

## Neural Embeddings Rank: Aligning 3D latent dynamics with movements

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Long-term and cross-hemisphere decoding in M1

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dia: -1.2 off: -2.1 dia: 0.76 off: 0.7

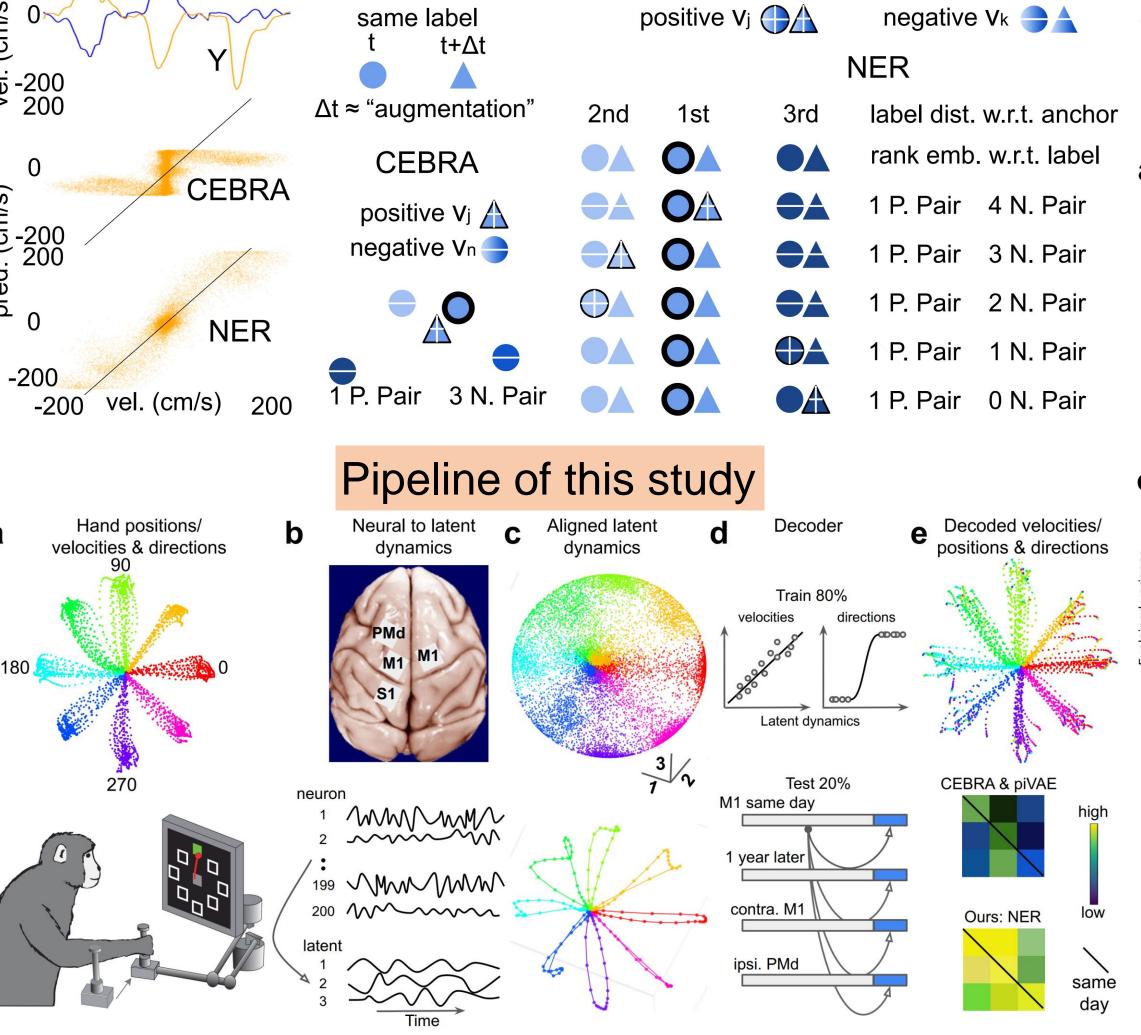
https://github.com/NeuroscienceAl/NER NeurIPS 2024 + NeuroAI and SSL Workshops (Oral)

Aligning neural dynamics with movements is a fundamental goal in neuroscience and brain-machine interfaces. However, there is still a lack of dimensionality reduction methods that can effectively align low-dimensional latent dynamics with movements. To address this gap, we propose Neural Embeddings Rank (NER), a technique that embeds neural dynamics into a 3D latent space and contrasts the embeddings based on movement ranks. NER learns to regress continuous representations of neural dynamics (i.e., embeddings) on continuous movements. We apply NER and six other dimensionality reduction techniques to neurons in the primary motor cortex (M1), dorsal premotor cortex (PMd), and primary somatosensory cortex (S1) as monkeys perform reaching tasks. Only NER aligns latent dynamics with both hand position and direction, visualizable in 3D. NER reveals consistent latent dynamics in M1 and PMd across sixteen sessions over a year. Using a linear regression decoder, NER explains 86% and 97% of the variance in velocity and position, respectively. Linear models trained on data from one session successfully decode velocity, position, and direction in held-out test data from different dates and cortical areas (64%, 88%, and 90%). NER also reveals distinct latent dynamics in S1 during consistent movements and in M1 during curved reaching tasks.

## Inspiration and motivation of this study

We are **inspired** by the fact that many features, including movements, are continuous, and that the function of many biological neurons is not classification but regression. For example, many neurons exhibit monotonic tuning to light intensity and sound levels. Even for discrete features like faces, face cells exhibit ramp-shaped tuning to different features. We are motivated by the fact that CEBRA treats continuous labels as many discrete classes, which cannot be well separated in low-dimensional space. These classes are also highly imbalanced, with many more near-zero classes.

anchor Vi



## NER reveals consistent & aligned latent dynamics in M1 2016-10-21 2015-03-13 Latent dynamics in PMd & decoding between M1 & PMd Explained variance using linear decoders References and Acknowledgments

Schneider et al, Nature, 2023; Zhou and Wei, NeurIPS, 2020; Zha et al, NeurIPS, 2023 We greatly appreciate the Miller and Shenoy labs for publicly releasing their experimental data on macaque monkeys. We also thank the Mathis lab for the CEBRA code, which served as the basis for our NER. This work was supported by NIDCD grant DC003180.

## dia: 0.94 off: 0.93 dia: 0.75 off: 0.74 Different movements have different latent dynamics 3 pairs of straight-curve 3 pairs of curve-curve move

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