INDIVIDUAL STRATEGIC BEHAVIOR IN A TEAM FORMATION AGENT-BASED SIMULATION

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ABSTRACT

The modern knowledge worker is faced with managing their time across multiple projects. To ensure the successful completion of one project, the worker might be inclined to put more time into that project than was originally intended, at the expense of other projects with which they are involved. This paper looks at the impact of this type of strategic behavior on the output of research teams. Our model was an adaption of Bakshy and Wilensky's team assembly model which looked at the formation of academic teams to complete some collaborative research task. The agents, who represent researchers, make strategic decision to increase their prestige through the selection of the teams they work with. The results indicate that the average size of the disjoint components, sets on connected agents, decreases when prestige is introduced. This implies a smaller, more cliquey, "invisible" college is formed within a given field of study.

Keywords: agent-based modeling, agent-based simulation, group assembly, group formation, organizational structure

1 INTRODUCTION

Current organizational theory tends to assume that knowledge workers are cogs in a machine, that is, they will fulfill a purpose in an organization with robotic like efficiency. This generic worker approach has led to criticism by some; for example, Sarah Mei said, "your team is an immutable data structure. Every time you modify it, you're actually making a whole new one" (Mei 2016). On the other hand, group dynamics looks at the human interplay within small groups to determine the best group organizational and management practices based on the individuals needs and skills. However, the group dynamic research focuses at the single group level, or on multiple small groups, in a very controlled time-restricted setting with no interfering other project pressures.

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An individual employee might work within a single group on a single large project but he or she might also be working on multiple projects over multiple teams. The employee may be allocated a certain amount of time for each project, based on its funding or importance. Whether an employee actually spends that much time on each project is a different matter. Ebbs and flows of project work mean it is hard for an employer to keep track of effort place on a project, e.g., a pending deadline might require an employee to work exclusively on one project and catch up on the others later. Even if a knowledge worker does spend the allotted time on a project, their productivity on the project will vary depending on their energy level. Their energy level may vary depending on the time of day and their individual excitement to the project (e.g., a pending deadline or project on a topic of interest).

A project might take more time (energy) of a team member than is specified due to external and internal factors. External factors are those that are externally influencing a team member, e.g., overly demanding team leader, a badly scoped project, or pending deadlines. Internal factors are personnel reasons that an employee might choose to take more time on a project, e.g., desire to perform for a certain project leader. The same goes for a team member spending less time (energy) on a project for external reasons, e.g., unclear direction from project leadership, or internal factors, e.g., the project is boring, or dislike of the team leader. Since administrative tasks tend to be adsorbed within bookable overhead time, a team member might spend even less time on the projects tasks because they are booking administrative tasks within it, e.g., time-sheet preparation, generic team meetings, etc.

A team member's choice on how much they work on a project might be environmental/cultural, emotional/social, or strategic. Environmental/cultural reasons might be that the organization always spends more/less time on projects for certain customers or that unrealistic time-lines are expected from the type of project (e.g., literature reviews are usually given short shrift effort when a proper systemic review can take several months (Liberati et al. 2009)). Emotional/social reasons might include desire to gain approval from others. Strategic reasons include fulfilling projects needed for promotion, gain/retain membership to an "informal" team, or other prestigious perk of the job (project involves good exposure or has longevity). This research investigates the impact of this strategic element on team selection.

To achieve this investigation, we adapt an existing agent-based simulation (Bakshy and Wilensky 2007), that represents academics, within an emerging field of study, forming research collaborations to produce a single peer-reviewed publication. The academics can be involved in multiple teams and, thus, build a collection of active co-authors. Good research output increases prestige but so does working with more prestigious academics.

The next section discusses some relative literature. This is followed by a description of the model. Finally, results and conclusions are given.

2 LITERATURE REVIEW

Generally speaking, team formation patterns are of great interest as their dynamics can reveal important patterns about sociality and cooperation. However, taking an overly simplistic view of team formation risks creating models which are inapplicable to real world situations. For example, many models operate under the assumption of single task assignment or only look at collaboration within a single area (such as an academic field).

Modeling team or group formation is not new within ABMS (Martínez-Miranda and Pavón 2011, Celik et al. 2011, Jiang, Hu, and Wang 2010). An example of group formation adapted into an ABMS includes a probabilistic model of creative team formation (or assembly) (Guimera et al. 2005). They were trying to estimate the probabilities that best explained the formation of collaborative networks in the scientific disciplines (and the Broadway musical industry). These probabilities were the chance a collaborative team would incorporate a newcomer and the chance of a team taking advantage of existing relationships (see Bakshy and Wilensky (2007) for a version of the model in NetLogo). The results indicated the formation of collaborative networks undergoes a phase change. In early stages of the simulation, the collaborative network had many smaller sub-groups in the environment. However, as the simulation progresses, a single giant-component is observed in the network. This resembles the so-called "invisible college," a web of social and professional contacts linking scientists across universities originally proposed by de Solla Price (Price 1963).

Another variation was developed to explore the impact of agents' heterogeneous characteristics on group formation (Lungeanu et al. 2015). Their approach was to utilize a hybrid agent based system dynamics model in order to better incorporate heterogeneity within their model than that which is provided by the system dynamics approach. They found, from parameter fitting real-world data in the field of oncofertility, that team assembly is greatly affected by the prestige of individuals, particularly the seniority and reputation of a team member. Additionally, they revealed that external variables, such as funding from large grant-making institutions can also have significant effects.

Some models have utilized game theory in order to simulate cooperative team formation. These models assume that the agents are rational actors in game theoretic paradigms. Furthermore, models, such as Collins and Frydenlund (2016a), utilize core values as the measure of rational optimality, rather than an individual level measure. As such, it assumes that not only are all agents rational decision makers, but they all have access to the same information and will manipulate it to create the most optimal core set of all given possibilities. However, the rationality assumption is not well founded given the theories from organizational and cognitive psychology. In order to address this, models should strive to incorporate empirically demonstrated heuristics and biases in order to better model psychological propensities of decision making (Lane 2013; Sun & Hélie 2013); this is discussed further below.

Previous models have a number of deficiencies that can be addressed within an agent based modeling paradigm. Primarily, these fall into two categories, commitment constraints and psychological biases. Commitment constraints include those logistical aspects of collaboration, such as the external factors noted above. Primarily, all real-world actors are limited in their time commitments. Simulations which use real world time commitment measurements show that this has a massive effect on human sociality and cooperation (Arnaboldi et al. 2015). However, models such as those presented by Guimara, Uzzi et al. (2005) (and therefore Bakshy and Wilensky (2007) model) and Lungeanu, Sullivan et al. (2015), assume that agents interact over discrete time intervals (years) without any internal constraints on the time in which they have to allocate to a project. Rather, they appear to assume that agents can interact indefinitely within a model's discrete time interval, which is later interpreted as a time interval relevant to human actions (i.e. a calendar year).

Additionally, humans have evolved psychological biases, that will further constrain with whom we choose to interact. For example, humans often have a bias toward interacting with other individuals who have a greater level of prestige, a concept denoting freely conferred deference, as opposed to dominance or coercion (Henrich & Gil-White 2001). Prestige has also been an important topic for anthropologists for nearly a century (Radcliffe-Brown 1922), who have noted that individuals tend to be attracted to prestigious individuals and prefer to work with individuals with greater prestige, particularly in smaller groups.

The way in which prestige biases can effect human decisions are numerous, and can affect the way in which we chose to mimic another individual or learn from their actions (Bell 2013; Atkisson et al. 2012) and these abilities develop early on in childhood (Chudek et al. 2012). However, it is less clear how prestige can affect preferential treatment decisions during team formation in the workplace. Evolutionary psychologists have investigated how, over the course of human evolution, teams for tasks such as foraging and resource gathering have created hierarchical dynamics where some individuals have greater prestige than others (Price & Van Vugt 2014). This has resulted in the current psychological literature positing that prestige mechanisms are adaptations to aid in group formation. As such, prestige is a viable and interesting theoretical mechanism to be included in ABMs of team formation.

3 MODEL

Our model adapted the team assembly model of Bakshy and Wilensky (2007), which was written in the NetLogo modeling language (Wilensky 1999). Their model was based on the work of Guimera et al. (2005). The model focused around academic network formation, within a particular field, where the nodes represent researchers and the arcs represent existing or previous collaboration on a peer-reviewed publication. There are two types of agents (nodes) with the model: incumbents and new-comers. Incumbents are individuals that have already published in the field of study (i.e., are present on the network) and new-comers are not present on the network (i.e., newly created nodes). Their model used three mechanisms to determine the network formation: (1) probability 'p' of working with an incumbent; (2) probability 'q' of choosing a previous collaborator, if an incumbent is chosen; and (3) a fixed team size of four individuals per collaboration.

To limit the size of the network, agents are removed if they do not form a new collaboration within a set period. This represents the "publish or perish" phenomenon in academia. We set this value to 52 time-steps (weeks) within all our runs.

We adapted this model by including some strategic behavior within the simulation. The agents are assumed to want to obtain the most prestigious publications at the minimum effort. Prestige is a measure of how an agent is viewed by the academic community, in terms of their research output. It is assumed a publication's prestige is determined by the most prestigious team member (because we have not model citations explicitly here). A lack of effort into a collaboration will result in a mediocre publication, which will degrade the prestige of the team members. Thus, agents rank other connected agents by the outcome of previous collaborations as opposed to their prestige alone. For this reason, links are given a prestige value, as well as agents, which represents the prestige of the previous collaboration between the two connected agents.

The adaption from the Bakshy and Wilensky model occurs at the team formation stage, when agents are deciding which other agents to include in their team. There are two potential selection processes in the model, namely (1) when current team members are deciding which existing contacts to join to their team and (2) when deciding to connect to agents that have not already connected to the current team. The formula for the first case is given by:

$$b_{max}(Connected) = \underset{b \in A}{argmax}\{V(l_{ab}) : a \in T \subset A, I_{ab} = 1\}$$

Where b_{max} is the agent selected for addition to team T. The agent must be connect to the team via some link l_{ab}, where I_{ab} is the indicator function for whether agents a and b are linked. *V(.)* is the current prestige value of a link or agent. If there does not exist an agent that satisfy the criteria (i.e., the current team is only connected to itself) then the team will connect to an agent not already in the team. This is determined by:

$$b_{max}(Unconnected) = \underset{b \in A}{argmax}\left\{V(b) \leq \max_{a \in T} V(a) : \forall a \in T, I_{ab} = 0\right\}$$

If no agents satisfy the criteria, then a random agent is added to the team.

Once the team is formed, the agents decide how much effort to place into the collaboration. This is determined by each agent scoring the collaboration in context of their other previous collaborations. Thus for a collaboration to be successful:

$$|N| + \sum_{a \in T \setminus N} \frac{\sum_{b \in T} V(l_{ab})}{\sum_{b \in A} I_{ab} V(l_{ab})} > 1$$

Where N is a subset of T such that any agent in N does not have a link of non-zero value, like a newcomer (who puts all their effort into the current collaboration paper). If enough effort is put in the collaboration then a successful publication is produced and the agents update their values as follows:

$$\forall a, b \in T, \qquad V_{t+1}(a) = \lambda V_t(a) + (1-\lambda) \max_{c \epsilon T}(V_t(c) + 1) \tag{1}$$

$$V_{t+1}(l_{ab}) = \max_{c \epsilon T}(V_t(c) + 1)$$

Here t represents an time-step and λ is the smoothing factor. Note that every team member's prestige will grow under this formula. If, however, the effort is not reached (less than one) then all the team members prestige decreases by a factor of λ. We assume that the value of links deteriorate over time by some factor μ (set to 1%):

$$\forall a, b \in A, \qquad V_{t+1}(l_{ab}) = (1-\mu)V_t(l_{ab})$$

These new mechanics were incorporated into the Bakshy and Wilensky model. A brief description of the simulations algorithm is given below:

1. With probability (1-P), create a new comer to join the team and skip to step 4.
2. With probability (1-Q), group all the incumbents, not currently in the team, that have a prestige value less than the existing highest prestige of the team. Pick the incumbent with highest prestige from the group to join the team. Skip to step 4.
3. Pick the incumbent, not currently in the team, that is connected to any of the current team member which has the highest value link to the team.
4. Repeat from step 1 until four team members selected.
5. Link all team members
6. Determine effort and update prestige

This process was completed 5000 times to ensure that steady-state was reached.

4 RESULTS

The simulation was run for varying values of the smoothing factor, λ, with each parameter batch repeated 100 times. The original Bakshy and Wilensky simulation was also run for comparison purposes. A screenshot from the simulation is shown in figure 1. Where possible, standard default values were used: P was set 40% and Q to 65% (which were the default values from the original simulation). There were 5,000 time-steps in each run to ensure steady-state was reached.

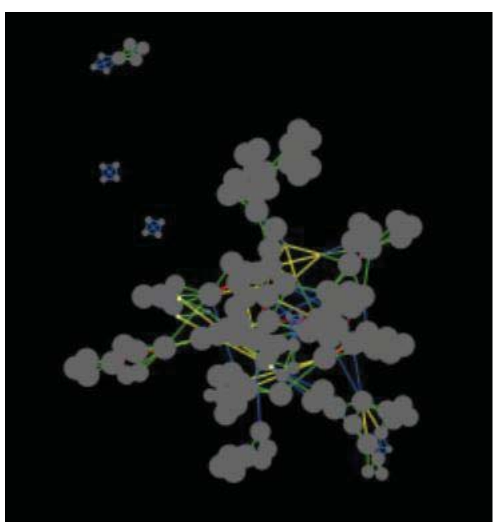

Figure 1: A screenshot of a formed network of the NetLogo model. The agents (grey circles) prestige is shown by their size.

We look at two sets of output data in this paper: the final average agent prestige value and the final average component size, for each run. A component is defined as connected set of agents thus there could be multiple components at any point in a simulation run, which will grow or decrease over time. Figure 1 shows a screenshot with 4 components: 3 small and one very large. The average values, over the 100 runs per smoothing factor, are shown in Table 1.

Table 1: The mean, minimum and maximum of the final average prestige and final average component size, for the 100 runs of each λ value

	Final Prestige			Final Av. Component Size		
	Min.	Mean	Max.	Min.	Mean	Max.
0	4.49	7.84	18.26	6.96	10.58	21.42
0.1	3.43	5.52	9.11	6.72	9.48	13.08
0.2	2.96	4.03	5.85	6.80	10.03	17.66
0.3	2.16	2.97	3.98	6.88	10.35	21.71
0.4	1.62	2.18	2.79	6.62	9.77	16.33
0.5	1.25	1.52	1.85	6.60	10.91	23.43
0.6	0.89	1.07	1.40	7.27	10.60	19.62
0.7	0.61	0.71	0.92	6.81	10.12	20.00
0.8	0.34	0.42	0.51	5.93	10.15	17.00
0.9	0.16	0.19	0.21	6.78	10.19	48.66
1	0.00	0.00	0.00	7.48	14.75	41.00
Original	0.00	0.00	0.00	8.29	15.31	32.60

As the smoothing factor increases, the average prestige value decreases. This is expected because λ determines the growth rate of prestige, as shown in Equation (1). When the smoothing factor has a value of one, then there is no updating to prestige and each agent's prestige value remains at zero. When the smoothing factor is zero, then each successful collaboration results in all the collaborators prestige increasing significantly. The relationship between prestige and the smoothing factor is shown in figure 2.

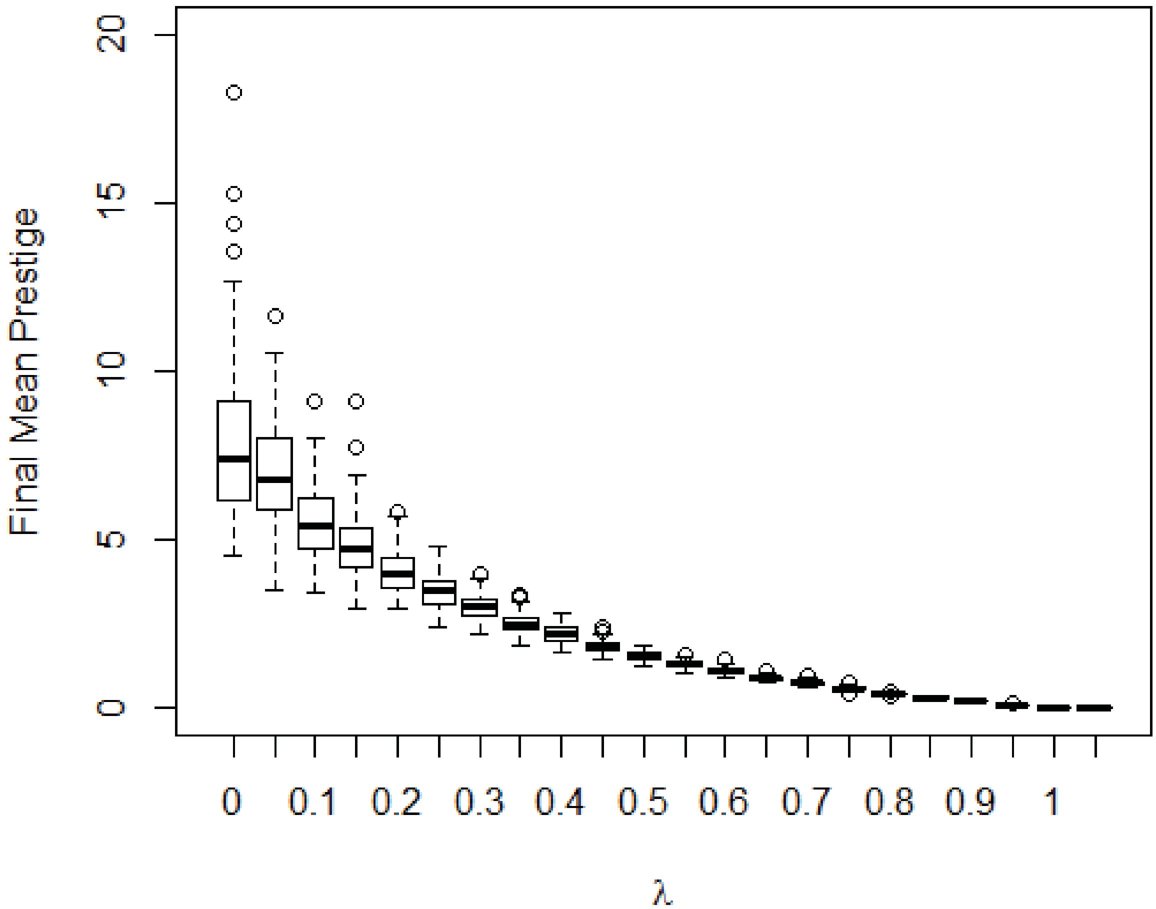

Figure 2: Boxplot chart of the final mean prestige as λ varies. The final box is the results from the original model.

The Pearson's product moment correlation between the smoothing factor and logarithm of the final average prestige was -0.972 for cases when the smoothing factor was less than one. This result was statistically significant at the 95% confidence level. This shows that there is exponential growth in prestige in relation to the smoothing factor.

There was no relationship found between the final average component size and the smoothing factor. When the smoothing factor equals one, it is the same as when prestige is not considered, this was shown to be statistically the case (via a Welch two-sample t-test with p-value 0.4736 at 95% confidence level). The cases which considered prestige seemed to have similar final average component sizes as each other.

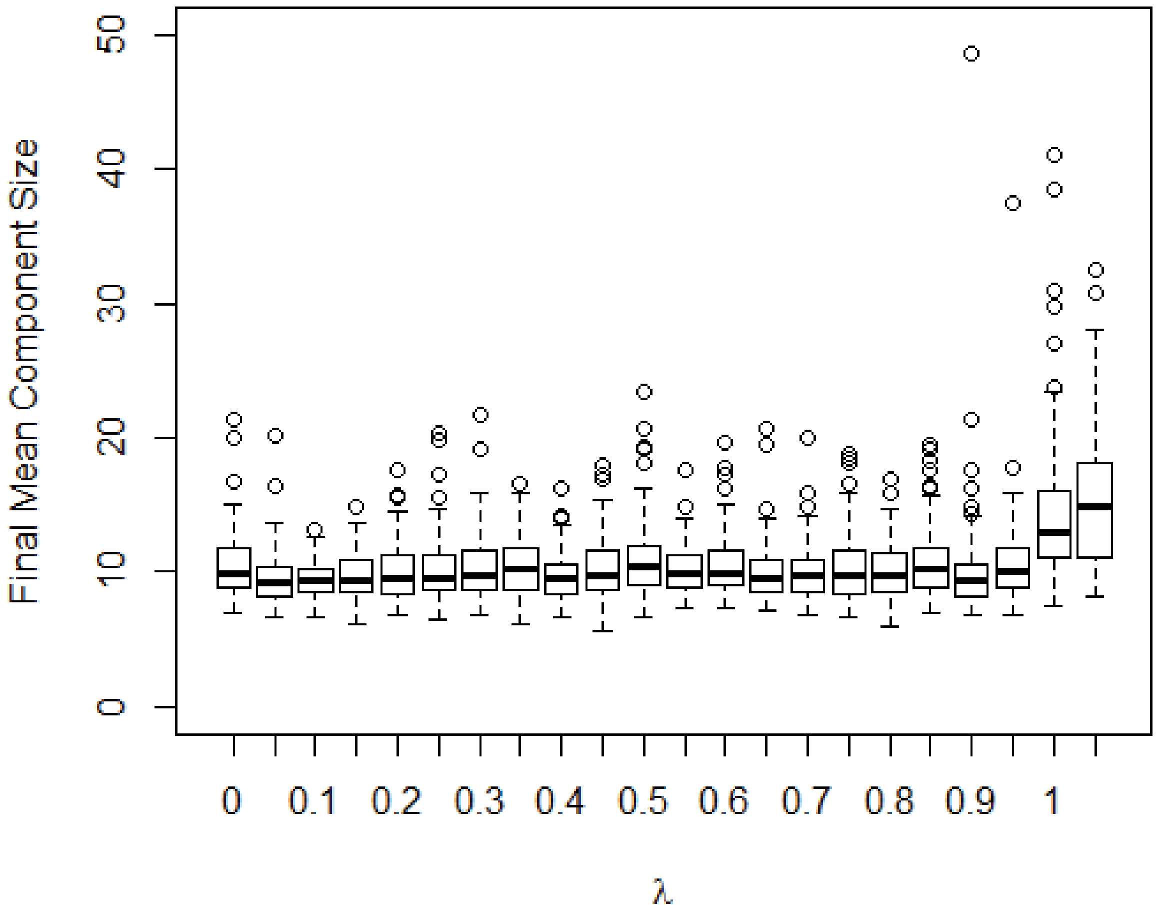

Figure 3: Boxplot chart of the final mean prestige as λ varies. The final box is the results from the original model.

However, there was a difference when prestige is considered versus when it is not. The "no prestige" case and the smoothing factor of one case were grouped and compared against the rest. They were shown to be statistically different from the other cases (a p-value of 3.599e-12 at 95% confidence level). It was concluded that including prestige fundamentally changes the average component size and, thus, component sizes in general; thus prestige results in smaller groups.

4.1 Validation

Since the simulation is based on purely theoretical principles, it is difficult to validate the results. The simulation results provide insight into the potential of the proposed hybrid approach to strategic group formation and possibly will inspire others to use our strategic group formation concepts within their research. How to actually validate ABMS is a major issue for the community (Collins et al. 2015) and several different, sometimes conflicting, approaches have been proposed (McCourt, Ng, and Mitchell 2012, Niazi 2011, Ligtenberg et al. 2010, Gore and Reynolds 2010, Champagne and Hill 2007). Thus, we argue our hybrid ABMS approach be used for theory building (Poile and Safayeni 2016) or the validation methodology be chosen based on the actual application domain. Future directions could potentially validate the model against historical co-authorship networks in specific academic disciplines with small numbers of active researchers, such as the scientific study of religion.

5 CONCLUSIONS

This paper looked at the impact of individual strategic behavior on group formation. An example based around the development of collaborative groups in an emergent academic field was used as the bases of our model. The agents want to strategically work with the most prestigious people they can to increase their own prestige. We found that concern about prestige decreased the size of the component social networks that the agents were a part; thus making the research output more incestuous.

The next stage for this research includes subgroup formation, where agents decide to form their own separate components. This will be done using the same hybrid cooperative game theory / agent-based modeling approach as Collins and Frydenlund (2016b).

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