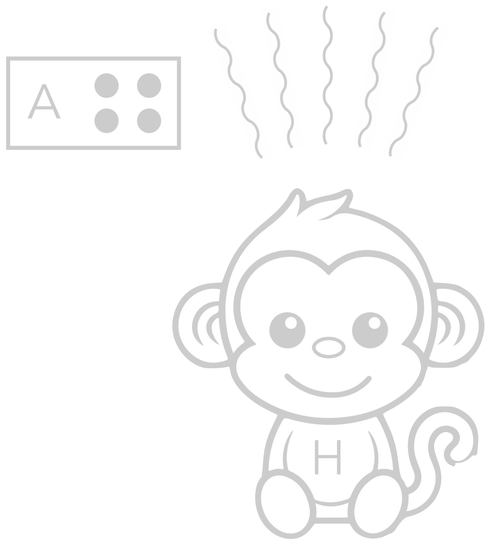
Experimentally Informed Signal Processing with Supervised Independent Component Analysis

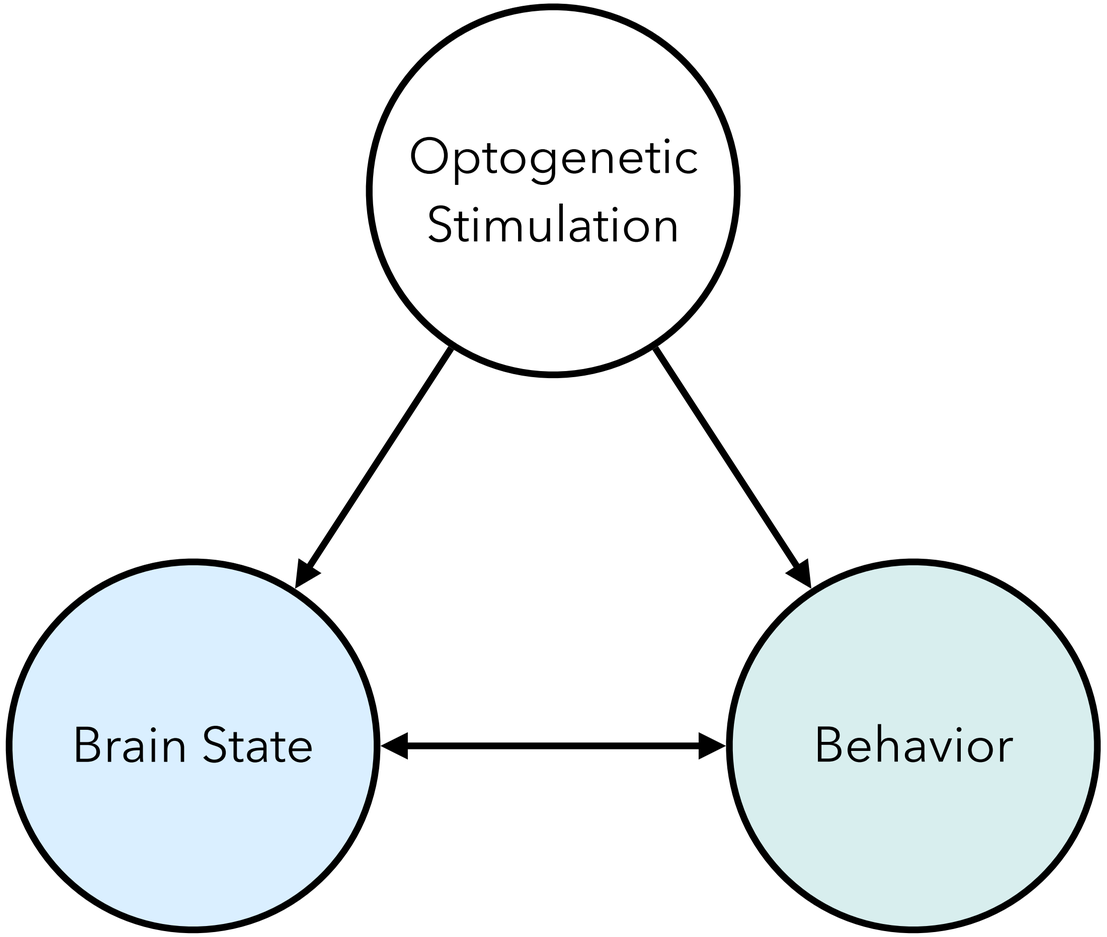
Optostim × XAI Retreat

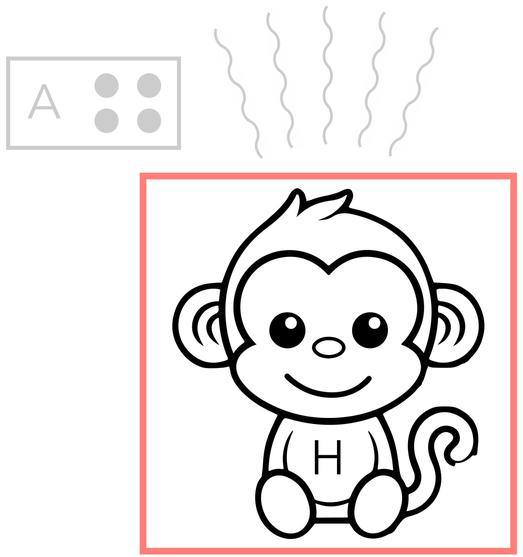
February 05, 2025

Ronak Mehta

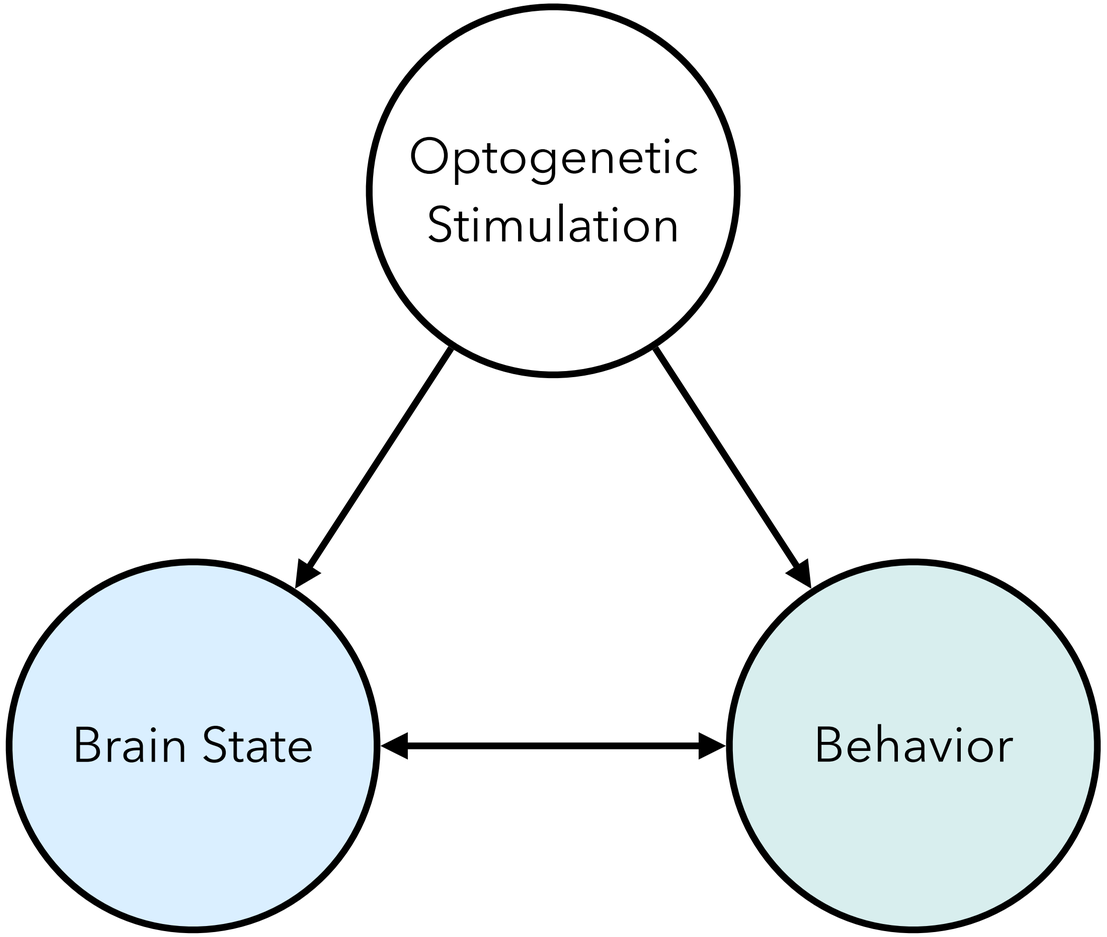
Observed Data
Brain State
Behavior

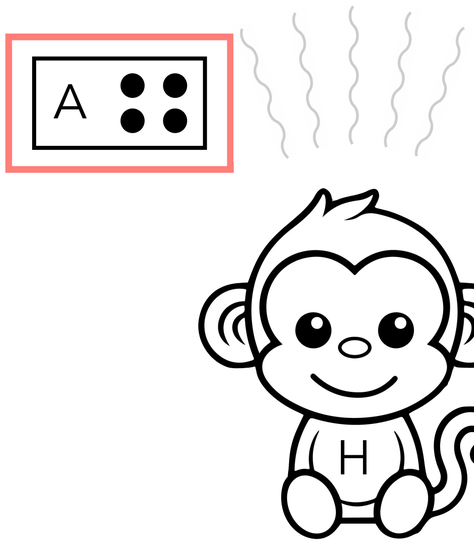

A
H


Optogenetic Stimulation
Brain State
Behavior

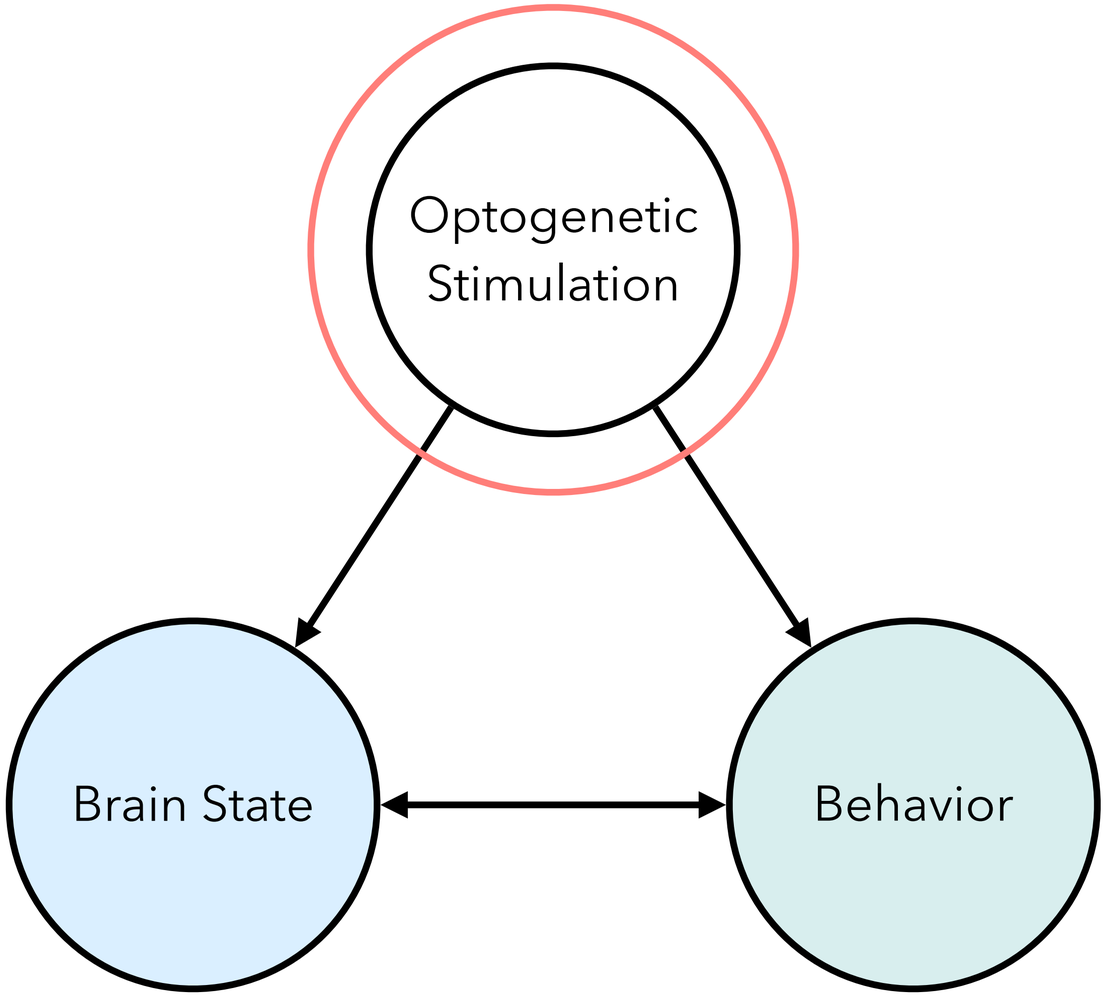


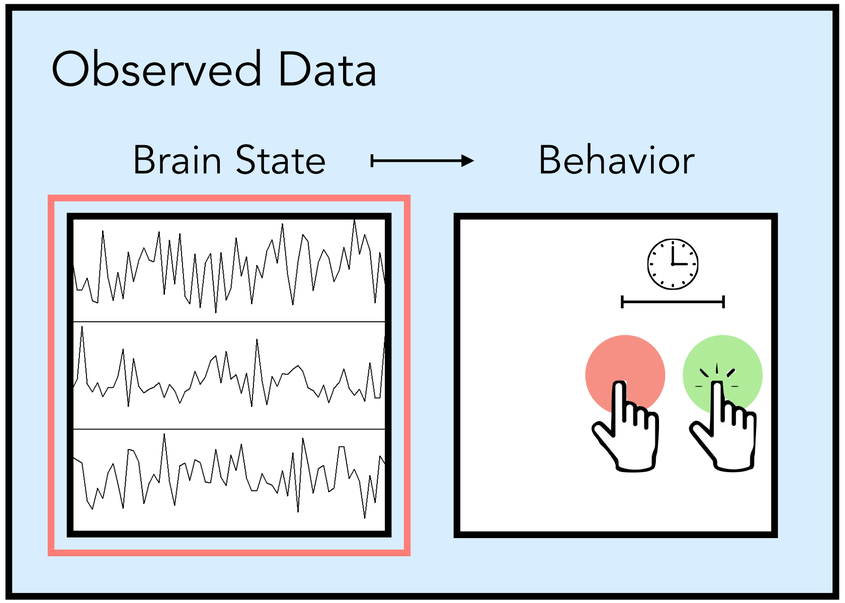
Adult male rhesus macaque monkey.



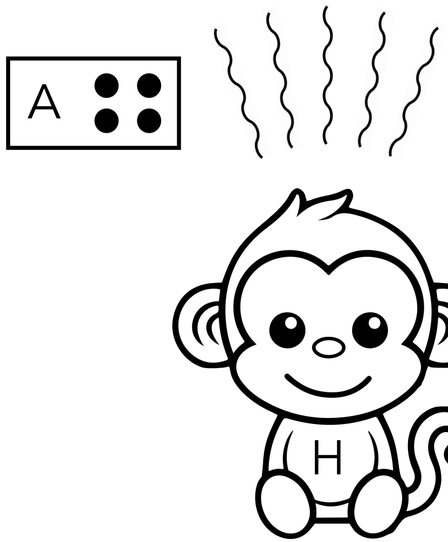


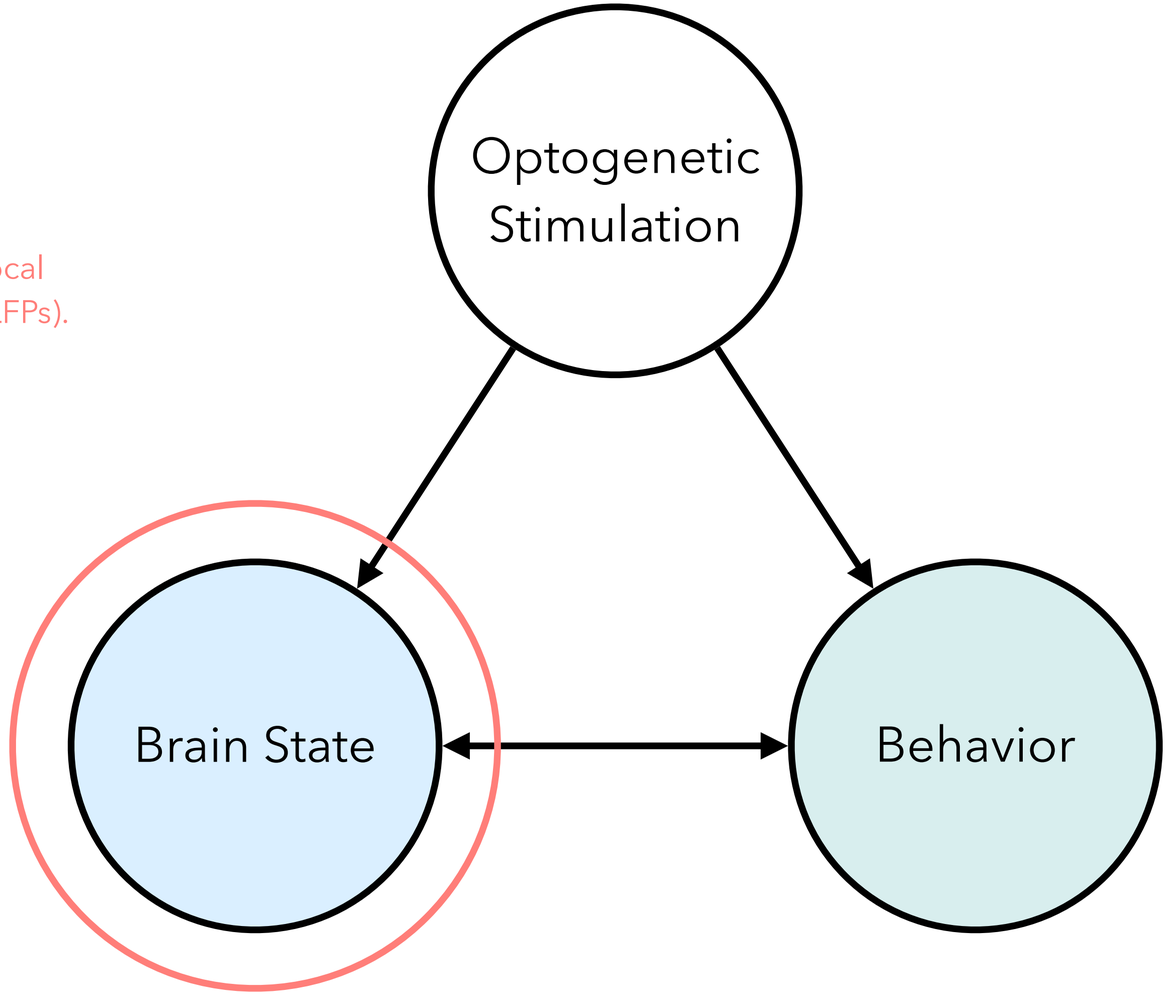
Multi-model artificial dura (MMAD) implanted over PPC with optogenetic interface.

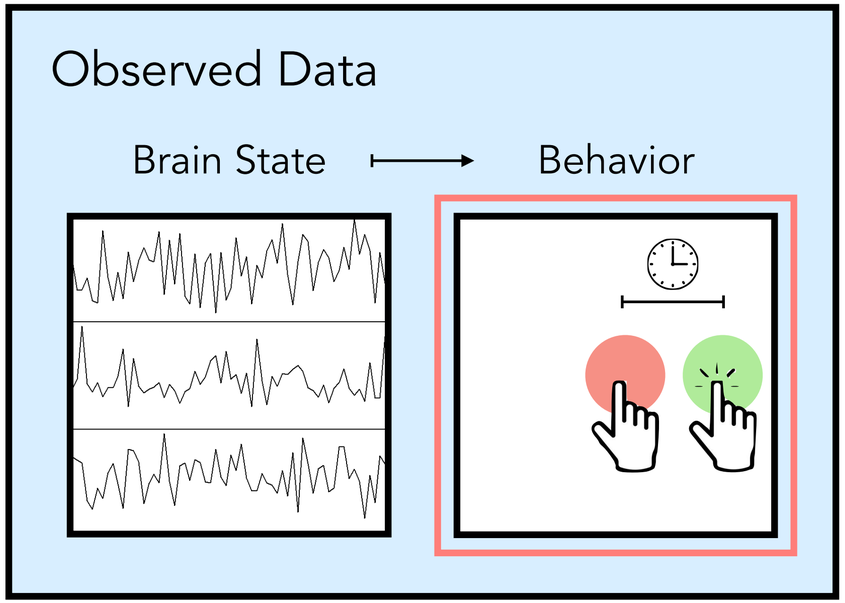




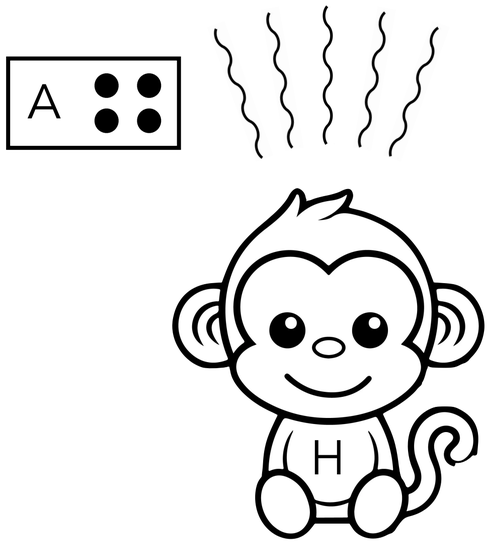
Light-evoked local field potentials (LFPs).

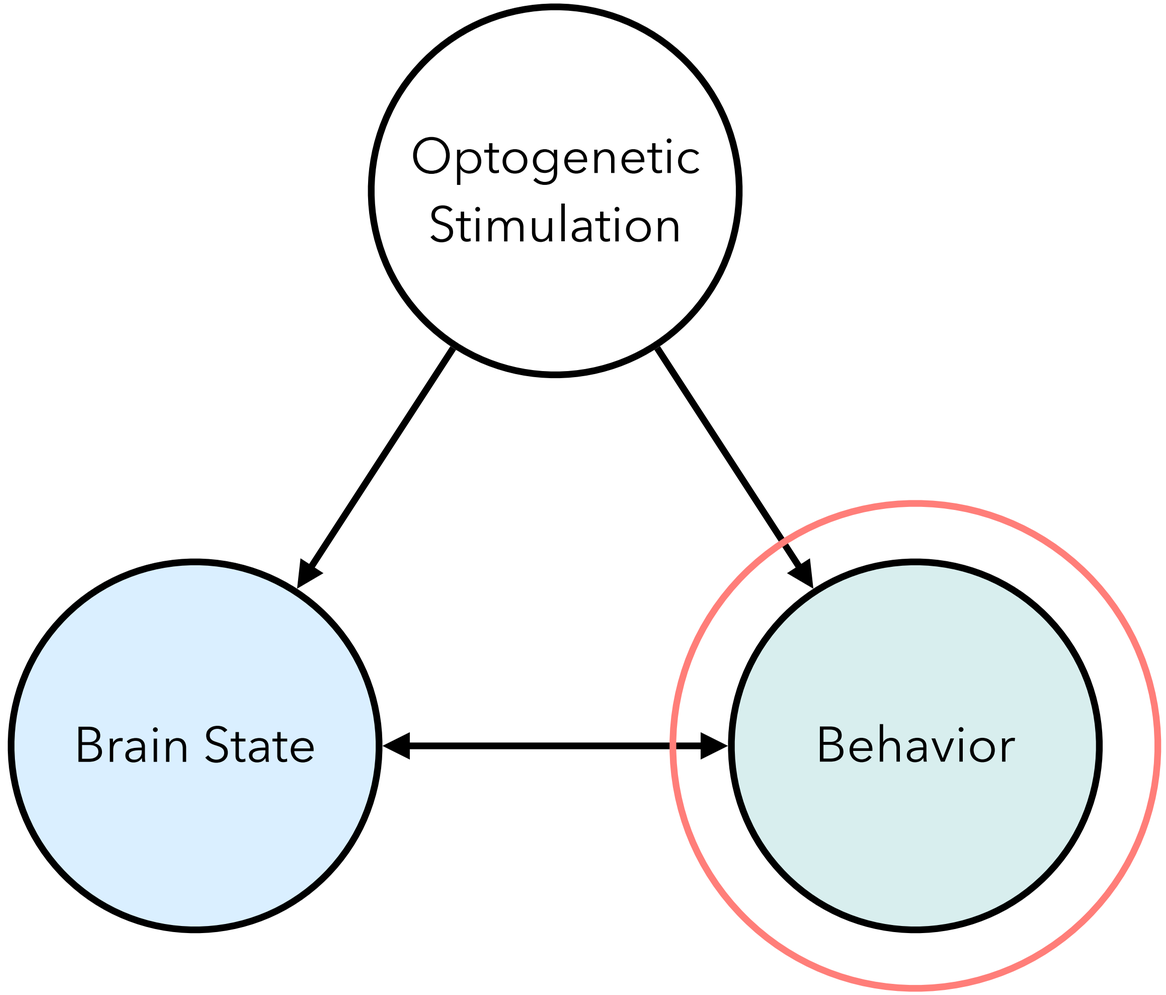




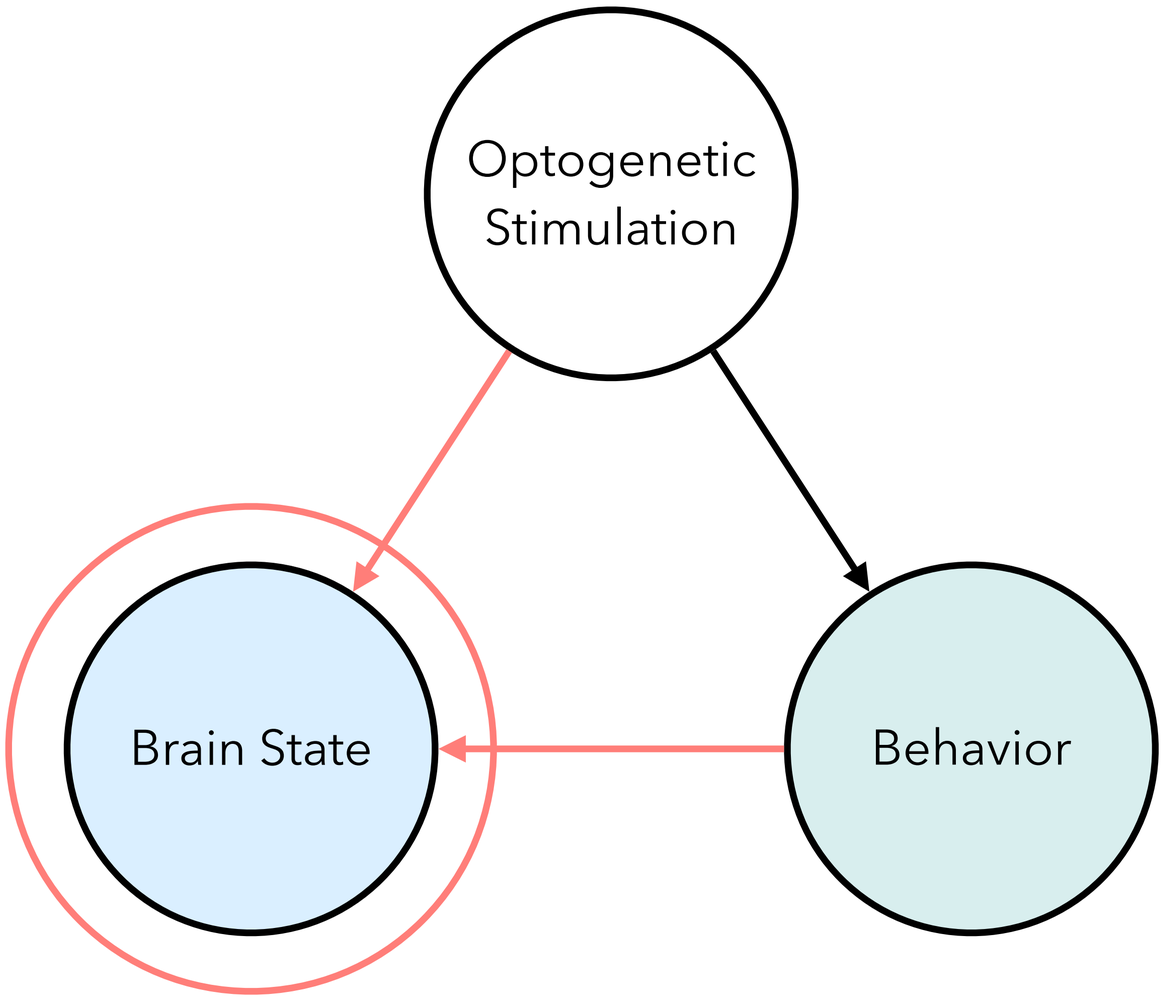


Delayed center outreach task.





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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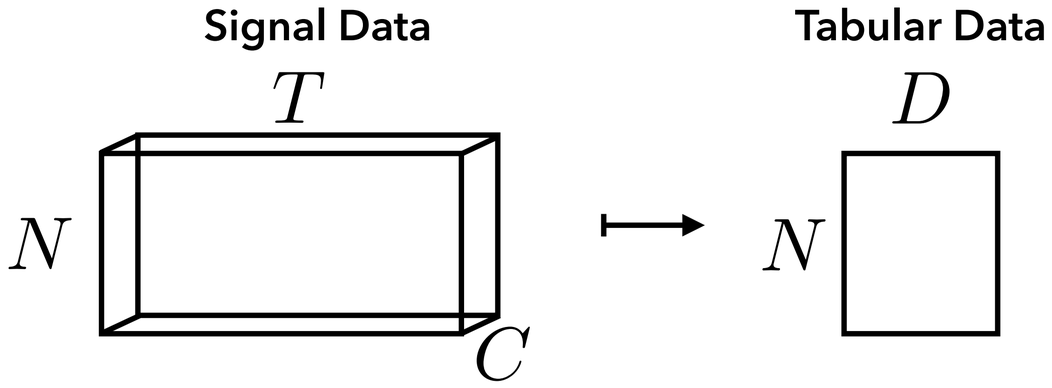
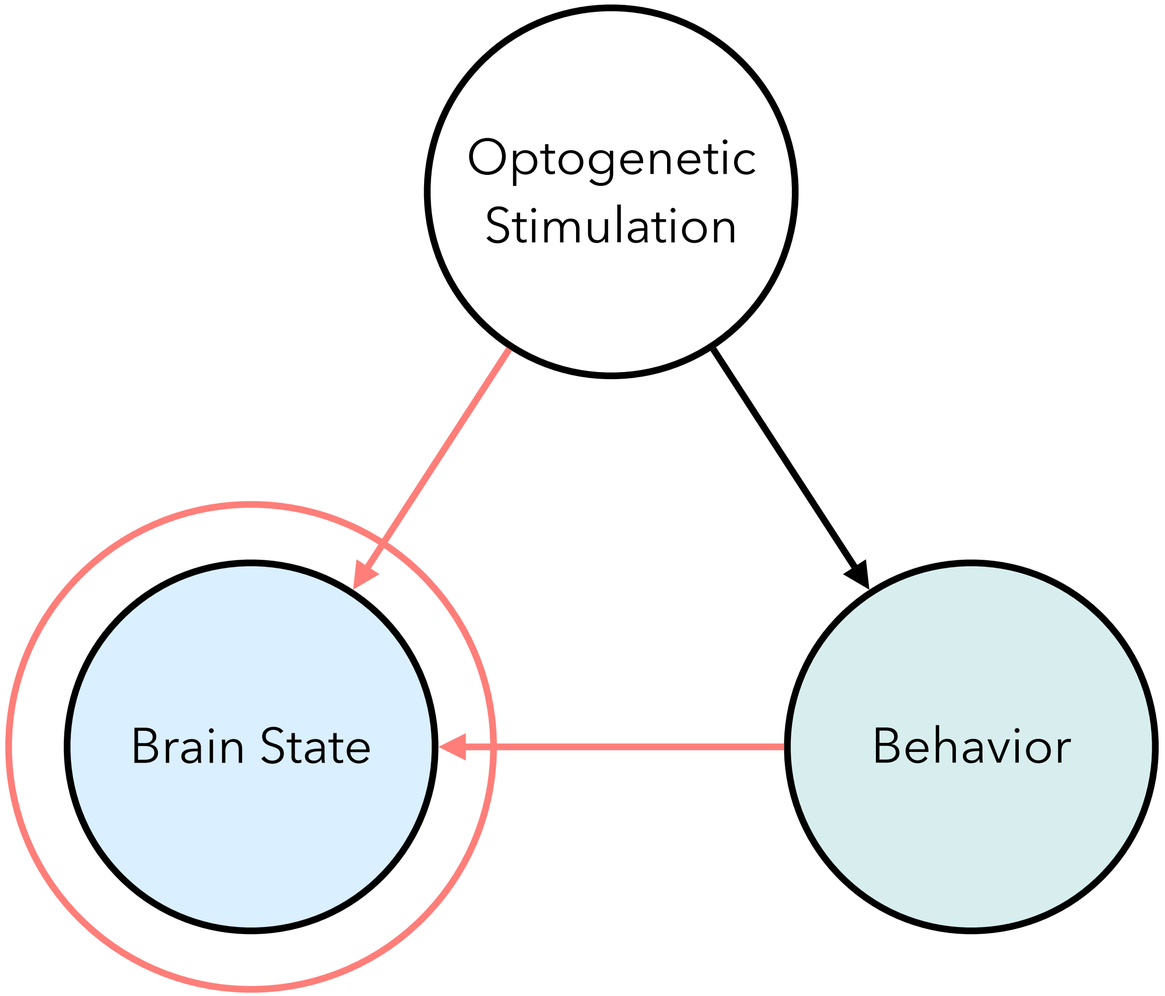
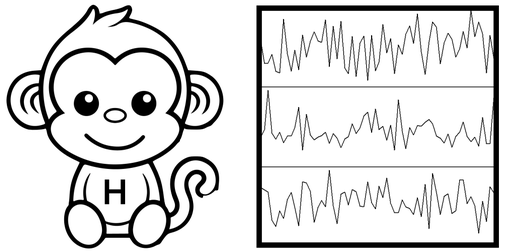


N Trials
T Samples
C Channels
D Dimensions



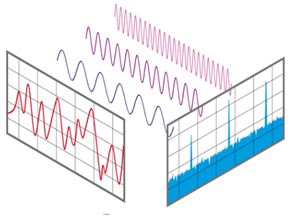
A Common Pipeline

Input Signal

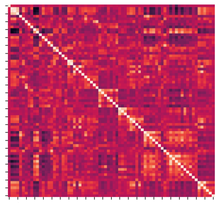


Signal Processing

Fourier Analysis

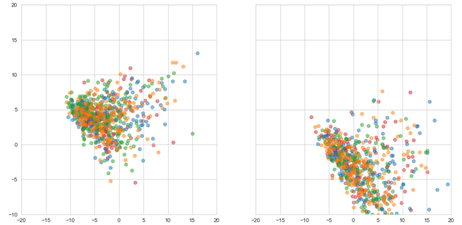


Model Correlations



Dimension Reduction

PCA



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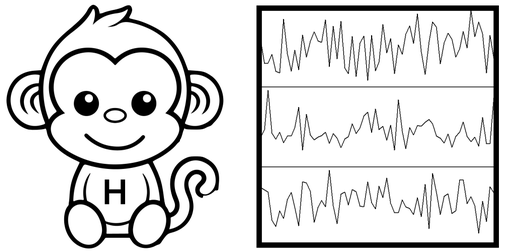

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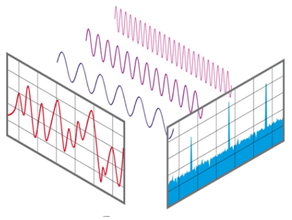

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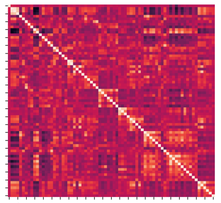

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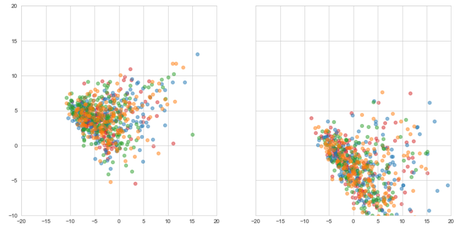

Challenging due to:
1) high-dimensional data,
2) alignment of representations across trials, and
3) possible ambiguities of graph-based methods.

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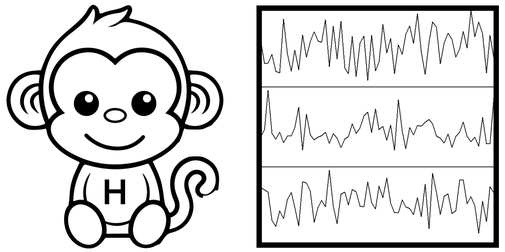

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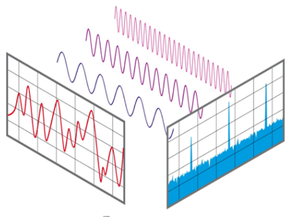

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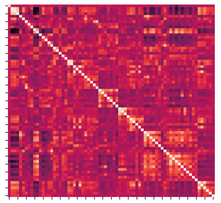

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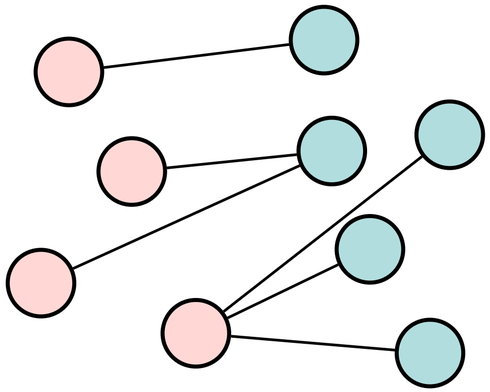
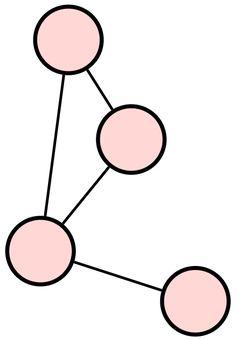
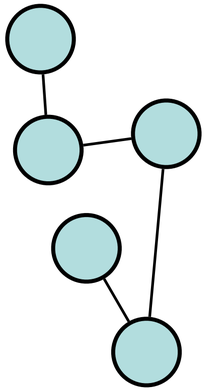
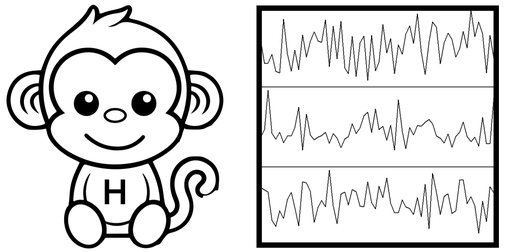






Proposed Pipeline

Input Signal



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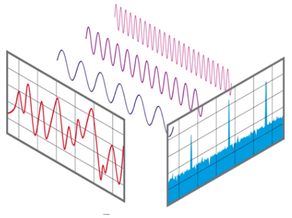

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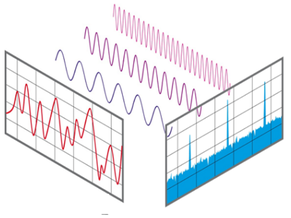

Dimension Reduction

PCA

Proposed Pipeline

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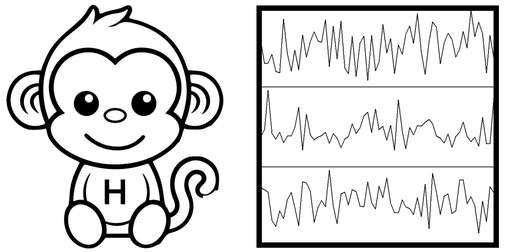
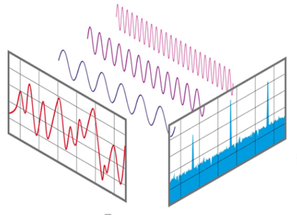


Signal Processing

Unmixing (ICA)

Fourier Analysis



Dimension Reduction

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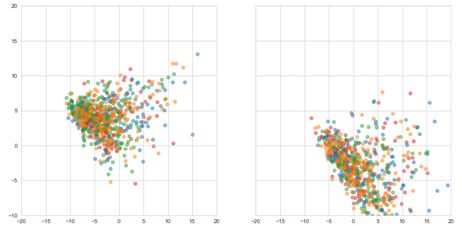

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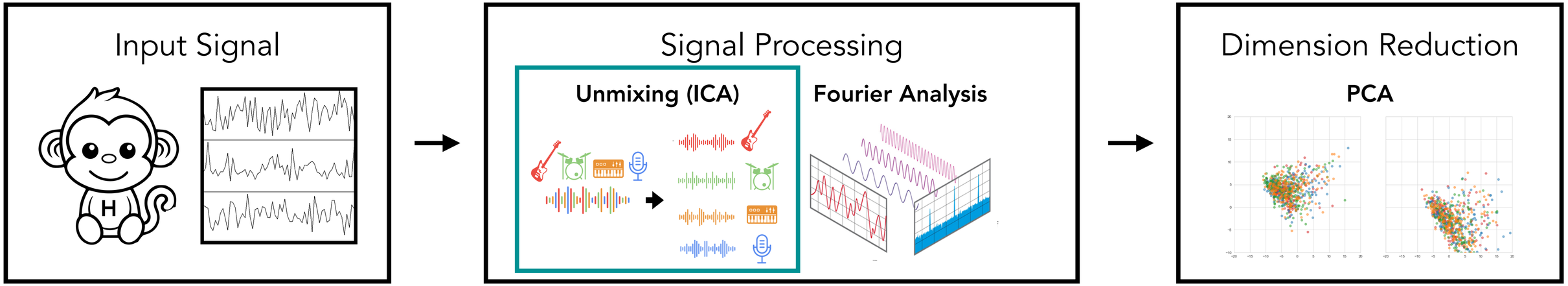


Independent component analysis (**ICA**) separates the signals into **independent source** signals that have no correlation structure but recover the original signal when combined.

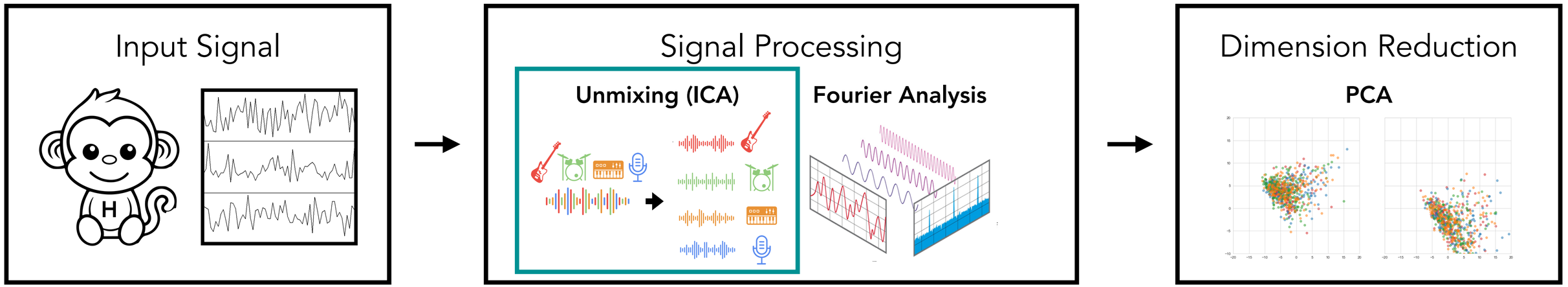
$$\mathbf{x} = \mathbf{A}\mathbf{s}$$

Observed Signal — Mixing Matrix — Source Signal

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

Unmixing Matrix

Proposed Pipeline



Contributions: a novel ICA algorithm that:

1) has runtime independent of N and T,
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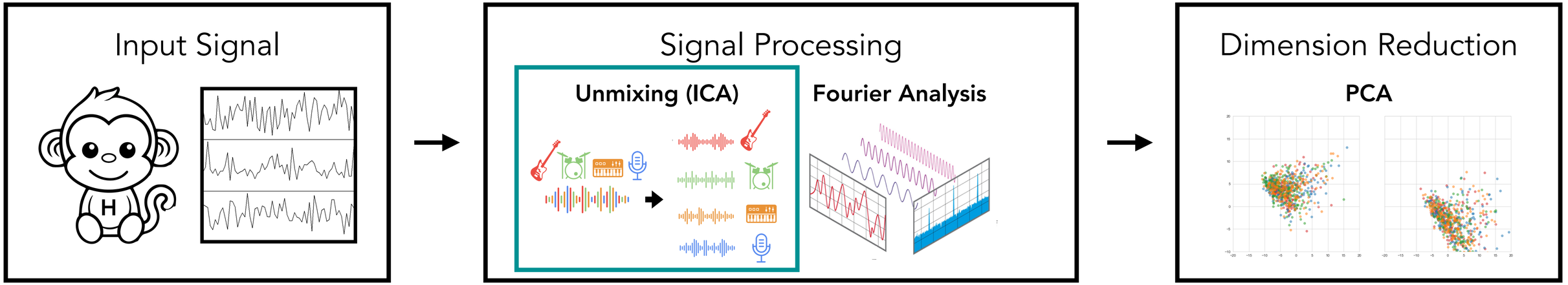

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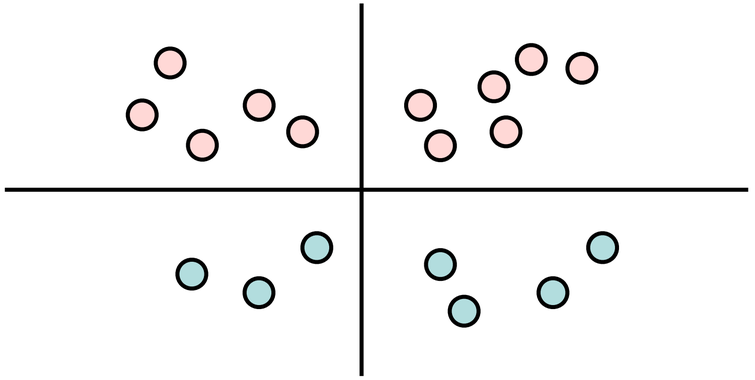

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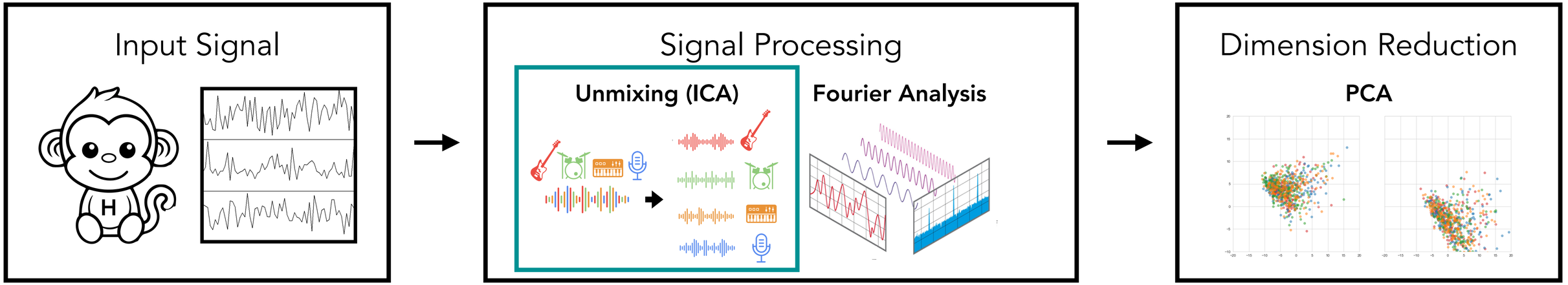

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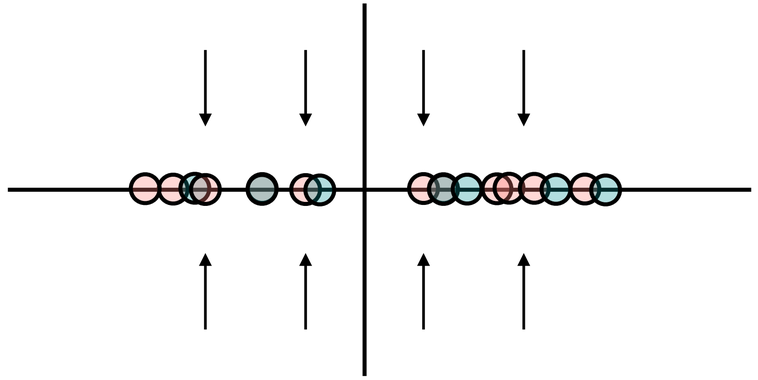
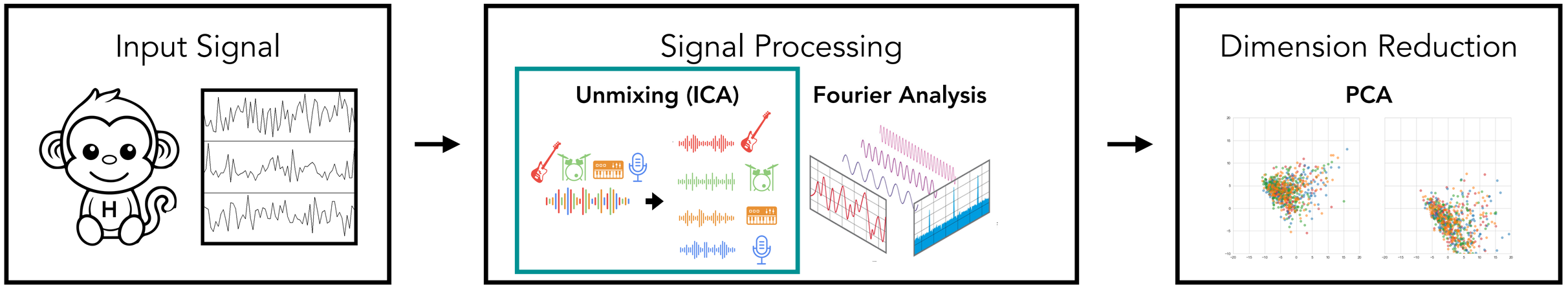


Projection onto the first principal component destroys task information.

Proposed Pipeline



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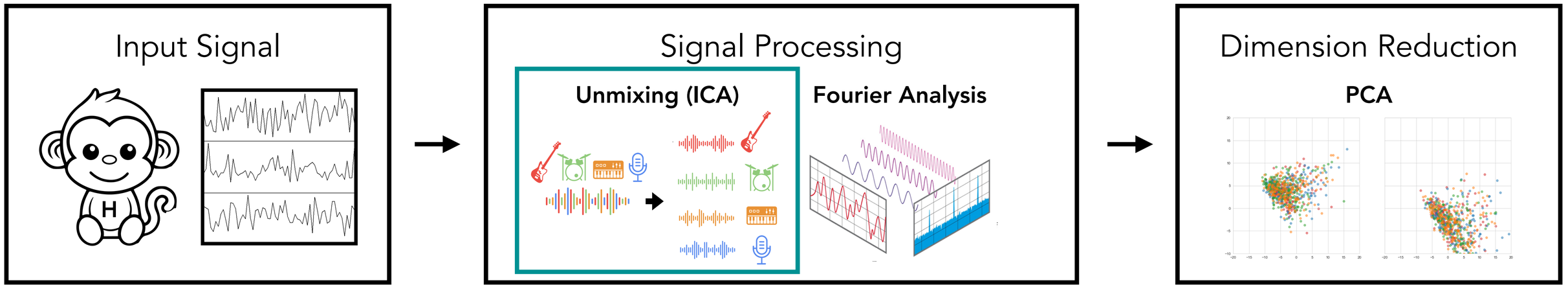

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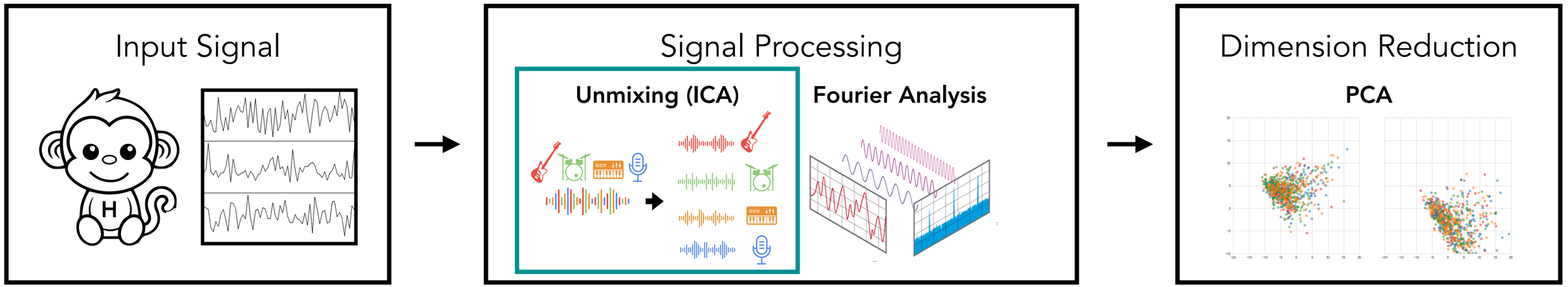

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Prediction loss term enforces **experiment information**.

$$R_i(\mathbf{W}) := (f_\theta(\mathbf{W}\mathbf{x}_i) - y_i)^2$$

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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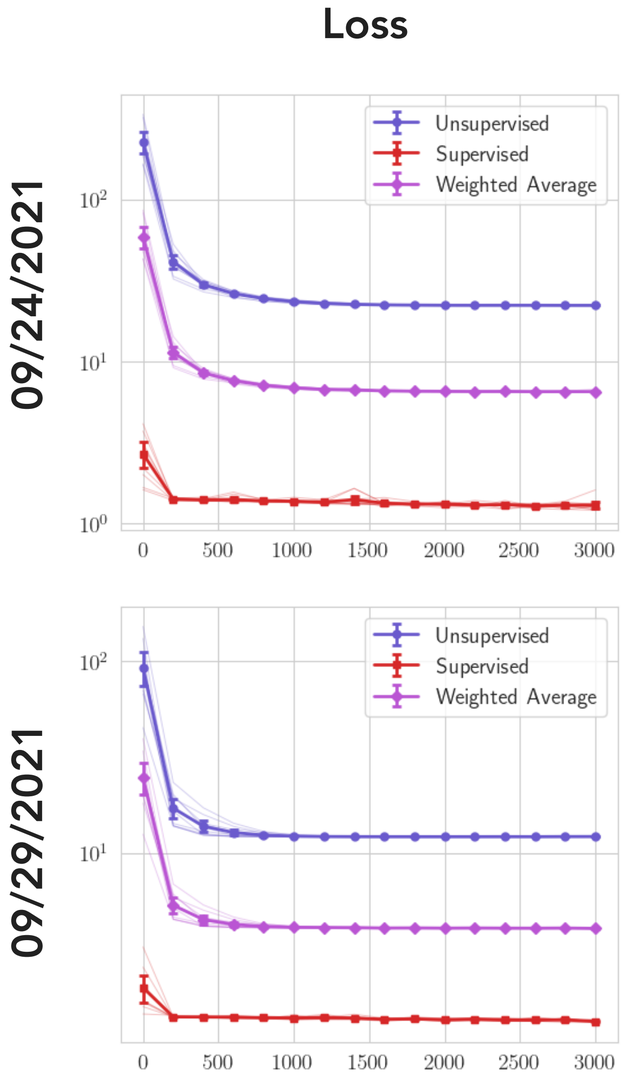

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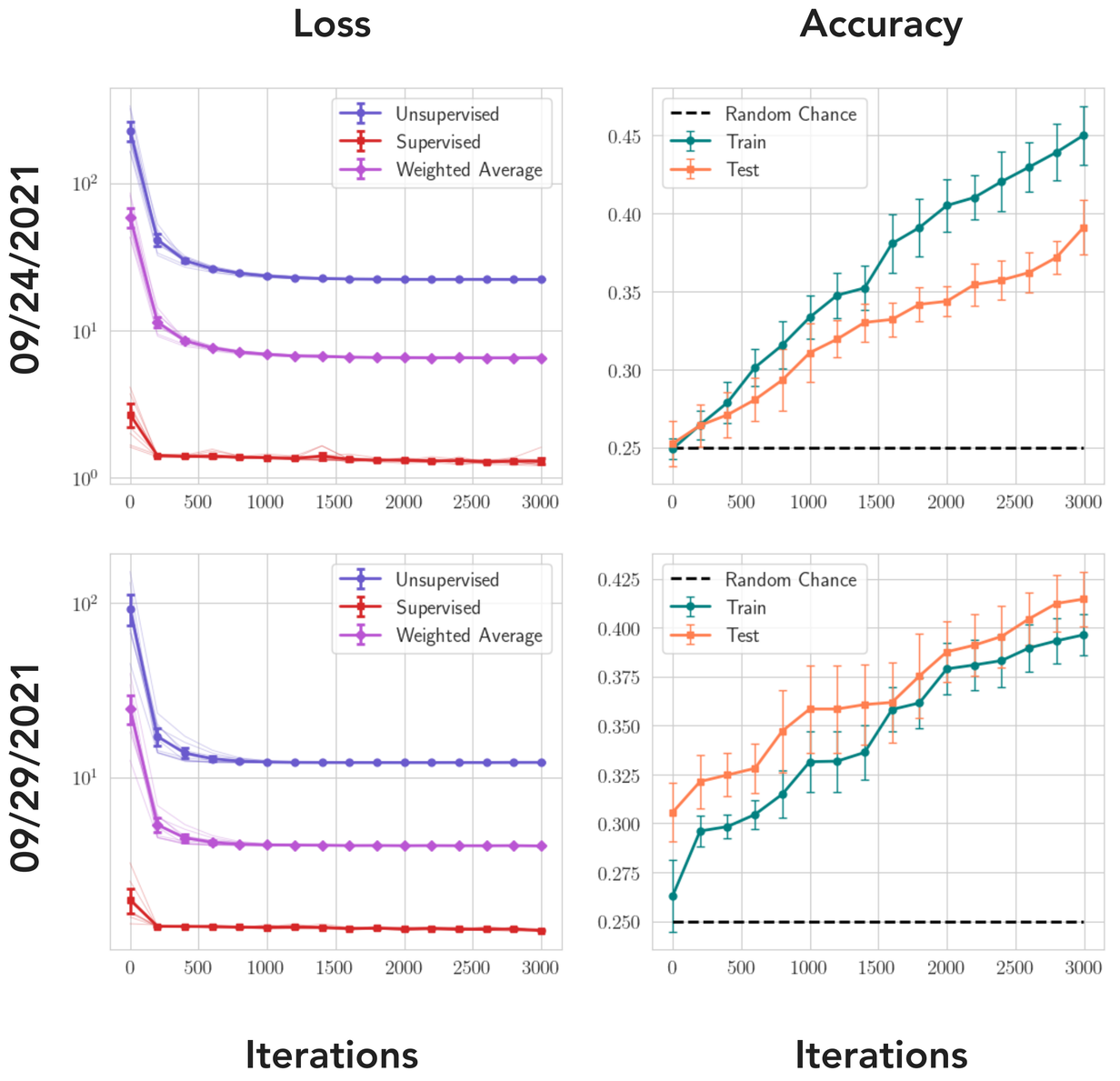

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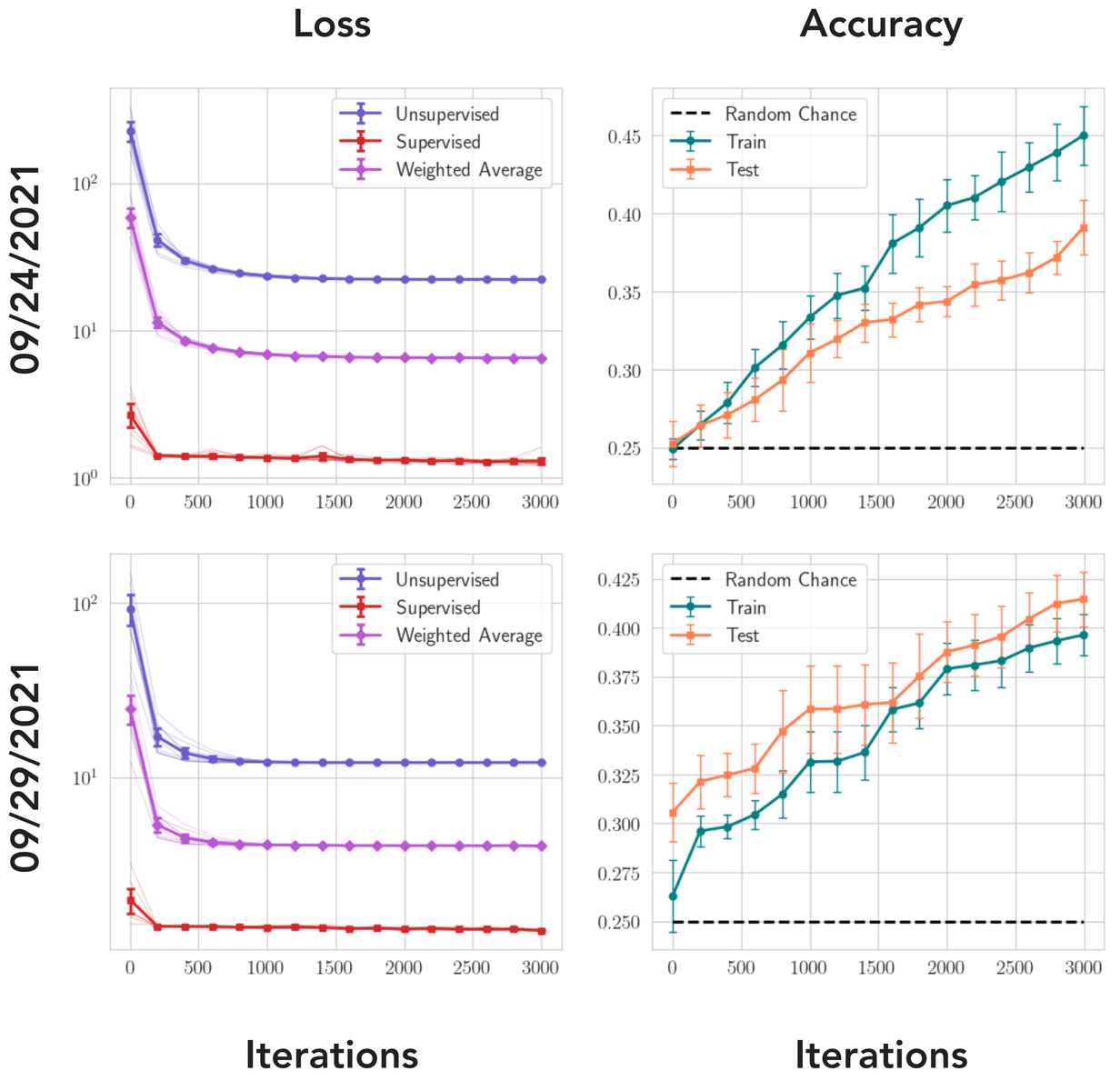
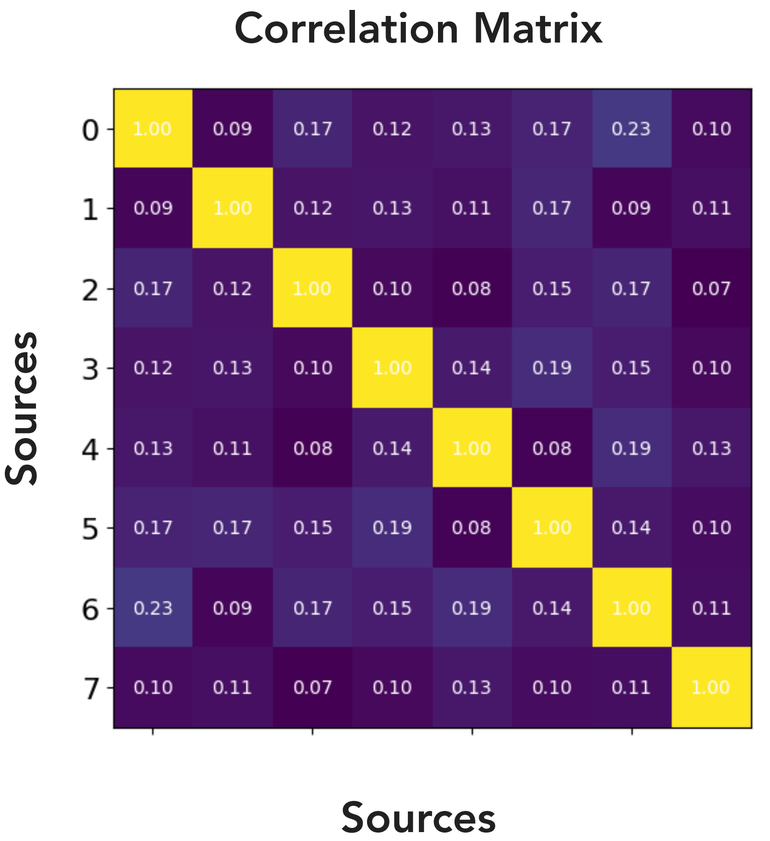
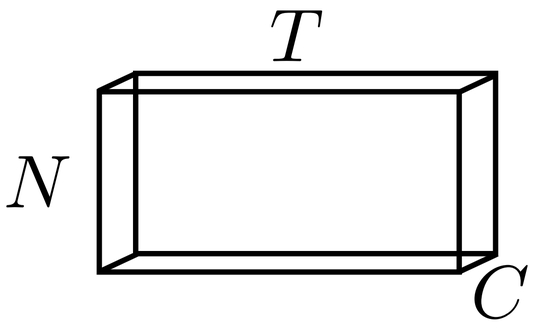
Can the sources predict the outcomes from the experiment?

Are the separated sources actually independent?

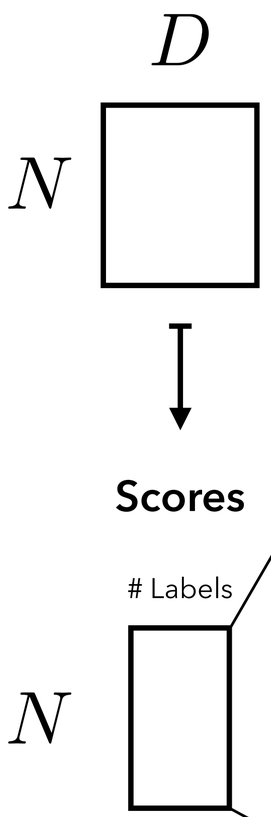


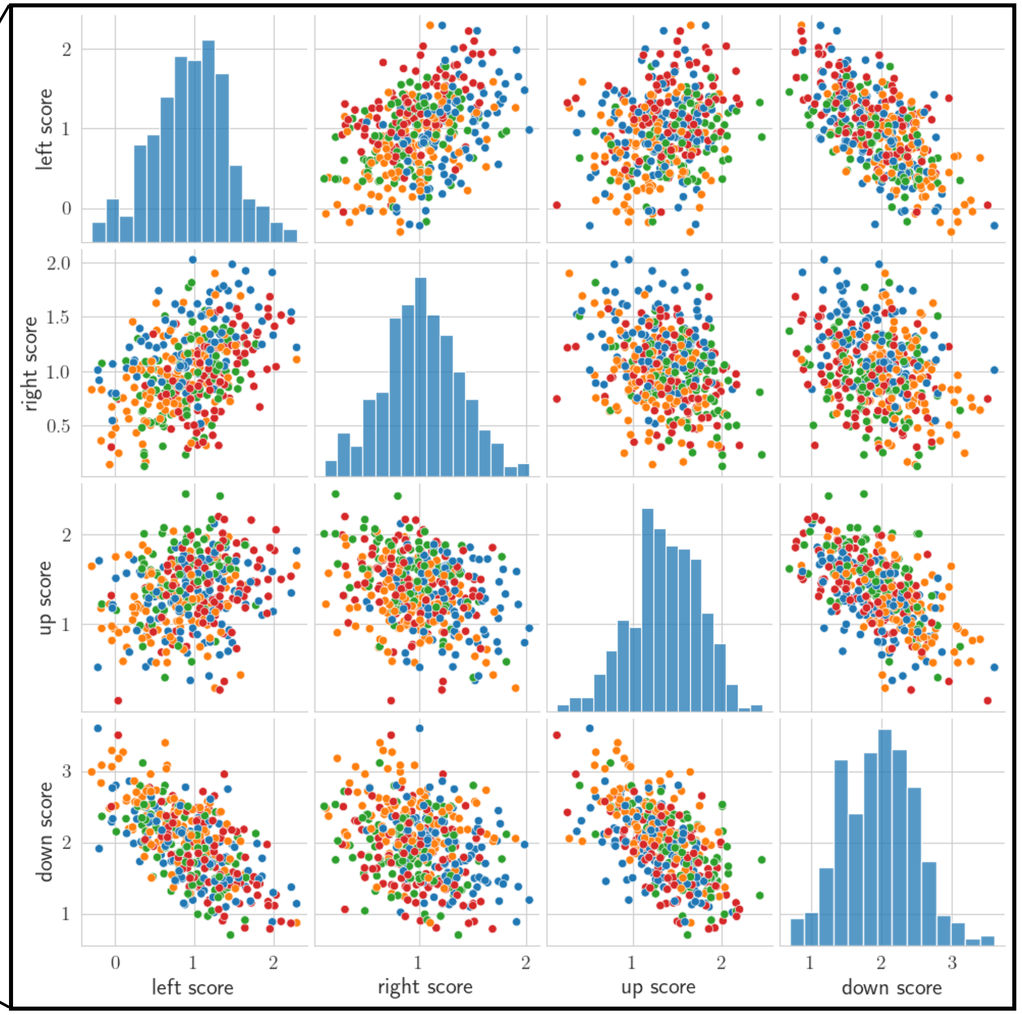


Signal Data



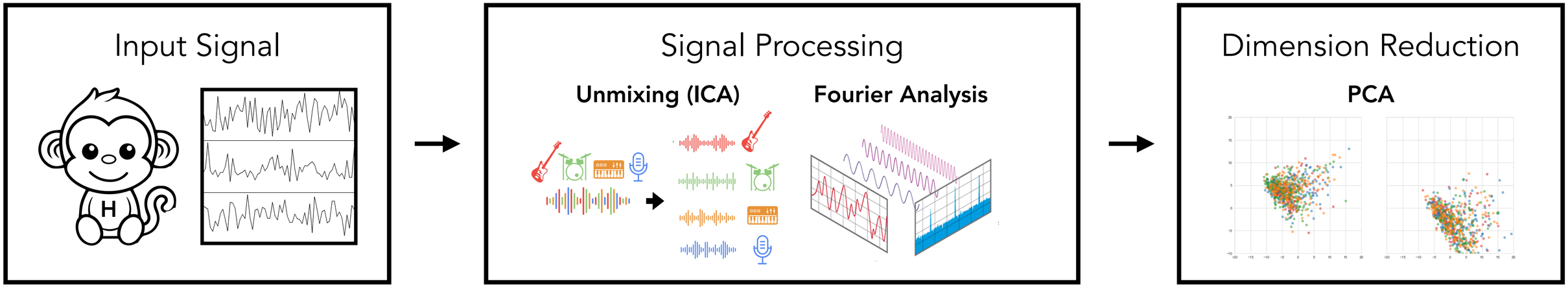
Tabular Data





Conclusion

- We develop an ICA algorithm for source separation which disentangles correlated signals while preserving important experimental information.
- Future scientific work involves using time-dependent labels (labeled periods of the center outreach task).
- Future algorithmic work involves further scalability improvements using advanced techniques from randomized optimization.



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Optostim × XAI Retreat

February 05, 2025

Thank you! Questions?

Ronak Mehta