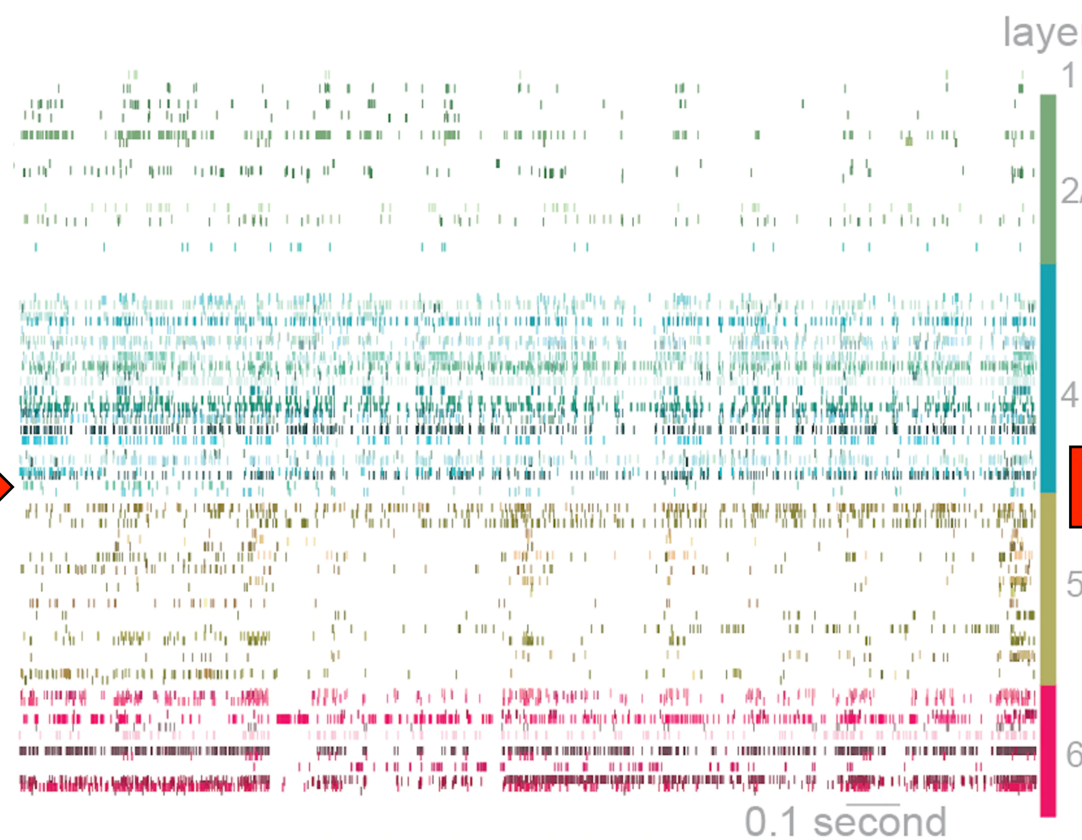
NeuroAI:
How to harness Artificial Intelligence Research for understanding the brain

GERGŐ ORBÁN

computational systems neuroscience lab
Dept Computational Sciences

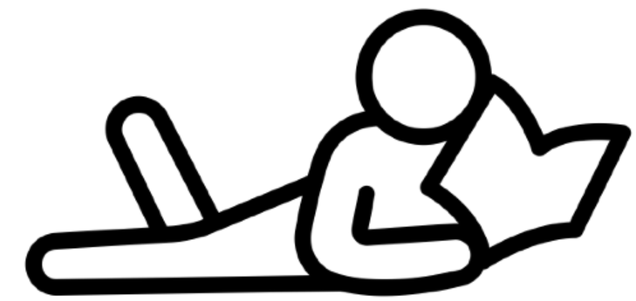
Wigner Research Center for Physics

Reading the neural code

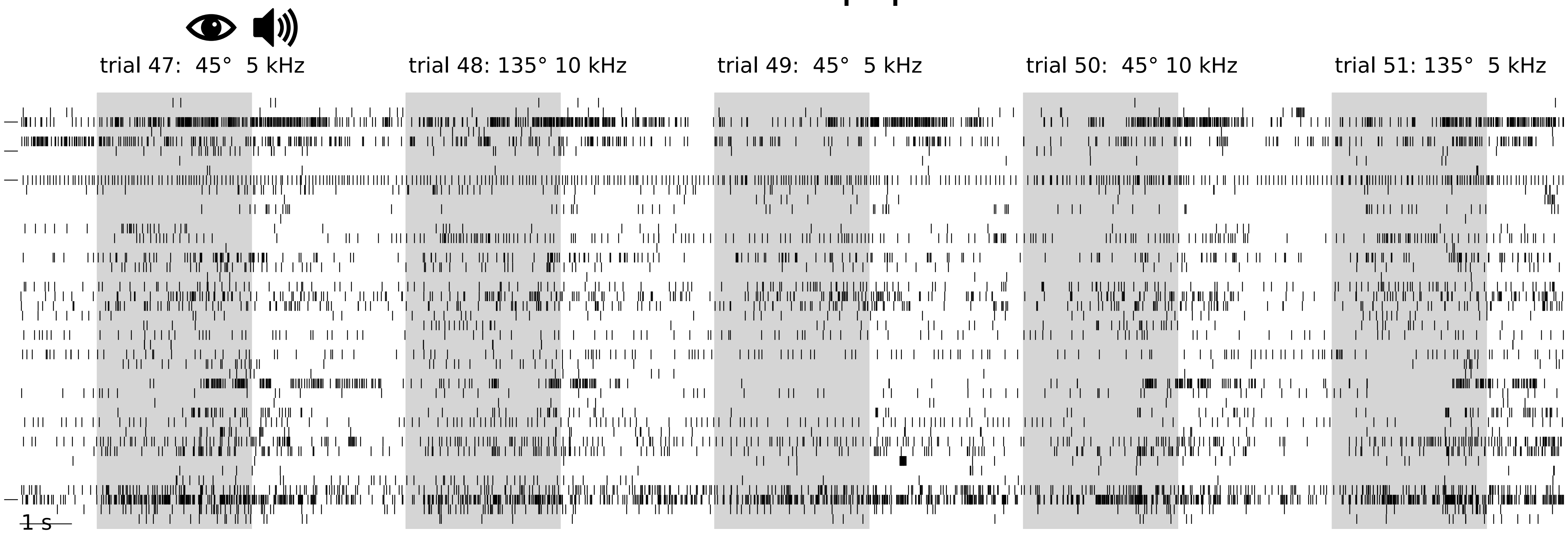


source: Allen Brain Observatory

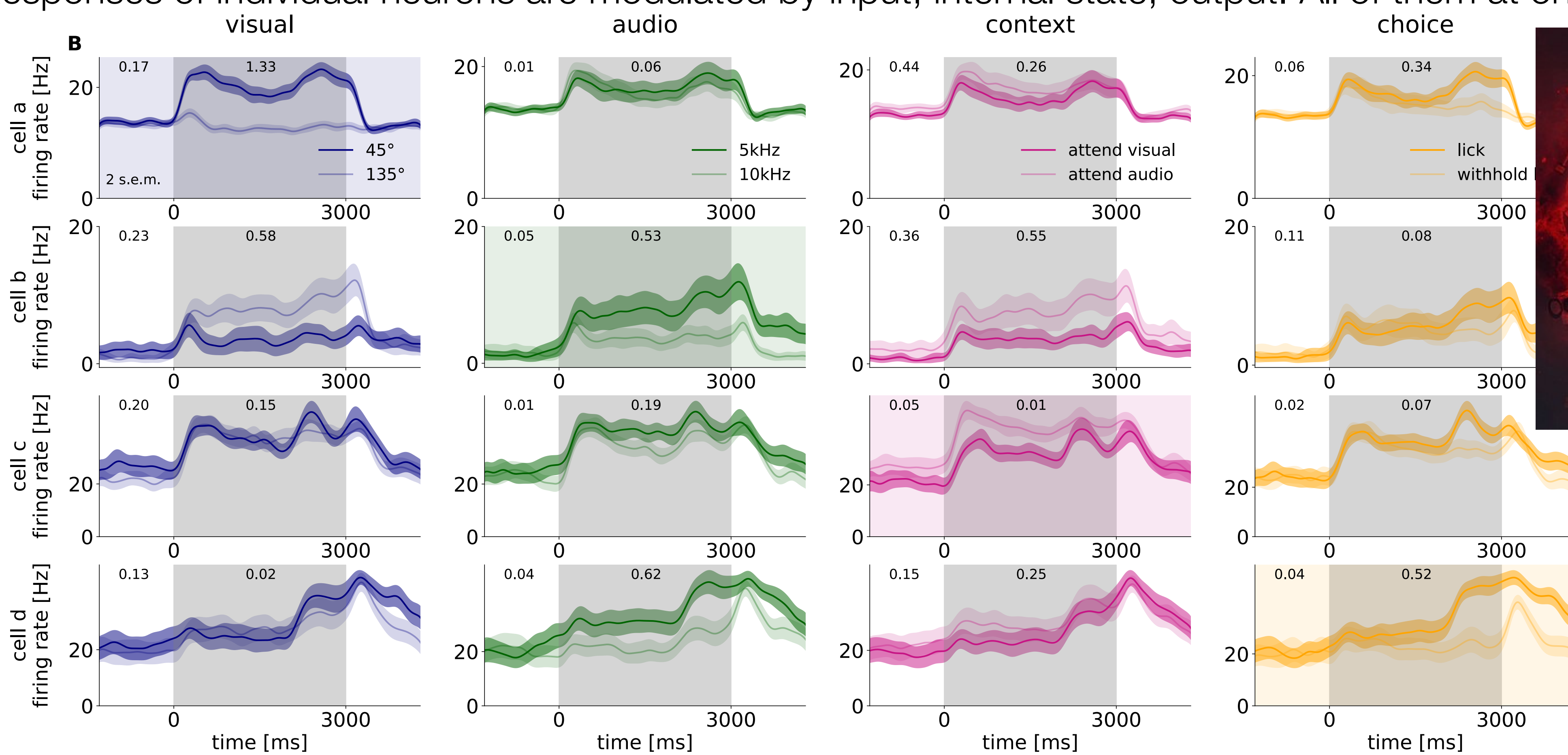
?



Data-driven approaches

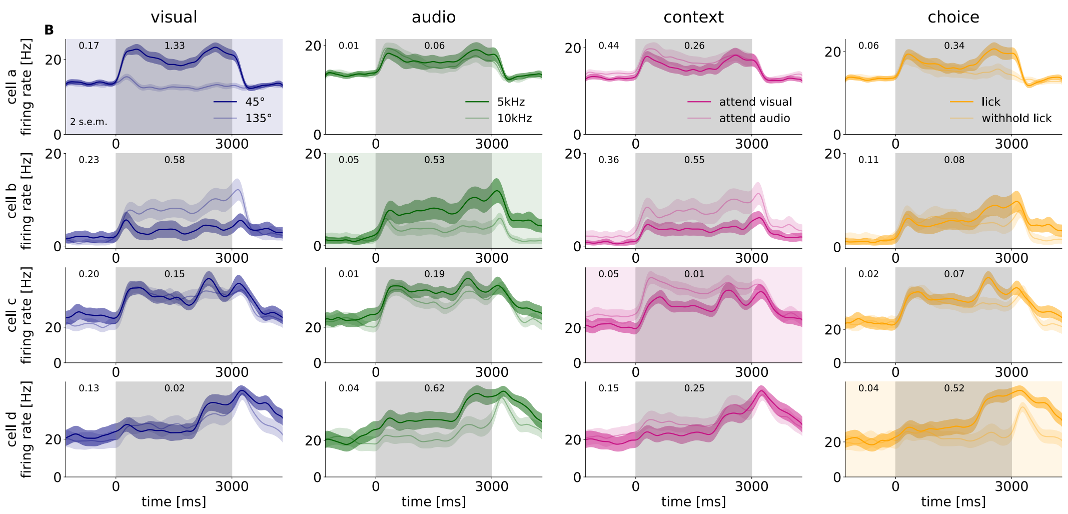


Responses of individual neurons are modulated by input, internal state, output. All of them at once.



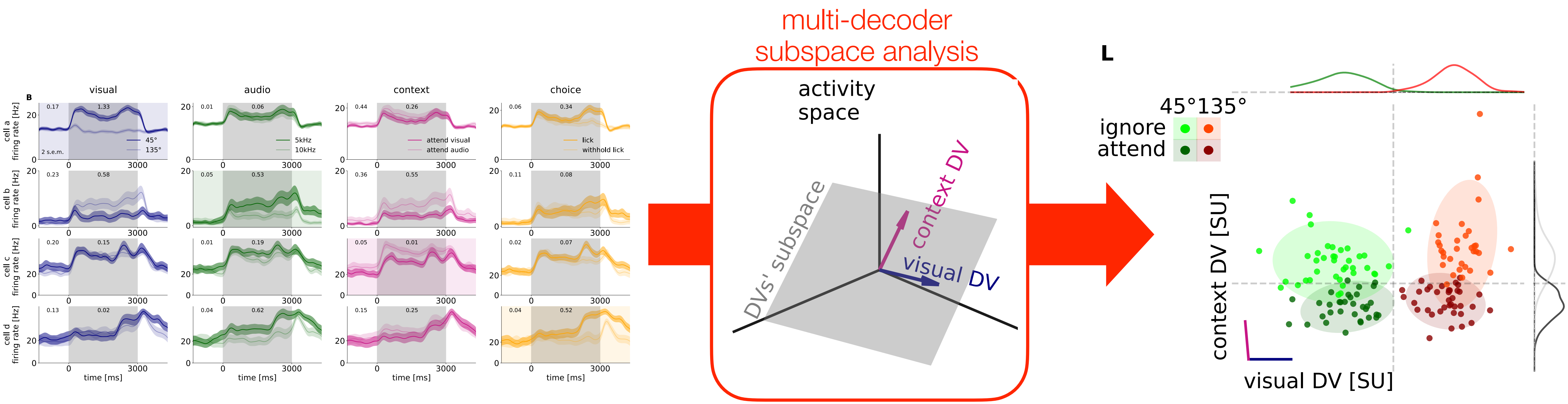
Hajnal et al (2023) Nature Communications

Data-driven approaches



Hajnal et al (2023) Nature Communications

Data-driven approaches



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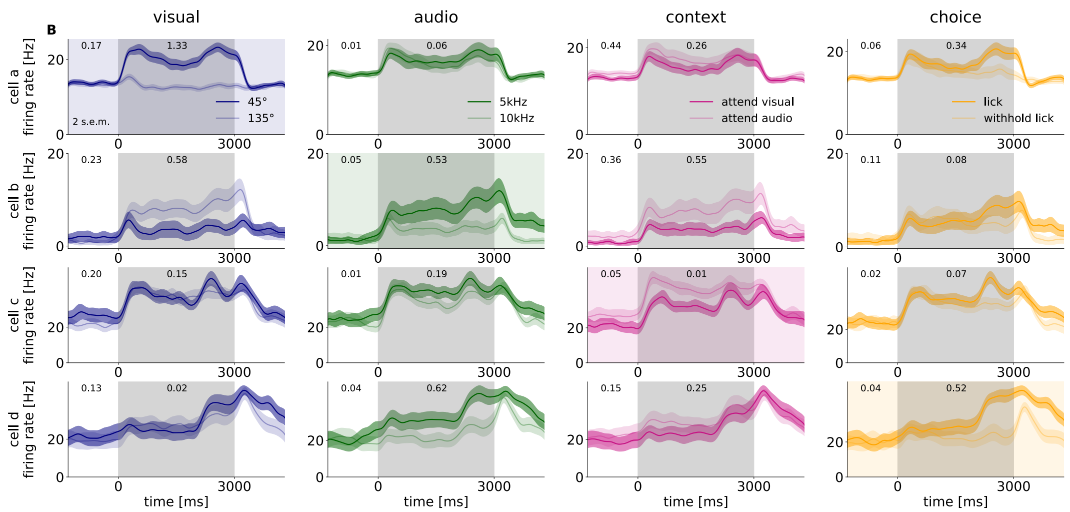
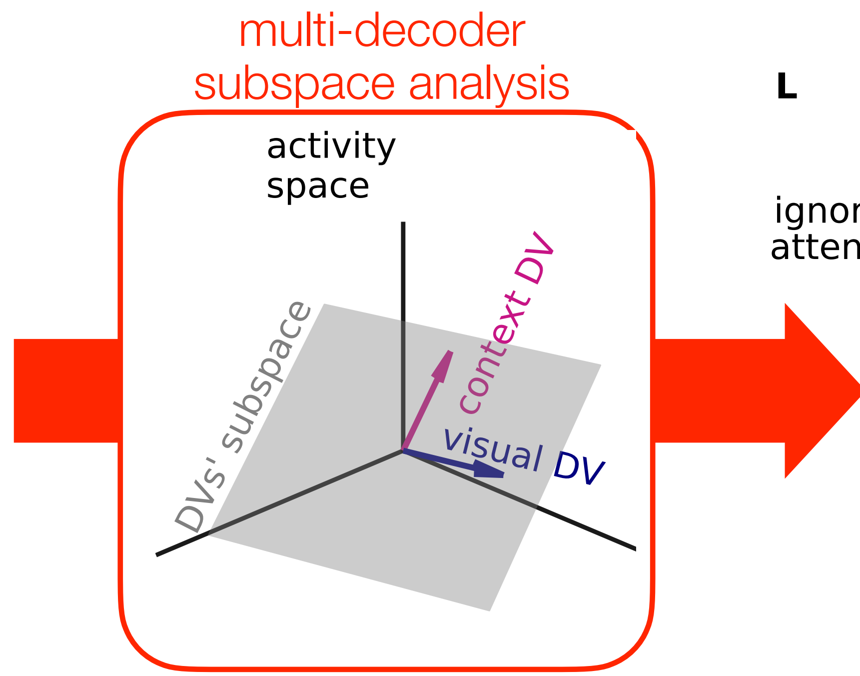
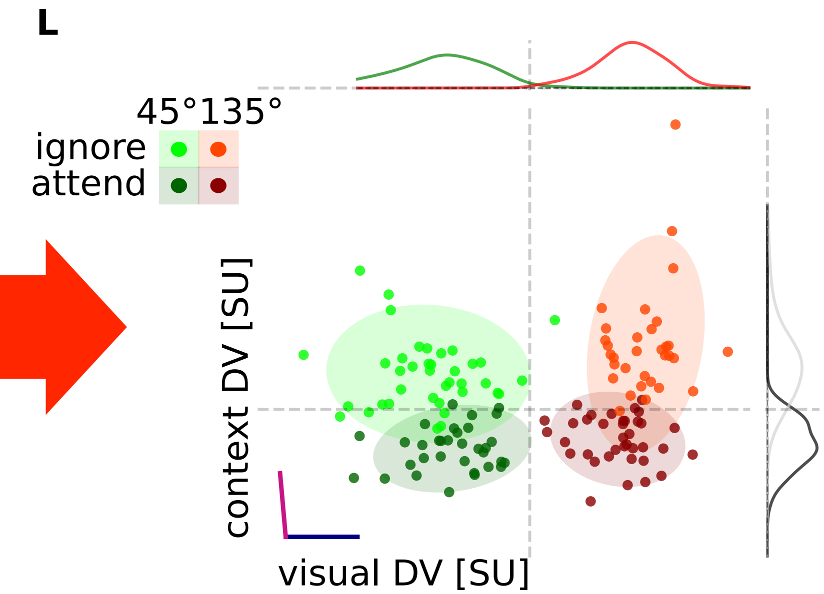
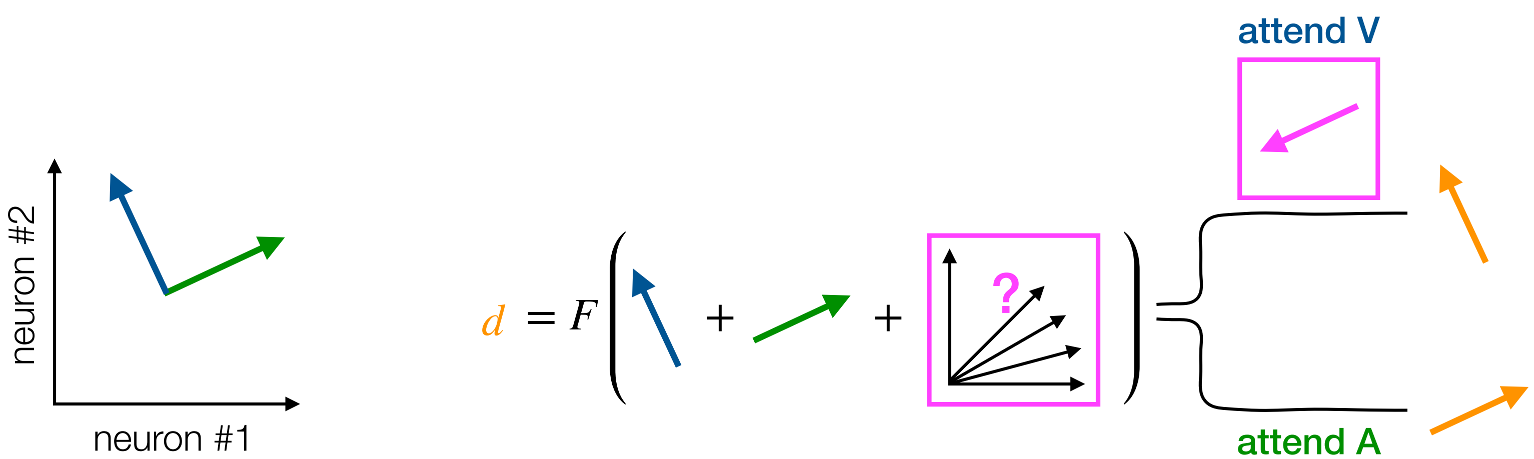
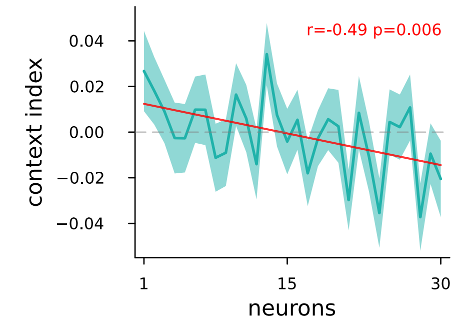




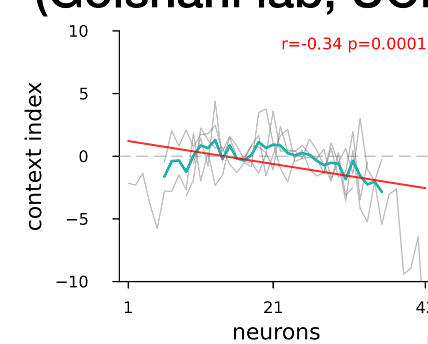




PREDICTION



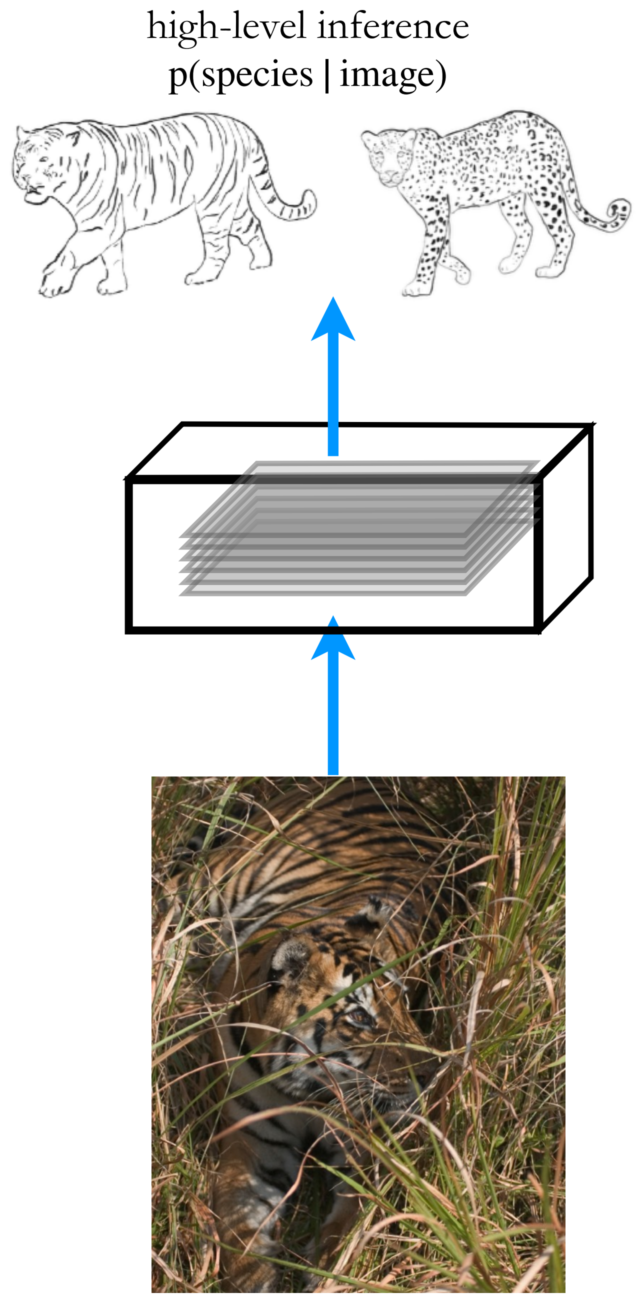
MOUSE RECORDINGS (Golshani lab, UCLA)

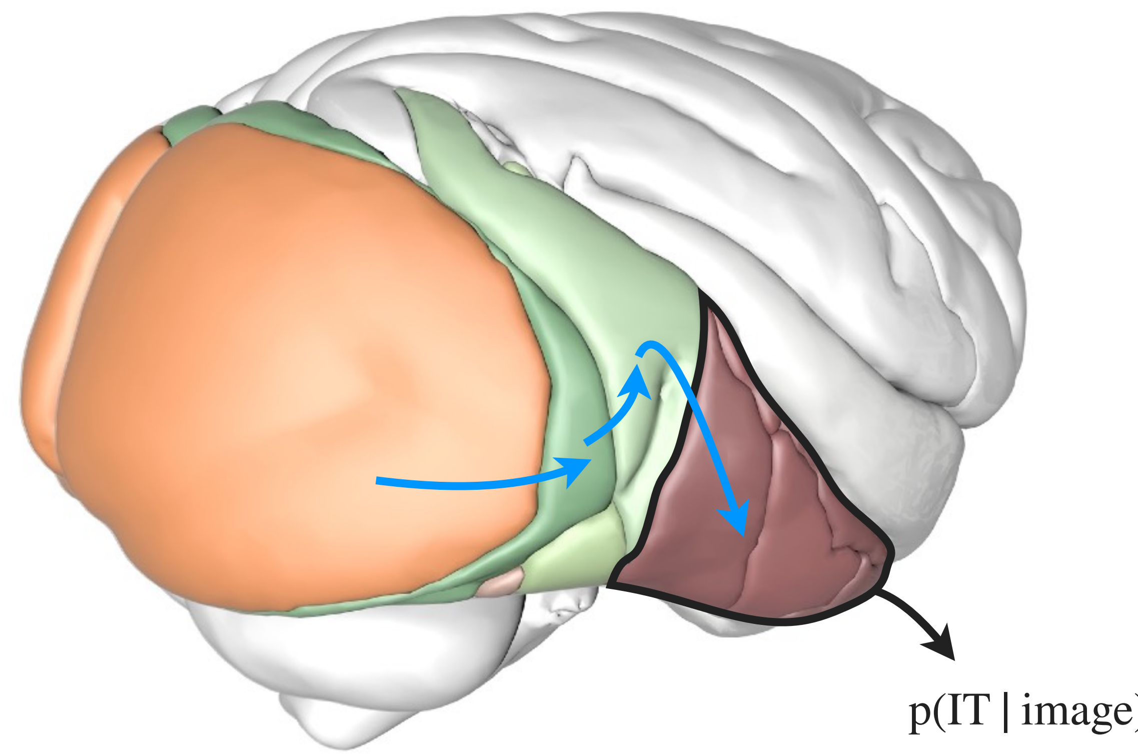


Hajnal et al, in prep

Hajnal et al (2023) Nature Communications

Adaptation-based approaches
deep **discriminative** models





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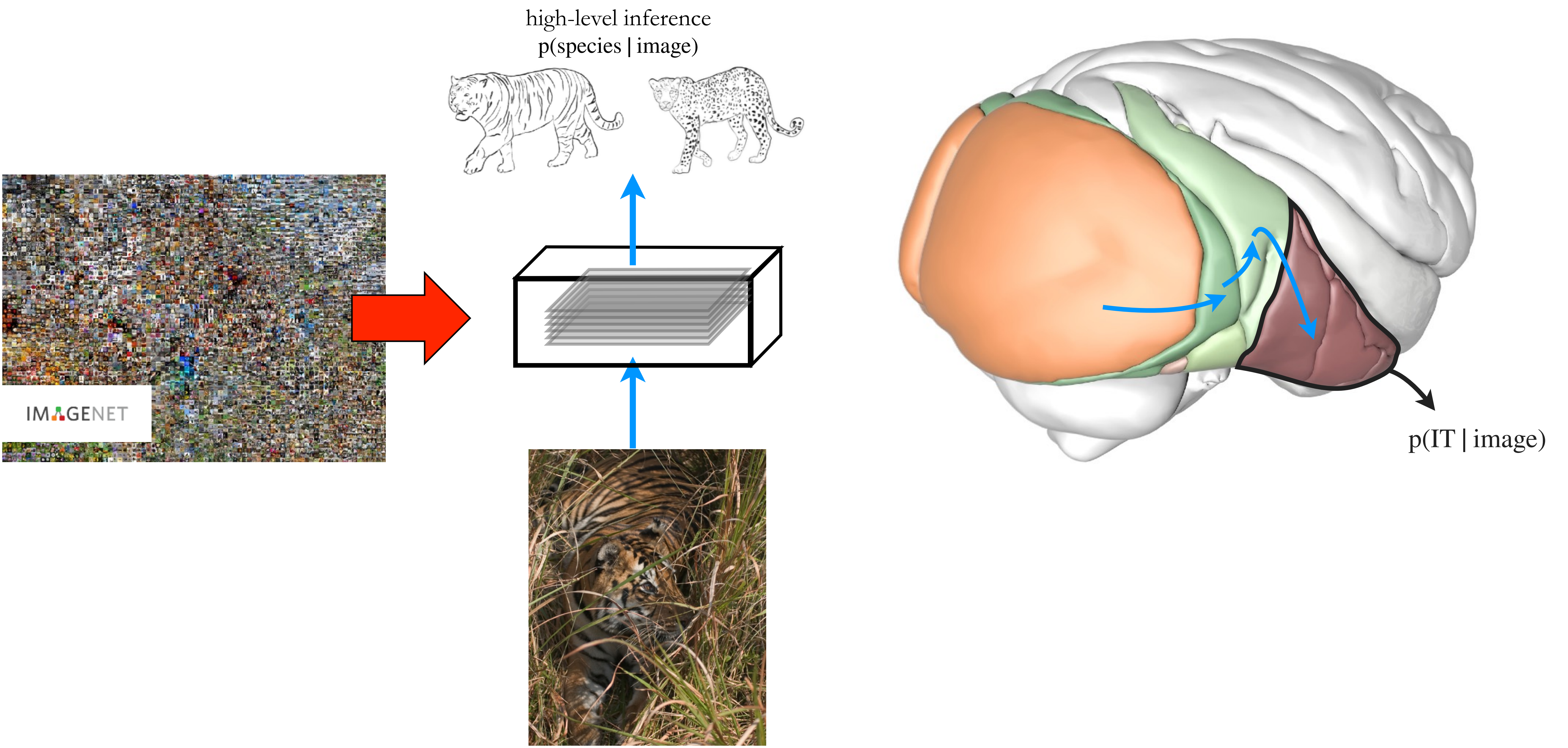
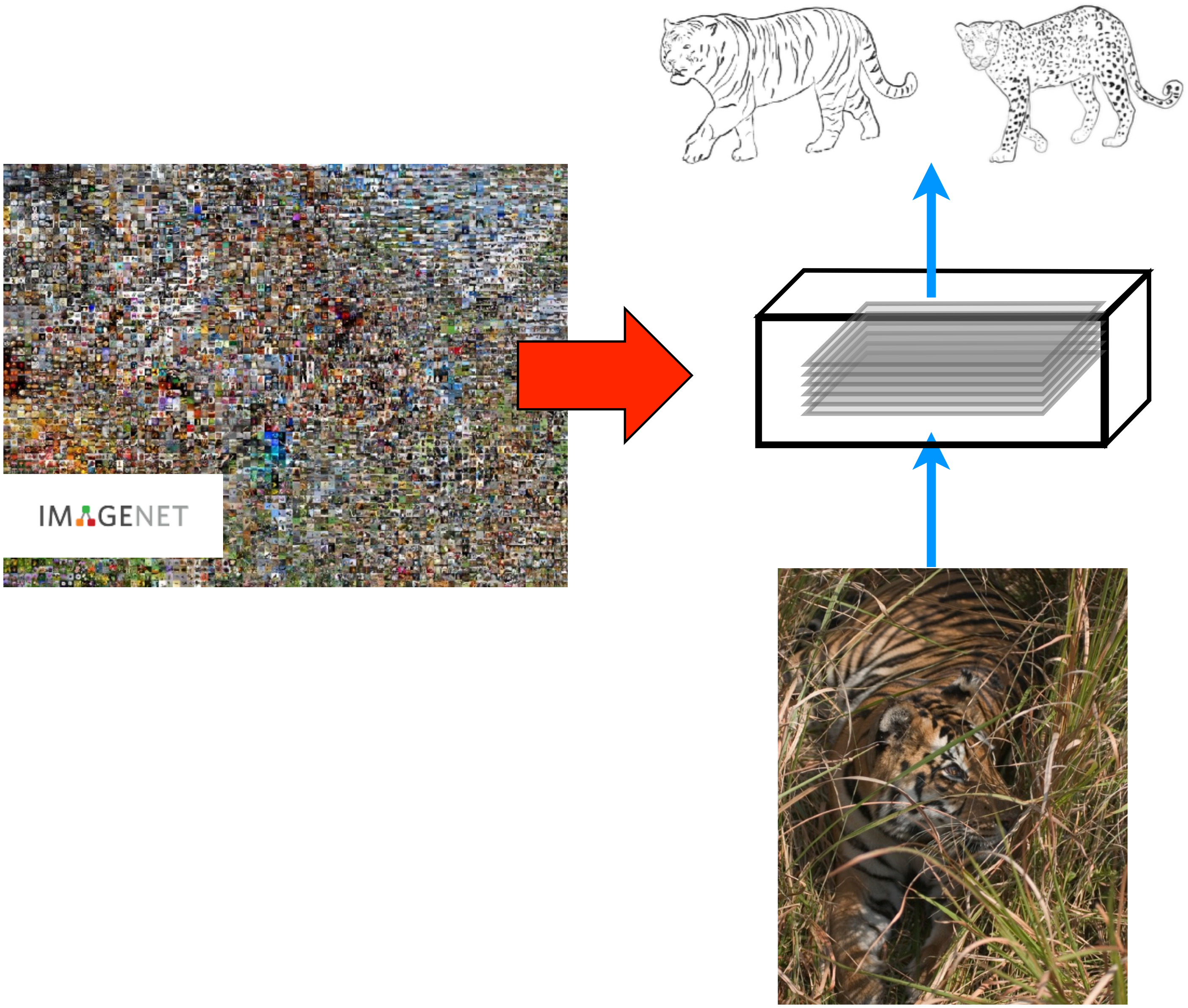
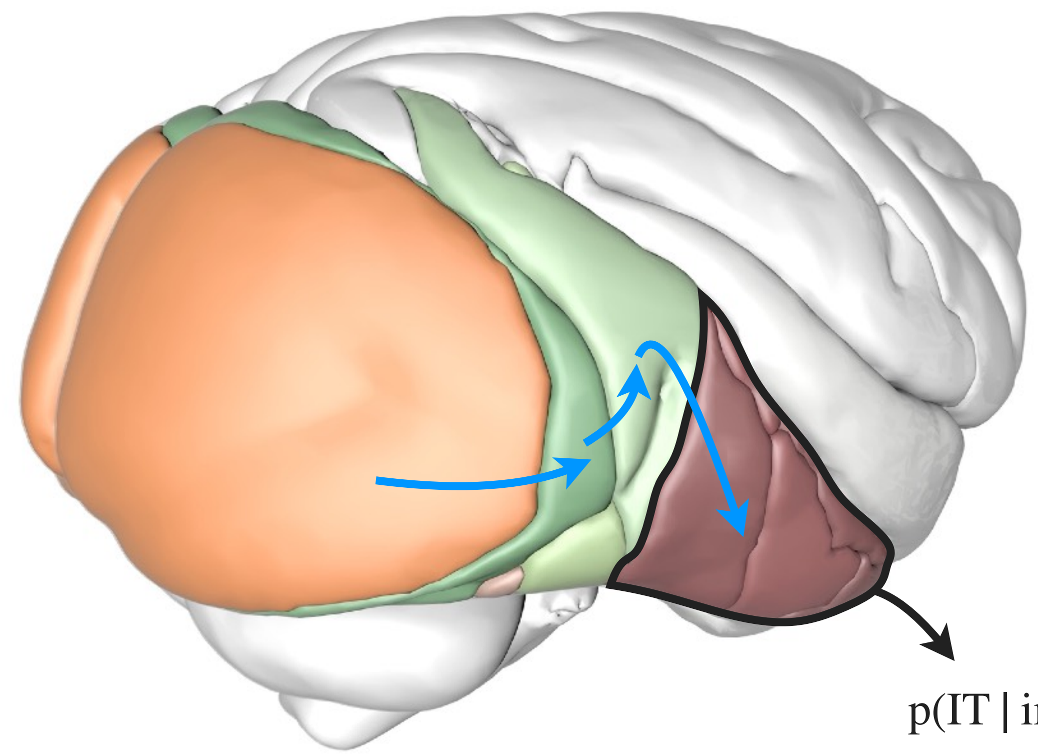


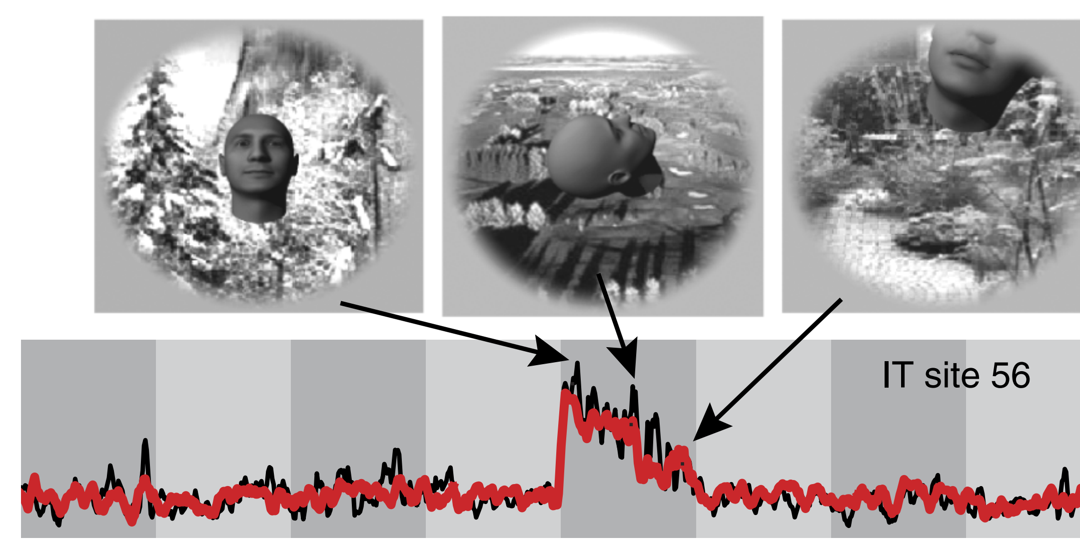
Adaptation-based approaches
deep **discriminative** models

high-level inference
p(species | image)





p(IT | image)



1600 unseen test image (sorted by category)

Yamins et al (2016) Nat Neurosci

Adaptation-based approaches
deep **generative** models

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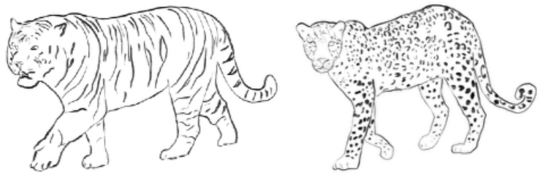
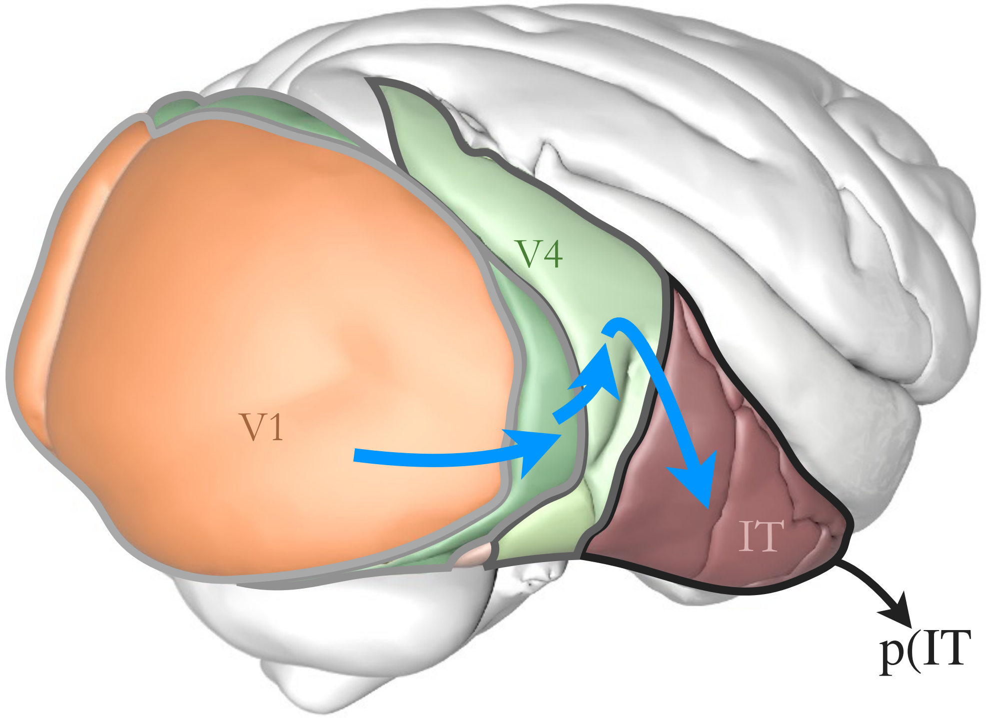
p(species | image)





Meszéna et al (2022) NeurIPS
Csikor et al, in prep

Adaptation-based approaches

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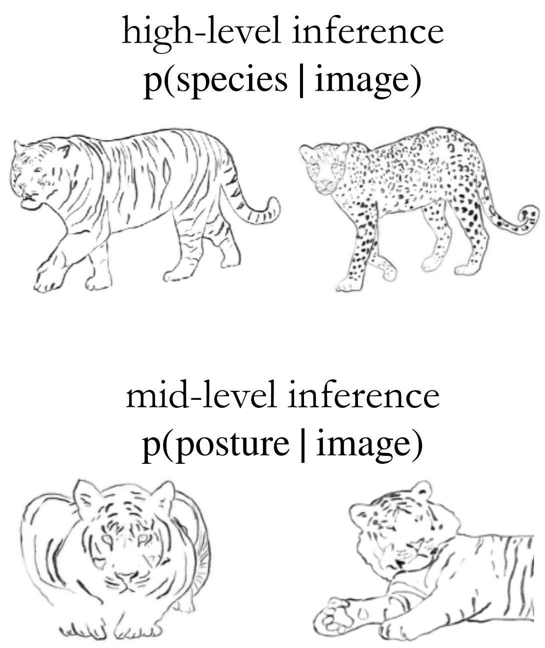

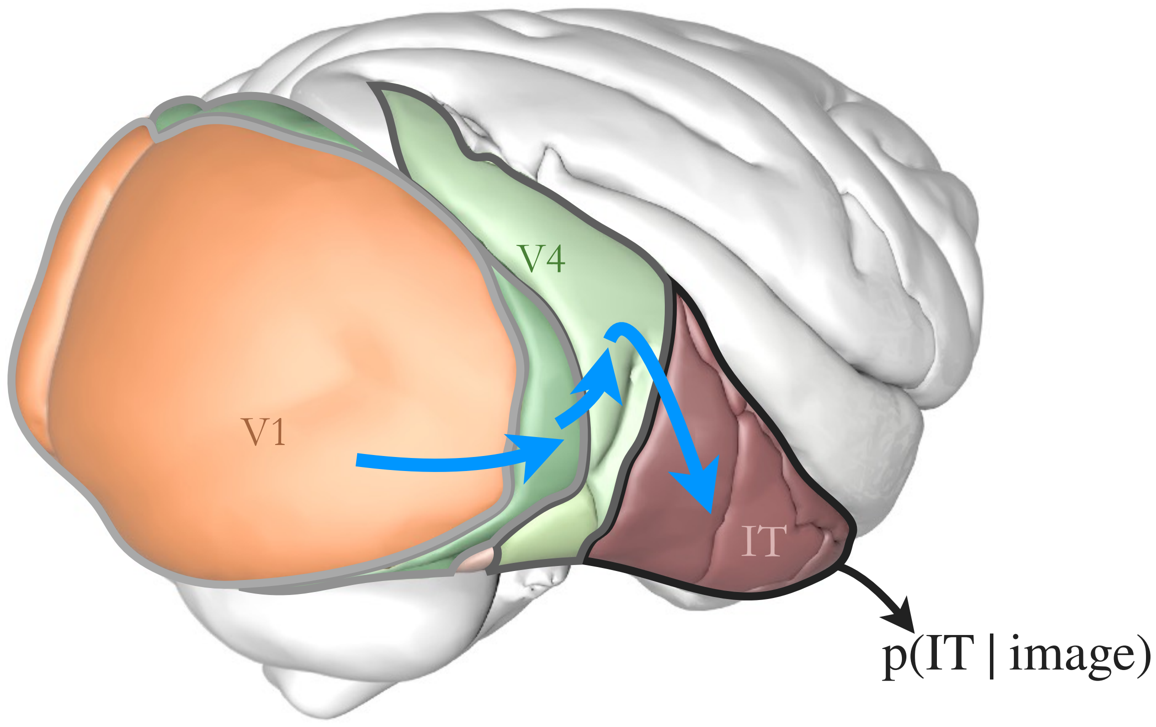

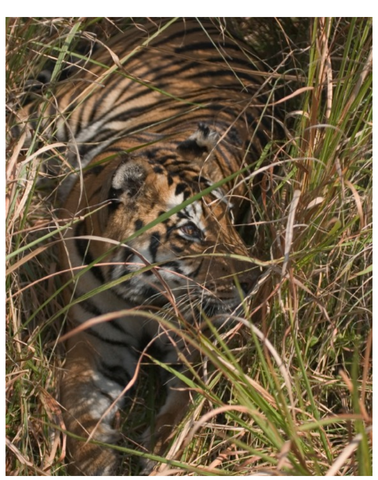

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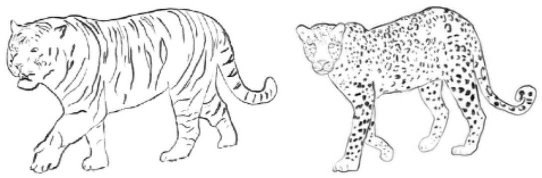
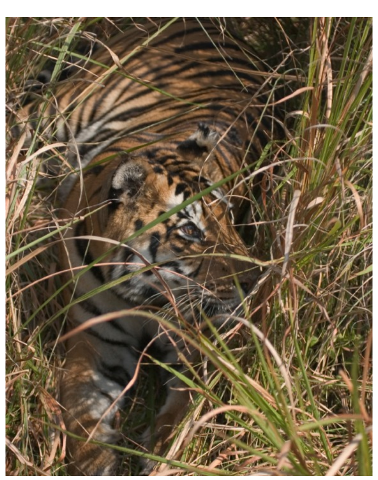
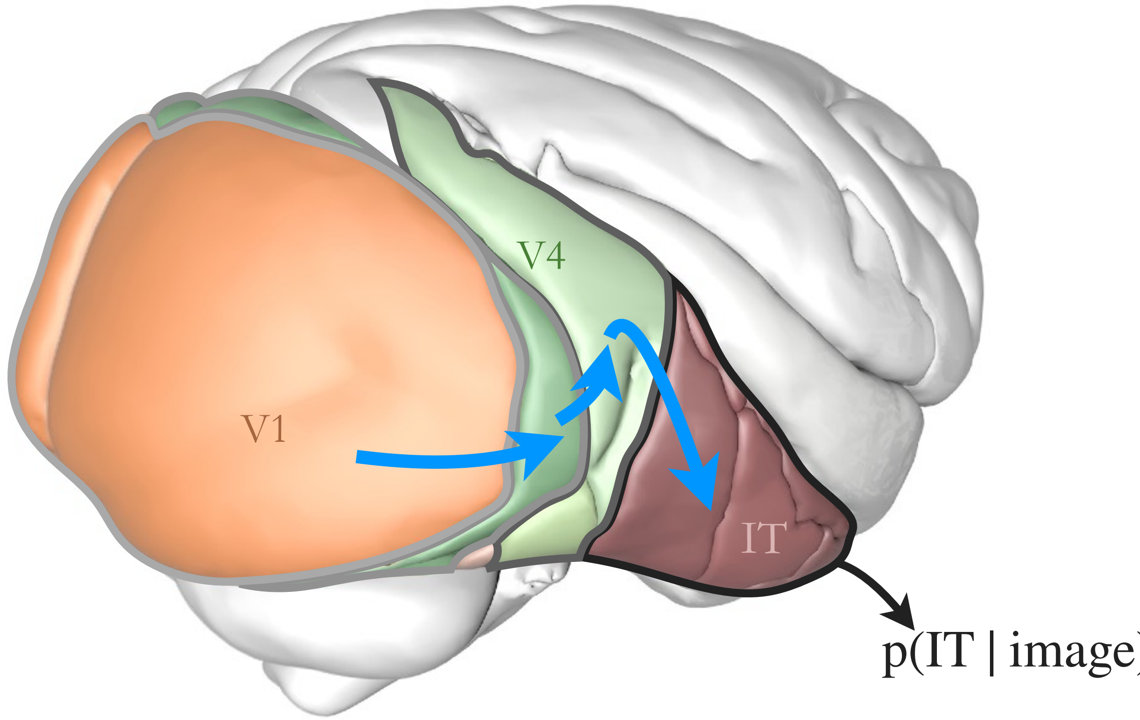


mid-level inference
p(posture | image)

low-level inference
p(compositional features | image)





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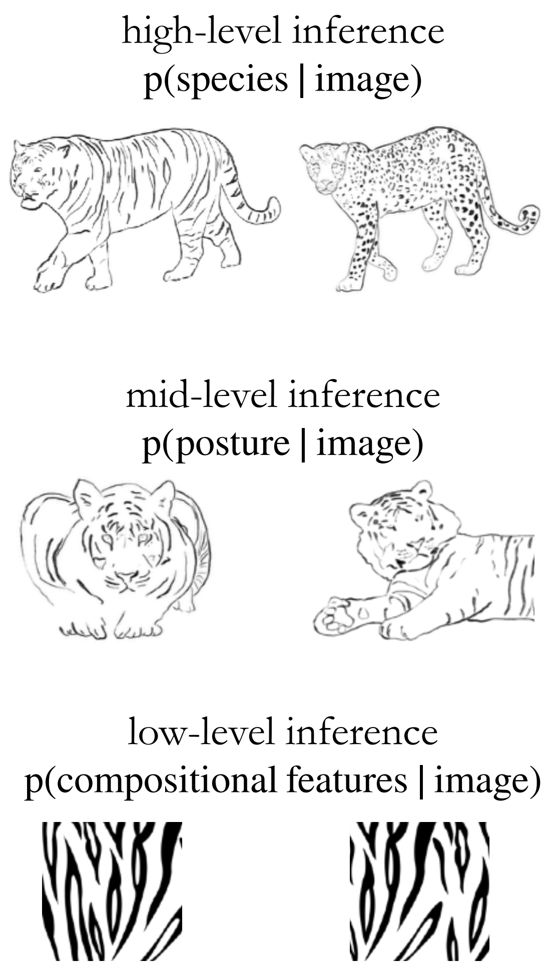

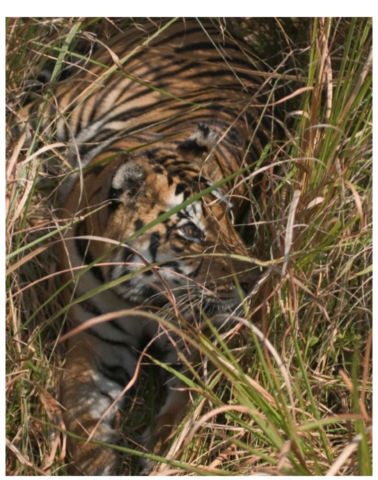

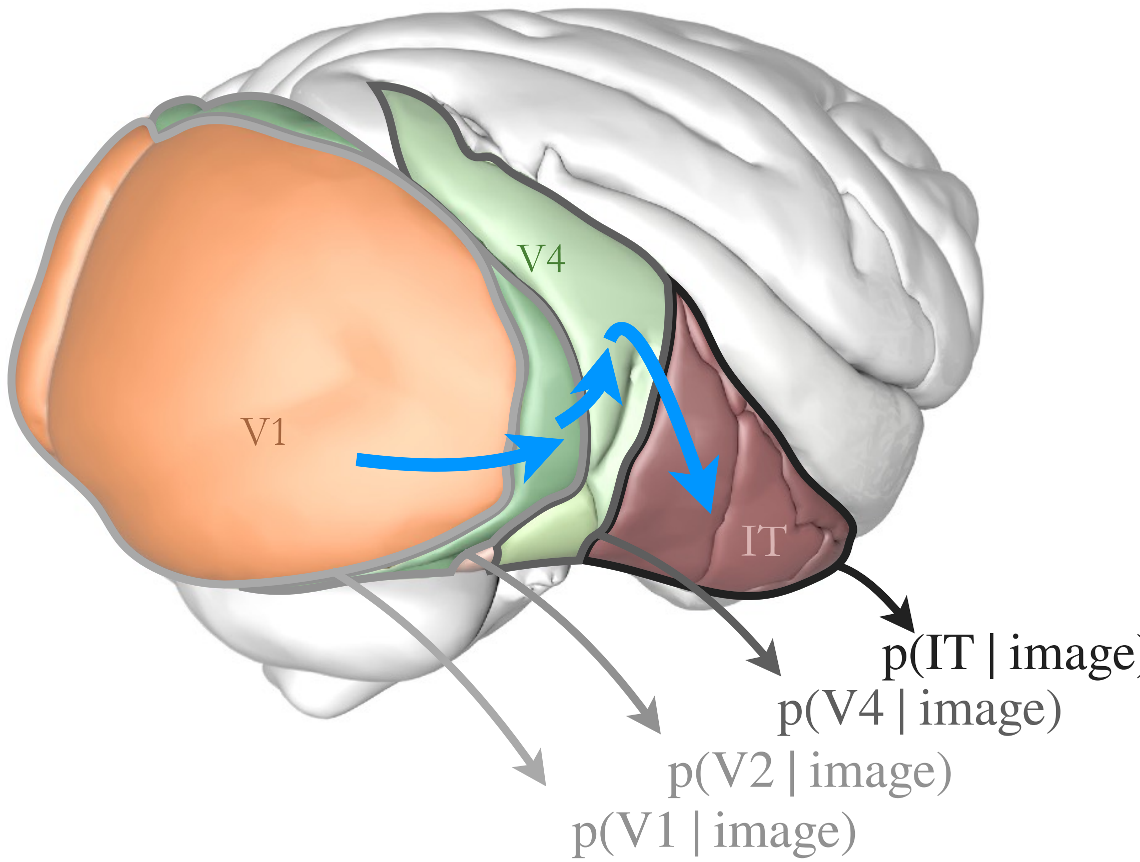

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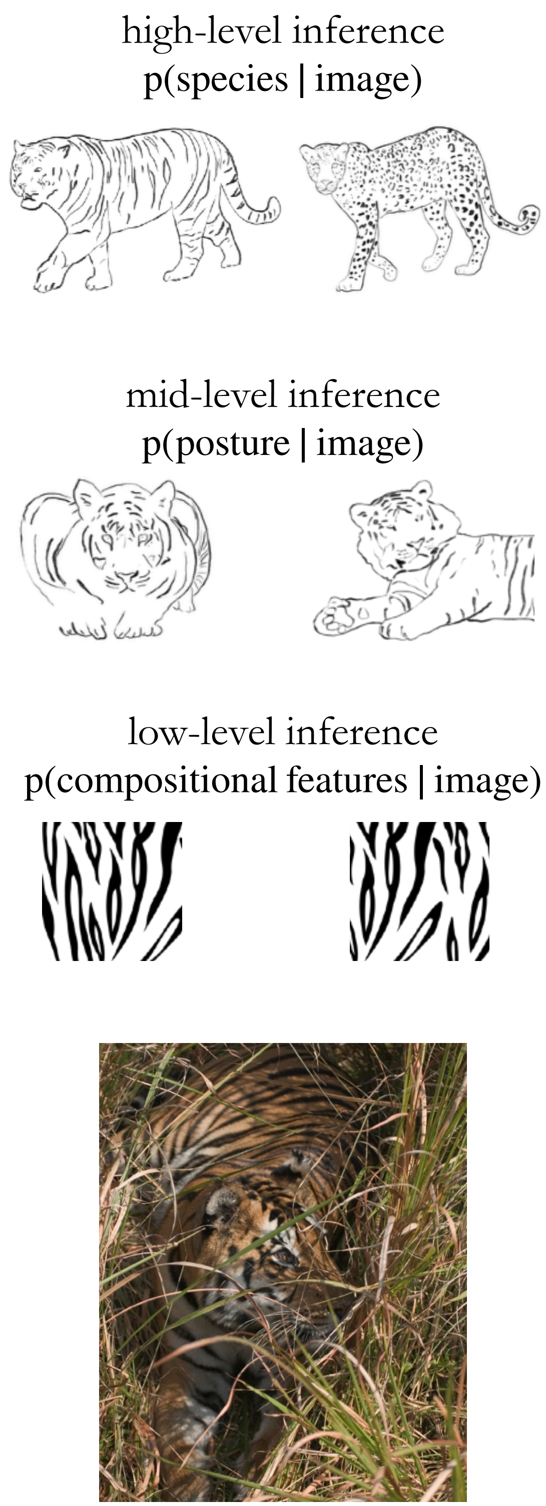

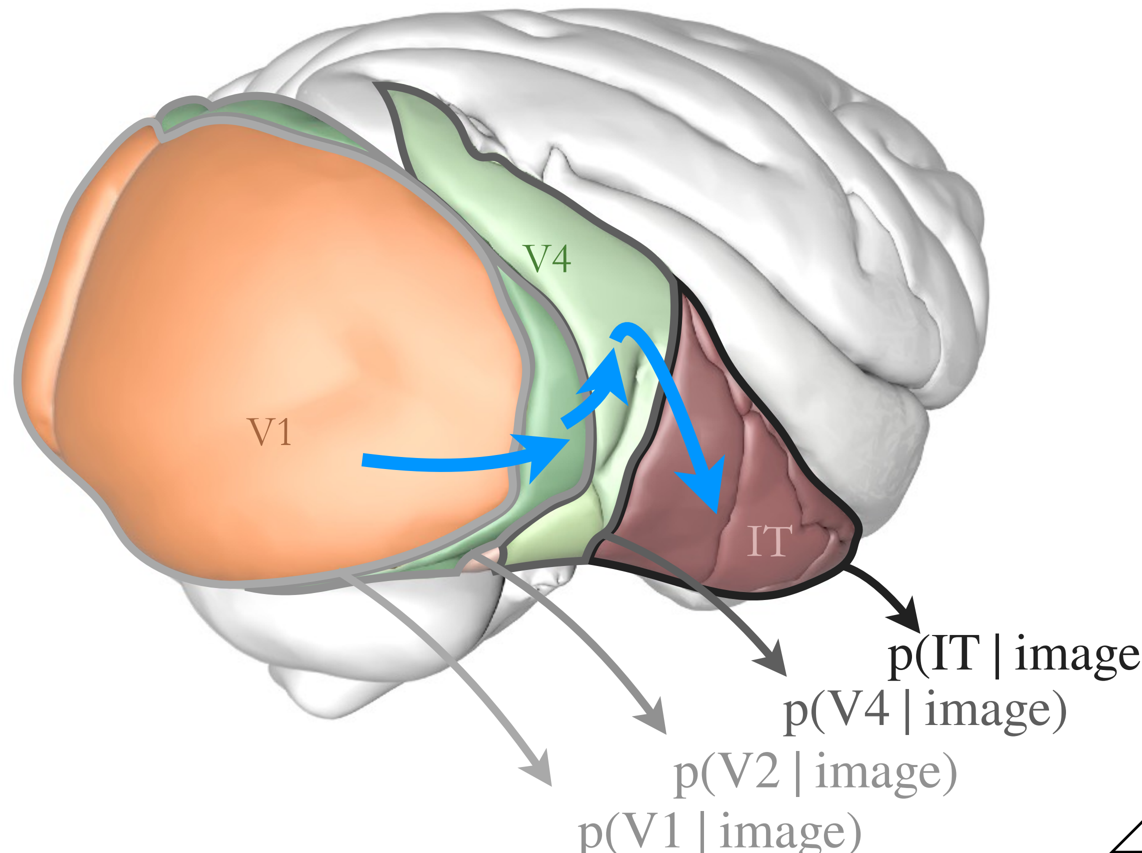

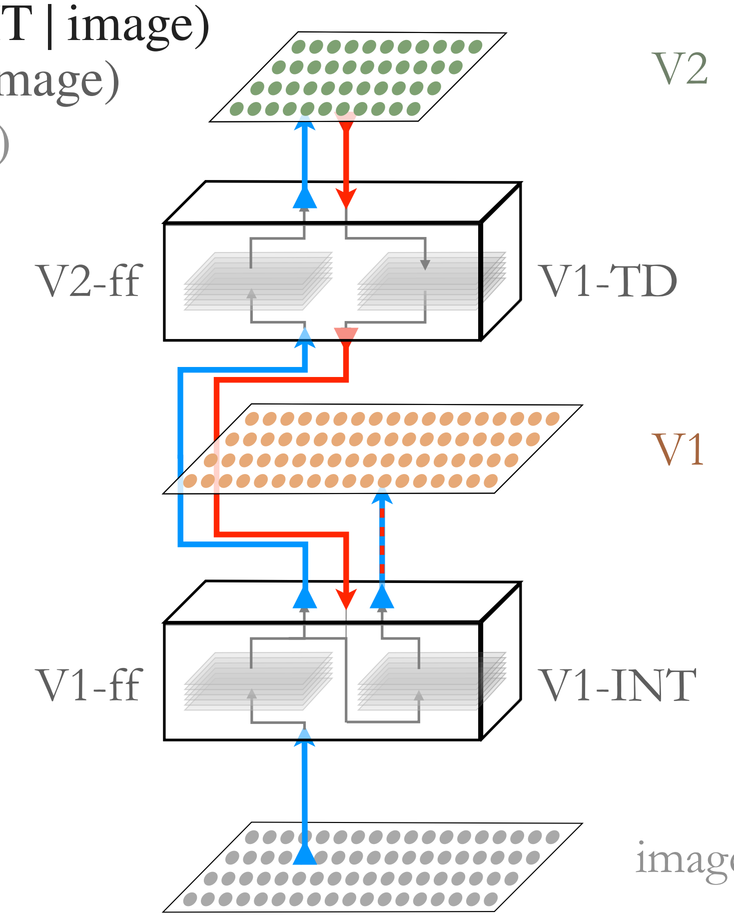

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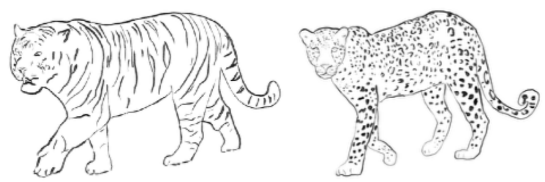

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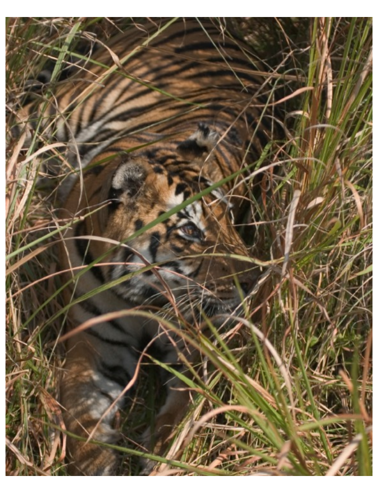

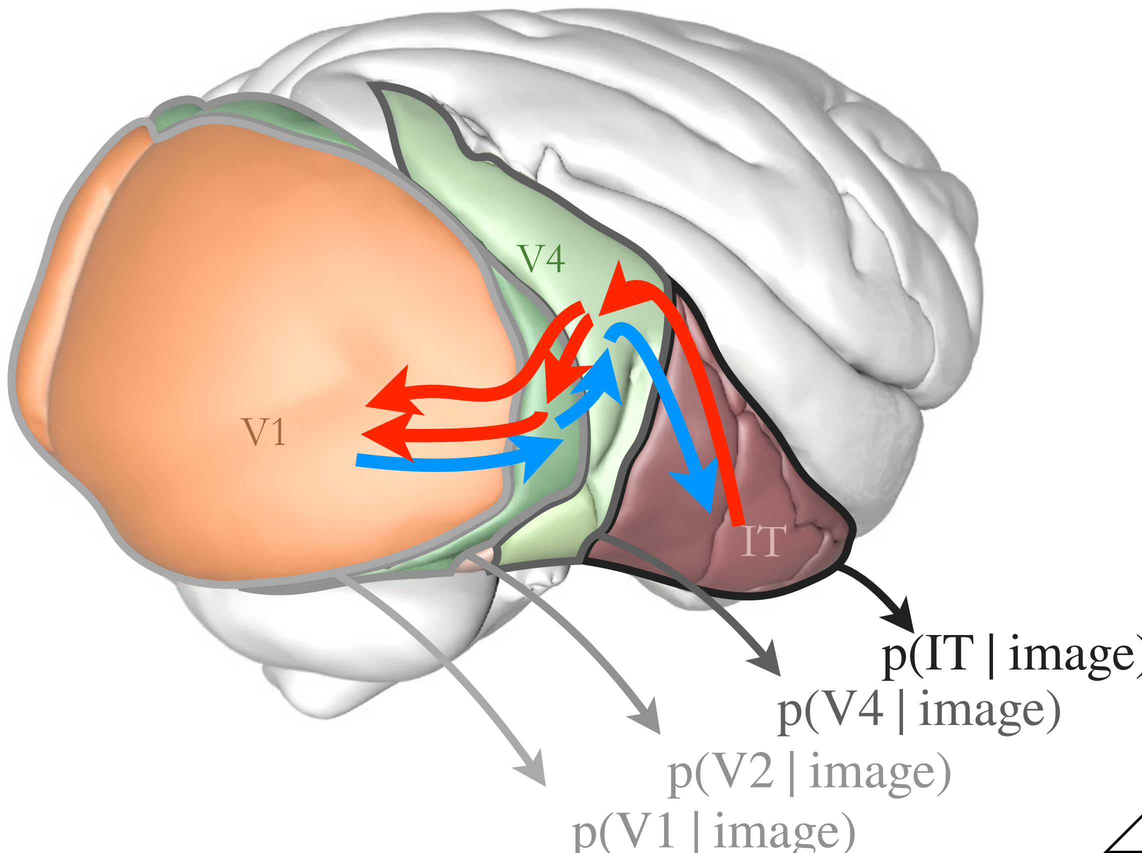

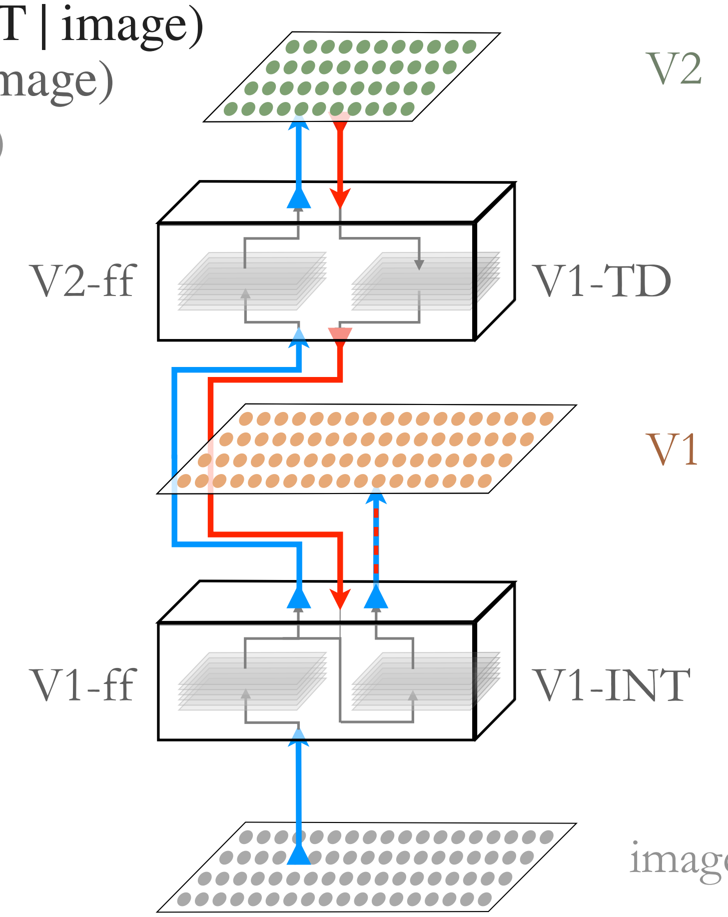

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Interpreting the neural code: ML insights

Approximate inference

probability distributions need to be represented

Orbán et al (2016) Neuron

Bányai et al (2019) PNAS

Interpreting the neural code: ML insights

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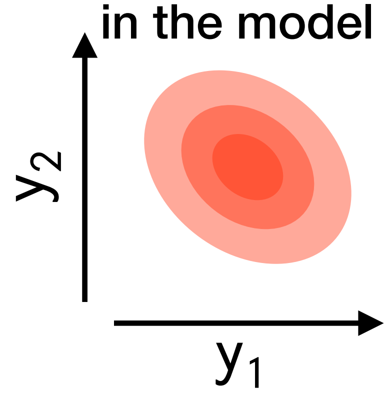
inference in the model



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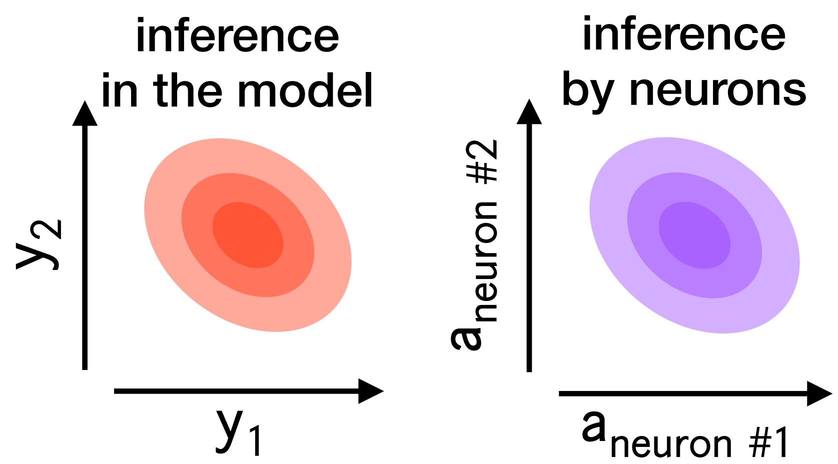

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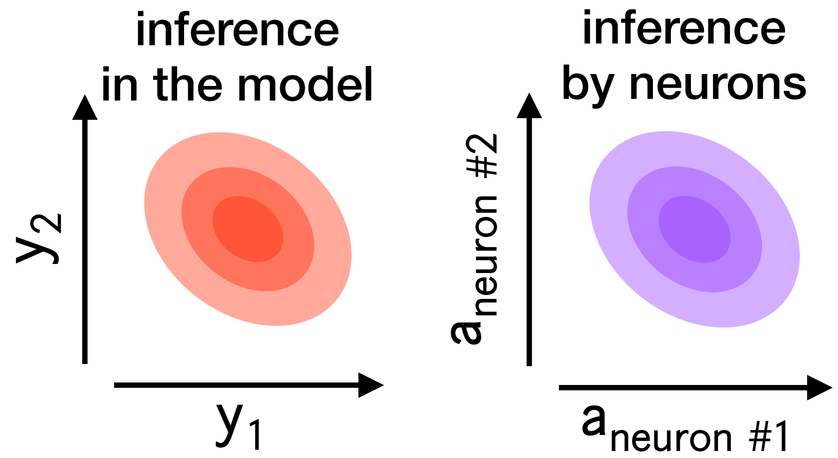

stochastic sampling ⤳ variable membrane potential

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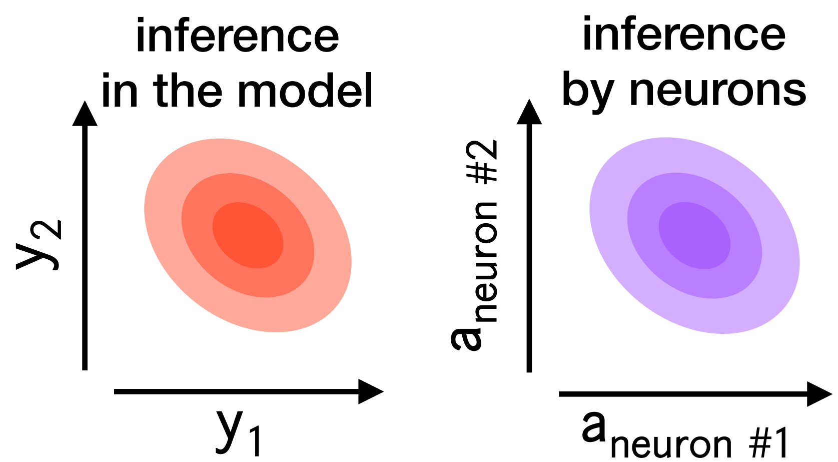

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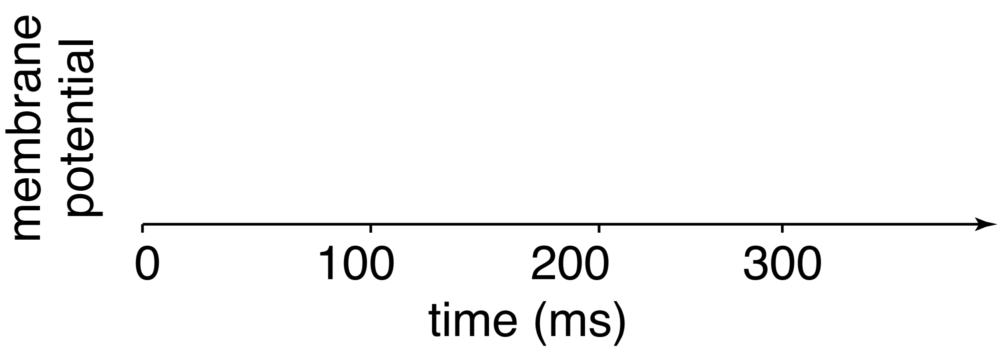

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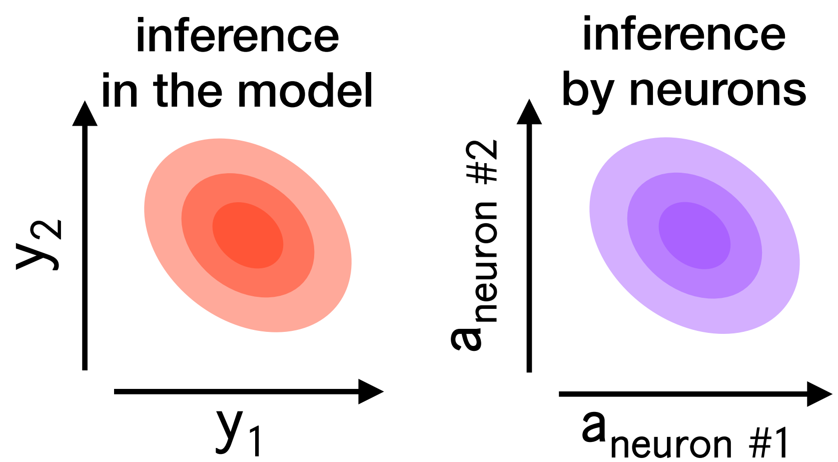

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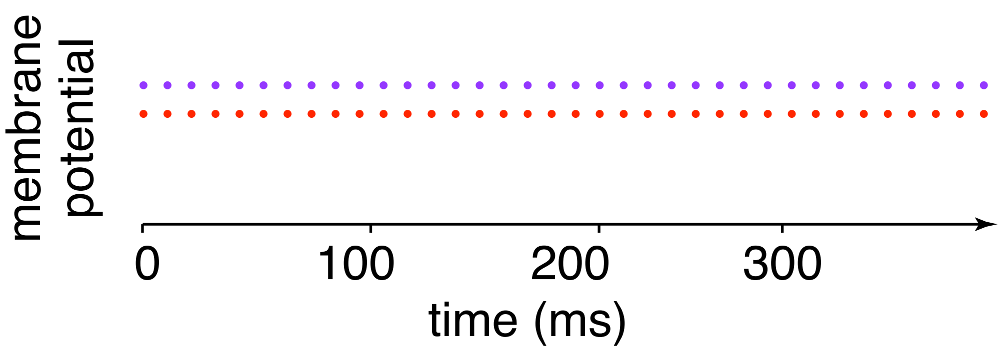

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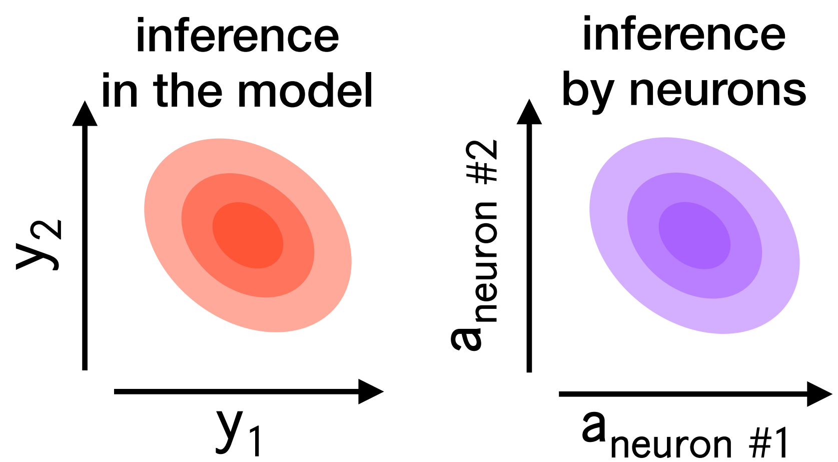

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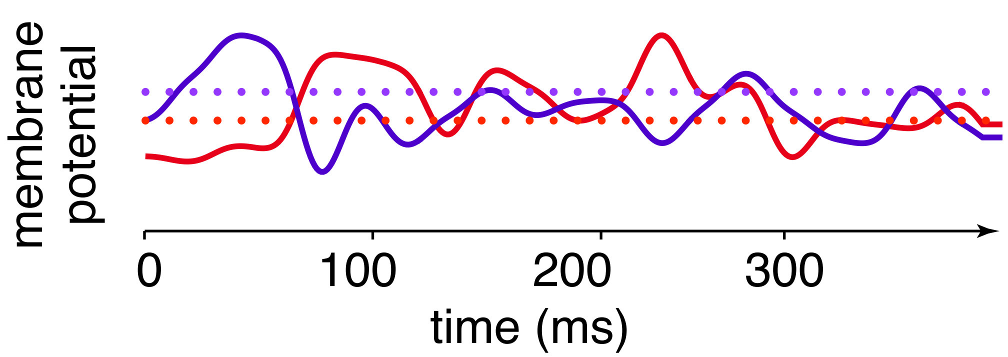

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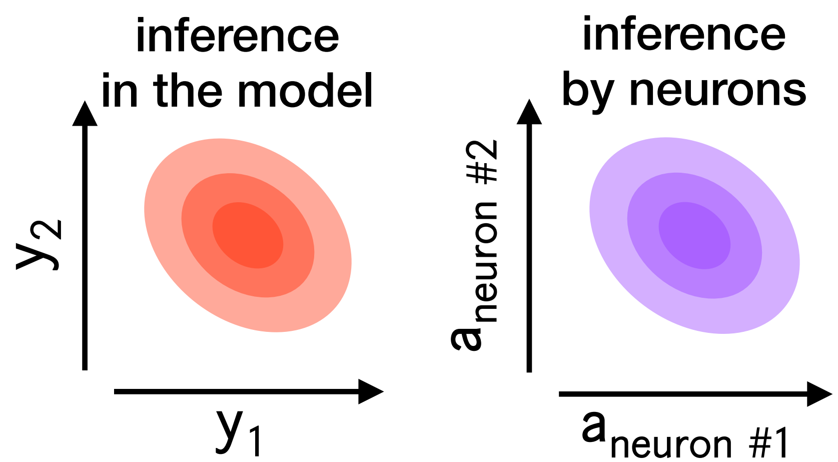

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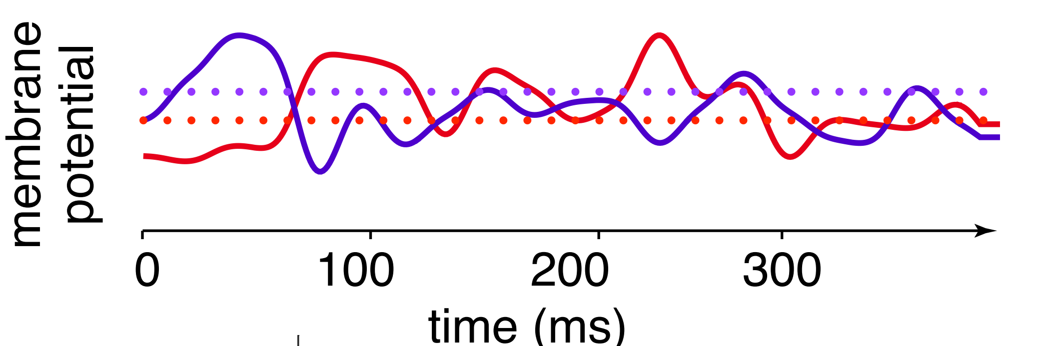

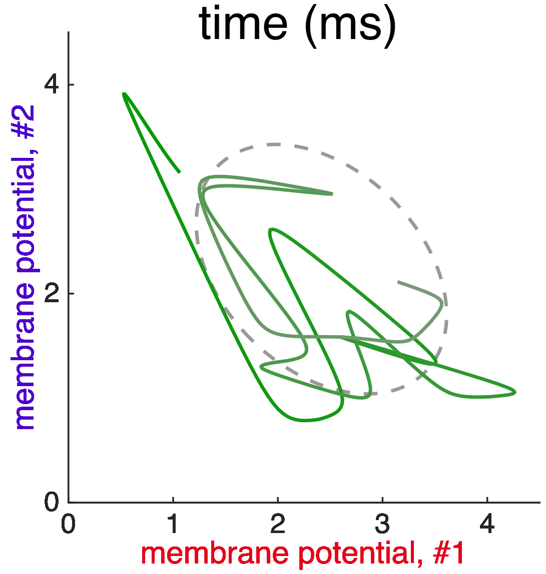

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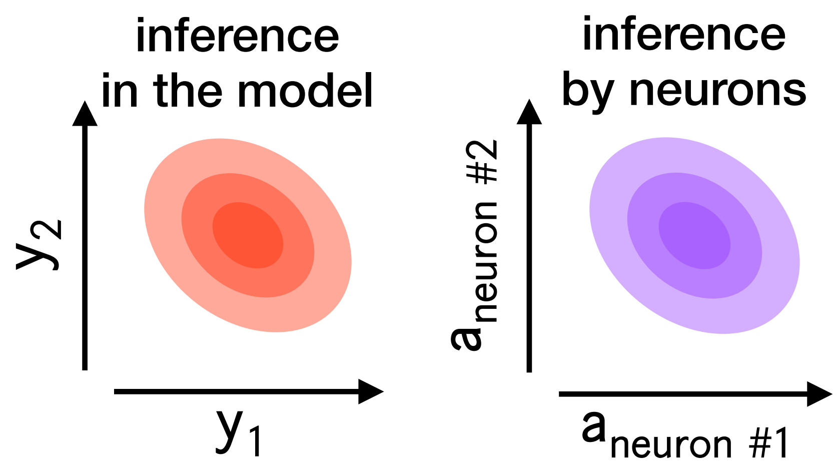

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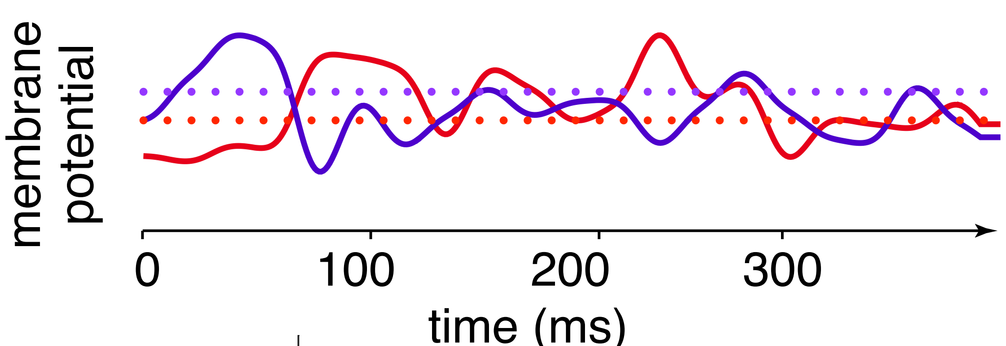

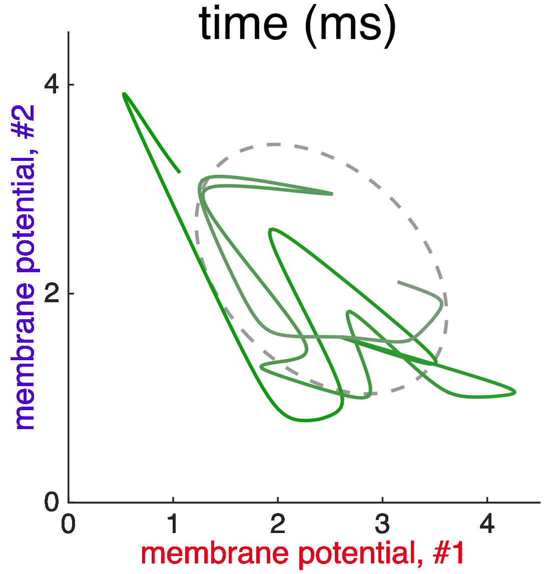

response variability ⇔ subjective uncertainty

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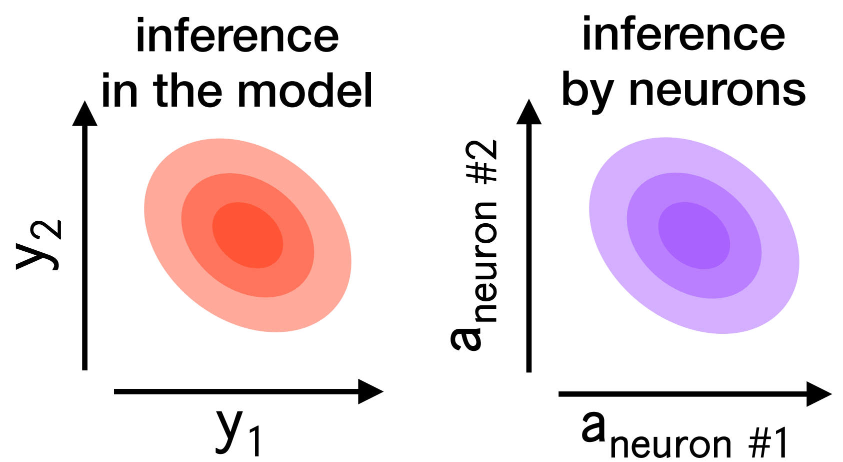

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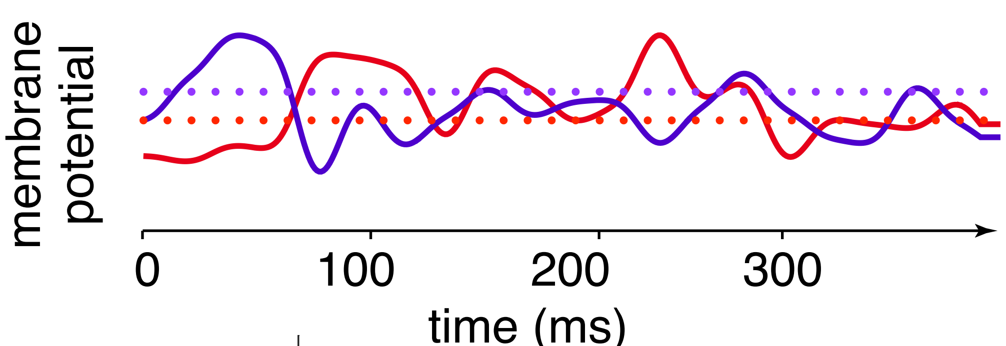

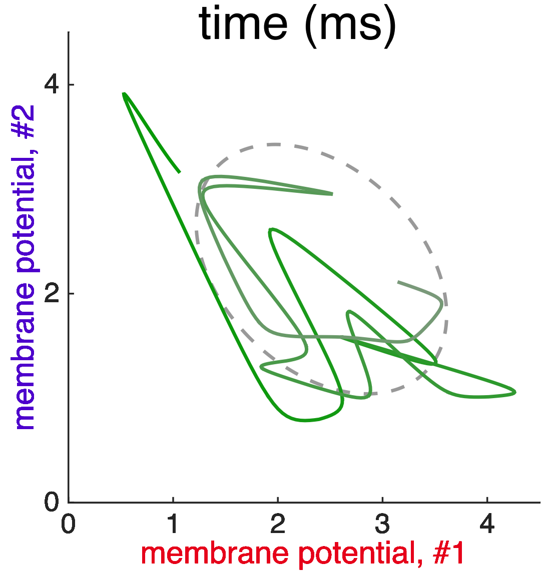

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Orbán et al (2016) Neuron

Contextual prior

learning exploits regularities, regularities change from context-to context

Bányai et al (2019) PNAS

Interpreting the neural code: ML insights

Approximate inference

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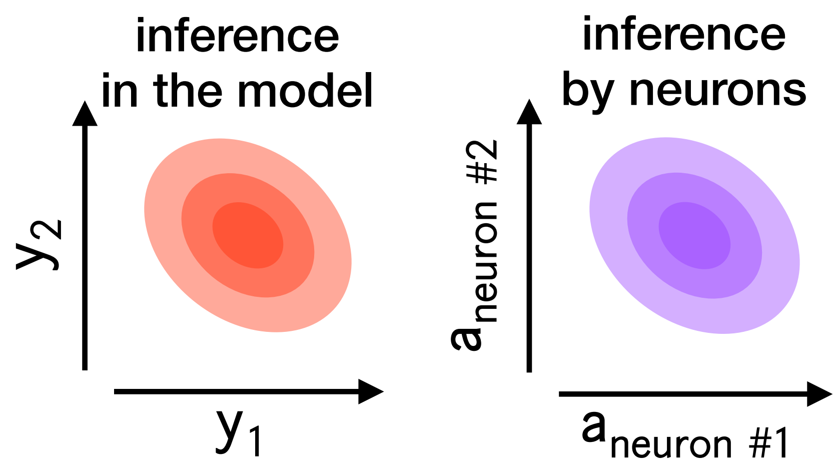

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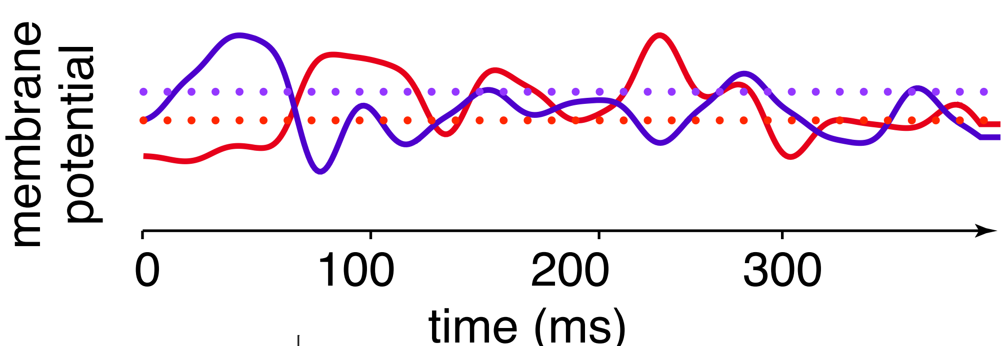

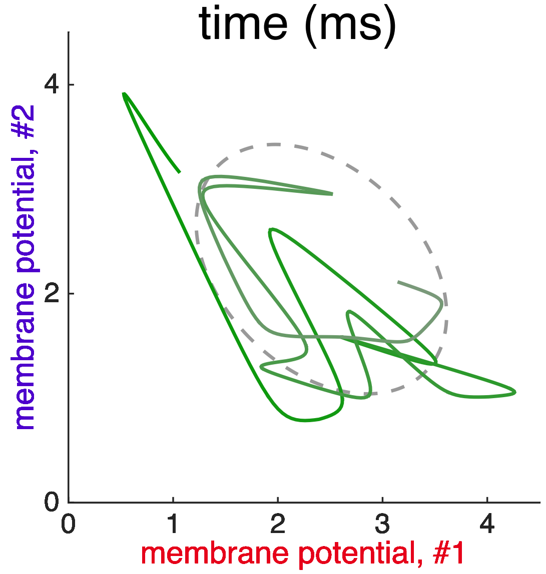

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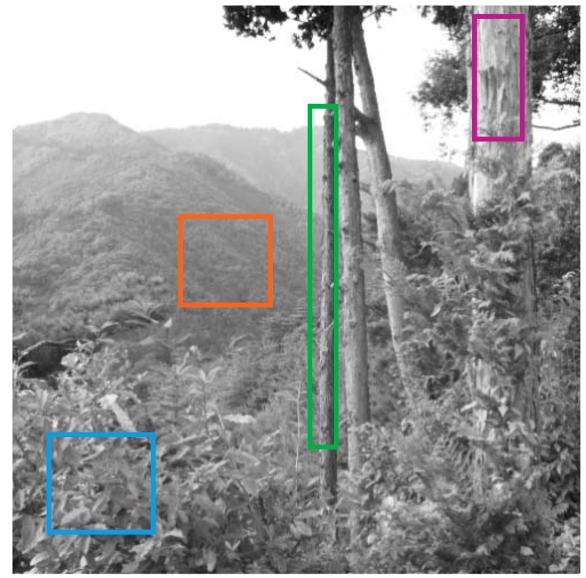

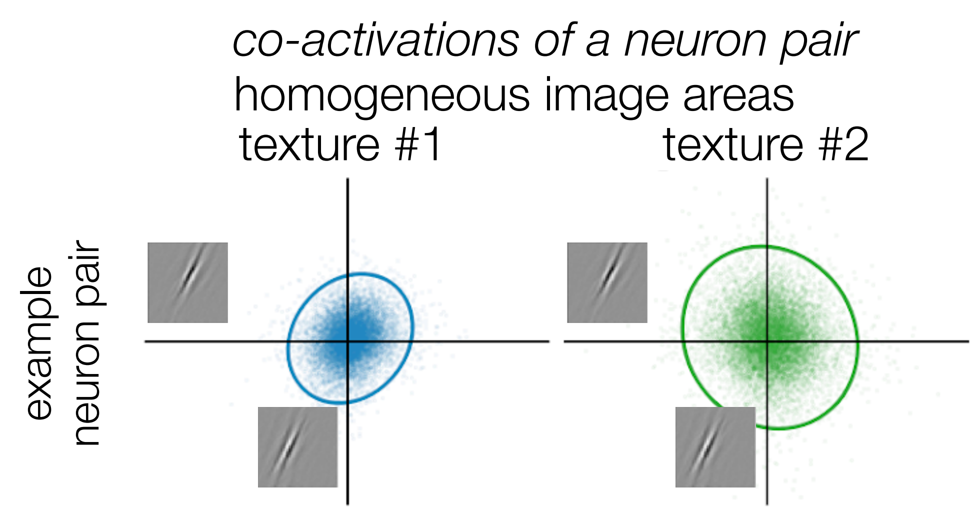

Bányai et al (2019) PNAS

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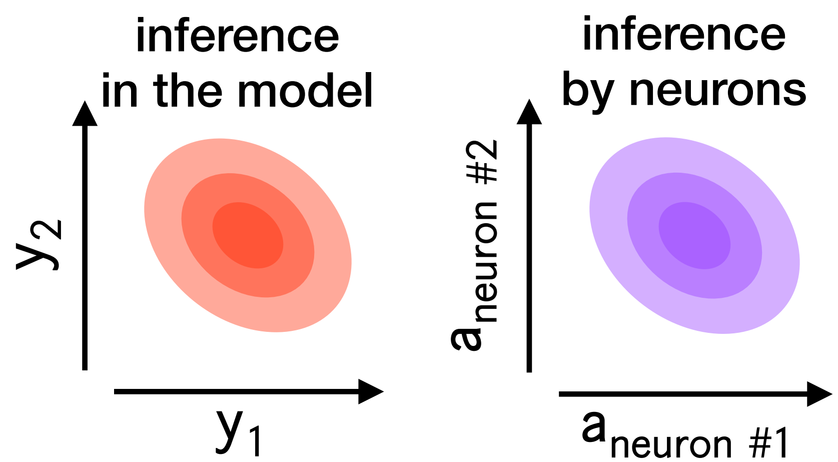

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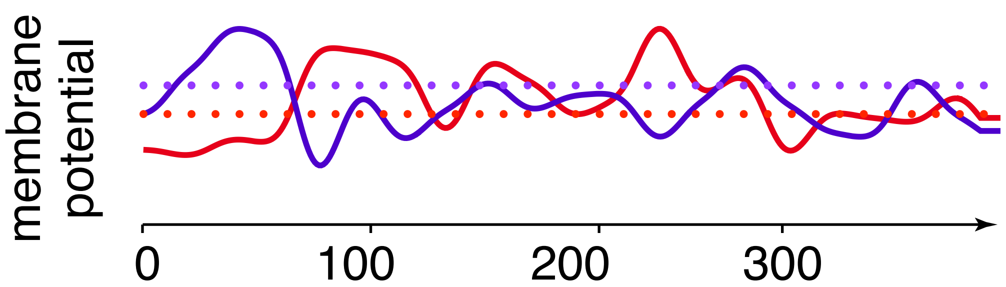

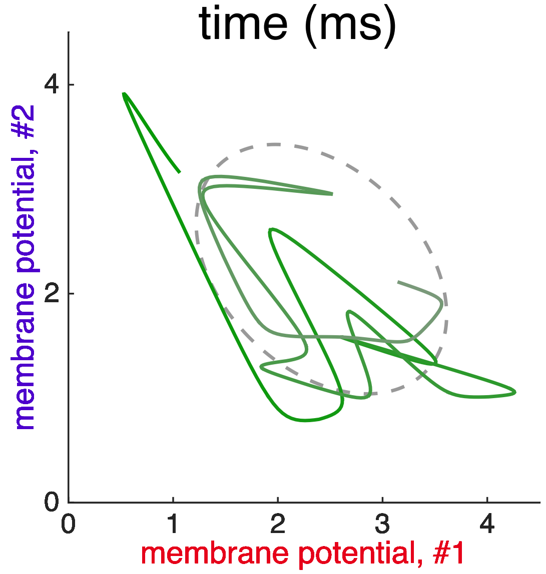

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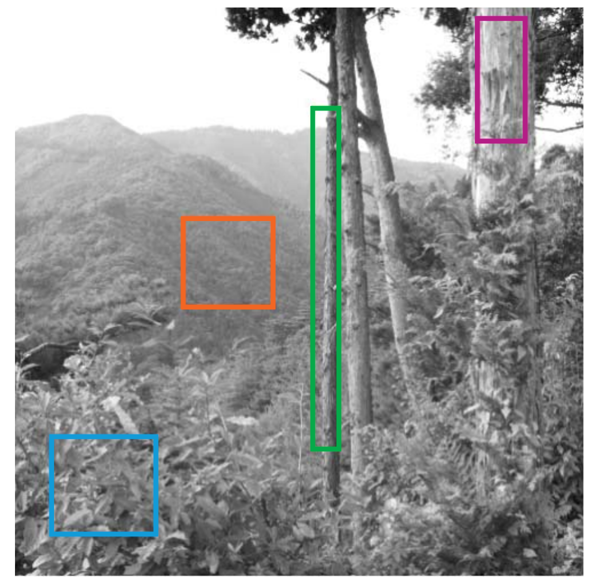
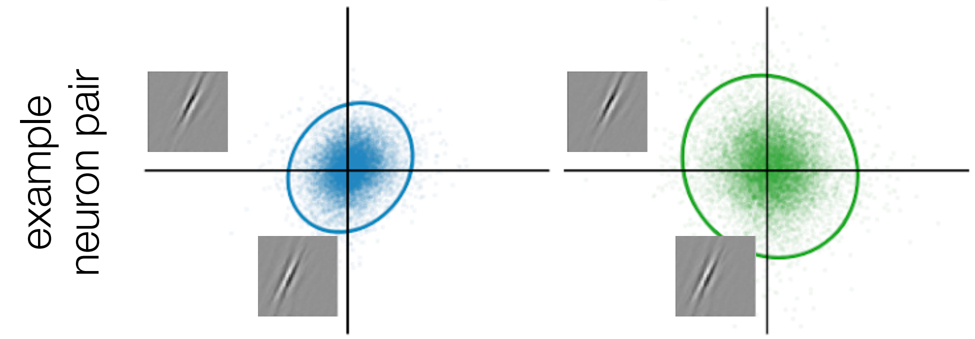
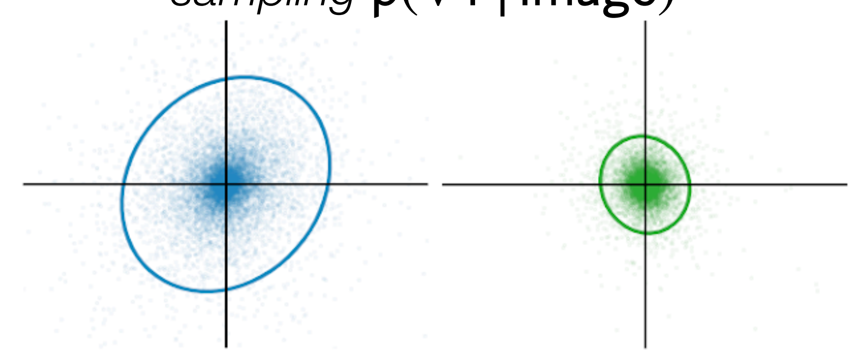




neural ensembles represent distributions
⤳ context-dependent correlations in priors

sampling p(V1 | image)

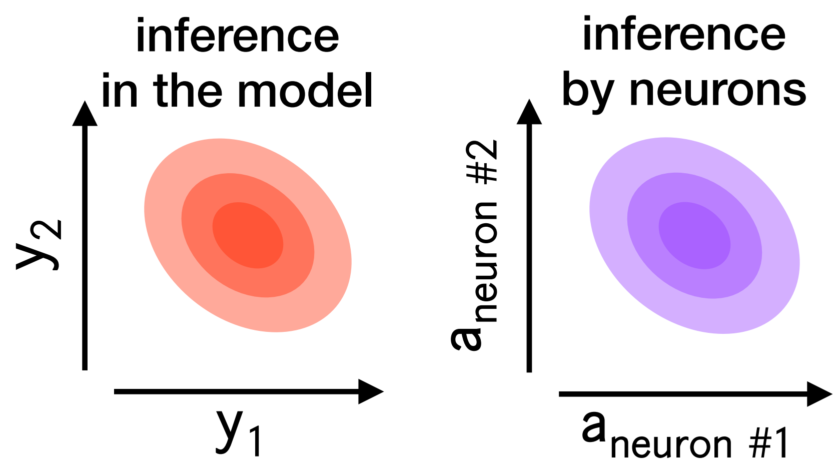


Bányai et al (2019) PNAS

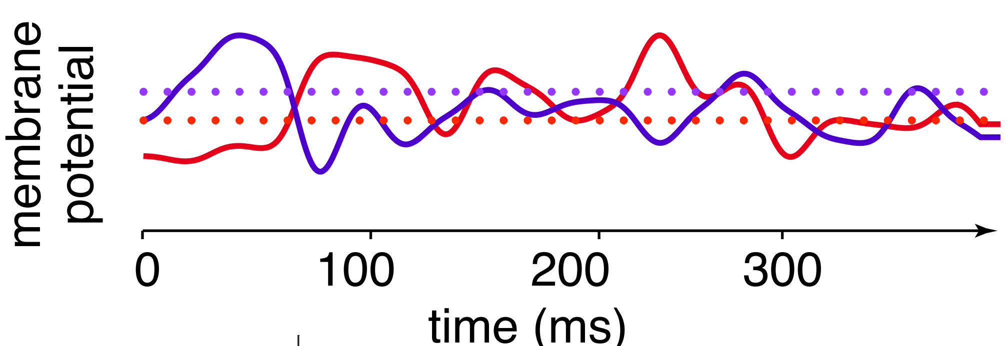
Interpreting the neural code: ML insights

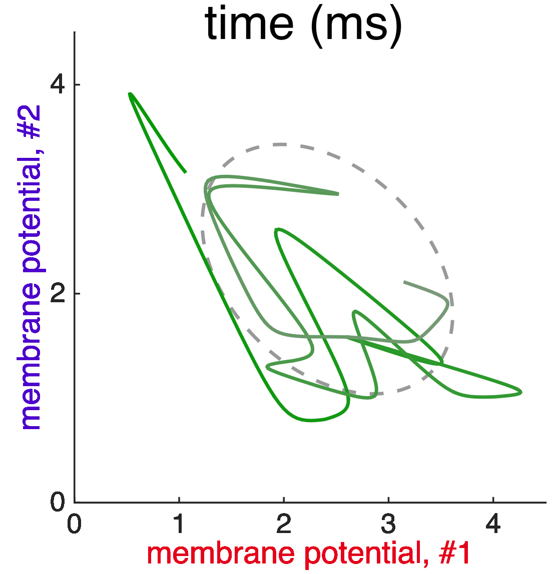
Approximate inference

probability distributions need to be represented



stochastic sampling ⇝ variable membrane potential



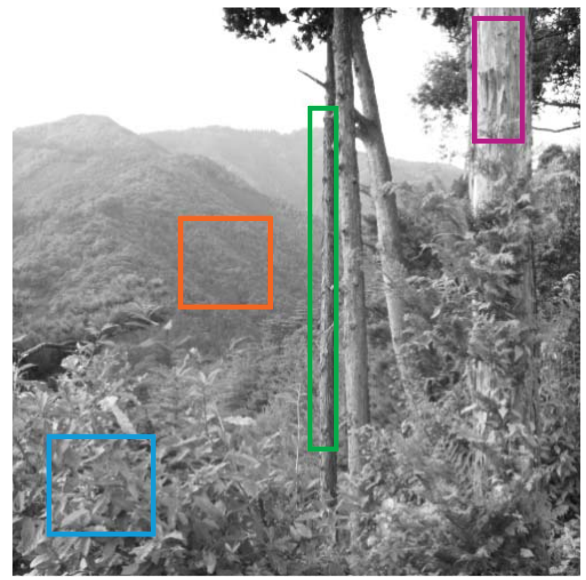


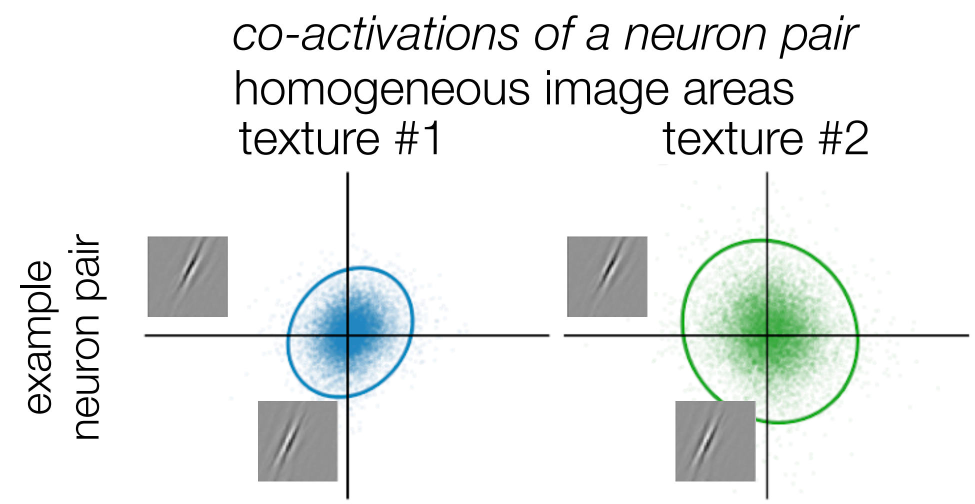
response variability ⇔ subjective uncertainty

Orbán et al (2016) Neuron

Contextual prior

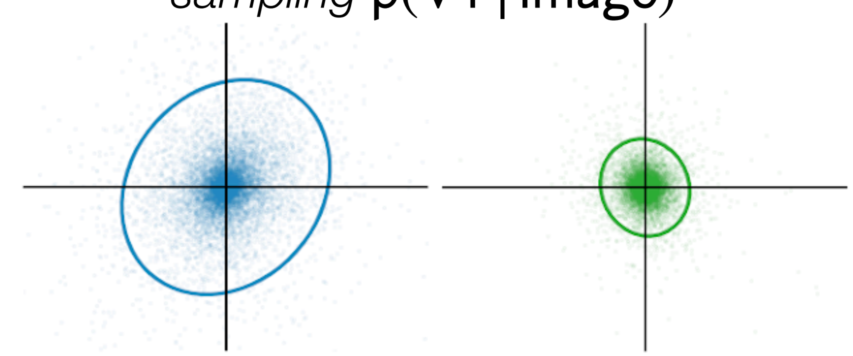
learning exploits regularities, regularities change from context-to context





neural ensembles represent distributions
⇝ context-dependent correlations in priors

sampling p(V1 | image)



response correlations ⇔ correlations in priors

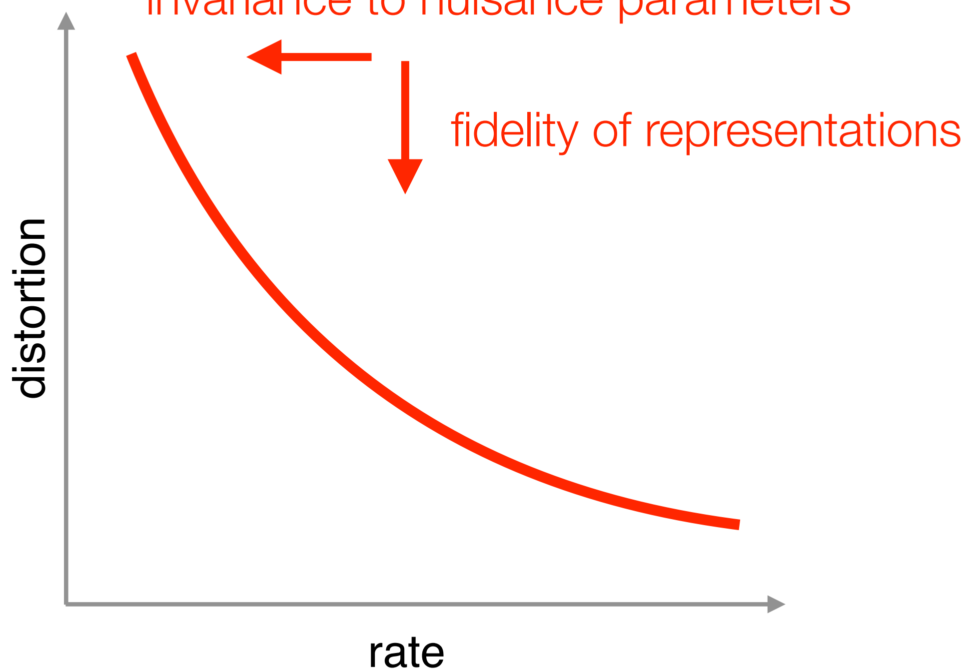
Bányai et al (2019) PNAS

Interpreting the neural code: ML insights

Hierarchical inference

learning captures invariances increasingly complex invariances
⤳ gradual compression

theory of lossy compression
invariance to nuisance parameters



Nagy et et al (2020) PLoS CB
Meszéna et et al (2022) NeurIPS
Csikor et et al, in prep

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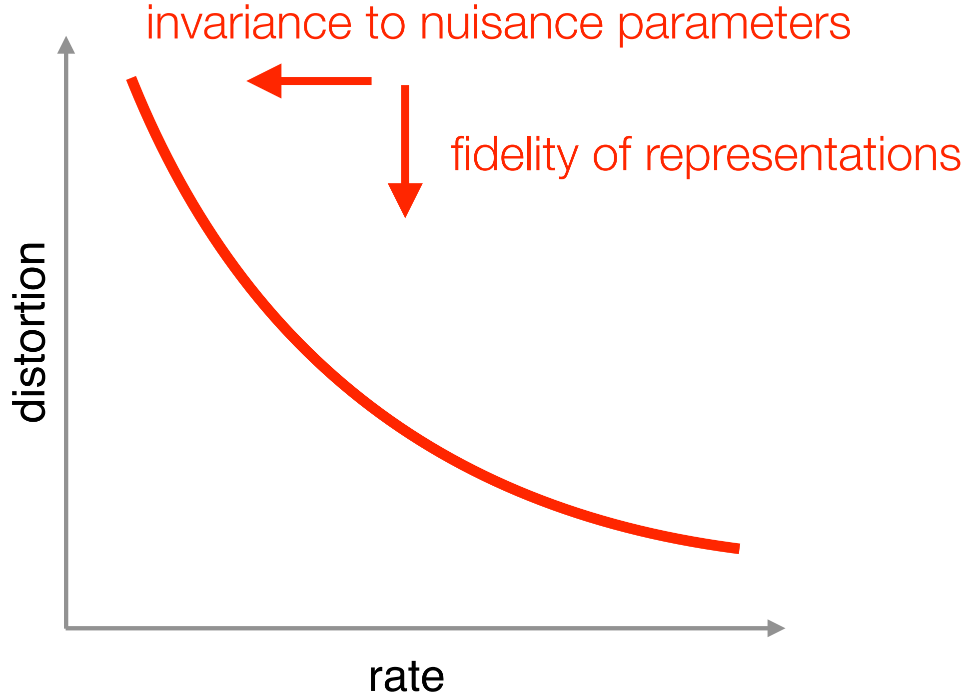

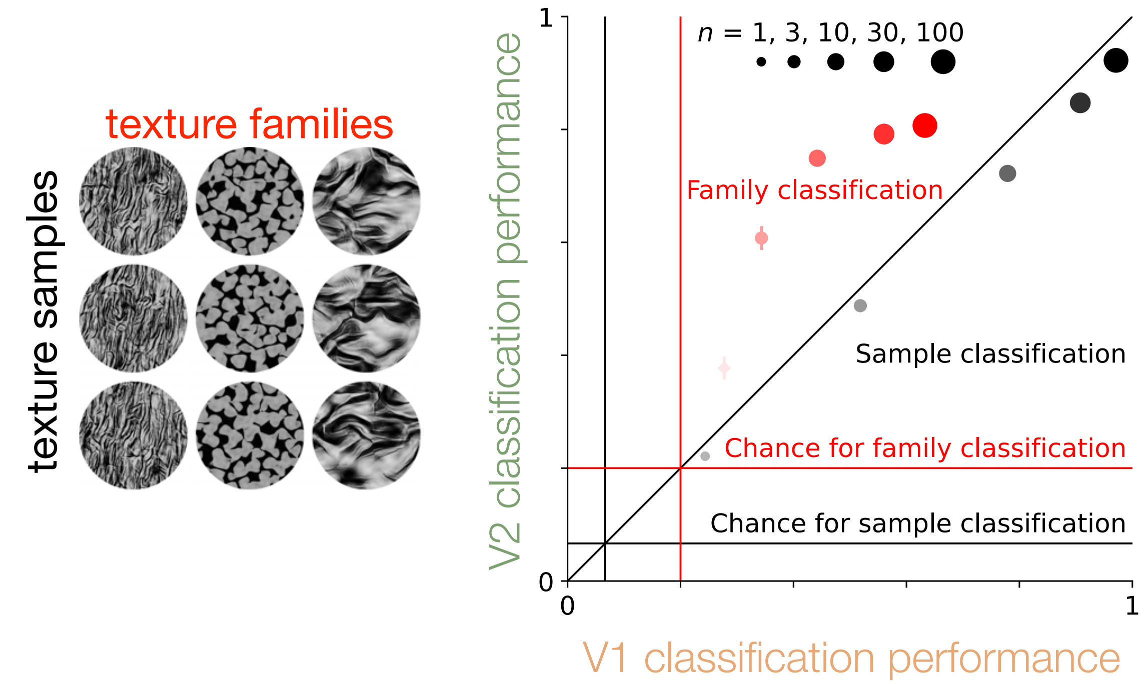

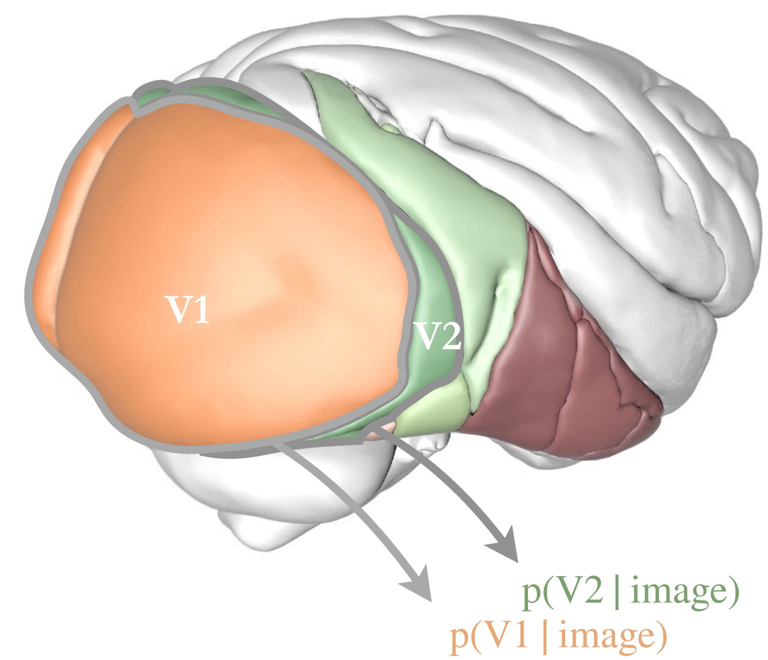

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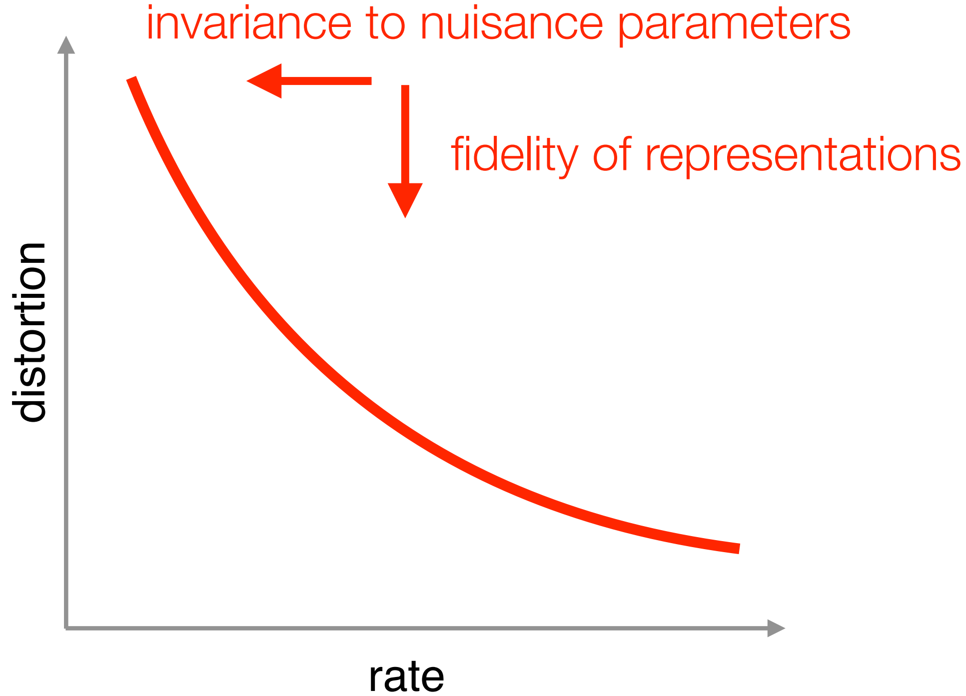

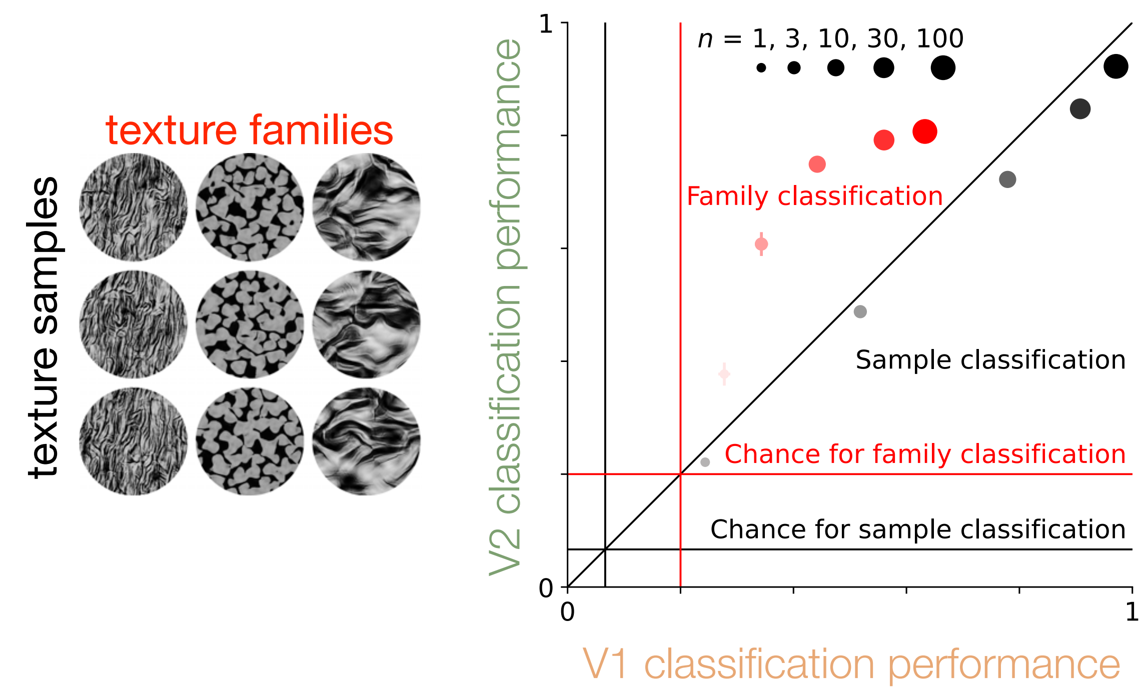

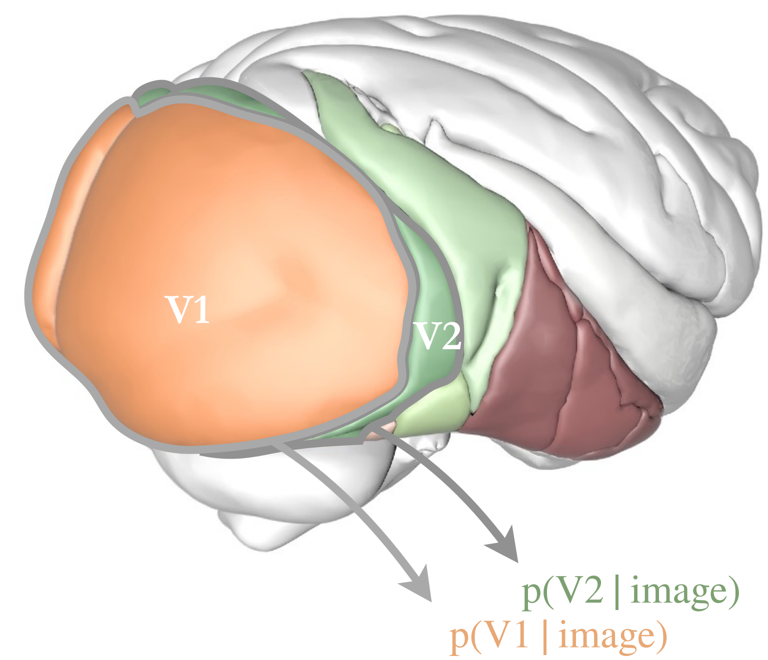

optimally losing information during processing

Nagy et et al (2020) PLoS CB
Meszéna et et al (2022) NeurIPS
Csikor et et al, in prep

Outlook: A testbed for theories

$$ELBO = \mathbb{E}_{q(V1\,|\,\mathrm{image},V2)}[p(\mathrm{image}\,|\,V1)] + \mathrm{KL}\,[q(V2\,|\,\mathrm{image})\,||\,p(V2)] + \mathbb{E}_{q(V2\,|\,\mathrm{image})}\left[\mathrm{KL}\,[q(V1\,|\,\mathrm{image},V2)\,||\,p(V1\,|\,V2)]\right]$$

Outlook: A testbed for theories

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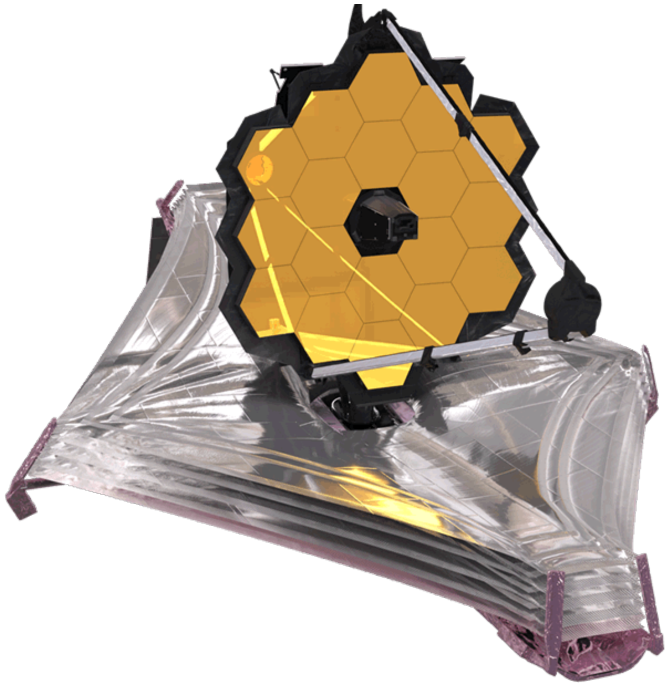
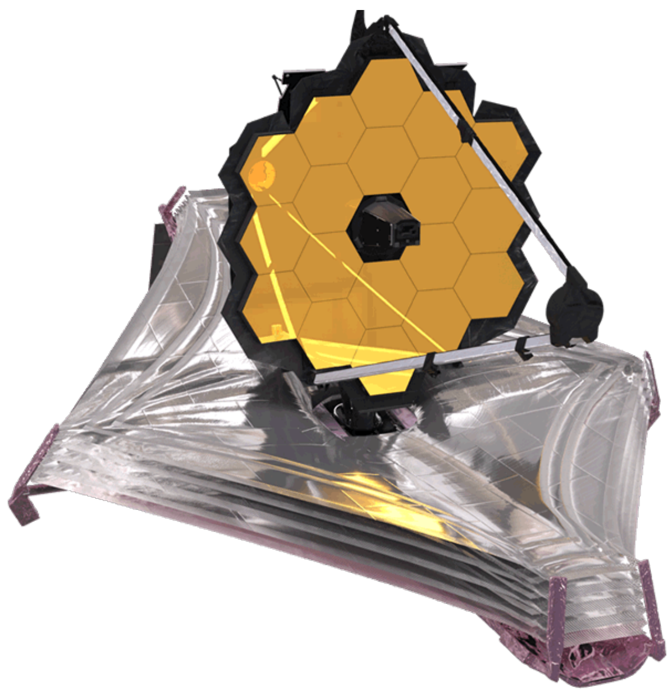


Space Telescope Science Institute Office of Public Outreach

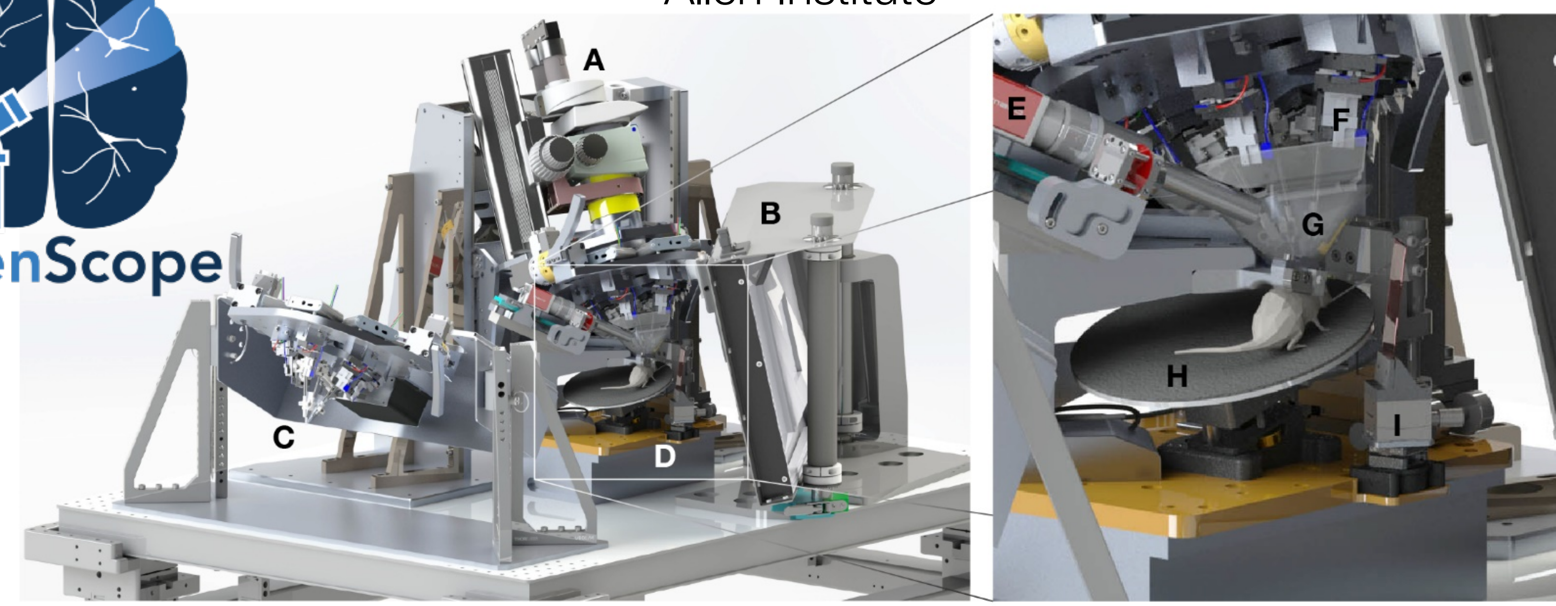
Outlook: A testbed for theories

$$ELBO = \mathbb{E}_{q(V1\,|\,\text{image},V2)}[p(\text{image}\,|\,V1)] + \text{KL}\,[q(V2\,|\,\text{image})\,||\,p(V2)] + \mathbb{E}_{q(V2\,|\,\text{image})}\big[\text{KL}\,[q(V1\,|\,\text{image},V2)\,||\,p(V1\,|\,V2)]\big]$$



OpenScope

Allen Institute



Space Telescope Science Institute Office of Public Outreach

Outlook: A testbed for theories

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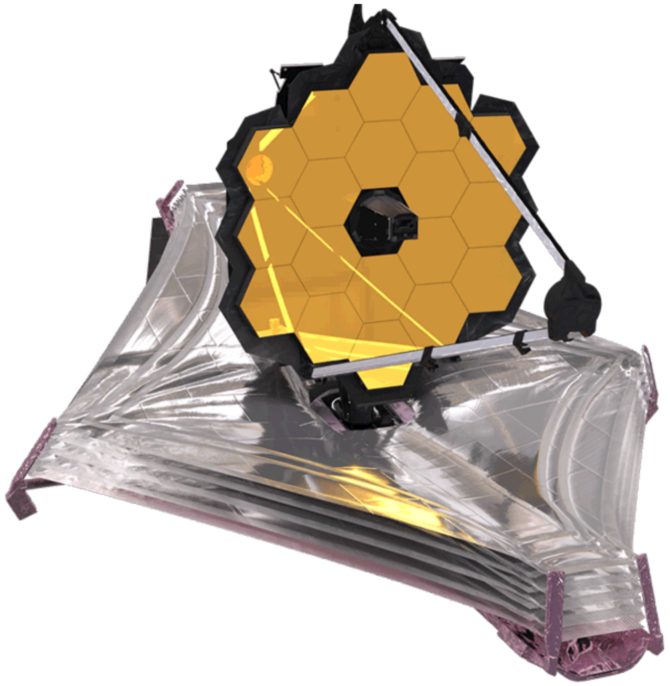

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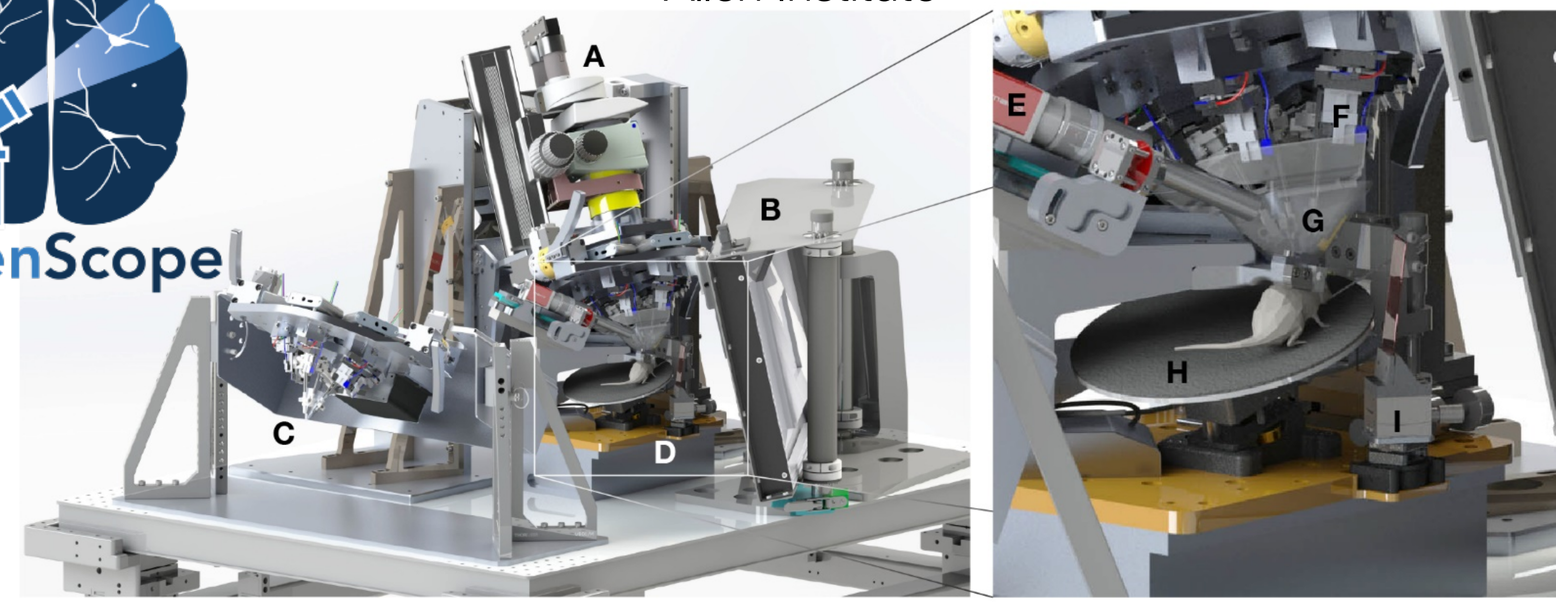

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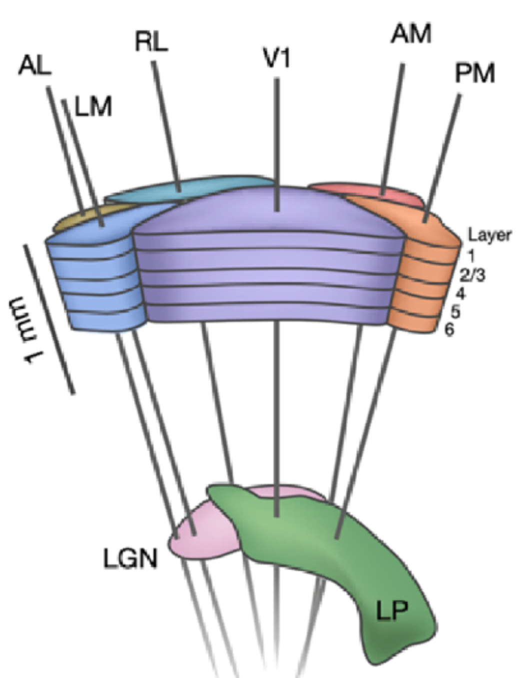

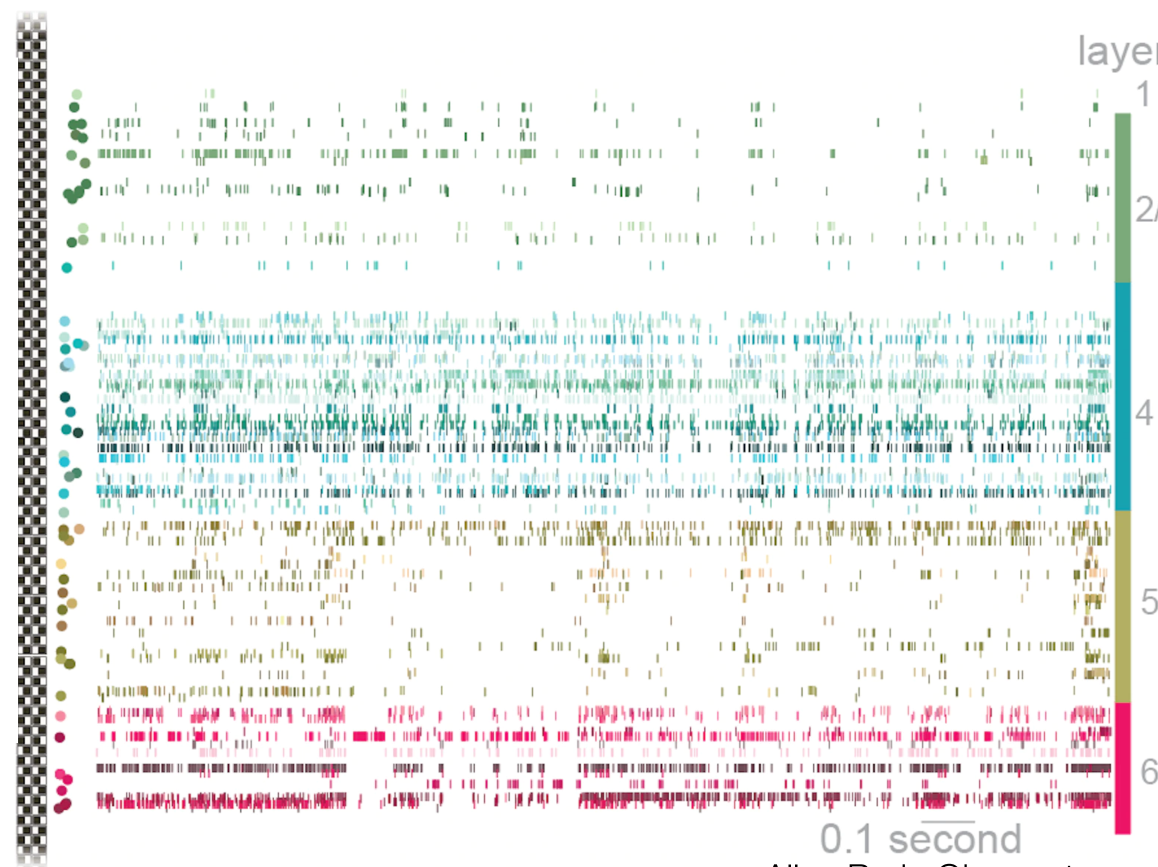

source: Allen Brain Observatory

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