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EMERGENCE OF CONVENTIONS IN SOCIAL NETWORKS

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Abstract. *In this work is considered the problem of the emergence of conventions in a society through distributed adaptation by agents from their on-line experiences at run time. The agents are connected to each other within a fixed network topology and interact over time only with their neighbors in the network. Agents recognize a social situation involving two agents that must choose one available action from multiple ones. The study confirms the emergence of system-wide conventions via the process of social learning where an agent learns to choose one of several available behaviors by interacting repeatedly with randomly chosen neighbors without considering the identity of the interacting agent in any particular interaction.*

Keywords: social network, social interaction, convention, scale-free topology, multi-agent systems, machine learning.

1. Introduction

Favored by the large support of mass-media and of Internet, new ways for interaction and collaboration between individuals has arrived in the form of social networking.

The tendency to group a growing number of entities (in particular individuals) is typical for complex systems, and this it done not by cluster size, but by the huge number of mutual interactions between members.

Recent (let say the last twenty years) specialty literature indicated that networks are the best fit for this structure, and among these Scale-free Networks (SFN) having both topology and dynamic behavior (expressed by the flow of information) independent of scale representation seem to capture best the behavioral characteristics

(Internet remains the best example, with its fractal topology and self-similar patterns exhibited in the informational traffic).

In the same time, one can affirm that the main characteristic of complex systems with SFN structure is self-organization.

Self-organization is the way due to which following rules (usually simple) of behavior emerges a new organizational structure and new interactions entities also appear in the system.

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The term self-organization is used to describe the dynamics of complex systems and related emergent processes. Most often the interactions are nonlinear and the evolution is nondeterministic (somehow chaotic), but may lead to a new hierarchical order in the system.

In this way, emergence is a step in the evolution of complex systems allowing their adaptation to changes in the environment and can also bring new ordering relationships, for example by limiting the degrees of freedom of movement.

Through its relationships with social entities, an organization overcomes the entities' cognitive, physical, temporal, formal and informal barriers and thusly, through its formalism of group affiliation, its procedures, objectives and restrictions imposed to its members, it persists despite the fact that, alone or at group level the agents (i.e., the members of a social entity or of an organization) do not interact.

Consequently, the organizations enjoy the advantages of its own purely formal structures which can exist independently of the individual objectives, actions and intentions of the agents, which it actually coerces to act in a certain manner, such as through objective differentiation and therefore though material benefits differences, with the objective of reaching the organization's goals.

Conversely, an organization's formalism can become its disadvantage due to the inherent rigidity of the roles and structures of its makeup, which every so often are slow to react to open, dynamic and unpredictable environments.

In order to compensate this disadvantage, the organization must employ complex social interaction capacities, such as cooperation and negotiation, as well as adaptability and efficiency in overcoming the problems of its members (e.g., loss of interest, lack of interaction etc.).

Based on the above, we can conclude that organizations (i.e., systems composed of multiple agents/individuals) exist, react and persist due the common objectives and simultaneous actions of its members, and cannot be modeled like the social systems where, sociologically, the change of the systems' structure is due to the interaction between its members but not due to their intentions, which can be different.

Taking into account the needs of those organizations to respond quickly to the specific challenges of a hyper connected world, in this paper we study the emergence of conventions in a society of artificial agents through the repeated interactions between its members.

An on-line (or run-time) convention means that agents can tailor their decision to the current environment. Each agent learns from its interactions concurrently and over repeated interactions with randomly selected neighbors.

Hence, it is important to study mechanisms that lead to emergence of a convention from on-line interaction experience.

Two particular approaches have been proposed to determine the development framework of this model: multi-agent system organization to observe how the members of such a system relate (for explanation of some elements of social emergence, such as collaboration, consensus, confidence) and respectively scale-free networks for evidence of some elements of organizational emergence (growth mechanisms and degree of interconnectivity).

2. Related works

The emergence of social conventions in multi-agent systems has been rigorously analyzed first in the seminal work of Delgado [1], with reference to settings where every agent may interact either with every other agent or with nearest neighbors, according to some regular underlying topology.

These networks, one of the main examples being the Internet, are what is called complex, that is, either graphs with the small-world property or scale-free graphs. In this note is studied the efficiency of the emergence of social conventions in complex networks, with the conclusions that scale-free graphs make the system much more efficient than regular graphs with the same average number of links per node.

The problem of cooperation in multi-agent systems was largely discussed in [2]. The novelty consists in proposing the use of machine learning techniques to automate the search and optimization process.

Additionally, the authors discuss direct and indirect communication between agents in connection with learning, plus open issues in task decomposition, scalability, and adaptive dynamics.

Successive progress in resolving the issue of emergence has been brought about by the work of a group of authors ([3], [4], [5], [6]) that have started from the definition of convention by reference to social norms and have studied different network structures, in order to compare and evaluate the effects of different network topologies on the success and rate of emergence of social conventions.

Additionally they proposed a reward metric that takes into consideration the past action choices of the interacting agents, based on classical game theory.

Finally, we mention some more recent developments ([7], [8], [9]) that simultaneously address the three trends highlighted in social systems research: machine learning algorithms for evaluating cooperation mechanisms in multi-agent systems, evolutionary games to determine the effectiveness of social interactions and accuracy of social networks models based on free-scale topologies.

Their contributions explain the emergence of cooperation, model the co-evolution of multiple network event streams to allow for more complex data structures with many types of nodes and events and introduce network statistics to reflect the potentially complex dependencies among agents.

3. Basic principles of the General Theory of Information

Definition of social interactions

Let consider a population of N interacting agents. Although in the general case a convention could involve an interaction between many agents at the same time, in our study we discuss only the case of bilateral interactions, the most common in practice. For our definition of a bilateral social interaction, we consider (similar to the definition given in [6]) that each agent plays a specific role: first role (or row role) and second (or column) role, where the rows and columns are elements of a matrix (the payoff matrix) reflecting the preferences between the different outcomes of the interaction for each agent like in a normal-form game.

Of course, we consider that each agent can experience both roles. The agent has to select an action in the set A_r of actions available to the row role, respectively in the set A_c of actions available to the column role). Each agent models the situation with a payoff matrix P_i of size $| A_r | \times | A_c |$.

Definition 1 (*Social interaction*) A social bilateral interaction is a 4-tuple $\{N,A_r,A_c,(P_i)_{i\in N}\}$ where:

– agent i gets $P_i\ (a_r,a_c)$ when i is the row agent and chooses action a_r and the other agent is the column agent that chooses a_c.

– agent i gets $P_i\ (a_r,a_c)$ when i is the column agent and chooses action a_c and the other agent is the row agent that chooses a_r .

We assume that all agents have a similar understanding of the social situation: all the agents share the same ordinal preference over the different outcomes of the game, but they may have different cardinal preferences. This assumption excludes from consideration situations where agents that have different preferences between the outcomes.

By the other hand, we allow the actual payoffs to differ from agent to agent, and we allow indifference: if some agents strictly prefer outcome a over outcome b, then no agent strictly prefer b over a, but some may be indifferent over them.

Topologies of social networks

Agents are connected by a interconnection graph G of a fixed topology that restricts their interactions only with their direct neighbors (we represent agent relationships with nodes and links).

Every node *i* represents an agent (actor) *i* within the network and links (*i, j*) denote social ties between agents *i* and *j*.

More of that, we decorate each link (*i, j*) with the strength of the social tie or the amount of information flowing through it, hereafter called link weight $w_{i,j}$.

The statistical analysis of link weights $w_{i,j}$ between pairs of vertices in the social network indicates an heterogeneous pattern of interactions, typically following a power law: $P(w_{i,j}) \sim w_{i,j}^{-\lambda}$ where $P(w_{i,j})$ is the probability of having a link with weight $w_{i,j}$.

In addition, the heterogeneous distribution of link weights might be related to the hierarchical organization of the social network.

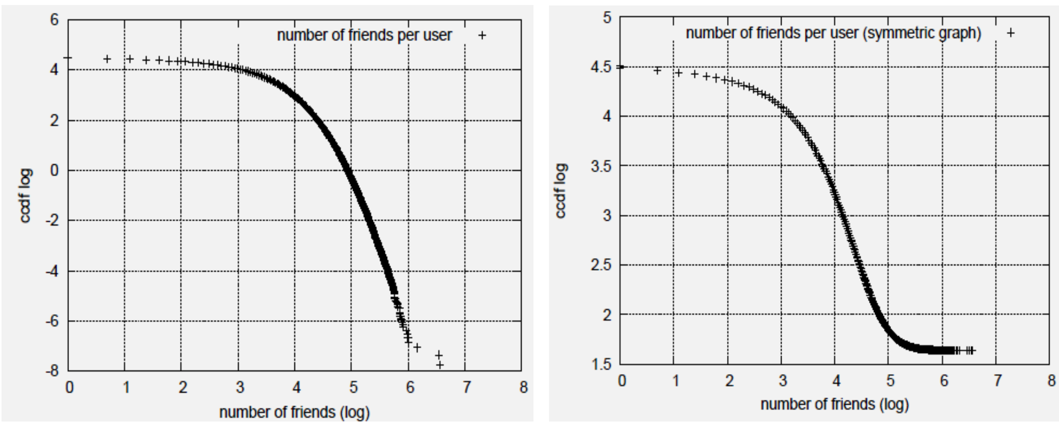
In this aim, we define $\vec{P}(w_{i,j}) \sim w_{i,j}^{1-\lambda}$ as the cumulative distribution function (cdf) of $P(w_{i,j})$ and $\overleftarrow{P}(w_{i,j}) = 1 - P(w_{i,j})$ as the complementary cumulative distribution function (ccdf), or simply the tail distribution.

For example, in **fig. 1** are represented the tails for the distribution of the number of agents (friends) per user in a simulation of a small social network with around 500 users, were each user is represented as a node in a graph. Each node is encoded with an integer.

The analysis of the graph was made for two cases, depending of the social relation between two users A and B, which can be asymmetric or symmetric.

An asymmetric relation (**fig. 1 a**) means that if node A has an edge to node B, this does not mean that B also has an edge to A.

Of course, in the symmetric relation (fig. 1 b) there is a bidirectional link between A and B.



a. **b.**

Fig. 1. ccdf of the friendship graph: **a)** asymmetric; **b)** symmetric.

Both distributions seem to be heavy tailed, which means that the properties of the graph do not change if the edges in the graph are directed or undirected.

For these reason in all other simulations we have considered only the symmetric version of the graph, which is more appropriate with the real case of open social networks (OSS).

There is a characteristic pattern of symmetric interaction, where a few strong units dominate the activity of the whole OSS. Interestingly, the distribution of link weights in large software communities also follows a power-law; with an exponent consistent with the observed in the small software communities.

Most real networks typically contain parts in which the nodes (units) are more highly connected to each other than to the rest of the network. The sets of such nodes are usually called clusters, communities, cohesive groups, or modules having no widely accepted, unique definition.

This remark leaded us to consider that the most suitable topology of a social network is that of a scale free network [10].

Fig. 2 illustrates the topology of a free scale network with 128 nodes that started from an initial core of 4 nodes; in the connection of other nodes we have applied the law of the preferential attachment.

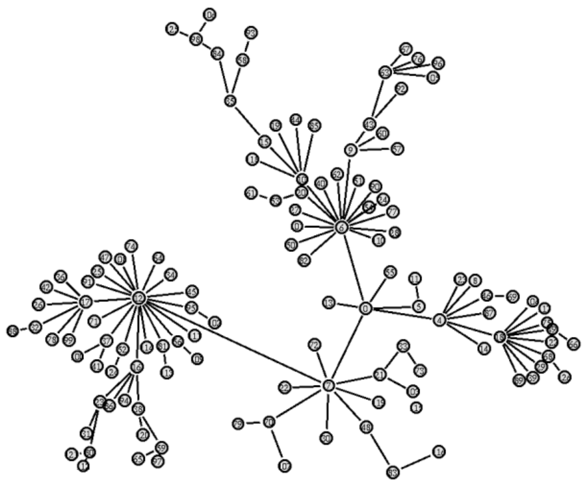


Fig. 2. A network with scale-free topology.

Social interaction protocol

To resume, we consider in our model a population of N of $n = |N|$ agents located in a graph G that faces a social situation involving two roles, with their corresponding action set A_r, A_c, and each agent i models the social situation with a game having a payoff matrix Pi. Hence, we represent the social situation as a tuple $\{N,G,A_r,A_c,P_1, . . . ,P_n\}$.

The simulation of the system progresses in discrete steps. At each iteration, many distinct pairs of agent are randomly generated. To make a pair, an agent is first chosen from the set of agents that has not already been selected, and is paired with a randomly selected neighbor that has not yet been selected. This selection process is iterated until no more pairs can be formed, i.e., when there are no more neighbor agents that have not been selected.

In the case of a fully connected graph, this algorithm will produce N/2 pairs at each iteration, and all the agents will learn at the same speed.

However, when agents do not have the same number of connections, the agents that have more neighbors are more likely to experience an interaction at each iteration.

This selection imbalance introduces a bias: agents with more connections will accumulate more experience and will learn faster than agents with a small number of connections.

Because of the topology of the graph, agents with many connections will also have a greater influence on others.

4. Theoretical approaches in the Information Science

Definition of a social convention

The behavior of an agent in repeated play of a bilateral stage game is characterized by its actions when it plays respectively the row role and the column role.

More formally, given a social interaction $\{N,G,A_r,A_c,P_1, . . . ,P_n\}$, the behavior of an agent i is a pair (r^i , c^i) that consists of a pure strategy $r^i \in A_r$ for the row role and a pure strategy $c^i \in A_c$ for the column role (the strategies are the actions available to the agents). A convention corresponds to an equilibrium strategy profile for all pairs of agents in the population. It is a simplified form of the consensus principle used in Decision Support Systems (DSS) philosophy.

Definition 2 *(Social convention)* For a social situation $\{N,G,A_r,A_c,P_1, . . . ,P_n\}$, we say that the population uses a *convention* when for all pairs of agents (i, j), we have both that (r^i , c^j) is an equilibrium for the game $(P_i , P^T{}_i)$ and $((r^j , c^i)$ is an equilibrium for the game $((P^T{}_i, P_j)$where P^T is the transpose of P.

Not all equilibria are conventions, and in the following, we will consider that a convention is a pure strategy Nash equilibrium. The use of a Nash equilibrium ensures that the equilibrium is stable: knowing that other agents are following the convention, a given agent is incentivized to follow it as well.

We consider only pure strategies as, in practice, conventions are pure strategies.

In Nash equilibrium the two players adopt a pair of strategies such that neither player can get a better payoff by deviating from their strategy.

In other words, each strategy is a best response to the other. Depending on the game, there may be no Nash equilibrium, a unique one, or much equilibrium. Because in these strategies the players are not allowed to use randomness to decide their moves, they are called pure strategies.

Now is the moment when Machine Learning (ML) as technique Artificial Intelligence (AI) of meets Game Theory. Many situations involving many agents can be modeled as games where learning algorithms can then be used as decision making mechanisms. As a result, learning to play repeated games has been an active area of research in multiagent systems and in particular in social networks, when considering that all agents would adopt the same learning algorithm in a decentralized environment.

Machine learning algorithm

We assumed that the basic decision making mechanism of an agent is a learning mechanism. This allows the agents to adapt their behaviors to their current environment and reduces the need for the system designer to specify precise parameters for each environment.

We will further assume that agents try to learn a behavior at the level of a social interaction. For example, an agent does not try to learn a behavior that depends on the specific agent he interacts with. If an agent fails to learn an appropriate behavior at this level, we would assume that the agent would refine her model of the situation (e.g. consider different sub-situations or learn some exceptions). Then, the agent would be able to recognize a given situation and use the appropriate data to make a decision.

With the social learning framework, there is no theoretical guarantee that a convention does emerge and stabilize. The goal of the agents is not to learn or discover a convention. Rather, their goal, as rational agents, is to choose decisions to maximize their expected utility. In order to test whether it was possible for learners to choose a correct behavior, we chose reinforcement learning as our tool for decision making.

In this aim we are studying the emergence of a convention in a population of interconnected interacting agents. Each agent uses a learning algorithm to learn, from accumulated experience, how to behave in each role of the social situation. We will at first assume that the agents do not have any initial bias towards a particular equilibrium.

We want to observe whether the population is able to learn the same behavior, i.e., whether, in the long run, the population adopts a convention.

To learn a useful behavior, an agent needs to first explore its options and subsequently exploit its accumulated knowledge. Even when the behavior of other agents appears predictable, an agent will need to explore periodically to ensure that it is not using a sub-optimal strategy.

It is also important in case of a change in the environment or if they change environments. This is particularly important for open and dynamic agent societies that are of interest to us and to a large percentage of researchers in the multi-agent systems community.

Consequently, to identify the emergence of a convention, we adopted a common definition from literature [11].

Definition 3 (*Convention emergence*) For a social $\{N,G,A_r,A_c,P_1, . . . ,P_n\}$, a convention has emerged when the strategy profile $(r,c) \in A_r \times A_c$ is played by T % of the population in a given iteration. The threshold T is different in various contributions, but all the authors agree that it should be at least 90%.

Note that each agent must learn how to behave for each role of the social situation. In this paper, we assumed that both roles are learnt independently. Of course, this issue is relevant for interactions that are not symmetrical. For symmetric problem, we would simply need a single learning algorithm.

Now we consider agents situated in more restrictive interaction topologies. Each agent is represented by a node in the network and the links represent the possibility of interaction between nodes (or agents). We consider that agents form a one-dimensional lattice with connections between all neighboring vertex pairs. We can see that when increasing the neighborhood size, the convergence time is steadily reduced. This effect is due to the topology of the network. When the one dimensional lattice has a small neighborhood size, on average, the diameter of the graph is high and therefore agents located in different parts of the network need a higher number of interactions to communicate their decisions or arrive at a consensus.

When agents have a small neighborhood size, they will interact often with their neighbors, resulting in diverse sub conventions forming at different regions of the network. We note that in each interaction, both agents are learning from it, therefore agents reinforce each other in each interaction. Such divergent sub conventions conflict in overlapping regions. To resolve these conflicts, more interactions are needed between agents in the overlap area between regions adopting conflicting sub conventions.

Unfortunately, the agents in the overlapping regions may have more connections in their own sub convention region and hence will be reinforced more often by their sub conventions, which makes it harder to break sub conventions to arrive at a consistent, uniform convention over the entire society.

On the other hand, when neighborhood sizes are large, and hence network diameters are small, agents interact with a large portion of the population. As a result, it is less likely that sub conventions are created or sustained.

Emergence of conventions in scale-free networks

We observe an interesting phenomenon for scale-free networks: sub-conventions might be persistent and the entire population fails to converge to a single convention. This phenomenon can be explained by some particular structure of the network.

In general, each node i of a network can be characterized by a membership number m_i, which is the number of communities the node belongs to. In turn, any two communities α and β can share $s^{ov}_{\alpha,\beta}$ nodes, which we define as the overlap size between these communities.

Naturally, the communities also constitute a network with the overlaps being their links. The number of such links of community α can be called as its community degree, d^{com}_{α}.

Finally, the size of any community α can most naturally be defined as the number of its nodes. To characterize the community structure of a large network we introduce the distributions of these four basic quantities. In particular, we will focus on their cumulative distribution functions denoted by $P(s^{com})$, $P(d^{com})$, $P(s^{ov})$, and $P(m)$, respectively.

The basic observation on which our definition for community relies is that a typical community consists of several complete (fully connected) subgraphs that tend to share many of their nodes.

Thus, we define a community, or more precisely, a k-clique-community (the term was introduced in [12]) as a union of all k-cliques (complete subgraphs of size k) that can be reached from each other through a series of adjacent k-cliques (where adjacency means sharing $k-1$ nodes).

This definition is aimed at representing the fact that it is an essential feature of a community that its members can be reached through well connected subsets of nodes.

There are other parts of the whole network that are not reachable from a particular k-clique, but they potentially contain further k-clique-communities.

In turn, a single node can belong to several communities. All these can be explored systematically and can result in a large number of overlapping communities. Notice that in most cases relaxing this definition (e.g., by allowing incomplete k-cliques) is practically equivalent to lowering the value of k.

In the same time any k-clique (complete subgraph of size k) can be reached only from the k-cliques of the same community through a series of adjacent k-cliques (two k-cliques are adjacent if they share $k-1$ nodes). The algorithm for numerical determination of the full set of k-clique-communities is based on first locating all cliques (maximal complete subgraphs) of the network and then identifying the communities by carrying out a standard component analysis of the clique-clique overlap matrix [8]. We use our method for binary networks (i.e., with undirected and unweighted links).

An arbitrary network can always be transformed into a binary one by ignoring any directionality in the links and keeping only those that are stronger than a threshold weight w^*. Changing the threshold is like changing the resolution with which the community structure is investigated: by increasing w^* the communities start to shrink and fall apart. A very similar effect can be observed by changing the value of k as well: increasing k makes the communities smaller and more disintegrated, but at the same time, also more cohesive.

The extent to which different communities overlap is also a relevant property of a network. Although the range of overlap sizes is limited, the behavior of the cumulative overlap size distribution $P(s^{ov})$ is close to a power law for each network, with a rather large exponent.

5. Conclusions

We investigated a bottom-up process for the emergence of social convention that depends exclusively on individual experiences rather than observations or hearsay. The proposed social learning framework requires each agent to learn from repeated interactions for a given social situation, without using knowledge of the identity of the other agents involved in the interactions.

The goal of this work was to evaluate whether such social learning can successfully evolve and sustain a useful social convention that resolves conflicts and facilitates coordination between population members.

The experimental results confirm that such distributed, individual, and social learning is indeed a robust mechanism for evolving stable social conventions. The results also suggest that to deploy a multiagent system, one can use generic agents that use learning mechanisms which can, with no detailed knowledge of the environment, learn efficient and stable coordination behavior.

Additionally the results confirm that stable conventions arise in scale-free networks because of some inherent structural characteristics of these networks. For the future we plan to investigate, in further depth, the reasons why these conventions might be created and maintained, as well as, mechanisms to dissolve them.

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