The impact of betweenness in small world networks on request for proposal coalition formation problems.

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Abstract. The analysis of societies demonstrates the recurrent nature of small world topology in the interactions of elements in such worlds. The small world topology proves to have beneficial properties for system's performance in many cases, however there are also scenarios where the small world topology's properties negatively affect the system's outcome; thus in depth knowledge on the small world weaknesses is needed in order to develop new generations of artificial societies and new models of economic systems. In this paper, a multi-agent system based on request for proposal protocol and coalition formation organisational paradigm is used to analyse properties of small world social networks of agents. Experiments center on nodes in the network with high betweenness and in particular the distribution of agents in the population across these nodes. Results show that small world topology scenarios lose their beneficial properties when non-competitive agents are positioned as high betweeness nodes in the network.

Keywords. Network analysis, Small World, Request for proposal, Coalition formation

1. Introduction

Interactions are the cause and effect of any society. In human societies, the number of those interactions is reduced because they are affected by geographic constraints and many other different events that bias the way people interact in an homophilic manner. A recurrent topology resultant on those constraints is the *Small World* [16], which beneficial properties have been studied for many different environments ([17,18] amongst many others), however, this topology is not exempt of weaknesses, as it has recently been revealed in [8], where small world networks are compared with other topologies proving faster convergence to near optimal outcomes but worse long term behavior. A similar result was obtained in [10] where high clustering coefficient in small world networks proved to be a handicap in some specific search problems. The present work extend those results giving an explanation on the negative effects observed in small world topologies.

The specific problem for which network analysis is performed is *Coalition Formation*. Coalitional systems are organisational mechanisms where agents have to explore a search space of agent group combinations in order to improve data flow, allocate resources efficiently, solve a problem in a coordinated manner, or to improve their outcomes by creating alliances. Those systems have been traditionally studied from a far-sighted perspective, and focused on the problem of finding stability concepts ([15,14] amongst many others) . Multi-Agent Systems research introduced the possibility of experimenting with coalitional systems with a limited number of possible interactions [1,12], and more recently myopic agents have been studied with concrete knowledge network topologies in team formation [5,6] as well as in firm formation models [2]. In this line, the work presented here defines a model that considers different small world underlying social networks on an specific type of electronic market allocation mechanism called Iterated Request For Proposal (RFP from now on). This model was first studied in [7], and further explored in [9], [11] and [10]. In this environment, an entity regularly issues a call for tender to provide specific goods or services with certain characteristics. Providers compete amongst themselves (either individually or in consortia – *coalitions*). Structures created are based on complementarity of their members. The more complementary they are, the better outcome they obtain. However structures do not grow in an uncontrolled manner, instead they optimise their size leaving out redundant members that would decrease the share of the eventual income of the coalition. There are many existent real systems that follow the RFP type procedures such as public building projects, competitive tender for government contracts or even collaborative research project grants. A main characteristic of the model is that instead of having agents that dynamically adjust their social connections [8,5] or that propagate/contaminate their neighbors through a social network [3,13], agents are constrained by a unmovable social network where no social capital is transmitted. However, agents can iteratively and incrementally form coalitions as long as there is a direct neighbor in the coalition – leading to an evolutionary process that converges to a Nash equilibrium. These dynamics gives shape to coalitions by putting together agents that can be far away from each other in the social network. Results obtained explain how the system performance is affected by the concrete capabilities of agents placed in specific positions of the social network. Concretely the positions studied are those with high betweenness [4]. Betweenness is a well known centrality measure that examines the extent to which an actor (node) is between all other actors within the network. This concept has been extensively used and adapted in network research area becoming one of the most important centrality concepts. In the present work evidence is provided to support the argument on the importance of betweenness central nodes in the network in the context of an iterated coalitional system, and specifically, experiments are addressed to provide data to explain the negative performance observed in small world networks in [10].

The rest of the paper is structured as follows: section 2 presents a formalisation of the RFP mechanism. Section 3.1 describes an specific metric that records the amount of dynamism that a certain topology generates as well as other metrics used to perform the analysis and the experimental setup. Results on the importance of positioning of agents with specific individual properties (*versatility* and *competitiveness*) in certain parts of the social network are provided and analysed in section 3.3. Finally, section 4 summarises the main conclusions.

2. Iterative RFP Coalition Formation Model

A population $I = \{1, 2, \ldots, n\}$ consists of a finite number of n individuals or *agents*. Agents compete for creating the best solution proposal to a given task *task* T. A *parti-*

tion $\sigma = \{\sigma_1, \sigma_2, \ldots, \sigma_p\}$ of the population I is a specification of p *coalitions* of agents $\sigma_i = \{\sigma_{i1}, \sigma_{i2}, \ldots, \sigma_{im}\}$, where σ_{ij} represents an agent from population I forming part of coalition σ_i. By forming coalitions, agents are able to increase their competitiveness towards the specified task, they are encouraged to do so as coalitions would be priced according to their ranking. Moreover they are encouraged to reduce coalition size hence increasing individual benefits by splitting the potential payoff amongst less members. Agents have heterogeneous capabilities, thus having different performance levels in different skills. A finite number of k *skills*, indexed from 1 to k is set for which each agent σ_{ij} has a fixed value: $\sigma_{ij} = \langle \sigma_{ij}^1, \sigma_{ij}^2, \ldots, \sigma_{ij}^k \rangle$. This way, it is possible to define a continuum of possibilities between agents that are *specialised* in the performance of a certain skill being unskilled for the rest of them, and agents that are *versatile*, being averagely apt for the performance of all the skills defined. A Task T is specified by a set of k skill requirements: $T = \langle T^1, T^2, \ldots, T^k \rangle$. Each one of the k skills have a degree of requirement. These requirements are modeled in the form of a number. In a coalition, skills of agents are aggregated in such a way that each agent gives the best of itself in a join effort to create a group as competitive as possible under the requirements of the Task. The coalition has a value in each skill representing the aggregated effort of its members. The aggregation for every skill $l : 1 \leq l \leq k$ in the coalition is modeled as:

$$\sigma_i^l = \max(\sigma_{ij}^l) : 1 \leq j \leq m \tag{1}$$

Each skill is considered as a necessary subtask for performing task T. By using the aggregation function shown in equation 1, the agent in a coalition which is the best fit for performing a certain subtask will be the one that performs it. This specific type of aggregation is chosen because it is characteristic of many different socio-economic processes. The aggregated effort of agents in equation 1 is used to measure an score $scr(\sigma_x, T)$ that indicates how well the agents in coalition σ_x perform together for accomplishing a task specification T. The score of a coalition is computed as the scalar product between σ_i and T. Amongst many possible choices, this metric is chosen because it captures in a simple way the different importance of subtasks T^l, and the additive valuation of all the required skills:

$$scr(\sigma_i, T) = \sum_{l=0}^{k} (\sigma_i^l * T^l) \tag{2}$$

2.0.1. *Agent Choices and Strategies*

Each player's strategic variables are its coalition choice to join σ_j and a set of agents in this coalition $\phi_{jk} : \{(\phi_{jk} \subset \sigma_j) \vee (\phi_{jk} = \emptyset)\}$ to eliminate. The possibility for optimisation responds to the change of value that certain agents can experiment when in their coalition they are out-skilled by a new member and so they become redundant. Only those actions accepted by a majority (more than the half) of members in the affected coalition, are performed. An agent that is requested to take an action can submit a finite number of requests in an specific order, in such a way that if an action is not accepted, the next action is checked and so on. If none of its action proposals is accepted, the agent stays in the same coalition where it was.

All the agents in the population follow the *Competitive Strategy* [9], that consists on proposing a set of actions that contain every proposal that either improves the score of the coalition the agent is in, or keeps the same score while reducing the size of the coalition. When they receive a proposal from an outsider, they accept if they are not in ϕ_{jk}'s proposal, and if the proposal improves the score or keeps it while reduce the coalition size.[1] Every agent j has a fixed social network α_j that is a non-empty set of agents. When considering to join a different coalition, agents are limited to just evaluating coalitions of agents in α_j.

2.0.2. RFP Iterated Model

At time 0, every agent is a coalition of just one element ($\sigma_i = \{\sigma_{ii}\}$). A task T is issued and a run of negotiation starts in which every agent, sequentially and following a random order, is asked about an action to take (see previous subsection). Agents have no knowledge on the order in which they are requested for an action, and when they are asked they can consider any action involving the coalitions in which there is some member of their social network. The run ends when all agents have been requested for an action. The process last as many runs as necessary until it converges to an stable state. Stability is reached when in a complete run, no agent is willing to leave the coalition is in or none of its actions are accepted by the hosting coalition.[2] When the system has reached equilibrium, coalitions' scores are captured for further analysis.

3. Experiments

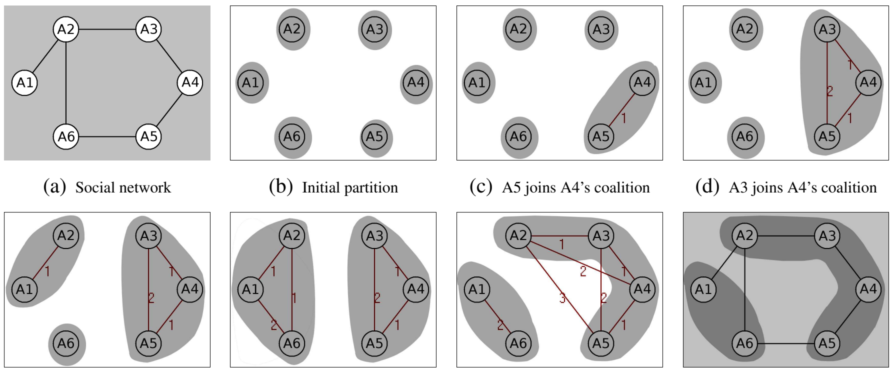
3.1. Metrics used in the experiments:

In order to measure how competitive an agent is in a simple way, every agent in the population is endowed with the same total number of skill capabilities, but distributed differently across skills. A highly competitive agent has higher concentration of capabilities in a reduced set of skills while a versatile agent is averagely apt in every skill. This way we can define a simple metric of *Competitiveness*: $com(\sigma_{ij})$, by just measuring the standard deviation in its skill values weighted by the task values. Analogously, *Versatility* is defined as the inverse of *Competitiveness*: ($ver(\sigma_{ij}) = 1/com(\sigma_{ij})$).

In order to test the dynamics that a certain underlying social network permits, a metric called *Historical Average Degree* (HAD from now on) is defined. This metric measures the distance that exists in the social network between agents in a coalition. What makes this metric different from the classical distance definition (minimal path length between two nodes), is that the distance is measured just using the links between the coalition members. The HAD value between two members does not change through the addition or abandon of partners. When an agent A joins a coalition there is at least 1 member (B) with path-length equal to 1, (otherwise this agent would not directly know any of the members of the coalition, hence it could not consider that coalition). The distance to the other members corresponds to 1 (distance from A to B) plus the minimal path length from B to the member of the coalition through a complete HAD valued network between members of the coalition. The coalition HAD value is the mean of each

[1] In [11] a payoff optimisation based strategy (conservative) is compared with the *competitive* approach used in here, resulting in worse general results for conservative populations

[2] In [11] it was shown how the system always converge to an stable state when the population follows an score maximizing strategy.



(a) Social network (b) Initial partition (c) A5 joins A4's coalition (d) A3 joins A4's coalition

(e) A1 joins A2's coalition (f) A6 joins A2's coalition (g) A2 joins A3's coalition (h) social net & coalitions

Figure 1. Example of iterated coalition formation process. Edge's values reflect the HAD between nodes. Shaded areas denote coalitions.

HAD value between each member of the coalition. This mean is computed for every coalition when the system has reached equilibrium. Figure1 exemplifies how the metric is computed during the process of coalition formation.

The global performance of the system is computed by measuring the quality (score) of the coalitions formed. It is assumed that for the entity who issues the RFP, it is important to obtain the higher score in the top coalitions rather than obtaining many coalitions with averagely high score. The concrete function used to measure this, is defined as follows: $Sc(\sigma) = \sum_{\text{rank}=0}^{p}(\text{scr}(\sigma_{\text{rank}}, T) * 1/2^{\text{rank}})$. This way, a certain experiment ends up with better or worse results depending on how efficient the best agents are in getting to know each other.

3.2. experimental set-up

In order to investigate the effects of the identity of agents in high betweenness positions, a significant number of experiments have been performed. A total of 1000 networks with 500 nodes have been tested, all of them are *Small World* networks (using the Watts-Strogatz model [16] with $p = 0.07$). For each one of the networks, 3 different mappings have been created in the following way: on the one hand, for every network, nodes are ordered decreasingly by *betweenness centrality*. On the other hand, 2 different orders of agents are created by computing *com*, and *ver* metrics in every agent (see section 3.1) and ordering agents decreasingly by each metric's values. Every experiment maps every agent in one of the 2 specific orders (*ver-ord* or *com-ord*), to a node according to its $betweenness$ order in the network. An additional random mapping *rdm-ord* has been used to create the third tested order. That creates a total setup of 3000 experiments: for each one of the 1000 different small world networks, 3 different sets of experiments are performed, each one with a concrete mapping between node betweenness and agent characteristics. Experiments are run until the system has converged to an equilibrium (see section 2.0.2).

For space restriction reasons, not all the experiments performed are shown. Some of the variables have been fixed. These variables are: the population composition (500 agents with 10 skills and, for every agent a total value of 100, heterogeneously distributed amongst the skills. The stdev. in the skill distribution is homogeneously distributed from 5 to 20. The task used in all the experiments is: $T = \langle 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 \rangle$ [3]. The connectivity degree k is also fixed to an average of 10.3 with very few deviation, hence connectivity is homogeneously distributed and results are not affected by the degree factor showed in [10].

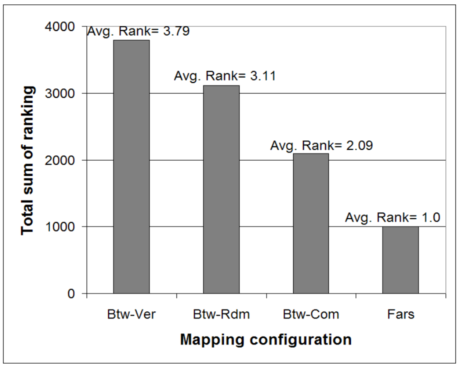
3.3. Experiments Results

Results obtained by each different mapping at the end of each experiment (each experiment has a different underlying network) are compared in terms of $Sc(\sigma^*)$ (see section 3.1). This way, each mapping gets a rank between 1 and 4 (as there are 4 different configurations under test). Figure 2(a) shows the sum of each ranking for each of the configurations tested through 1000 experiments. The main conclusion to drawn from those results is that *btw-com* is the mapping that gets better performance (preceeded, of course by farsighted setup, that permit the agents to have perfect sight of the population). This is indicating that when competitive agents (see metric description in section 3.1) are those with higher betweenness in the social network, performance of the system increases. Inversely, if versatile agents occupy the most betweenness-central positions, the system performance is clearly worse. As expected, random mapping is placed in between those two results, occupying the third ranking. The observed advantage of competitive agents has the following explanation:

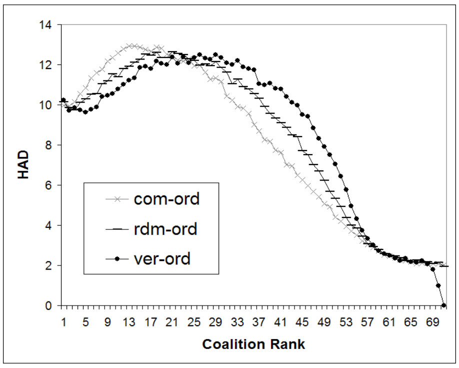
If the network would be a totally structured graph generated by Watts-Strogatz model (with parameter p=0), the coalition created by a competent agent could only improve its score by attracting agents longitudinally through tightly interconnected clusters. Watt-Strogatz small world model slightly break this structure and rewire some connections shortening the distance between different parts of the graph. Rewired nodes are those who have higher betweenness, as they are involved in many short paths between nodes in the graph. If agents with high attractive potential (competent agents) are situated in rewired nodes or nodes close to rewired nodes, competent coalitions will have more possibilities to grow up in more than one dimension –as it was the case of an structured network, hence increasing the opportunities of getting into touch with other competent and compatible agents.

A different perspective for analysing the advantage of positioning competitive agents in highly central positions is by monitoring the dynamism in the coalitions. Figure 2(b) shows the historical average degree (HAD) for each mapping. The three configurations have a similar shape: Starting in the first ranked coalition with a similar value, increasing until a critical point and decreasing. For explaining the reason and implications of their differences it is necessary to understand how the coalitional process is registered by the HAD metric: the best ranked coalition is usually the first one to converge. The process is top-down as during the formation process of the leading coalition, many agents are accepted and then made redundant of the coalition when they are outperformed by another joining agent. If an agent is made redundant from the leading coalition it creates dynamism in lower ranking coalitions, hence until top coalitions do not stabilise, lower ranking coalitions suffer changes. In *com-ord* configuration, as top ranking coalitions stabilise, those agents, that because of their capabilities are meant to form lower ranking

[3] the difference between values favors the diversity of Competitiveness and Versatility degrees (see section 3.1). None of the values is 0, so that all the skills are required (see section 2)



(a) Sum of the ranking of each configuration tested between them.



(b) Historical Average Distances (HAD) for each mapping.

Figure 2. Performance results measured in global score terms and dynamism. Competent agents placed in high betweenness positions prove the best results compared to Versatile or Random mappings.

coalitions, have more limited possible paths to get their way to each other. This is because possible paths through nodes in top ranking coalitions are blocked. As the stability process is top-down, second order coalitions reflect a higher HAD value because agents have to jump through alternative paths as long as their members have enough attraction power. After a critical point is reached, the HAD value start decreasing reflecting that agents are not able to find their way to get in contact. The only difference from the three lines in figure 2(b) is that *com-ord* (that is competitive agents occupying high betweenness positions) reaches the maximal point in a smaller ranking coalition. This fact indicates that the most competitive agents are concentrated in the top coalitions. Remaining agents have less attractive potential, hence they register lower dynamism in the coalitions created. The average convergence time registered for com-ord configuration is 20% lower than for ver-ord, this data supports the previous argument on the low dynamism in com-ord configurations.

4. Conclusions

Large scale multi-agent systems need to have a reduced agent's interaction space in order to avoid combinatorial explosion of interaction possibilities. Research on efficient social network topologies can be of great help in this area, however every interaction model requires specific research. In this paper it is shown that the two main properties of small world topologies (high clustering coefficient and low average path length) fail to create good global outcome in a general interaction model based on coalition formation organisational paradigm. On the one hand, as it was shown in [10], high clustering coefficient involves redundant connections and less possibilities of explorations than in other non-structured models. On the other hand, in this paper it has been shown that short average path length property is seriously compromised when low competitive agents are placed in highly betweenness-central nodes of the social network.

Betweenness positioning effects have been measured with two different methods: a quantitative metric on the aggregation of the coalitions scores and an analysis based on the HAD metric. While the former depends upon an explicit definition of a valuation of the results obtained, the HAD metric defined in the paper, permits a more abstract analysis just based on the social distances that separate each agent of the coalition. The HAD metric is an innovative analytical tool with interesting applications in the area of dynamic coalition formation. In this area, the research line followed in this paper takes an step further by studying in depth the combination of the use of social networks to map limited awareness of agents .

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