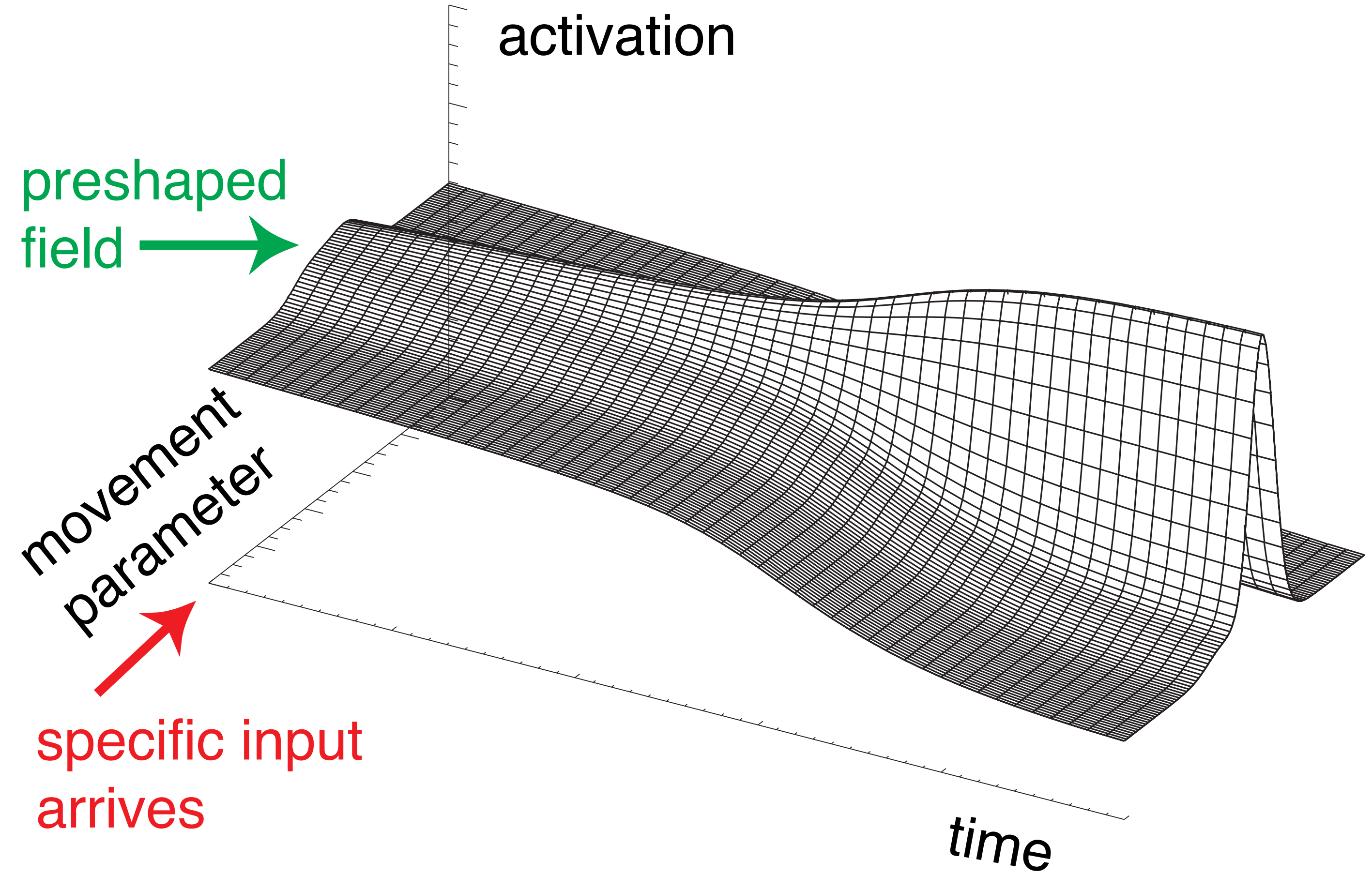
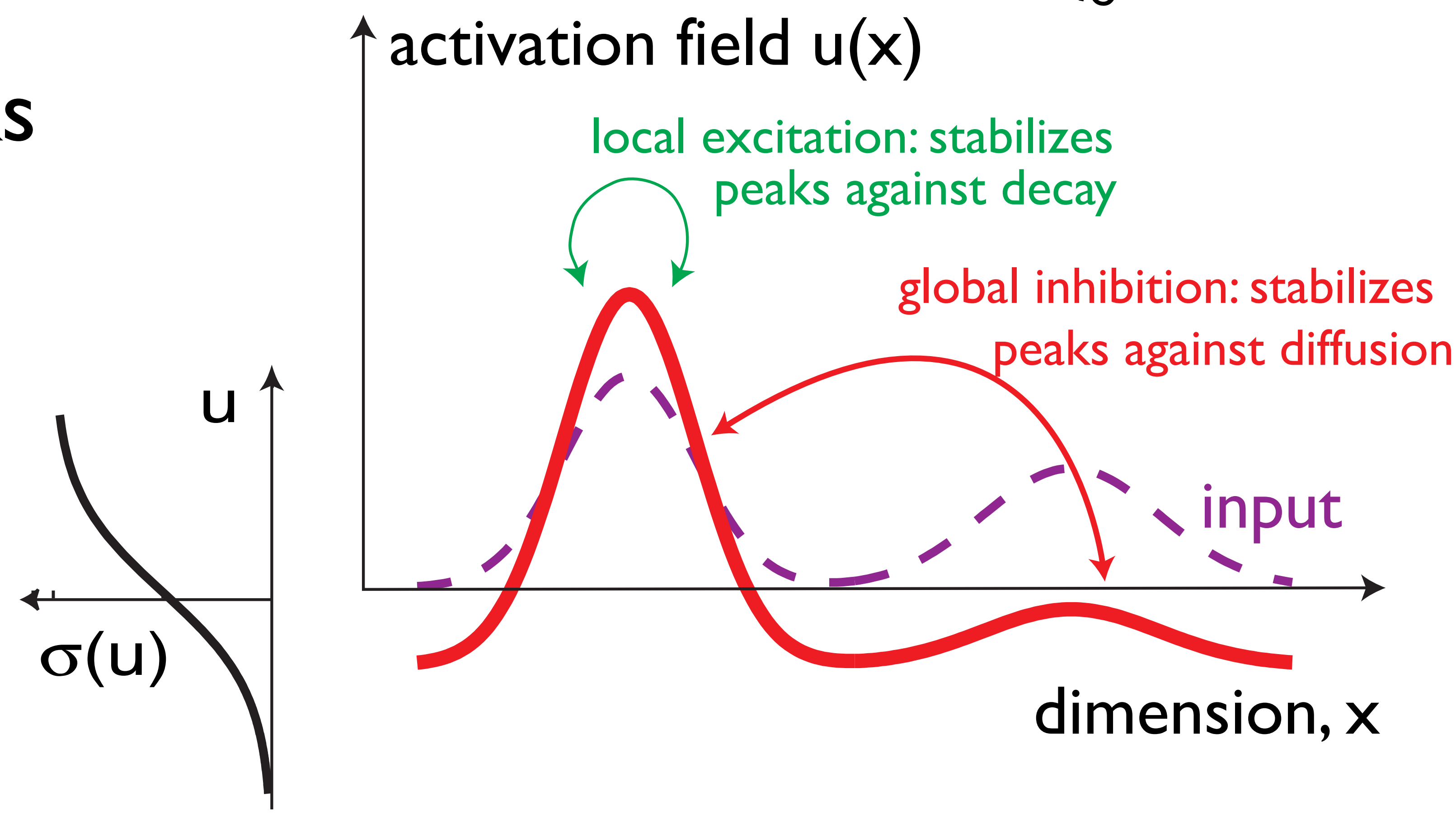
Higher-dimensional dynamics fields enable new cognitive function

Gregor Schöner

Core of DFT

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



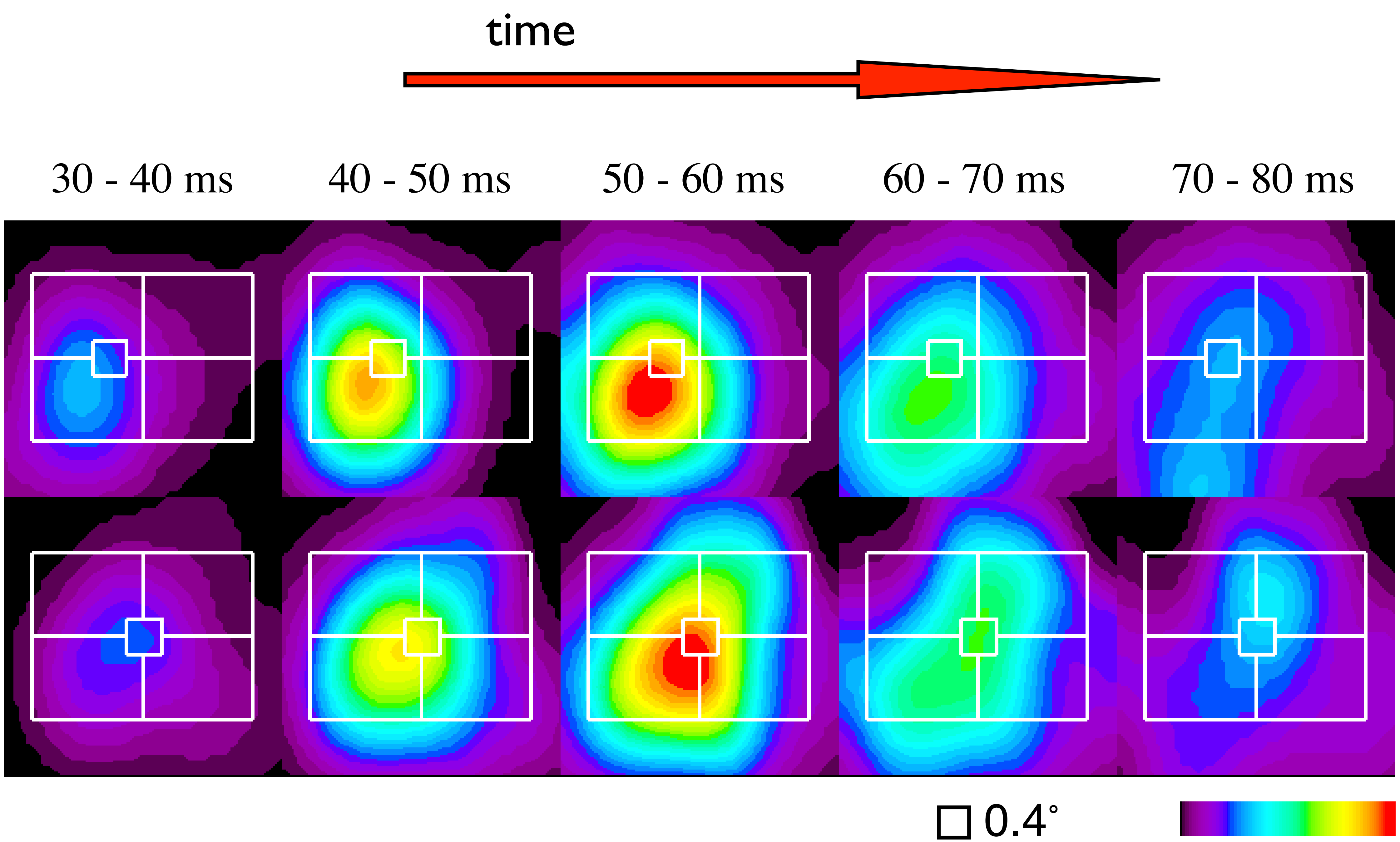


Dimensionality of fields

- 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

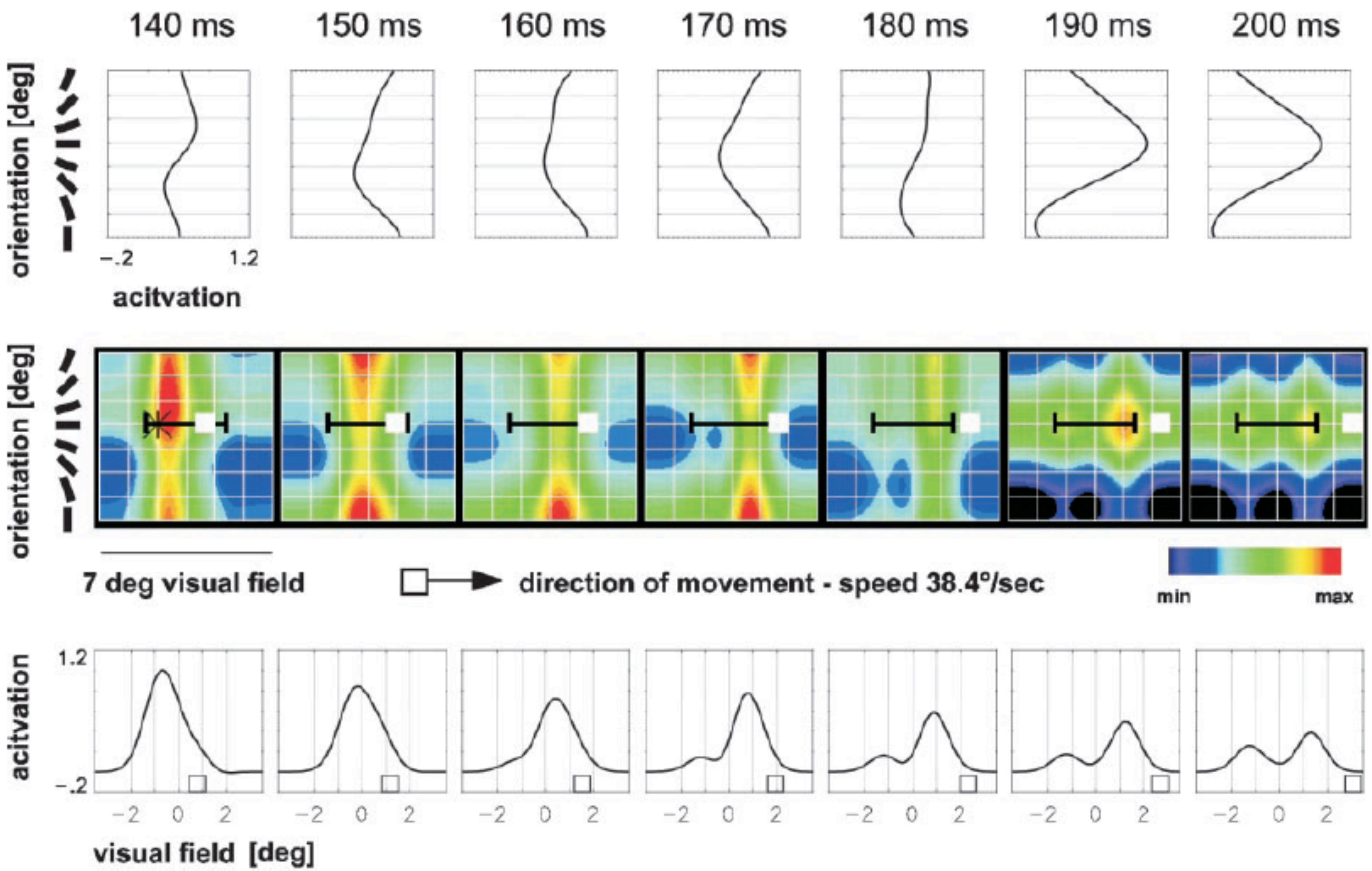
- obviously two-dimensional



[Jancke et al., 1999]

example: visual feature map

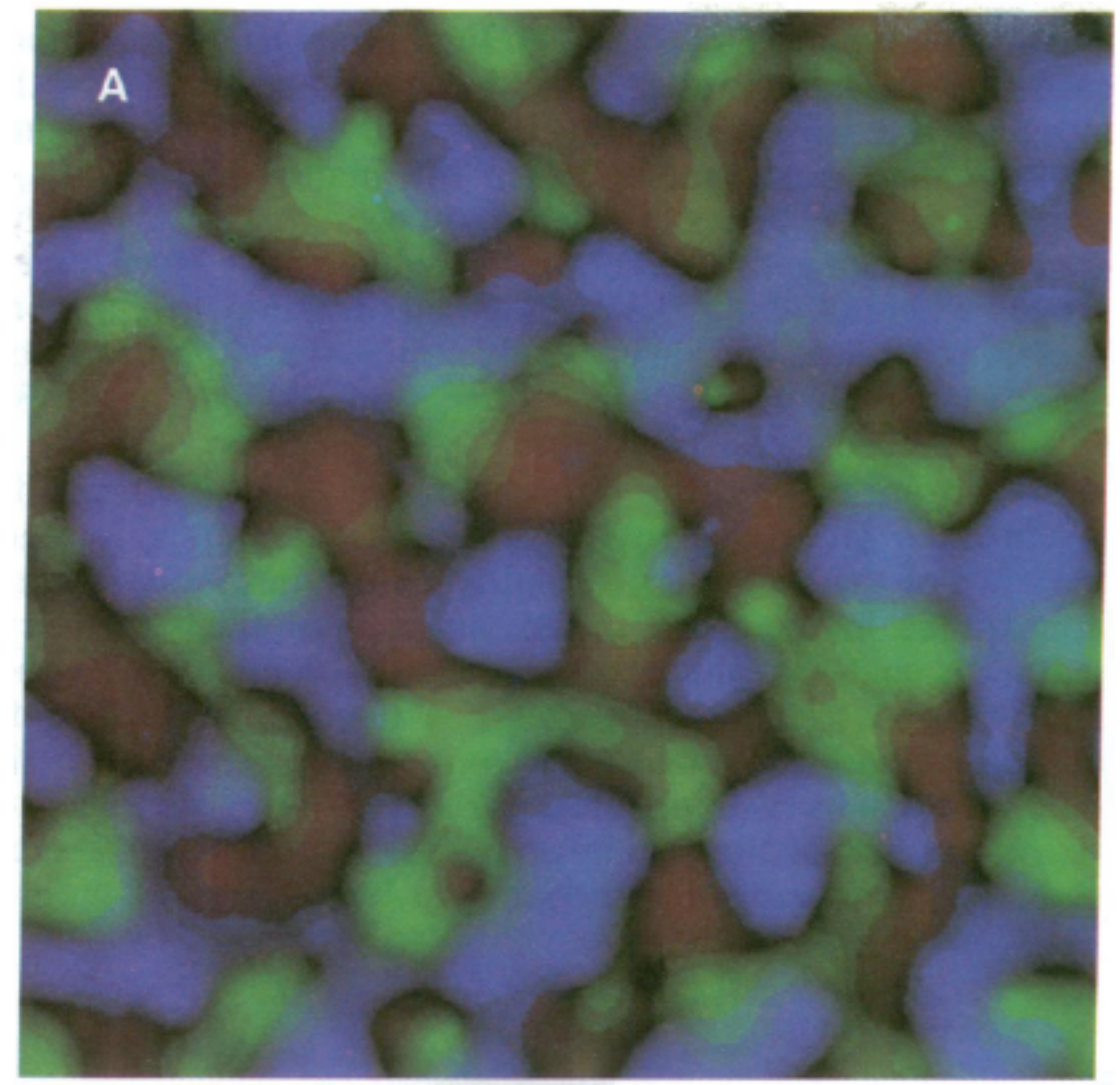
- orientation-retinal location



[Jancke, JNeursci (2000)]

example: visual feature maps

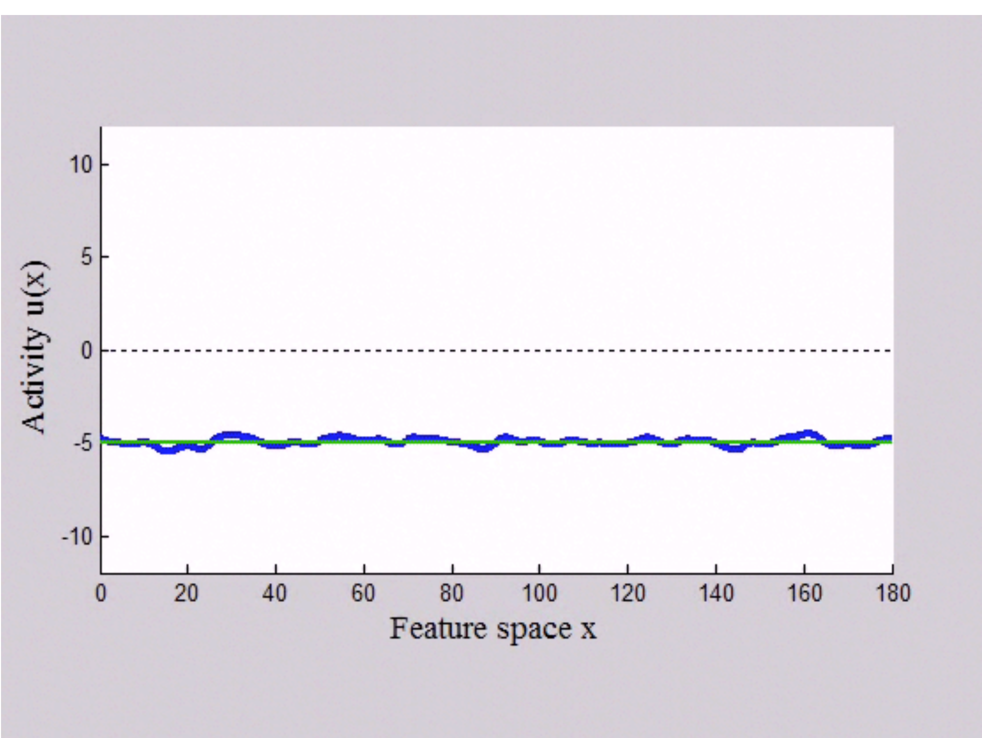
- the neural field representation a single feature (e.g. orientation) as well as retinal location is at least three-dimensional
- cannot be mapped onto cortical surfaces without cuts ...



Dynamic fields of higher dimensionality

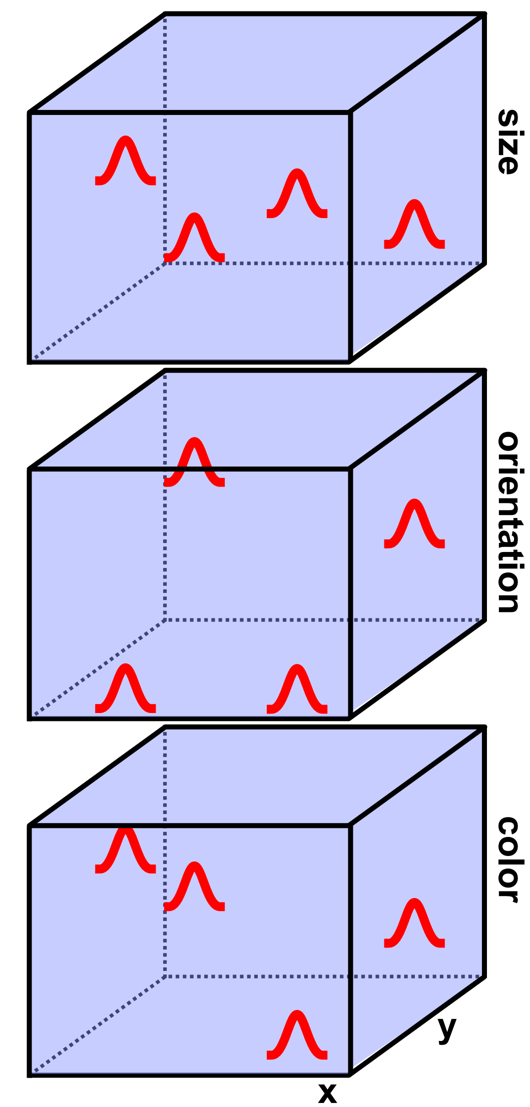
- 1, 2, 3, 4… dimensions: peak/ blob states …
- dynamics scale with dimensions

1-dimensional



2-dimensional

3-dimensional

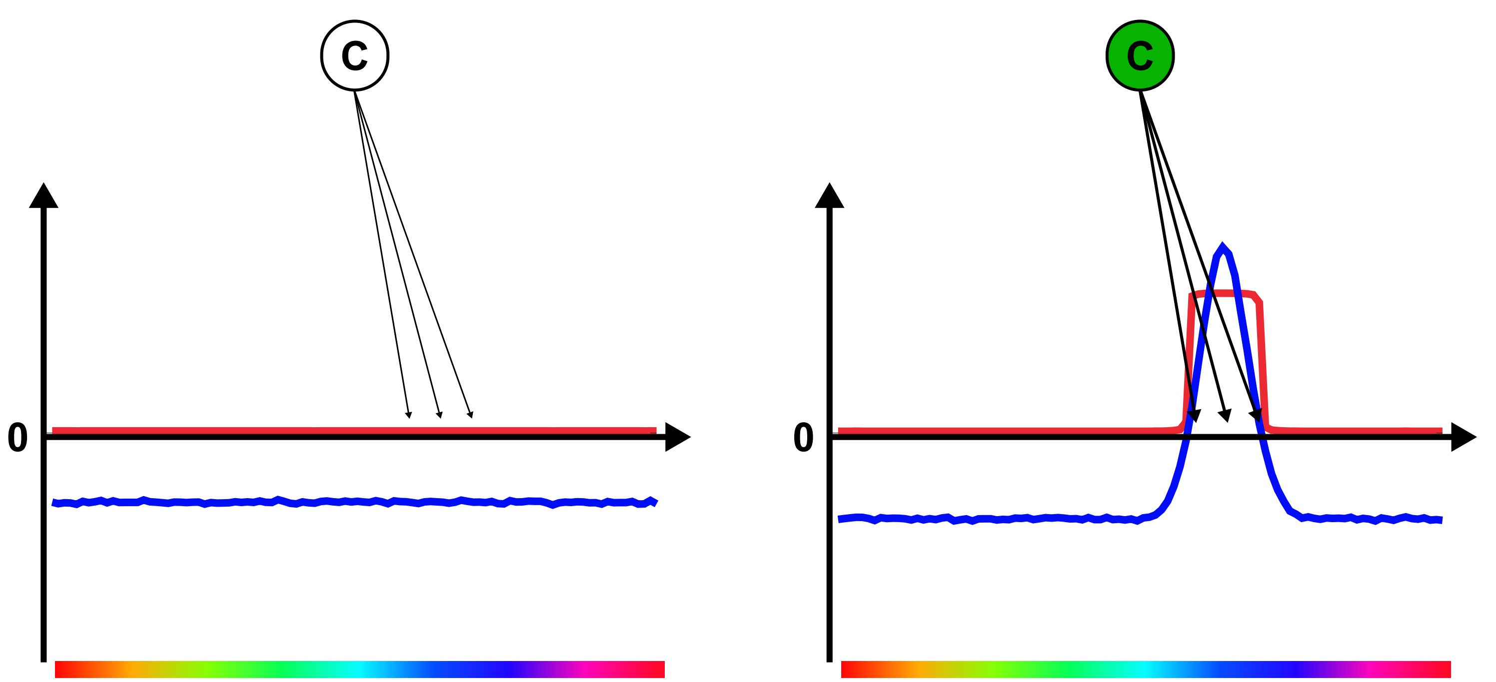


Nodes…

- represent discrete categories by virtue of their coupling to feature fields/feedforward NN
- typically embedded in populations of nodes that are inhibitorily coupled enabling selection among categories

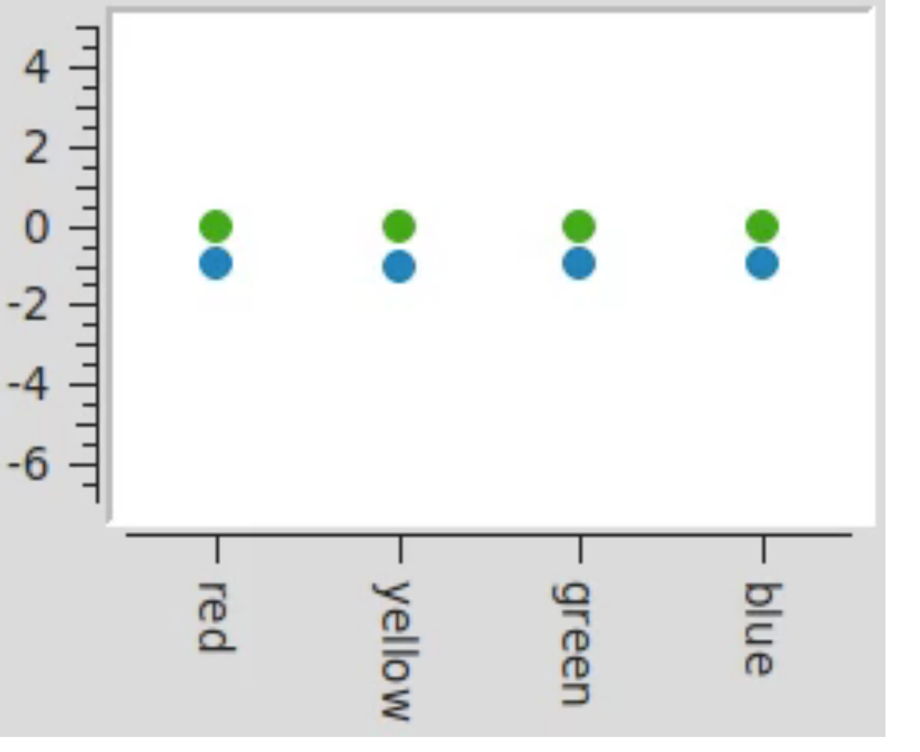
[Tekülve]

Concept Node "blue"



[Grieben]

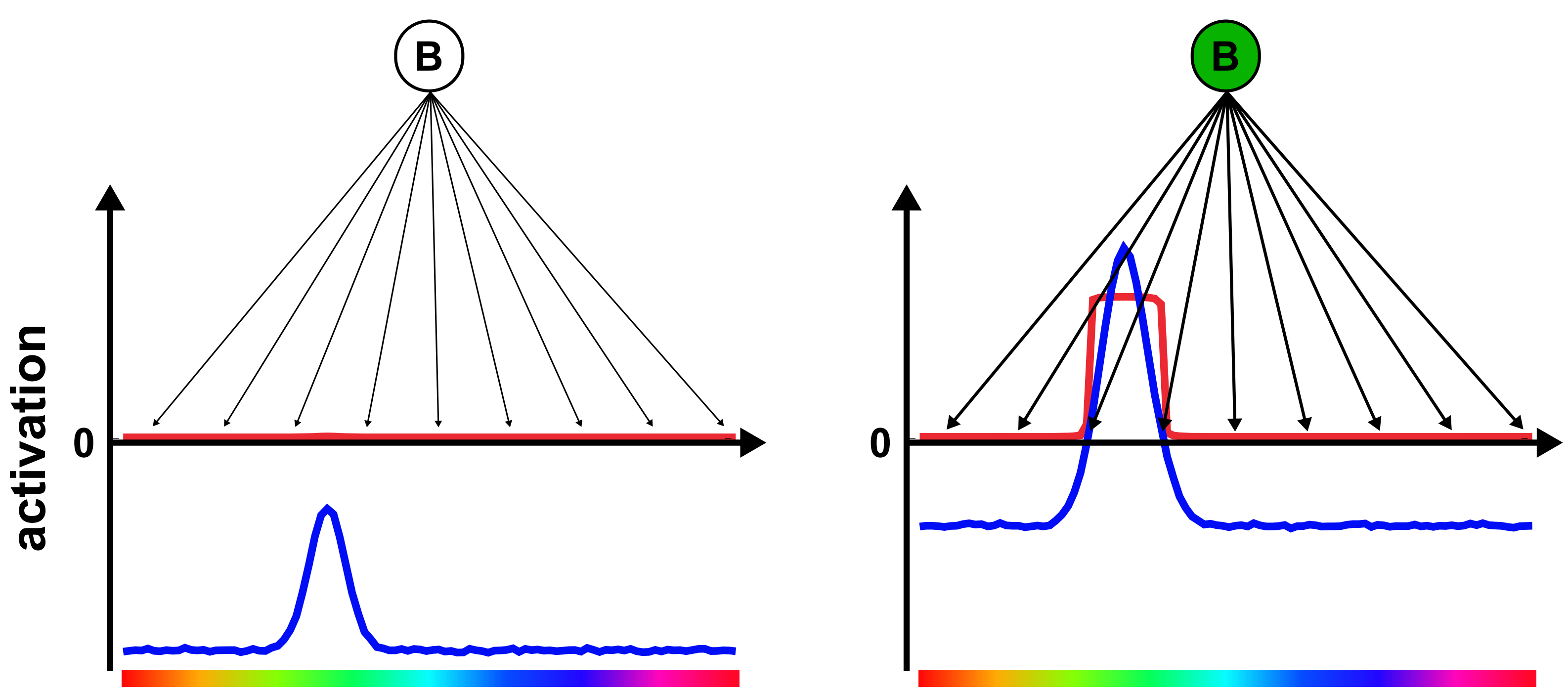
0-dimensional



Nodes…

- may also play a specific role to organizes fields within architectures..
- => we'll address this when talking about sequences

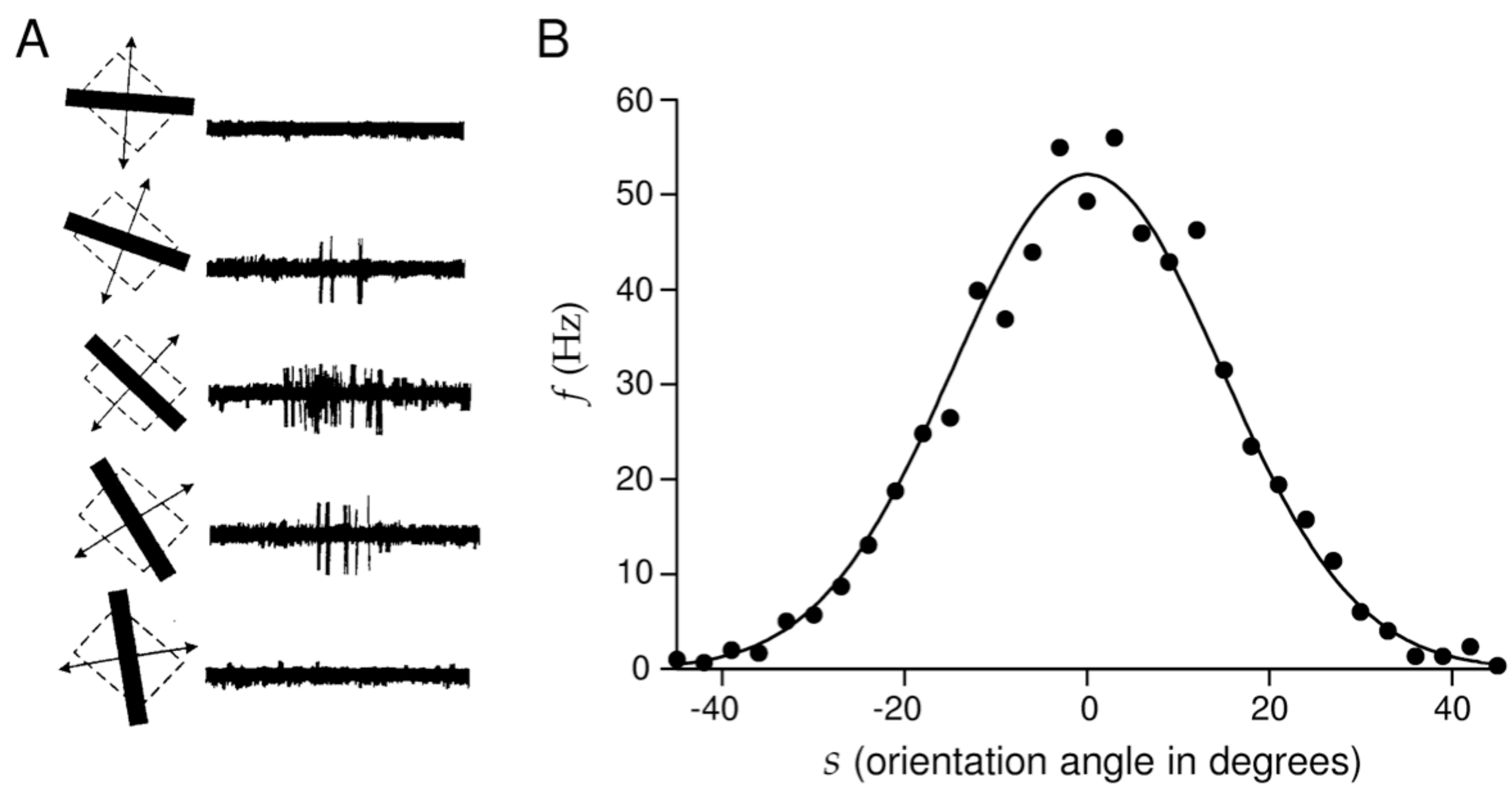
Boost Node



What do higher dimensional fields represent?

Combining different feature dimensions

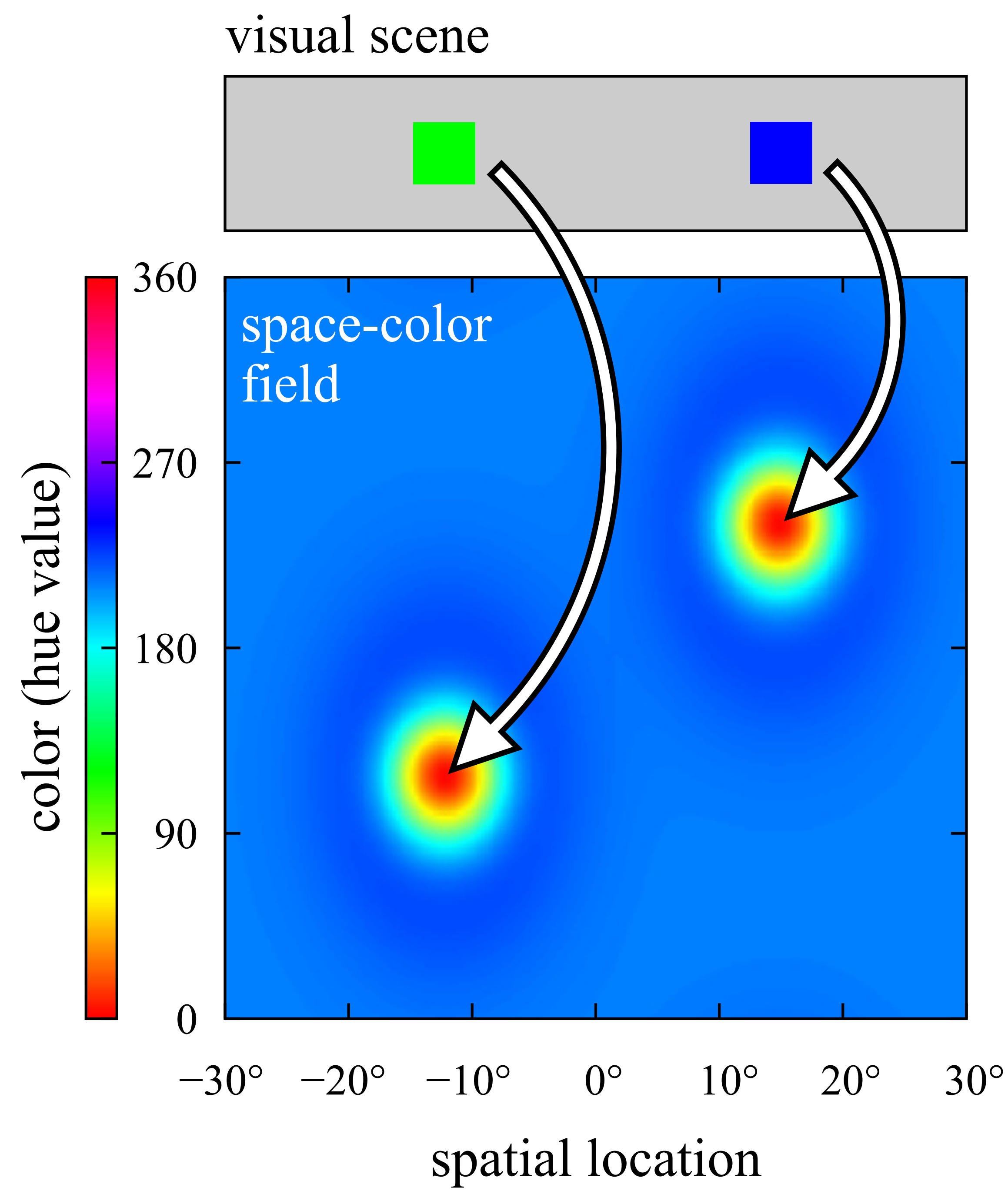
- neurons tuned to multiple dimensions
  - e.g. receptive field + direction tuning
  - => combines visual space and orientation
- “anatomical” binding



[Hubel, Wiesel, 1962]

Combining different feature dimensions

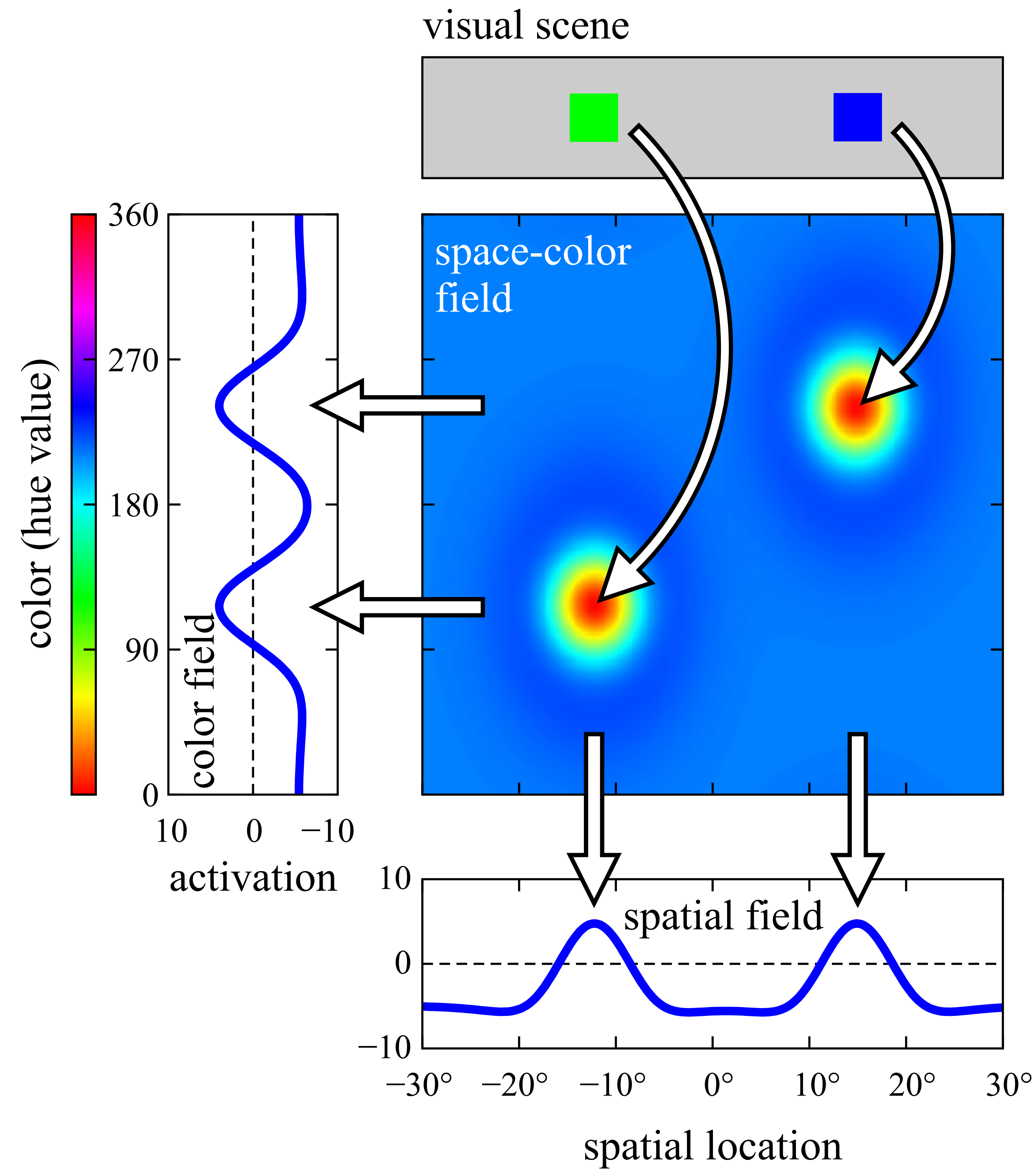
- example: a joint representation of color and visual space “binds” these two dimensions



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

Extract bound features

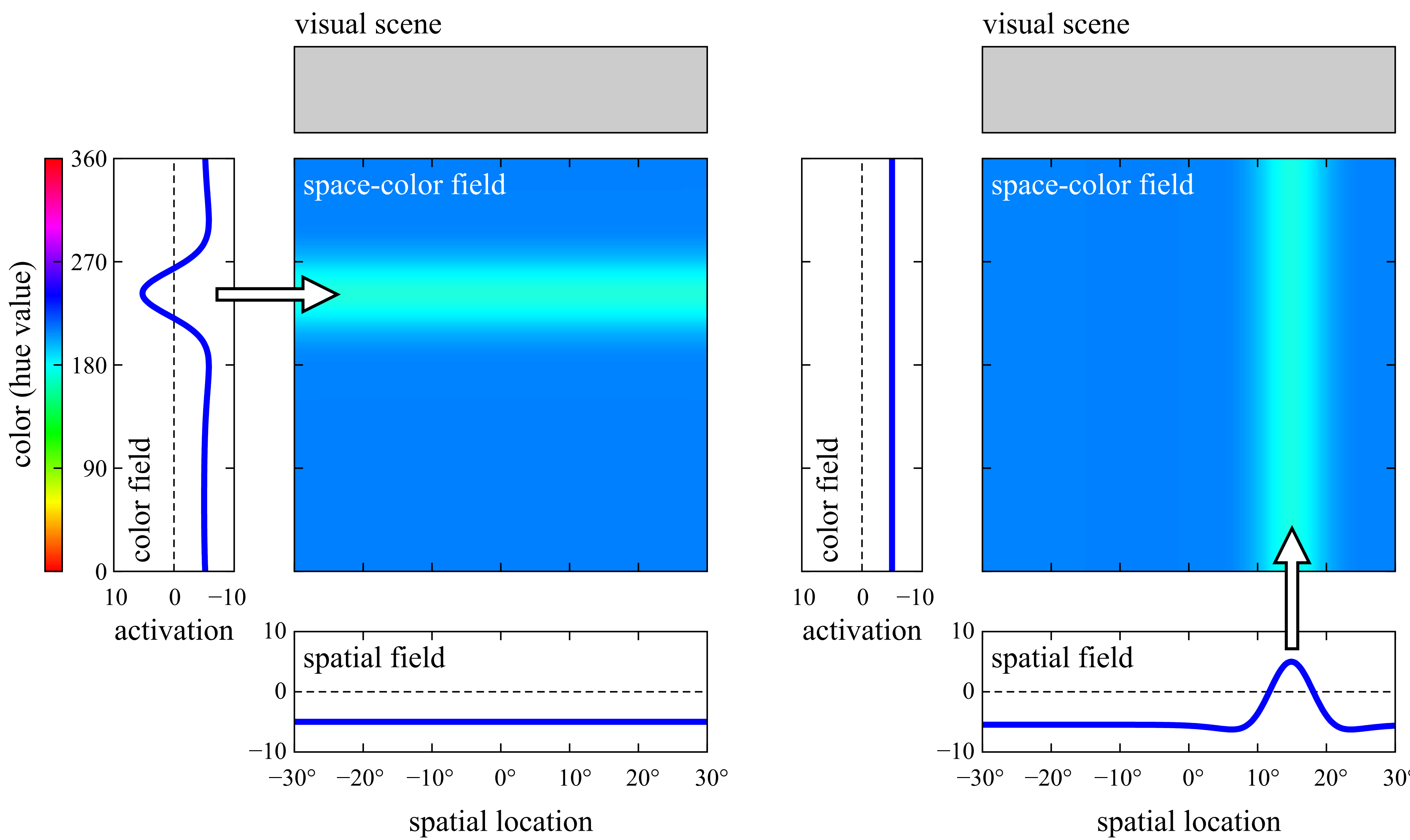
- project to lower-dimensional fields
- by summing along the marginalized dimensions
- (or by taking the soft-max)



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

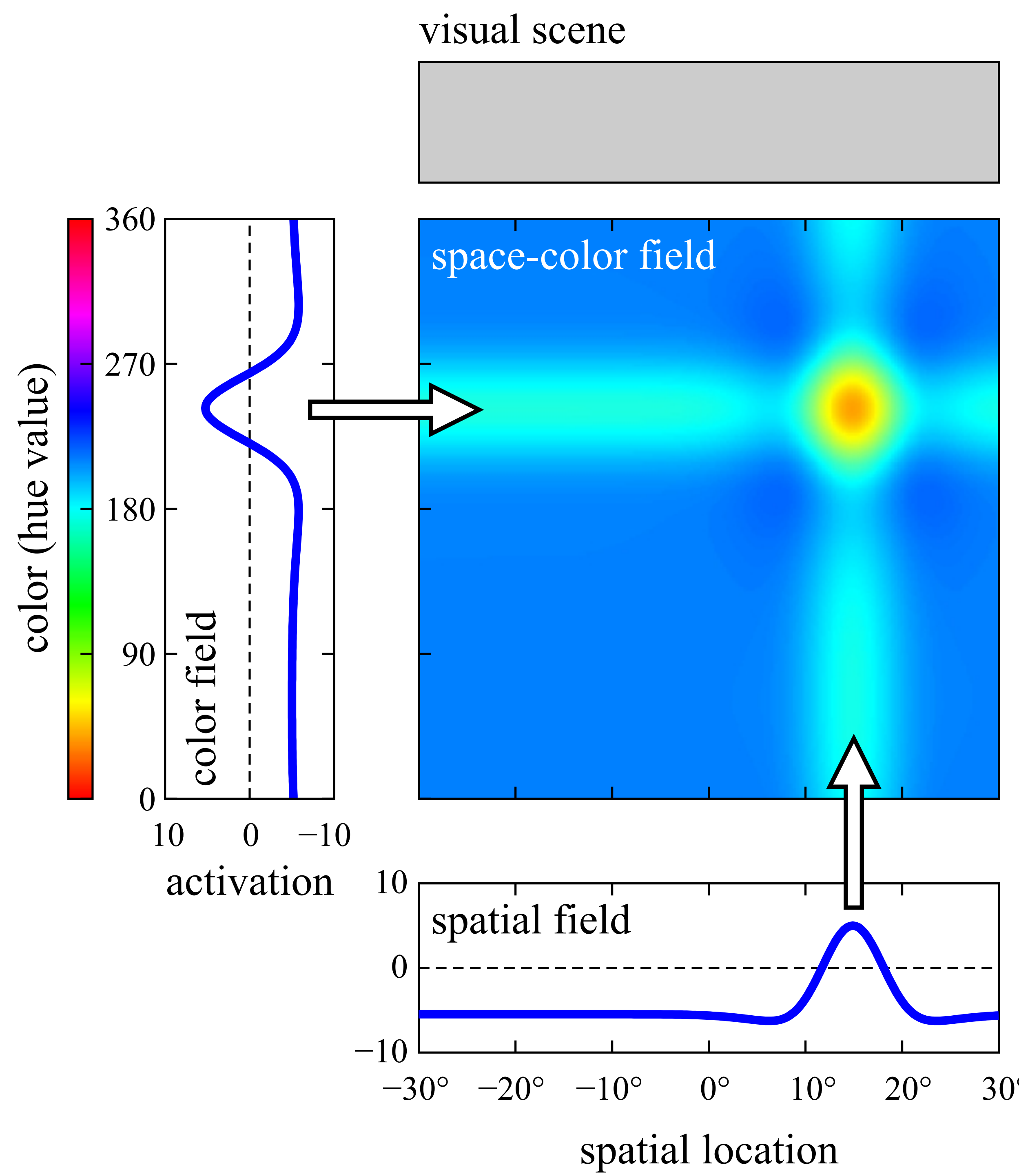
Assemble bound representations

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



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

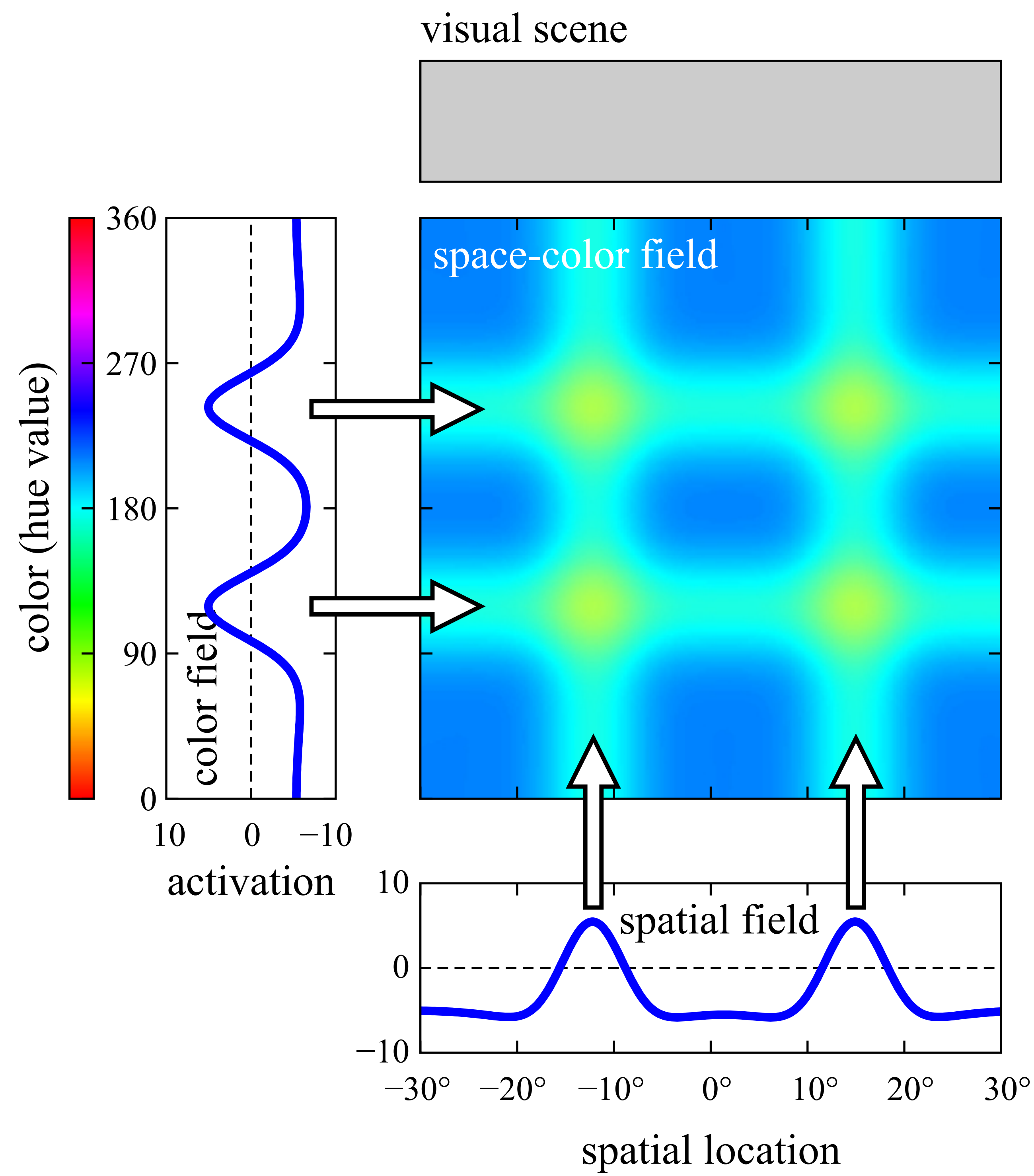
Assemble bound representations



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

Assemble bound representations

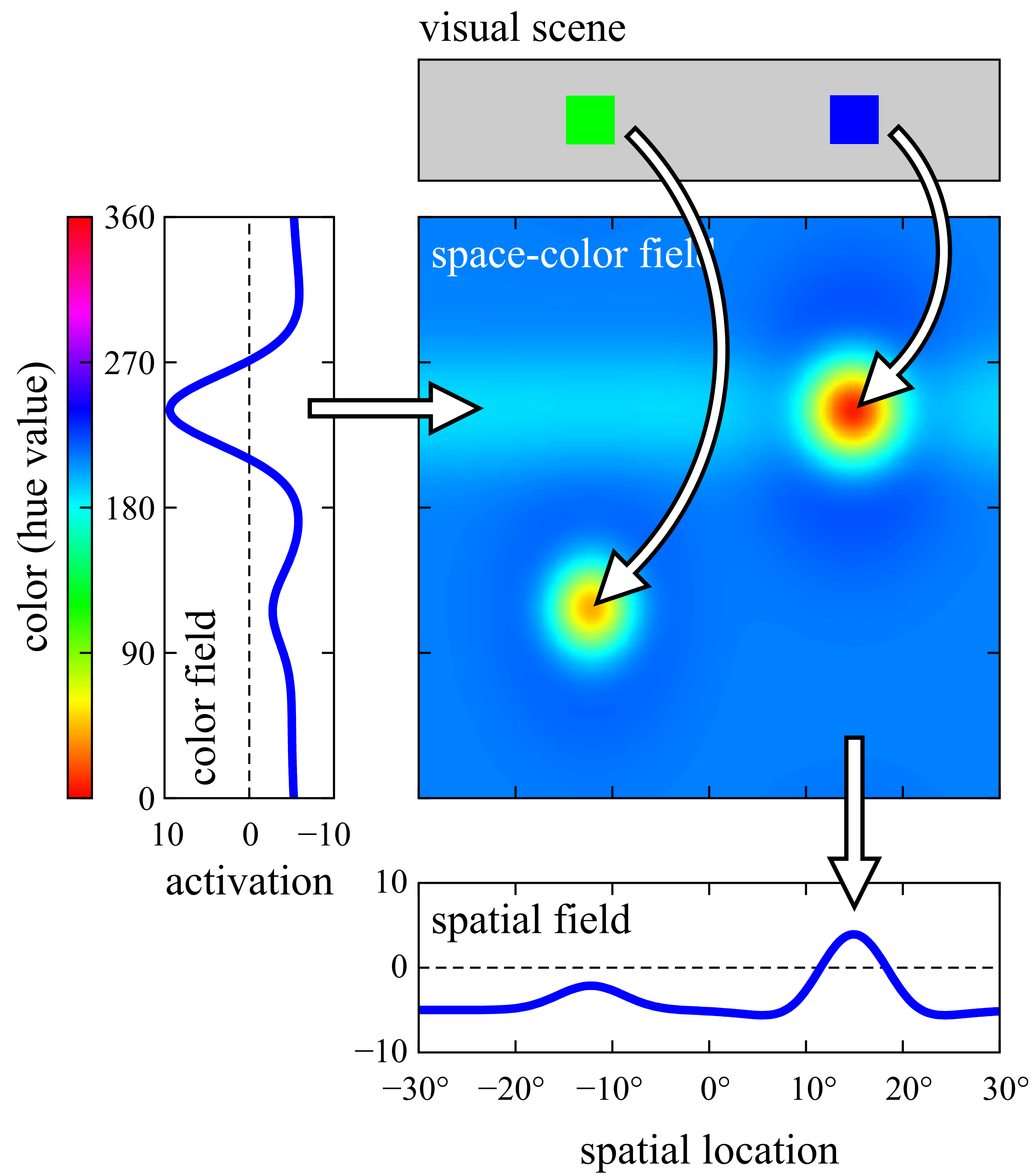
- binding problem: multiple ridges along lower-dimensional space lead to a correspondence problem
- => assemble one bound object at a time…
- => sequentiality bottle-neck!



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

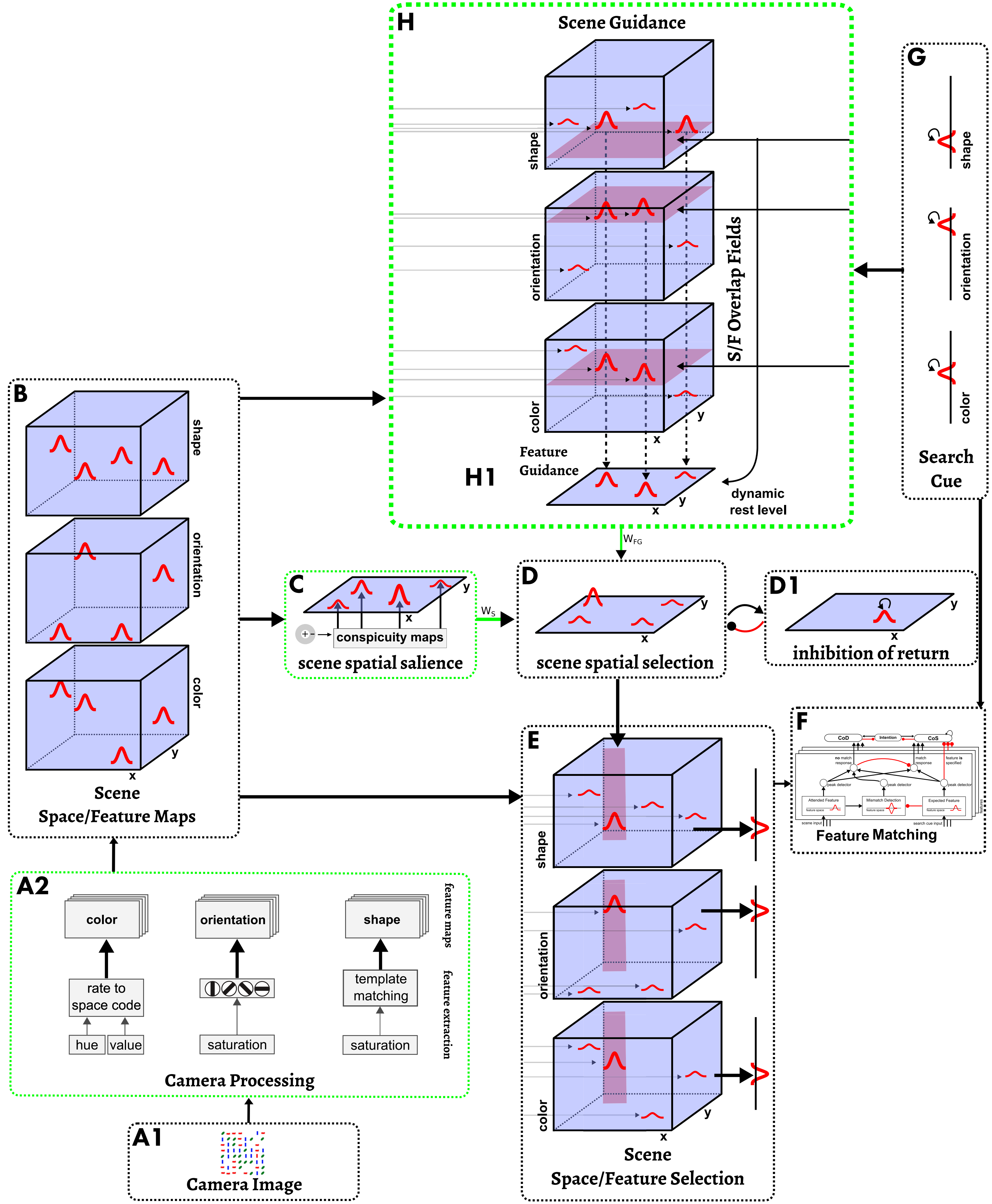
Search

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

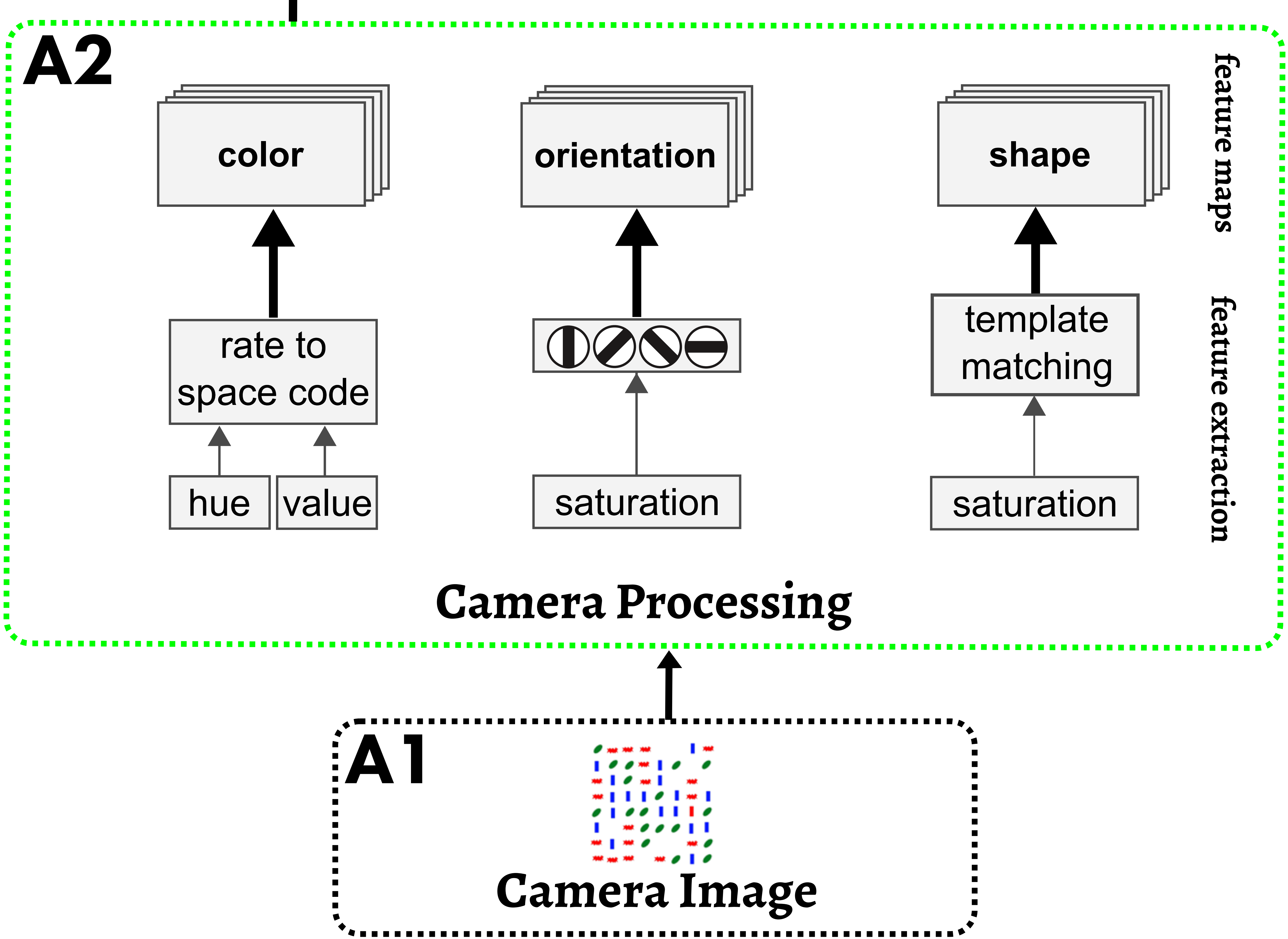


[Schneegans et al.,Ch 5 of *DFT Primer*, 2016]

Visual search



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


A2
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feature extraction
hue
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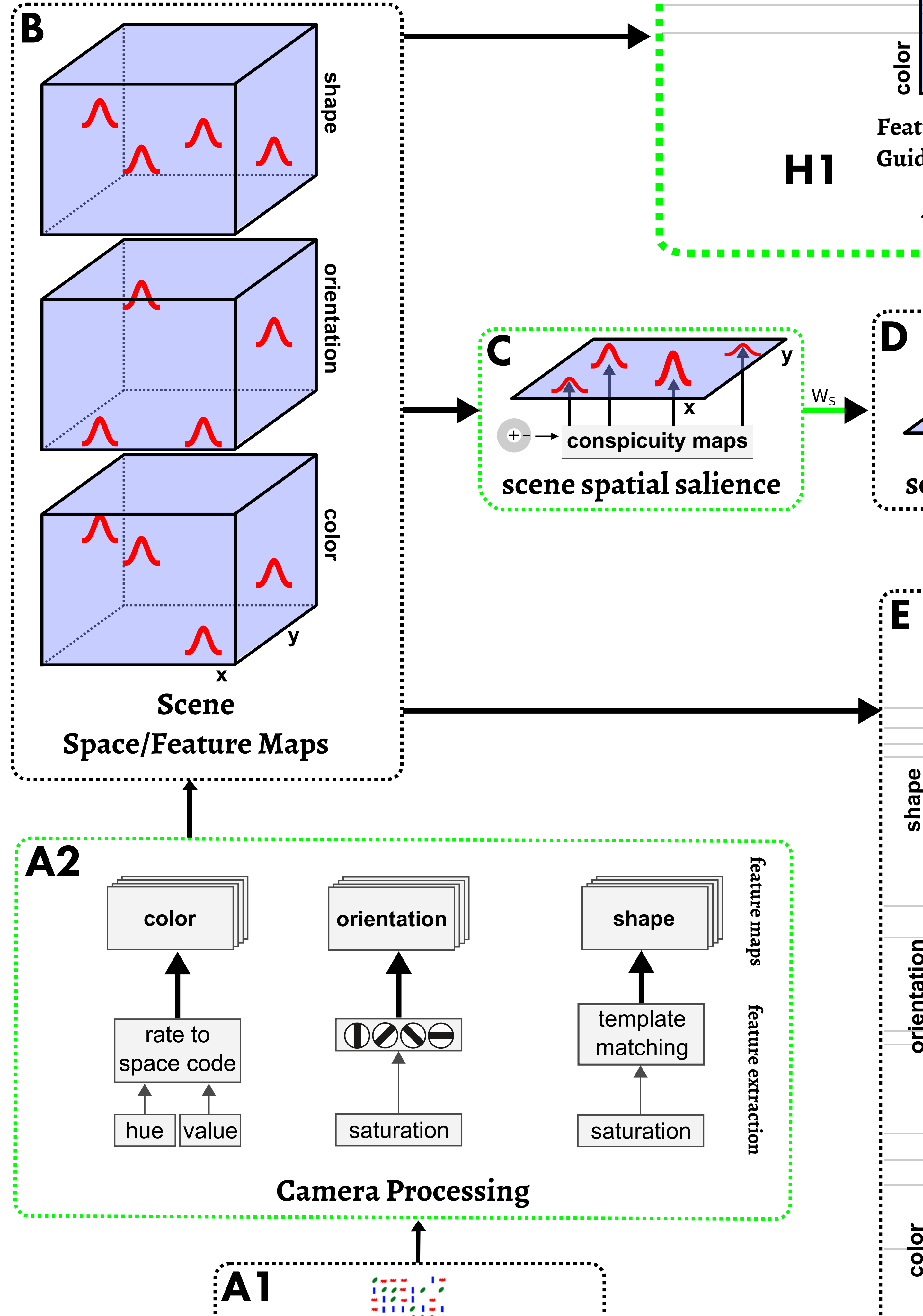
saturation
Camera Processing
A1
Camera Image



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feature extraction
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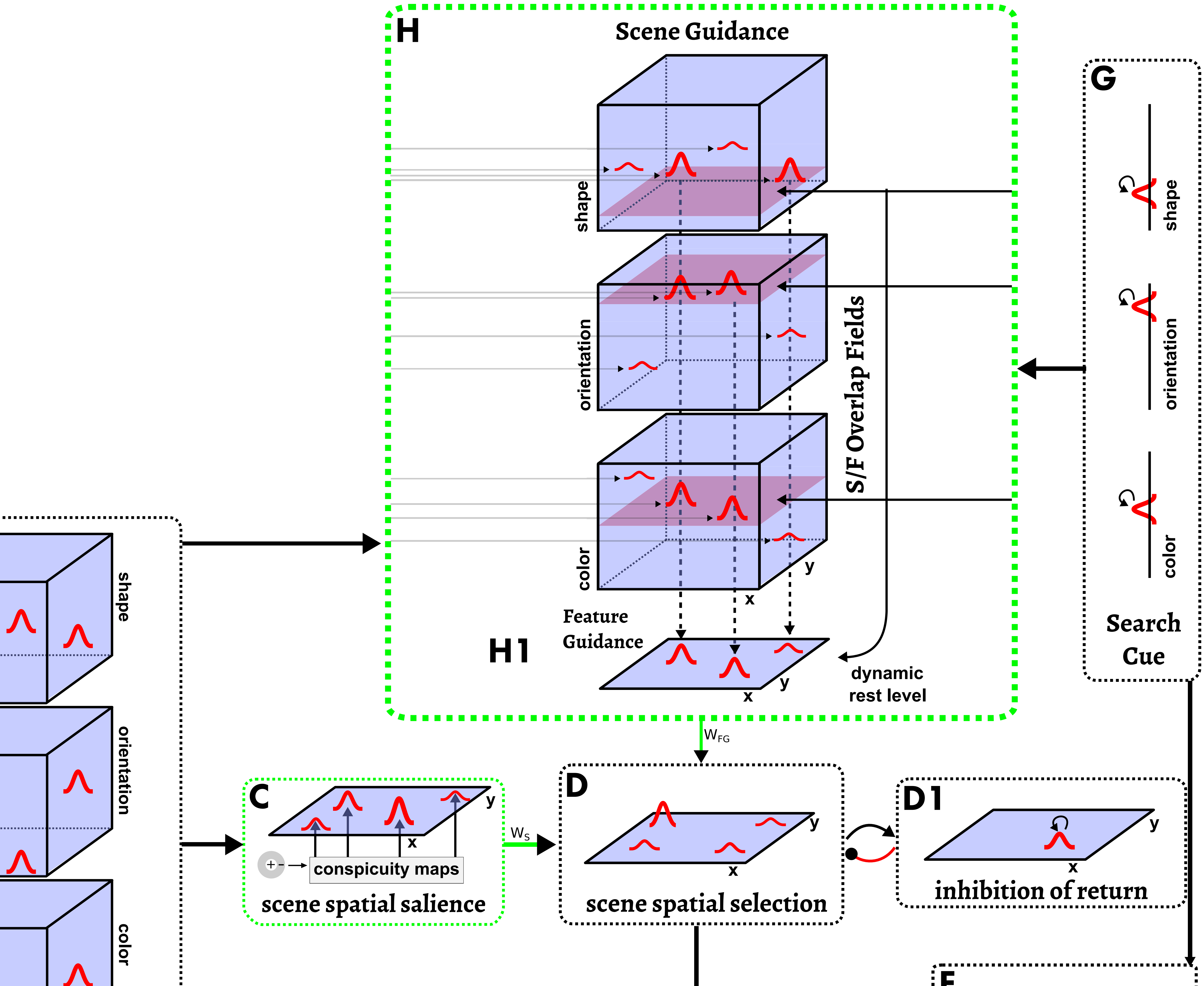
A1



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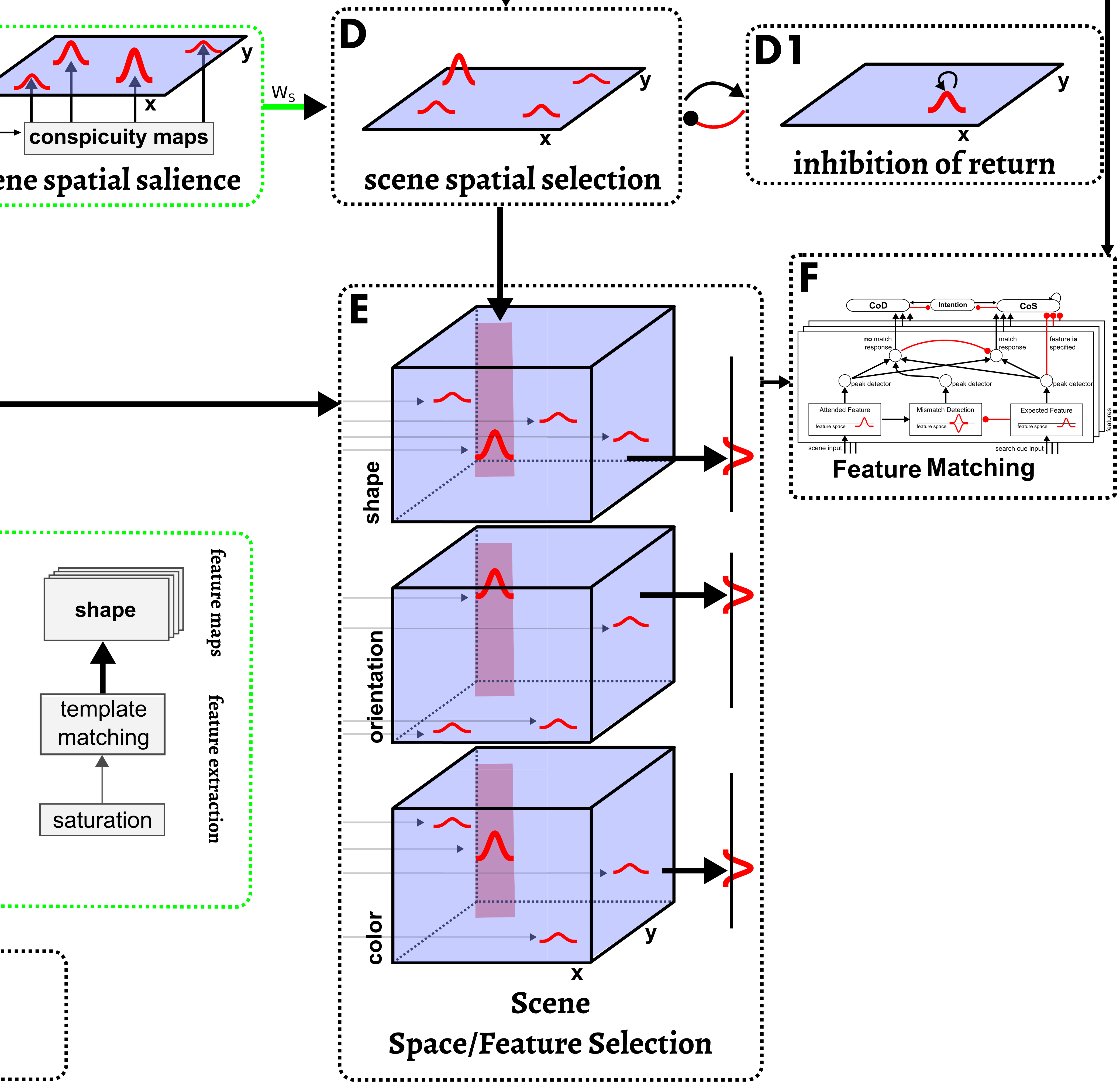

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Feature Matching
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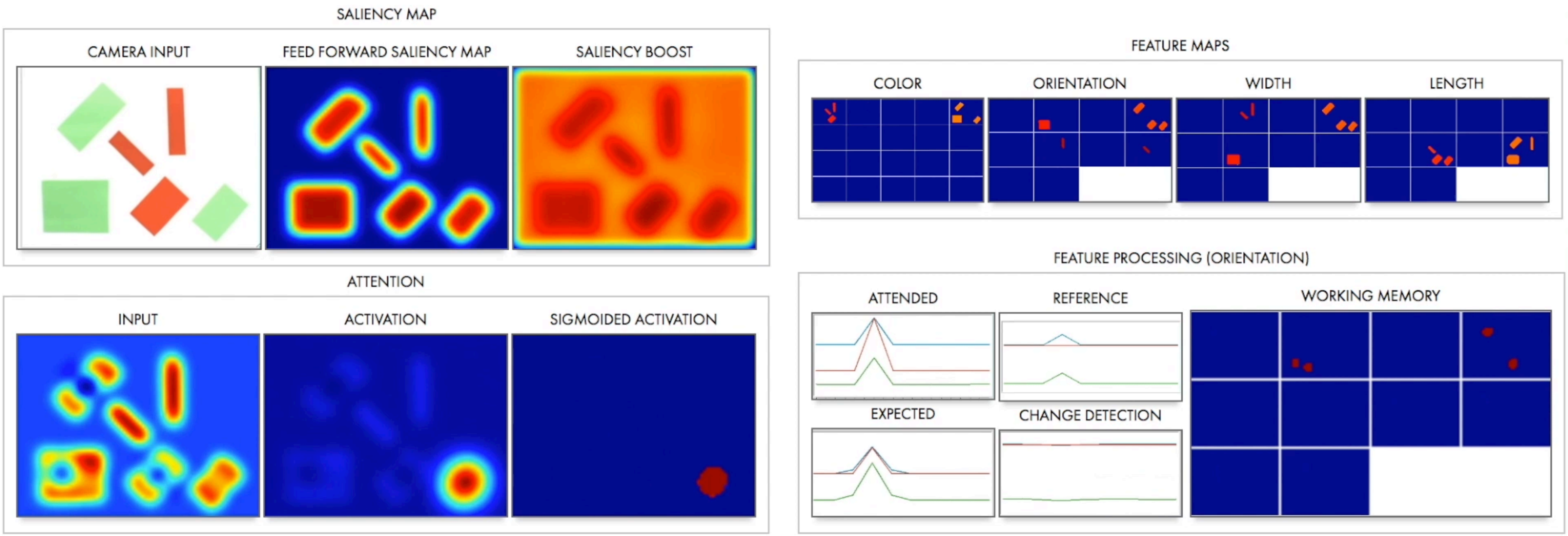
template matching
saturation
feature maps
feature extraction

Visual search



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

Binding

- “anatomical” binding does not scale
- binding through space
- localist vs. distributed representations
- learning

Scaling feature dimensions

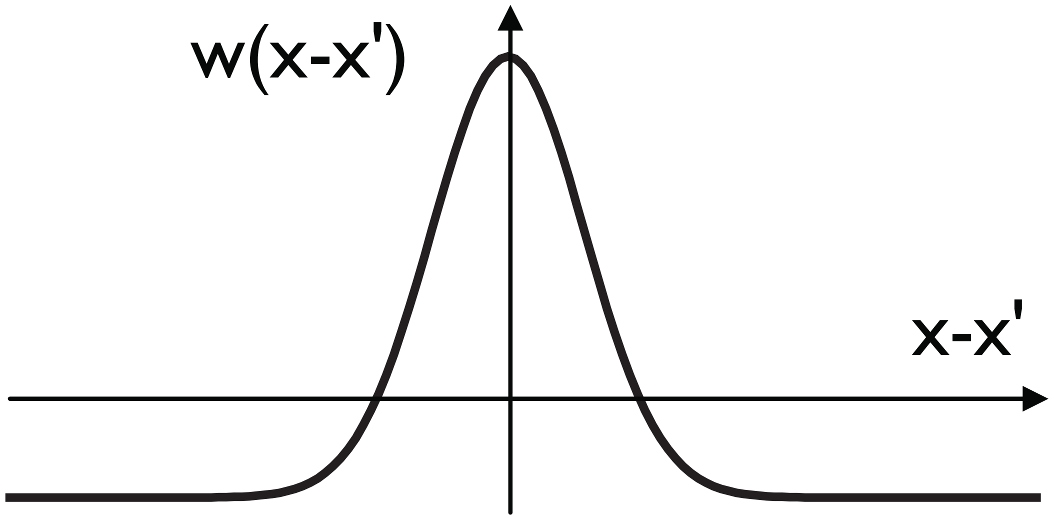
- 2 spatial dimensions
- depth
- orientation
- color
- texture
- movement direction
- size
- etc…

=>

- 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"

Localist vs. distributed

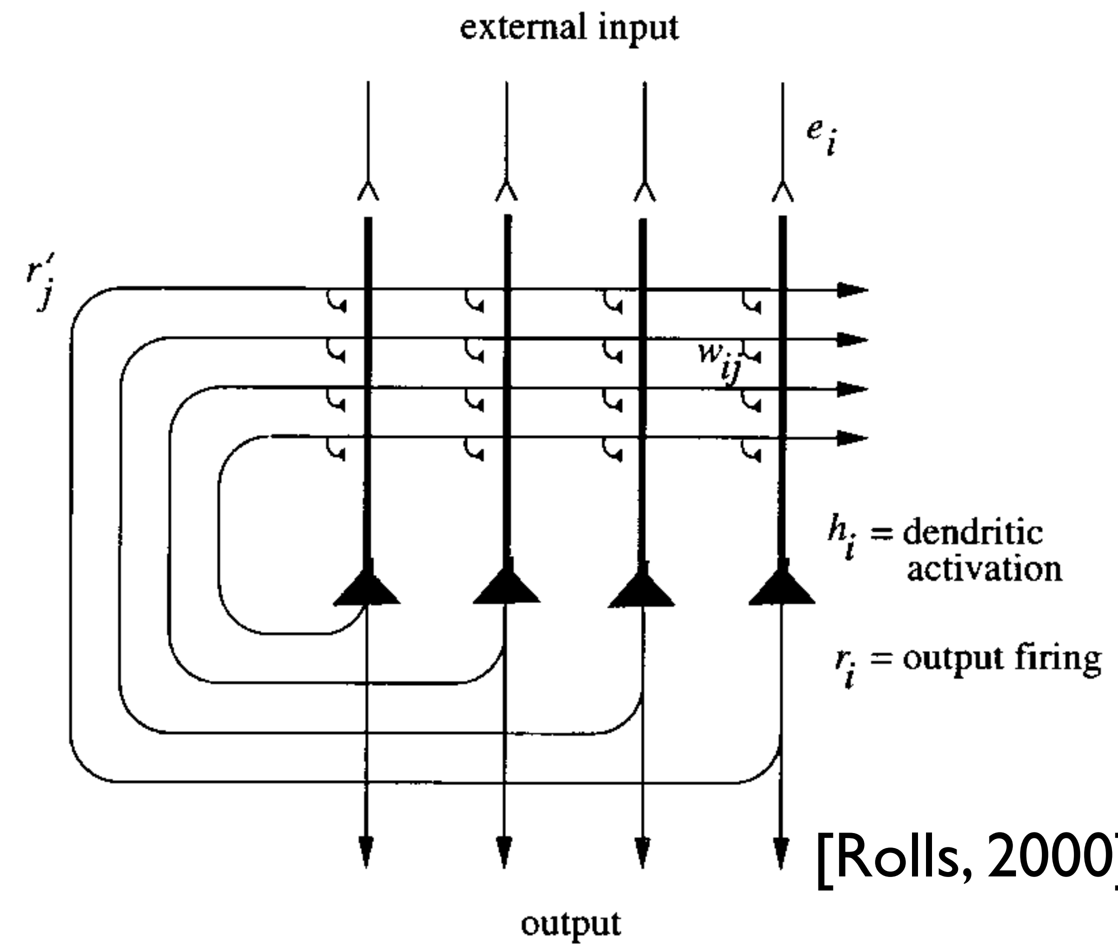
- scaling problem arises in localist representations
- distributed representations scale better



- but: localist representations enable stable states and thus cognitive function: detection, selection, working memory, (and sequence generation)
- that is why DFT sticks to the costly localist picture

Localist vs. distributed

- Hopfield networks have attractors for distributed representations, but these (and the synaptic weights) are specific to each memorized pattern

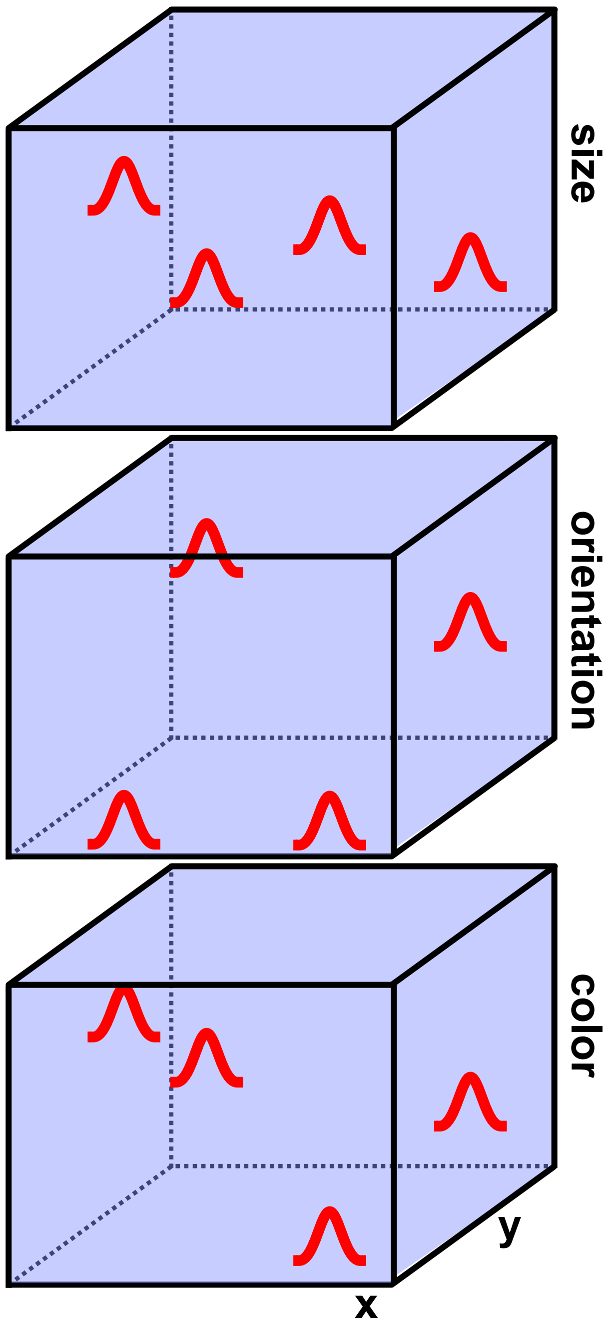


[Rolls, 2000]

- so the Hopfield networks lack flexibility that enables cognition…

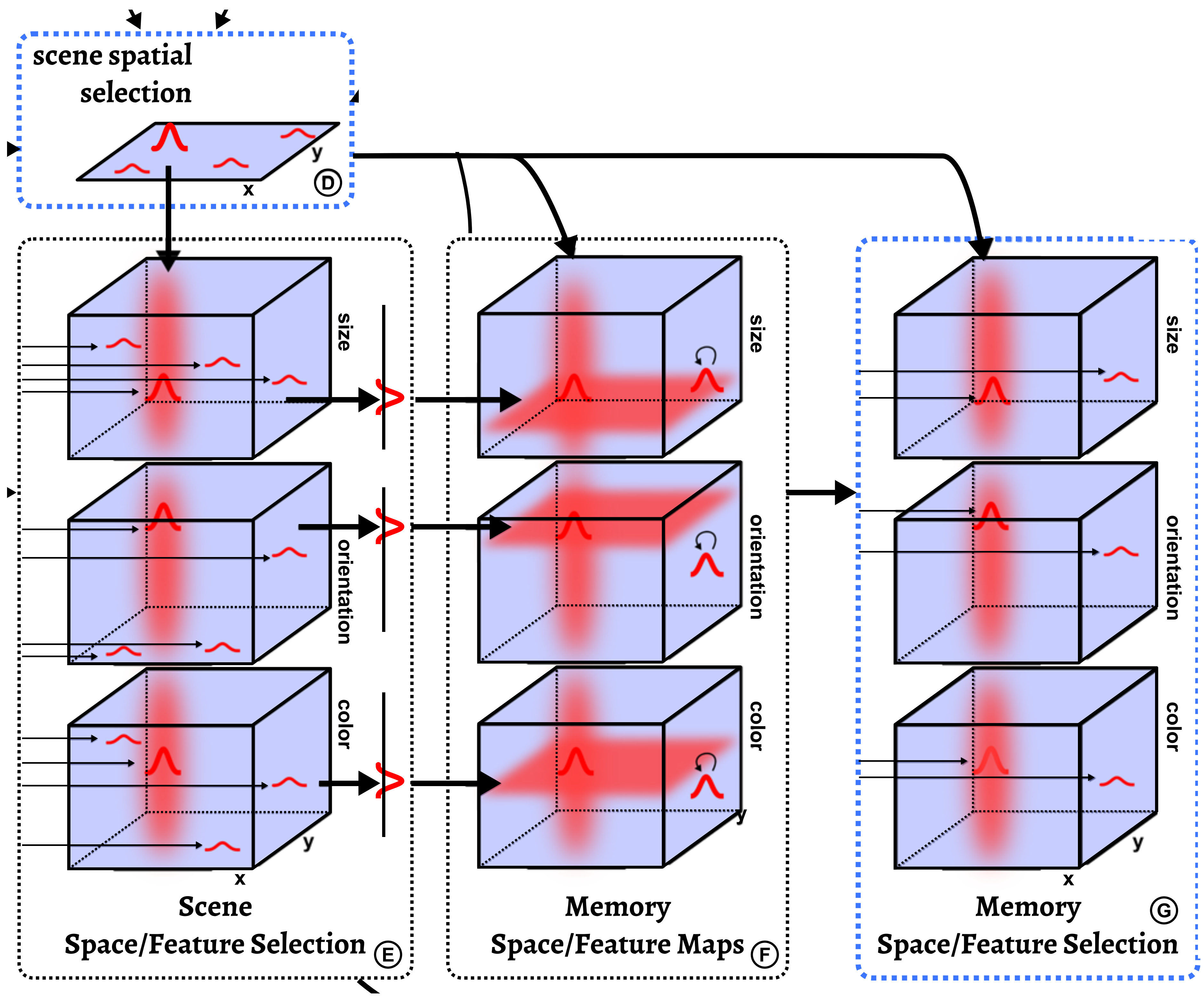
Binding through space

- 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)

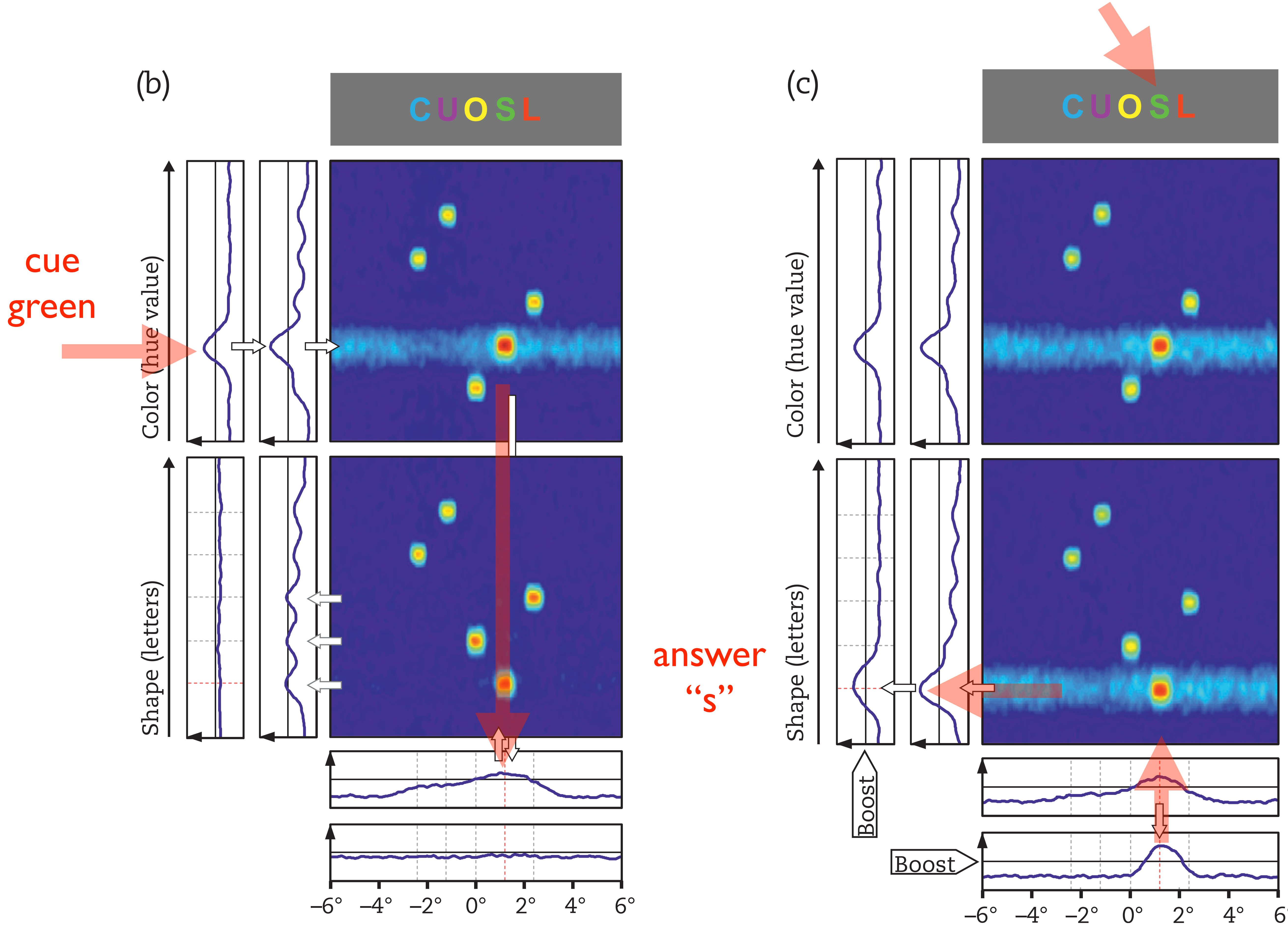


[Grieben et al. *Attention, Perception & Psychophysics* 2020]

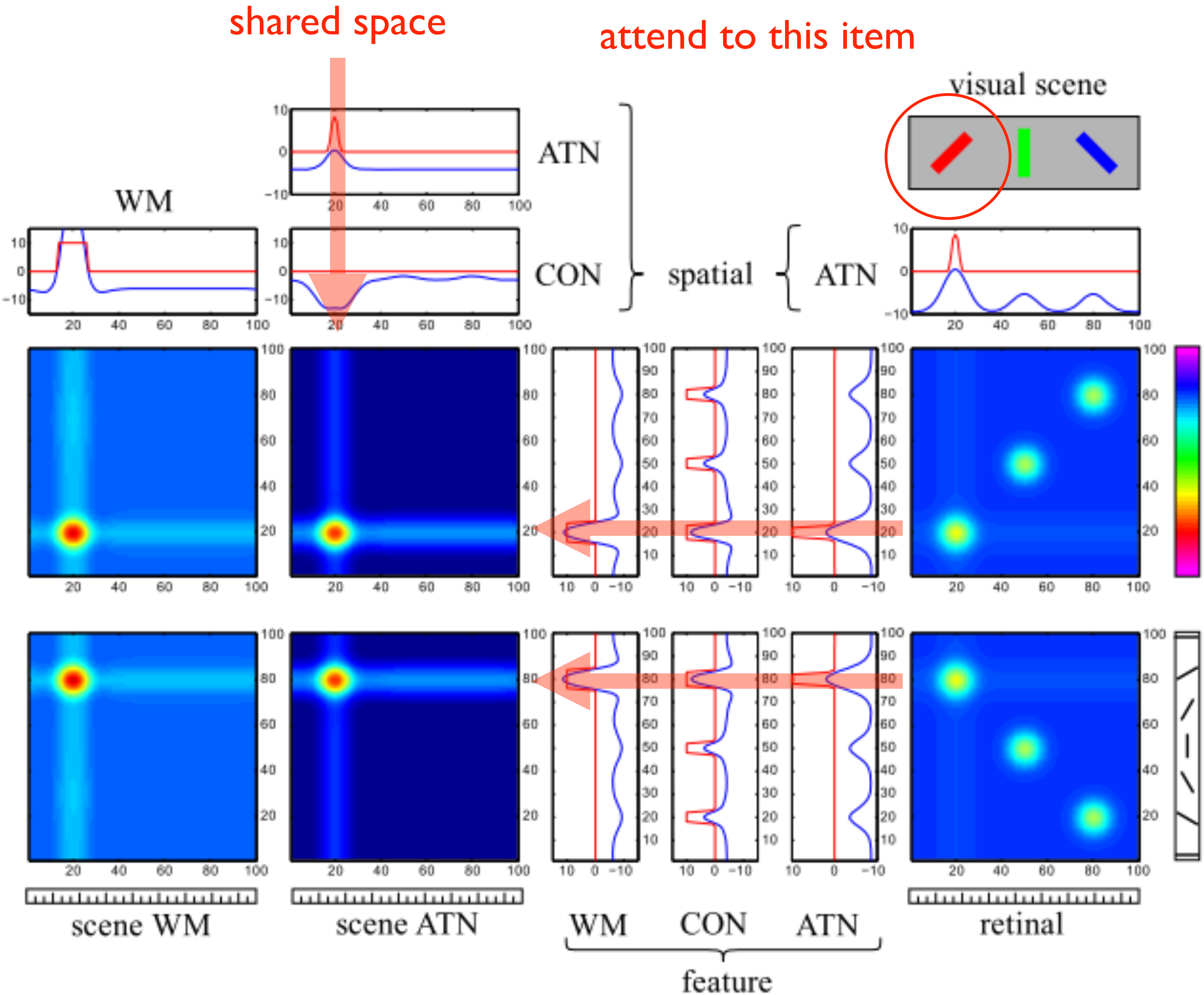
Binding through space



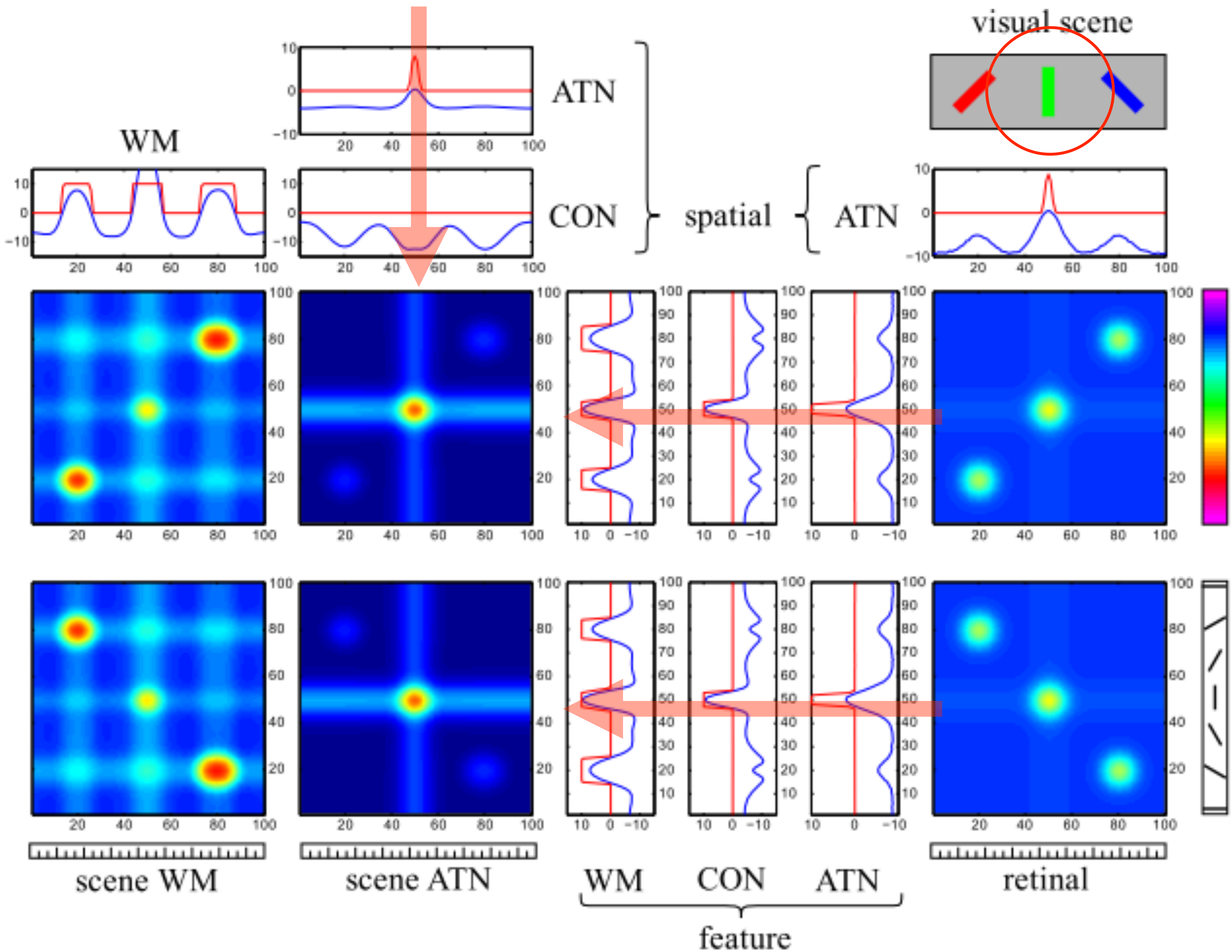
[Grieben et al. *Attention, Perception & Psychophysics* 2020]



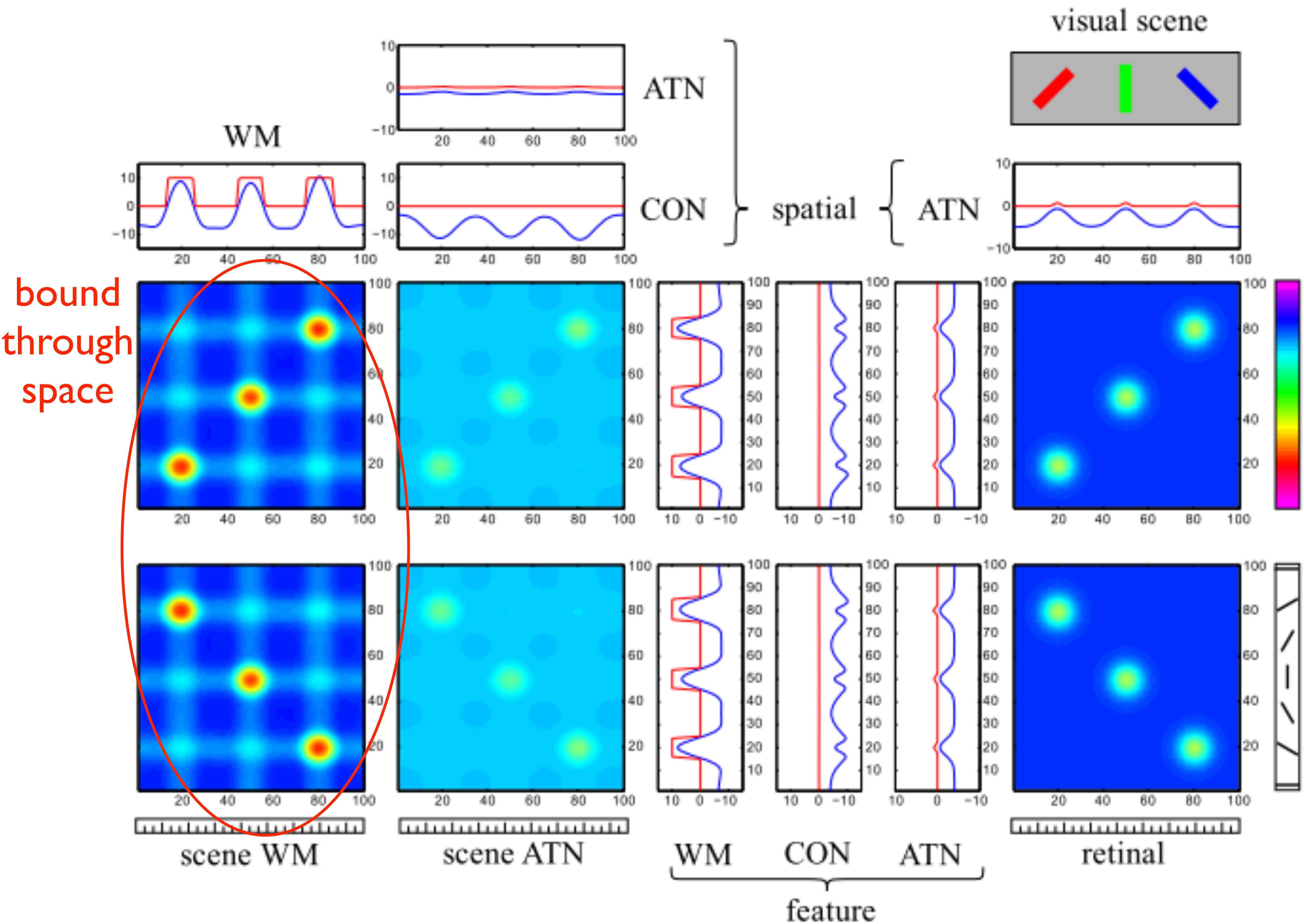
[Schneegans et al., Ch 5 of *DFT Primer*, 2016]



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



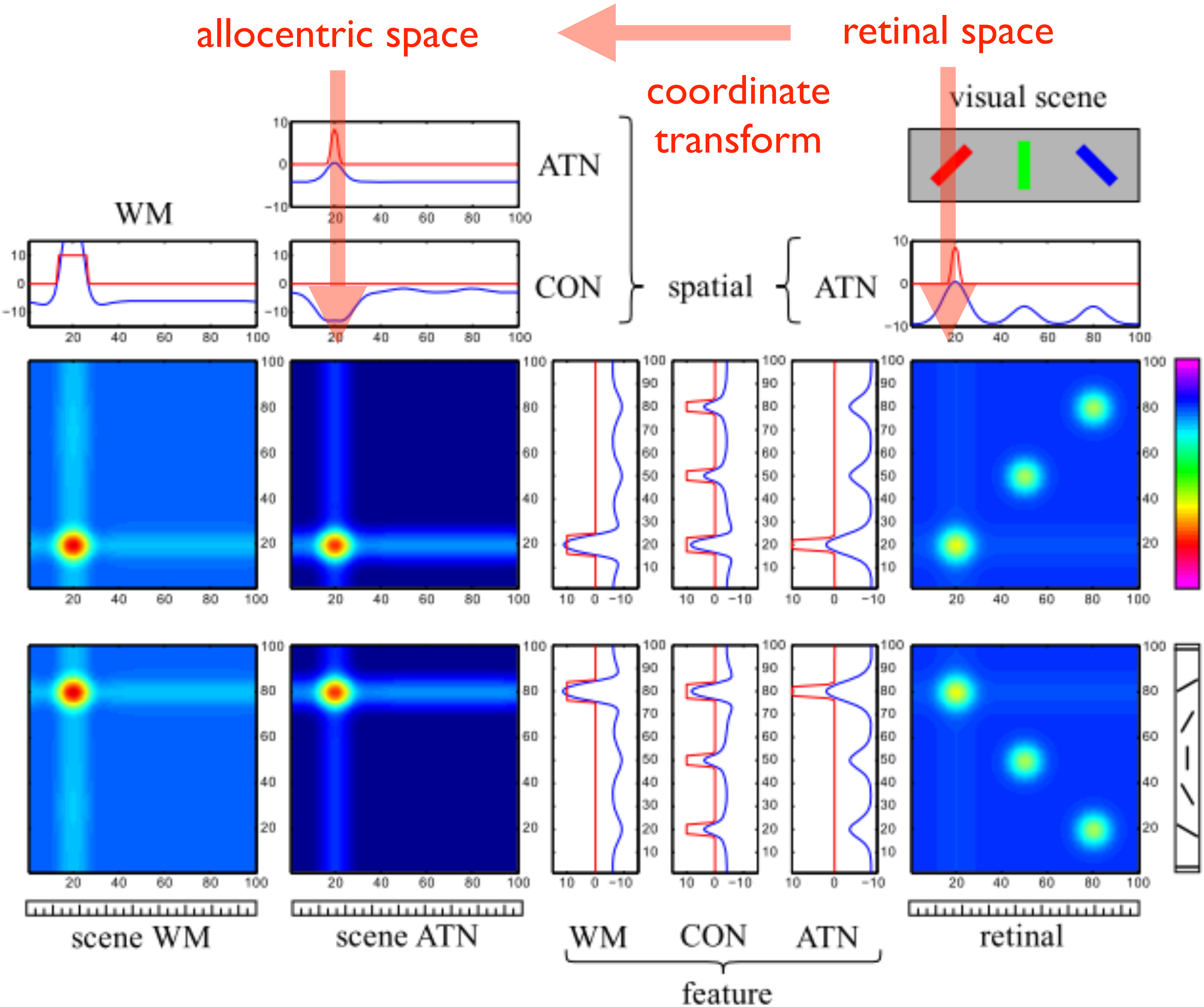
[Schneegans et al.,Ch 5 of *DFT Primer,* 2016]



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

Binding through space => sequential bottleneck

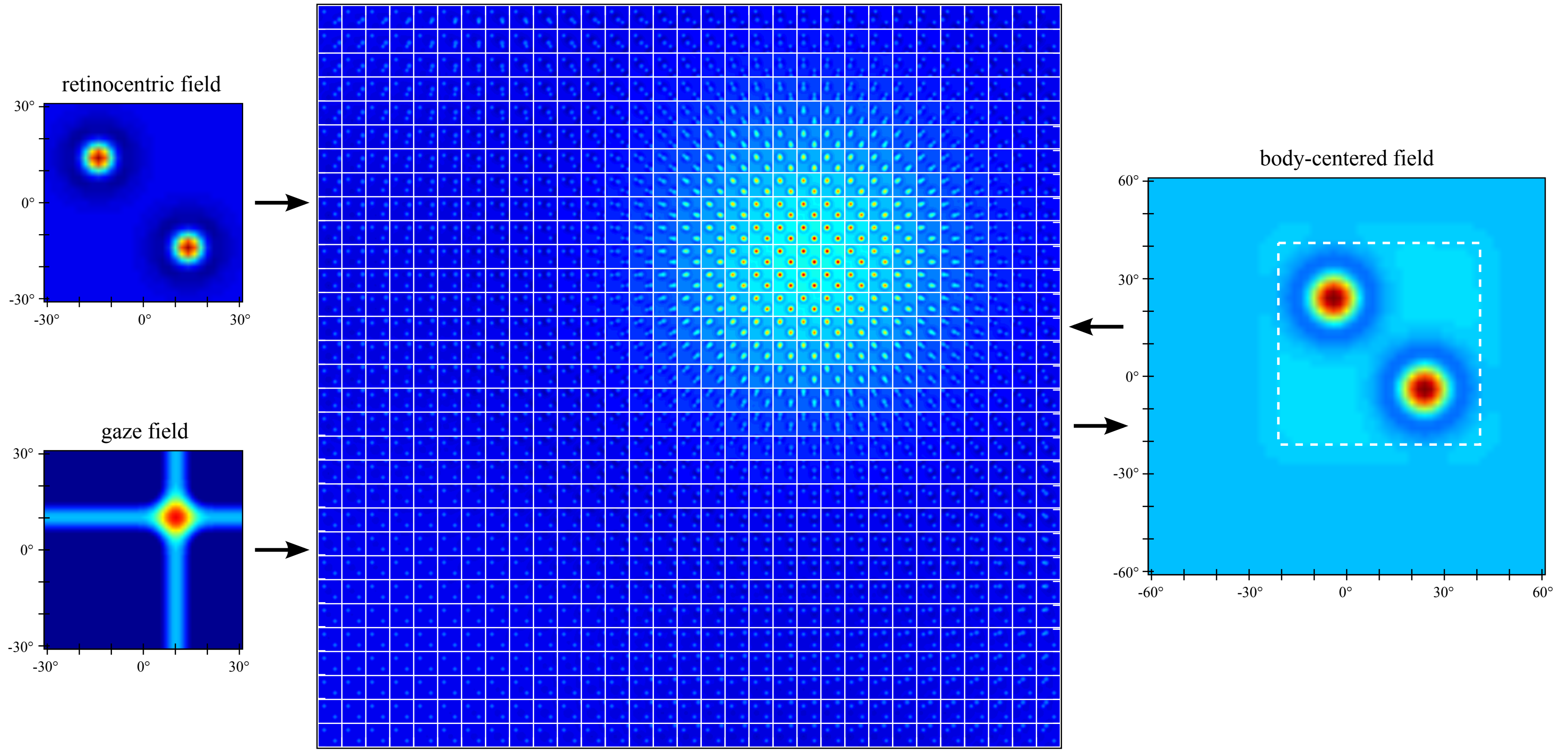
- binding through space must occur one time at a time..… to avoid binding problem
- => the sequential processing bottleneck may originate from this



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

Coordinate transforms and binding through space

- coordinate transforms: 2 by 2 spatial dimensions
- perform the coordinate transform in space only!
- no need to transport the feature values, which can be filled in by binding through space



[Schneegans, Schöner, 2012]

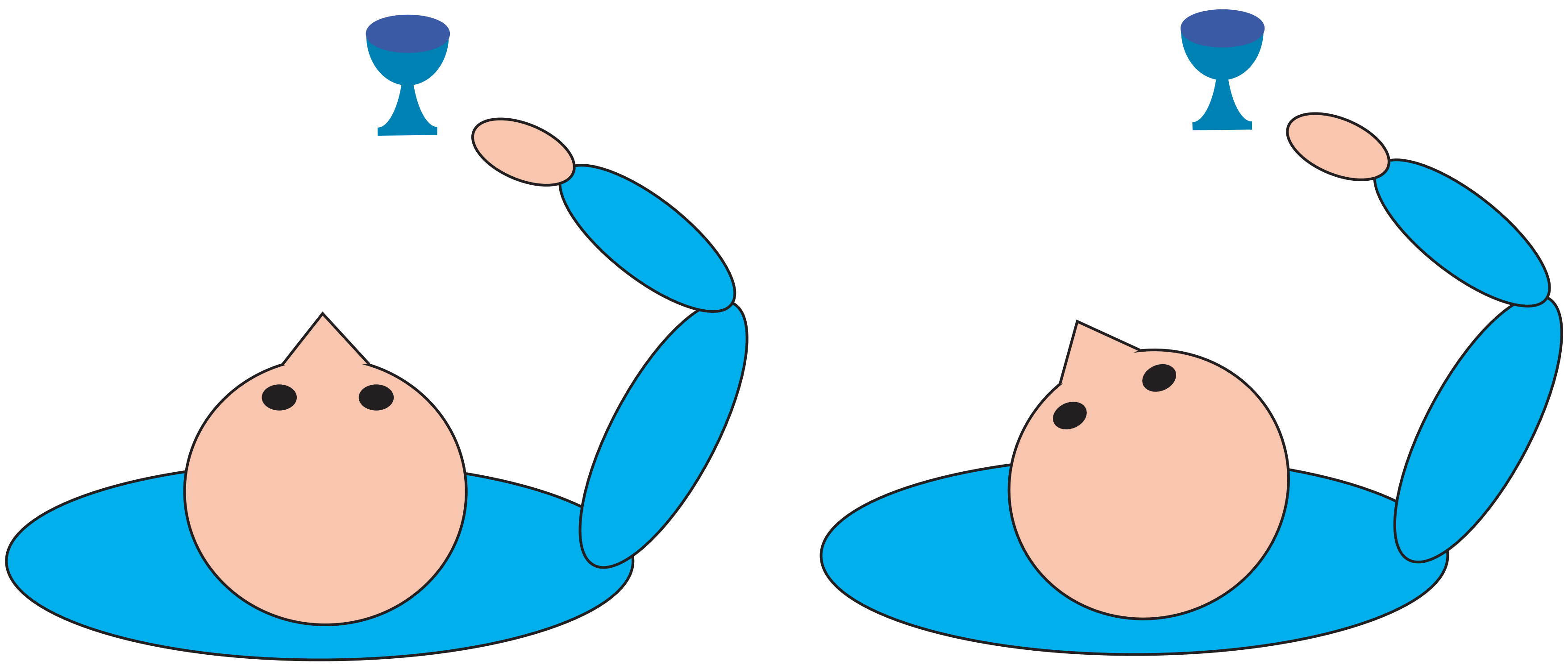
Generalization to other binding agents

- than space…
- a binding agent must be a shared neural dimension…
- can be discrete/categorical in nature
- e.g. can be an ordinal dimension, an “index”, a “label”
- => special lecture by Daniel Sabinasz on grounded cognition

Coordinate transforms

- are fundamental element to sensory-motor cognition
- [but critical also to mental operations!]

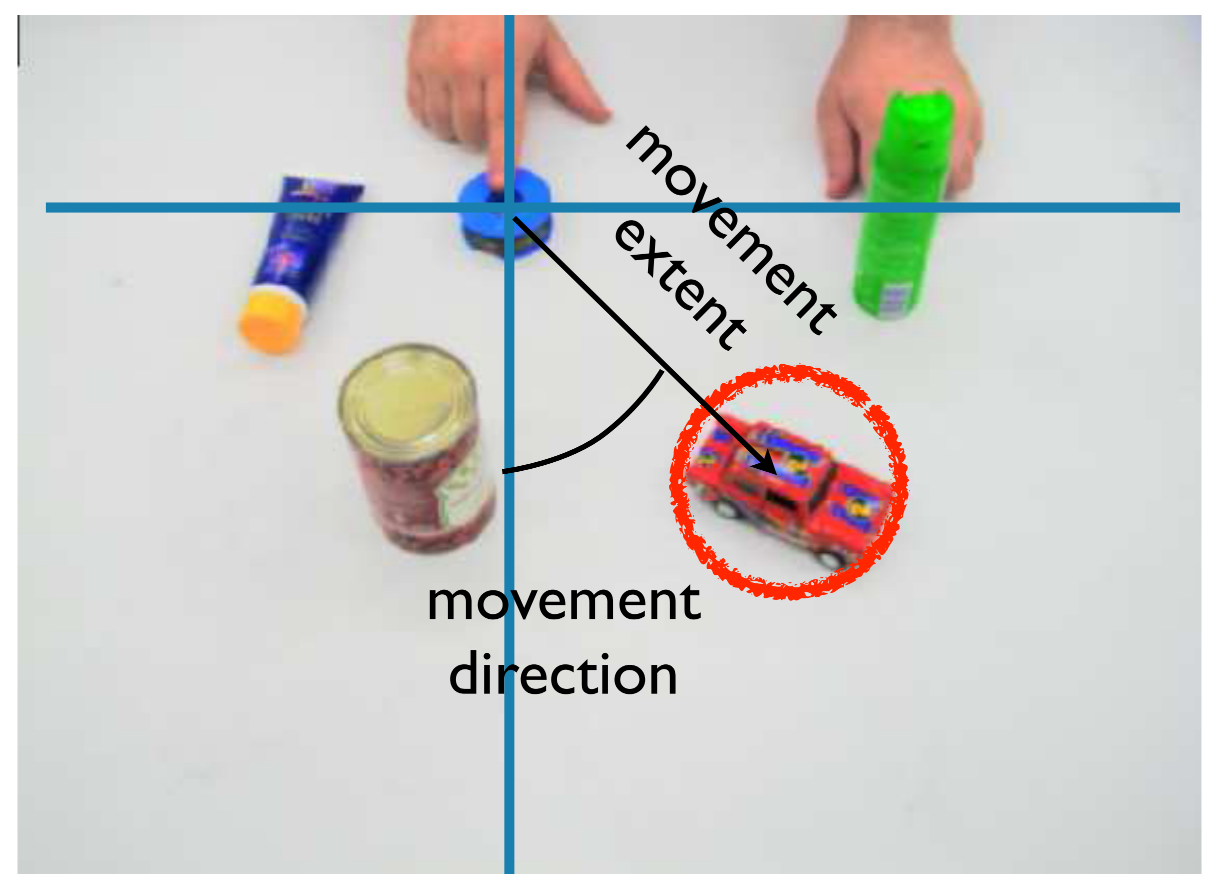
- example: reaching is guided by body-centered, not by retinal visual representation



Coordinate transforms

- are fundamental element to sensory-motor cognition
- [but critical also to mental operations!]

- example: movement parameters are extracted by representing movement target in coordinates centered in the initial position of the hand



Coordinate transforms

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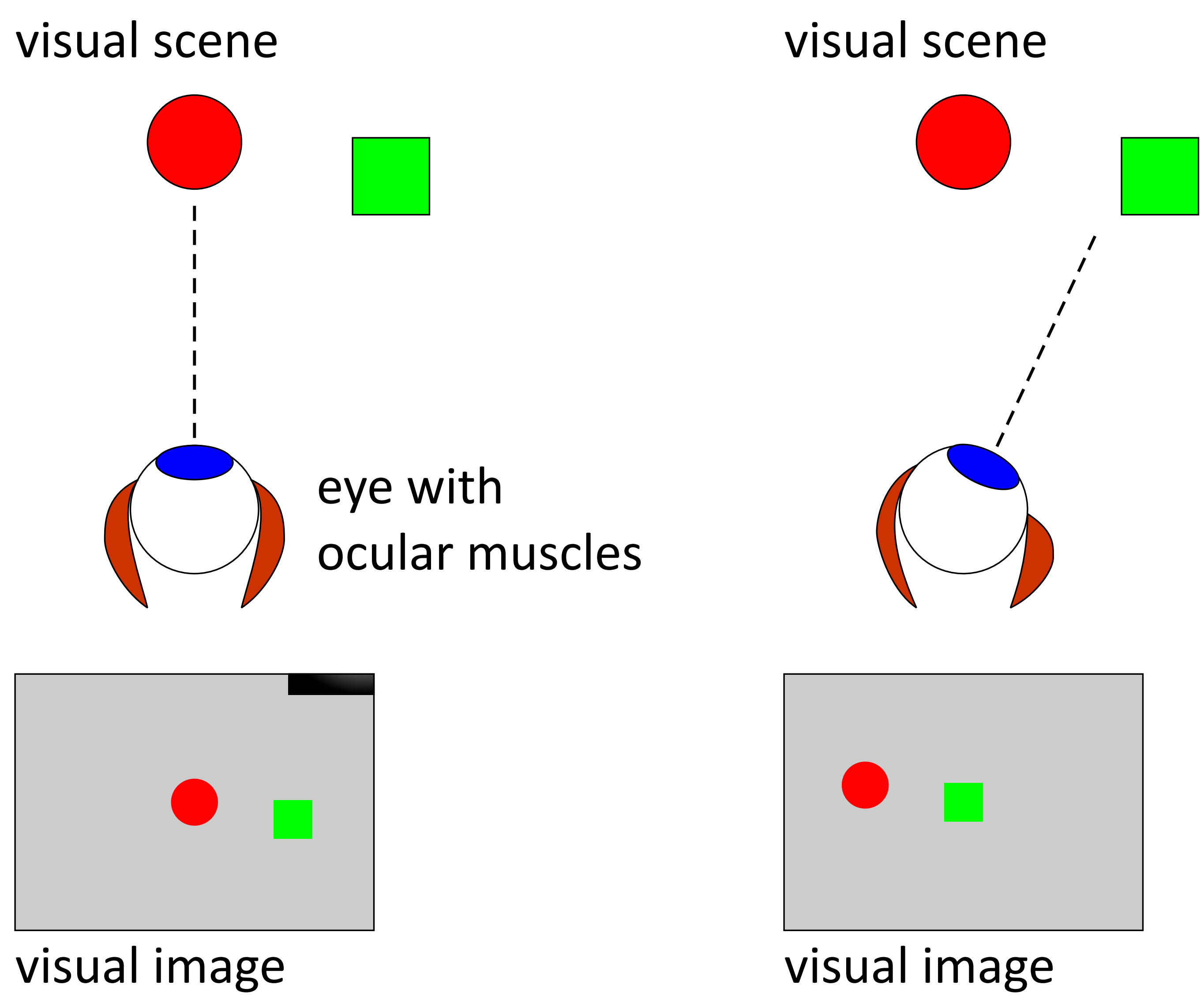


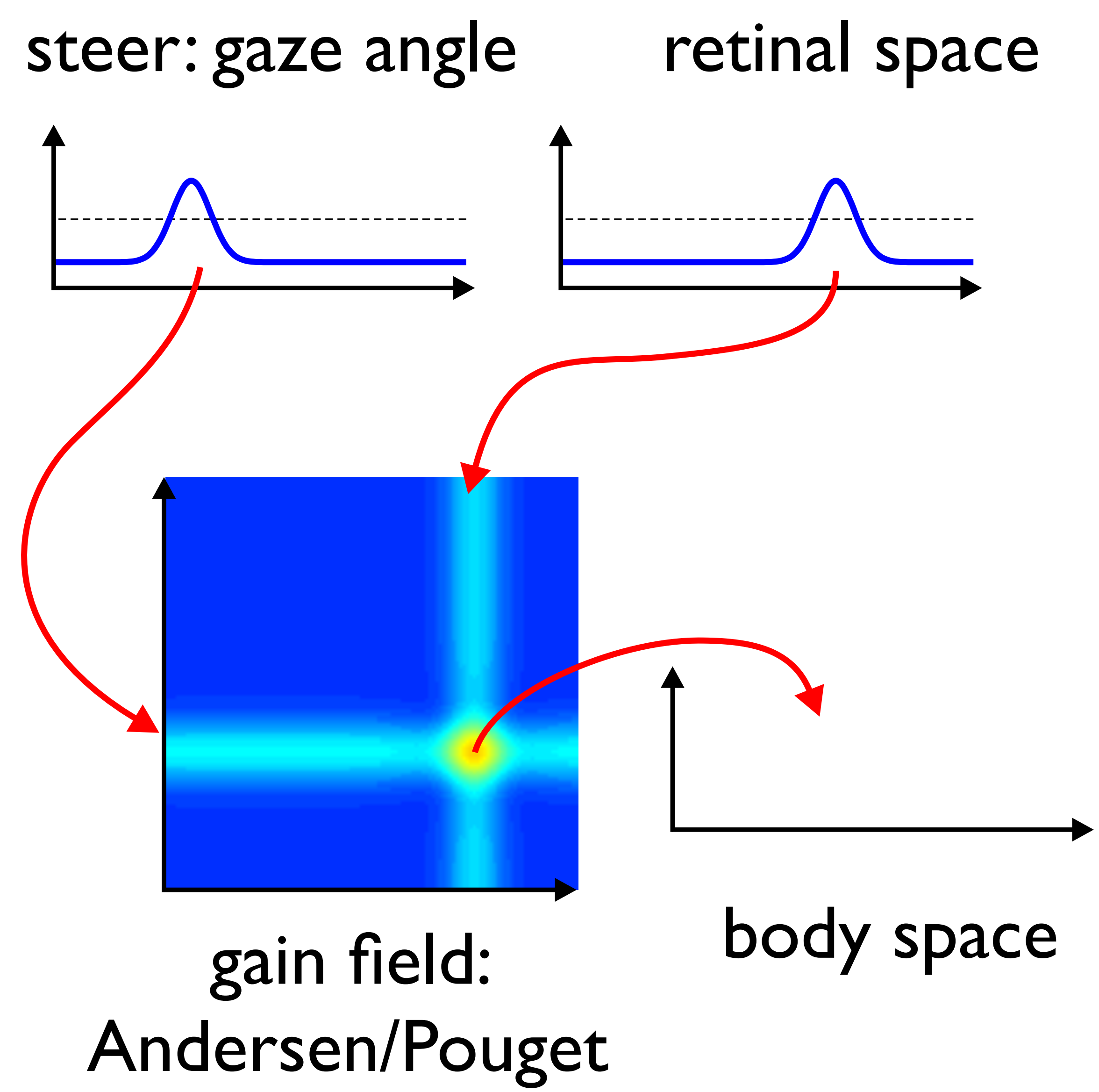
- worked example: from retinal to head-centered/ body-centered frame

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

Retina => body space

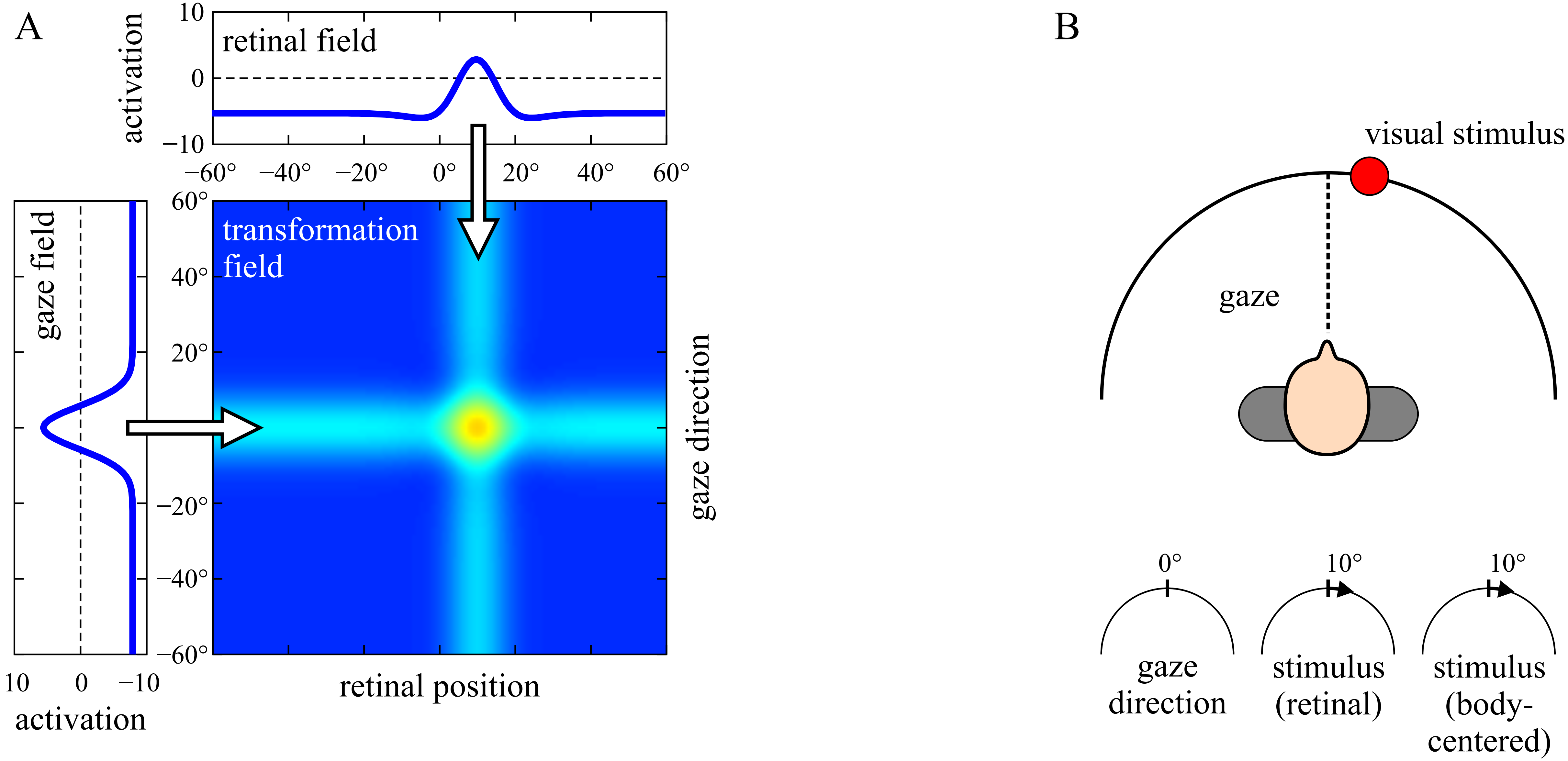
- transformation depends on the gaze angle = steering dimension

- need a bound neural representation of
  - retinal space
  - gaze angle
- obtained from ridge/slice input to bind these
- project to body space



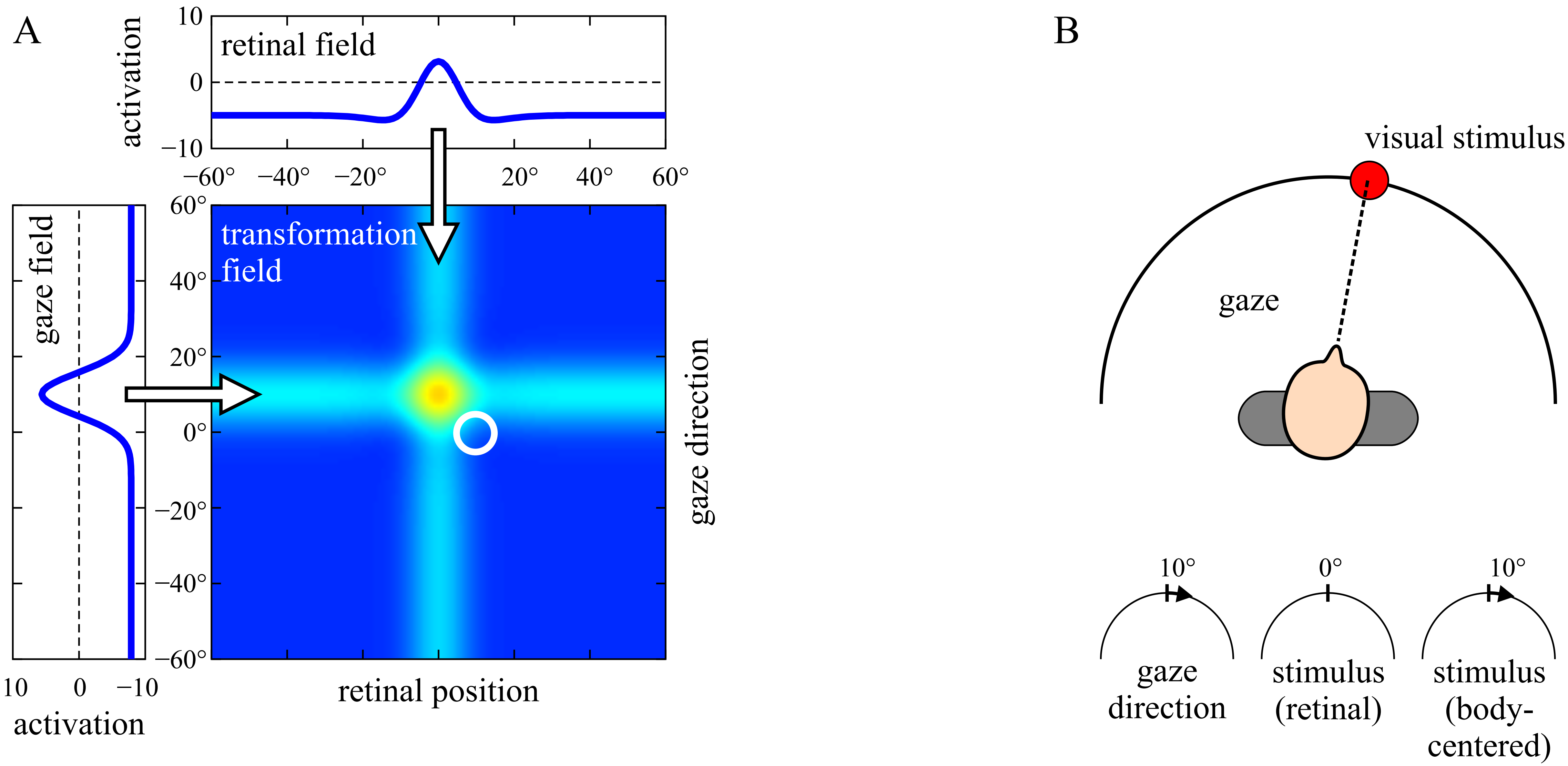
[Schneegans Ch 7 of *DFT Primer*, 2016]

Retina => body space



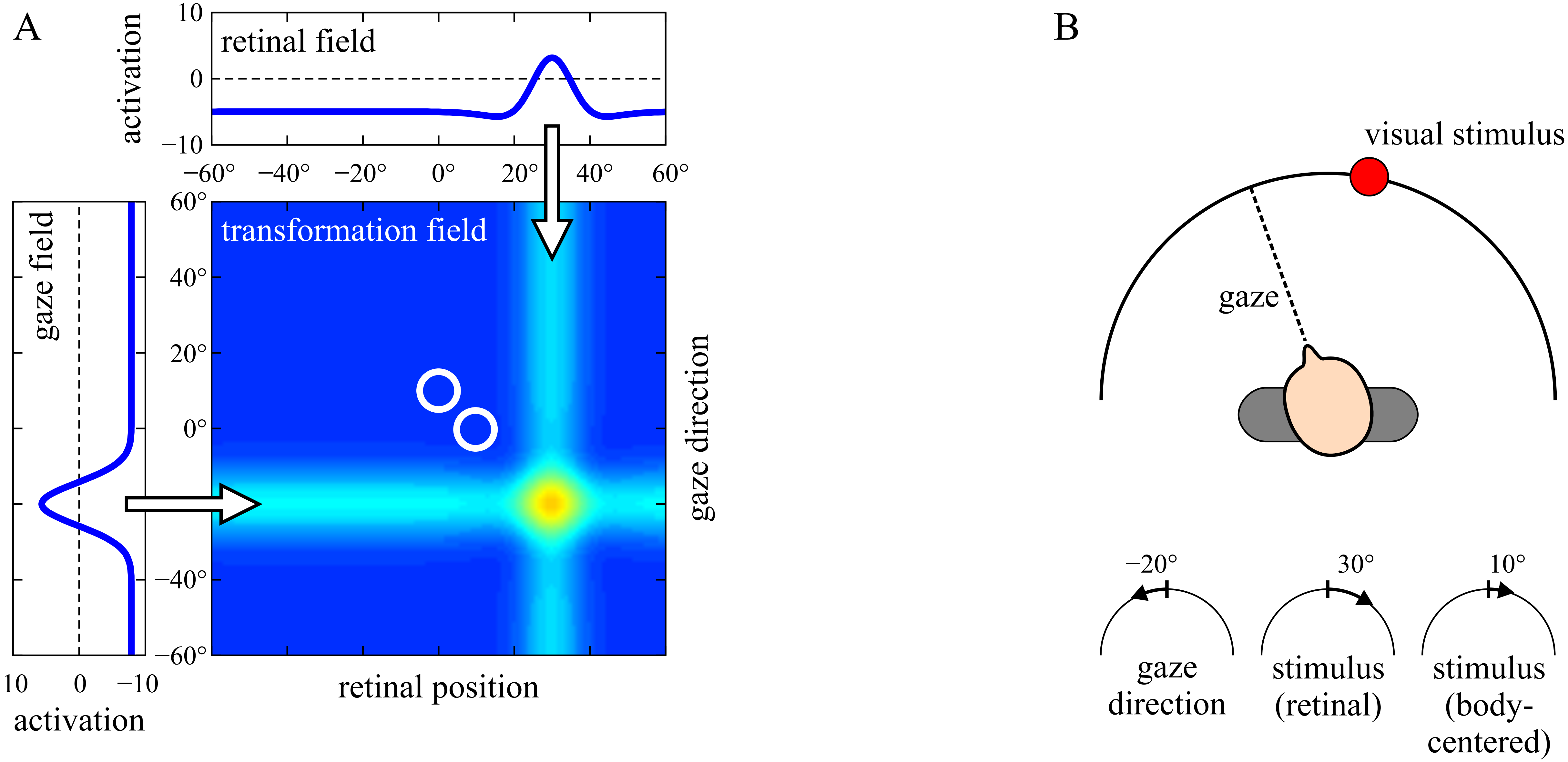
[Schneegans Ch 7 of *DFT Primer*, 2016]

Retina => body space



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

Retina => body space



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

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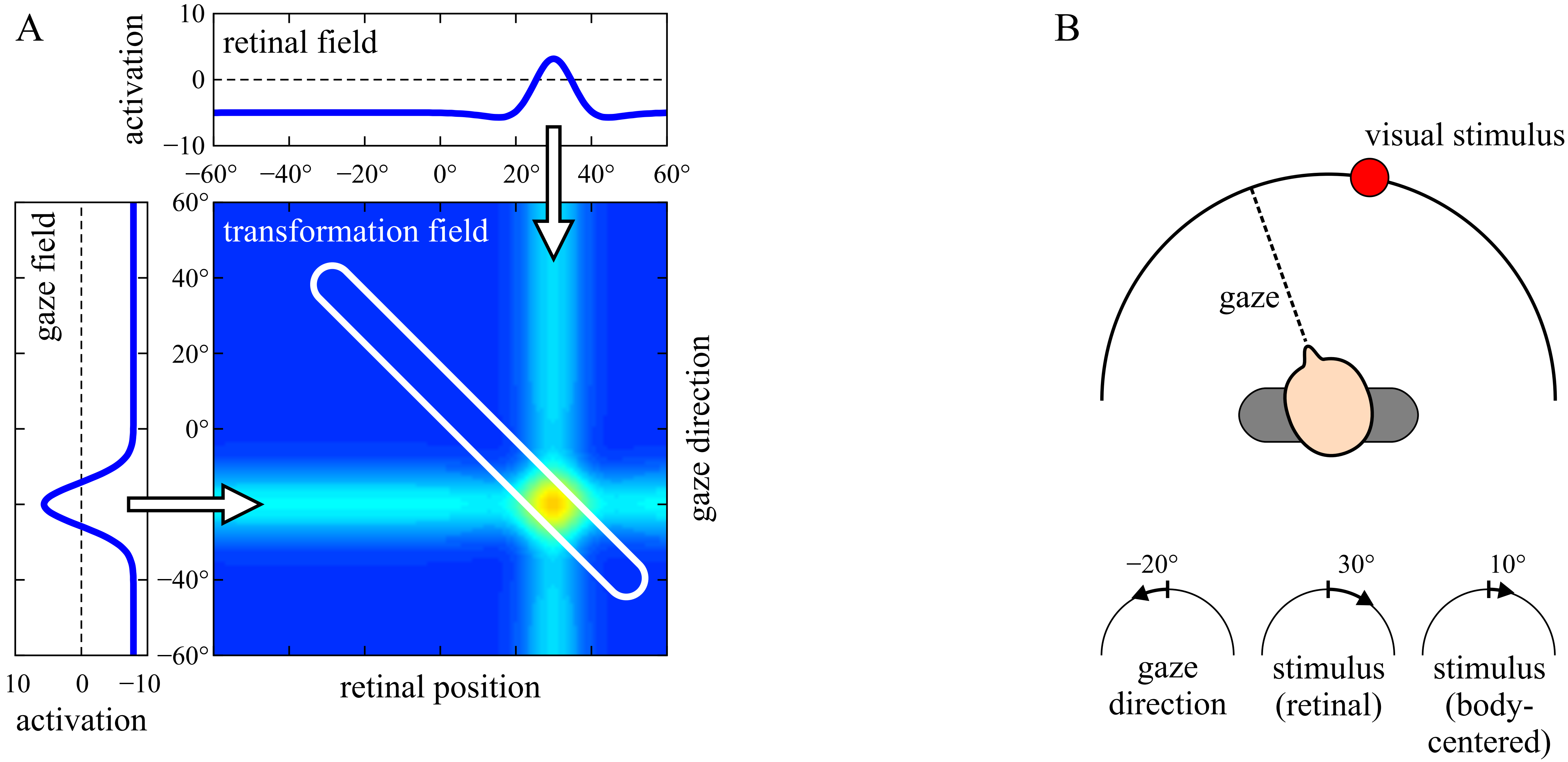
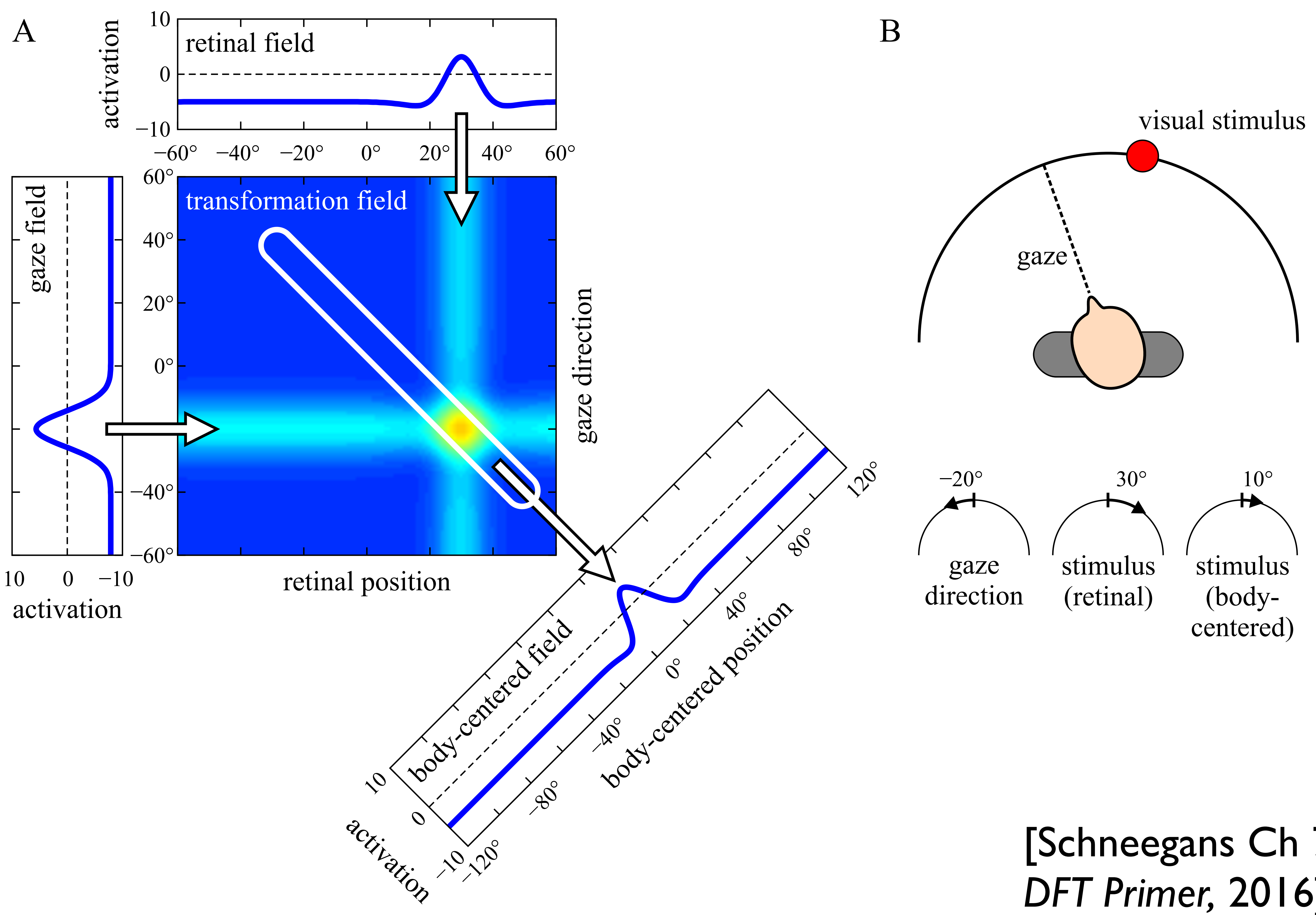


[Schneegans Ch 7 of *DFT Primer*, 2016]

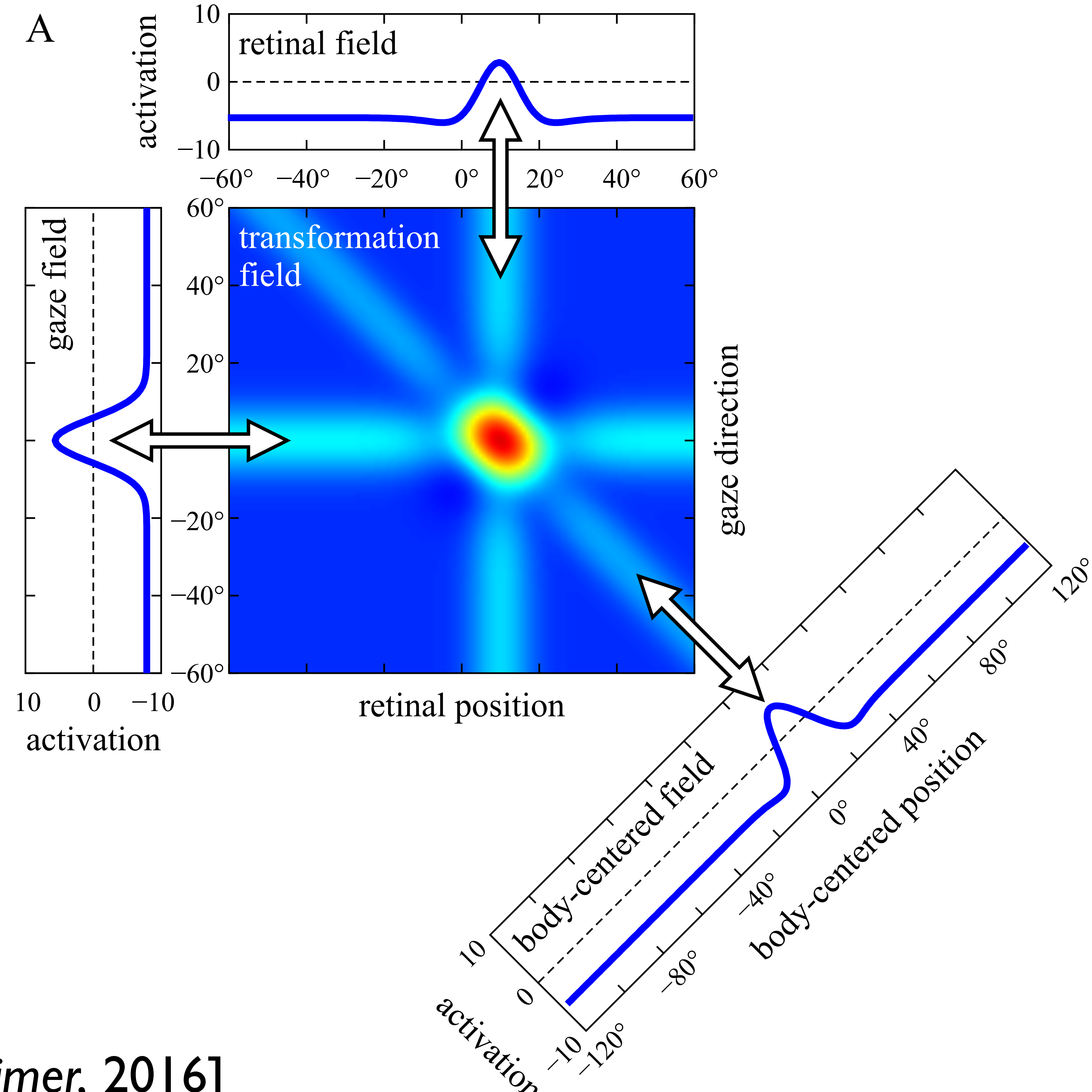
Retina => body space



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

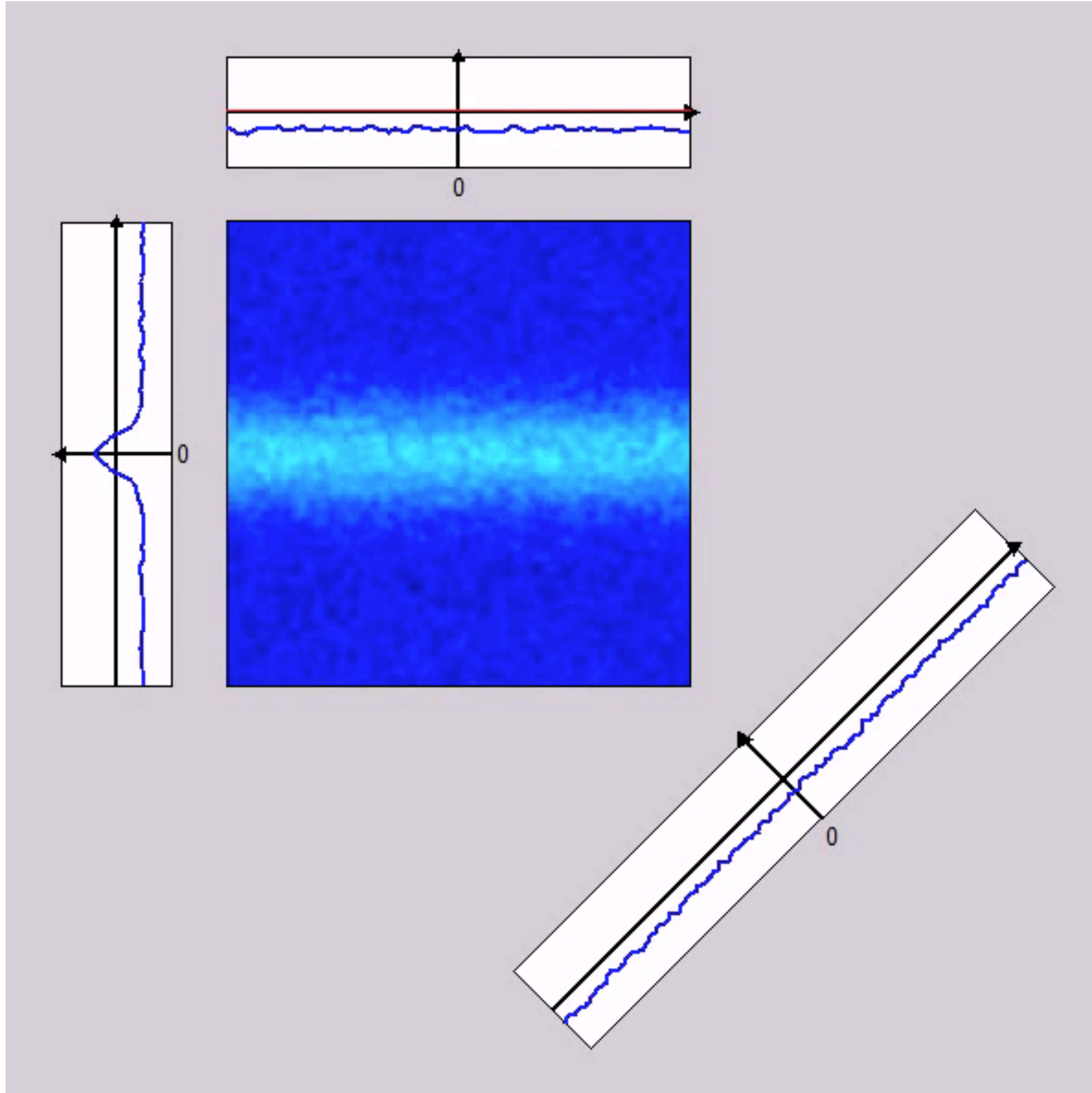
Retina => body space

- bi-directional coupling
- => predict retinal coordinates



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

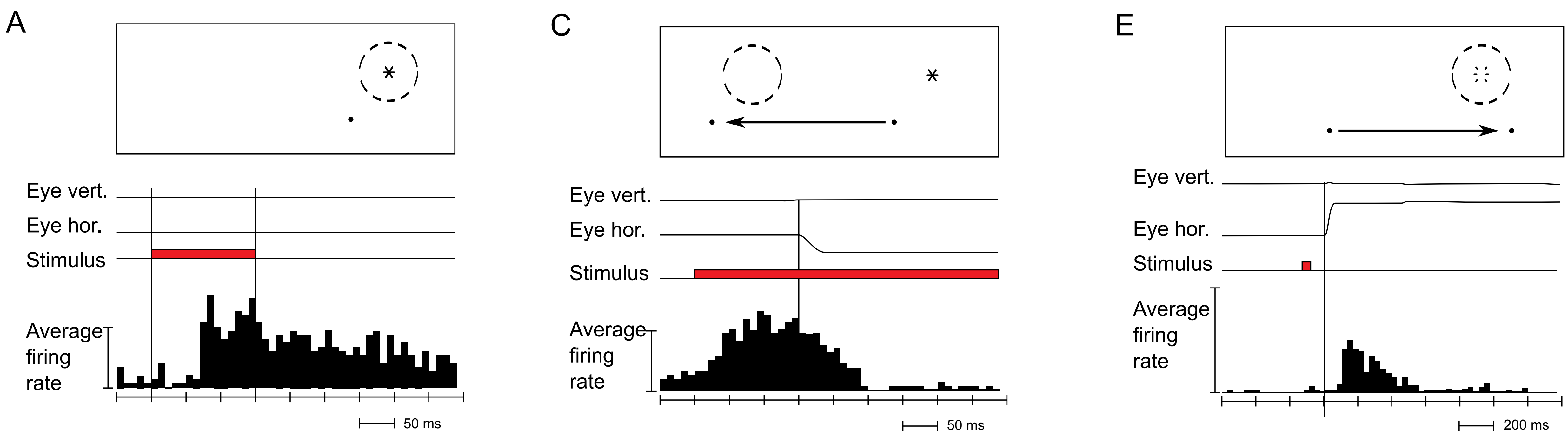
Spatial remapping during saccades



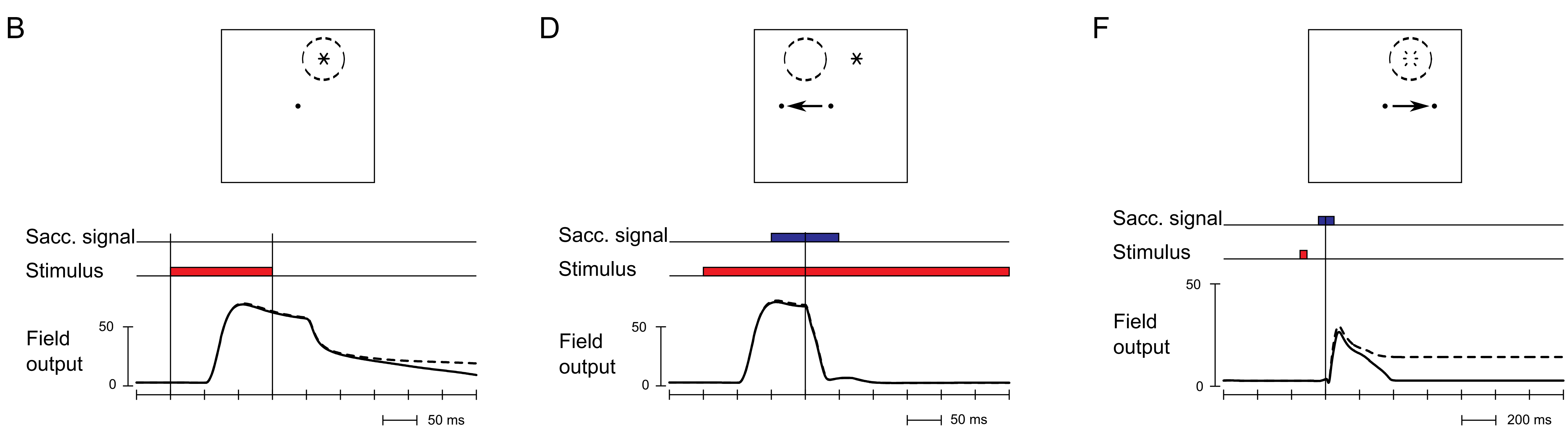
[Schneegans, Schöner *Biological Cybernetics* 2012]

Accounts for predictive updating

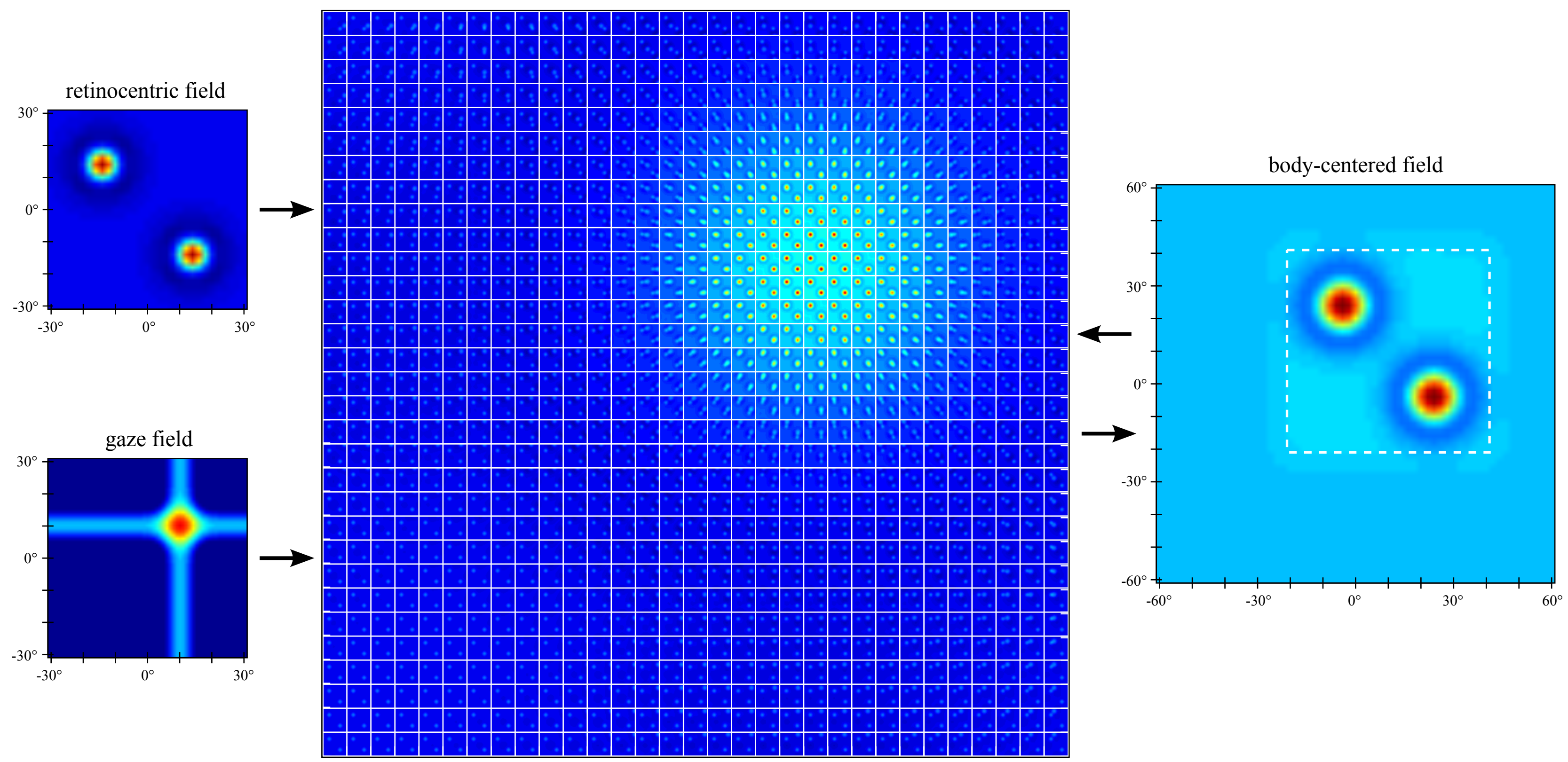
[neural data: Duhamel, Colby, Goldberg, 1992, LIP]



[model: Schneegans, Schöner *Biological Cybernetics* 2012]



Scaling



[Schneegans, Schöner, 2012]

Summary: higher dimensions

- representing different kinds of dimensions within a higher-dimensional field offers new (cognitive) functions
    - binding
    - search
    - coordinate transforms