# **Neuroformer: A Framework for Multimodal Neural Data Analysis**

Antonis Antoniades Yiyi Yu, Spencer Smith UCSB NLP Group, CS, ECE antonis@ucsb.edu

## Introduction

Weighted sum

#### Motivation

- Systems neuroscience experiments are growing in complexity
- Large datasets are acquired with multiple modalities, including visual, neural, reward, pose, eye-movement, environment and more
- No existing tools to unify training and analysis at this scale  $\bullet$



### $L = (\gamma)L_{vnc} + (\mu)L_{ce(I)} + (1 - \gamma - \mu)L_{ce(dt)}$ **Experiments**

(6)

### **Uncovering Ground-truth Connectivity**

- Simulated dataset of Hub Neurons ("Neurons that fire together, wire together")
- Attention can uncover ground-truth connectivity (20%) lacksquarevariability, compared to 13% for Pearson correlation)



### Neuroformer

#### Framework

- Re-frame Neuron IDs as token representations
- Align multiple modalities using contrastive learning
- Model Neural decoding as a sequential autoregressive process
- Optimize using MLE

### Architecture

Iteratively fuse the "Neural State" with all other modalities using

### **Multi-region Mouse Cortex Recordings**

- Wide-field-of-view 2-photon imaging of V1 + AL brain areas
- Mouse watching a naturalistic video lacksquare
- Neuroformer can generate high-precision simulations of lacksquareground-truth trials over 32 seconds
- Cross-Attention between Neurons and Video reveals salient lacksquare
- a cross-attention transformer that unrolls recurrently in space
- Decode using a causal transformer decoder with two projection outputs, one for temporal prediction, and one for classification

### Optimization

- Alignment (contrastive objective)  $s(F,I) = g_f(F_{p,c})^T g_i(I_c)$  $s(I,F) = g_i(I_c)^T g_f(F_{p,c})$  $p_m^{if} = \frac{\exp(s(i_m, f)/\tau)}{\sum_{m=1}^{M} \exp(s(i_m, f)/\tau)}$ (2)  $p_m^{fi} = \frac{\exp(s(f, i_m)/\tau)}{\sum_{m=1}^M \exp(s(f, i_m)/\tau)}$ (1) $L_{vnc} = \frac{1}{2} \mathbb{E}_{(F,I)\in d} [H(\boldsymbol{y}^{fi}(F), \boldsymbol{p}^{fi}(F)) + \boldsymbol{y}^{if}(I), \boldsymbol{p}^{if}(I))]$ (3)
- Spatio-temporal Decoding (MLE)

(4) 
$$L_{ce(I)} = \frac{1}{2} \mathbb{E}_{(I)\sim d} H(\boldsymbol{y}_I, \boldsymbol{p}_I) \qquad \qquad L_{ce(dt)} = \frac{1}{2} \mathbb{E}_{(dt)\sim d} H(\boldsymbol{y}_{dt}, \boldsymbol{p}_{dt}) \qquad (5)$$



![](_page_0_Figure_34.jpeg)

![](_page_0_Figure_35.jpeg)