Disentangling the roles of dimensionality and cell populations in neural computations

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Introduction

- How the two key concepts of cell classes and low-dimensional trajectories interact to shape neural computations ?
- We propose a method which combines artificial neural networks training and a recent theory linking dimensionality and connectivity structure [1] .
- We generate network models of low dimensionality and fixed number of cell classes which implement a series of behavioral tasks and allows us to explore the roles played by dimensionality and cell classes in neural computations.

Approach

Train minimal rank RNN → Reverse-engineer: Study dynamics [2] ⇅ Find minimal number of populations → Construct a class of minimally parametrized solutions

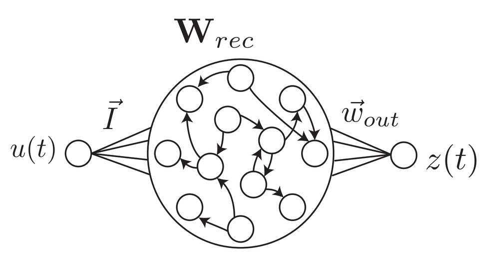
Task	Minimal rank	Minimal number of populations
Perceptual decision-making [Gold and Shadlen 2007]	1	1
Multi-sensory decision-making [Raposo et al 2014]	1	1
Parametric working memory [Romo et al 1999]	2	1
Context-dependent decision-making [Mante et al 2014]	1	2
n-Context-dependent decision-making	1	n
Delay-match-to-sample [Miller et al 1996]	2	2
Delay-non-match-to-sample	2	2

Classes of networks

flexibility ↑ ↓ interpretability

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

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



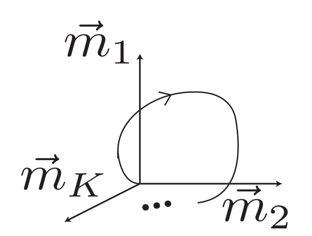
Low-rank RNN: $\mathcal{O}(N)$ parameters

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

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

Dynamics on K-dimensional subspace

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



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

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

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

Analytically tractable dynamics:

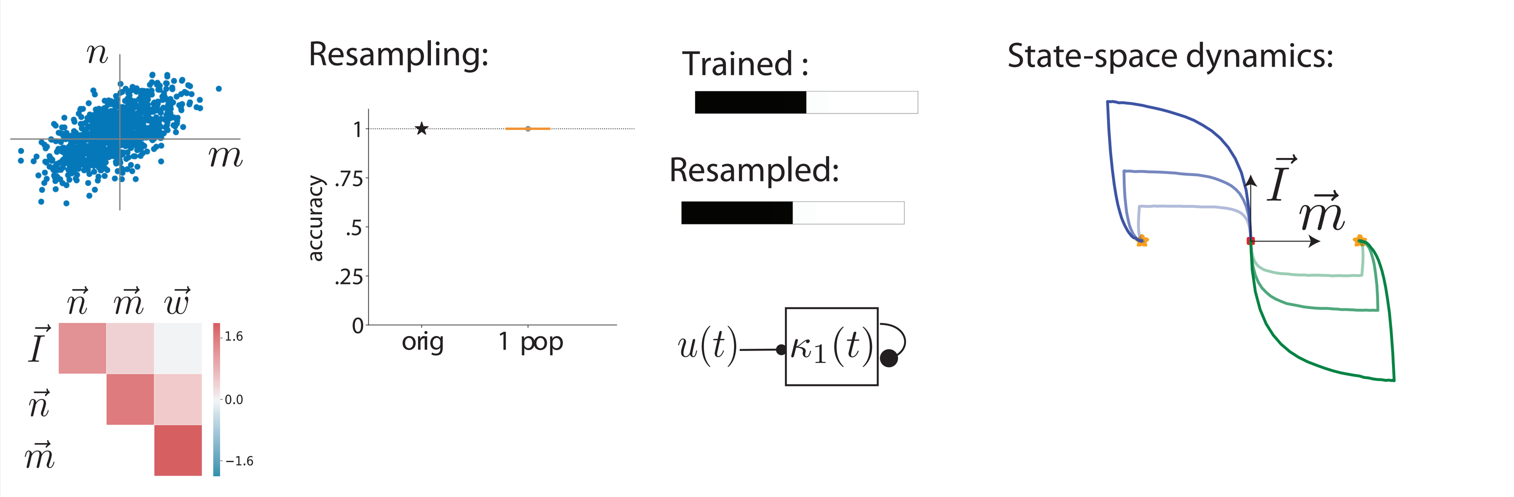
$$\dot{\kappa}_1 = -\kappa_1 + \tilde{\sigma}_{n_1 m_1}\kappa_1 + \tilde{\sigma}_{n_1 m_2}\kappa_2 + \tilde{\sigma}_{n_1 W_{in}} u(t)$$
$$\dot{\kappa}_2 = -\kappa_2 + \tilde{\sigma}_{n_2 m_1}\kappa_1 + \tilde{\sigma}_{n_2 m_2}\kappa_2 + \tilde{\sigma}_{n_2 W_{in}} u(t)$$

with functional connectivities:

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

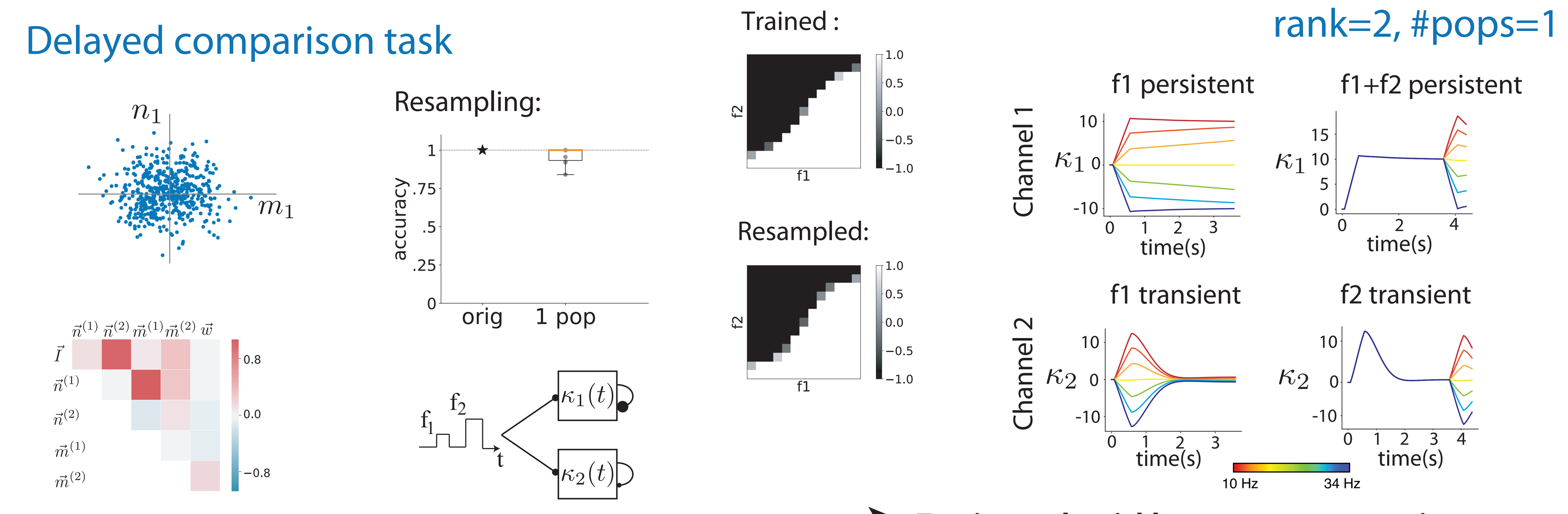
Increasing rank with a single population

Random dots motion task — rank=1, #pops = 1



➤ One internal variable : accumulation of evidence

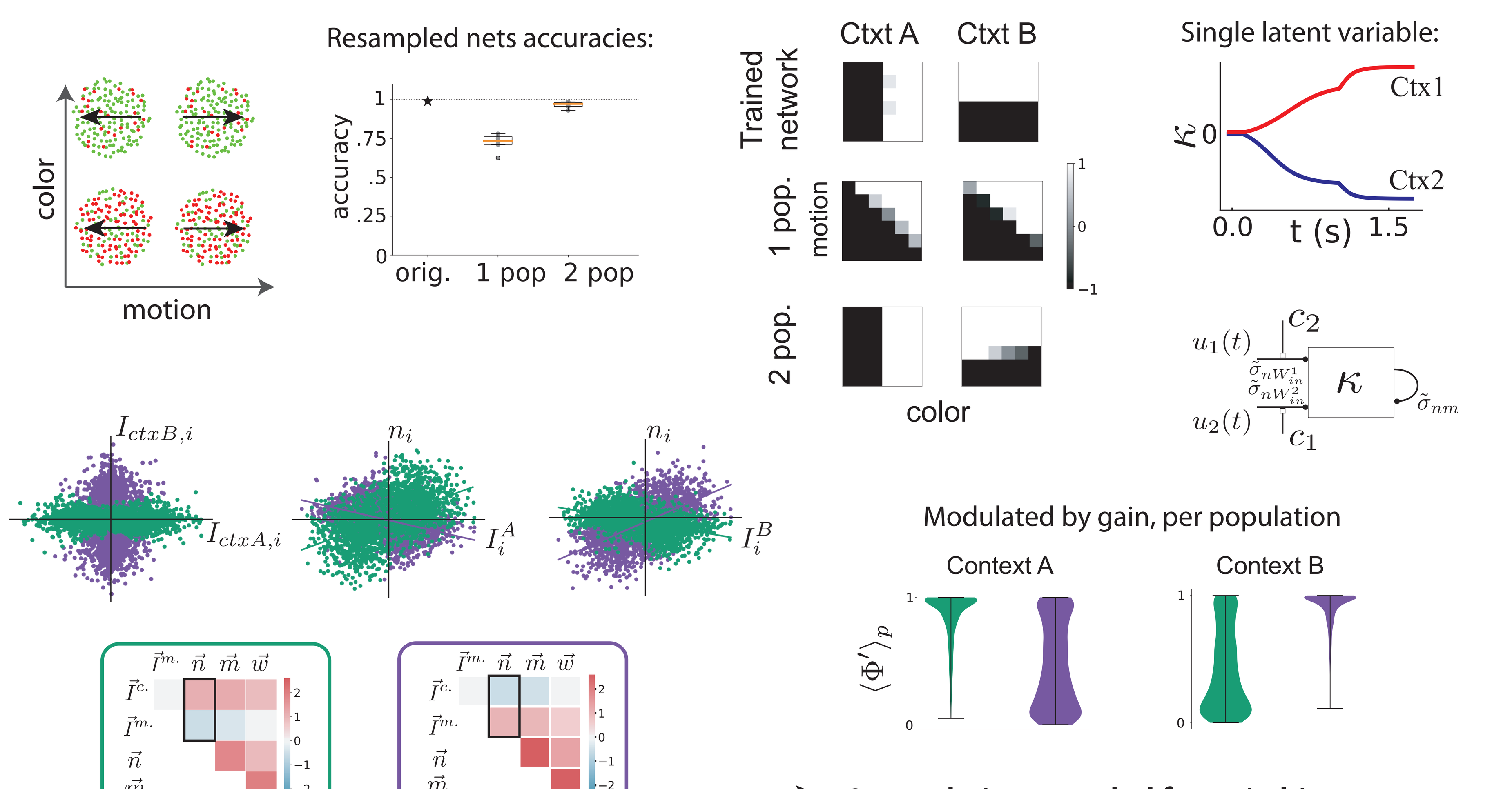
Delayed comparison task — rank=2, #pops=1



➤ Two internal variables: memory + compariso

Flexible tasks require multiple populations

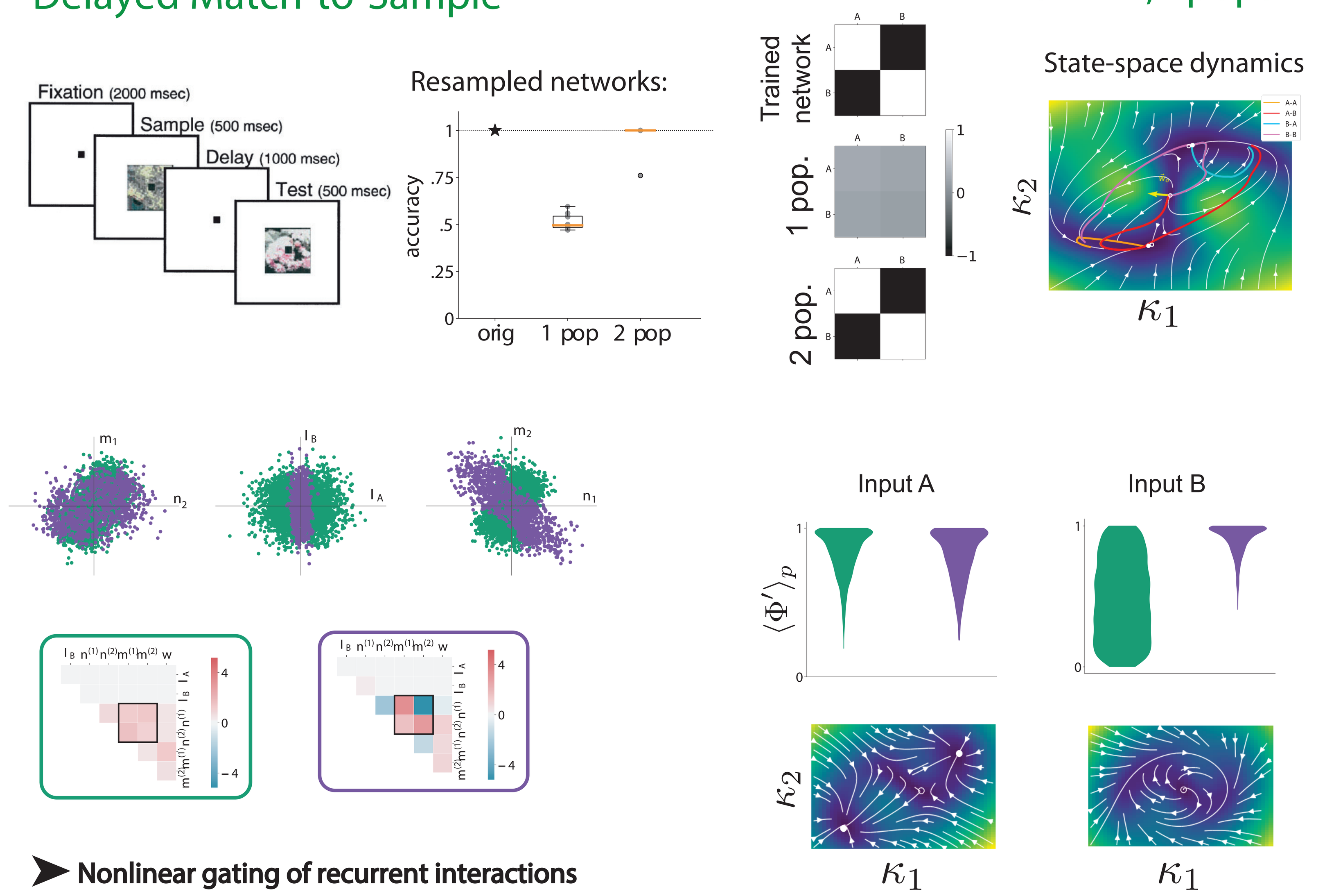
Context-dependent integration — rank=1, #pops=2



➤ 2 populations needed for switching

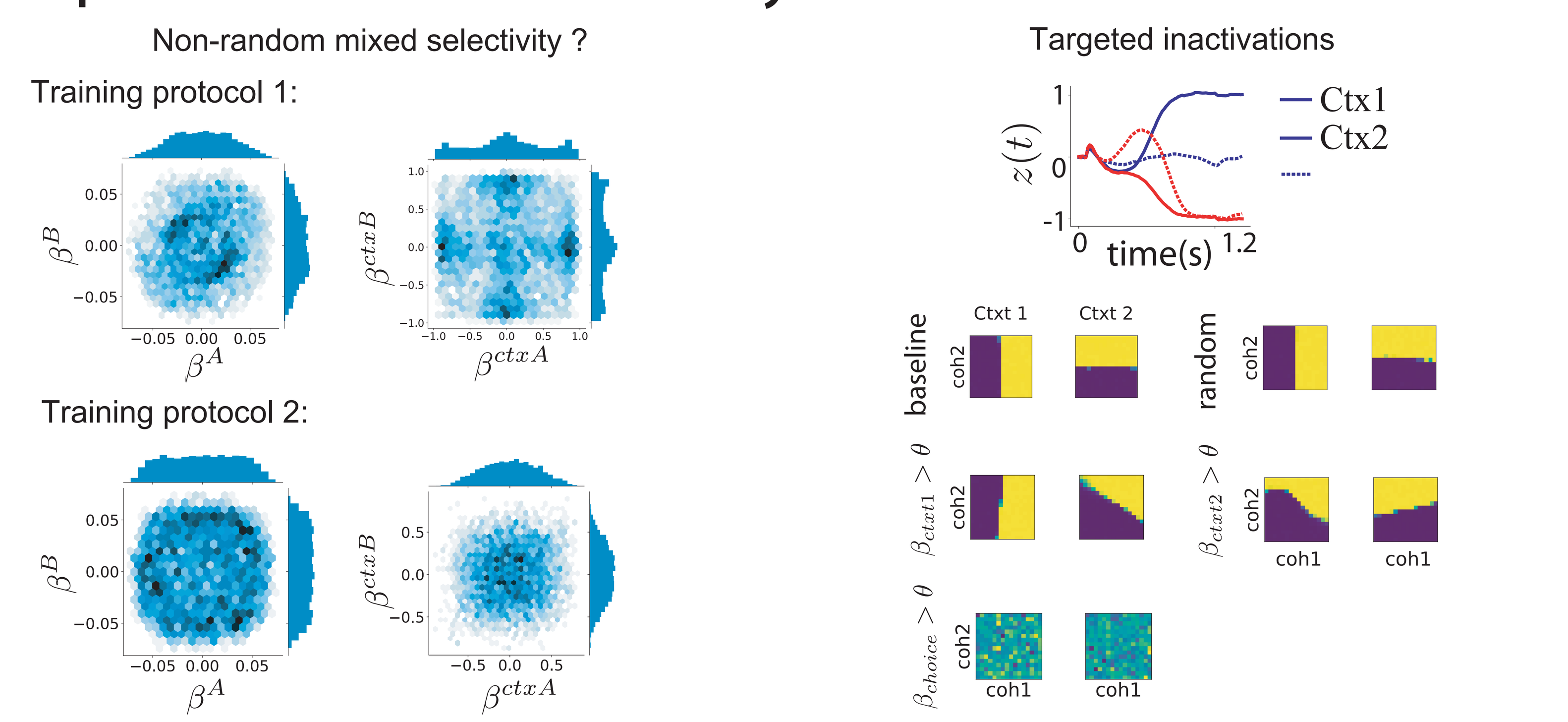
➤ Nonlinear gating of integrated inputs

Delayed Match-to-Sample — rank=2, #pops=2



➤ Nonlinear gating of recurrent interactions

Implications for cortical dynamics



➤ Connectivity structure can be parralelled by structure in selectivity, but not necessarily

➤ Targeted inactivations reveal connectivity structure

Conclusions

➤ Dimensionality of recurrently generated neural activity corresponds to the number of latent variables used in a computation.

➤ Having multiple cell classes is required to solve XOR-like task requiring to change the input-output relationship of networks

References

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[5] Yang et al. Task representations in neural networks trained to perform many cognitive tasks. *Nature Neuroscience* (2019)