

# Pervasively neural cognitive architectures: What they entail, what they may deliver, how they remain elusive

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# Neural inspiration in autonomous driving/robotics

- has returned center stage largely through Deep Learning, primarily in vision
- past discomfort about lack of theoretical penetration/proof of competence has faded as performance has become better
- rely on benchmarks with an eye for super-human performance

# Neural inspiration

- acceptance is helped by fact that NN are used in a narrow way...
- essentially as intelligent filters that extract information for neural representations... on which action/decisions are based
- decision making, planning, coordination, and control remain to a large extent outside the neural metaphor

# Neural inspiration

- this helps circumscribing the problem on limited verifiability
- but is also a limitation in itself... => underusing a potential revolution...
- => embodied cognition in closed loop rather than static representations and plans

# Cognition in the wild...

- attention/gaze
- active perception/working memory
- action plans/decisions/sequences
- goal orientation
- motor control
- background knowledge
- learning from experience

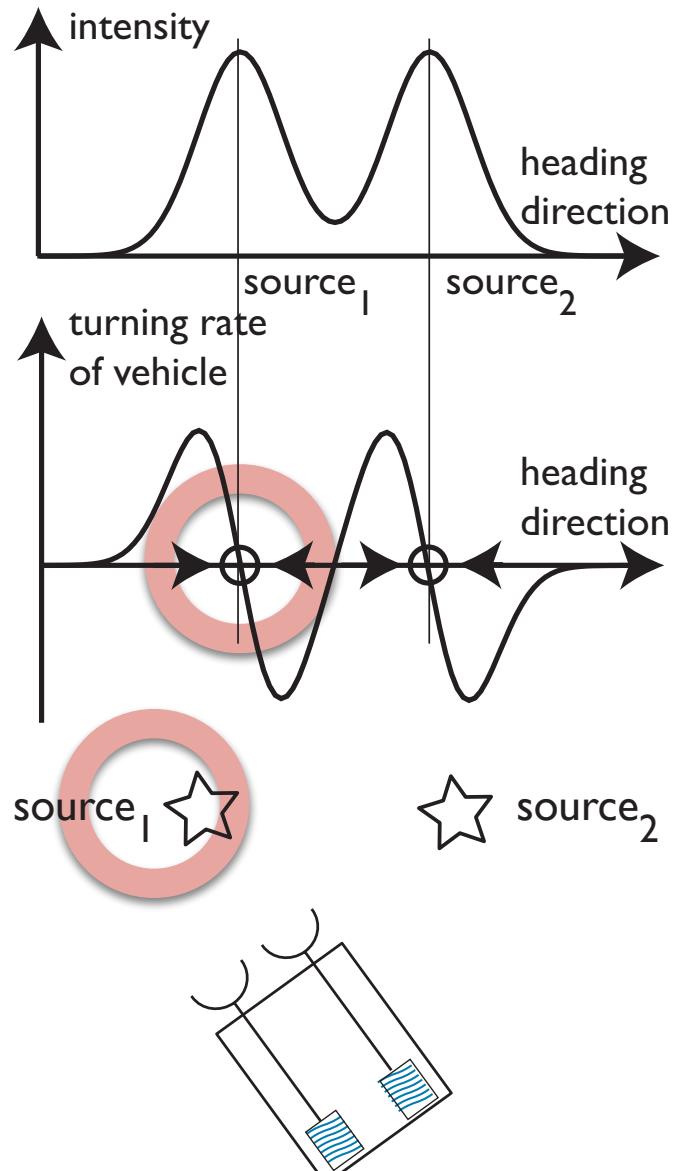


# => underlying neural processes have dynamic properties

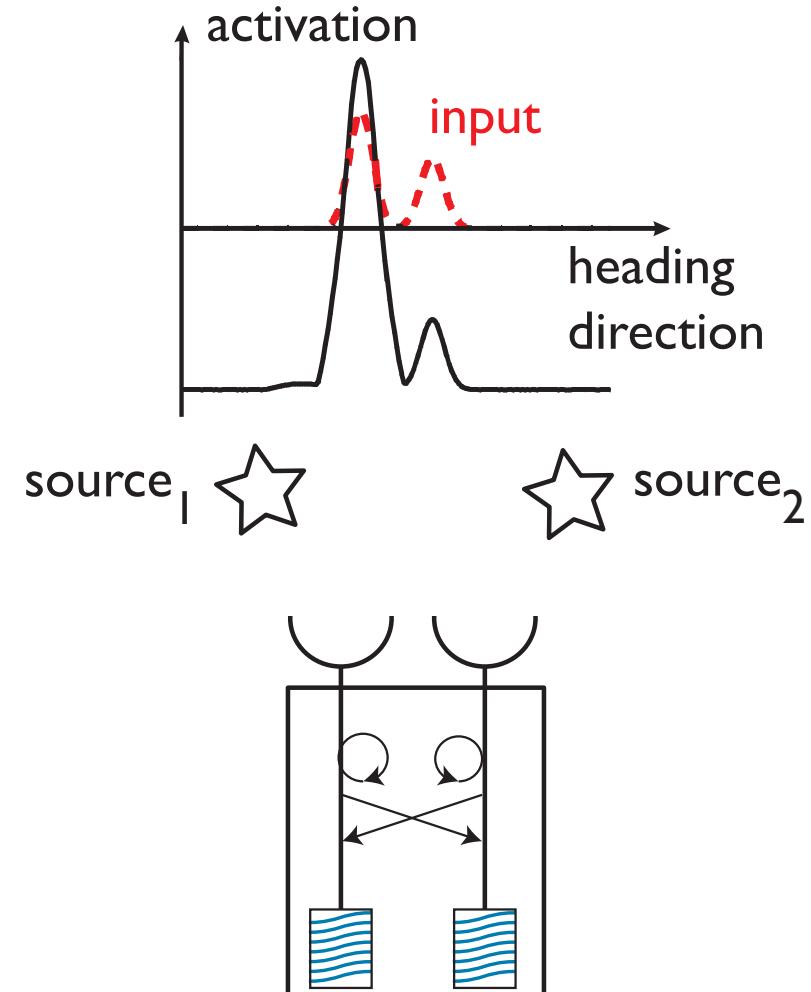
- graded state
- continuous time
- from which discrete events and categorical behavior emerge
- continuous/intermittent link to the sensory and motor surfaces in closed loop
- => dynamics
- => stability



# Two forms of dynamics



behavioral dynamics



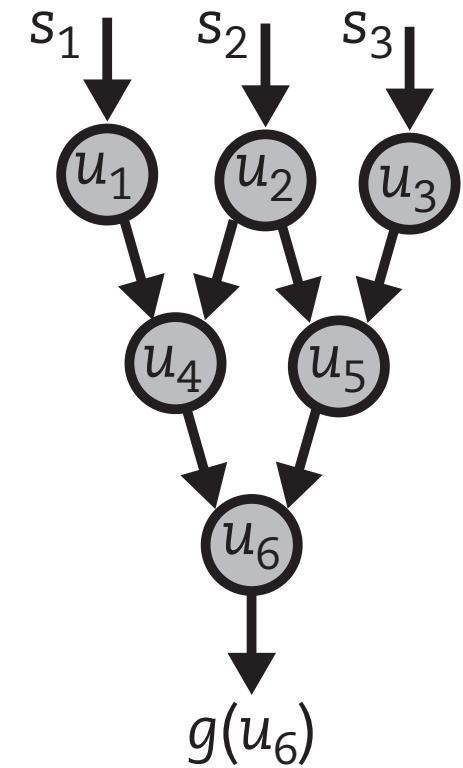
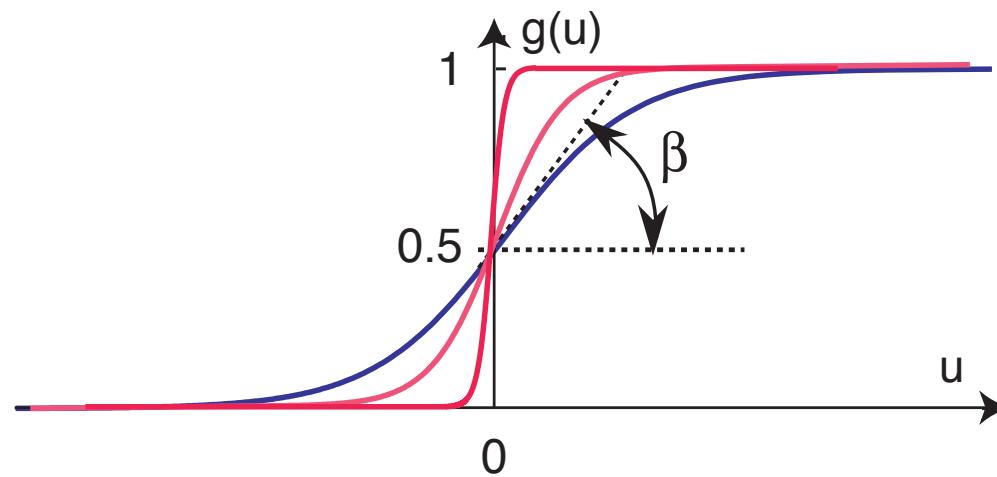
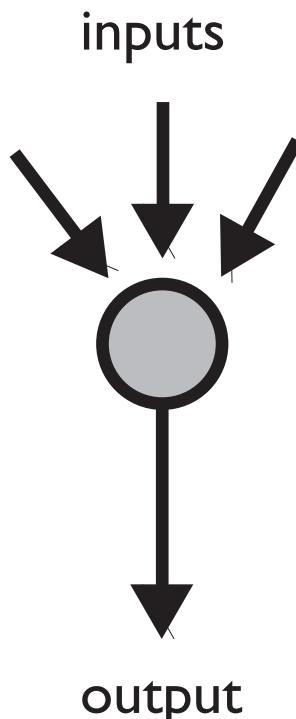
neural dynamics

# Embodiment hypothesis

- all cognition is like soccer  
playing = has the properties  
of embodied cognition
- => embodied cognition  
reaches all forms of  
cognition, including “higher”  
symbolic reasoning

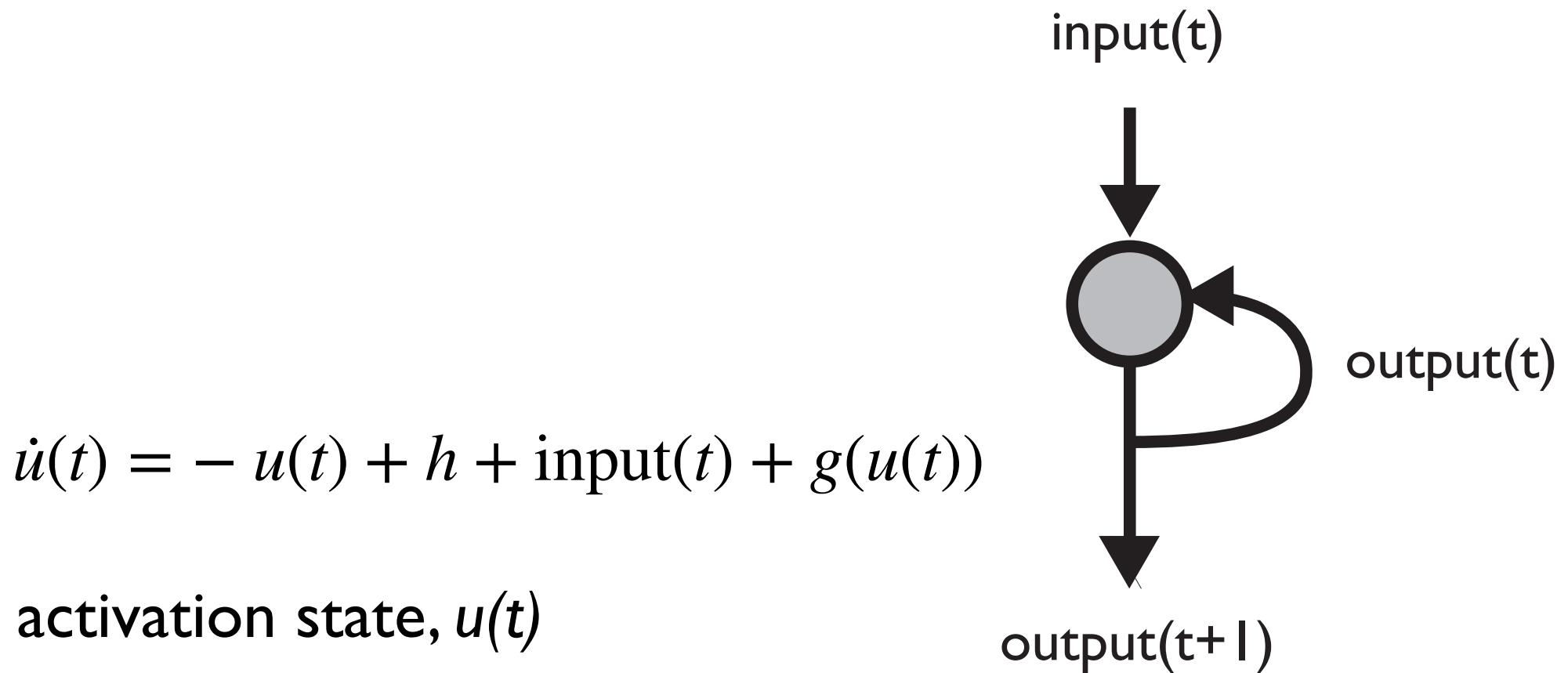


# Forward neural networks form input-output mappings/functions



$$\text{output} = g \left( \sum (\text{inputs}) \right)$$

# Recurrent neural networks require concept of (continuous) time => neural dynamics

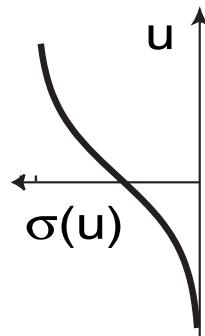
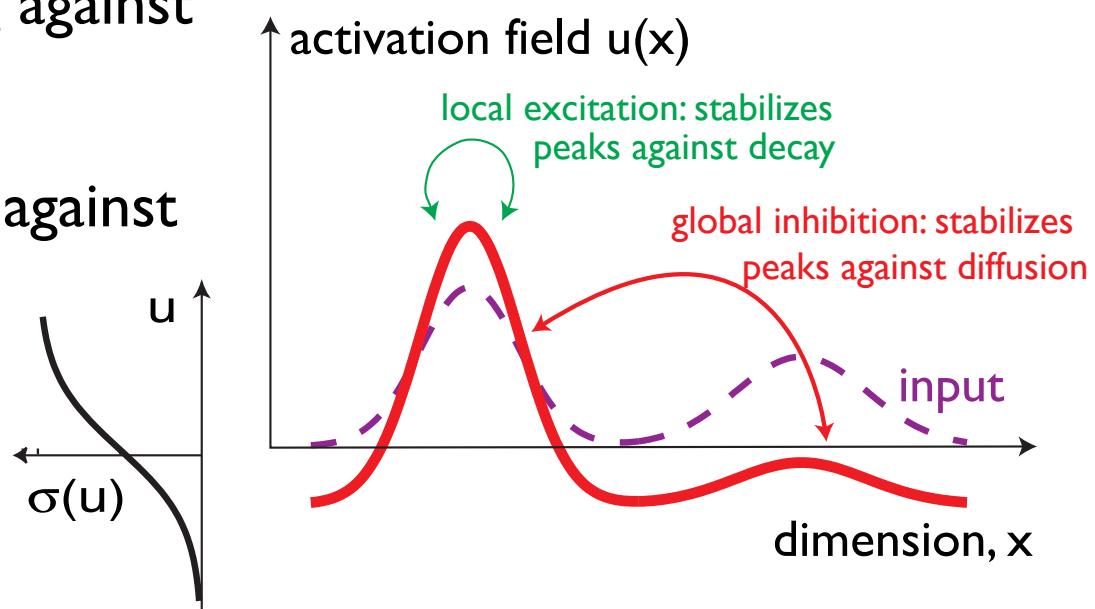


# Self-generated/self-stabilized activation patterns in neural dynamics

- key to cognition... !
- activation generated/sustained by recurrent connectivity (rather than by input)
- who recurrently excites who?
- => need for embedding in low-dimensional space

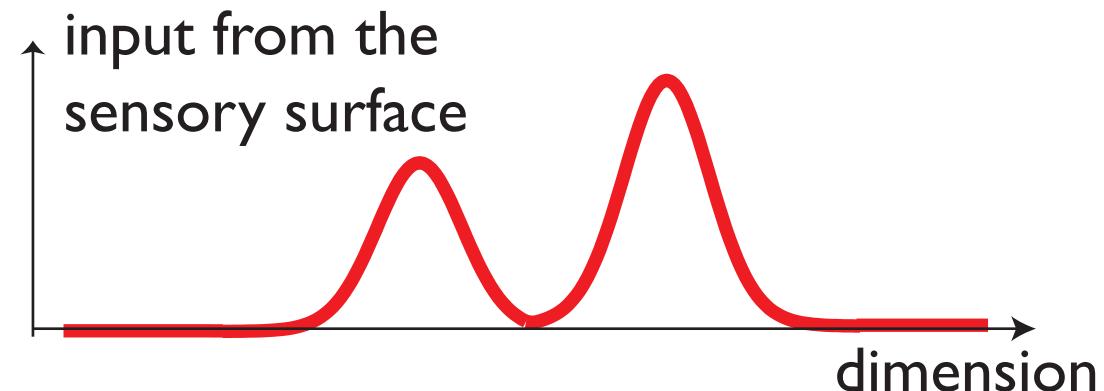
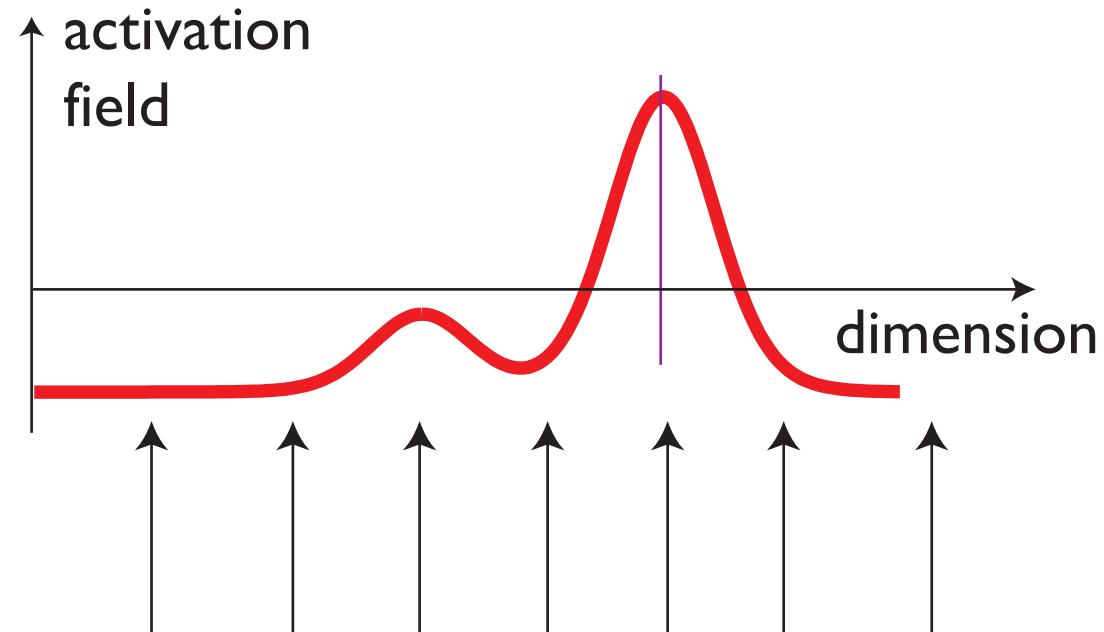
# Dynamic neural fields

- localized activation patterns stabilized by regular pattern of recurrent connectivity
- stabilized by excitatory coupling against decay
- stabilized by inhibitory coupling against diffusive spread
- => attractors



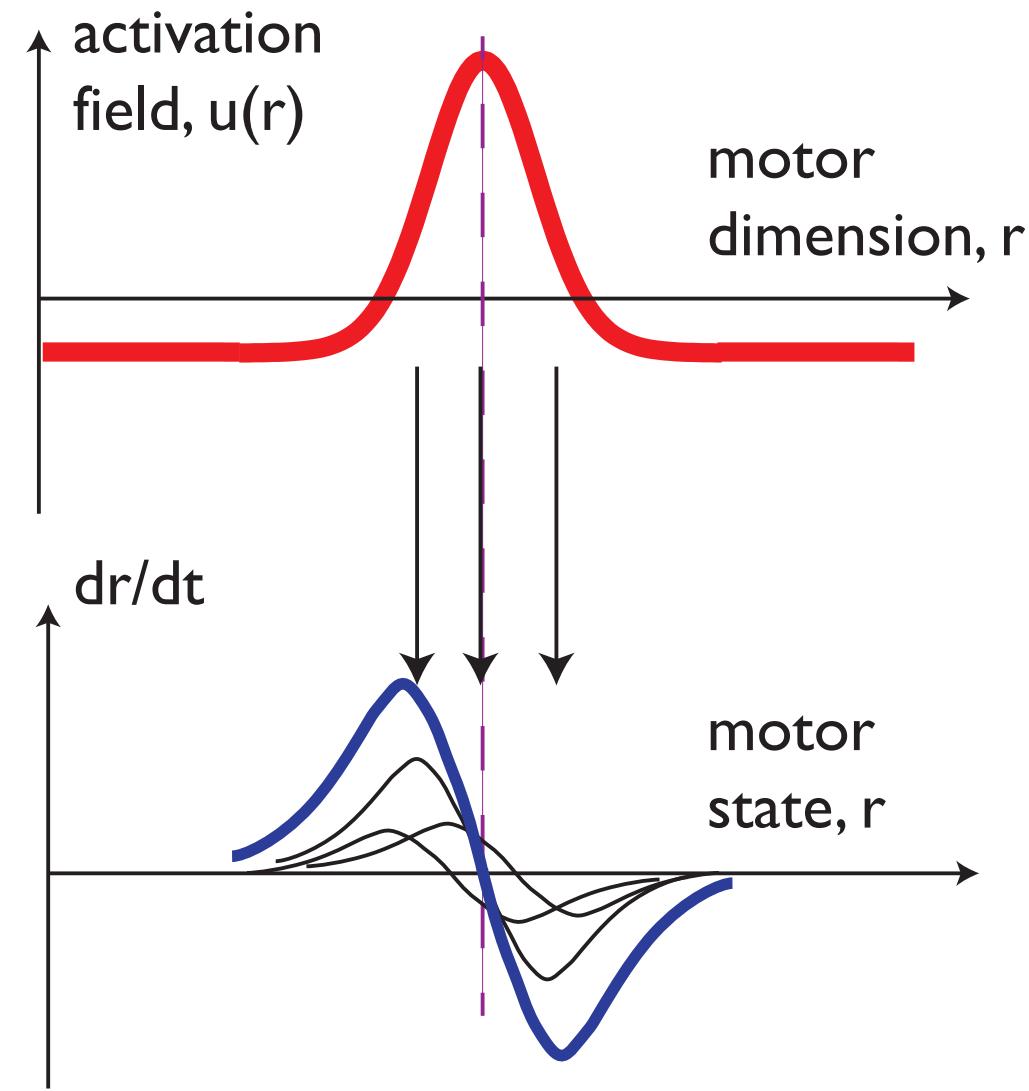
# Embedding in low-dimensional space

- through forward connectivity from sensory surface
- e.g., feature maps...
- e.g. deep networks...



# Embedding in low-dimensional space

- through forward projections onto motor surfaces...
- => behavioral dynamics
- e.g., through peripheral reflex loops



=> simulation

# Dynamic Field Theory

## ■ attractor activation states

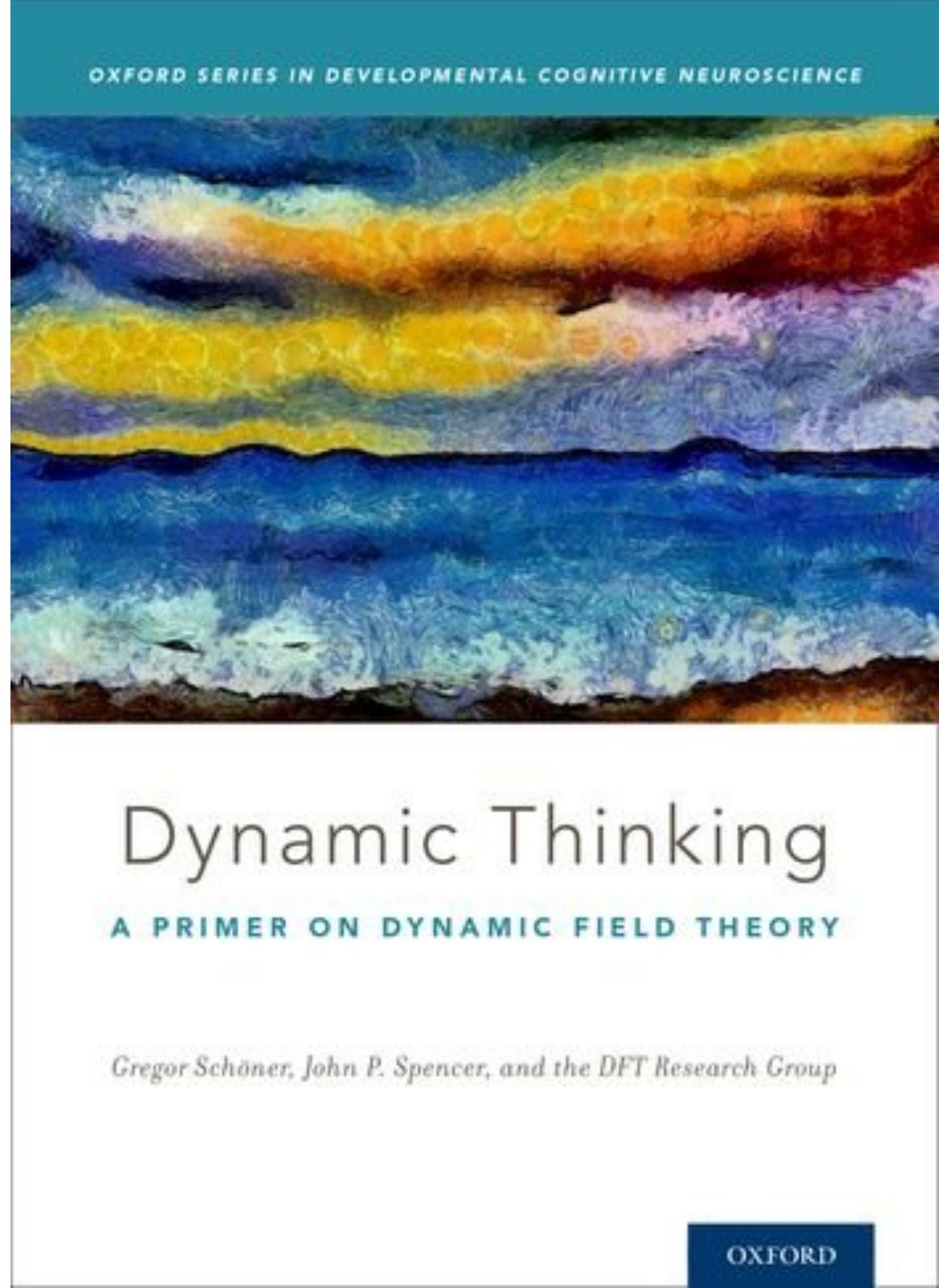
- input driven solution (sub-threshold)
- self-stabilized solution (peak, supra-threshold)

## ■ instabilities

- detection/reverse detection => events
- selection => decision making
- memory => WM
- boost driven detection: => categories, switching

# => Dynamic Field Theory

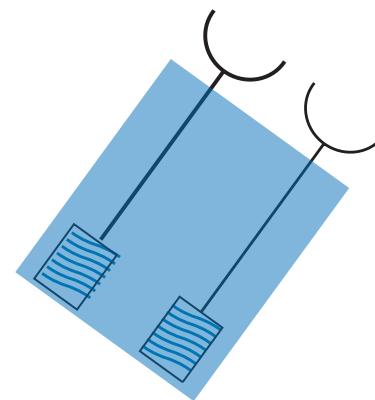
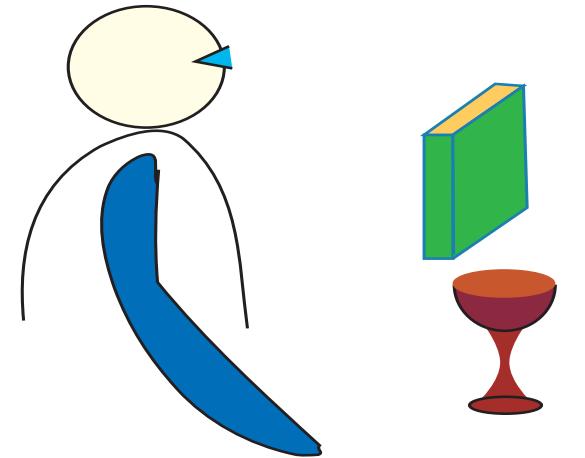
- “pervasively” neural processing accounts of behavior and cognition
- [dynamicfieldtheory.org](http://dynamicfieldtheory.org)



# Building embodied cognition

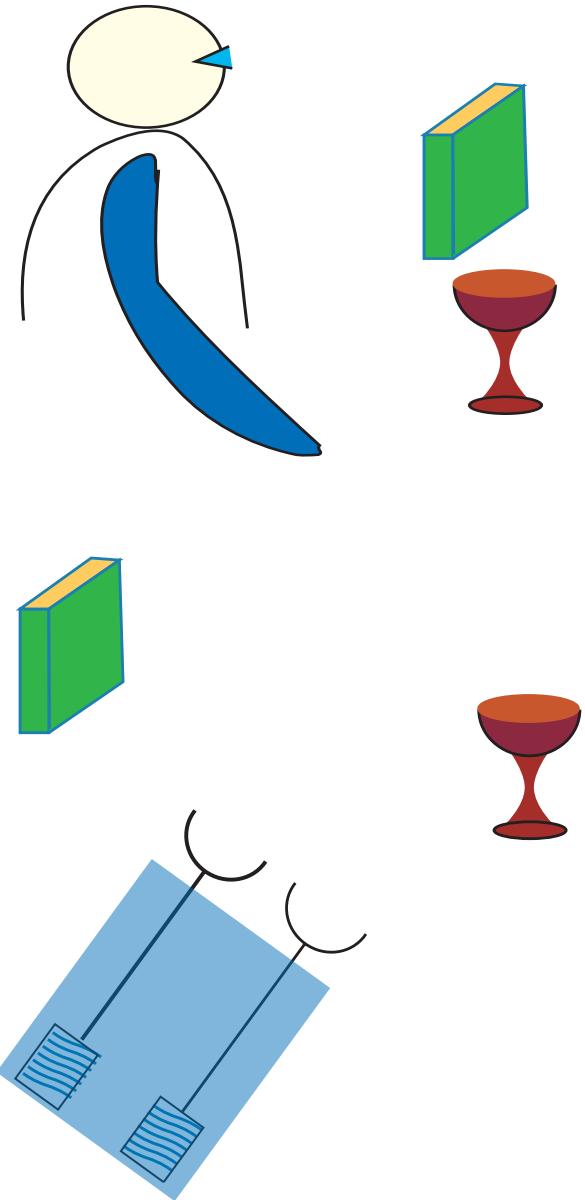
## ■ two scenarios

- “table-top”: directing action or thought at objects in a scene
- “navigation”: generating actions while moving through a world



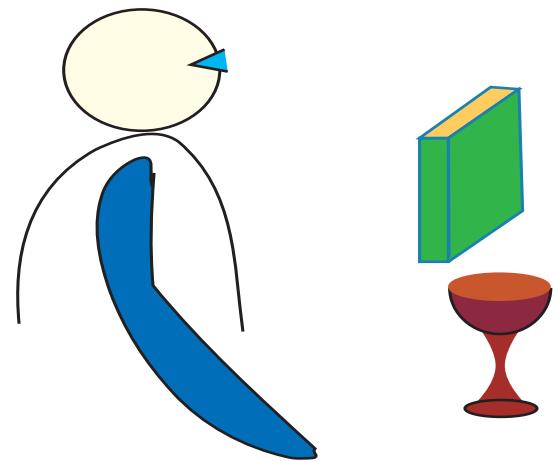
# Building embodied cognition

- notions in both scenarios
  - scene representation
  - generating sequences
  - concepts
  - goals, knowledge, problem solving

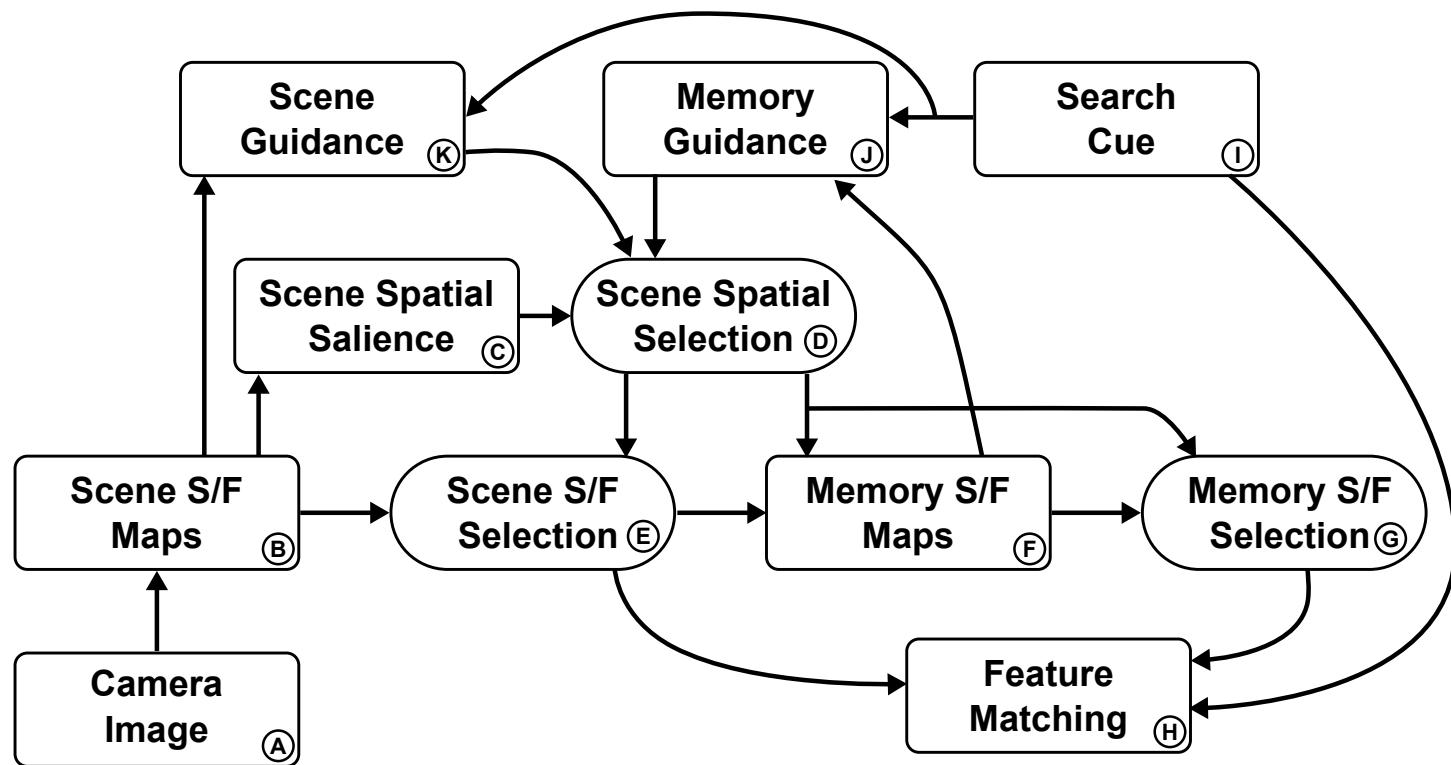


# Scene representation

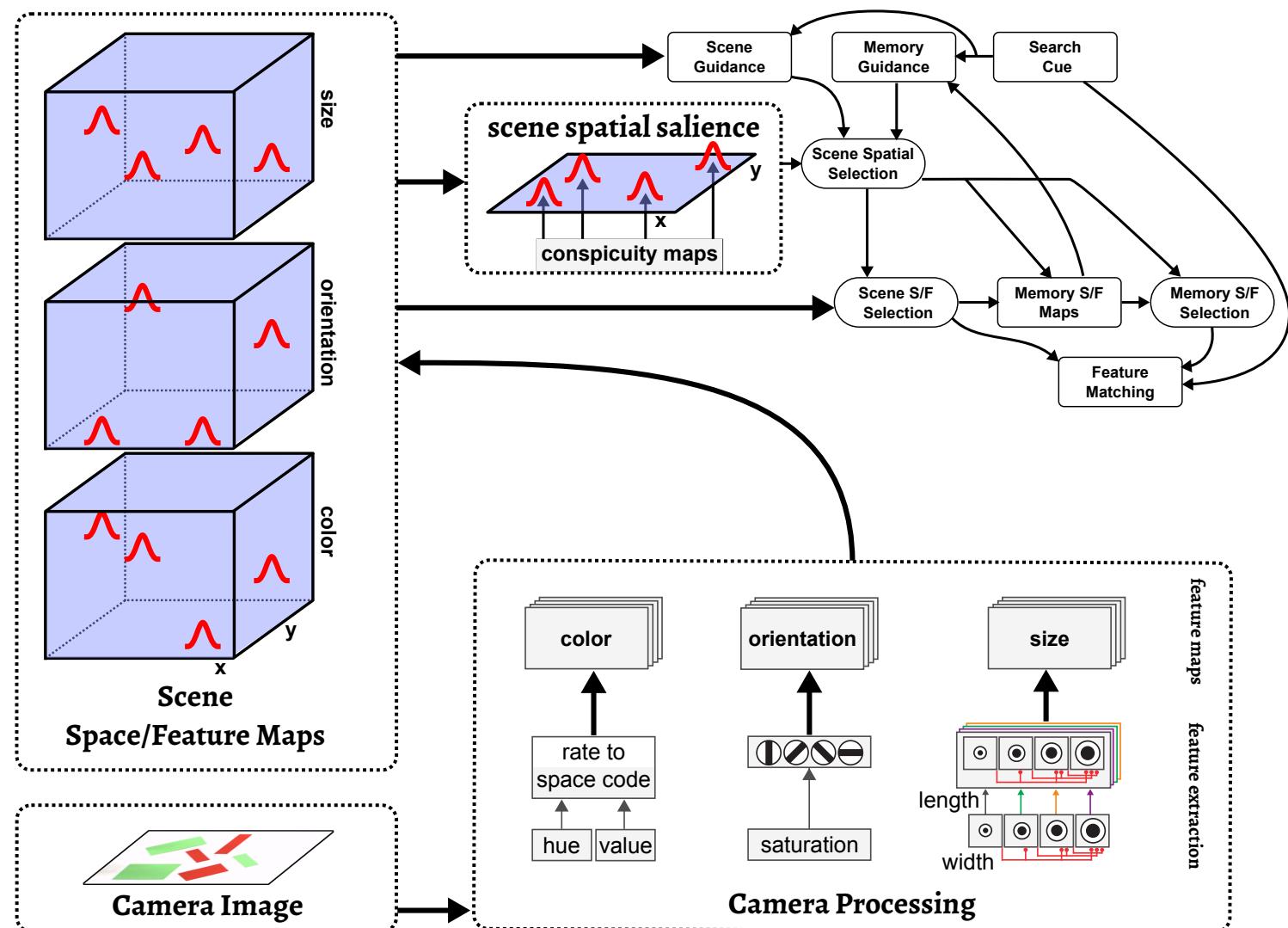
- any action directed at an object begins with bringing the object into the attentional foreground
  - visual search
  - attentional selection in scene memory
  - (selection within mental maps)



# Neural dynamic architecture of scene memory and visual search



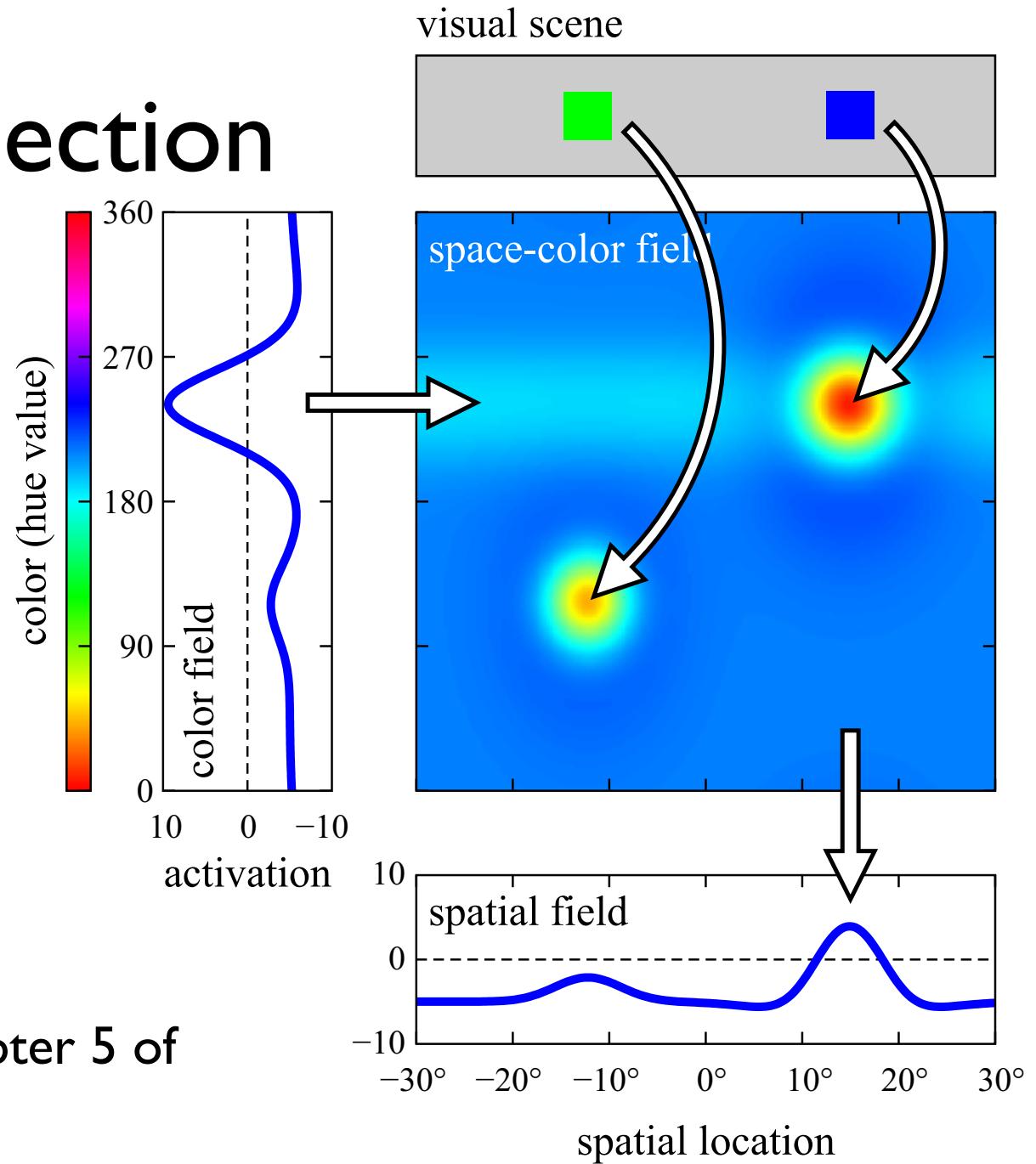
[Griebel et al, Attention, Perception & Psychophysics, in press]



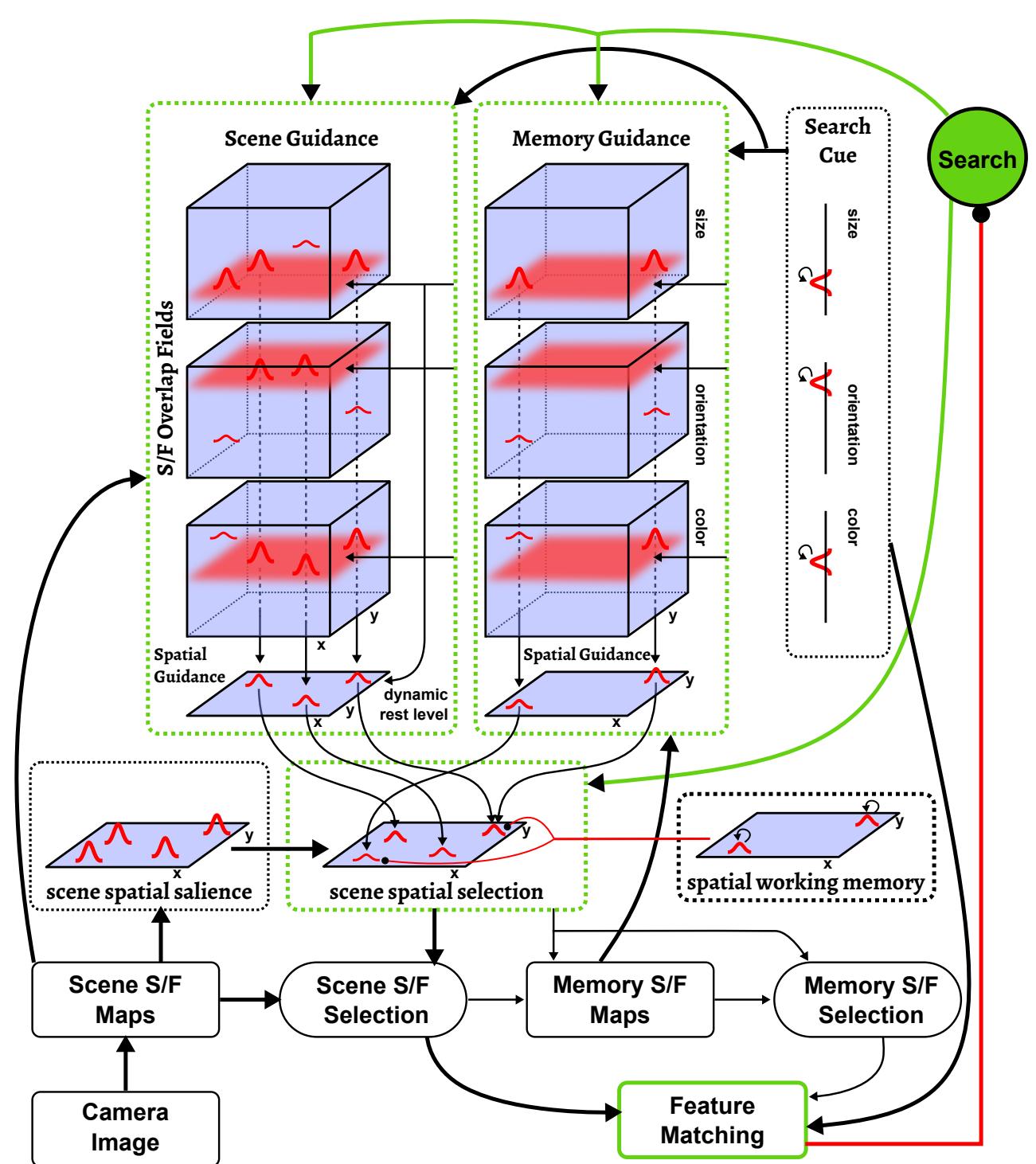
[Grieben et al, Attention, Perception & Psychophysics, in press]

# Attentional selection

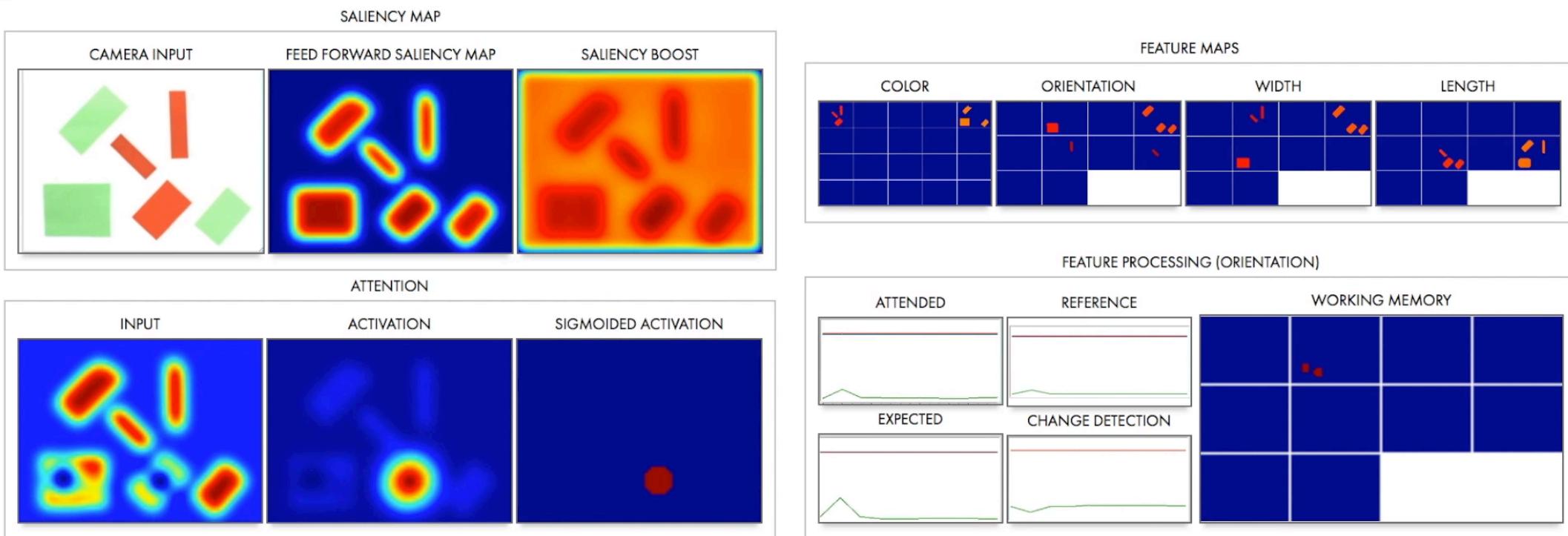
■ boost driven detection instability



[Schneegans, Lins, Spencer, Chapter 5 of DFT Primer, 2016]

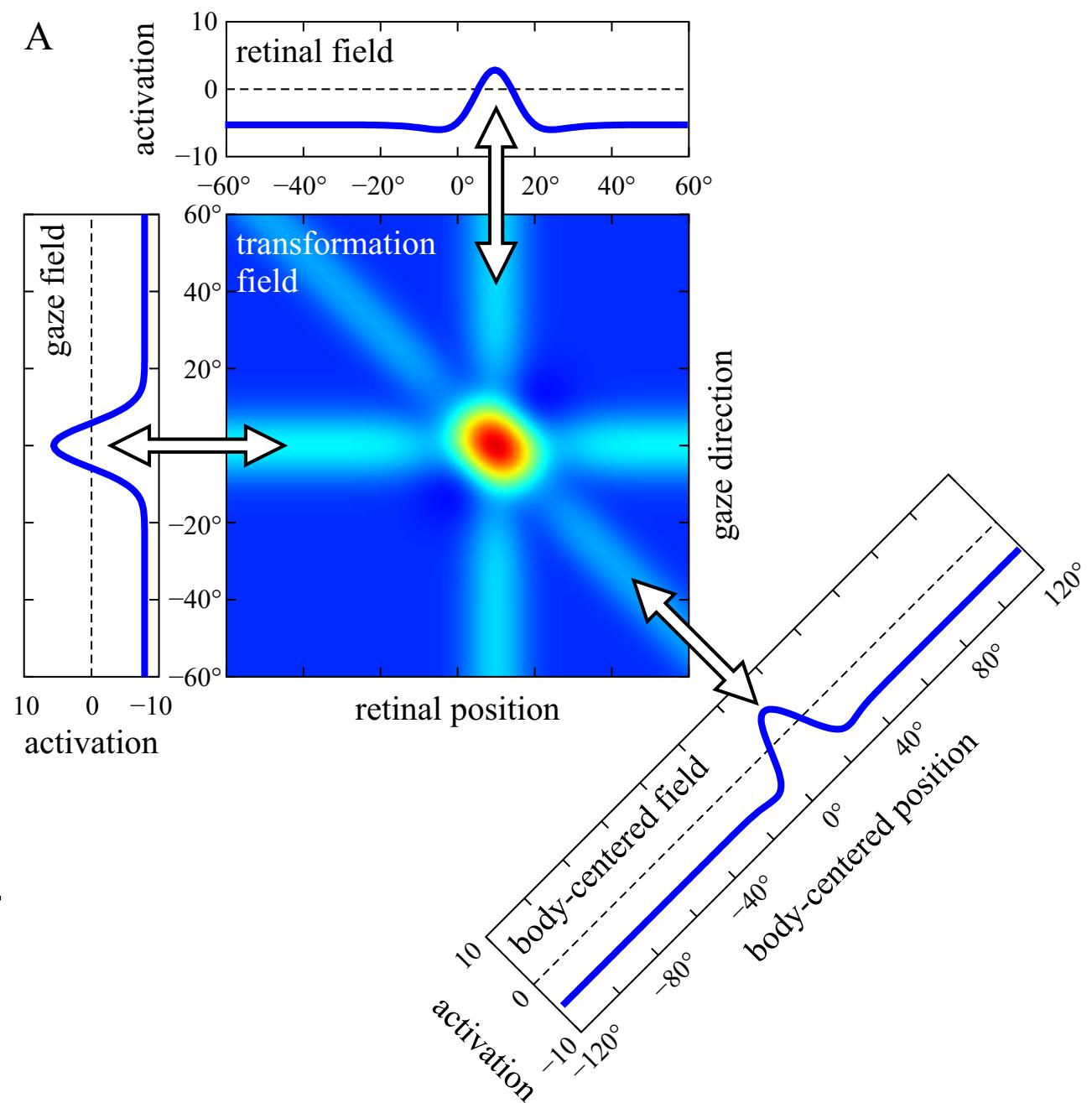


# Autonomous sequences of visual exploration and cued visual search



# Coordinate transformation

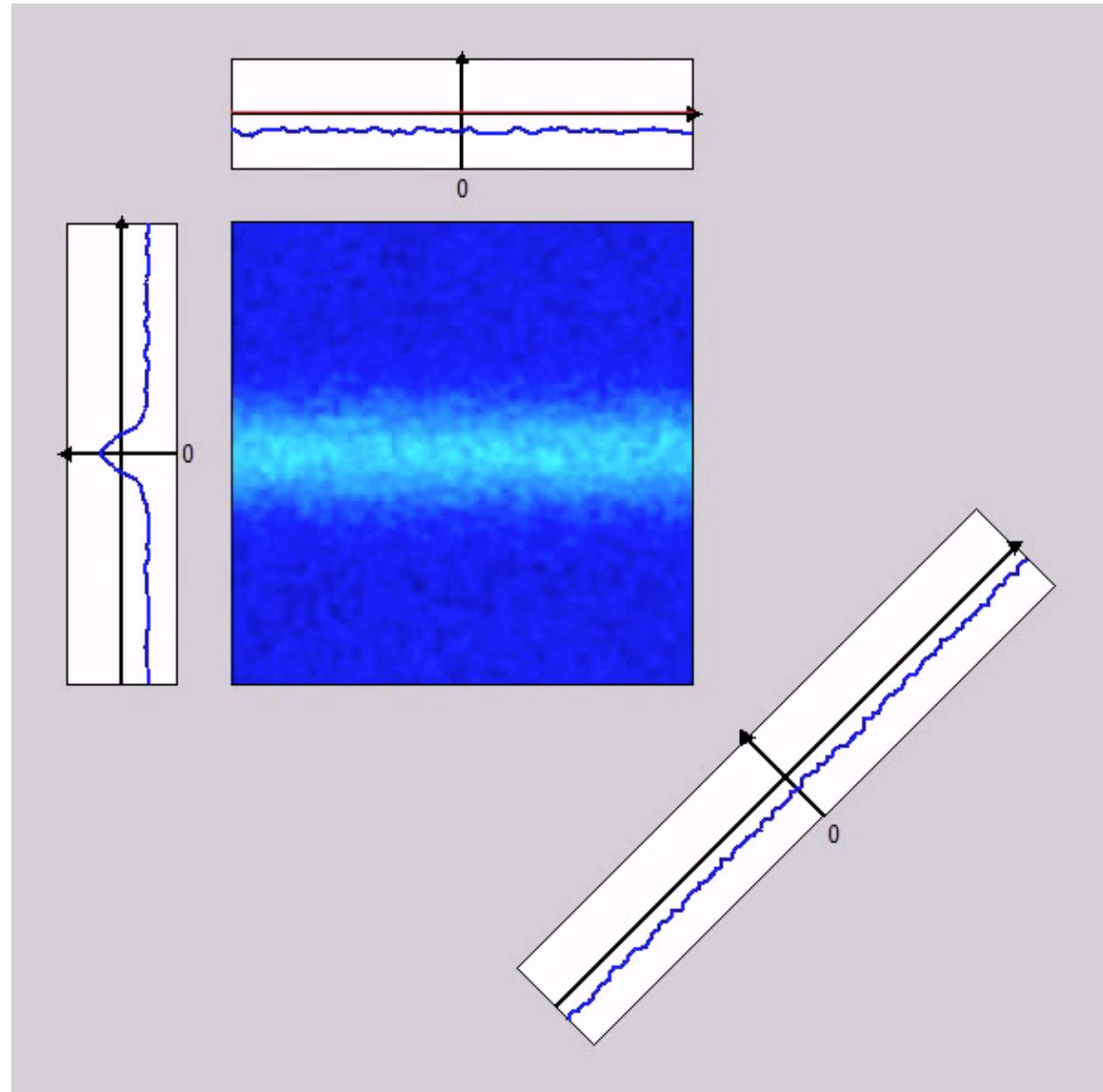
- are another function of multi-dimensional activation fields



[Schneegans, Chapter 7 of DFT Primer, 2016]

# Coordinate transformations

- are another function of multi-dimensional activation fields



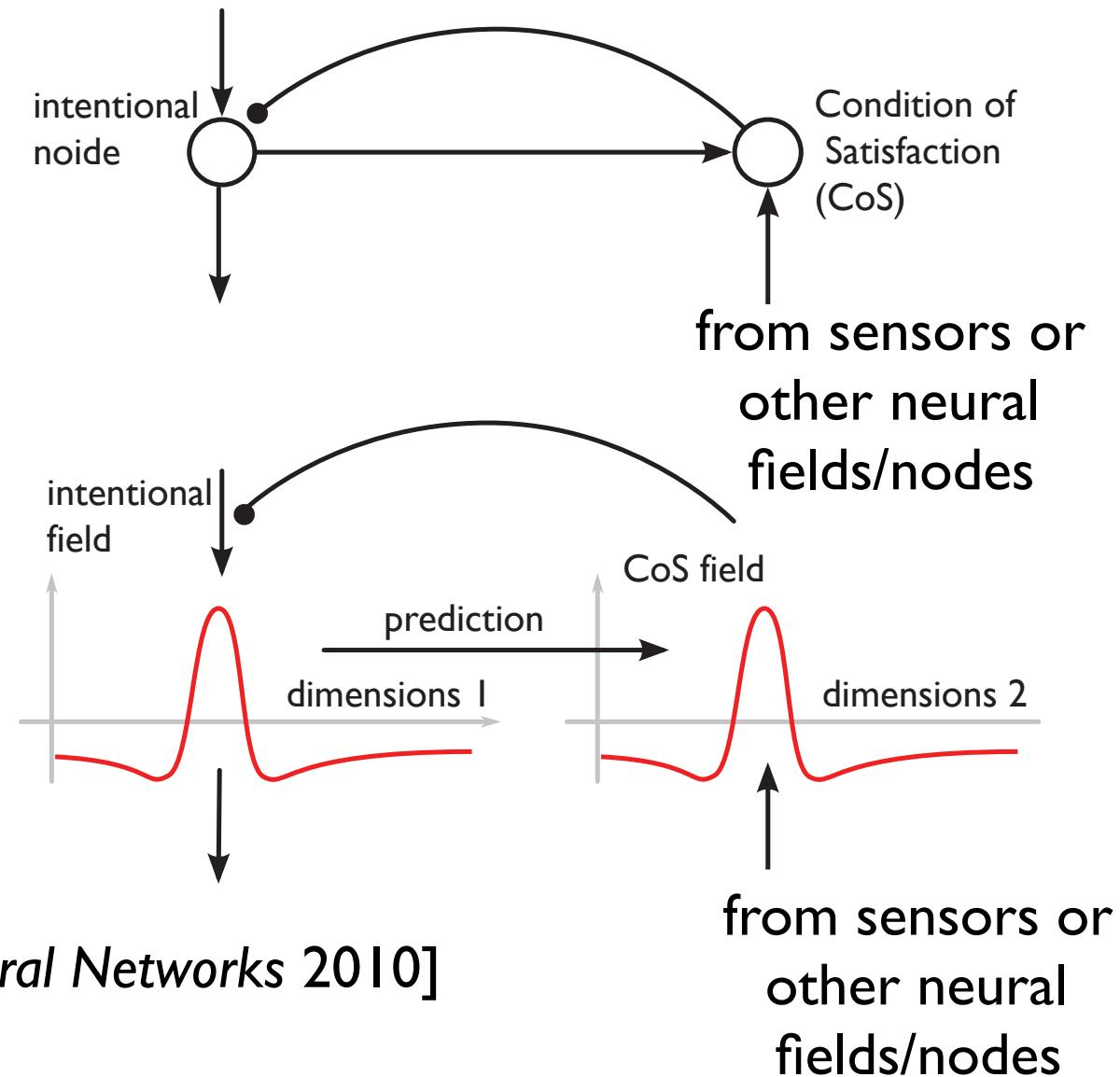
[Schneegans, Chapter 7 of DFT Primer, 2016]

# Sequence generation

- Actions and thoughts consist of sequences of mental states that unfold autonomously
  - not necessarily “triggered” by external inputs

# Sequences in neural dynamics

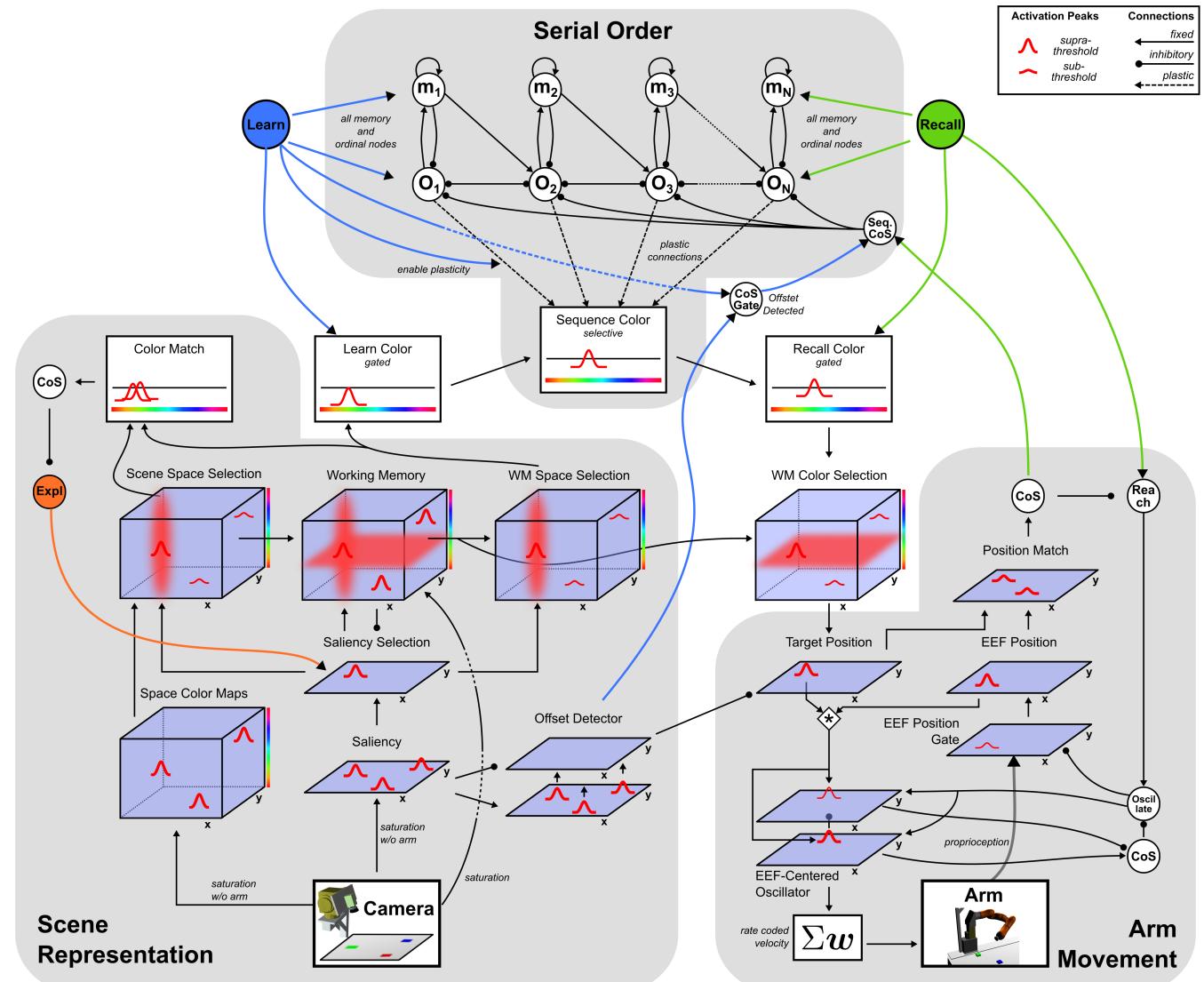
- intentional states predict/pre-activate their CoS=Condition of satisfaction
- match of prediction activates CoS and inhibits the intentional state



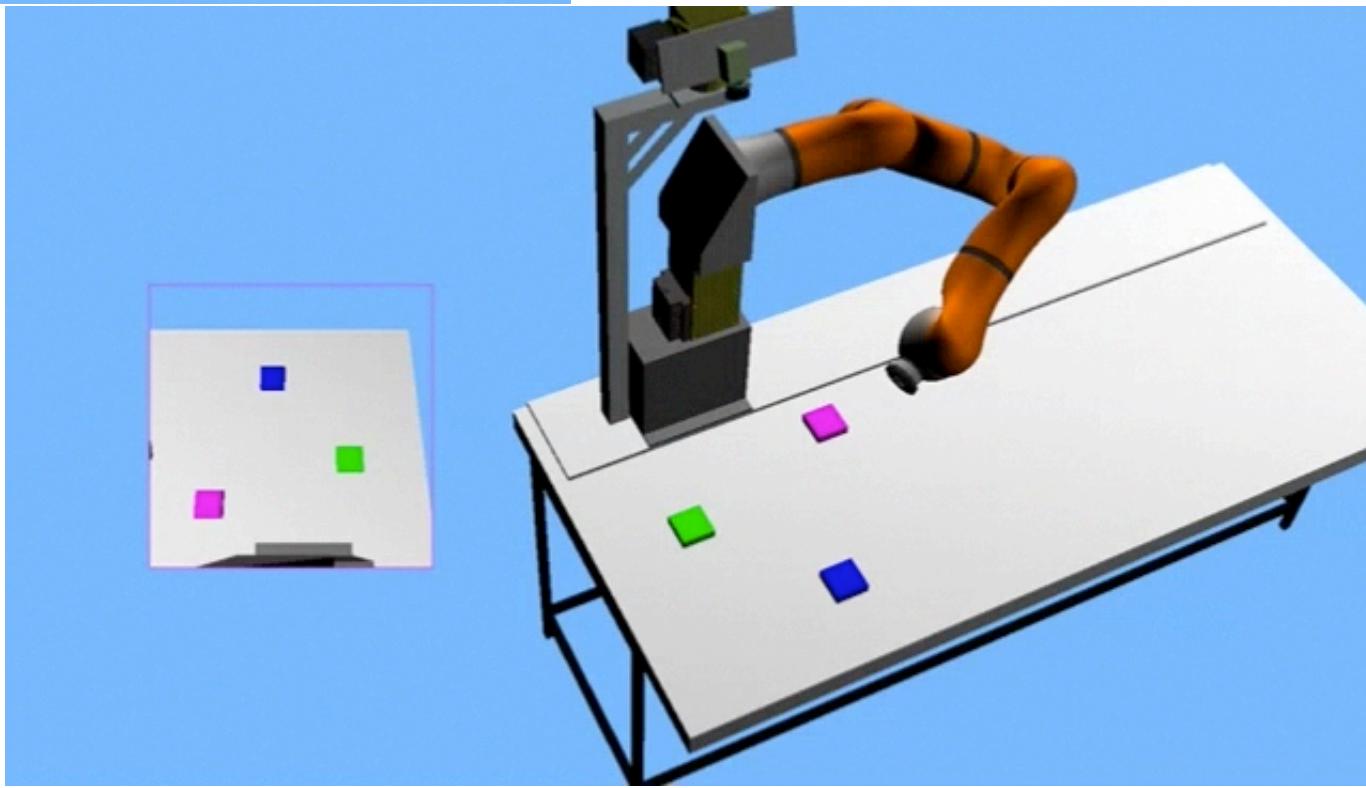
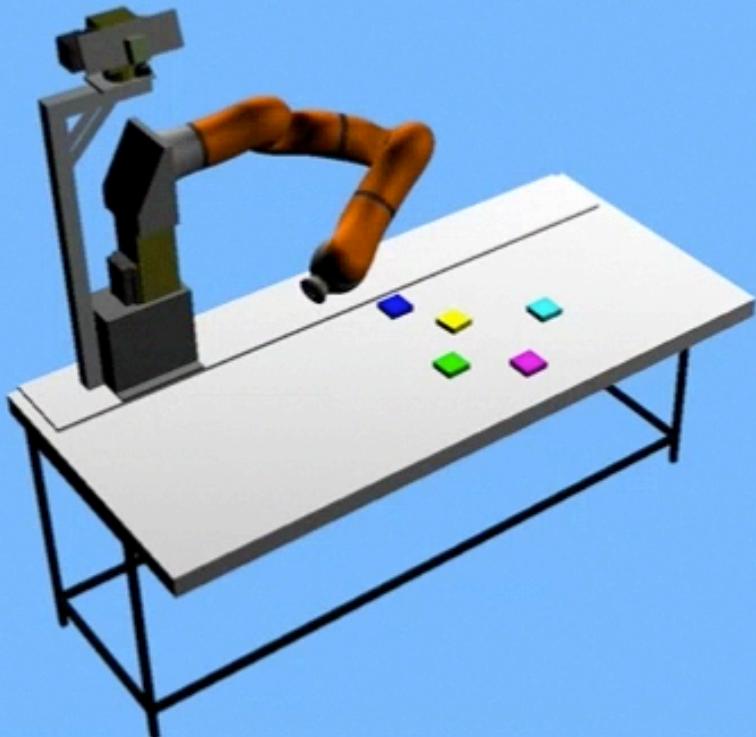
[Sandamirskaya, Schöner, *Neural Networks* 2010]

# Sequence generation directed at objects

- serial order from demonstration
- => sequence of pointing movements



[Tekülve et al., *Frontiers in Neurorobotics* (in press)]

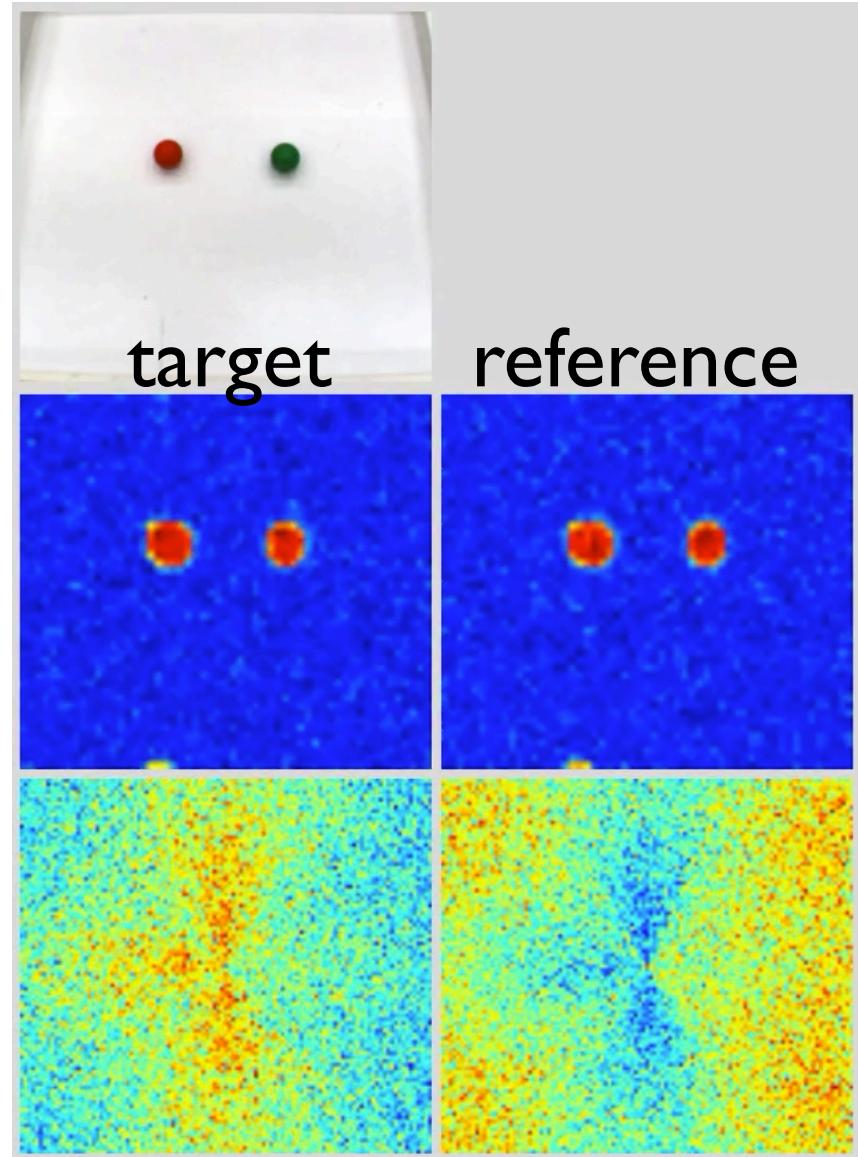


# Concepts, relational thinking

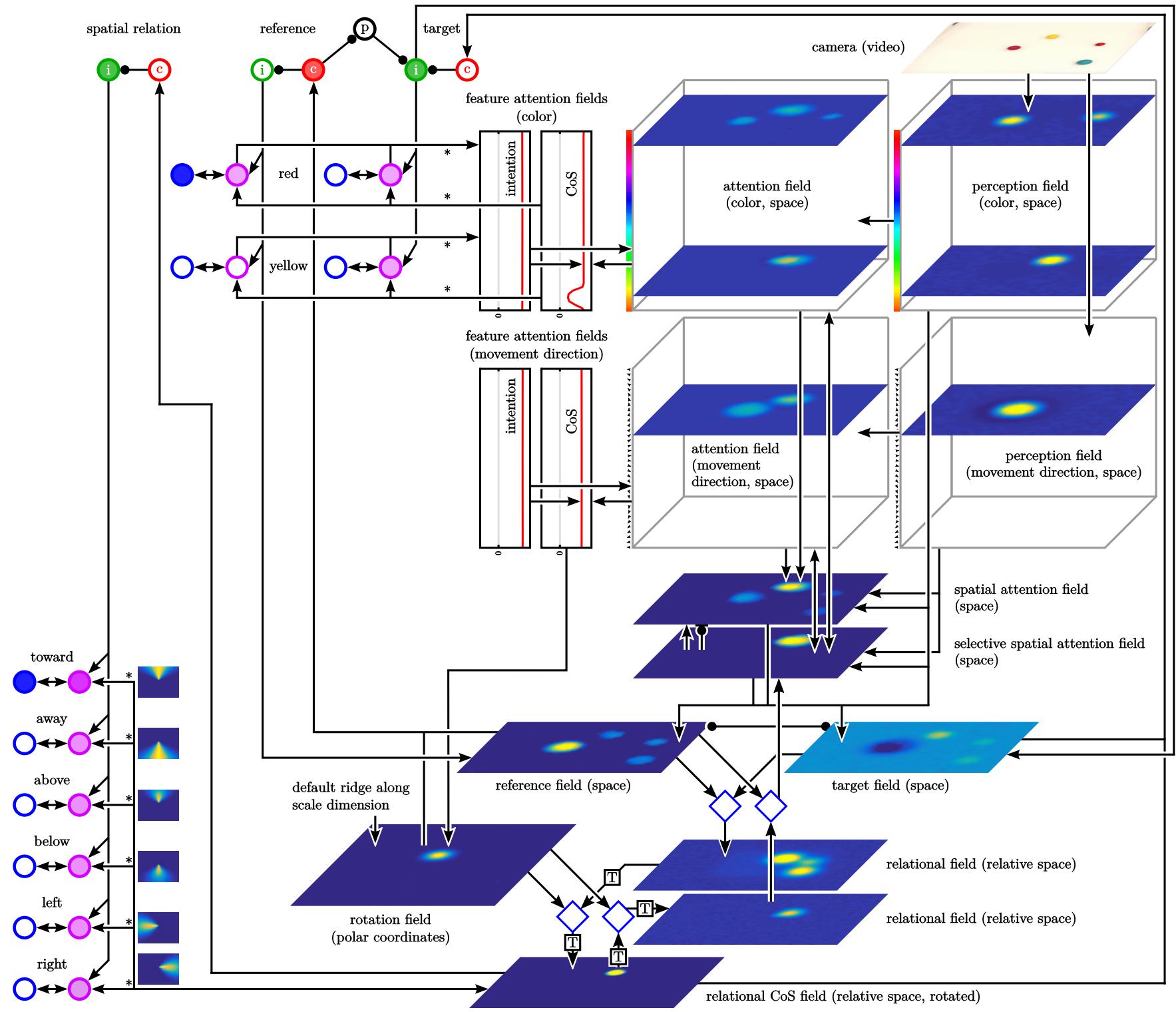
“red to the left of green”

- Talking about objects entails bringing the targeted object into the attentional foreground

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



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



# role filler binding

spatial relation

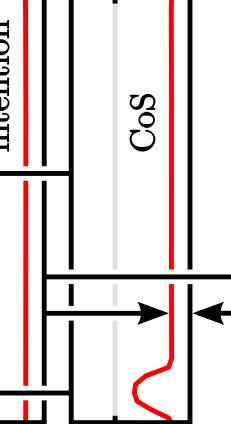
reference

target



feature attention fields

(color)



red

red

intention

CoS

yellow

yellow

intention

CoS

color  
concepts

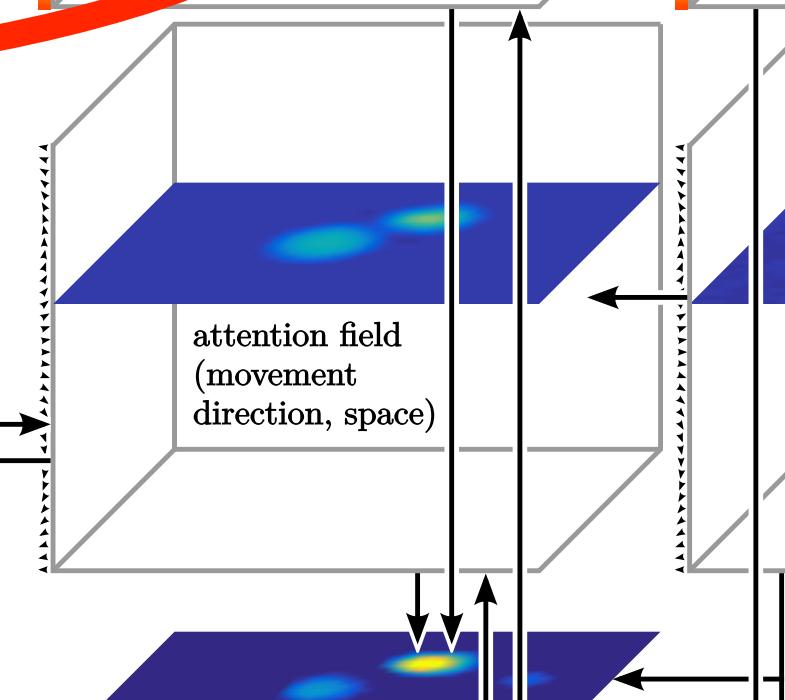
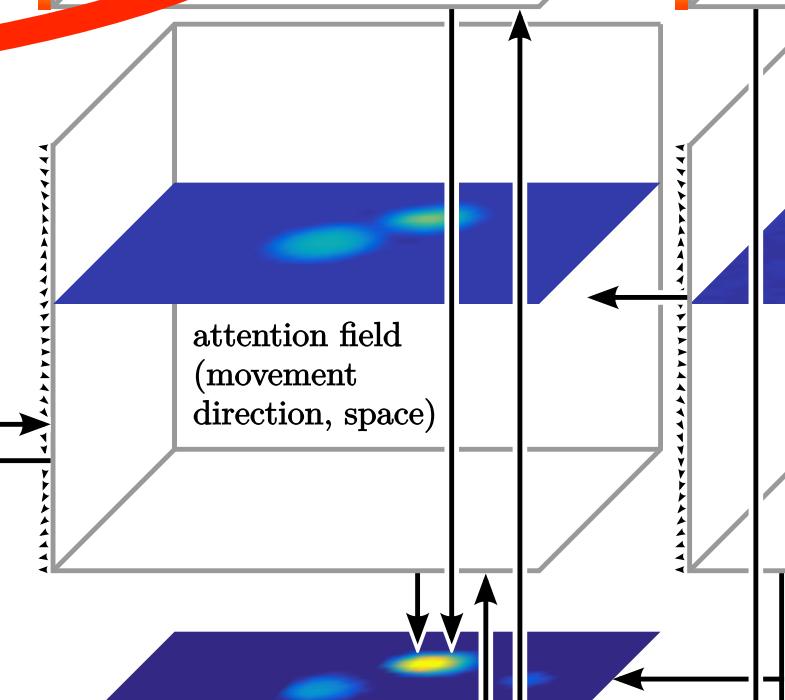
feature attention fields  
(movement direction)

intention

CoS

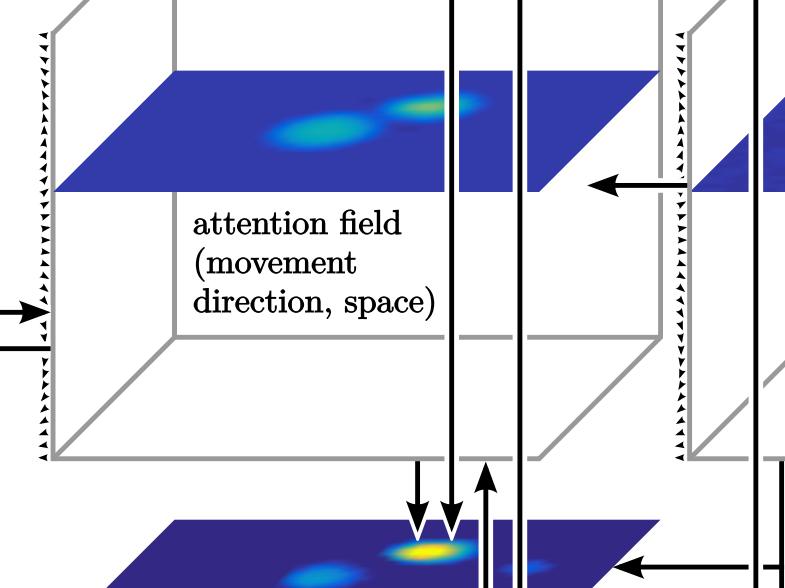
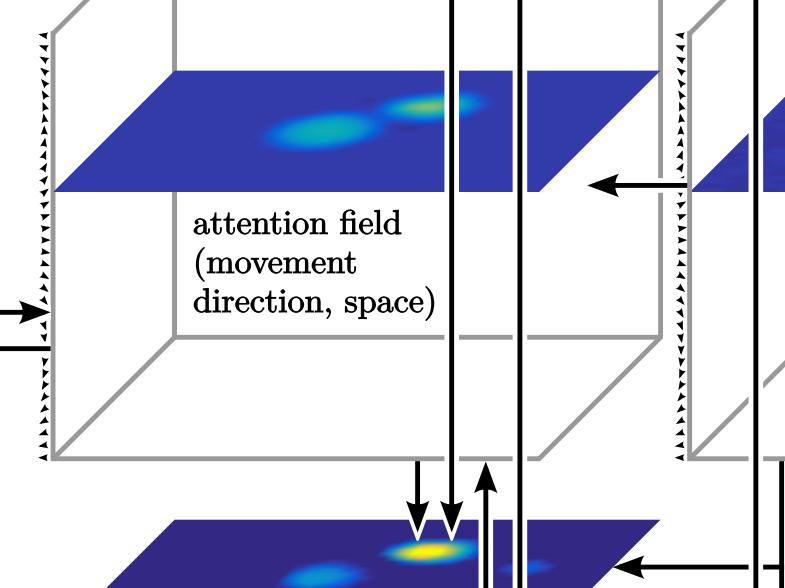
intention

CoS

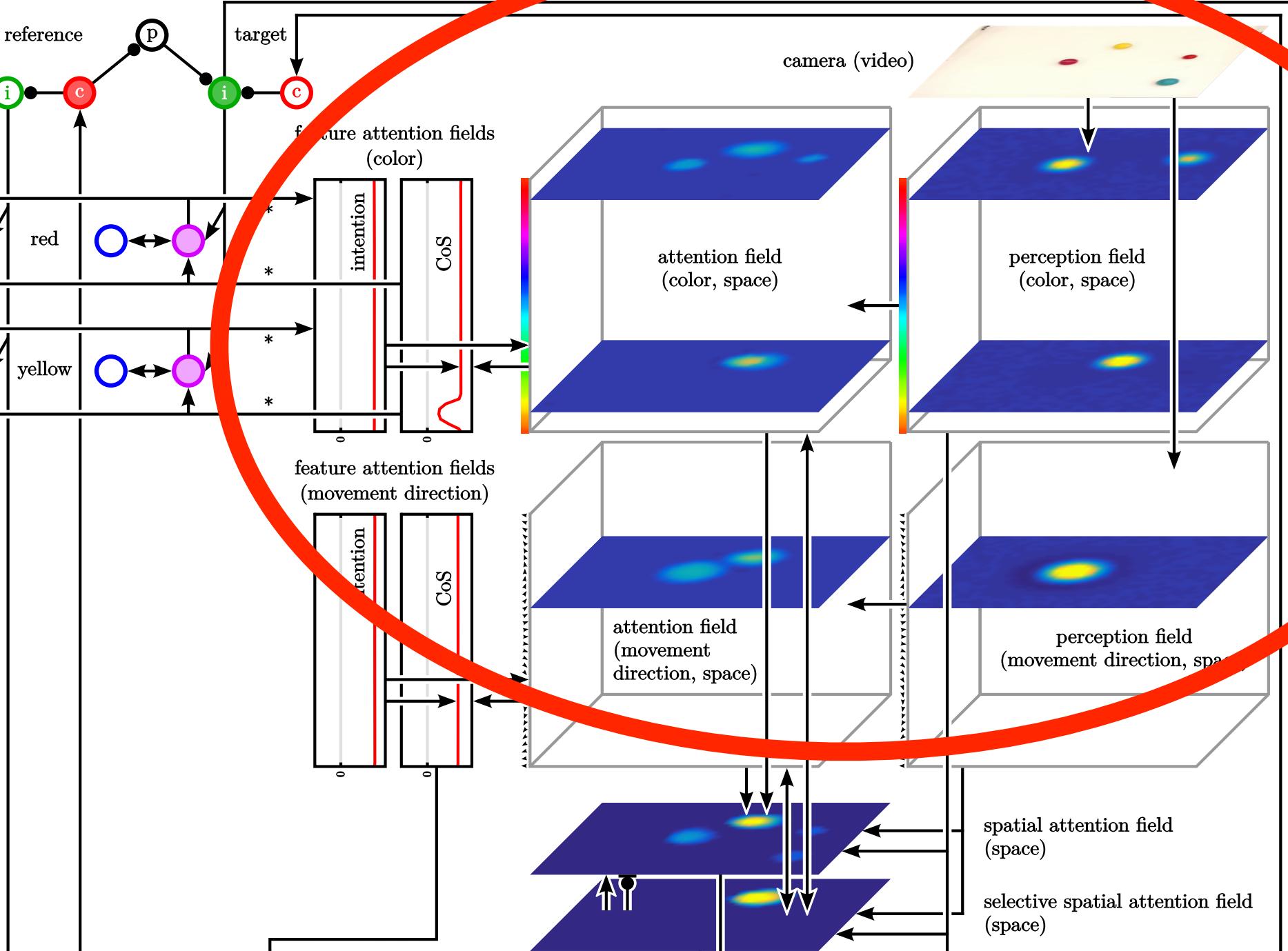


camera (video)

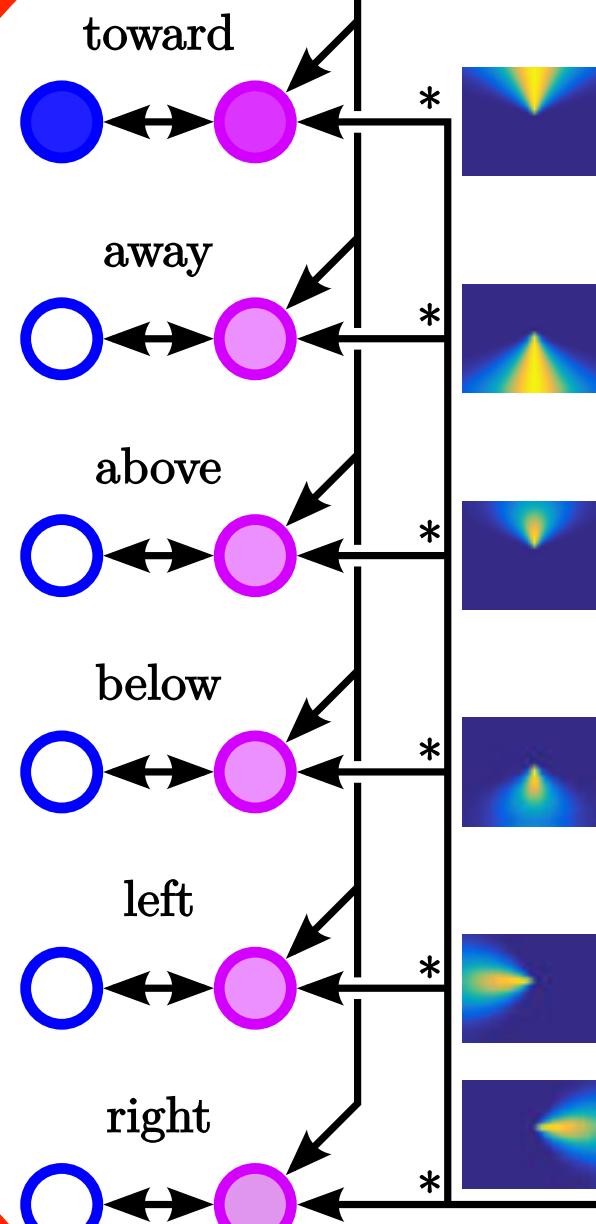
attention field  
(color, space)



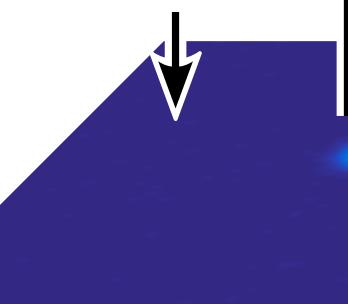
# cued visual search



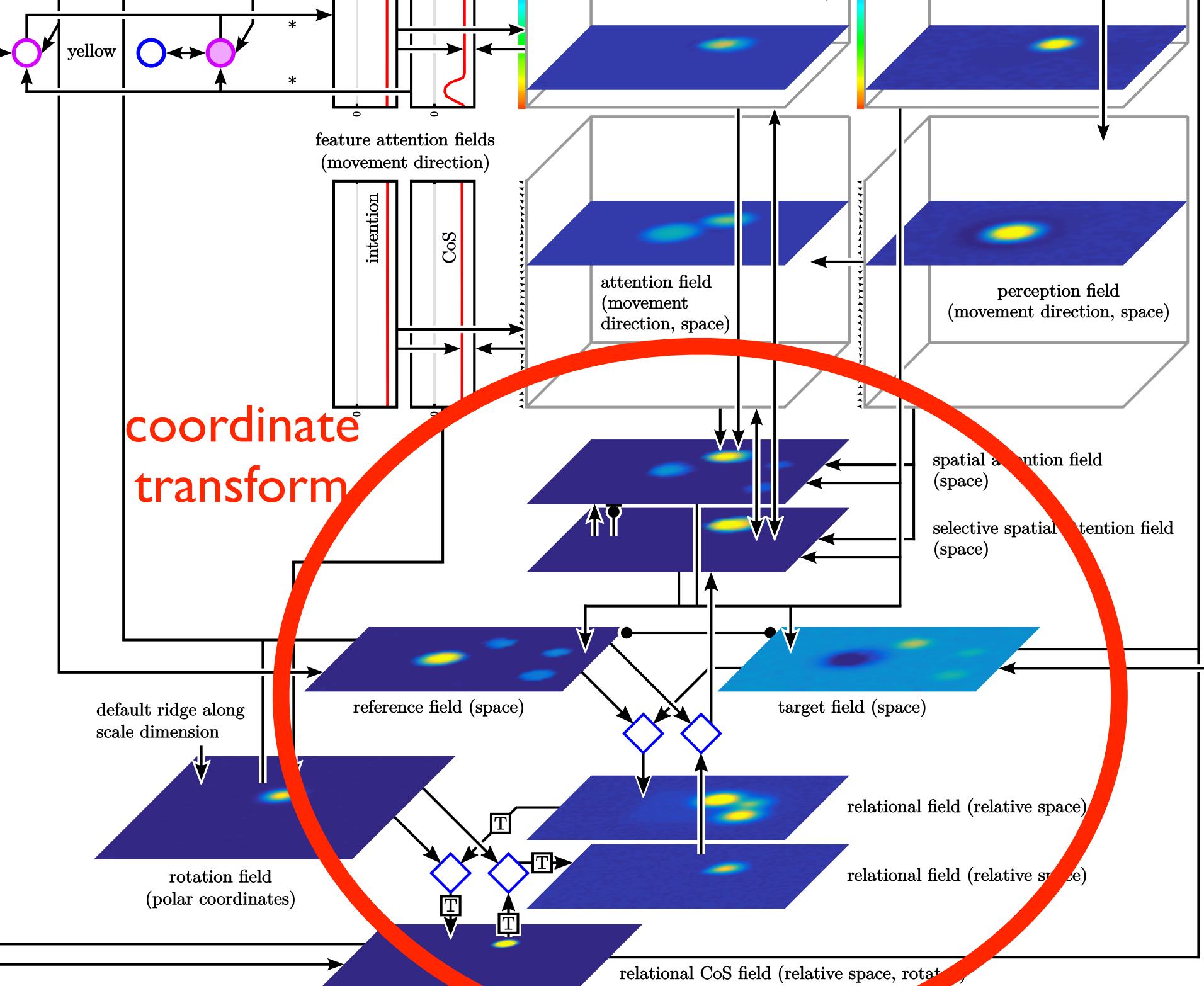
# relational neural operators



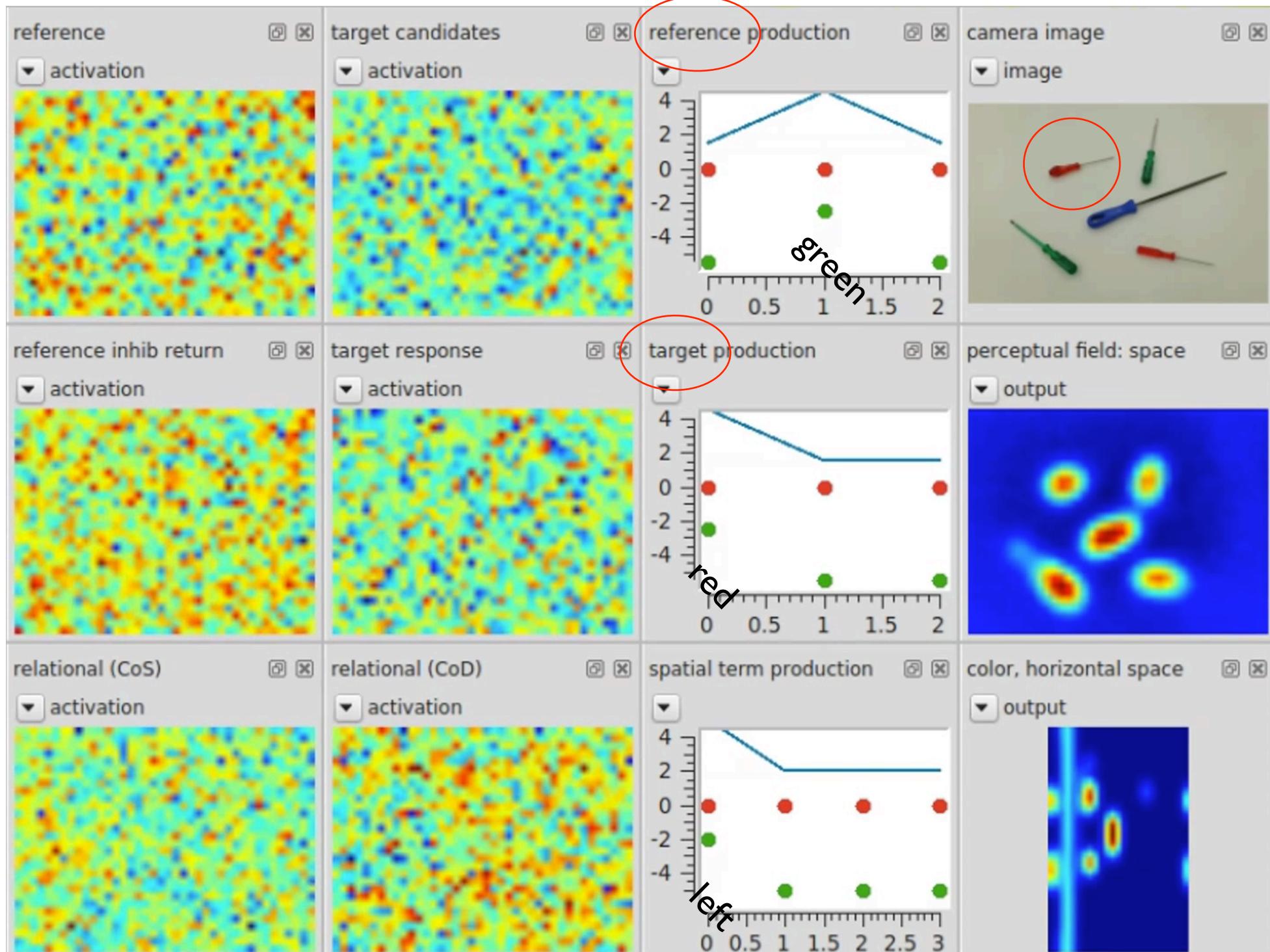
default ridge along  
scale dimension



rotation field  
(polar coordinates)



“red to the left of green”



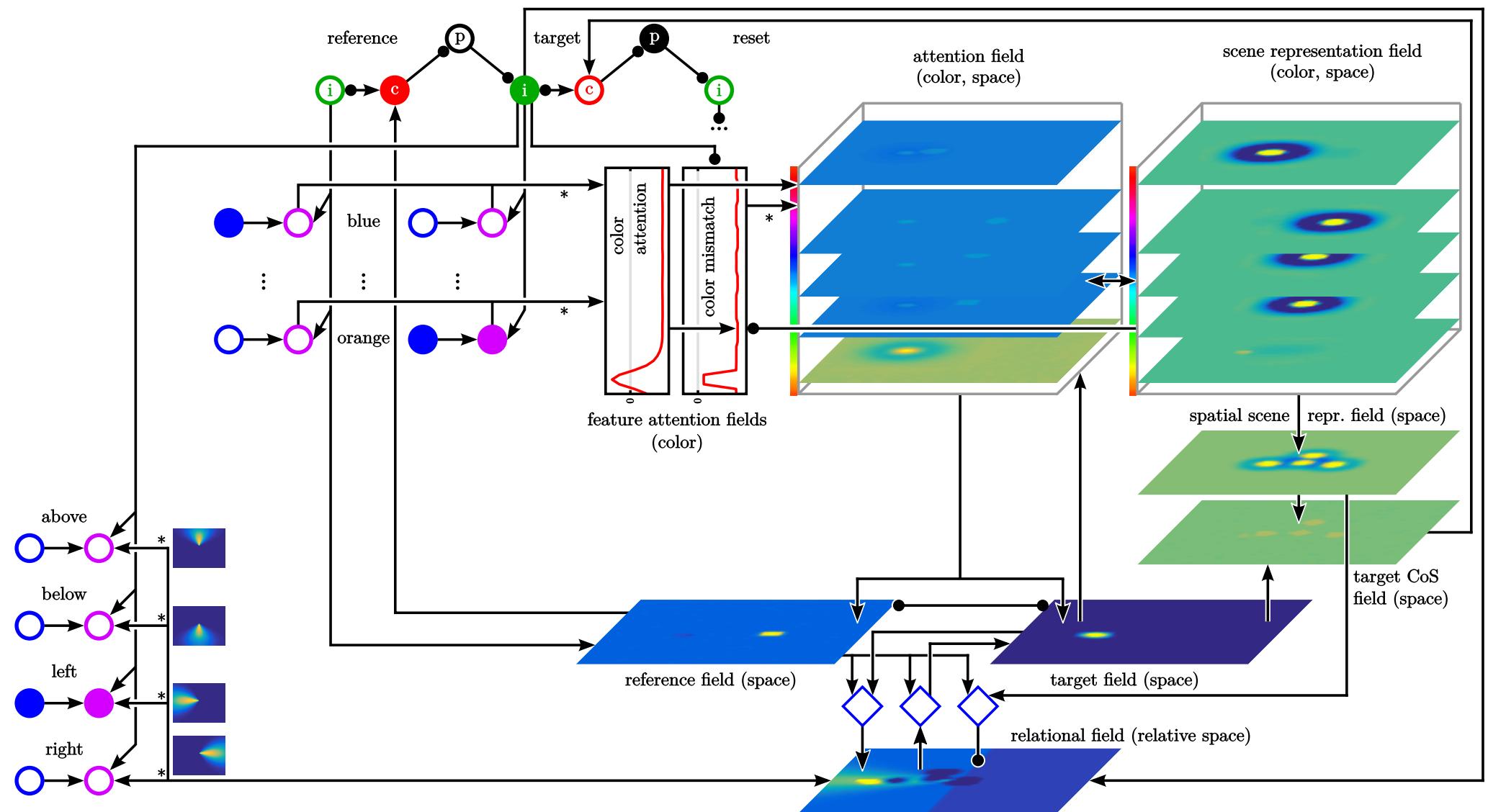
# purely “mental” scene representation

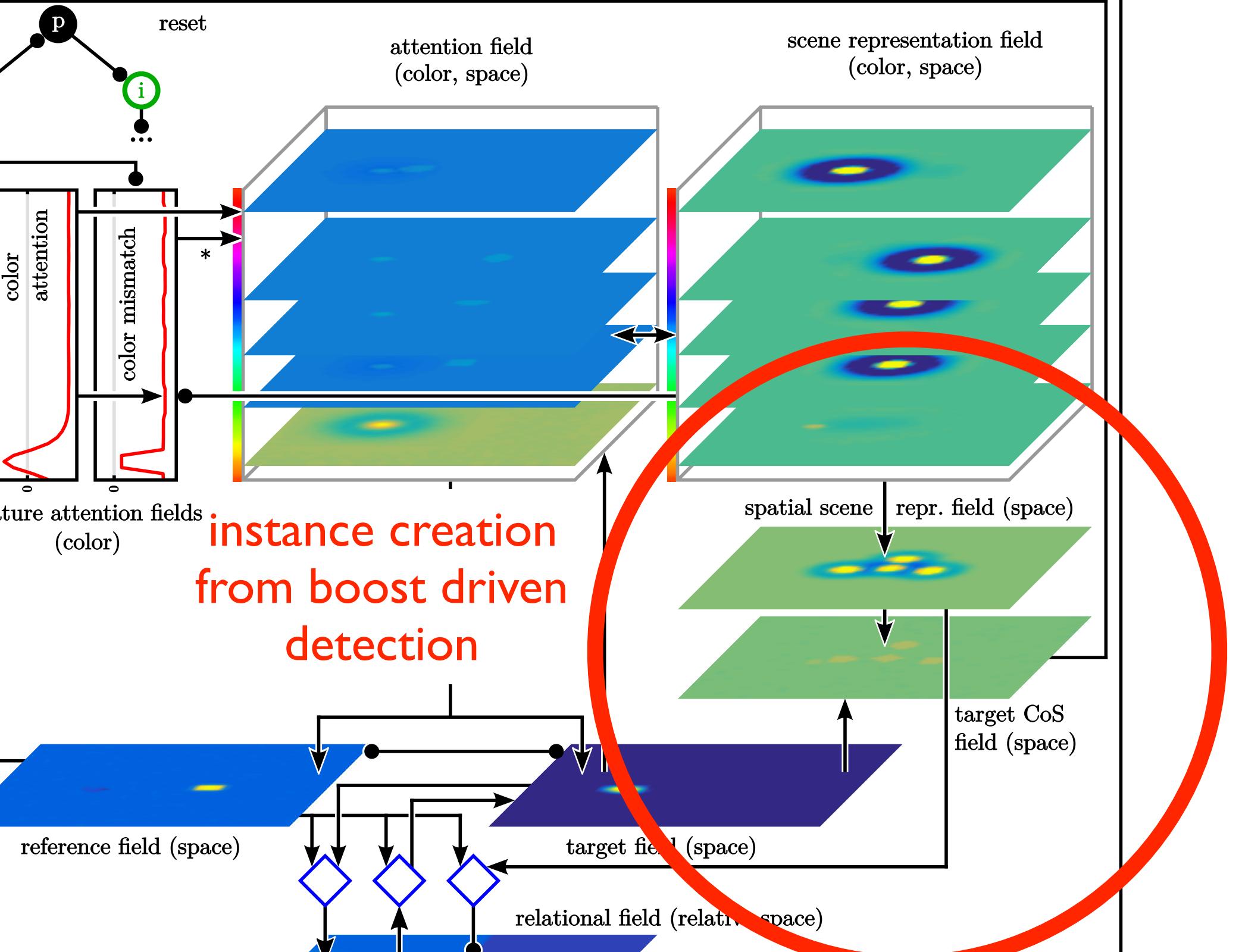
## ■ from propositions

- “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.”

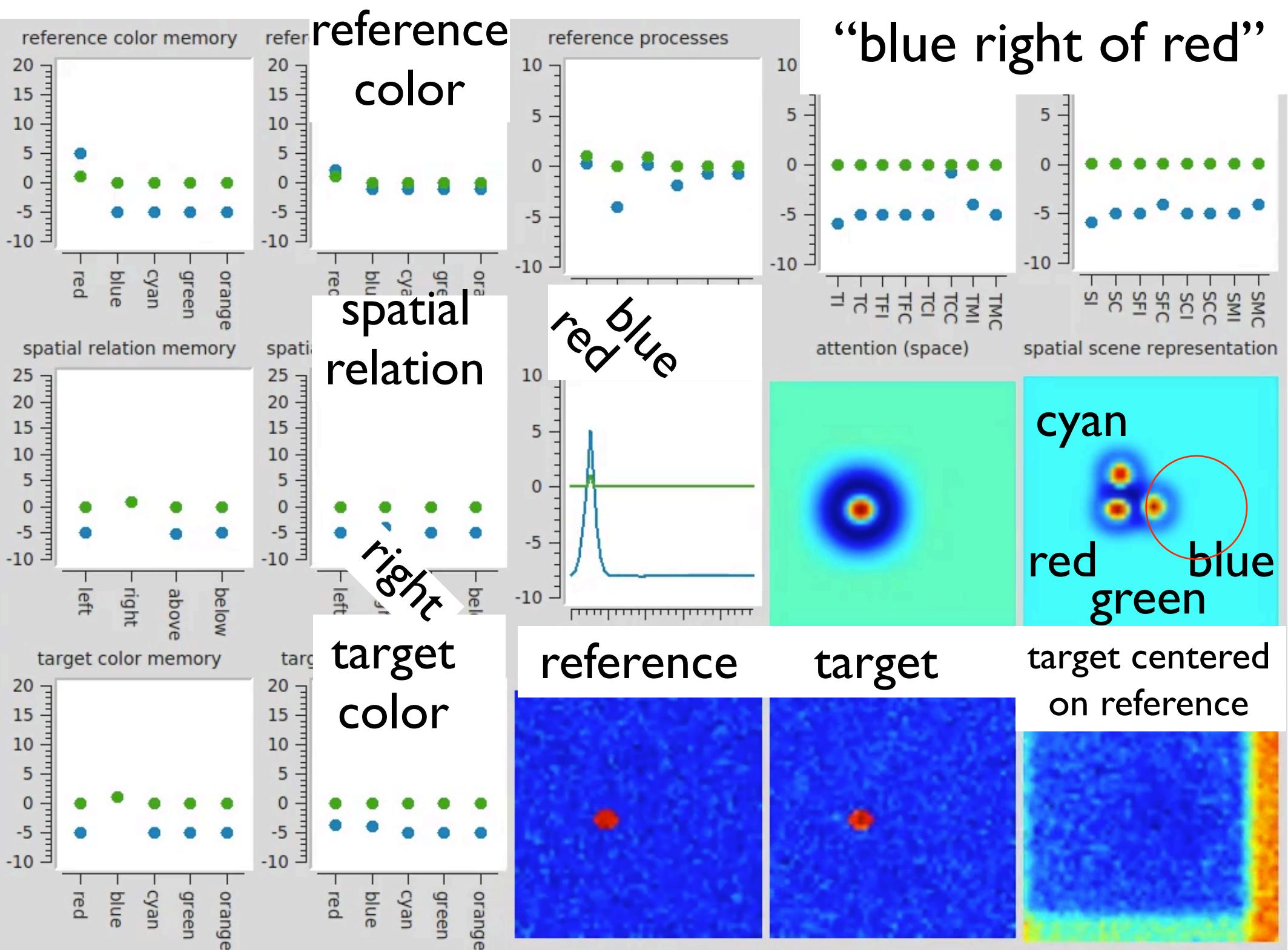
## ■ inference

- “Where is the blue object relative to the red object?”



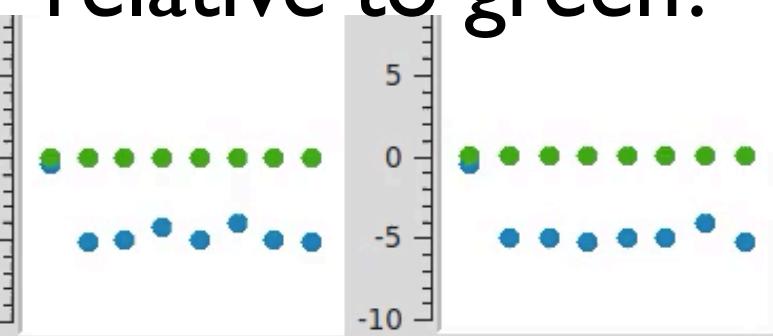
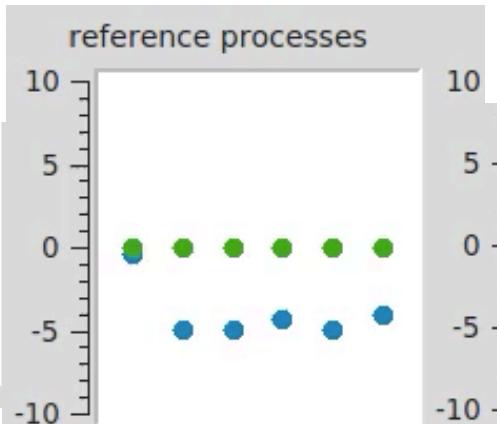
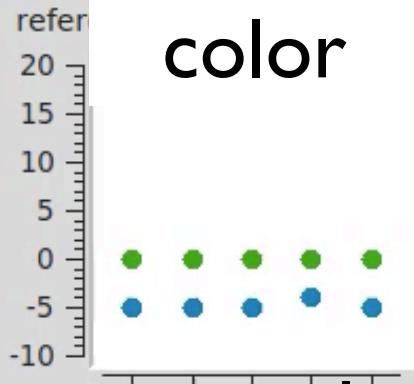
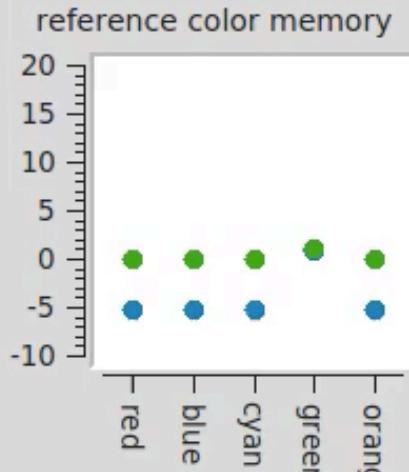


“blue right of red”

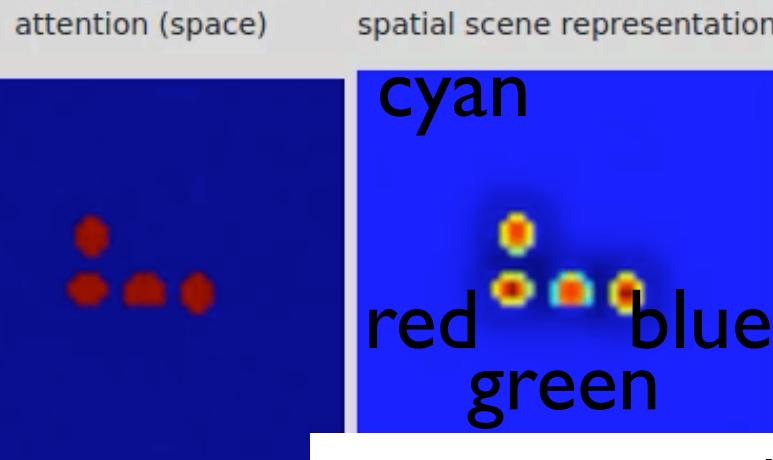
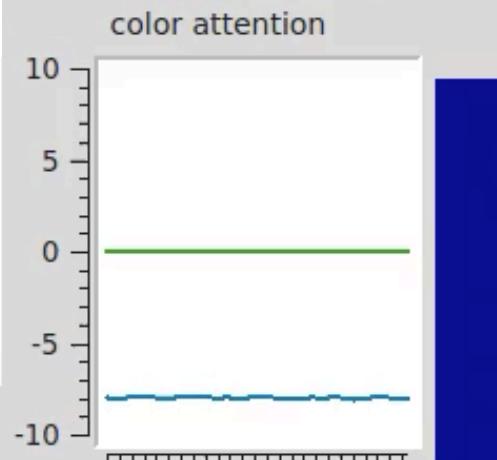
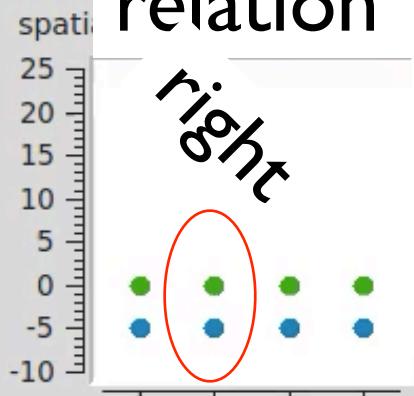
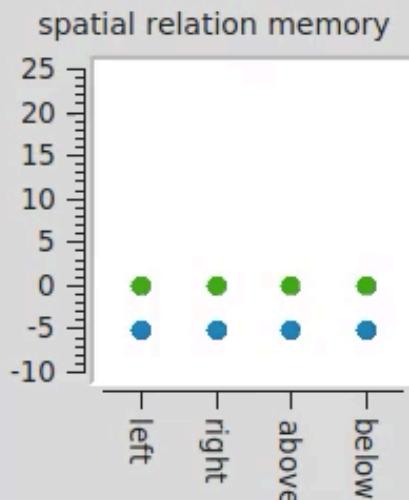


“where is blue  
relative to green?”

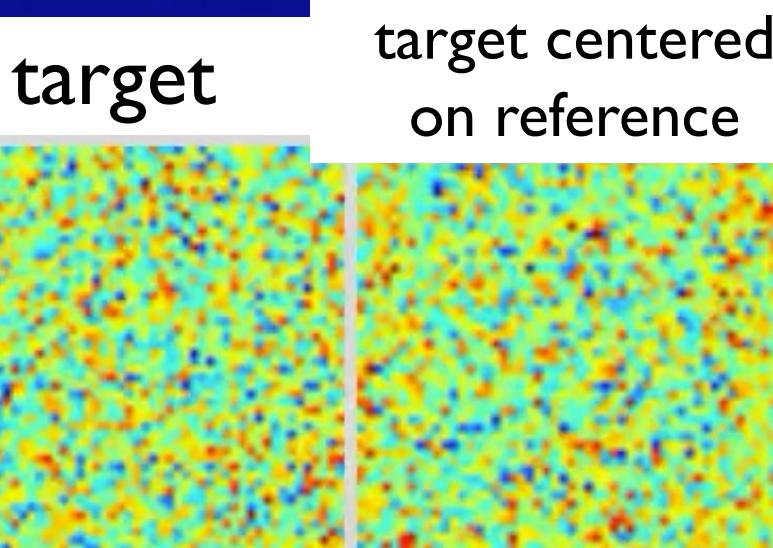
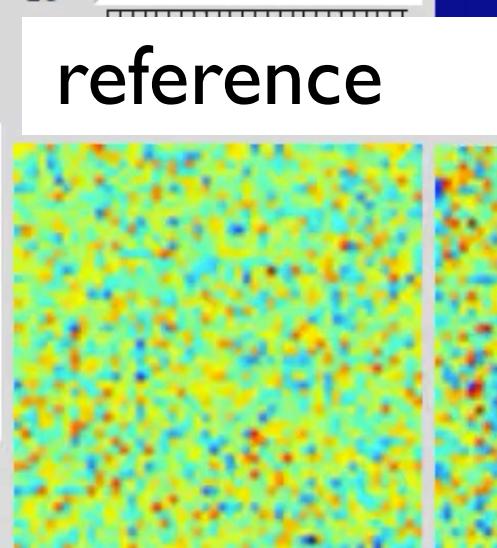
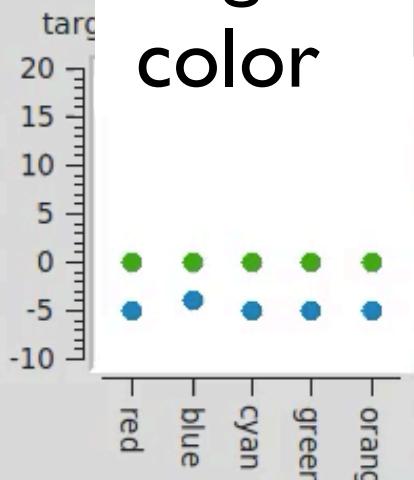
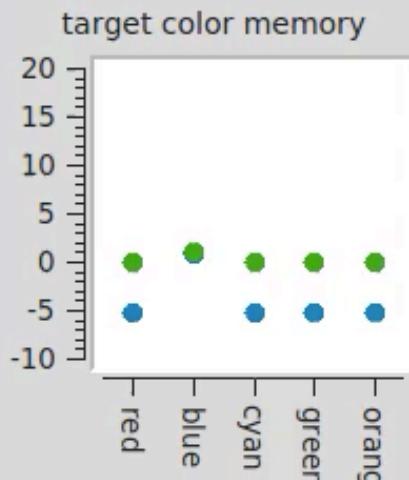
reference  
color



spatial  
relation

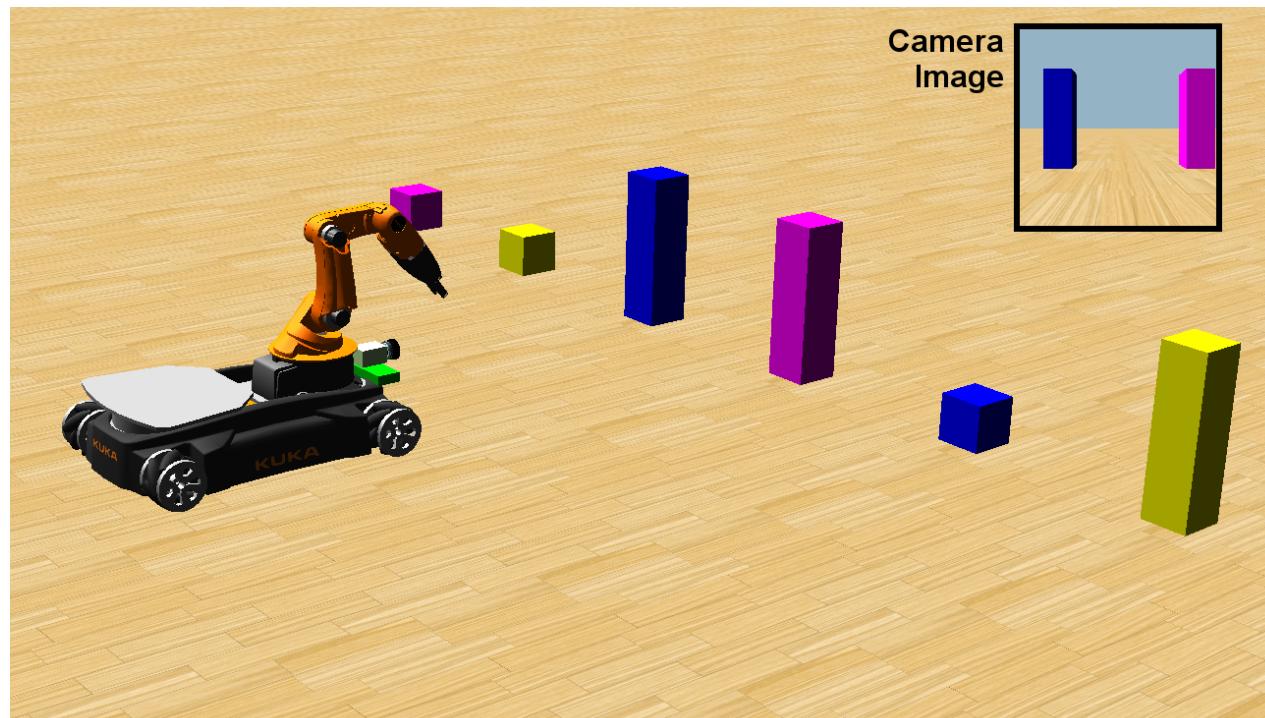


target  
color



cyan  
red  
blue  
green  
target centered  
on reference

# Goals, knowledge, problem solving



## world

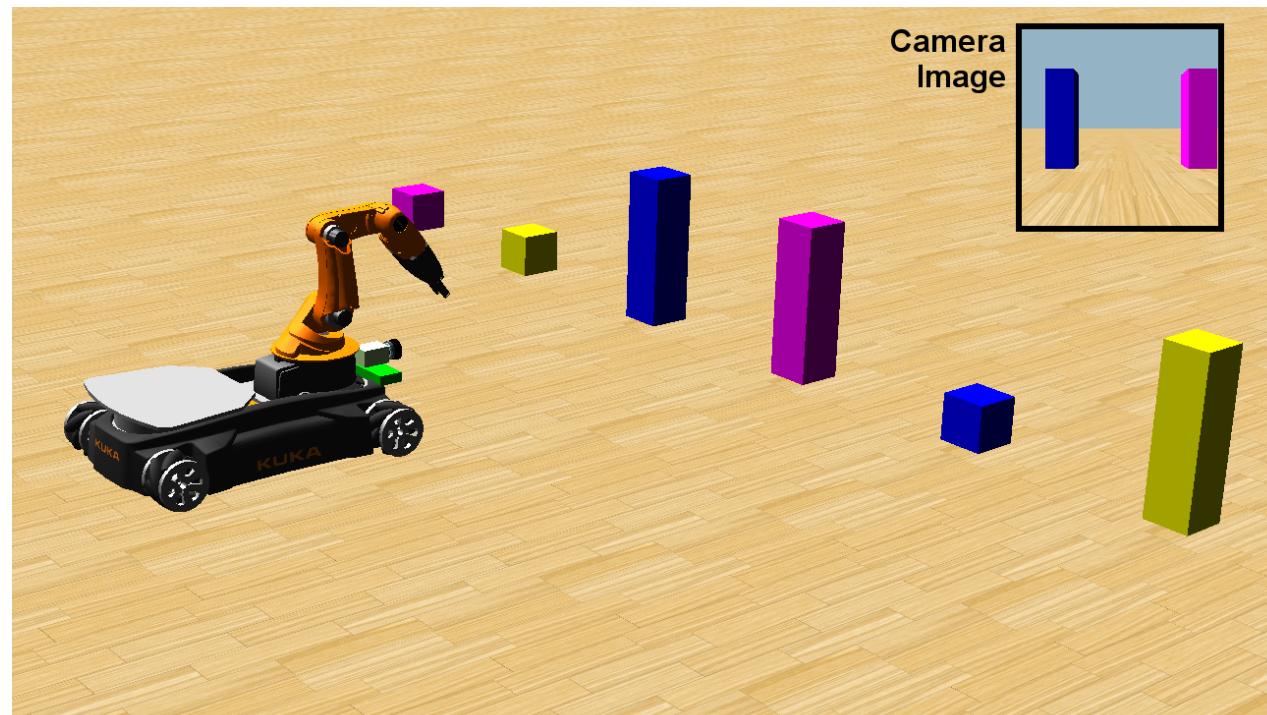
- colored objects (small)
- paint buckets (tall)
- vehicle with arm

## perception

- see color/feature
- sense position, arm, paint in gripper

## intention in action

- move in 1D
- reach to take up paint
- reach to apply a coat of paint



# memory

- of visual scene

# prior intentions

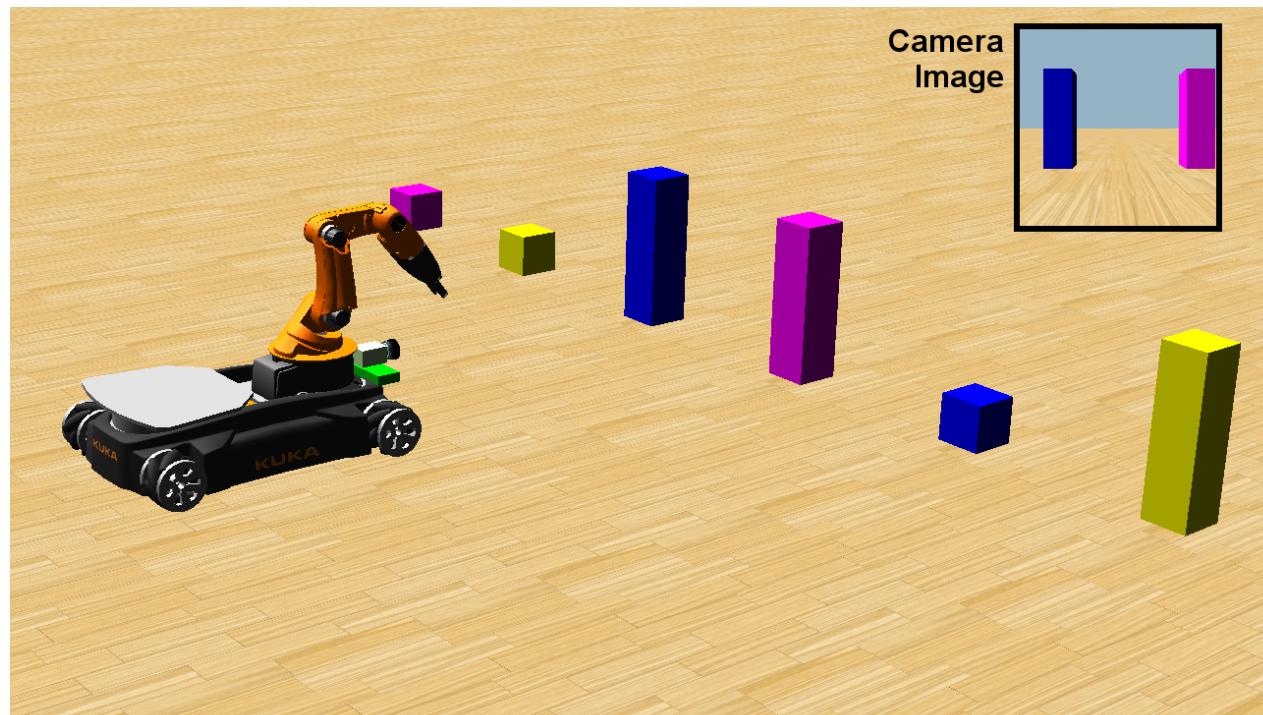
- search to paint
- search to load paint
- reach to apply paint
- move to a recalled location

# beliefs

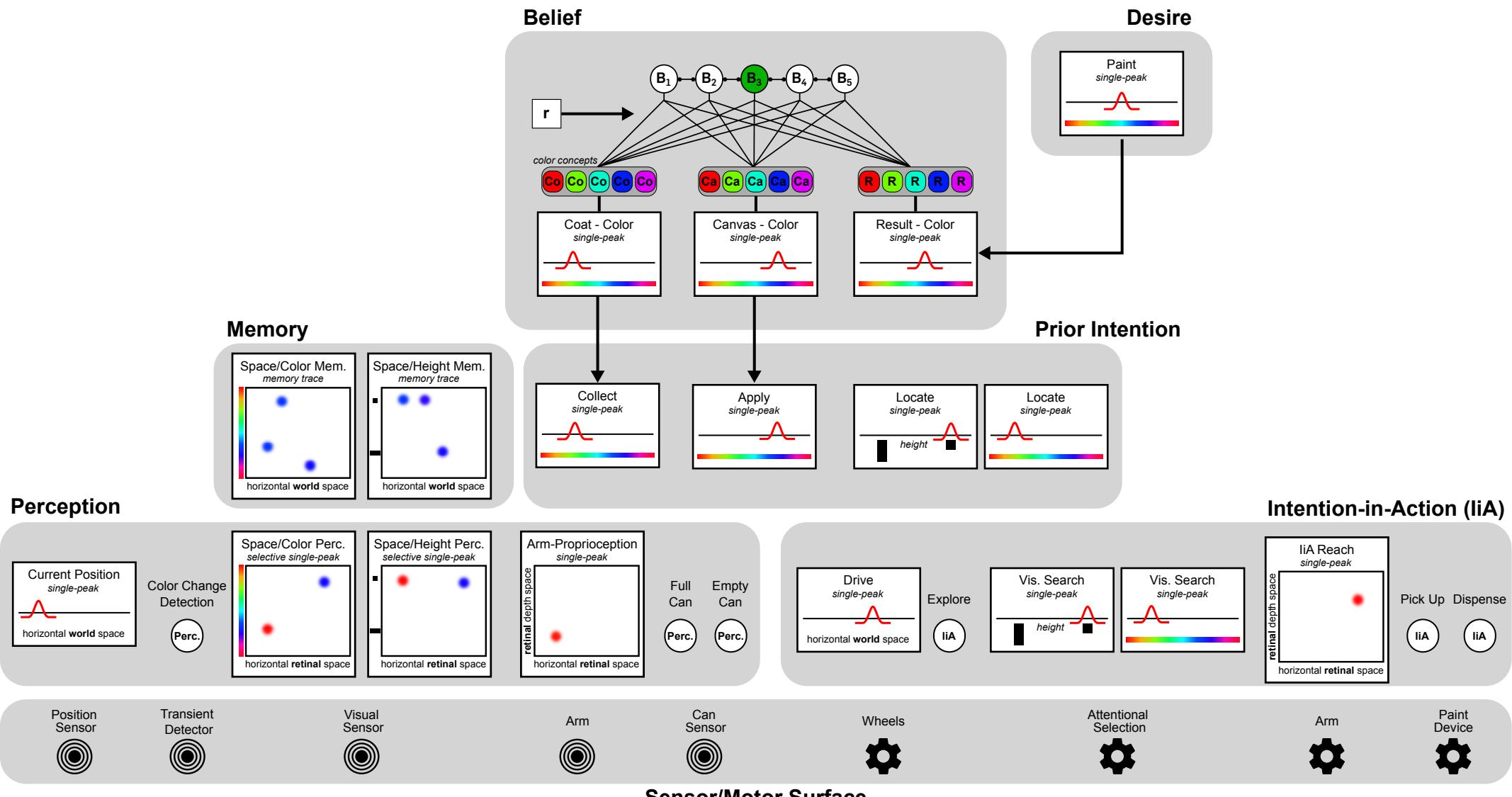
- rules linking color concepts:  
which paint on which canvas  
generates which new color

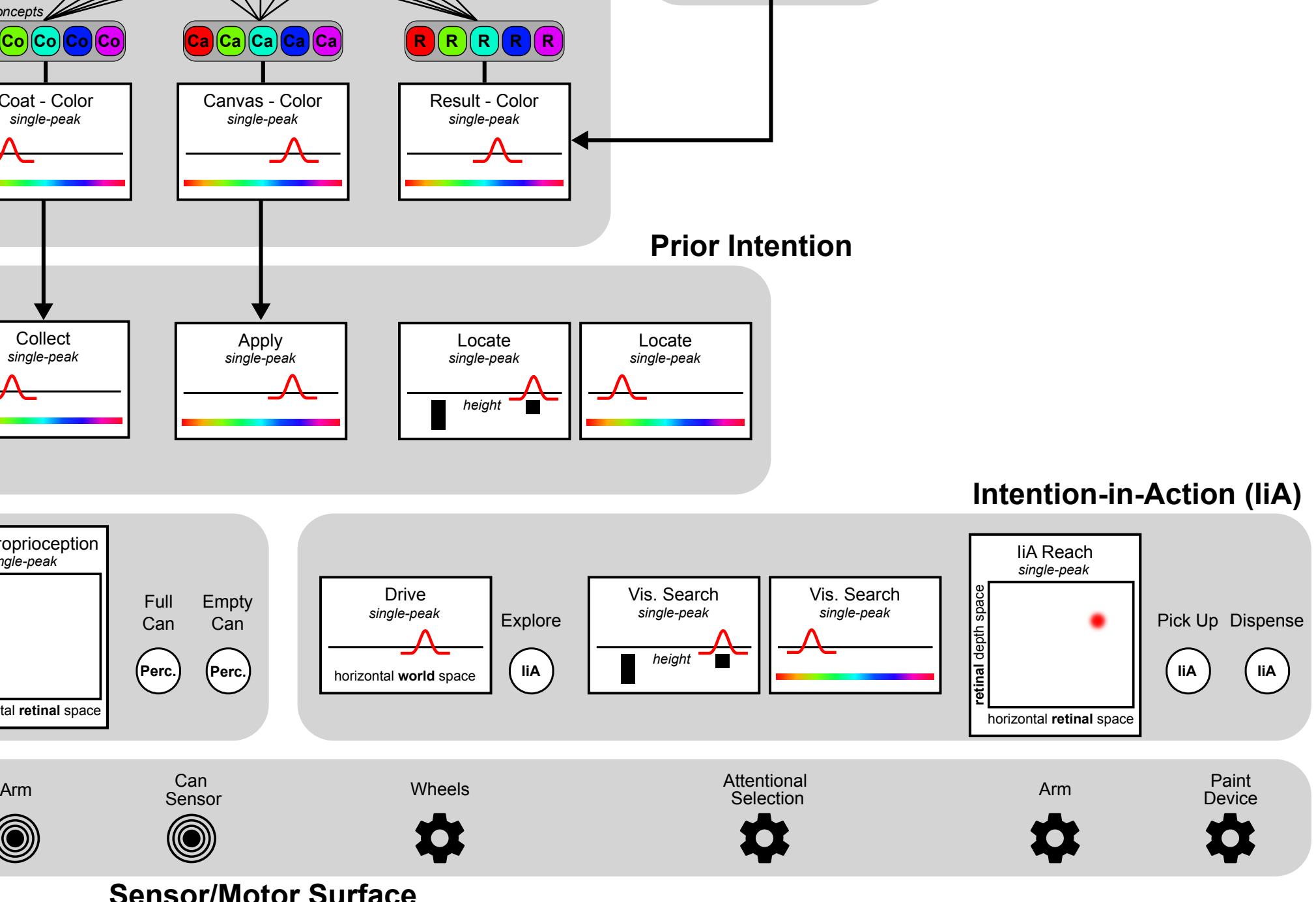
# desires

- for cubes of a particular  
color

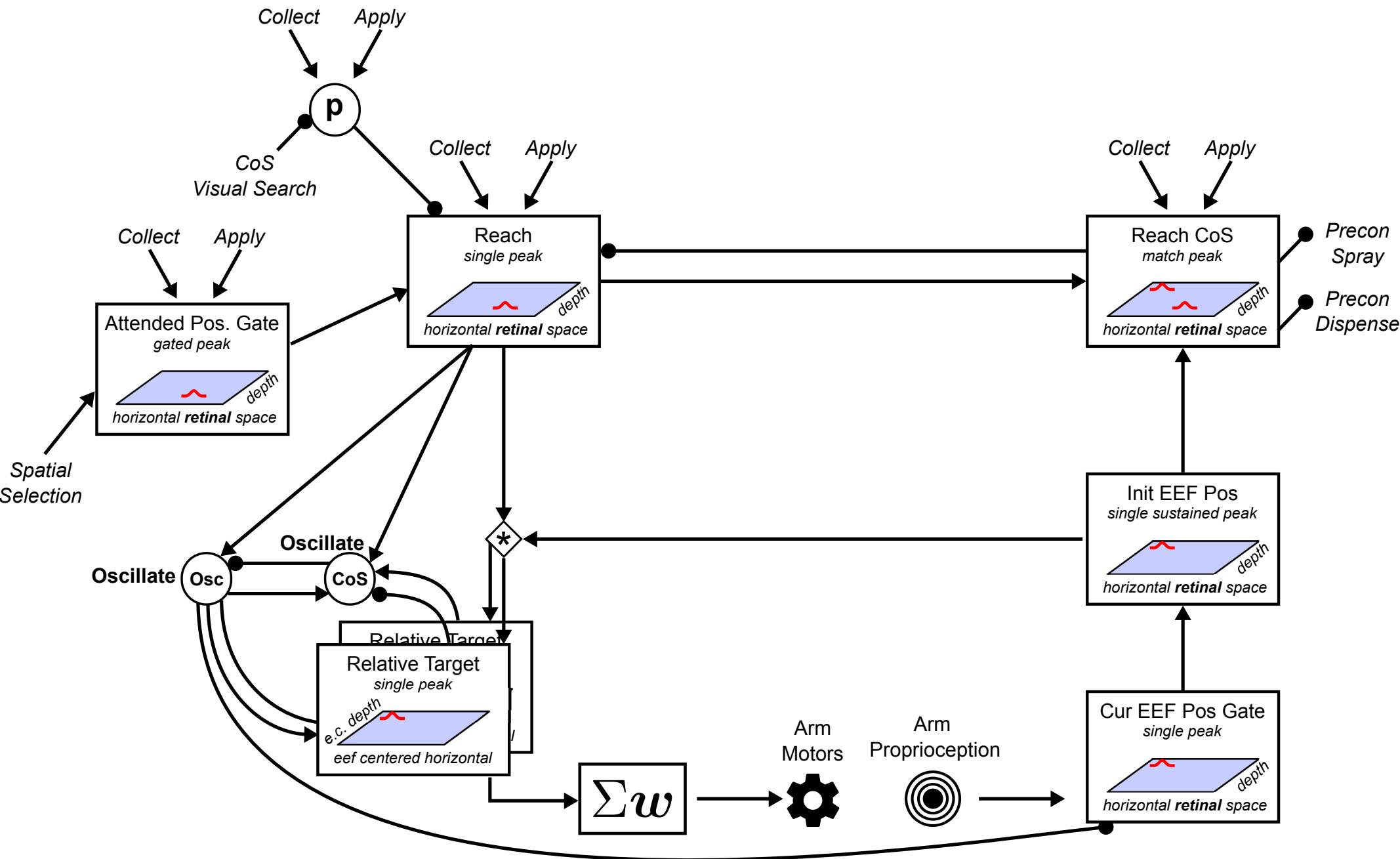


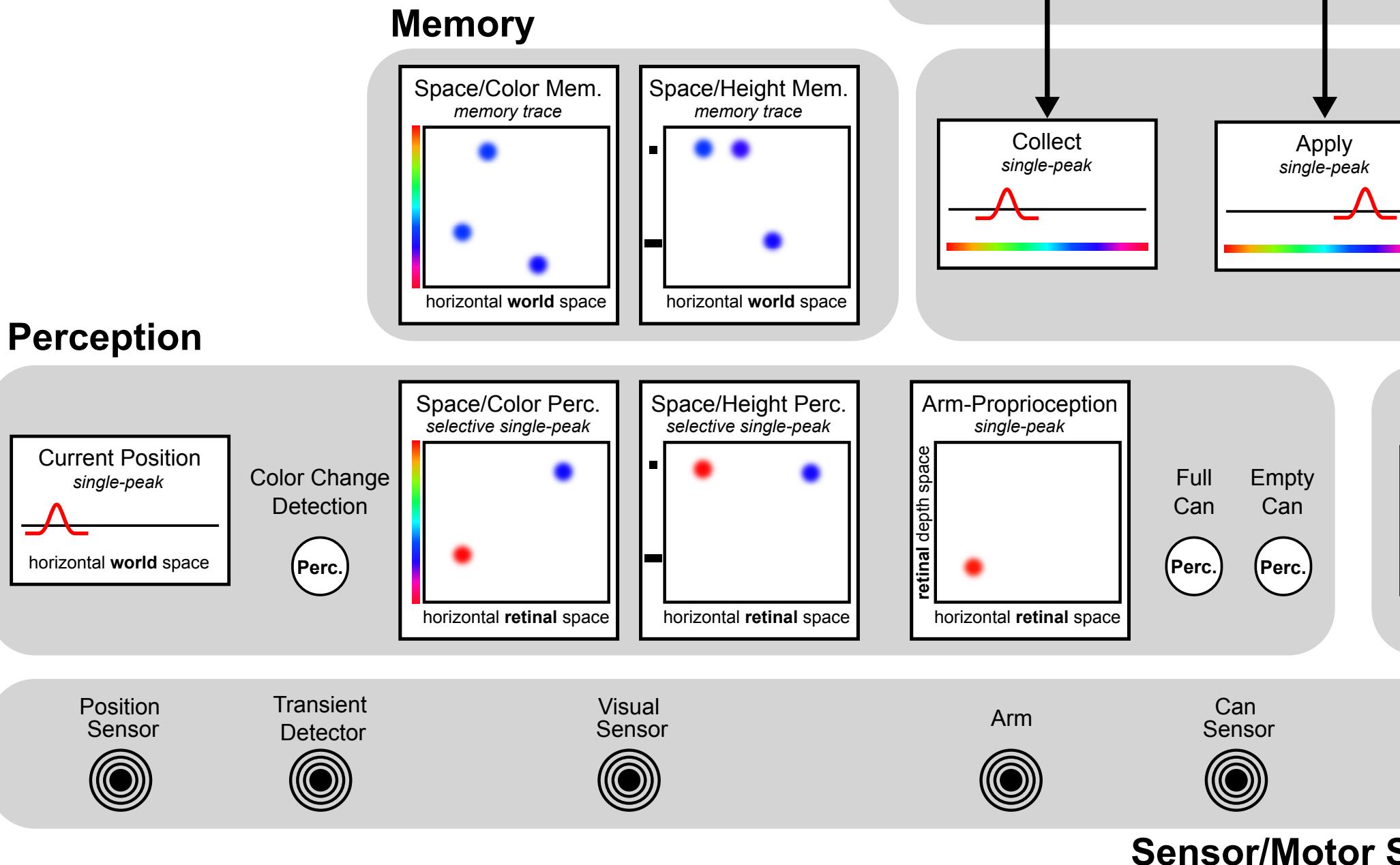
# Neural dynamic architecture



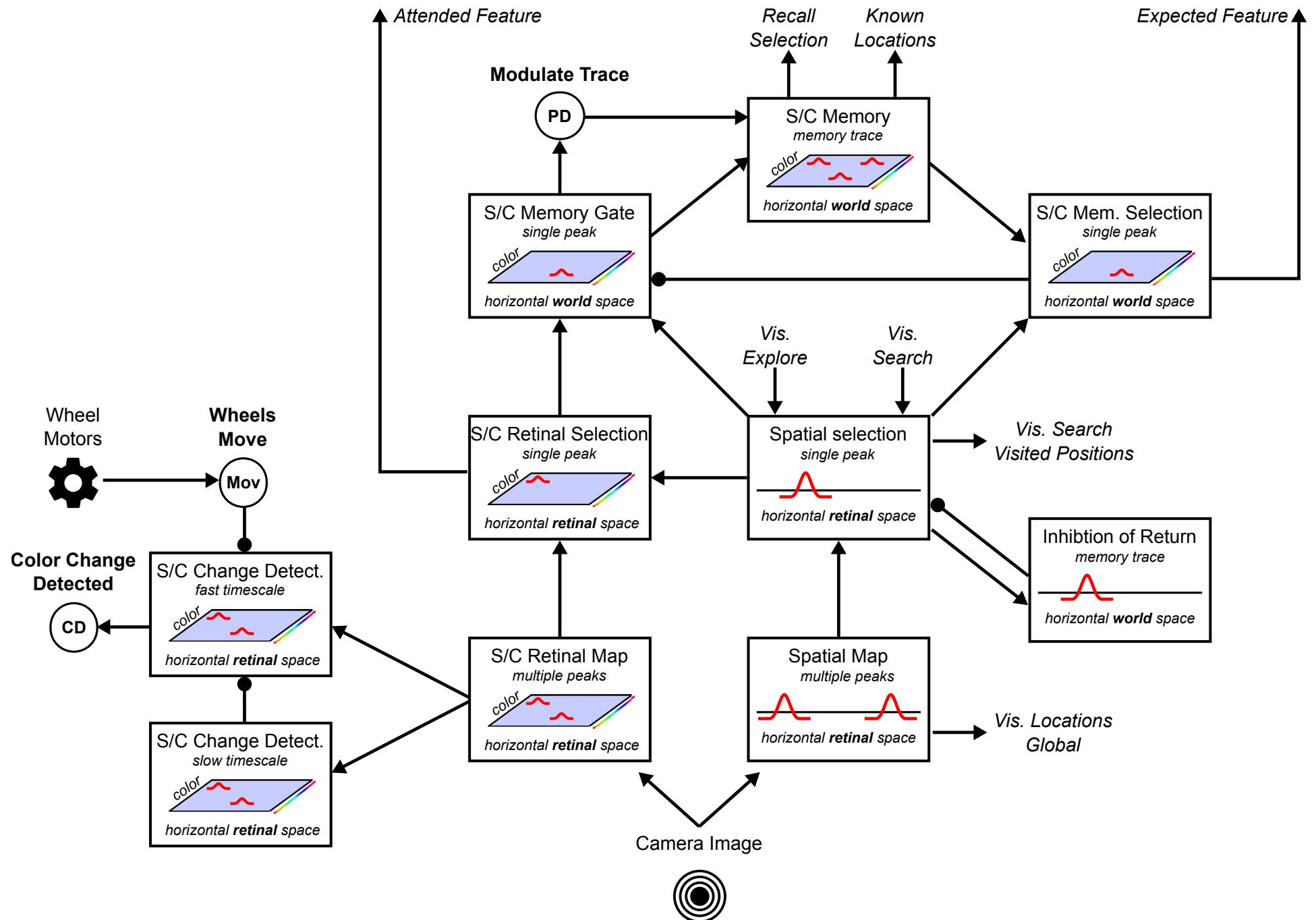


# Intention in action: reach

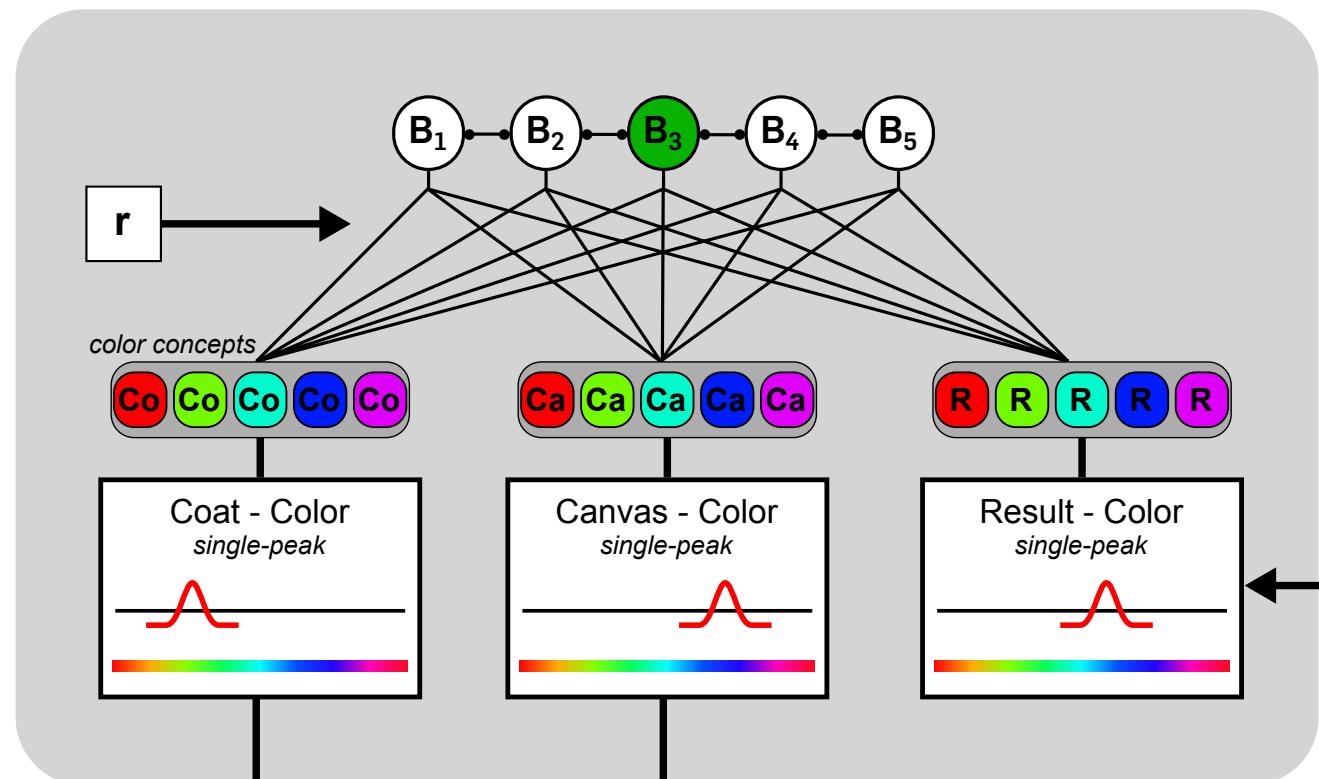




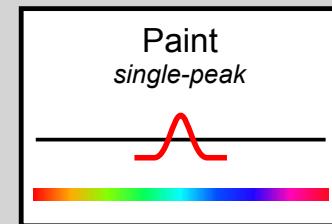
# Perception and memory



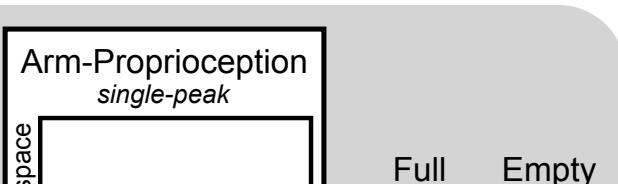
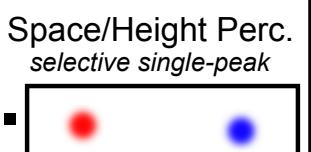
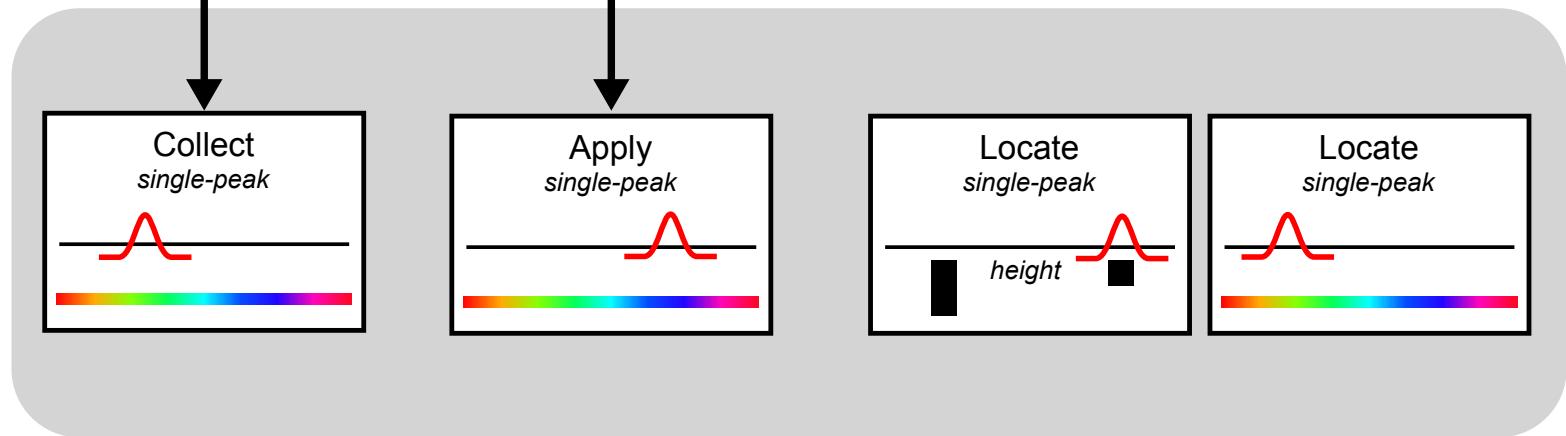
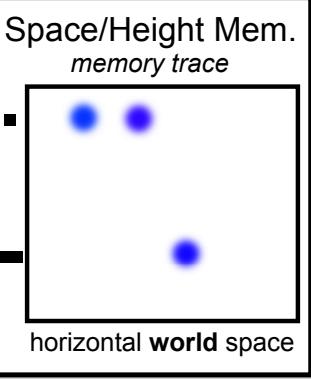
# Belief



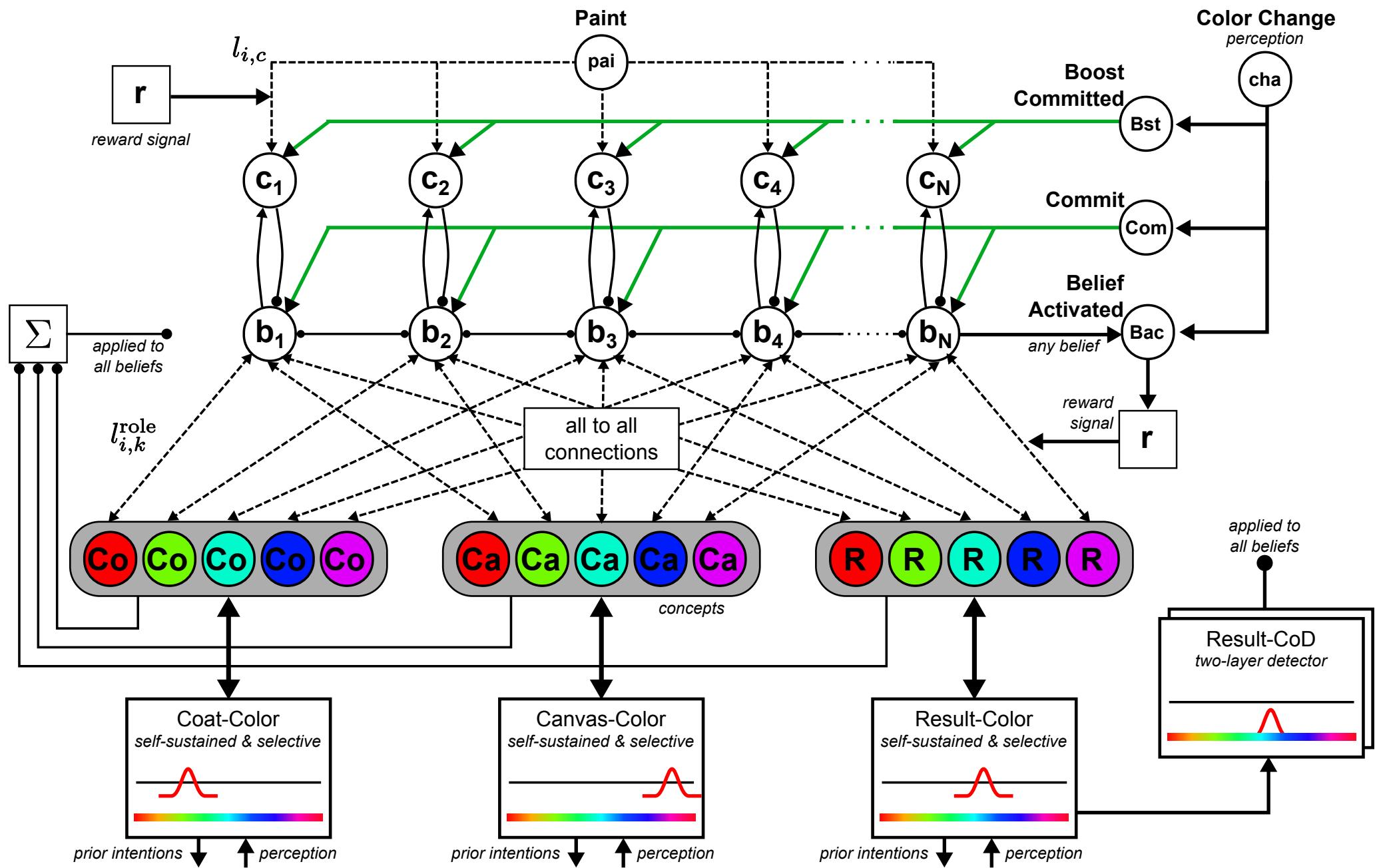
# Desire



# Prior Intention



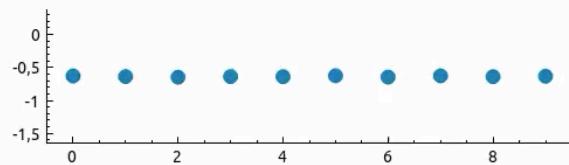
# Learning a new belief



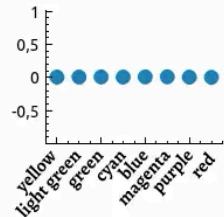
# Learn a new belief

[while exploring: applying blue paint to yellow cube]

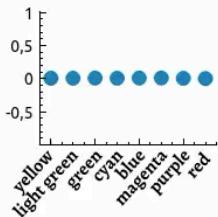
Belief Nodes



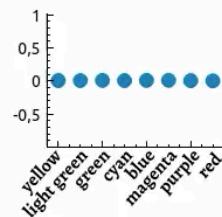
B1 Coat  
Weights



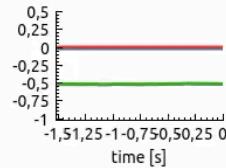
B1 Canvas  
Weights



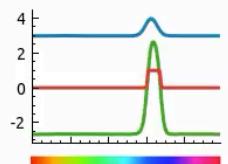
B1 Result  
Weights



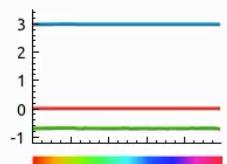
Reward  
Node



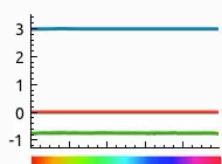
Coat Color



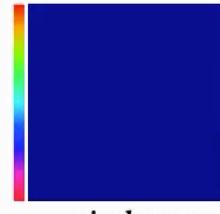
Canvas Color



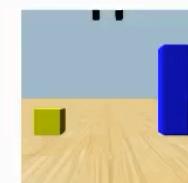
Result Color



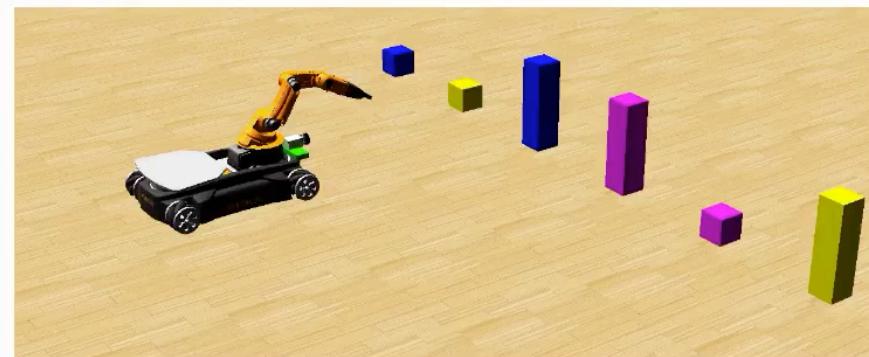
S/C Change  
Detector



Camera

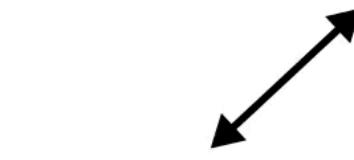
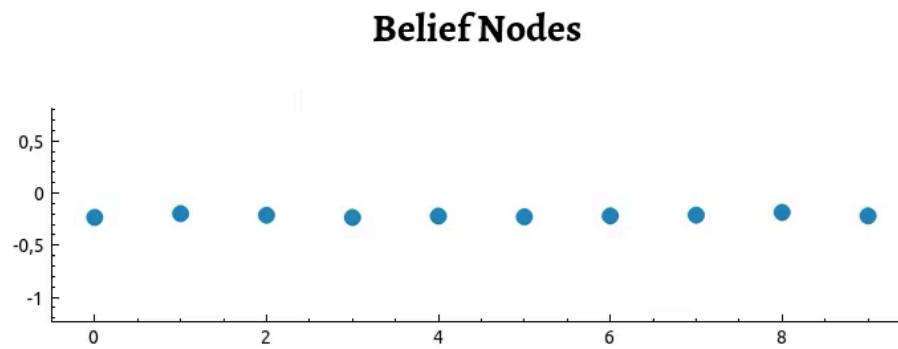


Scene



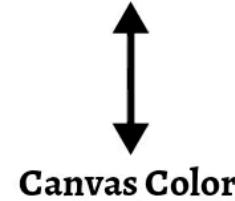
# Recall a belief

[triggered by a desire and objects in scene memory]

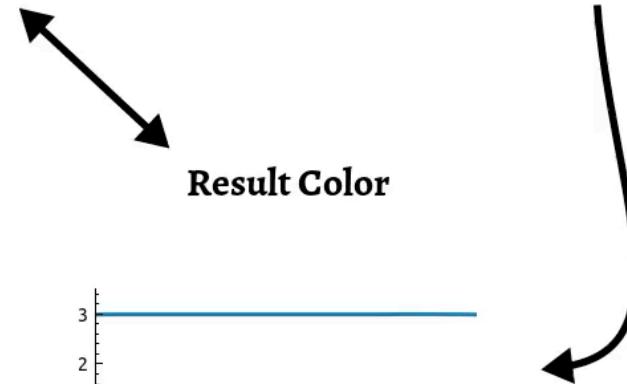
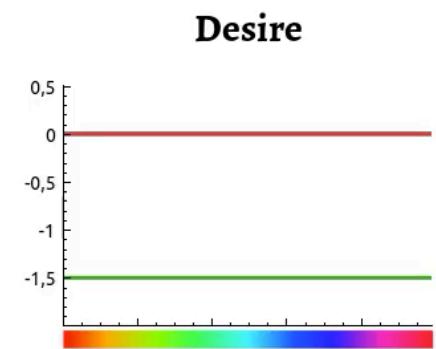


**Coat Color**

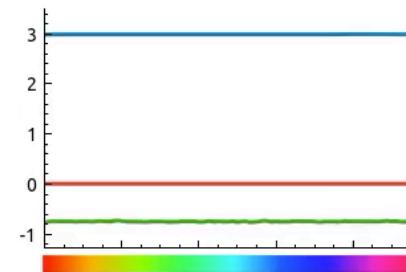
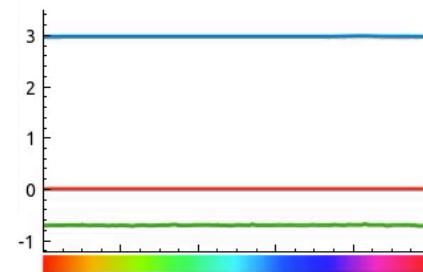
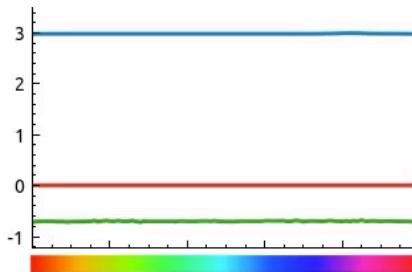
**Belief Nodes**



**Canvas Color**

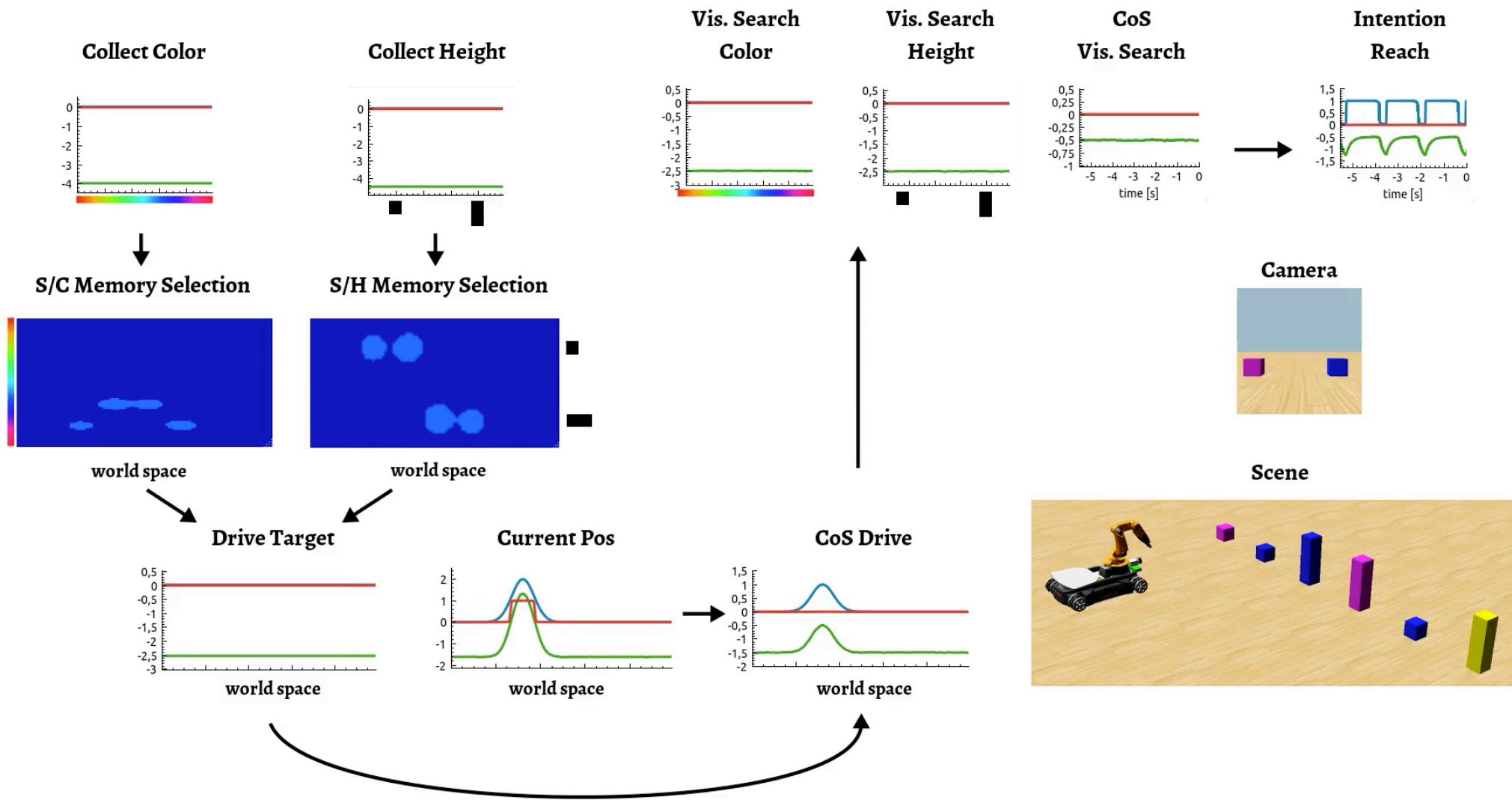


**Result Color**



# Recall-drive-search

[based on a desire and an activated belief,  
looking for a tall pink object, which is in memory]



# Summary

- low-dimensional activation fields enable the autonomous generation of sequences of mental states
  - events emerge from detection decisions
  - attentional foreground from selection decisions
  - low-dimensional activation fields as substrates for scene and mental maps
  - concepts, neural operators, and coordinate transforms enables generalization, inference
- stability => robustness => architectures
- enables autonomous learning

# Conclusions

- a privileged level of description for “pervasively neural” process accounts for behavior and thinking



**TOPICS**  
TOPICS IN COGNITIVE SCIENCE



Topics in Cognitive Science (2019) 1–15

The Dynamics of Neural Populations Capture the Laws  
of the Mind

Gregor Schöner

# What would pervasive neural processing “buy us” ?

- embodiment for “free”: updating, control, coupling
- coherent architectures: understandable
- learn back-ground knowledge (rather than program many special cases)
- autonomous learning
- low-energy implementations => Yulia Sandamirskaya

# A long way off?

- not necessarily... framework is becoming visible
- scaling to realistic scenarios as a challenge
  - use learning (deep learning?) to extract the low-dimensional representations within which neural dynamic cognition may work
- autonomous learning within this vision... still a challenge
  - develop the process infrastructure for that...
  - but also: study implications for its use