“the red cup to
the left of
the green cup”

Dynamic Field Theory: higher cognition

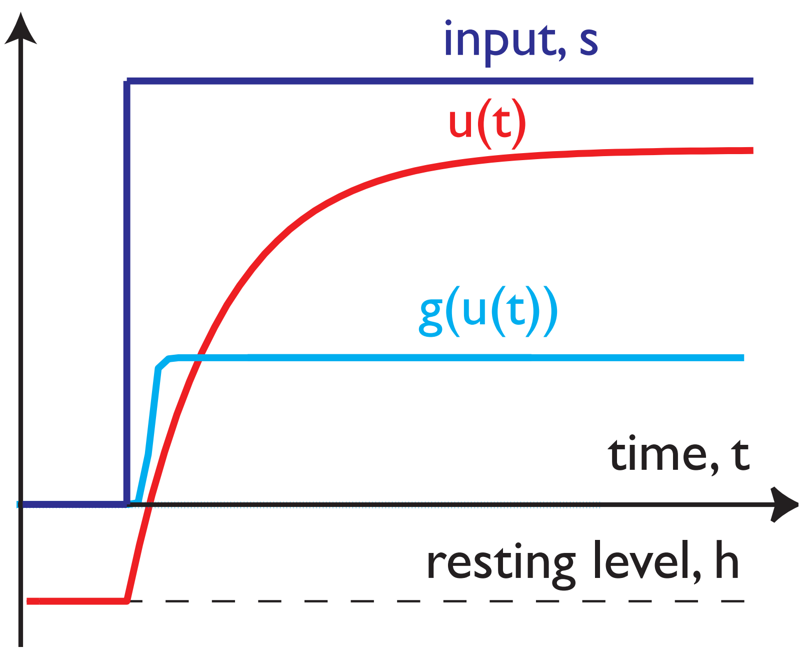
Gregor Schöner
Institute for Neural Computation (INI)
Ruhr-University Bochum, Germany
dynamicfieldtheory.org
gregor.schoener@rub.de

Recall

Embodied cognition

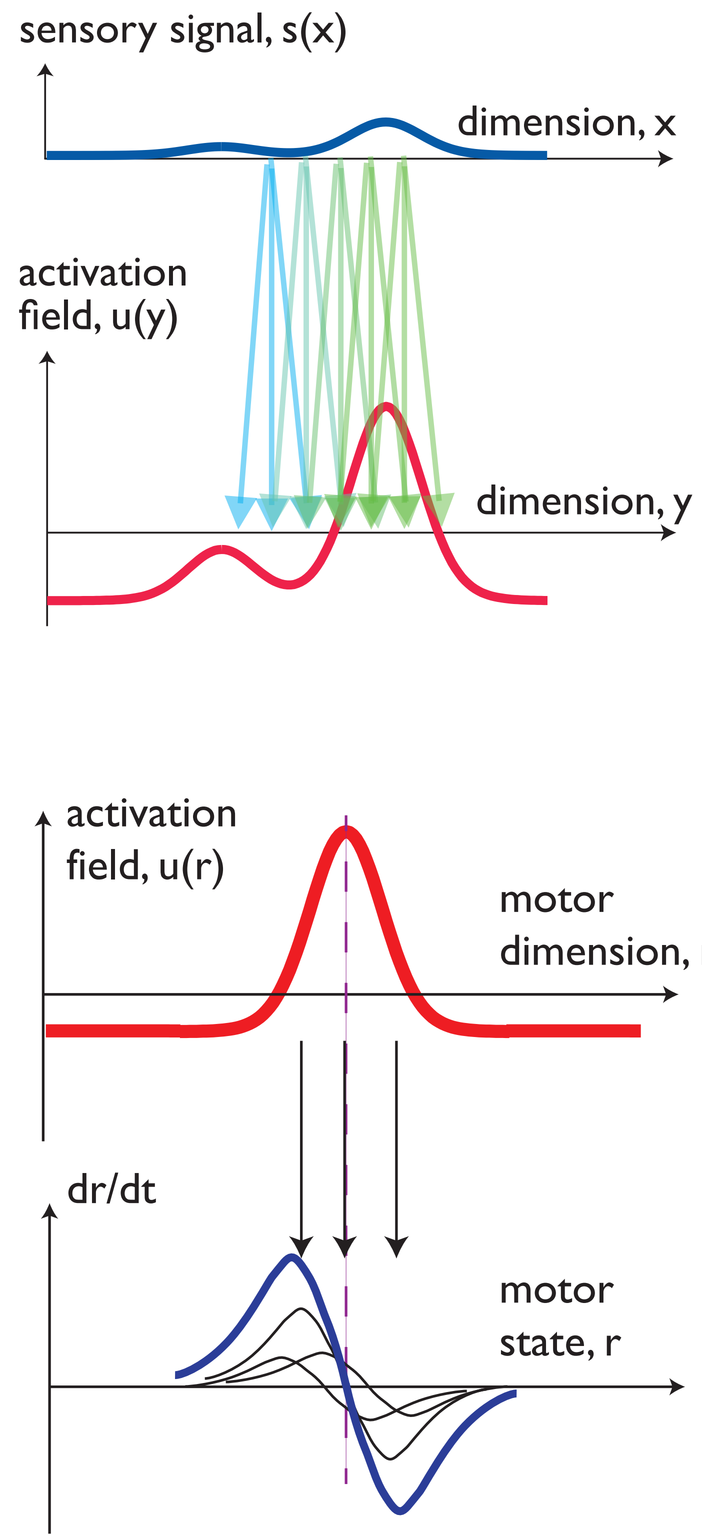
- neural dynamics generate time courses of activation variables/fields that can be linked to time-varying sensory input

$$\tau\dot{u}(t) = -u(t) + h + s(t)$$



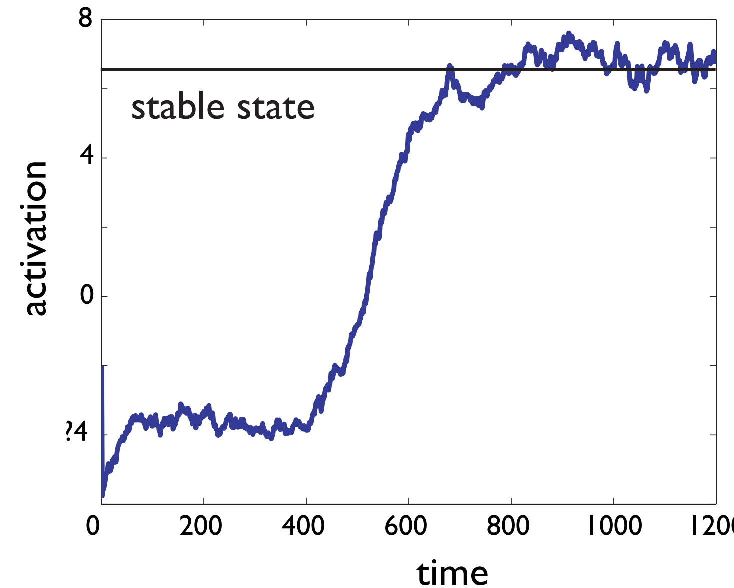
Embodied cognition

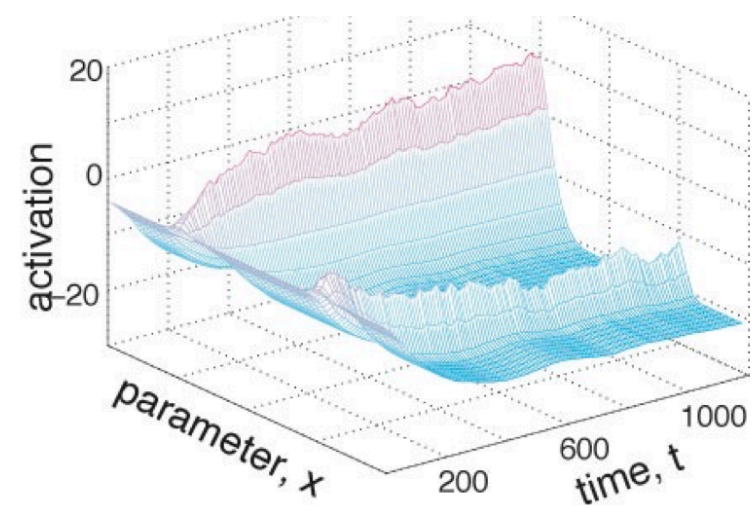
- the contents of these sensory-motor representations is determined by the forward connectivity from the sensory surfaces / to the motor surfaces



Embodied cognition

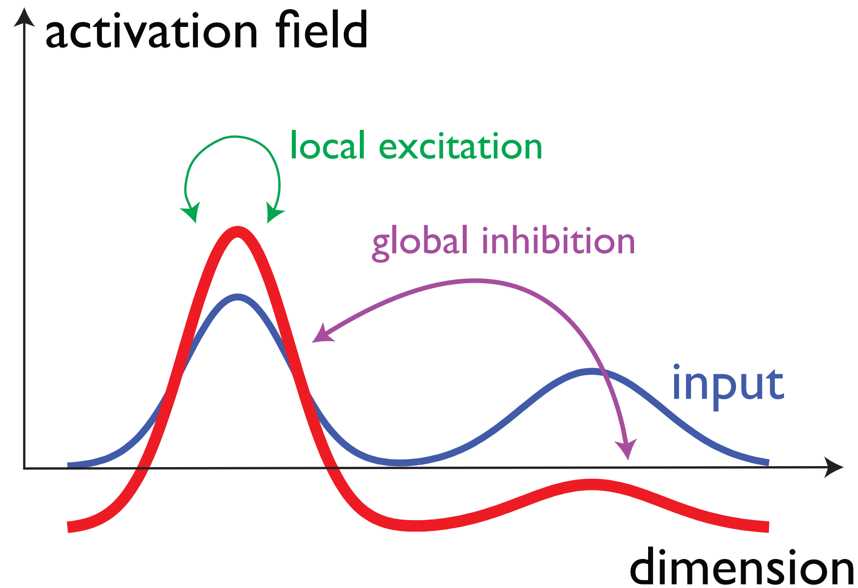
- sensory-motor cognition is not mere input-output mapping, but entails decisions
  - detection/initiation
  - selection
  - entry into working memory
  - categorization





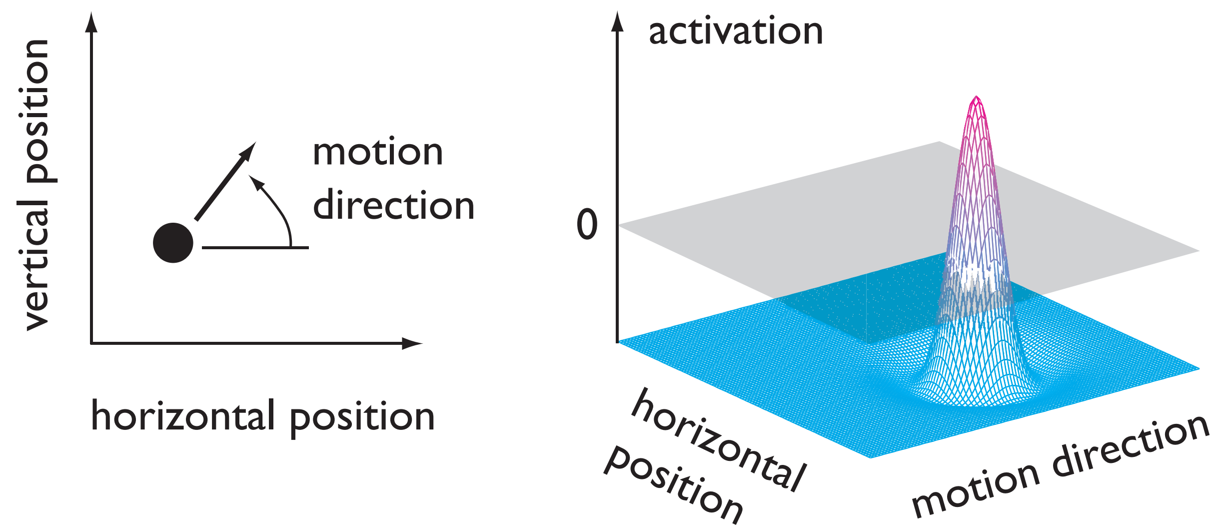
Embodied cognition

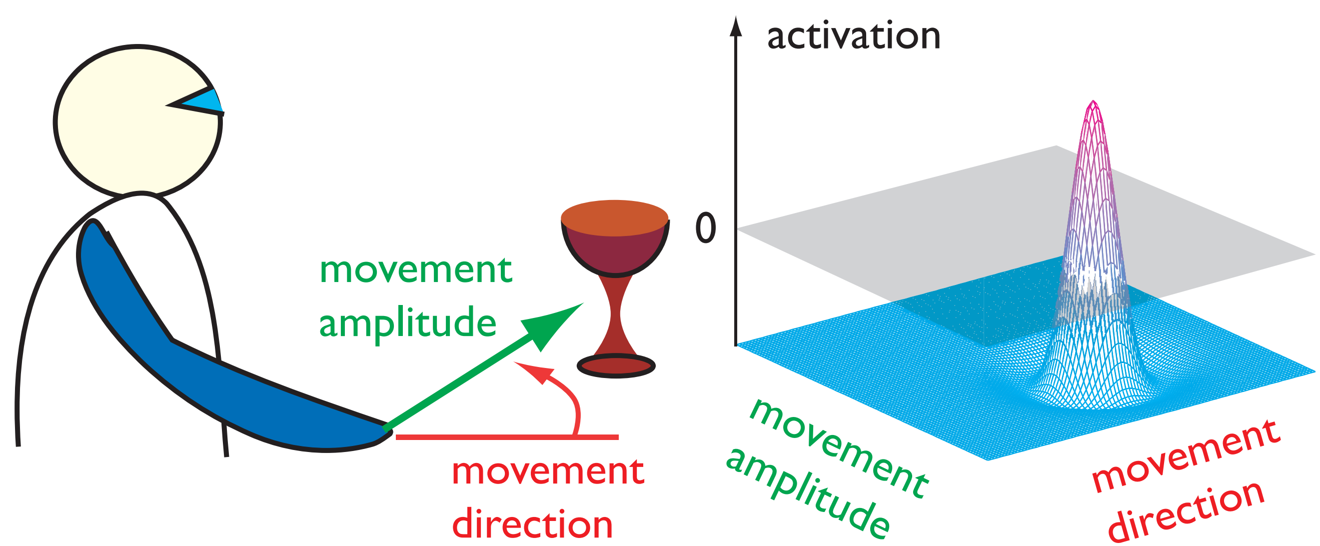
- decisions emerge from neural interaction within dynamic activation fields
- organized to make peaks stable states



Peaks as units of representation

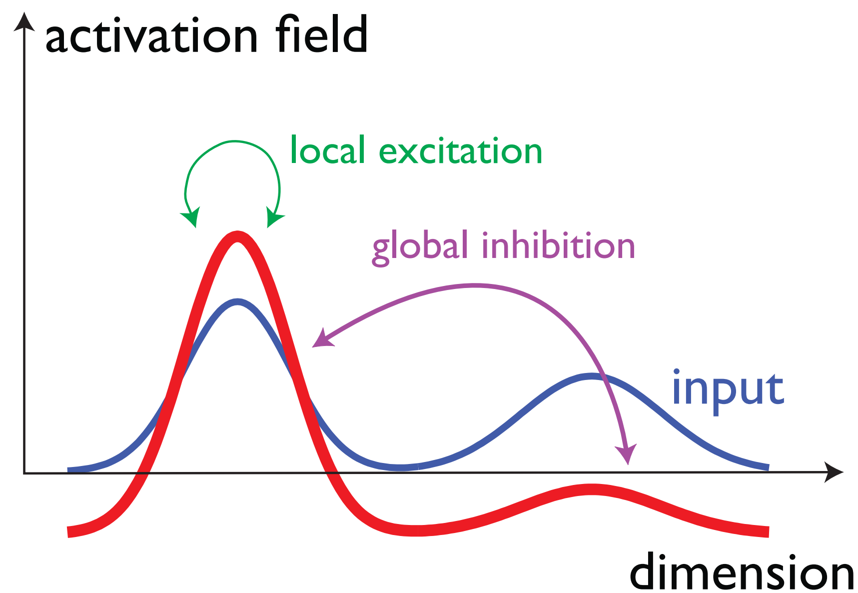
- representing perceptual states
- or motor states





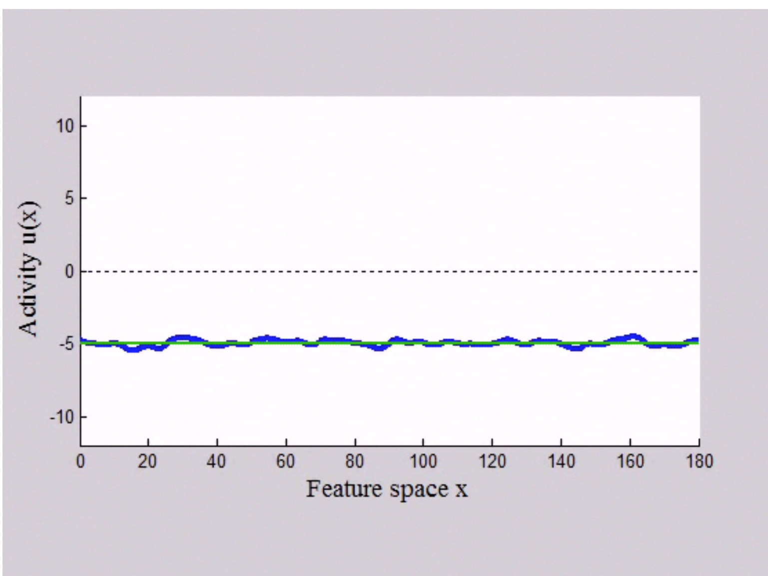
Peaks as units of representation

- => localist neural representation…
- <=> the uniform spatial organization of interaction to make stables states…
- only possible in low-dimensional feature spaces…
- … more later



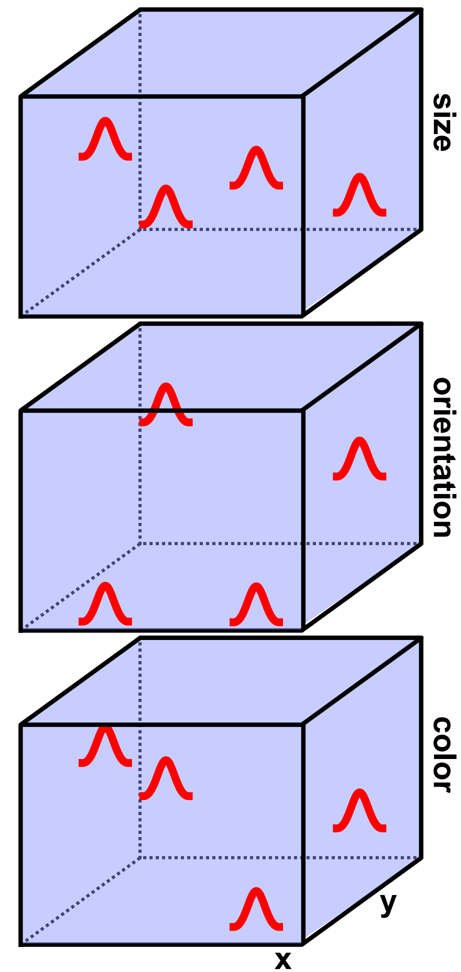
Dynamic fields of varying dimensionality

1-dimensional



2-dimensional

3-dimensional

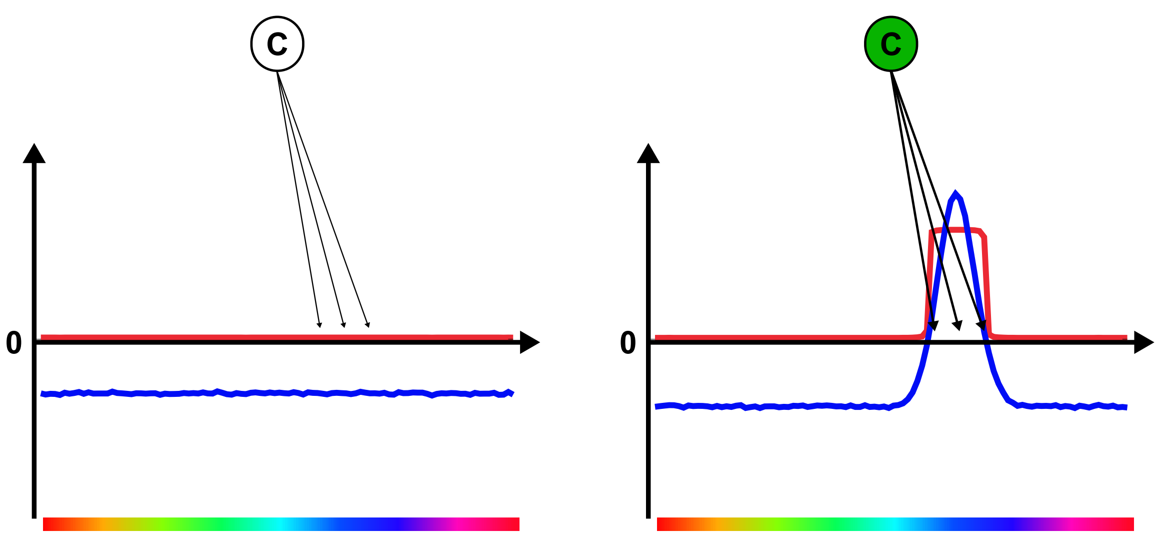


Nodes…

- 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

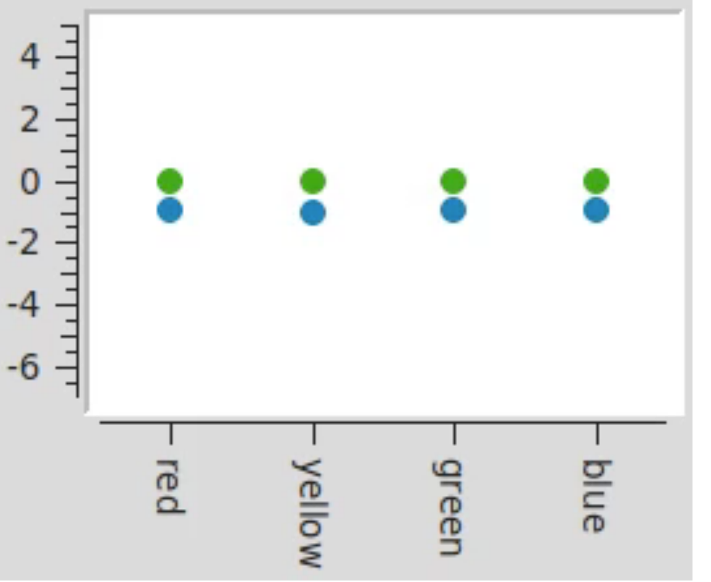
[Tekülve]

Concept Node "blue"



[Grieben]

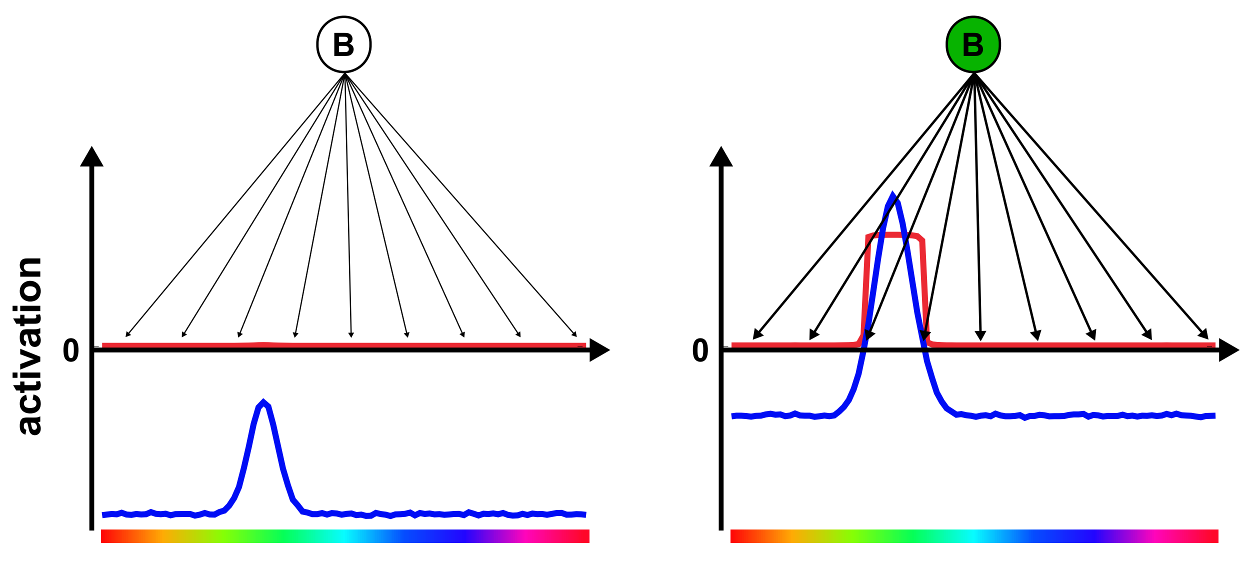
0-dimensional



Nodes…

- may have specific coupling structure that organizes fields within architectures and/or the order of instabilities
- => lecture 3

Boost Node



Roadmap

Higher dimensions

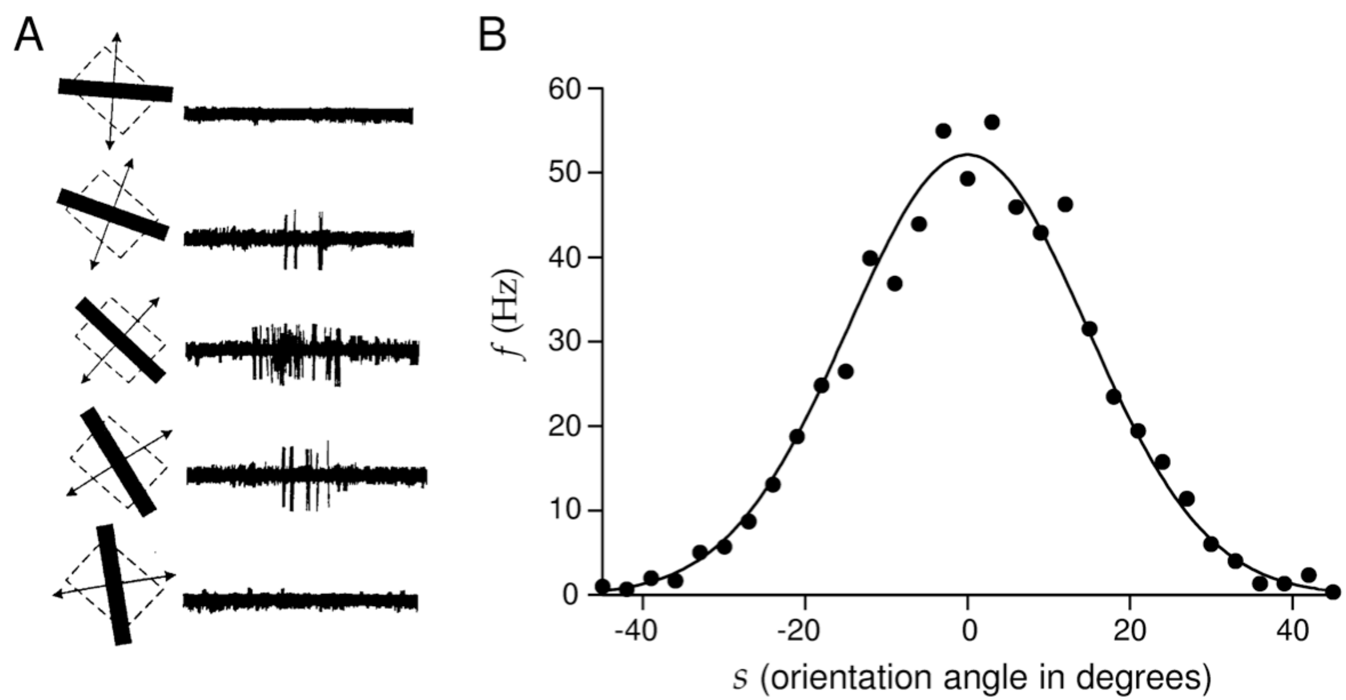
- representing different kinds of dimensions within a higher-dimensional field offers new (cognitive) functions
  - binding
  - search
  - coordinate transform

Feature dimensions

- beyond the spatial dimensions of sensory surfaces..
- visual features: local orientation, motion, texture, color, scale…
- auditory features: pitch, formants …
- motor features: movement direction, force direction …
- cognitive features: ordinal position …

Combining different feature dimensions

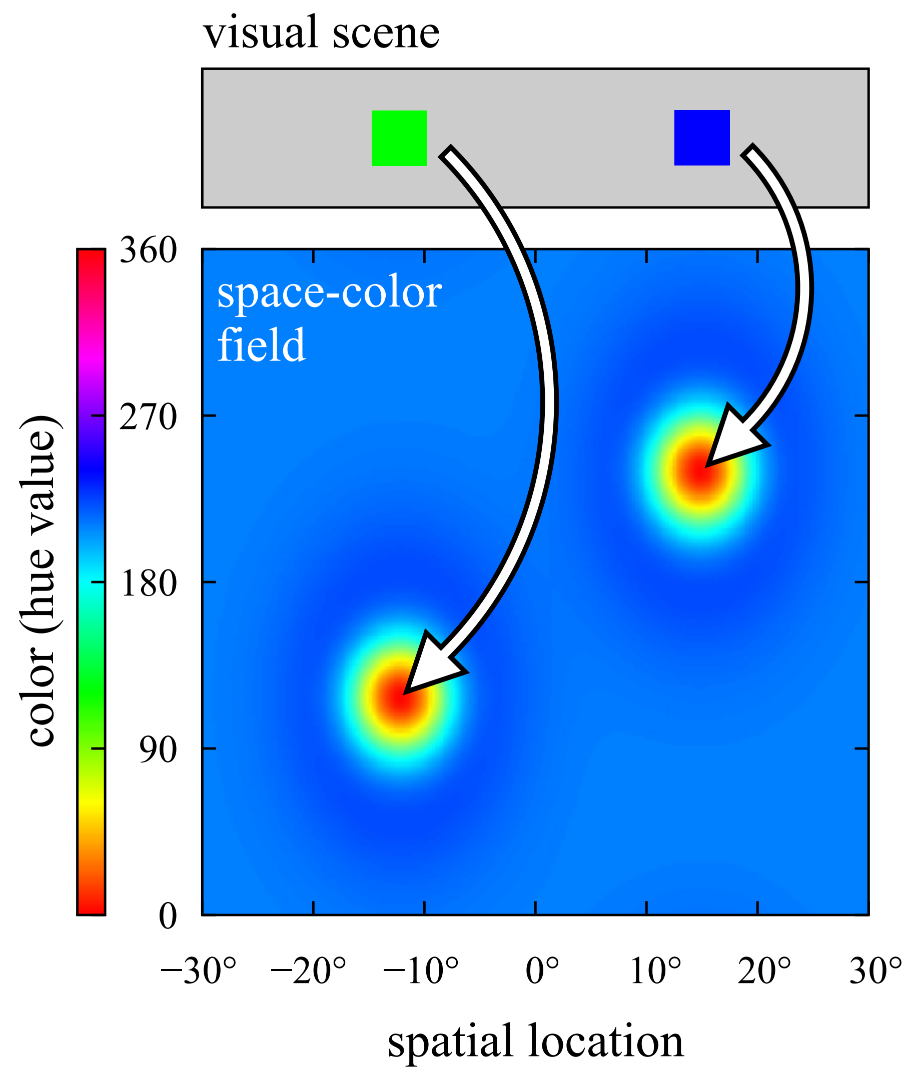
- neurons tuned to multiple dimensions
  - e.g. receptive field + direction tuning
  - => combines visual space and orientation
- “anatomical” binding



[Hubel, Wiesel, 1962]

Combining different feature dimensions

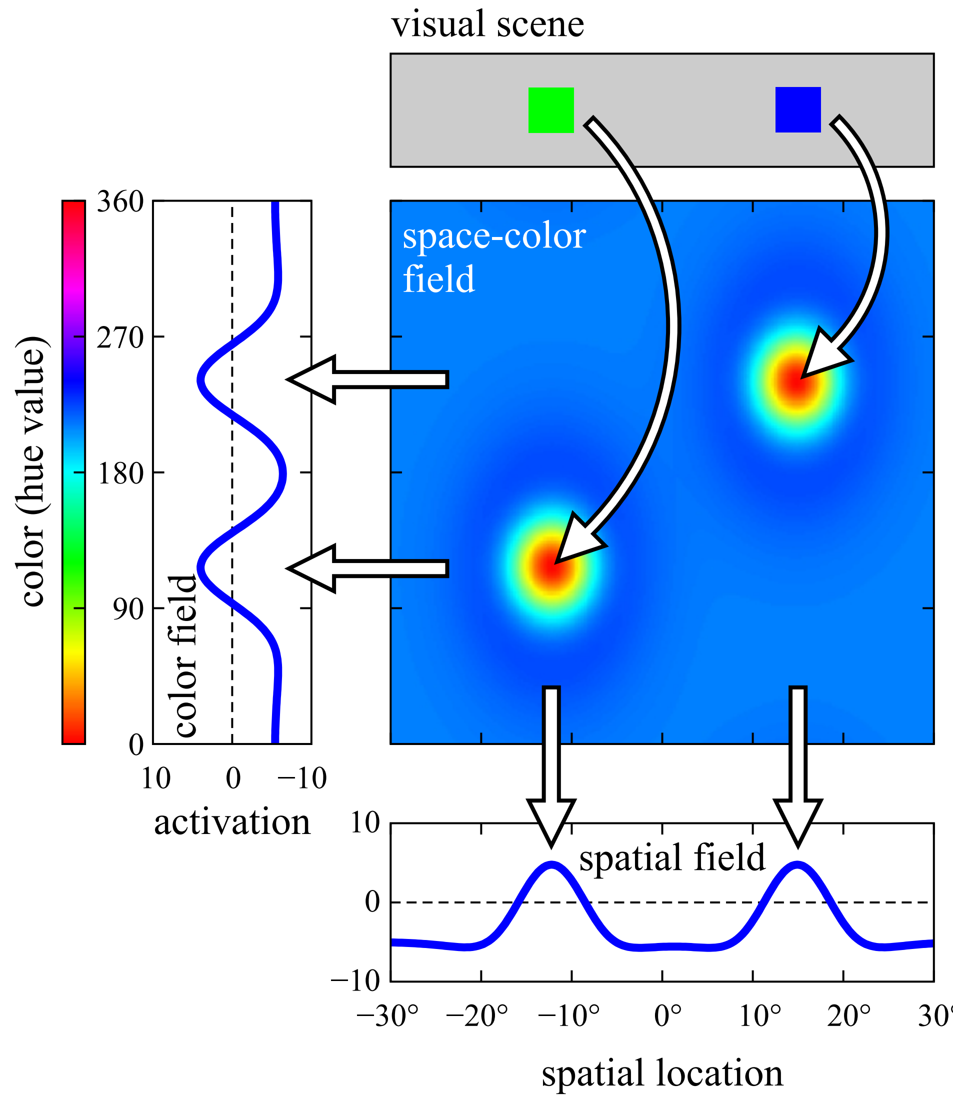
- example: a joint representation of color and visual space "binds" these two dimensions



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

Extract bound features

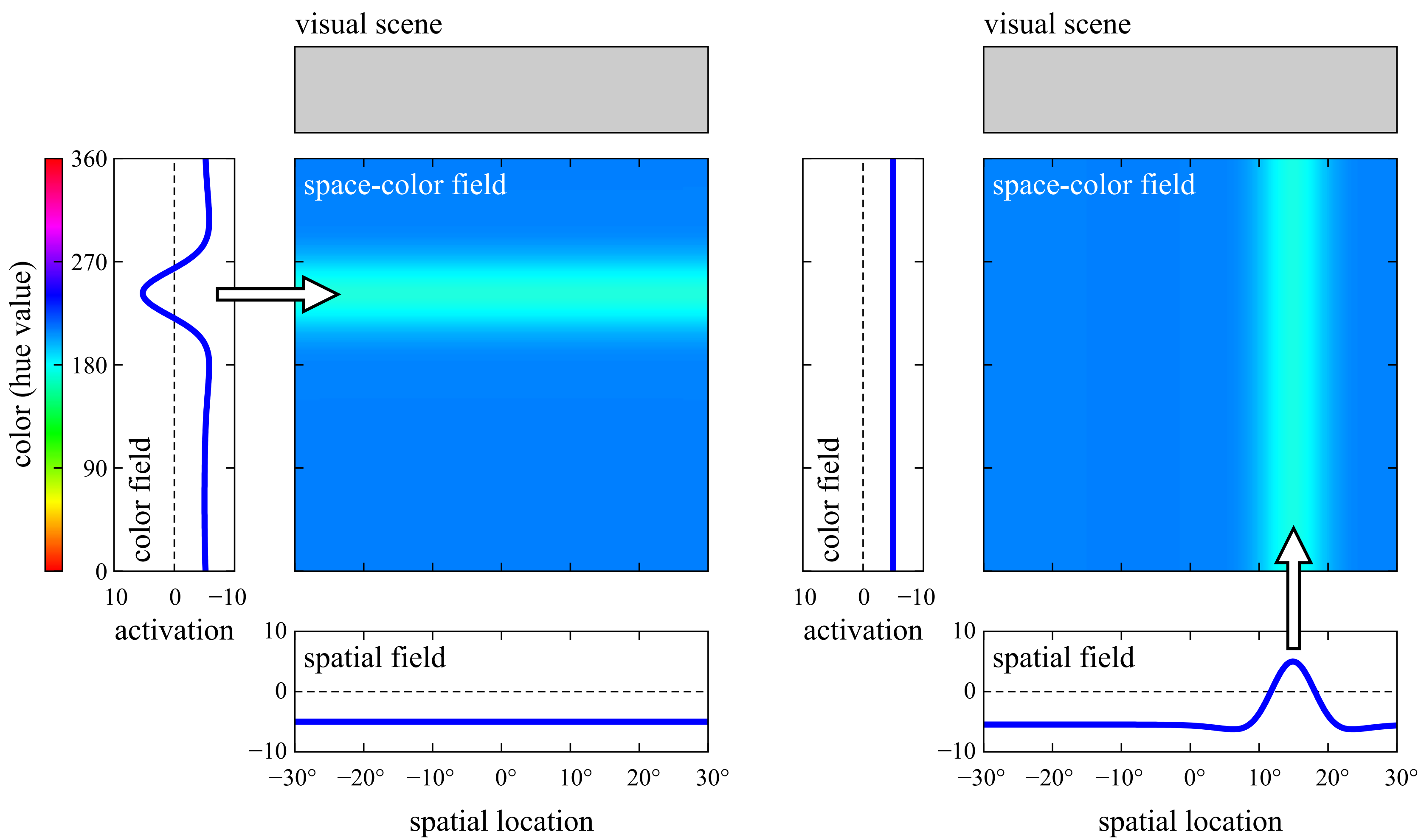
- project to lower-dimensional fields
- by summing along the marginalized dimensions
- (or by taking the soft-max)



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

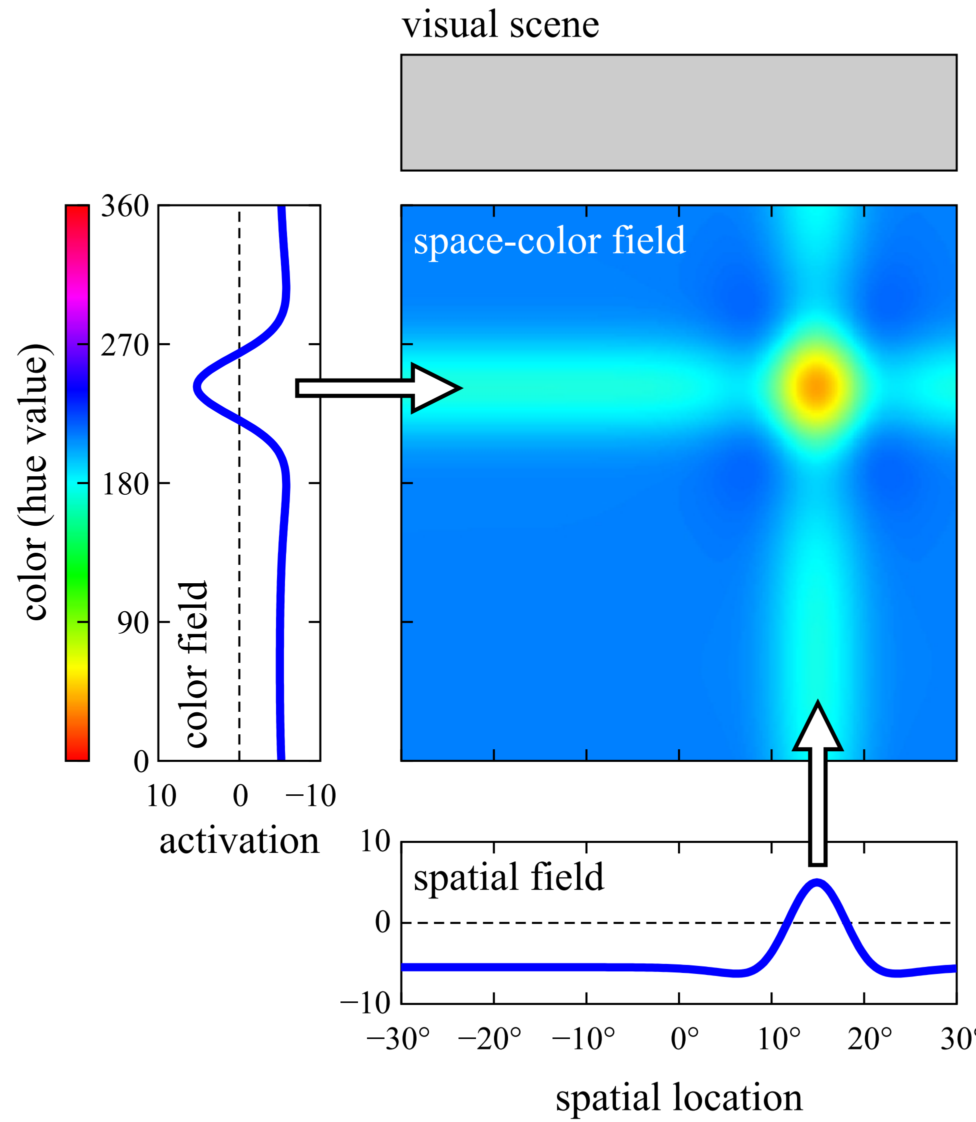
Assemble bound representations

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



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

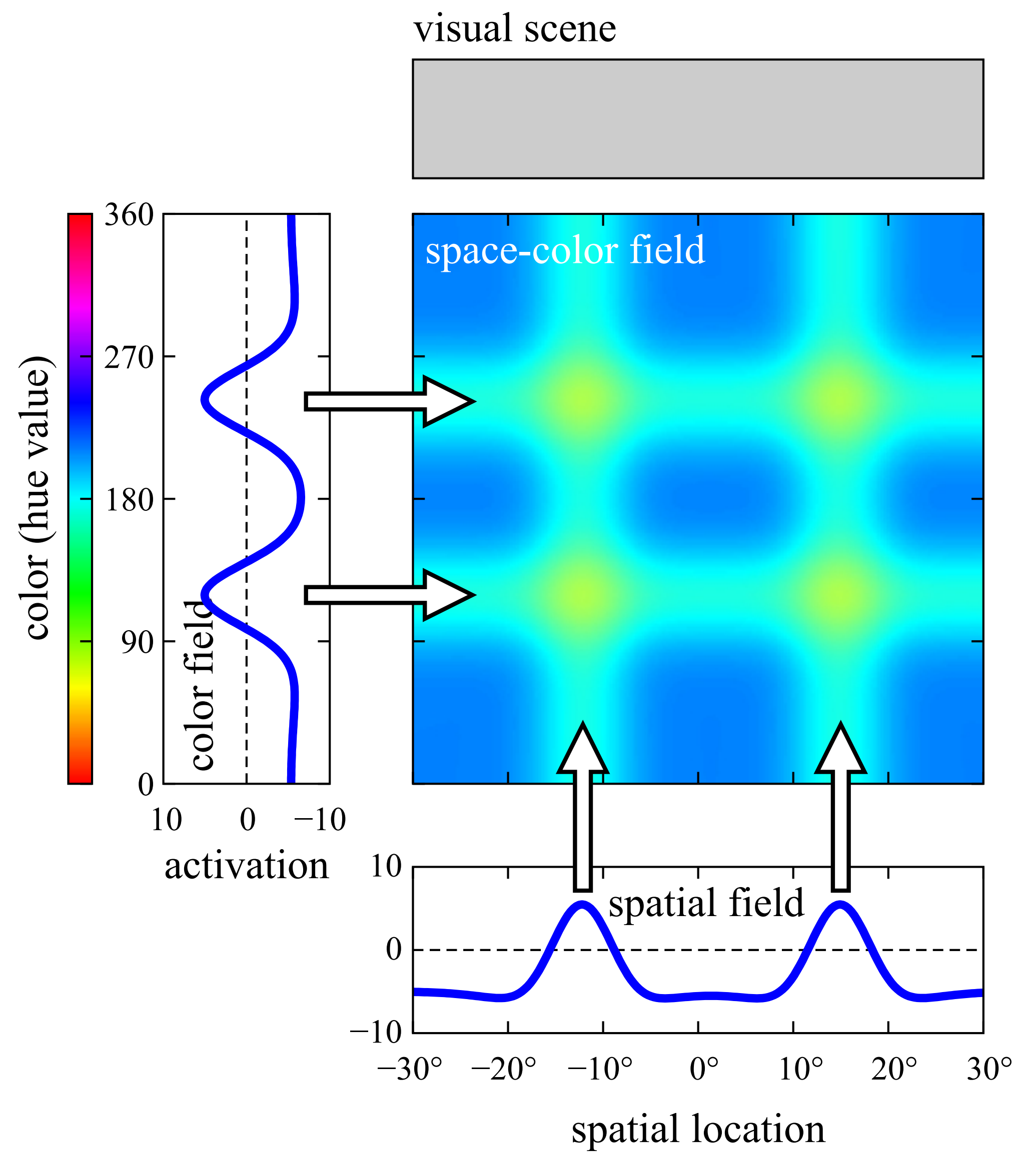
Assemble bound representations



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

Assemble bound representations

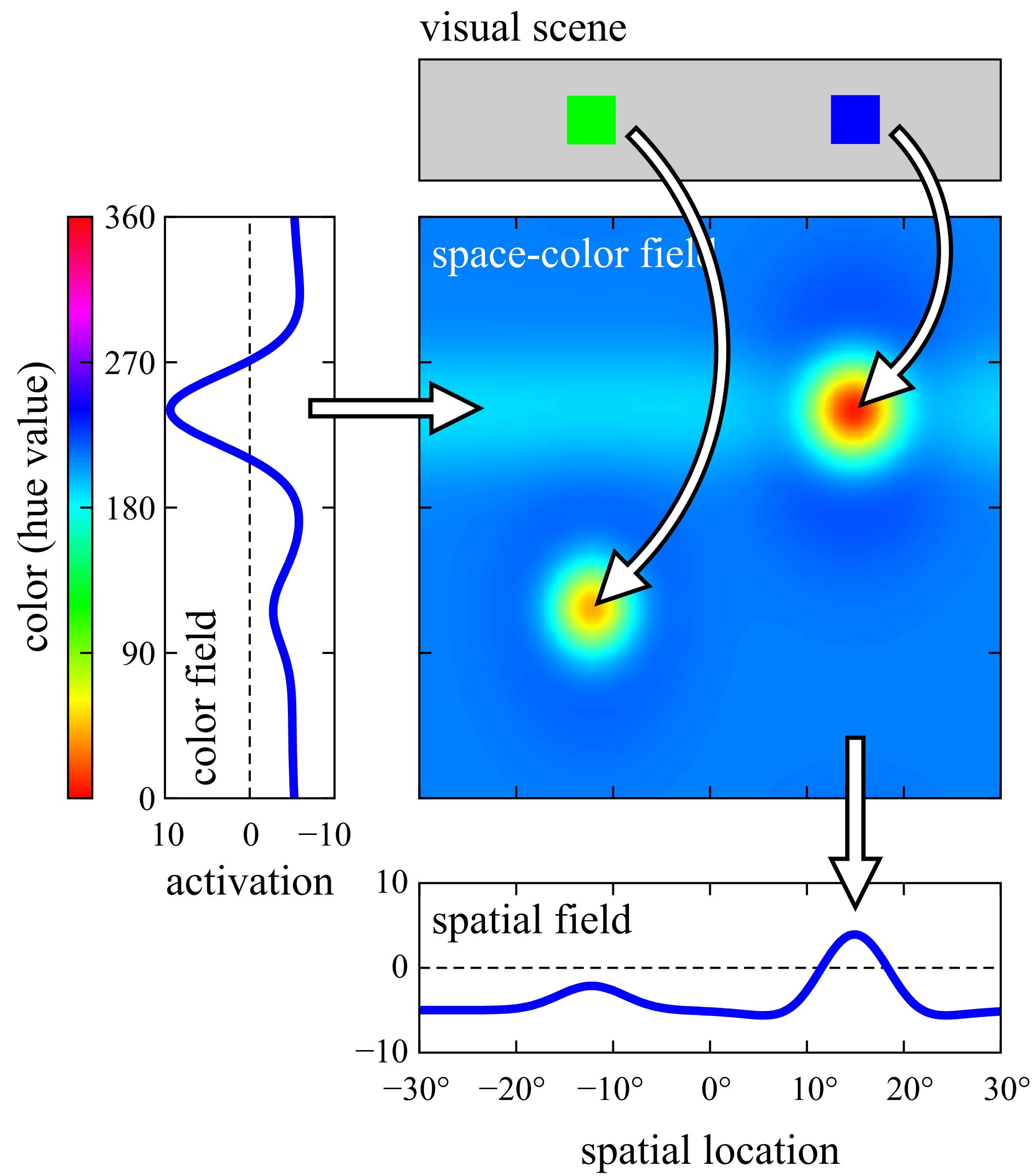
- binding problem: multiple ridges along lower-dimensional space lead to a correspondence problem
- => assemble one bound object at a time…
- => sequentiality bottle-neck!



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

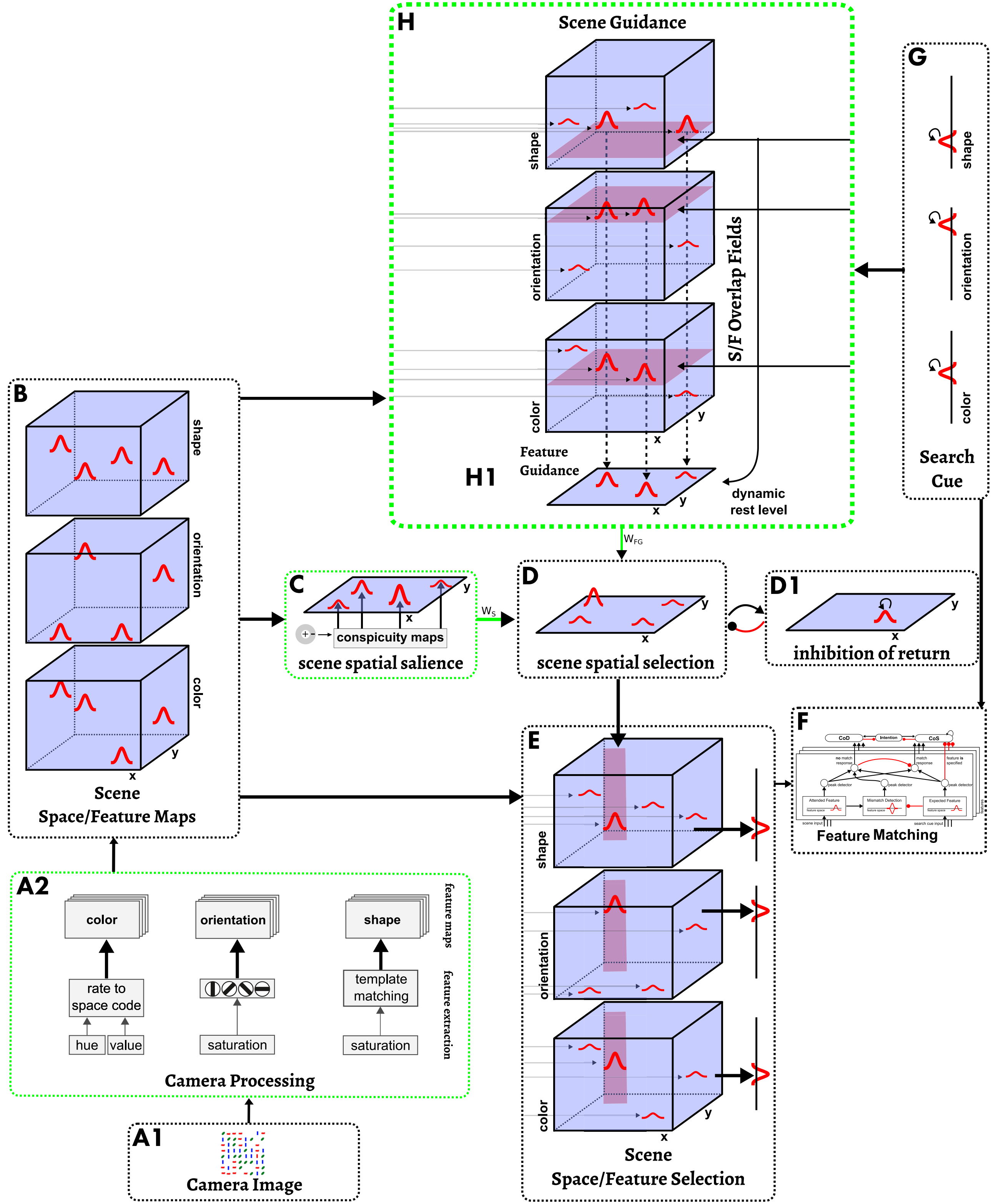
Search

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

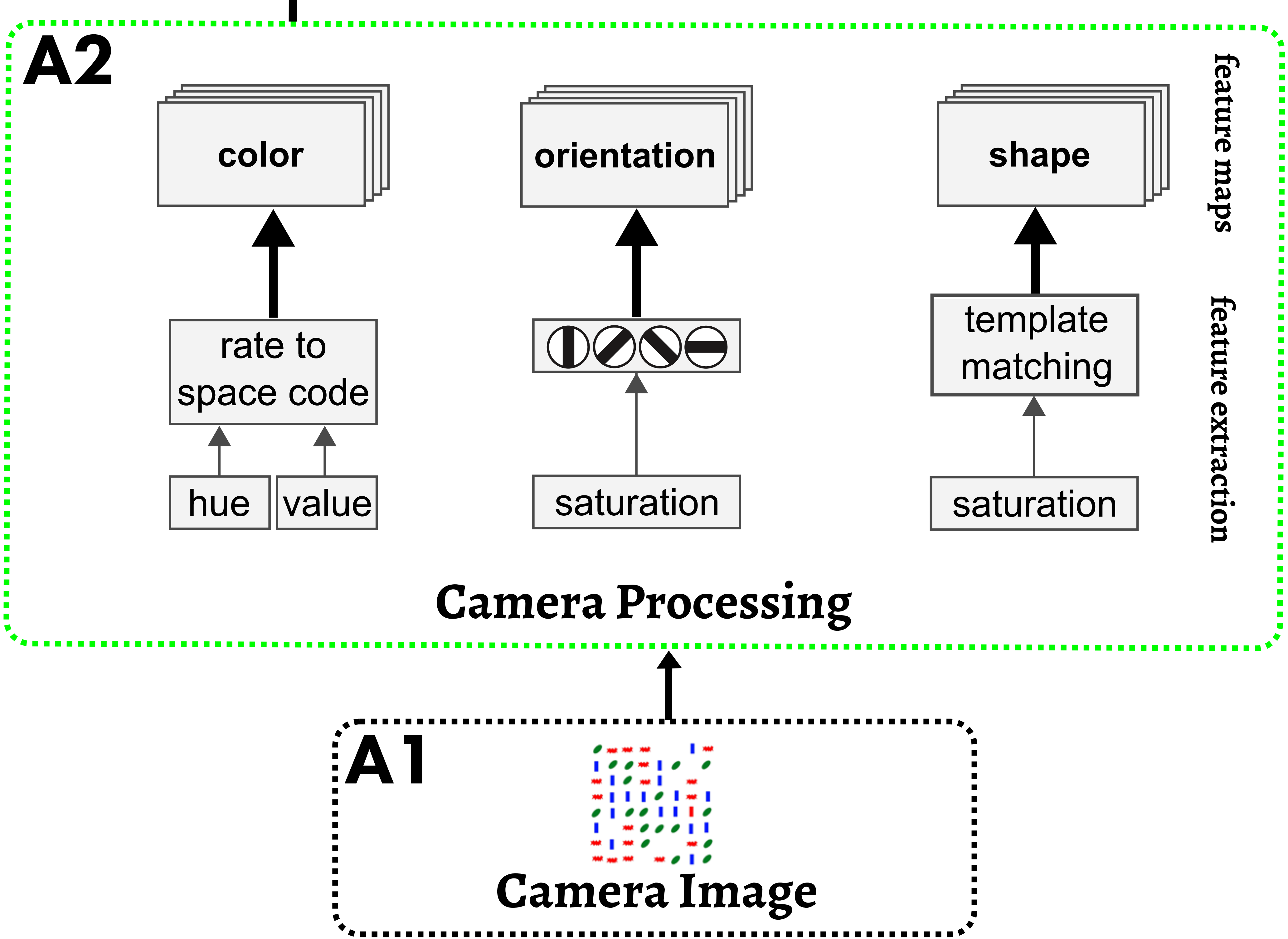


[Schneegans et al., Ch 5 of *DFT Primer*, 2016]

Visual search

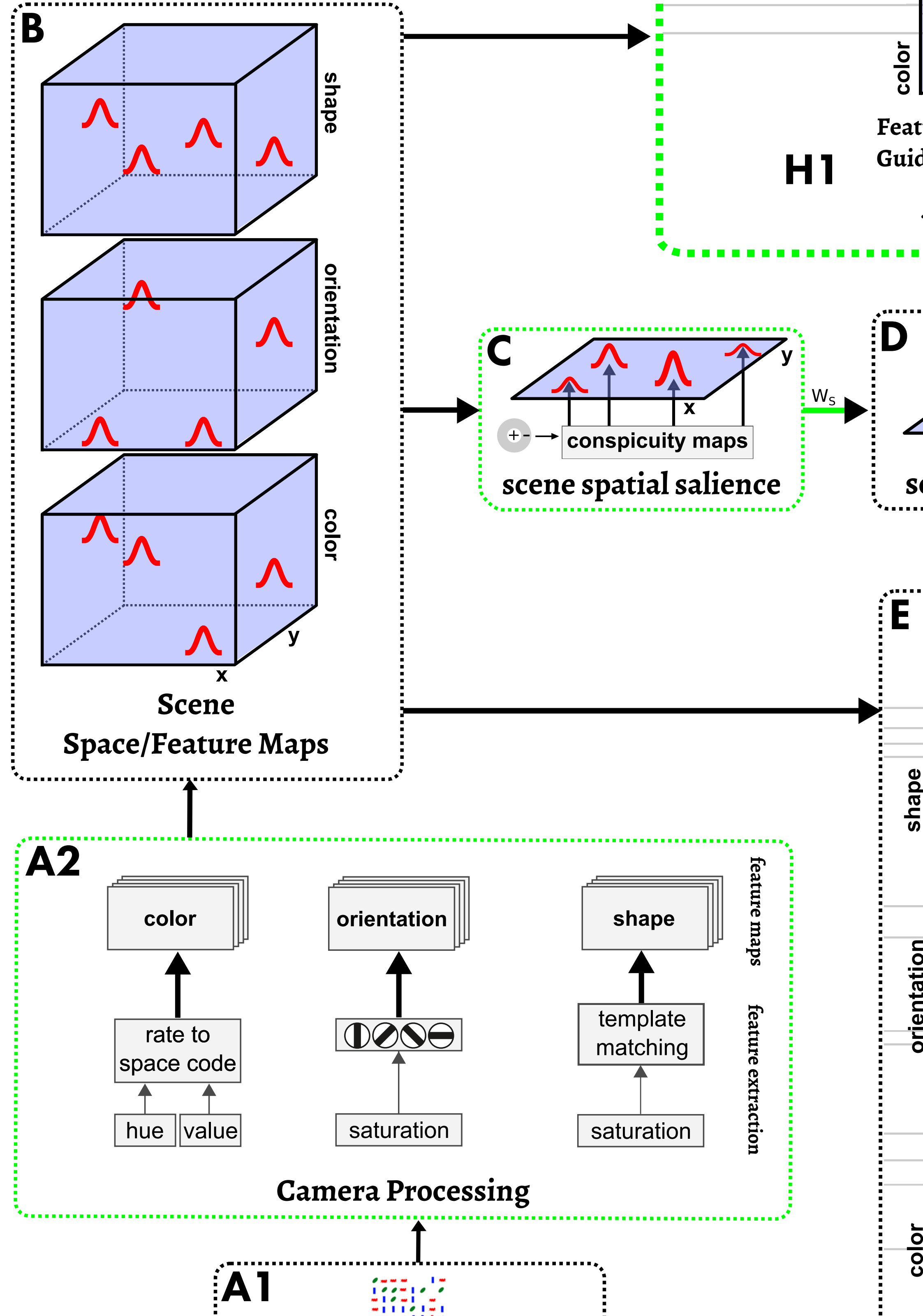


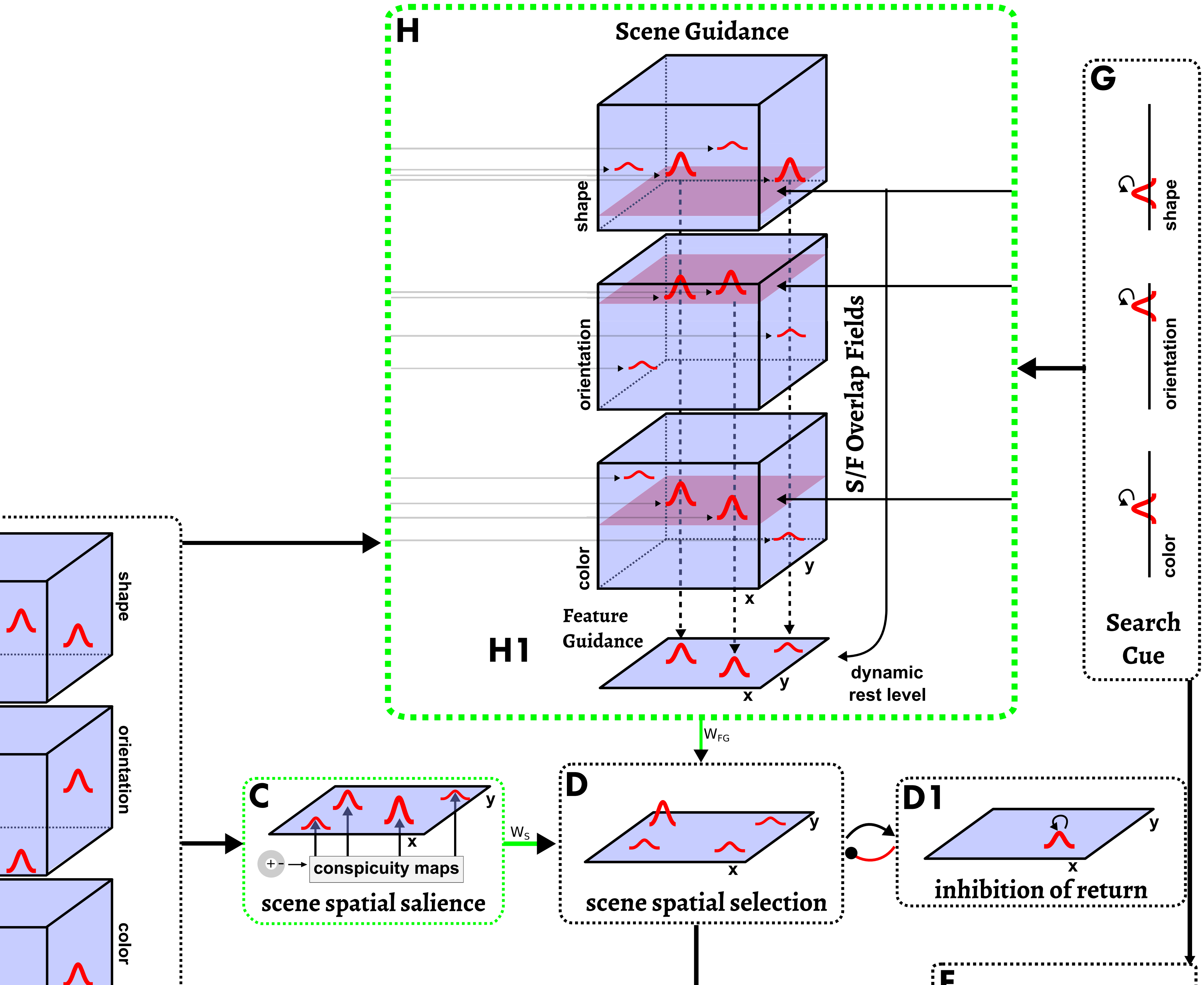
[Grieben et al. *Attention, Perception & Psychophysics* 2020; *CogSci* 2021]



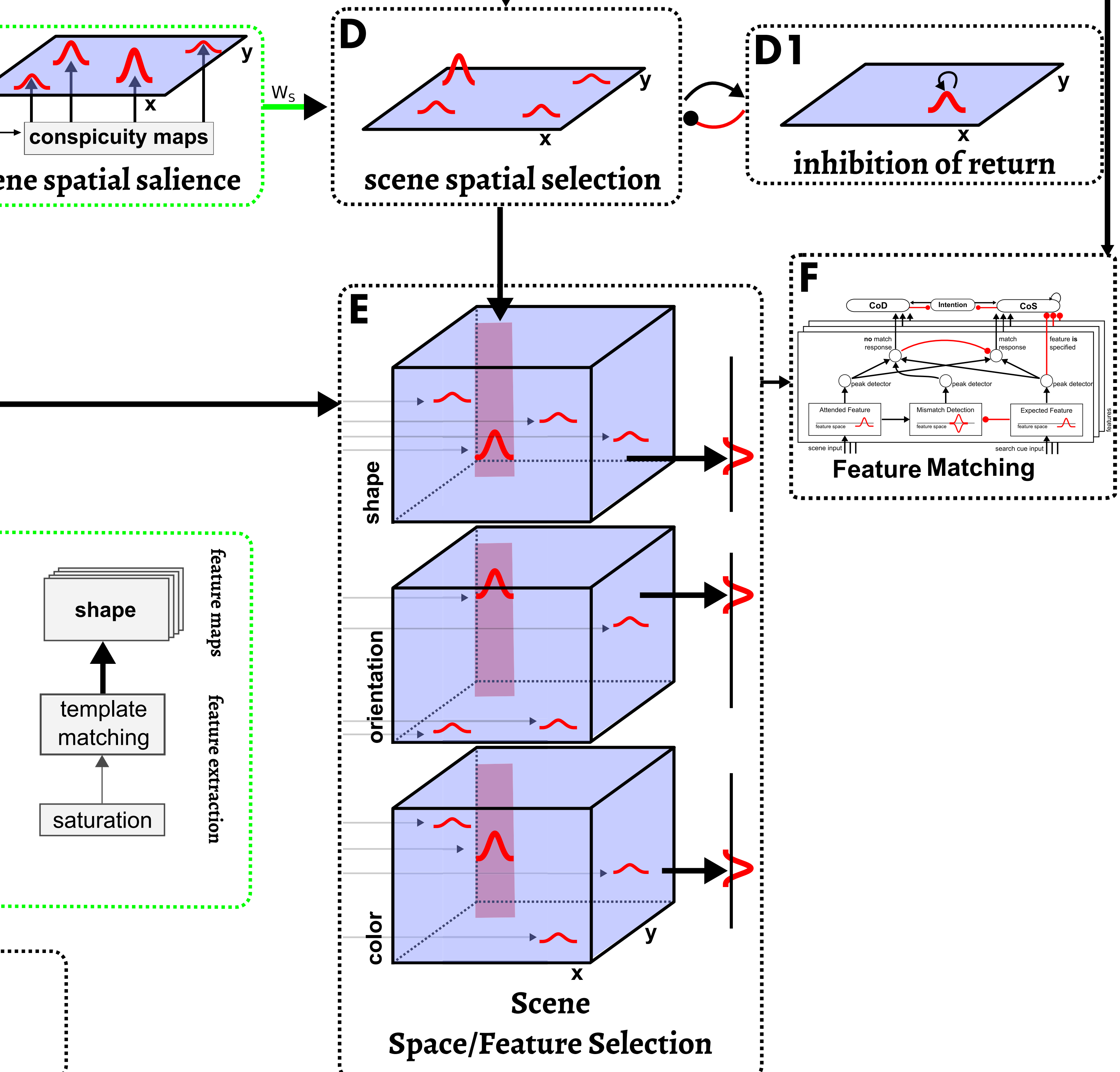
A2
color
orientation
shape
feature maps
rate to space code
template matching
feature extraction
hue
value
saturation
saturation
Camera Processing
A1
Camera Image

- => special lecture by Raul Grieben on Thursday



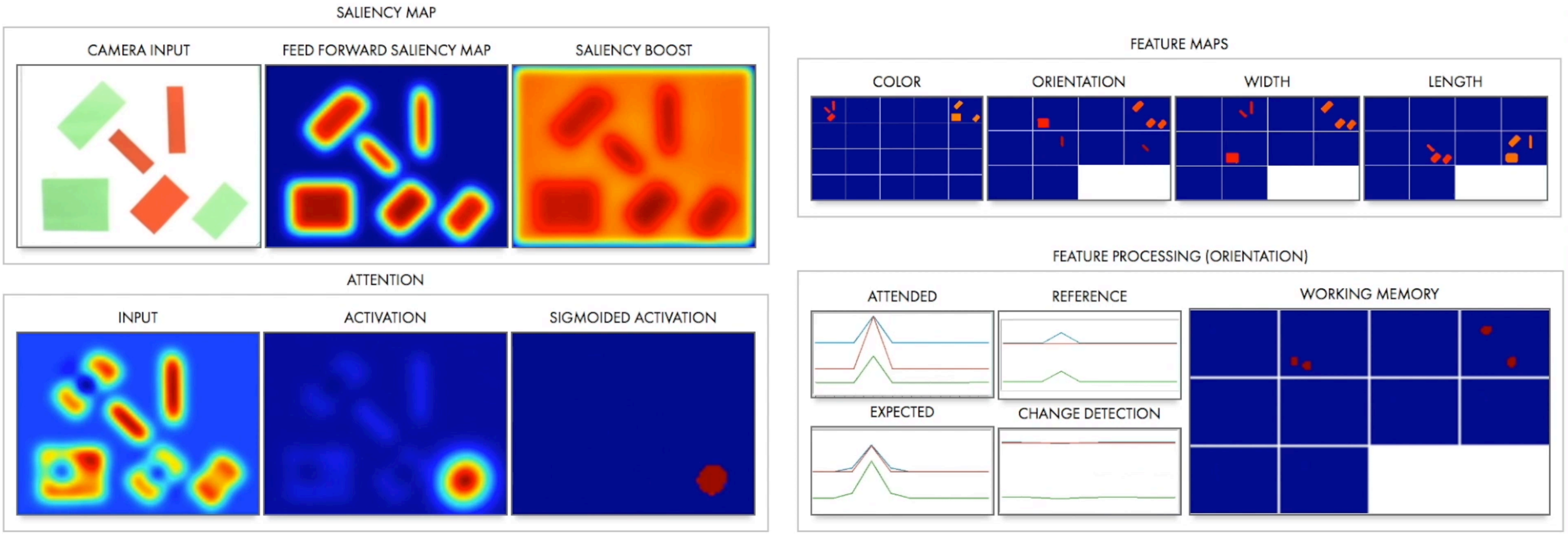


H
Scene Guidance
shape
orientation
color
S/F Overlap Fields
x
y
Feature Guidance
H1
dynamic rest level
G
shape
orientation
color
Search Cue
W_{FG}
C
conspicuity maps
scene spatial salience
W_S
D
scene spatial selection
D1
inhibition of return
E


y
x
conspicuity maps
ene spatial salience
Ws
D
y
x
scene spatial selection
D1
y
x
inhibition of return
E
shape
orientation
color
y
x
Scene
Space/Feature Selection
F
CoD
Intention
CoS
no match response
match response
feature is specified
peak detector
peak detector
peak detector
Attended Feature
feature space
Mismatch Detection
feature space
Expected Feature
feature space
features
scene input
search cue input
Feature Matching
shape
template matching
saturation
feature maps
feature extraction

Visual search

- => special lecture by Raul Grieben on Thursday



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

Roadmap

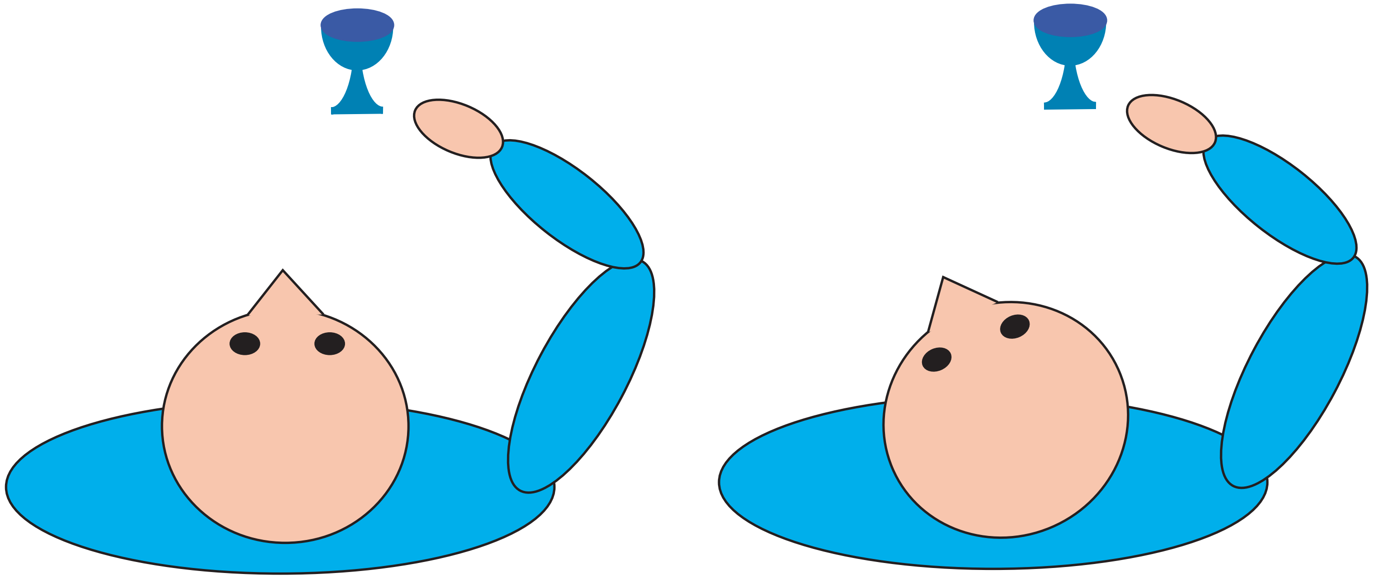
Higher dimensions

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

Coordinate transforms

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

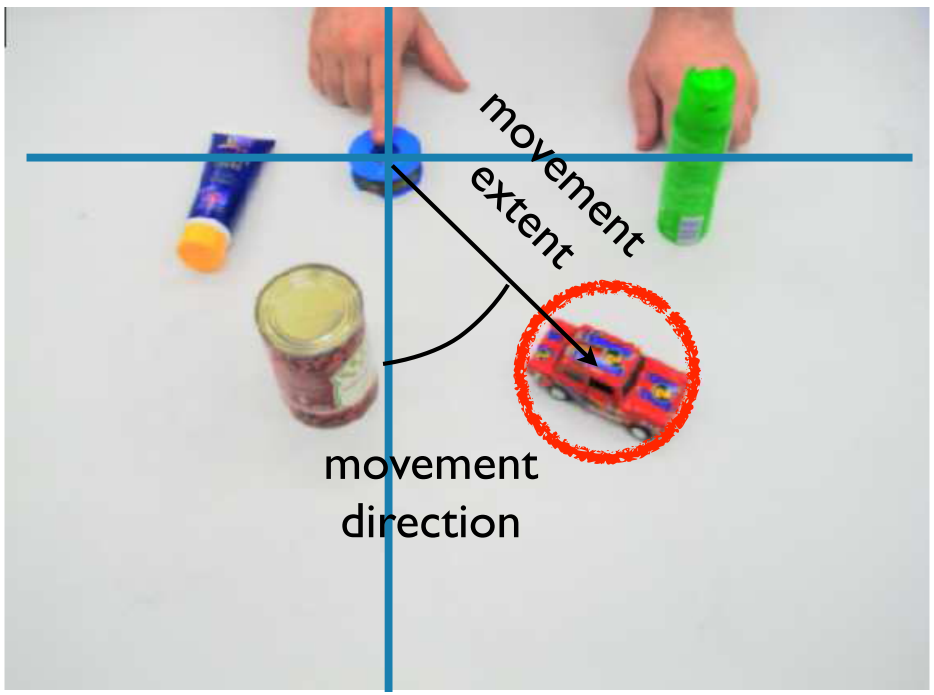
- example: reaching is guided by body-centered, not by retinal visual representation



Coordinate transforms

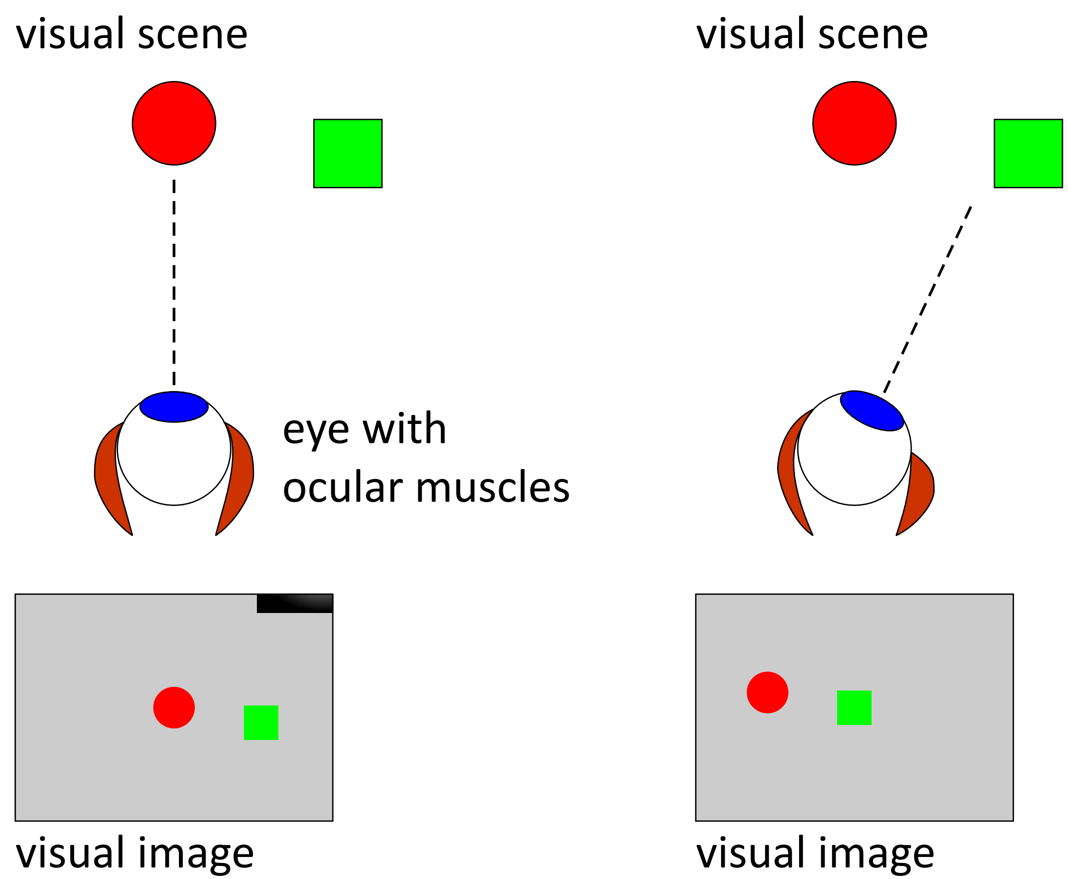
- are fundamental element to sensory-motor cognition
- [but critical also to mental operations!]

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



Coordinate transforms

- are fundamental element to sensory-motor cognition
- [but critical also to mental operations!]
- worked example: from retinal to head-centered/ body-centered frame

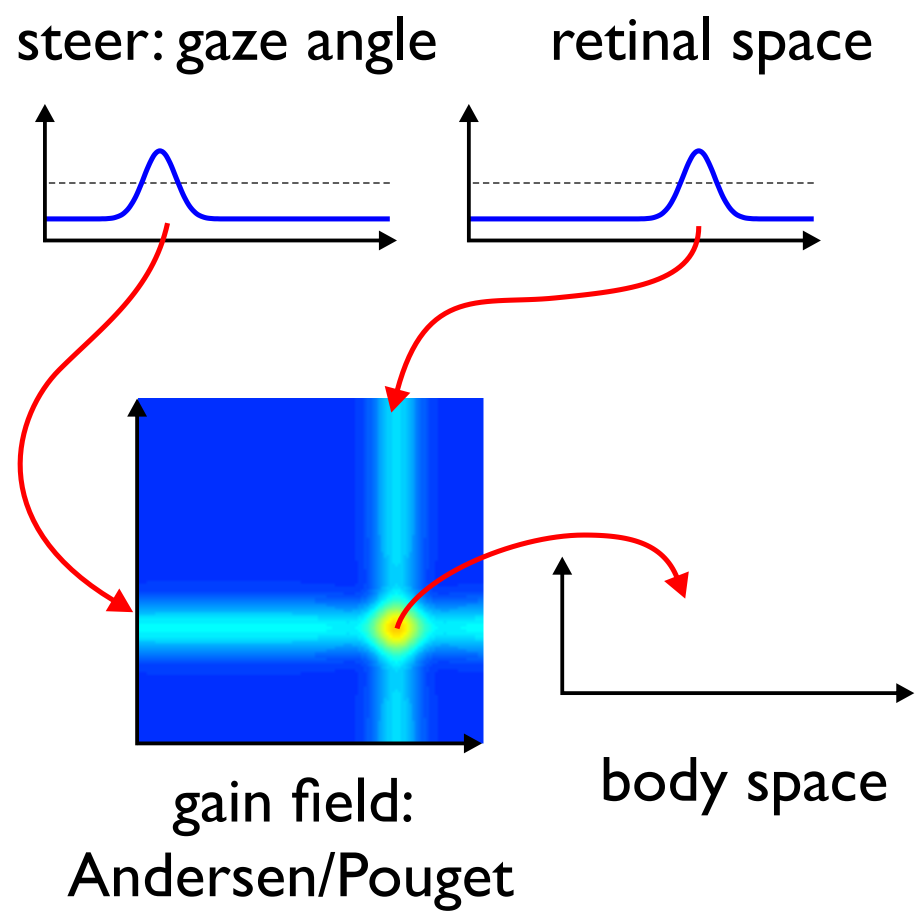


[Schneegans Ch 7 of *DFT Primer*, 2016]

Retina => body space

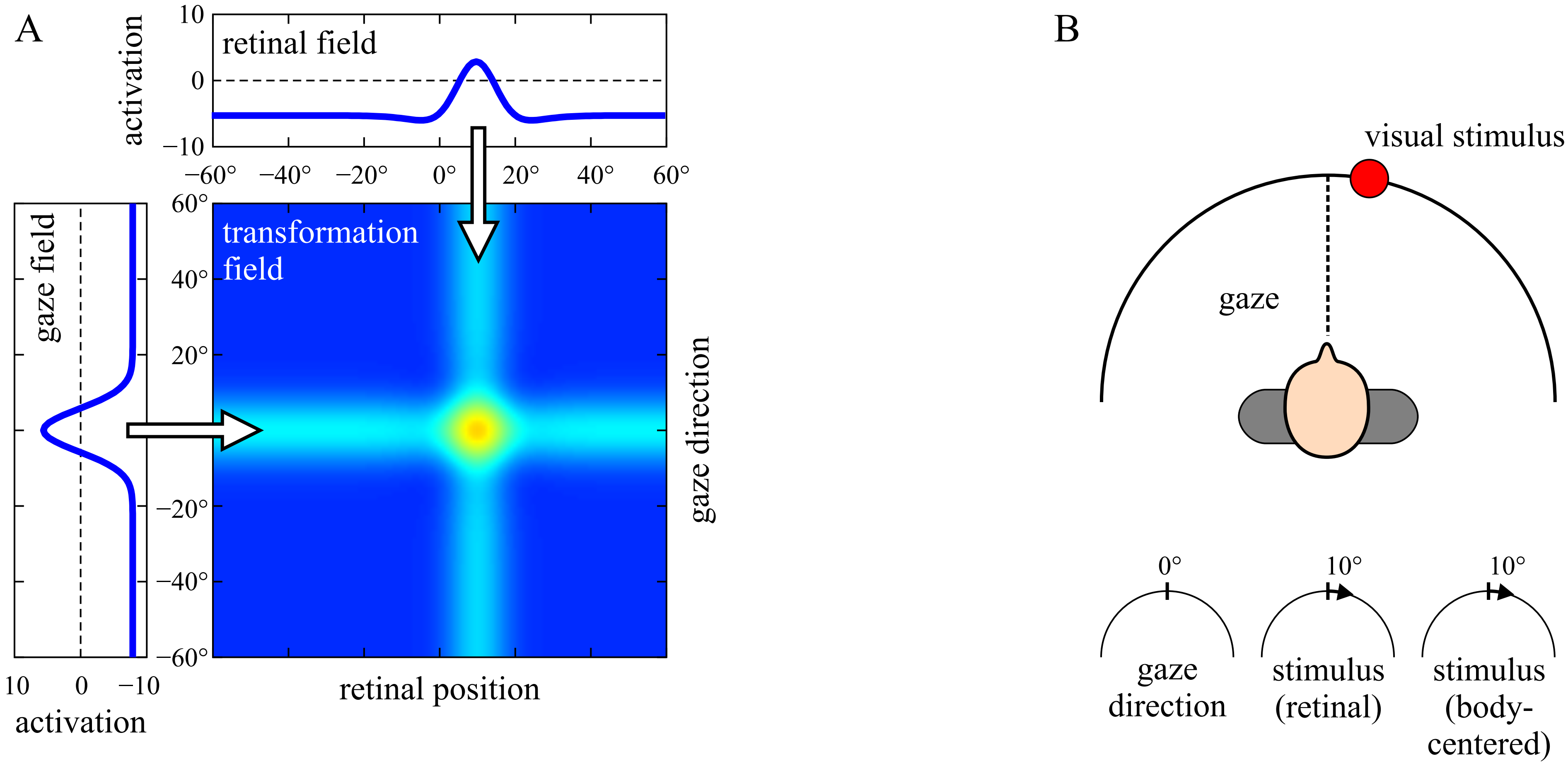
- transformation depends on the gaze angle = steering dimension

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



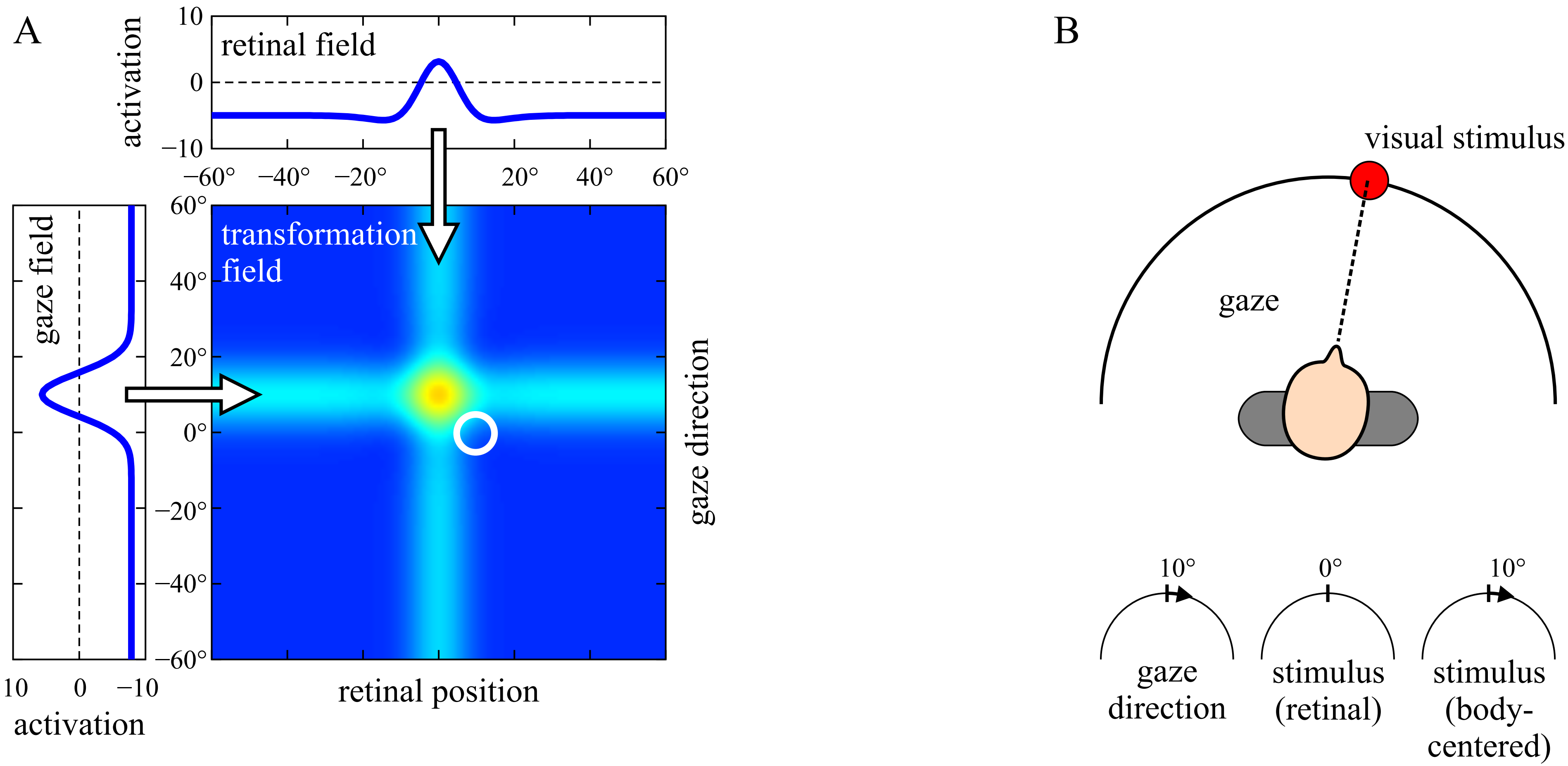
[Schneegans Ch 7 of *DFT Primer*, 2016]

Retina => body space



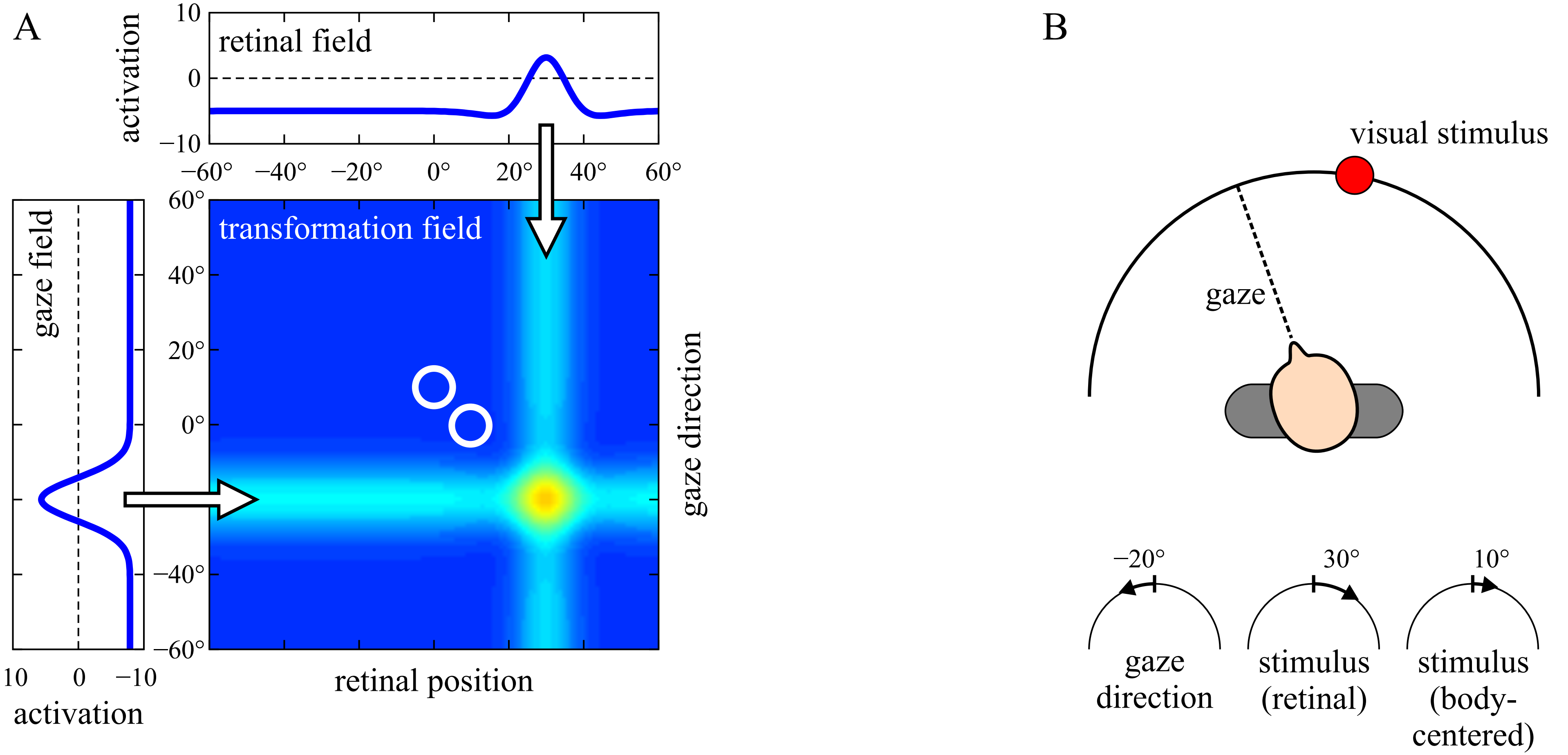
[Schneegans Ch 7 of *DFT Primer*, 2016]

Retina => body space



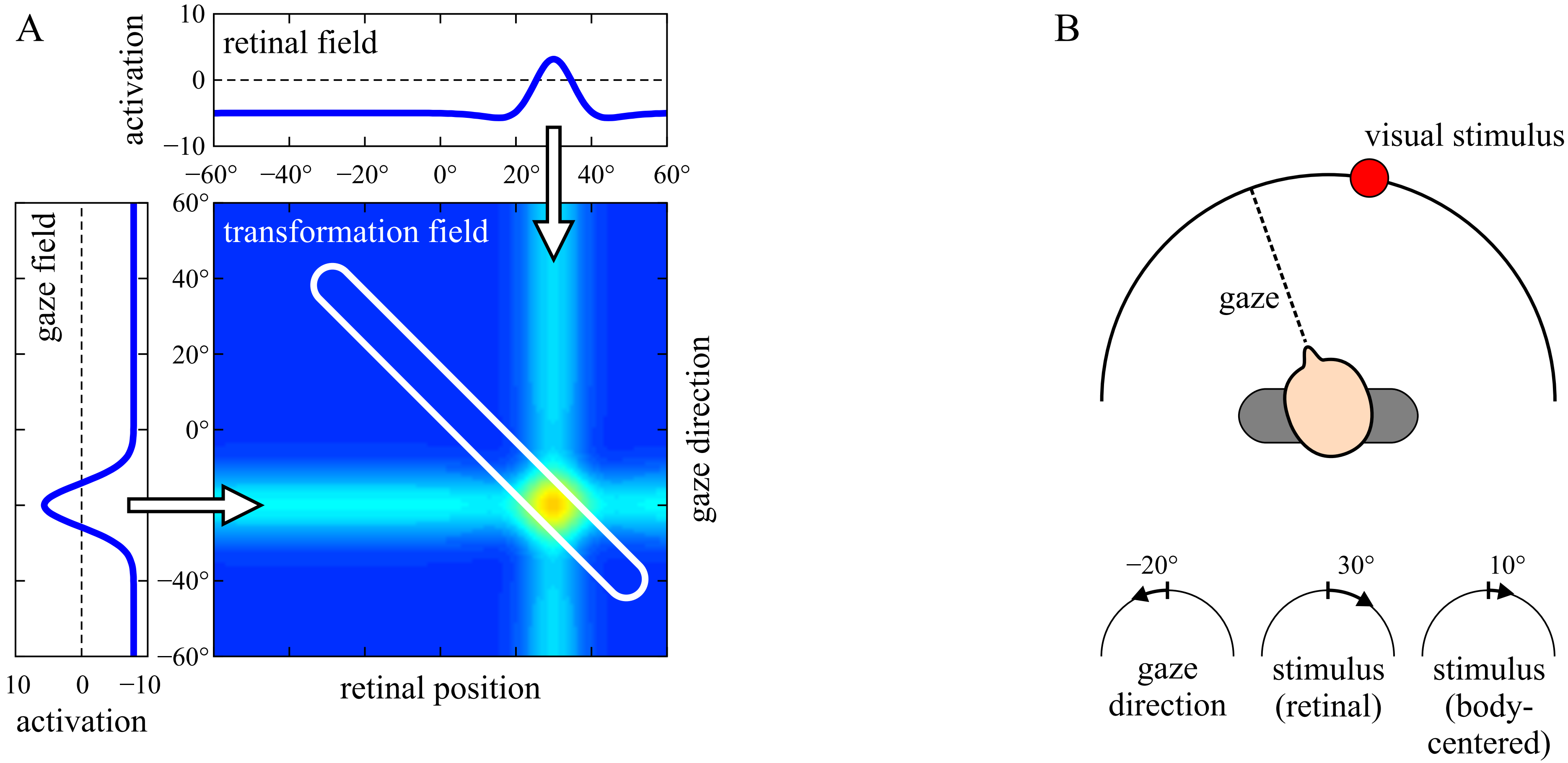
[Schneegans Ch 7 of *DFT Primer*, 2016]

Retina => body space



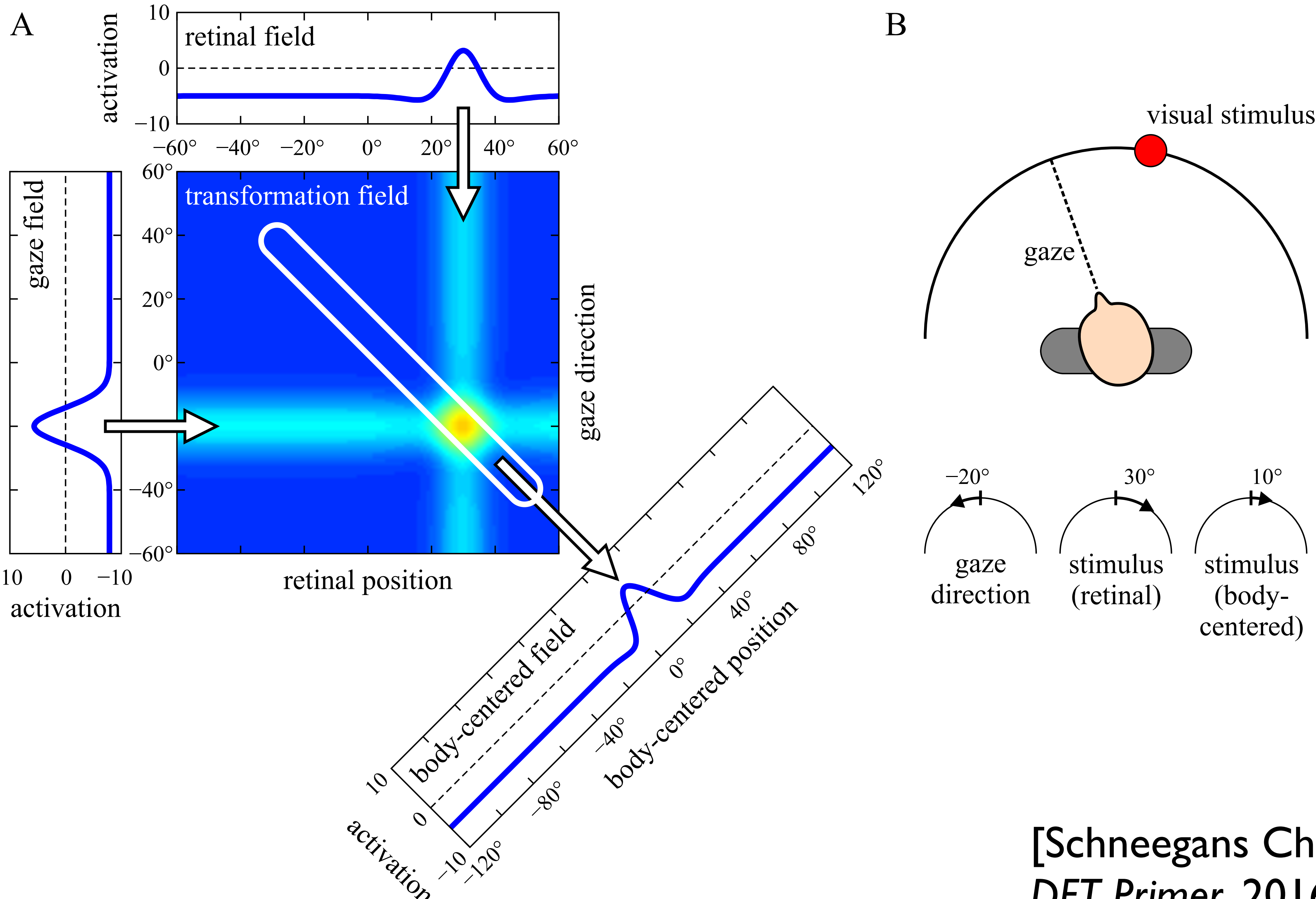
[Schneegans Ch 7 of *DFT Primer*, 2016]

Retina => body space



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

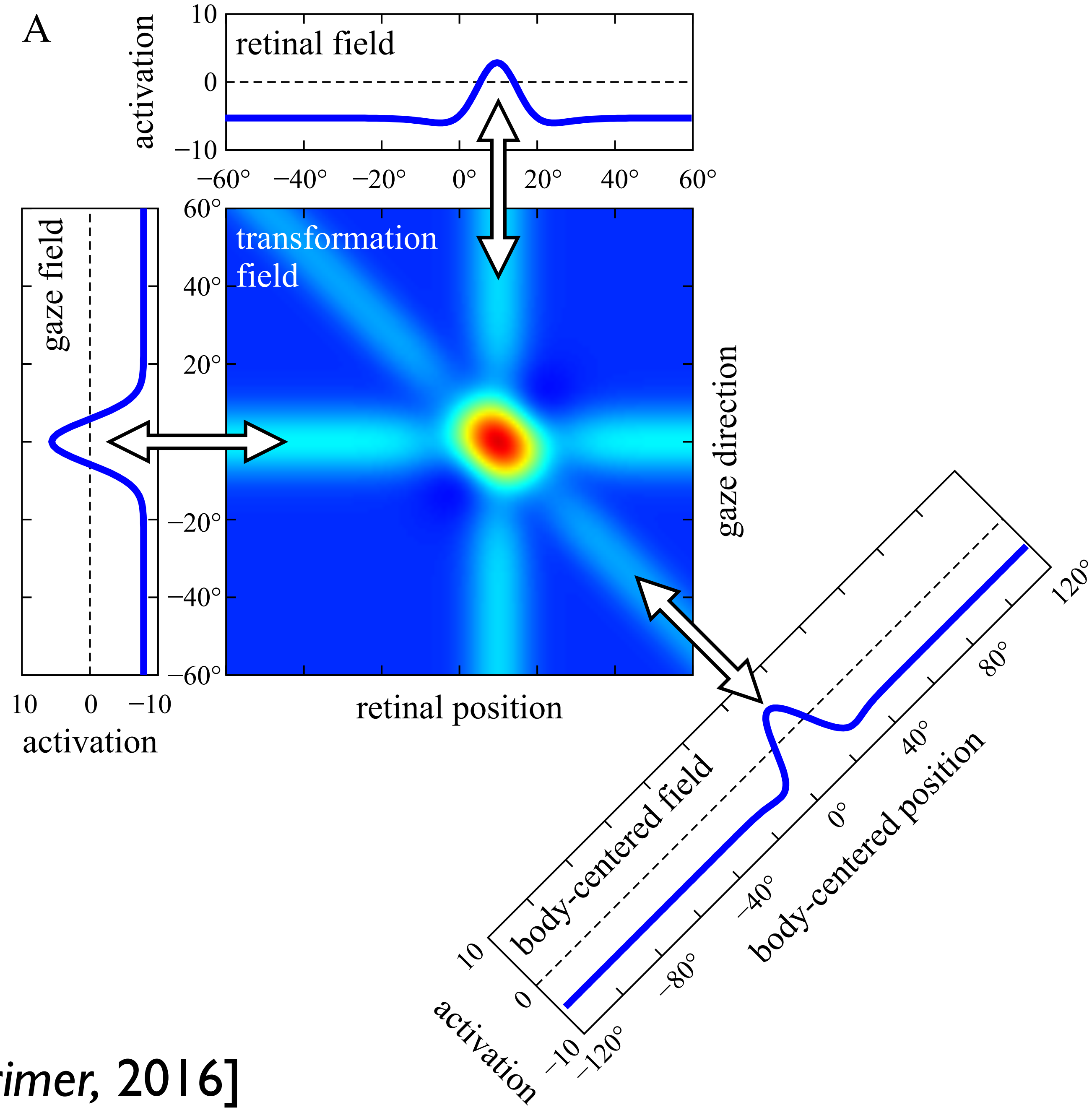
Retina => body space



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

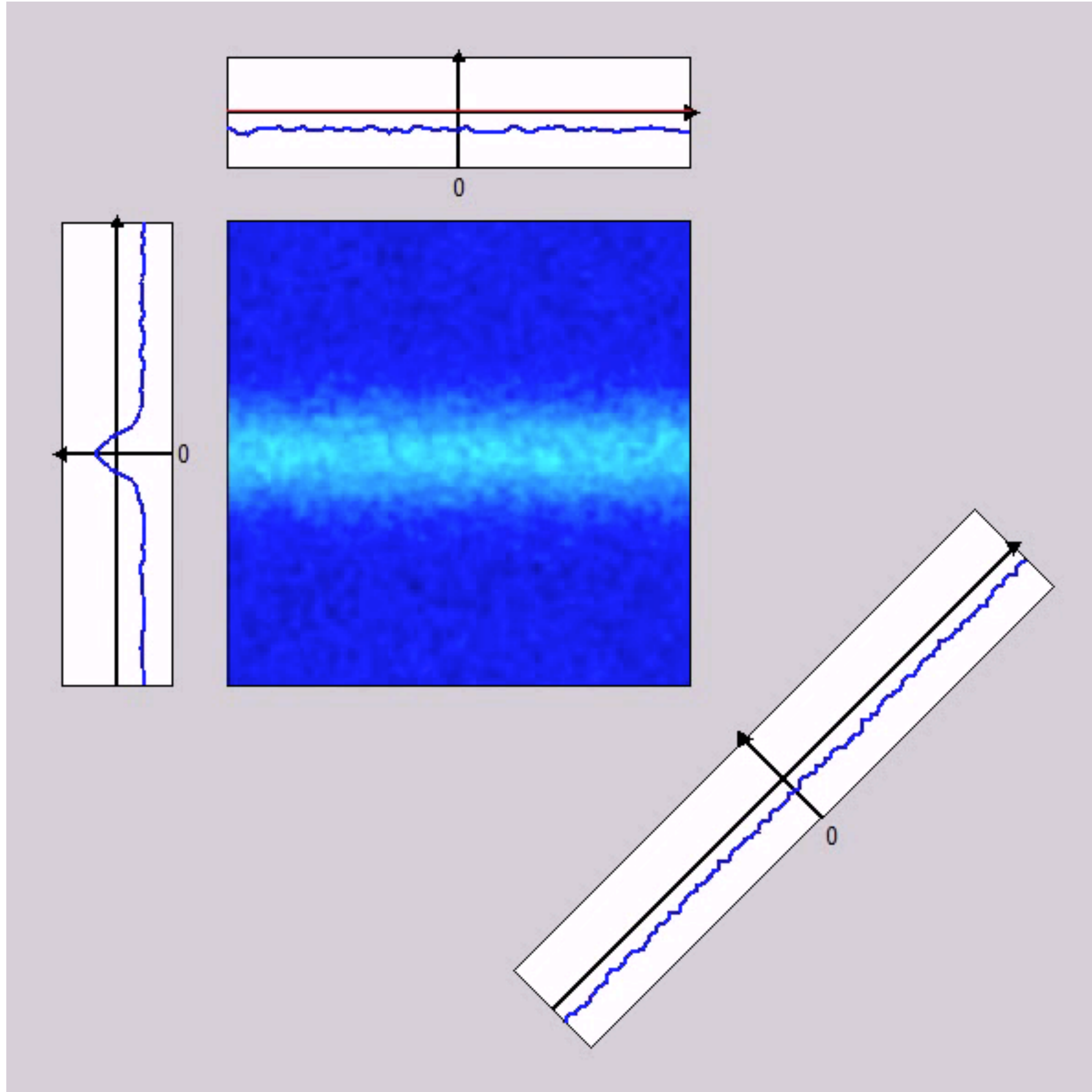
Retina => body space

- bi-directional coupling
- => predict retinal coordinates



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

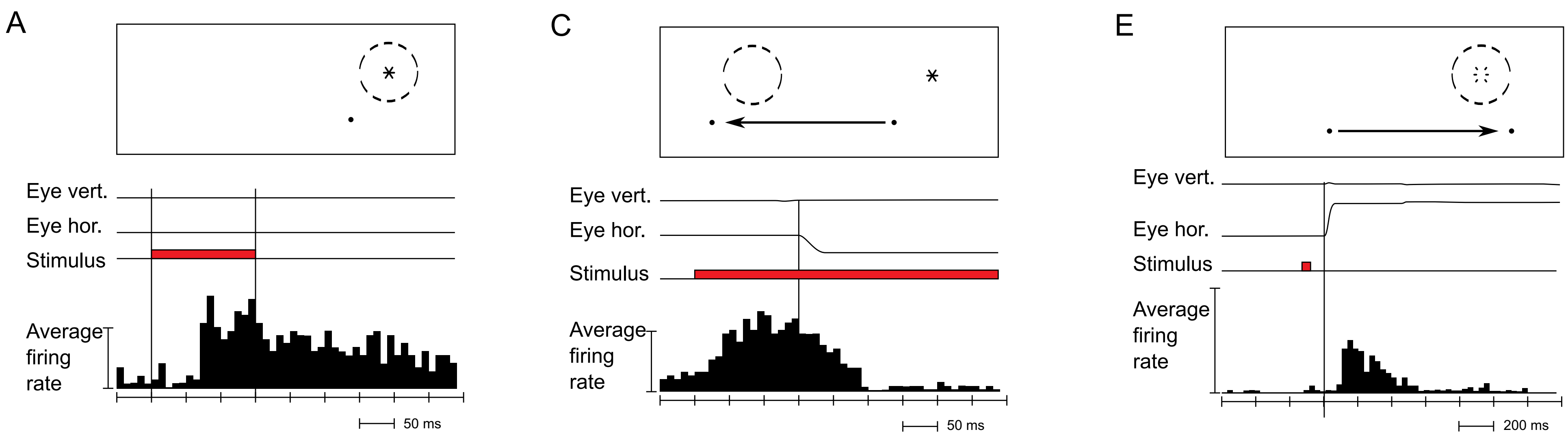
Spatial remapping during saccades



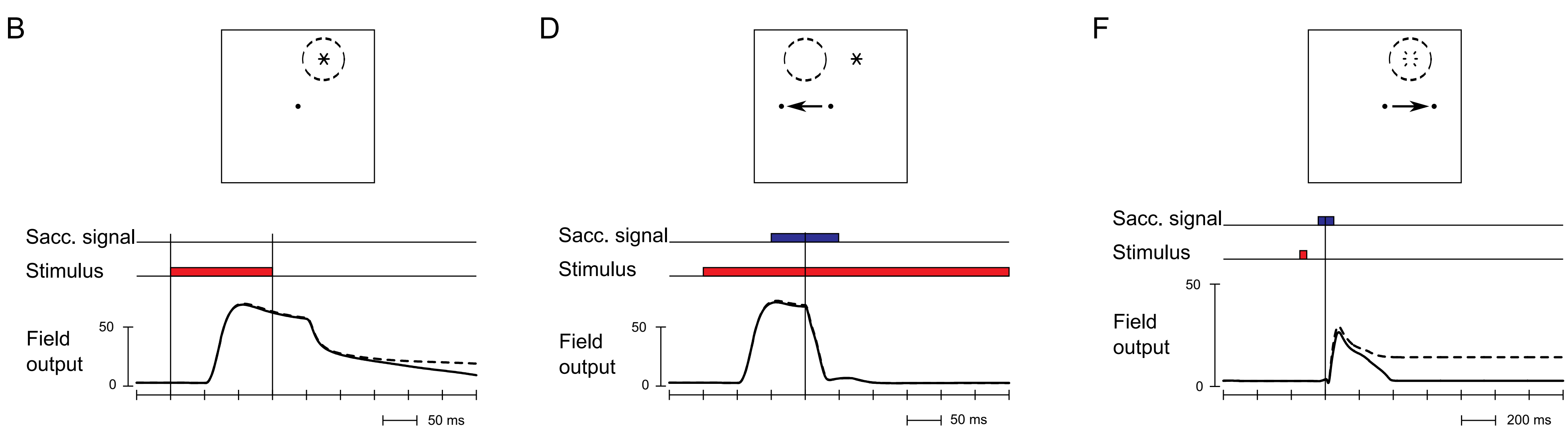
[Schneegans, Schöner *Biological Cybernetics* 2012]

Accounts for predictive updating

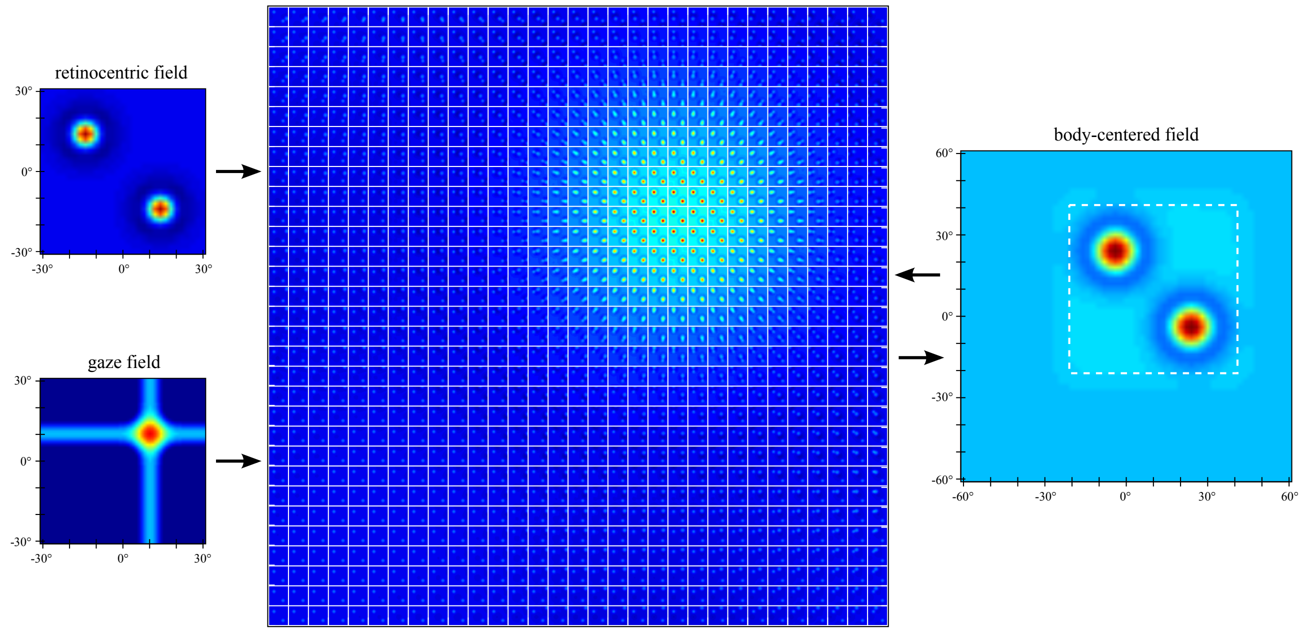
[neural data: Duhamel, Colby, Goldberg, 1992, LIP]



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



Scaling



[Schneegans, Schöner, 2012]

Roadmap

Binding

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

Scaling feature dimensions

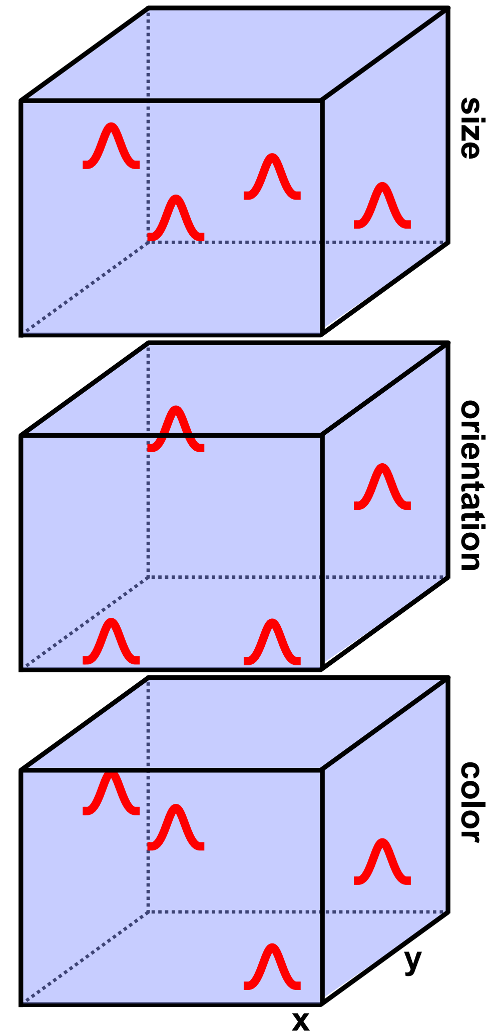
- 2 spatial dimensions
- depth
- orientation
- color
- texture
- movement direction
- size
- etc…

=>

- 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”

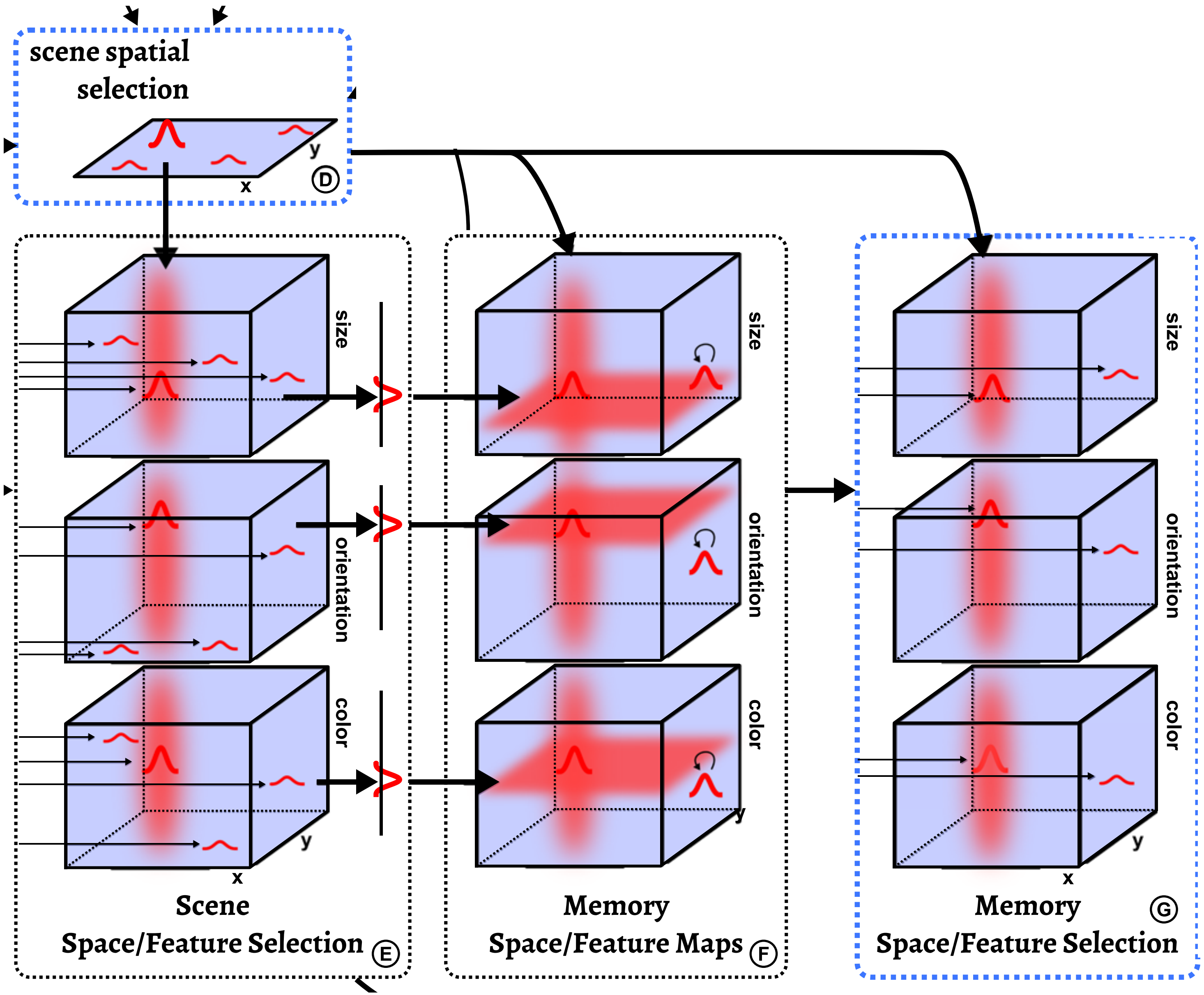
Binding through space

- 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)

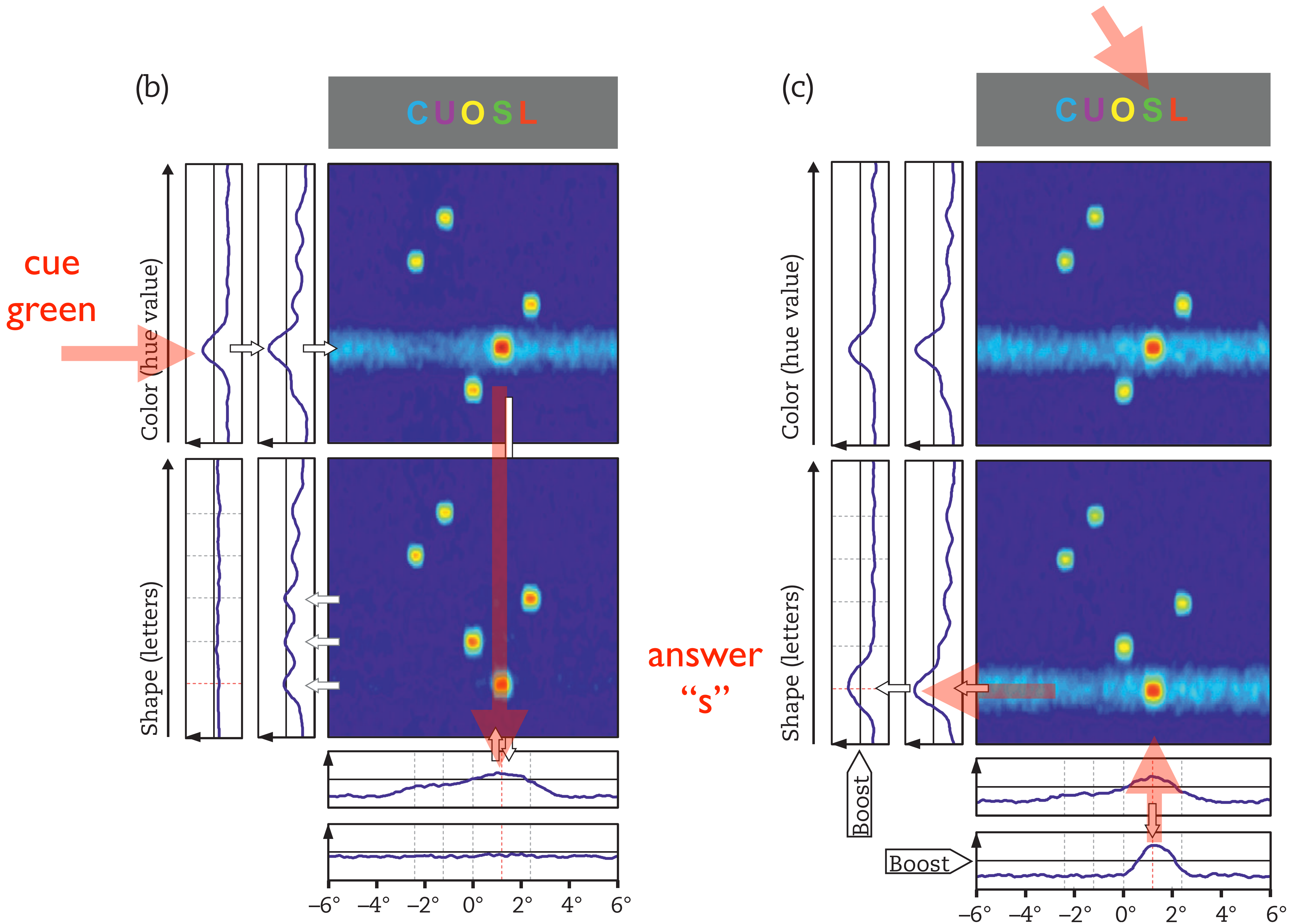


[Grieben et al. *Attention, Perception & Psychophysics* 2020]

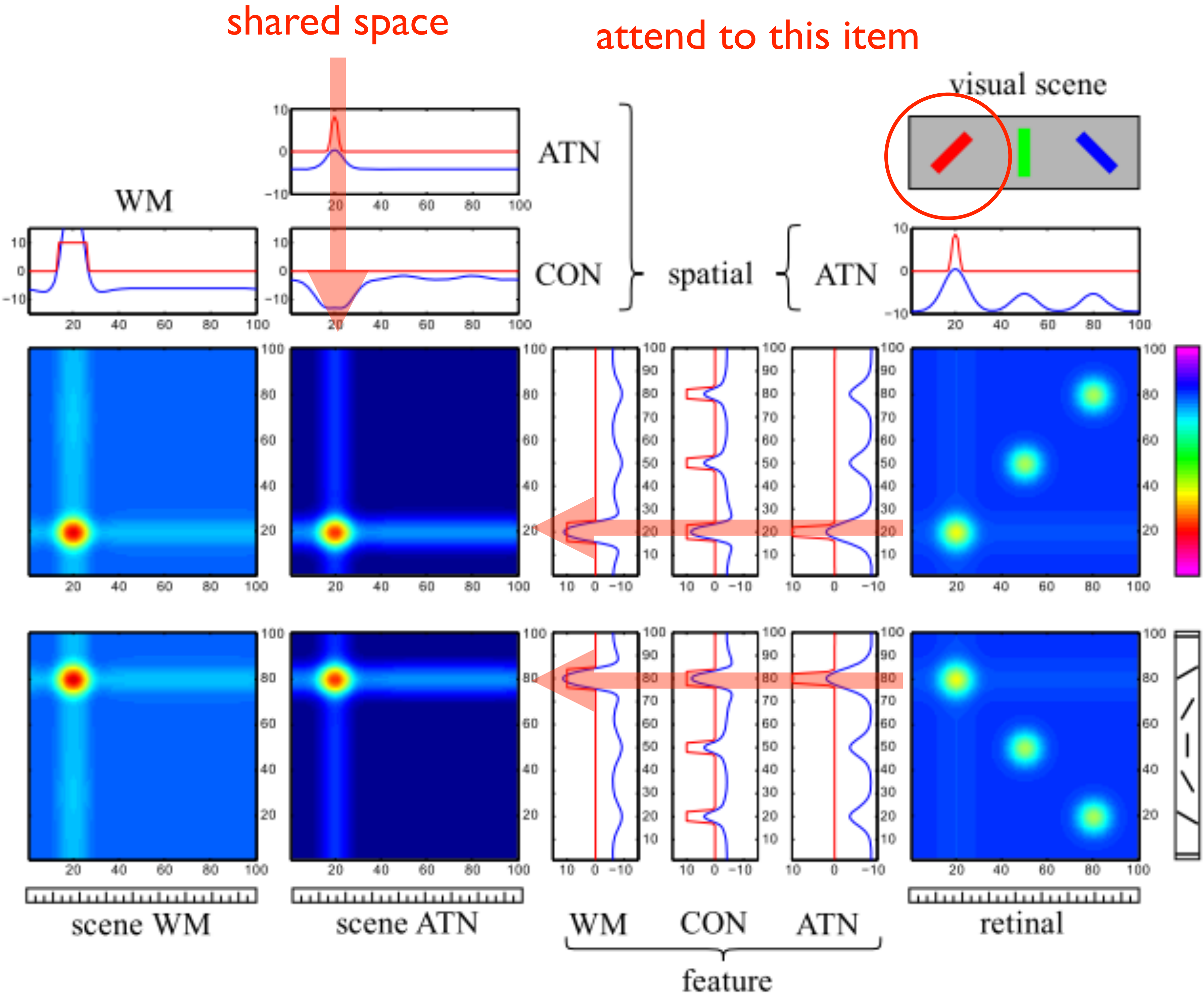
Binding through space



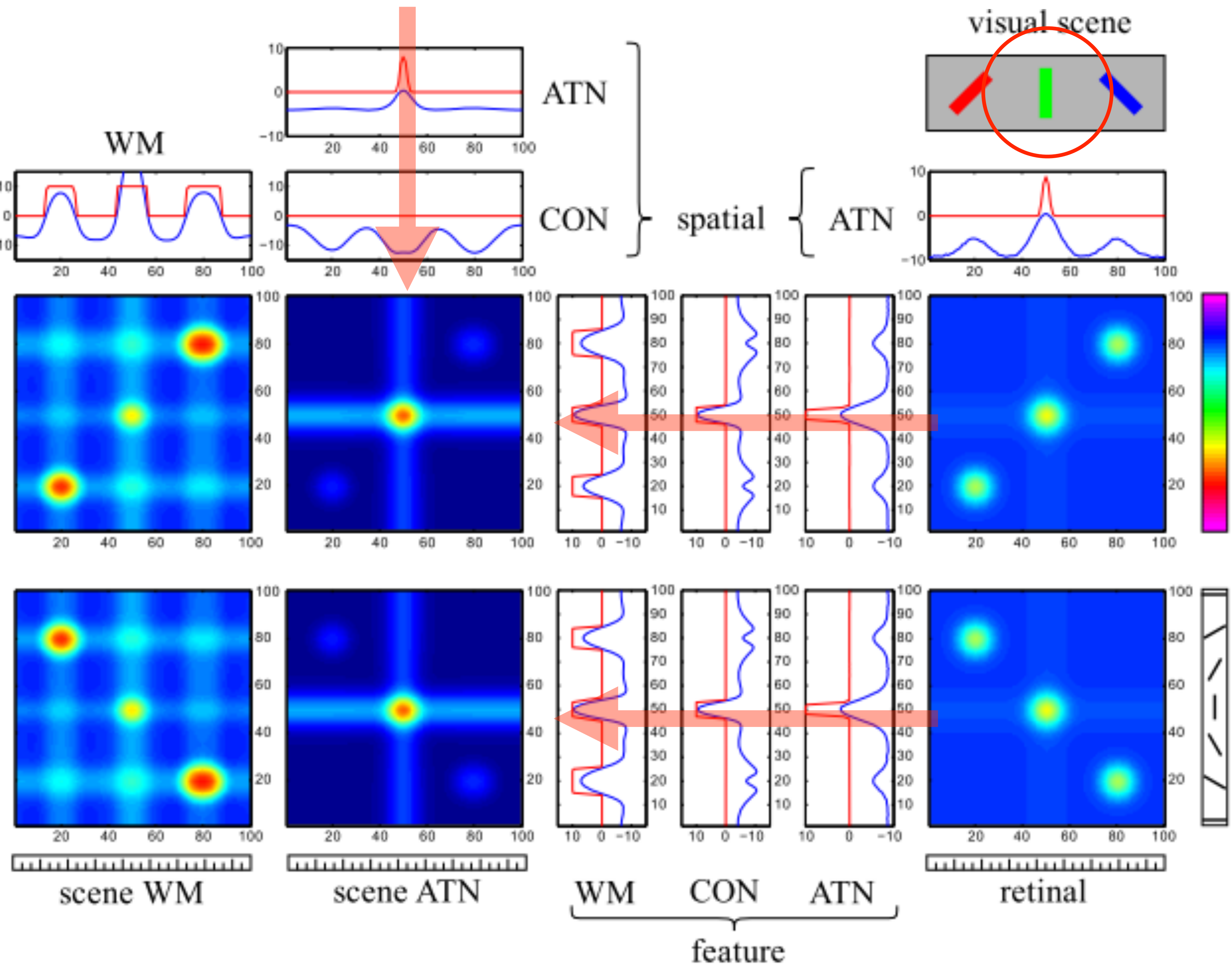
[Grieben et al. *Attention, Perception & Psychophysics* 2020]



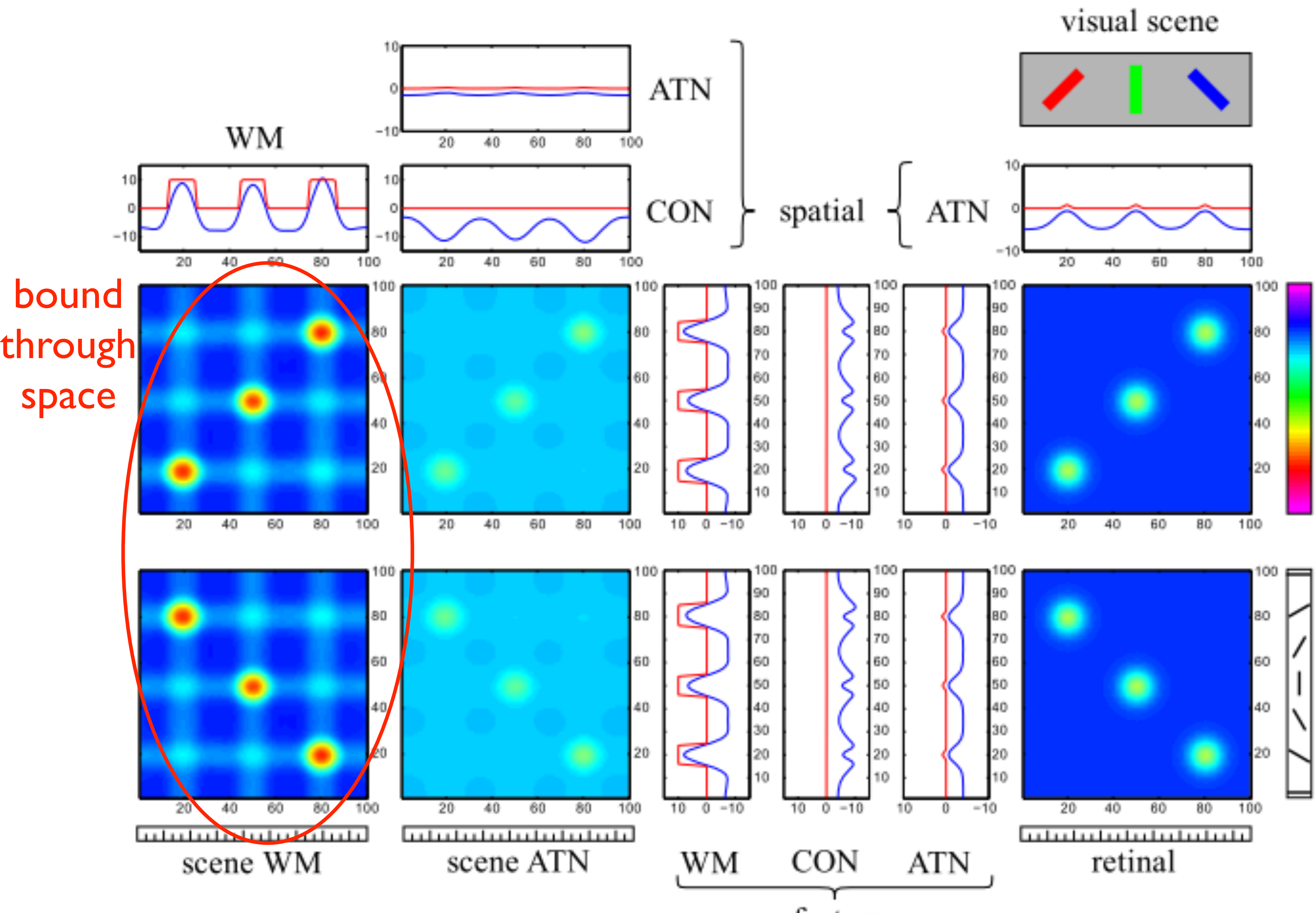
[Schneegans et al.,Ch 5 of *DFT Primer*, 2016]



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



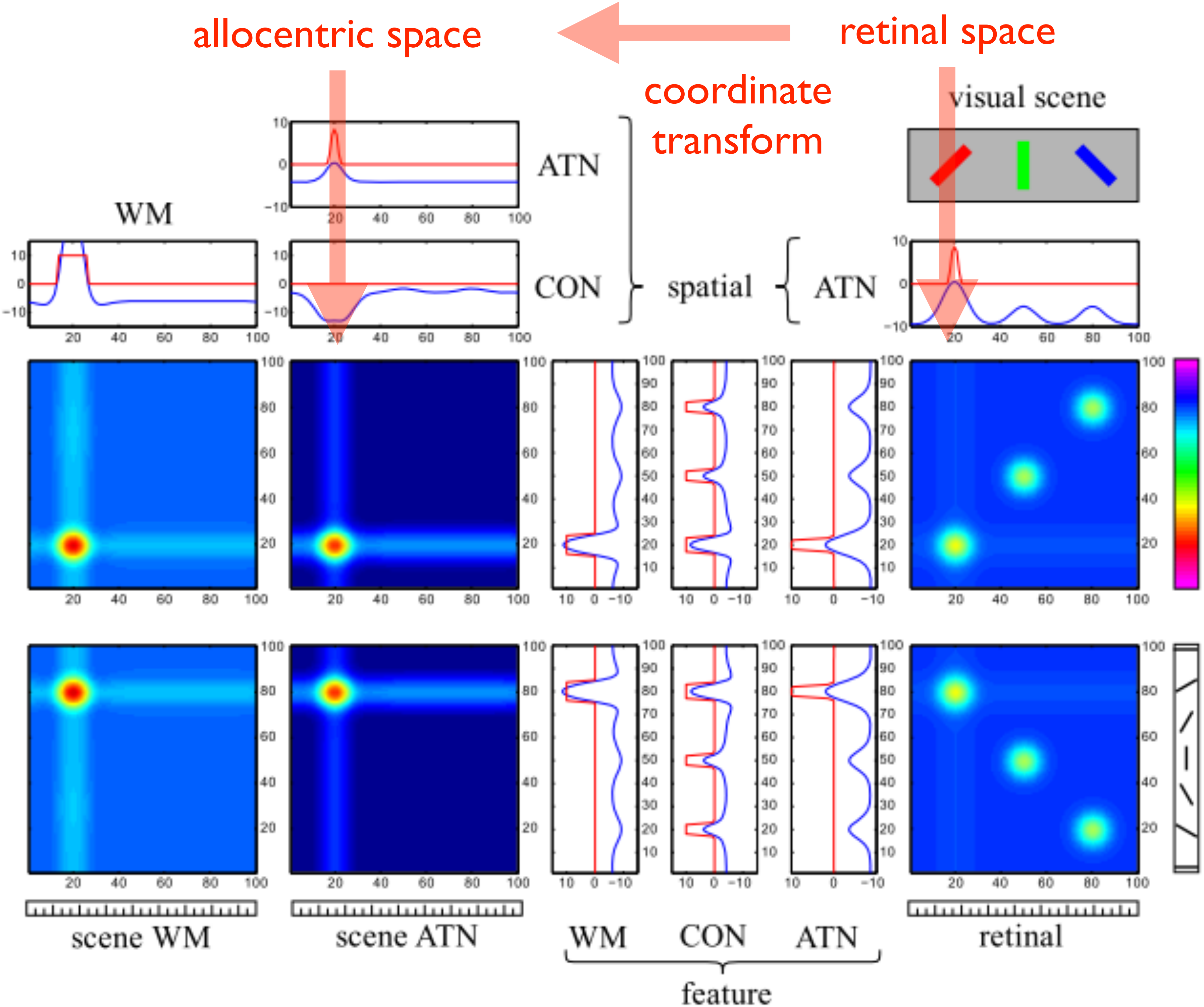
[Schneegans et al.,Ch 5 of *DFT Primer*, 2016]



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

Binding through space => sequential bottleneck

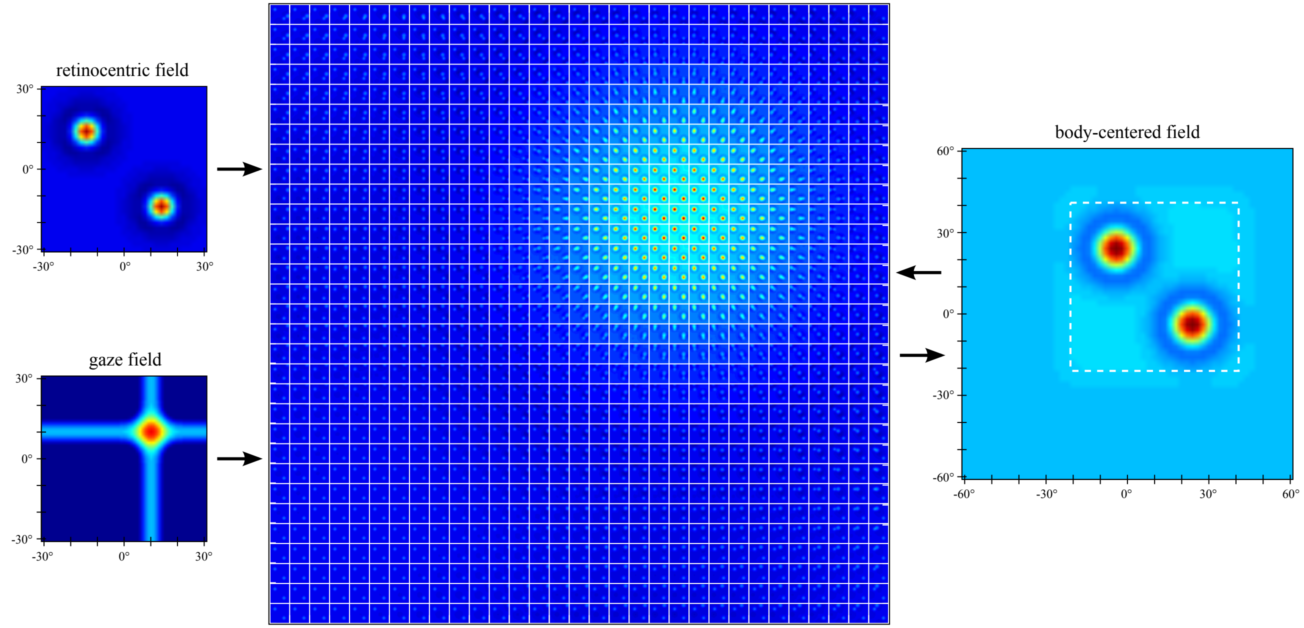
- binding through space must occur one time at a time..… to avoid binding problem
- => the sequential processing bottleneck may originate from this



[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



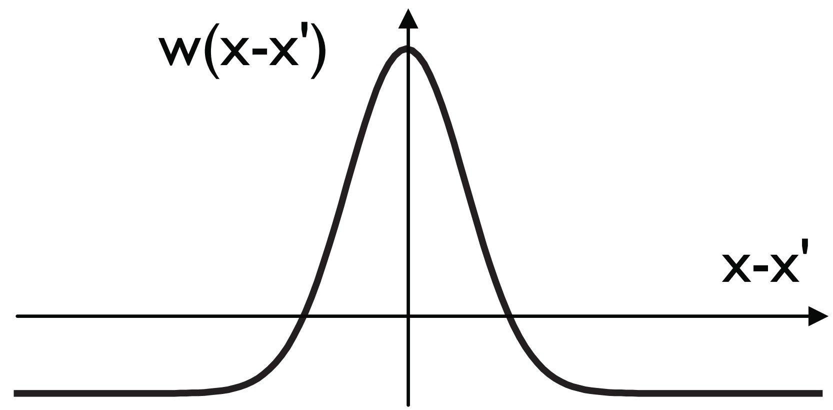
[Schneegans, Schöner, 2012]

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

Localist vs. distributed

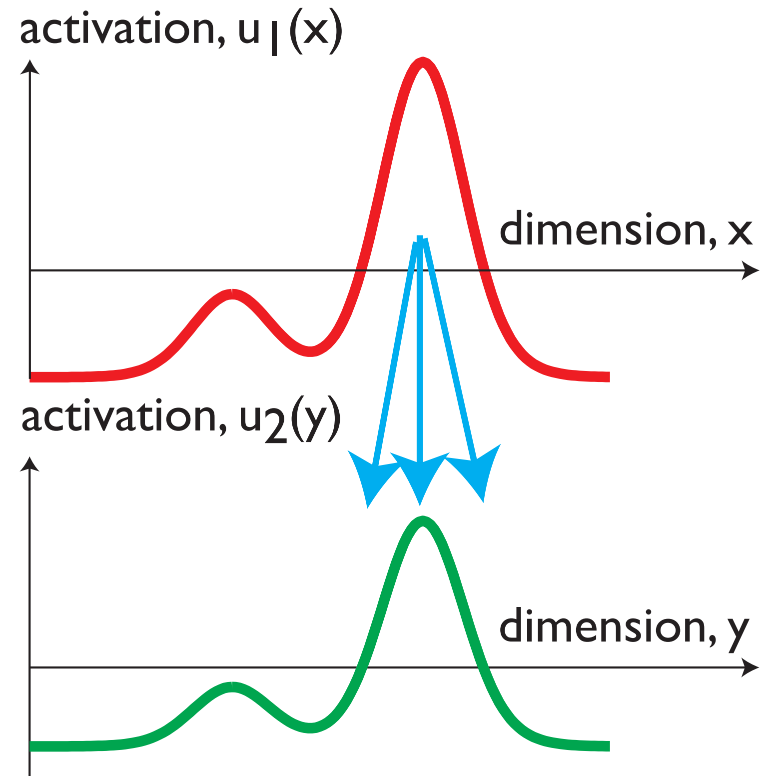
- scaling problem in localist representations
- required to create attractors with homogenous interaction



- distributed representations scale better, but: how to create attractors?
- Hopfield networks have attractors for distributed representations, but these (and the synaptic weights) are specific to each memorized pattern
- but Hopfield networks lack flexibility… => lecture 3

Hebbian learning

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

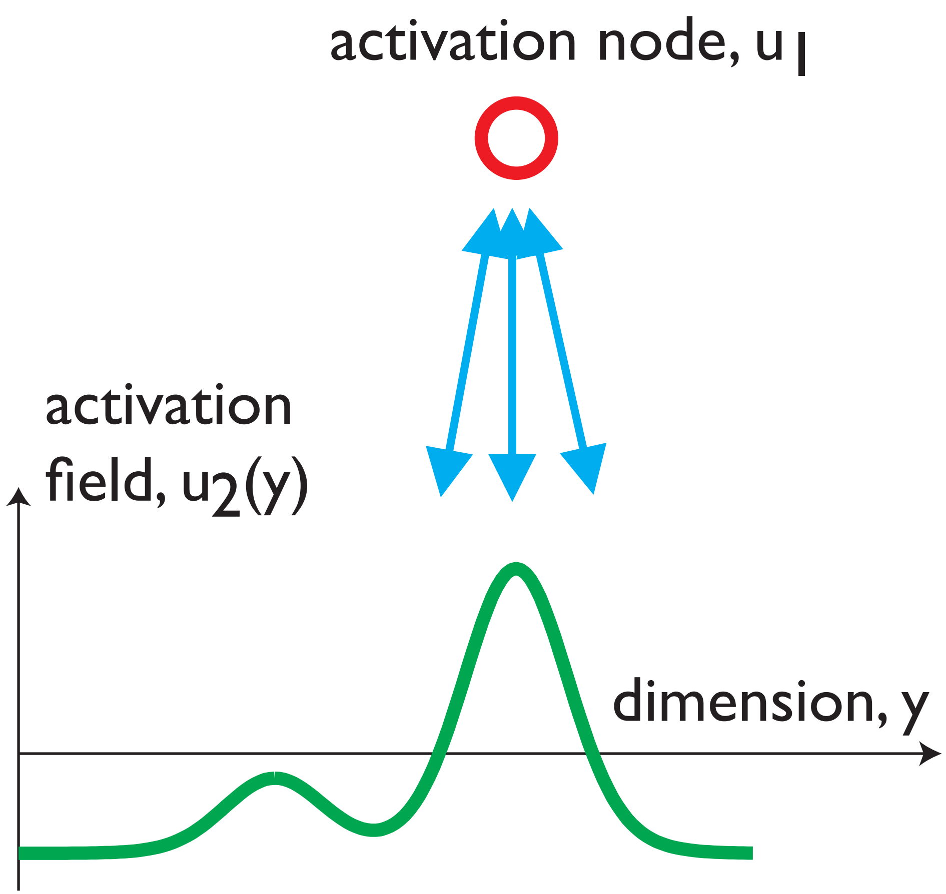


$$\tau \dot{W}(x, y, t) = \epsilon(t)\Big(- W(x, y, t) + f(u_1(x, t)) \times f(u_2(y, t))\Big)$$

[Sandamirskaya, Frontiers Neurosci 2014]

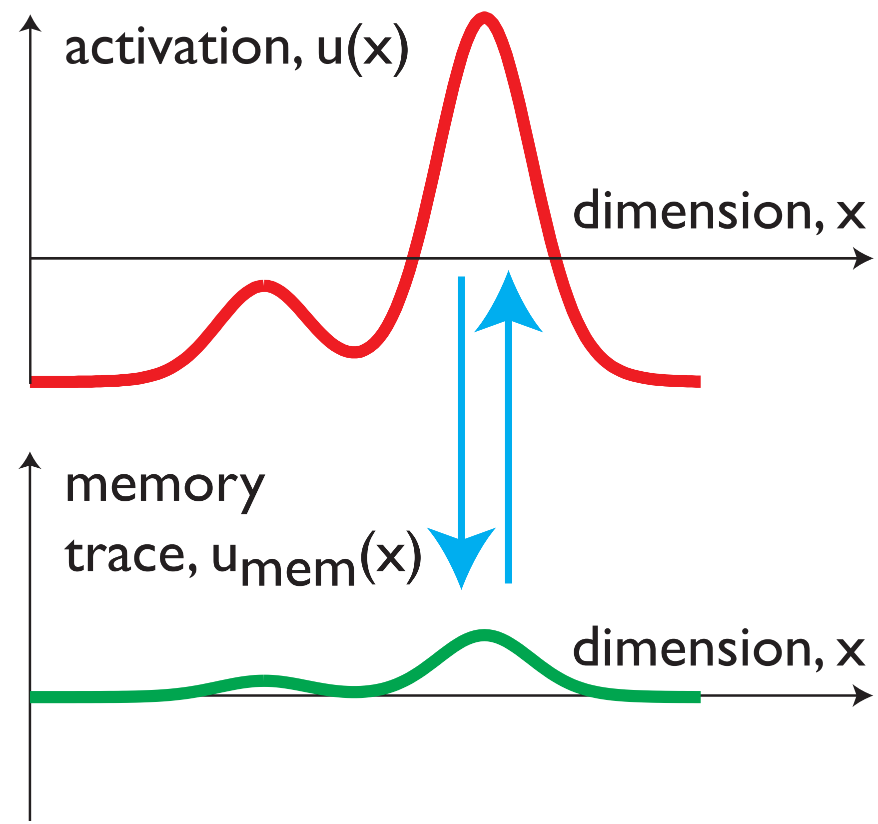
Hebbian learning

- learning reciprocal connections between zero-dimensional nodes and fields
- => grounded concepts
- analogous to the output layer of DNN
- => ensembles of such nodes coupled inhibitorily from 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

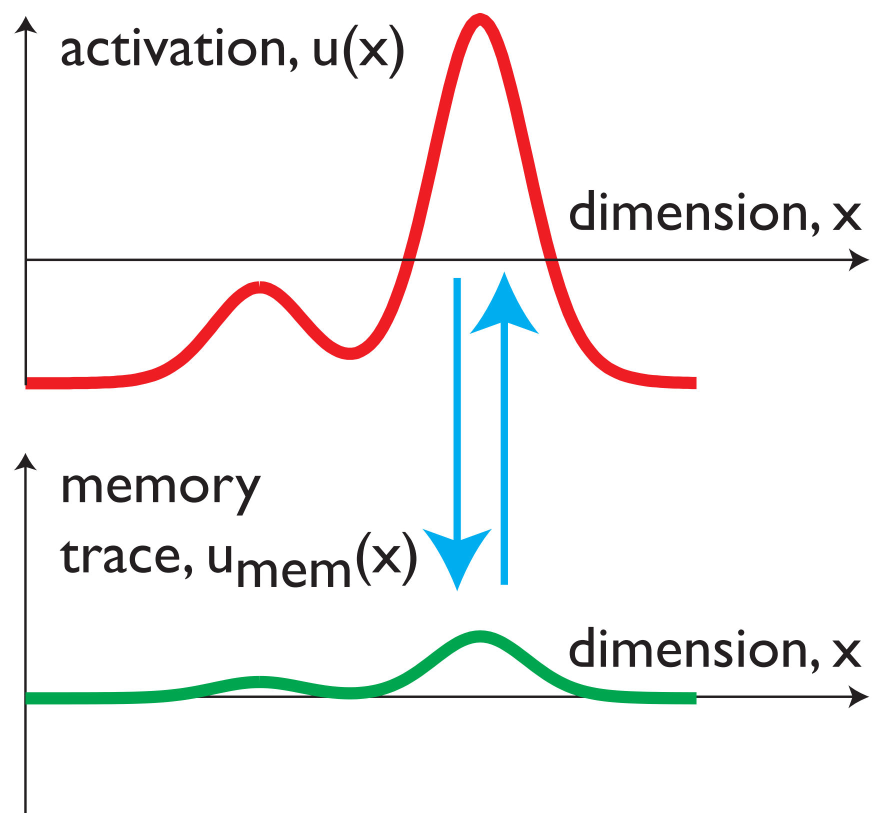


The memory trace

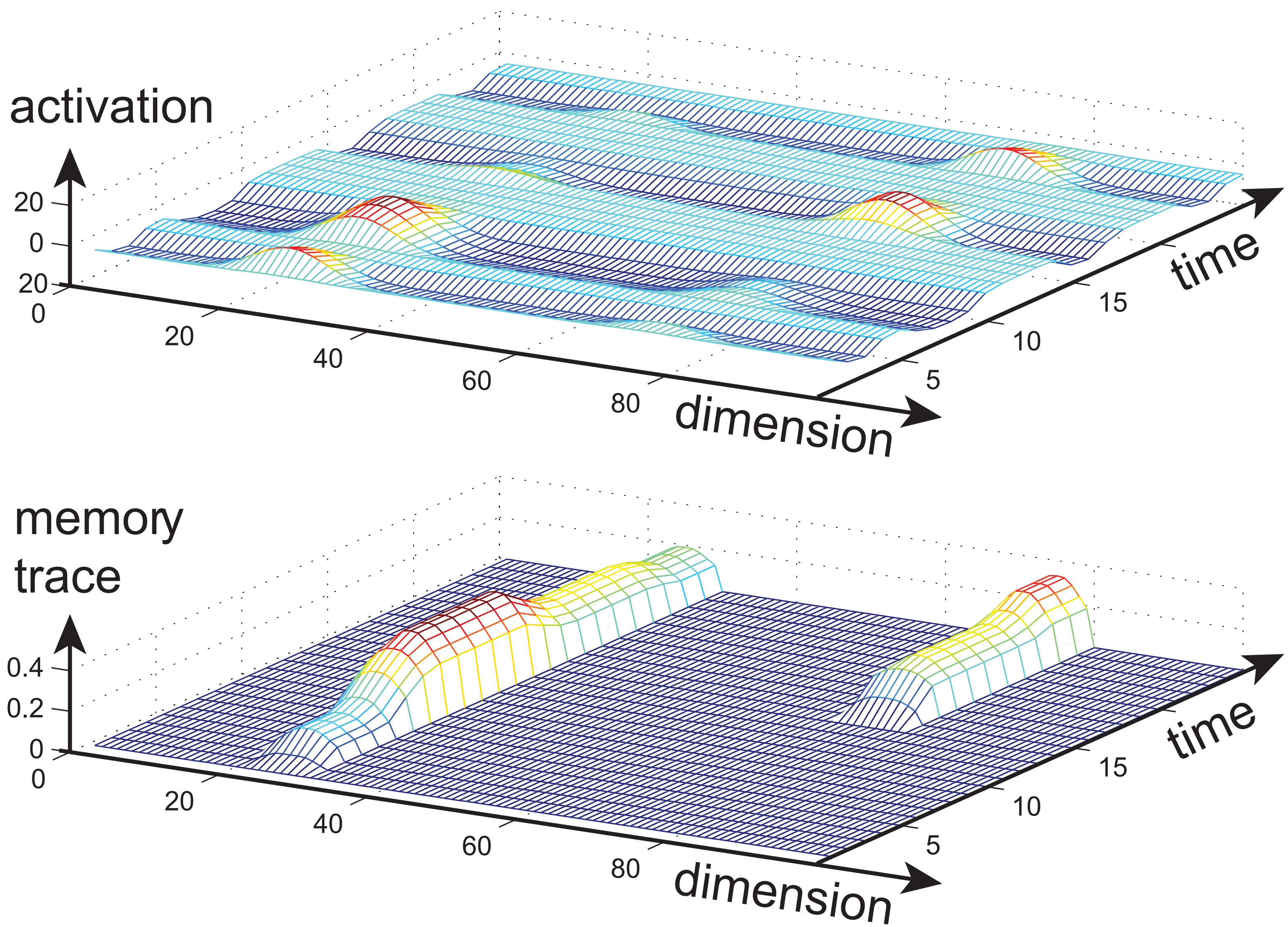
$$\tau \dot{u}(x,t) = -u(x,t) + h + s(x,t) + \int dx' w(x-x')\ \sigma(u(x',t)) + u_{\text{mem}}$$

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

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

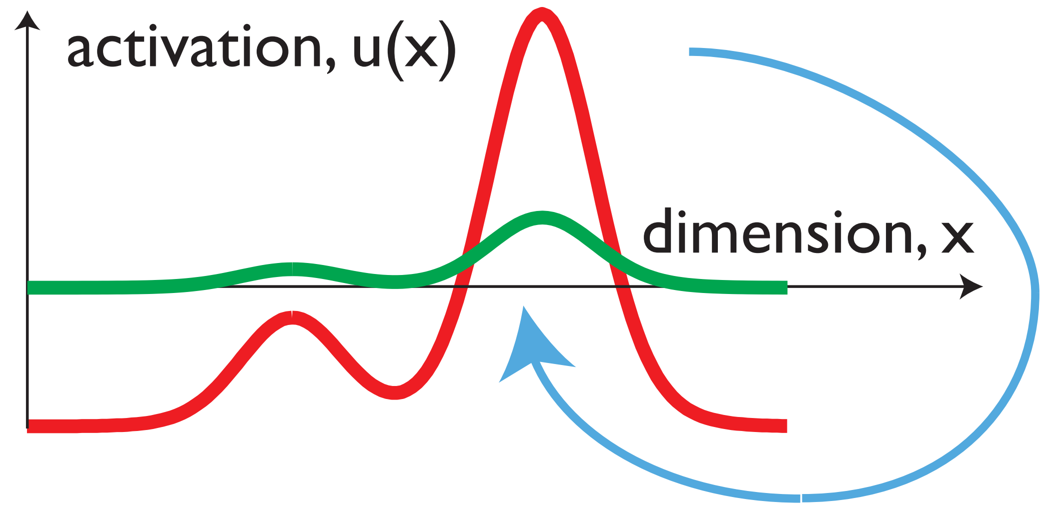


=> the memory trace reflects the history of detection decisions



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

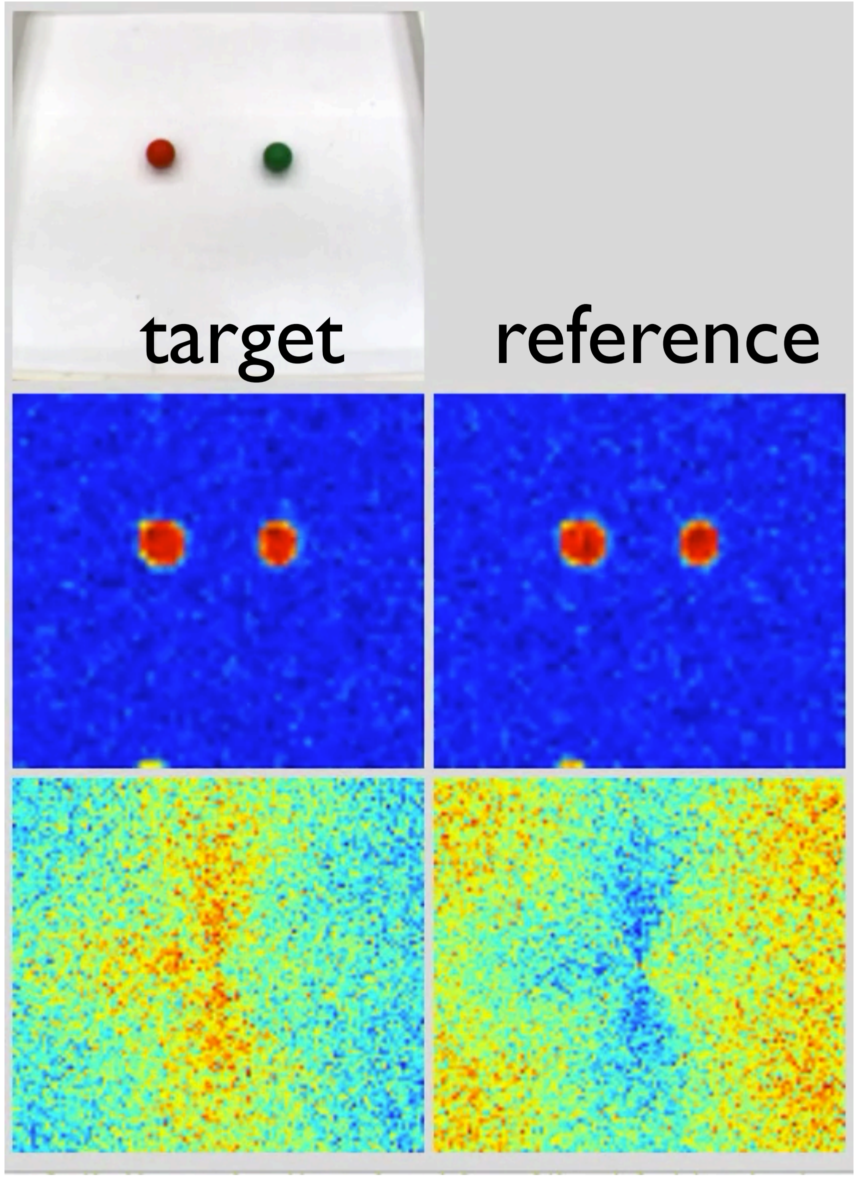
- the memory trace enables the re-activation of a past pattern of activation even when the input that caused the past pattern of activation is absent
- this is the basis for free and cued recall in DFT
- (compare live simulation in lecture 1)
- => Guest lecture Spencer

Higher cognition

- perceptual grounding of relational concepts
- generating descriptions
- mental mapping

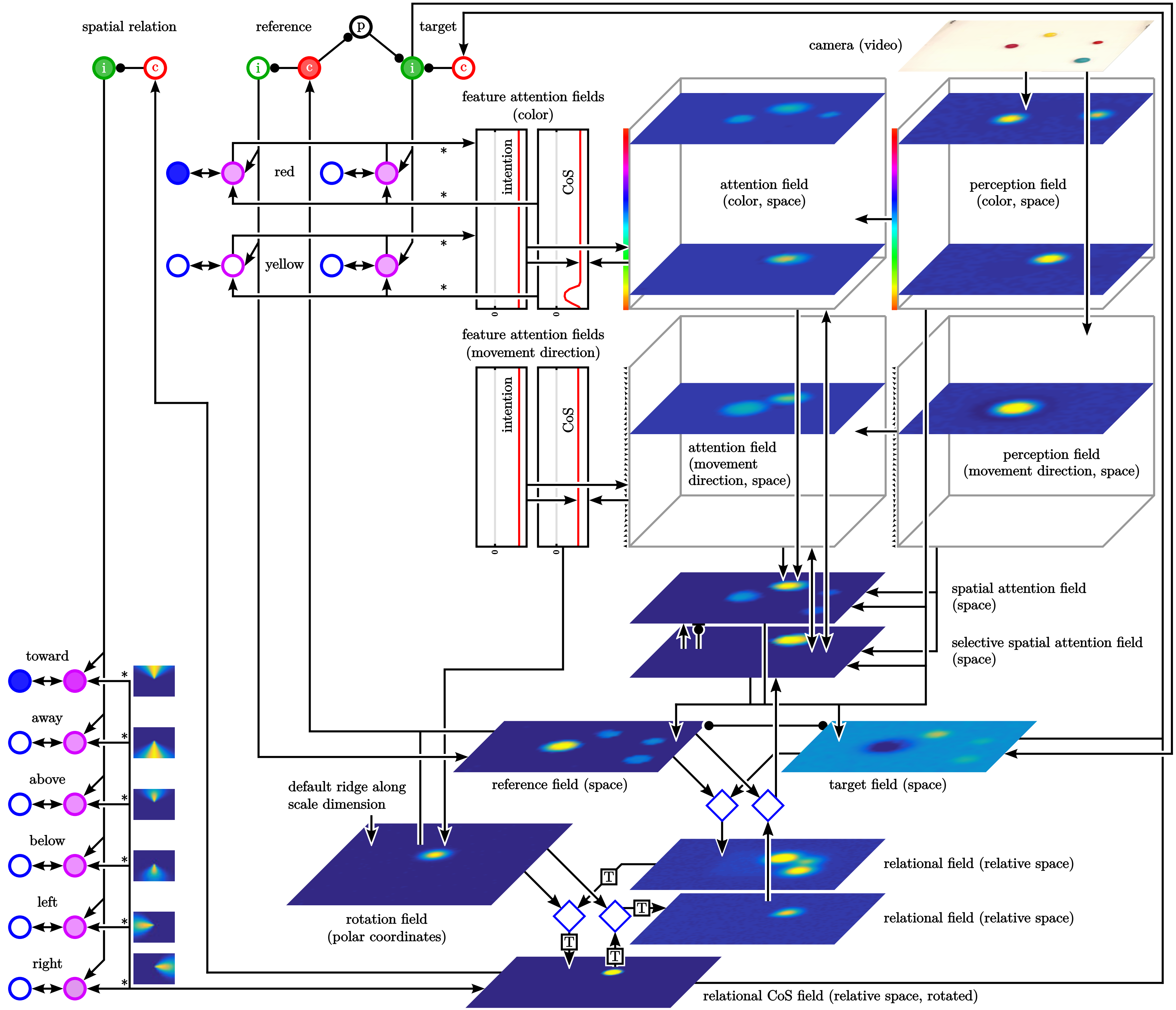
Concepts, relational thinking

"red to the left of green"



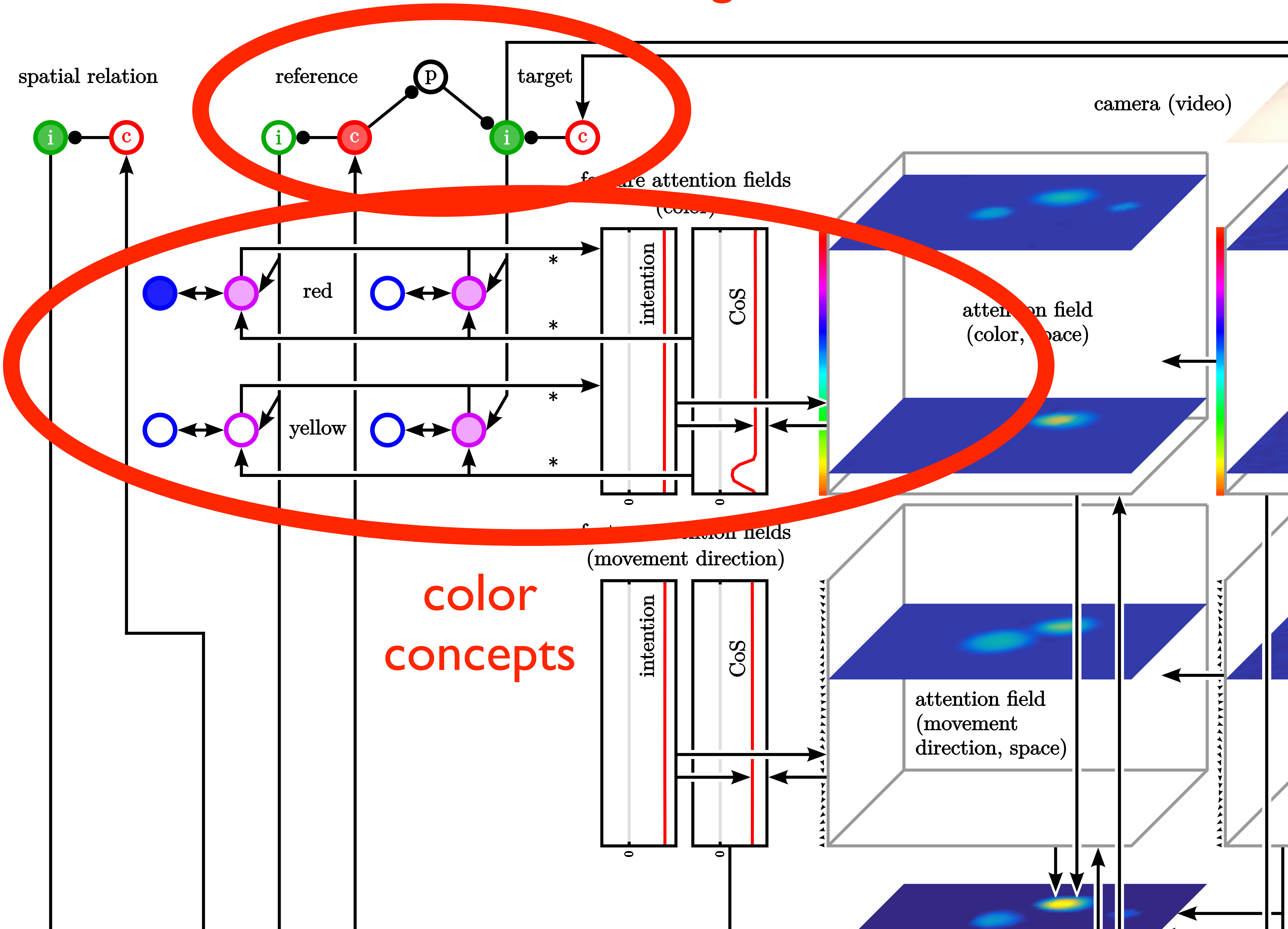
- talking about objects: bringing the target object into the attentional foreground

[Lipinski, Sandamirskaya, Schöner 2009
… Richter, Lins, Schöner, *Topics* 2017]

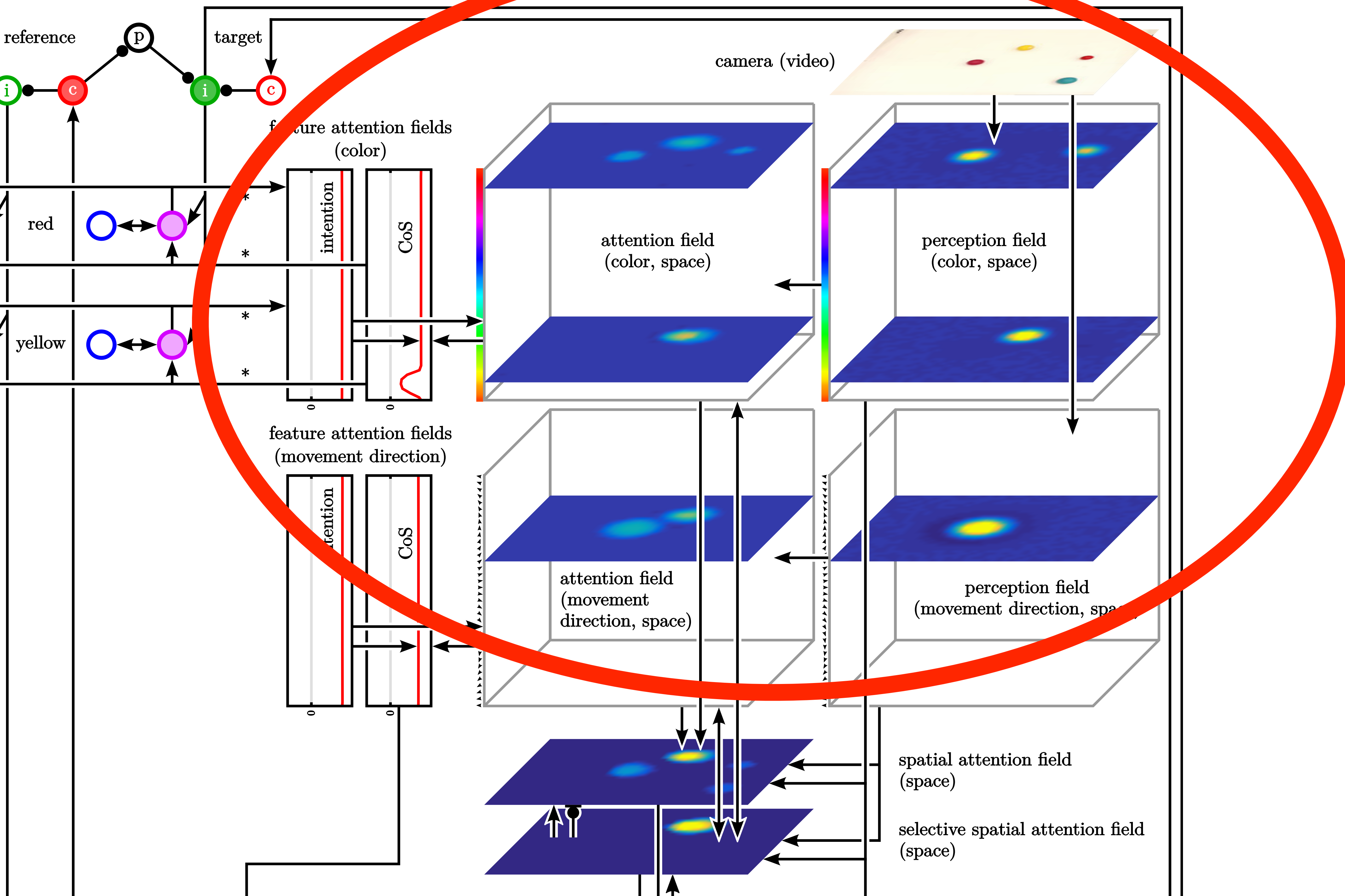


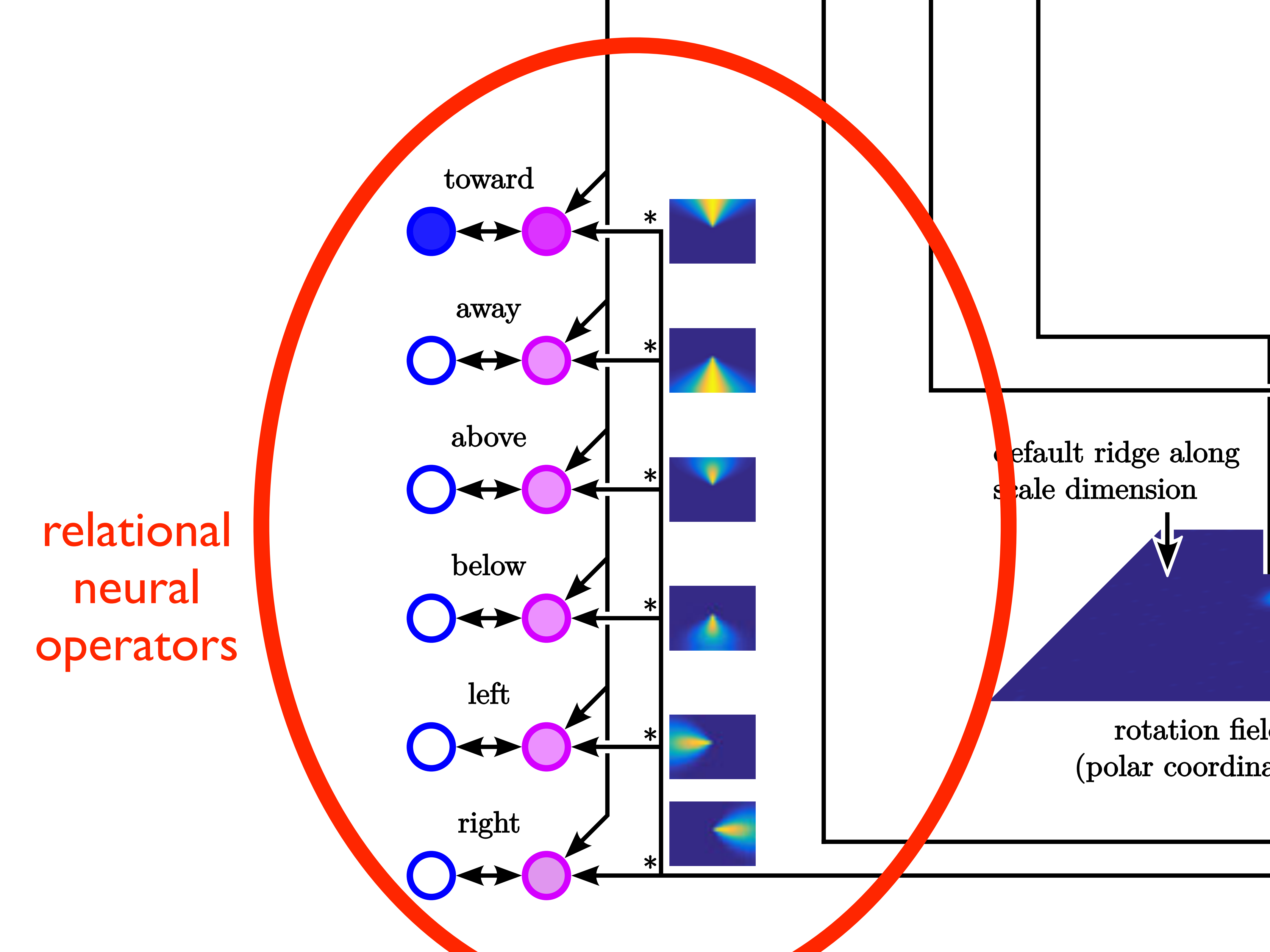
[Richter, Lins, Schöner, ToPiC (2017)]

binding to role

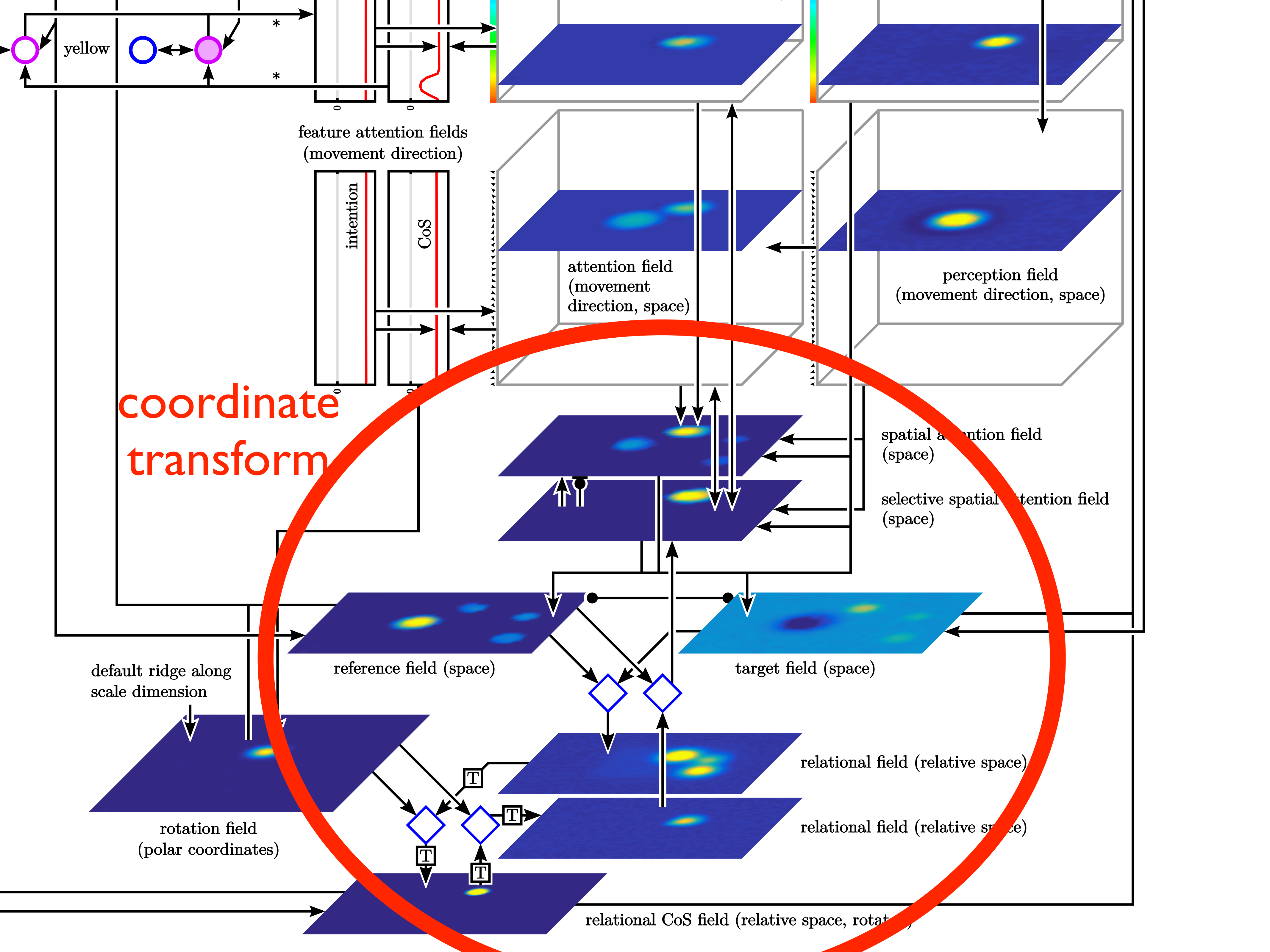


cued visual search



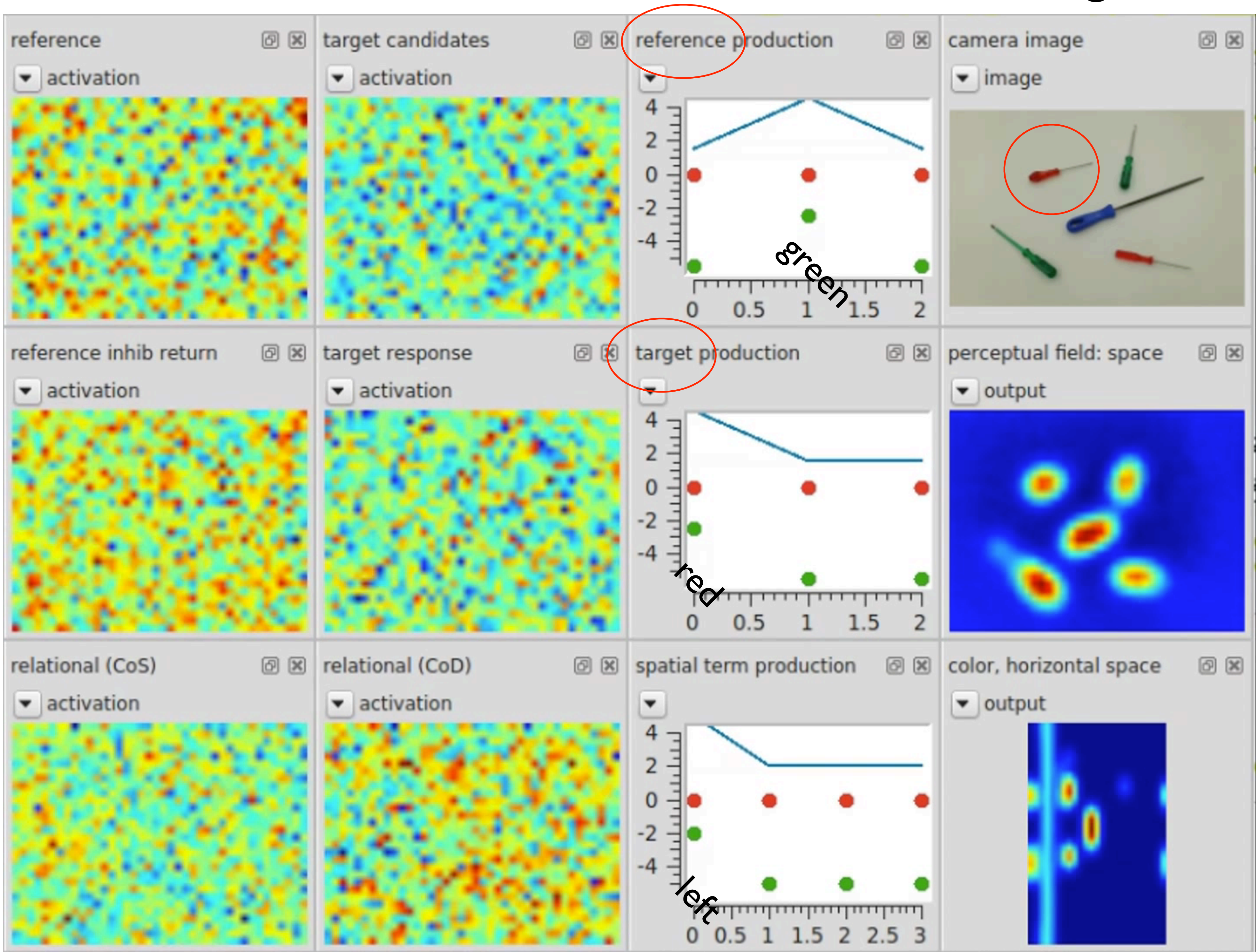


relational
neural
operators
toward
away
above
below
left
right
efault ridge along
s ale dimension
rotation fiel
(polar coordina



yellow
feature attention fields
(movement direction)
intention
CoS
attention field
(movement
direction, space)
perception field
(movement direction, space)
coordinate
transform
spatial a ntion field
(space)
selective spatial tention field
(space)
reference field (space)
target field (space)
default ridge along
scale dimension
relational field (relative space)
relational field (relative sp ce)
rotation field
(polar coordinates)
relational CoS field (relative space, rotat)

“red to the left of green”



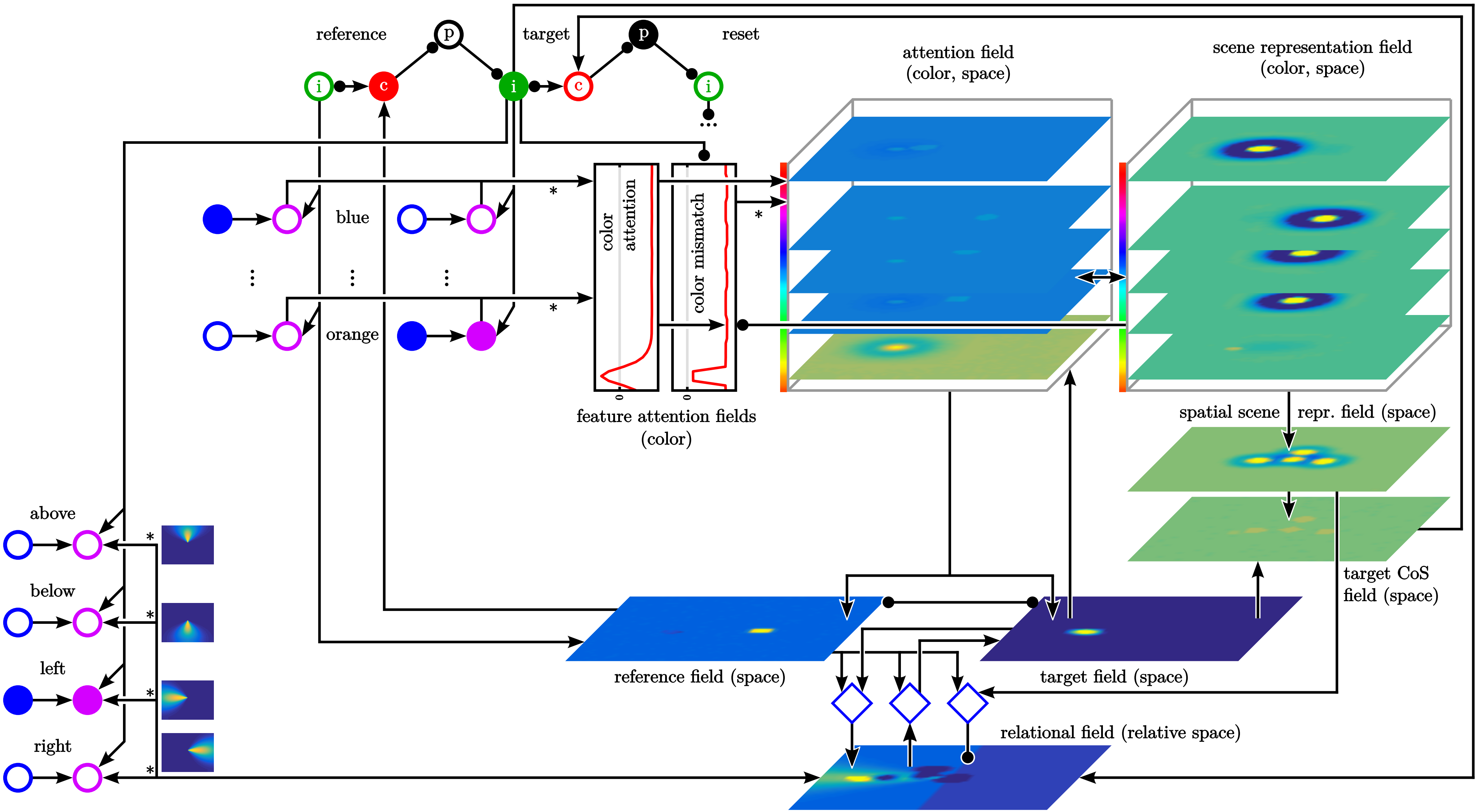
Concepts, relational thinking

- => special lecture by Daniel Sabinasz on Thursday
- how the sequence of processing steps arises… => next core lecture

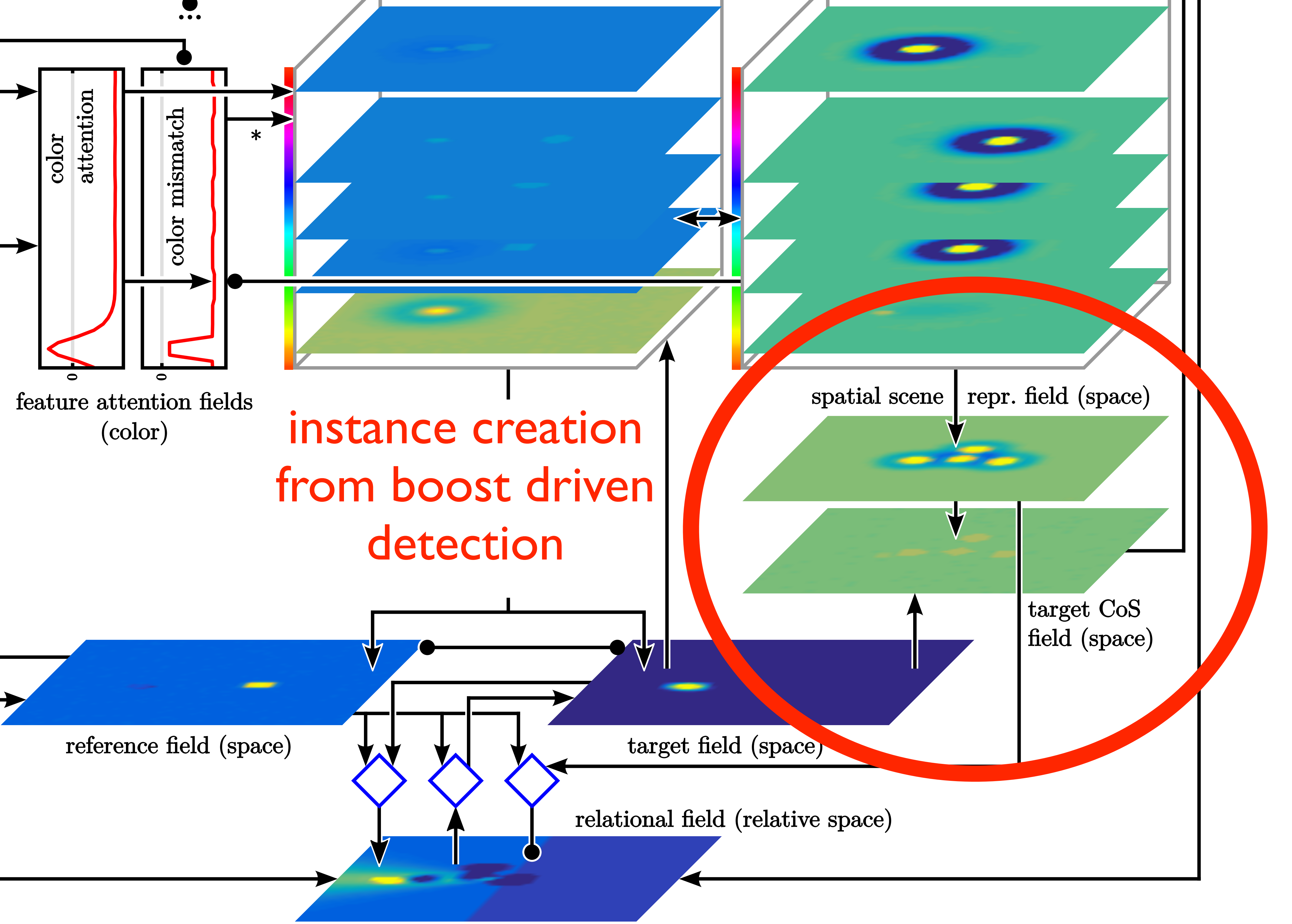
Mental mapping and inference

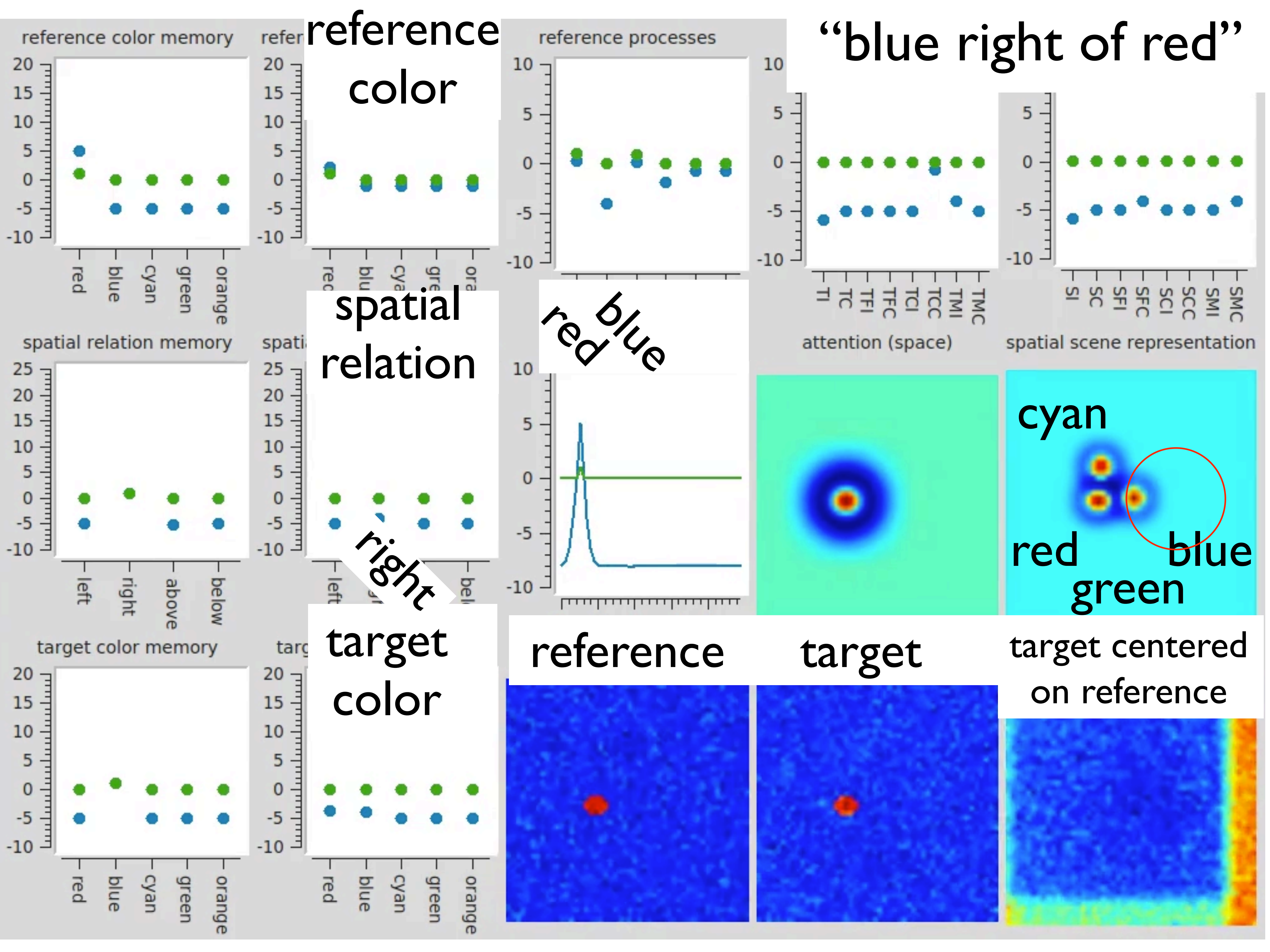
- propositions
  - “There is a cyan object above a green object.”
  - “There is a red object to the left of the green object.”
  - “There is a blue object to the right of the red object.”
  - “There is an orange object to the left of the blue object.”
- inference
  - “Where is the blue object relative to the red object?”

[Ragni, Knauff, *Psych Rev* 2013]

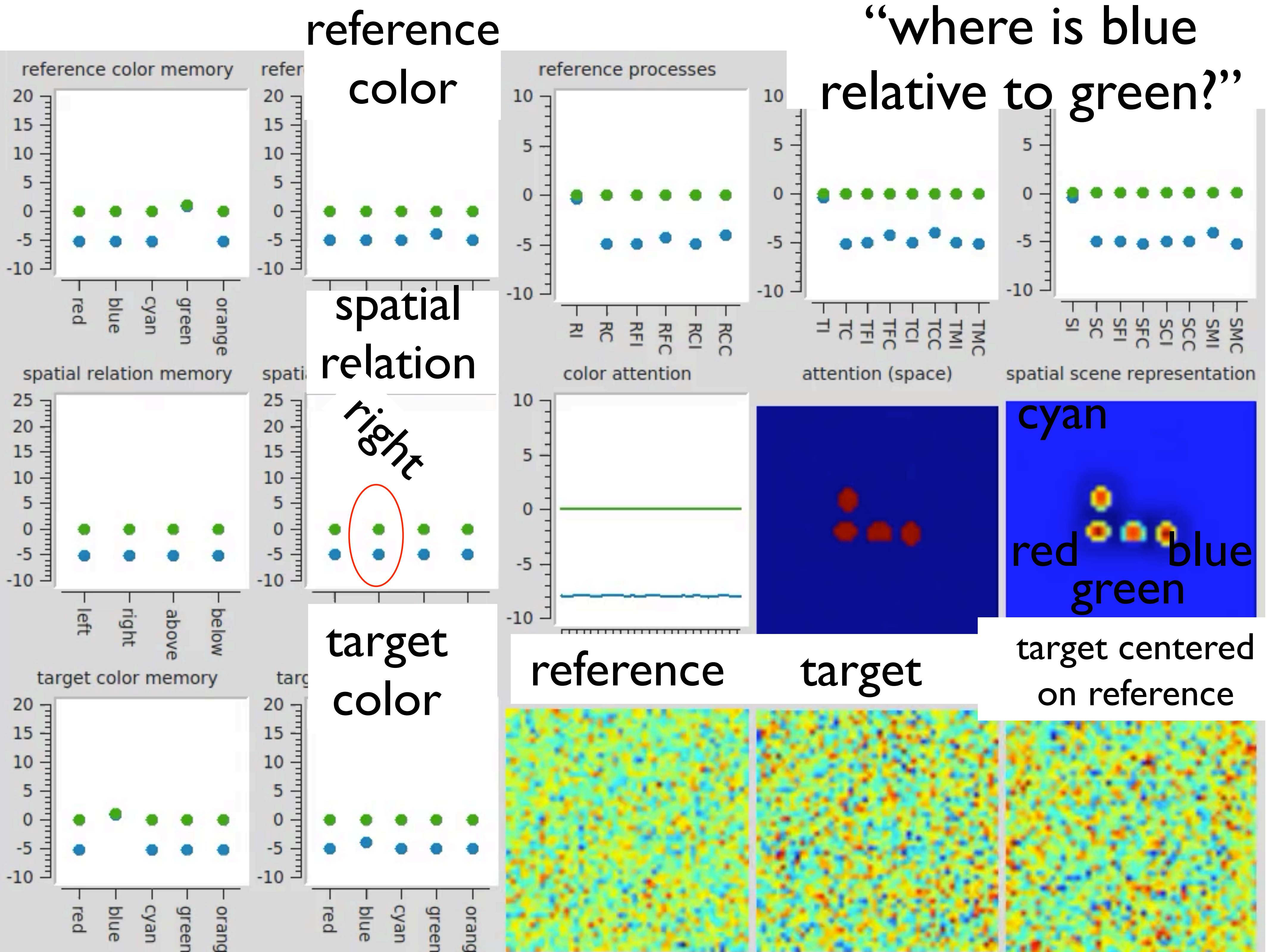


[Kounatidou, Richter, Schöner, CogSci 2018]


color attention
color mismatch
0
0
*
feature attention fields (color)
instance creation from boost driven detection
spatial scene repr. field (space)
target CoS field (space)
reference field (space)
target field (space)
relational field (relative space)



"blue right of red"
reference color memory
reference color
reference processes
red
blue
cyan
green
orange
TI
TC
TFI
TFC
TCI
TCC
TMI
TMC
SI
SC
SFI
SFC
SCI
SCC
SMI
SMC
spatial relation memory
spatial relation
blue
red
attention (space)
spatial scene representation
cyan
red
blue
green
left
right
above
below
target color memory
target color
reference
target
target centered on reference



"where is blue relative to green?"
reference color
spatial relation
right
target color
reference color memory
reference processes
spatial relation memory
color attention
attention (space)
spatial scene representation
target color memory
red
blue
cyan
green
orange
RI
RC
RFI
RFC
RCI
RCC
TI
TC
TFI
TFC
TCI
TCC
TMI
TMC
SI
SC
SFI
SFC
SCI
SCC
SMI
SMC
left
right
above
below
cyan
red
blue
green
reference
target
target centered
on reference

Conclusion

- dynamic fields across different feature spaces enable new cognitive functions: binding to space, search, coordinate transforms, binding through space, concepts, grounding/ descriptions, mental mapping
- next: how do sequences of neural attractor states come about?