Analyzing the Effects of Memory Biases and Mood Disorders on Social Performance

Extended Abstract

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ABSTRACT

Realistic models of decision-making and social interactions, considering the nature of memory and biases, continue to be an area of immense interest. Emotion and mood are a couple of key factors that play a major role in decisions, nature of social interactions, size of the social network, and the level of engagement. Most of the prior work in this direction is generally focused on a single trait: behavior or bias. However, this work builds an integrated model that considers multiple traits such as loneliness, the drive to interact, the memory, and mood biases in an agent among many others. The agent system comprises of rational, manic, depressed, and bipolar agents. The system is also modeled with an interconnected network, and the size of the personal network of each agent is based on its nature. We consider a game of iterated interactions where an agent cooperates based on its past experiences with the other agent. The agent's type determines its willingness to participate in each round, thus modeling the different levels of engagement observed in reality. In this work, emotional bias is modeled using two different gradients for encoding happy and sad episodes. Through simulation, the effects of various biases and comparative performances of agent types is analyzed. Taking the performance of rational agents as the baseline, bipolar agents do slightly better, manic agents do much better, and depressed agents do much worse. The payoffs also exhibit an almost-linear relationship with the extent of mania.

KEYWORDS

emotion; mood disorder; memory biases; mood-congruent retrieval; mania; depression; bipolarity

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1 INTRODUCTION

Individual and group decision-making and social interactions have been studied for long and continue to remain of interest. Some early models were fairly simplistic [13, 30], and they assumed perfectly rational behavior which is often not the case in reality. Time and again, research in the domains of psychology and behavioral sciences asserts that humans, as well as animals, are subject to a wide array of cognitive biases [7, 15]. Later works moved away from the assumption of perfect rationality and started incorporating various cognitive biases into decision models [16, 33, 34]. However, the effects of emotion and mood disorders on decisions and interactions still need to be explored.

A great deal of research has focused on the impact of emotion on memory but the findings have been extremely diverse, with some claiming emotional memories are indelible [6], while others claim that emotion has no effect whatsoever on memory [26]. Mood has been seen as the summary of recent emotions [25]. While emotions change after each episode, mood maintains a historical context, yet staying temporally relevant. Mood also affects memory retrieval; *mood dependence* is the phenomenon where past events whose emotional state match the current mood are more likely to be retrieved [24]. There seems to be no prior model capturing this effect of mood on memory.

Mood disorders are prevalent in humans, and studies indicate that about 20% of U.S adults experience some class of mood disorder in their lifetimes [3]. There have been many computational models of various mood disorders [9–11, 17], but most of these assume independent agents without any social interactions or social networks. The extent and frequency of social interactions are intricately linked to mood disorders, with studies indicating that chronically depressed people have smaller social networks than healthy controls [4, 35]. Empirical studies also conclude that depressed phases are connected with lower energy, interest, and drive [18, 31, 38]. Prior models do not take this into account.

We give an integrated model of decisions and social interactions which takes into account the roles of emotion, mood, and memory biases.

2 MODEL

Consider two agents A and B paired in an interaction at time t. Now, agent A's expectation of B's level of cooperation in this interaction is the average of past levels of cooperation of B that are still in A's memory. The primary assumption of this model, in line with studies [1, 27], is that A cooperates at the same level at which it expects B will cooperate.

The interaction is based on the Continuous Prisoners Dilemma (CPD) [19, 36]. In the standard Iterated Prisoners' Dilemma, agents are restricted to only two actions—cooperate or defect. However, not all interactions can be realistically modeled with such restricted behavior. In the CPD, agents can cooperate at any level between 0

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and 1, where 0 and 1 correspond to the cases of completed defection and cooperation respectively. The concept and related payoff structure are adopted from Verhoeff [36].

Agents with mood disorders such as mania, depression, and bipolarity are considered in addition to perfectly rational agents. Such an agent society is modeled with an interconnected social network, where agents interact only with their neighbors, and agents broadcast their experiences to their neighbors. Also, the size of the personal network of each agent is determined by its type, which helps fill one significant gap in many prior models that consider agents in isolation.

Agents are also modeled with different levels of engagement or drive. In each round of interaction, an agent has the choice to decide if it wants to participate. Manic agents are modeled with a higher drive and depressed agents with a lower drive, as is consistent with clinical observations [14, 28].

The simulation consists of multiple rounds of interactions, and all agents are not active in all the rounds. At any such round t, an agent A is randomly paired with another agent B if and only if A and B are neighbors and are active at t.

Emotion is modeled in line with the appraisal theory [2, 22]. The emotion of the agent A at time t, δ_A^t is therefore the difference between reward and expectation *i.e.*, $c_B - c_A$. To model the effect of emotion on memory, we define the initial strength of a trace as a linear function of emotion. We use two different gradients for positive and negative emotions, allowing us to model both positively and negatively biased agents.

The mood dependence effect is modeled as a probabilistic retrieval of traces using a triangular distribution centered around the current mood of the agent. This ensures traces with similar emotional states have higher chances of being retrieved than others, which is the condition of mood dependence [24, 32]. Forgetting is modeled using exponential decay, in line with prior work [29, 37].

One of depression's common symptoms is anhedonia [28], the inability or the diminished ability to enjoy pleasurable events; in mania, the opposite is true [5]. In line with existing work in computational models of mood disorder [12, 17], we use reward sensitivity to model perceived rewards to be different from actual rewards in individuals with mood disorders. The perceived reward is modeled as the product of actual reward and the agent's reward sensitivity (β_A). If agent A is depressed, then $0 \leq \beta_A \leq 1$ to model diminished rewards. If A is manic, then $\beta_A > 1$.

3 RESULTS

A system of 200 agents with representation from all four types—rational, manic, depressed, and bipolar is simulated for 2000 rounds of interaction. In each round, agents are paired with one of their neighbors subject to availability. The agents interact, update their payoffs, emotion, mood, and their availability for the next round. Different parameters of agents are varied in each experiment and their impacts on total payoff are studied.

With equal representation (25%) from all 4 types, we find that payoffs are highest for manic agents and least for depressed agents (Fig. 1). Although bipolar agents show vastly different payoffs between themselves, on average the payoff of bipolar agents is greater than that of rational agents by about 10%. It is also seen that the average payoff of manic agents is about 70% higher than the average payoff of rational agents. When compared with rational agents, an average depressed agent's payoff is roughly 60% lower.

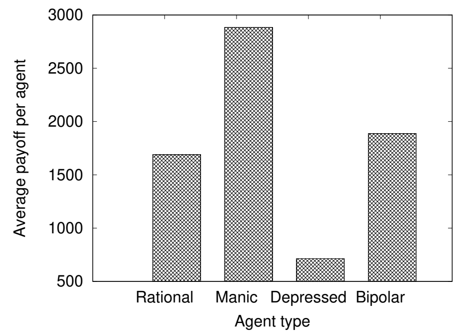
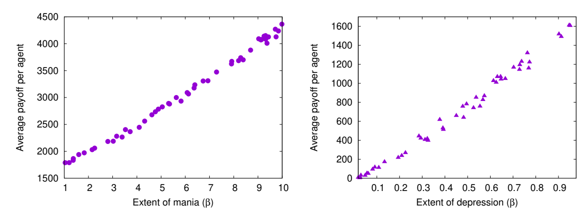


Figure 1: Comparing all types of agents

The reward sensitivity β is a measure of the extent of mania or depression. Fig. 2a depicts the almost-linear relationship between β and average payoff. It is observed that payoffs increase with increasing mania, which is fairly obvious because the higher the mania, higher is the drive in our model. An almost-linear relationship between β and payoff is observed in depressed agents also (Fig. 2b). It is also clear from Fig. 2, that depressed agents at any level perform worse than manic agents.



(a) Mania and Payoff **(b) Depression and Payoff**

Figure 2: Effect of levels of mania and depression

4 CONCLUSION

Models that capture the effect of mood and emotion on decisions realistically are essential and relevant. We use an agent-based modeling approach to understand the effects of various biases on performance. Unlike most prior work, we present a multi-faceted model that takes into account various aspects such as levels of engagement, nature of social interactions, and size of social networks. As this is an agent-based simulation, parameters such as the extent of mood disorders, population mixes, etc., can be varied to understand various scenarios, which may not be feasible in clinical trials.

Based on simulation of an agent society with different types of agents, the we obtain results about relative payoffs and other aspects that are in agreement with, and extend, published studies. Our results concur with psychological studies that establish a relationship between severity of depression and lower performance [20]. Clinical studies also suggest diminished performance in depressed individuals and improved performance in cases of mania [8, 21, 23], as also seen in our model.

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