Experimentally Informed Signal Processing with Supervised Independent Component Analysis

CoNECTome

May 16, 2025

Ronak Mehta

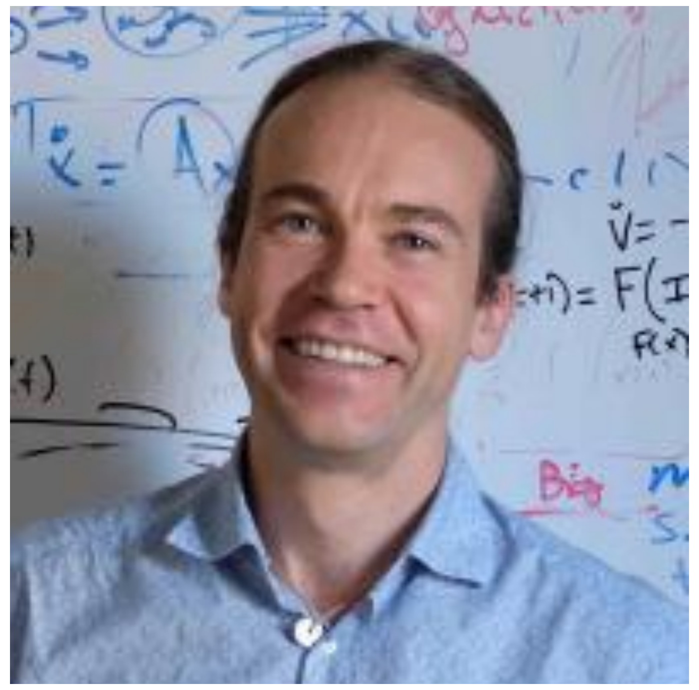
Team

Ronak Mehta
Statistics

Noah Stannis
Bioengineering

Azadeh Yazdan
Bioengineering

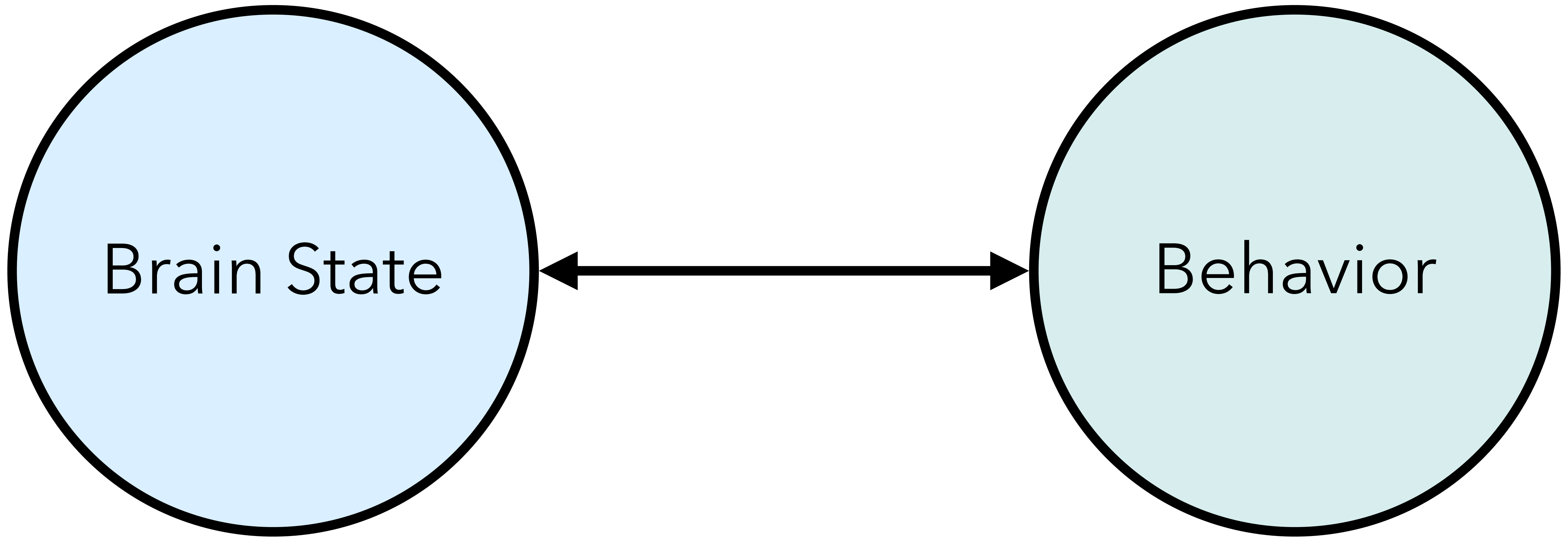
Ali Shojaie
Biostatistics



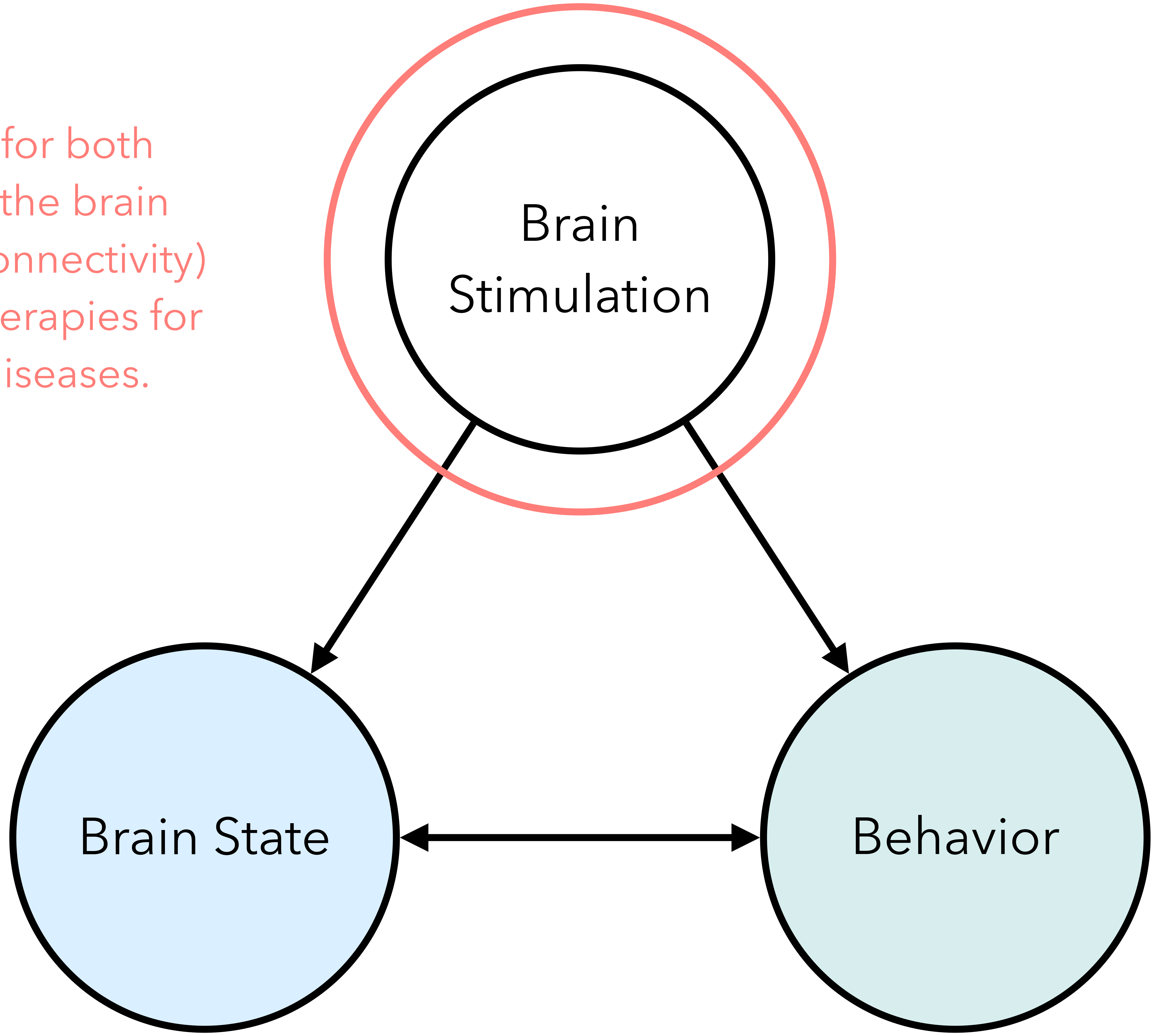
Eric Shea-Brown
Applied Mathematics

Zaid Harchaoui
Statistics

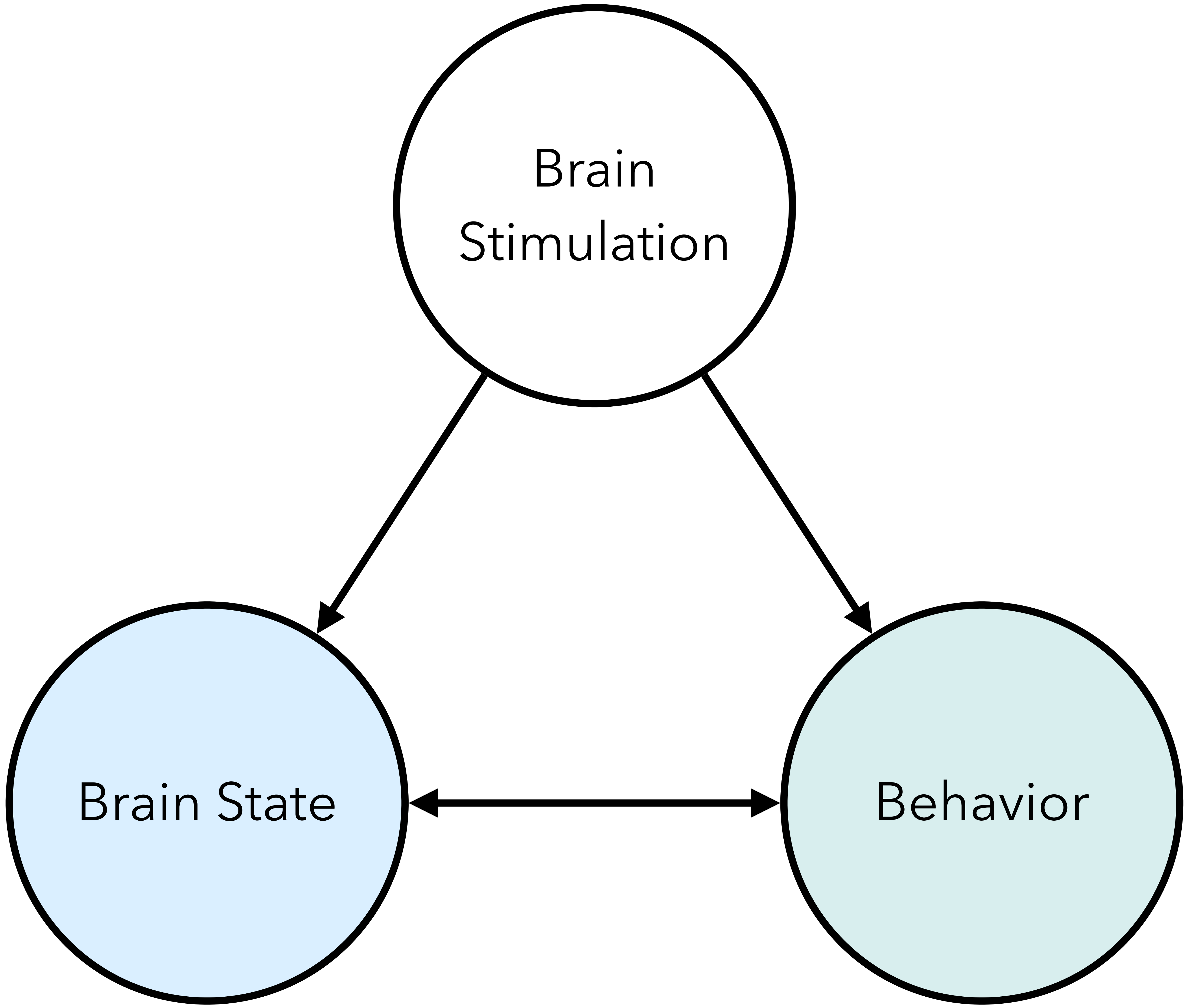
National Institutes of Health

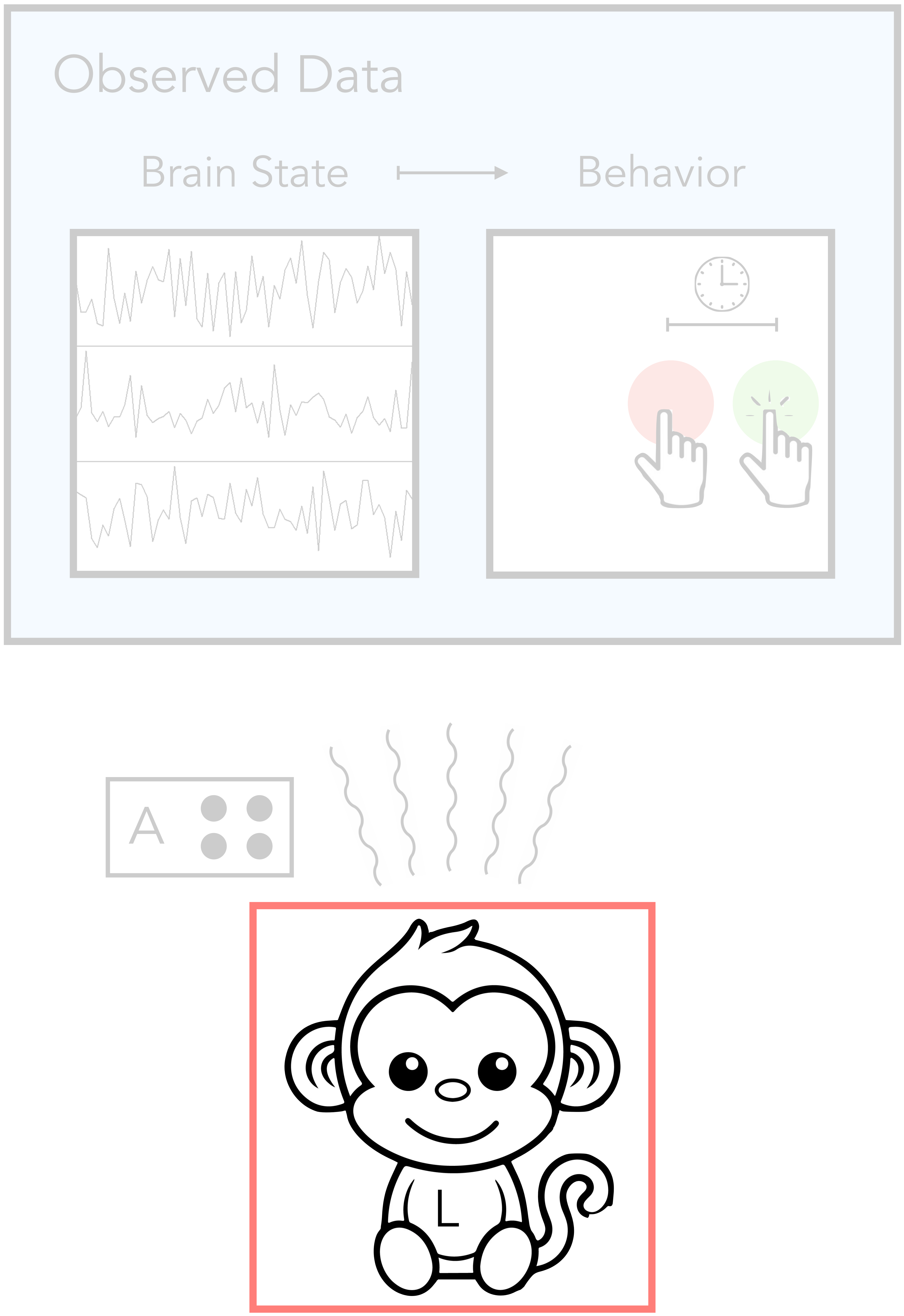

Brain State
Behavior

Opportunities for both understanding the brain (e.g. functional connectivity) and designing therapies for neurological diseases.

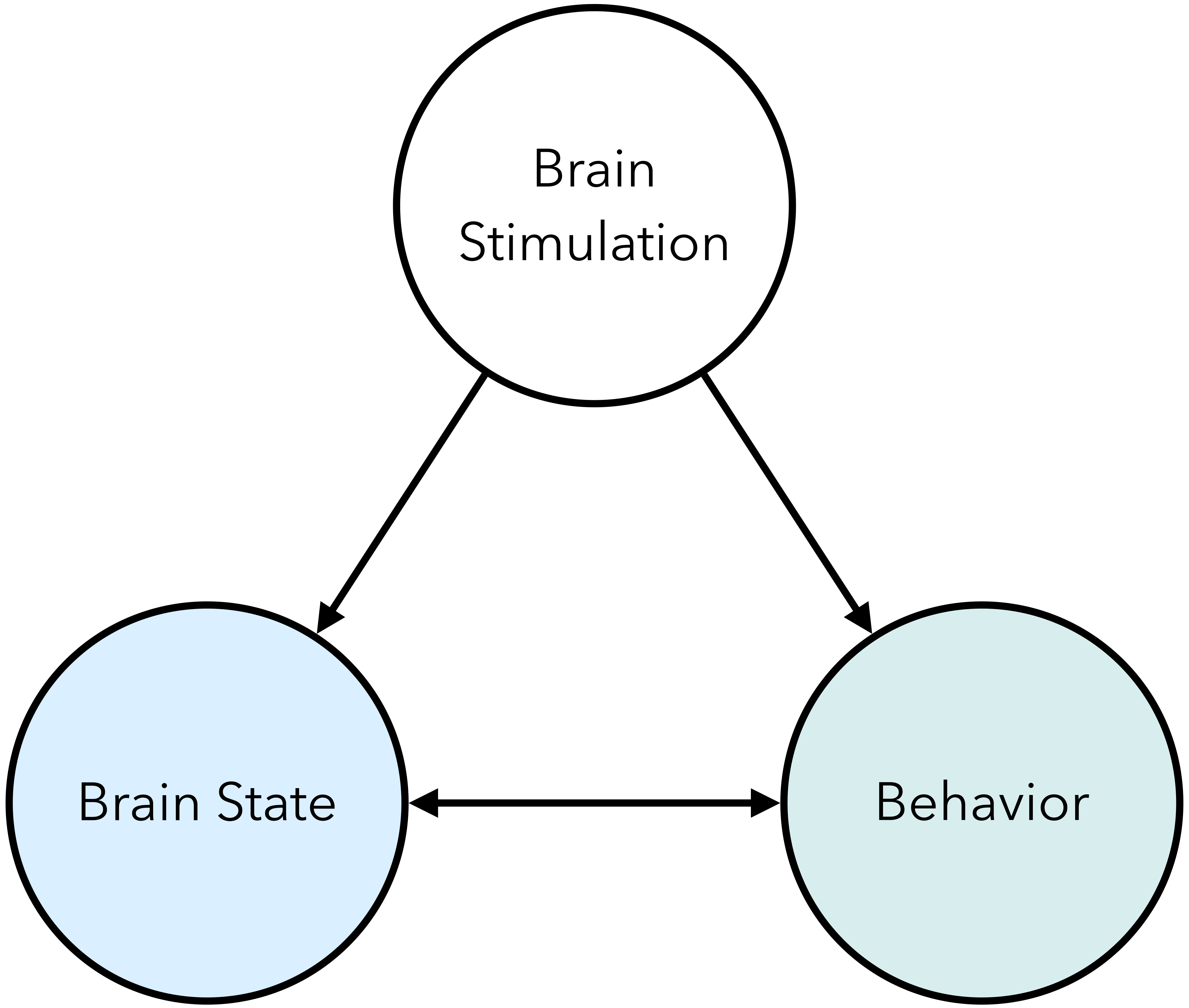


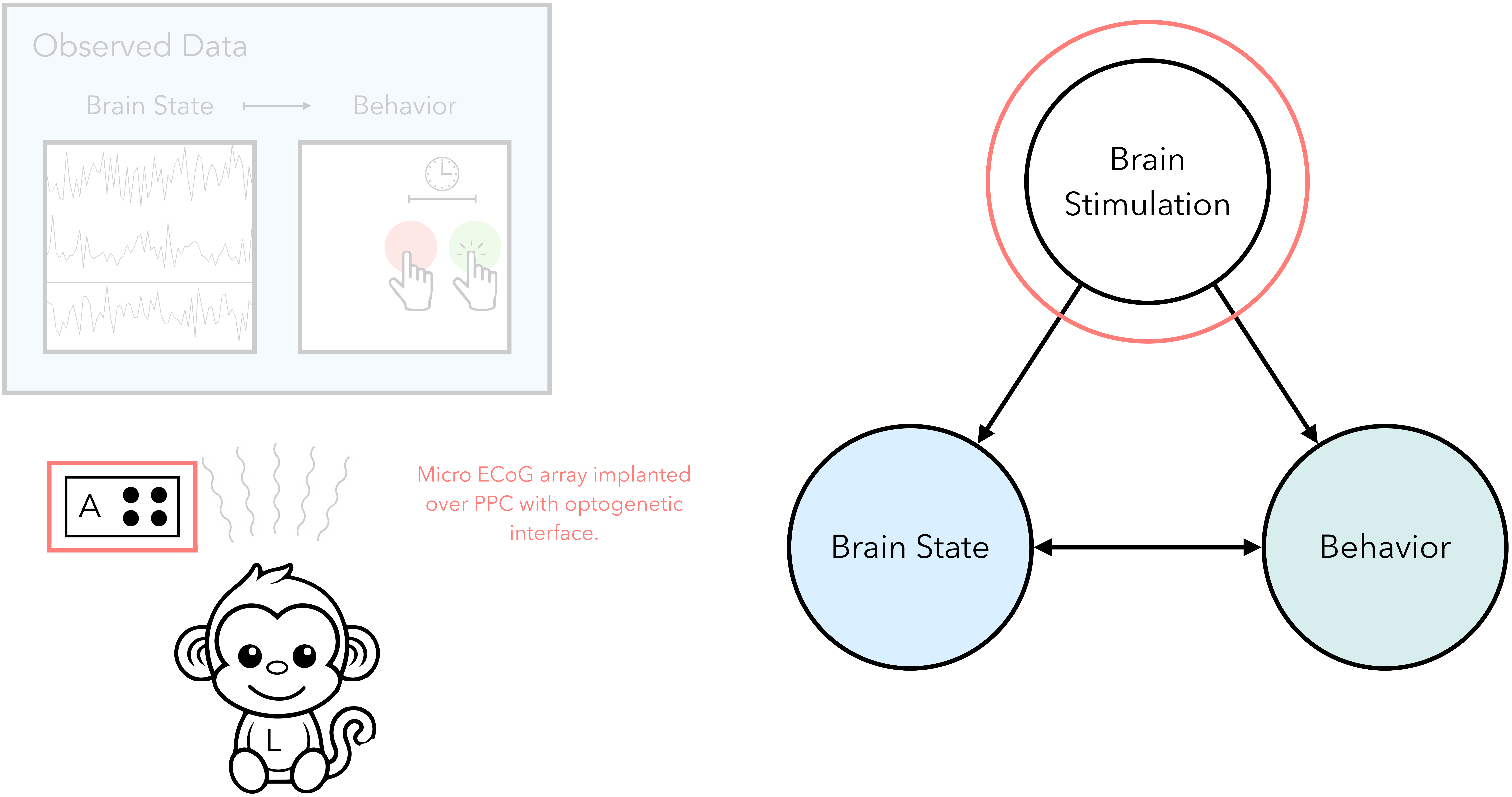
Observed Data
Brain State
Behavior
A
L

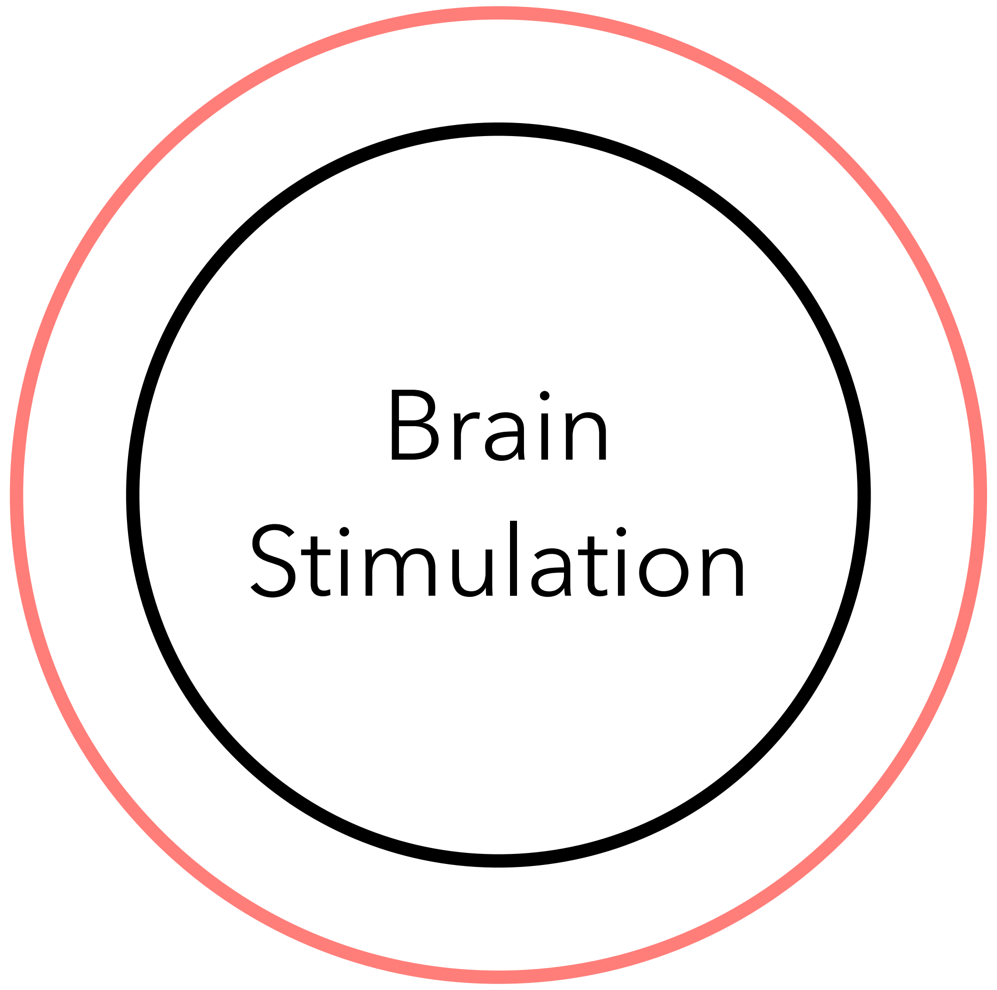

Brain Stimulation
Brain State
Behavior

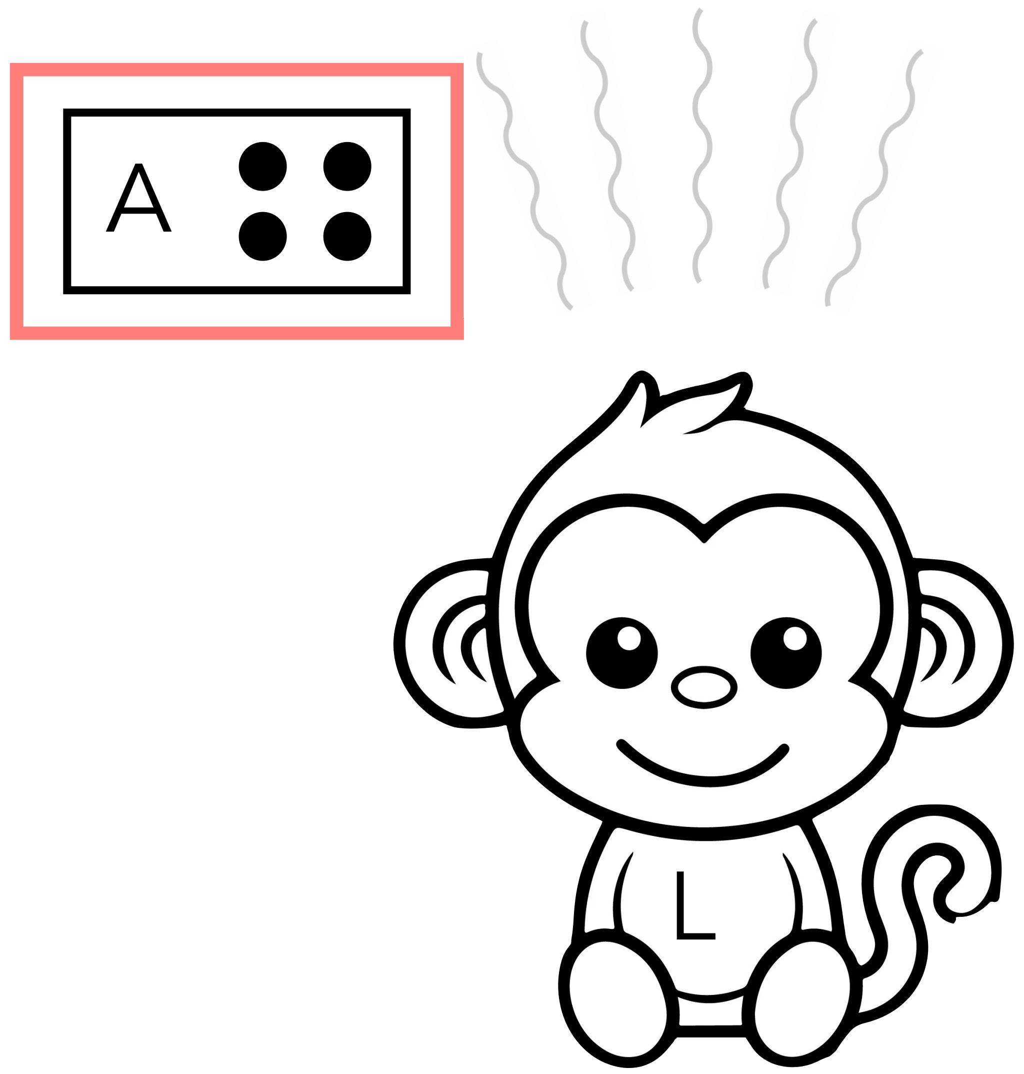


Adult male rhesus macaque monkey.

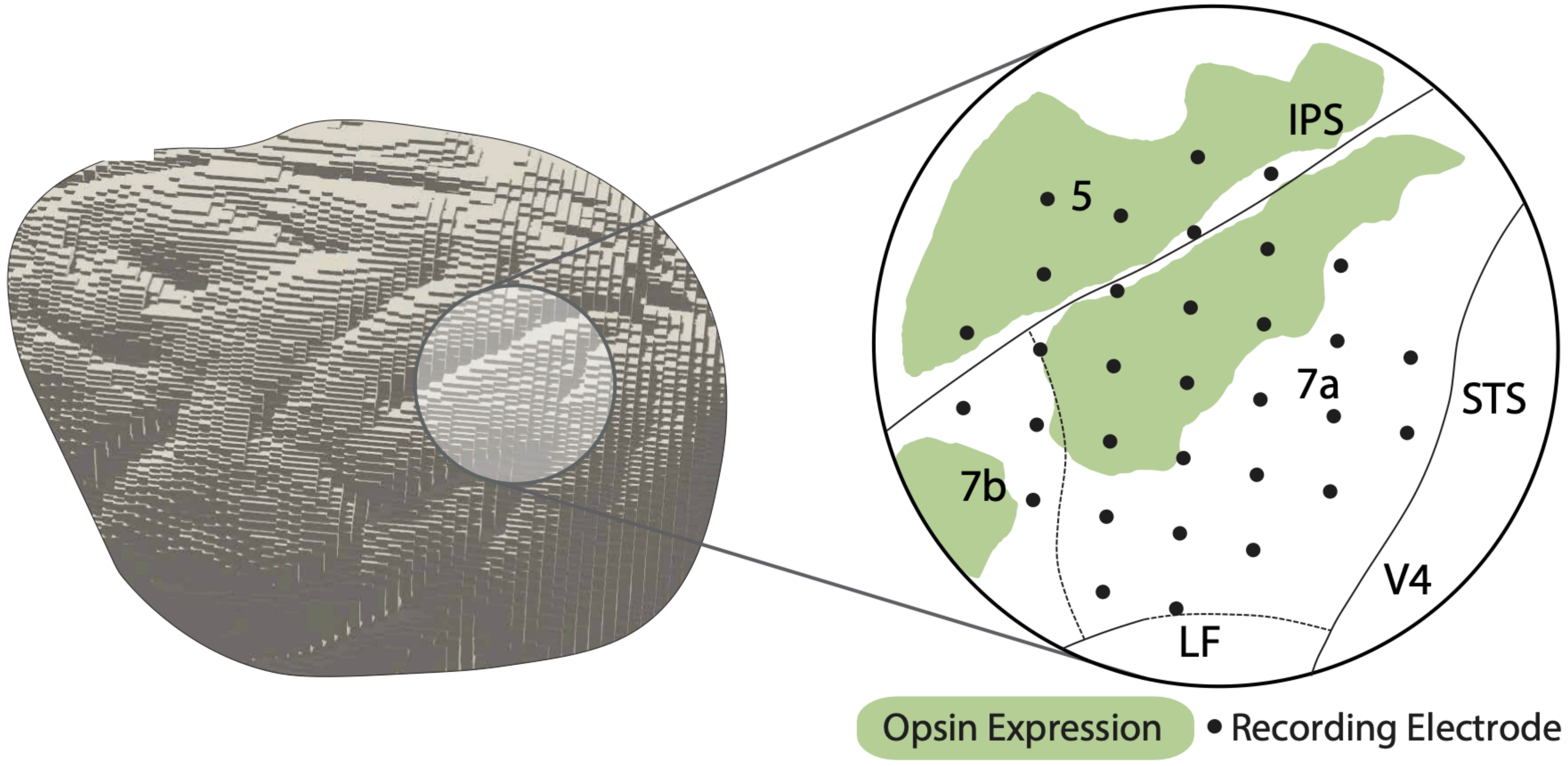



Observed Data
Brain State
Behavior
A
L
Micro ECoG array implanted over PPC with optogenetic interface.
Brain Stimulation
Brain State
Behavior

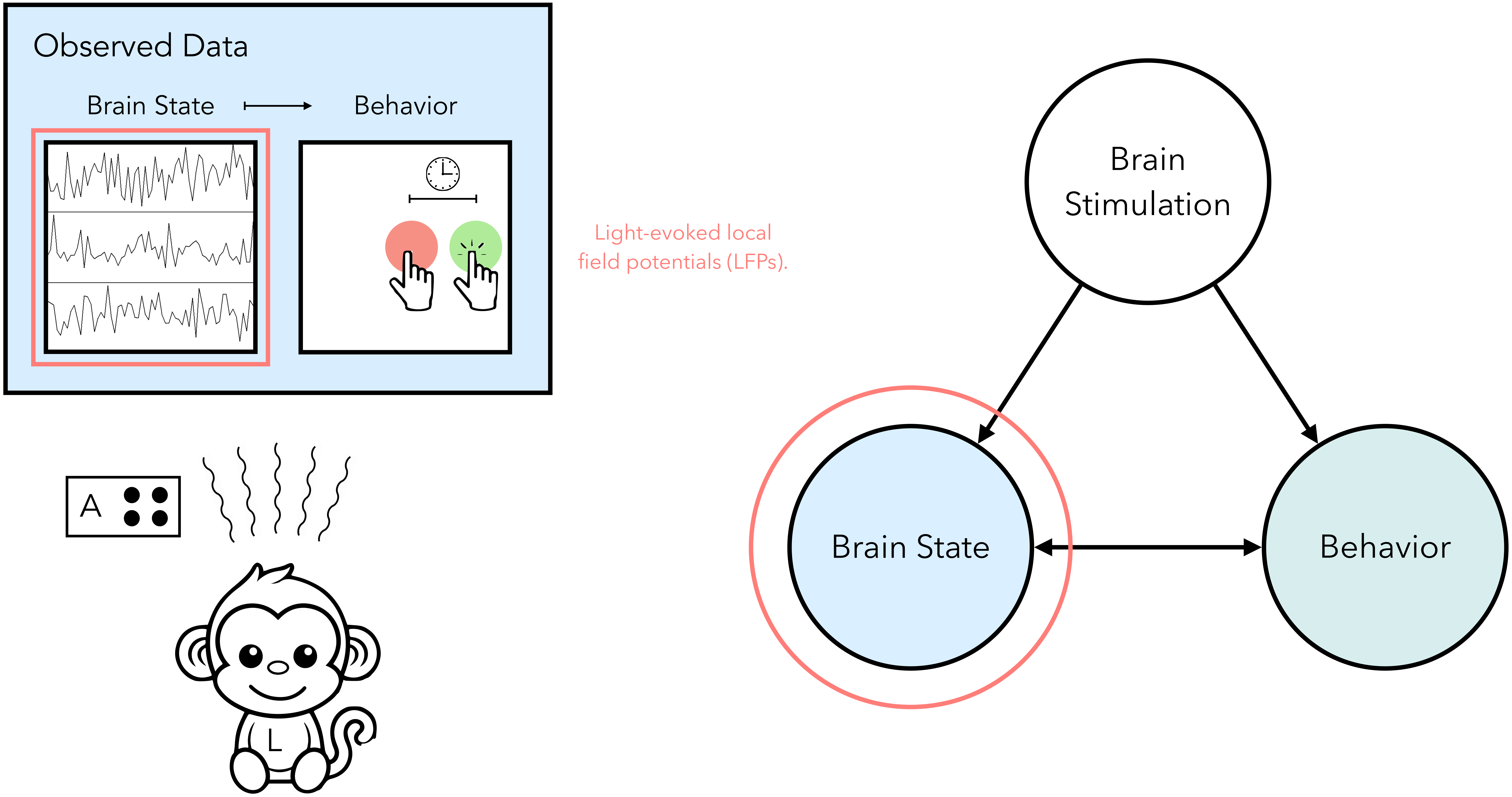


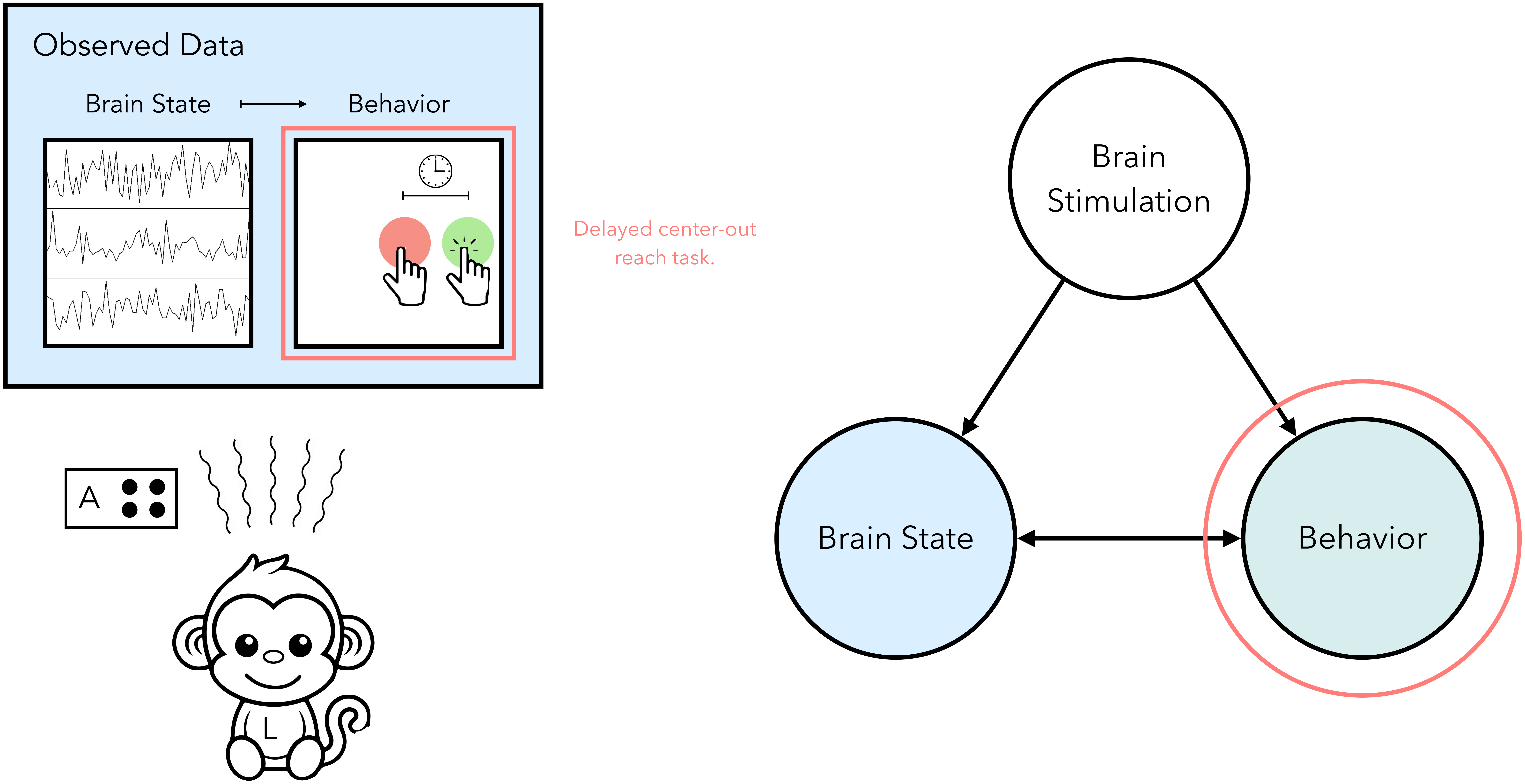


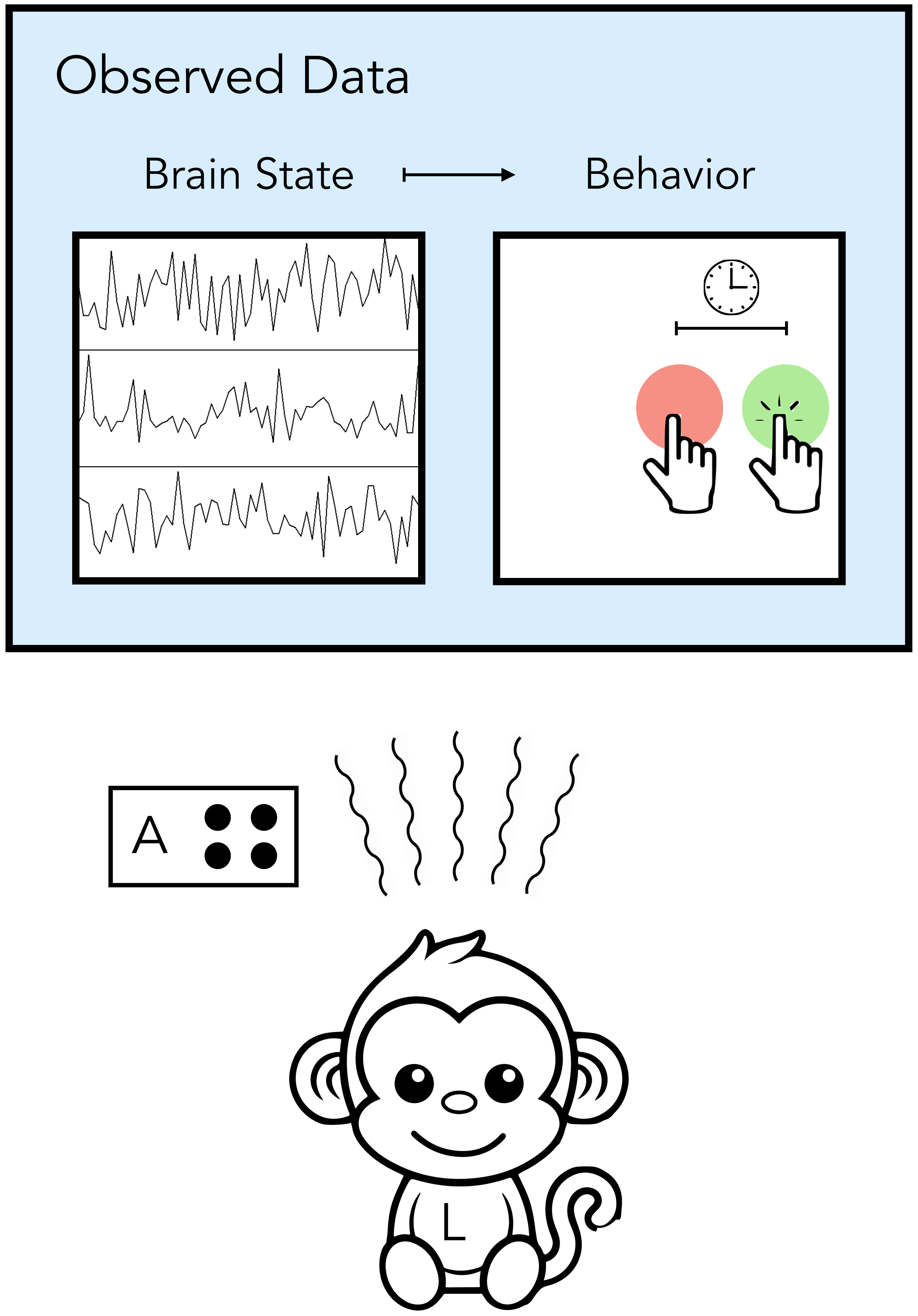
Micro ECoG array implanted over PPC with optogenetic interface.

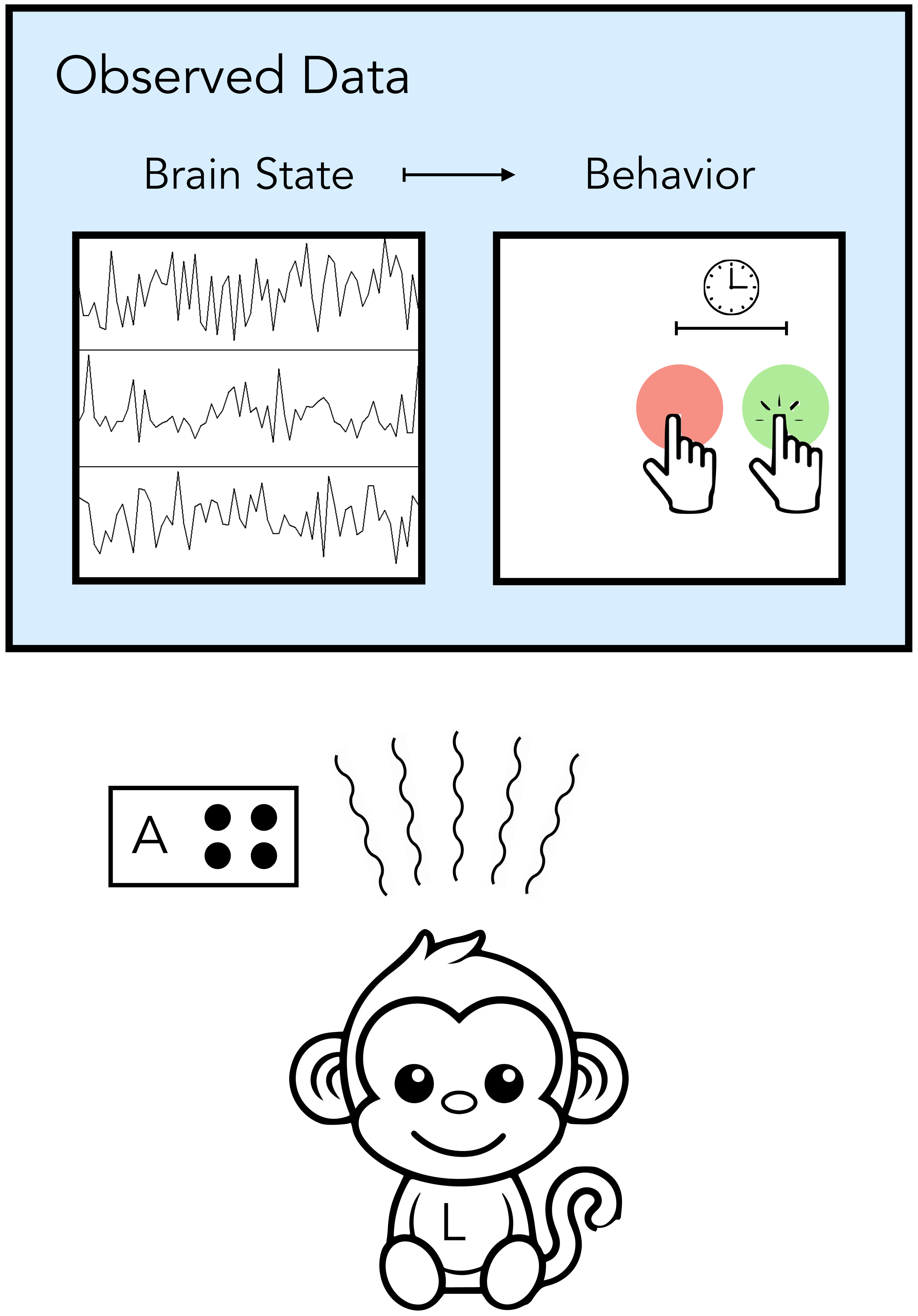


*pan neuronal inhibitory optogenetic viral vector (AAV8-hSyn-Jaws-GFP, UNC Vector Core, NC, USA)

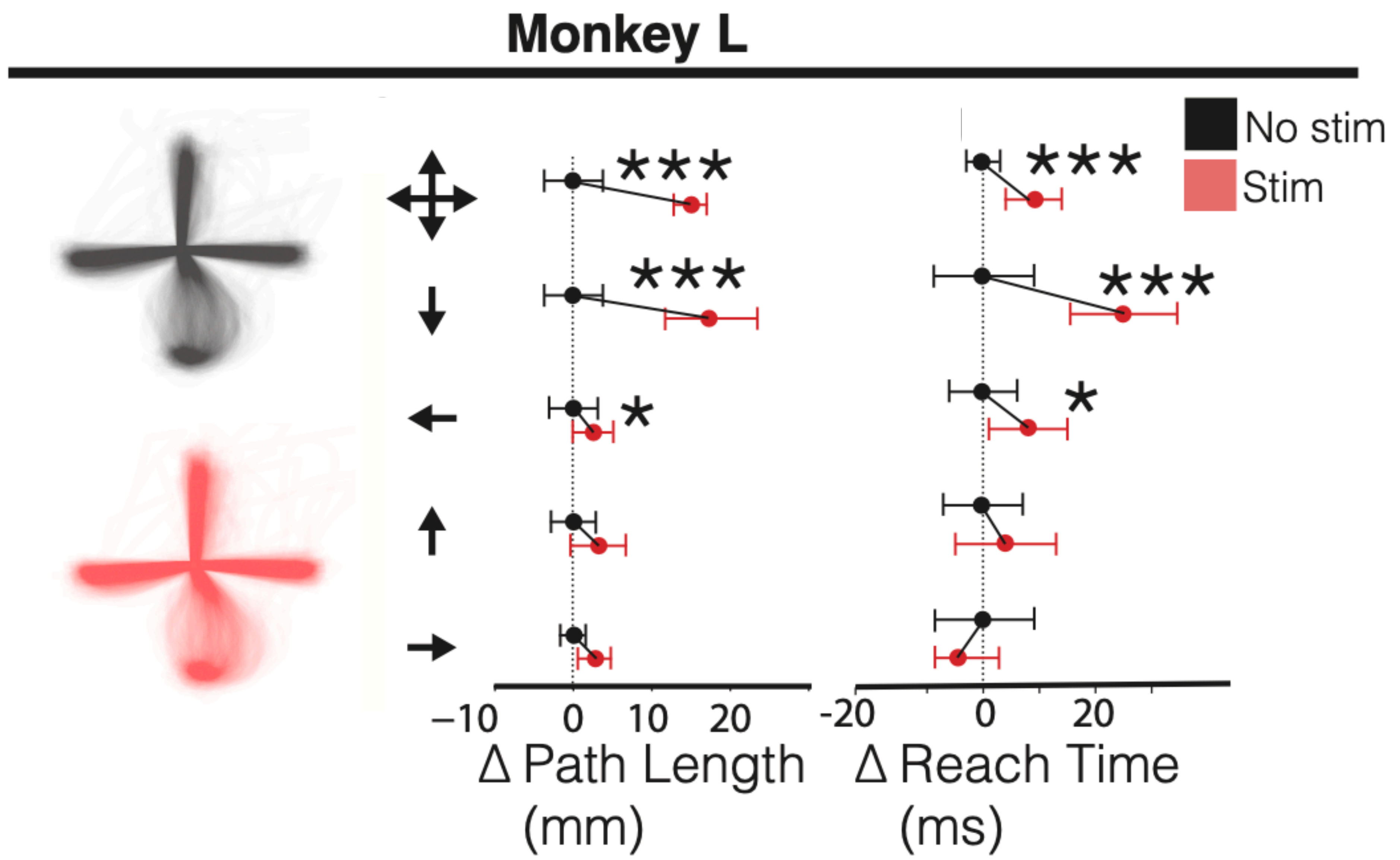

Observed Data
Brain State
Behavior
A
L
Light-evoked local
field potentials (LFPs).
Brain
Stimulation
Brain State
Behavior


Observed Data
Brain State
Behavior
Delayed center-out
reach task.
A
L
Brain
Stimulation
Brain State
Behavior

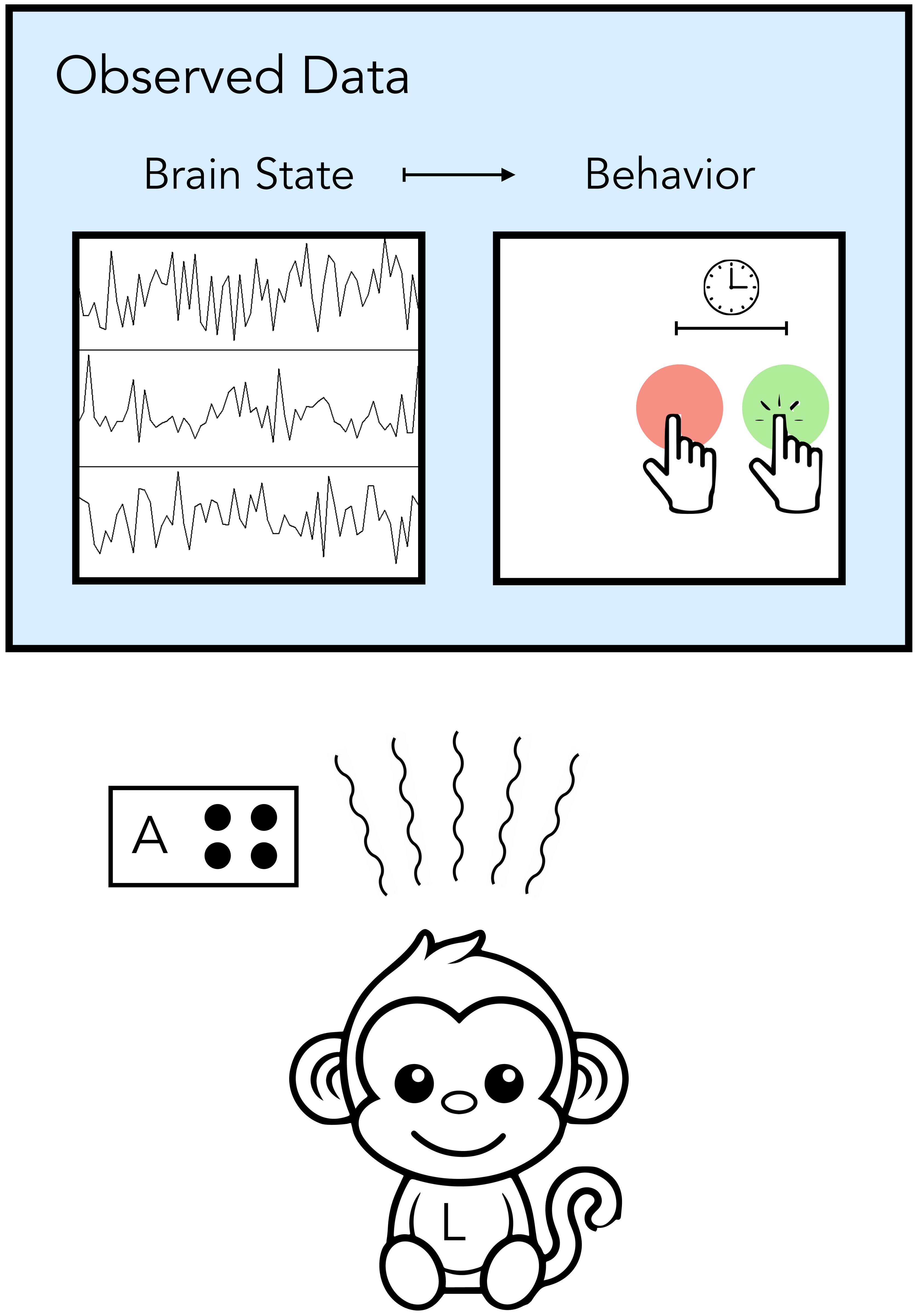

Observed Data
Brain State
Behavior
A
L



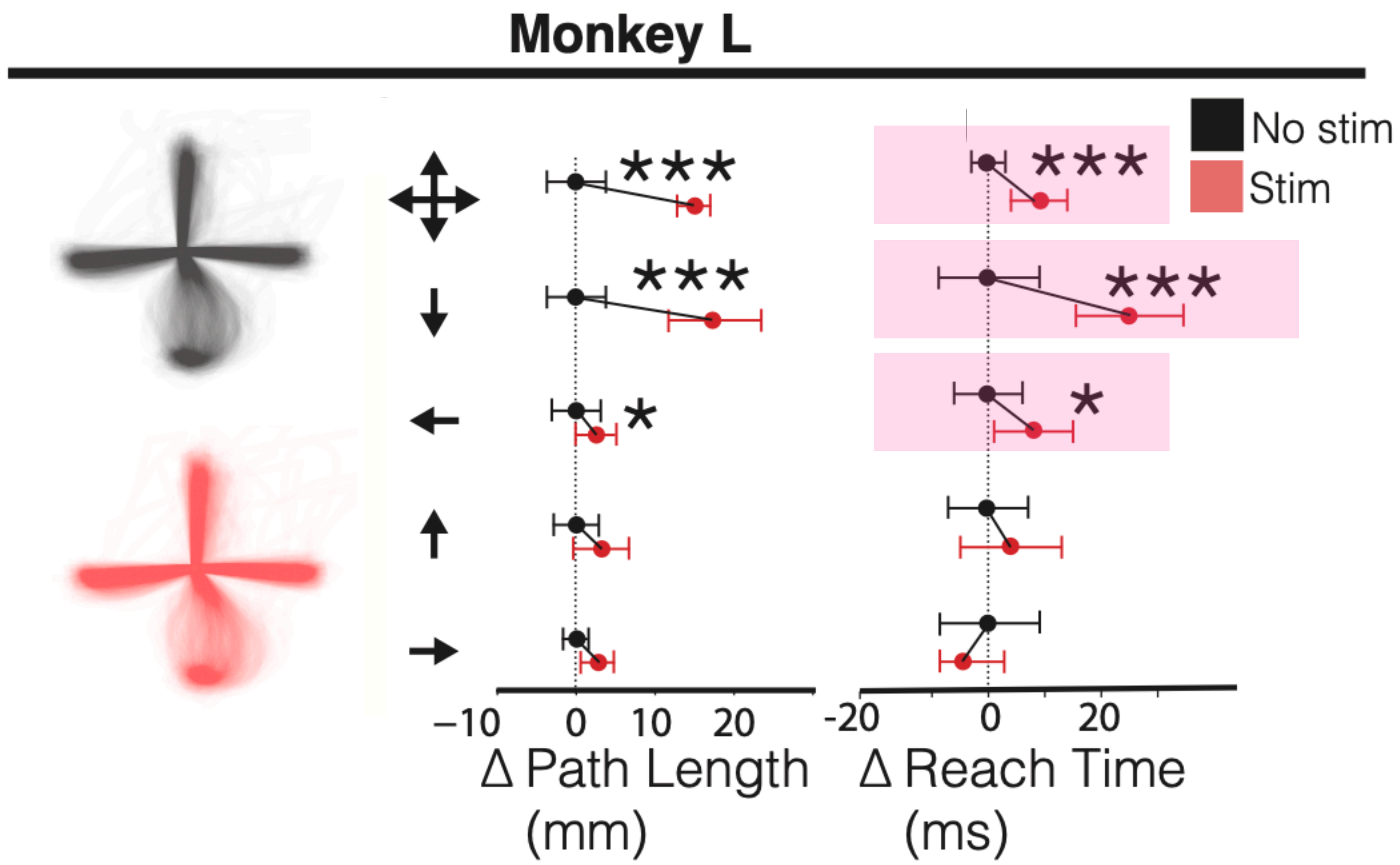
Observed Data
Brain State
Behavior
A
L



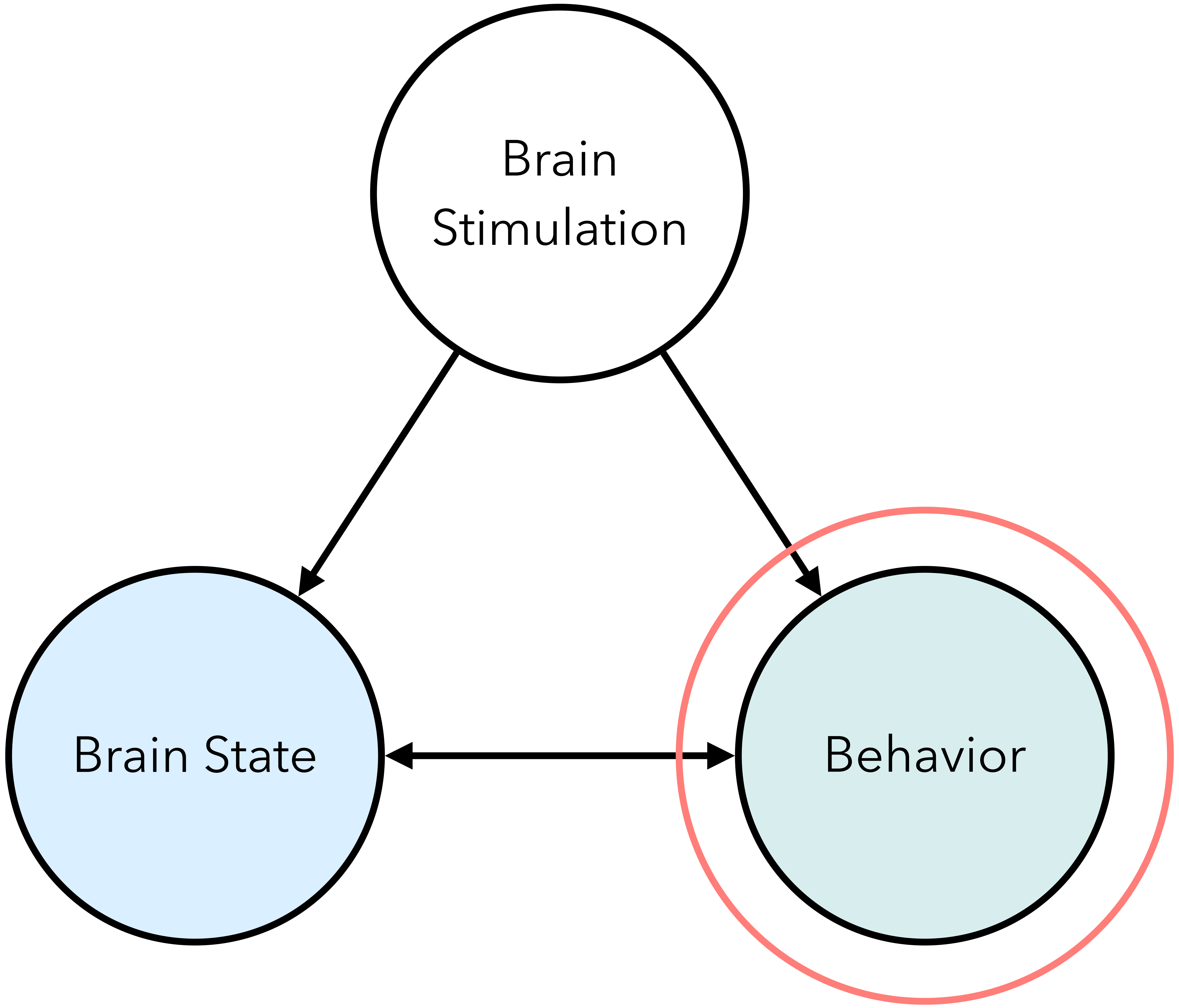
Monkey L
No stim
Stim
***
***
*
***
***
*
−10
0
10
20
-20
0
20
Δ Path Length (mm)
Δ Reach Time (ms)



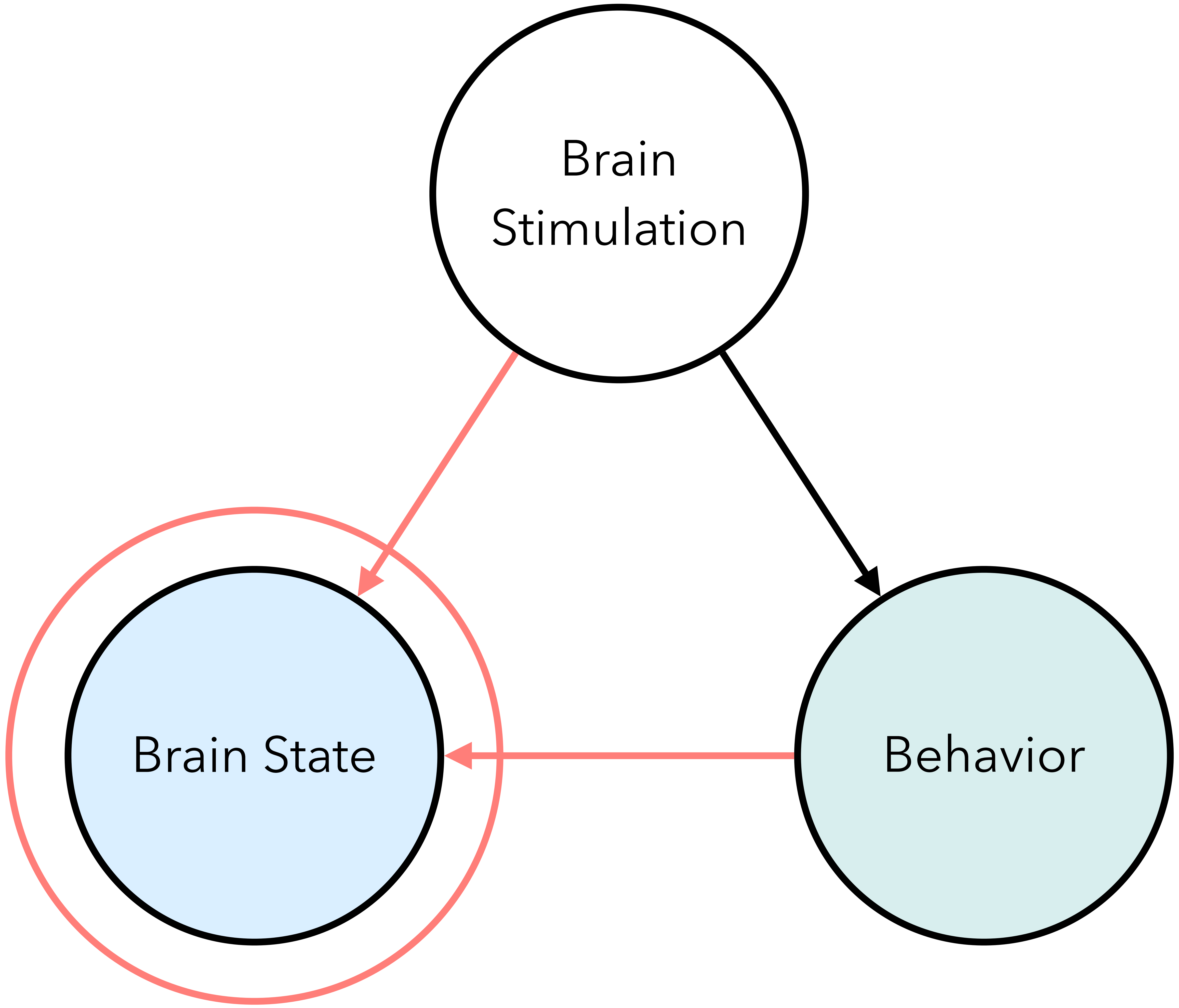
Optogenetic stimulation + inhibitory opsins result in delayed reach times.



We observed changes in a one-dimensional measurement of behavior (reach time).



Can we design **low-dimensional feature representations** of brain state to **test hypotheses** about changes induced by optogenetic stimulation and/or behavior?



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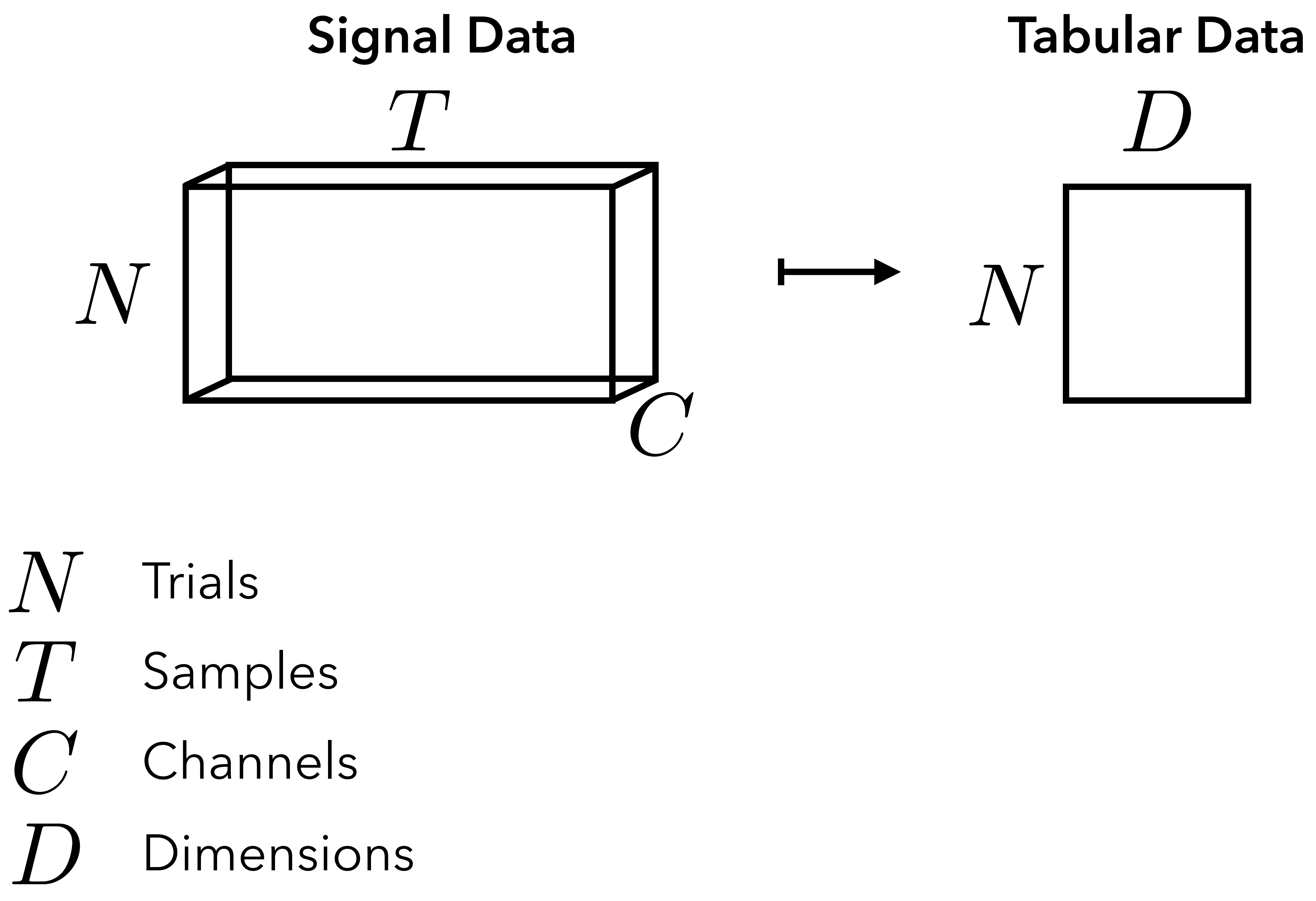
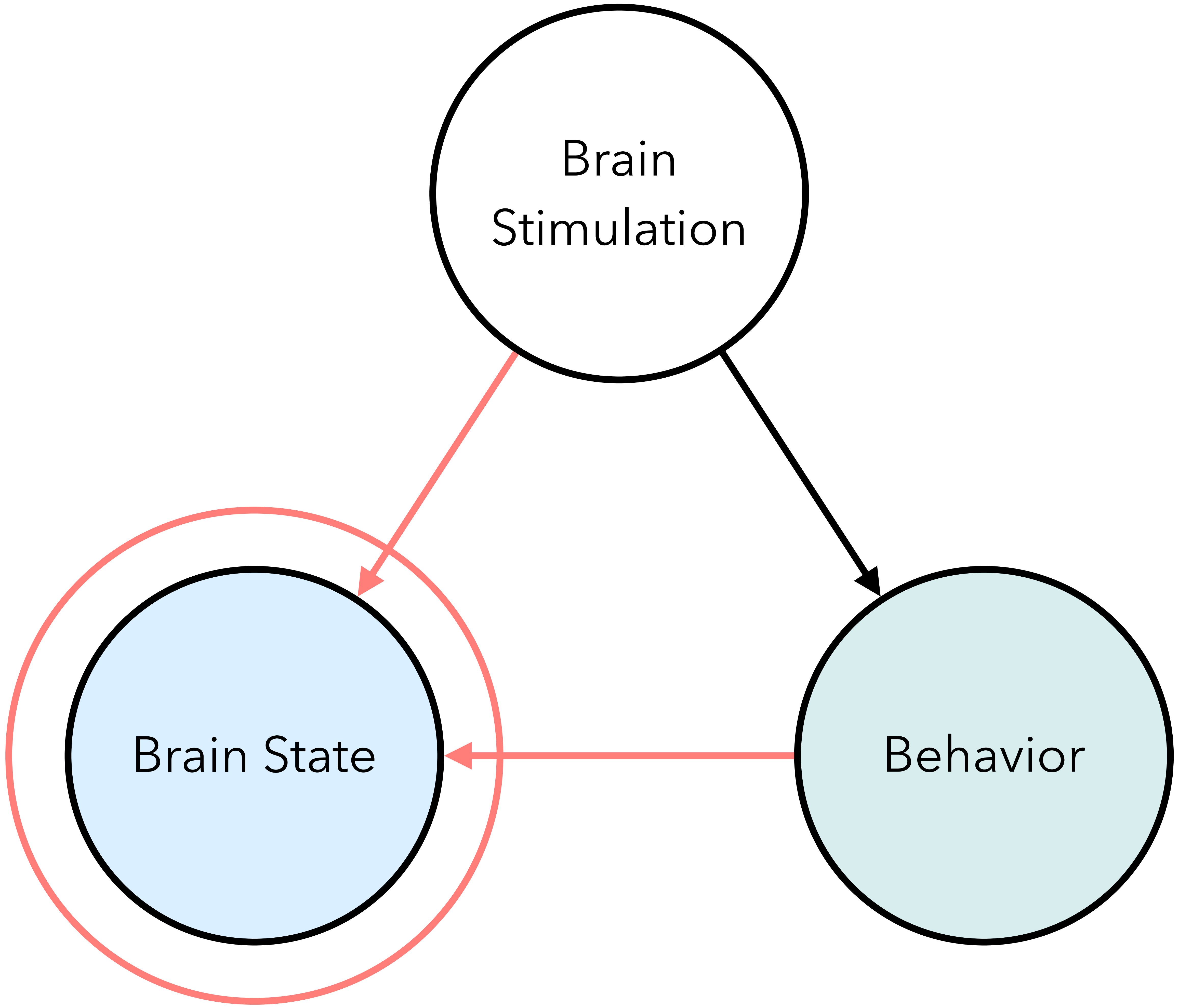
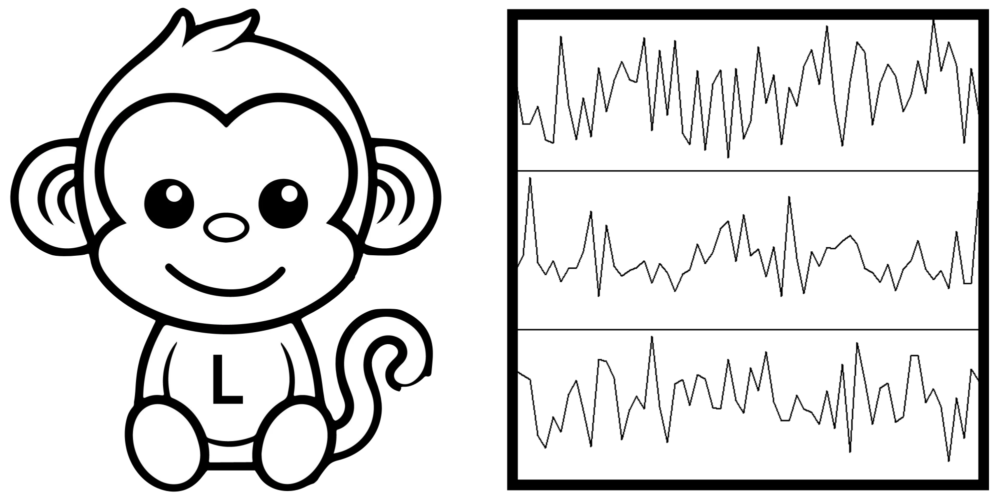




A Possible Pipeline

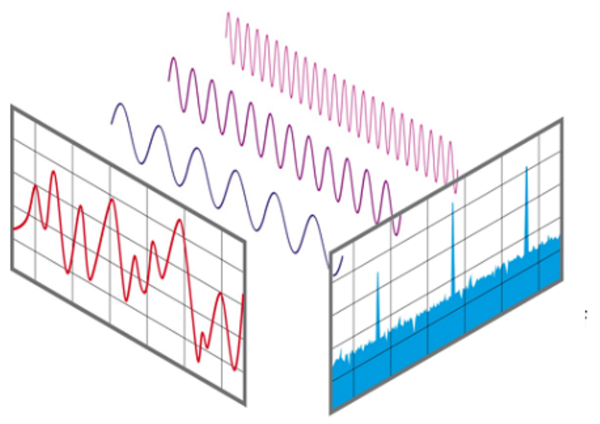
Input Signal



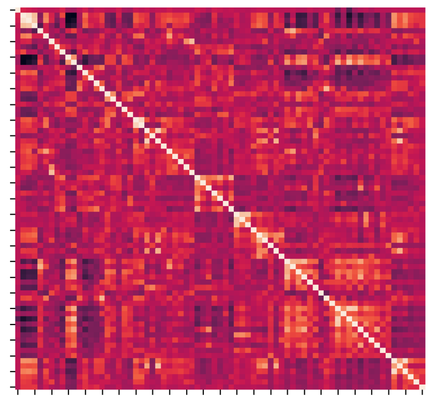
→

Signal Processing

Fourier Analysis



Model Correlations



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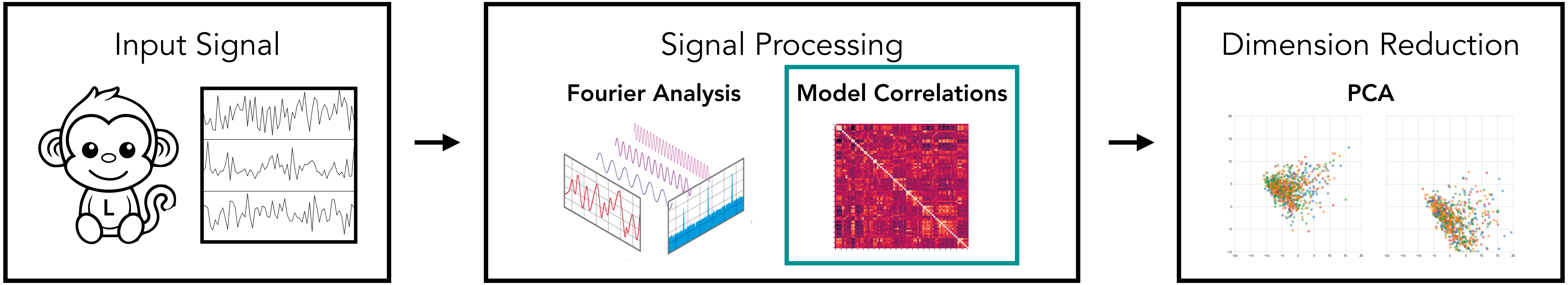
Dimension Reduction

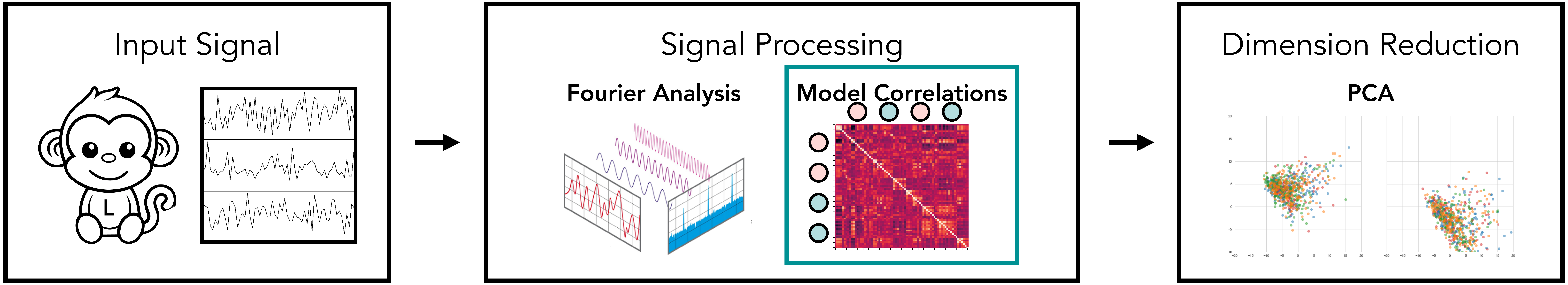
PCA

A Possible Pipeline



Challenging due to:
1) high-dimensional data,
2) alignment of representations across trials, and
3) possible ambiguities of network-based methods.

A Possible Pipeline



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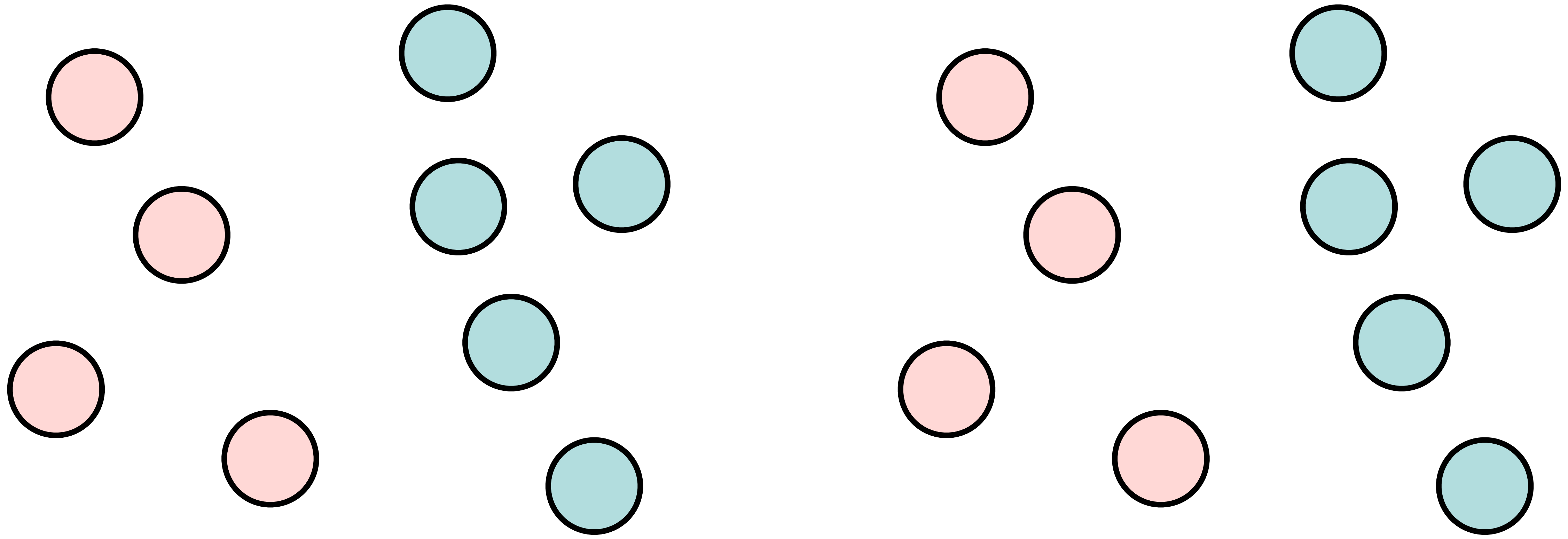

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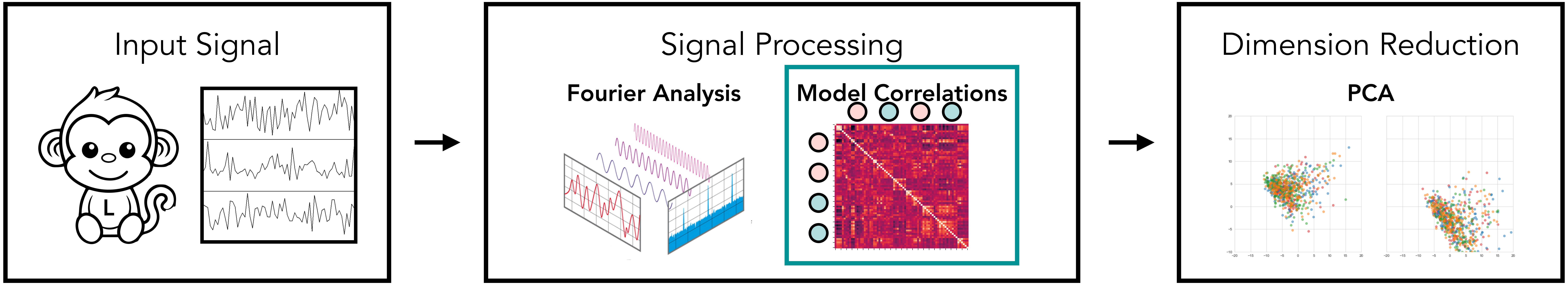

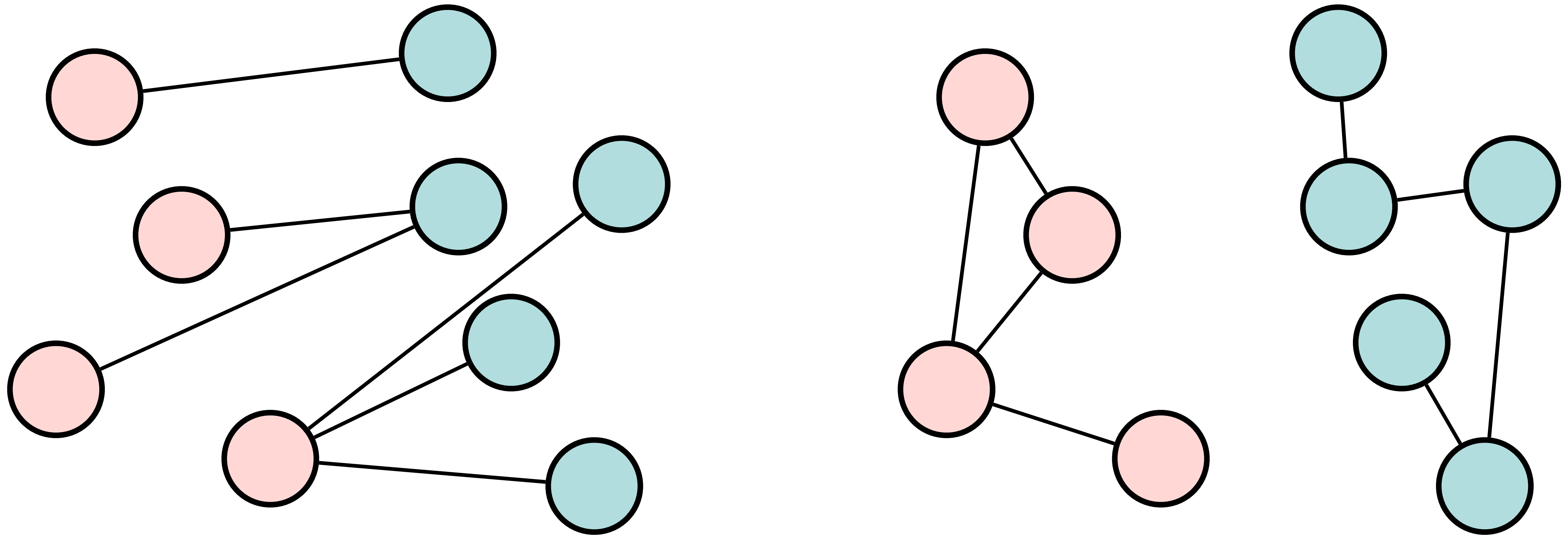

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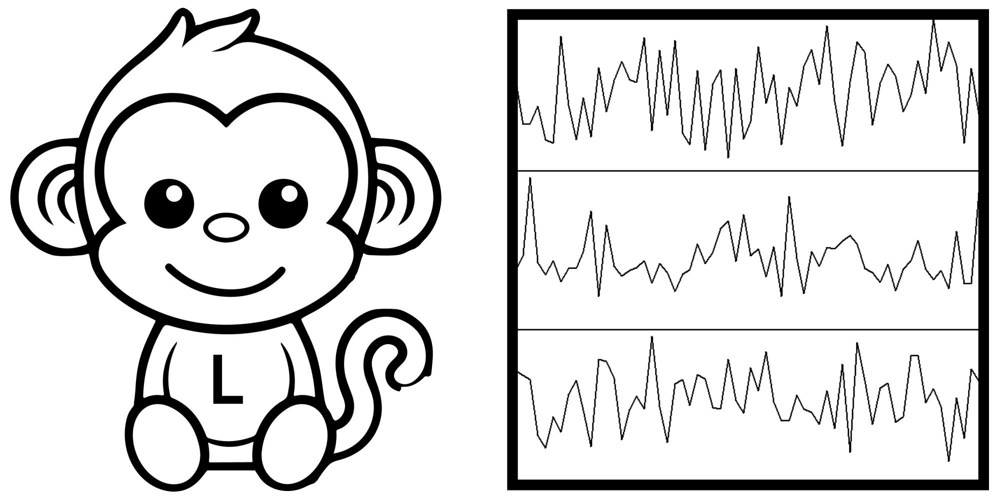
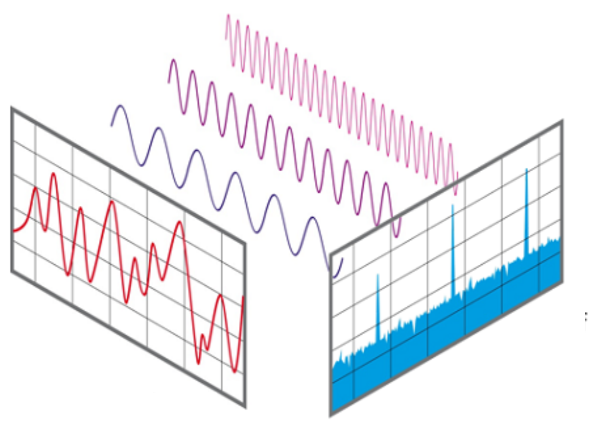
Proposed Pipeline

Input Signal



Signal Processing

Fourier Analysis

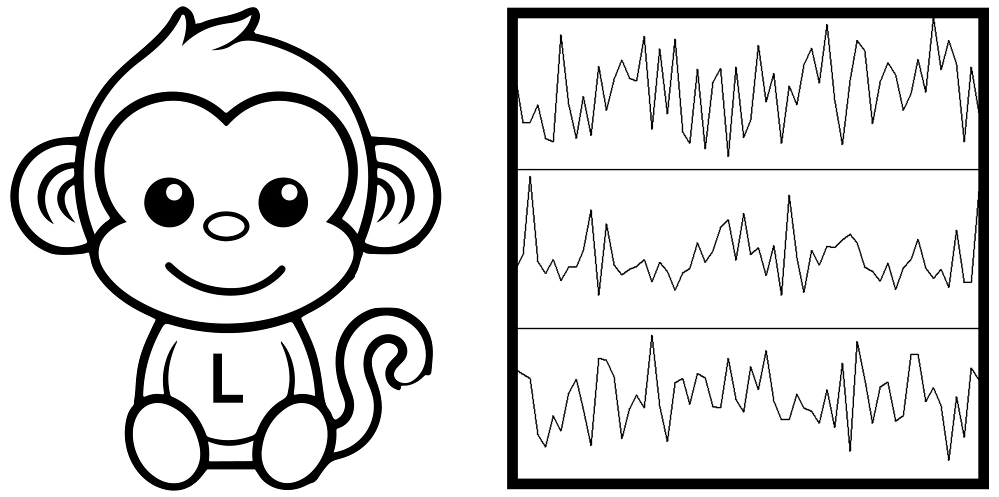


Dimension Reduction

PCA

Proposed Pipeline

Input Signal



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Signal Processing

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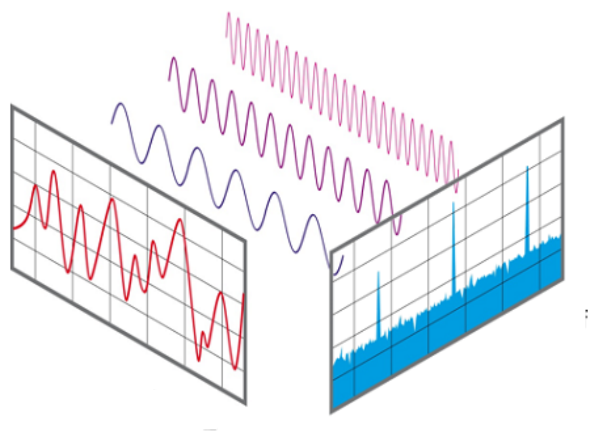

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PCA

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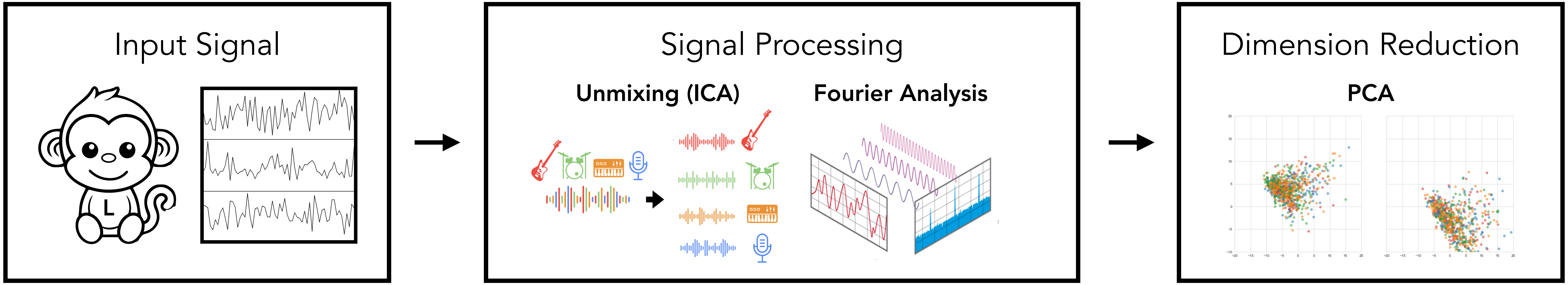

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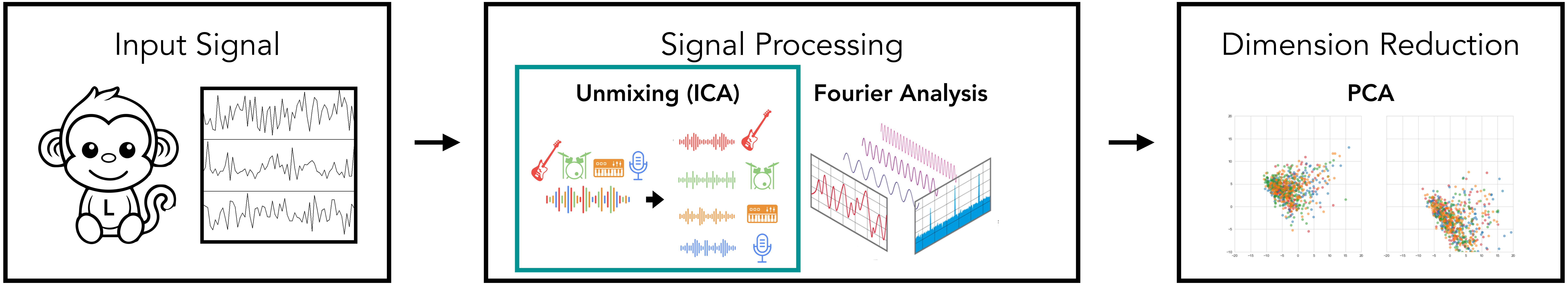


Independent component analysis (**ICA**) separates the signals into **independent source** signals that have no correlation structure but recover the original signal when combined.

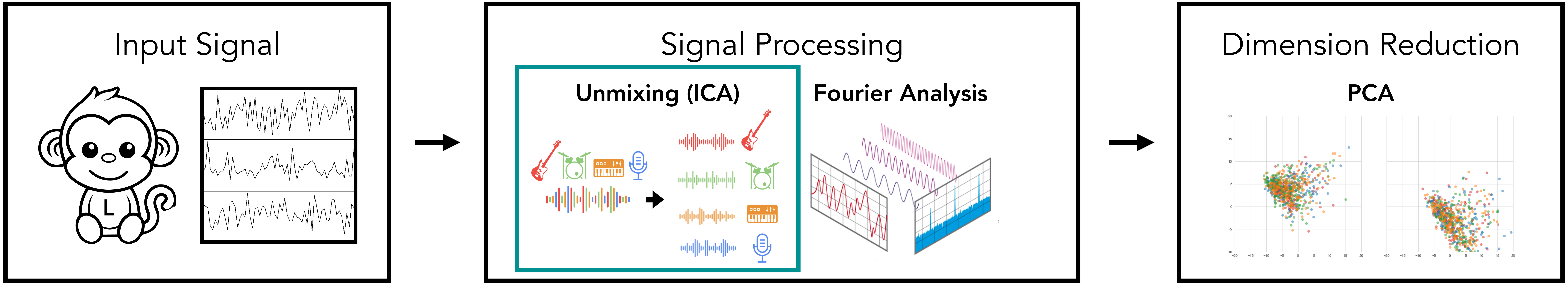
$$\mathbf{x} = \mathbf{A}\mathbf{s}$$

Observed Signal   Mixing Matrix   Source Signal

$$\mathbf{W}\mathbf{x} = \mathbf{W}\mathbf{A}\mathbf{s} \sim \mathbf{s}$$

Unmixing Matrix

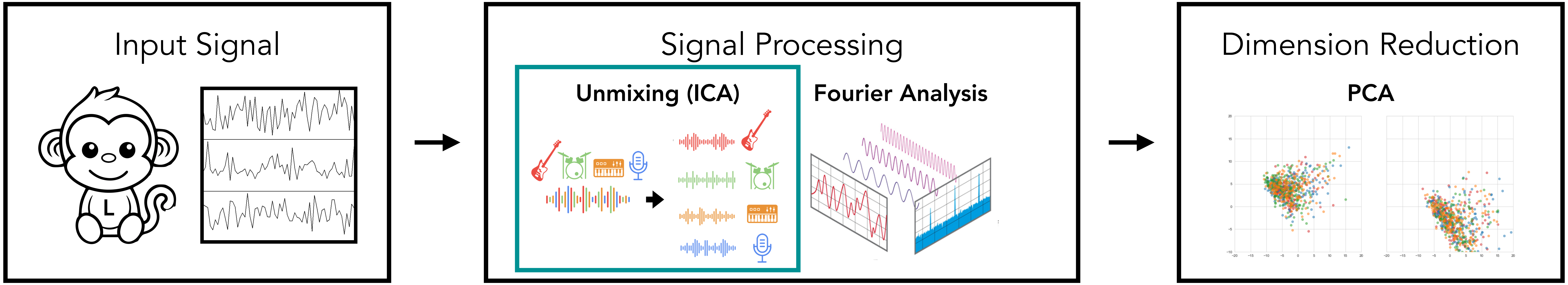
Proposed Pipeline



<u>**Contributions:**</u> a novel ICA algorithm that:

1) has runtime independent of N and T,
2) can use the same **unmixing matrix for multiple signals** from each trial, and
3) can create sources that are **both independent and encode experiment information** (such as reach direction and stimulation type).

Proposed Pipeline



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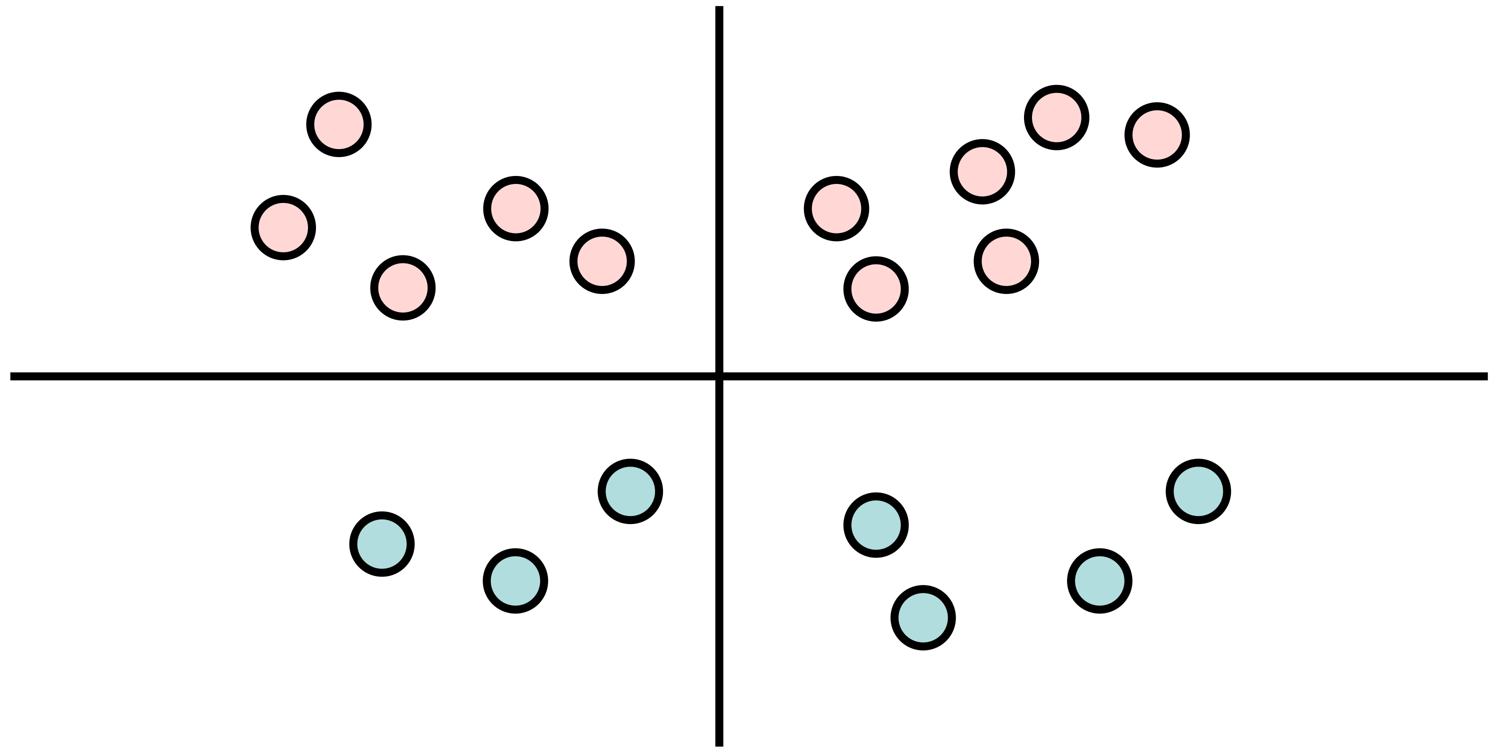

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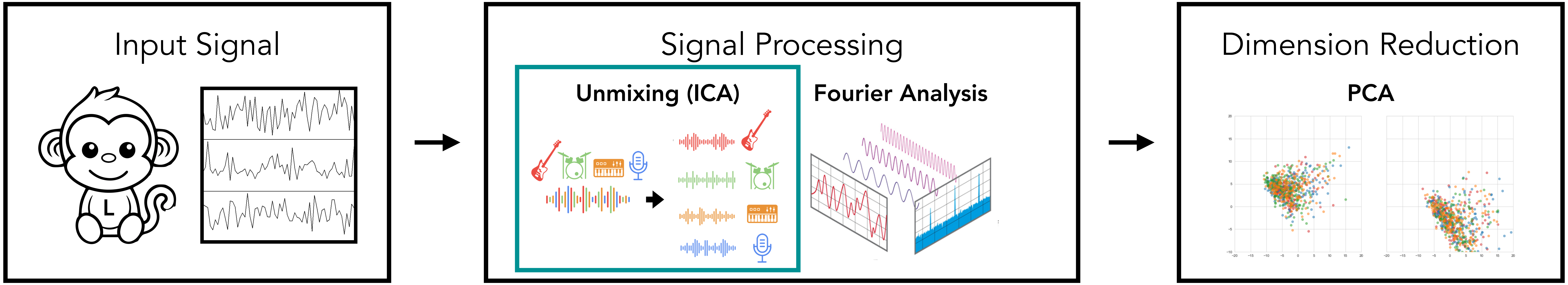

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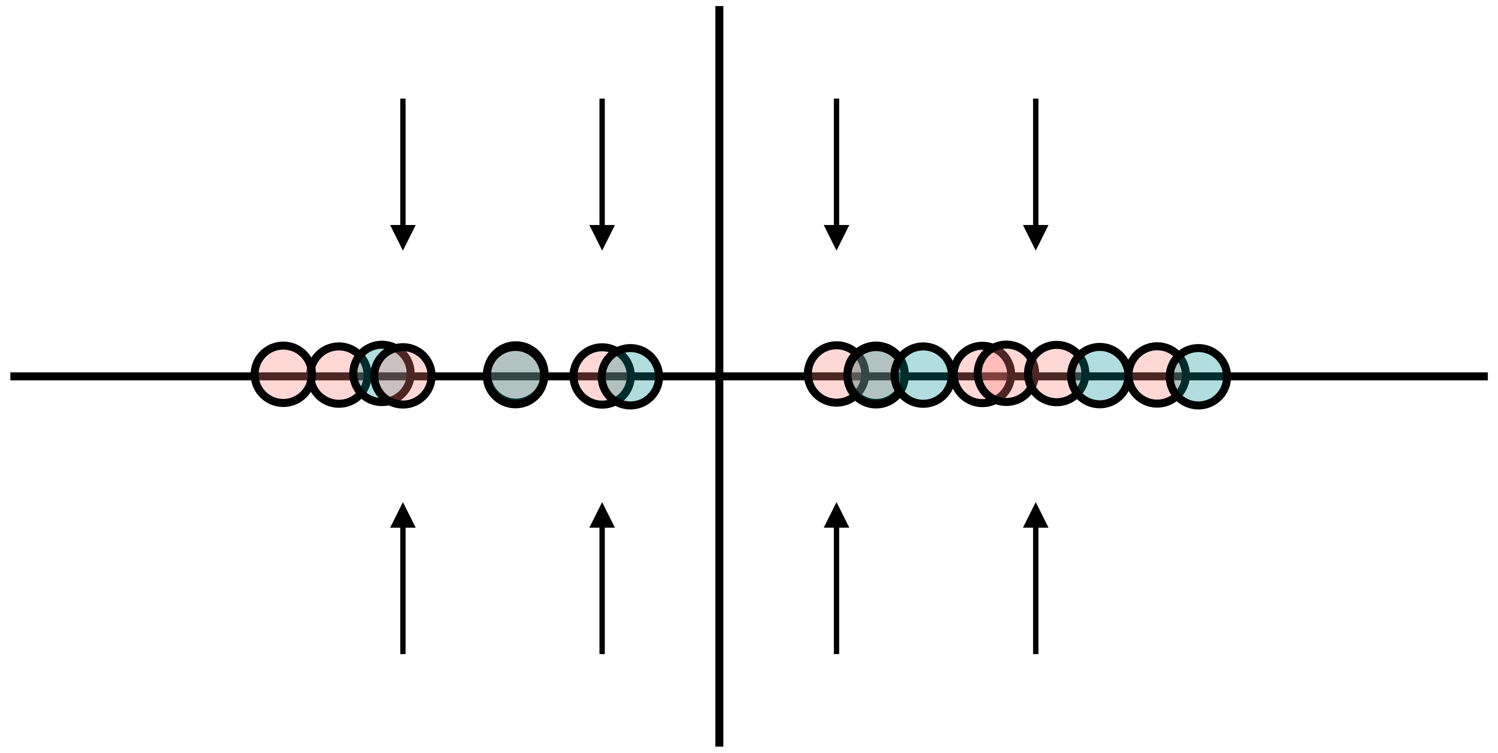
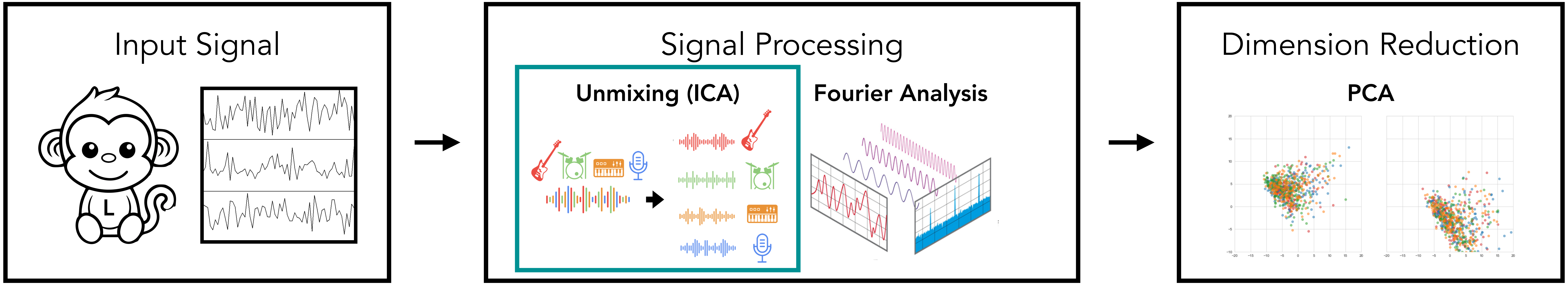


Projection onto the first principal component destroys task information.

Proposed Pipeline



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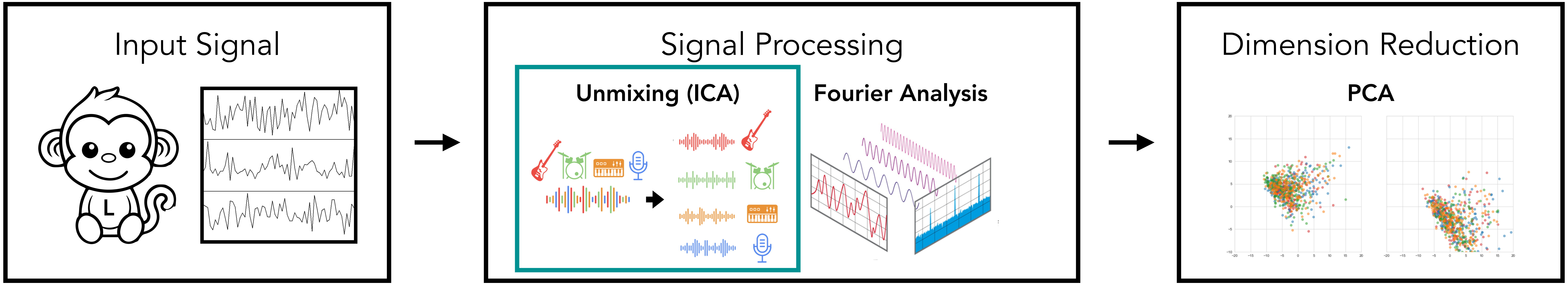
$$\min_{\mathbf{W},\theta} \left\{ \mathcal{L}(\mathbf{W}) + \lambda \left(\sum_{i=1}^{N} \ell(\mathbf{W}\mathbf{x}_i, y_i; \theta) \right) \right\}$$

Proposed Pipeline



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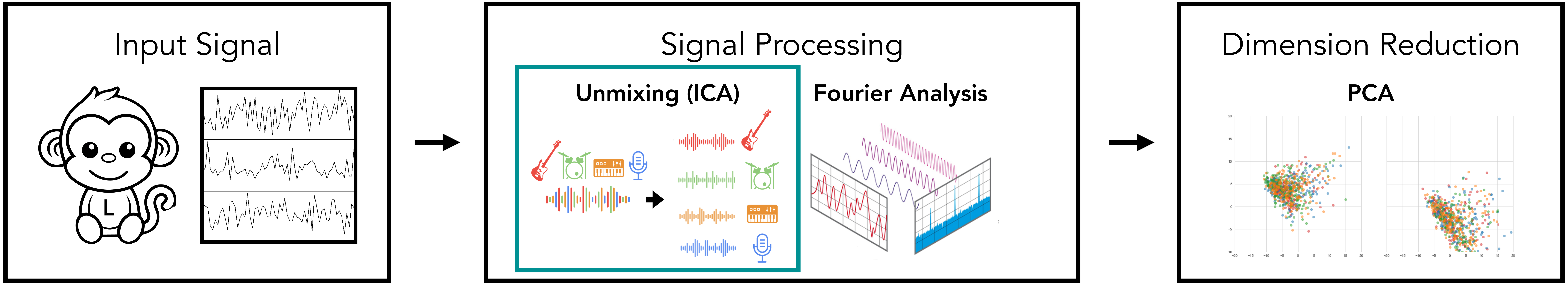
Negative log-likelihood term enforces **independence**.

Proposed Pipeline



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Prediction loss term enforces **experiment information**.

$$\ell(\mathbf{W}\mathbf{x}_i,y_i;\theta)=(f_\theta(\mathbf{W}\mathbf{x}_i)-y_i)^2$$

We use a simultaneous optimization scheme for the unmixing matrix and predictor parameter θ.

Does the mini-batch stochastic optimizer work on this objective?

Can the sources predict the outcomes from the experiment?

Are the separated sources actually independent?

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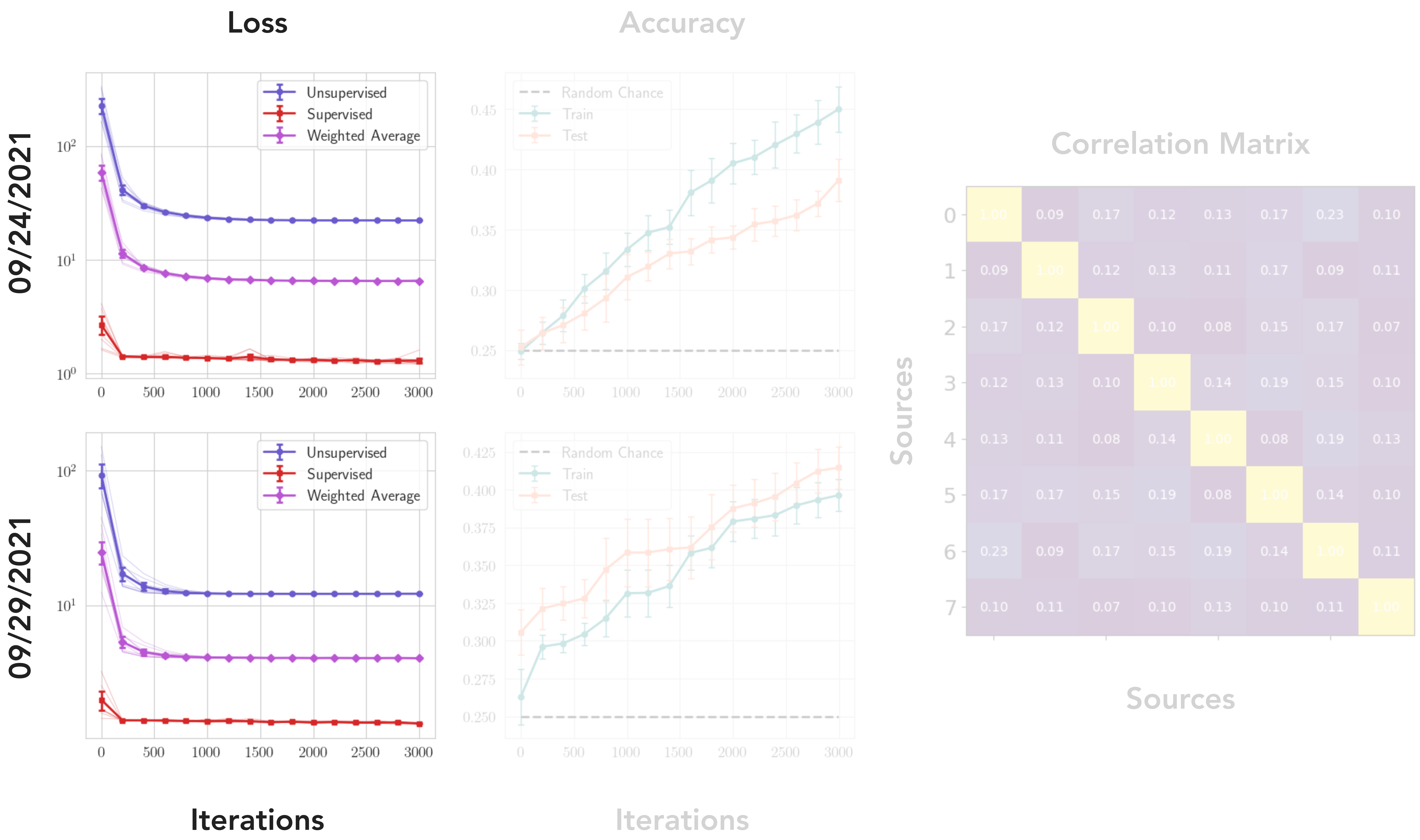

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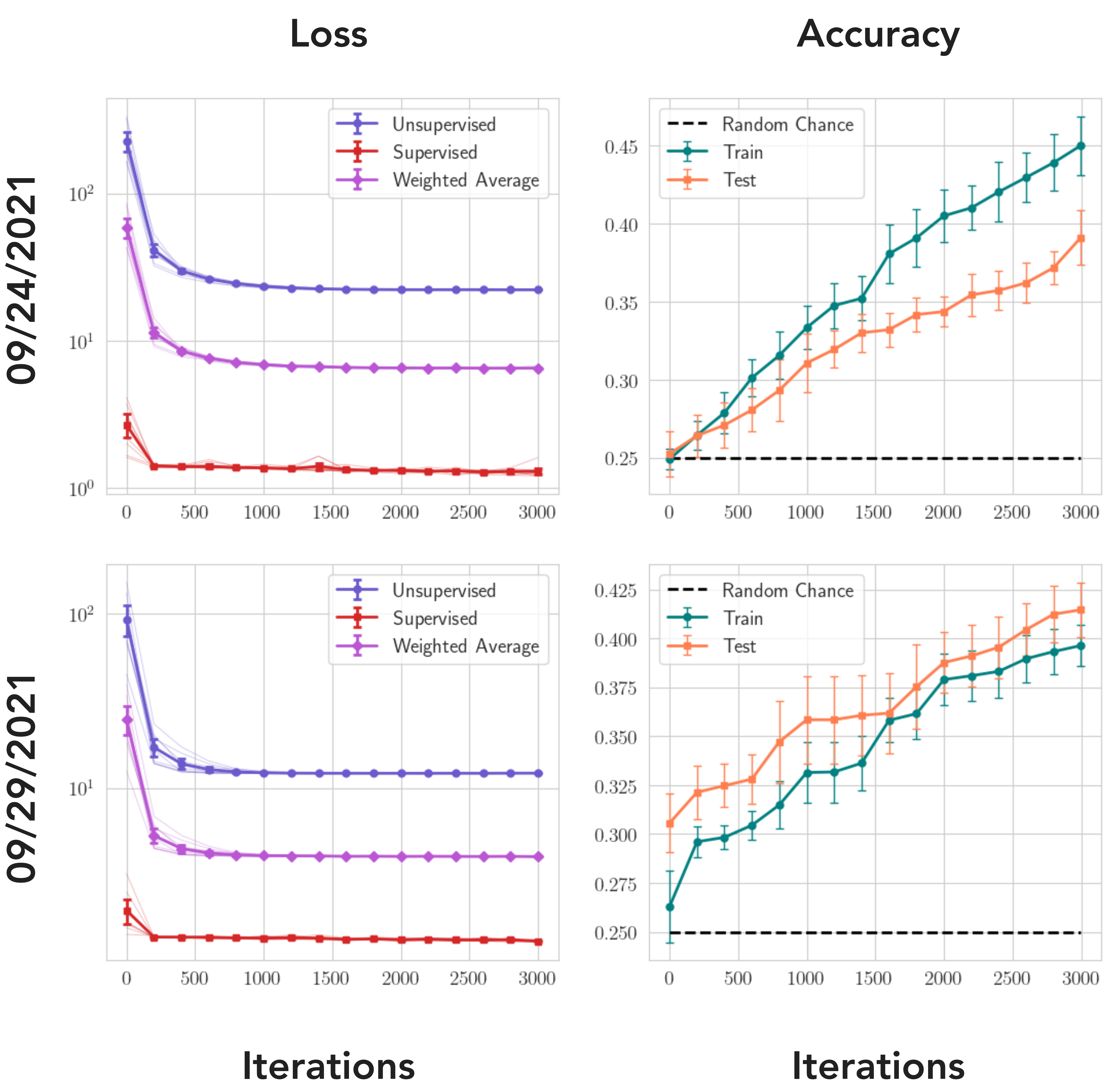

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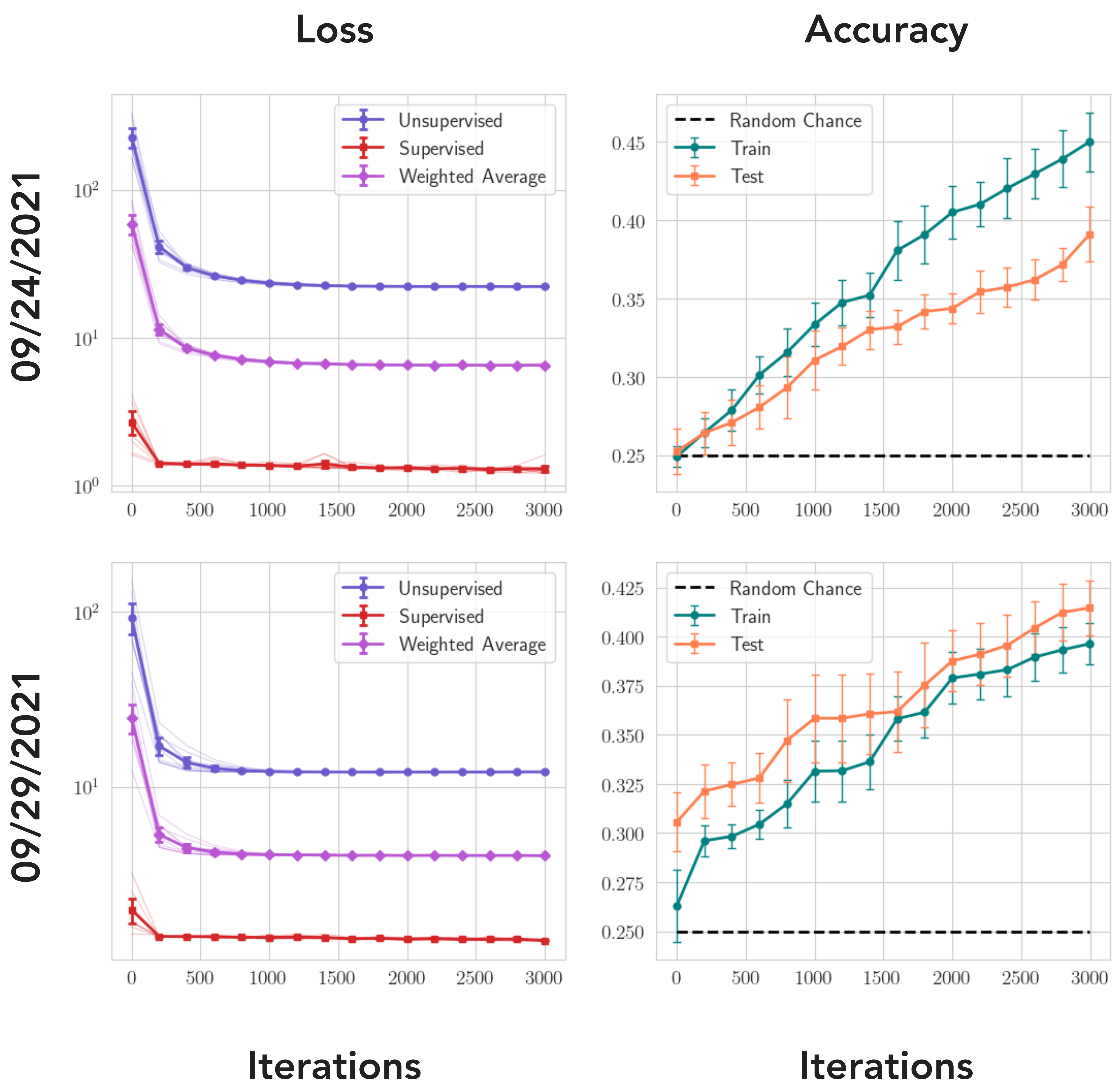

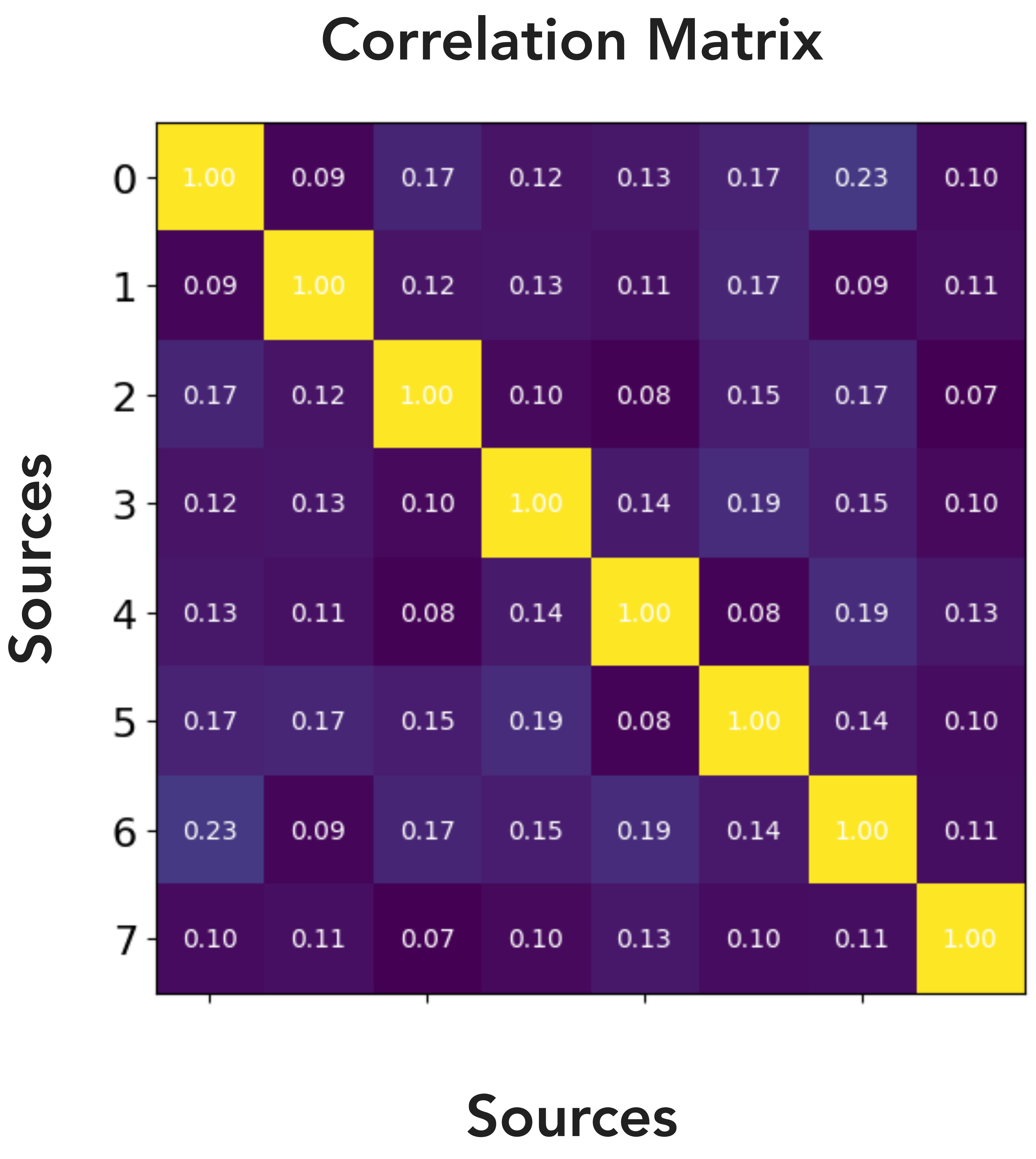

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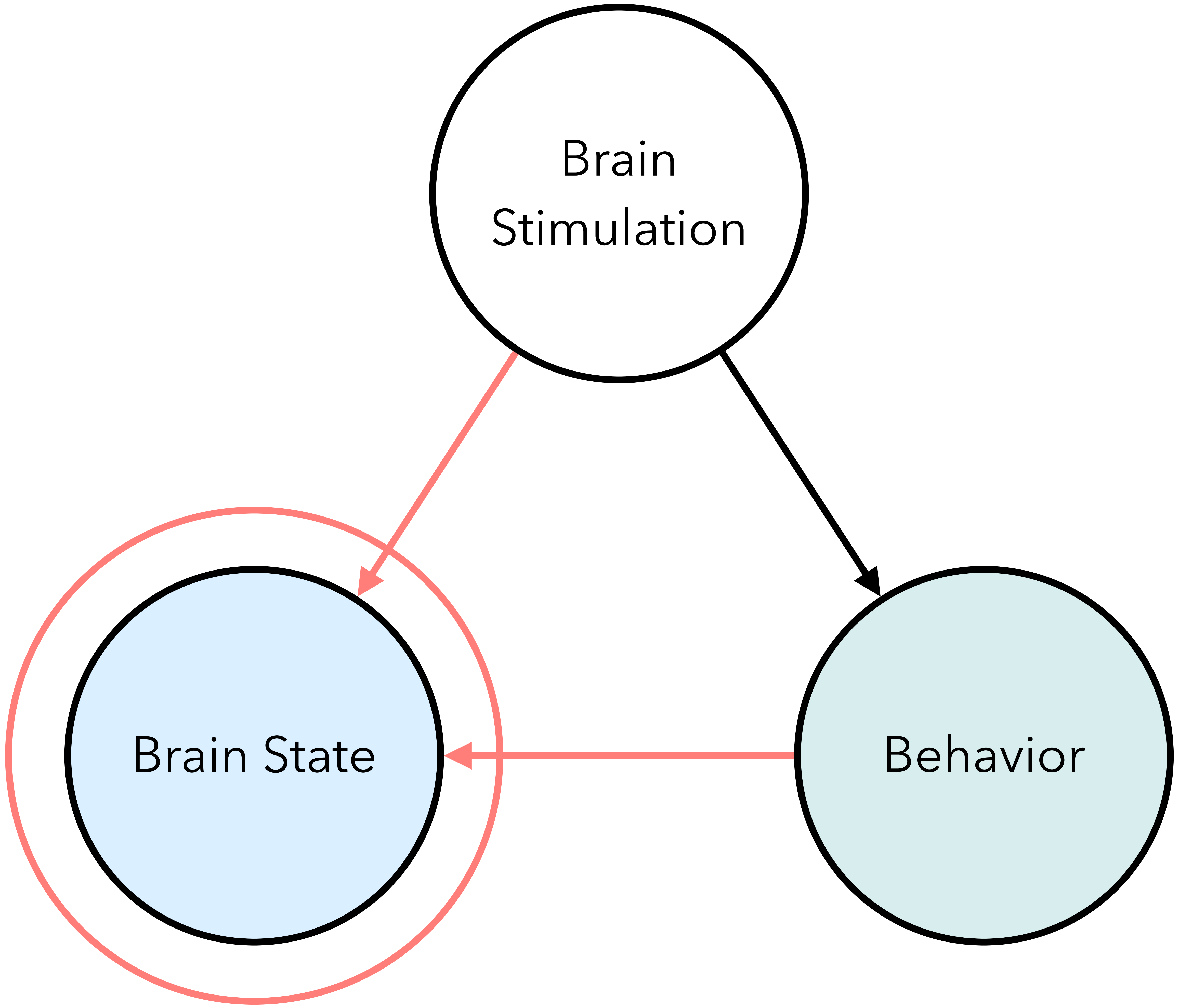

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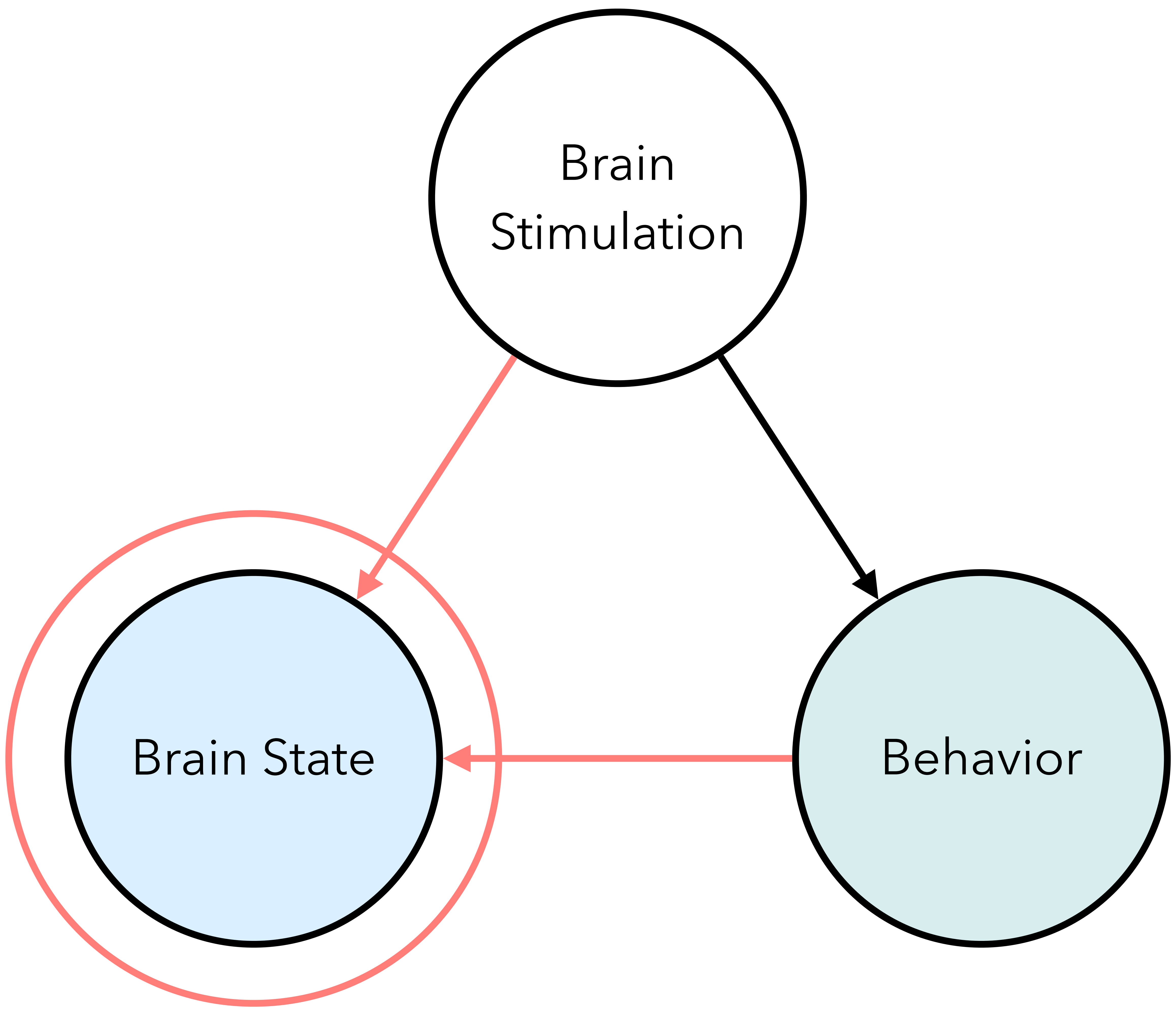

Ongoing Work:

1) Analysis of downstream feature representations and interpreting the unmixing matrix $\mathbf{W}$.
2) Using supervision to unmix **ill-conditioned** matrices.
3) Incorporating other applications such as audio data.

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Thank you! Questions?

Ronak Mehta

Can the additional **supervision** improve optimization performance for the unsupervised objective for **ill-conditioned** mixing matrices?

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Goal:

$$\mathbf{x} = \mathbf{A}\mathbf{s} \qquad \mathbf{W}\mathbf{x} = \mathbf{W}\mathbf{A}\mathbf{s} \sim \mathbf{s}$$

Can the additional **supervision** improve optimization performance for the unsupervised objective for **ill-conditioned** mixing matrices?

Goal:

$$\mathbf{x} = \mathbf{A}\mathbf{s} \qquad \mathbf{W}\mathbf{x} = \mathbf{W}\mathbf{A}\mathbf{s} \sim \mathbf{s}$$

Ill-conditioned = inversion is numerically unstable.

Can the additional **supervision** improve optimization performance for the unsupervised objective for **ill-conditioned** mixing matrices?

Objective:

$$\min_{\mathbf{W},\theta} \left\{ \mathcal{L}(\mathbf{W}) + \lambda \left(\sum_{i=1}^{N} \ell(\mathbf{W}\mathbf{x}_i, y_i; \theta) \right) \right\}$$

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- **Data:** Laplace(1, σ) sources. Mixing matrix is designed using Hilbert matrix, with <u>controllable</u> condition number κ.

$$\mathbf{A} = \begin{bmatrix} 1 & \frac{1}{2} & \frac{1}{3} & \frac{1}{4} & \frac{1}{5} \\ \frac{1}{2} & \frac{1}{3} & \frac{1}{4} & \frac{1}{5} & \frac{1}{6} \\ \frac{1}{3} & \frac{1}{4} & \frac{1}{5} & \frac{1}{6} & \frac{1}{7} \\ \frac{1}{4} & \frac{1}{5} & \frac{1}{6} & \frac{1}{7} & \frac{1}{8} \\ \frac{1}{5} & \frac{1}{6} & \frac{1}{7} & \frac{1}{8} & \frac{1}{9} \end{bmatrix}.$$

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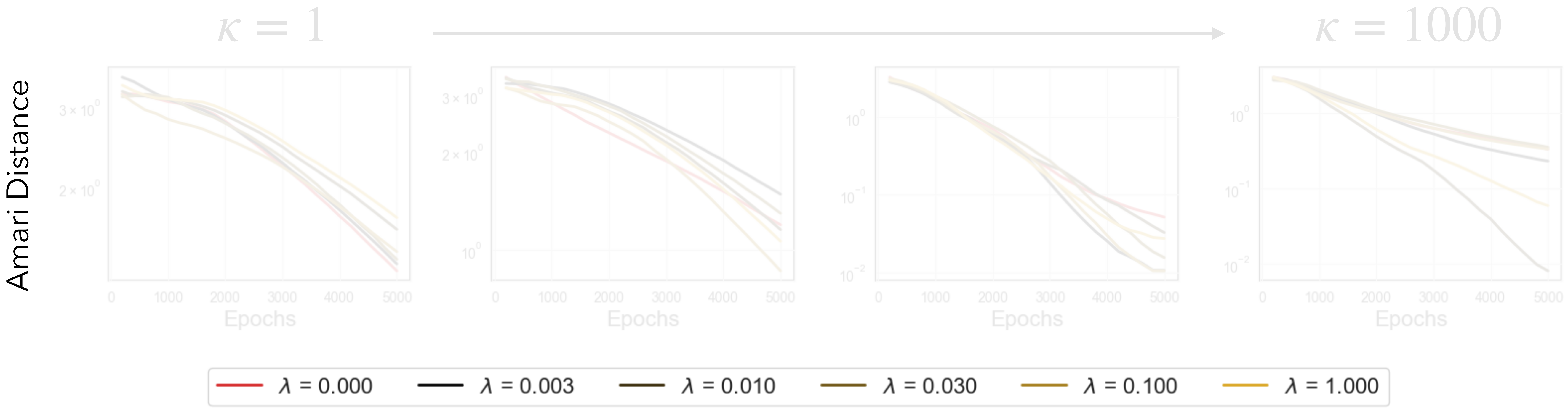
- **Model:** Mean response of original source supplied as supervision.

$$\mathbf{A}=\begin{bmatrix} 1 & \frac{1}{2} & \frac{1}{3} & \frac{1}{4} & \frac{1}{5} \\ \frac{1}{2} & \frac{1}{3} & \frac{1}{4} & \frac{1}{5} & \frac{1}{6} \\ \frac{1}{3} & \frac{1}{4} & \frac{1}{5} & \frac{1}{6} & \frac{1}{7} \\ \frac{1}{4} & \frac{1}{5} & \frac{1}{6} & \frac{1}{7} & \frac{1}{8} \\ \frac{1}{5} & \frac{1}{6} & \frac{1}{7} & \frac{1}{8} & \frac{1}{9} \end{bmatrix}.$$

Can the additional **supervision** improve optimization performance for the unsupervised objective for **ill-conditioned** mixing matrices?

Objective:

$$\min_{\mathbf{W},\theta} \left\{ \mathcal{L}(\mathbf{W}) + \lambda \left(\sum_{i=1}^{N} \ell(\mathbf{W}\mathbf{x}_i, y_i; \theta) \right) \right\}$$



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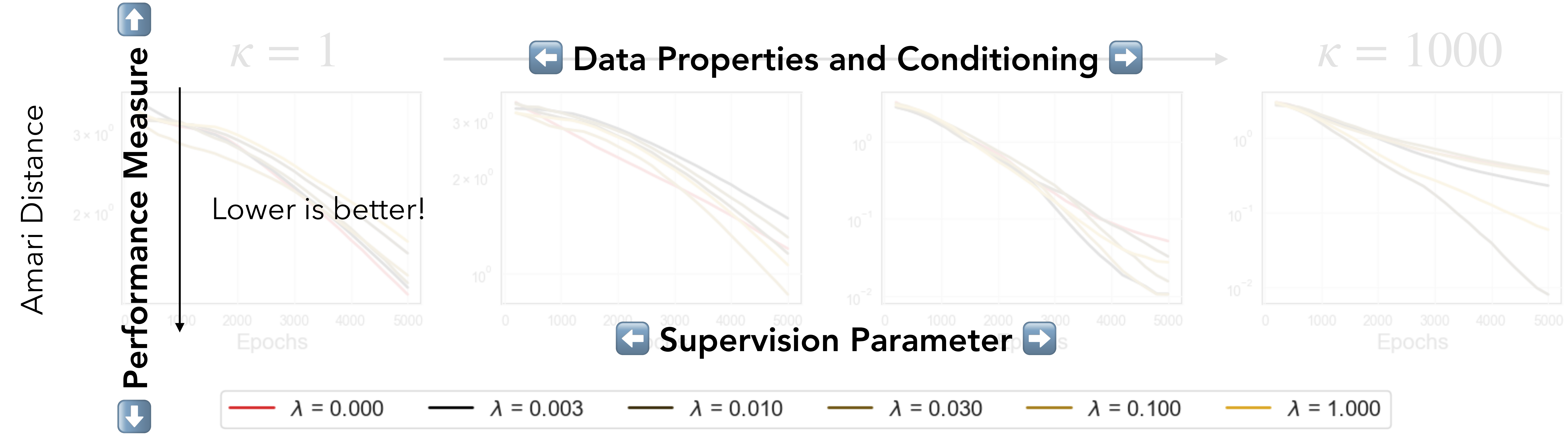

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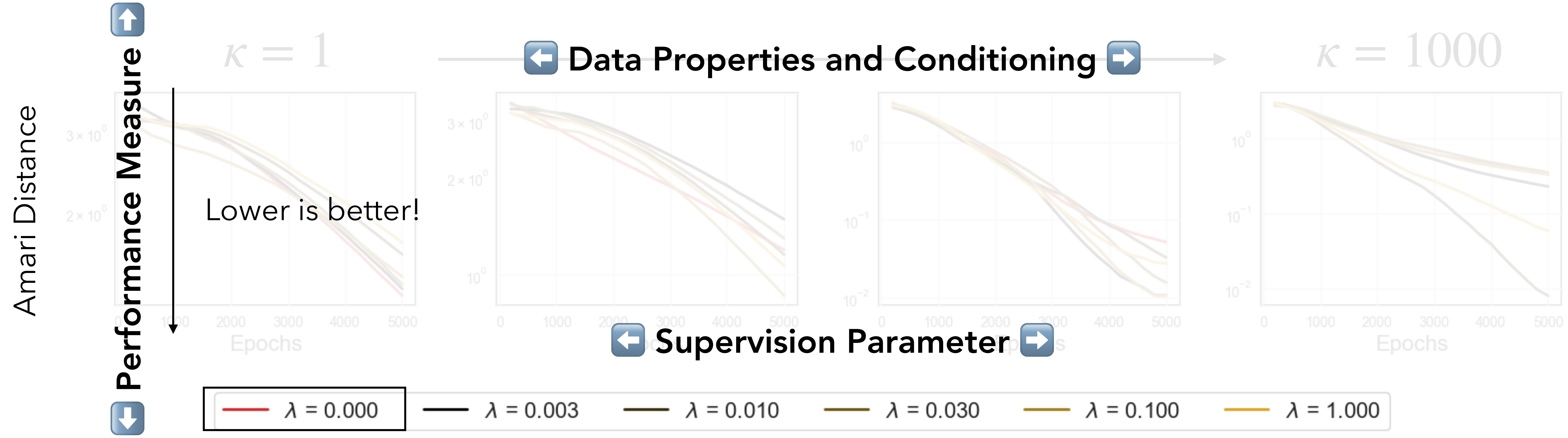

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$\kappa = 1$ → $\kappa = 1000$