Project specification report – network biology research labs

Spring 2024

This report should be submitted only after the supervisor(s) approval

Project name: Latent Variable Models of A Learning Brain
Supervisor's name: Kabir Dabholkar Omri Barak
Student's name: Arnold Cheskis
Main goals of the project: Latent variable models (LVMs) are used to capture the dynamics of a neural circuits given recordings of signals from the brain. LVMs assume that the dynamical system remains fixed. However, the brain is continuously evolving with time, i.e. 'learning'. We study the novel scenario of fitting LVMs to a learning brain using a student-teacher setting. We model the changing brain as a series of models originating from perturbations from a starting model. We evaluate student-teacher similarity using various methods including those mentioned in the paper (K. Dabholkar, O. Barak; 2024).

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NETWORK BIOLOGY RESEARCH LABORATORIES

Future Tasks breakdown (try to make is as detailed as possible)

1. Replicating the student-teacher setting with HMMs, verifying that Likelihood converges as we increase training trials or increase the learning rate, teacher likelihood given the teacher's emissions test dataset should give the best performance, etc.

2. Given a teacher model with parameters T_1, i.e. our "ground truth", we will create a series of models from it ($T_2, T_3 \dots T_k$) by perturbing it. Such that $T_2 = T_1 + \epsilon$, $T_3 = T_2 + \epsilon$, and so on… Thus, $T_1, T_2 \dots T_k$ represent how the brain changes as it learns. We want to start by training students with several different curricula, $S_1, S_{11}, S_{12}, S_2, S_{22}$ respectively on $T_1, T_1 \rightarrow T_1, T_1 \rightarrow T_2$ and so on...

3. Repeating each curriculum with many randomly initialized students.

4. Visualize the distribution of students and teachers in a 2D plot using various dimensionality reduction methods.

5. Evaluating students S_1, S_{11}, S_{12}, S_2, and S_{22} on an unseen teacher T_3

6. Generalize the training to more complex curricula $S_1, S_{11}, S_{12}, S_2, S_{22} \dots S_{12 \dots k}$

7. We know models with similar log likelihood scores can have hidden differences (Dabholkar, Barak 2024). Can these training procedures reveal them?

Relevant papers in the project:

Dabholkar, K., & Barak, O. (2024). *When predict can also explain: Few-shot prediction to select better neural latents* (arXiv:2405.14425). arXiv. http://arxiv.org/abs/2405.14425

Duncker, L., & Sahani, M. (2021). Dynamics on the manifold: Identifying computational dynamical activity from neural population recordings. *Current Opinion in Neurobiology*, *70*, 163–170. https://doi.org/10.1016/j.conb.2021.10.014

Mathematical models of learning and what can be learned from them—PubMed. (n.d.). Retrieved August 4, 2024, from https://pubmed.ncbi.nlm.nih.gov/37043892/

Pei, F., Ye, J., Zoltowski, D., Wu, A., Chowdhury, R. H., Sohn, H., O'Doherty, J. E., Shenoy, K. V., Kaufman, M. T., Churchland, M., Jazayeri, M., Miller, L. E., Pillow, J., Park, I. M., Dyer, E. L., & Pandarinath, C. (2022). *Neural Latents Benchmark '21: Evaluating latent variable models of neural population activity* (arXiv:2109.04463). arXiv. https://doi.org/10.48550/arXiv.2109.04463

https://neurallatents.github.io/

Stanford document about HMM

Maybe:
Barak O. Recurrent neural networks as versatile tools of neuroscience research. Curr Opin Neurobiol. 2017 Oct;46:1-6. doi: 10.1016/j.conb.2017.06.003. Epub 2017 Jun 29. PMID: 28668365.

Working Environment (software/hardware..)

Virtual – using Python

Specific needs from the lab engineer

None (for now).