A Factorized Low-Rank RNN Framework for Uncovering Independent Neural Latent Dynamics and Connectivity

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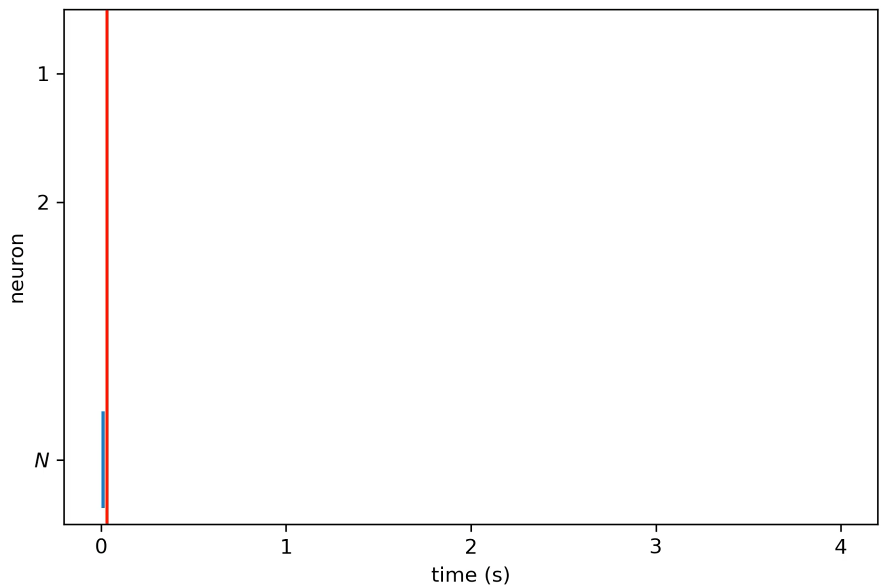
ICML 2026 Spotlight

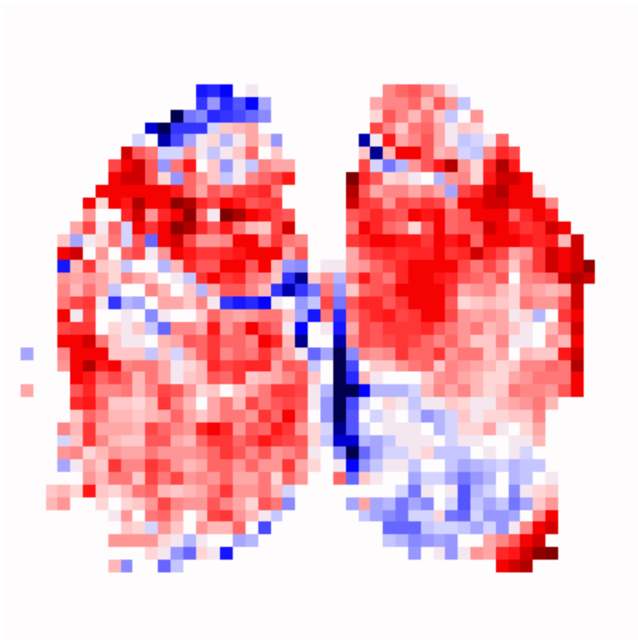
Neural data, what are they doing?

- Small scale: neuron-level spike train and underlying firing rates



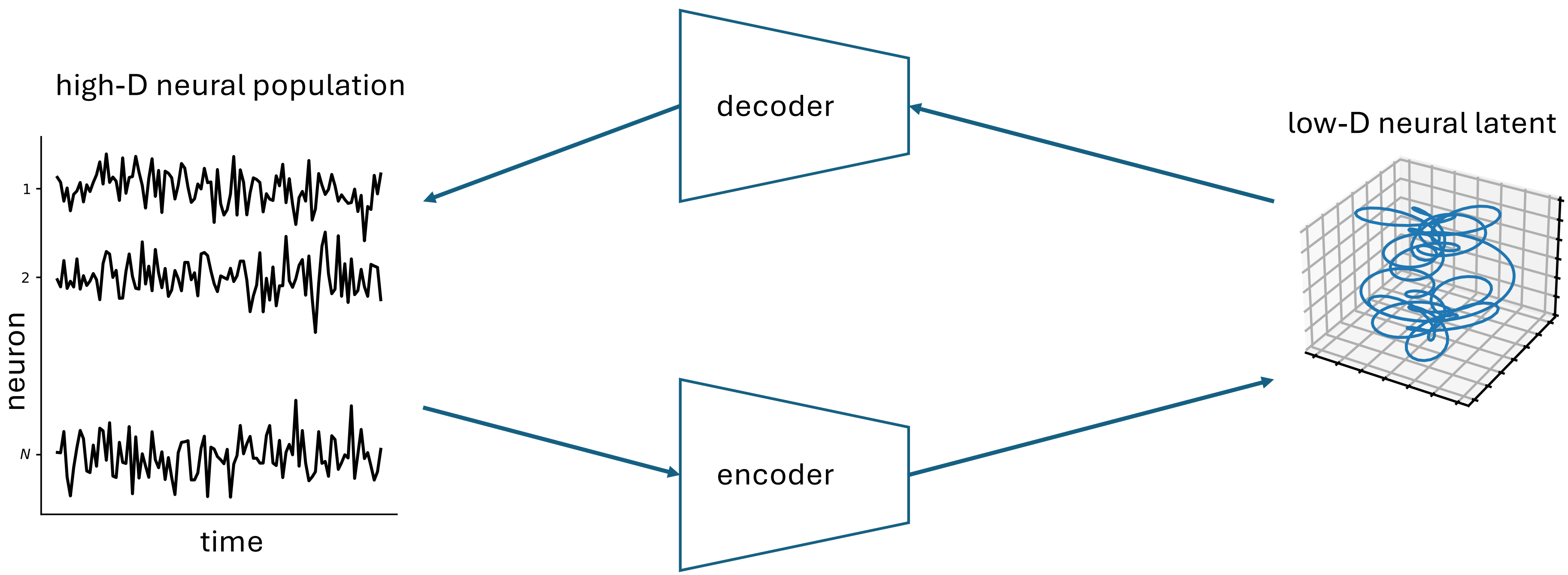
(Ramon et al., Nature Neuroscience, 2023)

- Large scale: voxel-level



(Lu et al., Nature Communications, 2023)

Low-D neural latent



Latent structure

- Plain VAE: no assumption
- PCA: orthogonal assumption
- Dynamical field
- and others…

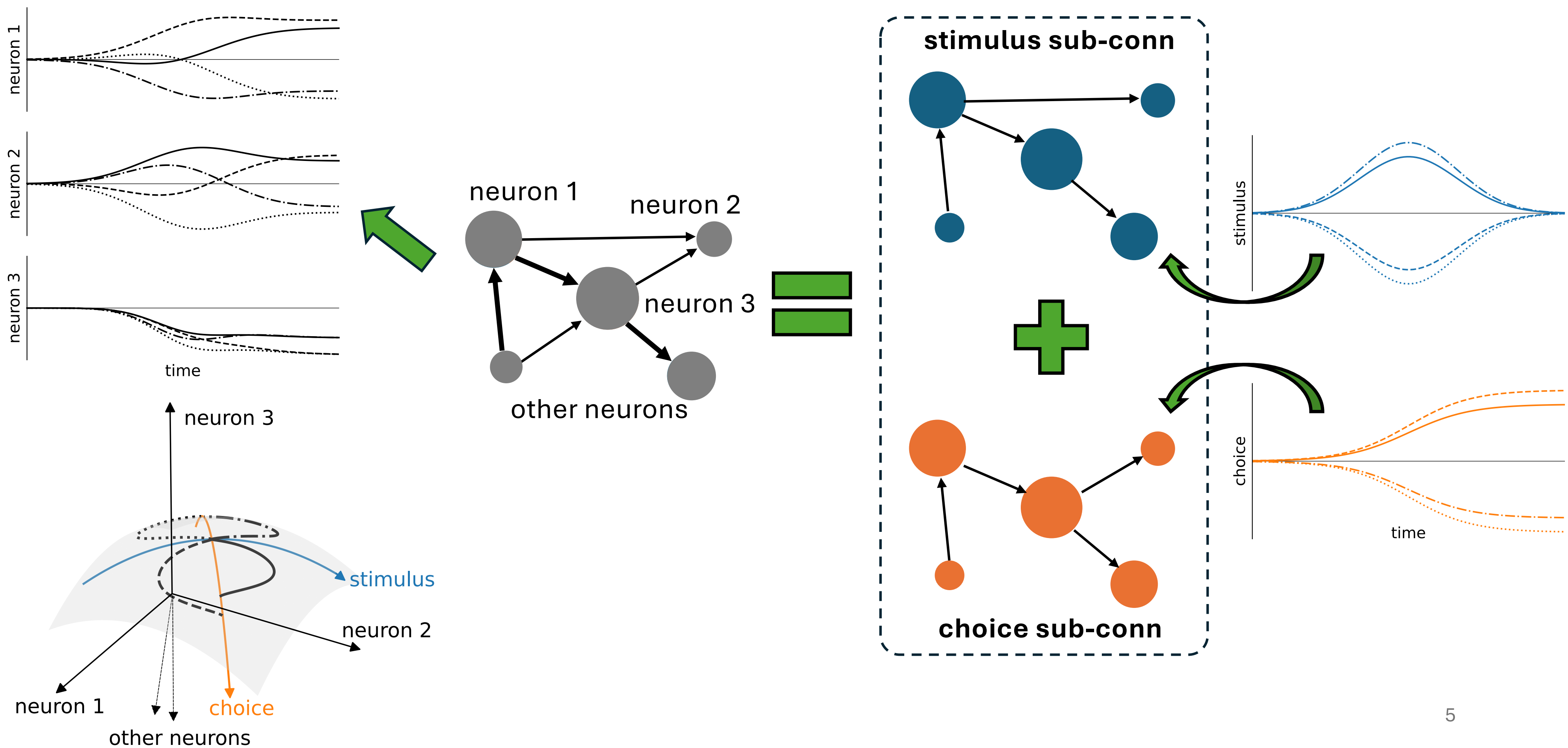
Pandarinath, C., O’Shea, D. J., Collins, J., Jozefowicz, R., Stavisky, S. D., Kao, J. C., ... & Sussillo, D. (2018). Inferring single-trial neural population dynamics using sequential auto-encoders. *Nature methods*, *15*(10), 805-815.

Cunningham, J. P., & Yu, B. M. (2014). Dimensionality reduction for large-scale neural recordings. *Nature neuroscience*, *17*(11), 1500-1509.

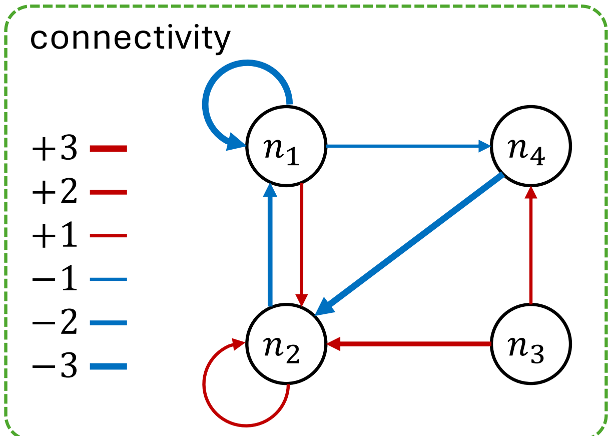
Luo, T. Z., Kim, T. D., Gupta, D., Bondy, A. G., Kopec, C. D., Elliott, V. A., ... & Brody, C. D. (2025). Transitions in dynamical regime and neural mode during perceptual decisions. *Nature*, *646*(8087), 1156-1166.

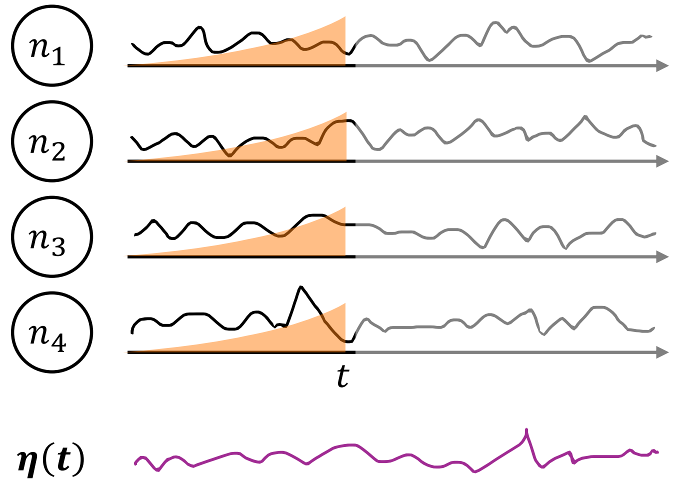
Aoi, M. C., Mante, V., & Pillow, J. W. (2020). Prefrontal cortex exhibits multidimensional dynamic encoding during decision-making. *Nature neuroscience*, *23*(11), 1410-1420.

Sub-connectivity of each latent subspace



Low-rank RNN (lrRNN)





external input

$$\frac{\mathrm{d}\boldsymbol{x}(t)}{\mathrm{d}t} = -\boldsymbol{x}(t) + \boldsymbol{W} \int_0^t \psi(\tau)\, \sigma\big(\boldsymbol{x}(t-\tau)\big)\, \mathrm{d}\tau + \boldsymbol{b} + \boldsymbol{\eta}(t) + \boldsymbol{\epsilon}(t)$$

convolved history | bias | noise

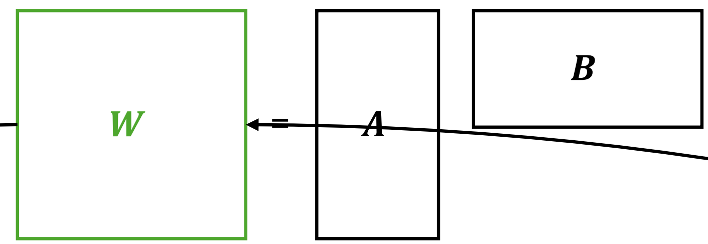
lrRNN

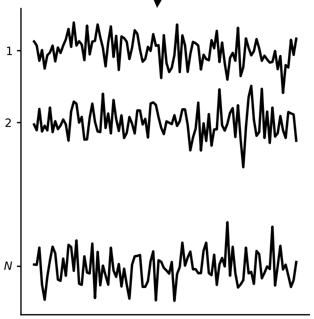
$$\frac{\mathrm{d}\boldsymbol{x}(t)}{\mathrm{d}t} = -\boldsymbol{x}(t) + \boldsymbol{W}\int_0^t \psi(\tau)\,\sigma\left(\boldsymbol{x}(t-\tau)\right)\mathrm{d}\tau + \boldsymbol{b} + \boldsymbol{m}(t) + \boldsymbol{\epsilon}(t)$$

$$\boldsymbol{x}^{(t)} \,|\, \boldsymbol{x}^{(t-1)} \ldots \boldsymbol{x}^{(t-L)} = \boldsymbol{W}\sum_{l=1}^{L} \sigma\left(\boldsymbol{x}^{(t-l)}\right) + \boldsymbol{b} + \boldsymbol{m}^{(t)} + \boldsymbol{\epsilon}^{(t)}$$

lrRNN

$$\boldsymbol{x}^{(t)} | \boldsymbol{x}^{(t-1)} \dots \boldsymbol{x}^{(t-L)} = \boldsymbol{W} \sum_{l=1}^{L} \psi_l \, \sigma\left(\boldsymbol{x}^{(t-l)}\right) + \boldsymbol{b} + \boldsymbol{\eta}^{(t)} + \boldsymbol{\epsilon}^{(t)}$$

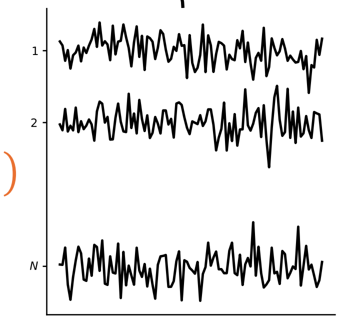




$\boldsymbol{x}^{(t)}$

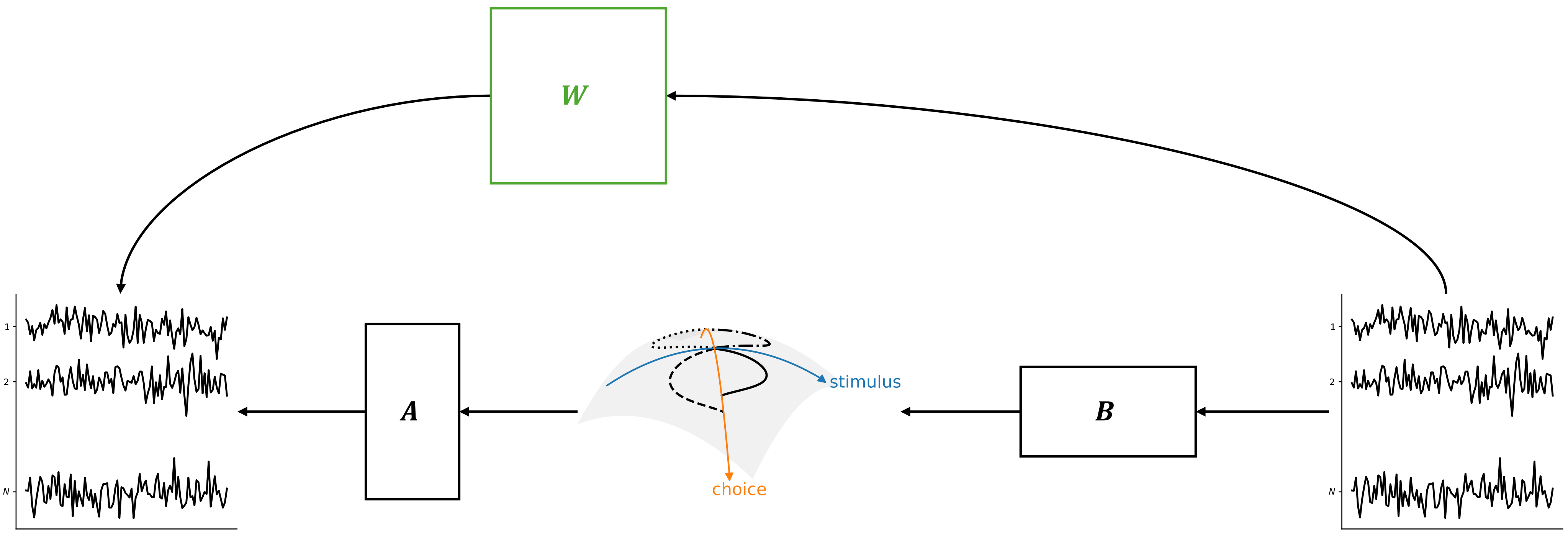
- lrRNN learns conn $\boldsymbol{W}$ by learning $\boldsymbol{A}, \boldsymbol{B}$
- No disentanglement
- LINT based on SVD has orthogonal latent
  - Hard to decompose biological meaningful subspaces
- How to achieve disentanglement?

$$\sum_{l=1}^{L} \psi_l \, \sigma\left(\boldsymbol{x}^{(t-l)}\right)$$



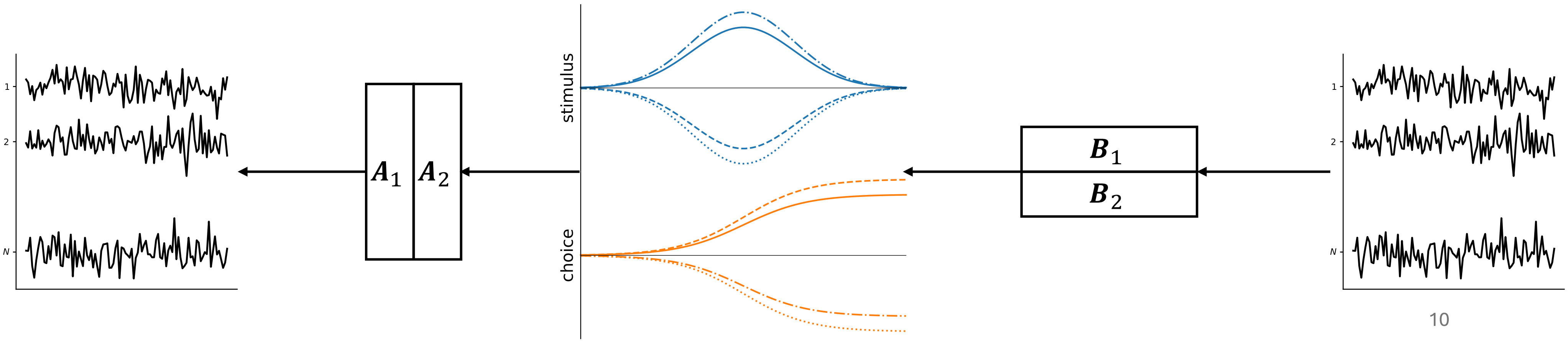
lrRNN as VAE

$$\boldsymbol{x}^{(t)}|\boldsymbol{x}^{(t-1)} \dots \boldsymbol{x}^{(t-L)} = \boldsymbol{W} \sum_{l=1}^{L} \psi_l \, \sigma\left(\boldsymbol{x}^{(t-l)}\right) + \boldsymbol{b} + \boldsymbol{\eta}^{(t)} + \boldsymbol{\epsilon}^{(t)}$$



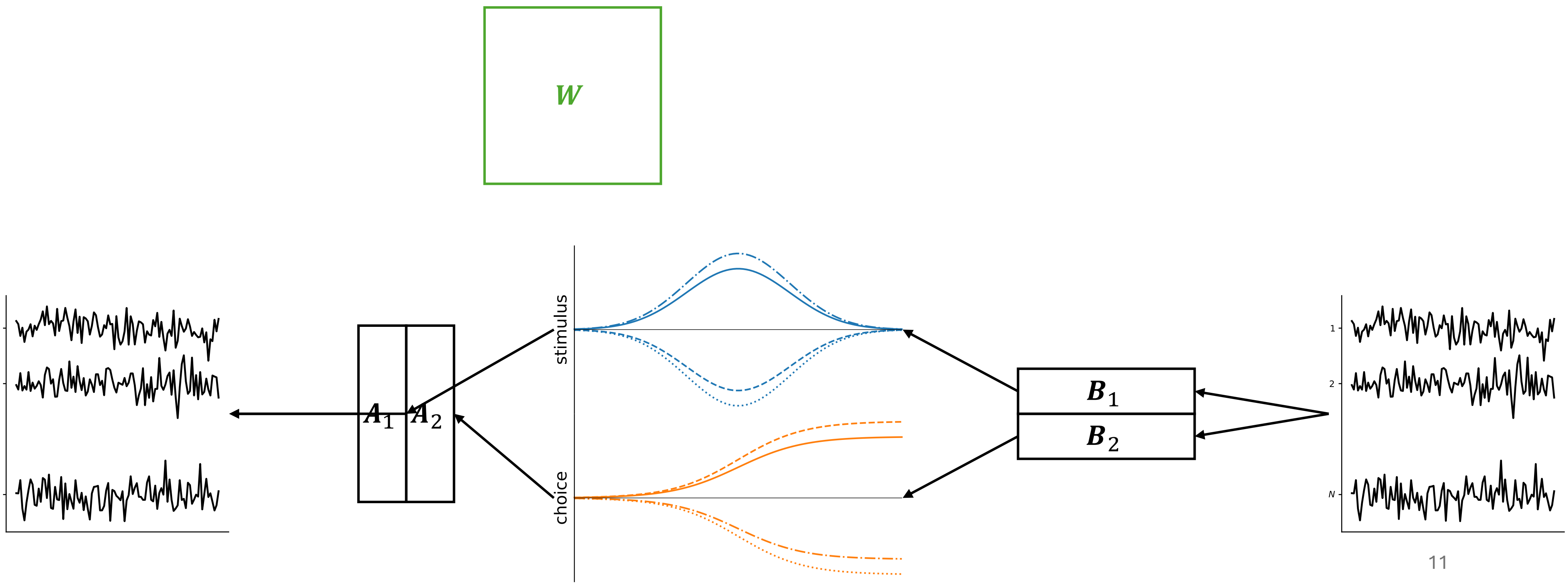
Latent disentanglement

$$\boldsymbol{x}^{(t)} | \boldsymbol{x}^{(t-1)} \dots \boldsymbol{x}^{(t-L)} = \boldsymbol{W} \sum_{l=1}^{L} \psi_l \, \sigma\left(\boldsymbol{x}^{(t-l)}\right) + \boldsymbol{b} + \boldsymbol{\eta}^{(t)} + \boldsymbol{\epsilon}^{(t)}$$



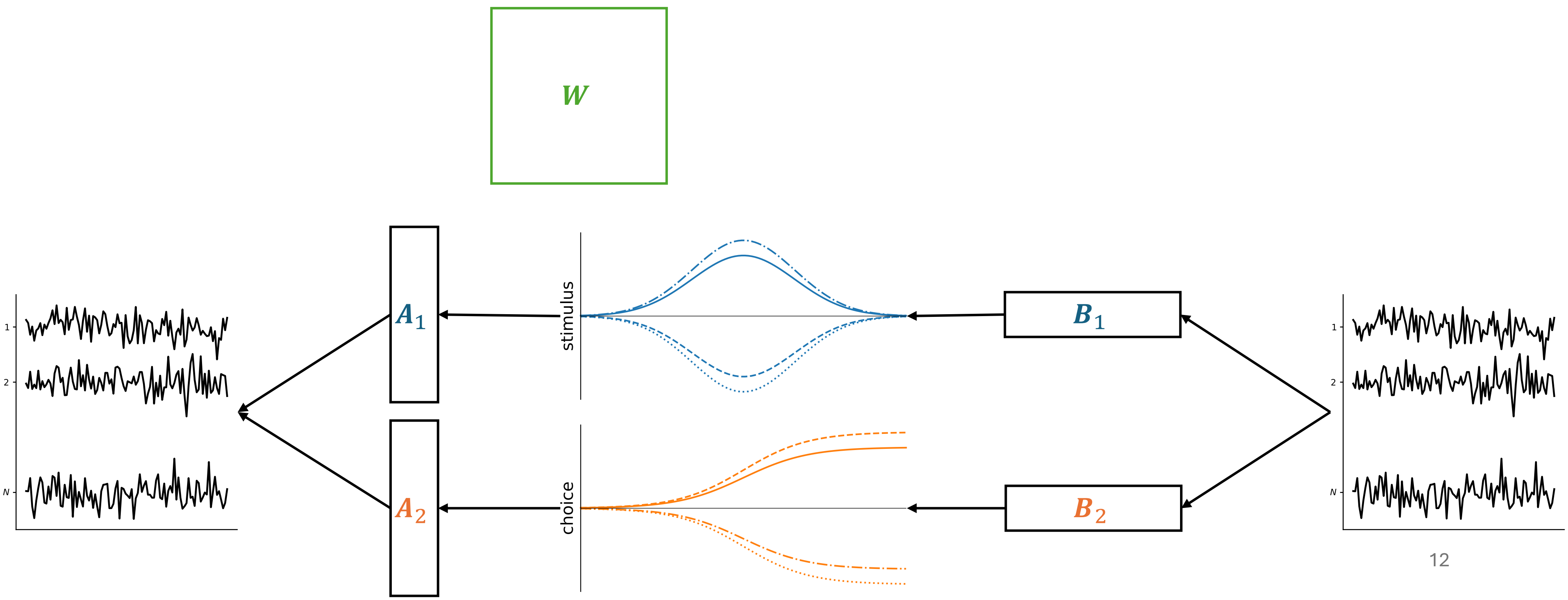
Latent disentanglement

$$\boldsymbol{x}^{(t)} | \boldsymbol{x}^{(t-1)} \dots \boldsymbol{x}^{(t-L)} = \boldsymbol{W} \sum_{l=1}^{L} \psi_l \, \sigma\left(\boldsymbol{x}^{(t-l)}\right) + \boldsymbol{b} + \boldsymbol{\eta}^{(t)} + \boldsymbol{\epsilon}^{(t)}$$



Latent disentanglement

$$\boldsymbol{x}^{(t)} \mid \boldsymbol{x}^{(t-1)} \dots \boldsymbol{x}^{(t-L)} = \boldsymbol{W} \sum_{l=1}^{L} \psi_l \, \sigma\left(\boldsymbol{x}^{(t-l)}\right) + \boldsymbol{b} + \boldsymbol{\eta}^{(t)} + \boldsymbol{\epsilon}^{(t)}$$



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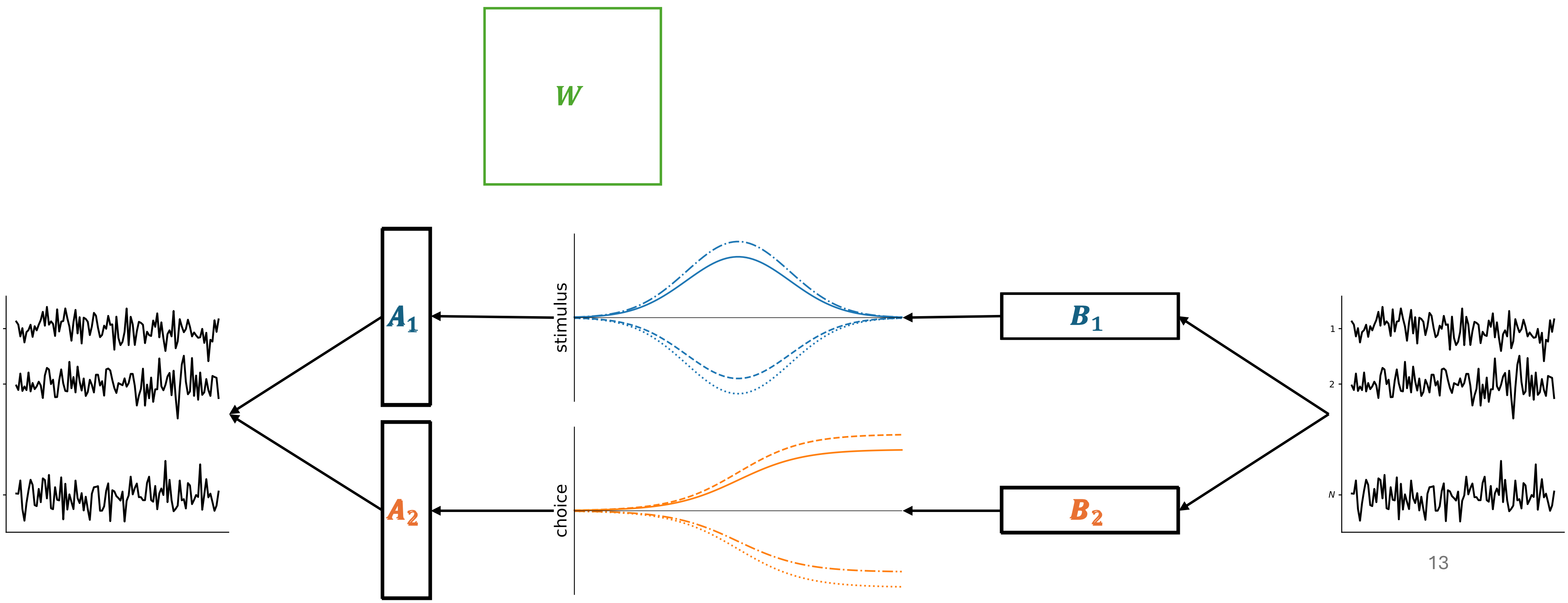

Latent disentanglement

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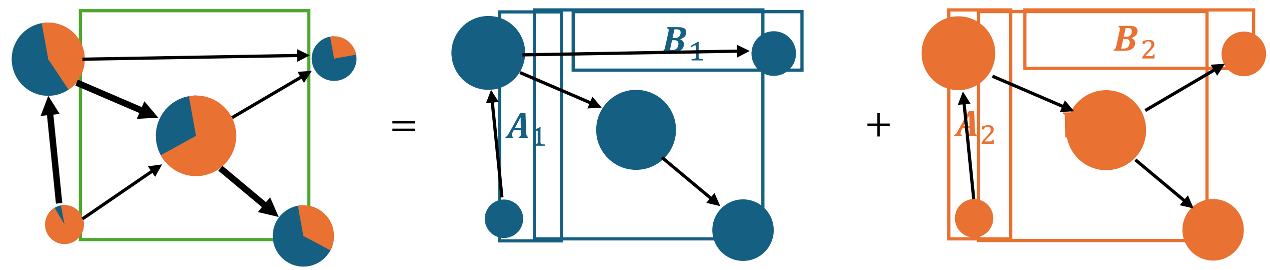
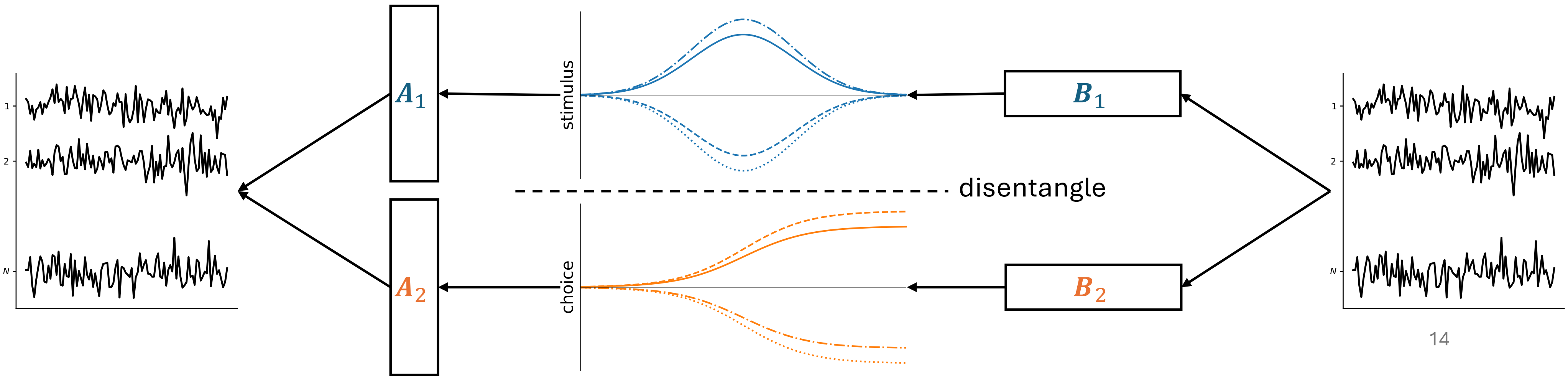




Disentangle the VAE latent

$$\mathcal{L} = \frac{1}{N}\sum_{n=1}^{N}\left(\mathbb{E}_q\left[\ln p\left(\boldsymbol{x}^{(n)}|\boldsymbol{z}\right)\right] - \mathrm{KL}\left(q\left(\boldsymbol{z}|\boldsymbol{x}^{(n)} \parallel p(\boldsymbol{z})\right)\right)\right) - \beta \cdot \mathrm{KL}\left(q(\boldsymbol{z}) \parallel q(z_1, z_2) \times q(z_3, z_4) \times q(z_5, z_6)\right)$$

Reconstruction

KL-divergence

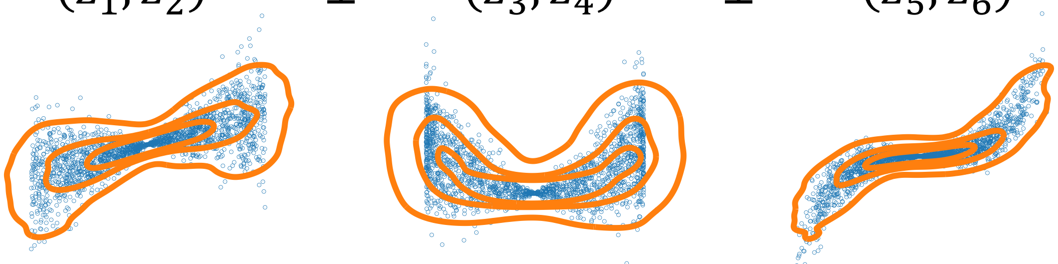
Partial correlation (PC)

penalize

$$q(z_1, \dots, z_6) = q(z_1, z_2) \times q(z_3, z_4) \times q(z_5, z_6)$$

$\Updownarrow$

$(z_1, z_2) \perp (z_3, z_4) \perp (z_5, z_6)$



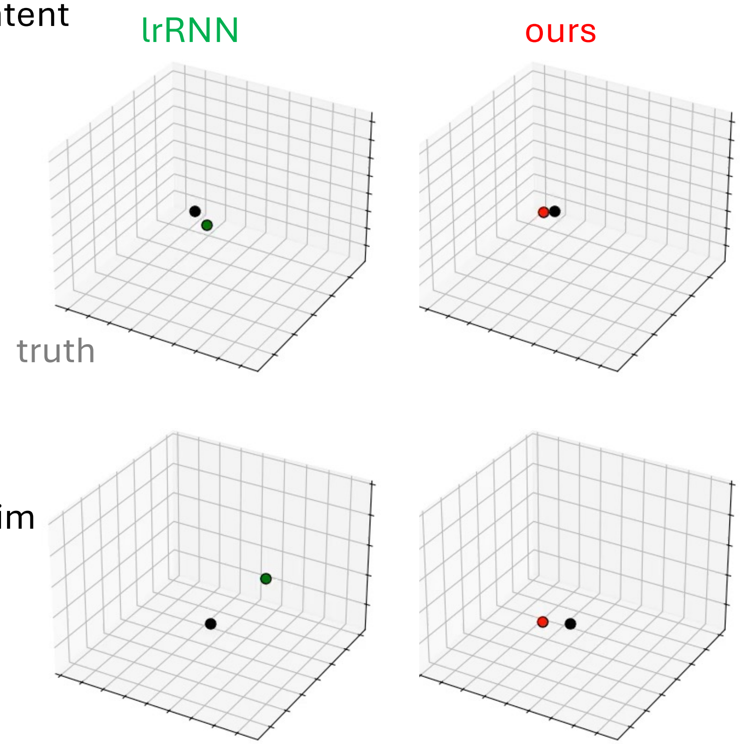
group 1 group 2 group 3

Lorenz + Thomas' cyclically symmetric latent dynamics

Simulate 6 dim latent

- First 3 dim
- Group 1
- Lorenz

- Remaining 3 dim
- Group 2
- Thomas

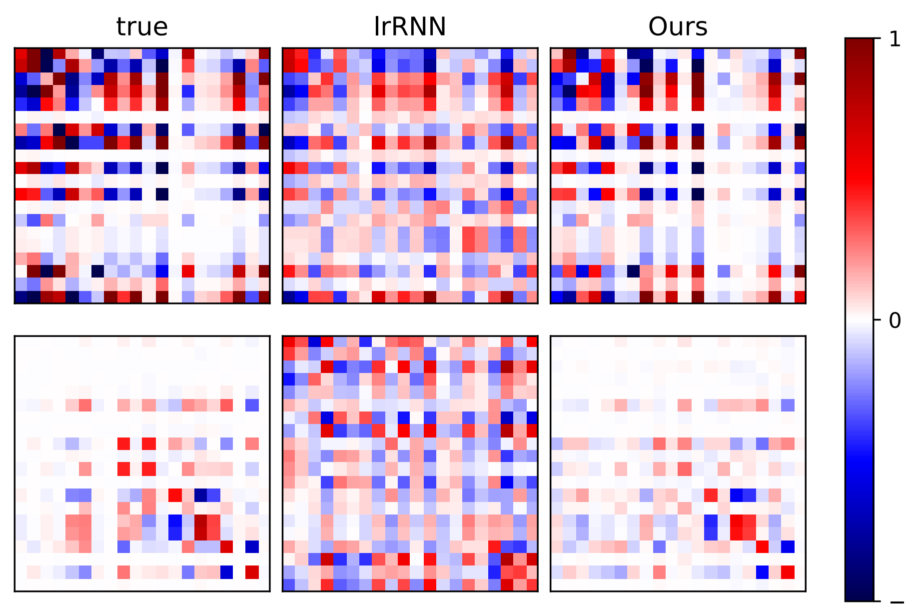


Sub-connectivities $\boldsymbol{W}$ of each group

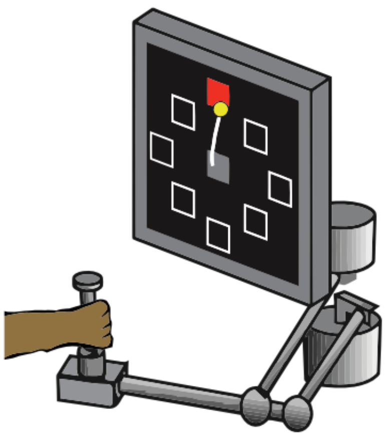
Row i, column j, $w_{i\leftarrow j}$, connectivity neuron $i \leftarrow$ neuron j

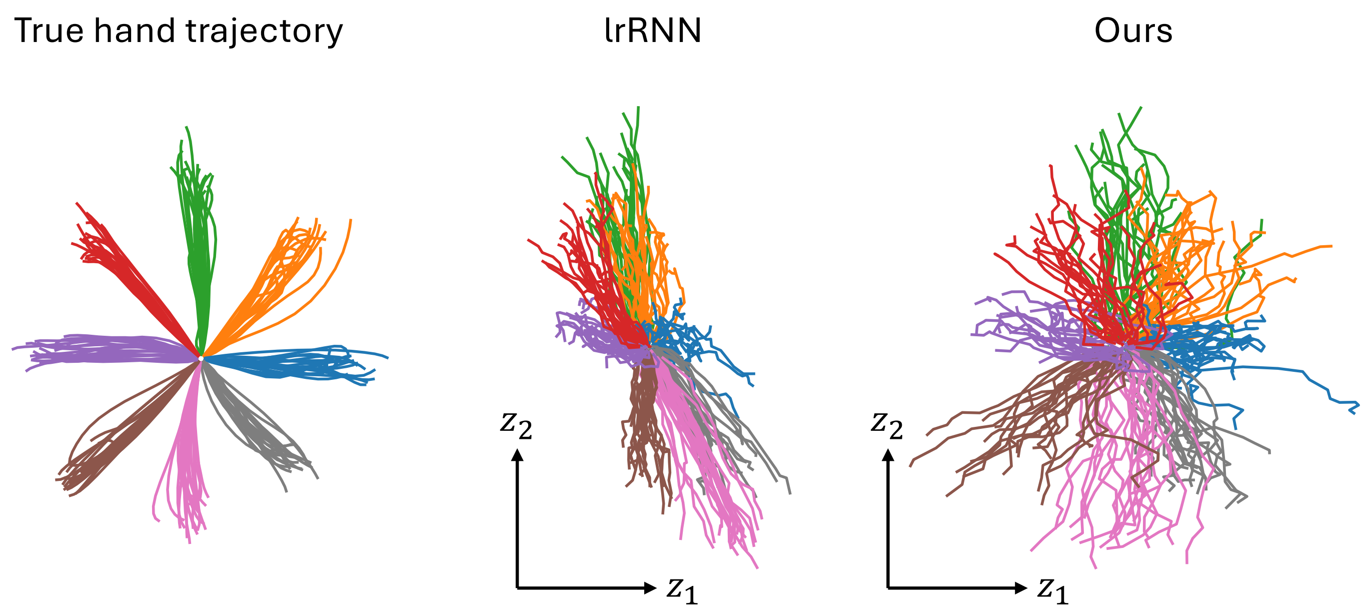
Red excitatory, blue inhibitory

Our sub-conn of each group matches the ground truth



Monkey reaching task

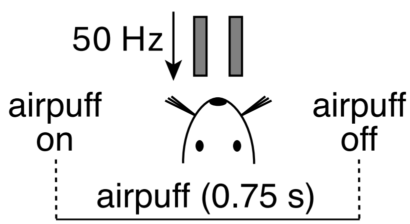




- Purely unsupervised, no hand movement info during model training.
- Our latent expresses hand movement better.

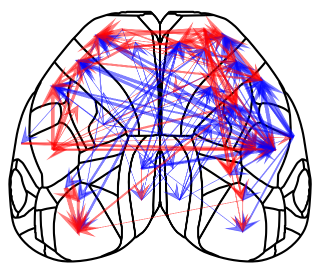
(Ma et al., elife, 2023)

Voltage imaging during air-puff

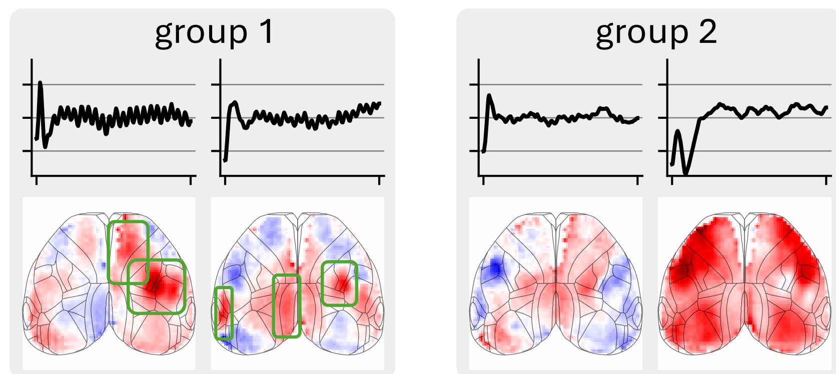


Provided by Yunmiao Wang
from Dieter Jaeger's lab

overall conn



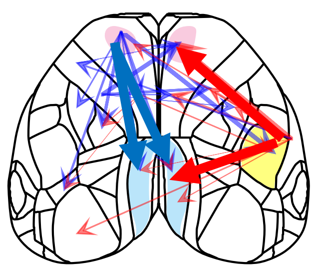
hard to interpret🙁



group …

Air-puff related 50 Hz oscillation concentrated only in group 1

group 1 conn



M2 (secondary motor cortex)

Right S2 (secondary somatosensory) -barrel

RSC (retrosplenial cortex)

- Right S2 → right M2
- Right S2 & left M2 → both sides of RSC
- RSC is responsible for memory
- Might be the formation of episodic memory of receiving the airpuff.

(Lu et al., Nature Communications, 2023)
(Anna et al., Brain and neuroscience advances, 2023)

Summary

- Our method captures both the latent dynamics of neural systems while allows group disentanglement.
- Unsupervisedly, we can reveal interpretable sub-connectivity that drives the corresponding latent subspace.
- The disentanglement method is generalizable to general representation learning.

Thanks for listening!