Cognitive Neuroscience

Analysis on behavioral tasks

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Contents

Part 1: Implicit Counterfactual Effect in Partial Feedback Reinforcement Learning: Behavioral and Modeling Approach

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Introduction

The research article examines the role of context in learning behaviors, particularly within reinforcement learning frameworks where only partial feedback is available. This study highlights the evaluative challenges that arise when only the outcomes of selected options are known, omitting counterfactual results that could potentially enrich the learning process. Behavior and decision-making are profoundly influenced by contextual factors, emphasizing the critical need to understand how learning adapts under conditions of limited feedback, in contrast to scenarios where both selected and unselected outcomes are disclosed.

This study employs both experimental and modeling approaches to investigate the impact of various feedback mechanisms on the learning process. It specifically addresses how the partial feedback paradigm can facilitate contextual learning effects, despite the absence of direct information about unselected options. This methodology aligns with neuroscientific evidence indicating that dopamine, a pivotal neurotransmitter in learning, exerts differential effects on neuronal populations, thereby influencing how values are assigned to different options. The research extends the analysis of reinforcement learning to encompass not just the probabilities but also the magnitudes of rewards, thereby expanding our understanding of contextual effects in value learning.

By implementing both partial and complete feedback paradigms, the study demonstrates that models which update the values of both chosen and unchosen options in opposing directions more accurately reflect behavioral data. The findings reveal that contextual effects transcend mere probabilistic evaluations, affecting reward magnitudes as well. Context is shown to play a crucial role in decision-making and reinforcement learning, though its impact on the latter has been relatively underexplored. Recent studies suggest that cognitive biases are likely a result of contextual influences during the value learning process.

This research focuses on two distinct learning paradigms: complete and partial feedback. In the complete feedback paradigm, participants are able to compare factual and counterfactual outcomes, which facilitates more effective value learning. However, the influence of context in the partial feedback paradigm remains less understood. Reinforcement learning processes involve updating the values of options based on prediction errors, which are encoded by dopamine in the brain. Inspired by dopamine's opposing effects on distinct populations of striatal neurons, the study introduces the Opposing Learning (OL) model. In this model, the outcomes of chosen options influence the values of both selected and unselected options.

Comparison Effect

Participants' behavior was studied to understand the impact of regret and relief on decision-making. Regret and relief occur when individuals compare the outcomes of their choices. This comparison influences whether they switch to a different option or stick with the same one. The study found a significant comparison effect in the complete feedback version but not in the partial feedback version, suggesting that participants' decisions were influenced more strongly by regret and relief in the complete feedback scenario.

Opposing Learning Model (OL)

A novel reinforcement learning model, the Opposing Learning (OL) model, was introduced, inspired by the striatal mechanism and built upon the standard Q-learning model. Unlike previous models focusing on the role of the unchosen outcome in updating chosen values, the OL model explains contextual effects by updating unchosen values based on chosen outcomes. This model correlates competing option values, leading to contextual effects during value learning. It also accounts for the influence of continuous reward magnitude on contextual effects. The OL model outperforms standard Q-learning models and offers insights into decision-making mechanisms.

Participants

Two groups of participants, comprising 35 and 42 individuals, engaged in the Partial and Complete versions of the experiment, respectively. Exclusions were made based on learning performance and reward expectation differences. Participants were healthy volunteers who provided informed consent and received monetary rewards based on task performance.

Behavioral Task

Participants underwent instrumental learning tasks with two versions: Partial and Complete. These tasks consisted of learning, post-learning transfer, and value estimation phases. In the learning phase, participants chose between stimuli pairs, gradually learning the most advantageous options. Feedback differed between the two versions, with only factual outcomes provided in the Partial version and both factual and counterfactual outcomes in the Complete version. The learning phase was followed by a transfer phase where participants made choices without feedback and a value estimation phase. The task design aimed to ensure participants learned reward associations and tested their decision-making abilities.

Code Implementation and Output Analysis

Nested Loop Execution

The implementation consists of a set of nested loops that iterates through a series of indices, printing the current index values for each level of the loop hierarchy. This was executed to simulate or iterate over a large number of combinations or states, with a half-second delay introduced between each print statement.

Data Loading

Multiple CSV files were loaded into pandas DataFrames, each representing different stages or types of data collected during an experiment. The datasets include partial and complete versions for estimation, learning, and transfer phases. This setup is crucial for further analysis and processing, providing the foundation for understanding the experimental data.

Data Processing

The data processing step involved initializing a counter to zero and then checking conditions within the DataFrame. Specifically, it counted the occurrences of a specific condition within the dataset, facilitating the identification of patterns or behaviors in the learning phase.

Data Overview

An overview of the partial learning DataFrame revealed the structure and content of the dataset. This DataFrame includes columns such as condition, stimuli positions, chosen actions, rewards, and reaction times, providing a comprehensive view of the experiment's data.
The dataset contains 10,500 rows and 8 columns, providing detailed records of the participants' interactions and responses throughout the learning phase of the experiment. Each row represents a single trial, capturing the conditions and decisions made by participants, as well as the corresponding feedback and reaction times.

Rate Calculation Function

The function calculate rates was implemented to compute the average rates of different options chosen by participants in the partial learning dataset. It iterates over the dataset, counting occurrences of each option and calculating average rates for each trial block. This process provides a detailed summary of participant choices across multiple trials. The resulting DataFrame contains the computed rates for each trial block, offering insights into the decision-making patterns of the participants.

Resulting Rates DataFrame

The calculate rates function produced a DataFrame summarizing the rates of each option chosen by the participants. This summary provides a clear view of how often each option was chosen during the trials, which is crucial for understanding the learning behavior of participants.

Computation of Rates per Trial

The function compute rates per trial was implemented to calculate the rates of options chosen by participants across different trials in the dataset. This function segments the data into smaller trial blocks and computes the rates for each block, offering a granular view of participant choices.

The function was applied to various datasets, including partial learning, partial transfer, complete learning, and complete transfer, resulting in summarized DataFrames for each dataset. The output of the function for each dataset is shown below:

- `partial learning` : 300 trials
- `partial transfer` : 24 trials
- `complete learning` : 360 trials
- `complete transfer` : 28 trials

Column Overview of Resulting DataFrames

An overview of the columns in the resulting DataFrames from compute rates per trial function shows a consistent structure across different datasets. The columns include:

- `ID`
- `Trial Block`
- `Count`
- `Opt1 Rate`
- `Opt2 Rate`
- `Opt3 Rate`
- `Opt4 Rate`

This structure ensures that the data is organized and easily comparable across different phases of the experiment.

Filtering and Aggregating Data

The next step involved filtering the learning rates partial and learning rates complete DataFrames to remove rows where both Opt1 Rate and Opt2 Rate are zero. This filtering ensures that only relevant data points are considered for further analysis. The filtered DataFrames were then sorted by Trial Block to facilitate aggregation. For each trial block, the mean rates of the options were calculated, resulting in an aggregated DataFrame that summarizes the average rates for each trial block. This aggregation provides a clearer picture of how the rates change over time across the trial blocks. The resulting aggregated DataFrames provide a comprehensive view of the average rates of options chosen by participants across different trial blocks, highlighting trends and patterns in the decision-making process.

Aggregated Data Overview

An overview of the aggregated data for the learning rates partial DataFrame shows the average rates for each option across the first few trial blocks. This summary highlights how participants' choices evolved over time.

- **Trial Block 0**: Opt1 Rate: 0.274, Opt2 Rate: 0.289, Opt3 Rate: 0.220, Opt4 Rate: 0.209
- **Trial Block 1**: Opt1 Rate: 0.291, Opt2 Rate: 0.291, Opt3 Rate: 0.209, Opt4 Rate: 0.203
- **Trial Block 2**: Opt1 Rate: 0.329, Opt2 Rate: 0.360, Opt3 Rate: 0.171, Opt4 Rate: 0.137
- **Trial Block 3**: Opt1 Rate: 0.337, Opt2 Rate: 0.371, Opt3 Rate: 0.163, Opt4 Rate: 0.129
- **Trial Block 4**: Opt1 Rate: 0.343, Opt2 Rate: 0.389, Opt3 Rate: 0.157, Opt4 Rate: 0.111

This detailed breakdown allows for an in-depth understanding of how learning and decision-making processes are reflected in the choices made by participants over the course of the experiment.

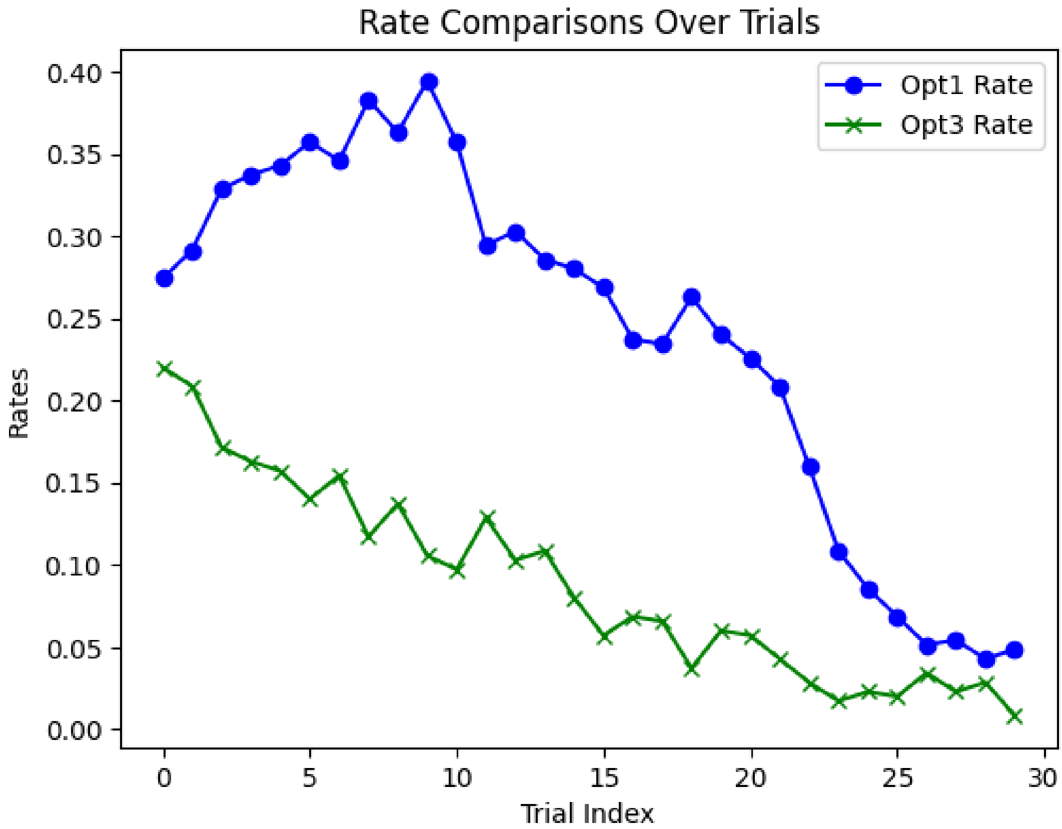

Figure 1: Rate Comparisons Over Trials

Rate Comparisons Over Trials

The figure below illustrates the comparison of rates for Opt1 and Opt3 over the trial blocks. This visual representation highlights the trends in participant choices for these options throughout the experiment. The plot shows that the rate for Opt1 increases initially, peaks around trial block 10, and then decreases. In contrast, the rate for Opt3 shows a steady decline over the trial blocks. This indicates that participants initially preferred Opt1 but gradually shifted away from it as the trials progressed.

Comparison of Opt2 and Opt4 Rates Across Trials

The figure below illustrates the comparison of rates for Opt2 and Opt4 over the trial blocks. This visual representation highlights the trends in participant choices for these options throughout the experiment. The plot shows that the rate for Opt2 increases initially, peaks around trial block 5, and then decreases. In contrast, the rate for Opt4 shows a steady decline over the trial blocks. This indicates that participants initially preferred Opt2 but gradually shifted away from it as the trials progressed, while the rate for Opt4 steadily decreased.

Rate Comparison of Opt1 and Opt3 Across Complete Data Trials

The figure below illustrates the comparison of rates for Opt1 and Opt3 across the complete data trials. This visual representation highlights the trends in participant choices for these options throughout the complete dataset. The plot shows that the rate for Opt1 fluctuates initially, with an overall increasing trend peaking around trial block 30, and then decreases sharply. In contrast, the rate for

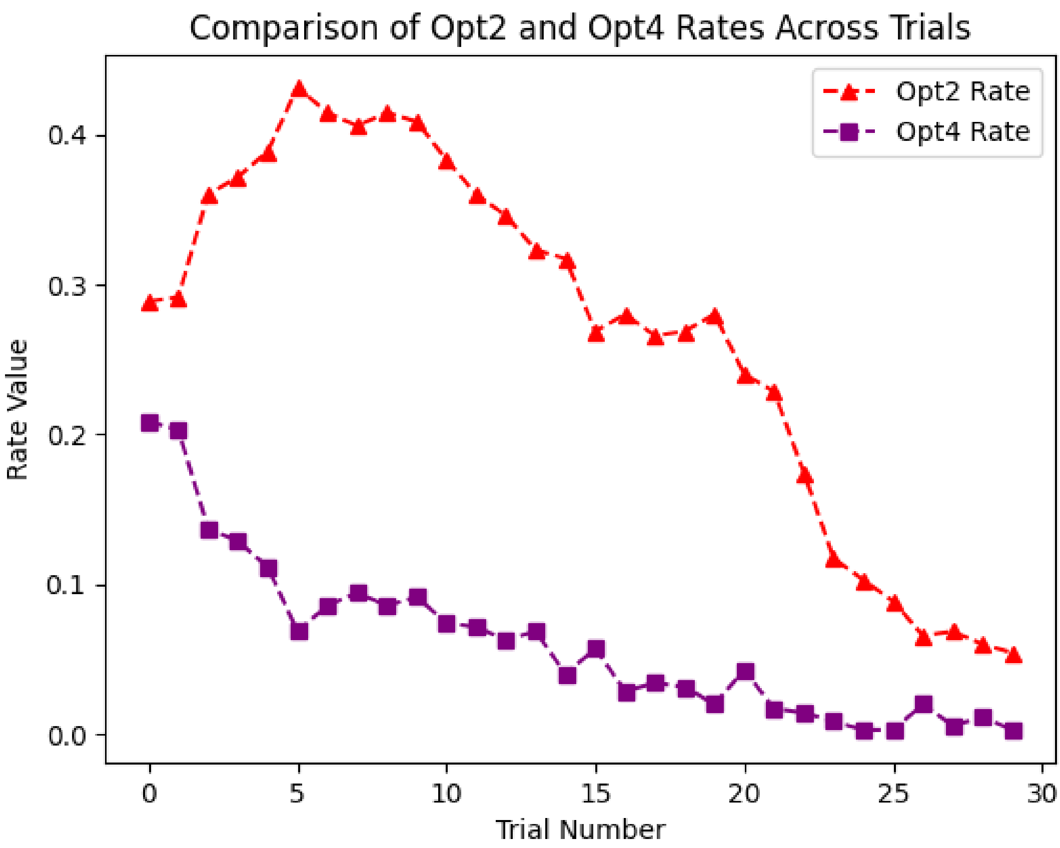

Figure 2: Comparison of Opt2 and Opt4 Rates Across Trials

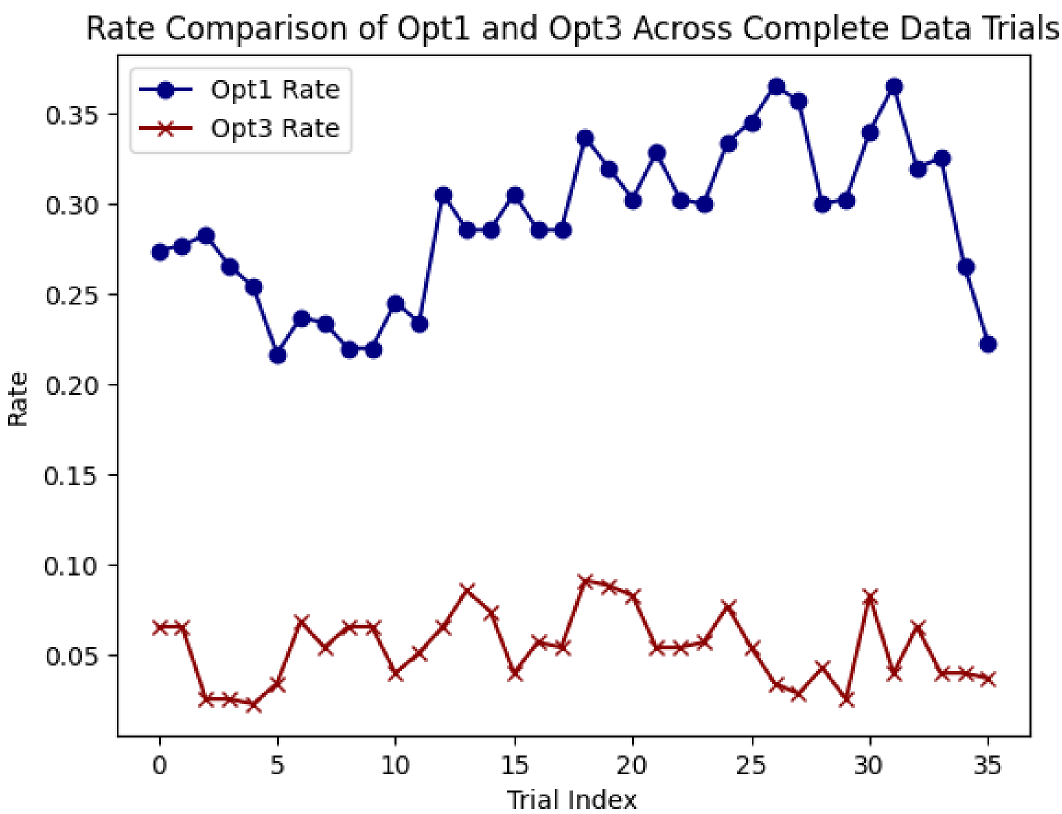

Figure 3: Rate Comparison of Opt1 and Opt3 Across Complete Data Trials

Opt3 remains relatively low with minor fluctuations throughout the trial blocks. This indicates that participants maintained a higher preference for Opt1 compared to Opt3 in the complete data trials.

Comparison of Opt2 and Opt4 Rates Over Complete Data Trials

The figure below illustrates the comparison of rates for Opt2 and Opt4 over the complete data trials. This visual representation highlights the trends in participant choices for these options throughout the complete dataset.

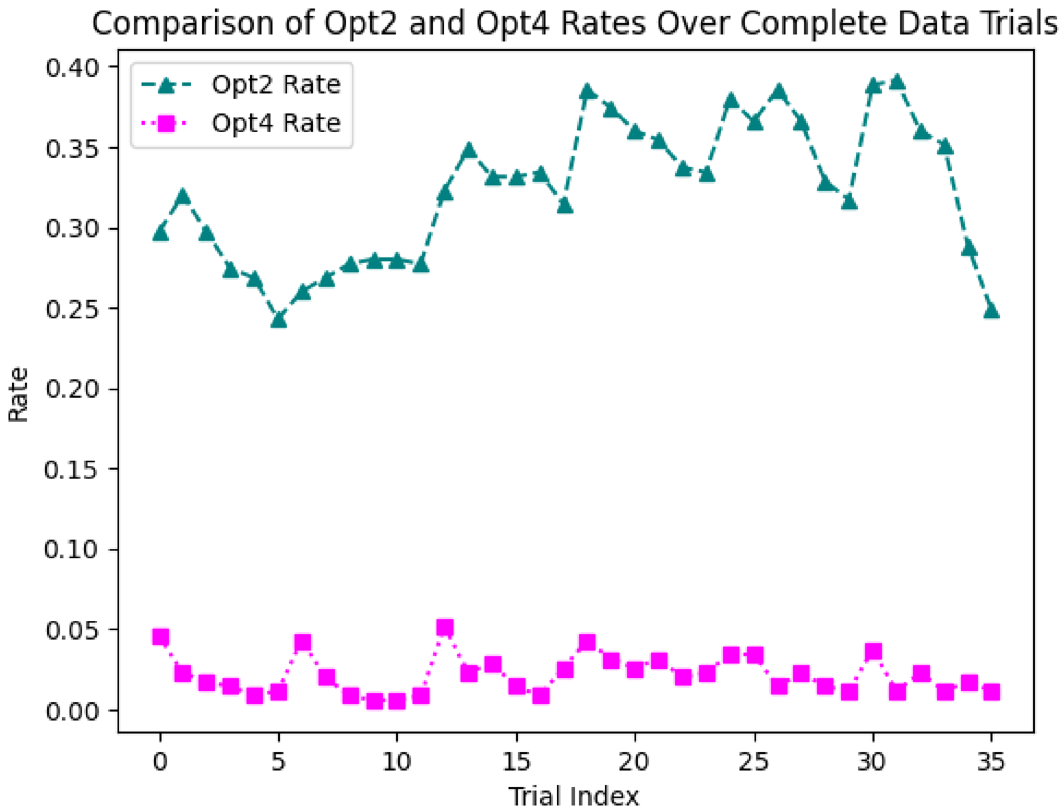

Figure 4: Comparison of Opt2 and Opt4 Rates Over Complete Data Trials

The plot shows that the rate for Opt2 increases initially, peaks around trial block 30, and then decreases. In contrast, the rate for Opt4 remains relatively low with minor fluctuations throughout the trial blocks. This indicates that participants maintained a higher preference for Opt2 compared to Opt4 in the complete data trials.

Average Rates Comparison for Partial Data

The figure below illustrates the average rates comparison for Opt1, Opt2, Opt3, and Opt4 in the partial dataset. This visual representation highlights the mean rate values for each option, providing insights into the overall preferences of the participants in the partial data trials.

The plot shows that Opt2 has the highest average rate, followed by Opt1, Opt3, and Opt4. This indicates that participants in the partial data trials had a stronger preference for Opt2 and Opt1 compared to Opt3 and Opt4.

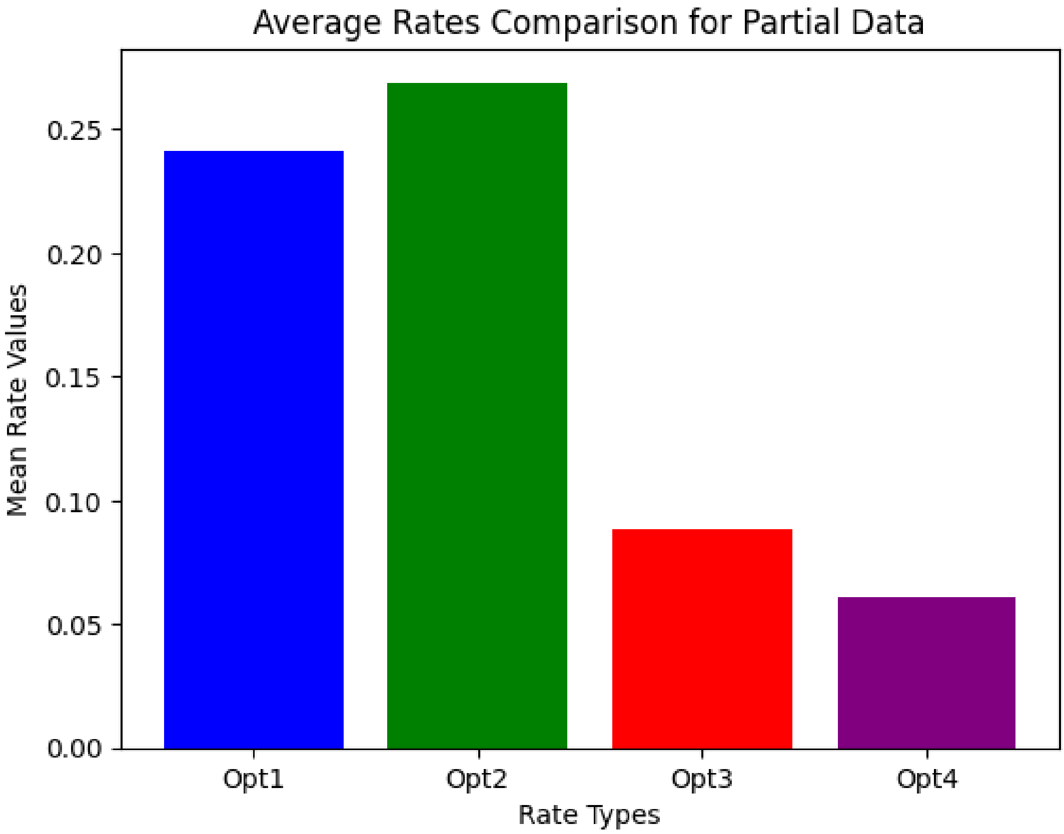

Figure 5: Average Rates Comparison for Partial Data

Average Rates Comparison for Complete Data

The figure below illustrates the average rates comparison for Opt1, Opt2, Opt3, and Opt4 in the complete dataset. This visual representation highlights the mean rate values for each option, providing insights into the overall preferences of the participants in the complete data trials. The plot shows that Opt2 has the highest average rate, followed by Opt1, Opt3, and Opt4. This indicates that participants in the complete data trials also had a stronger preference for Opt2 and Opt1 compared to Opt3 and Opt4.

Learning Rates with Standard Deviation as Confidence Interval

The figure below illustrates the bar plot of learning rates for the partial dataset, with the standard deviation as the confidence interval. This visual representation provides insights into the variability and spread of the learning rates across different options.

The plot shows that Opt2 has the highest average rate with the largest standard deviation, followed by Opt1, Opt3, and Opt4. This indicates that there is considerable variability in the learning rates for Opt2 and Opt1 in the partial dataset.

Complete Learning Rates with Standard Deviation as Confidence Interval

The figure below illustrates the bar plot of learning rates for the complete dataset, with the standard deviation as the confidence interval. This visual representation provides insights into the variability and spread of the learning rates across different options. The plot shows that Opt2 has the highest average rate with the largest standard deviation, followed by Opt1, Opt3, and Opt4. This indicates that there is considerable variability in the learning rates for Opt2 and Opt1 in the complete dataset.

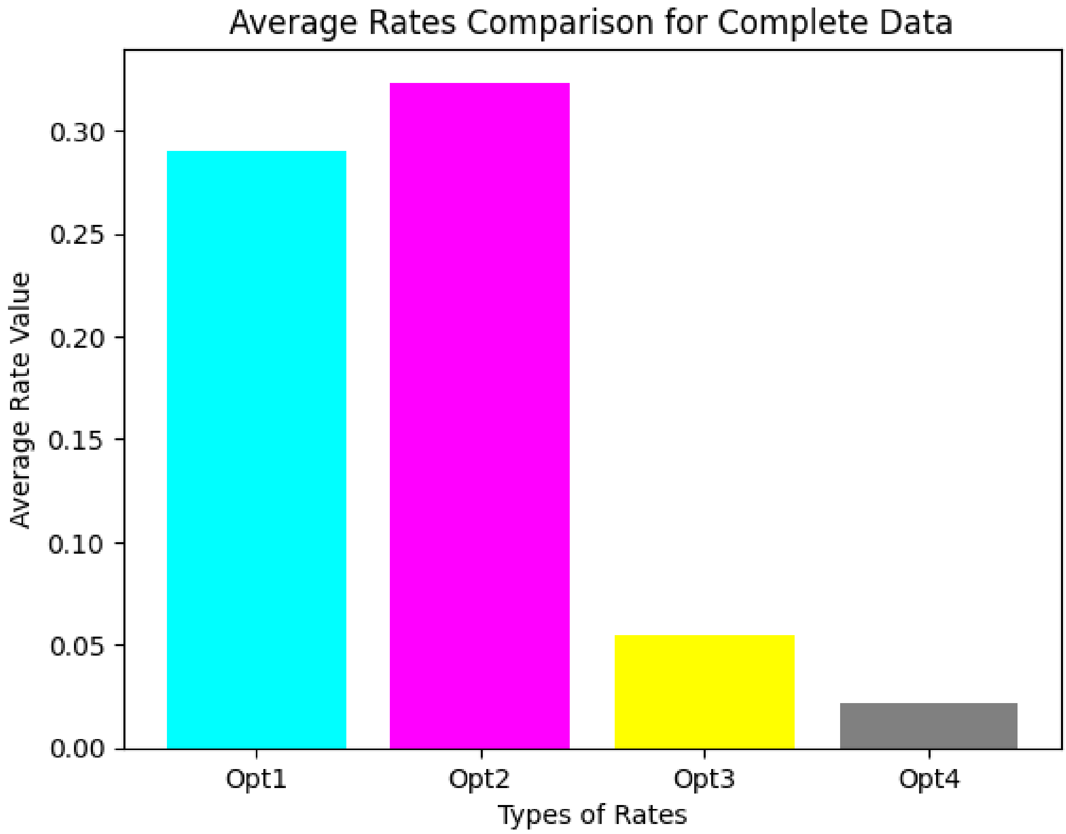

Figure 6: Average Rates Comparison for Complete Data

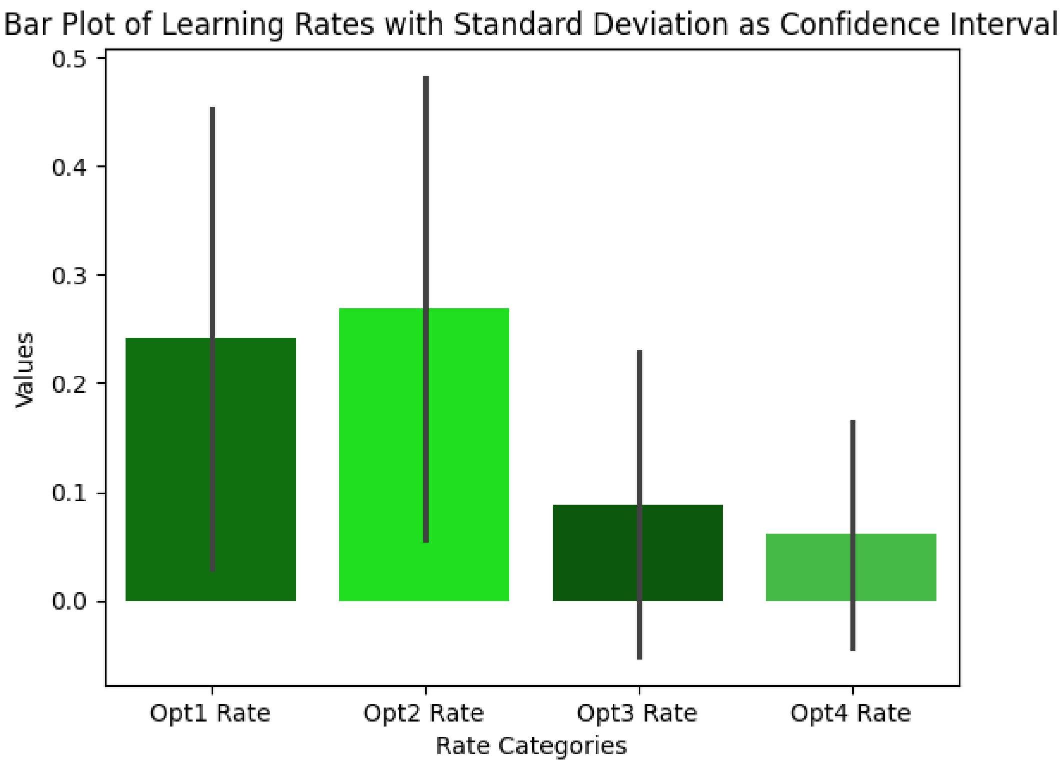

Figure 7: Bar Plot of Learning Rates with Standard Deviation as Confidence Interval

Partial Learning Rates Overview

The figure below illustrates the bar plot of partial learning rates. This visual representation highlights the average rate values for Opt1, Opt2, Opt3, and Opt4, providing insights into the overall learning

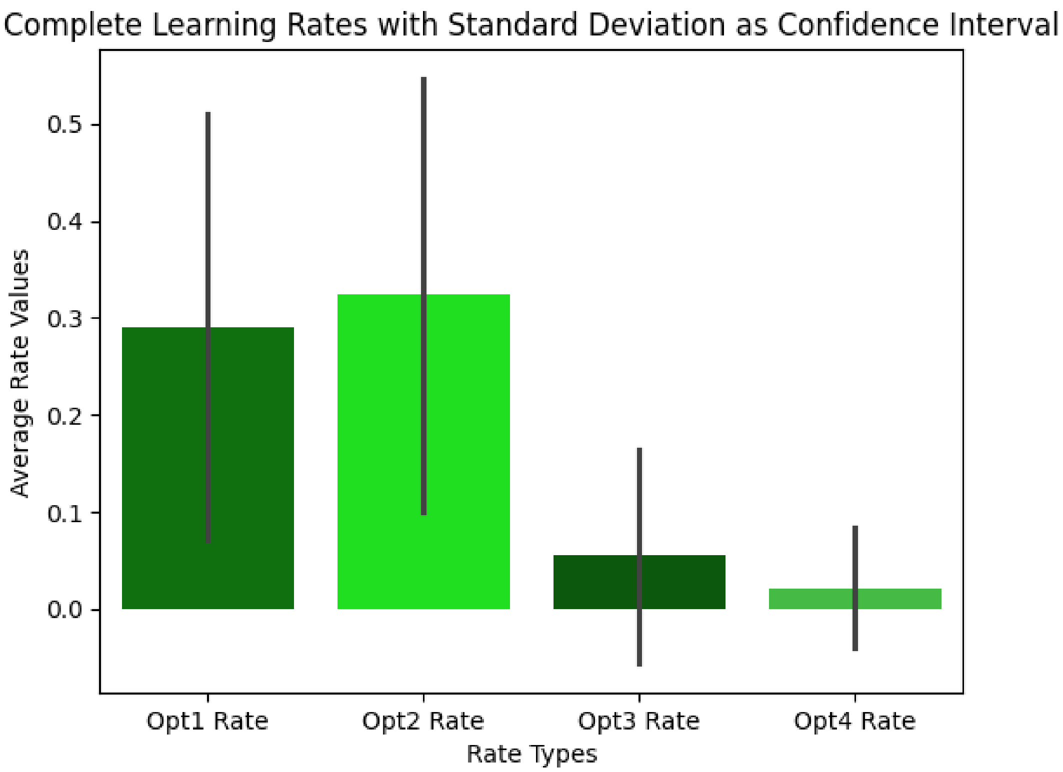

Figure 8: Complete Learning Rates with Standard Deviation as Confidence Interval

behavior of participants in the partial data trials.

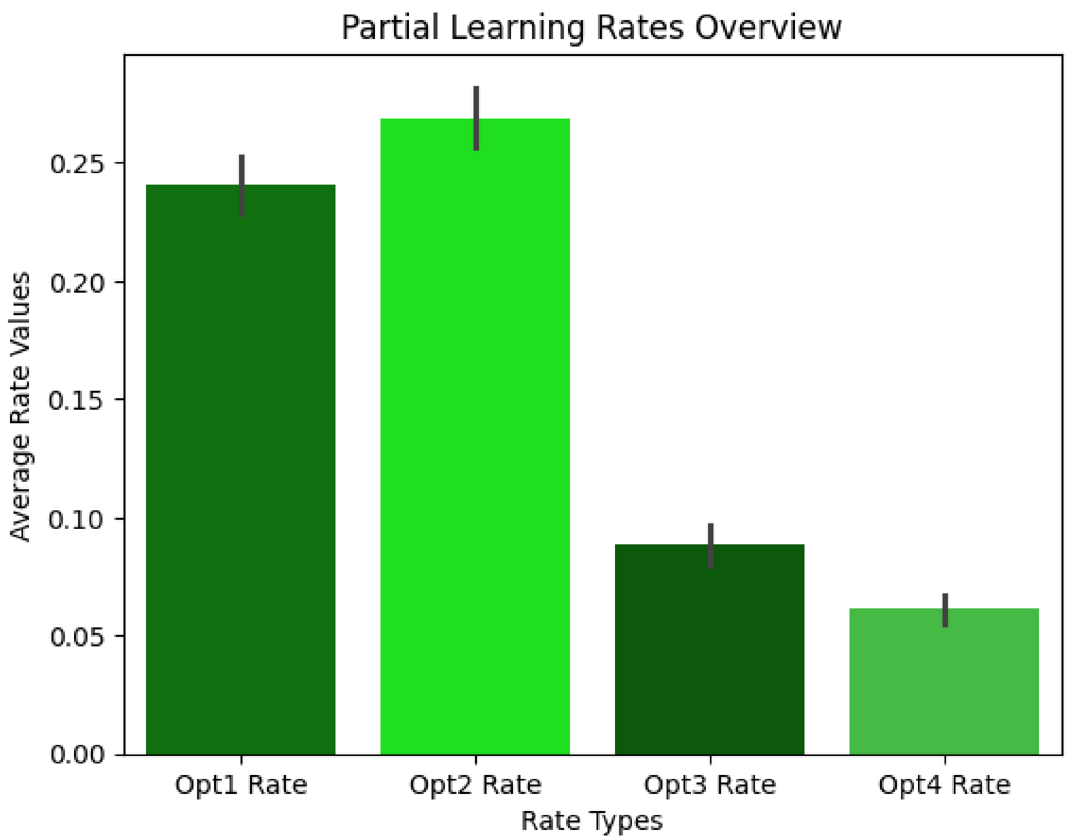

Figure 9: Partial Learning Rates Overview

The plot shows that Opt2 has the highest average rate, followed by Opt1, Opt3, and Opt4. This indicates that participants had a stronger preference for Opt2 and Opt1 compared to Opt3 and Opt4 in the partial learning trials.

Complete Learning Rates Overview

The figure below illustrates the bar plot of complete learning rates. This visual representation highlights the average rate values for Opt1, Opt2, Opt3, and Opt4, providing insights into the overall learning behavior of participants in the complete data trials.

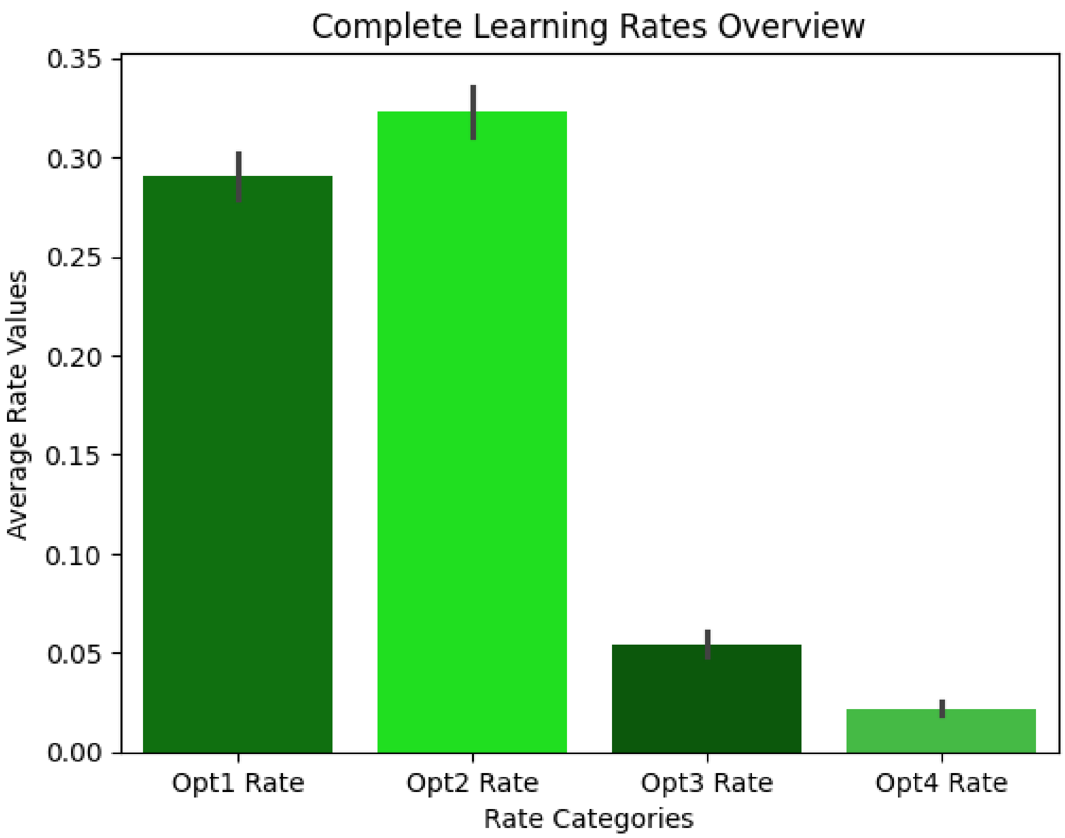

Figure 10: Complete Learning Rates Overview

The plot shows that Opt2 has the highest average rate, followed by Opt1, Opt3, and Opt4. This indicates that participants had a stronger preference for Opt2 and Opt1 compared to Opt3 and Opt4 in the complete learning trials.

Average Rates Comparison for Partial Data

The figures below illustrate the average rates comparison for Opt1, Opt2, Opt3, and Opt4 in the partial dataset. These visual representations highlight the mean rate values for each option, providing insights into the overall preferences of the participants in the partial data trials.

The plots consistently show that Opt2 has the highest average rate, followed by Opt1, Opt3, and Opt4. This indicates that participants in the partial data trials had a stronger preference for Opt2 and Opt1 compared to Opt3 and Opt4.

Average Rates Comparison for Complete Data

The figure below illustrates the average rates comparison for Opt1, Opt2, Opt3, and Opt4 in the complete dataset. This visual representation highlights the mean rate values for each option, providing insights into the overall preferences of the participants in the complete data trials. The plot

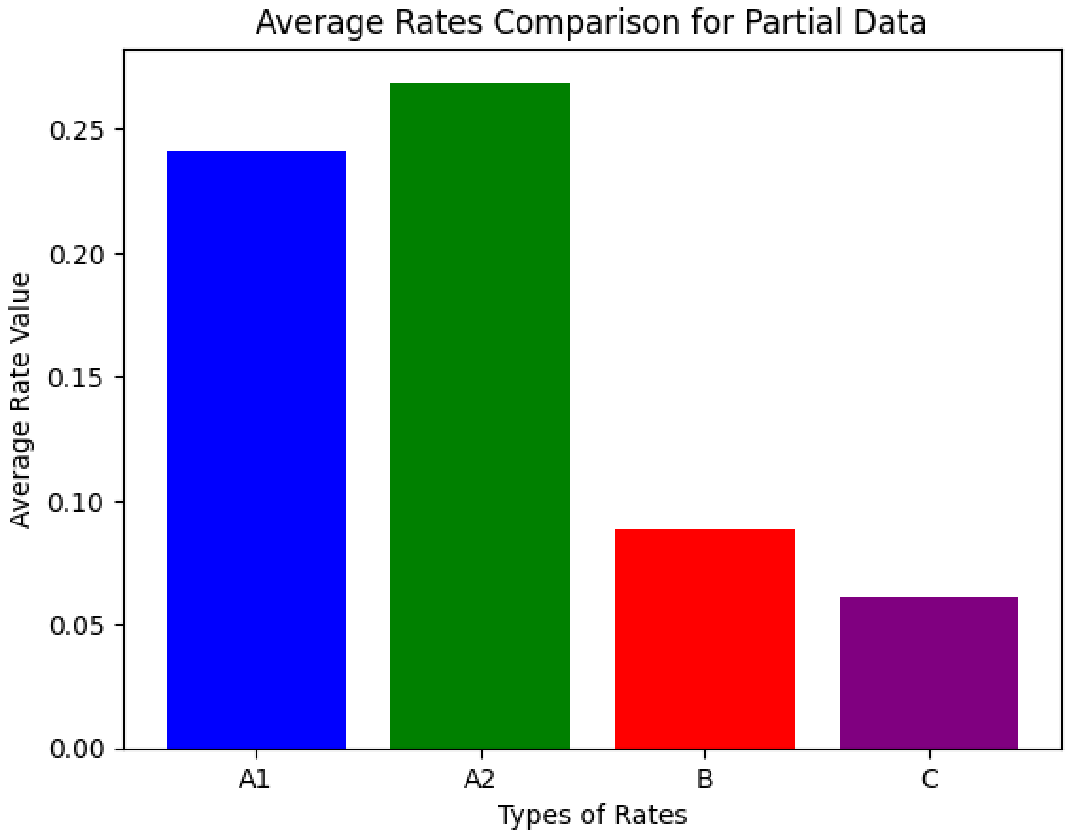

Figure 11: Average Rates Comparison for Partial Data (Figure 1)

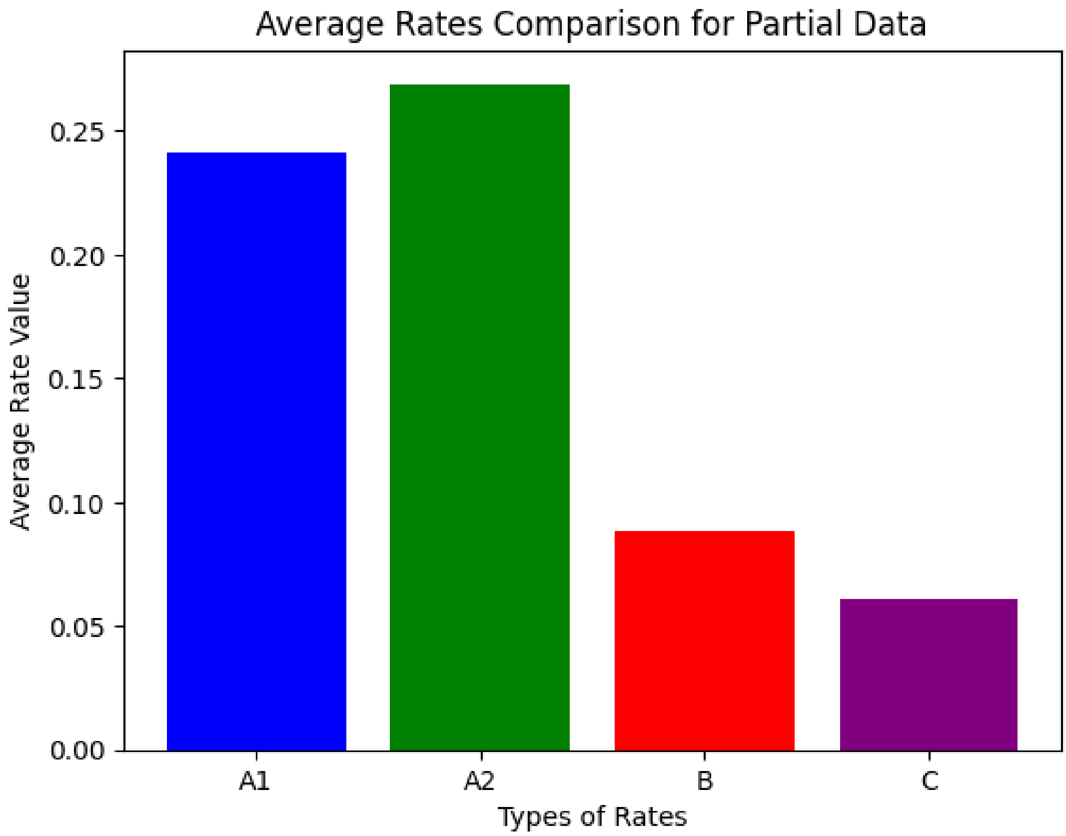

Figure 12: Average Rates Comparison for Partial Data (Figure 2)

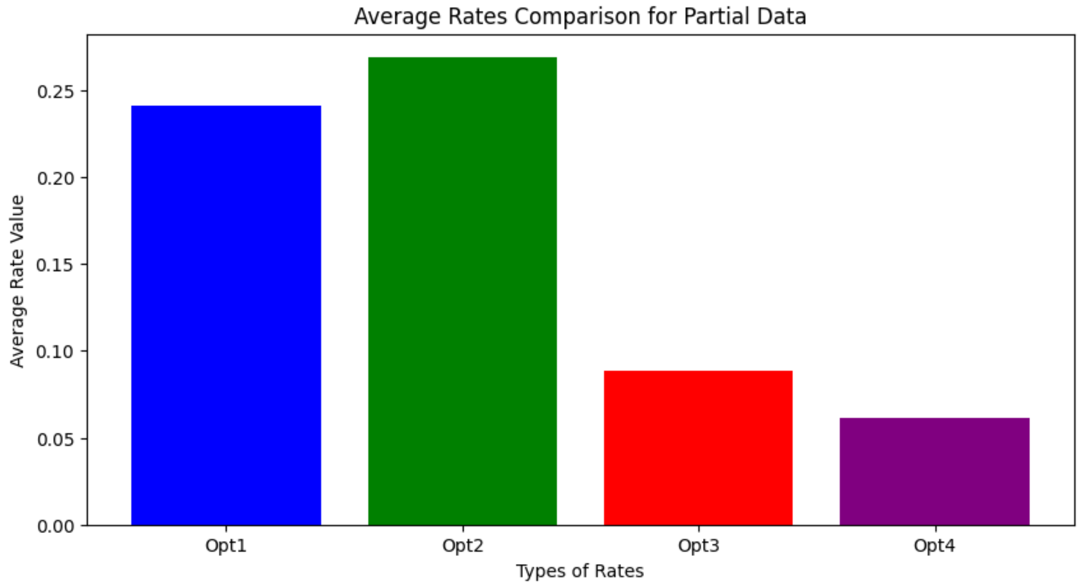

Figure 13: Average Rates Comparison for Partial Data (Figure 3)

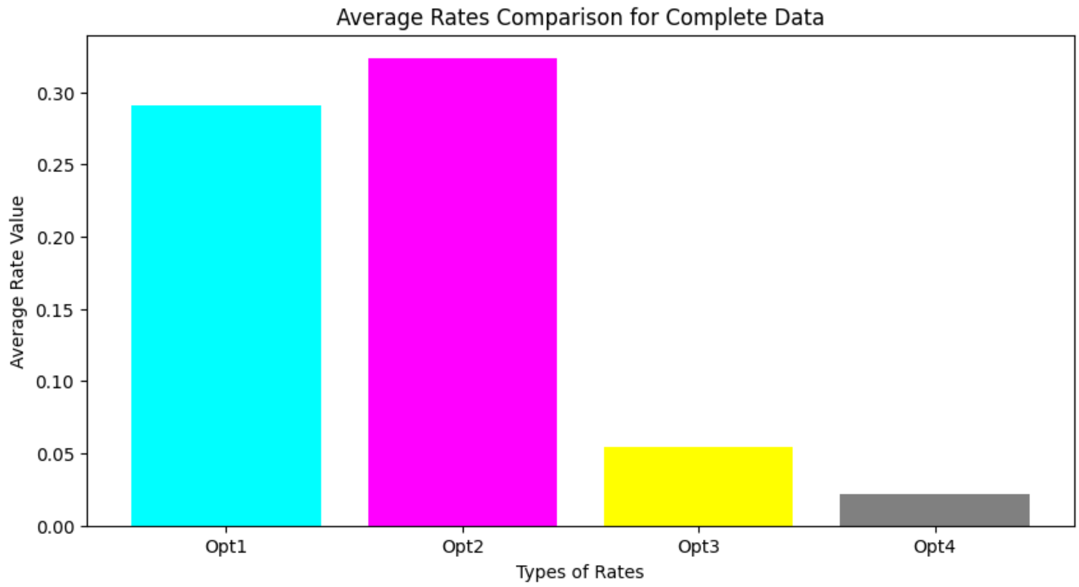

Figure 14: Average Rates Comparison for Complete Data

shows that Opt2 has the highest average rate, followed by Opt1, Opt3, and Opt4. This indicates that participants in the complete data trials also had a stronger preference for Opt2 and Opt1 compared to Opt3 and Opt4.

Statistical Analysis and Comparison

T-Test Analysis

To compare the learning rates for Opt1 and Opt2, a t-test was conducted for both the partial and complete datasets. The results are summarized below:

- **Partial Data**:
  - **T-statistic**: -0.9114
  - **P-value**: 0.3658

- **Complete Data**:
  - **T-statistic**: -3.2253
  - **P-value**: 0.0019

The difference in p-values between the partial and complete datasets is 0.3639, indicating a significant difference in learning rates between the two datasets.

Binomial Distribution Analysis

For the partial dataset, the binomial distribution was analyzed based on the mean rate values of Opt1 and Opt2. The following statistics were computed:

- **Partial Data**:
  - **Mean**: 0.0
  - **Variance**: 0.0
  - **Skewness**: ∞
  - **Kurtosis**: $-\infty$
- **Complete Data**:
  - **Binomial Mean**: 0.0648
  - **Difference in Binomial Means**: 0.0291

Variance Analysis

The variance of learning rates for Opt1, Opt2, Opt3, and Opt4 was calculated for the partial dataset:

- **Variance Opt1**: 0.0122
- **Variance Opt2**: 0.0146
- **Variance Opt3**: 0.0035
- **Variance Opt4**: 0.0029

Confidence Interval Calculation

The 95% confidence intervals for the difference in mean rates between Opt1 and Opt2 were calculated for both datasets:

- **Partial Data**:
  - **Confidence Interval**: (-0.0886, 0.0332)
- **Complete Data**:
  - **Confidence Interval**: (-0.0534, -0.0126)

These analyses provide a comprehensive understanding of the statistical differences and variability in learning rates between the partial and complete datasets.

Part 2: Behavioral Contagion Learning About Another Agent's Risk-Preferences Acts on the Neural Representation of Decision-Risk

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- **John P. O'Doherty** - Co-author, Computation and Neural Systems, California Institute of Technology, Pasadena, CA 91125.

Introduction

Understanding the neural mechanisms behind risk-taking behavior is pivotal across various fields including psychology, neuroscience, and behavioral economics. This study delves into behavioral contagion, where observing another individual's risk-taking behavior influences one's own risk preferences. Employing neuroimaging and computational modeling, this research aims to elucidate the neural foundations of this influence.

The experimental design involved 24 participants and utilized a series of trials to simulate decision-making under different risk conditions. The participants underwent three types of trials—Self, Observe, and Predict—each structured to provide insights into how individuals' risk preferences and decision-making strategies adjust when exposed to the behaviors of others.This research utilizes a mixed-methods approach, incorporating sessions that varied the risk conditions (risk-averse versus risk-seeking) observed by the participants. Such a design allows for a detailed analysis of how risk preferences might be contagiously altered, thereby modifying an individual's own neural assessment of risk.

The findings from this study offer significant implications for understanding the social components of economic decision-making. By analyzing the neural correlates of observed decisions, the research demonstrates that risk preferences are dynamically influenced through social interaction. This revelation holds profound implications for behavioral economics, psychology, and neuroeconomics, providing deeper insights into the factors that modulate decision-making processes.

Significance

Understanding why individuals engage in risky behavior at certain times and avoid it at others is crucial for various fields such as psychology, neuroscience, and behavioral economics. This study explores one potential mechanism for this variability: behavioral contagion. Behavioral contagion refers to the phenomenon where observing another individual's risk-taking behavior influences one's own risk preferences. By using neuroimaging combined with computational modeling, this study aims to identify the neural basis of this effect.

Methodology

The study is divided into five sessions, each designed to assess different aspects of risk preference contagion. Participants undergo multiple trials in which they either make decisions about gambles themselves, observe another person making similar decisions, or predict the choices of the observed person. Neuroimaging data is collected throughout the sessions to identify the brain regions involved in processing these decisions and their changes due to observed behavior.

Sessions and Tasks

Session 1: Self Trials

- **Description:** Participants make decisions on whether to accept or reject gambles. The gambles involve different probabilities and magnitudes, represented by pie charts. The range is random with probabilities varying from 0.2 for $60 to 1 for $10. Additionally, two 100% probabilities are interspersed to ensure proper engagement.
- **Number of Trials:** 28 Self Trials

Session 2: Mixed Trials (Risk-Averse)

- **Description:** Participants go through a series of blocks containing different trial types: Self Trials, Observe Trials (observing another person's choices), and Predict Trials (predicting the choices of another person). The observed individual exhibits risk-averse behavior. The sequence and authenticity of trials are manipulated to ensure control over exposure effects.
- **Number of Trials:**
  - 6 Predict Trials
  - 14 Observe Trials
  - 14 Self Trials
  - 14 Observe Trials
  - 14 Self Trials
  - 6 Predict Trials
  - 14 Observe Trials
  - 14 Self Trials
  - 14 Observe Trials
  - 14 Self Trials
  - 6 Predict Trials

Session 3: Self Trials

- **Description:** Similar to Session 1, participants make decisions about accepting or rejecting gambles.
- **Number of Trials:** 28 Self Trials

Session 4: Mixed Trials (Risk-Seeking)

- **Description:** Similar structure to Session 2, but the observed individual exhibits risk-seeking behavior.
- **Number of Trials:**
  - 6 Predict Trials
  - 14 Observe Trials
  - 14 Self Trials
  - 14 Observe Trials
  - 14 Self Trials
  - 6 Predict Trials
  - 14 Observe Trials
  - 14 Self Trials
  - 14 Observe Trials
  - 14 Self Trials
  - 6 Predict Trials

Session 5: Self Trials

- **Description:** Similar to Sessions 1 and 3, participants make decisions about accepting or rejecting gambles.
- **Number of Trials:** 28 Self Trials

Analysis of Decision-Making in Risky Choices

Data Preparation

Data from the experiment were loaded from a MATLAB file and processed using Python libraries such as *pandas* and *scipy*. The data set included several variables such as participants' choices, the associated probabilities, and potential rewards from risky and sure bets across different sessions. The sessions of interest for this analysis were sessions 1, 3, and 5, which focused primarily on decisions made by participants under varying conditions of risk.

Data Analysis

Initial Data Exploration

The analysis began with calculating the expected values and variances for each gamble based on its potential rewards and associated probabilities. This was crucial for understanding the decision-making process under risk.

Initial exploration included fitting a linear regression model to assess the impact of variance on the decision-making process, where the coefficient provided an estimate of risk aversion.

Utility Function Estimation

Utility functions were employed to model the cognitive processes underlying participants' choices. The first utility function considered was a linear combination of expected value and variance, where the coefficient on variance (α) indicated the degree of risk sensitivity. This parameter was estimated to be 0.01658870834858681, suggesting a modest level of risk aversion.

A more complex utility function incorporating non-linear preferences over rewards was also fitted. This function included a parameter (ρ) to model the curvature of the utility function, estimated using non-linear curve fitting methods. The estimated value of ρ was 0.03940693339307776, further characterizing the non-linear dynamics in participants' utility calculations.

Probabilistic Decision-Making Models

To understand how participants weighed the potential gains from gambles against sure rewards, logistic regression models were used. These models incorporated utility-based and exponential transformations of the gamble and sure outcomes to predict choice probabilities. Parameters such as α (risk preference) and β (decision noise) were estimated using optimization techniques to minimize the negative log-likelihood of observed choices. The final estimates were $\alpha = -0.02006520876590465$ and $\beta = 0.37176937949104827$, indicating a slight risk aversion and moderate decision consistency.

An exponential version of the utility function was also tested, where the risk preference parameter ρ was estimated to be approximately 0.9895621248468565, and β was 0.36848919454476714. This suggests that as the potential reward increases, the subjective value of the reward increases nearly linearly, indicating near-risk-neutral behavior.

Risk Preference Analysis

The overall risk preference was further quantified without the use of a model by comparing the average choice probability against a risk-neutral benchmark (0.5). The calculated value of -0.12767094017094016 indicates a general trend of risk aversion across participants, as the average choice probability of taking a risky gamble was less than the risk-neutral probability.

The comprehensive analysis suggests that while participants exhibit a baseline level of risk aversion, their responses to risk are influenced by both the variance and potential rewards of the options. The models fitted provide insights into the cognitive mechanisms participants use to evaluate risky choices, indicating a complex interplay between risk perception, potential rewards, and decision consistency. These findings contribute significantly to understanding decision-making processes in economic and psychological contexts.