
Computational modeling of human vision: Part II

Decoding

Kohitij Kar

Postdoctoral Associate

DiCarlo Lab

Recommended reading

Annu. Rev. Neurosci. 1998. 21:227–77
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SENSE AND THE SINGLE NEURON: Probing the Physiology of Perception

A. J. Parker

University Laboratory of Physiology, University of Oxford, Parks Road, Oxford, OX1
3PT, United Kingdom

W. T. Newsome

Howard Hughes Medical Institute and Department of Neurobiology, Stanford
University School of Medicine, Stanford, California 94305

Neuron
Perspective

Cell
PRESS

How Does the Brain Solve Visual Object Recognition?

James J. DiCarlo,^{1,*} Davide Zoccolan,² and Nicole C. Rust³

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Cambridge, MA 02139, USA

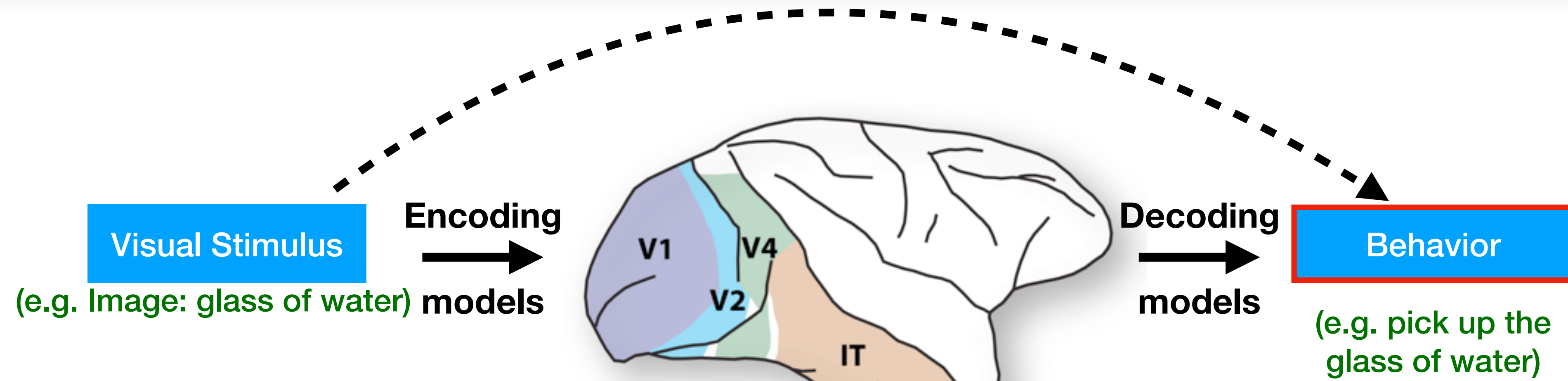
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DOI 10.1016/j.neuron.2012.01.010

How you might start to think about models of vision?



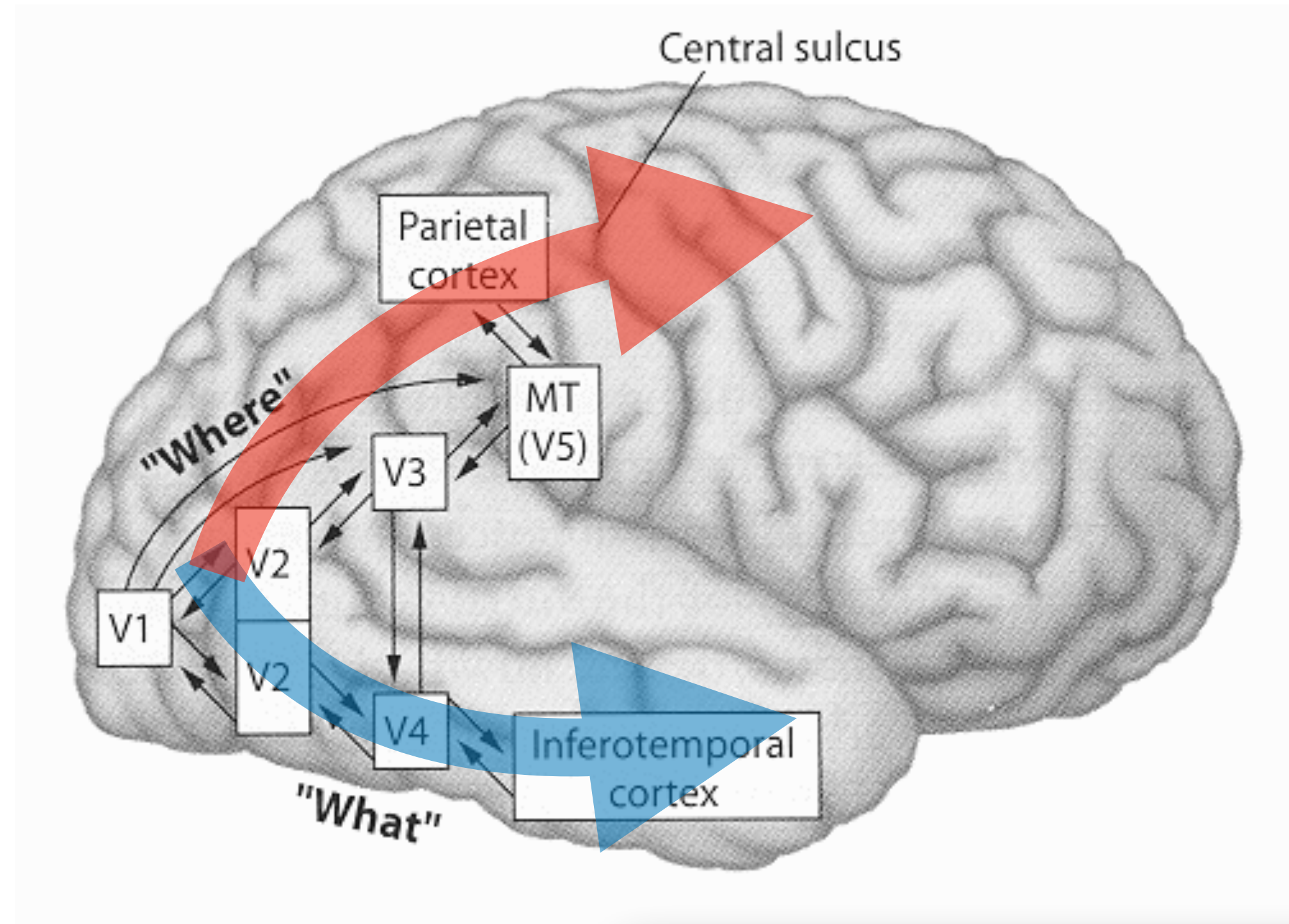
Encoding: How is the visual input represented in the brain?

Decoding: How is the representation used by the brain to carry out **behavioral tasks**?

What model is implemented in the brain?

This needs to be defined quantitatively to evaluate how **good** the decoding models are

Let's talk today about behaviors associated with the ventral stream



Visual Neuroscience (1996), 13, 87–100. Printed in the USA.
Copyright © 1996 Cambridge University Press 0952-5238/96 \$11.00 + .10

A relationship between behavioral choice and the visual responses of neurons in macaque MT

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²Howard Hughes Medical Institute and Center for Neural Science, New York University, New York

(RECEIVED February 24, 1995; ACCEPTED May 30, 1995)

* more on this during the **Psychophysics and data analysis tutorial**
Aug 15: 8-9 pm

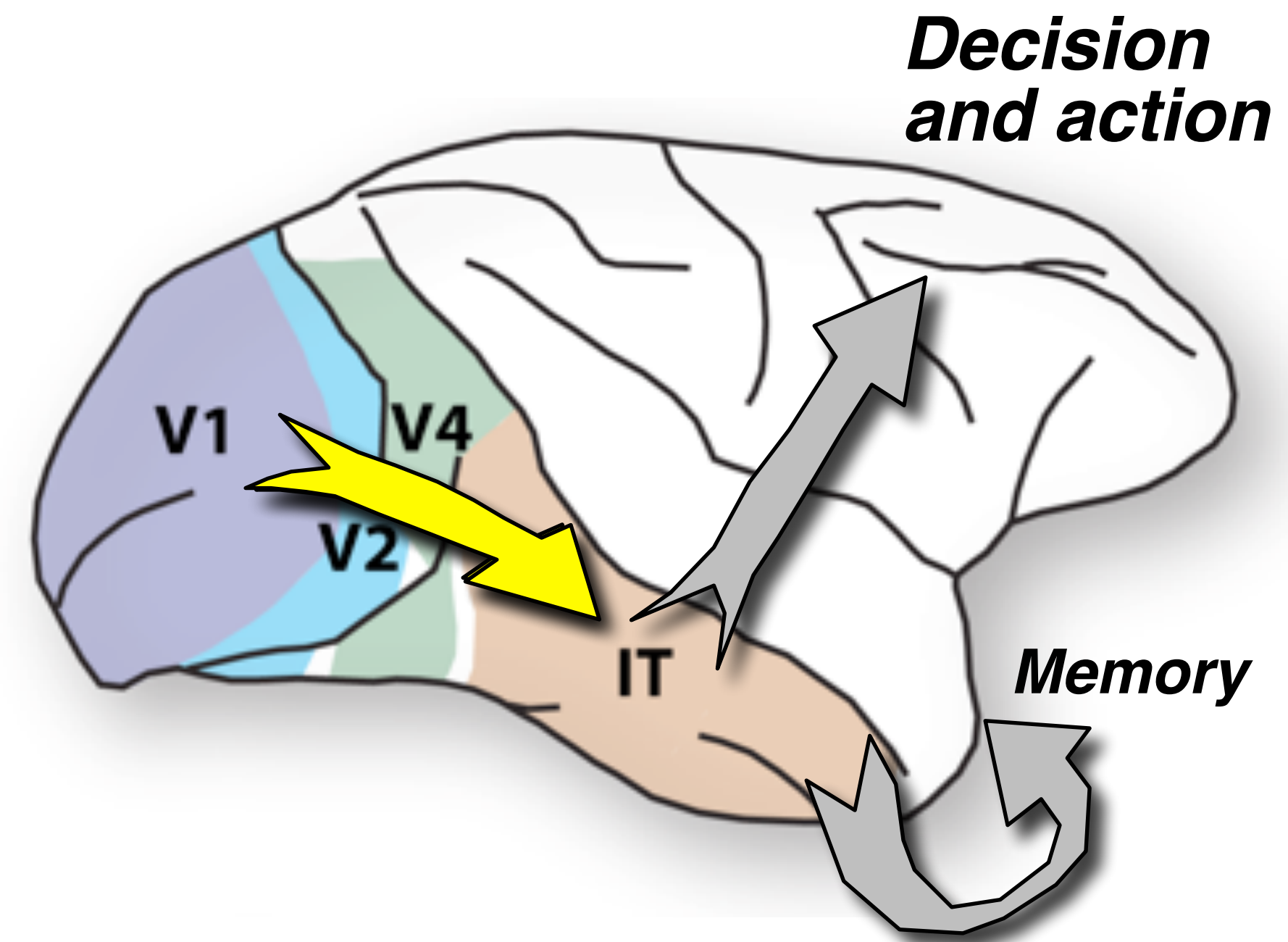
**Lets mainly talk about visual object
recognition today**

“Understanding how biological visual systems recognize objects is one of the ultimate goals in computational neuroscience.....” Riesenhuber and Poggio, 2000

Rapid object identity inference



Ventral Stream model of core object recognition



Behavioral Task

8 deg image at center of gaze, 100 msec viewing time

1

*Define &
operationalize a
behavior*



Behavioral Task

8 deg image at center of gaze, 100 msec viewing time

1

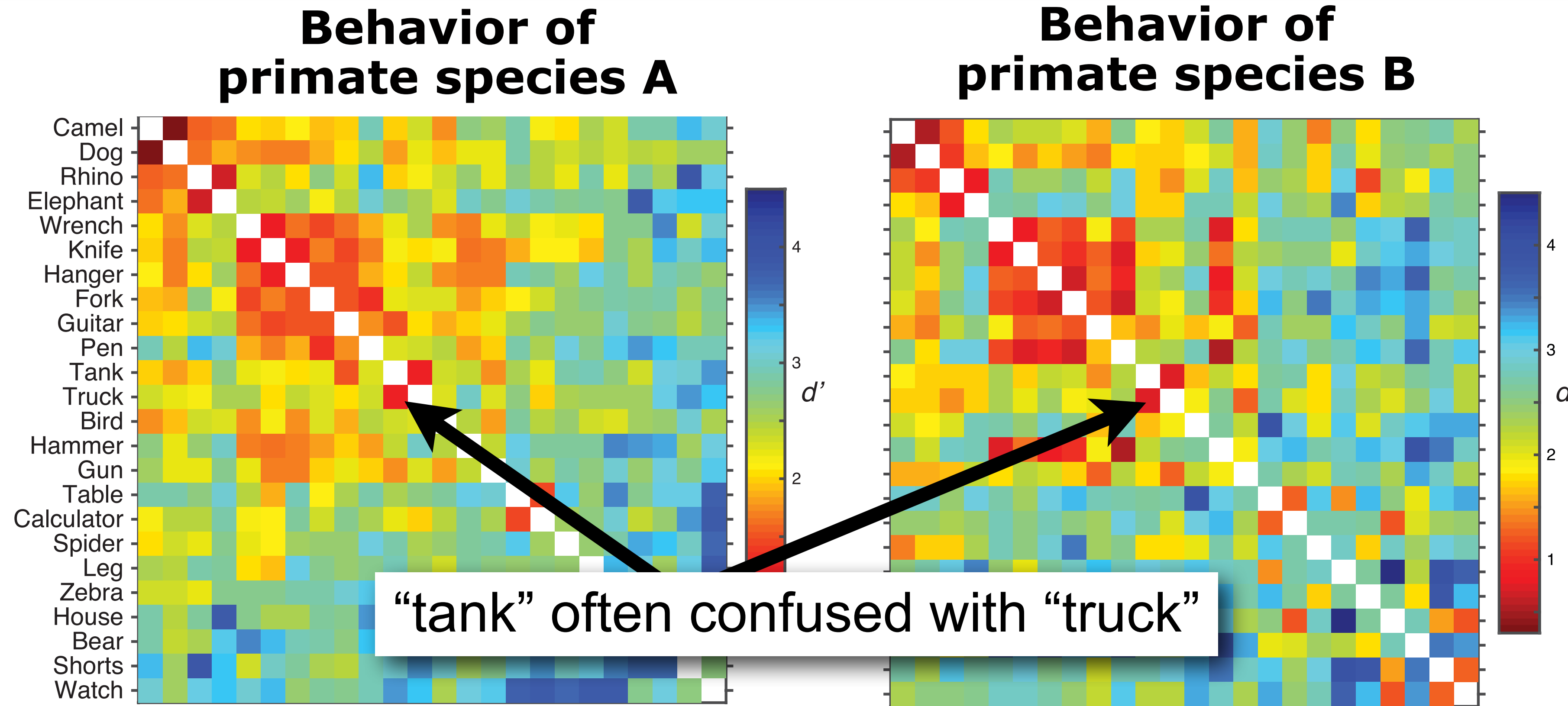
*Define &
operationalize a
behavior*



What animal model shall we choose to study the behavior?

2

Which animal model shall we choose?



Summary: human behavior = monkey behavior

Now go get more internal component measurements!

measure

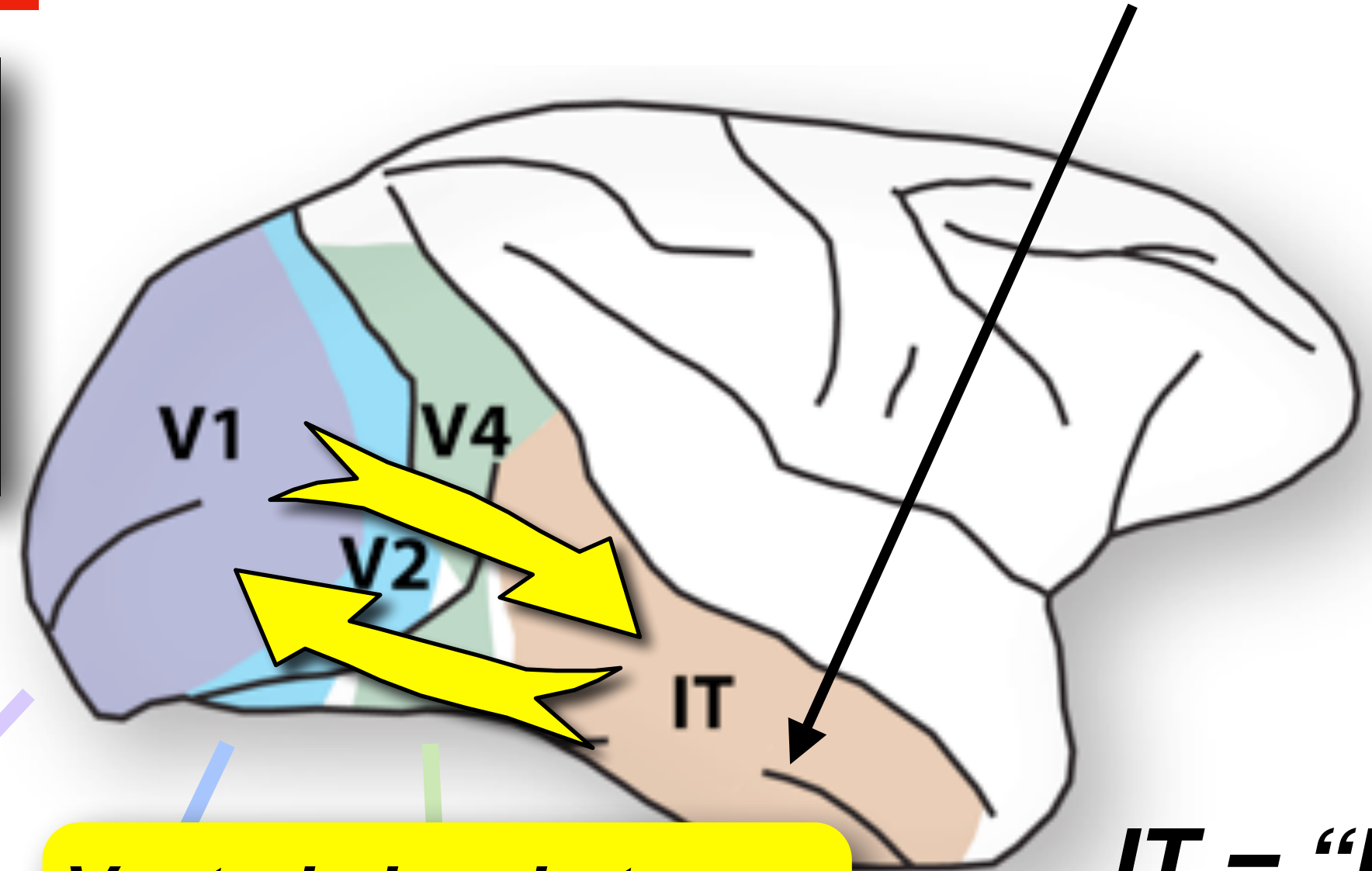
3

Where to look in the monkey brain?

Decades of neuroscience have provided measurements of macro- and meso- architecture

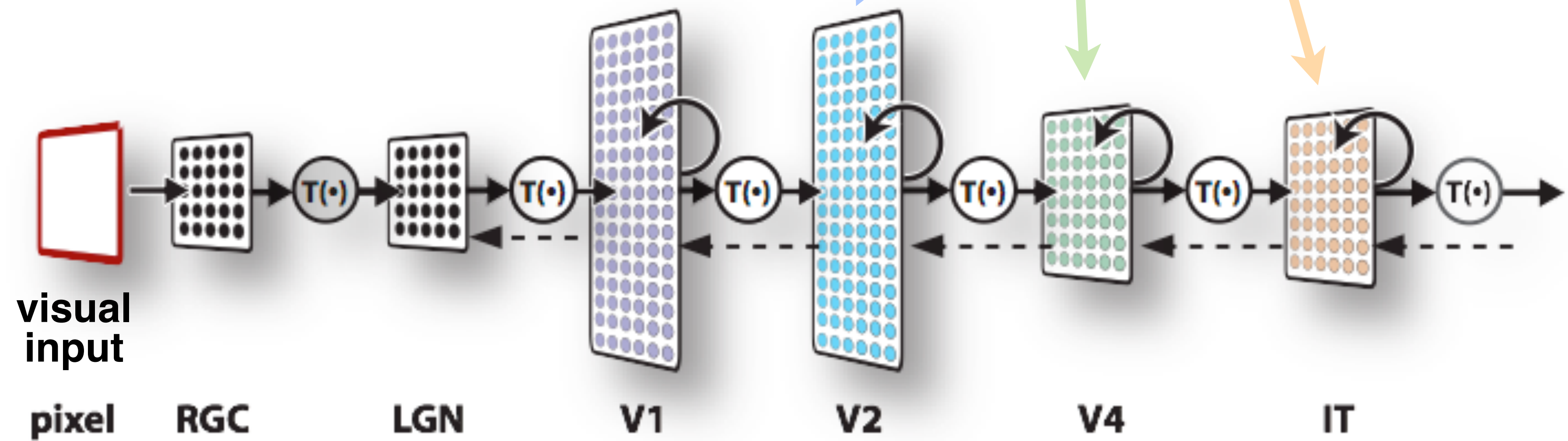
Get measurements of internal system components.

Lesions here result in deficits in visual recognition.



Ventral visual stream

IT = "Inferior temporal cortex"

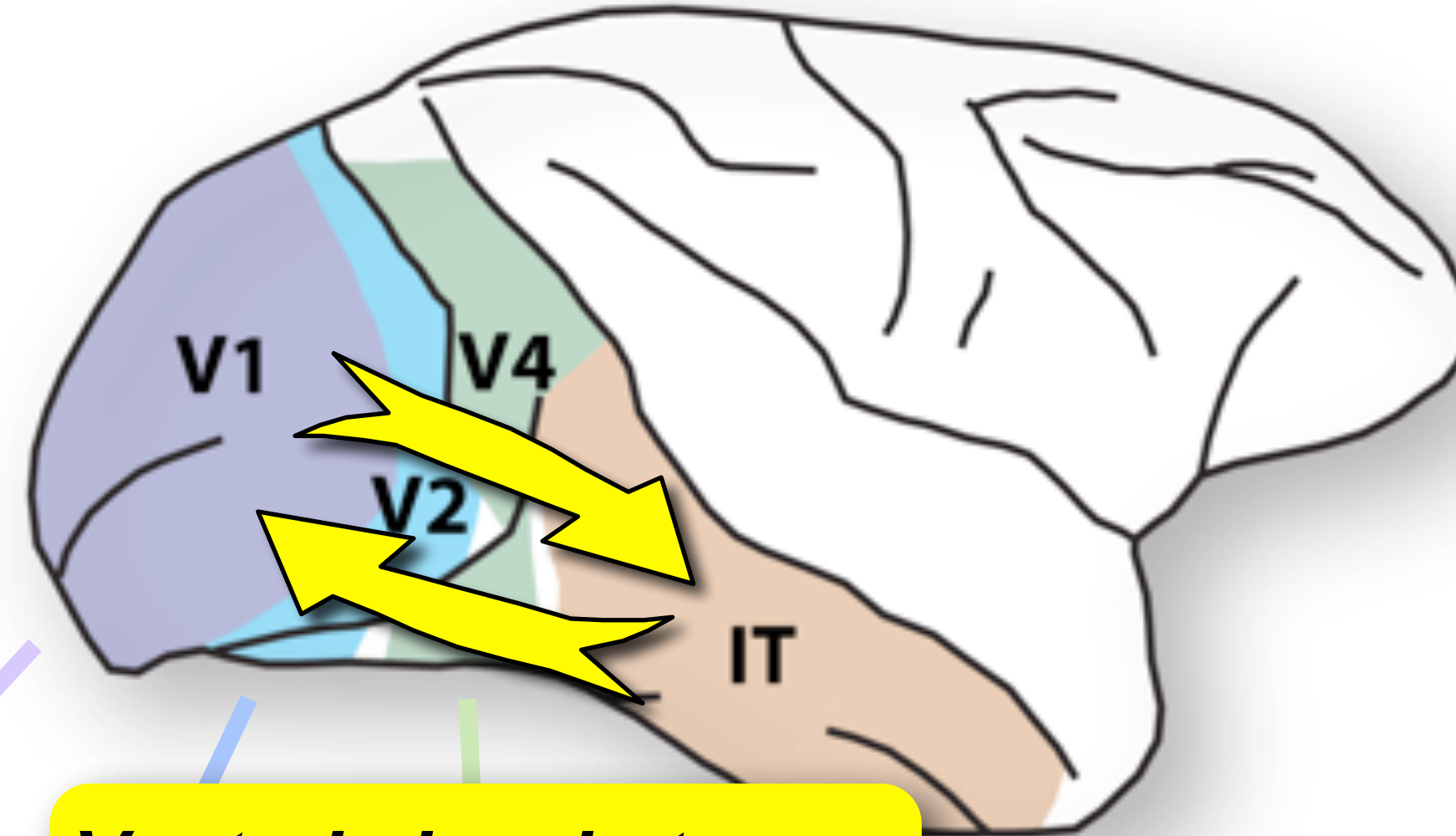


measure

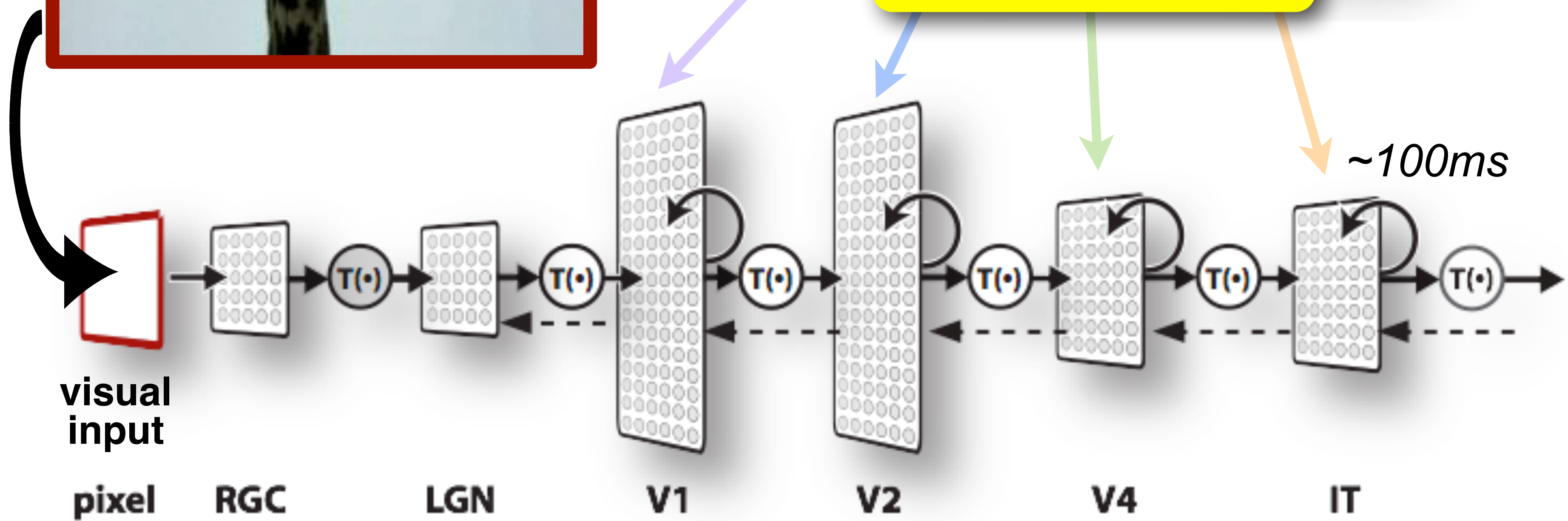
3

Get
measureme
of internal
system
components

**Decades of neuroscience
physiology:**



Ventral visual stream

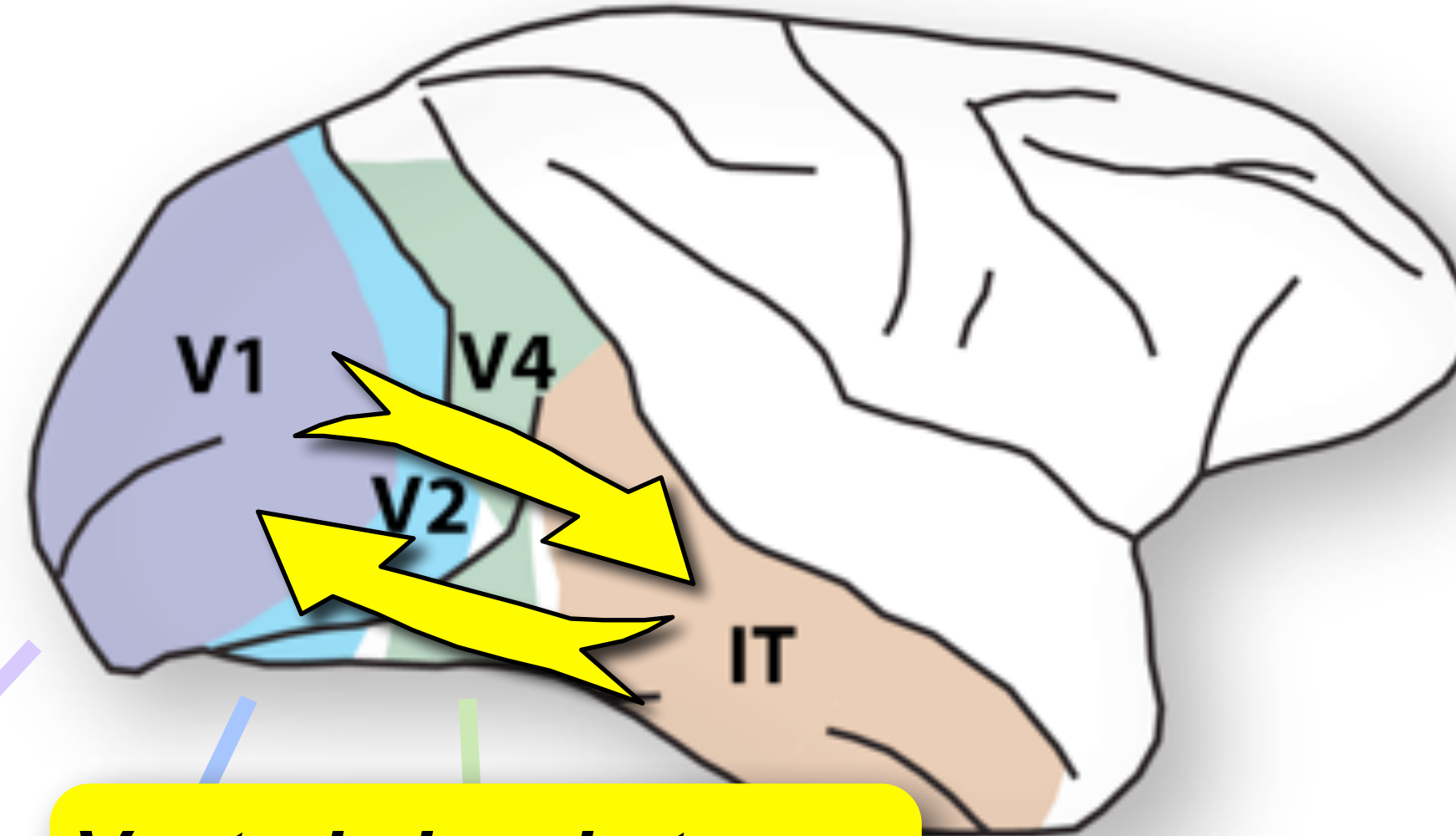


measure

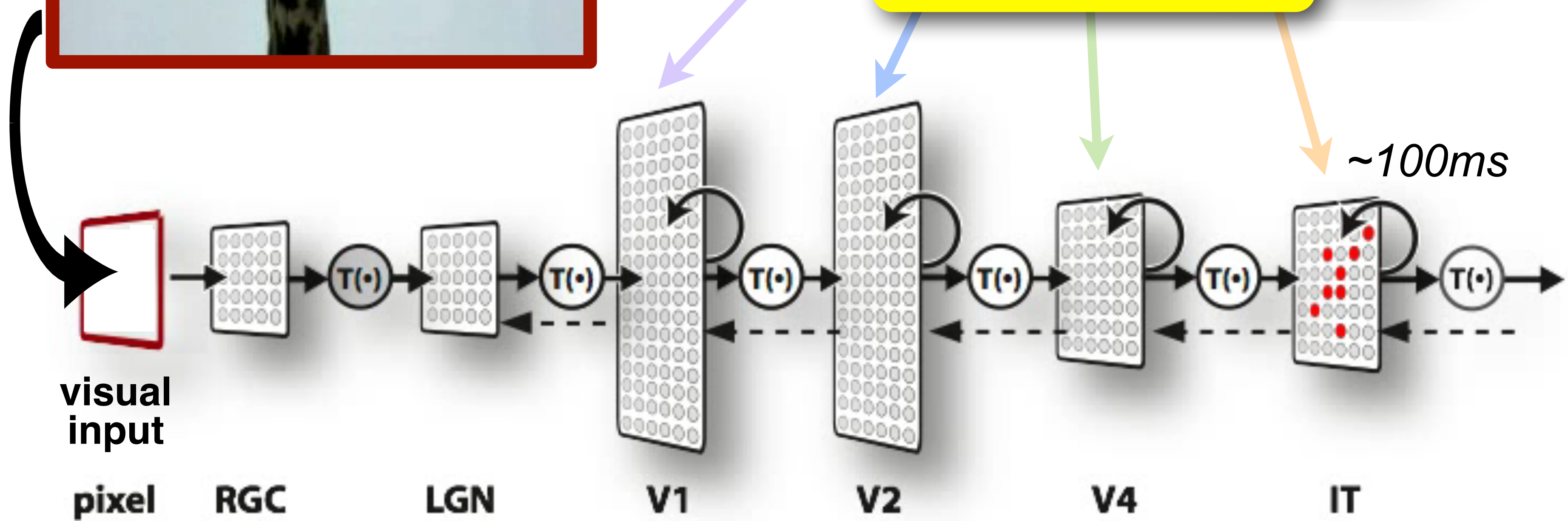
3

Get
measureme
of internal
system
components

**Decades of neuroscience
physiology:**



Ventral visual stream

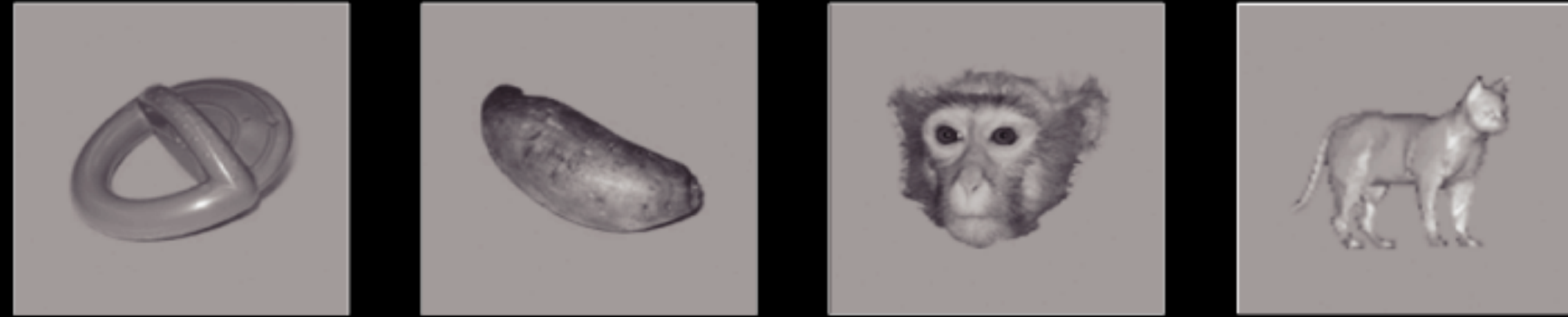


measure

3

Get measurement of internal system components

Examples of IT neuronal spiking responses

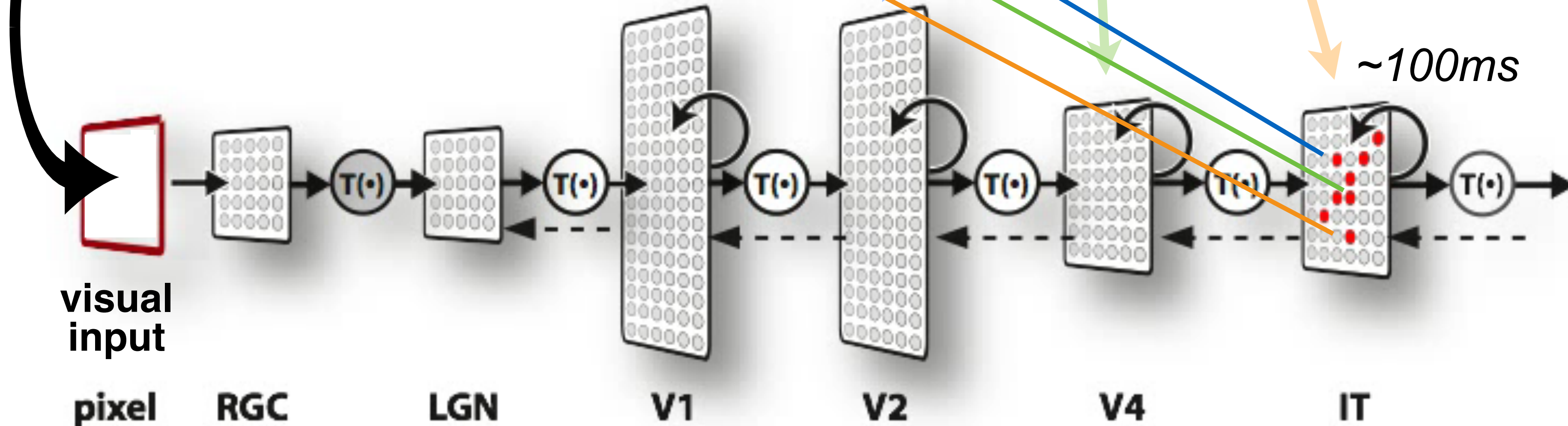


Site 1



Image duration
0 100 msec

Hung, Kreiman, Poggio, & DiCarlo *Science* (2005)



measure

3

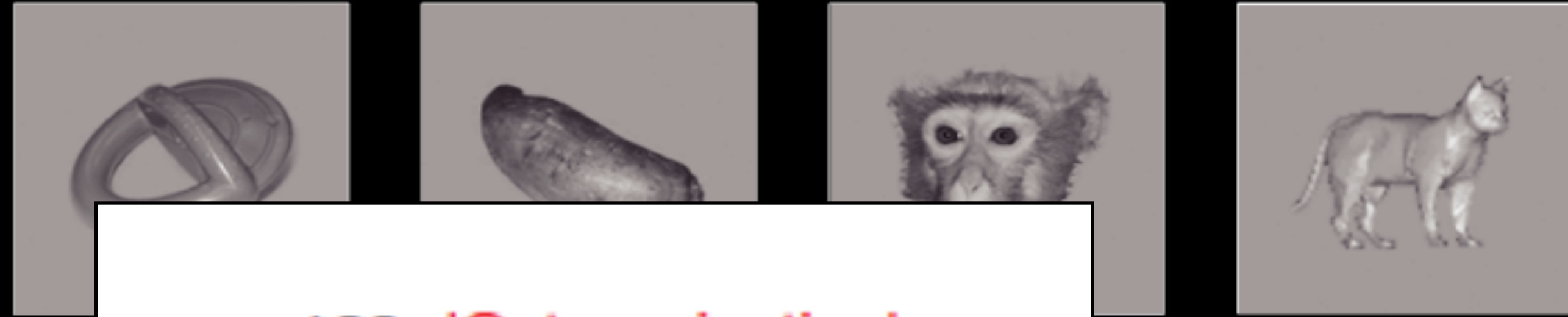
Get measurements of internal system components.

Examples of IT neuronal spiking responses

Site 1

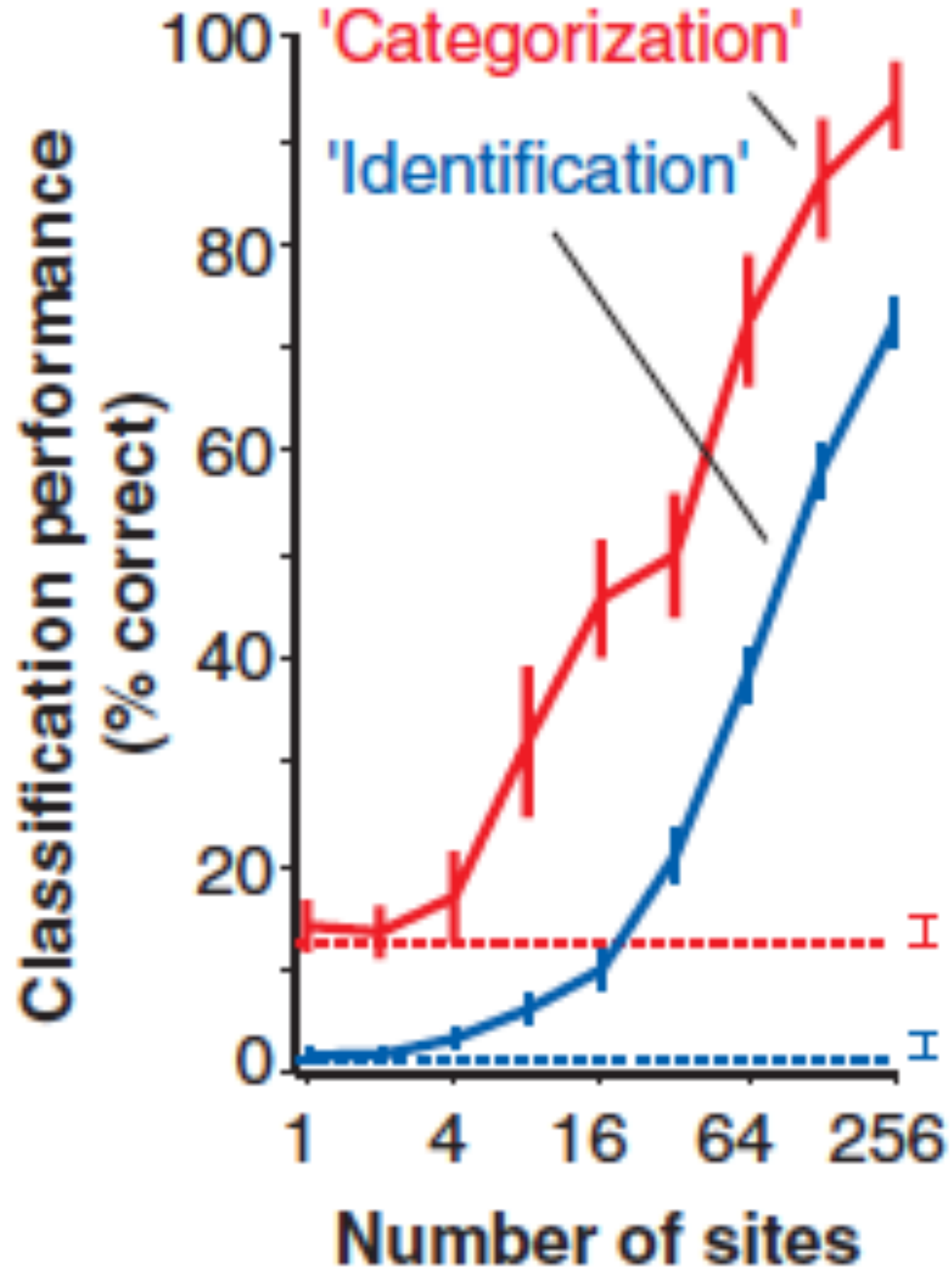
Image duration

0 ms



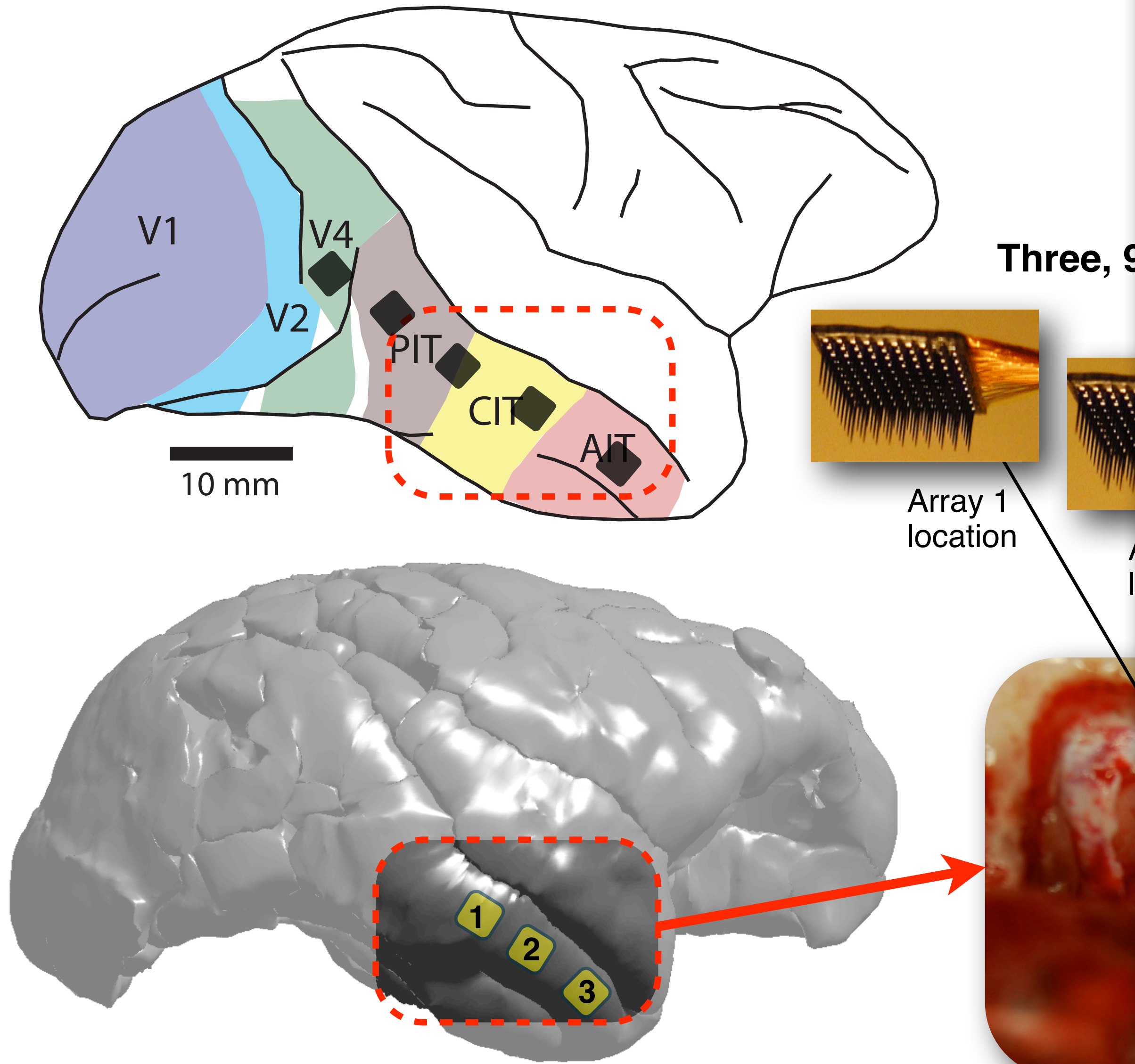
25

r = 7

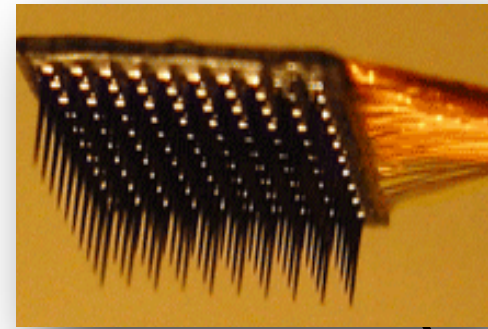


Hung, Kreiman, Poggio, & DiCarlo *Science* (2005)

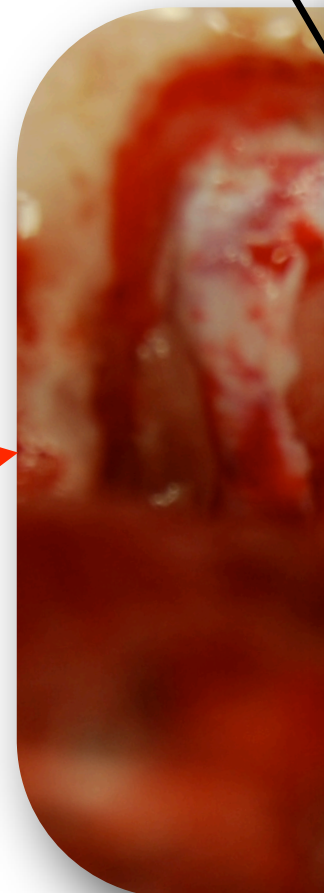
The data collection over the years have scaled up



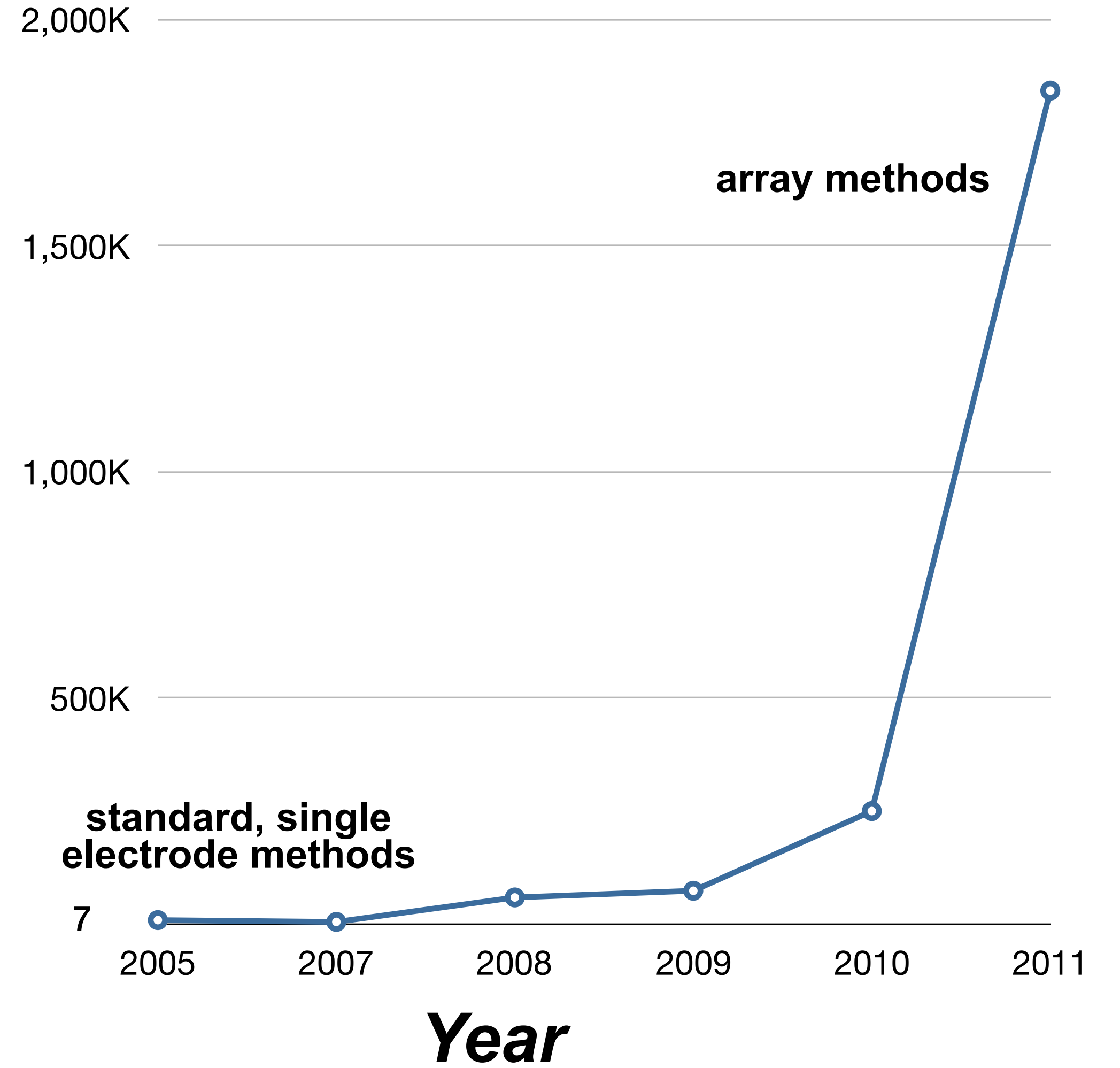
Three, 9



Array 1 location



Data collection rate
($nImages \times nSites$ per day)

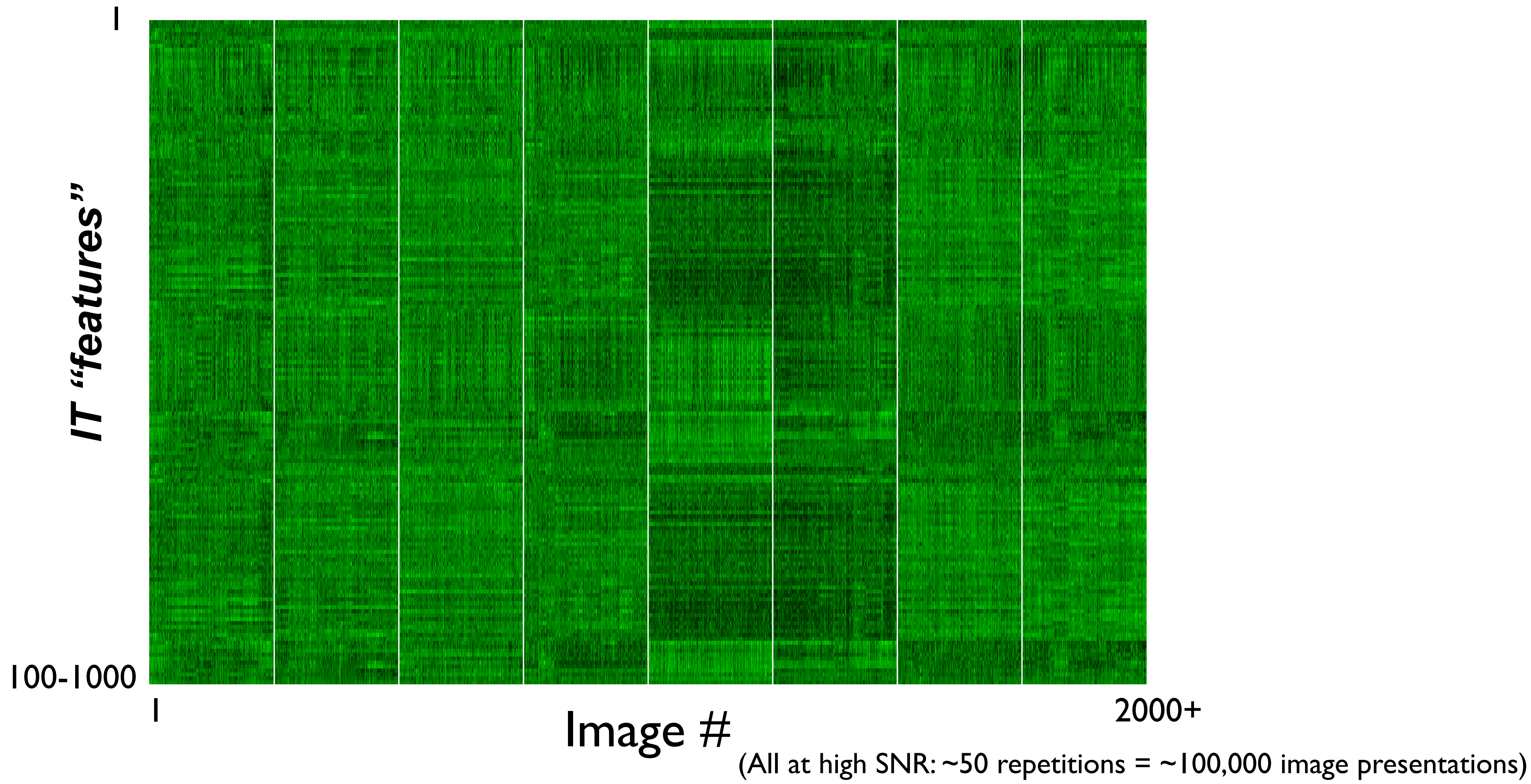


100-1000

IT "features"

I



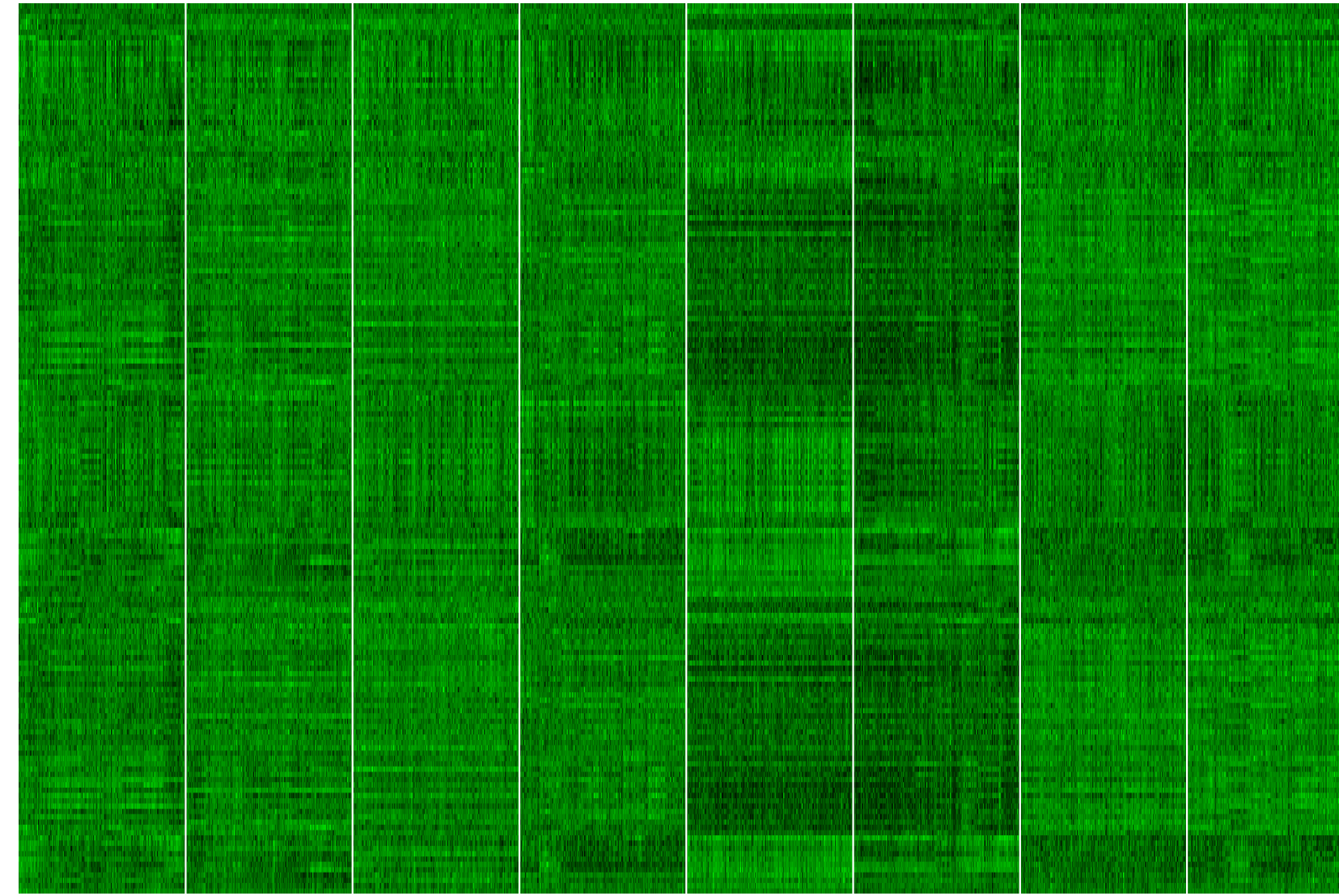


measure

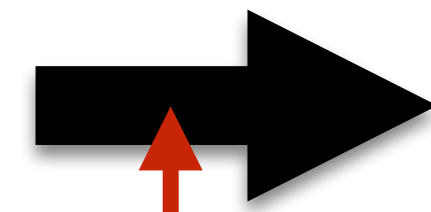
4

Test population decoding models that can fully explain behavior

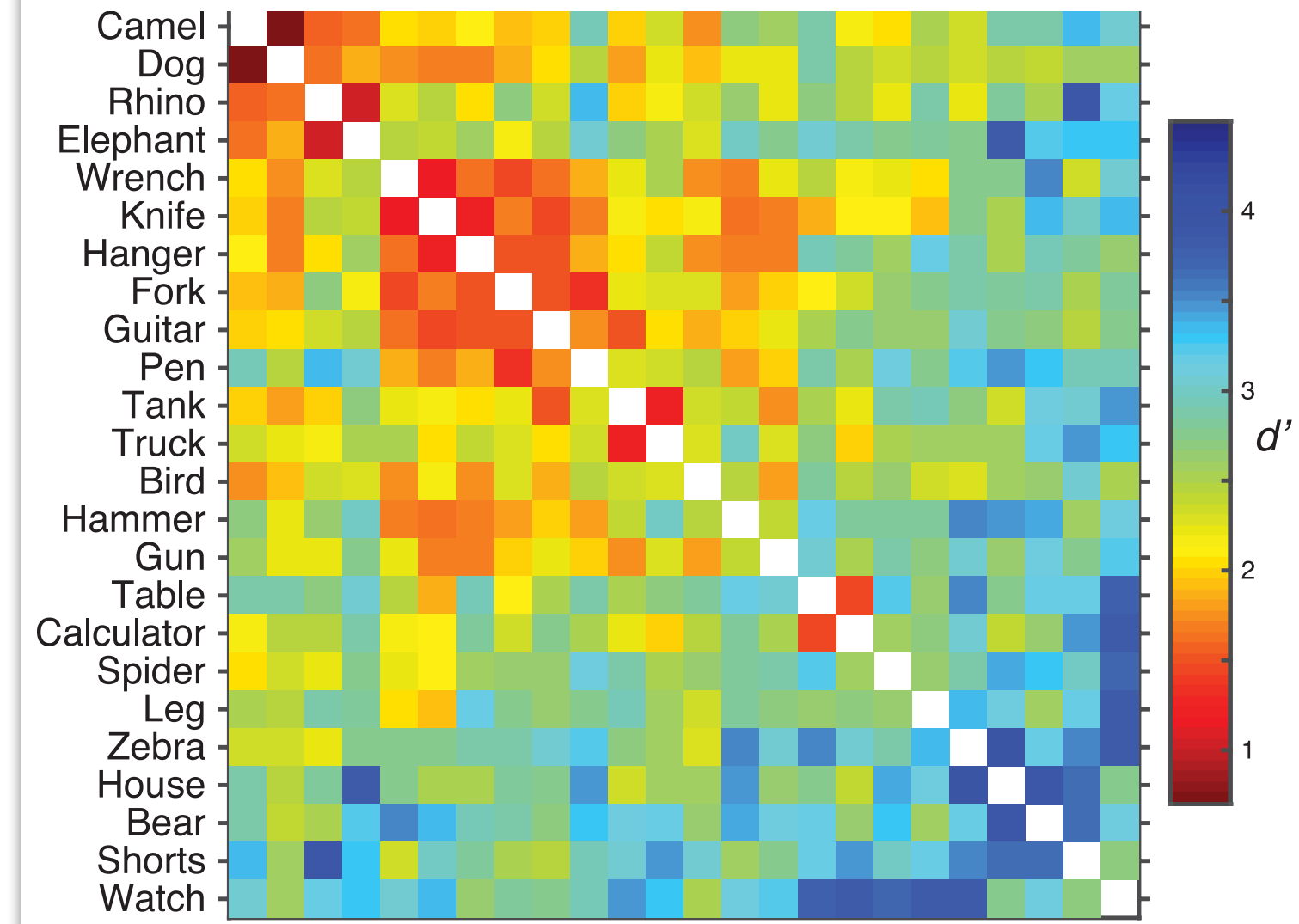
IT "features"



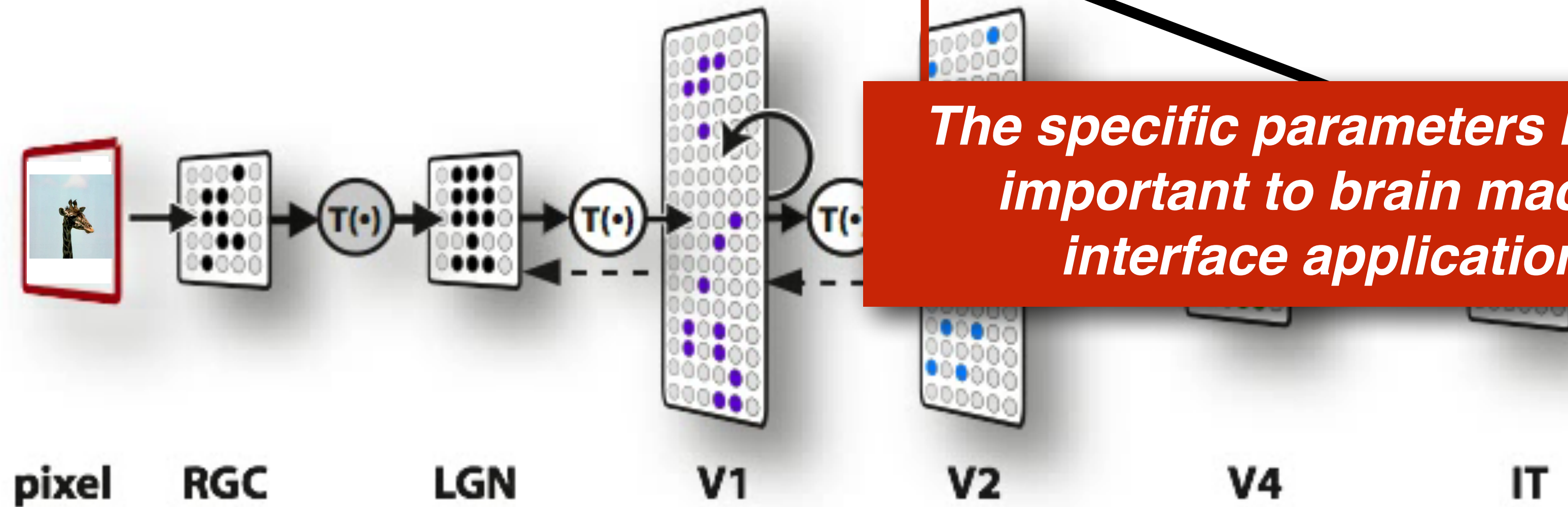
Linking neurons to behavior



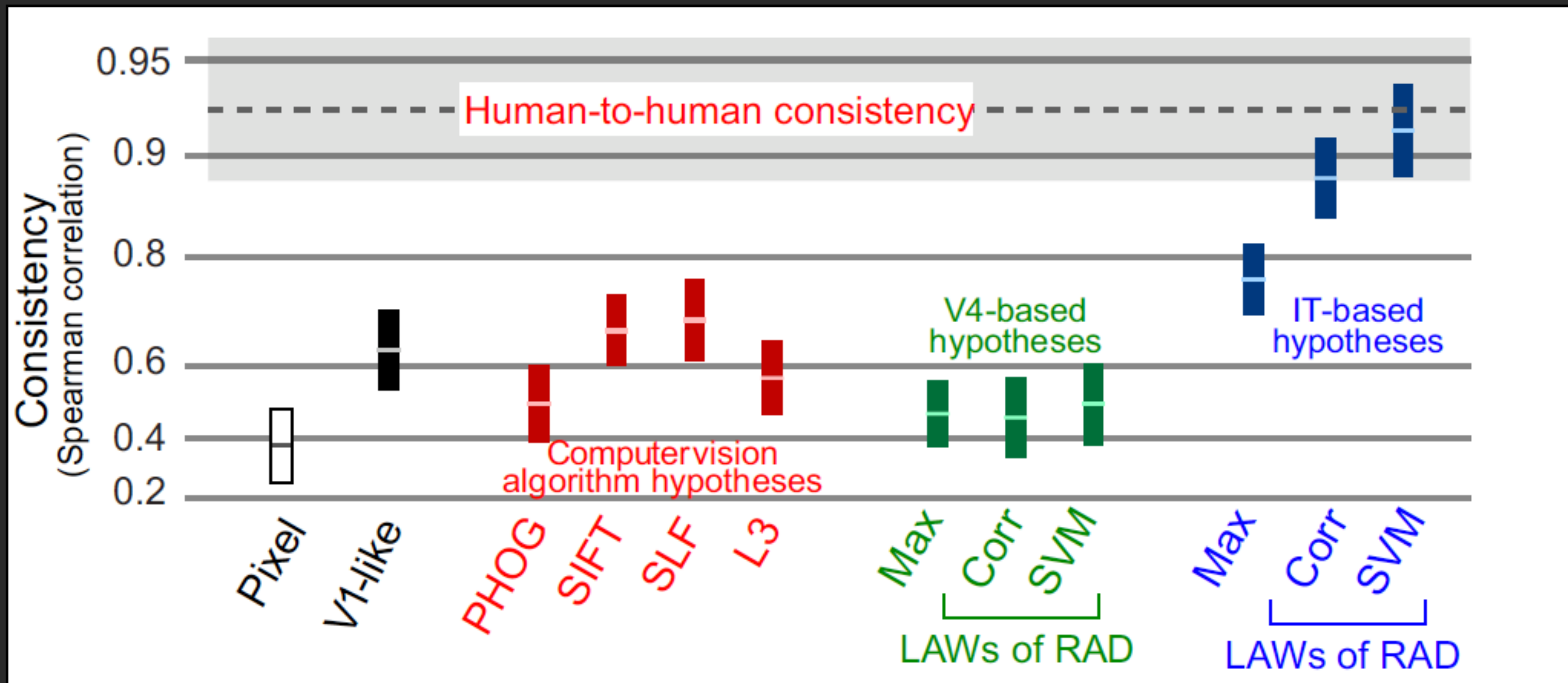
Behavioral performance on categorization tasks



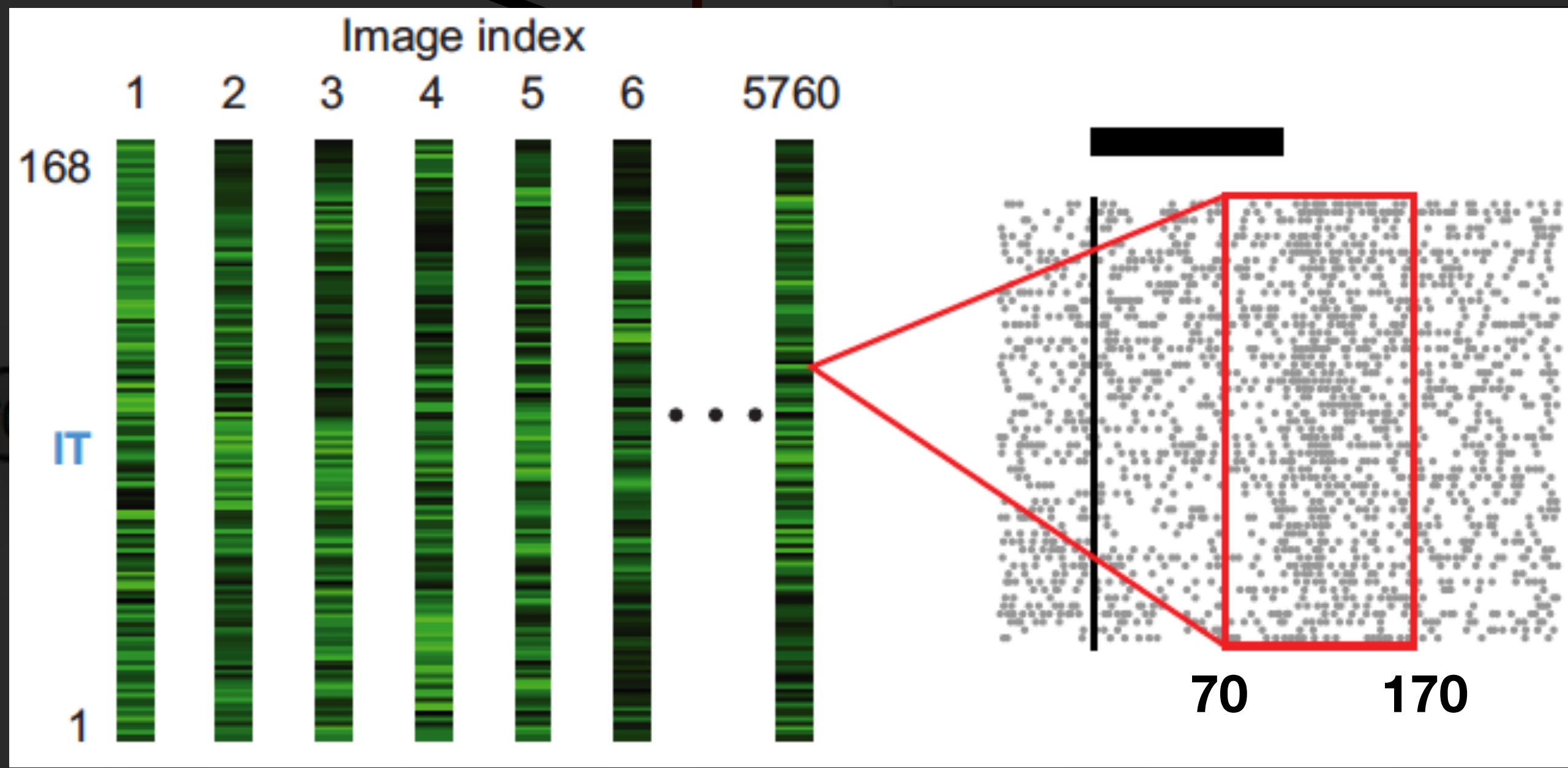
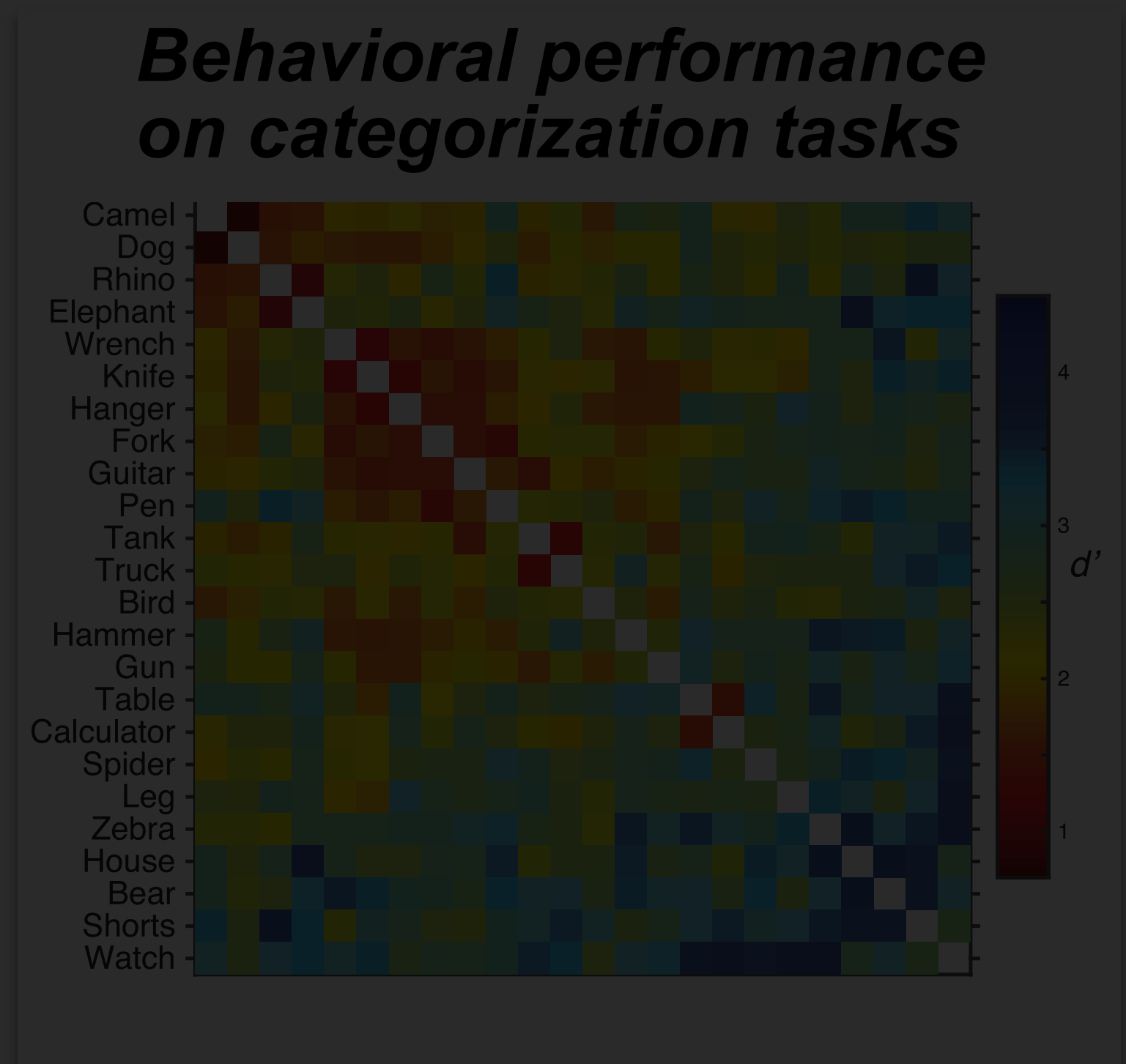
Majaj, Hong, Solomon, & DiCarlo, *J Neuro* (2015)
Hong*, Yamins*, Majaj & DiCarlo. *Nat. Neuro.* (2016)



The specific parameters here are important to brain machine interface applications.



Linking
hypotheses to
behavior

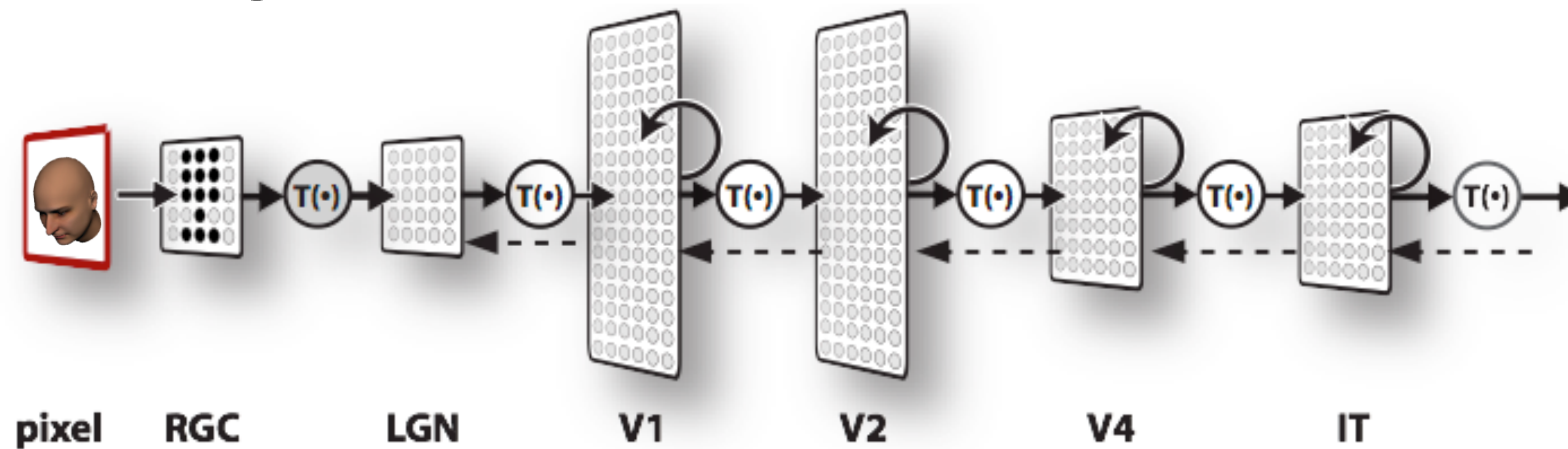
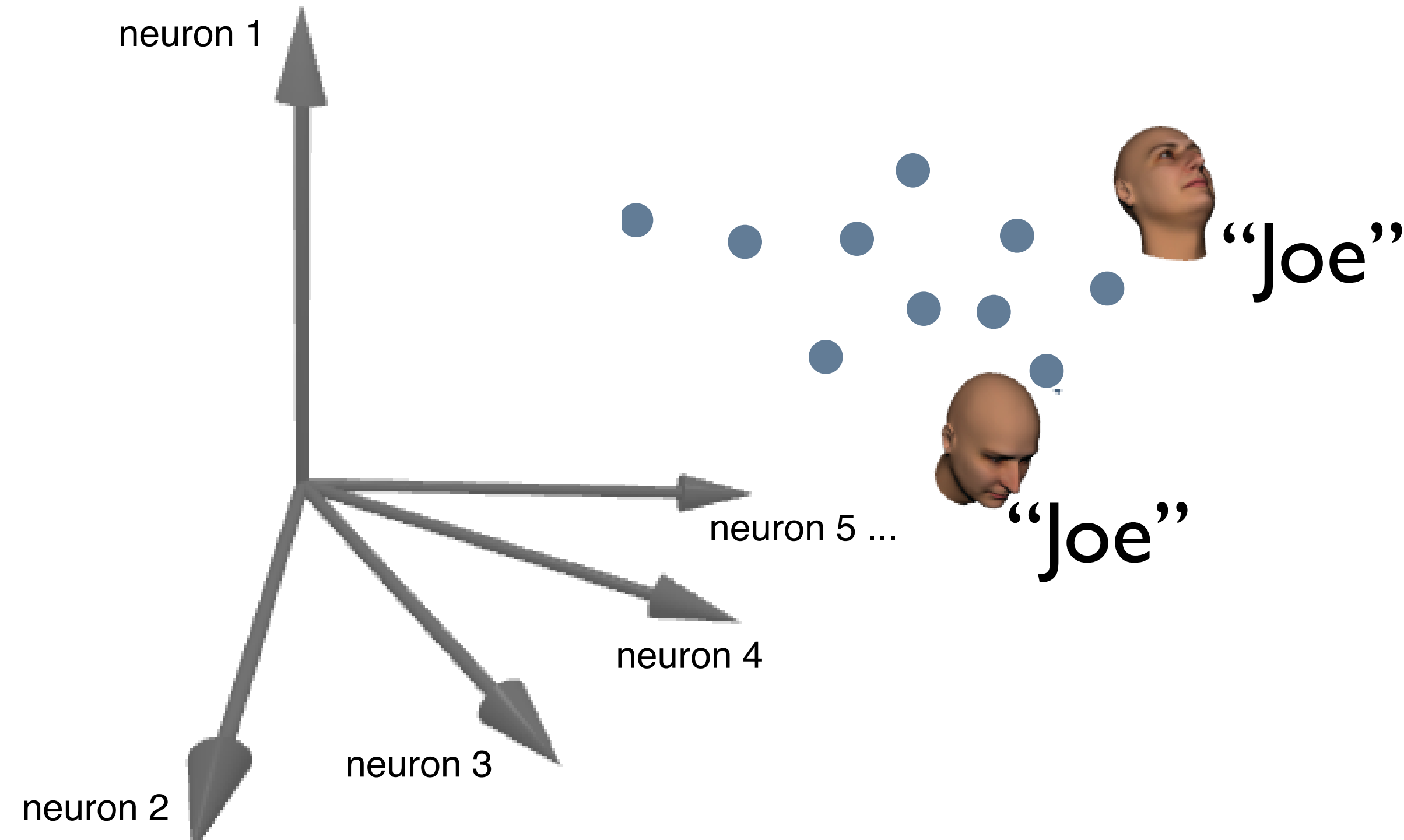


Neuro (2015)
Neuro. (2016)

are
e

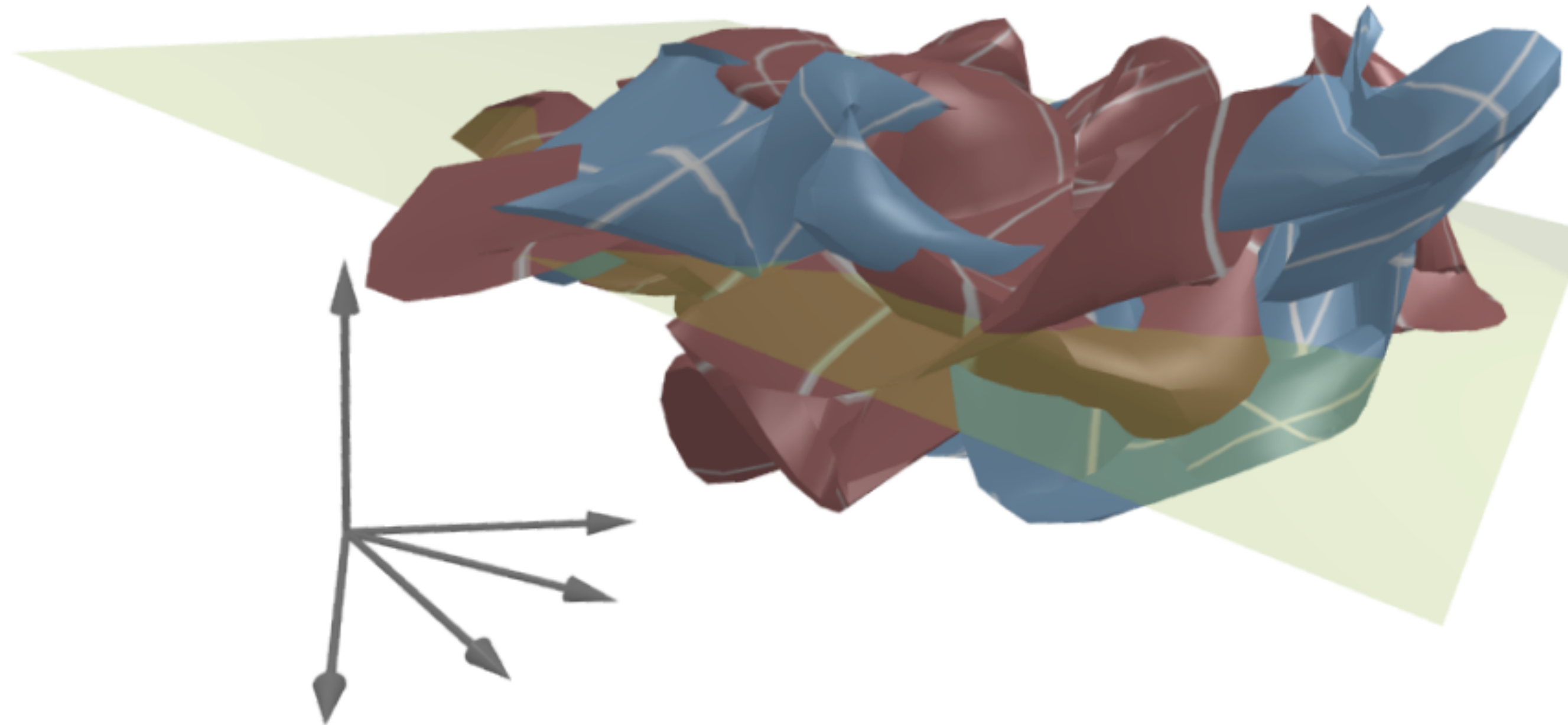
The visual brain represents the image as populations of visually-evoked “features”

“Joe’s” identity manifold



Object manifolds get untangled along the ventral stream

V1-like population representation



individual 2



ineffective
separating
hyperplane

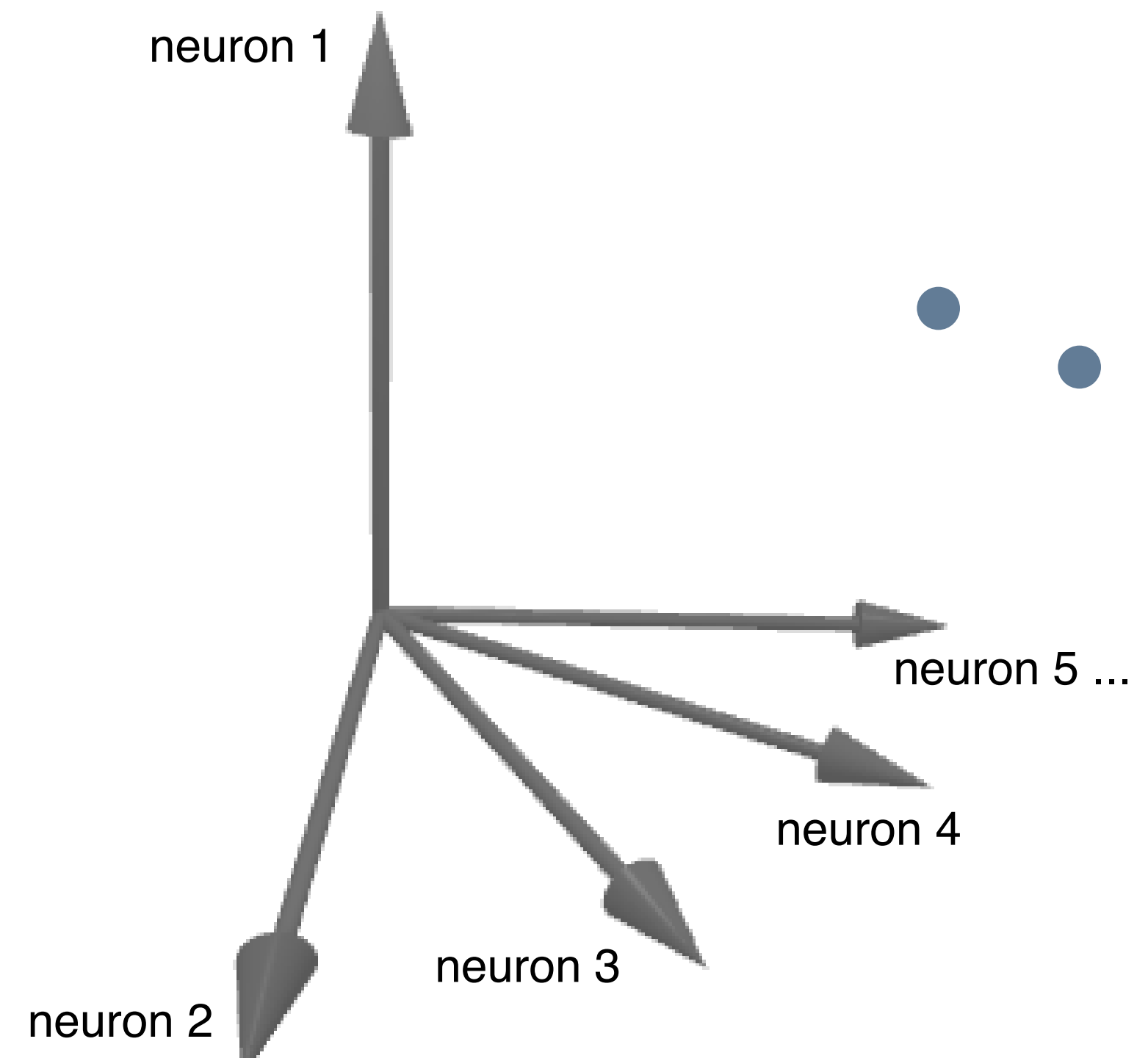


individual 1

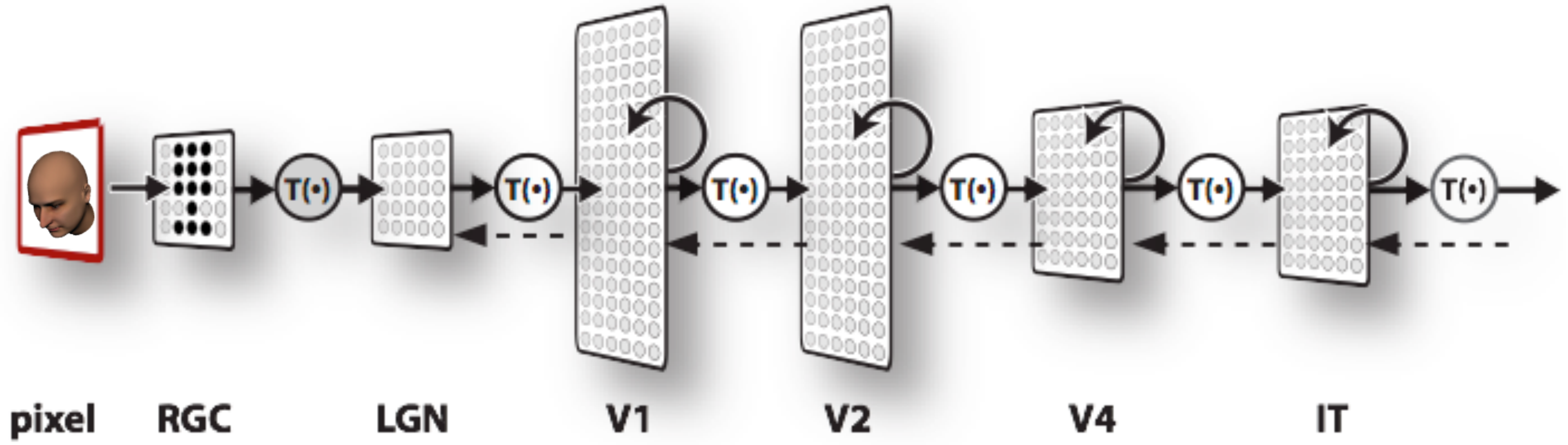
object manifolds are “tangled”

(Due to identity-preserving image variation.)

"Joe's" identity manifold



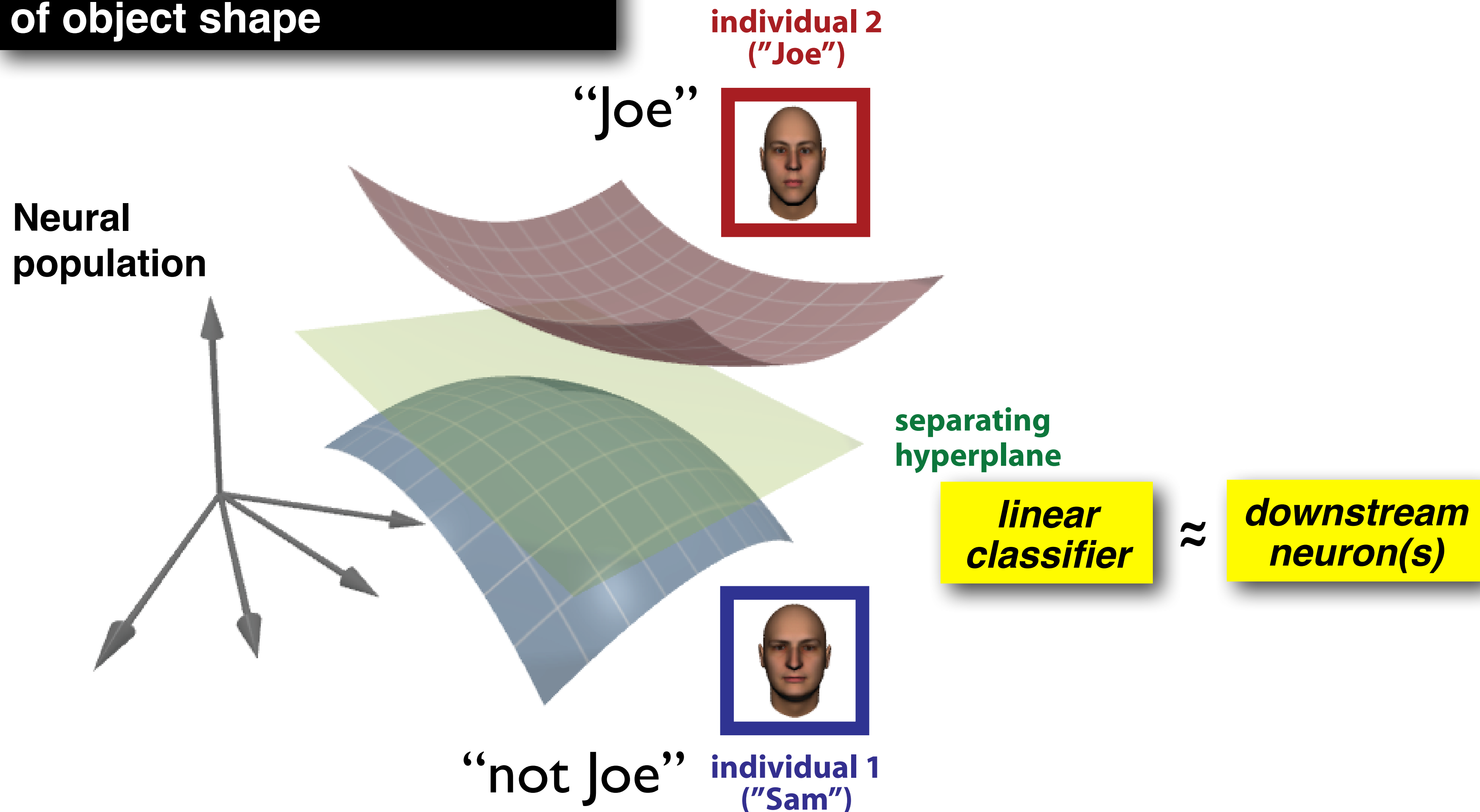
IT-like representation



The computational crux of object and face recognition

A “good” set of visual features: e.g. IT

== “Explicit” representation
of object shape

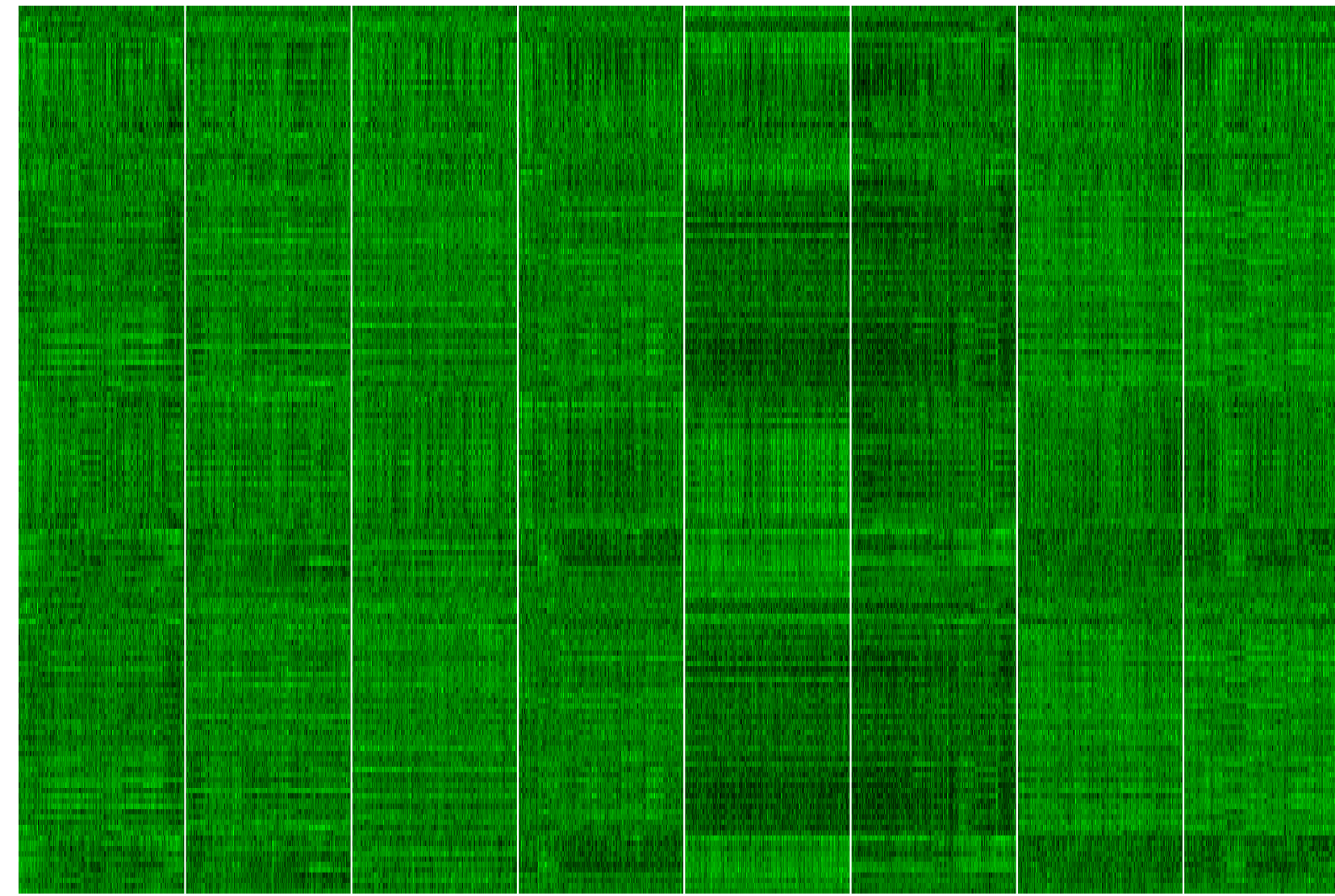


measure

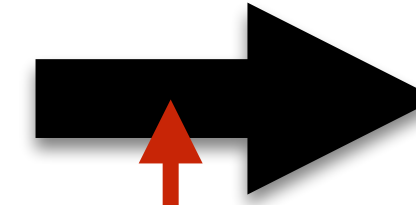
4

Test population decoding models that can fully explain behavior

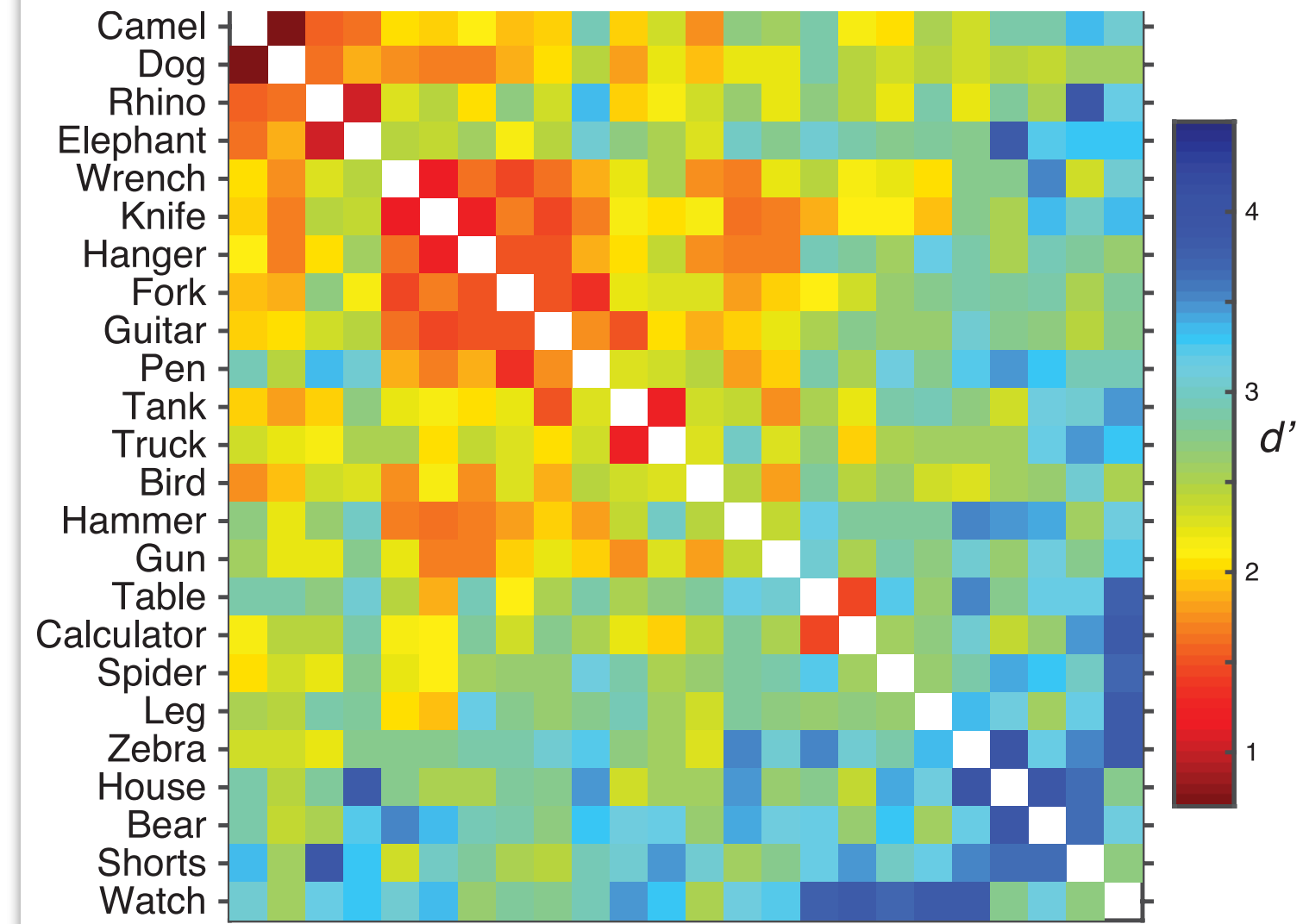
IT "features"



Linear decoder accurately predicts!

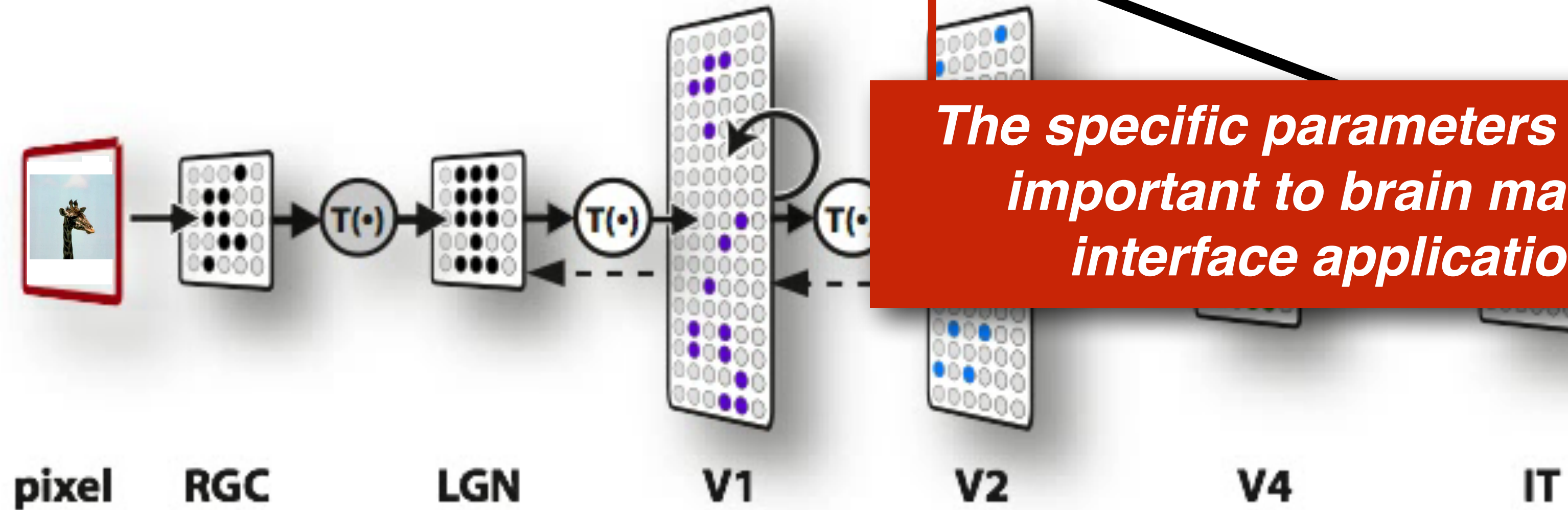


Behavioral performance on categorization tasks



Majaj, Hong, Solomon, & DiCarlo, *J Neuro* (2015)
Hong*, Yamins*, Majaj & DiCarlo. *Nat. Neuro.* (2016)

The specific parameters here are important to brain machine interface applications.



measure

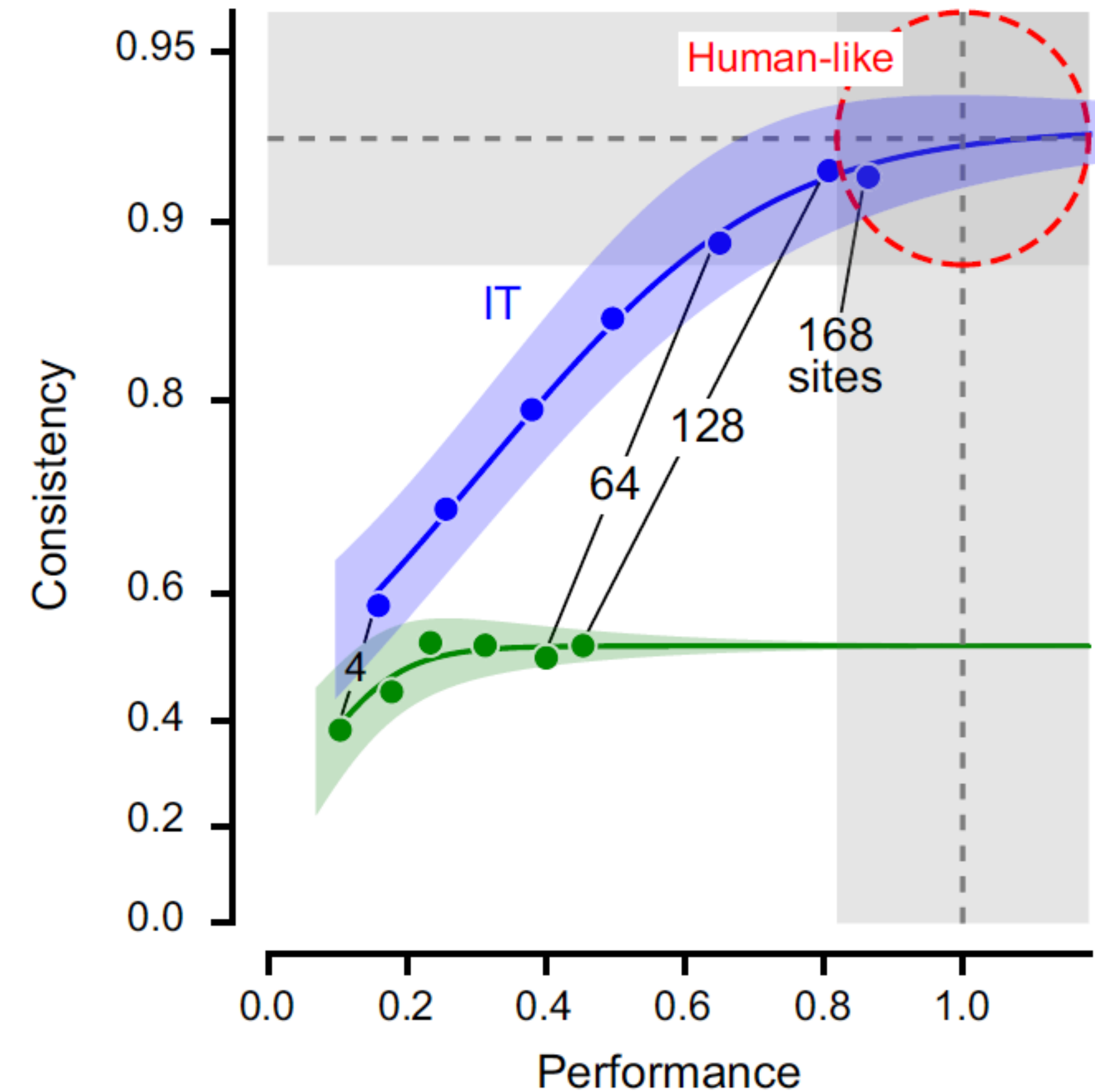
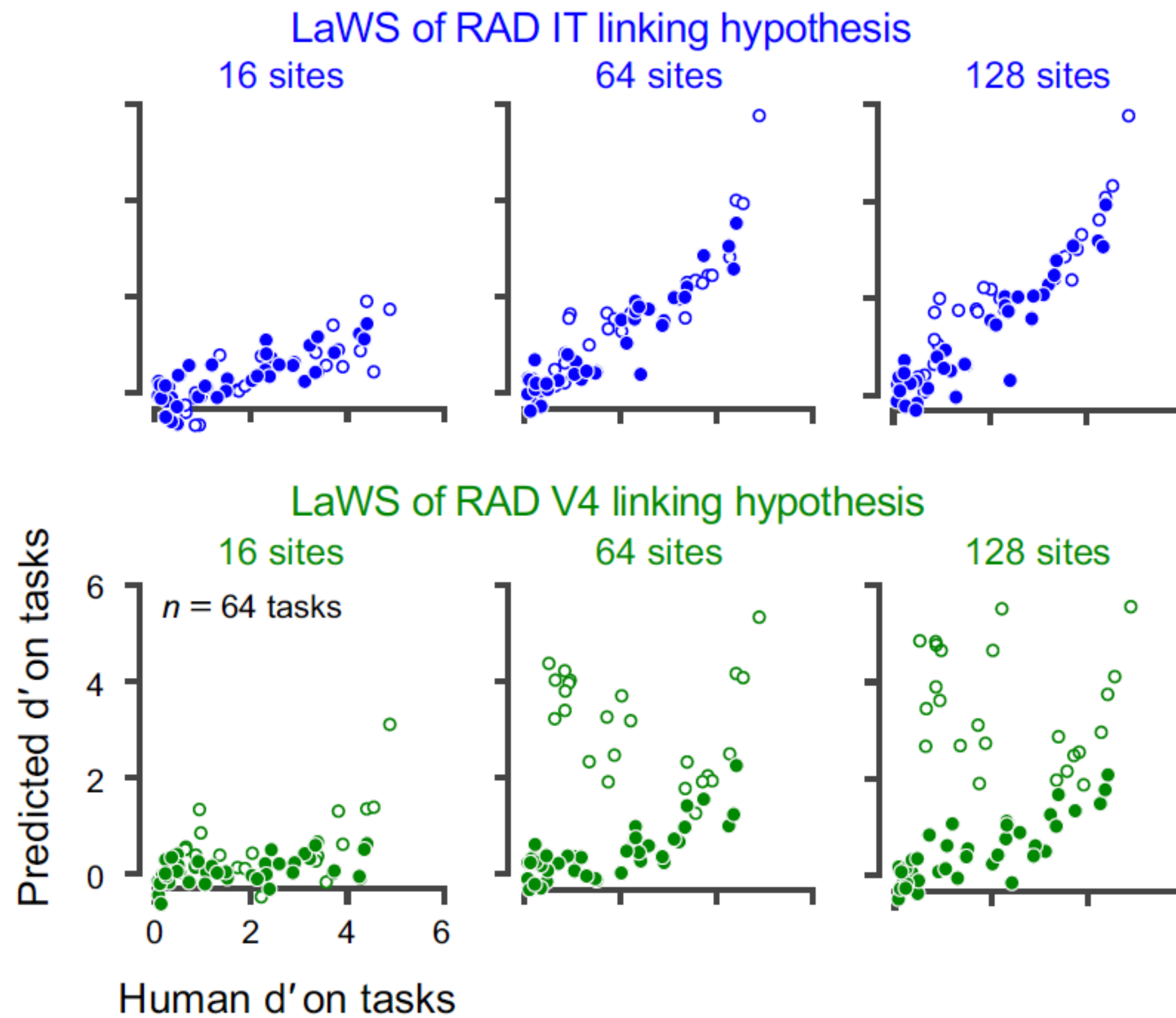
4

Test
deco
mod
fully
beha

Behavioral performance on categorization tasks

Camel
Dog

Linear



pixel

RGC

LGN

V1

V2

V4

IT

uro (2015)
Neuro. (2016)

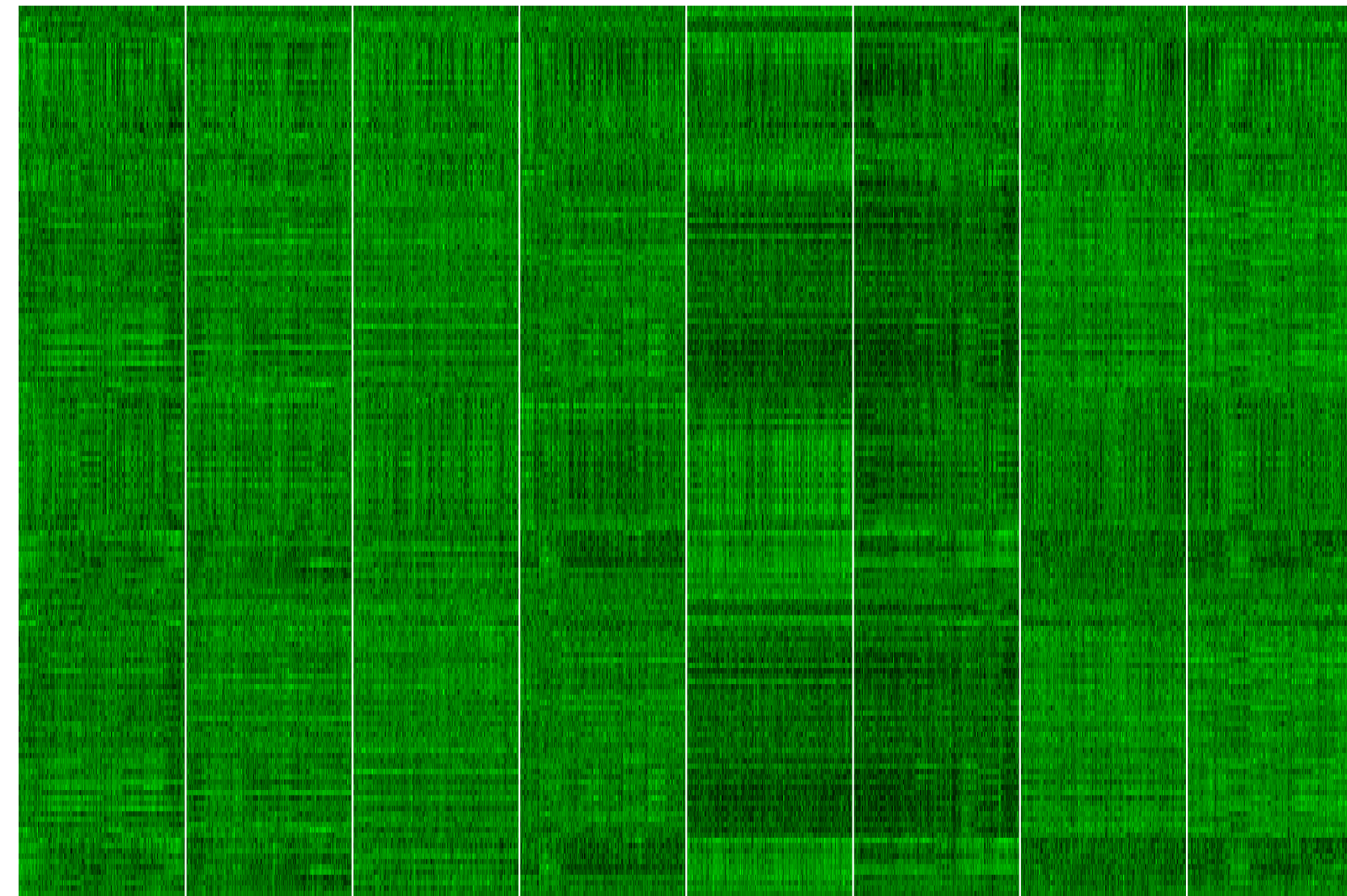
are
e

Test against finer grain behavior

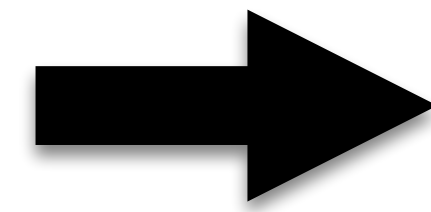
5

Test whether the same population decoding models can explain finer grain behavioral measurements

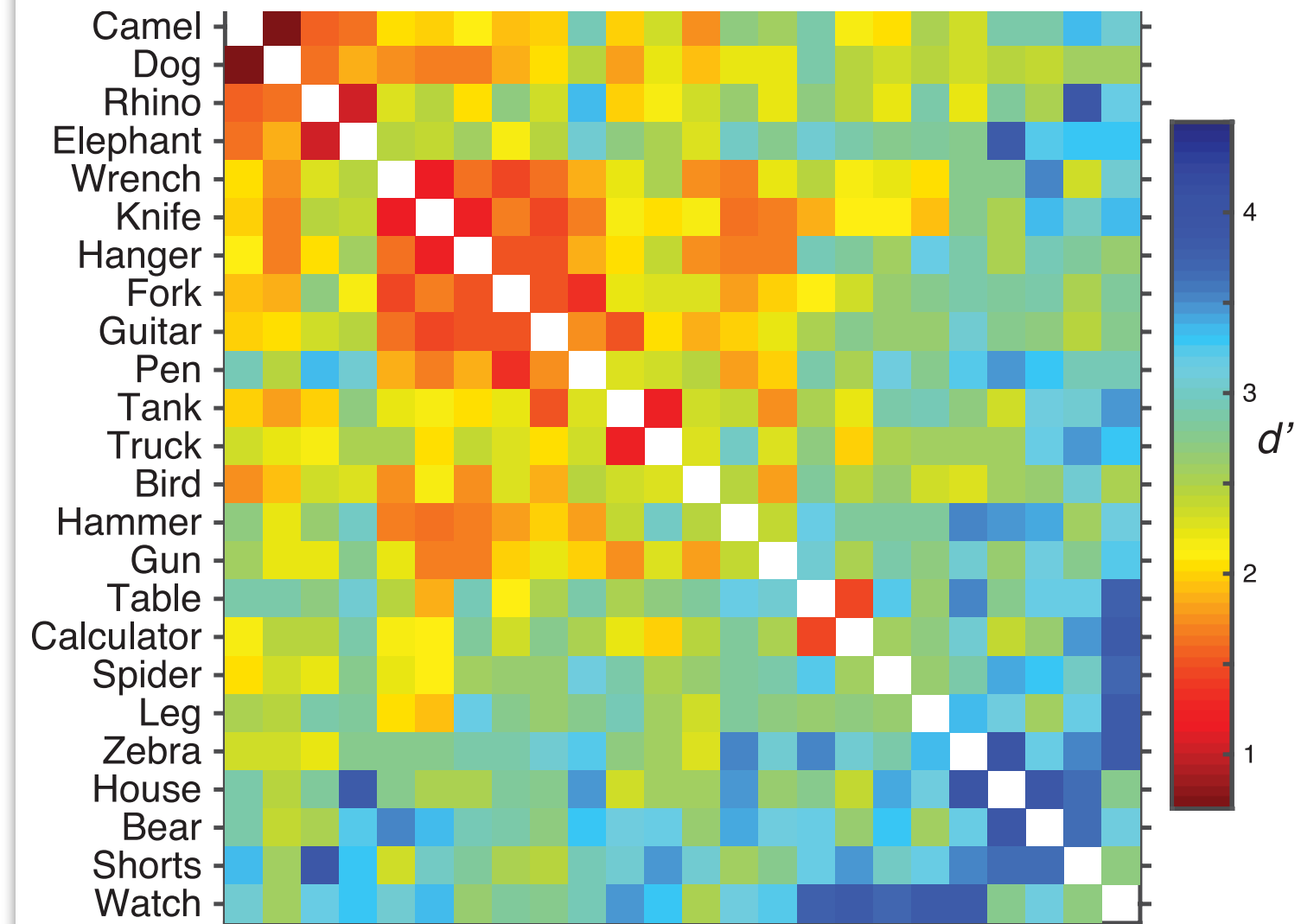
IT "features"



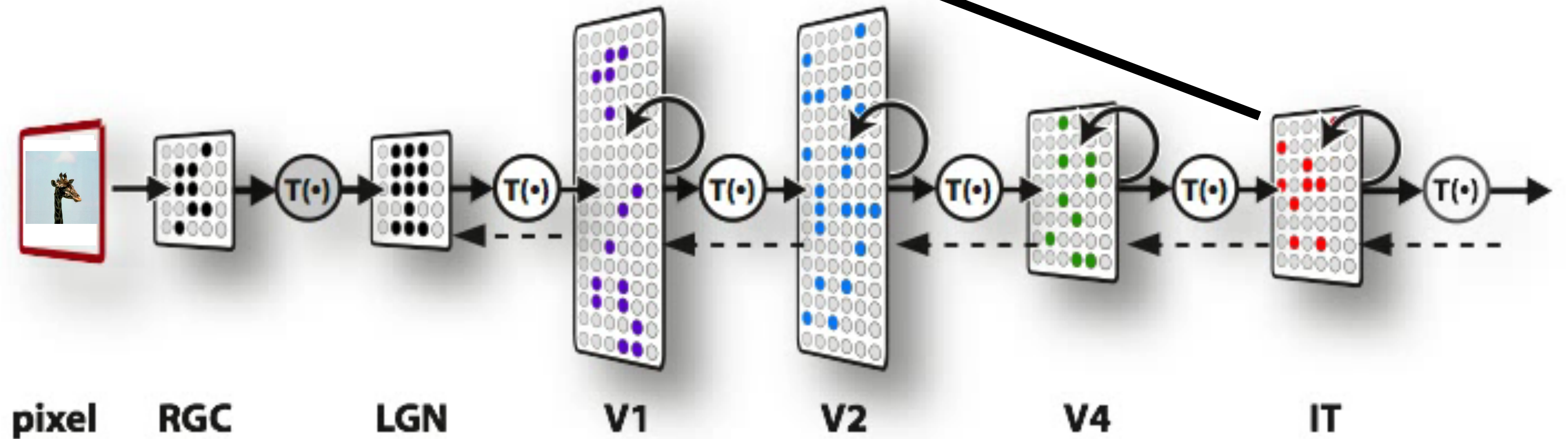
Linear decoder accurately predicts!



Behavioral performance on categorization tasks



Majaj, Hong, Solomon, & DiCarlo, *J Neuro* (2015)
 Hong*, Yamins*, Majaj & DiCarlo. *Nat. Neuro.* (2016)

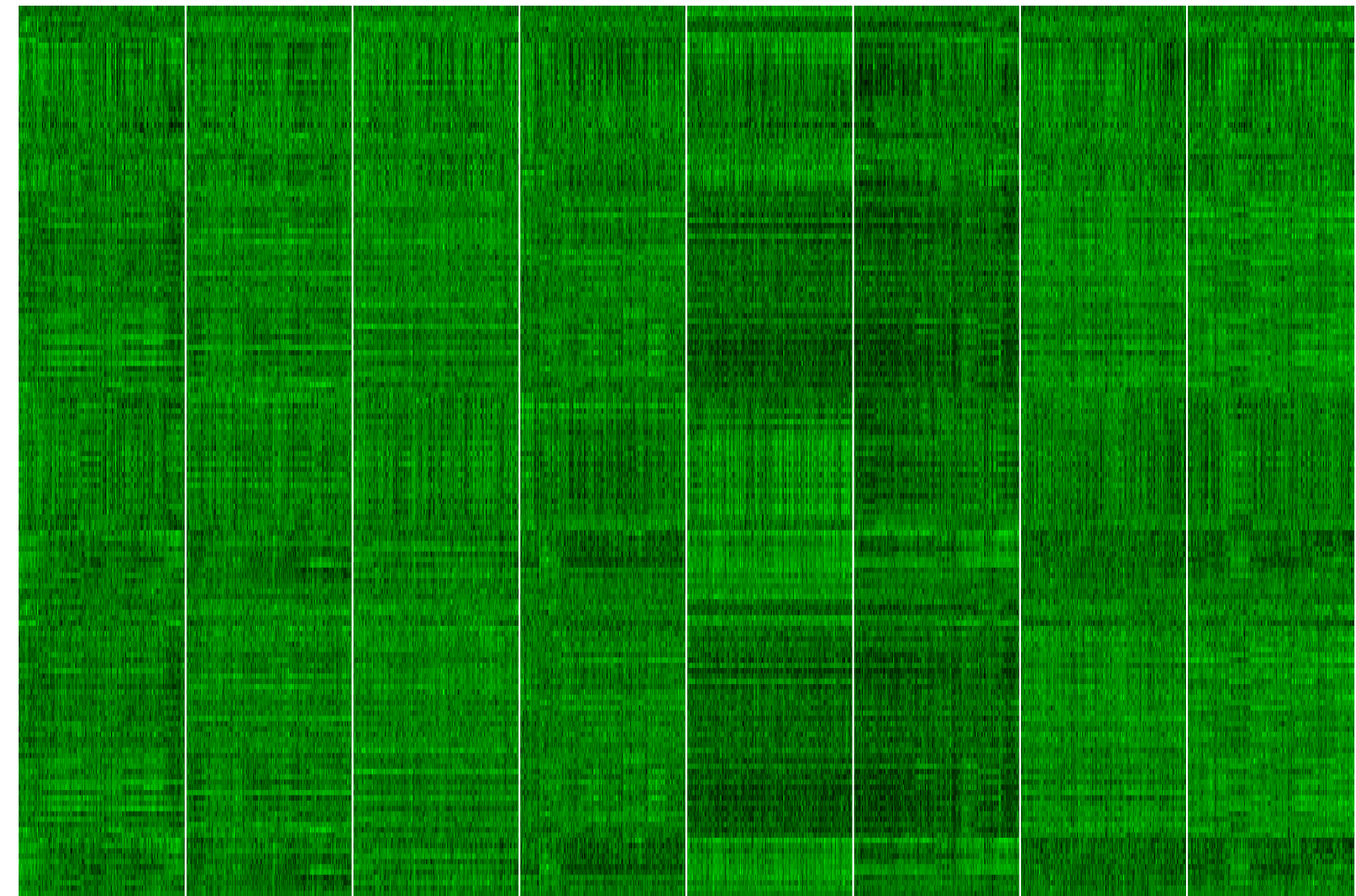


Test against finer grain behavior

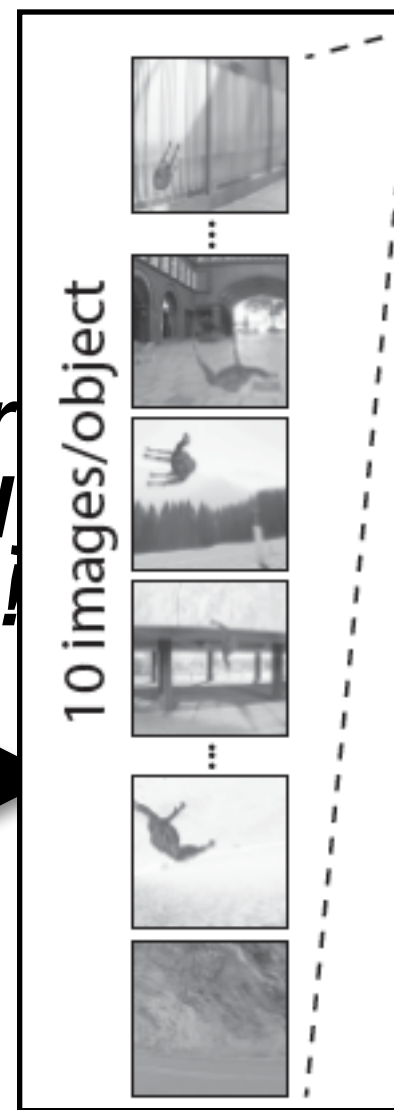
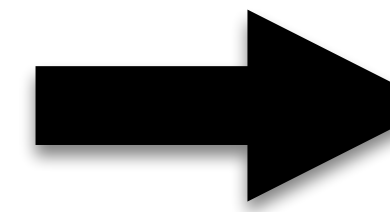
5

Test whether the same population decoding models can explain finer grain behavioral measurements

IT "features"

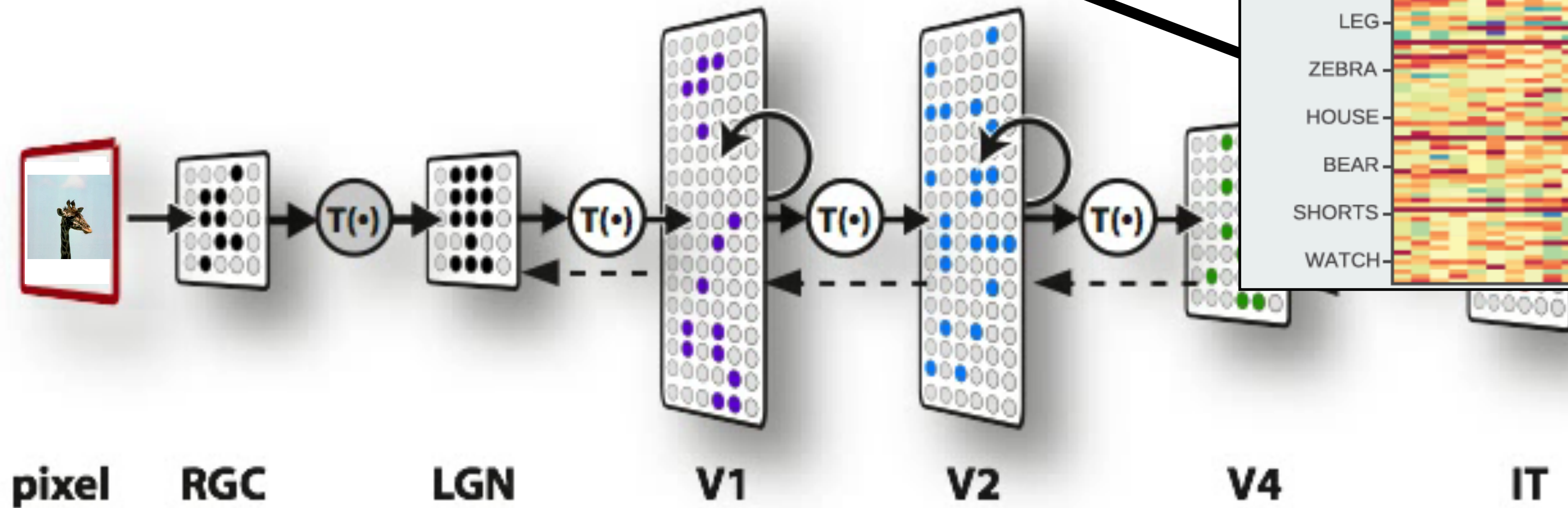
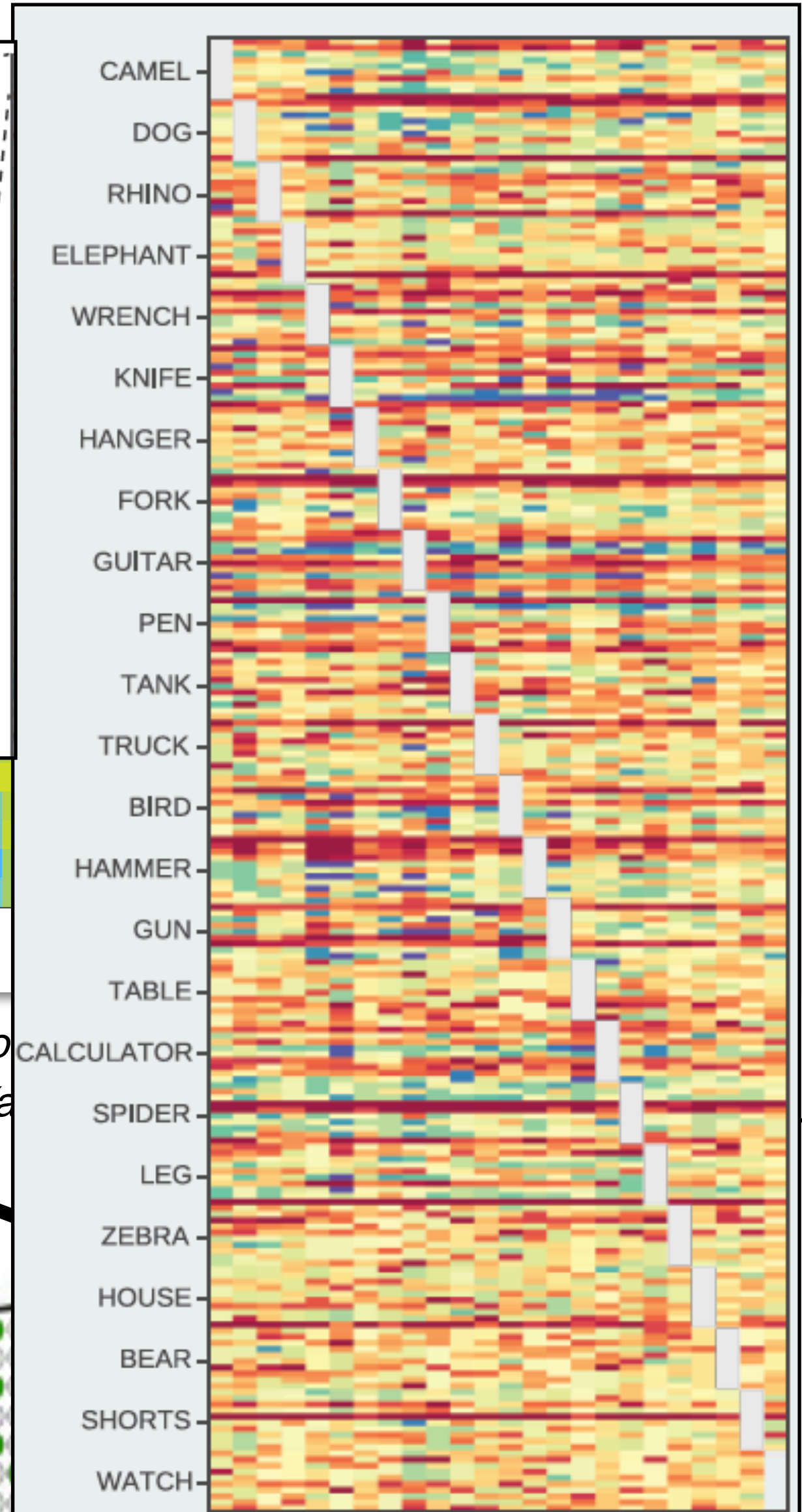


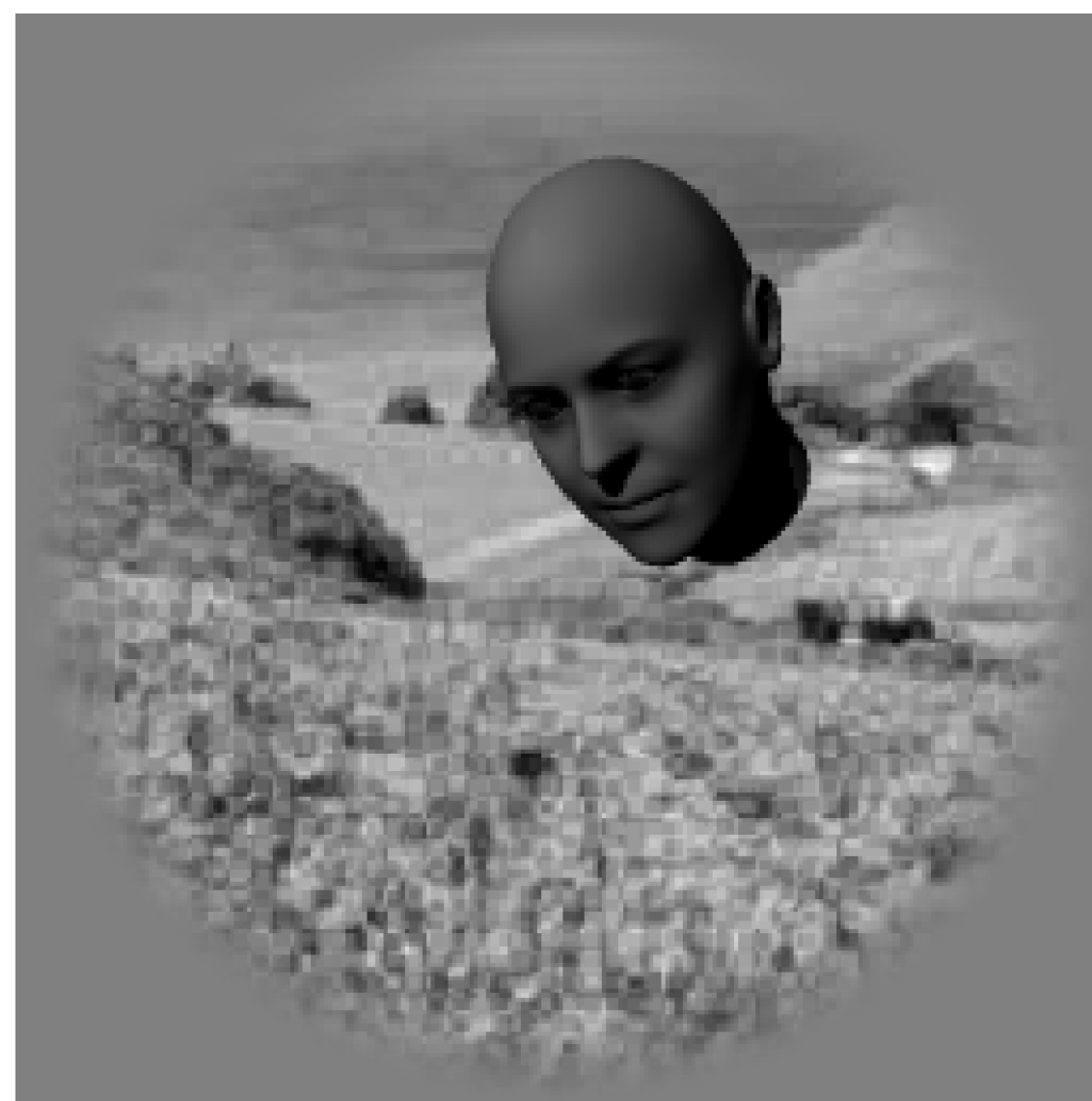
Linear decoder accurately predicts!



Zebra
House
Bear
Shorts
Watch

Majaj, Hong*, Ya

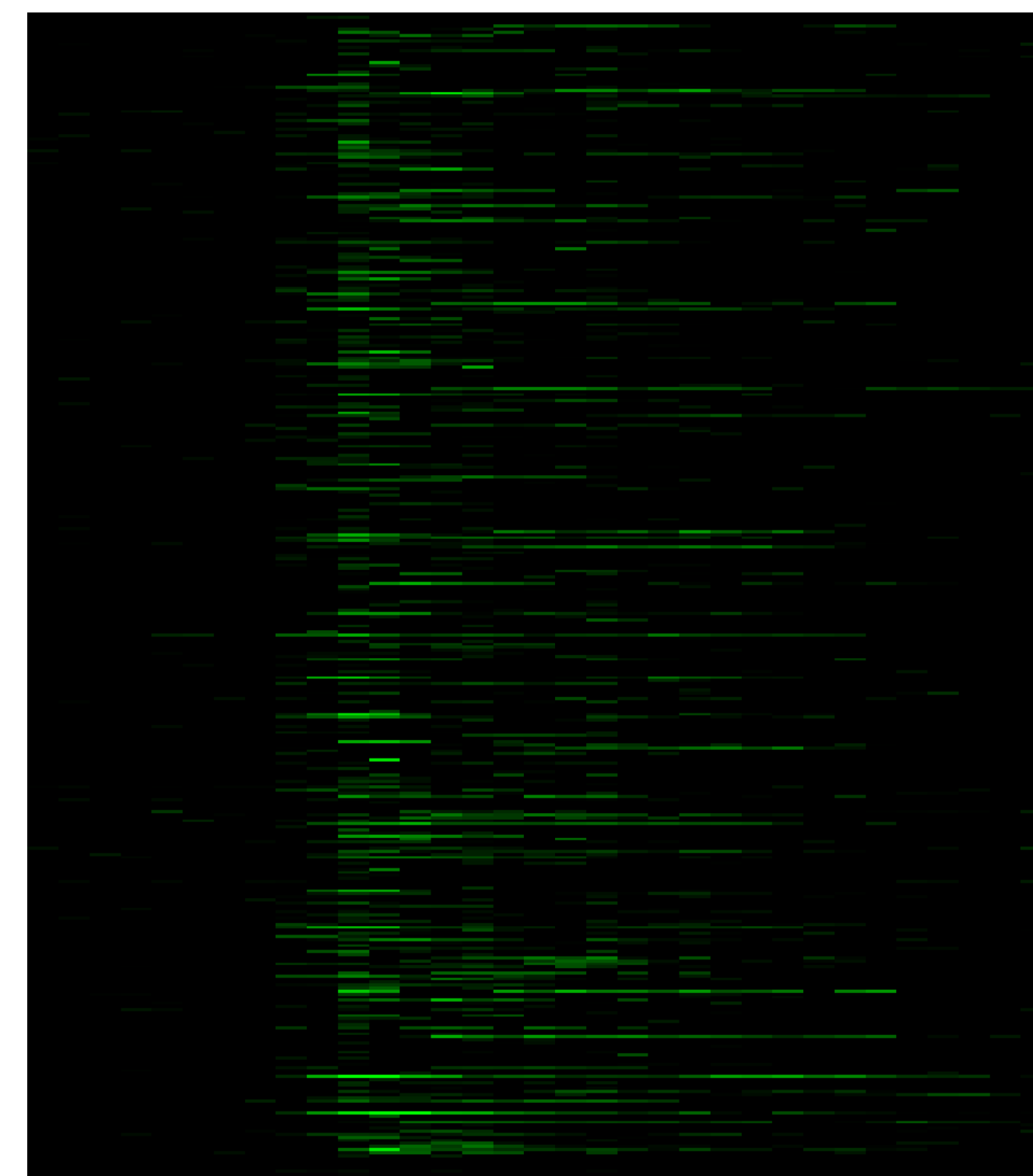




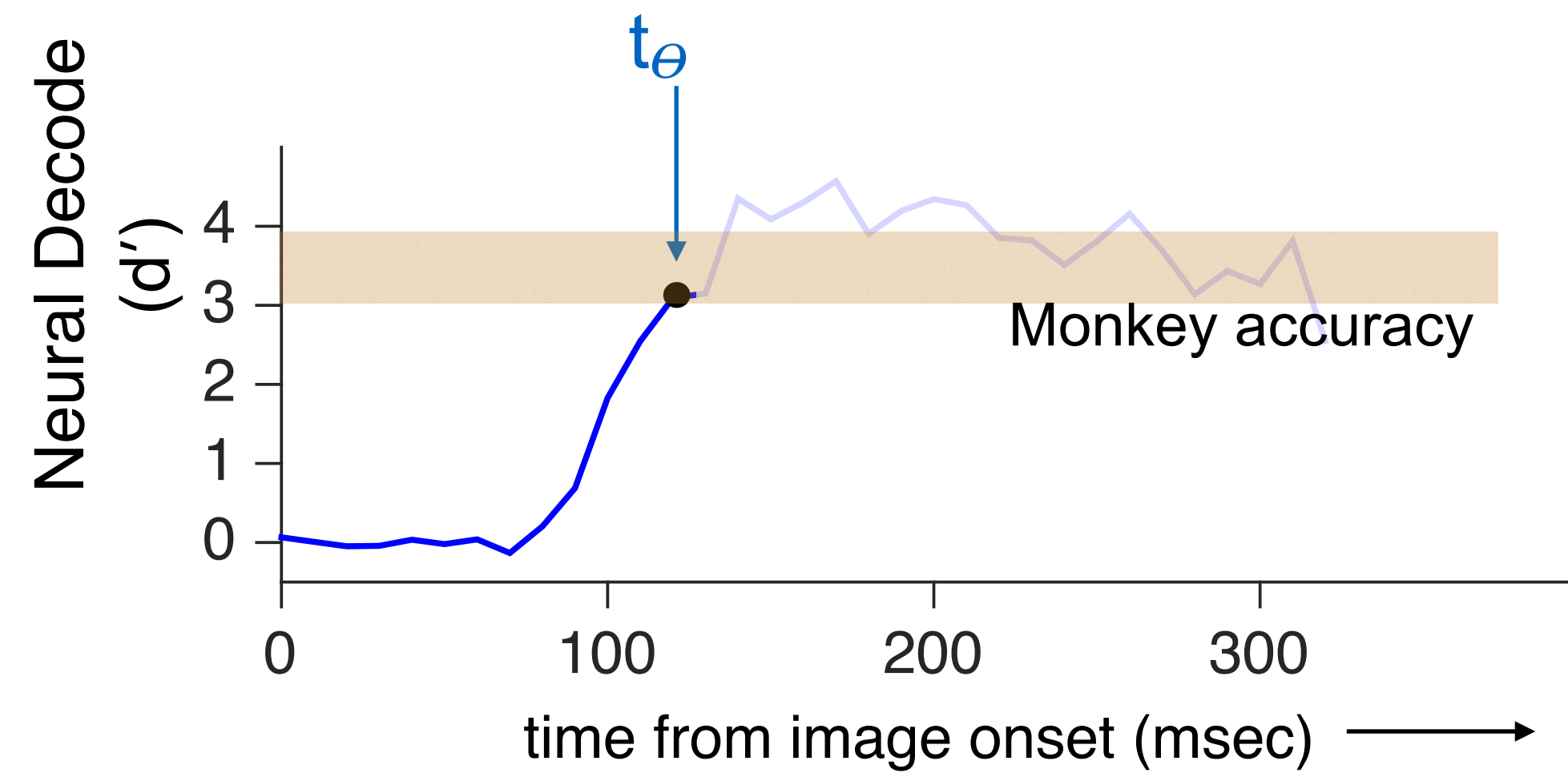
FACE

n=383

IT population vector



Neural activity level (au)

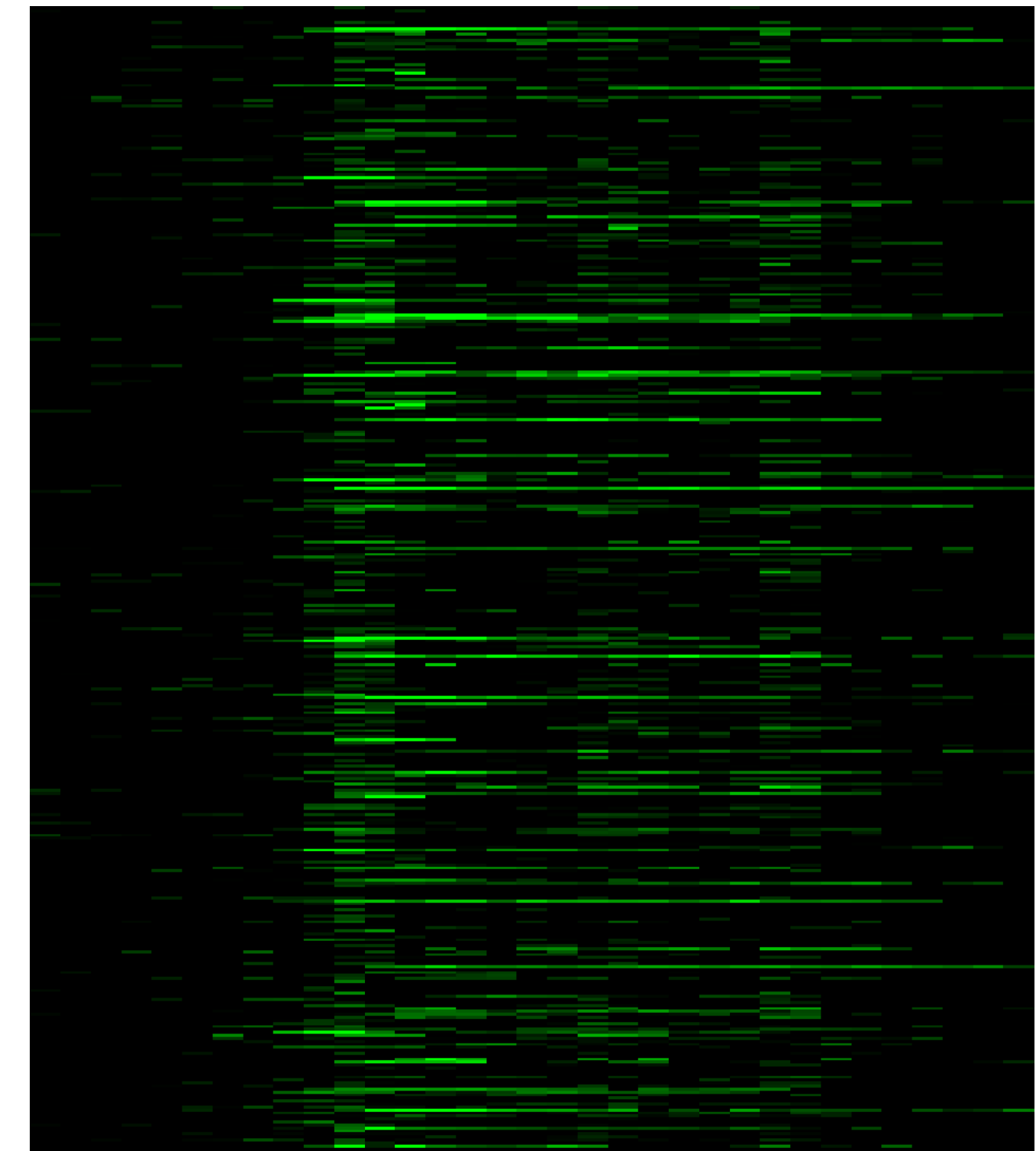




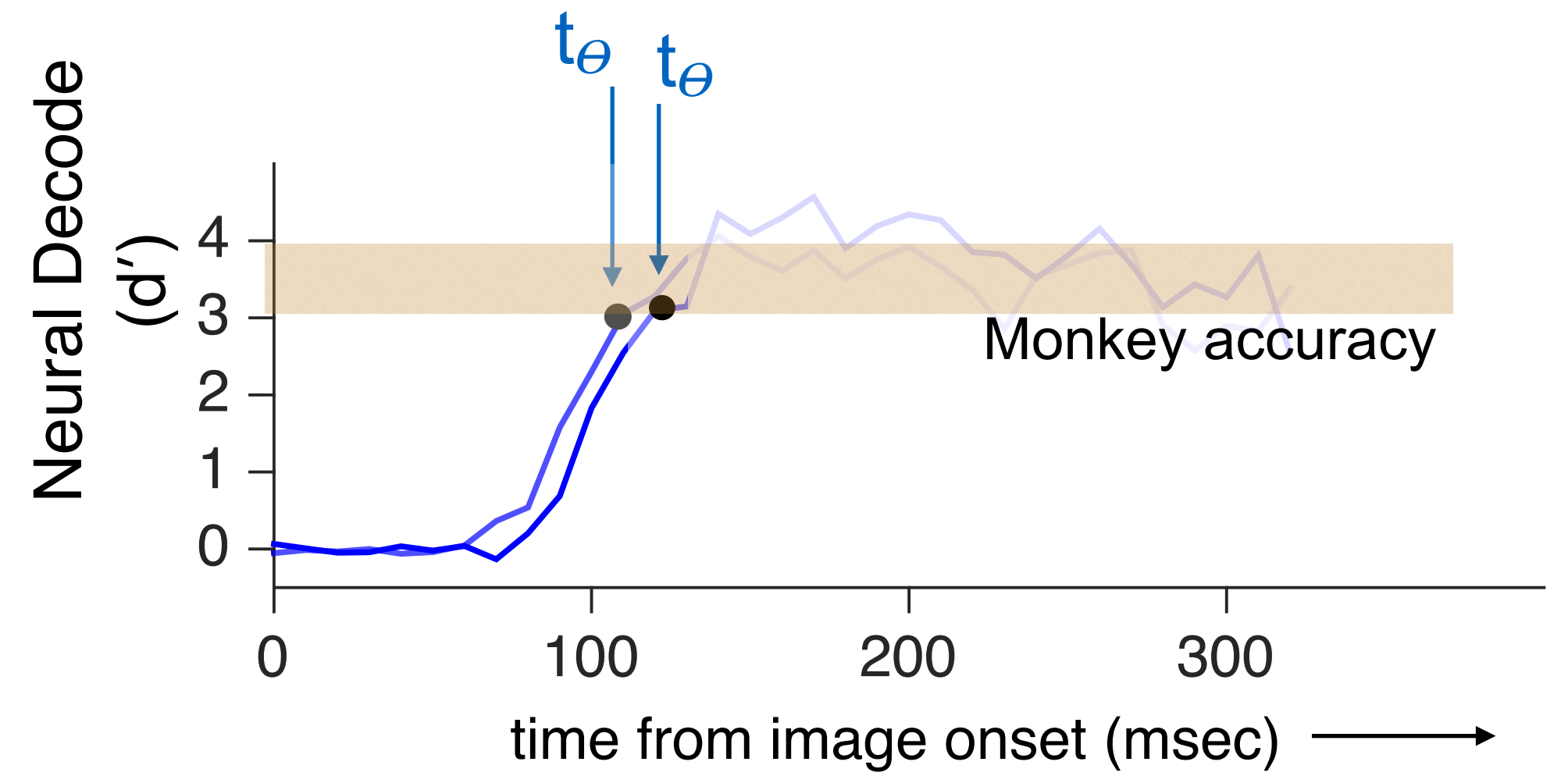
ZEBRA

n=383

IT population vector



Neural activity level (au)

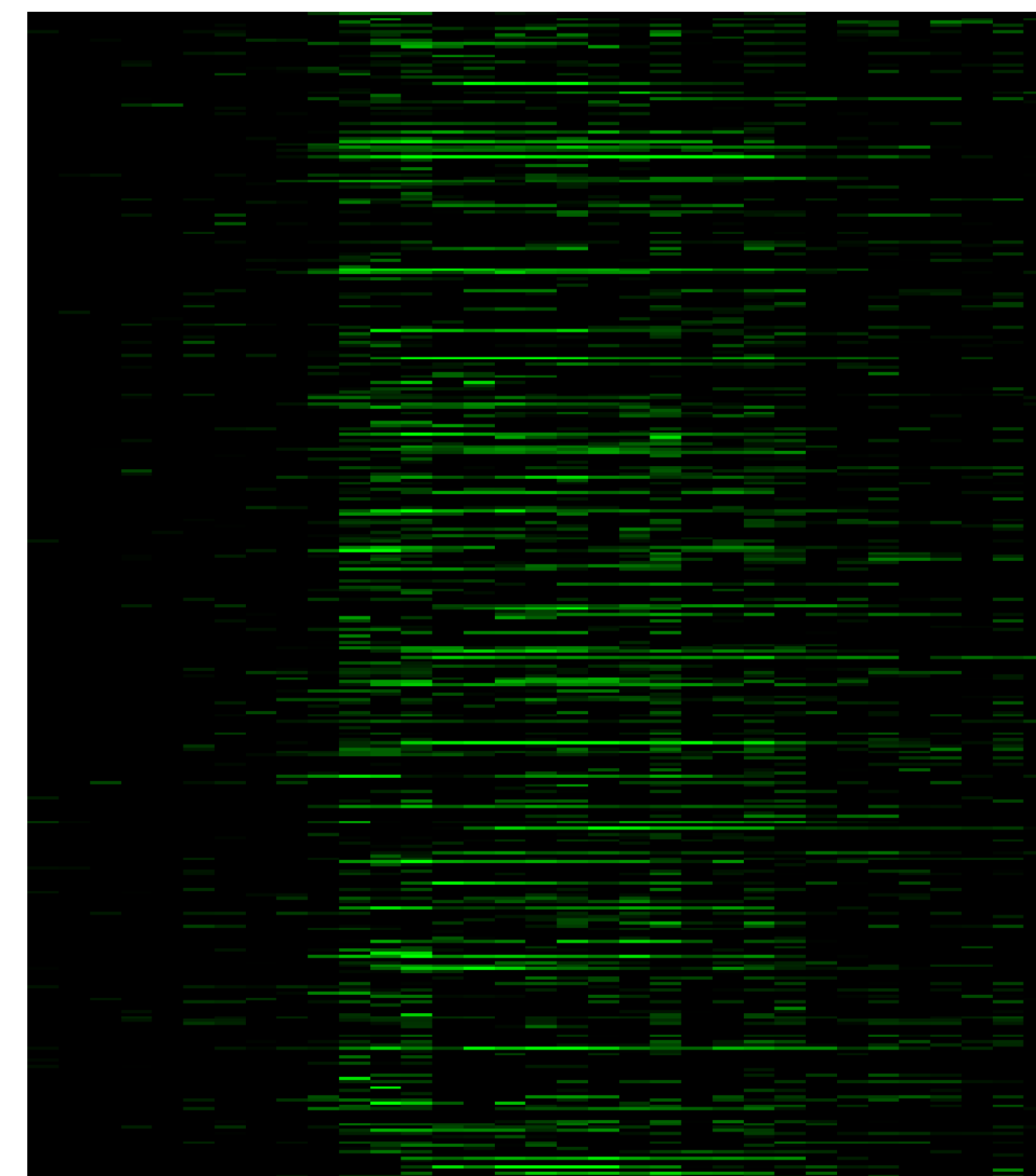




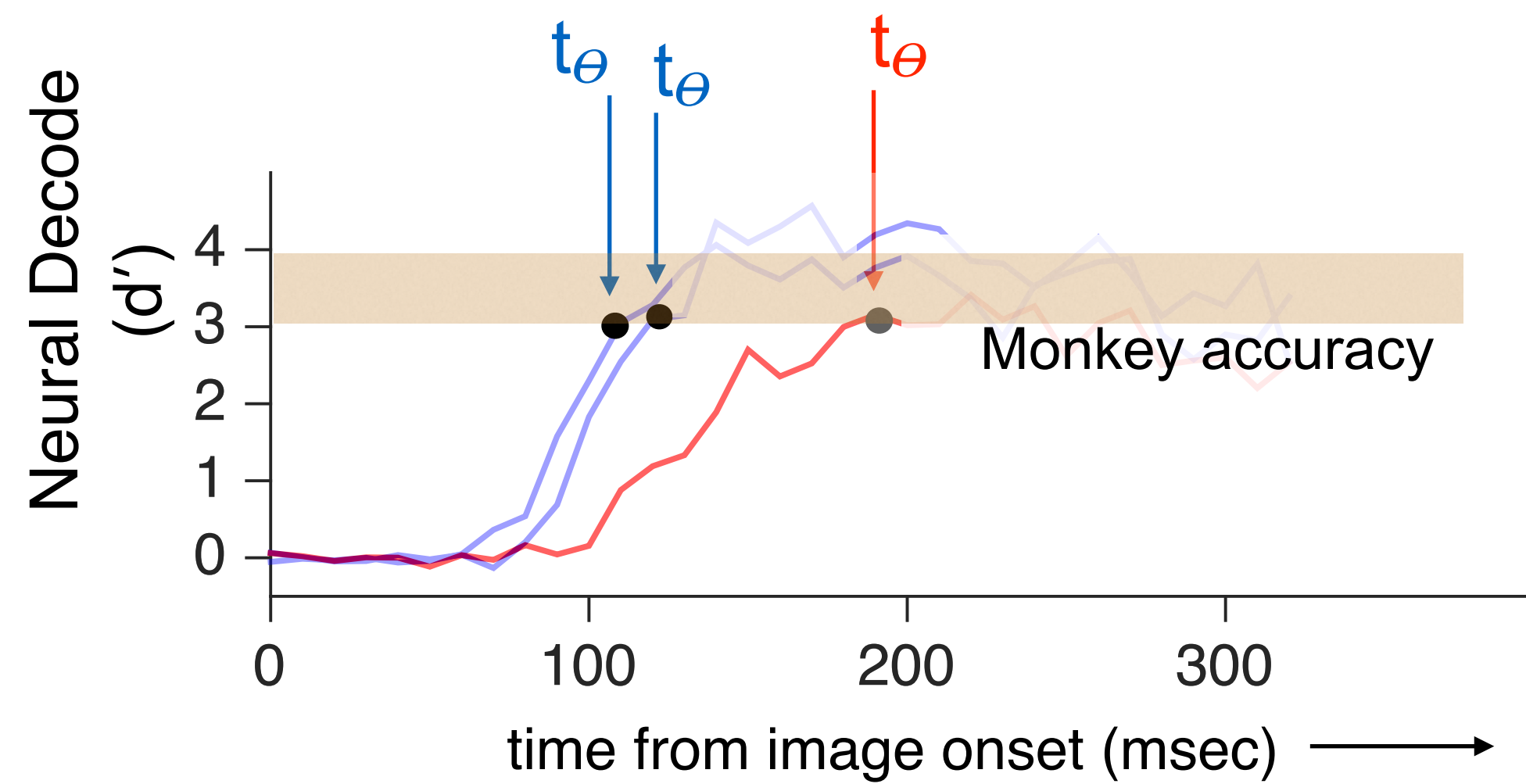
CAR

n=383

IT population vector



Neural activity level (au)

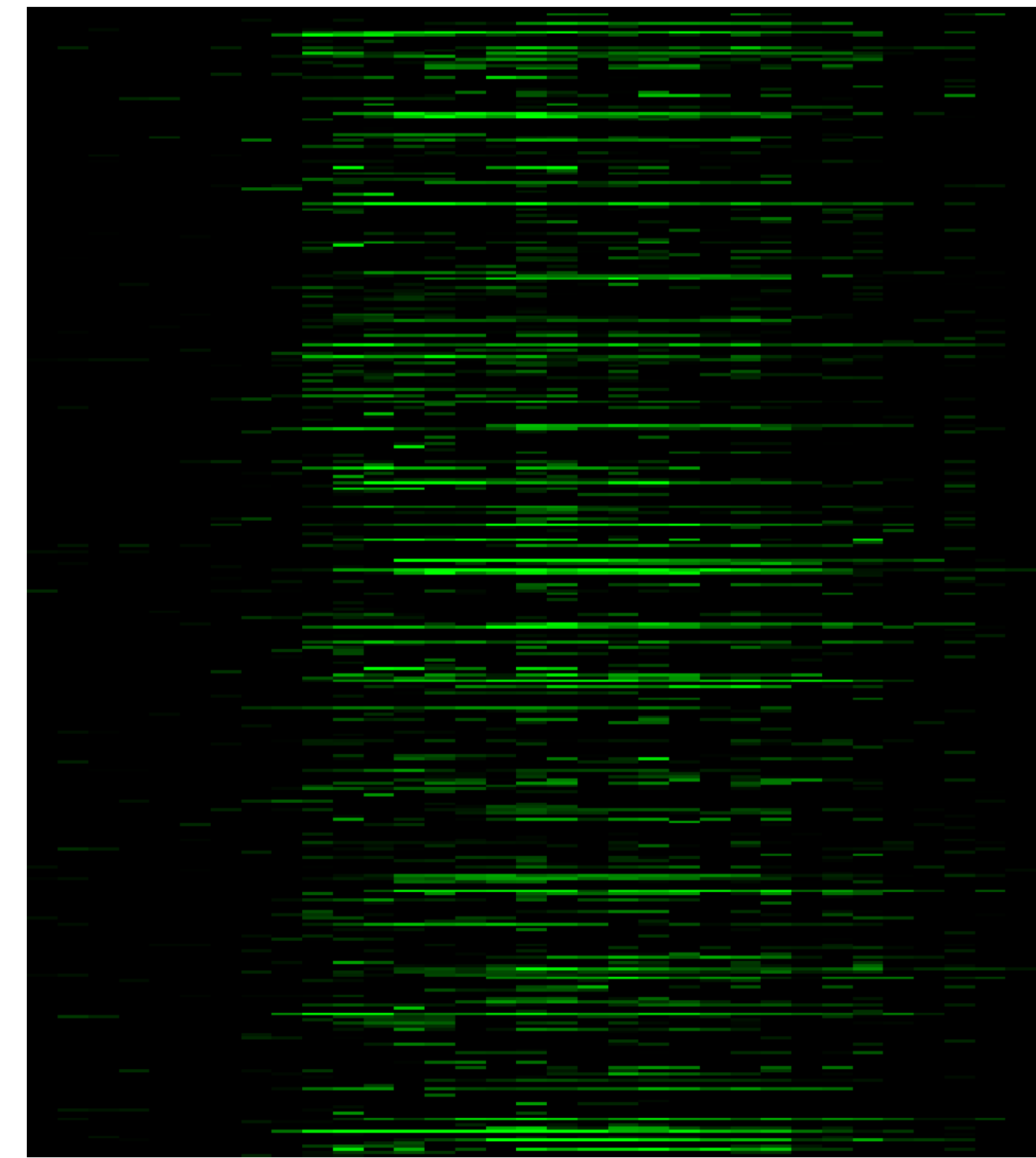




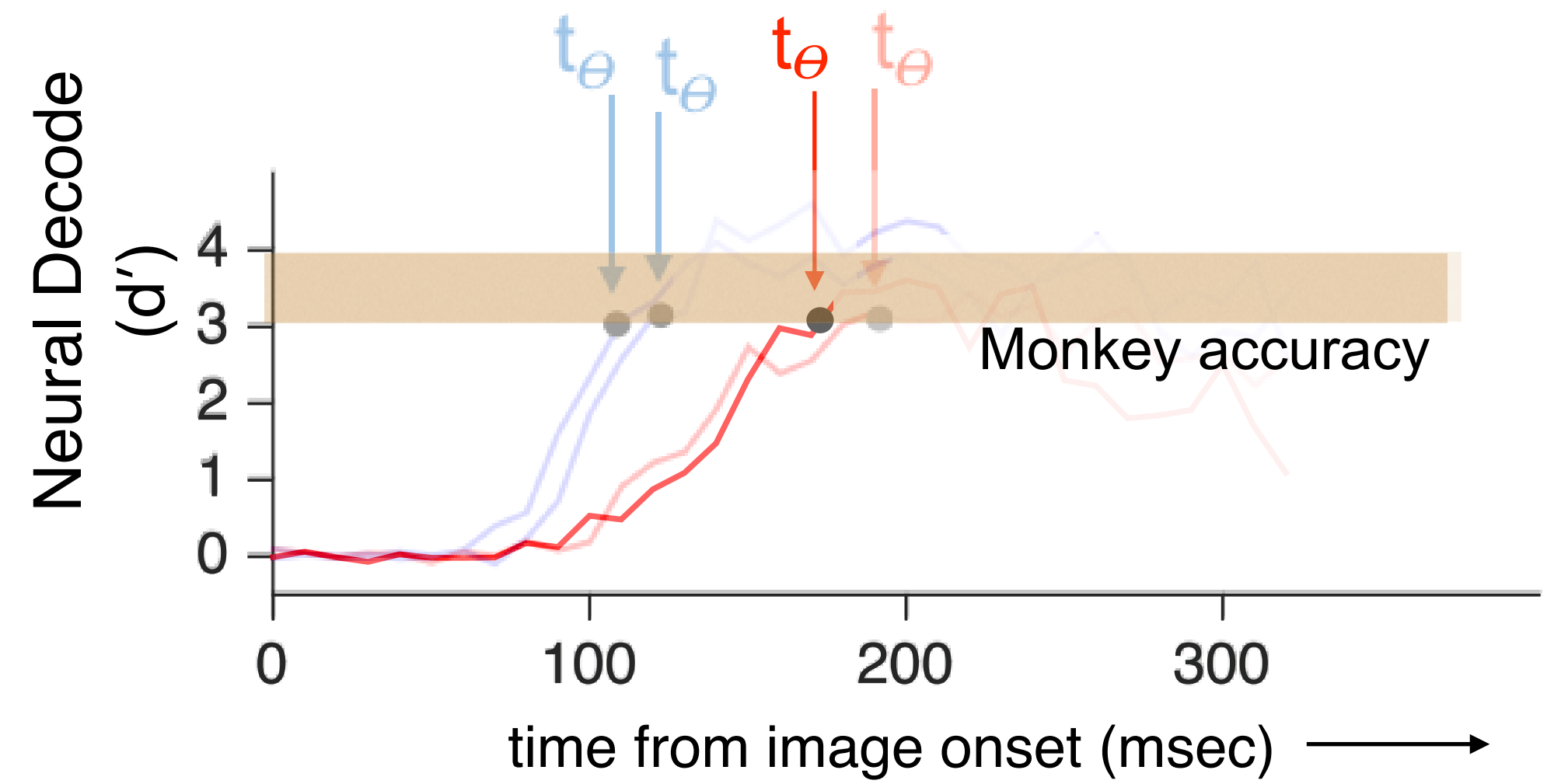
DOG

n=383

IT population vector

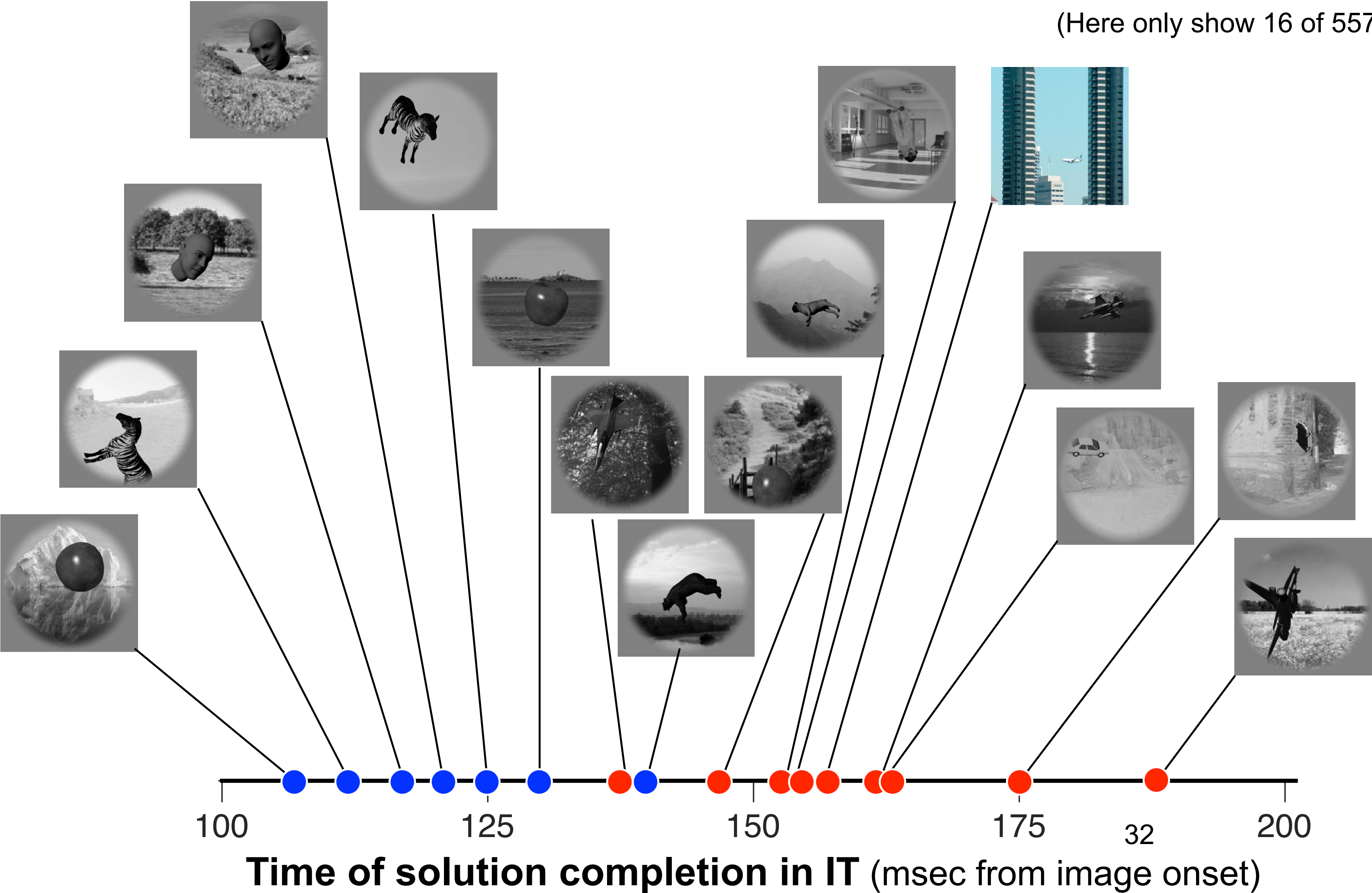


Neural activity level (au)



We precisely measured time of brain's penultimate solution product for thousands of images

(Here only show 16 of 5570 images measured)

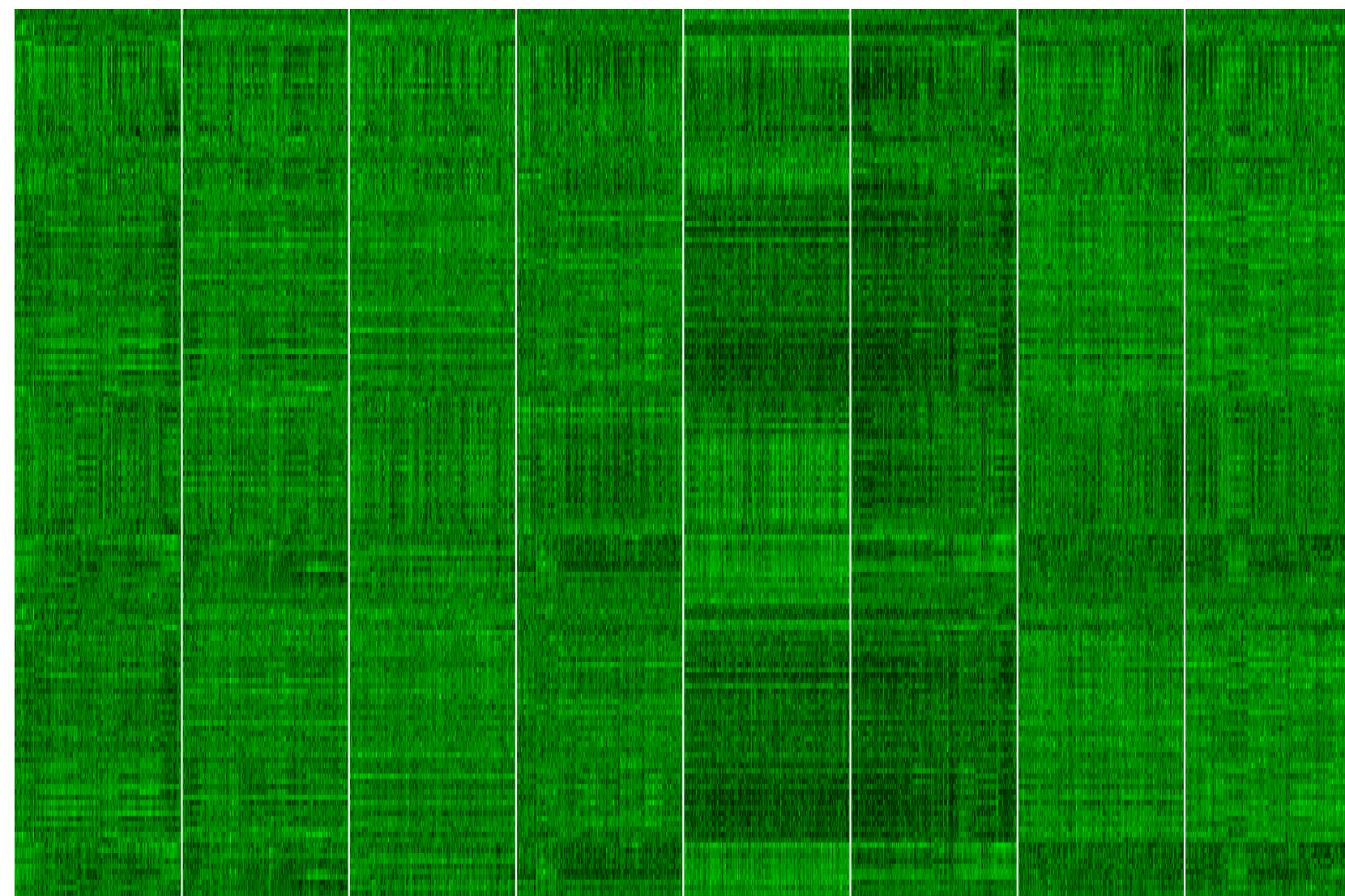


Test against finer grain behavior

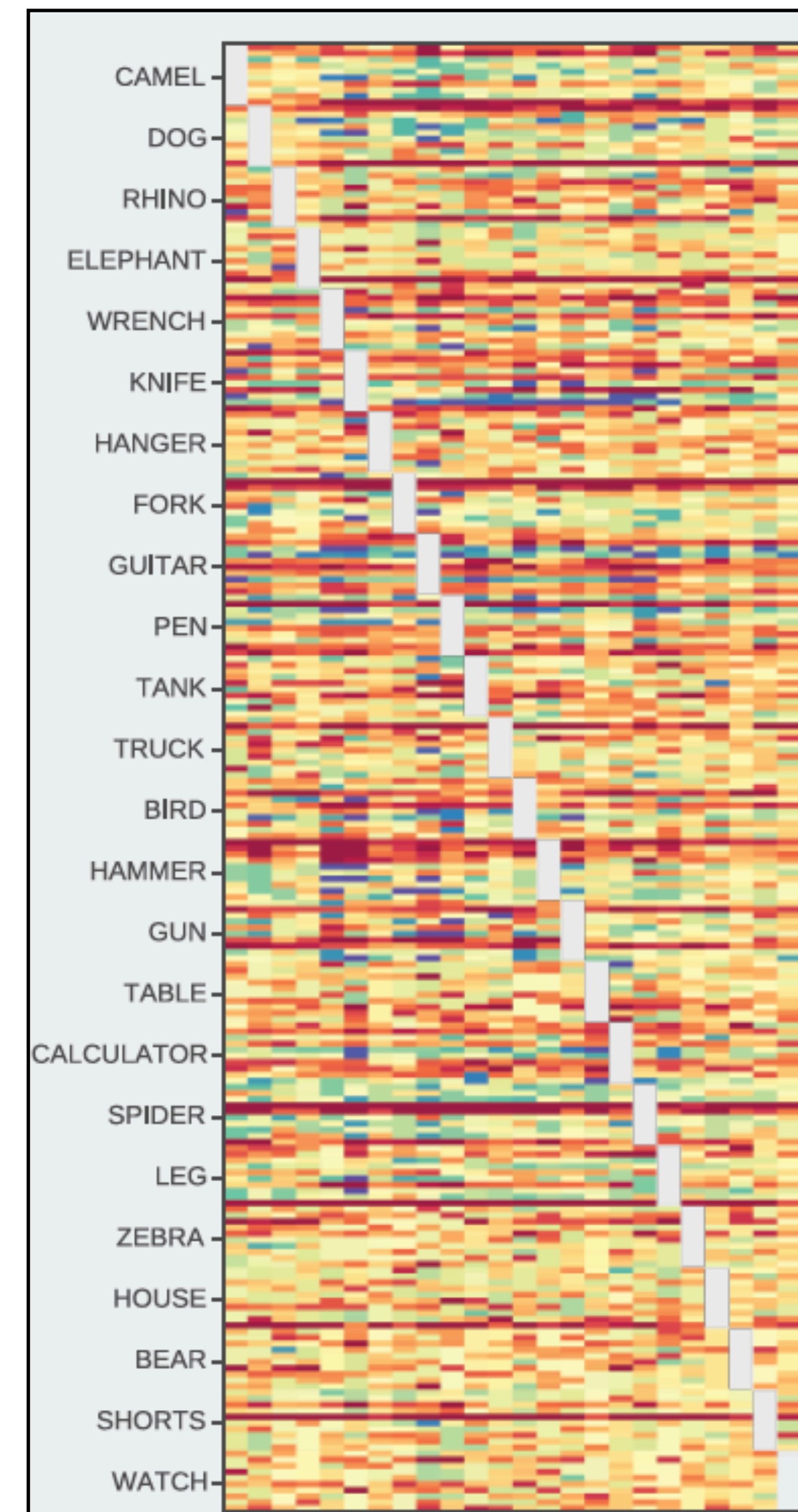
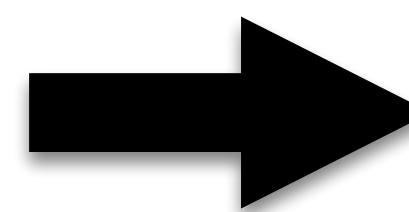
5

Test whether the same population decoding models can explain finer grain behavioral measurements

IT "features"



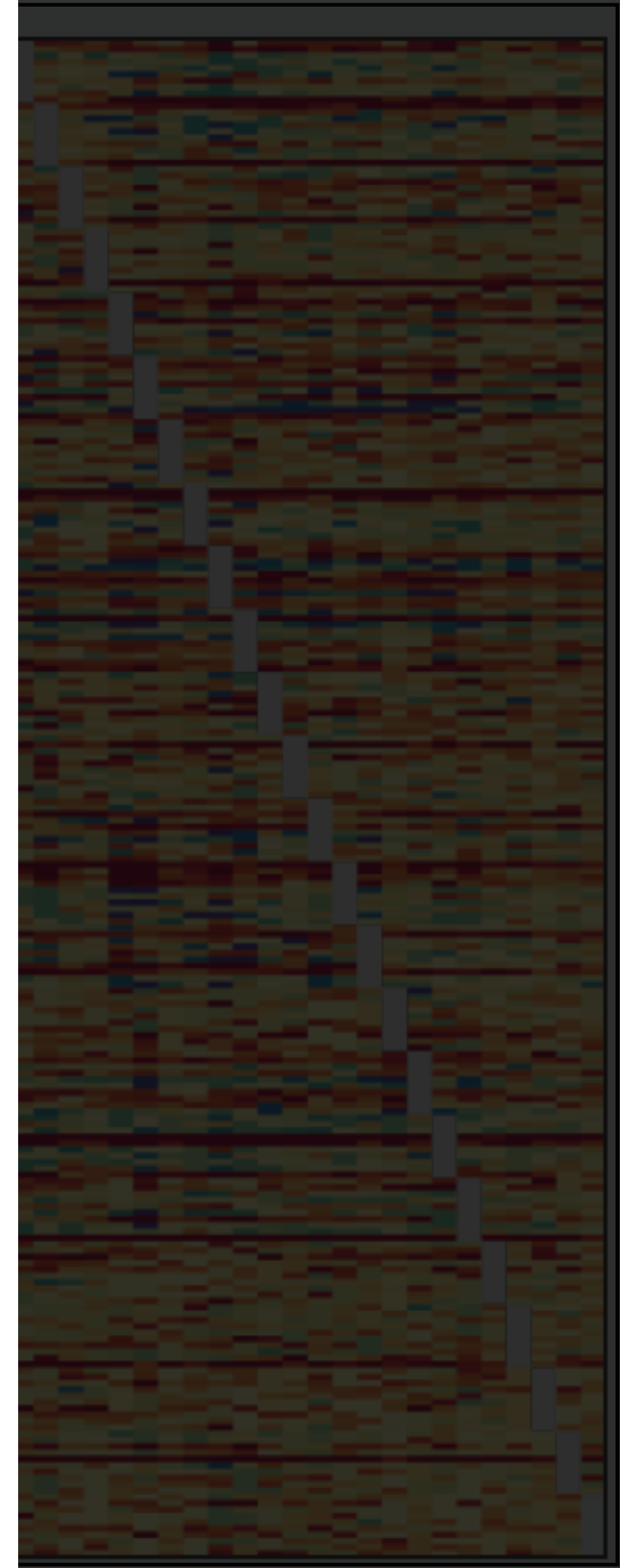
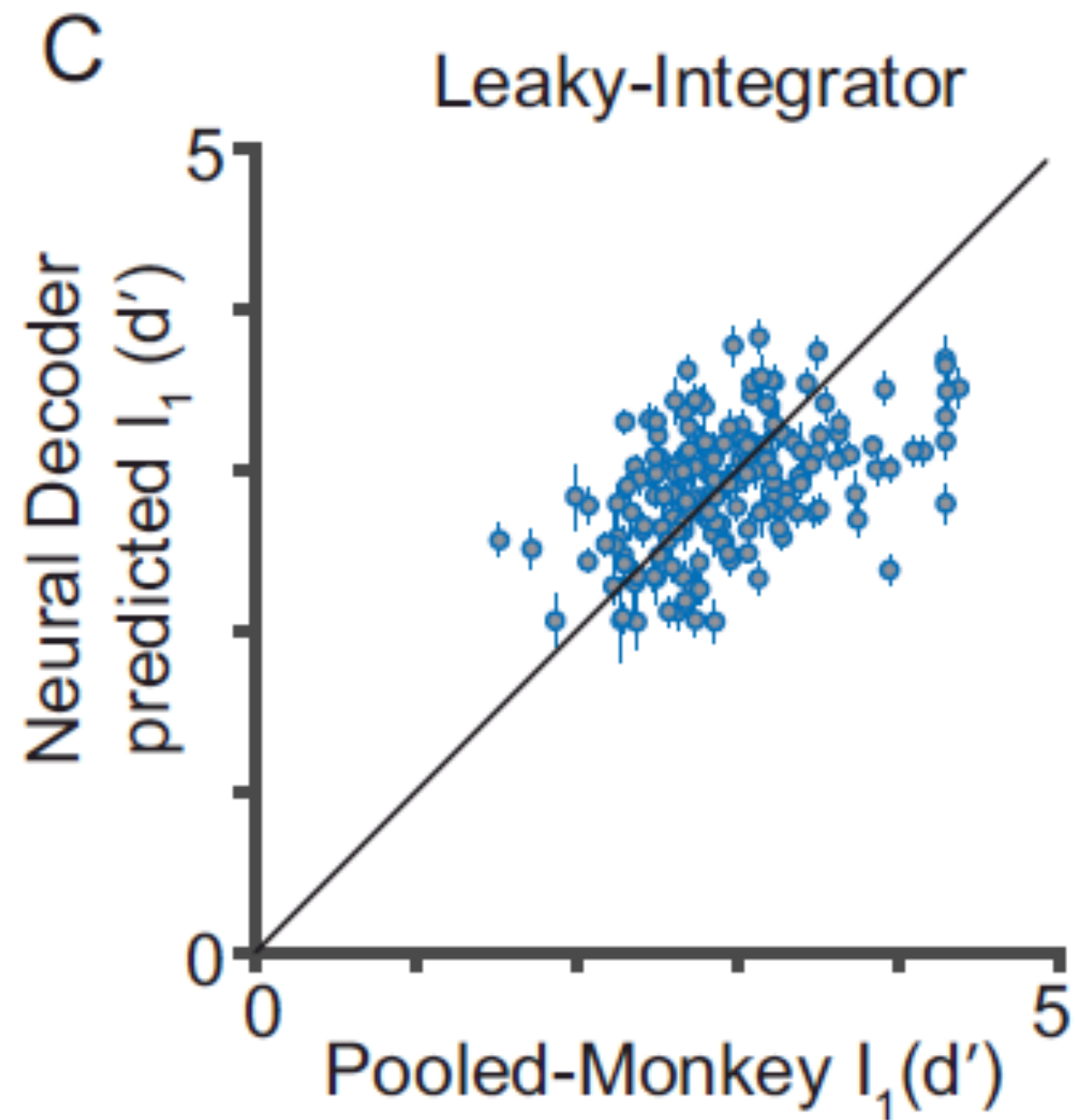
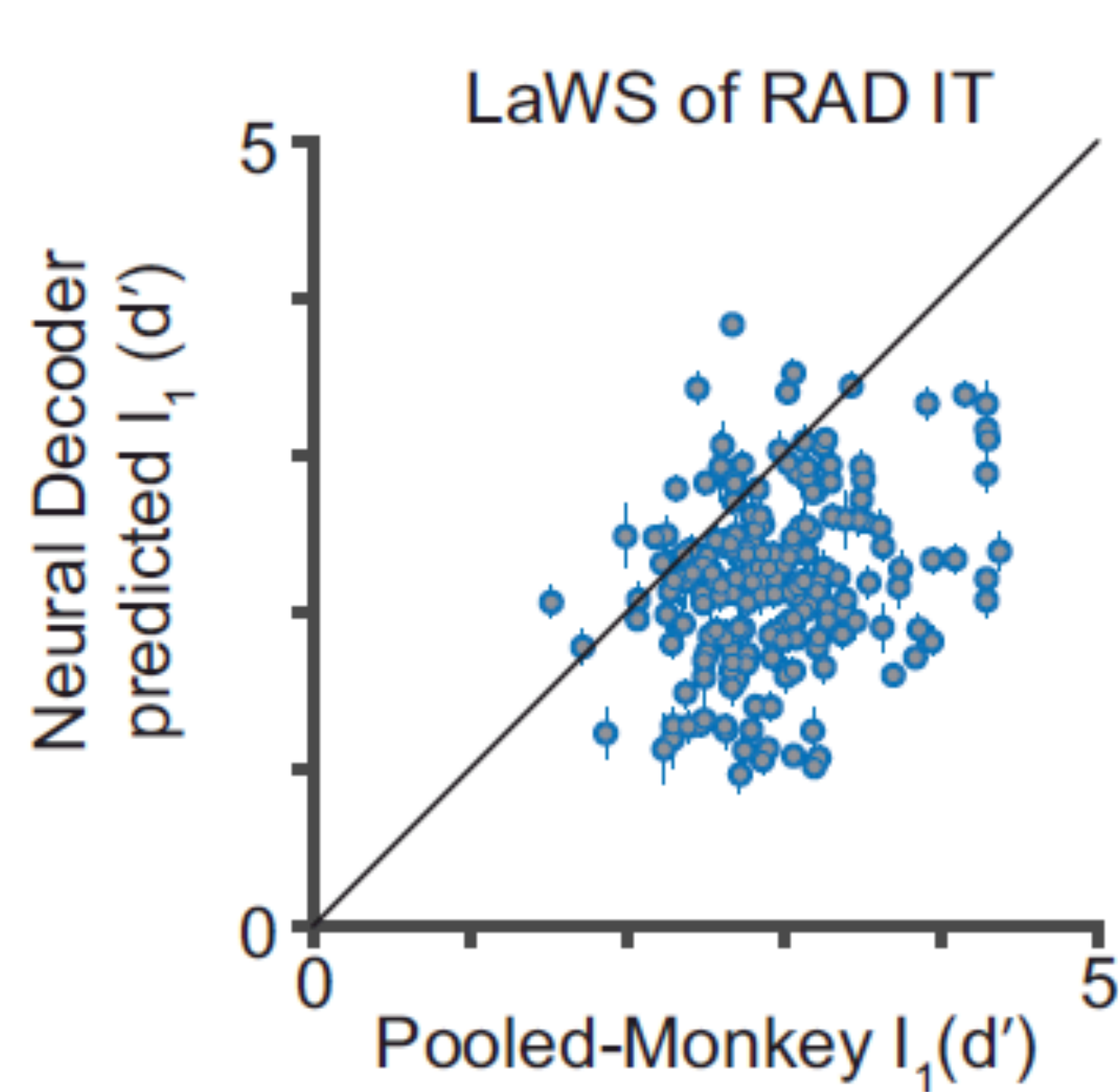
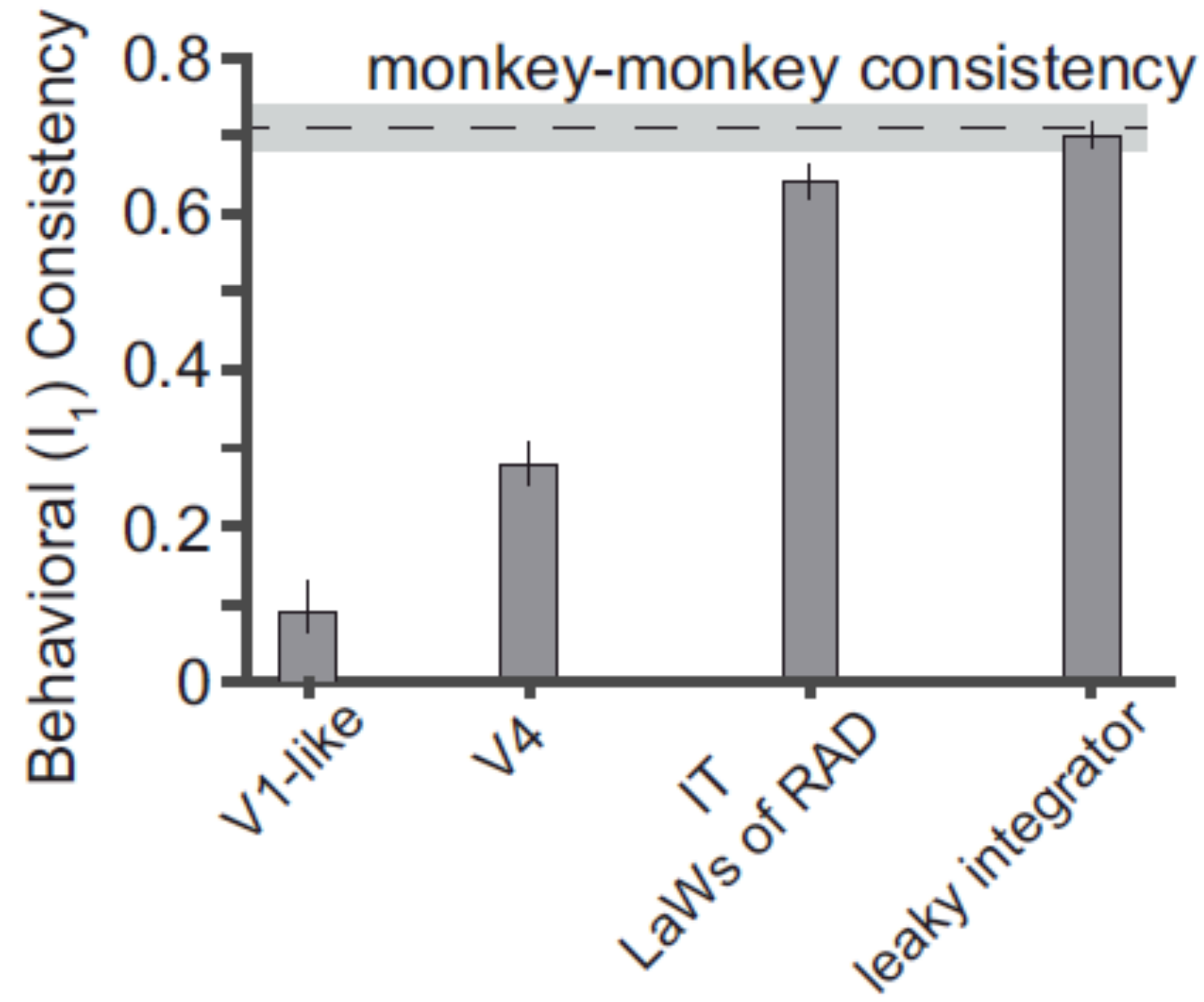
??



Test against finer grain behavior

5

Test whether the same population decoding models can explain finer grain behavioral measurements



THANKS ...

Now you have 19 more days to grill me
