

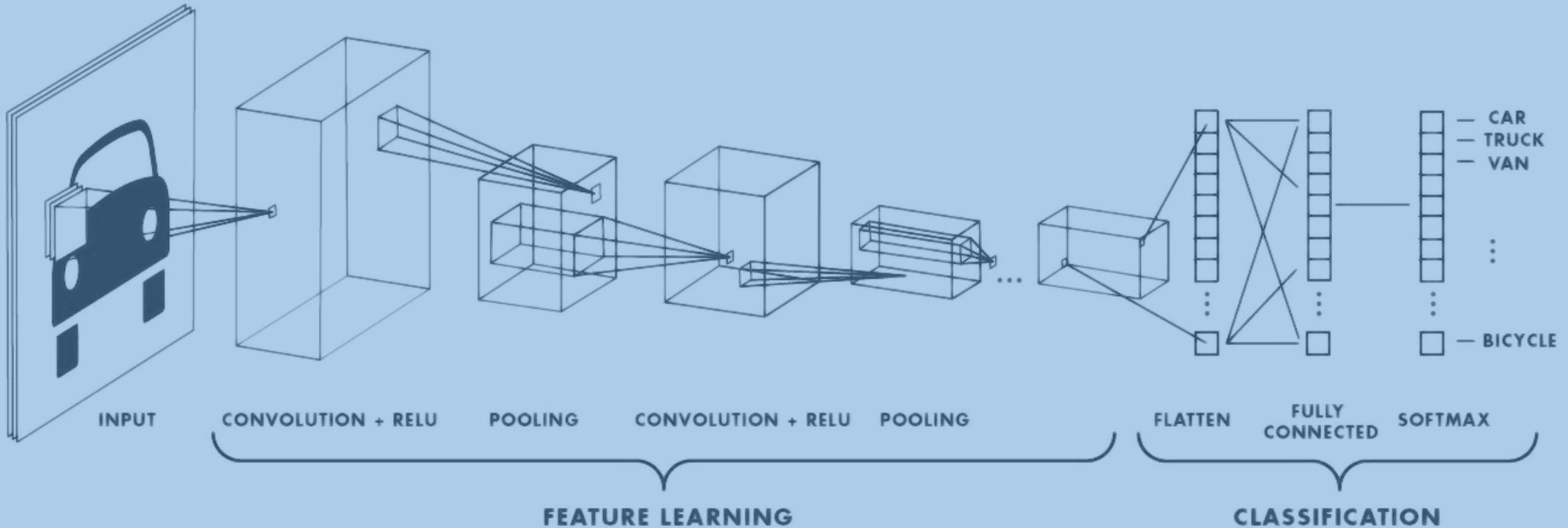
# Bridging DFT and DNNs:

A neural dynamic process model of scene representation, guided visual search and scene grammar in natural scenes

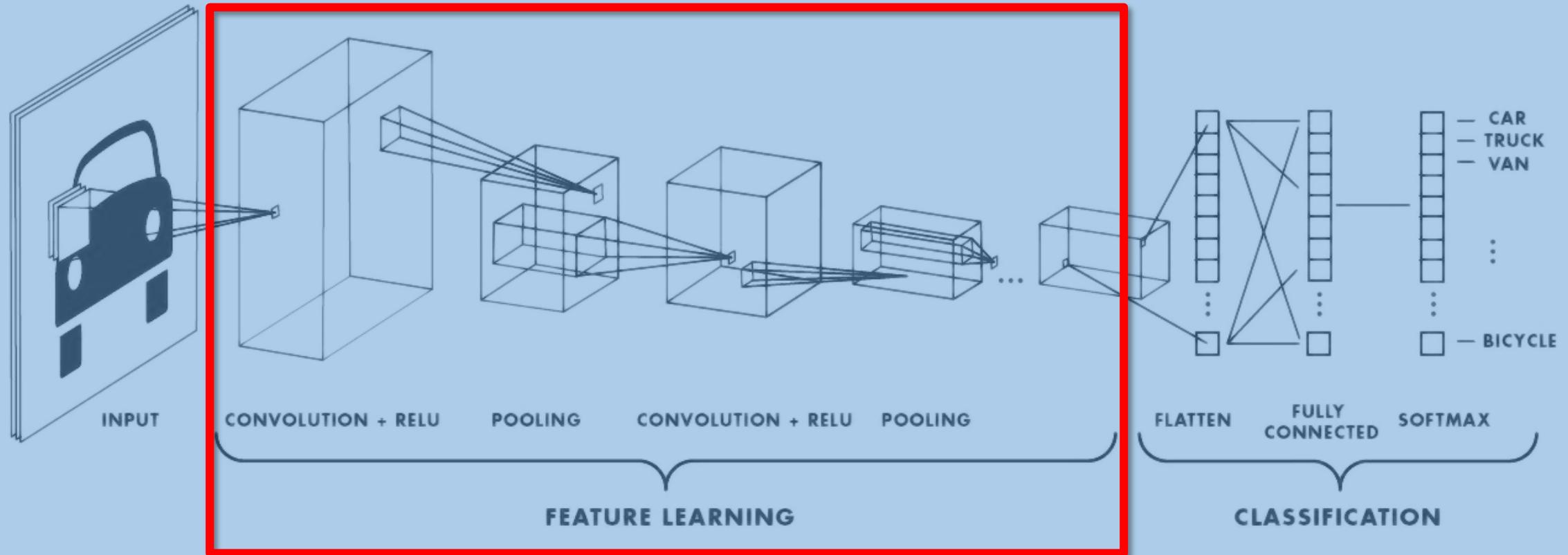
Raul Grieben

18.08.2022

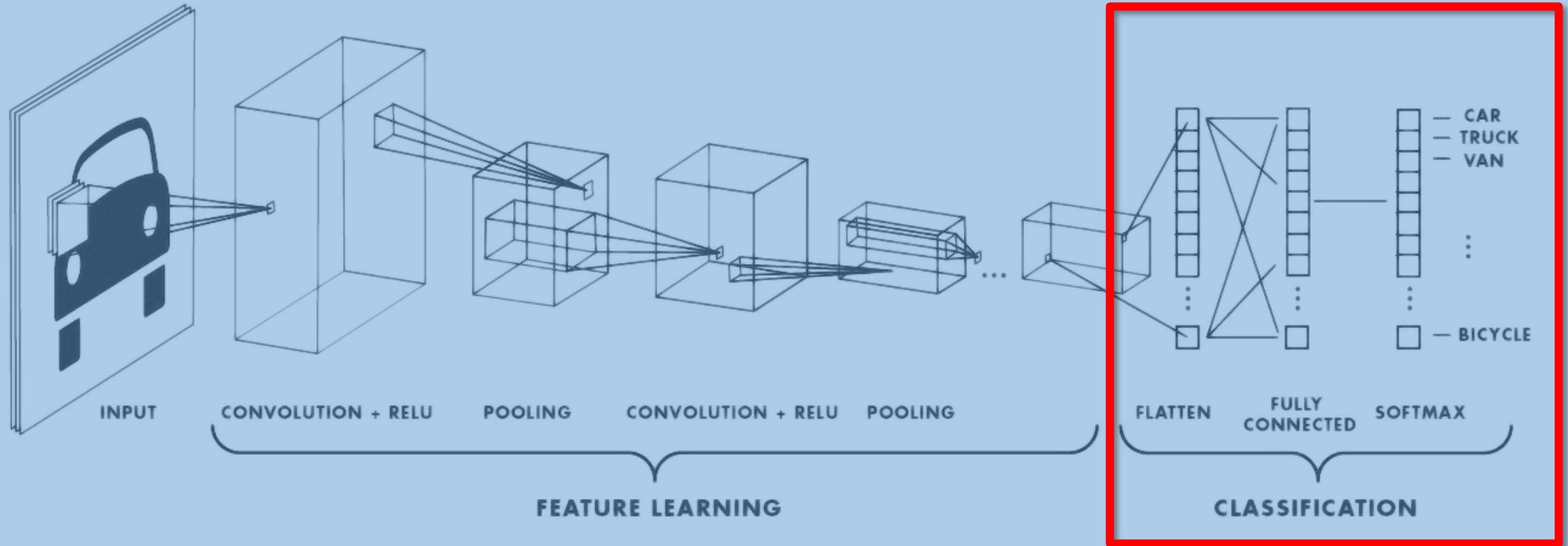
# Deep CNN



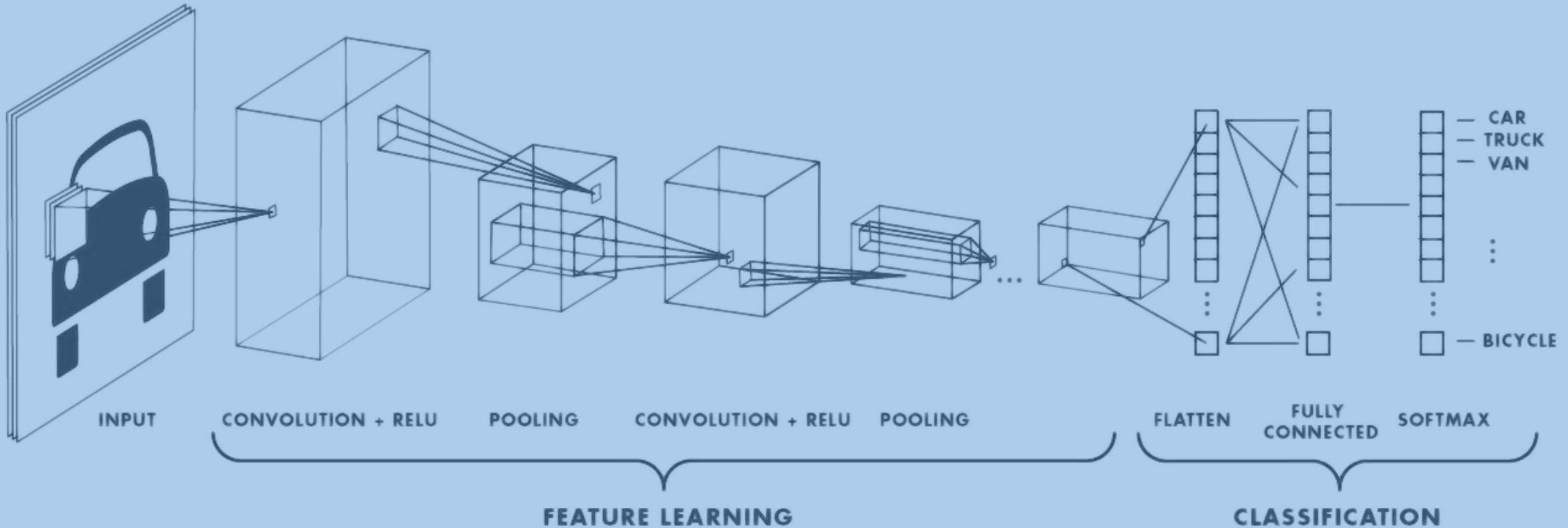
# Deep CNN



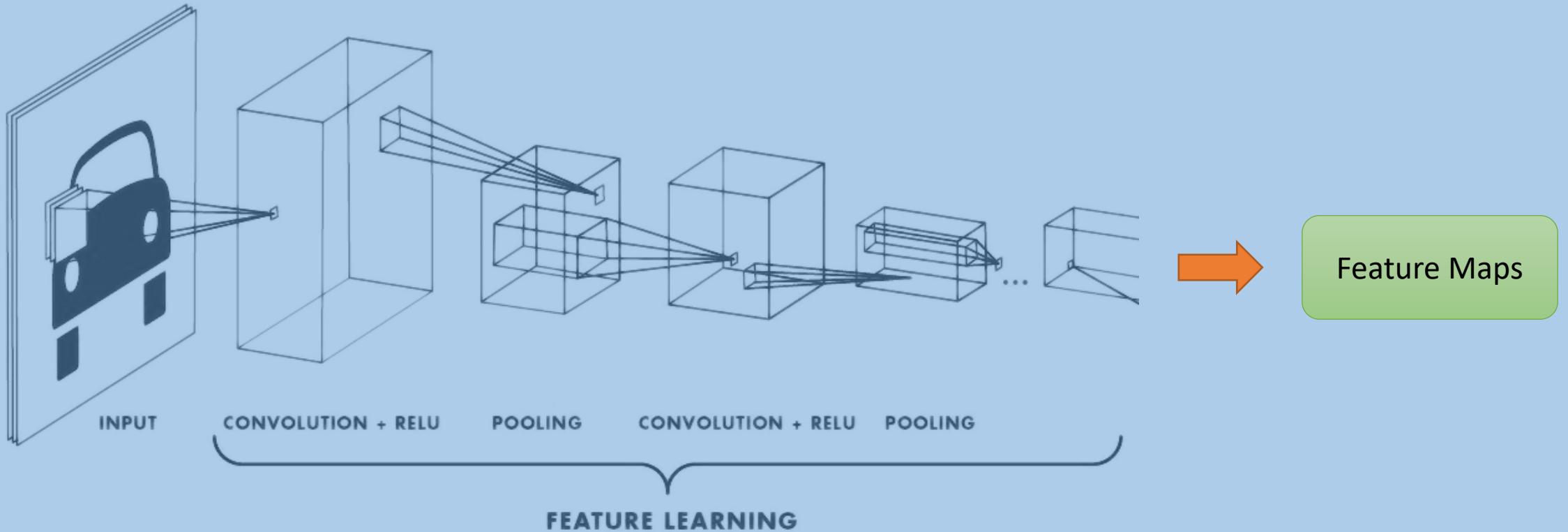
# Deep CNN



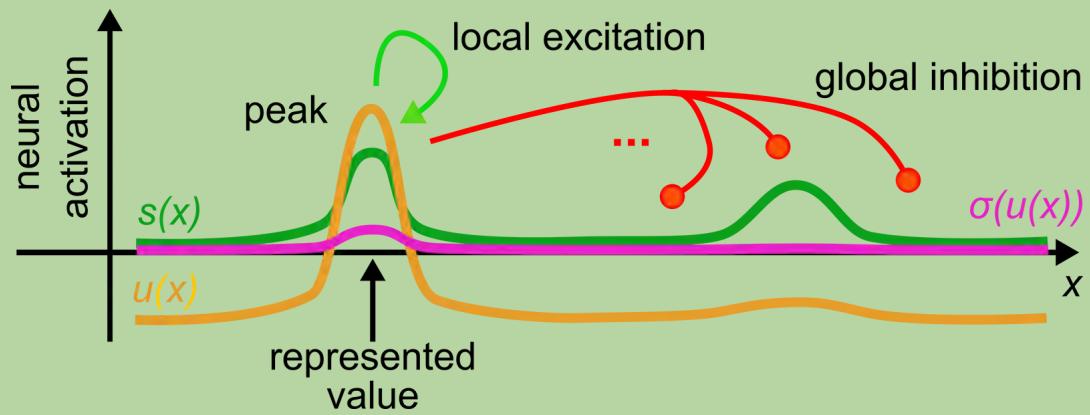
# Deep CNN



# Deep CNN

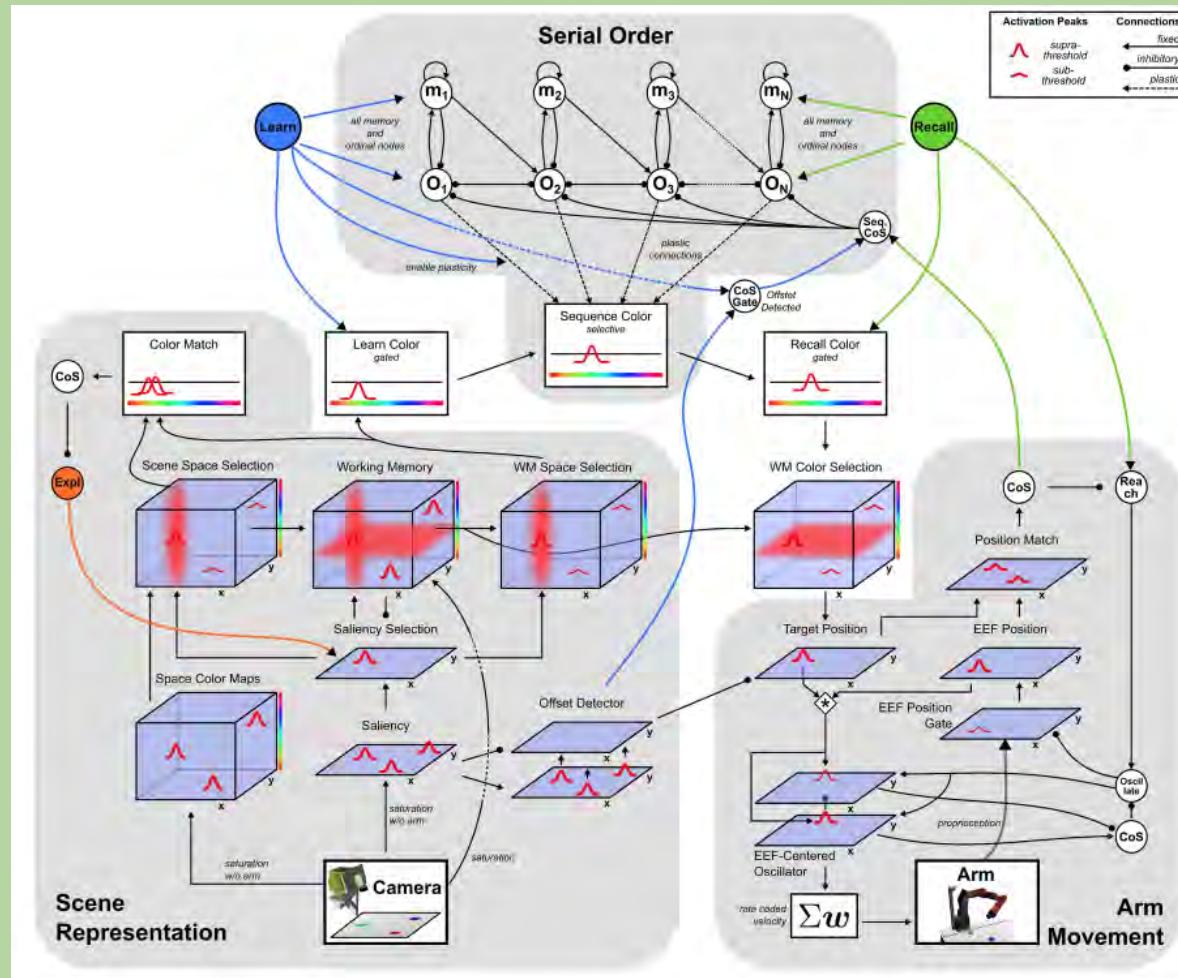


# Dynamic Field Theory

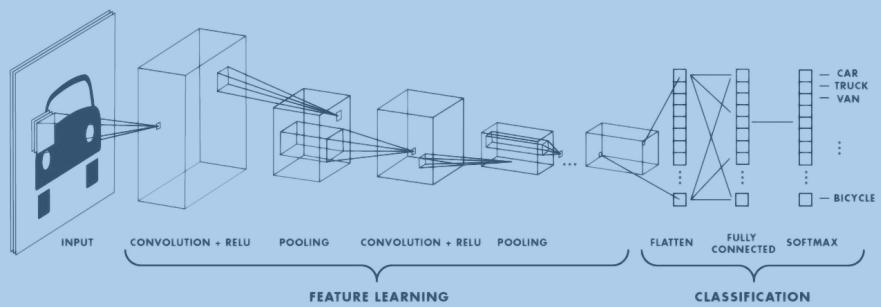


$$\begin{aligned}\tau \dot{u}(x, t) = & -u(x, t) + h + s(x, t) + \xi(x, t) \\ & + \int \omega(x - x') \sigma(u(x', t)) dx'\end{aligned}$$

# Dynamic Field Theory

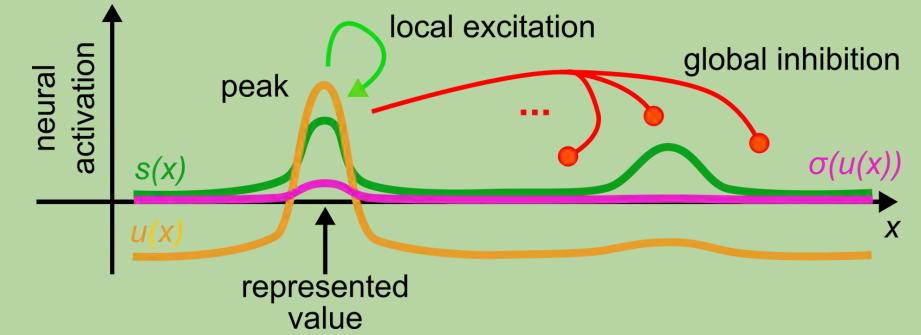


# Deep CNN



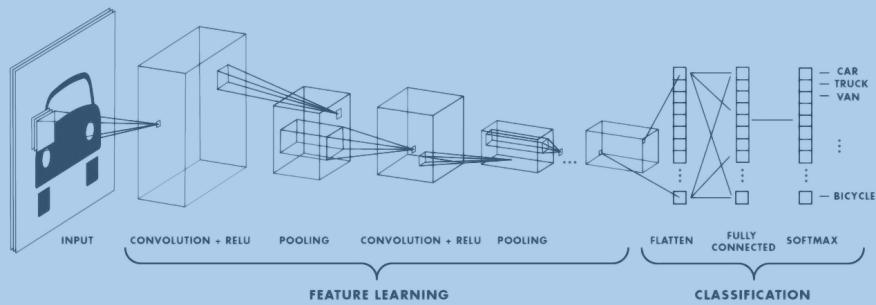
Feed-forward path

# Dynamic Field Theory



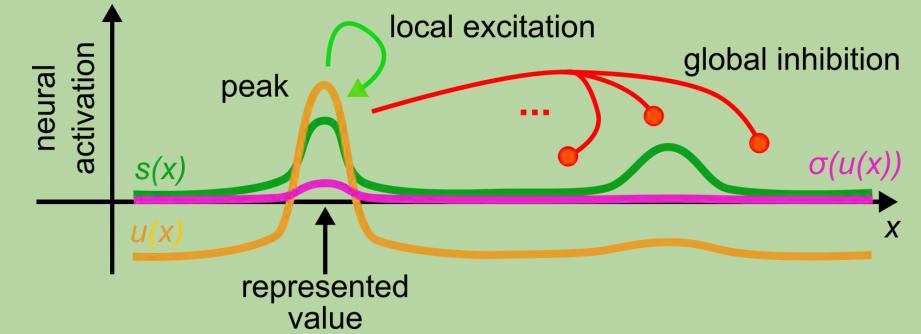
Higher cognition

# Deep CNN



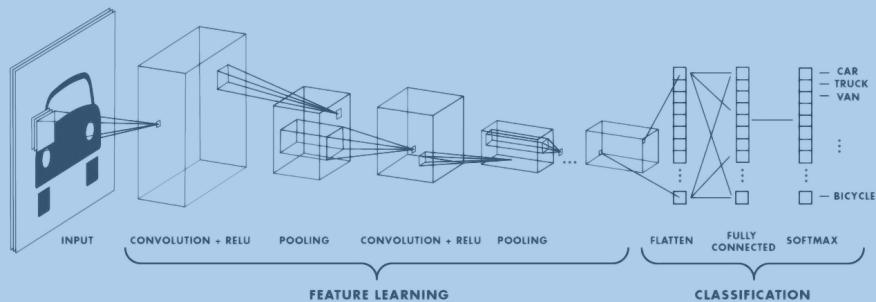
Feed-forward path

# Dynamic Field Theory



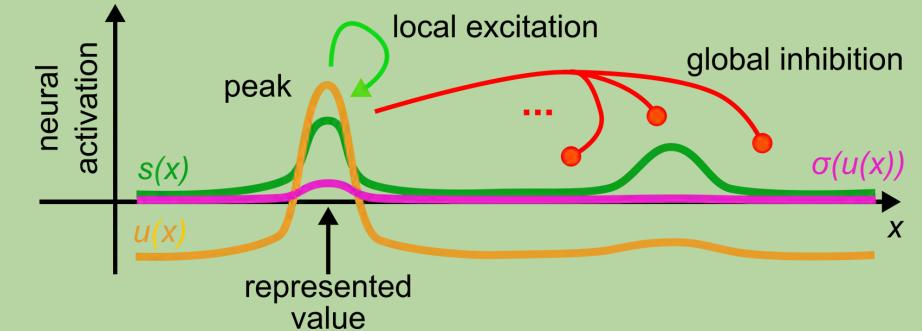
Higher cognition

# Deep CNN

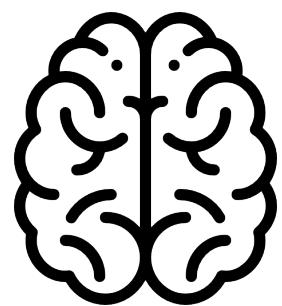


Feed-forward path

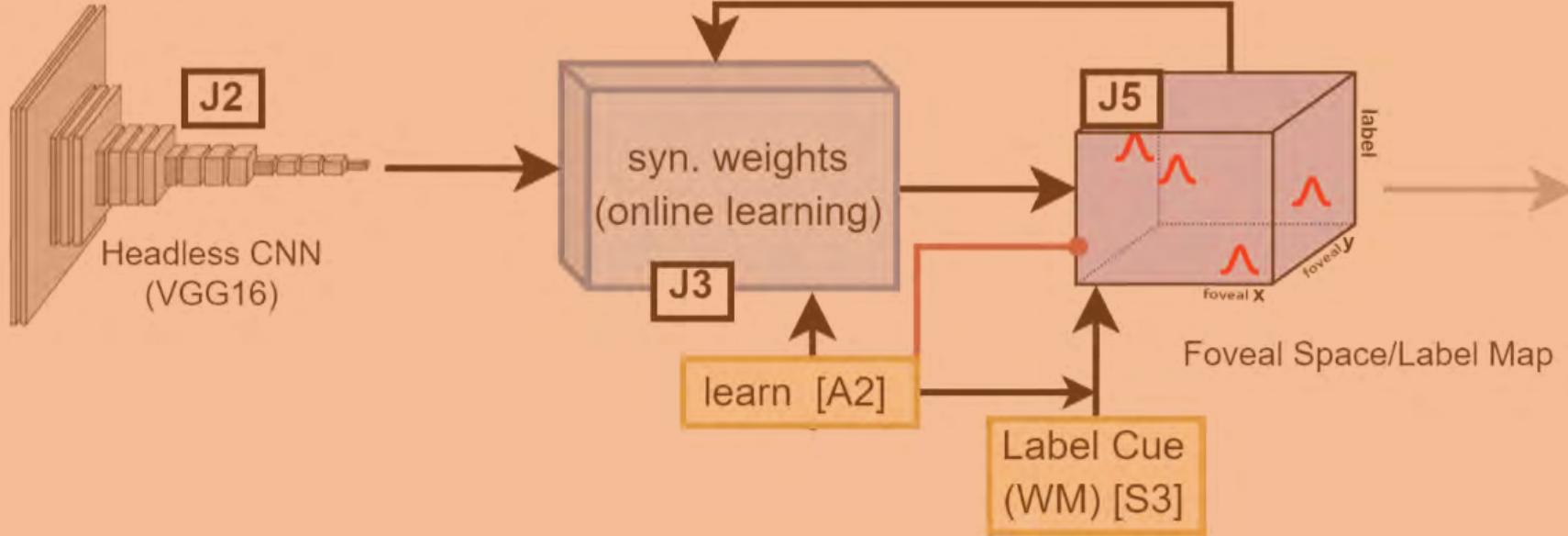
# Dynamic Field Theory



Higher cognition



# Interface

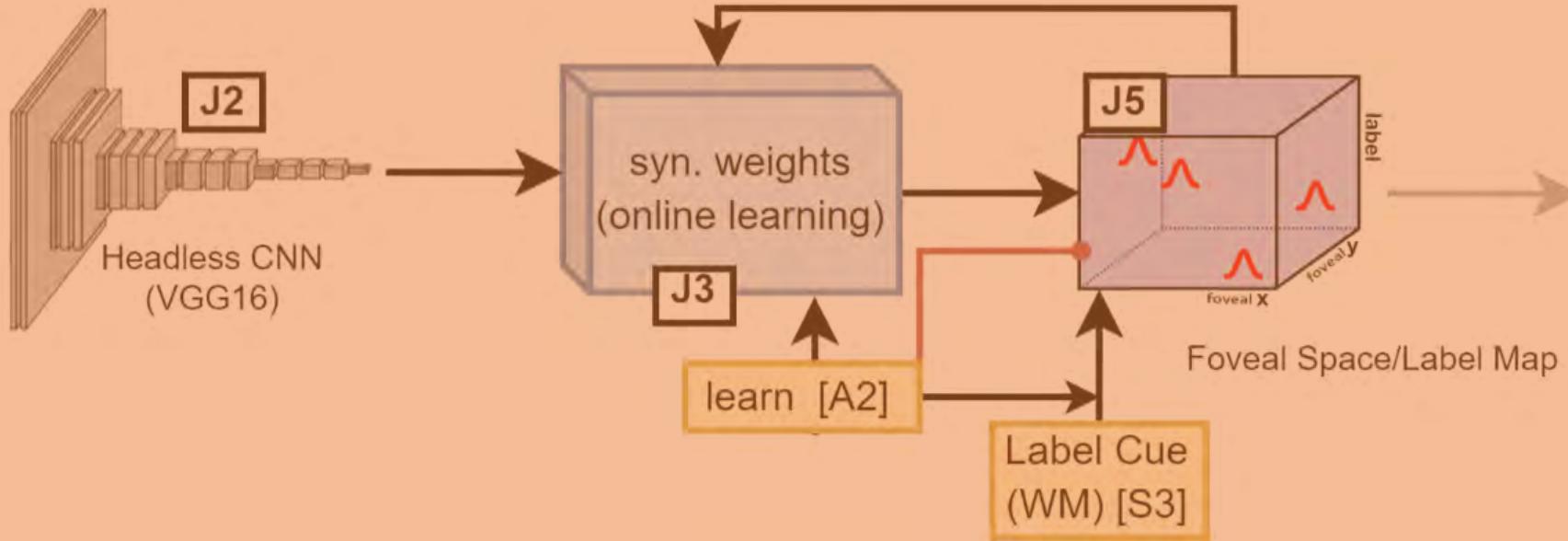


$$\tau_w \dot{w}_{m_f, u_{fsml}}(\mathbf{x}, t) = \eta \sigma(u_{\text{learn}}) y (y - \Theta) \frac{m_f(x_1, x_2, t)}{\Theta}$$

$$y = \sigma(u_{fsml}(\mathbf{x}, t))$$

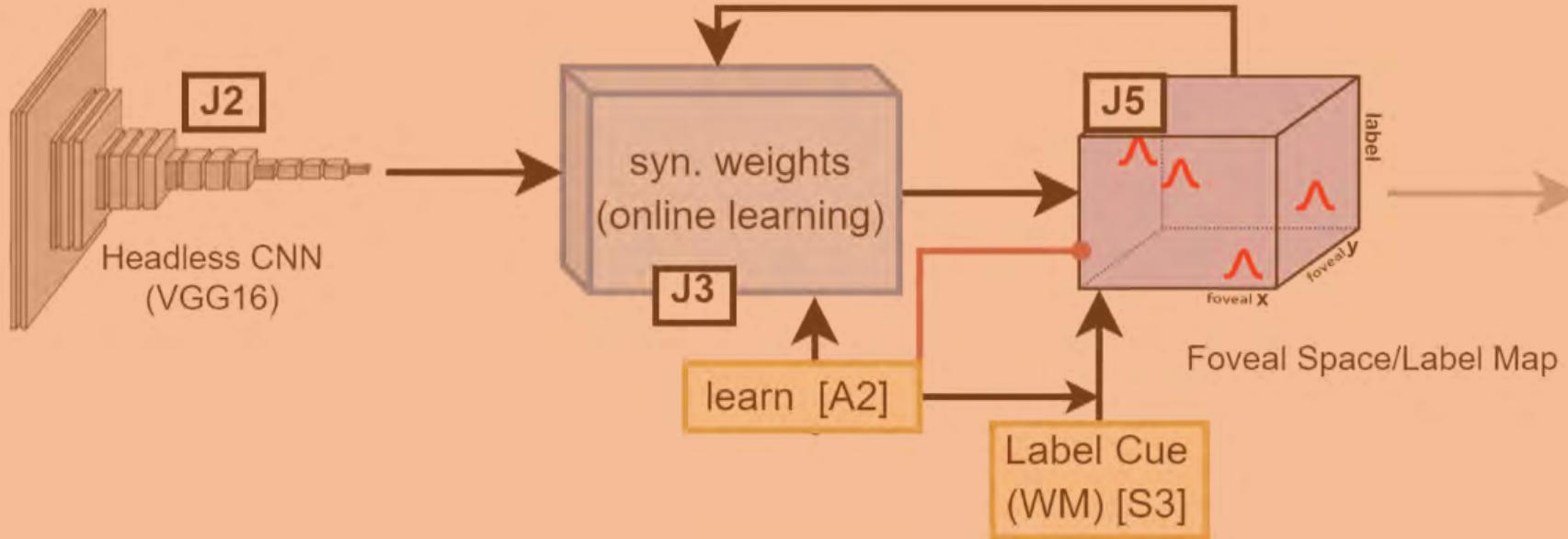
$$\tau_\Theta \dot{\Theta} = (y^2 - \Theta),$$

# Interface



$$\begin{aligned}\tau_w \dot{w}_{m_f, u_{fsml}}(\mathbf{x}, t) &= \eta \sigma(u_{\text{learn}}) y (y - \Theta) \frac{m_f(x_1, x_2, t)}{\Theta} \\ y &= \sigma(u_{fsml}(\mathbf{x}, t)) \\ \tau_\Theta \dot{\Theta} &= (y^2 - \Theta),\end{aligned}$$

# Interface



$$\begin{aligned} \tau_w \dot{w}_{m_f, u_{fsml}}(\mathbf{x}, t) &= \eta \sigma(u_{\text{learn}}) y (y - \Theta) \frac{m_f(x_1, x_2, t)}{\Theta} \\ y &= \sigma(u_{fsml}(\mathbf{x}, t)) \\ \tau_\Theta \dot{\Theta} &= (y^2 - \Theta), \end{aligned}$$



## Scene memory and spatial inhibition in visual search

A neural dynamic process model and new experimental evidence

Raul Grießen<sup>1</sup> · Jan Tekülve<sup>1</sup> · Stephan K. U. Zibner<sup>1</sup> · Jonas Lins<sup>1</sup> · Sebastian Schneegans<sup>2</sup> · Gregor Schöner<sup>1</sup>

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### Abstract

Any object-oriented action requires that the object be first brought into the attentional foreground, often through visual search. Outside the laboratory, this would always take place in the presence of a scene representation acquired from ongoing visual exploration. The interaction of scene memory with visual search is still not completely understood. Feature integration theory (FIT) has shaped both research on visual search, emphasizing the scaling of search times with set size when searches entail feature conjunctions, and research on visual working memory through the change detection paradigm. Despite its neural motivation, there is no consistently neural process account of FIT in both its dimensions. We propose such an account that integrates (1) visual exploration and the building of scene memory, (2) the attentional detection of visual transients and the extraction of search cues, and (3) visual search itself. The model uses dynamic field theory in which networks of neural dynamic populations supporting stable activation states are coupled to generate sequences of processing steps. The neural architecture accounts for basic findings in visual search and proposes a concrete mechanism for the integration of working memory into the search process. In a behavioral experiment, we address the long-standing question of whether both the overall speed and the efficiency of visual search can be improved by scene memory. We find both effects and provide model fits of the behavioral results. In a second experiment, we show that the increase in efficiency is fragile, and trace that fragility to the resetting of spatial working memory.

Grießen, R., Tekülve, J., Zibner, S. K. U., Lins, J., Schneegans, S., & Schöner, G.. (2020). Scene memory and spatial inhibition in visual search. *Attention, Perception, & Psychophysics*.

## A neural dynamic process model of combined bottom-up and top-down guidance in triple conjunction visual search

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Universitätsstraße 150, 44801 Bochum, Germany

### Abstract

The surprising efficiency of triple conjunction search has created a puzzle for modelers who link visual feature binding to selective attention, igniting an ongoing debate on whether features are bound with or without attention. Nordfang and Wolfe (2014) identified feature sharing and grouping as important factors in solving the puzzle and thereby established new constraints for models of visual search. Here we extend our neural dynamic model of scene perception and visual search (Grießen et al., 2020) to account for these constraints without the need for preattentive binding. By demonstrating that visual search is not only guided top-down, but that its efficiency is affected by bottom-up salience, we address a major theoretical weakness of models of conjunctive visual search (Proulx, 2007). We show how these complex interactions emerge naturally from the underlying neural dynamics.

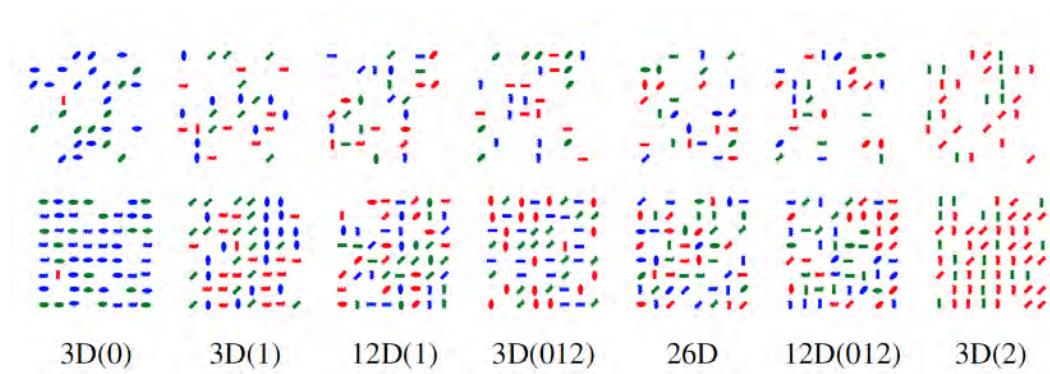
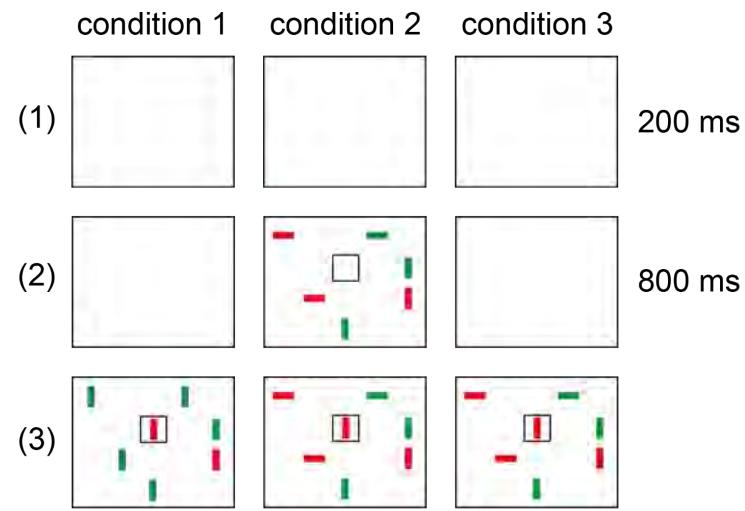
**Keywords:** neural dynamic process model; dynamic field theory; visual search; binding; feature sharing; grouping; triple conjunctions; bottom-up salience; top-down guidance;

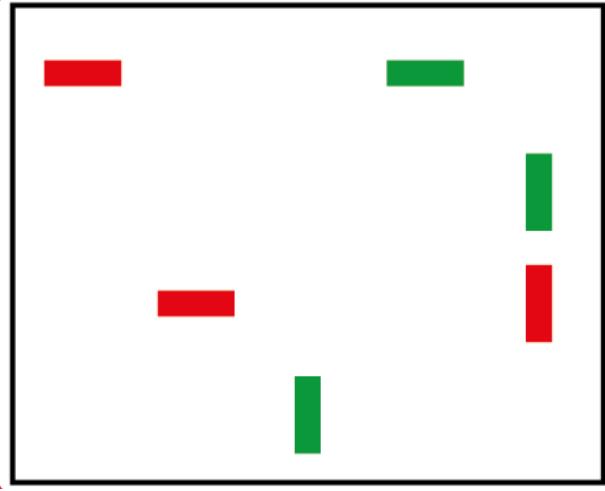
### Introduction

Finding an object in a natural visual scene is something we do all the time without thinking about it. Sometimes it can

Nordfang and Wolfe (2014) revisited triple conjunction searches and found evidence that both *grouping*, the number of different distractor groups in a search display, and *feature sharing*, the number of features shared between a distractor and the target, had a substantial effect on search efficiency. In the five experiments relevant for evaluation of our model (1a, 1b, 3, 4, and 6) they tested seven<sup>1</sup> conditions with distractor groups sharing zero features (3D(0)), one feature (3D(1), 12D(1)), two features (3D(2)) or with distractor groups composed of items with zero, one, and two shared feature values (3D(012), 12D(012), 26D). Three (3D conditions), 12 (12D conditions), or 26 (condition 26D) different distractor groups were pseudo-randomly pulled from 26 distinct triple conjunctions (*color* (red, green, blue) × *orientation* (0°, 45°, 90°) × *shape* (rectangular, oval, jagged)). The distribution of features in each condition was constrained: In condition 3D(0), no distractor could share any feature with the target. In conditions 3D(1), 3D(012), 12D(1), 12D(012), and 26D, each feature type was present in 1/3 of the items (1/3 were red, 1/3 green, and 1/3 blue, and so on). In condition 3D(2), the target

Grießen, R., & Schöner, G.. (2021). A neural dynamic process model of combined bottom-up and top-down guidance in triple conjunction visual search. Proceedings of the 43rd Annual Conference of the Cognitive Science Society.

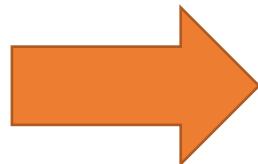




**laboratory stimuli**

**natural objects and scenes**

Basic feature  
guidance

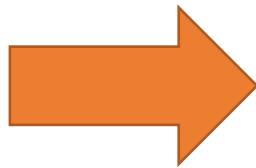


+ Categorical  
guidance

**laboratory stimuli**

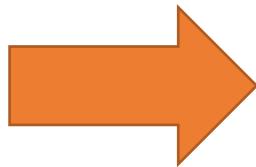
**natural objects and scenes**

Basic feature  
guidance



+ Categorical  
guidance

Basic feature  
matching



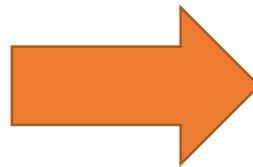
+ Object  
recognition



## **laboratory stimuli**

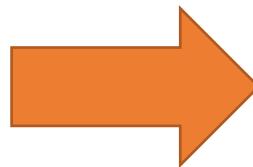
## **natural objects and scenes**

Basic feature  
guidance

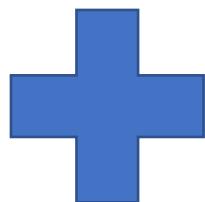


+ Categorical  
guidance

Basic feature  
matching

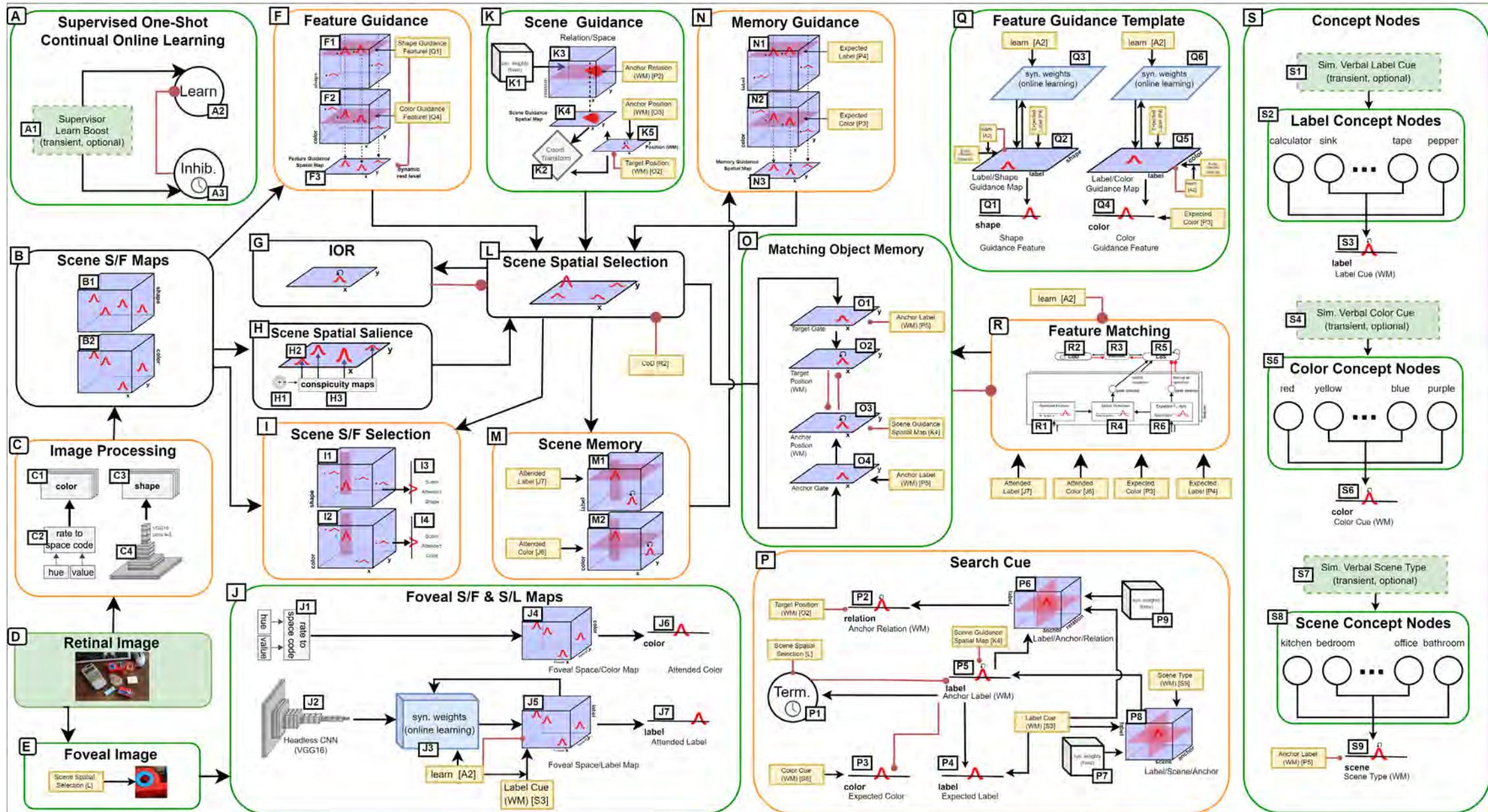


+ Object  
recognition

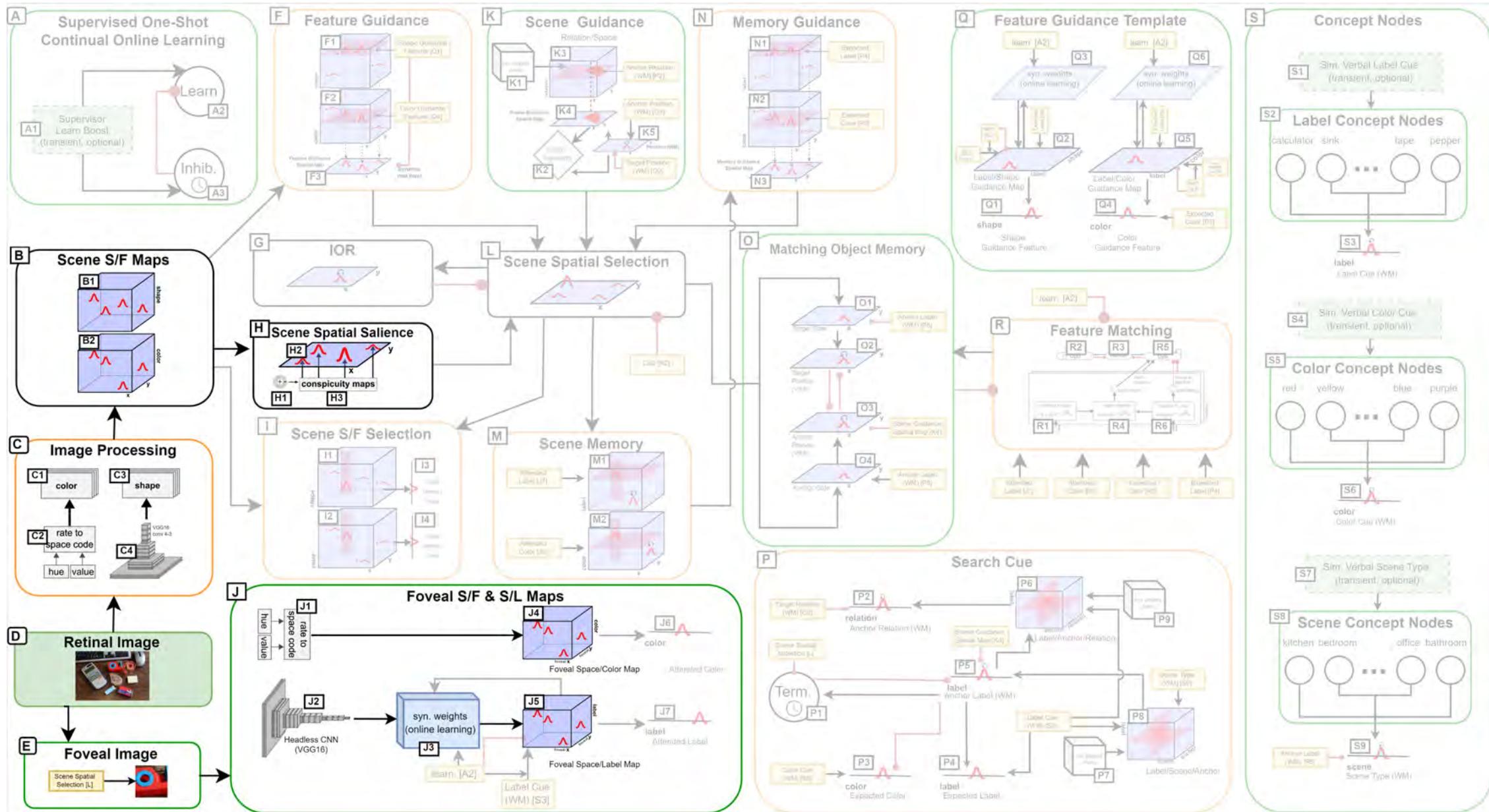


Scene grammar

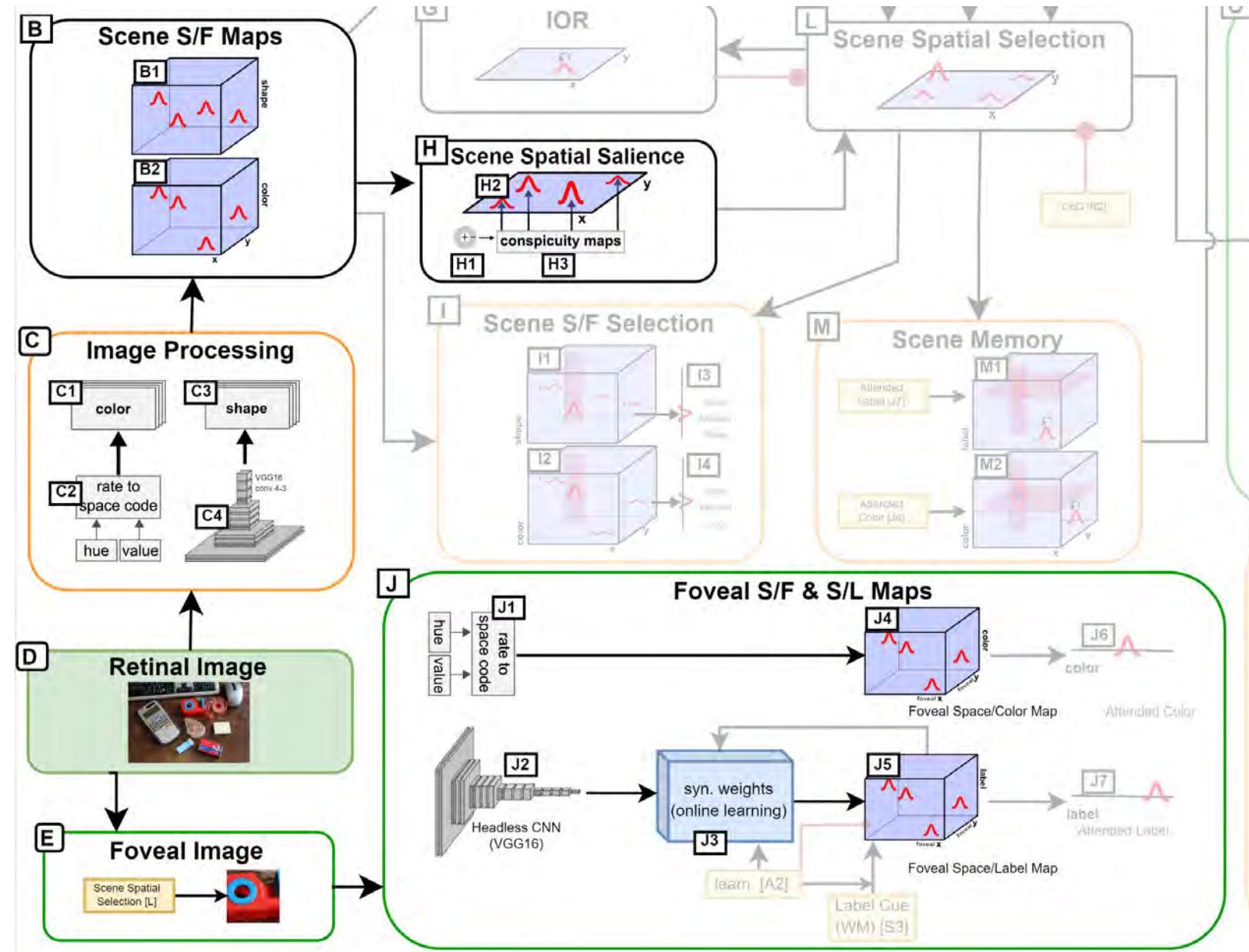
# The neural process model



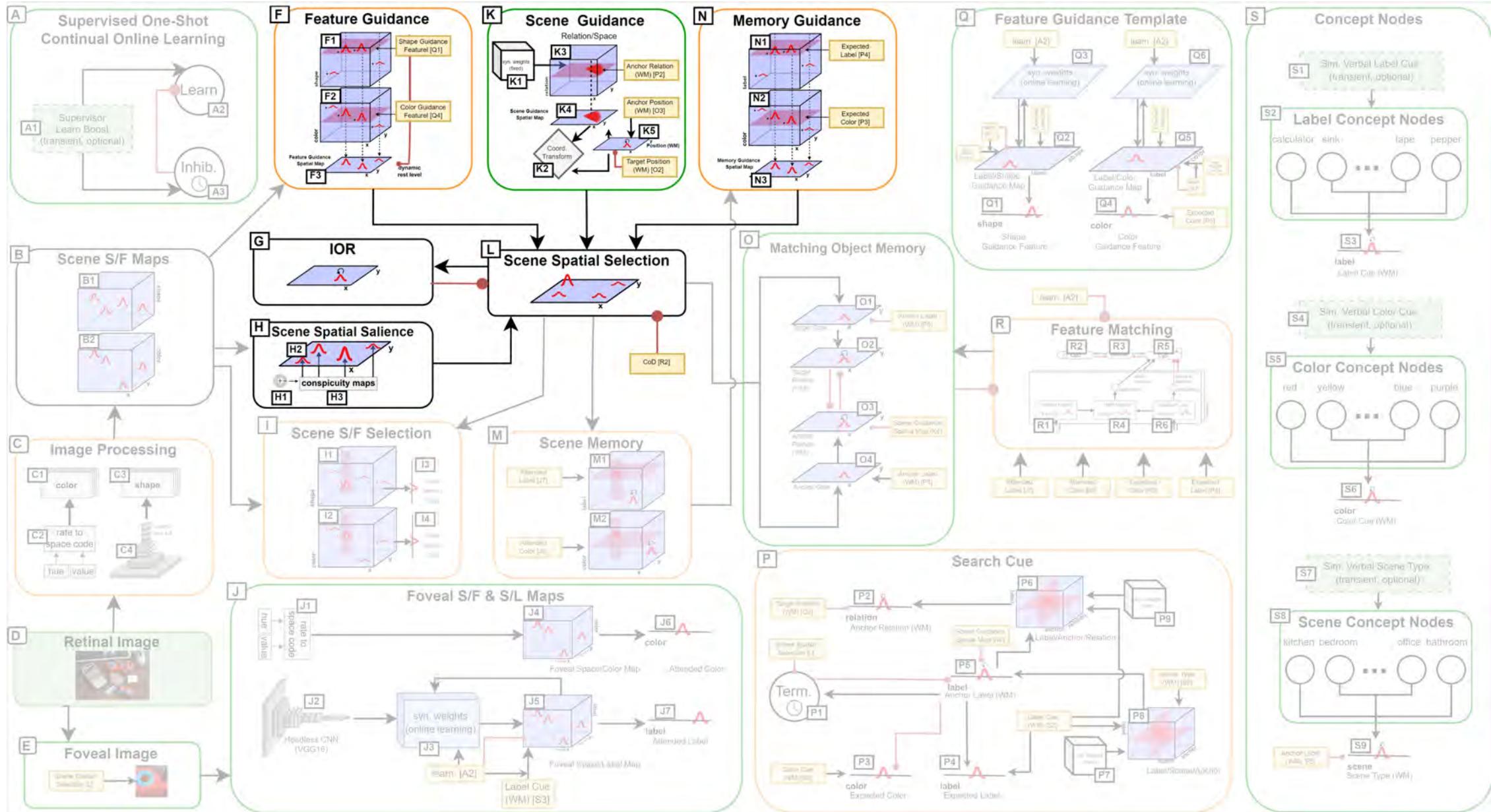
# Feed-forward feature and salience maps



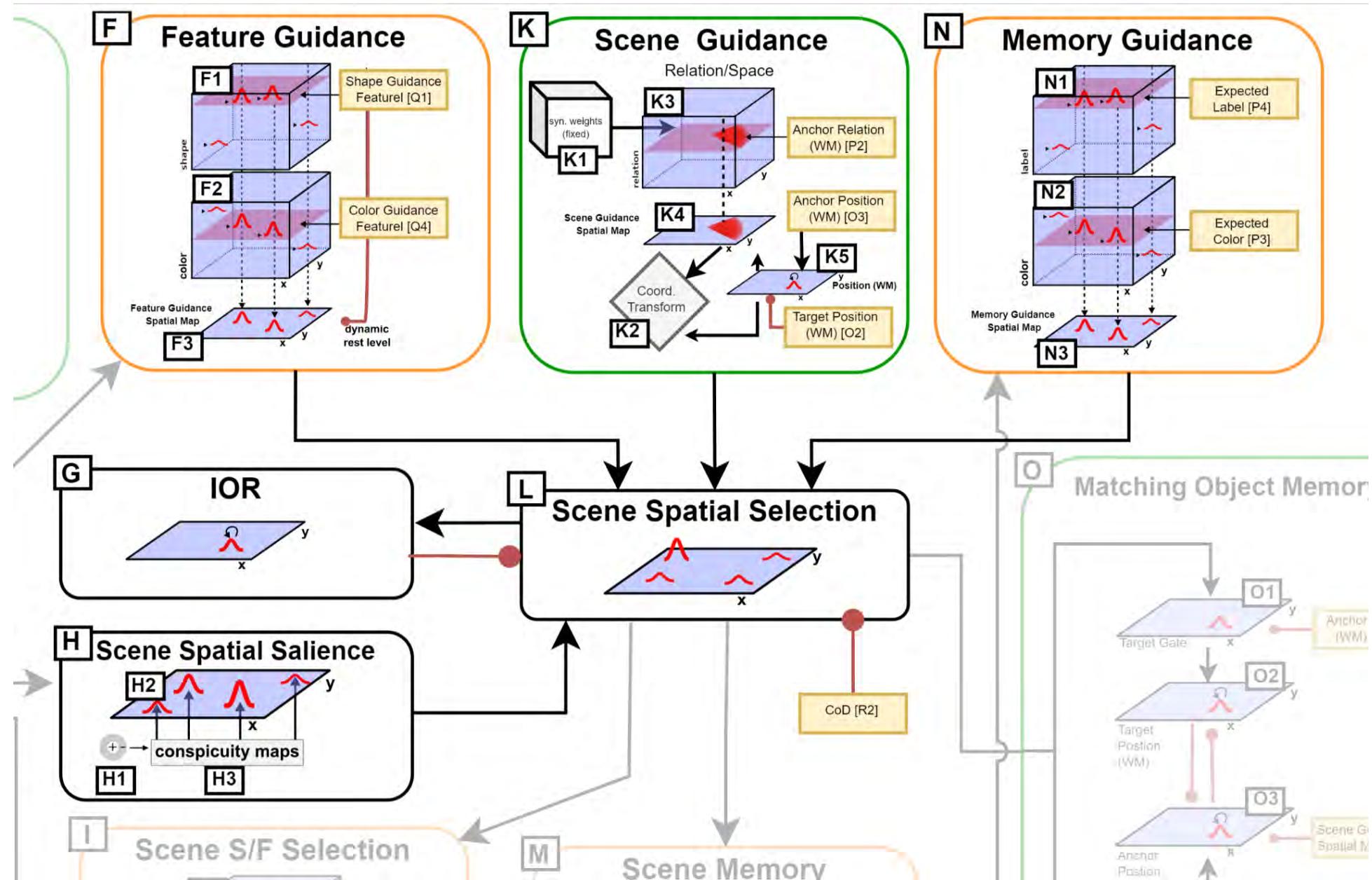
# Feed-forward feature and salience maps



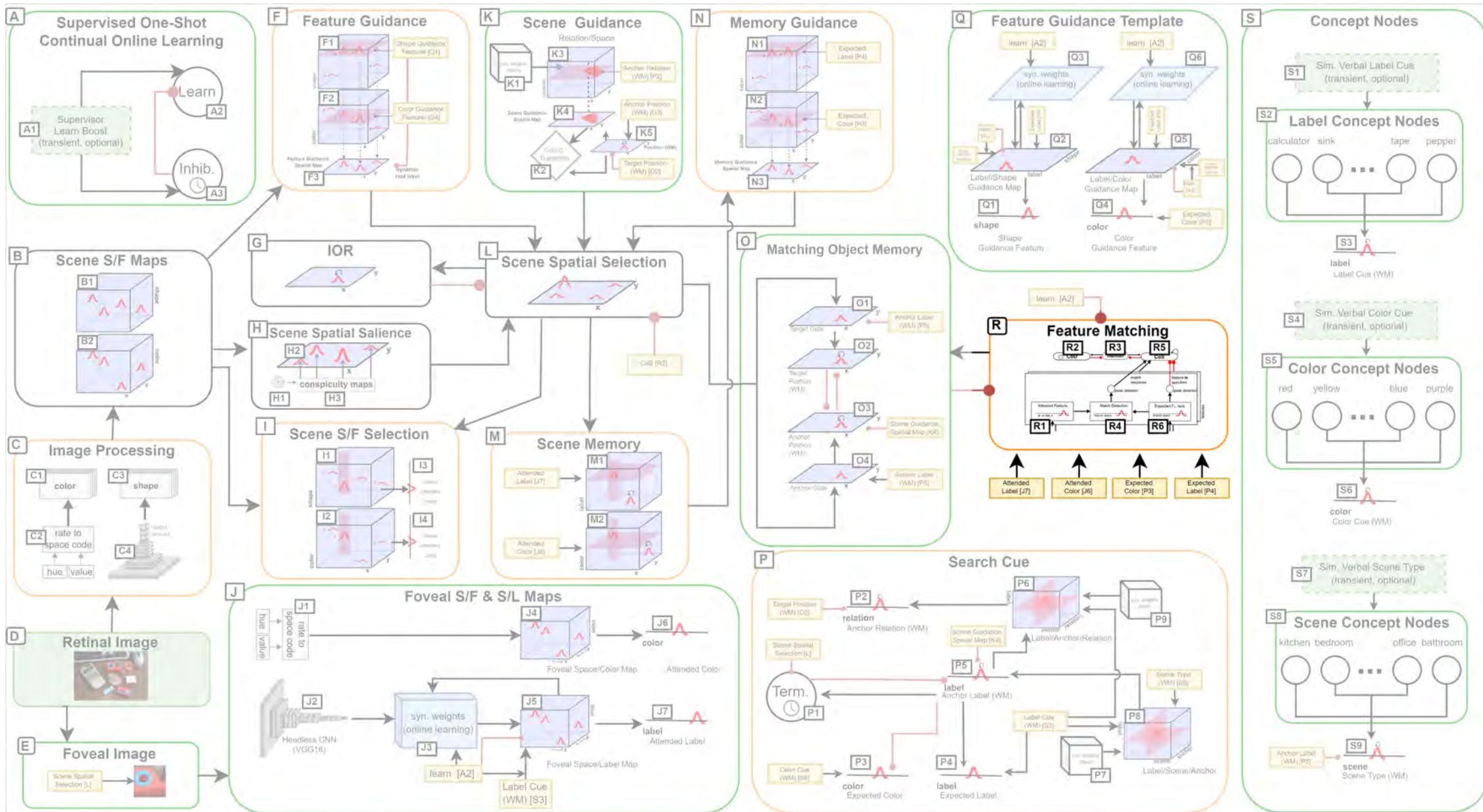
# Attentional selection through biased competition



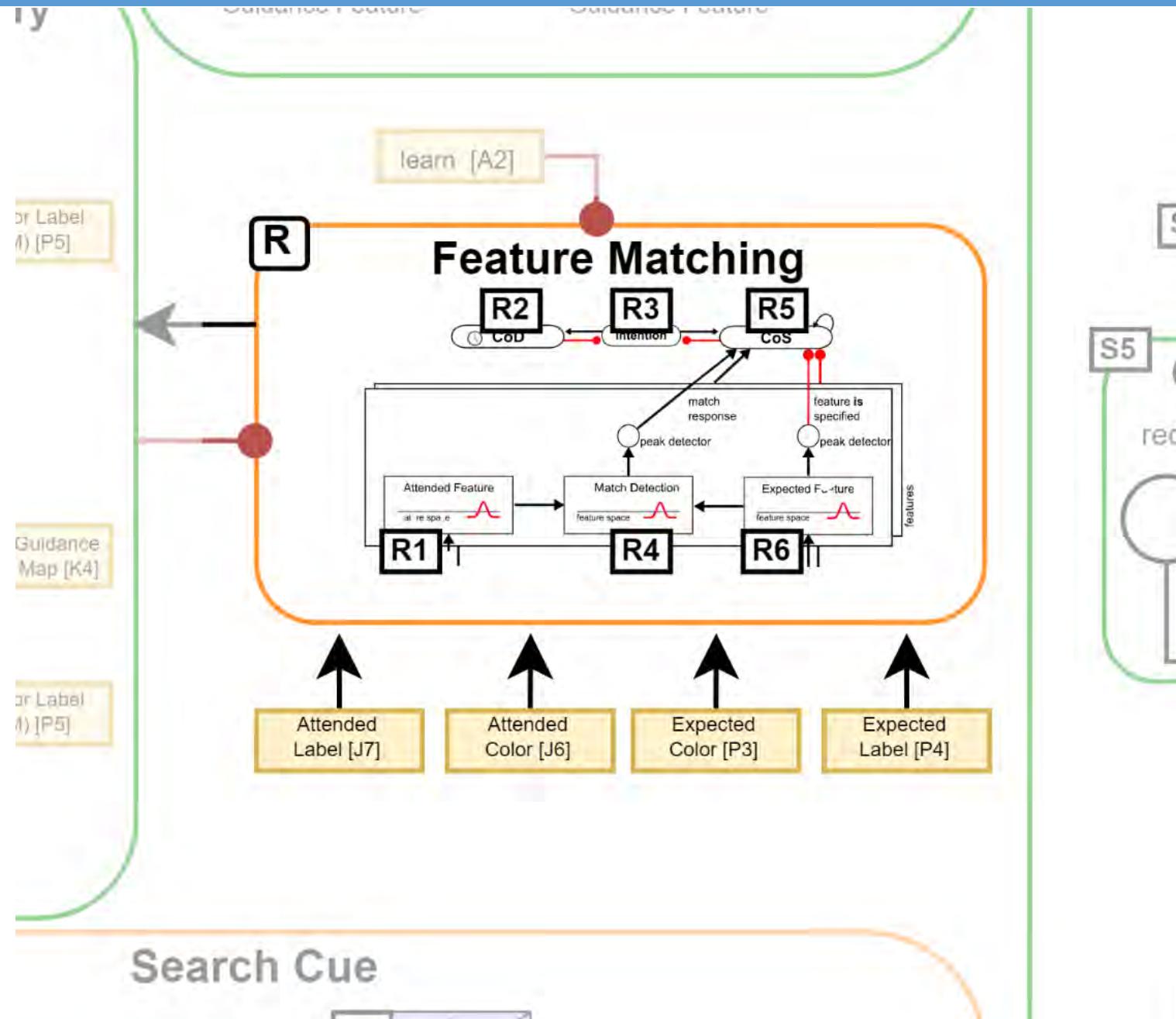
# Attentional selection through biased competition



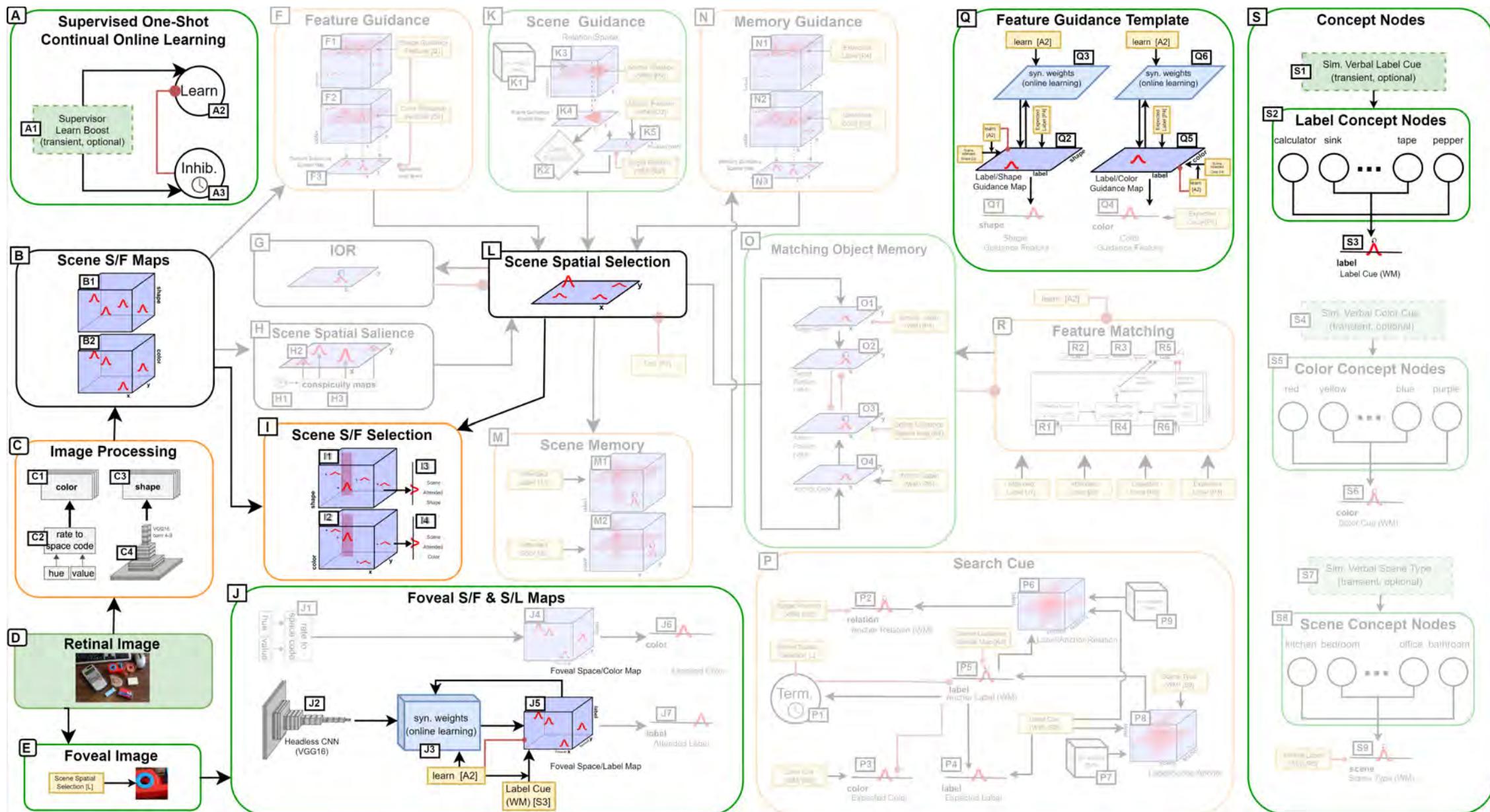
# Match detection



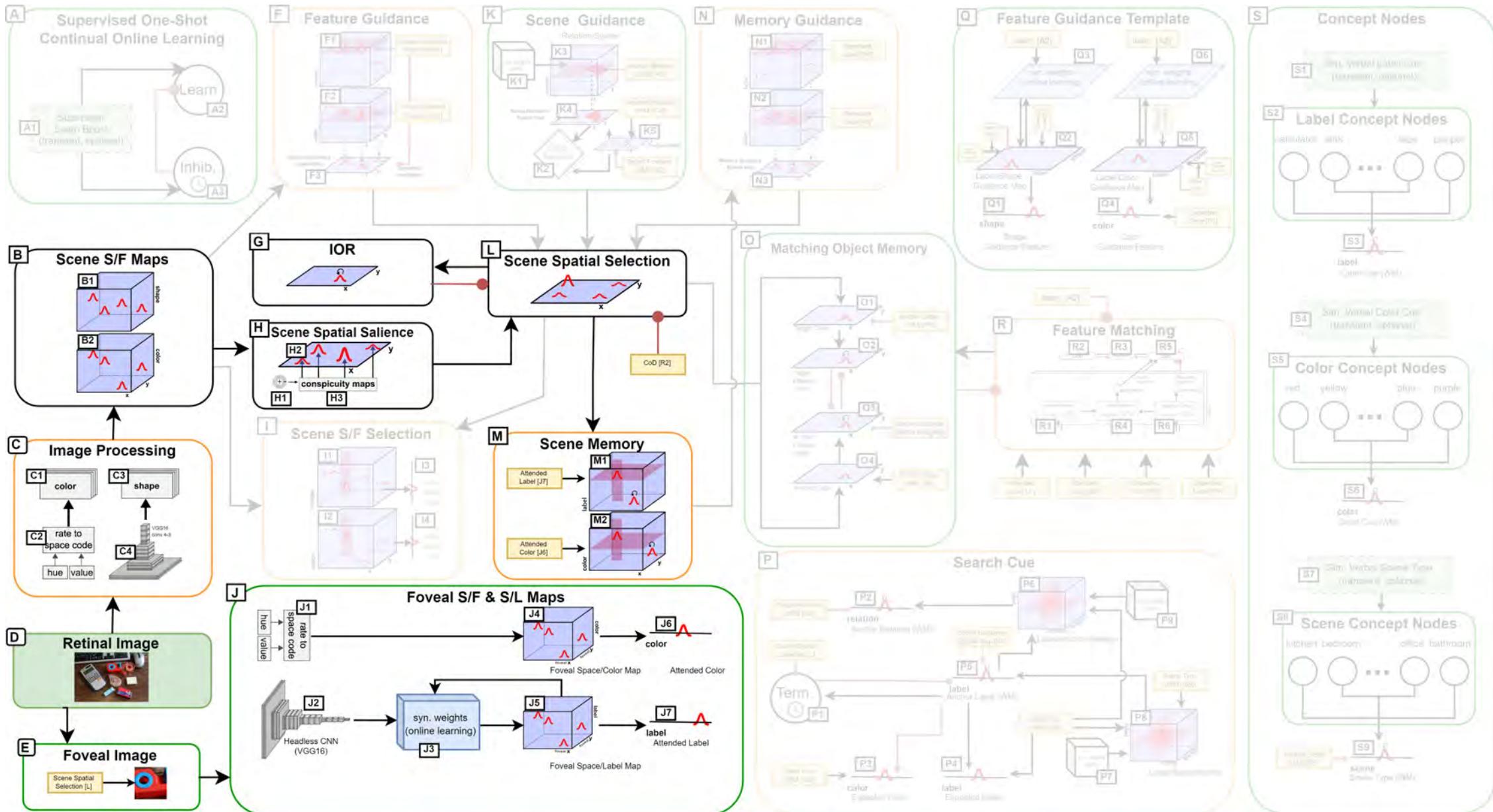
# Match detection



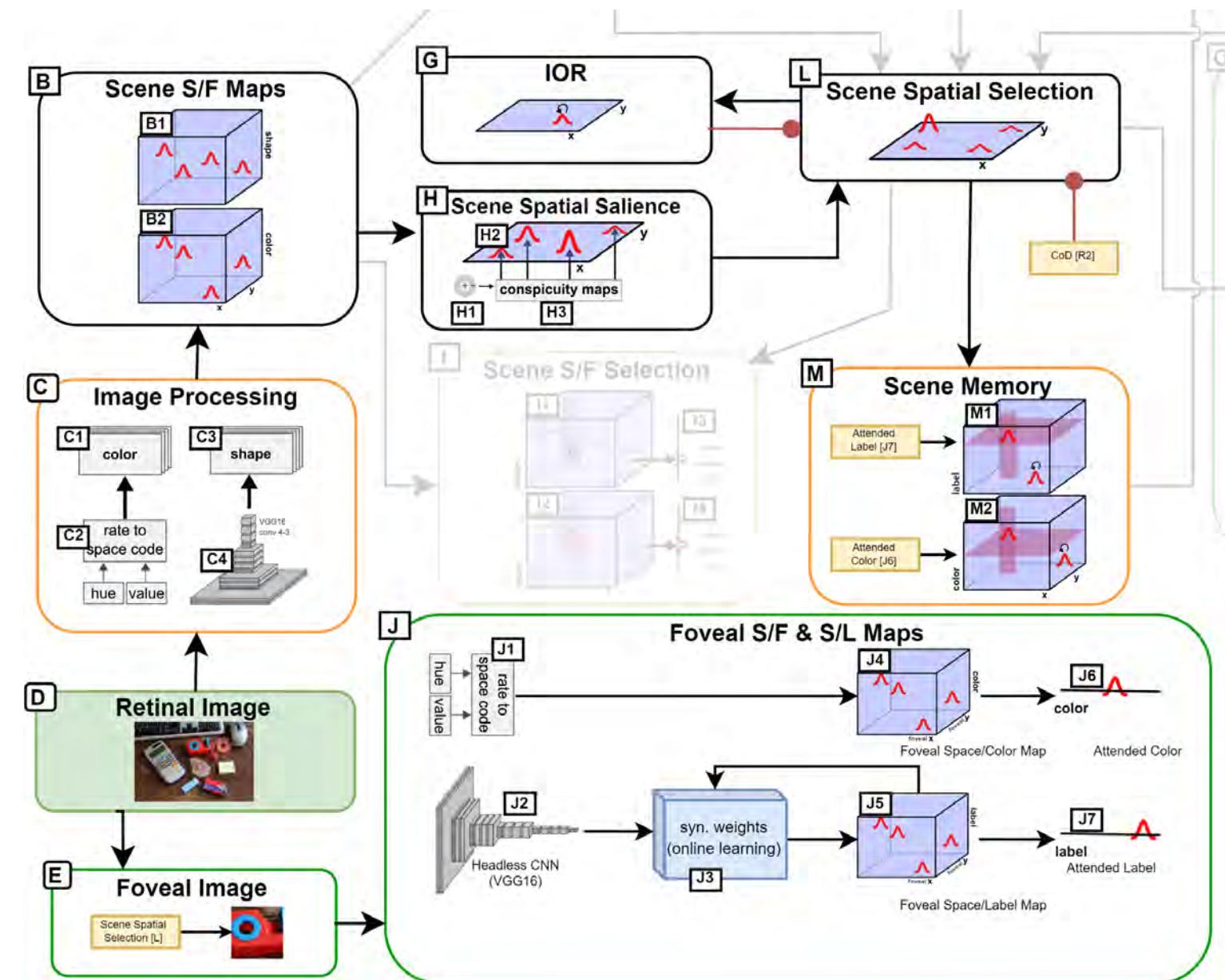
# Learning



# Autonomous visual exploration

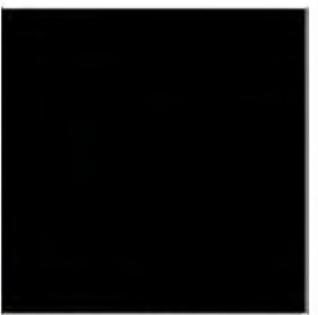


# Autonomous visual exploration

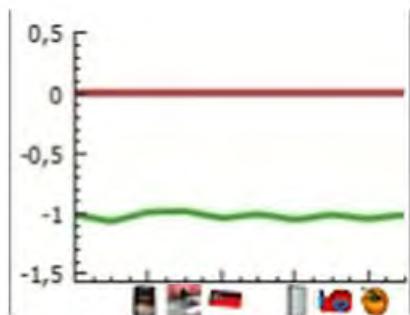




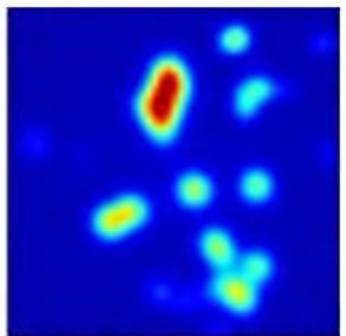
Camera Image



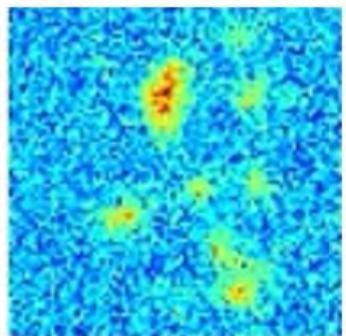
Foveal Image



Attended Label



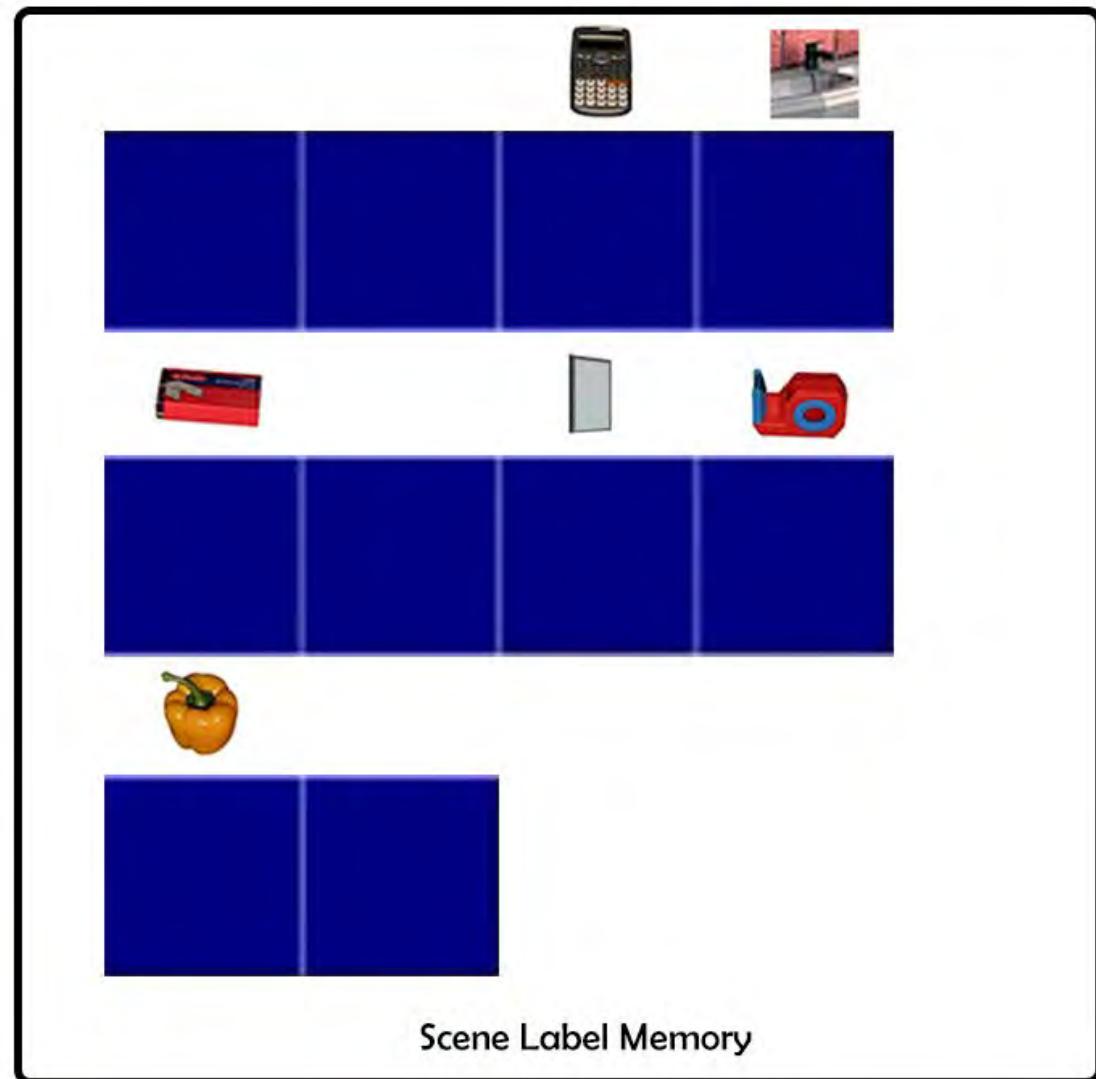
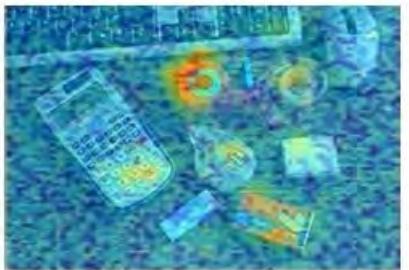
Attention (Input)



Attention (Activation)



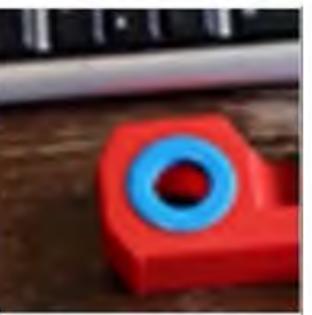
Attention (Sig. Activation)



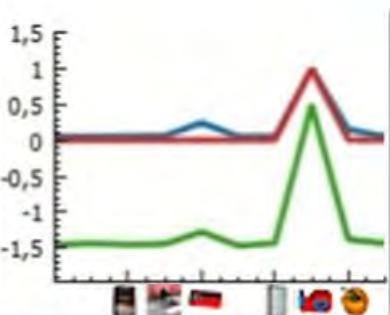
Scene Label Memory



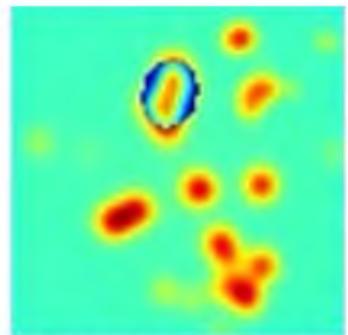
Camera Image



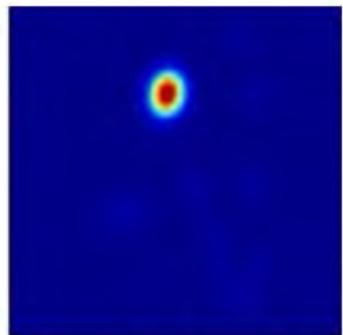
Foveal Image



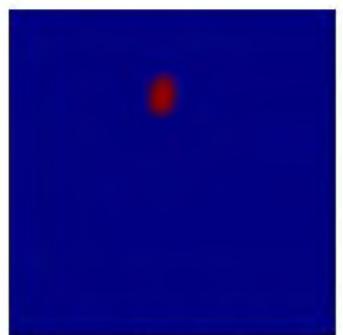
Attended Label



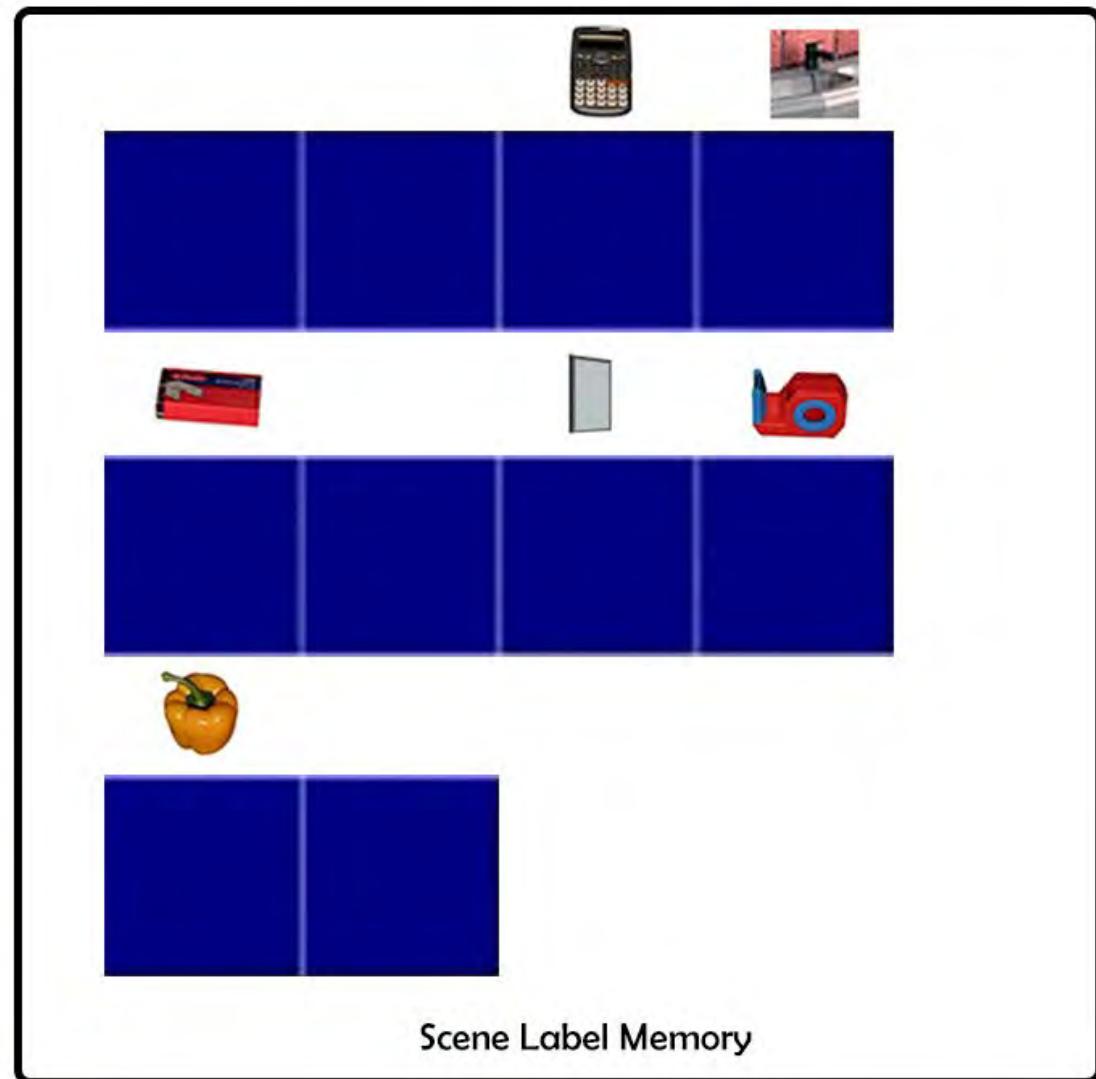
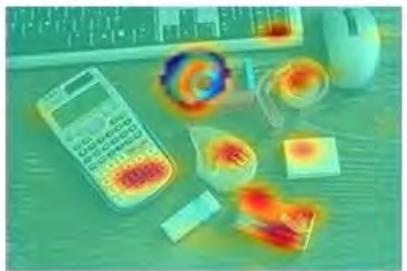
Attention (Input)



Attention (Activation)



Attention (Sig. Activation)



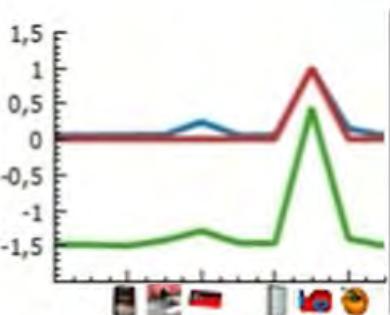
Scene Label Memory



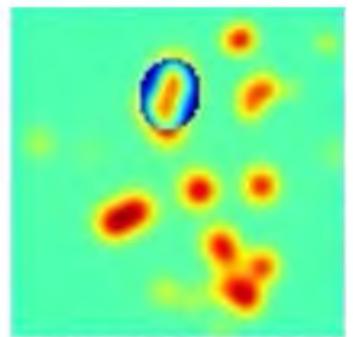
Camera Image



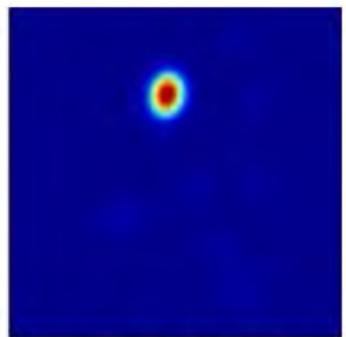
Foveal Image



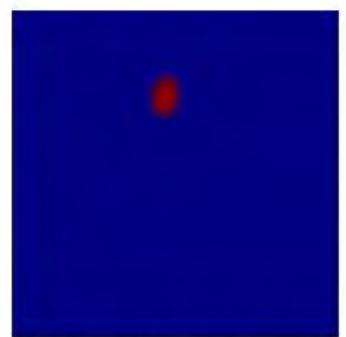
Attended Label



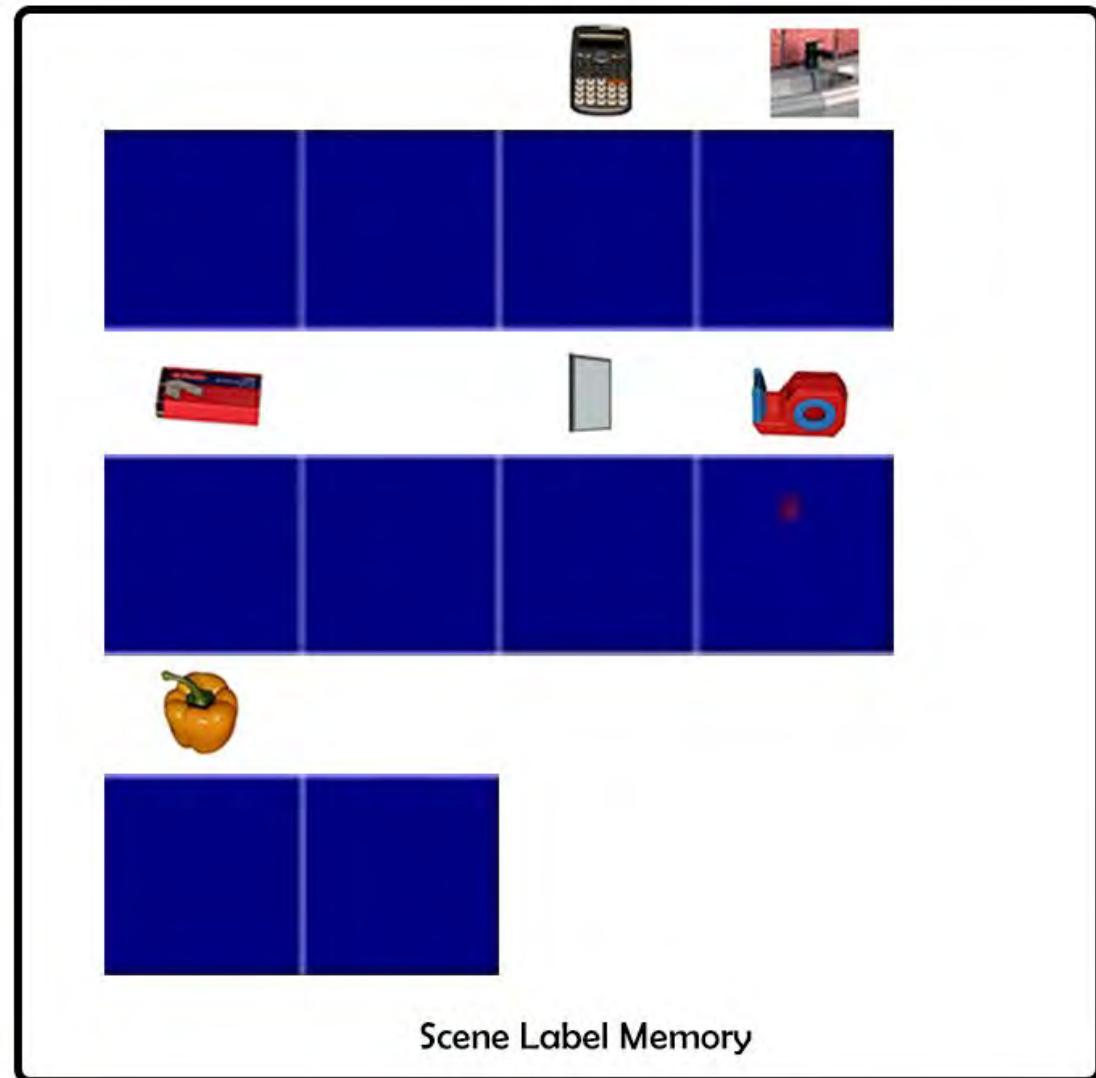
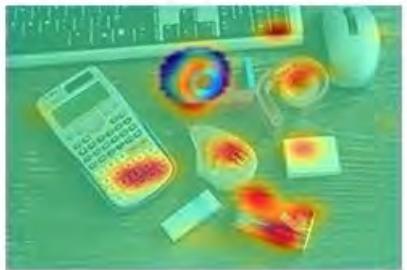
Attention (Input)



Attention (Activation)



Attention (Sig. Activation)

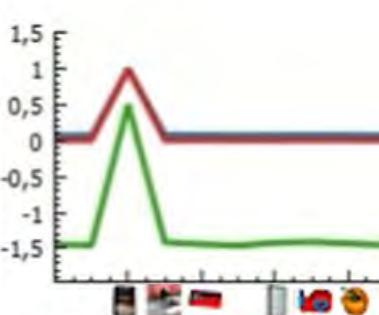




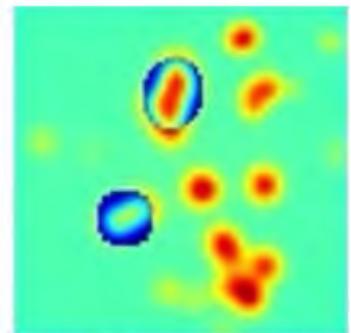
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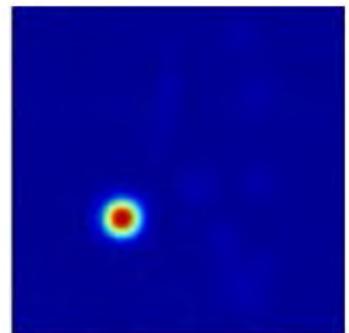
Foveal Image



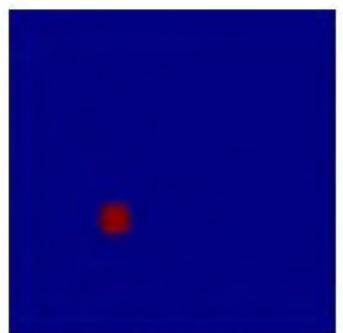
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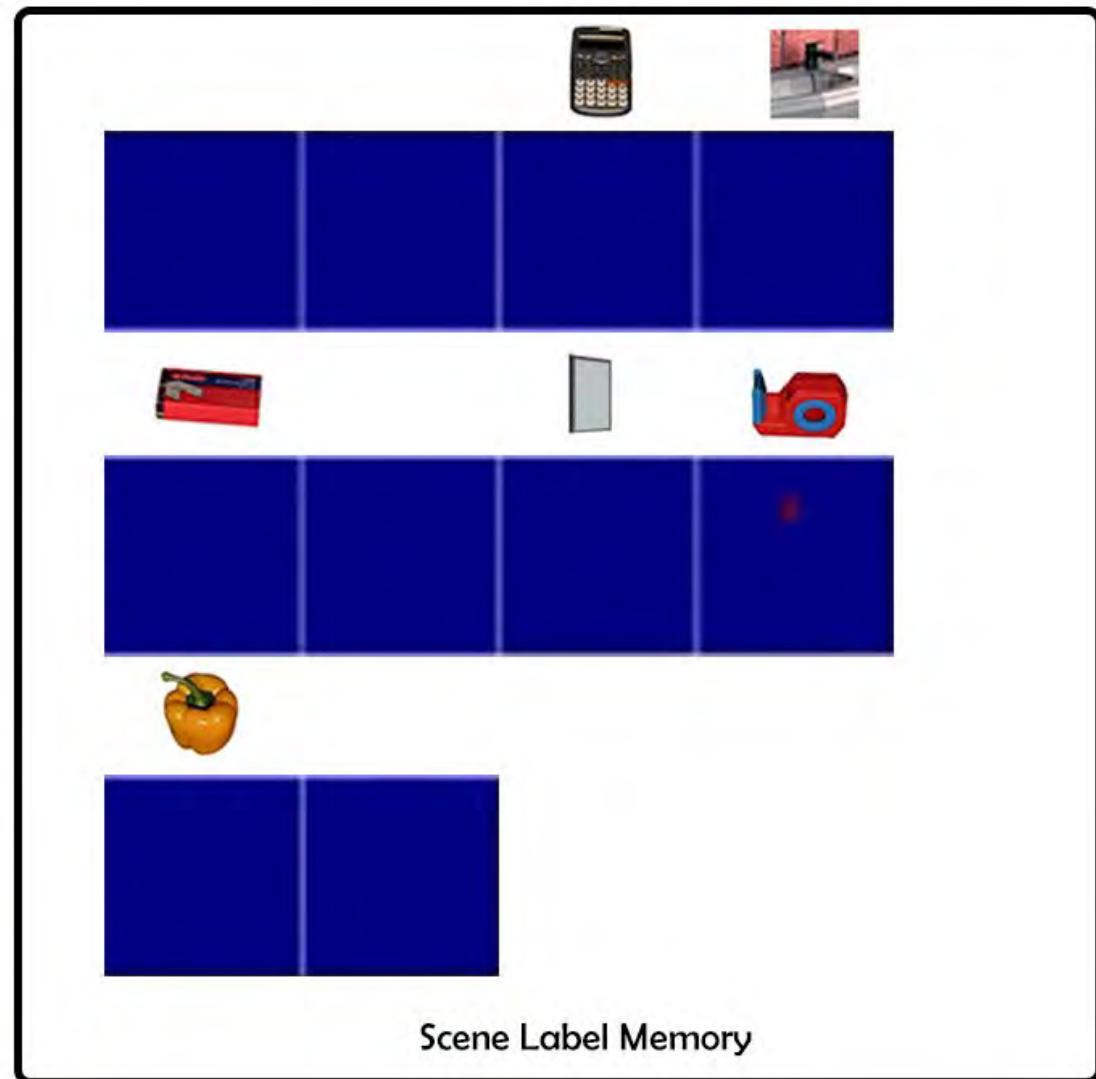
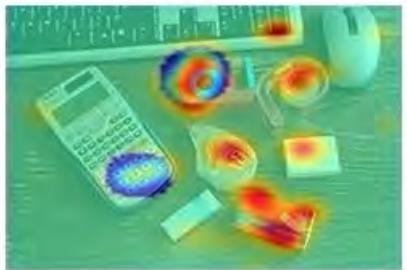
Attention (Input)



Attention (Activation)



Attention (Sig. Activation)

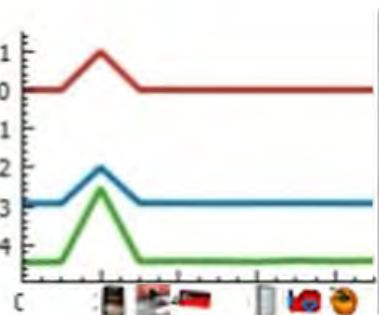




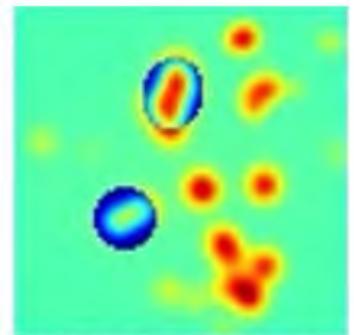
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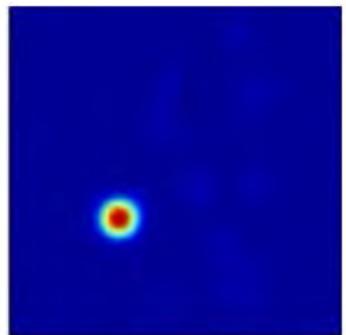
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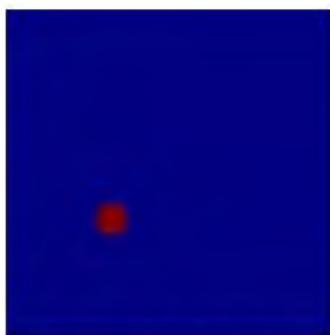
Attended Label



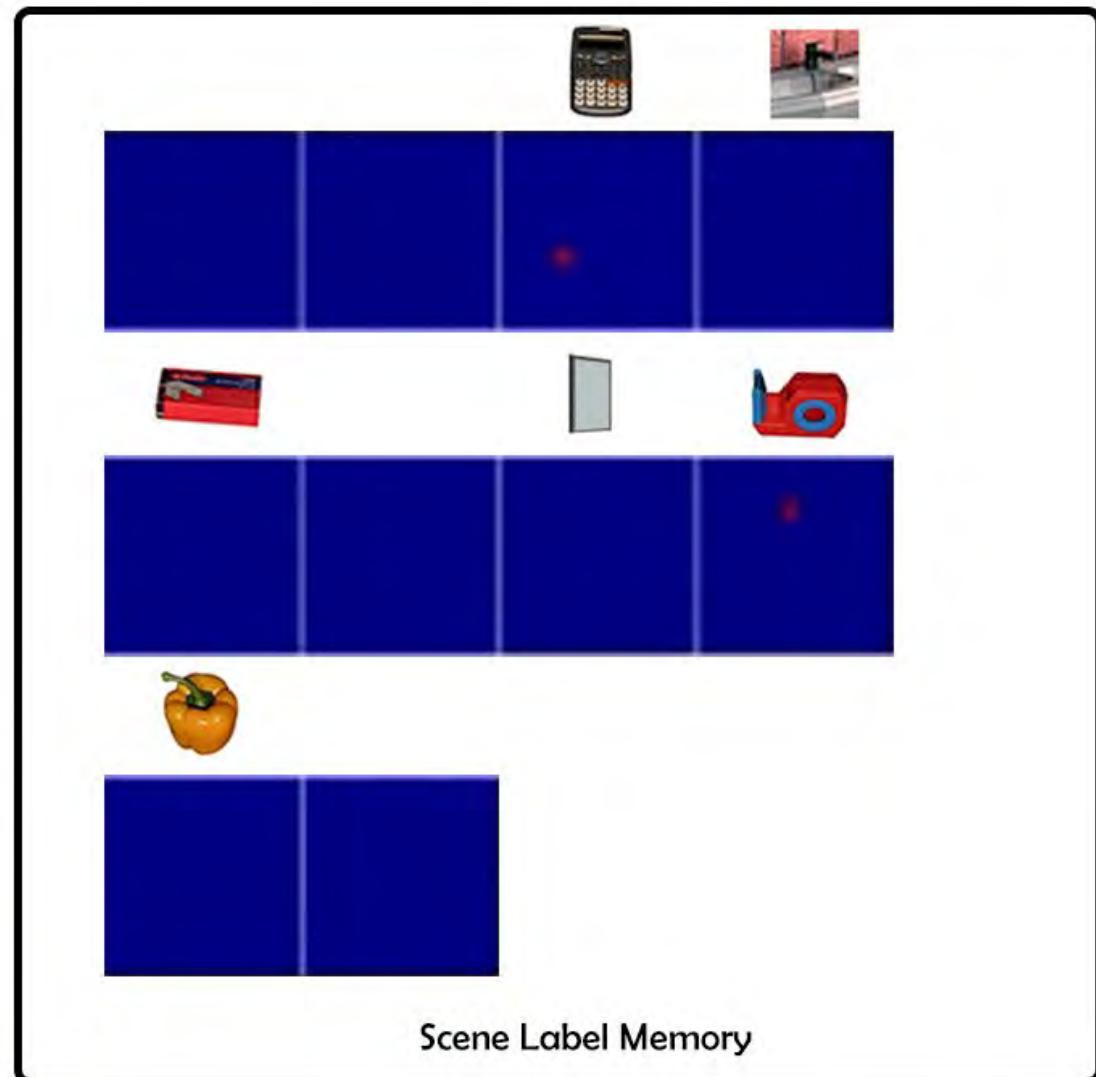
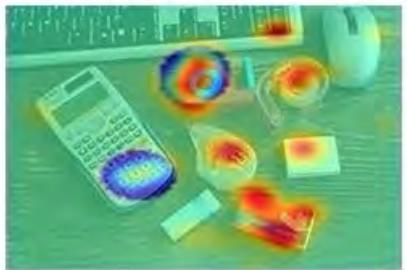
Attention (Input)



Attention (Activation)



Attention (Sig. Activation)

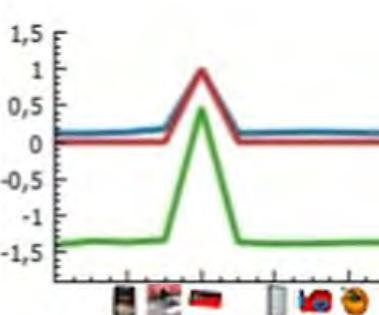




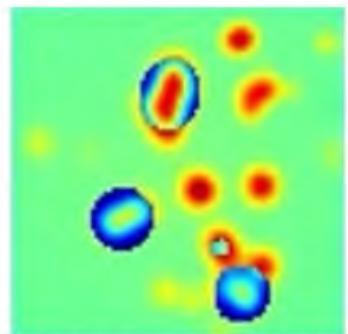
Camera Image



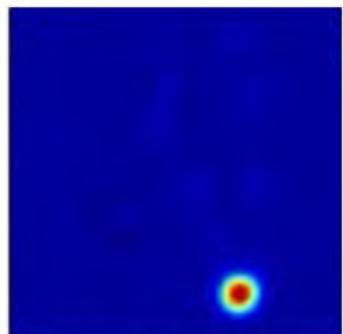
Foveal Image



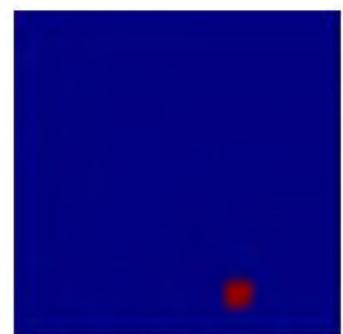
Attended Label



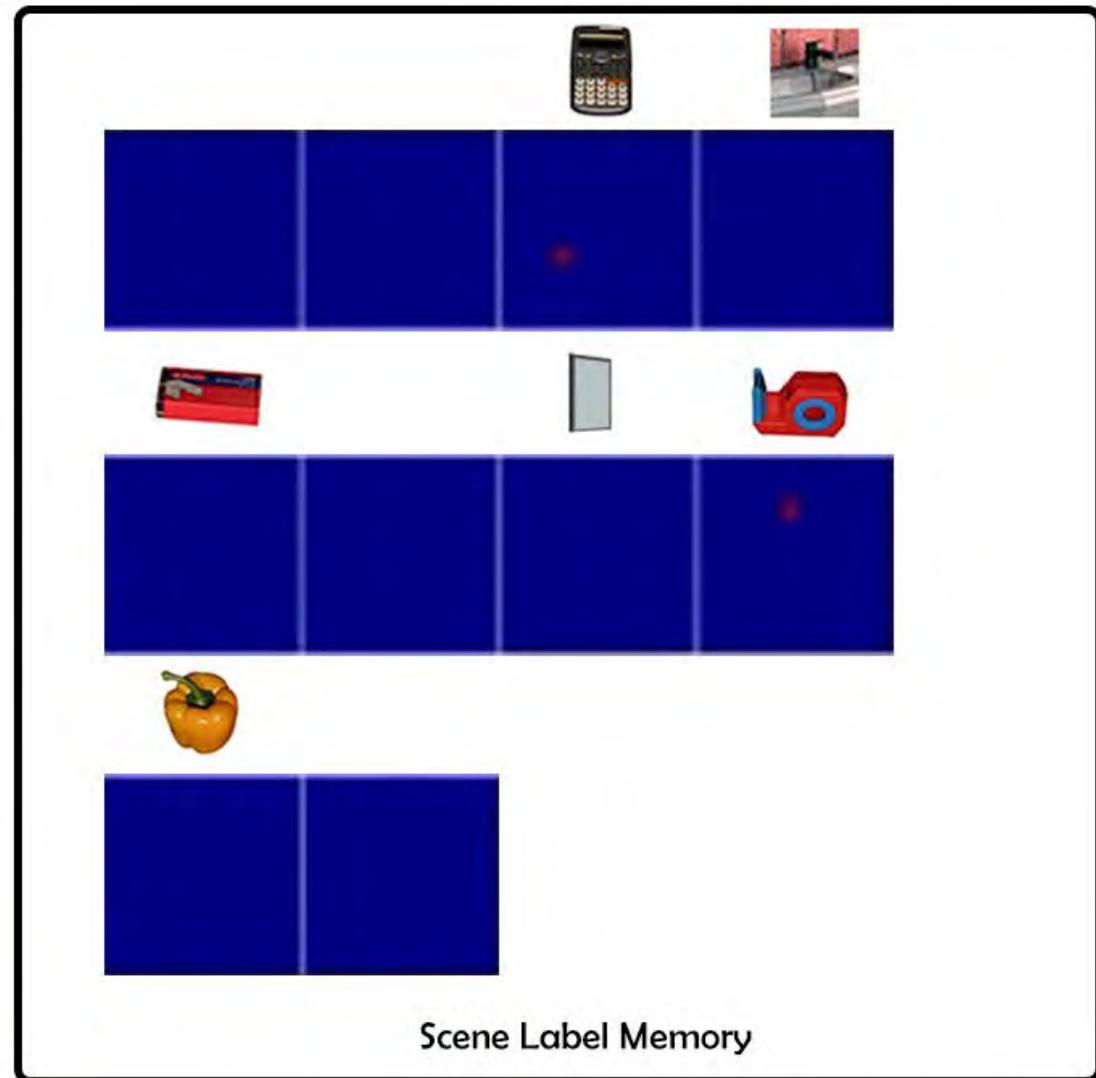
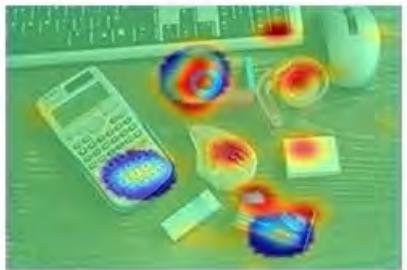
Attention (Input)



Attention (Activation)

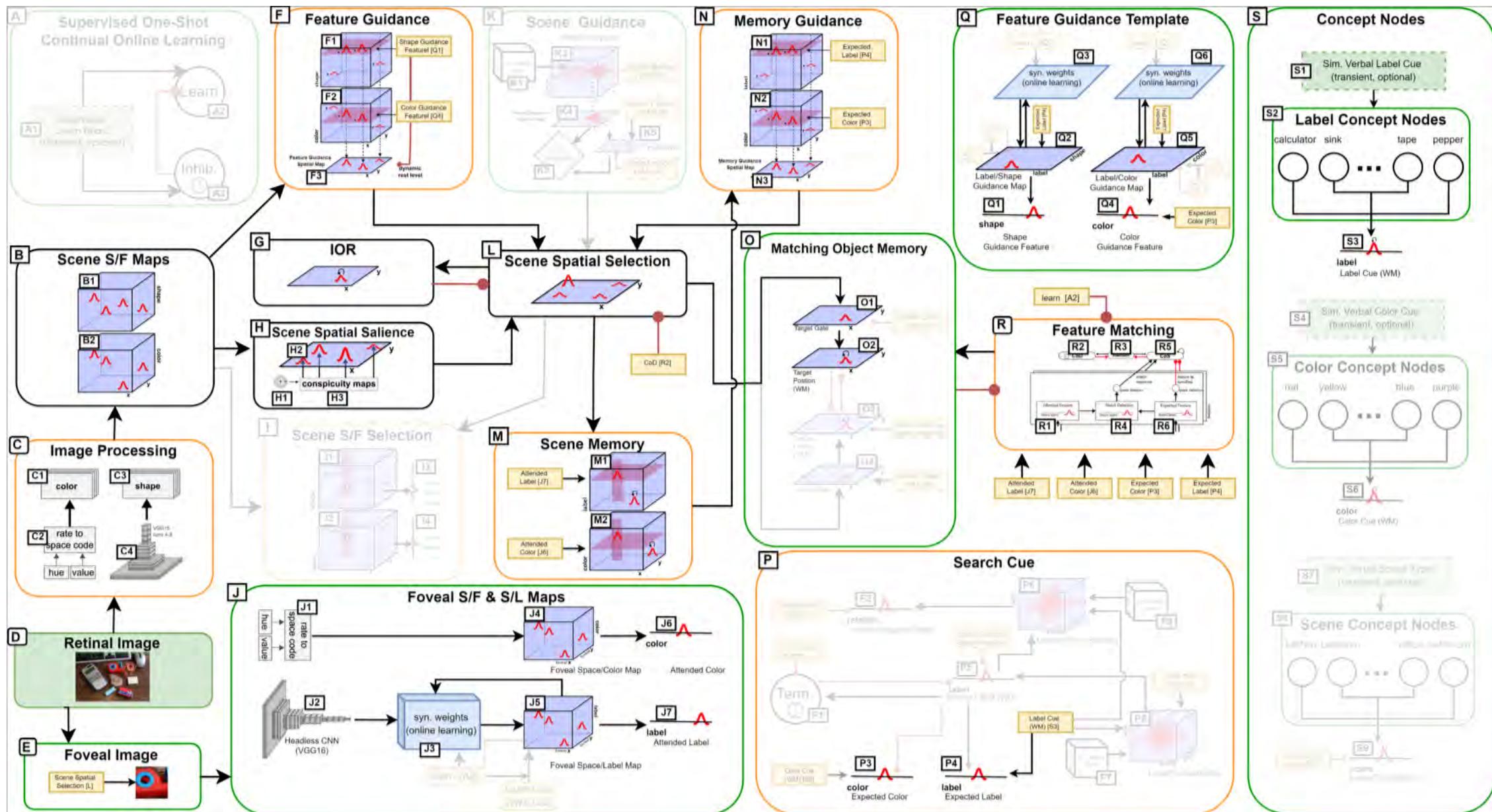


Attention (Sig. Activation)



Scene Label Memory

# Categorical visual search





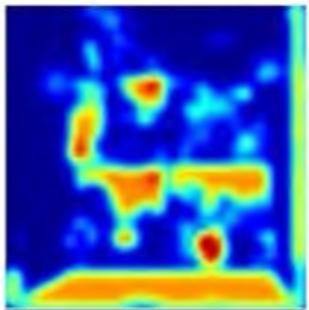
Camera Image



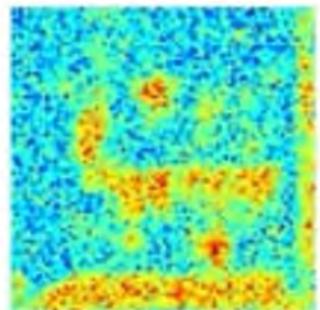
Foveal Image



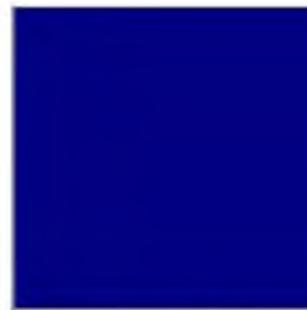
Target Position (WM)



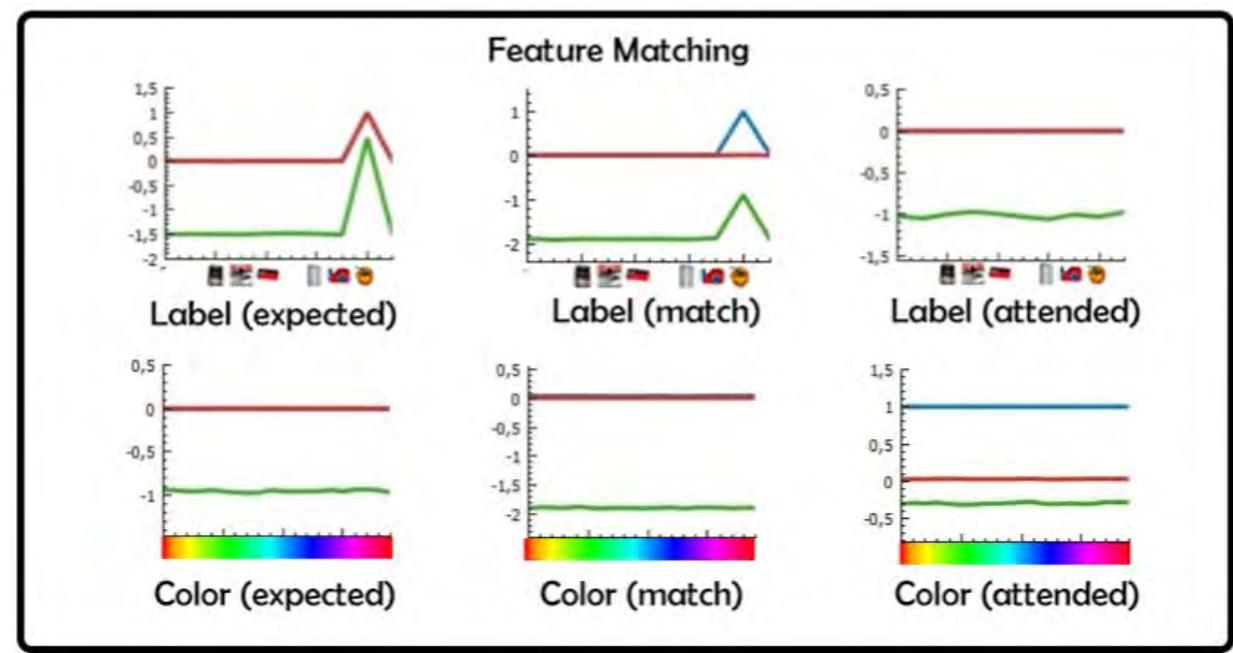
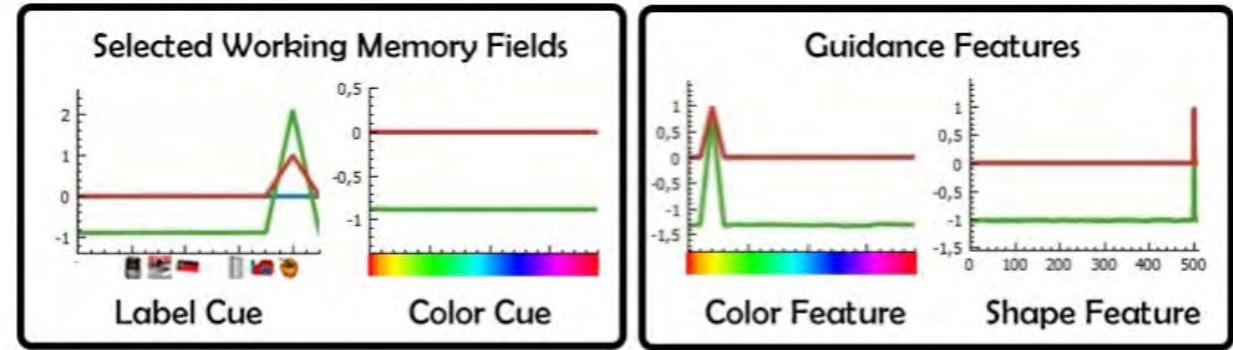
Attention (Input)



Attention (Activation)



Attention (Sig. Activation)





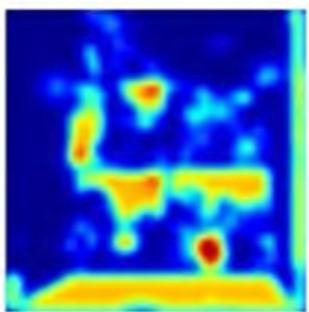
Camera Image



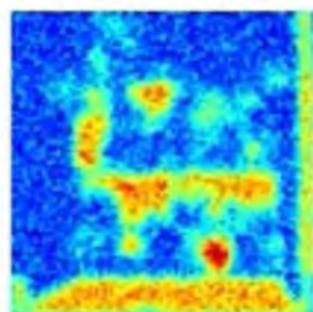
Foveal Image



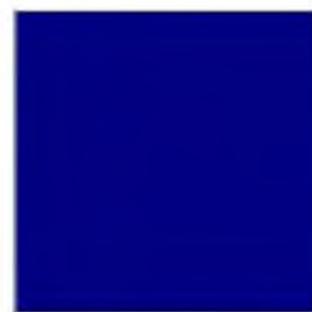
Target Position (WM)



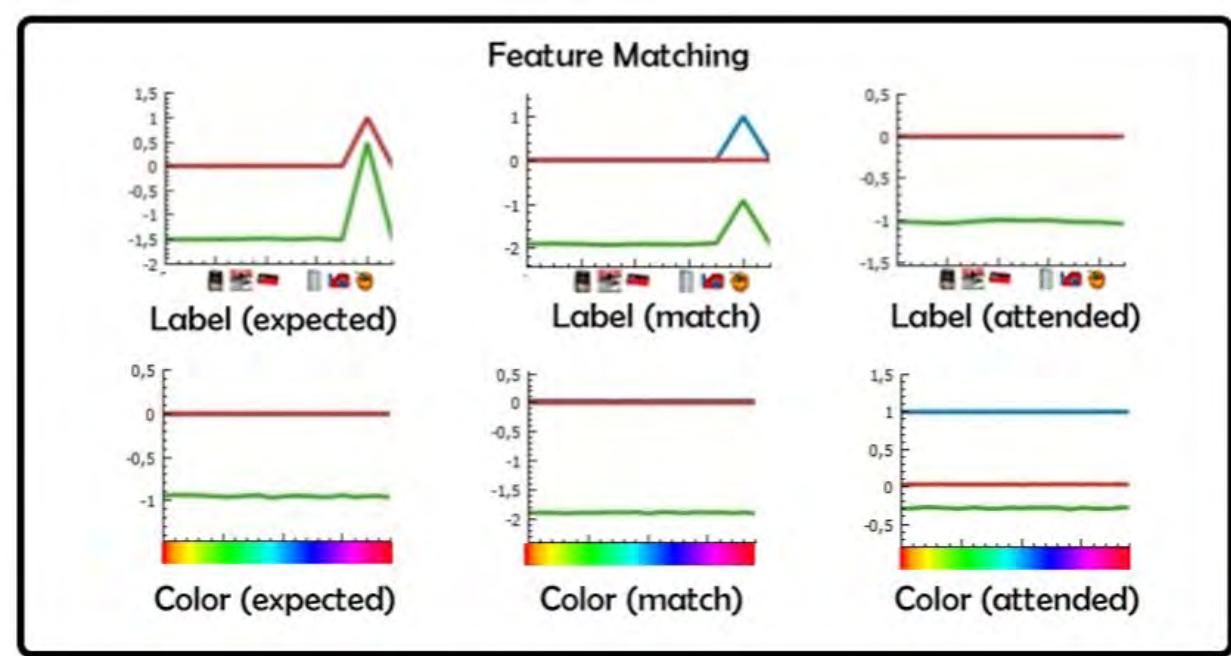
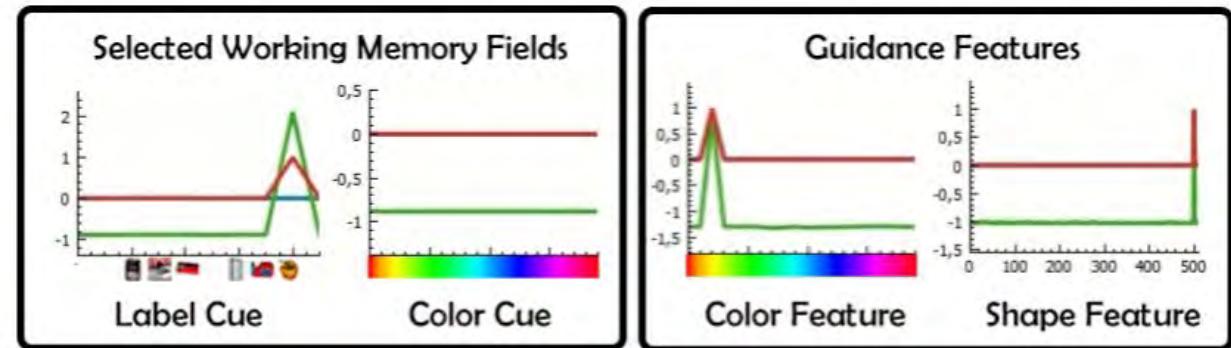
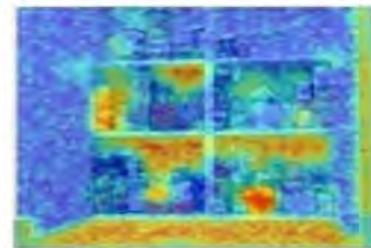
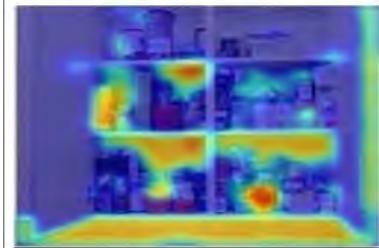
Attention (Input)



Attention (Activation)

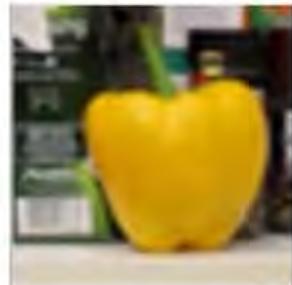


Attention (Sig. Activation)

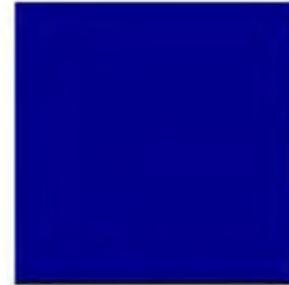




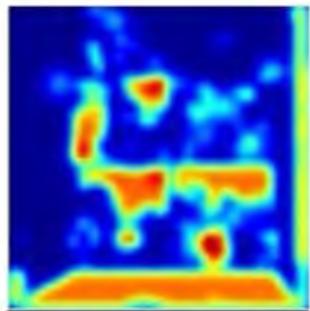
Camera Image



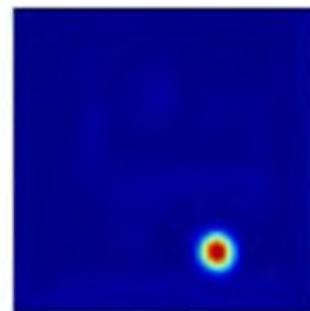
Foveal Image



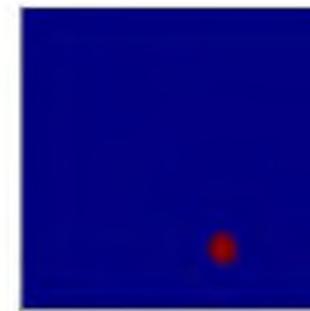
Target Position (WM)



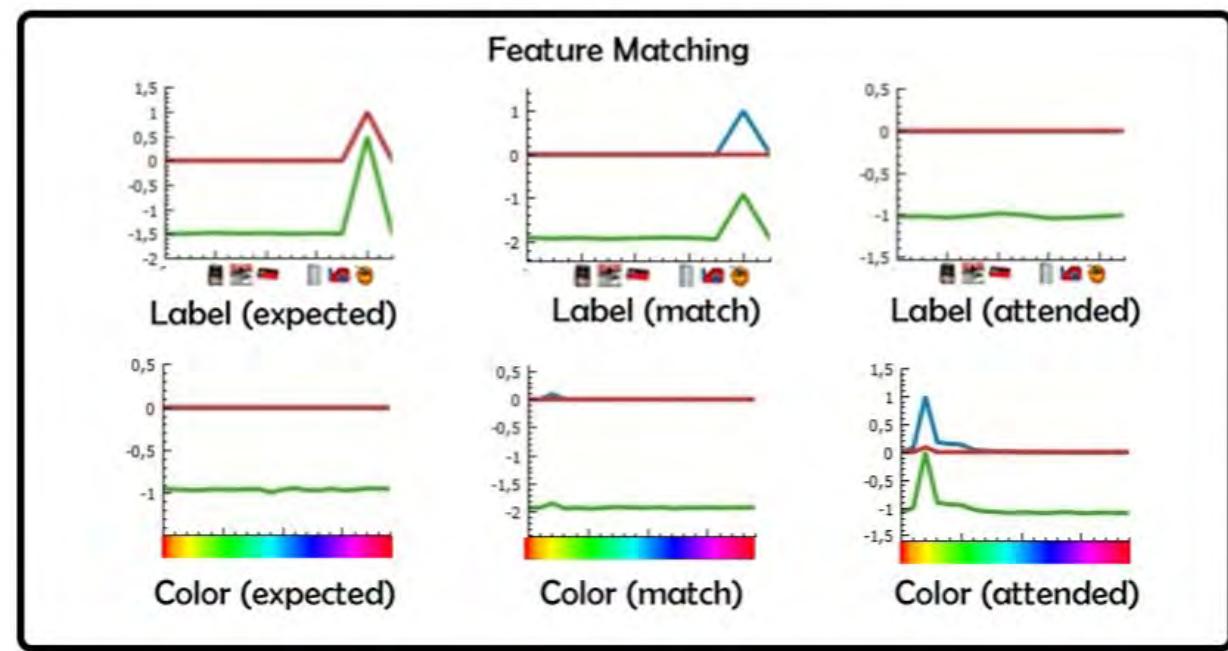
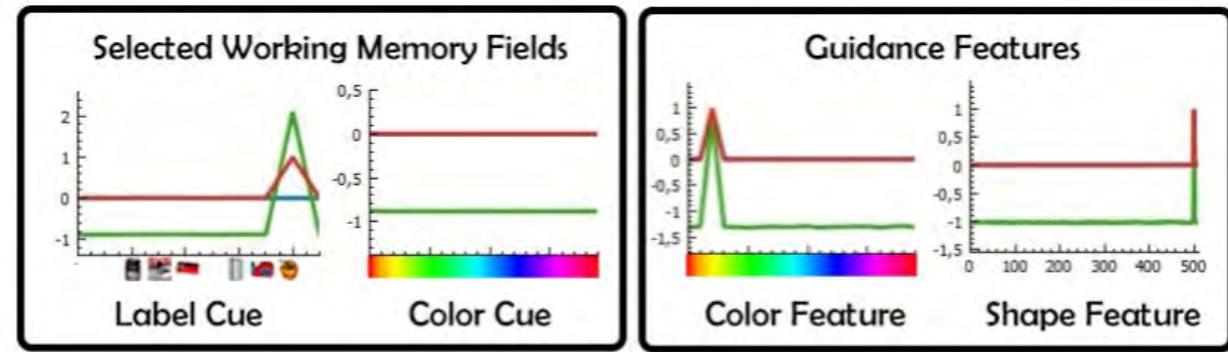
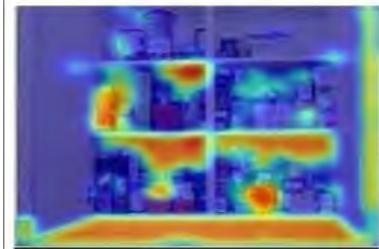
Attention (Input)



Attention (Activation)

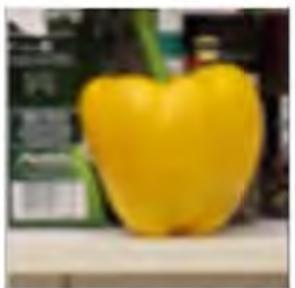


Attention (Sig. Activation)





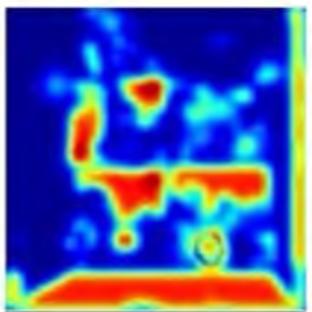
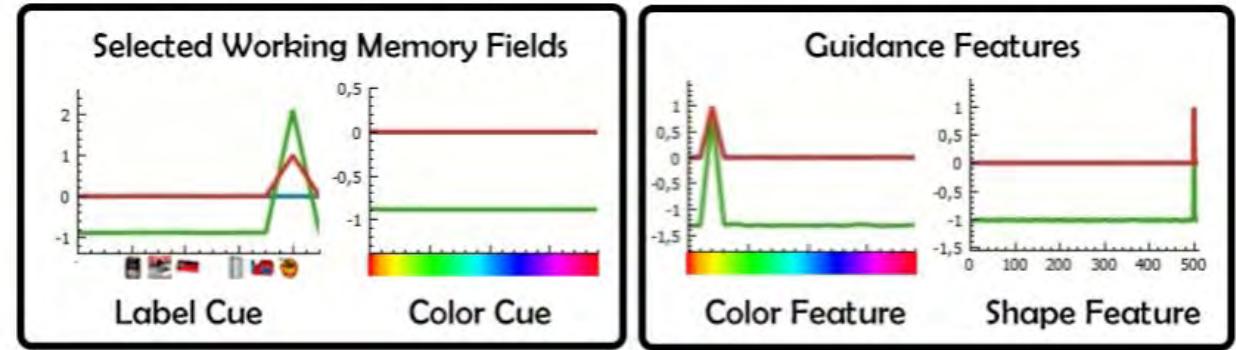
Camera Image



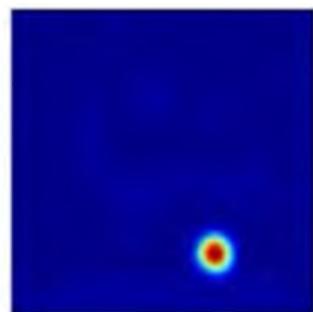
Foveal Image



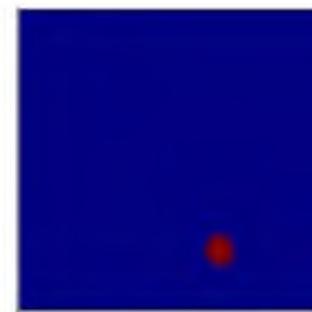
Target Position (WM)



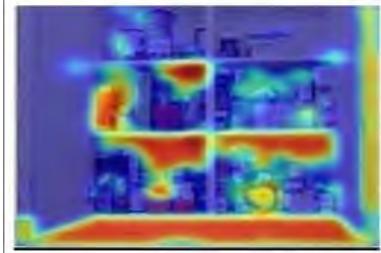
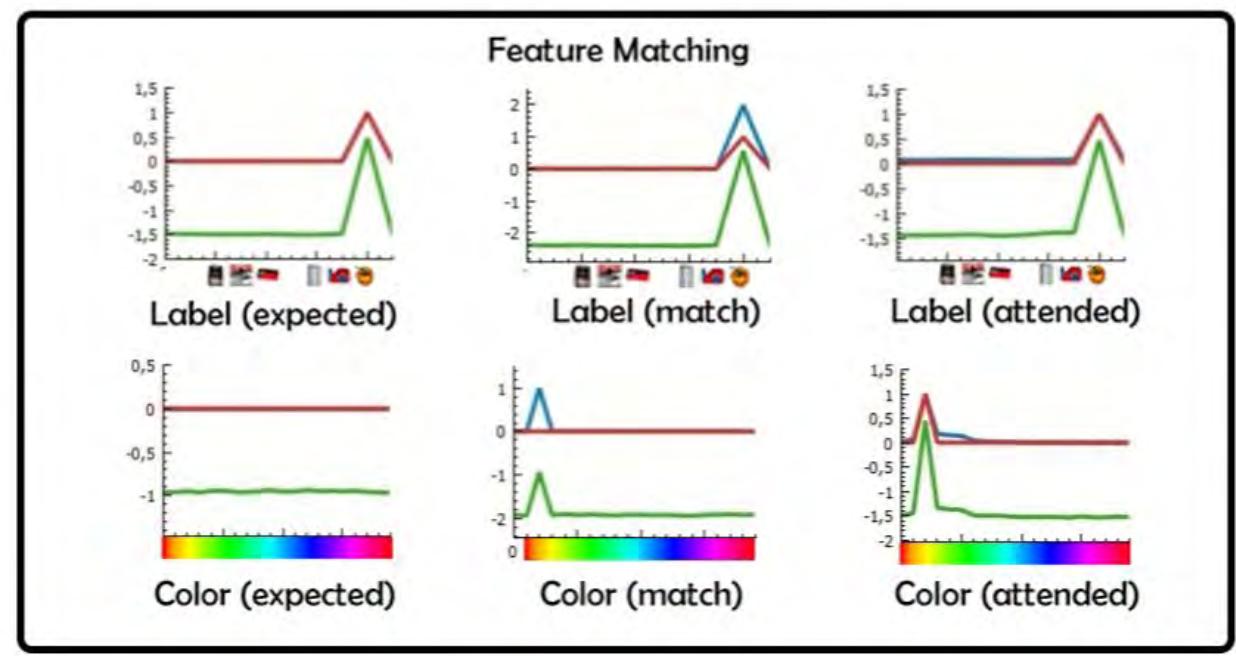
Attention (Input)



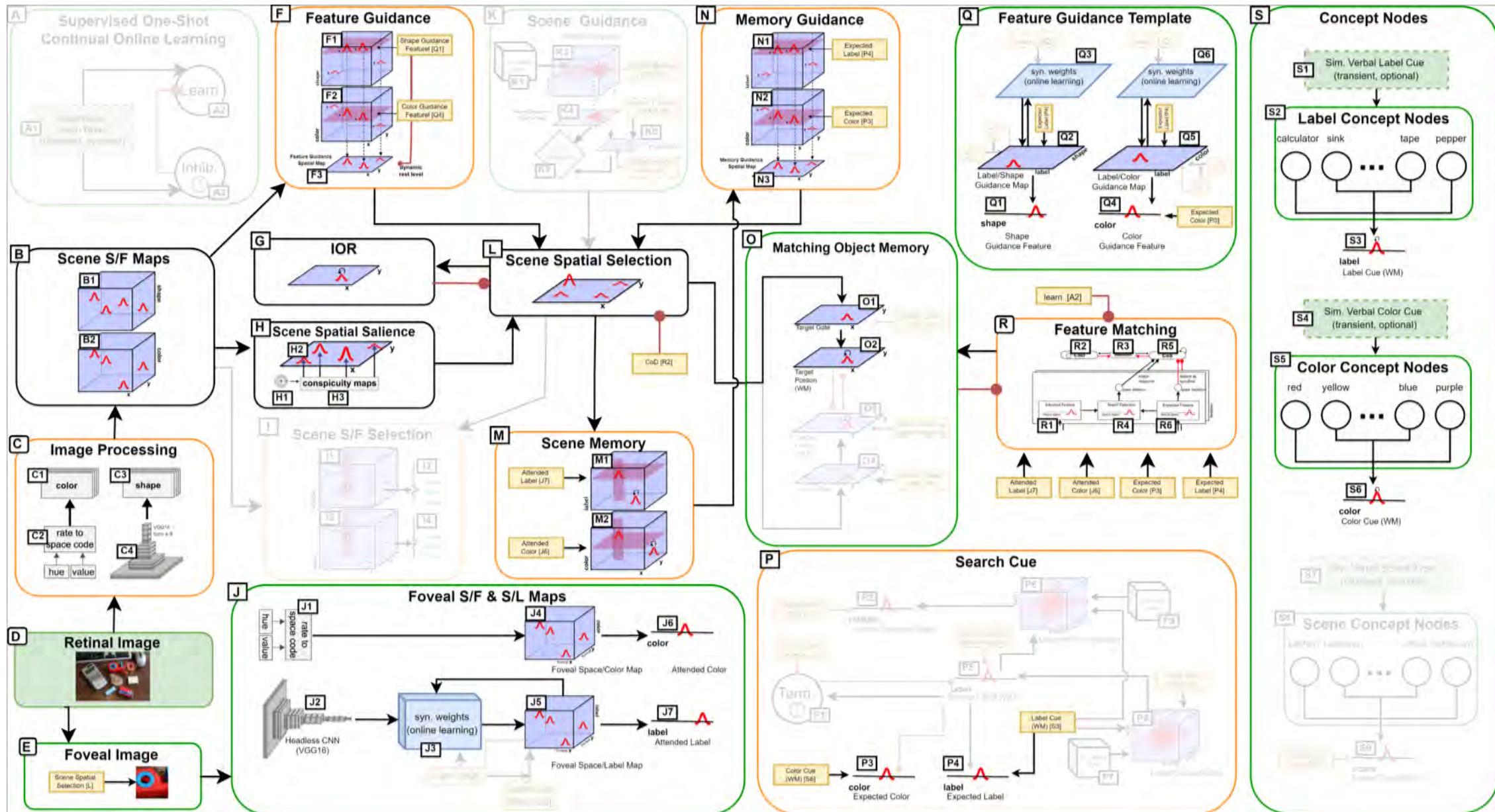
Attention (Activation)



Attention (Sig. Activation)



# Combined categorical and basic feature visual search





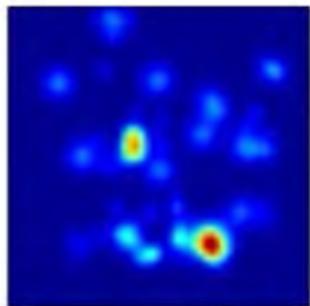
Camera Image



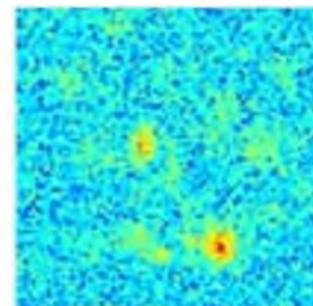
Foveal Image



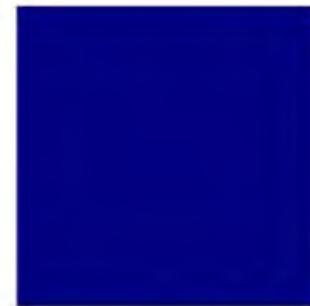
Target Position (WM)



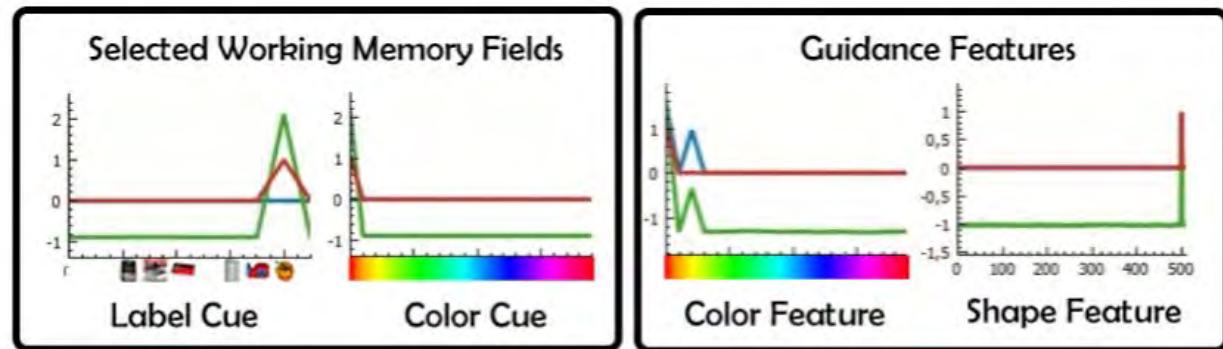
Attention (Input)



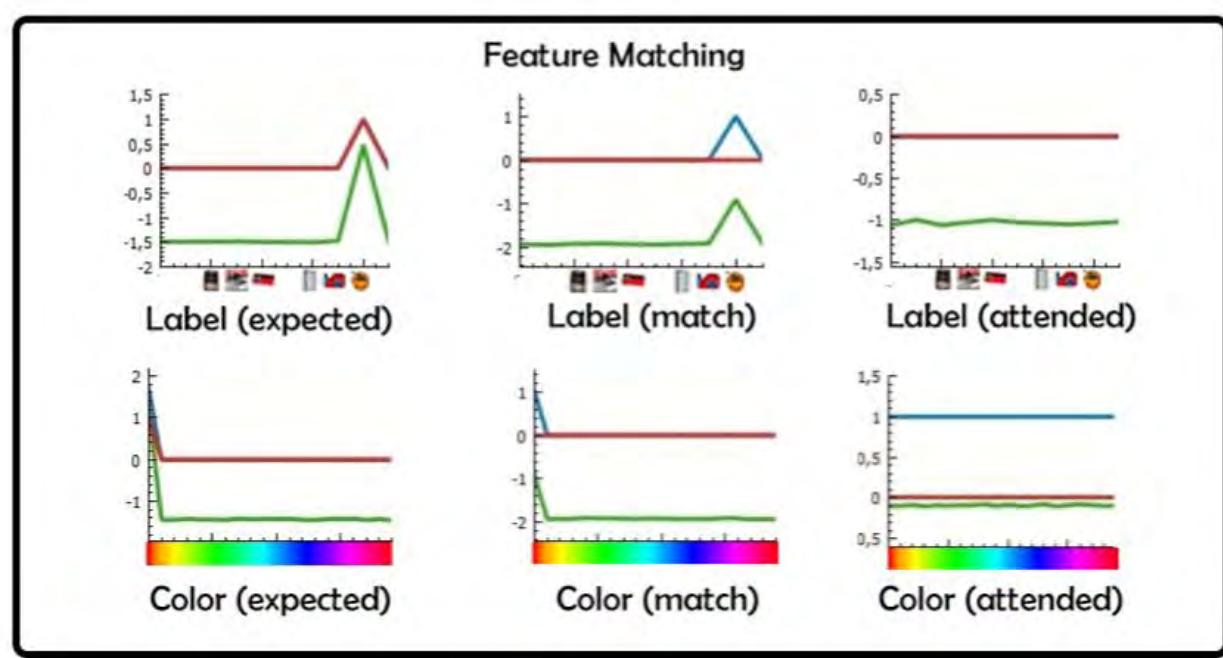
Attention (Activation)



Attention (Sig. Activation)

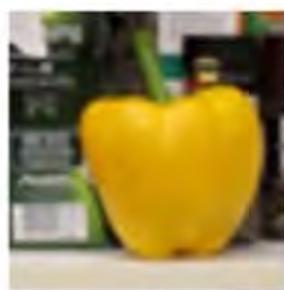


Color Feature      Shape Feature





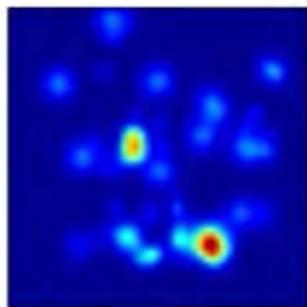
Camera Image



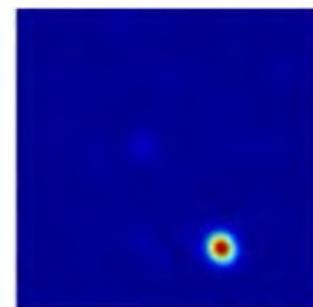
Foveal Image



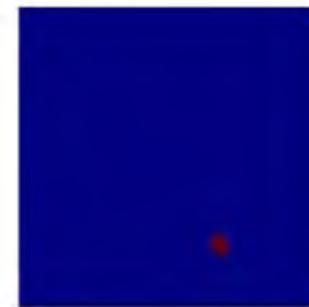
Target Position (WM)



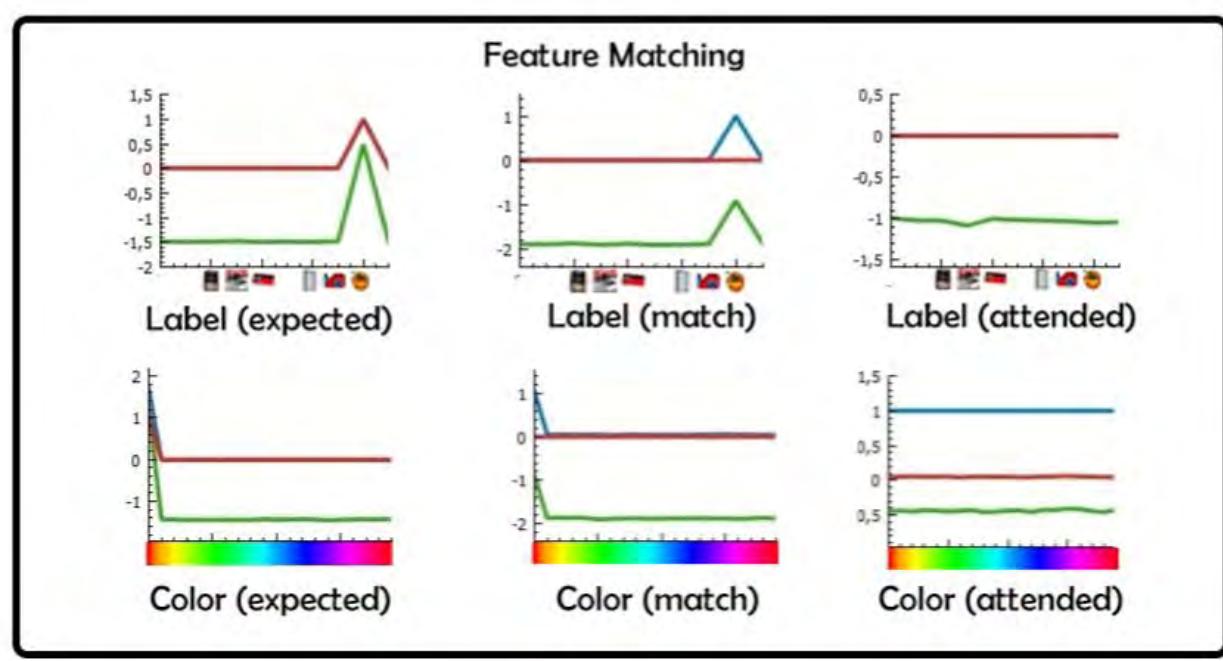
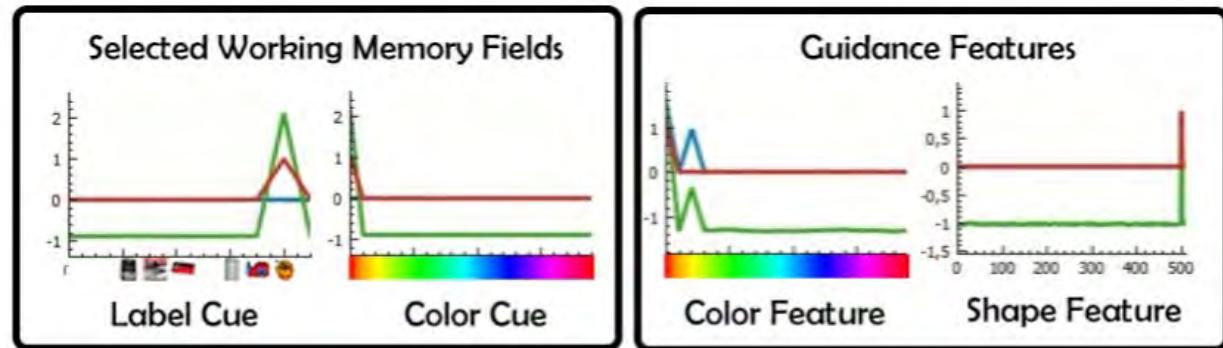
Attention (Input)



Attention (Activation)

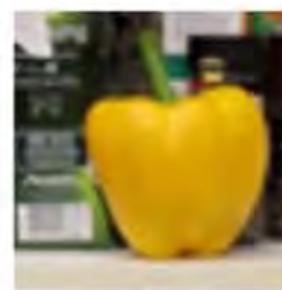


Attention (Sig. Activation)

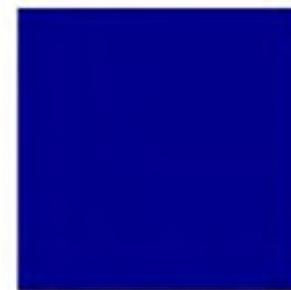




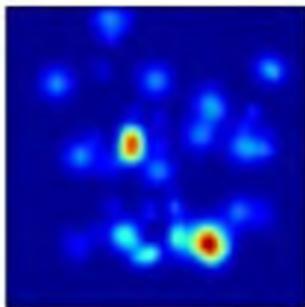
Camera Image



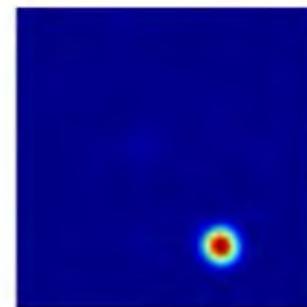
Foveal Image



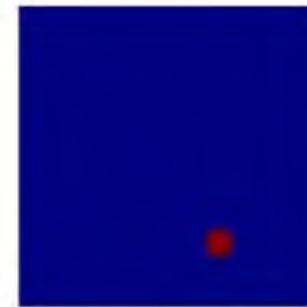
Target Position (WM)



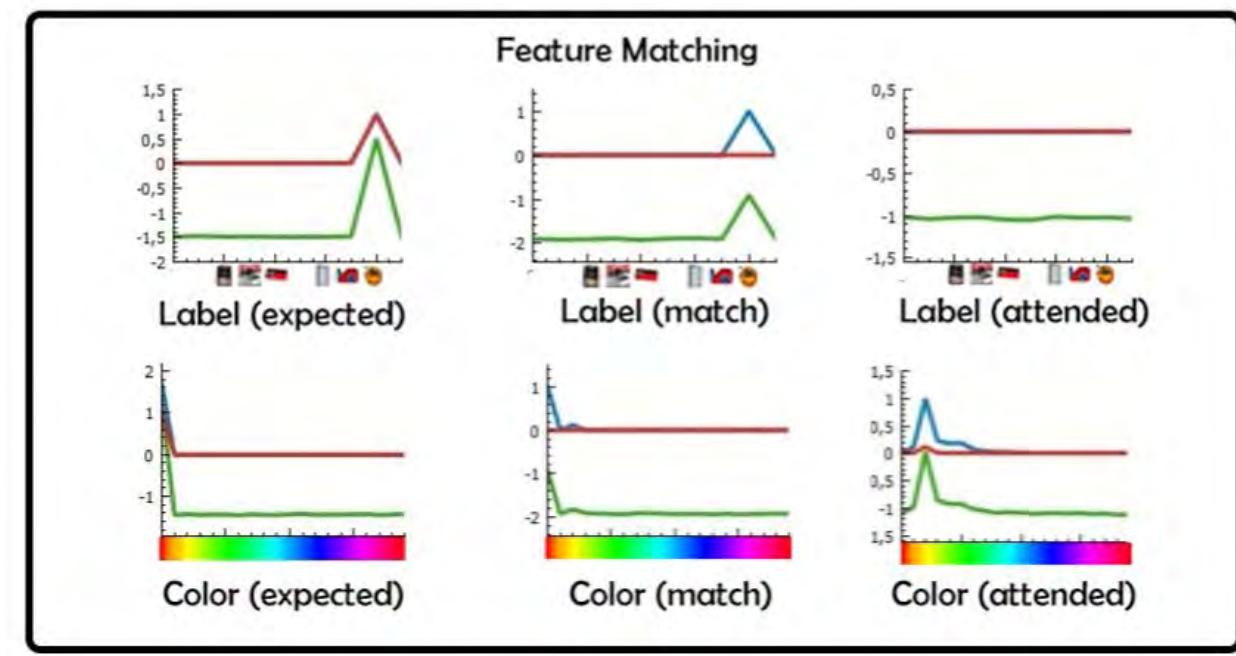
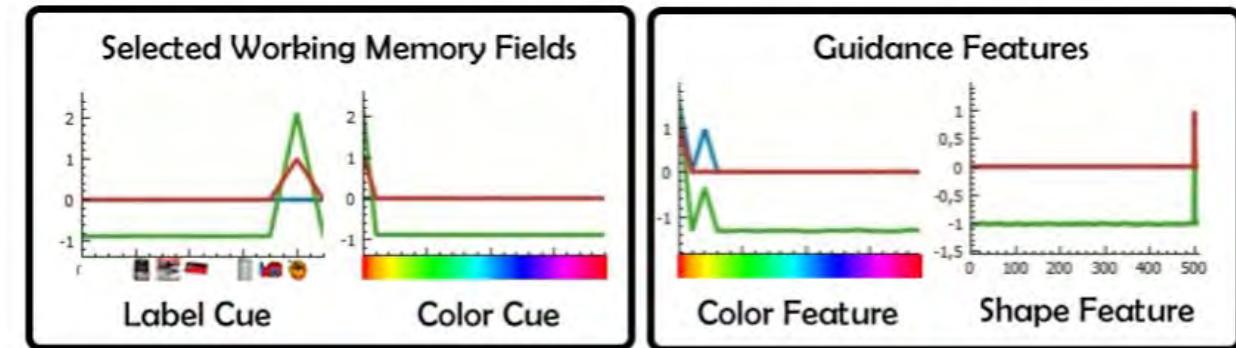
Attention (Input)



Attention (Activation)

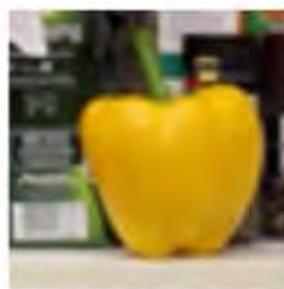


Attention (Sig. Activation)





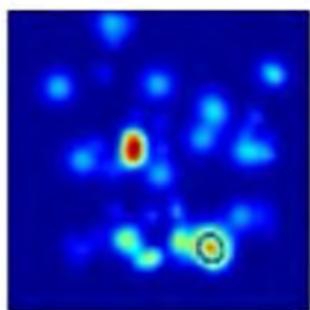
Camera Image



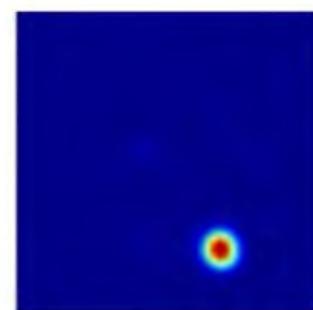
Foveal Image



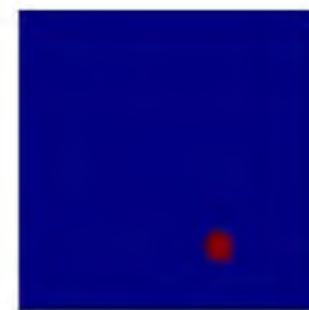
Target Position (WM)



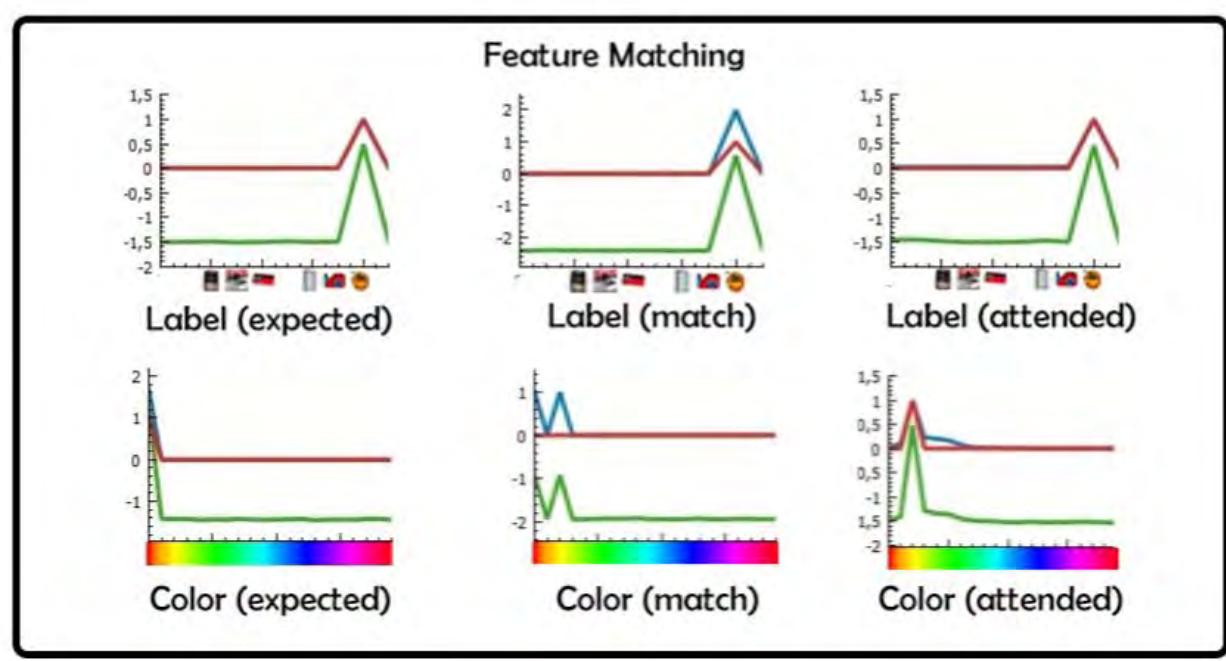
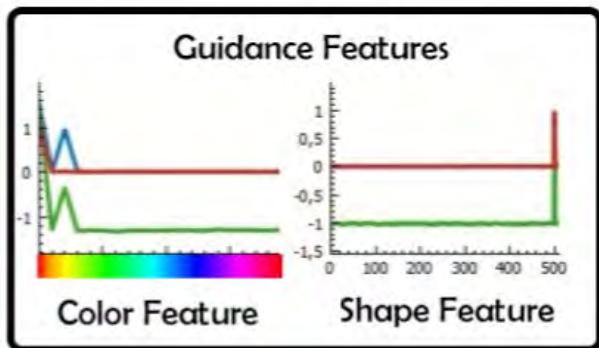
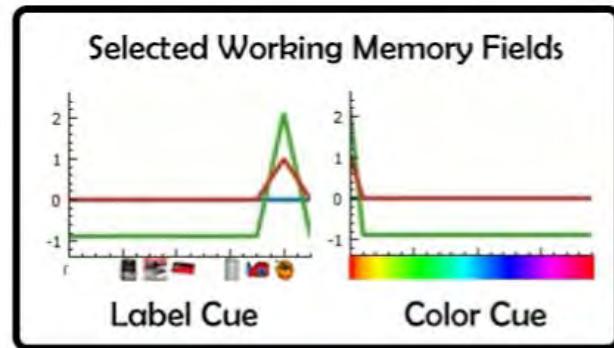
Attention (Input)



Attention (Activation)



Attention (Sig. Activation)





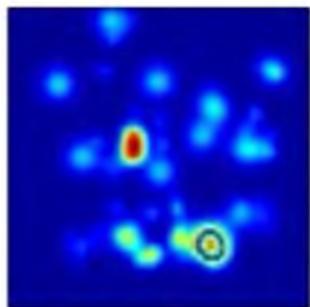
Camera Image



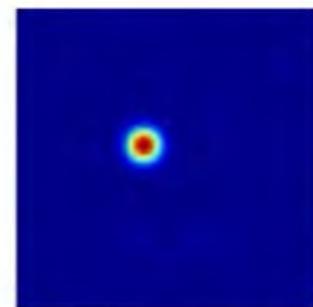
Foveal Image



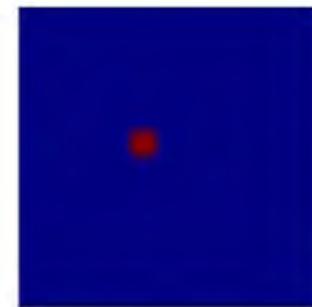
Target Position (WM)



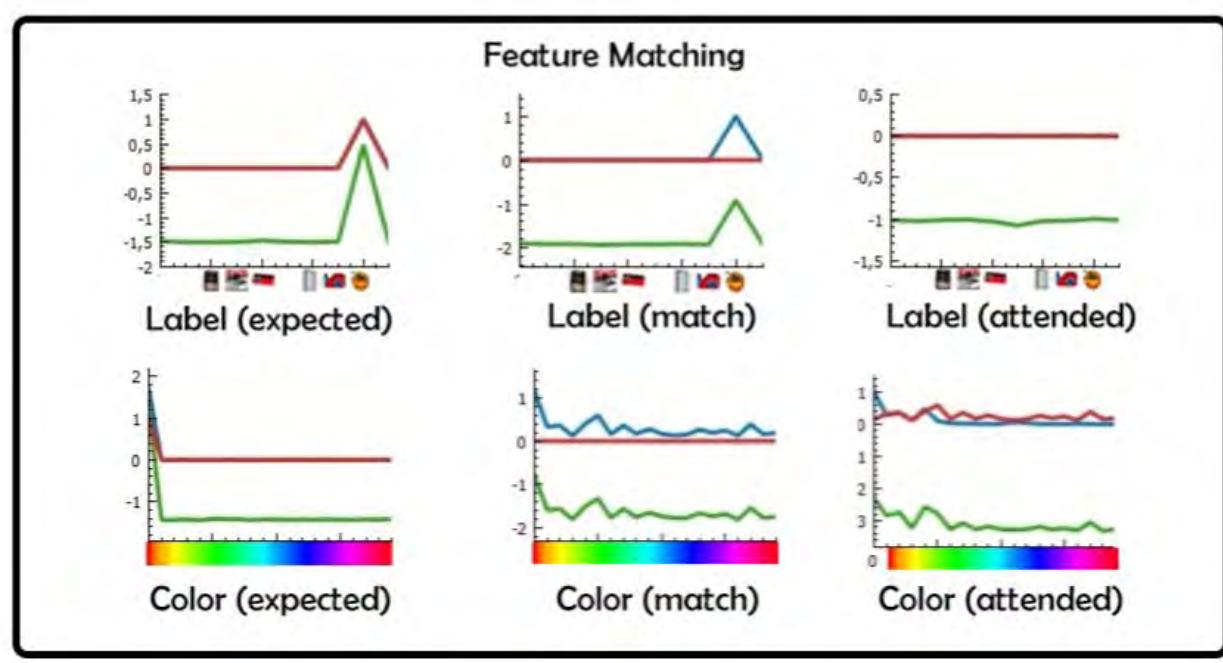
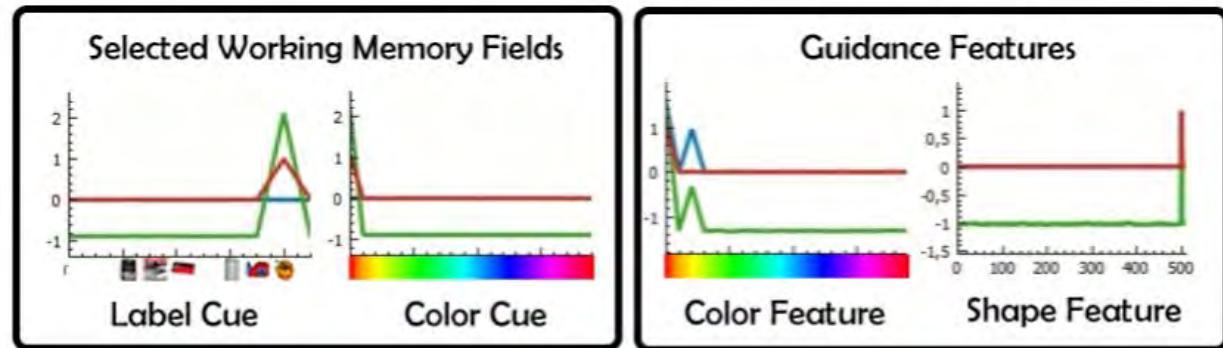
Attention (Input)



Attention (Activation)

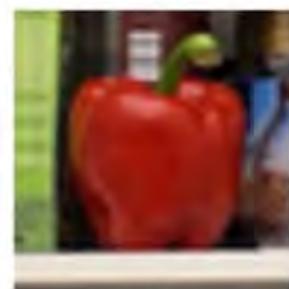


Attention (Sig. Activation)

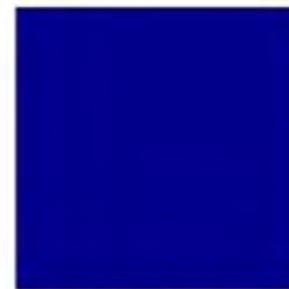




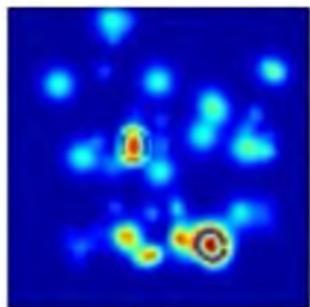
Camera Image



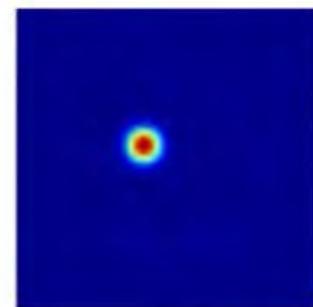
Foveal Image



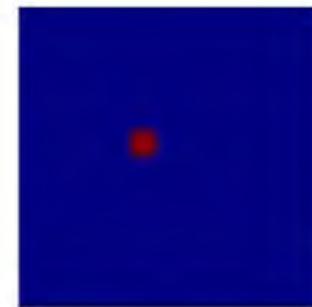
Target Position (WM)



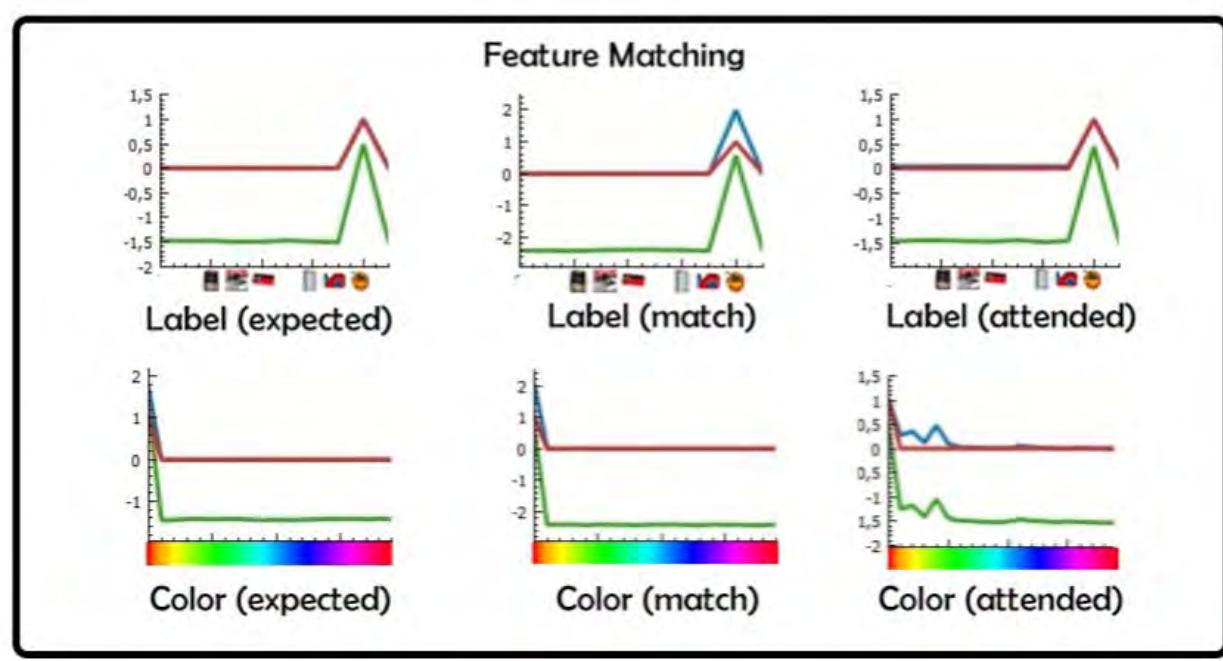
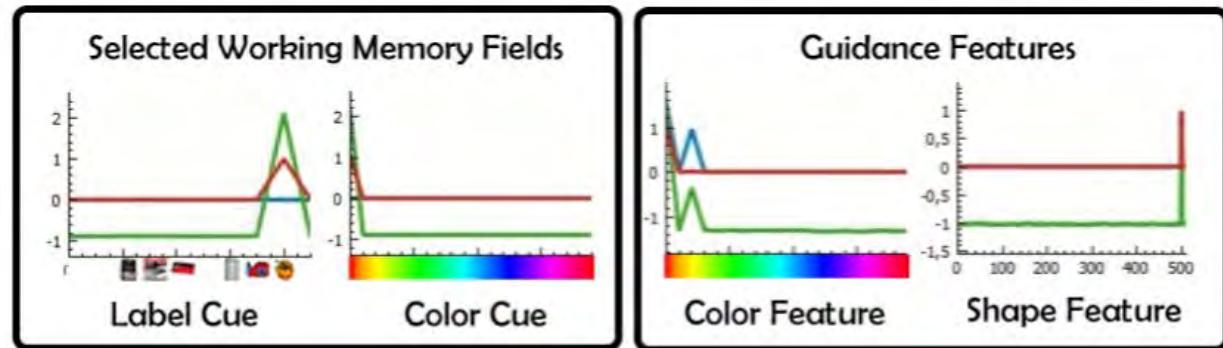
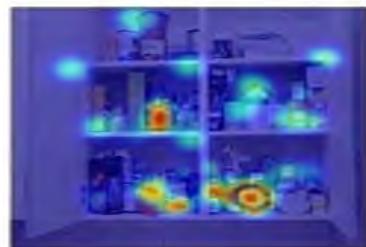
Attention (Input)



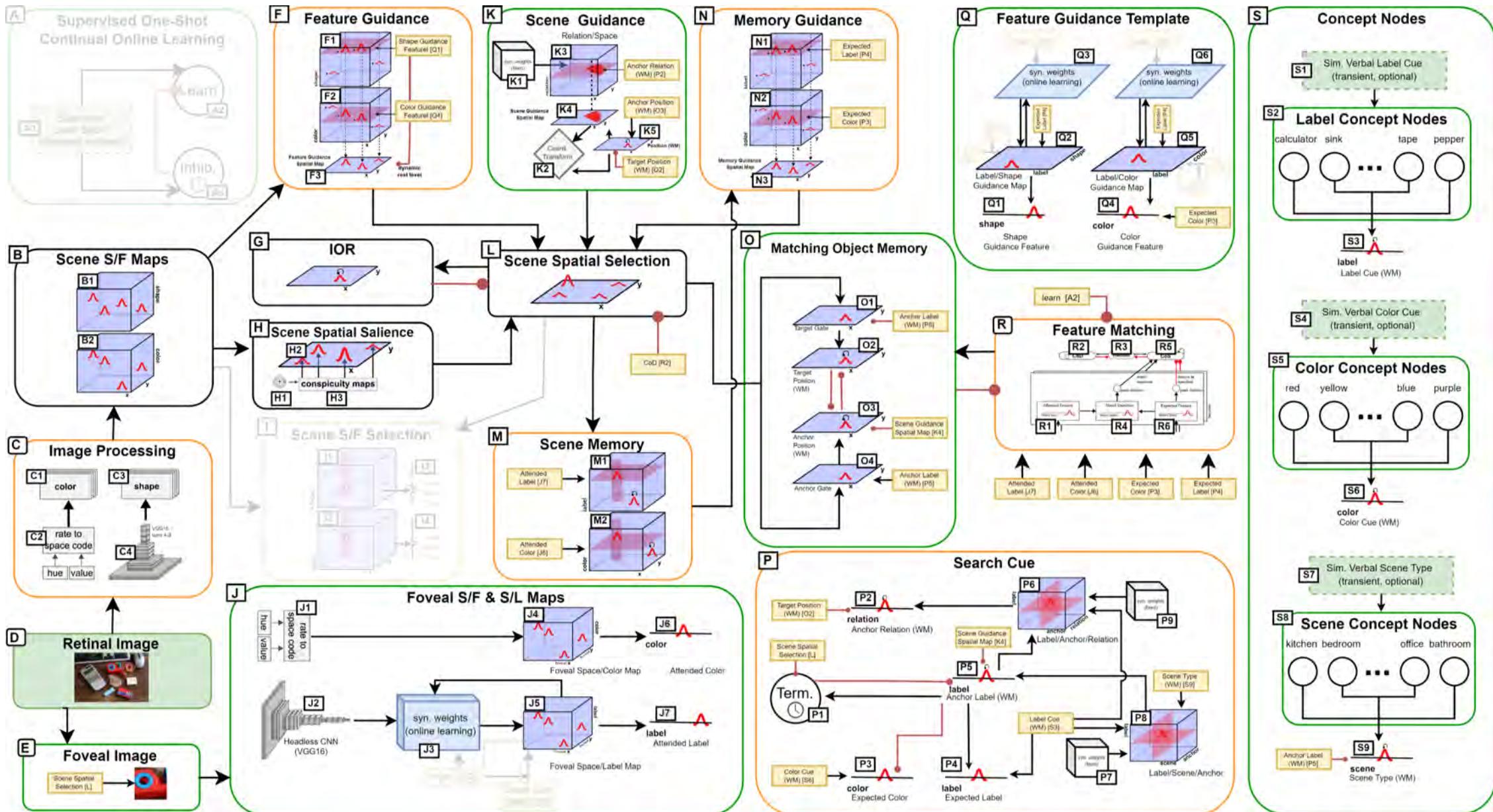
Attention (Activation)



Attention (Sig. Activation)



# Scene grammar

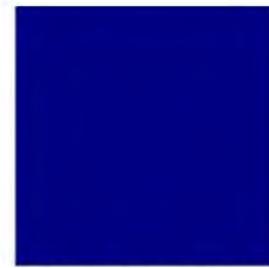




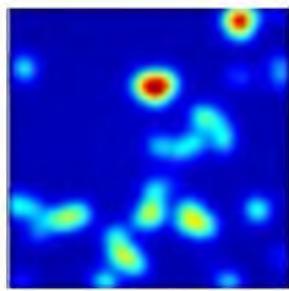
Camera Image



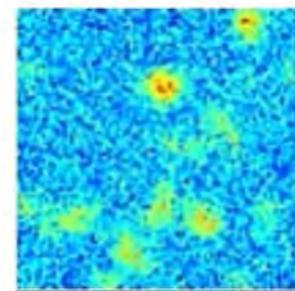
Foveal Image



Anchor Position (WM)



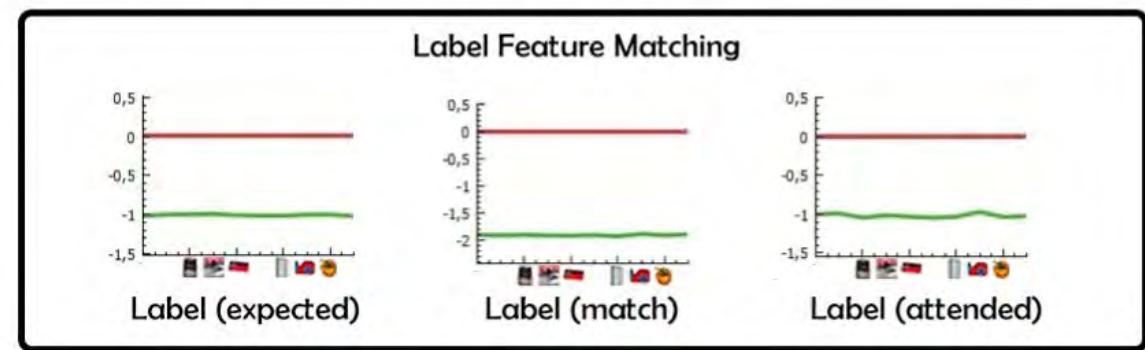
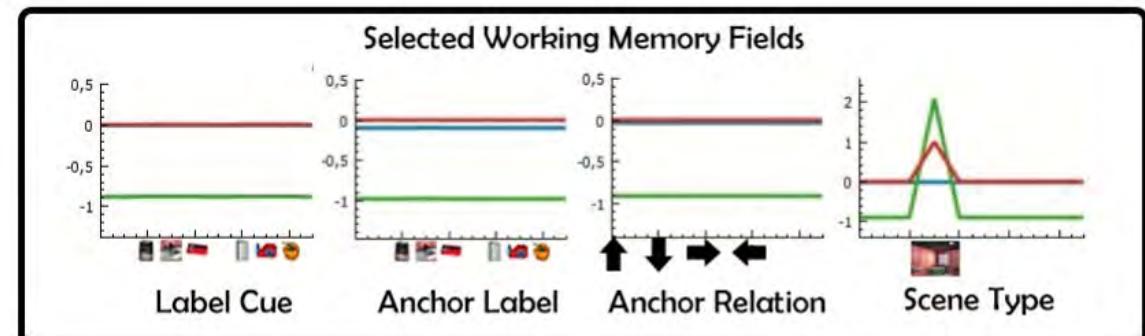
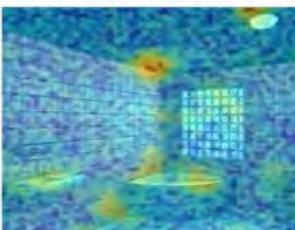
Attention (Input)



Attention (Activation)



Attention (Sig. Activation)





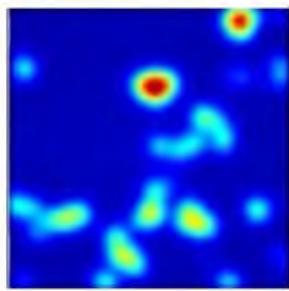
Camera Image



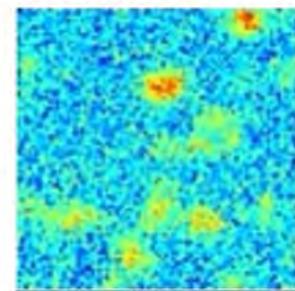
Foveal Image



Anchor Position (WM)



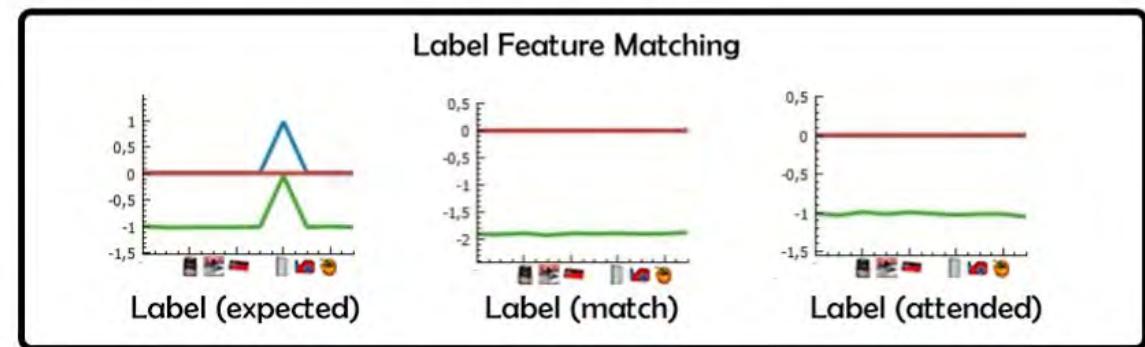
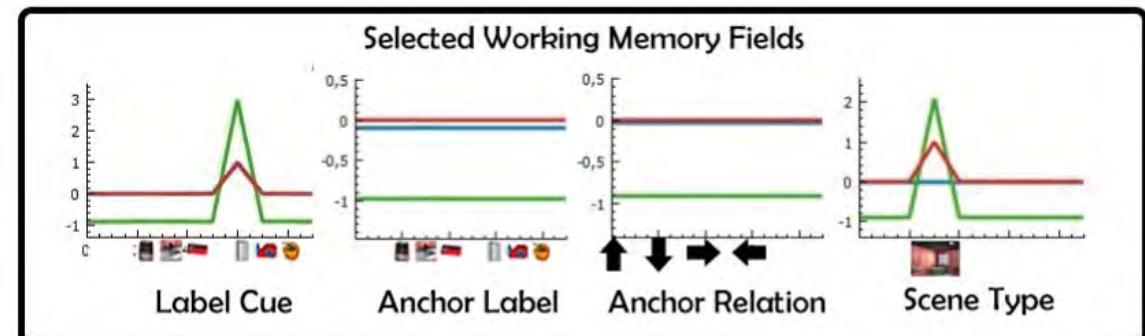
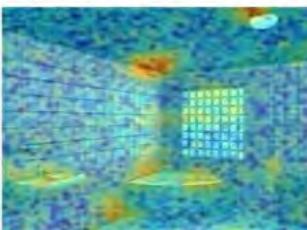
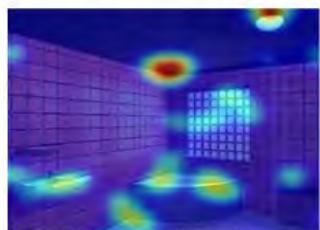
Attention (Input)



Attention (Activation)



Attention (Sig. Activation)

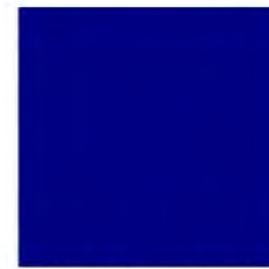




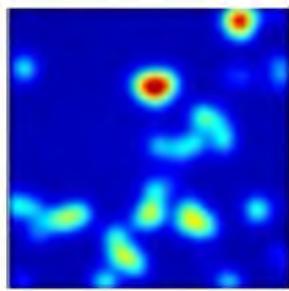
Camera Image



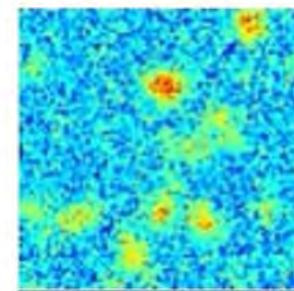
Foveal Image



Anchor Position (WM)



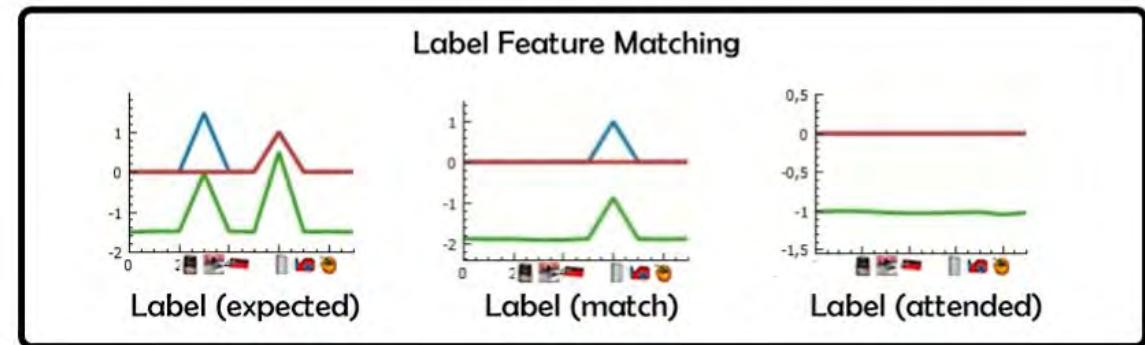
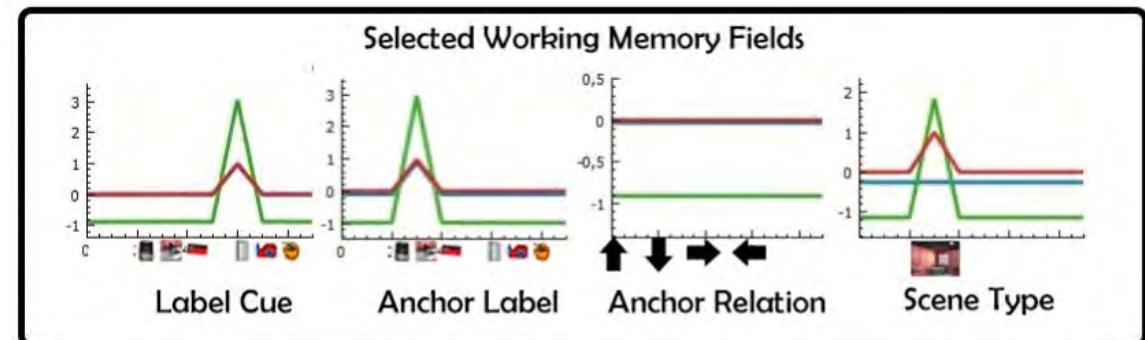
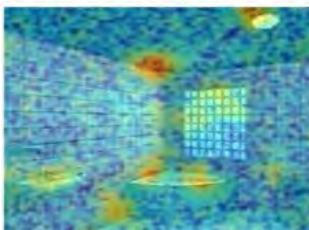
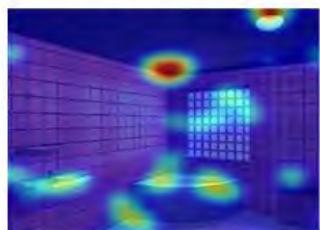
Attention (Input)



Attention (Activation)



Attention (Sig. Activation)

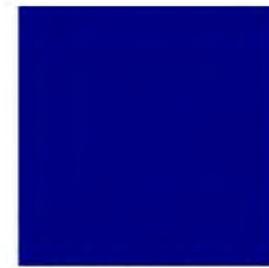




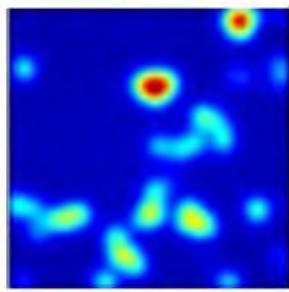
Camera Image



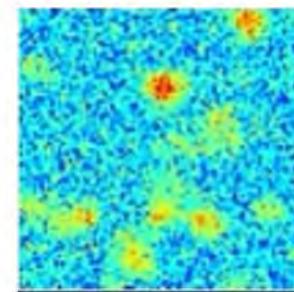
Foveal Image



Anchor Position (WM)



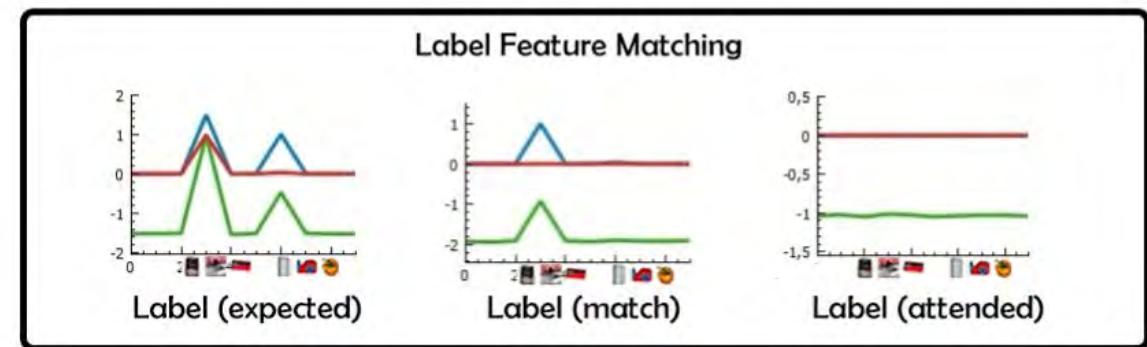
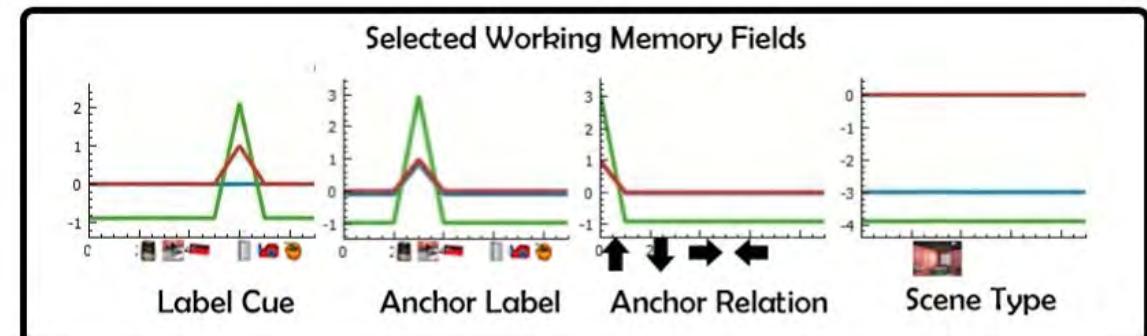
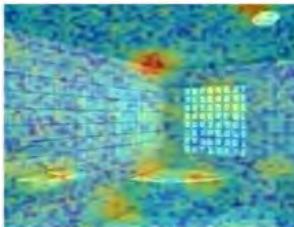
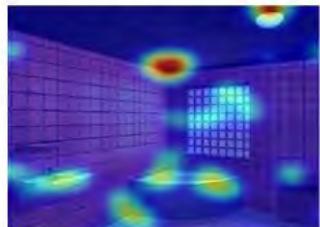
Attention (Input)



Attention (Activation)



Attention (Sig. Activation)

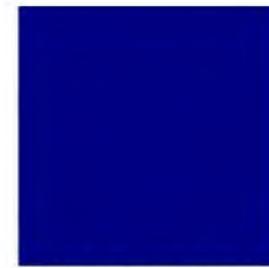




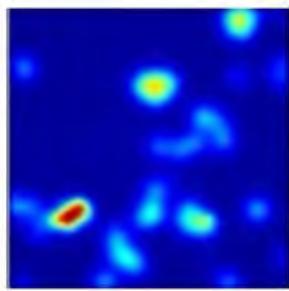
Camera Image



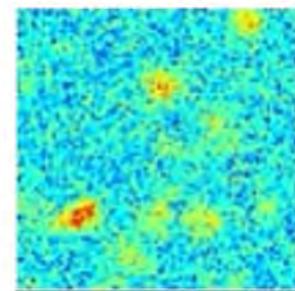
Foveal Image



Anchor Position (WM)



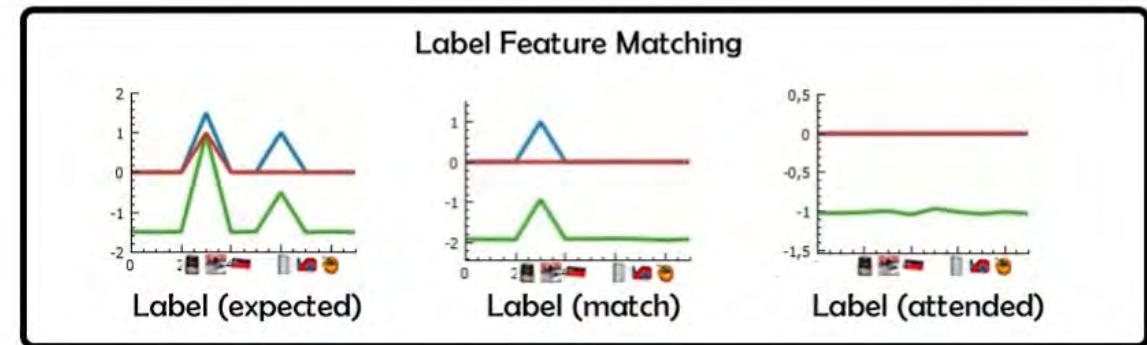
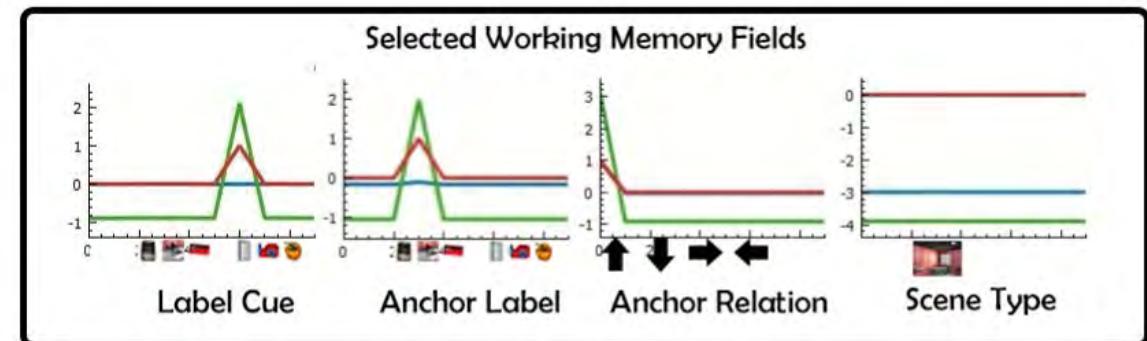
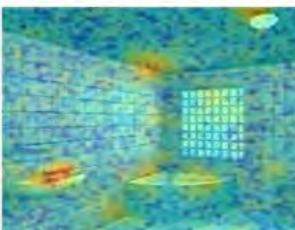
Attention (Input)



Attention (Activation)

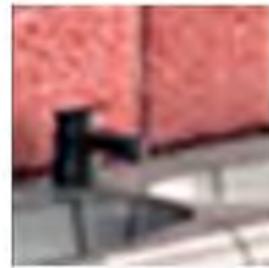


Attention (Sig. Activation)

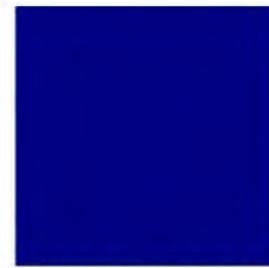




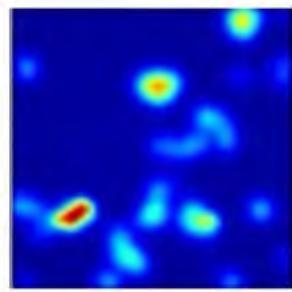
Camera Image



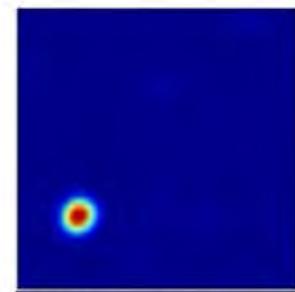
Foveal Image



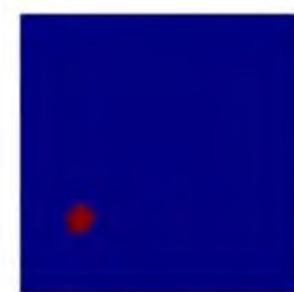
Anchor Position (WM)



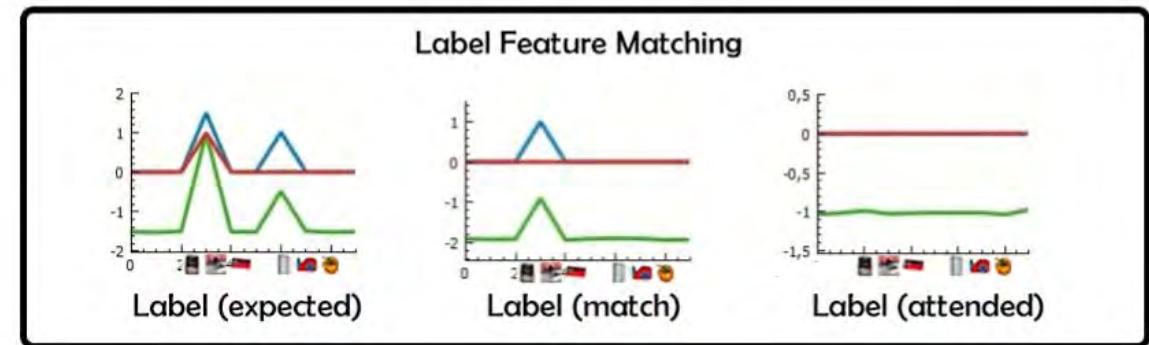
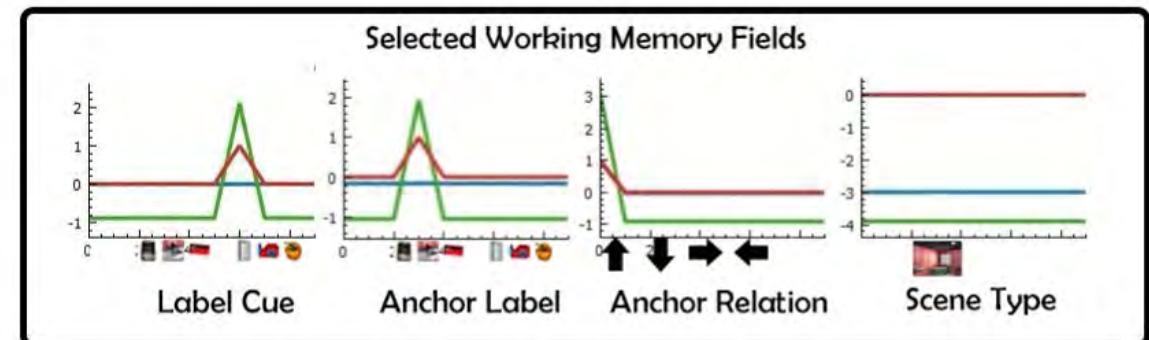
Attention (Input)

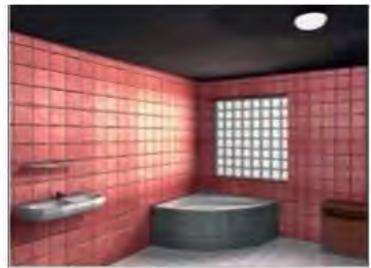


Attention (Activation)

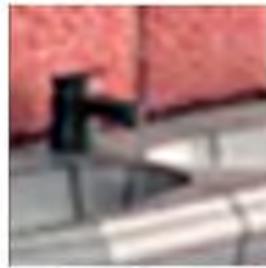


Attention (Sig. Activation)





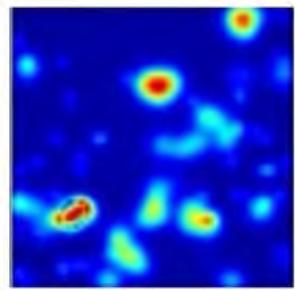
Camera Image



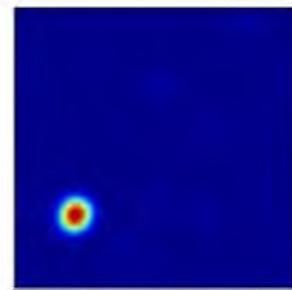
Foveal Image



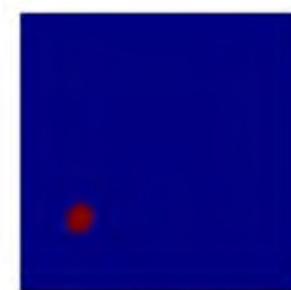
Anchor Position (WM)



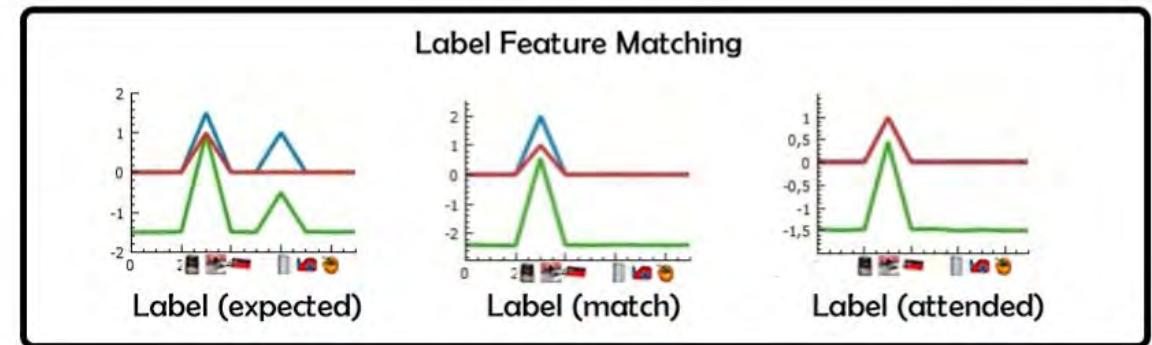
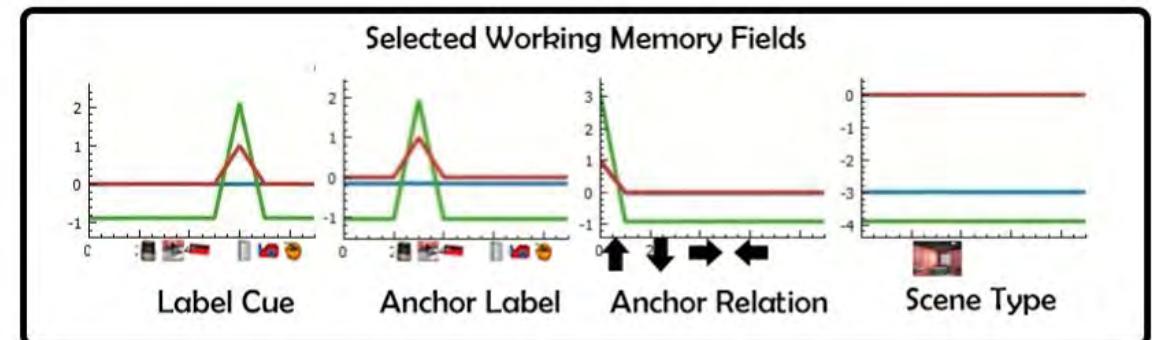
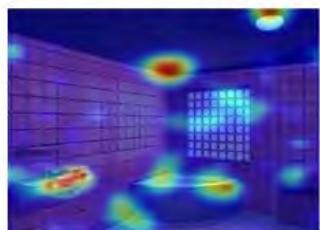
Attention (Input)

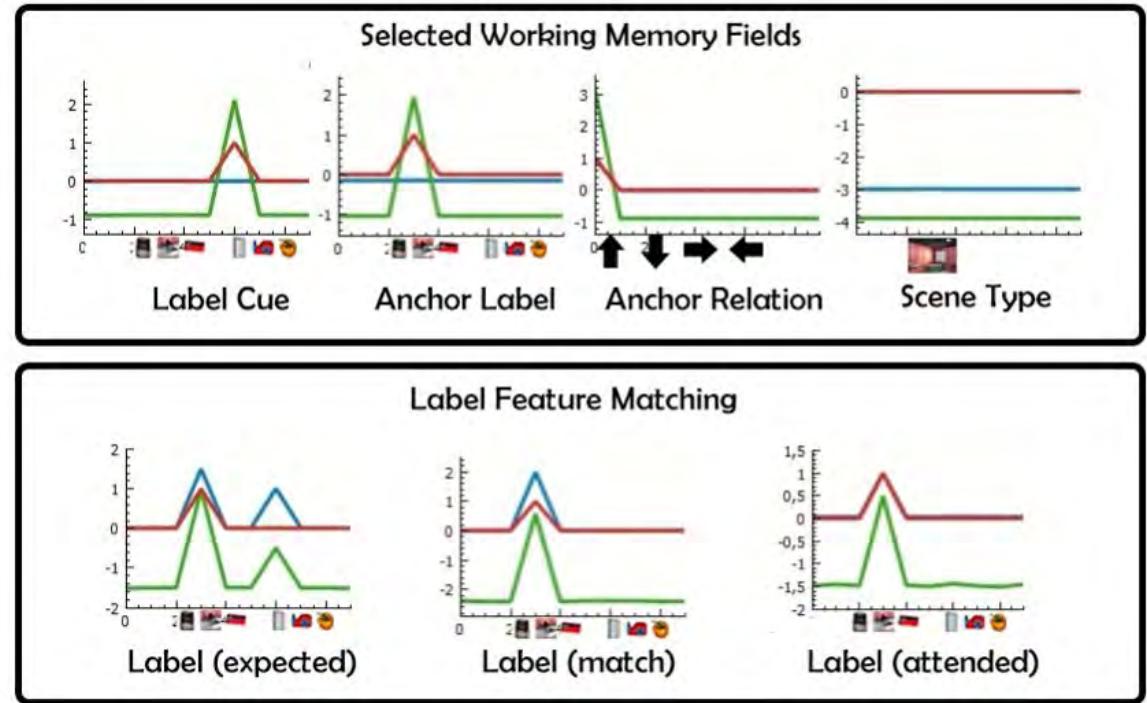
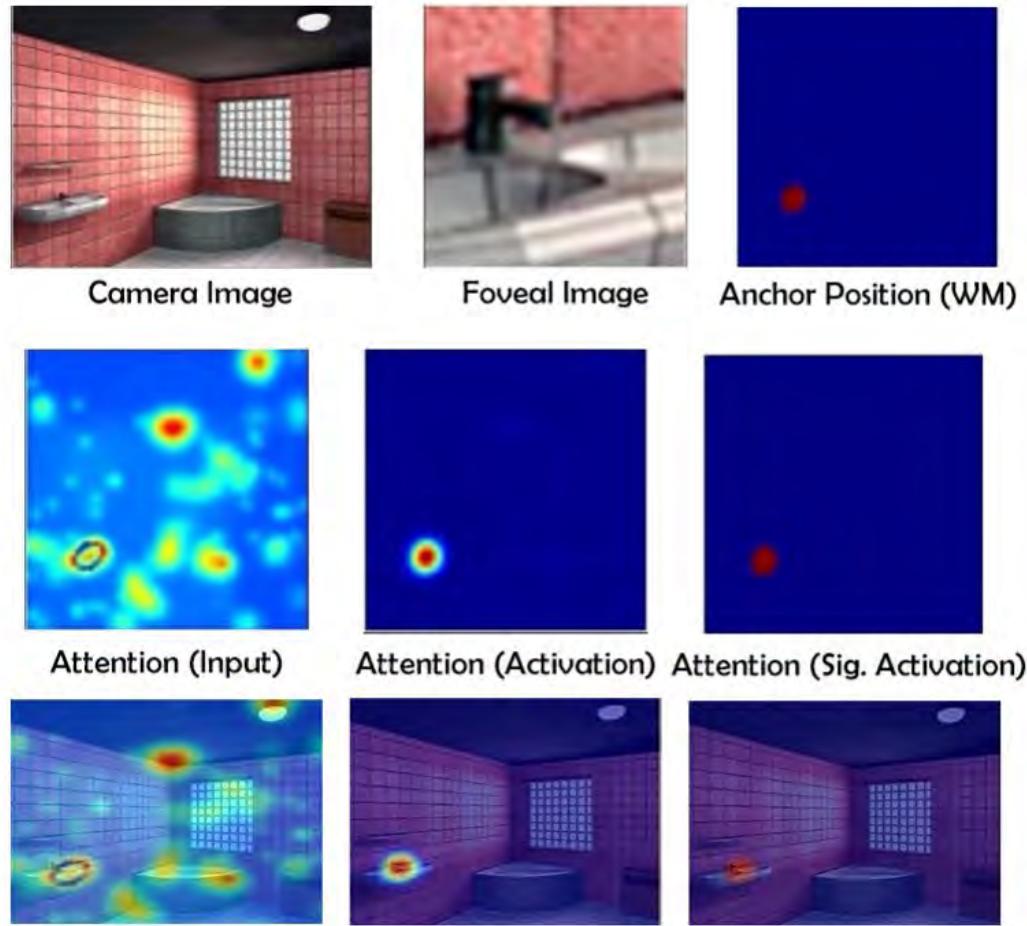


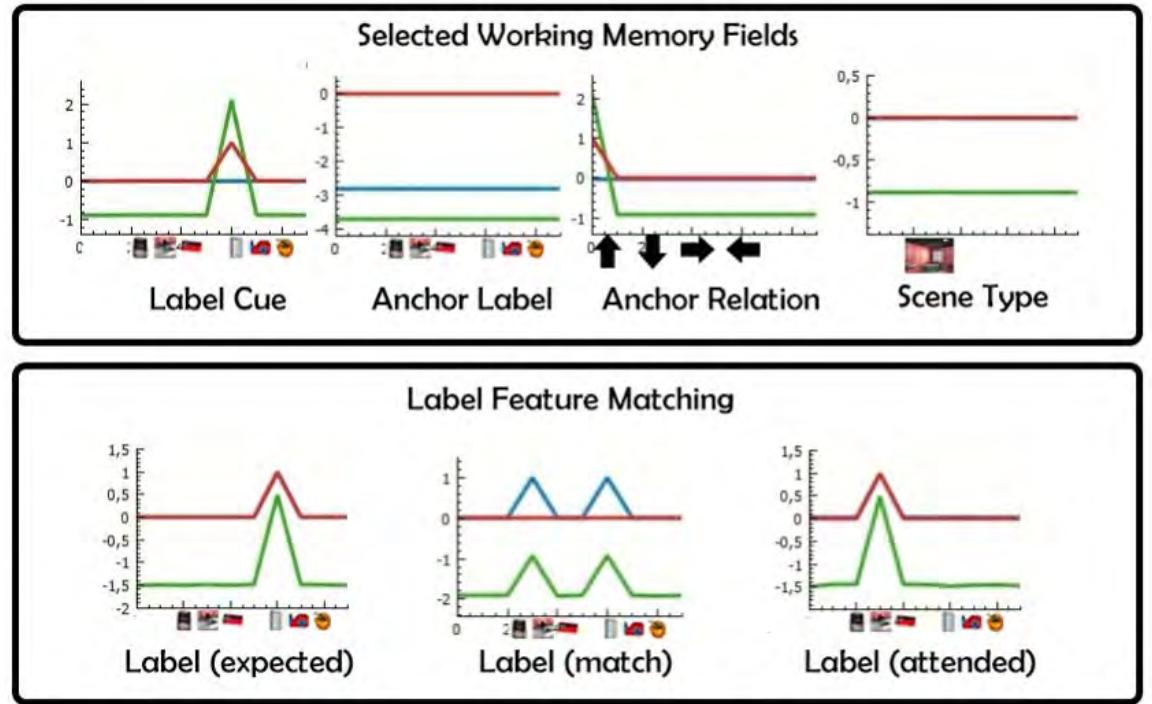
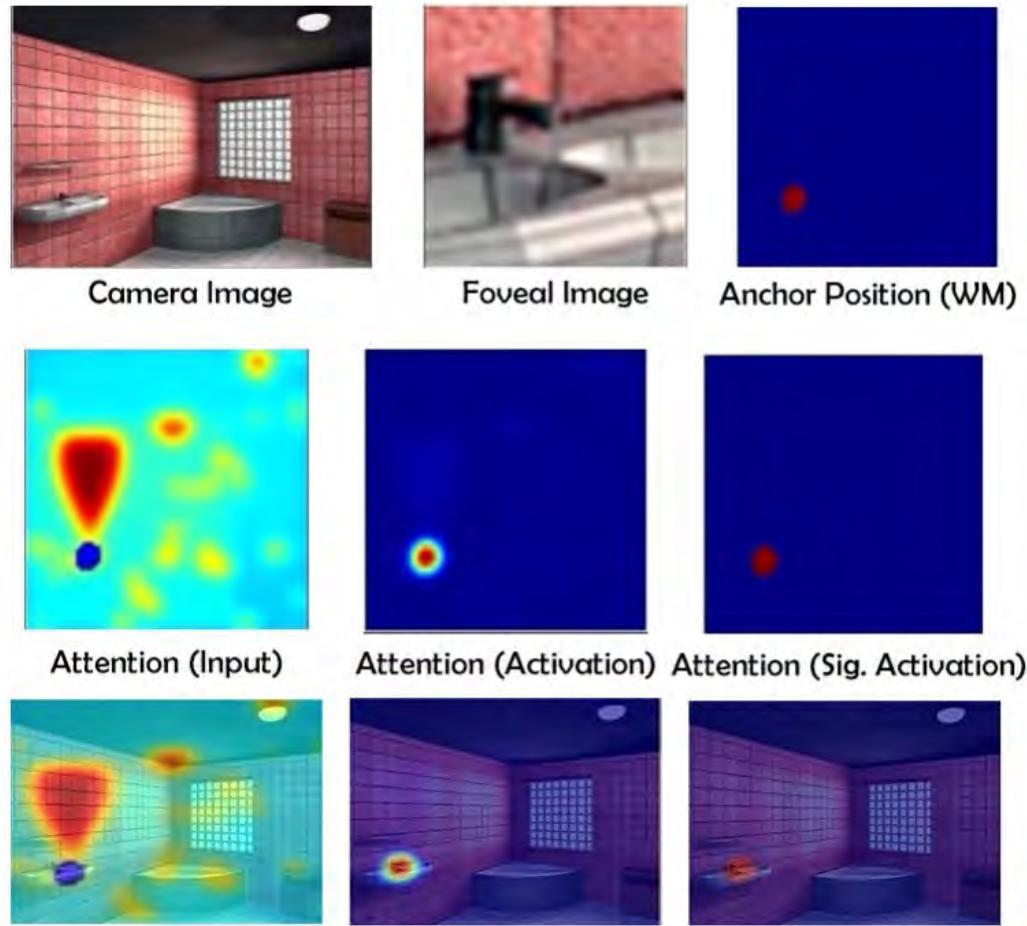
Attention (Activation)



Attention (Sig. Activation)







- We have shown a neural process account of visual search and scene memory that autonomously builds a scene representation and performs guided categorical visual search on natural scenes
- We found solutions for three important problems:
  - How the association between a categorical concept and preattentive shape can be learned from the intermediate layer of a CNN
  - How the distributed representation of the CNN feature maps can be mapped to the localist representation of a dynamic neural field
  - How scene grammar emerges from the underlying neural dynamics