Clusters, Symbols and Cortical Topography

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objective

talk briefly about work on cortical maps and their possible relevance to Soar:

- mapping from cortex to Soar
- biologically inspired clustering
    - competitive learning algorithm
    - sensory transduction
    - higher-order symbolic representations

agenda…

①	**mapping**	symbols with similarity
②	**model**	self-organizing maps (SOMs)
③	**demo task**	object categorization
④	**wrap-up**	a useful mapping?

mapping the cortex to *Soar*

attributes

- cortical areas correspond to attributes (color, shape, etc.)
- connectivity between attributes is architectural (fixed by “nature”, roughly)
- semantics of attributes are experiential (“nurture”)

values

- active representation in a cortical area, *winning cell*

(c12 ^shape round ^color red)

WM object **attributes** **values**

a complication in SOAR

- similarity relations are problematic

```
(b32  ^shape round   ^color red)
```

- symbols “red” and “pink” have no inherent similarity
- no guarantee that if “red and round” tends to activate “apple”, “pink and round” will do the same

red apple

pink apple

agenda…

①	**motivation**	symbols with similarity
②	**model**	self-organizing maps (SOMs)
③	**demo task**	object categorization

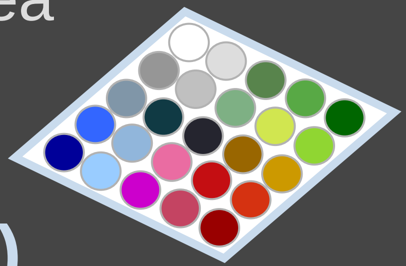
overview: self-organizing maps (SOM)

general features

- inspired by properties of cortical representations
- in class of competitive learning algorithms
- synaptic connectivity via “codebook vectors”
- single winning cell (attribute-value) via competition
- learn by moving winner’s vector closer to input

unique feature of SOMs

- winner ***and*** spatial neighbors moved towards input
- similarity via 2D location in cortical area

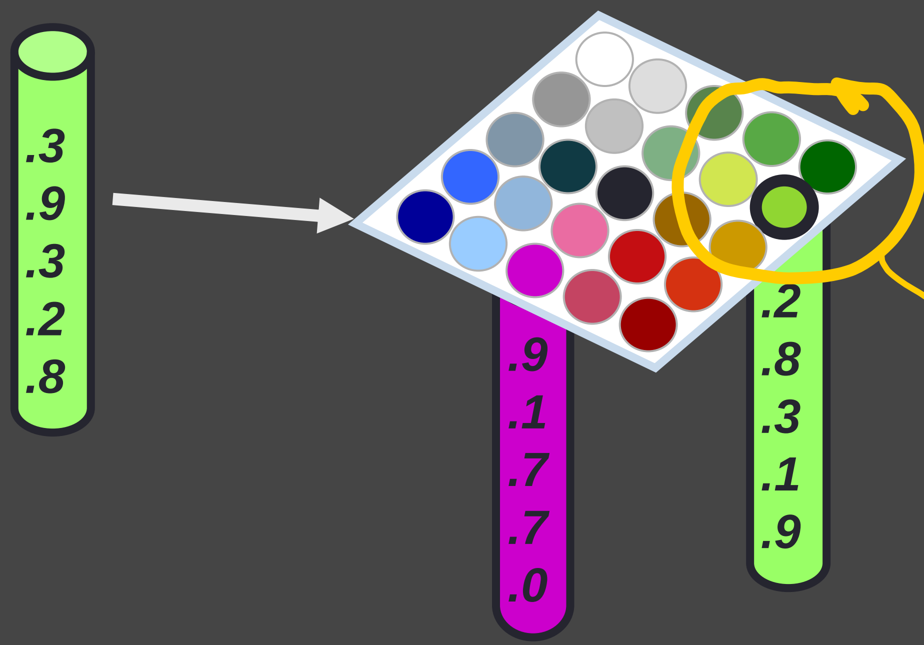


cortical map (SOM)

SOM learning algorithm (in a nutshell)

sensory stimulus

cortical map color attribute



winning cell
"yellow green"

1. winner's codebook vector moved closer to input vector
2. neighbors' codebook vectors moved closer to input vector (by less)

→ with experience, regions of similarity develop.

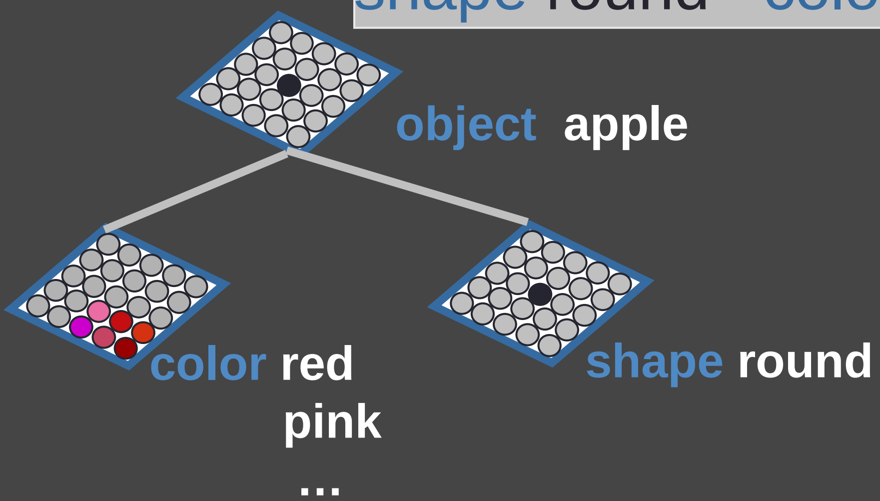
→ spatially proximal cells have similar receptive fields; winning cell is value for attribute.

SOMs and symbols

- **SOMs**
  - can transduce continuous sensory inputs
  - and provide similarity, via topography

i.e. similar cells in one cortical map tend to excite the same cells in other areas of cortex.

shape round color red excites fruit apple
shape round color pink excites fruit apple

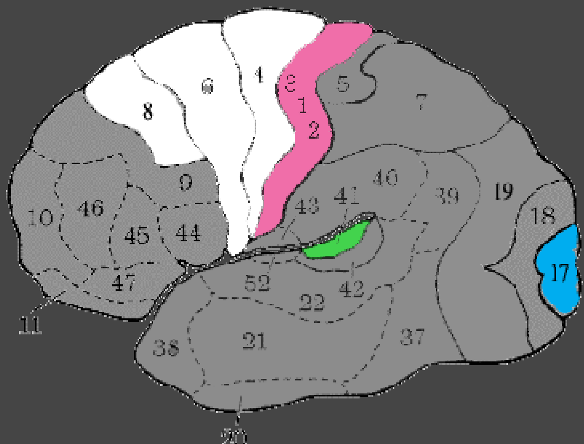


topography: important principle in brain

- **sensory cortex is topographically organized**
  - **visual**: *retinotopic* (based on retina, visual field)
  - **auditory**: *tonotopic* (based on auditory nerve, frequency)
  - **somatosensory**: *somatotopic* (based on location on the human body)
- **sensory topography not just in primary cortex**
  - starts in primary sensory cortex
  - continues to later stages of processing stream
- **when sensory-based topography ends, what comes next?**
  - no topography?
  - “semantic topography”?

taking SOMs to the next level…

- **situation:** SOMs work for sensory transduction, i.e. converting continuous valued inputs to symbols.
- **complication**: most cortical areas are **<u>not</u>** directly connected to sensory inputs, but to other cortical areas.



<u>Direct Connections to Sensation</u>

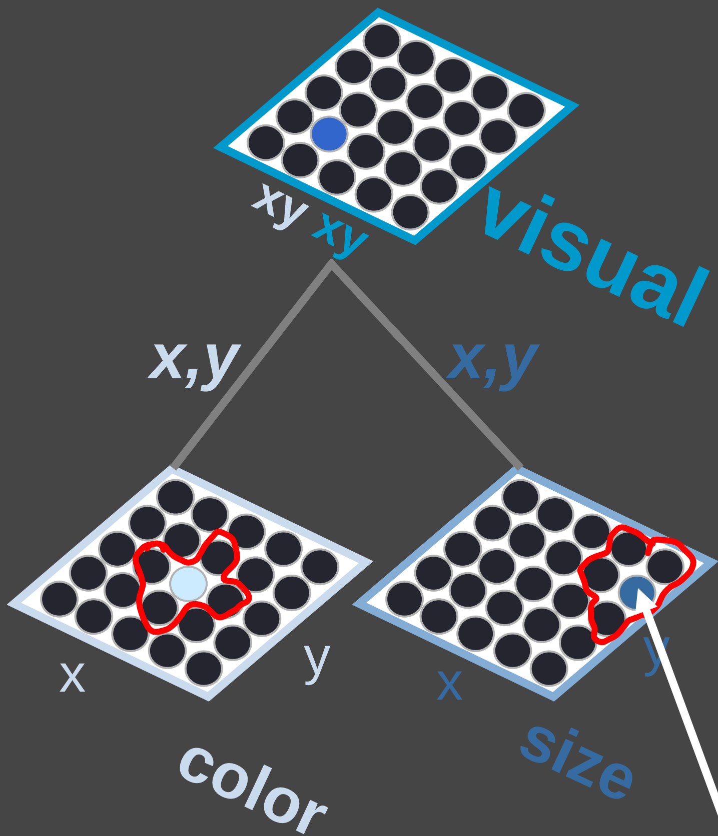
- Primary Visual
- Primary Auditory
- Primary Somatosensory

<u>CorticoCortical Connections</u>

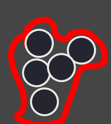
- Uni-, multi-modal association

- **question:** how are representations learned in higher-order maps receiving symbolic inputs from other maps…while preserving similarity relations?

idea: encoding via 2D “cortical coordinates”

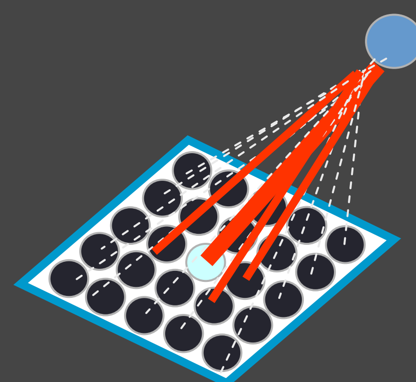


attribute-value
“large, horizontal orientation”



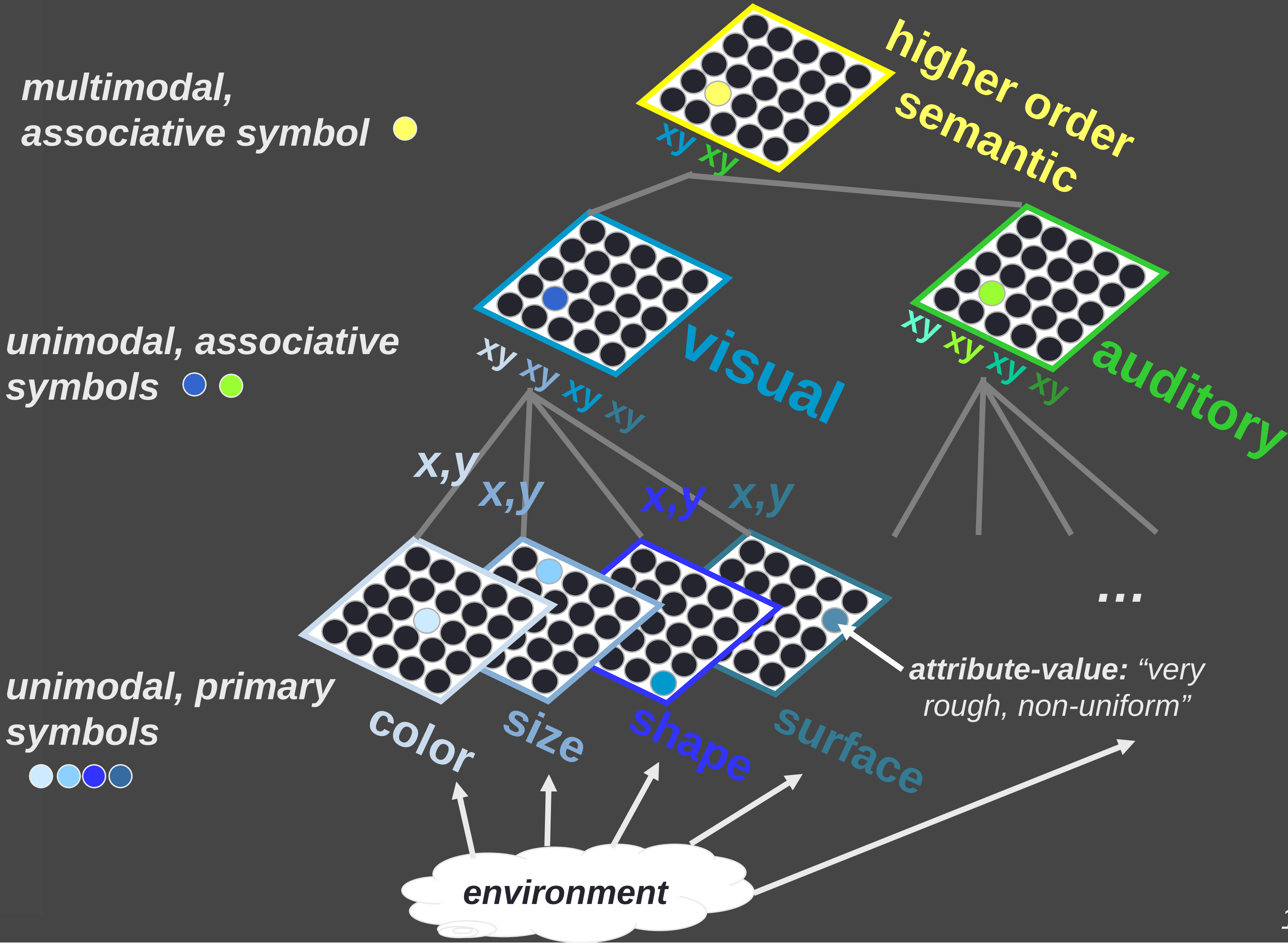
cell’s receptive field in
an afferent map

- x,y coordinate is a computational abstraction of the ***pattern*** of synaptic strength between a cell and all cells in an afferent map
- temporal coincidence of firing strengthens connections, “*fire together, wire together*”



(x,y): common language within a semantic network?

② **model**



agenda…

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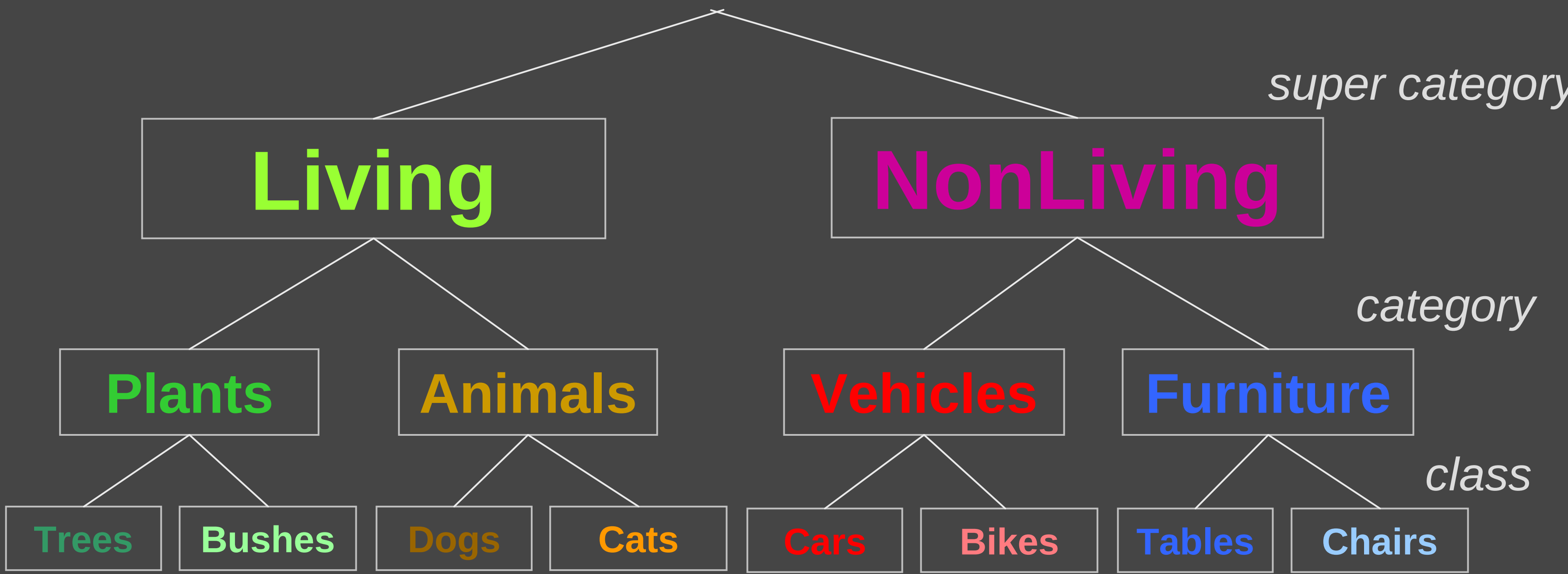
③	**demo task**	object categorization

example task: object categorization



- **96 exemplars, 12 per object class**

  e.g. 12 trees: 3 colors x 4 sizes

- **overlapping attribute-values**

  e.g. size: small dog ~ size large cat

  surface: car ~ table

stimulus attributes (assumed continuous valued)

Visual Perception

color	(hue, saturation, brightness)	[0..1]
size	($size_x$, $size_y$ $size_z$)	[feet]
shape	(roundness, complexity)	[0..1]
surface	(smoothness, uniformity)	[0..1]

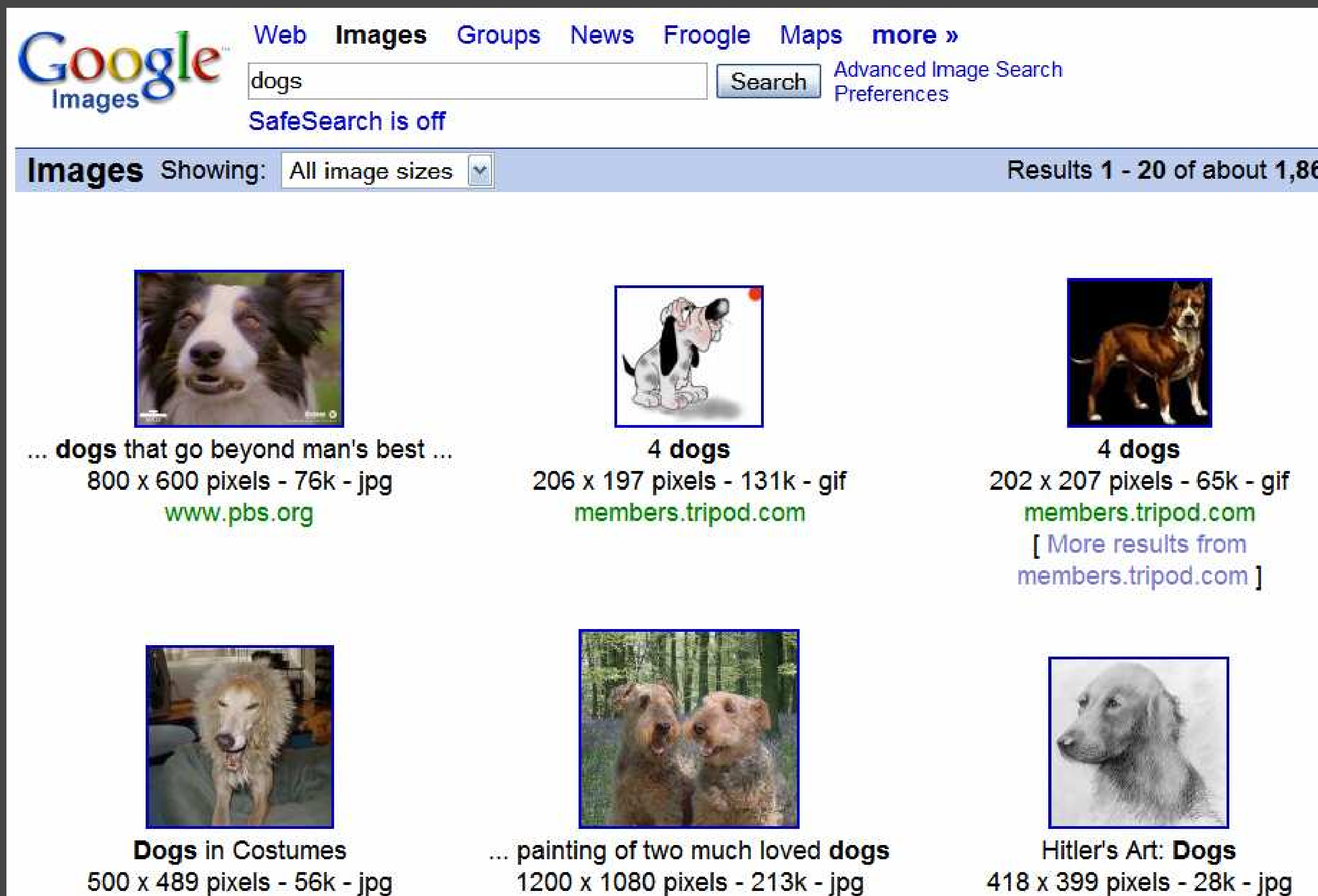
Auditory Perception

sound	(loudness, char. freq)	[0..1,Hz]

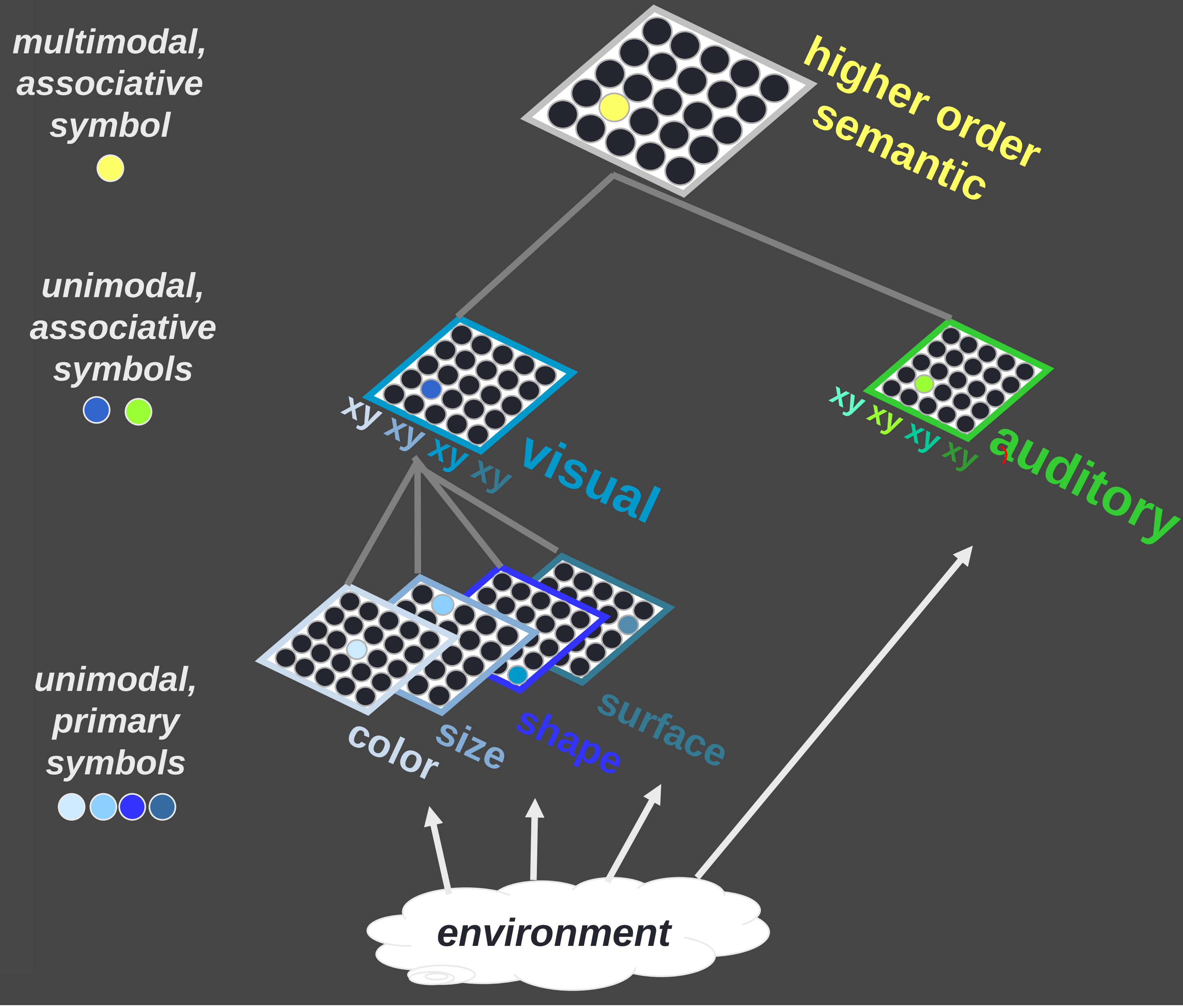
attribute coding: independently motivated

dog shape: (***roundness***: 0.85, ***complexity***: 0.15)

dog colors: (***H/S/B:*** (0.1,0.6,0.6), (0,0,0.1) , (0,0,1), (0,0,0.5))



model architecture

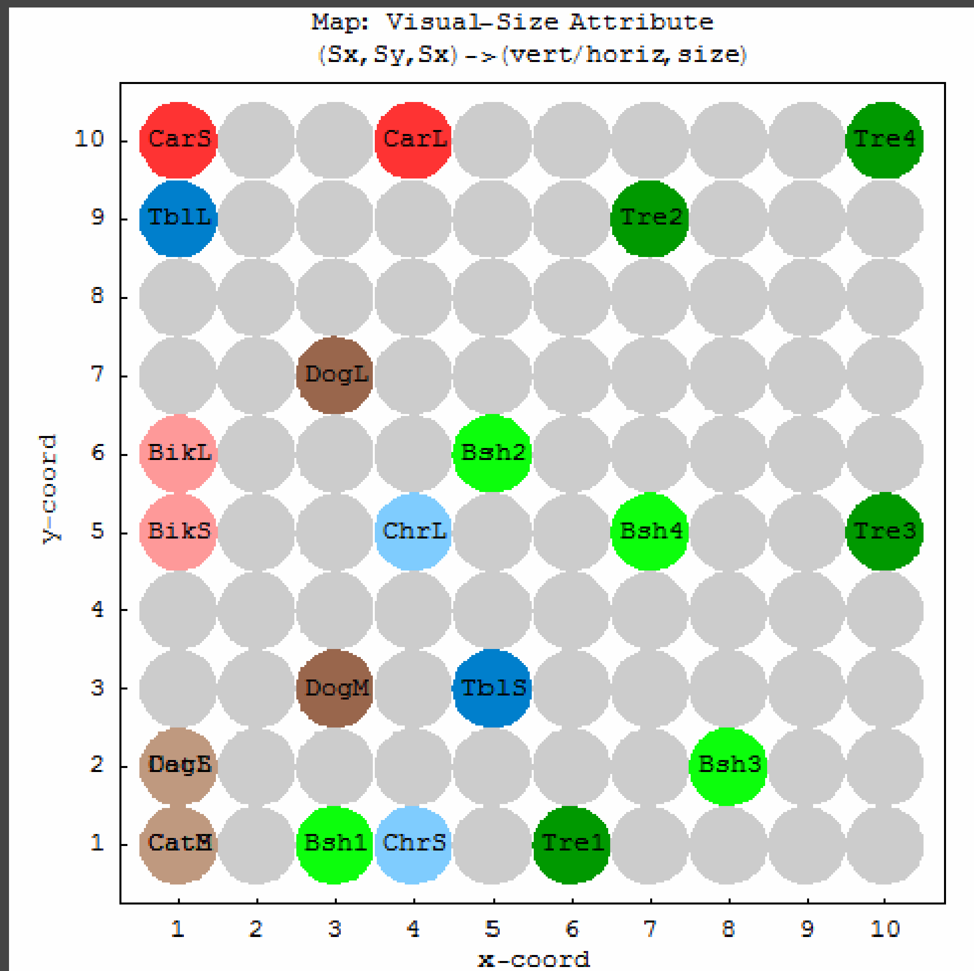


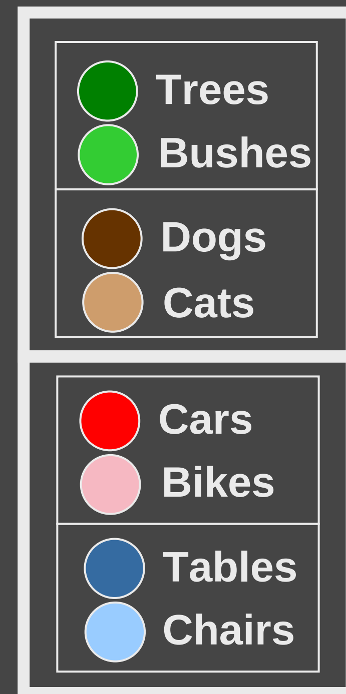
③ **task**

transduction example: size(x,y,z) to 2D-SOM

Larger

Smaller





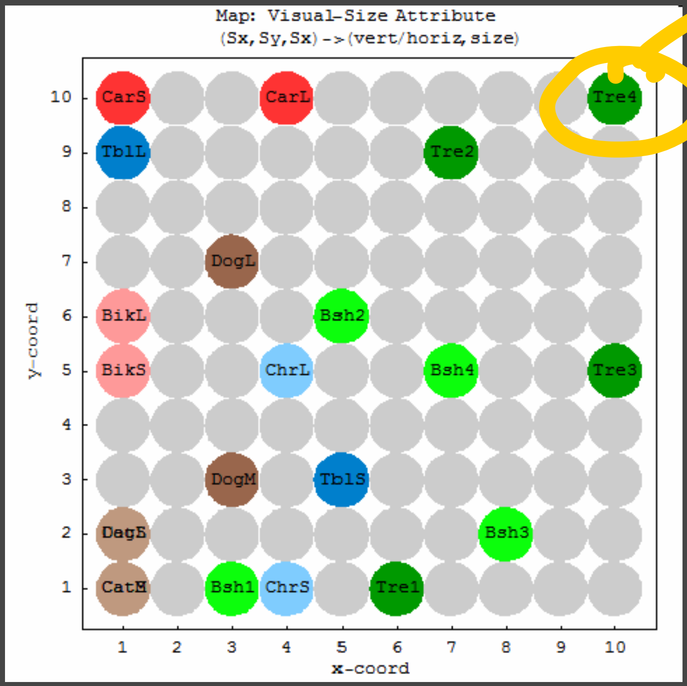
plot: winning cell for each class of object

Horizontally Oriented → **Vertically Oriented**

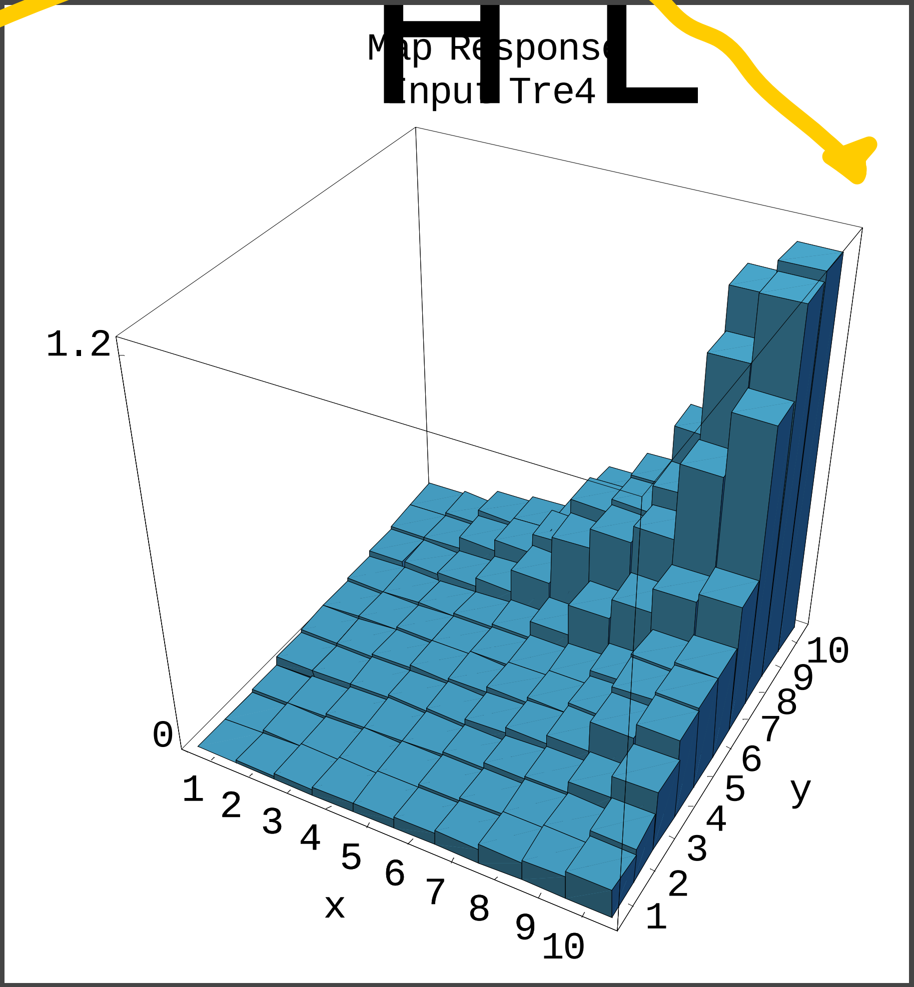
large x, relative to y,z

large y, relative to x,z

similarity via topography



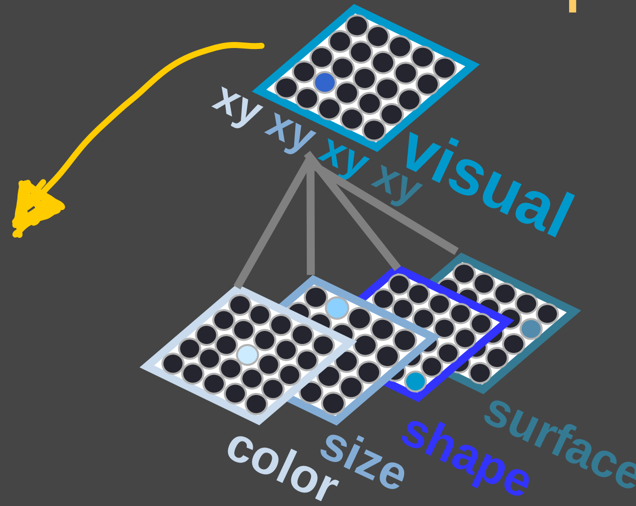
plot: winning cell for each class of object

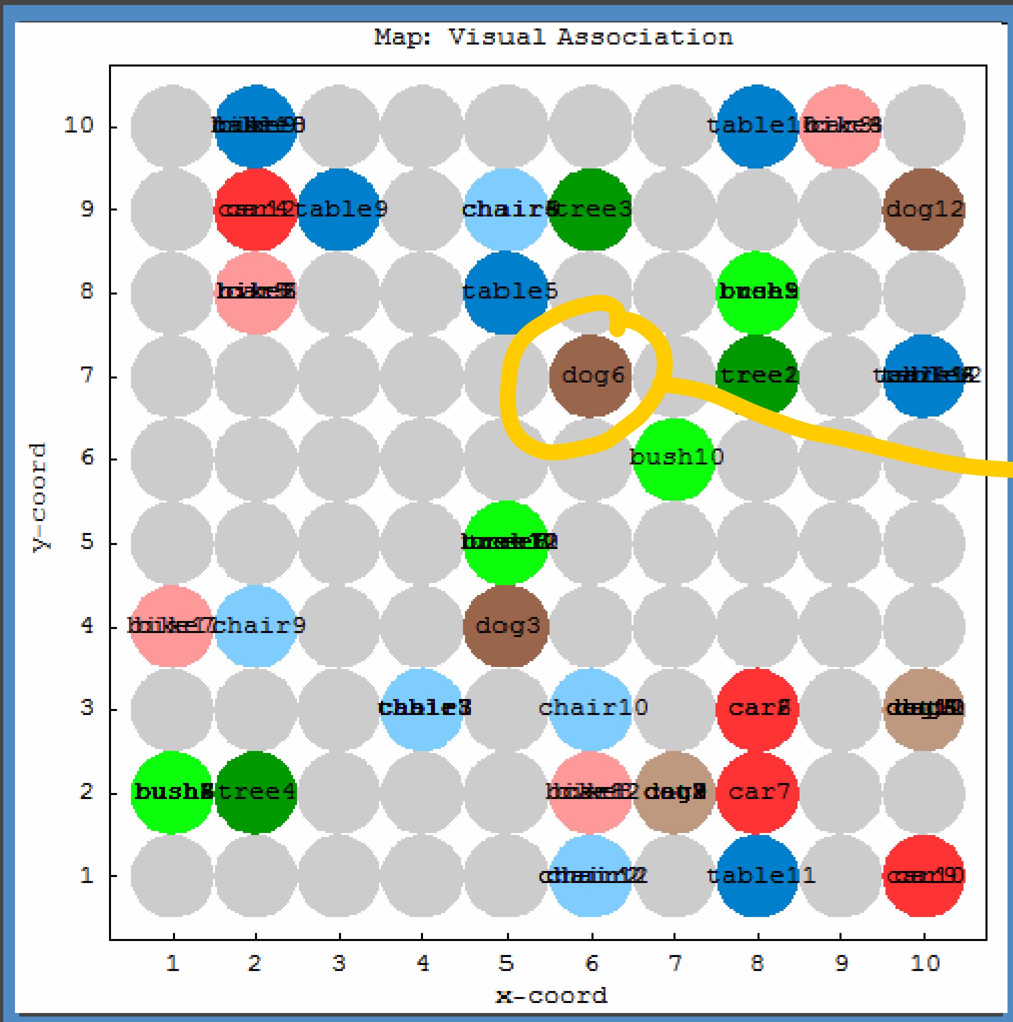


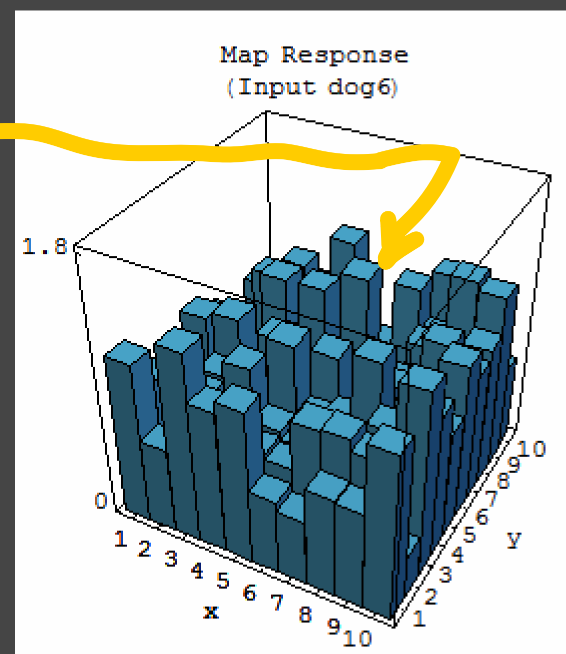
- winning cell, has largest response to Tree4 (tall, skinny tree)
- spatial neighbors have similar receptive field

higher order example: visual association map

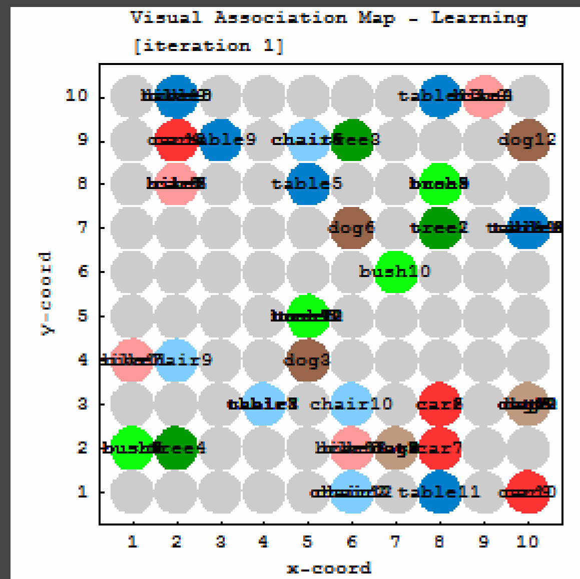
- initial map: random codevectors
- no pattern to winning cells







Learning - Movie

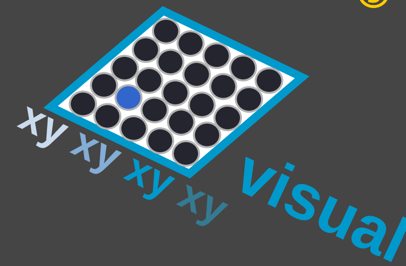


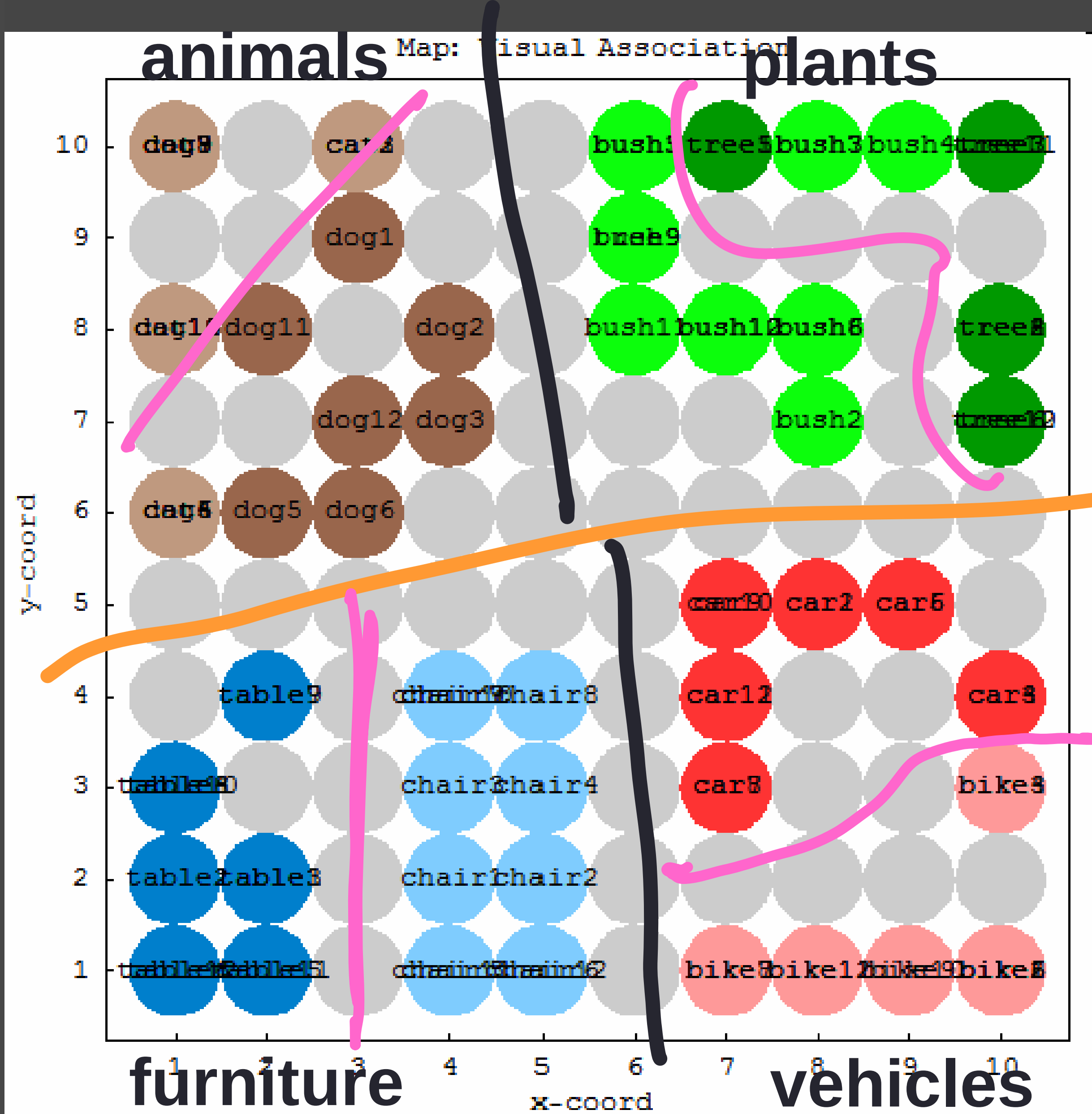
- 50 iterations (“iteration”, one pass through 96 training exemplars)
- Supercategory (living/nonliving) and category (plant, animal, vehicle, furniture) learned rapidly (a few iterations)
- Object classes (tree/bush, car/bike, etc) and individual exemplars learned later

..\Models\Object Demo\SOM Learning Movie.avi

results: visual map learning

③ task





living

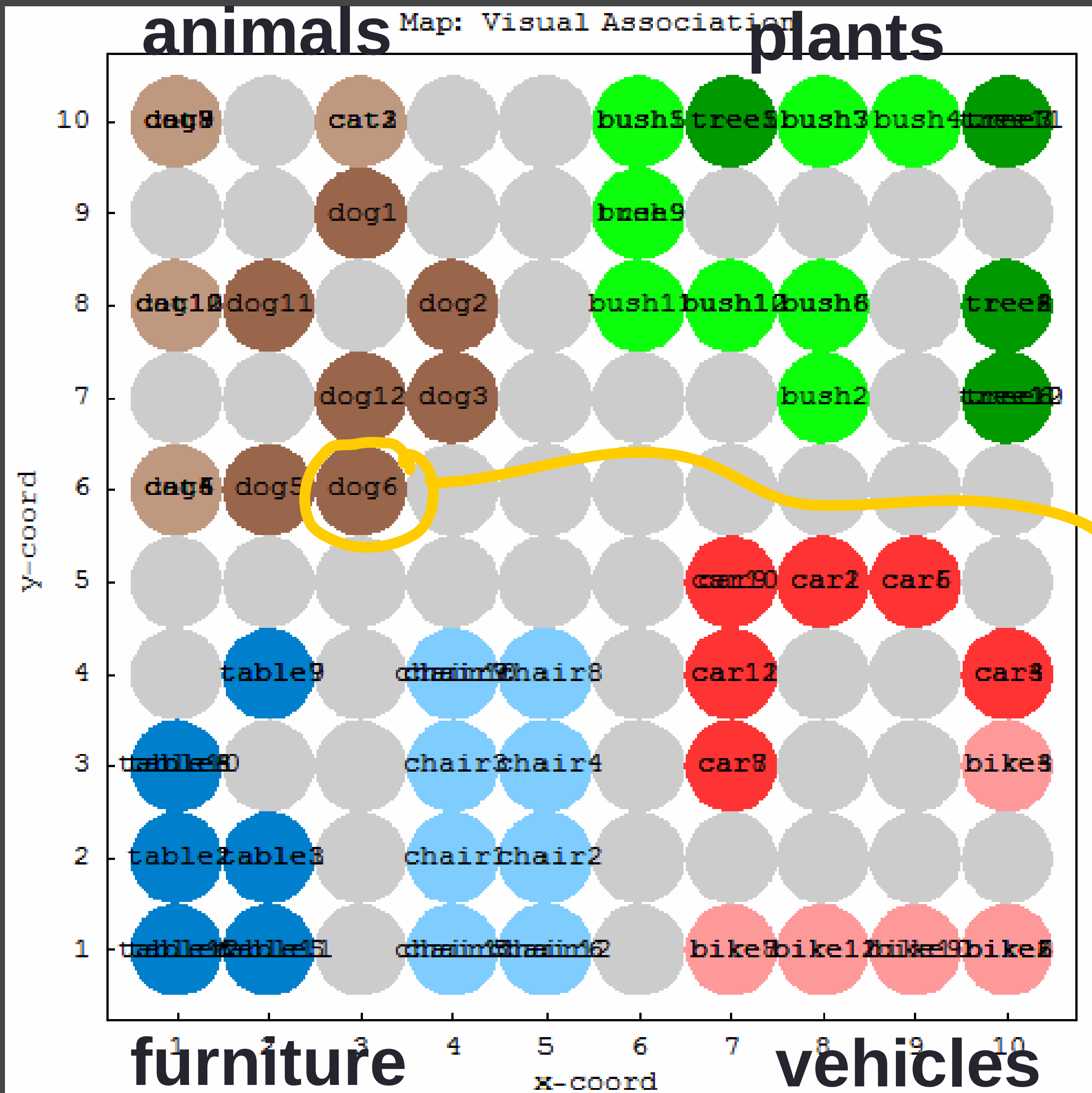
nonliving

Learned:

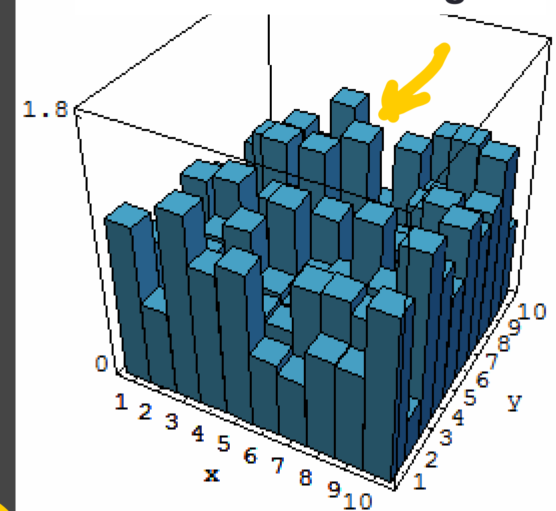
- super-category
- category
- most classes
- some exemplars

winning cells, within topography

③ task



Dog6 Response Before Training



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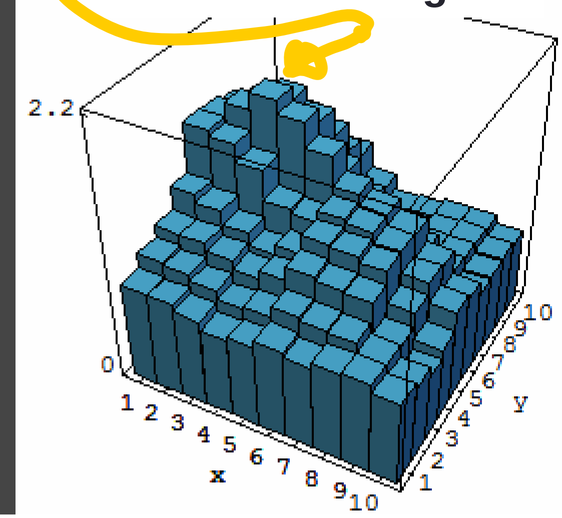
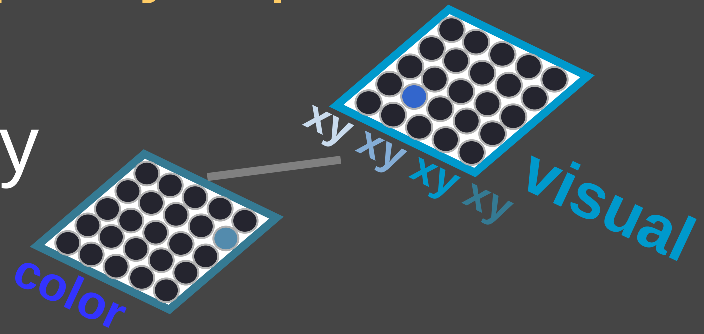
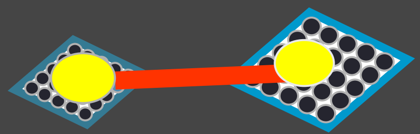


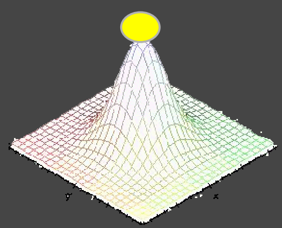
“cortical coordinates”: simple, yet powerful



- semantics determined by four key properties:
  - architecture (wiring)
    evolutionary experience



  - temporal coincidence (firing)
    individual experience
  - topography + conjunction (encoding)
    relations between stimuli / attribute-values



  - competition (excitation + inhibition)
    discretization at the level of cells/columns/patches

^nuggets golden

- **clustering & similarity** via neurally-inspired competitive learning
- **sensory transduction** to symbols
- **higher-order semantics** at increasing levels of abstraction, via cortical coordinates

^nuggets coal

- **top-down effects:** require additional extensions of SOM model (in progress)
- **attentional modulation:** allow relative weighting of attributes based on goals, context (in progress)
- **practical considerations:** viability of semantic network in Soar based on SOMs? training? exploitation of knowledge?