Learning to Compose: Geometric Reorganization of Prefrontal Dynamics Enables Flexible Multi-Task Control

Complex behavior requires neural circuits to compose elementary operations—maintaining memories, evaluating sensory cues, suppressing premature actions—into context-appropriate programs. How prefrontal dynamics reorganize to support such composition when task demands compete within a shared neural population remains unclear.

Here, we developed a dual-task paradigm in mice that combined a delayed paired-association (DPA) task with an olfactory Go/No-Go (GNG) discrimination embedded in the delay period. Mice learned the dual task rapidly, with early errors dominated by false alarms on unpaired DPA trials. Interference was asymmetric: Go cues disrupted performance more than No-Go cues, pinpointing premature action rather than memory failure as the central learning bottleneck. Population calcium imaging from medial prefrontal cortex (mPFC) showed that sample identity, choice tendency, and test identity occupied near-orthogonal subspaces of a shared low-dimensional manifold. As training progressed, sample representations remained stable while delay-period activity shifted away from the action-associated region.

To probe the underlying circuit mechanisms, we trained low-rank recurrent neural networks on the same paradigm. Networks developed a circular manifold on which memories were stored as attractors at distinct angular positions, and test stimuli acted as compositional rotation operators, routing stored memories to appropriate actions. Dual-task training relocated mnemonic attractors to a position that a reduced geometric model identified as Pareto-optimal—revealing a fundamental tradeoff in which optimizing one task necessarily impairs the other.

Consistently, optogenetic inhibition of ACC→mPFC projections during the delay displaced attractor geometry and selectively biased DPA versus GNG accuracy, matching the reduced model's prediction. Together, our results reveal how prefrontal circuits dynamically reshape attractor geometry through learning-dependent attractor fine-tuning, providing a mechanistic framework for how cortex resolves competing cognitive demands.