Ctrl-TNDM: Decoding feedback-driven movement corrections from motor cortex neurons

Citation for published version:
Kudryashova, N, Perich, MG, Miller, LE & Hennig, MH 2023, 'Ctrl-TNDM: Decoding feedback-driven movement corrections from motor cortex neurons', Computational and Systems Neuroscience (Cosyne) 2023, Montréal, Canada, 9/03/23 - 12/03/23.

Ctrl-TNDM: Decoding feedback-driven movement corrections from motor cortex neurons

Nina Kudryashova[1,*], Matthew Perich[2], Lee Miller[3,4], Matthias Hennig[1]

1. University of Edinburgh, UK; 2. Université de Montréal, Canada; 3. Northwestern Univ., USA; 4. Shirley Ryan AbilityLab, USA; *email: nkudryas@ed.ac.uk

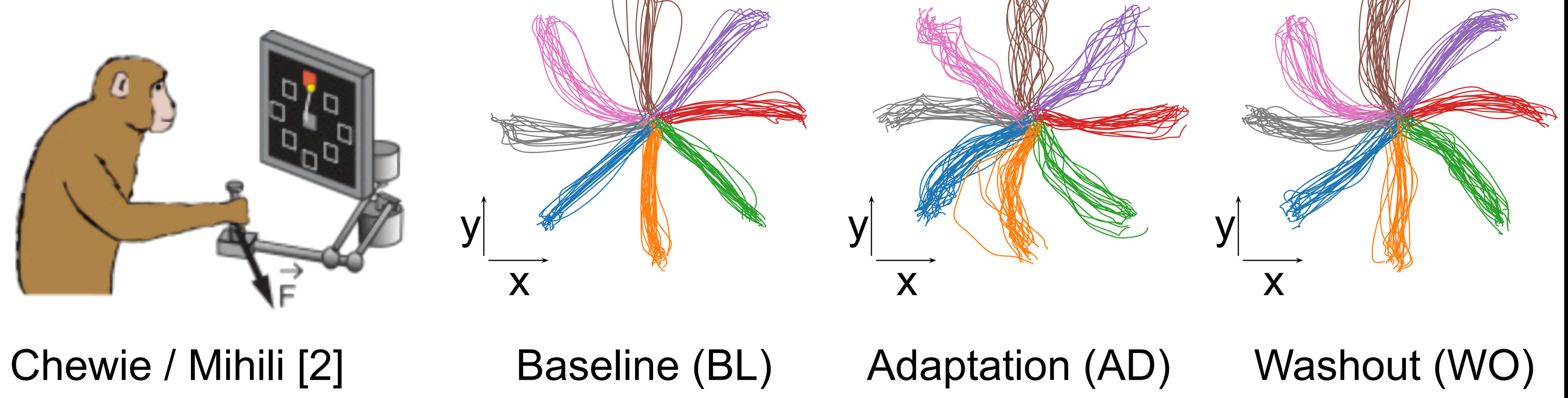
Motivation:

- Manifold hypothesis [1]: a low number of latent dynamical factors explain a large fraction of neural variability;
- Do these factors contain information about movement corrections during the trial?

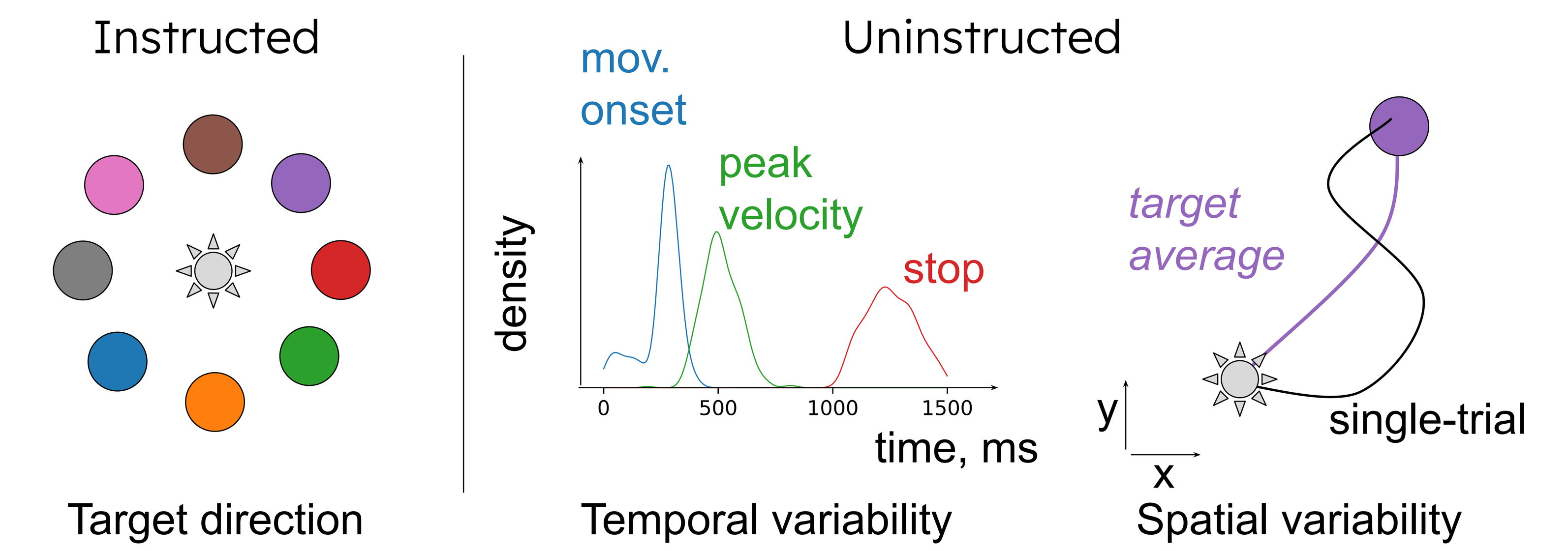
Approach:

- Disentangle sources of variability in behavioral data: instructed vs. **un**instructed
- Find latent dynamics in neural recordings from PMd/M1 of monkeys engaged in a center-out reaching task with perturbations that explains the **un**instructed behavior

A center-out reaching task, force field perturbation



Classic R^2 quantifies the total behavioral variability, which is dominated by the task instruction



Problem: a classic variance explained R^2 is insensitive to uninstructed variability

Example: knowing the correct task instruction allows to score $R^2_{pos} = 97\%, R^2_{vel} = 84\%$

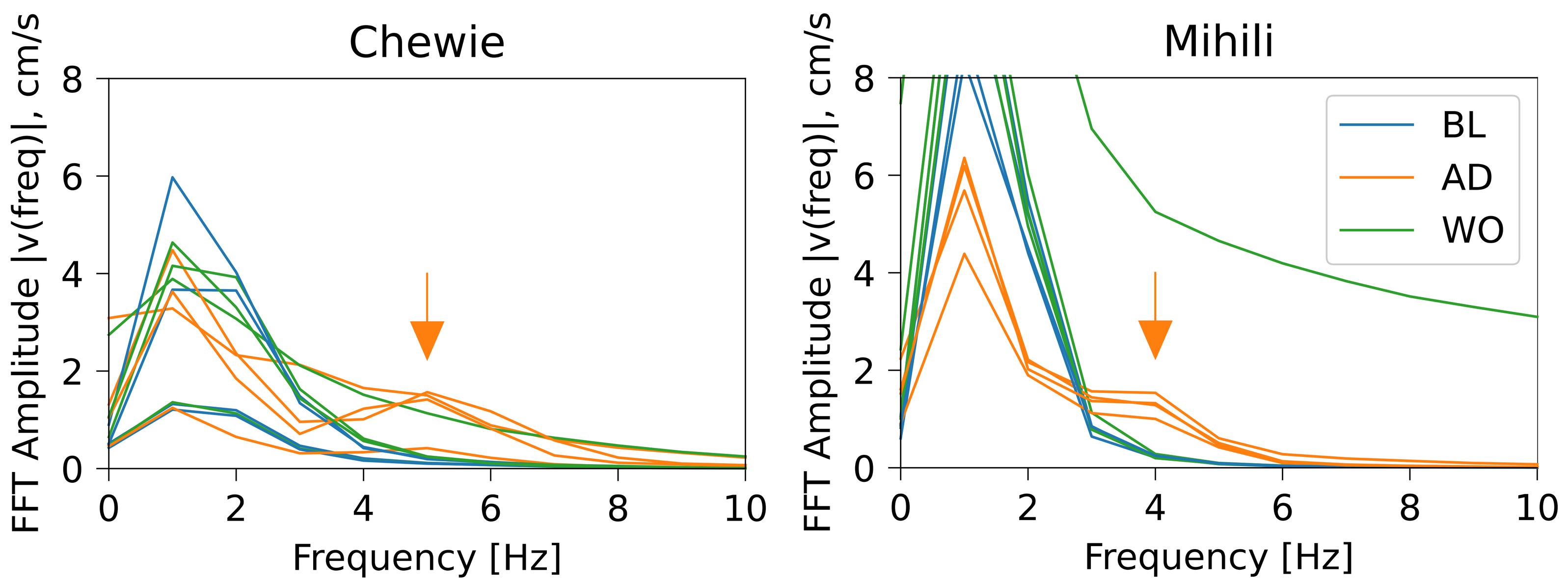
Solution: quantify the **un**instructed **v**ariance **e**xplained R^2_{UIVE}

$$R^2 = \left\langle 1 - \frac{\sum_{nt}(y_{ntb} - f_{ntb})^2}{\sum_{nt}(y_{ntb} - \langle y_{ntb} \rangle_{nt})^2} \right\rangle_b \quad \rightarrow \quad R^2_{UIVE} = \left\langle 1 - \frac{\sum_{n_d tb}(y_{n_d tb} - f_{n_d tb})^2}{\sum_{n_d tb}(y_{n_d tb} - \langle y_{n_d tb} \rangle_{n_d})^2} \right\rangle_d$$

here ***n***, ***t***, ***b***, ***d*** correspond to the trial number, time bin, behavioral component and **target direction**;
* we also treat the **behavior** (e.g. velocity) as a **2D vector**, and include **temporal variability**

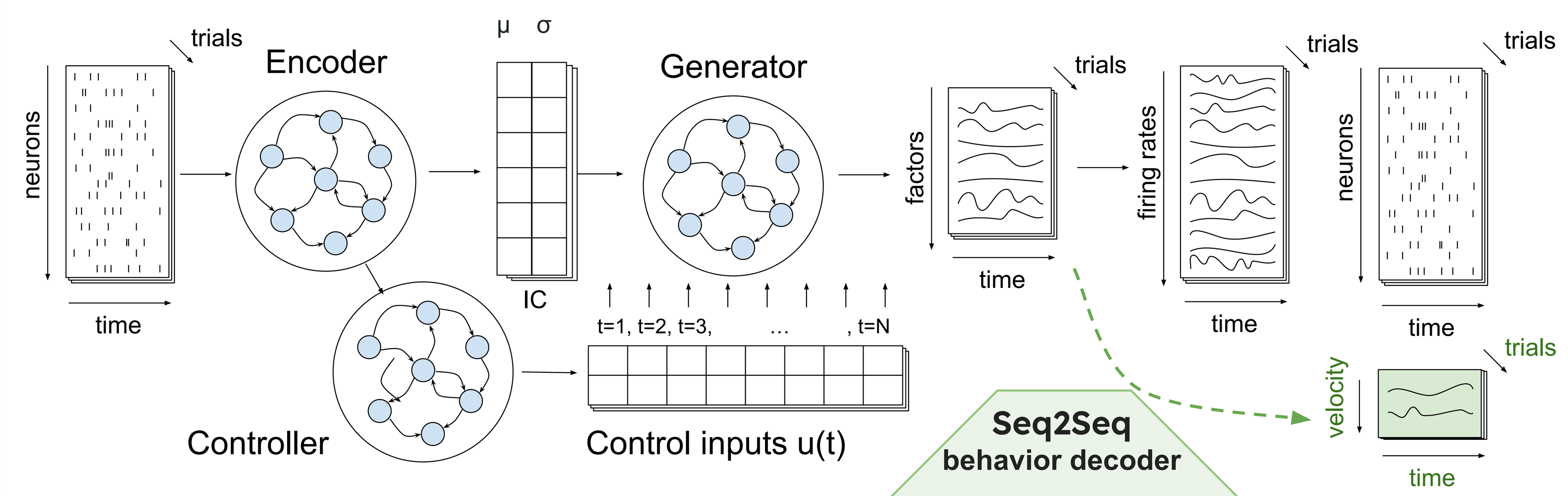
Hand velocity in adaptation trials exhibits ~4-5 Hz oscillations

Hypothesis: oscillations arise from a closed-loop feedback control

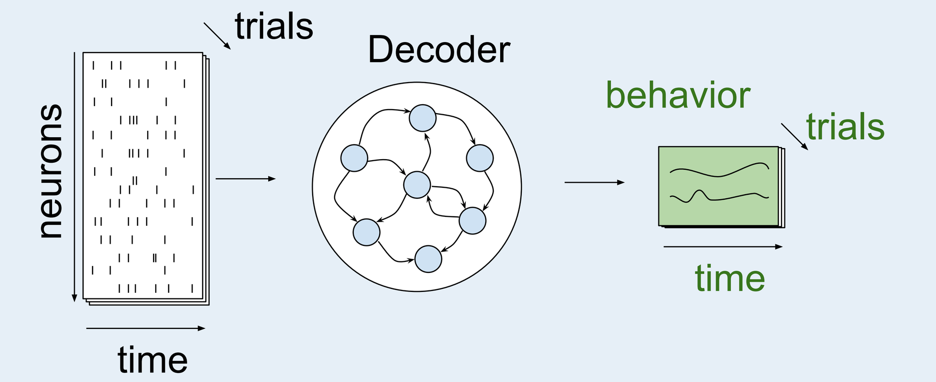


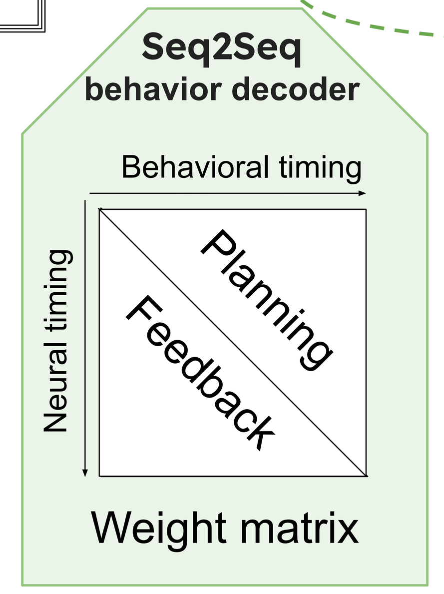
Ctrl-TNDM: controlled targeted neural dynamical model

Ctrl-TNDM: controlled targeted neural dynamical model is an extended LFADS [3] model with a controller that has an additional sequence-to-sequence behavior decoder (as in [4]) from inferred latent factors



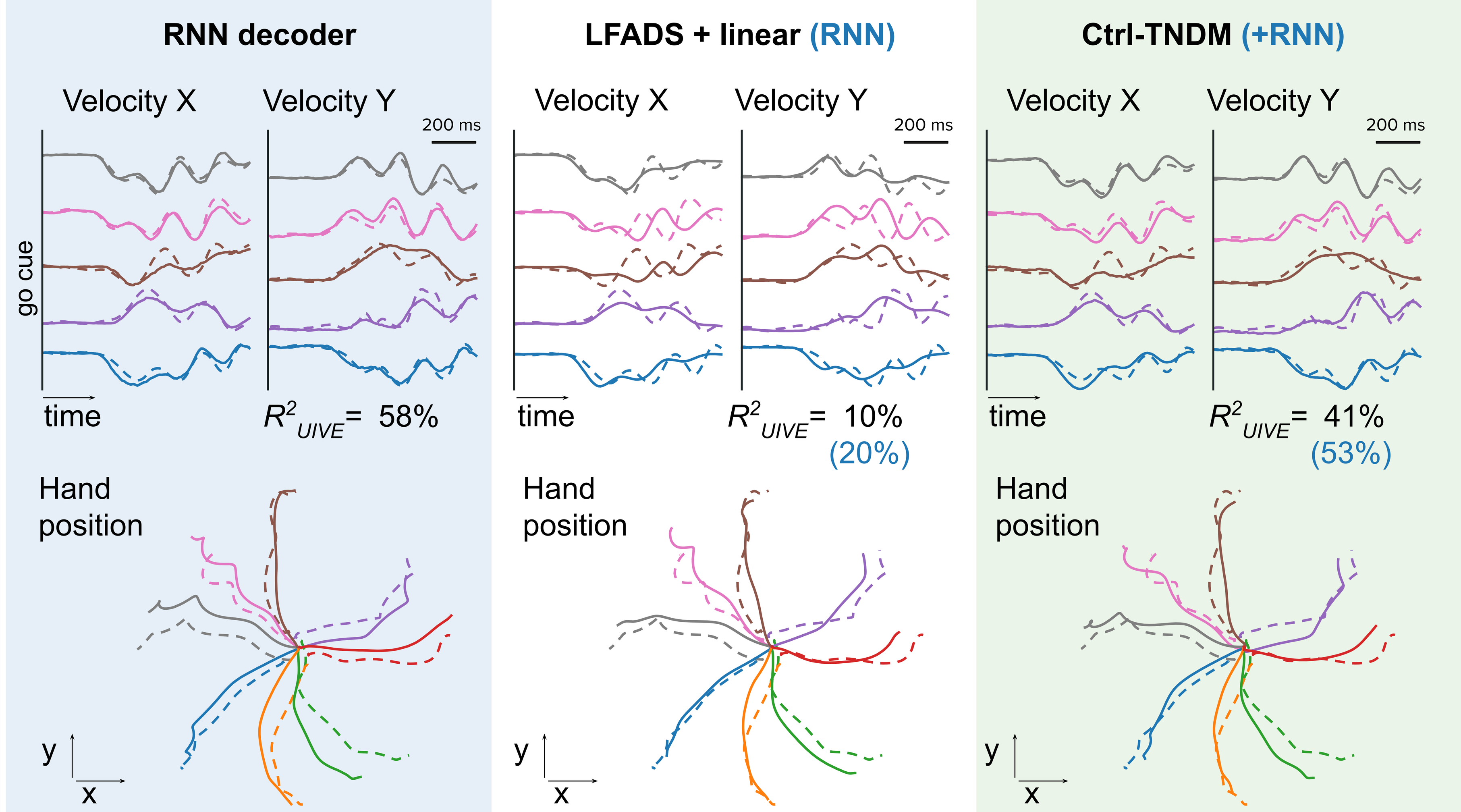
RNN decoder (estimates the best decoding)



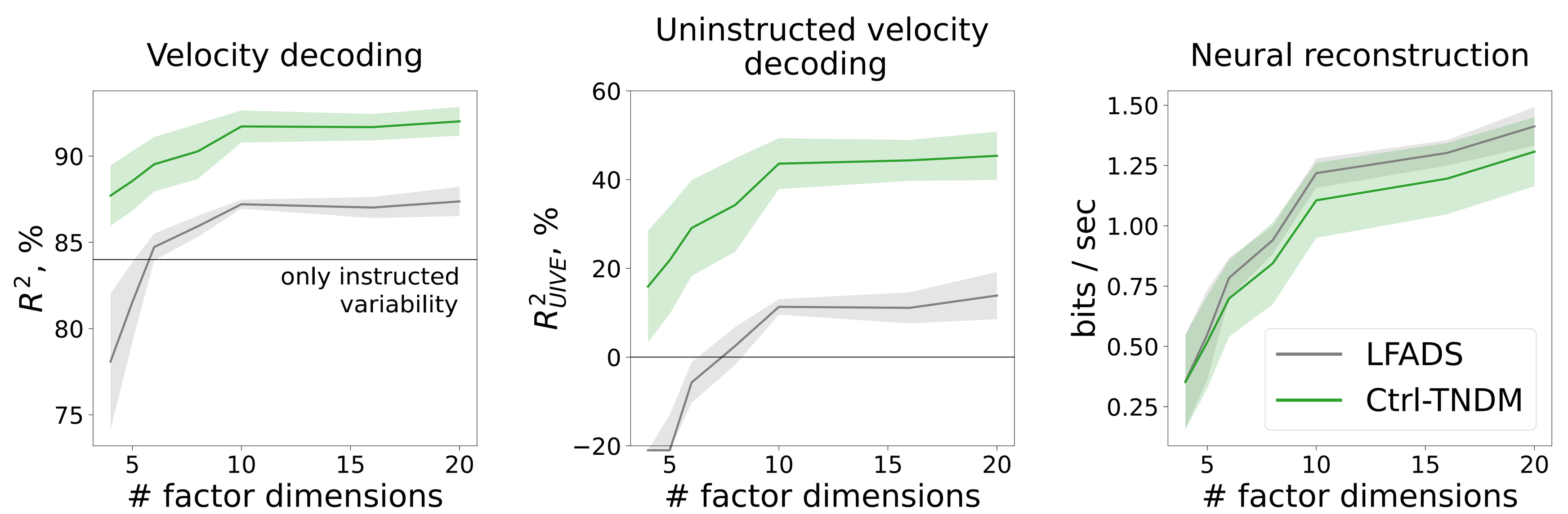


Learned weights reveal the relationship between neural dynamics and behavior (e.g. a diagonal matrix would mean perfect synchronization)

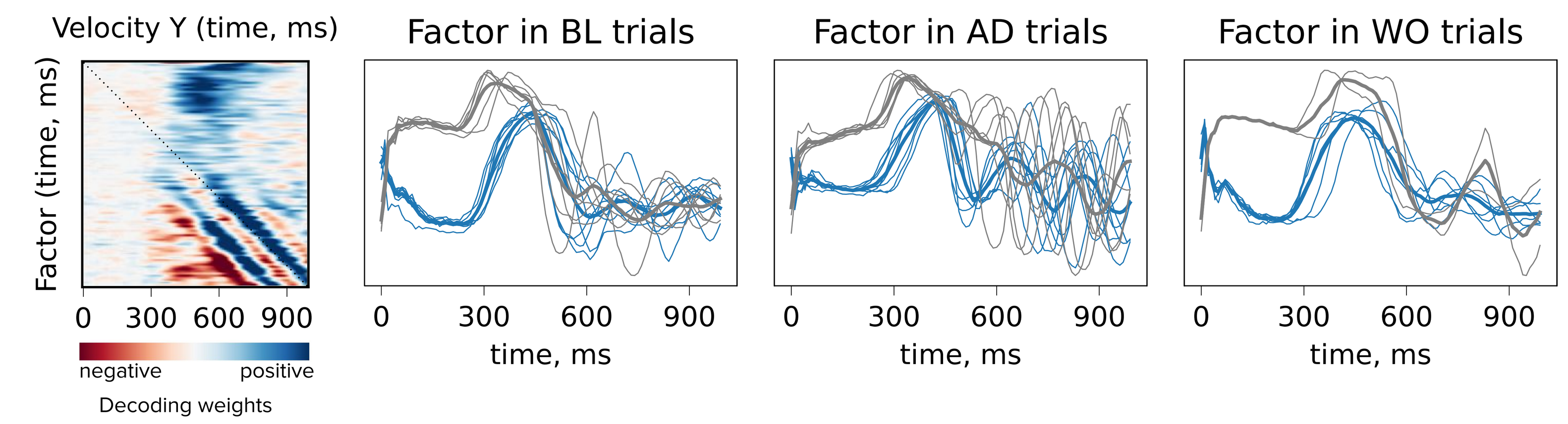
Without supervision, LFADS fails to capture the phase of the oscillations



Ctrl-TNDM even with 4 factors outperforms any LFADS model

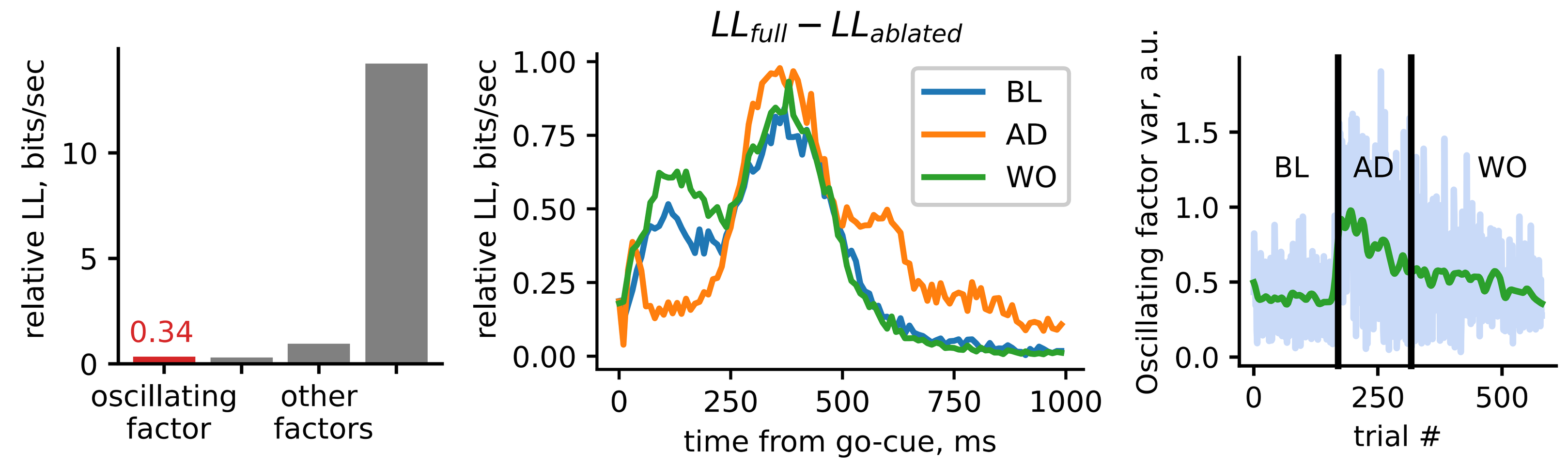


Ctrl-TNDM discovers oscillating factors, which oscillate more in AD

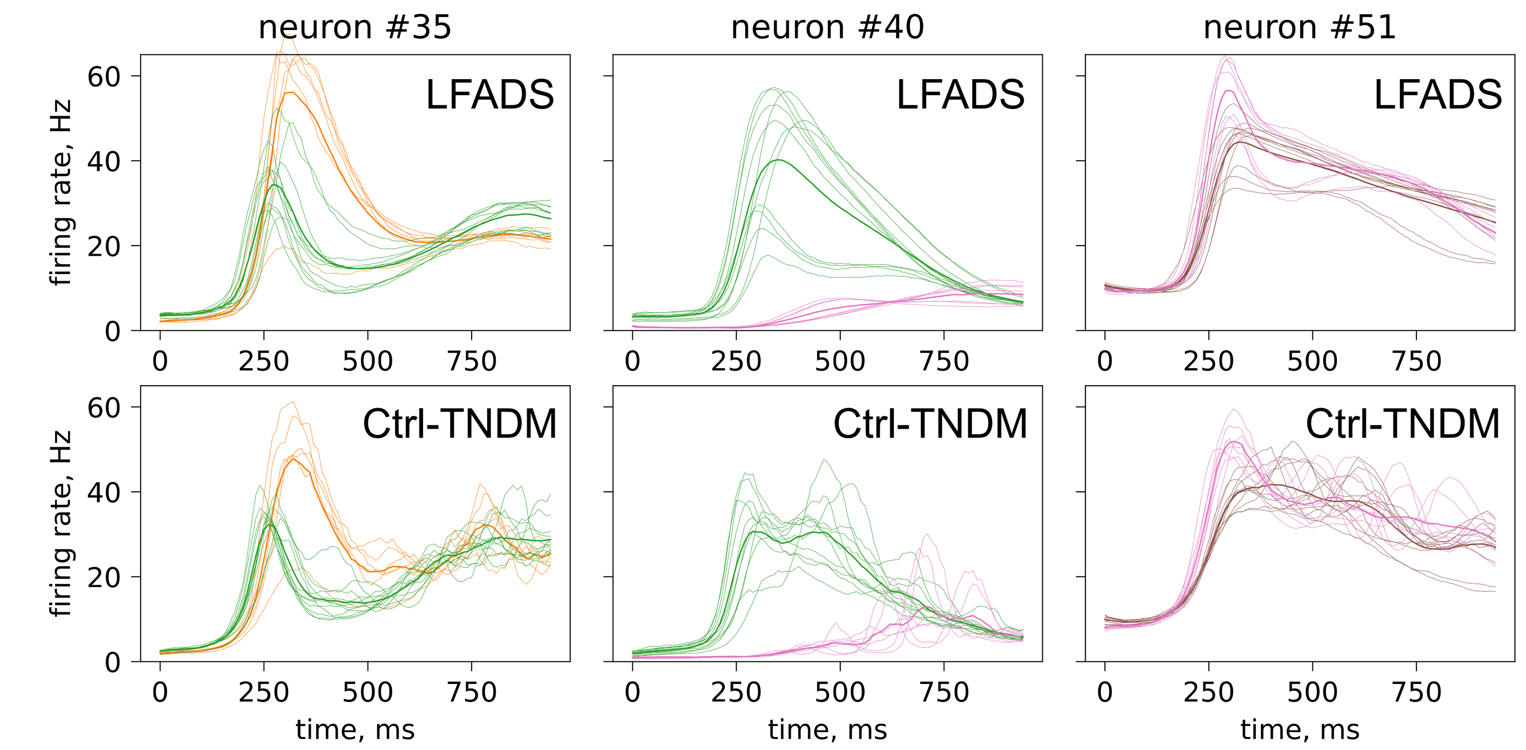


Oscillating factors explain a small portion of neuronal variability, mostly during movement and in AD trials

Example model with 4 factors:



Ctrl-TNDM captures neural activity related to hand velocity oscillations during movement, while predictions for the movement initiation phase remain similar to LFADS



Conclusion

Movement corrections during adaptation to the force field can be decoded from PMd/M1 neuronal activity. Yet, only a small portion of neuronal variability corresponds to movement corrections. Thus, unsupervised models (LFADS) discard this uninstructed variability, modeling it as noise. A weak supervision with behavioral output (velocity) enables detection of neuronal latent dynamics that corresponds to movement corrections.

References

[1] Gallego, Juan A., et al. "Neural manifolds for the control of movement." *Neuron* 94.5 (2017): 978-984.
[2] Perich, Matthew G., Juan A. Gallego, and Lee E. Miller. "A neural population mechanism for rapid learning." *Neuron* 100.4 (2018): 964-976.
[3] Hurwitz, Cole, et al. "Targeted neural dynamical modeling." *Advances in Neural Information Processing Systems* 34 (2021): 29379-29392.
[4] Pandarinath, Chethan, et al. "Inferring single-trial neural population dynamics using sequential auto-encoders." *Nature methods* 15.10 (2018): 805-815.