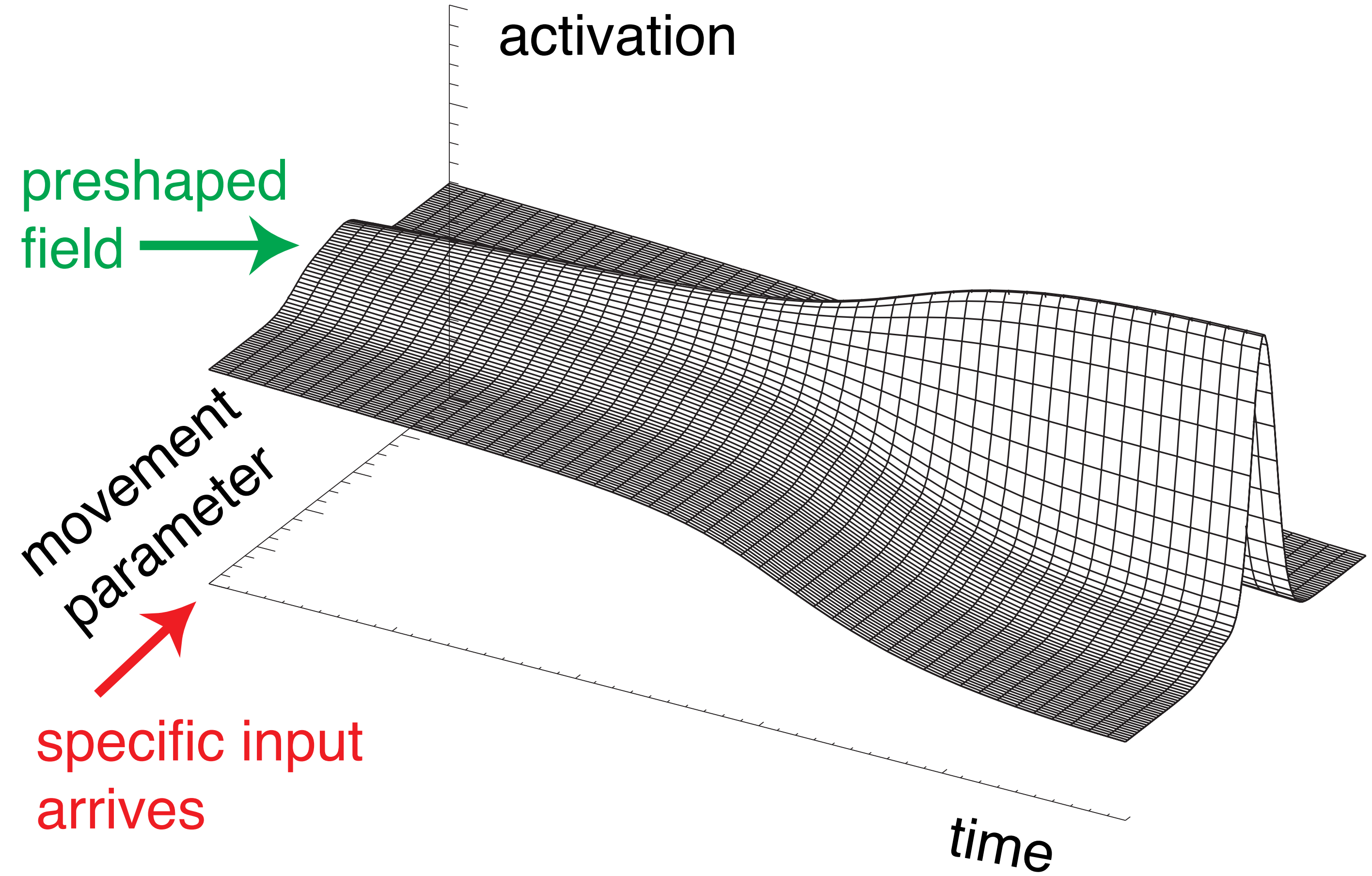
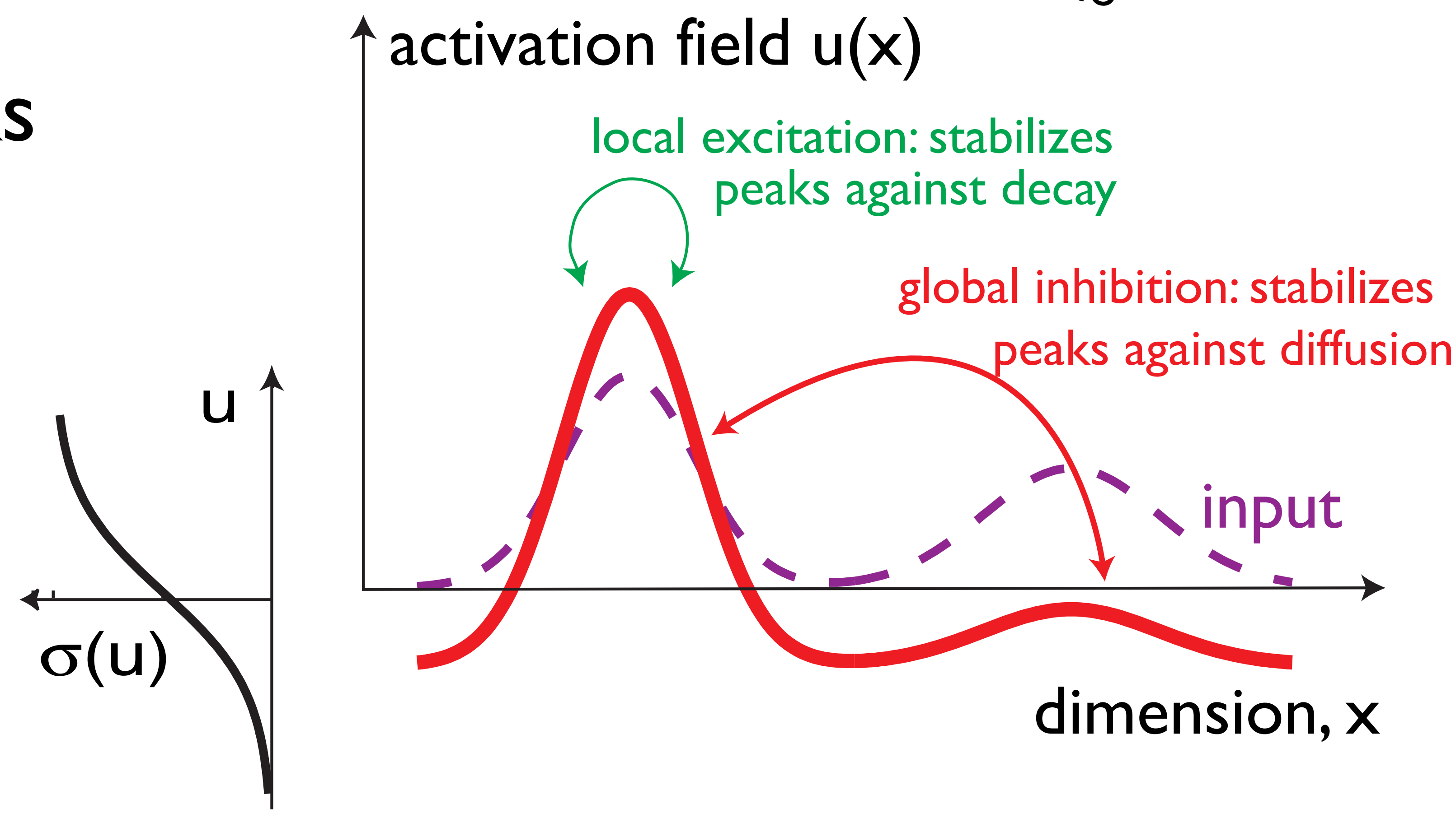
Higher-dimensional dynamics fields enable new cognitive function

Gregor Schöner

Core of DFT

- field dynamics combines input
- with strong interaction:
  - local excitation
  - global inhibition
- leading to stable peaks
- instabilities:
  - detection
  - selection
  - memory



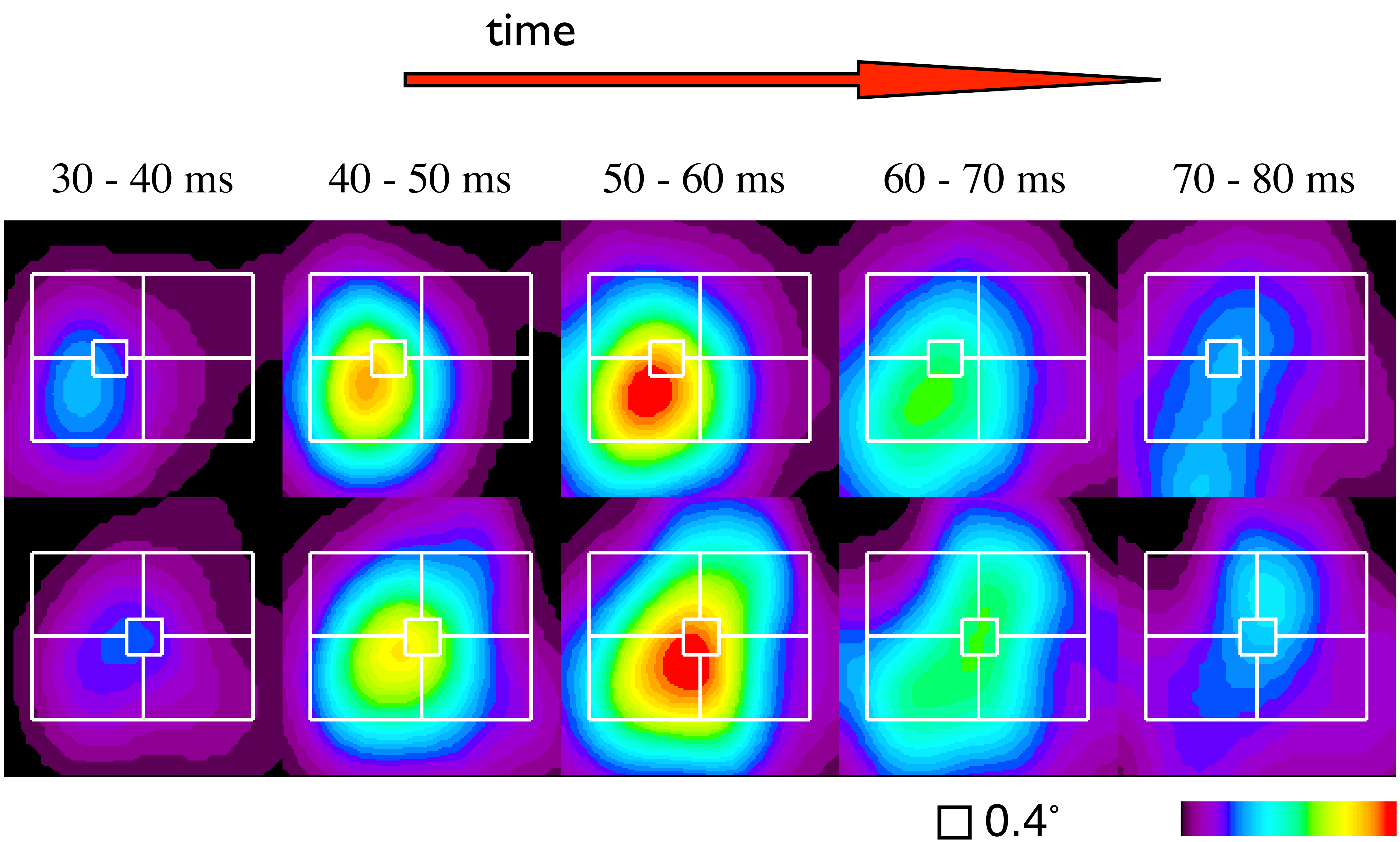


Dimensionality of fields

- all this was done primarily in fields defined over a single dimension…
- multi-dimensional fields are not per se fundamentally different….
- in particular, they have the same kind of dynamics as one-dimensional fields

example: retinal space

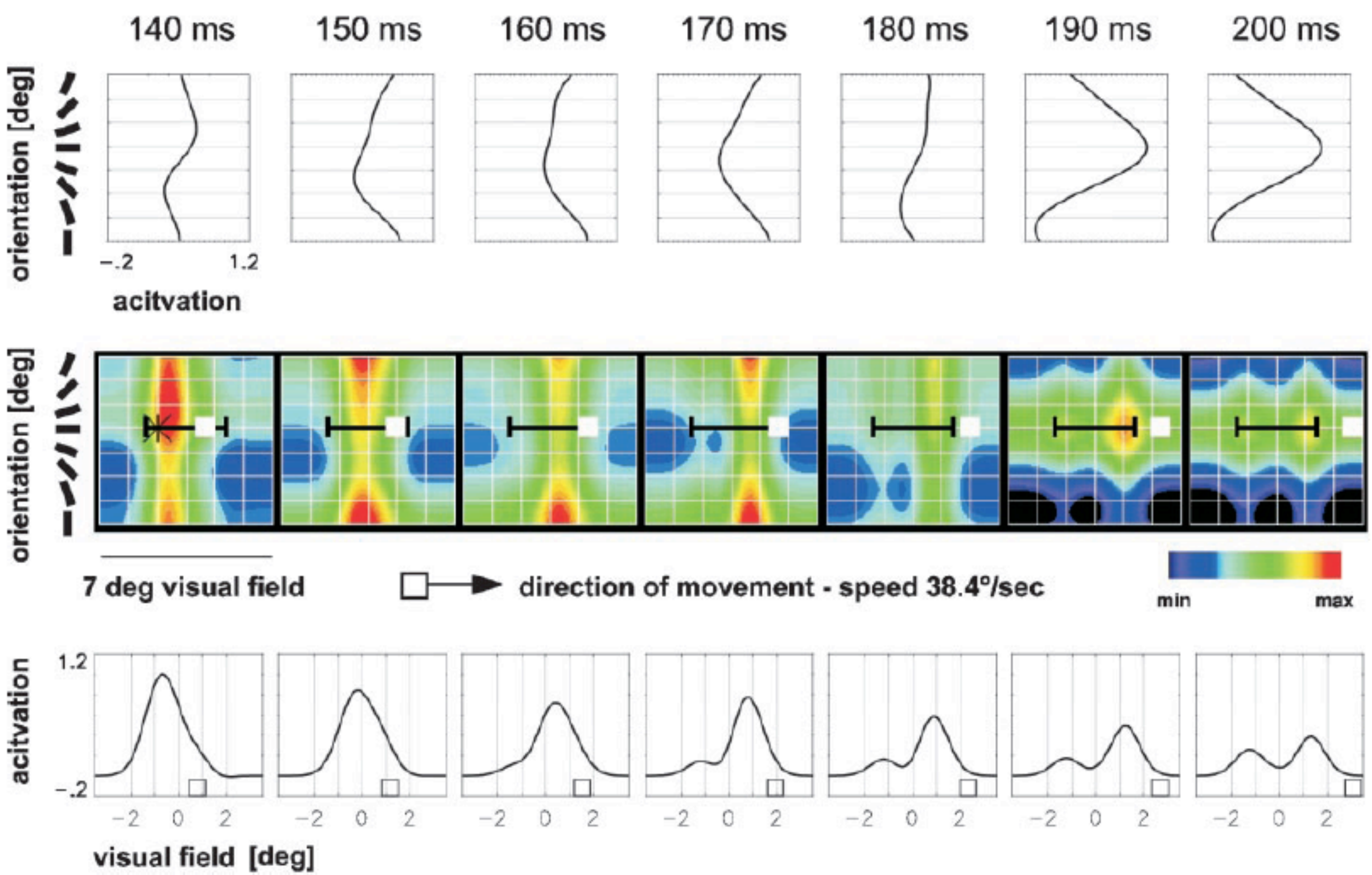
- obviously two-dimensional



[Jancke et al., 1999]

example: visual feature map

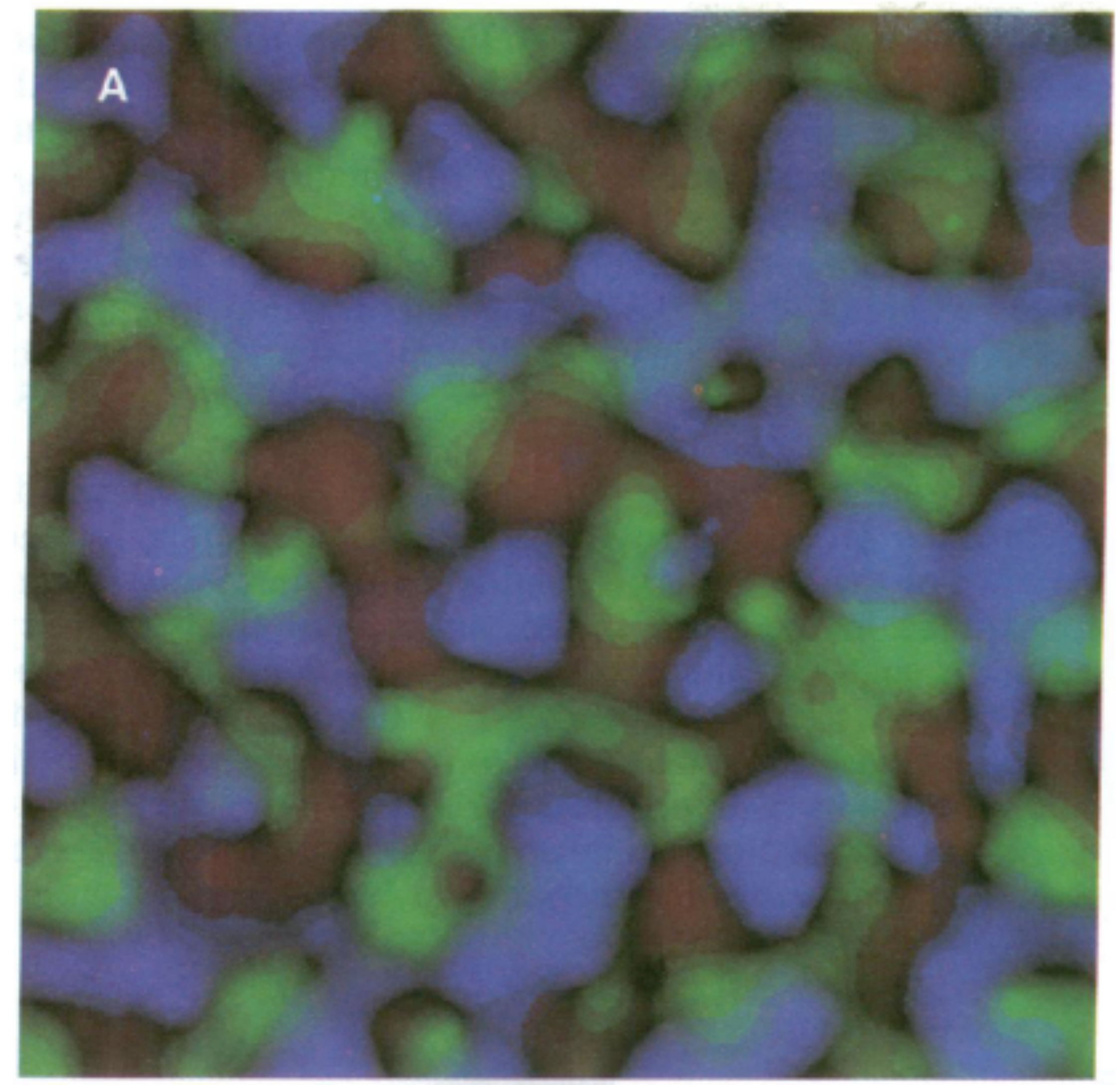
- orientation-retinal location



[Jancke, JNeursci (2000)]

example: visual feature maps

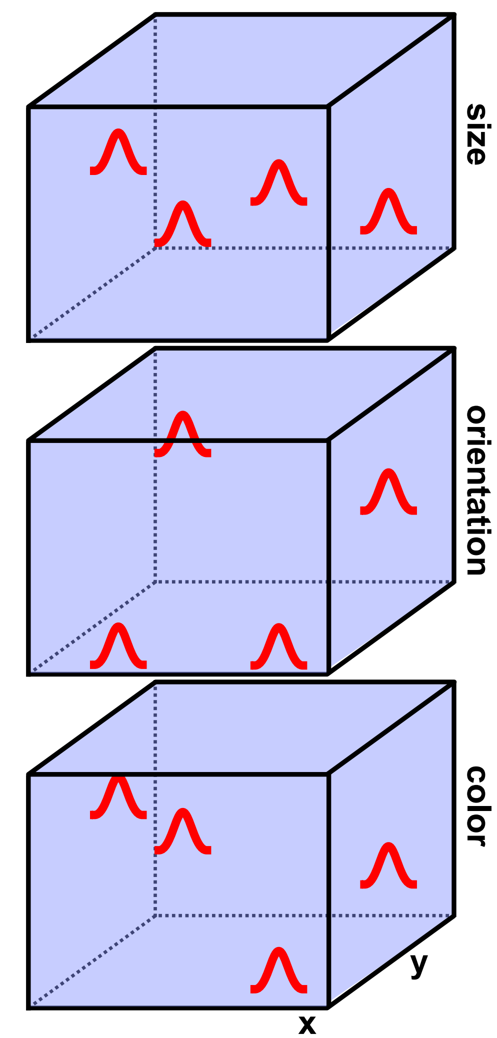
- the neural field representation a single feature (e.g. orientation) as well as retinal location is at least three-dimensional
- cannot be mapped onto cortical surfaces without cuts ...



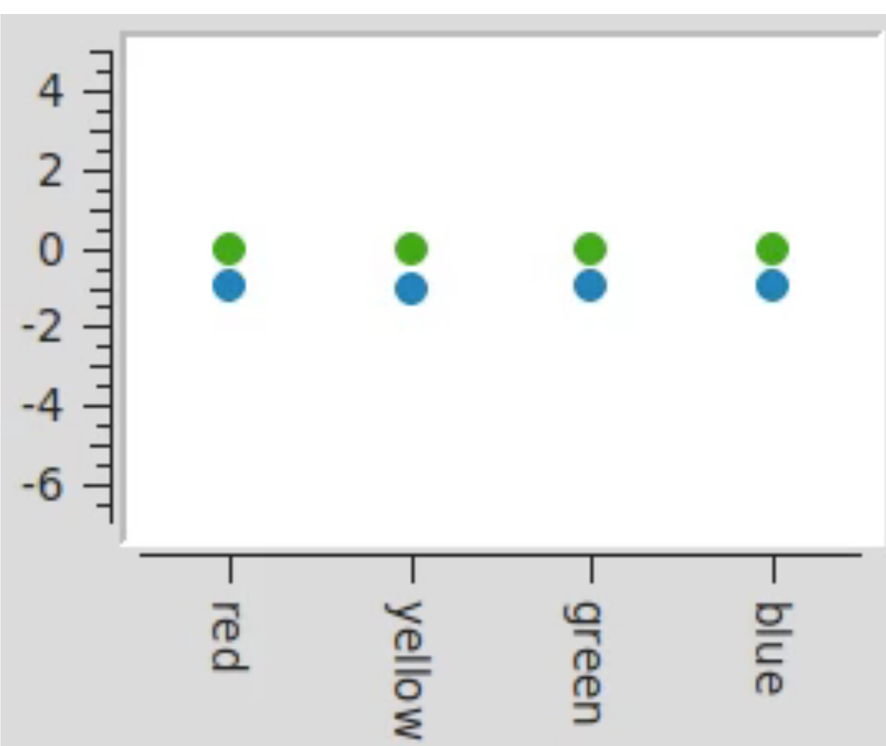
Dynamic fields of varying dimensionality

- 0-dimensional: nodes, “on” vs “off” states
- 1, 2, 3, 4… dimensions: peak/ blob states

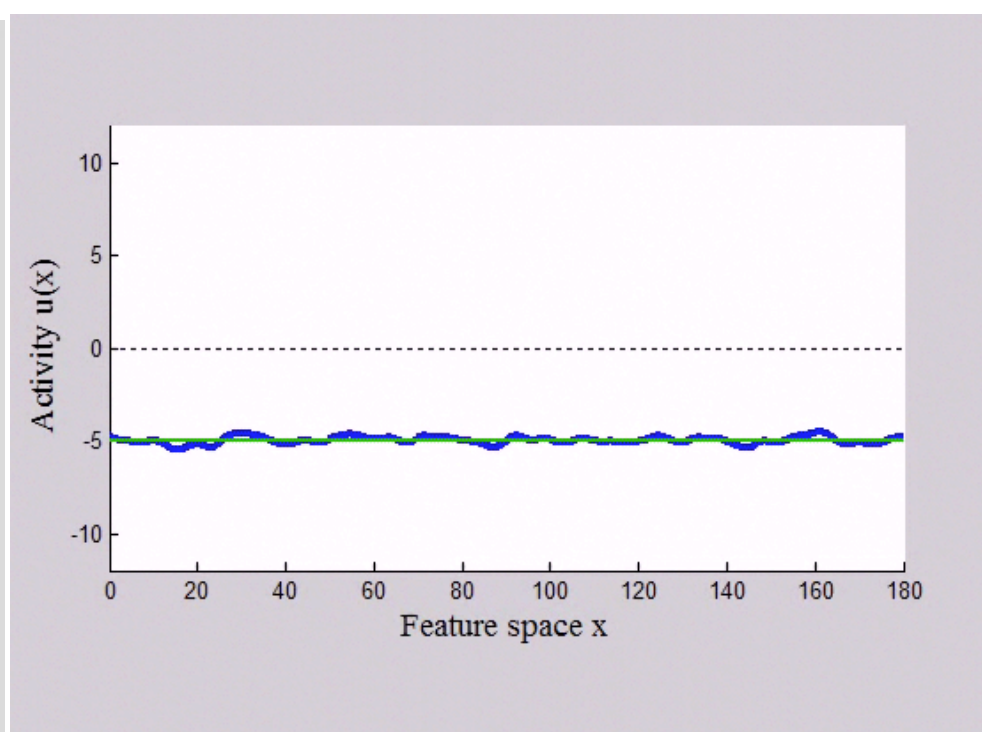
3-dimensional



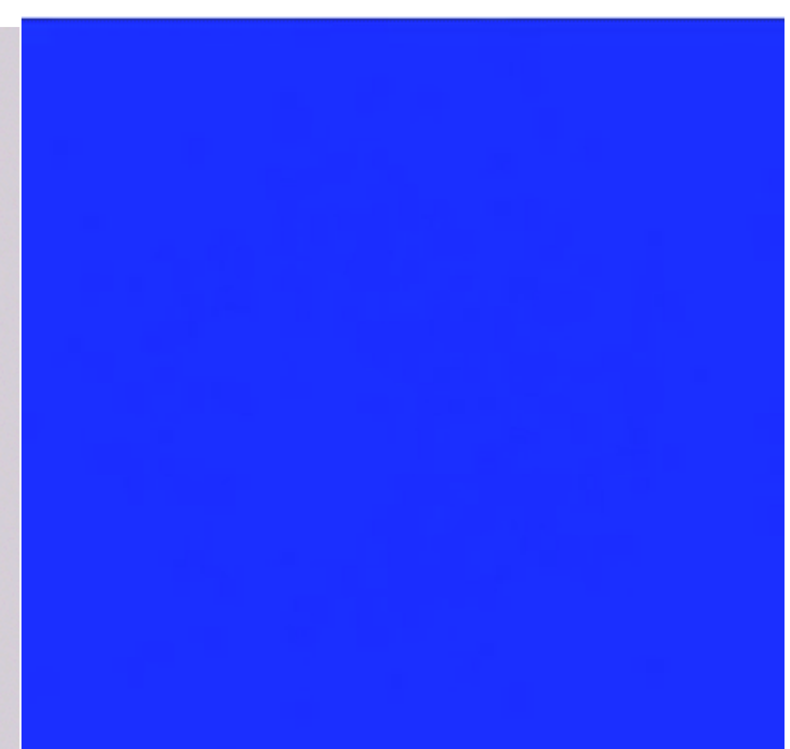
0-dimensional



1-dimensional



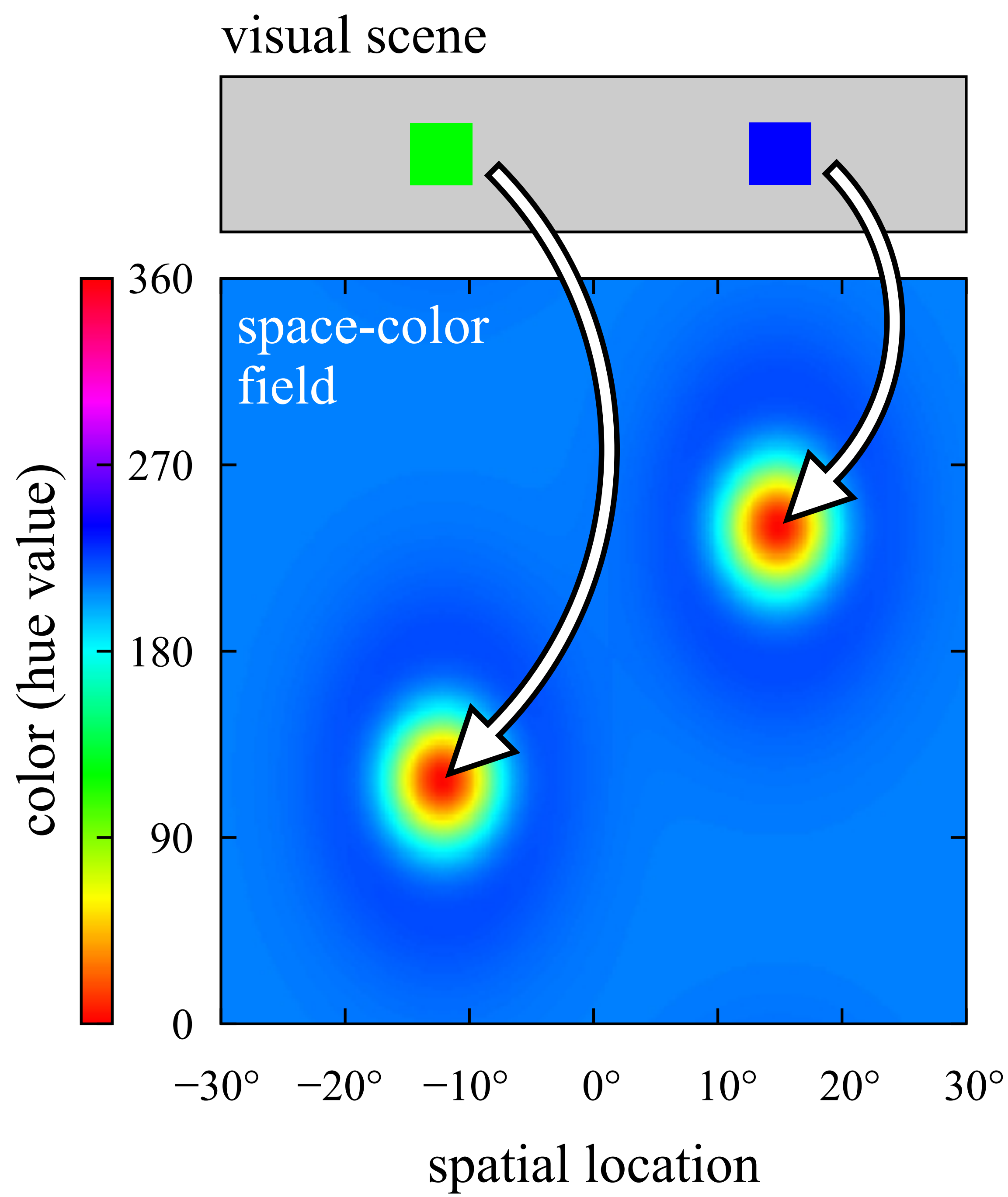
2-dimensional



New cognitive functions emerge as dimensionality is varied

Binding

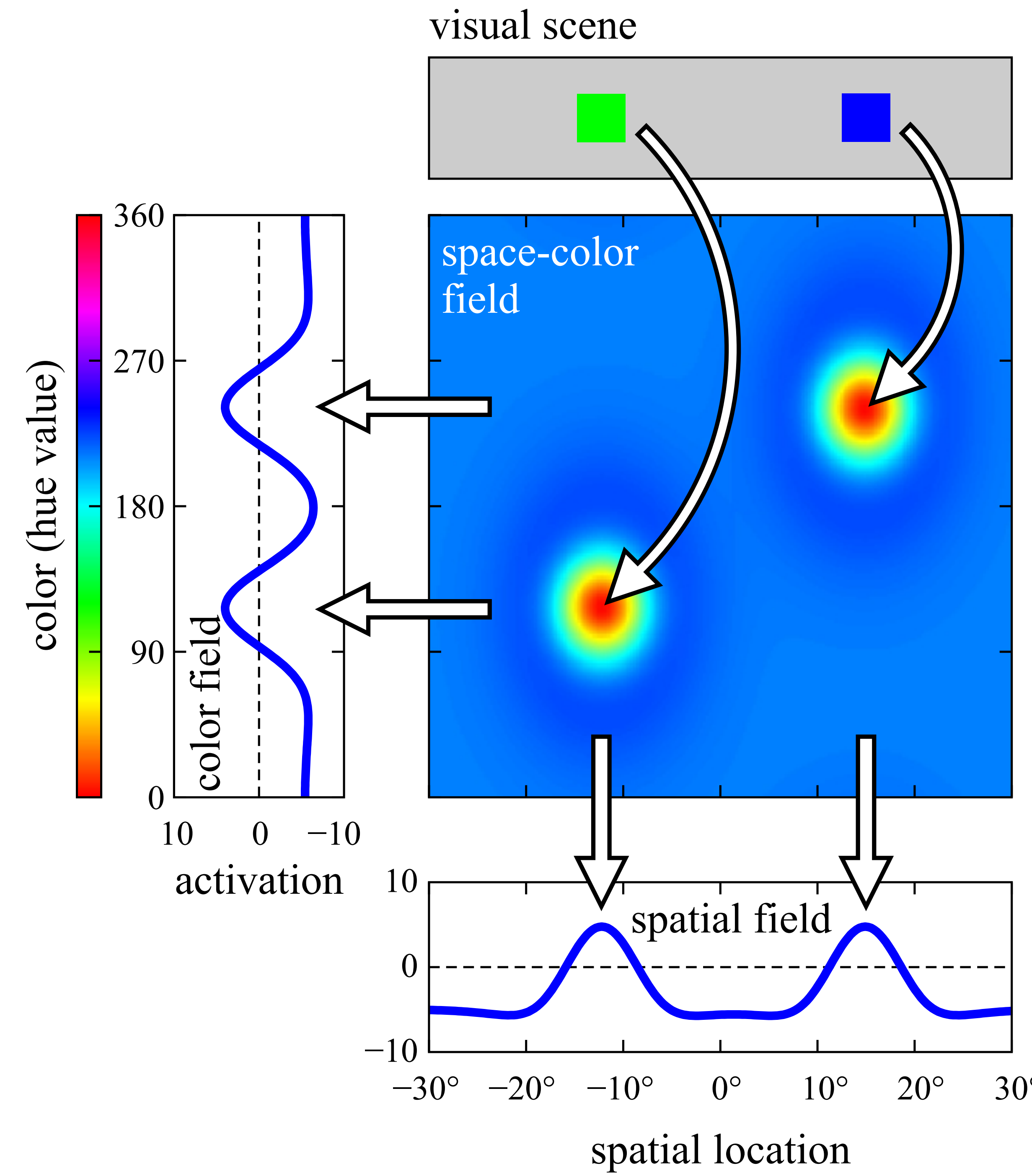
- a joint representation of space and color



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

Extract bound features

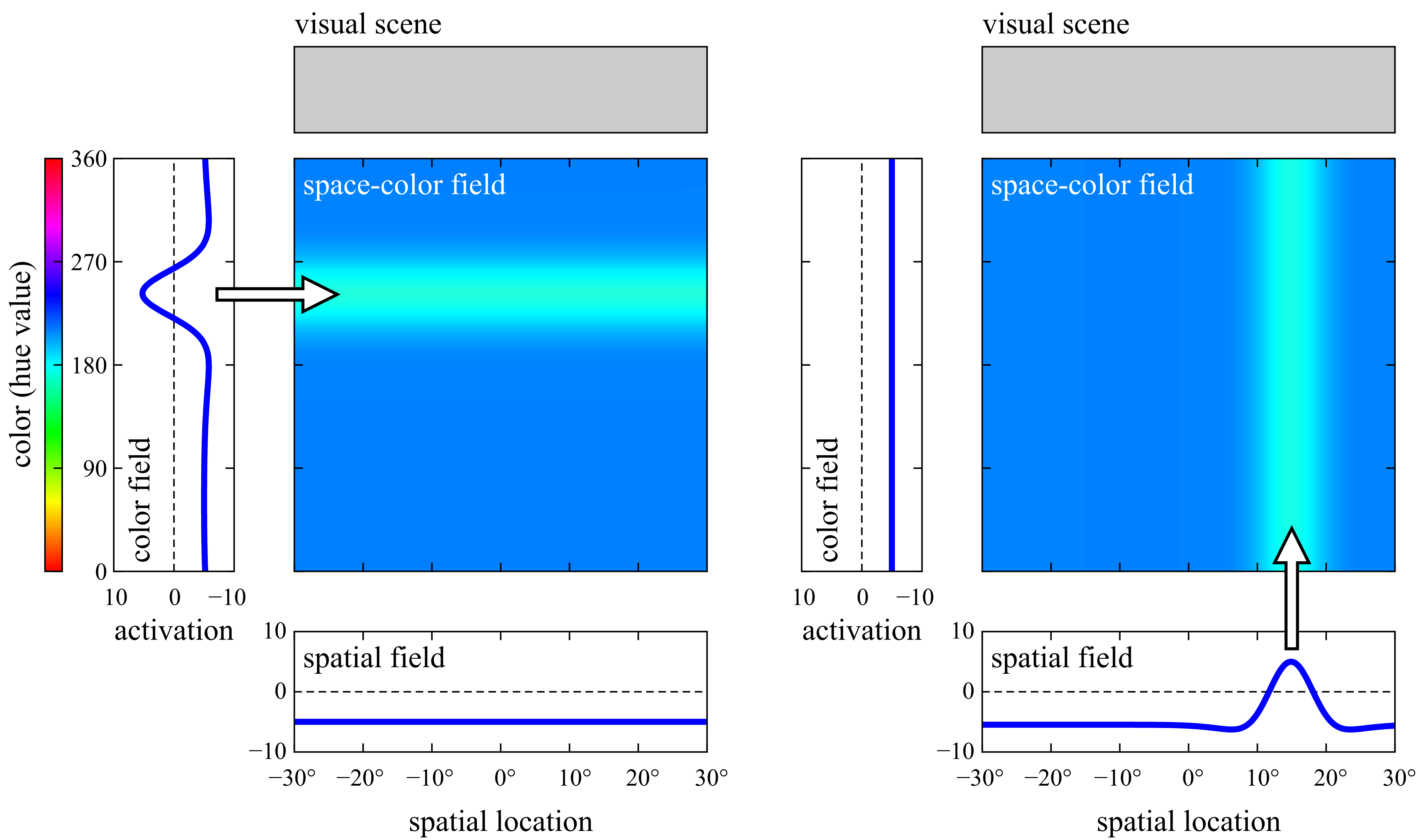
- by projecting to lower-dimensional fields
- summing along the marginalized dimensions
- (or by taking the soft-max)



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

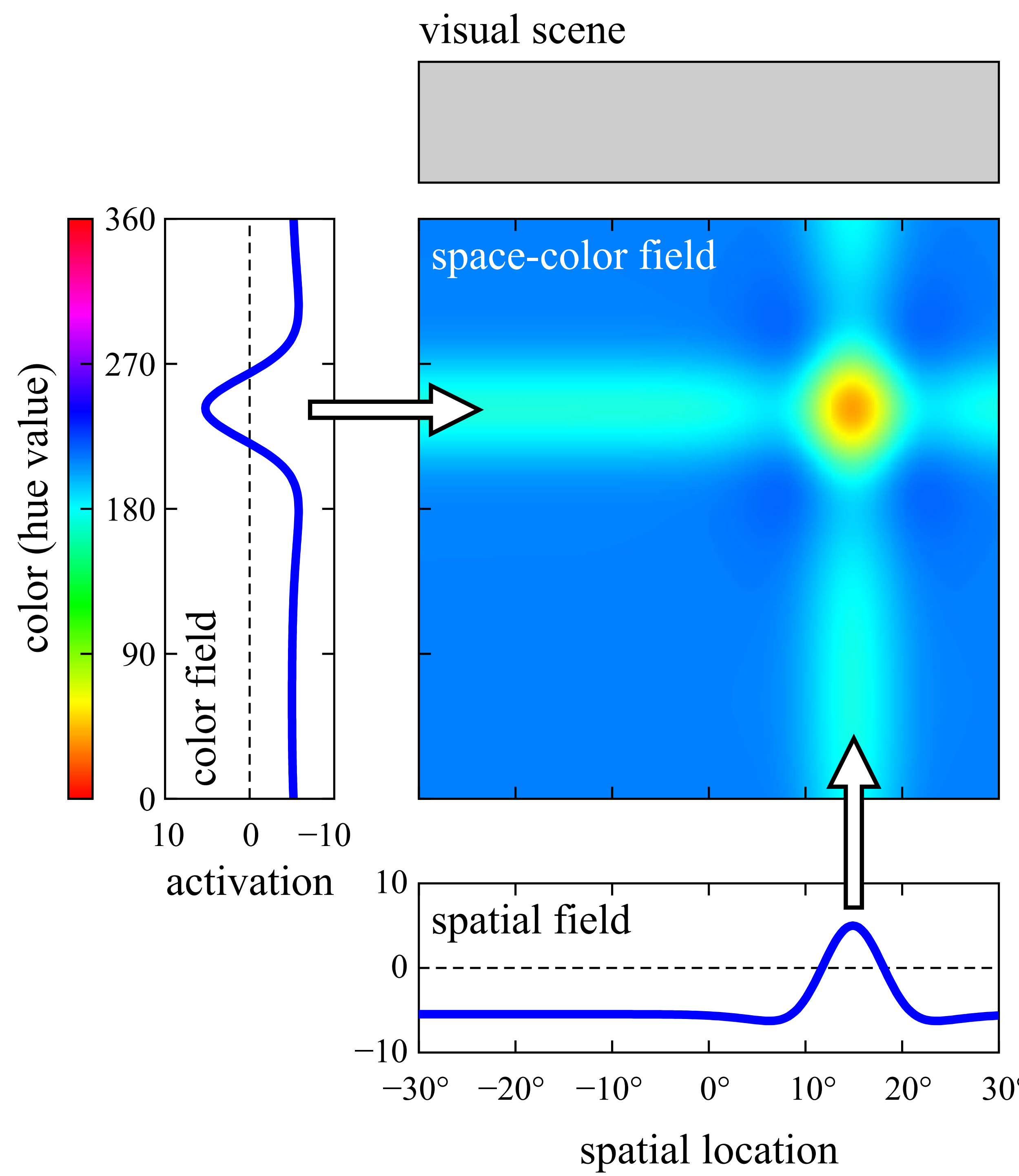
Assembling bound representations

- projecting into higher-dimensional field by "ridge input"



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

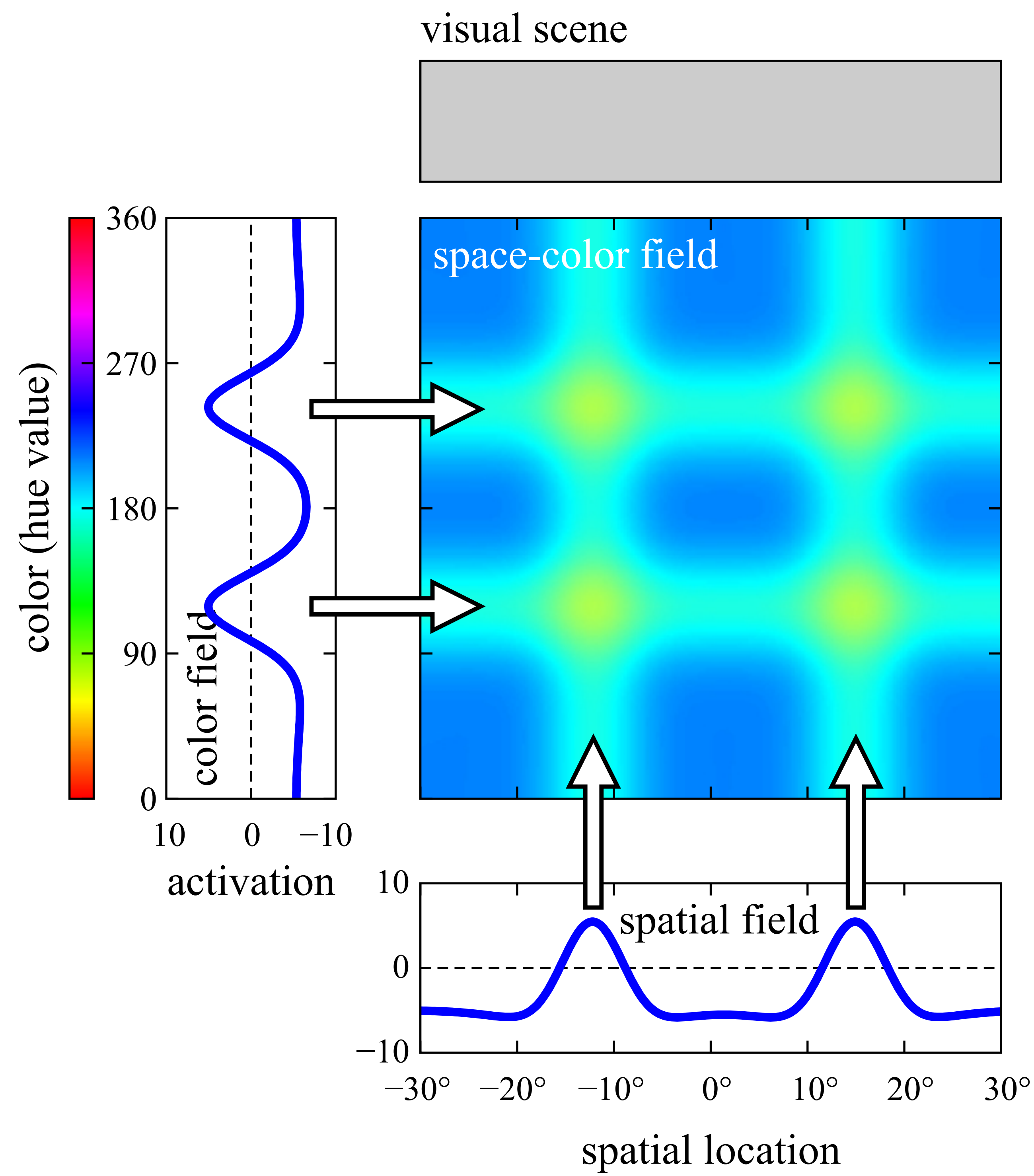
Assembling bound representations



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

Assembling bound representations

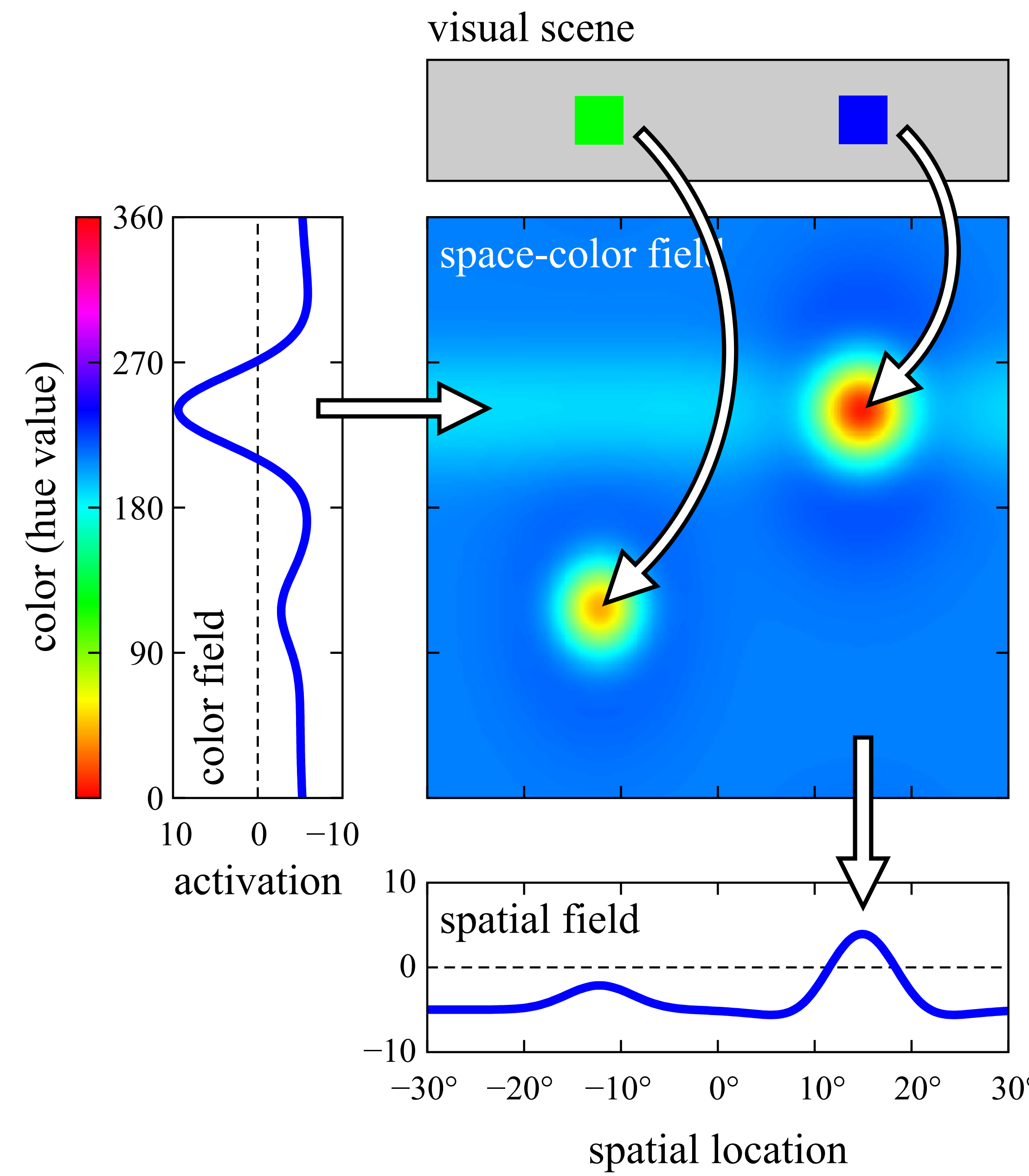
- binding problem: multiple ridges lead to a correspondence problem
- => assemble one object at a time… sequentiality bottle-neck!



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

visual search

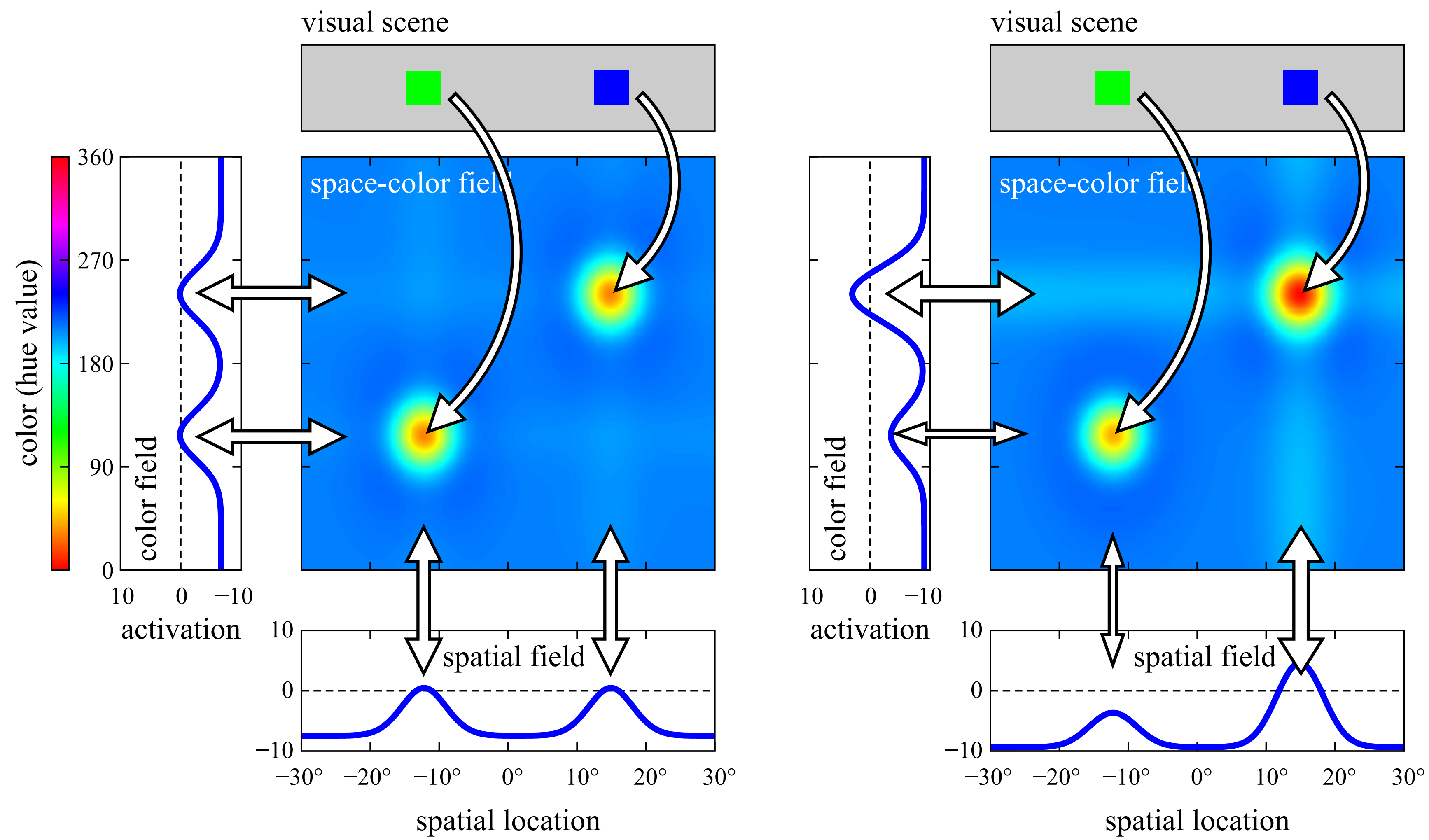
- combine 1D (ridge) input with 2D input..
- so that only those 2D locations can form peaks that overlap with ridge (boost driven detection)
- activates objects consistent with 1D feature value



[Slides adapted from Sebastian Schneegans,
see Schneegans, Lins, Spencer, Chapter 5 of Dynamic Field Theory-A Primer, OUP, 2015]

visual search

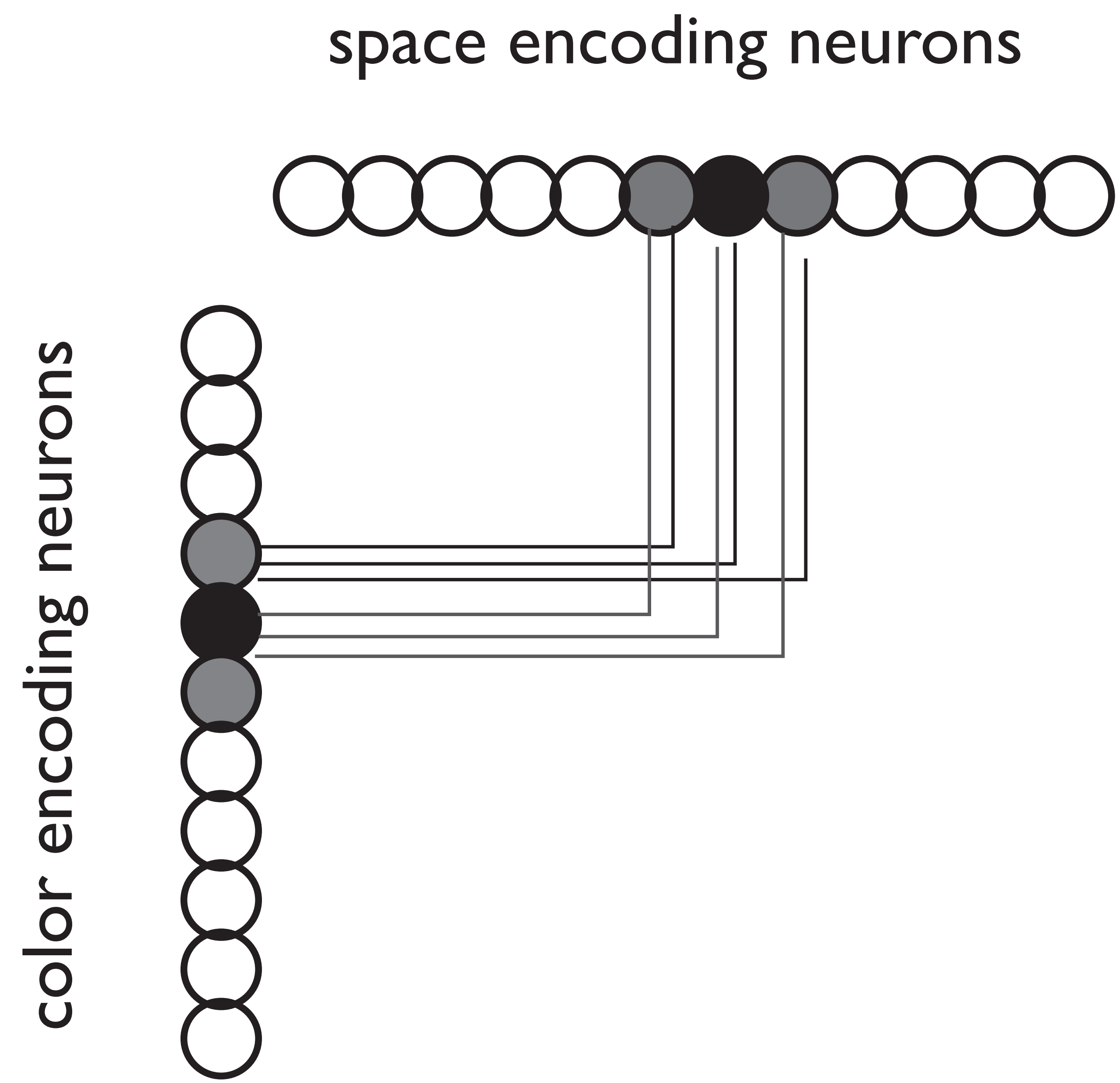
- the selection from visual search can be propagated to the 1D feature representations …



[Slides adapted from Sebastian Schneegans,
see Schneegans, Lins, Spencer, Chapter 5 of Dynamic Field Theory-A Primer, OUP, 2015]

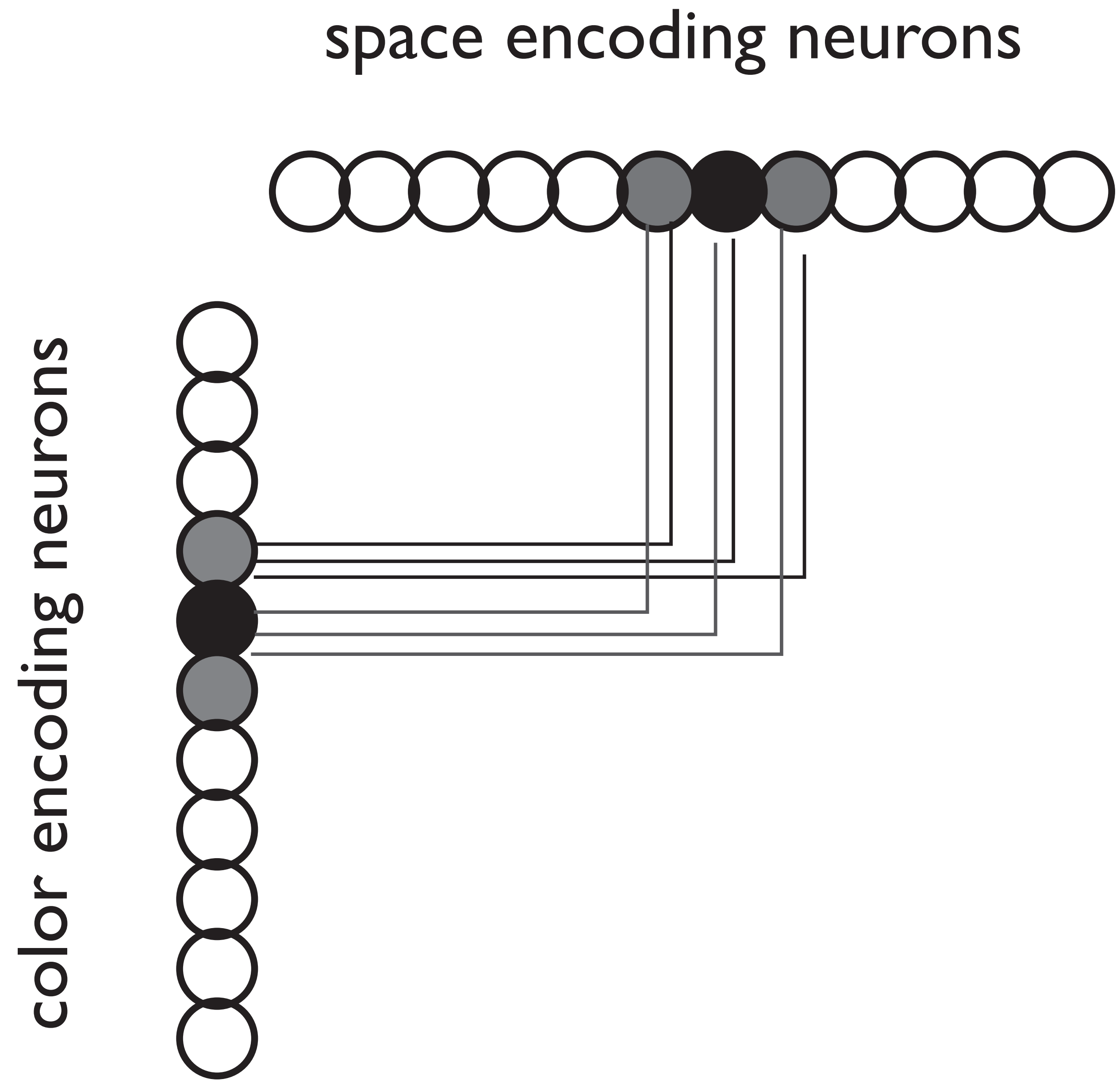
contrast: synaptic association

- in conventional connectionist networks associative relationships are learned by adjusting synapses between those color and space neurons that have been co-activated



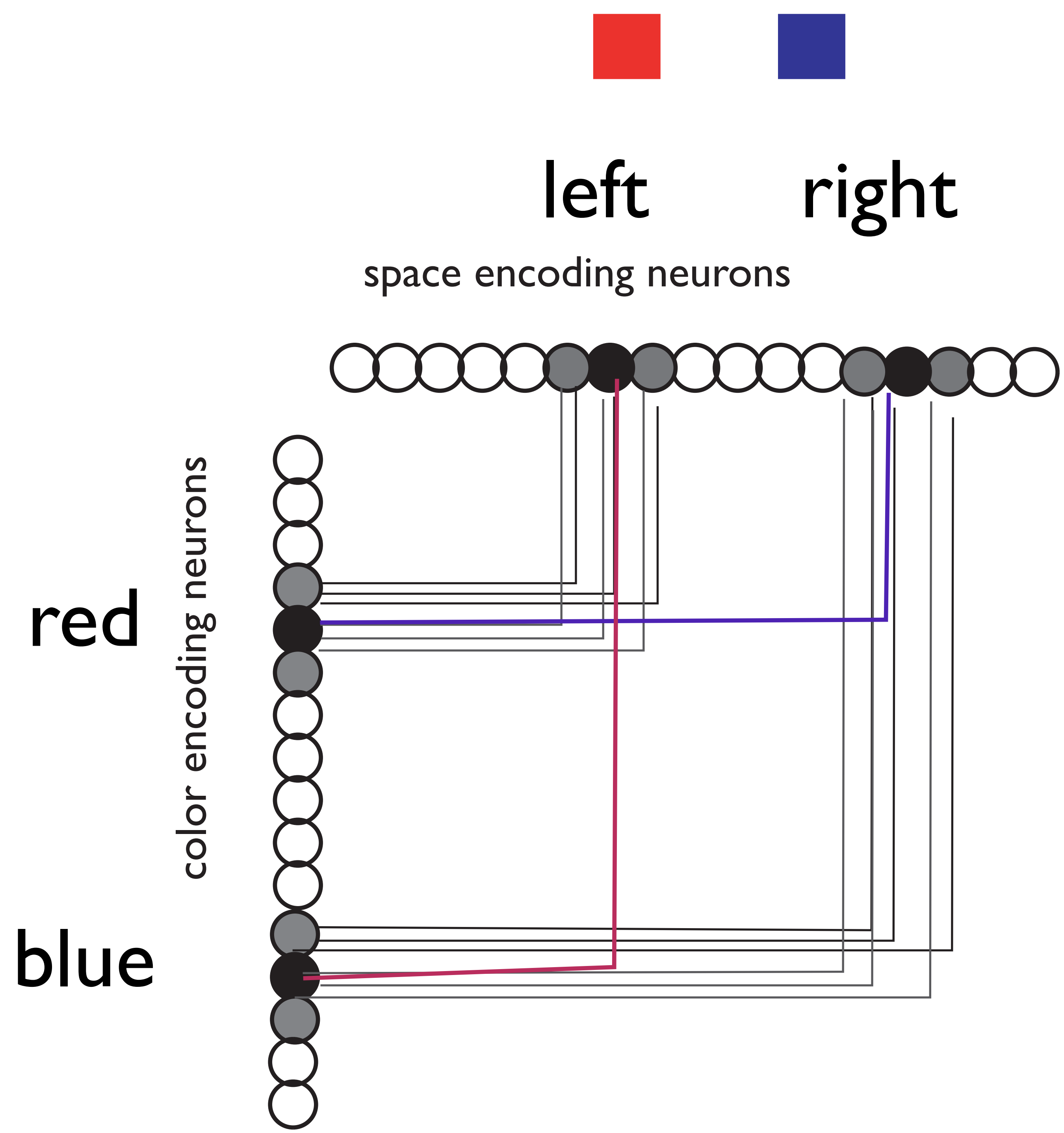
limitations of synaptic association

- connections must be learned, so does not account for how "where is the red square" works from current stimulation (seen for the first time ever)



limitations of synaptic association

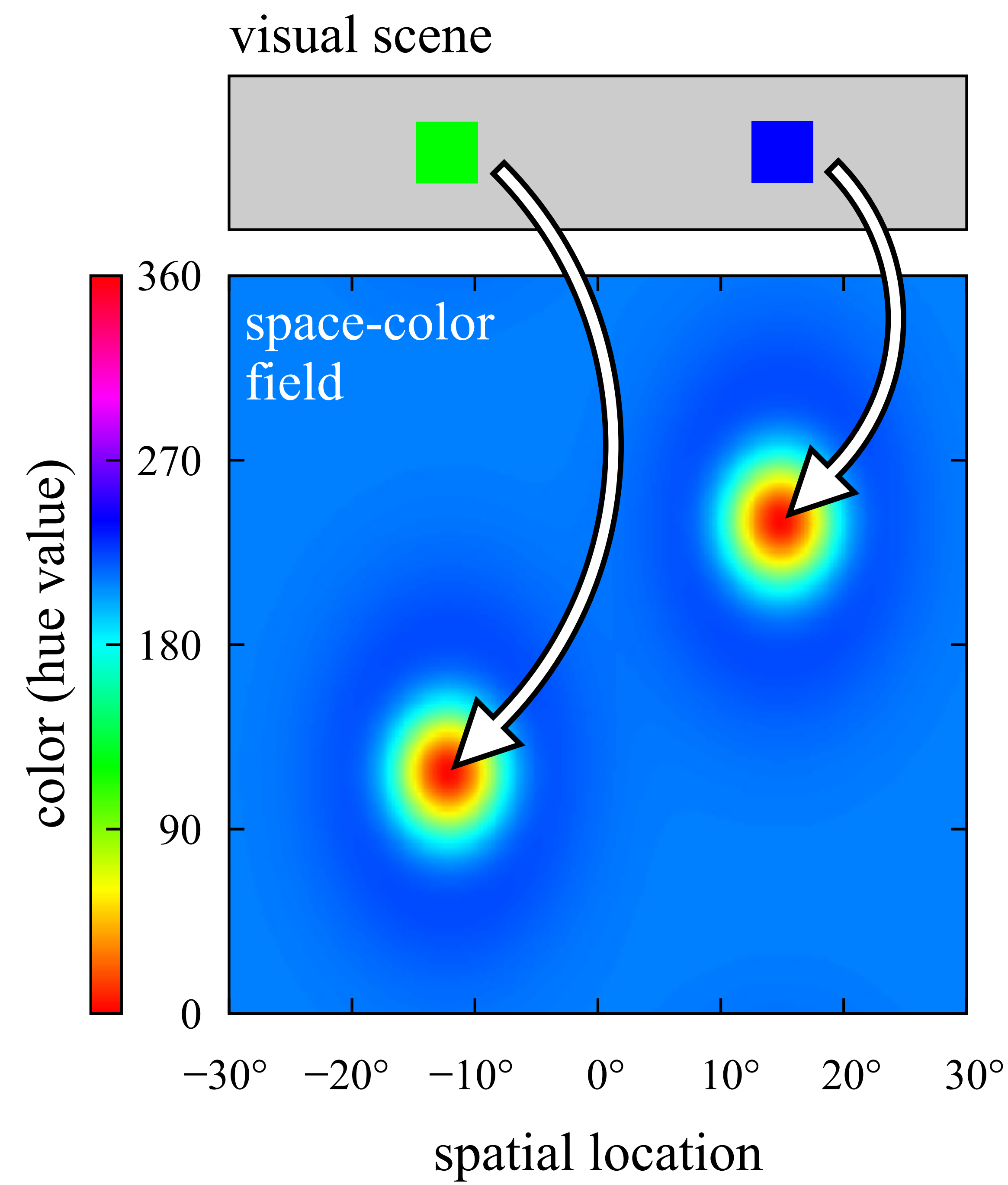
- learning multiple associations poses a binding problem:
- connectionist associators learn one item at a time and need separate presentation of individual items!



the network may associate blue with left and read with right

Binding by joint representations

- a “neuro-anatomical” form of binding
- => very costly



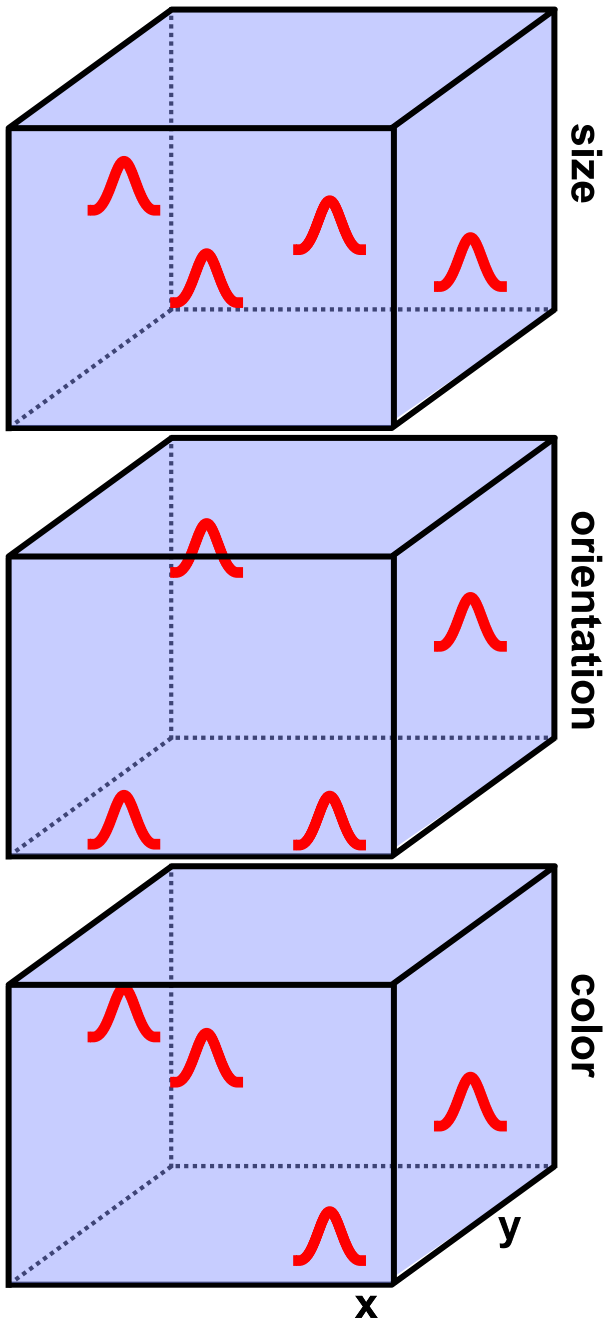
[Schneegans et al., Ch 5 of *DFT Primer*, 2016]

Binding by joint representations

- example: bind orientation, color, texture, scale, and 2D visual space => 6-dimensional field
- 100 neurons per dimension => 10^{12} neurons ~ the entire brain!

Binding through space

- separate 3 to 4 dimensional feature fields
- all of which share the 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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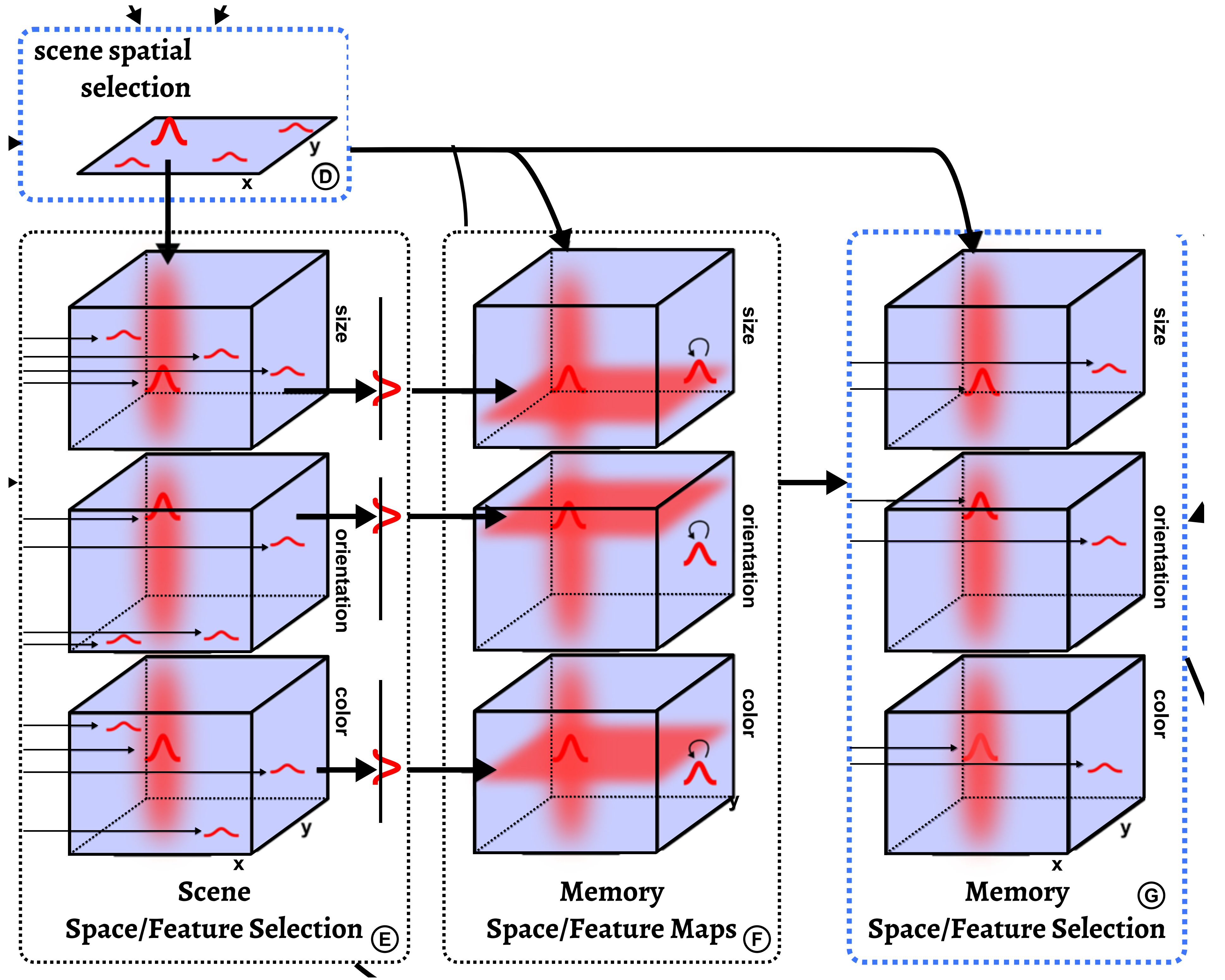

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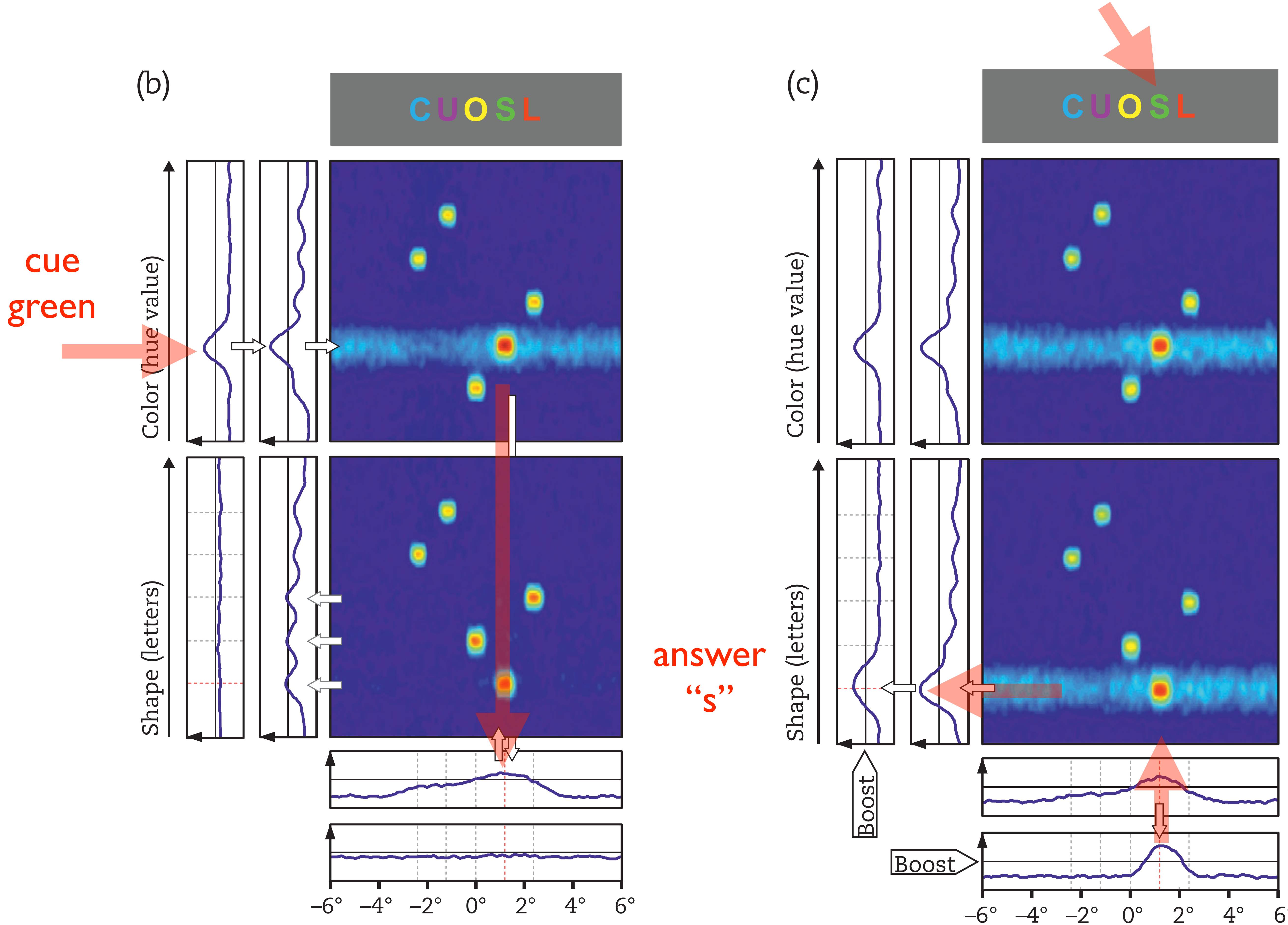
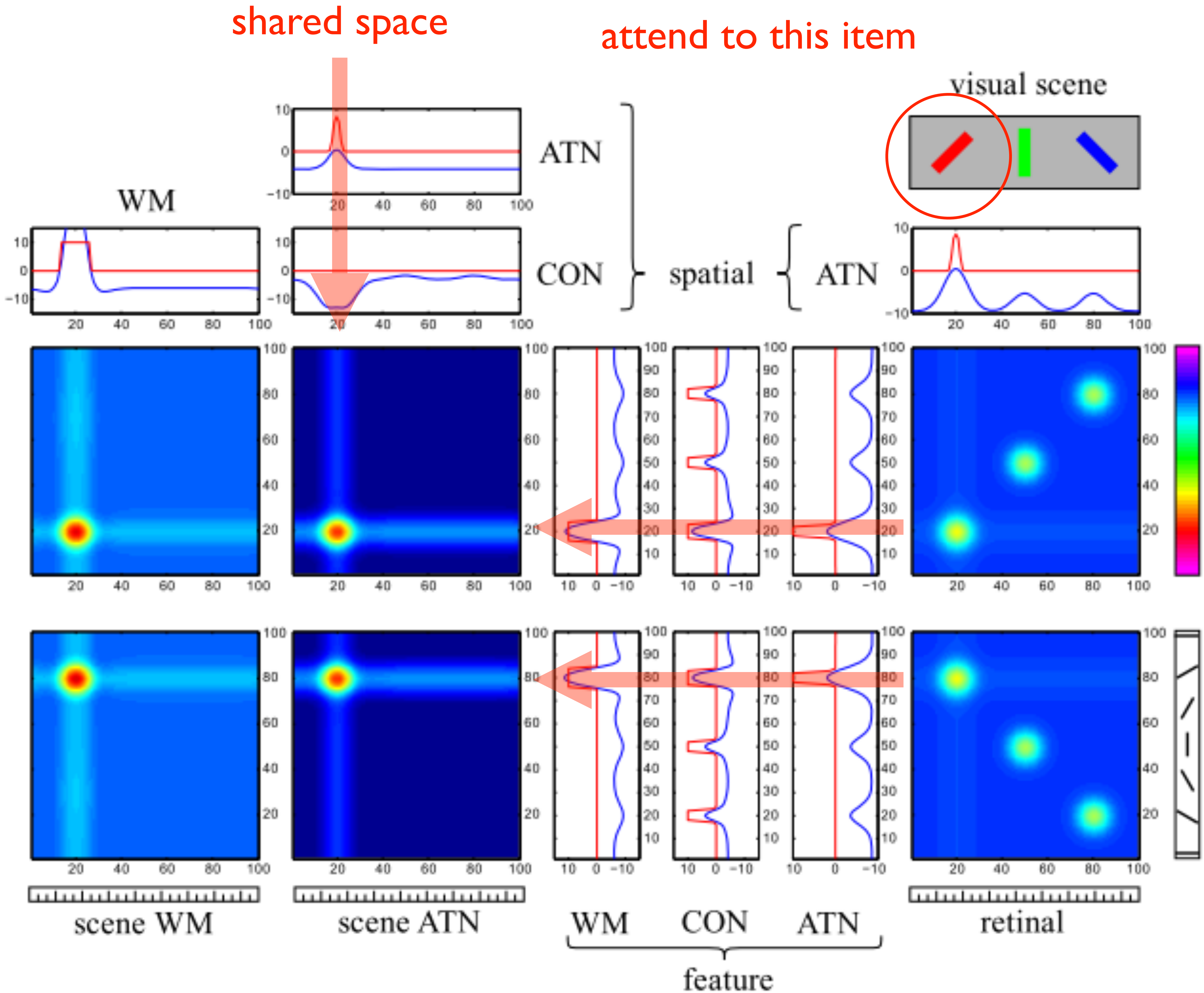
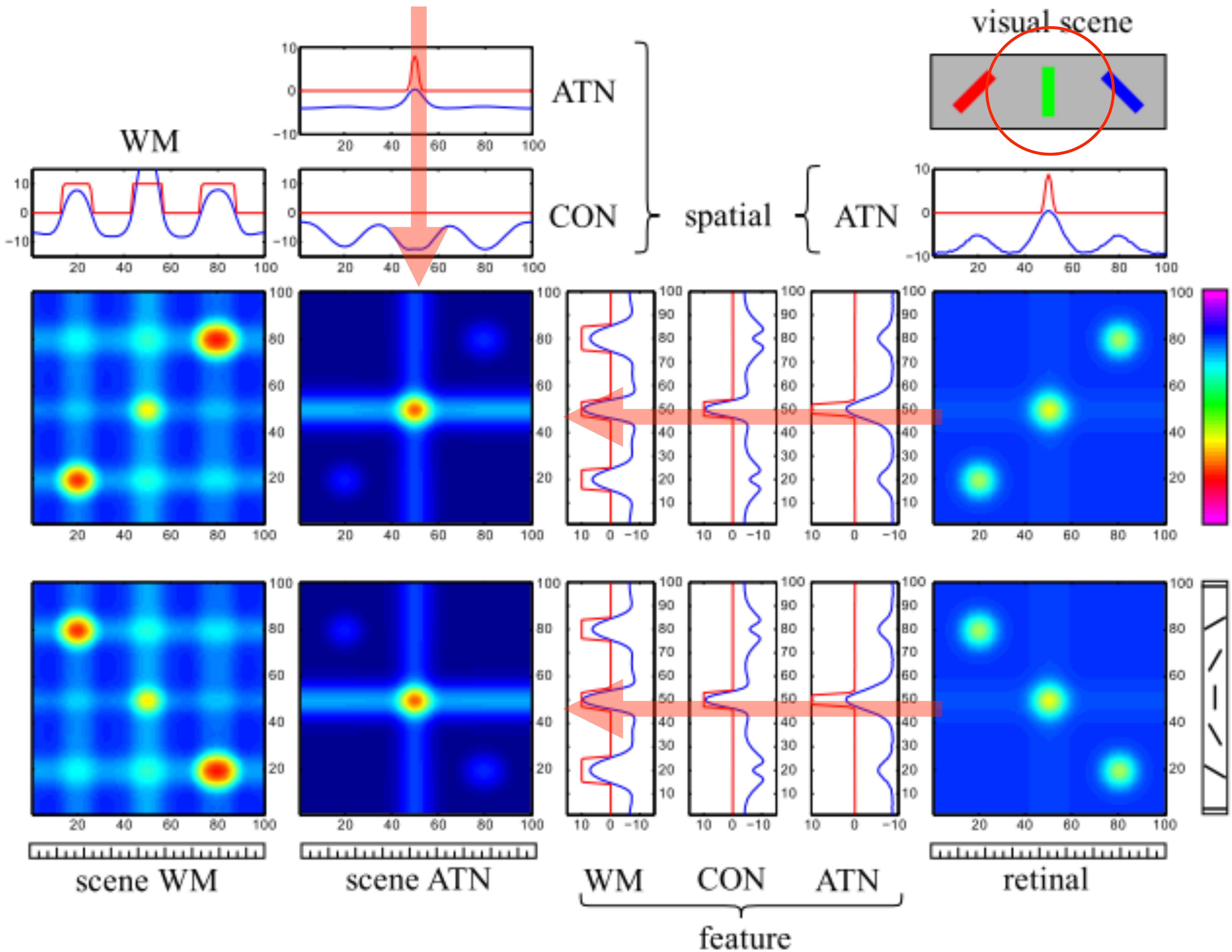


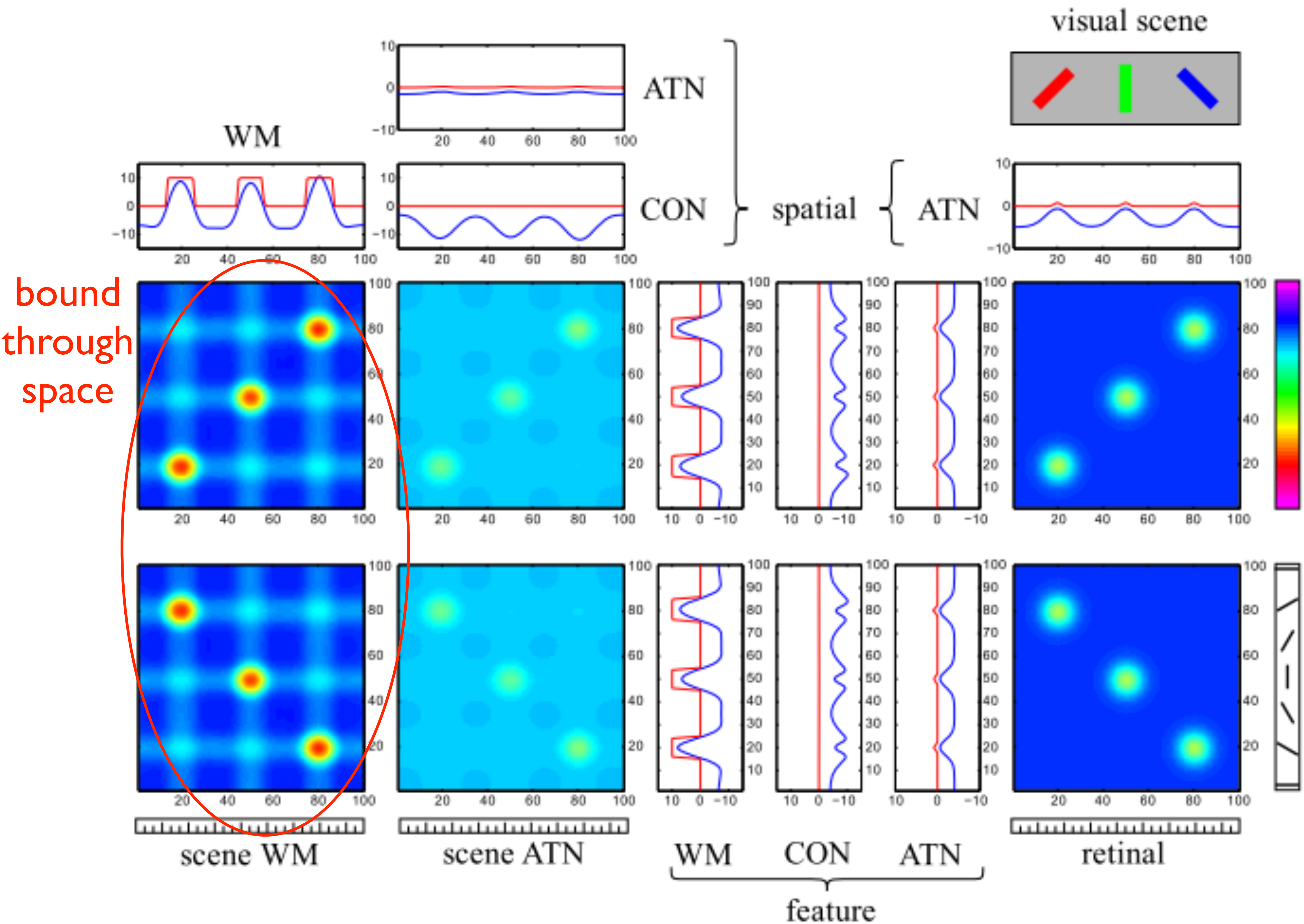
[Schneegans et al.,Ch 5 of *DFT Primer*, 2016]



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



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



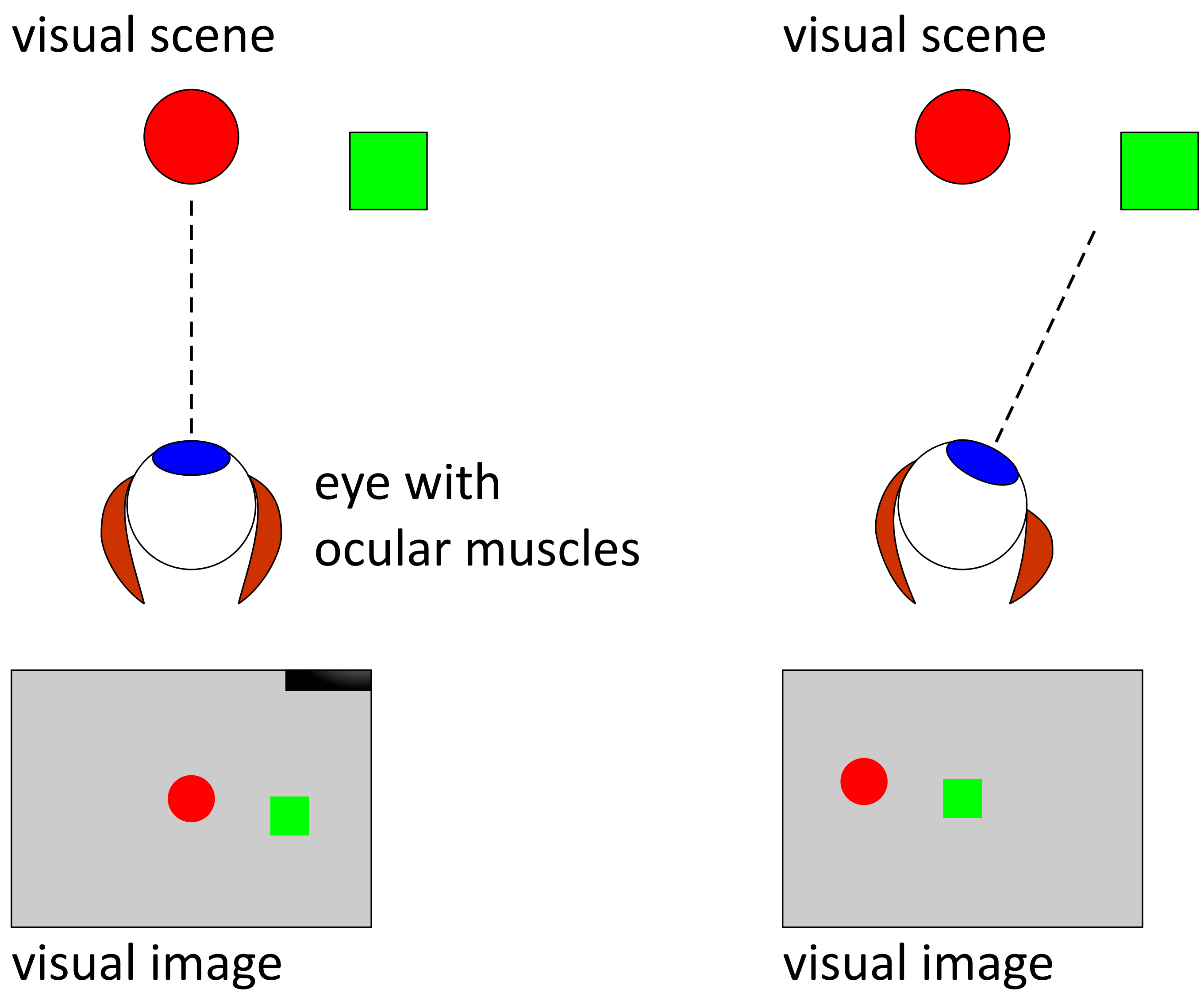
[Schneegans et al.,Ch 5 of *DFT Primer,* 2016]

Coordinate transforms

- fundamental element of sensori-motor, but also of mental operations!

Coordinate transforms

- eye movement: from retinal to body-centered representation (e.g. for reaching)



[Schneegans Ch 7 of *DFT Primer*, 2016]

Coordinate transforms

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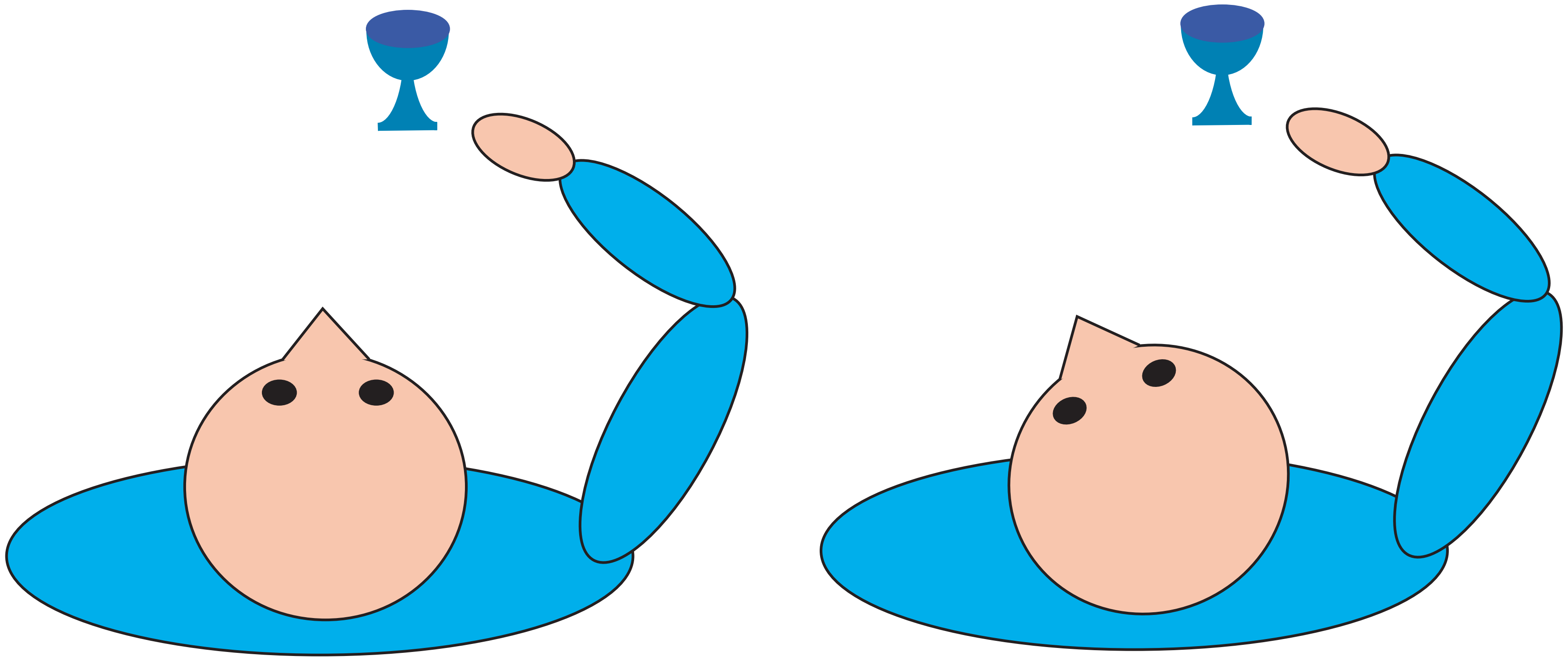
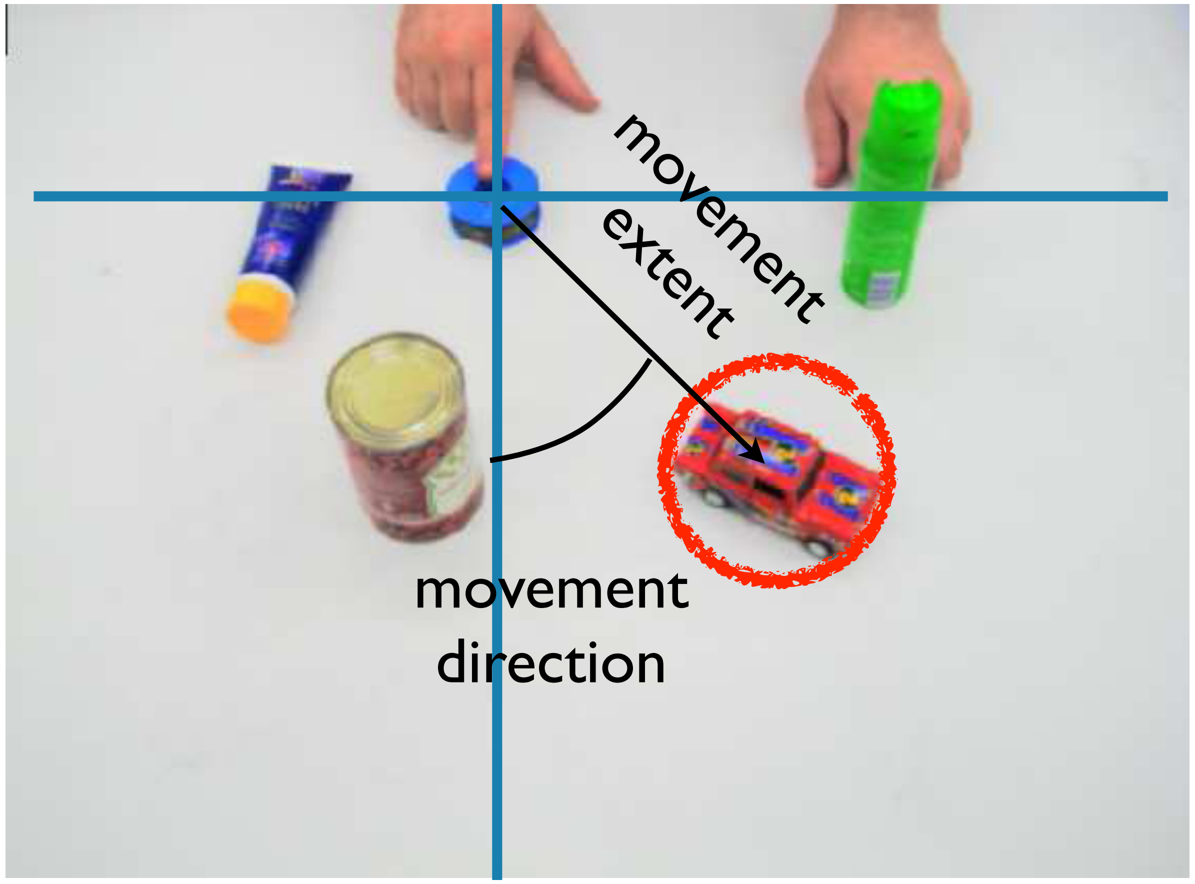


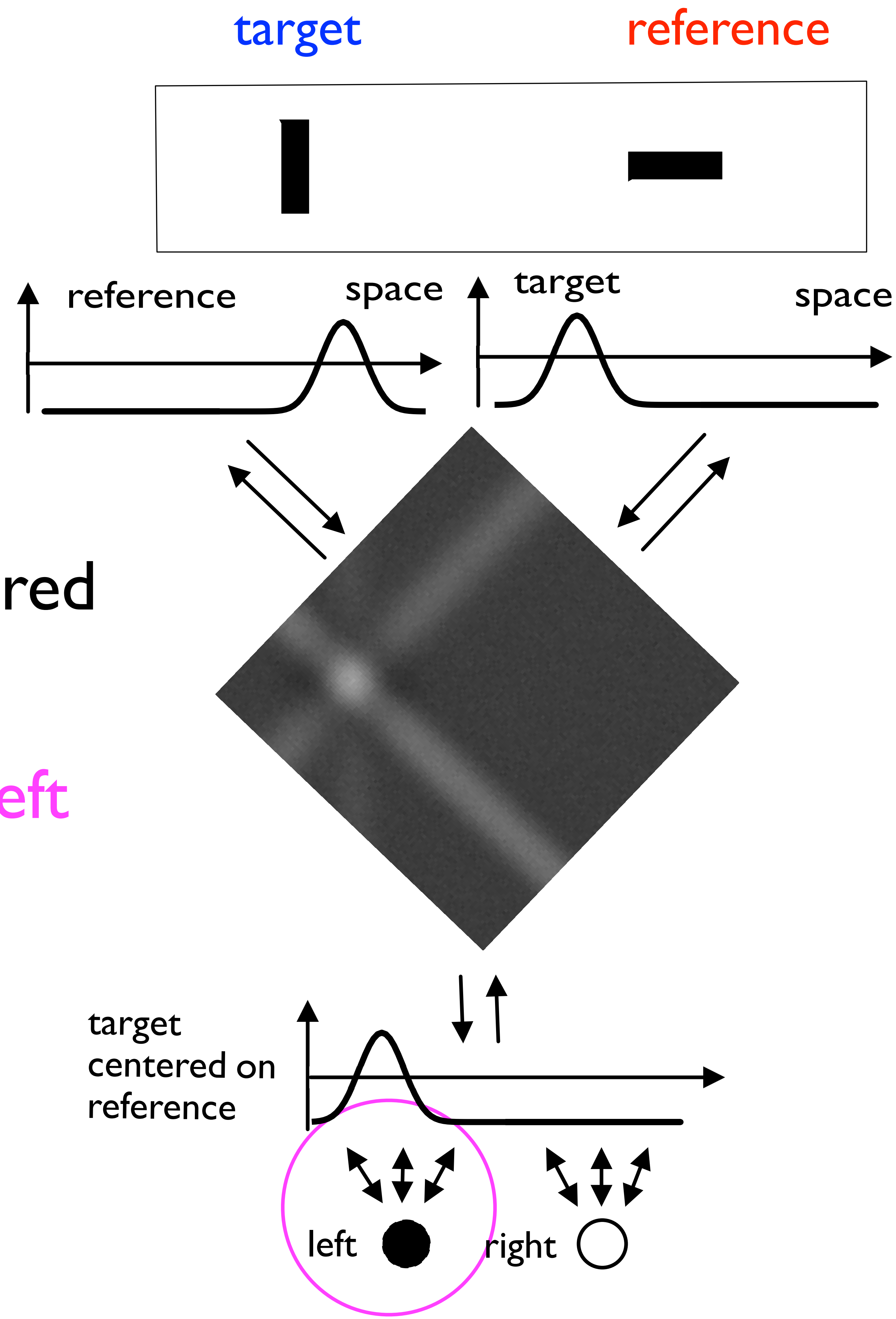
Coordinate transforms

- hand movement: from body-centered to hand-centered representation



Coordinate transforms

- relational concepts: from visual space to frame centered in reference object
- e.g. "vertical object to the left of horizontal object"



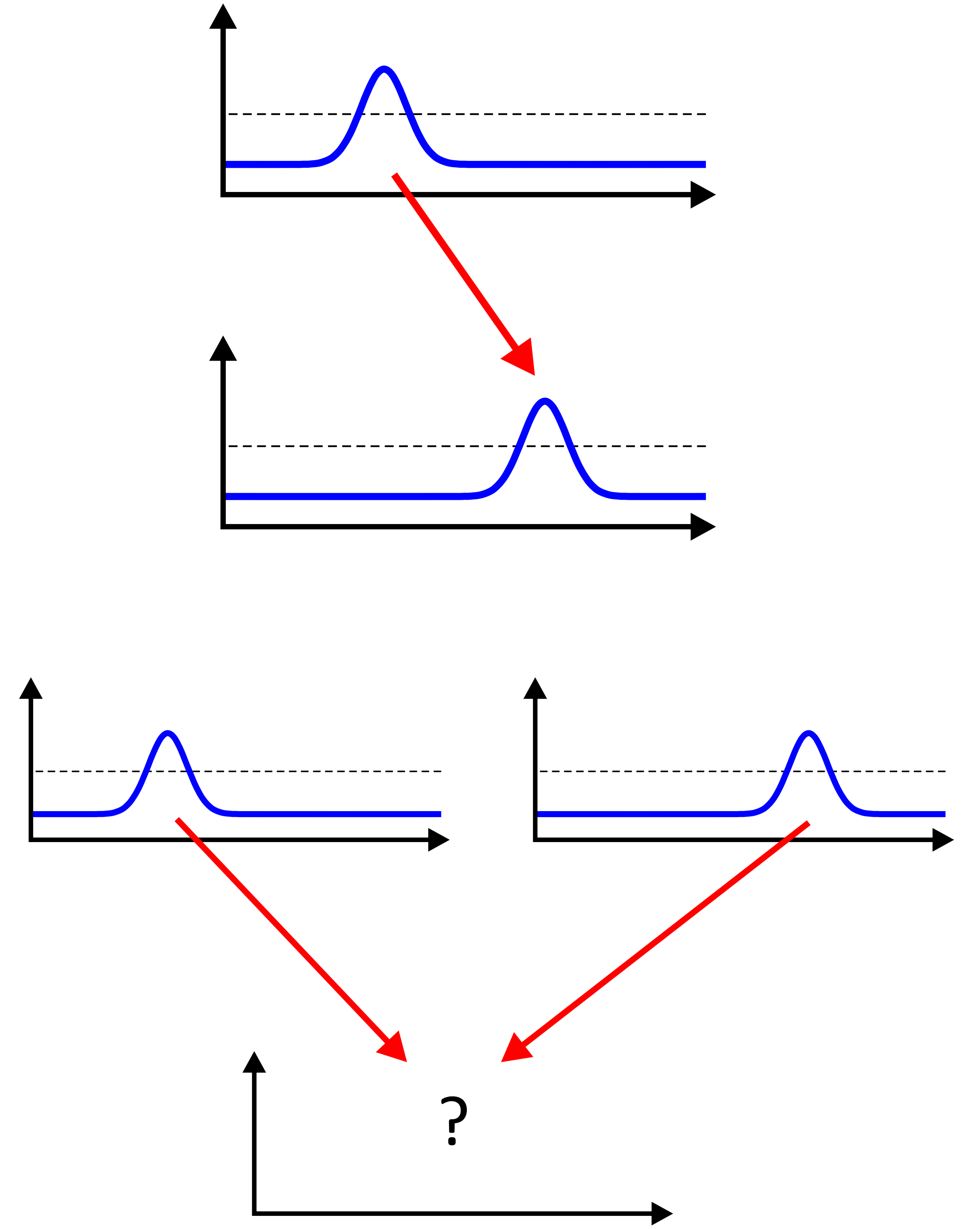
Coordinate transforms

- a mapping between two reference frame: e.g. retino-centric (moving with the eye) to body-centered (gaze-invariant)
- mapping=shift operation with amount of shift depending on current gaze direction
- $x_{\text{body}} = f(x_{\text{retinal}}, x_{\text{gaze}}) \approx x_{\text{retinal}} + x_{\text{gaze}}$
- but how to implement such functions neurally?

[Slides adapted from Sebastian Schneegans,
see Schneegans, Chapter 7 of Dynamic Field Theory-A Primer, OUP, 2015]

Coordinate transforms

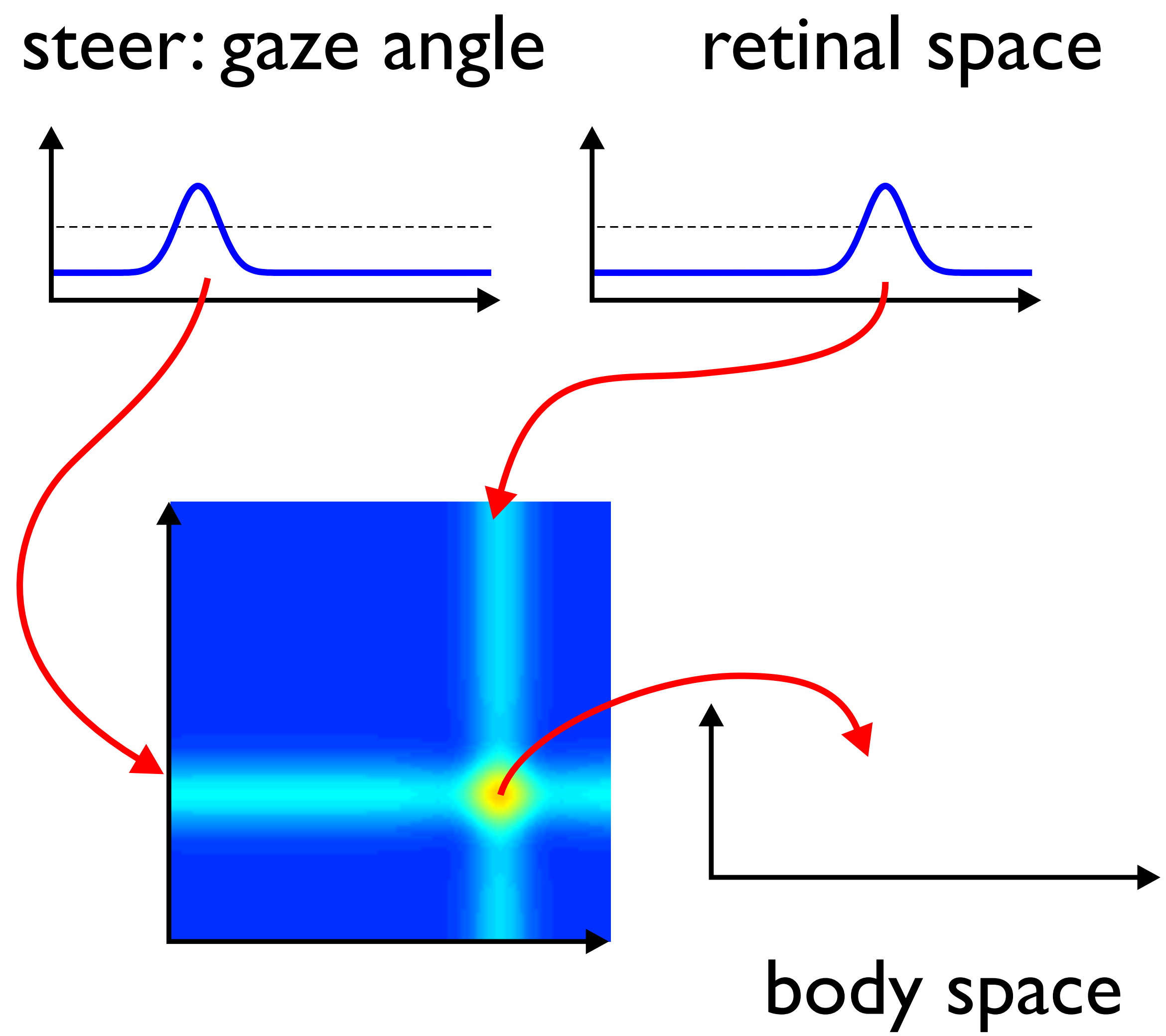
- fixed mapping: neural projection in a neural network
- flexible mapping steered by x
  - x=gaze direction
  - x=hand position
  - x=position of reference object



[Schneegans Ch 7 of *DFT Primer*, 2016]

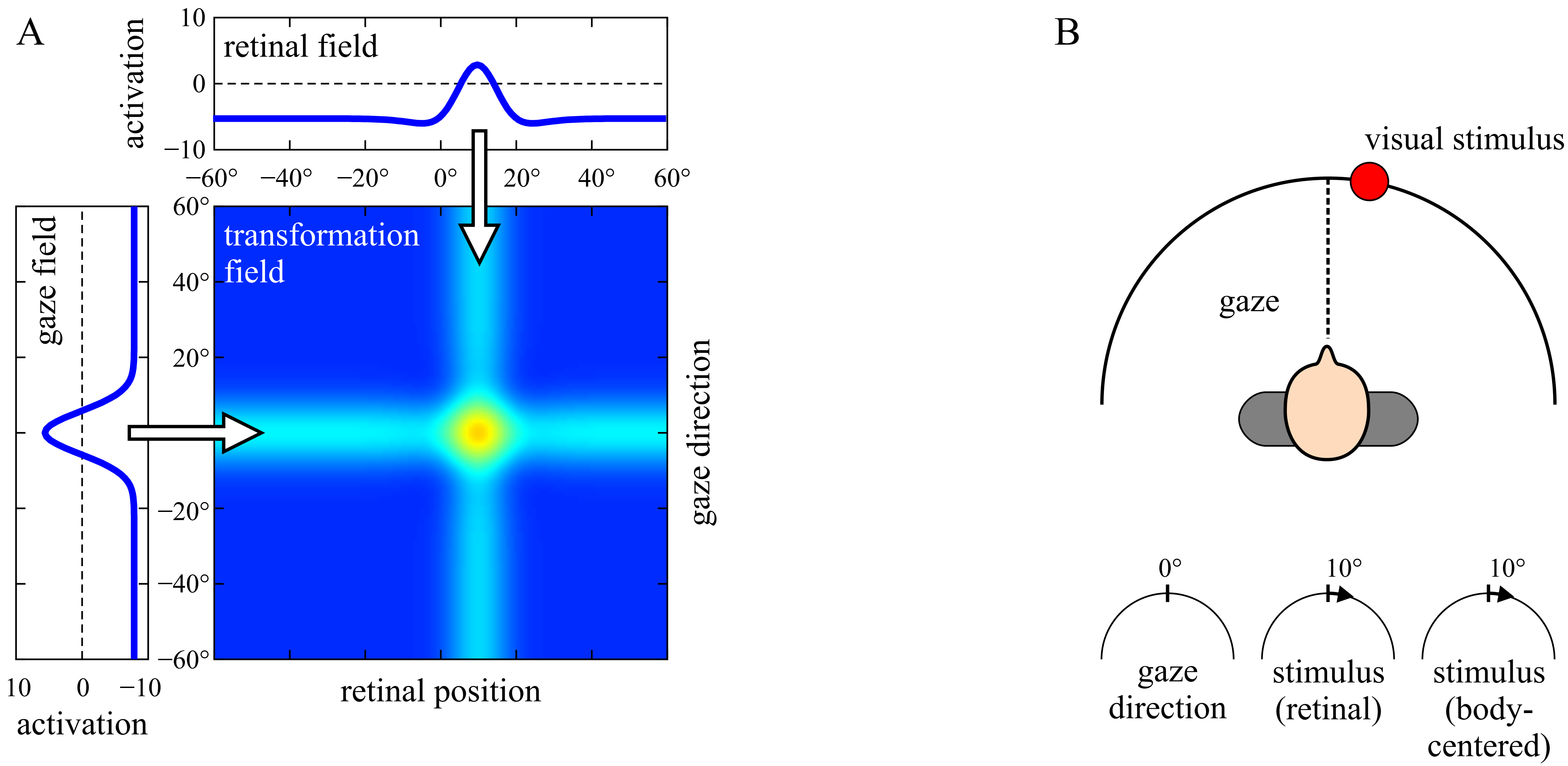
Coordinate transforms

- a joint representation of
  - the space to be mapped
  - the steering space
- bind the two spaces
- ridge/slice input
- peak
- project out to transformed space



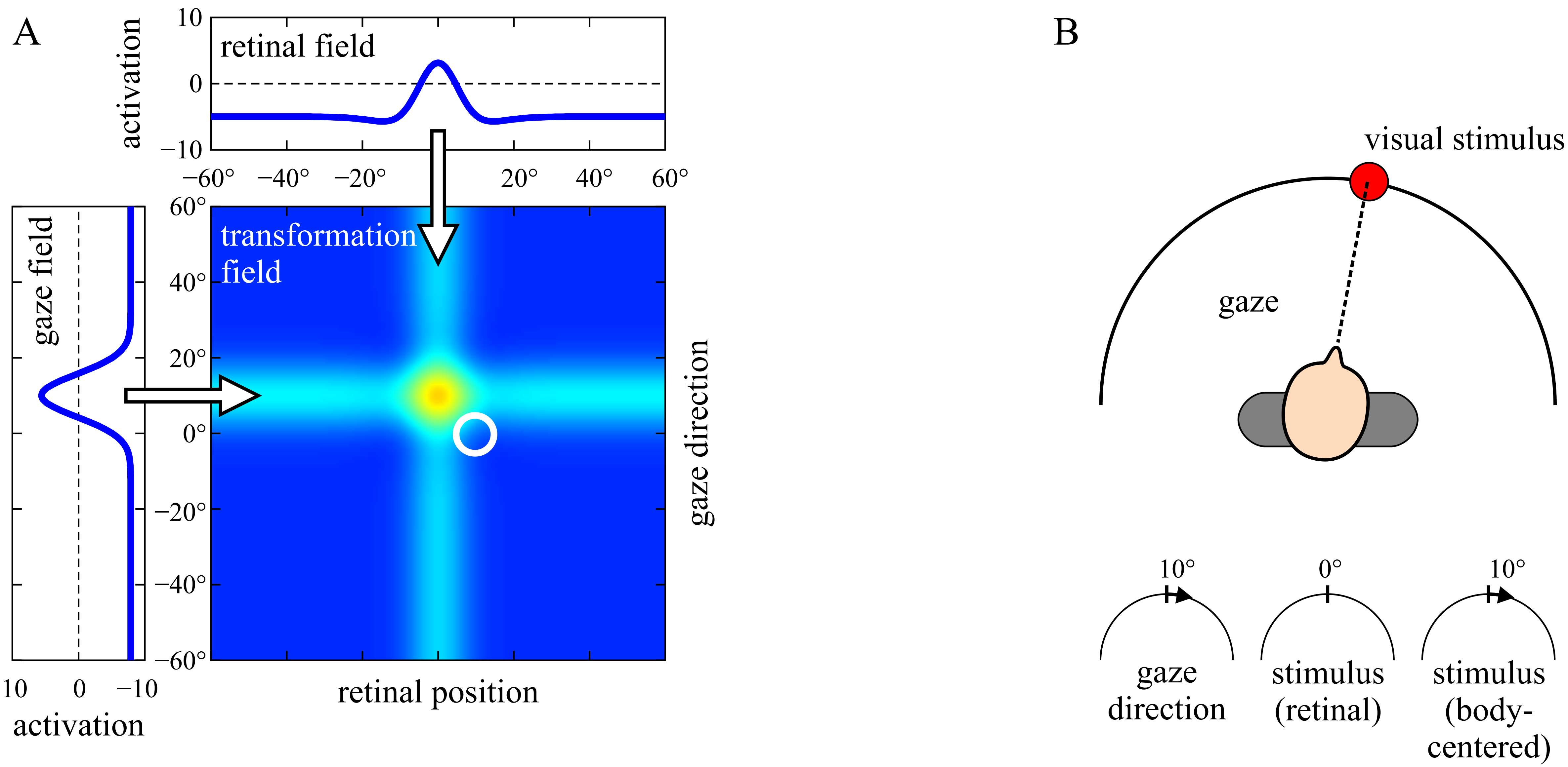
[Schneegans Ch 7 of *DFT Primer*, 2016]

Coordinate transforms



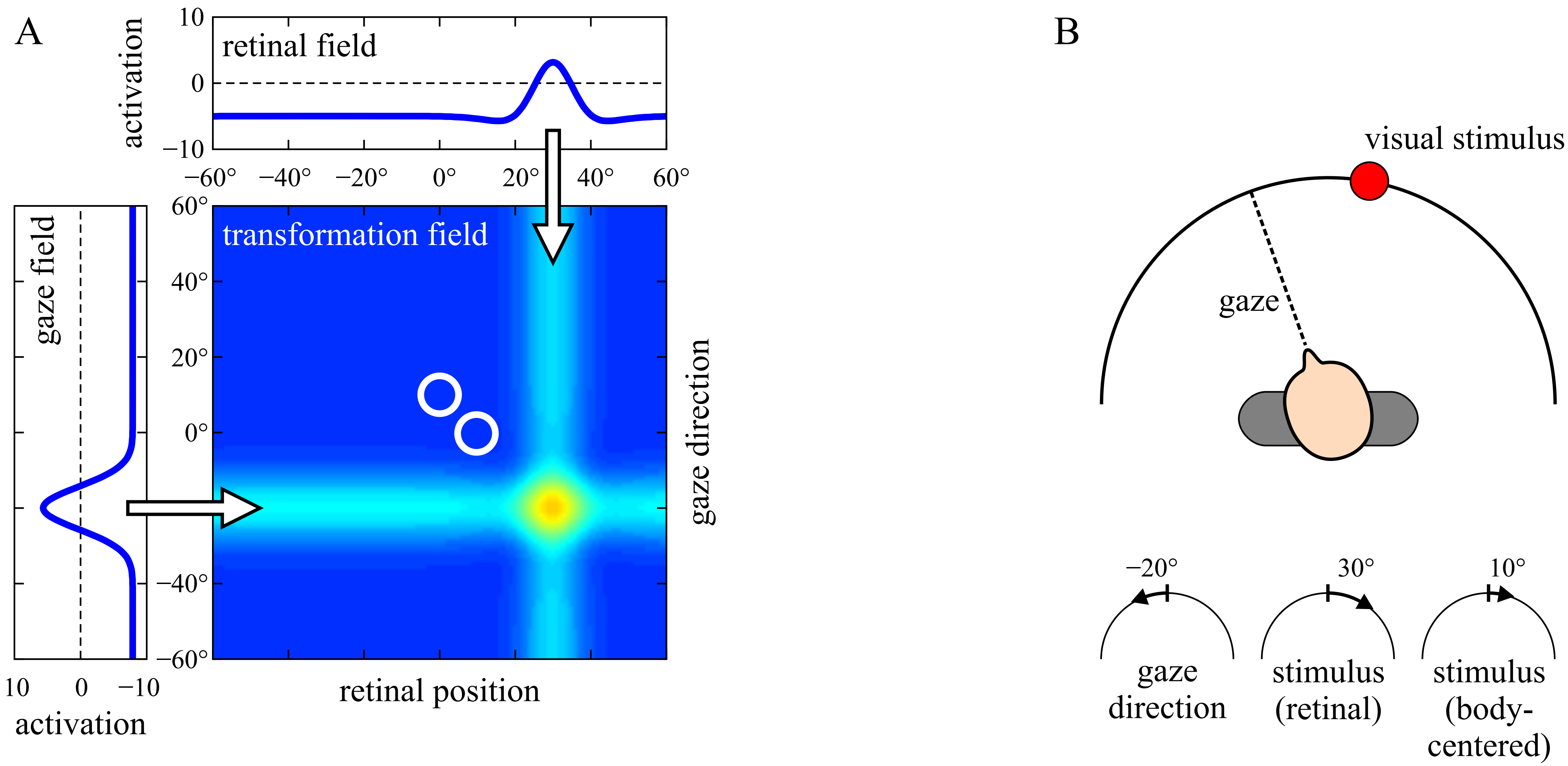
[Schneegans Ch 7 of *DFT Primer*, 2016]

Coordinate transforms



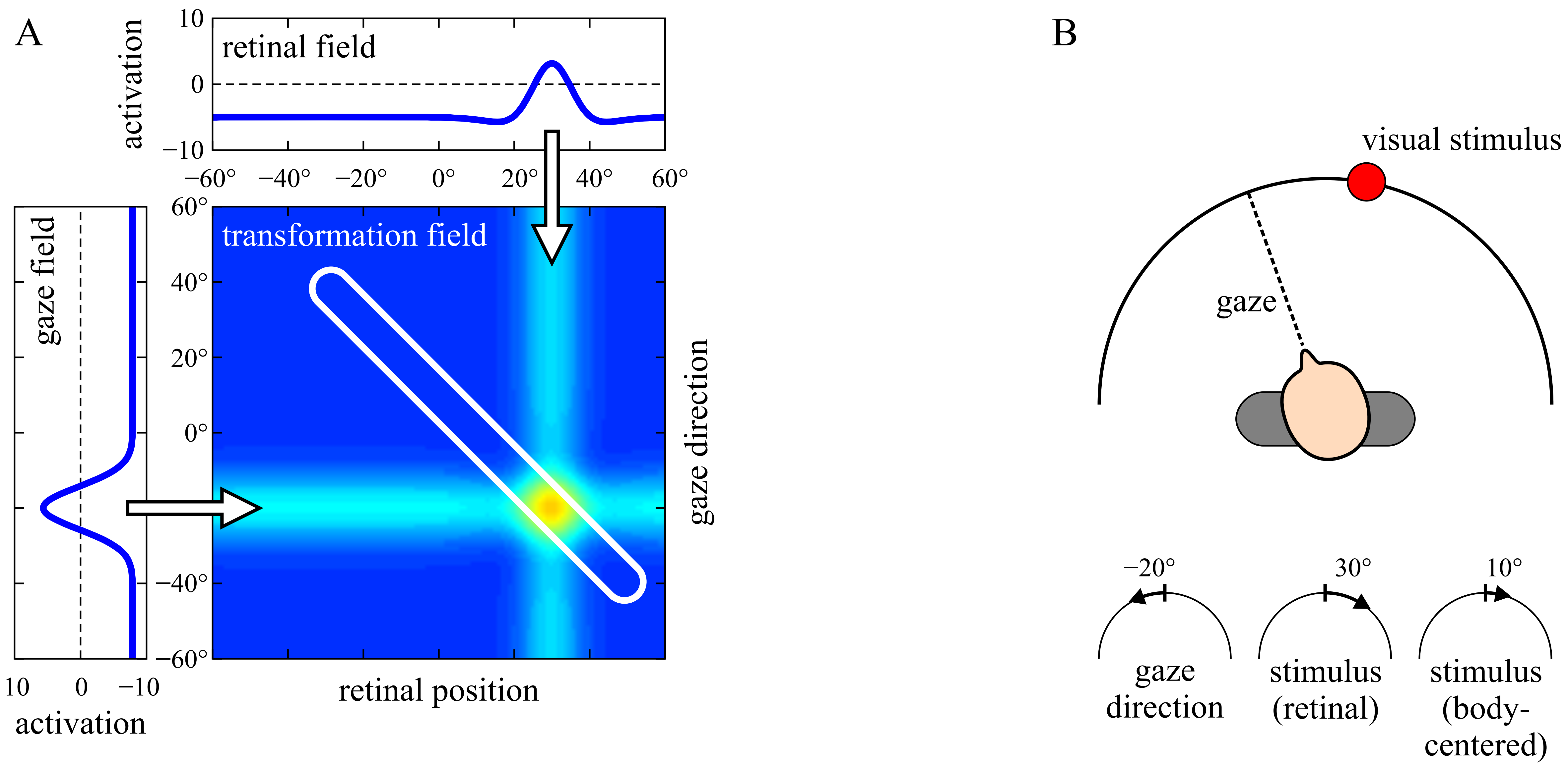
[Schneegans Ch 7 of *DFT Primer*, 2016]

Coordinate transforms



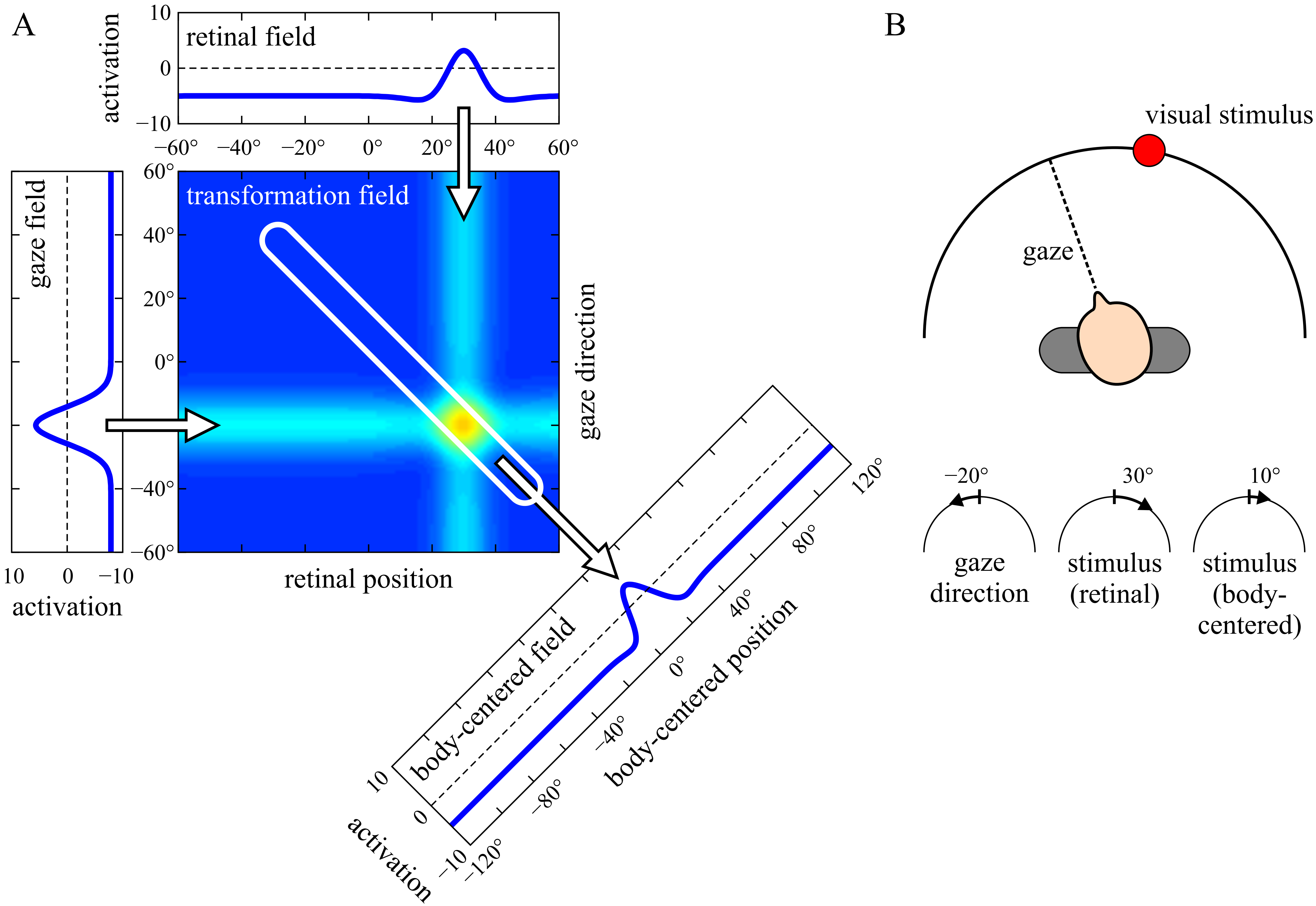
[Schneegans Ch 7 of *DFT Primer*, 2016]

Coordinate transforms



[Schneegans Ch 7 of *DFT Primer*, 2016]

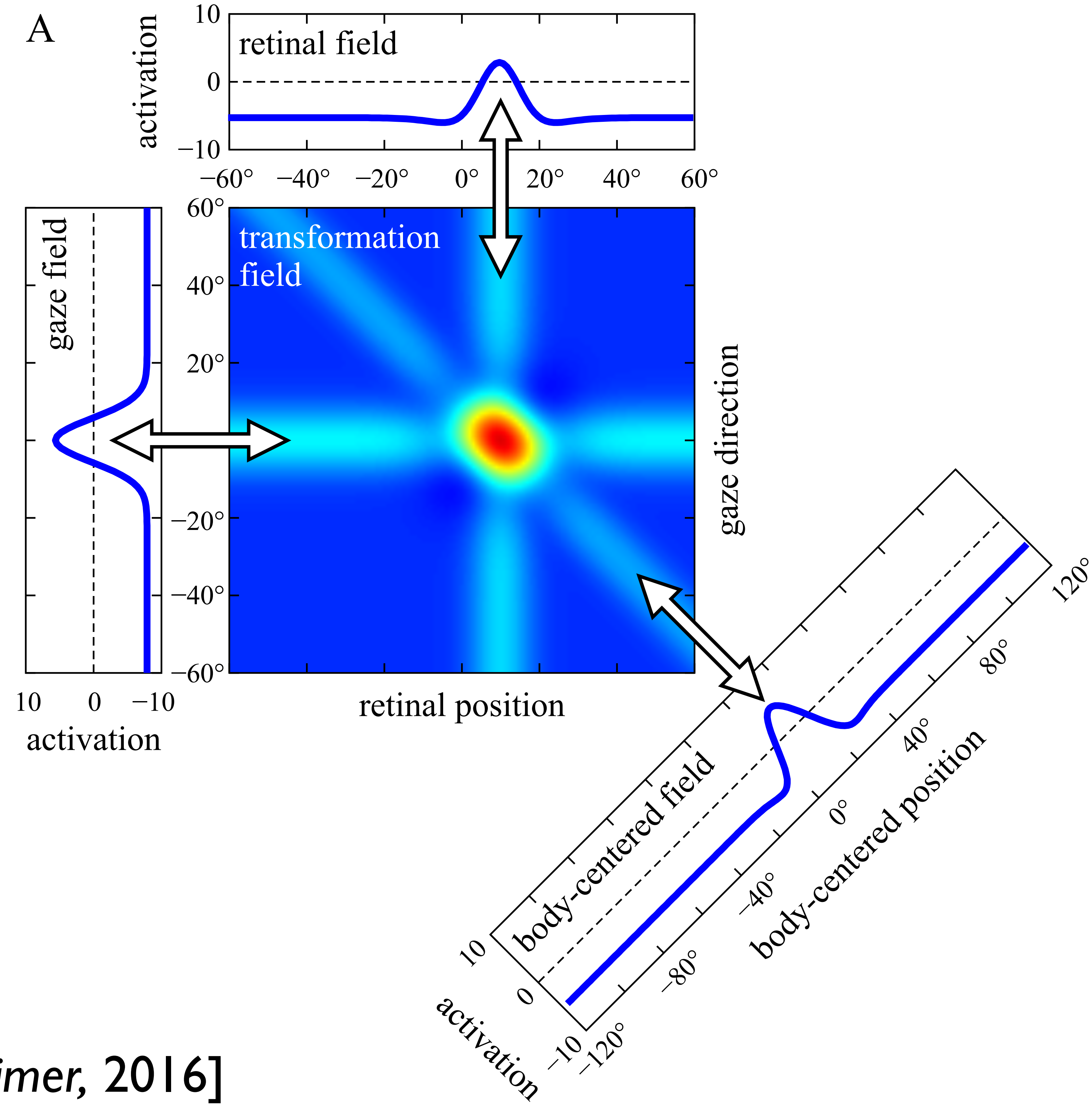
Coordinate transforms



[Schneegans Ch 7 of *DFT Primer*, 2016]

Coordinate transforms

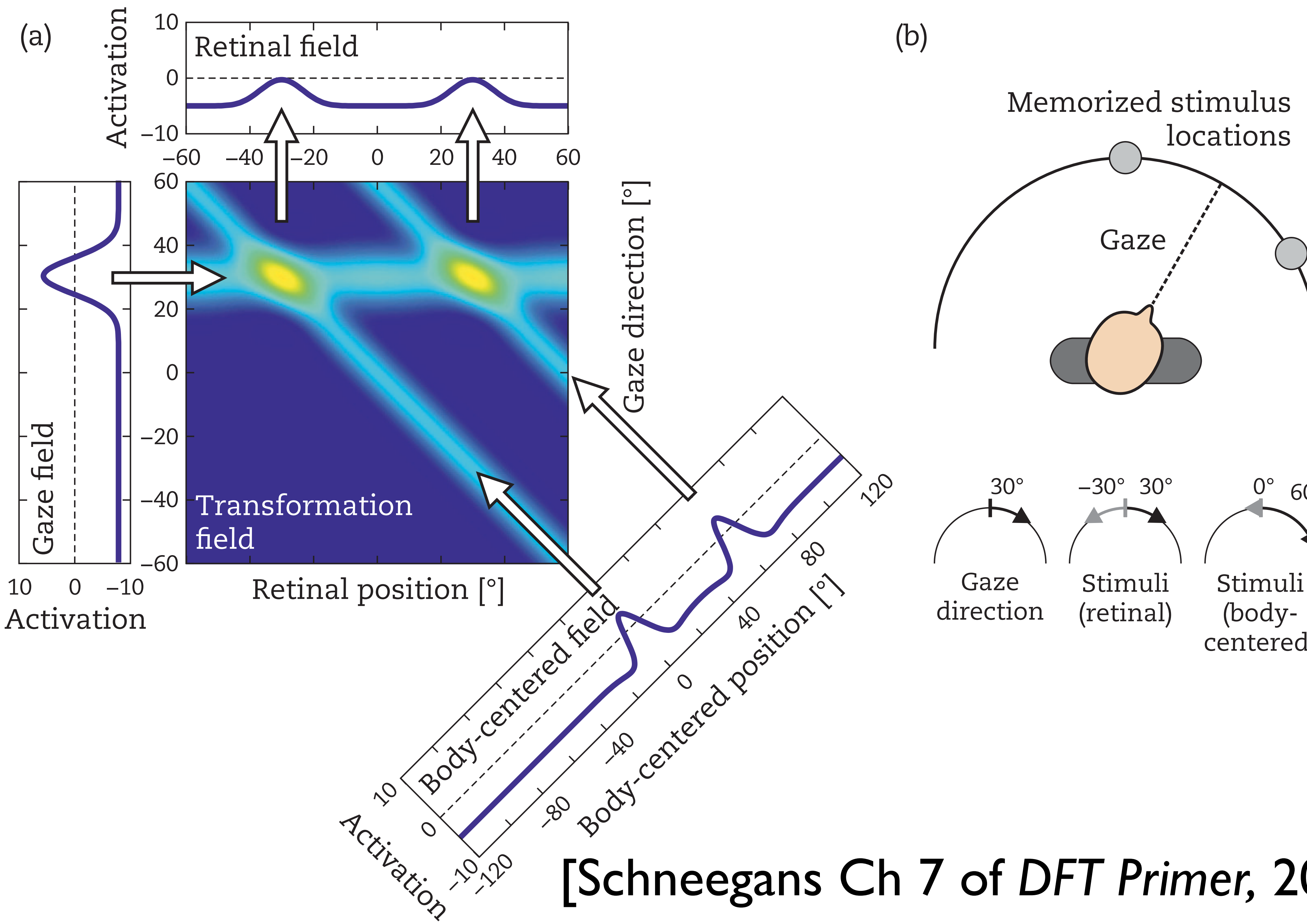
- bi-directional coupling
- enables new functions



[Schneegans Ch 7 of *DFT Primer*, 2016]

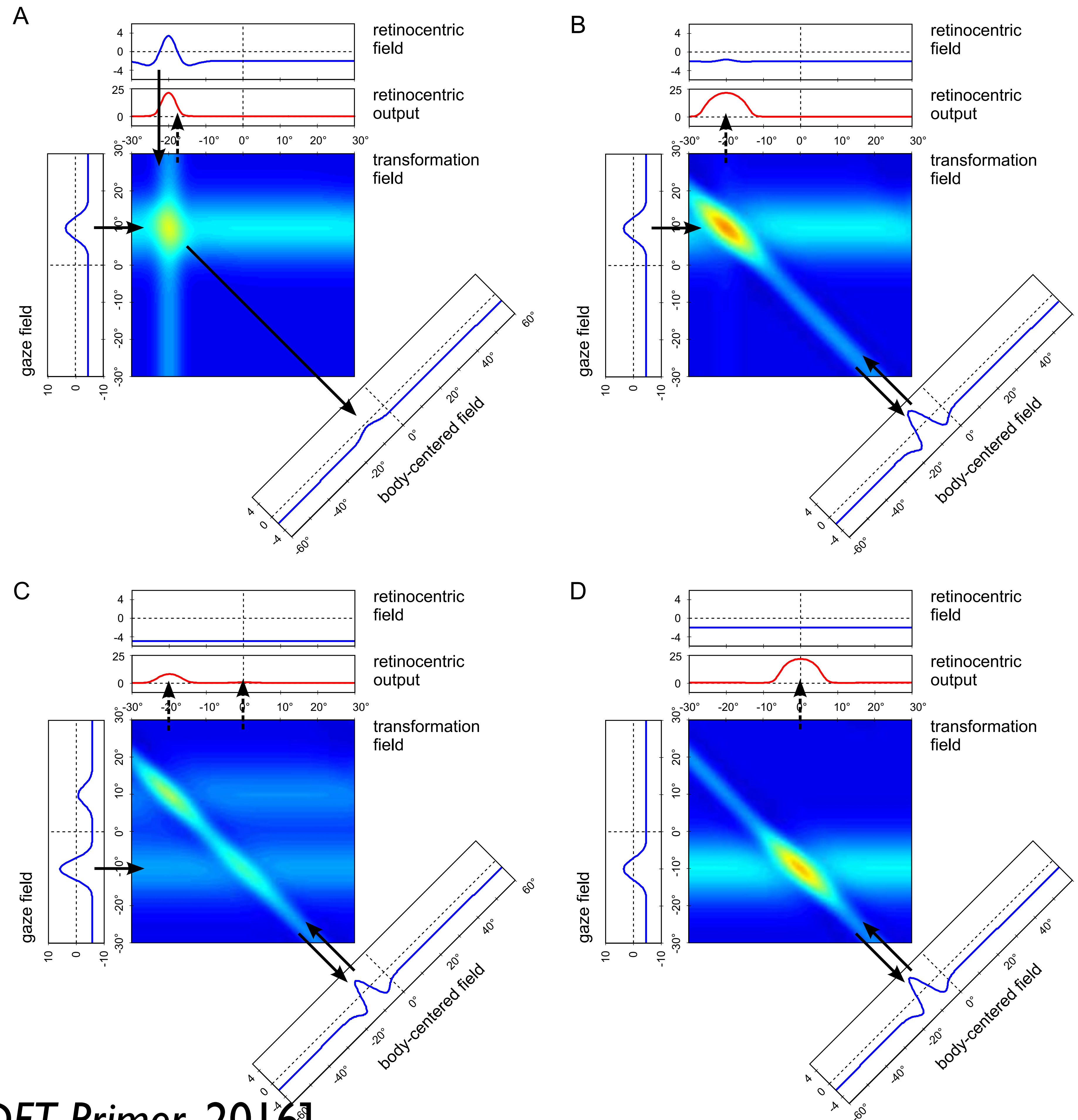
Coordinate transforms

- predict retinal image from memorized scene



[Schneegans Ch 7 of *DFT Primer*, 2016]

Spatial remapping during saccades



[Schneegans Ch 7 of *DFT Primer*, 2016]

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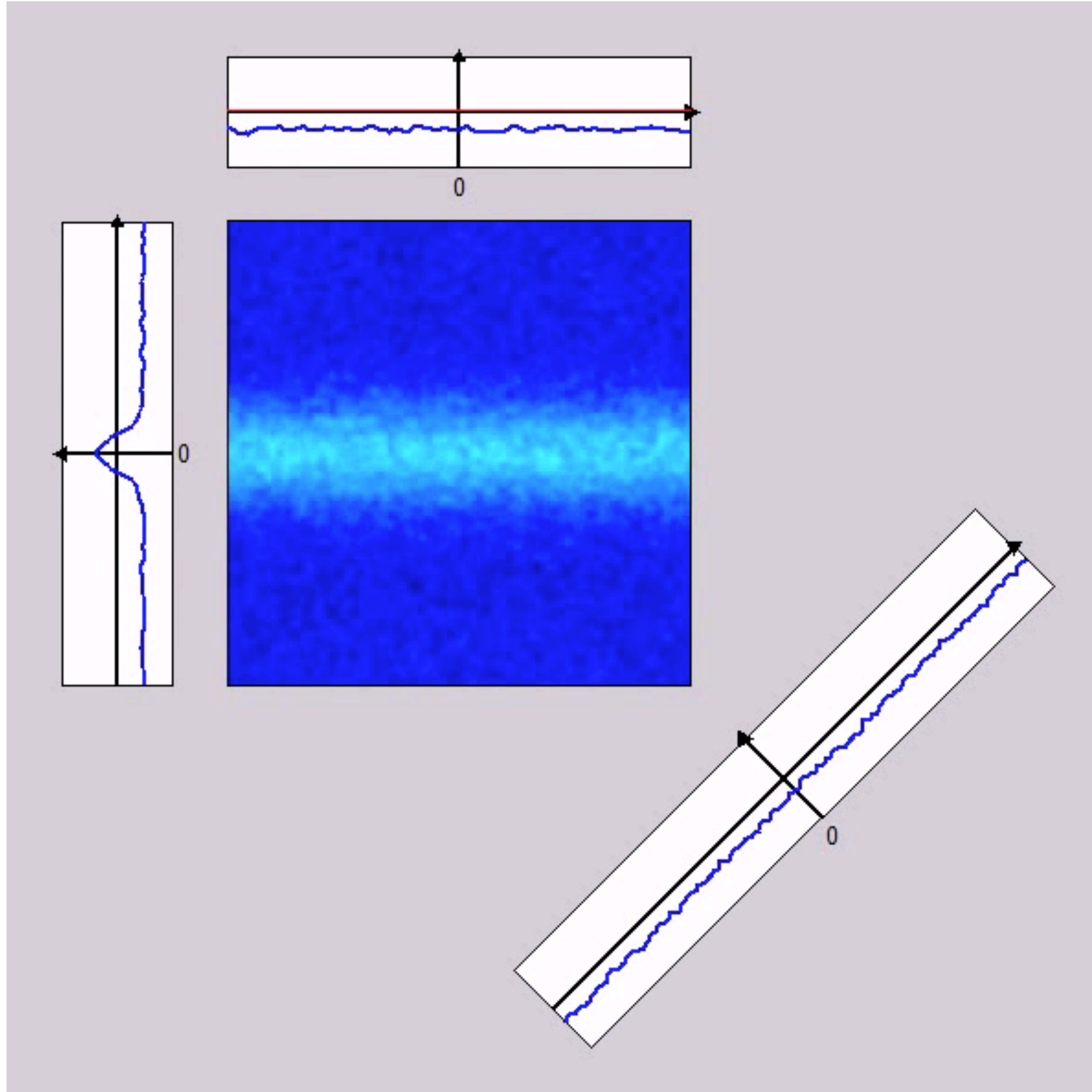
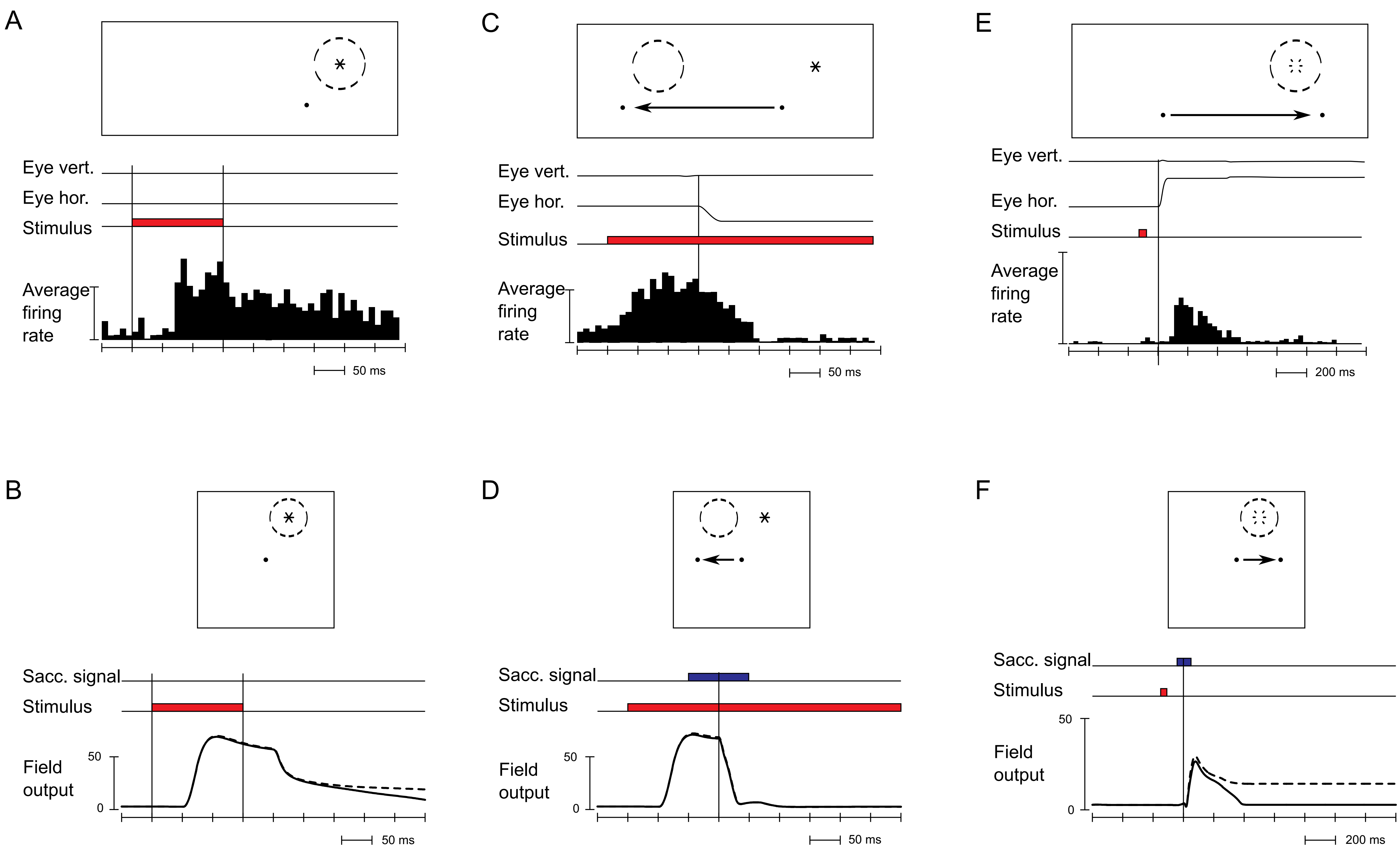


[Schneegans, Schöner *Biological Cybernetics* 2012]

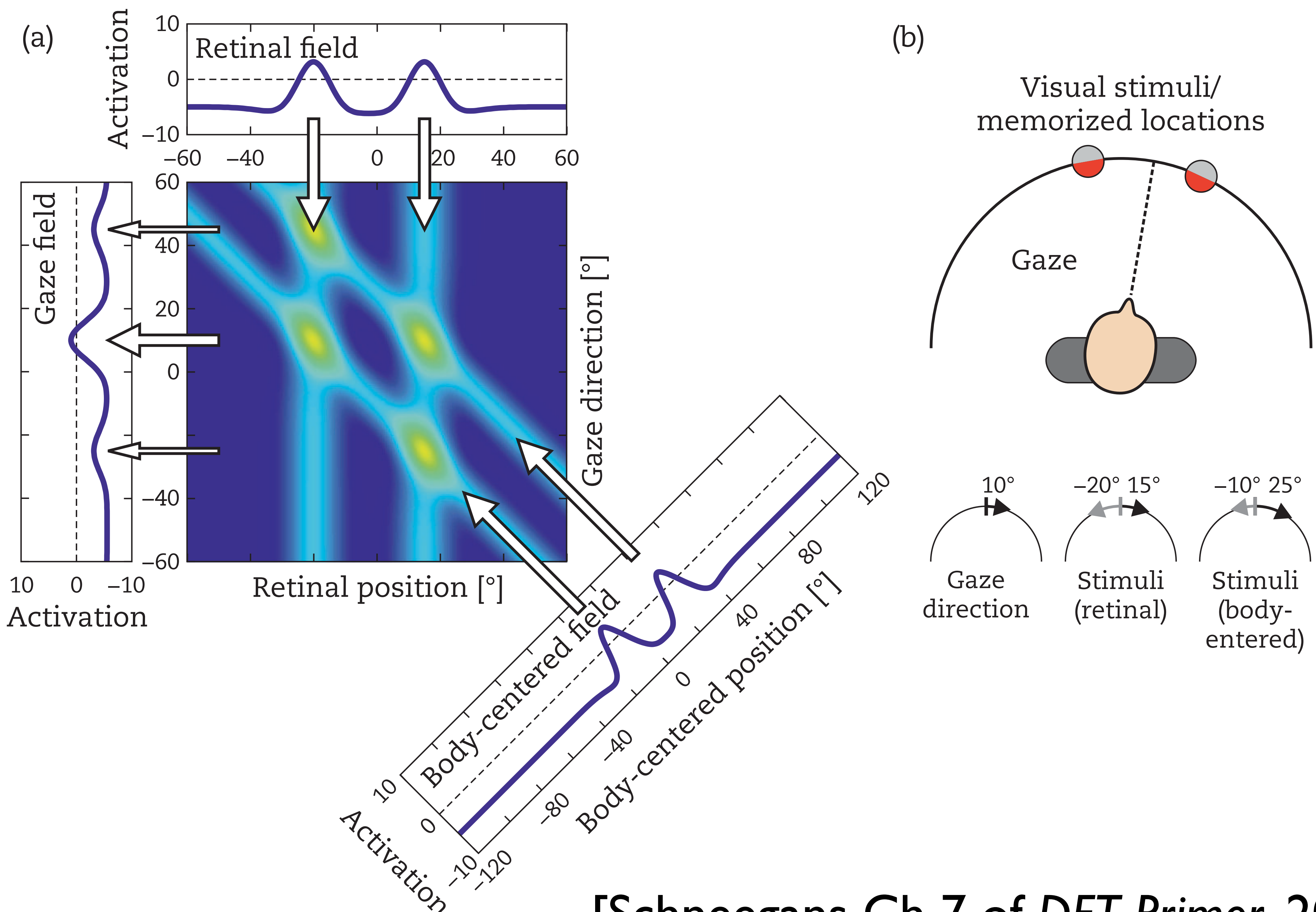


=> accounts for predictive updating of retinal representation

[Schneegans, Schöner *Biological Cybernetics* 2012]

Coordinate transforms

- estimate gaze by matching scene to memorizes scene



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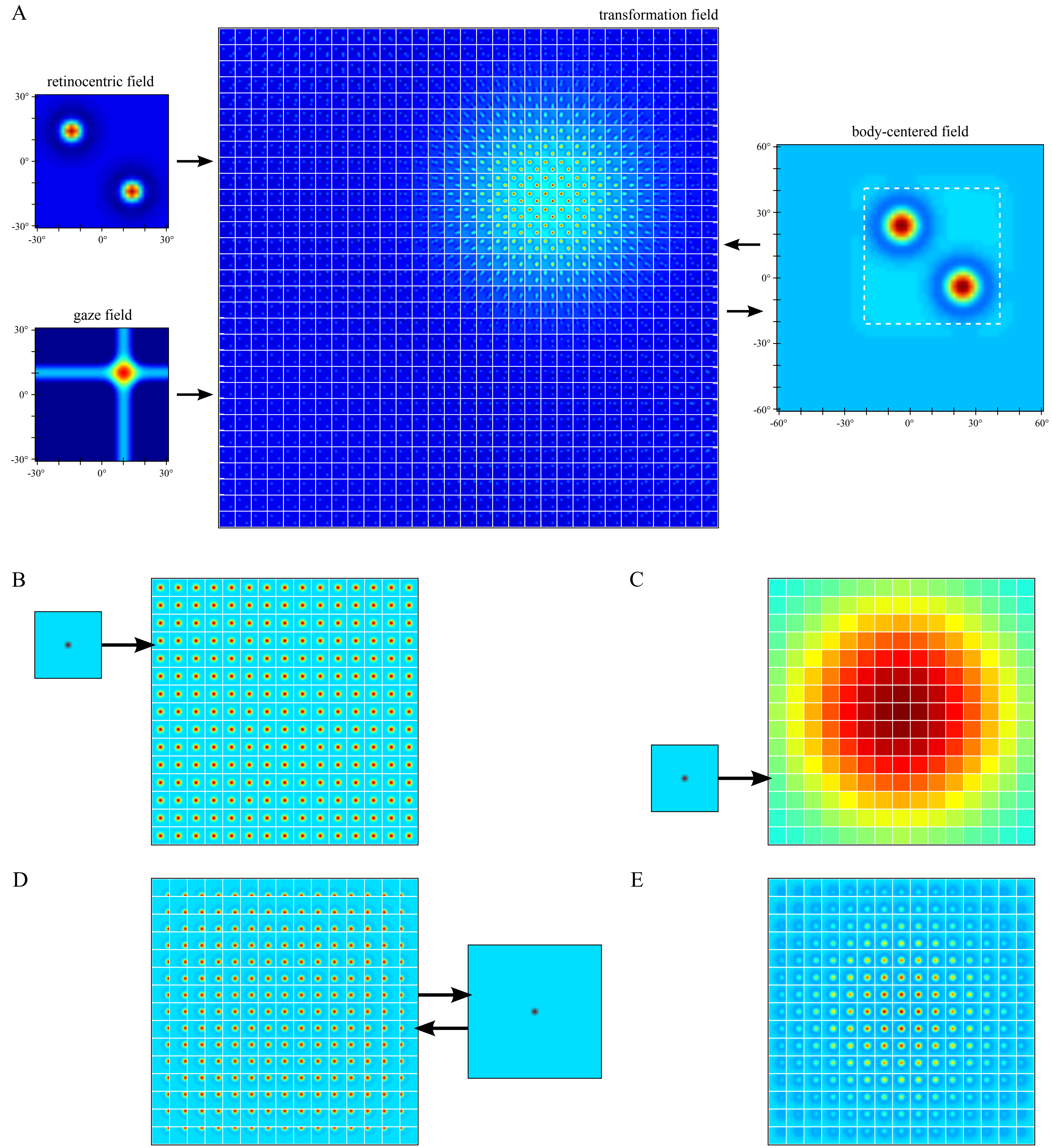
Scaling



[Schneegans Ch 7 of *DFT Primer*, 2016]

Scaling

- joint representation of steering and transformed space ~ 4 dimensions
- binding through space… enables transforming only space!
- => coordinate transforms are linked to the sequentiality bottleneck!

Summary

- higher-dimensional dynamic fields enable new cognitive functions: binding, attentional selection, matching, visual search, coordinate transforms