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DYNAMICS OF BETTING BEHAVIOR UNDER FLAT REWARD CONDITION

AYAKO ONZO* and KEN MOGI†
Sony Computer Science Laboratories, Takanawa Muse Bldg, 3-14-13, Higashigotanda, Shinagawa-ku, Tokyo, 141-0022, Japan
and
Tokyo Institute of Technology, 4259, Nagatsuta-cho, Midori-ku, Yokohama, 226-8502, Japan
**onzo@olive.ocn.ne.jp*
†*kenmogi@csl.sony.co.jp*

One of the missions of the cognitive process of animals, including humans, is to make reasonable judgments and decisions in the presence of uncertainty. The balance between exploration and exploitation investigated in the reinforcement-learning paradigm is one of the key factors in this process. Recently, following the pioneering work in behavioral economics, growing attention has been directed to human behaviors exhibiting deviations from the simple maximization of external reward. Here we study the dynamics of betting behavior in a simple game, where the probability of reward and the magnitude of reward are designed to give a "zero" expected net reward ("flat reward condition"). No matter how the subject behaves, there is on average no change in one's resources, and therefore every possible sequence of action has the same value. Even in such a situation, the subjects are found to behave not in a random manner, but in ways showing characteristic tendencies, reflecting the dynamics of brain's reward system. Our results suggest that brain's reward system is characterized by a rich and complex dynamics only loosely coupled with external reward structure.

Keywords: Reward; neuroeconomics; uncertainty; betting; dopamine.

1. Introduction

Animals, including humans, encounter novel stimuli in the course of life, incurring cognitive uncertainty. How animals coordinate their actions in such an uncertain environment is one of the crucial questions to be asked of cognition.

Metacognition is considered to be essential in the robust handling of uncertainty.[1–4] Hampton reported on the metacognitive ability of rhesus monkeys.[3] It was found that the monkey has a "metacognition" of its internal state, i.e., its own assessment of the likelihood of conducting the task successfully. This kind of cognitive process is likely to contribute to a more stable handling of uncertain situations.

Avoiding uncertainty is not necessarily adaptive. To keep exploiting only certain sources of reward is tantamount to dismissing opportunities to explore alternative sources of reward, and might work unfavorably for one's survival. The balance between exploitation and exploration is thus important for survival, and has been investigated in the reinforcement-learning paradigm.[5]

In the developmental process, the psychological safe base provided by caretakers is considered to be a necessary basis for the infant's voluntary exploration of novel stimuli.[6–7] Perception of safe base as a basis for exploration is likely to be relevant also in mature humans.

Shultz and his colleagues revealed that dopamine neurons code uncertainty itself.[8] There was a sustained increase in activity that grew from the onset of the conditioned stimulus to the expected time of reward. The peak of the sustained activation occurred at the time of potential reward, which corresponds to the moment of greatest uncertainty. These results suggest that dopamine neurons might respond to uncertainty itself and that uncertainty could be regarded as a secondary reward, providing a possible explanation for addiction to gambling. The temporal parameters involved in the learning of action-reward association, e.g., the discount rate, and their correlate in the dopamine system,[9–11] are expected to be important in the metacognition of uncertainty and related cognitive processes.

A variety of studies in economics have shown that humans make decisions under uncertainty based not on the expected value but on the subjective expected utility.[12–16] The tendencies of risk seeking or aversion[12–13] and of loss aversion[14–16] have been explained by taking the magnitude relationship of preference between the options into account. No matter how well a theory is developed to account for people's decision making, there is always a certain degree of uncertainty involved. People do not always make the same choice even under exactly the same condition. In this respect, it is important to clarify the nature of brain's internal dynamics related to uncertainty handling as is reflected in people's decision making.

Investigating people's betting behavior is one of the simple and effective tools for uncovering the nature of the cognition of uncertainty. In most studies, the game is designed in such a way that a change in betting behavior leads to a change in the expected gain, reflecting real life situations. On the other hand, it is possible that people's betting behavior exhibit internal dynamics of its own, in dissociation with externally defined reward structure.

Here we investigate the dynamics of betting behavior in a simple game where the expected net reward value is constant (zero) regardless of the action chosen (flat reward condition). We conjectured that this particular paradigm reveals the nature of internal neural dynamics involved in people's judgment under uncertainty, which is only loosely coupled with external defined reward.

2. Methods

We conducted a betting game that consisted of 20 trials. The participants were 12 healthy young adults (ages 22–29, 6M & 3F). The subjects were undergraduate and graduate students in several universities in Tokyo area, and possessed basic knowledge of probability. The subjects were aware that the outcomes of betting would be determined by the simulated random process in the computer, and that there was no way to influence the outcome by any system of betting. The subjects were instructed about the general conditions involved in the game beforehand and gave informed consent. The subjects started with an initial resource of 5 units, and tried to increase the amount as best as they could. The buttons and letters were displayed on a laptop computer (Sony VAIO PCG-505G/B).

In each trial, the subject had a choice of either betting or escaping, by pushing the "Bet" or "Escape" button that became active 5 seconds after pushing the "Next" button (Fig. 1). The trial number, probability of winning (=0.25, always the same), and the current resource were displayed. For the very first turn, the buttons became active 5 seconds after launching the game software. There was no explicit time pressure, and the subjects were allowed to use as much time as they liked when making the decisions. The delay from the activation of the "Bet" and "Escape" buttons to the moment when the subjects made the choice was recorded. When the subject pushed the "Bet" button, 1 unit was taken from the subject's resource. The probability of winning was fixed at 0.25. If the subject won, 4 units were added to the resource. The expected net gain when betting was therefore zero. When the subject pushed the "Escape" button, the resource remained the same. Thus, there was no change in the expected value of gain no matter what choice ("Bet" or "Escape") the subject made (flat reward condition). From the probabilistic point of view, the subject had no rational motivation to bet or escape with a particular strategy, and any deviations from a random betting pattern can only be explained in terms of cognitive bias and/or illusion, with no actual contribution to the net gain.

The feedback ("You Win!" "You Lose!" or "You Escape!") was displayed immediately after the subject pushed the "Bet" or "Escape" button. The screen remained the same until the subject pushed the "Next" button. The game was over when the resource became 0 or the trial number reached 20. Each subject repeated 30 games. When the 20 trials were over, the resource was set back to the initial value of 5, and the gains and losses were not carried over to the next session.

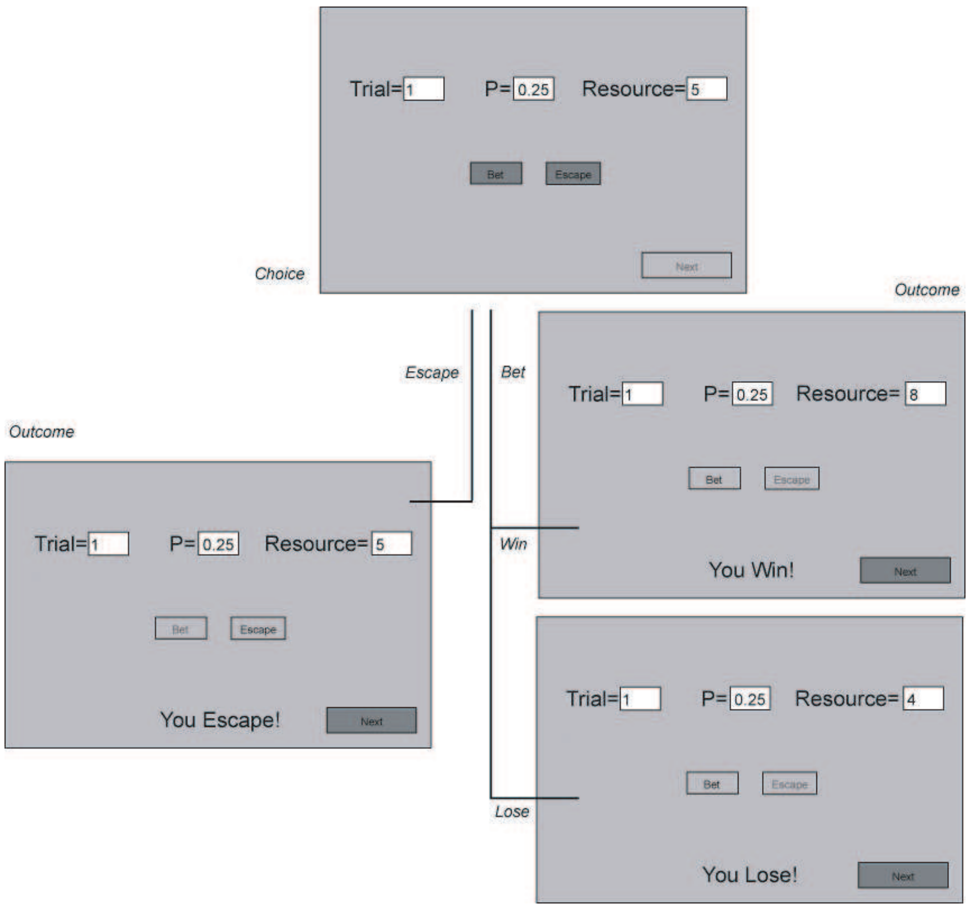

Fig. 1. Experimental protocol.

3. Results

The behavior of the subjects can be characterized by the probability of the subject to bet (betting rate), $N_{\text{bet}}/N_{\text{trial}}$, where N_{bet} and N_{trial} are the number of betting and trials, respectively. By obtaining the betting rate under various criteria, we characterized the behavior of the subjects.

From the probabilistic point of view, there is no rationale for the subjects to bet using any specific strategy. Any tendency away from the random betting behavior would suggest the existence of (unconscious or conscious) strategy that the subjects employed, in which the internal dynamics of the brain's reward and decision-associated areas is reflected.

Figure 2 shows the relation between the amount of resource and betting rate. The rate is flat for amount of resource up to ~16, and then again stays at a higher fixed level for larger amounts of resource.

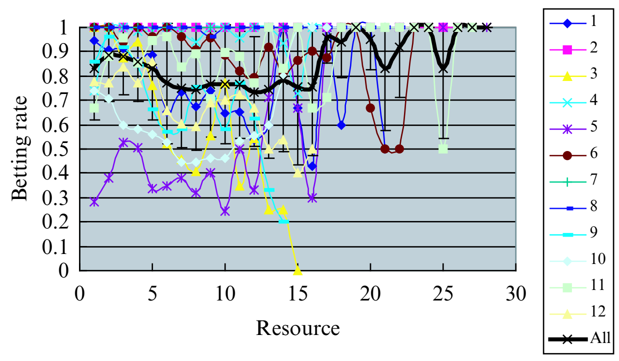

Fig. 2. Resource and betting rate.

As there are considerable individual differences, we plot the average as well as individual data in this and following figures. The subject numbers are used consistently throughout. Since the game is over when the resource becomes zero, it is psychologically natural to bet more frequently when more resource is accumulated through winning ("safe base" effect). Note that there is a slight increase of betting rate when the resource is small, which cannot be explained by the safe base effect.

The trial number could also influence the betting rate. A subject could, for example, take a greater risk towards the end of the 20 trials set within a game. Note that the subjects were aware of the trial number, as it is displayed clearly on the game screen (see Methods). Figure 3 shows the relation between the trial number and betting rate. There is no apparent tendency for the subjects to bet more frequently towards the end of the session. The absence of the effect of trial number is consistent throughout the subjects, although the betting rate differs among subjects.

Since the probability of winning in a trial is independent of past outcomes, there can be no rational explanation for the dependence of betting behavior, if any, on the previous outcomes. Figure 4 shows the dependence of betting rate on the immediately previous outcome (Lose, Win, or Escape). There is a statistically significant tendency to bet more frequently after losing, than winning ($p < 0.05$). Note the considerable individual differences in the betting rate.

When averaged over the subjects, there was no significant difference in the reaction time no matter which choice ("Bet" or "Escape") the subject made. In addition, no significant dependence of the reaction time on the previous outcome ("Escape", "Lose", or "Win") was found (Fig. 5). This statistical insignificance, however, is due to the large standard deviation in the reaction time. The individual plots for average reaction time for making the "Bet" or "Escape" choice indicate that the subjects do actually take longer when choosing to bet than

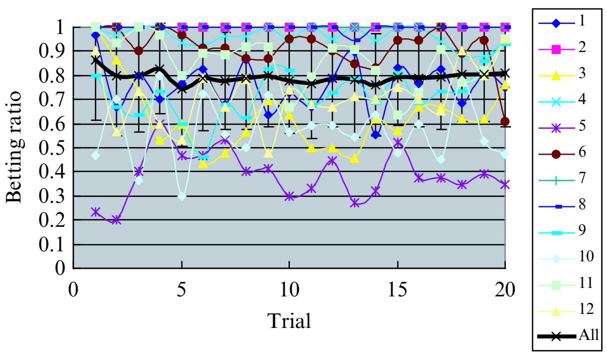

Fig. 3. Trial number and betting behavior.

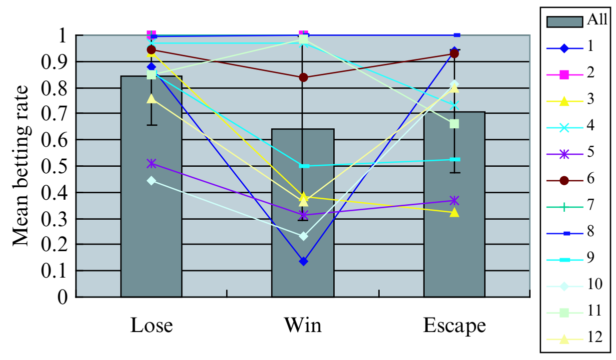

Fig. 4. Previous outcome and betting behavior.

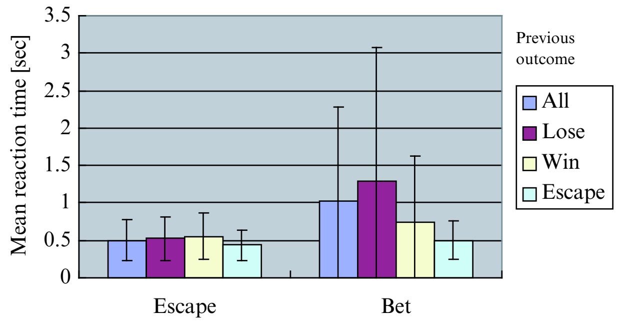

Fig. 5. Betting behavior and reaction time.

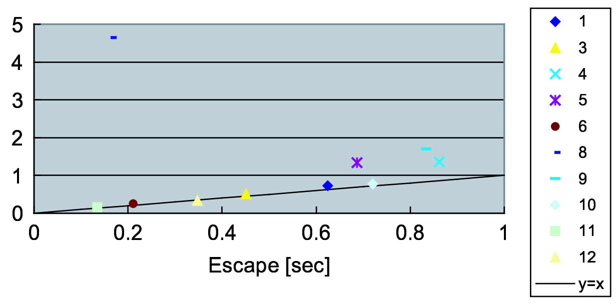

Fig. 6. Reaction time of individual subjects for "Bet" and "Escape" choices.

to escape (Fig. 6). The longer delay before deciding to "bet" likely reflects the nature of cortical processing involved. Note that two subjects (number 2 and 7) opted to keep betting and never escaped (often resulting in the termination of the game before 20 trials). Therefore, their data do not appear in Fig. 6.

Data analysis so far suggests that there are considerable individual differences in betting behavior. There are important aspects of betting dynamics that are not apparent when averaged. The dynamics of betting behavior might be heterogeneous even in an individual. It seemed possible that the betting behavior as is indicated in Fig. 2, which can be approximated as a Markov process, is actually composed of heterogeneous modes of betting dynamics, with the subjects behaving in distinct manners away from the random behavior.

Since there are 3^k possible outcomes for k consecutive trials, it is difficult to analyze all possible trajectories of betting behavior. After some preliminary analysis, we focused on a particular mode of betting behavior, where the subject keeps betting for several trials without escaping ("betting streak").

Figure 7 shows the "cornering effect" in a betting streak. Here, the betting rate is plotted against the number of consecutive choices of betting already made. The betting rate keeps increasing, away from the random behavior where the betting rate should stay at a constant level. When a subject keeps betting, it appears that he or she is "cornered" into a state where there the betting rate continues to increase, resource permitting.

It is possible that a betting streak is driven by consecutive winnings or losses. In consecutive winnings, the subjects might "feel good" and keep betting. In consecutive losses, they might be motivated to make up for the loss. We analyzed the betting rate in "winning streaks" (where the subject keeps betting and winning) and "losing streaks" (where the subject keeps betting and losing). Note that winning streaks and losing streaks are subsets of betting streaks. Comparison between the data suggests that the outcome does not have significant effect on the subject's behavior in a betting streak (Fig. 8). The subject seems to be determined to keep betting, regardless of the result.

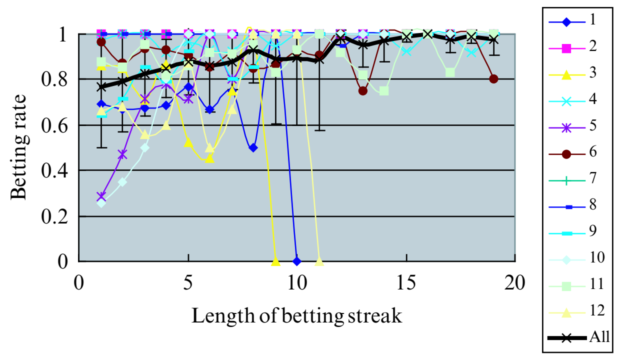

Fig. 7. Betting streak.

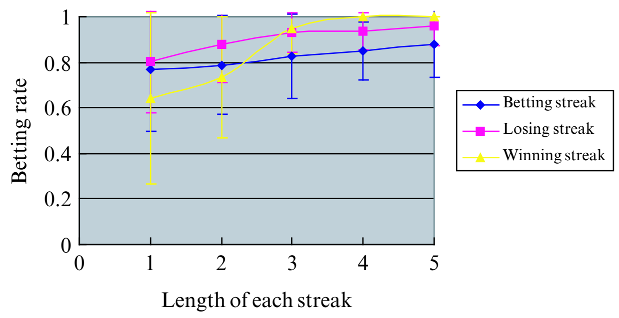

Fig. 8. Betting rate in betting, losing, and winning streaks.

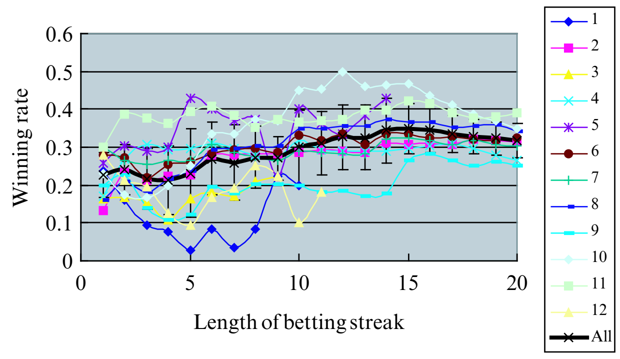

Fig. 9. Cumulative winning rate in a betting streak.

Although no statistically significant difference in betting rate was found in the comparison between the three kinds of streaks, there indeed was a small tendency that a betting streak is induced by consecutive winnings. Figure 9 provides evidence that supports the hypothesis that a betting streak is induced by winning repeatedly. When we calculate the cumulative winning rate (i.e., the average winning rate within a betting streak), it becomes significantly higher as the length of the betting streak is increased. This result suggests that at least some betting streaks are induced by an event where the subject had the fortune to win above the chance level of 0.25. Note that when averaged over all trials, the betting rate is higher after losing, rather than winning (Fig. 2). Thus, the behavior of the subjects in a betting streak is a phenomenon separate from the average tendency.

4. Discussions

The robust handling of uncertainty is important for survival. It is interesting to ask how we recognize and judge uncertainty, and choose appropriate actions.

Subjective bias and illusions are integral part of the brain's cognitive process of uncertainty handling, and merits investigation apart from the context of external reward optimization

A large variety of studies in economics and neuroeconomics have taken subjective factors that influence a subject's decision making.[13] For instance, Kahneman and his colleagues studied the introspective value of lotteries.[16] In their experiment, the subjects had to choose between lottery A and B. In A, there is a sure loss of \$750. In B, there is a 75% chance to lose \$1000 and a 25% chance to lose nothing. They found that although both lotteries had an identical expected value, a clear majority of respondents preferred B (13% of the subjects chose A and 87% chose B). This result suggests that there is a risk seeking preference on this kind of negative choice. They obtained a hypothetical value function by investigating people's preference. The value function is (a) defined on gains and losses rather than on total wealth, (b) concave in the domain of gains and convex in the domain of losses, and (c) considerably steeper for losses than for gains. Social factors can also influence people's perception of uncertainty.

It is important to study the cognition of uncertainty in the full richness of its dynamics, since our behavior is embedded in the constantly changing situations in daily life. In our experiment reported here, the subjects exhibited characteristic betting dynamics in a simply designed game. Since the expected gain is constant regardless of the subject's behavior, differential behavior cannot be explained on the basis of reward optimization. The differential behavior of the subject can only arise from the brain's internal dynamics, reflecting neural mechanism for evaluating reward and making decisions in an uncertain environment. Informal interviews with the subjects after the experiment suggested that they were in general unaware of the fact that they were behaving differentially depending on the previous outcome. Therefore, the betting dynamics is likely to reflect unconscious tendencies, rather than an application of conscious strategies.

Several factors seem to affect the betting behavior. The perception of the resource as safe base, memory of recent results, and perception of the probability of winning are some elements affecting the betting behavior observed. The complex neural computation involving the representation of these factors, finally culminating in a winner-take-all type decision-making, is likely to be an integral part of the robust handling of uncertainty. The betting dynamics under the flat reward condition is neutral to reward, and the evolution of the neural dynamics might be understood in a context neutral to the immediate reward.[17] At least some aspects of betting dynamics (e.g., higher betting rate after losing compared to winning) cannot be explained by the immediate optimization of gain. Needless to say, these cognitive processes need to contribute to, or at lease be compatible with, the efficient utilization of external reward in the environment. The enrichment of neural dynamics in a context neutral to expected gain might contribute to the final fitness. The exact logic behind such a development of neutral dynamics, however, needs to be clarified in future investigations.

Finally, there was a considerable individual difference of betting behavior. As already mentioned, two subjects chose to keep betting and never escape. Apart from these extreme cases, there is a wide variety of betting patterns among the subjects. Anecdotal evidence suggest that such heterogeneity of strategy is typically observed in gaming under the presence of uncertainty, and might reflect a general tendency of the neural system involved in the robust handling of uncertain situations. In particular, in situations involving interaction with another agent, such as the ultimatum game,[18] and prisoner's dilemma,[19] heterogeneity of strategies might induce rich interpersonal dynamics, increasing the complexity of social interaction and contributing to the overall fitness of the group of people involved.

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