EFFECT OF VARYING COMPUTATIONAL LOAD ON HOW PEOPLE EXPLORE AND RESPOND TO UNCERTAINTY

BSE662A: Decision Making and the Brain

Group G12

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End-sem Report

Introduction

In today's fast-moving world, it's super important to understand how people make decisions when they're short on time and unsure about what to do. This report is about how time pressure, like deadlines, and having a lot to think about at once, which we call computational load, affect our decisions. We're particularly interested in how these things influence how we explore different options and deal with uncertainty. Our main goal is to see how time pressure and computational load affect decision-making when things aren't clear. We're using a multi-armed bandit task game to mimic real-life decisions and see how people change their strategies under pressure. By observing how individuals adapt their approach when faced with cognitive constraints, we aim to shed light on the underlying mechanisms driving decision-making.

The importance of studying decision-making under various cognitive loads and time constraints cannot be overstated. Such research holds significant implications across diverse domains, from business and finance to healthcare. By unraveling the complexities of exploration-exploitation dilemmas in decision-making, we gain valuable insights into human behavior that can inform the design of effective decision-support systems and interventions.

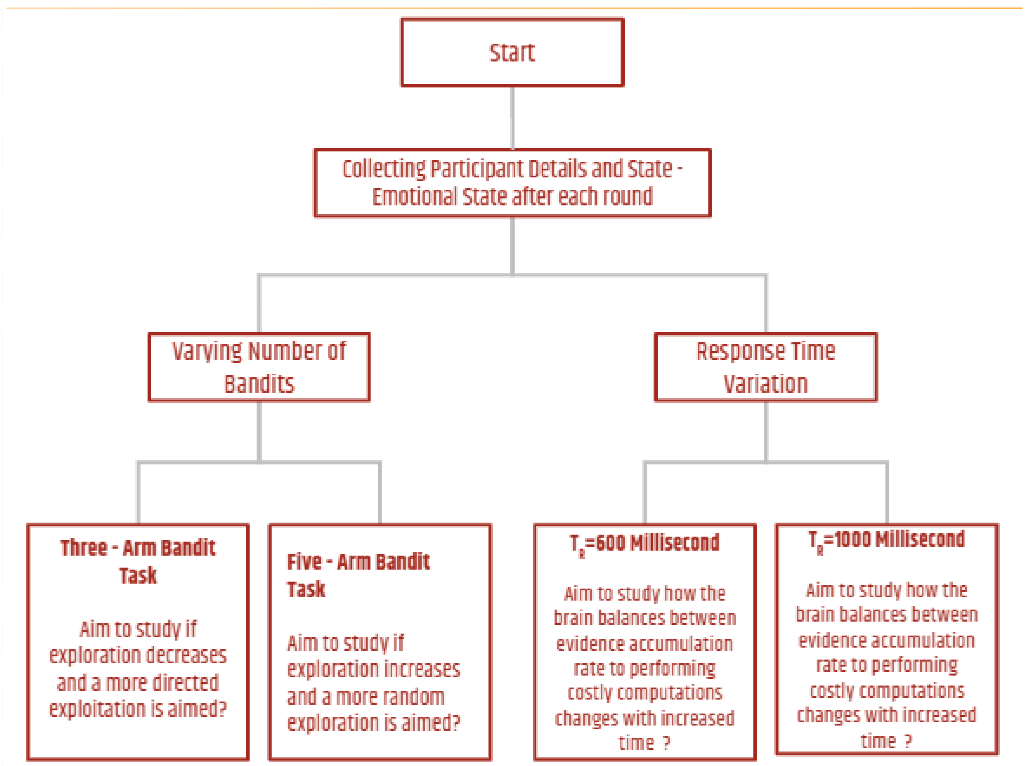
To help us with our research, we're using a computer program written in Python for the multi-armed bandit task. This program lets us create realistic decision-making scenarios and collect data from participants to analyze later. This model allows us to make controlled decision-making scenarios and collect data efficiently, enabling rigorous analysis of participant responses. By leveraging technology in this manner, we aim to capture nuanced nuances in decision-making behavior and discern patterns that may not be immediately evident.

Our study builds upon the foundation laid by previous research in the field. While past studies have often focused on individual factors such as time pressure or reward expectations, our approach seeks to integrate these elements, offering a more comprehensive understanding of decision-making processes. We aim to provide a holistic view of decision-making under cognitive constraints by examining the combined effects of time pressure and computational load.

In decision-making research, people usually focus on one thing at a time, like time pressure or how much stuff someone has to think about. But real life isn't that simple. We're trying something different by looking at how time pressure and having a lot to think about at once, which we call computational load, work together. This gives us a better understanding of how people deal with tough choices. We want to learn more about how people handle uncertainty and make decisions by studying how these factors interact.

Experimental Design: the Python setup

The Three-Arm Bandit Task aims to see if exploitation becomes more focused and less exploratory. In this task, participants are presented with three options, each with a different reward probability. Different time pressure conditions are introduced via varying response times, which affects how decisions are made. The Five-Arm Bandit Task aims to find out if more random exploration is preferred or if exploration increases. As in the Three-Arm Bandit Task, participants must choose from five options with varying reward odds. Once more, response times are adjusted to produce various time constraints, which modifies decision-making dynamics.



Experiment Workflow

Let's explore the circumstances mentioned:

1) 3-arm Bandit, 6–40 rounds: This condition probably intends to investigate how participants modify their decision-making tactics during several rounds with comparatively faster response times (TR=600 ms). Participants may first explore choices with fewer arms and a reasonable number of rounds, but as they gain more experience, they will eventually gravitate towards utilizing the most lucrative arm.

2) 5-arm Bandit, 6–40 rounds, examines how to make decisions in a more complicated setting with five alternatives. Because there are more arms, participants may explore more despite shorter response times (TR=600 milliseconds). This could result in more diverse choice patterns throughout the rounds.
3) 3-arm Bandit, 10–40 rounds: This condition aims to determine how participants balance exploration and exploitation over a longer time span by increasing the number of rounds while keeping the same response time (TR=600 milliseconds). If there are more rounds, players might have more chances to hone their decision-making techniques and show an earlier or more gradual trend toward exploitation.
4) 10–40 rounds, 5-arm bandit: Like the prior condition, this scenario has five possibilities and a more extended period. Participants may navigate the bigger choice area under time pressure, resulting in various exploration patterns, given the additional rounds and shorter response times (TR=600 milliseconds).

This design aimed to look into how decision-making processes should balance exploitation with exploration. On the other hand, the Time Bandit Task is a novel experimental design involving participants making choices using various keyboard keys, with each round's unique mappings. They finished 40 rounds, with 20 tries in each round. Time pressure and payment conditions are crossed and manipulated within the same subject in this design. Participants were given two options for manipulating time pressure: limited time rounds, where they were limited to 400 milliseconds for every selection, or unlimited time rounds, where they could take as much time as they wished for each selection. If participants exceeded the allotted time, negative feedback was delivered in time-limited rounds, while positive input was offered in unlimited time rounds. Inputs during the 400 millisecond feedback periods did not affect the subsequent trial. Both experiments investigate decision-making dynamics under various time constraints; however, the latter adds a more subtle manipulation of time constraints within a particular task paradigm, which balances the more general investigation in the first experiment.
The emotional value was assessed on a scale of -5 to 5 before the game started.-5 signified lousy mood, while 5 meant good mood. Subsequently, our objective was to explore potential differences in responses between individuals experiencing positive versus negative moods. Through meticulous analysis, we aimed to uncover the impact of emotional states on decision-making dynamics. This study delves deeply into the complex relationship between mood and response speed, offering valuable insights into the psychological nuances that shape decision tasks. By understanding these factors, we can better grasp the intricacies of human behavior in various contexts.

Data Collection :

To collect data for our study, we employed a systematic approach to capture various aspects of participants' decision-making behavior.

Game Setup and Environment: Participants played a Python-based game involving a three-armed and five-armed bandit task. They were instructed to choose between different sets of keys (Q, W, E and Q, W, E, R, T) and press them according to the game's instructions. All participants played the game in a controlled environment on the same device to ensure consistency. This approach aimed to minimize external factors that could influence decision-making.

Recording Decisions and Response Times: Throughout the game, we recorded every choice made by participants and the corresponding response times. This data provided insights into the speed and efficiency of decision-making under different conditions of time pressure and computational load. We aimed to capture participants' choices and how quickly they made them, allowing for a comprehensive analysis of decision-making strategies.

Emotional State Assessment: Besides recording decisions and response times, we asked participants to rate their emotional state before and after each game round on a scale of -5 to 5. This assessment provided valuable information about the emotional context in which decisions were made. By understanding how participants' emotional states fluctuated throughout the game, we could explore potential links between mood and decision-making behavior.

Reward System and Score Tracking: Each key press in the game generated a reward, contributing to participants' total scores. We meticulously tracked these scores to assess participants' performance and reward maximization strategies. By analyzing the relationship between crucial choices, rewards earned, and total scores, we gained insights into how participants approached decision-making tasks and sought to optimize their outcomes.

Uniformity and Familiarization: We implemented several measures to ensure uniformity and minimize data collection variability. Firstly, we ran trial rounds for each participant to familiarize them with the game mechanics and ensure they understood the task requirements. Additionally, participants were instructed to use their dominant hand for key presses to maintain consistency across trials.

Data Storage and Organization: All data collected during the study, including participants' choices, response times, emotional state ratings, and total scores, were meticulously recorded and stored in a structured Excel file. This organized approach facilitated subsequent analysis by allowing for easy retrieval and comparison of data points across participants and experimental conditions.

Implementing these data collection procedures, we aimed to gather comprehensive and reliable data to support our analysis of decision-making behavior under time pressure and computational load. These measures ensured that our study captured the intricacies of decision-making processes in a controlled and systematic manner, laying the groundwork for meaningful insights and interpretations.

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Data Analysis :

Expected observation:

1. Response Time:
   - In all scenarios, participants are operating under time pressure (TR=600 milliseconds). Participants are likely to make faster decision-making overall.
   - As participants become more familiar with the task and the number of rounds increases, they might exhibit a slight decrease in response time due to improved decision-making efficiency.
   - In the 3-arm Bandit scenarios, participants might have slightly quicker response times compared to the 5-arm Bandit scenarios, as they have fewer options to consider.

2. Learning Rate for High Reward Arm:
   - Initially, participants might explore all arms to understand their reward probabilities.
   - Over time, especially in scenarios with a higher number of rounds, participants are likely to learn the reward probabilities of each arm more accurately.
   - In the 3-arm Bandit scenarios, participants might learn the high reward arm relatively quickly, especially in the shorter rounds, leading to earlier exploitation.
   - In the 5-arm Bandit scenarios, due to the increased complexity, participants might take longer to identify and exploit the high reward arm compared to the 3-arm Bandit scenarios.

3. Exploration to Exploitation Time:
   - Initially, participants might engage in exploration, trying out different arms to gather information about their reward probabilities.
   - As participants gain experience, they are expected to transition from exploration to exploitation, focusing more on selecting the arm with the highest expected reward.
   - In scenarios with more rounds (10–40 rounds), participants might have a longer exploration phase before shifting towards exploitation, as they have more time to gather information and refine their decision-making strategies.
   - In scenarios with a higher number of arms (5-arm Bandit), participants might exhibit a more prolonged exploration phase due to the increased complexity of the decision-making environment.

Overall, these trends suggest that the interplay between response time, learning rate, and exploration-exploitation dynamics would likely vary based on the specific conditions of the experiment, such as the number of arms and rounds available to participants.

4. Repeat choices

- Repeated choices are expected to be higher in rounds with lesser time experimental condition (600 ms) and higher computational load - 5 arm.

Our Analysis:

Analysis for Response time variations;

In the context of the experimental conditions involving 3-arm and 5-arm bandit tasks with response times set at 600 milliseconds and 1000 milliseconds, discernible trends emerged regarding participants' average response times and the slope of the core-time plot. Notably, the average response time was observed to be elevated for the 5-arm task compared to the 3-arm task, irrespective of the response time constraint, thus indicating a consistent pattern across varying task complexities. Furthermore, analysis of the slope of the core-time plot revealed a notably steeper gradient for both response time conditions in the 1000 milliseconds case. This inclination suggests a more rapid accumulation of decision-related information over time compared to the 600 milliseconds case. These findings collectively underscore the nuanced interplay between task complexity, response time constraints, and the rate of information accumulation, elucidating fundamental aspects of cognitive processing and decision-making dynamics in uncertain environments.

Analysis for drift rate;

In the examination of drift rates within the experimental paradigm encompassing 3-arm and 5-arm bandit tasks under varying response time conditions, distinct observations emerged regarding the impact of response time on drift rates across task complexities. Specifically, in the 3-arm task, the drift rate exhibited a discernible acceleration when subjected to the 1000 milliseconds response time constraint compared to the 600 milliseconds counterpart. Conversely, in the 5-arm task, the drift rate demonstrated minimal variance between the two response time conditions. This discrepancy suggests that while response time constraints exert a notable influence on the drift rate in simpler decision-making contexts, such as the 3-arm task, their effect diminishes in more complex environments, such as the 5-arm task.

One plausible explanation for this phenomenon could be linked to cognitive resource allocation. In simpler tasks with fewer alternatives, participants may allocate additional cognitive resources under the extended response time condition, leading to a heightened drift rate as more deliberative processing occurs. Conversely, in more complex tasks, cognitive resources may already be maximally engaged, thereby attenuating the impact of response time variations on the drift rate. This underscores the nuanced interaction between task complexity, response time constraints, and cognitive processes underlying decision-making dynamics.

Entropy of the observed participant choices

The variance of entropy for the choices made by the participants is higher in the case of 5 arm task indicating higher exploration. Reduced entropy patterns are recorded in higher time pressure conditions hinting towards lower exploration and coupled with higher total scores imply higher exploitation approach in participant choices.

Our Final conclusion;
In the assessment of participant behavior within the experimental framework, a notable proportion remained engaged in random exploration despite the progression of the task. Particularly noteworthy was the observation of a comparatively higher repetition of choices in the initial stages of the 5-arm task when contrasted with the 3-arm task. This pattern persisted irrespective of the response time constraint, with the 600 milliseconds condition exhibiting a greater prevalence of repeated choices compared to the 1000 milliseconds condition.

Regarding performance metrics, an intriguing trend emerged in the analysis of the slope of increase, with a consistently higher gradient observed in the 1000 milliseconds response time condition compared to the 600 milliseconds condition. Specifically, while this trend held true for both the 3-arm and 5-arm tasks under the 1000 milliseconds constraint, a discrepancy emerged under the 600 milliseconds condition, with the slope of increase notably lower in the 3-arm task compared to the 5-arm task, thus presenting a contradiction to the anticipated pattern.

This contradiction suggests a potential interaction between response time constraints and task complexity, wherein the impact of response time on performance metrics may vary depending on the intricacy of the decision-making environment. Further investigation is warranted to elucidate the underlying mechanisms driving this phenomenon and reconcile the observed discrepancies.

Plots:

Performance vs rounds graph;
fig1 : plot signifies 3 arm 600
fig2 :plot signifies 3 arm 1000
fig3 :plot signifies 5 arm 600
fig4 :plot signifies 5 arm 1000

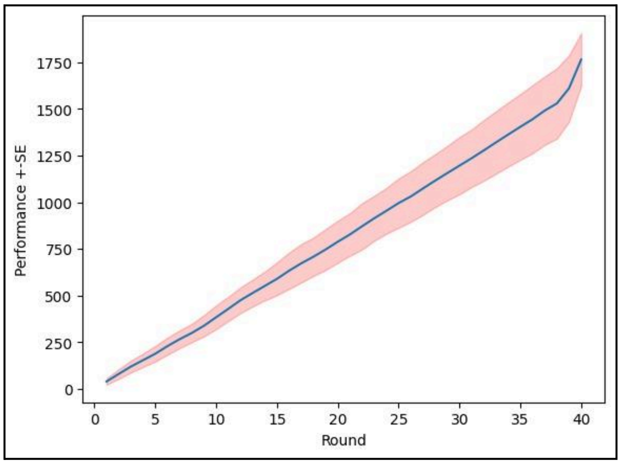

Fig1 :

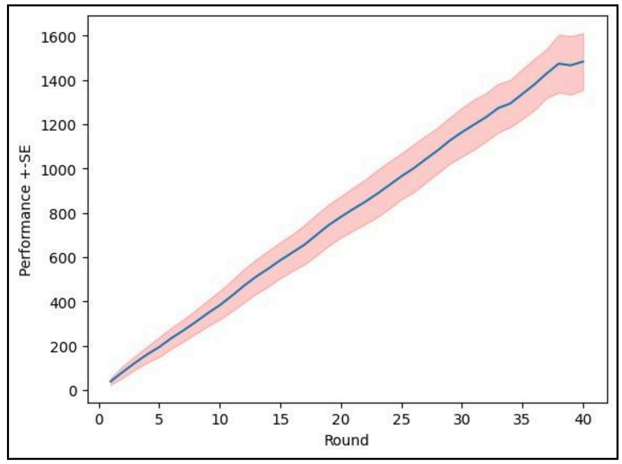

Fig2:

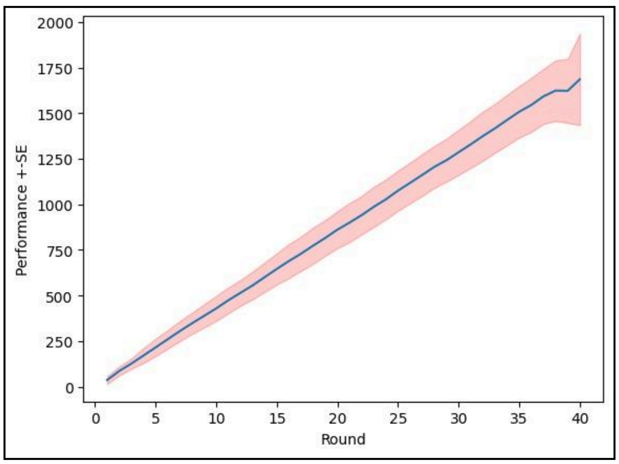

Fig3:

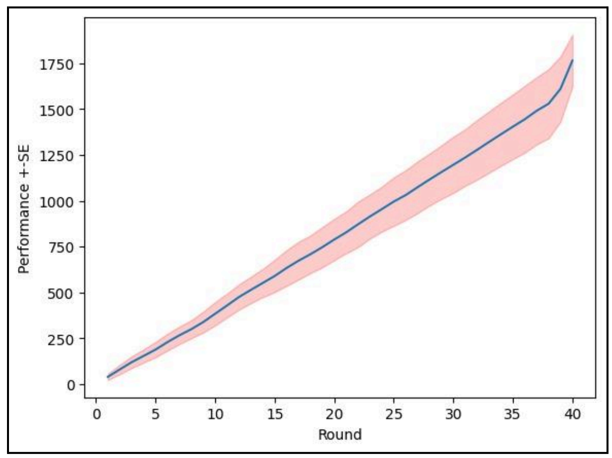

Fig4:

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