The dynamical modes framework: towards a biophysical interpretation of neural data

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Large scale recording techniques have enabled the simultaneous recording of activity from ensembles of neurons. Commonly used methods such as principal component analysis can effectively reduce the number of dimensions of the neural activity recorded during a particular task, but the extracted principal components may not necessarily be computationally relevant for this task. We propose that there is a potentially different set of activity patterns at the population level, 'dynamical modes', that do represent and/or carry out the necessary computations for successful task performance. We will outline a framework to identify dynamical modes in a neural data set based on the task set, i.e., a priori defined com- putational requirements for the task. We illustrate the framework on frontal cortical neurons that were recorded during a memory-guided decision task. Intuitively, dynamical modes correspond to neural activity patterns at the population level that subserve computations that produce behavior. A fundamental component of the framework we are proposing is to define dynamical modes within a precise mathematical formalism. We consider neural activity (e.g., trial-averaged histogram) as an N-dimensional vector $r(t) \in R+ N$ where N is the number of neurons in the data set, and R+ corresponds to the positive real numbers. We express the neural activity $r(t)$ in the 'full neural network basis' as: $r(t)=r1[1,0,0,...0] +r2[0,1,0,...0] +...$ (1) where ri is the firing rate of unit $i \in \{1, 2, ..., N\}$ and
ei is the canonical basis. This description is commonly referred to as the 'neural state space'.
We now consider a change of basis, that changes the representation of neural activity from one level of description to another. Generally, we can write: $r(t) = m1(t)P1 + m2(t)P2 + m3(t)P3 + ...$, (3), where mj(t) with $j \in \{1,2,...,K\}$ is a scalar function of time.
In this new basis, we introduced vectors Pj that reexpress neural activity to reveal potentially relevant computations contained in the functions mj (t). We can now formally define a dynamical mode as a component of the expansion of the neural activity in the new mode basis(Eq.3). In the expansion, we can distinguish mode directions - the vectors Pj - from mode projections - the scalar functions of time mj(t), both of which can be extracted from data (Figure 2). In the memory-guided response task, dynamical mode projections span the

different behavioral epochs - three are shown in Figure 2A. These projections reside along three directions in neural activity space, the dynamical mode directions, which constrain - though do not uniquely determine - the matrix P (Figure 2B). The neural circuits obtained via the dynamical mode projections, define a ’dynamical mode connectivity’ matrix J, which corresponds to the subspace of behaviorally-relevant computations. Finally, J and P determine the connectivity A of the full neural network (Figure 2C). Thus, we are able to obtain a full neural network in a data-driven manner that is constrained to exhibit dynamical modes. With the the full neural network, we can analyze the full neural network matrix A for, e.g., random and non-random features of the connectivity that are related to neural dynamics.