2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Stimulus to Action Neural Network by Inferring Connectomics

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***Abstract*— Artificial neural network (ANNs) models have emerged as an important tool to understand the brain function. By fitting real neural data to an ANN, we created a powerful test-bed model for evaluating brain function. We further causally tested the effects of lesions in the network and their effects on the predicted responses and performance.**

I. INTRODUCTION

With the emergence of large-scale electrophysiological data, artificial neural network and computational models are becoming critical for interpreting high-dimensional data [1]. In the past, fitting ANN to real data has proven difficult due to the insufficient sampling of individual neurons, relevant brain regions, and meaningful behavior. In this work, we use freely available data of *in-vivo* large-scale and multi brain region single-cell recordings from rodents while they engage in a visual decision making task [2]. We developed a test-bed neural network model platform, capable of testing hypotheses ranging from the number of neurons needed for computation, timing, and the causal role of specific brain regions for behavior.

II. METHODS

1) Data: We selected the sessions from [2] ($n = 14$) where both visual (V) and motor (M) cortical areas were recorded simultaneously ($\bar{n_V} = 102$, $\bar{n_M} = 96$). For each recorded unit, time averaged segments were taken by trial (n_t-number of trials) to create the activity matrices A_V - $(n_V \times n_t)$ and A_M-$(n_M \times n_t)$ by session. Stimulus contrast presentation p=$(n_t \times 3$ - includes bias) and binary responses r - $(n_t \times 1)$ are the behavior elements used to fit the model.

2) Model Fitting: The ANN model predicts a response for each trial given a stimulus and takes the following form:

$$\hat{r} = \sigma(s \cdot A_E \cdot A_{Tr} \cdot A_D) \quad (1)$$

Where $\hat{r}$ is the predicted response, σ represents the sigmoid function. The encoding matrix A_E-$(n_V \times 3)$ is fitted by solving $p = A_V \cdot A_E$. The decoding matrix A_D-$(n_M \times 1)$, is obtained by a logistic regression fitting of $r = \sigma(A_M \cdot A_D)$. Finally, the transforming matrix A_{Tr}-$(n_V \times n_M)$, is computed through linear regression by solving $A_M = (A_E \cdot p) \cdot A_{Tr}$.

3) Model Evaluation: A 5-fold cross-validation is used to evaluate model performance against the correct answer (TvM) and the animal's response (SvM), for each time bin of interest (0:-500ms-0; 1:0-500ms; 2: 500ms-1s). Invalid trials are excluded from fitting but were used for model evaluation: (1) no-go trials, no contrast difference, and subject responded; and (2) no-resp trials, trials with contrast difference but no response.

4) Model Perturbation: A randomly selected set of weights on each of A_E, A_{Tr} and A_D are set to zero, simulating a lesion. This allows to causally explore both the robustness of the model and the implied role of the regions in performing the task.

*[*]See github for affiliations: https://github.com/mgonzal1/wombats-malos

III. RESULTS AND DISCUSSION

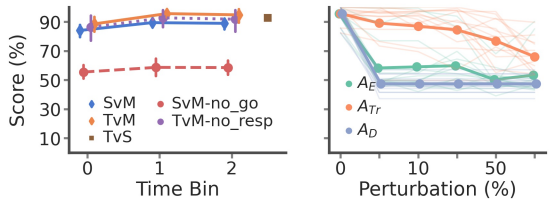

Fig. 1. **Left**. Performance against time for different trial types. **Right**. Performance decay by ablation percentage. Error bars 95%CI across sessions.

In Fig. 1 (left), we can see that the model matches the correct response (TvM) consistently more often than matching the behavior of the subject (SvM), and outperforms the actual behavior of the subject (TvS). Indeed, the model tracks the stimulus more than the response, as seen by the poor model predictions on no-go trials. Surprisingly, our model implies that there is sufficient information to predict the response in the pre-stimulus period, as demonstrated by the high performance in the 0 time bin (-500ms to 0). On the right plot, we observed that performance rapidly decays to chance as connections are ablated for the decoding and encoding matrices, while the transforming component is more robust to perturbations.

IV. CONCLUSIONS

We introduced a flexible test-bed ANN model to evaluate stimulus (encoding) to action (decoding) computations and to infer the possible connections between these (transform). Further research can optimize this approach by using non-linear approaches in the fitting process. Further, this work is also of scientific interest as it points to a decoder that tracks the stimuli more so than the subject's response.

REFERENCES

[1] Yuste, R. From the neuron doctrine to neural networks. Nat Rev Neurosci 16, 487–497 (2015).
[2] Steinmetz, N. A., et. al. Distributed coding of choice, action and engagement across the mouse brain. Nature 576, 266–273 (2019).