Extracting computational mechanisms from neural activity with low-rank networks

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Abstract

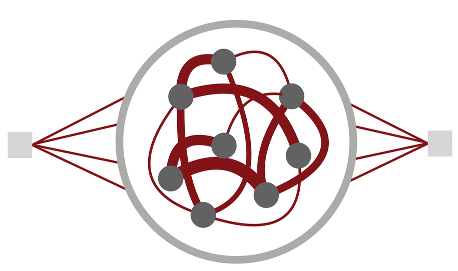
- We propose a new latent variable model based on low-rank RNNs [Mastrogiuseppe & Ostojic 2018, Beiran et al. 2021, Dubreuil et al. 2022]
- We train low-rank RNNs to reproduce neural activity neuron-by-neuron.
- We validate our approach by generating low-rank trajectories from low-rank RNNs and retrieving their connectivity with our method.
- We also train low-rank RNNs to reproduce activity of a pre-trained full-rank RNN. This leads to a compact model of the initial network, and testable predictions on inactivations of groups of neurons.
- Finally, we apply our method to neural recordings of macaque PFC, showing how our approach retrieves low-dimensional dynamics and a compact description of a network that generates them.

Classes of networks

flexibility

Full-rank RNN: $\mathcal{O}(N^2)$ parameters

Trainable $\mathbf{W}_{rec}, \vec{I}, \vec{w}_{out}$

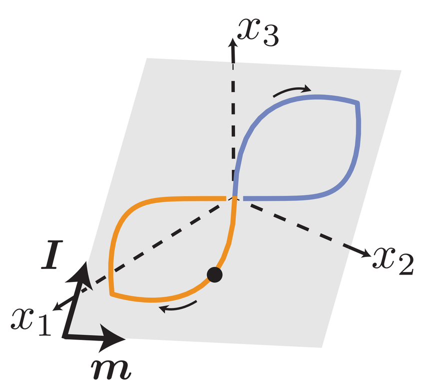


Low-rank RNN: $\mathcal{O}(N)$ parameters

[Mastrogiuseppe & Ostojic 2018]

$$W_{rec} = \frac{1}{N}\sum_{k=1}^{K} \vec{m}^k \vec{n}^{kT}$$

Trainable $\vec{m}^k, \vec{n}^k, \vec{I}, \vec{w}_{out}$



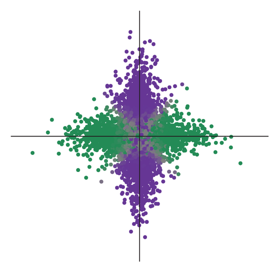
Dynamics on K-dimensional subspace

$$\vec{x} = \kappa_1 \vec{m}^1 + \cdots + \kappa_K \vec{m}_K$$

Gaussian-mixture RNN: $\mathcal{O}(1)$ parameters

[Dubreuil, Valente et al. 2020]

$$(m_i^1, n_i^1, I_i, w_{out}) \sim \sum_{p=1}^{P} \mathcal{N}(\vec{\mu}_p, \Sigma_p)$$



Trainable $(\vec{\mu}_p, \Sigma_p)$

Analytically tractable dynamics:

$$\dot{\kappa}_1 = -\kappa_1 + \tilde{\sigma}_{n_1 m_1}\kappa_1 + \tilde{\sigma}_{n_1 m_2}\kappa_2 + \tilde{\sigma}_{n_1 W_{in}} u(t)$$

$$\dot{\kappa}_2 = -\kappa_2 + \tilde{\sigma}_{n_2 m_1}\kappa_1 + \tilde{\sigma}_{n_2 m_2}\kappa_2 + \tilde{\sigma}_{n_2 W_{in}} u(t)$$

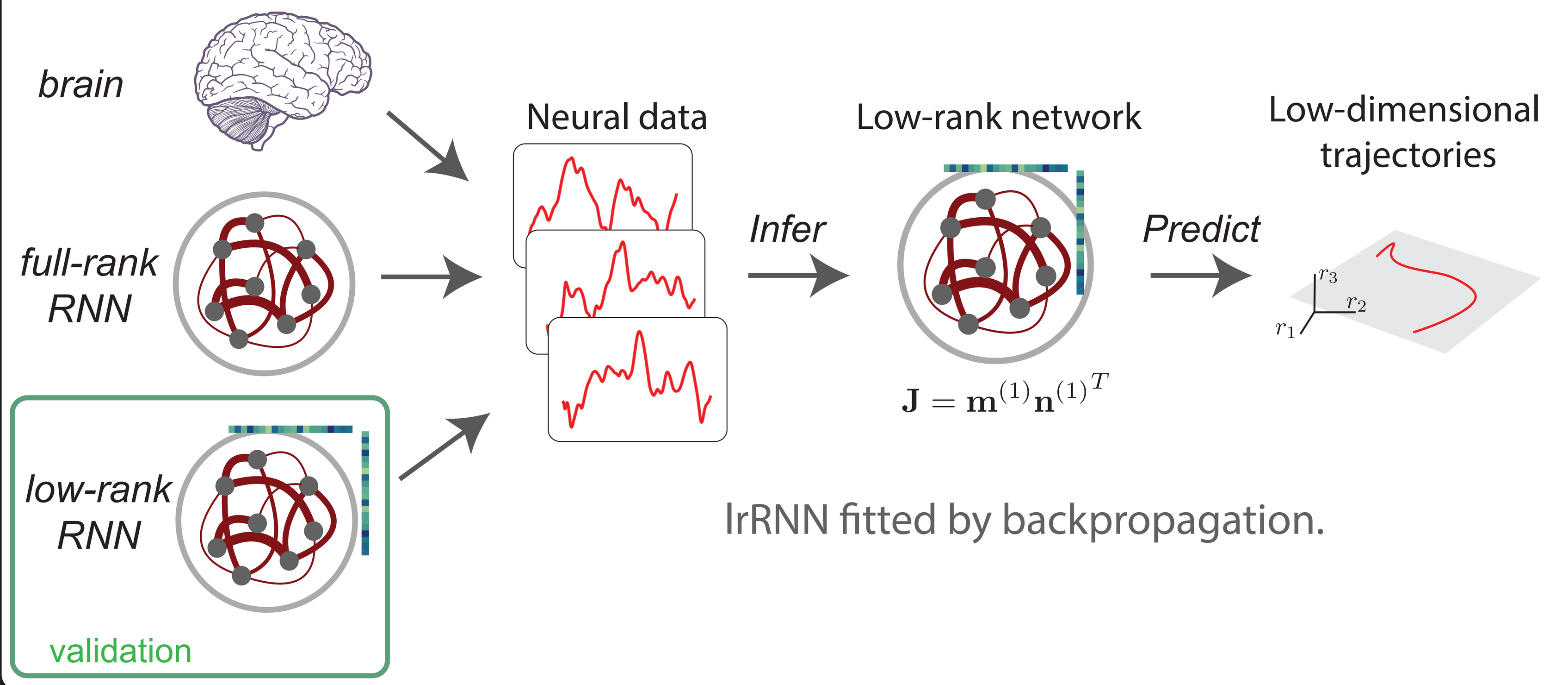
with functional connectivities

$$\tilde{\sigma}_{ab} = \sum_{p=1}^{P} \sigma_{ab}^{p} \langle \phi' \rangle_p$$

interpretability

paper blog

Approach: fitting low-rank RNNs to neural recordings

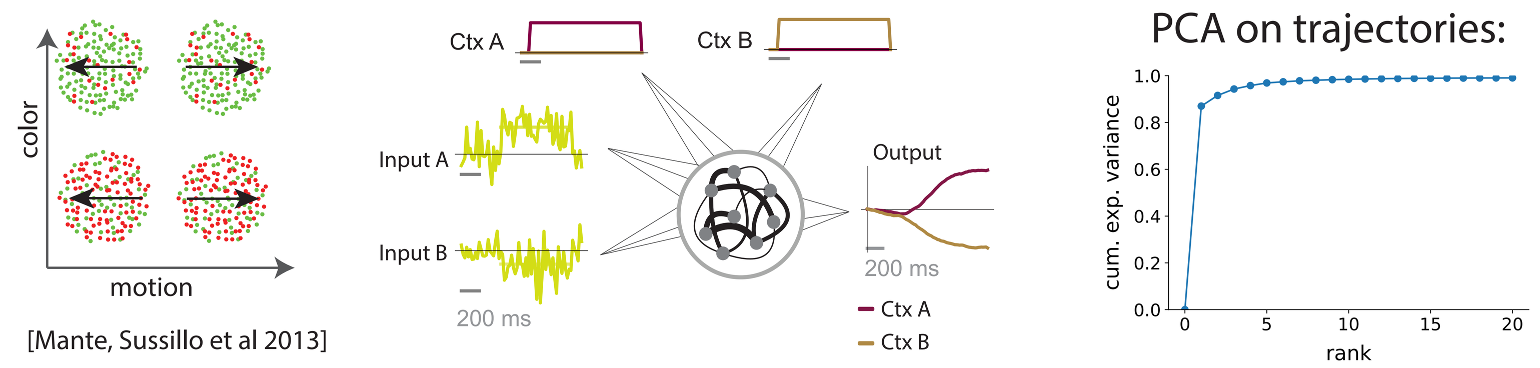


lrRNN fitted by backpropagation.

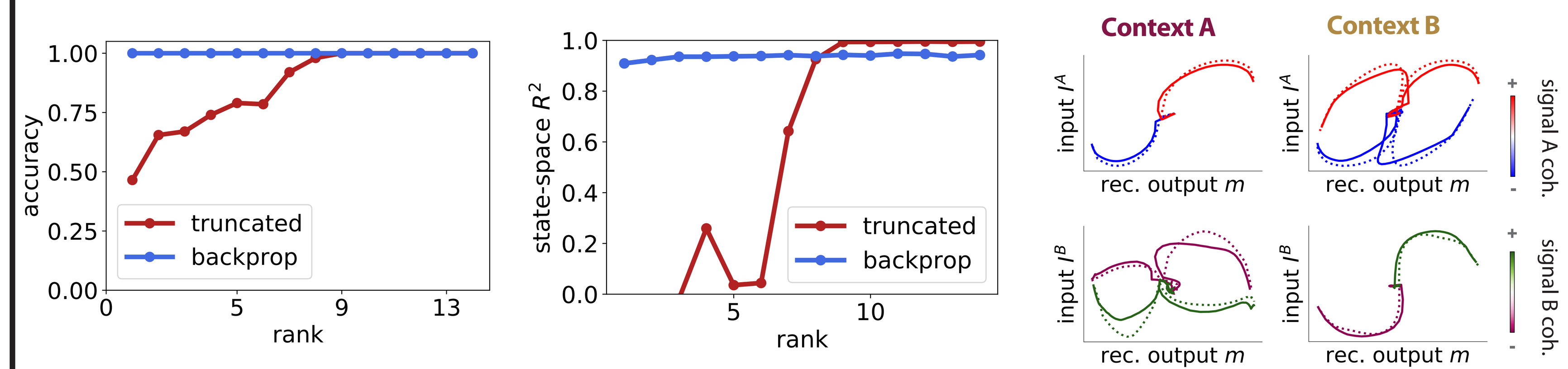
"Opening the black box" of a full-rank network

➤ **This method can give insights into the mechanism used by a full-rank network**

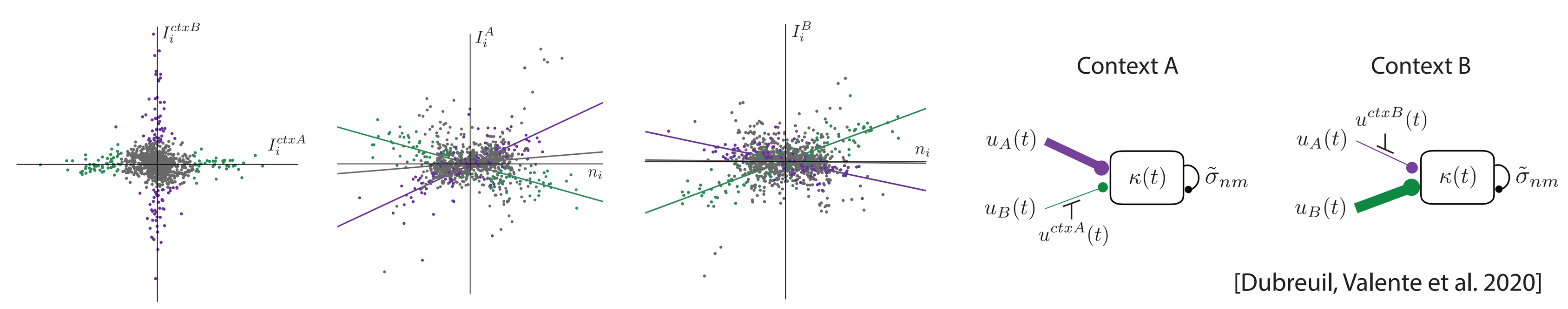
A full-rank network is trained on a context-dependent DM task:



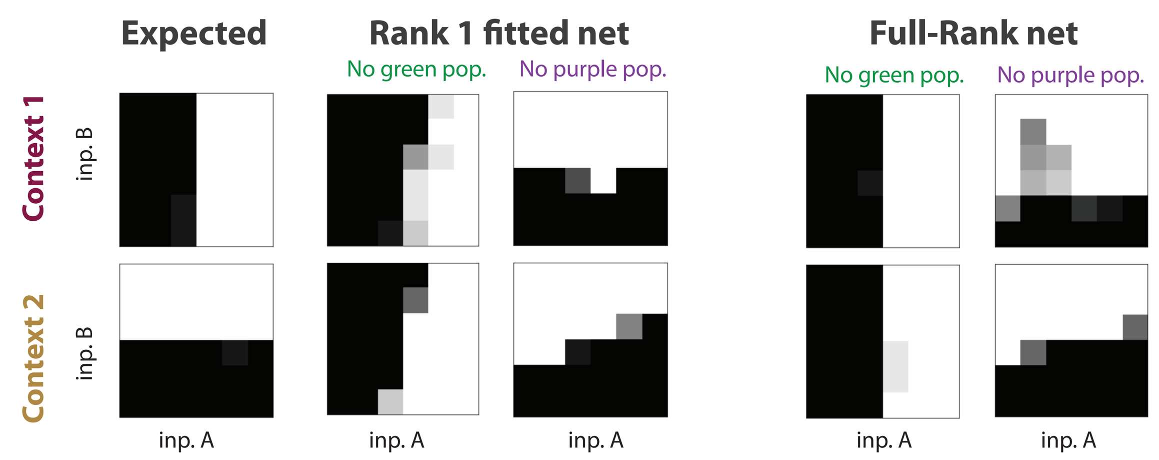
With backprop, a rank-1 network suffices to capture neural activity:



Reverse-engineering rank-1 connectivity shows role for two populations:



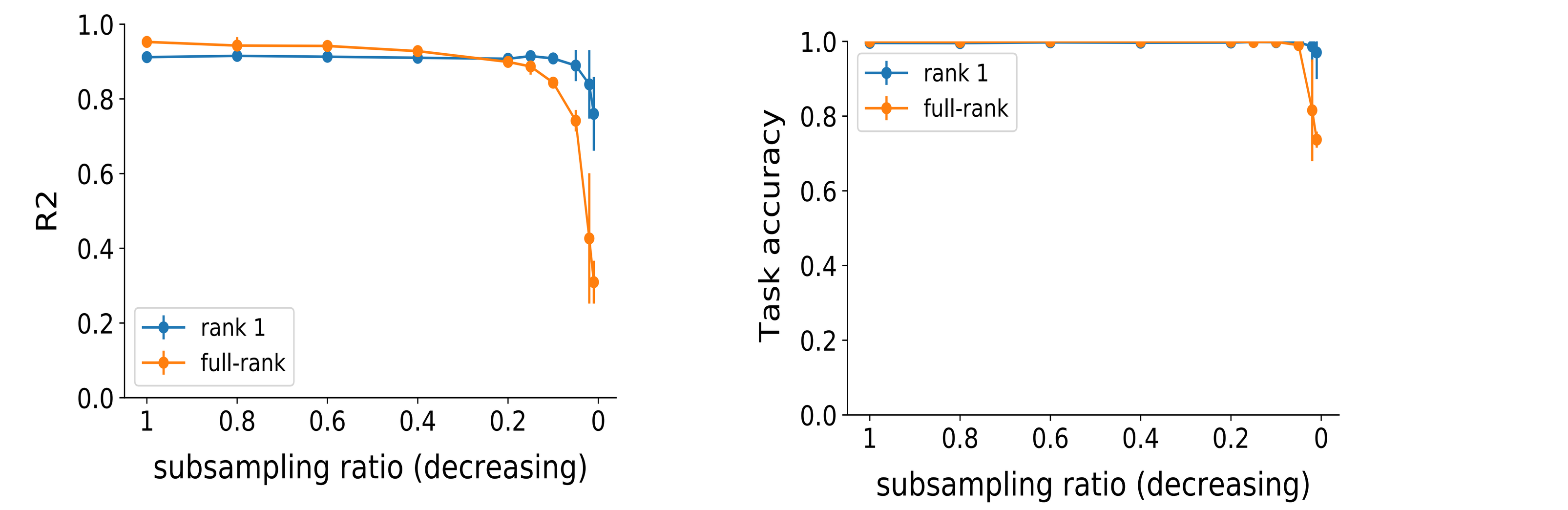
Specific predictions for inactivations of the original network can be done:



Neuron subsampling

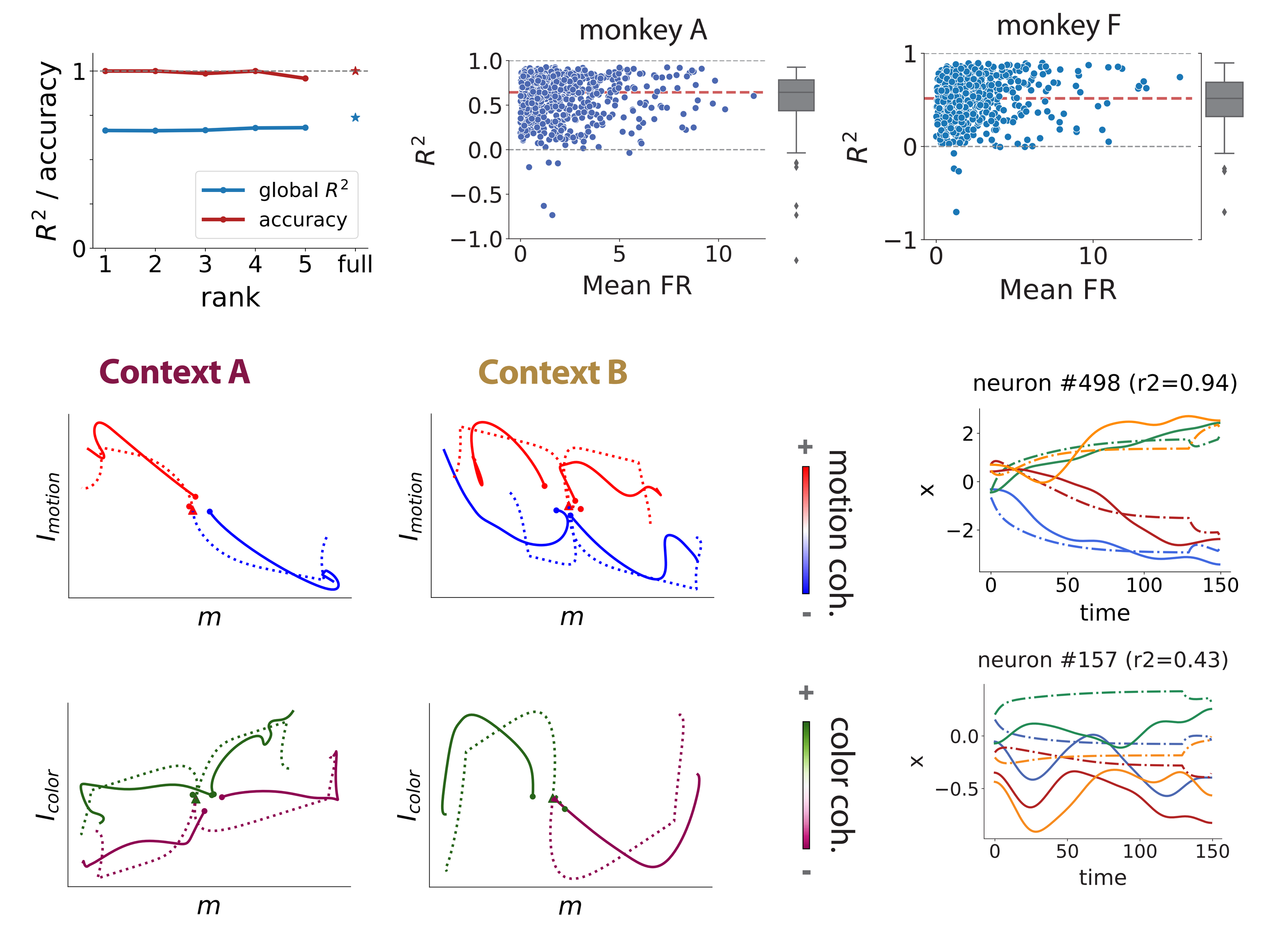
➤ **This method is very robust to subsampling**

Results for networks fitted to subsampled trajectories of a full-rank, 1000 neurons network



Neural recordings

➤ **Low-rank networks can capture neural activity recorded in behavioral tasks.**



Take-home messages

- Low-rank networks provide a compact and interpretable description of network dynamics.
- Fitted to neural data, they provide low-dimensional dynamics and testable predictions.
- They can be applied to understand full-rank RNNs, as well as to neural recordings.

Bibliography

- Mante, V., Sussillo, D., et al., "Context-dependent computation by recurrent dynamics in prefrontal cortex", Nature, 2013
- Mastrogiuseppe, F. and Ostojic, S., "Linking connectivity, dynamics and computations in low-rank recurrent neural networks", *Neuron*, 2018
- Beiran, M., et al., "Shaping dynamics with multiple populations in low-rank recurrent networks", Neural Computation, 2021
- Dubreuil, A., Valente, A., et al., "The role of population structure in computations through neural dynamics", Nature Neuroscience, 2022