

# TAVAE: A VAE with adaptable priors explains contextual modulation in the visual cortex

Balázs Meszéna<sup>1</sup>, Keith T. Murray<sup>1,2</sup>, Julien Corbo<sup>3</sup>, O. Batuhan Erkat<sup>3</sup>, Márton A. Hajnal<sup>1</sup>, Pierre-Olivier Polack<sup>3</sup>, Gergő Orbán<sup>1</sup>

- 1) Computational Systems Neuroscience Lab, Department of Computational Sciences, HUN-REN Wigner Research Centre for Physics, Budapest, Hungary
- 2) Princeton Neuroscience Institute, New Jersey, United States
- 3) Center for Molecular and Behavioral Neuroscience, Rutgers University, Newark, United States

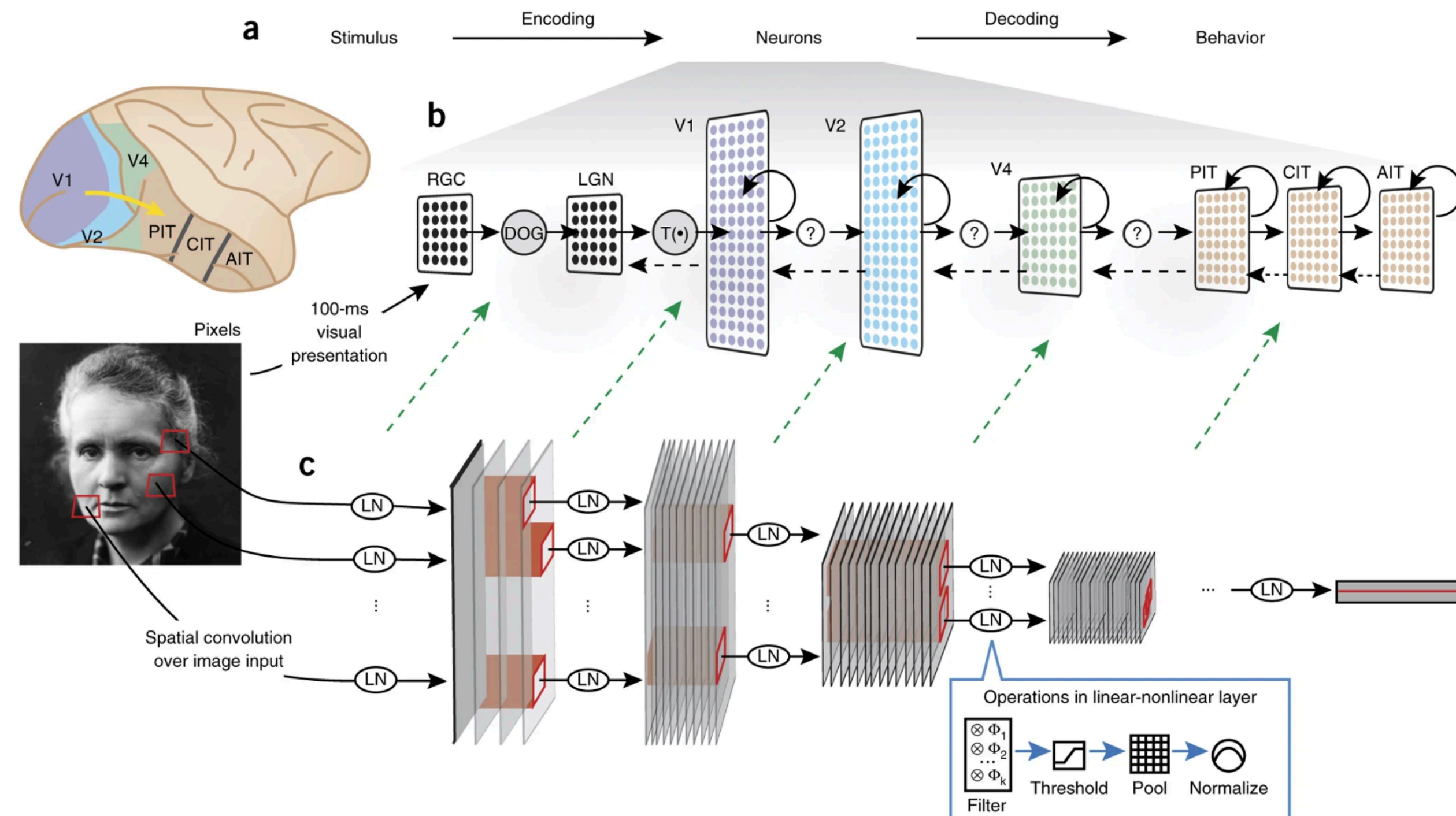




# Predicting neuronal responses in the visual cortex using deep neural networks

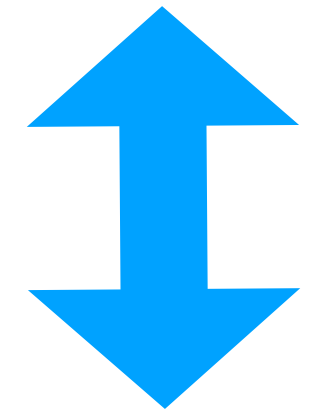


**Passive viewing**



*Yamins & DiCarlo, Nature Neuroscience, 2016*

**Biological neurons**

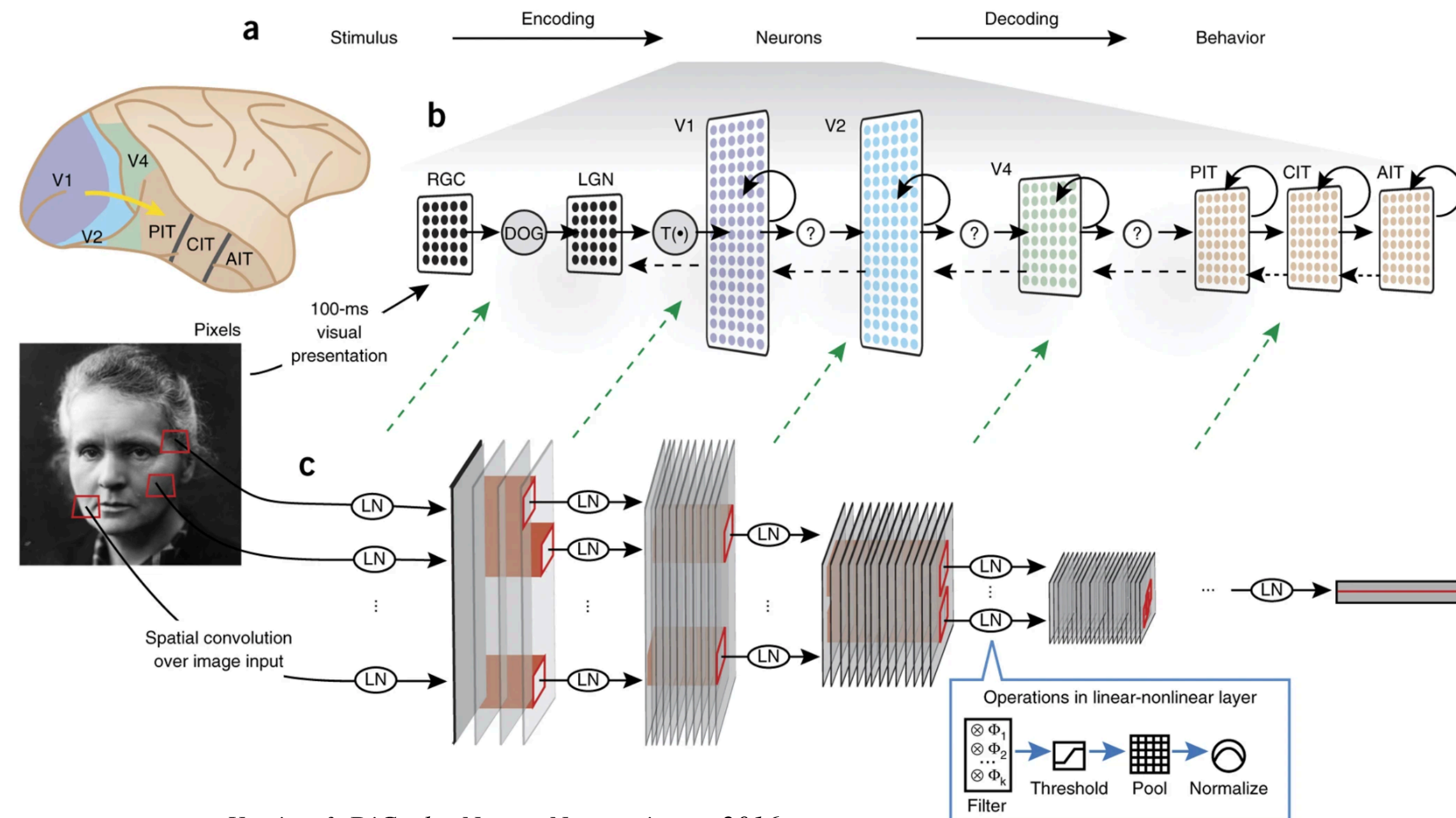


**Model CNN layers**

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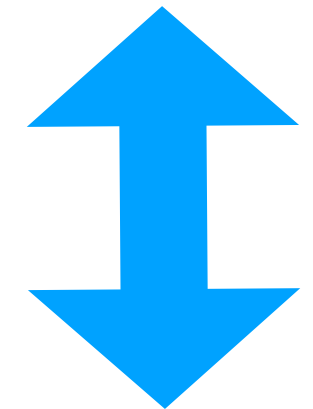


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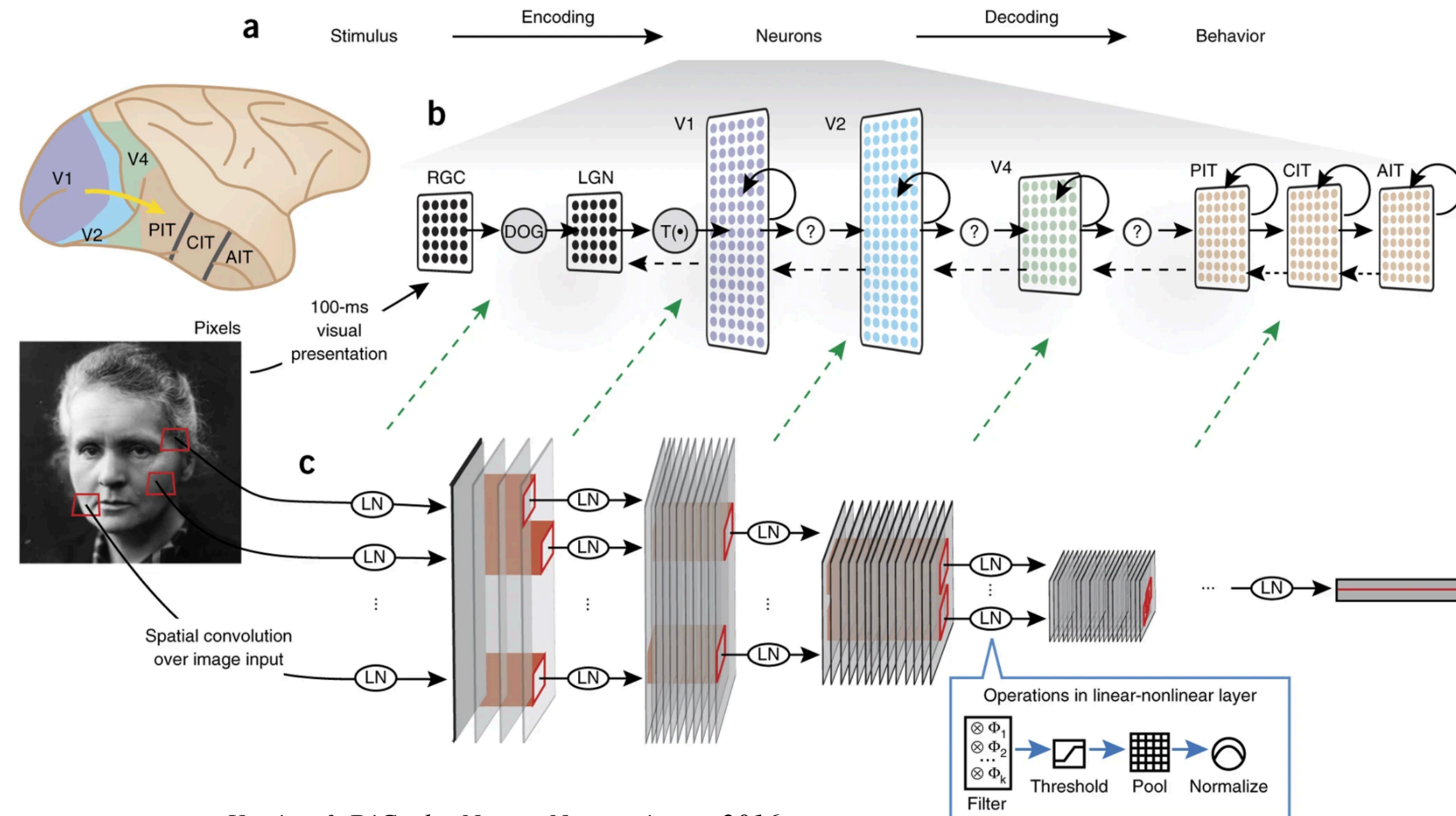
**Model CNN layers**

**Neuronal response is context dependent**

# Predicting neuronal responses in the visual cortex using deep neural networks

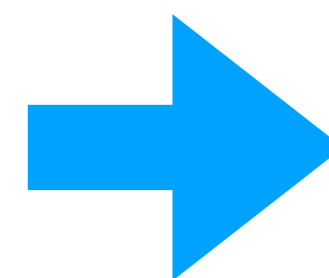


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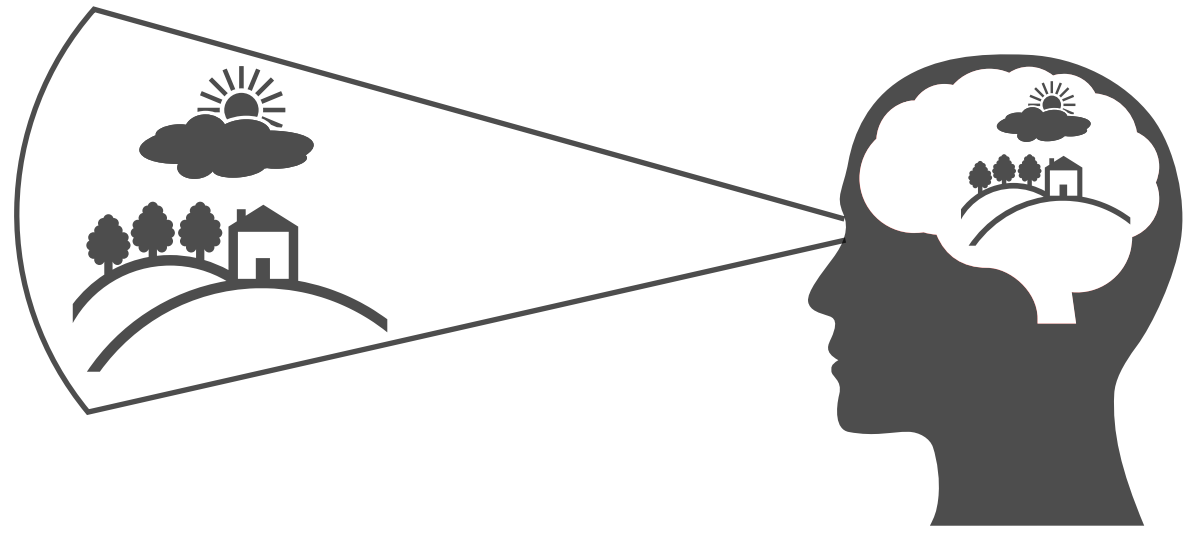
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**Neuronal response is context dependent**

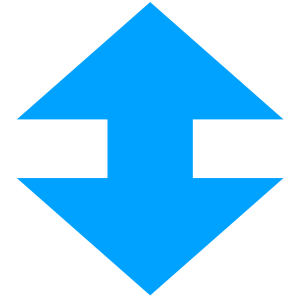


**During task?**

# Modeling vision with latent generative model

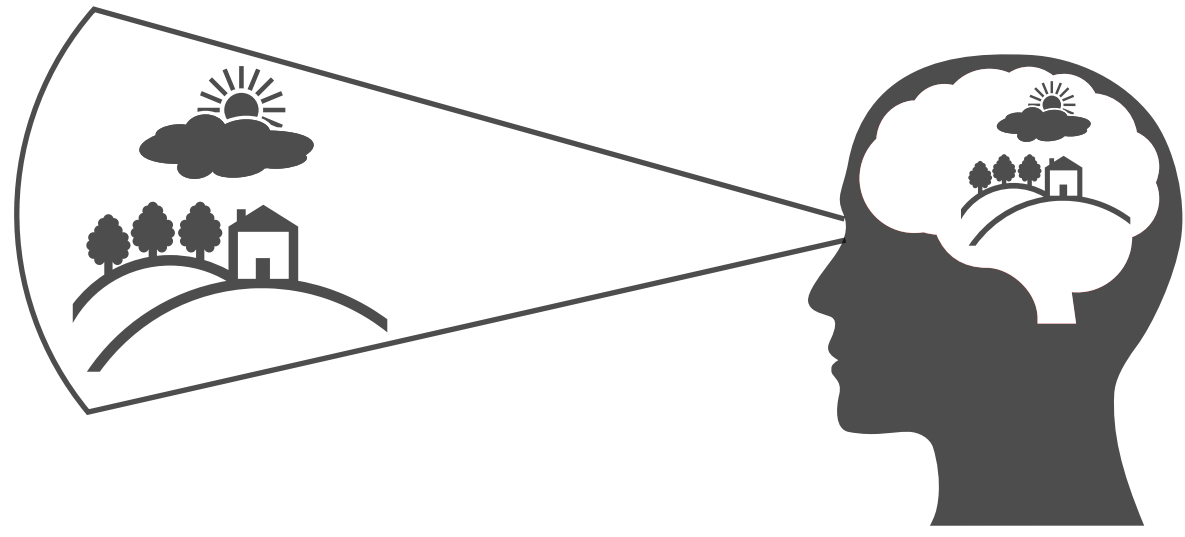


Visual cortex

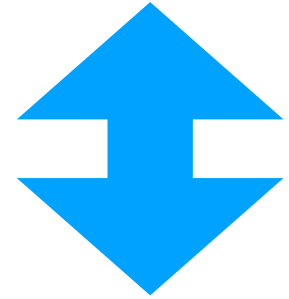


Generative model

# Modeling vision with latent generative model

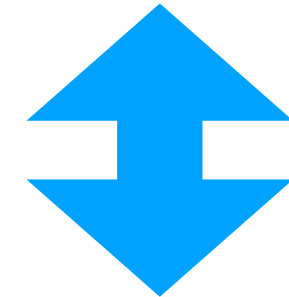


**Visual cortex**



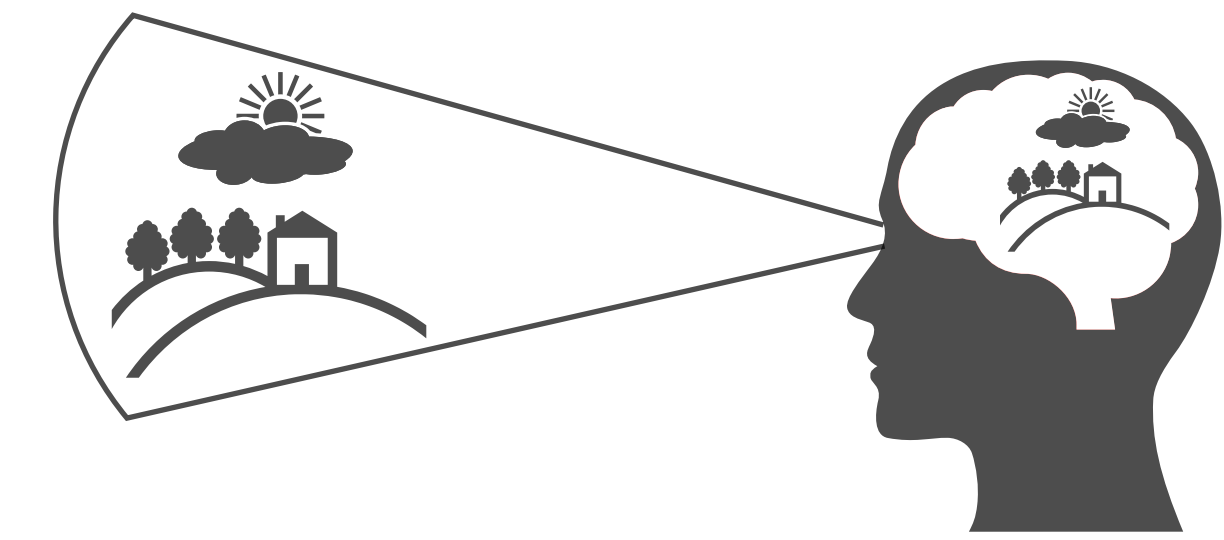
**Generative model**

**Neuronal response**



**Latent inference**

# Modeling vision with latent generative model

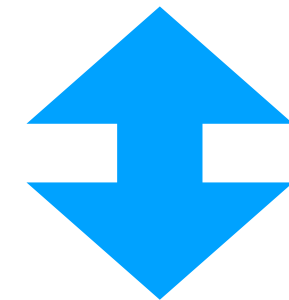
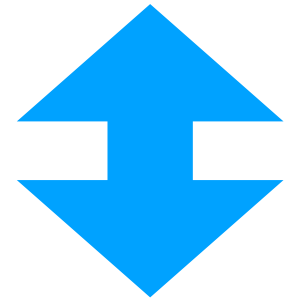


**Learning objective:**  
Learning regularities of natural images

$$p_0(\mathbf{x}) = \int p(\mathbf{x} | \mathbf{z}) p_0(\mathbf{z}) d\mathbf{z}$$

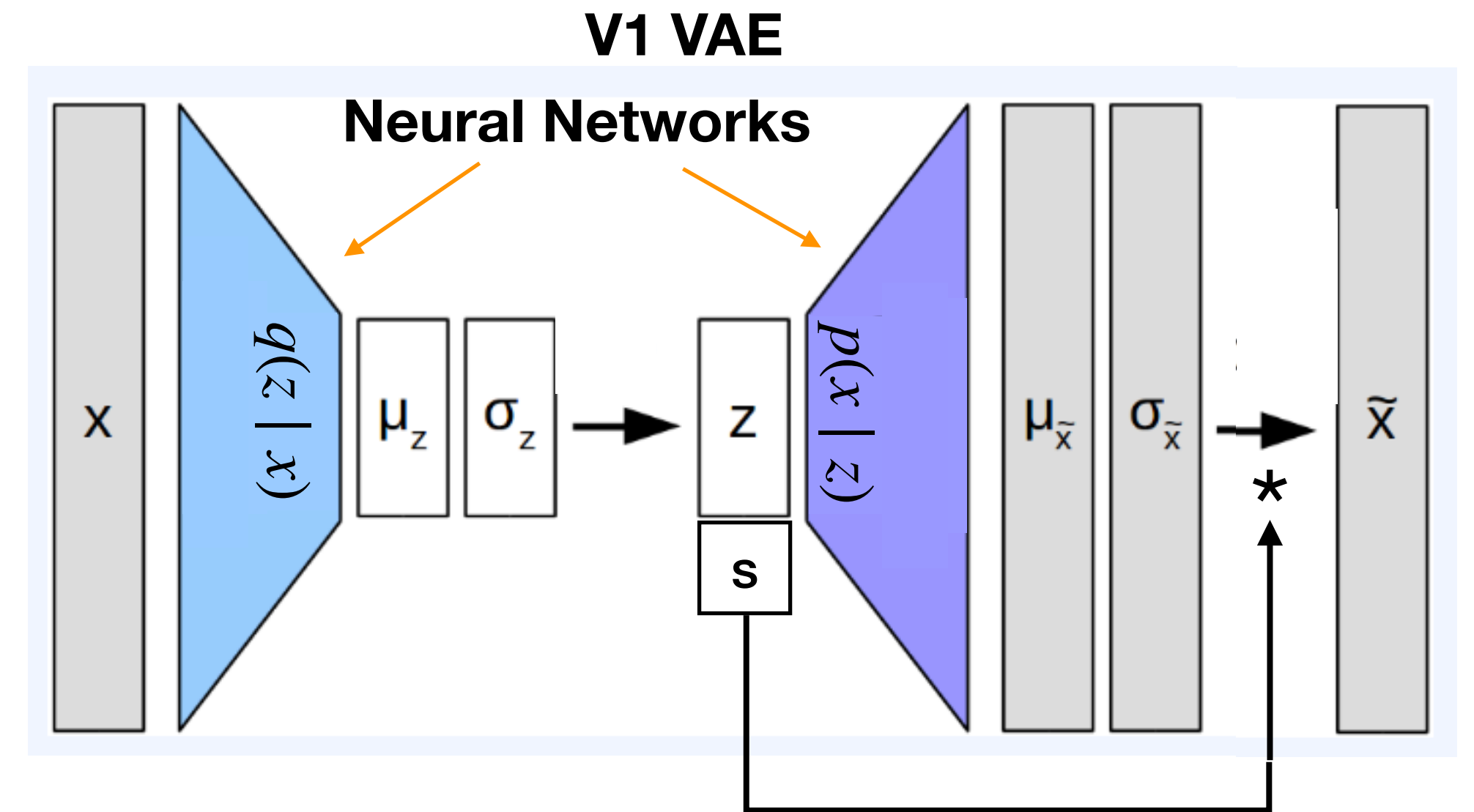
Visual cortex

Neuronal response

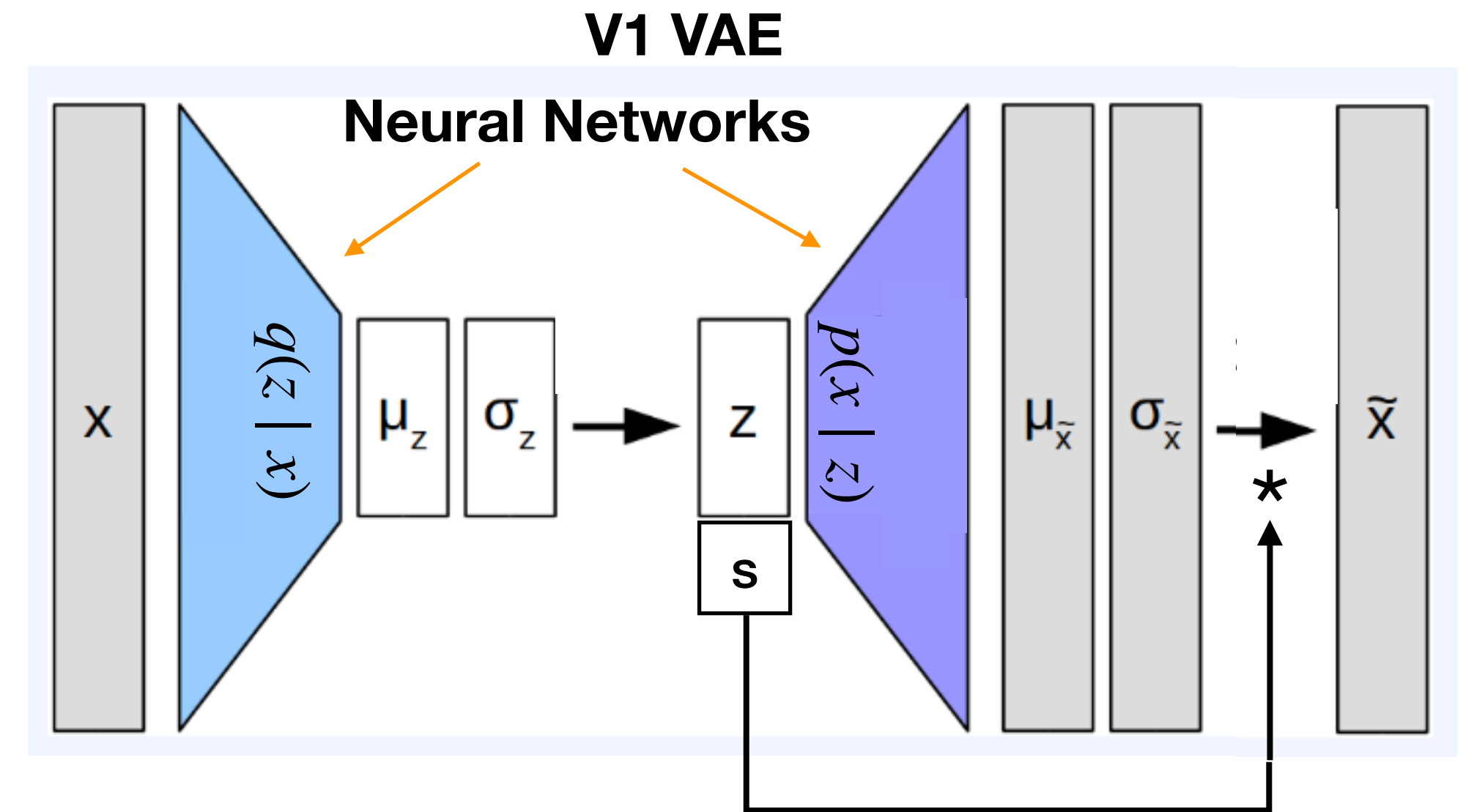
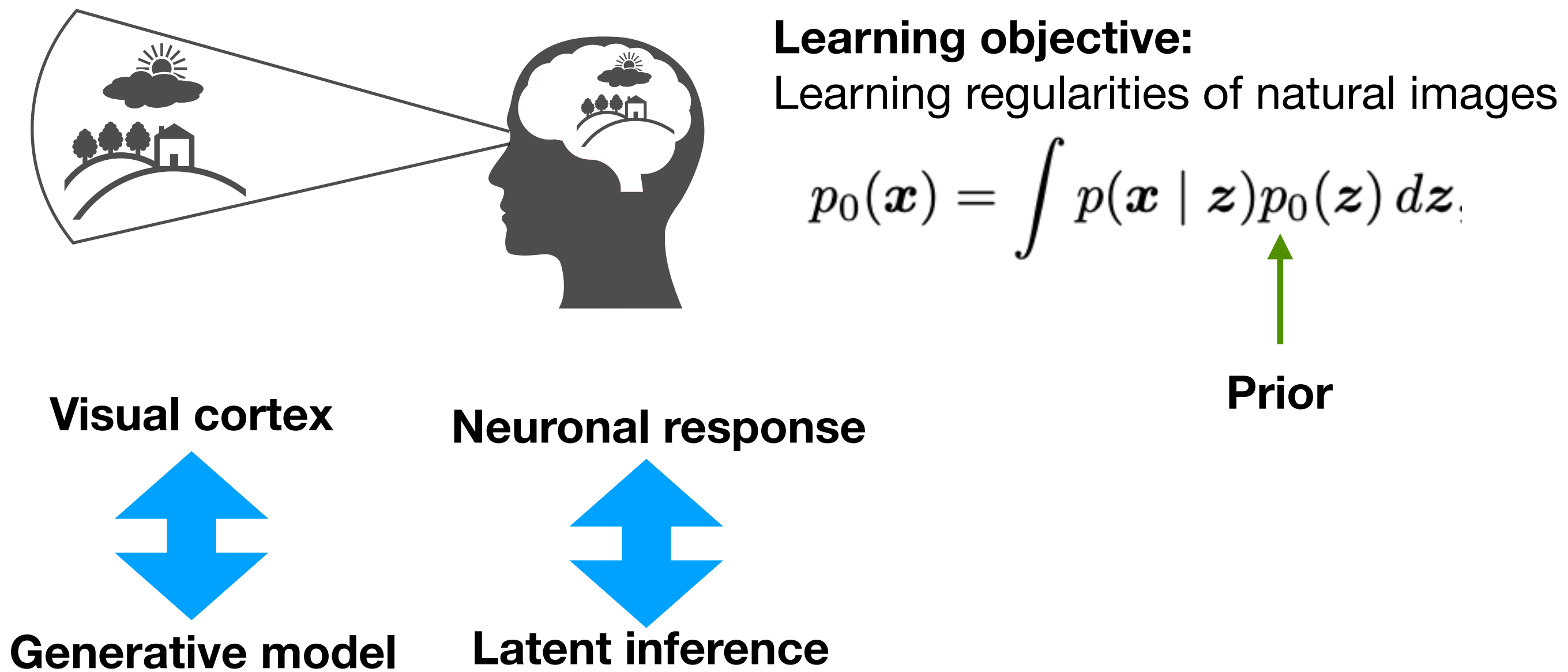


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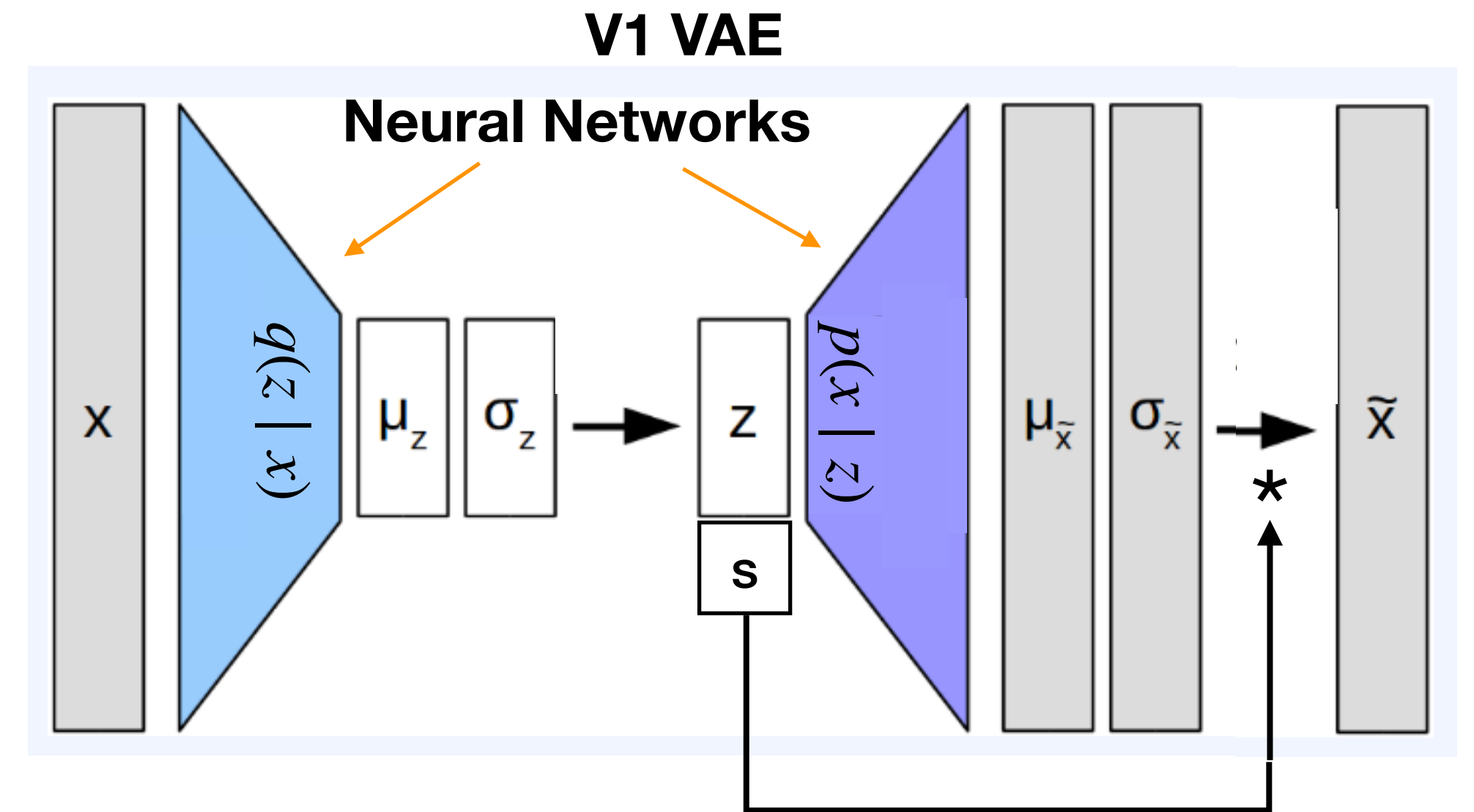
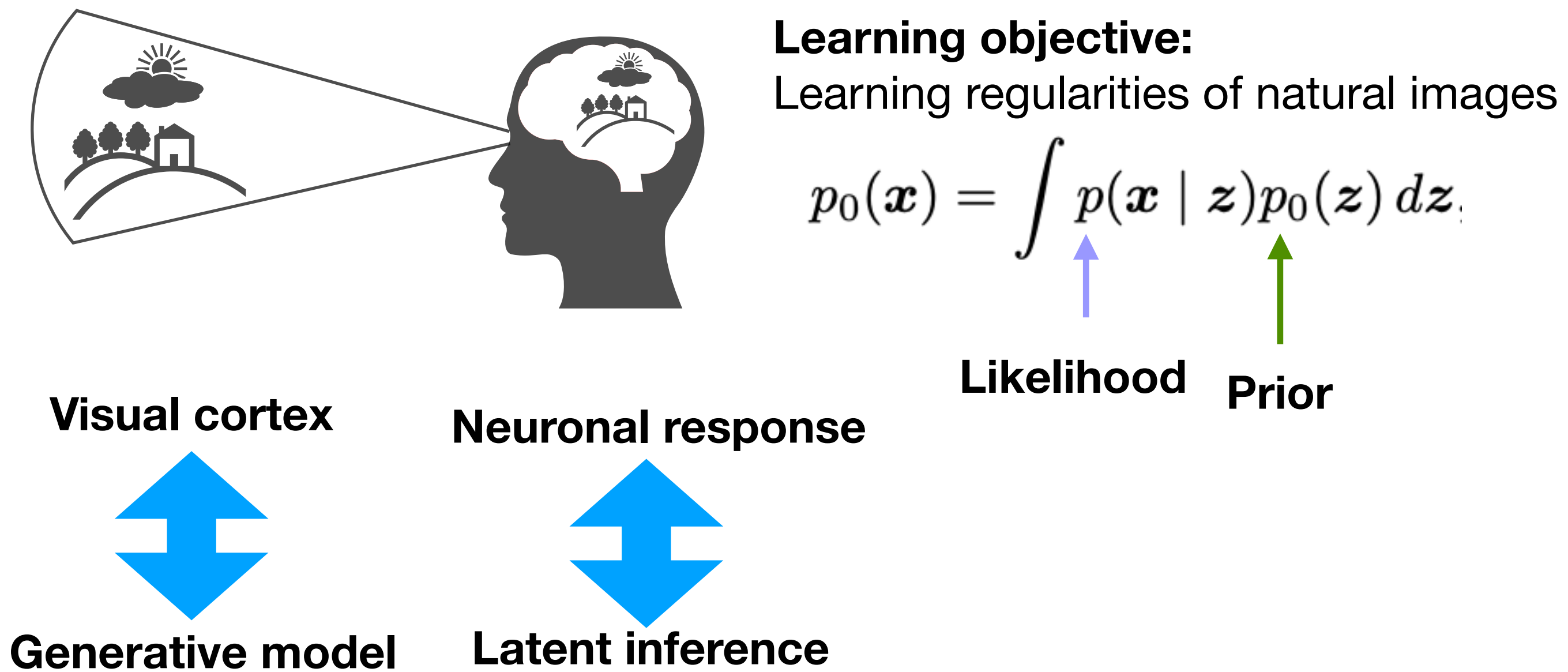
Latent inference



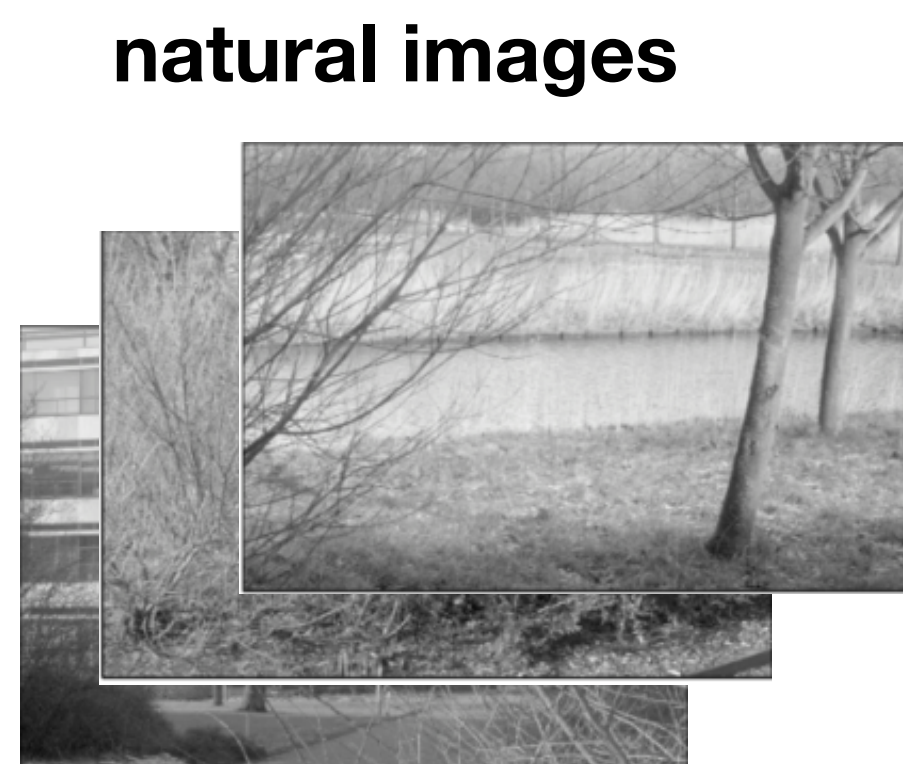
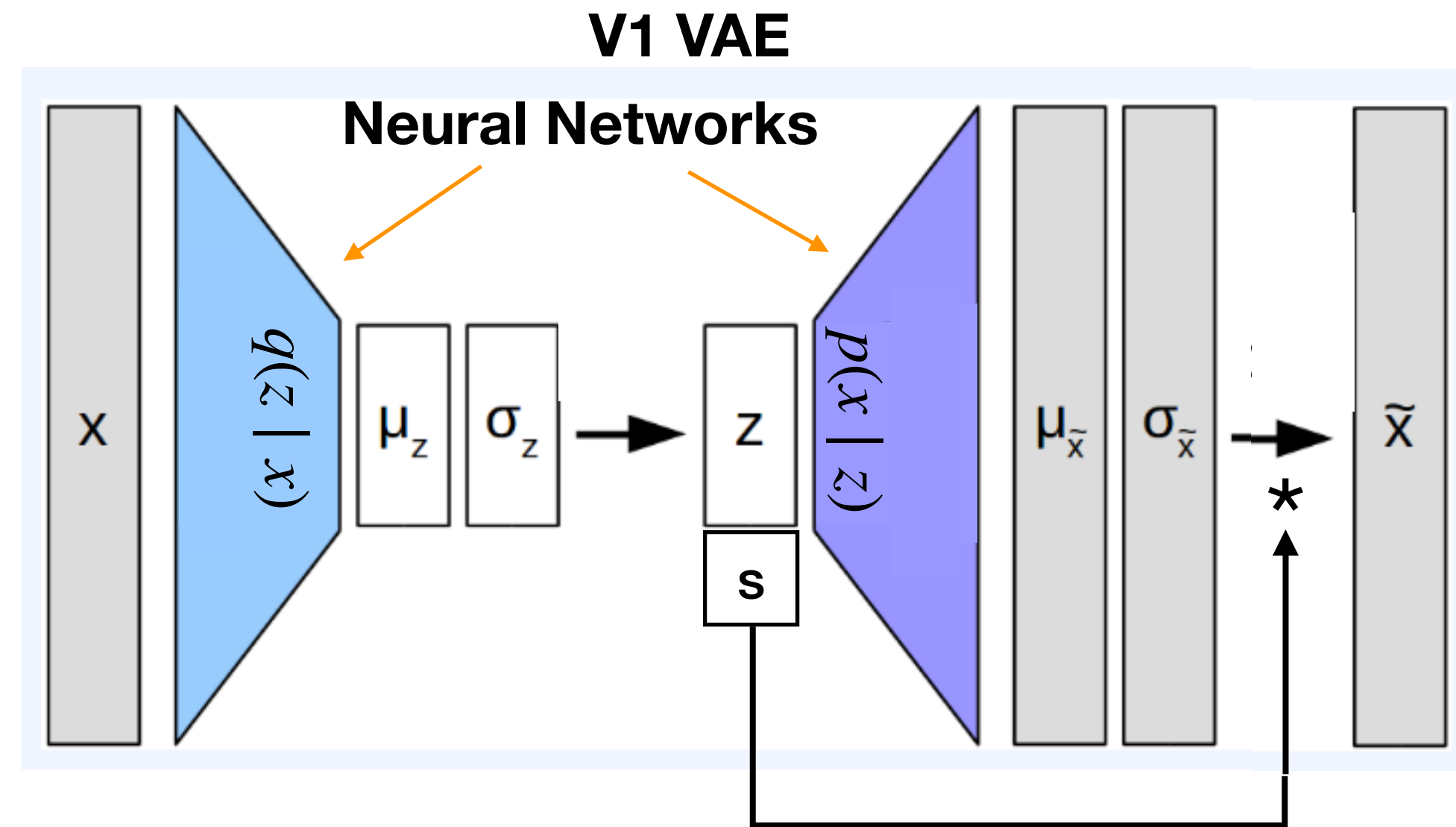
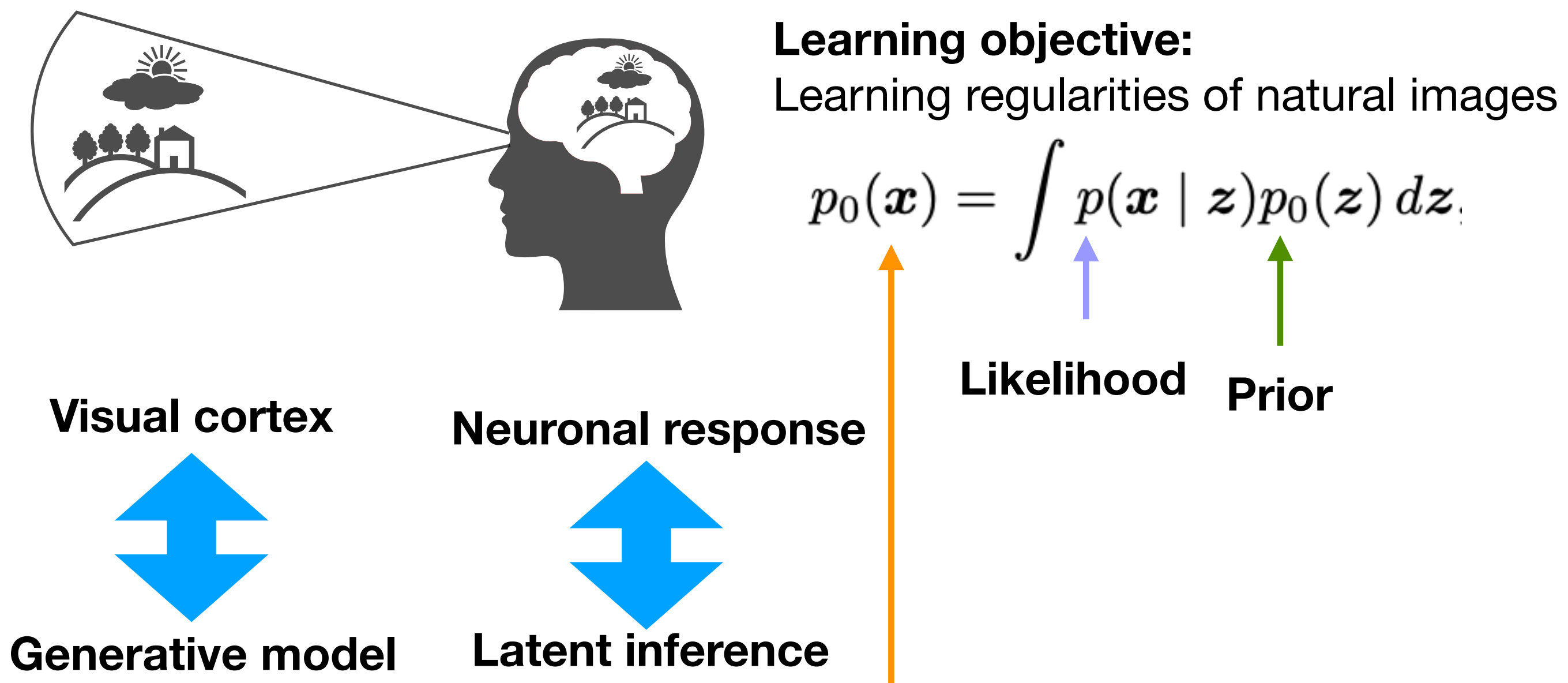
# Modeling vision with latent generative model



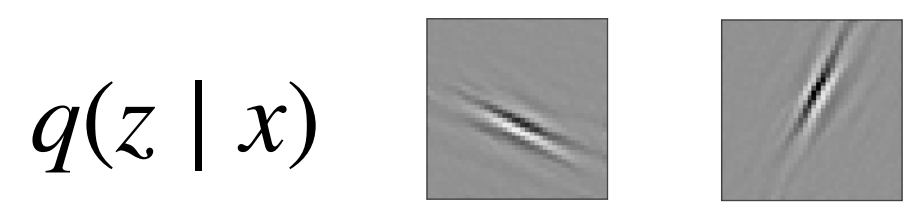
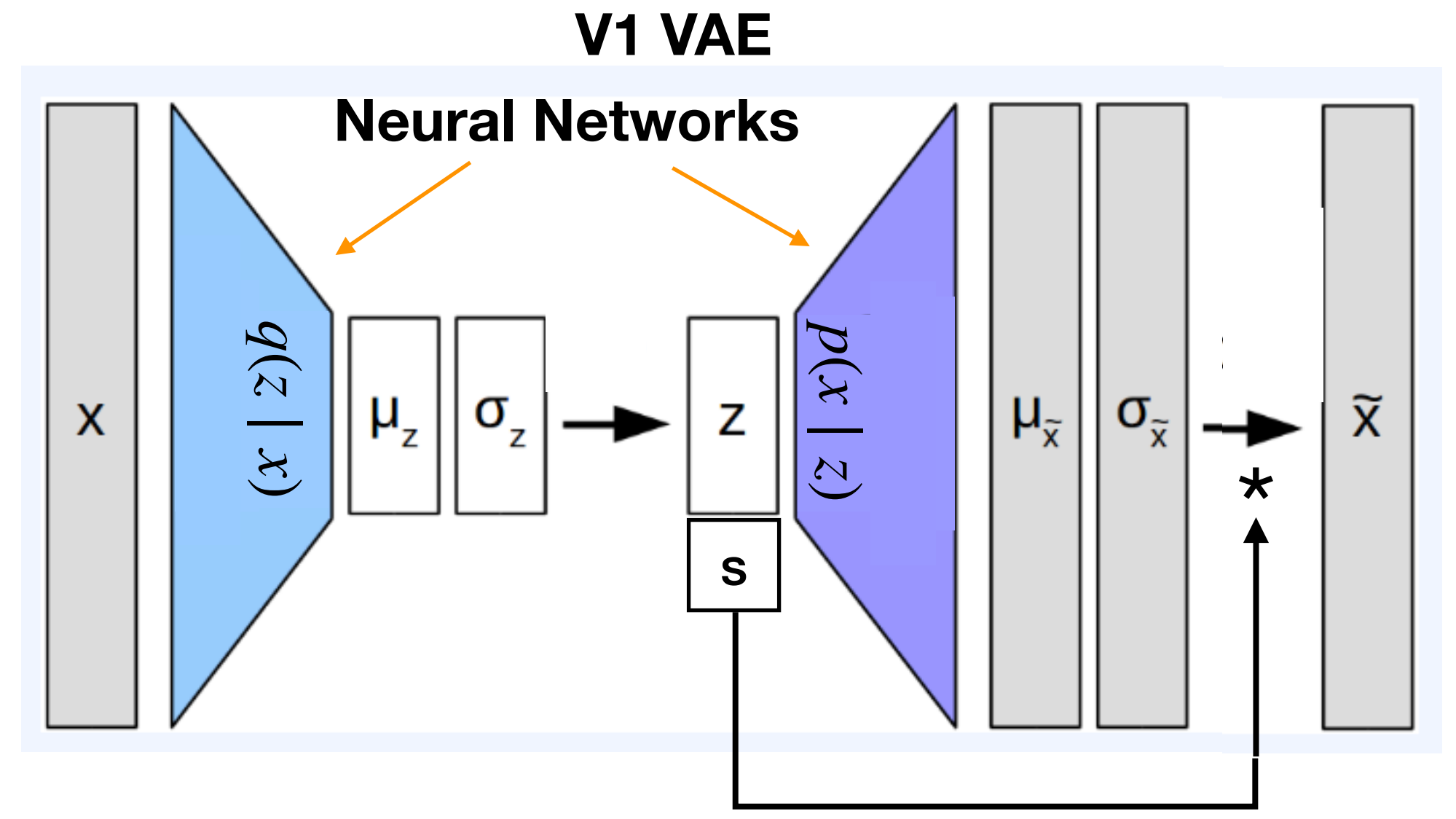
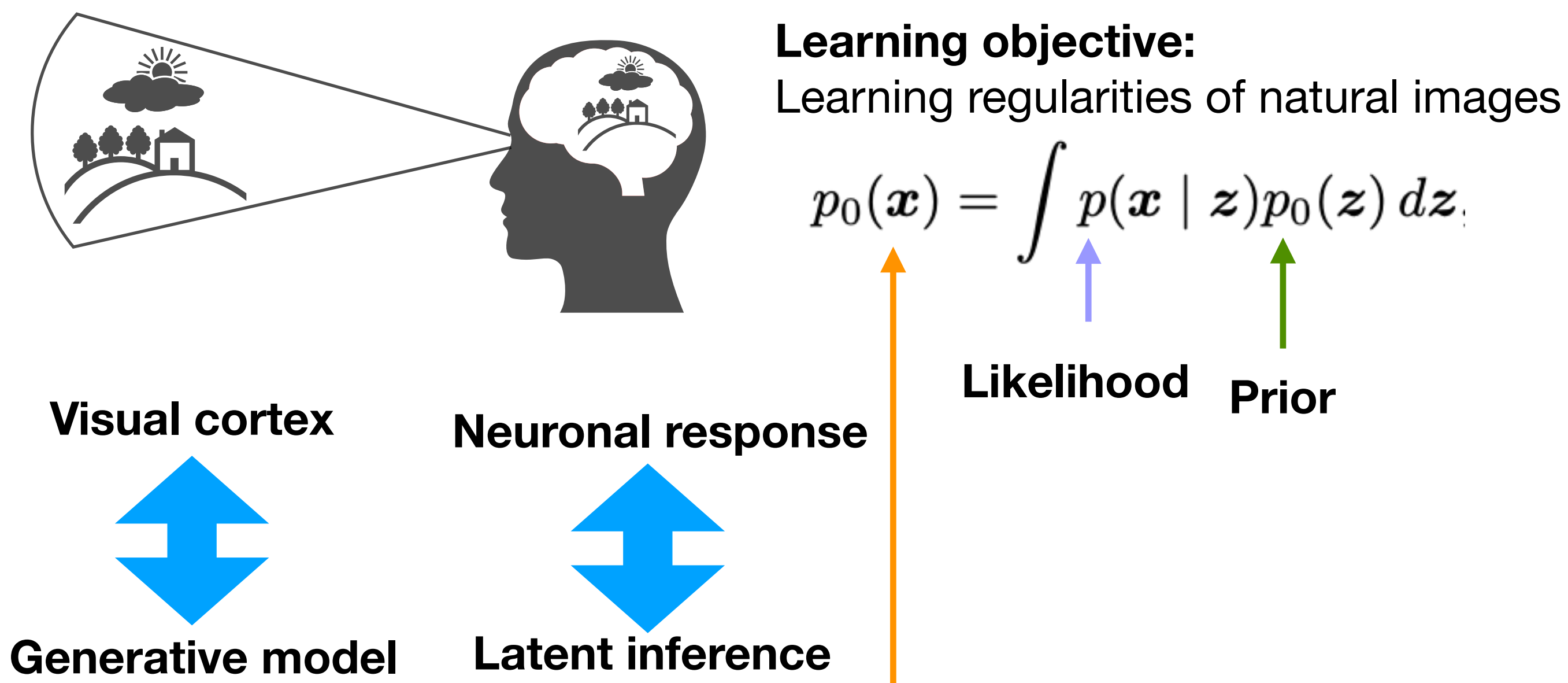
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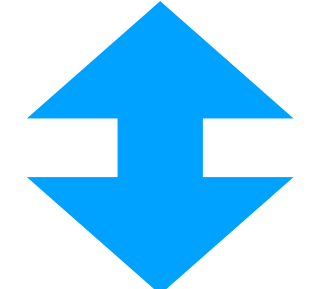
# Modeling vision with latent generative model



# Modeling vision with latent generative model



**Variational posterior**



**Neuronal response**

# Task adaptation in generative models

$p_0(\mathbf{x})$

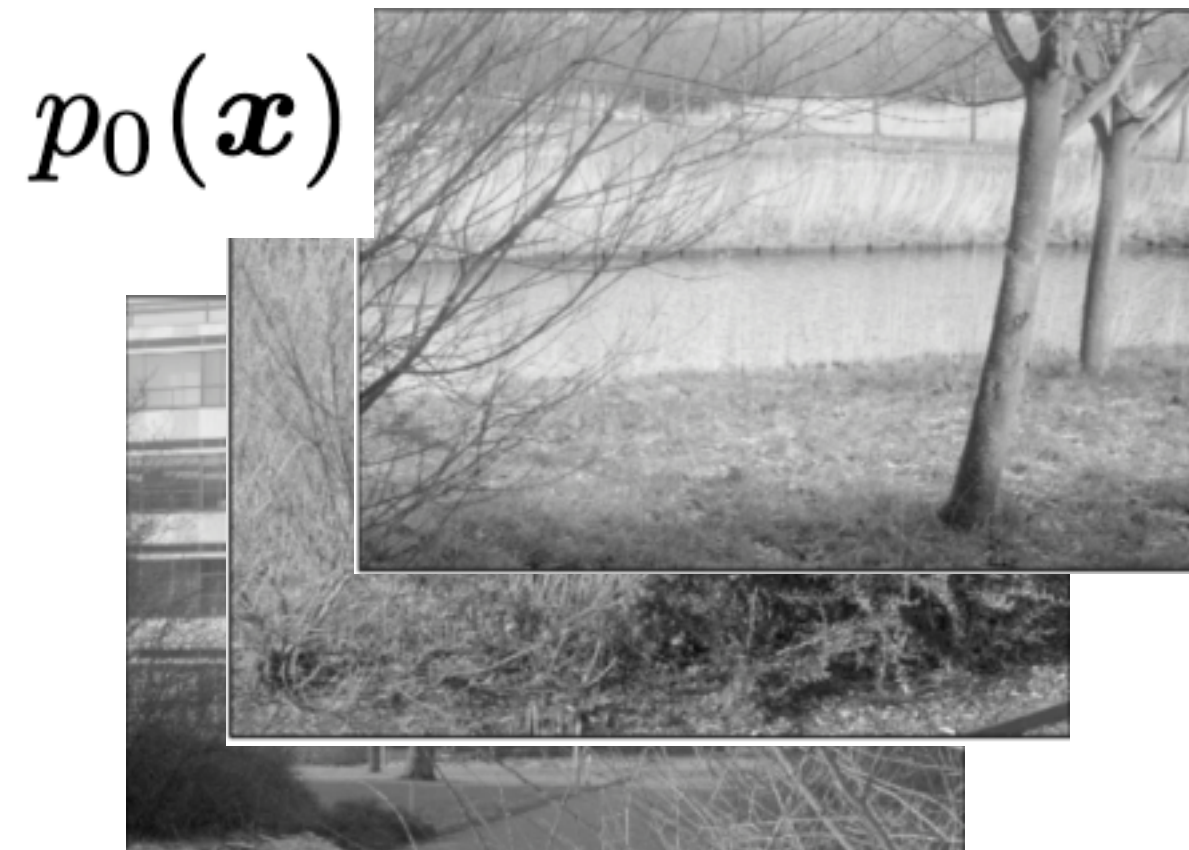


# Task adaptation in generative models

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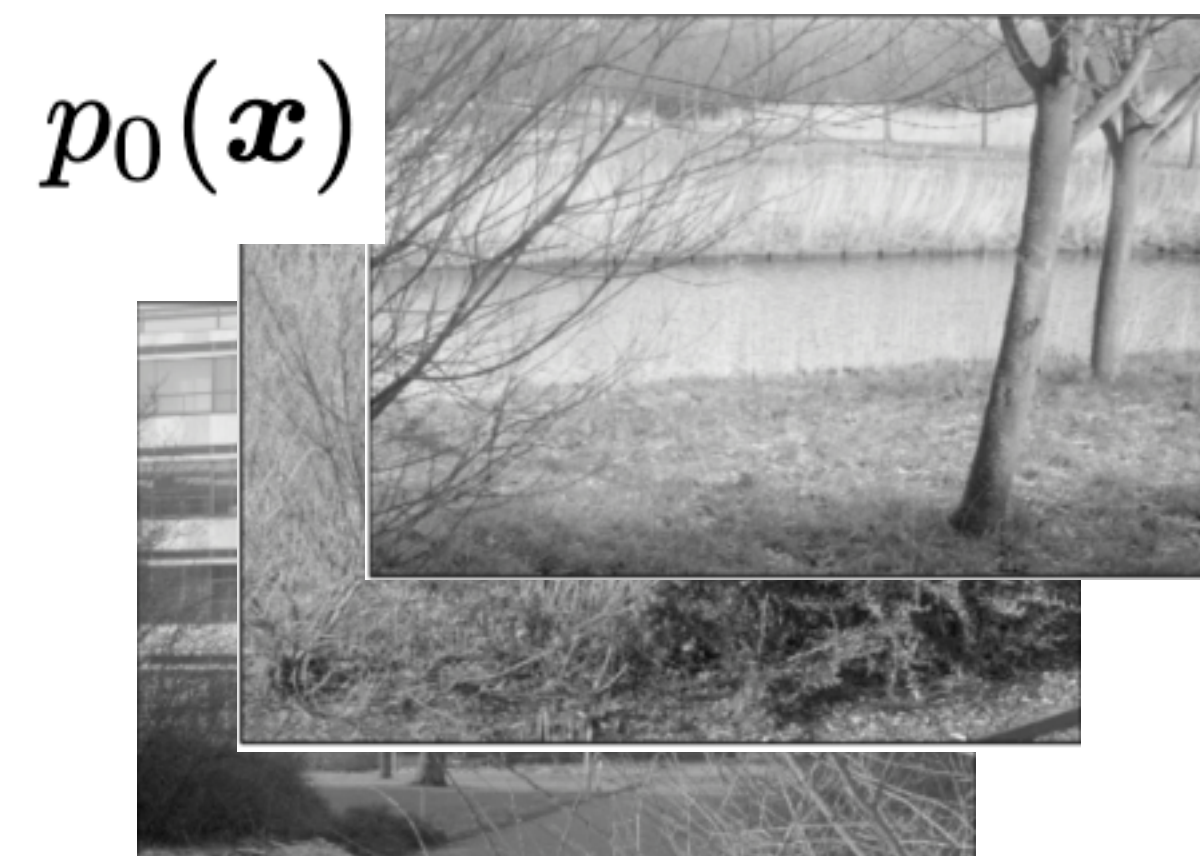
# Task adaptation in generative models



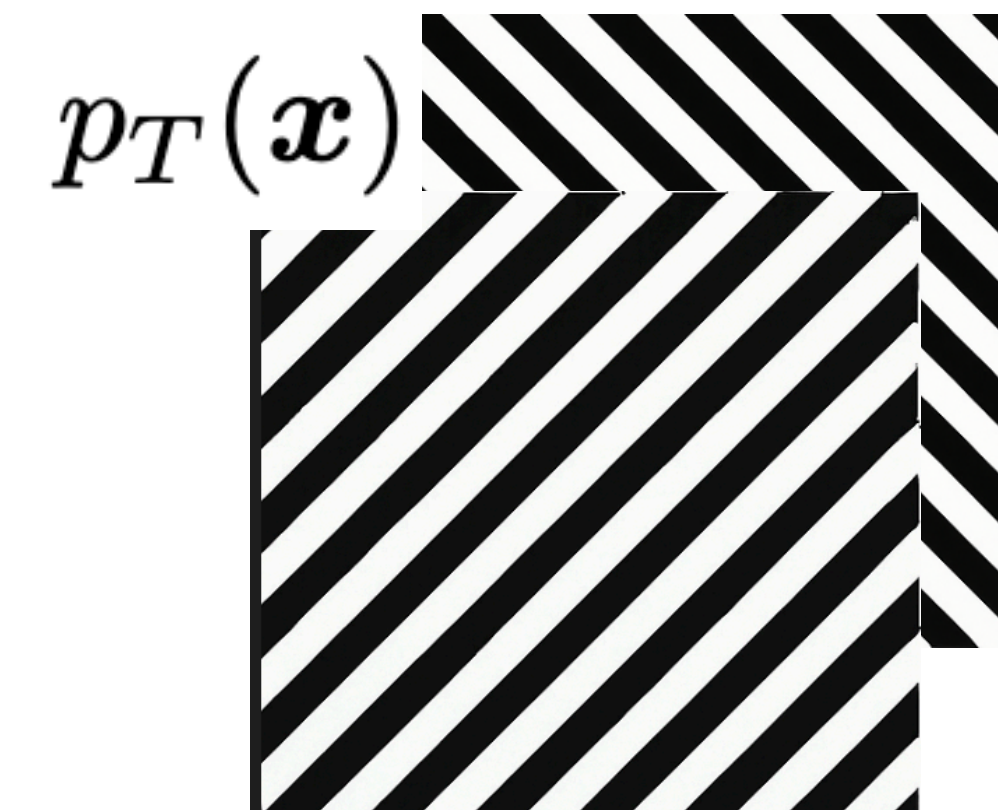
**How do we incorporate task adaptation?**



# Task adaptation in generative models



Change in stimulus statistics

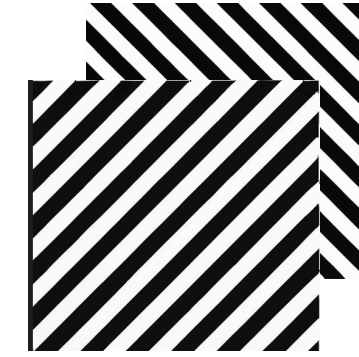


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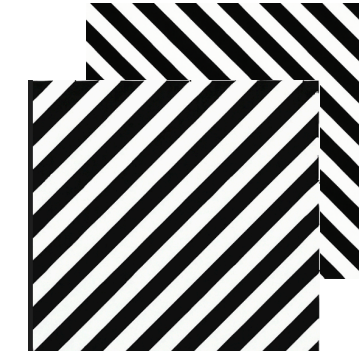
# Task adaptation in generative models

Brute force: train new VAE for the new image set



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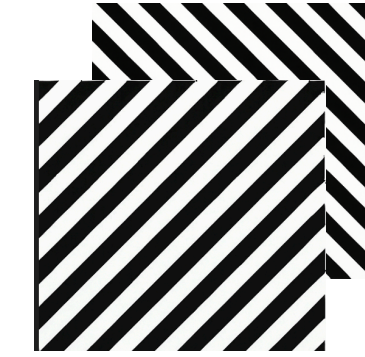


Not enough data



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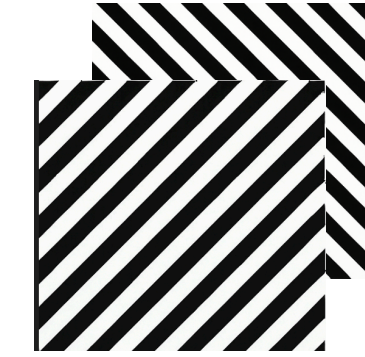


Tune away important representation



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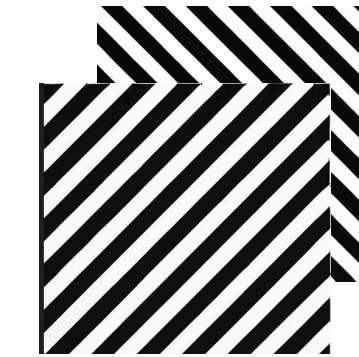
Instead: computational efficient, biologically plausible solution

$$p_T(\mathbf{x}) = \int p(\mathbf{x} | \mathbf{z}) p_T(\mathbf{z}) d\mathbf{z}$$

Retain likelihood

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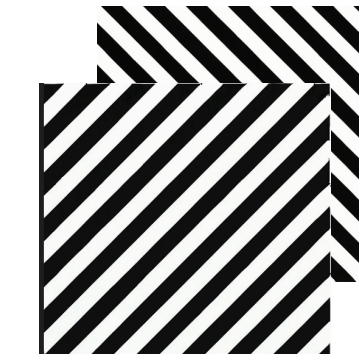
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Cheap optimization

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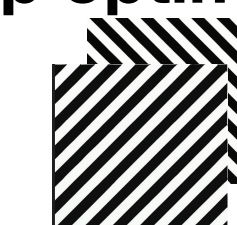
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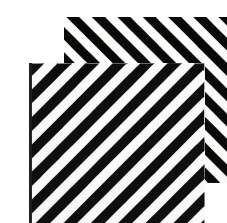


$$q_T(\mathbf{z} | \mathbf{x}) \propto \frac{q(\mathbf{z} | \mathbf{x}) p_T(\mathbf{z})}{p_0(\mathbf{z})}$$

Cheap optimization

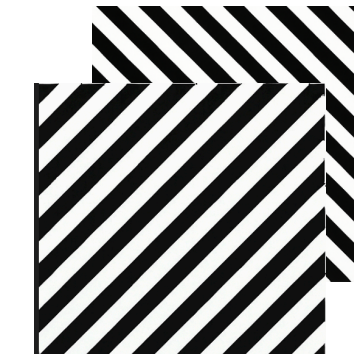


Inference in task



# Task adaptation in generative models

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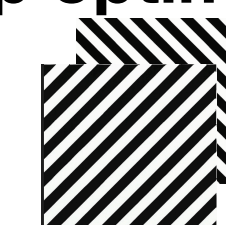
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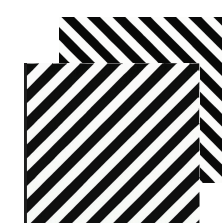
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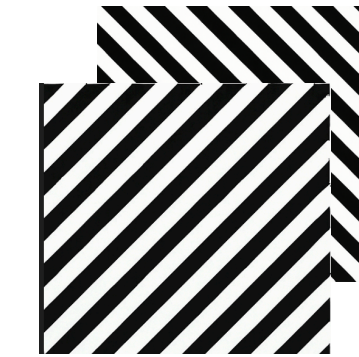


Context-free inference



# Task adaptation in generative models

Brute force: train new VAE for the new image set



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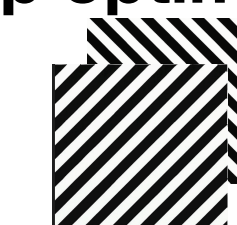
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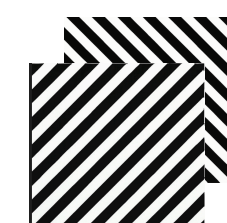


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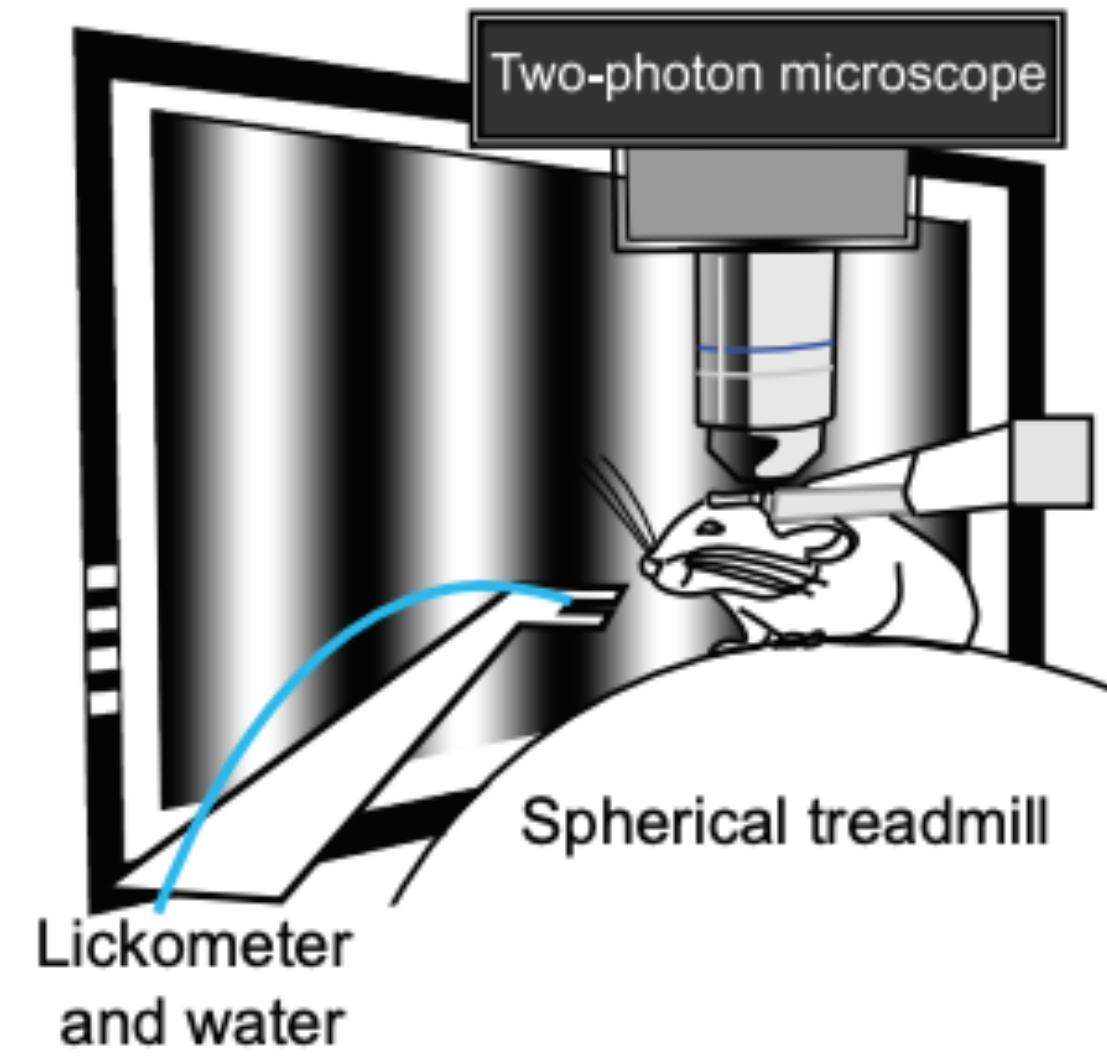
Inference in task



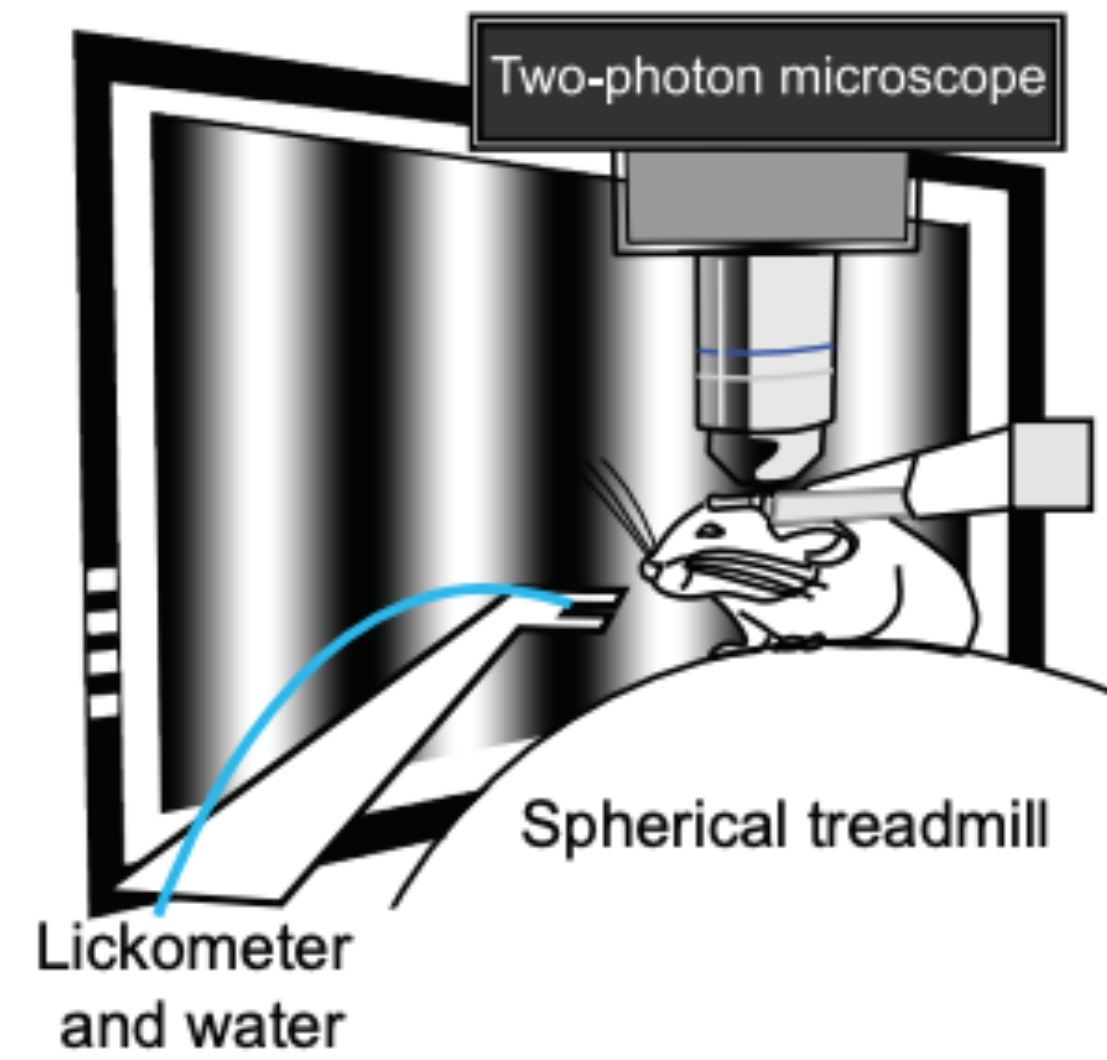
Context-free inference



# Experimental setup



# Experimental setup



9-18 days

Training

45°

Go

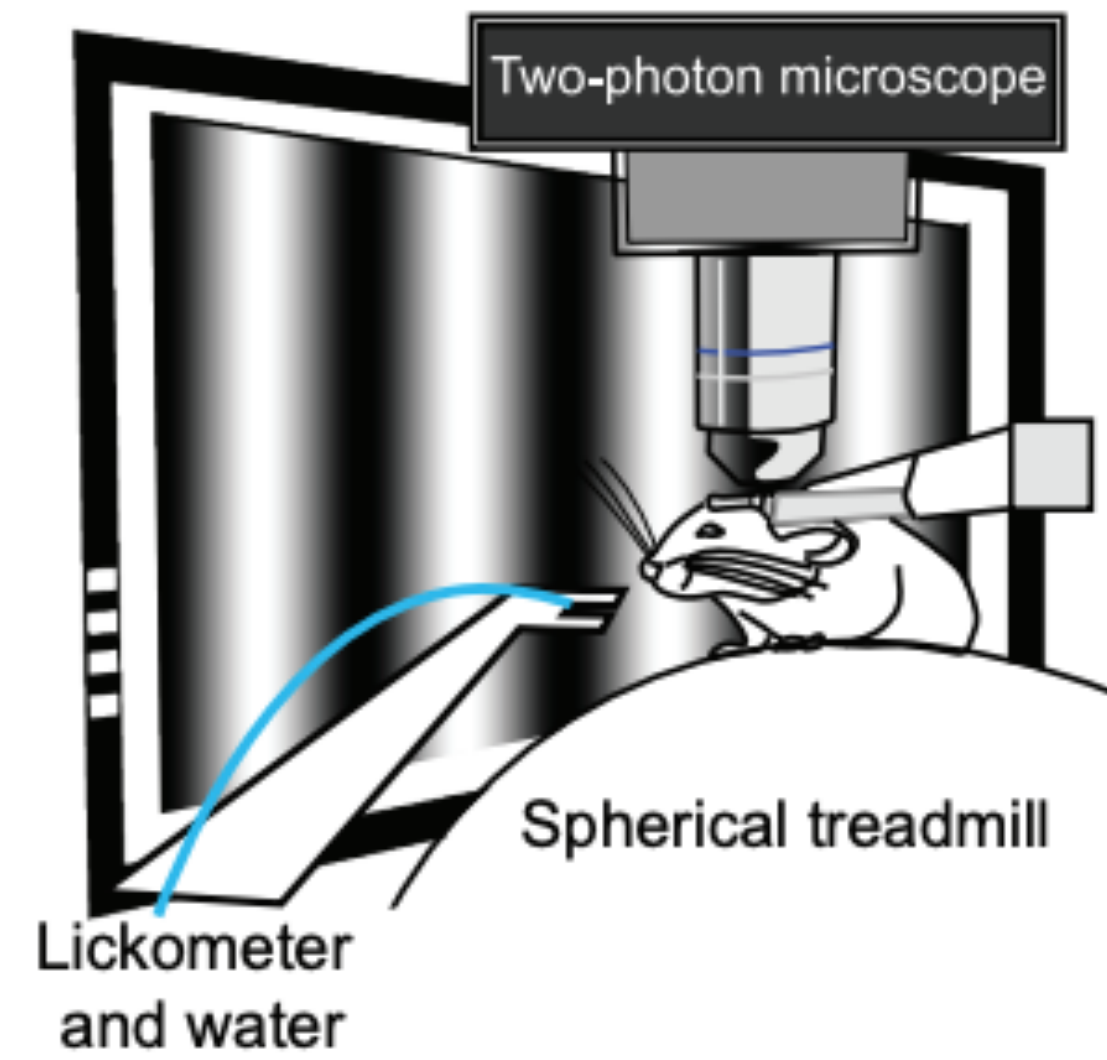


135°

NoGo



# Experimental setup



9-18 days

Test days

Training

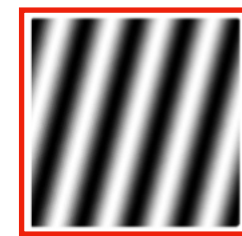
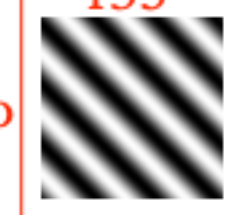
45°

Go

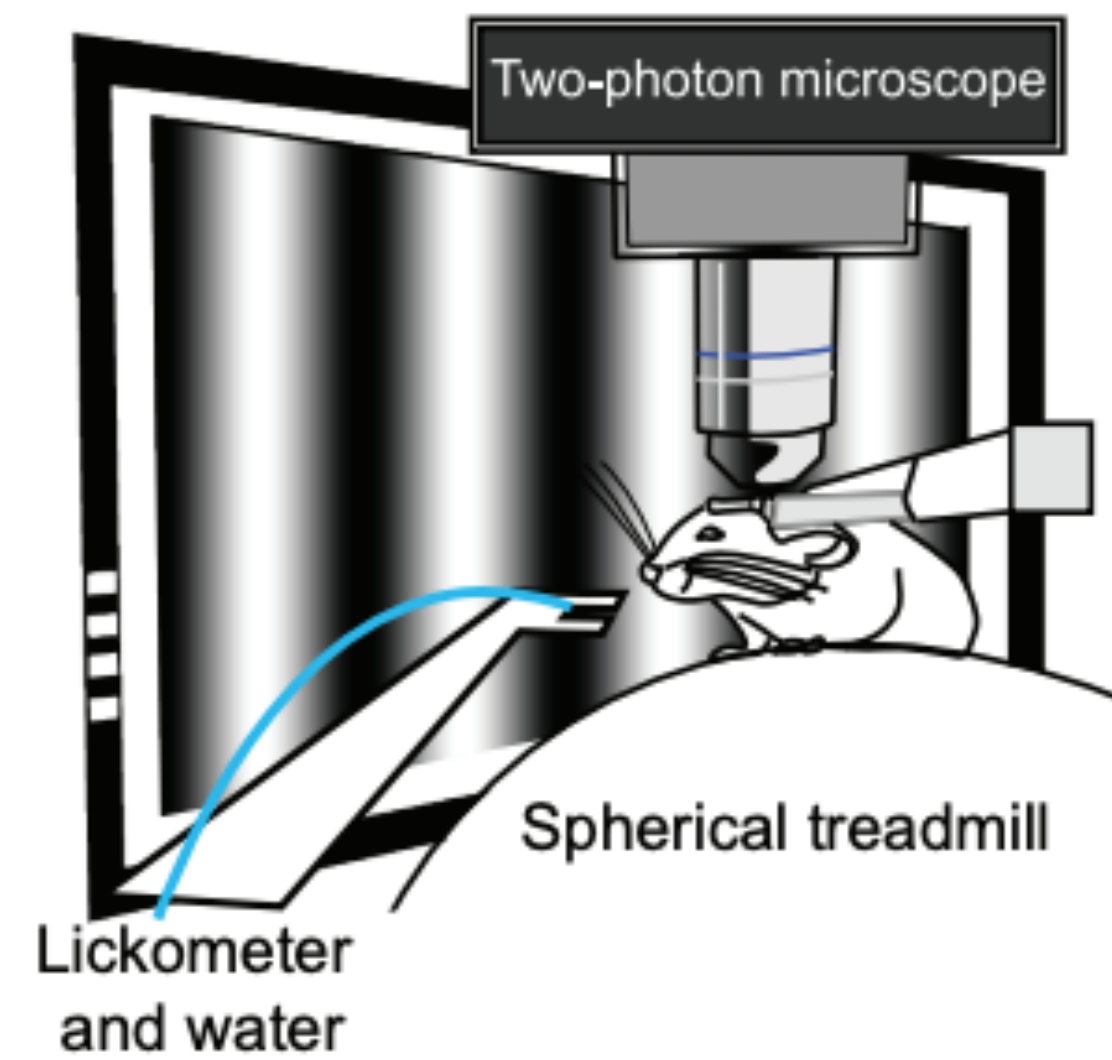


135°

NoGo



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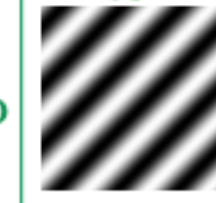
9-18 days

Test days

Training

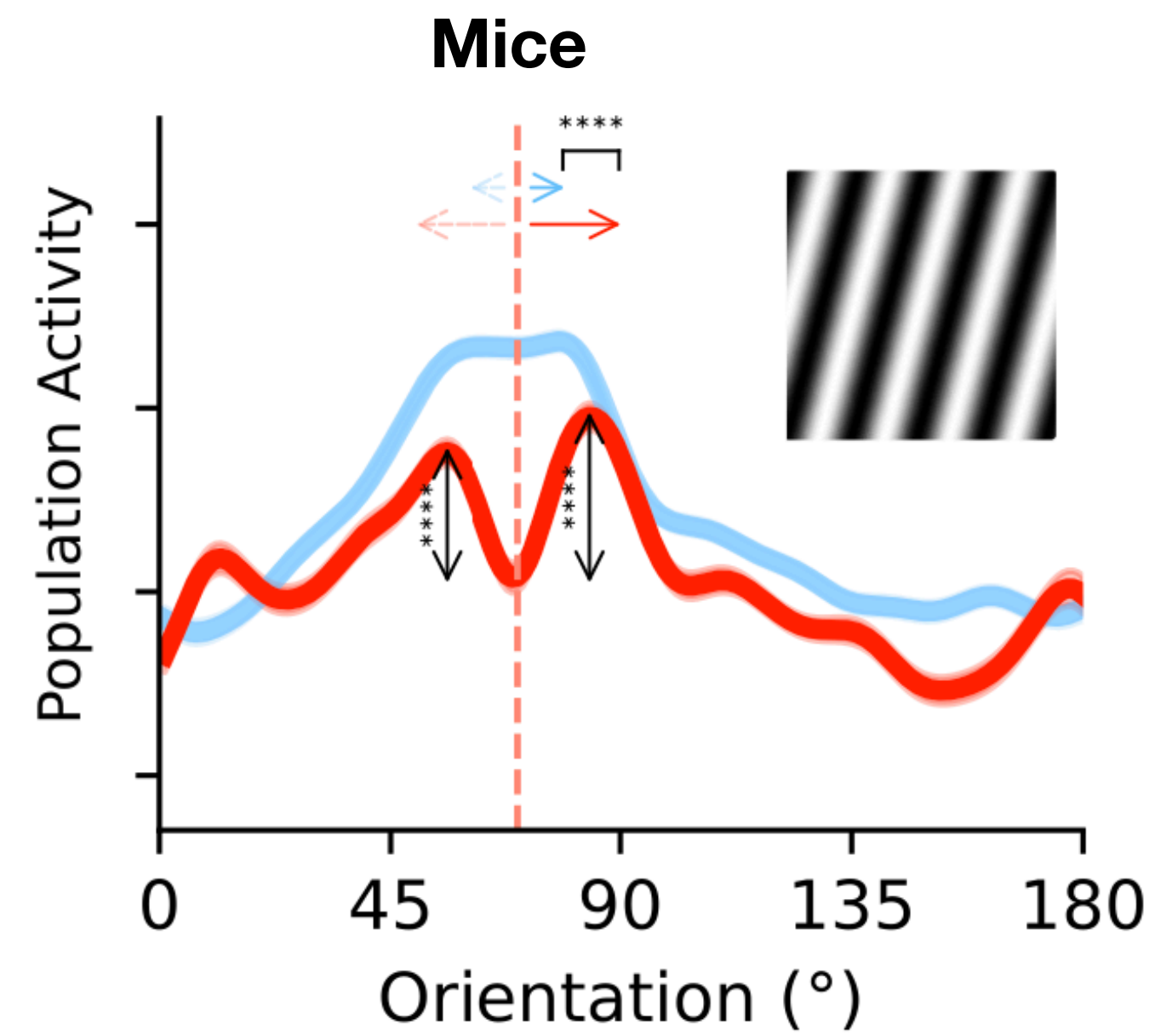
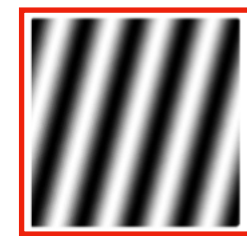
45°

Go

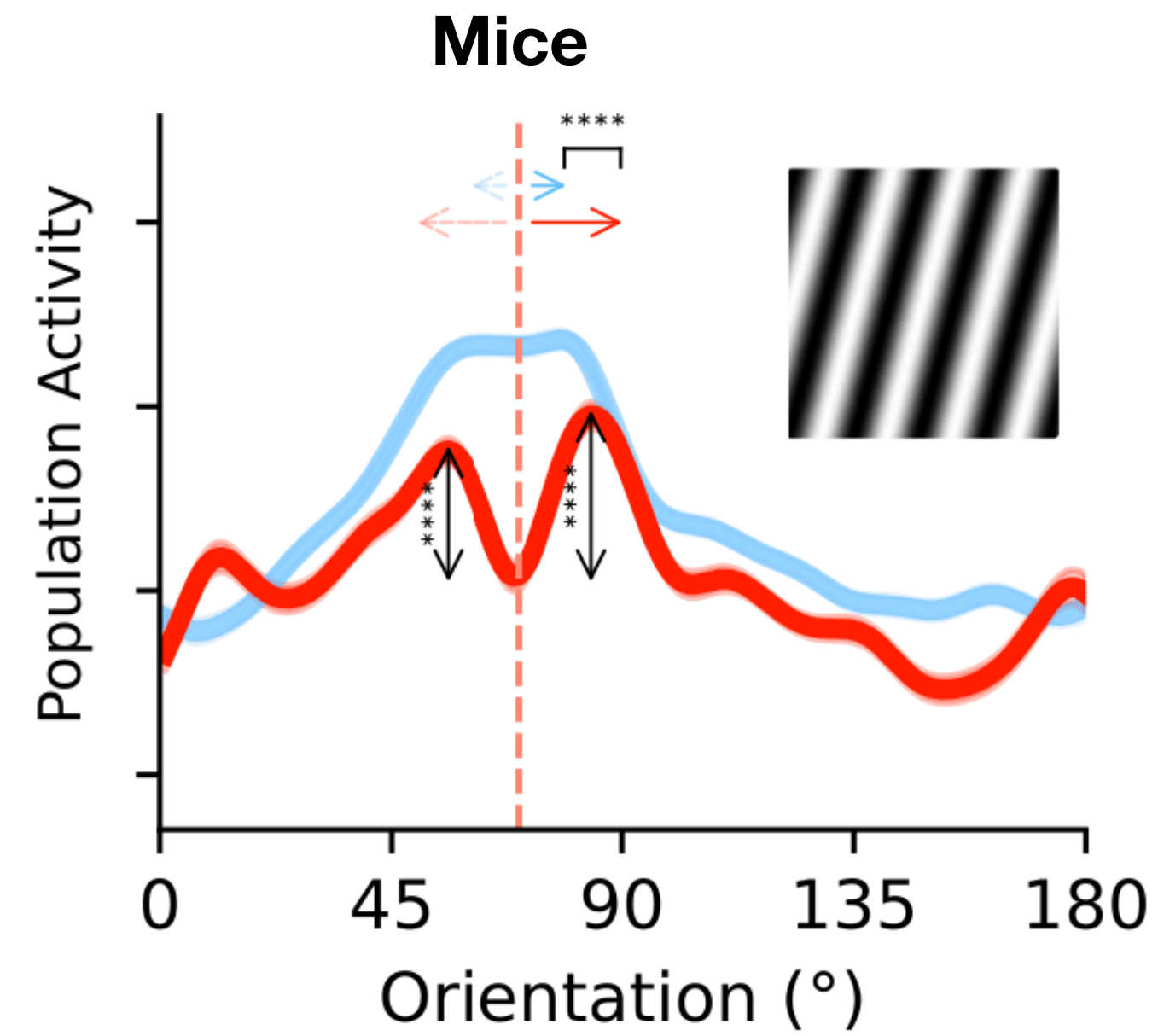
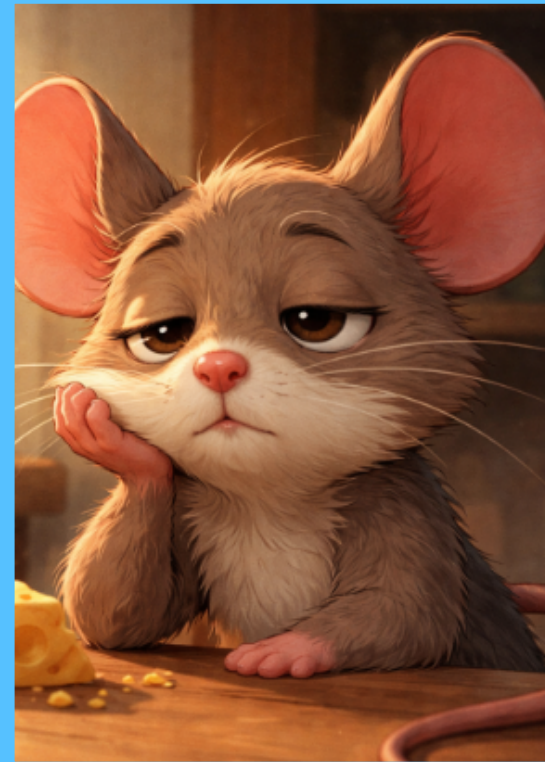
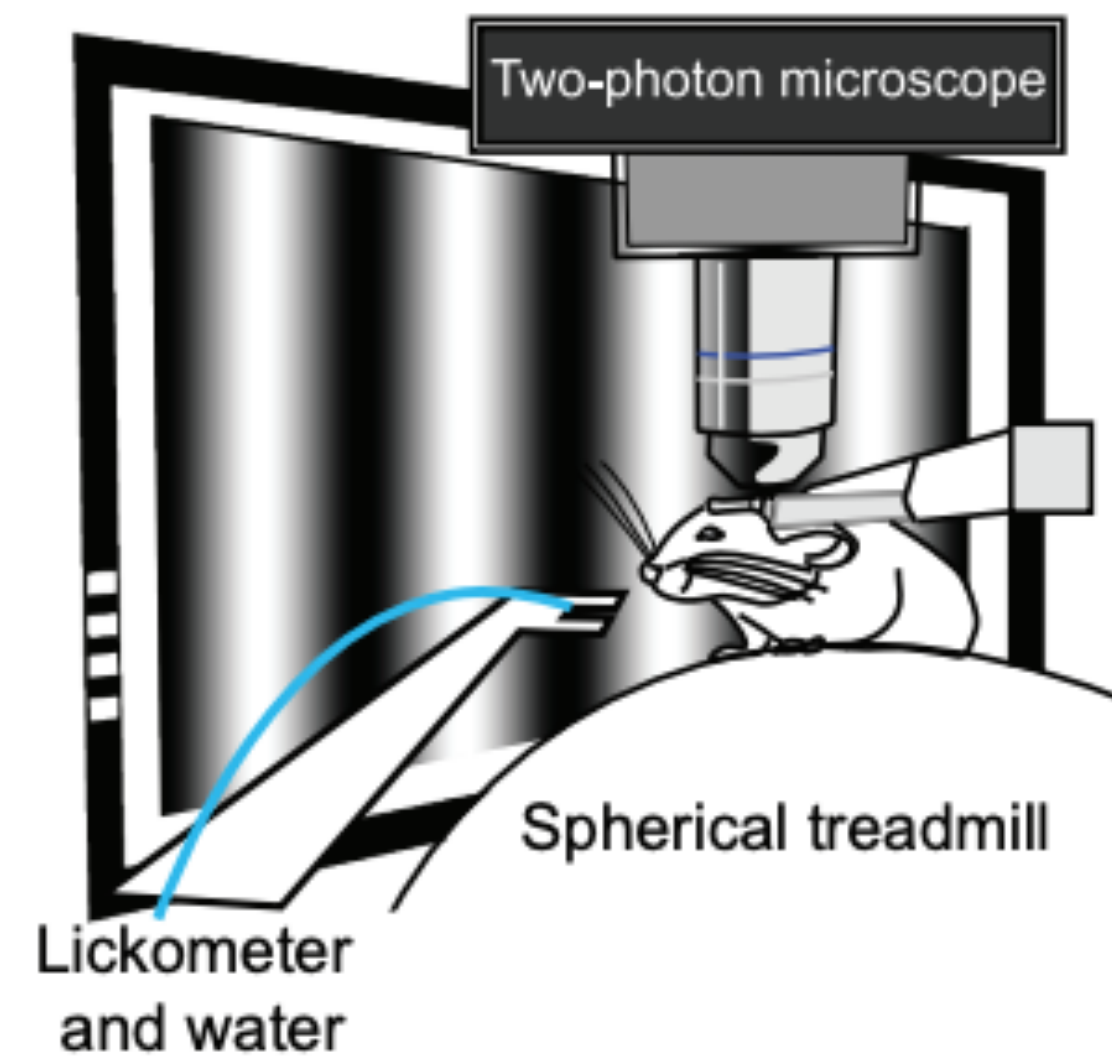


135°

NoGo



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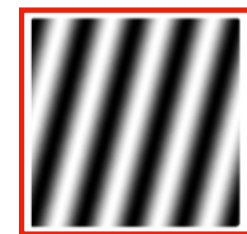
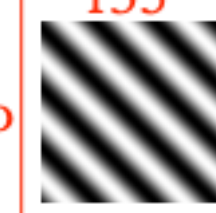
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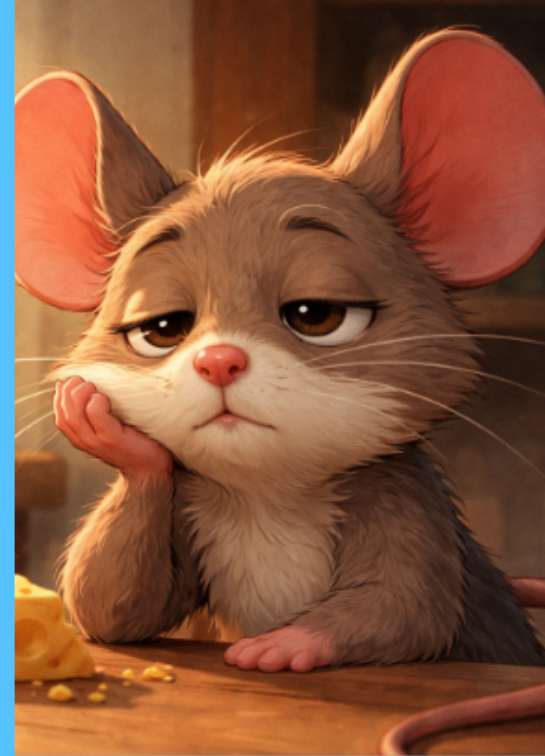
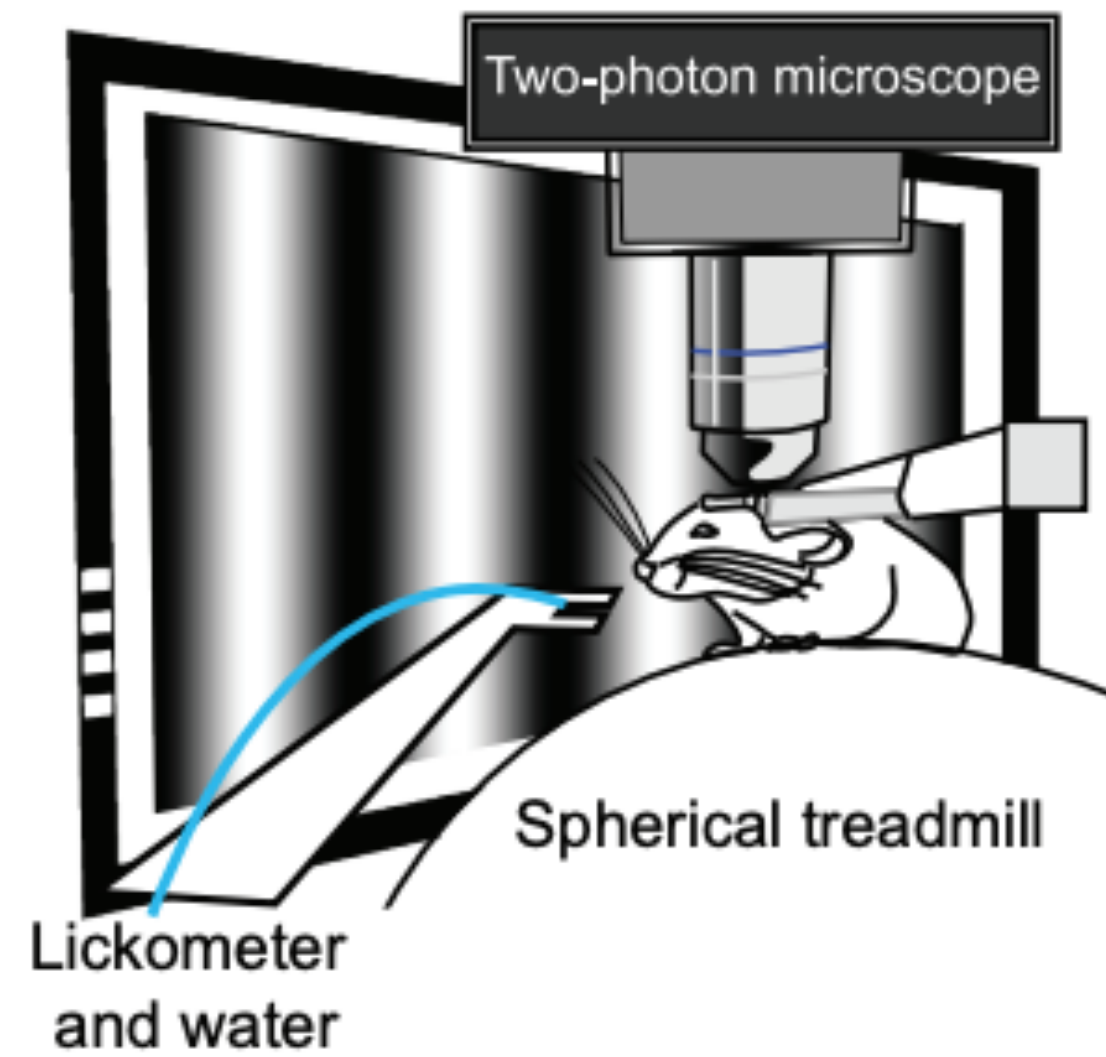


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# Experimental setup



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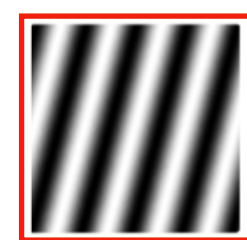
45°

Go



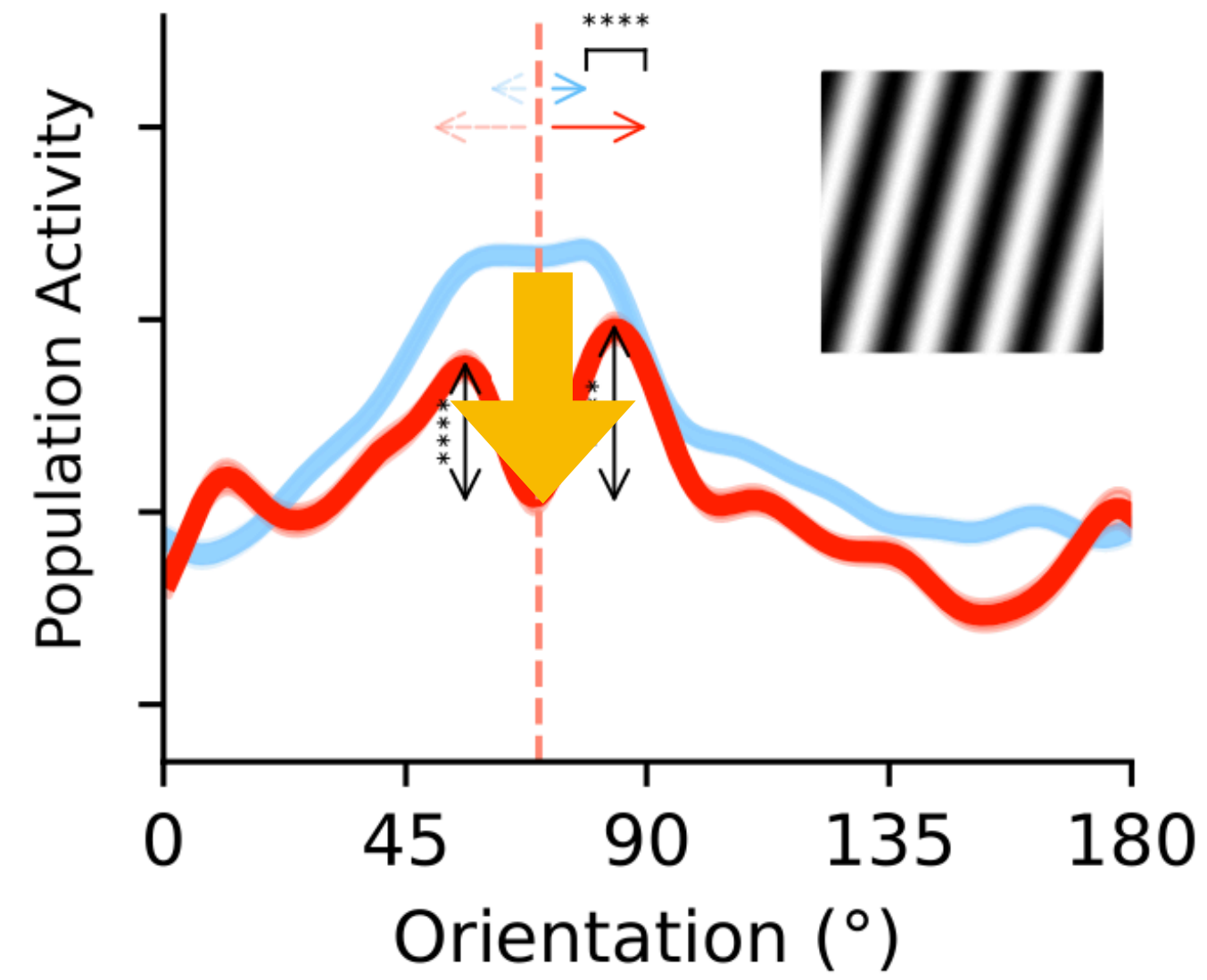
135°

NoGo

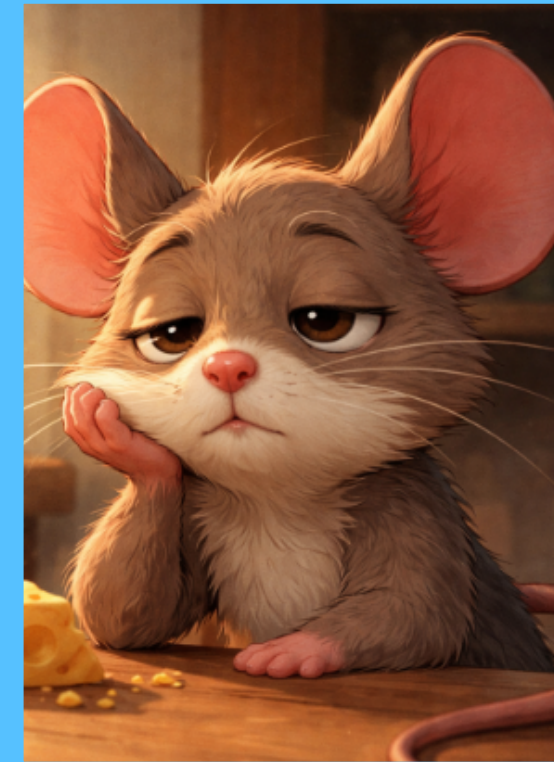
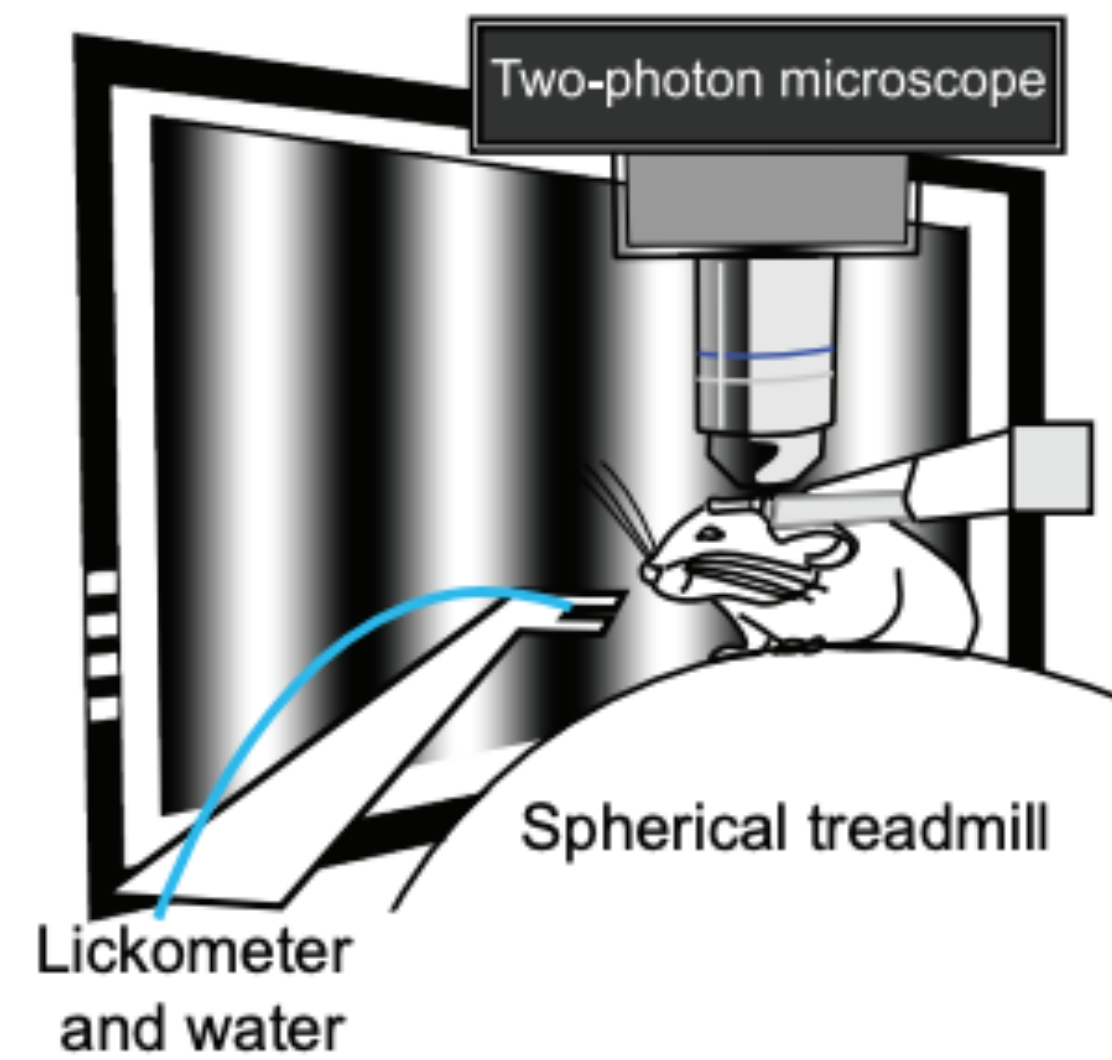


Bimodal response profile

Mice



# Experimental setup



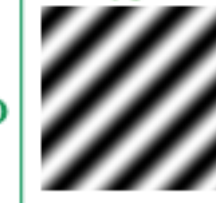
9-18 days

Test days

Training

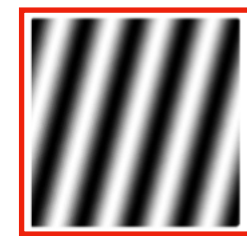
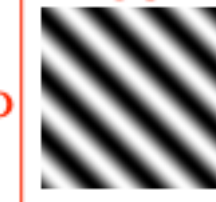
45°

Go



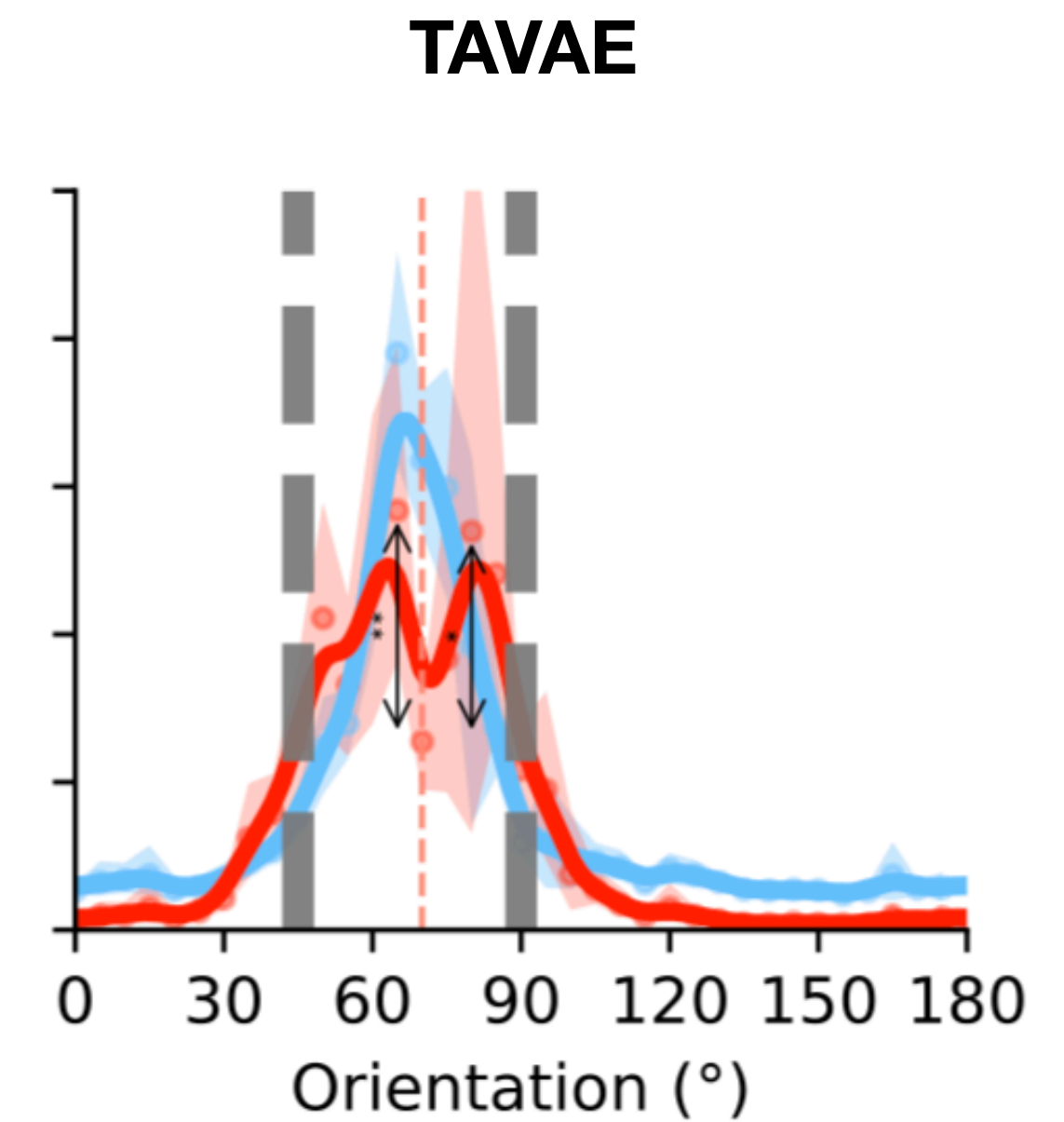
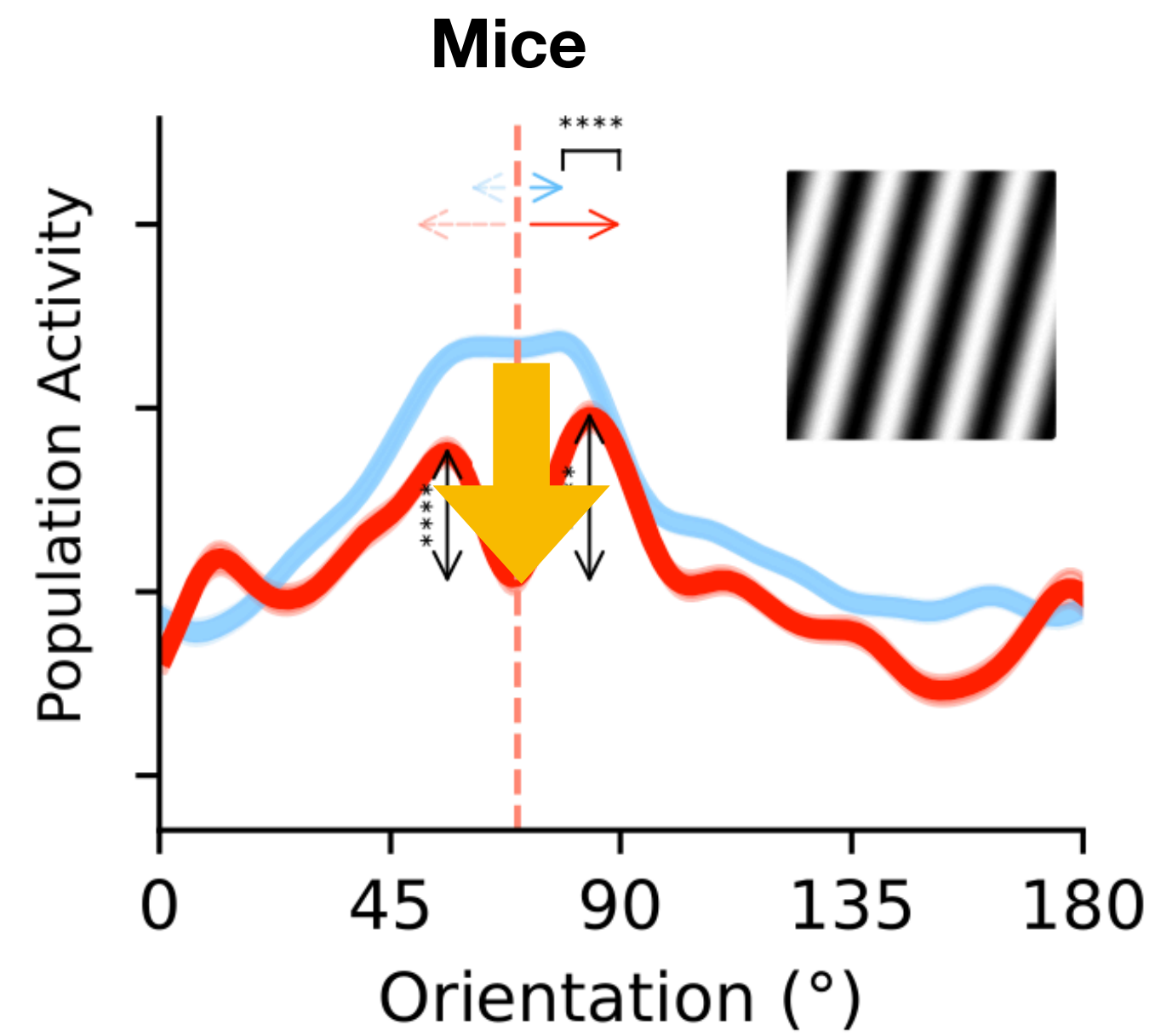
135°

NoGo



Bimodal response profile

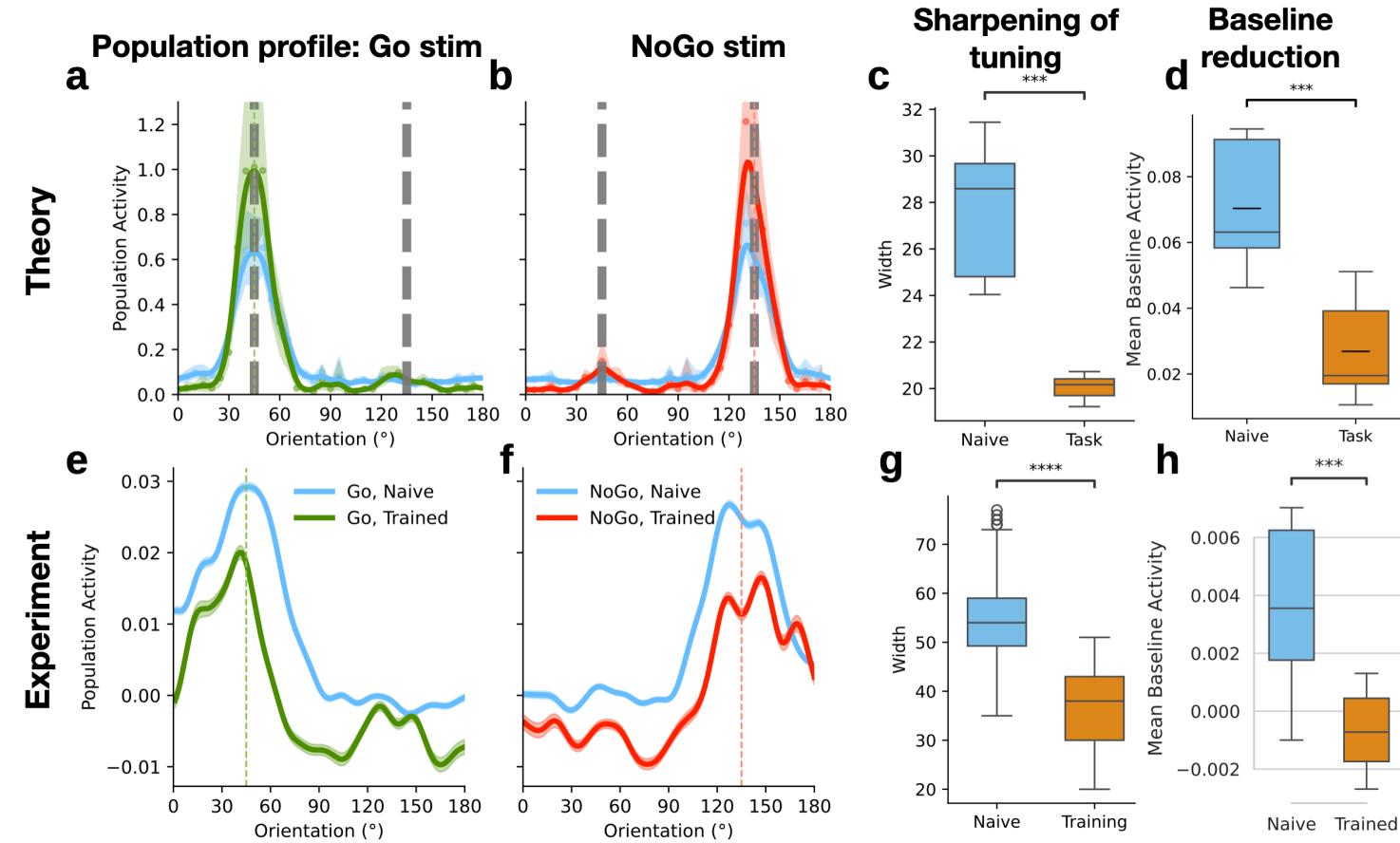
Model explains bimodality



# Detailed results in the paper!

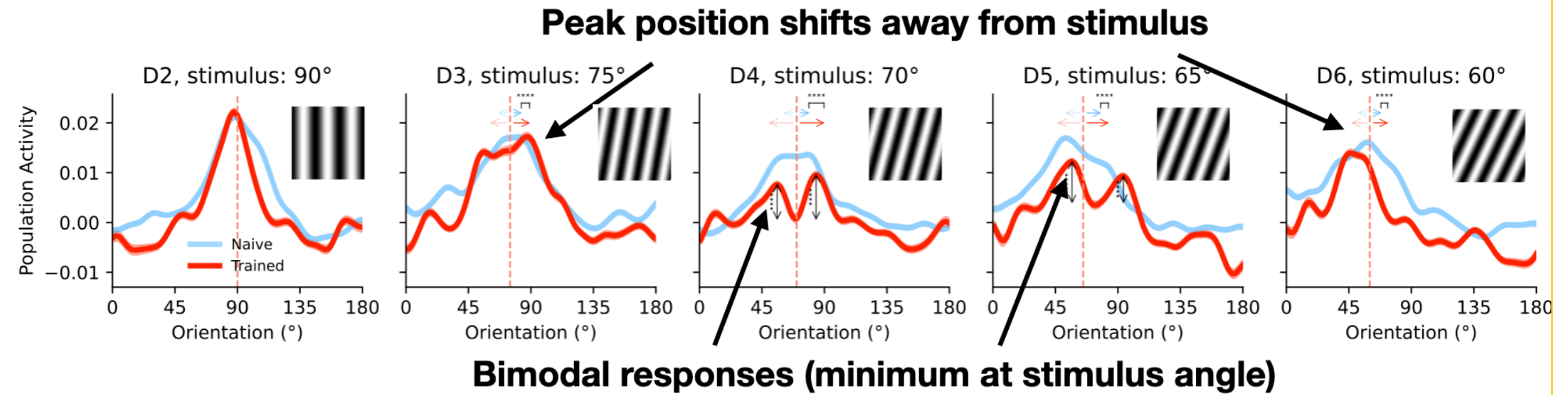
## D1: task congruent stimuli

Adapting to the discrimination task: acquiring a contextual prior



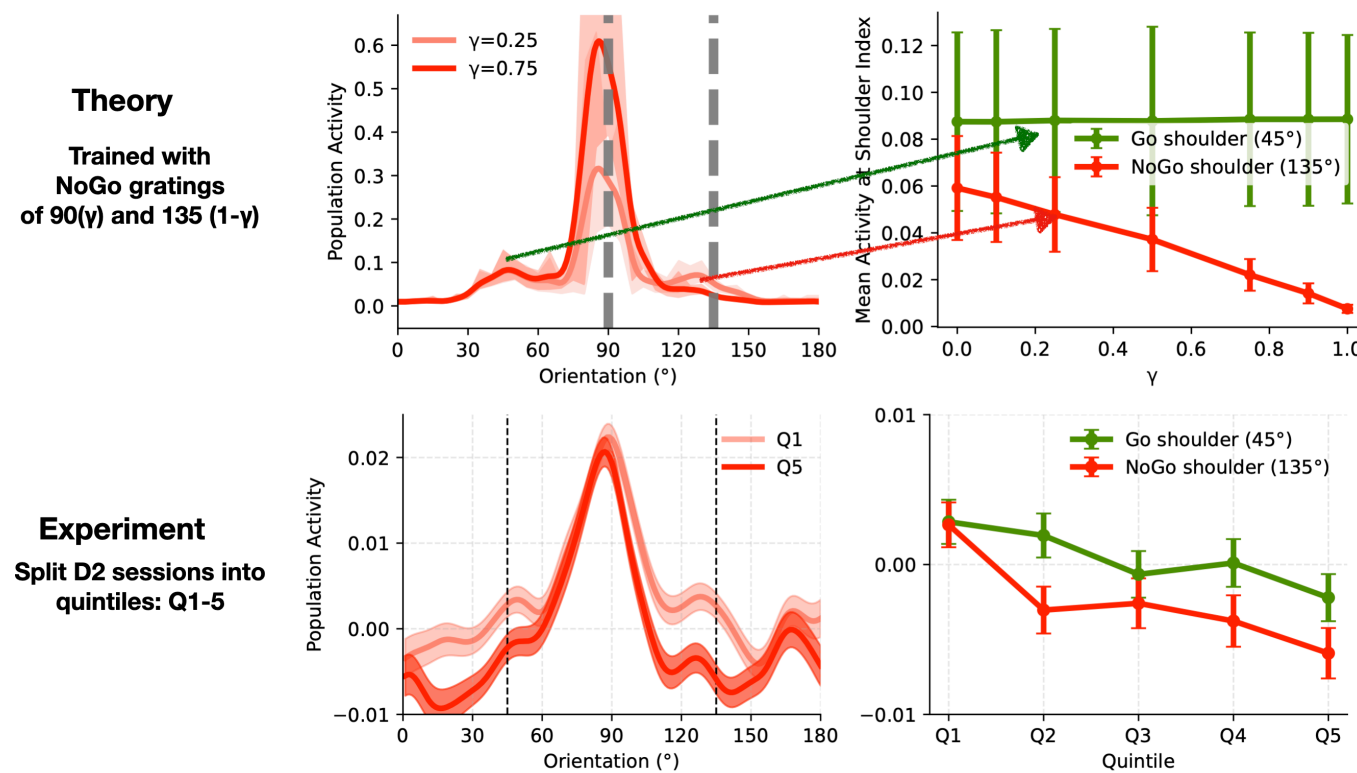
## D2-D6: task-stimulus mismatch

Violation of trained stimulus statistics: biased responses through contextual prior

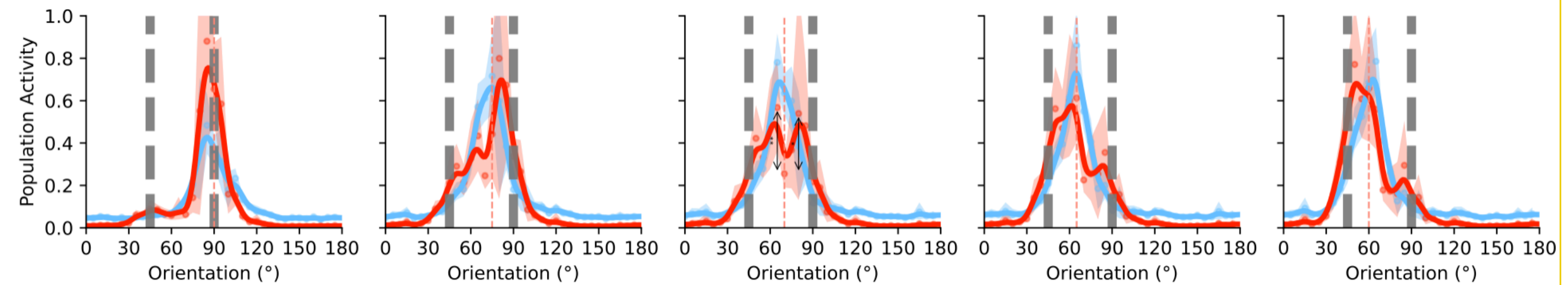


## Gradual update of the prior upon stimulus mismatch (D2)

The contextual prior can adapt to clear violations of learned statistics: unfounded hypotheses early in a session are gradually discredited



- Partial adapter model: Adaptation to D2 stimuli then retain D2 in later sessions



## Predictive power of alternative accounts

	TAVAE (45, 90)	VAE	TAVAE (45, 135)	TAVAE (EAGER)
$r(\text{TASK})$	$0.78 \pm 0.02$	$0.53 \pm 0.12$	$0.54 \pm 0.10$	$0.53 \pm 0.11$
$r(\text{TASK-NAIVE})$	$0.58 \pm 0.09$	—	$0.32 \pm 0.17$	$-0.10 \pm 0.23$