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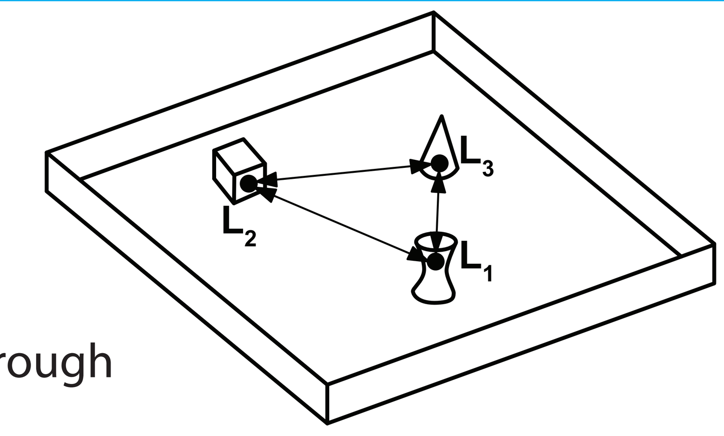
Unsupervised Learning of Relative Landmark Locations Using Grid Cells

Overview



Background

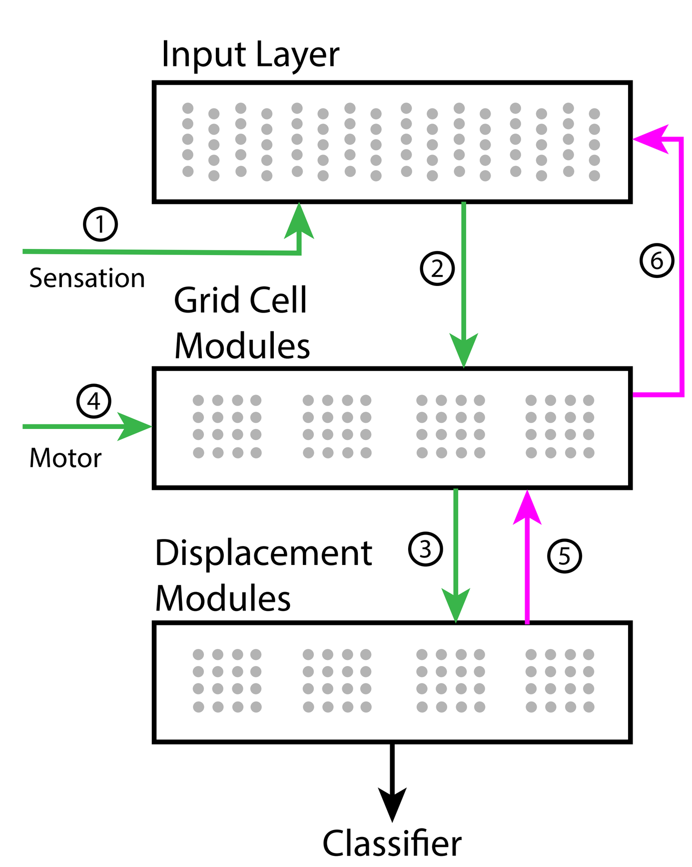
• Grid cells provide location codes, spatially related through path integration[1]
• Multiple grid cell modules provide unique location codes for many large environments[2]
• We have shown that displacement modules encode spatial relationships between grid cell reference frames[3]

Contributions

• We propose that displacement cells encode the relative position of pairs of landmarks and that sets of displacement cells provide robust representations of environments
• Simulations show the model's ability to learn and distinguish among many complex environments with high noise tolerance

Network Model

1. Sensory inputs drive the input layer
2. Input layer activity drive cells in the location layer based on learned connections
3. Pairs of cells in each location module drive displacement cells that encode the relative positions
4. Motor input shifts the active location layer cells
5. Displacement cells plus newly active location cells drive additional cells in the location modules
6. The set of active location layer cells provide lateral input to the sensory input layer, predicting the next sensory input



Results

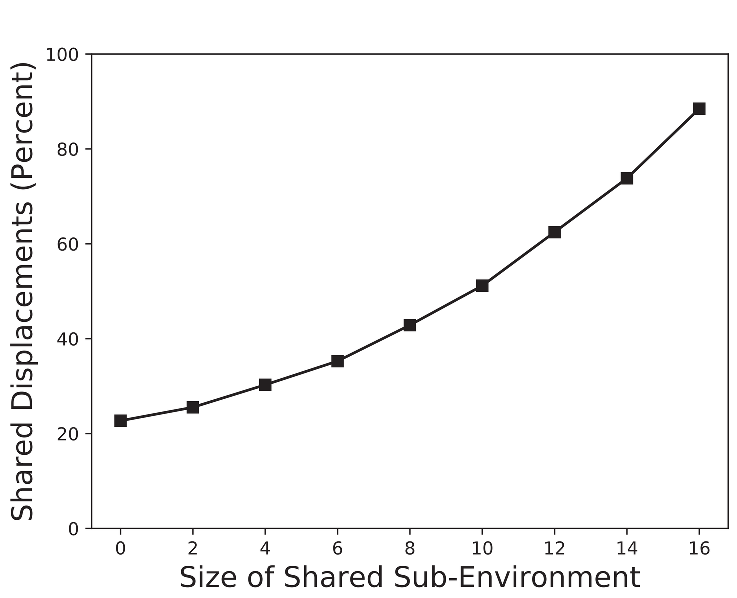
• Network trained on 1000 environments , each with 16 locations containing random landmarks from a pool of 5 unique landmarks
• The network is able to distinguish between environments with substantial noise, with only minor degradation from ideal
• A bag-of-features model is not able to distinguish environments due to the small number of unique landmarks

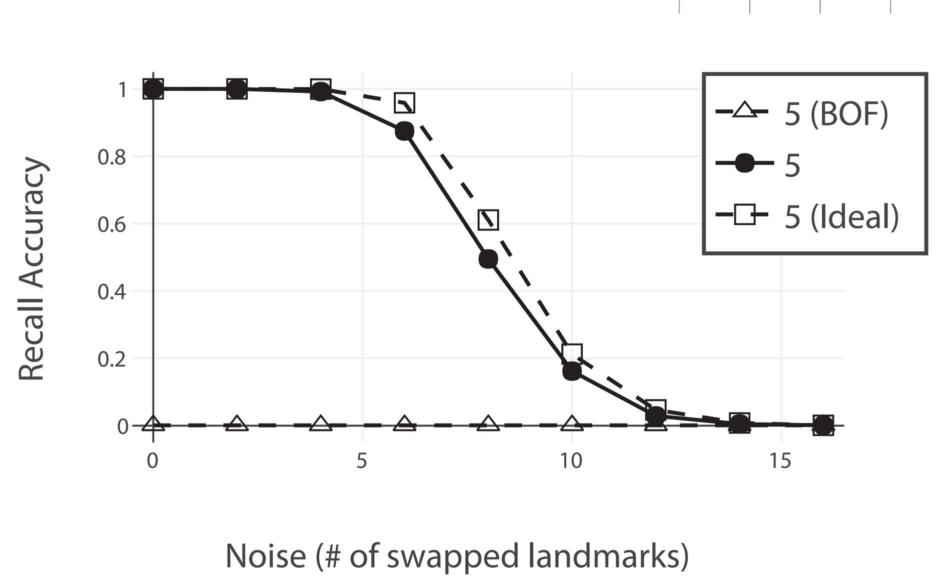
Environment 1

D	F	D	B
J	I	E	C
J	G	G	F
E	I	A	D

Environment 2

A	G	I	J
G	J	E	E
D	D	A	F
G	C	C	H



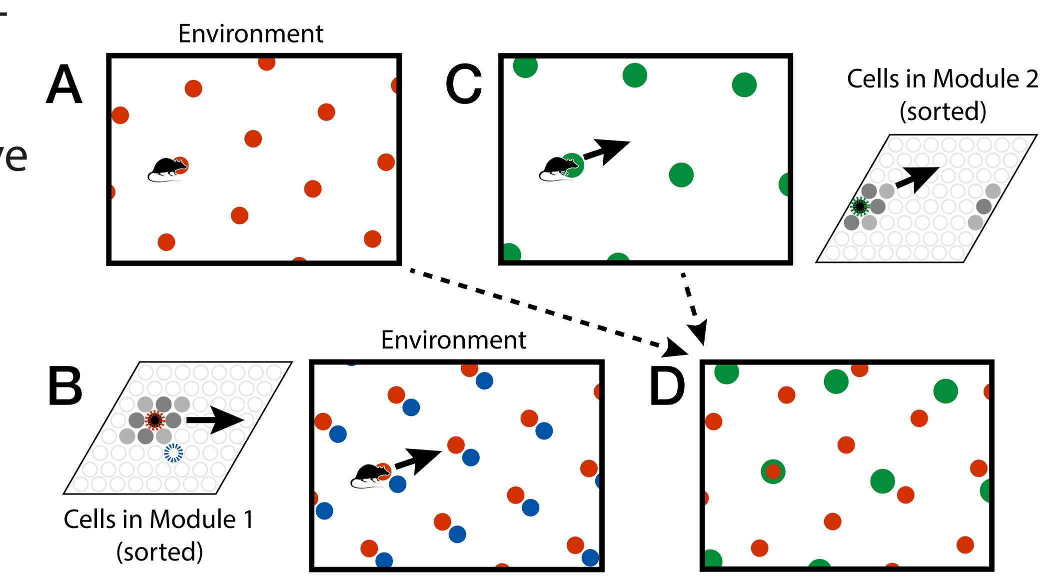


Key Properties

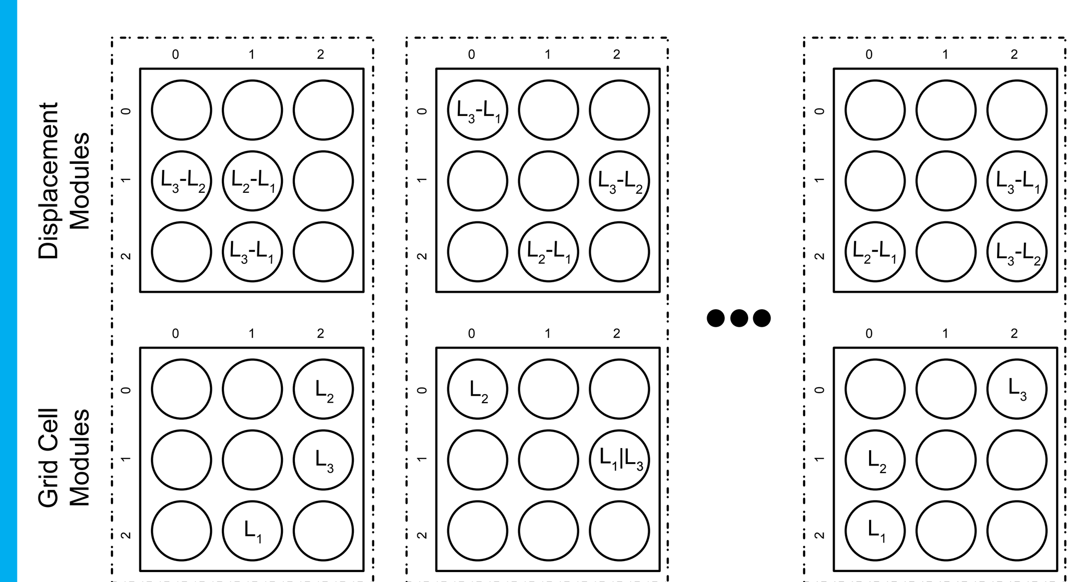
• Representations of environments through neural activity, without learning
• Displacement cells provide generalization
• Required number of displacement cells grows quadratically with the size of the location layer union
  • Learning more complex landmarks mitigates the issue
  • Composition of environments in a hierarchical network is possible

Grid Cells

A. Single cell firing fields form a hexagonal lattice over environments
B. Grid cells in the same module have different phases but the same scale and orientation
C. Other modules have different scales and orientations
D. Multiple modules uniquely encode locations over many large environments



Displacement Modules



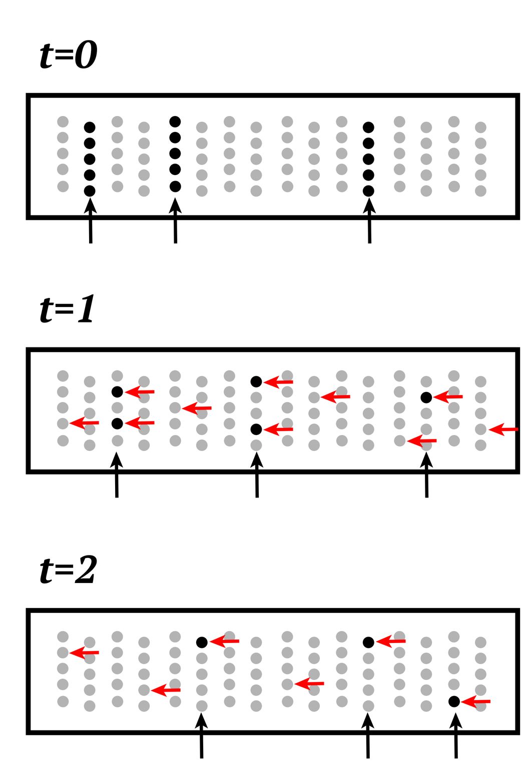
• Grid cell modules maintain a union of recent activity. Path integration shifts this activity with each movement.
• Displacement modules encode the relative locations of landmarks
• Two environments that share relative landmark configurations will share displacements
• The same displacements will be activated for any traversal order

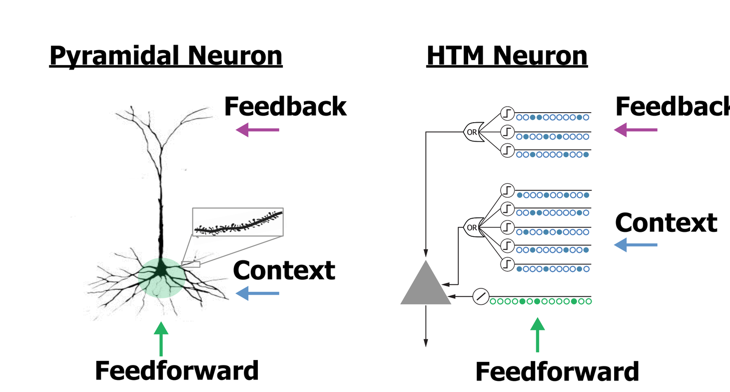
Input Layer Predictions

Sensory input causes mini-column "bursting" with no predicted cells

Distal input causes cells to be predicted and win out

A single cell per column uniquely encodes the context for inputs





This model assumes compartmental neurons with separate proximal basal and distal basal dendrites. See Hawkins and Ahmad, 2016[6].

Discussion

• We predict that there is stable neuron activity that represents a local environment independent of context
• Analogous circuits exist in the neocortical circuit[7]

• Substituting a temporal signal rather than spatial motor command for path integration may provide a mechanism for learning temporal sequences
• Integration of multiple sensors and hierarchical networks are future extensions
• Currently working on integrating orientaion

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