## Biological learning in mammals: A framework involving many manifolds

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The brain is a network of several cells. Changes in these cells and their components are ubiquitous. There are so many behavioral variables to be learnt as part of any learning task. The fundamental question is on how the brain performs task-specific learning involving different cells, within which several components undergo learning-induced changes? How does the brain network stay stable despite being subjected to changes in several components? How is the brain network capable of learning multiple tasks without forgetting the ones that were learned previously?

An elegant framework that makes these questions tractable involves what are known as manifolds. Let us consider a simple example involving neural activity. Although there are so many neurons in the brain, all of them *cannot* fire simultaneously. This is because some of these are inhibitory neurons, which suppress activity in neurons where they connect to. Thus, the connectivity patterns and the synaptic inputs ensure that the activity of a set of neurons do not span the entire possible space of firing rates but are *constrained* to fall within a *low-dimensional manifold*. These are referred to as **neural manifolds**, a framework that has provided important insights into how different neurons interact with each other in executing specific tasks. Similarly, the ubiquitous nature of plasticity does not imply that arbitrary combinations of components can undergo plasticity. There is a structured low-dimensional manifold referred to as a **plasticity manifold** that constrains plasticity involving different components. Finally, a **behavioral manifold** refers to the low-dimensional manifold that reflects constraints on the behaviors that can be elicited by the animal, given external and internal constraints.

Against this backdrop, a learning task can be defined as a change, that is constrained by the plasticity manifold, in the mapping from the neural manifold to the behavioral manifold. This project will be an exploration, involving both experimental (electrophysiological and/or behavioral) and computational (realistic network simulations and/or dimensionality reduction analyses) techniques, of how these disparate manifolds interact with each other towards achieving biological learning in the brain.

**Prerequisite**: A keen interest in learning new things and an attitude engrained in innovation and intellectual exploration.

## **Further reading**

- 1. Mishra, P., & Narayanan, R. (2021). Stable continual learning through structured multiscale plasticity manifolds. *Curr Opin Neurobiol*, 70, 51–63. <u>https://doi.org/10.1016/j.conb.2021.07.009</u>
- Vyas, S., Golub, M. D., Sussillo, D., & Shenoy, K. V. (2020). Computation Through Neural Population Dynamics. *Annual Review of Neuroscience, Vol 36*, 43, 249–275. https://doi.org/10.1146/annurev-neuro-092619-094115
- Jazayeri, M., & Afraz, A. (2017). Navigating the Neural Space in Search of the Neural Code. Neuron, 93(5), 1003–1014. <u>https://doi.org/10.1016/j.neuron.2017.02.019</u>
- Krakauer, J. W., Ghazanfar, A. A., Gomez-Marin, A., MacIver, M. A., & Poeppel, D. (2017). Neuroscience Needs Behavior: Correcting a Reductionist Bias. *Neuron*, 93(3), 480–490. https://doi.org/10.1016/j.neuron.2016.12.041