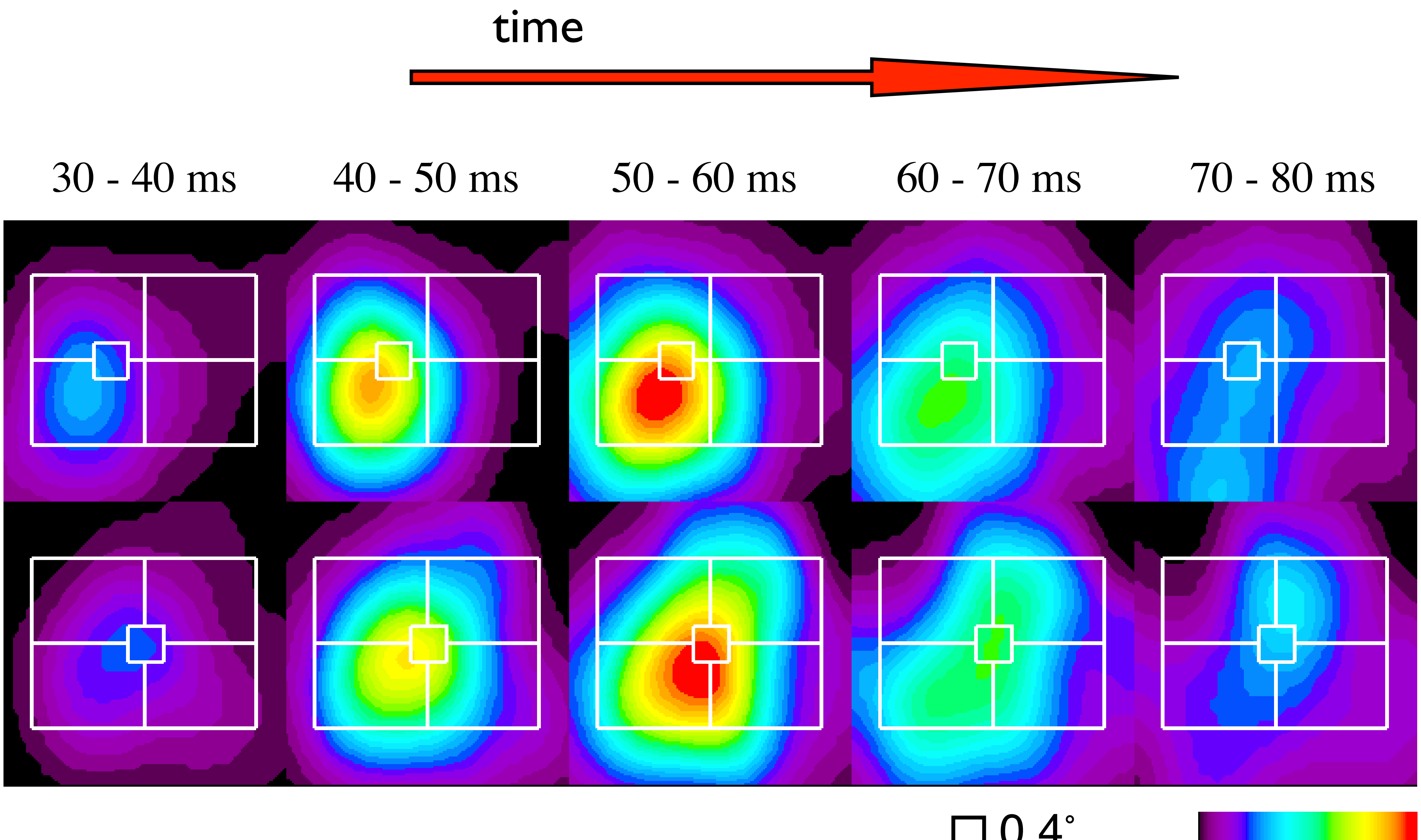
DFT in two dimensions or more ...

Gregor Schöner

example: retinal pace

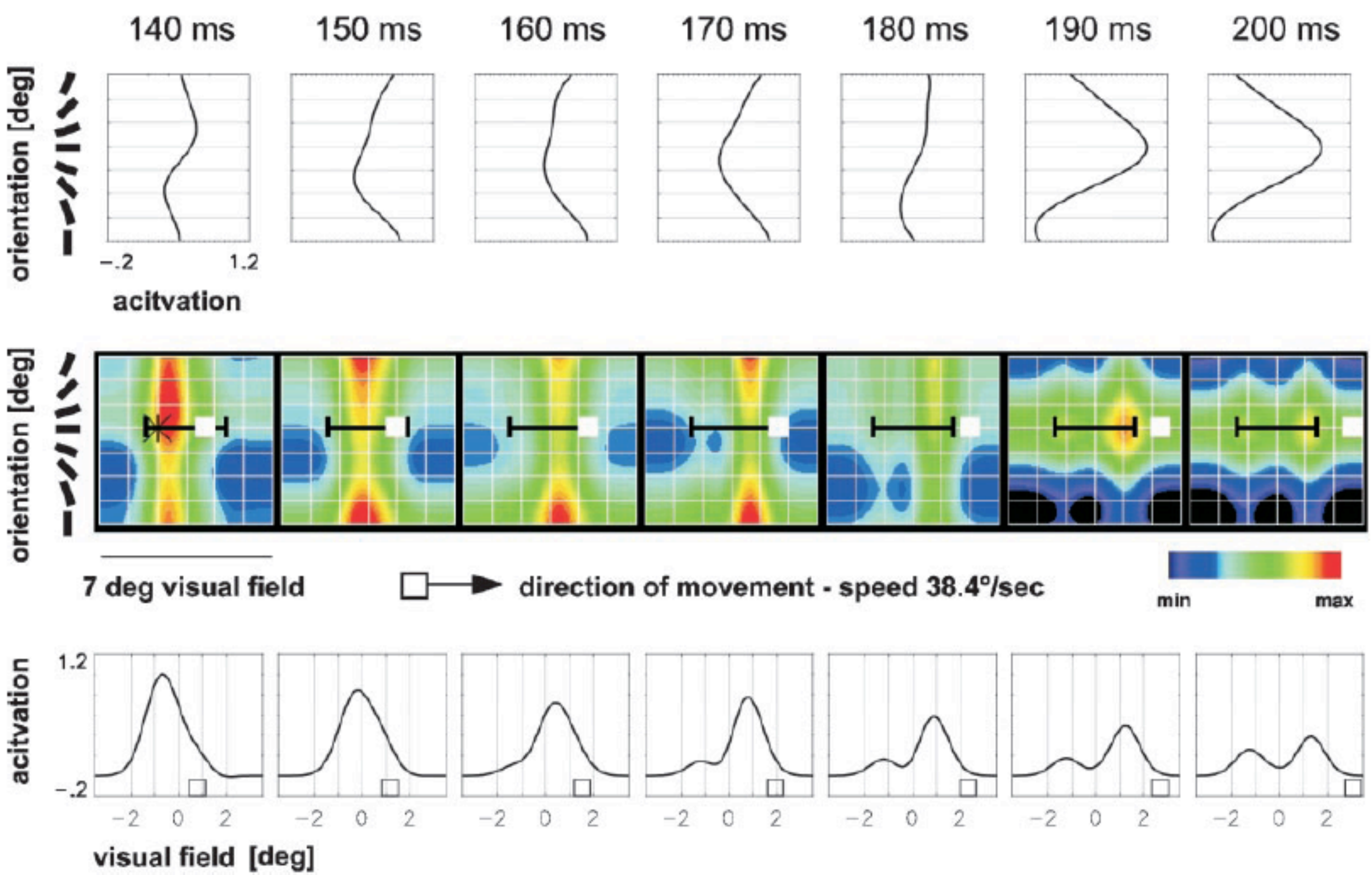
- obviously two-dimensional



[Jancke et al., 1999]

example: visual feature map

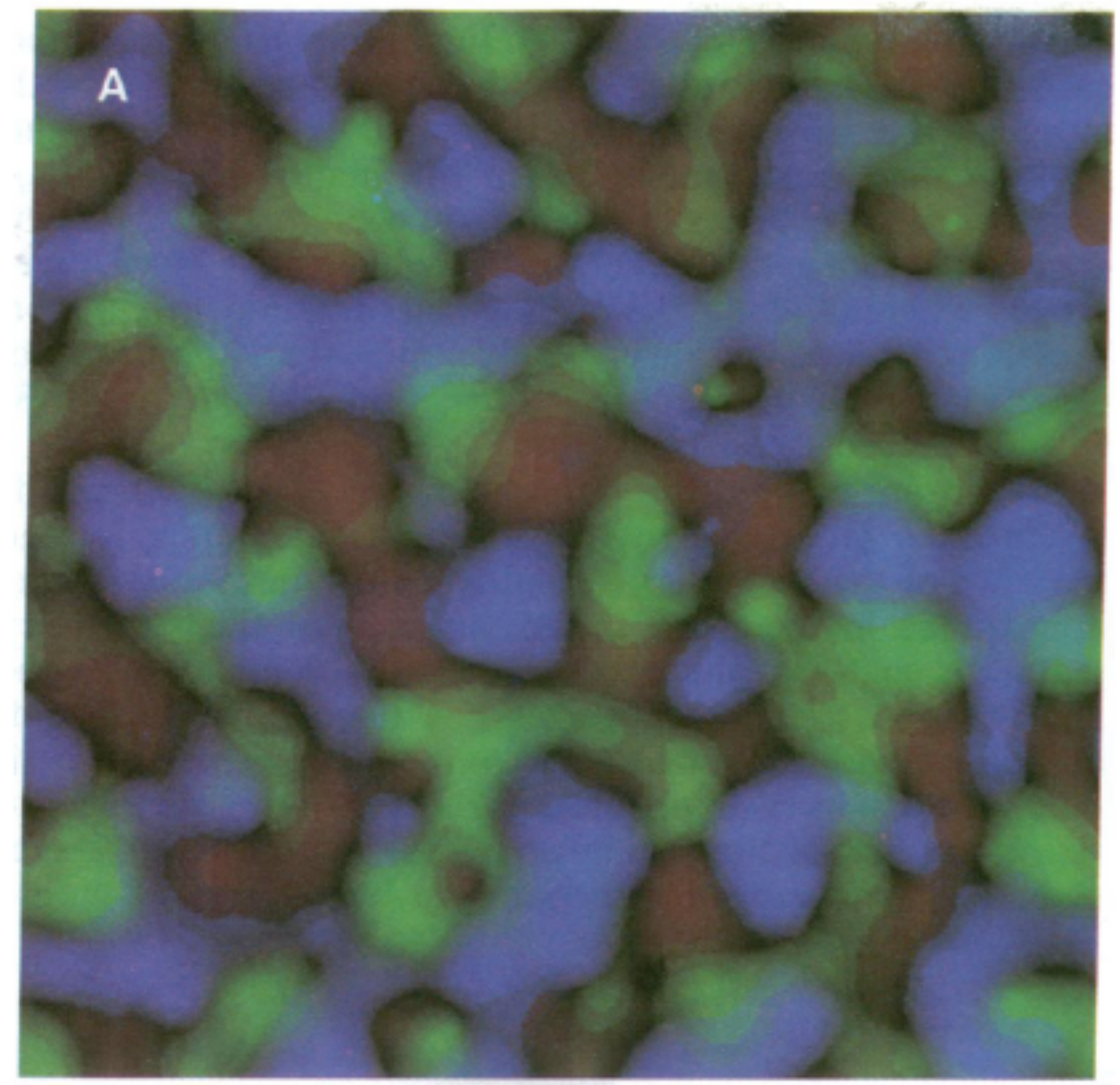
- orientation-retinal location



[Jancke, JNeursci (2000)]

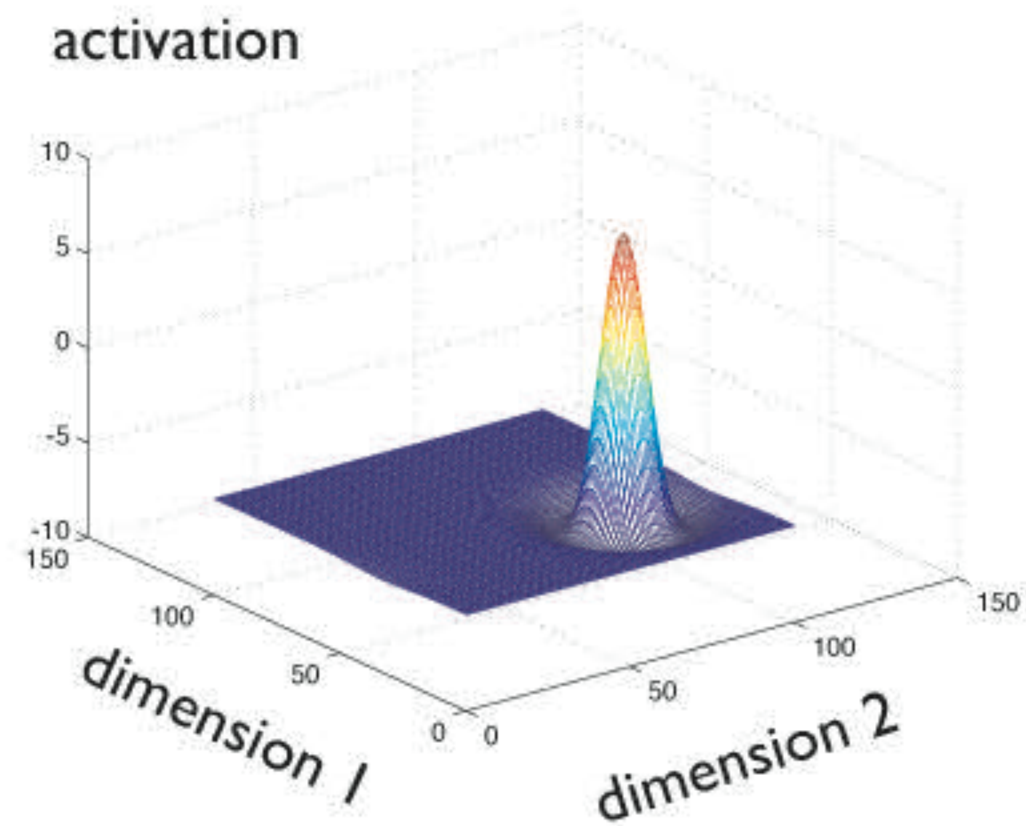
example: visual feature maps

- 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 ...



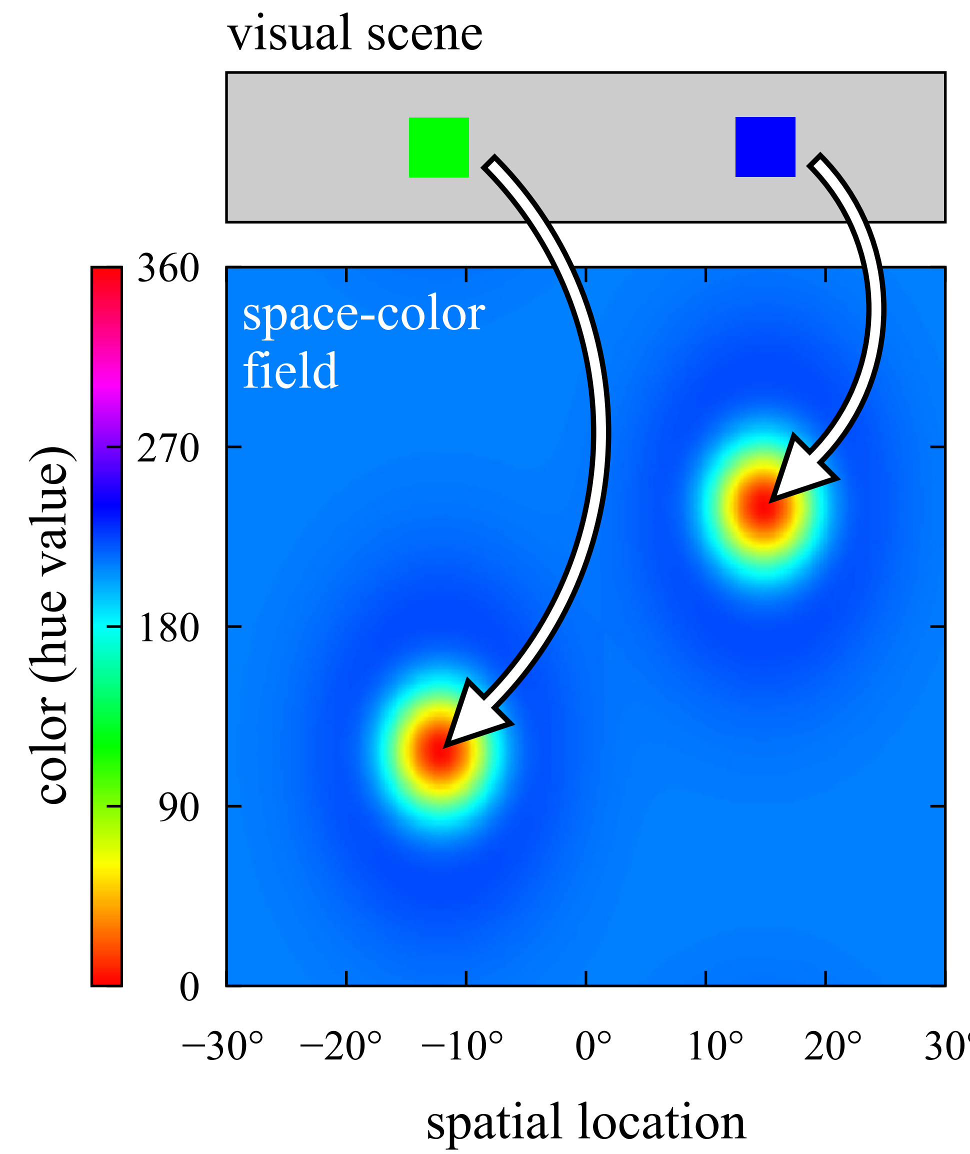
mathematics of 2D fields

- => simulation
- no problem ... self-stabilized peaks work just fine...



Example: Color-Space field

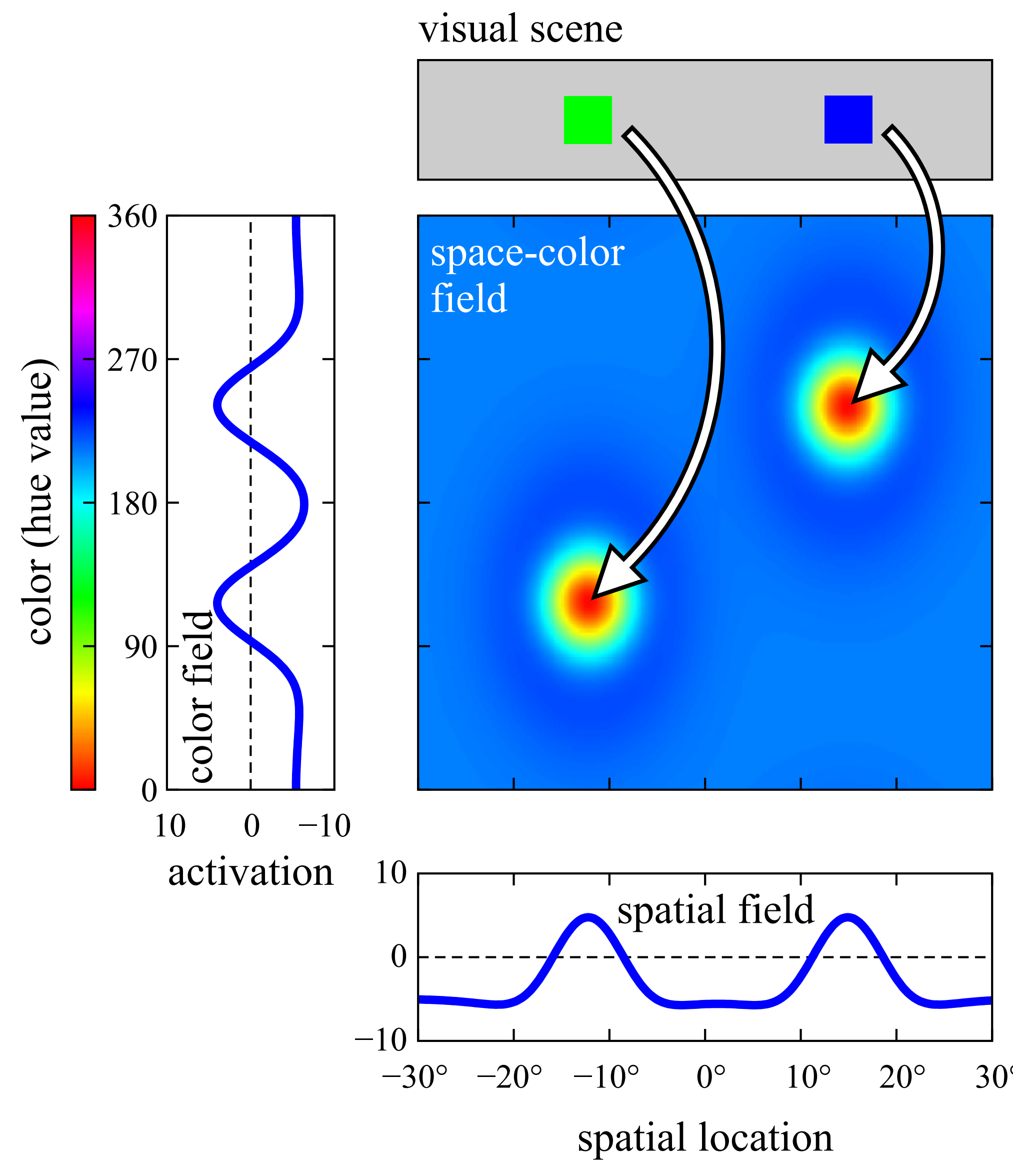
- 1D spatial location (for illustration)
- 1D color dimension (hue)
- visual input: 2D
- => 2D peaks



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

Example: Color-Space field

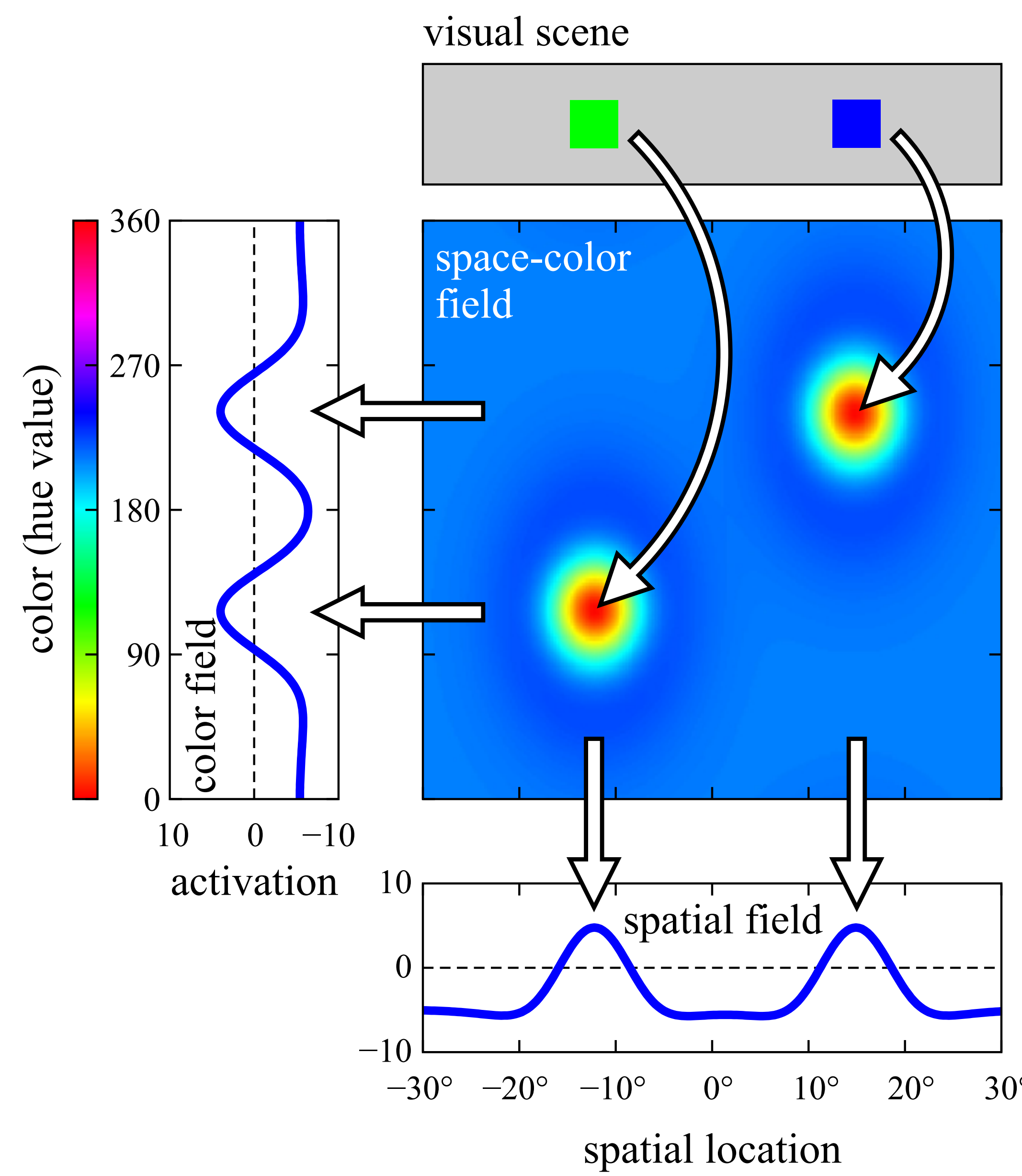
- separate fields for1D spatial location
- and 1D color dimension (hue)
- => combined vs. separate representations



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

Example: Color-Space field

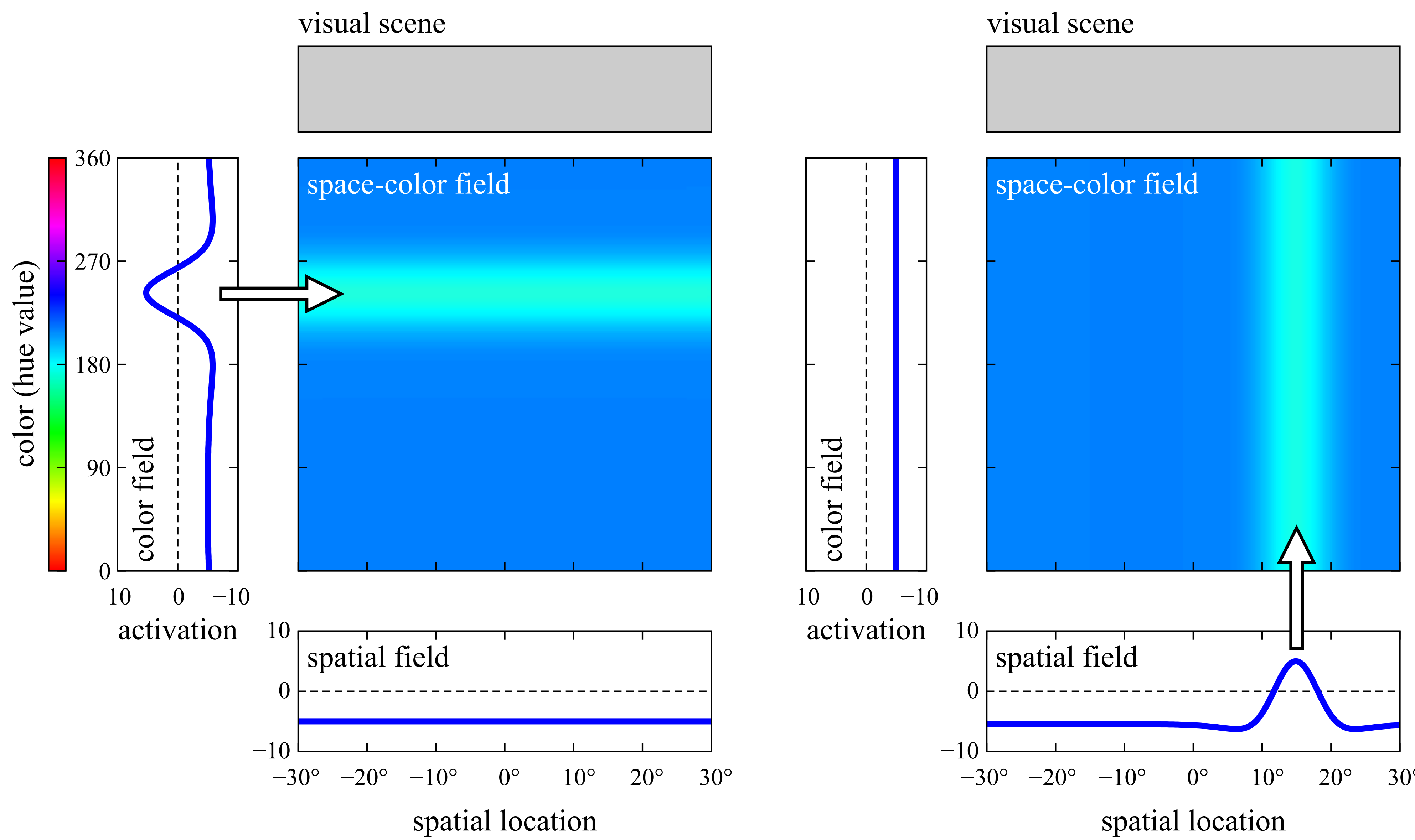
- read-out from 2D to 1D
- by projection
  - summing along the other dimension (marginalization)
  - or taking the (soft)max



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

Example: Color-Space field

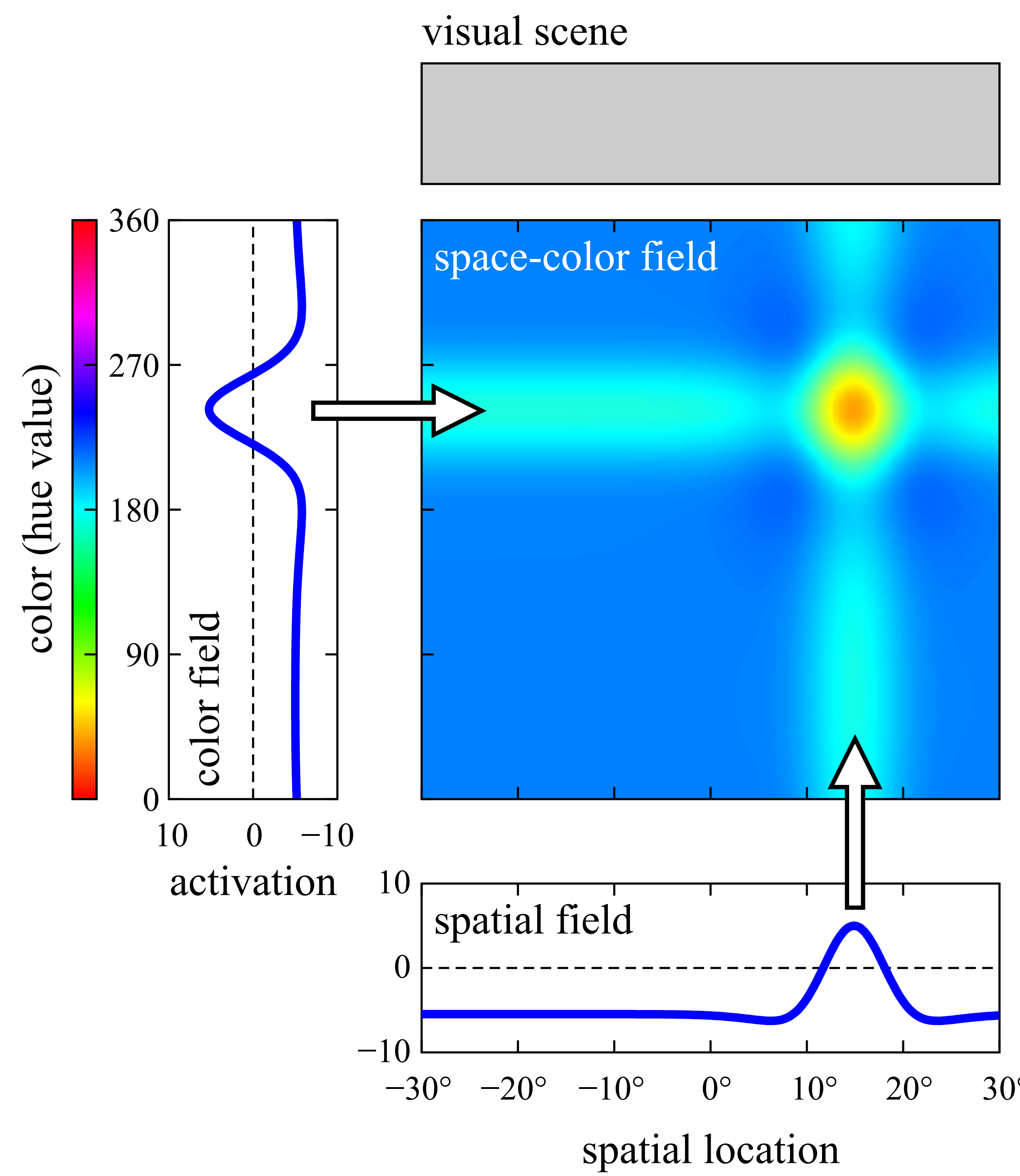
- input from 1D to 2D: ridge input that is constant along the other dimension



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

Example: Color-Space field

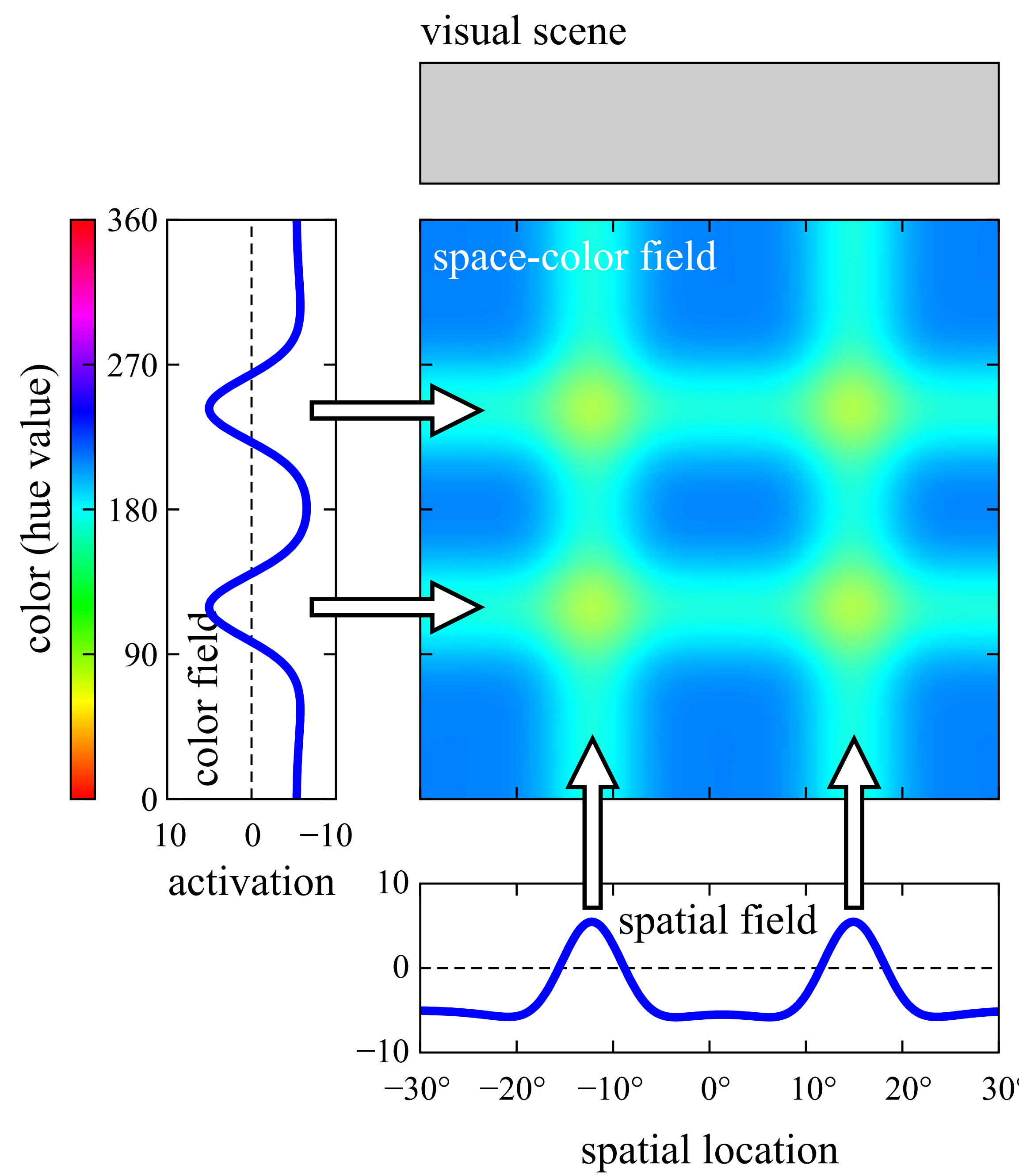
- peaks at intersections of ridges: bind two dimensions



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

Example: Color-Space field

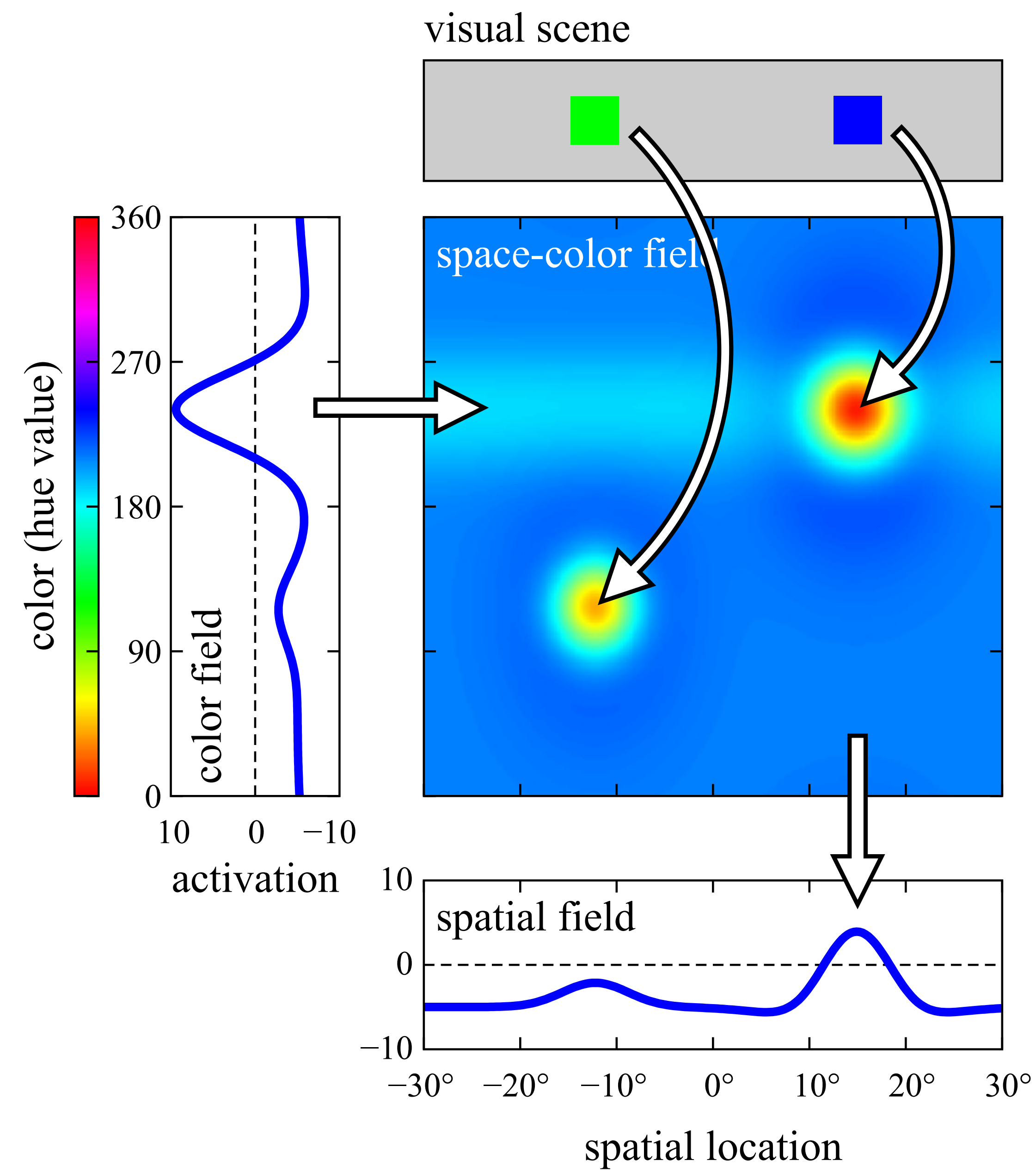
- feature-binding: multiple ridges lead to binding problem: correspondence problem



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

Example: Color-Space field

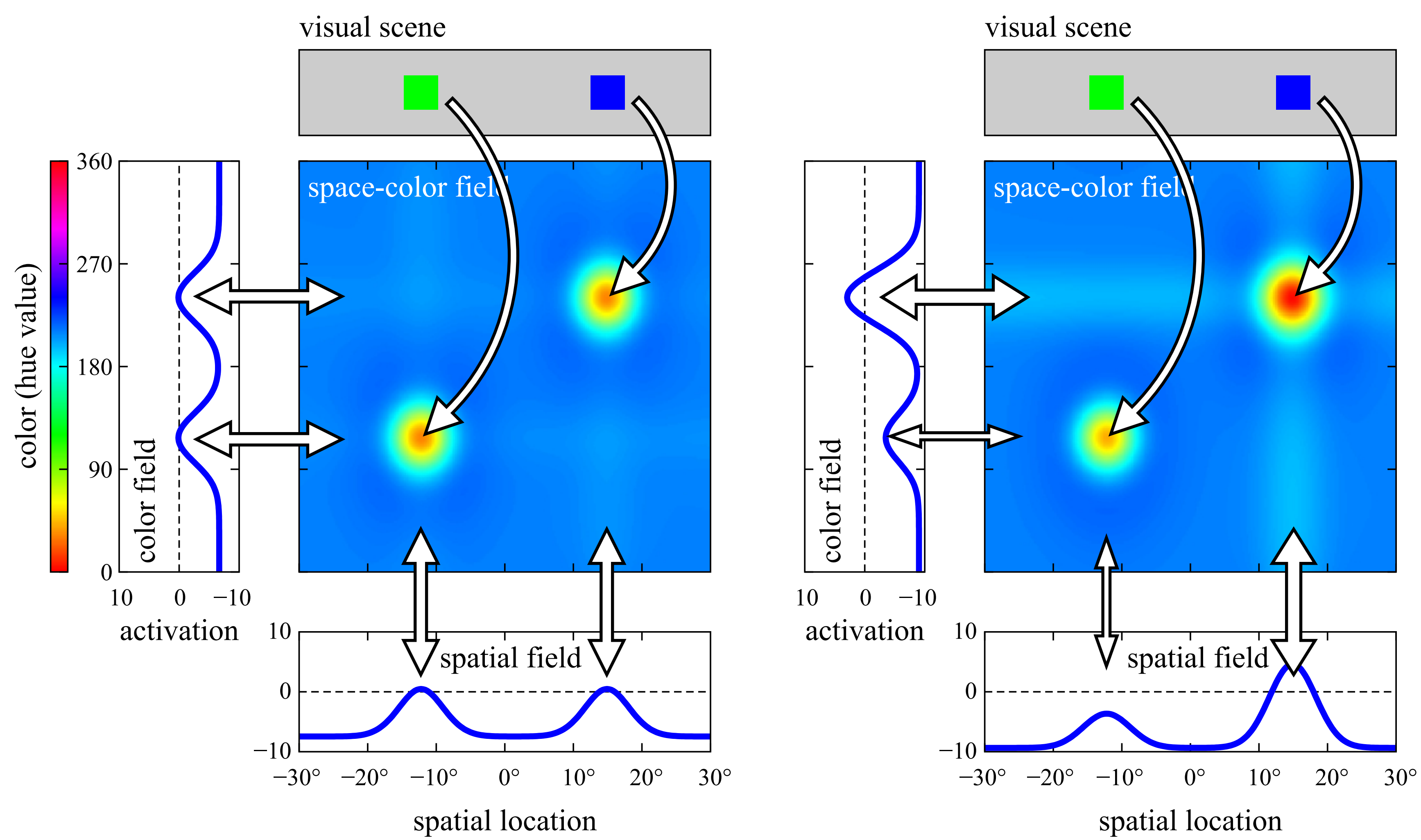
- visual search: combine ridge input with 2D input..



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

Example: Color-Space field

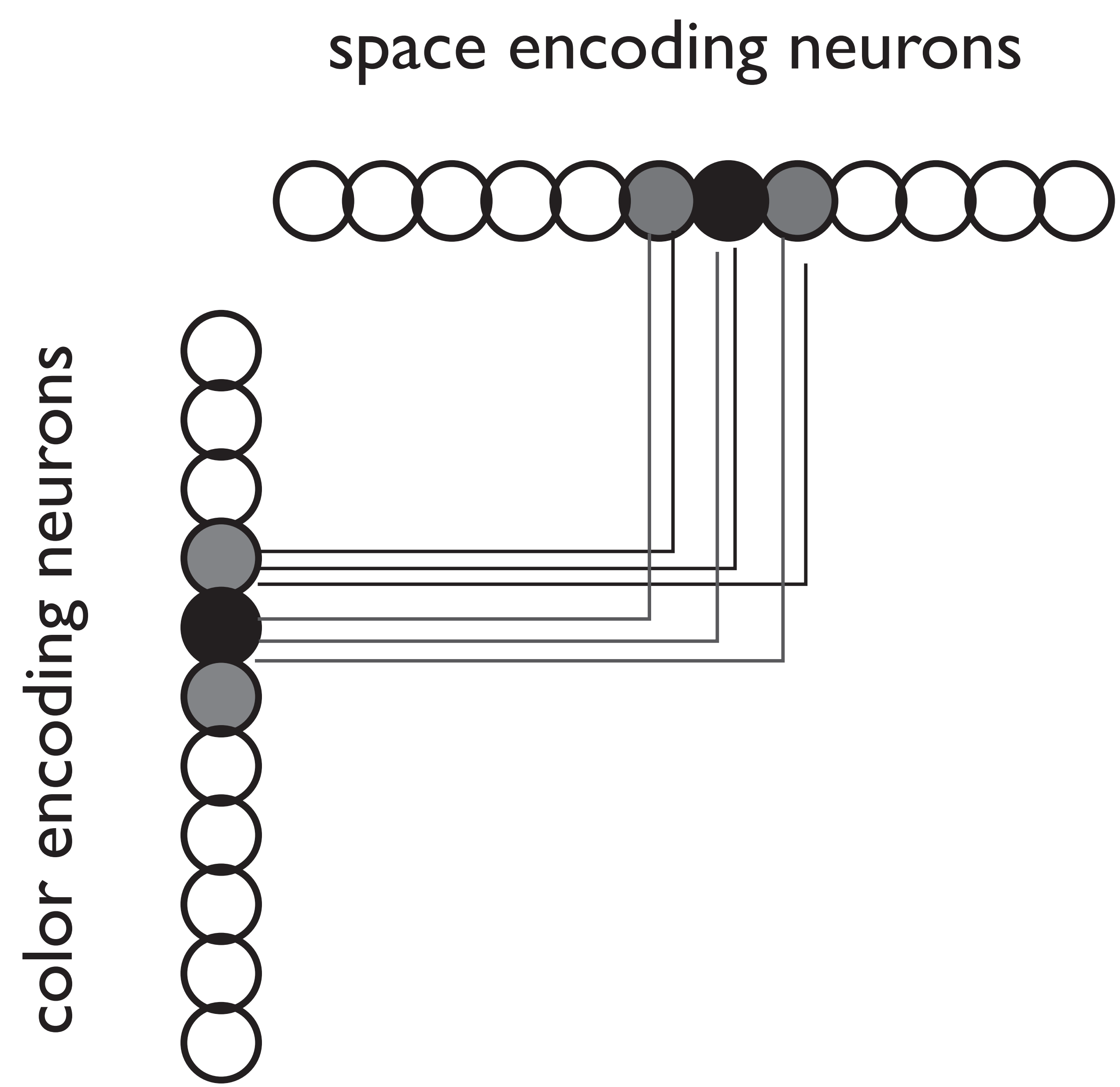
- joint selection in 2 1D fields, that are coupled across 2D field



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

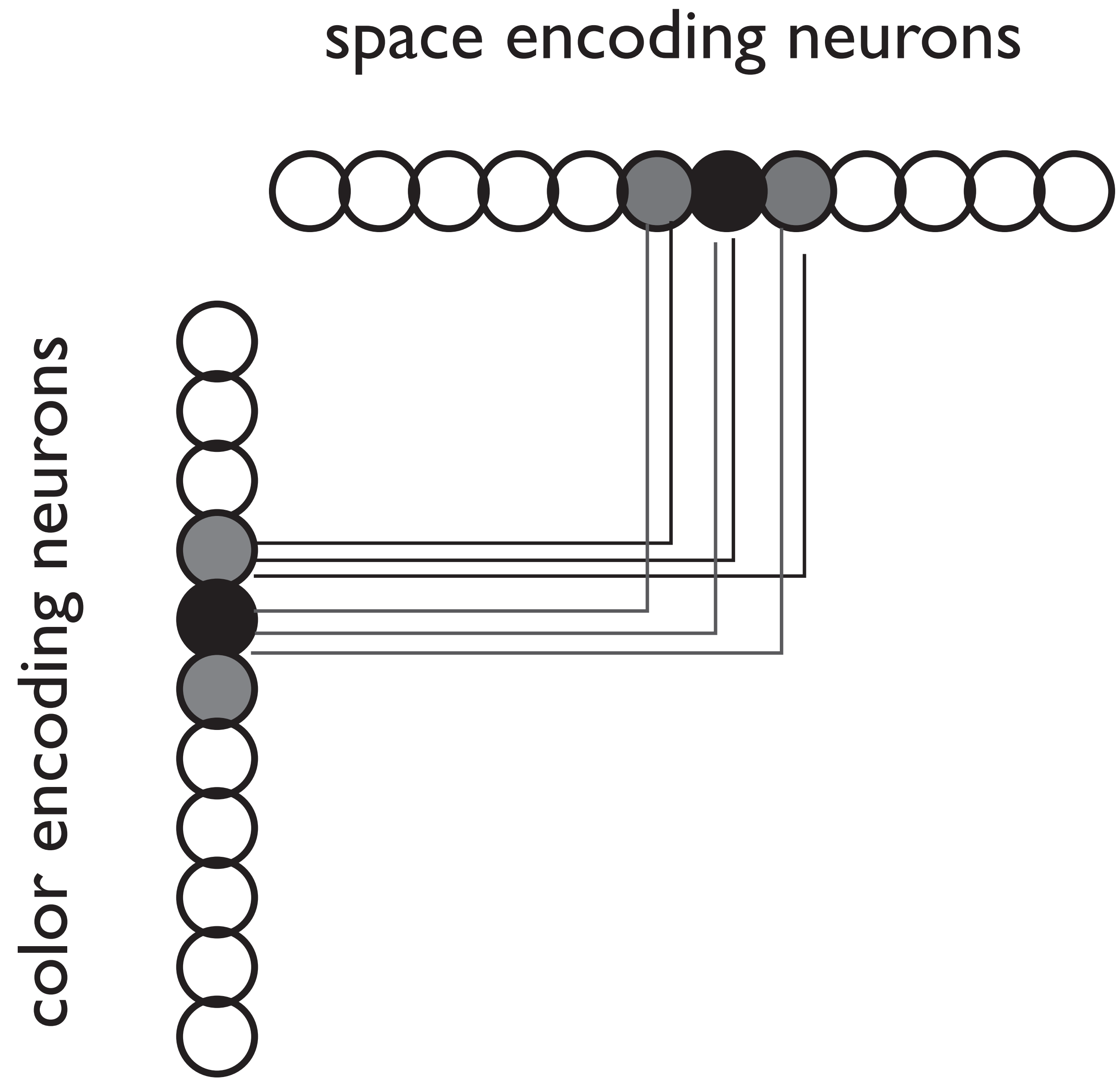
synaptic association

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



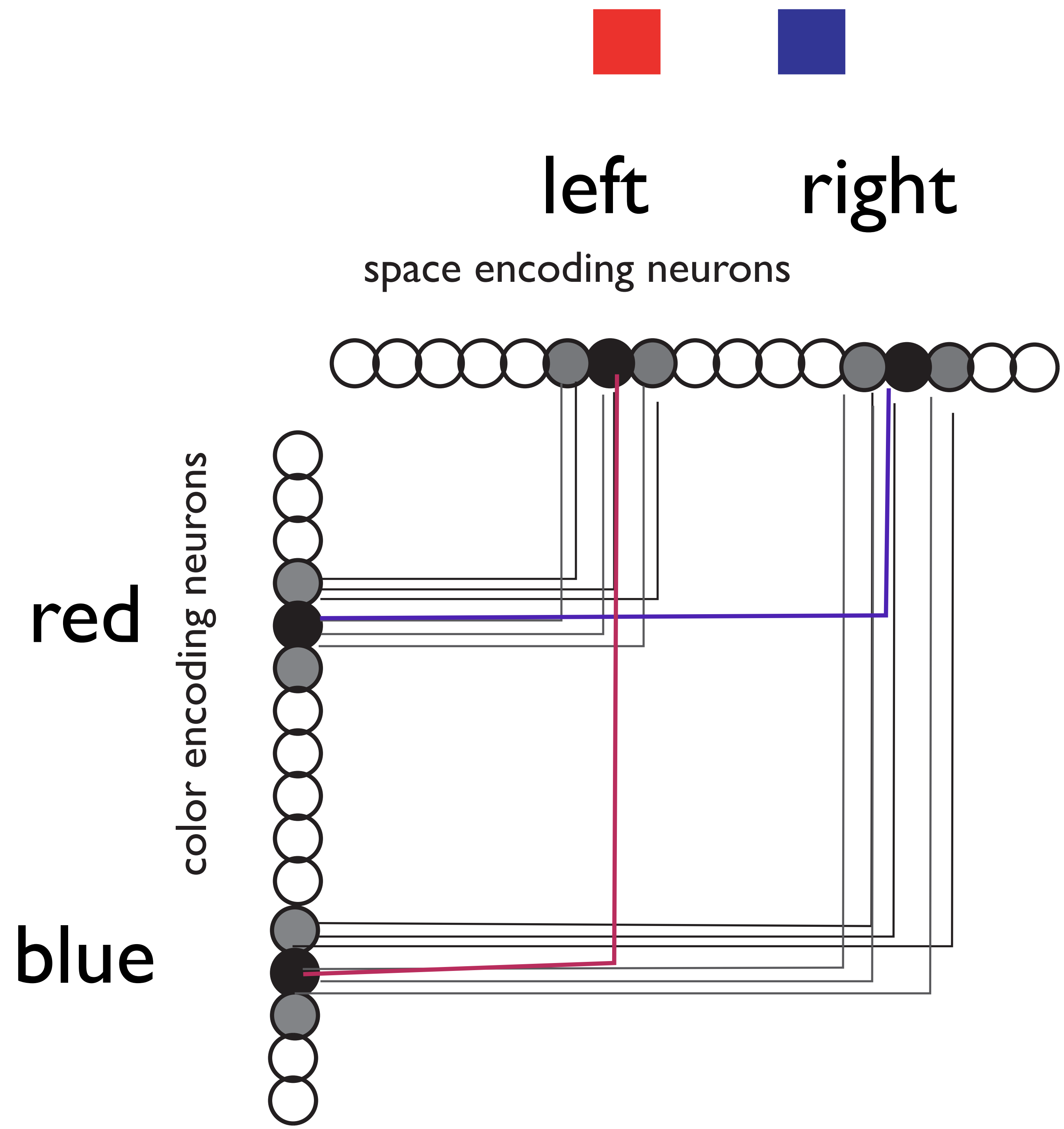
limitations of synaptic association

- 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!



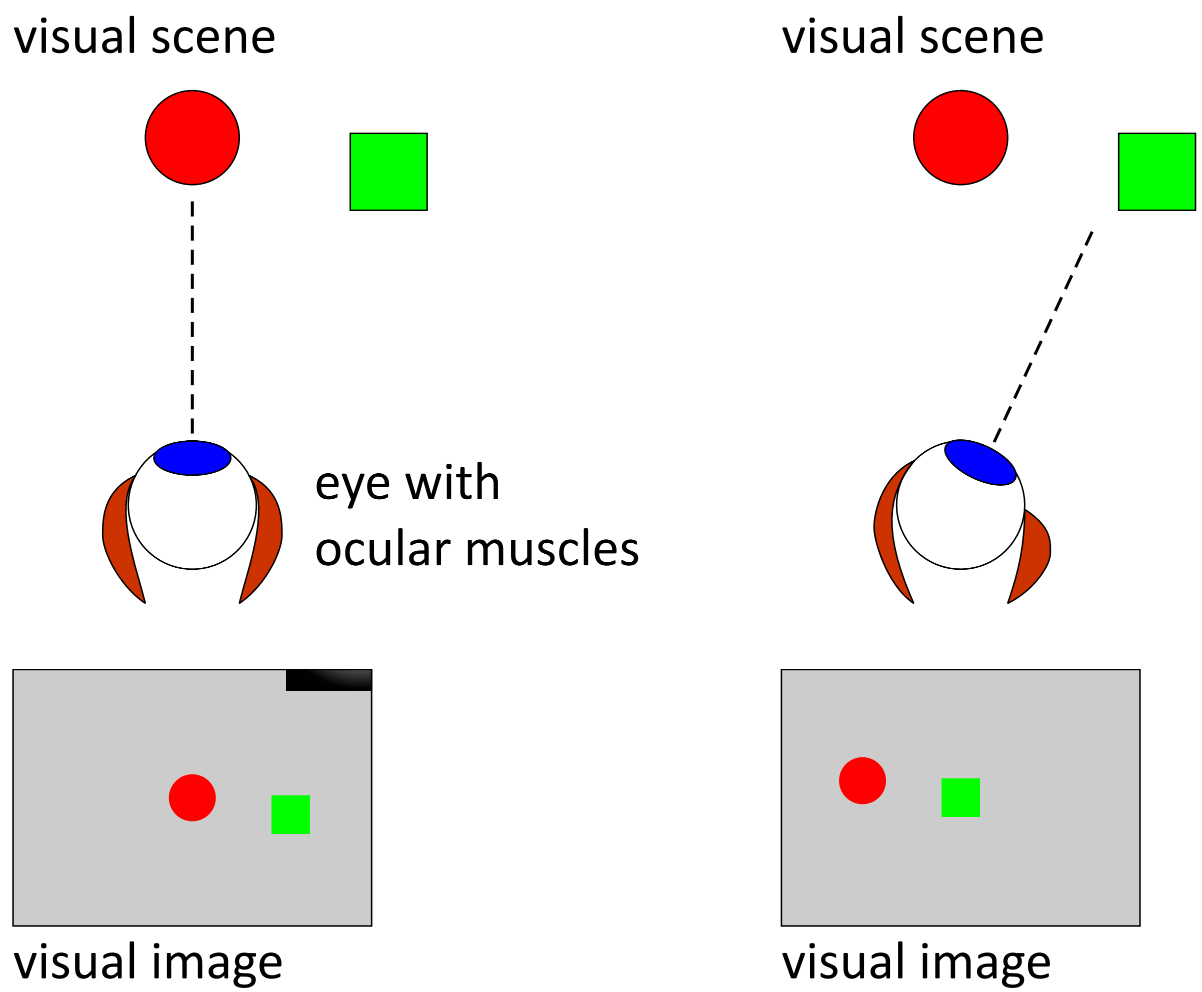
the network may associate blue with left and read with right

more functions for higher-dimensional fields: coordinate transformations

- which are analogous to the instantaneous associations between stimulus features demonstrated earlier

coordinate transformations

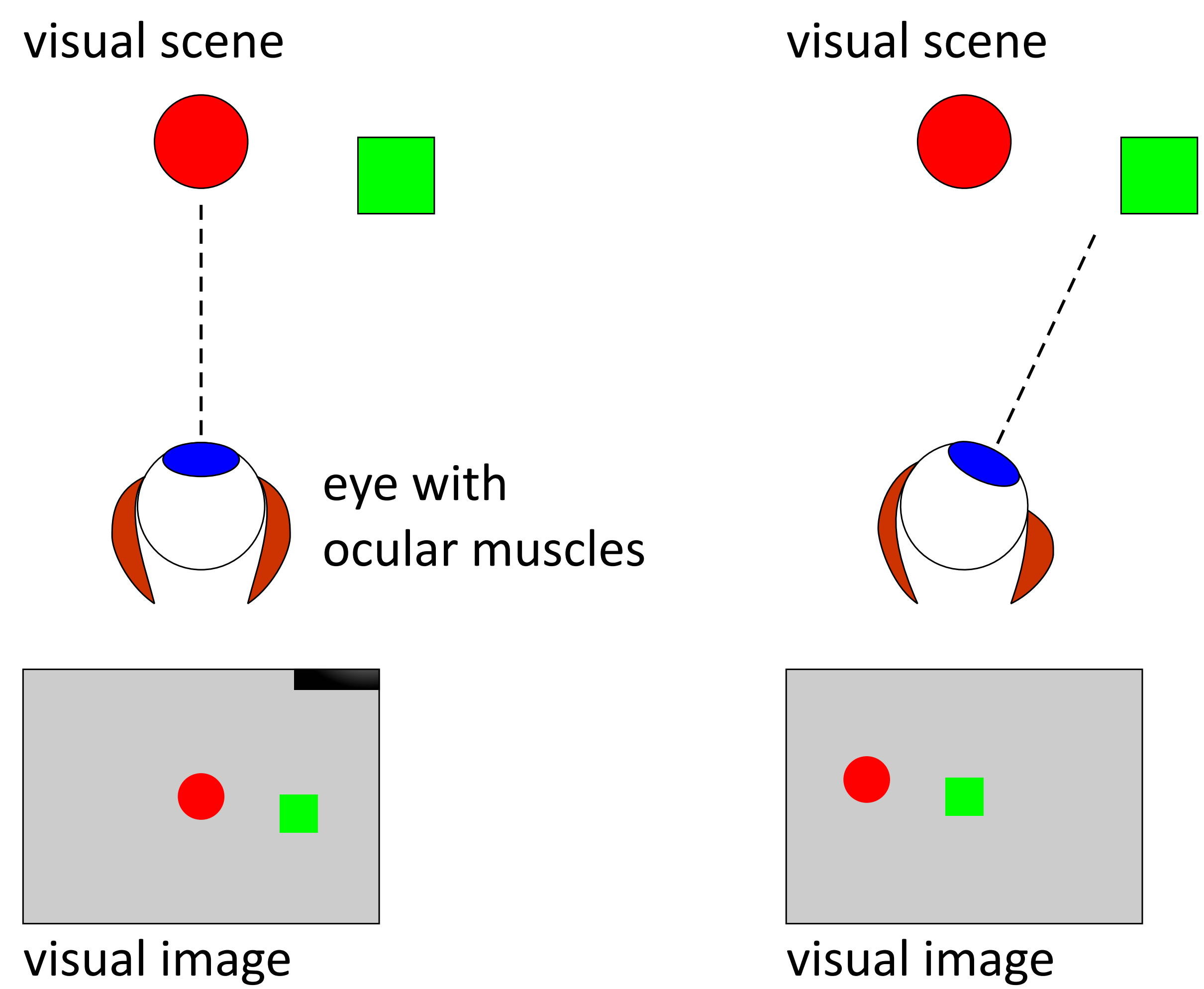
- eye movement: visual target from retinal representation to head-centered representation for reaching



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

coordinate transformations

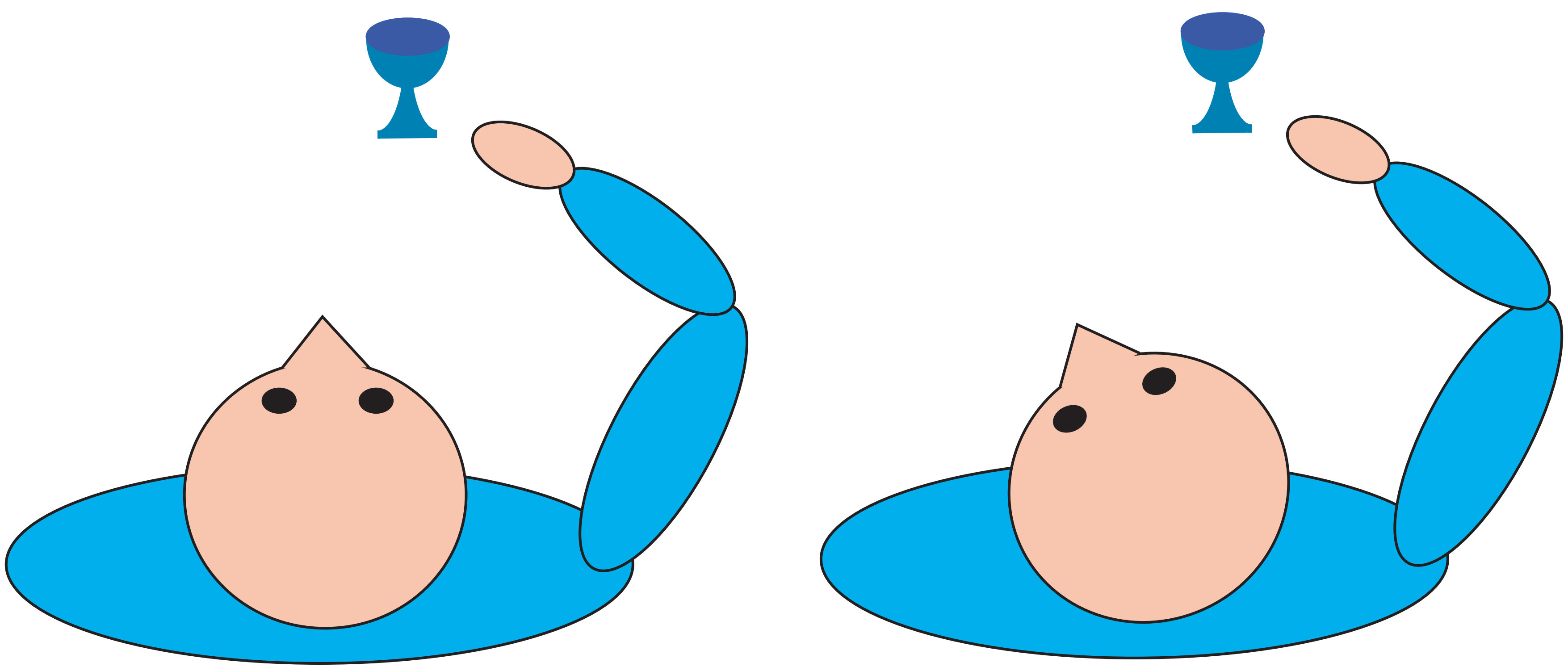
- every gaze shift changes the spatial reference frame of the visual perception
- how to memorize location when the reference frame keeps shifting?
- => transformation to gaze-invariant reference frame



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

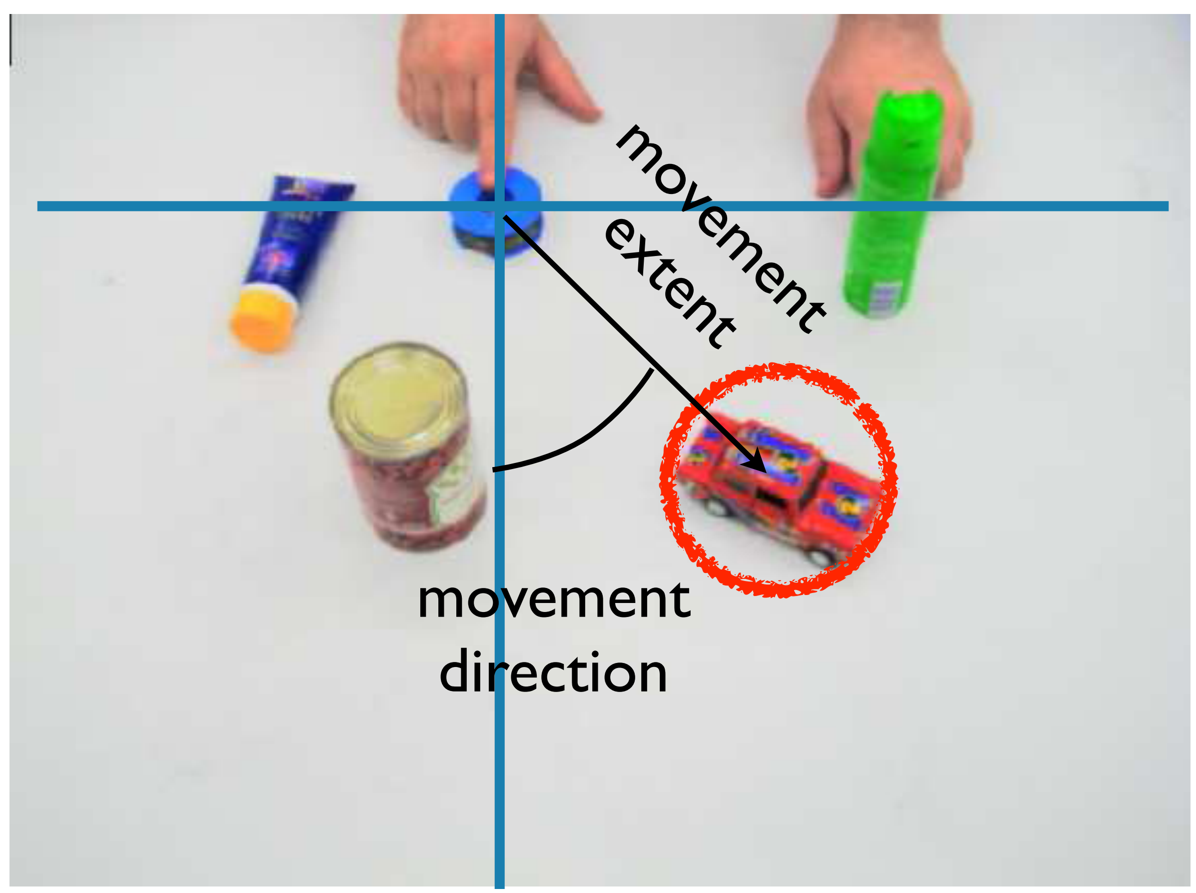
coordinate transformations

- head movement: transform visual target from retinal representation to body-centered representation



coordinate transformations

- hand movement: transform movement target from body-centered representation to hand-centered representation for reaching



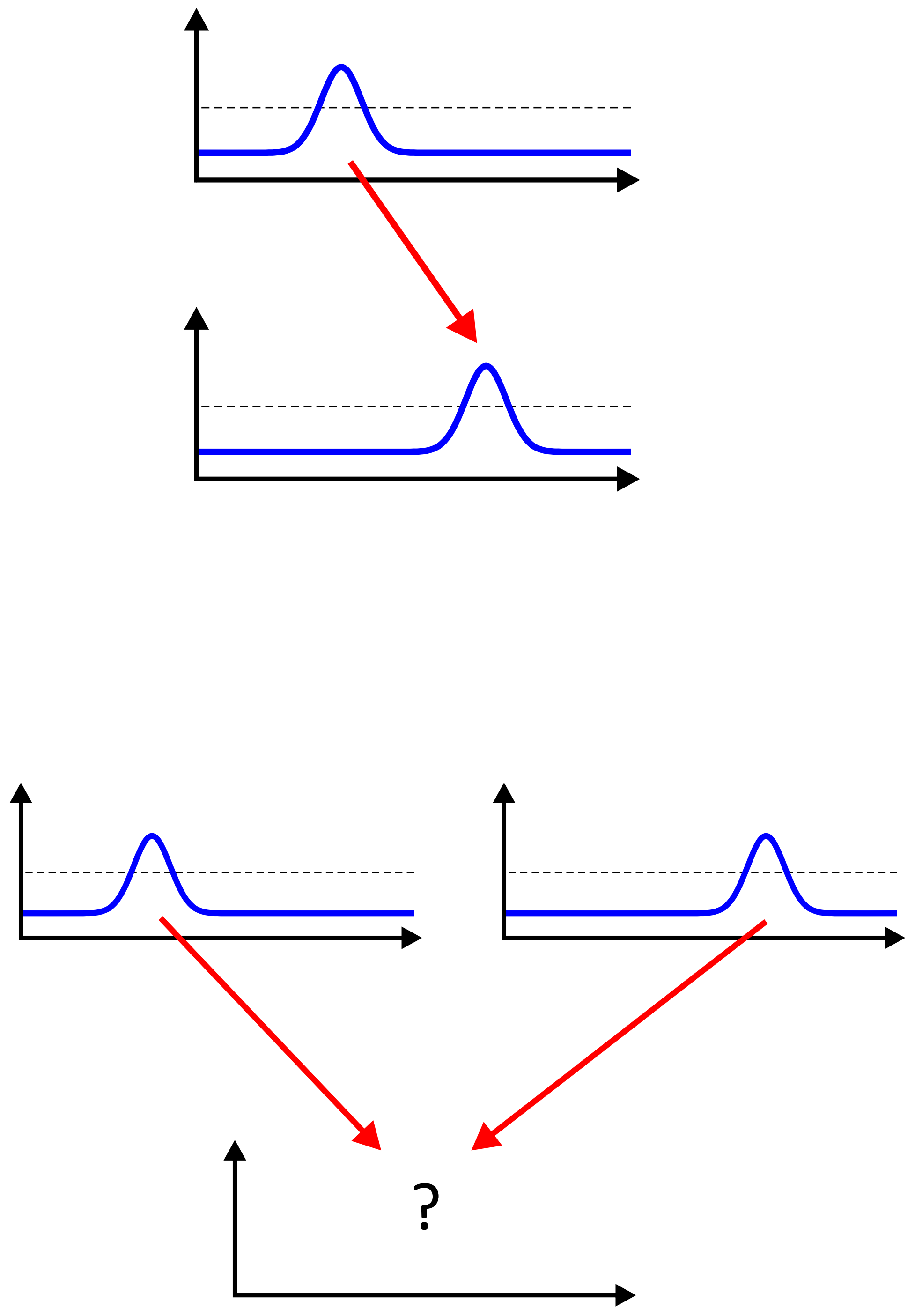
coordinate transformations

- need mapping between different reference frame: retinocentric (moving with the eye) to body-centered (gaze-invariant)
- mapping is a variable shift, depends on current gaze direction
- as a formula x body = x retinal + x gaze
- but how to implement this in DNFs, using space code representations?

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

coordinate transformations

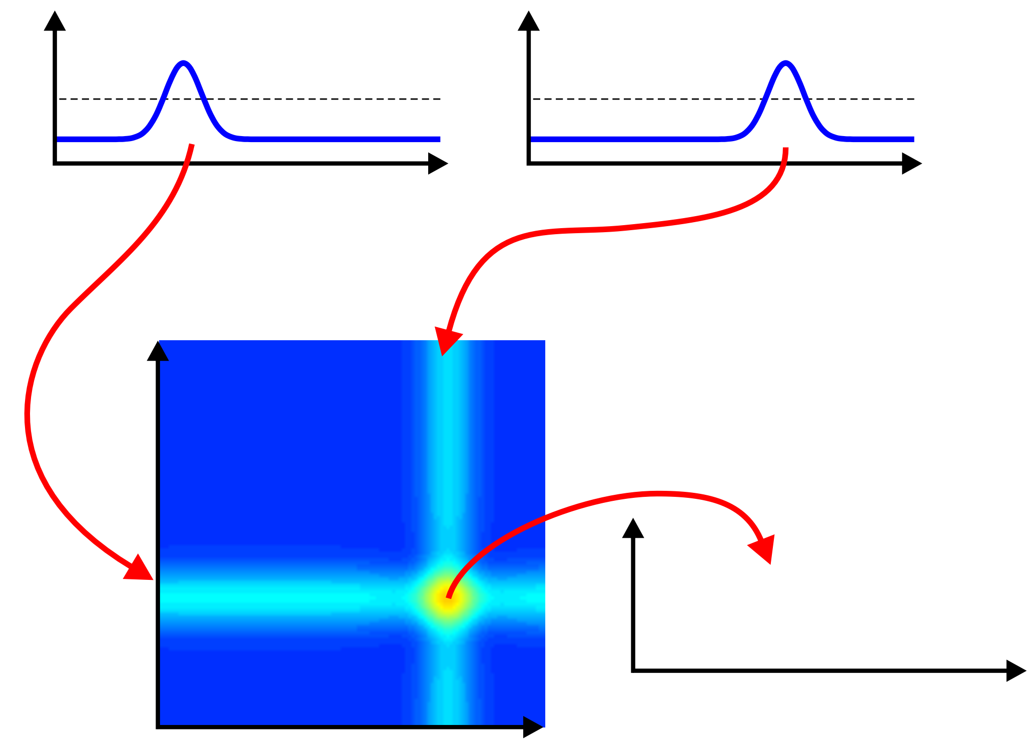
- fixed mapping: neural projection in a neural network
- flexible mapping that depends on gaze/eye position?



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

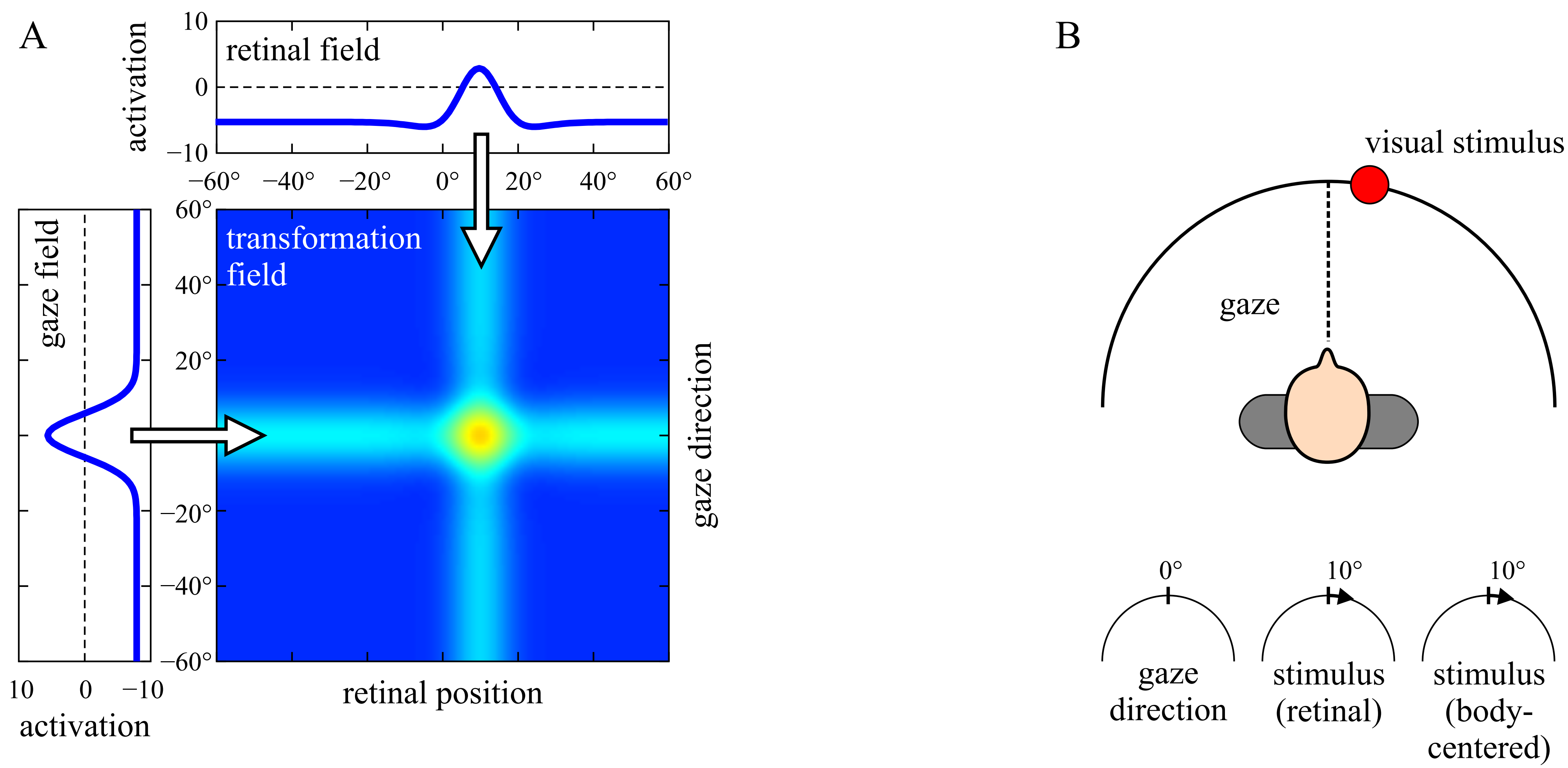
coordinate transformations

- expand into a 2D field
- free output connectivity to implement any mapping



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

coordinate transformations



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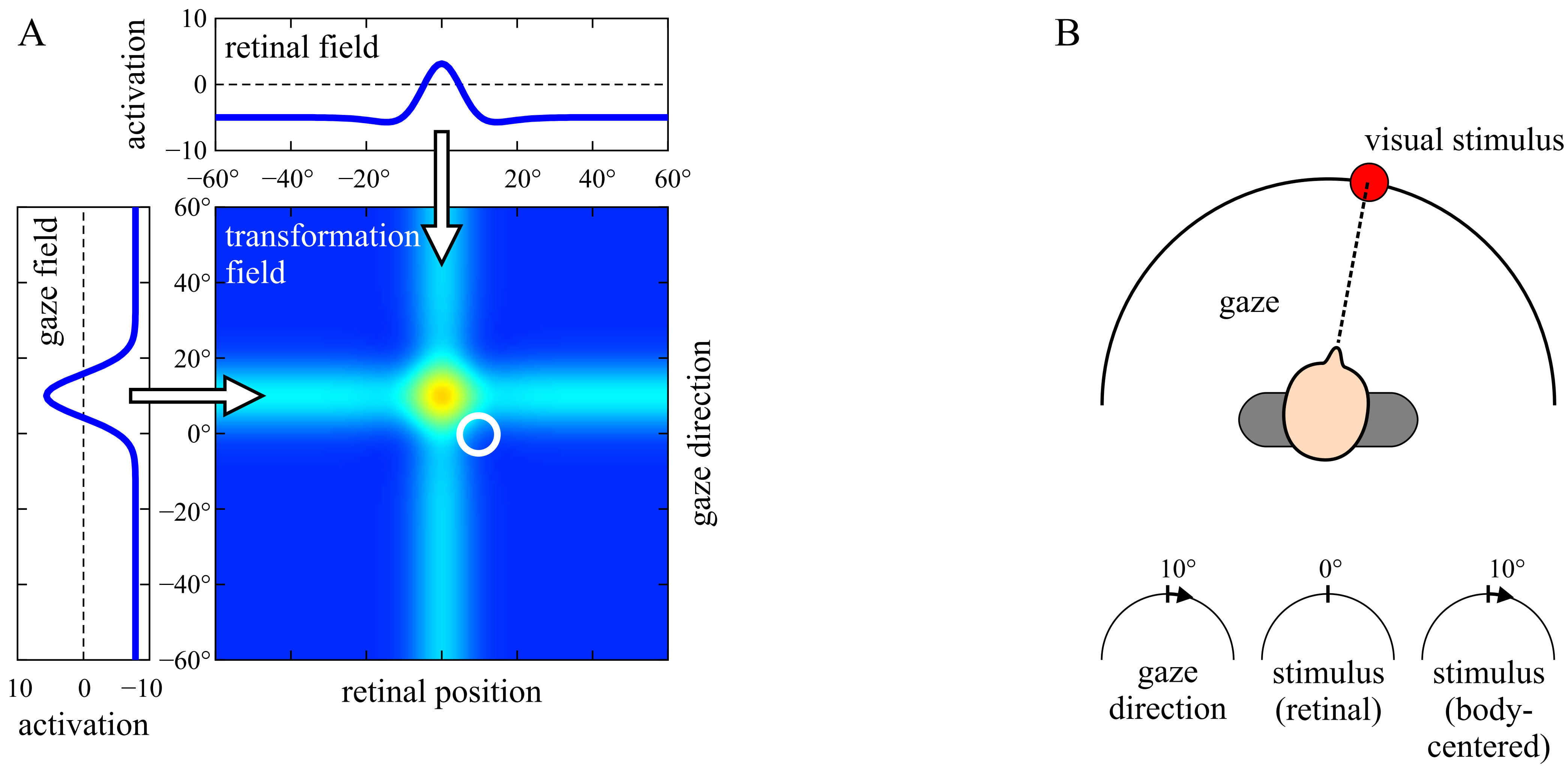
coordinate transformations



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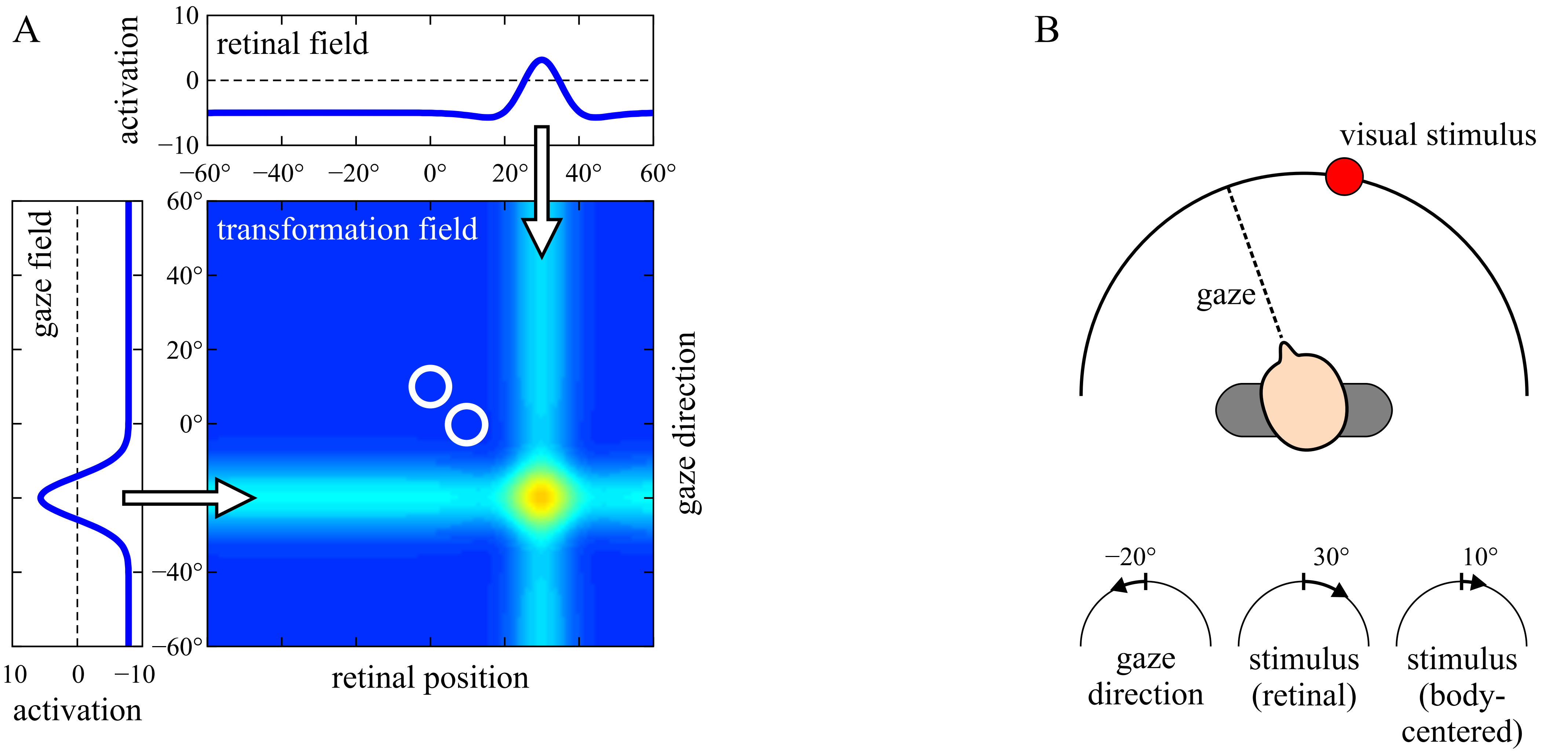
coordinate transformations



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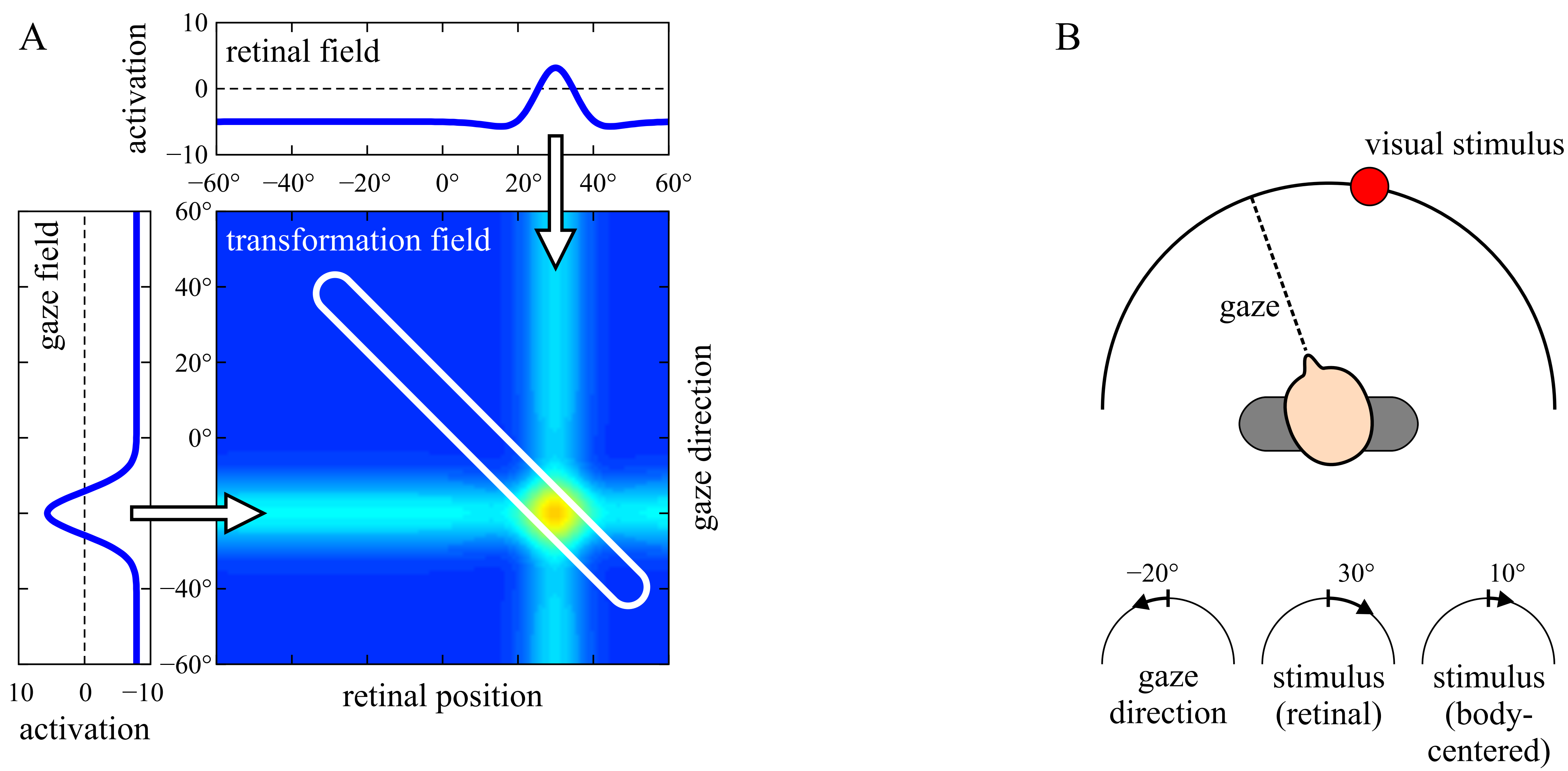
coordinate transformations



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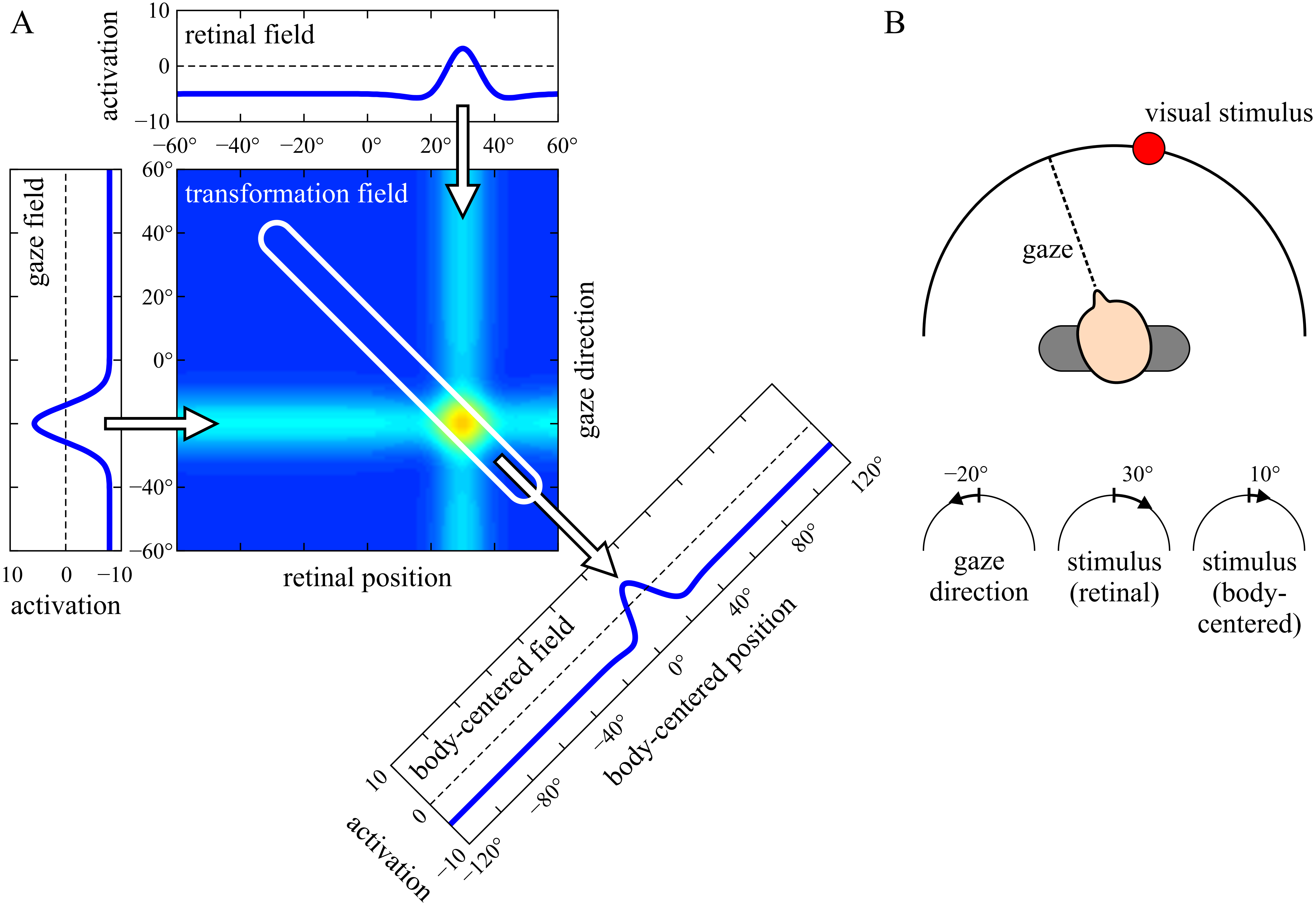
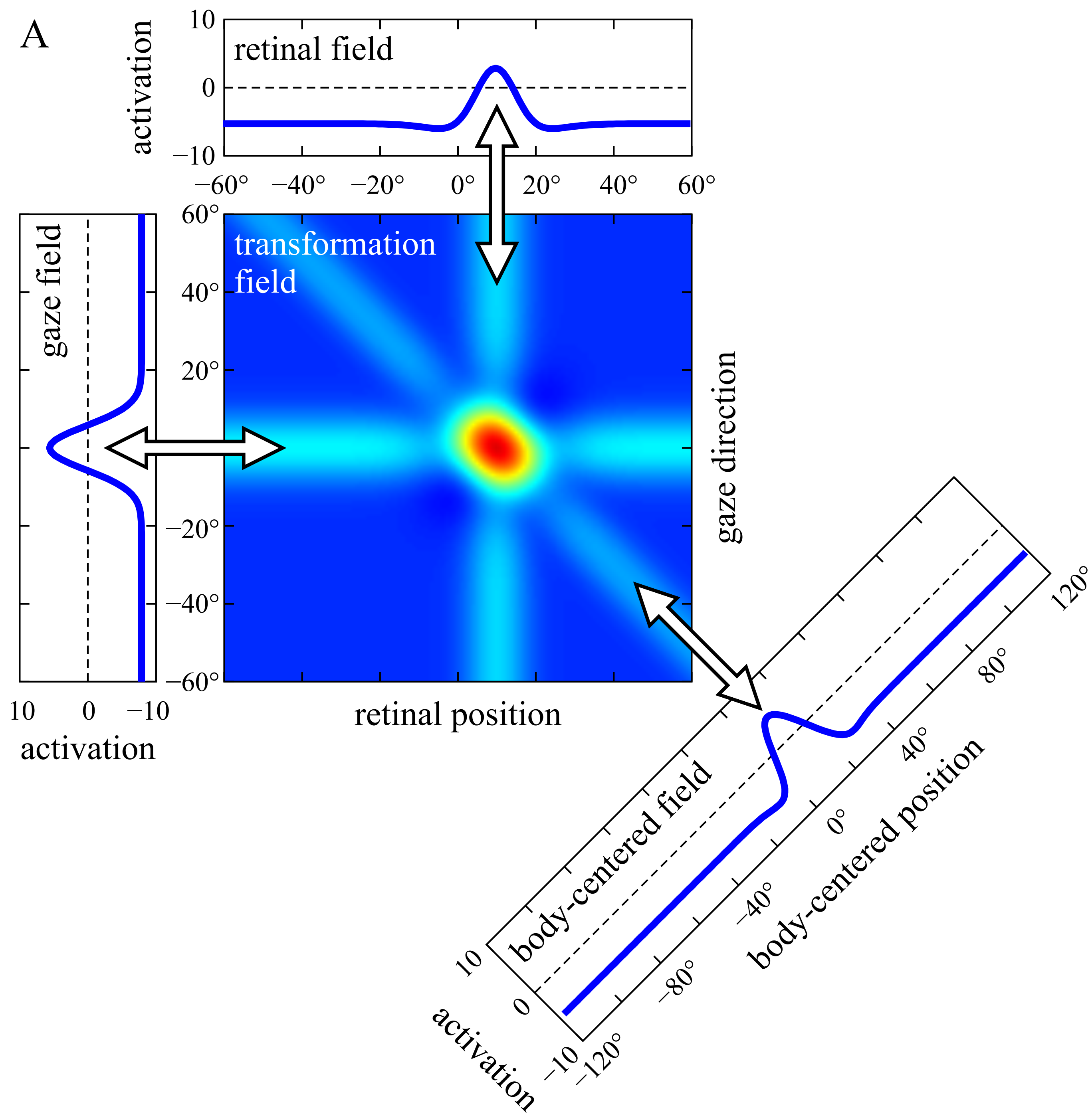
coordinate transformations



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

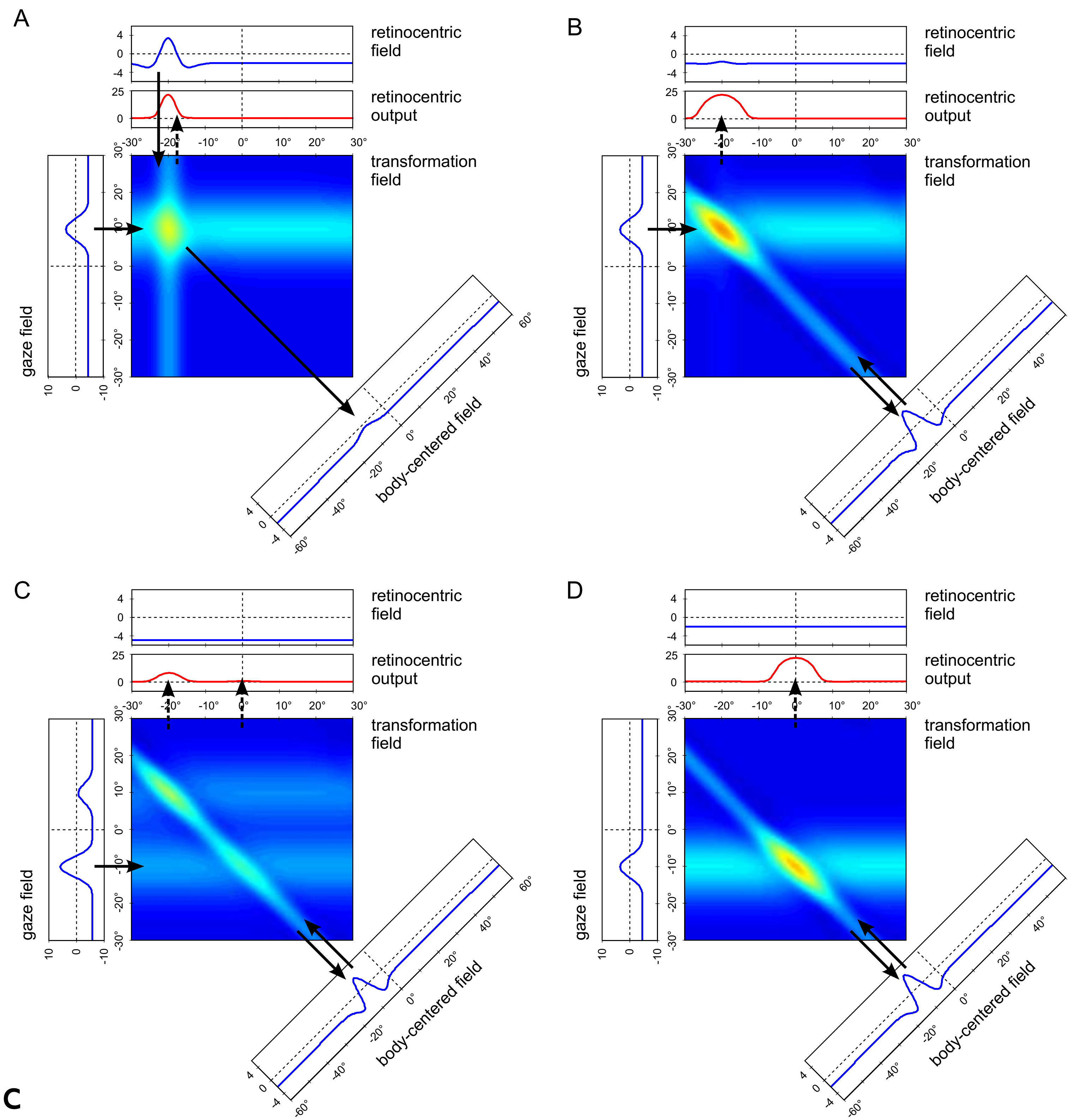
coordinate transformations

- bi-directional coupling: reversing the transformations

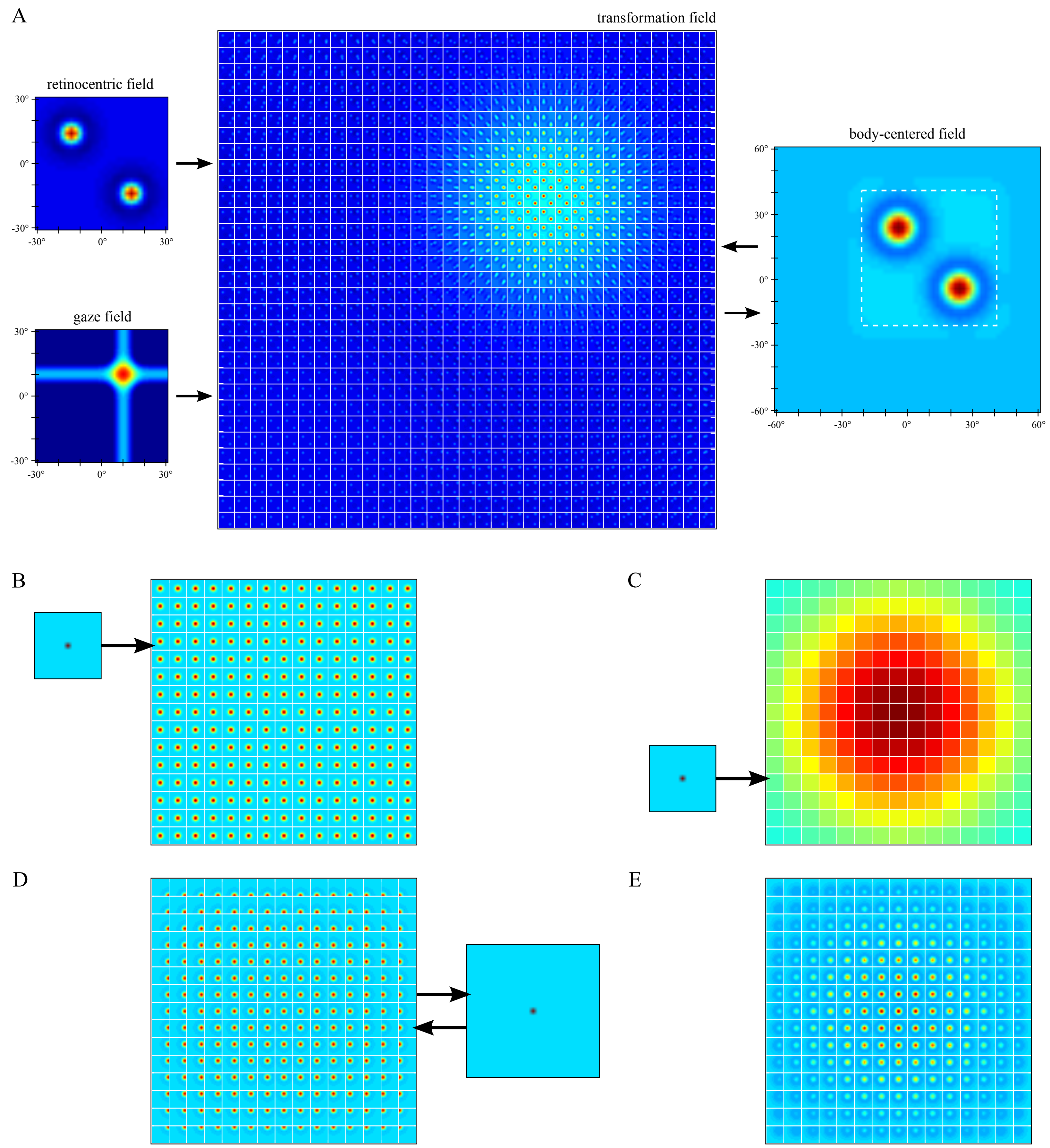


[Slides adapted from Sebastian Schneegans,
see Schneegans, Chapter 7 of Dynamic Field Theory-A Primer, OUP, 2015]

spatial remapping during saccades



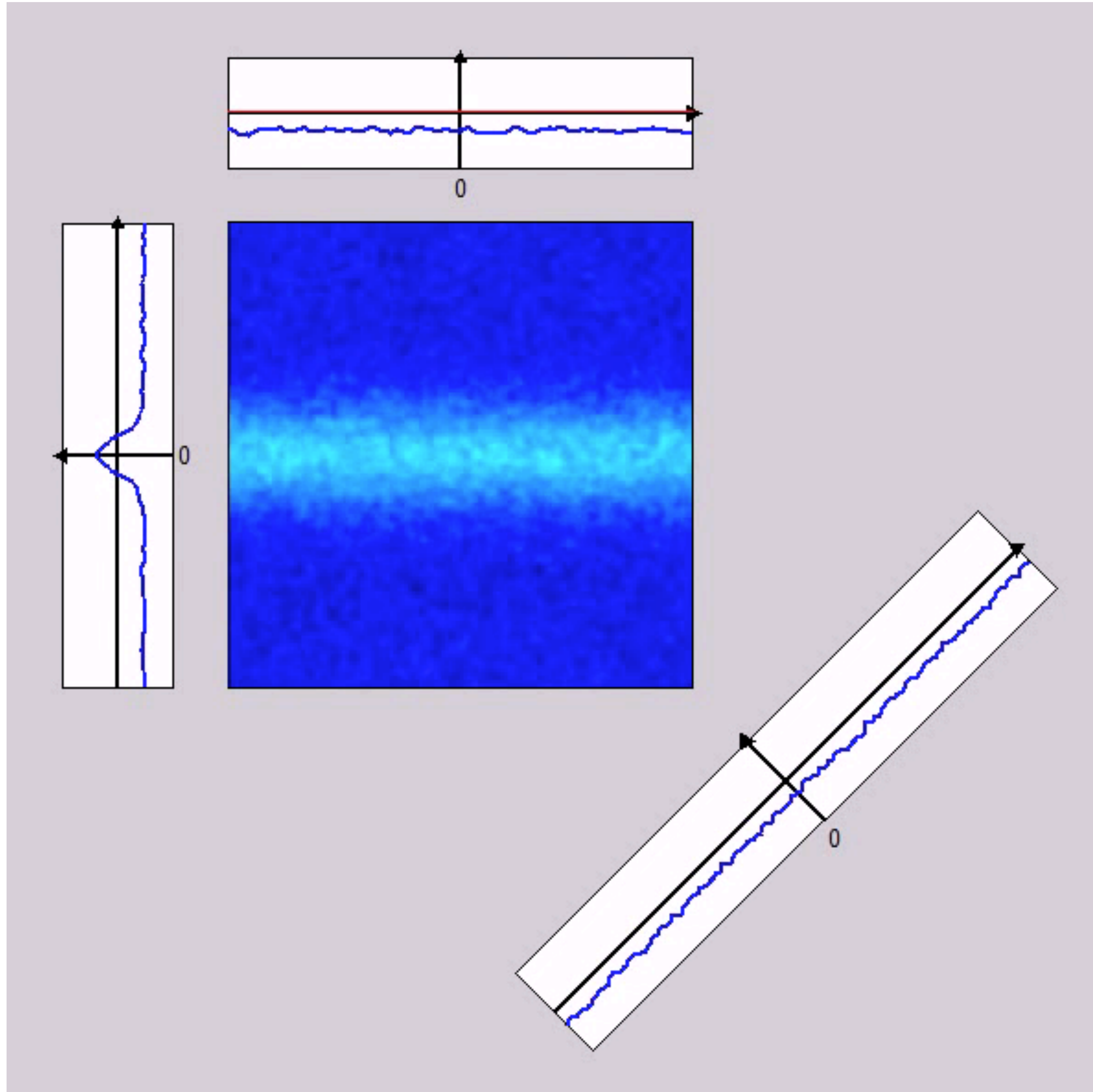
[Slides adapted from Sebastian Schneegans,
see Schneegans, Chapter 7 of Dynamic Field Theory-A Primer, OUP, 2015]



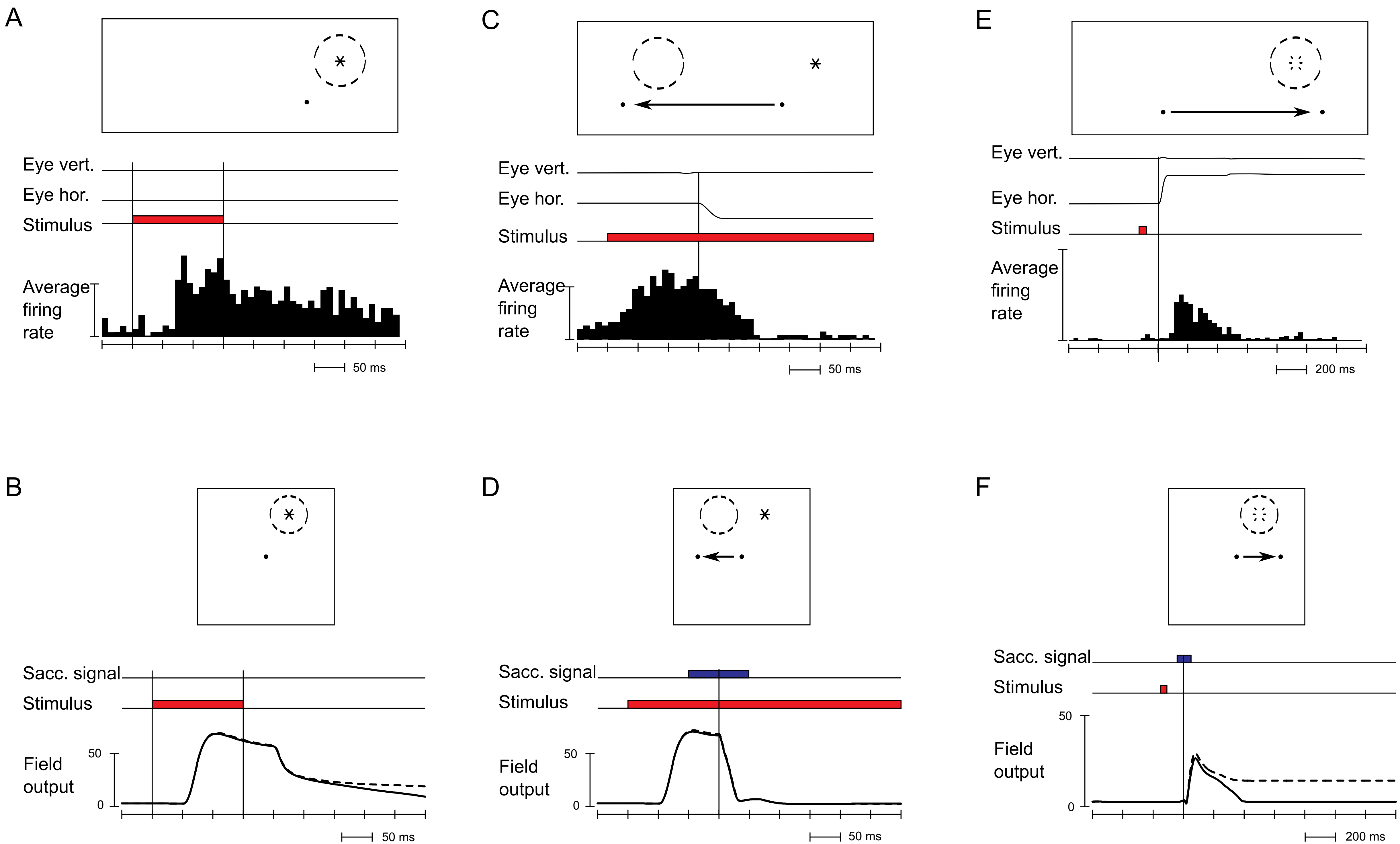
[Slides adapted from Sebastian Schneegans,
see Schneegans, Chapter 7 of Dynamic Field Theory-A Primer, OUP, 2015]

Coordinate transformations

- predict retinal location following gaze shift



[Schneegans, Schöner, BC 2012]



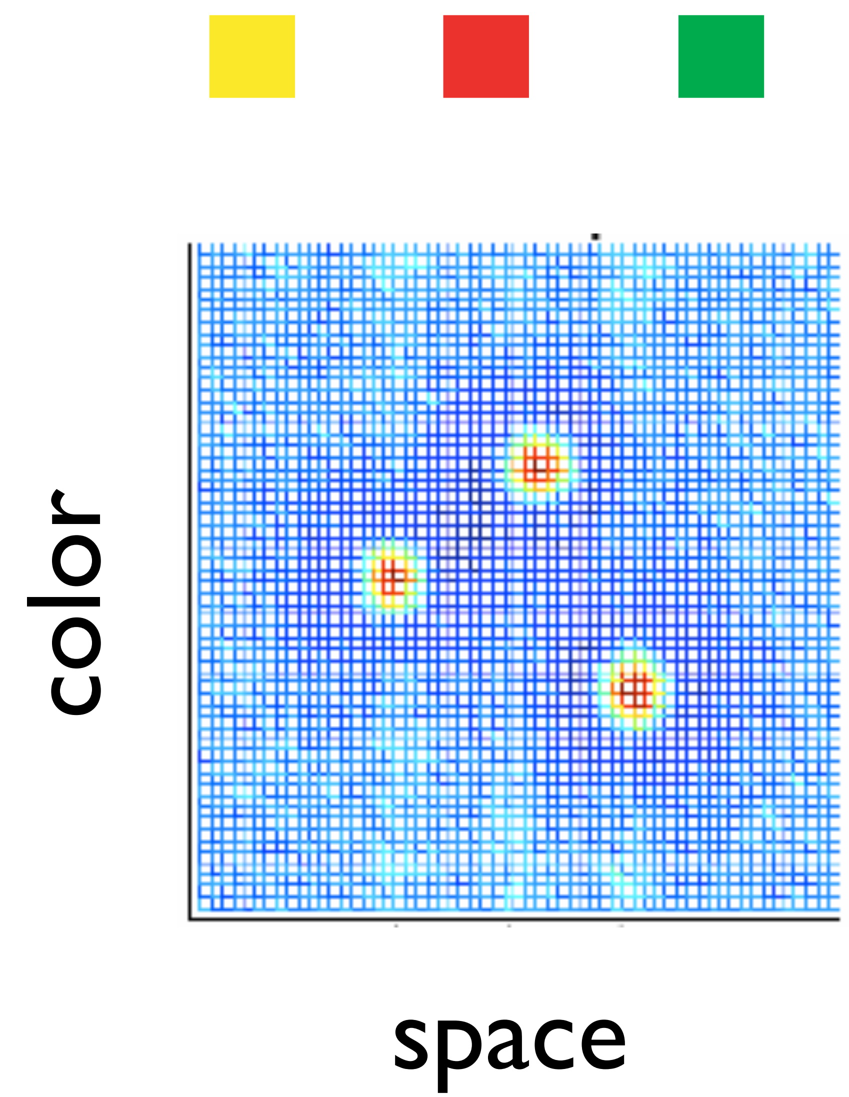
=> accounts for predictive updating of retinal representation

[Schneegans, Schöner, BC 2012]

Scaling dimensionality

multi-dimensional fields represent "bound" feature conjunctions

- the 2D fields representing the combinations of features (e.g., color, orientation, etc) and locations



Scaling dimensionality

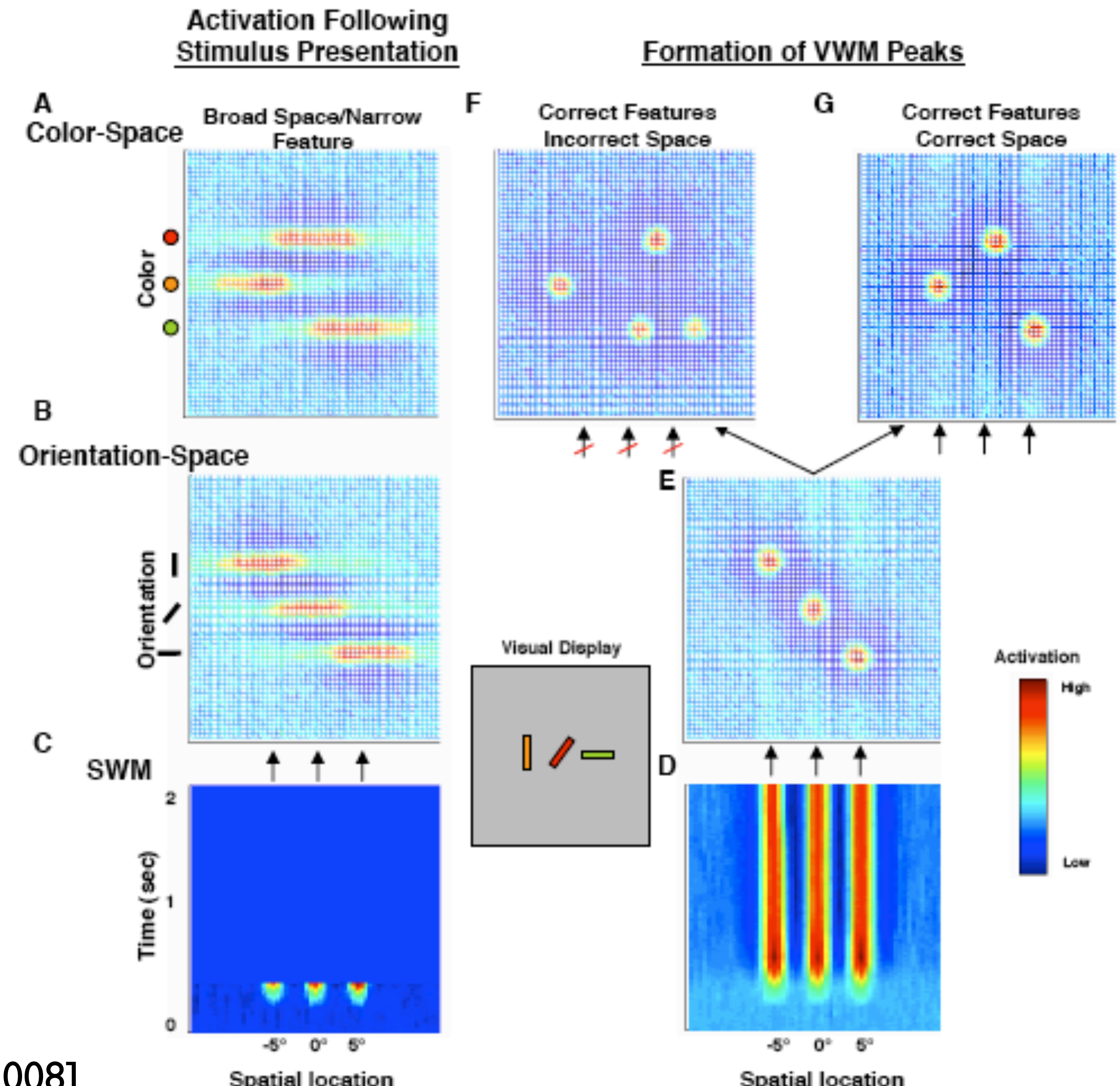
- example: 6-dimensional field (as needed for coordinate transformations from 3D to 3D)
- sample each dimension with 100 neurons: 10^12 neurons! problem: entire brain...

scaling

- many combinations of lower dimensional fields may do the job
- => binding

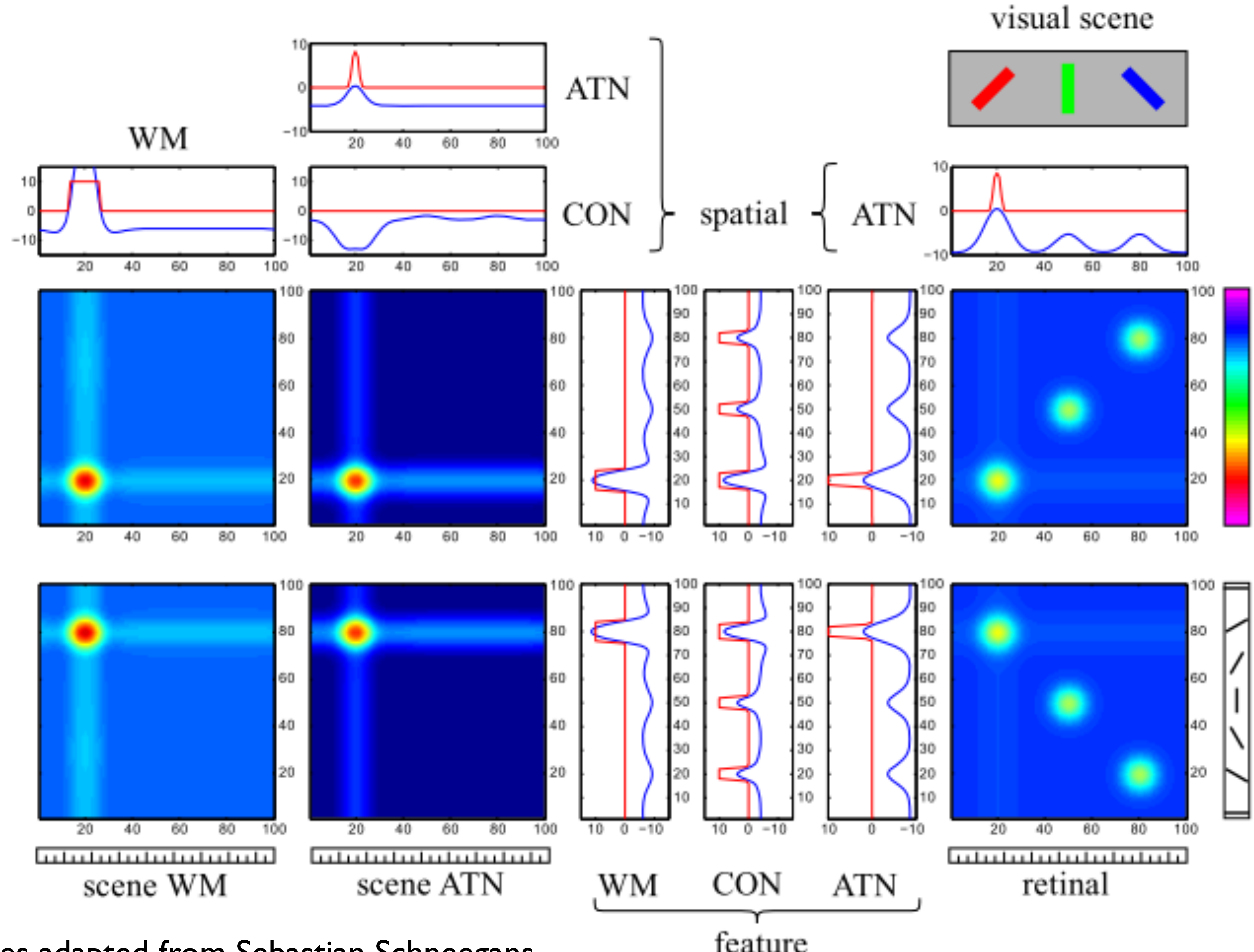
feature binding along space

- peaks in different feature-space fields are bound by local excitatory coupling along space



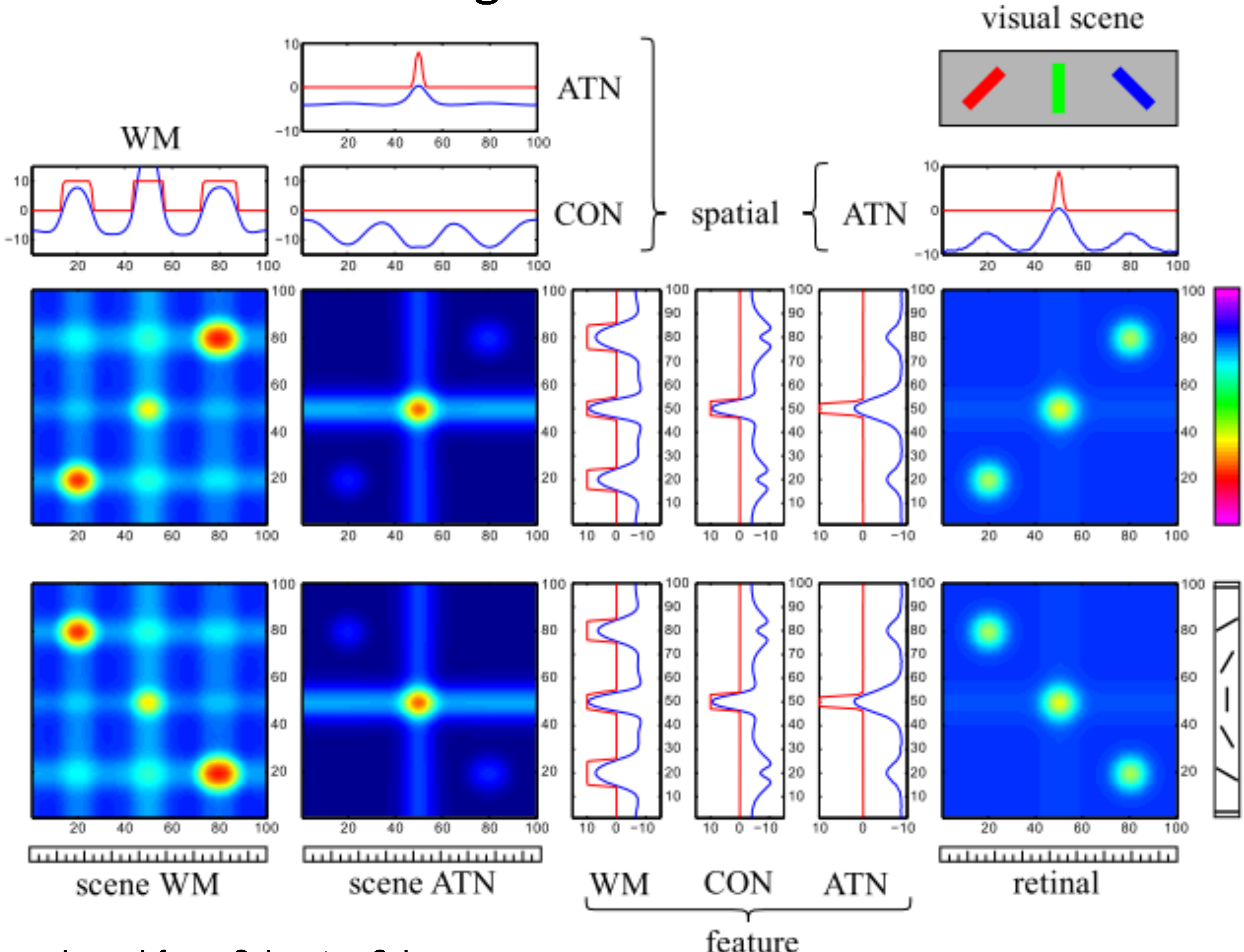
[Johnson, Spencer, Schöner, NIP 2008]

Memorization of left item



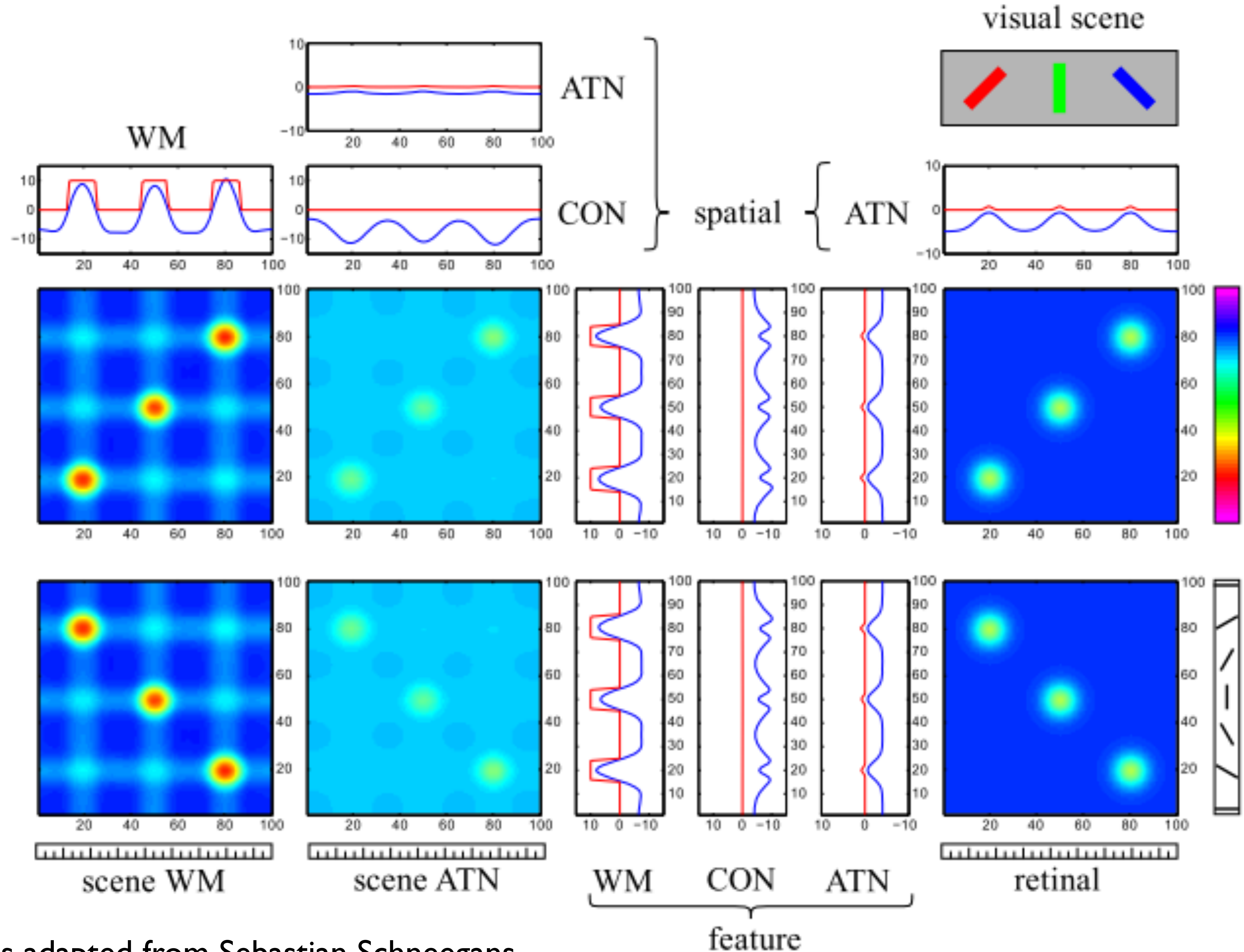
[Slides adapted from Sebastian Schneegans,
see Schneegans, Spencer, Schöner, Chapter 9 of Dynamic Field Theory-A Primer, OUP, 2015]

Adding third item to scene



[Slides adapted from Sebastian Schneegans,
see Schneegans, Spencer, Schöner, Chapter 9 of Dynamic Field Theory-A Primer, OUP, 2015]

Post sequential memorization of all three items



[Slides adapted from Sebastian Schneegans,
see Schneegans, Spencer, Schöner, Chapter 9 of Dynamic Field Theory-A Primer, OUP, 2015]

Scaling

- coordinate transforms as bottle-necks

Conclusion: multi-dimensional fields

- enable new cognitive functions that derive from association and cannot be realized by synaptic networks
  - instantaneous association or linkage (referral) enabling dimensional cuing
  - cued recall
  - coordinate transforms instantaneous real-time
  - representing associations, rules etc. in a manner that can be activated/deactivated

Conclusions continued

- need to span only a limited number of dimensions (2 and 3), which are expanded by binding through space
- span by small number of neurons

Outlook

- multi-dimensional fields help us move toward higher cognition