LR, indicating that the other metrics are unlikely to contribute significantly to influence prediction. We believe that 4LR is learning *which* metric is best to place by, given the results in Table 6.8, since the results from placing by 4LR are roughly equivalent to placing by the *best* performing metric (out of the four) for each network sample. In Gnutella, 4LR is always outperformed by PC or LR, indicating that met-

	Random			Stratified		
Network	PC	LR	4LR	PC	LR	4LR
arXiv-SNS	-0.08	0.164	0.19	0.71	**0.91**	0.90
arXiv-MHRW	0.018	0.10	0.11	0.67	**0.93**	0.92
arXiv-MRHWDA	-0.03	0.34	0.08	0.75	**0.88**	0.86
Enron-SNS	-0.03	0.16	0.13	0.69	0.80	**0.85**
Enron-MHRW	-0.10	0.17	0.21	0.71	**0.88**	0.87
Enron-MHRWDA	0.08	0.06	-0.03	0.73	**0.90**	0.89
Gnutella-SNS	-0.01	0.03	-0.10	0.33	**0.67**	0.58
Gnutella-MHRW	0.02	-	-	0.44	**0.75**	0.65
Gnutella-MHRWDA	0.09	-0.15	0.06	0.36	**0.73**	0.52

Table 6.9: Correlation of each learnt model with measured influence, using separate training and test data, over each class of network sample and learnt on both random and stratified node sampling. Bolded entries indicate the highest correlation for that network sample.

rics other than Degree, EC, HEE and HITS are indicative of influence in these networks. Moreover, the linear combination of metrics in each of these network samples outperforms placement by single metrics. The Gnutella network samples show a reduced potential for influence compared to the samples from the Enron and arXiv networks, and exhibit lower edge counts, average degree, and clustering coefficients, and higher diameters. All these properties reduce the ability of an agent to exert influence, and may provide an indication of the likely efficacy of our methodology prior to application.

Our results suggest that if computational expense is an issue, targeting by Degree (or EC, HEE or HITS) will yield significant gains in influence, but if computational expense is less important, then applying our methodology results in further gains. If our methodology is applied using online measurements of influence (i.e. not requiring repeated simulations), the computational cost is significantly reduced.

6.7.3 Targeting IAs in the coordination game domain

The results given above suggest that agents can attain significant gains in influence by exploiting knowledge of the topological structure connecting agents. However, the results given so far are only for the language coordination domain, and to demonstrate generality it is necessary to test the extent to which

Network	Average lexicon similarity				Number of wins (normalised)			
	PC	LR	4LR	Random	PC	LR	4LR	Random
arXiv-SNS	0.44	0.42	**0.58**	0.16	0.34	0.30	**0.50**	0.03
arXiv-MHRW	0.5	0.32	**0.62**	0.18	0.42	0.20	**0.55**	0.02
arXiv-MHRWDA	0.34	0.38	**0.6**	0.16	0.22	0.27	**0.50**	0.02
Enron-SNS	0.62	0.32	**0.68**	0.16	0.56	0	**0.62**	0.02
Enron-MHRW	0.2	0.5	**0.58**	0.16	0.30	0.36	**0.53**	0.02
Enron-MHRWDA	0.34	0.16	**0.52**	0.16	0.21	0.06	**0.43**	0.02
Gnutella-SNS	0.18	**0.46**	0.36	0.18	0.03	**0.37**	0.24	0.06
Gnutella-MHRW	**0.4**	**0.4**	0.24	0.16	0.27	**0.29**	0.10	0.02
Gnutella-MHRWDA	**0.38**	0.36	0.36	0.18	**0.25**	0.24	0.22	0.04

Table 6.10: Average lexicon similarity and normalised number of wins when placing an IA at a location chosen by the predictive models. The best performing placement strategies are shown in bold.

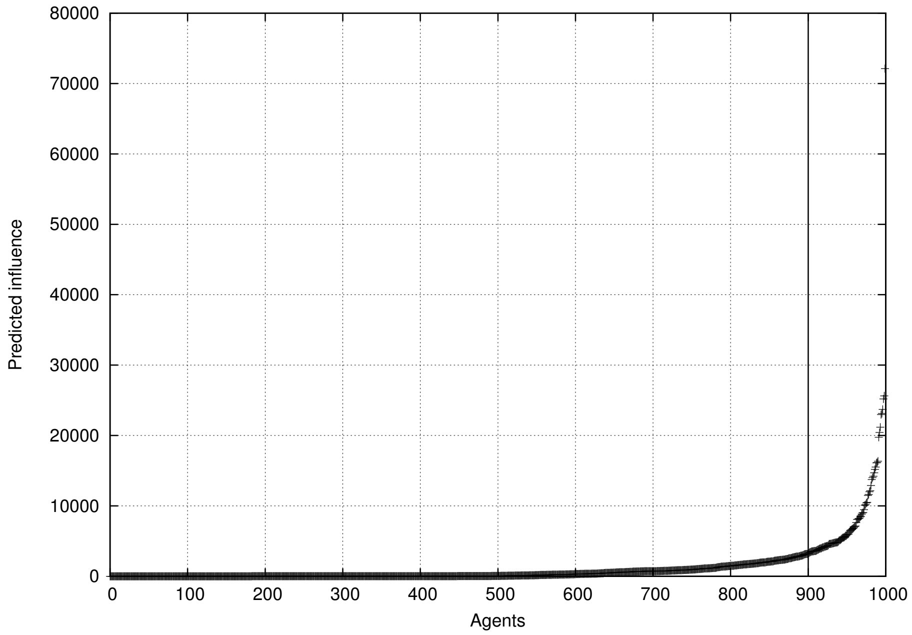


Figure 6.4: Predicted influence for each node in an example SNS sample from the arXiv network. Less than 10% of the individuals in the network account for almost all of its influence.

agents can gain influence from targeting placement according to a prediction model based on topological characteristics in another domain. Accordingly, in this section we present results from targeting IAs within the coordination game domain described in Section 6.6.2. We initially target locations predicted as influential by each of the four single metrics previously identified in Section 6.7.1. We build new prediction models with data generated from running coordination game domain simulations for the same (stratified by degree) node sets as those used in Section 6.7.2. This allows us to directly compare the quality of models learnt using different agent interaction processes and metrics of influence. In contrast, in Section 6.7.4 we use the actual models learnt in Section 6.7.2 in the coordination game domain to determine the extent to which these models predict influence across domains.

Table 6.11 shows the results from placing a single IA at the location maximised by each heuristic metric identified in Section 6.7.1. We can see roughly similar trends, in that the arXiv and Enron network samples see significant gains in influence while the Gnutella samples exhibit relatively small gains. The gains in influence are not as large as in the language coordination domain and this is likely to be because the combination of multiple co-existing conventions with similar numbers of adherents, agent exploration, and reduced convention space size result in a domain in which influencing the population is more difficult. It may also be that the scope for influence, as imbued purely by network structure, is reduced in this domain simply due to its inherent mechanisms. Nonetheless, there is still clearly potential for targeting individual locations for gains in influence.

Table 6.12 shows the normalised number of wins attained by applying the influence learning methodology using the coordination game and the coordination game domain. While increases in influence are clearly evident, with similar trends as those observed in the language coordination domain, the scale of influence gain is reduced, and is smaller than the gain obtained when placing by single heuristics compared to random placement. As discussed above, there

Network	Number of wins (normalised)				
	Degree	HEE	EC	HITS	Random
arXiv-SNS	**0.43**	0.33	0.41	0.40	0.11
arXiv-MHRW	0.39	0.35	**0.40**	0.36	0.10
arXiv-MHRWDA	**0.43**	0.42	0.38	0.33	0.09
Enron-SNS	0.38	**0.40**	0.33	0.38	0.10
Enron-MHRW	0.45	0.39	0.37	**0.47**	0.10
Enron-MHRWDA	0.42	0.38	**0.48**	**0.48**	0.09
Gnutella-SNS	0.28	0.23	0.23	**0.35**	0.09
Gnutella-MHRW	**0.18**	0.12	0.15	**0.18**	0.12
Gnutella-MHRWDA	0.12	0.23	**0.25**	0.18	0.08

Table 6.11: Normalised number of wins when placing an IA at a location selected by maximising each of the four heuristic metrics identified in Section 6.7.1 in the coordination game domain. Best performing metrics are highlighted in bold.

Network	Number of wins (normalised)			
	PC	LR	4LR	Random
arXiv-SNS	0.13	0.16	**0.25**	0.11
arXiv-MHRW	0.18	0.14	**0.26**	0.10
arXiv-MHRWDA	0.17	0.12	**0.22**	0.09
Enron-SNS	0.10	0.13	**0.23**	0.10
Enron-MHRW	0.12	0.10	**0.24**	0.10
Enron-MHRWDA	0.11	0.14	**0.23**	0.09
Gnutella-SNS	0.13	**0.17**	0.15	0.09
Gnutella-MHRW	**0.23**	0.19	0.15	0.12
Gnutella-MHRWDA	**0.19**	0.16	0.13	0.08

Table 6.12: Normalised number of wins when placing an IA at a location chosen by the predictive models, using the coordination game domain. The best performing placement strategies are shown in bold.

are a number of reasons for this (including agent exploration, smaller convention space and increased probability of similarly sized co-existing conventions). Accordingly, the variance in IA efficacy is much higher between identically configured runs, and there is more noise in the data learnt by the methodology. The predictions of influence are consequently less likely to be accurate.

Furthermore, there are only ten discrete strategies in the coordination game domain, and switching strategies can involve non-trivial costs. In particular, given that a number of conventions co-exist with similar membership sizes, an agent being influenced to a given strategy can directly result in subsequent costs if that agent interacts with a neighbour adhering to a different convention. In the language coordination domain, the convention space is quasi-continuous and switching convention is less likely to incur costs (consider that if an agent alters one mapping in a lexicon, that mapping may not be used in a communication for some time). This leads to two effects: (i) agents are less likely to incur costs as a result of altering convention in the language coordination domain, leading to increased likelihood of being successfully influenced (as opposed to being influenced, incurring a cost and switching to another strategy), and (ii) in the coordination game domain the methodology has to learn on the number of absolute wins, rather than the more fine grained measure of lexicon distance. As a result of the second issue, the learning algorithms have less detailed data on which to learn, further reducing the efficacy of the methodology.

6.7.4 Using learnt models in other domains

A major component of our hypothesis regarding the poorer results in the coordination game domain is that the data available is less suitable for accurate learning. To test this, we re-ran simulations in the coordination game domain, but placed IAs at the position predicted as most influential by the models learnt using data from the language coordination domain, which had resulted in models that appeared to predict more influential locations.

Table 6.13 plots the normalised number of wins attained in these exper-

Network	Number of wins (normalised)			
	PC	LR	4LR	Random
arXiv-SNS	0.3	0.21	**0.37**	0.11
arXiv-MHRW	0.16	0.19	**0.35**	0.10
arXiv-MHRWDA	0.16	0.15	**0.30**	0.09
Enron-SNS	0.40	0.14	**0.76**	0.10
Enron-MHRW	0.28	**0.45**	0.26	0.10
Enron-MHRWDA	0.15	0.15	**0.55**	0.09
Gnutella-SNS	0.11	0.1	**0.36**	0.09
Gnutella-MHRW	**0.19**	0.13	**0.19**	0.12
Gnutella-MHRWDA	0.19	**0.21**	0.20	0.08

Table 6.13: Normalised number of wins gained by placing an IA at a location chosen by the predictive models learnt on the language coordination data, using the coordination game domain. The best performing placement strategies are shown in bold.

iments. We can clearly see that using these models does result in gains in influence, despite using a model learnt on data from a different domain. This suggests that (i) the models learn intrinsic influence relating to the network structure itself, rather than as a result of the specific behavioural patterns exhibited by agents situated on the network, and (ii) that, to some extent, these models can be used to predict influence even when the behaviour of agents in the targeted domain is significantly different to that used to generate the data that teaches the models.

However, there are a number of interesting points exhibited in the data. Firstly, the gains in influence are, on average, less than those attained when using predictions within the same agent interaction domain. This may be either due to the coordination game domain having less potential for influence, or that the different agent behaviour models have different influence characteristics which undermines the predictions. Secondly, there is far higher variation in the results, especially with respect to the Enron network samples. We believe this to be a result of the coordination game domain itself having far higher variation in the outcomes of individual simulation runs. Finally, the Gnutella network samples display inconsistent behaviour in terms of which learnt models are best, and the learnt models appear to have fairly similar predictive power in this context.

Overall, we can conclude that learnt models for predicting influence from topological metrics, for the large part, do translate between different interaction domains. If a target domain does not have easily definable on-line influence metrics or off-line agent models, it may therefore be possible to use a simple interaction domain, such as the language coordination setting, to generate data on which to apply our methodology and still retain significant efficacy.

6.7.5 Deriving the properties of an ideal influence metric

These results demonstrate the importance of choosing an appropriate metric of influence. The interaction domains evaluated in this chapter both show similar gains in influence for placement by single metrics but differing gains in influence using learnt models. As discussed above, a major component of this disparity is due to the influence metric in the coordination game domain (i.e. the number of exact "wins") containing less information about the effect of the IA. We can subsequently hypothesise the properties that an *ideal* influence metric would exhibit, as follows.

1. *Continuous:* An ideal influence metric measures the *extent* of an agent's influence, and not simply whether it has influenced the majority of the population.

2. *Proportional:* An ideal influence metric maps linearly to the influence that an agent has exerted.

3. *Ease of measurement:* An ideal influence metric is easily measured. Both of the metrics for influence described in this chapter are measurable only with access to data for repeated simulations, however in some cases influence metrics may be easily measurable online (e.g. the number of re-tweets on Twitter).

4. *Signal to noise ratio:* The influence metric in the coordination game domain is subject to much higher variance than the metric in the language

coordination domain since (i) agents explore, and (ii) the smaller convention space implies that there is a higher probability of a win being the result of chance. An ideal metric should be particularly robust to noise and have a low variance in order to increase the accuracy of learnt models.

6.8 Conclusions and further work

In this chapter, we have proposed a methodology for learning the influence of nodes in a network. We evaluated our methodology using two representative domains of convention emergence on networks sampled using a variety of techniques from three real-world datasets. We corroborate results in the literature that degree is highly indicative of influence, and show that Eigenvector Centrality, Highest Edge Embeddedness, and HITS are also linked to influence. When placed at locations selected through application of our methodology, agents gain significant influence compared to random placement. In the arXiv and Enron network samples, the 4LR model, learnt on just node degree, EC, HEE, and HITS, gives gains in influence equivalent to targeting by the individual metric (of those four) that best predicts influence in that network sample. This indicates that the linear regression model learns which metric most predicts influence in that network sample. In the Gnutella network samples, the learnt models typically outperform single metric placement, and, in general, supervised learning using linear regression almost always outperforms unsupervised learning using PCA.

The models learnt on the arXiv and Enron network samples and on the Gnutella network samples are significantly different, indicating that the structural characteristics that imbue influence are, to some extent, unique to each class of network samples (and, potentially, to each individual network sample). The Gnutella network samples demonstrate (i) that using single metric heuristics does not guarantee optimal influence, and (ii) that different network structures exhibit significantly varied ranges of potential influence. We believe that the important global network metrics (such as average degree, clustering coefficient, or diameter) may indicate the potential for maximising influence in a given network, and we intend to explore this in future work, along with other agent interaction domains to ensure that our methodology generalises.

As discussed in Section 6.5, the differences in important topological metrics between different datasets is far greater than the differences in metrics in network samples taken from a single dataset. This implies that each network, and sub-networks sampled from them, have unique structures that can be characterised by structural analysis. In future work, it may be useful to determine if different classes of network with similar influence characteristics exist (as appears to be the case between sub-networks sampled from the Enron and arXiv datasets), and learn influence models for each class to be applied as necessary. This would remove, in many cases, the need to apply our full methodology repeatedly.

CHAPTER 7

Manipulating established conventions

In the previous two chapters, we have demonstrated how to manipulate conventions and how to exploit topological information to increase manipulation efficacy, but the IA mechanism was only tested during the initial emergence phase. As discussed in Chapter 4, there has been relatively little research into the middle and latter stages of the convention lifecycle. At this point, conventions have become established and the forces of precedence make influencing the population more difficult. In this chapter, we investigate how to manipulate conventions after establishment, by giving agents one-off rewards, and equipping IAs with sanctions and incentives to apply in their interactions, in an attempt to strengthen their influence and overcome the forces of precedence. We show that, after establishment, IAs are the most effective strategy (out of those investigated) for manipulating convention adoption, as long as there is a minimal level of population churn.

7.1 Introduction

Conventions, socially accepted standards of behaviour, have shown considerable promise in supporting coordinated behaviour in modern open MAS domains. As discussed in Chapter 1, we can expect these domains to be characterised by large, time-varying populations, uniform levels of authority, lack of centralised control, and a variety of stakeholders inserting agents with heterogeneous capabilities and goals. Conventions reduce costs associated with malcoordination and increase social welfare, and are particularly applicable since they can emerge in a decentralised manner. In Chapter 4, we discussed the significant progress in understanding the mechanisms by which conventions are established, but there has been comparatively little progress in understanding their behaviour in what we term the middle and latter stages of the convention life-cycle.

In particular, there may be a need to manipulate conventions, through either adding support or destabilisation, once they have become established. We can identify four major reasons for why interested parties may wish to manipulate conventions. Firstly, an inferior convention may be dominant in the population, in the sense that switching convention may increase levels of coordination. Secondly, environmental change may necessitate transitioning to a more appropriate convention. For example, encouraging "green" behaviour in the face of climate change illustrates the necessity and difficulty of such convention changes. Thirdly, an interested party may wish to encourage a more personally beneficial convention — if we consider brand preference as conventional behaviour, then each stakeholder has an interest in changing the convention to one favourable to their brand. Lastly, there may be an inappropriate number of conventions established to produce optimal behaviour. Typically, this can be interpreted as there being multiple conventions where the ideal situation is one, but in some situations (e.g. the El-Farol bar problem (Arthur, 1994)) the ideal goal is the co-existence of multiple conventions.

Since conventions typically emerge via agents modifying their interaction choices in response to previous history, there are significant feedback effects which can amplify the influence of targeted interventions. Determining which interventions are most effective is thus key to understanding how to manipulate conventions. Using a model of convention emergence with realistic assumptions, including heterogeneous learning mechanisms, complex network structures restricting interactions, and time-varying populations, we examine three mechanisms for manipulating conventions: (i) through one-off rewards targeted at specific individuals, (ii) through a small group of agents introduced into the population by interested stakeholders (that is, using the IA technique introduced in Chapter 5), and (iii) through a small group of agents applying sanctions and incentives in interactions in which they participate. The three mechanisms are embodied in the two strategies that we evaluate in this chapter, namely rewarding specific individuals at specific timesteps (i.e. an implementation of the first mechanism), and using IAs who are equipped with the ability to sanction or incentivise individuals with whom they interact (i.e. an implementation of the second two mechanisms).

We show that (i) one-off incentives are most effective when most of the population is undecided and conventions have not become significantly established, but lose almost all their efficacy as the forces of precedence stabilise and establish conventions, (ii) small proportions of agents can significantly influence populations to a given convention, for which incentives provide a small but measurable boost in efficacy, and (iii) sanctions, also applied in interactions by small proportions of agents, are ineffective, in our model of convention emergence, at manipulating conventions to any significant degree and are often counterproductive. Interestingly, this is contrary to some investigations into the role of sanctions (for example, Axelrod's (1986) evaluation of the role of sanctions in enforcing norms), and we discuss this further in Section 7.5.2. We also show that a minimal rate of population churn, in which agents join and leave the system, facilitates convention manipulation in systems where conventions are established and stable.

7.2 Background

In this section, we review the relevant literature surrounding the manipulation of conventions and the role of network structure in convention emergence.

7.2.1 Network structure

Network structure has been shown to have significant impact on the behaviour of conventions. Delgado (2002) has shown that conventions on complex networks (i.e. those that have scale-free degree distributions and logarithmically bounded shortest path lengths) emerge as efficiently as on fully connected networks, and Pujol *et al.* (2005) have shown that clustered networks allow more stable conventions to emerge under a wider range of conditions than non-clustered networks. High degree nodes are known to be important (e.g. Albert & Barabási (2002), Chen *et al.* (2009)), and have been shown to play a more influential role in convention emergence than low-degree nodes (Franks *et al.*, 2013) (as demonstrated in Chapters 5 and 6).

Given that we consider MAS in which agents join and leave freely, we can reasonably expect real-world instantiations to exhibit dynamic network topologies, with both the set of individuals and the connections between them changing over time. However, investigation into dynamic network topologies is still in its infancy, and accurately modelling dynamic topologies is likely to require a deep understanding of the domain-specific mechanisms that generate topological features. Consequently, static networks are used in the majority of research as a useful middle-ground between well-mixed populations and dynamic networks. While algorithms for generating dynamic networks that exhibit complex properties exist (e.g. Gonzalez *et al.* (2006)), there has been relatively little research into their efficacy in modelling specific domains, and we cannot therefore guarantee their generality. Accordingly, in this thesis we focus on time-invariant network topologies.

7.2.2 Manipulating conventions

Compared with the process of convention emergence, there has been comparatively little research into how conventions might be manipulated. Sen and Airiau (2007) demonstrated that a small proportion of agents can influence societies many times as large, but only used two possible conventions. Garlick and Chli (2009) have shown that "policemen" agents can be effective at limiting social unrest in an agent-based model. In Chapter 5, we extended these ideas and introduced the *Influencer Agent* (IA) concept, in which a small proportion of agents are inserted with goals and strategies chosen specifically to influence the population to adopt appropriate conventions (Franks *et al.*, 2013). We show in Chapter 5 that (i) IAs can significantly manipulate which convention emerges in a population, even with a large convention space, and (ii) positioning IAs using topological information can significantly increase their efficacy. Villatoro (2011) proposed local network rewiring and observation of neighbouring agents' actions as possible mechanisms for undermining meta-stable subconventions, with the goal of emerging a single unified convention across the entire population. Given the self-reinforcing nature of conventions, manipulation after establishment may be difficult.

Boyer and Orlean (1992) have examined convention manipulation from a socio-economic perspective, and propose four situations in which convention change might occur: (i) a general collapse may alter the existing convention structure, (ii) an external group adhering to an alternate strategy may invade the population, (iii) a certain compatibility between conventions may reduce transition costs[1], and (iv) individuals may agree to change conventions through collective agreement. Since situation (iii) does not translate effectively into many convention emergence models, and situation (iv) in most cases requires a centralised authority, we consider situations (i) and (ii) as the most directly applicable to MAS research.

[1] Transition costs may be environmental, as in the costs associated with switching which side of the road a country drives on, or personal, as when an individual switches convention and subsequently encounters an individual using a contrary convention.

These both represent special cases of a change in the environment, which we consider to include the payoff function, the agent population, the set of strategies available, and the underlying network structure constraining interactions between agents. Depending on the domain, some or all of these may be open to manipulation by interested parties. Targeted changes to the payoff structure can encourage agents to pick alternate strategies, and external invasion by groups of agents demonstrates to other individuals the efficacy of alternate strategies. Both techniques then trigger the precedence feedback loop and may allow the targeted strategy to gain adherents.

7.3 Mechanisms for manipulating convention emergence

To effectively manipulate conventions, we potentially only need to encourage a small proportion of agents to act as desired, and subsequently allow the forces of precedence to propagate the choice throughout the population. We can do this in one of two ways: (i) encouraging the agent to choose an action by altering the reward it gets from its choices, or (ii) altering the behaviour that the agent observes and incorporates into its calculations on precedence. In this chapter, we explore strategies designed to implement one or both of these mechanisms.

Specifically, we identify two strategies that implement (i) alteration of agent rewards, (ii) alteration of observed behaviour, and (iii) both alteration of rewards and behaviour. We propose one-off incentives to reward agents for certain choices, the insertion of small groups of agents in the form of IAs, with single fixed strategies, and equipped with incentives and sanctions for the interactions in which they participate. The use of IAs corresponds to instantiations, at different parameter settings, of strategies (ii) and (iii), while one-off incentives implements strategy (i). We believe these to be realistically implementable strategies: for example, a variety of companies already use one-off rewards or employed individuals to aid brand propagation (Delre *et al.*, 2010) in a manner analogous to strategies (i) and (ii).

IAs are an attractive solution to problems of convention emergence since they are applicable to highly decentralised systems, do not require modification of agent architectures, strategies or goals, and are effective at manipulating populations many times their size. Therefore, IAs are highly suited for practically applying incentives and sanctions in several real-world domains.

7.4 Model of convention emergence and experimental setup

To evaluate our strategies for manipulating conventions, we require a model of convention emergence that accounts for the kind of conventions typically observed in open MAS. Specifically, we assume that agents use heterogeneous learning algorithms, incorporate notions of social imitation, are situated on realistic network structures, and that the population changes over time.

Our model of convention emergence is loosely based on Sen and Airiau's model of private learning (Sen & Airiau, 2007) and Walker and Wooldridge's model of convention emergence with local information (Walker & Wooldridge, 1995). The interaction regime (IR) is defined as follows: each timestep, every agent in turn engages in an interaction with a randomly chosen neighbour, with the payoff function ($P_{x,d,r}$) using a coordination game with ten possible choices (Table 7.1).

	0	1	...	9
0	4,4	-1,-1	...	-1,-1
1	-1,-1	4,4	...	-1,-1
⋮	⋮	⋮		⋮
9	-1,-1	-1,-1	...	4,4

Table 7.1: Payoff structure for coordination game.

A variety of research has demonstrated two key sources for information on which to base decision making (e.g. Sen & Airiau (2007), Young (1996)), namely,

(i) *personal*, using an individual's direct interaction history, and (ii) *social*, using the interactions that an individual has observed but not directly participated in. We model this by splitting an agent's learning along these lines, with separate mechanisms selecting a choice based on each source. In a given interaction, agents choose between personal and social choice according to a system-wide parameter α, where $\alpha = 0$ indicates that agents will always use personal experience alone to make strategy selections, $\alpha = 1$ indicates social choice alone, and $\alpha = 0.5$ indicates an agent will randomly choose between personal and social experience, using each roughly half the time. Research on the role of social imitation in convention emergence is limited: personal experience is sufficient for convention emergence (Sen & Airiau, 2007), but observation of behaviour has also been shown to be an effective mechanism by which norms can emerge (Axelrod, 1986). Young has argued that observation of behaviour is key to propagating information regarding established conventions (Young, 1996). Parameterising the system with α facilitates exploration of the impact of social observation and imitation in the emergence and manipulation of conventions.

With regards to social experience, we use the parameter *obs* to determine the proportion of the neighbours of interaction participants that observe the results of interactions. When $obs = 0$ only the participants of an interaction will know the results, whereas when $obs = 1$ every neighbour observes the outcome. When $obs = 0.5$ exactly half of the neighbours are randomly chosen to observe an interaction.

In typical real-world open MAS, we can assume that agents will have a wide variety of goals, architectures, and internal algorithms. To model this heterogeneity, we use a variety of strategy selection mechanisms. For personal experience, agents' strategy selection ($ss_{x,d,r}$) and strategy update ($su_{x,d,r}$) are implemented using either Q-learning (Waktins, 1989) or WoLF-PHC (Bowling, 2001). When selecting a strategy based on social experience, an agent learns using either Q-learning, WoLF-PHC, Highest Cumulative Reward (HCR) (Shoham & Tennenholtz, 1997), or Most Recently observed (MR). At the start of the simulation, each agent is initialised with the mechanisms for personal and social choices chosen uniformly at random, giving a total of 8 possible agent configurations. Agents explore in 10% of interactions by selecting a strategy uniformly at random.

We situate agents on an underlying network structure that restricts their interactions to immediate neighbours. The impact of network structure on aggregate population behaviour is significant and, as discussed above, has been shown to influence the emergence of conventions in a variety of ways. Consequently, using realistic networks is fundamental to ensuring the generality of our results. As in Chapter 6, we use the arXiv general relativity collaboration network and a P2P network formed using the Gnutella file-sharing program, and we also use the email network of an EU institution[2].

These networks are too large to practically be used in simulations, and so we sampled networks of 1,000 nodes using Snowball Sampling (SNS), Metropolis-Hastings Random Walk (MHRW) (Gjoka *et al.*, 2010), and Metropolis-Hastings Random Walk with Delayed Acceptance (MHRWDA) (Lee *et al.*, 2012). SNS provides good local coverage of a network but has been shown to be biased towards high-degree nodes (Gjoka *et al.*, 2010). MHRW provides a uniform sampling and preserves the degree distribution of sampled networks (Gjoka *et al.*, 2010), but in our experiments we have found that it does not necessarily preserve the small-world nature of networks (i.e. where the characteristic path length of networks is bounded by the logarithm of the number of nodes). MHRW-DA follows MHRW, except that it modifies the transition probabilities of the random walk to reduce the chance of traversing parts of the network that have already been visited (Lee *et al.*, 2012). While ideal sampling techniques, which preserve every structural feature of interest from the sampled network, do not exist, we believe the combination of SNS, MHRW and MHRWDA allows us to test our strategies for manipulating conventions on a large set of realistic structures. We create one network sample using each sampling algorithm on each dataset,

[2]All taken from the Stanford large network dataset collection http://snap.stanford.edu/data

resulting in 9 distinct networks on which we evaluate our strategies.

IAs are modelled as agents with a single fixed strategy, namely the strategy that is being targeted for manipulation. As discussed above, one of our strategies for manipulating conventions is equipping IAs with sanctions and incentives. This is instantiated by each IA being able to modify the payoff received by interaction participants in any interaction containing an IA. If the interaction participant chooses the IA strategy (i.e. both agents choose the same strategy), then the IA multiplies the payoff received by the partner by a factor of $incentive = \{1, 2, 5, 10\}$. If the interaction partner chooses a different strategy (and the agents do not subsequently coordinate), then the IA can multiply the payoff by the partner received by a factor of $sanction = \{1, 1.5, 5, 10\}$. Recall that this payoff will be negative due to non-coordination. Note that for the first non-trivial multiple, we use 2 for incentives and 1.5 for sanctions. Since sanctions are likely to be applied more often (in any interaction, there are 9 possible "wrong" choices, but only 1 "correct"), we are more interested in determining if small sanctions have any effect, since these will result in lower expenditure. As a result, we evaluate sanctions using 1.5 as an arbitrary multiplier that is lower than 2.

One-off incentives are modelled by giving each targeted agent a single payoff of size $r = 5, 10, 50, 100$ for the targeted strategy, as though that agent had selected the targeted strategy in an interaction. Since the typical payoff for choosing a coordinated strategy is 4 (that is, when no sanctions or incentives are applied), these values of r equate to 1.25, 2.5, 12.5, or 25 times the maximum payoff receivable in interactions. These are therefore much larger than the incentives applied by IAs, but differ in that they only occur once in the simulation.

In typical real-world domains, we can expect the population to change significantly over time as agents join and leave. We model this using a simple instantiation of population churn, with the following limiting constraints: (i) we do not change the network structure over time and (ii) we hold the population size constant. Dynamic network structures, while more realistic, are difficult to accurately model. Given the importance of realistic network structures noted above, we believe that introducing dynamic network topologies would undermine the generality of our work. Consequently, we model churn using a parameter $PC = \{0, 0.001\}$ that represents the proportion of churn in the population: each timestep PC agents are entirely reset (i.e. their personal and social experience is deleted and new learning algorithms are chosen). As such, this simple model of population churn allows us to test the effect of new agents on the forces of precedence, but not the effects of changing network structure.

The proportion of interactions in which an agent selects a given strategy s over the last 20 interactions is called the *adherence* of that agent to s. Following Lewis' definition of convention as a regularity in behaviour (see Chapter 4 for more detail), we call a strategy a convention if at least one agent has an adherence of at least 0.9. Such agents are *members* of the convention. To evaluate the efficacy of our manipulations, we measure a convention's *membership*, the number of members, and its *rank* in terms of membership. To measure the relative cost of each of our strategies, we also calculate the total *expenditure* in terms of the amount of additional payoff awarded to agents throughout the simulation. Although this is an abstract measure in our model, in real-world domains incentives will typically translate into costs for the incentivising party — for example, companies promoting brand adherence may reward targeted individuals with products, with each product having a cost to the company. Since we make no assertions on how our payoff structures translate to real-world value, we use total expenditure as a guide for ranking the relative efficiency of our strategies.

We use 4000 timesteps in all simulations, and statistical significance is tested using Pearson's Correlations with a confidence of 95%. Data for each manipulation strategy is averaged over 30 runs for each configuration given on each network. Unless otherwise stated, we use $\alpha = 0.5, obs = 1$.

Table 7.2 summarises the parameter settings used for experiments presented in this chapter.

Parameter	Values	Description
$\|\Sigma\|$	10	Number of possible strategies/conventions
α	$\{0, 0.5, 1\}$	Probability of using social experience in strategy selection
obs	$\{0, 1\}$	Probability of each neighbour observing an interaction
Social $su_{x,d,r}$	WoLF-PHC Q-Learning HCR Most Recent	Strategy update for social experience
Personal $su_{x,d,r}$	WoLF-PHC Q-Learning	Strategy update for personal experience
G	arXiv-SNS arXiv-MHRW arXiv-MHRWDA Gnutella-SNS Gnutella-MHRW Gnutella-MHRWDA EU-Email-SNS EU-Email-MHRW EU-Email-MHRWDA	Network structures used
$incentive$	$\{1, 2, 5, 10\}$	Incentive factors applied by IA
$sanction$	$\{1, 1.5, 5, 10\}$	Sanction factors applied by IA
r	$\{5, 10, 50, 100\}$	One-off rewards
PC	$\{0, 0.001\}$	Population churn
t	4000	Simulation length

Table 7.2: Table showing the key parameters used throughout simulations in Chapter 7

7.5 Results

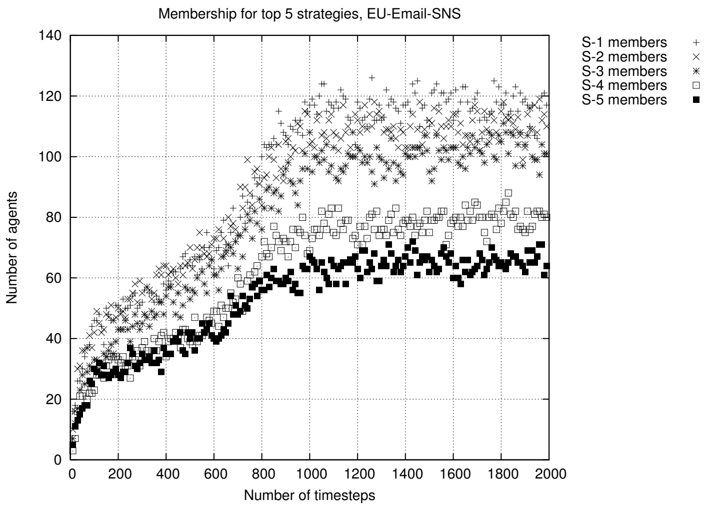
We consider three primary configurations of our model in which to test our strategies for manipulating conventions. The first configuration is with no population churn, and we introduce our strategies at $t = 0$. This represents an idealised situation — there are no pre-existing conventions and no agents have any historical data on which to base their decisions. In our second configuration, we introduce each strategy individually at $t = \{500, 1000, 1500\}$. In this setting, conventions are either already established or on their way to becoming established, and the forces of precedence are therefore far stronger. Finally, in our third configuration we introduce a small amount of population churn and apply each strategy individually at $t = \{500, 1000, 1500\}$. This setting is the most realistic of the three, with conventions pre-existing in a population and agents joining and leaving over time. We first present an overview of the general behaviour of our model and subsequently treat each configuration separately.

7.5.1 Baseline behaviour

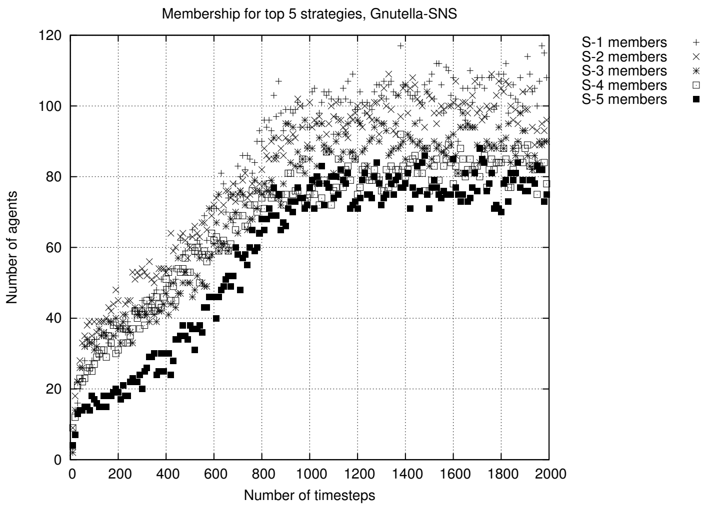
Initially, we analyse the general behaviour of our model without applying any of our strategies for convention manipulation.

Figures 7.1(a), 7.1(b), and 7.1(c) show the 5 top strategies, in terms of the number of agents that adhere to the strategy more than 90% of the time, for individual representative runs from the SNS network samples from each dataset. For reasons of space, we have omitted results for the MHRW/MHRWDA samples, but note that they display substantially the same behaviour as the SNS samples. We can see that the conventions that emerge (recall that we call any strategy with at least one member adhering to it 90% of the time a convention) stabilise in terms of adherents after around 1000—1200 timesteps, and that although one convention may dominate, there is always at least one other convention with a non-trivial number of adherents. Our model thus produces a set of conventions that co-exist and are stable. We have plotted each figure up to $t = 2000$ since the system stabilises and no further significant changes occur. The fluctuations in convention membership are largely due to the effect of agent exploration. For comparison, Figure 7.2 shows the membership for the top 5 strategies for a run with an identical configuration as Figure 7.1(c) except that agents do not explore, which leads to membership counts being far more stable.

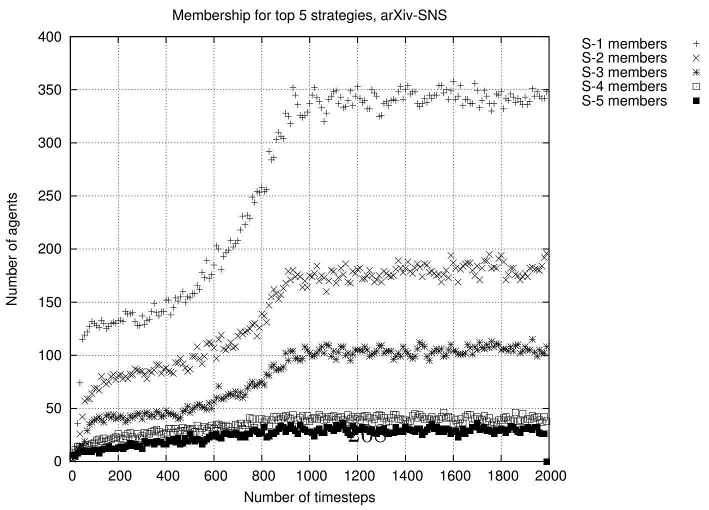
There are interesting differences in the behaviour between each network type. The arXiv network samples converge on a stable set of conventions around 200 timesteps earlier than the EU-Email and Gnutella network samples, and display a transition period during which convention membership starts rising rapidly and then stabilises. Conversely, the Gnutella and EU-Email network samples exhibit constant rises in membership counts until stabilisation, and also give rise



(a)



(b)



(c)

Figure 7.1: Membership counts for the top 5 strategies on (a) EU-Email-SNS and (b) Gnutella-SNS networks, and (c) arXiv-SNS, using $\alpha = 0.5$.

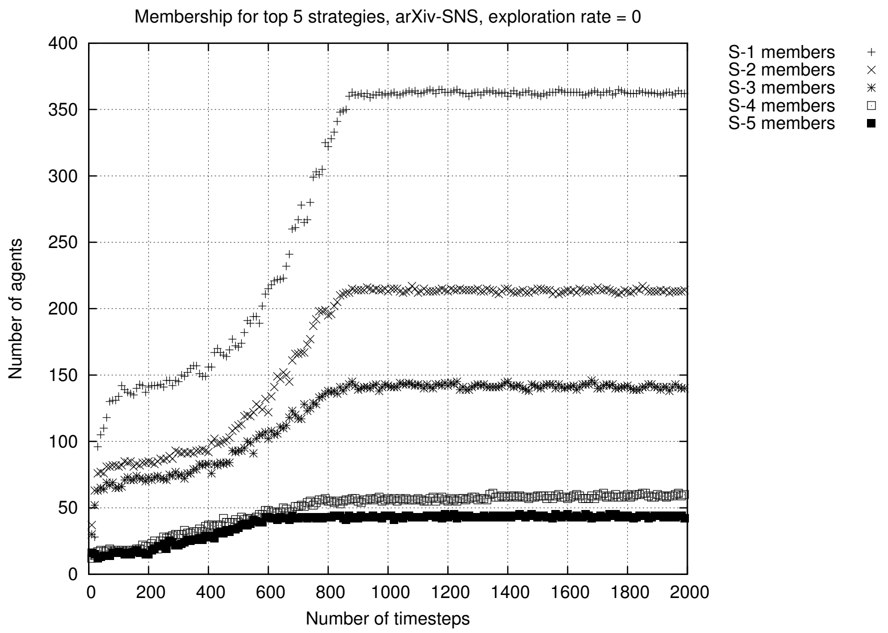
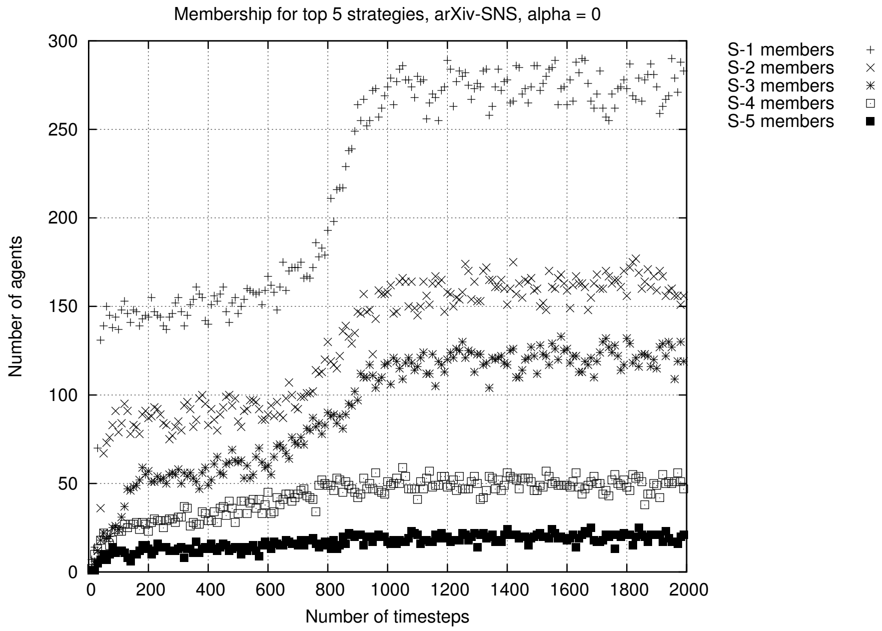


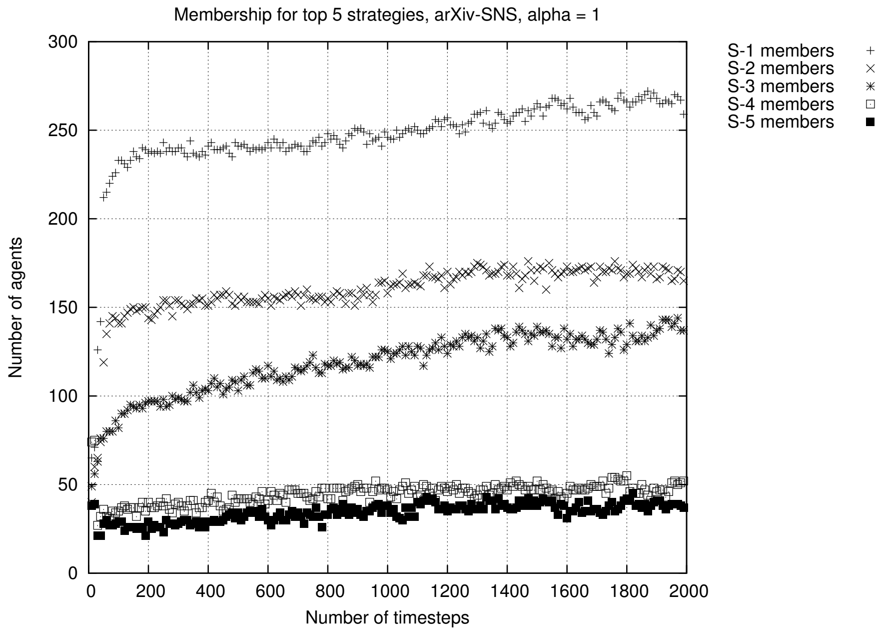
Figure 7.2: Membership counts for the top 5 strategies on arXiv-SNS with no agent exploration, and $\alpha = 0.5$.

to conventions that have much closer membership counts. The arXiv samples have much higher clustering coefficients than the other network samples (around 0.5 for arXiv compared to 0.005 for Gnutella), and this clustered structure may account for the faster emergence of conventions (Pujol *et al.*, 2005). Although there are differences in convergence behaviour between the networks, the macro-level behaviour is similar: agents converge on a set of co-existing conventions with up to 350 members (at the very highest) which remain largely stable after 1000—1200 timesteps and for the remainder of the simulation.

Although we test our strategies in the remainder of this chapter with $\alpha = 0.5$, such that there is an equal mix of personal and social experience being used by agents, there are differences in system behaviour evident from using $\alpha = 0$ or $\alpha = 1$. Figures 7.3(a) and 7.3(b) show representative runs on an arXiv-SNS network sample with each boundary value of α. The other network samples display substantially the same behaviour, and as such we have omitted detailed figures for them here. The behaviour with $\alpha = 0$ is similar to $\alpha = 0.5$, although



(a)



(b)

Figure 7.3: Figure showing membership counts for the top 5 strategies on arXiv-SNS with (a) $\alpha = 0$ and (b) $\alpha = 1$.

Prop. Rewarded	0.01			0.1		
Reward Amnt.	10	50	100	10	50	100
Random	0.6 (12)	1.2 (19)	1.0 (18)	1.6 (24)	2.6 (70)	2.5 (66)
Degree	0.1 (20)	2.1 (34)	2.2 (29)	3.2 (34)	4.7 (135)	4.7 (206)

Table 7.3: Increase in rank and membership (in parentheses) of targeted convention after rewarding a proportion of individuals at $t = 0$, selected either randomly or by highest degree, with $\alpha = 0.5$.

the membership of each convention is slightly reduced compared with $\alpha = 0.5$. When $\alpha = 1$, and agents use only social experience in determining which strategy to use, convergence is extremely quick and convention memberships only change gradually after around 200 timesteps. Membership counts for individual conventions are again slightly lower, and for both $\alpha = 0$ and $\alpha = 1$ the total number of agents that are members of a convention are lower. For the remainder of this chapter, we use $\alpha = 0.5$, as we believe it realistic to assume that agents will take into account both personal and social experience when determining what strategies to choose.

Figure 7.4 shows the results of introducing population churn on the arXiv-MHRWDA samples, such that one agent is randomly reset each timestep. We see two main consequences: (i) conventions are less stable and membership counts fluctuate more, and (ii) overall membership counts are reduced by up to 150 agents per convention. This is to be expected, since newly joined agents are not counted as part of any convention until they reach 90% adherence over their 20 most recent interactions. As such, it takes at least 20 timesteps before an agent is counted as part of a convention.

7.5.2 Configuration 1: static population with no pre-existing conventions

One-off incentives

The first strategy we examine is one-off incentives, wherein we reward either 10 or 100 targeted agents (i.e. a proportion of 0.01 or 0.1) by varying amounts, up to 25 times the size of the maximum payoff attainable in a single interaction.

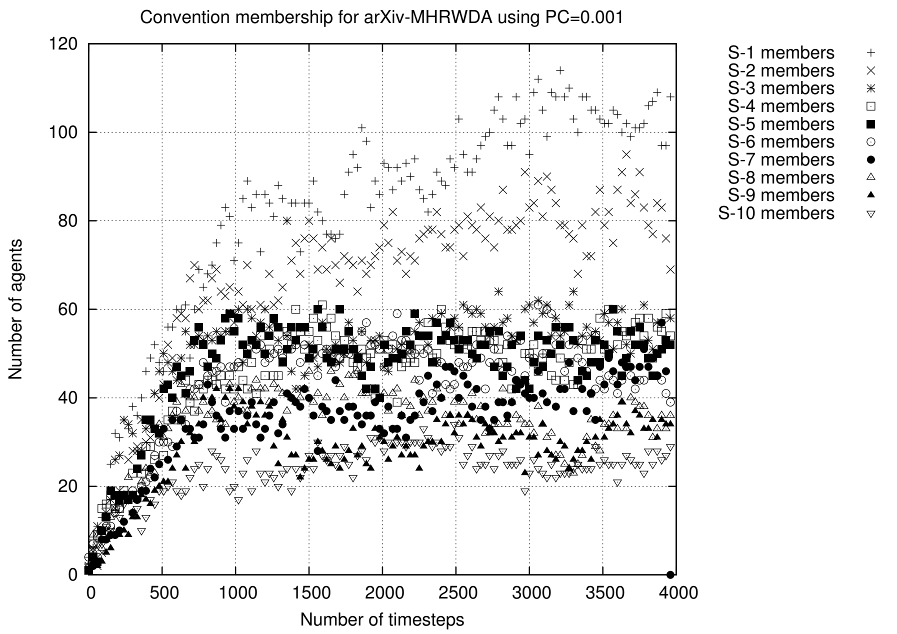


Figure 7.4: Membership counts for each strategy on the arXiv-MHRWDA sample with one agent randomly reset every timestep, $\alpha = 1$. There is a much greater variability in convention membership, with lower average membership counts, allowing IAs greater influence over which strategy becomes dominant in the population.

Table 7.3 shows that membership of the targeted convention rises, with a corresponding increase in membership rank with (i) increased reward size and (ii) increased proportion of agents rewarded. For rewards above 12.5 times the maximum interaction payoff (i.e. for a reward of over 50), there are no further gains in rank and these results are statistically indistinguishable (although there is still a gain in the number of agents adhering to the targeted convention). Rewards of around 12.5 times the maximum interaction payoff appear to form a threshold over which there are hugely diminished returns. However, rewarding more agents continues to be beneficial. The increase in rank and membership rises proportionally with the total expenditure (i.e. in this case, the reward amount times the number of agents targeted) up until the threshold mentioned above. We also see significant gains in targeting high-degree agents compared to random targeting. This corroborates research demonstrating the importance of high degree nodes (e.g. Chen *et al.* (2009)), and rewarding these agents results in large gains in both convention rank and membership.

To attain a significant increase in convention membership requires large expenditure using one-off incentives, with a maximum average gain of 206 members for a total reward expenditure of 5,000 — that is, the targeted convention gains a maximum of 206 members, and this occurs when the total additional payoff applied to agents is 5,000 (and is targeted by degree). Although translating our values for utility to real-world costs is difficult, the fact that this is so much greater than the reward that agents can attain in individual interactions suggests that it is impractically costly to apply this form of reward. Although we only report results for $\alpha = 0.5$, we note that the results for $\alpha = \{0, 1\}$ are statistically indistinguishable from these.

Inserting IAs

Table 7.4 shows the results from inserting either 1 or 50 IAs into a population, either randomly or placed by node degree. We use $\alpha = 0.5$, and there is no population churn. We have indicated the best result in each row in bold, and

	Obs.	0				1			
	IA Prop.	0.001		0.05		0.001		0.05	
Inc.	Sanc.	R	D	R	D	R	D	R	D
1	1	1.1 (14)	2.2 (132)	4.5 (202)	4.6 (316)	0.6 (6)	2.1 (132)	4.5 (196)	**4.6 (321)**
1	1.5	1.7 (11)	2.8 (132)	5 (187)	**5.1 (339)**	*1.2 (23)*	2.4 (131)	4.8 (210)	4.9 (338)
1	5	0.4 (2)	1.0 (86)	3.5 (123)	4.5 (298)	0.6 (5)	0.9 (74)	3.2 (132)	**4.8 (332)**
1	10	-0.6 (-5)	0.9 (91)	3.2 (112)	4.5 (277)	-0.8 (-10)	0.5 (88)	3.4 (128)	**4.6 (298)**
2	1	*1.8 (17)*	3.3 (149)	4.9 (235)	**5 (394)**	0.6 (7)	2.6 (147)	*4.2 (262)*	4.3 (372)
2	1.5	1.5 (-9)	*3.1 (150)*	4.7 (263)	***4.8 (402)***	1.1 (-1)	*3.3 (151)*	4.8 (261)	*4.9 (399)*
2	5	0.7 (18)	1.0 (78)	3.9 (178)	**4.3 (351)**	0.8 (22)	1.1 (73)	4.1 (192)	4.2 (331)
2	10	1.0 (2)	1.3 (97)	3.4 (162)	4.4 (308)	0.9 (5)	1.4 (98)	3.7 (144)	**4.4 (322)**
5	1	0.8 (6)	2.3 (85)	4.4 (222)	4.7 (332)	0.6 (4)	1.2 (78)	4.5 (214)	**4.2 (340)**
5	1.5	0.6 (6)	1.3 (82)	3.3 (201)	4.6 (321)	0.7 (2)	1.4 (80)	3.9 (228)	**4.5 (338)**
5	5	0.9 (9)	0.9 (37)	2.9 (198)	4.2 (298)	0.9 (5)	1.1 (90)	3.3 (182)	**4.1 (302)**
5	10	1.2 (15)	1.0 (73)	2.9 (167)	**4.3 (301)**	1.1 (12)	1.1 (72)	3.0 (172)	4.2 (298)
10	1	0.5 (6)	1.4 (107)	*3.5 (278)*	**4.7 (388)**	0.5 (5)	1.9 (78)	3.6 (260)	4.6 (370)
10	1.5	0.6 (6)	1.5 (116)	3.1 (266)	**4.7 (376)**	0.6 (8)	1.3 (77)	2.9 (258)	4.6 (358)
10	5	0.5 (4)	1.1 (104)	3.1 (277)	4.3 (301)	0.5 (3)	0.9 (80)	3.3 (288)	**4.3 (312)**
10	10	0.9 (4)	1.0 (114)	3.0 (251)	4.1 (299)	0.8 (1)	1.3 (104)	3.3 (248)	**4.2 (313)**

Table 7.4: Convention rank increase and (in parentheses) membership increase (over average numbers for simulation runs with no interventions) for the targeted convention when varying proportions of IAs use incentives and sanctions within their interactions. IAs are placed either Randomly (R) or by Degree (D). We use $\alpha = 0.5$ and $PC = 0$ (i.e. no population churn). The best result, in terms of membership increase, in each row is shown in bold and the best result in each column is italicised. "Inc." indicates incentives, and "Sanc." indicates sanctions.

italicised the best result in each column. A number of interesting effects are exhibited. Incentives are effective, but we witness a similar threshold effect as with rewards: the best results are attained by doubling the reward of an agent, but beyond that we observe no further increases in convention rank or membership.

Conversely, sanctions appear to be counter productive — as we increase the sanctioning amount, we see statistically significant decreases in convention rank and membership counts. We believe this to be due to the non-selective manner of sanctions: a heavy sanction will conclusively deter an agent from choosing the sanctioned strategy again, but does not give any information about which strategy *should* be chosen. This reduces the number of strategies that an agent will choose from and may push it to choose another (non-targeted) strategy which subsequently performs successfully. Sanctioning would thus have the effect of strengthening adherence to other strategies, and only occasionally would that strengthening effect be for the targeted strategy.

Observability of interactions has no statistically distinguishable effect on

		Placement	
Inc.	Sanc.	Random	Degree
1	1	3.6 (65)	4.6 (80)
1	1.5	3.4 (82)	4.5 (81)
1	5	2.1 (33)	4.4 (55)
1	10	2.0 (28)	4.4 (51)
2	1	3.9 (72)	4.6 (102)
2	1.5	3.9 (68)	4.5 (98)
2	5	3.1 (38)	4.5 (75)
2	10	3.1 (38)	4.1 (68)
5	1	2.9 (40)	4.3 (69)
5	1.5	2 (41)	4.5 (73)
5	5	2.6 (25)	3.6 (53)
5	10	2 (24)	3.5 (26)

Table 7.5: The change in convention rank and membership for the targeted convention when introducing 10 agents at $t = 0$ using incentives and sanctions, placed either randomly or by degree in a static population, with $\alpha = 0.5$ and $obs = 1$.

either convention rank or membership counts, and using one IA placed randomly gives statistically significant effects in only around 50% of cases (see Table 7.4). Furthermore, the increases in membership and rank from using incentives, while statistically significant, are slight, and whether these benefits outweigh the cost will be highly domain dependent. On average, an IA will participate in at least 4,000 interactions over the course of a simulation. Assuming an equal number of adherents for each strategy, it will likely apply incentives in, on average, 1 in every 10 interactions (given 10 strategies, and one targeted strategy). This results in at least 400 interactions where the IA at least doubles the reward attained by the interaction participant. Assuming a doubling of reward (i.e. the most effective incentive amount), this results in an additional expenditure of 800, for (i) an average increase in rank of around 0.3 and (ii) around 50-60 extra convention members. IAs are, however, much more cost effective than rewards: IAs without incentives will cost around 800 and can add around 130 agents to the targeted convention.

Table 7.5 shows the results from using 10 IAs (i.e. a proportion of 0.01) under the same configuration. We can see that 10 agents, placed by degree, are sufficient to make the targeted convention dominant within the population. However, the increases in convention membership are smaller, and scaling to 50 IAs results in further significant increases in membership. We see the same effects regarding sanctions and incentives: sanctions are counter-productive, and incentives produce a small increase up to a threshold level.

We note that Tables 7.5 and 7.4 show, for small numbers of IAs, a drop in incentive efficacy as the incentive factor rises. This only occurs for small numbers of IAs, and only when introduced at $t = 0$. It is unclear why this is the case, but this effect does not translate to larger numbers of agents or our results introducing IAs later on in the simulation. Since we believe that the latter configuration is more realistic, we leave determination of the mechanism behind these results to further work.

In summary, we draw the following conclusions when our strategies are applied in a static population with no pre-existing conventions.

- Both rewards and IAs are highly effective at manipulating conventions when there are no pre-existing conventions in the population and the population does not change over time.

- Targeting each mechanism by degree facilitates large increases over random targeting.

- Sanctions, applied by IAs in interactions, can be counter-productive, which we believe is due to their non-specific nature. Interestingly, this runs counter to other investigations into sanctions, such as Axelrod's (1986) investigation into norm enforcement. We believe that the reduction of efficacy in sanctions that we observe to be a result of the increased convention space (as discussed above) and other effects unique to our model.

- One-off rewards applied to individuals can add up to 200 individuals to the targeted convention for a cost of around 5,000 (or an expenditure of 25 per additional member), while IAs can add around 130 individuals for a cost of around 800 (or an expenditure of around 6 per agent). IAs are

Prop. Rewarded	0.01			0.1		
Reward Amnt.	10	50	100	10	50	100
Random	0.3 (10)	0.2 (1)	-0.1 (-1)	0.6 (13)	0.2 (6)	0.5 (13)
Degree	-0.3 (-5)	0.4 (11)	0.6 (10)	0.4 (11)	0.6 (9)	0.6 (11)

Table 7.6: Increase in rank and membership (in parentheses) of the targeted convention (compared to average) after rewarding a proportion of individuals at $t = 500$ selected either randomly or by highest degree, and using $\alpha = 0.5$.

therefore much more cost effective than one-off rewards when manipulating conventions.

7.5.3 Configuration 2: static population with pre-existing conventions

The configuration considered in the previous section is an idealised case. In practical instantiations of open MAS, we can expect the system to have been running for some time before attempts to manipulate conventions are implemented by interested parties. As such, conventions are likely to already be established or be in the process of establishment when interventions occur. To model this, we evaluated one-off rewards and IAs that are inserted into the population at $t = \{500, 1000, 1500\}$. As noted in Section 7.5.1, the model transitions to a stable state between $t = 1000$ and $t = 1200$, such that at $t = 500$ there will be significant precedence for each convention, and at $t = \{1000, 1500\}$, we can expect conventions to be becoming, or have become, stable and established.

When we introduce one-off rewards of IAs later in the simulation, their efficacy is drastically reduced. Table 7.6 shows the results for one-off rewards, and Table 7.7 shows the results for IAs (with Table 7.5 plotting the results for IAs introduced at $t = 0$, under the same configuration, for comparison). We find that the reduction in efficacy is statistically indistinguishable for all three non-zero values of t, indicating that the reduction in efficacy occurs due to the early and middle stages of convention emergence. IAs perform significantly better than rewards, and a proportion of 0.01 (i.e. 10 IAs) introduced from $t = 500$ onwards facilitates, roughly, an increase of 1 rank in the targeted

		Placement	
Inc.	Sanc.	Random	Degree
1	1	1.3 (12)	1.3 (13)
1	1.5	1 (8)	1.3 (13)
1	5	1.2 (13)	1.5 (19)
1	10	1.6 (16)	1.2 (15)
2	1	0.8 (10)	1.4 (15)
2	1.5	1 (9)	1.7 (16)
2	5	1.8 (17)	1 (17)
2	10	0.2 (6)	1.1 (15)
5	1	1.9 (20)	1 (9)
5	1.5	2 (20)	1.3 (14)
5	5	2.6 (25)	2 (23)
5	10	1 (14)	1.5 (16)

Table 7.7: The change in convention rank and membership for the targeted convention when introducing 10 agents at $t = 500$ using incentives and sanctions, placed either randomly or by degree in a static population, with $\alpha = 0.5$ and $obs = 1$.

convention, when such a proportion introduced at $t = 0$ results in an increase of 3 or 4 ranks, and often allows the targeted convention to dominate. Rewards give no statistically significant increases after $t = 500$. These results indicate that as the forces of precedence and mutual expectations become entrenched, manipulation of conventions becomes correspondingly more difficult. In entirely static populations manipulating established conventions is likely to be extremely difficult, but static populations are not a realistic assumption: in typical real-world open MAS we can expect some degree of population churn over time. We hypothesise that a non-static population would be considerably more amenable to manipulation, due to a larger number of agents that have not implacably settled on a given convention.

7.5.4 Configuration 3: time-varying population with pre-existing conventions

Our third configuration introduces a small amount of population churn: every timestep, we reset one agent to represent an agent leaving and a new agent joining. As discussed in Section 7.4, this is a very simple model of population

		Placement	
Inc.	Sanc.	Random	Degree
1	1	1.1 (14)	3.1 (129)
1	1.5	2.1 (21)	3.1 (129)
1	5	2.4 (22)	3.1 (88)
1	10	1.9 (29)	2.9 (92)
2	1	2.2 (39)	2.9 (123)
2	1.5	2.4 (39)	3 (128)
2	5	1.9 (9)	3.2 (132)
2	10	1.7 (11)	2.9 (125)
5	1	2.1 (17)	3.2 (125)
5	1.5	2.2 (24)	3 (124)
5	5	2.2 (17)	3 (124)
5	10	2 (13)	2.7 (121)

Table 7.8: The change in convention rank and membership for the targeted convention when introducing 10 agents at $t = 500$ using incentives and sanctions, placed either randomly or by degree in a population with 1 agent being replaced per timestep, with $\alpha = 0.5$.

		Placement	
Prop. Rewarded	Amount	Random	Degree
0.01	10	0 (0)	0.4 (36)
	50	0.8 (8)	0.3 (35)
	100	1.0 (21)	1.5 (56)
0.1	10	0.6 (8)	1.2 (40)
	50	1.4 (10)	1.5 (48)
	100	1.3 (9)	1.4 (43)

Table 7.9: The change in convention rank and membership when applying one-off rewards to agents at $t = 500$ with $PC = 0.001$.

churn, chosen such that we do not run into problems associated with modelling dynamic network topologies.

Table 7.8 shows the results of inserting IAs at $t = 500$ with a population churn of $PC = 0.001$, and Table 7.9 shows the results of applying one-off rewards at $t = 500$, also with churn. Population churn appears to allow IAs to retain their effectiveness when conventions are established or in the process of becoming established (although there is still a small drop in efficacy), while rewards only regain marginal effectiveness. One IA is not sufficient to create a measureable difference (and so we have not shown these results), but 10 IAs are sufficient to attain significant gains in rank and membership for the targeted convention. Under population churn, we see a much higher degree of variance between results, but there are clear trends. Firstly, incentives are much less effective than when IAs are inserted at the start of the simulation, whether with population churn or not. The biggest increases are still gained from the presence of IAs at all, rather than their manipulation of the payoff structure.

Overall, the presence of population churn and 10 IAs results in a change of around 3–4 ranks for the targeted convention, which is significantly closer to the baseline results with IAs introduced at $t = 0$ and no churn. Placement by degree results in large increases in convention membership, although we do not necessarily see such a large increase in convention rank. However, changes in both rank and membership when placing by degree are statistically significant. Our results support the intuitive hypothesis that conventions are most easily manipulated when a large proportion of the society is undecided, and as conventions become more established the potential for influence is drastically reduced. Rewards and incentives are effective in these early stages, but do not make a large impact after the early stages of emergence. In the middle and latter stages of convention establishment, simply attempting to propagate a convention by consistently adhering to a given convention has the greatest effect assuming a minimal level of turnover in the population.

We hypothesise that since IAs are present over time, as opposed to the one-off nature of rewards, they can continue to nudge the population as new agents join and so can influence convention emergence more efficiently. In this respect, IAs are equivalent to rewarding individuals small amounts over time rather than large one-off payments. This hypothesis fits the framework of conventions: the force of precedence is strengthened, by definition, by repeated choices in interactions. A one-off reward may generate a small number of repeated "correct" choices, where correct means that the agent uses the targeted strategy, but if the individual is embedded in a topological area where another convention dominates, the effect of the reward will quickly dissipate and the precedence of other conventions takes over. Conversely, IAs generate a large number of identical choices over time, and this significantly strengthens the force of precedence for the targeted strategy over time. Moreover, IAs are more likely to influence "churned" agents (i.e. newly joined agents) due to their longevity, whereas the effect of rewards may well have waned by the time a new agent joins.

7.6 Conclusions

In this chapter, we have evaluated a variety of strategies for manipulating conventions in a model with realistic assumptions. We show that one-off rewards and Influencer Agents (IAs) applying incentives in interactions are highly effective in the early stages of convention emergence, when large parts of the population are undecided, but their efficacy quickly wanes as the forces of precedence stabilises conventions. A small group of IAs (essentially corresponding to Boyer and Orlean's (1992) external invaders) attempting to propagate a single convention are much more effective, both in terms of real gains in convention membership and rank, and in terms of expenditure versus the size of one-off reward needed to attain significant increases.

The IA technique remains effective throughout the stages of convention establishment, as long as there is a minimal level of population churn introducing new individuals into the population. Our results suggest that using many small interventions is more effective than a small number of large interventions, particularly in the presence of population churn. In a static population, conventions appear to be too stable to significantly influence once established, and we believe techniques to destabilise conventions would be needed in such cases (e.g. such as Villatoro & Sabater-Mir's (2011) social instruments). Population churn is a realistic assumption to make in many open MAS domains and our results support the notion that established conventions in such domains can be manipulated.

Sanctions appear to be almost entirely ineffective, and often result in a reduction in rank and membership for the targeted convention. We believe that this is because a sanction only reduces the probability of an individual choosing a given strategy, and in a space with a wide variety of strategy choices the agent may well be encouraged to use other strategies in subsequent interactions that reinforce a convention other than the one targeted, creating the counter-intuitive effect. In future work, we plan to investigate the use of more intelligent sanctioning and rewarding strategies, to target incentives, sanctions and rewards at those agents that are most likely to be either influential or amenable to change.

CHAPTER 8

Discussion and conclusions

The work outlined in this thesis investigates how mechanisms for cooperative and coordinated behaviour can be applied to the specific challenges of open multi-agent systems. Broadly, we focus on two factors which underpin the interaction processes of agents in such systems, that is, information propagation and network topology. In this chapter, we review the contributions made in this thesis and (i) discuss the extent to which it has fulfilled its original aims, (ii) evaluate the major limitations of the work presented and (iii) identify directions for future research.

Our initial aims, described in Section 1.5, outlined the general directions for our research. Our objectives were to (i) investigate the role of information propagation and network structure in the emergence of cooperative and coordinated behaviour, (ii) enhance the robustness of simple reputation mechanisms to the challenges of open MAS, (iii) identify limitations in current models of convention emergence and determine how to manipulate conventions and norms, and (iv) determine how to exploit knowledge of the network structure constraining agent interactions. In general, we have fulfilled these aims as follows. Chapters 3 and 6 specifically deal with information propagation and network structure (i.e. our first objective), and these processes are key themes in Chapters 5 and 7. The investigations described in Chapter 3 demonstrate gossiping as an effective way to improve the robustness of reputation mechanisms (i.e. our second objective). Chapters 4, 5, and 7 present work identifying limitations in current convention models and propose techniques for manipulating conventions and norms (i.e. our third objective). The work in Chapter 6 demonstrates how knowledge of the network structure can be exploited, in fulfilment of our fourth objective.

8.1 Contributions

- **Using gossiping to mitigate the negative effects of incomplete information and underlying network structures**

  In Chapter 3, we demonstrated that incomplete information and topological structure can significantly affect the operation of simple reputation mechanisms. Insufficient and incomplete information are key factors through which support for cooperative behaviour is undermined in reputation mechanisms, and we have demonstrated two configurations under which simple reputation mechanisms are particularly vulnerable: (i) when there is *insufficient* information about potential partners, such as when agents are first entering a system, and (ii) when there is *incomplete* information regarding potential interaction partners, such as when there is a very high rate of interactions. We further identified the overall strategy distribution of the population as a driver of incomplete information: if there is a uniform mix of strategies in a population, there is increased uncertainty over an individual's strategy and decisions made on the basis of incomplete information are more likely to be incorrect. Norms and conventions, which increase the certainty with which certain actions are selected, are therefore useful techniques to reduce the effects of insufficient and incomplete information and increase support for cooperative behaviour. Gossiping mechanisms are shown to be an effective substitute for direct observation of agent behaviour, and significantly increase the levels of cooperative behaviour in a system. Our investigations were, however, limited in two key respects: (i) the population size, and (ii) the form of the underlying network structure. The majority of experiments were run with $n = 100$ agents, and while we validated our contributions with a small number of experiments with $n = 1000$, it will be necessary to perform more large-scale experiments in future work. The majority of the experiments were performed on synthetic networks, which are poor models of real-world network structures (as demonstrated in Chapter 6). We intend to test our techniques on a wide range of real-world networks in future work.

- **Developing a new model of convention emergence**

  In Chapter 4, we identified several limitations in the descriptive power of the current theory of convention emergence and used aspects of convention emergence literature from several fields to synthesise a formalism for describing convention emergence in open MAS. The key limitations are that (i) typical definitions regard a single universal convention as the ideal goal, when in practice this may not be desirable or attainable, and (ii) current models do not propose ways of quantitatively measuring a convention's quality, support or stability. Furthermore, typical investigations into convention emergence use disparate models that are not easily comparable. Our formalism is a response to these limitations in which many models of convention emergence can be expressed and compared in a uniform manner.

  We subsequently introduce a model of convention emergence that is based on Lewis' (1969) idea of conventions as *regularities*, and which removes the limitations of assuming that a single convention is the ideal goal. Specifically, our model explicitly allows for the co-existence of multiple conventions and can quantify the quality, support and stability of a convention. Our model facilitates investigations into the middle and latter stages of the convention lifecycle, which have been previously under-explored. The work described in Chapter 4 opens up a variety of avenues for future research. Firstly, we propose a number of new metrics describing convention support, quality and stability, and in this thesis we have started to evaluate whether they can aid our understanding of the behaviour of conventions at different points in the lifecycle. Extending this evaluation to the variety of metrics proposed in Chapter 4 is an important direction for future research. Secondly, we propose linking notions of topological structure into our metrics (for example, with the notion of connected convention components), but an empirical evaluation of whether these additional concepts are useful or not is beyond the scope of this thesis. Finally, one of our key aims was to re-orient the definition of conventions to allow for multiple conventions co-existing as an ideal aim. The quintessential example of such a system is the El-Farol bar problem (see Chapter 4 for more details), and evaluating how our approach applies is key to validating its usefulness.

- **Using Influencer Agents to manipulate convention emergence**
  In Chapter 5, we demonstrate the Influencer Agent (IA) concept, which uses small groups of agents under the direction of interested parties to control which convention emerges in a population. We show that (i) small numbers of Influencer Agents are sufficient to manipulate the emergent dominant convention, and (ii) Influencer Agents provide significant gains in both the number of agents adhering to a convention and the speed of convergence. IAs are very simple: they attempt to "lead-by-example" by perpetually choosing a single strategy. This aids the establishment of precedence for that strategy, and it consequently quickly spreads throughout the population. We show that placing agents by degree, a common

proxy for agent influence, leads to significantly increased efficacy in manipulating which convention a population settles on.

- **Using knowledge of the underlying network structure to identify influential individuals**
  We further explore targeting the location of IAs in Chapter 6, which proposes a methodology for learning the network value of an individual in terms of its ability to influence the rest of the population. While corroborating previous research linking node degree with influence, we also show that HITS, Eigenvector Centrality, and Edge Embeddedness are strong predictors of the influence a given individual holds. We build prediction models to identify particularly influential locations by exploiting knowledge of the underlying network structure. Applying these models allows significant gains in agent influence. In 2 of the 3 networks we investigate, the best prediction models learn *which* of the four heuristics identified above best indicate agent influence. In 1 of the 3 networks, the best prediction models identified a linear combination of metrics that predict influence better than any single metric. Finally, we demonstrate the insufficiency of typical synthetic network generation algorithms in modelling structures found in the real-world, and show that the wide variety of structures found in such domains require adaptive mechanisms for efficient exploitation.

- **Manipulating conventions in the middle and latter stages of the convention lifecycle**
  In Chapter 7, we show that population churn is a key process for allowing established conventions to be manipulated, and analyse the effectiveness of sanctions, incentives, and one-off rewards in detail. Our approach to sanctions and incentives, in which they are applied by IAs in individual interactions, is designed to model how these mechanisms might be realistically applied, and we demonstrate that they are, in general, not cost-

effective. We show that many small interventions are much more effective at manipulating convention emergence than a small number of large interventions, and that in static populations none of our proposed techniques are effective at manipulating conventions once the forces of precedence have established and stabilised a convention.

8.2 Directions for future research

Aside from the specific future work described for some of the contributions above, we can identify a number of general directions in which to take the work developed in this thesis.

- **Combining trust, reputation, norms and conventions**
  In Chapter 3, the strategy distribution of the population is identified as a potential driver of incomplete information, which subsequently increases the number of "incorrect" choices that agents make in interactions. These choices have two consequences: the agent incurs personal costs, and the level of cooperation in the overall population falls. Norms and conventions, which reduce the diversity of the strategy distribution of the population, may be an effective complement to trust and reputation systems in supporting coordinated and cooperative behaviour. In this thesis, we have not investigated this hypothesis and evaluating the extent to which norms and conventions aid populations of agents equipped with trust and reputation mechanisms is therefore a key direction for future research. Supplementing norms and conventions with trust and reputation (i.e. as opposed to supplementing trust and reputation with norms and conventions) may also be beneficial, in that agents could decide on whether to adopt a norm or convention based on the reputation of those already adhering. This would reduce the influence of agents adopting undesirable conventions.

- **Practical validation of our convention formalism and theories of convention emergence**

The work described in Chapter 4 attempts to re-orient traditional theories of convention emergence so as to account for several identified limitations. We propose a formalism with which models of convention emergence can be described in a unified manner, with the aim of facilitating direct comparison. We further propose a new definition of convention and develop several metrics for describing their quality, stability and support. While a fundamental first step, practical validation of the usefulness of these contributions is necessary. For example, it may be valuable to measure the evolution of convention metrics over time in traditional models (e.g. Sen and Airiau's (2007) or Salazar *et al.*'s (2010b)) and evaluate what additional insight they provide in the original results. We believe that empirical experiments into how these metrics change over time may reveal much about the nature of convention emergence.

- **Extending IAs**

  The preceding three chapters (i.e. Chapters 5, 6 and 7) primarily use the IA mechanism as a tool for manipulating convention emergence. We have demonstrated that they are particularly effective, but their implementation remains simplified. We expect that significant gains in efficacy could be made with more complex IA strategies, including intra-IA collaboration. Furthermore, we have only tested IAs in two models of convention emergence. Future work must therefore involve (i) identifying further strategies IAs can use to influence a population and (ii) determining how to apply IAs in real-world application domains.

- **Further validation on real-world networks**

  A particular focus of this thesis is the effect of the underlying network structure. For Chapters 3, 5, and part of 6, our investigations were based on networks generated by synthetic network generators, which attempt to model features of networks found in the real world (i.e. the small-world and scale-free properties). While we perform a small number of experiments that suggest that these results generalise to real-world networks, we find in Chapter 6 that synthetic generators create particularly poor models of real-world networks. While Chapters 6 and 7 demonstrate that the IA mechanism is generalisable, our work in Chapter 3 requires more validation on real-world networks before we can truly claim that it can be generalised.

- **Linking network structure with conventions**
  In Chapter 4, we discuss how the metrics that quantify convention support, stability, and quality might be linked with notions of topological structure: for example, determining if conventions are more stable when the network induced by adhering agents is connected. Network structure is known to have a significant impact on convention emergence (e.g. Pujol *et al.* (2005)) and incorporating notions of network structure into our models of convention emergence is a key step in understanding these processes more fully.

- **Dynamic network topologies**
  In real-world applications we can also expect network topologies to be constantly changing: that is, they are *dynamic* rather than static. We have not included models of topological dynamism in our research for two reasons: (i) research into dynamic networks is still in its infancy, and given our results with static network generators we do not feel that incorporating notions of topological dynamism would necessarily increase the applicability of our results, and (ii) the processes which alter network topology (namely, how and when agents join and leave a network, and how connections between agents are created) are highly domain-specific and implementing specific rules for dynamism would reduce the generality of our work. However, our work is still limited by its use of static network topologies, and in the future we will investigate the techniques introduced in this thesis in the context of topological dynamism.

- **Further topological extensions**

A minor limitation of our work is that all the networks used are treated as undirected. While there do exist domains in which edges must be treated as directed, in many typical open MAS the edge represents reflexive concepts, such as being able to mutually communicate or observe behaviour. We, in general, believe our work generalises to directed graphs, although this must be tested in future work. We note one exception to this, namely that the random-walk based sampling techniques described in Chapter 6 (such as MHRW and MHRW-DA) are not defined for directed graphs, and substitutes would have to be used. Initial work investigating substitutes for directed graphs does exist, such as that proposed by Wang *et al.* (2010).

8.3 Final remarks

In this thesis, we have examined trust, reputation, norms and conventions and their use in supporting cooperative and coordinated behaviour in open MAS. We have significantly extended the theory of conventions and shown how they can be manipulated, using a mechanism highly applicable to the challenges of open MAS (i.e. Influencer Agents), at all stages of the lifecycle. Conventions and norms are powerful mechanisms for coordinating large populations, and our work in Chapter 3 suggests that they can significantly reduce the impact of incomplete information when used together with techniques for trust and reputation.

There are two major themes which run throughout this thesis, namely that of network structure and that of information propagation.

The role of network structure cannot be understated. In each chapter in this thesis, the underlying network structure had significant impacts on the behaviour of agent populations. In Chapter 6, we demonstrated that there exists a huge gap between the structures generated by synthetic network generation algorithms and those that are found in the real world, and the complexity and properties of real-world networks remains an open research area. We believe that conventions and network structure can be linked, as discussed in Chapter 4, and this linking may illustrate further influences of network structure on the behaviour of conventions.

The propagation of information throughout a population also has significant impact. In Chapter 3, the use of gossiping to increase available information regarding potential interaction partners significantly reduced the levels of selfishness. In Chapter 5, IAs manipulate convention emergence by making other agents observe their strategy selection repeatedly, which then gets propagated through the population.

These two factors influence the behaviour of agents in all open multi-agent systems, and determining how they impact mechanisms that support the emergence of cooperative and coordinated behaviour is fundamental to applying such techniques in open MAS. We believe that the work in this thesis is a key step towards this goal.

APPENDIX A

Network structures

Complex network structures underpin the majority of open MAS domains. Accordingly, a thorough understanding of the impact of network structure is necessary when designing mechanisms for promoting cooperative and coordinated behaviour. In this appendix, we review the network concepts at the core of the research presented in this thesis, and review common issues in research into network structure and its impact on open MAS. While investigation of the impact of network structure is an important theme throughout this thesis, we investigate networks in most detail in Chapter 6.

A.1 Introduction

In many investigations into conventions, norms, trust and reputation in multi-agent systems, agents interact with others that are selected randomly from the entire population (e.g. Axelrod (1986), Nowak & Sigmund (1998), Vylder (2007)). This is as an idealised situation, since in practice an agent's choice of interaction partner is constrained by notions of connectivity or location. For example, nodes in a P2P network can only interact with those they are connected to, and nodes in MANETs or wireless sensor networks can only interact with those within transmission range. Agents wishing to interact with others outside their immediate neighbourhood depend on intermediate agents to re-transmit their communications. The network structures that typically constrain the connectivity of agents in this way are highly complex (Albert & Barabási, 2002) and have a number of common properties, such as power-law connectivity distributions or logarithmically-bounded path lengths.

Network analysis can significantly enrich understanding of complex systems in a variety of fields (Stephenson, 1989), including biology (e.g. McDonald (2007)), computer science (e.g. Delgado (2002)), and economics (e.g. Delre *et al.* (2010)), and networks have been shown to have significant influence on the behaviour of agent populations (Cohen *et al.*, 2001; Delgado, 2002; Nowak, 2006; Pujol *et al.*, 2005; Szabó & Fath, 2007; Villatoro & Sabater-Mir, 2011). We are only just beginning to understand the complexity of networks found in the real world, and many features remain under-investigated (Abdallah, 2010).

We are interested in understanding how the aggregate behaviour of individual agents affects the trajectory of the entire society, and as such the study of MAS is intimately linked with the study of topological structure. The spread of conventions, social norms and information (such as trust assessments) relies on the pattern of connections between agents, and the robustness and stability of these systems is intertwined with their social structure.

Since networks model a wide variety of systems, there is considerable disparity between fields as to the exact interpretation of many terms and concepts. In this chapter we define the terms and concepts we use in the remainder of this thesis, so as to avoid confusion. Where not explicitly referenced, definitions are taken from Easley and Kleinberg (2010), Barabási and Albert (2002) or West (1996).

A.2 Network concepts

This section introduces the core network concepts used throughout this thesis.

A.2.1 Basic definitions

We define a graph G as a set of vertices, or nodes, and a set of edges connecting those nodes as

$$G = (V, E)$$

Graphs can be either *directed* or *undirected*, mandating that edges are either an ordered or unordered (respectively) pair $e_i = (v_i, v_j) : v_i, v_j \in V, e_i \in E$. In this thesis we concentrate on undirected graphs, since (i) we typically define connections as representing reflexive concepts such as direct communication or interaction ability and (ii) certain sampling techniques (discussed in Section A.3.4) do not generalise to directed networks. Edges can be associated with *weights* representing concepts such as bandwidth, trust assessments, or geographic distance. Such graphs are called *weighted graphs*. In this thesis we focus on *unweighted* graphs, and we define most concepts with respect to unweighted, undirected graphs, unless otherwise stated.

The *degree*, k, of a node is the number of edges incident to that node. The *neighbourhood* or *neighbour set* of a node v_i contains all those nodes that are directly connected, such that

$$N(v_i) = \{v_k : v_k \in V, (v_k, v_i) \in E\}$$

Typically, an agent is only able to directly communicate or interact with those in its neighbourhood. The degree of a node is equal to the neighbourhood size $k_i = |N(v_i)|$.

Paths

A *path* between two nodes is an ordered list of nodes defining a traversable route from one node to another, meaning that every consecutive pair of nodes in the list must be joined by an edge. The *shortest path* is the path between two nodes with the fewest hops, which is also called the *geodesic* path. We are often interested in the shortest path length as a useful measure of graph structure, since small shortest path lengths confer significant benefits on a population (see below). The *diameter* of a graph is typically defined as either the average shortest path length over all pairs of nodes, or the largest shortest path length over all pairs of nodes. Both are useful metrics, and so we use the definition that the diameter is the largest shortest path length, so as to measure the upper bound, and we refer to the average shortest path length as the *characteristic* path length (Watts & Strogatz, 1998).

Connectivity

We say a graph is *connected* if there exists a path between every pair of nodes. In practice, this may not be the case, in which case we call the largest subsets of nodes that are connected *connected components.* Typically, in real-world networks we see one *giant* component, which may account for upwards of 90% of the nodes in the graph, with a few small connected components existing separately. We can further say that a graph is *completely connected* if every single node is connected to every other node, in which case there are $n(n-1)/2$ edges in a graph with n nodes.

Static/Dynamic

Finally, we say that a graph is *static* if the set of nodes and edges remains constant throughout the period for which we consider, and *dynamic* if either or both sets change (either through addition or deletion) with time. Realistically, we expect an element of malleability in both the set of nodes and edges, since agents can join or leave a system, and potentially rewire their connections. The study of dynamic topologies is less developed than that of static topologies, and static topologies are often implemented in models as a useful middle ground between the completely-connected abstract space of idealised situations and the highly dynamic practicalities of real-world domains.

A.2.2 Global graph properties

The topology of the network through which agents communicate or interact with each other has important implications for the efficiency of information propagation, robustness to targeted and random malicious action, and support for social constructs such as reputation or social norms. Consequently, there have been varied and extensive attempts to conceptualise the local structure of connections around a node using more advanced metrics. Although many metrics are heavily dependent upon each other, they each capture different aspects of network structure. These properties are used to characterise network samples throughout the thesis.

Characteristic path length

The characteristic path length is an important metric for quantifying how easily information can propagate across a network. Typical real-world networks tend to have proportionally low characteristic path lengths, implying low communication overheads.

Clustering Coefficient

The *local clustering coefficient* (LCC), initially introduced by Watts and Strogatz (1998), measures the probability that any given neighbour of a node v_i is also connected to another neighbour of that node. It is thus calculated by taking the number of edges that exist between the neighbours of v_i, which we denote E_i, and dividing by the total number of edges that could exist. Accordingly, LCC is calculated as

$$C_i = \frac{2 \times E_i}{k_i(k_i - 1)}$$

For directed graphs, the result is divided by 2. The LCC can also be equivalently defined in terms of *triadic closure*, since a neighbour forming a connection to another neighbour is creating the third side of a triangle consisting of the node under consideration and the two neighbours.

A high LCC value indicates that most neighbours are also connected to other neighbours. This often indicates the presence of *community structure* (see below for details). A node in a group with significant clustering is highly visible, in the sense that neighbours can easily communicate with each other about an individual's activities even if only a small sub-set actually observe such activities. Furthermore, information can be propagated very quickly throughout a highly clustered group, with direct connections between a large proportion of the agents. Real-world networks are typically highly clustered.

We often refer to the clustering coefficient of an entire graph to characterise the general structure in aggregate. This can be defined either as the average LCC over all nodes, or using the ratio of closed triangles to connected triples of nodes. Both definitions give the same value, and for the purpose of this thesis we adopt the former definition, such that the Global Clustering Coefficient (GCC) of a graph G is given by

$$GCC(G) = \frac{1}{n} \sum_{v_i \in V} LCC(v_i)$$

Average Neighbour Degree and Joint Degree Distribution

Intuitively, nodes with a high degree are likely to be more important than nodes with a low degree, increasing the connectivity and clustering of a network and acting as components of many more shortest paths. However, if a highly connected node is connected only to nodes with a low degree, that importance might be diminished. Conversely, a node connected to many other highly connected nodes is able to reach a much larger sub-set of the population in only 2 hops. As such, we need a measure of whether a node tends to be connected to high degree or low degree nodes. We call this the Average Neighbour Degree (AND), defined as

$$AND_i = \frac{\sum_{v_k \in N(v_i)} N(v_k)}{|N(v_i)|} : v_i, v_k \in V$$

An extension of this idea is the *Joint Degree Distribution* (JDD), which measures the probability of a given node of degree k_i connecting to nodes of degree k_j. Mislove et al. (2007) approximate this using the degree correlation function k_{ij}, which maps the degree of node i with the average degree of all nodes connected to i. This approximation is equivalent to the AND metric, and as such AND approximates the full JDD. We do not use the JDD as a metric in this thesis since it is a statistical measure that characterises a full network. Instead, we use AND, where relevant, as a property of an individual node.

Related to this is the *scale-free* metric, proposed by Li *et al.* (2005) as a response to perceived problems with scale-free characterisations in the literature (see below for discussion of scale-free networks). The scale-free metric measures the extent to which a graph displays scale-free properties (Li *et al.*, 2005). It is defined for a given graph G as

$$s(G) = \sum_{(v_i, v_j) \in E} (k_i \times k_j)$$

If s_{max} is the maximum value of this metric for all graphs with an identical degree distribution as G, then

$$S(G) = \frac{s(G)}{s_{max}}$$

When this value tends to one, the graph is considered scale-free. Theoretically this measure allows a strong characterisation of how scale-free a graph structure is, but typically it is impractical to calculate, especially given the difficulty of determining s_{max}.

Li *et al.* (2005) have incorporated the node degree distribution and the joint degree distribution into a single measure — the scale-free metric is maximised when highly-connected nodes tend to connect to other highly-connected nodes, and minimised when highly-connected nodes tend to connect to nodes with low degree.

Together, these metrics allow us to characterise not just the properties of single nodes (or entire populations), but the local structure of nodes and edges around a given node. This local structure has been implicated in a number of varied and surprising effects, and understanding local network structure is key to understanding the operation of social processes on that network.

Network heterogeneity and density

The density of a network is the normalised form of the average node degree, such that a network with density 1 is indicative of a completely connected clique, and a density of 0 indicates a network with no edges. Density is thus highly correlated with clustering coefficient.

Network heterogeneity is defined by Dong and Horvarth (2007) as the standard deviation of node degree values divided by the mean node degree. As such, it encapsulates the tendency for nodes to be hubs, wherein a high value indicates that there exist nodes in the network with disproportionately above-average node degrees. Hubs have been implicated in a wide variety of network properties, such as the weakness of scale-free networks to targeted attacks and their converse robustness to random malicious action, and the low characteristic path lengths of many real-world networks.

A.2.3 Metrics of topological location

In the same way that the properties described above characterise entire networks, it is possible to characterise the properties of an individual node and its location within a network. Node degree, discussed above, is the quintessential example, but there also exist a huge number of other metrics. We look at these metrics of individual location in detail in Chapter 6, in which we investigate the extent to which knowledge of topological structure can be used to increase the level of influence that an agent has over the rest of the population. Accordingly, we give a detailed description of common metrics in Section 6.4.

A.2.4 Network structures

Much research in recent years has focused on the complex structures exhibited by typical real-world networks. These structures give the networks intriguing properties, the most important of which are (i) a scale-free degree distribution, (ii) path lengths bounded by the logarithm of the number of nodes in the network (i.e. the *small-world* property) and (iii) highly clustered communities. Newman (2003) reviews these properties in significant detail. Throughout this thesis, we use results derived from simulations incorporating real-world network structures that display these properties. Aside from characterising the structure of these networks, these properties often provide an explanatory mechanism for agent interaction behaviour.

Scale-free degree distribution

Real-world networks typically exhibit a power-law degree distribution, where the probability of a node having a given degree k is given by $p_k \propto k^{-\gamma}$, with γ being specific to the network in question. Cohen and Havlin (2003) have shown that scale free networks with $2 < \gamma < 3$ have diameter $d \propto lnlnN$, and Albert and Barabási (2002) have shown that a huge variety of real-world networks exhibit scale-free degree distributions, including the internet (also shown by Faloutsos *et al.* (1999)), the world-wide web, protein folding networks, and many instantiations of the human social network including sexual contact networks and academic collaboration networks. Mislove *et al.* (2007) have demonstrated scale-free and small-world (see below) properties in Flickr[1], YouTube[2], LiveJournal[3] and Orkut[4].

[1]http://flickr.com
[2]http://youtube.com
[3]http://livejournal.com
[4]http://orkut.com

In practice, a scale-free degree distribution results in the existence of *hub* nodes which have significantly greater than average degree and act to link disparate clusters of individuals. This means that scale-free networks are highly resistant to randomised malicious action (since the majority of random attacks will miss the hub nodes) but vulnerable to targeted attacks. Albert *et al.* (2000) found that randomly removing 5% of nodes did nothing to change network connectivity, but removing the top 5% most connected nodes doubled the diameter. In networks that are not scale-free, but instead show an exponential decay in degree (e.g. random networks), the change in connectivity increases monotonically with the number of nodes removed no matter what order those nodes are chosen in.

Small-world path lengths

The term *small-world* describes networks in which the characteristic path length is small compared to the number of nodes in a network. In general, the small-world property is taken to mean that the characteristic path length grows logarithmically with the population size (Watts & Strogatz, 1998). Kleinberg's model of small-world networks (Kleinberg, 2000) generates graphs on which nodes can communicate along shortest paths using local information only. Accordingly, small-world networks have highly desirable properties concerning information propagation, and most real-world networks exhibit small-world properties (Wang, 2003).

Community Structure

Especially in the natural world, networks often display *community structure*: groups of nodes with high levels of internal connectivity compared to the rest of the network. These clusters, characterised by large LCCs, facilitate internal communication between nodes and, due to the high internal connectivity, render agent behaviour more visible to others. Determining community structure in networks remains an open research problem, however Newman and Girvan (2004) have demonstrated promising results using edge betweenness metrics[5]. Leskovec *et al.* (2009) have shown that clusters of nodes remain highly internally connected and sparsely connected to the external network up to sizes of around 100 nodes, but after this the structure merges with the larger network and the community structure disappears. Clustering, and by extension community structure, can have significant impacts on agent processes (e.g. Pujol *et al.* (2005)).

Other structural properties

A number of other structural properties can be used to characterise typical real-world networks. For example, Sridharan *et al.* (2011) have shown that the embeddedness distribution in online social networks shows a scale-free distribution, and that a random k-tree network model can capture this behaviour, and Palla *et al.* (2005) have shown that the size of communities of overlapping cliques also exhibits a power-law distribution. The full implications of these are yet to be realised and there are likely to be a wide variety of as yet undocumented structural properties found in real-world networks that impact on the internal processes of open MAS.

A.3 Issues in topological research

This section discusses typical issues encountered in research into network structure, and its impact on open MAS. These issues underpin the work presented in this thesis and demonstrate the significant influence of network structure on agent systems.

A.3.1 Dynamism of networks

Given that we consider MAS in which agents join and leave freely, we can reasonably expect real-world instantiations to exhibit dynamic network topologies,

[5]See Chapter 6 for a discussion of betweenness.

with both the set of individuals and the connections between them changing over time. However, investigation into dynamic network topologies is still in its infancy, and accurately modelling dynamic topologies is likely to require a deep understanding of the domain-specific mechanisms that generate topological features. Consequently, static networks are used in the majority of research as a useful middle-ground between fully-connected populations and dynamic networks. While there are a small number of algorithms for generating dynamic networks that exhibit complex properties (e.g. Gonzalez *et al.* (2006)), there has been relatively little research into their efficacy in modelling specific domains, and we cannot therefore guarantee generality. Accordingly, the work in this thesis focuses on static network topologies.

A.3.2 Impact of network structure in MAS

As discussed above, network structure has significant impact on the behaviour of agent populations. This section provides a brief overview of work investigating the importance of the underlying network constraining agents.

Delgado (2002) has shown that the speed of convention emergence is highly dependent on underlying network structure and that scale-free networks are as efficient as fully-connected graphs in this context. Kittock (1993) also demonstrates significant impacts on convention emergence, and Pujol *et al.* (2005) have implicated clustering in the efficiency of convention emergence.

Since information propagation is fundamental to mechanisms that support cooperative behaviour, and since information requirements may be high (Bolton *et al.*, 2005), the ease of propagation of information in networks characterised by scale-free degree distributions and small-world path lengths is particularly interesting. Infections are particularly easily spread through such networks (Huang *et al.*, 2008; Pastor-Satorras & Vespignani, 2001), and Glinton *et al.* (2010) note that network structure and density can impact the correctness of beliefs assessed from uncertain evidence provided by neighbours.

Introducing constraints on agent interactions in the form of overlay networks has been shown to support cooperation and increase system efficiency. Cohen *et al.* (2001) use a tag-based model of cooperation, equivalent to imposing an overlay network constraining agent neighbourhoods, and show subsequent support for cooperative behaviour in repeated Prisoner's Dilemmas. Condie *et al.* (2004) have shown that modifying the topology in file-sharing P2P networks can give significant gains in system efficacy and resistance to malicious action.

There has been significant research interest in non-computational fields regarding how systems are affected by their constraining network structure, and whether the location of a node in that structure is predictive of some notion of power or influence. McDonald (2007) shows that *information centrality*, a metric quantifying an individual's location in a network similar to closeness centrality (introduced in Chapter 6), is predictive of male reproductive success in long-tailed manakins. Bonacich (1987) proposes a measure of centrality that predicts power in exchange networks (networks in which individuals bargain with items of value), where it has since been shown that traditional centrality measures were ineffective (Cook *et al.*, 2010). Fagyal *et al.* (2010) have demonstrated that both central and peripheral individuals have significant roles in the spread of linguistic innovations. These results demonstrate the power of network analysis in enhancing our understanding of complex systems but also illustrate how different domains are affected in highly disparate ways by the underlying network. In Chapter 6, we investigate in detail the extent to which knowledge of network structure can be exploited by designers looking to increase levels of cooperation and coordination.

A.3.3 Synthetic networks

Many algorithms have been proposed to generate artificial networks that exhibit features of networks found in the real world for research purposes. While these algorithms are effective at reproducing the few structural properties under consideration, there are currently no algorithms to generate networks that exhibit the full range of structural properties observed in the real world. Ultimately, real-world networks tend to be scale-free, small-world and highly clustered, whereas networks generated algorithmically exhibit at most two out of these three properties.

Erdös-Renyi Random Graphs

Random networks are those in which each pair of nodes is connected with constant probability p. They were initially studied by Erdos and Renyi (1960), and have been extensively investigated since. While random networks are no longer thought to be accurate models of real-world networks, their insights have inspired innumerable contributions since, and they are useful as a baseline for comparison with networks that display more complex structures.

Barábasi-Albert

Barábasi and Albert proposed a network generation algorithm based on *network growth*, in which new nodes are iteratively added to the network through *preferential attachment* (Albert & Barabási, 2002), in which nodes with a higher degree have an increased probability of connection to new nodes. These concepts are observable in the majority of complex real-world networks, such as the internet (new websites are more likely to link to well-known sites than those that are not) and the human social network (well-connected people are further introduced to more people).

The algorithm proceeds by iteratively adding new nodes (until reaching some pre-defined size) and connecting each new node to m (where m is a parameter of the algorithm) existing nodes with a probability proportional to the current degree of each existing node under consideration. The model generates scale-free networks with $\gamma = 3$. The networks are also small-world, with a characteristic path length that increases with the logarithm of the number of nodes.

Eppstein power-law

Eppstein and Wang's (2002) generation algorithm was developed to model the world wide web without requiring incremental growth. The algorithm proceeds as follows, while maintaining constant size and density.

1. A random node, v, with degree greater than zero, is chosen.
2. Pick u randomly from the neighbour set of v.
3. Pick another node x at random.
4. Pick a further node y with probability proportional to y's degree.
5. If x and y are not the same node and there does not exist an edge connecting x and y, then add this edge and remove the edge connecting u and v.

This process is iterated r times, where r is in the order of millions. As $r \to \infty$, the degree distribution of the network tends to a scale-free power law, with γ typically around 1.5.

Kleinberg small-world

Kleinberg's small-world generation algorithm (Kleinberg, 2000) is based on the observation that short paths in real-world networks are often not only present but determinable using only local information. Kleinberg's algorithm starts with a toroidal lattice of nodes, such that each node has initial degree four, and adds additional long-range edges between nodes with a probability inversely proportional to the Manhattan distance between them, i.e. $P(connection) \propto D^{-\alpha}$. Kleinberg found that at $\alpha = 2$, the time for a decentralised greedy algorithm to find the shortest path between two nodes is $O((logN)^2)$.

A.3.4 Sampling real-world networks

Given the limitations described above concerning algorithmically generated network topologies, several different real-world network datasets have been used in research in conjunction with networks generated artificially. Verification of empirical results across generated and real-world datasets support the conclusions in this thesis, and analysis of the differences between generated and real-world networks helps identify the limitations and specific properties or motifs of each.

Since real-world networks are typically very large, it is often necessary to generate smaller samples that reproduce the structural properties observed in the full network. In this section, we briefly discuss common sampling mechanisms, and we provide a more detailed discussion in Chapter 6.

There are a number of sampling techniques. Each starts at a random node, and progressively adds nodes to a sample set until a threshold is reached.

1. **Breadth-first search (BFS)**

   In each iteration of BFS, all the neighbours of sample set nodes that are not already in the sample set are added, until the threshold is reached.

2. **Snowball-sampling (SNS)**

   SNS proceeds identically to BFS, except that within each iteration, if adding all the new neighbours to the sample set would push the sample set past the threshold, neighbours are chosen randomly from those available until the threshold is reached.

3. **Random-walk (RW)**

   A random walk adds one node at a time, by following a random walk through the network from the start node. Each neighbour is chosen with uniform probability.

4. **Metropolis-Hastings Random Walk (MHRW)**

   A random-walk with transition probabilities biased away from high-degree nodes, in an attempt to generate a uniform sampling of nodes from the network. Initially investigated by in the context of real-world sampling by Gjoka *et al.* (2010), who demonstrated that MHRW produces a uniform sampling of nodes from the full network and effectively preserves the node degree distribution, which is an essential component in the study of complex networks (Gjoka *et al.*, 2010).

5. **Metropolis-Hastings Random Walk with Delayed Acceptance (MHRW-DA)**
   Initially introduced by Lee *et al.* (2012), MHRW-DA is the same as MHRW with an additional modification of transition probabilities to reduce the likelihood of revisiting nodes. MHRW-DA covers more of the network when sampling, increasing the estimation accuracy.

6. **Albatross sampling**
   Introduced by Jin *et al.* (2011), Albatross sampling is a random walk with modified transition probabilities and a chance of randomly jumping to another node in the network, in order to gain greater coverage and avoid problems associated with sampling networks with multiple connected components.

BFS, SNS and RW are all known to be biased towards high-degree nodes, distorting the structure of the sampled network away from that of the full network (Gjoka *et al.*, 2010). However, BFS and SNS produce good coverage of the local area around the start node. As such, they are subject to greater variation between samples but may be useful for ensuring that a wide variety of structural properties are tested. MHRW, MHRW-DA and Albatross have all been shown to converge towards the node degree distribution exhibited in the full network being sampled. There are no guarantees about the reproduction of any other metrics or structural properties.

A.4 Conclusions

In this appendix, we have described the important features of networks, discussed the significant role network topology has in agent research, and discussed typical issues in network research that impact the work described in this thesis.

The role of network topology cannot be underestimated and is a key theme throughout this thesis. In particular, we focus on network structure in Chapter 6, and we provide further detailed discussion regarding networks in Sections 6.2.1, 6.4, 6.4.2, and 6.5.

APPENDIX B

Common convention emergence models

This appendix demonstrates how common models of convention emergence can be expressed using the formalism developed in Chapter 4. Specifically, we focus on (i) Sen and Airiau's (2007) model of social learning with private interactions, (ii) Walker and Wooldridge's (1995) model of conventions focusing on strategy update mechanisms, and (iii) Villatoro *et al.*'s (2009b) model with interaction payoff based on agent history. We provide a brief summary of each model before describing them in detail using our formalism. All the notation we use is defined in Chapter 4, in which it is summarised in Tables 4.2, 4.3, and 4.4.

B.1 Social learning with private interactions

In the scenario proposed by Sen and Airiau (2007), agents are paired randomly from the population and engage in a coordination game, analogous to vehicles meeting at an intersection and deciding whether to yield or go. Interactions are private, with no external observers, and participants know the payoff and strategy of the other participant (although identities are hidden). The payoff that agents receive is determined by a static payoff matrix. Agents are chosen as either row or column player (with respect to the payoff matrix), and learn independent strategies for each situation.

B.1.1 Model description

Using our formalism, we can describe this scenario as follows.

The interaction regime, given in Algorithm 3, returns a set of interactions with each agent participating at least once (i.e. $ip = 1$) with a neighbour chosen uniformly at random. The underlying network structure G is completely connected in the formulation used by Sen and Airiau (i.e. each agent is connected to every other agent).

Algorithm 3 Interaction regime for Sen and Airiau's model of social learning

//I is set of interactions
//d is the current dimension being investigated
for all $Agent \in Population$ **do**
  $Partner \leftarrow getRandomNeighbour(Agent)$
  $I \leftarrow I \cup \langle d, \langle Agent, \sigma_1, row\rangle, \langle Partner, \sigma_2, column\rangle\rangle$
end for
return I

The agents' payoffs are given by a static payoff matrix. Sen and Airiau use two different matrices: (i) a standard coordination game, and (ii) a social dilemma game. The payoffs are given in Table B.1. Sen and Airiau's motivating example of cars meeting at an intersection doesn't translate to the coordination game, and accordingly strategies are labelled 1 or 0 instead of go or yield. The coordination game is analogous to other rules of the road, such as driving on the left or right.

Since there are two payoff functions, with different equilibria, we split the model

	0	1
0	4,4	-1,-1
1	-1,-1	4,4

(a)

	Go	Yield_L
Go	-1,-1	3,2
Yield_R	2,3	1,1

(b)

Table B.1: Payoff matrices for (a) the coordination game and (b) the social dilemma game.

into two dimensions, each with two roles, such that

$$D = \{\text{junction}, \text{coordination}\}, R_{\{junction,coordination\}} = \{\text{row}, \text{column}\}$$

Both roles have the following possible strategies in their respective dimensions:

$$\Sigma_{junction,\{row,column\}} = \{\text{go}, \text{yield}\}$$

$$\Sigma_{coordination,\{row,column\}} = \{1, 0\}$$

These dimensions represent the different games used by Sen and Airiau. The junction dimension involves agents deciding whether to yield or go at a junction, whereas the coordination dimension involves agents deciding whether to coordinate their actions, perhaps by selecting a side of the road to drive on or which side to overtake on. As such, they represent independent interaction models.

The observability settings for each role are the same, such that

$$R_{row} = R_{column} = \langle ID = false, S = true, P = true, U = false, p = 1\rangle$$

That is, agent strategy and payoff are always observable, but agent identity and overall utility are private.

Agents update and select their strategies using one of a variety of learning algorithms, including Q-learning, WoLF, and Fictitious Play. Although agents are assumed to use the learning technique for each role, the strategies for the roles are learnt independently (i.e. strategies are learnt either as row player or column player). The strategy update and selection mechanisms for agents are given in Algorithm 4. Recall that $su_{x,d,r}(M, I, ss_{x,d,r})$ is the strategy update function, which takes the set of agents' memories (M), the interaction (I), and the strategy selection function of the agent ($ss_{x,d,r}$) as arguments. For a full summary of the notation used in this appendix, see Tables 4.2, 4.3, and 4.4 in Chapter 4.

Algorithm 4 Strategy selection and update for Sen and Airiau's social learning

```
//d is current dimension
//learner is one of Q-learning, WoLF, or Fictitious Play
//Strategy update
procedure su_{x,d,r}(M, I, ss_{x,d,r})
    learner_r.update(I, M)
end procedure
//Strategy selection
function ss_{x,d,r}(I, M)
    return learner_r.select(I, M)
end function
```

B.2 Walker and Wooldridge's convention emergence

Walker and Wooldridge (1995) introduced one of the first investigations into the role of local information and agent strategy update on convention emergence. They introduce a formalism to describe convention emergence models, which forms the basis of our formalism, and subsequently use a model of agents traversing a grid in search of food to investigate the impact of strategy update rules on convention emergence. Agents move horizontally or vertically along the grid in search of food, and can see one square ahead. Moving incurs a cost to the agent's food *budget*. If they see an item of food, they move to that square, and otherwise they move to a randomly selected square. If more than one agent makes a bid for the same food, and neither agent attacks, then the agent that takes the food is selected randomly. If one agent attacks another (i.e. attempts to move to a square with either an agent already occupying it or another agent attempting to move there simultaneously, and chooses to attack that agent), both agents incur a food cost and the agent with the largest food budget wins.

Walker and Wooldridge define four possible strategies for agents to follow with regards to whether to attack a square: (i) giving precedence to agents in the square above (i.e. not attacking northwards), (ii) giving precedence to agents to the left, (iii) giving precedence to the right, or (iv) giving precedence to the square below. There are four main strategy update functions, broadly based on which strategies the updating agent has observed as most common. Variations to these functions give a total of sixteen possible strategy update rules.

B.2.1 Model description

Agent interactions are a little more complex in this model than in other typical approaches, since agents move around an abstract world, and interactions with other agents occur as a result of these movements. We assume that individual movements are dealt with outside of our formalism, since the only part of the model concerned with conventional behaviour is when two agents wish to eat the same food, which we call here a *conflict*. When this occurs, each agent can either yield or attack the other agent. Whether the agent yields or not depends on which of the four strategies it selects: Yield up, down, left or right.

The interaction regime for this model is given in Algorithm 5. Since interactions are symmetric, there is only one role, which we call *conflicter*. Similarly, there is only one dimension, which for the purposes of this description we call *FoodSearch*. The payoff for an agent is not specified, and the costs associated with attacking and other actions are also unknown.

Agents learn by observing the strategies employed by other agents, but do not utilise agent identity or payoff. As such, for the conflicter role, only agent strategy is observable:

$$R_{conflicter} = \langle ID = false, S = true, P = false, U = false, p = 1\rangle$$

Algorithm 5 Interaction regime for Walker and Wooldridge's model of convention emergence

//I is set of interactions
$Conflicts \leftarrow getConflictsFromAgentMovement()$
for all $FoodSquare \in Conflicts$ **do**
  $I_{new} \leftarrow \langle FoodSearch \rangle$
  for all $Agent \in getConflictingAgents(FoodSquare)$ **do**
    $I_{new} \leftarrow I_{new} \cup \langle Agent, \sigma_1, conflicter \rangle$
  end for
  $I \leftarrow I \cup I_{new}$
end for
return I

Strategy selection by each agent simply returns the currently adopted strategy, out of the four possible. Strategy update, the focus of Walker and Wooldridge's paper, involves one of sixteen possible update rules, based on four base rules from which all the variants are created. We reproduce the four base rules here, but omit full descriptions of all sixteen variants, since generating each variant is trivial. Algorithms 6, 7, 8, and 9 show the four base rules. We note that for the "Simple majority with communication by agent type" update mechanism, agents are required to be able determine if other agents in the interaction are of the same type. We assume this function is available, despite it not being expressed within our formalism.

Algorithm 6 Walker and Wooldridge's strategy update rule: Simple majority

function $su_{x,d,r}(M, I, ss_{x,d,r})$
  $highestObserved \leftarrow -1$
  for all $\sigma \in \Sigma_{FoodSearch,conflicter}$
    if $obsHist_{x,FoodSearch}(\sigma) > highestObserved$ **then**
      $highestObserved \leftarrow obsHist_{x,FoodSearch}(\sigma)$
      $\sigma_i \leftarrow \sigma$
    end if
  end for
  return σ_i
end function

Algorithm 7 Walker and Wooldridge's strategy update rule: Simple majority with memory restart

```
function su_{x,d,r}(M, I, ss_{x,d,r})
    highestObserved ← −1
    for all σ ∈ Σ_{FoodSearch,conflicter}
        if obsHist_{x,FoodSearch}(σ) > highestObserved then
            highestObserved ← obsHist_{x,FoodSearch}(σ)
            σ_i ← σ
        end if
    end for
    M ← ∅
    return σ_i
end function
```

Algorithm 8 Walker and Wooldridge's strategy update rule: Simple majority with communication by agent type

```
function su_{x,d,r}(M, I, ss_{x,d,r})
    highestObserved ← −1
    //Agents of the same type in the interaction
    AT ← I.getAgentsOfSameType(x)
    for all σ ∈ Σ_{FoodSearch,conflicter}
        if obsHist_{AT,FoodSearch}(σ) > highestObserved then
            highestObserved ← obsHist_{AT,FoodSearch}(σ)
            σ_i ← σ
        end if
    end for
    return σ_i
end function
```

Algorithm 9 Walker and Wooldridge's strategy update rule: Simple majority with communication on success

function $su_{x,d,r}(M, I, ss_{x,d,r})$
    $highestObserved \leftarrow -1$
    //Agents in the interaction
    $AS \leftarrow I.getAgents()$
    //Agents with a certain amount of success communicate
    //their successful memories
    $M_{success} \leftarrow M$
    for each $Agent \in AS$
      if $Agent.isAboveSuccessThreshold()$ **then**
        $M_{success} \leftarrow M_{success} \cup Agent.getSuccessfulMemories()$
      end if
    end for
    for each $\sigma \in \Sigma_{FoodSearch,conflicter}$
      if $obsHist_{M_{success},FoodSearch}(\sigma) > highestObserved$ **then**
        $highestObserved \leftarrow obsHist_{M_{success},FoodSearch}(\sigma)$
        $\sigma_i \leftarrow \sigma$
      end if
    end for
    return σ_i
end function

B.3 Payoff based on agent interaction history

Villatoro *et al.* (2009b) propose a convention emergence scenario in which the payoff that agents receive is determined by the number of times a strategy has been selected by the interaction participants. They situate agents on one of three network topologies: a one dimensional lattice, a scale-free network and a completely-connected stars network. Agents are associated with a finite size memory, and cannot observe overall utility, strategy selection, or payoff of others in interactions. Agents use Q-learning to update their strategies based on their payoffs.

B.3.1 Model description

Expressing Villatoro *et al.*'s model is simple using our formalism. The interaction regime (given in Algorithm 10) is identical to that given in Algorithm 3, except that there is only one possible role, which we term here *participant*. Villatoro *et al.* model two learning regimes: mono-learning, in which only one agent learns in each interaction, and multi-learning, in which both do. For brevity, we only describe the multi-learning configuration, but note that description of the mono-learning configuration is trivial[1]. There are two possible strategies, and one dimension, such that

$$\Sigma = \{A, B\}$$

,

$$R = \{participant\}$$

Agents explicitly cannot observe any aspect of their interaction partner's choices:

$$R_{participant} = \langle ID = false, S = false, P = false, U = false, p = 0 \rangle$$

Algorithm 10 Interaction regime for Villatoro *et al.*'s model of convention emergence

```
//I is set of interactions
for all Agent ∈ Population do
    Partner ← getRandomNeighbour(Agent)
    I ← I ∪ ⟨d, ⟨Agent, σ1, participant⟩, ⟨Partner, σ2, participant⟩⟩
end for
return I
```

The payoff function, the focus of Villatoro *et al.*'s investigation, is given in Algorithm 11. The strategy update and selection functions are the same as for Sen and Airiau's model, except with the learning algorithm constrained to Q-learning only.

B.4 Illustrative comparative analyses

A useful feature of our formalism is that it facilitates comparative analysis of disparate models of convention emergence from the literature, in order to allow researchers to identify generalised conclusions despite the apparent differences

[1]Briefly, expressing the mono-learning configuration would involve using two roles for each interaction, where for one of which the agent updates their strategy and for the other the agent does not.

Algorithm 11 Payoff function for Villatoro *et al.*'s model of convention emergence

function $P_{x,d,r}(I, \mathcal{P}(M))$
  for each $Agent \in I.getAgents()$
    $TotalAActions \leftarrow obsHist_{Agent,d}(A)$
    $TotalBActions \leftarrow obsHist_{Agent,d}(B)$
  end for
  if $TotalAActions \leq TotalBActions$ **then**
    return $\dfrac{obsHist_{x,d}(B)}{TotalBActions}$
  else
    return $\dfrac{obsHist_{x,d}(A)}{TotalAActions}$
  end if
end function

in models used. In this section, we demonstrate such a comparative analysis, using Villatoro *et al.*'s model (2009b) and Sen and Airiau's model (2007).

Villatoro *et al.*'s model can be seen as a simplified version of that used by Sen and Airiau. The key differences to examine are strategy update mechanisms, observability, and payoff. In terms of observability, Sen and Airiau allow agents to observe their participant's strategy and payoff. However, this is only a result of the use of payoff matrices for the payoff function: if an agent knows its own payoff and the strategy it chose, it therefore knows what the opponent chose, and their payoff. Only Fictitious Play actually uses the knowledge of the opponent's strategy selections. Restricting strategy update/selection mechanisms to Q-learning or WoLF therefore renders the observability identical between the two models for all practical purposes.

In Sen and Airiau's model, there are two roles in each dimension, where there is only one in Villatoro *et al.*'s work. In the coordination game dimension in Sen and Airiau's model, agents are rewarded for selecting the same strategy, as they are in Villatoro *et al.*'s. The key difference in the reward between the two models is that Villatoro *et al.*'s model incorporates an agent's strategy selection history in the calculation of payoff. The interaction regimes are identical, save for the difference in the number of roles. We can therefore directly compare results, where those results are reported for similar conditions. We find one such configuration when each model is run with a completely connected network, all agents using Q-learning, and (in Villatoro *et al.*'s case) low memory sizes.

Under these conditions, populations in Villatoro *et al.*'s formulation take at least 1000 timesteps to converge (with convergence time increasing with memory size), whereas Sen and Airiau's populations converge in just 100. There are two main differences between the models at this point: the use of a different number of roles for each dimension and the incorporation of history into payoff function. It is unclear why having two roles would result in *faster* convergence, since it means that each learning algorithm has less information for the same number of interactions (as compared to using one role), whereas there is an attractive hypothesis for why incorporating history results in slower convergence. Specifically, incorporating history means that "wrong" choices in the past affect an agent's payoff for longer, whether as a result of exploration or adherence to a convention that no longer holds. As a result, it takes longer for an agent to receive the full benefit of switching to a new convention in Villatoro *et al.*'s formulation, whereas in Sen and Airiau's model an agent can instantaneously and completely benefit from a switch in strategy. Expressing each model in our formalism has thus allowed us to identify specific differences in configuration and determine which of these might account for observed differences in results — although empirical evaluation is still necessary to confirm this hypothesis.

Comparison with Walker and Wooldridge's model is more difficult. While expressable within our formalism, the interaction regime and payoff structure are of completely different forms to those used by Villatoro *et al.* or Sen and Airiau. However, usage of our formalism allows us to design experiments that test the impact of each specific difference. For example, Walker and Wooldridge find that some of their strategy update rules converge in around 300 timesteps. To test whether this is a comparable rate to that of Sen and Airiau, or Villatoro *et al.*, we can easily implement the update rules in these other models. However, if we believe Walker and Wooldridge's model to be more applicable to our domain of interest, we can use our formalism to design experiments to examine each component individually.

For example, the interaction regime, which determines the rate and participants of interactions in the model, can be easily swapped for the regime from Villatoro *et al.* or Sen and Airiau. Further simulations will allow us to determine if the interaction regime has any significant effects on the convergence rate within Walker and Wooldridge's model. Further, we could alter the payoff function to use a payoff matrix or Villatoro *et al.*'s payoff incorporating interaction history. This would further corroborate or refute the analysis above regarding the effect of incorporating history into payoff calculations, and allow us to determine the extent to which the unique payoff structure of Walker and Wooldridge's work affects the reported convergence rates.

B.5 Summary

In this appendix, we have shown how three common convention emergence scenarios can be expressed in a single unified interaction formalism. By using a common formalism, many of the features and characteristics of the various techniques proposed for convention emergence in these scenarios can now be directly compared, and experiments for illuminating the causes of empirical differences between results can be more easily designed. We have demonstrated this by (i) analysing Sen and Airiau's (2007) model with respect to that of Villatoro *et al.* (2009b), and demonstrating that the use of interaction history in calculating agent payoff may be a cause for slower convergence and (ii) discussing experiments that can be run to determine which aspect of Walker and Wooldridge's (1995) model results in their faster convergence.

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