# Hippocampal Encoding of Abstract Cognitive Maps Supports Navigation in a Real-World Social Network

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**Abstract:**

**Despite the complex relational structure of human social networks, people adeptly navigate their communities. Recent work suggests people accomplish this by building predictive cognitive maps of others' social relations, but little is known about how the brain encodes these representations. Here, we interrogate two representational formats differing in their assumptions about how information flows through large human networks: sequential transmission vs simultaneous propagation. Evidence from a real-world social network reveals that people's cognitive maps of social ties are built to track simultaneous propagation of information, and that the anterior hippocampus encodes these predictive representations to support social navigation.**

**Keywords: Social Networks; Cognitive Maps; Representation Learning; Hippocampus**

## Introduction

To flourish, human beings must learn to navigate complex social environments in order to access the rich resources embedded in networks (Bourdieu, 1986). Thus, people's ability to successfully navigate social networks depends on their ability to construct an accurate mental representation of the social relations comprising the network. Past work suggests that predictive maps of transition probabilities between members of a social network might be a plausible format of representation akin to sequential spatial navigation (Successor Representation SR: Gershman, 2018; Momennejad et al., 2017; Son, Bhandari, et al., 2023; Son, Vives, et al., 2023; Stachenfeld et al., 2017). However, these representations appear ill-suited to capture information flow which might propagate simultaneously across multiple paths in the network, largely because they strip away information about the absolute strength of associations between network members. Here, we hypothesize that an adaptive cognitive map of social networks would instead retain this information to afford flexibility across different navigation contexts (Katz Communicability, KC: Katz, 1953), and investigate whether the hippocampus, a region critical for spatial navigation, encodes predictive maps of social relations to facilitate *social* navigation.

## Methods

### Procedures

We recruited 187 first-year undergraduates (100 Female, 83 Male, 4 Other) from a network of three dormitories at Brown University. We measured the 'ground-truth' structure of the friendship network by asking participants to identify who their friends are amongst the 186 other participants. We then probed participants' (N=100) knowledge and inferences about friendships between other members of the network (personalized sub-samples of 30 individuals based on their graph distance from each participant) by asking participants to indicate whether each individual was friends with every other individual. A further subset of participants (N=98) completed a third task requiring inferences about how information flows through the network (i.e., whether news about X reaches Y, using a stimulus subsample of 25 individuals from the previous 30). Finally, 43 participants who participated in all previous sessions underwent fMRI while passively viewing images of 22 other network members (subsampled from the previous 25 stimuli).

### Models of Representation

The SR is a matrix M of size n x n such that M(*j*, *k*) encodes the probability of transitioning from state *j* to *k* (Stachenfeld et al., 2017). Given a transition matrix T, the SR is simply the discounted sum of the powers of the transition matrix, T (Eq. 1).

$$SR = \sum_{t=0}^{\infty} \gamma^t T^t \qquad (Eq. 1)$$

In the case of social networks, the transition matrix T can be computed from the friendship network's adjacency matrix A, which indexes whether a network member *j* is friends with network member *k,* A(*j*, *k*). We define the underlying friendship structure in the network as reflecting pairs of network members who mutually identified each other as their friends. However, because we had no objective metric of the participants' observations in this real-world social network, we assumed participants acquired information about pairs of friends in the network with a probability $p^d$ that decreases with participants' graph distance *d* from the pair, which approximates a perceived adjacency matrix A' for each participant. Correspondingly, T is computed from A'. In contrast, KC represents the association strength between two network members using the distance-weighted adjacency matrix A' directly (Eq. 2).

$$KC = \sum_{t=0}^{\infty} \alpha^t A'^t \qquad (Eq. 2)$$

Crucially, this distinction formalizes KC's assumption that the dynamics of information flow in a network derive from a propagation model based on leaky cascades as opposed to SR's model of discrete random-walks (Zamora-López & Gilson, 2024).

## Results

### Network knowledge

Overall, participants demonstrated relatively accurate knowledge of friendships in the network (Accuracy: M = 0.838, SD = 0.046; d-prime: M = 0.991, SD = 0.491; d-prime $\neq$ 0: t(99) = 20.203, p < .001). However, participants also made systematic errors in their friendship judgments: they more frequently inferred friendship between non-friend pairs who are closer to each other in the network (b = -1.318, SE = 0.077, z = -17.080, p < .001; Figure 1). These 'inaccurate' inferences also depended on how closely connected the individual was to each pair: inaccurate inferences became less likely for pairs further away (interaction b = 0.644, SE = 0.0582, z = 11.064, p < .001).

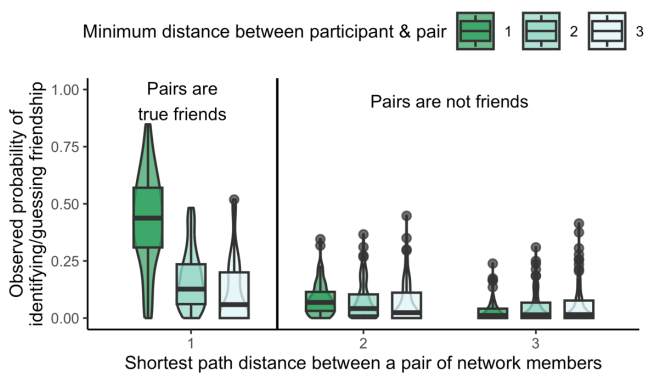


**Figure 1:** Participants' friendship judgments for pairs of network members.

To investigate the format of participants' social network representations, we fit both a SR and KC model with a logistic response function to participants' judgments about friendships between pairs. Posterior predictive checks revealed that both models reproduced empirically observed errors in participants' judgments (SR: interaction b = 0.771, SE = 0.059, z = 13.152, p < .001; KC: interaction b = 0.744, SE = 0.054, z = 13.778, p < .001). However, model comparisons provided strong evidence that participants' behavior was better explained by the KC model ($\Delta BIC_{SR\text{-}KC}$: M = 99.825, SD = 75.953, t(99) = 13.143, p < .001; 93/100 participants $\Delta BIC \geq 10$), suggesting that participants' friendship inferences were guided by a predictive representation that tracks the communicability of information between network members across simultaneous paths.

### Hippocampal encoding of predictive maps for social navigation

How does the brain encode such an abstract representation of the social network? We constructed participant-level representational dissimilarity matrices, computing cross-validated Mahalanobis (crossnobis) distances for each pair of network members presented in the scanner (Diedrichsen et al., 2021; Walther et al., 2016). Sign-inverted crossnobis distances thus index neural pattern similarity. We found that the model-estimated KC value of network pairs significantly predicted neural pattern similarity in anterior hippocampus (aHC: b = 0.431, SE = 0.188, t(29) = 2.286, p = .030), but SR did not (b = -0.061, SE = 0.060, t(85) = -1.018, p = .312). Control region V1 tracked neither KC nor SR (ps $\geq$ .520). These results suggest that aHC encodes a person's identity as a function of their social connectedness to the broader network.

To demonstrate that neural encoding of KC in aHC is functionally deployed for social navigation, we then conducted an out-of-sample test of its predictive power in the information flow task. We not only found group-level evidence that neural pattern similarity in aHC predicts inferences about information flow (b = 0.168, SE = 0.076, z = 2.193, p = .028), but also that this effect is significantly modulated by individual differences in how strongly KC predicts aHC neural pattern similarity (interaction b = 0.256, SE = 0.104, z = 2.454, p = .014; Figure 2). Again, control region V1 does not predict out-of-sample inferences about information flow (p = .845) In other words, neural activity in aHC supports social navigation in the information flow task only when it encodes the communicability of information between network members.

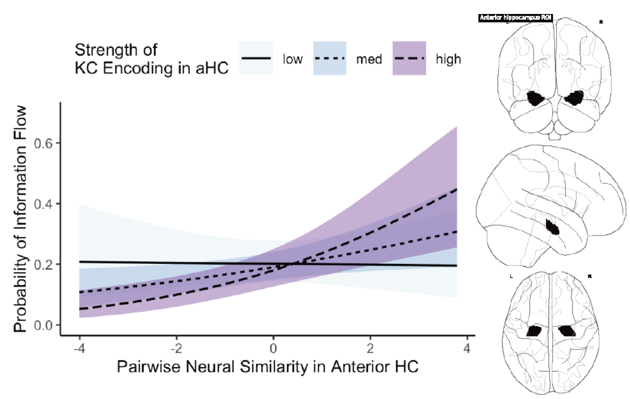


**Figure 2:** Predictive encoding of Katz in aHC predicts out-of-sample inferences about information flow

## Conclusion

Our results suggest that people's cognitive maps of their real-world social networks retain critical information about the absolute strength of pairwise relations. Encoded in the anterior hippocampus, these predictive representations facilitate social navigation by supporting people's ability to infer how information propagates simultaneously through their network.

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