**Christian Machens – CNeuro Lectures 2021**

**Lecture 1 (Basic):**

Population Coding and Distributed Representations in the Brain

Information in the brain is often distributed across large populations of neurons. For instance, when we study animals performing specific behavioral tasks, we find a complex dependency of neural activities on experimental parameters, such as stimuli, decisions, or motor responses. In higher-order areas of the brain, we find that single neurons 'mix' both sensory and motor-related signals. These mappings from (carefully chosen) experimental parameters to population activities appear to be typical and stable across tasks, brain areas, and animals, and have led to the notion of distributed representation. I will review modern methods of analyzing such population activities and discuss experimental finding over a variety of different brain systems. Within this view point, information in neural circuits is represented in lower-dimensional subspaces (or manifolds) of the neural activities. I will specifically focus on the idea that 'encoding is non-linear while decoding is linear' and discuss the underlying assumptions.

These are the papers most closely related to the talk:

Keemink, S. W., & Machens, C. K. (2019). Decoding and encoding (de) mixed population responses. Current opinion in neurobiology, 58, 112-121.

Kobak, D., Brendel, W., Constantinidis, C., Feierstein, C. E., Kepecs, A., Mainen, Z. F., ... & Machens, C. K. (2016). Demixed principal component analysis of neural population data. Elife, 5, e10989.

These are a few papers that provide some context:

Saxena, S., & Cunningham, J. P. (2019). Towards the neural population doctrine. Current opinion in neurobiology, 55, 103-111.

Humphries, M. D. (2020). Strong and weak principles of neural dimension reduction. arXiv preprint arXiv:2011.08088.

Sadtler, P. T., Quick, K. M., Golub, M. D., Chase, S. M., Ryu, S. I., Tyler-Kabara, E. C., ... & Batista, A. P. (2014). Neural constraints on learning. Nature, 512(7515), 423-426.

Stringer, C., Pachitariu, M., Steinmetz, N., Carandini, M., & Harris, K. D. (2019). High-dimensional geometry of population responses in visual cortex. Nature, 571(7765), 361-365.

Wohrer, A., Humphries, M. D., & Machens, C. K. (2013). Population-wide distributions of neural activity during perceptual decision-making. Progress in neurobiology, 103, 156-193.

**Lecture Abstracts**

**Lecture 2 (Advanced):**

A Geometric View on Spiking Networks and Distributed Representations.

In the classical picture of neural networks, the single rate neuron is the fundamental computational unit. While immensely successful (both in neuroscience and AI), this view has also created several persistent puzzles about the organization of neural systems. One puzzle are (unreliable) spikes, which have largely remained a nuisance, rather than a feature of neural systems. Another puzzle is robustness to perturbations, which is

ubiquitous in biology, but largely ignored in neural network modeling. I will show that these puzzles can be resolved if we shift our perspective of how neural systems operate from a single-neuron to a population-perspective. Based on only two assumptions - that the effective output of a neural network can be extracted via linear decoding, and that each neuron only fires to bound an error on this output, I will show how to derive a spiking network of integrate-and-fire neurons that exhibits irregular and asynchronous spike trains, balance of excitatory and inhibitory currents, and robustness to perturbations. I will provide geometric intuitions for the network's functionality, discuss the non-linear embedding of input signals in the state space, and show how such networks can learn distributed representations from scratch.

These are the papers most closely related to the talk:

Calaim, N., Dehmelt, F. A., Gonçalves, P. J., & Machens, C. K. (2020). Robust coding with spiking networks: a geometric perspective. bioRxiv.

Brendel, W., Bourdoukan, R., Vertechi, P., Machens, C. K., & Denéve, S. (2020). Learning to represent signals spike by spike. PLoS computational biology, 16(3), e1007692.

These are a few papers that provide some context:

Denève, S., & Machens, C. K. (2016). Efficient codes and balanced networks. Nature neuroscience, 19(3), 375-382.

Abbott, L. F., DePasquale, B., & Memmesheimer, R. M. (2016). Building functional networks of spiking model neurons. Nature neuroscience, 19(3), 350-355.

Boerlin, M., Machens, C. K., & Denève, S. (2013). Predictive coding of dynamical variables in balanced spiking networks. PLoS computational biology, 9(11), e1003258.

Eliasmith, C. (2005). A unified approach to building and controlling spiking attractor networks. *Neural computation*, *17*(6), 1276-1314.