Movement Classification From Corticomotor neuron Activity: Cross Subject Generalization

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Deep learning for physiological signals - 3360209

Experimental Design

2 **Rhesus monkeys** (Chip, Gabby) were trained to perform **12 cued movements** (flexion/extension **of digits 1–5 and the wrist)**

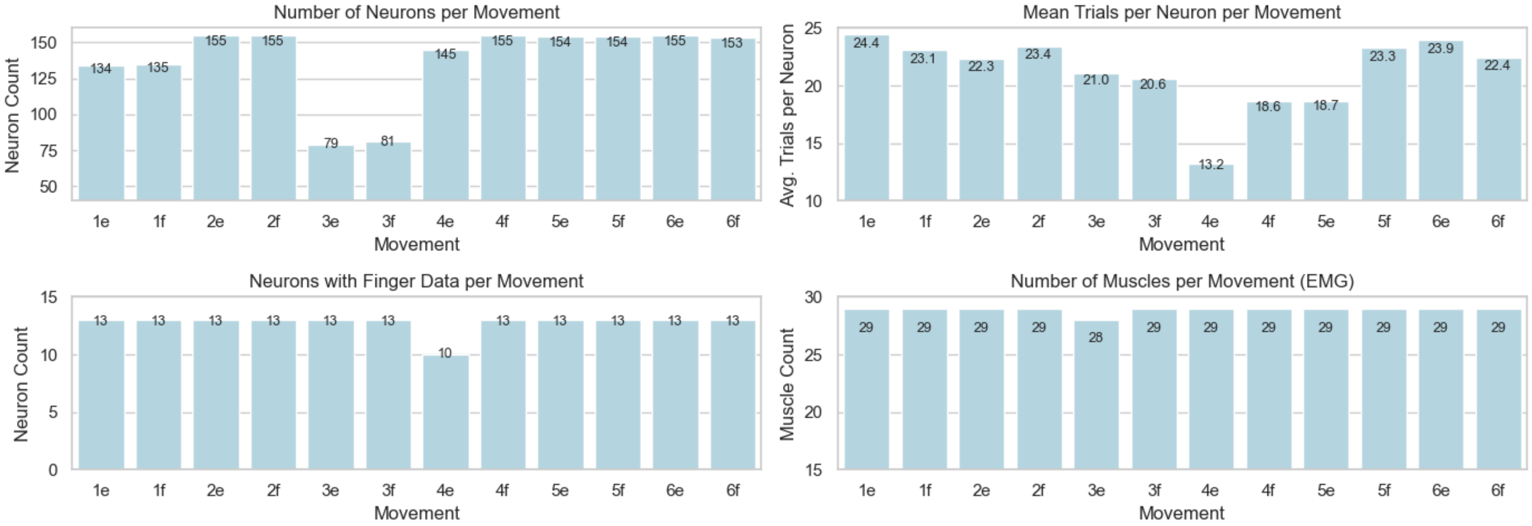
Each trial cued via LEDs; monkeys made brief, isolated digit/wrist movements.

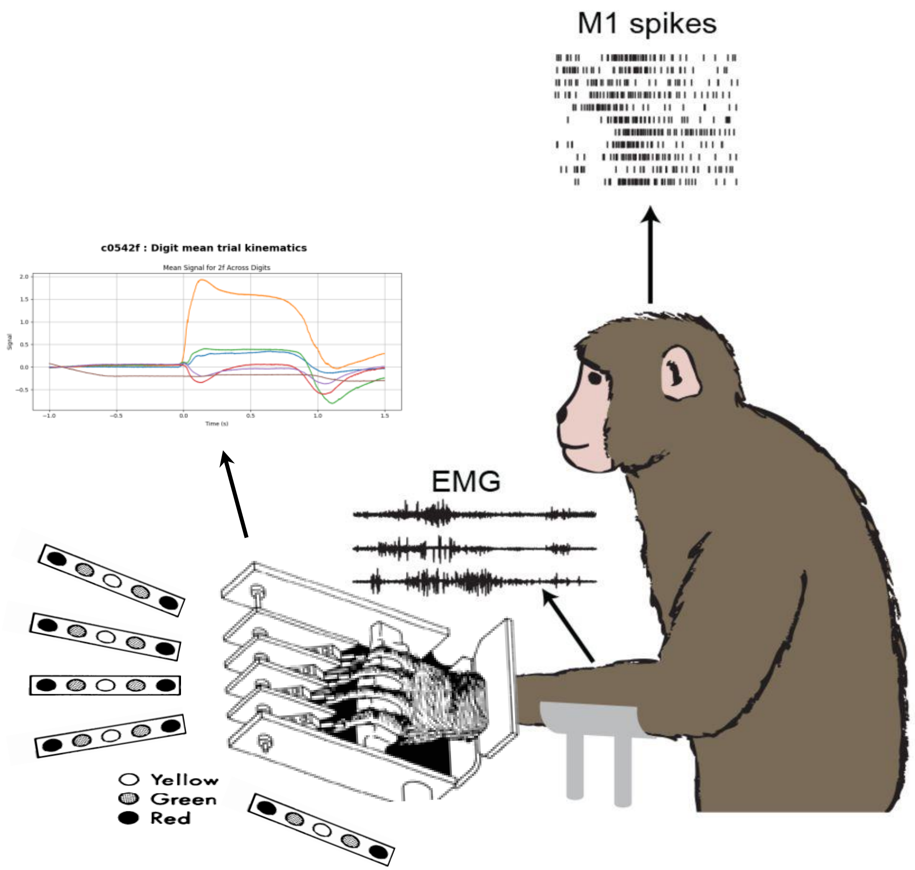
While performing each task:

➡ **Single CM cell activity** was recorded (n=179,119, respectively)

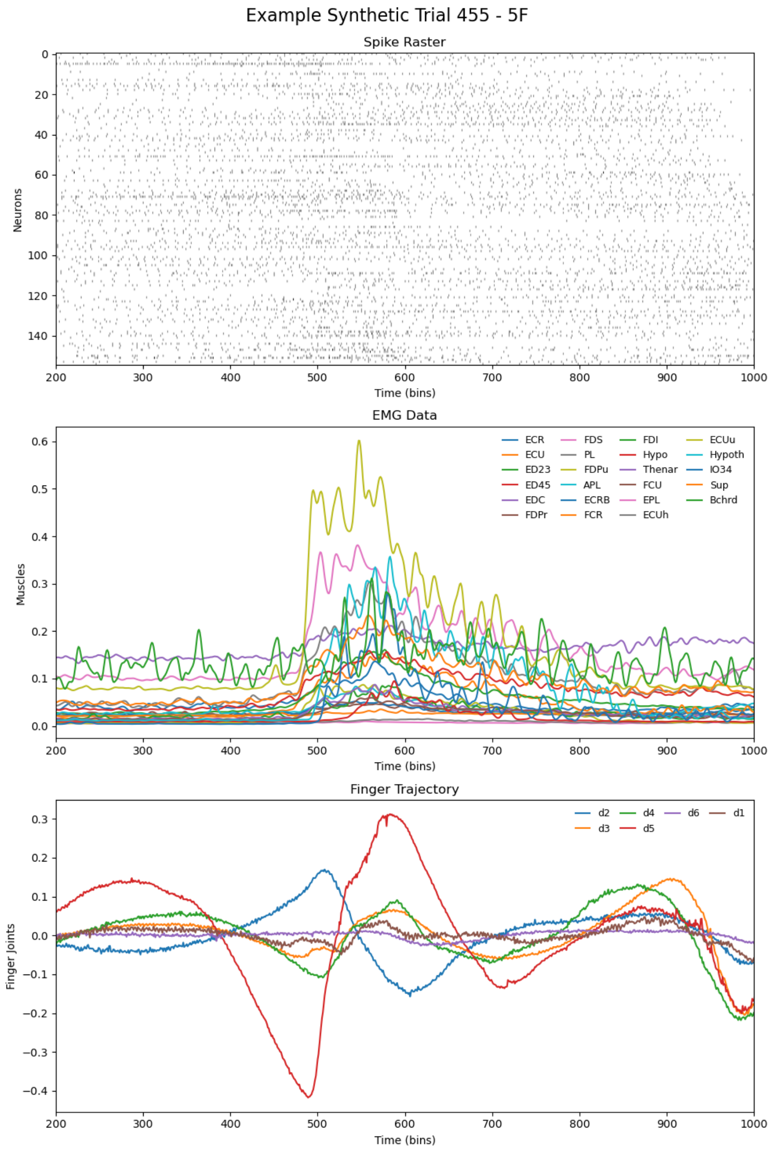
➡ Forearm/hand muscles' **EMG** was recorded (m=30,22)

➡ Finger and wrist **movements** tracked with strain gauges and microswitches

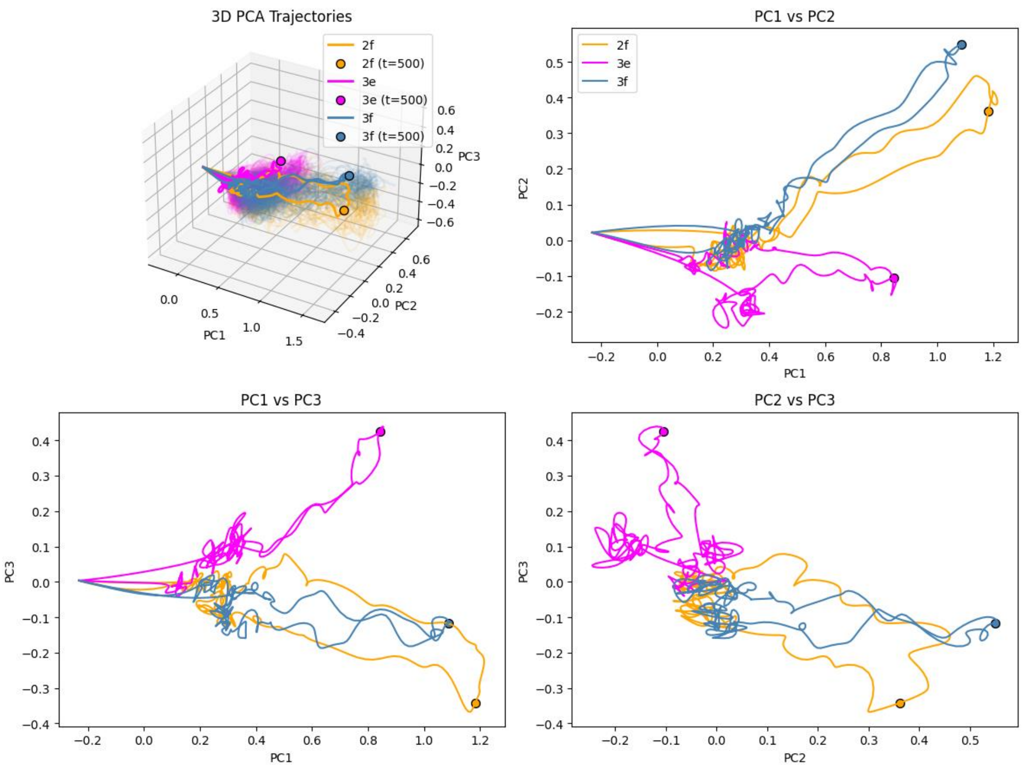


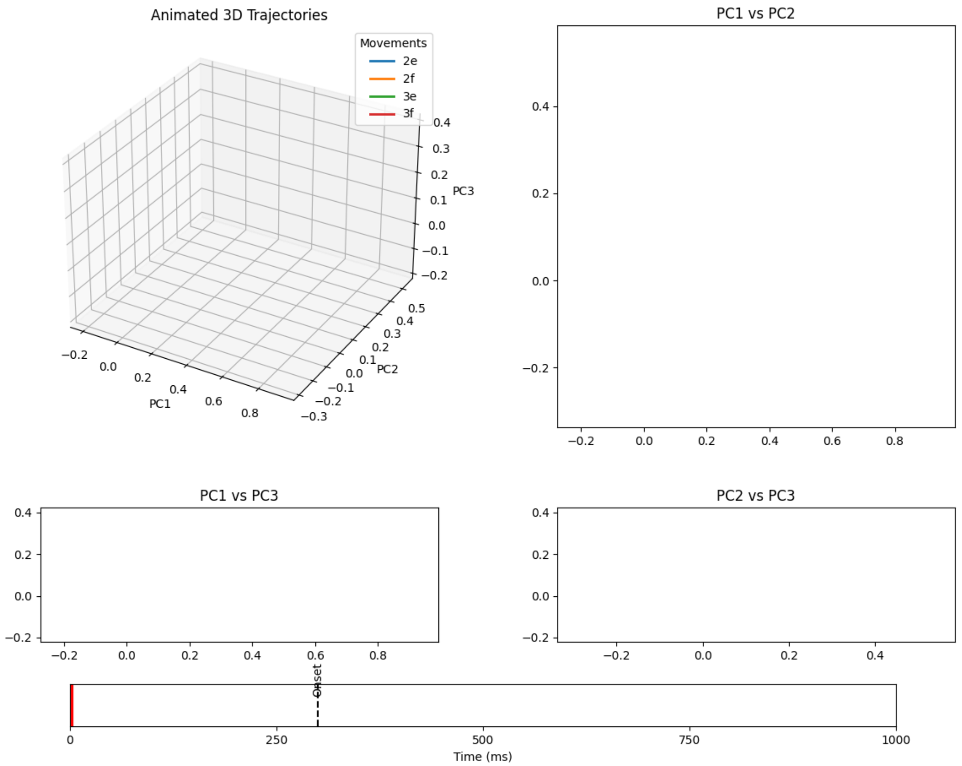


Data Synthesis

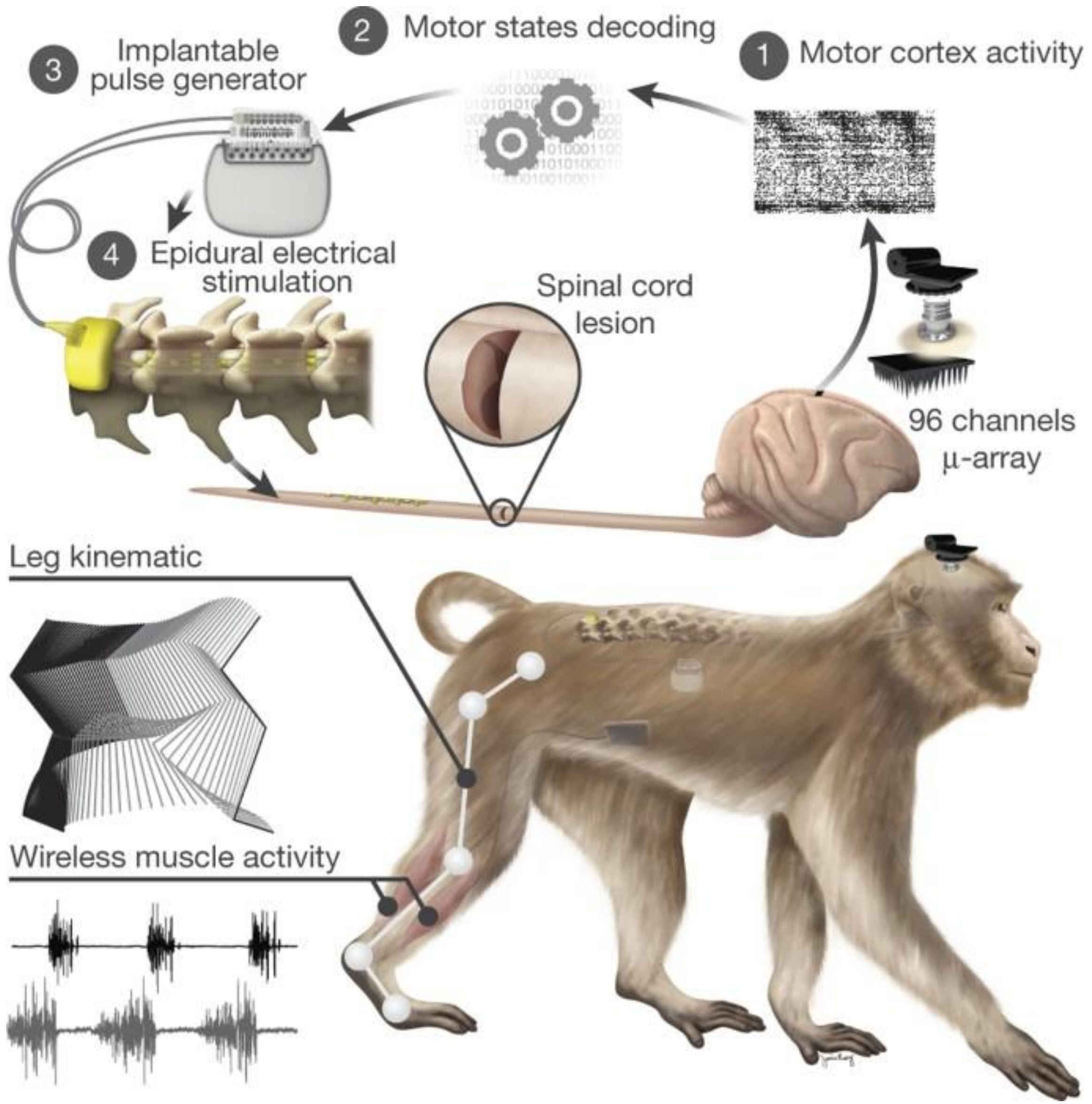


Neural Space PCA



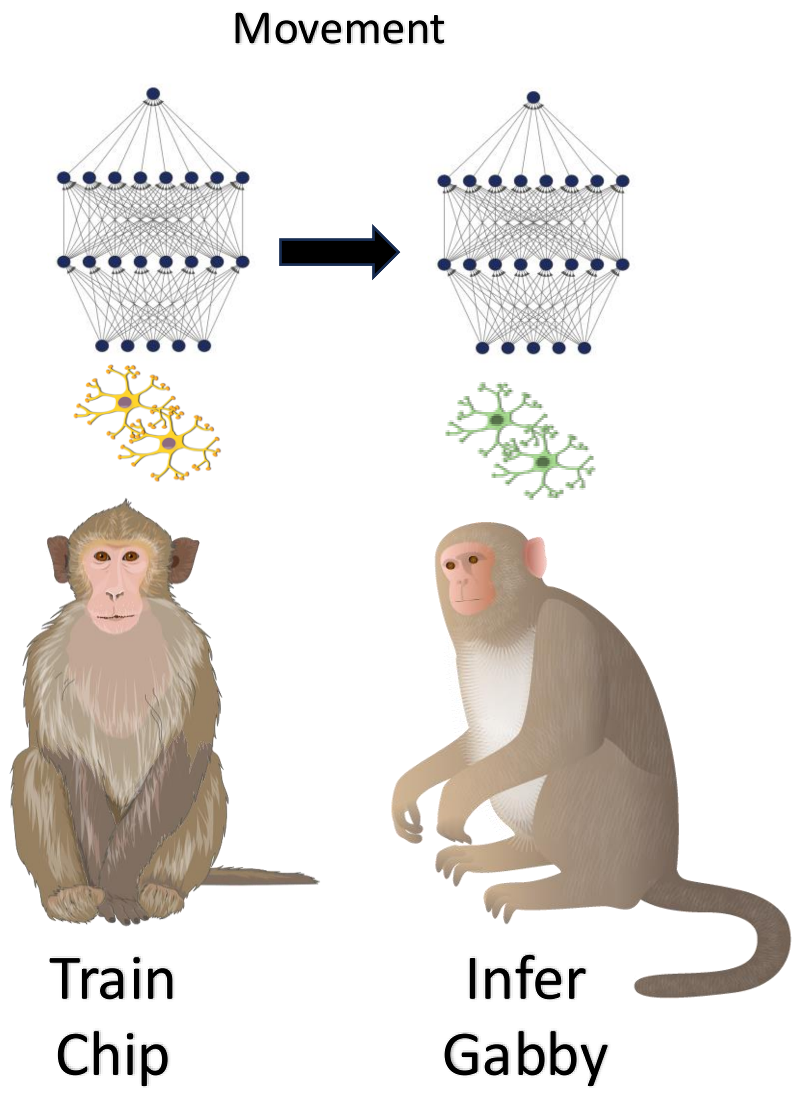


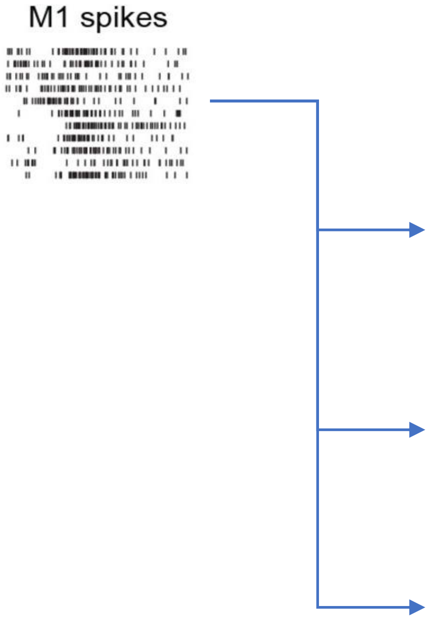
Motivation



2 Motor states decoding
1 Motor cortex activity
3 Implantable pulse generator
4 Epidural electrical stimulation
Spinal cord lesion
96 channels
μ-array
Leg kinematic
Wireless muscle activity

Goal: Cross Subject Generalization

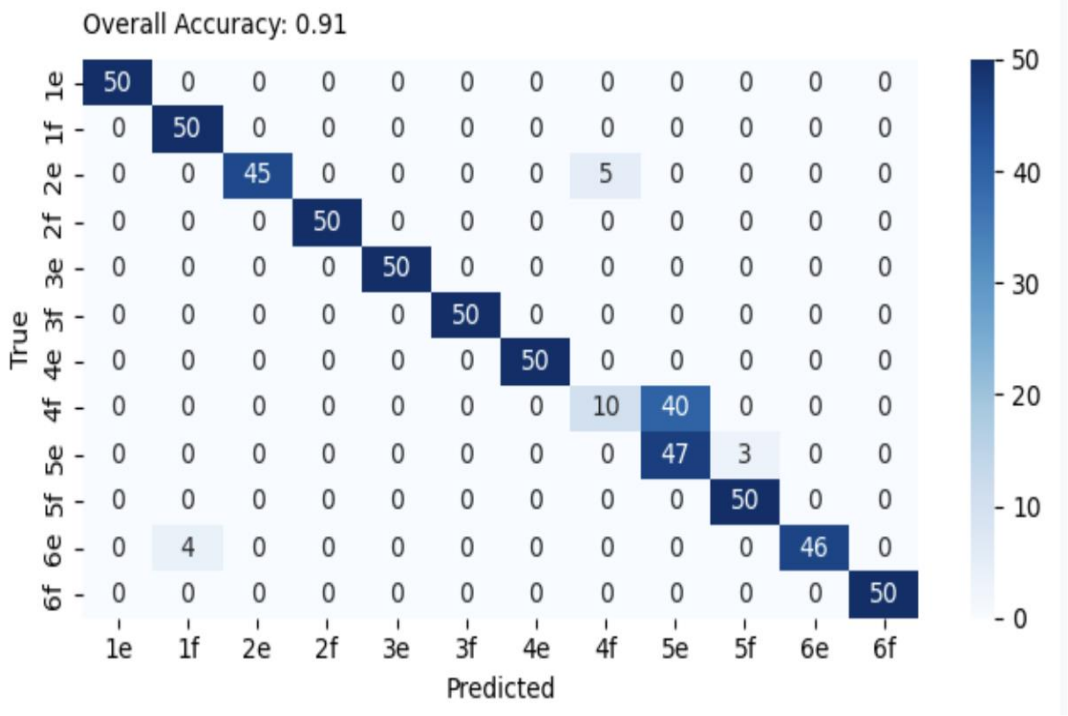




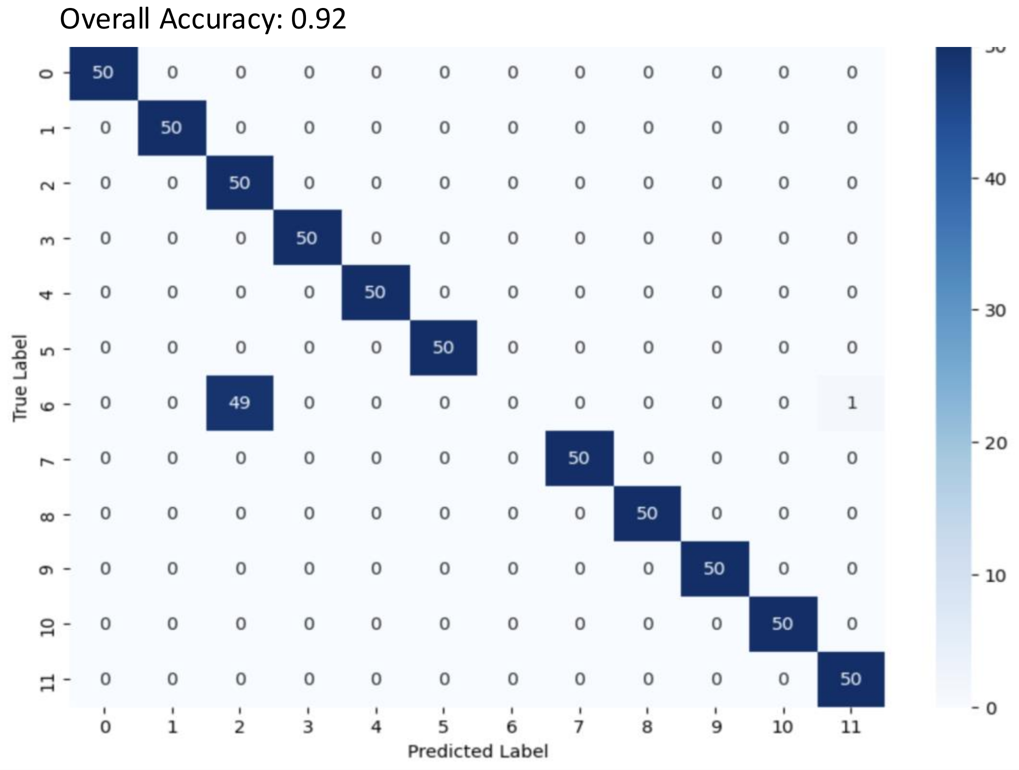
- Logistic regression
- CNN
- LFADS + CNN

Primary results

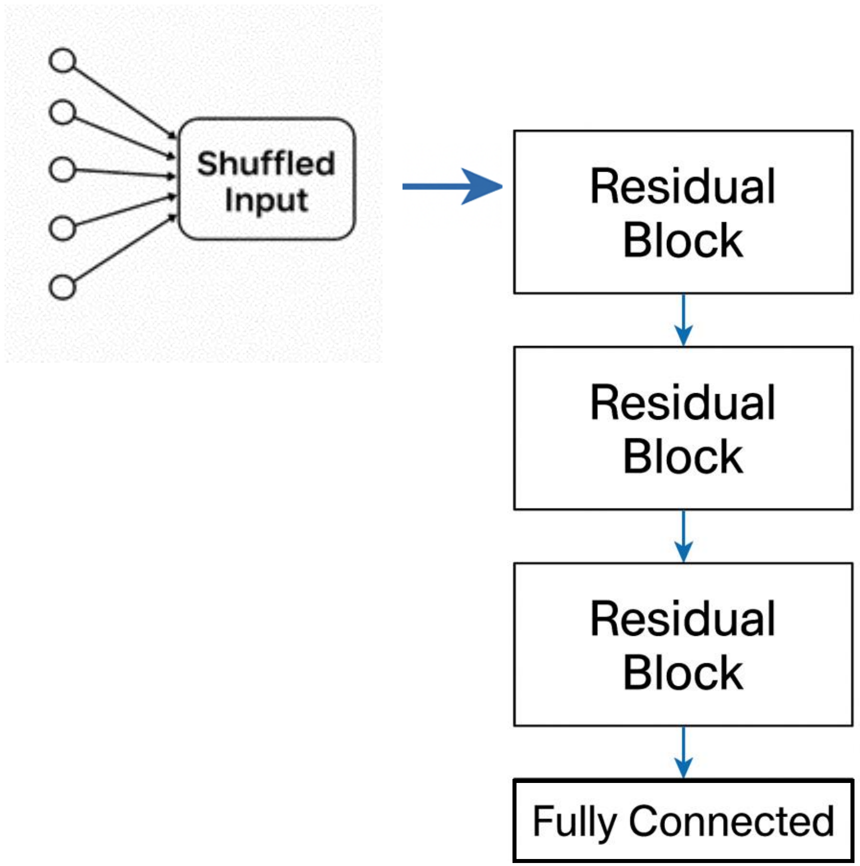
1D-resCNN model

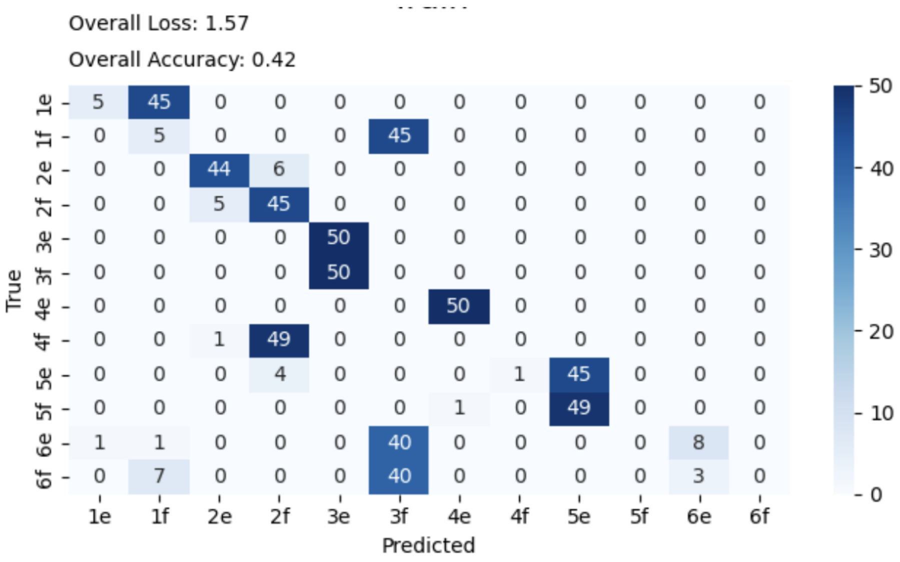


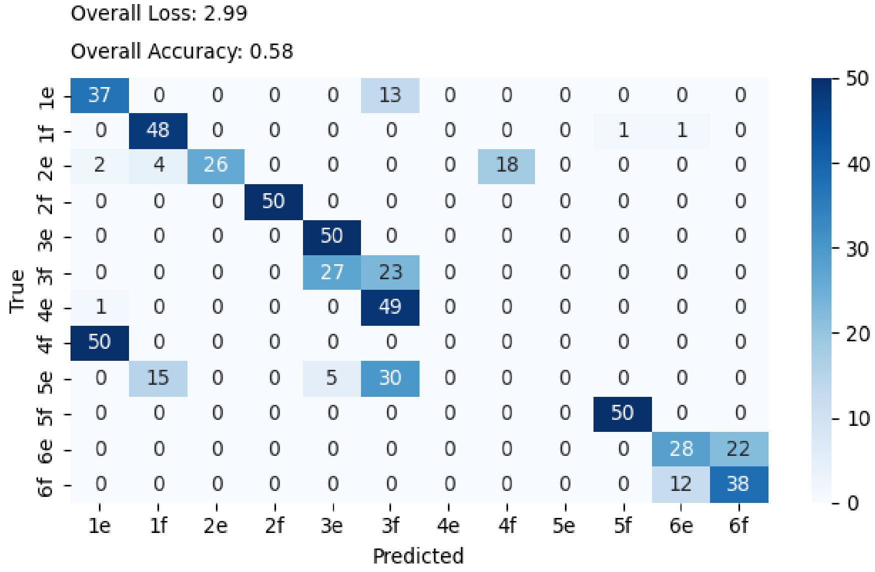
Logistic regression ML model



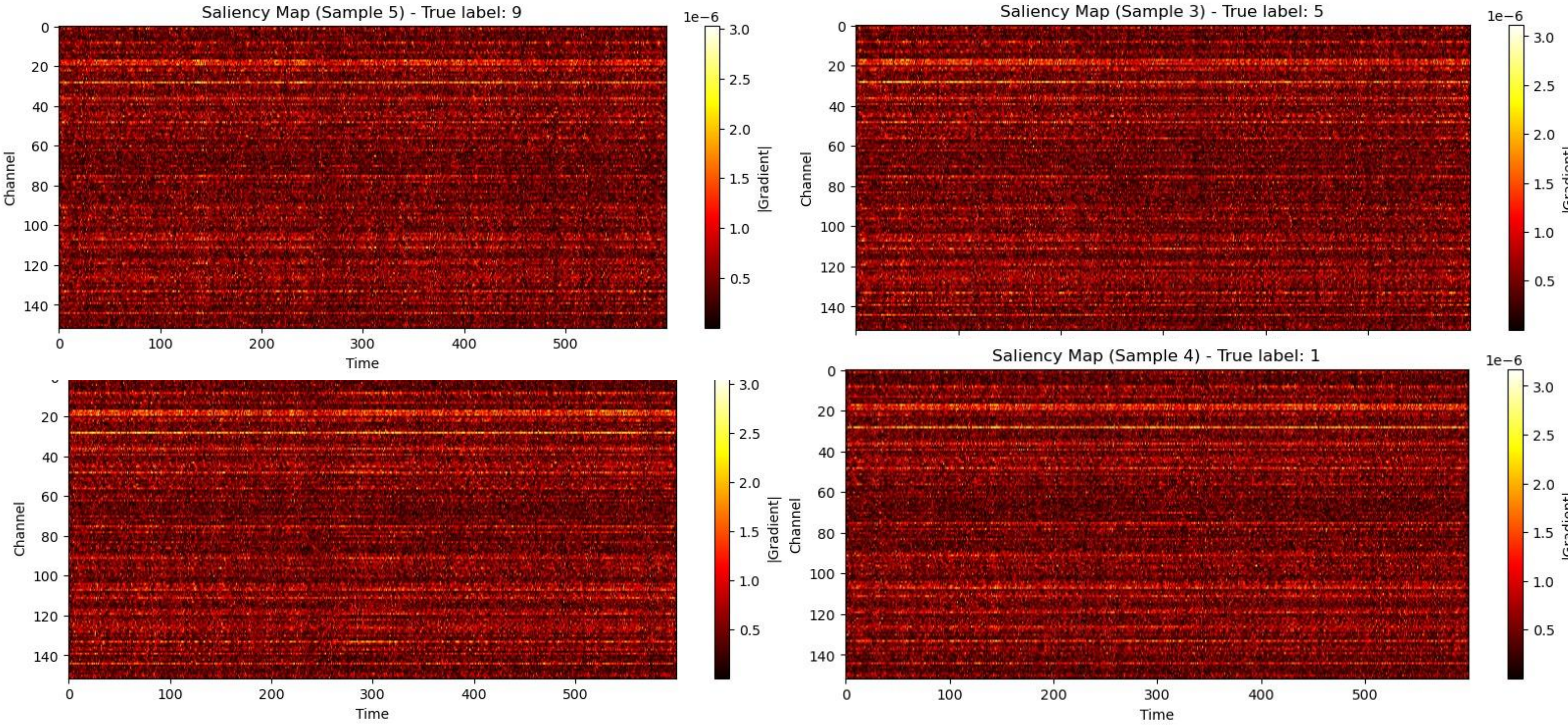
Shuffled input







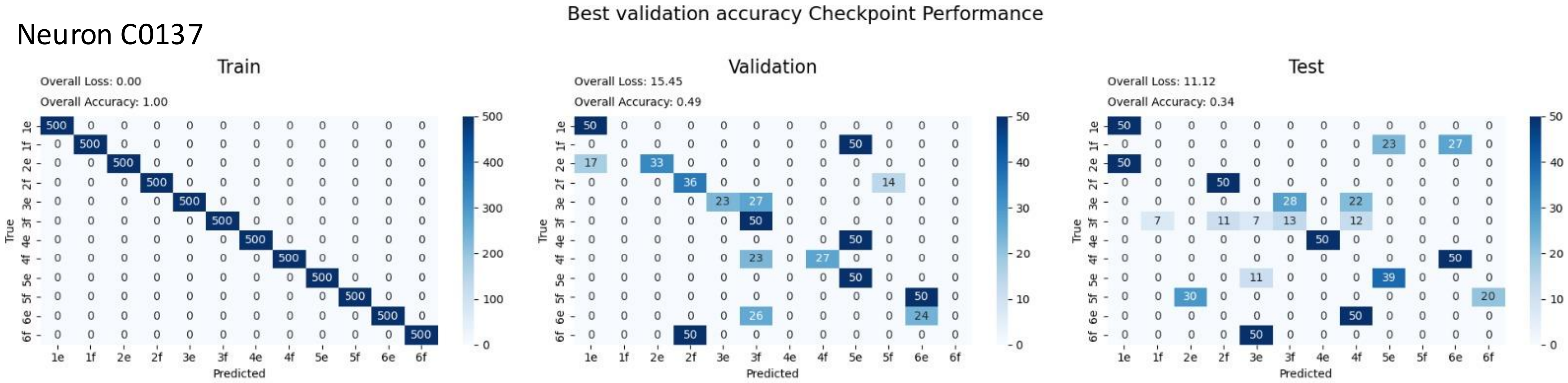
Interpretability - Attention map

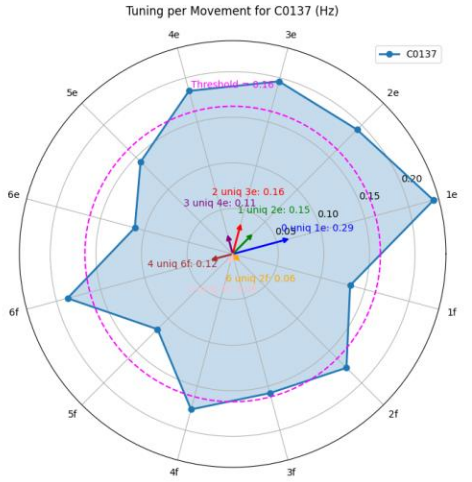


Broadly tuned neurons

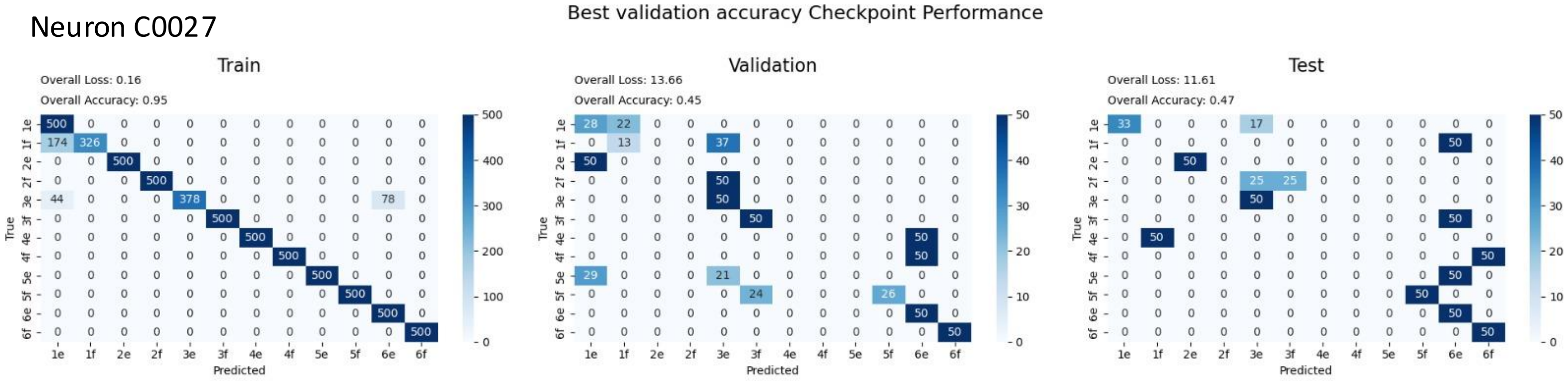
Top 5 most important channels: ['C0137', ‘C0027', 'C0115', 'c0491', 'C0235']

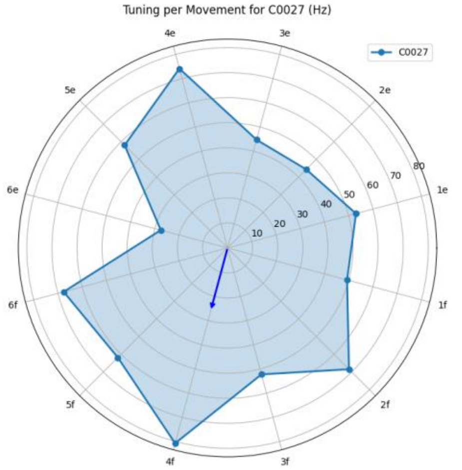
Neuron C0137



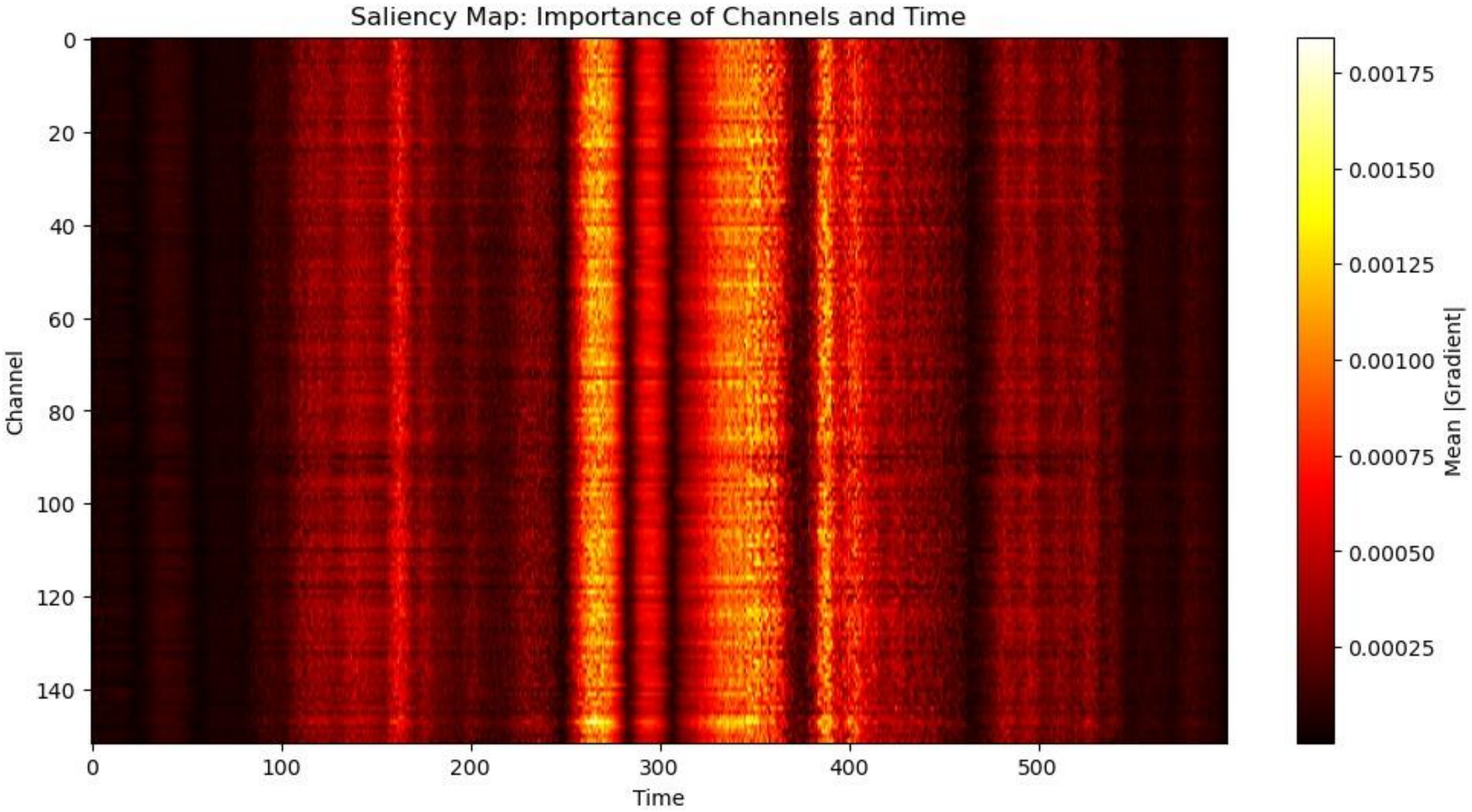


Neuron C0027





Interpretability - Attention map



Article

Full title: Monkey-to-human transfer of brain-computer interface decoders

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Abstract:
Intracortical brain-computer interfaces (iBCIs) enable paralyzed persons to generate movement, but current methods require large amounts of both neural and movement-related data to be collected from the iBCI user for supervised decoder training. We hypothesized that the low-dimensional latent neural representations of motor behavior, known to be preserved across time, might also be preserved across individuals, and allow us to circumvent this problem. We trained a decoder to predict the electromyographic (EMG) activity for a “source” monkey from the latent signals of motor cortex. We then used Canonical Correlation Analysis to align the latent signals of a “target” monkey to those of the source. These decoders were as accurate across monkeys as they were across sessions for a given monkey. Remarkably, the same process with latent signals from a human participant with tetraplegia was within 90% of the with-monkey decoding across session accuracy. Our findings suggest that consistent representations of motor activity exist across animals and even species. Discovering this common representation is a crucial first step in designing iBCI decoders that perform well without large amounts of data and supervised subject-specific tuning.

`lfads-torch`: A modular and extensible implementation of latent factor analysis via dynamical systems

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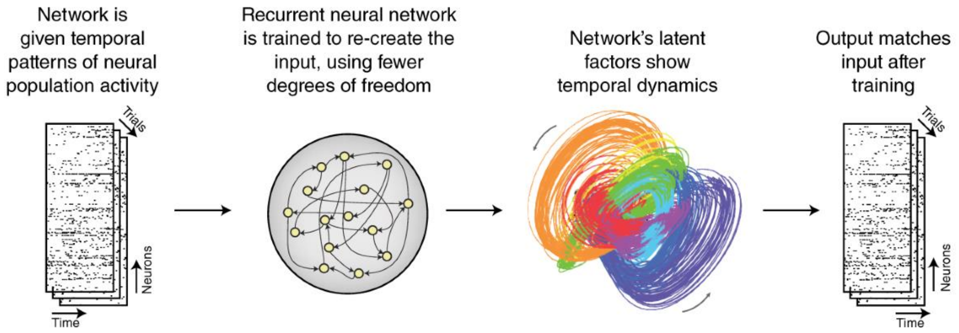
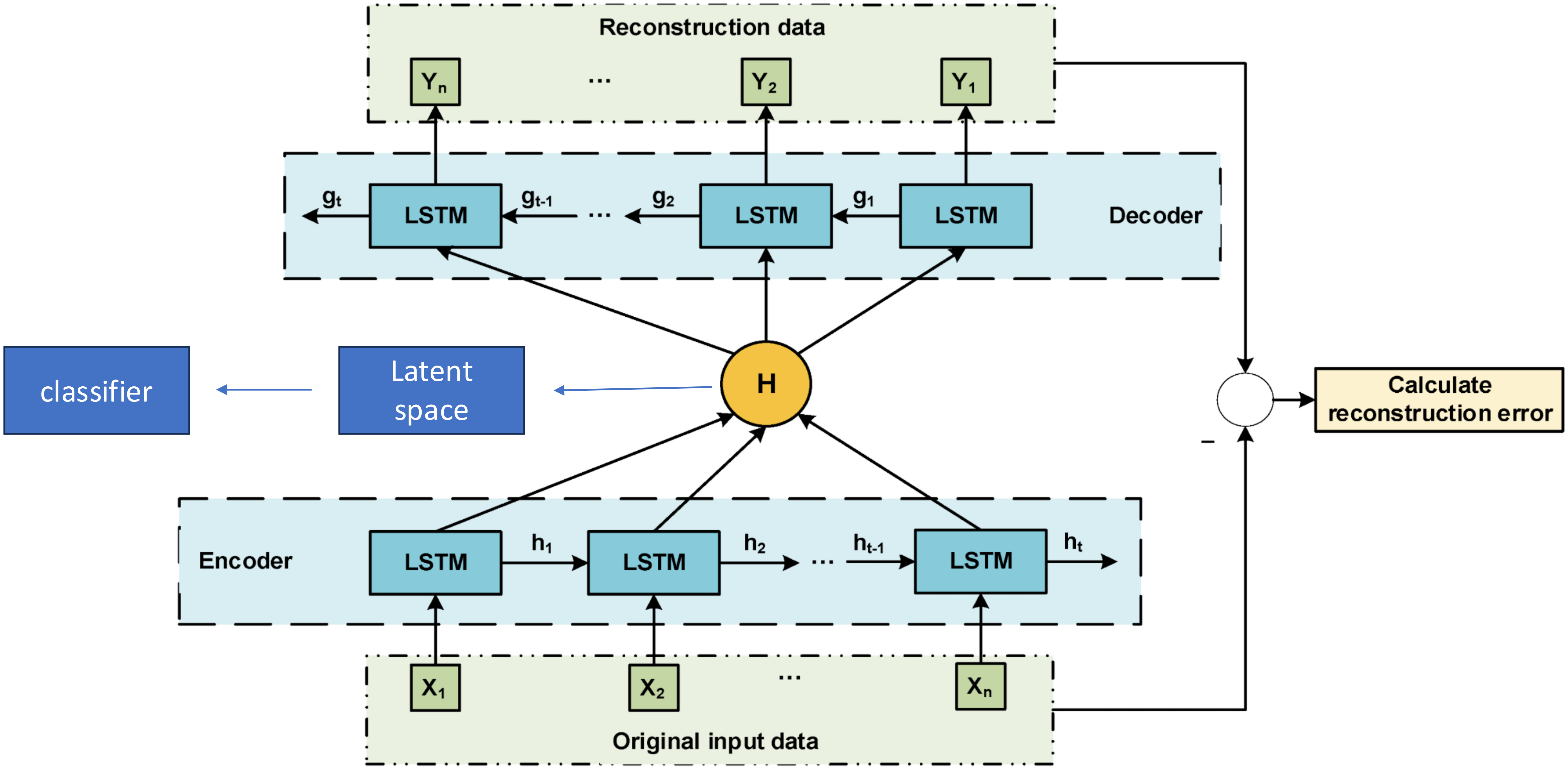
Abstract

Latent factor analysis via dynamical systems (LFADS) is an RNN-based variational sequential autoencoder that achieves state-of-the-art performance in denoising high-dimensional neural activity for downstream applications in science and engineering. Recently introduced variants and extensions continue to demonstrate the applicability of the architecture to a wide variety of problems in neuroscience. Since the development of the original implementation of LFADS, new technologies have emerged that use dynamic computation graphs, minimize boilerplate code, compose model configuration files, and simplify large-scale training. Building on these modern Python libraries, we introduce `lfads-torch`—a new open-source implementation of LFADS that unifies existing variants and is designed to be easier to understand, configure, and extend. Documentation, source code, and issue tracking are available at: `https://github.com/arsedler9/lfads-torch`.

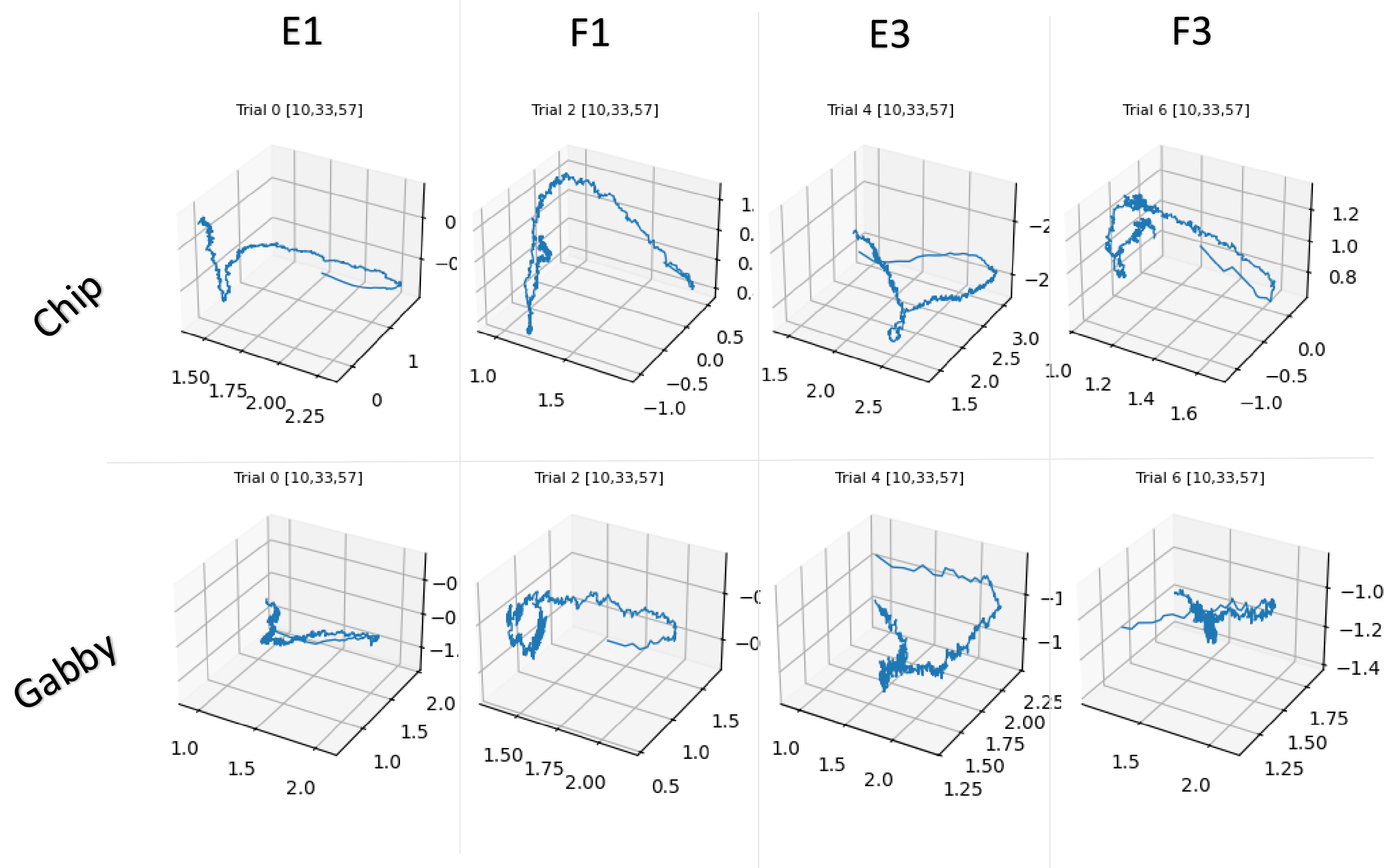
Keywords: deep learning, neuroscience, dynamical systems

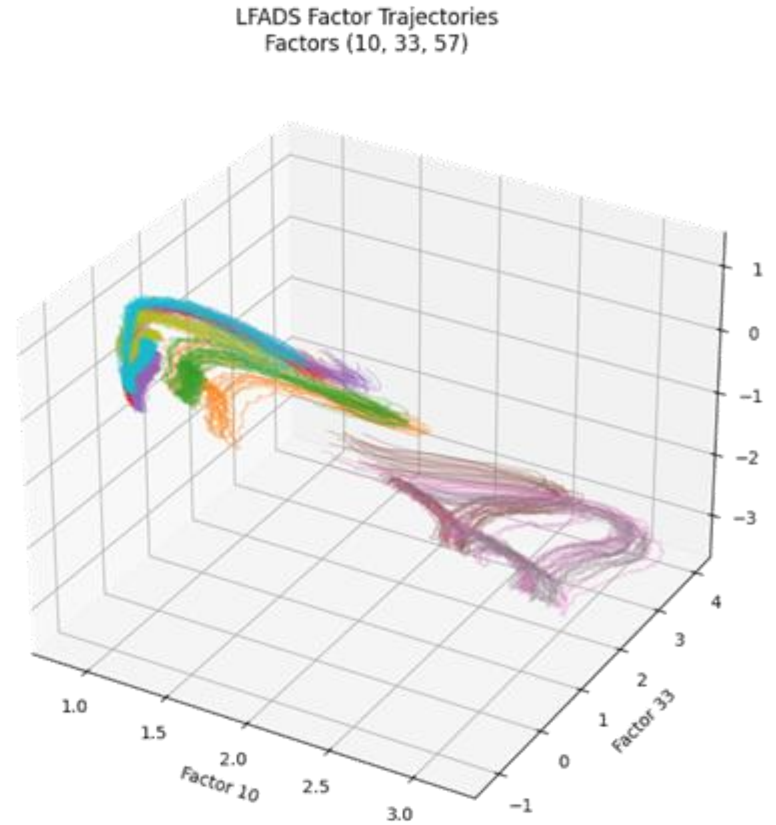


Architecture-model

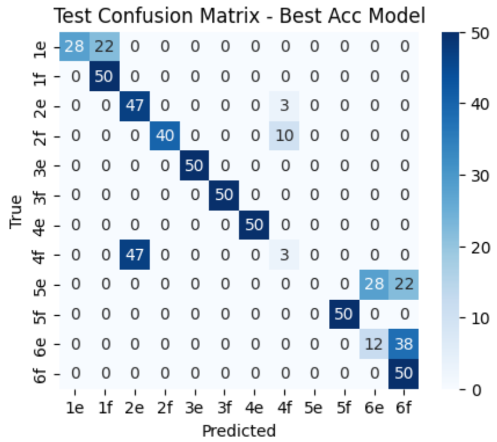


LFADS latent space

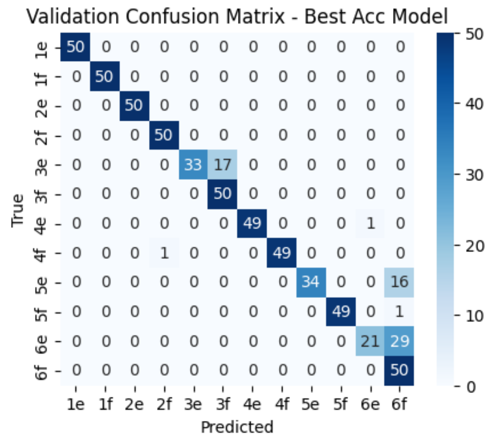




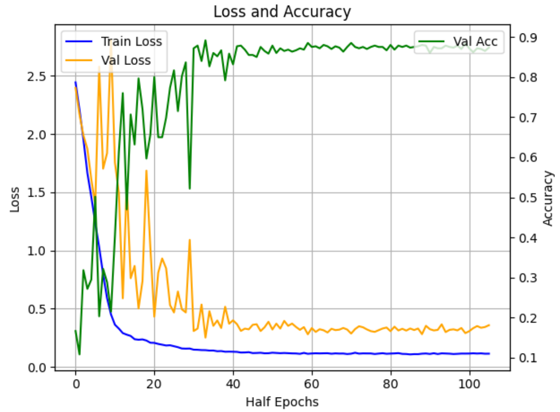
LFADS: Results - Chip



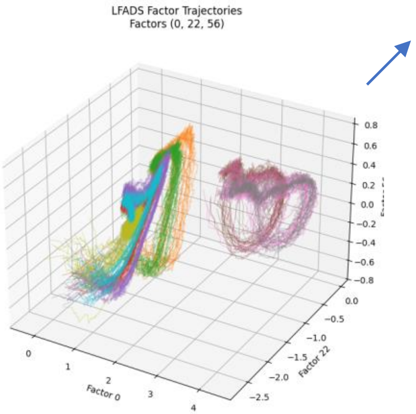
Test Loss: 0.7133 | Test Acc: 0.7167

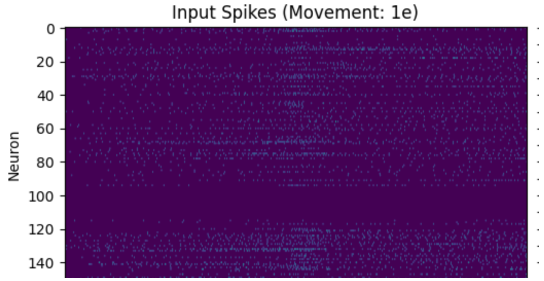


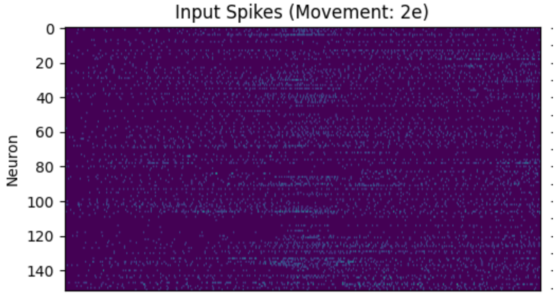
Val Loss: 0.2515 | Val Acc: 0.8917

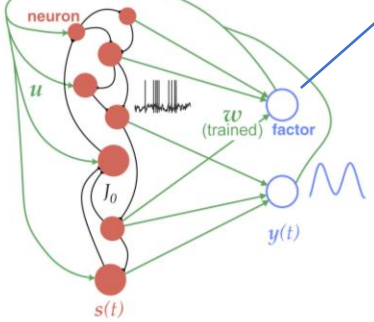


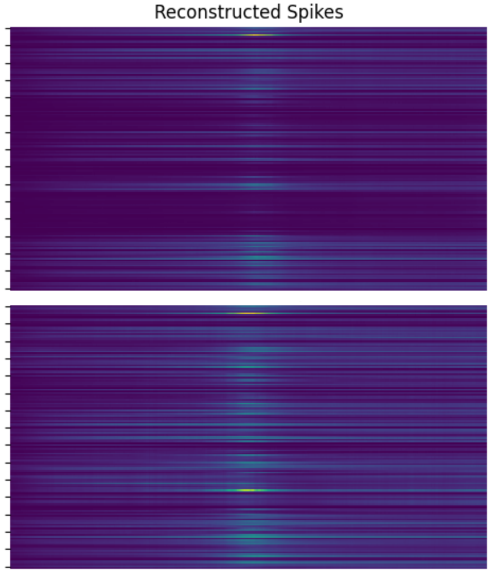
Movement











LFADS: Results - Gabby