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# Step 1

## Our preliminary questions

1. How to reflect the (fully trained) mouse’s internal state at time point of decision making - and how to tell different states apart based on

* eg., erroneous prior decision to impact upcoming decision / perseveration - timing difference? - upcoming decision should be “better” (in our case: correct)?
* eg., signal contrast correlation to response time?
* e.g., signal contrast correlation to accuracy?
* e.g., response time to accuracy?
* e.g., position of stimulus to response time?

1. Does bias impact learning rate?

## What exact aspect of data needs modeling?

* Answer this question clearly and precisely! Otherwise you will get lost (almost guaranteed)
* Write everything down!
* Also identify aspects of data that you do not want to address (yet)
* “classic” lapse model does not reflect different decision strategies / dynamic decision strategy
* **do we want to model the learning process or decision making process once mice have been fully trained?**
* how can we tell the mouse’s internal state at time point of decision making
  + is stimulus duration relevant for decision making?
  + speed of wheel?
  + is the mouse bored?
  + ITI?
  + is there a time-out for stimulus duration?
* how can a model represent / capture potentially different states or a change in states prior to decision making?
* How do these (different) states impact the final decision? (Which aspects of the internal states?)
* **in trained mice**: use relationship between different data points to investigate whether there are different internal states / whether these can be modeled?
  + eg., erroneous prior decision to impact upcoming decision / perseveration - timing difference? - upcoming decision should be “better” (in our case: correct)?
  + eg., signal contrast correlation to response time?
  + e.g., signal contrast correlation to accuracy?
  + e.g., response time to accuracy?
  + e.g., position of stimulus to response time?
* regression towards the mean
* **in mice during training**: use a step-wise function?

## Define an evaluation method!

* How will you know your modeling is good?
* E.g., comparison to specific data (quantitative method of comparison?)
* split data into training and test -> run model on test data

## For computational models: think of an experiment that could test your model

* You essentially want your model to interface with this experiment, i.e. you want to simulate this experiment

# Step 2: Literature search

## HMM (W3D2)

## Roy et al. → Nitika

## Ashwood et al. → Sam

## Urai et al. → Sonja

### Adaptive History Biases Result from Confidence-Weighted Accumulation of past Choices (Braun et al, 2017)

* done in humans → “challenging visual motion discrimination task near psychophysical threshold”
* choice history bias depends on confidence, past decision

### Confirmation Bias through Selective Overweighting of Choice-Consistent Evidence (Talluri et al., 2018)

* humans
* decisions more effective if stimulus motion in second trial was consistent with decision taken during first trial
* explaining mechanisms underlying confirmation bias

### Choice history biases subsequent evidence accumulation (Urai et al., 2019)

* humans
* evidence challenging the hypothesis that choice history bias impacts starting point of evidence accumulator towards the threshold reflecting past decision:
* “individual history biases in overt behavior were consistently explained by a history-dependent change in the evidence accumulation, rather than in its starting point. Choice history signals thus seem to bias the interpretation of current sensory input, akin to shifting endogenous attention toward (or away from) the previously selected interpretation.“

### Reinforcement biases subsequent perceptual decisions when confidence is low, a widespread behavioral phenomenon (Lak et al., 2020)

* mice, rats, humans, and across different sensory modalities
* “past rewards bias future choices specifically when previous choice was difficult and hence decision confidence was low. “ → effect of reward not consistent
* → added statistical decision confidence into model for choice-updating strategy

## Prince’s paper → Prince

# Step 3

1. What parameters / variables are needed?
   1. fully trained mice data -> 200 trials with 80% correct → percent correct
   2. look across labs → do not separate btwn labs
   3. trial response time → from stim onset to mouse response
   4. signal contrast → does it impact lapse rate? and response time?
   5. incorrect answer → does it impact response time? (prior?)
   6. lapse rate
   7. ITI
   8. is there a time-out for stim presentation → seems it is self-timed
   9. bias →
   10. probability correct
2. Variables needed to describe the process to be modeled?
   1. Do a PCA / lasso regression or something to constrain / identify the relevant parameters which may constitute internal states?
   2. Define internal states (through HMM or whatever; W3D2)

# Step 4

Response time = stimulus onset through response (turning the wheel)

1. You think about the hypotheses in words by relating ingredients identified in Step 3
   1. When giving an incorrect response in the prior trial, the next trial’s response time will be longer. (consider penalty / longer ITI in case of incorrect answer.)
   2. Longer response times (compared to individual overall average) indicates “different/distracted/bored” state.
   3. ITI might cause state transition → correct-to-correct vs incorrect-to-correct → longer ITI (based on incorrect response) will result in change in internal state: from disengaged to engaged
   4. correct-trial-ITI leads to mice remaining in engaged/same state → self-transition; incorrect-trial-ITI leads to mice to transition from disengaged to engaged state.
   5. disengaged is related to more lapses
   6. longer response times lead to more errors / longer response time is indicator for error (or change in response time)
   7. if incorrect response in prior trial, then increase in response time which may lead to correct response in next trial. → transition from disengaged to engaged.
   8. if correct response in prior trial, an increase in response time would lead to an erroneous response in next trial → transition from engaged to disengaged.
   9. assumption: error rate is indicator for boredom / disengagement

State characteristics

* disengaged state
  + related to more errors / less accuracy
* engaged state
  + related higher accuracy

1. You then express these hypotheses in mathematical language by giving the ingredients identified in Step 3 specific variable names.

# The hypothesis

Does a post-error slowing happen in mice?

Confidence:

* low signal contrast = not easy → low confidence (everything < 50%)
* high signal contrast = easy → high confidence (100%, 50%)

Outcome = response time → post error slowing

1. longer response times correlate with prior / choice history bias of incorrect and leads to correct response in next trial
2. longer response times correlate with “bored/disengaged” state
3. Longer response times correlate with making error next trial

Parameters

* prior response: correct/incorrect \*see whether duration of history has an impact or just last trial
* ITI (if it is different btwn correct/incorrect in fully-trained mice): 1s/2s
* feedback (if it’s used in fully-trained mice): sugar water / noise burst
* Outcome variable: response time

# Project proposal → latest version [here](https://docs.google.com/document/d/1xM8y8MjNX6neIaVWP0ZWXOP_F-qcfTzHY5wIKpGw9cQ/edit#heading=h.l2cj2nbn90x9)

## Research question

Is there post-error slowing in mice?

## Background / Introduction

In a perceptual decision task, noisy evidence is accumulated until a threshold is reached, that is, a decision occurs. However, our responses are not always correct, and adapting to an error is crucial for learning and survival. It is therefore assumed that the evidence accumulation process for each decision is dynamically updated based on choice history, among other things.

Post-error slowing (PES) refers to the phenomenon of reduced reaction time to a stimulus after an erroneous response. While PES itself has been reliably replicated in humans, there are conflicting findings to whether PES may lead to increased or decreased performance in the upcoming task [(Wessel, 2018)](https://www.zotero.org/google-docs/?sLf99i). Several theories try to determine why it may occur and how it works mechanistically [(see for example, Ceccarini & Castiello, 2018; Dames & Pfeuffer, 2021)](https://www.zotero.org/google-docs/?zAyRdD). An additional challenge seems to lie in the precise and unbiased measurement of PES [(Derrfuss et al., 2022)](https://www.zotero.org/google-docs/?PS9Yn0).

Based on the IBL data for a 2AFC perceptual decision making task in mice we want to investigate whether there is detectable difference in post-error versus post-correct response times which may replicate a PES phenomenon in mice. Furthermore, we aim to train both a GLM and classifier model to reliably predict (reduced) response times based on previous response, ITI duration, and signal contrast. Findings may add to and substantiate the idea of different internal states in mice which are thought to dynamically update the mice’s decision strategy throughout a multi-trial session [(Ashwood et al., 2022)](https://www.zotero.org/google-docs/?yb3pux).

## Hypothesis

In the trial after an incorrect response is recorded, there will be an increase in response time.

We believe that, given <input variables>, there is a reliable method to predict response times in subsequent trials.

<input variables> =

* ITI and/or Previous Trial Correct
* Signal contrast and location
* Response time and/or full trial time and/or time between start of trial and stimulus onset

## Methods

1. Normalize all variables
2. Check, using paired t-test, whether there is a significant difference in response times after correct vs incorrect responses.
3. Build GLM to predict response time, given variables of interest. We will use data from one lab.
   1. Analyze weights in order to determine importance placed on previous trial
4. Build a classifier to check for generalizability of data: Train on one lab, evaluate on the others.

Bonus: Update GLM to include more than one previous trial. This may cause us to modify our classifier as well.

## Expected Results

We expect that there will be a significant increase in response time following an incorrect trial. We believe that, given information from the previous trial, there will be a method to reliably predict response times.

## Relevance

*Suggestion: try the approach on mice from one lab; and then prove generalisability across labs to increase the power of the model.*

## 

## Background ideas

In a perceptual decision task, noisy evidence is accumulated until a threshold is reached, that is, a decision occurs. However, the perceptual or sensory input is not weighted objectively but influenced by context including the personal history of past decisions and the confidence with which past decisions were reached. It is therefore assumed that the evidence accumulation process for each decision is dynamically updated based on choice history, among other things.

An observable difference in the decision making process in mice in a 2AFC task lies in the individual response time, that is, on a trial basis, the time it takes the mouse to accumulate sufficient evidence for the response to be executed, hence the time between stimulus onset and the turning of the wheel. We hypothesize that this response time is influenced by features such as signal contrast (aka, task difficulty), probabilistic task setup (aka, designed consistency of the stimulus to occur at the expected position, i.e., 20%, 50%, or 80%), and the feedback provided (aka, sugary water and shorter ITI in case of correct response; noise burst and longer ITI in case of incorrect response).

In addition, however, we assume latent variables to influence the response time which may constitute internal states of a mouse to reflect the update strategy preceding the upcoming choice. As such we hypothesize that, similar to the phenomenon of post-error slowing in humans, the response time will increase after an erroneous past choice but then most likely result in a correct upcoming response.

Longer response times, however, might also occur if the mouse got disengaged (e.g., distracted, bored, transitioned into automated behavior e.g. due to high probability rates of stimulus position, i.e., 80% condition). In this latter case we assume a longer response time to more often than chance lead to an incorrect response.

Extra:

* Increased response time due to past error; (eventually leading to correct response in next trial. *disengaged → engaged transition)*

# Abstract: IBL data - Post-Error Slowing → [final abstract here](https://docs.google.com/document/d/1pLjLkWOeysDfGtwOmfNwVEVw1D9Q-p0w388JA32b9PE/edit#heading=h.esf59ff1q65a)

* **What is the phenomena**? Here summarize the part of the phenomena which your modeling addresses.
  + Response time slows down after an incorrect trial. In Humans, this is known as post-error slowing (PES).
* **What is the key scientific question?**: Clearly articulate the question which your modeling tries to answer.
  + What is the most impactful predictor of prolonged response times: prior response (correct/incorrect response), signal contrast, or delay of stimulus onset?
* **What was our hypothesis?**: Explain the key relationships which we relied on to simulate the phenomena.
  + Prior incorrect response can predict prolonged response time in subsequent trials.
* **How did your modeling work?** Give an overview of the model, its main components, and how the modeling works. ''Here we ... ''
  + Normalize all variables
  + Gaussian GLM with: limit to fully trained mice. Train model on data of one lab and test on the same lab. In a second step, test the model on the other labs.
    - y: response time upcoming trial (continuous)
    - x1: prior response (correct / incorrect)
    - x2: signal contrast (100, 75, 50, 25)
    - x3: signal position (left / right)
    - x4: delay of stimulus onset (continuous?)
    - x5: session phase (early, mid, late)
* **What did you find? Did the modeling work?** Explain the key outcomes of your modeling evaluation.
  + Expected results: we expect the largest weight in the GLM will be on x1, that is, the prior response.
* **What can you conclude?** Conclude as much as you can *with reference to the hypothesis*, within the limits of the modeling.
* **What are the limitations and future directions?** What is left to be learned? Briefly argue the plausibility of the approach and/or what you think is essential that may have been left out.