

## **The Power of Social Cognition**

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### **Abstract**

As human beings, we understand and make sense of the social world using social cognition. Social cognitions are cognitive processes through which we understand, process, and recall our interactions with others. Most agent-based models do not account for social cognition; rather, they either provide detailed models of task-related cognition or model many actors and focus on social processes. In general, the more cognitively realistic the models, the less they explain human social behavior and the more computationally expensive it is to model a single agent. In contrast, in this research an agent-based model containing an explicit model of social cognition is developed. Results from this model demonstrate that adding social cognition both improves the model veridicality and decreases computation costs.

# Introduction

Scholars define social cognition, broadly, as the way humans understand and process their interactions with others (Greenwald & Banaji 1995). This includes interpreting human interaction, drawing inferences from spoken and unspoken communication, and developing an understanding of group dynamics. Like any notion of cognition, social cognition can be studied at various levels of abstraction. At the neurological level, scholars have made inroads in understanding social cognition's biological origins (Frith & Frith 2008). One level "up" on the abstraction hierarchy, cognitive psychologists have developed models of how stereotypes are embedded within interpretable, but cognitively faithful, mental representations (e.g. Bem 1981, Brashears et al. 2013). Social psychologists have studied how human actions are a function of culturally shared affective meanings, represented as a parsimonious set of numerical values (Heise 2007), and the cognitive turn in sociology has wrought about similar sorts of empirical models of cognition and culture (Goldberg 2011; Lizardo 2014).

Recent work has begun integrating theory and data at multiple cognitive abstraction levels. For example, Schröder and Thagard (2013) integrate biological, cognitive and social psychological research into a unified model of how social behavior emerges from a neuropsychological theory of semantic pointers. A long-standing question, however, is how to integrate model based theories of cognition with model based theories of social structural dynamics (e.g. Carley 1991; Lizardo & Strand 2010). One reason why theorizing about this intersection is difficult is that methods to capture empirical data for theories linking social structure and cognition are difficult to collect and measure (Brashears 2013). An alternative approach is to link cognition and structure via theory implemented as computer simulation (e.g. Carley 1991), specifically *agent-based models*. As suggested by Schröder and Thagard (2013 pg. 275), "Multiagent models, simulating communication between multiple virtual agents in artificial societies ... might one day shed light on how stable, consensual structures of affective meaning are generated and maintained in cultures."

The present work focuses on an advancement of an existing, empirically validated agent-based model called Construct (Schreiber & Carley 2013) with an approach to social cognition that is significantly more faithful to cognition than prior iterations. Interestingly, this increase in faithfulness is achieved by more faithfully modeling *limitations* (rather than features) of human cognition. Within the agent-based modeling literature, the proposed approach is novel, but its goals are not (Bainbridge et al. 1994).

Socially realistic models tend to be lax in terms of the "cognitive" representation of socio-cognitive processes. Extant dynamic network socio-cultural models (e.g., Carley & Ren 2001) may have representations of alters in the "cognitions" of agents, and what those alters think or believe, but the informative mechanisms of social cognition are deterministically noisy perceptions of the simulation's ground-truth. This is not sufficient because it is not a good model of how we create or inform inferences of others. Humans can, and often do, draw and even act on inferences about what others think and know merely from their first glance at them, before they have even spoken their first word. Thus, agent-based models should be able to represent such a social cognitive

mechanism, while still retaining the computational efficiencies of socially realistic, cognitively-poor agent-based models.

This research addresses this gap in simulation technologies and social theory. The proposed approach connects existing cognitive, social psychological abstractions of social cognition into an overarching model of dynamic social structure. While the model described lacks faithfulness to many conceptualizations of social cognition, it provides an efficient formalization to span these abstraction levels while retaining complexity.

The behavior of this model is examined and validated by examining its capability to replicate a number of “stylized facts” (Kaldor 1961) that have been shown to exist empirically. For example, the model’s capability to faithfully represent known interactional patterns between members of different social groups (Tajfel and Turner 1979) is explored. The model’s ability to accurately portray these facts is determined via both quantitative and qualitative evaluation of model output, a form of “docking” (Axtell, Axelrod, Epstein, & Cohen 1996). This approach is taken rather than simply running more simulations as statistical significance is guaranteed to be achieved by running more simulations; whereas, examining qualitative patterns provides better theoretical guidance.

In all cases, model output is compared to an existing agent-based model that provides a less faithful and more computationally expensive representation of social cognition. The results of the virtual experiment demonstrate that the proposed model provides outputs that better match empirical data. Further, a combination of theoretical analysis and experimentation is used to prove that the proposed model is computationally more efficient than this prior work.

## **Related Work**

This section contains a brief review of extant approaches to social cognition in agent-based models, and lessons that can be learned from these models, as well as prior implementations of a theory of mind implemented as transactive memory system. While significant work focuses on social cognition and its intersection with social interaction and social structure, the present discussion is restricted chiefly to work that is germane to computationally modeling these processes.

## **Modeling Social Behavior**

Several models have employed aspects of social cognition to examine inter-agent behavior without ascribing to a rigorous general cognitive model. For example, De Weerd, Verbrugge, and Verheij (2013) showed the competitive advantage of modeling an adversary’s thought processes. Chavalarias (2005) used game-theoretic models to explore how imitation behaviors can lead to social differentiation. Paul, Pickett, Sherman, and Schank (2012) used Optimal Distinctiveness Theory (Brewer 1991) to inform a Schelling-esque model (1971) of how different social configurations could stabilize, showing that a social space’s initial configuration strongly affects the persistent patterns of group identity. Friedkin (2006) demonstrated the movement of individual’s to group norms via a social influence process on opinion formation.

Deep models of individual cognition, such as those implemented in Soar (Laird 2012) or ACT-R (Anderson et al. 2004), are rarely implemented in situations where inter-agent communication is required, let alone collaboration or coordination. When they are, model developers create specific code and working memory elements that represent alters but there are not explicit architectural mechanisms for social cognition or theory of mind. Examples of domain-specific implementations include inferences on enemy locations in adversarial agent-simulations (Best, Lebiere, & Scarpinato 2002) or assigning tasks to flight squadron members (Jones et al. 1999). There has been interesting work placing ACT-R modeling within an organizational context (Helmhout 2006). However, such models are computationally infeasible to utilize when one wishes to perform simulations of large numbers of agents. Recent cognitive models with some social cognition scale successfully into the hundreds of agents (Kaulakis et al. 2012).

## Prior Implementations of Theory of Mind

The proposed model is a formalization of a theory of mind, an element of general social cognition, to improve agent-based simulation of human actors. At the core of this theory of mind is a multi-level *transactive memory* system. Transactive memory is an explanatory mechanism of “how groups process and structure information” (Wegner 1987). Wegner suggests that humans both encode information internally and encode the location of external information resources. These external resources can include notebooks, file cabinets, databases, and, most importantly, other human beings. A person may not know, for example, how to diagnose a problem with a car, but that same person may know that a mechanic is a good starting point. This encoding capacity is essential to both what allows groups to be efficient, and allows people to specialize usefully in their work.

Prior simulation efforts have modeled this human capacity as a three-element tuple,  $ijs$ . Each agent  $i$  has for alter  $j$  a perception of alter  $j$ 's knowledge of information set  $s$ . Palazzolo and his collaborators (2006) had a continuous value (from 0 to 1) for this three-element tuple, representing perceived likelihood of an alter having information of use related to that knowledge set. Carley and Ren (2001) represented each sub-element in each agent's representation of alters as a binary. Thus, agents may believe an agent knows or does not know a specific piece of knowledge (an information element in one or more sets  $s$ ). Construct (Carley 1991), the agent-based dynamic-network simulation model extended herein, integrates the model of transactive memory as described in Carley and Ren (2001), and then further extends it to account for multiple modes of interaction and diverse communication modalities (Carley, Martin, & Hirshman 2009).

These prior efforts are functional, but are necessarily scale limited. As the agent population increases, the computer memory requirements increase exponentially. However, humans are able to function socially despite being conceptually aware of thousands, if not millions, of other human beings. Consistent with the Carnegie School (Cyert & March 1963; March & Simon 1958; Simon 1957) theoretical position the proposed model is predicated on the assumption that human memory capacity is not functionally infinite. Instead, it is argued that humans are boundedly rational (Simon, 1991) and must have a mechanism that conserves memory capacity yet retains functionality.

## Theoretical Approach: The Generalized Other to inform Transactive Memory

As a candidate mechanism, humans are modeled as being capable of holding detailed transactive memory representations for a limited number of people. For others, humans hold coarser representations inferred from group membership. In other words, humans hold stereotypes, or prejudices, that inform their perceptions of what others know. While the terms stereotype and prejudice have functionally distinct meanings in the social psychological literature (Hewstone et al. 2002), the concept that group memberships inform one individual's perceptions of others is a core component of social cognition.

Mead's (1925) Generalized Other is a foundational root in the study of human stereotyping. Mead argued that people make and retain persistent inferential statements on ethical behavior, such as "people of type X tend to do thing Y". Multiple such statements may be active at the same time, and in aggregate, Mead called these the "Generalized Other". People, Mead claimed, use the Generalized Other to regulate their own behavior by acting in compliance with the statements applicable to themselves. People can also use the Generalized Other to understand the behavior of others. It is assumed that Mead would also be comfortable with the idea that people can make similar inferential statements, "people of type X tend to know or believe thing Y" for he wrote (1925, pg. 275), "[s]ocial control depends, then, upon the degree to which the individuals in society are able to assume the attitudes of others who are involved with them in common endeavor."

From Mead's work springs a rich collection of psychological, sociological and social psychological research on stereotypes. For example, Stryker's (1980; 2008) sociological and structural take on symbolic interactionism definitively argues that humans perform stereotyping on different "types" of others. From a psychological perspective, many scholars have addressed an immediate following question, how are "types" of people identified? Mead suggested that there exists a large common group, called in his work "society", but also that humans concurrently maintained additional inferential statements for all relevant types. In the proposed model, embodies the theory that external, that is, clearly visible group memberships may be sufficient to distinguish "types". Thus, types are a fixed and uniformly agreed upon set, which is a simplification of human experience. This representation is a formalization of the "minimal" group paradigm suggested by Tajfel, Turner and their colleagues (1979; 1981). In the paradigm, group memberships are clearly and universally defined (by, e.g., the color of one's shirt in an experimental setting; see Tajfel, Billig, Bundy, and Flament 1971). Importantly, this representation is a limitation of this implementation, not the overall model's theoretical underpinnings. Even including this limitation, the salience and precise representations of different group memberships are informed entirely from individual experience. Thus, each agent may have its own wildly different understanding of its social context.

From the literature referenced above, three transactive memory tiers essential to the proposed multi-level implementation are identifiable:

- **Personal:** I know this individual and have specific perceptions about what they do and do not know.

- **Group:** I do not know this individual, but I have perceptions about groups to which I believe they belong.
- **Global:** I do not know this individual, and I do not have perceptions about the groups to which I believe they belong.
- 

Scholars often discuss both the Generalized Other and stereotyping within schema theory's (Rumelhart 1978; 1980) cognitive framework. In this context, a schema represents a memory structure for retaining generic concepts. In schema theory, each individual has a hierarchy of schema applicable to specific environmental conditions. Schemata that help us understand who other people are and what they are likely to know "Social Schema" (Kuethe 1962). These produced social schema are culturally dependent (Little 1968), but their production mechanism is expected to be endemic to the human condition and not to be culturally dependent.

In schema theory, environmental cues determine schema availability. Individuals use available schema to make inferences about their environment. Unavailable schema do not burden the individual's resources. In cognitive agent systems (Anderson 1996), schema-like representations have been used to produce human-like cognition as agents learn tasks, and agents may have many schema (implemented as production rules, a specific form of schema that use if-then structures) active simultaneously. Work by Duong and Reilly (1995) used a hierarchy of neural-networks to implement schema theory and model Mead's Symbolic Interactionism (Mead 1925), producing a hiring model showing racial bias.

Anderson and his collaborators (2004) suggest, and give empirical evidence, that chunks of human memory are "activated" when they are used. This activation decays over time with non-use. An actor's schemas can be associated with an "activation score", allowing one to determine the accessibility of the schema to the agent. These activation scores, according to Anderson, determine if an agent is able to recall a chunk. If the agent cannot recall the chunk, it must do without it.

The proposed model takes advantage of this approach's computational tractability, but changes the activated chunk's granularity. Rather than each chunk representing a single schema-object, of which there are many per alter, each chunk represents a specific alter or group. Each interaction with an alter is treated as an activation-event, and thus alters (and their groups), which are frequently contacted, will have high activation scores. An agent may also receive information about an alter or group, and this is also an activation-event. Thus, what schema are used to inform behavior are contextually dependent on recent activities and current social structure, an important aspect to realistic social cognition (Edmonds 2014). Brashears (2013) showed that social schema are active in understanding group structures. This research goes further to suggest that schemas are necessary to conserve limited cognitive resources and allow humans to interact intelligently (if heuristically) with unknown others.

For more information on the approach's implementation, see Joseph, Morgan, Martin, and Carley (2014). The remainder of the paper is organized as follows. First, the utility of a multi-level transactive memory system is reviewed. Then two virtual experiments for assessment are outlined. Then a proof of the computational savings from a multi-level system is provided. Finally, results from the virtual experiments are provided, followed by a discussion of limitations and potential future work. The results suggest that the multi-level implementation improves model fidelity,

conserve's the agent's limited cognitive resources, and improves the model's sensitivity to important initial conditions.

## Modelable Social Phenomena

The proposed model, Construct-SC, is an extension of Construct (Carley et al. 2009) to include a social-cognition adaptation of aforementioned multi-level transactive memory system. Construct is a network-centric agent-based simulation of knowledge diffusion within groups. Agents communicate information to other agents. Agents may forget knowledge they possess. How information diffuses within a group depends on multiple factors: the preferences of individual agents, the initial knowledge of each agent, and the social ties between those agents. In Construct, a central tenant is that as individuals learn and change what they know, they also change their position in the social network, and thus their most likely interaction partners. There are multiple biases for preference for interaction, including:

- Homophily, agents prefer interacting with people like themselves (McPherson, Smith-Lovin, & Cook 2001)
- Expertise, agents prefer interacting with people with valuable knowledge (Carley & Hill 2001)
- Propinquity, agents prefer interacting with people nearby (Allen 1984)

Both homophily and expertise require perceptions of people's knowledge. Earlier iterations of Construct used an error-prone and stochastic perception of ground-truth. However, later work with Construct implemented transactive memory as outlined in Carley and Ren (2001). Agents maintain persistent alter representations as transactive memory vectors. Agent interactions inform these vectors. In Construct-SC (Social Cognition), the Construct system is modified by:

- Adding transactive memory vectors for groups, of similar form to those for alters;
- Assigning transactive memory vectors activation scores which change over time;
- Allowing transactive memory vectors to be lost (or "forgotten") through disuse.

In both Construct-SC and Construct's transactive memory system (Carley & Ren 2001), a "schema" is a transactive memory vector – a series of K bits, where K represents the number of knowledge pieces, or "facts", in the system. Each bit represents the ego's perception of the alter's, group's, or Generalized Other's knowledge of a fact. While Construct has a single vector for each alter, in Construct-SC these schemas are arranged hierarchically. An ego determines what an alter knows by starting at the **personal** level. If that schema is activated above the threshold, then the agent uses the alter's transactive memory vector. If not, the agent will "construct" the alter's knowledge vector from the relevant **group** schema. If the alter belongs to no relevant groups, then the agent uses the **Generalized Other's** transactive memory vector.

With these changes, Construct-SC should be able to model social and human phenomena that Construct could not. Construct-SC should also replicate results from Construct. In Table 1, a set of observations on human social behavior are presented. For each of these observations, an "X" is used to denote whether that observation is reflected in Construct or Construct-SC respectively.

| Table 1. Stylized facts of Construct and Construct-SC  |   |           |              |
|--|---|-----------|--------------|
| Designed   | Citation                                  | Construct | Construct-SC |
| Individuals interact with others.  |   | X         | X            |
| People interact with others based on their perceptions of them.  |   | X         | X            |
| Individuals reason about a generalized other.  | Mead 1925                                 |           | X            |
| Individuals have perceptions of groups.  | Stryker 1980                              |           | X            |
| Perceptions of unknown individuals are based on their known group affiliations.  | Tajfel and Turner 1979                    |           | X            |
| Group perceptions can be informed by interactions with members of that group.  | Carley 1991                               |           | X            |
|  |   |           |              |
| Emergent   | Citation                                  | Construct | Construct-SC |
| Diffusion of new information follows an S-Shaped Curve.  | Rogers 2010                               | X         | X            |
| Heterogeneous groups are more likely to discover novel information from outside the group than are homophilous groups.               | Granovetter 1983; 2005                    | X         | X            |
|  |   | X         | X            |
| Groups with some heterogeneity outperform purely homophilous groups.   | Ancona & Caldwell 1992                    | X         | X            |
| Individuals are more likely to interact in-group than out-group.   | Blau 1977; Tajfel & Turner 1979           | X         | X            |
| The improvement in task competency of cliquish groups will have significantly more marginal variation over time.                     | West, Barron, Dowsett, & Newton 1999      |           | X            |
| Perceptions of others are often based upon things such as expected roles, social norms, and social categorizations.                  | Greenwald & Banaji 1995; Heise 1979; 2007 |           | X            |
| Arbitrary and even meaningless distinctions between groups can trigger a tendency to favor one's own group at the expense of others. | Tajfel et al. 1971                        |           | X            |
| Transactive memory should preserve computational resources.  | Wegner 1995                               |           | X            |

Those factors that are “designed” are actual mechanisms built in to the model implementation. Those factors that are “emergent” are results that emerge from the model in the virtual experiments.

As Table 1 documents, Construct-SC is a formalized theory that allows for a richer representation of the social group phenomena. Table 1 is used to inform the construction and simulation outputs of interest for the primary virtual experiment outlined in the next section.

## Virtual Experiment Design

Two different virtual experiments inform the results. Virtual Experiment 1 focuses on the question “Is this a better model of human behavior?”. Virtual Experiment 2 is used to address the question “Is this a more computationally efficient implementation of human behavior?”.



## Virtual Experiment One: Modeling Human Behavior

In the first experiment, Construct-SC is evaluated as a model of human behavior. It is anticipated that Construct-SC will model successfully the stylized facts from Table 1. For this experiment, the agent count, the knowledge count, the number of simulation turns, and the task-size (in bits) for performance evaluation are kept constant.

Several factors are manipulated that influence the distribution of knowledge. One of these is the group structure of the social space. Group structure is controlled by two variables: 1) whether there was a single dominant social group, or whether all groups were the same size, and 2) the disparity in size between the dominant and non-dominant groups (if there was a dominant group).

The distribution of knowledge across groups is also varied. Three knowledge distributions are considered: 1) Group-Based, 2) Random, and 3) Fuzzy Groups. In the Group-Based condition, knowledge is distributed based on group affiliation. Each group's size, relative to the total number of agents, indicates how many of the knowledge bits 'belonged' to the group, and the group's knowledge bits are assigned stochastically to group member. In the Random condition, knowledge is distributed without reference to group membership. In the Fuzzy Group condition, knowledge is distributed primarily, but not entirely, based on group membership.

The social space is also differentiated by whether individuals may be members of multiple groups. In the "single" condition, all individuals are members of exactly one group. In the "multiple" condition, all individuals are initialized as members of a single group, and then are given a random chance ( $0.25^{(\text{number of group-memberships})}$ ) to be a member of an additional group, with the new group chosen at random from groups to which that individual does not already belong. The first group, Group 0, is assumed to be highly interstitial: a person is twice as likely to be assigned membership to Group 0 as other groups.

Individuals in the social scene may be more or less driven by desire for interaction with others like themselves (Homophily), or with people with rare knowledge (Expertise). Frequently, these drives are co-present in people (Carley, Lee, & Krackhardt 2002), as shown, for example, by Valente (1996). Three settings are used for these values: 1) "100/0" where all interaction is driven by homophily preference; 2) "60/40" where homophily preference is dominant to expertise preference; and 3) "0/100" where all interaction is driven by expertise preference.

To contrast Construct and Construct-SC, two variants of the Transactive memory model (TM-Model) are used. The experimental condition "Full" represents the earlier implementation of Construct's Transactive Memory. The condition "Multi-Level" represents Construct-SC's new Transactive Memory implementation.

Agents are evaluated on several dependent variables, including in-group interaction probability, out-group interaction probability, knowledge diffusion over time, and task performance over time. In-group interaction probability is the average, across agents, of the summation of probabilities of interacting with fellow group members. Out-group interaction probability is, similarly, the

average, across agents, of the summation of probabilities of interacting with alters outside the group. Knowledge diffusion is the sum of each agent’s knowledge-bit count. Task performance is evaluated using a binary classification task (Carley 1992). In a binary classification task, agent knowledge is used as a mask over a binary string, and the task for the agent is to successfully guess whether a string is more 1s or 0s. To evaluate task performance, the set of knowledge bits is divided into ten contiguous blocks, each representing a task. Each turn, bits required per task are drawn at random from each block. An agent’s score each turn is the percentage of tasks they completed correctly. The first virtual experiment’s factors and constants are presented in Table 2.

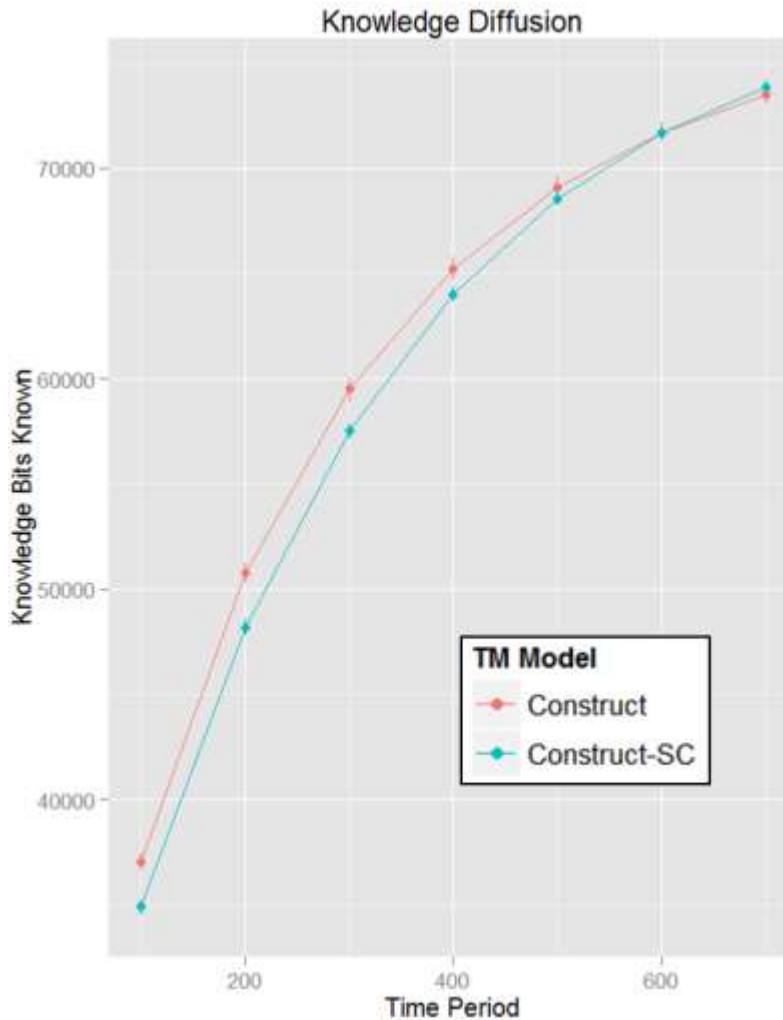
| <b>Table 2. Virtual Experiment 1 - comparing behavior versus Full (Construct) and Multi-Level (Construct-SC) implementations of transactive memory</b> |  |                    |
|--|--|--------------------|
| <b>Factors</b>   | <b>Values</b>  | <b># of Values</b> |
| Group Size and Number  | Single-Dominant (60%, Large), Single-Dominant (60%, Small), All-Equal (Large), All-Equal (Small) | 4                  |
| Knowledge Distribution (Random, Group-Based)   | Group-Based (0.01, .3), Random (.1, 0.0), Fuzzy Groups (0.03, .25)                               | 3                  |
| Group Membership   | Single, Multiple   | 2                  |
| Interaction Drives (Homophily/Expertise)   | 100/0, 60/40, 0/100  | 3                  |
| Transactive Memory   | Full, Multi-Level  | 2                  |
|  | Total Combinations   | 144                |
|  | Runs Per Condition   | 10                 |
|  | Total Runs   | 1440               |
|  |  |                    |
| <b>Constants</b>   |  |                    |
| Agent Count  | 200  |                    |
| Knowledge Count  | 400  |                    |
| Sub-Tasks  | 10   |                    |
| Time   | 800  |                    |
|  |  |                    |
| <b>Outcomes</b>  |  |                    |
| In-Group Interaction Probability   | Average of each agent’s summed probabilities of interacting in-group                             |                    |
| Out-Group Interaction Probability  | Average of each agent’s summed probabilities of interacting out-group                            |                    |
| Knowledge Diffusion  | Summation of each agent’s knowledge-bit count  |                    |
| Task Competencies  | Binary Task Classification (see above)   |                    |

| <b>Table 3. Virtual Experiment 2 - comparing run-time results</b> |  |                    |
|---|--|--------------------|
| <b>Factors</b>  | <b>Values</b>                            | <b># of Values</b> |
| Agent Count   | 1000, 5000, 10000, 15000                 | 4                  |
| Transactive Memory  | Full, Multi-Level                        | 2                  |
|   | Total Combinations                       | 8                  |
|   | Runs Per Condition                       | 10                 |
|   | Total Runs                               | 80                 |
| <b>Constants</b>  |  |                    |
| Group Size and Number   | All-Equal                                |                    |
| Knowledge Distribution (Random, Group-Based)                      | Fuzzy Groups (0.03, .25)                 |                    |
| Group Membership  | Multiple                                 |                    |
| Interaction Drives (Homophily/Expertise)                          | 60/40                                    |                    |
| Knowledge Count   | 1000                                     |                    |
| Sub-Tasks   | 10                                       |                    |
| Time  | 365                                      |                    |
| <b>Outcomes</b>   |  |                    |
| Run Time  | Average turn length in seconds per agent |                    |

## Virtual Experiment Two: Empirical Observation of Achieved Efficiencies

Virtual Experiment 2, described in Table 3, is used to evaluate Construct and Construct-SC's run-time costs. It is anticipated that the simulations using Construct-SC will have a much faster run-time. A formal analysis of Construct-SC's memory complexity is provided next; however, evaluating Construct-SC's time-complexity is highly dependent on a modeler's choices. Thus Virtual Experiment 2 was run to demonstrate achieved efficiencies for typical usage based on prior experience. For these experiments, the group structures, knowledge distribution, interaction drives, knowledge count, sub-task count, time, and machine configuration are controlled. A powerful machine with 60 processors and 0.5 TB of memory to minimize noise in run-time results was used to run the virtual experiment. In each case, Construct was run on a single thread.

The number of agents (agent count) in the simulation world, and the transactive memory model were varied. The primary outcome variable was run-time, which was measured as average turn length per agent to make the results more easily comparable across the wide variation in number of agents.



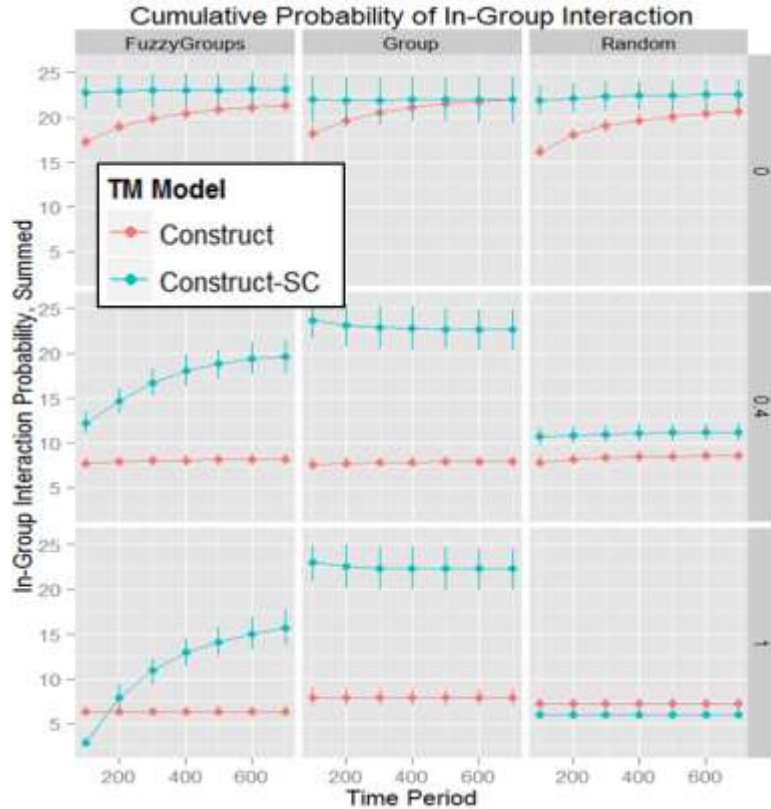
**Figure 1. Information Diffusion in Construct and Construct-SC. Both Models predict overall diffusion of information at similar rates across other variables.**

## Results

Following the pattern established by the virtual experiments, the results are presented in subsections, related to the modeling of human behavior and to run-time results.

### An Improved Model of Human Behavior

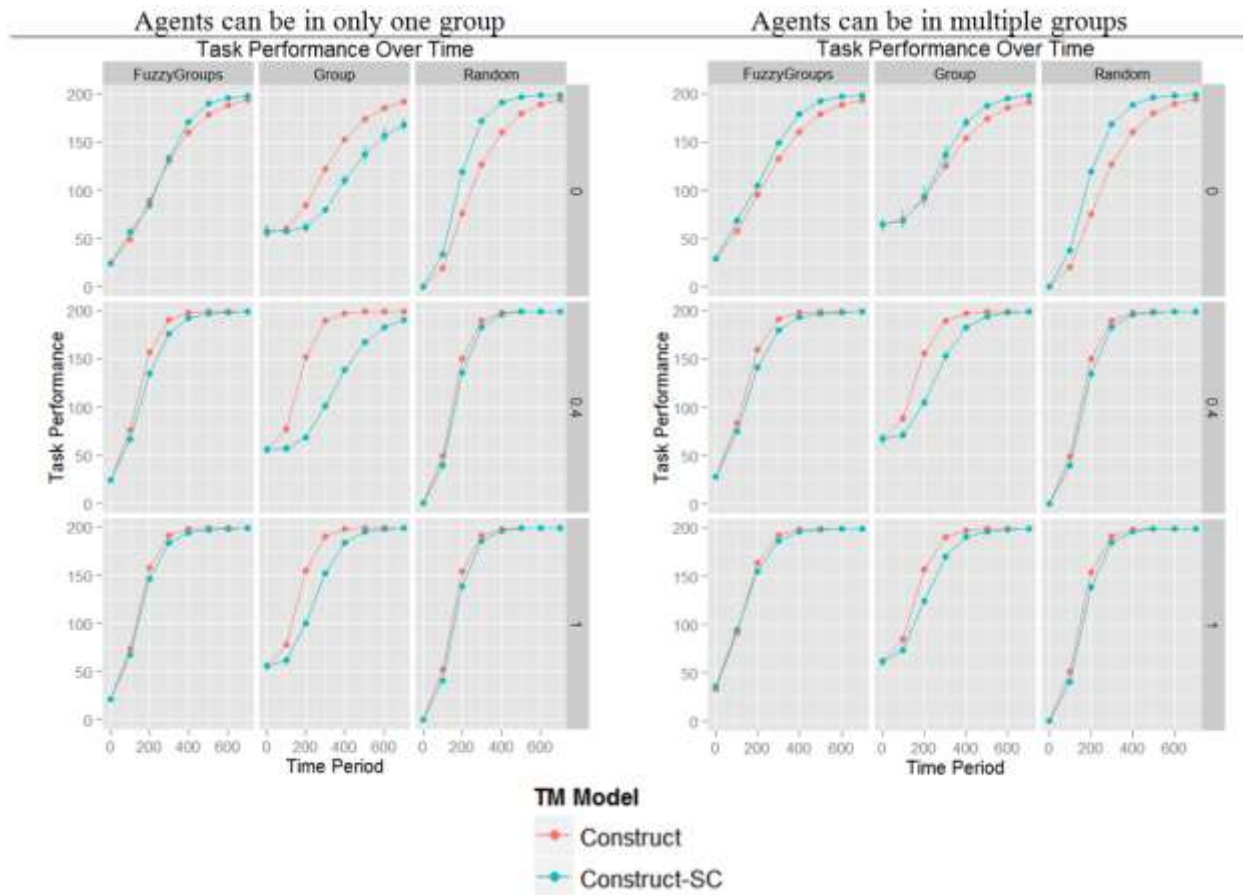
By improving the theory of mind implementation over that Construct, it is anticipated that the improved model, Construct-SC, will better represent the stylized facts described in Table 1. The results demonstrate that adding social cognition is a theoretical win; i.e. the model with improved theory of mind produces results which better match Table 1's stylized facts.



**Figure 2. Construct-SC actors prefer to interact in-group unless only rare knowledge is valued and group membership is arbitrary**

In this section, Table 1 is used to guide the analysis of the results. First, both models should replicate information diffusion’s S-Shaped curve. The results in Figure 1, demonstrate that both models predict similar levels of information diffusion over time across all condition groups. Clearly, the curves represented do not show the traditional “bottom” of the expected S-shaped curve, but otherwise follow the expected pattern. The apparent difference from the traditional S-shaped curve, however, can be readily attributed to the initial conditions of the model, which was set to ensure a reasonable run time. More specifically, because initial information density was set high, simulations essentially skip the ‘discovery’ phase for most knowledge bits. As is demonstrated, when considering multiple knowledge bits together to measure task performance, the familiar S-shaped curve returns (Figure 3).

Construct-SC allows for group reasoning and group biases. People often privilege interaction with people within their social groups, even when those groups do not imply shared knowledge or understanding. Figure 2 is a series of line plots, showing the distribution of in-group bias with Construct and Construct-SC compared in every sub-graph. The separate columns represent how knowledge is distributed a priori; the separate rows represent the weighting of the expertise drive. Each sub-graph represents cumulative bias towards the in-group, with the X-axis being time. As shown in Figure 2, Construct-SC agents prefer to interact more with members of their own group than Construct agents in nearly all cases. The exceptions occur in the somewhat unlikely social situation where only the expertise drive is active, and thus only rare knowledge is valued. In the

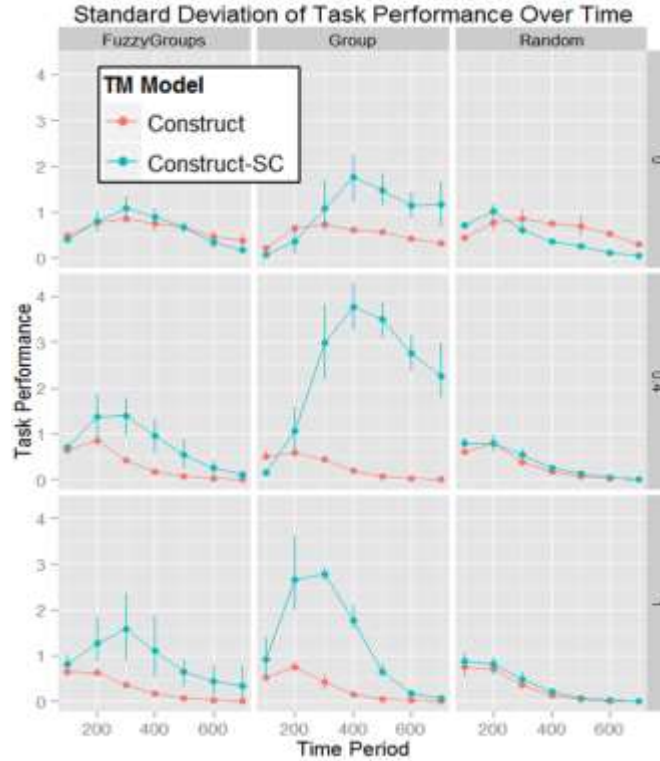


**Figure 3. Task performance of different groups are compared over time. Important social structures of the simulation drive variation in Construct-SC task adoption outcomes.**

fuzzy-group knowledge distribution, Construct-SC agents find value in interacting outside the group, at first, until enough members of their own group gain rare knowledge. In the random-case, Construct-SC agents tend to attribute knowledge they already possess to in-group members which does not offer any group cohesion.

In task performance, it is anticipated that there will be variation over time in highly cliquish groups (West, et. al 1999), i.e., groups that prefer to interact with the in-group over interacting with people outside the group. Based on the findings from Figure 2, it is assumed that groups that are entirely homophily-driven (the top row) fit this definition. Construct-SC agents are, in general, more cliquish.

Figure 3 is a series of line plots, showing the distribution of task performance with the Construct and Construct-SC compared in every sub-graph. Two separate graphs are presented, one where agents can be members of multiple groups, and one where they can only be a member of a single group. In both cases, every agent is a member of at least one group. Within each graph, the separate columns represent knowledge distribution, and the separate rows represent the weighting of the expertise drive. Each sub-graph represents the task performance of the population, with the Y-Axis being the summation of all agents' capabilities to complete a large complicated task. The task was



**Figure 4. Variation in task performance outcomes over time - Construct-SC shows a more pronounced U-Shape curve over time in all group-based knowledge distributions.**

defined as follows. First the knowledge was divided into ten parts using contiguous sets of knowledge bits. Then the bits required for each sub-task at each point in time were drawn from all bits related to that sub-task. Thus, performance on each task should be expected to vary over time, but as agents gain knowledge, they will become better able to contribute to the overall task, until nearly every agent can perform nearly all sub-tasks involved. The X-axis indicates time. Construct-SC allows for much more variation in outcomes, and that variation is due to the simulation’s social structure.

Figure 3 shows that simulation outcomes are sensitive to social structure. The more agents are motivated by expertise, the faster performance tends to improve. Knowledge distributed a priori by group tends to diffuse slower, probably due to in-group biases shown in Figure 2. Construct-SC agents, with their stronger in-group biases in general, tend to distribute task-knowledge more slowly. Multi-group memberships mitigate the effect.

Figure 4 shows that outcome metric variations are different between Construct and Construct-SC. Construct-SC’s task performance outcome variations have a distinctive U-shape curve over time when knowledge is not randomly distributed – this pattern is muted in original Construct. Note that this is not merely the addition of more noise to the simulation model – instead the perceived additional variability is, in the outcome variable, structural in nature. When group membership is salient to performance (because knowledge is distributed through group memberships), there is low variability in performance both at the beginning and at the end of the simulation, i.e. at both

| Table 4. Symbols used in analysis of the computational complexity |  |
|---|--|
| Symbol  | Meaning  |
| $I$   | Number of instances (e.g.  SO-TMV ) is the number of instances in the SO-TMV                             |
| $G$   | Number of groups   |
| $N$   | Number of agents   |
| $K$   | Number of knowledge bits   |
| $SOTM$  | Agent perception of individuals ( <b>S</b> ignificant <b>O</b> thers <b>T</b> ransactive <b>M</b> emory) |
| $GTM$   | Agent perception of groups ( <b>G</b> roup <b>T</b> ransactive <b>M</b> emory)                           |
| $NIntPerTurn$   | Number of interactions an agent can have per turn  |
| $Thresh$  | Threshold of activation at which agent “forgets” an agent or group                                       |

observed areas of the diffusion curve. . Rather than adding noise, social cognition reduces variation and so noise when group membership is salient.

## Better Behavior, Better Performance

In general, as models become more veridical they become more computationally complex. In other words, the better the model of cognition, the longer it takes to simulate group behavior, and the more computer resources are required. In this section, Construct-SC’s computational performance is analyzed. The results demonstrate that adding a multi-level theory of mind is a computational win; i.e. to model the same number of agents in Construct-SC versus Construct requires less memory and runs faster.

From a computational perspective, the new mechanism’s chief advantage is that it reduces the computer memory required to maintain transactive memory by implementing a variant of ACT-R’s activation equations. In this section, a formal proof of this fact is provided, followed by an empirical demonstration that this space saving does not come at the cost of the simulation’s run-time speed. These memory and run-times make it feasible to run much larger simulations in Construct-SC. Table 4 provides an overview of the symbols used in the derivations in this section.

In Construct-SC the implementation of ACT-R’s activation equations are a variant of Petrov’s (2006) approximation. In this variant, agents “forget” information if its activation score is below a threshold. In Construct-SC, agents “forget” their perceptions, or transactive memory, of other agents and groups if they have not interacted with them recently. “Time” is represented by simulation turns, and thus bounds can be set on the amount of time before an agent “forgets” based on the number of simulation turns that have elapsed and a particular setting of the variables in the ACT-R equation. The following derivation utilizes this idea to bound the model’s memory requirements.

In Table 4, the variables needed to calculate the algorithm’s complexity are defined. Then in Table 5, the major mechanisms for Construct and Construct-SC are compared – defining their space complexity. As is clear, retaining perceptions of alters dominates the space complexity in Construct. Assuming that there will be many more agents than groups ( $N > G$ ), the same is true of



| Table 5. Computational complexity per agent of the social cognitive system |                             |                                   |
|--|-----------------------------|-----------------------------------|
| Object   | Space Complexity- Construct | Space Complexity- Construct- SC   |
| Agent Knowledge  | $O(NK)$                     | $O(NK)$                           |
| Alter to Group Matrix  | N/A                         | $O(NG)$                           |
| Activation Mechanism   | N/A                         | $O(N*( SOTM  +  GTM ))$           |
| Perceptions of others' knowledge   | $O(N^2K)$                   | $O(N*( SOTM + GTM )*K)$           |
| <b>Total</b>   | $O(N^2K)$                   | $O(\max(NG, N*( SOTM + GTM )*K))$ |

Construct-SC. The primary question that must be answered is thus the size of  $|SOTM| + |GTM|$  relative to  $N$ , as this will identify the space savings obtained.

To make this determination, assume that  $|GTM| = G$ , and again that  $G$  is small relative to  $N$  for this simulation model. In other words, assume that the number of groups that an agent can be in is insignificant as compared to the number of agents. The primary concern now becomes comparing  $|SOTM|$  and  $N$ . Assume that an agent has interacted with another agent  $T$  turns ago. Then, given the activation equations described by Petrov (2006) and the mechanism described, the following must be true for the agent to not “forget” the alter (where  $K$  is some initial, small, constant activation value to ensure Equation 1 is defined when  $T = 0$ ):

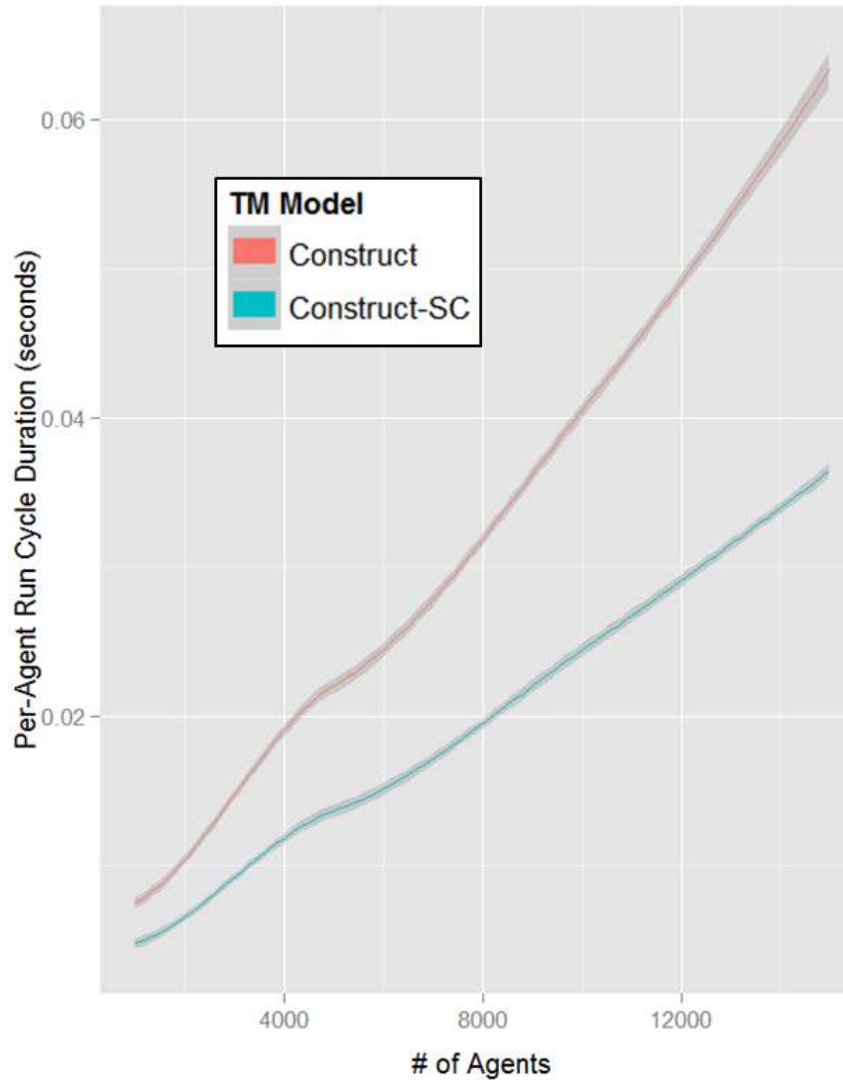
$$\log\left(\frac{1}{\sqrt{K+T}}\right) > Thresh \quad (1)$$

With some straightforward algebraic manipulation, results in an equation which defines the number of time steps, or simulation turns before which an agent will “forget” an alter that it interacted with once,  $T$  turns ago:

$$T < \frac{1}{\exp(2 * Thresh)} - K \quad (2)$$

If an agent interacts with an alter only once,  $T$  turns ago, then the agent will forget the alter after a number of turns determined by the threshold parameter. In the pathological case where an alter interacts with  $NIntPerTurn$  unique alters each turn, then  $|SOTM|$  will be the minimum of  $N$  or the product  $NIntPerTurn * Equation 2$ . Modelers can tune parameters such that there are no space savings, where there are few agents and many allowed interactions. However, even at the most loose settings utilized in Virtual Experiment 2, where  $K=1$ ,  $NIntPerTurn=2$ ,  $Thresh=-1$ , then  $|SOTM|$  is at most 15 agents large. This value is constant and does not depend on  $N$ , thus Construct-SC, with realistic parameter settings, is an order of magnitude (in  $N$ ) more space efficient than Construct.

A formal analysis of Construct-SC’s time complexity is not provided because such an analysis would be dependent on the modeler’s choices, and thus could not be broadly generalized. Instead, an empirical assessment is provided as guidance, via Virtual Experiment 2, of a typical use of



**Figure 5. Construct-SC takes less time to run for a similar number of agents.**

Construct, noting the same limitation. In Virtual Experiment 2, knowledge sizes were kept constant, but the number of agents was varied (from 1000 to 15,000). Figure 5 above shows a run-time comparison of Construct and Construct-SC. Construct-SC runs faster across all population sizes. Note that Construct-SC's time complexity does depend on the number of groups, but it is anticipated that the number used in Virtual Experiment 2 (10 groups) are typical of usage.

## Discussion

In implementing Construct-SC, a multi-level model of group-based inferences, we see that stereotypes preserve resources and improve model behavior compared to models where agents retain transactive memory of all potential alters. Specifically, the model with group-based inferences:

**Table 6. Summarization of Results Using the Stylized Facts**

| Emergent Phenomenon   | Citation                                  | Construct        | Construct-SC                         |
|---|---|------------------|--------------------------------------|
| <b>Diffusion of new information follows an S-Shaped Curve.</b>  | Rogers 2010                               | Fig.1, Fig. 3    | Fig.1, Fig. 3                        |
| <b>Heterogeneous groups are more likely to discover novel information from outside the group than are homophilous groups.</b>               | Granovetter 1983; 2005                    | Fig.2            | Fig.2                                |
| <b>Groups with some heterogeneity outperform purely homophilous groups.</b>   | Ancona & Caldwell 1992                    | Expertise: Fig.3 | Expertise: Fig.3<br>K-Distro: Fig.3  |
| <b>Individuals are more likely to interact in-group than out-group.</b>   | Blau 1977; Tajfel & Turner 1979           | Homophily: Fig.2 | All except Random+/Expertise: Fig. 2 |
| <b>The improvement in task competency of cliquish groups will have significantly more marginal variation over time.</b>                     | West, Barron, Dowsett, & Newton 1999      |                  | Fig. 4                               |
| <b>Our perceptions of other people are often based upon things such as expected roles, social norms, and social categorizations.</b>        | Greenwald & Banaji 1995; Heise 1979; 2007 |                  | Fig.2                                |
| <b>Arbitrary and even meaningless distinctions between groups can trigger a tendency to favor one's own group at the expense of others.</b> | Tajfel et al. 1971                        |                  | Fig.2                                |
| <b>Transactive memory should preserve computational resources.</b>  | Wegner 1995                               |                  | Table 4<br>Fig.5                     |

- Allows for arbitrary groupings of agents to significantly impact interaction between agents;
- Shows significant in-group bias;
- Supports wider variances in task performance, with that variance better supported by the structure of the knowledge space;
- Runs faster and requires less memory.
- 

Using the stylized facts from Table 1, the results of Virtual Experiment 1 are summarized in Table 6.

Limiting the ability of agents to retain perceptions of alters and providing a group-based inference mechanism, resulted in agent behavior that is more true to established “stylized facts”. This suggests that people behave the way they do because they have finite cognitive resources which forces them to retain group-level schemas for actors they do not personally know. This research finding recalls the variety of work done with cognitive biases – and how these biases inform both extant social structures and how network researchers collect data on these structures. This work suggests an approach towards modeling the rich variety of socially relevant cognitive biases.

Although a significant advancement in agent modeling, this work still has several limitations. First, and most significantly, the model of groups could be improved in a variety of ways. In Construct-SC groups are universal and group membership is immediately visible to others. This implementation of groups is best fit for superficial grouping characteristics, such as coarse-grained representations of age, gender and race. A more advanced group model would include spontaneous group formation, a process by which agents infer group membership, and the ability for agents to leave groups. Despite these limitations, the relevance of groups in the current model is not uniform to every agent; it is based on who these actors tend to interact with. Thus, the abstractions of groups themselves may be lost over time.

This model could be further explored by being placed in a specific interesting context, such as a small town or village with well-defined demographics; where group sizes are not roughly equivalent, and membership in multiple groups is constant. Comparing the spread of knowledge and beliefs in Construct and Construct-SC in such a context, with perhaps a comparison to a historical situation of interest, would be worthwhile.

The group inference mechanisms assume that these group inferences are generally, if not perfectly, accurate. This model ignores the ability of agents to select media and other sources of information that bias their inferences. However, this model does allow for agents to have more or less personal bias in their understanding of alters, but this does not entirely overcome the issue of bias in media sources.

The ability to use group membership to inform an implemented theory of mind is a useful extension to the agent literature that other models could learn from. The results demonstrate that group stereotypes allow agents to conserve resources, make decisions faster, and better emulate human behavior.

Overall, this paper demonstrates the value of implementing social cognition in models of human social behavior. By adding a multi-level model of theory of mind to a network interaction model, the emergent behavior better reflects real human social behavior and reduces computational complexity. The complexity reduction reduces costs in time and in computational hardware, making it feasible to model substantially larger populations. For a modeler, this is a clear win. Theoretically, it suggests that social cognition provides humans with a fast heuristic approach for processing vast quantities of data with less effort. It further suggests that peculiarities of social behavior may be the consequence of cognitive limitations that admit inferences about individuals and groups given social generalizations.

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