

Learning the code of large neural populations using sparse random projections

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We present a new class of accurate, efficient, and scalable models for the activity patterns of large neural populations. These models rely on sparse, random, and nonlinear projections and are highly accurate in representing the codebook of populations of hundreds of neurons, requiring surprisingly small amounts of training data, while also being scalable and computationally efficient. Interestingly, these models have a biologically plausible implementation via shallow, simple neural circuits that use random, sparse, and nonlinear projections, and can learn using a simple, noise-driven learning rule. We further show that homeostatic synaptic scaling enhances both the efficiency and accuracy of learning such models for very large neural populations. Finally, we discuss how these models may enable the brain to perform Bayesian decoding and to learn metrics over the space of neural codes and external stimuli.

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