Using Machine Theory of Mind to Learn Agent Social Network Structures from Observed Interactive Behaviors with Targets

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*Abstract*— Human social interactions are laden with behavioral preferences that stem from hidden social network representations. In this study, we trained a neural network (NN) to learn and predict human social preferences based on implicit information from the way agents and social targets behaviorally interact with each other. Our findings have implications for machine applications that seek to infer hidden information structures solely from third-person observation of behaviors.

# INTRODUCTION

# The use of artificial intelligent machines that dynamically interact with people is proliferating across many aspects of human life such as in interactive live service platforms [] and socially assistive robots []. Nevertheless, the efficacy of such social machines is limited by the naturalness of their interactions with people. Specifically, human-machine interactions are typically hampered because the interactive actions engaged by machines are often contextually aberrant and do not fit human social behavioral norms []. Thus, learning algorithms that help social machines display more human-like contextually relevant interactive behaviors should enhance their intended functionality.

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# One characteristic driving fluent human social interactions is access to information about the underlying social network of persons involved, which is often implicit []. For example, suggesting a friend call Bill Gates about a lunch appointment would be absurd unless one knew that he is a common acquaintance. Also, one might talk about sensitive matters with a sibling amongst other family members but avoid such topics with the sibling when amongst colleagues. In these above scenarios, knowledge of the collocutor’s social network is implicitly required to determine if a given interactive action would be contextually pertinent or not. Similarly, naturalistic human-machine social interactions would require machines to represent and leverage on information about the underlying social networks governing behavioral interactions between humans.

# Social networks, however, are abstract constructs in human minds that are hidden with respect to third-party observers such as another person or a machine. A social network exists only because the persons involved preferentially interact with each other in specific ways. As such, the nature of social connections between persons must be inferred from observations of their interactive behaviors. Critically, other work has shown that artificial neural networks implementing Theory of Mind (e.g. ToMnet []) can observe past social interaction outcomes between agents and targets (derived from predetermined interaction rewards) and form internal representations of agents’ hidden false beliefs.

# In this study, we adapted the work in [] to construct ToMnet+ and evaluated how its operation might represent hidden social networks underlying observed interactions between agents and targets. Such a demonstration has implications on how neural models might be engaged to infer deep relational structures in apparently disparate observations across various classes of data problems. In addition, as mentioned, an artificial neural network developed along these lines might also be integrated as a dynamic module in social software services or robots to enhance human-machine interactions across various functional contexts.

# Core to our approach in this work is simulating plausible social networks that constitute ground truth against which to assess performance of ToMnet+ (Fig. 1). These simulated social networks consisted of agents with different inter-personal connection weights to targets. Importantly, connection weights were based on the range of scores from the Social Support Questionnaire (SSQ) commonly used in Psychology to evaluate real human social dependencies on specific persons []. In general, people more readily approach and interact with persons in their network whom they perceive as providing them with greater social support [].

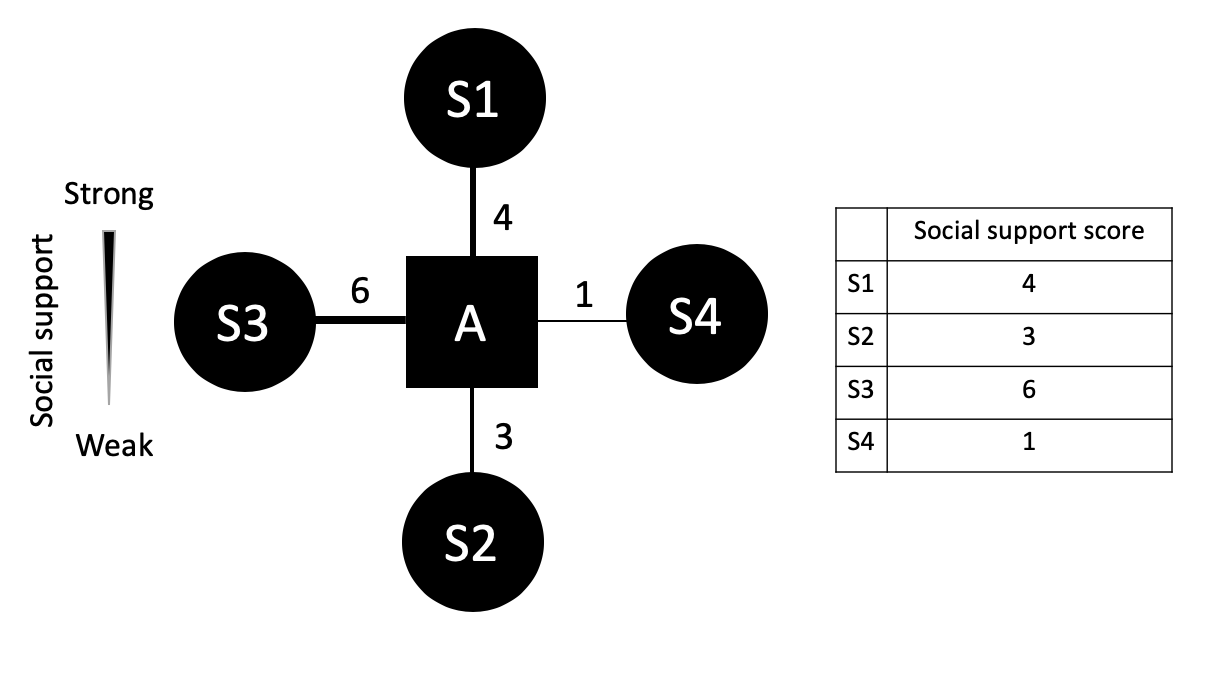


Fig. 1. An example simulated social support network of agent, *A*, and four targets, *S*. Connections between the agent and targets are modulated by the degree of social support the agent perceives receiving from each target.

# Simulated social support networks were thus used to generate sets of agent interactions with targets in different social contexts from which ToMnet+ learned. To test for a hidden social support network representation, we asked ToMnet+ which target an agent would preferentially interact with over various novel combinations of social contexts. We considered that the rank order of agent-target social support weights captures the base topology of our simple simulated social networks. As such, the goal is to determine if ToMnet+ judgment of agent-target social interaction preferences during test has a similar rank order as the social support weights.

# In the following, Section II expands on the notion of social support and its influence on human social interaction as well as considers relevant findings on machine learning of human social preferences. Section III covers our methodology regarding the SSQ, simulation generation, additional real human social interaction data acquisition for ecological validation, and ToMnet+ architecture and implementation. Section IV reports ToMnet+ performance results for the simulation data as well as human data. Section V discusses the findings and conclusion.

# Background and Related Works

## A. Social Support Networks

Studies have investigated associations between human interaction behaviors and their underlying social support networks. [] was the first study to coin the term “social network” to describe a small Dutch community …

Subsequently, it is well noted that the social network of persons is a critical factor for the sort of social interactions a person might engage in or not. Specifically, persons will seek out support from persons in their social network for help to address certain needs []. Interestingly, support may not always be sought out from persons close in the social network. Rather, persons in more distal networks or weak networks might at times be more favored for some life or psychological needs [].

Thus, while a person might maintain several different types of social network, one of the most important of these is a person’s social support network. Critically, one’s social support network likely drives many everyday social interactions with different people. As such, there is a need to quantify a person’s social support network.

Several approaches have been implemented to characterize social support networks. Of these, Sarason’s Social Support Questionaire [] has been one of the most commonly used. The SSQ consists of 27 items. …

In this study, we simulated a social network of a virtual agent (A) with four social targets (s) based on the degree of social support the agent perceives about each target as in the SSQ [].

## B. Machine Theory of Mind

## C. Social Machines

# Methodology

## A. System Overview

We simulated a social network of a virtual agent (*A*) with four social targets (*s*) based on the degree of social support the agent perceives about each target []. We then placed agents and selected targets in locations in a grid world randomly generated with barriers (Fig. 2). Using these social agent parameters, we simulated agent movement behaviors to targets by contrasting the physical distances, , which is the number of steps between agent and targets, and attraction, , which is calculated as,

Where , and and are the nth personal and associative parameters of target s, respectively. Then,

such that the agent was set to move toward the social target with largest , constituting a grid world trajectory instance (green arrows in Fig. 2). We simulated 10,000 grid world trajectories in total. In addition, a real human participant also indicated four friends (targets) with social parameter information obtained using questionnaires [3][4][5]. The participant was then placed in randomly generated grid world scenarios and was tasked to reach one of the targets with minimal moves, yielding 9,830 real human trajectory data. We then applied a modified ToMnet consisting of a deep-learning architecture with a character network and a prediction network. The character network consumes the agent’s past grid world trajectories to summarize the acting agent’s “character”. The prediction network then consumes the 8-dimensional character vector and, with a given new grid world state, predicts which target the agent will approach. The character and prediction networks consist of a residual network (resnet) and a long-short term memory network (LSTM) meta-layers that summarize the agent’s spatiotemporal grid world movement behaviors. The model was applied using a 8:1:1 training, validation, and testing split on simulated and human data separately using Tensorflow [6]. The trained model was used to infer the underlying preference of the simulated/human agents by feeding the model with start grid world states with four targets equidistant from agents. The probability of approaching each target output using softmax function were agents preference scores for each target.

## B. ToMnet+

The ToMnet+ is inspired by the ToMnet [8]. ToMnet+ is composed of a character network and a prediction network. The character network consists a resnet with 5 layers followed by an average pooling layer and then a single-layer LSTM. The input of the character network is a batch of trajectories, Each trajectory is a 4d tensor of size 10×12×12×11, where 10 is the number of steps in the trajectory, 12 is the width and height of the grid world. 11 is the number of features of each

consumes the agent’s past grid world trajectories to

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# Experimental results

## A. Simulation Data

Performance of the trained models in predicting the agents’ final targets from test grid world start states is shown in Table 1 for both simulated and human data. Model performances as measured by the accuracy in predicting the agent’s final target given test start states in grid world. S1~S4 are 4 potential targets across the grid world instances, each with different personal and associative social parameter values constituting their underlying social network structures. Preference scores are normalized prediction probabilities (see Methods).

Because there were 4 potential targets in the test grid worlds, the chance prediction was 25%. Critically, the models which observed nothing more than the agents’ grid world behaviors were capable of inferring the agents’ underlying preference rankings.

1. Multi-target preference prediction performance

| Data Type | Final Target Accuracy | Predicted Preference Score | True Preference Score |
| --- | --- | --- | --- |
| Simulated | 80.14% | S4 (1.16)  >S3(0.83)  >S2(0.76)  >S1(0.62) | S4 (1.15)  >S3(0.79)  >S2(0.72)  >S1(0.72) |
| Human | 73.26% | S4 (0.71)  >S3(0.28)  >S2(0.01)  >S1(0.00) | S4 (0.95)  >S3(0.83)  >S2(0.83)  >S1(0.83) |

## B. Human Data

# Conclusions

Our findings highlight the potential of machine applications that infer implicit human preferences from third-person behavioral observation data. This is distinct from most current applications that are focused on dissociating explicit signals (e.g. recognizing emotional categories from facial expressions). This is also distinct from the previous study, which used ToMnet to extract preference from simulated agents without hidden associative structures [2]. We demonstrate that a NN such as ToMnet can also model real hidden social networks reflected in human social preferences. Aside from artificial intelligence and robotics applications, our findings also have implications in neuropsychological research. In principle, the human brain is also a neural network, albeit more complex, that operates by integrating observations of how other humans behaviorally interact to generate an internal hypothesis about real social networks [7]. As such, it is intriguing to consider such model implementations of learning and behavior as formal theory about the information mechanisms at work in human brains. With this initial platform, future work expanding on different formats of behavioral information and NN architectures can then be used to better understand how the human mind grasps reality.

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