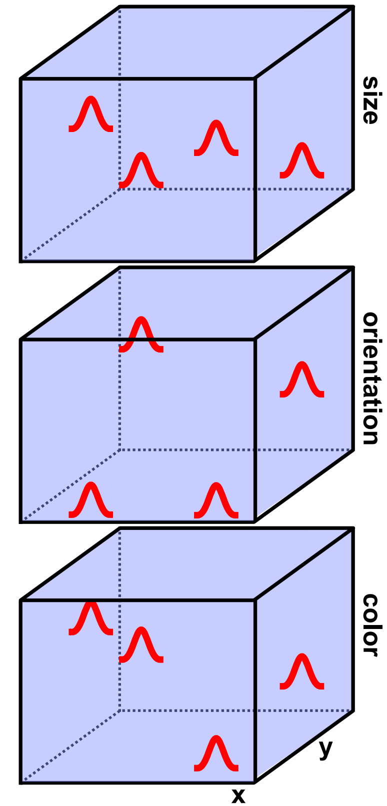
Advanced concepts of DFT

Gregor Schöner

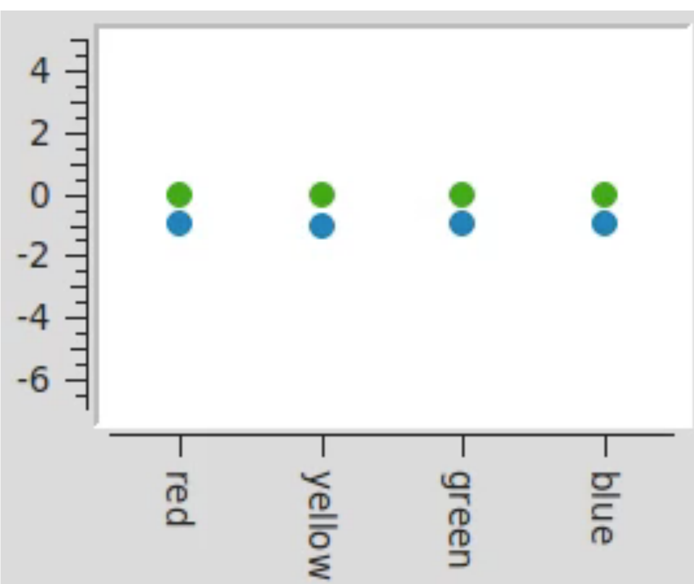
Dynamic fields of varying dimensionality

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

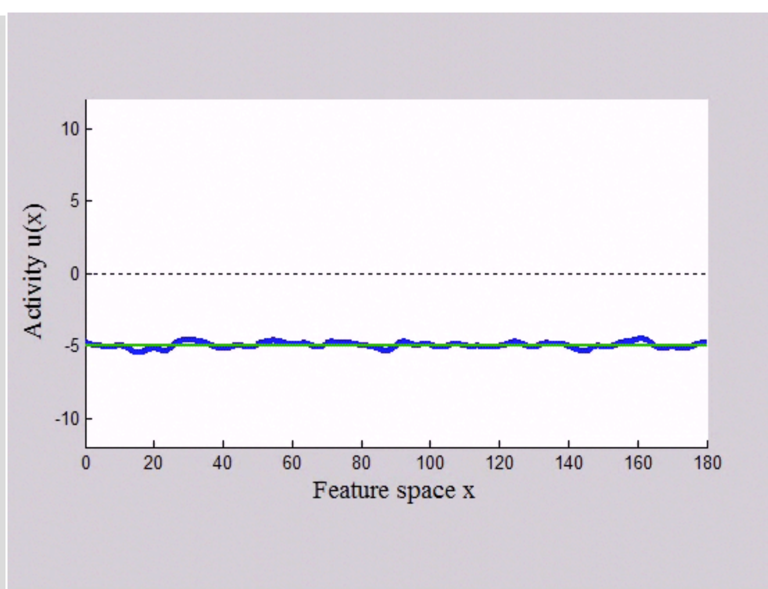
3-dimensional



0-dimensional



1-dimensional

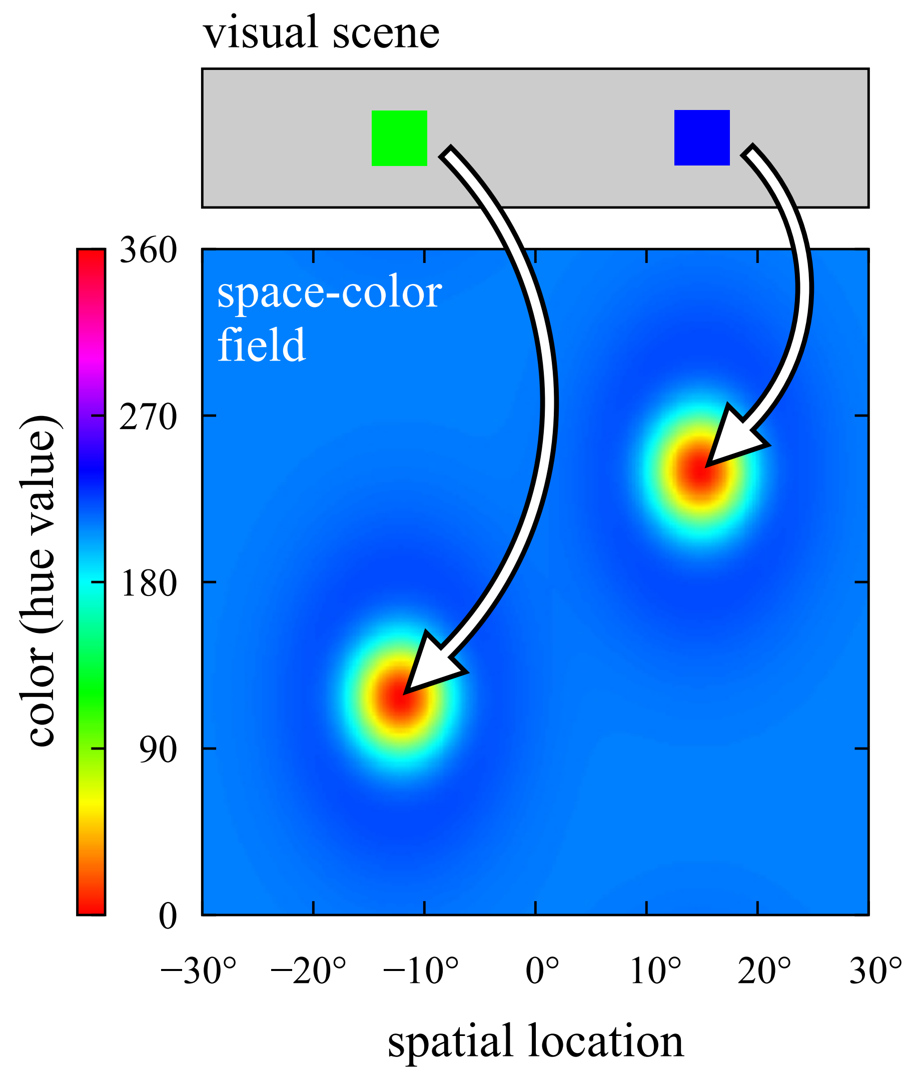


2-dimensional

New cognitive functions emerge as dimensionality is varied

Binding

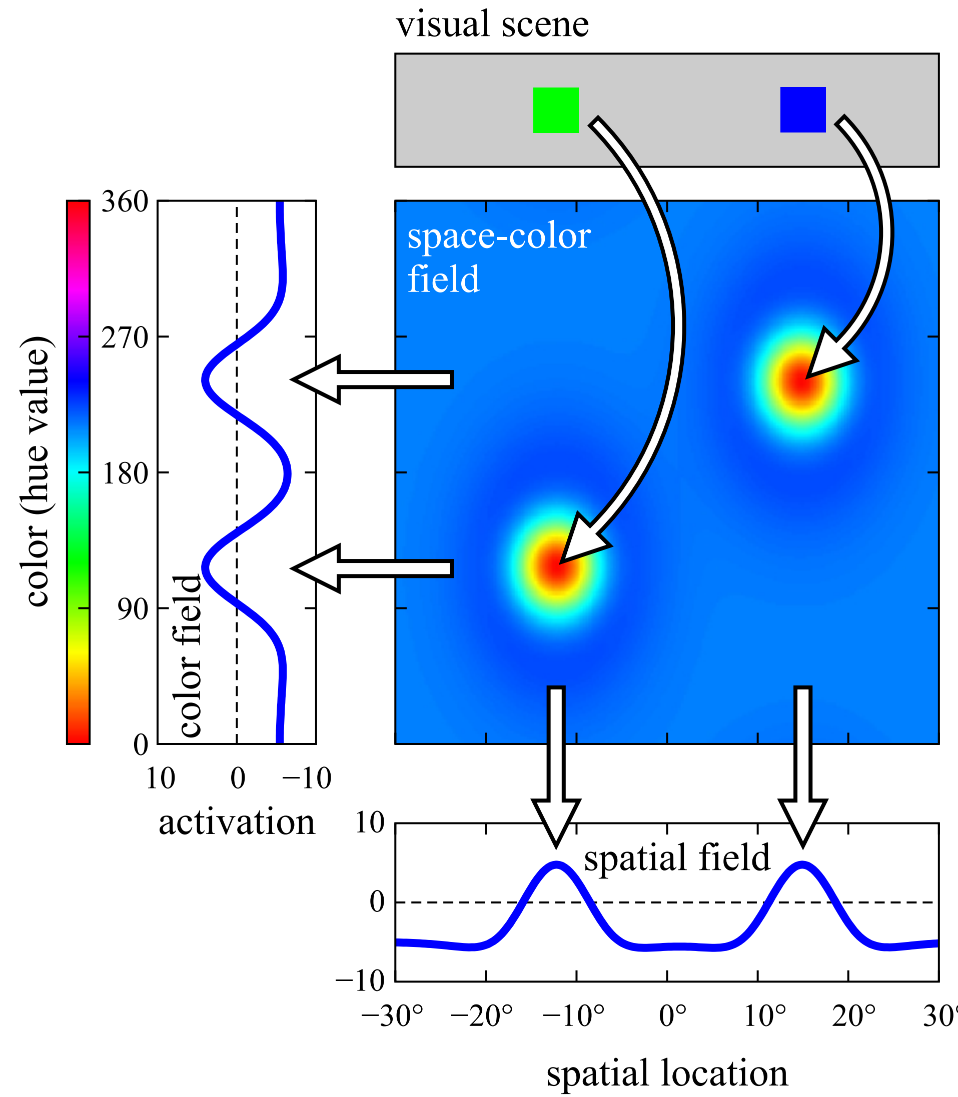
- a joint representation of space and color



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

Extract bound features

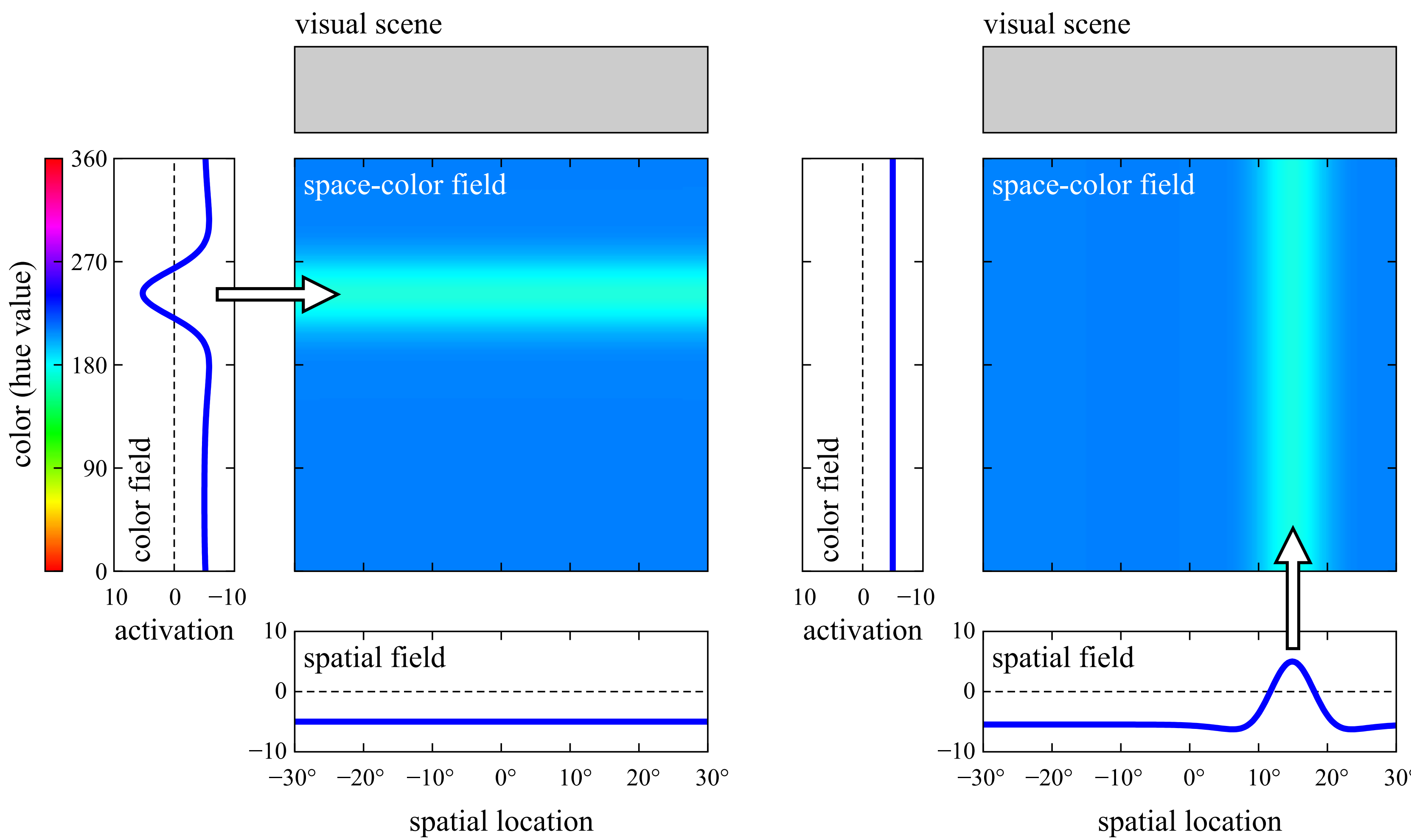
- by projecting to lower-dimensional fields
- summing along the marginalized dimensions
- (or by taking the soft-max)



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

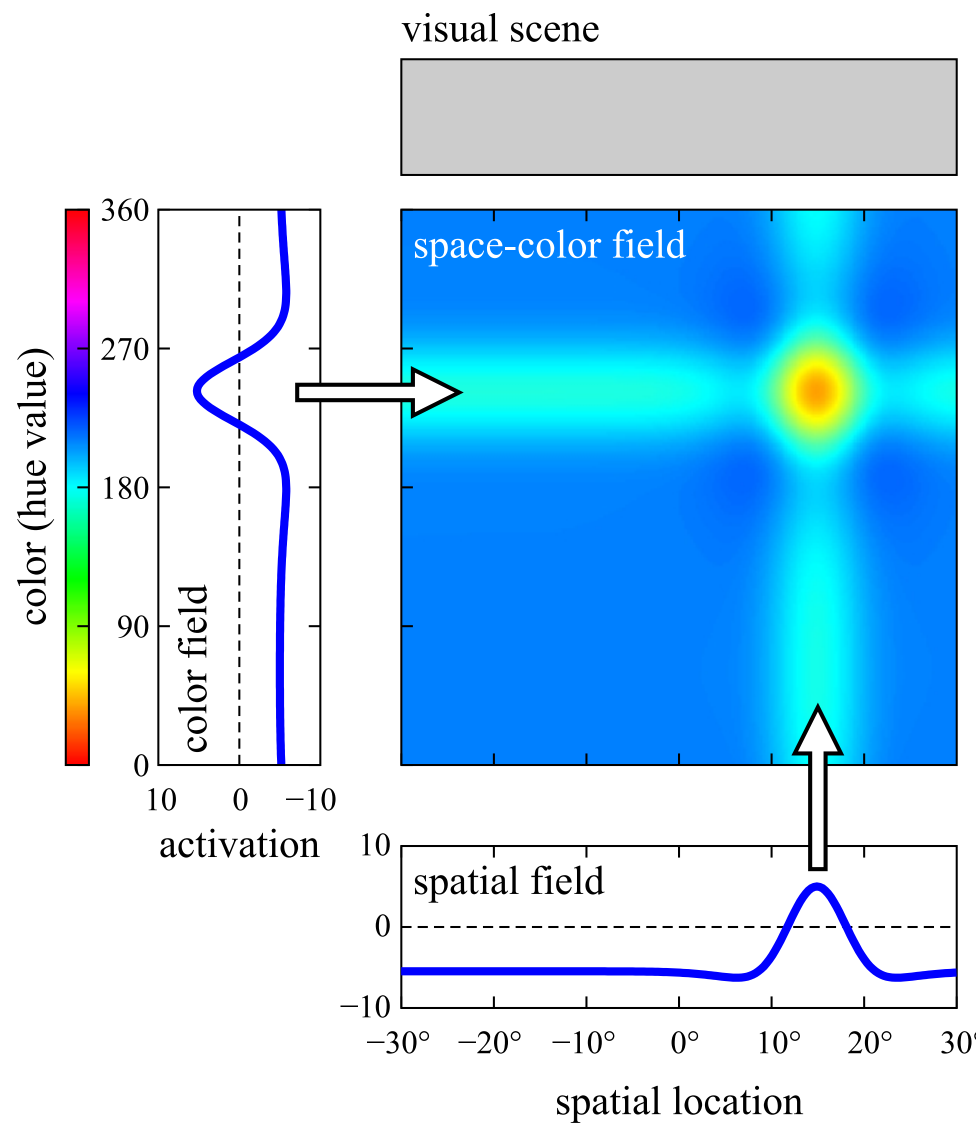
Assembling bound representations

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



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

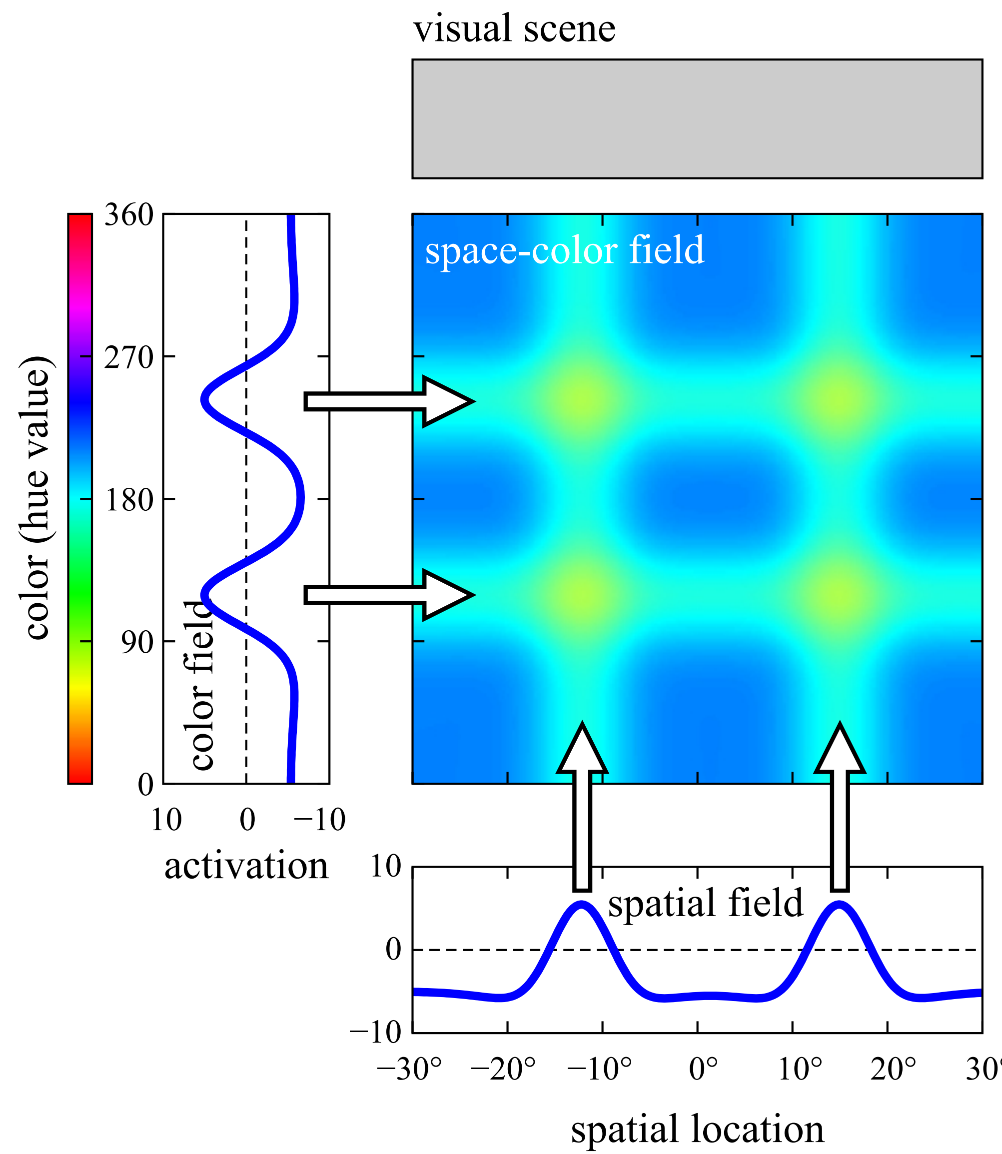
Assembling bound representations



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

Assembling bound representations

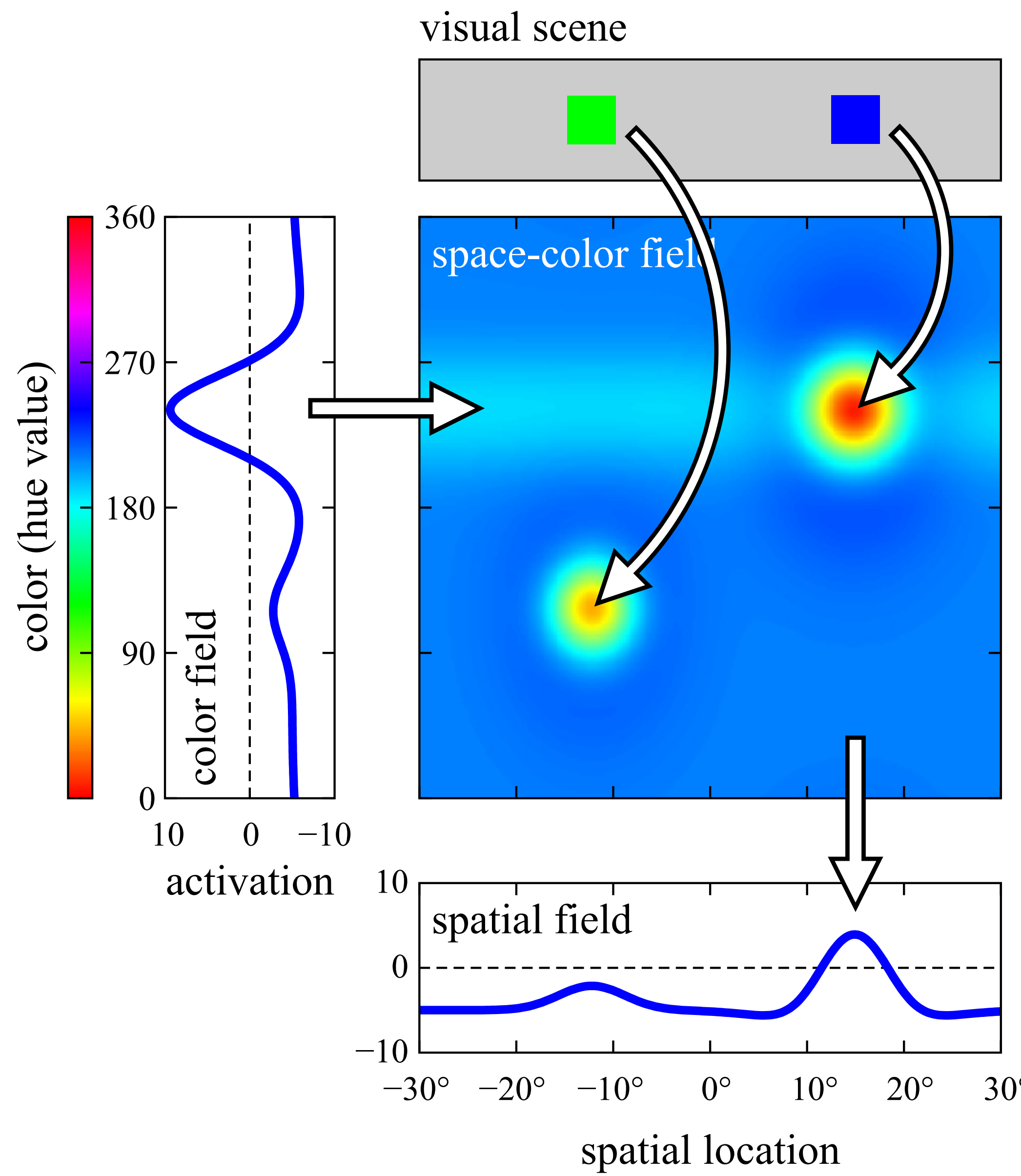
- binding problem: multiple ridges lead to a correspondence problem
- => assemble one object at a time… sequentiality bottle-neck!



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

Visual search

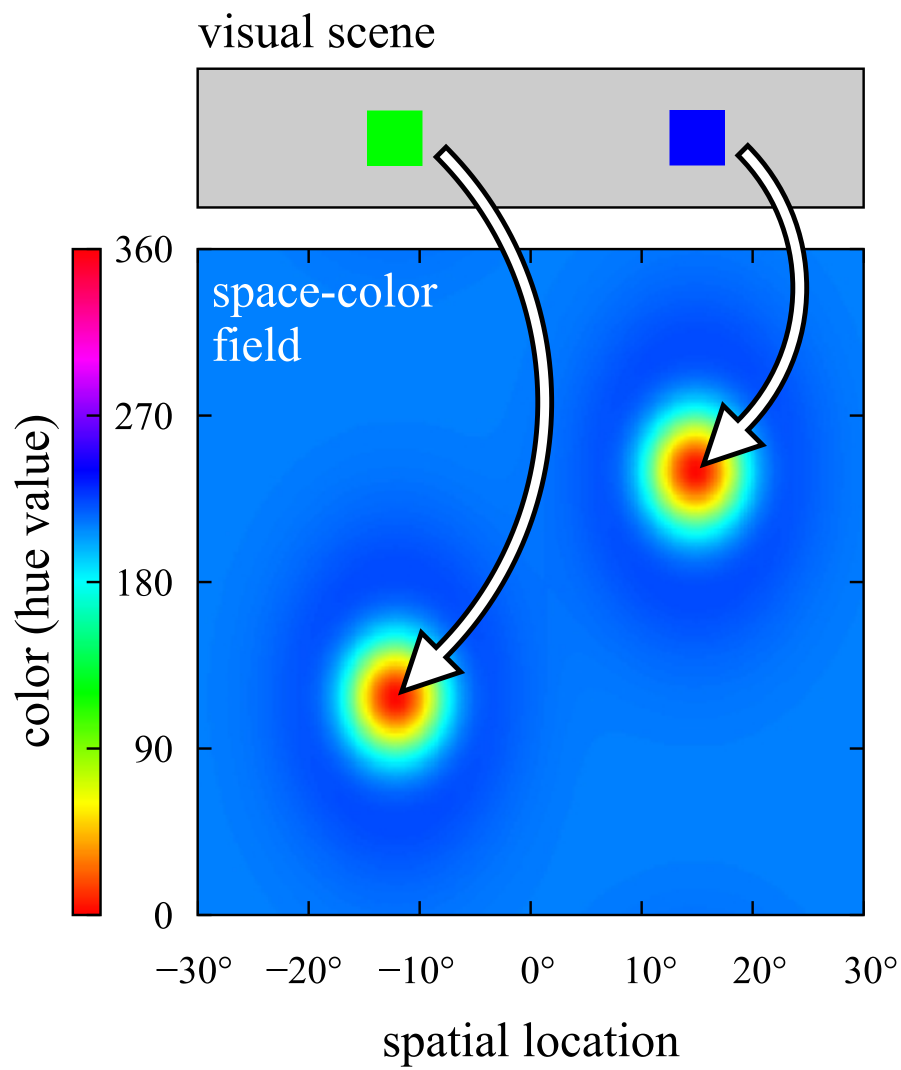
- => Raul Grieben's case study



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

Binding by joint representations

- a "neuro-anatomical" form of binding
- => very costly



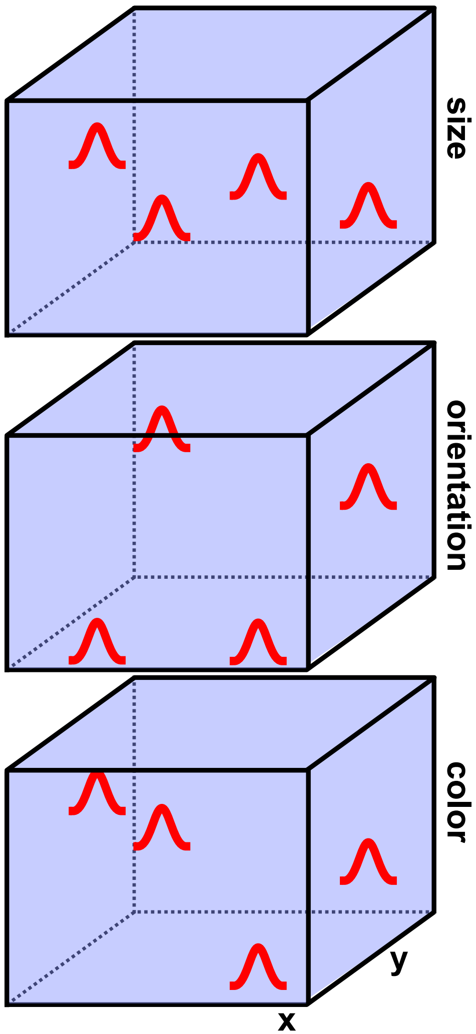
[Schneegans et al., Ch 5 of *DFT Primer*, 2016]

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

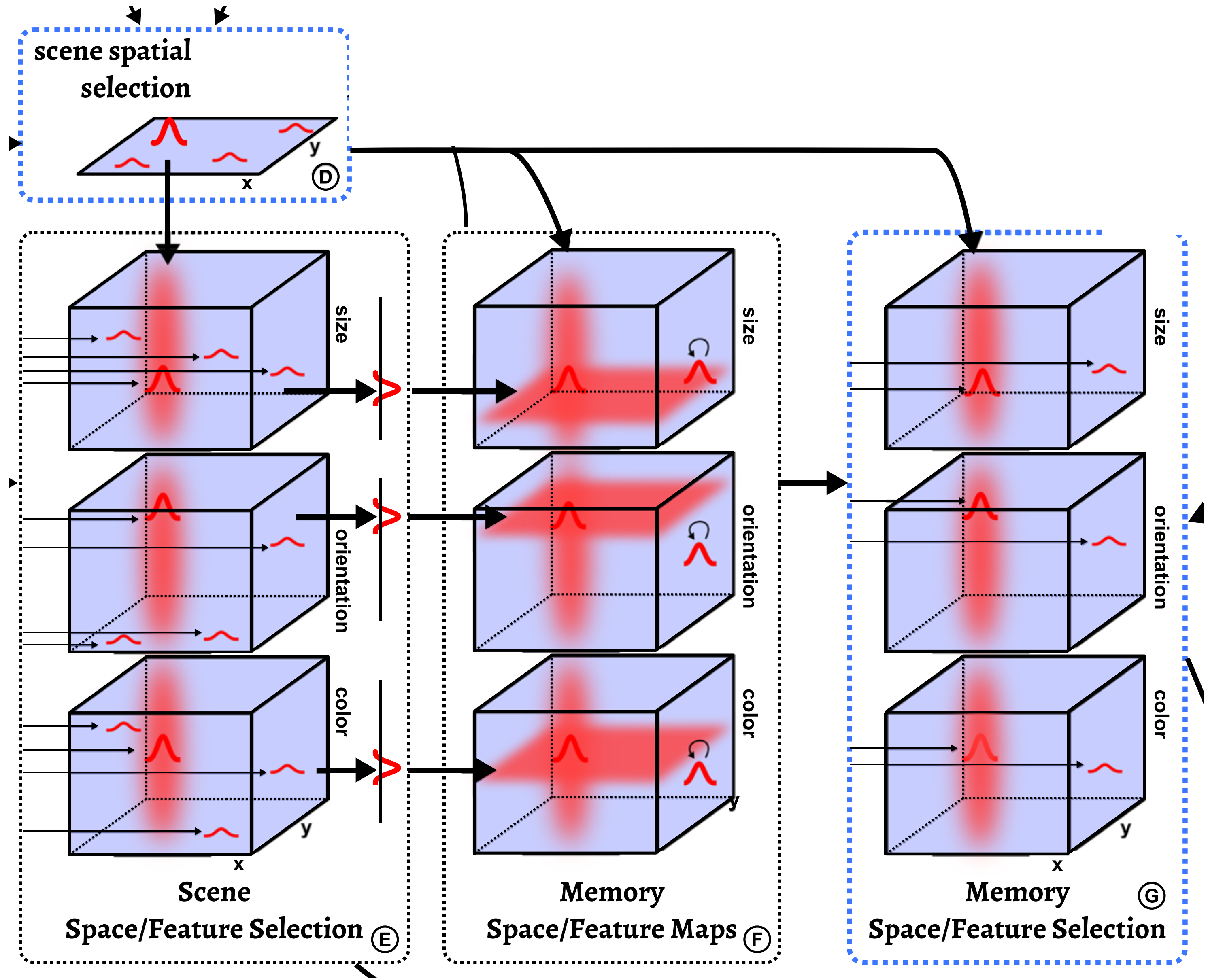
- separate 3 to 4 dimensional feature fields
- all of which share the dimension visual space (~all neurons have receptive fields)
- bind through space à la Feature Integration Theory (Treisman)



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

Binding through space

- bind through space à la Feature Integration Theory (Treisman)



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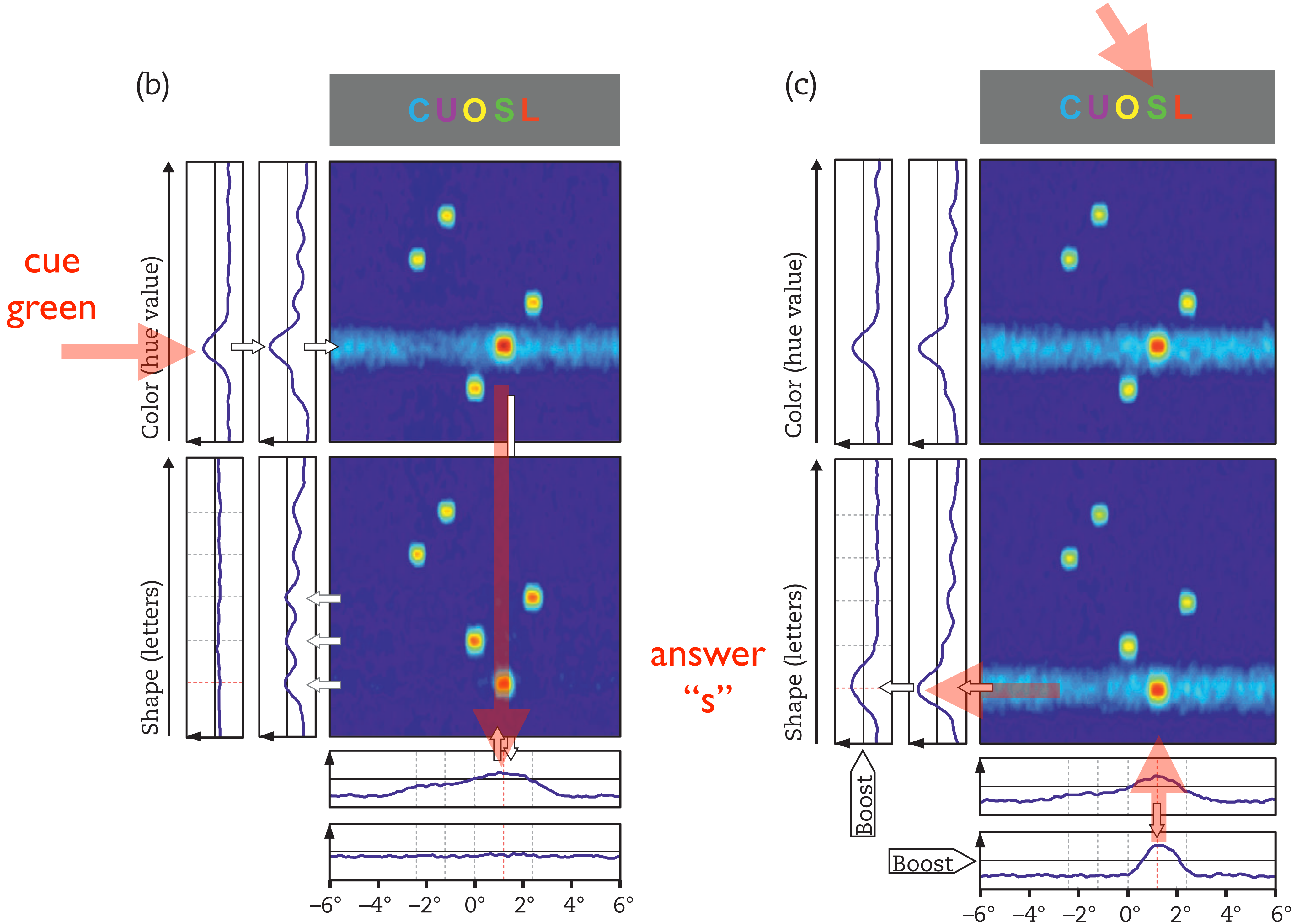
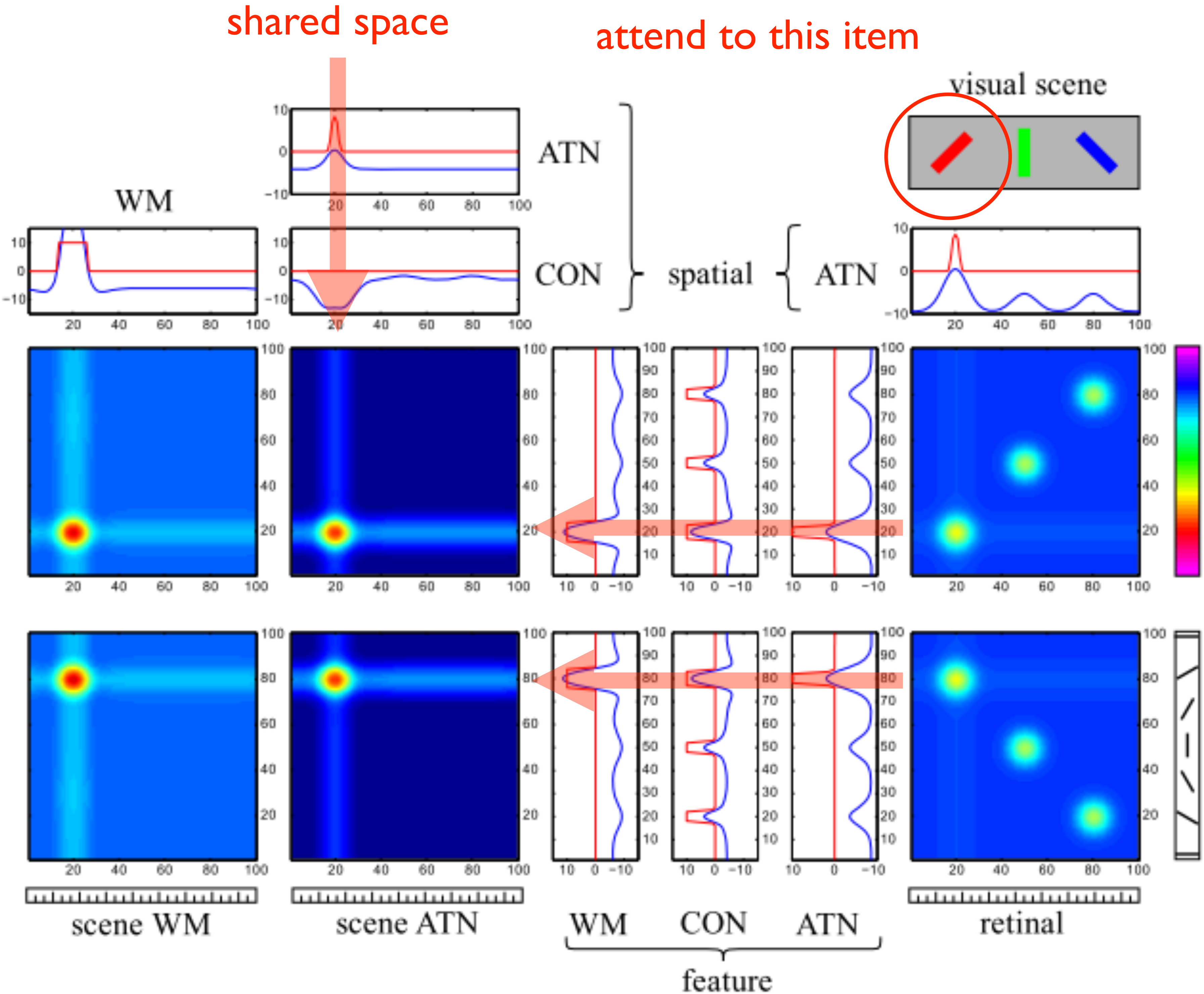
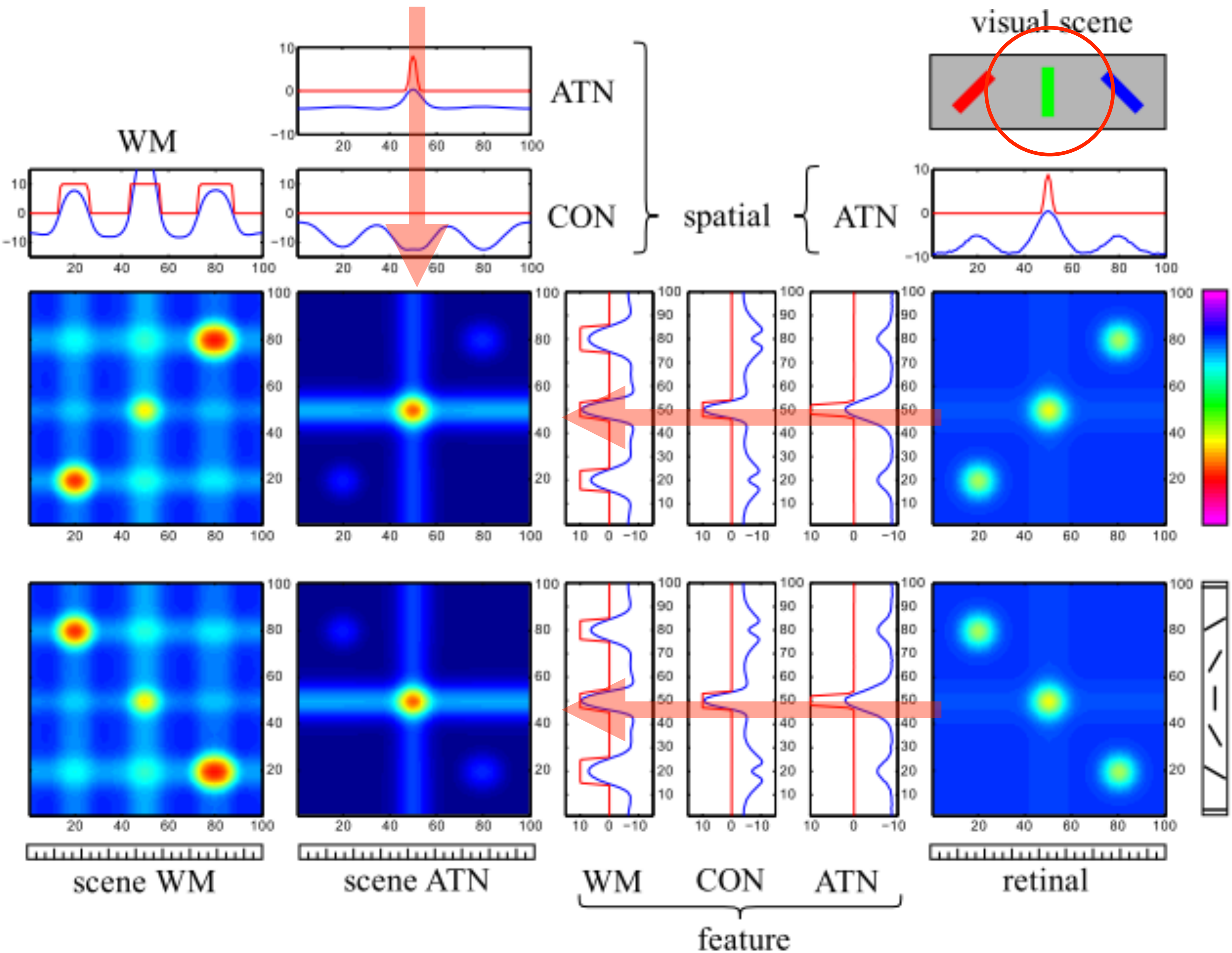


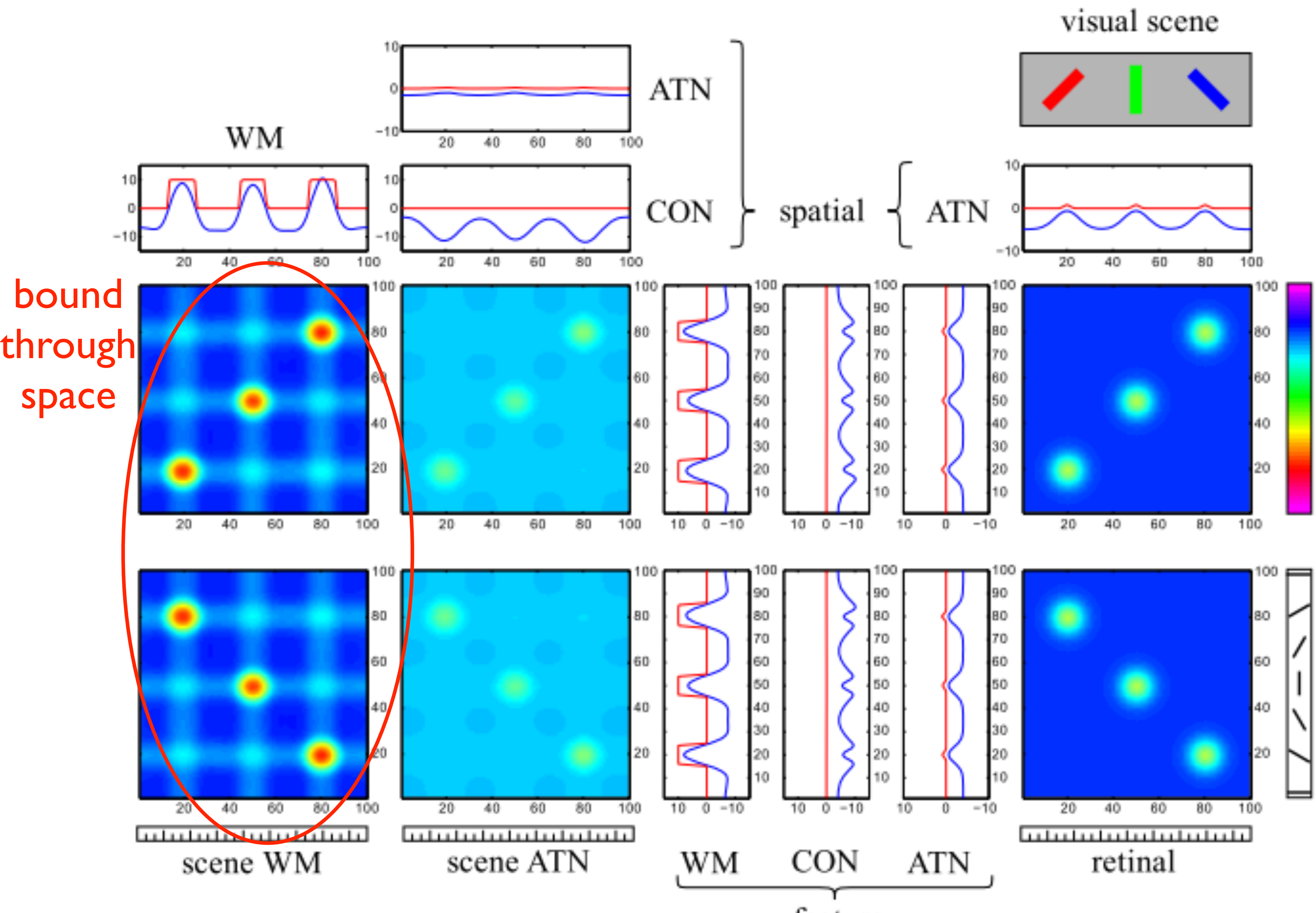
[Schneegans et al.,Ch 5 of *DFT Primer*, 2016]



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



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



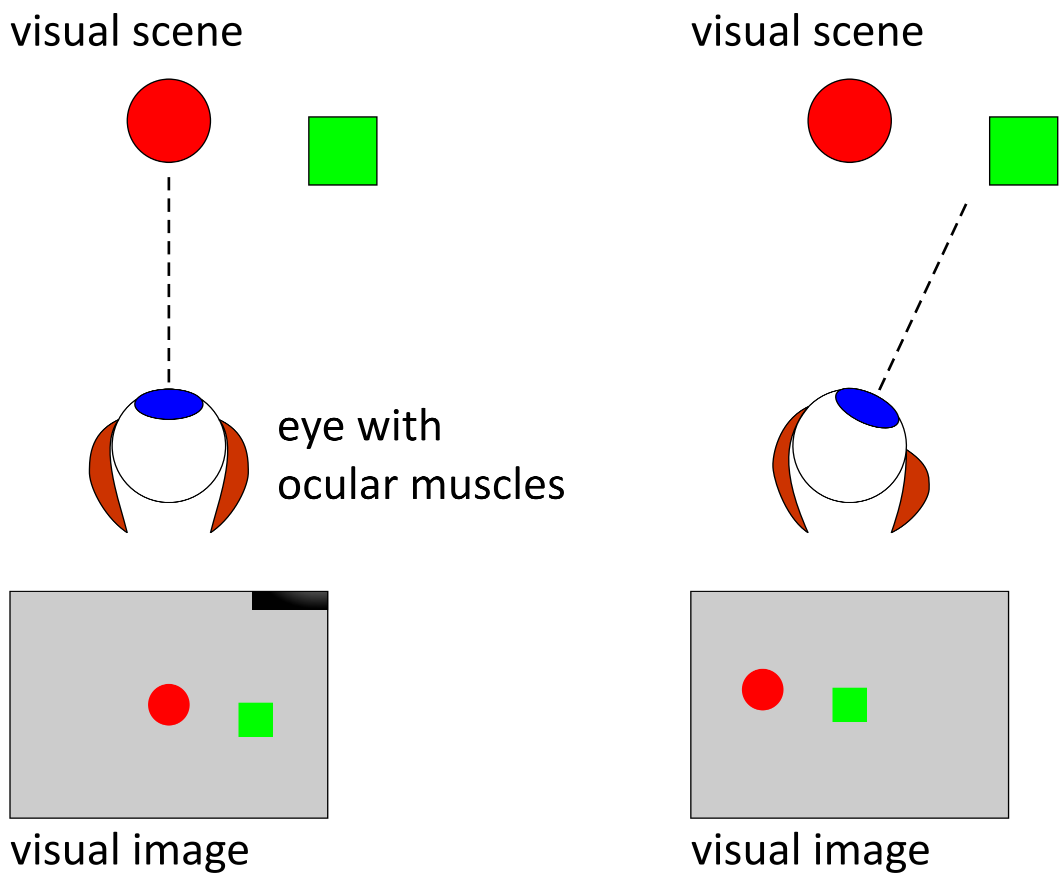
[Schneegans et al.,Ch 5 of *DFT Primer,* 2016]

Coordinate transforms

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

Coordinate transforms

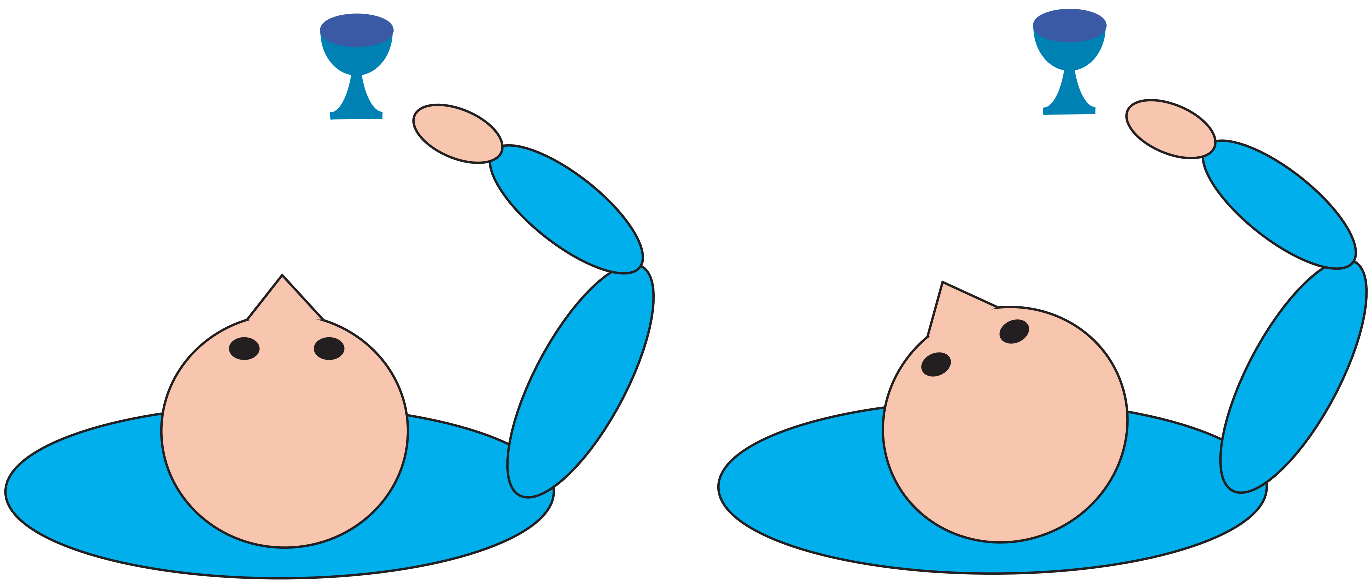
- eye movement: from retinal to body-centered representation (e.g. for reaching)



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

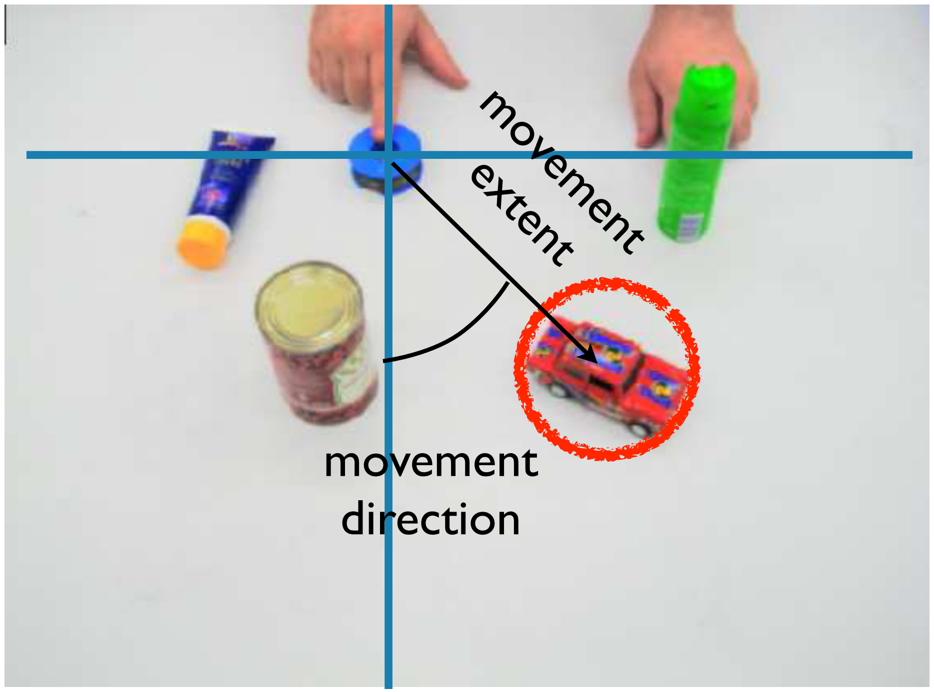
Coordinate transforms

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



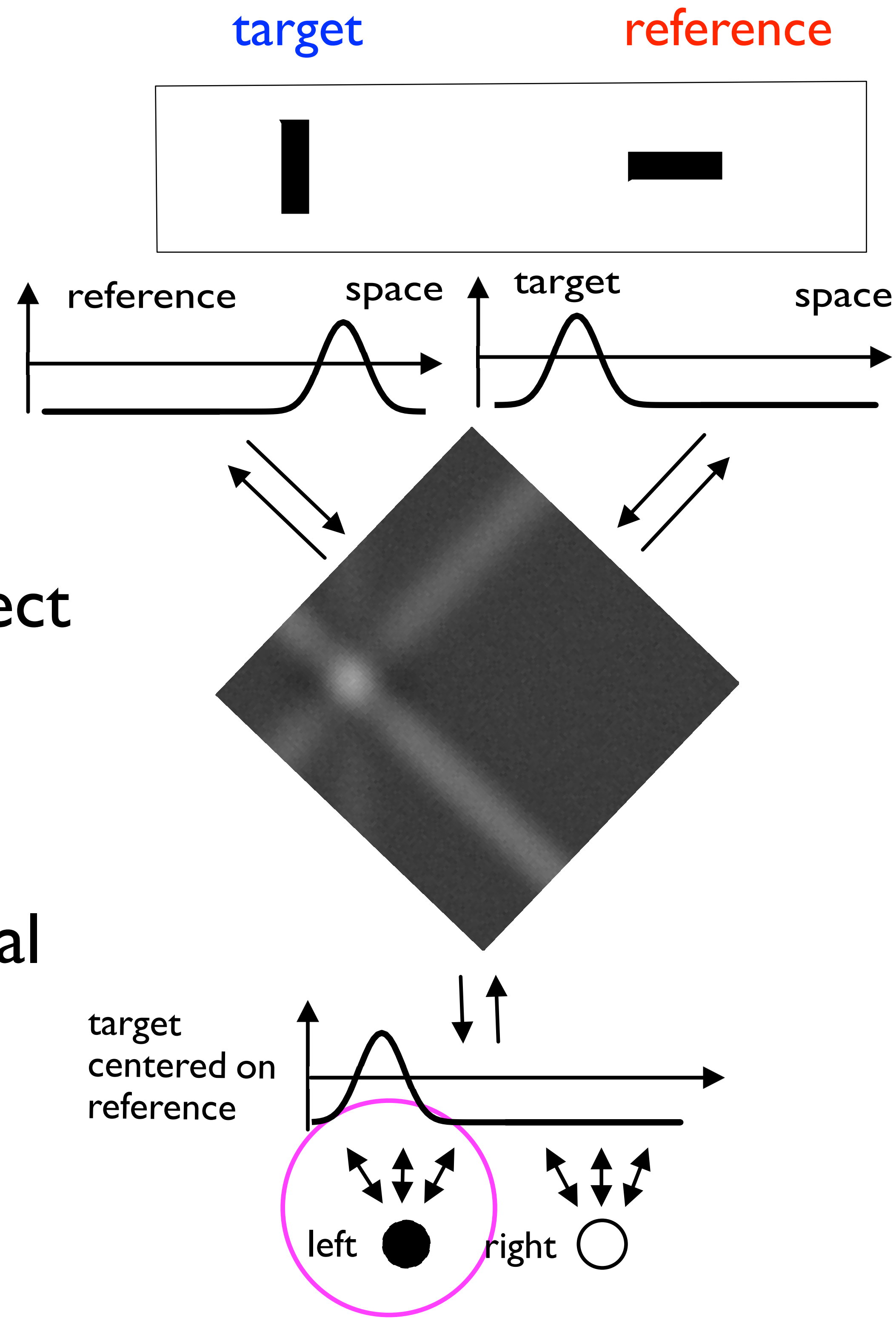
Coordinate transforms

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



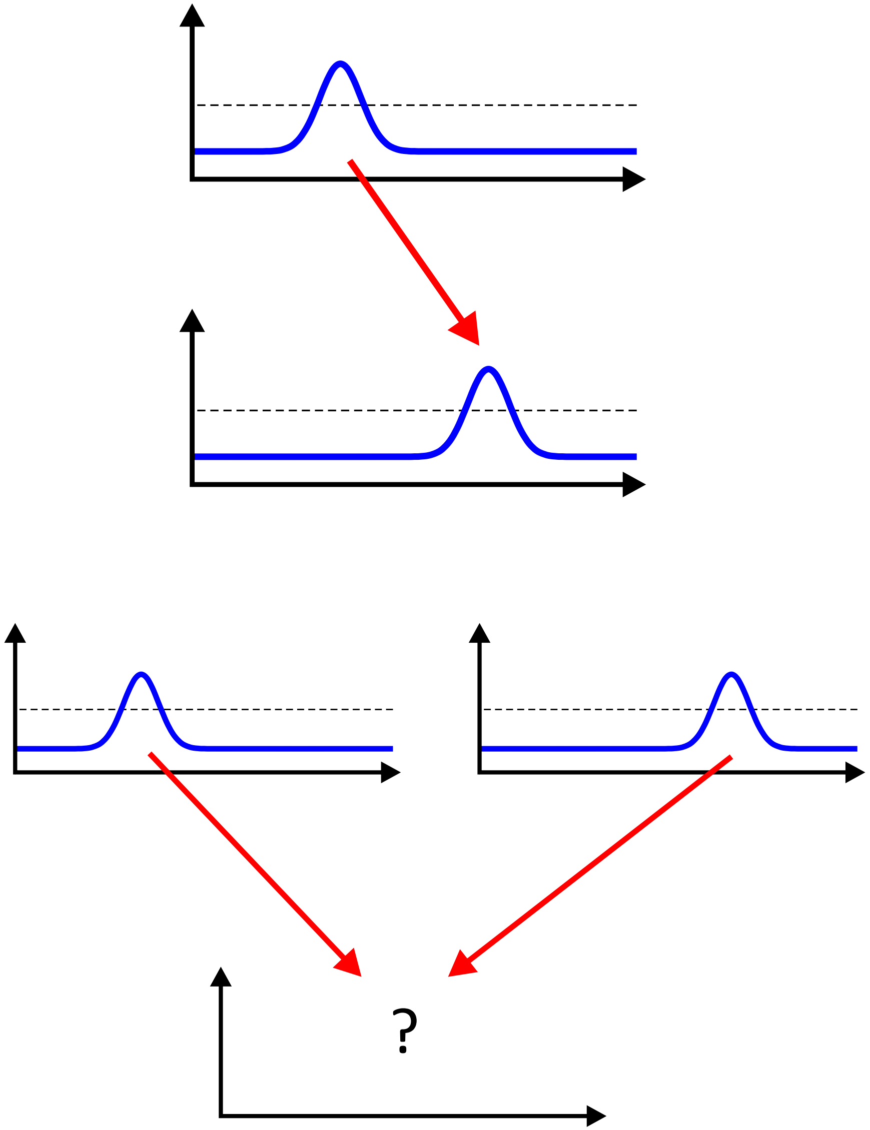
Coordinate transforms

- relational concepts: from visual space to frame centered in reference object
- e.g. “vertical object to the left of horizontal object”
- => Mathis Richter’s tutorial



Coordinate transforms

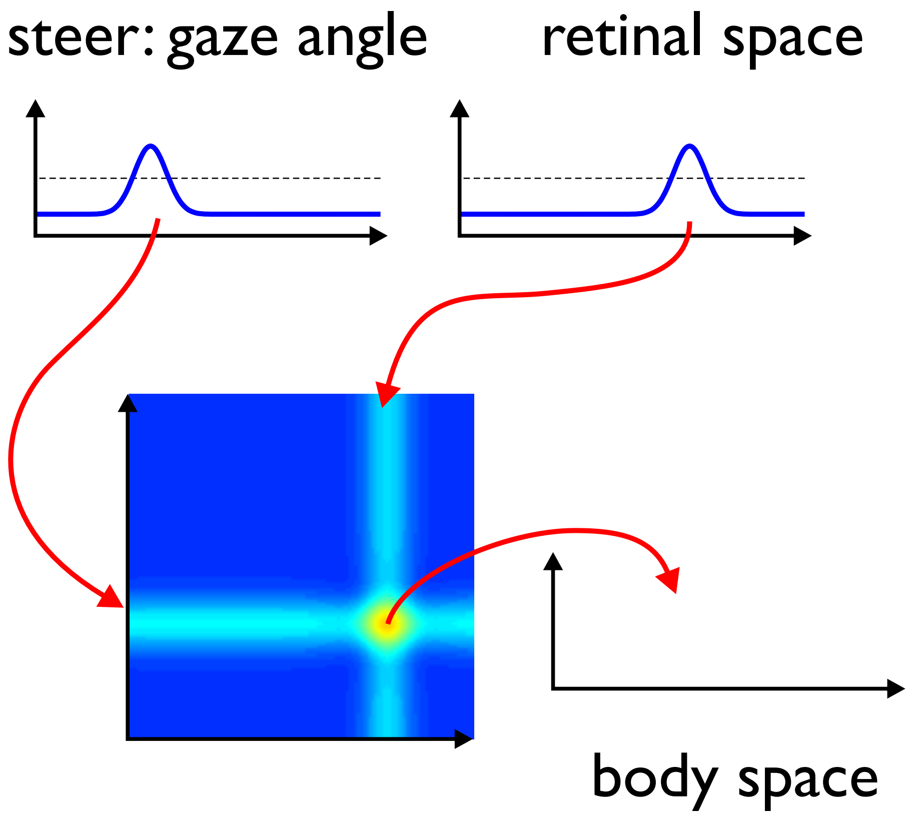
- fixed mapping: neural projection in a neural network
- flexible mapping steered by x
  - x=gaze direction
  - x=hand position
  - x=position of reference object



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

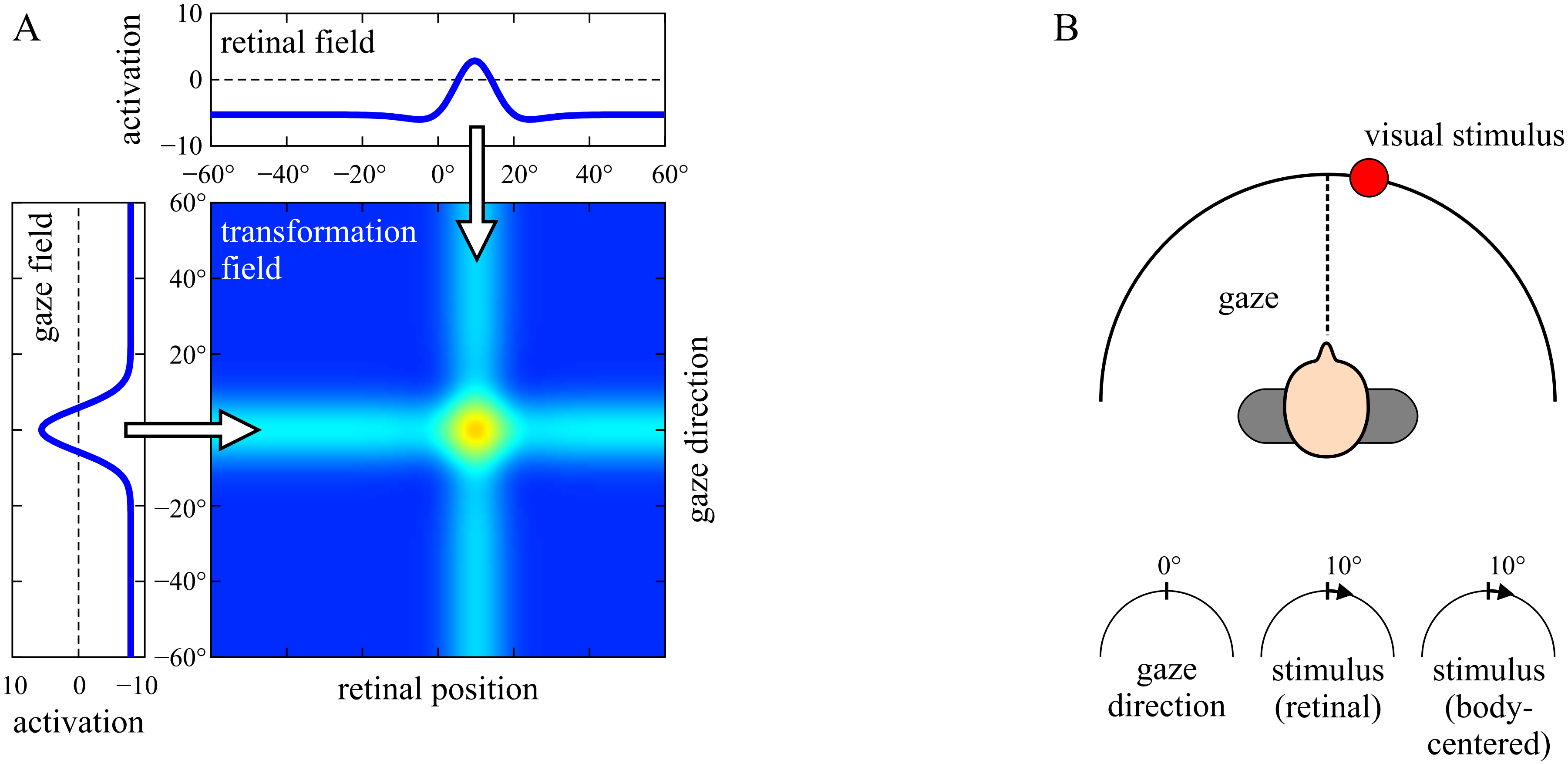
Coordinate transforms

- a joint representation of
  - the space to be mapped
  - the steering space
- bind the two spaces
- project out to transformed space



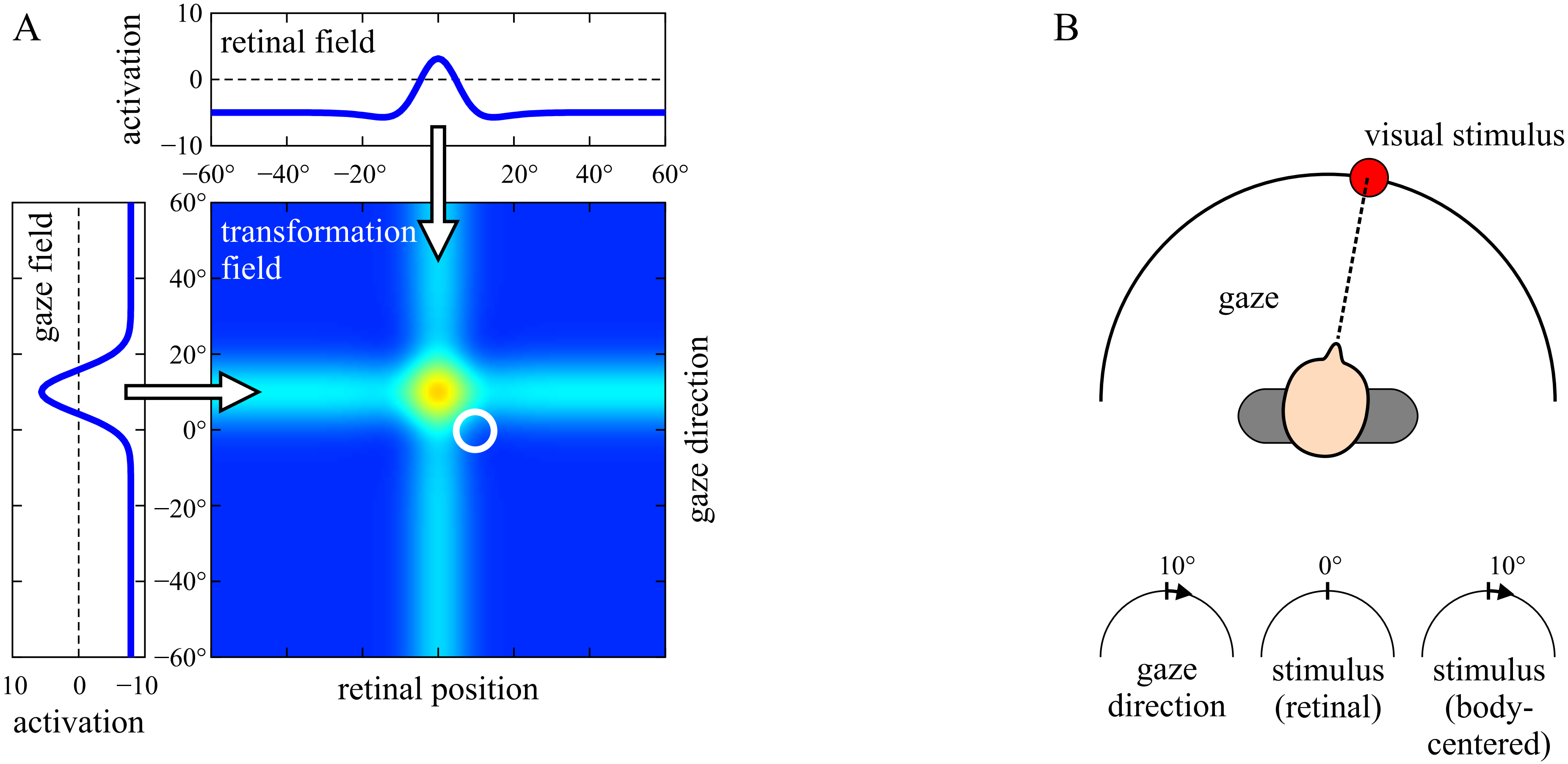
[Schneegans Ch 7 of *DFT Primer*, 2016]

Coordinate transforms



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

Coordinate transforms



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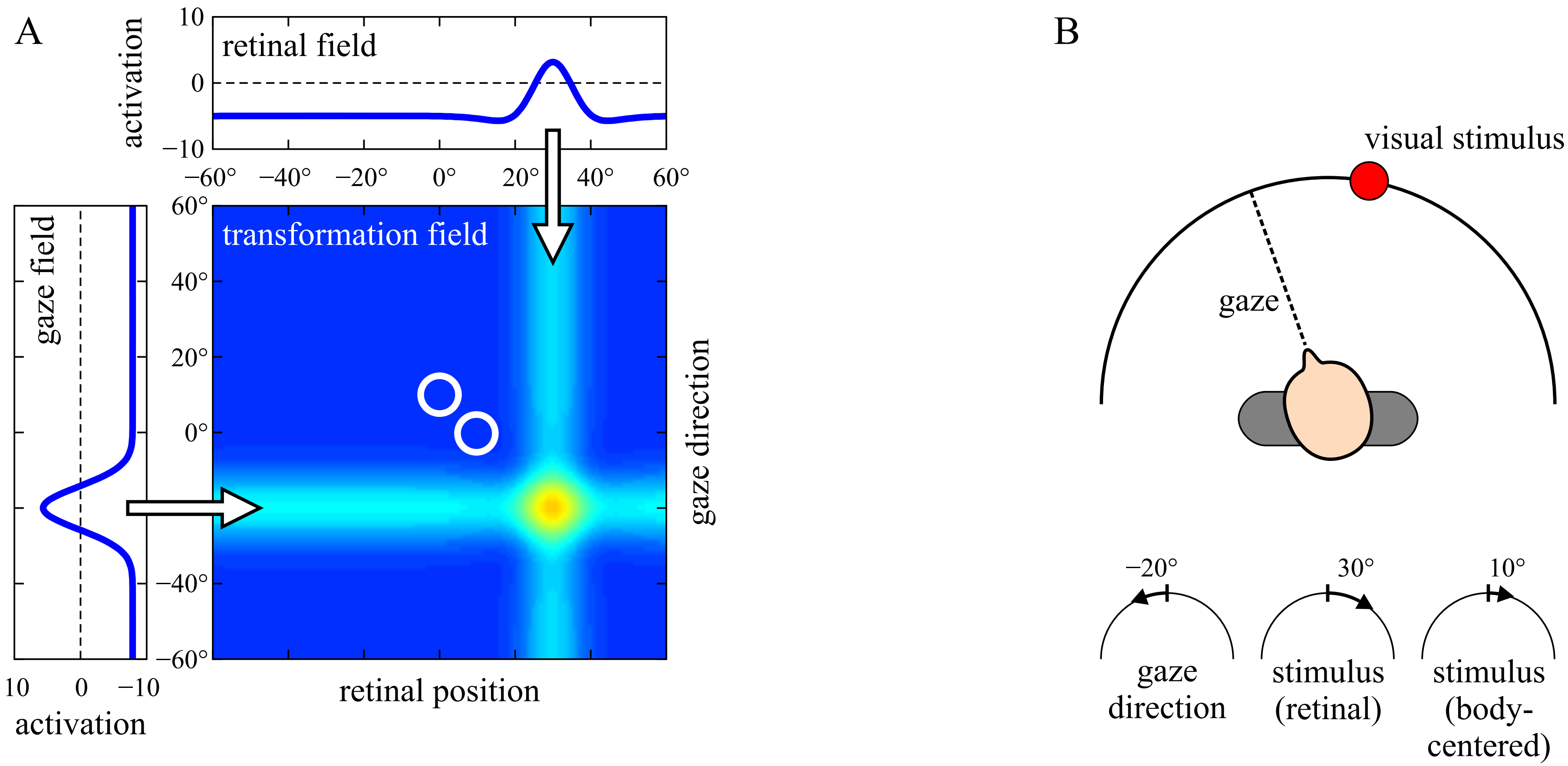
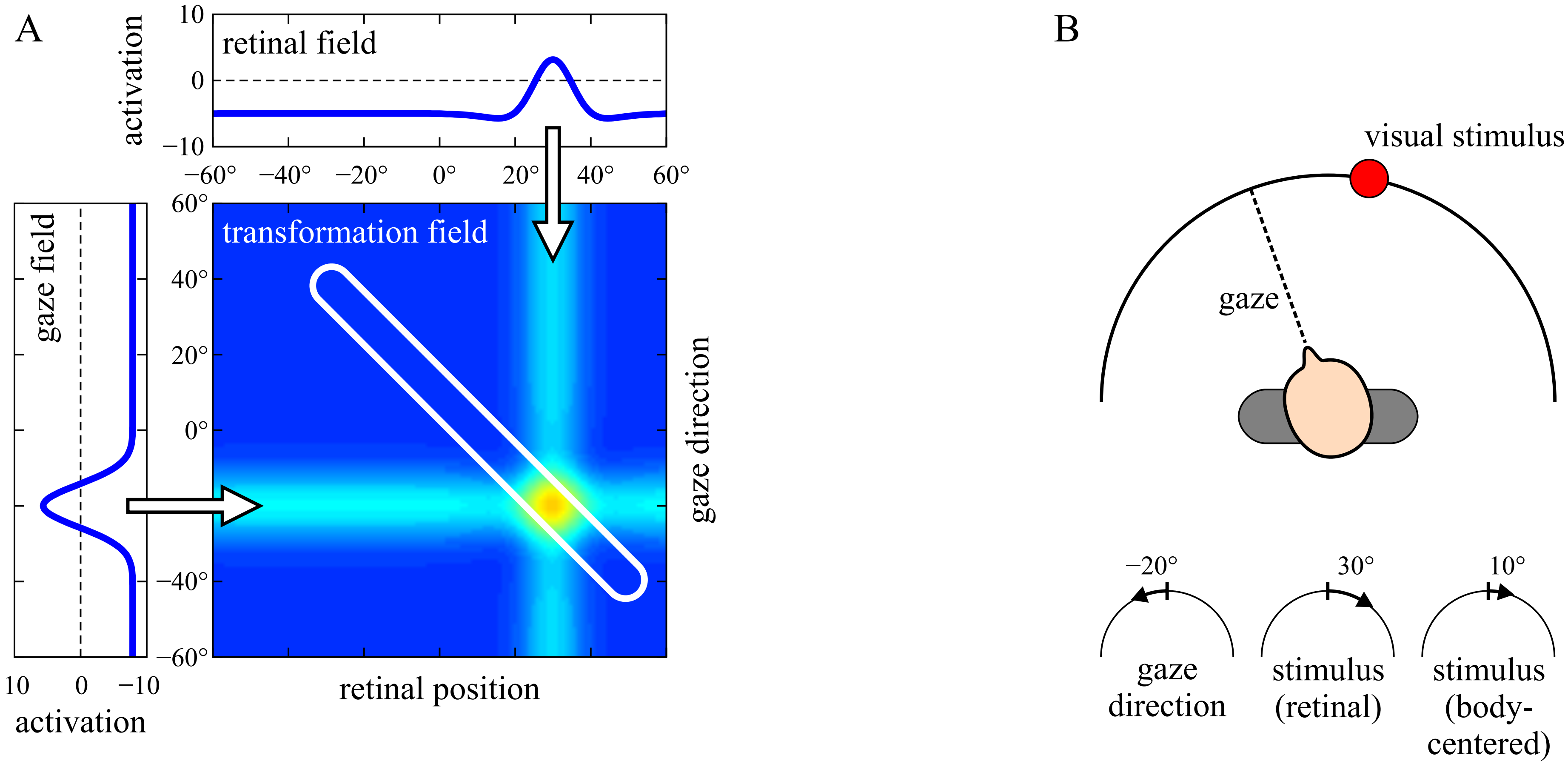
Coordinate transforms



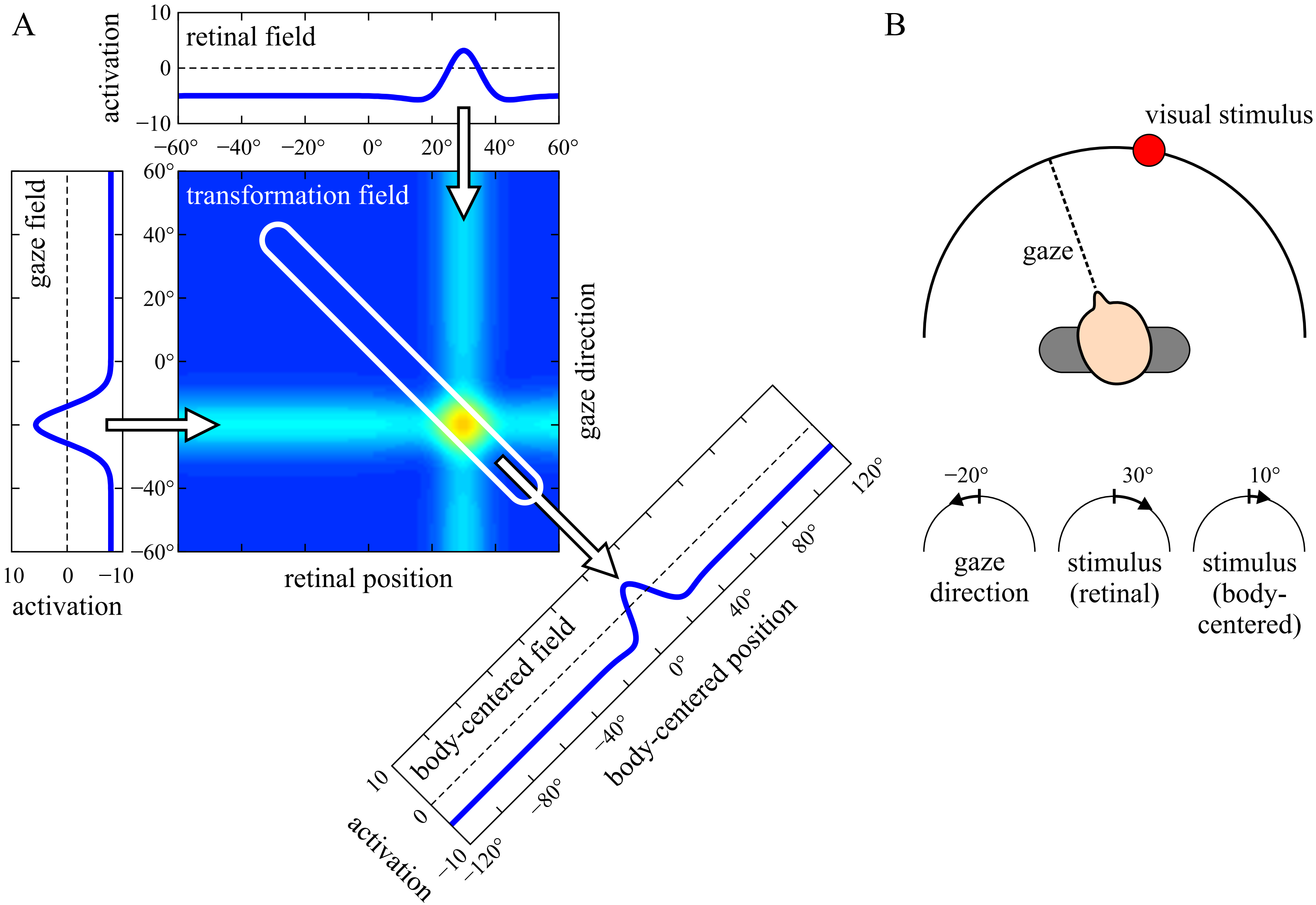
[Schneegans Ch 7 of *DFT Primer*, 2016]

Coordinate transforms



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

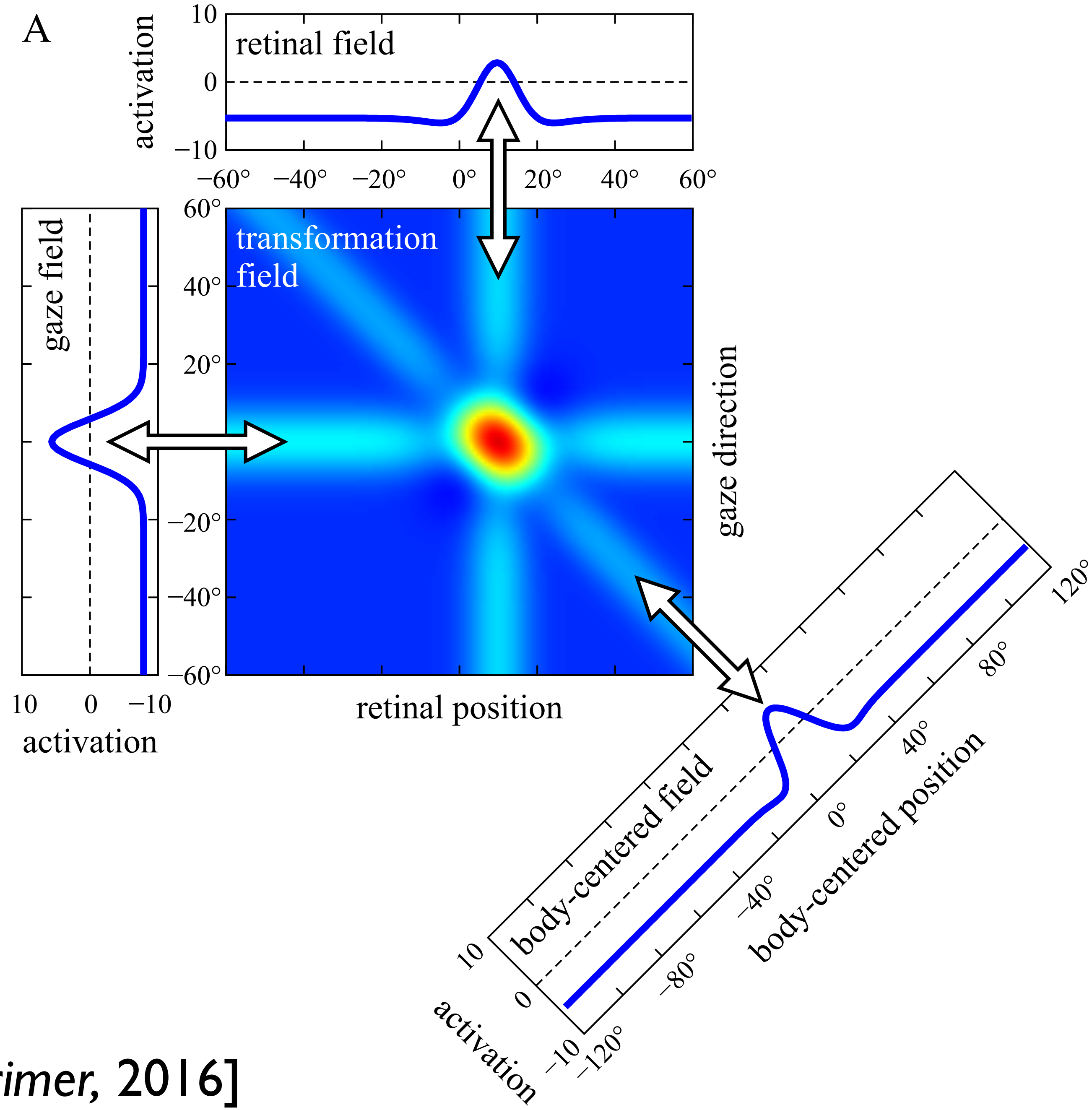
Coordinate transforms



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

Coordinate transforms

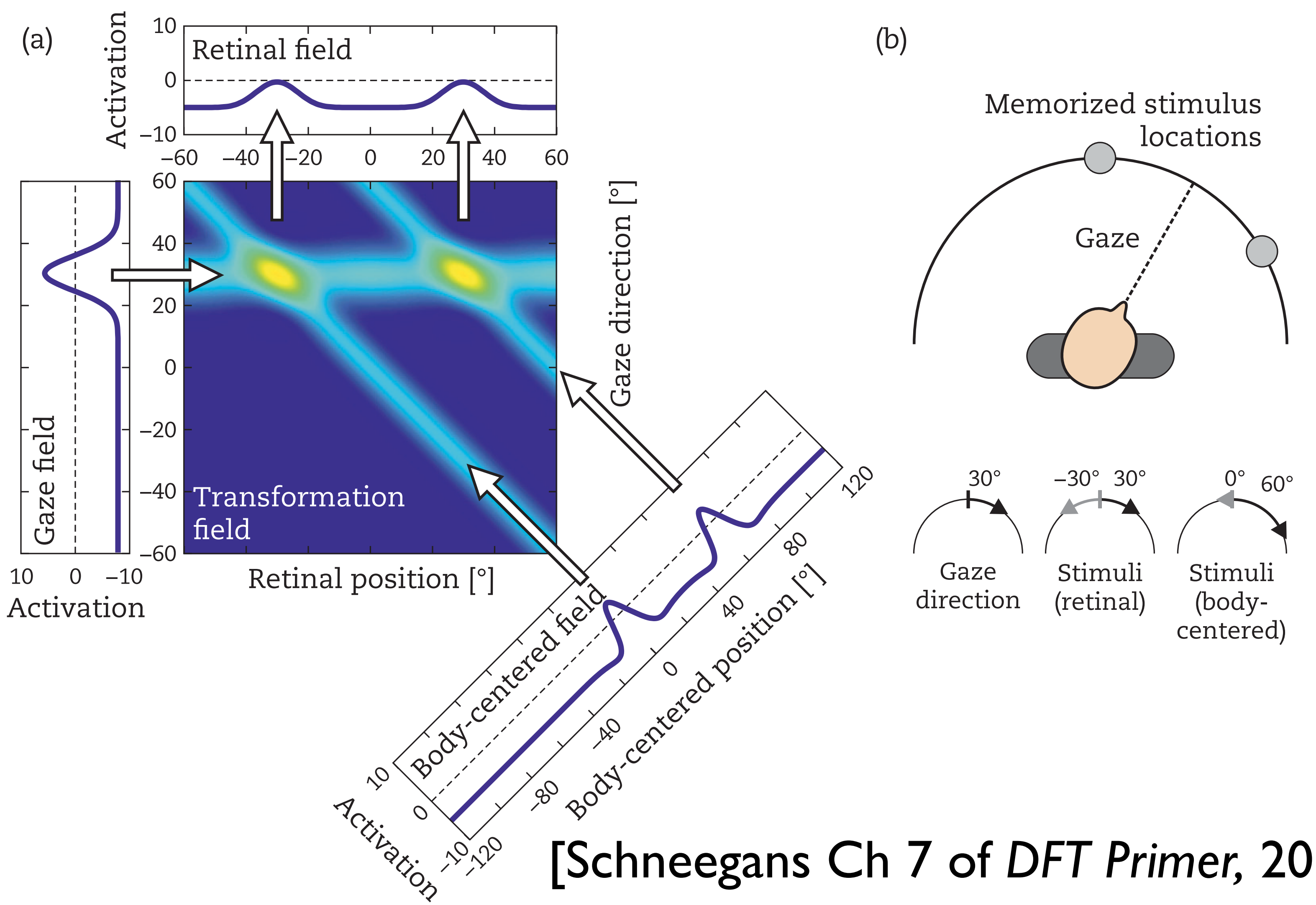
- bi-directional coupling
- enables new functions



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

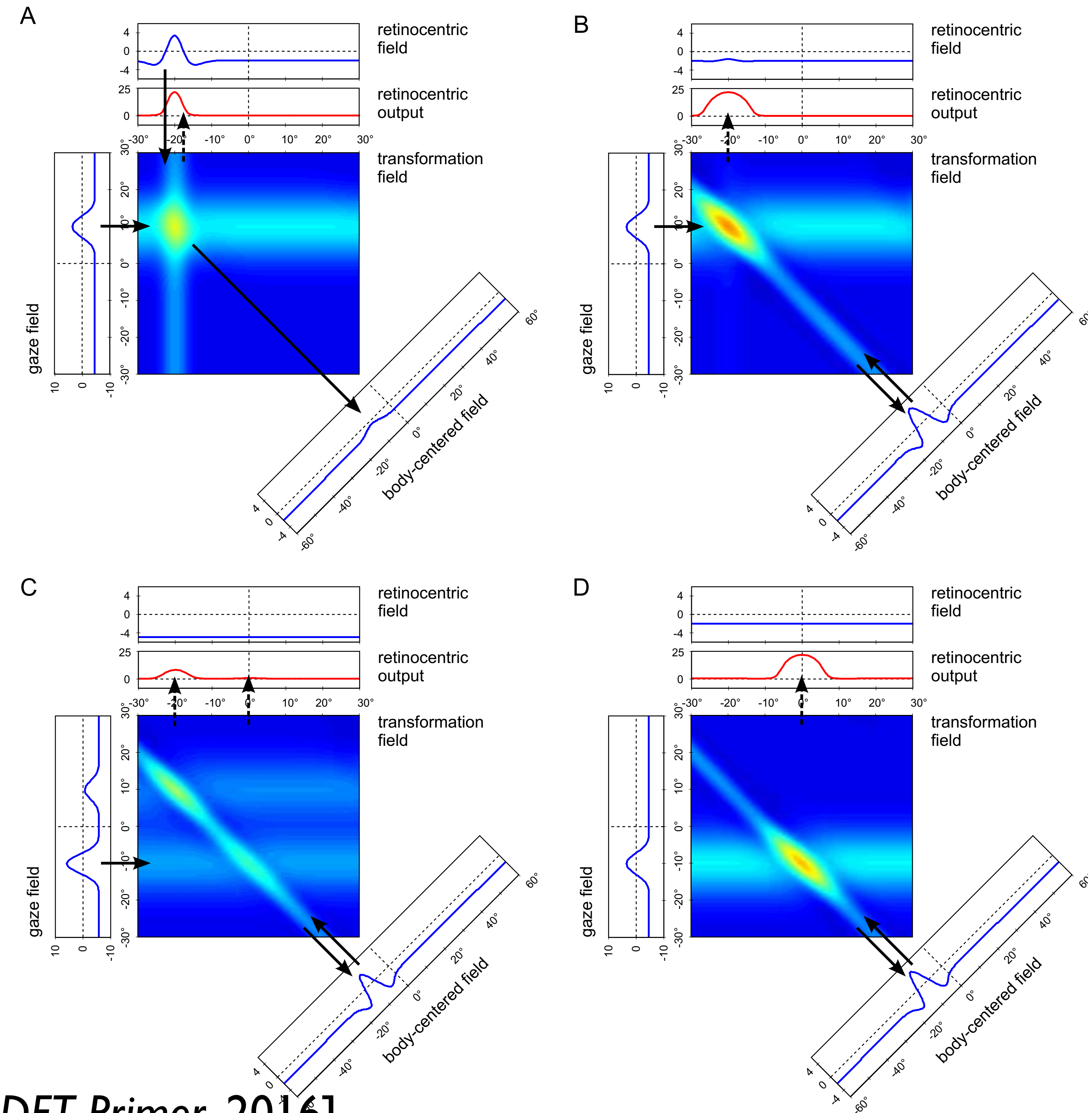
Coordinate transforms

- 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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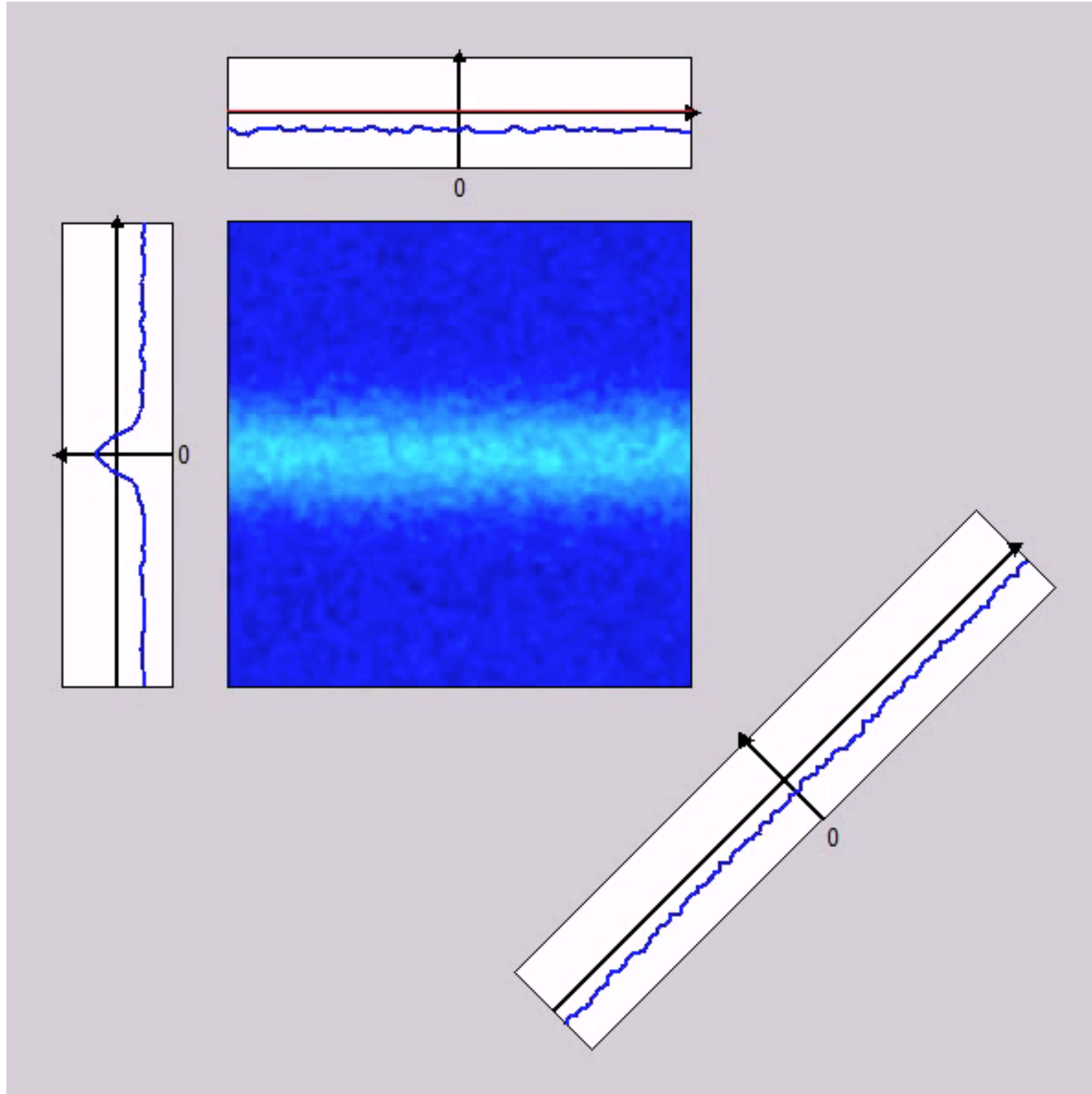
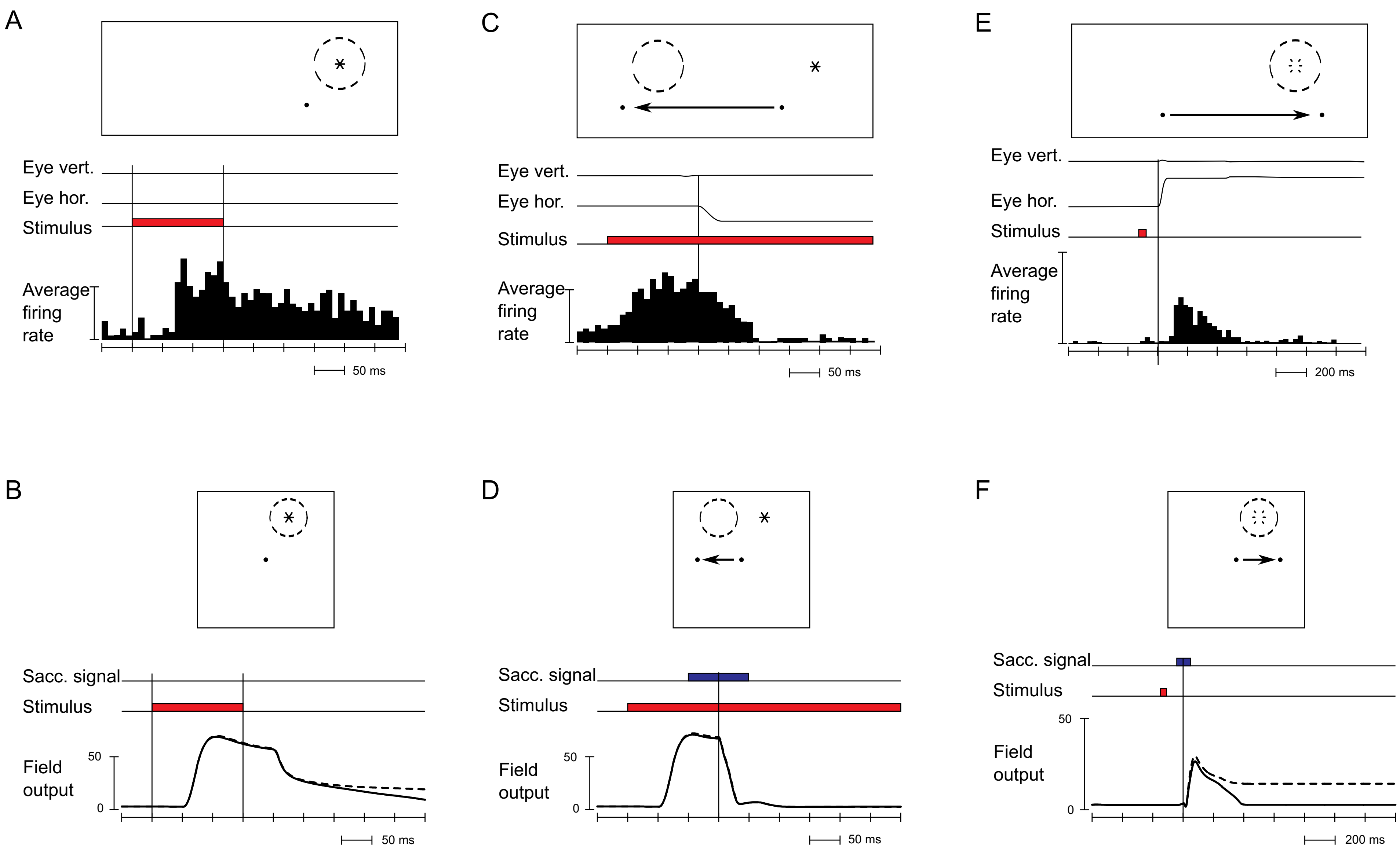


[Schneegans, Schöner *Biological Cybernetics* 2012]

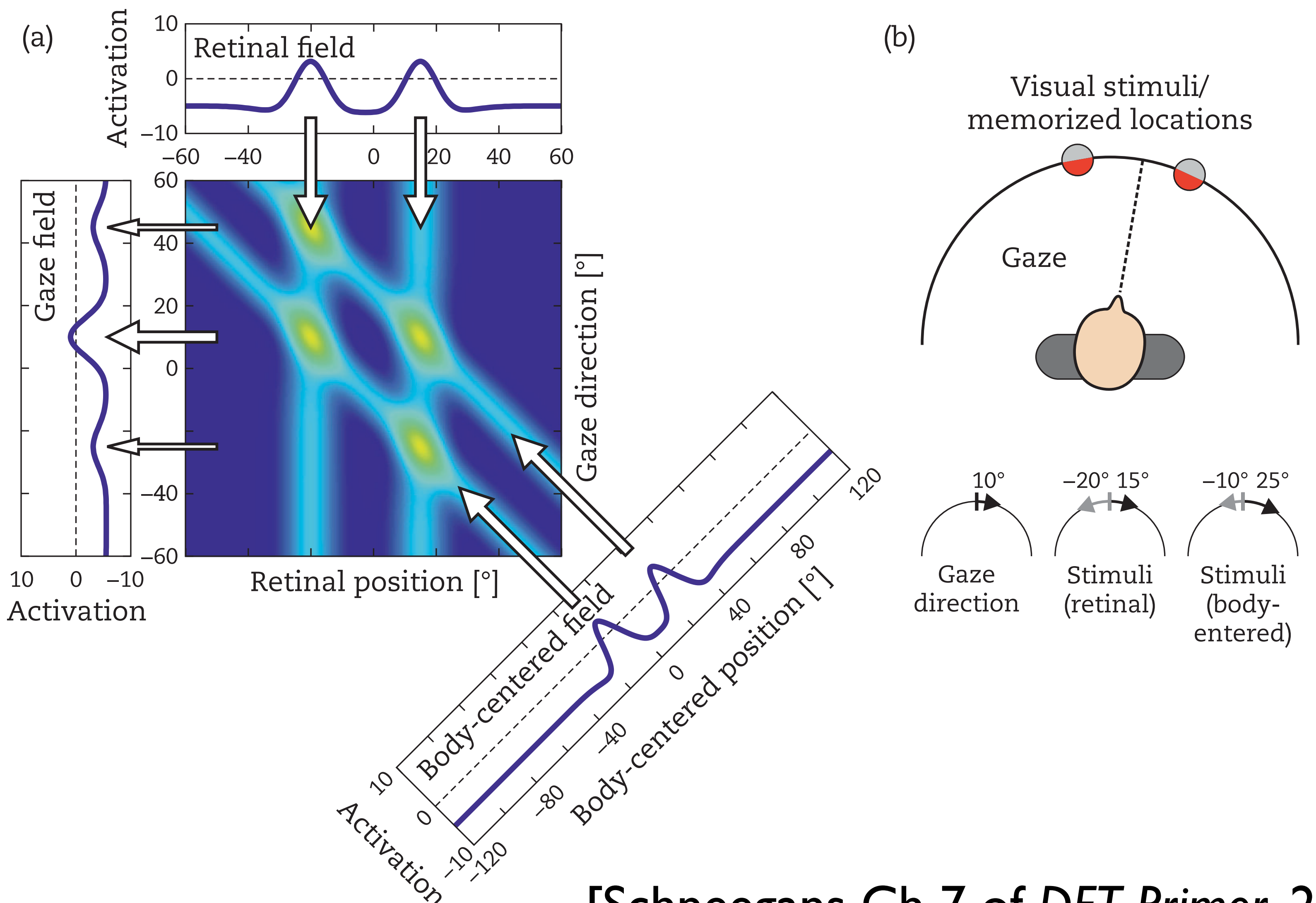


=> accounts for predictive updating of retinal representation

[Schneegans, Schöner *Biological Cybernetics* 2012]

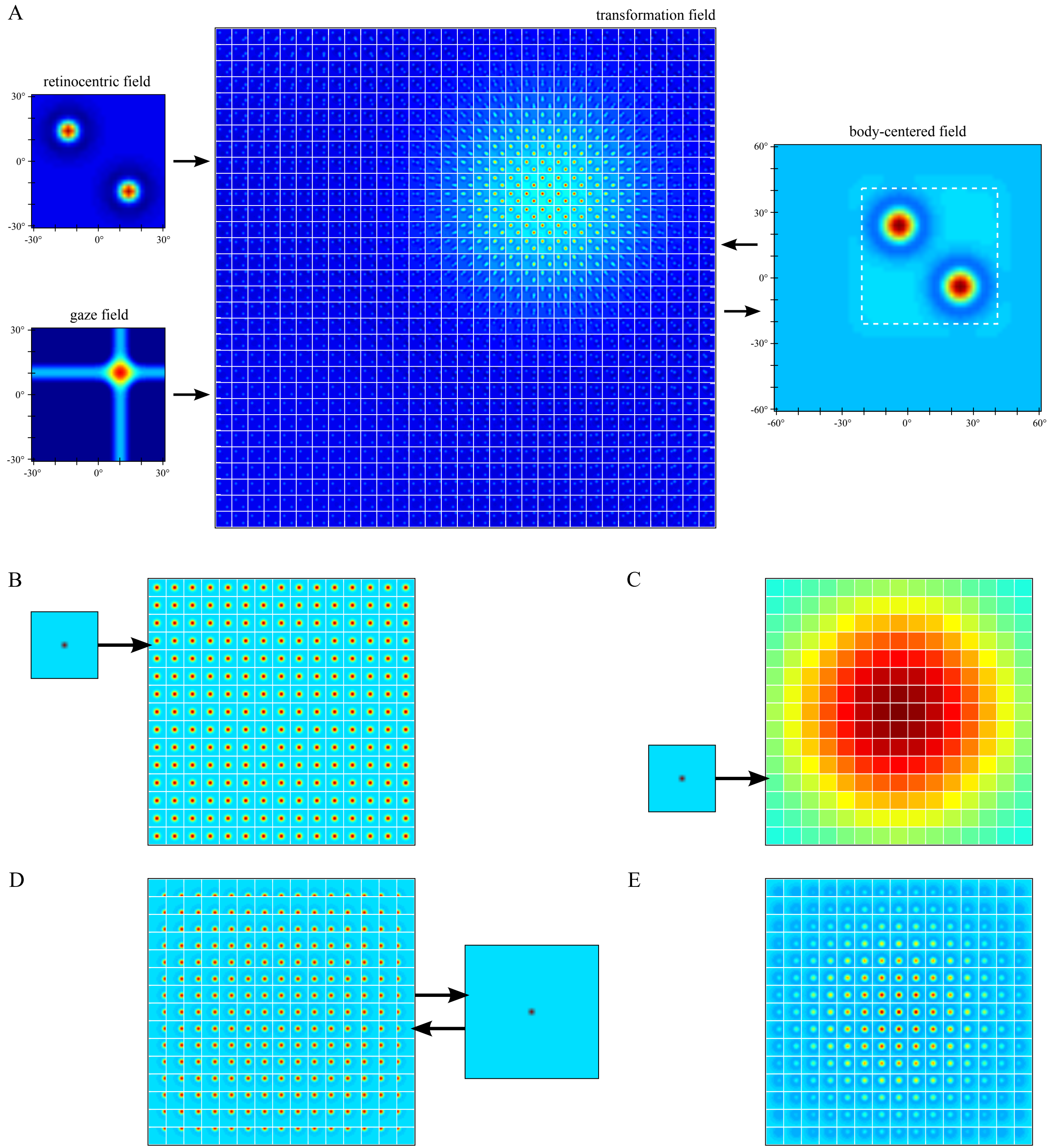
Coordinate transforms

- estimate gaze by matching scene to memorizes scene



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

Scaling



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

Scaling

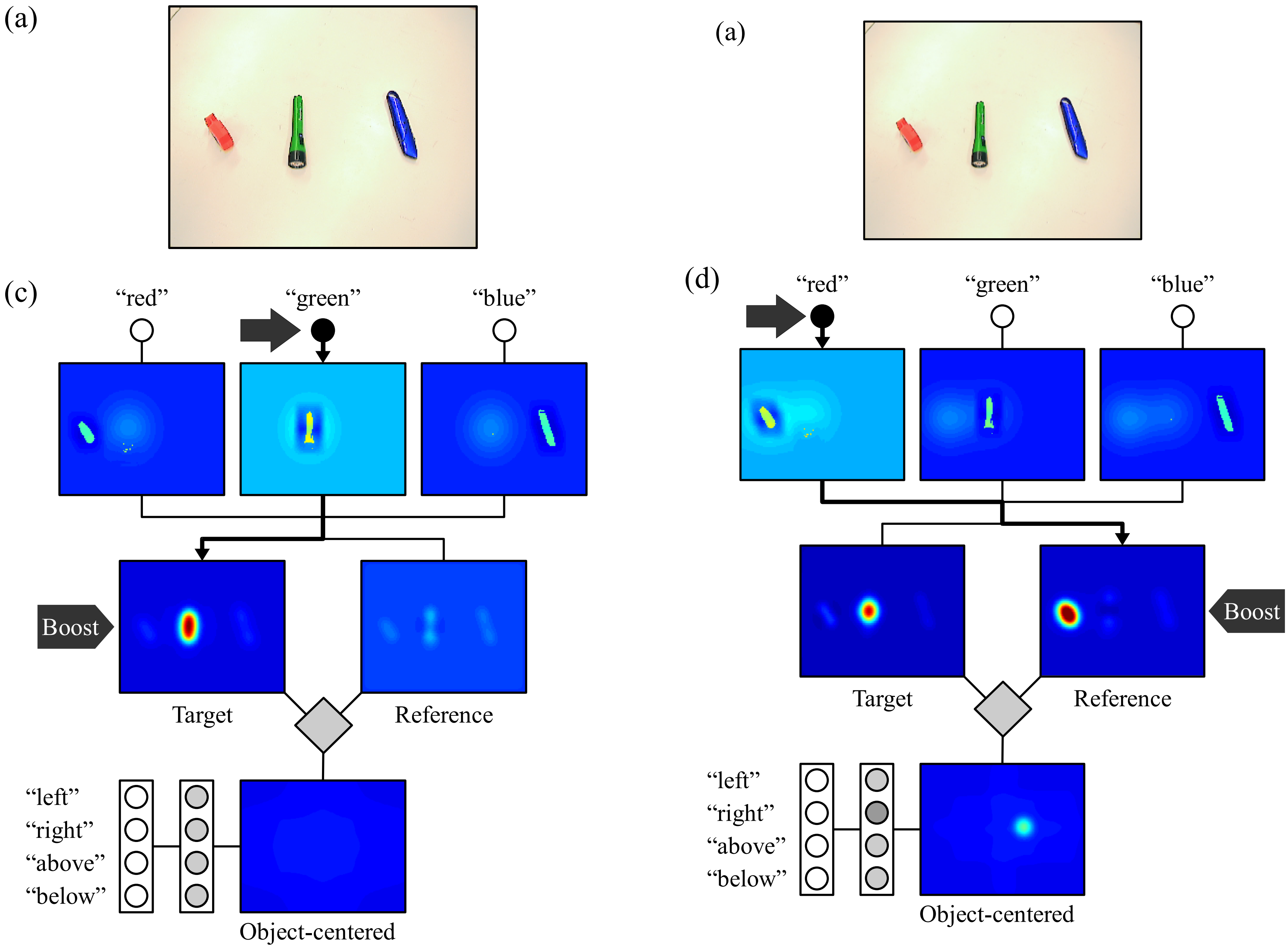
- joint representation of steering and transformed space ~ 4 dimensions
- binding through space… enables transforming only space!
- => coordinate transforms are linked to the sequentiality bottleneck!

DFT architectures

- why are the peaks and their instabilities preserved as we couple fields into architectures?
- stability => structural stability=robustness
- = invariance under change of the dynamics

DFT architectures

- controlling the instabilities of fields in an architecture is a source of flexibility
- example: architecture for perceptual grounding of spatial relations
- (=> tutorial by Mathis Richter)



[Lipinski et al: *JEP:LMC* (2011)]

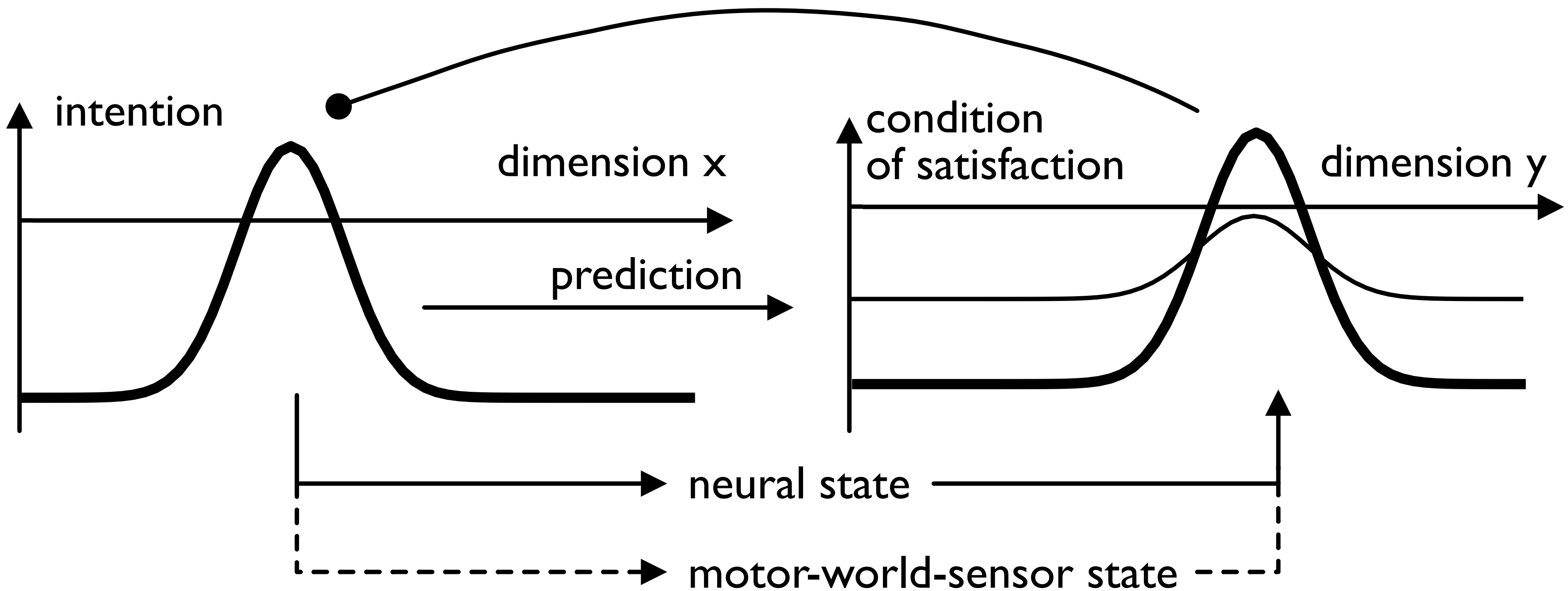
DFT architectures

- enabling a field go through the detection instability or not homogeneous input (boost)
- reweighs the effective coupling in an architecture
- ~gating

Sequence generation

- how would such boosts arise autonomously, from within the architecture?

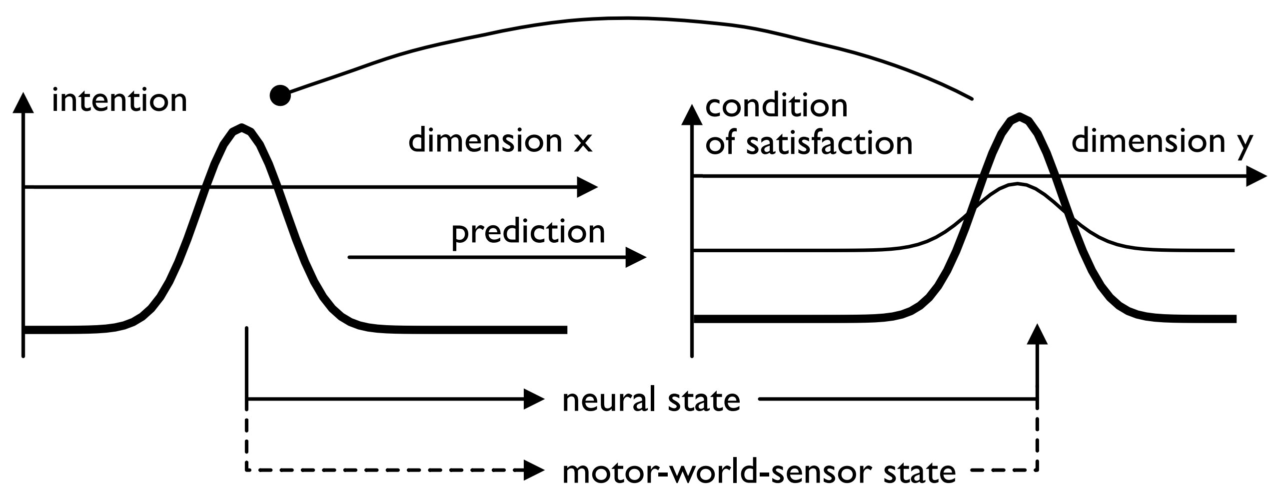
Condition of satisfaction



[Sandamirskaya, Schöner, *Neural Networks* 2010]

Condition of satisfaction

- detection instability in CoS as prediction and input match
- reverse detection in intention field
- reverse detection in CoS field
- => active transient



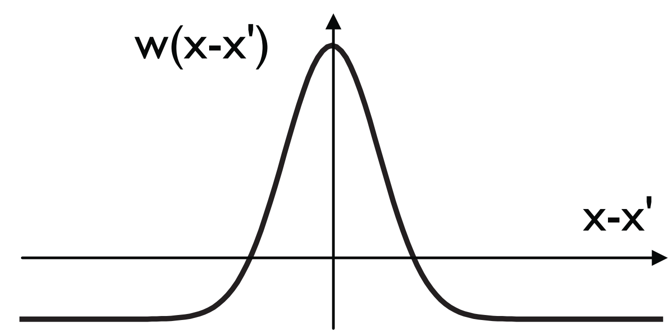
[Sandamirskaya, Schöner, *Neural Networks* 2010]

Sequence generation

- => Jan Tekülve's tutorial

How do DFT architectures compare to DNN architectures ?

- in DFT: commitment to localist representation, in which regular form of interaction enables continuum of attractor states
- => low-dimensional spaces
- (Hopfield networks have attractors that exploit distributed representations, but weights are specific for each attractor)



How do DFT architectures compare to DNN architectures ?

- Attractors and their instabilities enable
  - architectures
  - binding, coordinate transforms
  - autonomous sequential processing
- => toward neural processes accounts for higher cognition

How do DFT architectures compare to DNN architectures ?

- Output/classification layer of DNN often invoke "winner takes all" localist representations..
  - => could be the interface to DFT
  - high-dimensional distributed representation would be the efficient discrimination machine that works while high-dimensional input is present
  - while low-dimensional localist DFT representation would be the neural dynamic cognition machine that works autonomously not dependent on ongoing input
- => DFT as neural account for symbolic processing?

DFT vs VSA

- Vector-symbolic architectures (VSA) are a theoretical alternative
  - high-dimensional distributed representations as vectors that are symbols
  - afford combination (information processing) while preserving the original vector
  - classical version is not neurally feasible
  - and creates the symbol grounding problem at encocding

DFT vs VSA

- Neural engineering framework (NEF) is proposed as a possible neural implementation of VSA
  - vectors represented by (small) populations of spiking neural networks
- But: to preserve original vectors, connectivity in architectures is very special
  - connectivity takes into account the original encoding
  - => non-local dependence of connectivities on each other… that may not be compatible with neural principles

Summary

- DFT is based on the hypothesis that the dynamics of neural populations = privileged level of description for neural process accounts of behavior and thinking
- units of representation are attractors in low-dimensional activation fields that can be linked to the sensory/motor surfaces
- stability => robustness, enables architectures
- through binding, coordinate transforms, and sequence generation to higher cognition

[Schöner *TopiCS* 2019]