

# Fragmented spatial maps from surprise and affordances

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## Summary

When animals explore complex environments, their neural representations of the space often fragment into multiple maps. What determines these map fragmentations?

We pose the problem of environmental map fragmentation as a problem of spatial clustering, and show that remapping decisions may be driven by surprise or prediction error augmented by navigational affordances as they are potentially encoded by boundary vector cells.

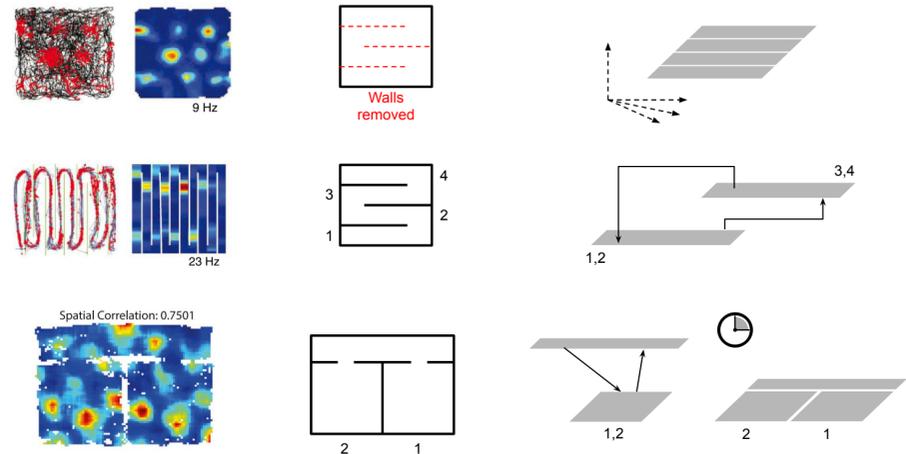
So far the literature on models of map fragmentation and grid remapping roughly falls into two categories: The first assumes that remapping is mainly driven by similarity of sensory observations and can only remap to regions one has visited before (Grievens et al., Cheung). Note that in an environment with no sensory ambiguity there would be no grid remapping in this case.

The second approach considers Eigenvectors of different types of transition matrices, e.g. Eigenvectors of the successor representation (Stachenfeld et al.) and Eigenvectors of the graph Laplacian of the adjacency matrix (Machado et al.). In both cases it is not clear how remapping decisions would be driven in a novel environment upon first visit because state transition information has yet to be collected.

In contrast, our model remaps even in an environment without sensor ambiguity and also in a novel environment upon first visit.

**References:**  
Derdikman et al., *Fragmentation of grid cell maps in a multicompartement environment*, 2009, Nature Neuroscience  
Carpenter et al., *Grid cells form a global representation of connected environments*, 2015, Current Biology  
Ankerst et al., *OPTICS: ordering points to identify the clustering structure*, 1999, ACM Sigmod record  
Fairfield et al., *Segmented SLAM in three-dimensional environments*, 2010, Journal of Field Robotics  
Grievens et al., *A boundary vector cell model of place field repetition*, 2018, Spatial Cognition & Computation  
Machado et al., *A Laplacian framework for option discovery in reinforcement learning*, 2017, ICML  
Cheung, *Probabilistic Learning by Rodent Grid Cells*, 2016, PLOS Computational Biology  
Stachenfeld et al., *The hippocampus as a predictive map*, 2017, Nature Neuroscience

## Fragmented spatial maps in MEC



**Fig: Map fragmentation in MEC.** Left, Middle: Firing fields of a grid cell in the environments illustrated in the middle column (Derdikman et al., Carpenter et al.). Right: Schematic illustration of map fragmentation. Gray regions illustrate submaps embedded in the neural state space of grid cells. Arrows indicate grid realignments which we interpret as map transitions

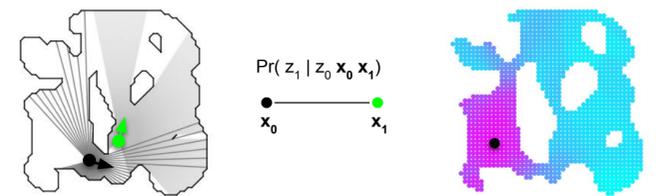
The ability for path integration and the potential to enable vector-based navigation lend grid cells to provide the base for a cognitive map in the sense of Tolman. But the accumulation of path integration errors impedes the formation of a consistent map. This is a well-known challenge in the problem of simultaneous localization and mapping (SLAM). One of the attempts to overcome the problem of error accumulation is to divide the environment into smaller regions where the error is negligible.

Recordings from the medial entorhinal cortex (MEC) of rats show that they also form fragmented spatial maps reminiscent of the local maps above: The neural activity of grid cells while running through a 1-dimensional maze of zig-zagged compartments (hairpin maze) showed repetitive firing patterns across arms with similar running directions implying that the grid representation was fragmented into repeating submaps (Derdikman et al.). Interestingly the fragmentation occurred irrespective of the type of wall, including transparent walls, suggesting that it depends on features encoding navigational affordances as they are encoded by boundary vector cells for instance.

Another indication for the fragmentation of maps comes from the Barry lab (Carpenter et al.). Grid cells were recorded in an environment containing two perceptually identical compartments connected via a corridor. The initial firing patterns in both compartments were similar, suggesting a shared submap for both compartments. However, with experience, a single, continuous grid pattern spanning both compartments formed. The fragmentations seem to align with environmental features like doorways and corridors for instance.

We interpret a realignment of the grid fields of entorhinal grid cells as a transition between submaps, and call it *grid remapping*. In contrast to typical hippocampal remapping experiments, in which the environment changes while the agent remains stationary, we are interested in remapping during exploration of a static (potentially big) environment, where observational changes are caused only by a change in location.

## Map fragmentation via clustering



**Fig: Similarity measure on pose space.** Left: Two agents at two different poses and their field of view. The overlap of their observations defines a prediction similarity. Right: For a fixed pose the remaining poses are colored by their predictability.

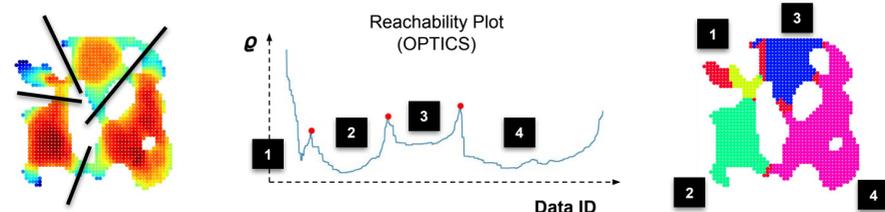
In robotics a contiguous region is loosely defined as follows (Fairfield et al.): "While a robot is within a contiguous region, its range sensors are likely to collect measurements that lie within the contiguous region and unlikely to collect measurements in different regions."

Put it differently, any observation made in a contiguous regions can be inferred from any other observation made in that region. In that light we consider segmentations induced by clusters in the space of pairs of locations  $x$  and measurements  $z$  with respect to a prediction model  $Pr(z_i | z_0, x_0, x_i)$ . This prediction similarity is explained in the figure above.

Our cluster algorithm of choice is OPTICS (Ankerst et al.), a density-based cluster algorithm that we apply to the set of locations  $X$  endowed with a similarity matrix  $D$  whose entries are defined by the observation model above. The segmentation for an organically shaped environment is shown below.

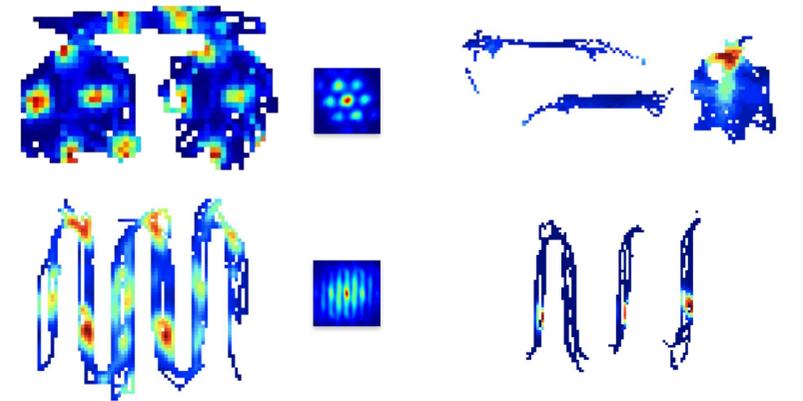


**Fig: Geometry of pose space.** Left: Both circles are of the same fixed radius with respect to prediction similarity. Right: Isomap embedding of the pose space with respect to prediction similarity. The embedding illustrates that contiguous regions correspond to dense regions.



**Fig: Map fragmentation from density-based clustering.** The OPTICS algorithm returns an ordering of the data points and their reachability. The valleys in the plot can be interpreted as clusters and the resulting segmentation is shown on the right.

## Map fragmentation from online model

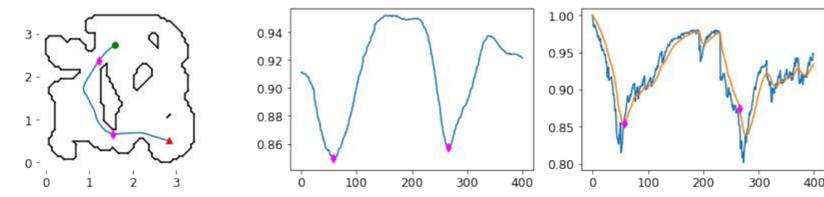


**Fig: Map fragmentation of the online model.** Left: Firing fields of a grid cell in the two compartment environment and the hairpin maze. The grid firing patterns are replicated between the two rooms (square shows spatial correlation between rooms). The firing fields in the hairpin maze do not form a global hexagonal pattern (square shows spatial autocorrelation). Right: Map fragments computed by the online model. Each colored pixel corresponds to a grid code that is associated with an observation vector (here BVCs). The fragments are colored by comparing the associated observation with a fixed reference observation.

The model integrates noisy velocities estimates of an agent exploring an environment and updates its internal position estimate (grid cells). Additionally it stores associations between its position estimate and sensory observations given by a local occupancy map represented through a population of BVC's.

Note that contiguity is a local property, and hence we can try to compute it online. We borrow ideas from *segmented SLAM* (Fairfield et al.), and predict the current observation from an observation made a fixed amount of timesteps in the past. If this prediction signal falls below a previously fixed threshold a remapping event is triggered. At this point either a new map is formed, or the model has to relocate (through the associative memory) to a previously visited position that matches the current observation.

The probability to remap to a previous location depends on strength of the association and hence is proportional to the number of visits.



**Fig: Online computation of remapping signal.** Left: Example path through an environment. Middle: Smoothed remapping signal from offline cluster computation. Right: Online remapping signal from comparing the BVC activity at time  $t$  with BVC activity at time  $t - \Delta$ . We trigger a remapping event when the signal falls below a (potentially dynamic) threshold  $\theta$ .