Back To The Future

By: Siobhan Hall, Saptarshi Ghosh, Conor Keogh, Holly Wilson
Hungry Silkworms

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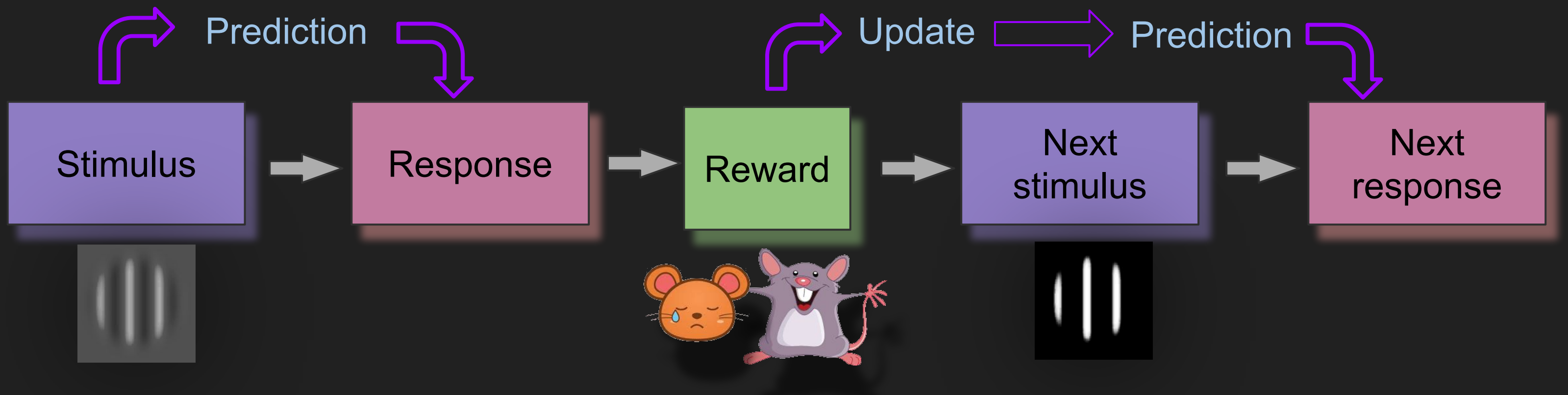
Introduction



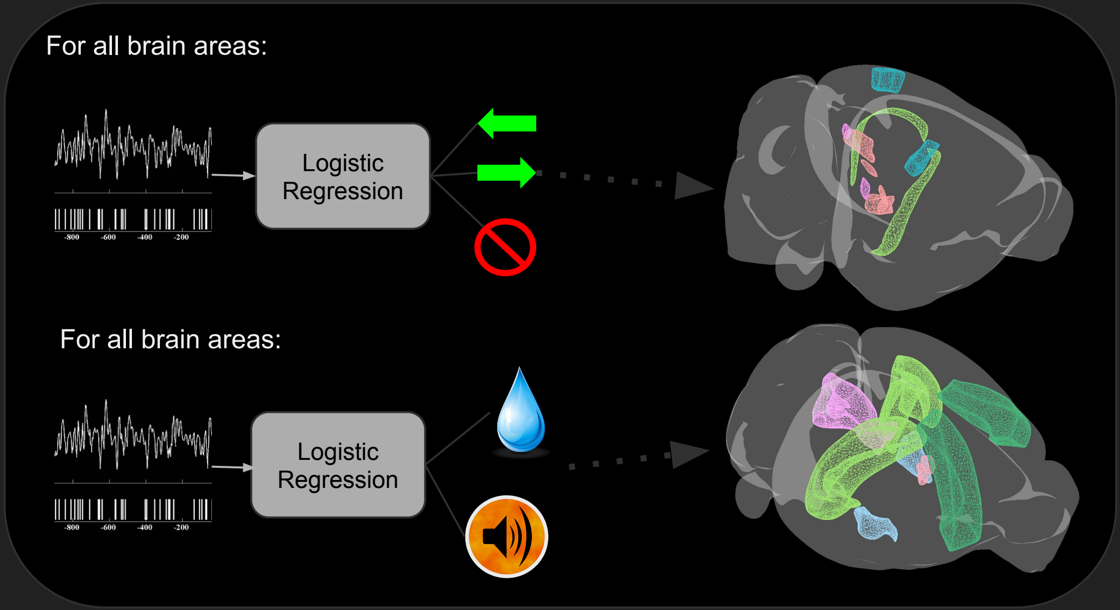
Aim: Determine whether feedback integration from a trial is evident in the subsequent trial

Hypothesis: Feedback integration from a trial is used to update predictions in subsequent trials (single trial history) at a neural level.

Dataset: Dataset from Steinmetz et al. Nature 576, 266-273 (2019)

Decoding 

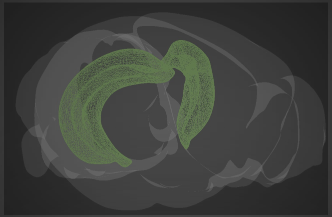
Which brain areas and time window optimally represents response and reward?



Optimise different size and index of time windows:

Reward: 1.1 seconds (time-locked to reward at time 0)

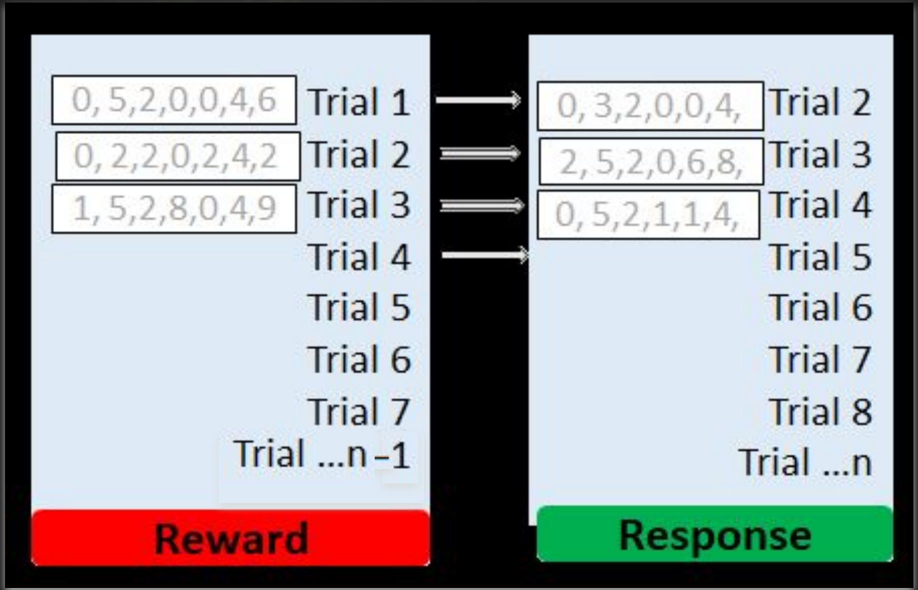
Response: -0.8 seconds (time-locked to the response at 0)



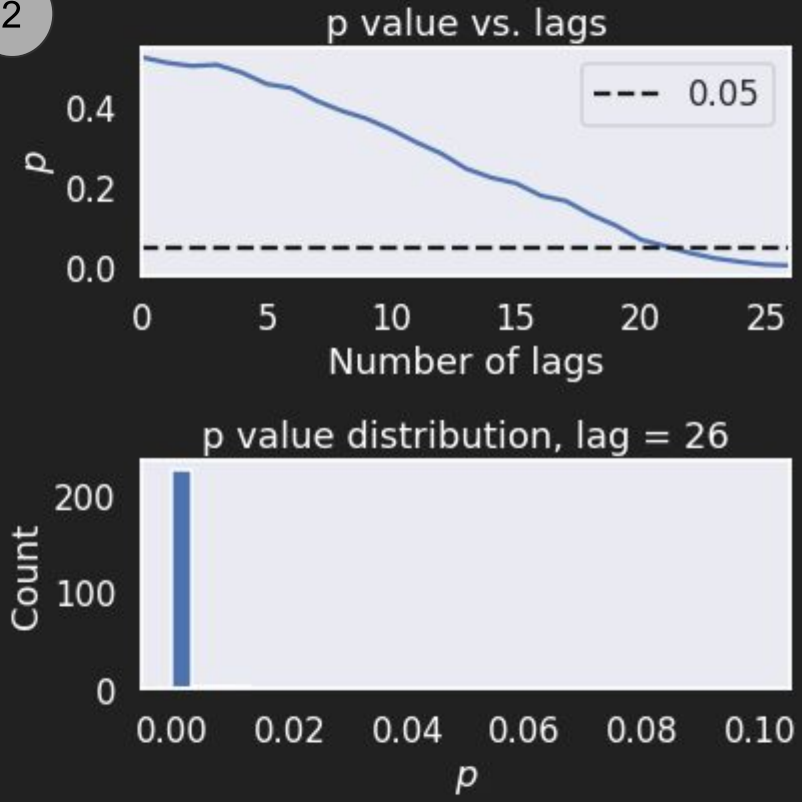
Granger Causality

1

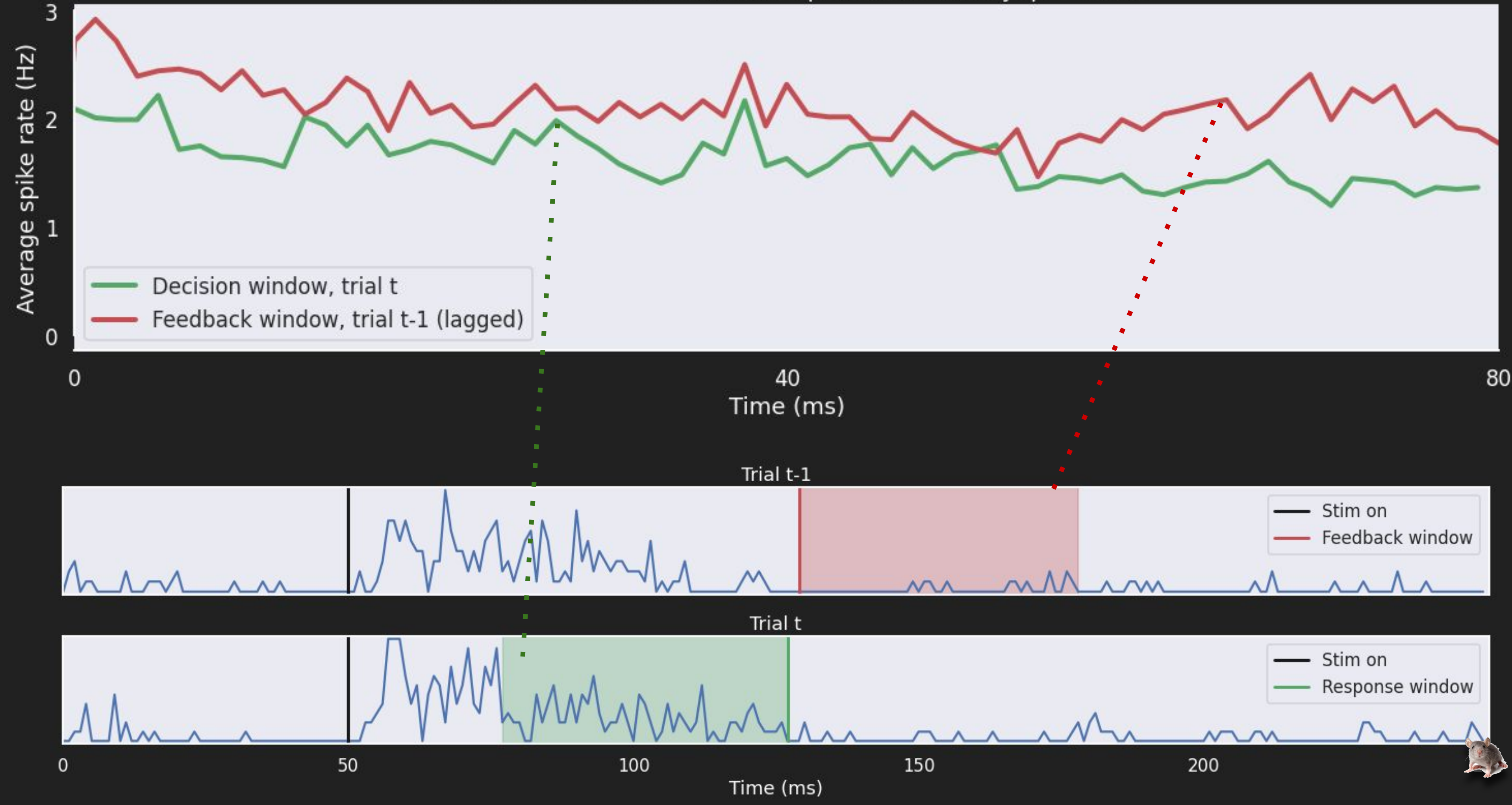
Granger causality on each trial (and subsequent trial)



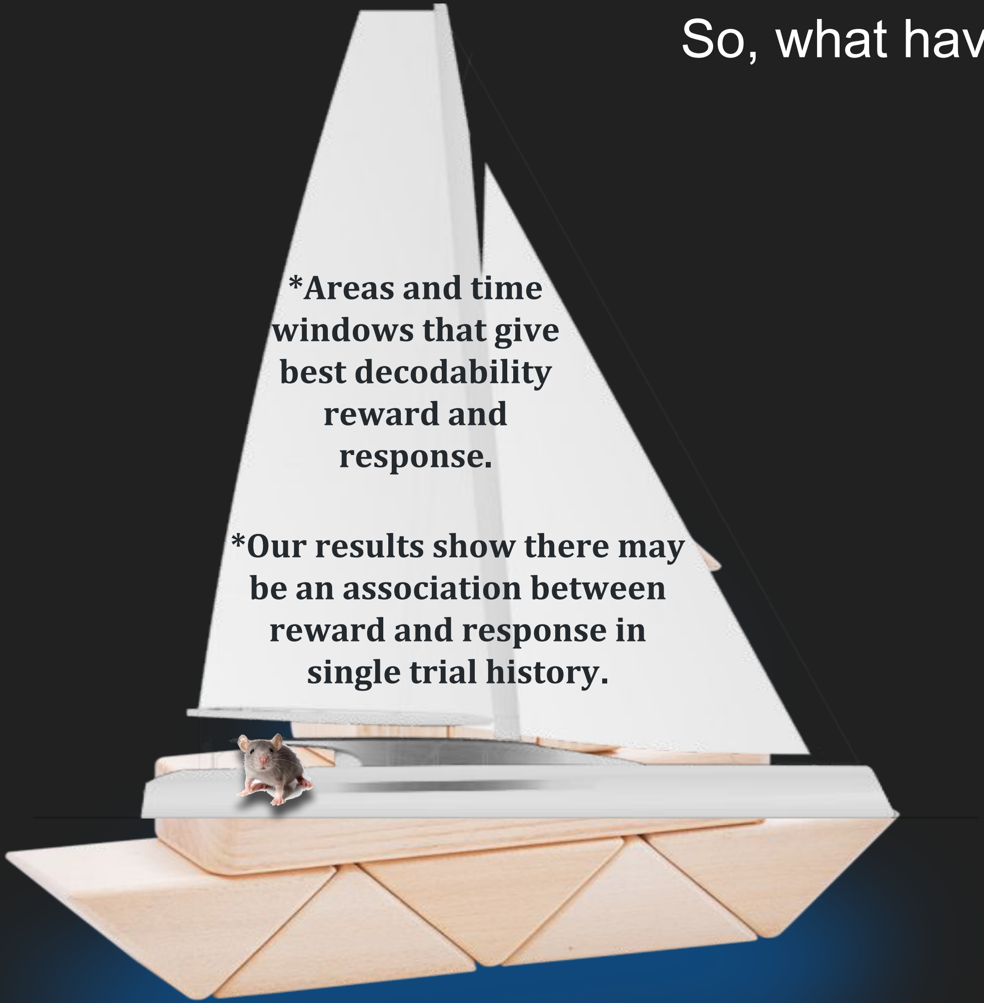
2

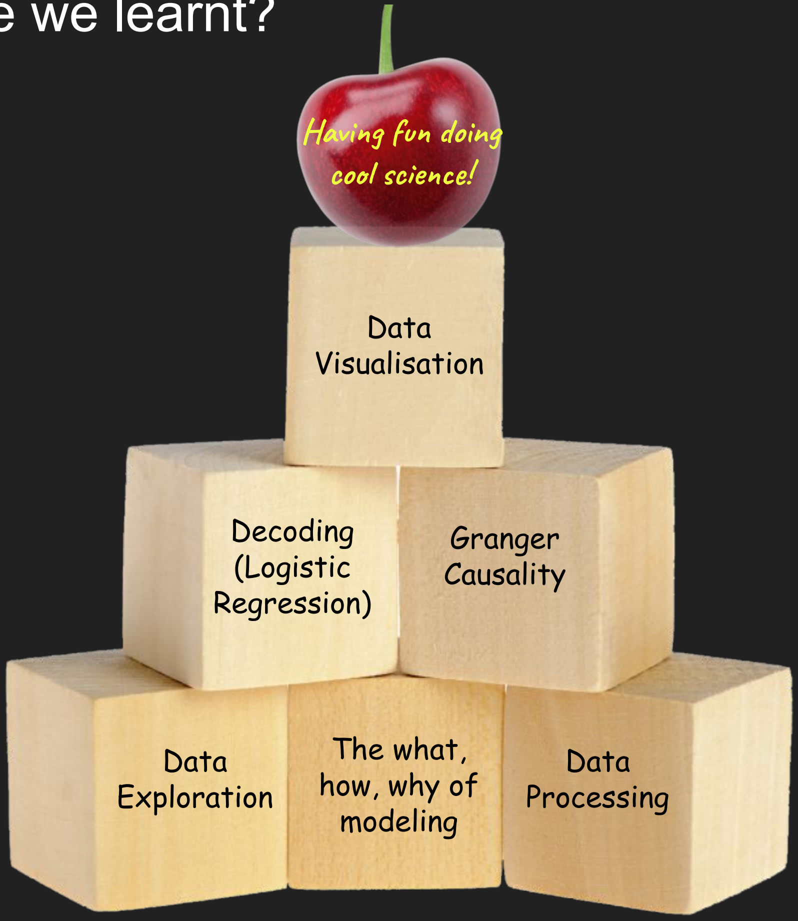


Interaction between feedback & prediction activity; $p < 0.001$



So, what have we learnt?





Mentors

@NeuralCompLab

@mfatimachado

Team

@sapta15

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@ConKeogh

@hollywilsh

Go Hungry SilkWorms

<--- Code

& Zoom, Google Image, G-Office Suite

Information transfer in Steinmetz dataset

Manolo Martinez, Sergio Grueso, Marc Schwartz and Juan Sustacha
(@074 Aquatic Iguanas)

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Motivation

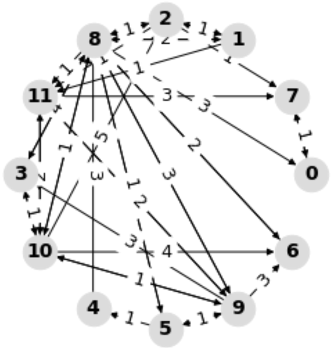
- **What**: How much information flows from stimulus to behavior through the recorded neurons, and how much bypasses them?
- **Dataset:** Steinmetz
- **Who**: Aquatic Iguanas
- **How:** Information Theory

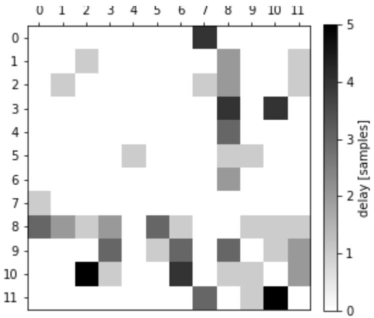
Multivariate transfer entropy análysis:

- 12 x 340 time series corresponding to 12 brain areas recorded during the session, in 340 trials..
- The activities of neurons in each of the areas is averaged and discretized per trial, using maximum-entropy binning (4 values).
- Only statistically significant edges and time lags are shown.

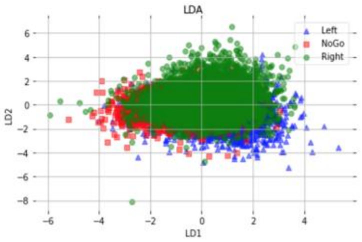
Results:

The Subiculum appears to be a hub of sorts in this particular network (why?)

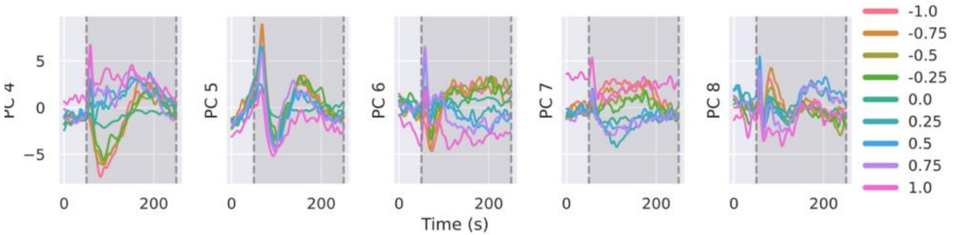




Dimensionality Reduction

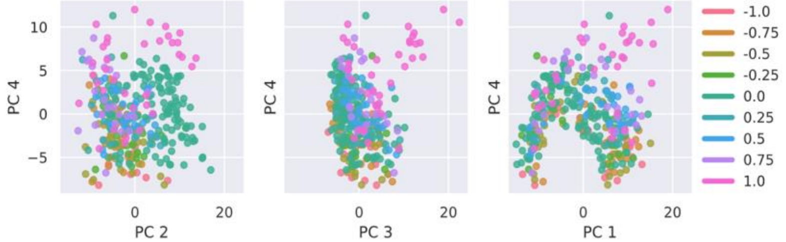


LDA analysis

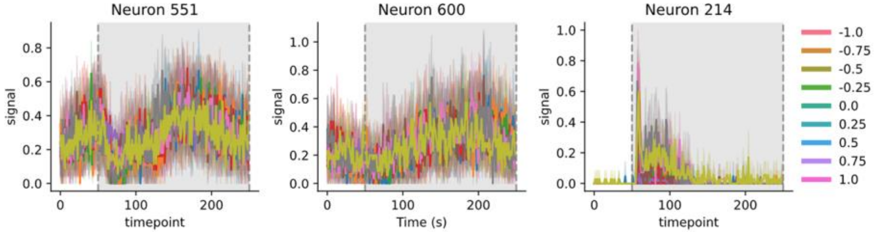


PC4 shows a structure differentiating between trial types

Three neurons mapping to the three eigenvectors explaining the most variance



PC plotted one against the other (from 1st to 4th PC). Legend represents the difference in contrast between stimuli (trial types)



MD (thalamus) **LH** (thalamus) **VISp** (visual cortex)

Experience

- We realized how important is to carefully preprocess your data in a clean and readable manner

- It is important to understand conceptually the analytical methods and the assumptions it makes

- We realized how computing some measures (i.e. transfer entropy) can be both computationally (time) costly and difficult to interpret as number of dimensions increase

Metastable attractors predicting motor actions

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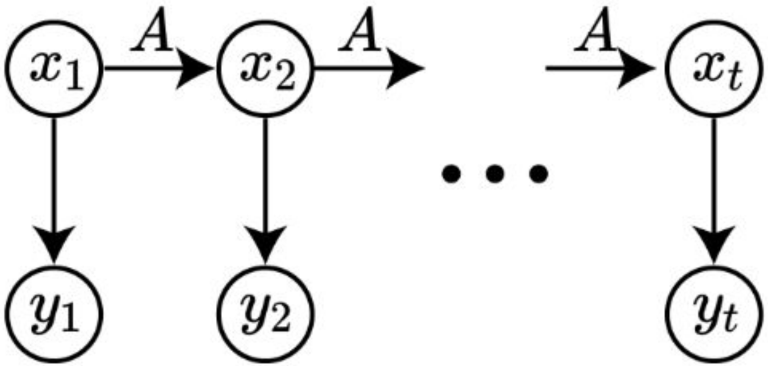
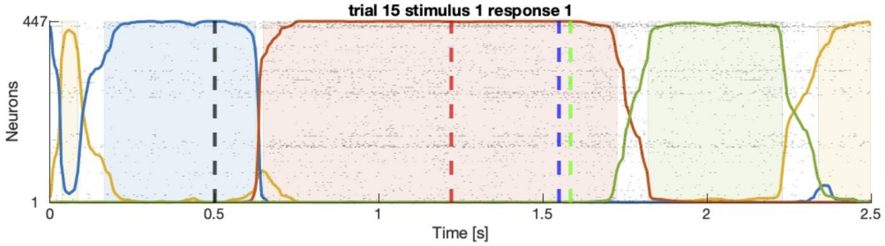
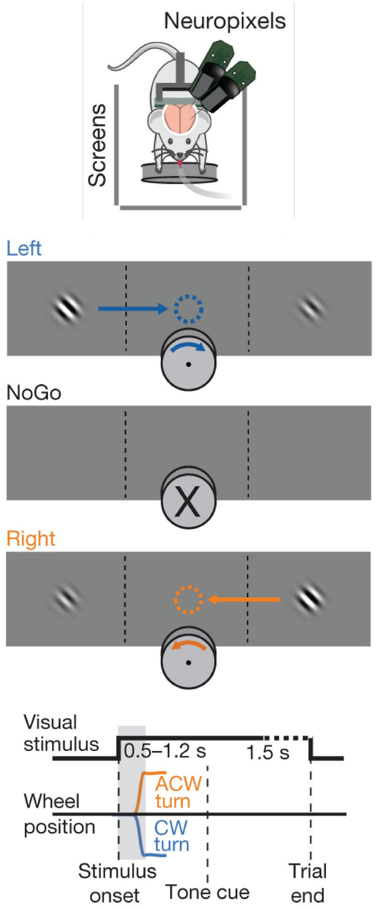
Elena Menichini
Magdalena Sabat
Miguel Angel Casal Santiago

Background





trial 15 stimulus 1 response 1
447
1
Neurons
0
0.5
1
1.5
2
2.5
Time [s]

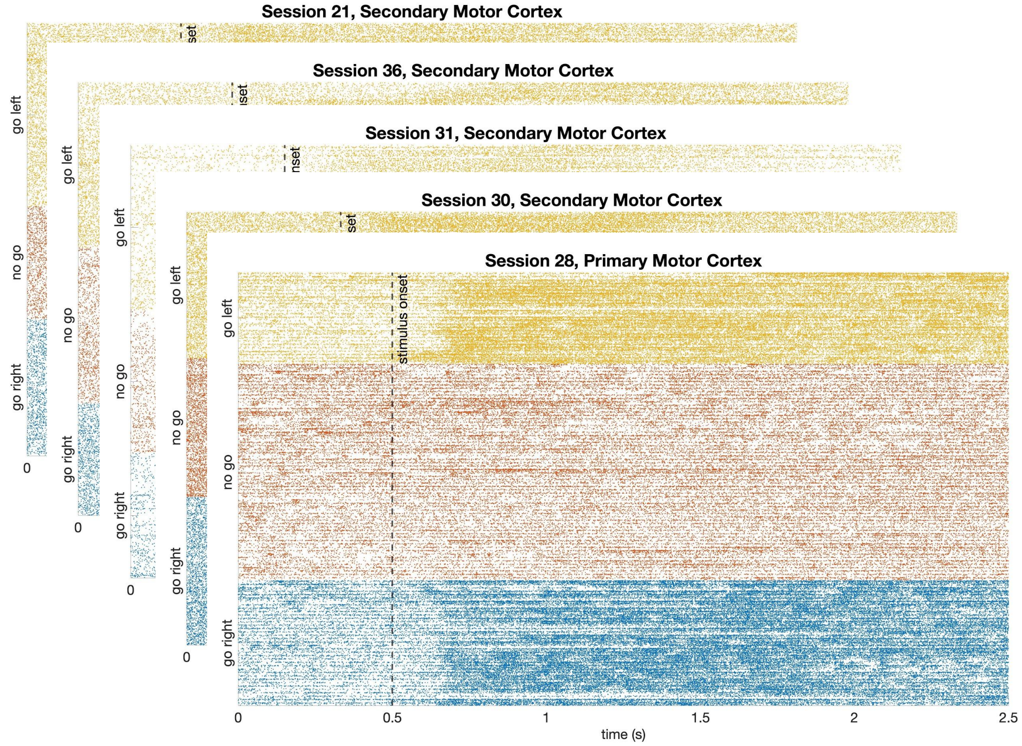


Neuropixels
Screens
Left
NoGo
Right
Visual stimulus
0.5–1.2 s
1.5 s
Wheel position
ACW turn
CW turn
Stimulus onset
Tone cue
Trial end

Scientific Question

Can **hidden states** in **brain dynamics** **predict** behavioral **events**?

The dataset: raw data structure



39 sessions

Maaaaaaaaaaaany areas

10th session

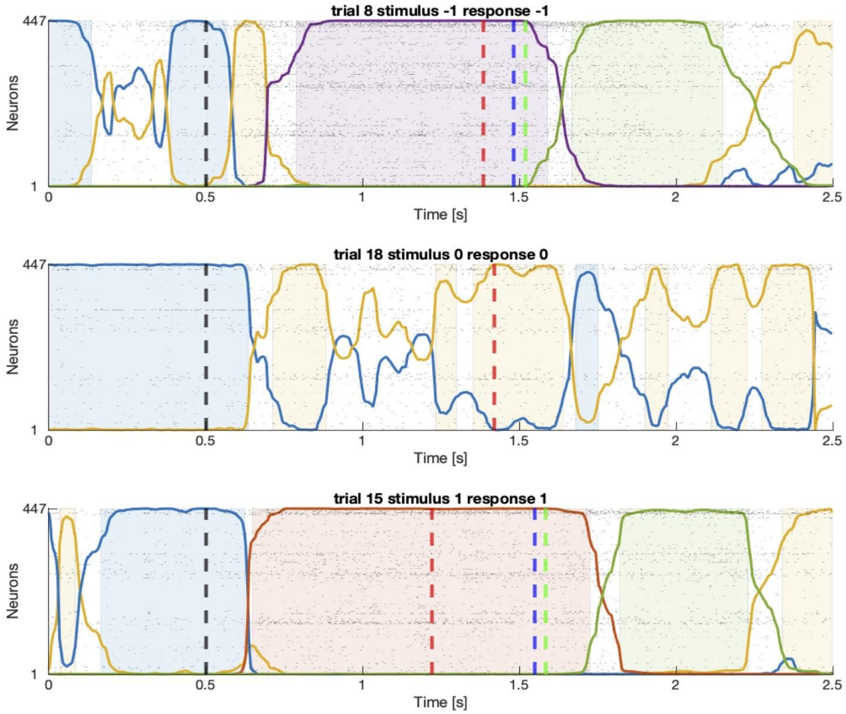
Primary Motor Cortex

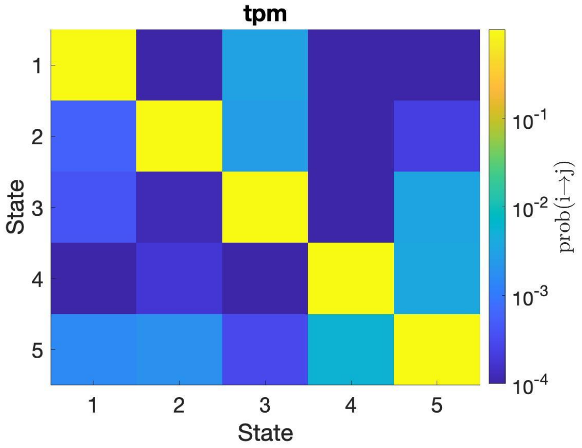
State sequences

go right

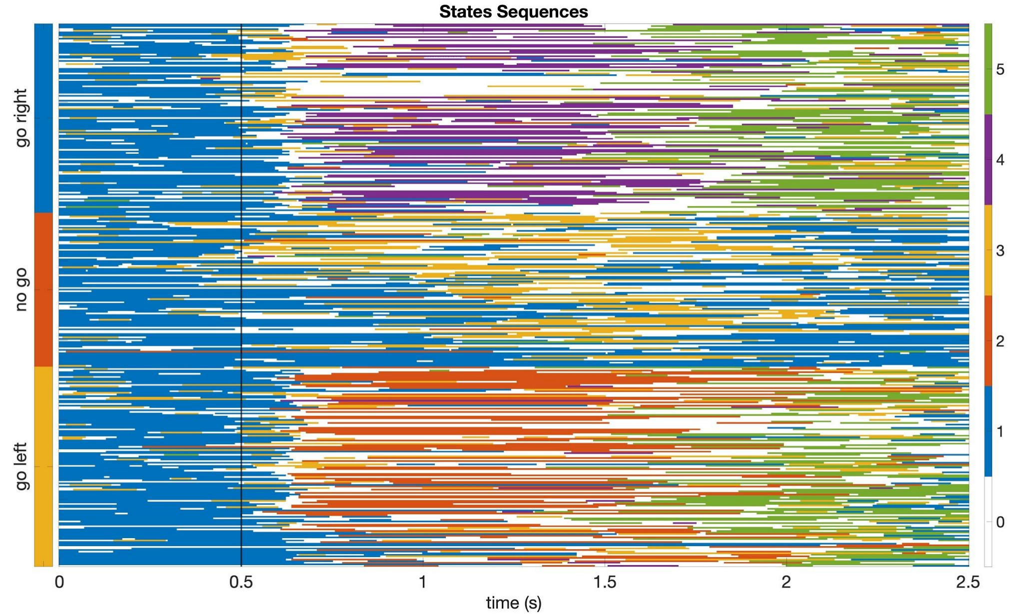
no go

go left

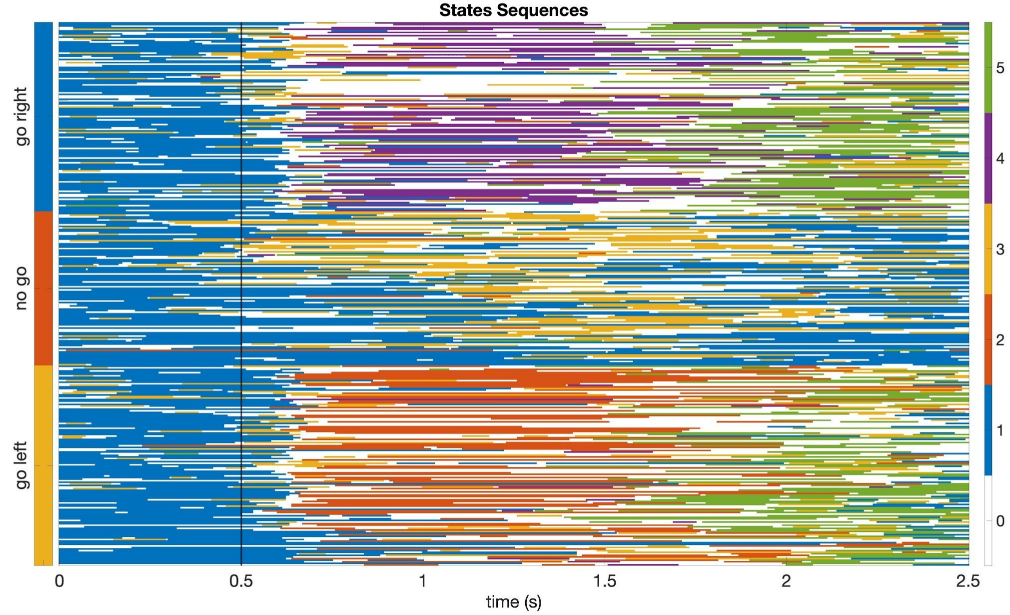


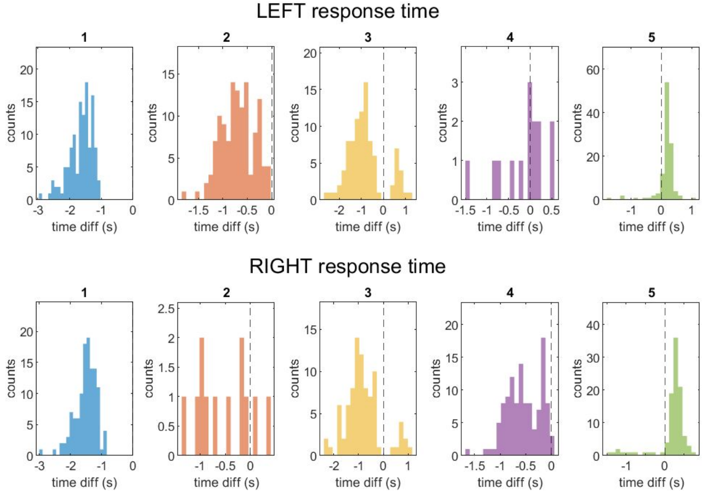


Sequences


States Sequences
go right
no go
go left
0
0.5
1
1.5
2
2.5
time (s)
5
4
3
2
1
0

State sequences





Conclusion

Yes, **hidden states** in **brain dynamics** **can predict** behavioral **events**

Acknowledgements

Our TA **Marina Fridman**

Our Mentors **Arthur Valencio** and **Luca Mazzucato**

Our **pod 135-malachite-giraffe** James McManus, Arne Nix, Sthitapranjya Pati, Alejandro Pequeño, Oscar Savolainen, Pongsakorn Wechakarn

The **Neuromatch Organizing Committee and volunteers**

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State sequences in V1 and M2 population dynamics

By: Asude Aydin, Ivan Orsolic, Marcel Jüngling
Pod: 141-gregarious-sambar

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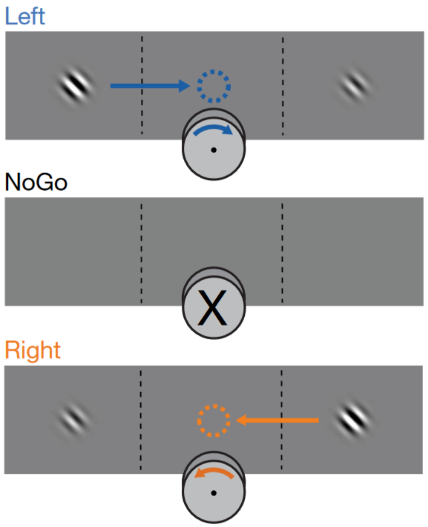
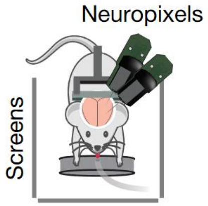
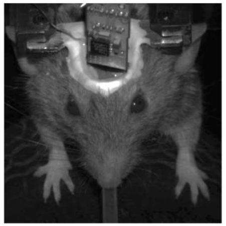
Research question





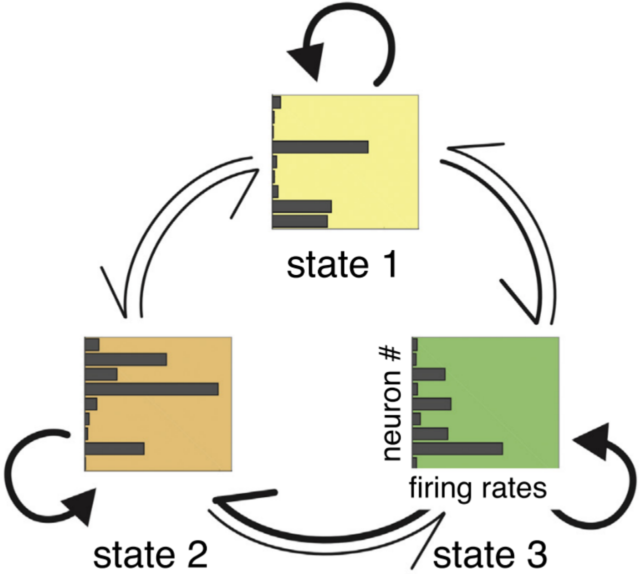


Steinmetz et al. 2019

Decoding analysis:

Can we infer behaviour from neural activity in the mouse cortex?

Research question



La Camera et al. 2019

- Can neural activity in the mouse cortex be described by discrete firing rate state sequences that reflect behaviour?

What did we do?

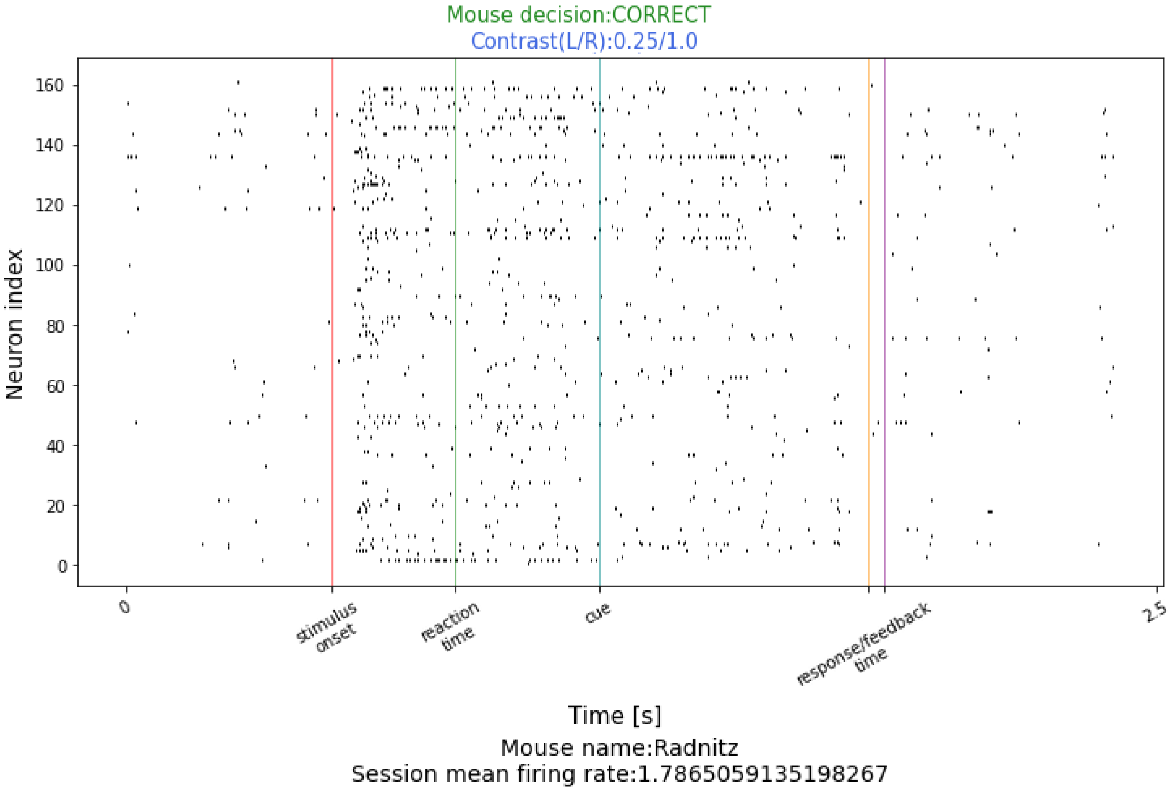
Fit HMM model to
experimental data

Implement the HMM

Compare results to behavioural
data and fits to simulated data

Explore the raw data
➡ decide on brain areas to study

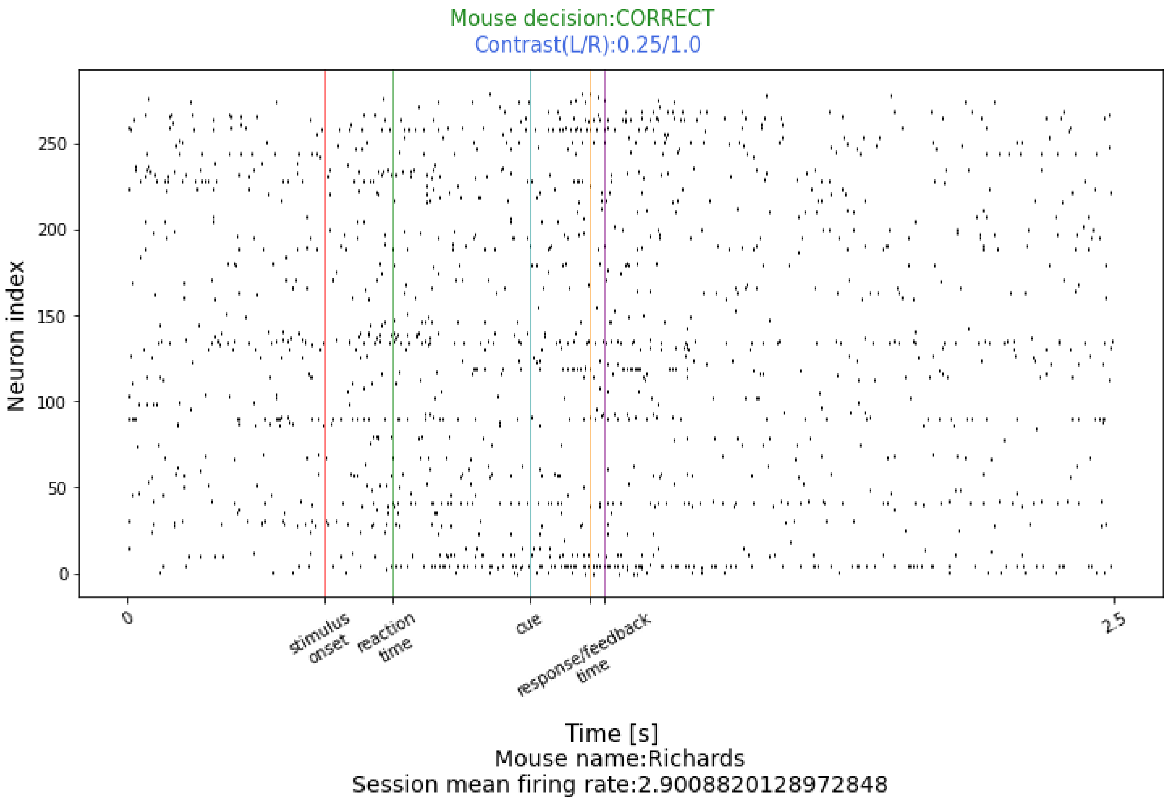
Neural activity in V1 changes during the task



Stimulus onset: visual grating stimuli
Reaction time: Start of wheel movement
Cue: Auditory cue, stimulus & movement coupled
Response time: Mouse finishes the task
Feedback time: Mouse receives reward (correct) or white noise sound (incorrect)

- Visually – we expect at least two states
- Only trial with strong right contrasts were chosen (recordings from monocular region)

Neural activity in M2 slightly changes during the task

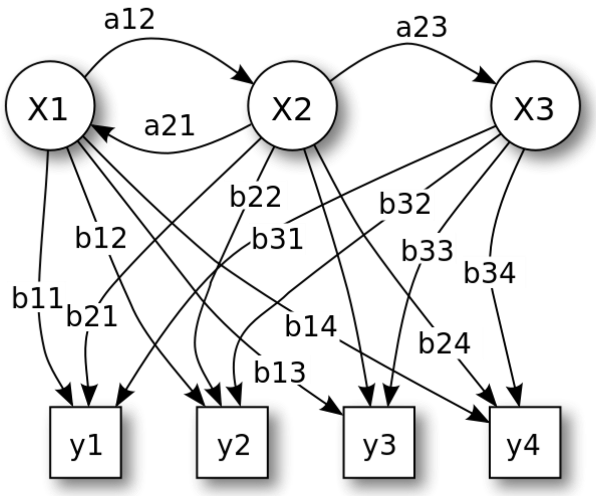


Stimulus onset: visual grating stimuli
Reaction time: Start of wheel movement
Cue: Auditory cue, stimulus & movement coupled
Response time: Mouse finishes the task
Feedback time: Mouse receives reward (correct) or white noise sound (incorrect)

- Different activity states are visually not easy to recognise
- Only trials with wheel movements to the right were chosen

How can we quantify this?

→ Apply Hidden Markov Model (HMM)



http://faculty.washington.edu/eliezg/teaching/StatR503/CourseMaterials/Week8/HMM.html

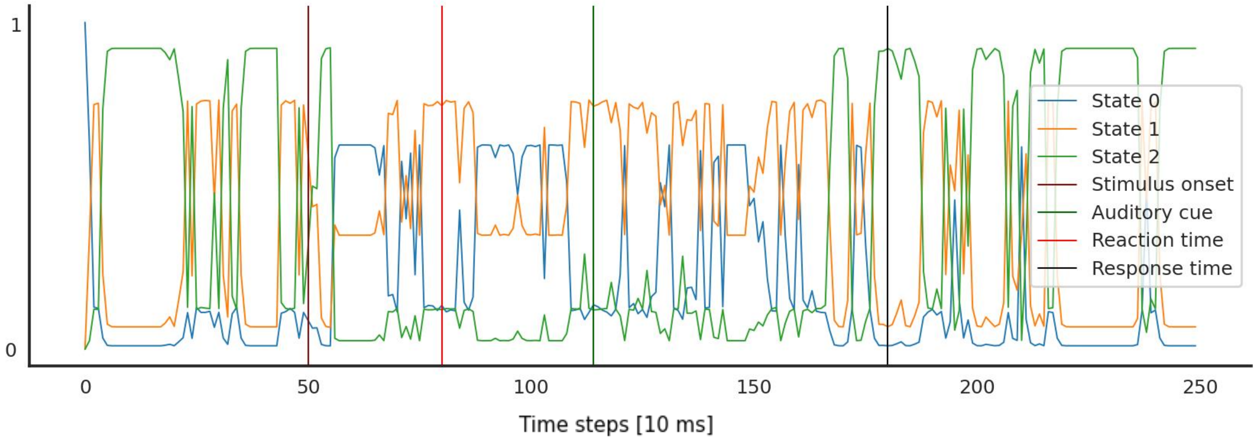
x: hidden states – firing rate vectors

a: state transition probabilities

b: output probabilities – Poisson distribution

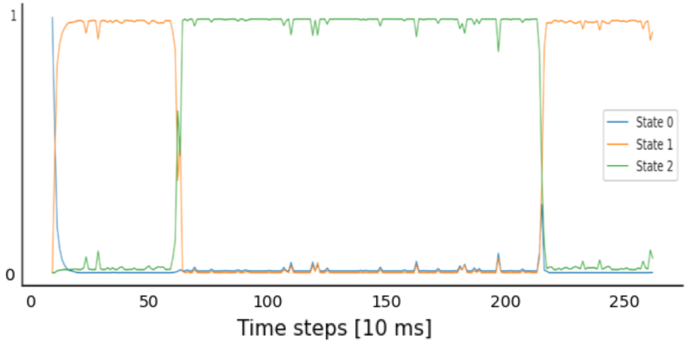
y: observations – spike count matrices

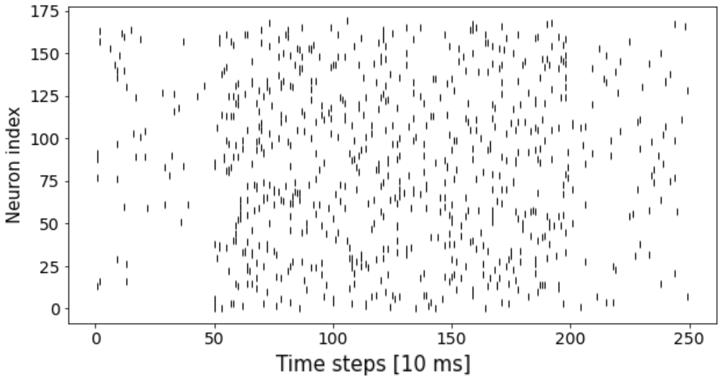
Three-state model for V1



- Fitting 3 or more states to 29 trials seemed to capture a lot of noise
- No strong correlation between behaviour and states
- Compare to simulated data

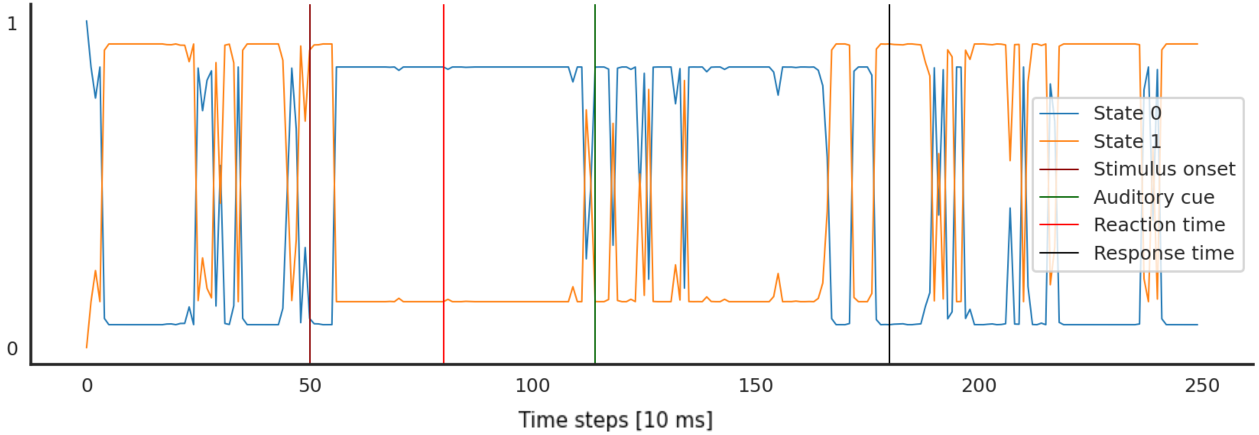
Three-state model for simulated data





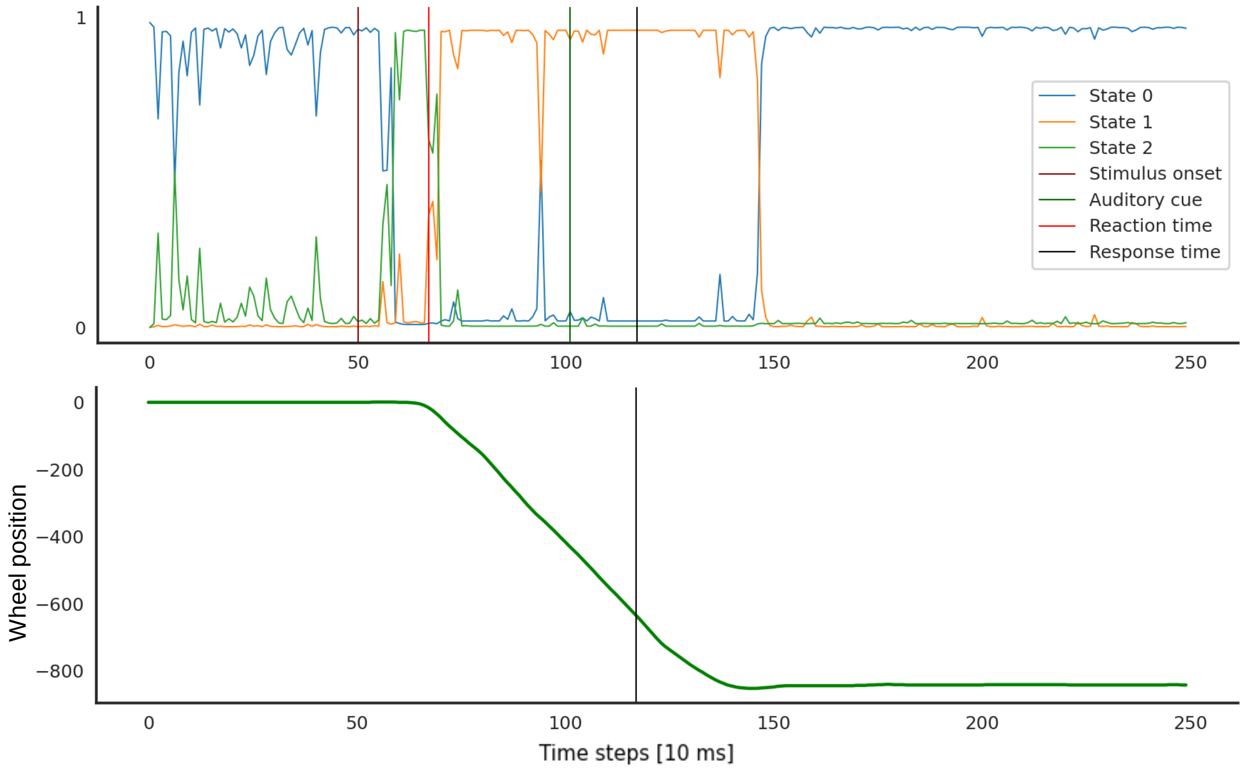
- Fitting 3 state to 29 trials of simulated data works quite well
- Either more experimental data is needed **or**
- discrete state sequences are not a good description of activity in V1 **or**
- state sequences in V1 represent more complex features

Two-state model for V1



- Even if quite noisy – the two-state model seems to capture the onset of the visual stimulus as well as the task end

Three-state model for M2



For the M2 data the HMM states correlate with behaviour

- State 0: no locomotion
- State 2: Movement initiation
- State 1: Movement

Who are we?

Asude Aydin

BSc **Electrical and Electronics Engineering**,
Middle East Technical University, Turkey

Starting this fall:
MSc **Neural Systems & Computation**,
ETH & UZH Zürich, Switzerland

Interests: Neuromorphic cognitive robots

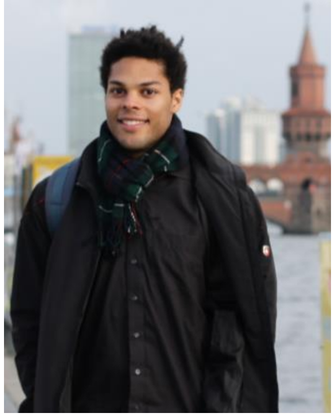
Ivan Orsolic

BSc **Information and Business Systems,**
University of Zagreb, Croatia

MSc **Information and Software Engineering**,
University of Zagreb, Croatia

Interests: Neuromorphic computing, spiking neural networks, robotics

Marcel Jüngling



BSc and (currently) MSc **Biophysics,**
Goethe University Frankfurt, Germany

Starting this fall:
PhD at the MPI for Brain Research, Frankfurt

Interests: Synaptic plasticity, neural network dynamics

We would like to thank

- **Zane Mitrevica,** for being an awesome TA
- **Dr. Benjamin Scholl,** for mentoring throughout project work
- **Dr. Patricio Orio,** for mentoring the initial project phase
- **Anastasiia Gorshkova,** for starting out this project with us
- Our whole pod, **the gregarious sambars,** for a great time
- And of course the whole **neuromatch community**!

neuromatch academy

Neuromatch Academy Project
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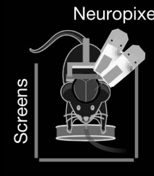
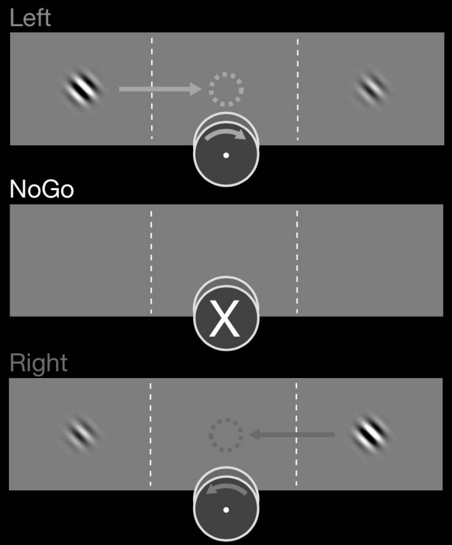
Heitor Rapela Medeiros (hrm@cin.ufpe.br)
Mentor: Michael Okun (THANK YOU SO MUCH)

Dataset: Steinmetz *et al. 2019*



Spiking activity recorded from
~30k neurons in 42 brain regions

2 alternative forced choice w/ go-nogo



Goal: *infer wheel rotation from spiking activity*

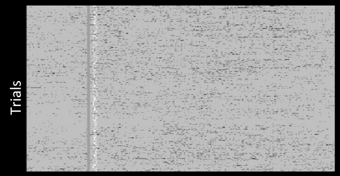
Considerations

Neurons that care about *choice* can/usually differ from *action* neurons
(choice precedes action and may indicate wheel rotation direction)

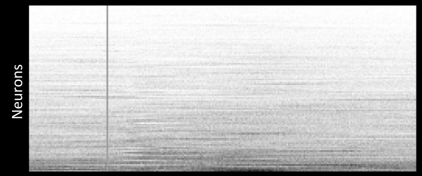
Choice leads to wheel rotation that causes stimuli movement on screen
> *infer choice based on primary visual cortex (V1) activity?*
> *compute wheel rotation from stimulus movement encoded in V1?*

Initial approach

Profile V1 activity using raster/peristimulus time histograms of neuronal activity



Single neuron response across trials

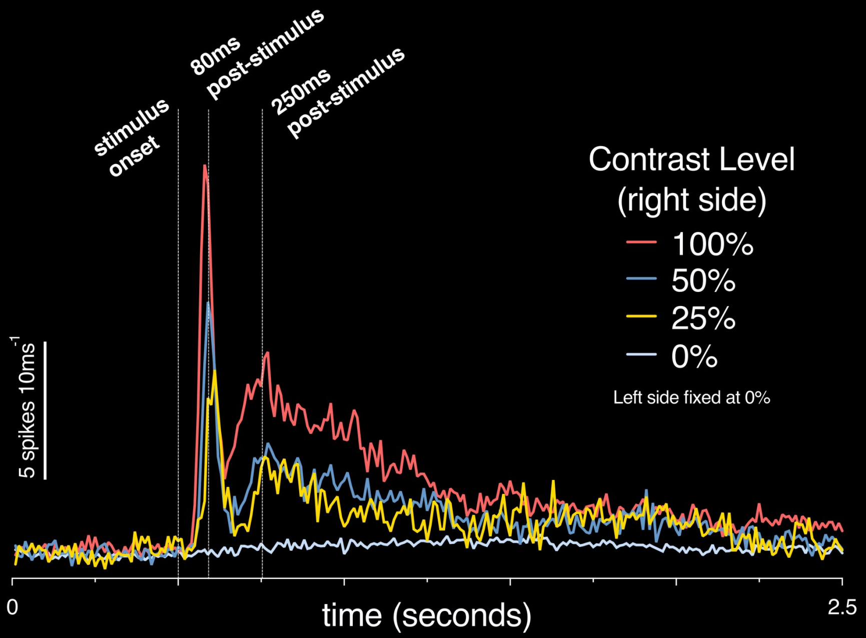


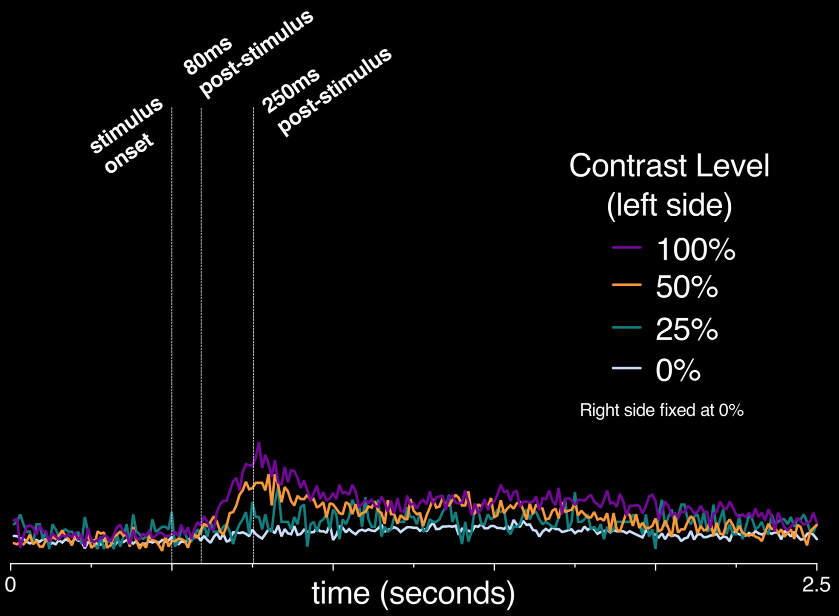
Average (smoothed) activity over many trials

Second approach

Select V1 neurons that best predict *outcome* (wheel direction)
> multiple regression with cross-validation (8-fold)
> select top 50 neurons

Selected V1 neurons average activity for different stimuli (right side is contralateral to recording)





Neurons that best predict outcome respond differently for different levels of contrast

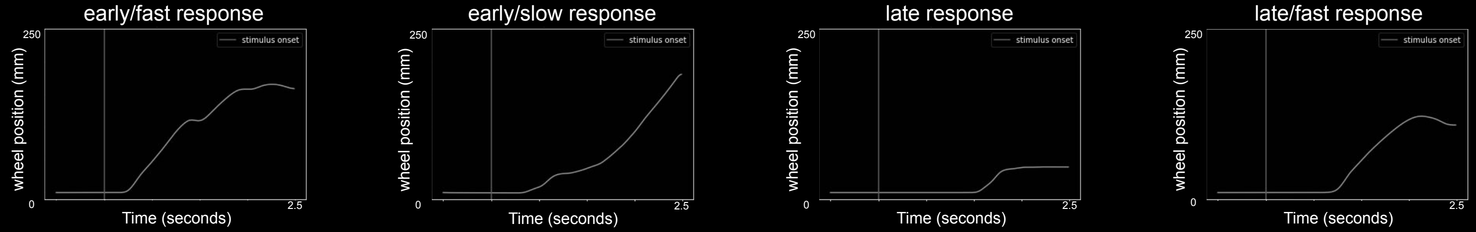
But… mice were well trained! ~98% correct choices when contrast at 100%

Neurons that predict outcome may actually encode stimuli location

Unfinished analysis:

Investigate neuronal activity in V1 for different wheel dynamics for the stimulus of the same contrast on either side.

Cluster trials by wheel dynamics



If V1 neurons respond differently to different wheel dynamics, inferring wheel rotation may be possible from visual perception encoding alone.

Then...

Redo analysis in motor and action encoding neurons

Modelling mice decision making

By: David Medina, Aleksander Nitka, Nahuel Salem-Garcia & Max Townsend
Crazy Octopus / The Generalised Linear Krakens
Support from: Richard Rosch and Lucas Pinto

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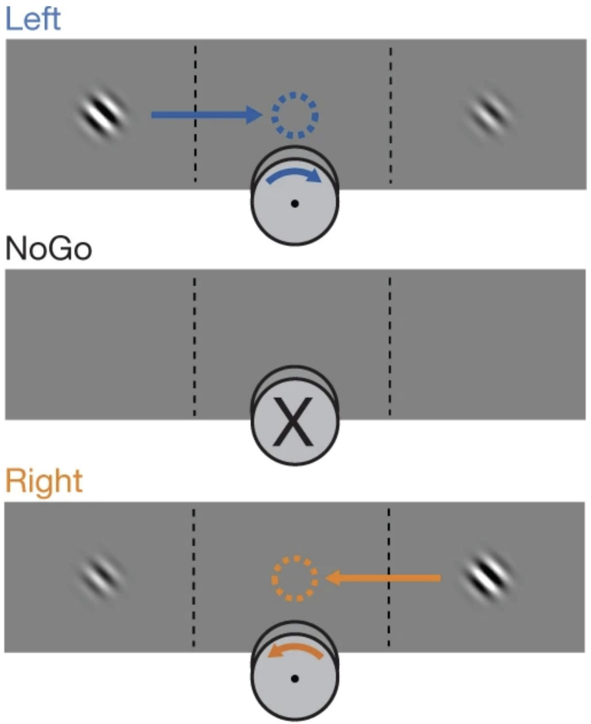
How perceptual decisions are affected by trial history?

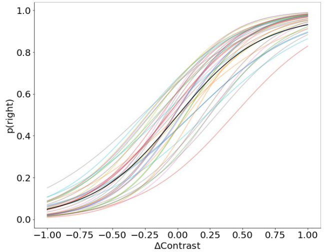
- Steinmetz dataset
- Constraints and problems:
  - Design
  - Data
  - Methods
  - Time, workload and life



Steinmetz, Zatka-Haas, Carandini & Harris, 2019, https://doi.org/10.1038/s41586-019-1787-x

How do we try to answer this question?

Logistic regression, additional decision models (e.g. adding probability of simply switching from last option)

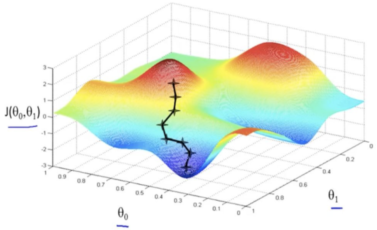


Two binary decisions:

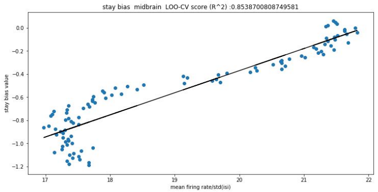
1. Go vs no go
2. Left vs right

1. **Perceptual variables:** contrast (left) and contrast (right)
2. **Other variables**: previous reward, previous choice, number of trials elapsed

Model optimization (gradient descent, differential evolution)



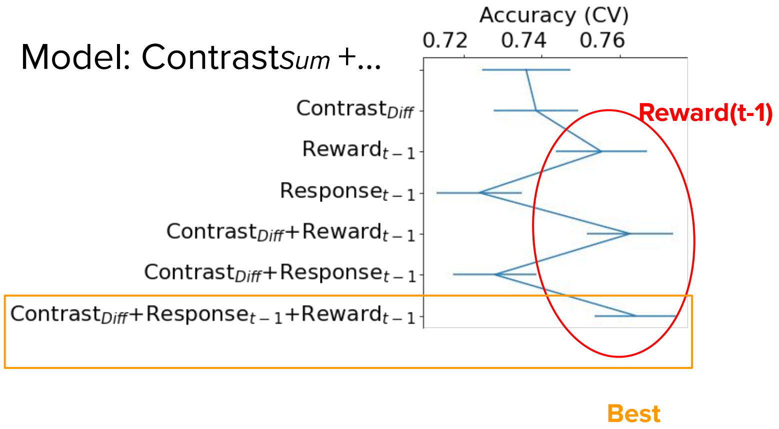
Correlate model parameters with firing rates



Results. Go/NoGo decisions are biased

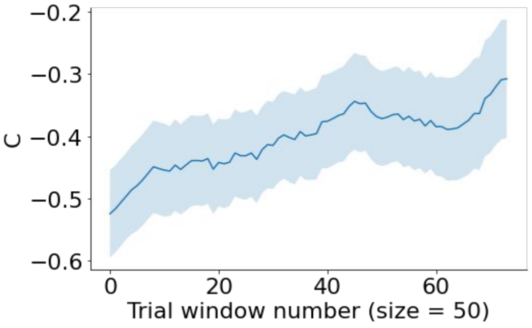
Logistic regression:
P(go) predicted by previous reward

Model: $Contrast_{sum}$ +...

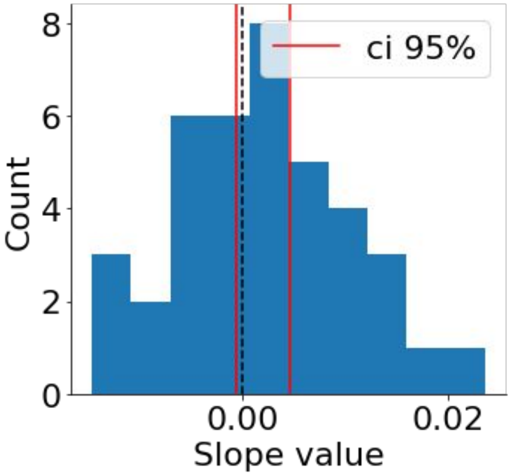


Change in action threshold across trials (C<0 : “Go” tendency)

Average



Slope distribution over sessions



Results: Biases are non-stationary.

- Modelling latent features of mouse behaviour
  - Q-Learning
  - Sensory integration with time-varying biases