Modeling Neural Dynamics: a data-driven approach

Quantitative Life Science

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Overview

Introduction

Short term memory:

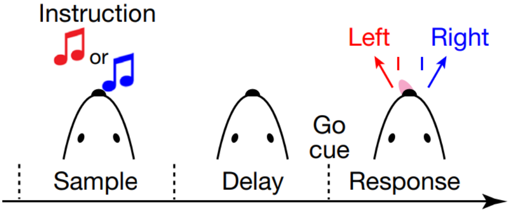
- Neurons in the frontal cortex show persistent changes in spike rate, that correlate with the maintenance of short-term memories.
- In[1], investigation on the principles that underlie this behaviour.
  - ? Continous attractor dynamics.
  - ? Discrete attractor dynamics.

Goal: replication of the dynamics.

[1] Inagaki et al., "Discrete attractor dynamics underlies persistent activity in the frontal cortex".

Experimental setup

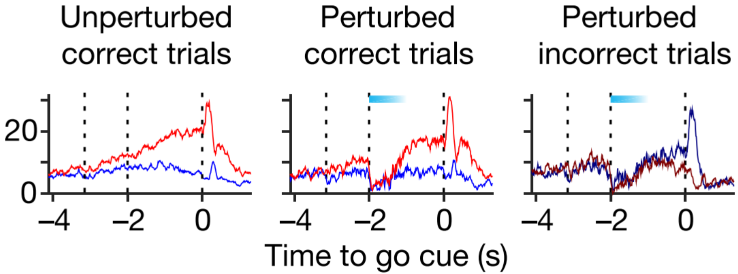
- Delayed response task.
- Mouse anterior lateral motor cortex (ALM).
- Optogenetic perturbations.



Analysis of single cell and population activity.

Analysis: Single cell

- Single selective cell.
- Spike rate comparison.



Cell with left selectivity. Red: spike rate in left trial.
Blue: spike rate in right trial

Analysis: Population dynamics

Population dynamics

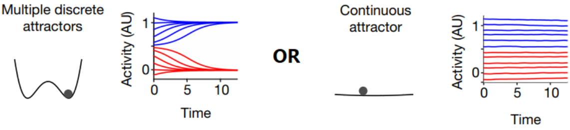
20 sessions, 755 neurons (small subset in each session) and 6 mice.
Flow for a single session:

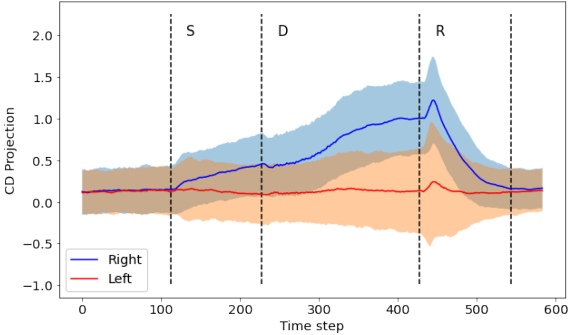
1. Select 50% of the trials.
2. Compute the coding direction (CD) : w

   $$w = \langle r(t)_{\text{right trial}} - r(t)_{\text{left trial}} \rangle$$

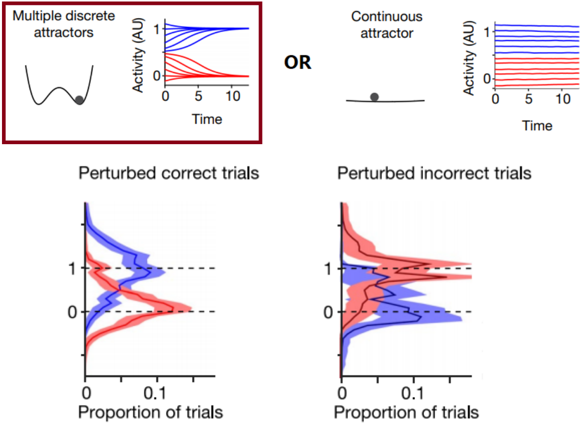
   where $r(t) = (r_i(t) \quad \text{for i} = 1, \ldots, \# \text{ neurons})$
   Mean on trials and on delay time-steps.
3. Project the test trials on w.

Attractor dynamics (I)

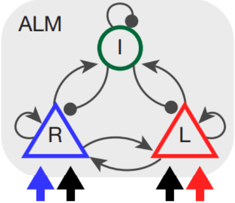


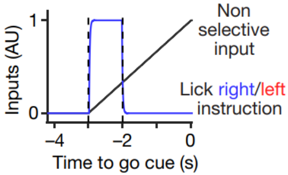


Attractor dynamics (II)



Standard framework



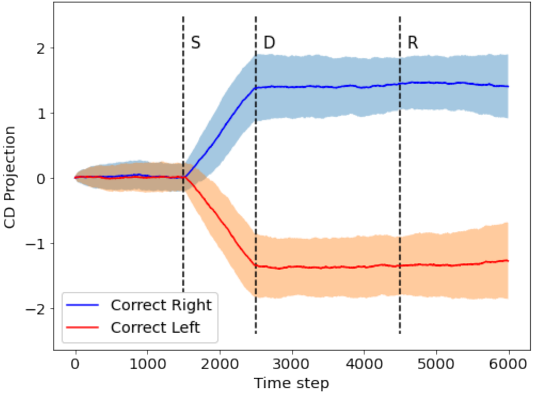


$$\tau_i \frac{dh_i(t)}{dt} = -h_i(t) + \sum_{j=L,R} \widetilde{W}_{ij} G_E(h_j(t)) + \widetilde{I}_i^{nonsel}(t) + I_i^{sel}(t) + \eta_i(t)$$

$$\widetilde{W}_{ij} = W_{ij} - \frac{W_{iI} W_{Ij}}{1 + W_{II}}, \qquad \widetilde{I}_i^{nonsel}(t) = I_E^{nonsel}(t) - \frac{W_{iI} I_I^{nonsel}}{1 + W_{II}}$$

$G_E(h_i) = f(g(h_i))$, where $g(h_i)$ is a sigmoidal activation function.

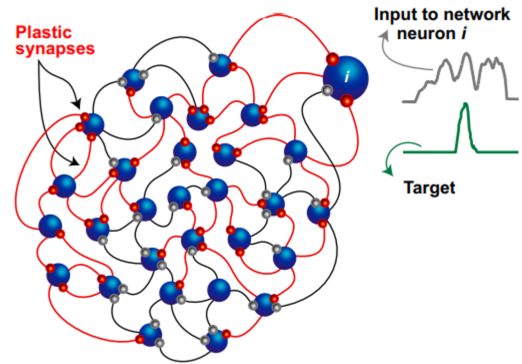
Standard framework: dynamics



Dynamics of two selective neuron populations for 500 trials. Red: spike rate projection for left-selective. Blue: spike rate projection for right-selective

Data-driven framework: FORCE

Internal synaptic modifications can be used to alter the chaotic activity of a recurrently connected neural network and generate complex but controlled outputs.[2]



[2] Sussillo and Abbott, "Generating coherent patterns of activity from chaotic neural networks".

Data-driven framework: FORCE

Problems in the online training of a Recurrent Neural Network:

- The synaptic modification can give rise to delayed effects that deviate the dynamics from the target.
- Training in face of chaotic spontaneous activity.

First Order Reduced Controlled Error

The goal of training is not significant error reduction, but rather reducing the amount of modification needed to keep the errors small.

Data-driven framework: FORCE

Recursive least squares algorithm (RLS)

1. Error estimation:

$$e_- = \mathbf{J}^T(t-\Delta t)\ \vec{r}(t) - f(t)$$

2. Synaptic modification:

$$\mathbf{J}(t) = \mathbf{J}^T(t-\Delta t) - e_-\mathbf{P}(t)\vec{r}(t)$$

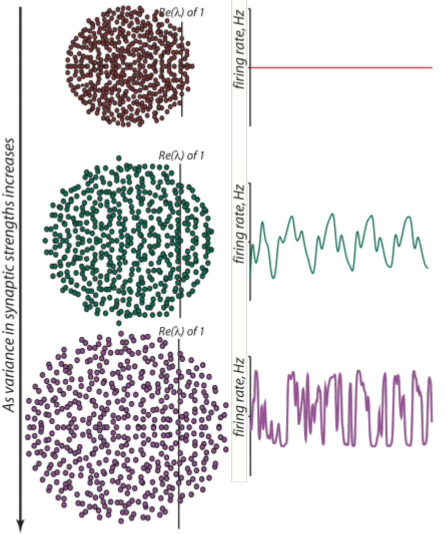
where:

$$\mathbf{P}(t) = \mathbf{P}(t-\Delta t)\ -\ \frac{\mathbf{P}(t-\Delta t)\ \vec{r}(t)\ \vec{r}^T(t)\ \mathbf{P}(t-\Delta t)}{1+\vec{r}^T(t)\ \mathbf{P}(t-\Delta t)\ \vec{r}(t)}, \qquad \text{where } \mathbf{P}(0) = \frac{\mathbf{I}}{\alpha}$$

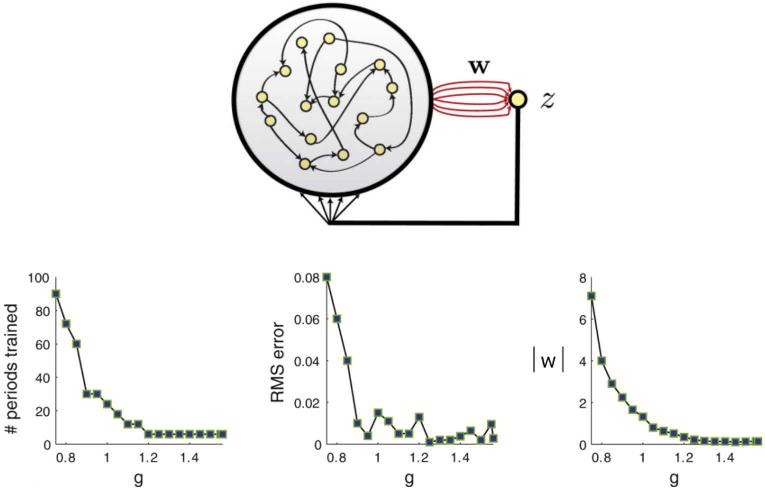
FORCE : chaotic activity (I)

$$\mathbf{J} \sim \mathcal{N}\left(0, \frac{g^2}{N}\right)$$

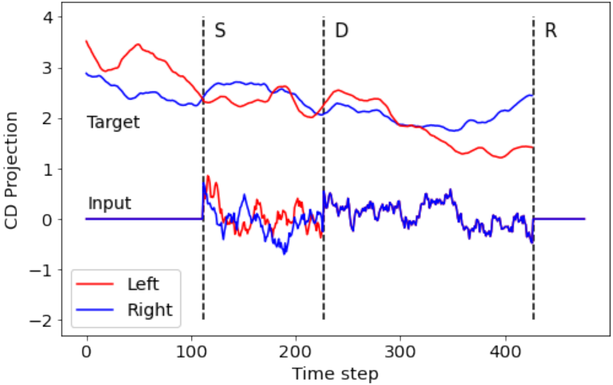
$$\begin{cases} g < 1 \rightarrow \text{inactive} \\ g > 1 \rightarrow \text{chaotic} \end{cases}$$



FORCE : chaotic activity (II)



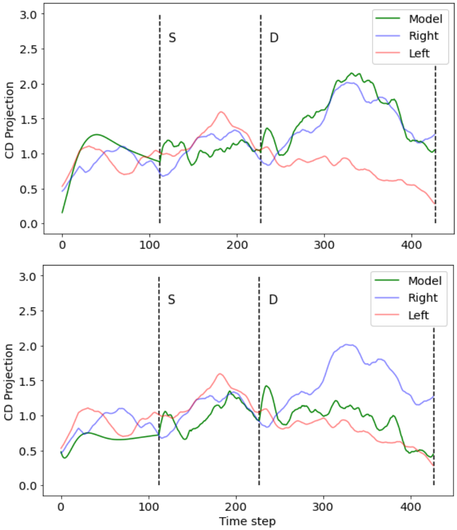
Data-driven framework: setup[3]



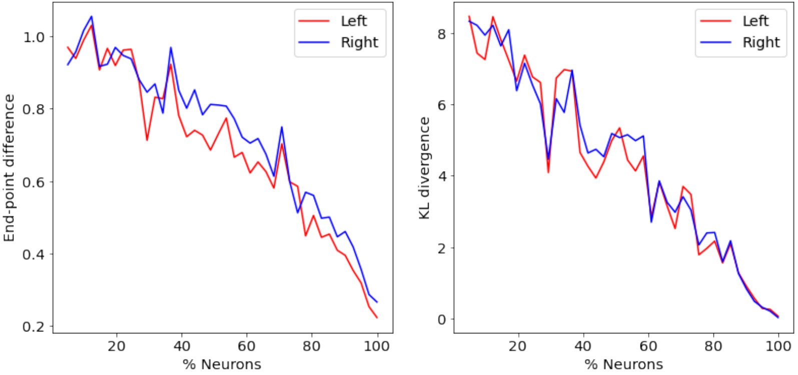
$$\tau \frac{\mathrm{d}x_i}{\mathrm{d}t} = -x_i + \sum_j^N J_{ij}\phi(x_j) + h_i, \quad \phi(x) = \frac{1}{1+e^{-x}}$$

[3] Rajan, Harvey, and Tank, "Recurrent network models of sequence generation and memory".

Data-driven framework: results



Data-driven framework: results



Conclusion: summary

- The activity of ALM neurons move toward discrete end points that correspond to specific movement directions.
- The discrete attractor dynamics behavior can be replicated using standard techniques with parameters fine-tuning.
- A learning framework is also possible, and it is able to retrieve the real data dynamics.

Conclusion: future developments

- Test the robustness of learning, injecting noise during the sample epoch.
- Analyse the performance adding hidden neurons to expand the activity space.
- Study the properties of the connectivity matrix after learning.

Thank you for your attention

References

Inagaki, Hidehiko K et al. "Discrete attractor dynamics underlies persistent activity in the frontal cortex". In: *Nature* 566.7743 (2019), pp. 212–217.

Sussillo, David and Larry F Abbott. "Generating coherent patterns of activity from chaotic neural networks". In: *Neuron* 63.4 (2009), pp. 544–557.

Rajan, Kanaka, Christopher D Harvey, and David W Tank. "Recurrent network models of sequence generation and memory". In: *Neuron* 90.1 (2016), pp. 128–142.