



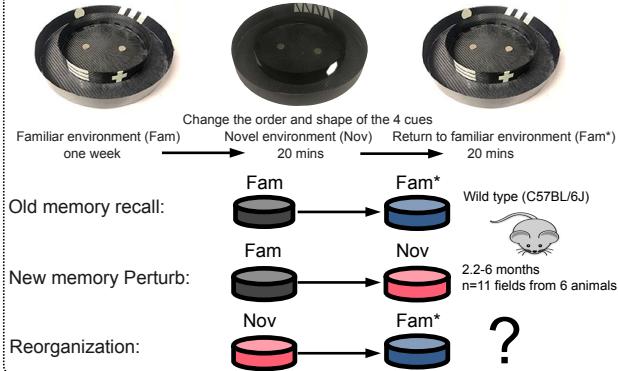
Multi-scale neural dynamics underlying memory encoding and recall in hippocampal area CA1

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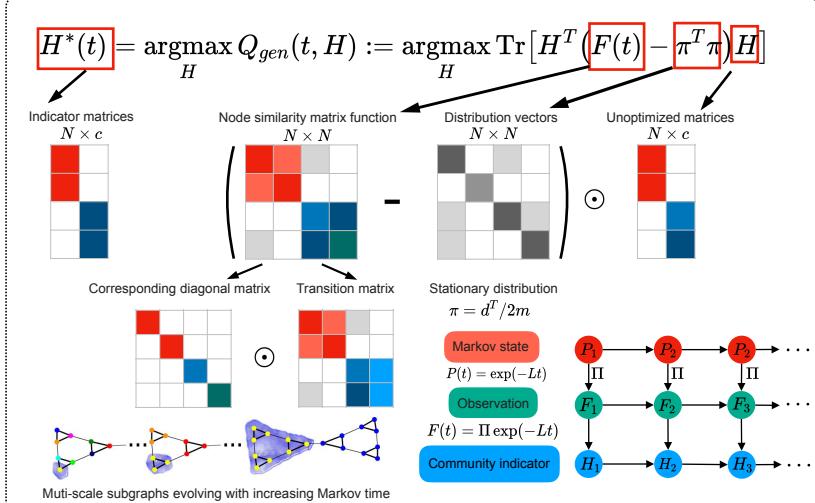
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Motivation & Experiment design

Question: How does learning a new memory reorganize the functional network topology of an old memory in hippocampal area CA1?



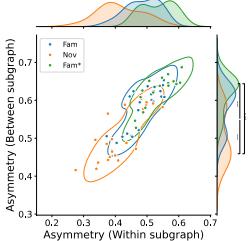
Multi-scale subgraph detection with generalized Markov Stability



Asymmetry of connections between subgraphs & within subgraph

Figure.5 As the scale of the subgraphs transitioned from coarse to fine granularity, both the intra-subgraph and inter-subgraph asymmetry exhibited an increase. Furthermore, the perturbation introduced by new memories led to a **decrease** in the asymmetry of connections within and between subgraphs, indicating a higher degree of homogenization in the functional networks.

During the subsequent reorganization process, the asymmetry of connections within and between subgraphs was **elevated** in the fam* condition compared to the fam condition.



Ongoing directions - Simulate neural dynamics of memory recall with perturbation

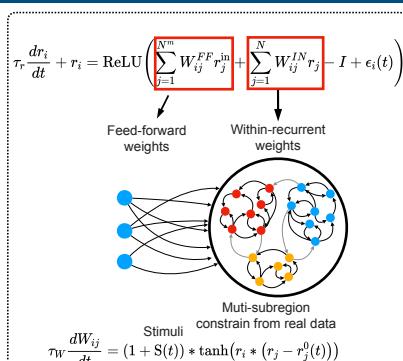


Figure.6 By conducting rest simulations at different time scales, we aim to observe the impact of the consolidation process duration following perturbation on the reorganization during recall.

Initial result.

Modeling networks of different environments by self-organizing processes.

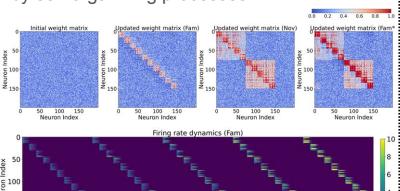
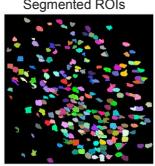


Figure.7 To simulate perturbation, we designed receptive fields based on the graph structure we inferred. Initial findings suggest that when returning to the initial environment, **greater** inhibitory neuron weights are required to maintain stable neural dynamics.

Approach of dynamic functional connection



Segmented ROIs
2-photon microscope
Water immersion
Dental cement
Skull
Cover glass
CA1
CA3
DG
Directed graph

$$B \parallel A \parallel f_A(t) \\ F_{AB} = \frac{1}{N_{AB}} \sum_{i=1}^{N_B} f_A(t_i^B) \\ f_A(t_i^B) = \xi_{\text{exc}}(t_i^B - t_{\text{last}}^A) = e^{-(t_i^B - t_{\text{last}}^A)/\tau}$$

Perturbation (encoding) results at the network level

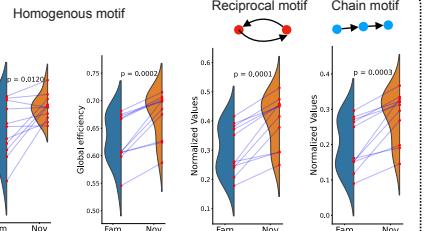


Figure.1 At the network level, a **higher** average clustering coefficient and global efficiency with exploring the novel environment. In fam*, these returned to the level of fam.

In the novel environment, both the **Chain motif** and **Reciprocal motif** exhibited an increase, resulting in the emergence of **homogeneous structures**.

Reorganization (recall) results at the subgraph level

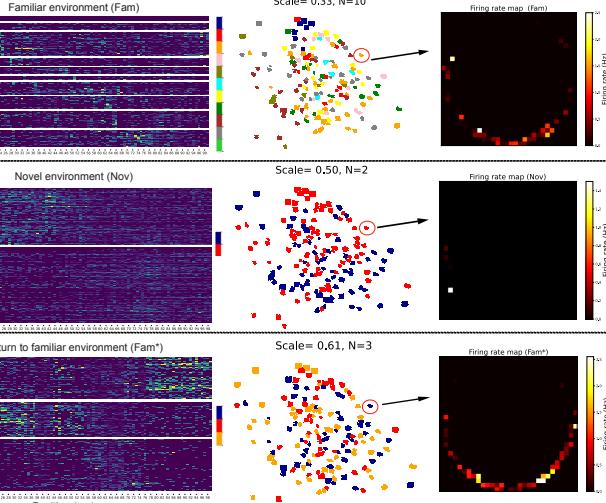


Figure.2 At certain time scales that exhibit considerable stability, our method demonstrates the capability to detect highly **reliable** subgraphs. These subgraphs effectively capture neurons that possess similar firing fields.

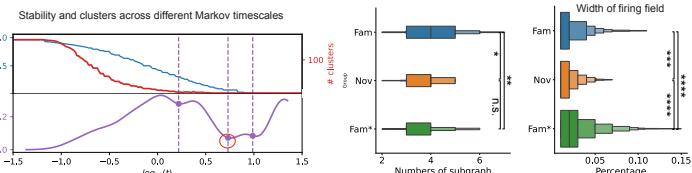


Figure.3 During the reorganization process, we observe that the stable subgraph scales become **coarser**, indicating a **reduction** in the number of stable subgraphs in the Fam*. This effect appears to be a consequence of the previous perturbation. Furthermore, among ~1761 cells analyzed, a significant **broadening** of the firing rate map was discovered.

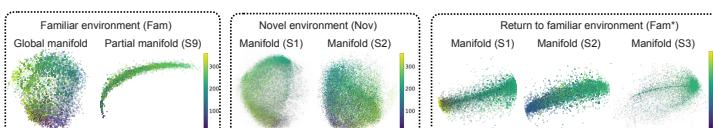


Figure.4 The perturbation process initially disrupted the previously stable global manifold. Further analysis of the manifolds corresponding to each neural subpopulation revealed that, compared to the Fam, the sub-population manifold spanned **broader** local field during the reorganization process in Fam*.

Conclusion and discussion

- The perturbation (new memory encoding) initially led to the homogenization of the CA1 network.
- Population structure exhibits differences across spatial scales.
- During the reorganization (recall) process, neurons extended their firing fields, resulting in a reduction in the number of functionally distinct subpopulations.
- However, the asymmetry of the existing subpopulations was enhanced.