Dimensionality reduction of multi-trial neural data by tensor decomposition

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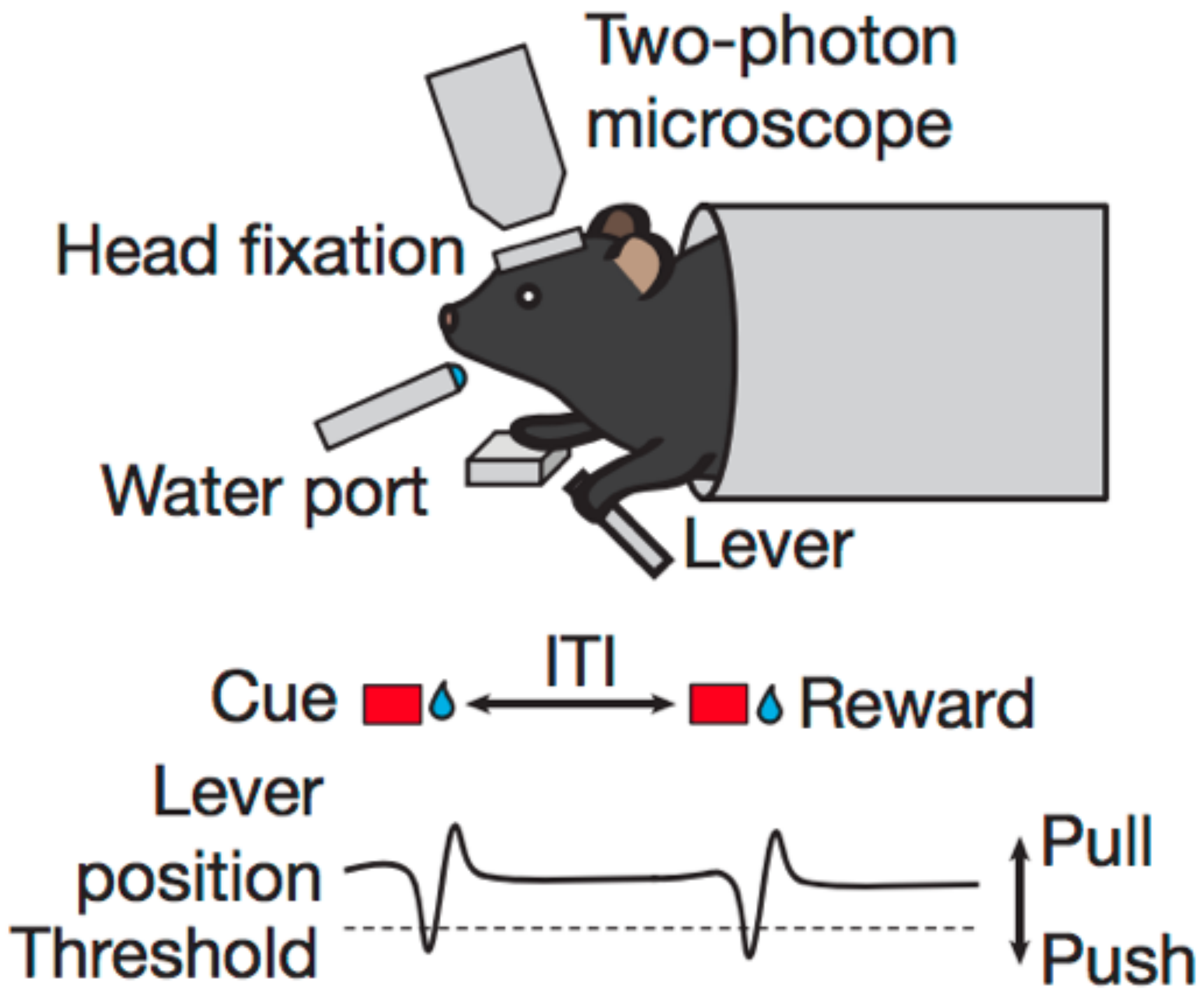
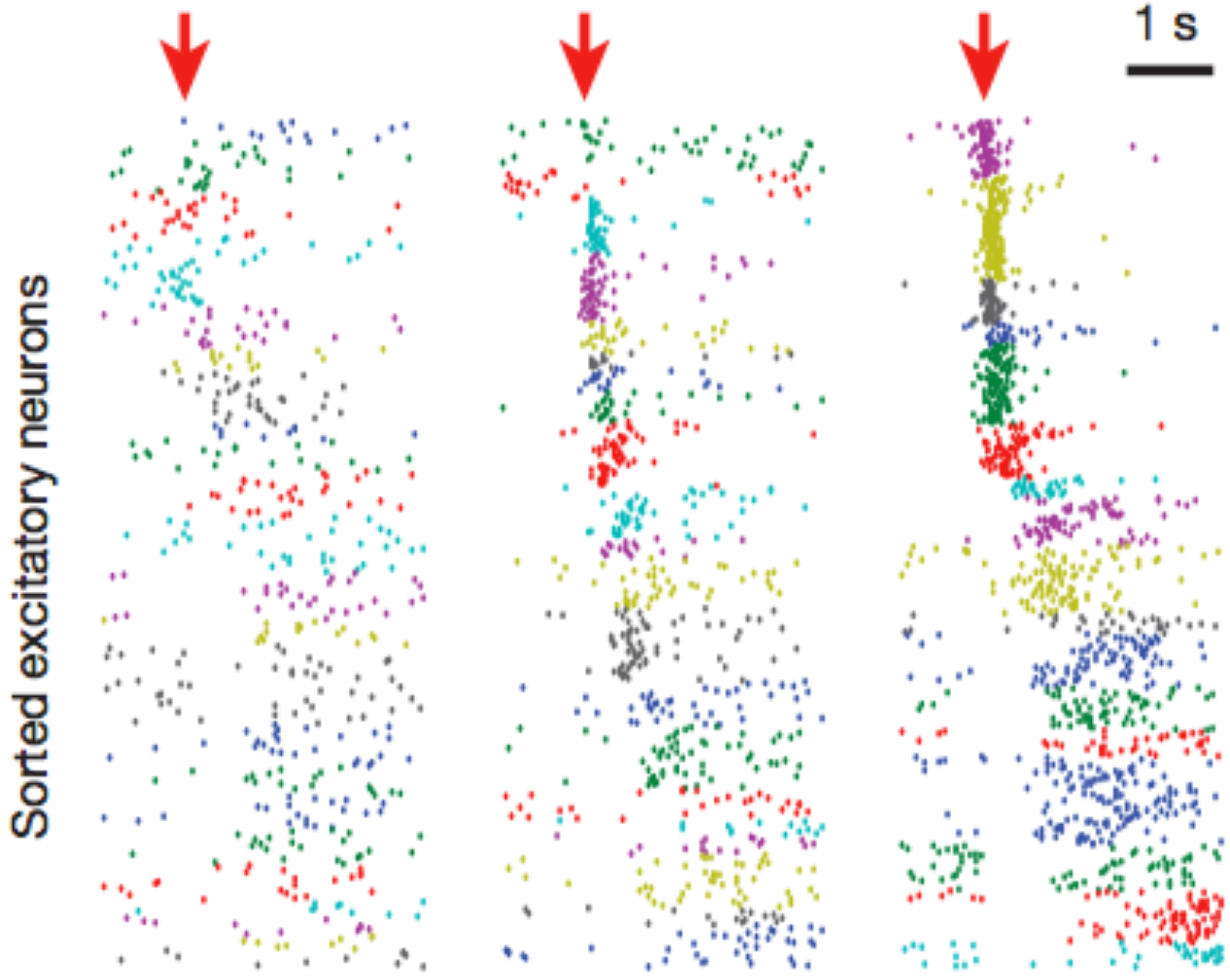
Modern experiments capture a large range of timescales in neural data



(Peters et al., 2014)

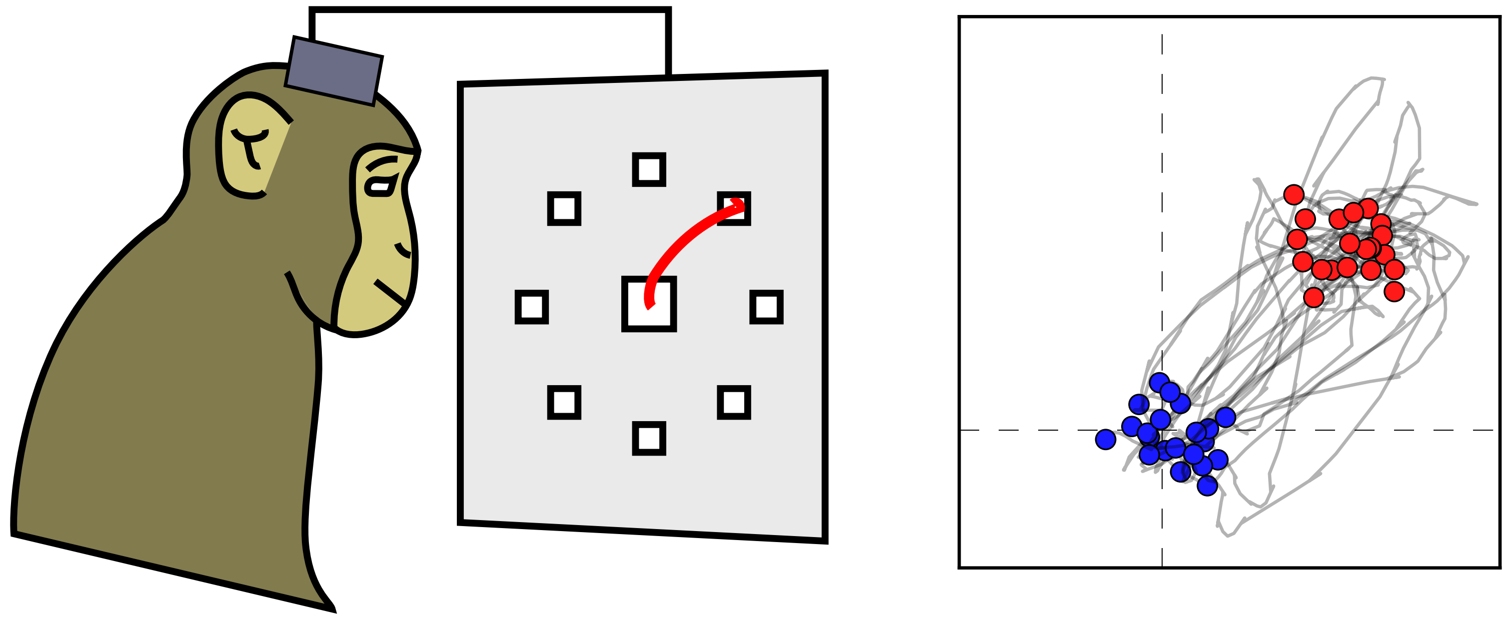


session A session B session C

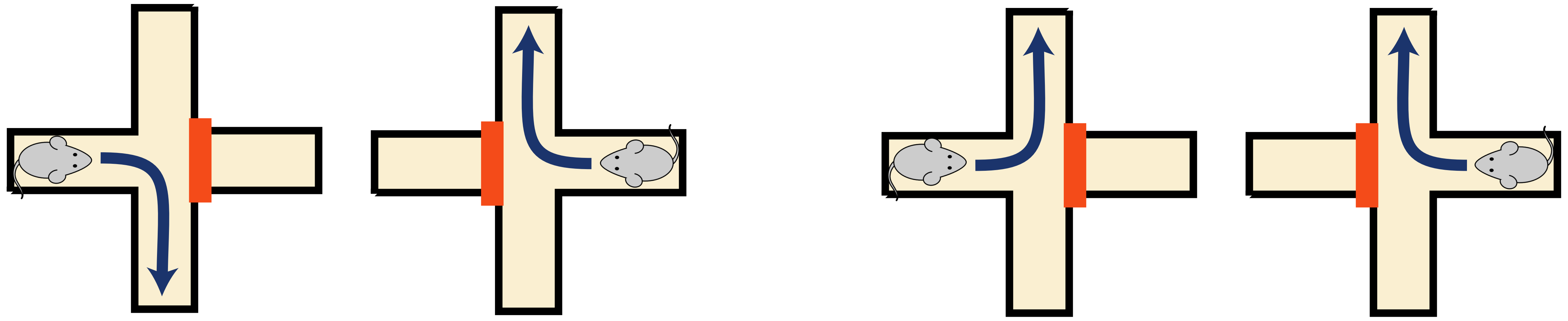
Neural data is large, *along multiple dimensions*

- Ability to record from **thousands of neurons**, over **thousands of trials**.
- Existing dimensionality reduction techniques (e.g. PCA) do not separate **within-trial** dynamics from **across-trial** components.
- We propose **tensor decomposition** as a framework for systems neuroscience to attack this problem.
- We recover low-dimensional descriptions of learning in two datasets:

Macaque - BMI learning

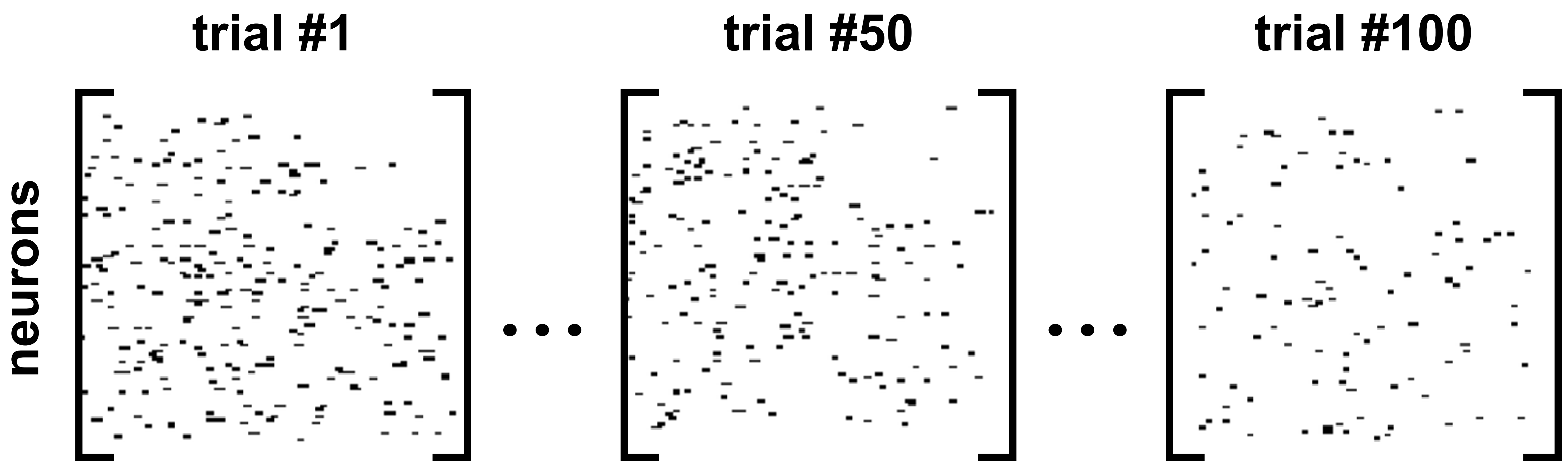


Mouse - navigational strategy switching



“turn right” **“go north”**

Trial-averaged PCA



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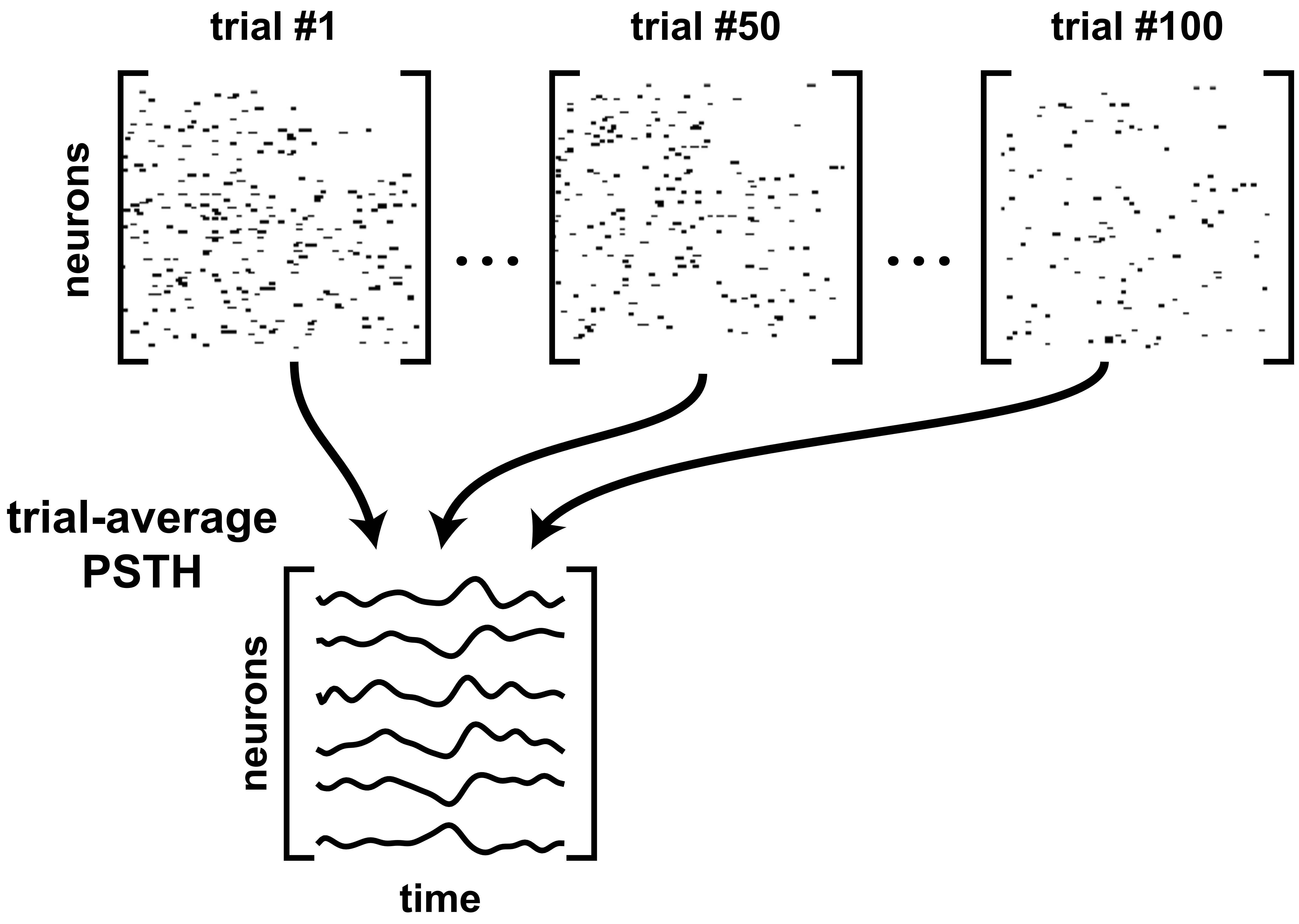

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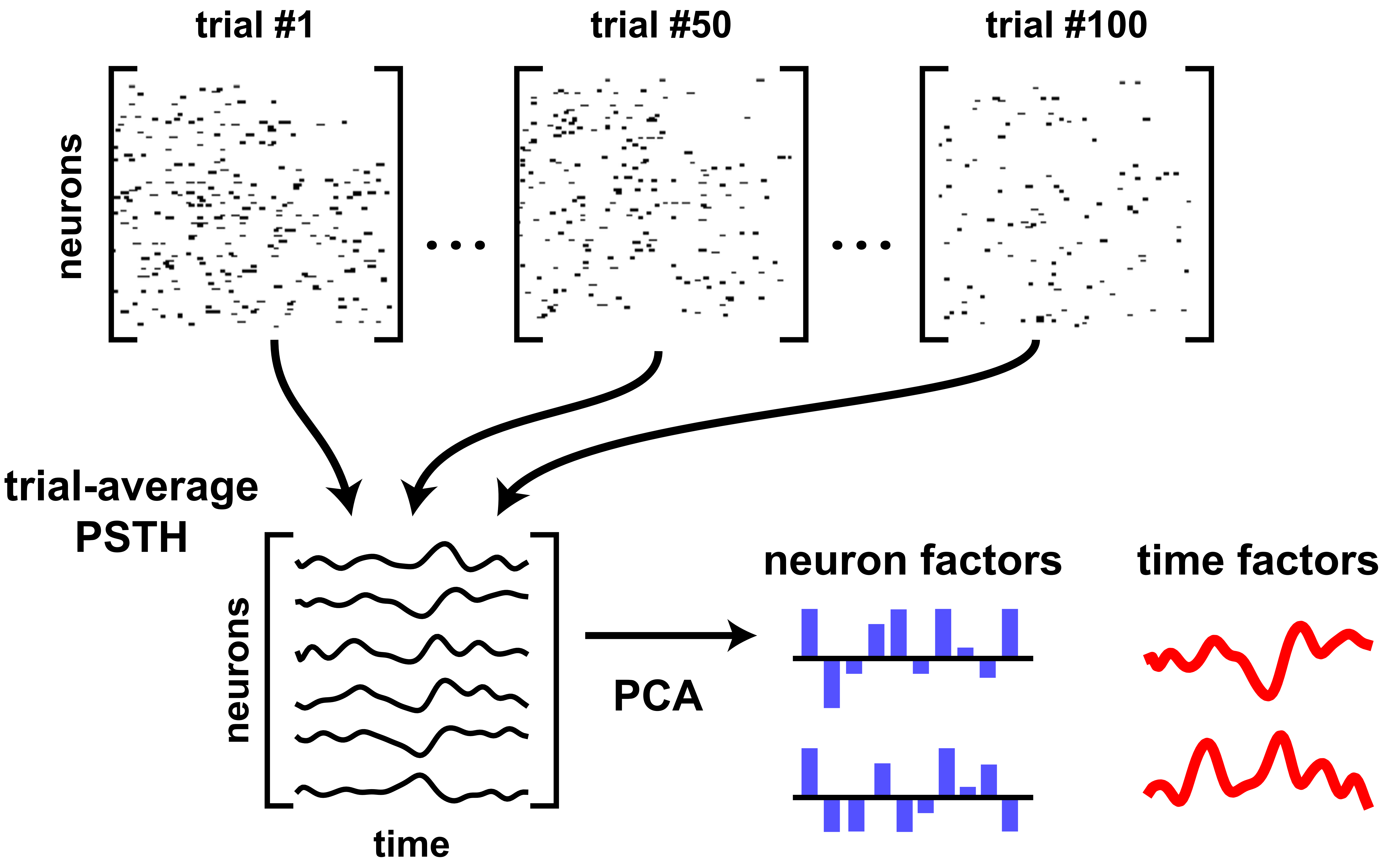

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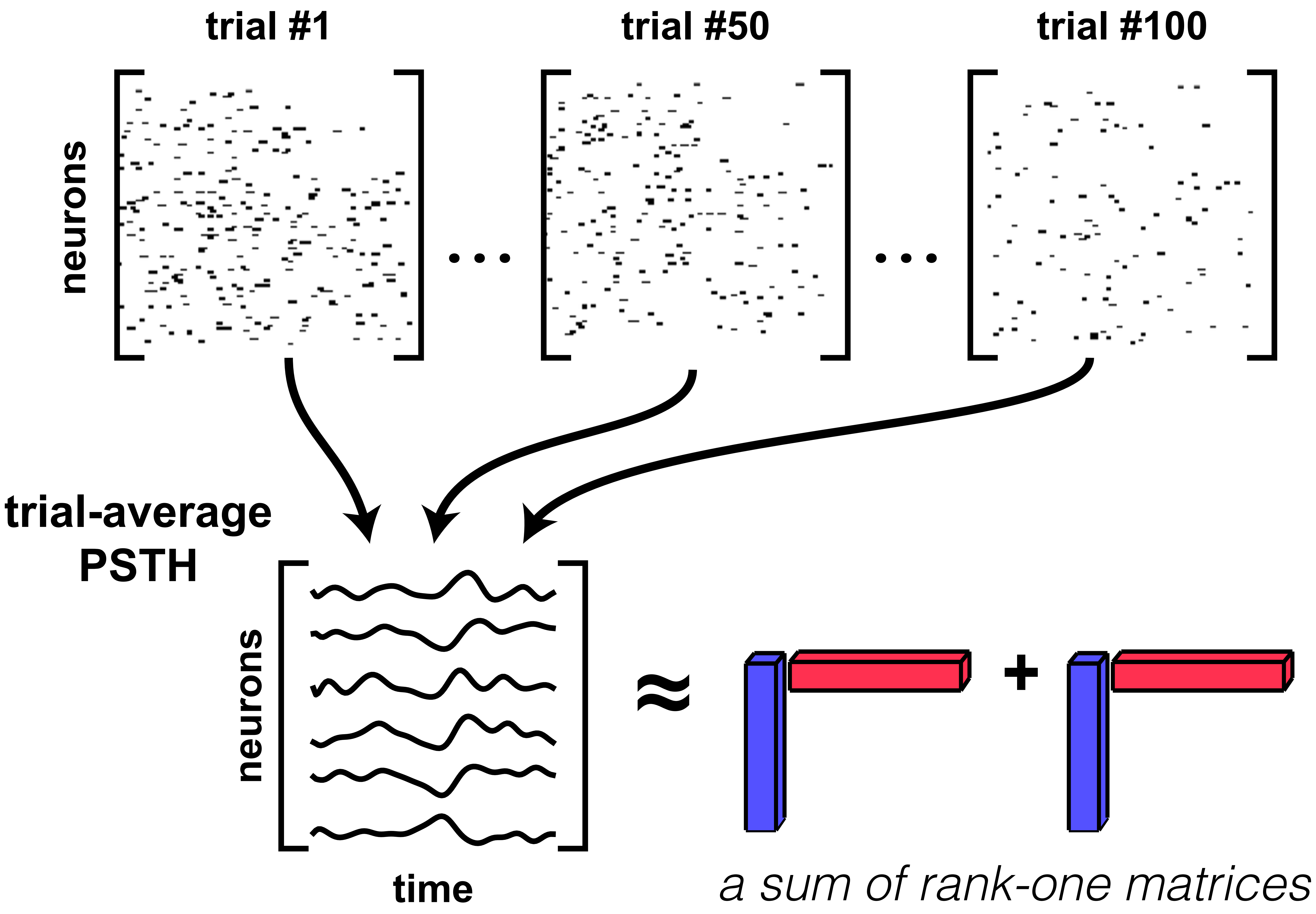

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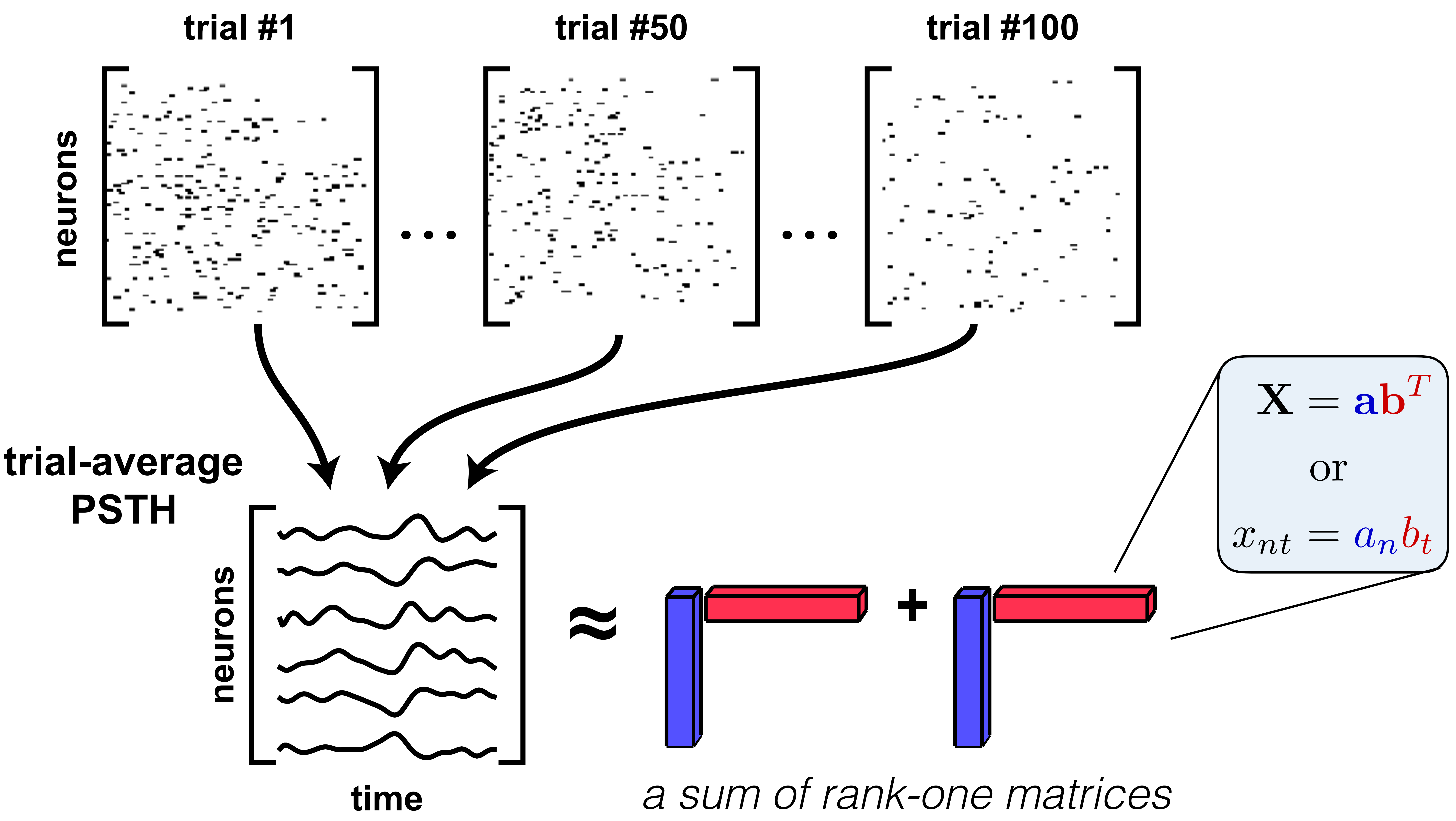
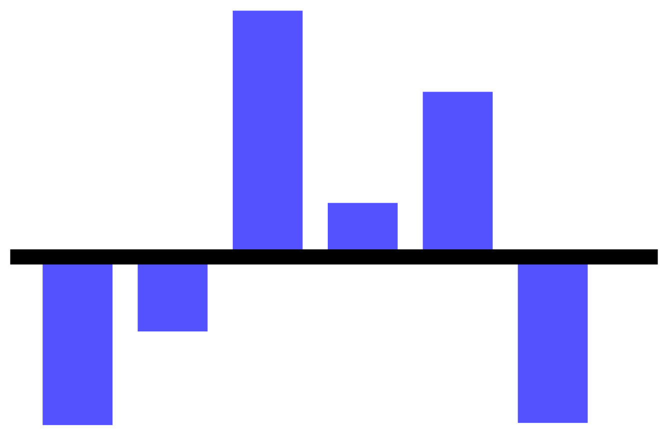


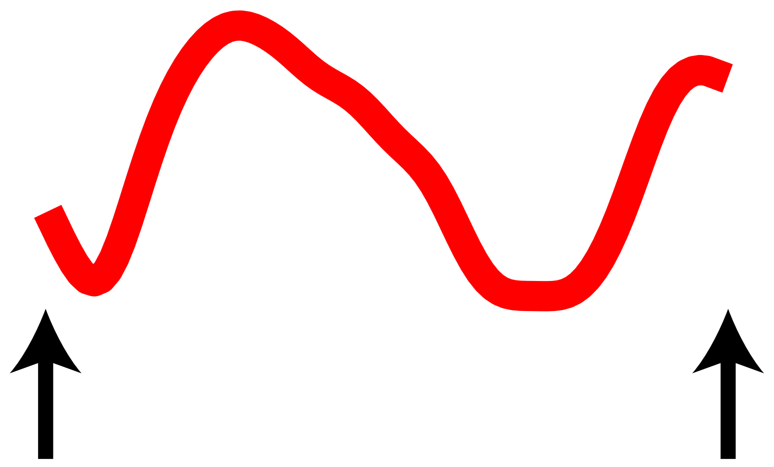
Our Goal: Find compact representation for within- and across-trial neural dynamics

neuron factors



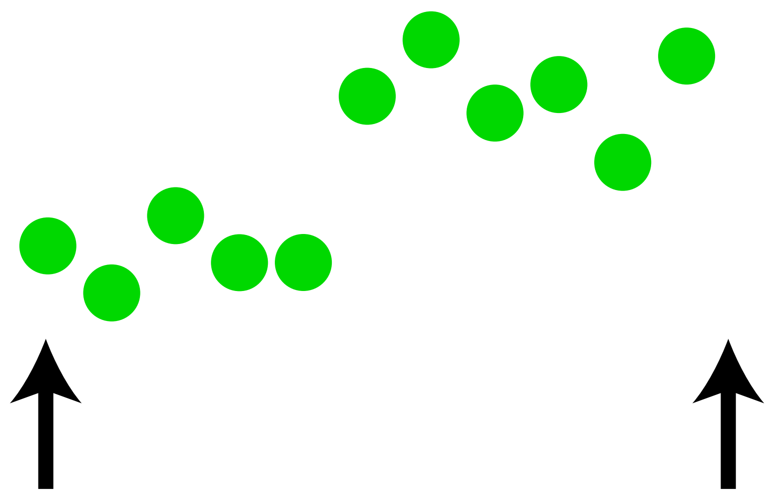
functional cell types

temporal factors



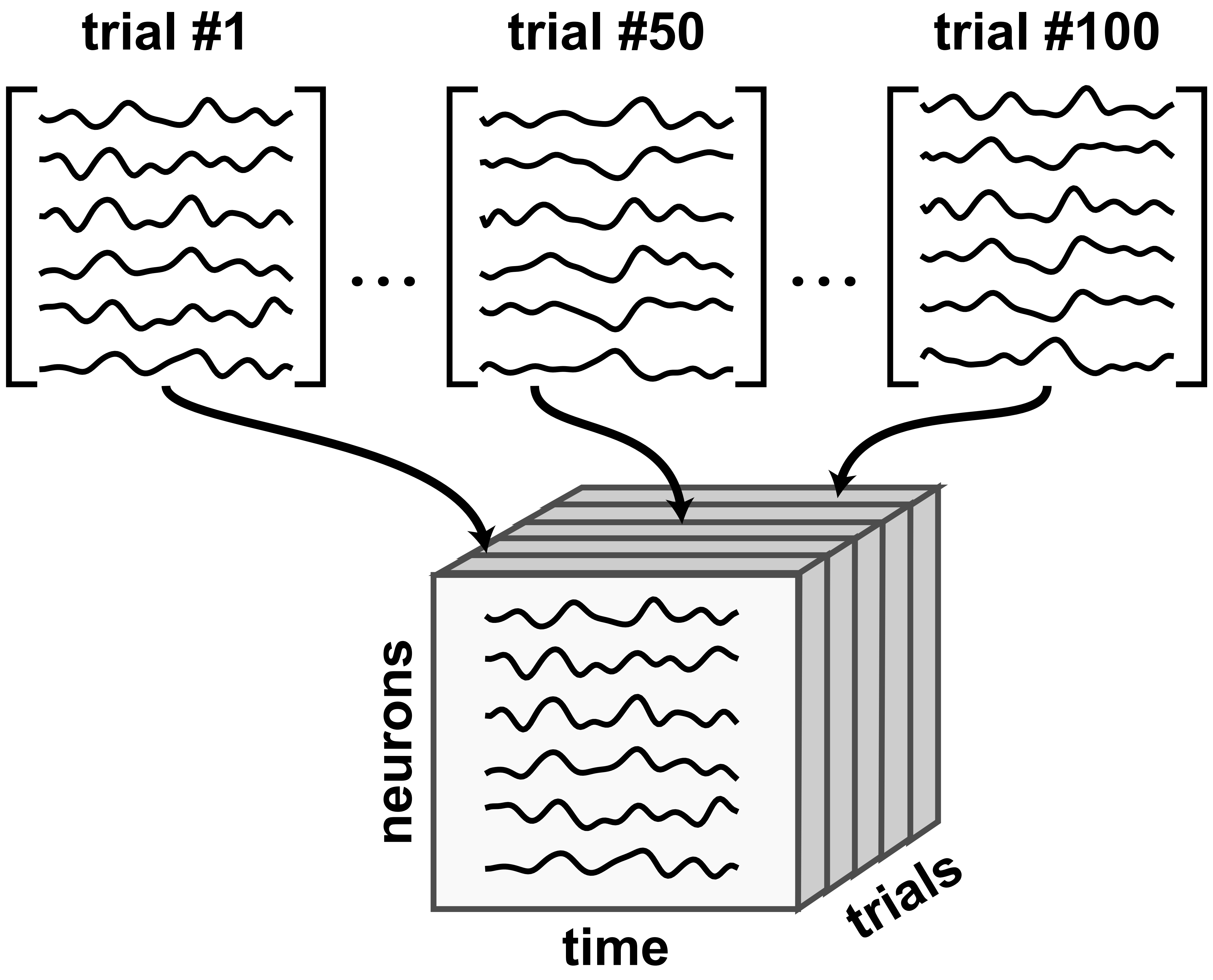
within trial dynamics

trial factors



learning dynamics

We represent multi-trial data as a third-order tensor and use **<u>Canonical Polyadic (CP) decomposition</u>** to perform dimensionality reduction.



data tensor

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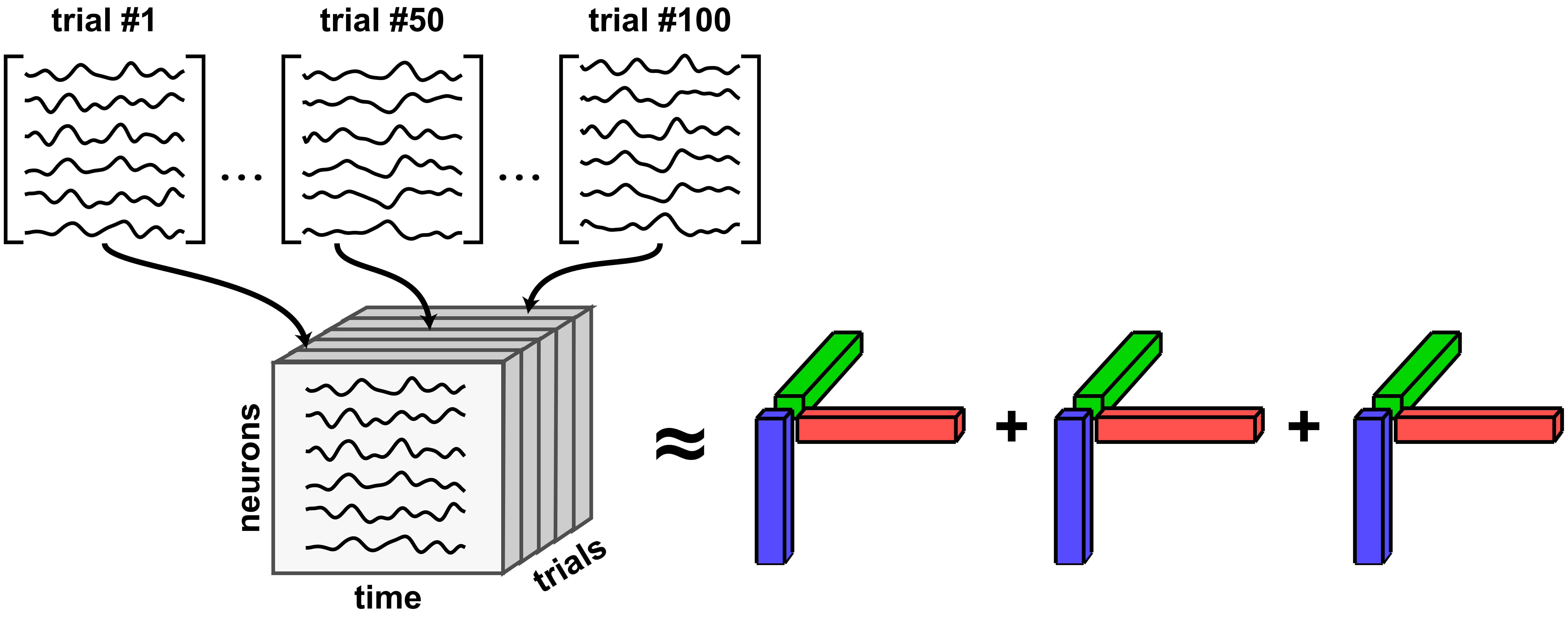

data tensor

a sum of rank-one tensors

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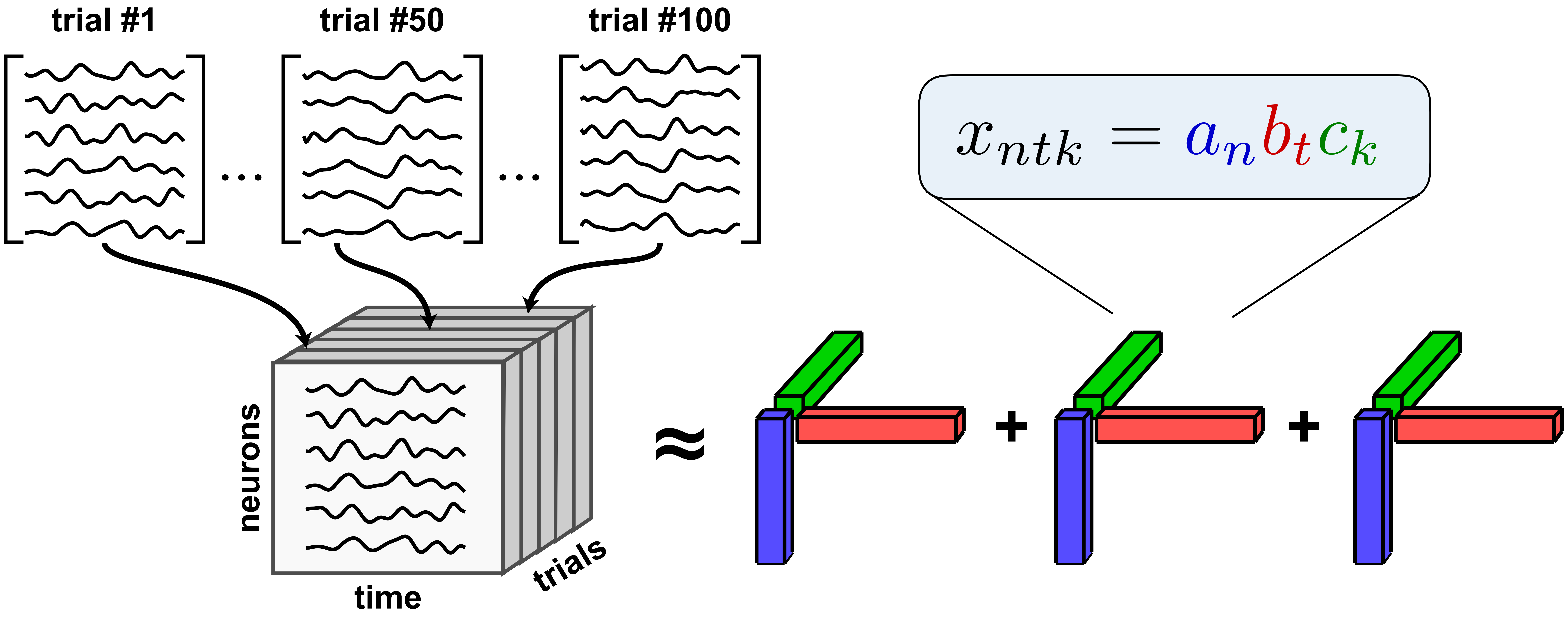

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A neuroscientist's perspective:

CP tensor decomposition is a linear network with gain modulation — an influential principle of cortical computation (e.g., Carandini and Heeger, 2012)

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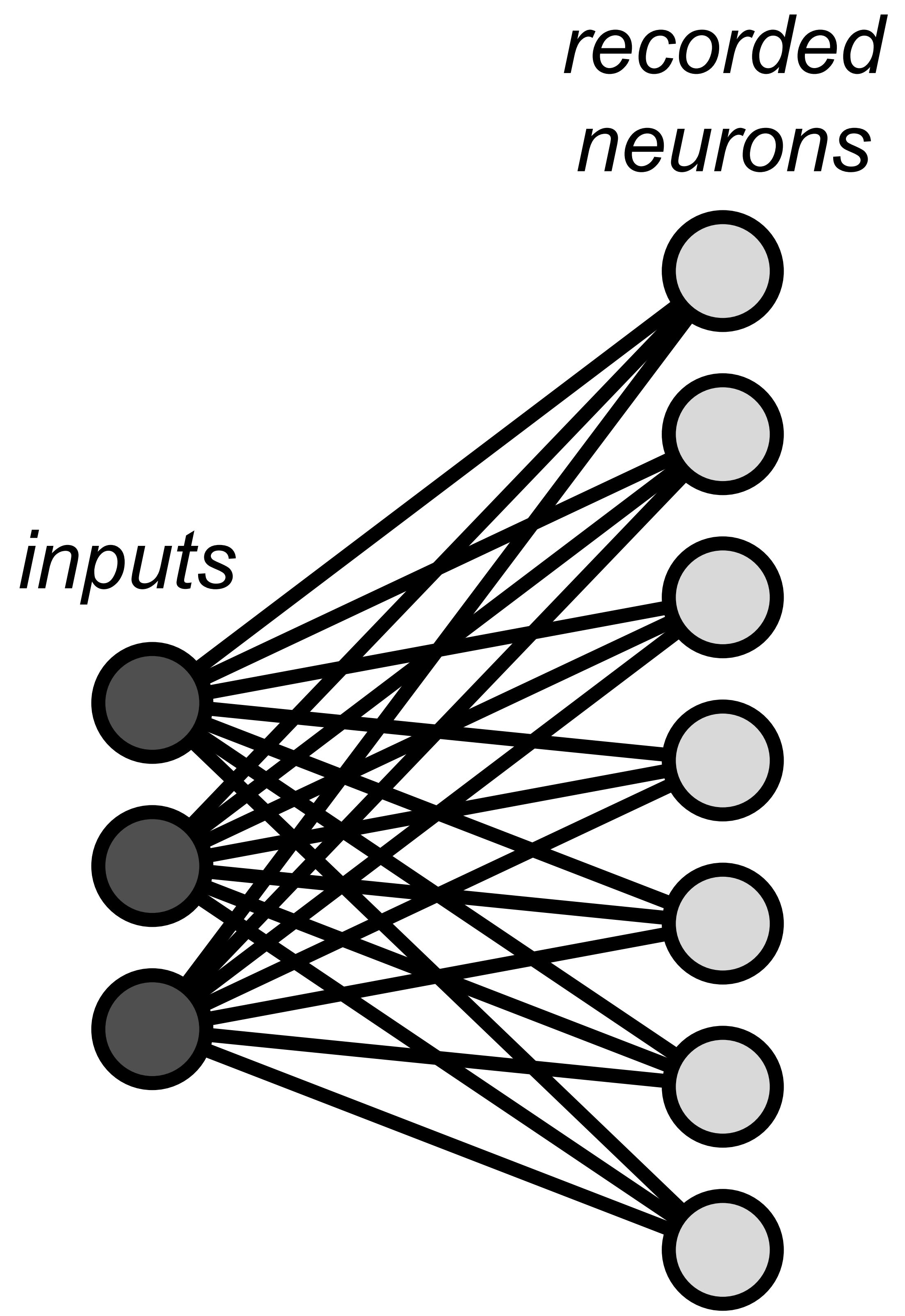
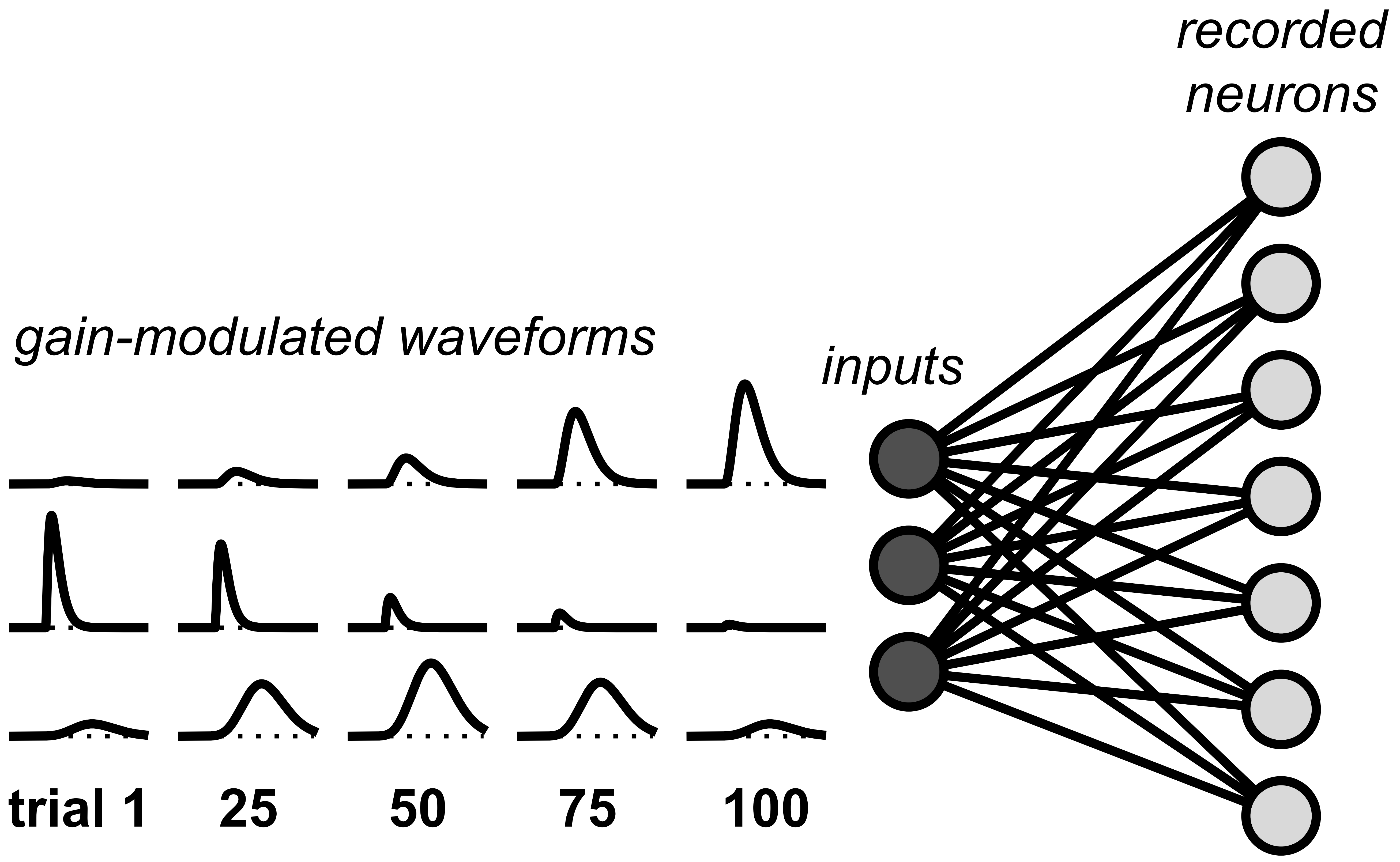


A neuroscientist's perspective:

CP tensor decomposition is a linear network with **gain modulation** — an influential principle of cortical computation (e.g., Carandini and Heeger, 2012)



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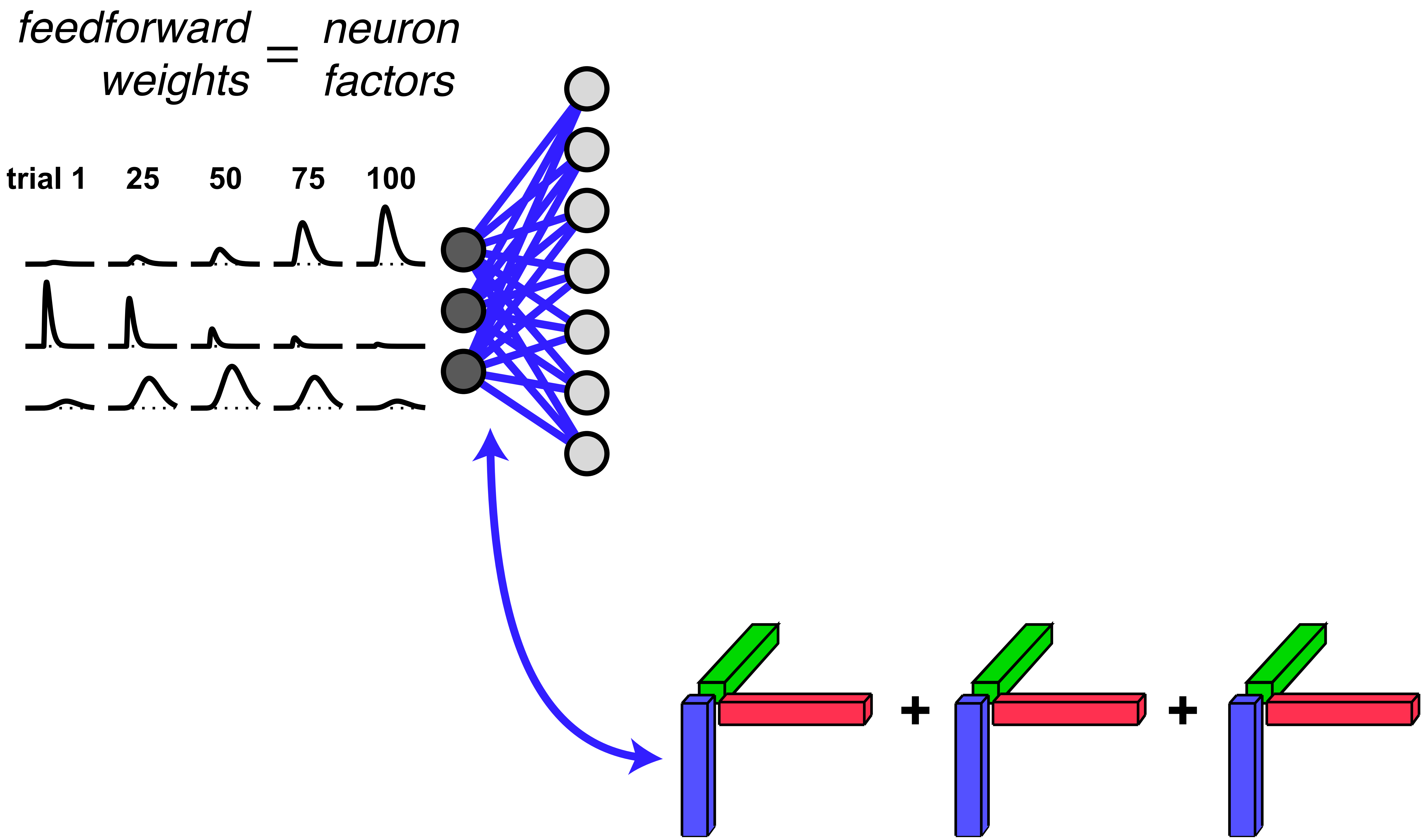

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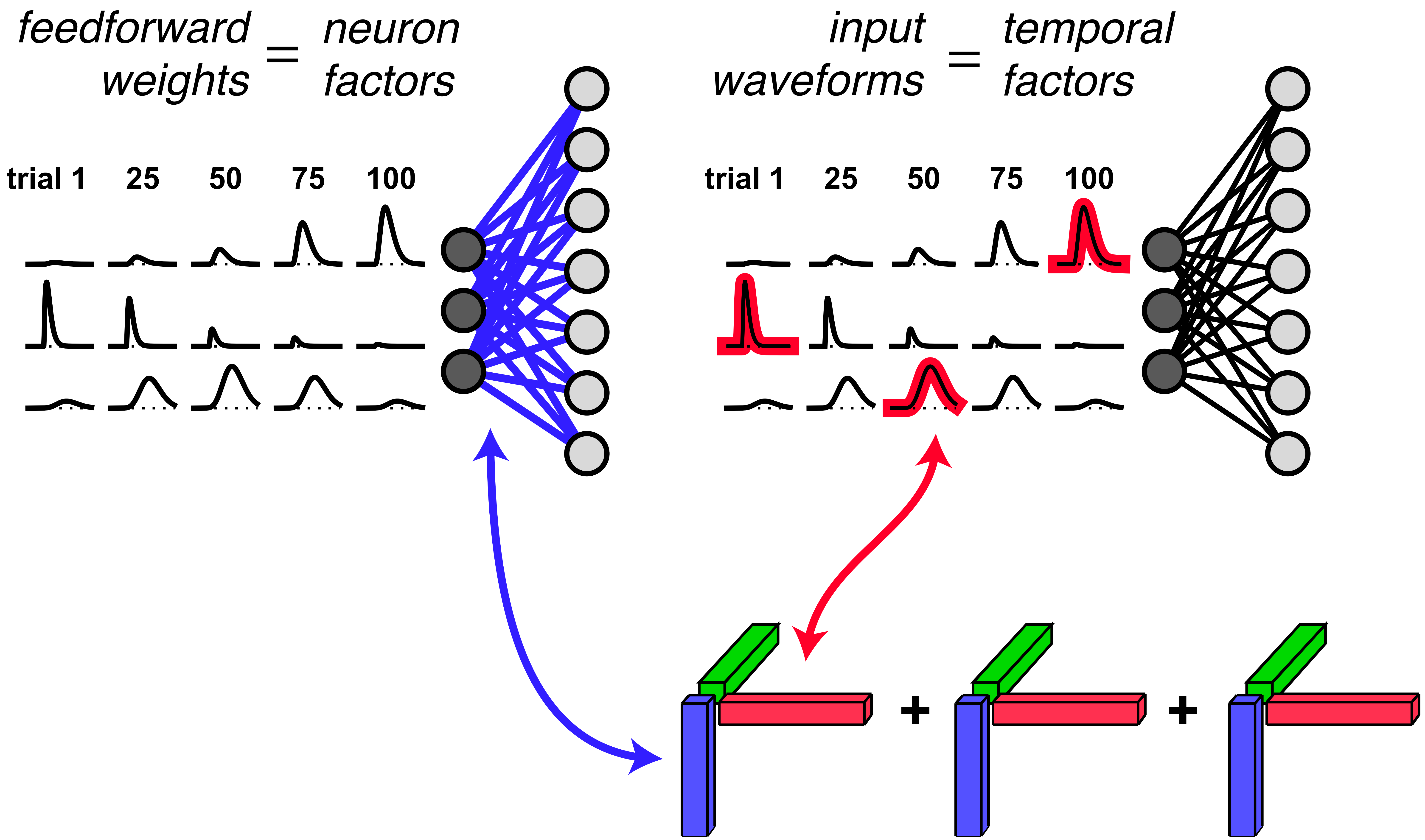

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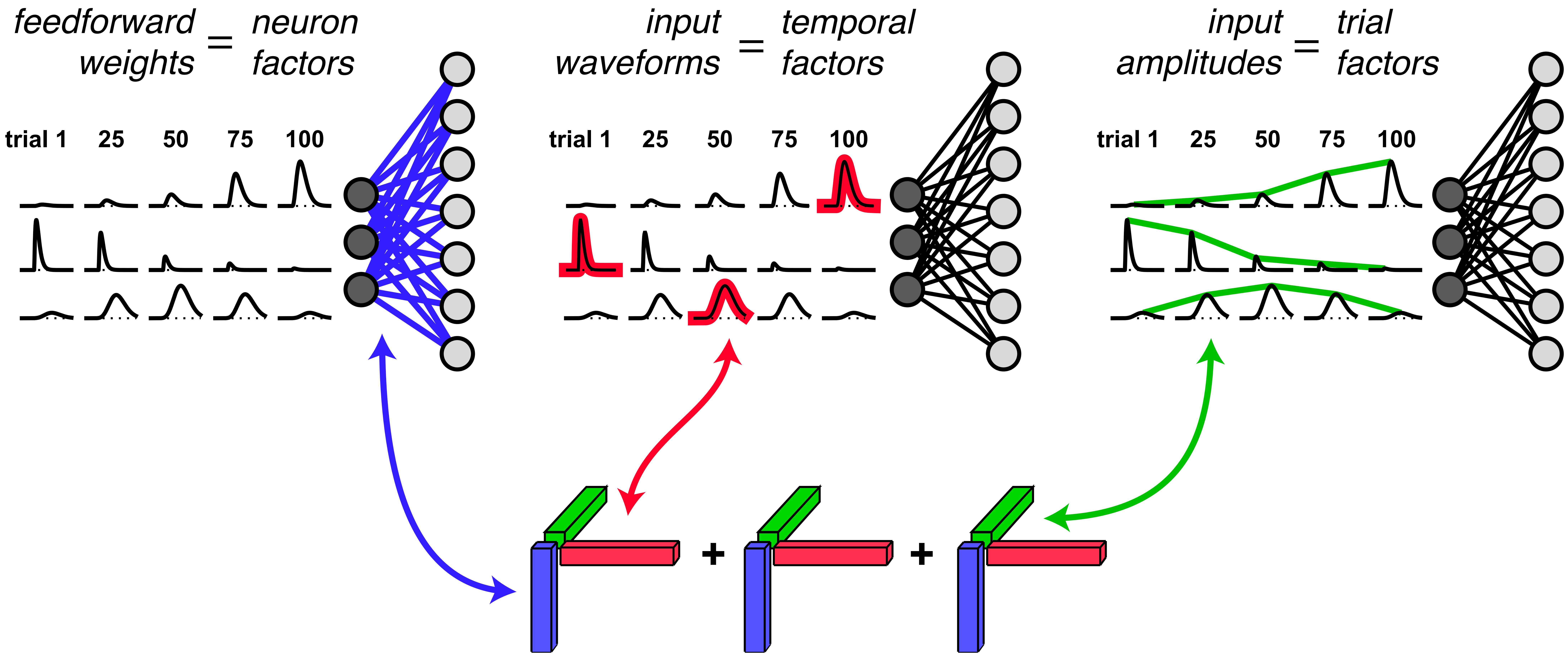
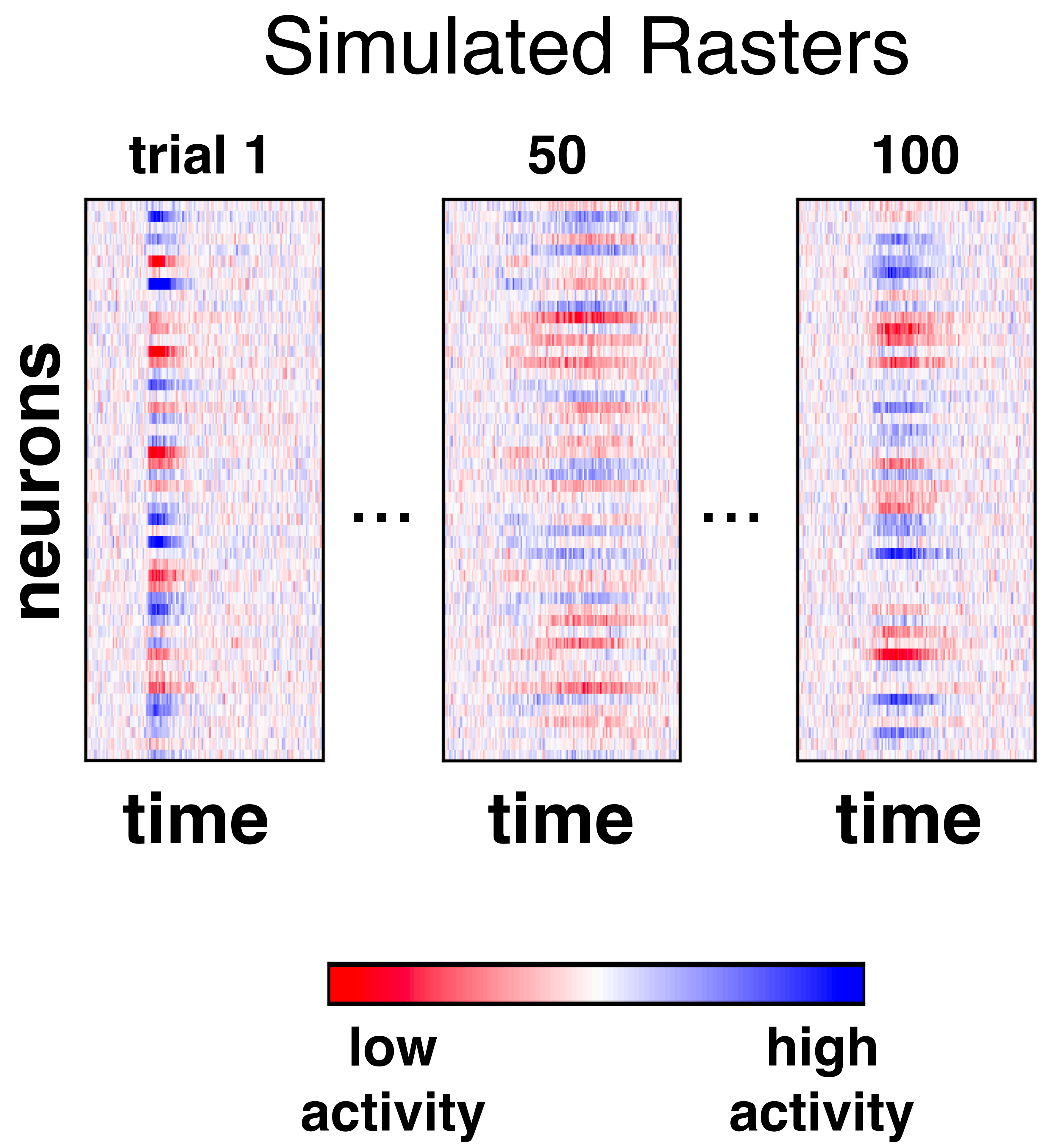


PCA fails to recover network parameters from simulated data



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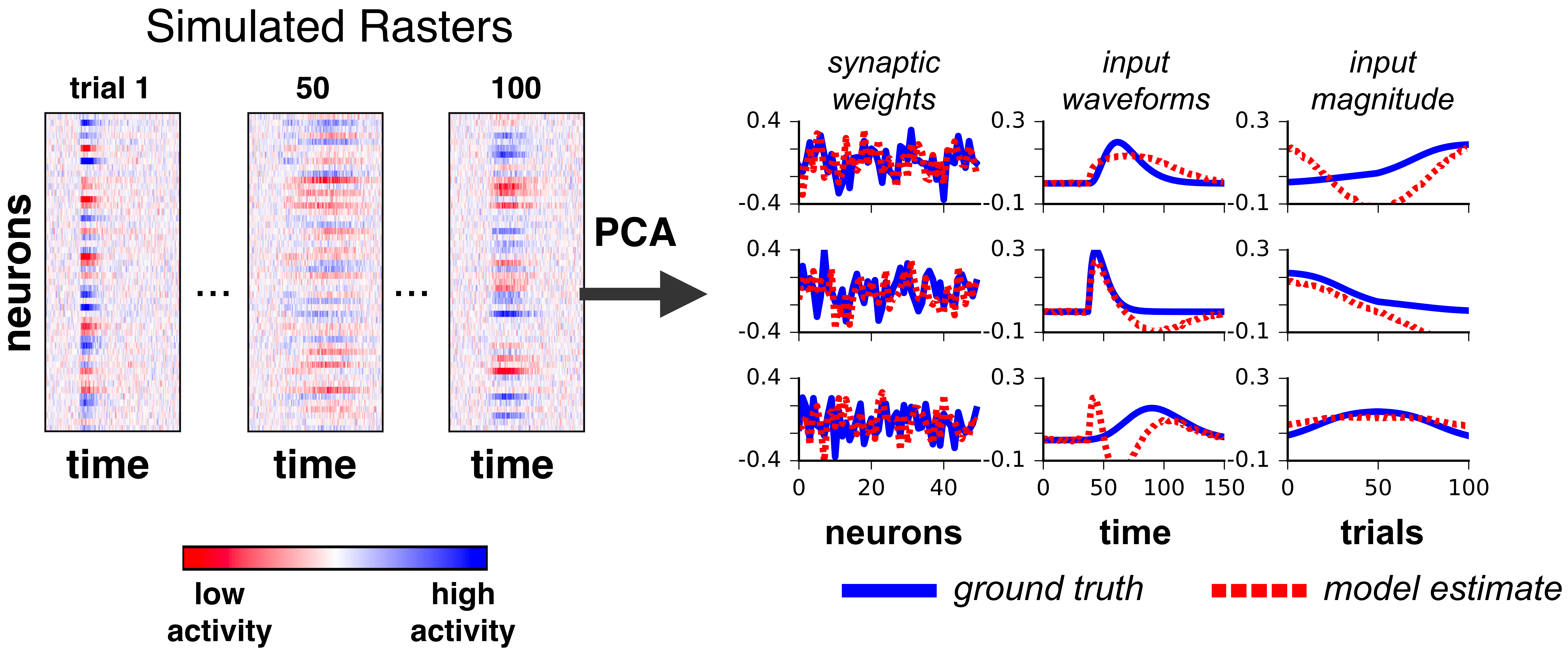
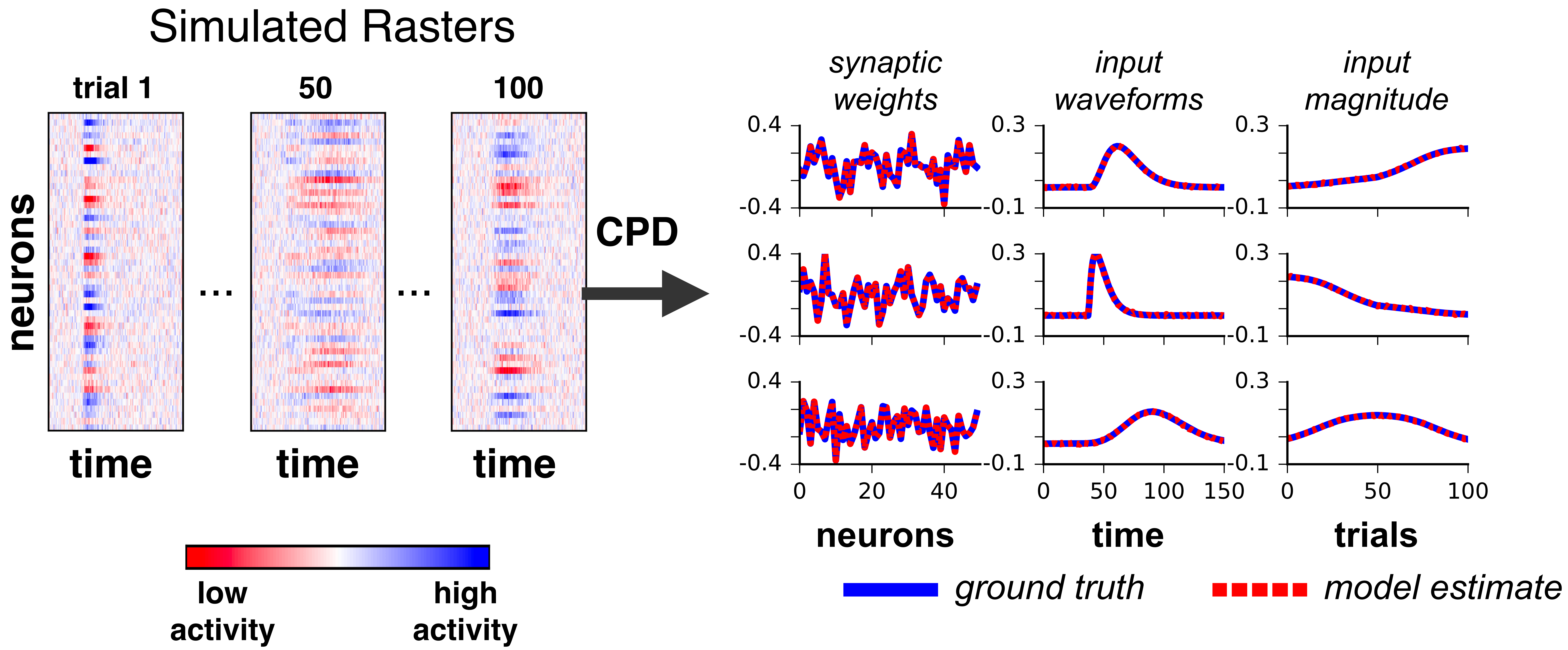
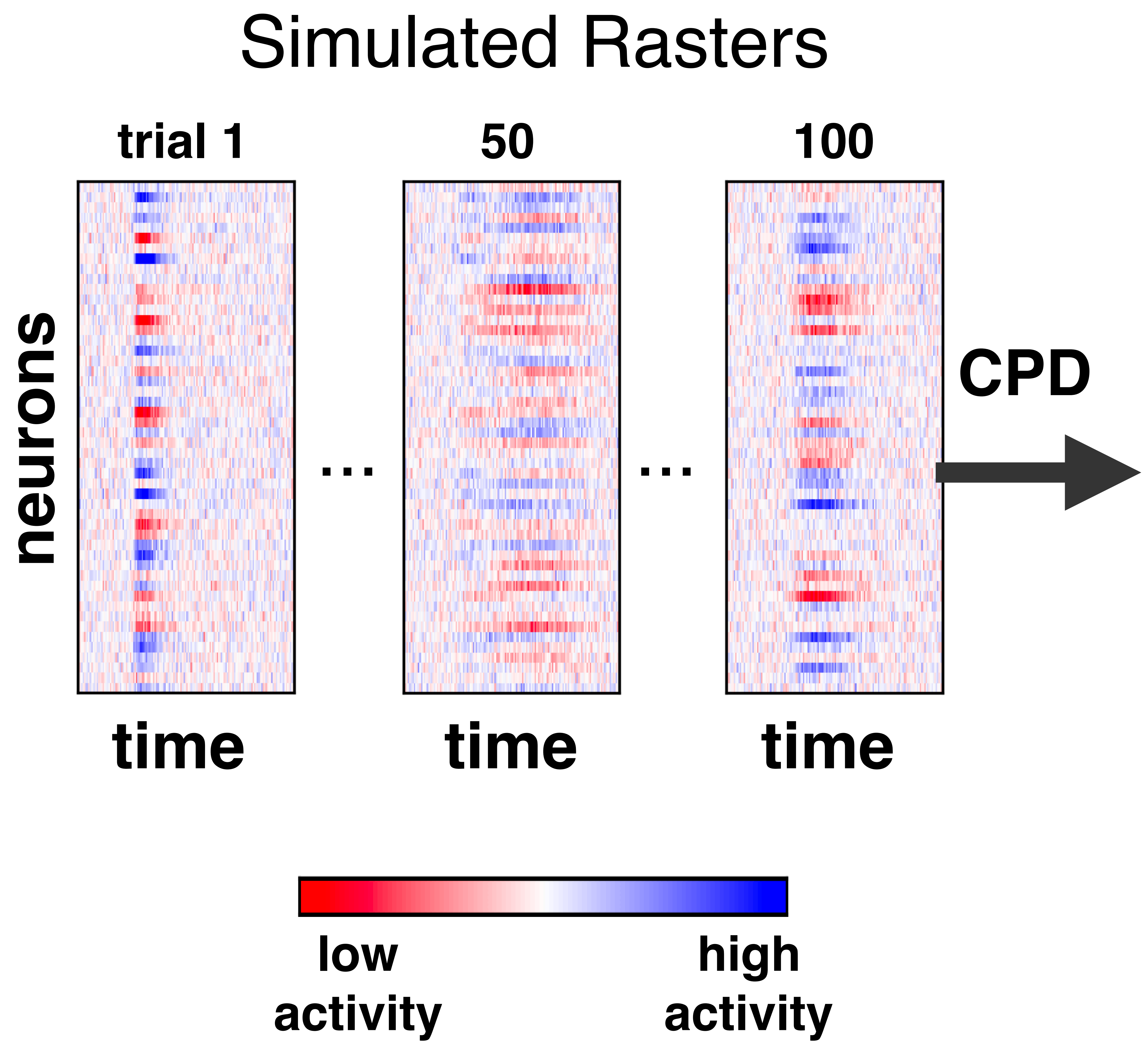


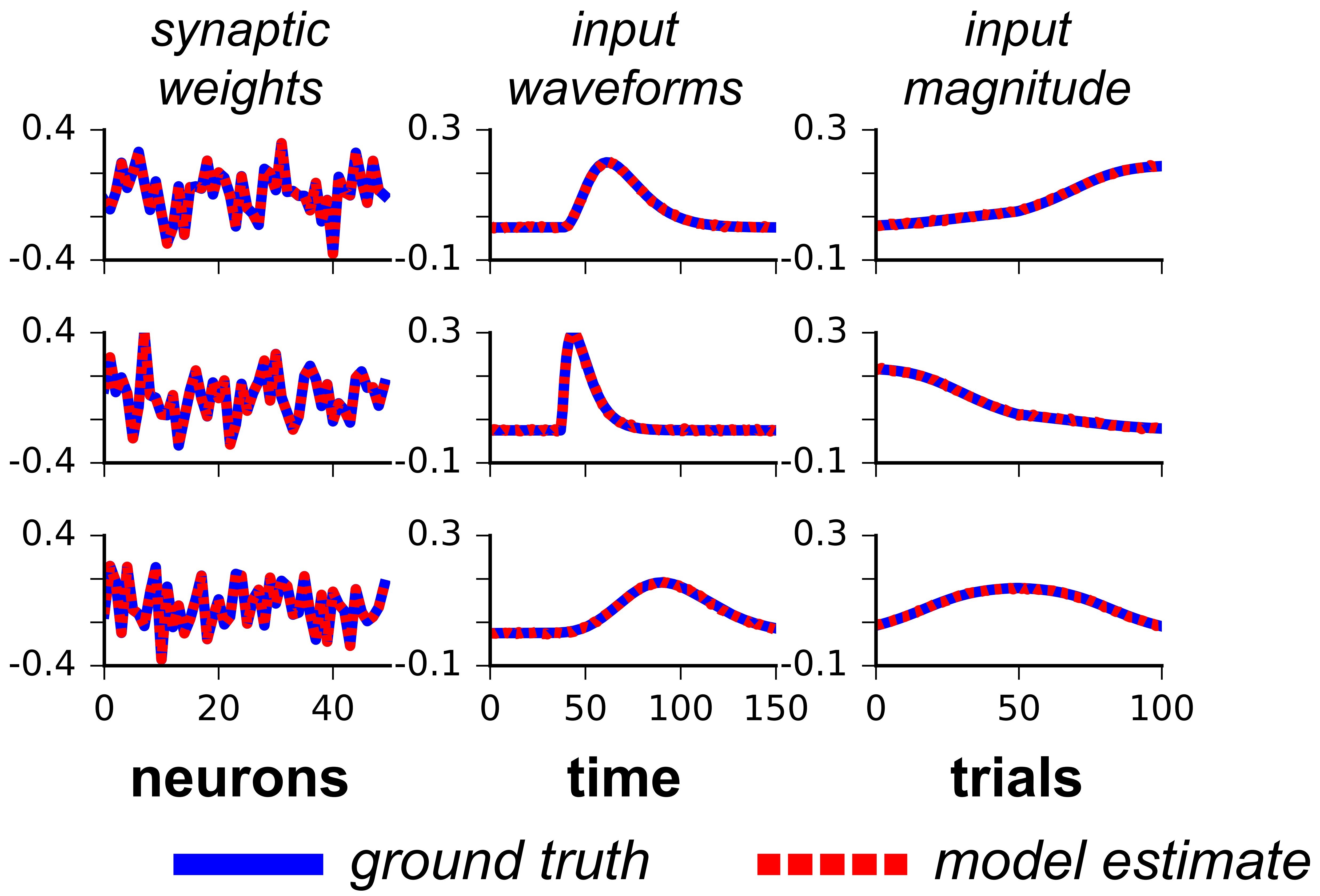
CP decomposition *precisely* recovers network parameters



CP decomposition p
network pa

Why this works: CP decompositions are unique when latent factors are linearly independent [Thm Kruskal ’77]

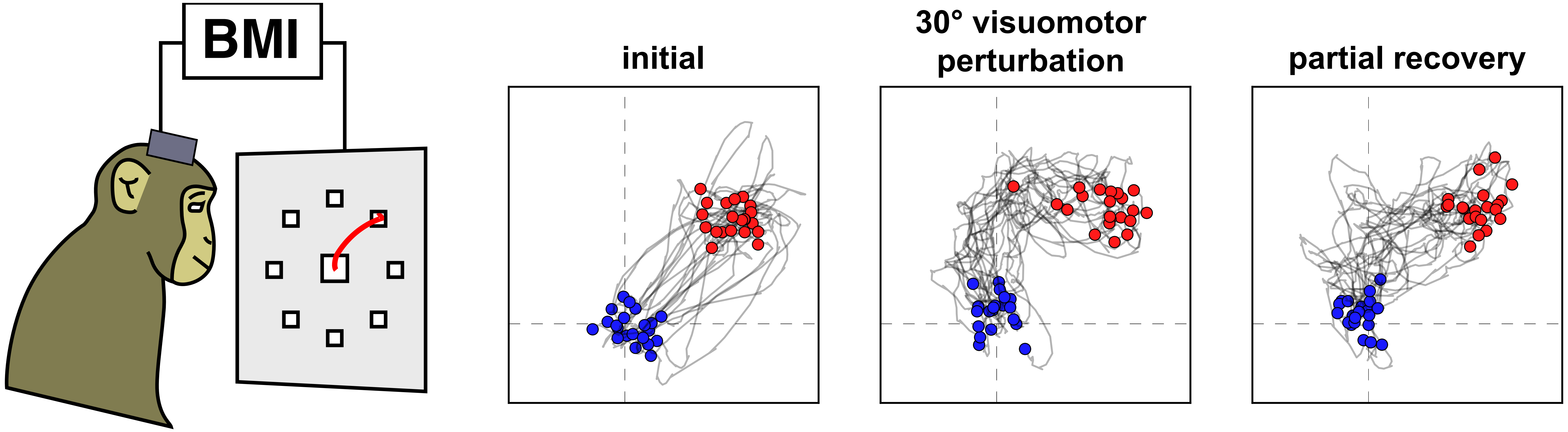




Application #1: learning cursor control with a brain machine interface (BMI)

Saurabh Vyas

Krishna Shenoy



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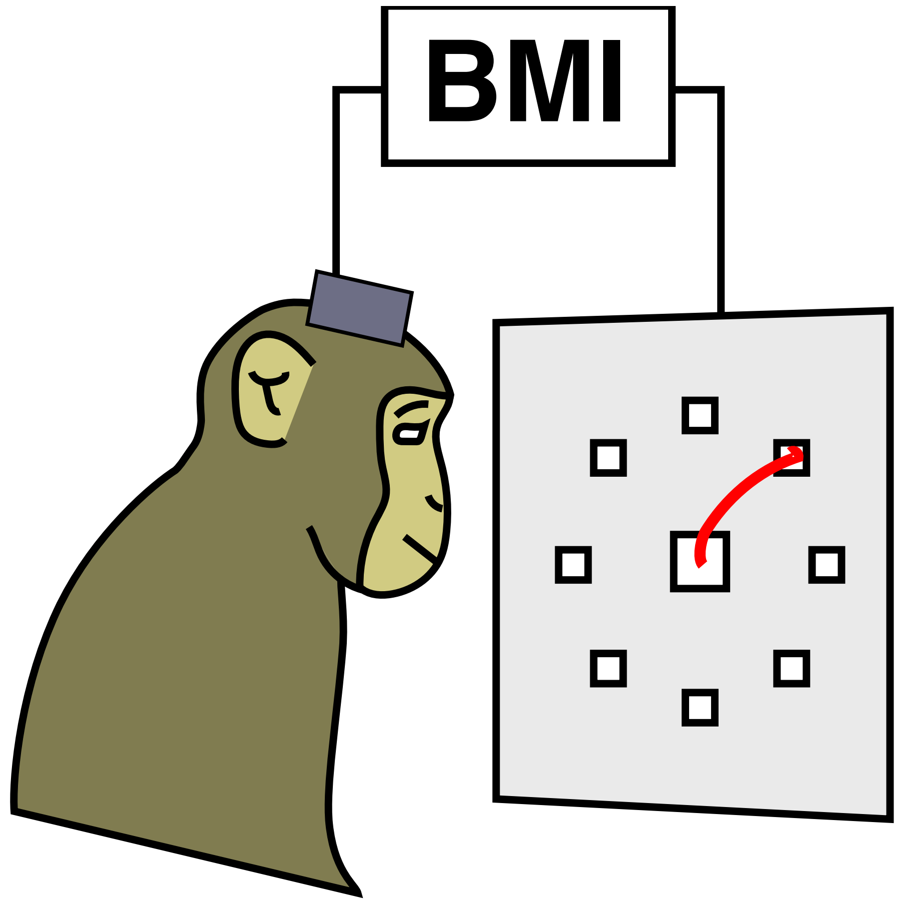

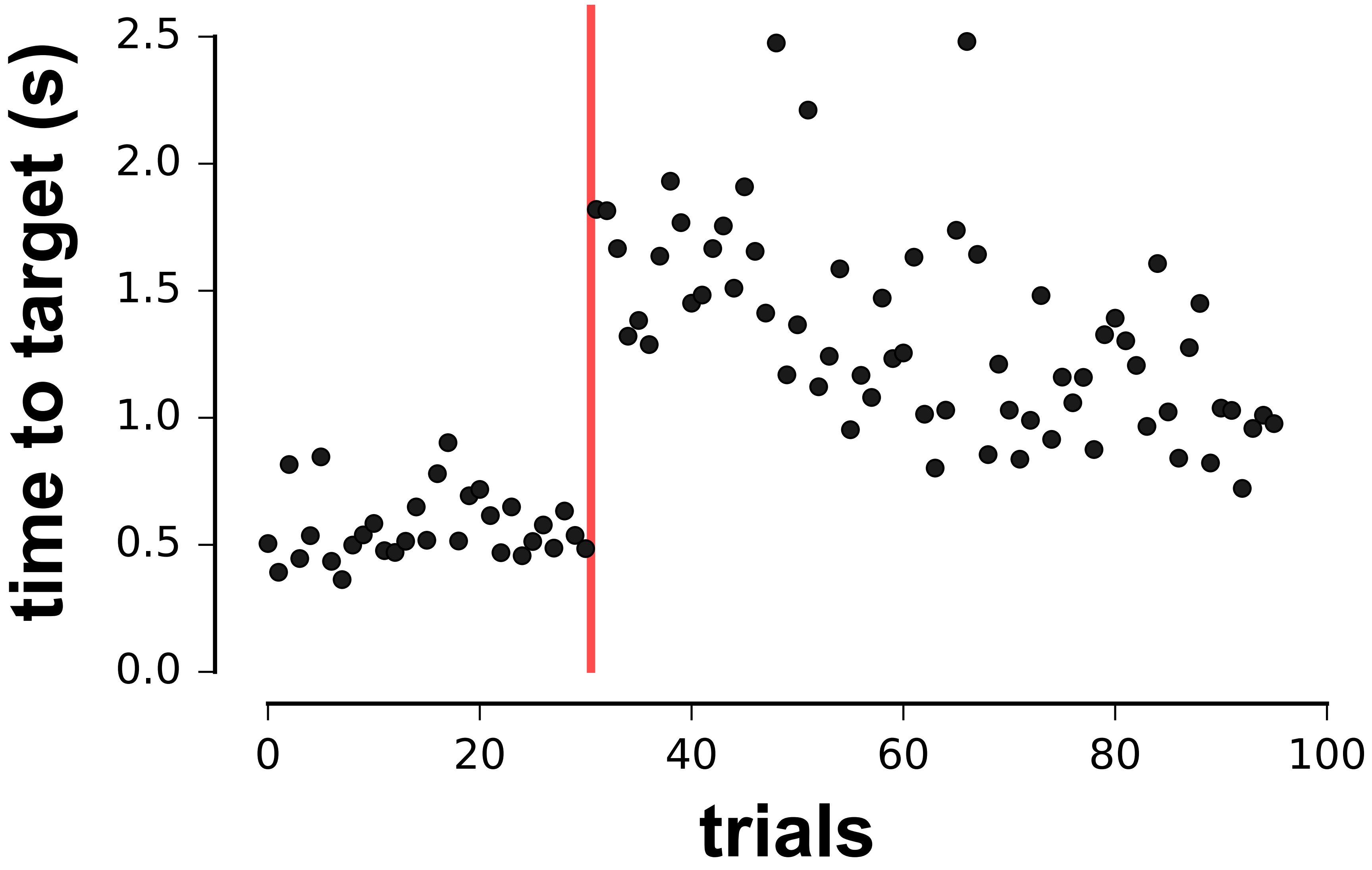

CP decomposition identifies early- and late-responding dynamics in response to the BMI perturbation.

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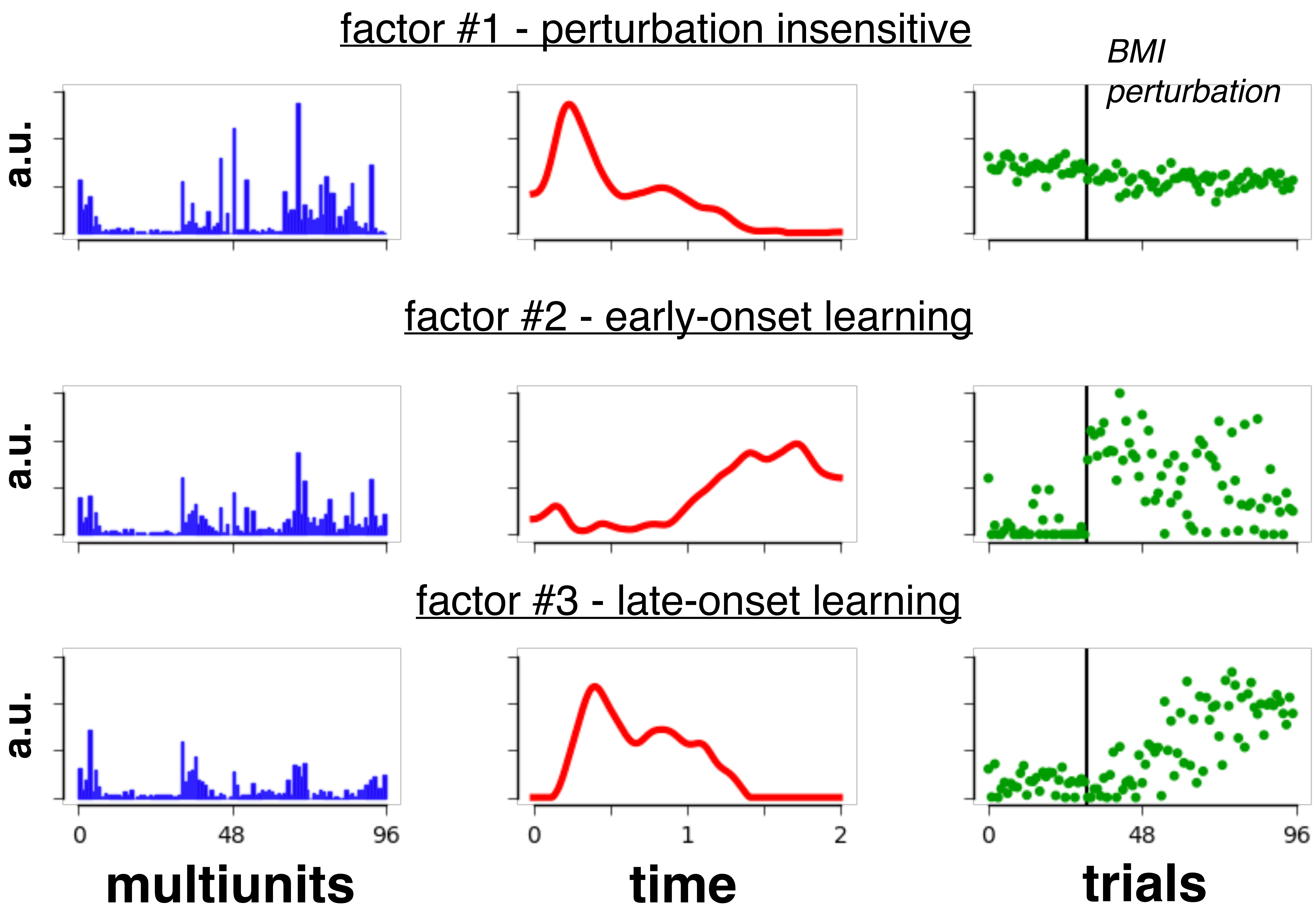
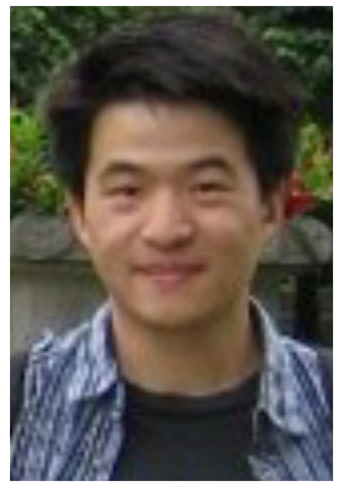


Application #2: response to reward contingency shift during spatial navigation



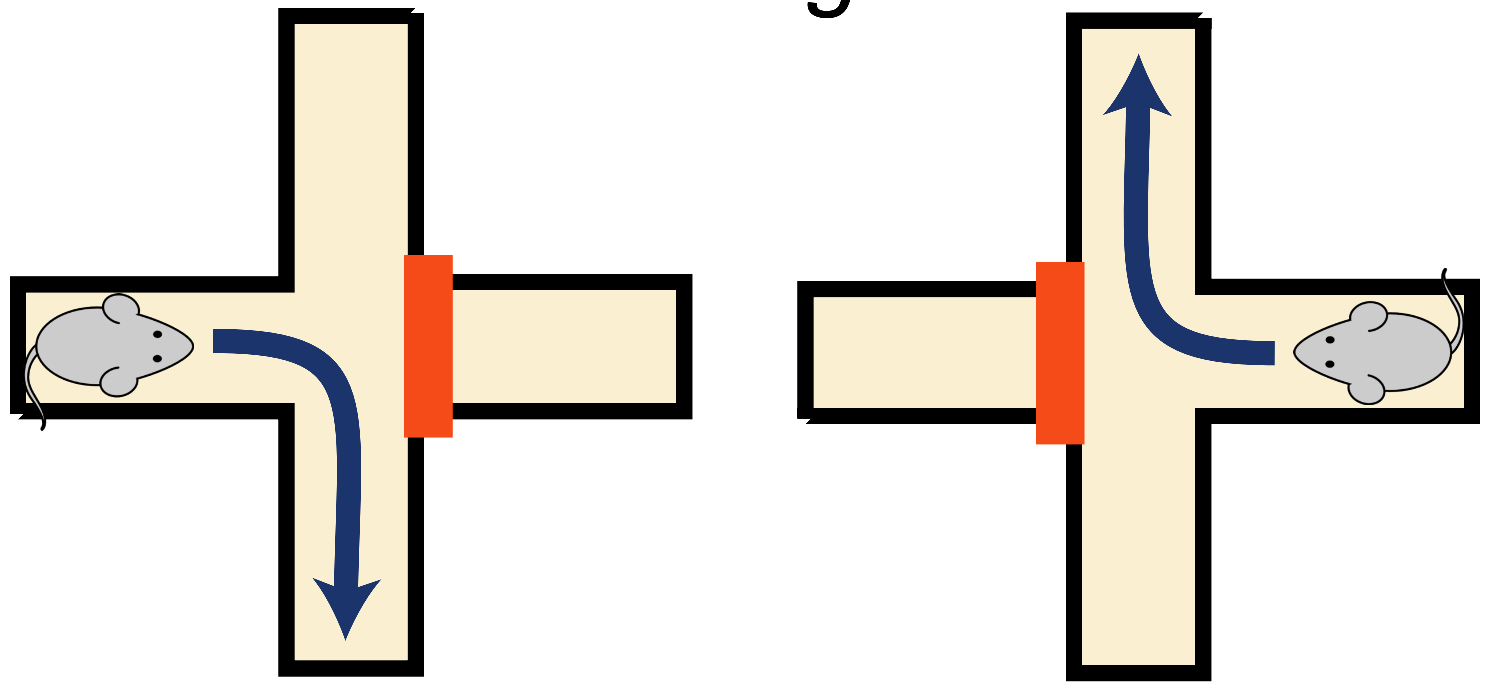
Tony Kim

Fori Wang

Mark Schnitzer

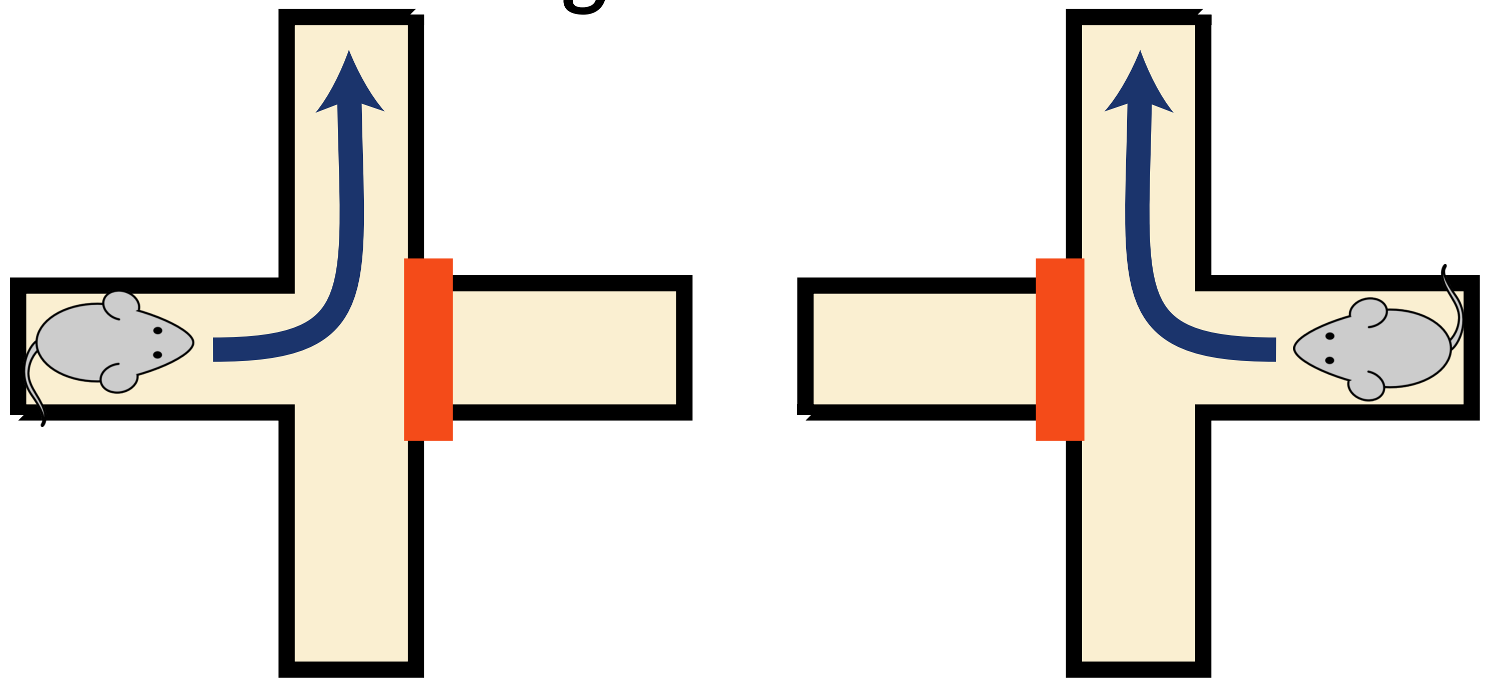
Egocentric Condition

turn right

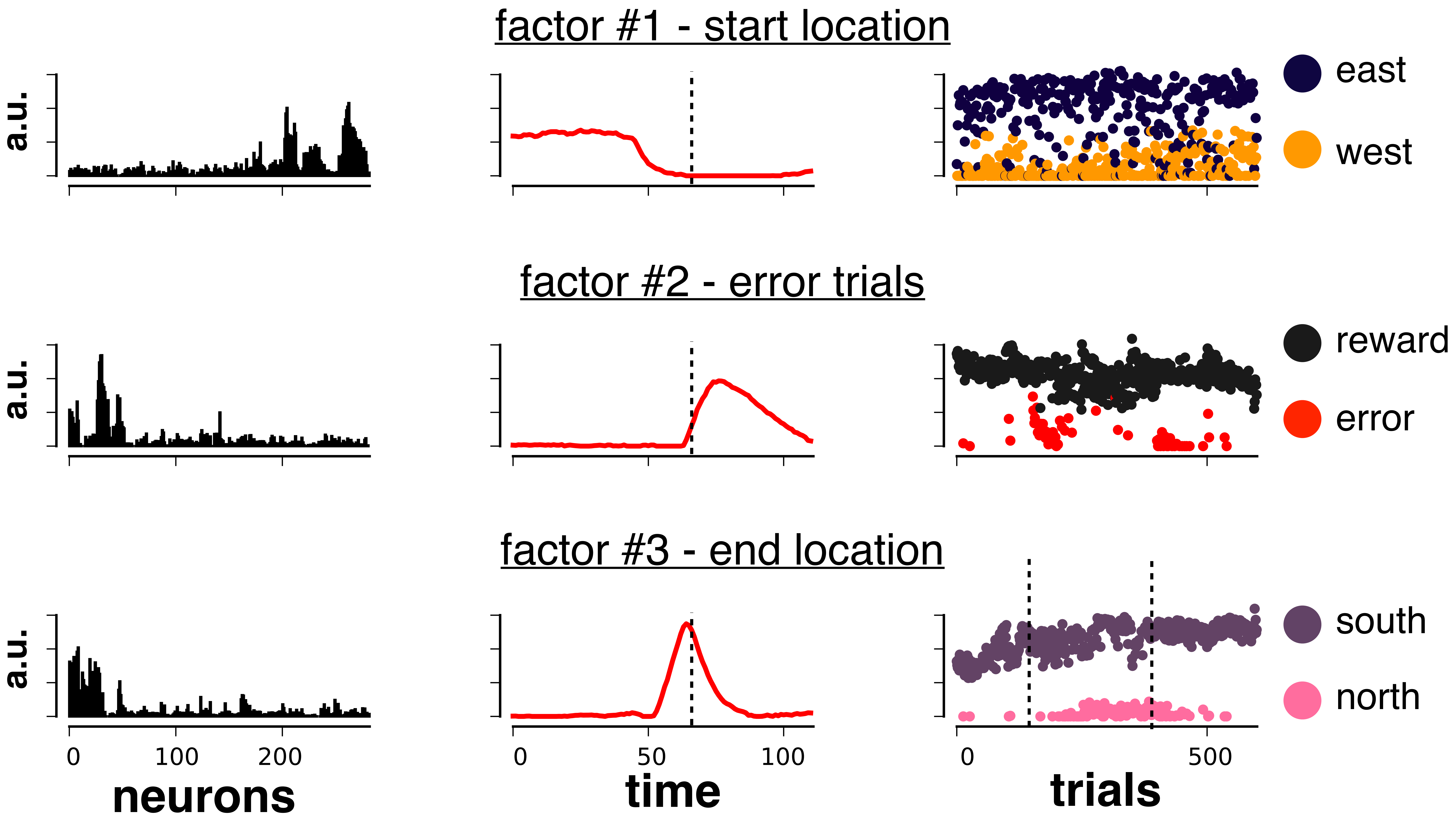


Allocentric Condition

go north



CP factors are highly interpretable, often "demixed" representations of task-variables



Summary

- CP tensor decomposition is a generic tool that is applicable to many datasets
- Avoids trial-averaging, separates within-trial and across-trial dynamics
- Fully unsupervised technique
- Practical and theoretical principles can be leveraged from existing research:
  - Proofs of theoretical properties/advantages over PCA.
  - Specialized, scalable optimization methods.

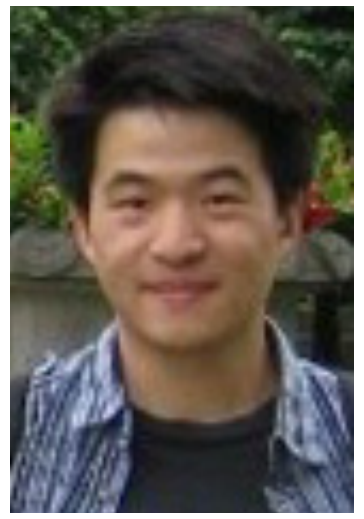
Code : github.com/ahwillia/tensor-demo

Contact : ahwillia@stanford.edu

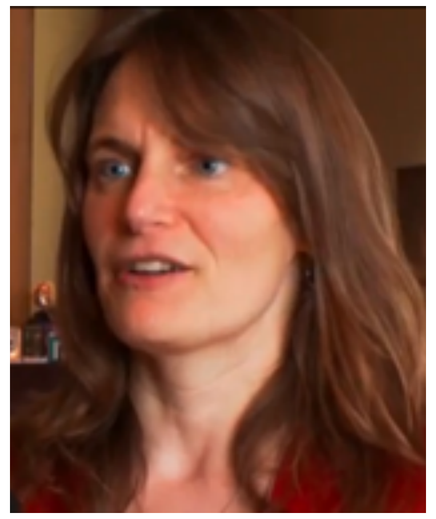
Slides : alexhwilliams.info/pdf/cosyne17.pdf

Code : github.com/ahwillia/tensor-demo

Co-authors






Tony Kim	Fori Wang	Mark Schnitzer	Saurabh Vyas	Krishna Shenoy	Tammy Kolda	Surya Ganguli

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- Chris Stock
- Lane McIntosh
- Sarah Harvey
- Aran Nayebi