



清華大學  
Tsinghua University

# Towards Large-Scale Neural Representation Learning for Calcium Population Dynamics

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# Contents

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**Background and Significance**  
**Related Work**  
**Methods and Results**  
**Conclusion and Future Work**

\* Some concept and pipeline figures are generated by AI to provide better illustration.



# Contents

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## **Background and Significance**

- Large-scale, heterogeneous calcium imaging makes it possible to ask whether reusable neural representations can support multitask prediction, transfer, and biological interpretation.

## **Related Work**

## **Methods and Results**

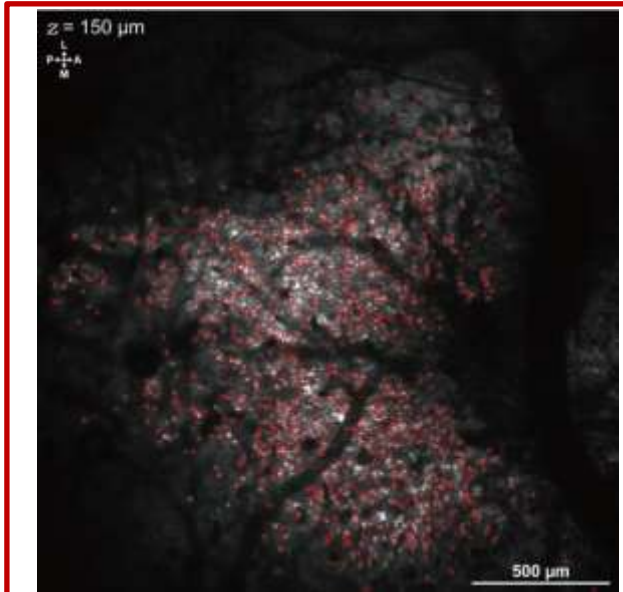
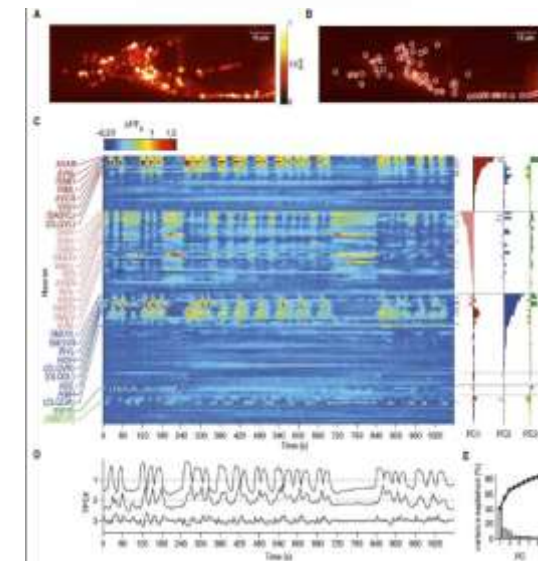
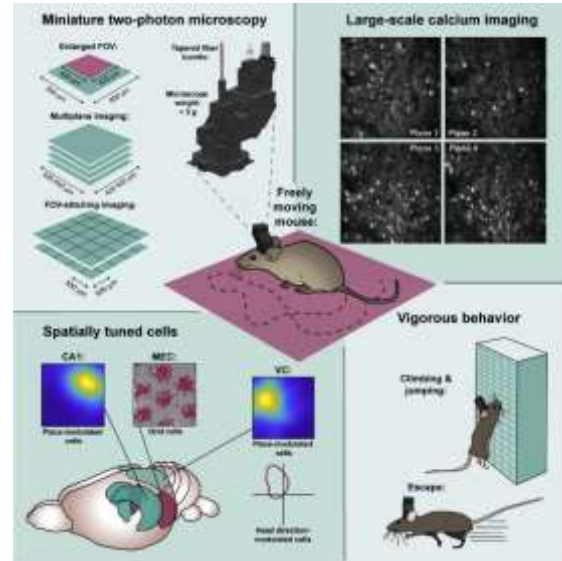
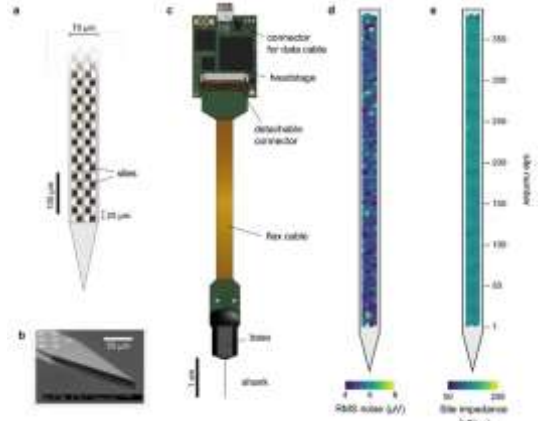
## **Conclusion and Future Work**



# Background

## Large-scale neural observation creates a new data regime:

Record tens of thousands of neurons once at a time  
Data heterogeneity for animals, experimental paradigms and species

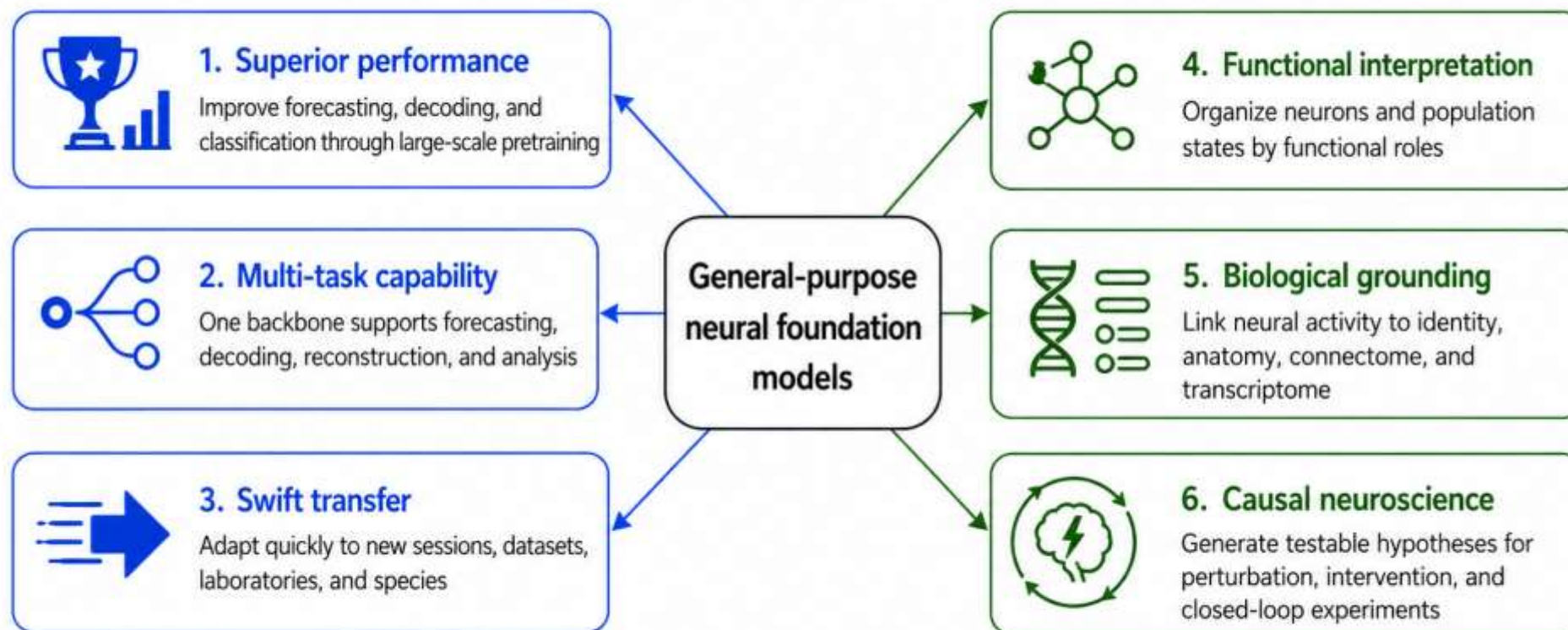




# Significance

## From prediction tools to functional coordinates:

### Why general-purpose NFM matters



Toward reusable, transferable, and biologically grounded neural representations.



# Contents

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## Background and Significance

## Related Work

- Spike/electrophysiology models provide early templates for foundation-style neural modeling, while calcium-trace models directly motivate multitask modeling, transfer, and biological interpretation.

## Methods and results

## Conclusion and Future work



Liam Paninski



Eva Dyer

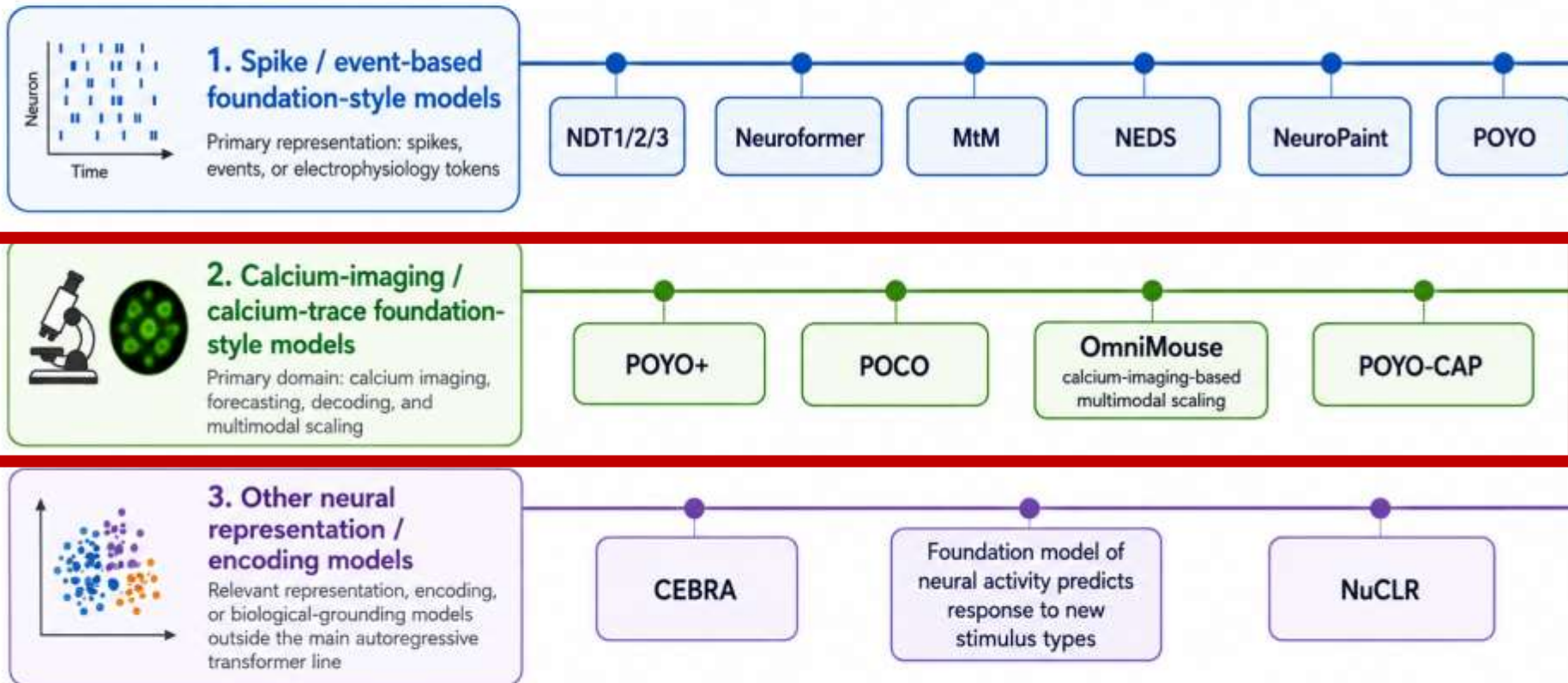


# Related Work

## Overall lines of **Transformer for neural data**:

### Three lines of related work

Neural representation learning for population activity



Discuss methods on spike/neuropixels and calcium data here.

For computational and systems neuroscience.

CaIM and CAPT are discussed separately as the main works of this talk.



# Related Work and Roadmap

## General technical lines:

- POYO series are widely acknowledged.
- Masked modeling is predominated.
- **Adaptive modules (session-specific projection, session / neuron embeddings)** are used for cross-session, cross-animal data.

## What has been finished:

- Modeling on spike data ==> Masked modeling (MtM, NEDS), decoding (POYO),
- Modeling on calcium trace ==> behavior decoding (POYO+), forecasting (POCO), scaling law (OmniMouse)

## What we want to construct for general-purpose NFM:

- A model with standard **pre-training, fine-tuning paradigm** for **diverse functions** on calcium trace datasets.
- A model capable of **transferring** to different sessions, animals, datasets, and even species.
- A model enabling **functional interpretation or multimodal biological analysis**.



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**Background and Significance**

**Related Work**

**Methods and results:**

- **CalM: A Self-Supervised Foundation Model for Population Dynamics in Calcium Imaging Data**

**Conclusion and Future Work**



Zhang



Qian

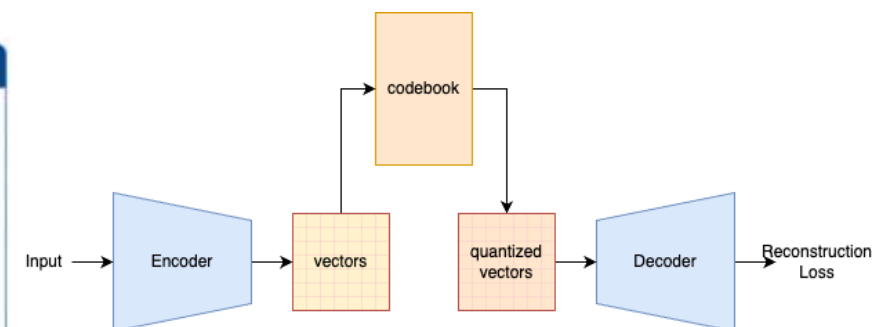
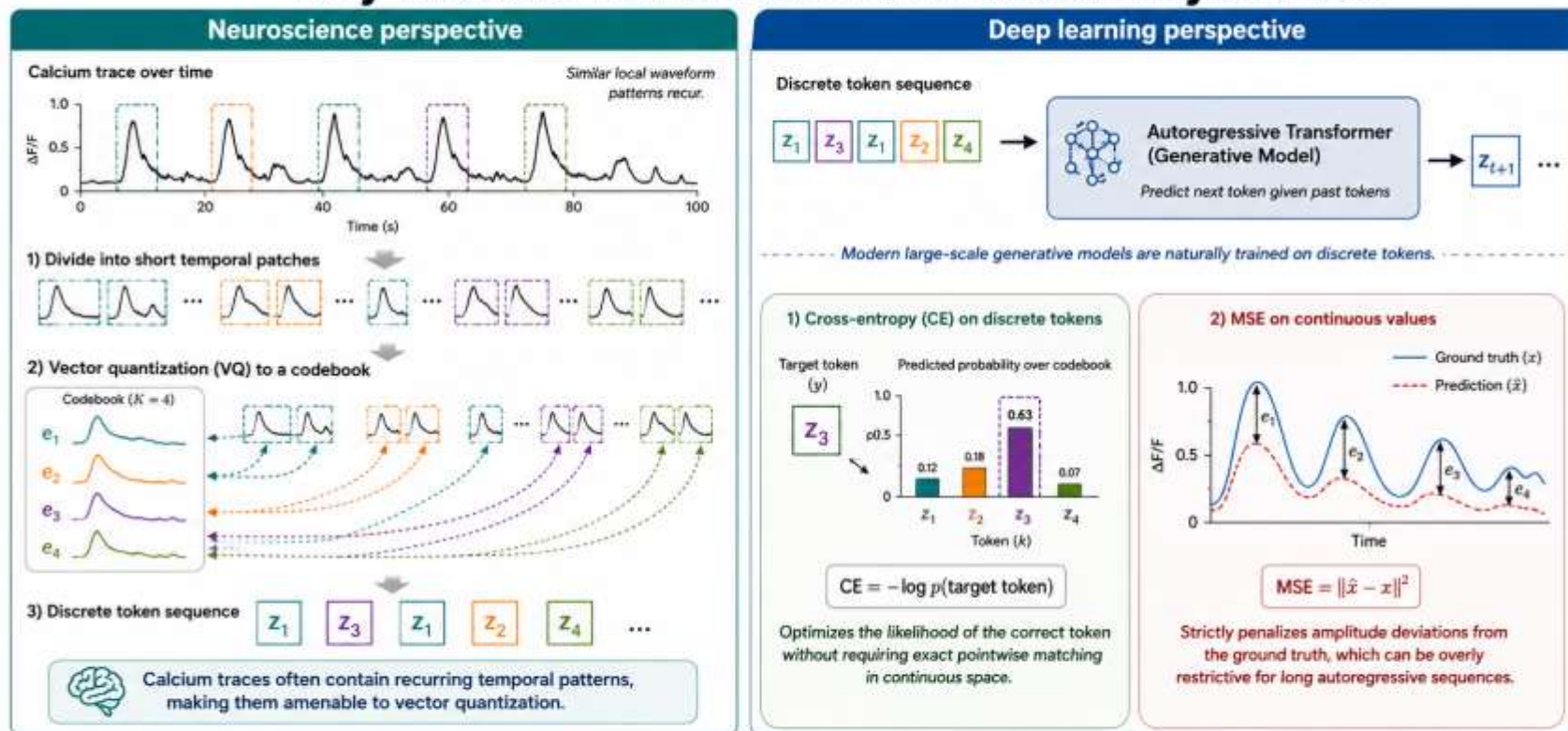


# CaIM: Method

## Intuition from 2 perspectives:

- Neuroscience: calcium traces show **periodic pattern**, which can possibly be tokenized by **VQ net**.
- DL: modern large-scale generative models are predominantly trained to **predict discrete tokens**.

### Why Discrete Tokenization for Calcium Dynamics?



Vector-quantization  
Variational autoencoder  
(VQ-VAE)

Explore autoregressive models for calcium data here.



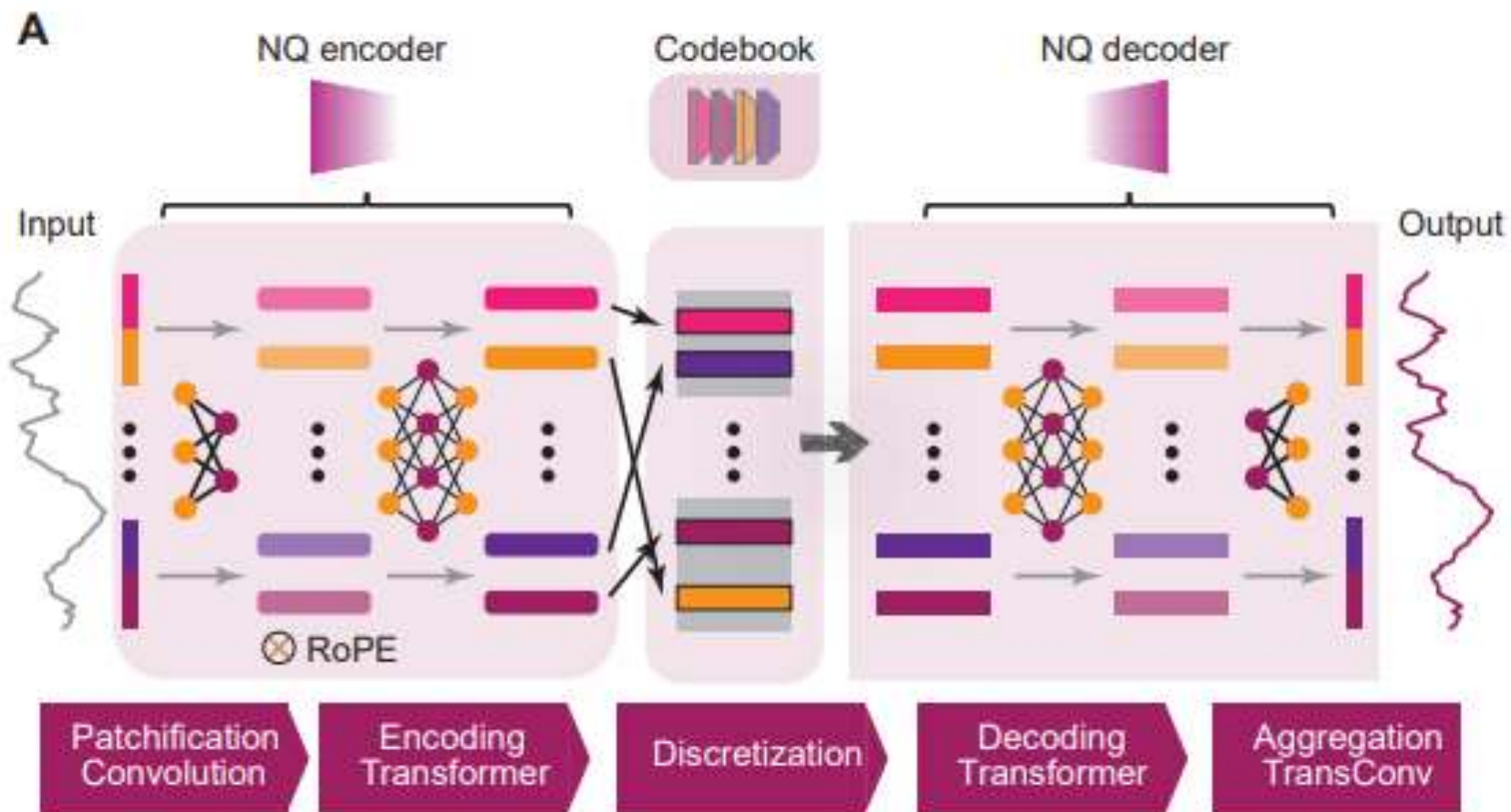
Discrete VQ tokens connect recurring calcium dynamics with token-based autoregressive training.



# CaIM: Method

## Neural quantizer (NQ, stage 1):

- NQ is a VQ net that discretizes single neural traces into discrete tokens.



Lossy compression

Auxiliary AR head

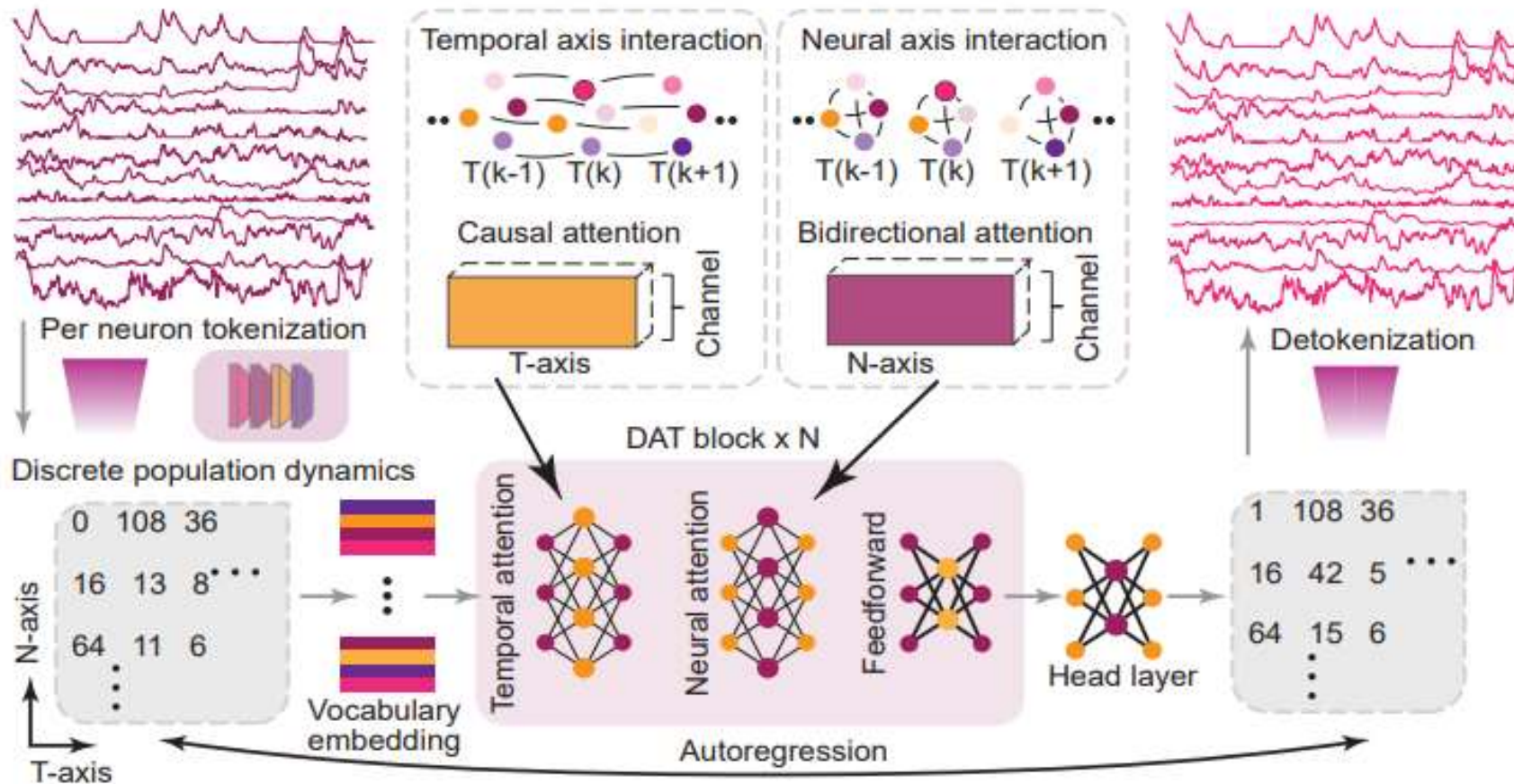
Gumbel-softmax  
reparameterization



# CaIM: Method

## Dual-axis Transformer (DAT, stage 2):

- DAT is pretrained to **autoregressively predict the next tokens of all neurons given the history.**
- **Session embeddings and neural embeddings** are cooperated into the model for training and fine-tuning.



Computational complexity ?

Forecasting task ?

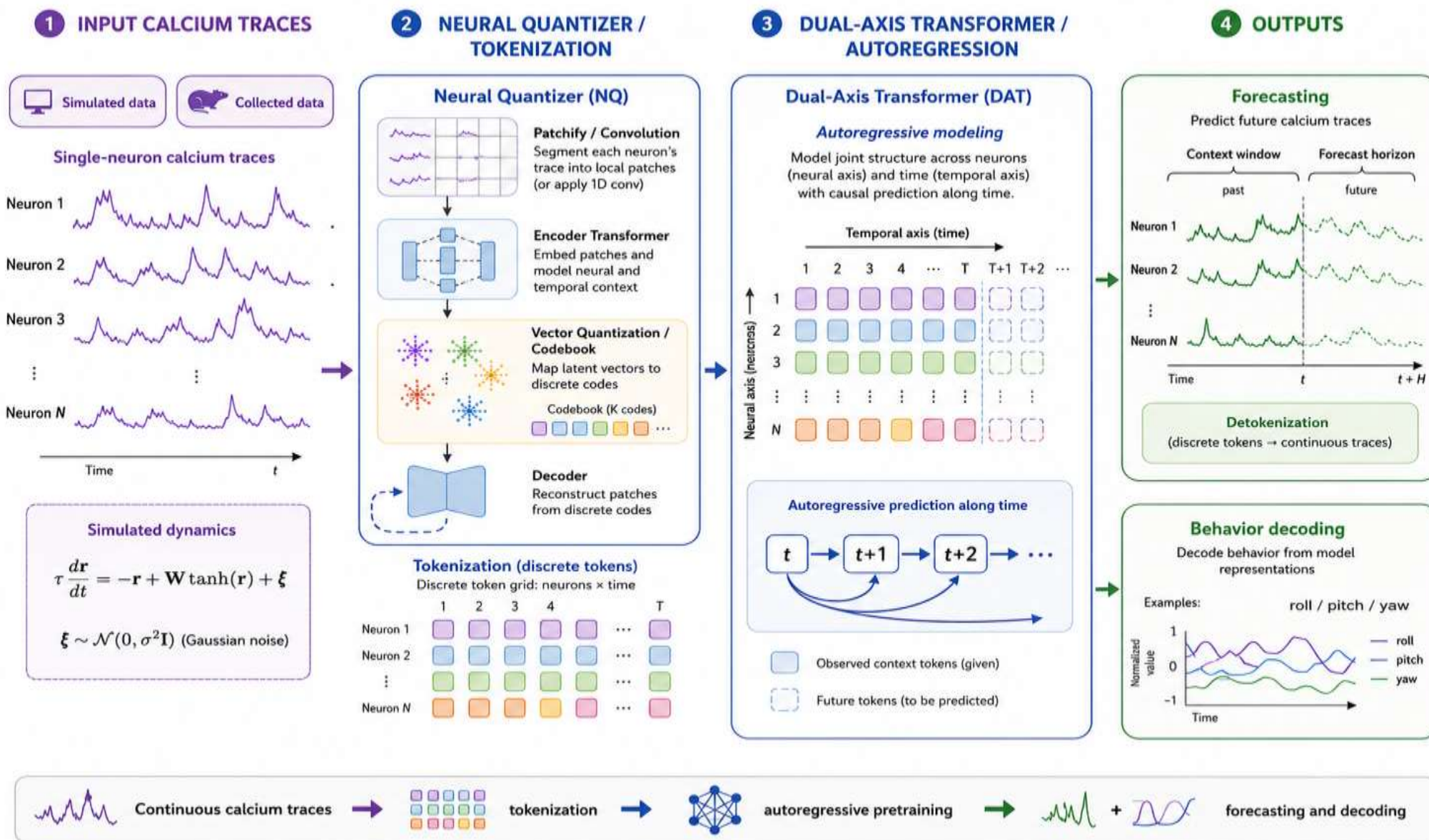
Scheduled Sampling (SS)

Neighborhood Replacement (NR)



# CaIM: Method

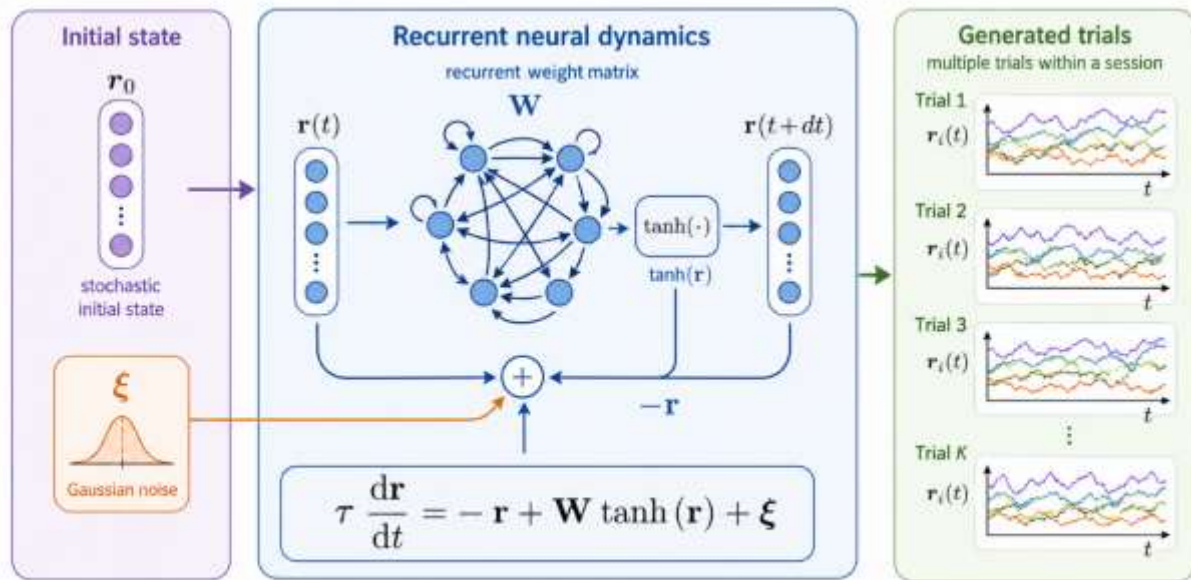
## Overall Pipeline:





# CaIM: Datasets

## Simulation with linear dynamical system:

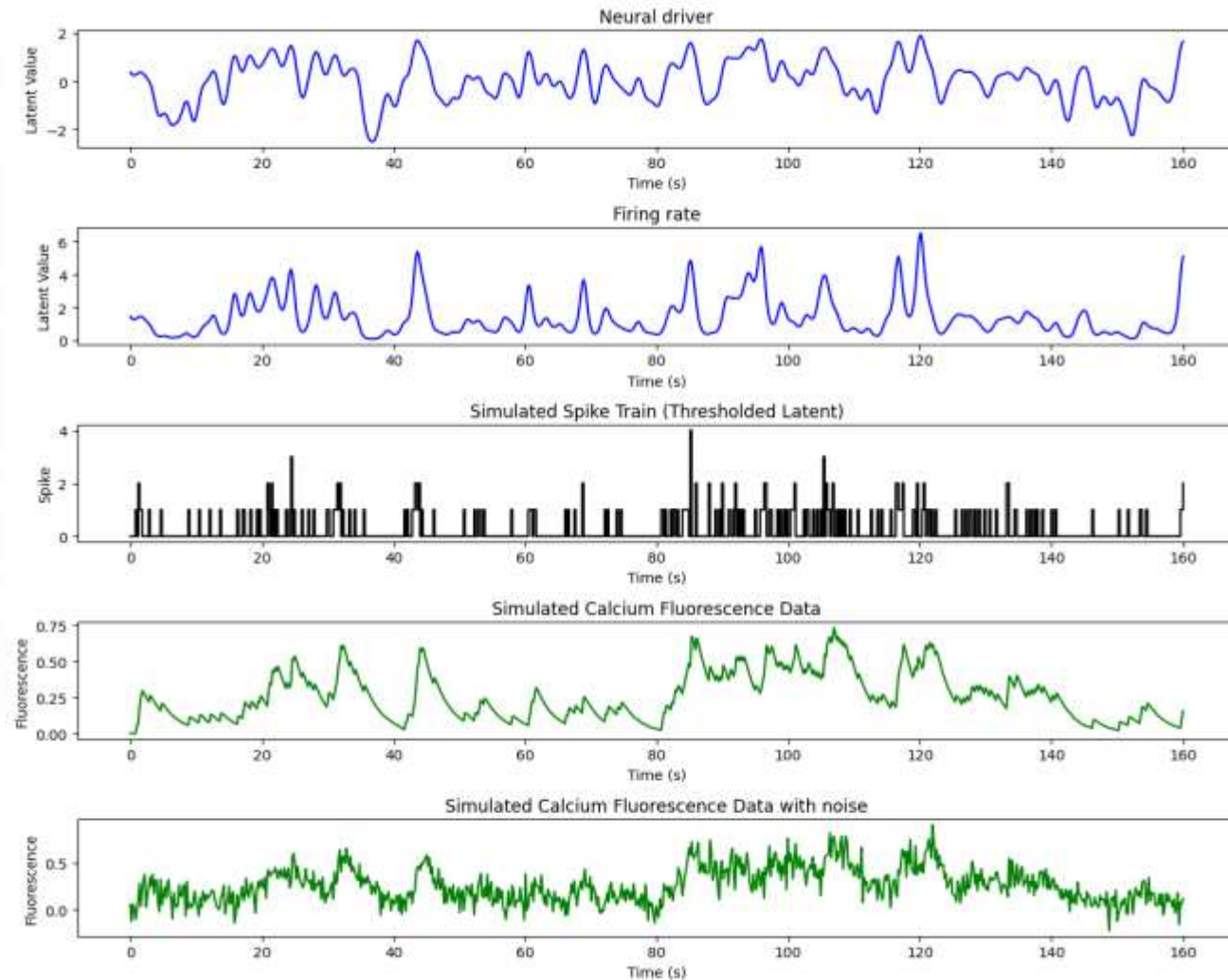


*Simulated data:* recurrent neural dynamics generate multiple trials within a session.

**Fixed connectivity  $W$  within a session**

200 Neurons with 400 trials

100 time points at 5 Hz

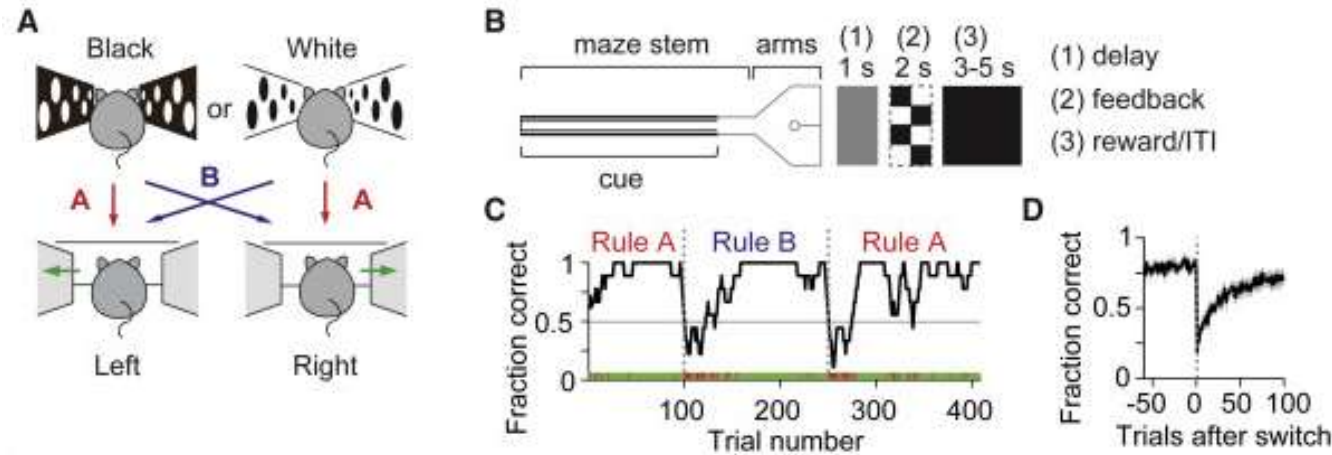




# CaIM: Datasets

## Collected large-scale open-source datasets:

- Tseng. Dataset: Contains calcium activity from 6 different cortical areas in mouse posterior cortex.



Model	Subjects	Sessions	Neurons / Units
NEDS	73	74	27,380
POCO (Harvey mice)	4	12	~1.6K
POYO+	256	1,335	>110,000
NeuroPaint (IBL)	20	20	21,568
CaIM	8	286	273,770

Comparison with  
other methods

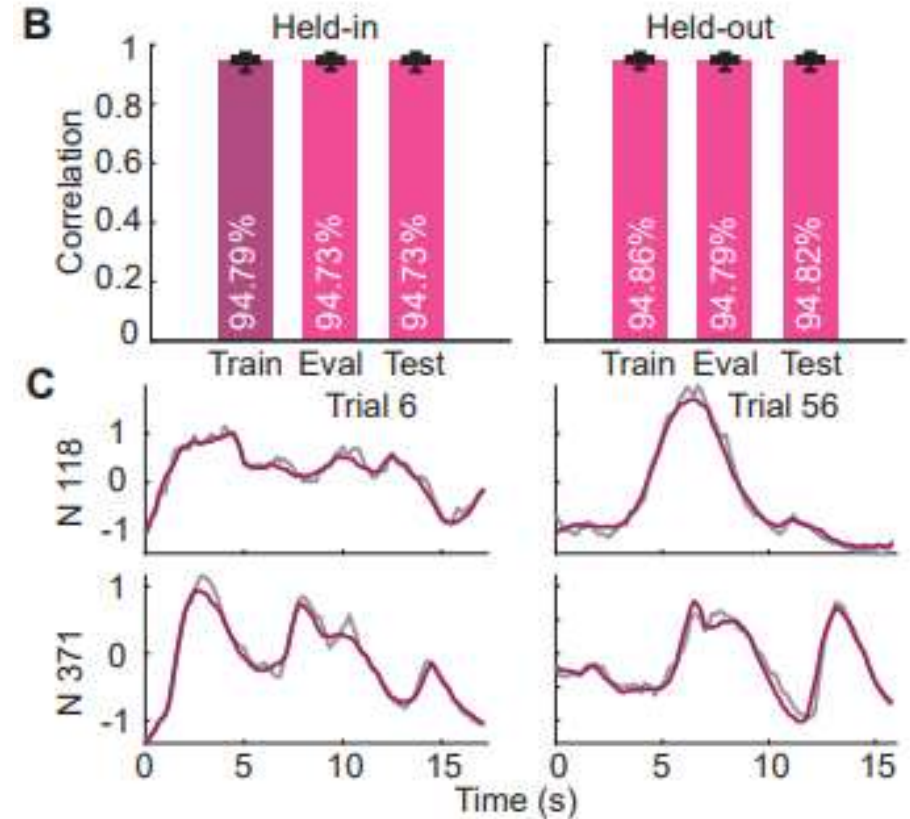
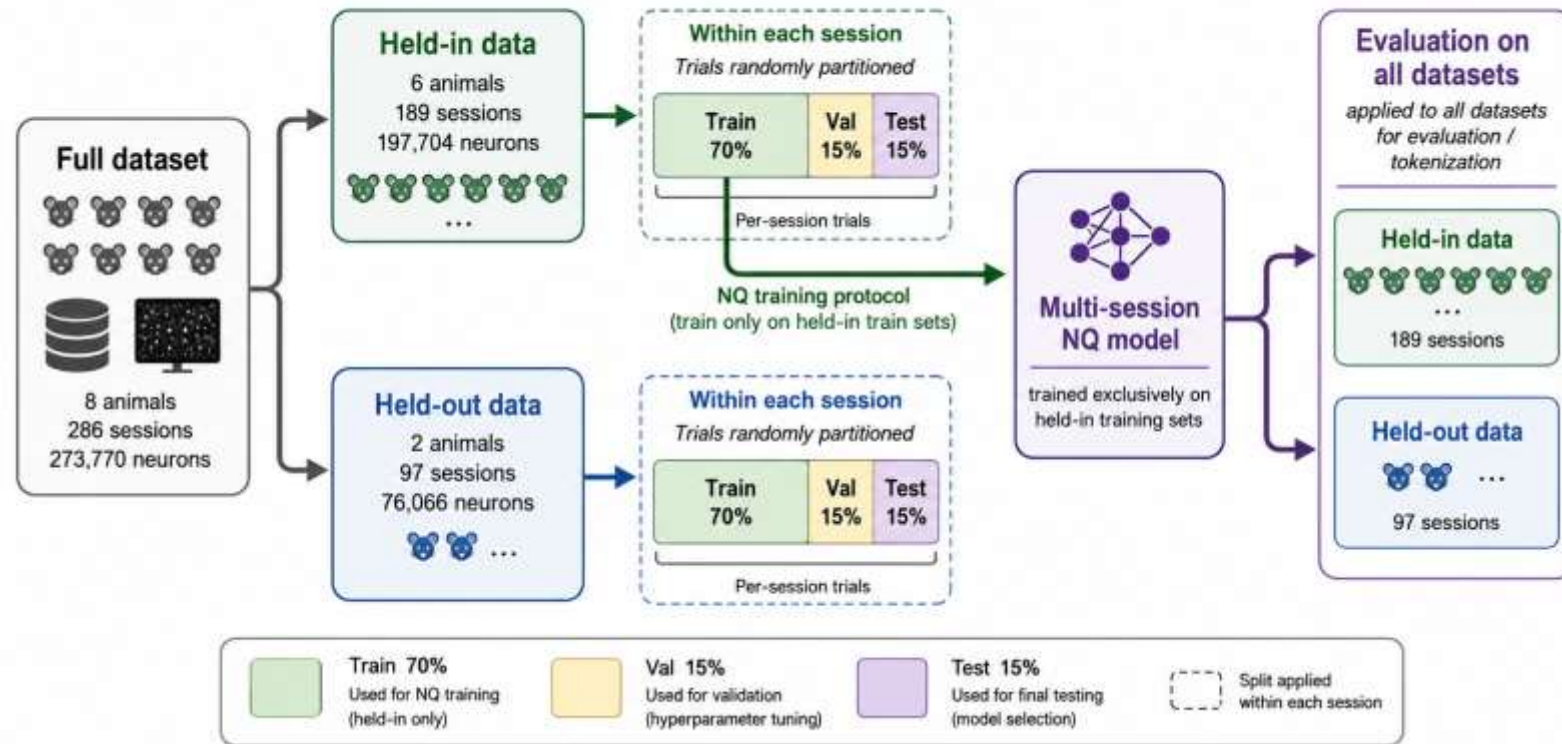


# CaIM: Predictive Performance

## Data splitting and NQ performance:

- Reconstruction quality and generalization are ensured.

### Dataset split for multi-session experiments

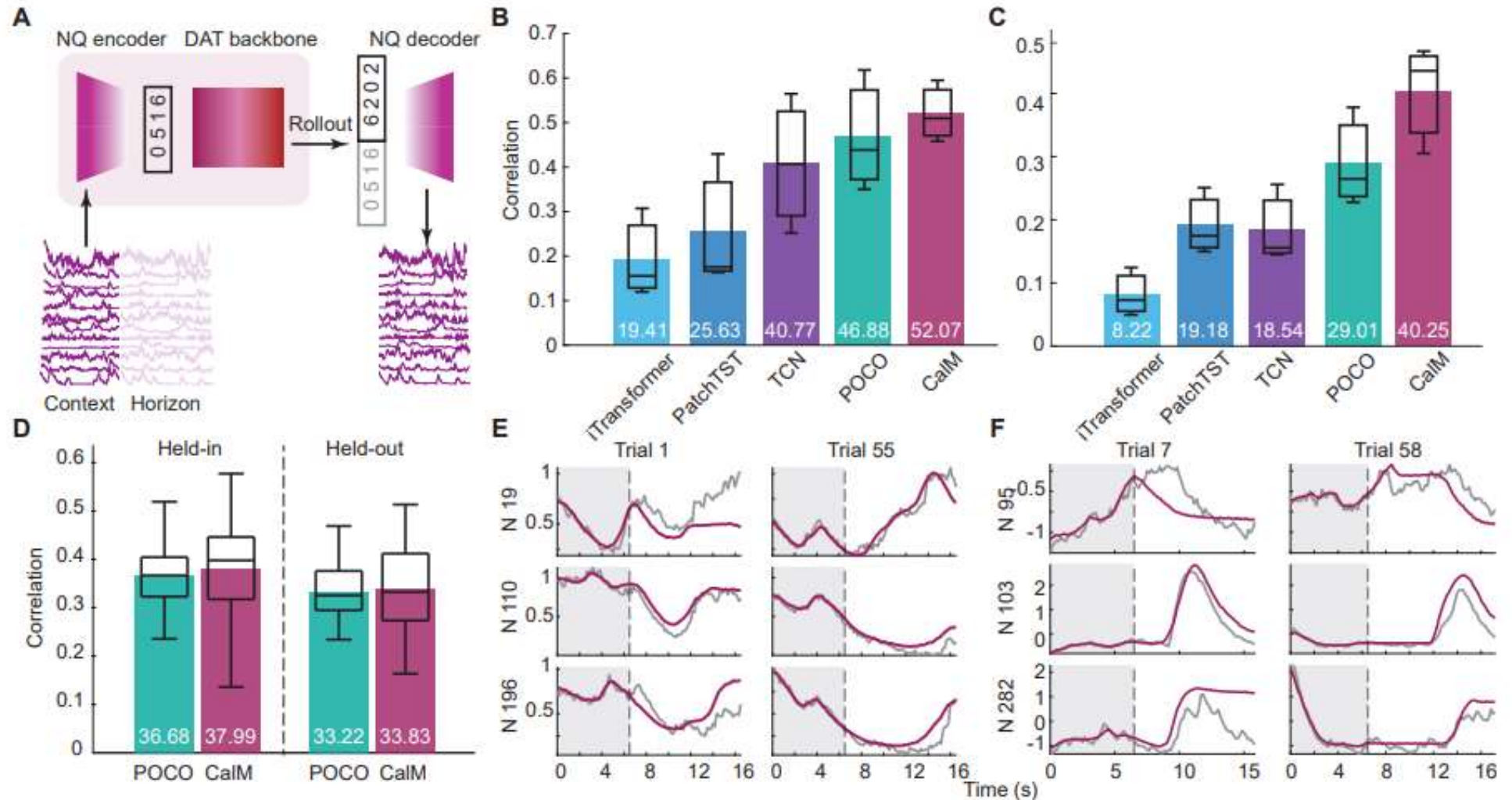




# CaIM: Predictive Performance

## Neural dynamics forecasting:

- Fine-tuning just requires adding extra session and neuron embeddings with backbone frozen.

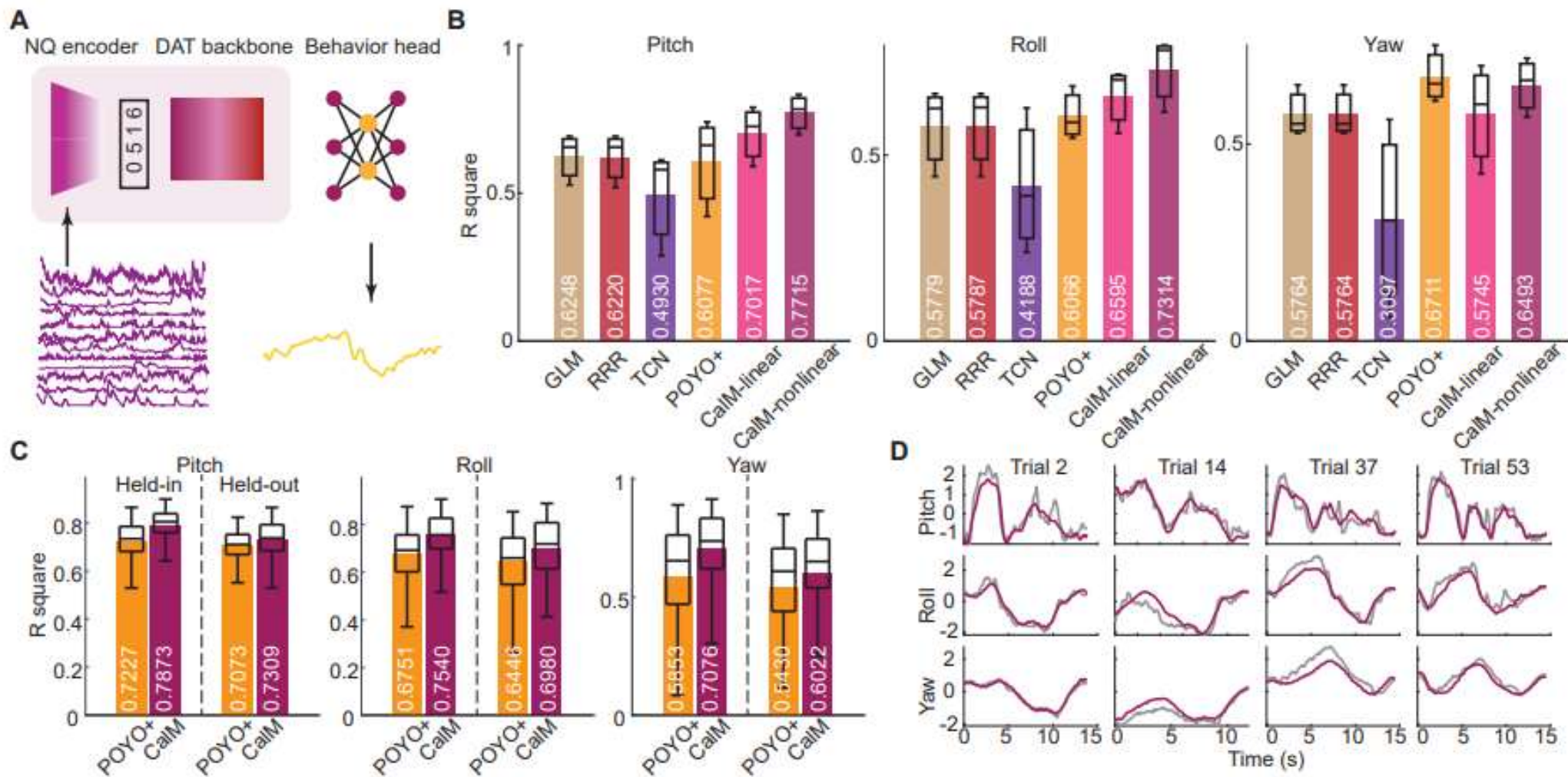




# CaLM: Predictive Performance

## Behavior decoding:

- We freeze the backbone and replace final layer with a behavior decoding head.



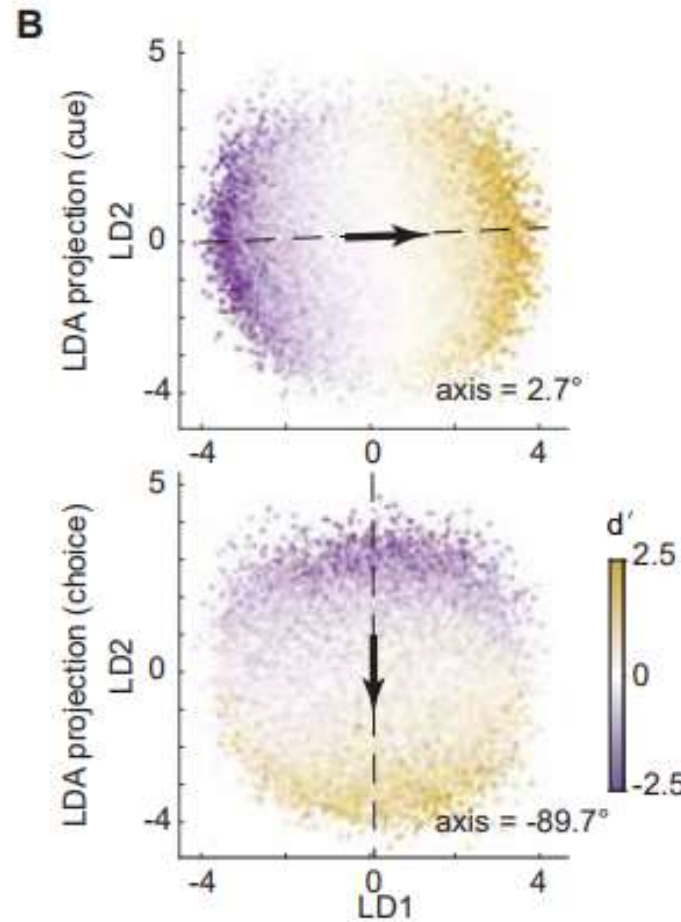
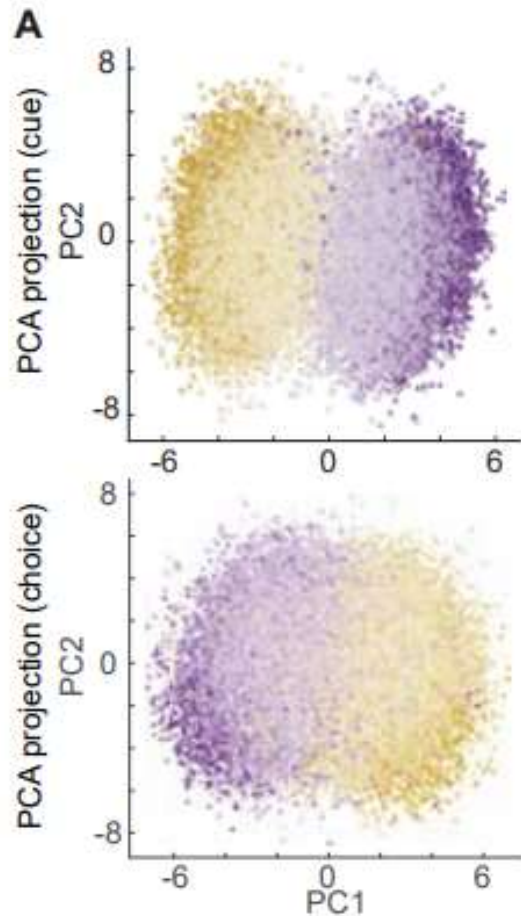
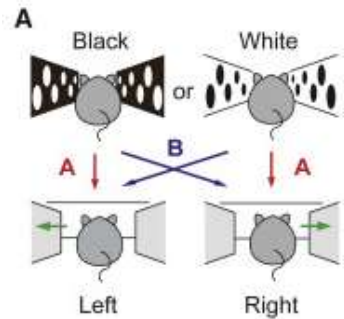


# CaIM: Linear Functional Study

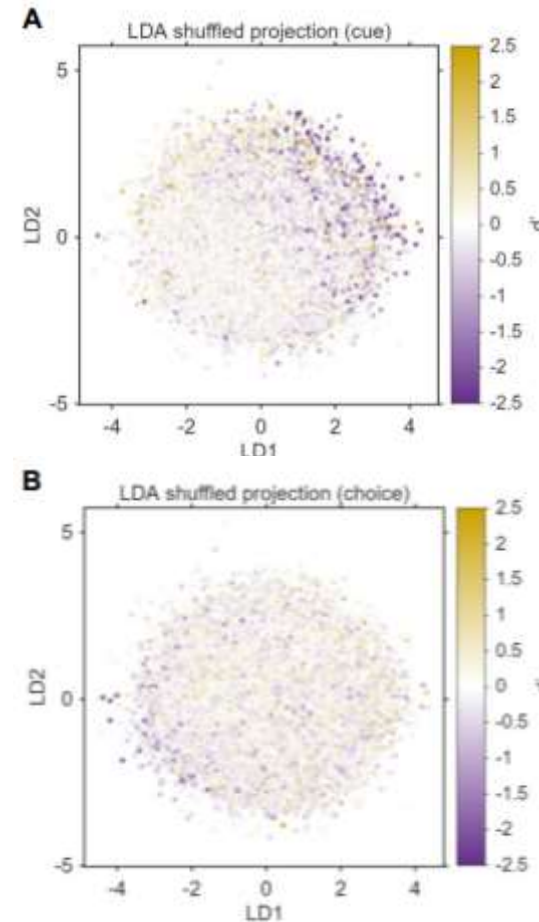
## Interpretability:

- Unsupervised and supervised dimensional reduction demonstrates clear function separation for neurons.

Use  $d'$  as functional labels



Shuffled control



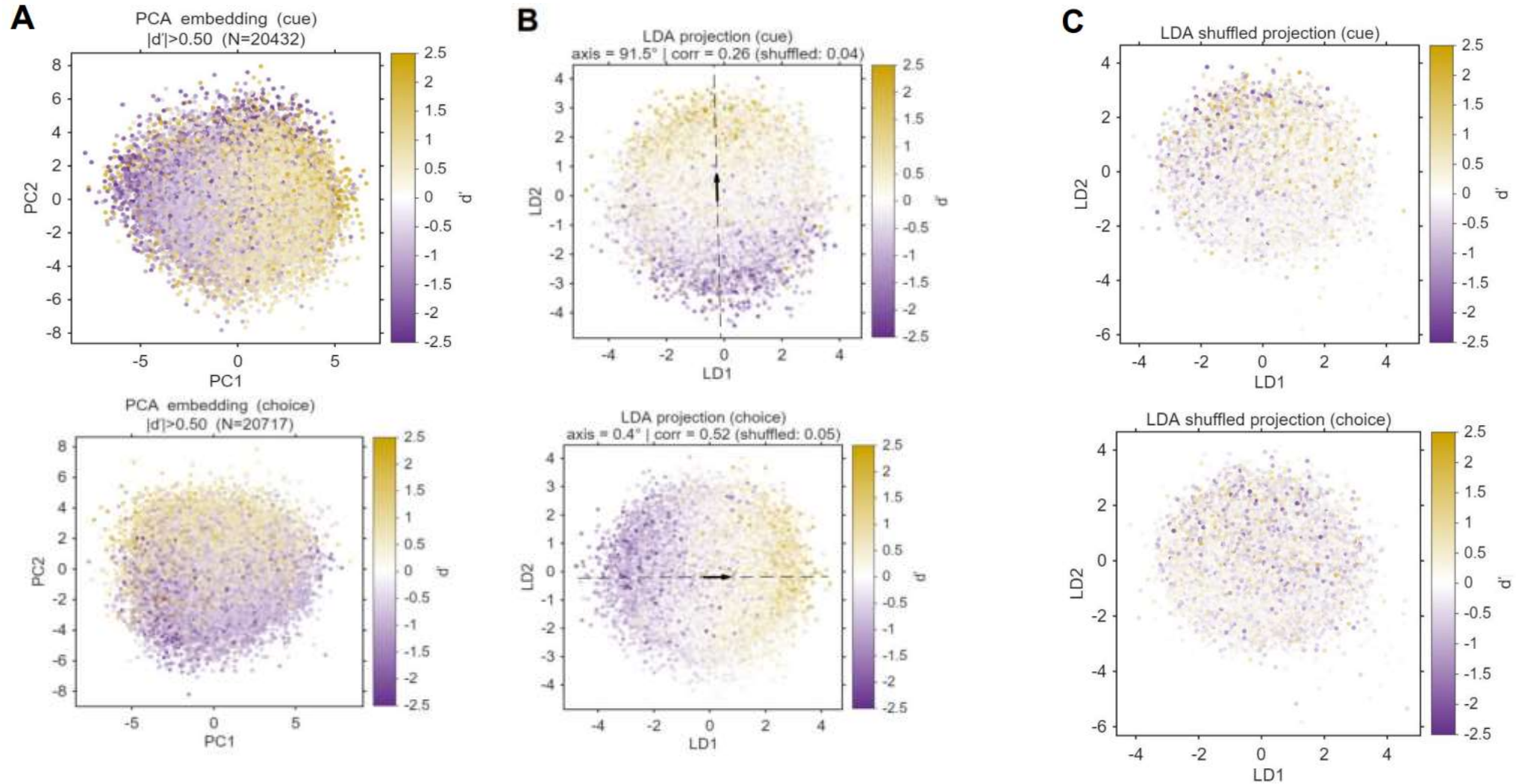
Shared functional coordinate



# CaIM: Linear Functional Study

## Interpretability:

- The same results are revealed in held-out part.



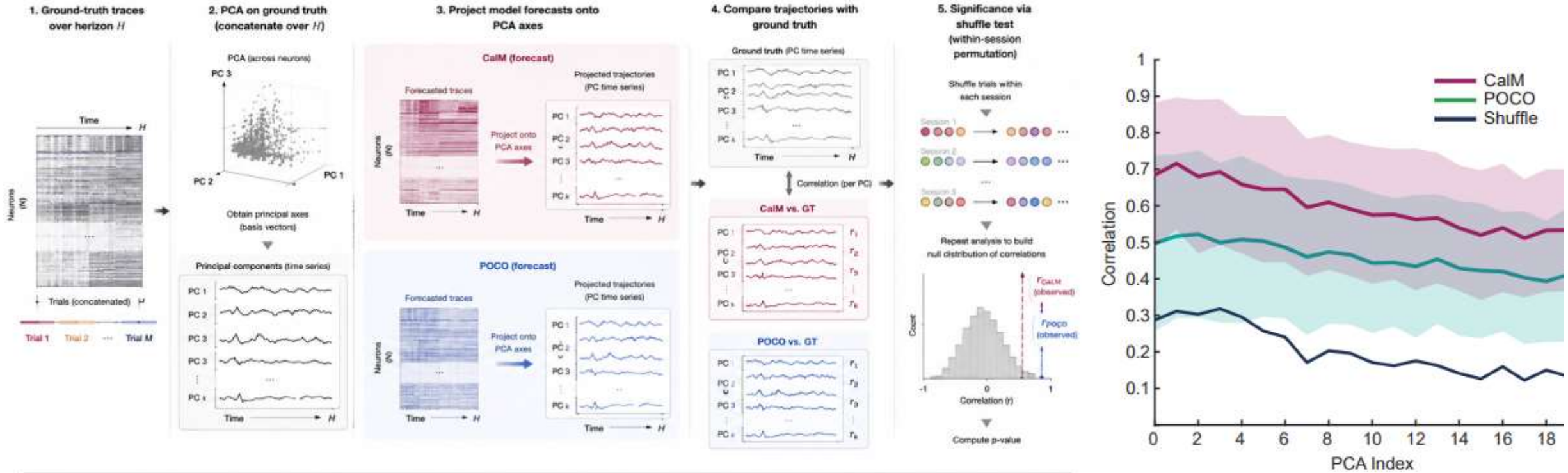


# CaIM: Linear Functional Study

## Interpretability:

- Linear dynamics preservation despite pointwise forecasting error.

### Low-dimensional dynamics analysis



**What does it measure?**

How well the model's low-dimensional trajectories align with the ground-truth dynamics along each principal component.

**Correlation (per PC)**

$$r_k^{CaIM} = \text{corr}(PC_k^{CaIM}, PC_k^{GT}), \quad r_k^{POCO} = \text{corr}(PC_k^{POCO}, PC_k^{GT})$$

Average over  $k$  PCs to summarize performance.

— Ground truth (PC time series)

— CaIM (forecast)

— POCO (forecast)

**Higher correlation & significant p-value**  
 → better preservation of intrinsic dynamics



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- CalM suggests that calcium NFMs should be multi-task capable, transferable and biologically interpretable, but general-purpose calcium NFMs will require broader pretraining, multimodal grounding, and causally validated biological interpretation.



# Conclusion

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## Take-home messages:

### CalM:

- Leverages DAT together with NQ tokenization strategy with autoregressive training.
- Effectively bridges **generative and discriminative tasks**.
- Linear analyses for interpretability demonstrate that the learned representations exhibit clear functional segregation and preserve dynamics.



## I: Broader calcium corpus pretraining:

- General-purpose models require broader pretraining across: brain regions, calcium indicators, sampling rates, laboratories, experimental paradigms, species.
- Current models are still limited by source-domain bias and relatively narrow pretraining distributions.

## Key questions:

- Does performance improve with more sessions, neurons, species, and tasks ?
- Is transfer limited by **model size, data diversity, or source-domain bias** ?
- Can **scaling laws** be observed for calcium neural data ?
- Can **few-shot / zero-shot learning** be implemented ?

The next stage is not only larger models, but larger and more diverse calcium pretraining corpora.



# Future Work

## II: Functional coordinates and multimodal grounding:

- A functional coordinate is a learned representation space where neurons, sessions, or population states can be compared by functional and biological structure.

### Key questions:

- Do embeddings align with known **cell identities or anatomical classes** ?
- Can embeddings predict **neurotransmitter type, connectomic, or transcriptomic similarity** ?
- Can functional coordinates reveal **new biologically meaningful neuron groups**?

The goal is not only to improve prediction, but to align learned neural representations with biological structure.



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**Thanks for the attention !**



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