The Emergence of Semantic Topography and Category-Specific Impairments in a Neurally-Inspired Computational Model

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Introduction

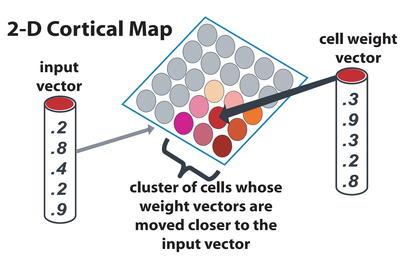
Representations in primary sensory cortices are organized topographically. In the visual system, a sensory-based retinotopy exists across multiple levels of processing and eventually gives way to more complex object-based representations in inferotemporal (IT) cortex[1,2]. While there is evidence for a higher-order topography in IT cortex[2,3,4], at present its structure is poorly understood.

Simulations of learning in cortical maps using self-organizing algorithms have faithfully reproduced primary visual topographies.[5,6] In this work we use these self-organizing algorithms to investigate how higher-level semantic representations might develop based on cortico-cortical inputs from topographic sensory maps rather than directly from sensory stimuli. We also investigate whether random lesions to the model produce the types of category-specific deficits reported in patients[7,8].

Methods

Self-Organizing Maps (SOMs)[9,10]

- Computational abstraction of 2-D cortical maps.
- Maps learn topographic representations based on regularities in their inputs.
- Cells within maps have weight vectors representing their receptive fields.
- Cells within a map compete to represent an input.
- Learning occurs when a spatial cluster of cells change their receptive fields to be more responsive to the current input.



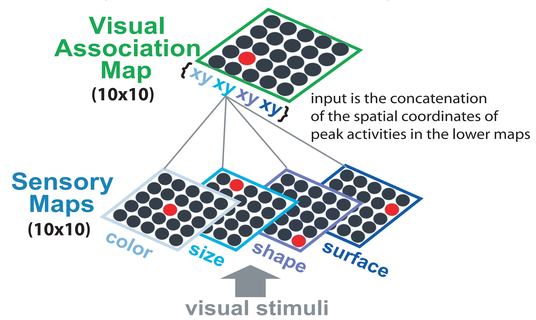
Model Architecture

Sensory Maps

- A simplification of early- and mid-stage processing of the visual attributes of stimuli.
- Each map receives *sensory* input: an input vector representing a single visual attribute of a stimulus.

Visual Association Map

- Map receives *spatial* input: an input vector encoding the locus of activity in the lower-level sensory maps.
- Spatial coordinates are a computational proxy for each cell's receptive field in lower-level maps.



Stimuli

- 96 exemplars: 8 object classes (trees, bushes, dogs, cats, bikes, cars, tables, chairs); 12 variants per class.
- Exemplars respresented by vectors encoding four visual attributes:

color:	{hue, saturation, brightness}	[0,1]
size:	{$size_x$, $size_y$, $size_z$}	[feet]
shape:	{roundness, complexity}	[0,1]
surface:	{smoothness, uniformity}	[0,1]

Learning Procedure

(1) Initialization: Randomized weights in all maps.

(2) Sensory Map Learning: Stimuli presented (500 iterations, random order) and weight vectors are updated based on SOM learning algorithm.

(3) Visual Association Map Learning: As stimuli are presented to the Sensory Maps, concatenated coordinates of peak activities are provided as inputs to the Visual Association Map. Weight vectors are updated based on SOM learning algorithm.

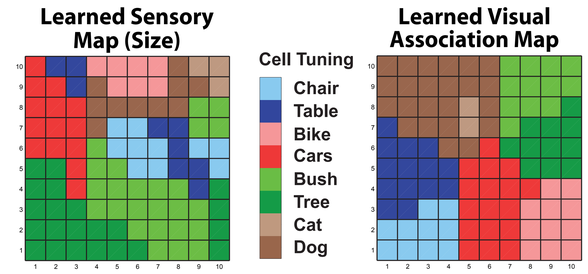
Results I: Learning

Sensory Maps

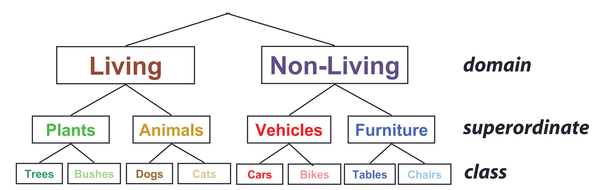
- The figure below (left) shows an example of a sensory map (Size Map) after learning. Cells are colored based on the object class that generates the maximum response.
- Self-organization results in topography; stimuli with similar attribute-values are spatially proximal.
- At the level of Sensory Maps, no single map allows all object classes to be distinguished.

Visual Association Map

- The figure below (right) shows the Visual Association map after learning. A *semantically* structured topography has emerged, e.g. trees near trees, chairs near chairs.



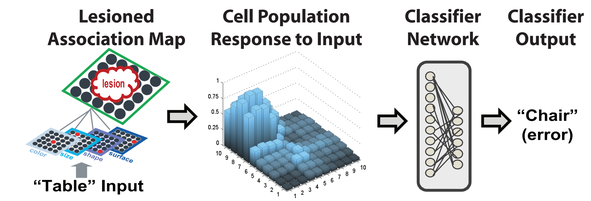
- Furthermore, the spatial structure of the emergent topography exhibits multiple levels of a semantic hierarchy (below).



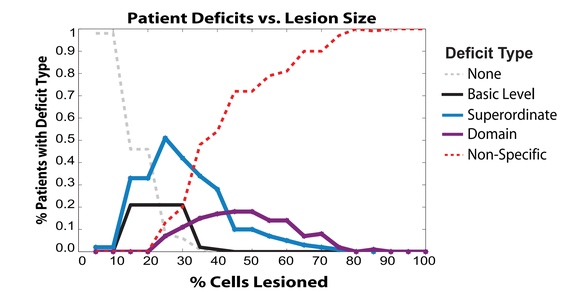
- Note: A hierarchical clustering algorithm applied to the same stimuli fails to capture category semantics at all levels.

Results II: Lesioning

- Simulated patients by imposing 2000 lesions of varying size and location on the Visual Association Map.
- Classifier network trained and used to "read out" the population response to each input.



- With small lesions, the model exhibits basic level and superordinate deficits; with larger lesions, domain-level distinctions emerge as well as global semantic deficits.



Conclusions

- Semantic representations can be learned based on same principles of computation operating in sensory cortex.
- Emergent topography reflects semantics at multiple levels of abstraction (e.g. cats vs. dogs, animals vs. plants, living vs. non-living).
- Population responses in a topographically structured representation produce the types of category-specific semantic impairments observed in patients.

References

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