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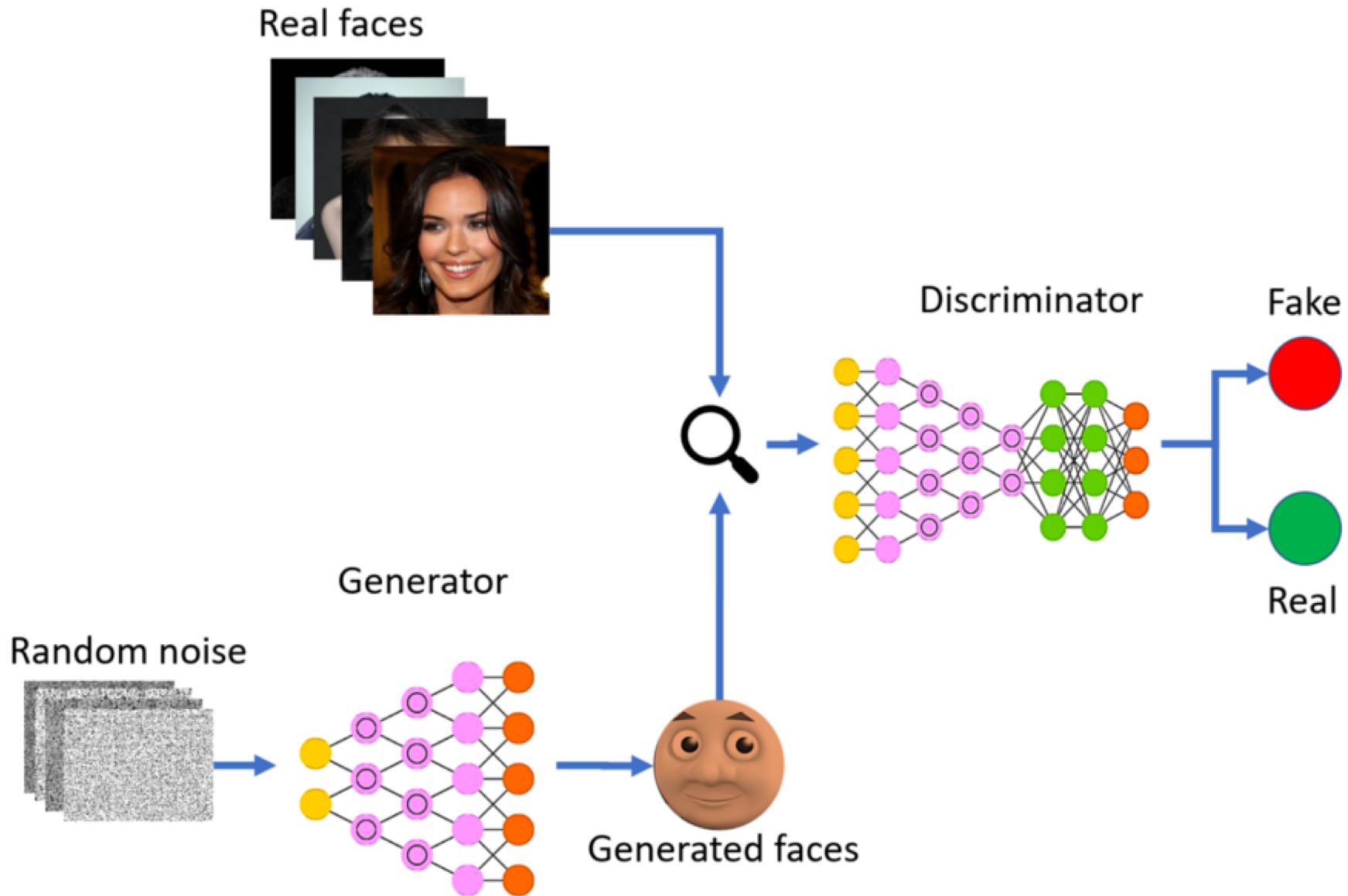
Brain and Mind
Research Institute

Workshop on Applied Deep Learning in Intracranial Neurophysiology

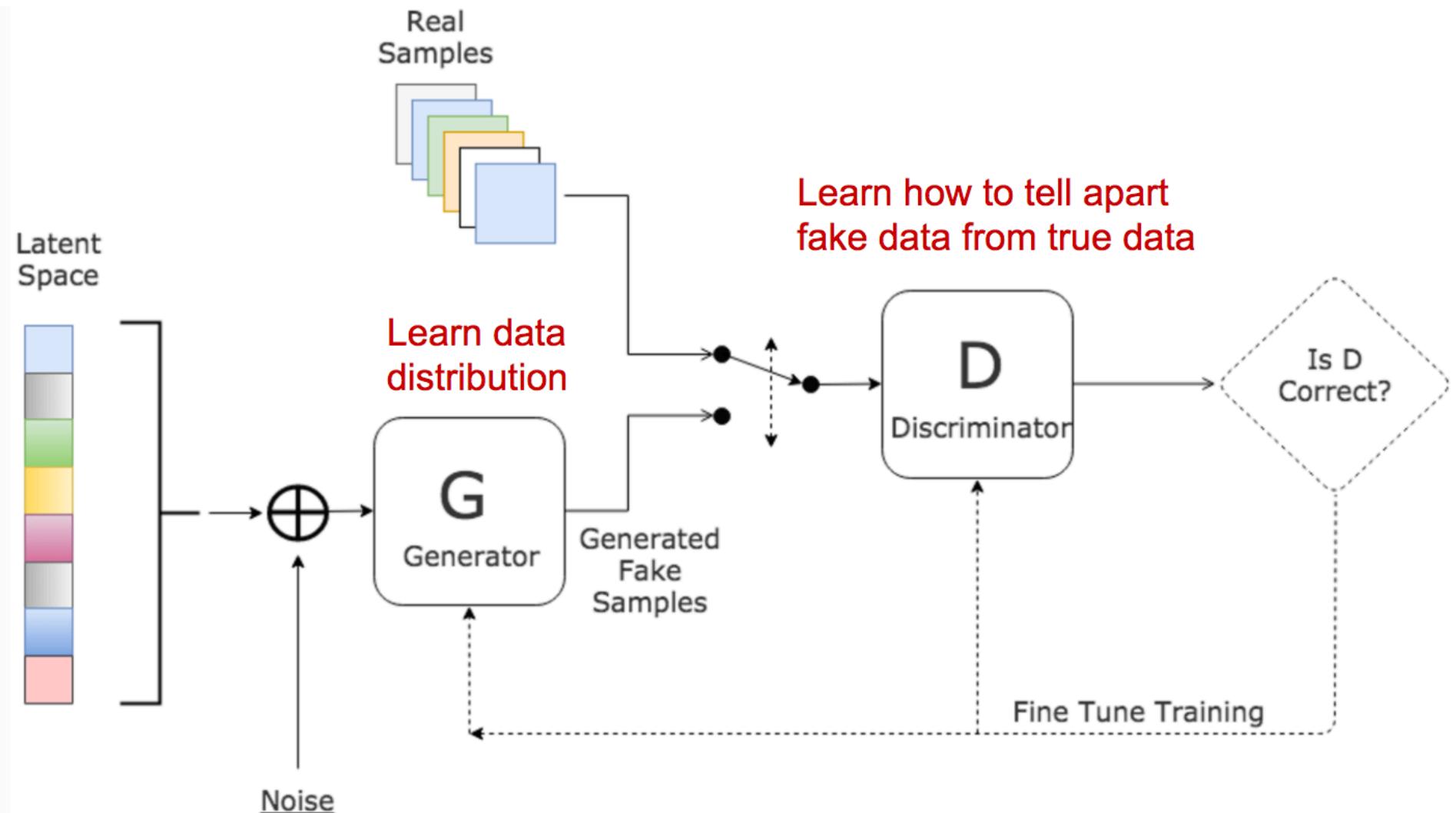
Part 8 – Adversarial Domain Adaptation
September 17, 2019

Presented by Chadwick Boulay, MSc, PhD
Sachs Lab

Intro to GANs



Intro to GANs





Ian Goodfellow
@goodfellow_ian



4.5 years of GAN progress on face generation.

arxiv.org/abs/1406.2661 arxiv.org/abs/1511.06434 arxiv.org/abs/1606.07536 arxiv.org/abs/1710.10196 arxiv.org/abs/1812.04948



1:40 AM · Jan 15, 2019 · Twitter Web Client

- thispersondoesnotexist.com



Trained generative model has representation of real data structure.
We can then explore the model latent space.

Interpolation in Latent Space





smiling
woman



neutral
woman



neutral
man



smiling man

Style-GAN

- <https://youtu.be/kSLJriaOumA?t=28>

- A Brief Review on: MRI Images Reconstruction using GAN
- Generative Adversarial Networks for the Creation of Realistic Artificial Brain Magnetic Resonance Images

- Brain MRI super-resolution using 3D generative adversarial networks

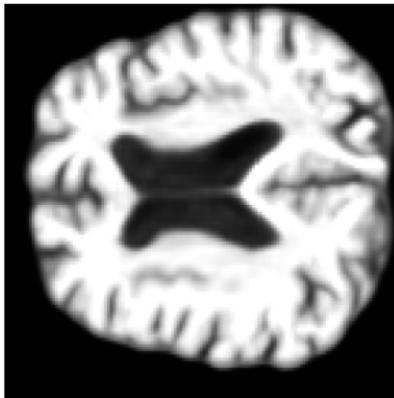
Original image



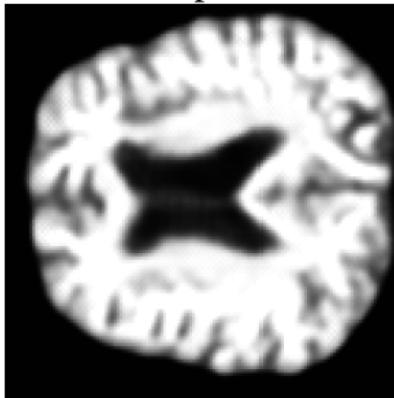
Cubic spline interpolation



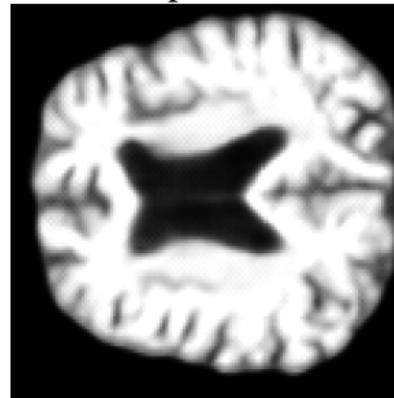
Resize convolution



Subpixel



Subpixel-NN



- Excellent youtube video here:
 - <https://www.youtube.com/watch?v=dCKbRCUyop8>
- Along with notebook:
 - https://drive.google.com/drive/folders/1LBWcmnUPoHDeaYIRiHokGyjywldyhAQb?usp=drive_open

ADVERSARIAL DOMAIN ADAPTATION FOR STABLE BRAIN-MACHINE INTERFACES

Ali Farshchian, Juan A. Gallego, Lee E. Miller & Sara A. Solla

Northwestern University, Evanston, IL, USA

{a-farshchiansadegh, juan.gallego, lm, solla}@northwestern.edu

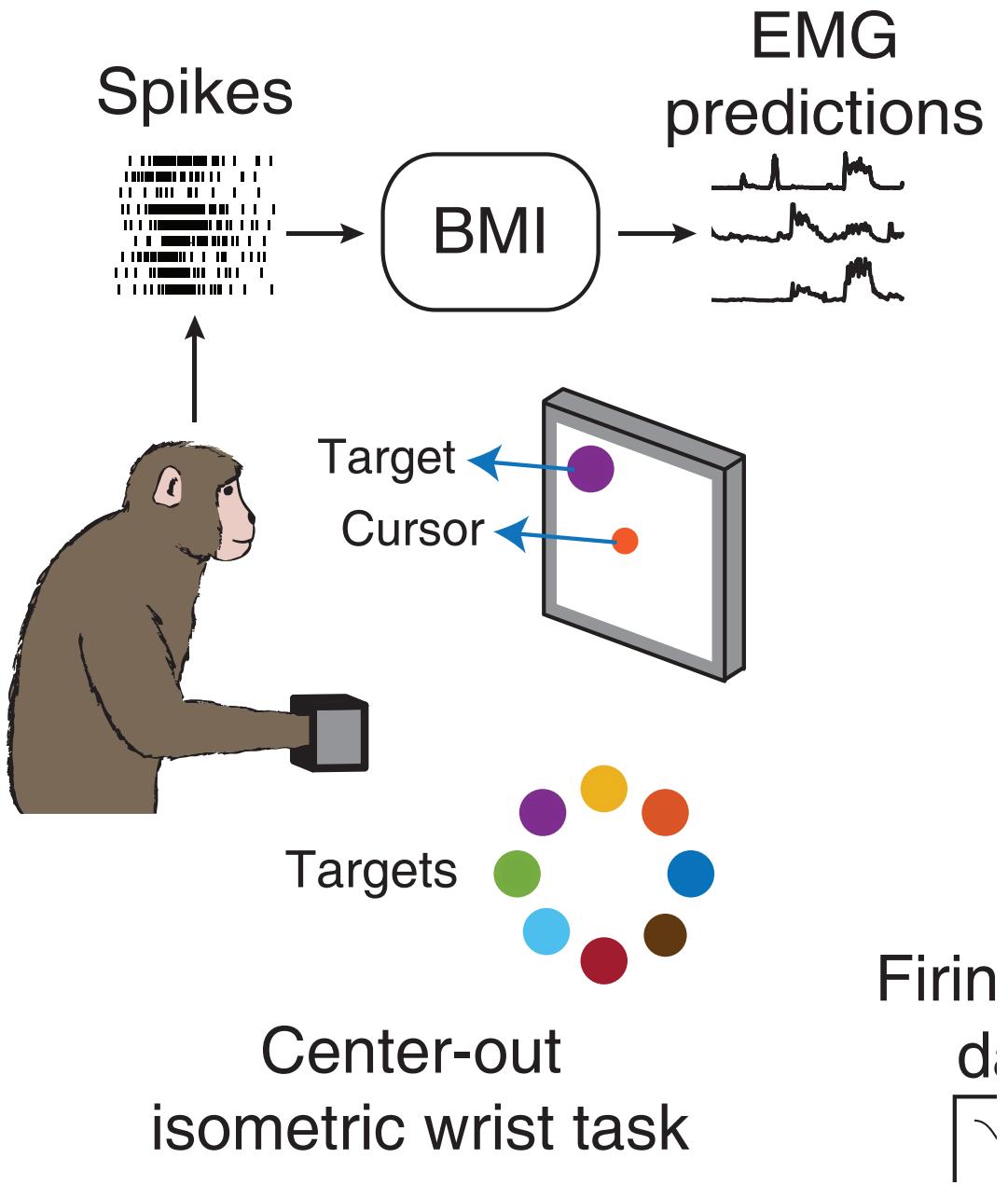
Joseph P. Cohen & Yoshua Bengio

University of Montreal, Montreal, Canada

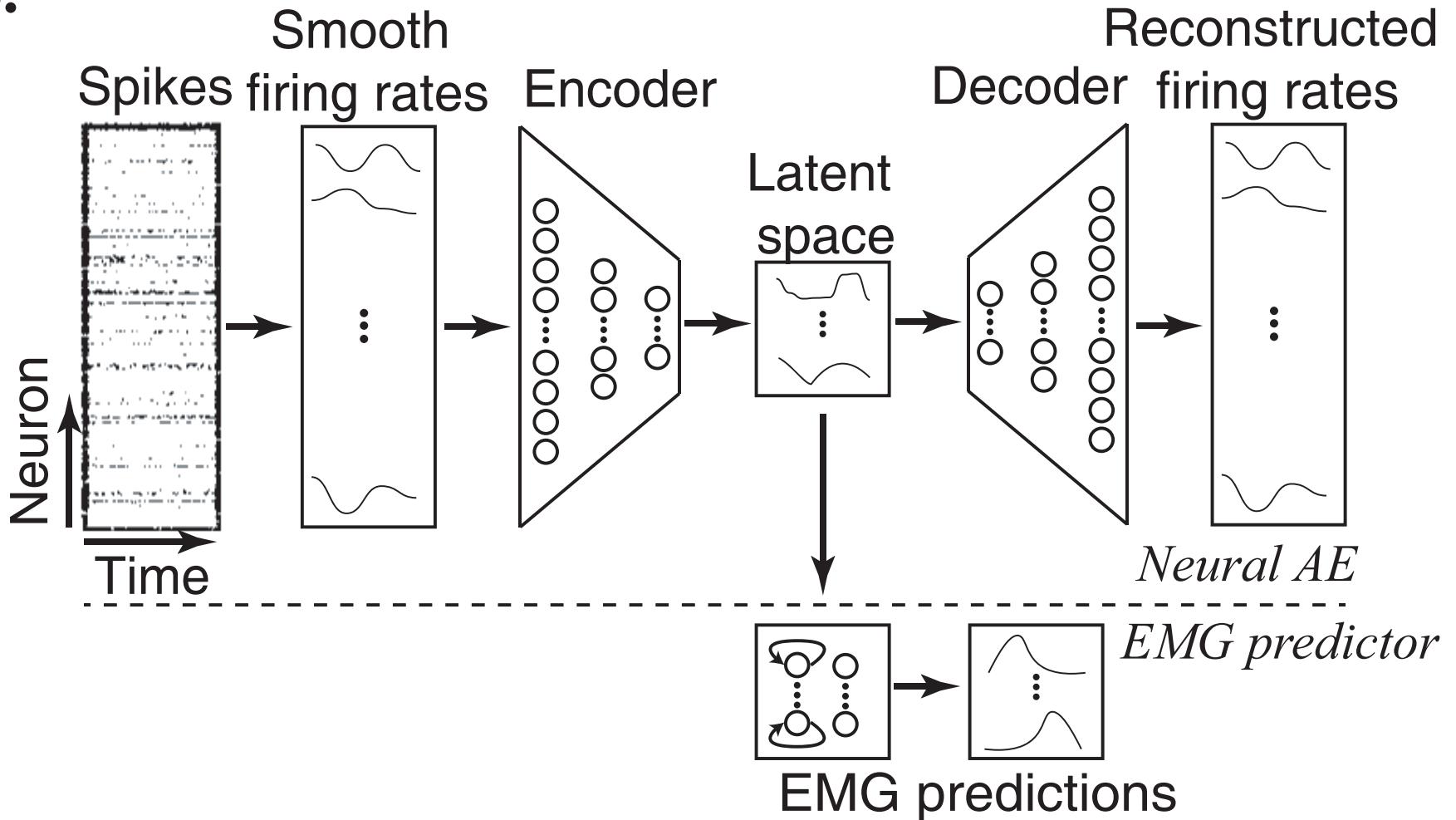
cohenjos@iro.umontreal.ca, yoshua.bengio@umontreal.ca

ADAN Motivation

- 40% turnover in recorded neurons per week
- Old and new neurons alike participate in same low-dimensional manifold.
- Train DNN: (V)AE; latent space → motor commands
 - Similar to LFADS with different implementation details
- Align PDFs of reconstructed signal residuals on day k with PDF of day 1.
 - Results in alignment of neural latent space.
- Assumes relationship between latent space and movement remains constant across days.



B.



$$\mathcal{L} = \lambda \mathcal{L}^x + \mathcal{L}^y = \frac{1}{T} \sum_{t=1}^T \left(\lambda \|\hat{\mathbf{x}}_t - \mathbf{x}_t\|^2 + \|\hat{\mathbf{y}}_t - \mathbf{y}_t\|^2 \right)$$

$$\lambda = \frac{\mathcal{L}^y}{\mathcal{L}^x}$$

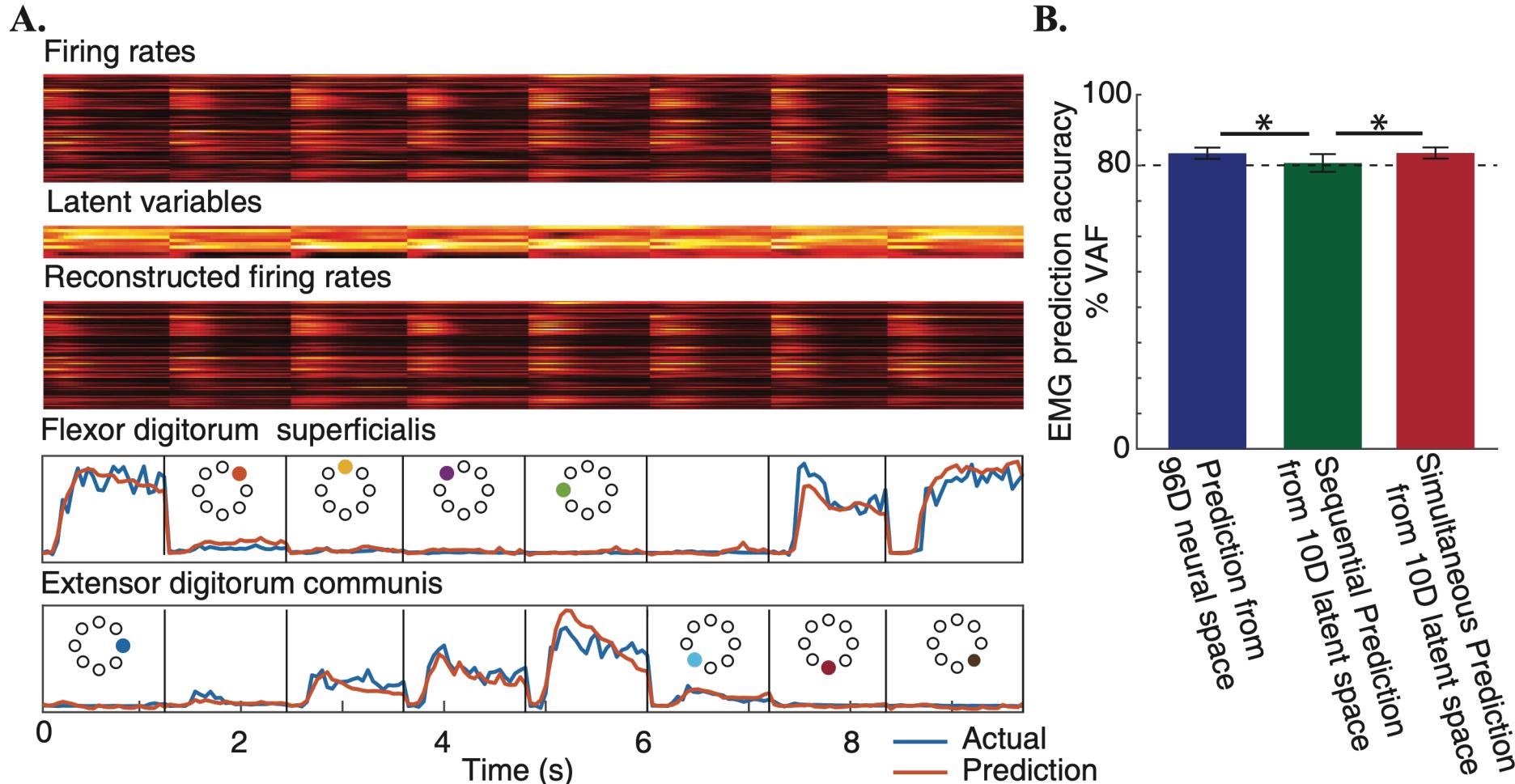
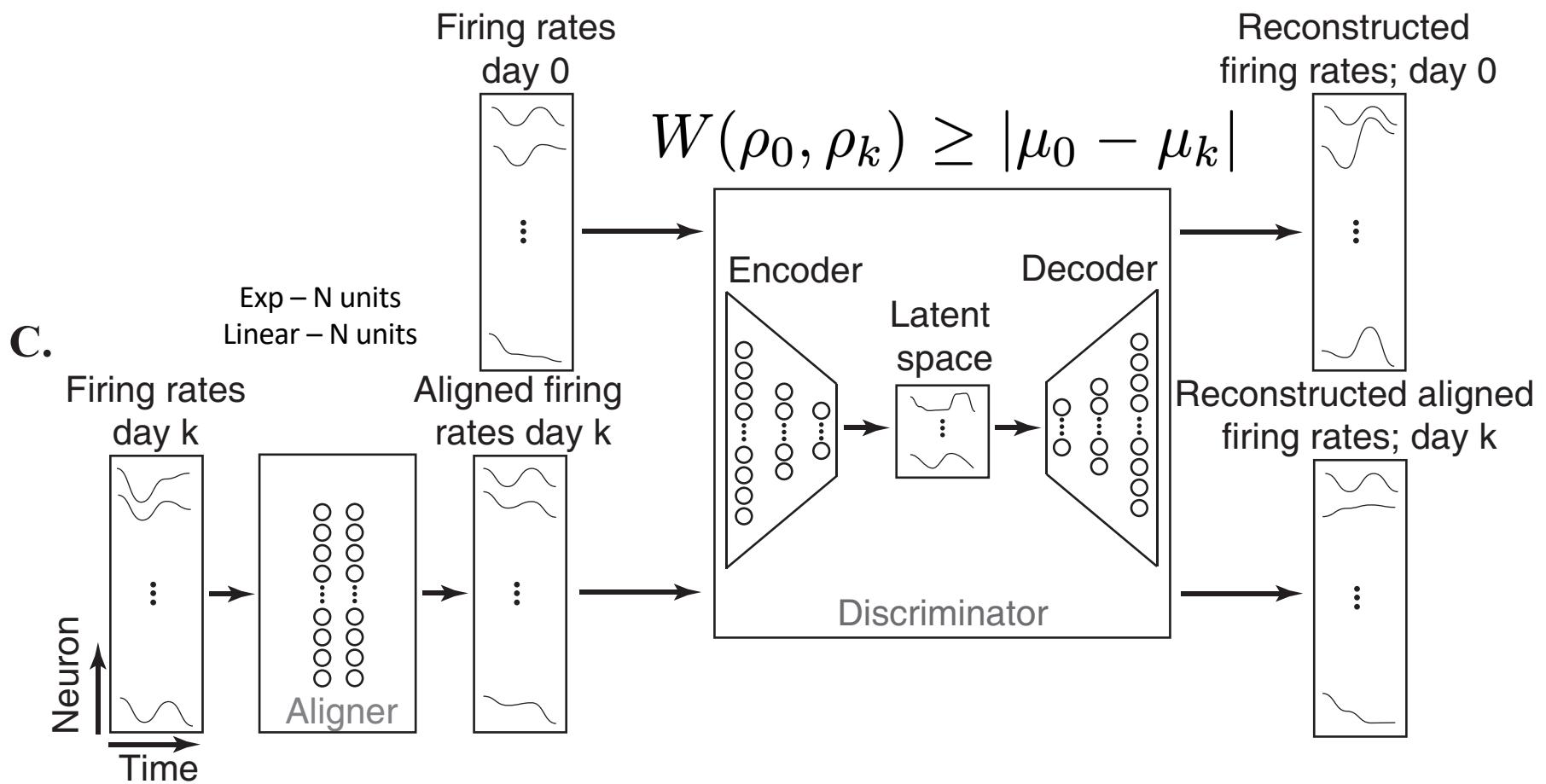
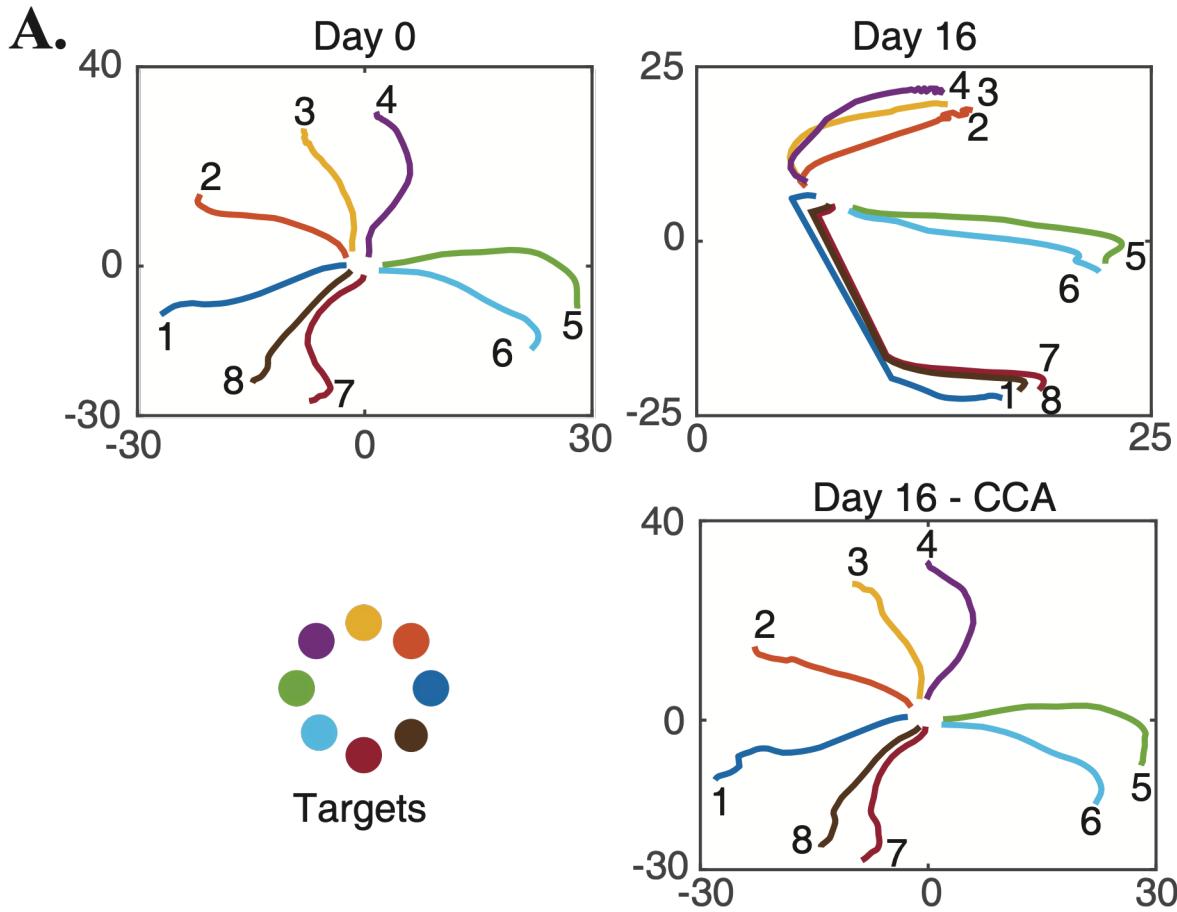


Figure 2: Neural to muscle BMI. **A.** Example firing rates recorded from the hand area of primary motor cortex while the monkey performed the isometric wrist task; we also show latent variables and reconstructed firing rates. The quality of EMG predictions is illustrated by comparison to actual EMGs for two representative muscles, for each of the eight target directions. **B.** Performance comparison between EMG predictions from n -dimensional firing rates (blue) and EMG predictions from l -dimensional latent variables, obtained either by training the predictor sequentially (green) or simultaneously (red) with the neural AE. Error bars represent standard deviation of the mean.

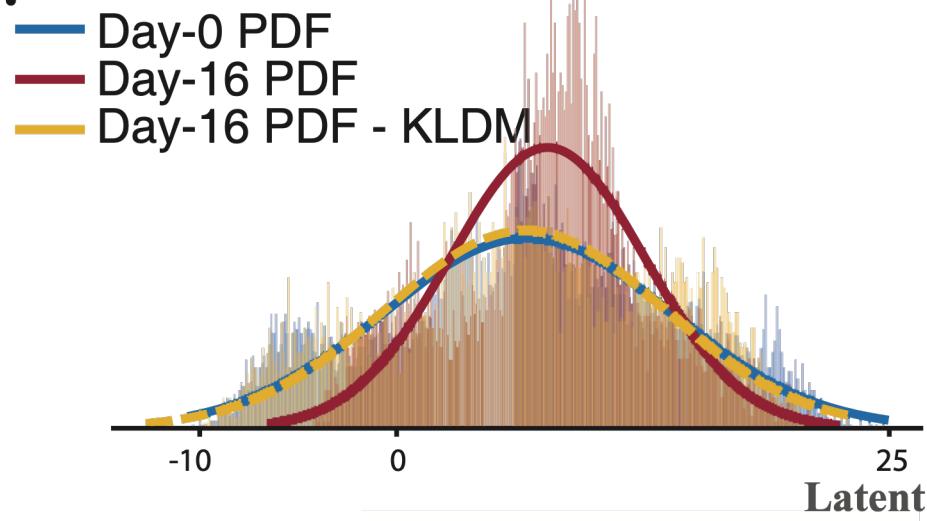
ρ_0, ρ_k : Distributions of scalar losses


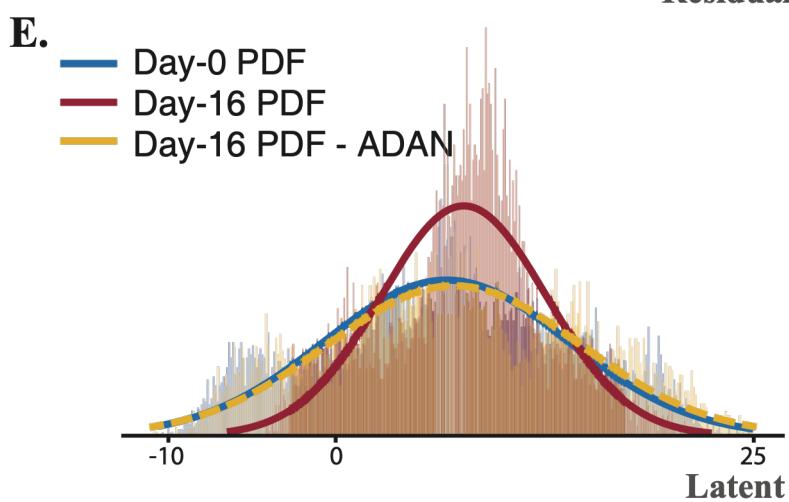
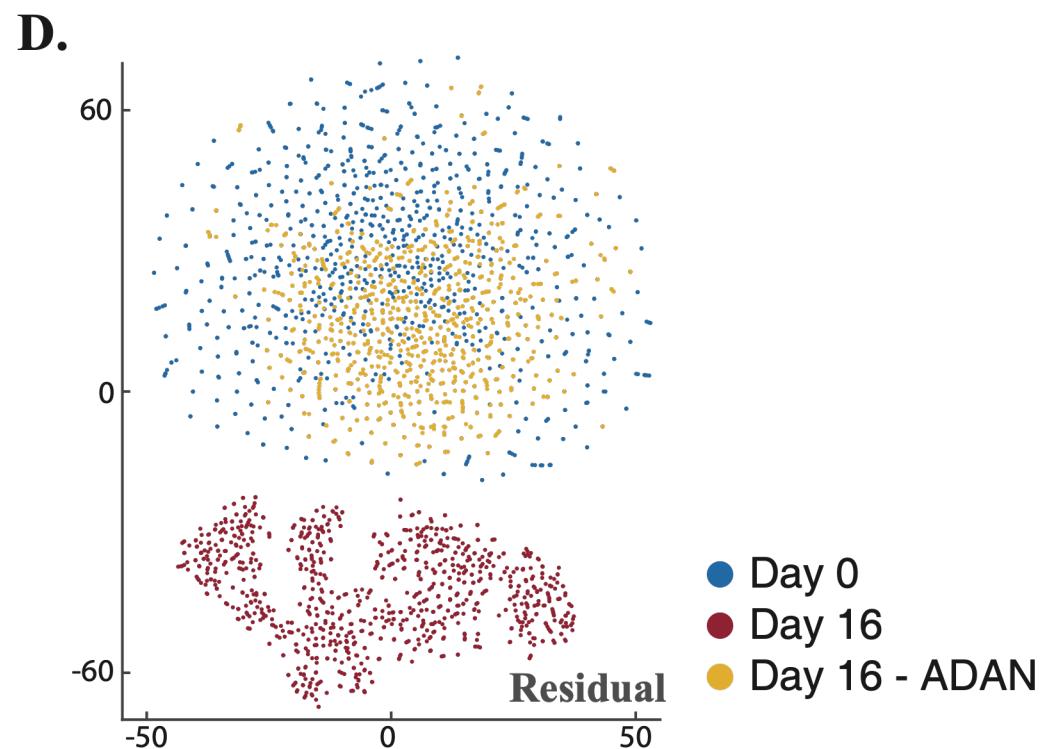
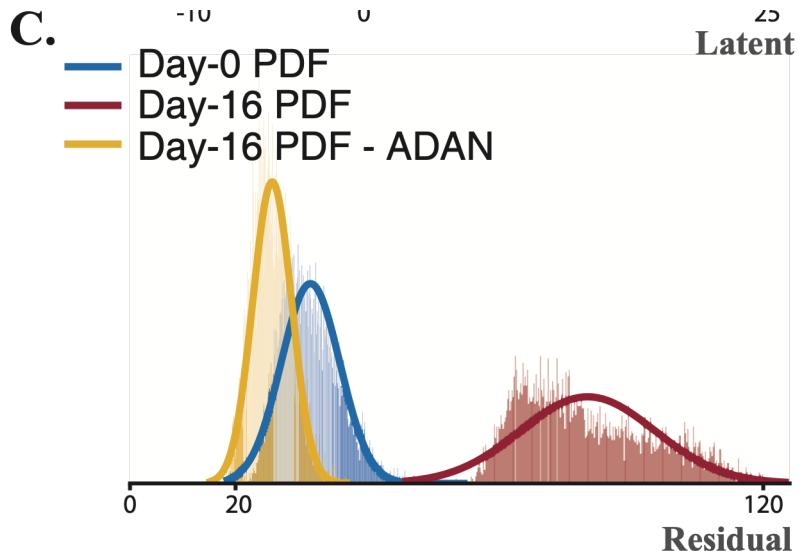
$$\begin{cases} \mathcal{L}_D = \mu_0(\mathbf{X}_0; \theta_D) - \mu_k(A(\mathbf{X}_k; \theta_A); \theta_D) & \text{for } \theta_D \\ \mathcal{L}_A = \mu_k(A(\mathbf{X}_k; \theta_A); \theta_D) & \text{for } \theta_A \end{cases}$$

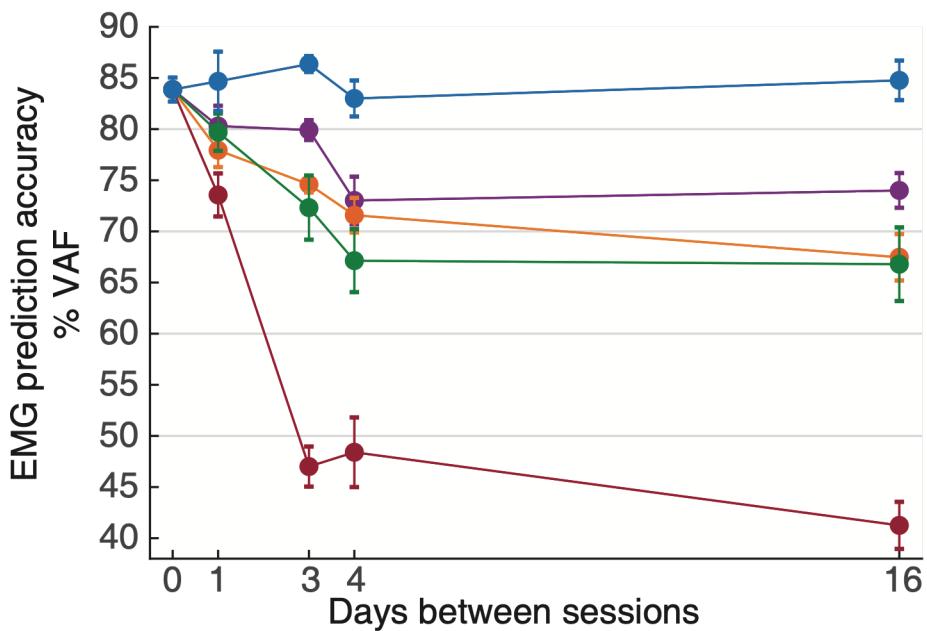
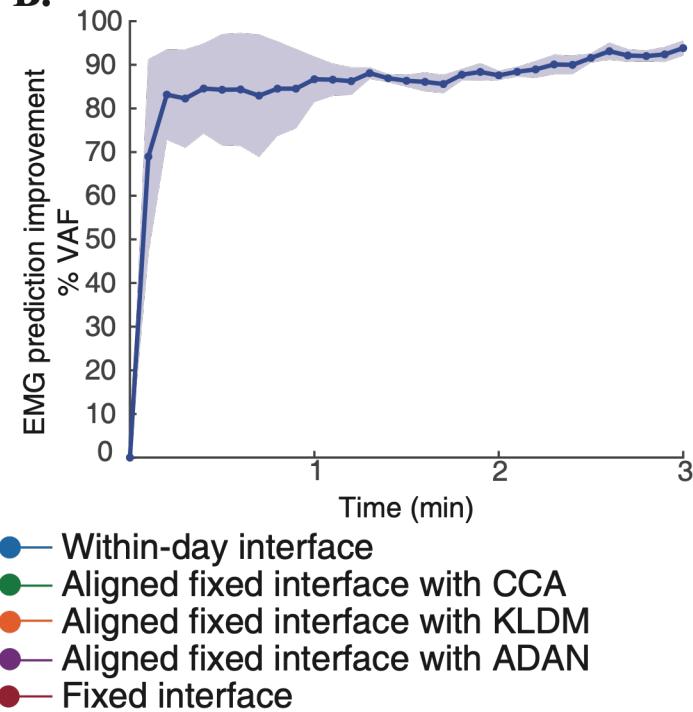


t-SNE of latent neural trajectories
CCA alignment requires many labeled trials on day 16.

B.





A.**B.**

- Notebook [08_01_ADAN.ipynb](#)