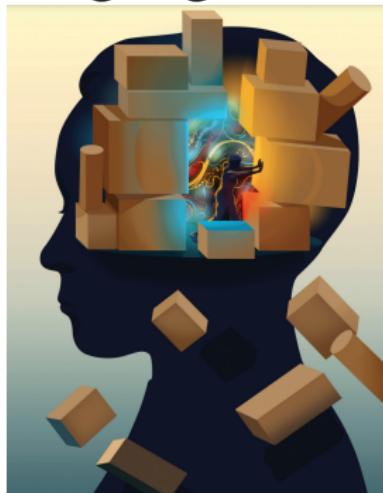


The Importance of Forgetting: Recovering Topology from Spike Train Data with Zig Zag Persistence



Brantley Vose

CSE 5339: Week 5

We have learned a lot of theory...

- Neuroscience introduction
- Persistent homology
- Zig-zag and multiparameter persistence

It's time to focus in on an application!

Review

The Space Reconstruction Experiment

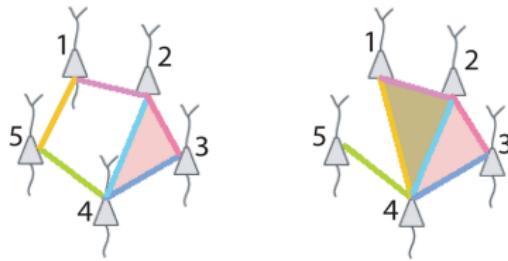
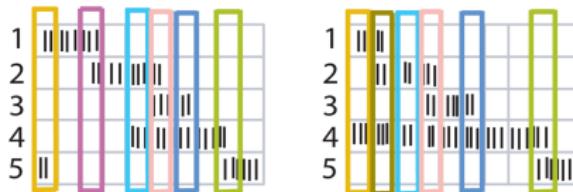


Given spike train data from the hippocampus, can we reconstruct geometric or topological aspects of the arena?

First Strategy: Nerve Complex and Persistent Homology

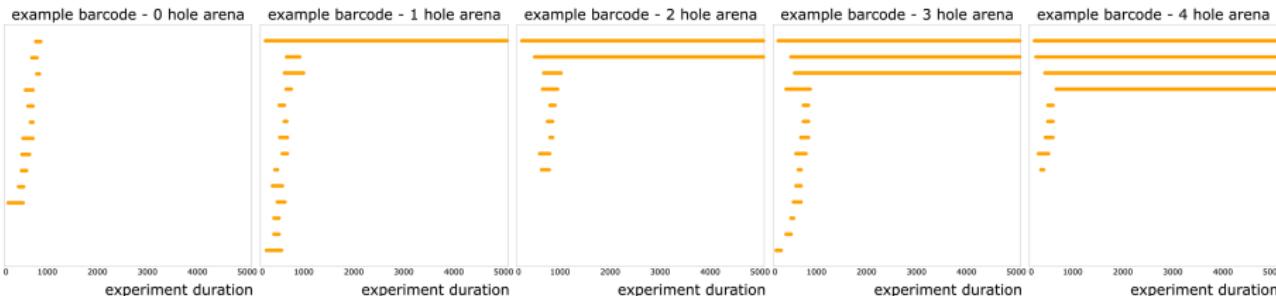
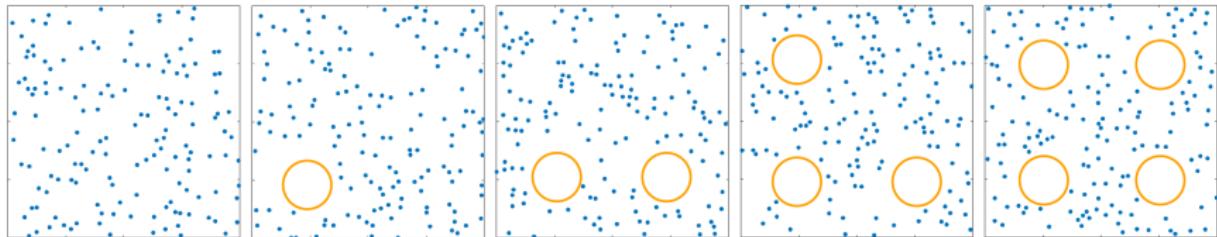
Previous strategy from [CI08]:

- ① Collect spike train data from place cell ensemble as mouse explores.
- ② Approximate the nerve complex by watching for cofiring.
- ③ Persistent homology should reflect homology of the arena.

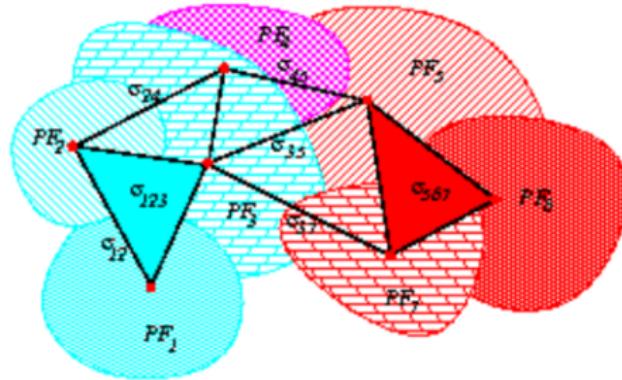


First Strategy: Nerve Complex and Persistent Homology

The hope: the resulting barcodes reflect the topology of the arena.



The Question: Limited Memory

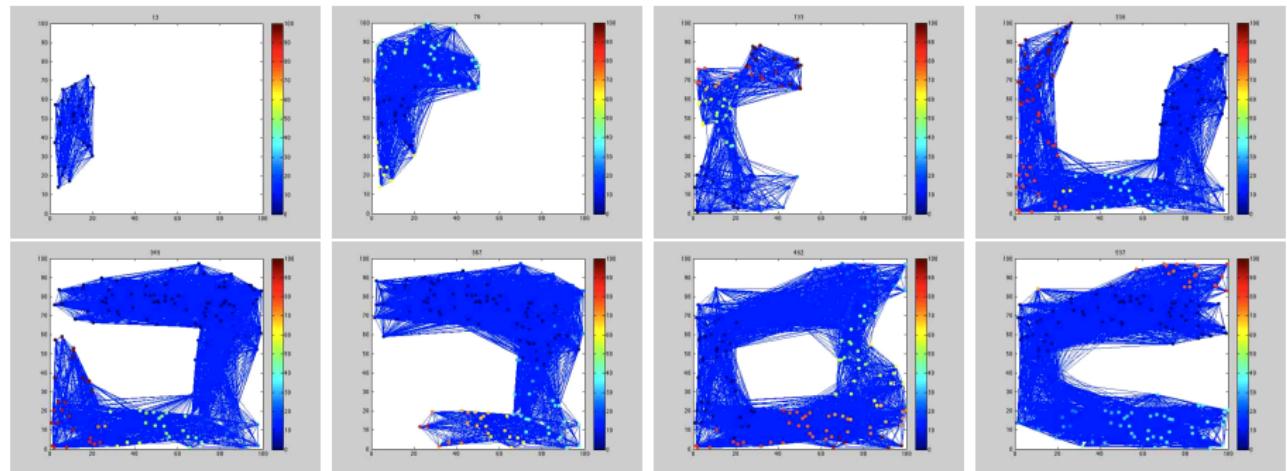


This method uses “perfect memory,” i.e. the complex at the end of the experiment includes data gathered at the very beginning.

Question: How does Limited Memory Affect the Reconstruction of the Topology?

One Extreme: Very Short Memory

What would happen if we “forgot” the simplices in our complex after some amount of time?

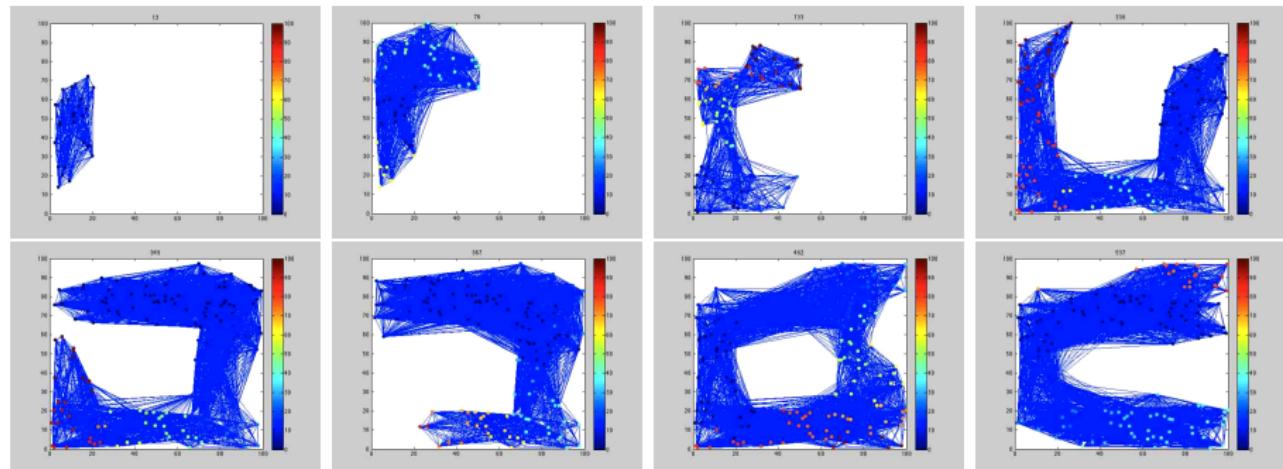


(Not pictured: Obstacle in center of arena, and higher-dimensional simplices.)

If simplices are forgotten too quickly, our complex struggles to capture the topology.

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(Not pictured: Obstacle in center of arena, and higher-dimensional simplices.)

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Expectation: Longer Memory Should be Better

The Setup

Modeling Limited Memory

Recall the filtered complex with **perfect memory**:

- Fix a window size $\epsilon > 0$ and a threshold $n_0 \in \mathbb{N}$. We say a collection $\{v_0, \dots, v_k\}$ of cells *cofire* at time t if

$$|s(v_i) \cap [t - \epsilon, t + \epsilon]| \geq n_0$$

for all $i = 0, 1, \dots, k$, where $s(v_i)$ is the spike train for place cell i .

- Let V be the collection of observed place fields. Suppose the experiment runs from $t = 0$ to $t = T$. The filtration is given by

$$K_t = \{\sigma \subset V \mid \text{the cells in } \sigma \text{ have cofired by time } t\}$$

for integers $t \in [0, T]$

Modeling Limited Memory

What about with **limited memory**? The authors of [CDM18] modify the above model by adding a memory length parameter.

Definition

Fix a memory length $\tau > 0$. The *synaptic potentiation complex with memory length τ* (or simply the *potentiation complex*) is given by

$$K_t^\tau = \{\sigma \subset V \mid \text{the cells in } \sigma \text{ have cofired at some time in } [t - \tau, t]\}$$

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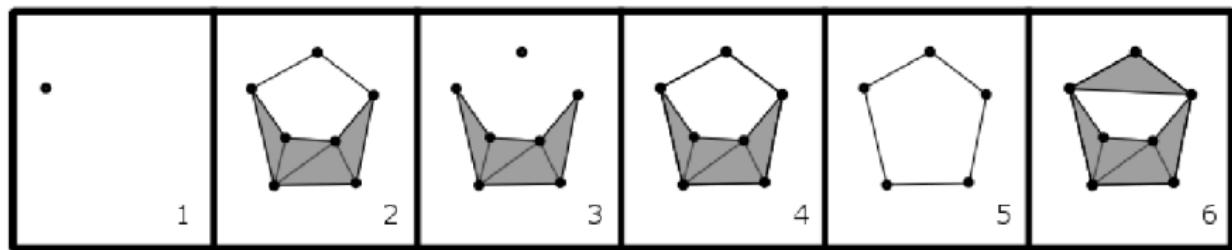
for integers $t \in [0, T]$.

Problem: This is often **not a filtration!** There is no guarantee that $K_t^\tau \subseteq K_{t+1}^\tau$, since some simplices might be **forgotten** between time t and $t + 1$.

Using Zig-Zag Persistence

Solution: **Zig-zag persistence!**

The potentiation complex K_t^τ may not be a filtration, but it is a zig-zag filtration! We can still get barcode with zig-zag persistence.



The Experiment

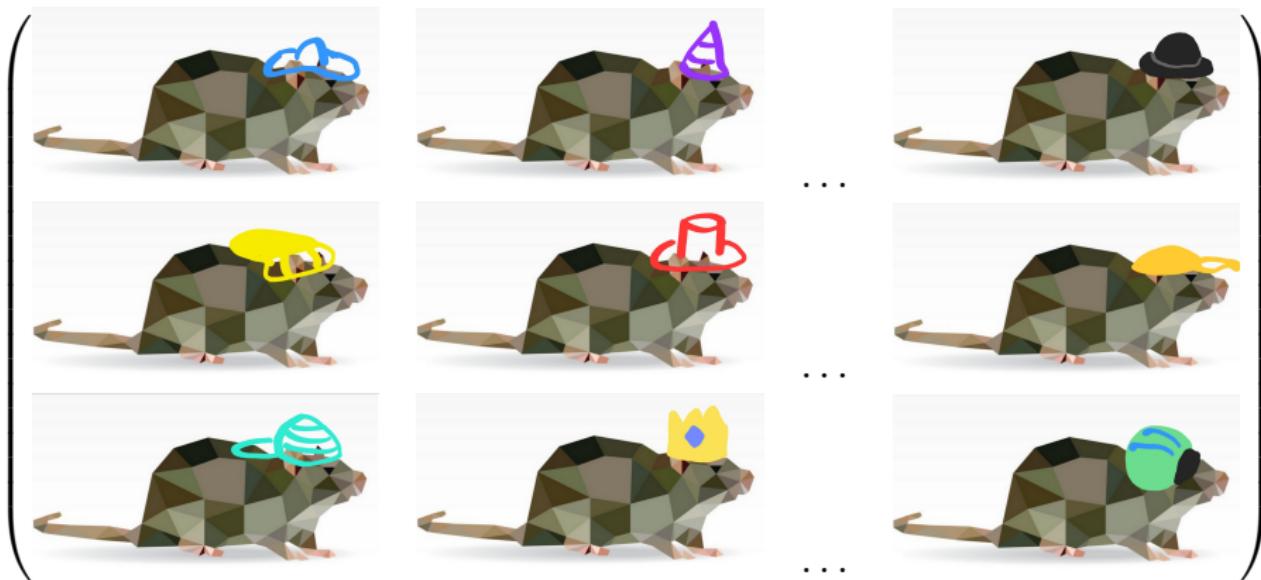
The Experiment

The experiment has three parts.

- ① Generate a datasets by simulating mice in arenas.
- ② Try to recover the topology of the virtual arenas with potentiation complexes and zig-zag persistence. Try many values of τ .
- ③ Analyze the results. Do the barcodes tell us which arena our simulated rats were in? **How does limited memory affect the reconstruction of arena topology?**

Step 1: Generating the Dataset (The Mice)

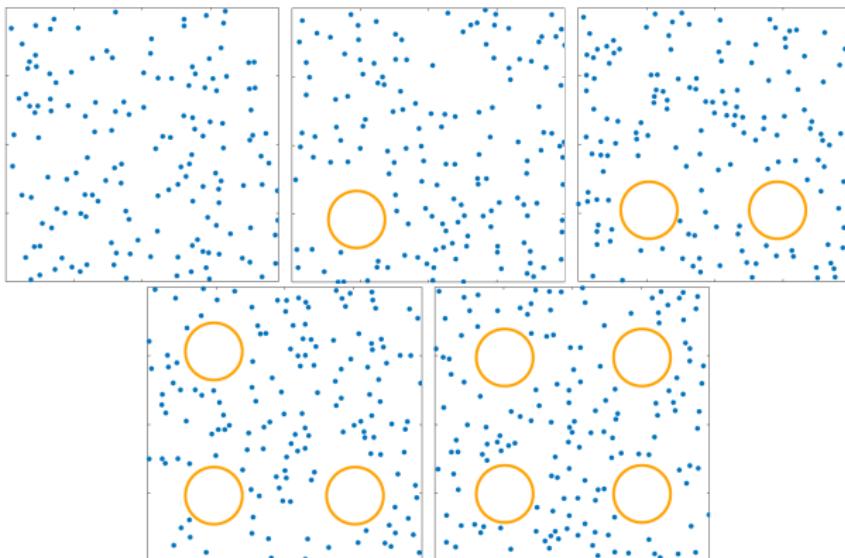
Meet our virtual test subjects:



15 combinations of activated firing rate (12, 14, 16, 18, or 20Hz) and place field radius (14, 15, or 16cm).

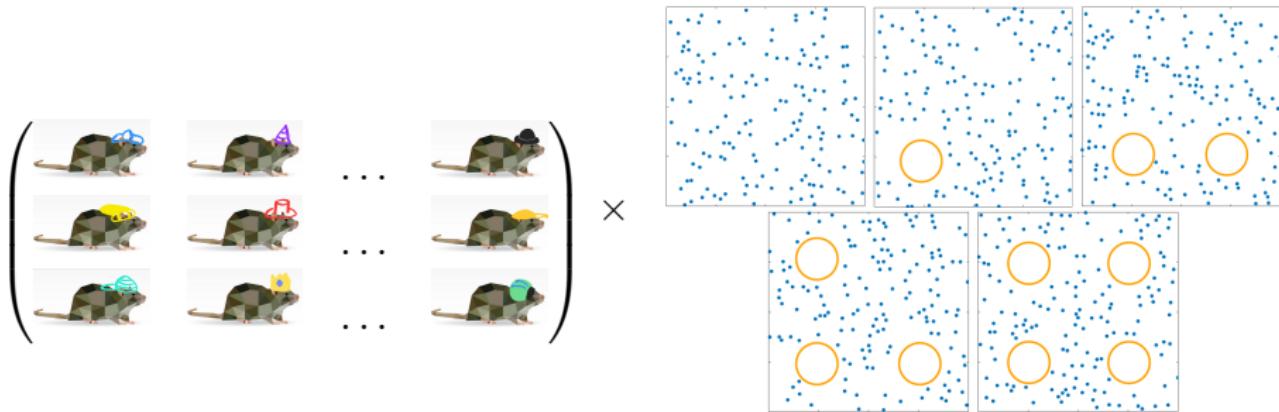
Step 1: Generating the Dataset (The Arenas)

Our virtual laboratory:



5 arenas with different homotopy types.

Step 1: Generating the Dataset



Run each mouse in each arena 10 times and collect simulated spike train data. Total spike train datasets: $15 \times 5 \times 10 = 750$.

Step 2: Reconstruct Topology of Arena with Limited Memory

- Discretize spike trains into 5000 time bins.
- For each memory length $\tau \in [50, 5000]$ in increments of 50, construct potentiation complex $(K_t^\tau)_{t=1}^{5000}$.
- Compute barcodes using zig-zag persistence.

$(750 \text{ spike trains}) \times (100 \text{ memory lengths}) = 75,000 \text{ barcodes.}$

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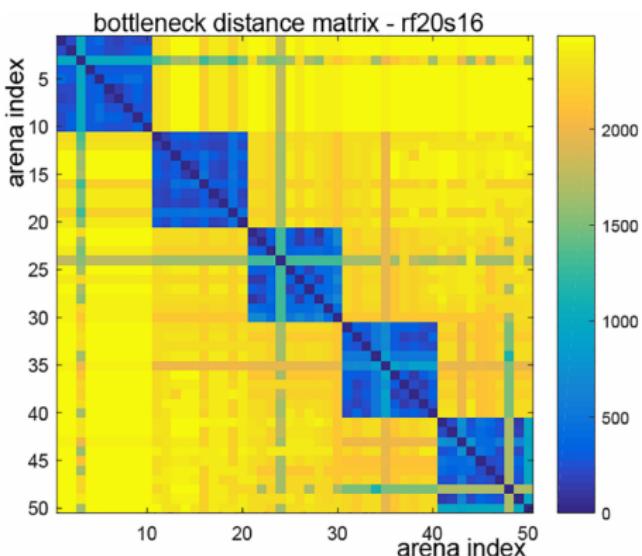
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Step 3: Analyzing the Results

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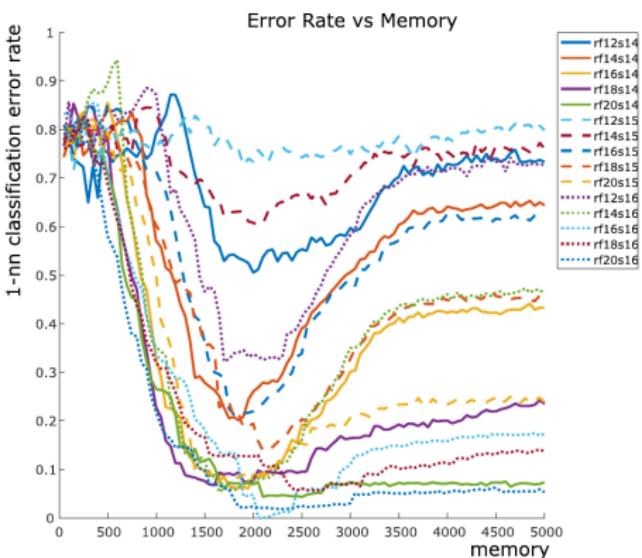
- Pick a mouse and a memory length τ .
- Take the 50 barcodes generated by that mouse at that memory length.
- Calculate the pairwise bottleneck distances between the barcodes.
- Determine the 1-nearest neighbor error rate in predicting the arena.



Step 3: Analyzing the Results

Results:

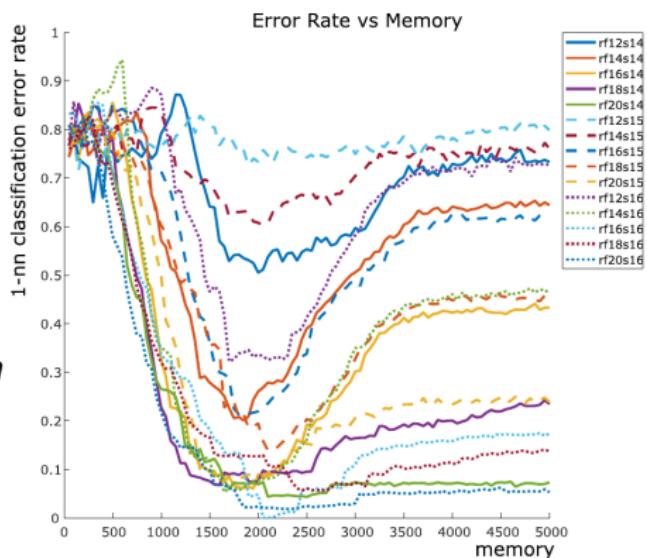
- As predicted, very small τ leads to no topological information.
- Surprisingly, error rate reaches a minimum around $\tau \approx 2000$, *then rises again*.



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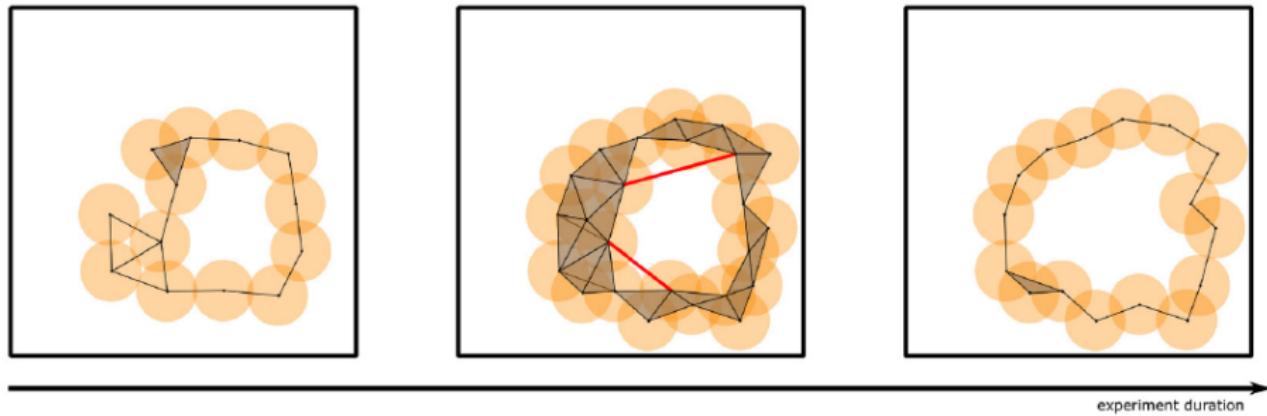
More memory is not always better?

Intermission

Why is More Memory Not Always Better?

We expected more memory to be better, but this is not always the case.
Why?

Theory: The problem could be **spurious firing**. Simplices may be added due to noise.



Two ways for mistakes to get fixed:

- Fill in the extra loop with more simplices.
- Forget the mistaken edge.

Testing the Hypothesis

Is spurious firing really the reason more memory is sometimes worse?

As good scientists, we change up the model and see if the effect persists.

Modification 1: Change mouse trajectory model.

- Results so far simulated mouse movement as “billiards”.
- Replace with a “random walk” model.

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Result: Same effect! Error rate minimized around $\tau \approx 2000$.

Testing the Hypothesis

Modification 2: Remove randomness from firing model.

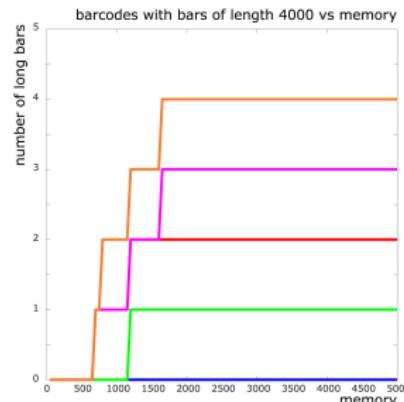
- Firing rate so far modeled with a random Poisson process. A place cell has high firing rate while mouse is inside the place field, low firing rate otherwise.
- Replace with a more deterministic *binary* model. Cell fires while mouse is inside the place field, stops when it leaves.

Testing the Hypothesis

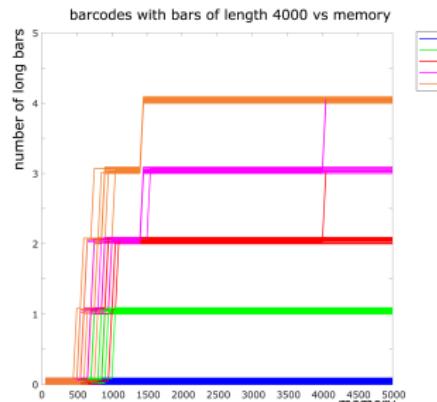
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Result: Effect vanishes!



Deterministic firing model



Random firing model

Testing the Hypothesis

Modification 3: Reintroduce spurious firing.

- Replace firing model with a *fuzzy binary model*.
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Testing the Hypothesis

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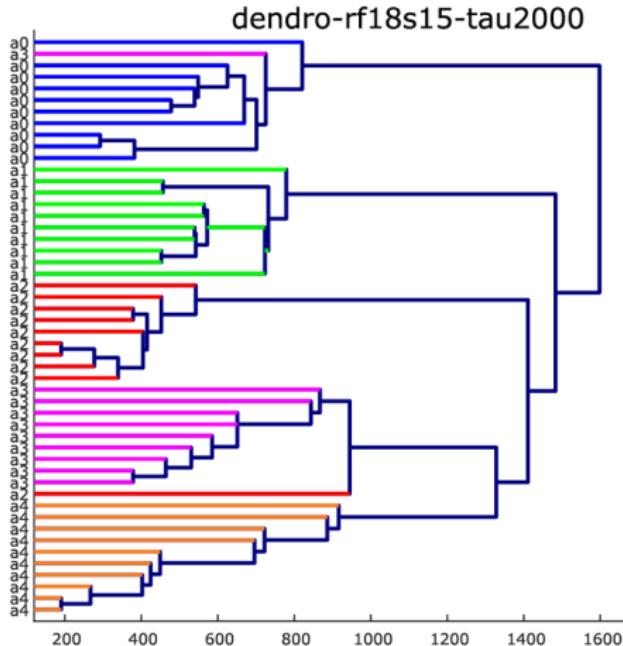
- Replace firing model with a *fuzzy binary model*.
- Deterministic firing while mouse is in the place field, random firing while outside.

Result: Effect reappears!

Conclusion: The error rate “valley” really is caused by spurious firing.

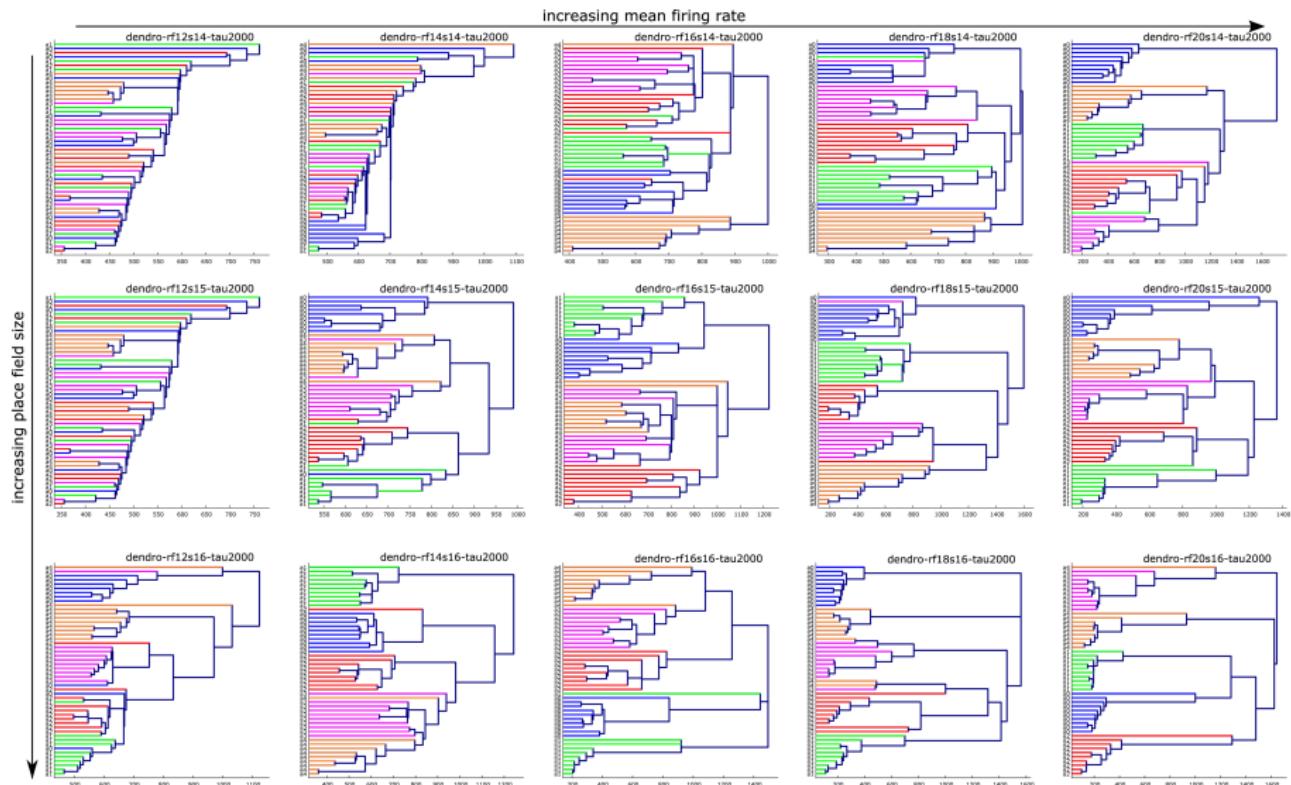
Sanity Checks

Do the barcodes actually form five clusters? Break out the dendrograms.



Sanity Checks

Make one dendrogram for each mouse.



Sanity Checks

Using the single-linkage dendrograms, we can perform statistical tests.

- The barcodes from most mice do fall in 5 statistically significant clusters.
- In all but one case, the clusters do have a statistically significant correspondence with the arenas.
- Clustering is best when firing rate is high and place fields are large.

Table 1. *p*-values for single linkage dendrograms in Fig 8.

		mean firing rate (Hz)				
		12	14	16	18	20
place field size (cm)	14	0.200	0.637	0.957	0.011*	0*
	15	0.998	0.956	0*	0*	0*
	16	0.891	0.001†	0*	0*	0*

Table 2. 1-nearest neighbor classification error rates at $\tau = 2000$.

		mean firing rate (Hz)				
		12	14	16	18	20
place field size (cm)	14	0.729	0.603	0.216	0.192*	0.087*
	15	0.496	0.269	0.090*	0.078*	0.069*
	16	0.340	0.862†	0.047*	0.123*	0.022*

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- Zig-zag persistence with an intermediate memory length actually performs better than a perfect memory if place cells can mistakenly fire.

Thank You!

Further Reading

Nature article summarizing findings on the importance of forgetting.



The importance of forgetting

Long thought to be a glitch of memory, the ability to forget is actually crucial to how the brain works, researchers are realizing.

BY LAUREN GRANT

ROLE OF FORGETTING

Different types of memory are created and stored in different parts of the brain. Some areas of the brain are old, processing the details, but others are new, processing the whole story — those of events experienced personally — begin to take lasting form in a set of neurons that fire together every time the person thinks about the event. These neurons are interconnected through synapses — junctions between these cells that enable it to pass signals along. Each neuron can be connected to thousands of others in this way. Through a process called synaptic plasticity, neurons constantly produce new synapses and strengthen existing ones, such as the receptors for these chemicals. This is a normal process. The stronger the memory, the stronger its neural network becomes. As more and more neurons recall the memory, it becomes embedded in the brain. In the end, the memory is stored in a single area that exists independently in the cortex, where it is put away for long-term storage.

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Link on course webpage.

References I

-  Samir Chowdhury, Bowen Dai, and Facundo Mémoli, *The importance of forgetting: Limiting memory improves recovery of topological characteristics from neural data*, PloS one **13** (2018), no. 9, e0202561–e0202561 (eng), 30180172[pmid].
-  Carina Curto and Vladimir Itskov, *Cell groups reveal structure of stimulus space*, PLOS Computational Biology **4** (2008), no. 10, 1–13.