A Computational Framework for Studying Social Cooperation in Rats

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Introduction

Understanding the neural mechanisms that drive social cooperation is crucial for advancing our knowledge of social behavior and developing treatments for conditions such as autism spectrum disorder and early-life stress. Animals such as rats can model these mechanisms, though their behavioral variability makes analysis inherently challenging. While reinforcement learning (RL) has emerged as a promising framework for modeling animal behavior, multi-agent RL algorithms have not yet been applied to the study of social cooperation.

In order to test the validity of RL, we used experimental data of a freely behaving cooperative task in rats from Jane Taylor's Lab to attempt to analyze the extent to which the models capture animal behavior.

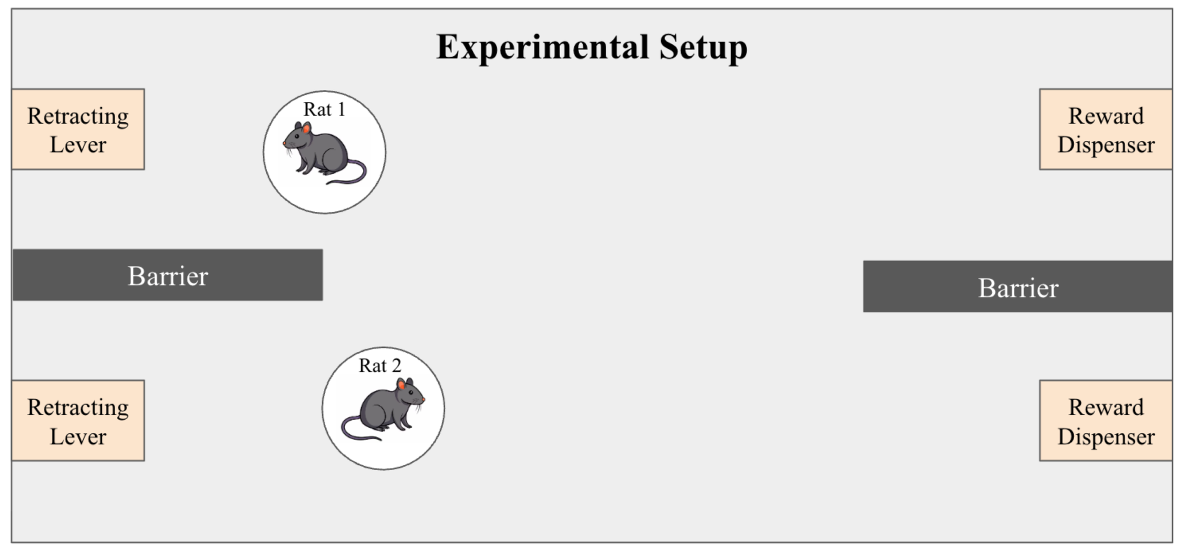
Methods

Training:

- Pavlovian Conditioning – Associate sound queue with reward
- Instrumental Training – Associate lever press at sound queue with reward

Sessions:

- Two rats in a cage with two levers on the left side and two reward dispensers on the right side with barriers in between
- Rats rewarded if levers pressed within 1 second of each other



Experimental Modifications:

- Training Partners – pairs of rats that have trained together
- Unfamiliar – pairs of rats that have been trained but have not seen current partner

Fiber Photometry

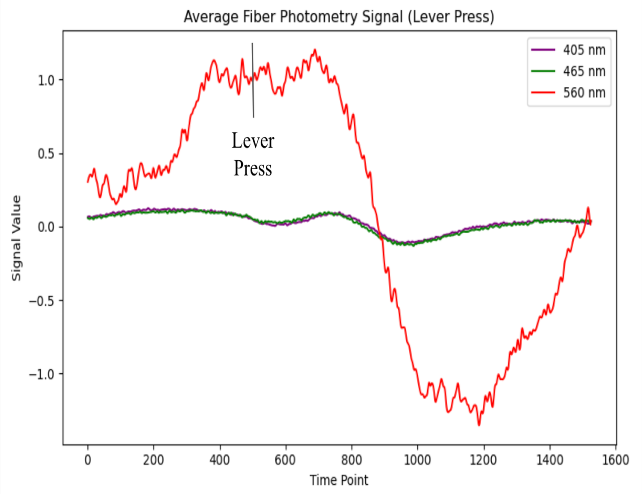


FIGURE 1. Neural Signals before and after lever press

Fiber photometry data was collected in the Anterior Cingulate Cortex (ACC), specifically in the pathways to the Basolateral Amygdala (BLA) and Anterior Insulate Cortex (AIC); these brain regions have previously been found to be associated with cooperation [].

Control (405 nm)

ACC → BLA (465 nm)

ACC → AIC (560 nm)

Cooperative Strategies

Synchronization

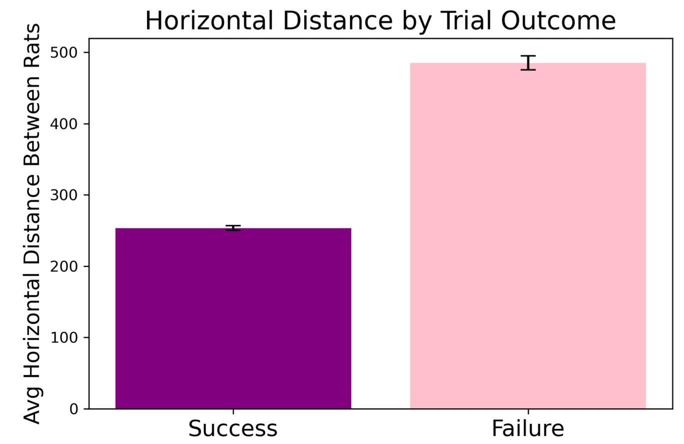


FIGURE 2. Rats appear to be more synchronized in successful trials where greater synchronization.

Waiting Before Cue

FIGURE 3. Strong correlation between waiting near the levers before they come out and cooperative success rate.

Waiting Before Press

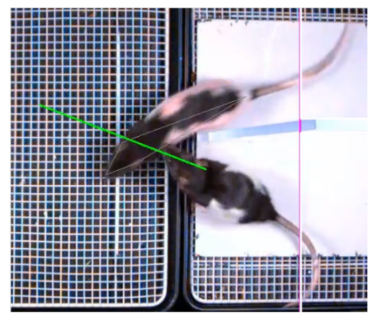
FIGURE 4. The further away a rat's partner is from the lever, the longer they take to press it.

FIGURE 5. # of Rats near Lever at Cue is strong indicator of success. However, synchronization is also an indicator of success independently

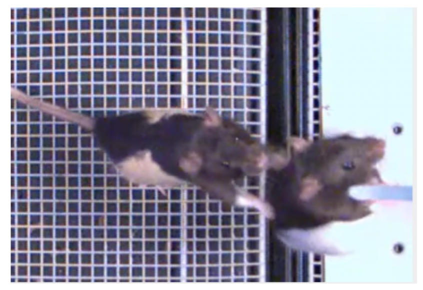
FIGURE 6. As rats train together more, they learn to go to lever before cue more often. Meanwhile/Similarly, synchronization decreases/increases over sessions.

How Behaviors Influence Success

FIGURE 7. Percent of frames gazed is negatively correlated with cooperative success rate across sessions.



Gazing



Physical Interaction

Gazing defined as head base, nose vector intersecting other rat for 1/3+ seconds

Interacting defined as close proximity for 1/3+ seconds

FIGURE 8. Percent of frames physically interacted is negatively correlated with cooperative success rate across sessions.

Effects of Familiarity

Figure 9. Unfamiliar rat pairs exhibit significantly lower gazing percentages than rat pairs who are training partners.

Figure 10. Trained rats have significantly lower gazing percentages than untrained rats.

FIGURE 11.
Gazing decreases throughout training.
Physical Interactions decrease throughout training.
Success increases throughout training.

Behavioral Conclusions

I. Rats exhibit different overarching cooperative strategies such as synchronizing their movement, waiting near the levers before the cue, and waiting to press the lever if their partner is far away, demonstrating an awareness of their partners position.

II. These strategies are not mutually exclusive. In fact, waiting might act as a mechanism to synchronize.

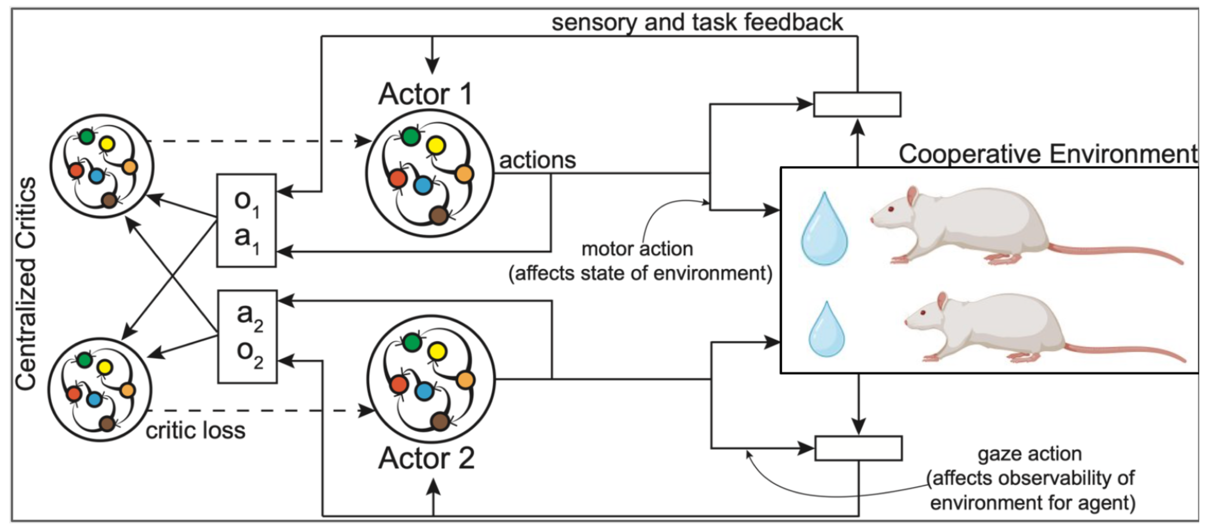
III. Over training rats learn that waiting near the levers is the most effective strategy to succeed.

IV. Contrary to the initial hypothesis, social behaviors such as gazing and physical interaction in familiar rats seem to serve as distractions rather than a way of communicating.

V. However, those social behaviors do seem to be a tool for rats to familiarize themselves with their partners, initially.

Modeling Approach

Since we are interested in modeling cooperation, we are using the multi-agent deep deterministic policy gradient (MADDGP) algorithm [2] in order to accurately model the cooperative aspect of the task.



Moving forward, we can compare the behaviors of strategies of the model with that of the experimental data and assess the extent to which the model captures the real results. This will allow is to …

1) Gain an insight into the neural computations underlying the behaviors and strategies required for social cooperation.
2) Test the validity of RL models in studying social paradigms.

References

[1] Allsop, S. A., Wichmann, R., Mills, F., et al. (2018). Corticoamygdala transfer of socially derived information gates observational learning. *Cell*, *173*(6), 1329–1342.e18. https://doi.org/10.1016/j.cell.2018.04.004

[2] Lowe, R., Wu, Y., Tamar, A., Harb, J., Abbeel, P., & Mordatch, I. (2017). *Multi-agent actor-critic for mixed cooperative-competitive environments.* arXiv:1706.02275

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Link to examples and code.

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