**Project specification report – network biology research labs**

**Spring 2024**

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

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| **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 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). |
| **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 , i.e. our “ground truth”, we will create a series of models from it () by perturbing it. Such that = + ,  = , and so on… Thus, represent how the brain changes as it learns. We want to start by training students with several different curricula, respectively on 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 on an unseen teacher 6. Generalize the training to more complex curricula 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). |