

## T-29. Low-rank non-stationary population dynamics can account for robustness to optogenetic stimulation

Lea Duncker<sup>1,2</sup>  
 Daniel O'Shea<sup>3</sup>  
 Werapong Goo<sup>3</sup>  
 Krishna Shenoy<sup>3</sup>  
 Maneesh Sahani<sup>1,2</sup>

DUNCKER@GATSBY.UCL.AC.UK  
 DJOSHEA@STANFORD.EDU  
 WERAPONG.GOO@GMAIL.COM  
 SHENOY@STANFORD.EDU  
 MANEESH@GATSBY.UCL.AC.UK

<sup>1</sup>Gatsby Computational Neuroscience Unit

<sup>2</sup>University College London

<sup>3</sup>Stanford University

Genetically or anatomically targeted perturbations can provide invaluable insight into the functional role of sub-populations within neural circuits, but may be difficult to interpret. We have shown previously [O'Shea et al. COSYNE14] that focal optogenetic stimulation in primate motor cortex drives large concurrent changes in firing rates across a local population of neurons — perturbing, at least in part, patterns of activity correlated with the behavioural task — and yet decays rapidly with only subtle effects on reaction time and the kinematics of upcoming or ongoing movements. Does such robustness in the circuit require corrective influences from other populations [Li et al. Nature 2016] or could it arise within the local population itself? If the dynamics of population activity are low-rank, then robustness to stimulation could arise because the perturbation projects into the nullspace of the dynamical operator. However, a non-normal dynamical system may produce systematic, task-relevant output in this nullspace, and so it cannot be characterised by methods that depend purely on variance or regression to task parameters. We developed an efficient algorithm to learn a non-stationary, low-rank, population dynamical model from data. We applied this model to population recordings from macaque dorsal premotor cortex (PMd) during an instructed-delay center-out reaching task with optogenetically perturbed trials. The model captured the evolution of population activity throughout reach initiation and execution, successfully recovering the robust evolution of the neural population on stimulated trials. Examination of the model parameters revealed that indeed evolution was robust because the optogenetic stimulation projected into a nullspace of the identified low-rank dynamics. Ultimately, a clear understanding of the functional and behavioural role of neural populations will depend on a better understanding of both the effects of perturbation, and the dynamics that govern the evolution of the neural population.

## T-30. Hippocampal coding arises from probabilistic self-localization across many ambiguous environments

Ingmar Kanitscheider  
 Ila R Fiete

IKANITSCHIEDER@MAIL.CLM.UTEXAS.EDU  
 FIETE@MAIL.CLM.UTEXAS.EDU

University of Texas at Austin

How do animals self-localize accurately enough that their neurons exhibit spatial tuning over  $\approx 10$  – *minute* trajectories while their motion estimates are noisy enough that path integration would lead to disorientation over this time? Landmarks help, but can be spatially extended (walls) or resemble other landmarks, providing ambiguous information and leading to complex, multi-peaked posterior distributions over position. Robotics algorithms solve the problem by sequential probabilistic inference, but despite the rich literature on the brain's spatial representations it is unclear how neural circuits execute similar computations. We study the problem of localization with noisy motion cues in environments of different geometry, where walls are sensed only upon contact. We take a “model-free” approach—constrained by task but not neural tuning—and train recurrent neural networks to localize. We scrutinize the resulting performance and representations. The trained network exploits motion cue and environmental geometry statistics to vastly outperform path integration and methods that update a best single estimate of position using motion and landmark cues, even in novel environments of unknown specific shape. In an environment of known geometry, performance matches the Bayes-optimal particle filter. After training in