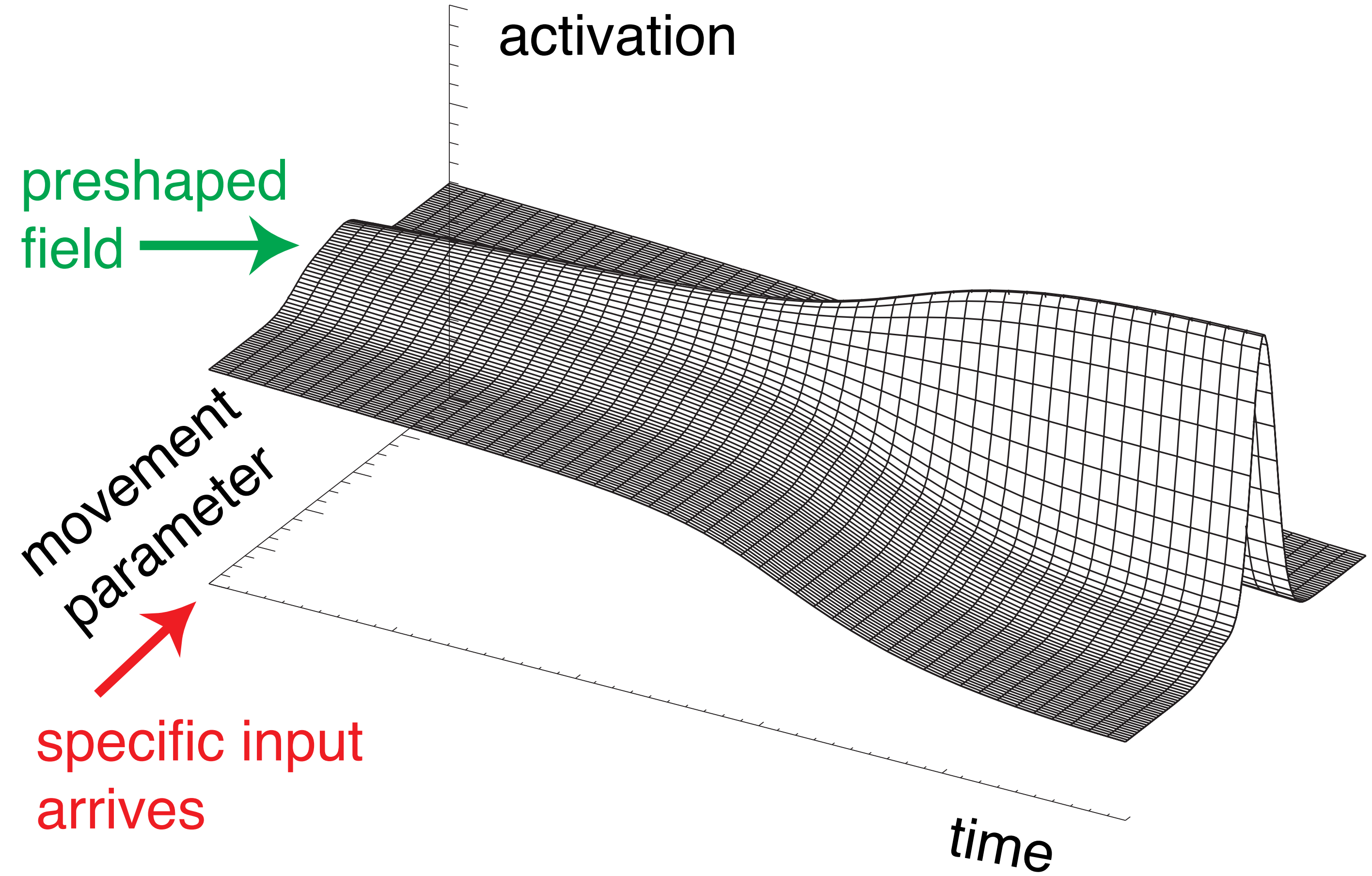
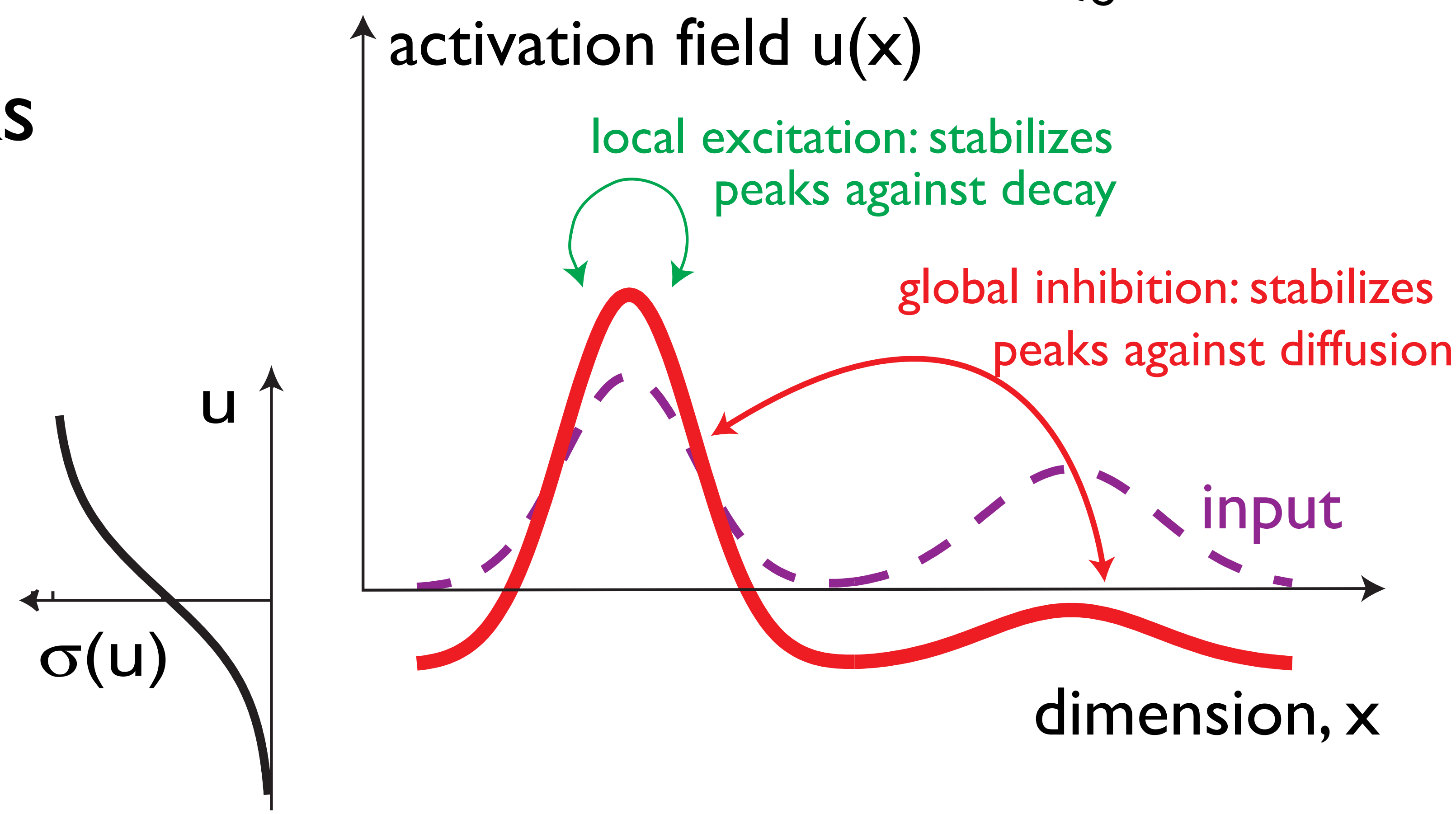
Higher-dimensional dynamics fields enable new cognitive function

Gregor Schöner

Core of DFT

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



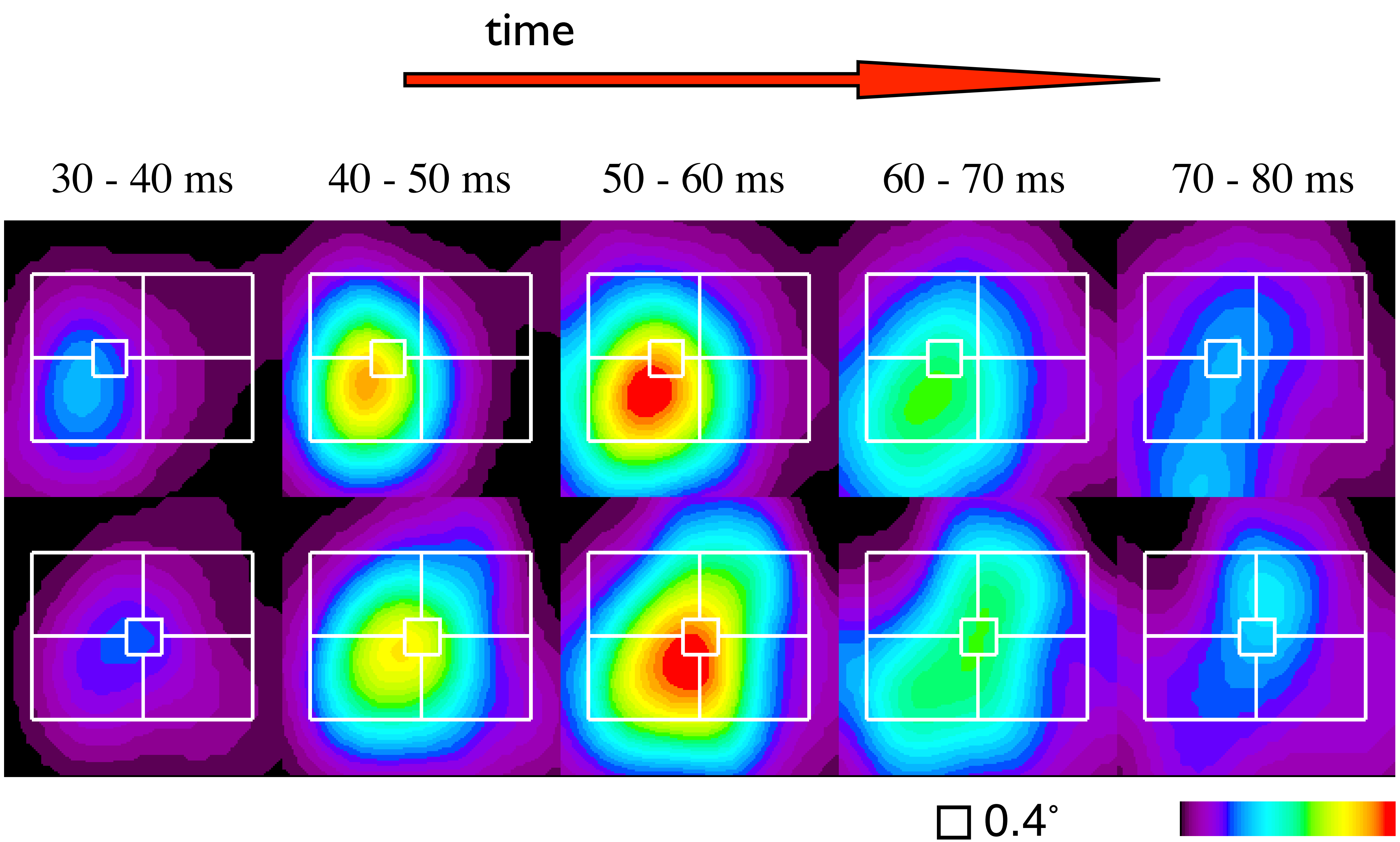


Dimensionality of fields

- 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

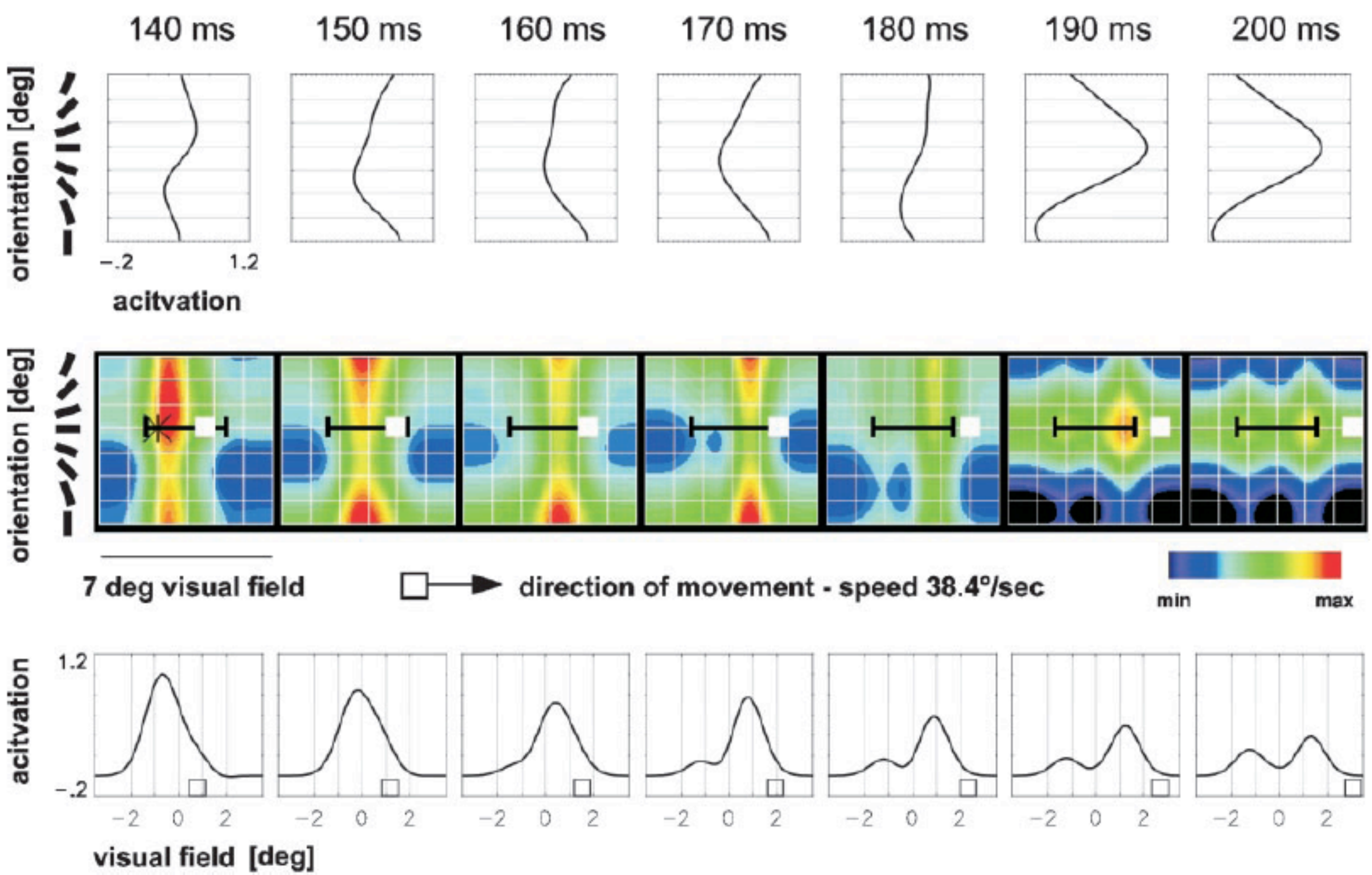
- obviously two-dimensional



[Jancke et al., 1999]

example: visual feature map

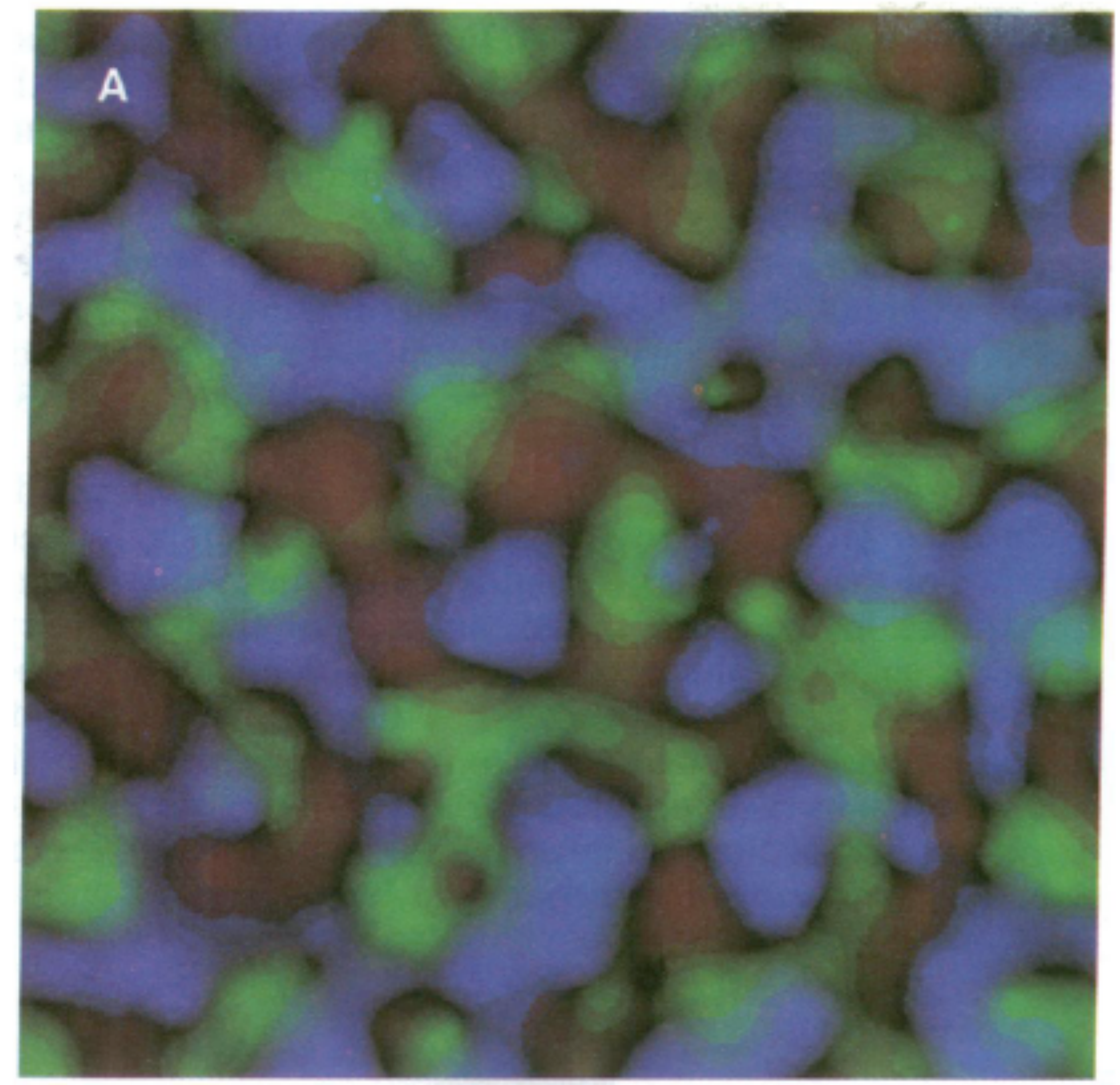
- orientation-retinal location



[Jancke, JNeursci (2000)]

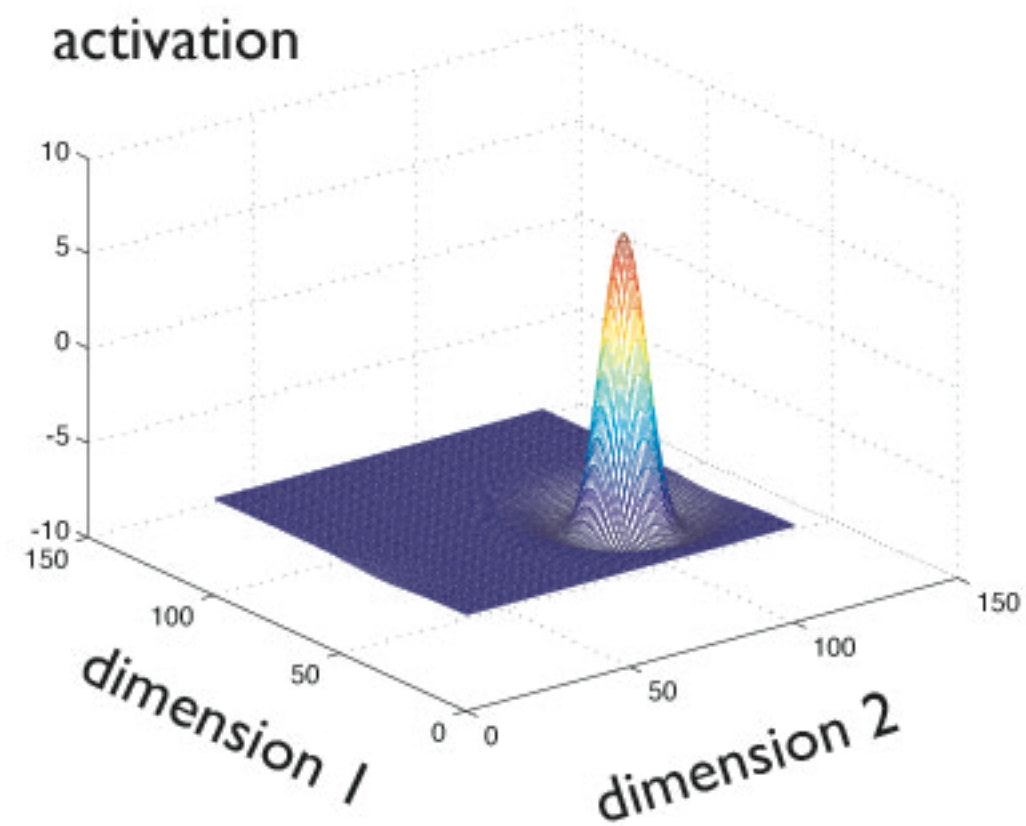
example: visual feature maps

- 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 ...



dynamics of 2D fields

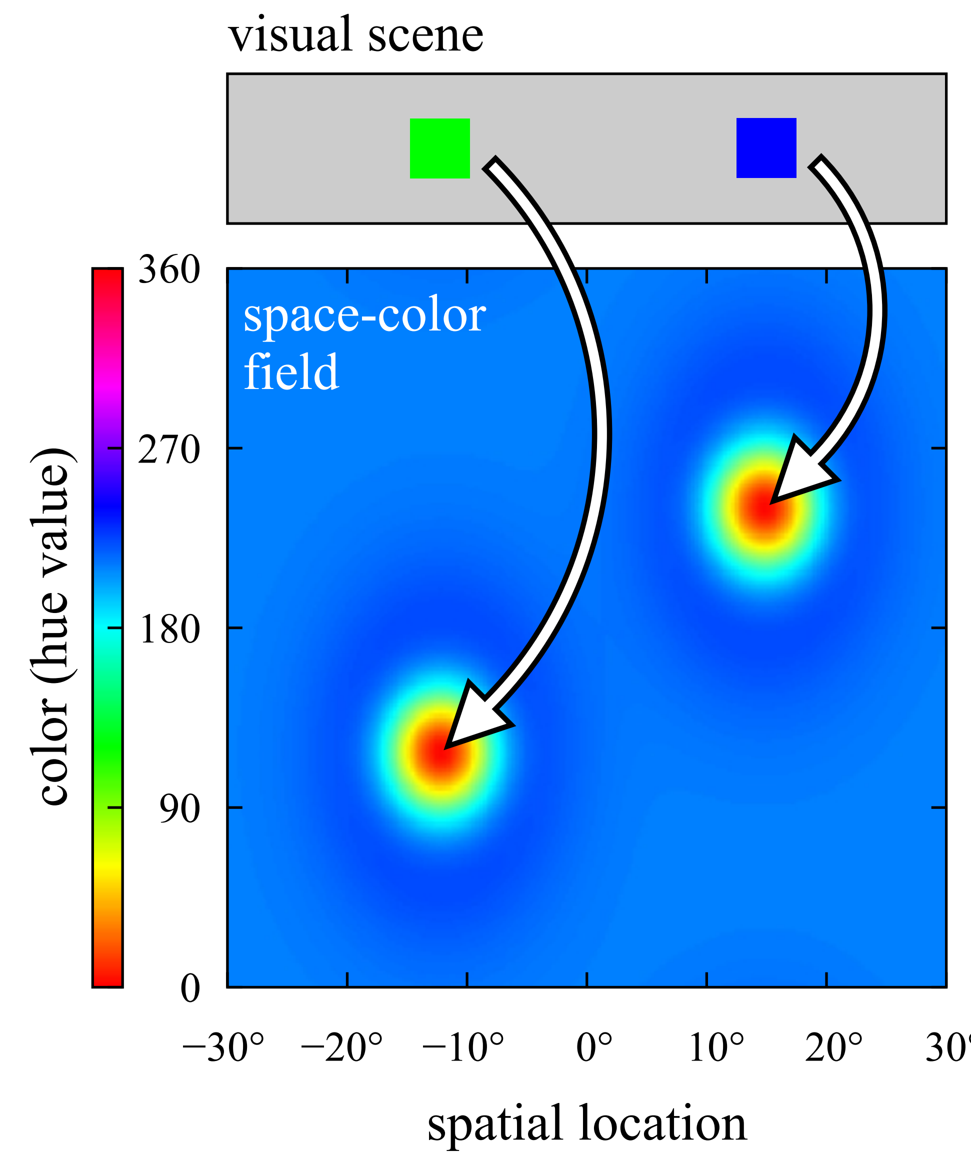
- => simulation
- no problem ... self-stabilized peaks work just fine...



But: higher-dimensional fields enable new cognitive functions

Example1: Feature binding

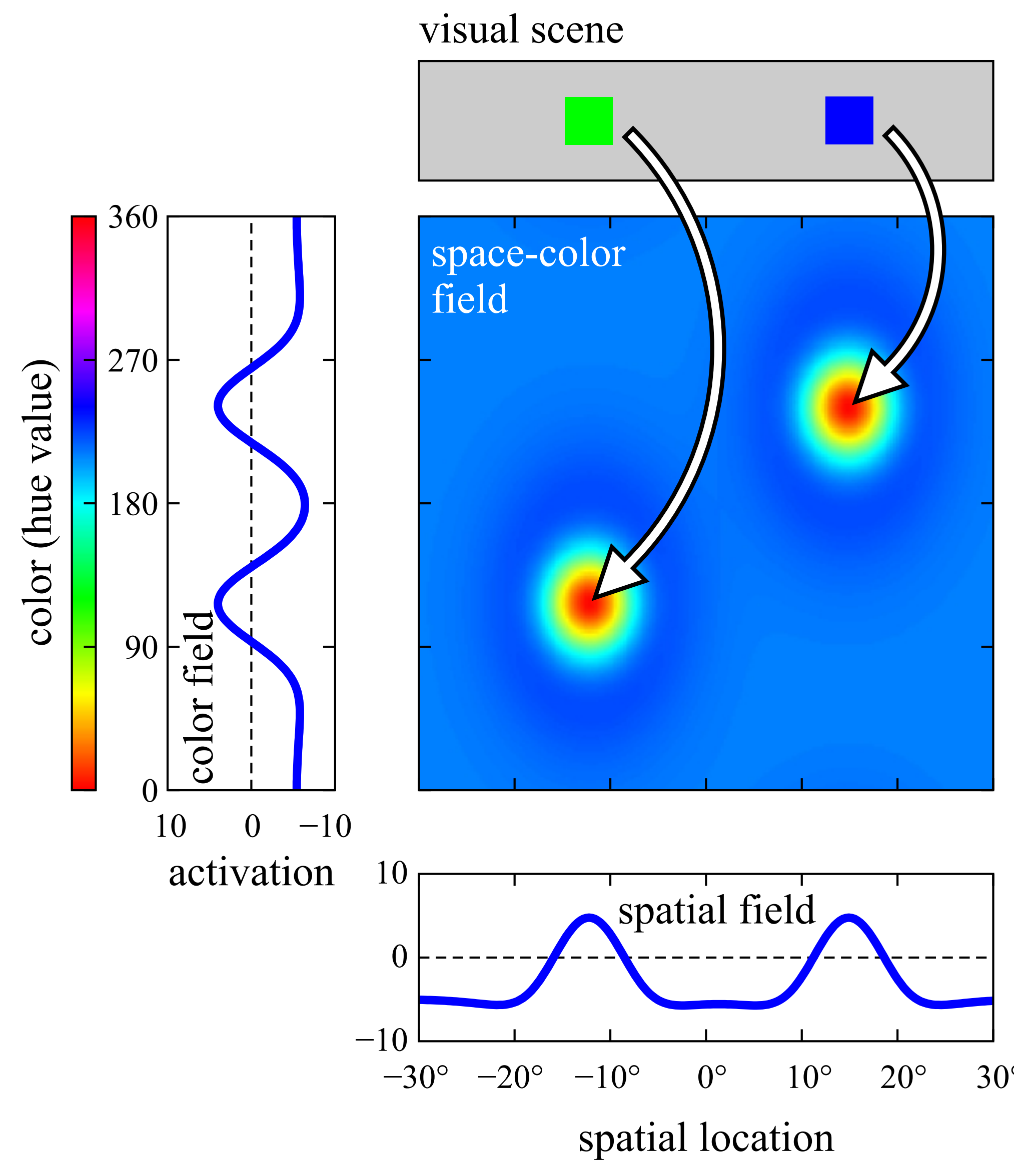
- 1D spatial location (for illustration)
- 1D color dimension (hue)
- visual input: 2D
- => 2D peaks



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

2D input

- creates 2D peaks that form combined (bound) representations of objects



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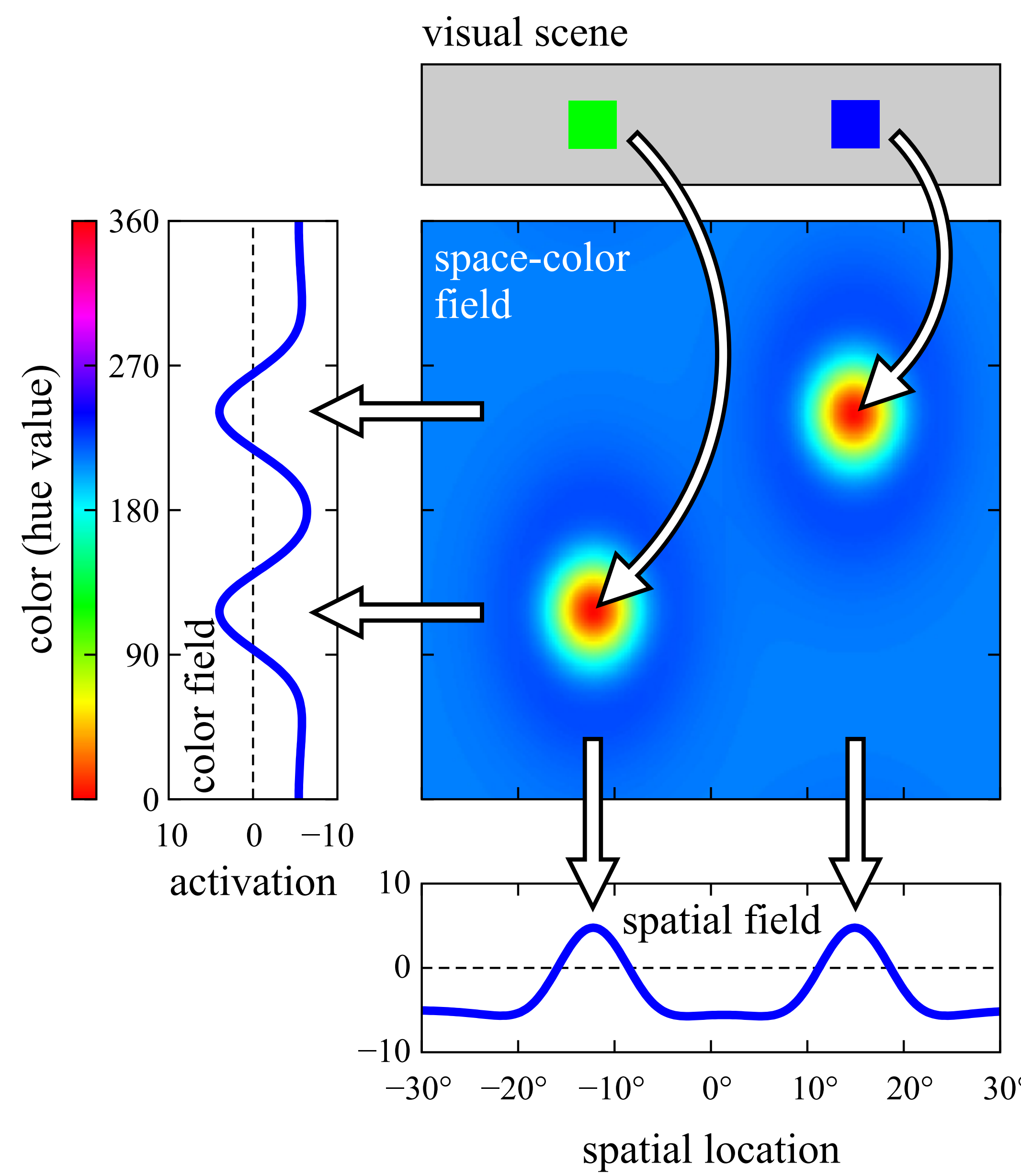
extracting features

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



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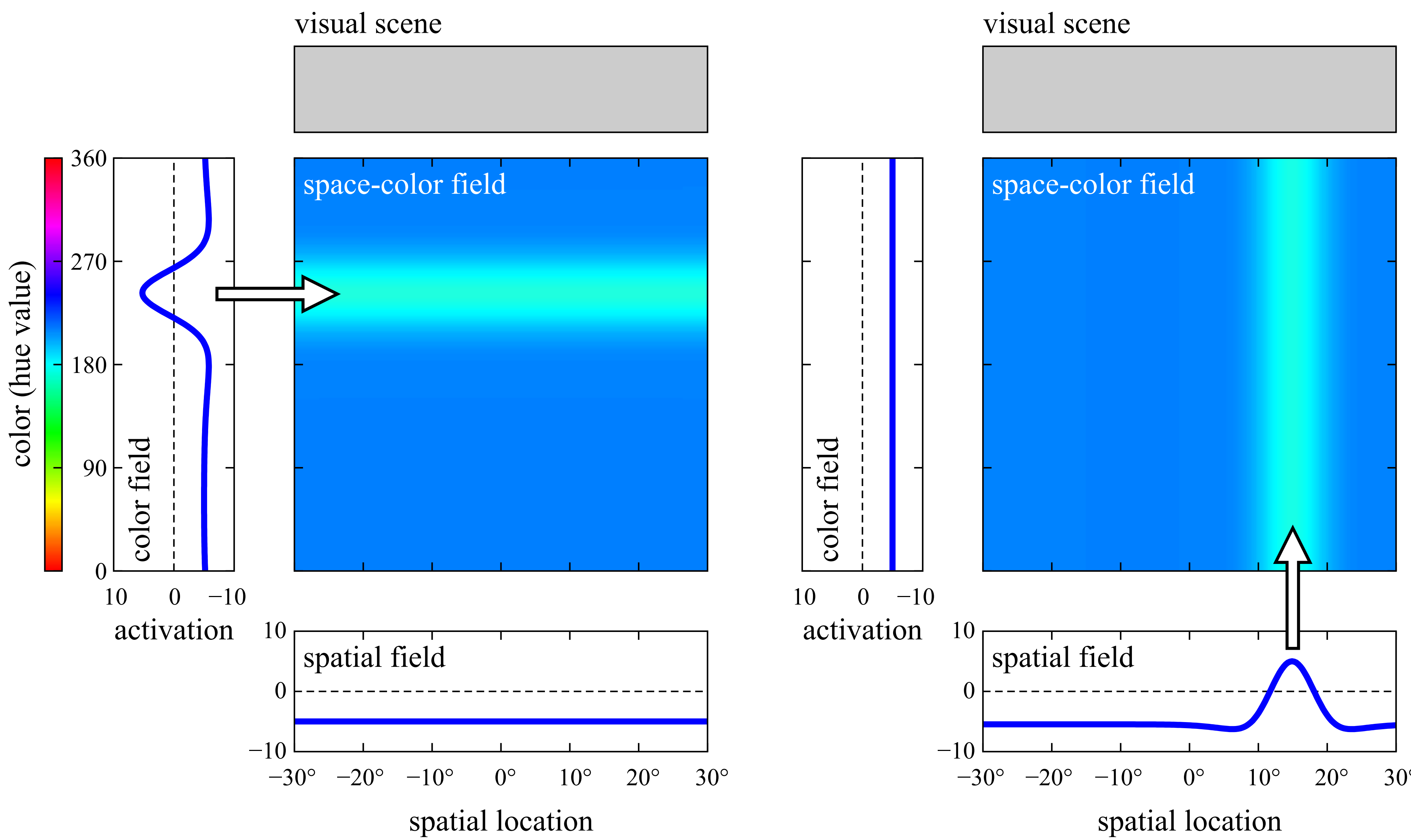
assembling bound representations

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



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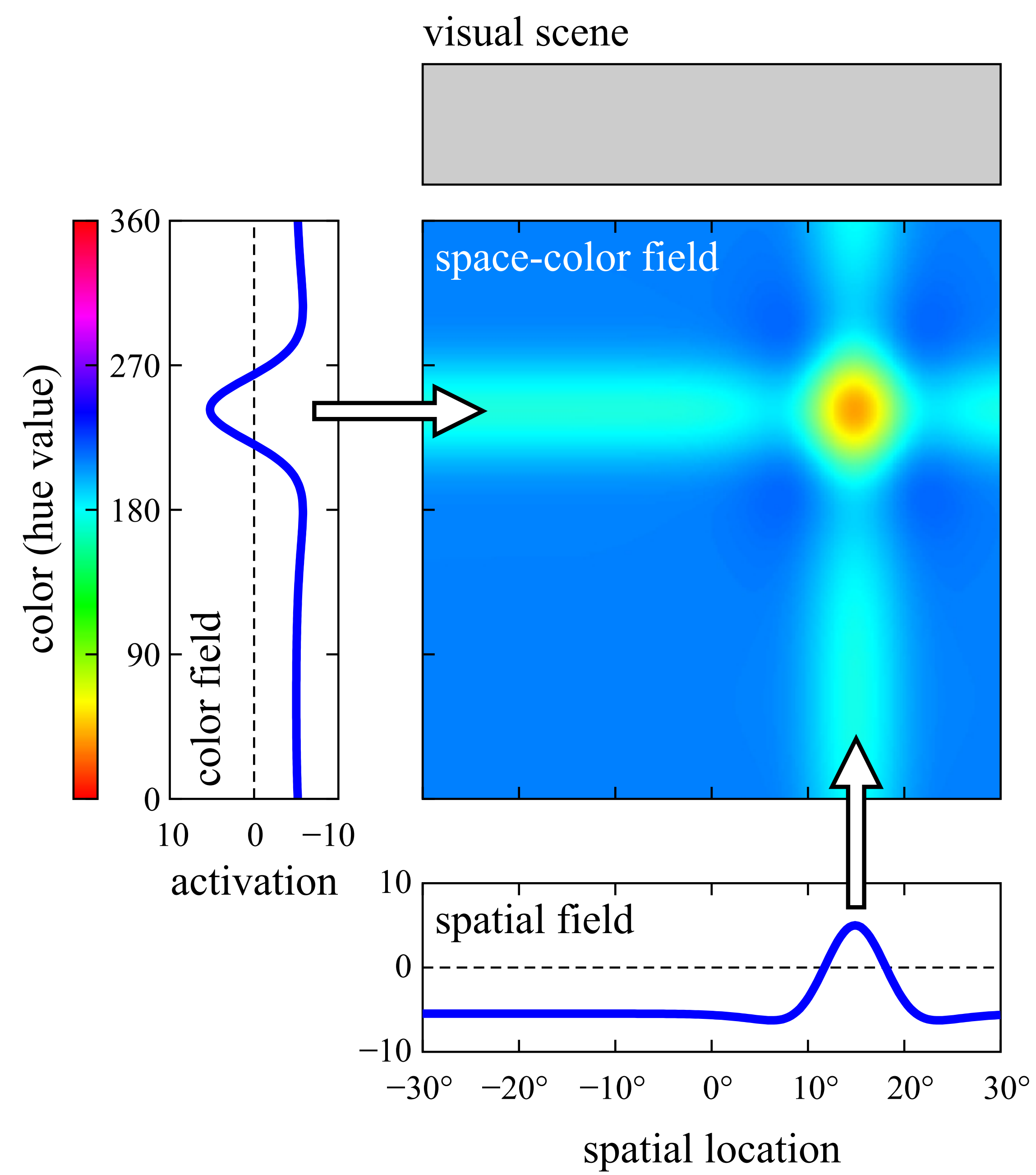
assembling bound representations

- peaks form at the intersections of ridges and form bound representations of the two dimensions



[Slides adapted from Sebastian Schneegans,
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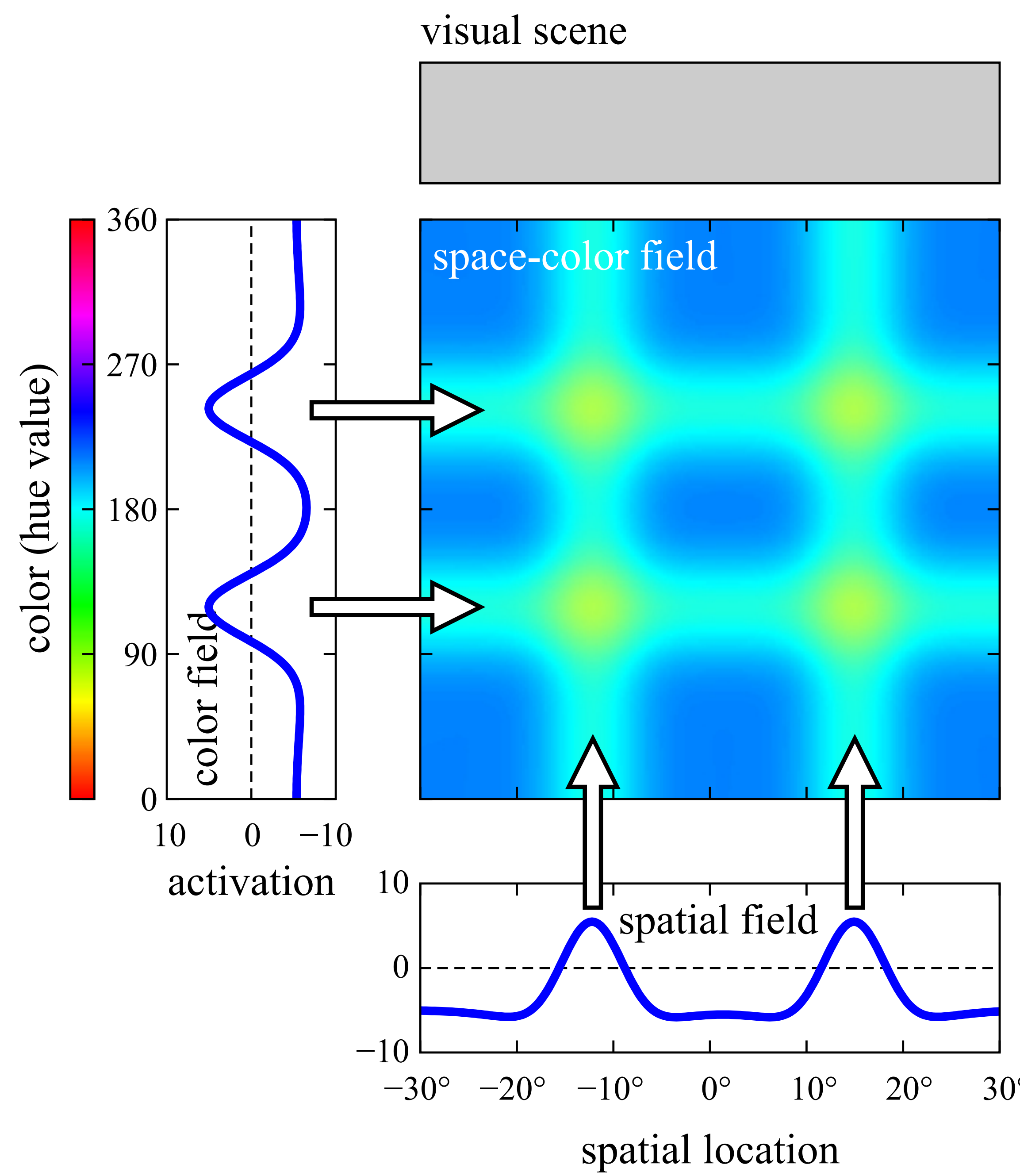
assembling bound representations

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



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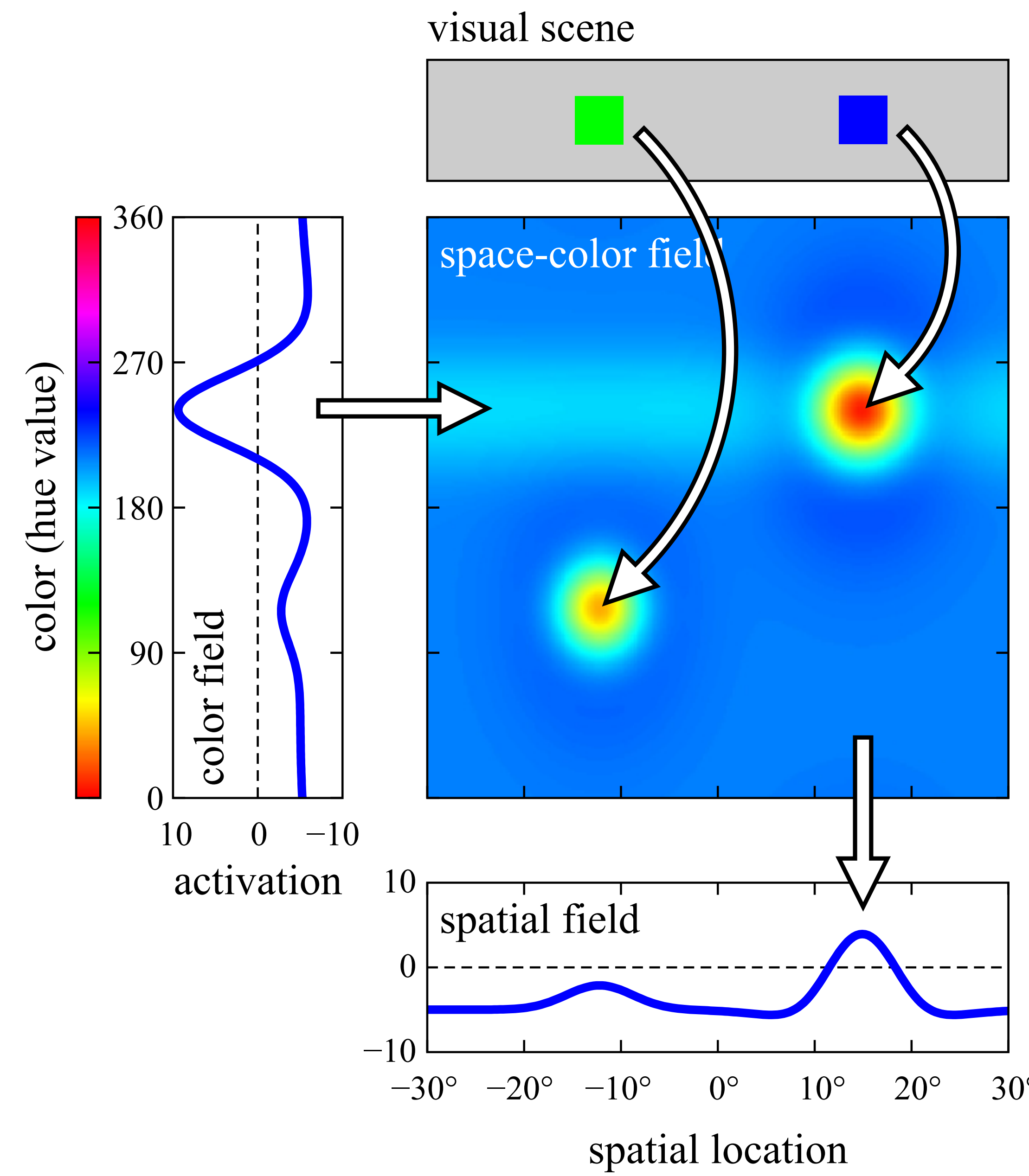
visual search

- 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



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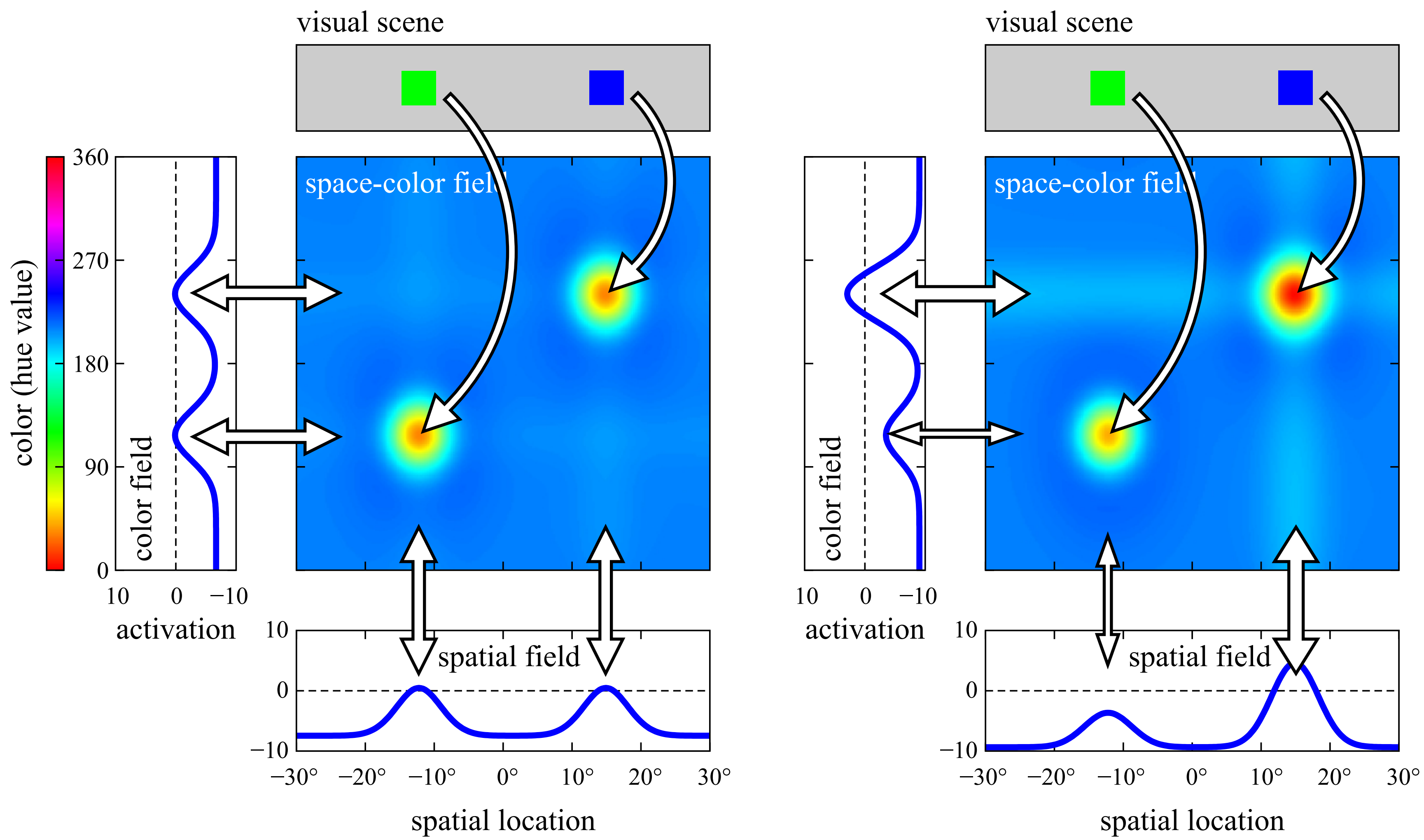
visual search

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



[Slides adapted from Sebastian Schneegans,
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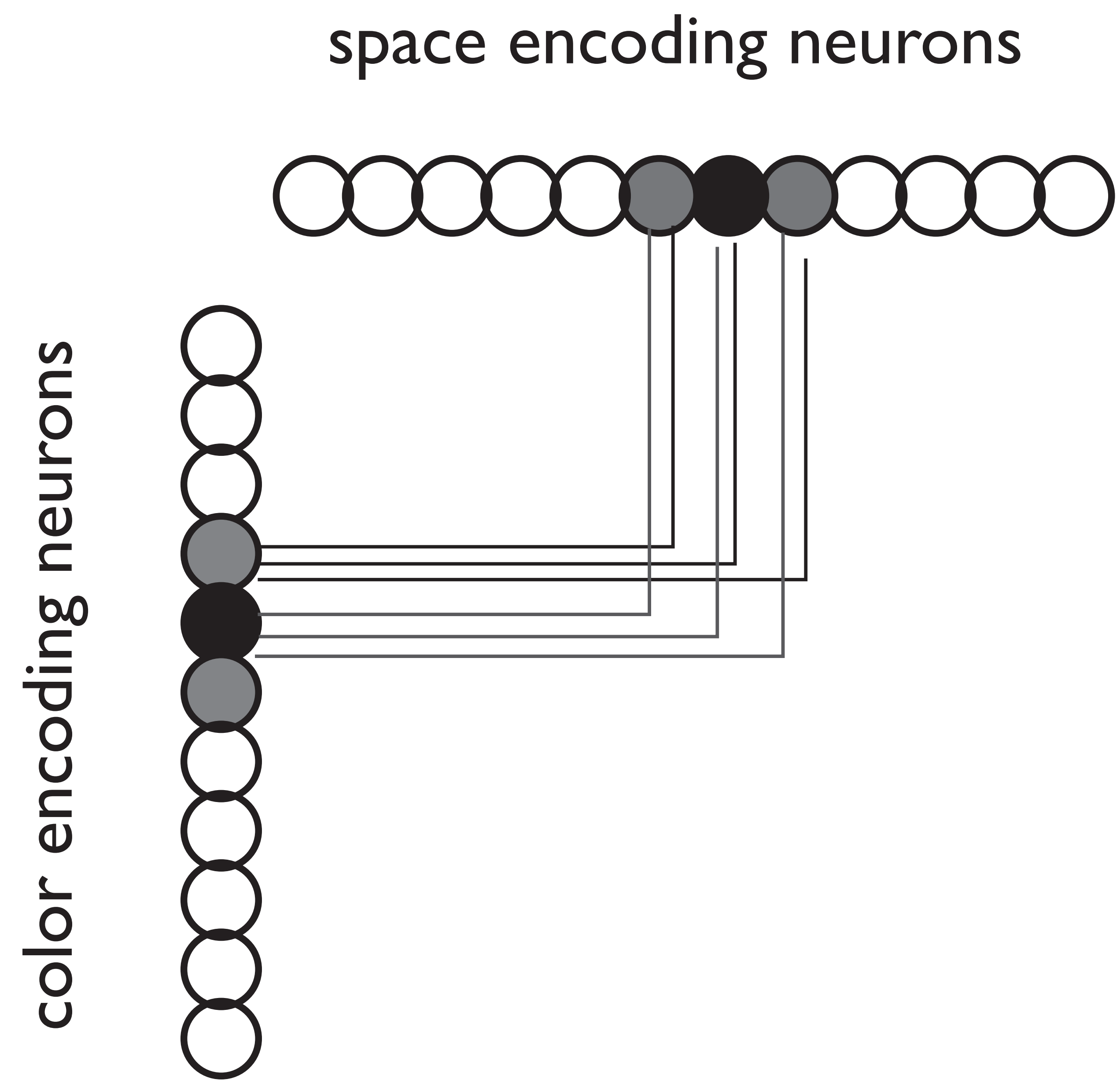
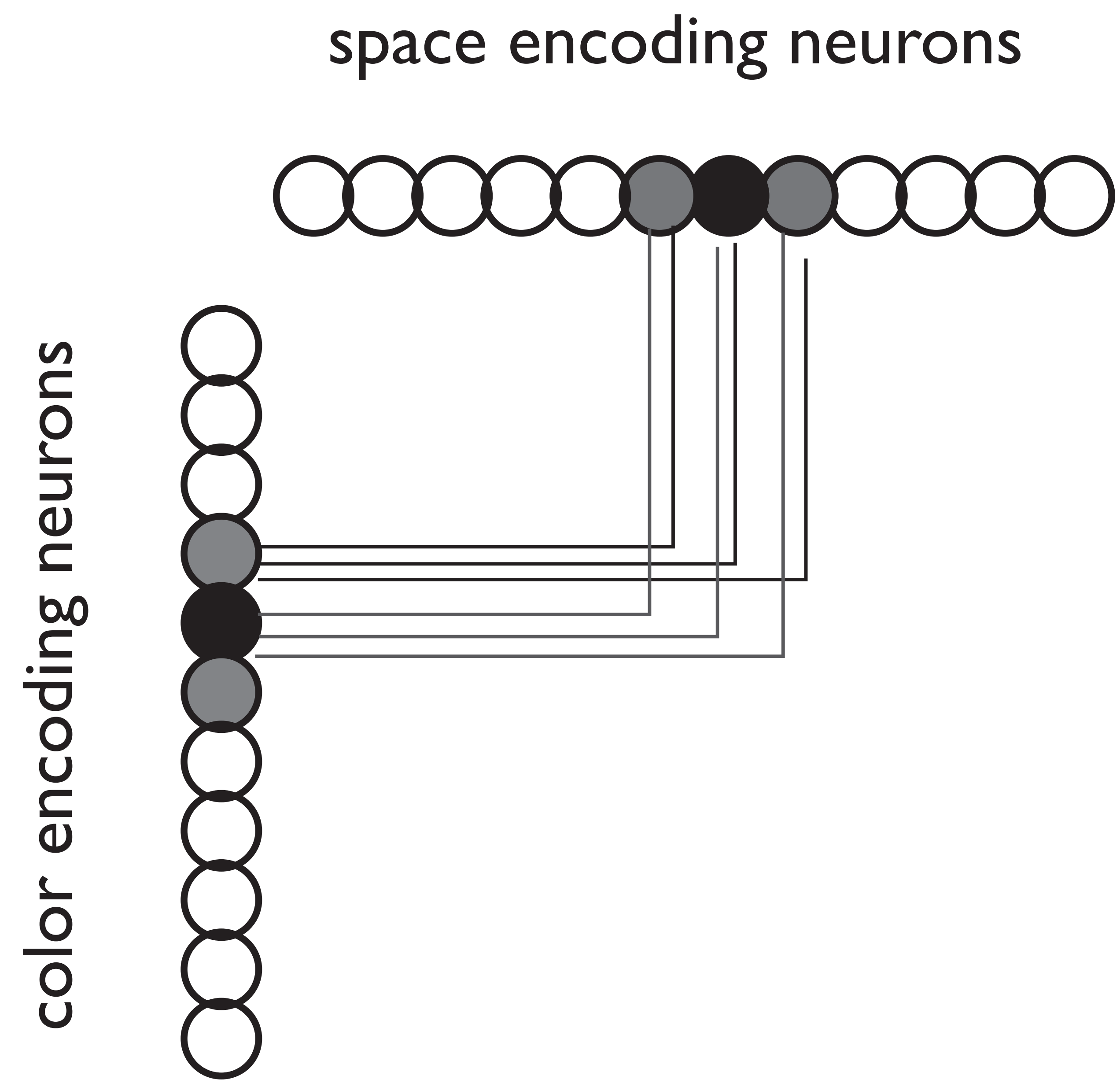
contrast: synaptic association

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



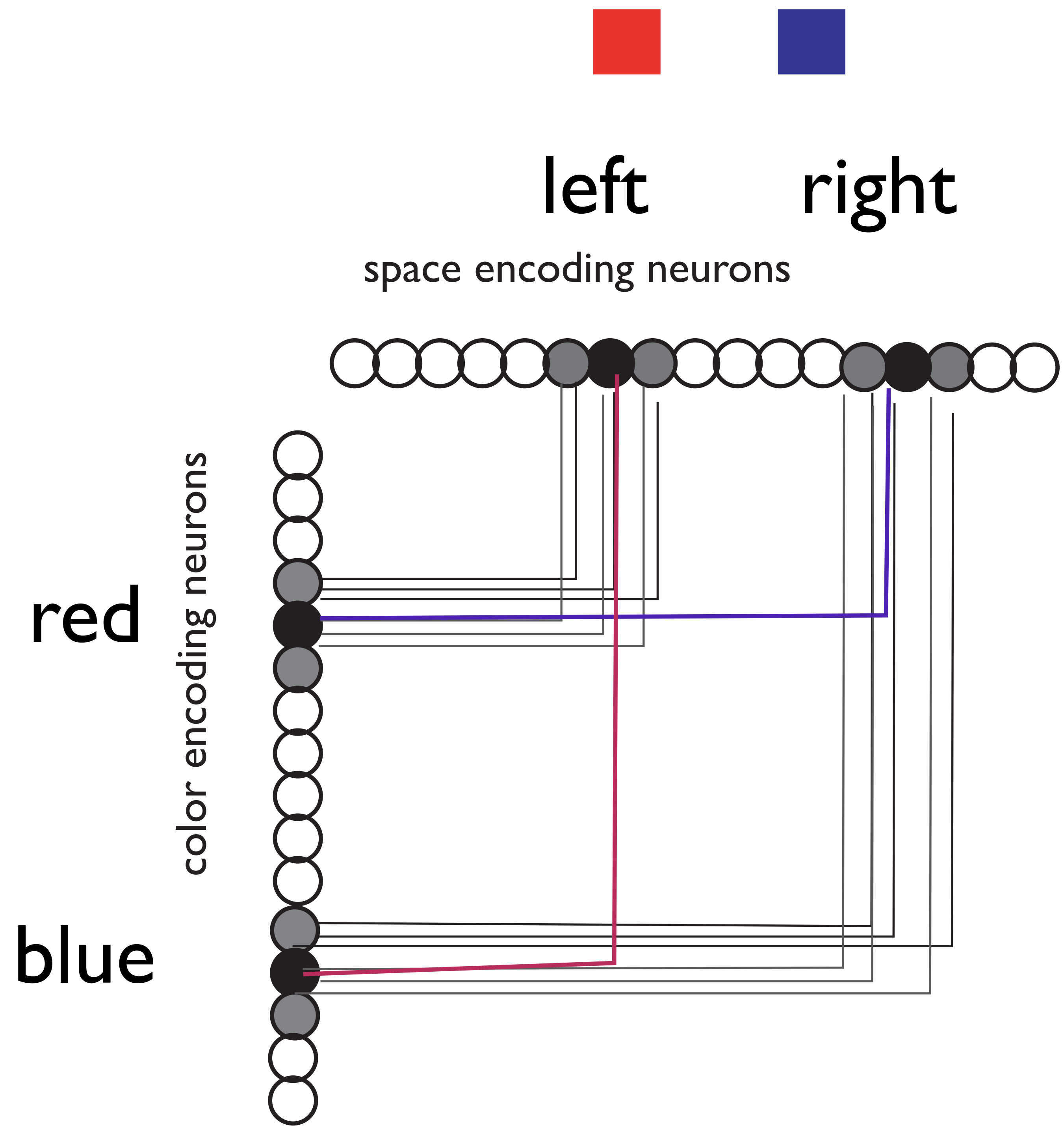
limitations of synaptic association

- 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!



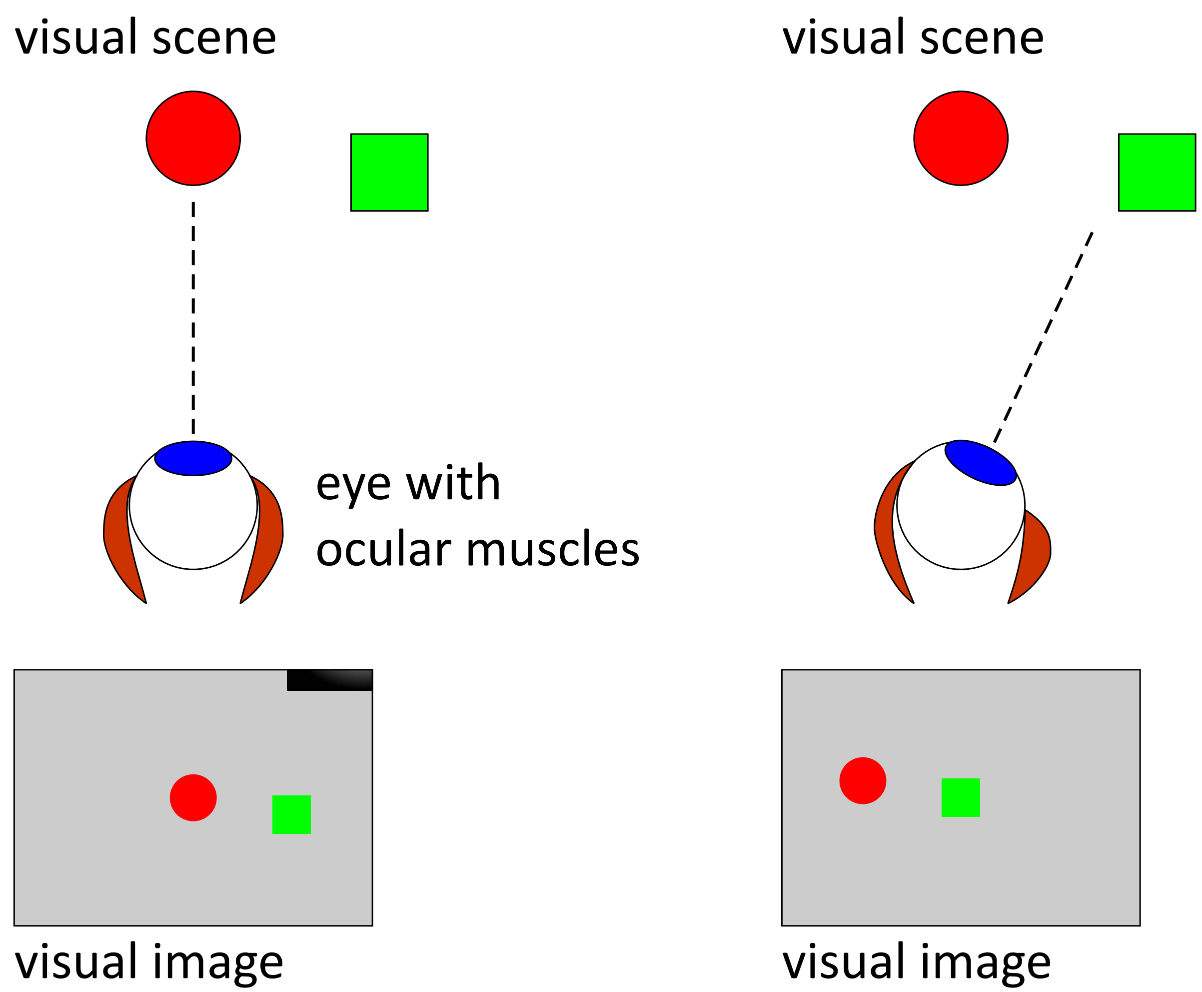
the network may associate blue with left and read with right

Example 2: 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



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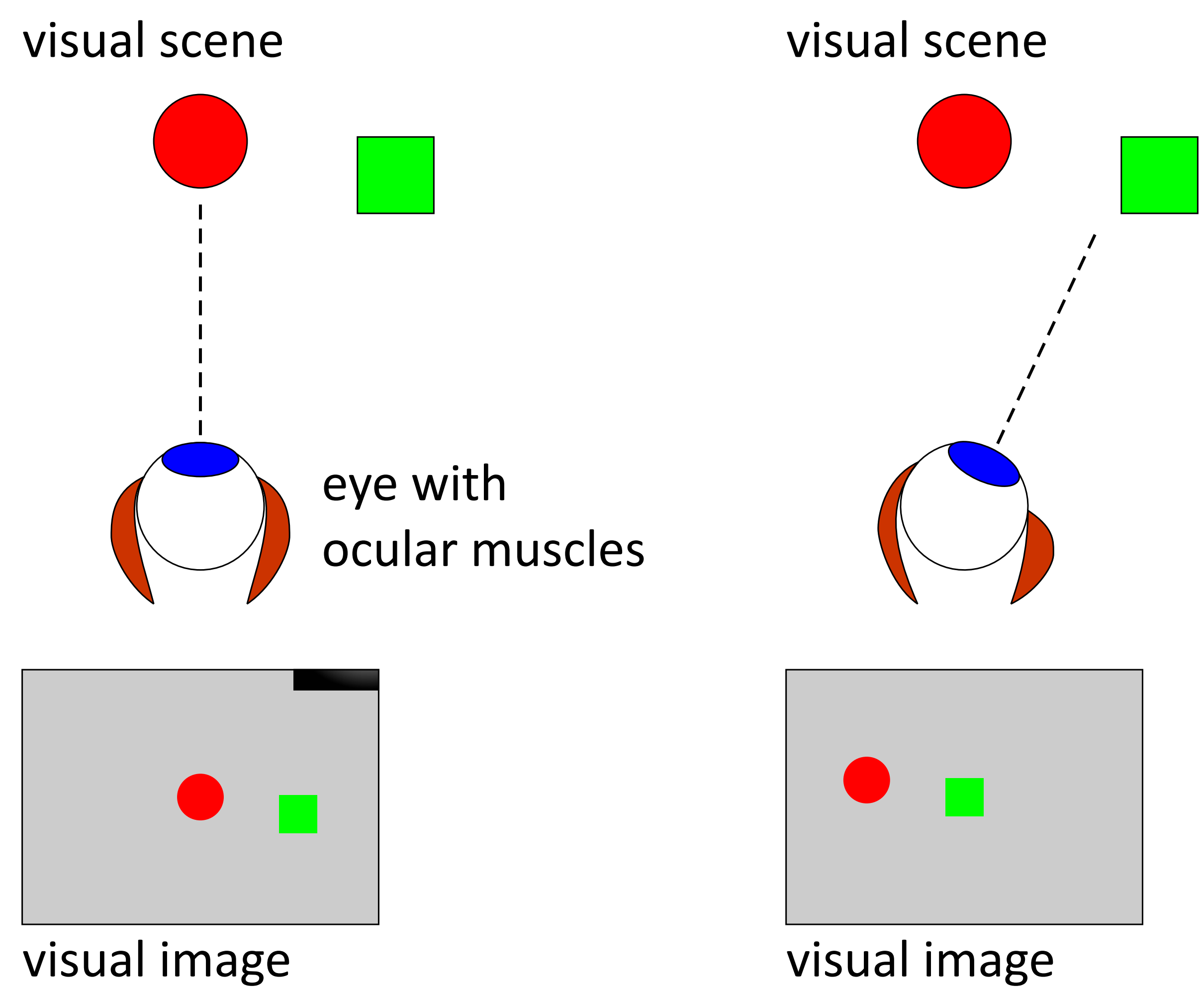
see Schneegans, Chapter 7 of Dynamic Field Theory-A Primer, OUP, 2015]

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



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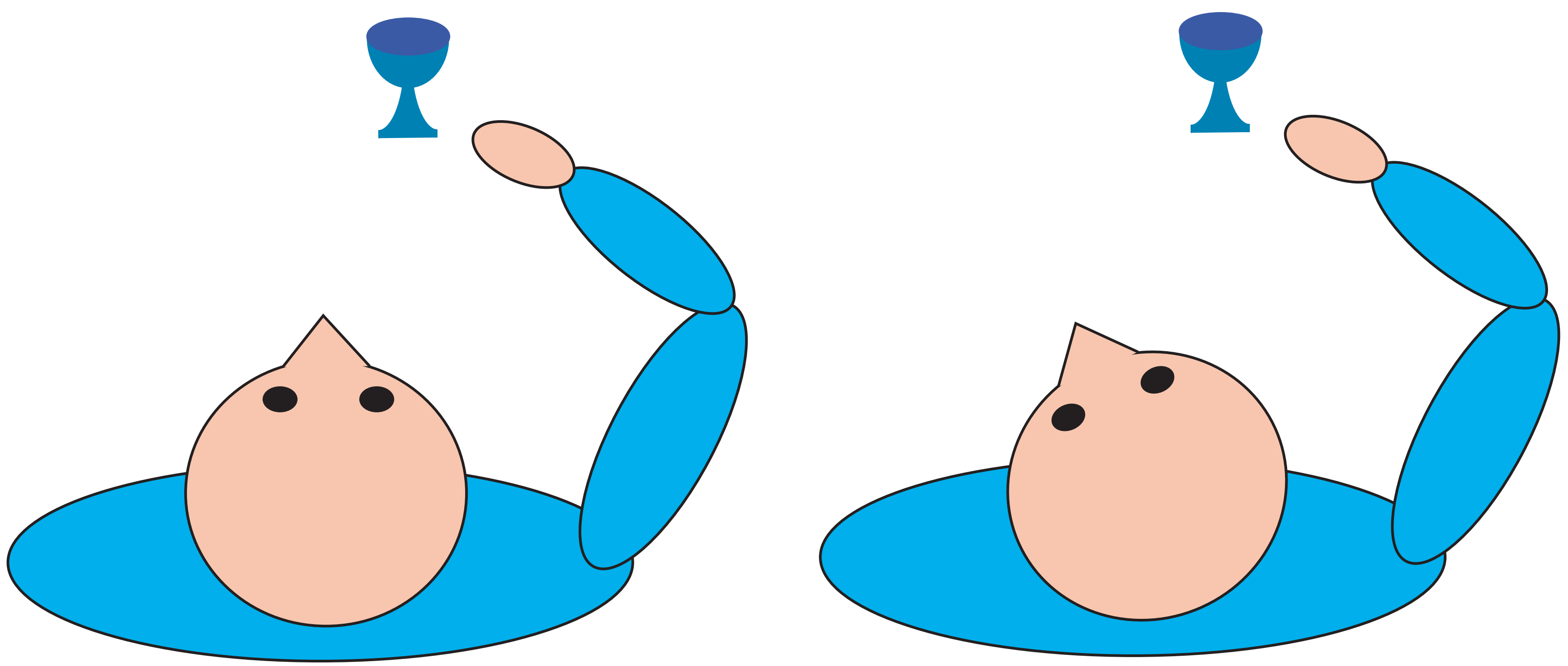
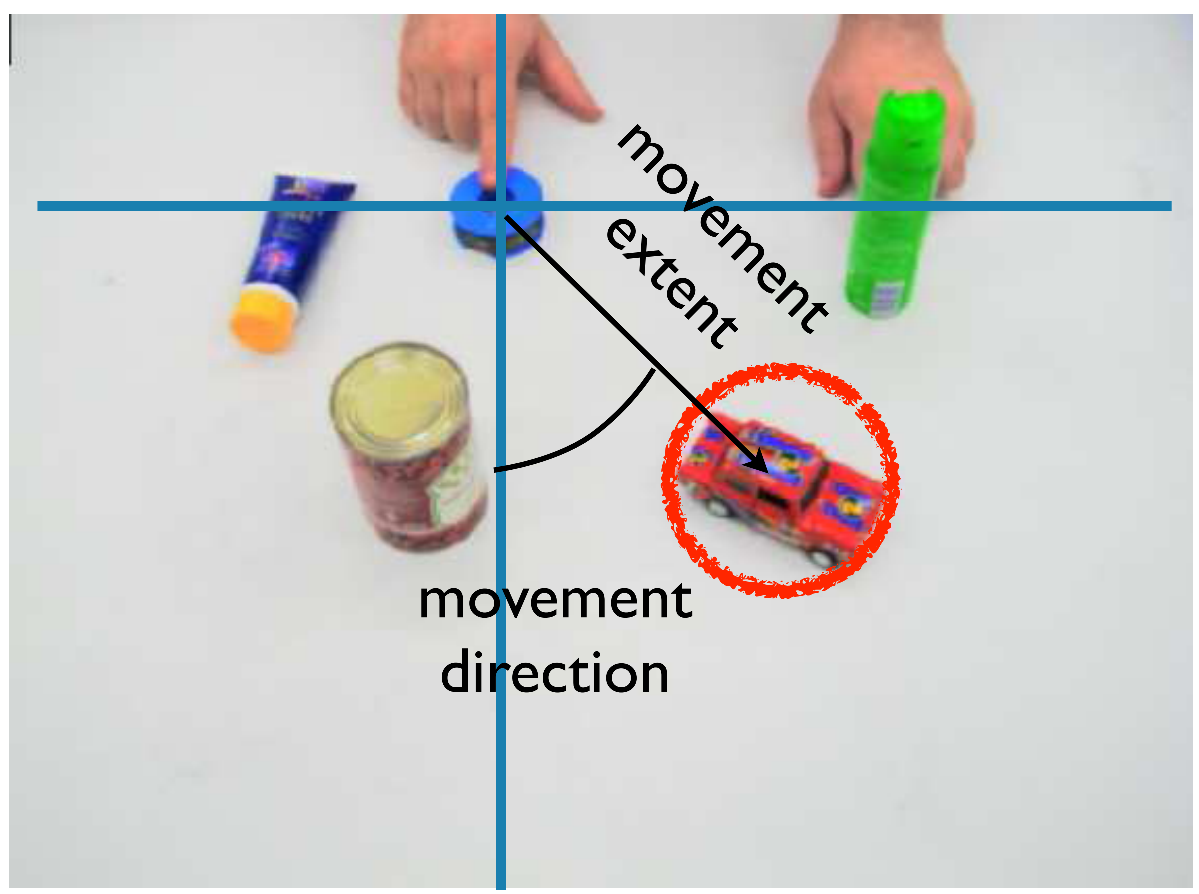
coordinate transformations

- 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,
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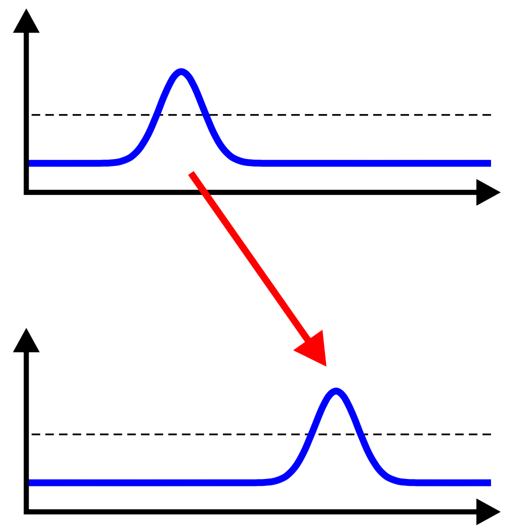
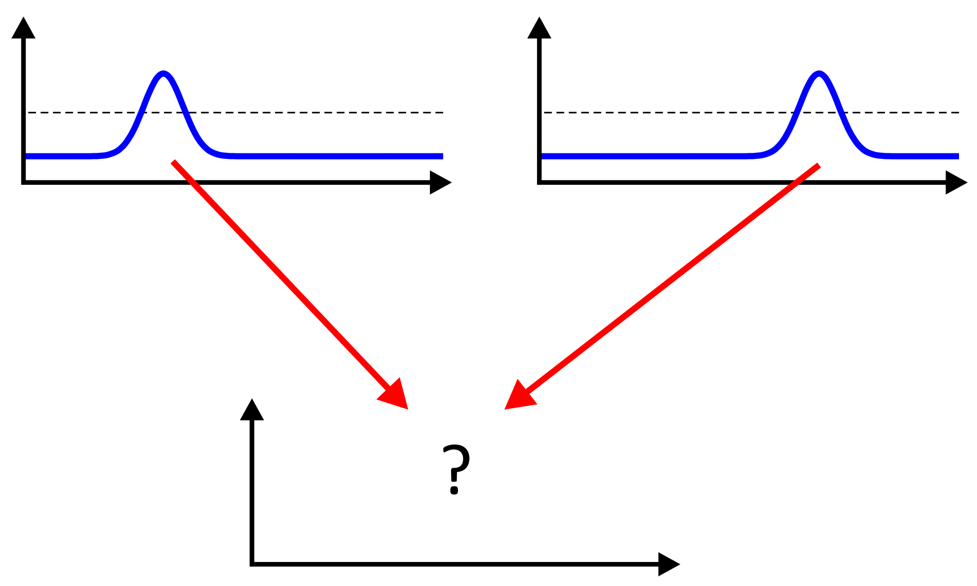
coordinate transformations



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



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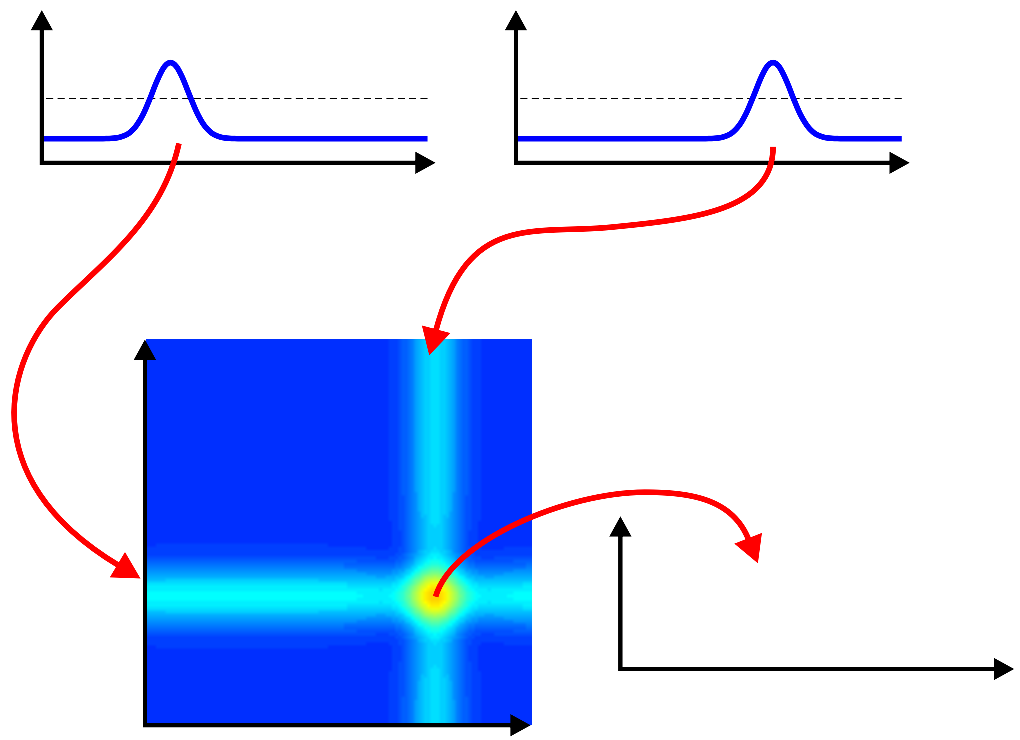
coordinate transformations

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



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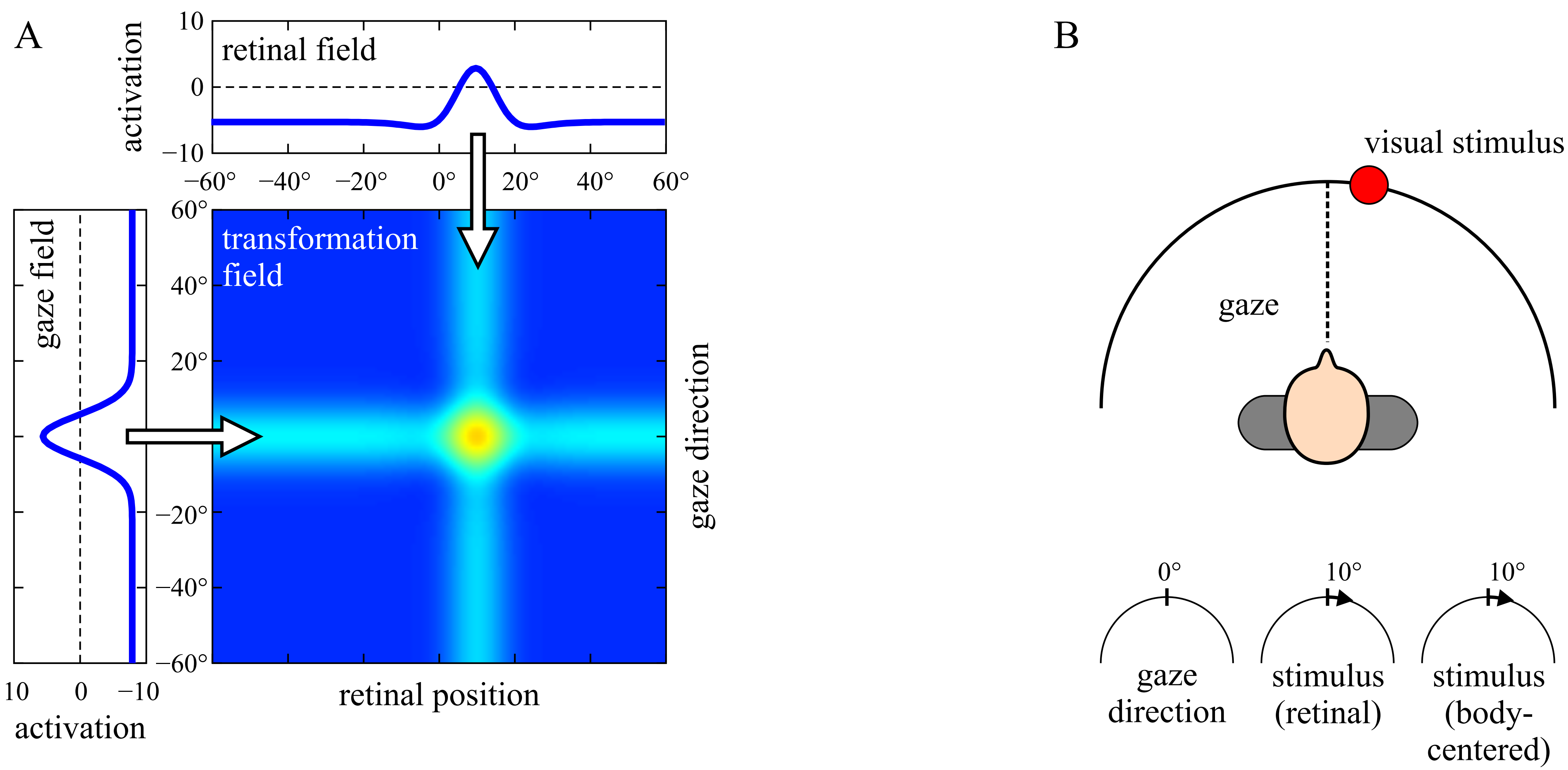
coordinate transformations



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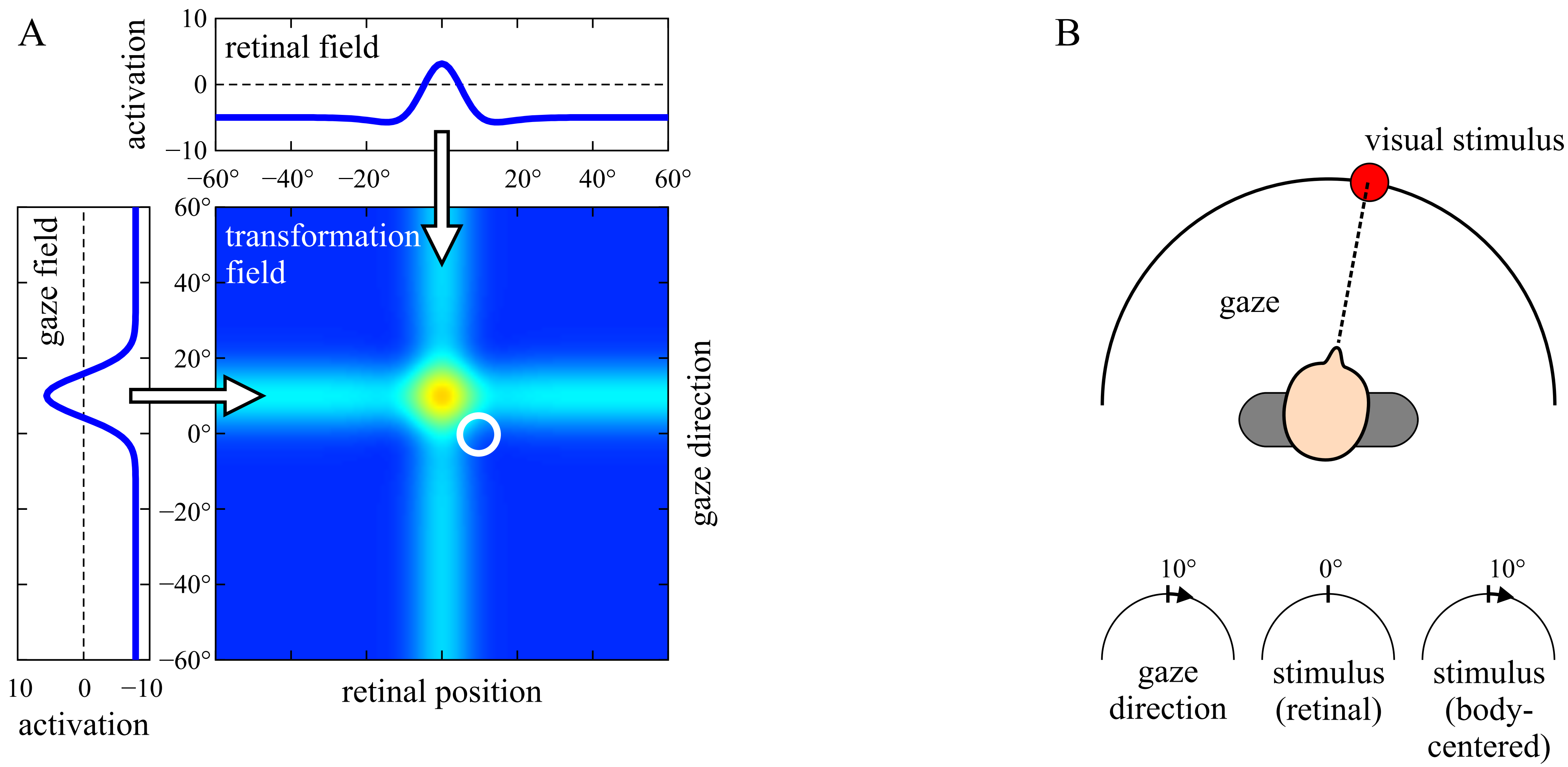
coordinate transformations



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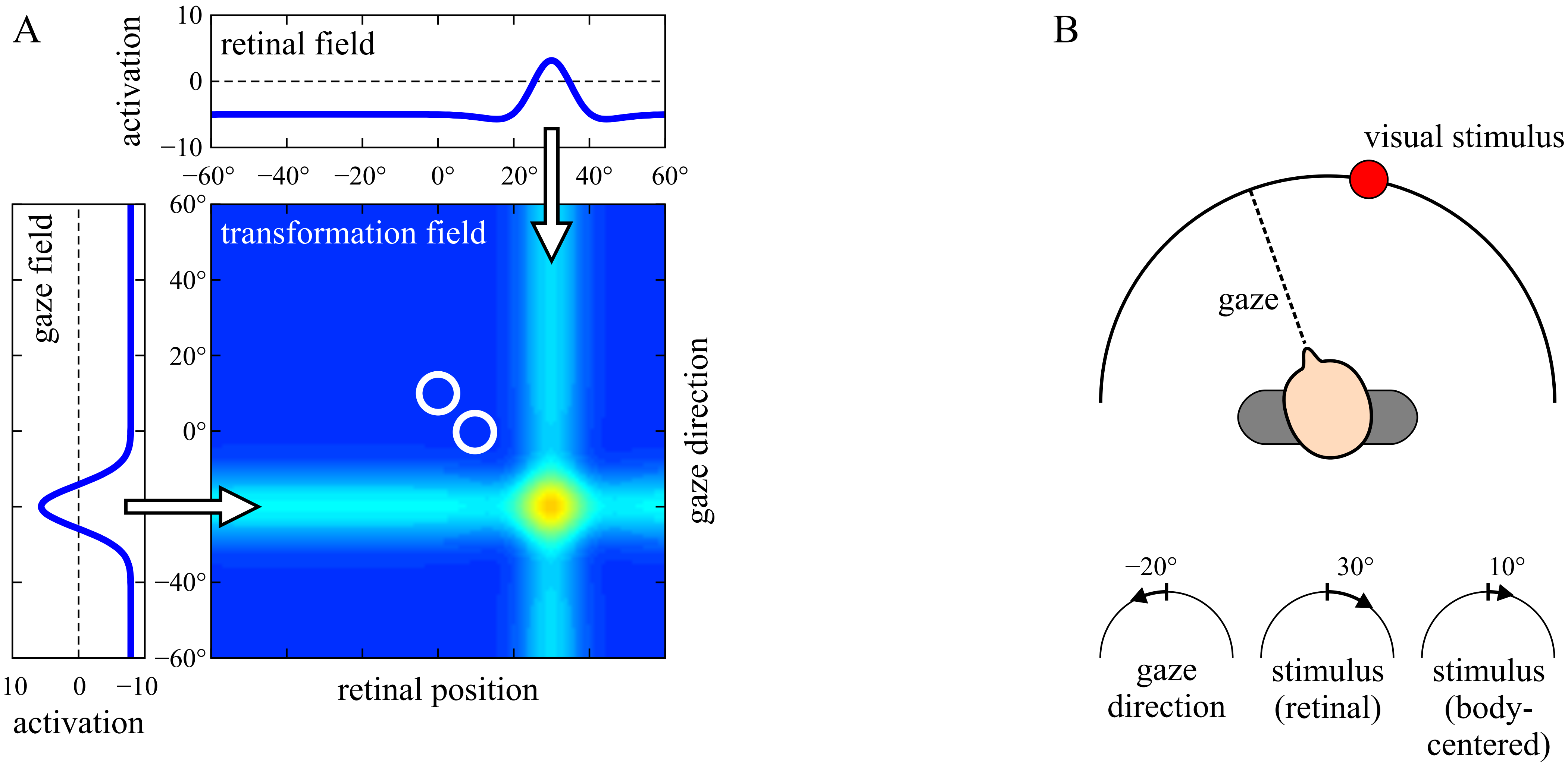
coordinate transformations



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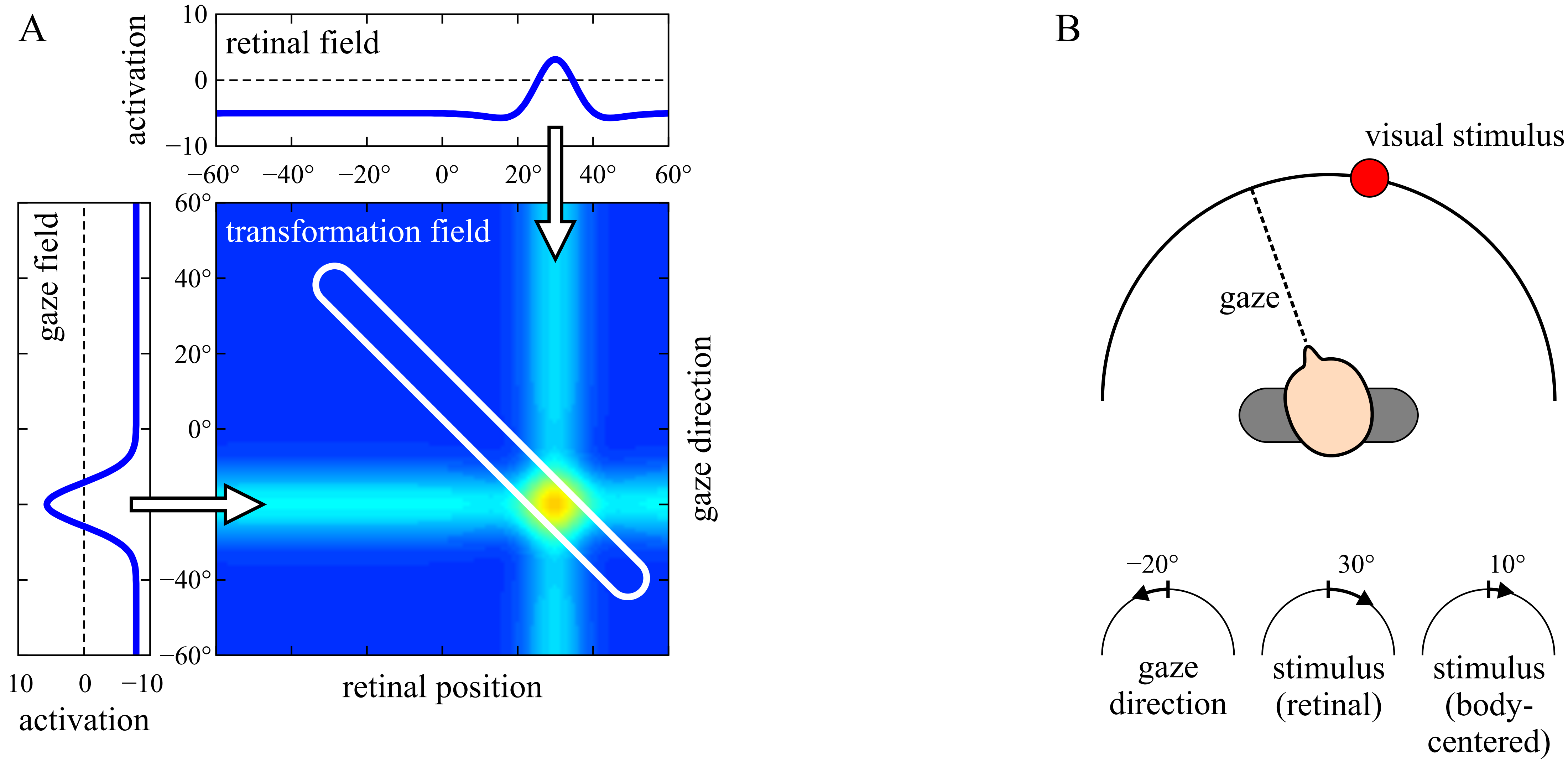
coordinate transformations



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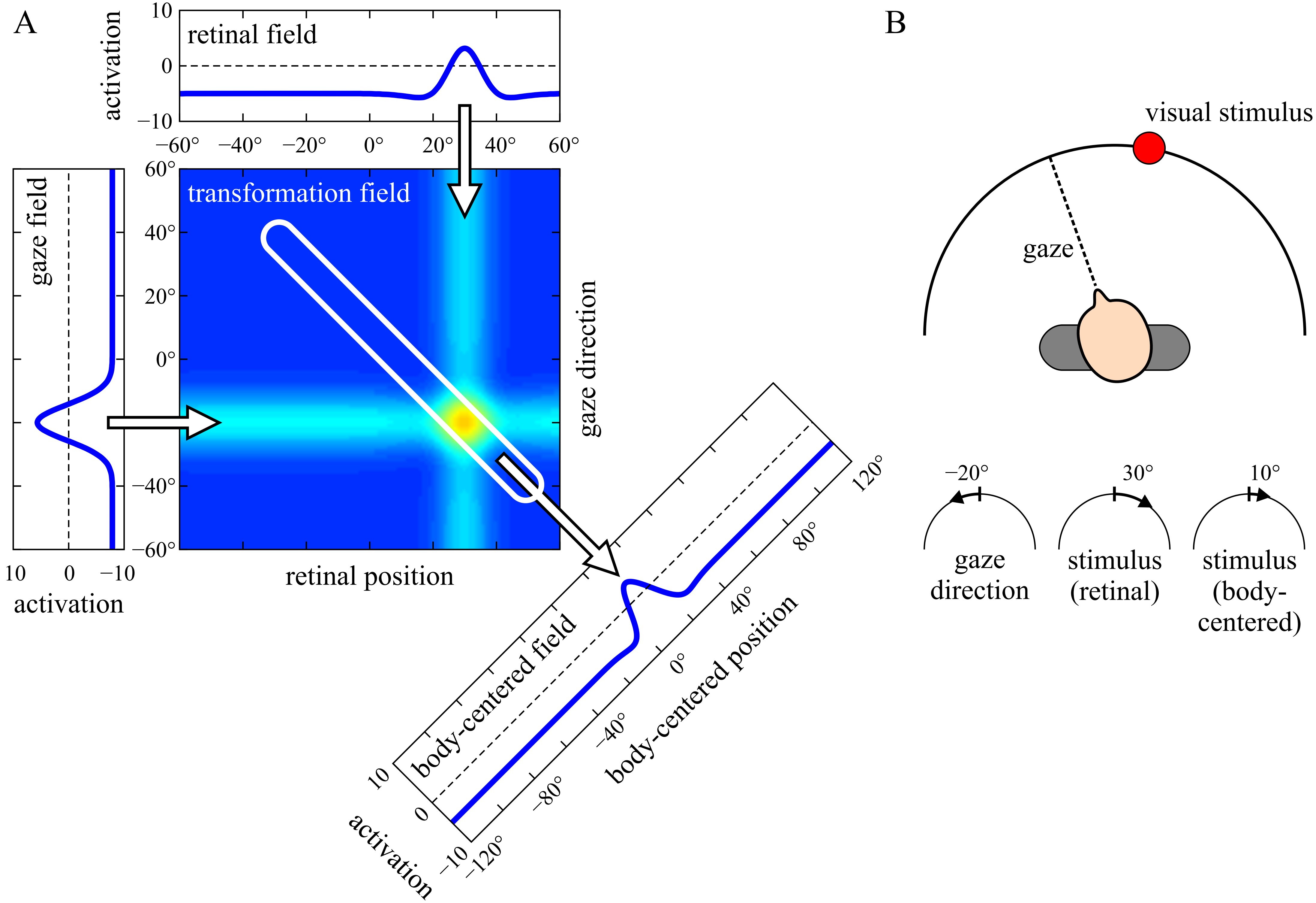
coordinate transformations



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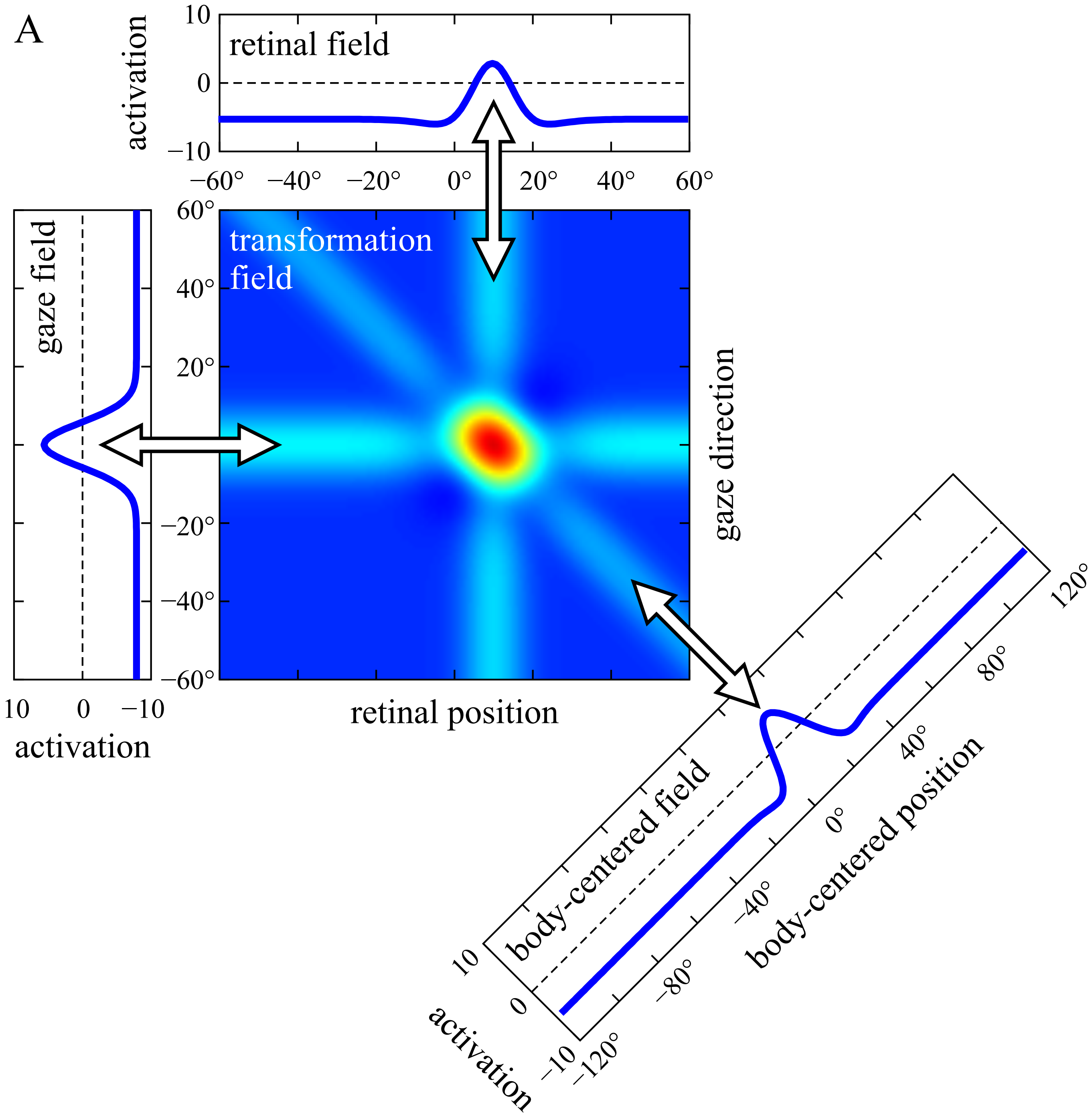
coordinate transformations

- bi-directional coupling: reversing the transformations



[Slides adapted from Sebastian Schneegans,
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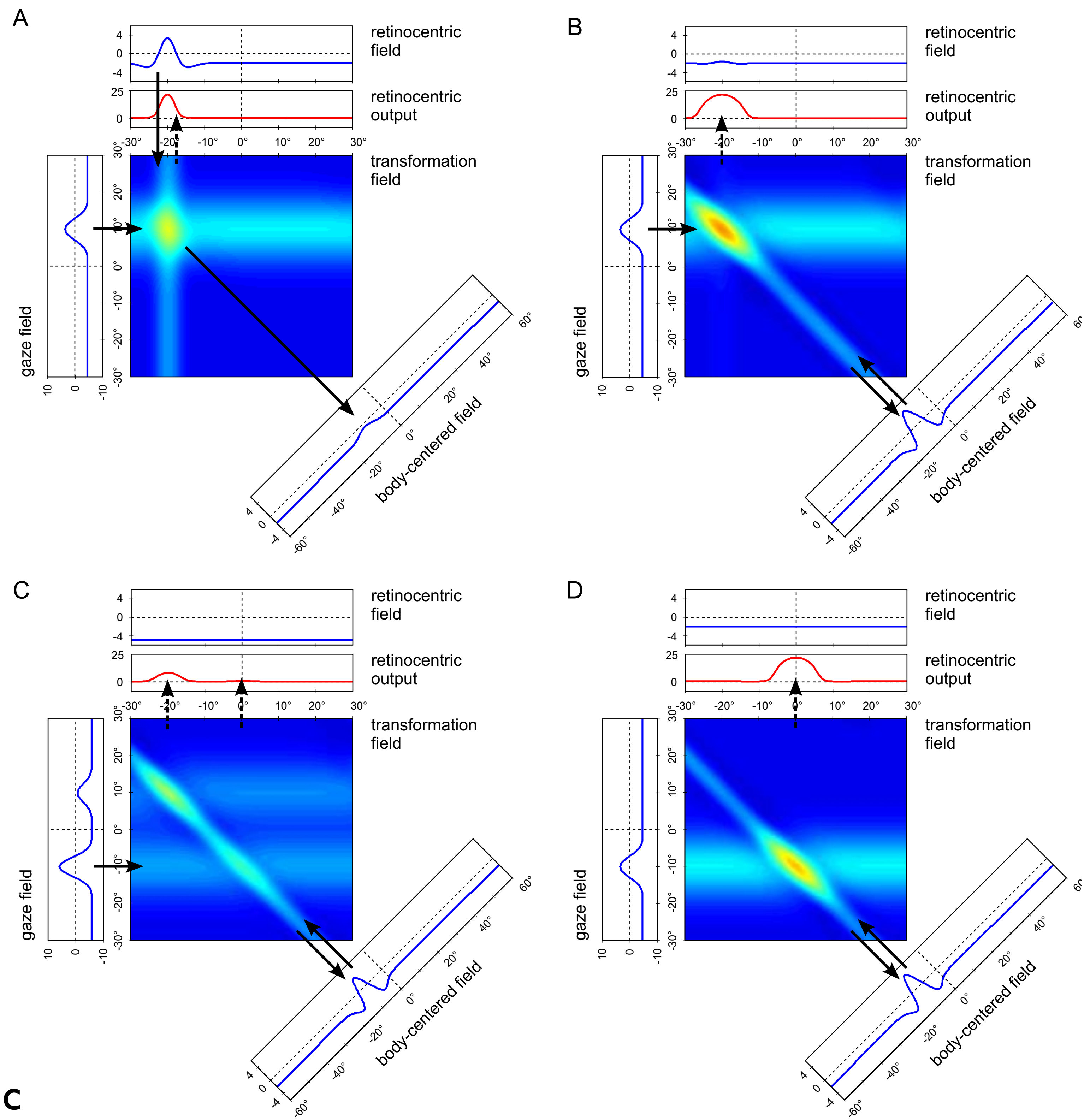
spatial remapping during saccades



[Slides adapted from Sebastian Schneegans,
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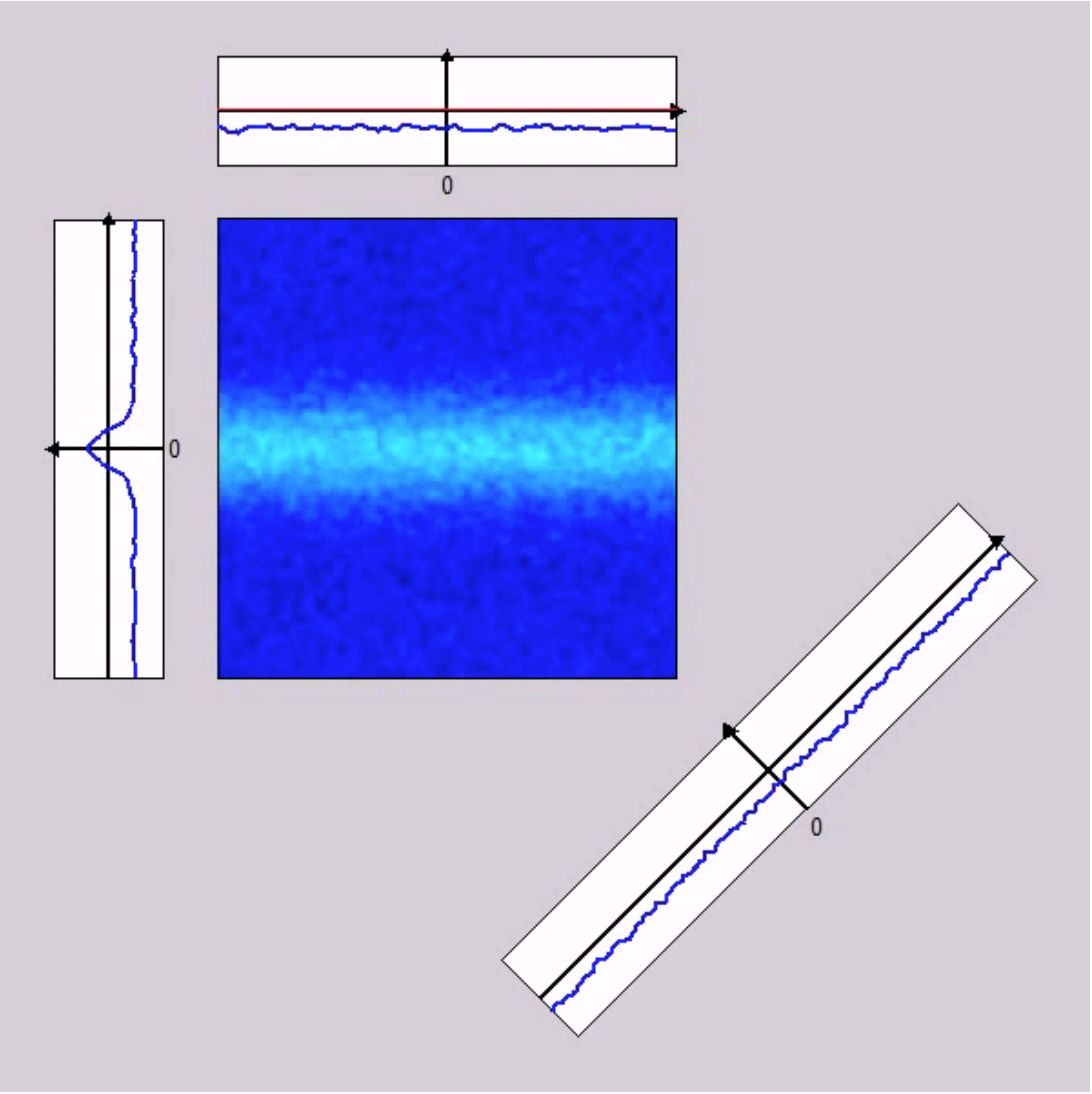
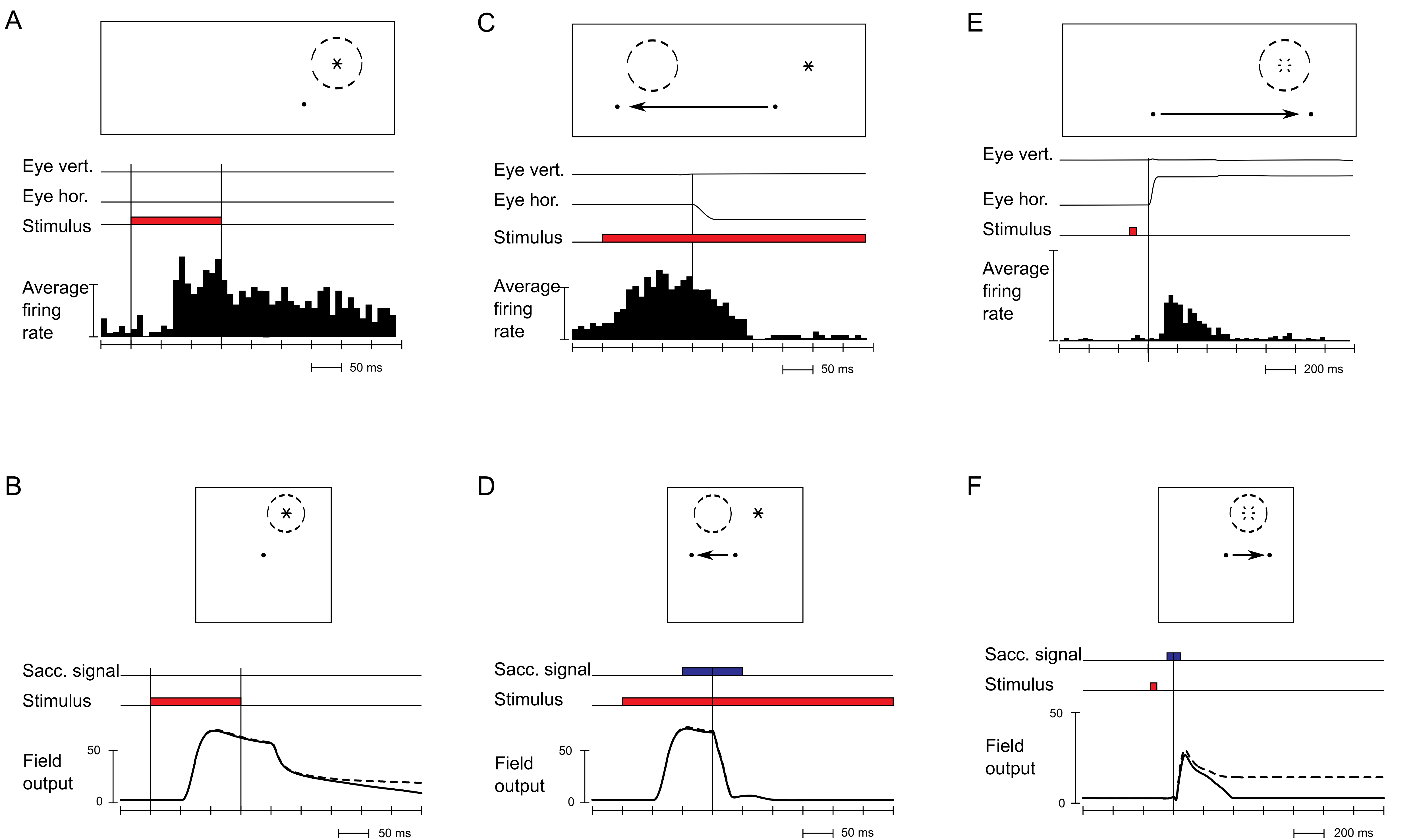
Coordinate transformations

- predict retinal location following gaze shift



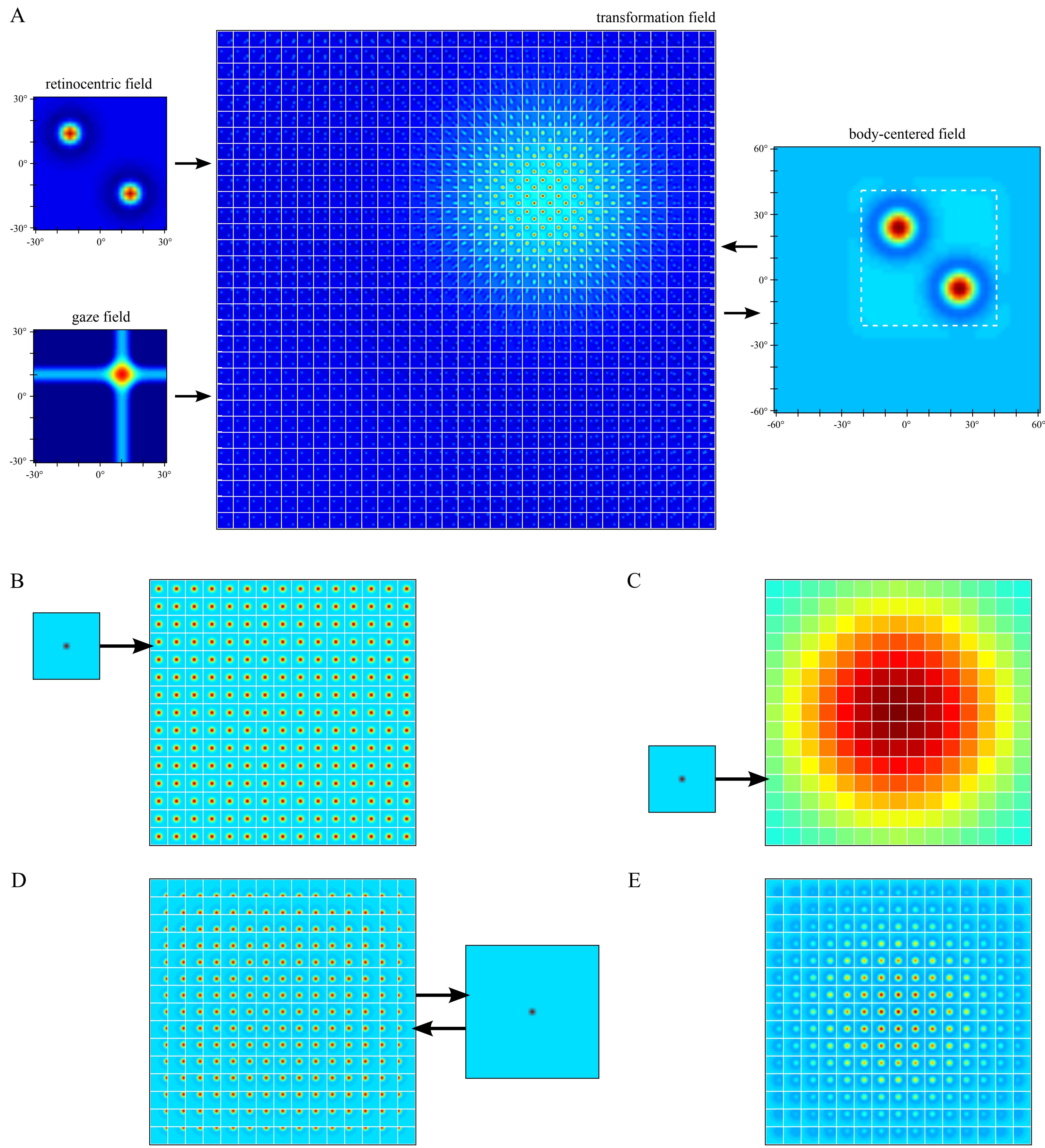
[Schneegans, Schöner, BC 2012]



=> accounts for predictive updating of retinal representation

[Schneegans, Schöner, BC 2012]

Scaling dimensionality



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Scaling dimensionality

- example: a single 6-dimensional field is needed to transform the coordinates of a 3D field:
  - 1 feature dimension X 2 spatial dimensions on input side
  - 1 feature dimension X 2 spatial dimensions on output side
- sample each dimension with 100 neurons: 10^12 neurons = entire brain!

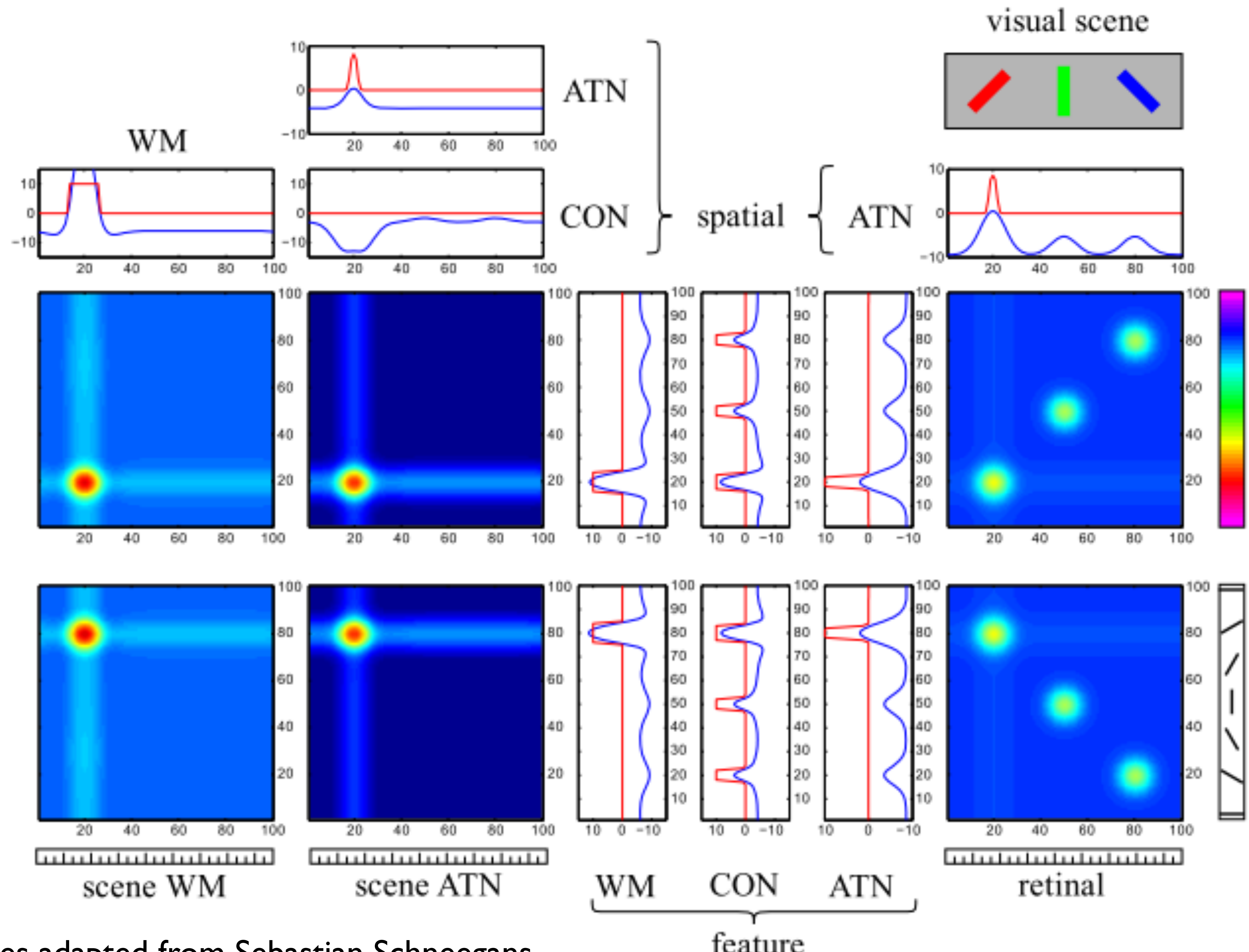
Scaling dimensionality

- Example: a few features over space
  - color
  - orientation
  - disparity
  - line-length
  - 2D space
- => 6 dimensions ~10^12 neurons!

solution

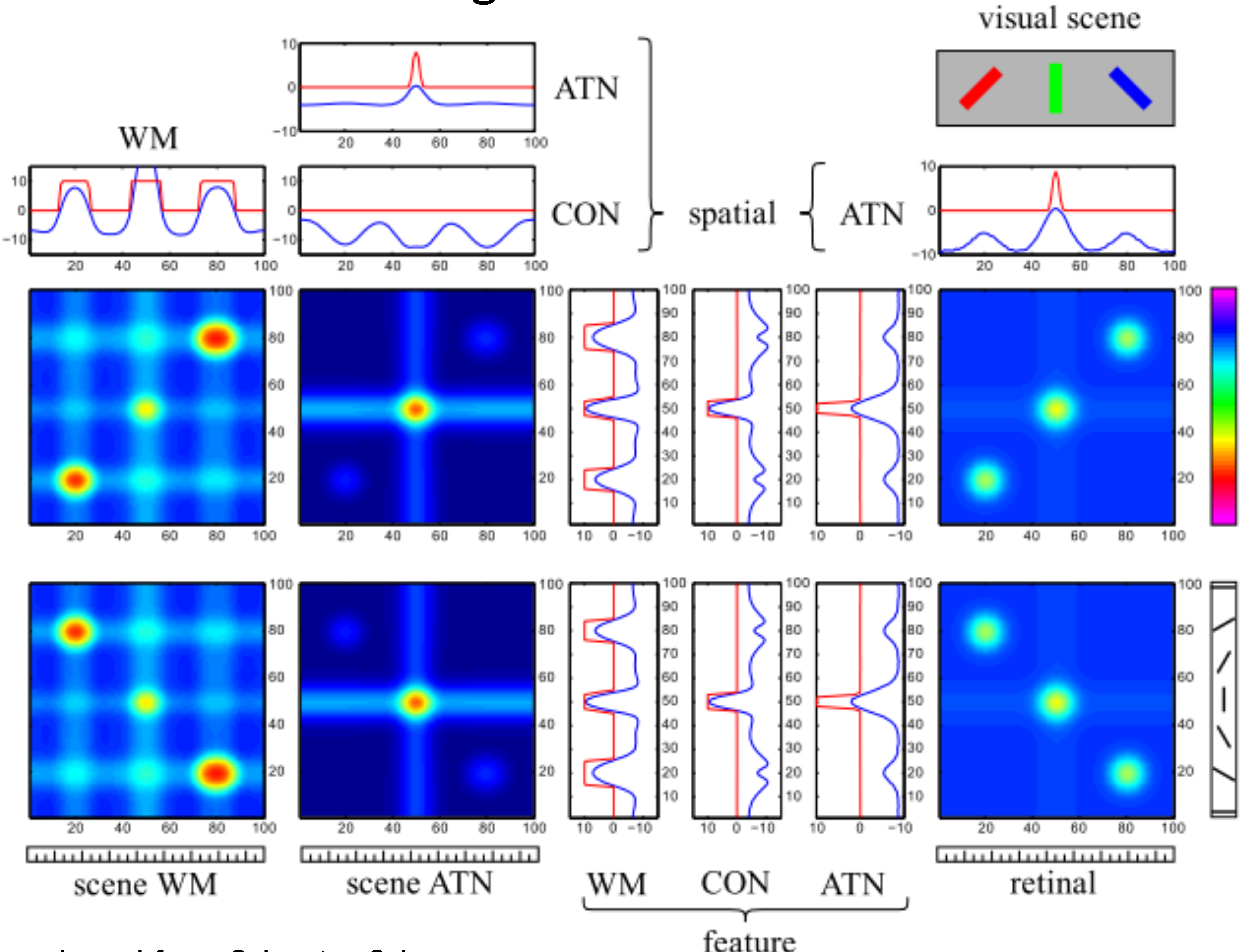
- break down the feature fields into many low dimensional fields… all 3 or maximally 4 dimensional
- coordinate transform only space…
- and bind the features to space by combining the ridge values: operating sequentially!
- => coordinate transforms are at the origin of the binding bottleneck

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



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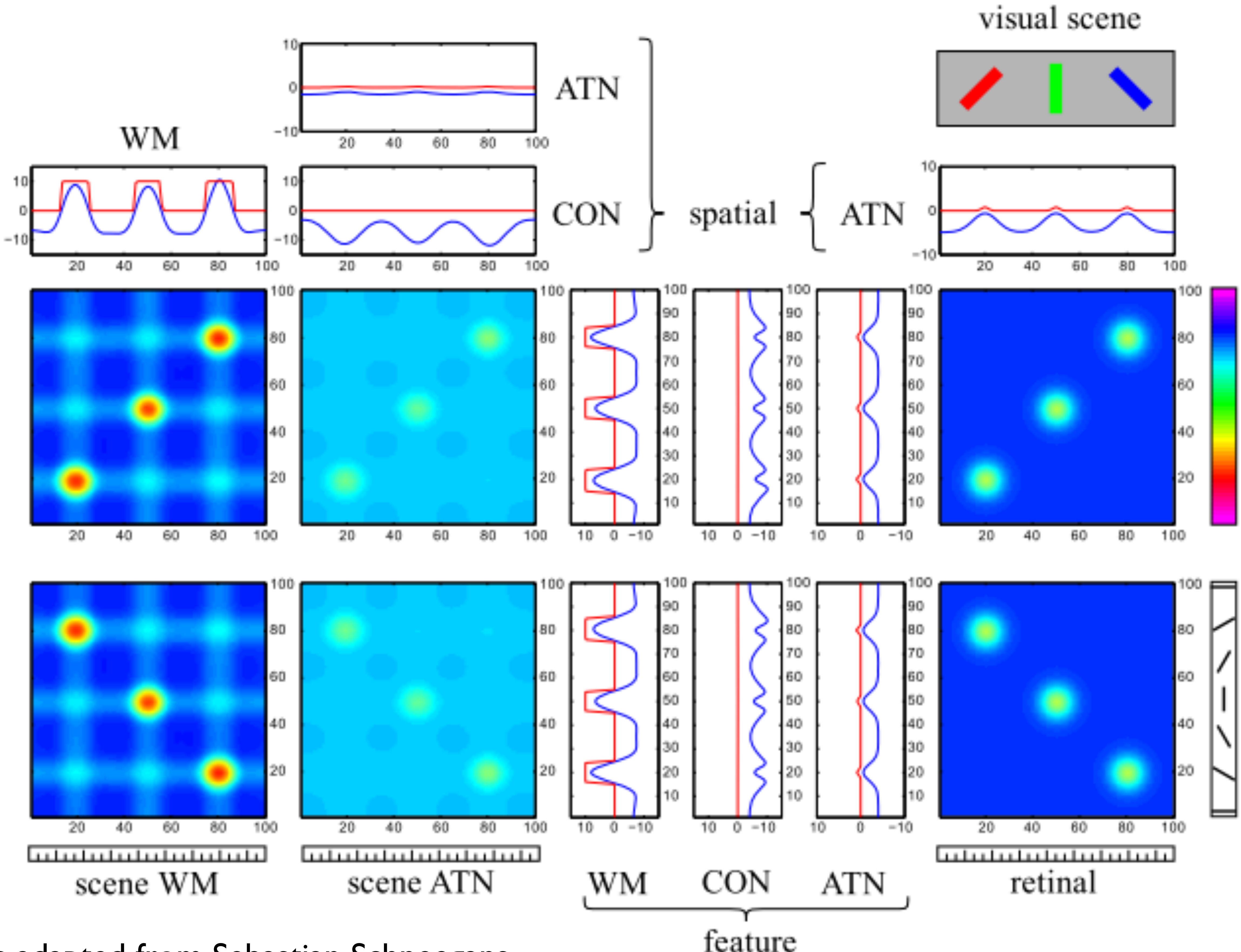
Post sequential memorization of all three items



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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