



Published in final edited form as:

J Exp Psychol Learn Mem Cogn. 2019 February ; 45(2): 253–271. doi:10.1037/xlm0000580.

Individual Differences in Learning Social and Non-Social Network Structures

Steven H. Tompson^{1,2}, Ari E. Kahn^{1,2,3}, Emily B. Falk^{4,5,6}, Jean M. Vettel^{1,2,7}, and Danielle S. Bassett^{1,8}

¹Department of Bioengineering, University of Pennsylvania

²Human Sciences Campaign, U.S. Army Research Laboratory

³Department of Neuroscience, University of Pennsylvania

⁴Annenberg School of Communication, University of Pennsylvania

⁵Department of Psychology, University of Pennsylvania

⁶Marketing Department, The Wharton School, University of Pennsylvania

⁷Department of Psychological and Brain Sciences, University of California, Santa Barbara

⁸Department of Electrical & Systems Engineering, University of Pennsylvania

Abstract

How do people acquire knowledge about which individuals belong to different cliques or communities? And to what extent does this learning process differ from the process of learning higher-order information about complex associations between non-social bits of information? Here, we employ a paradigm in which the order of stimulus presentation forms temporal associations between the stimuli, collectively constituting a complex network. We examined individual differences in the ability to learn community structure of networks composed of social versus non-social stimuli. Although participants were able to learn community structure of both social and non-social networks, their performance in social network learning was uncorrelated with their performance in non-social network learning. In addition, social traits, including social orientation and perspective-taking, uniquely predicted the learning of social community structure but not the learning of non-social community structure. Taken together, our results suggest that the process of learning higher-order community structure in social networks is partially distinct from the process of learning higher-order community structure in non-social networks. Our study design provides a promising approach to identify neurophysiological drivers of social network versus non-social network learning, extending our knowledge about the impact of individual differences on these learning processes.

Keywords

social network learning; statistical learning; social cognition

Consider the important, yet daunting, challenge of learning a social network at a new job. Some connections are dictated by management structure, such as who supervises whom, project assignments, and administrative burden. Other connections may reflect personal connections from shared personal interests, proximity of offices, kids on the same sports team, or spouses who are friends from college. Individuals may also cluster together into cliques or communities based on these individual work or personal connections. This intricate web of human interactions reflects a rich social network of relationships between individuals. Navigating these interwoven layers of social connections is critical for success at the workplace but also in a much broader range of social interactions with friends, family and strangers (Balkundi & Harrison, 2006; Fitzhugh & DeCostanza, 2016; Jehn & Shah, 1997; Orvis & DeCostanza, 2016). Understanding how people learn relational information and update their representations of social network connections and communities may provide key insights into a broad range of important questions about human behavior.

Research on statistical learning may provide insights into how people learn relational information. People are able to implicitly learn and pick up on spatial and temporal associations between objects grouped into communities (Halford, Wilson, & Phillips, 2010; Karuza, Thompson-Schill, & Bassett, 2016). Learning relational information about how objects or individuals are related to one another in space, time, or content is important for reasoning, language, and other higher cognitive processes (Halford, Wilson, & Phillips, 2010). This information enables individuals to form internal representations of the external world (Fiser & Aslin, 2002, 2005; Gómez, 2002; Jenny R. Saffran, Newport, & Aslin, 1996; Turk-Browne, Isola, Scholl, & Treat, 2008) which facilitate efficient information processing (Fine, Jaeger, Farmer, & Qian, 2013; Karuza, Farmer, Smith, Fine, & Jaeger, 2014; Turk-Browne, Scholl, Johnson, & Chun, 2010). By learning the relationships between objects or between individuals, people understand visual patterns, produce language (Friederici, 2005), form knowledge (Bousfield, 1953), develop social intuition (Gopnik & Wellman, 2012), exercise logical deduction, and attain expertise in their line of work (Moon, Hoffman, Novak, & Canas, 2011). Since social networks are inherently about the relations among individuals, learning relational information also likely confers advantages for successfully understanding social structure.

Collectively, relational data can be described as a network in which nodes might represent concepts, objects, or individuals, and in which edges might represent shared content, social relationships, or conditional probabilities (e.g., Moon et al., 2011). Yet, how the organization and content of such a network impacts our ability to learn the data is far from understood. Progress has been stymied by two critical limitations in both methodology and conceptualization. First, methodologically, research has predominantly focused on the learning of object pairs or concept pairs, rather than on the learning of higher-order, non-pairwise relationships present in real-world systems. Recent work suggests that human learners are sensitive to higher-order relational information beyond adjacent and immediately non-adjacent probabilities (Chan & Vitevitch, 2010; Goldstein & Vitevitch, 2014; Schapiro, Rogers, Cordova, Turk-Browne, & Botvinick, 2013). Yet, experimentally manipulating and studying these higher-order relationships requires a quantitative framework in which to characterize the higher-order relationships. The lack of such a

framework has challenged our ability to predict how people might learn such higher-order relational information.

Network science can provide a useful framework for characterizing complex patterns of relationships between pieces of information by conceptualizing the objects or concepts as a graph where the objects or concepts are nodes and relationships between the objects or concepts serve as edges (Newman, 2010). Network metrics can then be applied to describe higher-order patterns of relationships in the graph. For example, the degree to which words are clustered together into communities influences how easily a particular word is learned (Goldstein & Vitevitch, 2014). Moreover, individuals performing a basic perceptual learning task process stimuli more slowly if they lie in different communities (Karuza, Kahn, Thompson-Schill, & Bassett, 2017; Schapiro et al., 2013). Thus, the clustering or community structure is an important source of information about the higher-order relationships embedded in a network.

Second, conceptually, progress has been hampered by the lack of an understanding of the similarities and differences between learning relational content among objects, such as abstract shapes or verbal commands, and learning relationships among individuals, such as colleagues or friends. Categorization research has found that people use different strategies when processing information and assigning information to categories, and these strategies seem to be relatively consistent across different types of information (Baldwin, 1992; Murphy & Medin, 1985; Reed & Friedman, 1973). For example, people use similar strategies when categorizing individuals into social communities when the information about individuals is presented using conceptual information (age, demographics, etc.) and perceptual information (facial features; Reed & Friedman, 1973). But it is not known whether categorizing people and categorizing non-social targets operate using similar mechanisms.

Categories of objects or concepts are mathematically represented by sets, and are often colloquially referred to as clusters. If we connect these objects with edges indicating shared features, then objects or concepts in the same category will tend to be more densely interconnected than objects or concepts in different categories. In this context, a community is a set of objects or concepts whose elements are more densely interconnected with one another than expected in a random network null model. Thus, people may adopt similar strategies when learning the categories of different types of information or learning the community membership of that information.

However, much of the literature on categorization and statistical learning described above has focused on learning in one domain (social or non-social) and has not directly compared how people learn social versus non-social information. Although traditional views suggest that statistical learning of relational data may be relatively agnostic to data category (symbols, syllables, visual patterns; Reed & Friedman, 1973; Schapiro et al., 2013), emerging evidence demonstrates that category learning is influenced by salient goals (Chin-Parker & Birdwhistell, 2017). For example, infants are better at learning object properties when given additional social cues (Wu, Gopnik, Richardson, & Kirkham, 2011). This work

suggests that motivation influences how people process information and social content can further aid in learning individual features and categories.

Moreover, neurobiological mechanisms are differentially recruited for learning and processing social versus non-social information (Meyer, Spunt, Berkman, Taylor, & Lieberman, 2012; Meyer, Taylor, & Lieberman, 2015). The ability and motivation to process social information and non-social information is differentially associated with social traits, including perspective-taking (Meyer & Lieberman, 2016; Meyer et al., 2015). Furthermore, individuals who are more collectivistic tend to think about the self as being closely intertwined with others and are more sensitive to social relationships and contextual information (Chua, Boland, & Nisbett, 2005; Kim & Markus, 1999; Markus et al., 1991; Nisbett, Peng, Choi, & Norenzayan, 2001; Tompson, Lieberman, & Falk, 2015; Triandis & Gelfand, 1998), and may therefore be more likely to perceive relational information in social networks. It remains an open question whether there might be unique social, cognitive, or social-cognitive factors that predict learning of social versus non-social relational data, including higher-order community structure.

Here, we addressed these methodological and conceptual challenges by studying individual differences in the learning of higher order patterns of relationships. We defined *social network learning* to be the learning of inherently social relational data embedded on a network structure. We treated objects or individuals as nodes in a network, and we treated relationships (e.g., conditional probabilities or frequencies of co-occurrence) as edges in a network. For this study we focused on community structure (where nodes in a community are tightly interconnected to one another, with relatively few connections to nodes in other communities) as one type of higher-order network structure that could be important for individuals to learn.

Across five studies, participants completed a basic perceptual judgment where the order in which the stimuli were presented reflected previously defined relationships between the stimuli instantiated in a clustered network architecture. The network architecture was never explicitly shown to the participants, but we hypothesized that that architecture could be inferred by the temporal associations between stimuli. More specifically, stimuli were presented such that the stimulus presented on each subsequent trial was connected in a network to the stimulus presented on the previous trial. We then manipulated the cover story for the stimuli. To study social network learning, we emphasized that the stimuli represented people; to study non-social network learning, we emphasized that the stimuli represented abstract images or rock formations (depending on the study). Importantly, we used the same visual representations across both social and non-social tasks, and only changed the meaning ascribed to the stimuli. Using this task and a post-learning categorization task, we implicitly measured the degree to which participants learned the higher order community structure of social versus non-social networks, including the community assignment for each image.

Using an experimental paradigm that bridges social psychology, cognitive science, and network engineering, we examined three broad questions about social and non-social network learning. First, some researchers have suggested that learning relational data operates in a manner that is independent from the type of data being learned (Schapiro et al.,

2013). Thus, we hypothesized that people should learn the network structure for both social and non-social networks, and that this process should be indexed by our implicit measures of learning.

Second, we asked whether there were meaningful differences in the behavioral markers of social and non-social network learning despite their broad similarities. Although people should be able to learn both social and non-social network structures, previous work has found that the processing of social information can be performed independently from the processing of non-social information (Meyer & Lieberman, 2016; Meyer et al., 2012, 2015). We therefore hypothesized that individual differences in performance on social tasks might only show weak correlations with performance on non-social tasks.

Third, we investigated what traits predict social and non-social network learning. Previous work has demonstrated that processing social and non-social information is differentially associated with perspective-taking (Meyer et al., 2015), leading to our hypothesis that social traits (including perspective-taking and social orientation) should uniquely predict learning for social networks but not for non-social networks. Collectively, our results advance understanding of how people process complex relational information, and how that processing is influenced by the type of information being learned.

Overview

We recruited a total of 349 participants across five studies. In the first four studies, we recruited participants through Amazon Mechanical Turk. In Study 5, we recruited participants from the University of Pennsylvania using an online subject recruitment website (Experiments @ Penn). The protocol for all five studies was approved by the Institutional Review Board of the University of Pennsylvania.

We first employed a between-subjects paradigm in Studies 1 and 2 to test for implicit signatures of network learning in social and non-social networks. In Studies 3 and 4, we then examined whether the group difference between social and non-social network learning could be replicated at the individual level using a within-subject design. Finally, Study 5 investigated whether individual differences in traits could account for variability in learning social versus non-social networks.

In all five studies, participants viewed a sequence of fractal images and completed a rotation detection task where they judged whether each image was rotated 90 degrees. Each image was unique, and for each participant, each image was randomly assigned to a network node. The sequence of fractal images that each participant saw was generated by a random walk through the network (see Figure 1). This random walk ensured that the probability of one image being presented after the current trial was equivalent across trials and determined by the network structure. Each node was connected to exactly four other nodes, ensuring equivalent transition probabilities. The structure of transition probabilities is an important cue signaling event structure, which can influence how quickly participants learn information (Fiser & Aslin, 2005; Saffran, Aslin, & Newport, 1996; Turk-Browne, Jungé, & Scholl, 2005). Therefore, keeping the network structure uniform to remove transition

probabilities as a potential source of information about which trials to expect next is important for testing whether participants can learn higher-order network topology.

To measure implicit learning of the network structure, we computed differences in RT between *pre-transition trials* that occurred immediately before a transition from one cluster to another and *post-transition trials* that occurred immediately after a transition from one cluster to another. If participants learn the cluster membership, then they should anticipate seeing a within-cluster image rather than an image from another cluster. This *surprisal effect* should slow participants' response to the rotation judgment on the next trial (Karuza et al., 2017; Schapiro et al., 2013). The first two studies also included an odd-man-out test that measured learning based on categorization of images (described below) to provide additional evidence that participants' responses were influenced by the network structure. The fifth study included two trait questionnaires on social orientation and perspective-taking to examine individual differences that account for variability between social and non-social network learning.

Study 1

In the first study, we used a between-subjects design to test for implicit signatures of network learning in social and non-social networks. The primary goal of Study 1 was to establish that participants are capable of learning community structure for both social and non-social relational information. Intuitively, slower RT on post-transition trials and greater accuracy on the odd-man out task would indicate that individuals successfully learned the network structure. In this task, participants were presented with three images at a time and instructed to select one of the three images that “did not fit” with the other two. Importantly, two of the images on each trial were from the same cluster (i.e., same cluster nodes) and the third image (i.e., distant node) was at least three steps away from the other two images.

Study 1 Method

Participants—For the first study, we recruited 76 participants (37 non-social, 39 social) using Amazon Mechanical Turk. We excluded two participants who had accuracy lower than expected by chance (which we defined as 70%, given the proportion of rotated and unrotated trials in the task). None of the results in this study or any other study changed when participants with poor performance were included in analyses. Total compensation for a participant who completed all phases of either study ranged from \$6.25–\$9.00 (depending on performance bonuses).

Procedure—In Study 1, participants viewed a sequence of fractal images that we created using the Qbist filter (Loviscach & Restemeier, 2001) in the GNU Image Manipulation program (v.2.8.14; www.gimp.org), converted to grayscale, and then matched for average brightness. Each image was unique, and for each participant, each image was randomly assigned to a network node. The sequence of fractal images that each participant saw was generated by a random walk through the network (see Figure 1). Images were presented for 1500 ms. To ensure that participants were attending to the stream of images, they were instructed to press the J key with their right index finger if the image was rotated (30% of trials) and to press the F key with their left index finger if the image was not rotated (70% of

trials). The task was broken into 5 segments and participants were given a break between segments to reduce fatigue.

Participants completed a brief training procedure prior to starting the rotation detection task. First, they were shown each image in its non-rotated orientation. Then, they were shown the rotated and non-rotated versions side by side and asked to pick the non-rotated image. Next, they completed a practice version of the rotation detection task, where they saw each image once in random order. During the task, participants were also given audio feedback to assist learning the rotation of images. Specifically, they heard a high audio tone when they made an incorrect response and a low audio tone when they responded too slowly (greater than 1500 ms).

The network structure consisted of three clusters each composed of five nodes, and participants viewed a sequence of 1500 fractal images. Participants in the non-social condition were simply told that they would be judging whether abstract images were rotated. In the social condition, participants were told that “the images that you will see are taken from an online social media platform where people can choose one of these images as their avatar to represent themselves, much like you might use a photo to represent yourself on Facebook or Twitter. While completing the task (described in more detail on the next page), please make sure you focus on the people these avatars represent.”

After performing the image rotation judgment task, participants completed an odd-man-out test. On each trial, participants were simultaneously presented with three images in random order; two of the images represented nodes in the same cluster, and one image was drawn from nodes in a different cluster. Participants were told that the stream of images they just saw in the exposure phase adhered to a pattern, and they were instructed to select via button-press one of the three images that “did not fit” with the other two. We picked sets of images such that none of the images were boundary nodes (nodes that are connected to their own community and also connected to another community), and the probability of each image being presented with other images was equivalent. Each set of three images was then presented in all permuted orders giving 6 trials per set and 54 trials total.

Data Exclusions—To examine differences in RT due to the transition from one cluster to another, we excluded incorrect trials (11.2% data loss) and rotation trials (23.7% data loss) as well as trials with implausible response times (i.e., less than 100 ms or greater than 1500 ms; less than 1% data loss). We also excluded outlier data points greater than 3 standard deviations from the mean response time (less than 1% data loss). We also excluded a small number of trials (less than 1% data loss) where the random walk transitioned from one cluster to another and then immediately transitioned back to the first cluster, which resulted in the middle trial counting as both a pre-transition and post-transition trial. There were no significant differences in rates of data excluded for social versus non-social conditions.

Statistical Analysis—In our primary analyses, we tested whether previously identified indices of network learning in non-social domains might also index the learning of network structure in the social domain. Specifically, we examined cross-cluster differences in RT for the pre-transition and post-transition trials using linear mixed effects models, implemented

in R (v. 3.2.2; R Development Core Team, 2015) using the *lmer()* function (library lme4, v. 1.1–10). Intuitively, slower RT on post-transition trials would indicate that individuals successfully learned the community structure of the network. Linear mixed effects models are ideal for testing repeated measures designs which include both within-subject and between-subject variables (Bates, Mächler, Bolker, & Walker, 2015). Importantly, linear mixed effects models also allow us to account for between-subject differences in RT.

The primary mixed effects model in Study 1 included node type (pre-transition versus post-transition), condition (social versus non-social), trial number (standardized), and the two-way and three-way interactions between these variables, as predictors of RT (with node type and trial number included as within-subjects variables and with condition included as a between-subjects variable). For all models, we included the fullest set of random effects that allowed the model to converge, which included a random intercept for participant and a by-participant random slope for trial number and node type. All predictors were mean-centered to reduce multicollinearity (all $r_s < .280$). We then conducted simple effects analyses to examine whether the effect of node type was significant in both the social and non-social tasks. We also ran additional analyses including repetition priming effects (number of times the image was presented in the previous 10 trials, number of trials since the image was last presented) as additional variables in a mixed effects model. Including these variables did not alter the significance of the effects reported below, and thus we focus our discussion on the first set of analyses.

We also tested whether participants demonstrated network learning using the odd-man out task. In this task, participants were shown sets of three images where two images were in the same cluster and the third image was in a different cluster and at least 3 steps away from the other two images. Thus, if participants learned the network structure (either community structure or distance-based features of the network), they should be more likely to indicate that the image that was in a different cluster “did not fit” with the other two. To test for this behavior, we computed the percentage of trials where participants chose the different-cluster image and ran a one-sample t-test to examine whether this percentage was significantly greater than chance (33%). We tested this difference in percentage for each condition separately, and also ran a two-sample t-test to examine whether accuracy differed for the social and non-social tasks.

Study 1 Results

Commonalities in Social Versus Non-Social Network Learning—First, we investigated whether participants were able to learn the network architecture implicit in the temporal contingencies between stimuli. We fit a linear mixed effects model with node type (pre-transition versus post-transition), condition (social versus non-social), and trial number as predictor variables, using RT as the dependent variable. There was a significant main effect of node type (pre-transition versus post-transition), such that participants were significantly slower at responding to the post-transition trial than to the pre-transition trial for both social and non-social networks (see Table 1 and Figure 2A). There was no main effect of condition (social versus non-social), nor was the effect of node type moderated by condition. Follow-up analyses examining the cross-cluster surprisal effect for each condition

separately confirmed that participants showed a significant cross-cluster surprisal effect in both conditions. These results suggest that participants were surprised when the visual stream transitioned from one cluster to another, demonstrating that they learned the network structure of both the social and non-social networks.

Interestingly, we also found a significant three-way interaction between node type (pre-transition versus post-transition), condition (social versus non-social), and trial number (see Figure 2B). Participants demonstrated smaller cross-cluster surprisal effects at the beginning of the social network learning task (versus non-social network learning task) but this difference between social and non-social conditions diminished over time, such that the cross-cluster surprisal effects were equivalent at the end of the task. These results suggest that it may be more difficult to learn the social networks than the non-social networks, but that this effect disappears after sufficient practice.

A second measure of network learning is given by the participant's categorization accuracy on the odd-man out task. Participants were significantly more likely to indicate that the distant node "did not fit" with the other two same-cluster nodes in both the social task ($M=0.415$, $SD=0.134$, $t(38)=3.95$, $p<0.001$) and in the non-social task ($M=0.386$, $SD=0.127$, $t(34)=2.61$, $p=.013$), and there was no significant difference between the two conditions ($t(71.73)=0.93$, $p=.355$). These results provide additional evidence that participants learned the network structure of both social and non-social networks.

Study 1 Discussion

Study 1 provides converging evidence across two tasks that participants are capable of learning community structure of both social and non-social networks. Importantly, participants show similar signatures of learning across the two tasks. The primary difference between the two results is that participants in the social condition exhibited a stronger change in learning rate over the course of the task. This finding suggests that it may be more difficult to learn the social networks than non-social networks, but that this effect goes away after sufficient practice. There are, however, a few limitations to this first study which we aim to address in Study 2. Study 1 did not include a cover story and it is possible that differences in learning rate between tasks is simply due to added cognitive load of completing the image rotation judgment while thinking about the images as people. Nor did it include a test of how much participants were thinking about the abstract images as people in each condition. In Study 2, we aimed to correct for these limitations and test the generalizability of the results from Study 1.

Study 2

The second study is identical to the first study, except that 1) participants learned a different number of communities (two instead of three), 2) participants received a more elaborate cover story, and 3) participants were given a post-task manipulation test to measure whether they were more likely to think about the social stimuli as people. The purpose of this second study was to shorten the task and test for generalization of results across variable network size, explicitly control for potential differences in cognitive load, and directly test whether participants were more likely to think about the social stimuli as people.

Study 2 Method

Participants—For Study 2, we recruited 82 participants (40 non-social, 42 social) from Amazon Mechanical Turk. We excluded three participants who had accuracy lower than chance (70%). Total compensation for a participant who completed all phases of either study ranged from \$6.25–\$9.00 (depending on performance bonuses).

Procedure—The procedure for Study 2 was identical to Study 1, with three notable changes. First, we reduced the network size from 15 nodes to ten nodes to shorten the task and test for generalization of results across variable network size. In Study 2, the network structure consisted of two clusters each composed of five nodes, and participants viewed a sequence of 1000 fractal images. The only difference between the odd-man out task in Study 2 was that it had fewer trials than that in Study 1. Due to the smaller network size, there were also fewer potential unique combinations for the odd-man out task, and the odd-man out task therefore had fewer trials. Each set of three images in the odd-man out task was presented in all permuted orders giving 6 trials per set and 36 trials total.

Second, participants also read a cover story about the images in the non-social condition. The purpose of this manipulation in Study 2 was to explicitly control for potential differences in cognitive load created by instructing participants to think about the images as either people or rock formations. In the social condition, participants received the same instructions as in the first study, and were told that “the images that you will see are taken from an online social media platform where people can choose one of these images as their avatar to represent themselves, much like you might use a photo to represent yourself on Facebook or Twitter. While completing the task (described in more detail on the next page), please make sure you focus on the people these avatars represent.” In the non-social condition, participants were told that the “images were abstract patterns frequently found in rock formations. Some of these patterns are visible to the naked eye, whereas others are only visible with a microscope. These rock patterns are often created by natural forces, including tectonic plate shifts, wind and water erosion, and volcanic activity.” To enhance the cover story, we also had participants complete a pre-exposure choice where they were instructed to pick an image to serve as their avatar representing themselves (social condition) or to pick their favorite rock formation (non-social).

Third, participants completed a post-exposure rating task where they reported how much they thought about the images as people on a 5-point scale. We expected that participants would report thinking about the images as people more in the social condition than in the non-social condition.

Data Exclusions—Data exclusion criteria were identical to Study 1 and exclusion rates were similar (incorrect trials: 8.9%, rotation trials: 24.7%, implausible response times: less than 1%, outlier response times: less than 1%, and trials where the middle trial counted as both a pre-transition and post-transition trial: less than 1%). There were no significant differences in data loss across conditions.

Statistical Analysis—Analyses for Study 2 were identical to the analyses for Study 1.

Study 2 Results

Confirming Attributions of Social Meaning to Fractal Images—To interpret the results of our study as relating to social versus non-social network learning, it is imperative to first demonstrate that participants attributed social meaning to the fractal images in the social condition more so than to the fractal images in the non-social condition. To address this question, we tested whether participants were significantly more likely to report thinking about the images as people in the social condition than in the non-social condition. We found that there was a significant difference in post-task ratings ($t(75.01)=3.21, p=.002$), such that participants reported thinking about the images as people more frequently in the social condition ($M=2.97, SD=1.19$) than in the non-social condition ($M=2.00, SD=1.48$). These results suggest that participants were indeed more likely to think about the abstract images as people when told that they represented online avatars.

Commonalities in Social Versus Non-Social Network Learning—Next, we investigated whether participants were able to learn the network architecture implicit in the temporal contingencies between stimuli. We fit a linear mixed effects model with node type (pre-transition versus post-transition), condition (social versus non-social), and trial number as predictor variables, using RT as the dependent variable. Replicating the results from Study 1, there was a significant main effect of node type, such that participants were significantly slower at responding to the post-transition trial than to the pre-transition trial for both social and non-social networks (see Table 2 and Figure 3A). There was again no main effect of condition (social versus non-social), nor was the effect of node type moderated by condition. Follow-up analyses examining the cross-cluster surprisal effect for each condition separately confirmed that participants showed a significant cross-cluster surprisal effect in both conditions.

Replicating Study 1, we also found a significant three-way interaction between node type (pre-transition versus post-transition), condition (social versus non-social), and trial number (see Figure 3B). There was a stronger positive slope for social networks, such that participants demonstrated smaller cross-cluster surprisal effects at the beginning of the social network learning task (versus non-social network learning task), but by the end of the task the surprisal effect was actually larger in the social networks.

A second measure of network learning is given by the participant's categorization accuracy on the odd-man out task. Replicating the results from Study 1, participants were significantly more likely to indicate that the distant node “did not fit” with the other two same-cluster nodes in the social task ($M=0.413, SD=0.216, t(37)=2.37, p=.023$) and marginally more likely to indicate that the distant node “did not fit” with the other two same-cluster nodes in the non-social task ($M=0.375, SD=0.169, t(40)=1.69, p=.099$), and there was no significant difference between the two conditions ($t(70.05)=0.87, p=.386$).

Study 2 Discussion

Study 2 replicates Study 1 by showing that participants slow their responses following a transition from one cluster to another and are more likely to group images from the same community together. We also find that participants once again were slower at learning the

social network structure, despite adding a cover story to the non-social task to try to account for differences in cognitive load. Taken together, these results provide robust evidence that individuals are capable of learning community structure of both social and non-social networks. One limitation of both Study 1 and Study 2 is that they employed a between-subjects design. A stronger test of the potential overlap or independence of social and non-social network learning would involve having participants complete both tasks, to directly compare each individual's ability to learn community structure of both social and non-social networks.

Study 3

In our third study, we complemented the between-subject approach of the first two studies with a within-subject approach. Here, we directly examined whether individuals with better performance on the non-social network learning task also displayed better performance on the social network learning task. To the extent that these skills are independent, we would expect minimal relationship between performance on one task and performance on the other task. In contrast, if a common set of mechanisms underpins all types of network learning, then we would expect that performance on these two tasks would be correlated across subjects. Importantly, there could also be individual differences in motivation to learn social versus non-social networks, where some individuals are more motivated to learn social relationships than others. To reduce any potential participant fatigue induced by completing two 25-minute image rotation tasks (required due to the within subject design), we did not include the odd-man out task in this study.

Study 3 Method

Participants—For Study 3, we recruited 65 participants from Amazon Mechanical Turk. The order of the social and non-social conditions was counterbalanced across participants. We excluded one participant who had accuracy lower than chance (70%). Total compensation for a participant who completed all phases of either study variant ranged from \$6.25–\$9.00 (depending on performance bonuses).

Procedure—The procedure for Study 3 blended the procedures from Study 1 and Study 2 while adapting the task for a within-subject paradigm. As in the first two studies, participants completed a rotation detection task where the stimulus order followed a random walk along a modular community. Study 3 used the non-social cover story (abstract images) from Study 1, but the same community structure as Study 2. We used 10 unique fractals for each condition, and the images were randomly assigned to the social and non-social network for each participant. Images in each condition were organized into two clusters of five images, and participants completed 1,000 trials per condition.

Designing a within-subject version of the image rotation task required a few key modifications. First, we removed the odd-man out task to reduce fatigue for participants, since each condition of the image rotation task took 25 minutes. Second, to increase the degree to which subjects differentiated between the social and non-social conditions, we instructed participants as follows in the second variant: “In this study, we are interested in how the source and context of abstract patterns influences their representation. For each part

of the study, try to focus on the instructions and type of images that you are looking at IN THAT PART.”

Data Exclusions—Data exclusion criteria were identical to Studies 1 and 2 and exclusion rates were similar (incorrect trials: 9.2%, rotation trials: 24.5%, implausible response times: less than 1%, outlier response times: less than 1%, and trials where the middle trial counted as both a pre-transition and post-transition trial: less than 1%). There were no significant differences in data loss across conditions.

Statistical Analysis—As in the first two studies, we tested cross-cluster differences in RT for the pre-transition and post-transition trials using linear mixed effects models. The only difference between the mixed effects model in Study 3 and earlier studies is that condition is now treated as a within-subjects variable. We also ran an additional analysis including condition order as a between-subjects variable to the model to test whether the order in which participants completed the task influenced how they processed the images. Including condition order did not alter the significance of the effects reported below, and thus we focus our discussion on the first model.

Using the within-subjects design of Study 3, we were also able to test whether individuals who performed better in the non-social network learning condition also performed better in the social network learning condition. To isolate cross-cluster surprisal from individual differences in response time, we converted response times to *z*-scores (within-subject) and then computed the average difference in standardized RT for each subject. We then tested whether there was a significant correlation between the mean standardized RT difference between pre-transition and post-transition trials for social and non-social network runs. We also ran linear regression analyses adding condition order as a covariate to test whether the relationship between social and non-social network learning differed depending on the order in which participants completed the task. Finally, we also ran these analyses without first standardizing the response times within-subject and found the same effects when testing whether there was a significant correlation between the mean RT difference between pre-transition and post-transition trials for social and non-social network conditions.

Study 3 Results

Confirming Attributions of Social Meaning to Fractal Images—We first tested whether participants were significantly more likely to report thinking about the images as people in the social condition than in the non-social condition, in order to demonstrate that participants attributed social meaning to the fractal images in the social condition more so than to the fractal images in the non-social condition. Consistent with the effects from Study 2, we also found a significant difference in post-task ratings in Study 3 ($t(63)=4.34, p<.001$), such that participants reported thinking about the images as people more frequently in the social condition ($M=2.77, SD=1.16$) than in the non-social condition ($M=2.22, SD=1.33$).

Commonalities in Social Versus Non-Social Network Learning—Next, we investigated whether participants were able to learn the community structure implicit in the temporal contingencies between stimuli. To address this question, we examined RT

differences for pre-transition and post-transition trials; intuitively, slower RT on post-transition trials would indicate that individuals successfully learned the network structure. We fit a linear mixed effects model with node type (pre-transition versus post-transition), condition (social versus non-social), and trial number as predictor variables, using RT as the dependent variable. Replicating the effects from Studies 1 and 2, there was a significant main effect of node type, such that participants were significantly slower at responding to the post-transition trial than to the pre-transition trial for both social and non-social networks (see Table 3 and Figure 4A). Replicating Studies 1 and 2, there was again no main effect of condition (social versus non-social), nor was the effect of node type moderated by condition. Follow-up analyses examining the cross-cluster surprisal effect for each condition separately confirmed that participants showed a significant cross-cluster surprisal effect in both conditions.

The rate of learning effect found in Studies 1 and 2 did not replicate in Study 3. Specifically, the three-way interaction between node type (pre-transition versus post-transition), condition (social versus non-social), and trial number was not significant (see Figure 4B). This result diverges from the previous results found in Studies 1 and 2, where participants were slower in the social network learning condition. This effect might be in part due to the within-subject design and participants becoming more familiar with the task from the first version they completed to the second version, which reduces changes in cross-cluster surprisal over time.

Individual Differences in Social Versus Non-Social Network Learning—Next, we turned to an examination of individual differences in social versus non-social network learning. Specifically, we were interested in determining the degree to which people who are good at learning one type of network are also good at learning the other type of network. If we observed a correspondence in performance, it would suggest that the mechanism of learning social networks was similar to that of learning non-social networks. Conversely, if there was weak or no correspondence in performance, it would suggest the existence of distinct mechanisms or distinct motivations underlying social versus non-social network learning. To determine which explanation was supported by the data, we examined the correlation between each individual's cross-cluster surprisal effect in the social and non-social networks.

We observed no correlation between learning on the social and non-social tasks ($r(62) = -.026$, $p = .841$; see Figure 4C). These data are consistent with the notion that there may be distinct processes underlying social versus non-social network learning, either in terms of motivation or in terms of learning mechanism, and that different components may be stronger in one person than another. In other words, even though we observe no aggregate differences in learning social and non-social networks for the group as a whole, different people efficiently learn social and non-social network information.

Importantly, these results held even after controlling for condition order. The interaction between condition and condition order was not significant ($b = -0.27$, $SE = 0.28$, $t(60) = -0.96$, $p = .340$), and the association between social and non-social network learning was not significant when participants saw the social task first ($r(31) = -.139$, $p = .442$) and the non-

social task first ($t(29)=-.109, p=.569$). These results suggest that the lack of an association is not due to differences in condition order.

Study 3 Discussion

Study 3 shows that our cross-cluster surprisal measure of social and non-social network learning generalizes to a within-subjects task where participants complete both a social and non-social image rotation task. We did not replicate the differences in learning rate found in Studies 1 and 2, potentially due to the within-subject design and participants becoming more familiar with the task from the first version they completed to the second version. Importantly, this within-subjects design also allowed us to test whether individuals who were better at learning community structure in one type of network were also better at learning community structure in the other type of network. We found that there was no correlation between cross-cluster surprisal in the social and non-social tasks, such that people who were better at the social task were not necessarily better at the non-social task, and *vice versa*. This result may suggest that social and non-social network learning involve at least partially distinct mechanisms or motivation. This study suffered from the same limitation as Study 1, and in order to control for variation in cognitive load due to the social cover story, we ran an additional study with the same within-subjects design as Study 3, but adding in the rock formation cover story.

Study 4

Study 4 used an identical procedure as Study 3, except that participants were given the rock formation cover story for the non-social condition. This allowed us to test whether individuals who were better at non-social network learning were also better at social network learning while controlling for cognitive load induced by the cover story. To reduce order effects and bleed over of the cover story from the first task to the second task, we also included additional text between tasks to encourage participants to ignore the previous task when completing the second task.

Study 4 Method

Participants—In Study 4, we recruited 94 participants from Amazon Mechanical Turk. The order of the social and non-social conditions was counterbalanced across participants. We excluded five participants who had accuracy lower than chance (70%). Total compensation for a participant who completed all phases of either study variant ranged from \$6.25–\$9.00 (depending on performance bonuses).

Procedure—The procedure for Study 4 was identical to Study 3, with two notable changes. First, we added the rock formation cover story back in, in order to help account for differences in cognitive load due to the cover story. Second, to increase the degree to which subjects differentiated between the social and non-social conditions, we instructed participants as follows in the second variant: “In this study, we are interested in how the source and context of abstract patterns influences their representation. For each part of the study, try to focus on the instructions and type of images that you are looking at IN THAT PART.”

Data Exclusions—Data exclusion criteria were identical to Studies 1–3 and exclusion rates were similar (incorrect trials: 10.4%, rotation trials: 21.9%, implausible response times: less than 1%, outlier response times: less than 1%, and trials where the middle trial counted as both a pre-transition and post-transition trial: less than 1%). There were no significant differences in data loss across conditions.

Statistical Analysis—Analyses in Study 4 were identical to analyses in Study 3.

Study 4 Results

Confirming Attributions of Social Meaning to Fractal Images—We first tested whether participants were significantly more likely to report thinking about the images as people in the social condition than in the non-social condition, in order to demonstrate that participants attributed social meaning to the fractal images in the social condition more so than to the fractal images in the non-social condition. Replicating the results from Studies 2 and 3, we found a significant difference in post-task ratings ($t(88)=5.13, p<.001$), such that participants reported thinking about the images as people more frequently in the social condition ($M=2.86, SD=1.13$) than in the non-social condition ($M=2.26, SD=1.32$).

Commonalities in Social Versus Non-Social Network Learning—Next, we investigated whether participants were able to learn the community structure implicit in the temporal contingencies between stimuli. We fit a linear mixed effects model with node type (pre-transition versus post-transition), condition (social versus non-social), and trial number as predictor variables, using RT as the dependent variable. Replicating the results from Studies 1–3, there was a significant main effect of node type, such that participants were significantly slower at responding to the post-transition trial than to the pre-transition trial for both social and non-social networks (see Table 4 and Figure 5A). There was again no main effect of condition (social versus non-social). Unlike prior studies, we did find a two-way node \times condition interaction, such that participants showed greater cross-cluster surprisal in the non-social than the social condition.

Follow-up analyses examining the cross-cluster surprisal effect for each condition separately confirmed that participants showed a significant cross-cluster surprisal effect in both conditions, although this effect was larger in the non-social condition than in the social condition. Once again, we found that the three-way interaction between node type (pre-transition versus post-transition), condition (social versus non-social), and trial number was not significant (see Figure 5B). Thus, this interaction is significant in both between-subjects design studies but not significant in both within-subjects design studies.

Individual Differences in Social Versus Non-Social Network Learning—Next, we turned to an examination of individual differences in the learning of community structure in social versus non-social networks. Specifically, we were interested in determining the degree to which people who are good at learning community structure in one type of network are also good at learning the community structure in other type of network. Replicating the effect from Study 3, we observed no correlation between learning on the social and non-social tasks ($r(87)=.157, p=.141$; see Figure 5C). These data are consistent with the notion

that there may be distinct processes underlying the learning of community structure in social versus non-social networks, either in terms of motivation or in terms of learning mechanism.

Somewhat surprisingly, these results were influenced by condition order. There was a significant interaction between condition and condition order ($b=-0.47$, $SE=0.21$, $t(85)=-2.26$, $p=.027$), such that the association between learning on social and non-social networks was not significant when participants performed the social task first ($r(47)=-.110$, $p=.452$), but there was a significant correlation when participants performed the non-social task first ($r(38)=.400$, $p=.011$). Because this effect does not hold up in Study 3 and represents a small subset of the data, we cannot make a strong statement about this effect.

Study 4 Discussion

Taken together, all four studies discussed so far provide compelling evidence that participants learn community structure of both social and non-social networks. Importantly, Studies 3 and 4 also show that there is little association between learning rates within-subjects, suggesting that individuals who learn community structure in non-social networks are not also better at learning community structure in social networks, and *vice versa*. Interestingly, the one scenario where we did see an association between performance on social and non-social networks was when participants performed the non-social task first and were given a clear cover story for both tasks. Study 4 is also the only study that shows a significant difference in cross-cluster surprisal between the social and non-social conditions. However, this effect does not replicate in any of the other studies and a meta-analysis (described below) reveals this effect is not significant across studies. Further, given that our evidence so far for distinct mechanisms leading to social and non-social community learning is based on a lack of correlation (and hence limits our ability to make strong inferences), in the next study, we attempt to more directly show that different types of people are most efficient in learning community structure on social versus non-social networks.

Study 5 Introduction

Finally, our fifth study investigated whether learning the community structure of social and non-social networks is influenced by social traits. This study was identical to Study 4, with two notable changes. First, participants completed individual difference questionnaires designed to test social traits, including social orientation and perspective taking. The acquisition of this data allows us to more directly test whether social and non-social network learning are influenced by distinct processes. Second, to accommodate the longer study duration, we chose to recruit participants from the Philadelphia area who then completed the task in the lab. This change allowed us to more carefully monitor subject fatigue and replicate the earlier studies in a more controlled environment.

Study 5 Method

Participants—We recruited 33 participants from the University of Pennsylvania who completed the study in an on-site laboratory, and we excluded 2 participants due to missing data (server malfunction) and 1 participant who had accuracy lower than chance (70%). Total compensation for Study 5 ranged from \$20–\$30 (depending on performance bonuses).

Procedure—The procedure for Study 5 was identical to Study 4: it included cover stories for both the social and non-social conditions, and it also included extra instructions to encourage participants to differentiate between the instructions for the two conditions. The important new feature of this study was that we asked participants to complete two questionnaires measuring individual differences in social orientation and perspective-taking.

Social Orientation: The Triandis Individualism-Collectivism Scale (Triandis & Gelfand, 1998) consists of 15 items measured on a 7-point scale. It is designed to assess the extent to which an individual thinks about himself or herself as independent of and distinct from others (8 items) versus the extent to which an individual thinks about himself or herself as interdependent on and connected to others (7 items). Sample independent items include, “I’d rather depend on myself than others” and “My personal identity, independent of others, is very important to me” ($M=4.75$, $SD=0.75$, $\alpha=.700$). Sample interdependent items include, “I feel good when I cooperate with others” and “It is important to me that I respect the decisions made by my groups” ($M=5.43$, $SD=0.65$, $\alpha=.670$). For our composite social orientation score, we reverse coded interdependent items and computed the average response across all 15 items for each participant ($M=3.73$, $SD=0.56$, $\alpha=.722$).

Perspective-Taking: The Interpersonal Reactivity Index (Davis, 1980) consists of 28 items measured on a 5-point scale. It further consists of four subscales measuring different components of empathy, including perspective-taking, fantasy, empathic concern, and personal distress. In these analyses, we focused on the most cognitive component – perspective-taking – since we did not hypothesize any involvement of fantasy or emotional responses in the learning of community structure in networks. Sample items include, “I try to look at everybody’s side of a disagreement before I make a decision” and “I sometimes try to understand my friends better by imagining how things look from their perspective”. Two of the seven items in the perspective-taking subscale were reverse coded, and we computed the average response for each participant ($M=4.23$, $SD=0.67$, $\alpha=.733$).

Data Exclusions—Data exclusion criteria were identical to Studies 1–4 and exclusion rates were similar (incorrect trials: 8.7%, rotation trials: 26.2%, implausible response times: less than 1%, outlier response times: less than 1%, and trials where the middle trial counted as both a pre-transition and post-transition trial: less than 1%). There were no significant differences in data loss across conditions.

Statistical Analysis—As in Studies 3 and 4, we tested cross-cluster differences in RT for the pre-transition and post-transition trials using mixed effects modeling and tested whether individuals who are better at learning the community structure of non-social networks were also better at learning the community structure of social networks. However, information about task order for Study 5 was lost due to a technical malfunction, and therefore we were not able to analyze whether task order influenced the reported effects.

Using the additional individual differences measures collected in Study 5, we were also able to test whether differences in social orientation and perspective-taking accounted for differences between learning conditions. To examine individual differences in the learning of community structure in social and non-social networks, we first converted RT to z-scores

(within-subject) and computed the average standardized cross-cluster surprisal effect separately for the social task and the non-social task. We then fit linear mixed effects models with condition (social versus non-social) and scores on a single trait measure (either social orientation or perspective-taking) as predictor variables, and with standardized cross-cluster surprisal as a dependent variable.

Study 5 Results

Confirming Attributions of Social Meaning to Fractal Images—First, we tested whether participants were significantly more likely to report thinking about the images as people in the social condition than in the non-social condition. Consistent with the effects from Studies 2–4, we also found a significant difference in post-task ratings in Study 5 ($t(29)=2.90, p=.007$), such that participants reported thinking about the images as people more frequently in the social condition ($M=2.33, SD=0.99$) than in the non-social condition ($M=1.80, SD=1.06$).

Commonalities in Social Versus Non-Social Network Learning—Next, we investigated whether participants were able to learn the network architecture implicit in the temporal contingencies between stimuli. In order to test whether participants were significantly slower on post-transition trials than pre-transition trials, we fit a linear mixed effects model with node type (pre-transition versus post-transition), condition (social versus non-social), and trial number as predictor variables, using RT as the dependent variable. Consistent with the results from Studies 1–4, we found that there was a significant main effect of node type, such that participants were significantly slower at responding to the post-transition trial than to the pre-transition trial for both social and non-social networks (see Table 5 and Figure 6A). Moreover, there was no main effect of condition, nor was the cross-cluster surprisal effect moderated by condition. Follow-up analyses examining the cross-cluster surprisal effect for each condition separately confirmed that participants showed a significant cross-cluster surprisal effect in both conditions. As in Studies 3 and 4, we did not find a significant interaction between node type (pre-transition versus post-transition), condition (social versus non-social), and trial number (see Figure 6B). This 3-way interaction is significant in both between-subjects design studies but not significant in the three within-subjects design studies.

Individual Differences in Social Versus Non-Social Network Learning—Next we turned to an examination of individual differences in learning the community structure of social versus non-social networks. As in Studies 3 and 4, we were interested in determining the degree to which people who are good at learning community structure in one type of network are also good at learning community structure in the other type of network. Similar to Studies 3 and 4, we observed no correlation between learning during the social task and learning during the non-social tasks for Study 5 ($r(28)= -0.074, p=.697$); see Figure 6C. The combined correlation across the three within-subjects studies (Studies 3–5) was only 0.049 ($p=.512$).

To further examine the question of potentially distinct processes underlying the learning of community structure in social versus non-social networks, we asked whether social traits of

a participant predicted their ability to learn the community structure in social networks but not their ability to learn the community structure in non-social networks. We found that there was a significant interaction between social orientation and condition ($b=0.21$, $SE=0.08$, $t(28.00)=-2.61$, $p=.014$), such that individuals who reported greater collectivistic (*versus* individualistic) cultural values showed greater cross-cluster surprisal for the social networks ($t(28)=.492$, $p=.006$; see Figure 7A), but there was no association between social orientation and cross-cluster surprisal for the non-social networks ($t(28)=-.164$, $p=.387$). There was also a marginally significant interaction between perspective-taking and condition ($b=0.13$, $SE=0.07$, $t(56.00)=1.90$, $p=.063$; see Figure 7B), such that individuals who reported greater perspective-taking showed greater cross-cluster surprisal for the social networks ($t(28)=.412$, $p=.024$), but there was no association between perspective-taking and cross-cluster surprisal for the non-social networks ($t(28)=-.080$, $p=.674$). These results suggest that people who are more in tune with others, who think about the self as connected to others, and who frequently consider the perspectives of others, are more likely to learn the community structure when the network is social versus non-social. These data provide additional evidence that the learning of community structure in social networks is characterized by some processes that are independent from those implicated in the learning of community structure in non-social networks.

Study 5 Discussion

Study 5 replicated the key findings from the first four studies using an in-lab experiment. We find that participants were capable of implicitly learning the complex, higher-order structure of social networks. We also found that their performance in social network learning was uncorrelated with their performance in non-social network learning. Furthermore, social traits, including social orientation and perspective-taking, uniquely predicted learning social community structure but not learning non-social community structure. Our results suggest that the process of learning community structure in social networks displays clear distinctions from the process of learning community structure in non-social networks.

Mini Meta-Analysis

In order to test whether the results described above were robust across studies, we also conducted a mini meta-analysis (Goh, Hall, & Rosenthal, 2016) on each effect of interest that was included in at least 3 of our studies. Using this approach, we were able to estimate the effect size for each of four effects: manipulation check (Studies 2–5), cross-cluster surprisal effect (Studies 1–5), moderation of the cross-cluster surprisal effect by condition (social versus non-social; Studies 1–5), and the correlation between cross-cluster surprisal in the social and non-social tasks (Studies 3–5).

First, we tested whether there was a significant main effect of condition in our manipulation check in Studies 2–5 (there was no manipulation check in Study 1). Our mini meta-analysis estimated an effect size of $d=0.60$ (95% CI=[0.41,0.79]), confirming that participants were reliably more likely to report thinking about the stimuli as people in the social condition than in the non-social condition ($z=6.16$, $p<.001$).

Second, we tested whether participants reliably learned the community structure of the networks, as evidenced by a significant cross-cluster surprisal effect. We included the main effect of node type from the mixed effects models in Studies 1–5 (presented in Tables 1–5) in our mini meta-analysis. We estimated an effect size of $d=2.11$ (95% CI=[1.89,2.33]). Specifically, we found that participants were reliably slower when responding on post-transition trials than on pre-transition trials when examining all trials together ($z=18.80$, $p<.001$). Participants were also reliably slower when responding on post-transition trials than pre-transition trials when we estimated the effect size separately in the social task ($z=16.64$, $p<.001$, $d=1.72$, 95% CI=[1.52,1.92]) and non-social task ($z=16.77$, $p<.001$, $d=1.75$, 95% CI=[1.54,1.95]). These results suggest that participants are able to learn the community structure of both social and non-social networks.

Third, we also estimated the effect size for whether the cross-cluster surprisal effect was moderated by condition. We found that the cross-cluster surprisal is not reliably moderated by condition (node \times condition interaction meta-analysis: $z=0.58$, $p=.562$, $d=0.05$, 95% CI=[-0.12,0.22]), such that there is no difference in effect sizes across the social and non-social conditions. This result is intuitive given that the node \times condition interaction was significant in only one study (Study 4), and the direction of the effect varied across studies (negative slope in Studies 1 and 4, positive slope in Studies 2, 3, and 5). These results suggest that the cross-cluster surprisal effect does not differ across conditions.

Finally, across Studies 3–5 we also conducted a mini meta-analysis to test the correlation between conditions. We estimated an effect size of $r=.058$ (95% CI=[-.091,.203]), such that across studies there was not a significant relationship between the cross-cluster surprisal effect in the social and non-social conditions ($z=0.76$, $p=.447$). These results suggest that the process of learning community structure in social networks is not correlated with the process of learning community structure in non-social networks.

Discussion

The majority of real-world systems are complex networks characterized by patterns of relationships between elements in the network (Cong & Liu, 2014; Dorogovtsev, Goltsev, & Mendes, 2008). Higher-order information about the patterns of relationships is often not captured by simply measuring pairwise associations (Barrat, Barthélemy, & Vespignani, 2008) and is an important mechanism by which people learn complex information (Chan & Vitevitch, 2010; Goldstein & Vitevitch, 2014; Halford, Wilson, & Phillips, 1998).

While there has been a recent explosion in research on topological features of complex networks across the social sciences and biological sciences (Dorogovtsev et al., 2008; Girvan & Newman, 2002; Newman, 2010), research on how people learn relational data has mostly focused on pairwise relationships without considering the type of information. Thus, it is unclear how people learn information about higher-order clustering of social information, and whether the learning process shares any similar features with previously studied processes involved in learning relational data for non-social information (Karuza et al., 2017; Qian & Aslin, 2014; Qian, Jaeger, & Aslin, 2016; Schapiro et al., 2013).

Here we show for the first time that people are capable of implicitly learning the complex, higher-order structure of social networks. Our results suggest that the learning of community structure in social networks may be at least partially distinct from the learning of community structure in non-social networks: we observed little correlation between individual differences in the ability to learn community structure in social versus non-social networks. Finally, social traits, including social orientation and perspective-taking, uniquely predicted learning for social networks but not for non-social networks. These results advance our understanding of how people process complex relational information, and how that processing is influenced by the type of information being learned.

Expanding Experimental Paradigms from Non-Social to Social Network Learning

This study extends previous work that examined statistical relationships between non-social stimuli (Fiser & Aslin, 2002, 2005; Karuza et al., 2017; Qian & Aslin, 2014; Qian et al., 2016; Schapiro et al., 2013). In this literature, statistical relationships between stimuli are represented by temporal associations (stimuli frequently presented near each other in time; (Karuza et al., 2017; Qian & Aslin, 2014; Schapiro et al., 2013) or spatial associations (stimuli frequently presented at the same time; Qian et al., 2016). Individuals automatically bundle stimuli together into communities based on their temporal or spatial associations, such that stimuli that are strongly connected are processed more quickly, and people tend to respond more slowly when presented with stimuli that are not part of the current cluster (Karuza et al., 2017; Schapiro et al., 2013). Thus, individuals are capable of developing rich mental models of the higher-order topological information about the networks, even when they are not aware that such features exist (Qian et al., 2016).

Here, we observed that participants were significantly slower at responding to trials immediately following a transition from one cluster to another cluster for both social and non-social stimuli. Importantly, each node in the networks had an equivalent number of edges and thus the likelihood of moving from the pre-transition node to the post-transition node was equivalent to the likelihood of moving to any of the other within-cluster nodes that shared an edge with the current image. This architecture ensured that slower responses could not be due to differences in transition probabilities and instead is likely due to differences in cluster membership for the pre-transition and post-transition nodes. Thus, participants who responded slower to post-transition nodes had implicitly learned that the post-transition and pre-transition nodes belonged to different clusters.

Participants were also more likely to group together images that were closer together in the network, and these results did not differ for social and non-social networks, supporting the notion that participants successfully learned a higher order network structure. Again, the probability of any images being presented together in the odd-man out task was matched and all permutations were presented, and yet participants' responses suggest that they were biased by the higher-order network structure. Together, these results provide evidence for a common RT signature of network structure learning for social and non-social stimuli. Network learning for non-social stimuli plays a crucial role in cognitive performance in many other domains, including categorization, word-learning, reasoning, planning, and memory (Cong & Liu, 2014; Engelthaler & Hills, 2017; Goldstein & Vitevitch, 2014;

Halford et al., 2010). It is possible that social network learning might also play a crucial role in facilitating efficient performance on social cognitive tasks such as perspective-taking, social working memory, and social reasoning.

Individual Differences in Social and Non-Social Network Learning

However, the presence of a similar RT signature of learning in social and non-social networks does not necessarily mean that the underlying processes are identical. Previous work suggests that processing social information may rely on distinct processes from processing non-social information (Gamond et al., 2012; Meyer et al., 2012; Van Overwalle, 2011; Zahn et al., 2007). For example, brain regions recruited when reasoning about other people's mental states (mentalizing) are distinct from brain regions recruited during other reasoning tasks (Van Overwalle, 2011) and brain regions involved in mentalizing predict working memory performance for social but not non-social information (Meyer et al., 2012). The ways in which people learn categories are influenced by the type of category they are learning (Ashby & Maddox, 2005, 2011; Cunningham & Zelazo, 2007) and this extends to social categories (Gamond et al., 2012). However, none of this previous work has studied complex patterns of relational information.

Our data suggest that the ability to learn community structure in social and non-social networks are uncorrelated, and individuals who are good at learning community structure on one type of network are not necessarily good at learning community structure on the other type of network. While noise could obscure the relationship between social and non-social network learning, the reliability of this effect across studies suggests that the signal-to-noise ratio is unlikely to be a central limitation. Although we hesitate to draw too strong conclusions from null effects, this observation is particularly striking given that we observed equivalent effects on average for both tasks, and the experimental task was virtually identical except for the way in which the stimuli were described. The only difference was whether the images were described as online avatars representing people or described as non-social images (abstract images in Studies 1 and 3, and rock formations in Studies 2, 4, and 5). Results from a post-questionnaire confirmed the influence of the cover story where participants reported thinking about the images as people more frequently in the social condition.

Thus, it is possible that social and non-social network learning may be supported by independent processes and motivations. The strongest evidence in favor of this idea is that social, but not non-social network learning, was correlated with individual differences in perspective taking and social orientation. This observation highlights that different individuals, with different baseline motivations, performed the task differently. The lack of an interaction between node type (pre- vs. post-transition) and condition (social vs. non-social) in all but one of our study variants, however, leaves open the possibility that the underlying mechanisms may overlap and be called upon according to these differing motivational forces. Additional research is needed to disentangle these different possible interpretations.

We also found some evidence that the rate at which participants learn the social versus non-social stimuli also differs. In Studies 1 and 2, participants demonstrated smaller cross-cluster

surprisal effects at the beginning of the social network learning task (versus non-social network learning task) but this difference between social and non-social conditions diminished over time, such that the cross-cluster surprisal effects were equivalent at the end of the task (see Tables 1 and 2 and Figures 2B and 3B).

There are at least two plausible interpretations of this effect. First, this effect could be due to social network learning repurposing network learning of non-social information, much like other types of social cognition modify and repurpose other “ancestral” cognitive processes (Immordino-Yang, Chiao, & Fiske, 2010; Parkinson & Wheatley, 2015). This process might involve scaffolding of the social information on top of basic processing and would result in increased task demands and slower learning of the social network structure. Second, social information could actually be processed first and could instead bias the subsequent processing of detail. Both scenarios would lead to slower learning of the social network structure. However, it is important to note that the interaction between node type and time was only present in the between-subjects designs in Studies 1 and 2, and the interaction was not significant in the within-subjects paradigms used in Studies 3, 4, and 5. It is possible that the order in which the participants saw the two networks, or the fact that they saw both networks, obfuscated the interaction between node type and time, although further work is needed to directly test this possibility.

Social Traits Uniquely Predict Social Network Learning

Another important test of the similarities (or differences) in learning social vs. non-social network structure concerns the trait-level predictors of social and non-social network learning. To the extent that learning social networks and learning non-social networks involve independent processes, we would expect them to be predicted by different traits. Consistent with this hypothesis, we find that perspective-taking and social orientation uniquely predict the learning of community structure in social networks but not non-social networks. Thus, individuals who are more likely to consider the mental states of others and think about the self as being closely connected to others are more likely to learn the higher-order structure of the social networks.

People who are high in collectivistic social orientation are more likely to be concerned with social relationships and maintaining social harmony (Kim & Markus, 1999; Markus et al., 1991; Tompson et al., 2015; Triandis & Gelfand, 1998), and may therefore be more likely to pick up on relational information in social networks. Moreover, people from collectivistic cultures are more likely to attend to contextual information (Chua et al., 2005; Nisbett et al., 2001) and perceive relationships in the environment (Ji, Peng, & Nisbett, 2000). Our work suggests that people high in collectivistic orientation are uniquely sensitive to social relationships, as they are not more likely to pick up on non-social network structure.

This work also extends previous evidence suggesting that individual differences in ability to maintain social information in working memory is uniquely predicted by perspective-taking, whereas no such relationship exists for working memory for non-social information (Meyer & Lieberman, 2016; Meyer et al., 2012, 2015). We build on this earlier work to show that learning of social networks is also uniquely predicted by perspective-taking, and expand it to show that other social traits including social orientation also predict social network learning.

Real World Applications

Understanding how people learn complex social networks has important implications for many real-world domains. In fact, the majority of real-world systems can be described by complex patterns of relationships between elements in the network (Cong & Liu, 2014; Dorogovtsev et al., 2008). Furthermore, network structure is a key driver of group behavior and has been studied in the context of environmental disasters (Bosworth & Kreps, 1986), terrorist networks (Krebs, 2002), gangs (Van Gennip et al., 2013), and many other social and biological systems (Girvan & Newman, 2002). In an increasingly mobile world, people are frequently interacting, living, and working with novel groups of people. To successfully integrate into these new communities, it will be crucial for individuals to learn information about that network.

Methodological Considerations

One potential limitation of the current work is that data for Studies 1–4 were collected online through MTurk. This collection method allows for rapid collection of large samples of survey and behavioral data, but also introduces noise into the study. Although MTurk participants are at least as attentive as participants drawn from college samples (Hauser & Schwarz, 2016), there are risks associated with collecting data from a pool of participants who might complete dozens of surveys and experiments per month (Chandler, Mueller, & Paolacci, 2014; Crump, McDonnell, Gureckis, Romero, & Morris, 2013).

Moreover, our primary measure across all of the experiments was RT, which is likely influenced by variability in the computer, web browser, and internet quality used by each participant. However, our primary dependent variable focused on within-participant variability in RT, and thus any concerns about between-subject variability in RT are mitigated. Moreover, in Study 5 we recruited participants from the community around Philadelphia and had them complete the experiment in a laboratory under controlled experimental conditions. The mean RT, accuracy, and cross-cluster surprisal effect were very similar in the MTurk samples and community sample. Converging evidence across Studies 1–4 (MTurk samples) and Study 5 (community sample) helps to strengthen our confidence in these findings.

Another potential limitation is the small set of stimuli and single type of network structure. In order to demonstrate a clear effect with minimal variation across social and non-social networks, we chose to focus our experiments on abstract images chosen from a small set and only examined two network configurations with very clear clusters. It is therefore unclear whether the effects described here might be influenced by the structure, such that it might be more difficult to learn more complex network topologies or network topologies with more transition edges between communities. Moreover, our results show that participants are capable of learning which communities an individual node belongs to, but future research should examine whether individuals are capable of learning other network features, such as which nodes are most influential (degree) or how densely connected the network is (density).

Additionally, we did not test non-social traits. Given that social traits uniquely predicted social network learning, one potential hypothesis is that non-social network learning should be uniquely predicted by non-social traits (including working memory ability, intelligence, etc.). In addition, it is possible that familiarity with the type of information could influence how individuals learn network structure, such that individuals learn information they are familiar with better. Future work could address this hypothesis by examining individual differences in familiarity with both social and non-social types of information.

Moreover, if social information processing scaffolds on top of basic cognitive processing, then it is also possible that non-social cognitive abilities might influence both social and non-social network learning, even though social traits only influence social network learning. Future work should include additional measures of non-social traits to test these competing hypotheses.

Conclusion

In this paper, we discussed statistical learning of social and non-social network structures. Statistical learning is an important process whereby people learn the relationship between features or pieces of information based on their frequency of occurring near each other in space or time (Fiser & Aslin, 2002, 2005). While this topic has been heavily studied in the non-social domain (Karuza et al., 2017; Qian & Aslin, 2014; Qian et al., 2016; Schapiro et al., 2013), no research to date has examined this process in the social domain. However, it is likely that statistical learning plays a crucial role in learning social networks, such as when individuals start a new job or encounter a new social group. Taken together, these results suggest that individuals are able to learn the higher-order network structure of both social and non-social information. Importantly, although there are similarities in the implicit learning signatures, there also appear to be distinct processes or motivations involved in learning social and non-social network structures. These results advance understanding of how people build mental models of both social and non-social features of the natural world. This research has important implications for how quickly people will learn and adapt to new social contexts that require integration into a new social network. Future research should examine whether individual differences in these abilities are linked to psychological adjustment and well-being following a move or social transition.

Acknowledgments

This work was supported by an NSF CAREER award to DSB (CAREER PHY-1554488) and by an award from the Army Research Laboratory (W911NF-10-2-0022) to support collaboration between DSB, EBF, and JMV. DSB would also like to acknowledge support from the John D. and Catherine T. MacArthur Foundation, the Alfred P. Sloan Foundation, the Army Research Office through contract number W911NF-14-1-0679, the National Institute of Health (2-R01-DC-009209-11, 1R01HD086888-01, R01-MH107235, R01-MH107703, R01MH109520, 1R01NS099348 and R21-MH-106799), the Office of Naval Research, and the National Science Foundation (BCS-1441502, BCS-1631550, and CNS-1626008). EBF would also like to acknowledge support from NIH 1DP2DA03515601, DARPA YFA D14AP00048 and HopeLab. JMV acknowledges support from mission funding to the U.S. Army Research Laboratory. We would also like to thank Elisabeth A. Karuza for helpful feedback on the study design and manuscript. The content is solely the responsibility of the authors and does not necessarily represent the official views of any of the funding agencies.

References

- Ashby FG, Maddox WT. 2005; Human Category Learning. *Annual Review of Psychology*. 56(1):149–178. DOI: 10.1146/annurev.psych.56.091103.070217
- Ashby FG, Maddox WT. 2011; Human category learning 2.0. *Annals of the New York Academy of Sciences*. 1224(1):147–161. DOI: 10.1111/j.1749-6632.2010.05874.x [PubMed: 21182535]
- Baldwin MW. 1992; Relational schemas and the processing of social information. *Psychological Bulletin*. 112(3):461–484. DOI: 10.1037/0033-2909.112.3.461
- Balkundi P, Harrison DA. 2006; TIES, LEADERS, AND TIME IN TEAMS: STRONG INFERENCE ABOUT NETWORK STRUCTURE'S EFFECTS ON TEAM VIABILITY AND PERFORMANCE. *Academy of Management Journal*. 49(1):49–68. DOI: 10.5465/AMJ.2006.20785500
- Barrat, A; Barthélemy, M; Vespignani, A. *Dynamical processes on complex networks*. Dynamical Processes on Complex Networks. 2008.
- Bates D, Mächler M, Bolker B, Walker S. 2015; Fitting Linear Mixed-Effects Models Using **lme4**. *Journal of Statistical Software*. 67(1):1–48. DOI: 10.18637/jss.v067.i01
- Bosworth SL, Kreps GA. 1986; Structure as Process: Organization and Role. *American Sociological Review*. 51(5):699. doi: 10.2307/2095494
- Bousfield WA. 1953; The Occurrence of Clustering in the Recall of Randomly Arranged Associates. *The Journal of General Psychology*. 49(2):229–240. DOI: 10.1080/00221309.1953.9710088
- Chan KY, Vitevitch MS. 2010; Network structure influences speech production. *Cognitive Science*. 34(4):685–697. DOI: 10.1111/j.1551-6709.2010.01100.x [PubMed: 21564230]
- Chandler J, Mueller P, Paolacci G. 2014; Nonnaïveté among Amazon Mechanical Turk workers: Consequences and solutions for behavioral researchers. *Behavior Research Methods*. 46(1):112–130. DOI: 10.3758/s13428-013-0365-7 [PubMed: 23835650]
- Chin-Parker S, Birdwhistell J. 2017; Category learning with a goal: how goals constrain conceptual acquisition. *Journal of Cognitive Psychology*. 29(4):450–468. DOI: 10.1080/20445911.2017.1280499
- Chua HF, Boland JE, Nisbett RE. 2005; Cultural variation in eye movements during scene perception. *Proceedings of the National Academy of Sciences of the United States of America*. 102:12629–33. DOI: 10.1073/pnas.0506162102 [PubMed: 16116075]
- Cong J, Liu H. 2014; Approaching human language with complex networks. *Physics of Life Reviews*. 11(4):598–618. DOI: 10.1016/j.plrev.2014.04.004 [PubMed: 24794524]
- Crump MJC, McDonnell JV, Gureckis TM, Romero J, Morris S. 2013; Evaluating Amazon's Mechanical Turk as a Tool for Experimental Behavioral Research. *PLoS ONE*. 8(3):e57410. doi: 10.1371/journal.pone.0057410 [PubMed: 23516406]
- Cunningham WA, Zelazo PD. 2007; Attitudes and evaluations: a social cognitive neuroscience perspective. *Trends in Cognitive Sciences*. 11(3):97–104. DOI: 10.1016/j.tics.2006.12.005 [PubMed: 17276131]
- Davis MH, Davis MH, Davis MH. 1980; A multidimensional approach to individual difference in empathy. *JSAS CATALOG OF SELECTED DOCUMENTS IN PSYCHOLOGY*. 85
- Dorogovtsev SN, Goltsev AV, Mendes JFF. 2008; Critical phenomena in complex networks. *Reviews of Modern Physics*. 80(4):1275–1335. DOI: 10.1103/RevModPhys.80.1275
- Engelthaler T, Hills TT. 2017; Feature Biases in Early Word Learning: Network Distinctiveness Predicts Age of Acquisition. *Cognitive Science*. 41:120–140. DOI: 10.1111/cogs.12350 [PubMed: 26923664]
- Fine AB, Jaeger TF, Farmer TA, Qian T. 2013; Rapid expectation adaptation during syntactic comprehension. *PLoS ONE*. 8(10)doi: 10.1371/journal.pone.0077661
- Fiser J, Aslin RN. 2002; Statistical learning of higher-order temporal structure from visual shape sequences. *Journal of Experimental Psychology: Learning, Memory, and Cognition*. 28(3):458–467. DOI: 10.1037/0278-7393.28.3.458

- Fiser J, Aslin RN. 2005; Encoding multielement scenes: statistical learning of visual feature hierarchies. *Journal of Experimental Psychology. General.* 134(4):521–37. DOI: 10.1037/0096-3445.134.4.521 [PubMed: 16316289]
- Fitzhugh, SM, DeCostanza, AH. INSNA Sunbelt XXXVI. Newport Beach, CA: 2016. Organizational tie preservation and dissolution during crisis.
- Friederici AD. 2005; Neurophysiological Markers of Early Language Acquisition: From Syllables to Sentences. *Trends in Cognitive Sciences.* 9(10):481–488. DOI: 10.1016/j.tics.2005.08.008 [PubMed: 16139558]
- Gamond L, Tallon-Baudry C, Guyon N, Lemaréchal J-D, Hugueville L, George N. 2012; Behavioral evidence for differences in social and non-social category learning. *Frontiers in Psychology.* 3:291.doi: 10.3389/fpsyg.2012.00291 [PubMed: 22912624]
- Girvan M, Newman M. 2002; Community structure in social and biological networks. *Proceedings of the National Academy of Sciences of the United States of America.* 99(12):7821–6. DOI: 10.1073/pnas.122653799 [PubMed: 12060727]
- Goh JX, Hall JA, Rosenthal R. 2016; Mini Meta-Analysis of Your Own Studies: Some Arguments on Why and a Primer on How. *Social and Personality Psychology Compass.* 10(10):535–549. DOI: 10.1111/spc3.12267
- Goldstein R, Vitevitch MS. 2014 The influence of clustering coefficient on word-learning: How groups of similar sounding words facilitate acquisition. *Frontiers in Psychology.* 5Nov.:1307.doi: 10.3389/fpsyg.2014.01307 [PubMed: 25477837]
- Gómez RL. 2002; Variability and Detection of Invariant Structure. *Psychological Science.* 13(5):431–436. DOI: 10.1111/1467-9280.00476 [PubMed: 12219809]
- Gopnik A, Wellman HM. 2012; Reconstructing constructivism: Causal models, Bayesian learning mechanisms, and the theory theory. *Psychological Bulletin.* 138(6):1085–1108. DOI: 10.1037/a0028044 [PubMed: 22582739]
- Halford GS, Wilson WH, Phillips S. 1998; Processing capacity defined by relational complexity: implications for comparative, developmental, and cognitive psychology. *The Behavioral and Brain Sciences.* 21(6)doi: 10.1017/S0140525X98001769
- Halford, GS; Wilson, WH; Phillips, S. Relational knowledge: The foundation of higher cognition. *Trends in Cognitive Sciences.* 2010.
- Hauser DJ, Schwarz N. 2016; Attentive Turkers: MTurk participants perform better on online attention checks than do subject pool participants. *Behavior Research Methods.* 48(1):400–407. DOI: 10.3758/s13428-015-0578-z [PubMed: 25761395]
- Immordino-Yang MH, Chiao JY, Fiske AP. 2010; Neural reuse in the social and emotional brain. *Behavioral and Brain Sciences.* 33(4):275–276. DOI: 10.1017/S0140525X10001020
- Jehn KA, Shah PP. 1997; Interpersonal relationships and task performance: An examination of mediation processes in friendship and acquaintance groups. *Journal of Personality and Social Psychology.* 72(4):775–790. DOI: 10.1037/0022-3514.72.4.775
- Ji L-J, Peng K, Nisbett RE. 2000; Culture, control, and perception of relationships in the environment. *Journal of Personality and Social Psychology.* 78(5):943–955. DOI: 10.1037/0022-3514.78.5.943 [PubMed: 10821200]
- Karuza EA, Kahn AE, Thompson-Schill SL, Bassett DS. 2017; Process reveals structure: How a network is traversed mediates expectations about its architecture. *Scientific Reports.* 7(1): 12733.doi: 10.1038/s41598-017-12876-5 [PubMed: 28986524]
- Karuza, EA; Thompson-Schill, SL; Bassett, DS. Local Patterns to Global Architectures: Influences of Network Topology on Human Learning. *Trends in Cognitive Sciences.* 2016.
- Karuza E, Farmer TA, Smith FX, Fine AB, Jaeger TF. 2014 On-Line Measures of Prediction in a Self-Paced Statistical Learning Task. In. *Proceedings of the 36th Annual Meeting of the Cognitive Science Society.* :725–730.
- Kim HS, Markus HR. 1999; Deviance or uniqueness, harmony or conformity? A cultural analysis. *Journal of Personality and Social Psychology.* 77(4):785–800. DOI: 10.1037/0022-3514.77.4.785
- Krebs VE. 2002; Mapping Networks of Terrorist Cells. *Connections.* 24(3):43–52.

- Markus HR, Kitayama S, Cross SE, Fiske AP, Gilligan C, Givon T, Trian- H. 1991; Culture and the self: Implications for cognition, emotion, and motivation. *Psychological Review*. 98(2):224–253. DOI: 10.1037/0033-295X.98.2.224
- Meyer ML, Lieberman MD. 2016; Social Working Memory Training Improves Perspective-Taking Accuracy. *Social Psychological and Personality Science*. 7(4):381–389. DOI: 10.1177/1948550615624143
- Meyer ML, Spunt RP, Berkman ET, Taylor SE, Lieberman MD. 2012; Evidence for social working memory from a parametric functional MRI study. *Proceedings of the National Academy of Sciences of the United States of America*. 109(6):1883–8. DOI: 10.1073/pnas.1121077109 [PubMed: 22308468]
- Meyer ML, Taylor SE, Lieberman MD. 2015; Social working memory and its distinctive link to social cognitive ability: An fMRI study. *Social Cognitive and Affective Neuroscience*. 10(10):1338–1347. DOI: 10.1093/scan/nsv065 [PubMed: 25987597]
- Moon, B, Hoffman, RR, Novak, J, Canas, A. *Applied Concept Mapping: Capturing, Analyzing, and Organizing Knowledge*. CRC Press; 2011.
- Murphy GL, Medin DL. 1985; The role of theories in conceptual coherence. *Psychological Review*. 92(3):289–316. DOI: 10.1037/0033-295X.92.3.289 [PubMed: 4023146]
- Newman, M. *Networks: An Introduction*. OUP Oxford: 2010.
- Nisbett RE, Peng K, Choi I, Norenzayan A. 2001; Culture and systems of thought: Holistic versus analytic cognition. *Psychological Review*. 108(2):291–310. DOI: 10.1037/0033-295X.108.2.291 [PubMed: 11381831]
- Orvis, KL, DeCostanza, AH. *Communications Data for Enhanced Feedback in Interservice/Industry Training, Simulation, and Education Conference*. Orlando, FL: 2016. Utilizing Systems-based Training.
- Parkinson C, Wheatley T. 2015; The repurposed social brain. *Trends in Cognitive Sciences*. 19(3):133–141. DOI: 10.1016/j.tics.2015.01.003 [PubMed: 25732617]
- Qian T, Aslin RN. 2014; Learning bundles of stimuli renders stimulus order as a cue, not a confound. *Proceedings of the National Academy of Sciences of the United States of America*. 111(40):14400–5. DOI: 10.1073/pnas.1416109111 [PubMed: 25246587]
- Qian T, Jaeger TF, Aslin RN. 2016; Incremental implicit learning of bundles of statistical patterns. *Cognition*. 157:156–173. DOI: 10.1016/j.cognition.2016.09.002 [PubMed: 27639552]
- Reed SK, Friedman MP. 1973; Perceptual vs conceptual categorization. *Memory & Cognition*. 1(2):157–163. DOI: 10.3758/BF03198087 [PubMed: 24214510]
- Saffran JR, Aslin RN, Newport EL. 1996; Statistical learning by 8-month-old infants. *Science (New York, N.Y.)*. 274(5294):1926–8.
- Saffran JR, Newport EL, Aslin RN. 1996; Word Segmentation: The Role of Distributional Cues. *Journal of Memory and Language*. 35(4):606–621. DOI: 10.1006/jmla.1996.0032
- Schapiro AC, Rogers TT, Cordova NI, Turk-Browne NB, Botvinick MM. 2013; Neural representations of events arise from temporal community structure. *Nature Neuroscience*. 16(4):486–92. DOI: 10.1038/nn.3331 [PubMed: 23416451]
- Tompson S, Lieberman MD, Falk EB. 2015; Grounding the neuroscience of behavior change in the sociocultural context. *Current Opinion in Behavioral Sciences*. 5:58–63. DOI: 10.1016/j.cobeha.2015.07.004
- Triandis HC, Gelfand MJ. 1998; Converging measurement of horizontal and vertical individualism and collectivism. *Journal of Personality and Social Psychology*. 74(1):118–128. DOI: 10.1037/0022-3514.74.1.118
- Turk-Browne NB, Isola PJ, Scholl BJ, Treat Ta. 2008; Multidimensional visual statistical learning. *Journal of Experimental Psychology. Learning, Memory, and Cognition*. 34(2):399–407. DOI: 10.1037/0278-7393.34.2.399
- Turk-Browne NB, Jungé J, Scholl BJ. 2005; The automaticity of visual statistical learning. *Journal of Experimental Psychology. General*. 134(4):552–64. DOI: 10.1037/0096-3445.134.4.552 [PubMed: 16316291]

- Turk-Browne NB, Scholl BJ, Johnson MK, Chun MM. 2010; Implicit Perceptual Anticipation Triggered by Statistical Learning. *Journal of Neuroscience*. 30(33):11177–11187. DOI: 10.1523/JNEUROSCI.0858-10.2010 [PubMed: 20720125]
- Van Gennip Y, Hunter B, Ahn R, Elliott P, Luh K, Halvorson M, Brantingham PJ. 2013; Community detection using spectral clustering on sparse geosocial data. *SIAM Journal on Applied Mathematics*. 73(1):67–83. DOI: 10.1137/120882093
- Van Overwalle F. 2011; A dissociation between social mentalizing and general reasoning. *NeuroImage*. 54(2):1589–1599. DOI: 10.1016/j.neuroimage.2010.09.043 [PubMed: 20869452]
- Wu R, Gopnik A, Richardson DC, Kirkham NZ. 2011; Infants learn about objects from statistics and people. *Developmental Psychology*. 47(5):1220–1229. DOI: 10.1037/a0024023 [PubMed: 21668098]
- Zahn R, Moll J, Krueger F, Huey ED, Garrido G, Grafman J. 2007; Social concepts are represented in the superior anterior temporal cortex. *Proceedings of the National Academy of Sciences*. 104(15): 6430–6435. DOI: 10.1073/pnas.0607061104

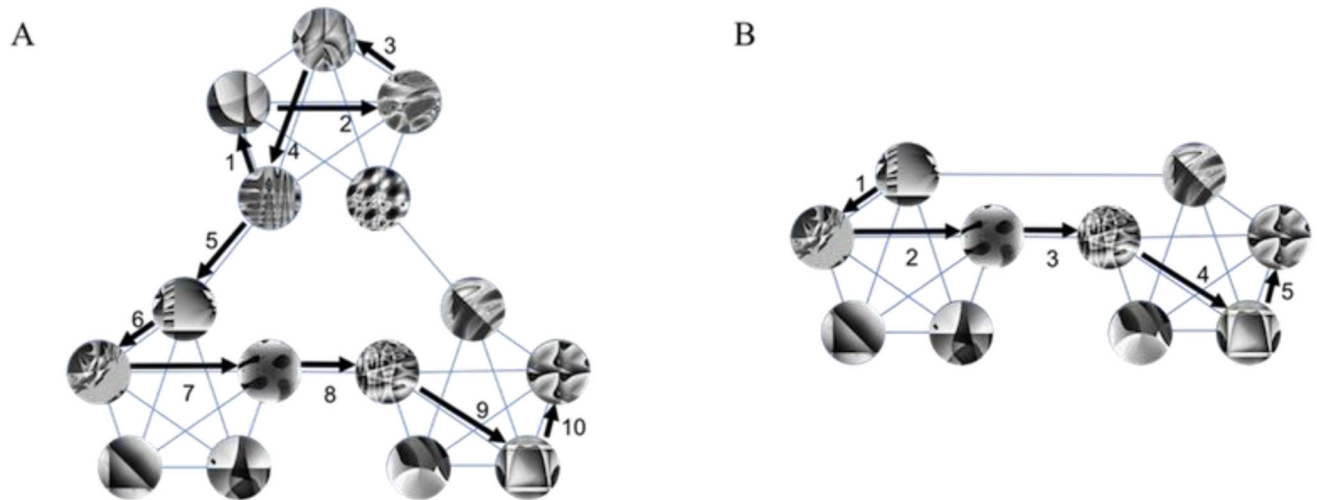


Figure 1.

Random walk through network of fractal images. Study 1 consisted of a random walk through three clusters of five images (Figure 1A) whereas all other studies consisted of a random walk through two clusters of five images (Figure 1B).

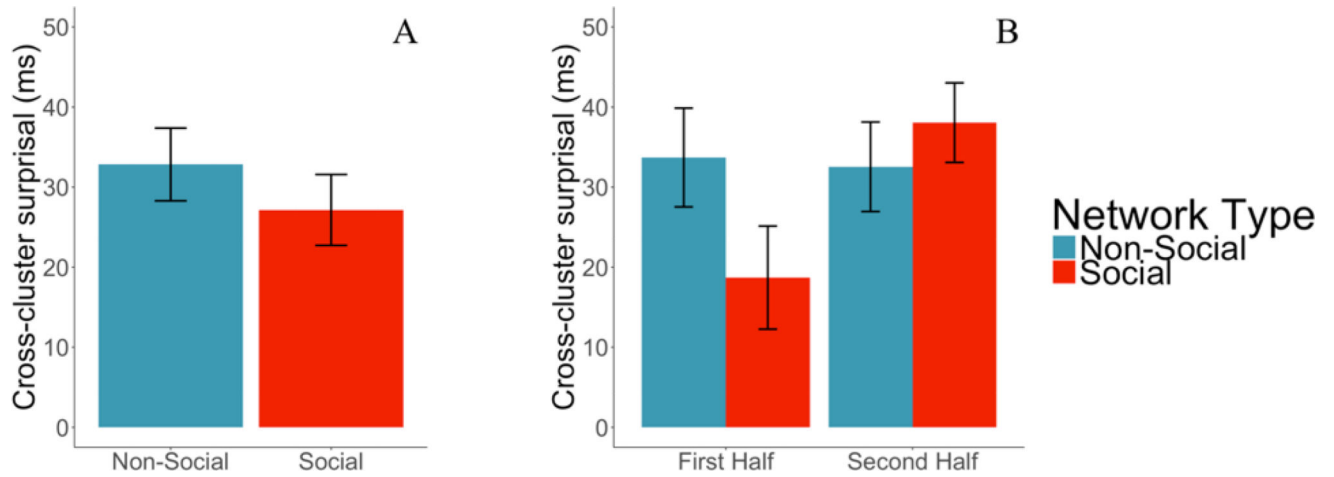


Figure 2.

Network learning in Study 1. 2A: Difference in RT for post-transition minus pre-transition trials for social and non-social networks. Participants responded significantly slower on post-transition trials than on pre-transition trials, and there were no significant differences between social and non-social tasks. 2B: Interaction between condition and time.

Participants in the social condition showed weaker cross-cluster surprisal to start, but by the end of the task the effect of condition was negligible.

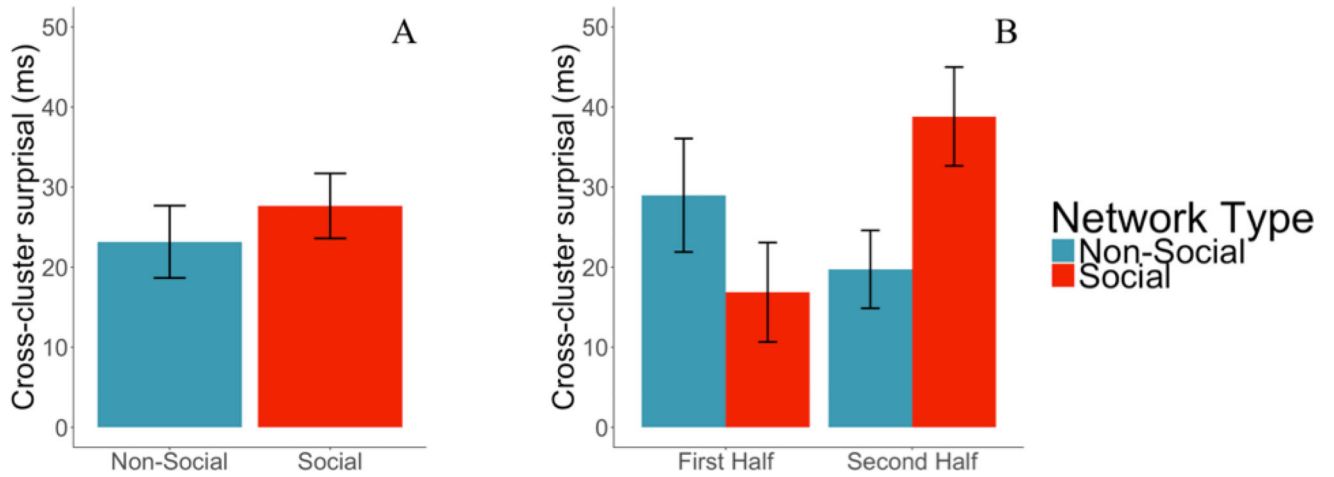


Figure 3.

Network learning in the Study 2. 3A: Difference in RT for post-transition minus pre-transition trials for social and non-social networks. Participants responded significantly slower on post-transition trials than on pre-transition trials, and there were no significant differences between social and non-social tasks. 3B: Interaction between condition and time. Participants in the social condition showed weaker cross-cluster surprisal to start, but by the end of the task the effect of condition was negligible.

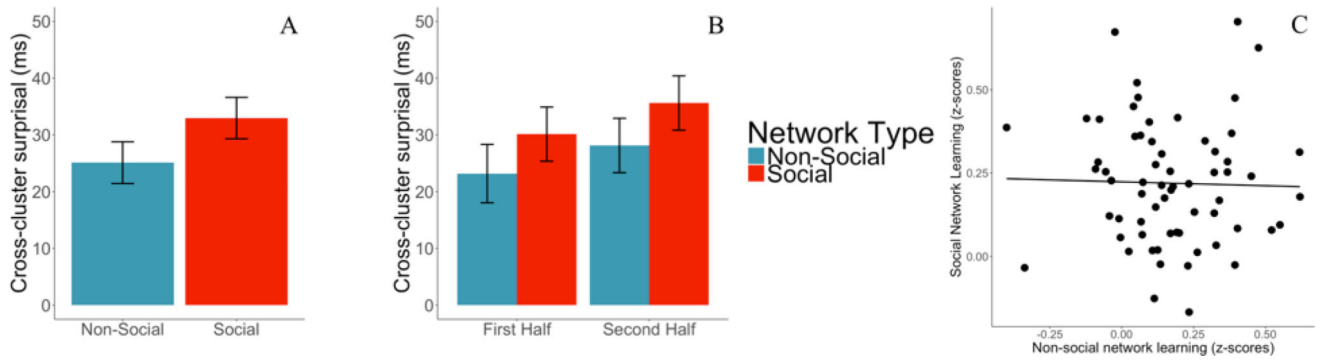


Figure 4.

Network learning in Study 3. 4A: Difference in RT for post-transition minus pre-transition trials for social and non-social networks. Participants responded significantly slower on post-transition trials than on pre-transition trials, and there were no significant differences between social and non-social tasks. 4B: Interaction between condition and time. There was no significant interaction between condition and time, such that participants showed similar cross-cluster surprisal effects at the beginning and end of both tasks. 4C: Correlation between each individual's cross-cluster surprisal effect (standardized within subject) for the social network and non-social network conditions. There were no significant associations between social and non-social network learning.

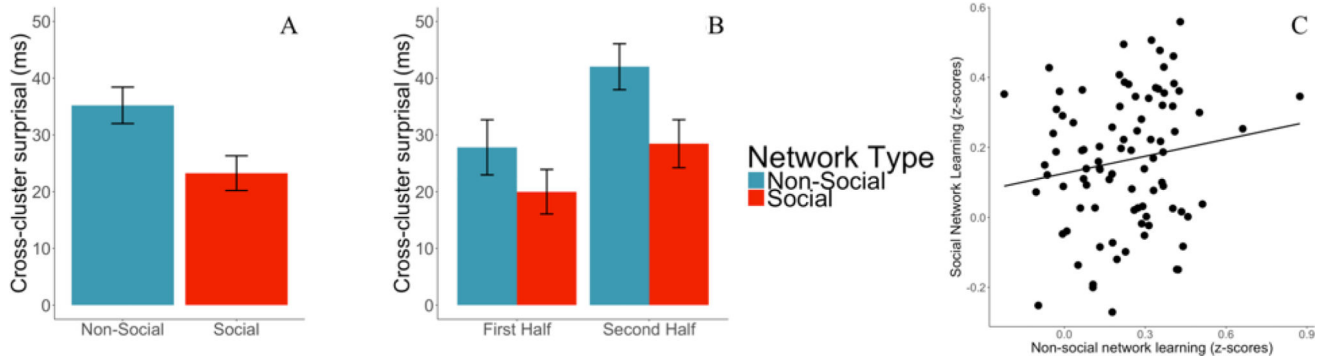


Figure 5.

Network learning in Study 4. 5A: Difference in RT for post-transition minus pre-transition trials for social and non-social networks. Participants responded significantly slower on post-transition trials than on pre-transition trials, and this effect was significantly larger for non-social networks. 5B: Interaction between condition and time. The difference in network learning for social and non-social networks did not significantly vary across the course of the tasks. 5C: Correlation between social and non-social network learning. Participants who were better at learning community structure in the non-social networks were not better at learning community structure in the social networks.

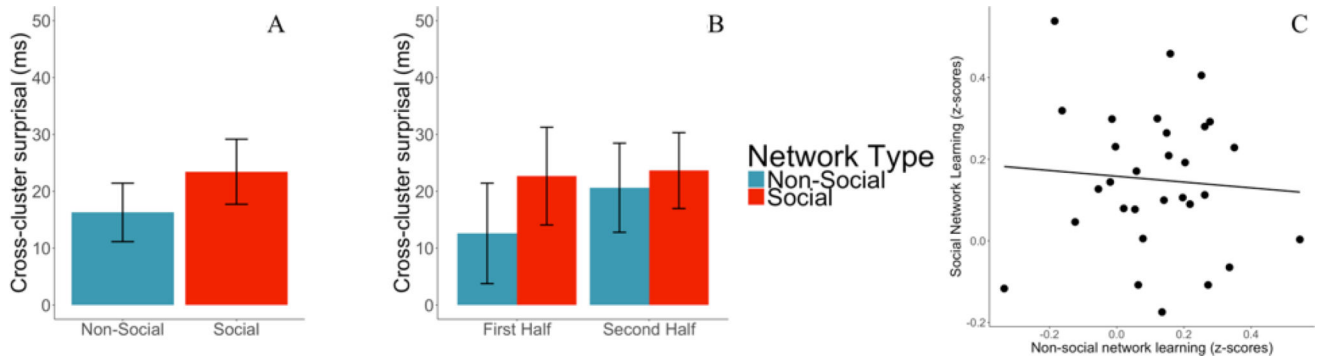


Figure 6.

Network learning in Study 5. 6A: Difference in RT for post-transition minus pre-transition trials for social and non-social networks. Participants responded significantly slower on post-transition trials than on pre-transition trials, and there were no significant differences between social and non-social tasks. 6B: Interaction between condition and time. There was no significant difference in cross-cluster surprisal across the course of the task. 6C: Correlation between each individual's cross-cluster surprisal effect (standardized within subject) for the social network and non-social network conditions. There were no significant associations between the learning of community structure in social and non-social networks.

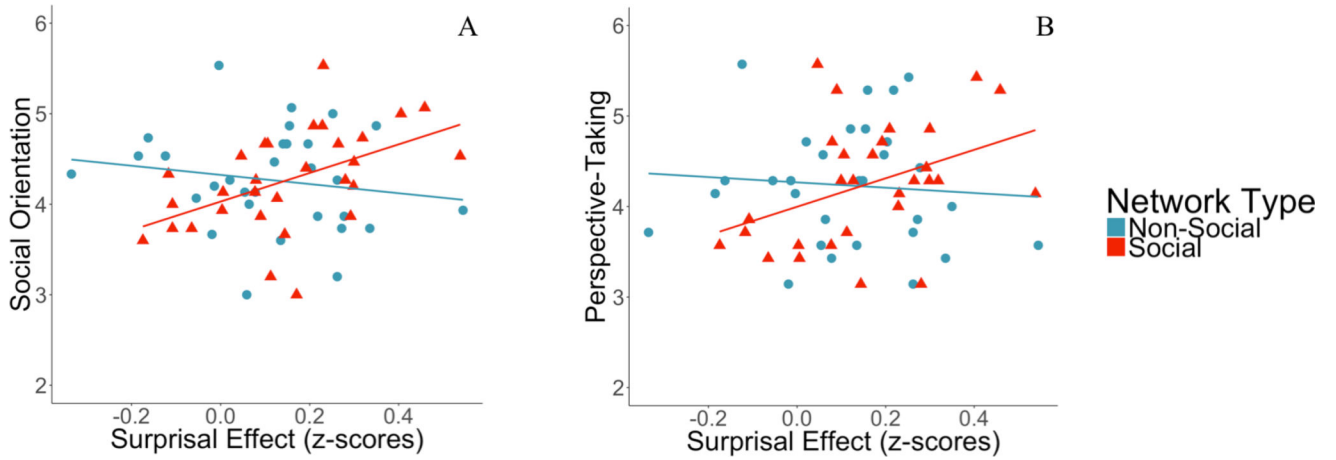


Figure 7.

Association between social traits and cross-cluster surprisal. People who are more collectivistic (Fig 7A) and people who are more likely to consider the perspective of others (Fig 7B) show stronger cross-cluster surprisal for the social networks, but not for the non-social networks. Higher values on the y-axis indicate more collectivistic (and less individualistic) scores (Fig 7A) and greater perspective-taking tendencies (Fig 7B).

Table 1

Summary of Study 1 results after fitting a mixed effects model.

	All Trials	Non-Social Network	Social Network
<i>Study 1</i>			
Main Effect of Node Type	b=15.05, SE=1.51, t(68)=9.99, p<.001	b=15.91, SE=2.23, t(34.04)=7.12, p<.001	b=14.25, SE=2.10, t(40.57)=6.78, p<.001
Main Effect of Condition	b=11.95, SE=8.63, t(72)=1.38, p=.171	n/a	n/a
Main Effect of Trial Number	b=-37.34, SE=2.82, t(72)=-13.23, p<.001	b=-32.29, SE=4.52, t(34.15)=-7.14, p<.001	b=-42.41, SE=3.47, t(37.14)=-12.21, p<.001
Node × Condition Interaction	b=-0.77, SE=1.51, t(68)=-0.51, p=.609	n/a	n/a
Node × Trial Interaction	b=1.81, SE=1.39, t(10,271)=1.30, p=.194	b=-2.94, SE=2.05, t(207.34)=-1.44, p=.152	b=6.56, SE=2.01, t(211.13)=3.27, p=.001
Condition × Trial Interaction	b=-5.01, SE=2.82, t(72)=-1.77, p=.080	n/a	n/a
Node × Condition × Trial Interaction	b=4.68, SE=1.39, t(10,271)=3.36, p<.001	n/a	n/a

Note. Significant effects are shown in bold.

Table 2

Summary of Study 2 results after fitting a mixed effects model.

	All Trials	Non-Social Network	Social Network
<i>Study 2</i>			
Main Effect of Node Type	b=11.91, SE=2.26, t(4,117)=5.28, p<.001	b=11.83, SE=2.27, t(546)=5.20, p<.001	b=14.32, SE=2.50, t(245)=5.74, p<.001
Main Effect of Condition	b=15.61, SE=18.85, t(77)=0.83, p=.410	n/a	n/a
Main Effect of Trial Number	b=-39.36, SE=4.41, t(77)=-8.92, p<.001	b=-39.42, SE=4.22, t(41)=-9.33, p<.001	b=-25.29, SE=4.83, t(37)=-5.24, p<.001
Node × Condition Interaction	b=2.45, SE=3.29, t(4,200)=0.74, p=.457	n/a	n/a
Node × Trial Interaction	b=-1.86, SE=2.25, t(7,414)=-0.83, p=.409	b=-1.86, SE=2.24, t(3,950)=-0.83, p=.407	b=5.54, SE=2.41, t(3,483)=2.30, p=.021
Condition × Trial Interaction	b=14.04, SE=6.38, t(78)=2.20, p=.031	n/a	n/a
Node × Condition × Trial Interaction	b=7.36, SE=3.29, t(7,415)=2.24, p=.025	n/a	n/a

Note. Significant effects are shown in bold.

Table 3

Summary of Study 3 results after fitting a mixed effects model.

	All Trials	Non-Social Network	Social Network
<i>Study 3</i>			
Main Effect of Node Type	b=14.52, SE=1.29, t(67)=11.29, p<.001	b=12.625, SE=1.77, t(64)=7.14, p<.001	b=16.14, SE=1.74, t(61)=9.30, p<.001
Main Effect of Condition	b=.01, SE=1.25, t(12,170)=0.01, p=.992	n/a	n/a
Main Effect of Trial Number	b=-24.44, SE=2.32, t(63)=-10.54, p<.001	b=-27.53, SE=3.35, t(61)=-8.22, p<.001	b=-23.29, SE=2.88, t(59)=-8.09, p<.001
Node × Condition Interaction	b=1.88, SE=1.24, t(12,130)=1.51, p=.131	n/a	n/a
Node × Trial Interaction	b=1.37, SE=1.24, t(12,160)=1.10, p=.270	b=1.38, SE=1.71, t(5,989)=0.81, p=.418	b=1.43, SE=1.70, t(6,050)=0.84, p=.399
Condition × Trial Interaction	b=2.48, SE=1.25, t(12,170)=1.99, p=.047	n/a	n/a
Node × Condition × Trial Interaction	b=-.05, SE=1.24, t(12,160)=-0.41, p=.685	n/a	n/a

Note. Significant effects are shown in bold.

Table 4

Summary of Study 4 results after fitting a mixed effects model.

	All Trials	Non-Social Network	Social Network
<i>Study 4</i>			
Main Effect of Node Type	b=14.33, SE=1.16, t(87)=12.39, p<.001	b=17.13, SE=1.51, t(432)=11.33, p<.001	b=11.78, SE=1.50, t(85)=7.87, p<.001
Main Effect of Condition	b=-0.21, SE=1.04, t(17,757)=-0.20, p=.839	n/a	n/a
Main Effect of Trial Number	b=-25.61, SE=2.09, t(88)=-12.23, p<.001	b=-24.84, SE=2.71, t(89)=-9.16, p<.001	b=-27.90, SE=2.76, t(85)=-10.11, p<.001
Node × Condition Interaction	b=-2.87, SE=1.04, t(17,741)=-2.77, p=.006	n/a	n/a
Node × Trial Interaction	b=2.20, SE=1.04, t(17,775)=2.12, p=.034	b=2.92, SE=1.44, t(8,831)=2.03, p=.042	b=1.04, SE=1.43, t(8,770)=0.73, p=.469
Condition × Trial Interaction	b=-1.35, SE=1.04, t(17,797)=-1.30, p=.195	n/a	n/a
Node × Condition × Trial Interaction	b=-1.11, SE=1.04, t(17,762)=-1.08, p=.282	n/a	n/a

Note. Significant effects are shown in bold.

Table 5

Summary of Study 5 results after fitting a mixed effects model.

	All Trials	Non-Social Network	Social Network
<i>Study 5</i>			
Main Effect of Node Type	b=8.53, SE=2.51, t(357)=3.40, p<.001	b=8.75, SE=2.63, t(52.94)=3.32, p=.002	b=12.14, SE=2.72, t(43.99)=4.47, p<.001
Main Effect of Condition	b=-5.93, SE=3.47, t(5,946)=-1.71, p=.087	n/a	n/a
Main Effect of Trial Number	b=-28.01, SE=3.39, t(54)=-8.26, p<.001	b=-28.39, SE=3.56, t(30.03)=-7.98, p<.001	b=-22.78, SE=4.55, t(29.46)=-5.01, p<.001
Node × Condition Interaction	b=3.54, SE=3.45, t(5,924)=1.03, p=.305	n/a	n/a
Node × Trial Interaction	b=0.04, SE=2.44, t(5,930)=0.02, p=.985	b=-0.12, SE=2.86, t(23.82)=-0.04, p=.967	b=0.13, SE=2.78, t(35.18)=0.05, p=.964
Condition × Trial Interaction	b=7.54, SE=3.48, t(5,937)=2.17, p=.030	n/a	n/a
Node × Condition × Trial Interaction	b=0.14, SE=3.45, t(5,927)=0.04, p=.967	n/a	n/a

Note. Significant effects are shown in bold.