Neural Dynamics For Embodied Cognition: Dimensions, binding

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Survey

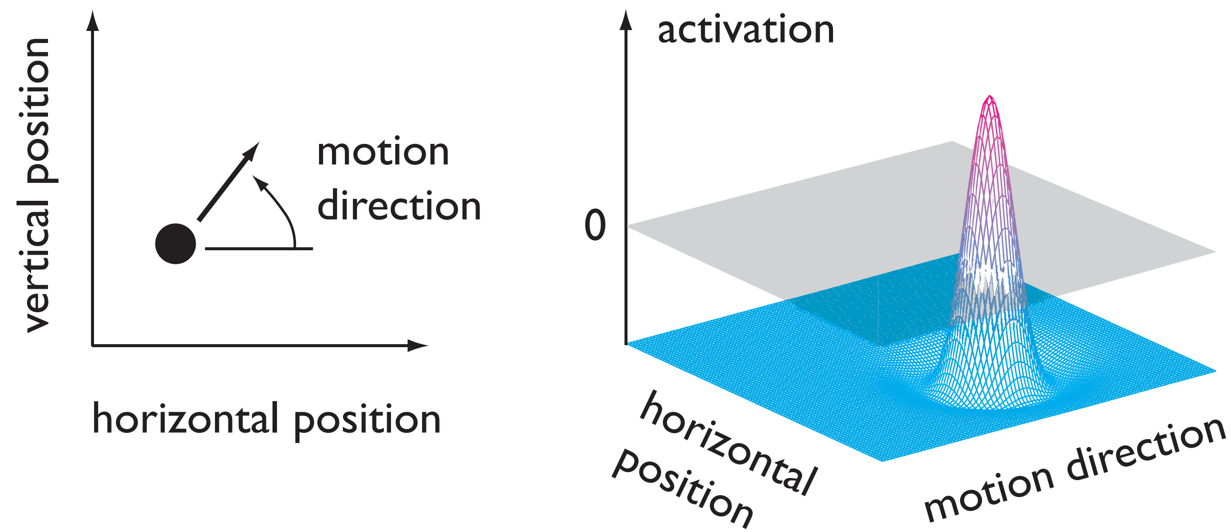
- Foundations 1: Neural dynamics [GS]
  - Introduction to Cedar/Instabilities in DFT [Stephan Sehring]
- Foundations 2: Dimensions/Binding [GS]
  - Cedar architecture: visual search [Raul Grieben]
- Foundations 3: Toward grounded cognition [GS]
  - Cedar architecture: relational grounding [Daniel Sabinasz]
- Foundations 4: Sequence generation [GS]
  - Cedar architecture sequence generation [Minseok Kang]

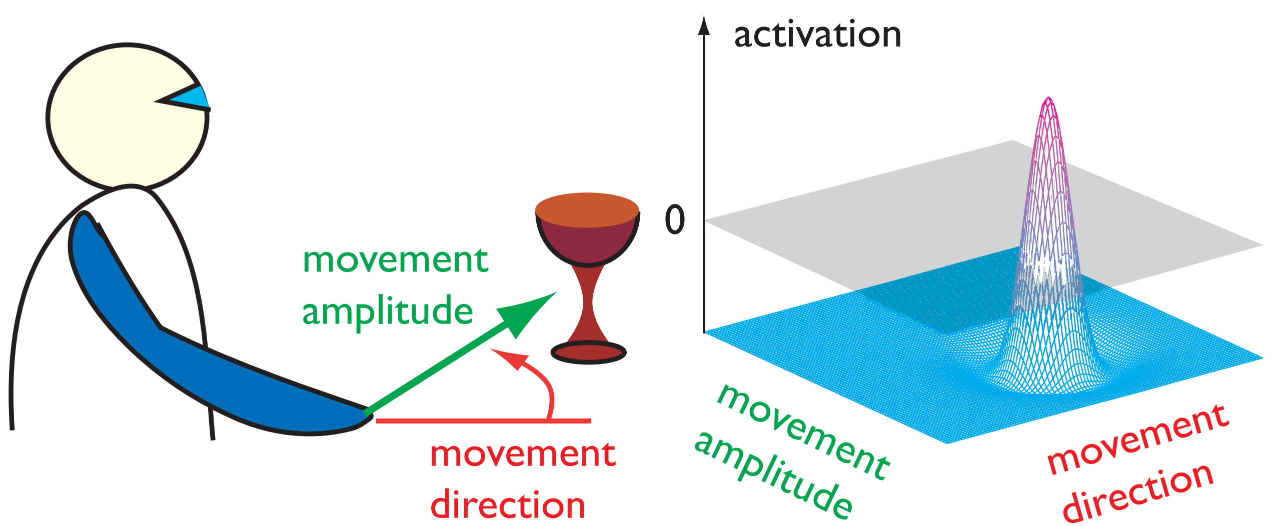
Foundations 2: Dimensions

- the dimension of neural fields
- two forms of binding
- scene representations
- visual search

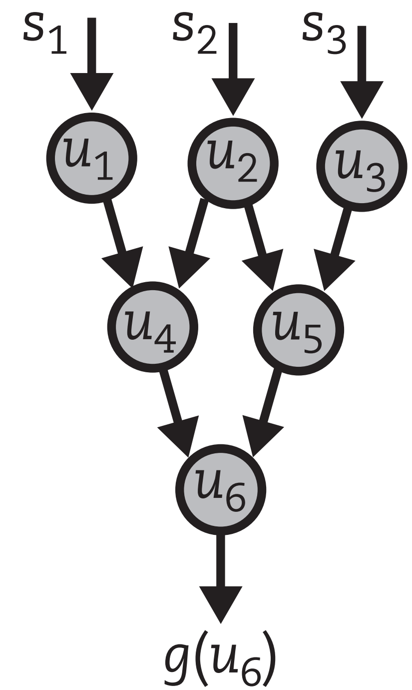
Where do the dimensions of neural fields come from?

- how do neural fields come to "represent" feature spaces?

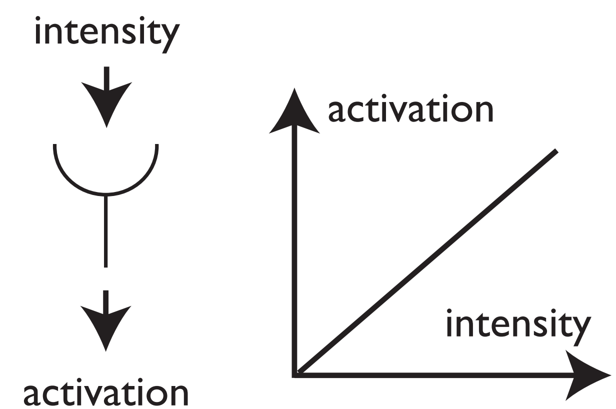


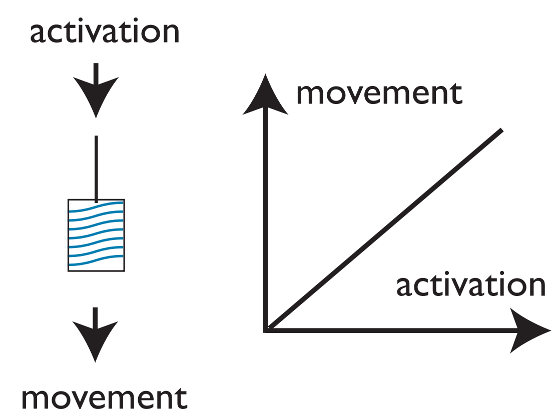


Neural networks



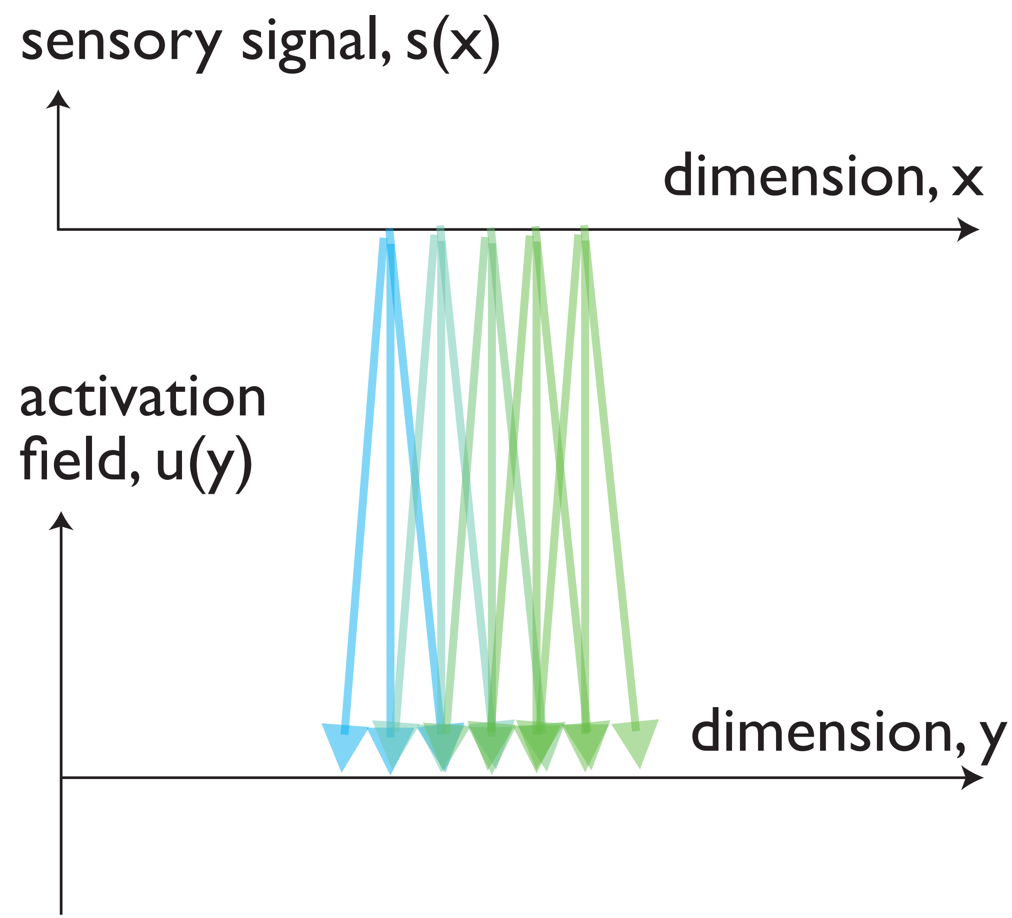
- forward connectivity determines "what a neuron stands for"= space code (or labelled line code)
- while the activation level may "stand for" intensities =rate code
- generic neural networks combine both codes





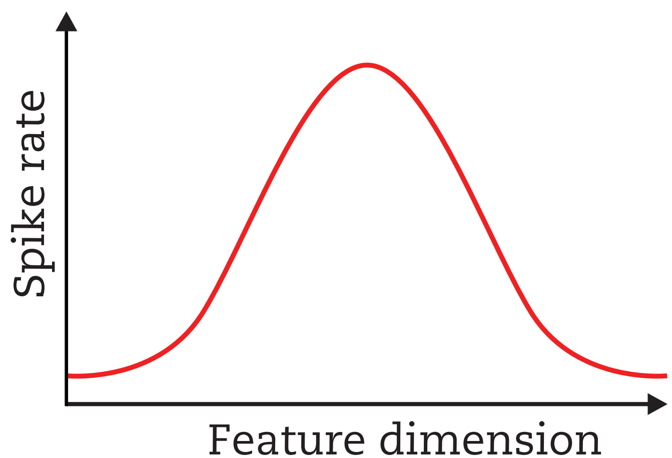
Neural fields

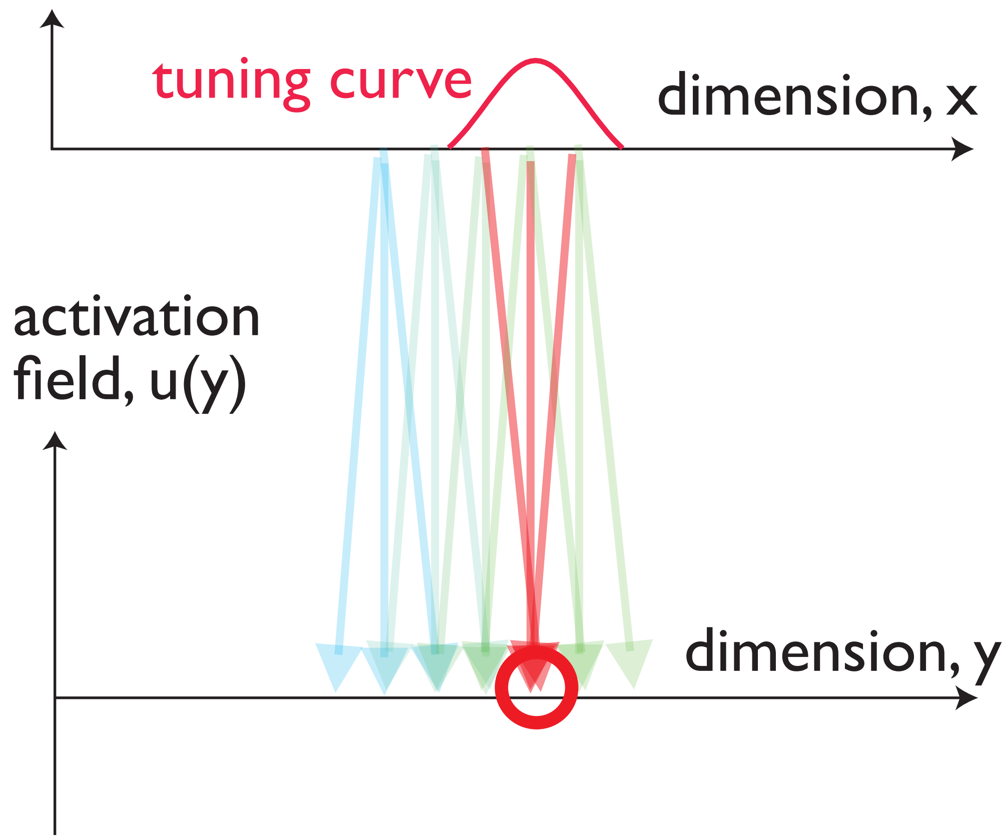
- forward connectivity from the sensory surface extracts perceptual feature dimensions



Neural fields

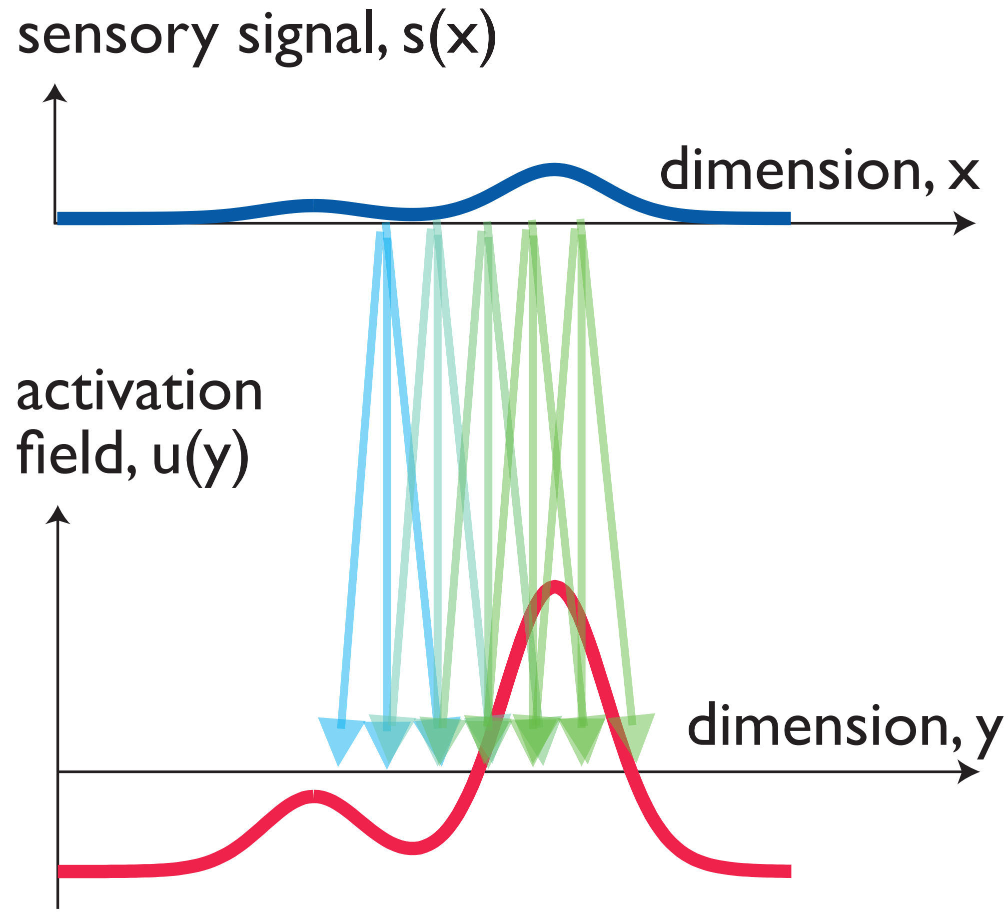
- as described by tuning curves or receptive fields





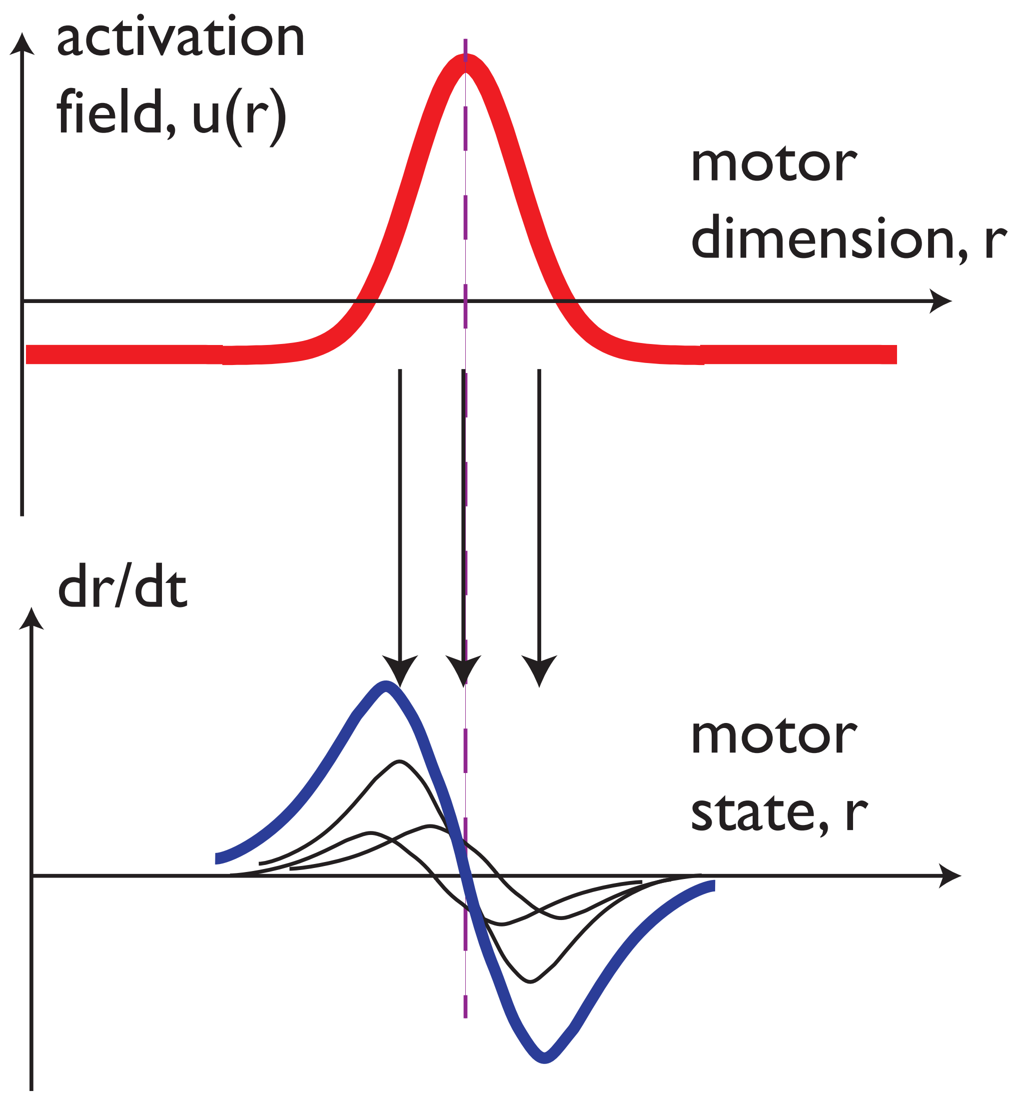
Neural fields

- => neural map from sensory surface to feature dimension
- neglect the sampling by individual neurons => activation field

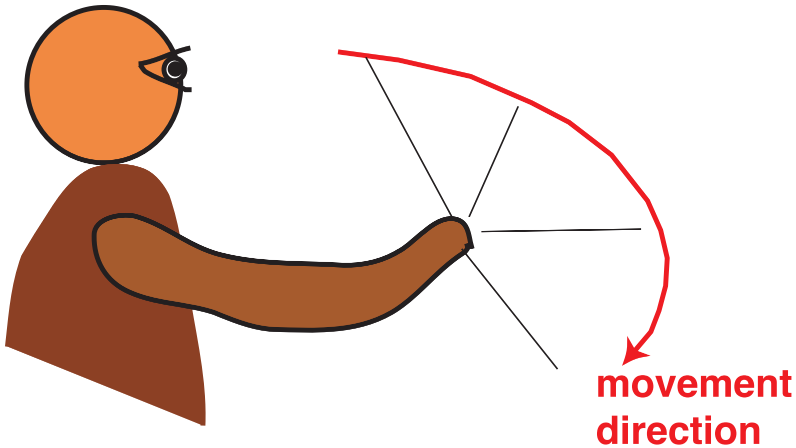


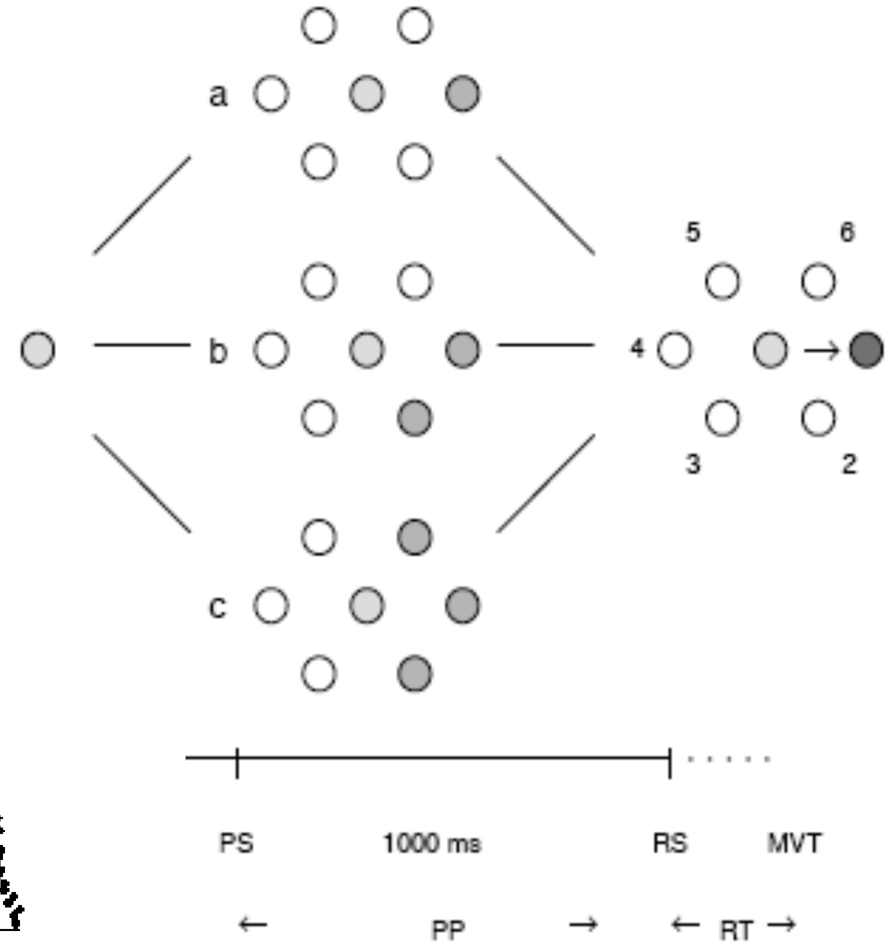
Neural fields

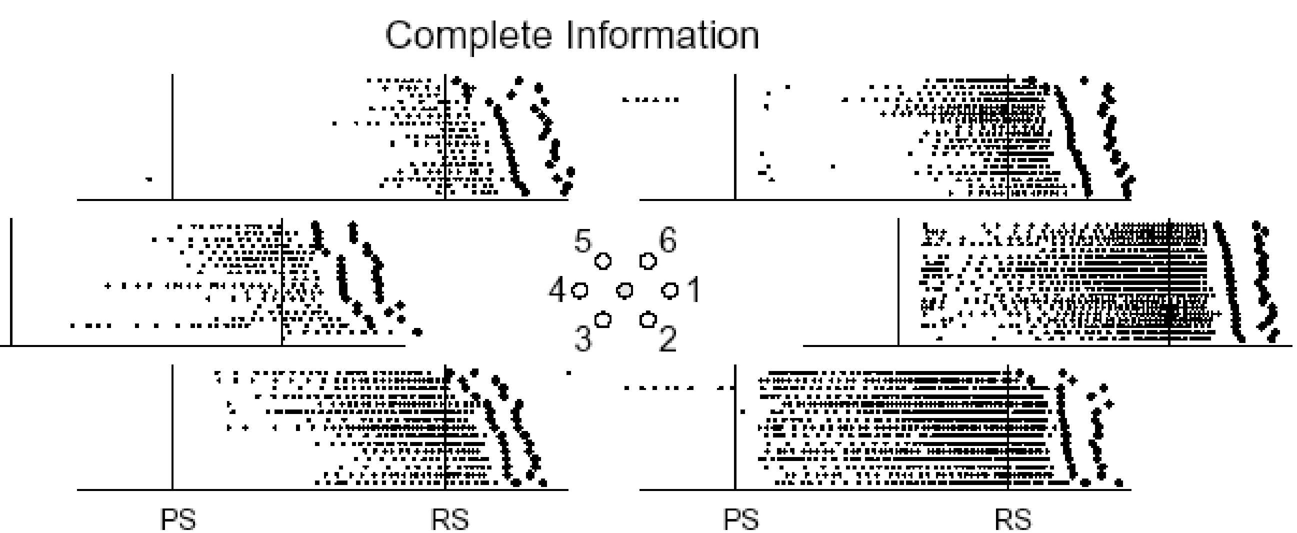
- analogous for projection onto to motor surfaces…
- which actually involves behavioral dynamics (e.g., through neural oscillators and peripheral reflex loops)



Neural estimation of fields



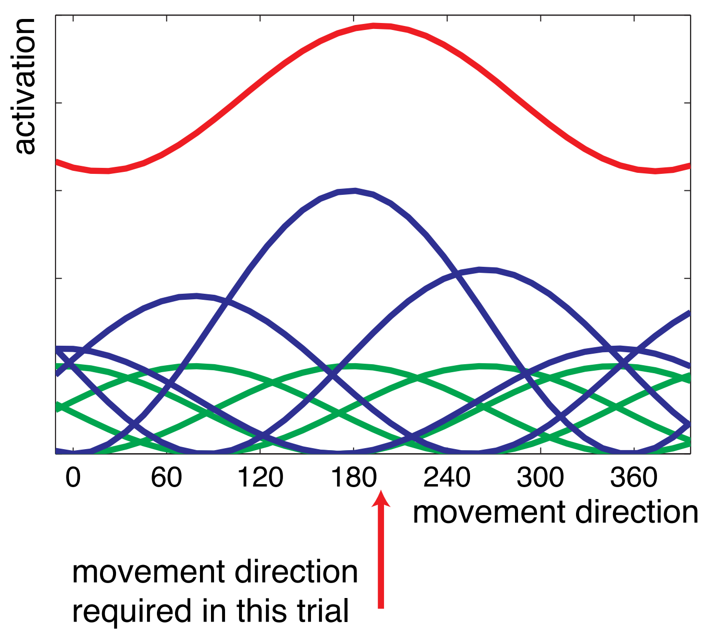


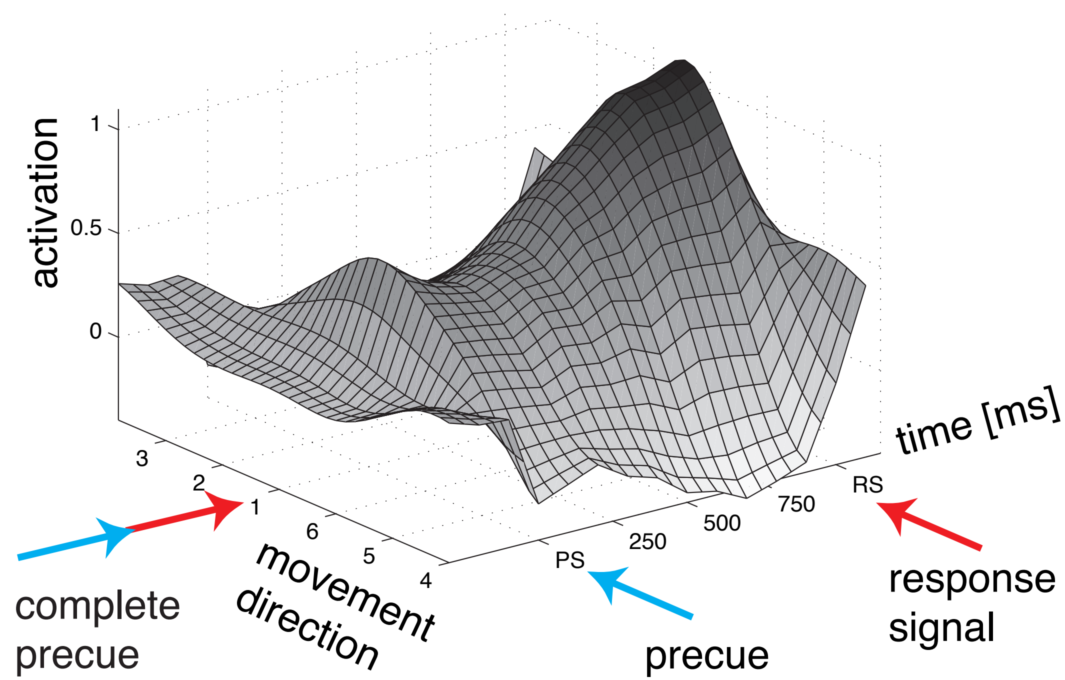


Bastian, Riehle, Schöner, 2003

Distribution of Population Activation (DPA) <=> neural field

Distribution of population activation = $\sum_{\text{neurons}}$ tuning curve * current firing rate

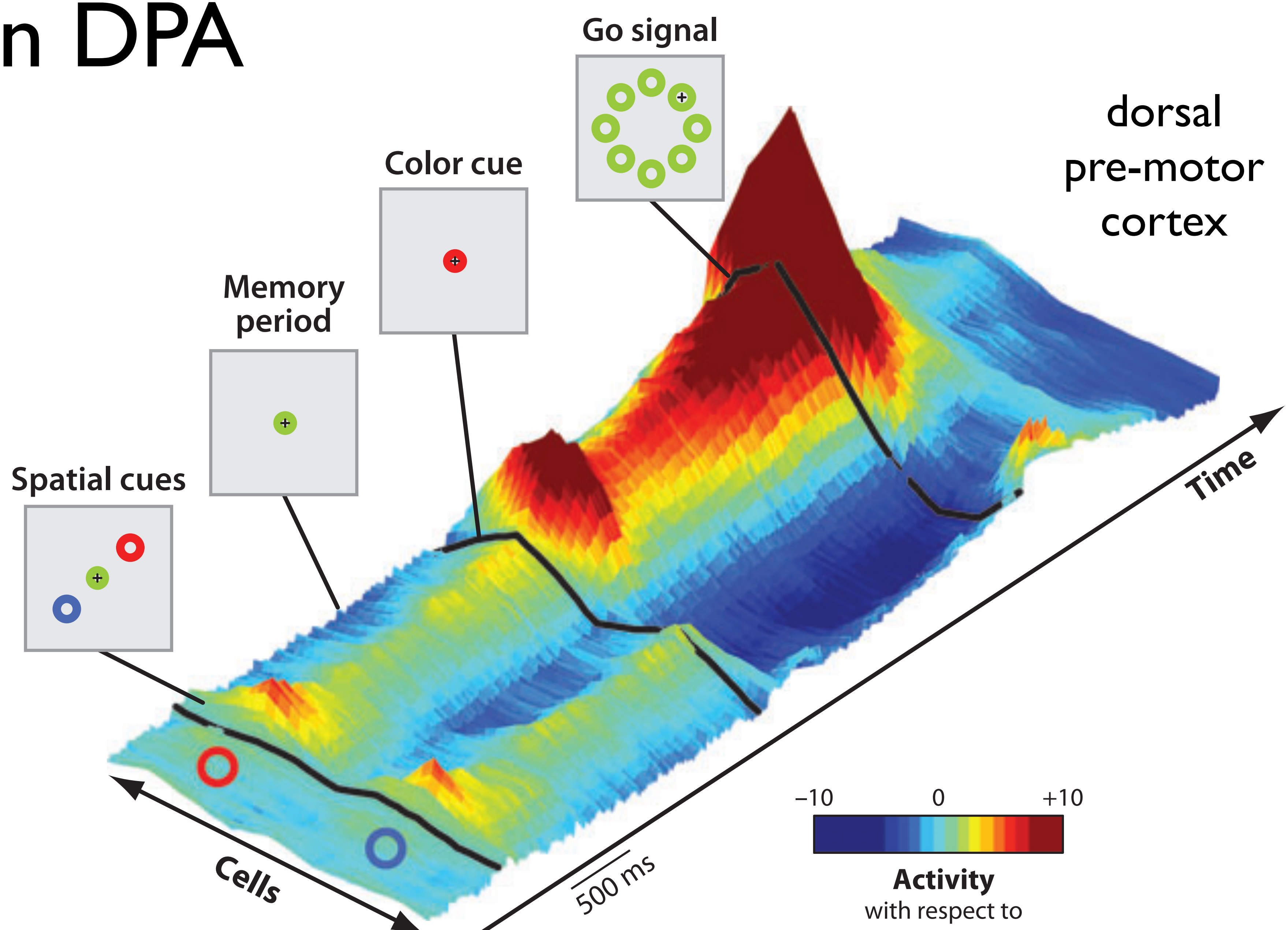




- note: neurons are not localized within DPA!

[Bastian, Riehle, Schöner, 2003]

Decision making in DPA



dorsal pre-motor cortex

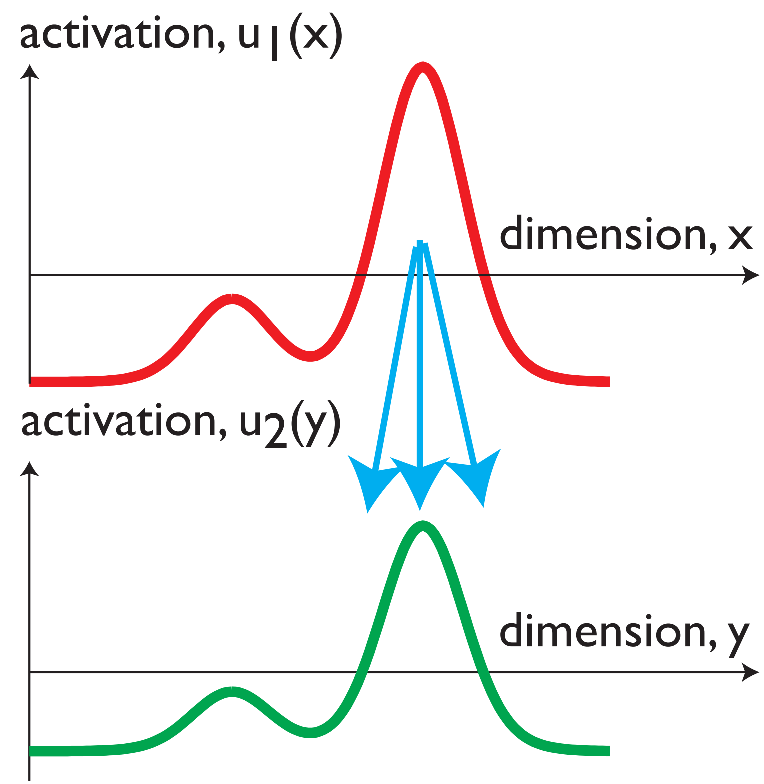
[Cisek, Kalaska 2005]

Patterns of connectivity gives neural fields meaning

- how does the connectivity arise?
- morphogenesis… modeled by fixed connectivity
- learning…

Hebbian learning

- Hebbian learning of projections
  - among fields
  - forward from sensory input to fields
- interaction leads to localized rather than distributed representations (SOM)

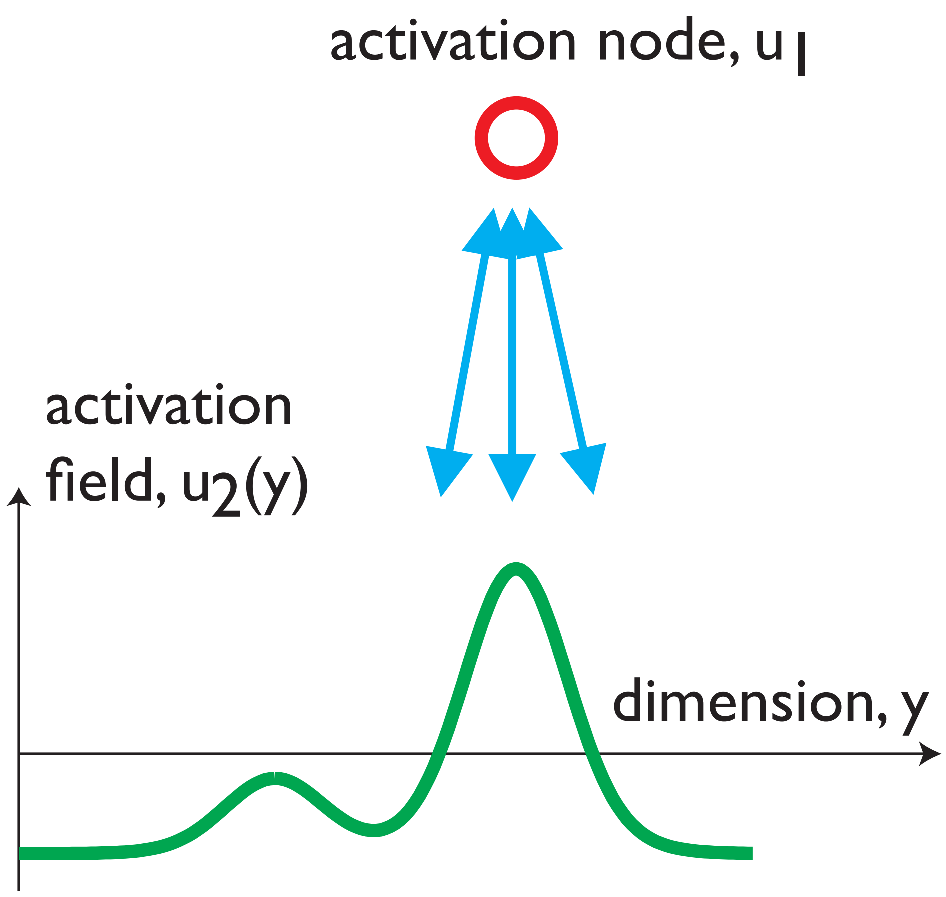


$$\tau \dot{W}(x, y, t) = \epsilon(t)\Big(- W(x, y, t) + f(u_1(x, t)) \times f(u_2(y, t))\Big)$$

[Sandamirskaya, Frontiers Neurosci 2014]

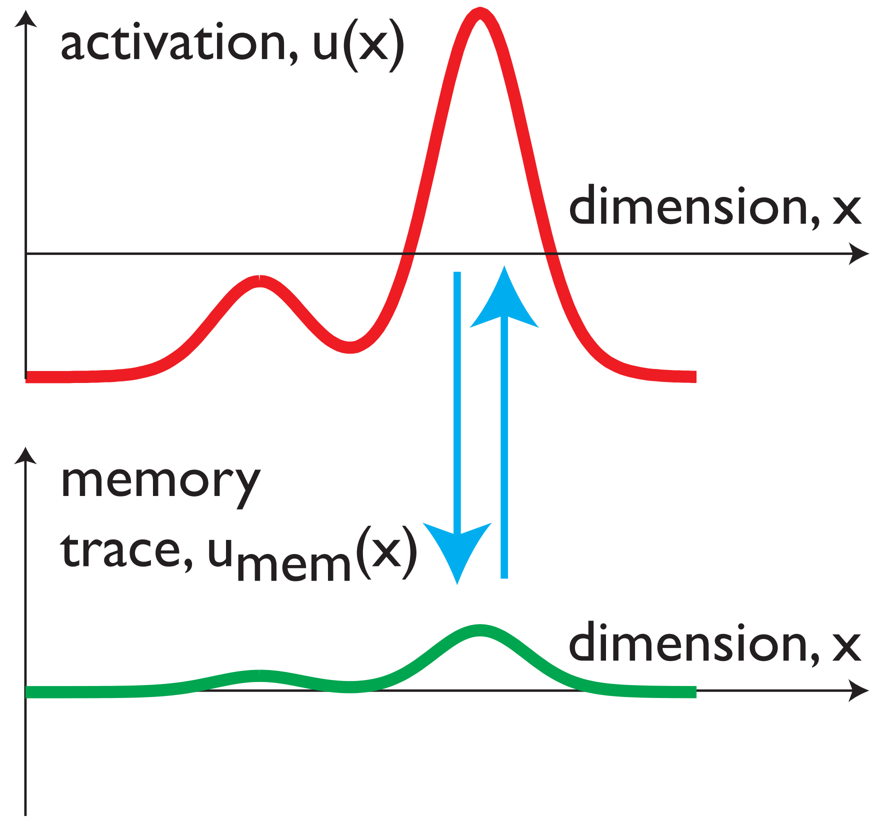
Hebbian learning

- learning reciprocal connections between zero-dimensional nodes and fields
- => grounded concepts
- analogous to the output layer of DNN
- => ensembles of such nodes coupled inhibitorily form the basis for conceptual thinking…



The memory trace

- facilitatory trace of patterns of activation
- in excitatory field: leads to sensitization
- in inhibitory field: leads to habituation

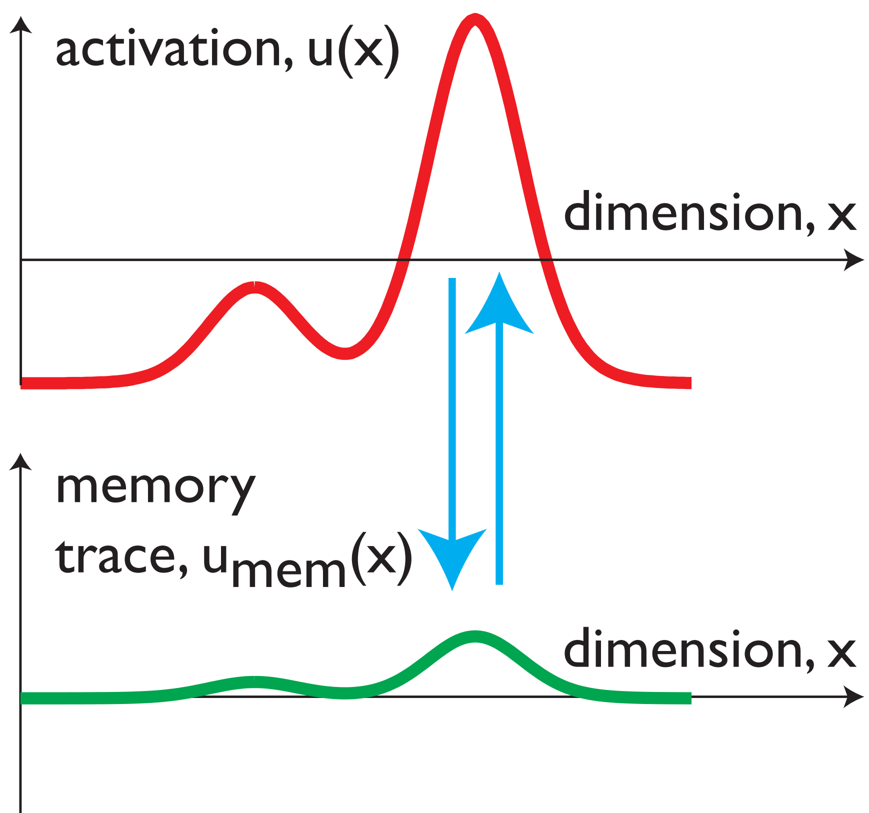


The memory trace

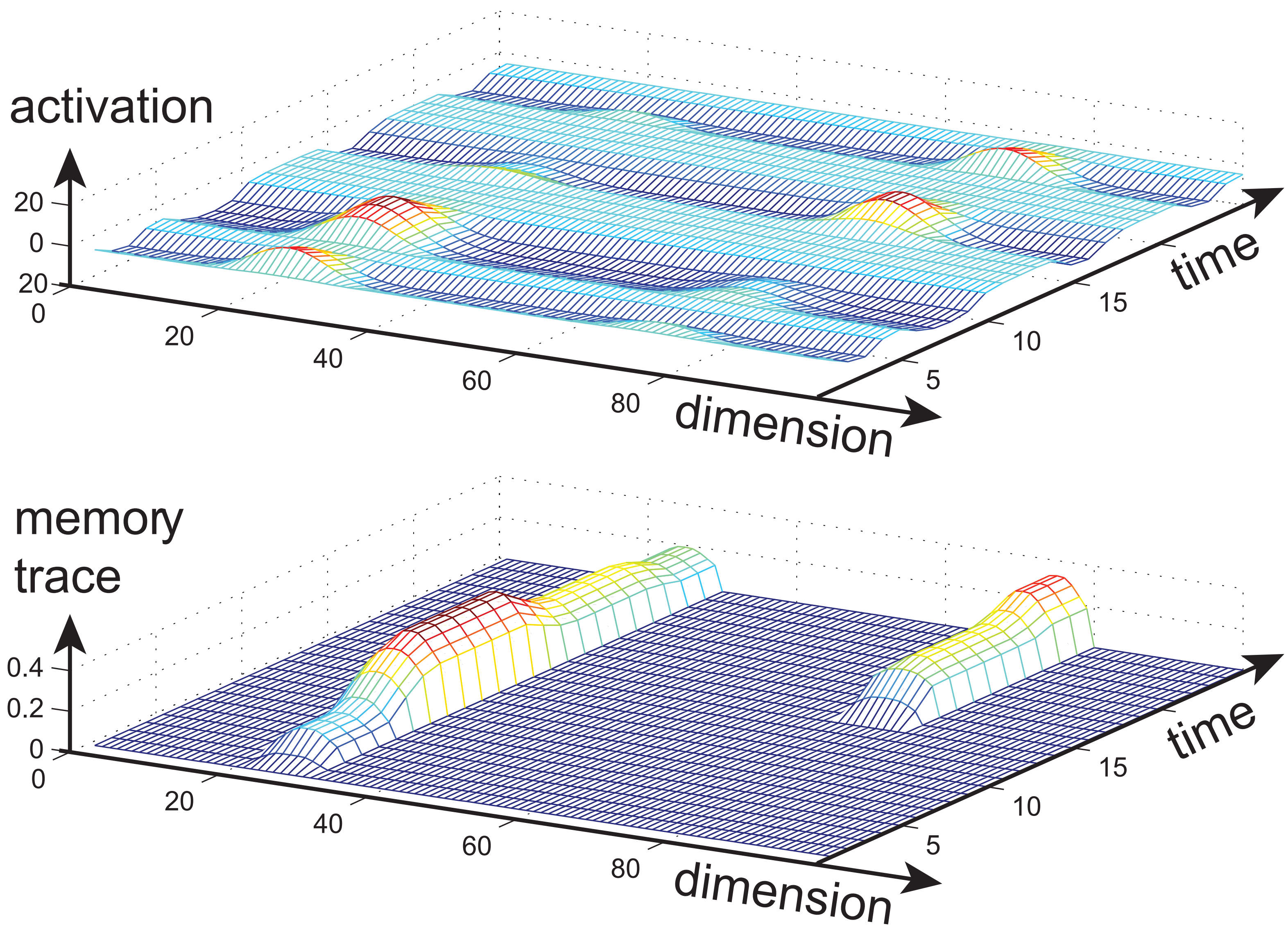
$$\tau \dot{u}(x,t) = -u(x,t) + h + s(x,t) + \int dx' w(x-x')\ \sigma(u(x',t)) + u_{\mathrm{mem}}$$

$$\tau_{\mathrm{mem}} \dot{u}_{\mathrm{mem}}(x,t) = -u_{\mathrm{mem}}(x,t) + \sigma(u(x,t))$$

$$\tau_{\mathrm{mem}} \dot{u}_{\mathrm{mem}}(x,t) = 0 \quad \text{if} \int dx' \sigma(u(x',t)) \approx 0$$

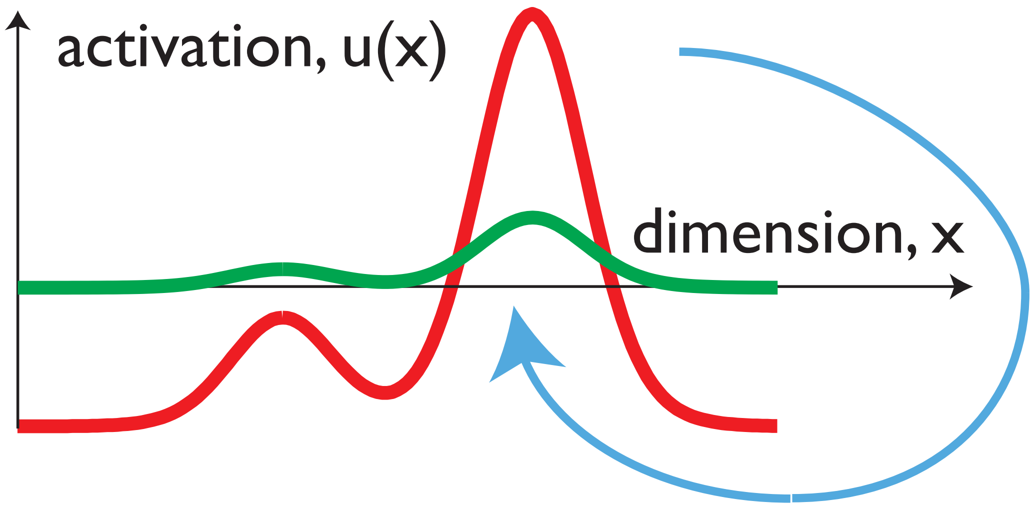


=> the memory trace reflects the history of detection decisions



Memory trace ~ first-order Hebbian learning

- increases local resting level at activated locations
- ~ the bias input in NN
- boost-driven detection instability amplifies small bias => important role in DFT



The memory trace is functionally different from conventional Hebbian learning

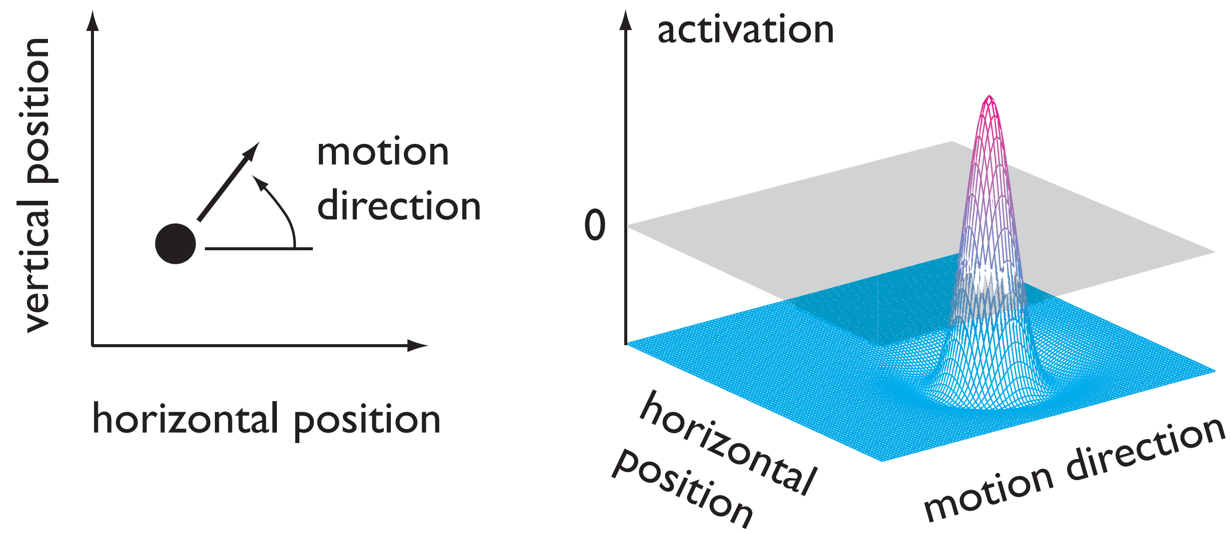
- the memory trace enables the re-activation of a past pattern of activation even when the input that caused the past pattern of activation is absent
- this is the basis for cued recall in DFT

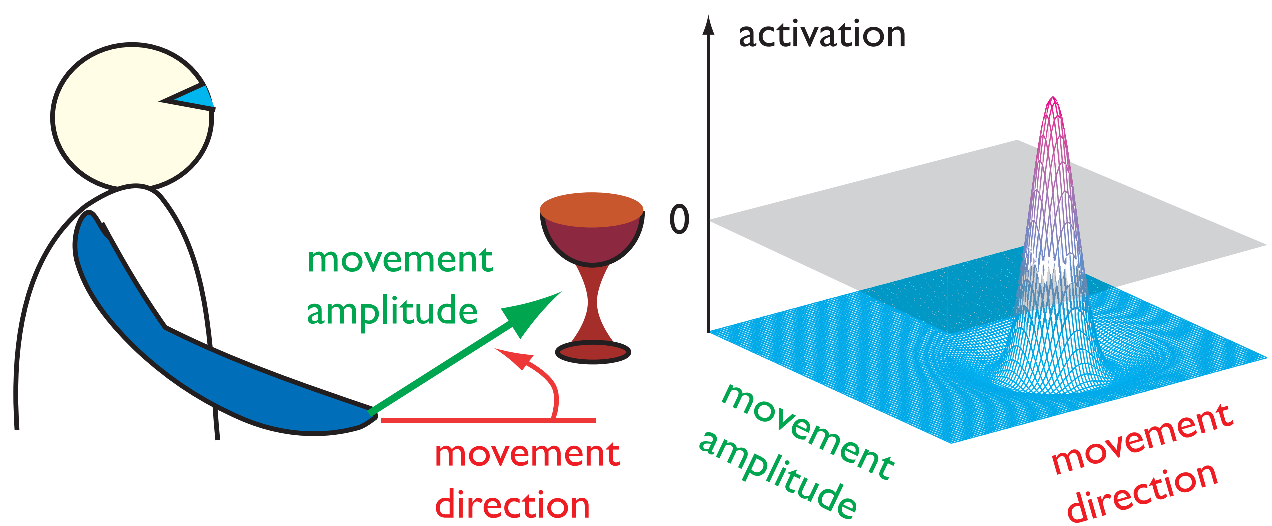
Roadmap

Foundations 2: Dimensions

- the dimension of neural fields
- two forms of binding
- scene representations
- visual search

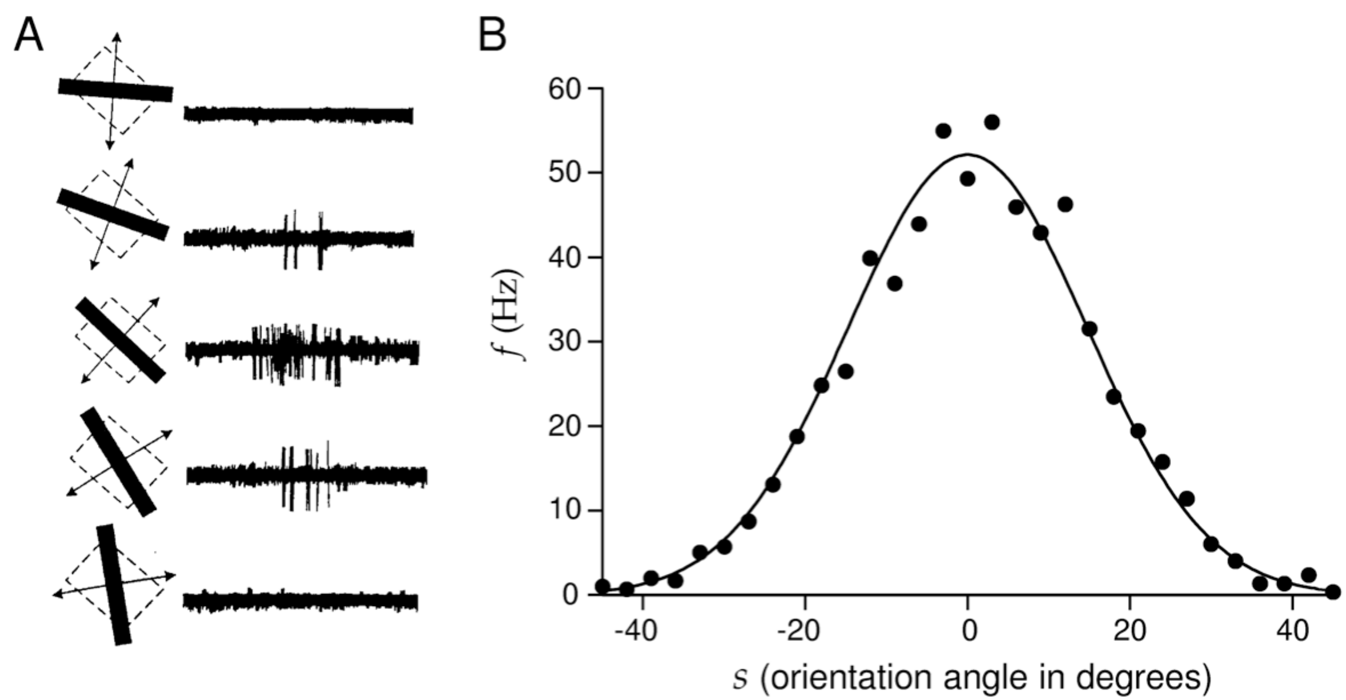
Fields may jointly represent different dimensions: examples





Neurons may be tuned to multiple different feature dimensions

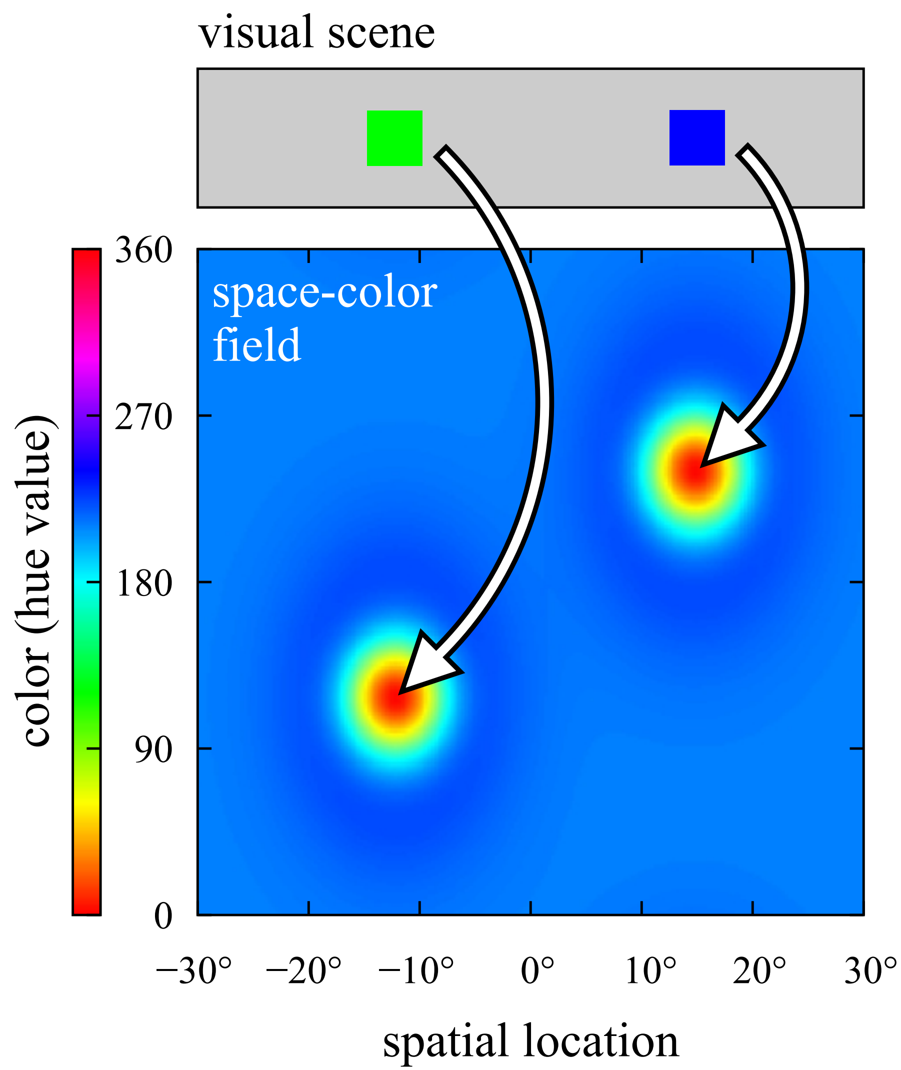
- example: receptive field + direction tuning
- => combines visual space and orientation
- => “anatomical” binding



[Hubel, Wiesel, 1962]

Combining different feature dimensions

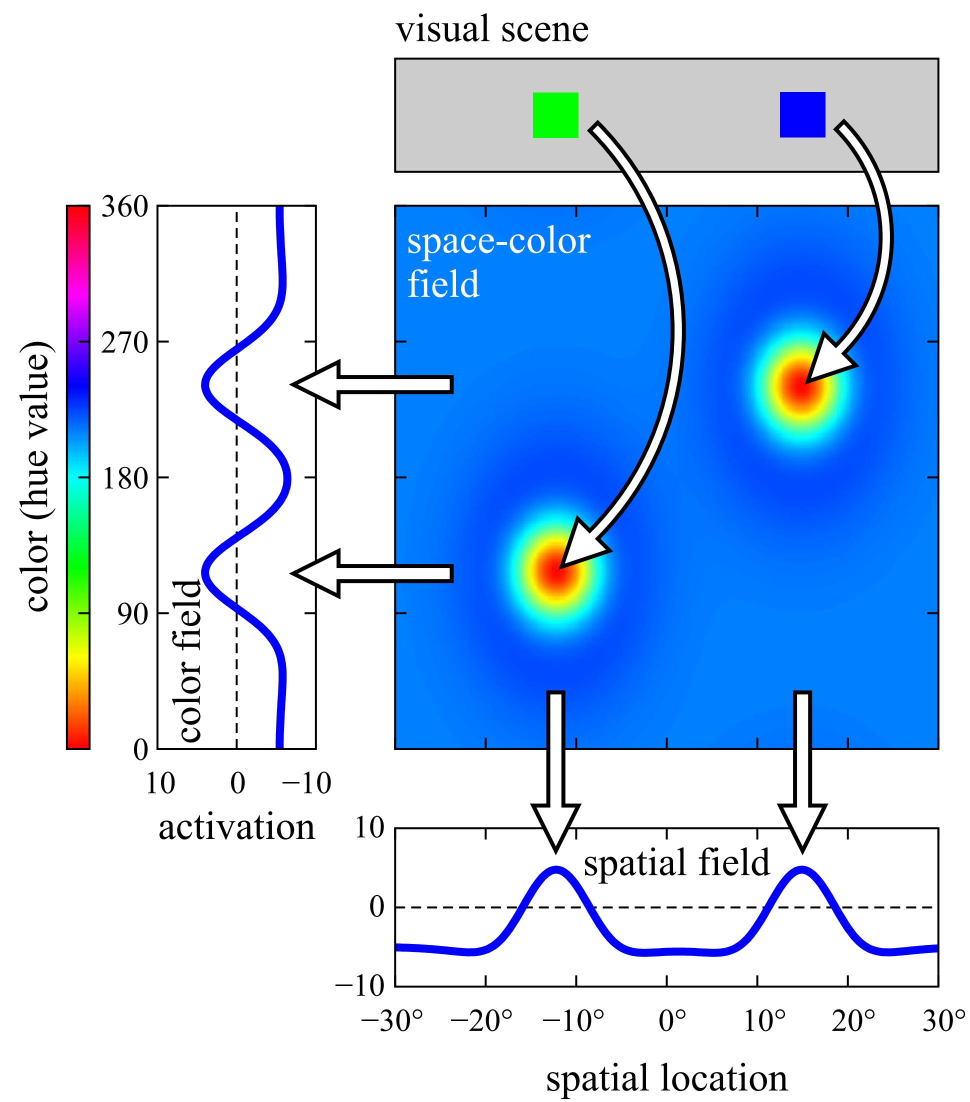
- example: a joint representation of color and visual space "binds" these two dimensions



[Schneegans et al., Ch 5 of *DFT Primer*, 2016]

Extract the bound features

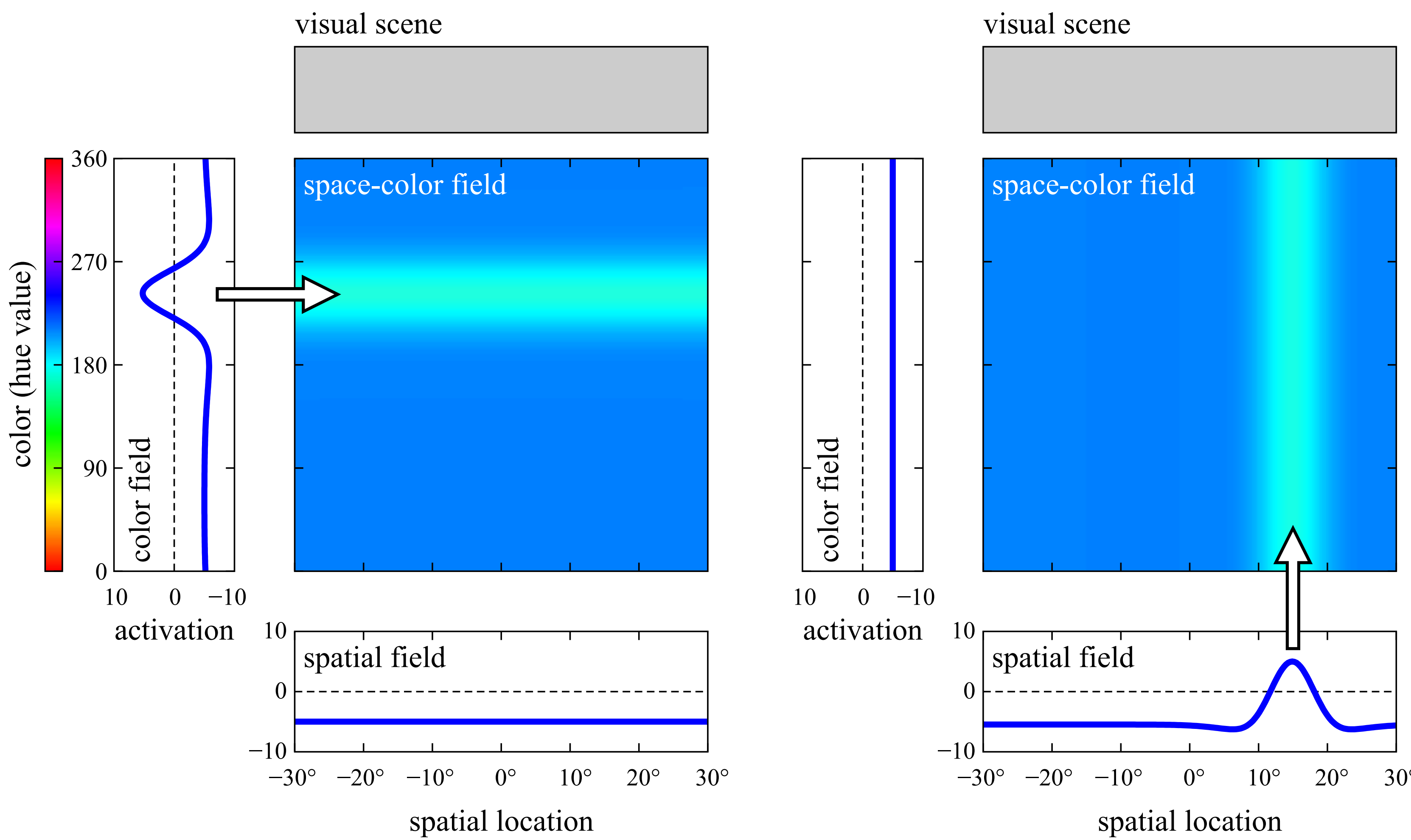
- project to lower-dimensional fields
- by summing along the marginalized dimensions
- (or by taking the soft-max)



[Schneegans et al., Ch 5 of *DFT Primer*, 2016]

Assemble bound representations

- project lower-dimension field onto higher-dimensional field as “ridge input”



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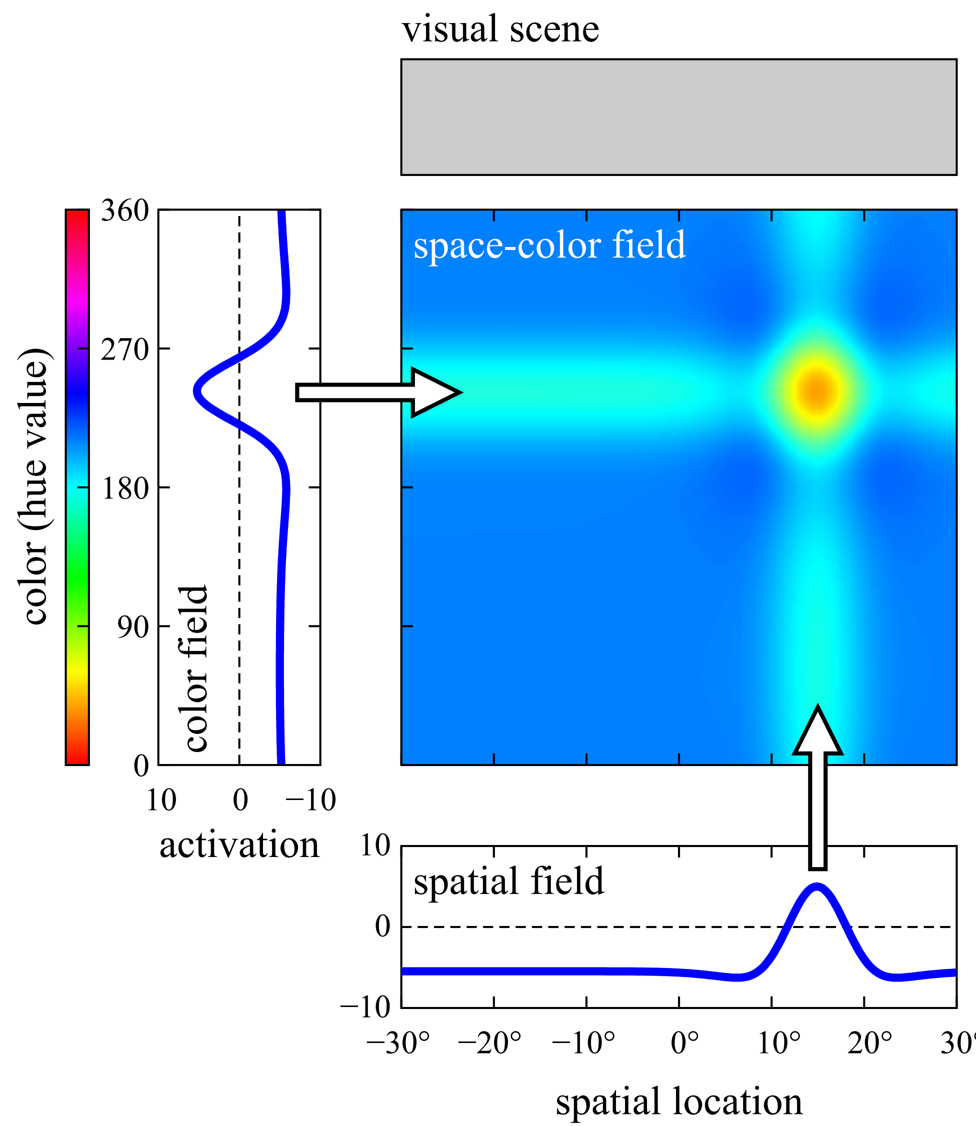
Assemble bound representations



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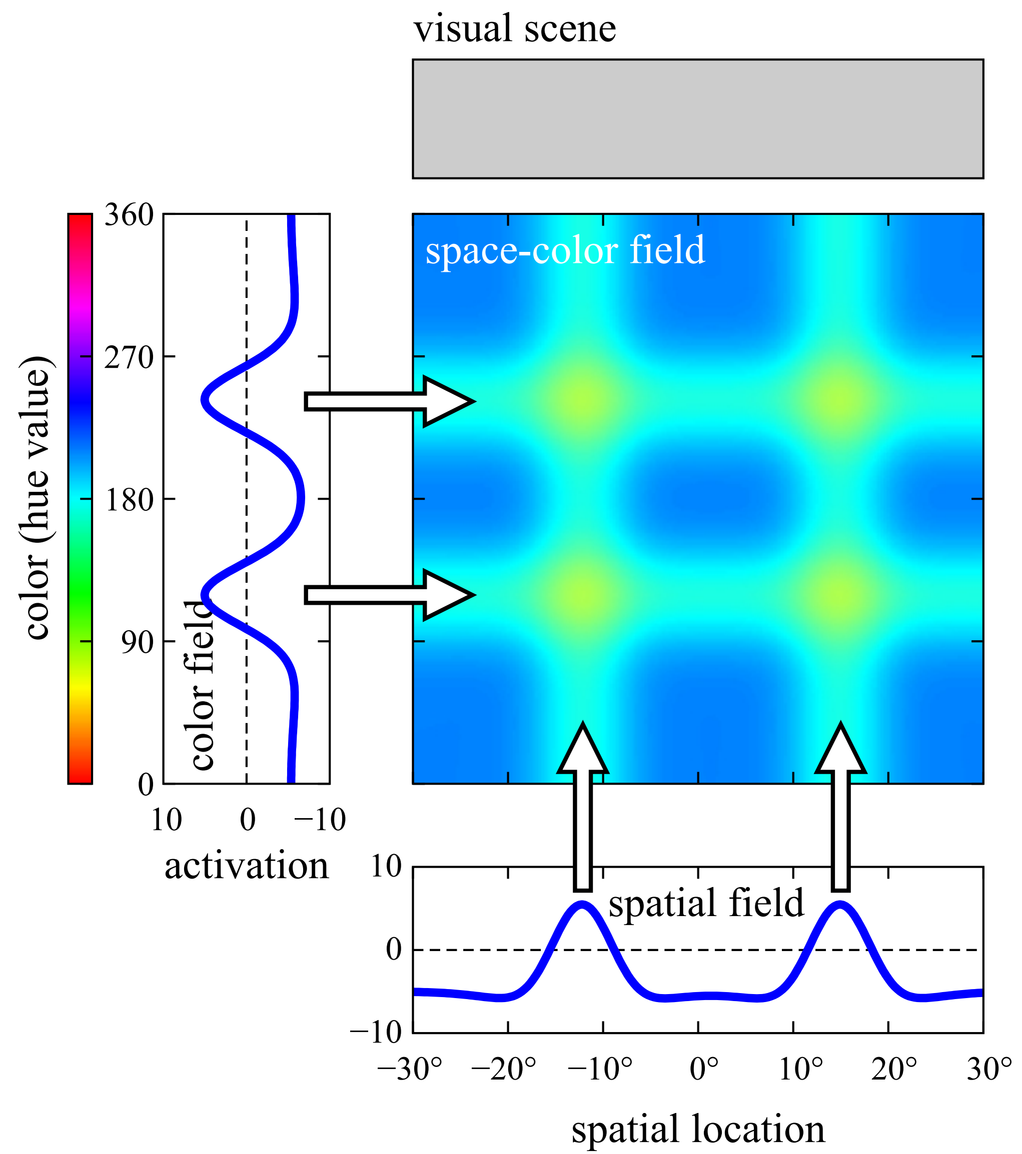
Assemble bound representations

- binding problem: multiple ridges along lower-dimensional space lead to a correspondence problem
- => assemble one object at a time…
- => sequentiality bottle-neck!



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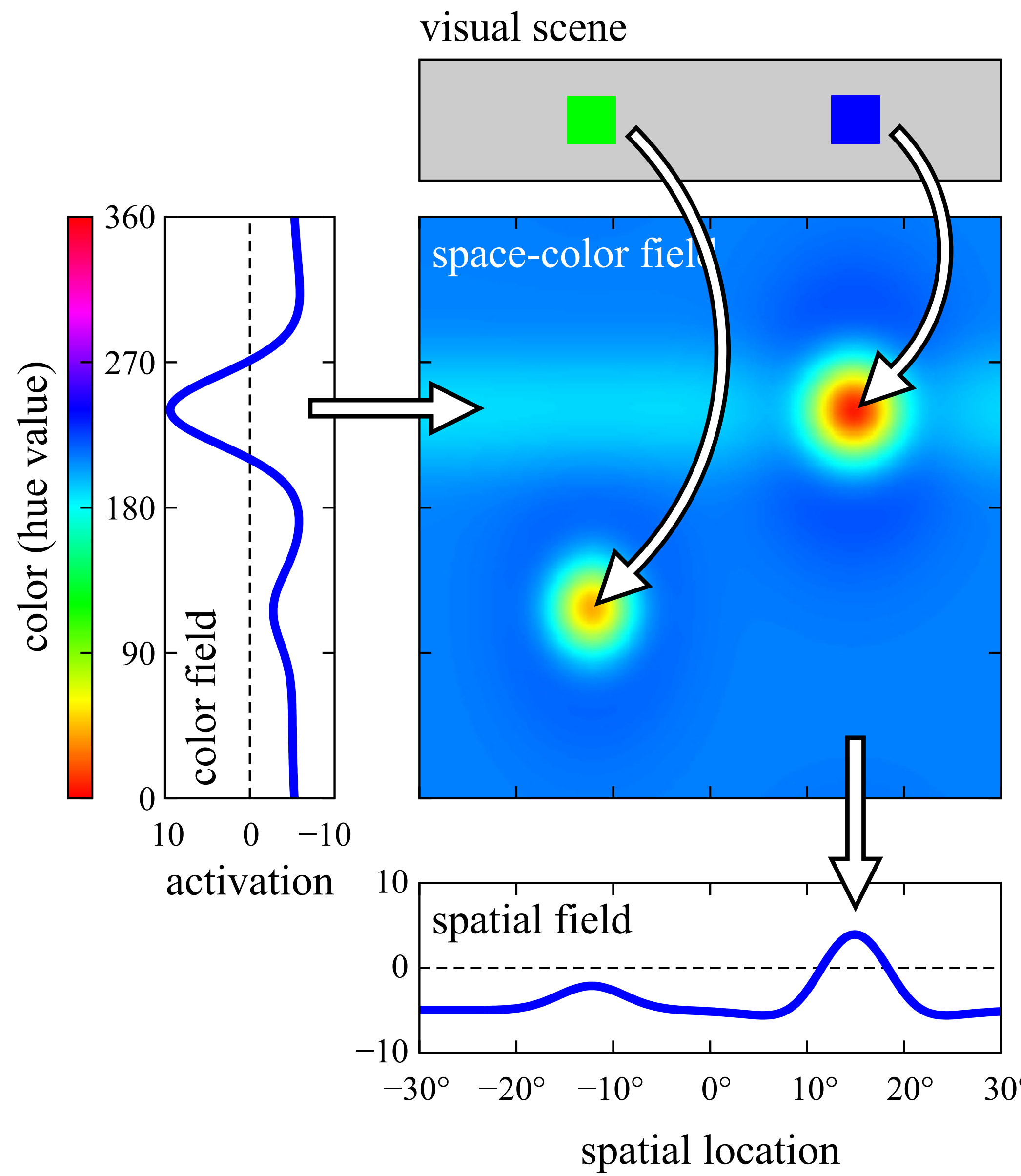
Search

- ridge input along one dimension extracts from bound representation matching objects
- other dimensions of those objects can then be extracted
- e.g. visual search



[Schneegans et al., Ch 5 of *DFT Primer*, 2016]

Scaling feature dimensions

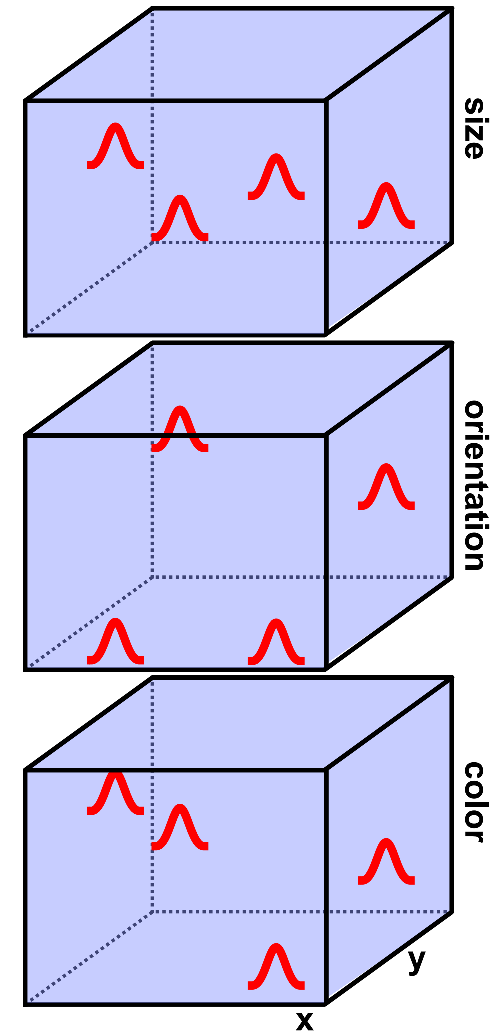
- 2 spatial dimensions
- depth
- orientation
- color
- texture
- movement direction
- size
- etc…

=>

- e.g. 8 dimensions
- 100 neurons per dimension
- $10^{2*8} = 10^{16}$!
- more than there are in the entire brain!
- => only small sets of feature dimensions can be bound "anatomically"

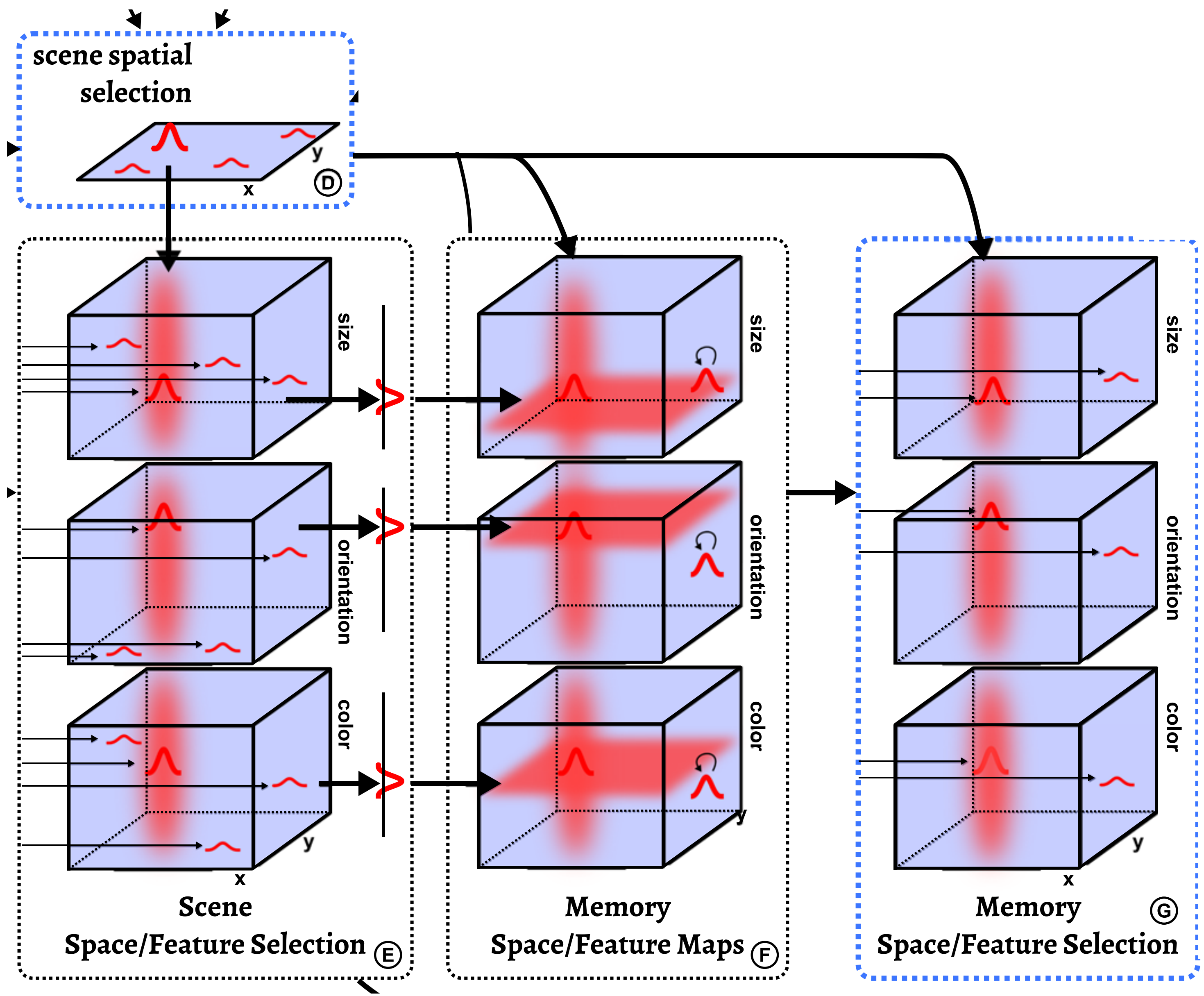
Binding through space

- many 3 to 4 dimensional feature fields
- all of which share the one dimension: visual space (~all neurons have receptive fields)
- bind through space à la Feature Integration Theory (Treisman)



[Grieben et al. *Attention, Perception & Psychophysics* 2020]

Binding through space



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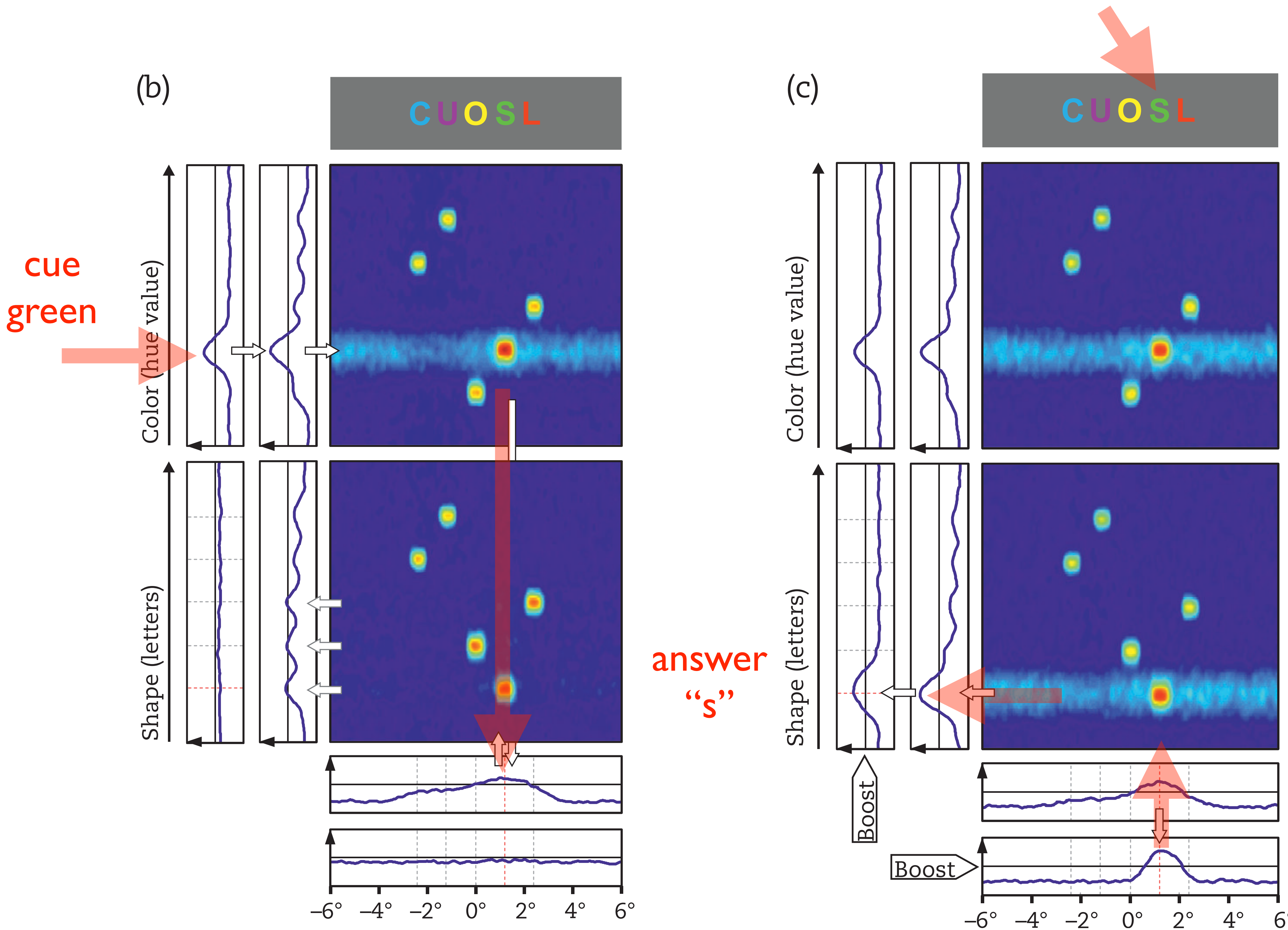

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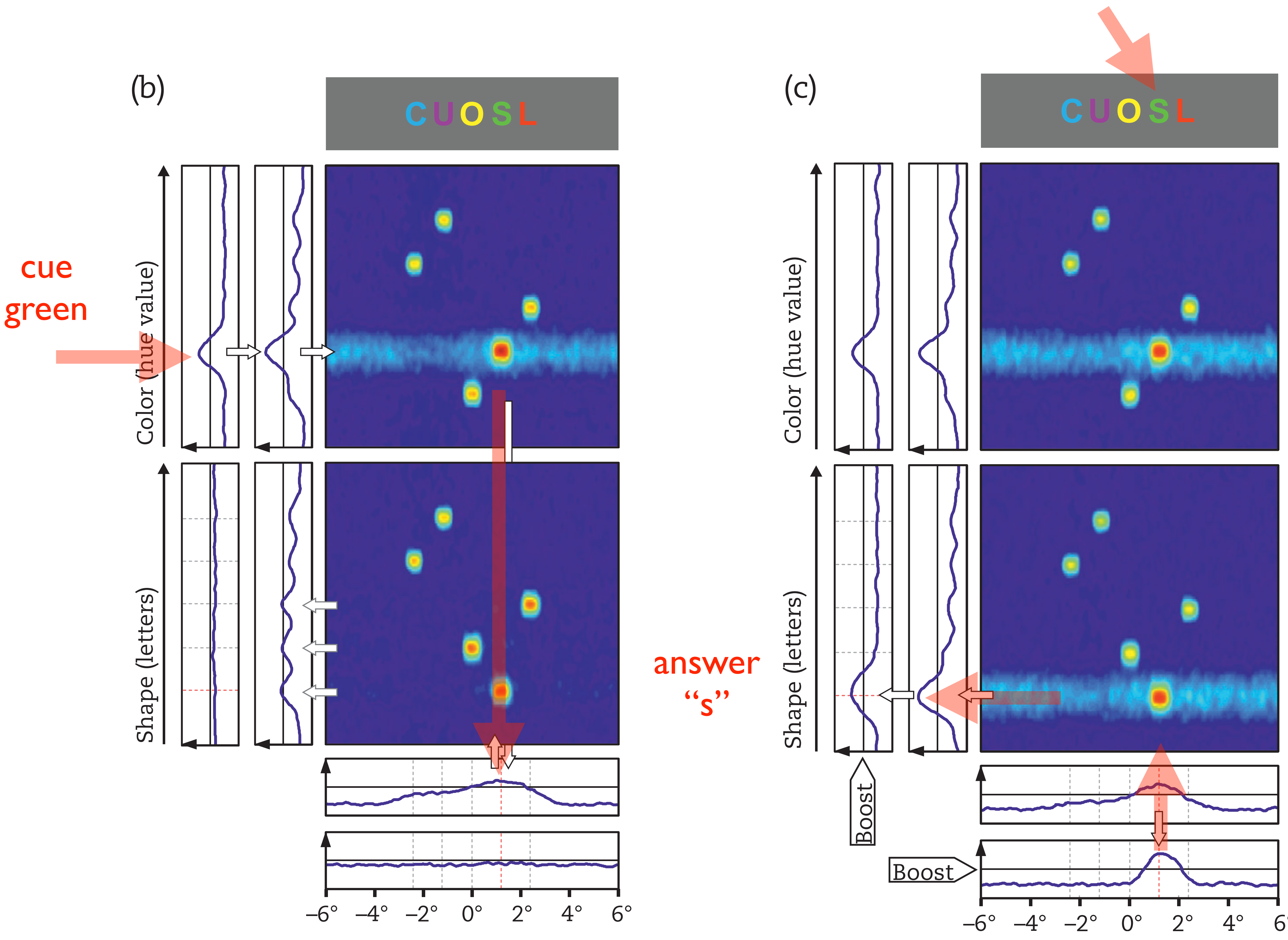

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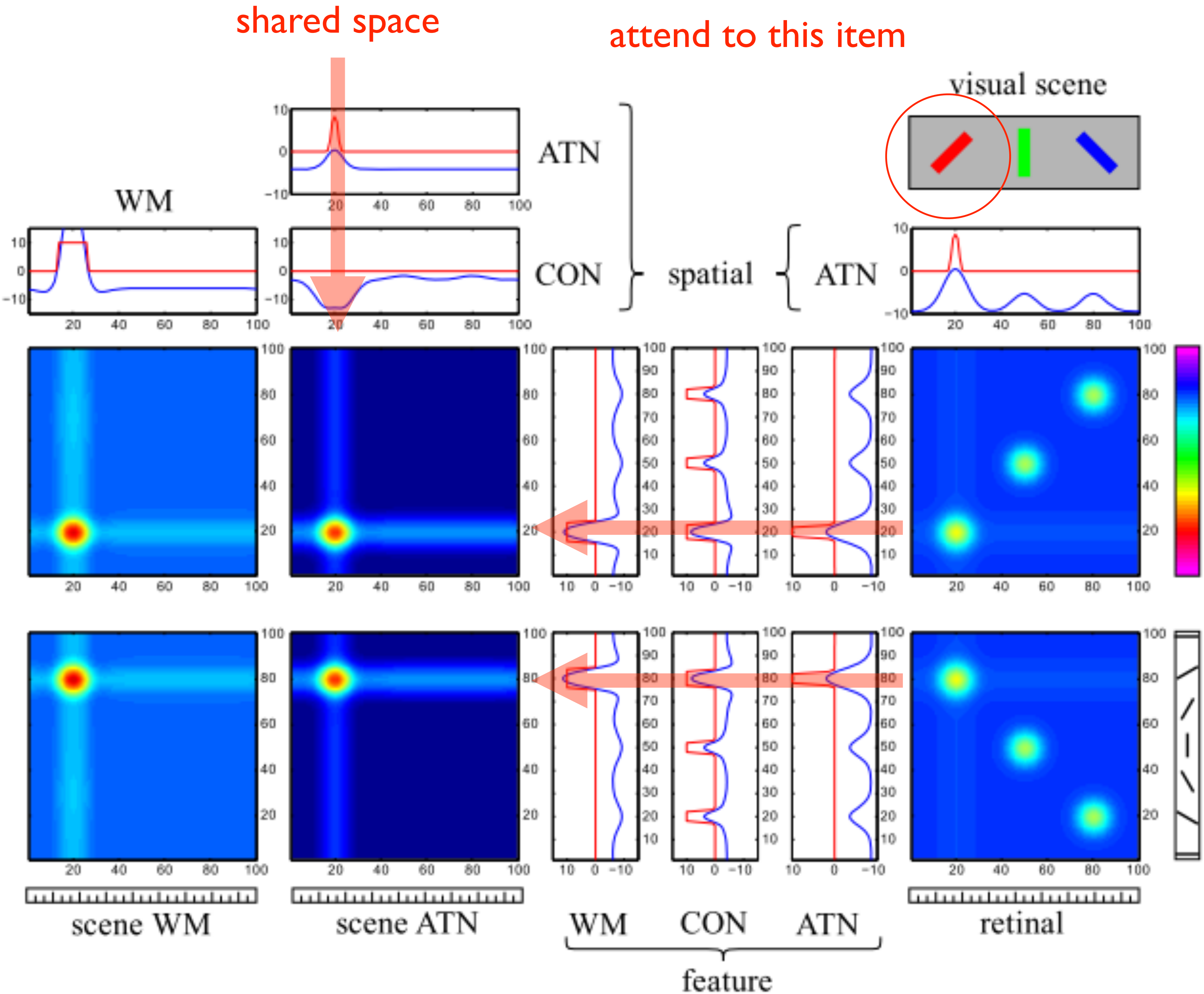
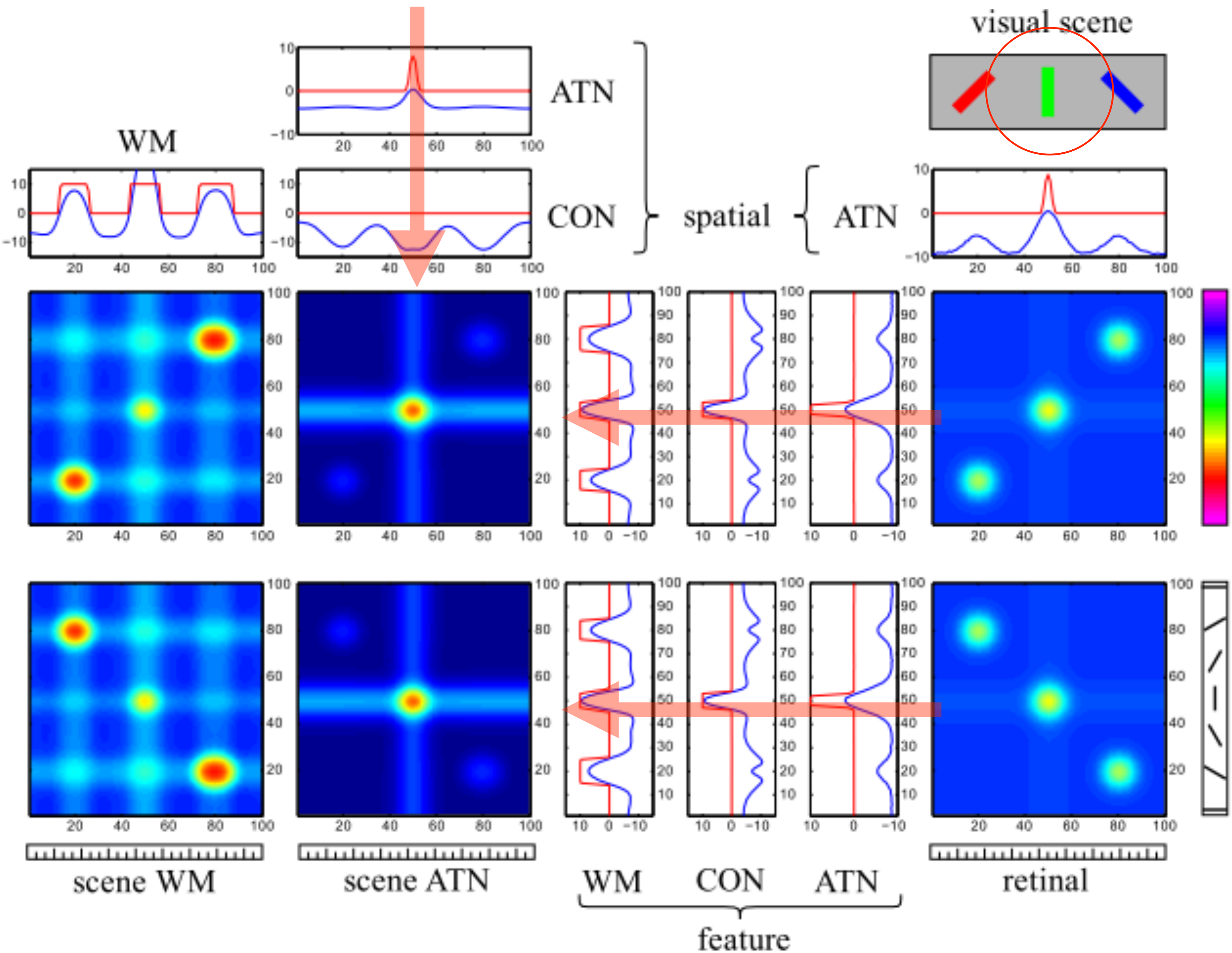


[Schneegans et al., Ch 8 of *DFT Primer,* 2016]



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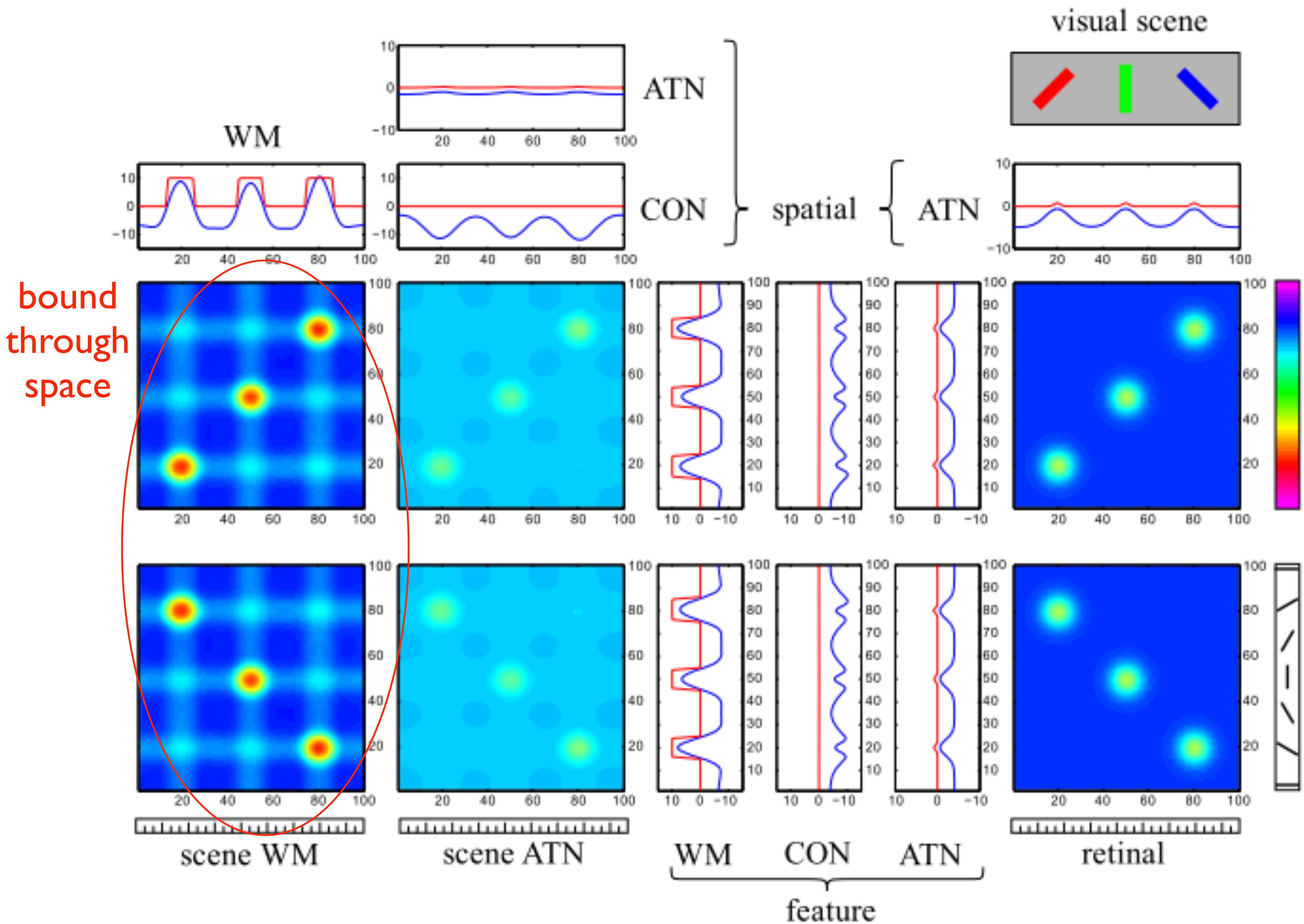

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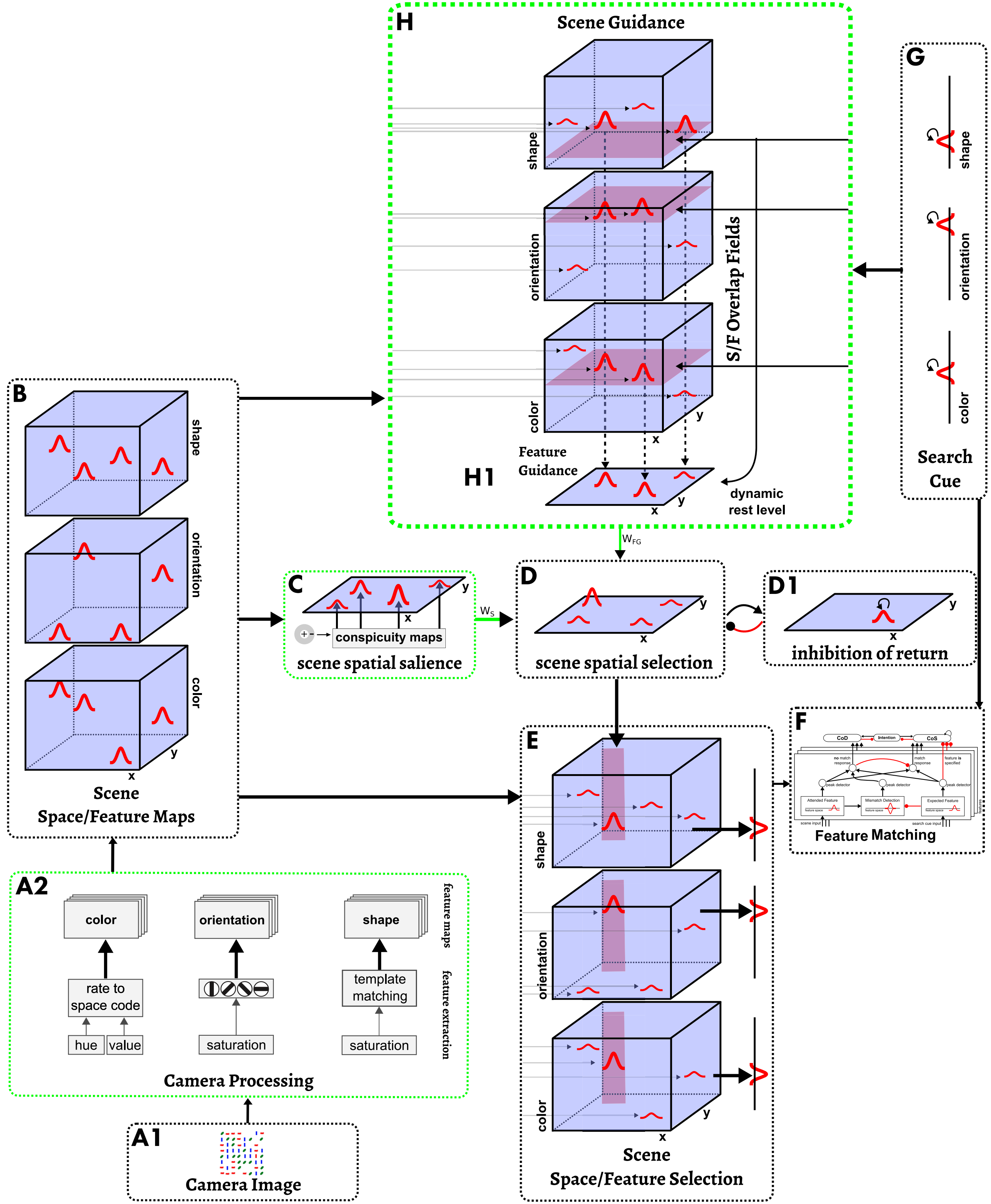
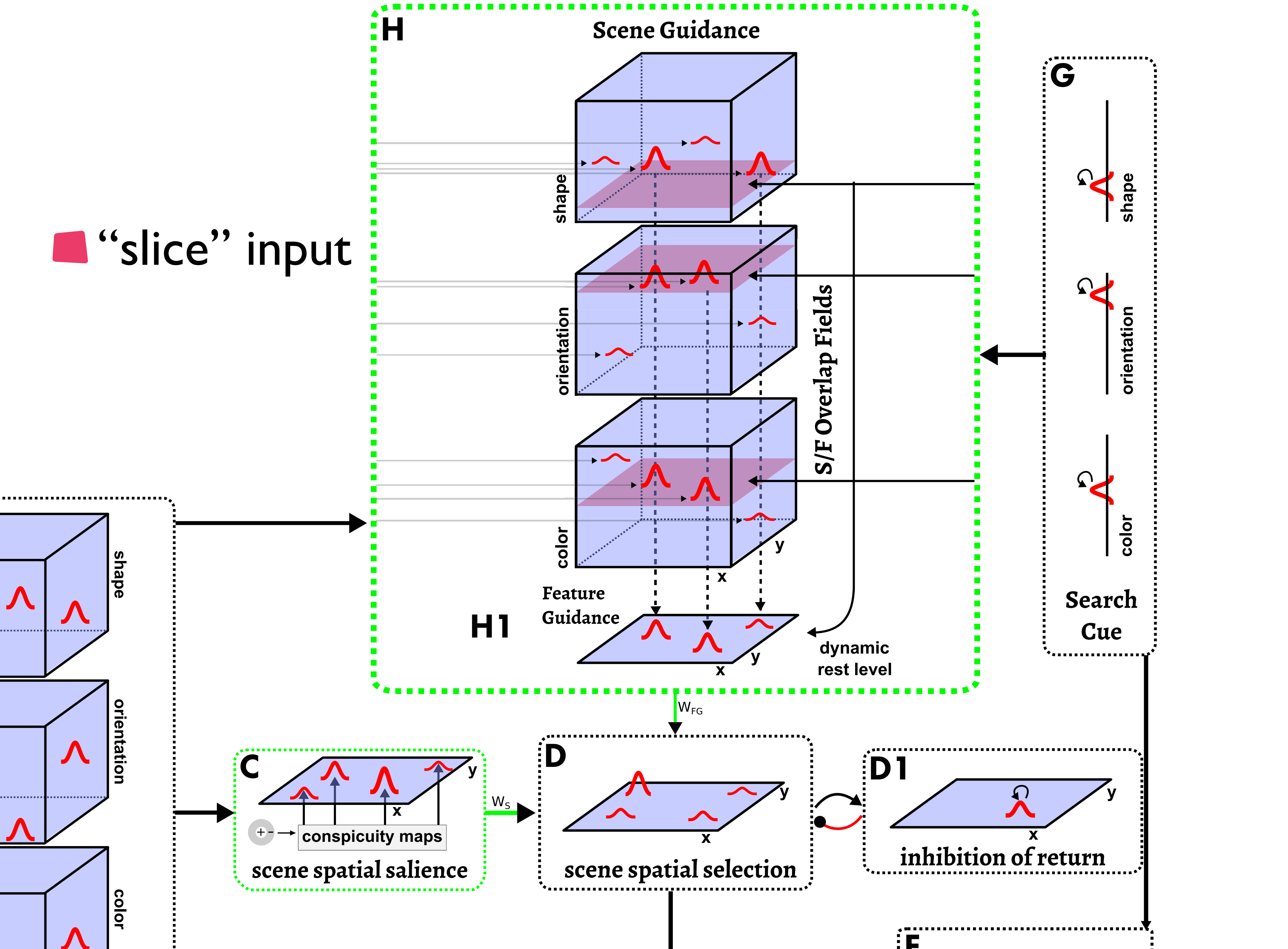
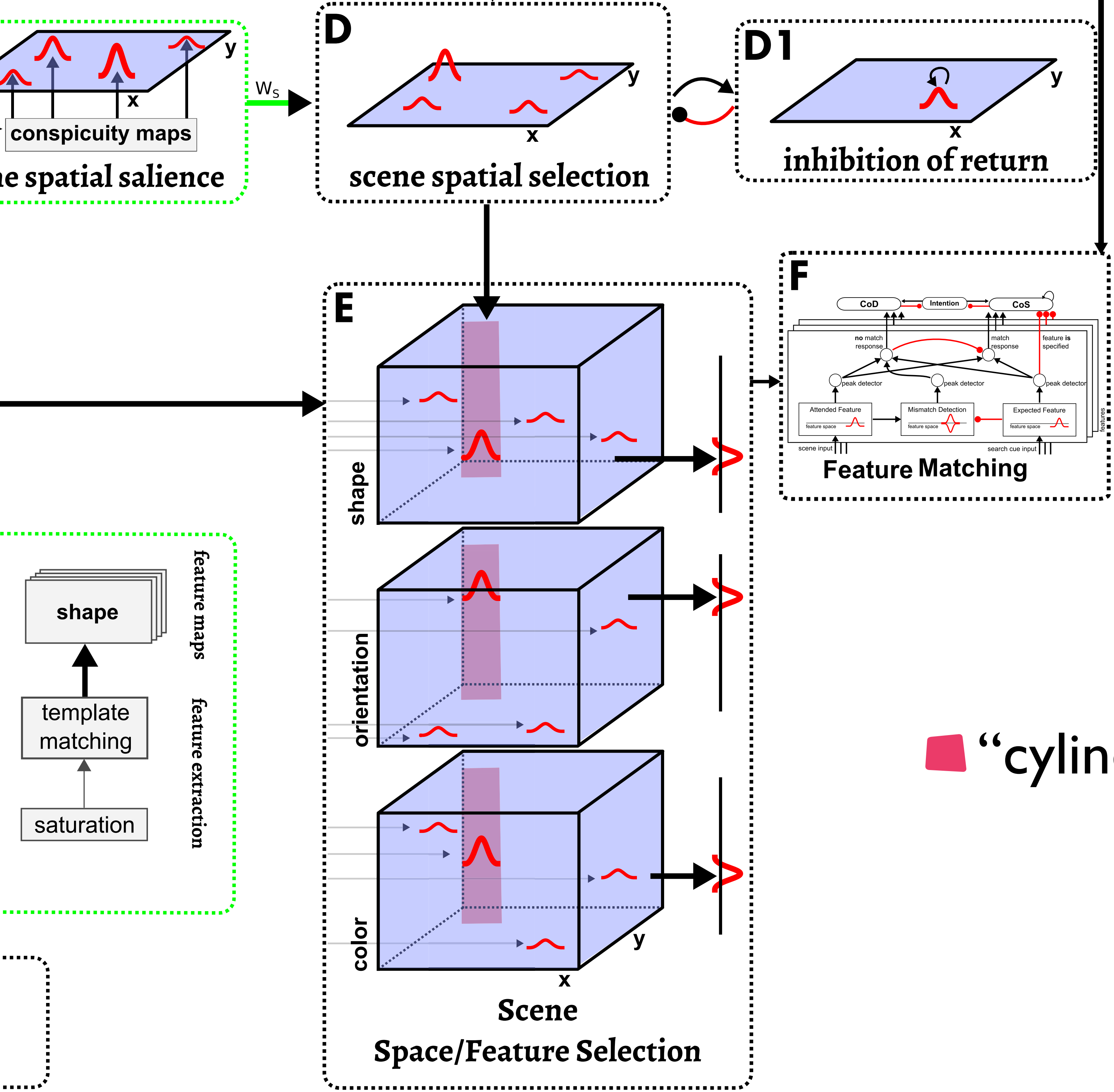
Conjunctive visual search



[Grieben et al. *Attention, Perception & Psychophysics* 2020; *CogSci* 2021]



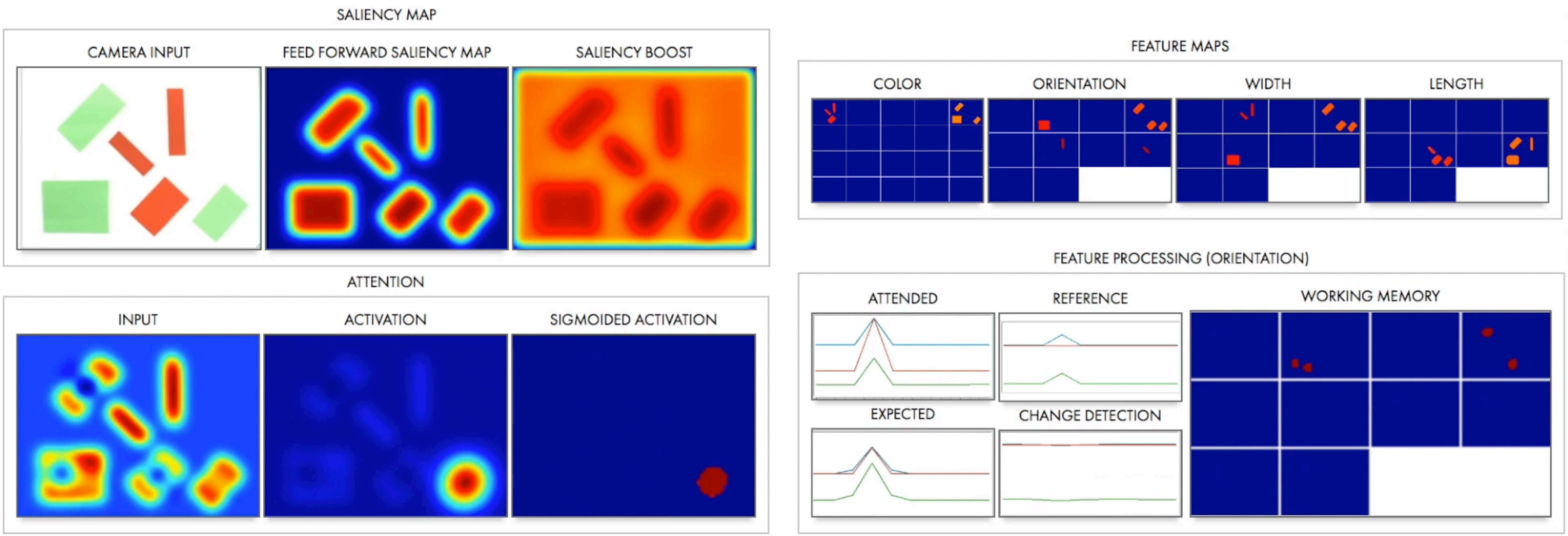
“slice” input
H
Scene Guidance
shape
orientation
color
S/F Overlap Fields
x
y
H1
Feature Guidance
dynamic rest level
G
shape
orientation
color
Search Cue
WFG
C
conspicuity maps
scene spatial salience
WS
D
scene spatial selection
D1
inhibition of return



“cylinder” input

Visual search

- => hands on exericse



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