USC Viterbi
Ming Hsieh
Department of Electrical and Computer Engineering

ICLR
International Conference On Learning Representations

BRAID: Input-driven Nonlinear Dynamical Modeling of Neural-Behavioral Data

Parsa Vahidi, Omid G. Sani, Maryam M. Shanechi

University of Southern California
Los Angeles, CA, USA

ICLR 2025

Input-driven Dynamical model for neural-behavioral data

Input-driven latent dynamical system

Latent state x^s_{k+1} Input u_k

$$x^s_{k+1} = A_{fw}(x^s_k) + K_{fw}(u_k)$$

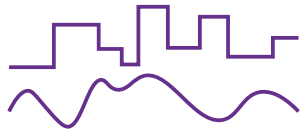
Neural activity Observations

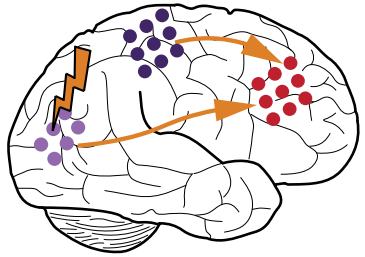
$$y_k = C_y(x^s_k, u_k) + v_k$$

Behavior Observations

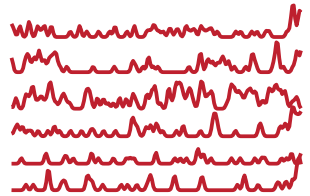
$$z_k = C_z(x^s_k, u_k) + \epsilon_k$$

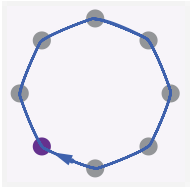
External inputs (u_k)





Neural activity (y_k)





Sensory,

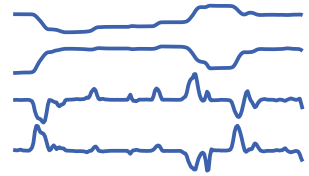
Neurostimulation,

Upstream brain region

Behavior (z_k)

Position

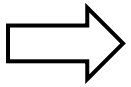
Velocity



Most existing approaches model neural activity as autonomous dynamical systems.

Do not model the effect of external inputs.

Autonomous approaches cannot distinguish intrinsic neural dynamics from effects of inputs.



✓ Learning explicit **representation** of **intrinsic** dynamics in presence of inputs

$$x_{k+1} = \boldsymbol{A_{fw}}(x_k) + K_{fw}(u_k)$$

Intrinsic **Input effect**

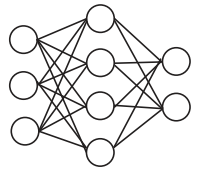
$$x_{k+1} = \boldsymbol{A}(x_k)$$

Mixture of **Intrinsic** & **input effect**

Input-driven Dynamical model for neural-behavioral data

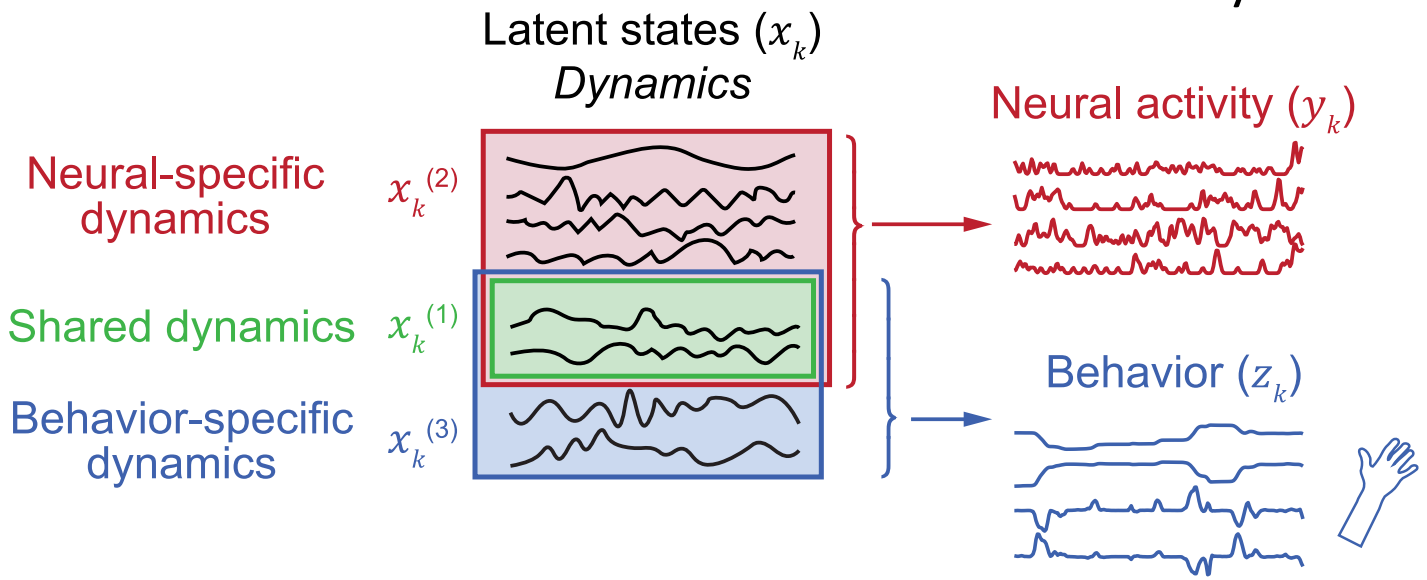
IPSID: Vahidi & Sani et al., *PNAS,* 2024 ⇨ Linear

✓ Model ***nonlinearity*** in neural-behavioral-input data. ⇨ **Nonlinear** model **MLP** transformations



✓ Intrinsic neural dynamics can be **relevant to behavior** or not. ⇨ **Prioritizing** neural-behavioral **shared** dynamics

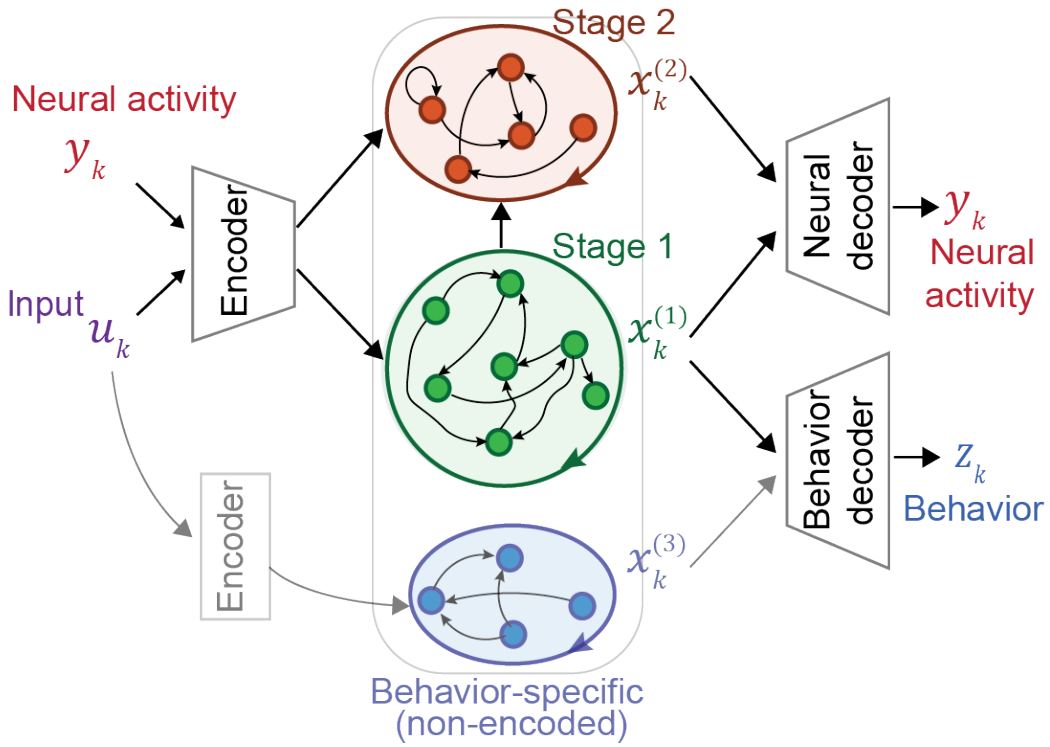
$$x_k \triangleq \begin{bmatrix} x_k^{(1)} \\ x_k^{(2)} \\ x_k^{(3)} \end{bmatrix}$$



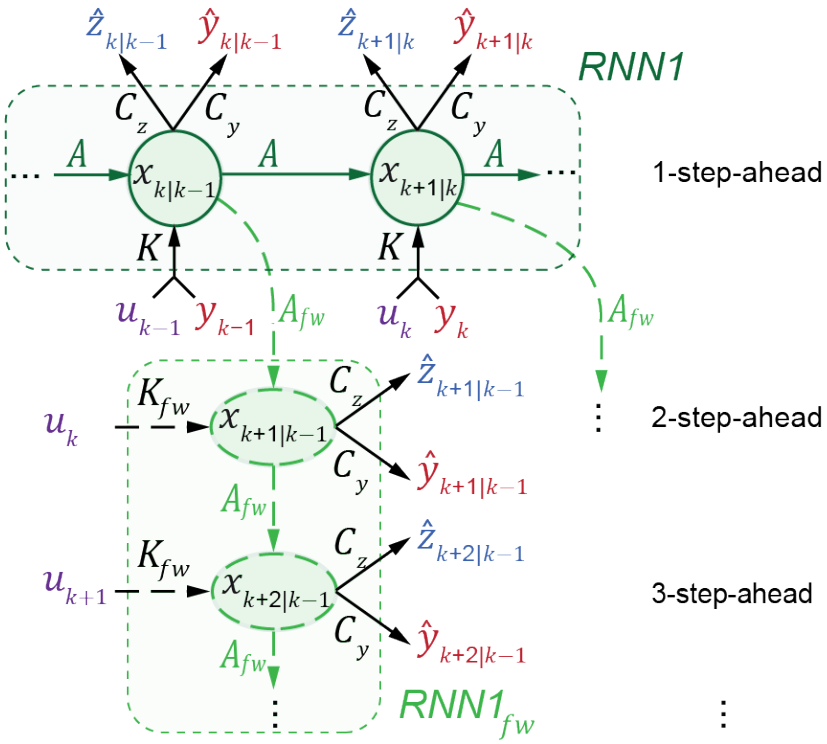
BRAID (behaviorally-relevant analysis of intrinsic dynamics): An input-driven, nonlinear method for disentangling intrinsic shared dynamics of neural-behavioral time-series from the effects of inputs and modality-specific dynamics

BRAID model

Multi-stage *RNN*



Predictor (1-step) VS Generative (m-step) form



Predictor model

$$x_{k+1|k} = A(x_{k|k-1}) + K(y_k, u_k)$$

$$\hat{y} = C_y(x, u)$$

$$\hat{z} = C_z(x, u)$$

K/K_{fw}: Encoder
A/A_{fw}: Recursion
C_y, C_z: Decoders

Objective:
m-step-ahead log-likelihood

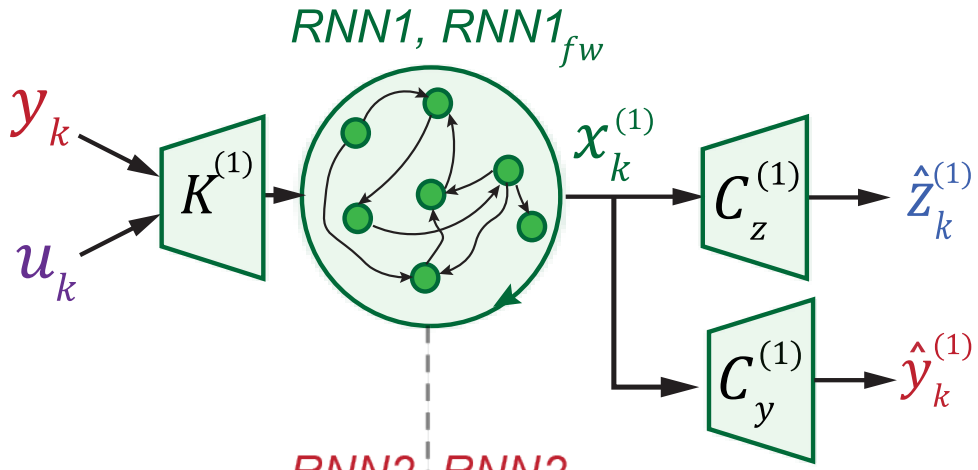
Generative (forecasting) model

$$x_{k+m|k} = \boldsymbol{A_{fw}}(x_{k+m-1|k}) + K_{fw}(u_k)$$

$for\ m > 1$: → **Intrinsic dynamics**

BRAID multi-stage learning

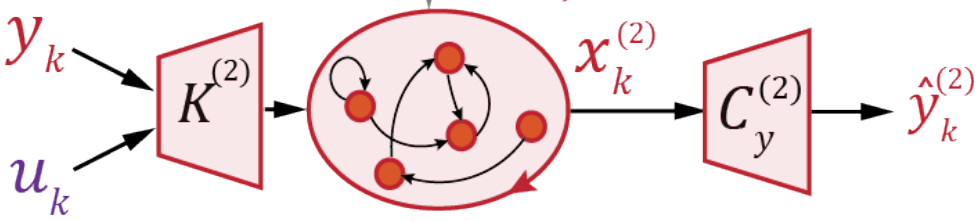
stage 1: learn intrinsic behaviorally relevant states $x_k^{(1)}$



$L_z(z, \hat{z}^{(1)})$

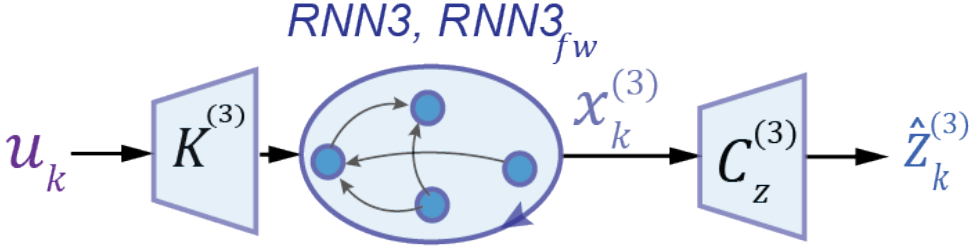
$L_y(y, \hat{y}^{(1)})$

stage 2 (Optional)



$L_y(y - \hat{y}^{(1)}, \hat{y}^{(2)})$

stage 3 (Optional)



$L_z(z - \hat{z}^{(1)}, \hat{z}^{(3)})$

Behavior prediction loss

$$L_z = \sum_{i=1}^{L} MSE(z_{k+m_i}, \hat{z}_{k+m_i|k})$$

Neural prediction loss

$$L_y = \sum_{i=1}^{L} MSE(y_{k+m_i}, \hat{y}_{k+m_i|k})$$

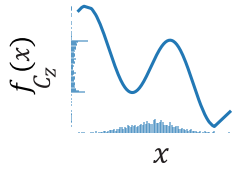
Experimental Results: Simulations

BRAID achieved optimal neural-behavioral predictive accuracy in nonlinear input-driven simulations

Simulated (true) model

$$x_{k+1} = A_{fw}x_k + Bu_k + w_k$$
$$y_k = C_y x_k + D_y x_k + v_k$$
$$z_k = f_{C_z}(C_z x_k) + D_z u_k + \epsilon_k$$

Nonlinearity



CC:
Pearson's Correlation Coefficient

Method	Behavior decoding CC	Neural prediction CC
IPSID	0.4567 ± 0.0527	**0.8901 ± 0.0304**
linear BRAID	0.4558 ± 0.0528	**0.8893 ± 0.0304**
DPAD *Nonlin* C_z	0.4958 ± 0.0620	0.3767 ± 0.0680
BRAID *Nonlin A*	0.4735 ± 0.0572	0.8127 ± 0.0528
BRAID *Nonlin K*	0.7680 ± 0.0467	0.6983 ± 0.0473
BRAID *Nonlin* C_y	0.4558 ± 0.0528	**0.8887 ± 0.0305**
BRAID *Nonlin* C_z	**0.8696 ± 0.0487**	**0.8913 ± 0.0305**
BRAID *Auto Nonlin*	**0.8693 ± 0.0487**	**0.8913 ± 0.0305**
True model (ideal)	**0.8737 ± 0.0486**	**0.8921 ± 0.0306**

Experimental Results: Simulations

BRAID Dissociated intrinsic dynamics from input dynamics

Normalized eigenvalue error $\frac{\sqrt{\sum_{i=1}^{n}\|\lambda_i - \hat{\lambda}_i\|^2}}{\sqrt{\sum_{i=1}^{n}\|\lambda_i\|^2}}$

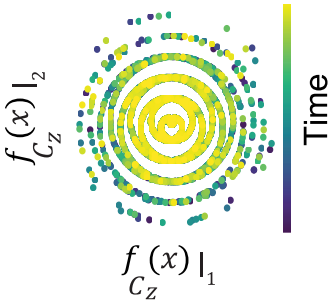
Intrinsic Dynamics

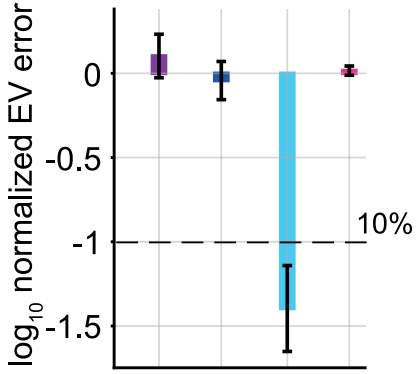
Ground truth $x^s_{k+1} = A^{True}_{fw}(x^s_k) + K^{True}_{fw}(u_k)$

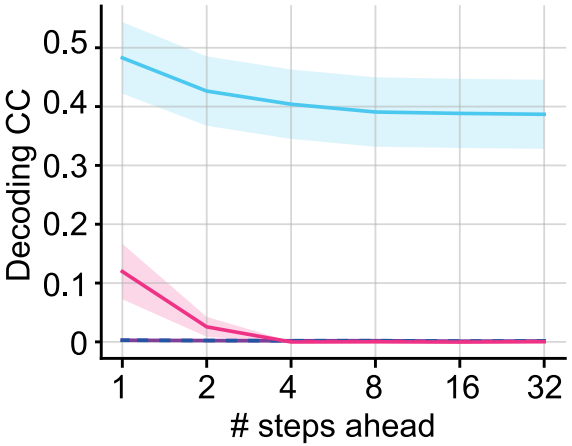
Eigenvalue error

Model $x_{k+1} = A_{fw}(x_k) + K_{fw}(u_k)$

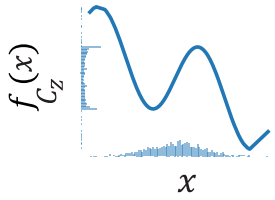
Spiral behavior manifold

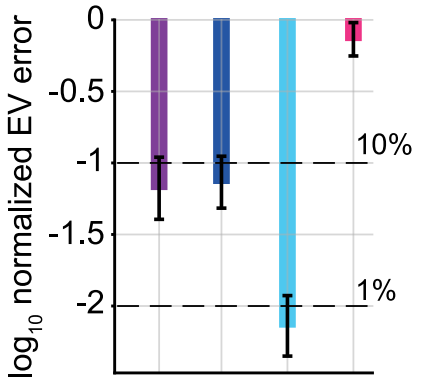






Trigonometric behavior manifold



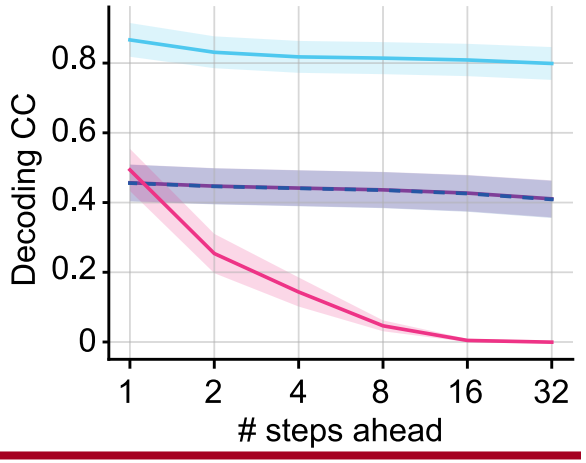


Ours BRAID *Nonlinear* C_Z (steps-ahead=[1,2,3,4,5])

Autonomous DPAD *Nonlinear* C_Z (steps-ahead=[1,2,3,4,5])

Linear Linear BRAID (steps-ahead=[1,2,3,4,5])

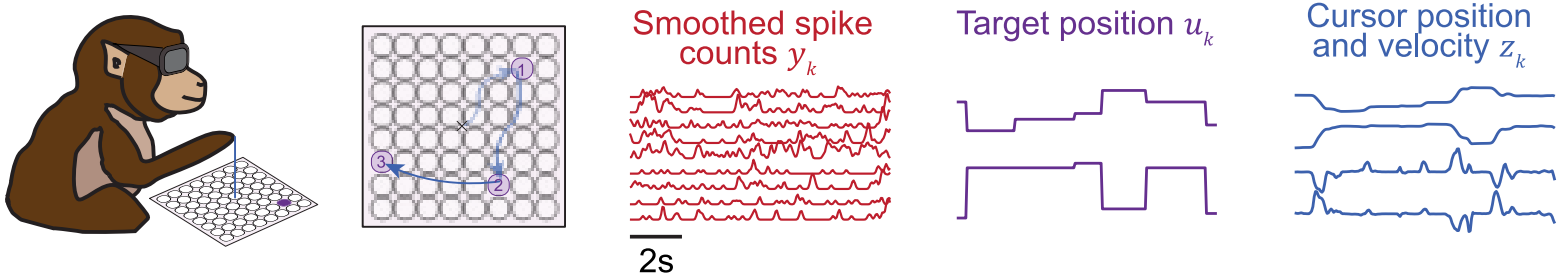
Linear IPSID



Experimental Results: NHP motor dataset

Public dataset by Sabes Lab

Non-human primate
Motor cortical activity (M1)
Reaching task

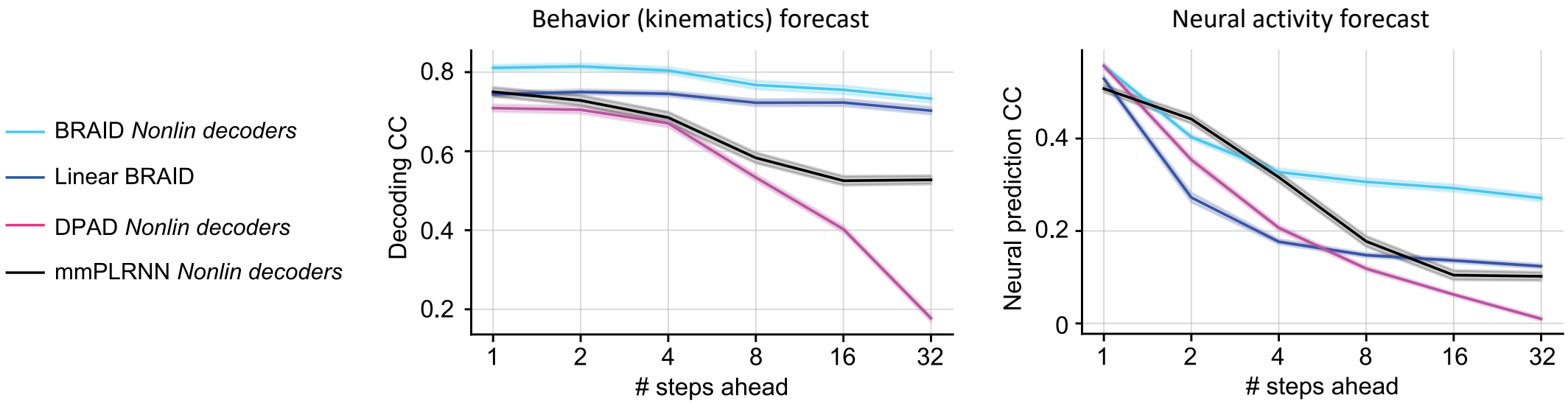


Exploring nonlinearities with BRAID

Model Nonlinearity	Behavior forecasting CC	Neural forecasting CC
Linear	0.7453 ± 0.0066	0.1767 ± 0.0054
Recursion (A, A_{fw})	0.7121 ± 0.0059	0.2719 ± 0.0061
Encoder (K, K_{fw})	0.7181 ± 0.0078	0.1646 ± 0.0049
Decoder (C_z, C_y)	$\mathbf{0.8042 \pm 0.0085}$	$\mathbf{0.3274 \pm 0.0078}$

Nonlinear decoders yield the best *4-step-ahead* neural-behavioral forecast

BRAID improves forecasting neural-behavioral data in NHP



Low-dim (Stage 1 only)

High-dim (Stages 1, 2)

Method	Behavior forecasting CC		Neural forecasting CC	
	$n_x = 16$	$n_x = 64$	$n_x = 16$	$n_x = 64$
Linear BRAID	0.7453 ± 0.0066	0.7409 ±0.0059	0.1767 ± 0.0054	0.3784 ± 0.0078
DPAD	0.6706 ± 0.0096	0.7352 ± 0.0079	0.2067 ± 0.0062	0.3611 ± 0.0080
U-BRAID	0.7663 ± 0.0069	**0.8049 ± 0.0068**	**0.4089 ± 0.0076**	**0.4185 ± 0.0074**
mmPLRNN	0.6851 ± 0.0143	0.7328 ± 0.0361	0.3162 ± 0.0107	0.3570 ± 0.0223
BRAID (ours)	**0.8042 ± 0.0085**	**0.7920 ± 0.0086**	0.3274 ± 0.0078	**0.4123 ± 0.0077**

Conclusions

- We developed BRAID, a novel input-driven nonlinear dynamical modeling method for disentangling the intrinsic shared dynamics between two observation modalities from the effect of inputs
- We validated BRAID in multiple simulated datasets and showed its ability to disentangle intrinsic dynamics from the effect of inputs, resulting in an interpretable representation of intrinsic dynamics
- We demonstrated that BRAID outperforms existing methods in forecasting neural-behavioral data in electrophysiological data recorded from NHP performing motor tasks

Acknowledgements

Shanechi Lab

NIH
R01MH123770
R61MH135407
RF1DA056402
DP2-MH126378

ONR
YIP
N00014-19-1-2128

ARO
MURI
W911NF-16-1-0368

FFOR

Thank you for your attention!