NEURAL INFORMATION PROCESSING SYSTEMS

浙江大學 ZHEJIANG UNIVERSITY

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Temporal **Co**nditioning **S**piking **L**atent **V**ariable **M**odels of the Neural Response to Natural Visual Scenes

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Author: Project link:

Background

Computation modeling of sensory circuits

- ➢ Hypotheses, in-silico validation, neural information processing mechanisms …
- ➢ Building AI algorithms (CNNs, Attention …)
- ➢ Brain-machine interface, neuroprosthetics …

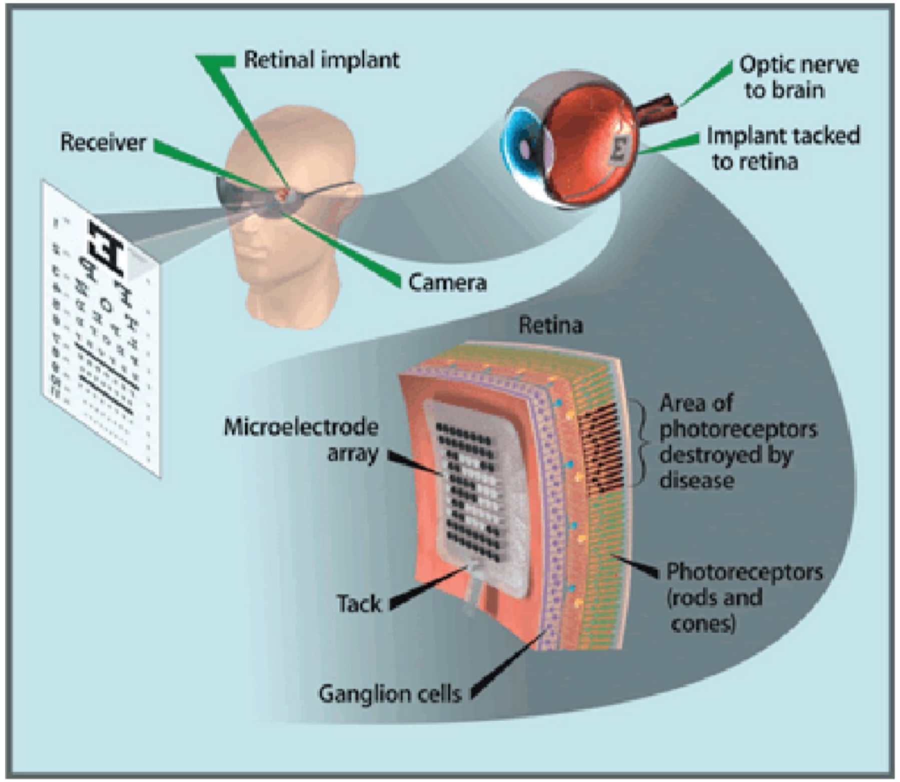


Image source: Jacob Granley 2022

① Yamins, Daniel LK, and James J. DiCarlo. *Nature Neuroscience*, 2016.
② Doerig, Adrien, et al. *Nature Reviews Neuroscience*, 2023.
③ Turner, Maxwell H., et al. *Nature Neuroscience*, 2019.

Background

Problem to solve: A computational model for the natural stimuli-neural response mapping

Challenge: these neural circuits involve numerous complex nonlinear processes.

Solution: Artificial neural networks

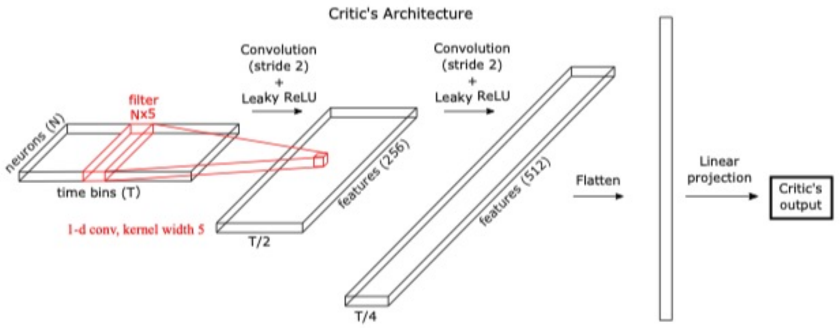


Image source: Manuel Molano-Mazon, 2018

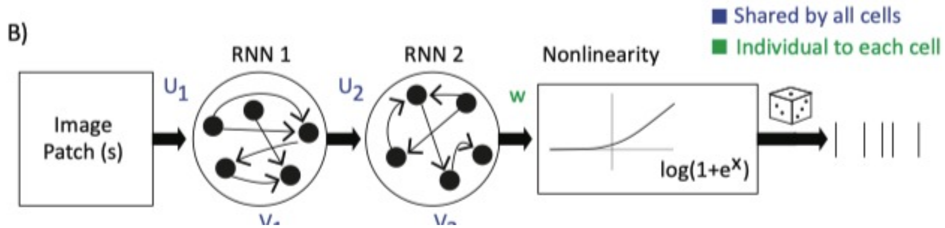


Image source: E. Batty, 2017

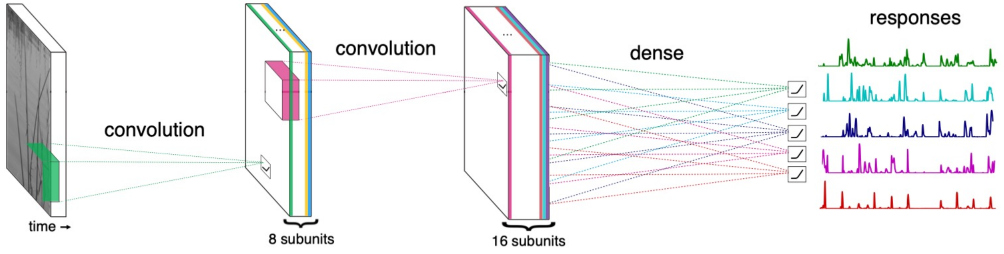


Image source: L. McIntosh, 2016

Motivation

Limit 1: Lossy Target

Most of the existing works focus on simulating the firing rates directly.

Firing rates *only characterize some aspects* of the original spike train, as a trial-averaged spike statistic.

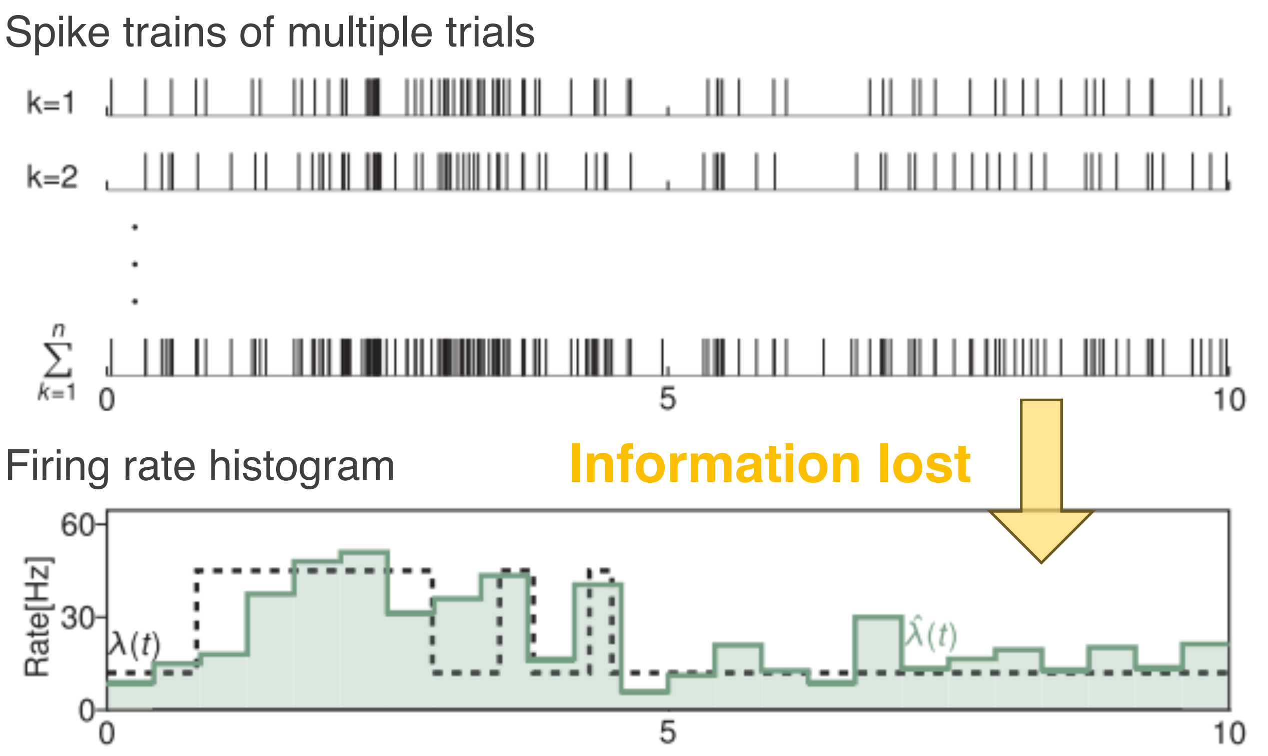


Image source: Rimjhim Tomar, 2019

① Gerstner, Wulfram, et al. PNAS, 1997
② Gerstner, Wulfram, et al. 2014.

Motivation

Limit 2: Unnatural Paradigm

Pre-defined fixed-length temporal filters:

- Bio-unrealistic
- Introducing more hyper-params
- Inflexible

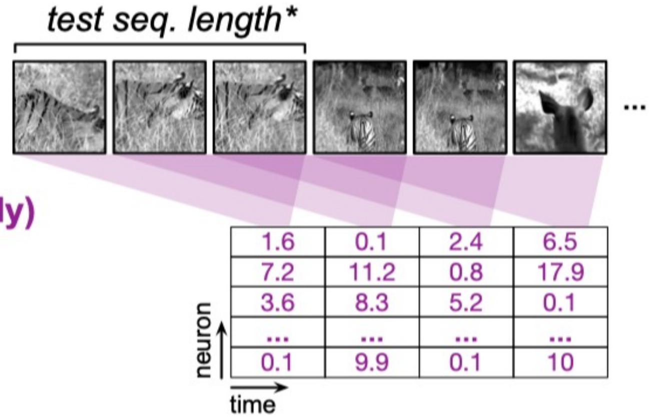
👇 Natural paradigm

long stimuli sequences
↓
response sequence

test seq. length: flexible, can be any length*

👇 Unnatural paradigm

long stimuli sequence
↓ split
short stimuli sequences
↓ **predict (separately)**
single step firing rates
↓ concat
firing rate sequence



test seq. length: fixed, pre-difined at the model learning phase*

Methodology: Problem formulation

Problem:

Modeling neural response to natural stimuli (visual stimuli in this work)

Formulation:

A sequence of visual stimuli: $\mathbf{x} = (\mathbf{x}_t)_{t=1\cdots T}, \mathbf{x}_t \in \mathbb{R}^{\dim[\mathbf{x}_t]}$

Neural poputation sequence (as our model's target): $\mathbf{y} = (\mathbf{y}_t) \in \{0,1\}^{T\times\dim[\mathbf{y}_t]}$, $\dim[\mathbf{y}_t]$ = number of RGCs

Latent neural codes, latent neural factors: $\mathbf{z} = (\mathbf{z}_t)$

At time *t:*

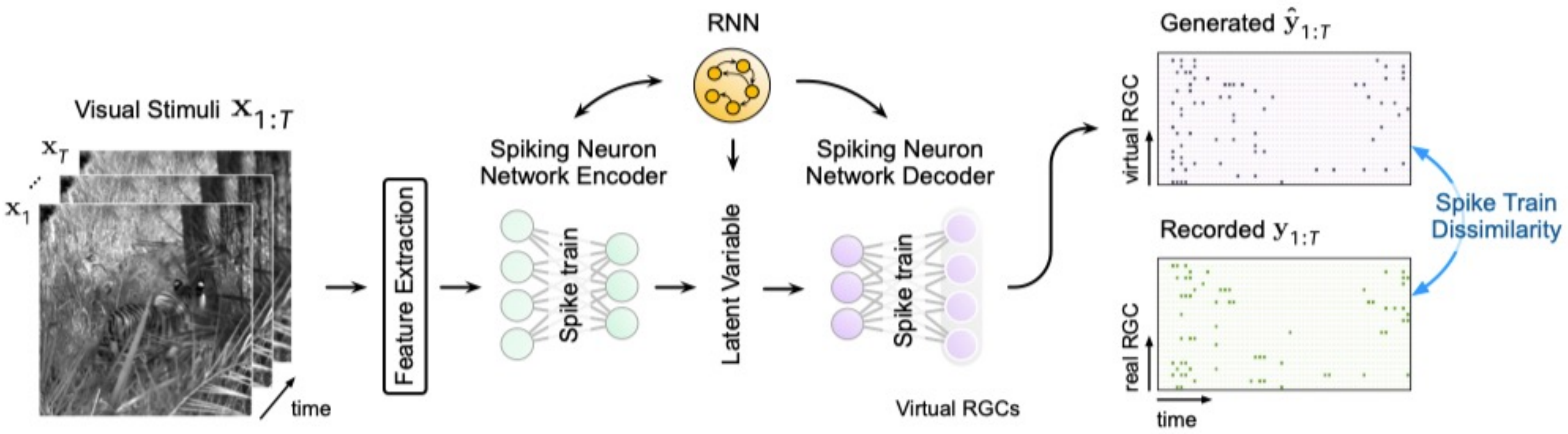
$$\mathbf{x}_t \xrightarrow{\text{Compressive mapping}} \mathbf{z}_t \xrightarrow{\text{Predictive mapping}} \mathbf{y}_t$$

Visual stimuli — Latent neural codes — Neural response

What we want to predict

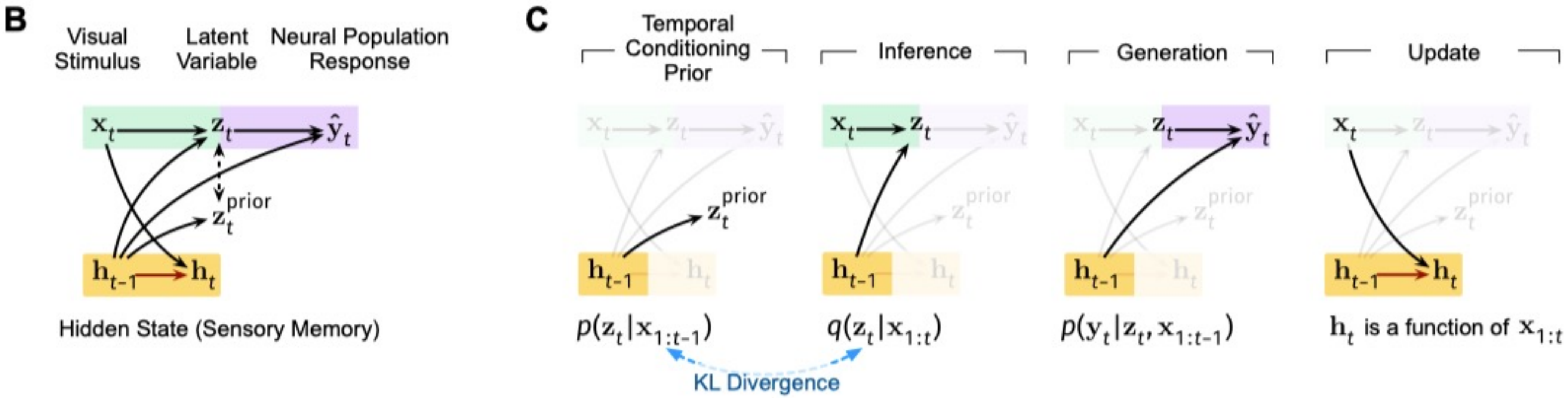
① Chalk, Matthew, Olivier Marre, and Gašper Tkačik. PNAS, 2018.
② Alemi, Alexander A., et al. ICLR, 2017.

To Tackle Limit 1 (lossy target)



① Akbarian, Amir, et al. Nature Communications, 2021.
② Gregor, Karol, et al. ICML, 2015.

To Tackle Limit 2 (unnatural paradigm)



① Chung, Junyoung, et al. NeurIPS, 2015.
② Whittington, James CR, et al. Cell, 2020.

Experimental Results 1

TeCoS-LVM Models Accurately Fit Real Spike Activities and Statistics

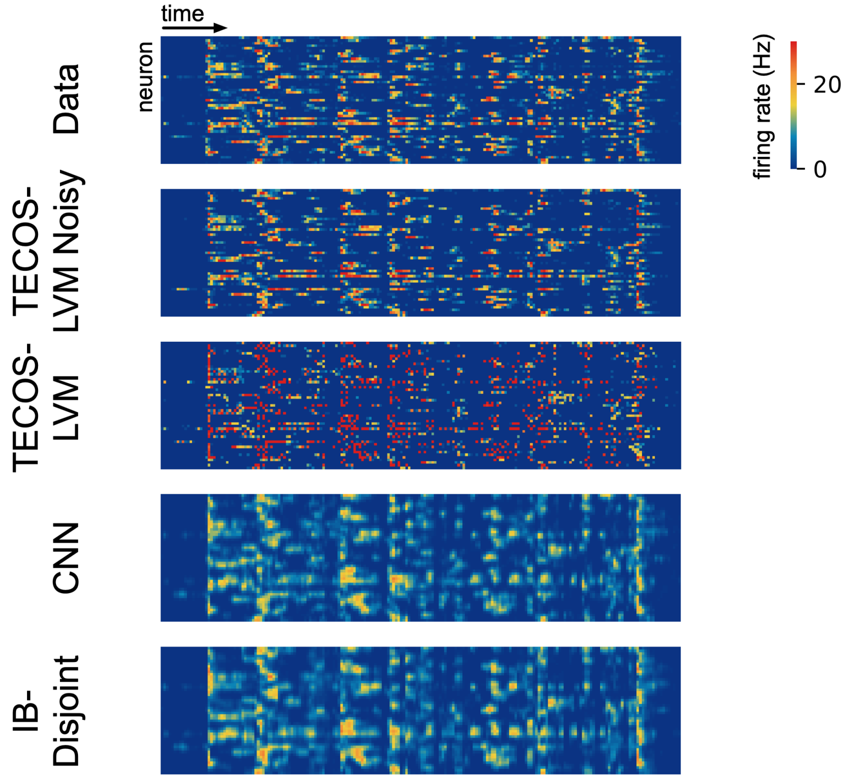


Figure 1. Firing rate prediction visualizations.

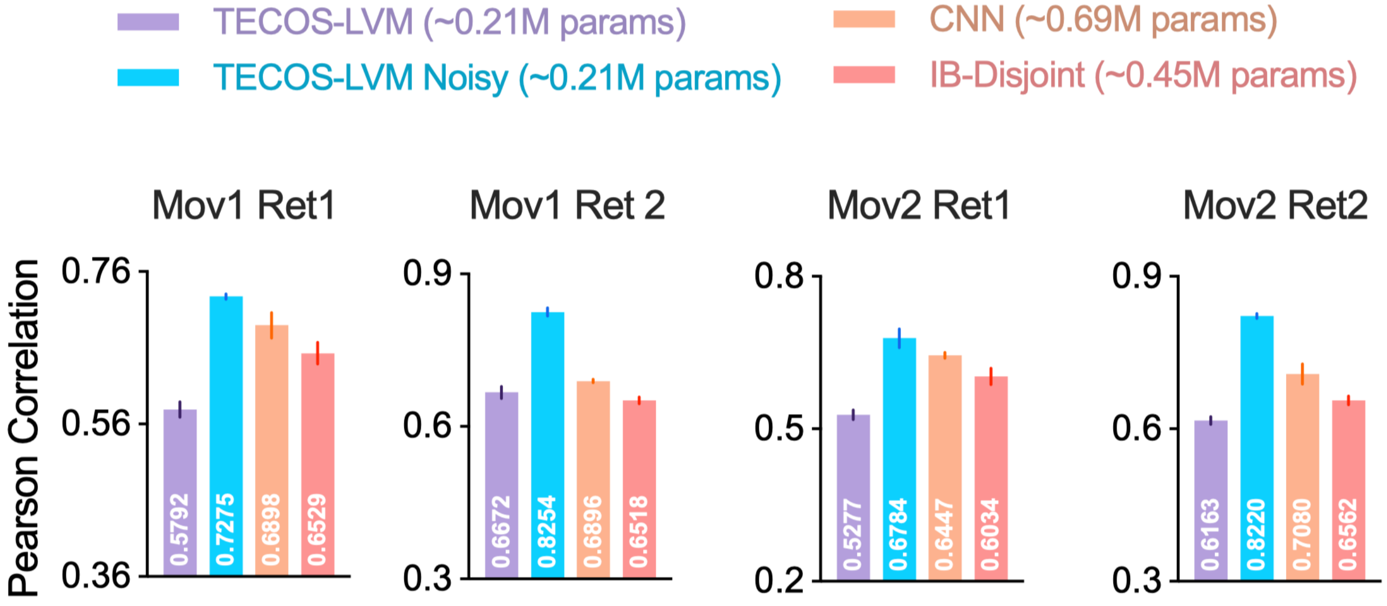


Figure 2. Firing rate prediction CC score comparison.

Experimental Results 2

TeCoS-LVM Models Accurately Fit Real Spike Activities and Statistics

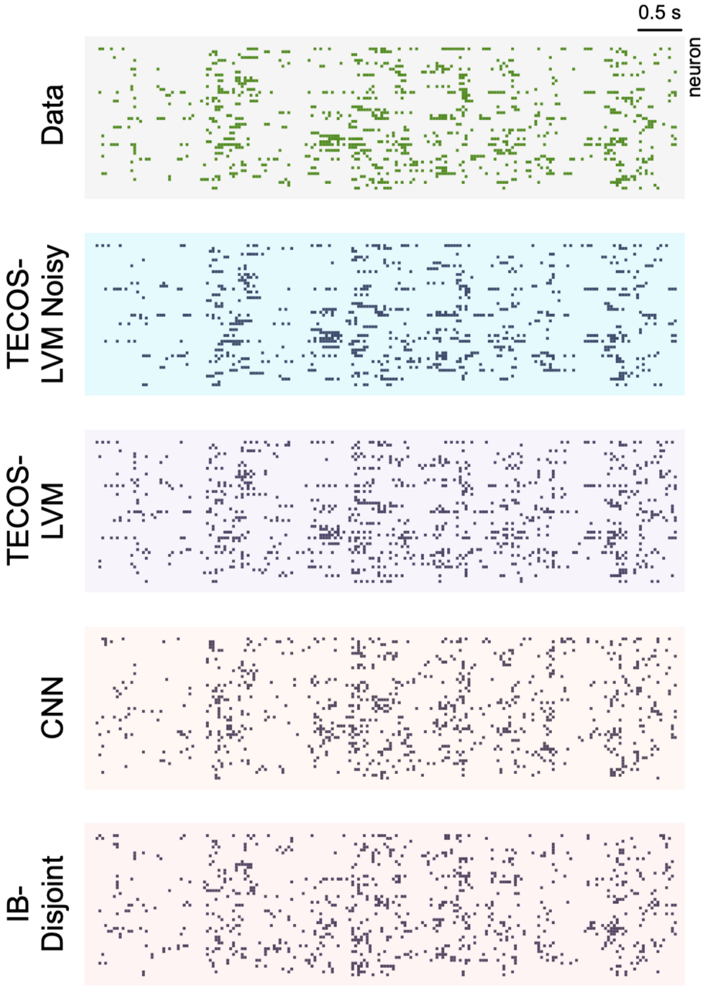


Figure 1. Spike train prediction rasters.

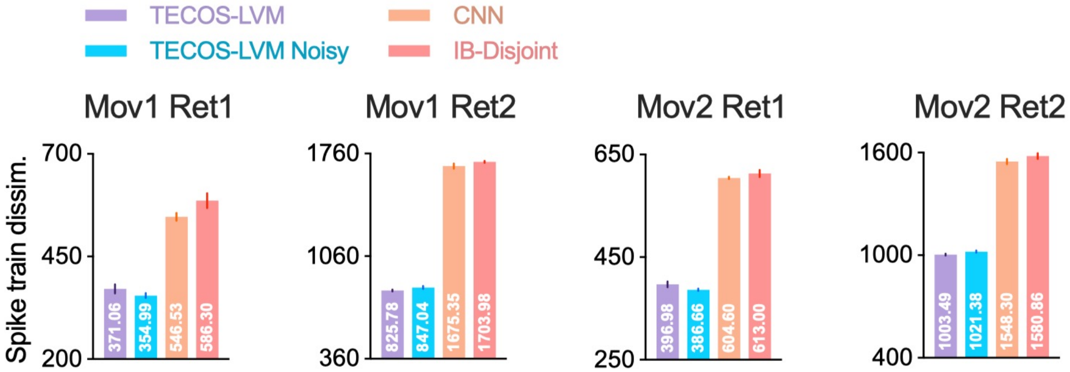


Figure 2. Spike train dissimilarity score comparison.

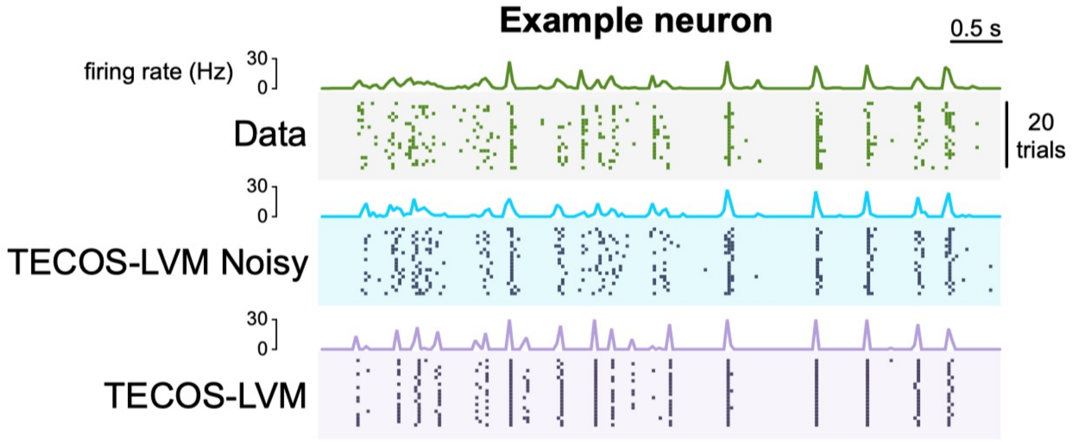


Figure 3. Multi-trial prediction rasters of an example neuron.

Experimental Results 3

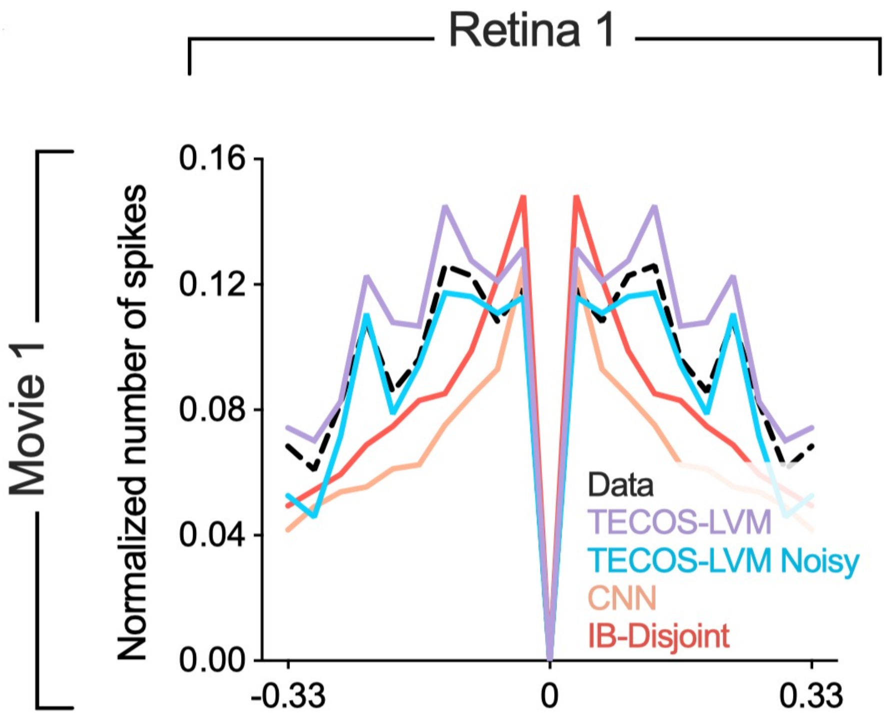


Figure 1. Spike autocorrelograms. Firing rate-targeted approaches loss spike autocorrelation information.

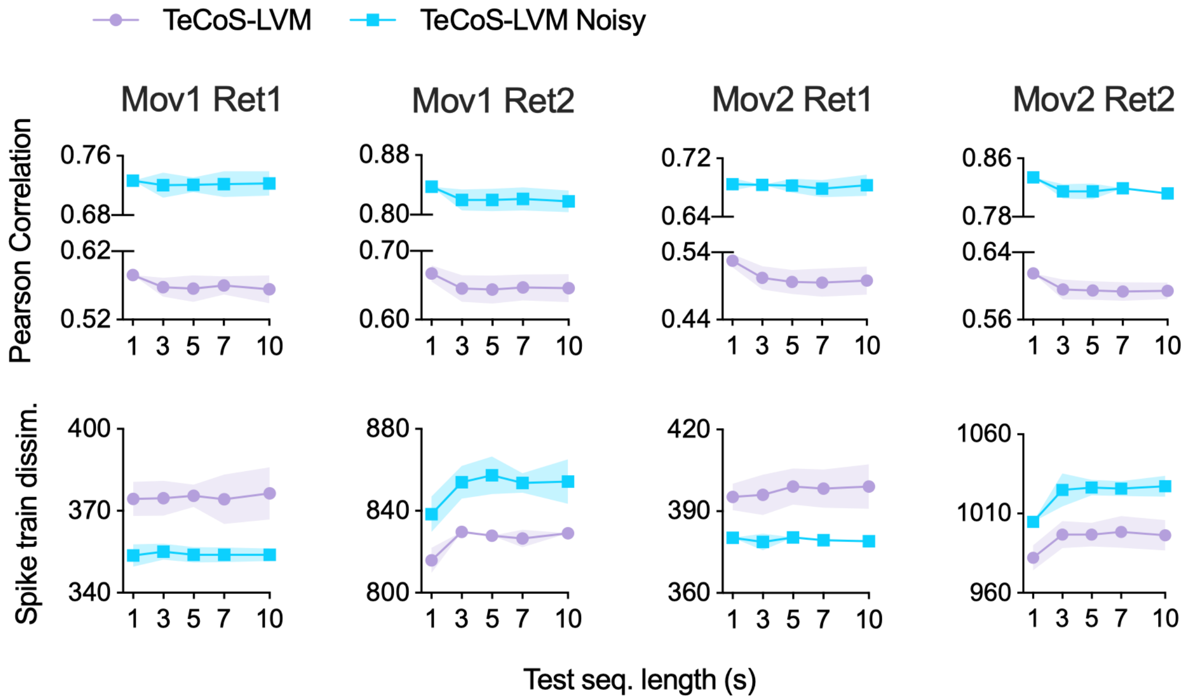
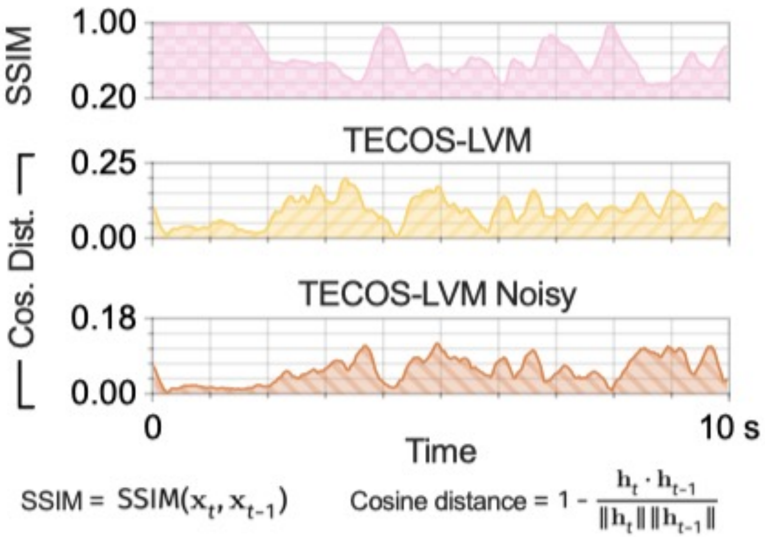
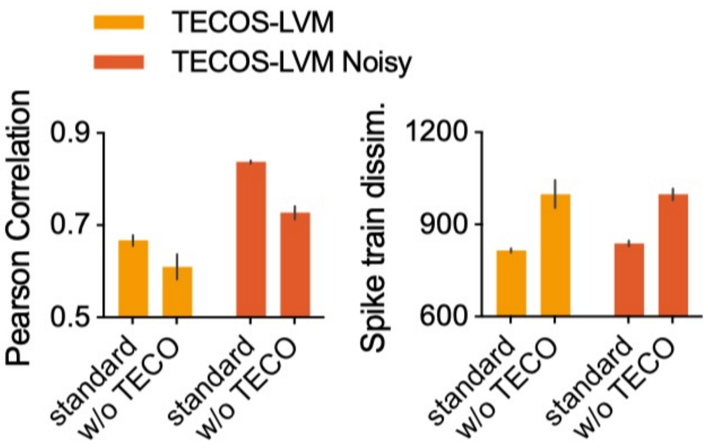


Figure 2. Learned TeCoS-LVM models generalize to longer time scales.

Experimental Results 4





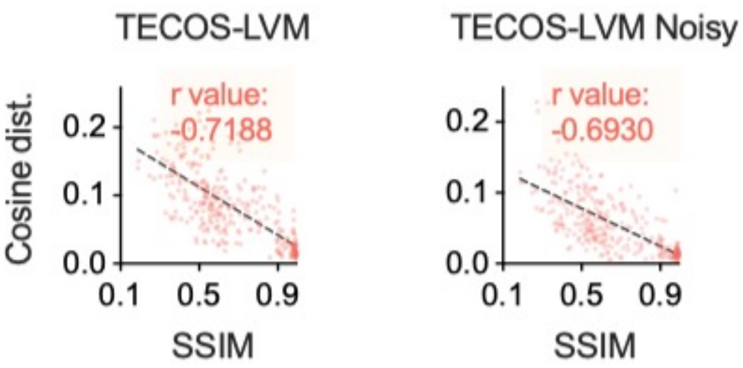
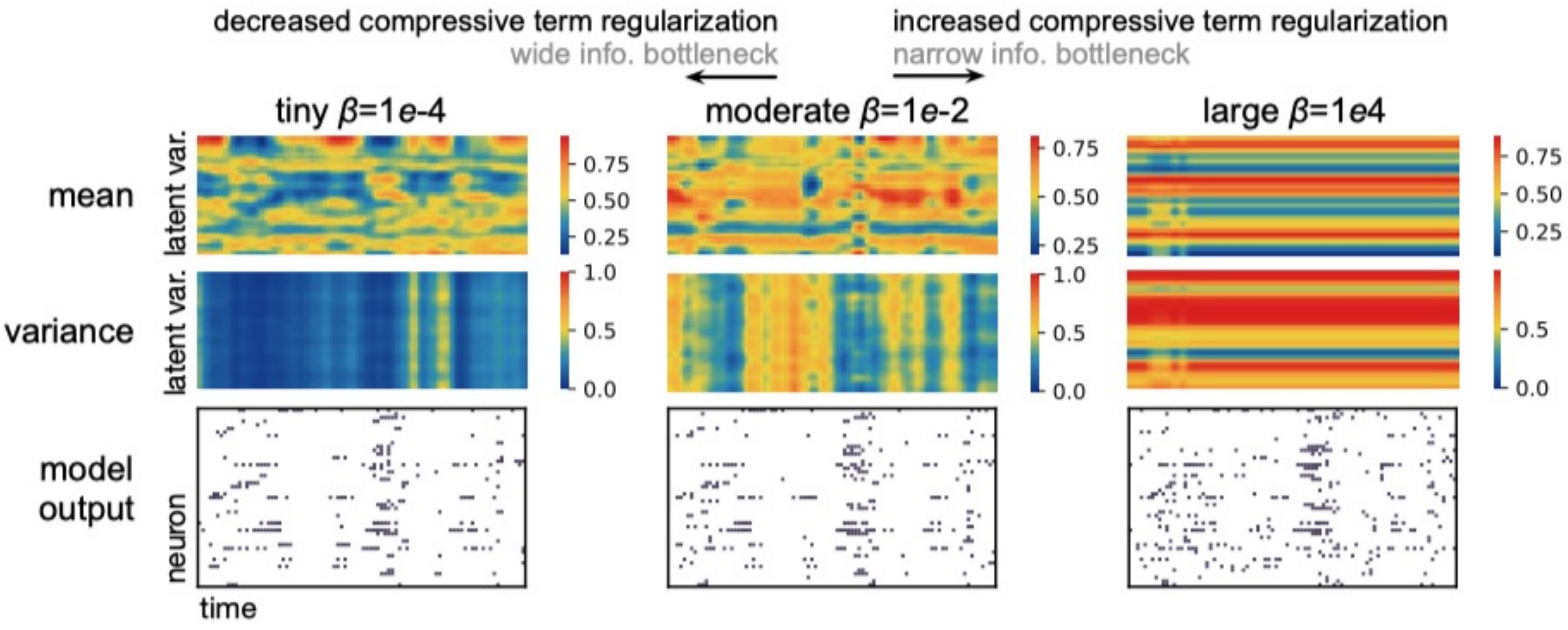


Table 2: Ablation results of using spiking hidden neurons. An ↑ indicates that the higher the value, the better, while a ↓ suggests the opposite. Results reported are averaged across multiple trials.

		Spiking hidden units	CC (↑)	Spike Train Dissim. (↓)	SPIKE (↓)	Victor-Purpura (↓)	van Rossum (↓)
Mov1 Ret1	TeCoS-LVM	Yes	**0.579**	**371.057**	**0.124**	**12.835**	**127.346**
		No	0.254	850.418	0.259	45.117	3416.557
	TeCoS-LVM Noisy	Yes	**0.728**	**354.989**	**0.155**	**14.024**	**238.614**
		No	0.653	370.099	0.167	14.805	291.706
Mov2 Ret2	TeCoS-LVM	Yes	**0.616**	**1003.489**	**0.123**	**22.666**	**574.298**
		No	0.471	1273.267	0.180	35.080	1890.910
	TeCoS-LVM Noisy	Yes	**0.822**	**1021.384**	**0.153**	**28.441**	**1135.805**
		No	0.748	1078.830	0.159	29.249	1144.087

Experimental Results 5



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Thanks for listening

Author Homepage:

Project link (in progress):