related with an animal's perceptual report [1]. The interpretation of this phenomenon (often summarized as choice probability (CP)) is complicated by the presence of correlations between neurons [2], which are often low-dimensional and shared across many neurons [3, 4, 5]. Here we extracted single-trial low-dimensional neural trajectory using variational latent Gaussian process (vLGP) algorithm [6] from population recordings in area MT [7] to understand how stimulus and choice are encoded across the population. The recovered neural trajectory captures the slow covariation in the population spike trains. The generative model of vLGP assumes multiplicative interaction among the latent processes in addition to an autoregressive point process observation model for each spike train. vLGP decomposes the population response as the shared variability (represented as neural trajectory) and individual neuron's private noise. We found that the neural trajectories strongly encoded the direction of the stimulus with similar temporal signature as single MT neurons. We then computed a time-weighted CP for the neural trajectories; this "population CP" was much higher than any single MT unit CP and increased over time unlike single MT unit CP. Most of the explanatory power of neural trajectories came from 2 latent dimensions, which were spatially localized along the recording electrode, suggesting anatomical organization correlated with functional information representation. Taken together, these observations offer new interpretive frameworks for population level activity in relation to perception.

T-28. Dimension reduction of multi-trial neural data by tensor decomposition

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Decision-making, sensation, and motor behaviors occur within fractions of seconds, while learned memories can require many hours, days, or years to mature. Technologies for long-term monitoring of neural activity enable examination of all these processes in a single experiment. However, exploratory analysis of these data is challenging due their size (thousands of neurons and behavioral trials) and diversity of timescales. Commonly used methods for dimensionality reduction identify low-dimensional features of within trial neural dynamics, but do not model changes in neural activity across trials. We propose to represent multi-trial data as a three-dimensional data array (a third-order tensor) with each entry indicating the activity of a particular neuron at a particular time on a particular trial (Fig 1). Approximating these data with the canonical polyadic (CP) tensor decomposition (reviewed in [3]) produces low-dimensional factors that summarize neural correlations, within-trial dynamics, and across-trial changes in dynamics. Applying CP decomposition to simulated multi-trial data precisely identified low-dimensional network inputs that varied across trials, whereas classical methods (PCA and ICA) failed to recover these signals. We then examined two experimental datasets: (a) prefrontal cortical neurons monitored by fluorescence microendoscopy in mice performing a spatial navigation task, and (b) multi-unit extracellular recordings in the premotor and motor cortices of a Rhesus monkey moving a virtual cursor through a brain-machine interface. In both cases, CP decomposition uncovered specific neural sub-populations with interpretable within-trial as well as across trial dynamics, reflecting task structure, strategies, rewards, and BMI perturbations. The CP decomposition is broadly applicable to common experimental designs in systems neuroscience, is simpler to fit and interpret than complex nonlinear models, and is more informative than classical techniques that represent neural data as a matrix.