Final Honors Thesis

Dynamical processes between teacher-student dyads in rat observational learning

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Background:

Observational learning is a type of learning that occurs when the learner watches and emulates the behavior of a teacher (Troha et al., 2023). Observation is critical to human development. As new beings in this world, babies are constantly sensing and processing information to gain familiarity. Even as adults, observational learning is intertwined with the way we acquire skills. Observational learning also provides an evolutionary advantage, as learning from observing others' trials and errors can keep you safe from danger and preserve your energy and resources (Troha et al., 2020). Observational learning is central to learning a new skill or task, as it applies the idea that an observer can learn how to accomplish something just by viewing a demonstrator do it. In terms of human-human interactions, studies have found that things like joint attention and verbal instruction are important to successful observational learning (Pagnotta et al., 2020). Overall, indicators of attention that require synchronized movement are important for successful observational learning to occur.

The importance of observational learning for skill acquisition or task completion has also been found to be consistent with rat studies (Troha et al., 2020). When placed in a task where an observer had to use a demonstrator's behavior to identify a reward location, it was found that the type of demonstrator had an impact on the success of the observer getting the reward. Compared to a non-social demonstrator (e.g. a ball), observers responded more quickly and accurately when they had a social demonstrator (e.g. another rat) (Troha et al., 2023). Presumably, this is because the observer rat is able to mirror another rat's behavior better than they are able to mirror a non-living object.

While observational learning has been a long standing concept, the use of recurrence quantification analysis (RQA) for understanding dyad interactions is a rather recent development. RQA refers to a nonlinear method of analyzing time series data. The key factor of RQA is that it looks at a certain variable and evaluates how that variable relates to itself at a different point in time. A specialty of RQA is that it allows for the dynamics of a system to be explained by any variable, not just one that has face validity (Carello & Moreno, 2005). This method of analysis can provide metrics like recurrence rate (i.e. the level of coordination between two time series) and determinism (i.e. the level of synchronization between two time series), which are all relevant in assessing the interactions between a dynamic system (Pagnotta et al., 2020).

In the case of a conversation between two people, studies have found that someone's postural sway (i.e. the way a body moves in terms of its center of mass) to be a better indicator of how engaged someone is, compared to more apparent features like similar gestures (Carello & Moreno, 2005). Using RQA, they looked at the time series data of two people in conversation and saw that there were high recurrence rates when they looked specifically at postural sway. In general, aspects of interpersonal coordination can provide a lot of information on the dynamics of an interaction (Paxton & Dale, 2017).

RQA is especially useful in analyzing observational learning tasks. In a human-to-human task that involved an observer having to put together a puzzle after watching a demonstrator do the task, RQA showed that there were high determinism values when the observer was looking at the same puzzle piece that the demonstrator was manipulating, as well as when the observer had audio accompanying the demonstration of the task (Pagnotta et al., 2020). This finding makes sense given the previous discussion on the importance of joint attention and verbal instructions.

When applying this phenomenon to rat observational behavior, we can draw similar hypotheses. Specifically, I will be looking at three sets of behavior: the independent behaviors of the teacher, the independent behaviors of the observer, and the interactions between the two.

Looking at these three aspects will tell us a lot about the types of behaviors that contribute to successful social learning; in essence, what are the rats doing individually and as a pair when they have a successful trial versus a failure trial? For my study, I will use RQA metrics mentioned previously, such as RR and DET, to determine by which behaviors the teacher and observer rats are most coordinated and to what degree they are synchronized. I hypothesize that there will be higher recurrence when the observer is exhibiting behavior that indicates attention towards the teacher. Specifically:

1. The recurrence rate and determinism values will be higher in trials where the learner gets it correct versus incorrect.
2. The recurrence rate and determinism values will be higher in trials where the teacher is behaving in a clear and direct manner (i.e. decreased hesitancy, straight path) and the observer is behaving in an attentive manner (i.e. facing teacher, straight path).

During this project, my responsibilities included frequent handling of the rats. Rats would be weighed and fed daily, and would also be handled during the observational learning task itself. I also assisted with running the animals in the observational learning task and collecting video recordings during this process. In terms of analysis, I worked with various softwares including DeepLabCut and SLEAP to generate predictions of the rat's coordinates throughout the videos, as well as building code to generate heatmaps and conduct recurrence analysis. This process included plenty of debugging, testing, and meeting with Dr. Paxton to understand the basics of RQA and the application to this specific experiment.

Methods:

Subjects:

A total of nine female Long-Evans rats (Envigo, Indianapolis, IN) were used for this study. Subjects included two teachers and seven observers approximately 15 months of age at the beginning of this study. All animals were maintained at 85% of their body weight. Rats were individually housed in cages in a 12 hour light/dark cycle (lights go on at 08:00). Unrestricted access to water was available in the home cages. The research protocols used were approved by the University of Connecticut Institutional Animal Care and Use Committee.

Behavioral Procedure:

This task involved a setup with two boxes, one for the teacher and one for the learner (Fig. 1). Three camera views were used (arial, left side, and right side). In both boxes, there was a signal light at the center of the edge of the box that was switched on to alert the rats that the nose-poke light(s) was going to be switched on. In a trial, the teacher's signal light was switched on and the teacher had to then place its nose in either the left or right nose-poke, depending on which light was on. If this is successfully done, a pellet was automatically dispensed for the teacher. In the other box, the learner had the same center light that goes off to alert the rat. However, for the learner, both nose-poke lights were on; the learner had to decide where to put its nose by watching the teacher. If the learner pokes its nose in the correct hole, they also receive an automatically dispensed pellet. We recorded 80 trials of this experiment and split up the trials between success and failure trials.

Fig. 1.

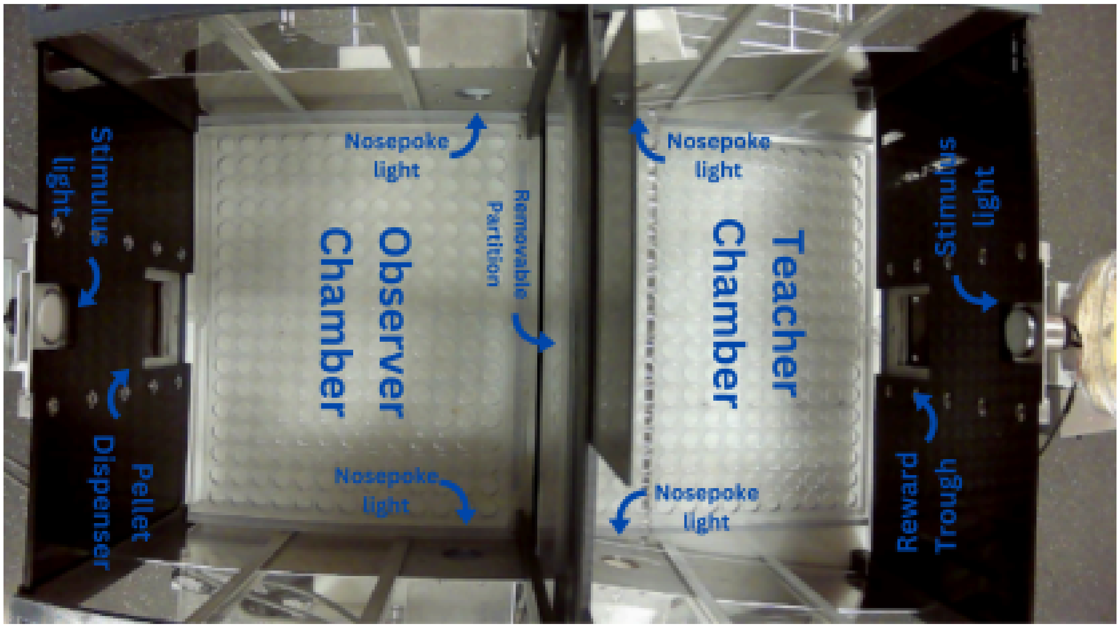

Figure 1: Diagram of the observational learning box. Note that the partition in the middle will be removed during the actual task, allowing the teacher and learner to see each other throughout the task.

Fig. 2.

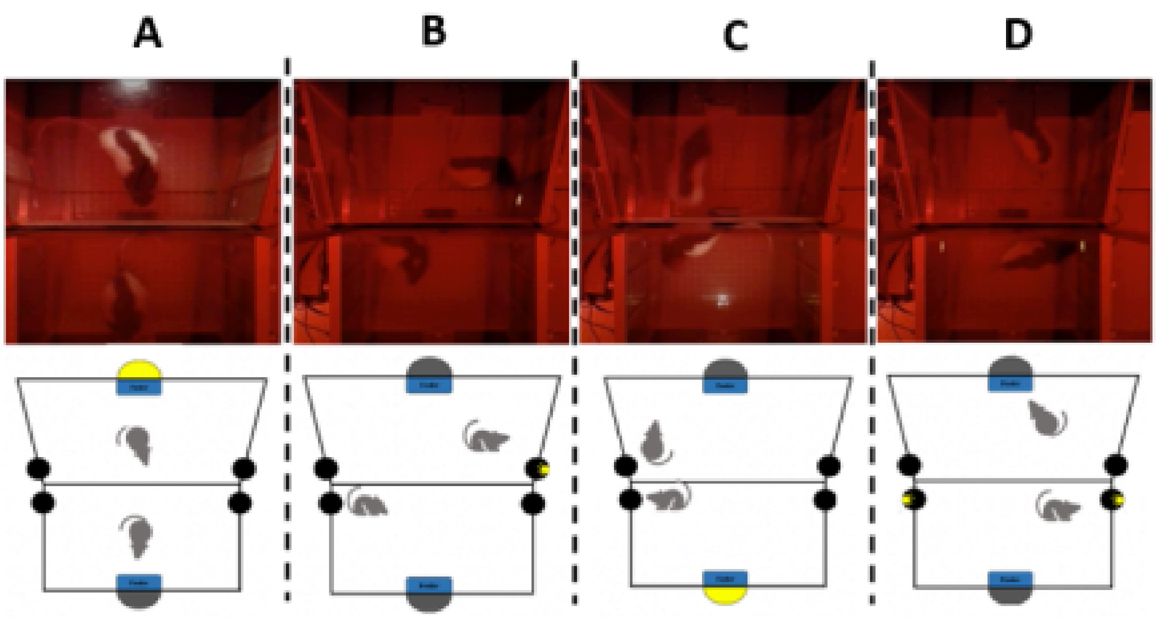

Figure 2: Diagram of stages of the task. Each trial can be broken down into four stages. (A) The

teacher's stimulus light comes on for 4 seconds, signaling their turn to respond. (B) The teacher's nose poke light comes on for a maximum of 4s, giving them a chance to respond. (C) The learner stimulus light comes on for 1s, signaling their turn to respond. (D) The learner nose poke lights come on for 4s, giving them a chance to respond at one of two nose pokes.

Data Analysis:

Behavioral Data:

During testing, each session was recorded. Each session had an aerial view, recorded with a camera placed in the same spots for each chamber. This was important because during tracking and position analysis, we needed the layouts of each video to be identical. Additionally, the program recorded how many trials each teacher rat and learner rat completed successfully or unsuccessfully. For analysis, we chose rats that had at least 10 incorrect trials, to compare the plots for correct versus incorrect trials.

Tracking and Position Analysis:

After recording our experimental trials, we needed a way to translate the videos into coordinate data. The two main software programs we used to achieve this were DeepLabCut (DLC) and SLEAP. DLC is a deep learning software that learns the position of key body parts using ResNet architecture. With as little as 200 labeled frames, DLC can create an accurate model that produces high probabilities for regions with user labeled points. While it can provide pose estimations that are accurate, training can be extensive (Luxem, 2023). On the other hand, SLEAP uses convolutional neural networks that allows for faster training compared to DLC. This architecture is more customizable to the dataset which allows for highly accurate pose estimation with as few as 100 labeled frames, with comparable accuracy to DLC and quicker training times (Luxem, 2023).

Heatmaps:

Our main method of "classic" analysis was to determine a visual way to represent where the rat was in a given trial. This would help us understand where the teacher and student rat tended to be in a given trial and how that differed based on whether the trial was successful or unsuccessful. To do this, we decided positional frequency heatmaps were our best option. We essentially had to create a matrix of where the rat was in their chamber based on their coordinate data, which we got from DeepLabCut outputs.

The heatmaps were created using Python, including packages like pandas, numpy, seaborn, and matplotlib. The process of creating the code to generate heatmaps started with preprocessing the data. With the DLC outputs, we had the accuracy percentage of the coordinate predictions for each body part that was tracked on the rat. For the heatmaps, we primarily used the rat's nose x and y coordinate data. Our first goal was to eliminate the coordinates where the accuracy was below 95%. Once doing that, we had to interpolate the missing values using the remaining values. After much discussion, we decided that the best method of interpolation was to find the difference between the first known value and the last known value, divide by the number of nulls, and then add that step to each value. Once we interpolated the null values, the next step was to create a matrix filled with all the values that corresponded to each section of the chamber. Using this matrix, we were able to generate a heatmap, as shown in Fig. 3, that depicts the position of the rat during a determined period of time, whether that is a whole 80 trial session, trial by trial, or second by second. Fig. 3 specifically depicts the path of the teacher during a correct trial. As we can see, the rat begins on the right side of the chamber, indicated by the red star, and then as the trial begins, goes to the correct nose poke on the left and then to the feeder at the top. The path appears to be direct and smooth throughout. Comparing this to Fig. 4, which depicts the path of the teacher when the learner gets it incorrect, in Fig. 4 we can see that the teacher's path to the nose poke is less direct, slower, and more hesitant. After creating the heatmaps, we had a better understanding of the general movements of the rat during the session. To extract further dynamics, we conducted recurrence quantification analysis.

Fig. 3.

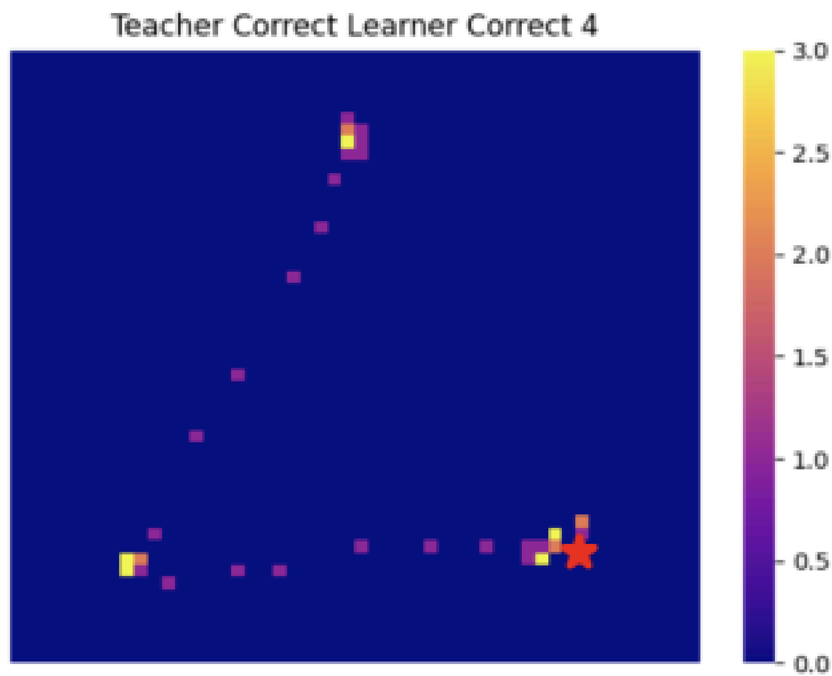

Figure 3: Heatmap of a 4 second trial of the teacher's movements when the learner chooses the correct nose poke.

Fig. 4.

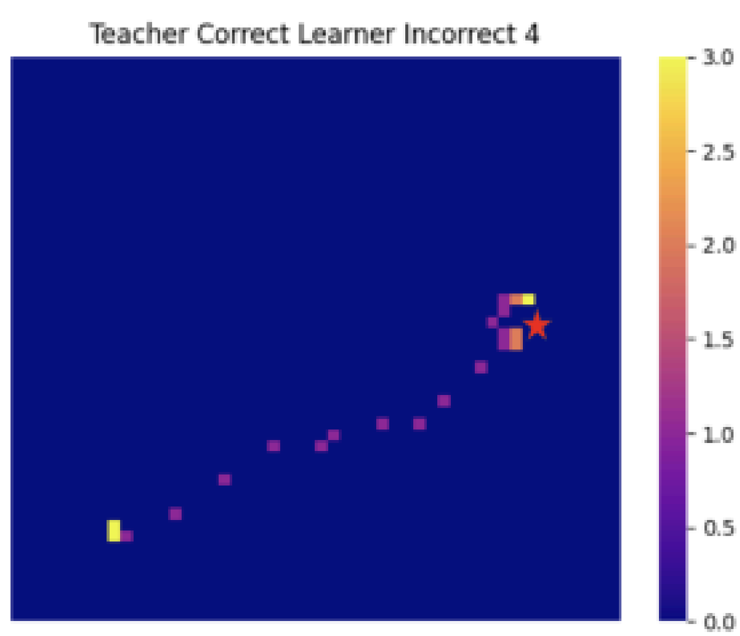

Figure 4: Heatmap of a 4 second trial of the teacher's movements when the learner chooses the incorrect nose poke.

Recurrence:

The majority of the RQA analysis was done using the programming language R. Through regular meetings with Dr. Alexandra Paxton, I learned the basics of how to conduct and interpret RQA. With the recurrence plots, we followed a similar approach to the preprocessing step for the heatmaps. First, we had to interpolate the null values that were less than 95% accurate for the rat's nose. We also did the same for the coordinate position of the signal light, as our metric for the recurrence plot was to calculate the distance from the rat to the signal light in a given trial. In terms of the actual recurrence, we mainly had to play with three different parameters: chosen delay, chosen embedding, and the radius.

The following figures depict the difference between the varying parameters. We can see how changing the radius affects the graph, by encapsulating more points to be considered as "recurrent". The chosen delay also makes an impact on the recurrence, as that is how much delay we are comparing the time series against itself by. We also played around with the chosen embedding dimension, which is the number of dimensions the system naturally lives in. By varying all these parameters, we were able to visualize the varying levels of recurrence within the session. After tweaking the parameters, we settled on using radius = 0.5, chosen delay = 30, and chosen embedding = 3 for the final plots, as these values seemed to represent the recurrence in the trials most accurately.

Fig. 5.

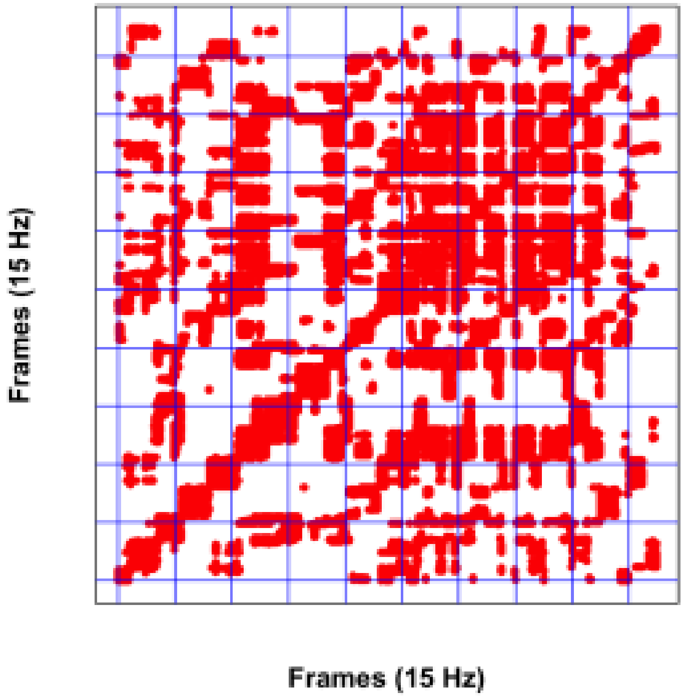

Figure 5: Recurrence plot where radius = 0.4, chosen delay = 30, chosen embedding = 2.

Fig. 6.

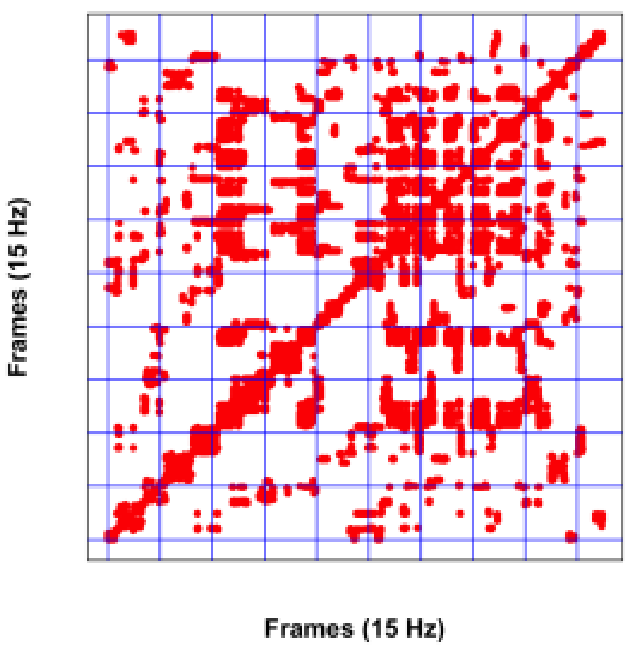

Figure 6: Recurrence plot where radius = 0.2, chosen delay = 30, chosen embedding = 2.

Fig. 7.

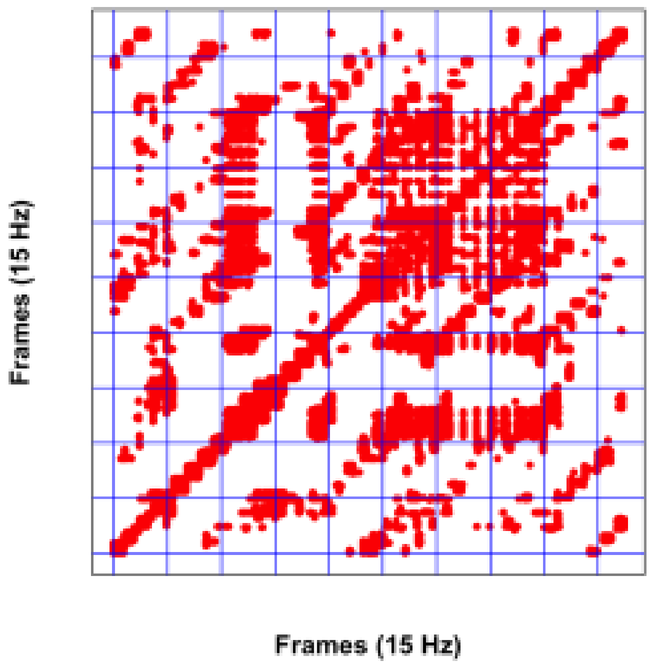

Figure 7: Recurrence plot where radius = 0.5, chosen delay = 15, chosen embedding = 3.

Results:

Our final analysis included comparing the recurrence plots between the teacher's movements and learner's movements during successful trials compared to unsuccessful ones. Fig. 8 shows a recurrence plot of the teacher's distance from the signal light throughout 10 correct trials (i.e. when the learner gets the correct nose poke). The recurrence rate (RR) was 0.145097 and the determinism (DET) was 0.975393. Fig. 9 looks at the teacher's movements except for 10 incorrect trials, where the learner does not get the correct nose poke. In this case, RR was 0.124550 and DET was 0.975644. Fig. 10 is now looking at the learner's movements (again, the distance from them to the signal light at any given frame) for the same 10 correct trials as the previous figure where the learner gets it correct. RR was 0.216805 and DET was 0.939381. The last plot (Fig. 11) looks at the learner's movements for the 10 incorrect trials. RR was 0.089811 and DET was 0.875498. To augment these recurrence plots, we have also included distance graphs, which depict the distance traveled from the teacher or learner rat to the signal light. We also have the heatmaps for each 4 second trial that the recurrence plots are made up of.

Fig. 8.

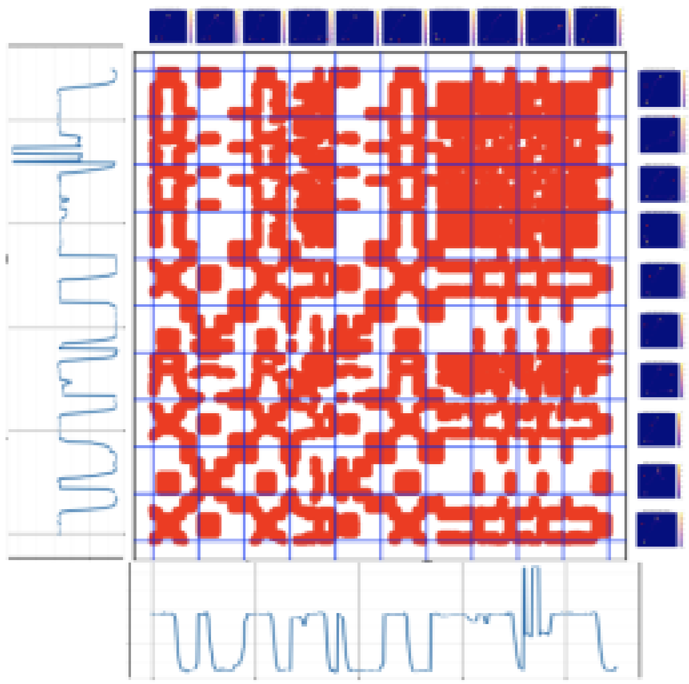

Figure 8: Teacher’s movement when learner is correct for 10 trials. On the x and y axes, we have the teacher’s distance from the light plotted and the corresponding heatmaps for each trial.

Fig. 9.

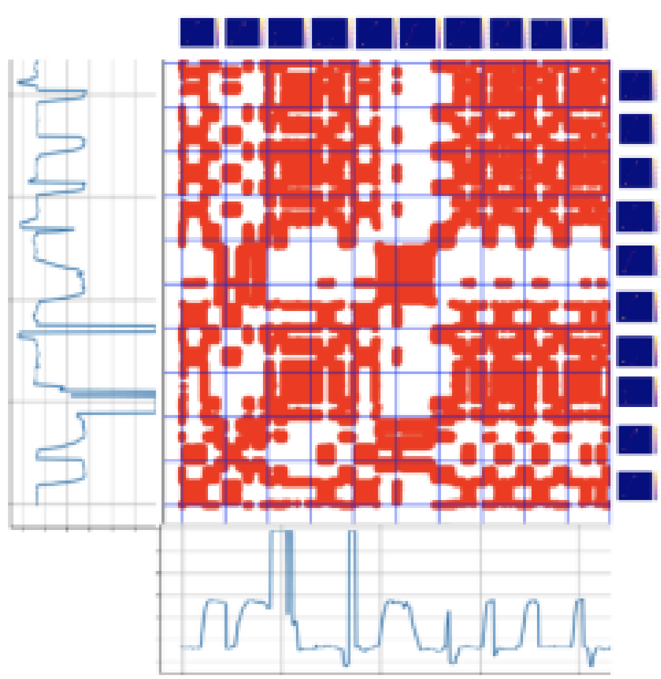

Figure 9: Teacher's movements when learner is incorrect for 10 trials. On the x and y axes, we have the teacher's distance from the light plotted and the corresponding heatmaps for each trial.

Fig. 10.

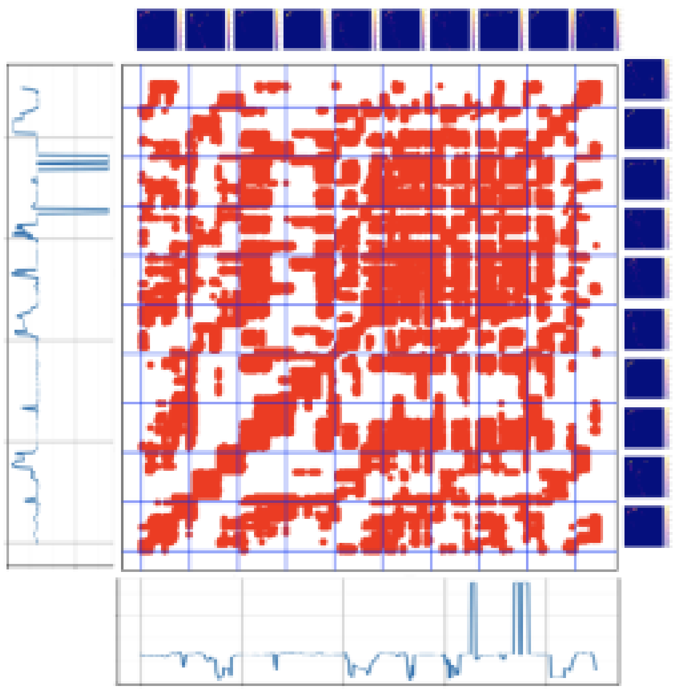

Figure 10: Learner's movements when learner is correct for 10 trials. On the x and y axes, we have the learner's distance from the light plotted and the corresponding heatmaps for each trial.

Fig. 11.

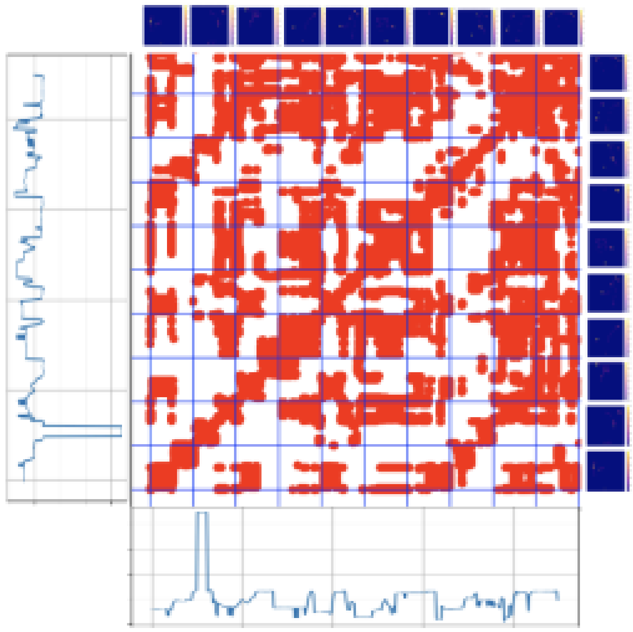

Figure 11: Learner's movements when learner is incorrect for 10 trials. On the x and y axes, we have the learner's distance from the light plotted and the corresponding heatmaps for each trial.

Discussion:

From this analysis, if we look at the plots visually, we can see that Fig. 8 appears very structured and more deterministic. When we compare this with Fig. 9, we see some similarities (similar concentrated boxes in the top right corner). However, from first glance, there are more white spots in Fig. 9 compared to Fig. 8, meaning there is less recurrence. Comparing Fig. 10 and Fig. 11, we can see that Fig. 10 looks a lot more structured and deterministic compared to Fig. 11, which does not have many boxy structures, meaning the movements could be more random. Fig. 10 has a lot more recurrence points, meaning the learner tends to have more structured movements during correct trials compared to the learner during incorrect trials.

In cases where there is recurrence that becomes more structured as the time series progresses, this could indicate that there was a lot more exploration in the first few trials compared to the last few. The teacher rats might have settled into a rhythm of movement as the trials went on, making the plots look increasingly deterministic in the top right corner of Fig. 8.

We also see some areas of dotted recurrence versus more blocks of recurrence, which could indicate a transition between states. With regards to this study, this could most likely be the teacher and/or learner rat going from a traveling and moving state to a stable state of sitting and resting.

Now looking at the distance graphs, we can see that the graphs for the correct trials look more deterministic, as they generally follow a more rigid pattern, whether we are looking at the teacher's movements or learner's movements. We also see that in the correct trials, there is a spike in the distance towards the latter trials, while in the distance graphs for the incorrect trials, we can see a spike happening in the first couple of trials, with the movement of the rest of the trials being a lot more irregular. This could indicate that once the rat makes a mistake, they find it hard to get back on track with the task, while when the rat is on a correct streak, they maintain that knowledge and continue those similar patterns of behavior. Taking a closer look at the heatmaps, we can also see how much more of a direct path the teachers and learners take towards the nose poke and signal light during correct trials versus incorrect trials. This solidifies that the teacher rat must have a characteristic movement that is clear and direct when the learner rat has a successful trial compared to an unsuccessful trial.

If we look specifically at the metrics of RR and DET, we can see that the recurrence plots for the correct trials had higher recurrence rates compared to their incorrect trial counterpart plots. Interestingly, we see that the DET values are all fairly similar for Fig. 8, 9, 10 but 11 is lower, meaning there was some level of synchronization between the teacher's movements when the learner got it wrong versus right, as well as the learner's movements when they got it right. This makes sense because in all these cases, the outcome of the target (teacher or learner) is a correct response. The only case where the target makes an incorrect response is in Fig. 11, where we look at the learner's movements when they get it wrong.

Future Directions:

In the future, we would want to continue our preliminary use of RQA and attempt to compare the teacher's movements against the learners' to see what synchronicities might appear in a successful trial compared to an unsuccessful trial. Additionally, in terms of the classic approach, we would want to figure out exactly what behaviors indicate good teaching and successful learning, whether this means teacher being close to the front of the chamber, closer to the learner, more or less grooming and rearing, heading angle from the teacher to the learner, etc. We would also want to continue to work with SLEAP and finetune our training process with that.

Appendix:

All figures mentioned in this paper are available here.

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