Prediction in the face of gradual and abrupt changes in the environment

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Introduction

Humans and other animals often face changes in their sensory input. Whether these fluctuations are attributed to randomness or actual changes in the generative process is an important problem they must solve. Additionally, animals have to discriminate the type of change encountered as it may influence the strategy of adaptation used. After abrupt changes, observations should be highly valuable as they provide information of the new situation. However, their relevance should be less in periods of stability as they convey already known information. On the other hand, if the generative process changes gradually over time, observed outcomes can be used to estimate its rate of change from trial to trial. These strategies have been implemented by error-driven algorithms but are usually tested separately in the face of abrupt and gradual changes. In this work, we tested subjects predictions in a perceptual task with no changes, gradual changes, abrupt changes and a combination of abrupt and gradual changes. In these four conditions, we tested three error-driven models that have been used previously in the literature.

Method

24 subjects performed a perceptual decision making task where they had to predict the position of a spaceship moving around planet Earth. Its position was generated from a Gaussian distribution where the mean could either remain constant, change abruptly, gradually, or change abruptly and gradually, which made our four experimental conditions. Each condition lasted 300 trials.

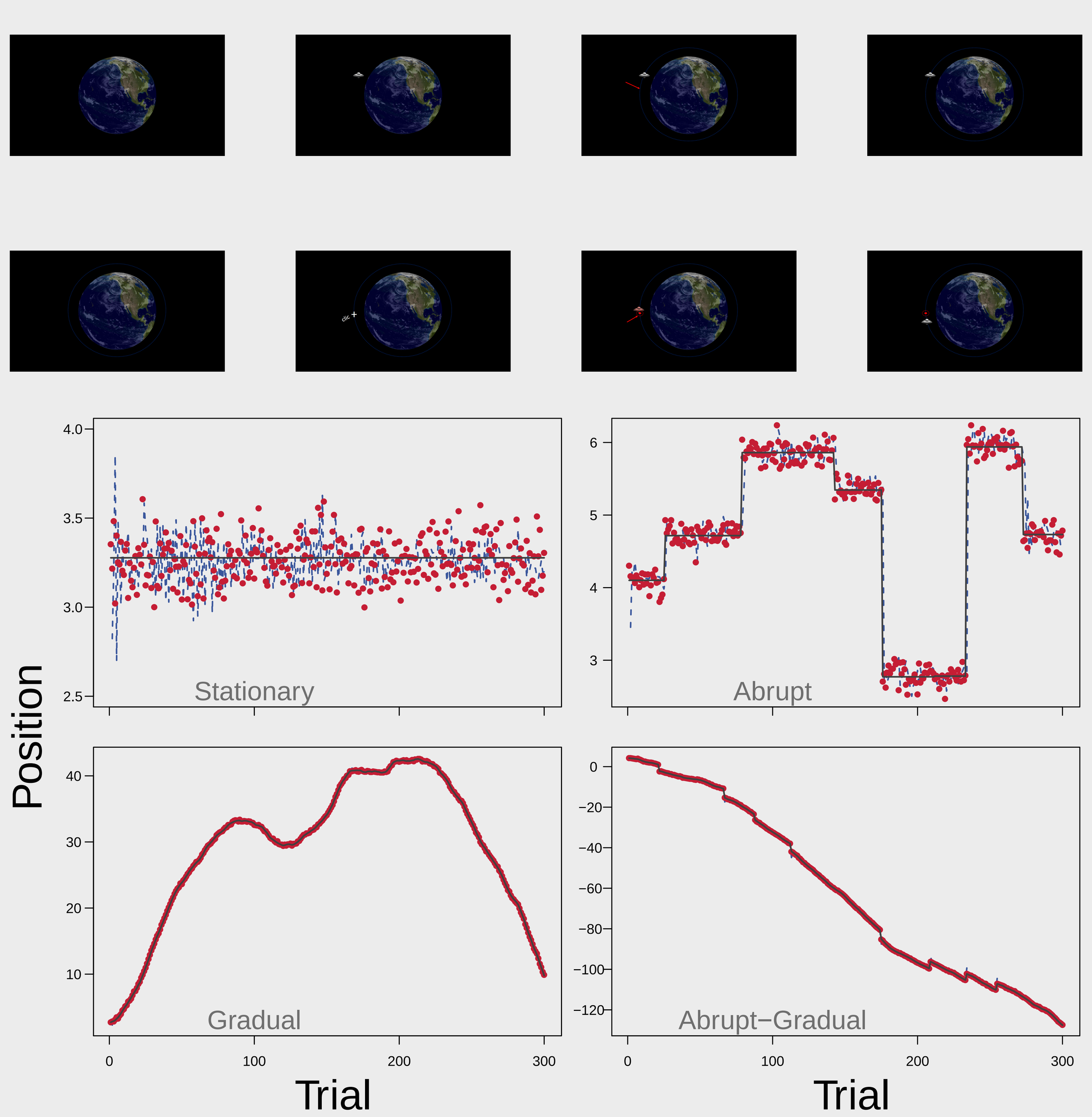

Figura: Example participant in the four experimental conditions. The dots represent the observed position of the spaceship, the dashed blue line represents the subjects' responses and the solid gray line represents the generative mean.

Results: errors

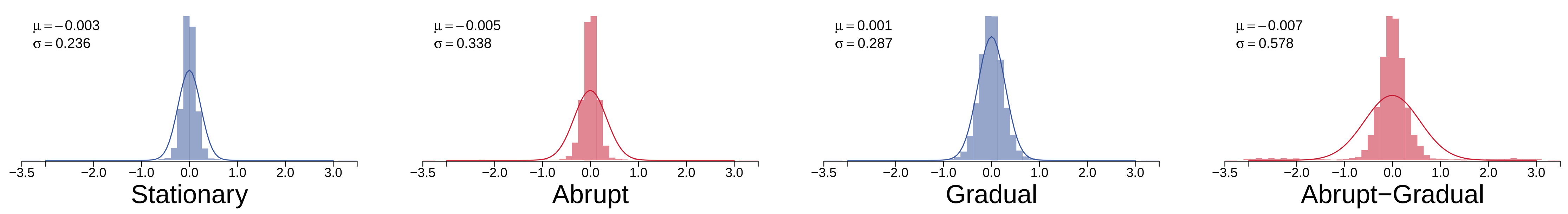

Figura: Histograms of error by condition

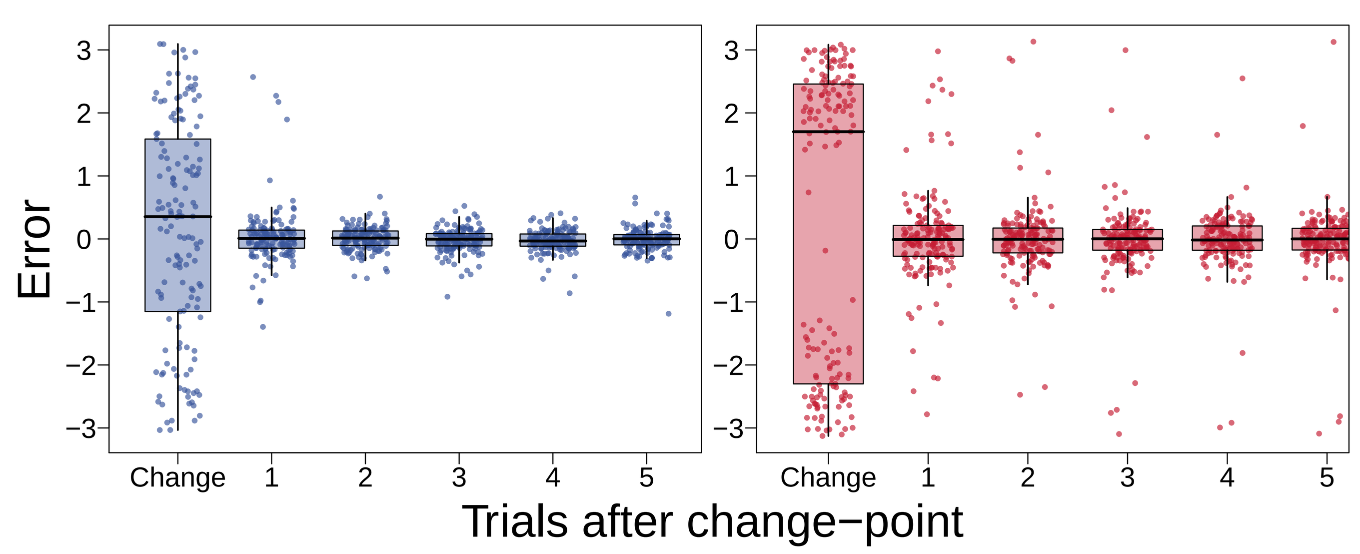

Figura: Prediction error after changepoint

Bayesian Modeling

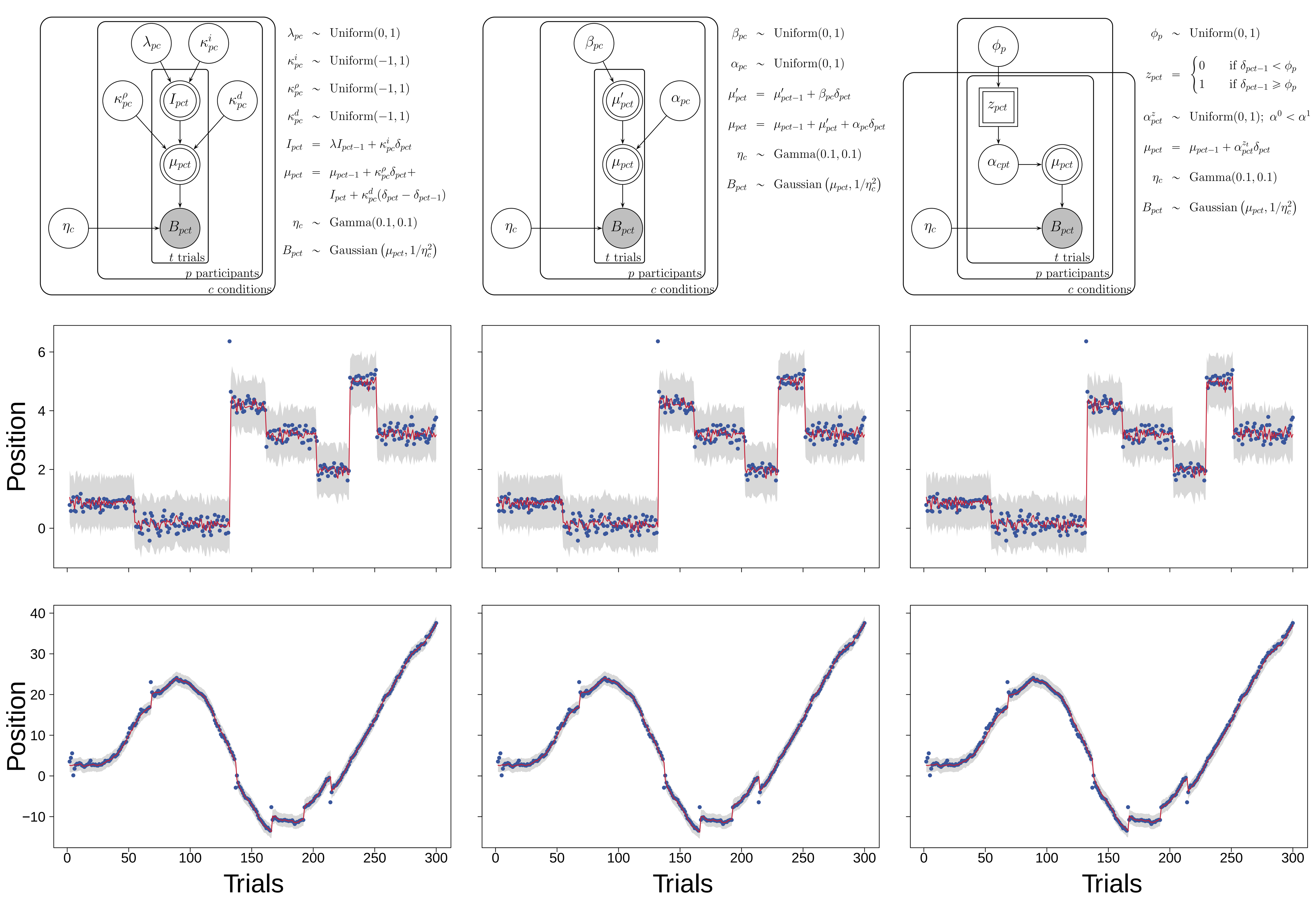

Figura: The first row shows the graphical representation of the three models used, the second row represents the 95 % High Posterior Density Interval for the predictions of each model in the abrupt-changes condition. The third one represents the predictions for the mixed condition. The first model is the PID, the second one is a delta-rule with a velocioty term, and the third one is a simple delta-rule model with a threshold that determines the learning rate.

Model Selection

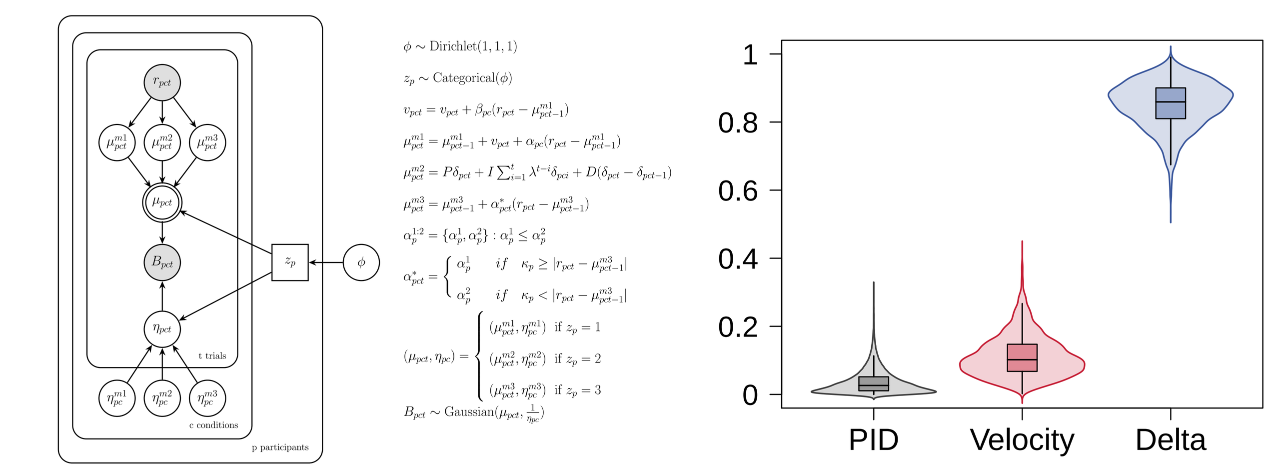

Figura: The first pannel presents the Bayesian graphical model used to select between the 3 learning rules. The pannel on the right presents the posterior distribution of the probability of each model.

Discussion

1) Subjects predicted accurately the generative mean of the spaceship in the four experimental conditions.
2) The second figure shows that for most of the change-points in the abrupt-changes condition the difference between participant's predictions and the mean of the generating process goes to 0 after just one observation. However, in the mixed condition, the difference between the true mean and the prediction shows more variance. Additionally, the errors in the change-point trials of this condition show a bi-modal distribution, which could be associated with subjects trying to predict the next position of the spaceship following the pattern (speed) from previous trials.
3) Using a Bayesian latent mixture model we observed that a delta-rule that switches between a high and low learning rates is favored by around 85 % of our subjects compared to a PID controller and a delta-rule with a velocity term.

References

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