Effects of Social Inhibition on Selection of Artifact Capabilities

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Abstract

Tool or artifact use is prevalent in the human race. Over time humans learn, evolve and modify these capabilities in order to achieve their goals facilitating their adaption in an ever changing environment. Once an artifact capability is learned however, humans are often faced with the decision making process of which capabilities to apply at any given time. These decisions are not only affected by their internal states but also the social environment in which they operate. In this study we present a computational multi-agent simulation model that investigates how social inhibition affects the artifact capability-selection process. Inspired by models of social inhibition in the field of specialization, we demonstrate that functioning in a social environment often leads to the inability to select and perform the capabilities that we inherently desire. The model also tests the effects of demand on the capability selection process. Experiments conducted demonstrate that at a group level social inhibition may contribute to a decline in the performance of the group. It is also observed that group performance increases alongside demand suggesting that higher demand may reduce the effects of social inhibition.

Introduction

Artifact capabilities refer to knowledge acquired by individuals for the use of artifacts towards the achievement of their goals. Philosopher Preston(1998) relates artifact use to human intelligence by contending that it demonstrates the high levels of human cognition. This has consequently lead to the use of artifact capabilities in the evaluation of intelligence (Wood, Horton, and Amant 2005). Byrne (2004) argues that a focus on the underlying cognitive elements of primate tool use can aid in better understanding the human intellect. These cognitive elements include not only how humans learn capabilities, but also how they choose which capabilities to learn as well as which capabilities among their possessed capabilities to apply. The notion of capability touches on various sub fields in Artificial Intelligence. Learning methodologies and Knowledge Discovery models are useful for understanding how humans develop capabilities. Knowledge Representation research is essential in representing what it means to have a capability. In the context of multi-agent systems complex capabilities gained by human interaction or cooperation can be explored. The field of Planning becomes essential as goals are set giving rise to the need to acquire the capability to achieve them either individually or as part of a group. Artifact use has been explored in robotics with the objective of building useful machines (Bluethmann et al. 2003; Amant and Wood 2005) and used in the area of artificial life to show social learning with animals (Noble and Franks 2002) among a variety of other fields. Learning, applying and evolving artifact capabilities have aided humans in dealing with changes in their environment. Over time these capabilities have contributed to the invention of new artifacts often accomplished by the combination or modification of existing ones. Ultimately functioning in a social world involves individuals combining these capabilities to acquire more complex ones towards accomplishing complex goals.

Scientists are always looking for new ways to improve on their understanding of the complexities of human societal behaviors (Gilbert 2004). In his study, Gilbert argues that human society is better analyzed as a whole in order to observe emergent behavior that otherwise would not be apparent. To this effect, several multi-agent based models where autonomous agents operate in virtual environments have been built to study different aspects of human society. One such aspect is the notion of social influence where an individual's behavior is affected by others in its environment. Such individual can also be inhibited from behaving in a manner which it inherently desires.

Artifacts have been defined as physical objects in the environment that provide some functionality that can be used by a human towards an adopted objective (Mokom and Kobti 2011b). A theoretical foundation for artifact capabilities rooted in the Belief-Desire-Intention (BDI) theory (Bratman 1987) was provided by Acay, Tildar, and Sonenberg(2008). In the model an agent is deemed to have a capability for an artifact if it has at least one plan (as part of its intentions) that specifies a way to use the artifact towards any of its goals. The model was extended to incorporate evolution and learning (Mokom and Kobti 2011b; 2011a) with the objective of demonstrating the superiority of learning artifact capabilities in a social context over learning individually.

In this study we explore the artifact capability selection

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process. Humans acquire several capabilities over time and may need to select which capability to apply at any given moment. For example one may possess the artifact capability to drive the artifact (car) but at any given time may decide to select the capability (drive the car), designate it to someone else (another person with the capability drives) or be prevented from selecting the capability by someone more influential. The need to drive the car, in the form of a task towards accomplishing some goal must also exist in the first place. In a social environment the decision to select a capability may be affected in a variety of ways. In specialization studies it has been demonstrated that internal and external factors influence an individual's selection of tasks to perform (Beshers and Fewell 2001). Some internal factors noted are genetics, the individual's emotional state, and experience in the sense that performance of a task may increase the individual's desire to perform it again. External factors on the other hand may include demand for the task or social influences from the individual's environment. While an individual's selection of an artifact capability may be partially driven by its objectives, similar to task selection it can also depend on the social environment in which the individual operates. Social inhibition models strive to demonstrate that an individual's actions may be affected both by the individual's inherent desires and the inhibitory effects of others in the individual's environment (Beshers and Fewell 2001). If one is part of a group for instance, then the capabilities possessed by other members will likely affect one's choices. Additionally if some individuals in the group have a greater influence over others then they may affect the capabilities they are able to perform.

Inspired by the social inhibition models in specialization studies (Naug and Gadagkar 1999; Cockburn and Kobti 2011) we design and implement a computational multi-agent simulation model to examine how social influences affect the selection of artifact capabilities. Agents possess a variety of artifact capabilities with different levels of skill and operate in groups. These groups have tasks that need to be fulfilled by its members with each task requiring different capabilities. Essentially this leads to groups having varying levels of demand for each capability. One objective is to examine how social influence affects group performance. A second objective is to explore the effects of demand on capability selection in the presence of social influence.

The next section provides some background on related work. It is followed by our model of artifact capability-selection agents. We then provide details on experiments conducted and results obtained. The final section provides conclusions deduced and future work.

Related Work

Selecting artifact capabilities is closely related to the studies conducted on task selection. In both instances individuals must decide on what actions to perform to accomplish their objectives in the presence of different factors. The difference lies in the notion that a task requires capabilities. A task may require a variety of capabilities and the same capability may be needed by completely different tasks. We contend that a computational model on capability selection may provide a micro view as opposed to the macro view provided by a model on task selection.

With the objective of studying the emergence of division of labor, task selection has been well explored in the biological sciences as well as in artificial intelligence. Beshers and Fewell (2001) provide a detailed review on a variety of specialization models demonstrating the emergence of division of labor based on how individuals select tasks to perform. Related to our work are the social inhibition models that demonstrate how task selection by individuals functioning in a social environment may be affected by their interaction with others (Naug and Gadagkar 1999; Cockburn and Kobti 2011). In Naug and Gadagkar's (1999) model an activator-inhibitor system was defined whereby individuals maintained two pods, one for its own state and the other that it transfers to others it comes across. The model was extended to include weights such that agents could divide their time among different tasks, in the presence of social inhibition (Cockburn and Kobti 2011). In an attempt to investigate whether specialization can emerge with the effects of experience, self reinforcement models for specialization (Theraulaz, Bonabeau, and Denuebourg 1998) address the notion that when an individual performs a task successfully, the probability of that individual choosing the task subsequently increases. The general objective of these models is to explain the origins of division of labor therefore, they do not examine the capabilities these agents possess. Essentially either all agents are deemed able to perform all tasks or the distinction among them is not detailed to the level of capabilities.

The task allocation problem whereby agents select tasks with the objective of maximizing their gains is another active area of research. In some models, agents bid for tasks with the ability to assign or exchange tasks among themselves (Sandholm 1998). Hanna and Mouaddib (2002) use a decision making approach, specifically a Markov decision process to address task selection in uncertain environments. Models for task allocation are utility based as they explore benefits and the distribution of payoffs where the agents' main objective is to maximize its expected utility. Our approach is complementary based where the focus is on the relevance of agents' knowledge and skills and how agents relate with each other.

Artifact Capability-Selection Model

In this section we present the specifications of our model for investigating the effects of social inhibition in the selection of artifact capabilities. The model supports agents that can select capabilities in the absence of and in the presence of social inhibition. We provide a definition for demand at the capability level and show how its effects on capability selection can be examined. The model supports agents operating in groups and allows for the extraction of behavior at the group level.

Approach

In our environment there exists a set of agents with varying ages arranged into groups. We assume that every agent can only belong to one group. There are a set of artifacts in the environment. Although the focus of our model is on artifact capabilities, we include artifacts themselves in order to put our capabilities in context. Each agent has learned a set of artifact capabilities with varying levels of experience or skill. There exists a set of tasks for each group specifying the tasks that the group is responsible for. Each task requires certain artifact capabilities. An agent can only select and perform one capability at a time, but can share tasks as the task may require different capabilities. It is assumed that all capabilities take the same amount of time to perform. Each agent has two objectives: to select a capability that has not yet been performed towards accomplishing any of the tasks in its group and to select the capability for which it is most skilled. The agent's age is used as an influence factor and is comparable such that for agent a and agent b, if $age(a) > age(b)$ then a is more influential than b. The same applies to the agent's skill or score for a capability: $sk_a(r) > sk_b(r)$ means agent a is more skilled than agent b for the artifact capability r. In our simulations we seek to investigate at group level how close the score of each selected capability is to the optimal score for that capability in the group. Additionally we explore how demand for a capability within a group may affect the selection process.

Environment Description

In our environment there are a set of agents A, a set of artifacts R, a set of tasks T and a set of groups G. Each $g \in G$ composed of a set of agents and tasks is defined as $g = \langle B, U \rangle$ where $B \subseteq A$ and $U \subseteq T$. Additionally, if $g_1, g_2 \in G$, and $g_1 = \langle B_1, U_1 \rangle$, $g_2 = \langle B_2, U_2 \rangle$ where $B_1, B_2 \subseteq A$ and $U_1, U_2 \subseteq T$ then $B_1 \cap B_2 = \oslash$. An agent can therefore belong to only one group. Since we do not explore the details of the agent using the artifact, we leave out the specifics of the artifacts R. A task $t \in T$ is made up of a set of capabilities: $t = \langle C_t \rangle$ where $C_t \subseteq C$. As with artifacts, we do not provide the specifics of the capability set C but assume that for every capability $d \in C$ there is a corresponding artifact $r \in R$ in the environment that the capability is for.

Each agent $ag \in A$ is defined as $ag = \langle a_{ag}, g_{ag}, D_{ag}, S_{ag}, P_{ag} \rangle$ where a_{ag} is a positive value for the agent's age, $g_{ag} \in G$ represents the group the agent belongs to, $D_{ag} \subseteq C$ represents the agent's capability set and S_{ag} represents the agents corresponding scores for its capability set. The capability score specifies the level of skill the agent has for the capability. As suggested by Cockburn and Kobti(2011), the agent has a set of pods P_{ag}. Agent pods are used to maintain the agent's preferences with regard to what capabilities in its capability set that it inherently wishes to select, along with exchanged inhibition for its capabilities. A $p(d) \in P_{ag}$ for an agent's capability $d \in D_{ag}$ is defined as $p_{ag} = \langle sa, ac, inh \rangle$. sa specifies the agent's self activator value, ac is the activator value and inh is the inhibitor value for the capability. Essentially, $|D_{ag}| = |S_{ag}| = |P_{ag}|$.

The self activator value $sa = (0, 1]$ is used to promote the agent's objective to perform the capability for which it has the highest score. This value is set to the capability score and is used in conjunction with the activator value in the capability selection process. In our model, each agent operates autonomously when selecting a capability and will always select the capability in its capability set with the highest $sa + ac$ as long as the capability has not already been selected by another agent. If multiple agents attempt to select the same capability at the same time then the selector among them is random. The idea is that with inhibition exchange manifested in the activator value ac prior to the commencement of each capability selection, it should still be possible to observe the effects of social inhibition. The determination of the capability's activator value ac and its inhibitor value inh are explained next.

Social Inhibition

Social inhibition is accomplished in our model via agents inhibiting each other by modifying the ac values in the agent pods. Agents can be implemented to influence each other when they interact (Cockburn and Kobti 2011), however in our model agents exchange inhibition with all members of their group for capabilities they share. Used as an influence factor, the agent's age is normalized to $(0, 1]$ representing how much influence the agent has. All agents set their inh values for each capability they possesss to their respective normalized age.

To exchange inhibition between ag_1 and ag_2 for a capability d that they both have, we obtain their respective pods for capability d. First each agent increases its own ac value by its inh value. Then the ac value in ag_1's pod is decreased by the inh value in ag_2's pod and the ac value in ag_2's pod is decreased by the inh value in ag_1's pod. Since inhibition is exchanged by all group members, its presence should result in a group configuration representing a social hierarchy of artifact capability selection based on the agent's age. The activator value ac for each agent's capability will depend on the size of the agent's group, the degree of influence of the group members and the number of agent's in the group sharing the capability.

Group Performance

The notion of group performance is introduced to evaluate how well agents in a group perform in the presence of social inhibition. Within each group, we define the exemplar for each capability as the agent with the highest score for the capability. Let the score for the exemplar x in a group g for capability c be $sc_x(c)$. When capability c is selected by some agent y that is a member of group g, with score $sc_y(c)$, we increment its performed score PS_c by: $\frac{sc_y(c)}{sc_x(c)}$ and increment a counter $Cntr_c$ that keeps track of how many times c is selected. A group's performance (GP) in a group requiring k distinct capabilities can then be defined as:

$$GP = \sum_{i=1}^{k} \frac{PS_i}{Cntr_i} \tag{1}$$

Since every agent's objective is to apply the capability for which it is most skilled, this objective is more likely to be accomplished in the absence of, rather than in the presence of social inhibition. In other words, group performance as defined here should decrease as the effects of social inhibition increase.

Demand

Demand within a group refers to the total effort required to complete all tasks relative to the available effort from members of the group (Jeanson et al. 2007). In our model, demand for a capability within a group means the number of times the capability is required across all of the group's tasks (N) relative to the number of agents in the group that have the capability (M). A group's demand GD in a group requiring k distinct capabilities can therefore be defined as:

$$GD = \sum_{i=1}^{k} \frac{N_i}{M_i} \tag{2}$$

In a group with low demand there are more agents that can perform capabilities than are required by the group. In such environments since more agents are competing to perform a capability, we suggest that agents should have a lesser chance of selecting their desired capability hence social inhibition should have a stronger effect. High demand within a group indicates that required capabilities exceed the number of agents within the group that can perform them. We contend that when demand is high agents should incur less inhibition within the group as there are fewer agents that can perform capabilities than are needed. In other words there should be less competition within the group when selecting capabilities. In this case social inhibition should have a weaker effect on the capability selection process thus resulting in better group performance. If our contention holds true then group performance should increase alongside demand.

Simulation Experiments and Results

The multi-agent simulation environment built to test the model contains agents generated with random ages $[25, 65]$ and organized into equal sized groups. It should be noted that the specific age range does not matter as the values are normalized to $(0, 1]$ prior to use. The range is simply used for ease of understanding. Agents are given random capabilities, each with a random score $(0.0, 1.0]$. Each group is assigned the same set of tasks, with each task composed of random capabilities. Experiments are conducted with multiple groups of the same size operating simultaneously in order to compute averages over the groups for group performance and group demand. Although group sizes are the same the agents are heterogeneous since capabilities are randomly assigned to agents. The expectation is that averages obtained over such groups operating concurrently to fulfill the same tasks will give more credibility to the simulation results. Agent pods are generated and the simulation begins with agents exchanging inhibition with each other. Every agent attempts to select a capability (not previously selected) from a required task in its group at every time step. Once an agent selects a capability for a required task within its group the capability is marked as selected. An agent is done when there are no longer any available capabilities for selection that the agent has in its capability set. The simulation ends when all agents are done.

In the first set of experiments we compare agents operating in an environment with no social inhibition with agents that deal with inhibition. We define two types of agents: AG_NOINH and AG_INH. AG_NOINH agents select capabilities in the absence of social inhibition. AG_INH agents operate in groups with social inhibition. We do not support a hybrid of groups. In the conducted experiments both types of agents have all the same capabilities and belong to groups with the same required tasks. This is to ensure that the same agents are being tested in the same environment except for the social inhibition effect. We maintain pods for both types of agents however the contents of the pods differ. All agents set the self activator value sa for each capability they possess to its respective score. AG_NOINH agents set their activator ac and inhibitor inh values to 0. They do not exchange any inhibition with other members of their group. The capability an AG_NOINH agent selects is solely dependent on its capability scores. AG_INH agents initialize their ac values to 0 and the inh values to their respective normalized ages. They then exchange inhibition with every member of their group modifying their respective ac values. The agents proceed to fulfill the requirements of their respective groups by selecting capabilities required by the groups tasks. In selecting a capability, the agent ranks its capabilities in descending order according to its total activator value $sa + ac$. The agents first attempt will involve the capability with the highest total activator value. If the agent can find a task required by its group with this capability and the capability has not been selected by another agent then the agent is free to select it. Therefore, while AG_NOINH agents will rank capabilities for selection based on their respective scores only, AG_INH agents will rank theirs based on their capability scores as well as how much inhibition they have exchanged with others. The simulation ends when there are no more capabilities for required tasks available that agents can select. At the end of each simulation run we calculate group performance for each group according to Equation 1 then compute the mean.

We tested with group size(10,20,100) of (50,100,500) agents respectively, number of tasks(5,10,20) and maximum number of capabilities $(maxcap)$ (10). The number of random capabilities given to agents and tasks are $[1, maxcap]$. In each experiment there were always 5 groups of agents. Table 1 shows the average group performance across groups of AG_NOINH and AG_INH agents. It can be observed from the last two columns that group performance is always higher for AG_NOINH agents than for AG_INH agents irrespective of the number of agents, group size, the number of tasks or the fact that at an individual level agents possess varying capabilities. This is in accordance with our expectations that social inhibition affects agent's selection choices and leads to a decrease in group performance due to agent's being inhibited from selecting capabilities for which they are most skilled. Although AG_NOINH agents always outperform AG_INH agents in this respect, they can still be limited from attaining the maximum potential of the group. Since every agent can only select one capability at a time, it

Table 2: Mean group demand (GD) and mean group performance (GP) of 100 AG_INH agents (group size 20)

# Tasks	GD	GP
5	0.339	0.681
10	0.504	0.698
20	1.221	0.725
50	2.496	0.727
100	5.168	0.731

is possible that the agent who gets there first is not the most skilled. With the assignment of random capabilities and capability scores to agents it is possible that the same agent may be the most skilled for more than one capability. Even when that agent can inhibit others and perform its chosen capability, it cannot stop any other agent from performing another capability once it is occupied at that time step. This occurs because the model allows agents to be autonomous rather than having the group designate capabilities. If capabilities were assigned to agents at group level we would expect AG_NOINH agents to outperform their AG_INH counterparts with an even greater margin.

The second set of experiments involve investigating the effects of demand on the selection of artifact capabilities in the presence of social inhibition. We utilize one type of agent from our first set of experiments: AG_INH. AG_INH agents initialize their ac values to 0 and the inh values to their respective normalized ages. They then exchange inhibition with every member of their group, rank their capabilities in descending order according to the total activator value $sa + ac$ and attempt in that order to select a capability. If an agent finds a task required by its group with the capability it wishes to select, then the agent is free to select it if it has not been selected by another agent. Agents are done when all tasks with required capabilities that they possess are completed. At the end of each simulation run we calculate group performance for each group according to Equation 1 and group demand for each group according to Equation 2 then calculate the respective mean.

We tested 100 agents organized in groups of 20 agents with tasks (5,10,20,50,100) and maximum number of capabilities ($maxcap$) (10). The number of random capabilities given to agents and tasks are $[1, maxcap]$. Table 2 shows the average group performance and average group demand levels. It can be observed that demand increases alongside group performance irrespective of the number of tasks or the fact that agents in the groups possess varying capabilities. We believe this suggests that an increase in demand may result in a lower "social inhibition effect". When demand is high there are fewer agents with capabilities to meet the capability needs of the group. The environment should thus be less competitive as there should be less inhibition exchanged. Since the first set of experiments show that social inhibition may cause a reduction in group performance then it follows the demonstration in the second set of experiments that a reduction in social inhibition among agents should result in an increase in group performance.

Conclusions and Future Work

The objective of this study was to evaluate how social inhibition affects artifact capability selection and investigate the role of demand in the process. Inspired by social inhibition models in the field of specialization, we implemented a computational multi-agent simulation model where agents select artifact capabilities in the presence of social inhibition. To model social inhibition we used agents' age as an influence factor. The simulation model accommodated agents with varying levels of skill for performing capabilities with the inherent preference to select the capability for which they are most skilled. Agents were organized into equal sized groups with random capabilities assigned to agents. Groups were assigned tasks where each task required random capabilities. The model tested the effects of social inhibition on the selection process by monitoring at group level how social inhibition affected the performance of the group. In addition, the model provided a definition for demand at capability level and investigated its effects on the selection process. Results obtained from conducted experiments demonstrate that social inhibition affects capability selection as agents operating in the absence of inhibition outperformed those operating in its presence. It was also demonstrated that demand can play a role in the selection process as experiment results suggested that group performance increases alongside demand possibly due to a reduction in social inhibition.

Although this study is domain neutral it can be applied to a variety of test cases. For example, a group can be defined as agents in a household. Objects such as different types of car seats could be defined as artifacts and agents could have varying levels of skills for their use (capabilities). A task may be driving a child to school which may require the capability to use a car seat. Demand for the car seat capability could be defined as how often the car seat capability is needed relative to how many people know how to use the car seat. Older agents could have more influence over younger ones (using age as an influence factor). Such a model could be used to study the effects of social inhibition in the decision process of "who gets to drive the kid to school?" It may be useful to test the model against a real-world case study to observe a possible predictive trend in the model when compared to reality.

The model uses a simple inhibition parameter, the agents' age. Inhibition in itself may not always result in a negative effect towards the overall objective of agents. A more complex inhibition parameter may be defined considering a scenario where the the inhibitor may have a positive effect on the objective in one context but have a negative effect in another.

The model used fixed group sizes but it may be useful to vary group sizes in the experiments. Agents are also restricted to a single group. It may be more beneficial to use social networks to define the agents' relationships, allowing agents to belong to multiple "groups" with the ability to select capabilities across groups. Experiments conducted in the model were at a group level. It may be useful to investigate the effects of demand at a population level, that is, agents belong to groups and groups exist in the population. Self reinforcement models in specialization theorize that di-

Table 1: Mean group performance (GP) of 5 groups of AG_NOINH and AG_INH agents

#Agents	Group Size	# Tasks	GP (AG_NOINH)	GP (AG_INH)
50	10	5	0.86	0.82
50	10	10	0.76	0.73
50	10	20	0.83	0.72
100	20	5	0.85	0.76
100	20	10	0.80	0.74
100	20	20	0.80	0.74
500	100	5	0.77	0.70
500	100	10	0.80	0.69
500	100	20	0.80	0.76

vision of labor can emerge due to experience (Theraulaz, Bonabeau, and Denuebourg 1998). This notion could be incorporated into our model such that agents capability scores improve when they select a capability and decline when a capability they possess has not been selected in a certain amount of time. Another important extension of our work is to examine the different hierarchies that may be formed as a result of social inhibition. This can lead to a model for group formation based on artifact capabilities. Finally, the model only investigates the selection of capabilities the agent already possesses. We intend to investigate the selection of new capabilities, that is, how the agent decides on what capabilities to learn. We expect this to be related to the capability demand which we have clearly defined in this study.

Acknowledgements

This work was supported in part by a grant from Auto21 and partial grants from CIHR and NSERC Discovery.

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