# Insights about the common generative rule underlying

# an information foraging task can be facilitated via collective search

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# **SUMMARY**

Social learning is beneficial for efficient information search in unfamiliar environments<sup>1,2</sup> ("within-task" learning). In the real world, however, possible search spaces are often so large that decision makers are incapable of covering all options, even if they pool their information collectively. One strategy to handle such overload is developing generalizable knowledge that extends to multiple related environments<sup>3</sup> ("across-task" learning). However, it is unknown whether and how social information may facilitate such across-task learning. Here, we investigated participants' social learning processes across multiple laboratory foraging sessions in spatially correlated reward landscapes that were generated according to a common rule. The results showed that paired participants were able to improve efficiency in information search across sessions more than solo participants. Computational analysis<sup>4</sup> of participants' choicebehaviors revealed that such improvement across sessions was related to better understanding of the common generative rule. Rule understanding was correlated within a pair, suggesting that social interaction is a key to the improvement of across-task learning.

## What's our research question?

Whether and how paired participants utilize social information across tasks and harness collective intelligence.

# METHODS

#### Participants

• 74 students were paired and simultaneously worked on the task in a separated cubicle (pair condition), while other 47 students participated alone (solo condition; between-subject design).

#### Task

- Participants worked on a "spatially-correlated" multi-armed bandit task with 165 options for 25 trials.
- They sequentially experienced six variants of search space ("session"), each of which was randomly sampled from a Gaussian Process prior with a common length-scale ( $\lambda$ =1.5; *i.e.*, magnitude of the spatial correlation).
- Thus, they could develop some understanding of the spatiallycorrelated structure of the environment and utilize the knowledge for information search.
- · Participants in the pair condition were provided with information about their partner's choice in the preceding trial prior to making a choice.



# **KEY FINDINGS**

- The superiority of the paired participants to the solo participants was more pronounced in later sessions.
- By fitting a computational model, inspired by the GP-UCB model<sup>4</sup>, we found that the paired participants had acquired some insights about the **common spatial correlation** underlying the reward landscape.
- The understanding of the spatial correlation was correlated within real pairs, suggesting that **social interaction** between participants played an essential role to foster insights about the common generative rule.

## REFERENCES

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4. Wu et al. Generalization guides human exploration in vast decision spaces. Nat. Hum. Behav. (2018).

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This paper has been published in Scientific Reports.

Website: https://naito-aoi.github.io/index\_en.html

# **COMPUTATIONAL MODELING**

- We consider a decision model with Gaussian Process regression (GP) and an Upper Confidence Bound policy (UCB)<sup>4</sup>.
- GP generates the spatial distribution of rewards in the environment as the mental representation.
- The magnitude of spatial correlation (the covariance between options in GP) are set by using a radial basis function kernel as below:

$$k_{RBF}(\mathbf{x}, \mathbf{x}') = \exp\left(-\frac{\|\mathbf{x} - \mathbf{x}'\|^2}{\hat{\lambda}}\right)$$
(1)

- UCB sampling provides the value function of options at each trial, based on estimates about mean rewards  $m(\mathbf{x})$  and the underlying uncertainty  $s(\mathbf{x})$  from GP.
- Furthermore, to consider the effects of social information in the pair condition, we added value accruing from imitation to the UCB value:

$$V(\mathbf{x}) = m(\mathbf{x}) + \beta \cdot s(\mathbf{x}) + \gamma \cdot k_{RBF}(\mathbf{x}, \mathbf{x}_{partner})$$
(2)



The overall valuation function was combined according to a softmax choice rule:





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### **BEHAVIORAL RESULTS**

- Collapsed across all sessions, participants in the pair condition outperformed those in the solo condition (LMM, 95% CI: [1.41, 5.16]).
- The difference in performance between the solo and pair conditions increased in later trials (LMM, 95%CI: [0.04, 0.47]).



Among the 4 parameters, only  $\hat{\lambda}$  was significantly correlated between paired participants (Spearman's Rank Correlation test,  $\rho$ =0.15, P<0.01).



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