Behavioral mechanisms of volatility monitoring during perceptual and reward-guided decision-making

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INTRODUCTION

In this study, we were interested in decision-making under uncertainty, hence how human subjects took decisions when they have incomplete information and have to use probabilistic inferences.



SIMULATION

Qualitative reproduction





Environment is ruled by probabilities that can change through time. **Volatility** : rate of change of the rules.

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Low volatility ~ stable. High volatility ~ frequent change.

Humans are able to take into account the volatility of the environment when they take decisions[1], but the eventual differences between each kind of decisions is unknown.

Experiment

Successions of cards drawn from an orange deck (mostly orange, sometimes blue) and a blue deck (the opposite) following a Von Misses distribution.



Two tasks : Observer and Actor. Two conditions : Low and High volatility. Game : A task and a condition. Subjects do all 4 games twice.

Marginal likelihood



1) Inference noise model explain all qualitative effect
2) beats the softmax model.

Results

Behavioral level

- Effect of volatility on accuracy (trivial)
- No effect of volaitility or tasks in reversal time
- Effects of volatility AND tasks in Mutual Information (MI) between each choice : smaller MI with High volaitlity, smaller MI in Observer tasks than Actor ones.

Computational level



Interpretation of H (how subjects perceive volatility)



Trivial effect of volatility, significant effect of task.

Model

Accumulation of information

Glaze normative model[3] : how subjects accumulate information.

$$L_{t} = L_{t-1} + \ln\left(\frac{1-H}{H} + e^{-L_{t-1}}\right) - \ln\left(\frac{1-H}{H} + e^{L_{t-1}}\right) + LLR_{t}$$
(1)
$$L_{0} = 0$$

CONCLUSION

Subjects take into account the variation of volatility in the two tasks, but there is no evidence it is taken into account differently depending on the task.

A model using Glaze [3] model and Inference noise [2] fit well with the subjects behavior and seems to confirm the use of Inference noise to describe errors in choices as it qualitatively reproduce all the effects, and is quantitatively close to the subjects behavior after fitting (not shown here).

 L_t : belief of the subject at t. H: perceived volatility. LLR_t : present evidence.

Two models for decisions

Softmax Classical interpretation : Subjects use L either to *stay* or to *change* with a given probability :

$$p_{stay}(L) = \frac{1}{1 + e^{-\beta L}}$$

 β : so-called exploration exploitation parameter. Hypothesis : Errors of the subjects are **exploration**.

Inference noise However, subjects have no reason to explore. Hypothesis : Errors comes from **internal computational errors**[2] when inferring the evidence.

 $LLR_{inf} = LLR + n_{cards}\sigma_{inf}N(0,1)$ (3)

The error σ_{inf} grows with the number of cards and propagate during the whole game. (1) + (3) \rightarrow choice using $sign(L_t)$ with each sign associated with one of the two possibility. Volatility is perceived as higher in the Observer task than in the Actor one. An interesting hypothesis to explain that would rely in the notion of agentivity : it would seems that in reward-guided decision tasks, the subject would feel more active than in perceptual tasks. Thus, one could think that with higher agentivity comes a feeling of control over the environment, hence thinking the environment is more stable in such tasks than in perceptual ones.

References

(2)

 Timothy E. J. Behrens et al. Learning the value of information in an uncertain world. en. In: Nature Neuroscience 10.9 (Sept. 2007)
Jan Drugowitsch et al. Computational Precision of Mental Inference as Critical Source of Human Choice Suboptimality. In: Neuron 92.6 (Dec. 2016)
Christopher M Glaze, Joseph W Kable, and Joshua I Gold. Normative evidence accumulation in unpredictable environments. In: eLife 4