Inferring low-rank network models from neural activity

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Abstract

- Trained RNNs can offer good descriptions of collective neural activity but are difficult to interpret.
- Low-rank networks keep similar characteristics yet offer great interpretability.
- We present LINT *(Low-rank Inference from Neural Trajectories)*, a method to infer interpretable connectivity from recordings.
- Our method retrieves low-dimensional task-related subspaces, as well as computational mechanisms at the circuit level.

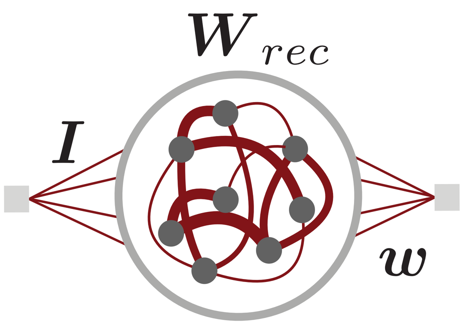
Classes of networks

flexibility

interpretability

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

Trainable $\boldsymbol{W}_{rec}, \boldsymbol{I}, \boldsymbol{w}$



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

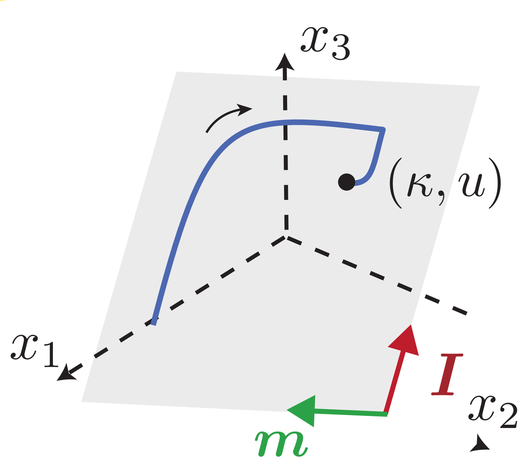
[Mastrogiuseppe & Ostojic 2018]

$$\boldsymbol{W}_{rec} = \sum_{r=1}^{R} \boldsymbol{m}^{(r)} \boldsymbol{n}^{(r)T}$$

Trainable $\boldsymbol{m}^{(r)}, \boldsymbol{n}^{(r)}$

Dynamics on R-dim subspace:

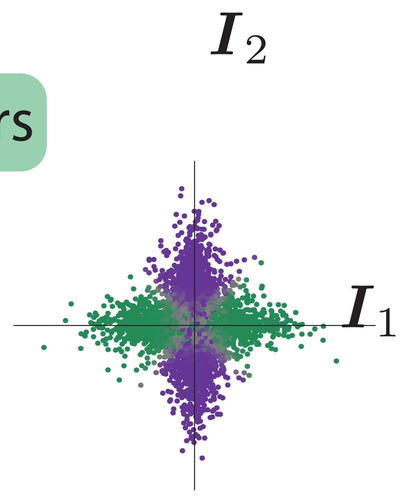
$$\boldsymbol{x}(t) = \sum_{r=1}^{R} \kappa_r(t) \boldsymbol{m}^{(r)} + \sum_{s=1}^{N_{in}} v_s(t) \boldsymbol{I}^{(s)}$$



Multi-population RNN: $\mathcal{O}(1)$ parameters

[Dubreuil, Valente et al. 2022]

$$(m_i^1, n_i^1, I_i, w_i) \sim \sum_{p=1}^{P} \mathcal{N}(\boldsymbol{\mu}_p, \boldsymbol{\Sigma}_p)$$



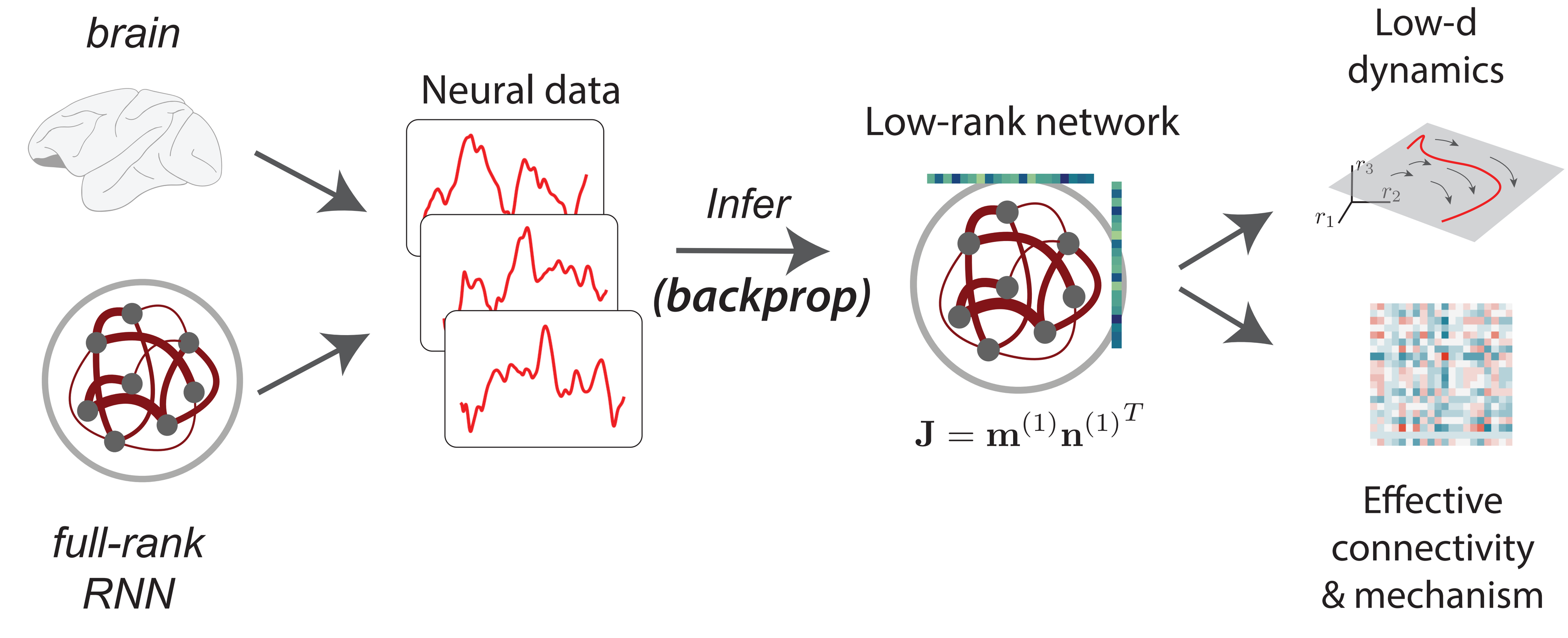
Trainable $(\boldsymbol{\mu}_p, \boldsymbol{\Sigma}_p)$

Analytically tractable dynamics:

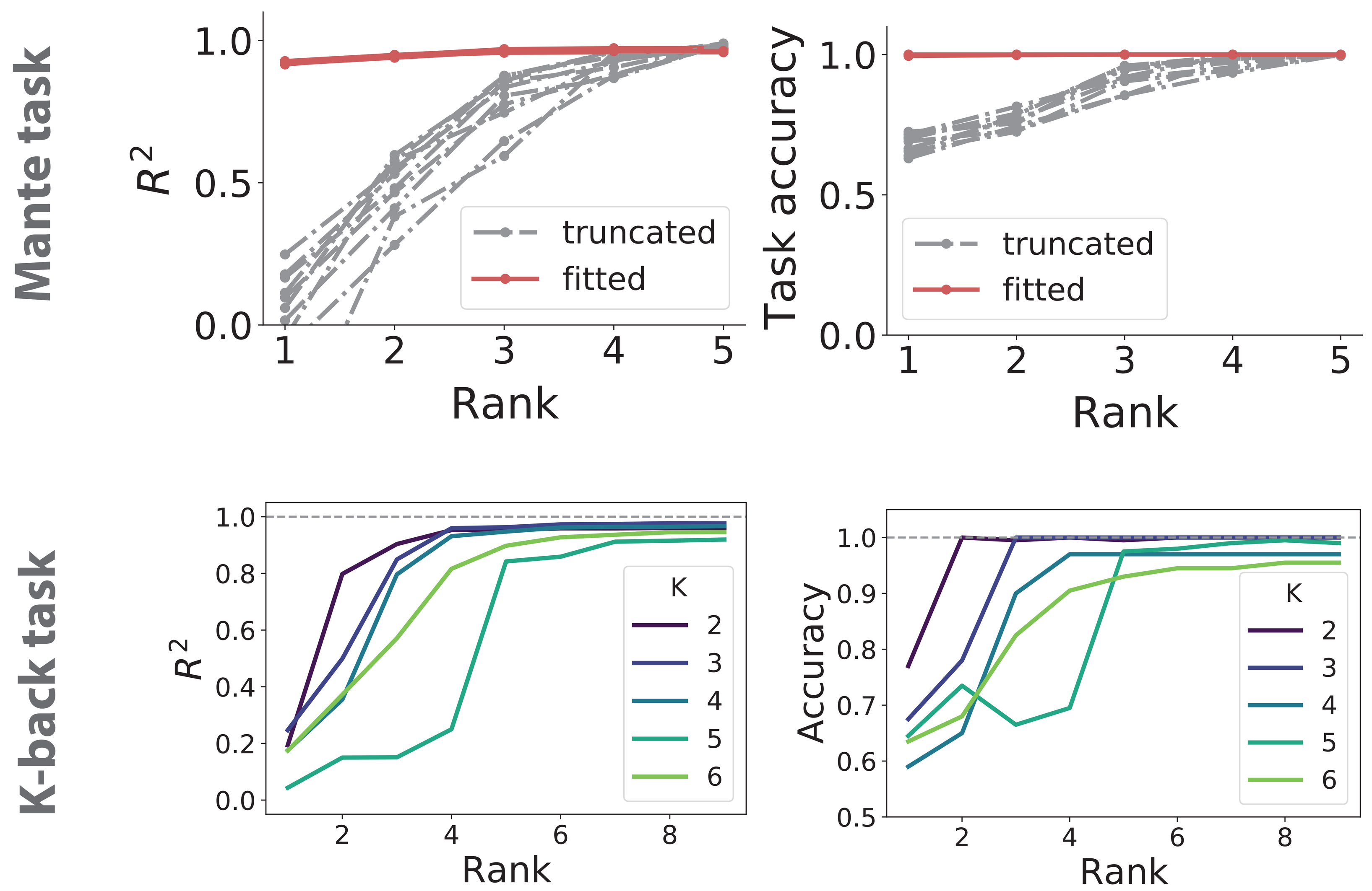
$$\dot{\kappa}_1 = -\kappa_1 + \tilde{\sigma}_{n_1 m_1} \kappa_1 + \tilde{\sigma}_{n_1 m_2} \kappa_2 + \tilde{\sigma}_{n_1 W_{in}} u(t)$$
$$\dot{\kappa}_2 = -\kappa_2 + \tilde{\sigma}_{n_2 m_1} \kappa_1 + \tilde{\sigma}_{n_2 m_2} \kappa_2 + \tilde{\sigma}_{n_2 W_{in}} u(t)$$

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

Approach: fit low-rank RNNs to neural recordings

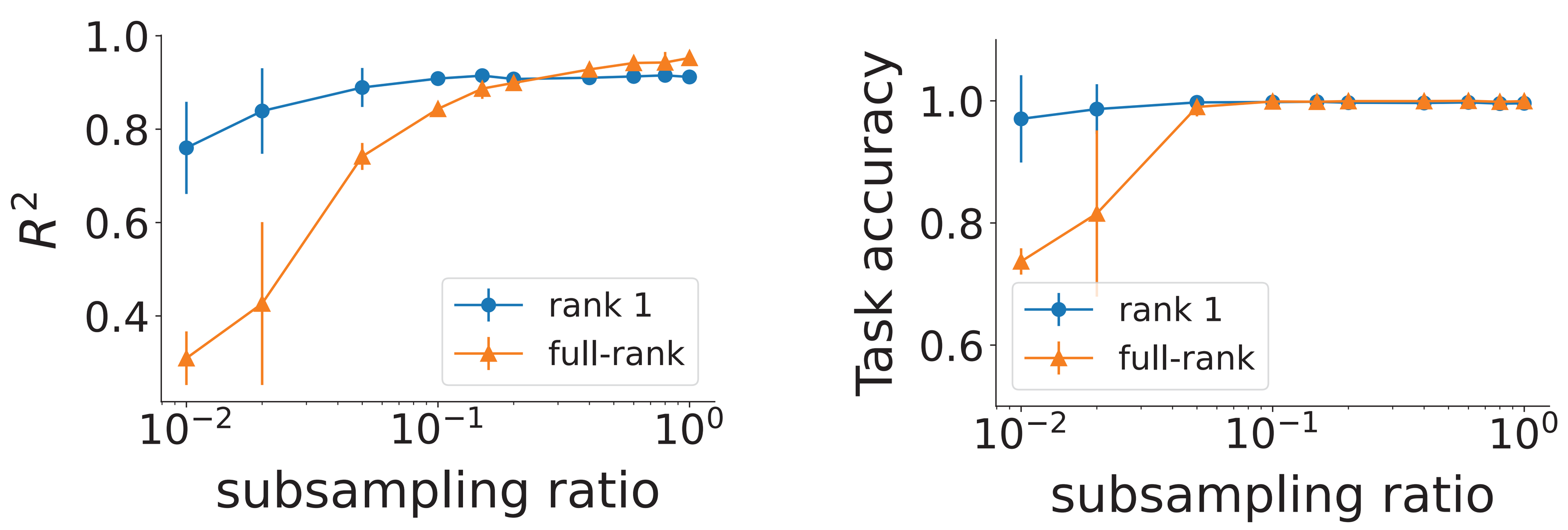


Reproducing full-rank nets with low-rank ones



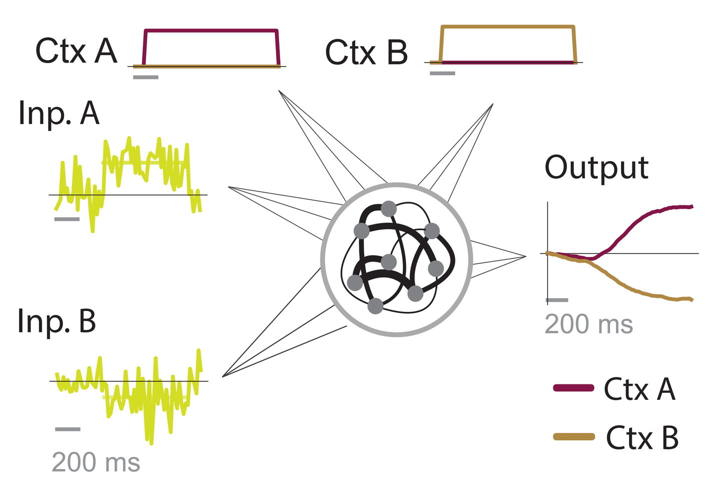
Neuron subsampling

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

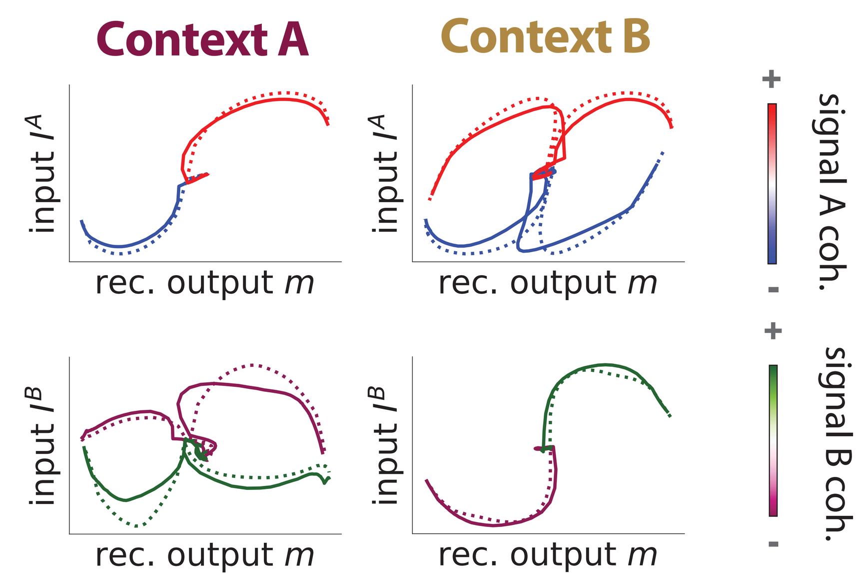


"Opening the black box" of a full-rank network

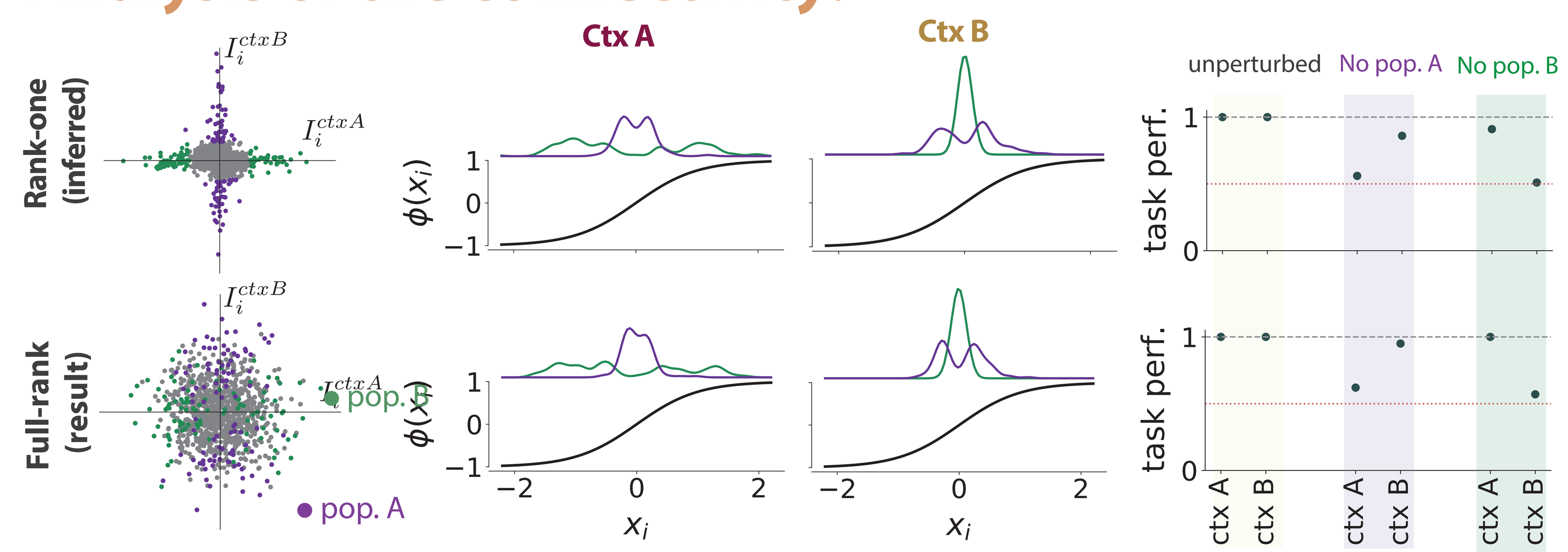
Task:



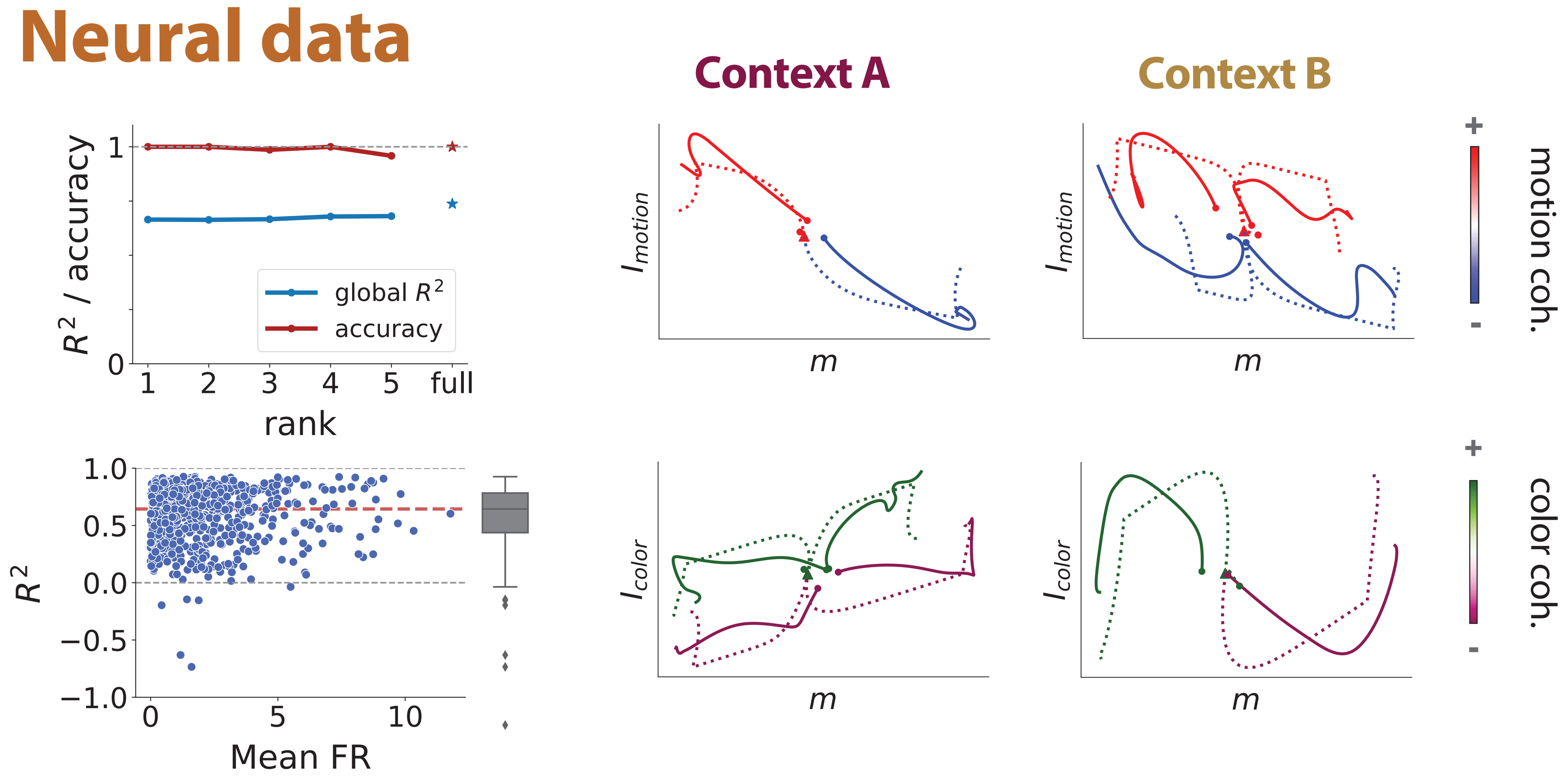
Low-dimensional dynamics:



Analysis of the connectivity:



Neural data



Take-home messages

- Networks with a very **low-rank connectivity** can capture the main aspects of dynamics of unconstrained RNNs and recorded neural data.
- They provide a way to dissect mechanisms in black-box RNNs and make them more **interpretable**.
- They bridge **dimensionality reduction** with the **computational requirements** of the studied task.

Bibliography

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