Joined Colloquium of SFB 1287 and SFB 1294

on the **27.11.2020** at **3 pm**

"Cognitive computational neuroscience of vision"

by Prof. Nikolaus Kriegeskorte, PhD

Zuckerman Institute, Columbia University New York, US

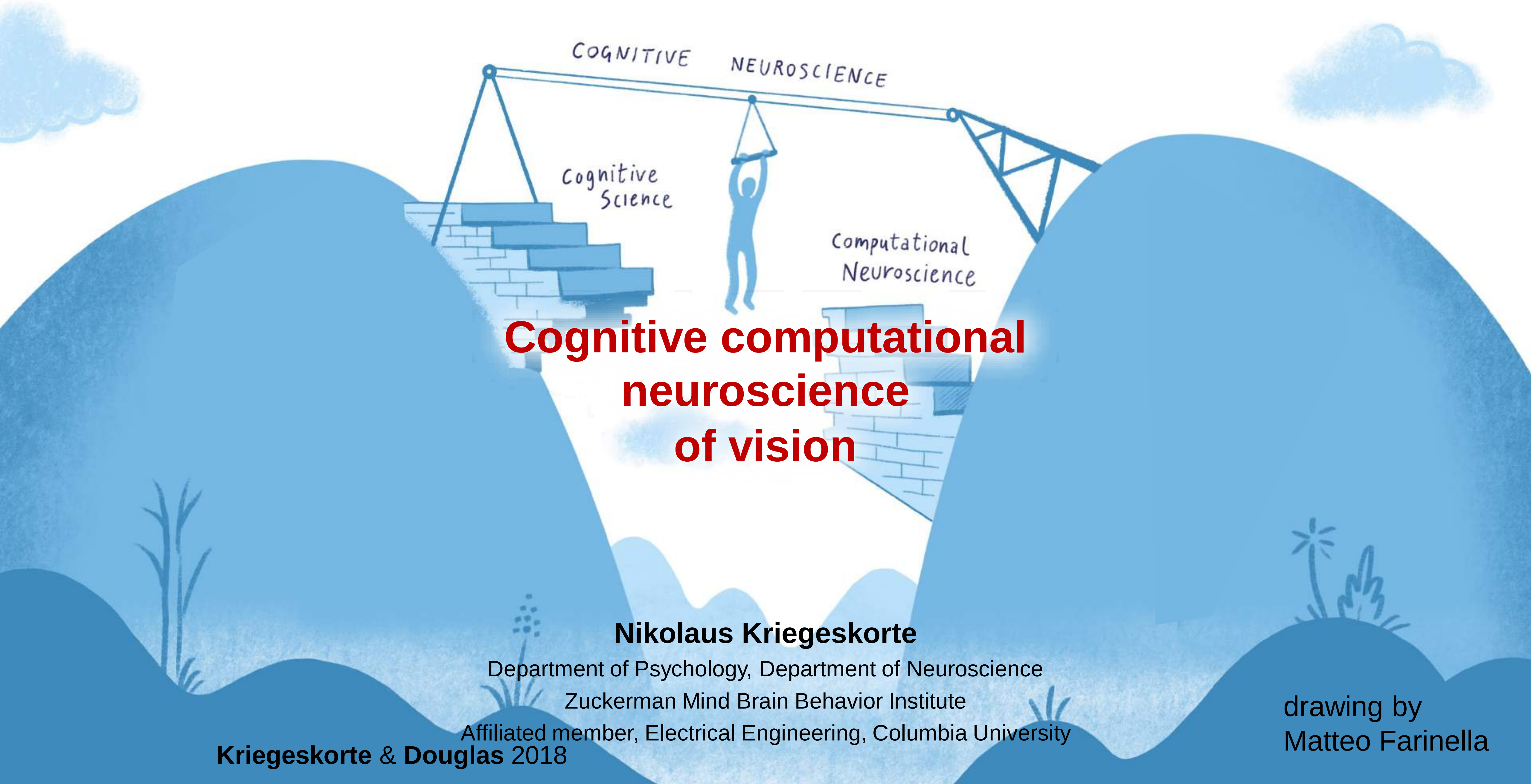
Online via Zoom - we will send out an invitation via our email lists. If you are not on a mailing list, please send an email up front to Liv.Heinecke[at]uni-potsdam.de to receive the link.

Abstract: To learn how cognition is implemented in the brain, we must build computational models that can perform cognitive tasks, and test such models with brain and behavioral experiments [1]. Modern technologies enable us to measure and manipulate brain activity in unprecedentedly rich ways in animals and humans. However, experiments will yield theoretical insight only when employed to test brain-computational models. Recent advances in neural network modelling have enabled major strides in computer vision and other artificial intelligence applications. This brain-inspired technology provides the basis for tomorrow's computational neuroscience [1, 2]. Deep convolutional neural nets trained for visual object recognition have internal representational spaces remarkably similar to those of the human and monkey ventral visual pathway [3]. Functional imaging and invasive neuronal recording provide rich brain-activity measurements in humans and animals, but a challenge is to leverage such data to gain insight into the brain's computational mechanisms [4, 5]. We build neural network models of primate vision, inspired by biology and guided by engineering considerations [2, 6]. We also develop statistical inference techniques that enable us to adjudicate between complex brain-computational models on the basis of brain and behavioral data [4, 5]. I will discuss recent work extending deep convolutional feedforward vision models by adding recurrent signal flow and stochasticity. These characteristics of biological neural networks may improve inferential performance and enable neural networks to more accurately represent their own uncertainty.

[1] **Cognitive computational neuroscience.** Kriegeskorte, N., & Douglas, P. K. (2018). *Nature neuroscience*
[2] **Deep neural networks: A new framework for modeling biological vision and brain information processing** Kriegeskorte N (2015) Annu. Rev. Vis. Sci.
[3] **Deep Supervised, but Not Unsupervised, Models May Explain IT Cortical Representation** Khaligh-Razavi SM, N Kriegeskorte (2014) PLoS Computational Biology
[4] **Representational models: A common framework for understanding encoding, pattern-component, and representational-similarity analysis** Diedrichsen J, Kriegeskorte N (2017) PLoS Computational Biology
[5] **Inferring brain-computational mechanisms with models of activity measurements** Kriegeskorte N, Diedrichsen J (2016) Philosophical Transactions of the Royal Society B
[6] **Recurrent Convolutional Neural Networks: A Better Model of Biological Object Recognition** Spoerer CJ, McClure P, Kriegeskorte N (2017) Frontiers in Psychology

An **introductory seminar** to the topic of the colloquia will be given beforehand by Alma Lindborg online from **2 to 2:45 pm** for all junior scientist.

Funded by: DFG

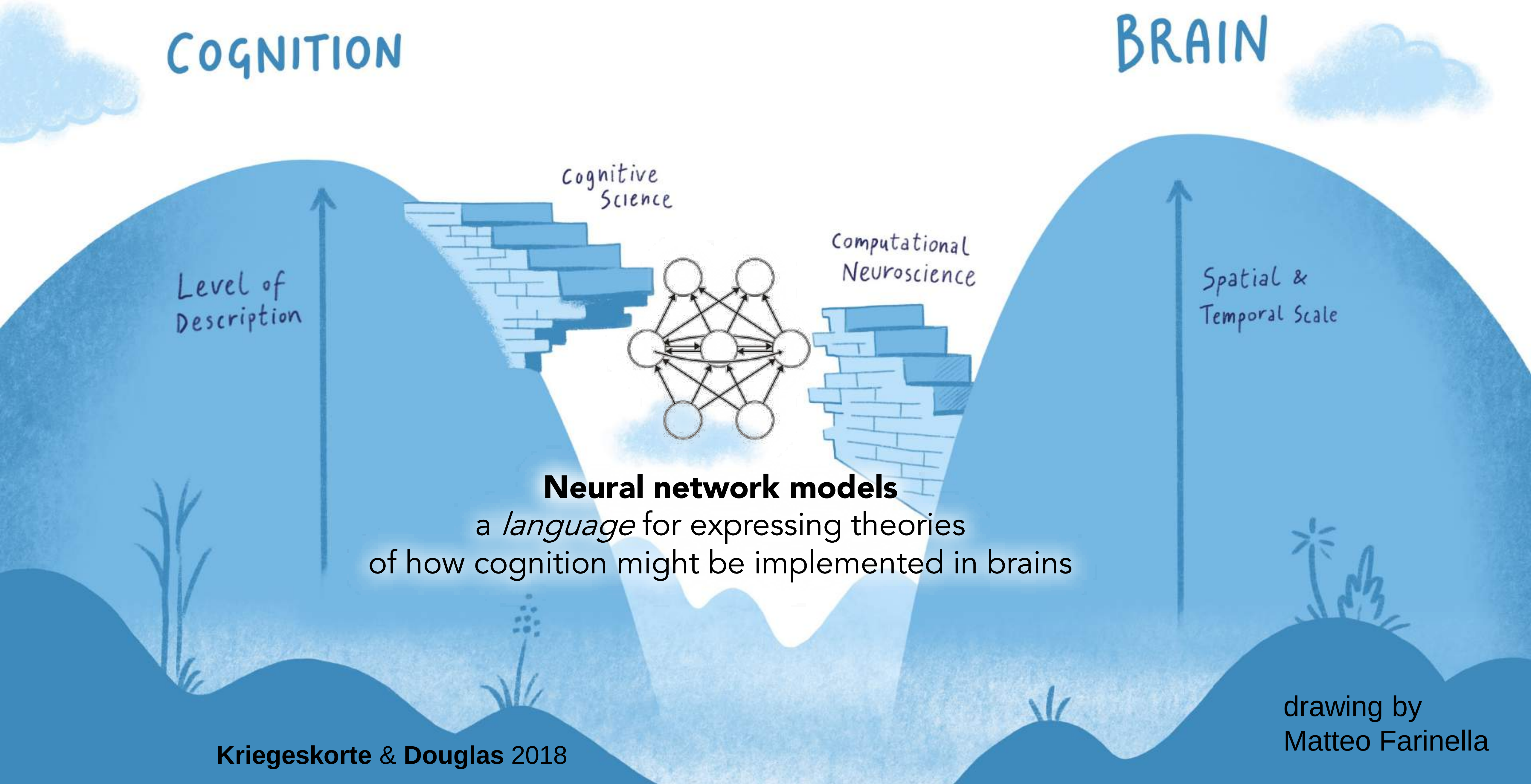


Cognitive computational neuroscience of vision

Nikolaus Kriegeskorte
Department of Psychology, Department of Neuroscience
Zuckerman Mind Brain Behavior Institute
Affiliated member, Electrical Engineering, Columbia University

Kriegeskorte & **Douglas** 2018

drawing by
Matteo Farinella

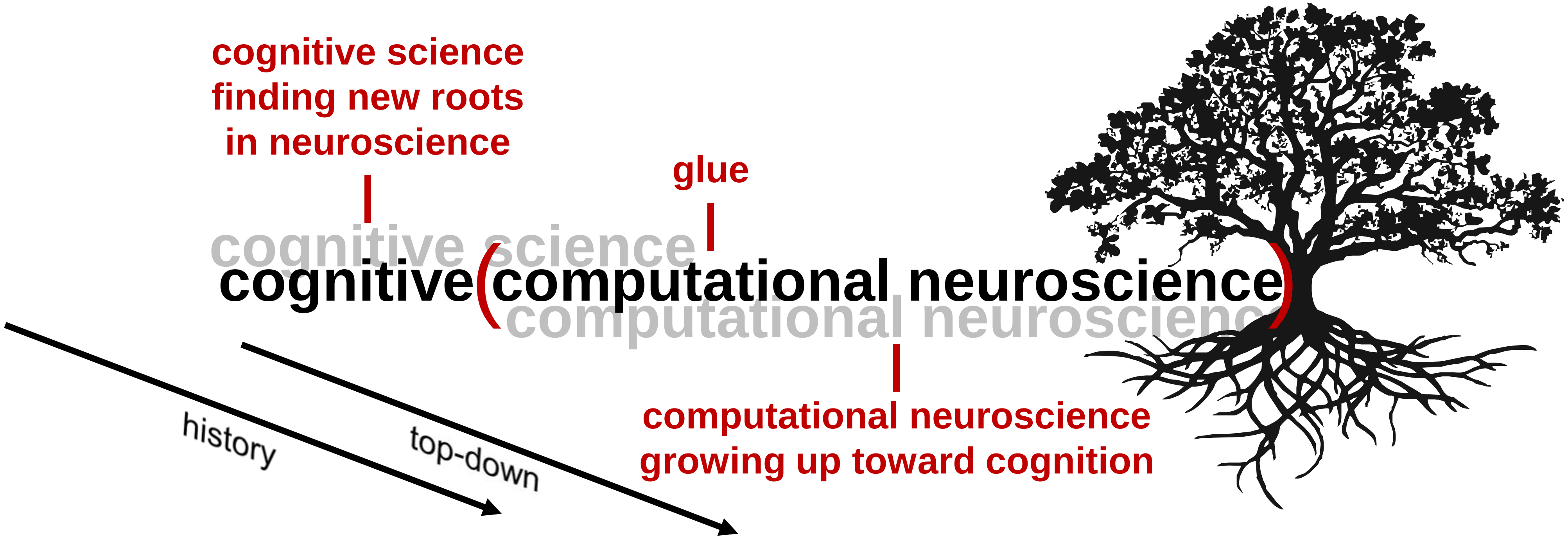


Neural network models

a *language* for expressing theories
of how cognition might be implemented in brains

Kriegeskorte & **Douglas** 2018

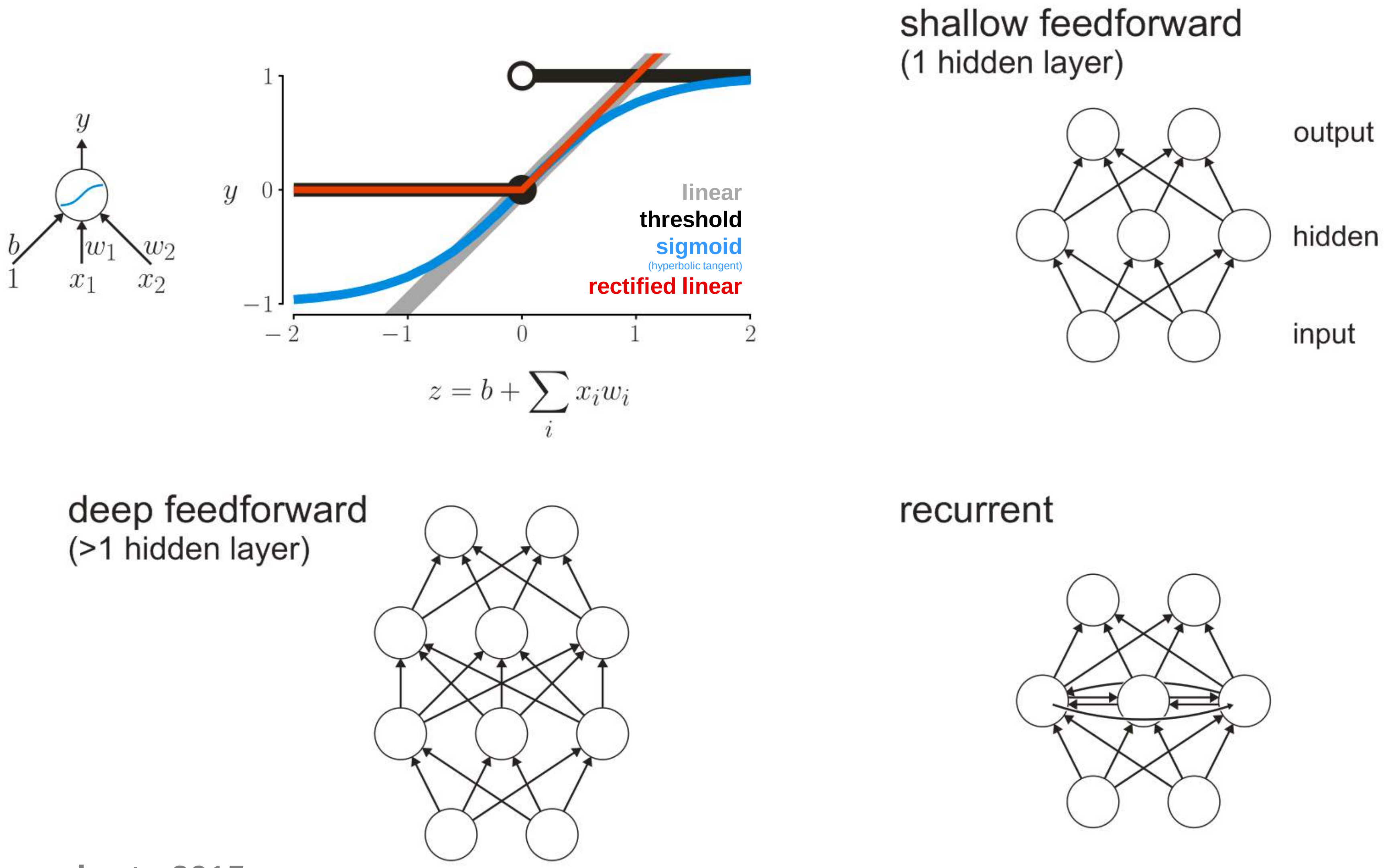
drawing by
Matteo Farinella



Kriegeskorte & Douglas 2018

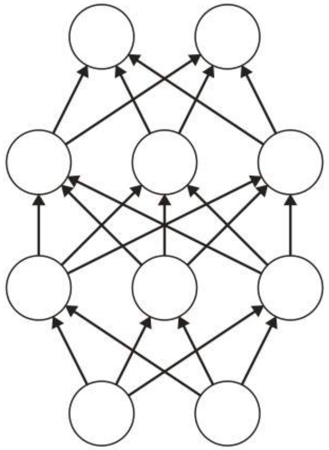
Neural network models

Neural network models



Kriegeskorte 2015

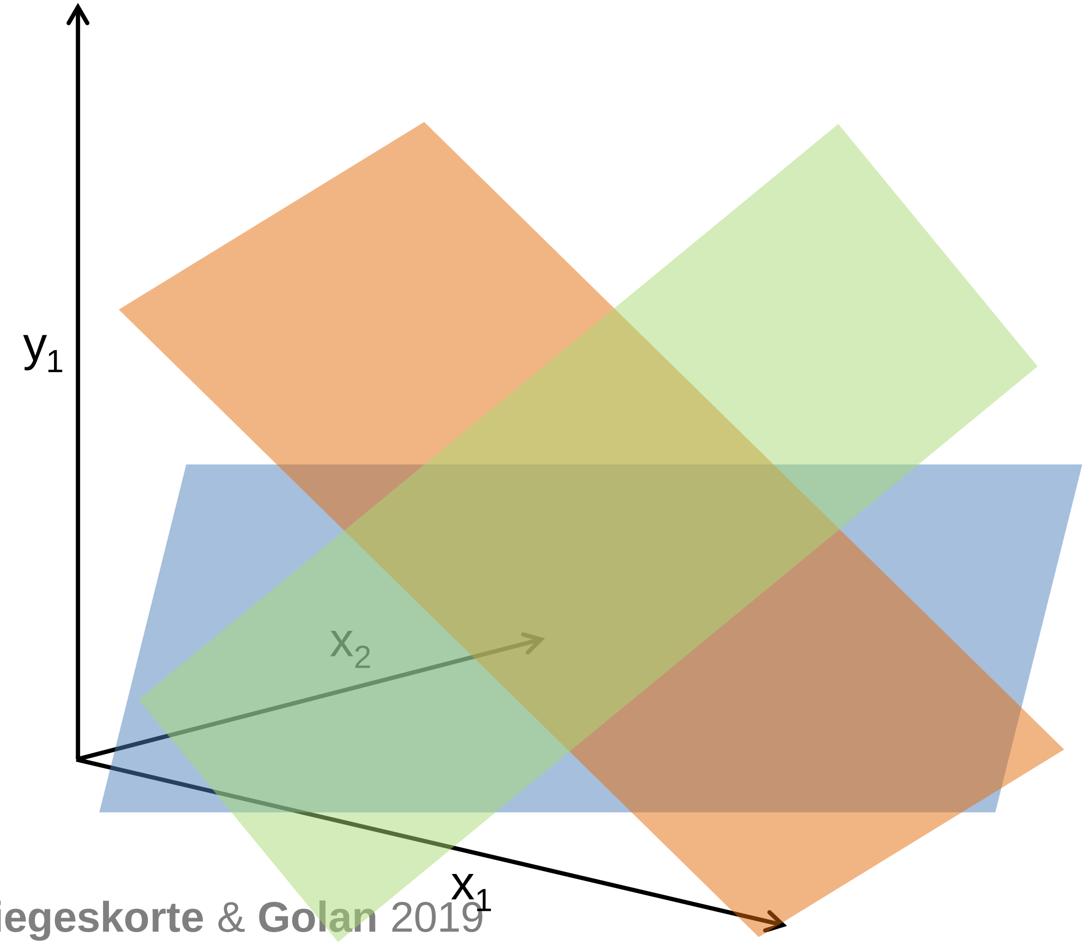
Neural network models

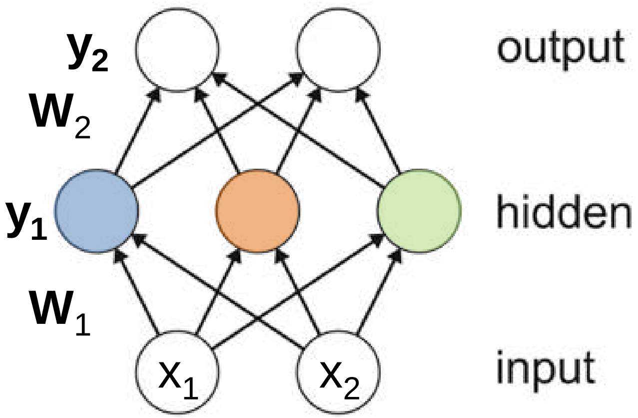


Kriegeskorte 2015

Nonlinear activation function needed to make a hidden layer useful

linear activation functions





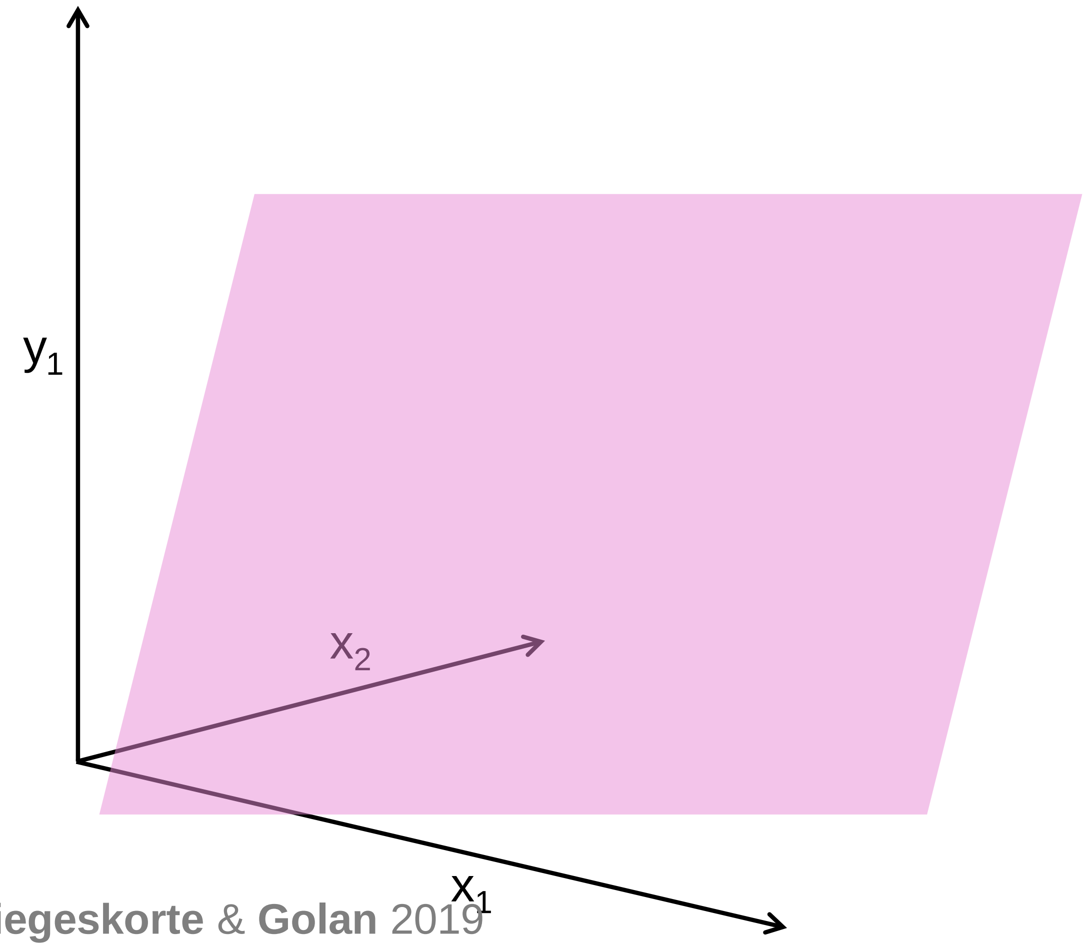
$\mathbf{y}_2 = \mathbf{x}\ \mathbf{W}_1\mathbf{W}_2$

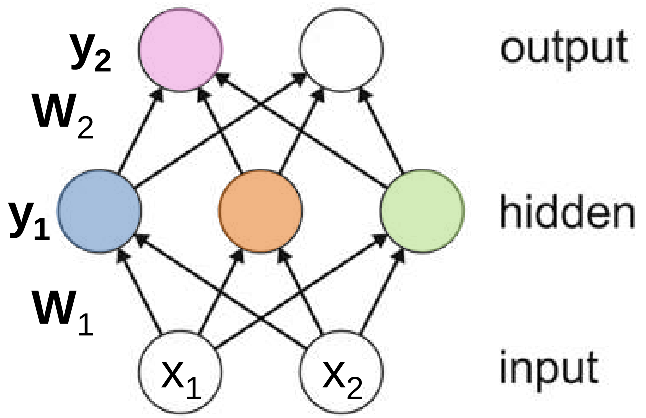
$\mathbf{y}_2 = \mathbf{x}\ \mathbf{W'}$

Kriegeskorte & Golan 2019

Nonlinear activation function needed to make a hidden layer useful

linear activation functions





$\mathbf{y}_2 = \mathbf{x}\ \mathbf{W}_1\mathbf{W}_2$

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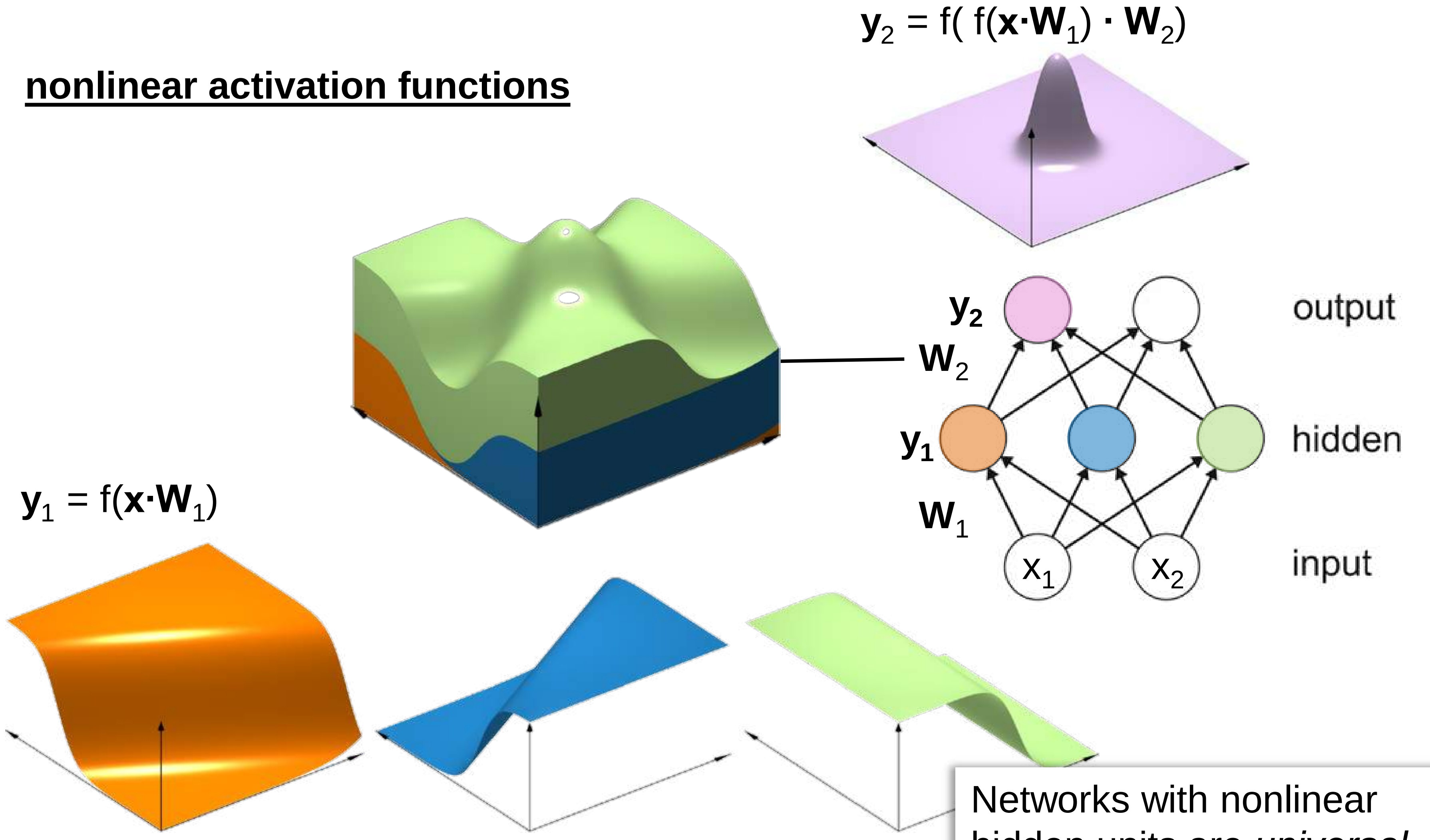
Kriegeskorte & **Golan** 2019

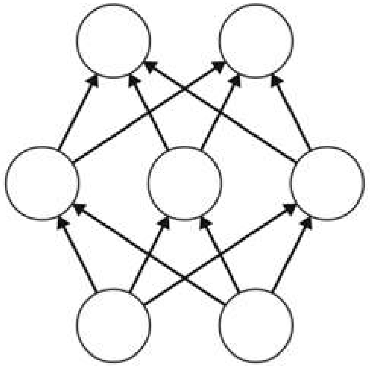
Nonlinear activation function needed to make a hidden layer useful



Networks with nonlinear hidden units are *universal* function approximators.

Kriegeskorte & Golan 2019 (primer for biologists)

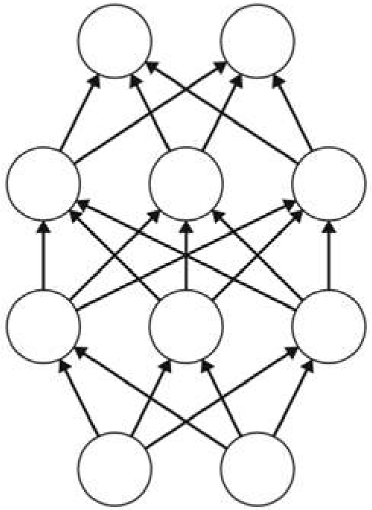
Why deep? Why recurrent?



shallow

1 hidden layer

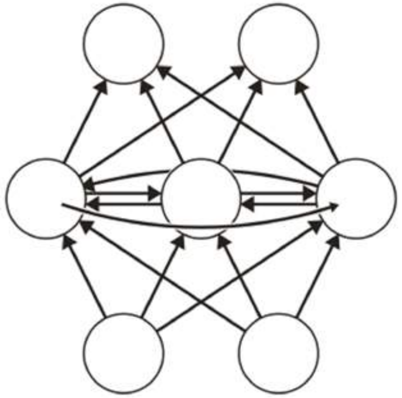
Networks with nonlinear hidden units are *universal function approximators*.



deep

>1 hidden layer

Deep nets can
- *reuse features* downstream
- represent many complex functions more concisely (fewer units and weights).



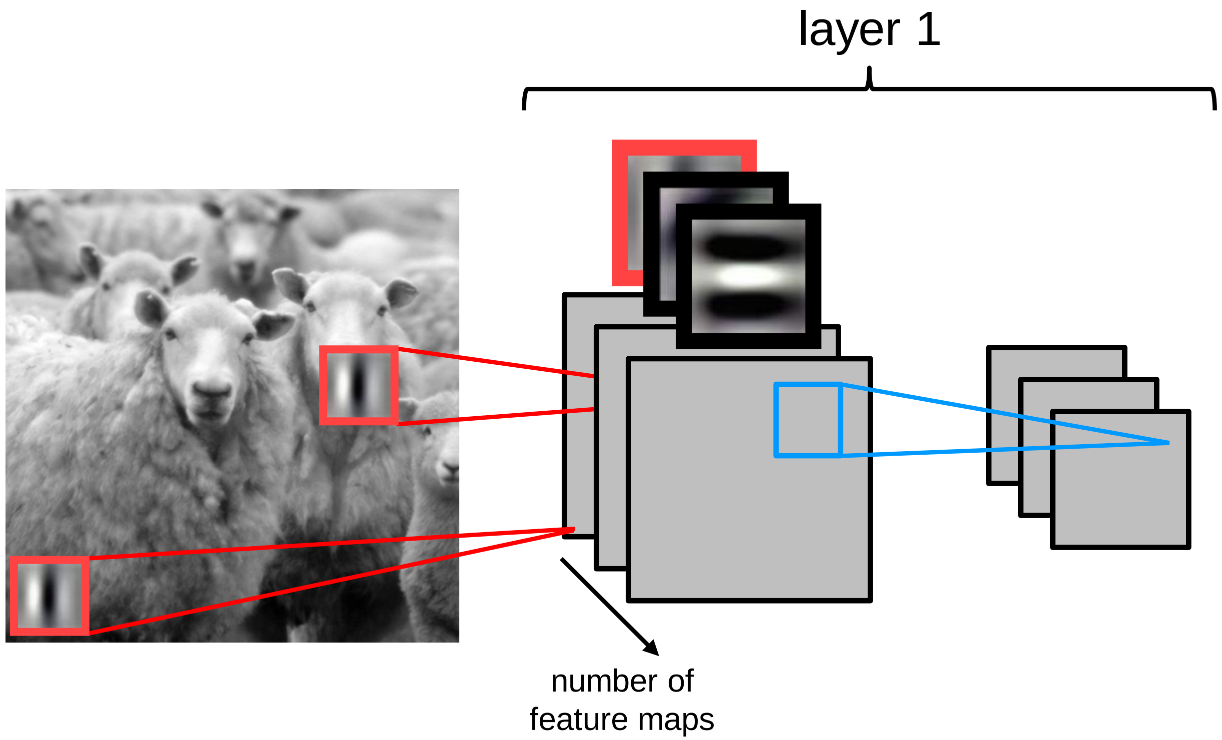
recurrent

Recurrent networks
- can *recycle weights and units* over time
- are *universal approximators of dynamical systems*.

hidden units are *universal* function approximators.

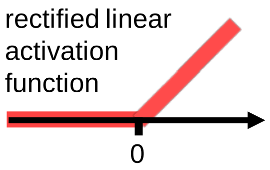
Kriegeskorte & **Golan** 2019 (primer for biologists)

Deep *convolutional* feedforward neural networks



deep:
> 1 hidden layer,
typically many layers

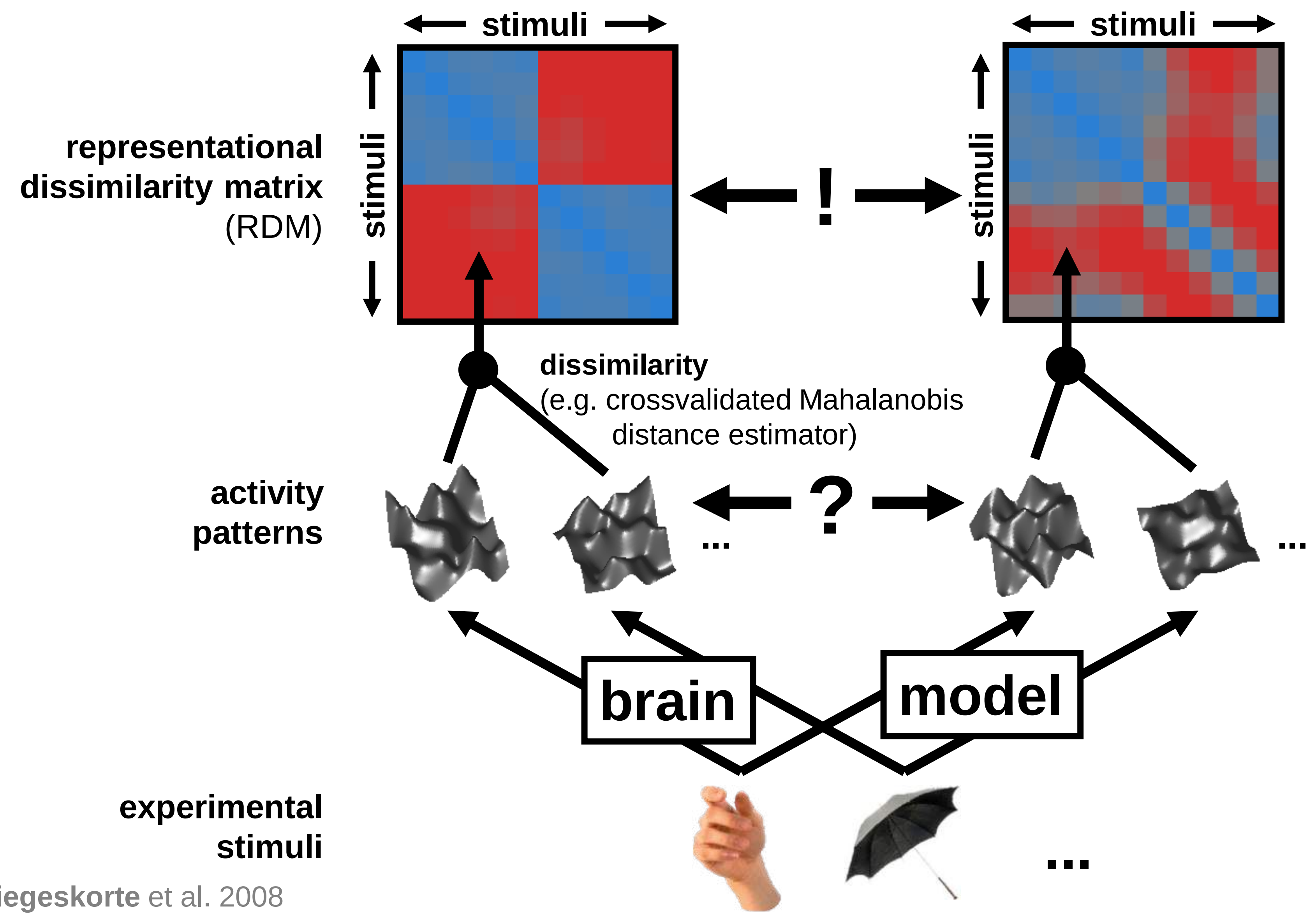
(1) convolution (2) nonlinearity (3) local pooling (3) local normalisation



local max
or avg

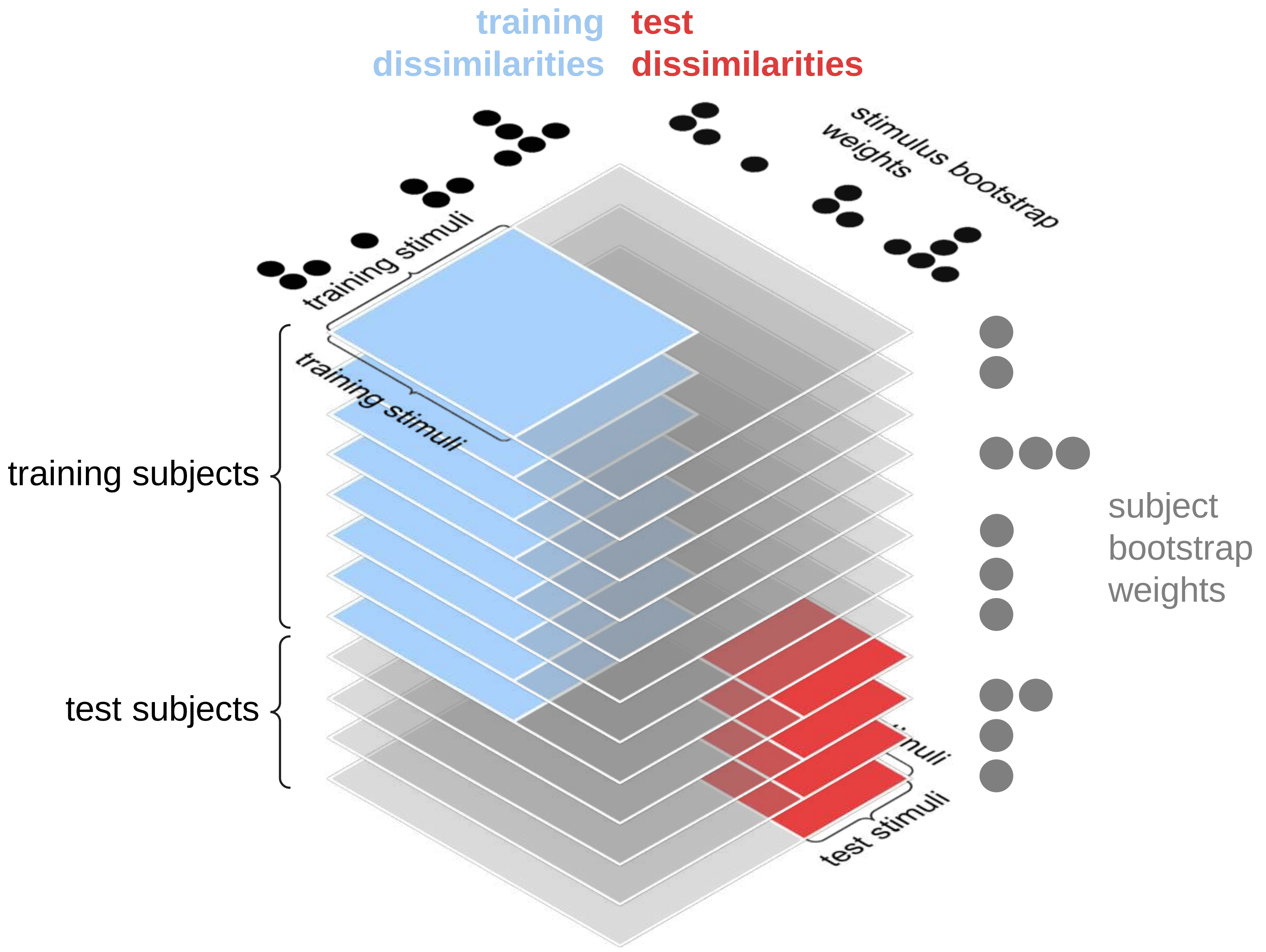
Testing neural network models with brain-activity data

Representational similarity analysis

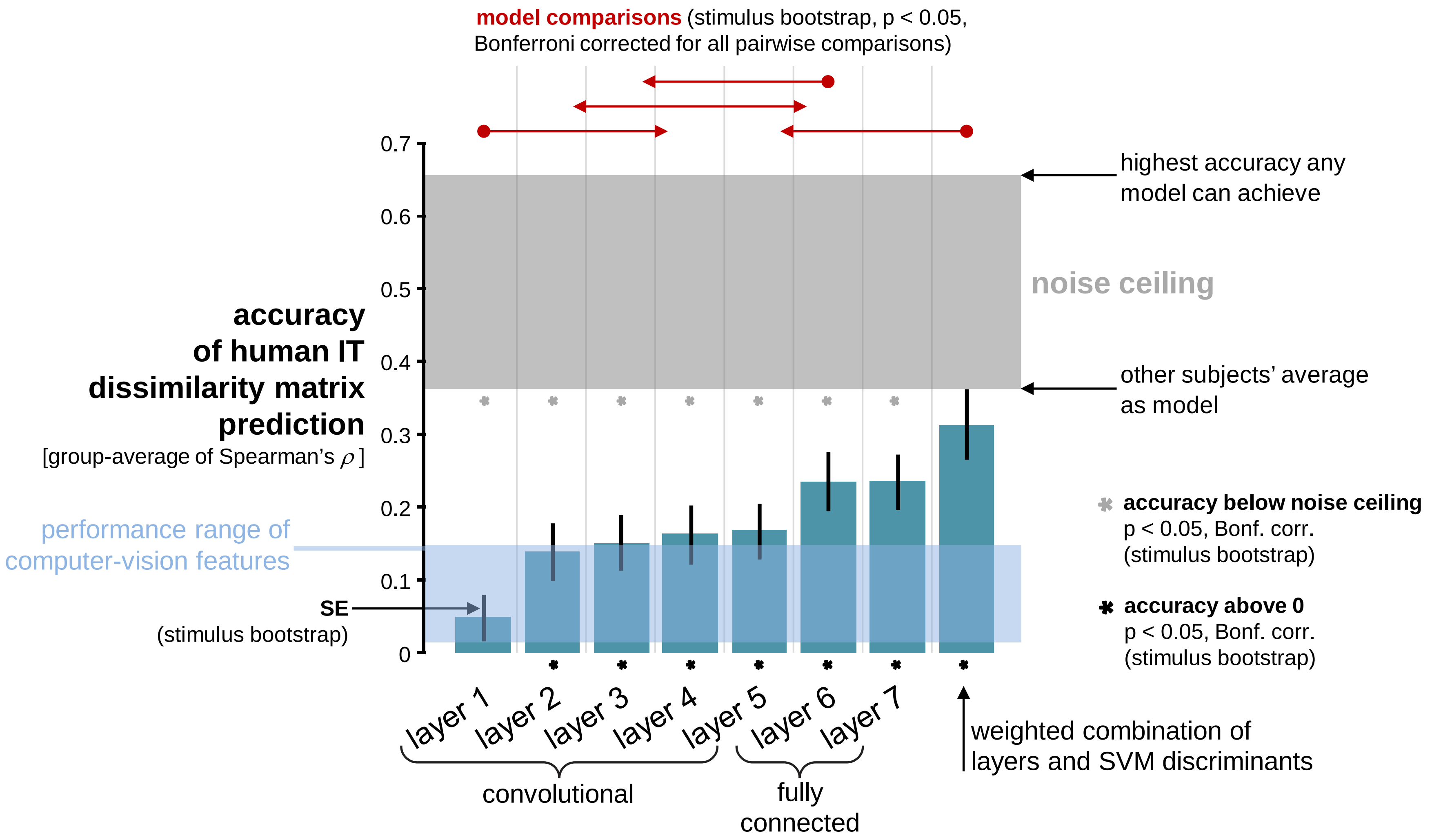


Kriegeskorte et al. 2008

Training and testing in crossvalidation

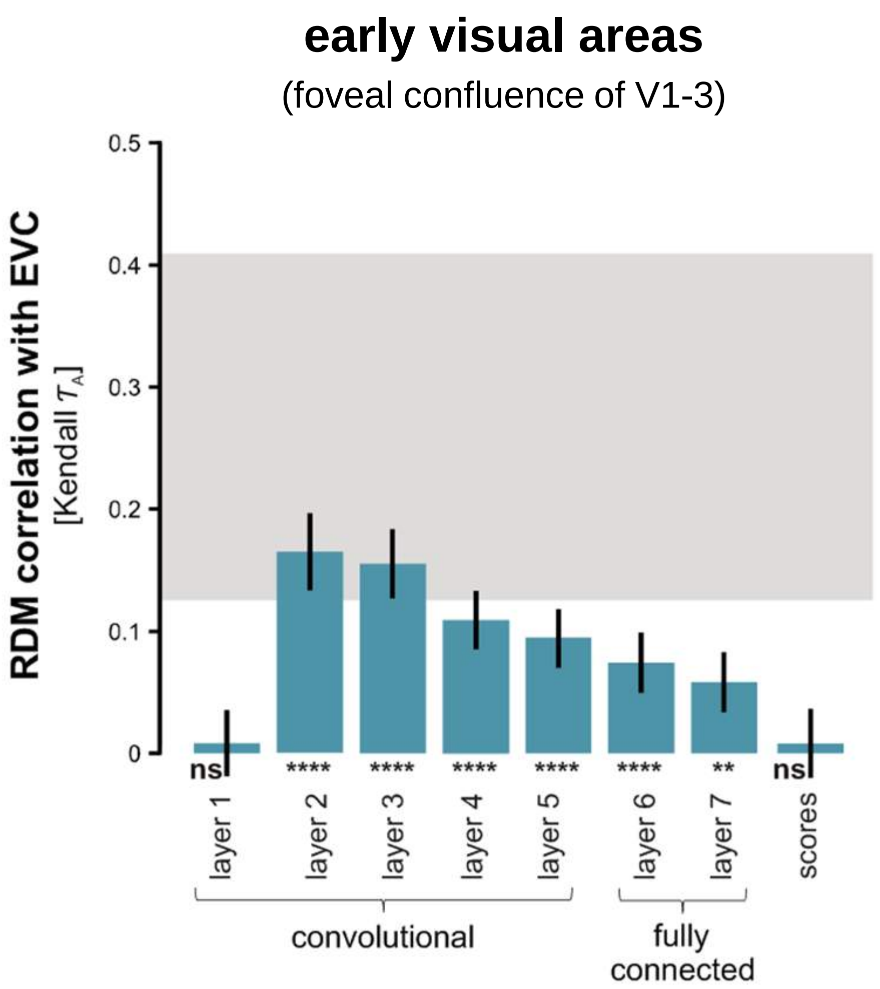


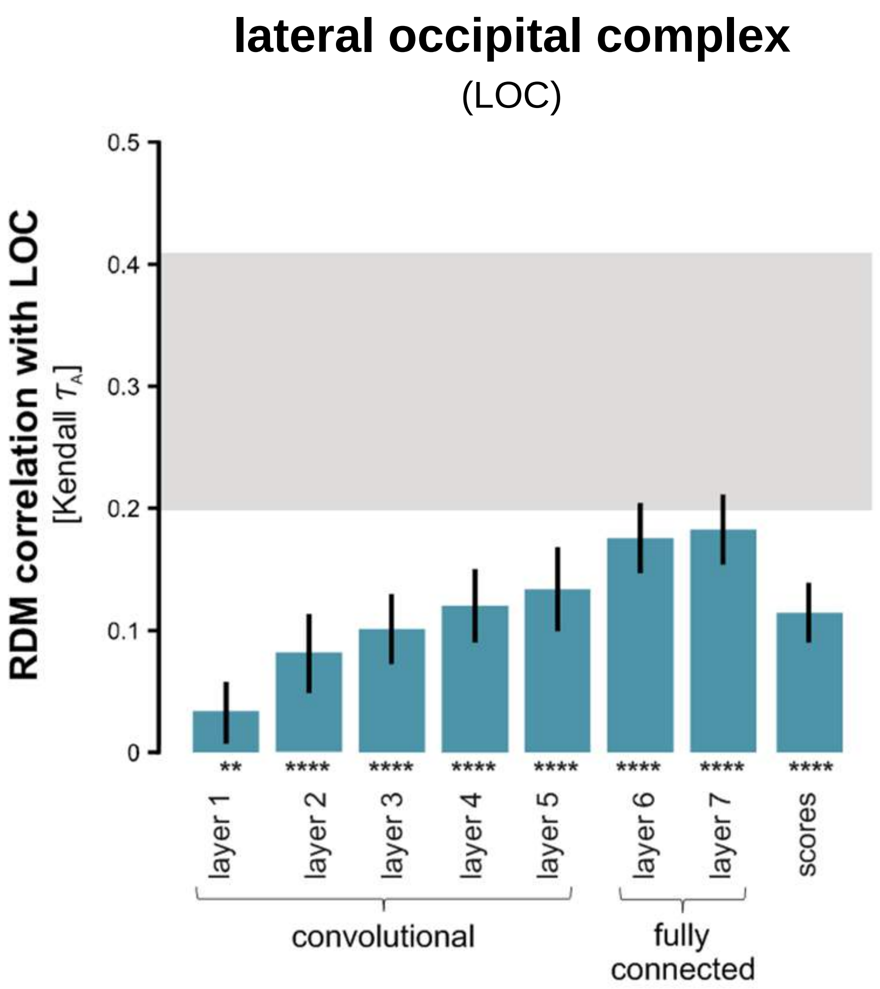
Deep convolutional feedforward networks predict IT representational geometry



Khaligh-Razavi & **Kriegeskorte** 2014, **Nili** et al. 2014 (RSA Toolbox), **Storrs** et al. (in prep.)

Deep-net layers correspond to stages of the ventral visual stream





Khaligh-Razavi & **Kriegeskorte** 2014, **Nili** et al. 2014 (RSA Toolbox)

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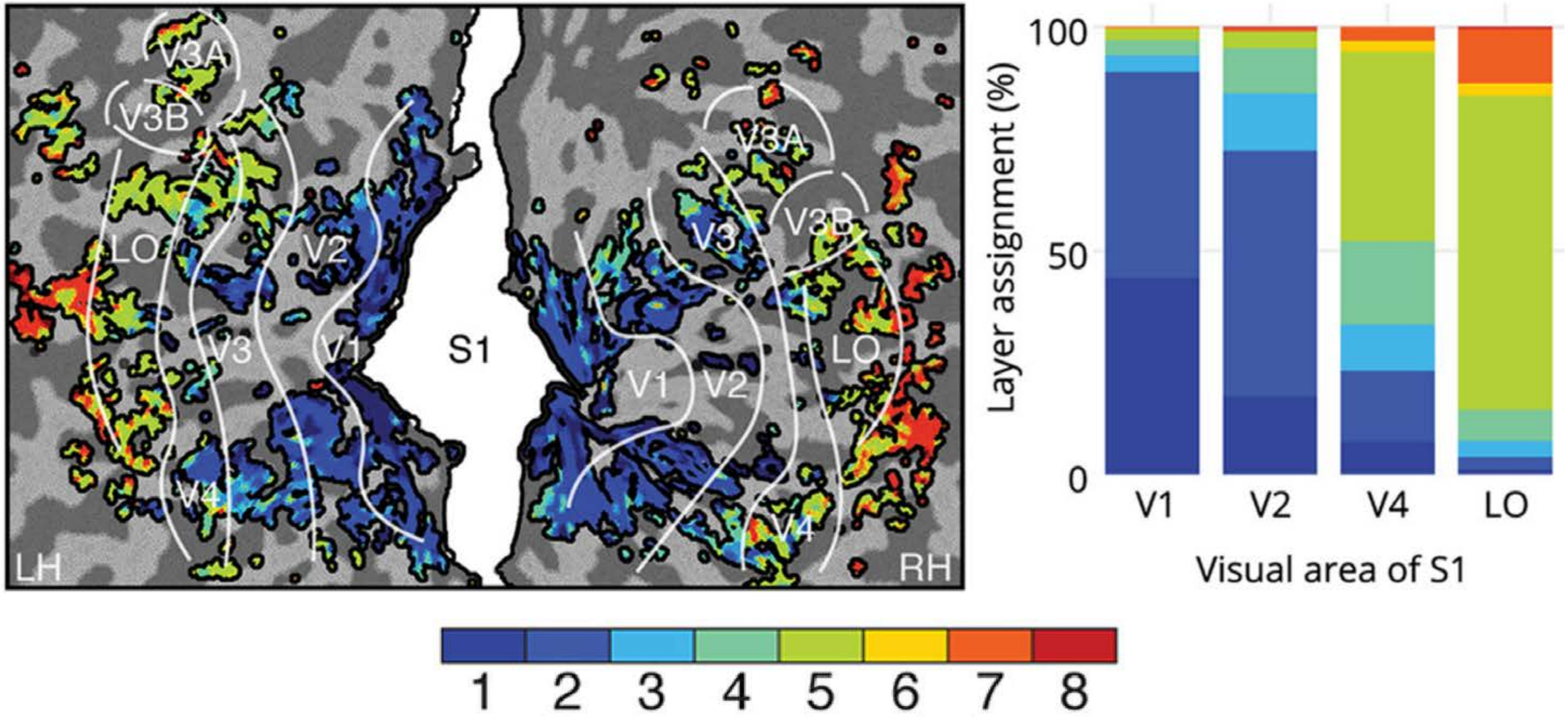
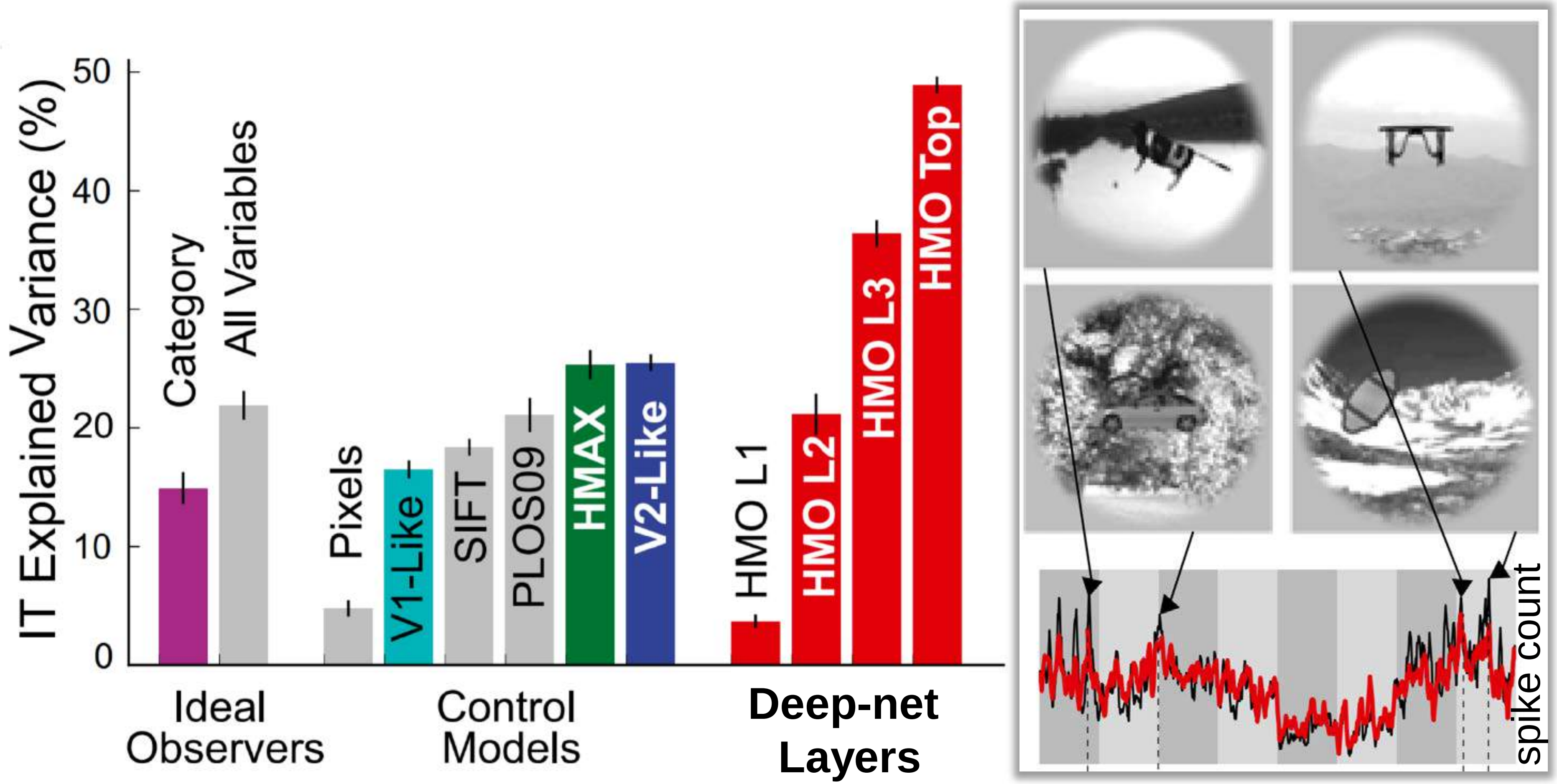


deep-net layer that best explains each voxel

Güçlü & **van Gerven** 2015, data from **Kay** et al. 2008

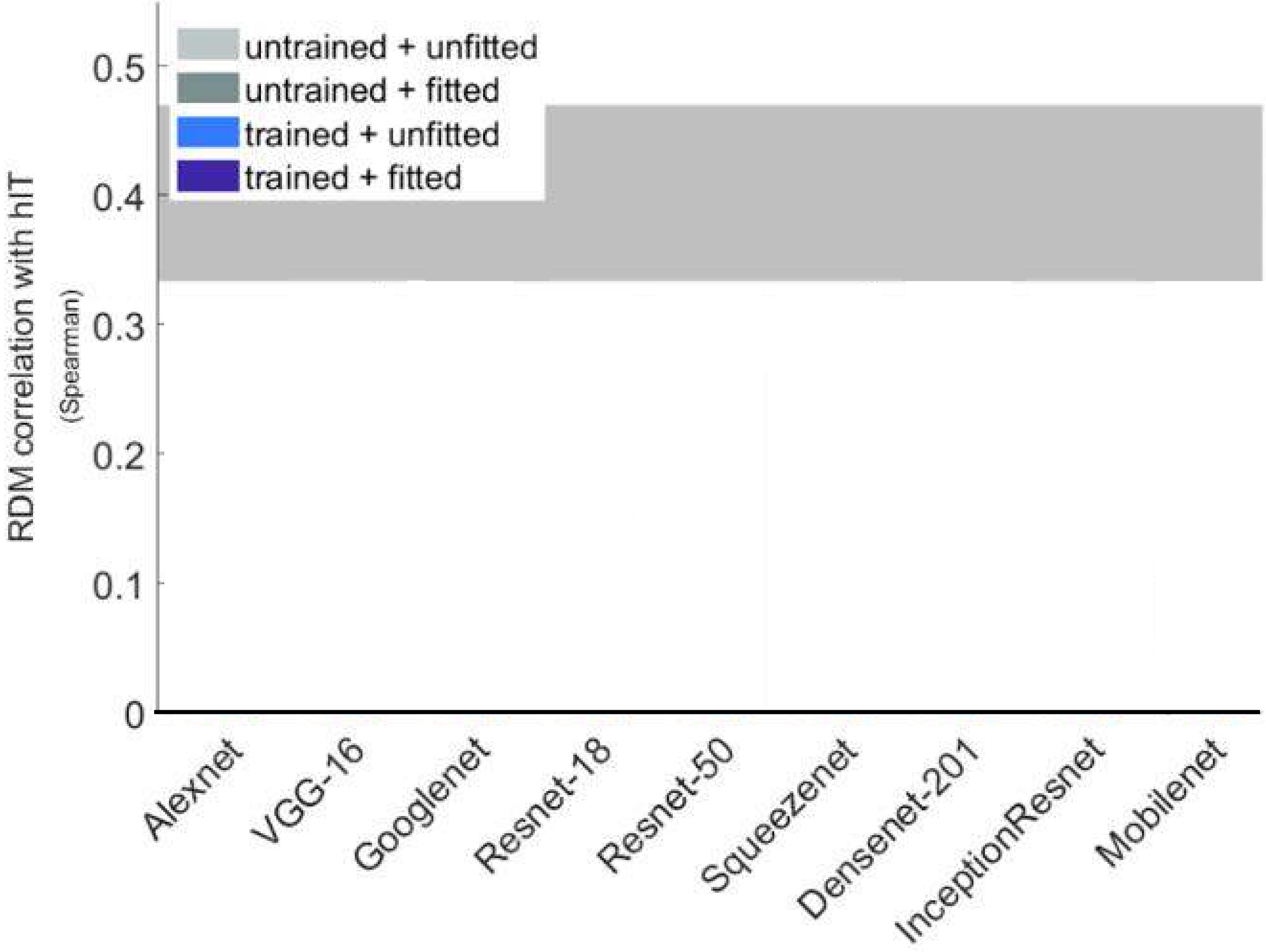
High explained variance for IT neuronal recordings



— single neuronal recording site
— deep-net predicted response for novel image

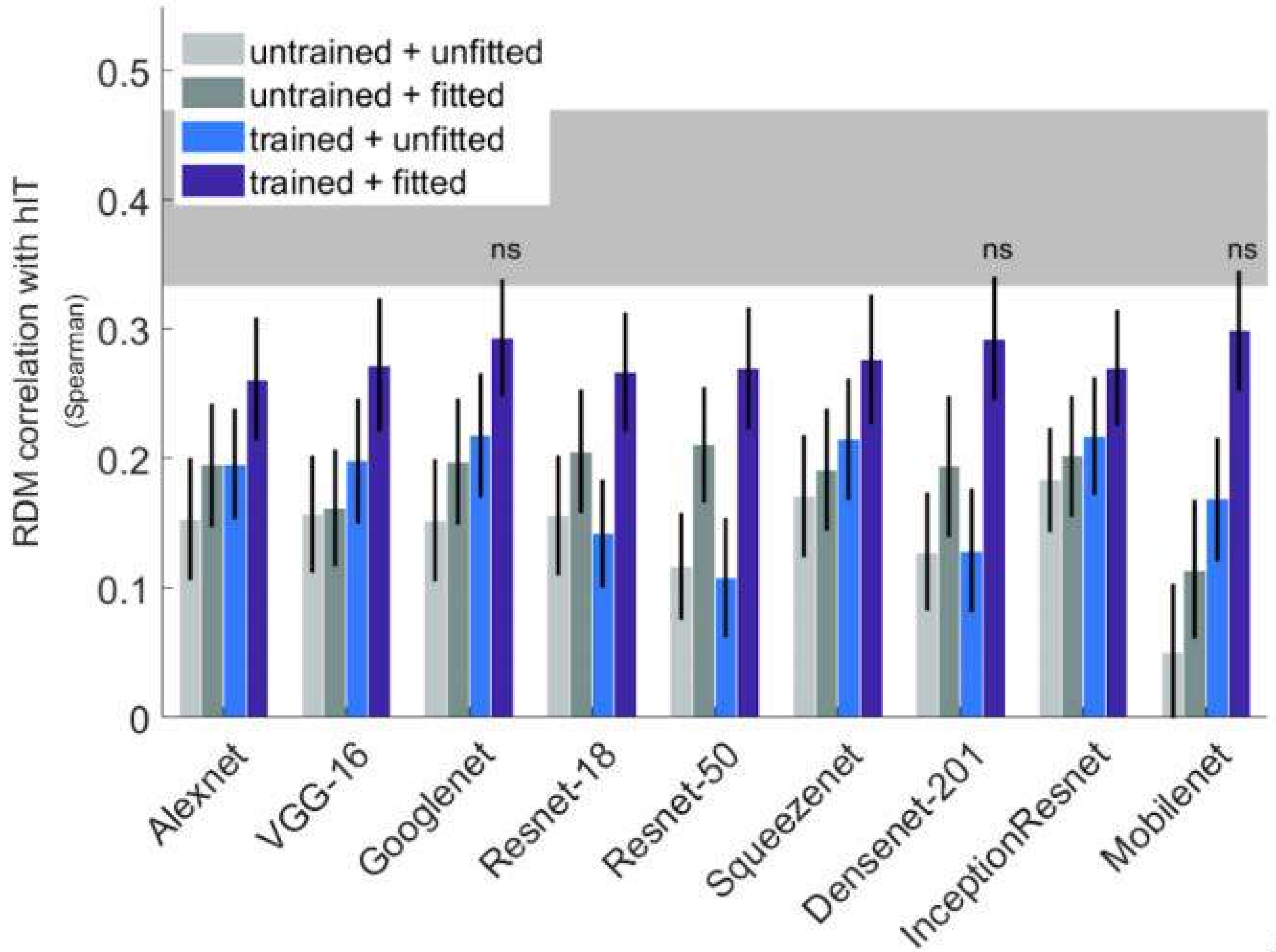
Yamins et al. 2014

Diverse deep feedforward neural networks predict IT, after *task-training* and *IT-fitting*

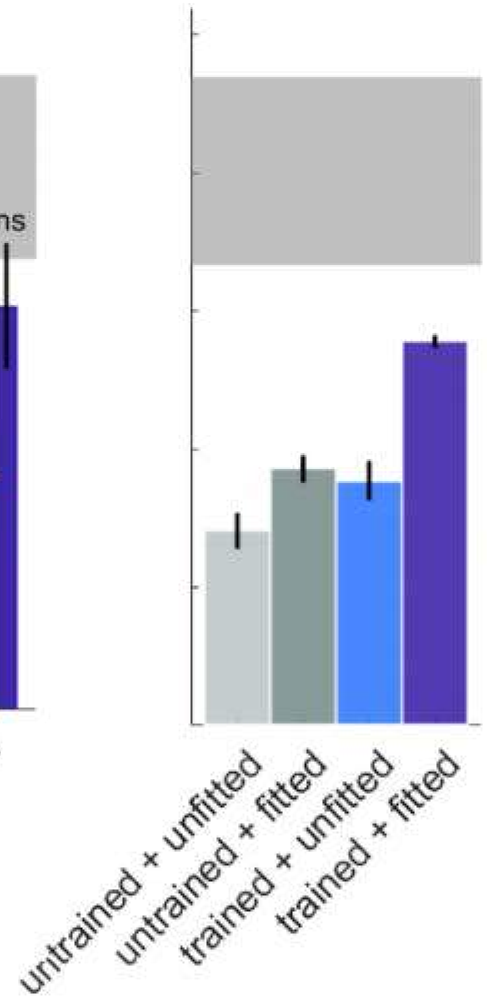


Storrs et al. pp2020

Diverse deep feedforward neural networks predict IT, after *task-training* and *IT-fitting*



Average across models



Storrs et al. pp2020

The converging feedforward story…

- Deep convolutional feedforward neural networks explain how the initial sweep through the primate visual hierarchy enables recognition at a glance.
- They predict representations of novel images better than any alternative current models.
- Both the *architecture* of the model and the *task training* contribute substantially to these successes.

However, we need to build models whose architecture more closely resembles the visual hierarchy.

A major feature of biological neural networks is recurrent signal flow.

Overview

1. Recurrent neural network models

2. Controversial stimuli

Overview

1. Recurrent neural network models

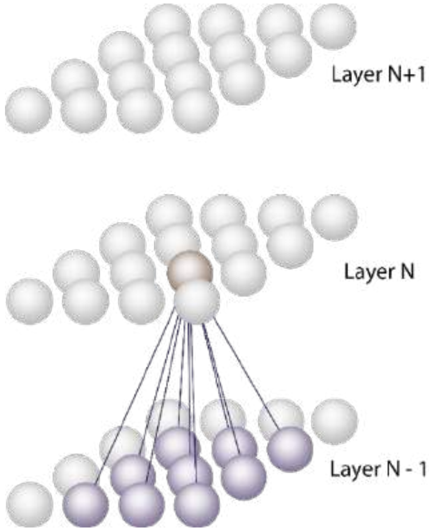
2. Controversial stimuli

Do *recurrent* convolutional neural networks provide better models of vision?

Courtney Spoerer

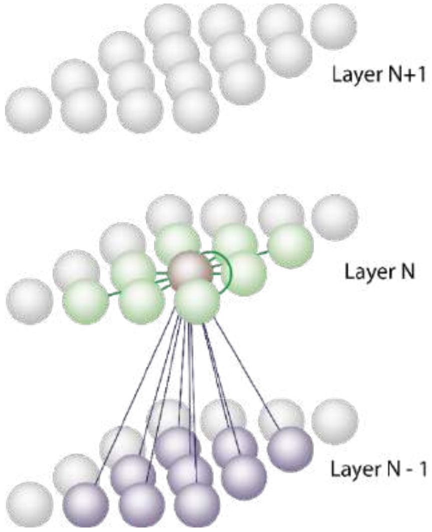
Recurrent convolutional neural networks

B (FF-CNN)



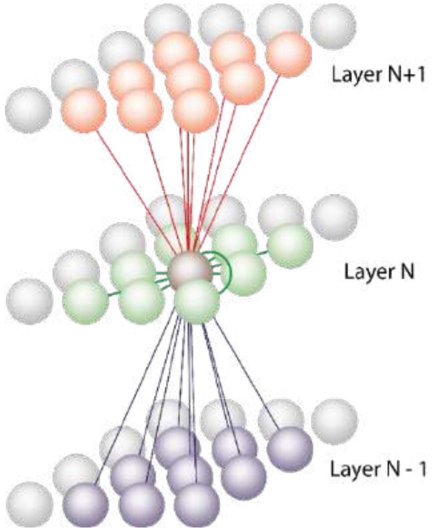
$$\sigma(h_B)$$

BL (RCNN)



$$\sigma(h_B + h_L)$$

BLT (RCNN)

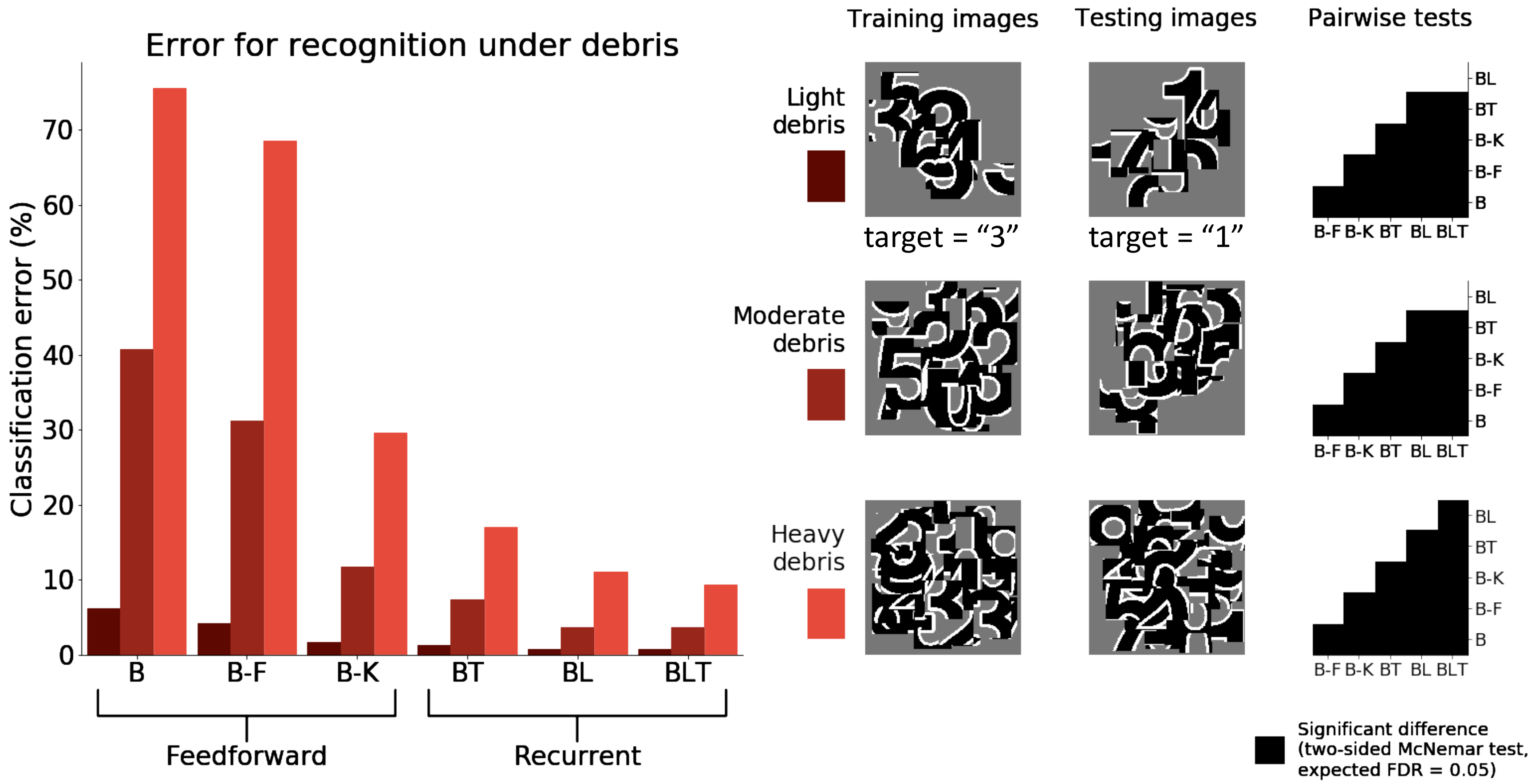


$$\sigma(h_B + h_L + h_T)$$

σ - non-linearity
h_x - convolution

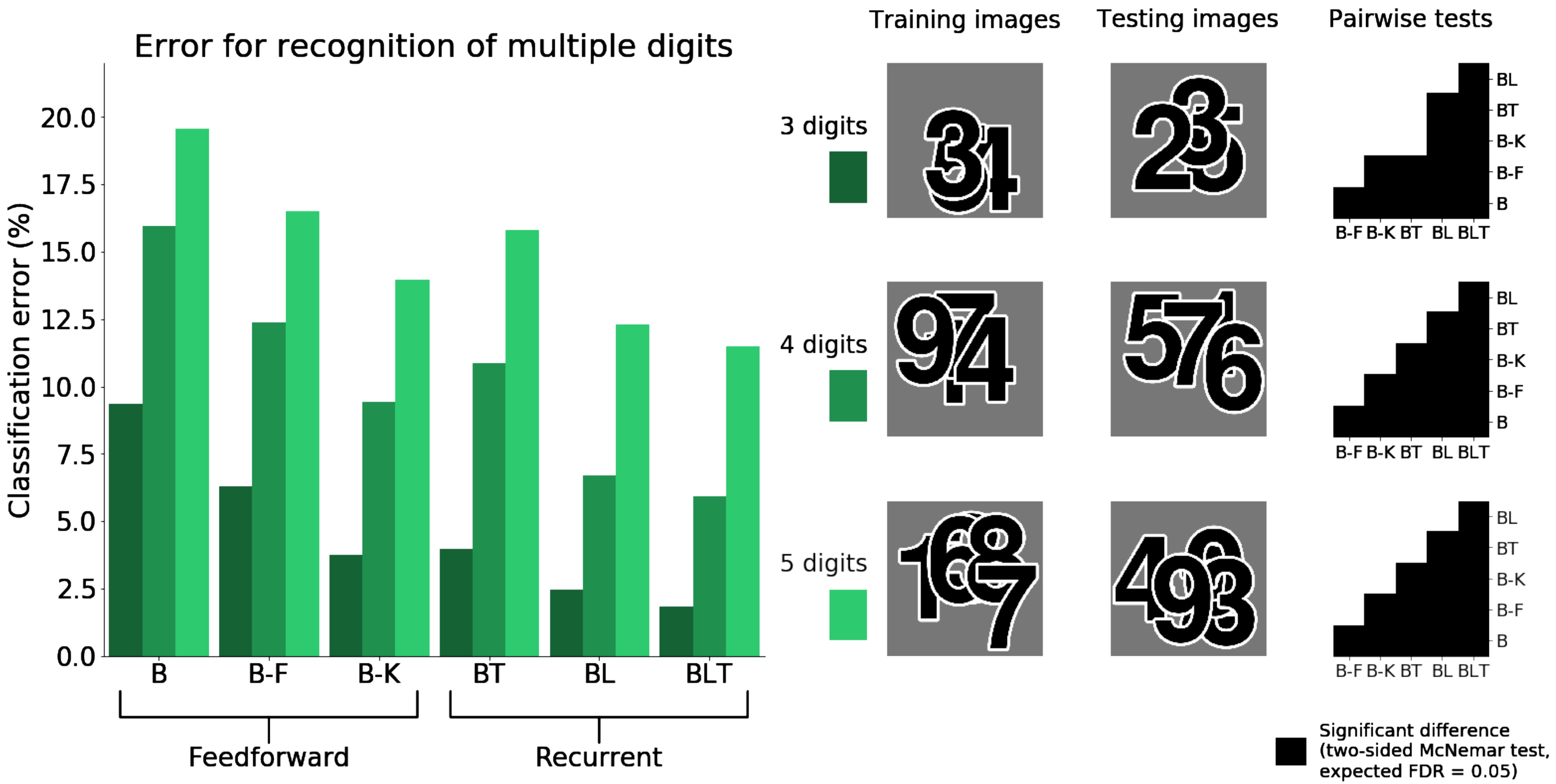
Liang & **Hu** 2015, **Spoerer** et al. 2017

Digit debris: recognition under occlusion



Spoerer et al. 2017

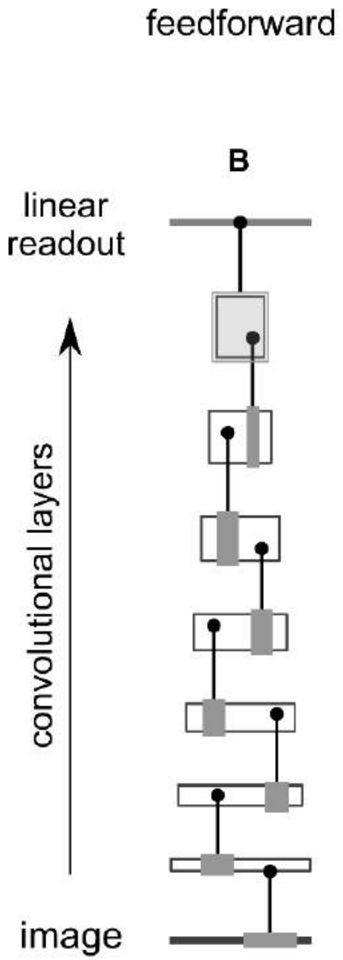
Digit clutter:
Multiple digit recognition



Spoerer et al. 2017

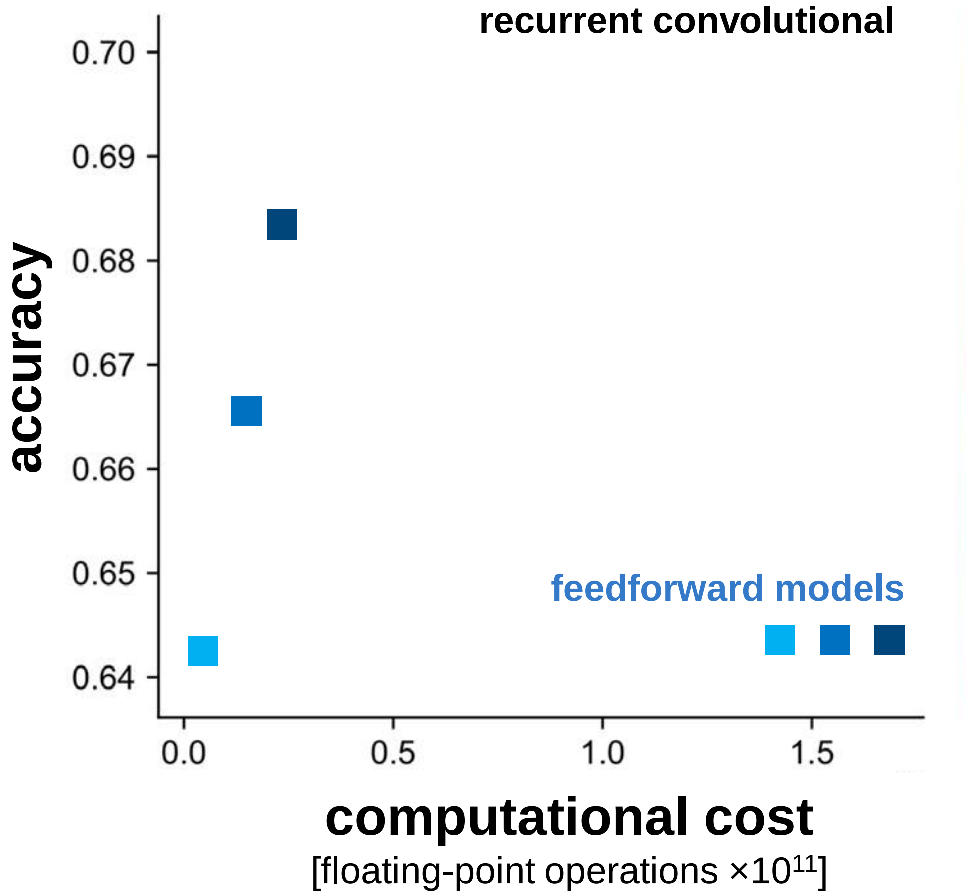
Can recurrent convolutional networks be scaled up to process natural images?

Recurrent convolutional networks trained to recognize natural images



Spoerer et al. 2020

Recurrent models can trade off speed of computation for accuracy



Spoerer et al. 2020

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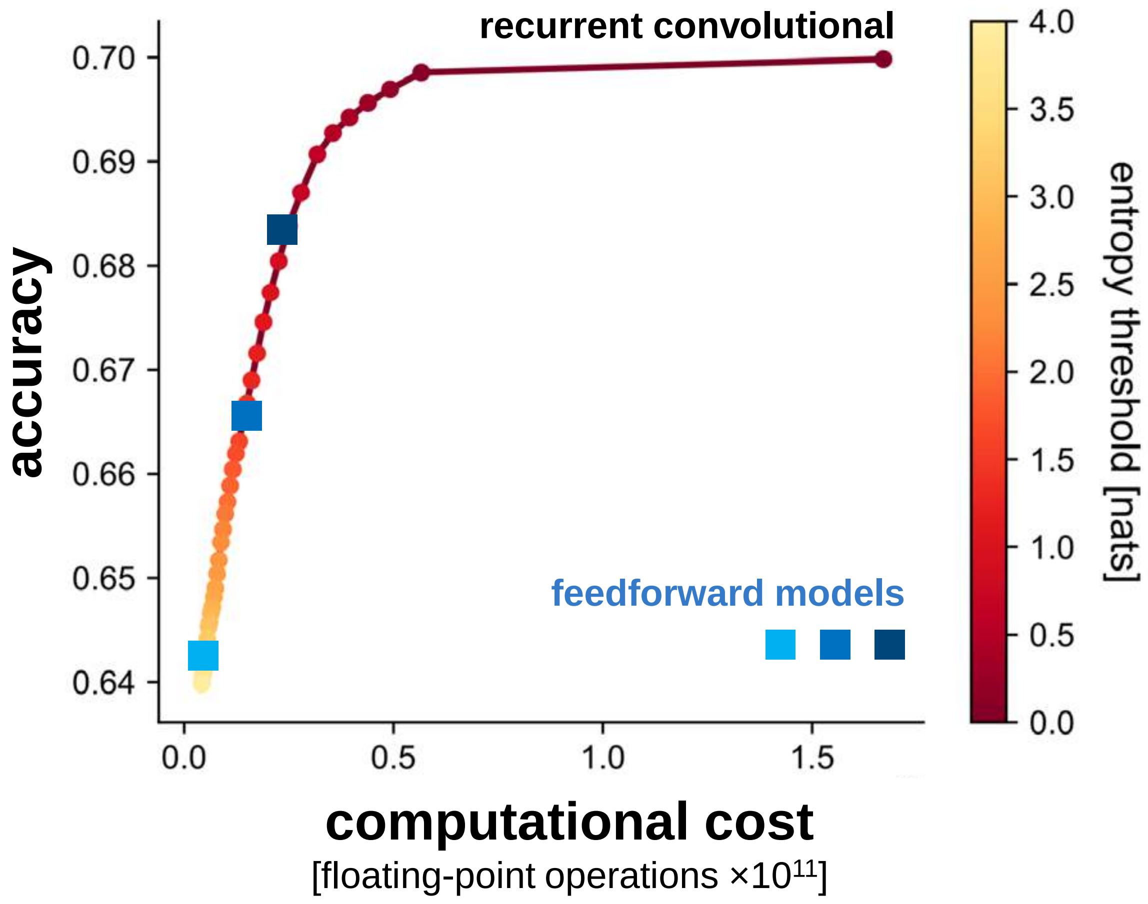
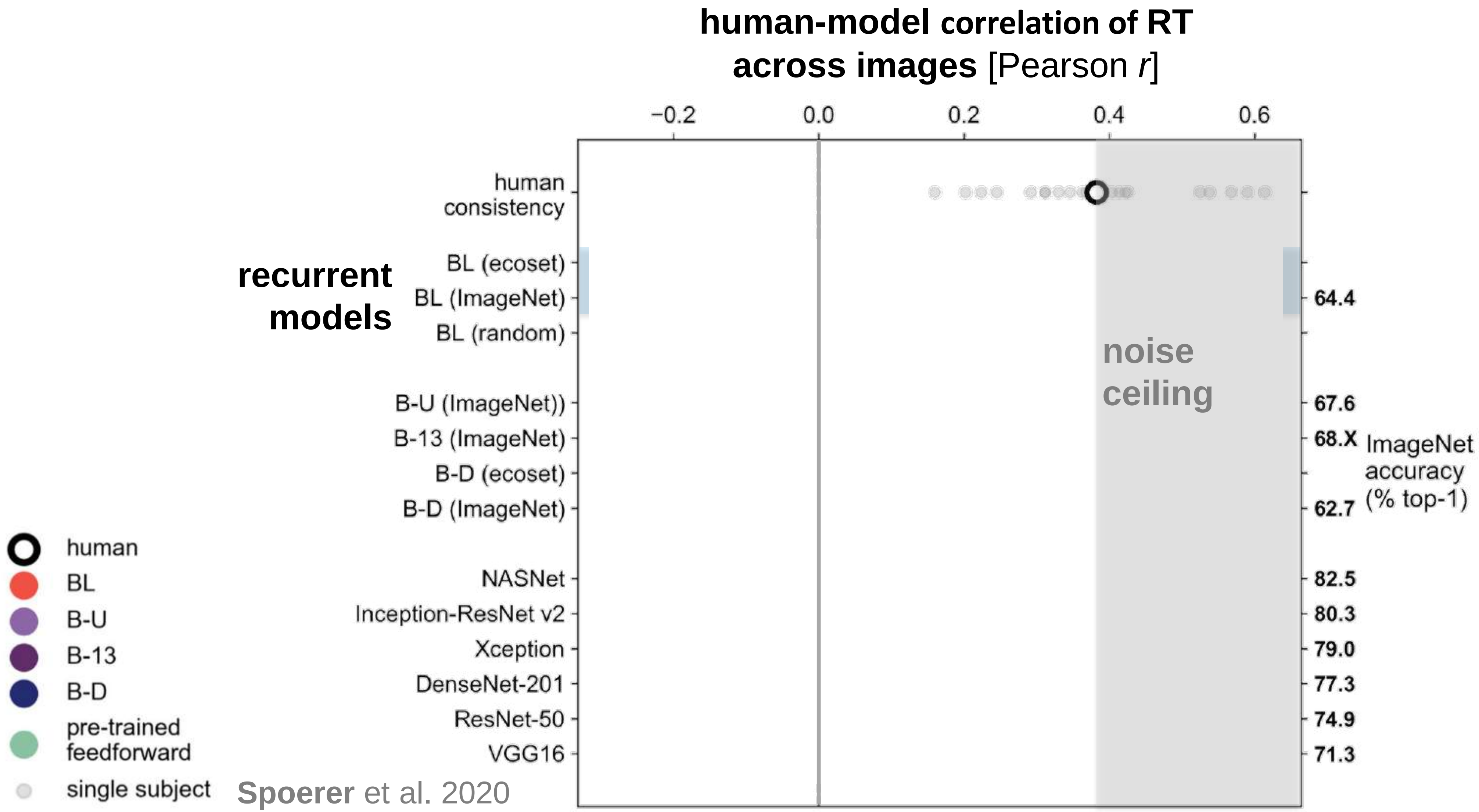


Spoerer et al. 2020

RCNNs predict human reaction times



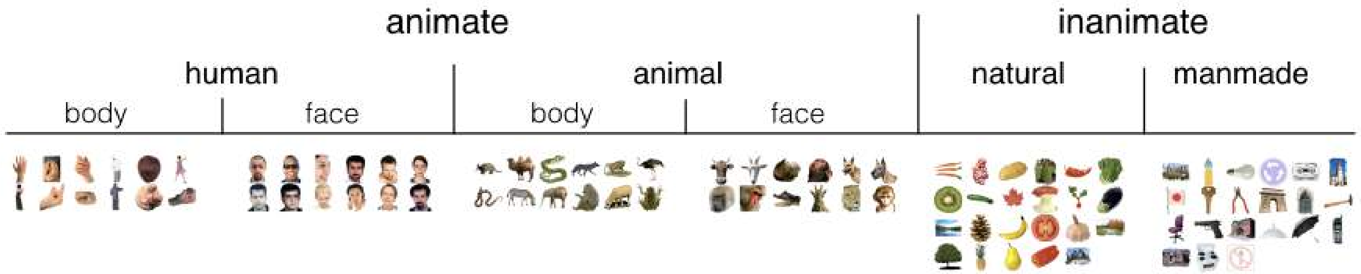
Spoerer et al. 2020

Tim Kietzmann

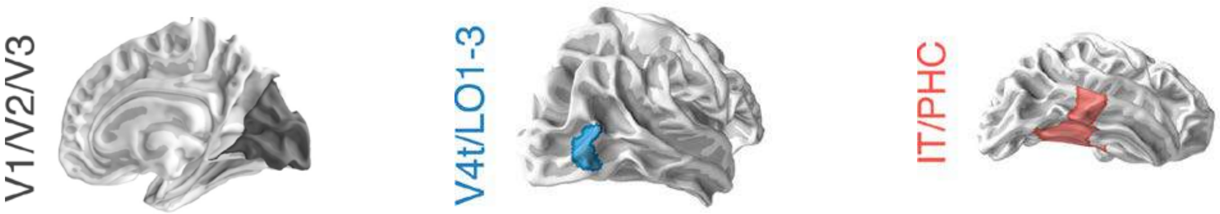
Can recurrent neural network models capture the representational dynamics in the human ventral stream?

Representational dynamics

stimuli



brain regions

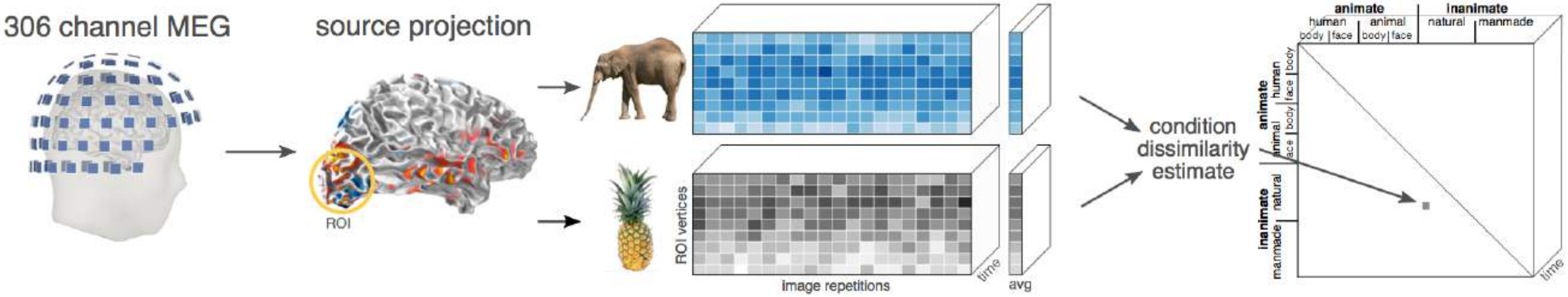


"early"

"intermediate"

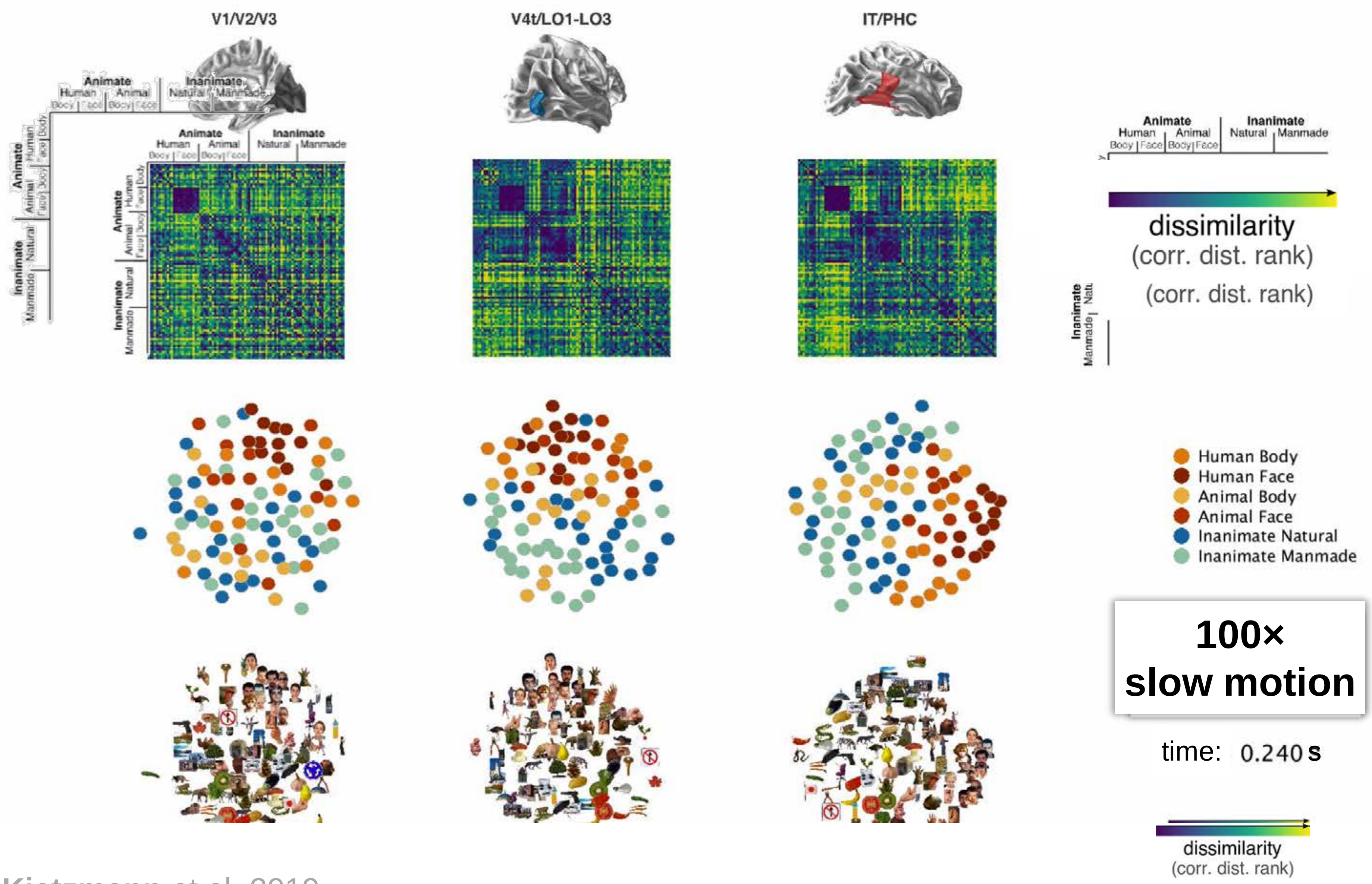
"high-level"

human magnetoencephalography



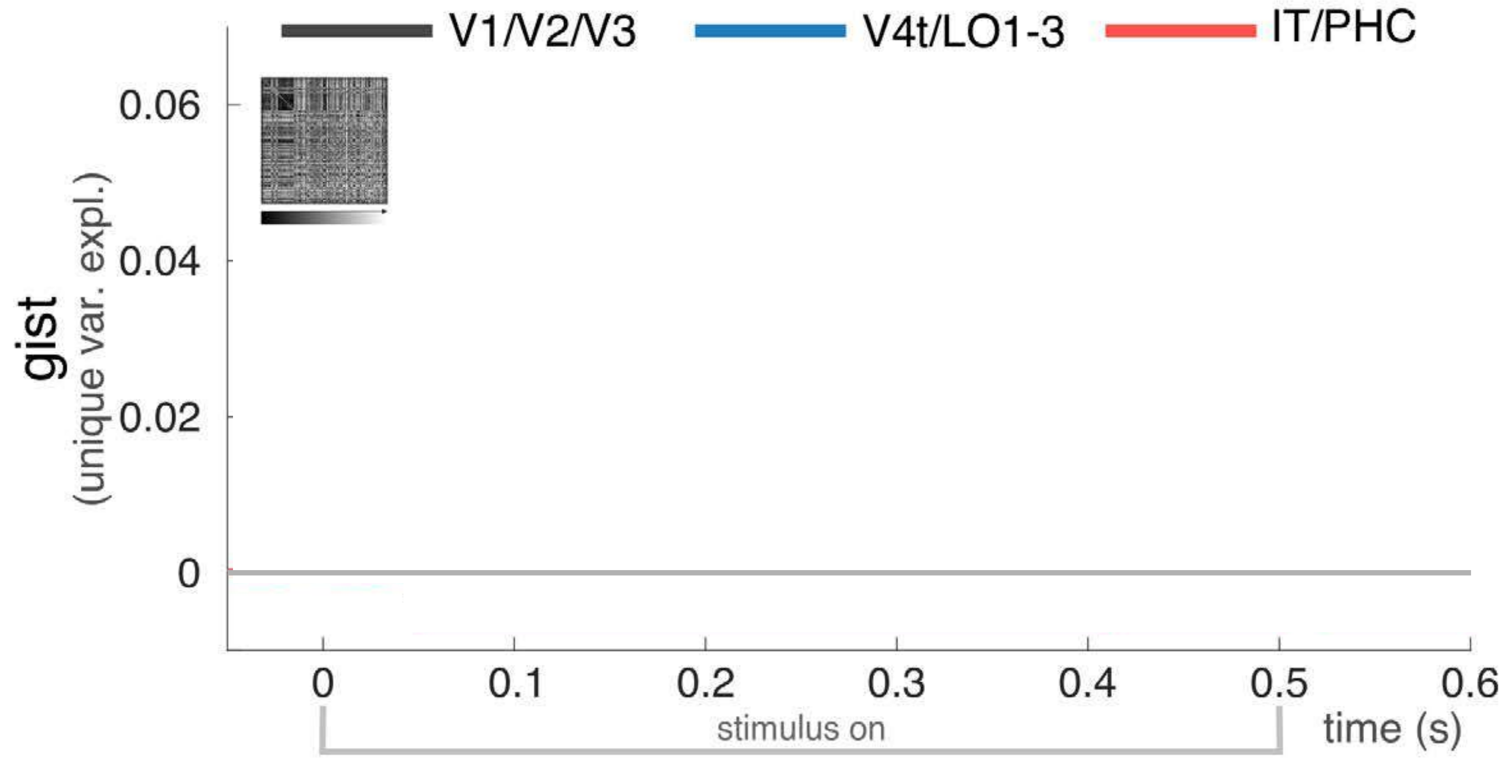
Kietzmann et al. 2019, Cichy et al. 2015

Movie time



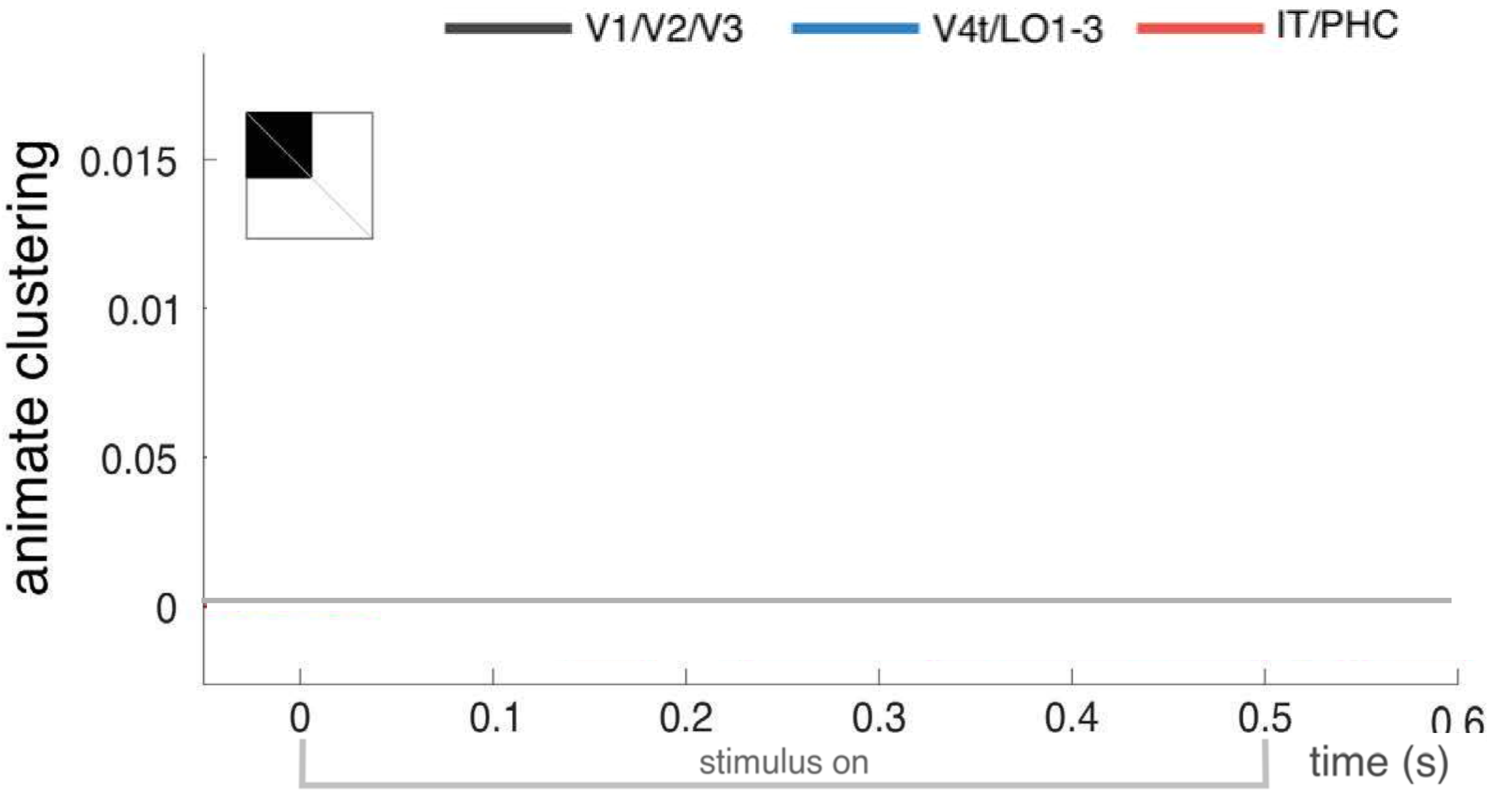
Kietzmann et al. 2019

Low-level features: gist model



Gist-like geometries first emerge in early visual areas, where they remain stronger throughout.

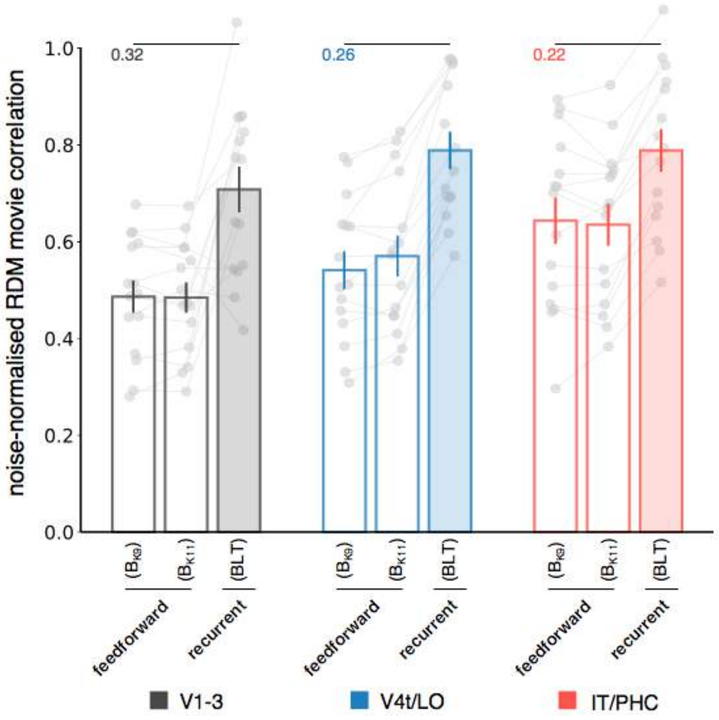
Categorical clustering: animacy



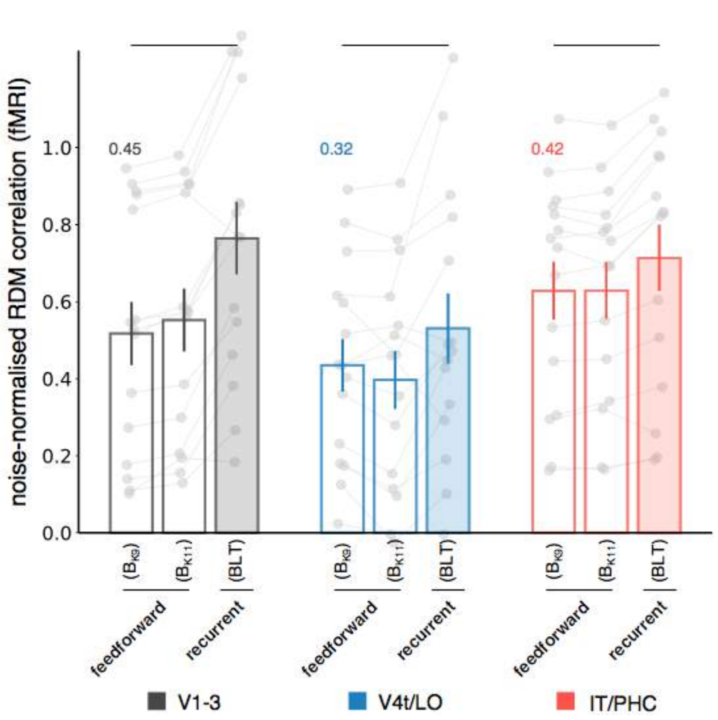
Animacy emerges first in IT/PHC, and only later in V4t/LO1-3.

Recurrent models better explain representations and their dynamics

magnetoencephalography



functional magnetic resonance imaging



feedforward recurrent

Kietzmann et al. 2019

The emerging recurrent story…

- Recurrent neural networks provide a **more neurobiologically realistic and computationally powerful** modeling framework.
- Recurrent processing can enable a network to
  - **recycle its computational resources**,
  - perform **more robust inferences**, and
  - **flexibly trade off speed and accuracy**.
- Recurrent models also **better explain the representational dynamics** of the human ventral stream.

Controversial stimuli: pitting neural networks against each other as models of human recognition

Golan et al. 2020

Controversial stimuli

Golan et al. 2020

Controversial stimuli: motivation

- Theoretical progress depends on experiments for which competing theories make distinct predictions.

- We can implement competing theories in testable NN models.

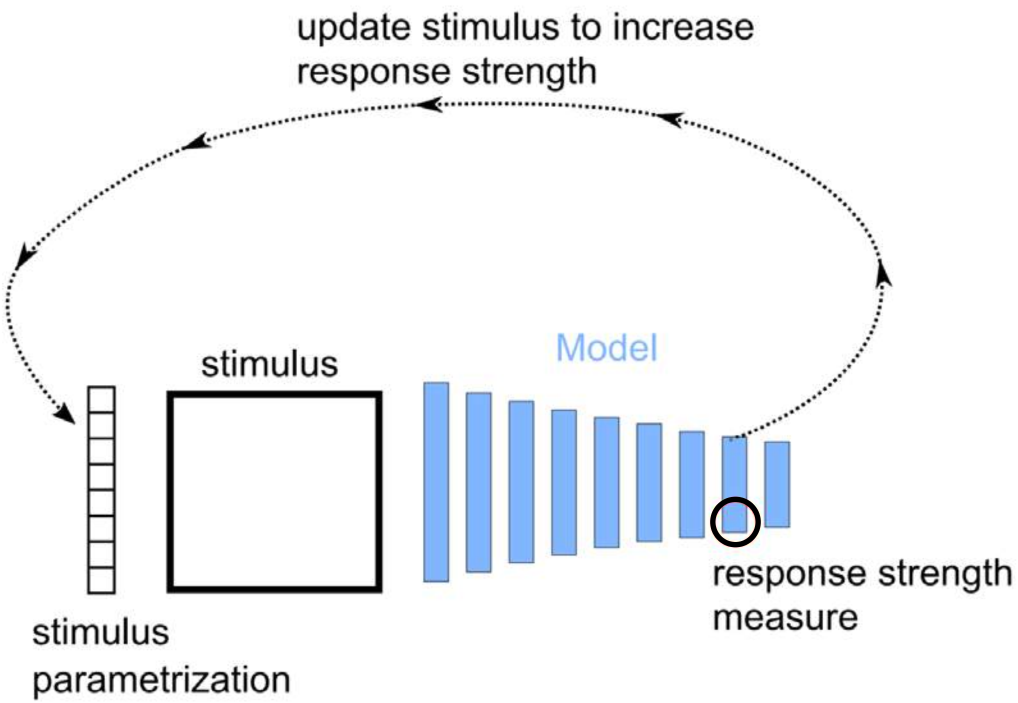
- However, NN models have many parameters, and theoretically distinct models often make similar predictions for natural stimuli.

Insight 1: To elicit models' distinct *inductive biases* we can test models on a population of stimuli not used in training (*out of distribution*).
  - natural stimuli drawn from a different stimulus population
  - synthetic stimuli (optimized to elicit bolder predictions, e.g. superstimuli, adversarial stimuli, and metamers)

Insight 2: Since our goal is to adjudicate among models, we can create synthetic stimuli optimized to elicit distinct predictions from different models: stimuli that are ***controversial*** among the models.

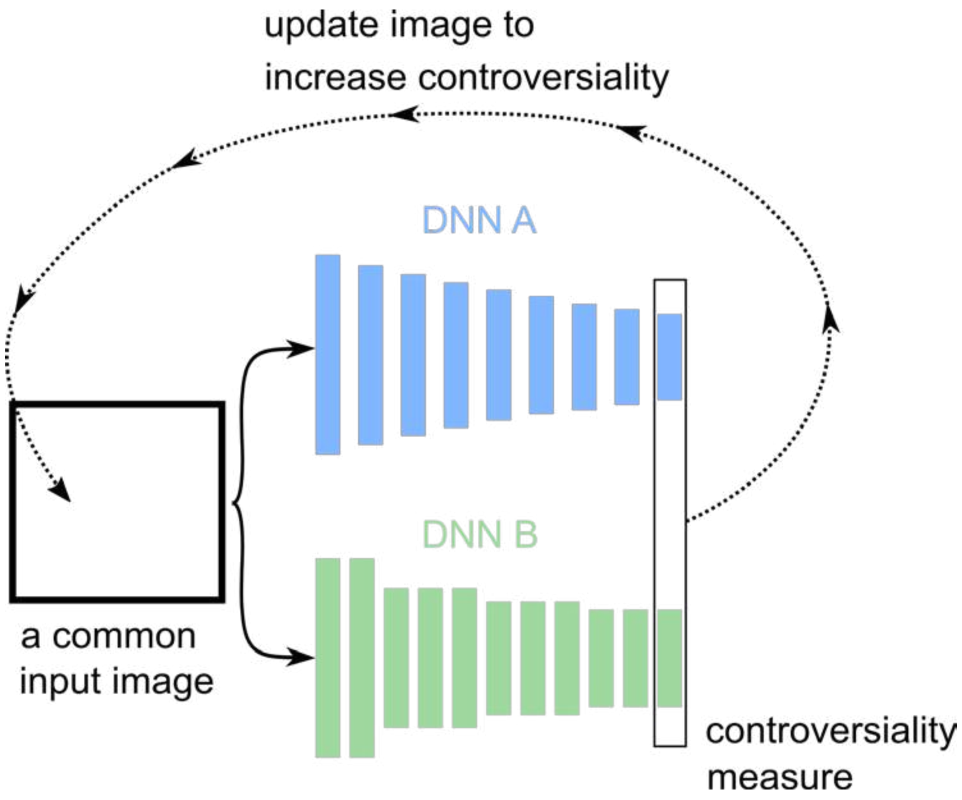
Golan et al. 2020, **Wang** & **Simoncelli** 2008

Superstimulus



Abbasi-Asl et al. 2018, **Malakhova** 2018,
Ponce et al. 2019, **Bashivan** et al. 2019,
Walker et al. 2019

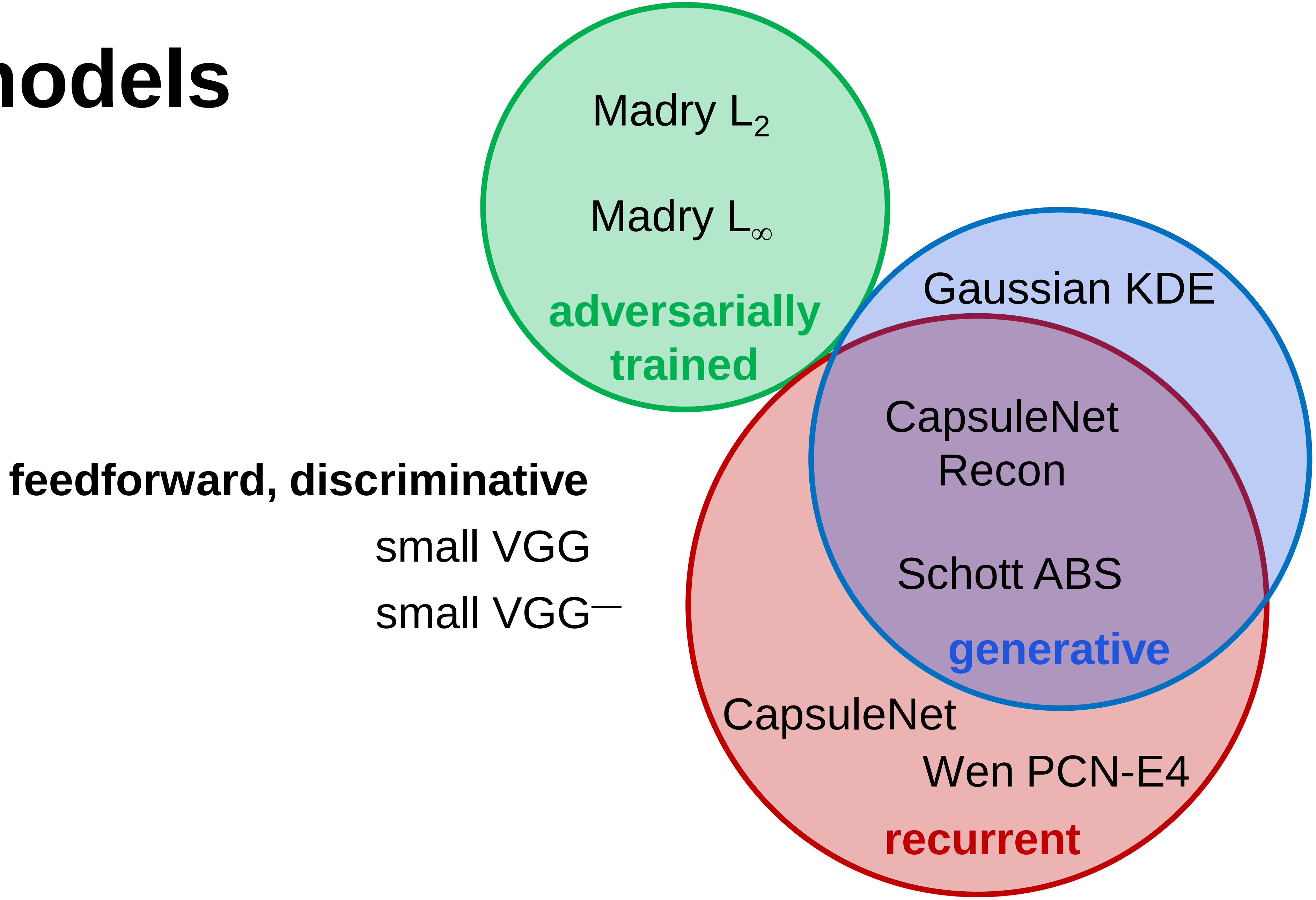
Controversial stimulus



Golan et al. 2020

MNIST

Tested models



Controversiality index

digit pair

$$c_{A,B}^{d_a,d_b}(x)$$

model pair

image

model **A** detects digit **a** **and** not digit **b**

and model **B** detects digit **b** **and** not digit **a**

Golan et al. 2020

Controversiality index

digit pair

model **A** detects digit **a**

and

not digit **b**

$$c_{A,B}^{d_a,d_b}(x) = \mathbf{min}\left\{\hat{p}_A(d_a \mid x), 1 - \hat{p}_A(d_b \mid x),\right.$$
$$\left.\hat{p}_B(d_b \mid x), 1 - \hat{p}_B(d_a \mid x)\right\},$$

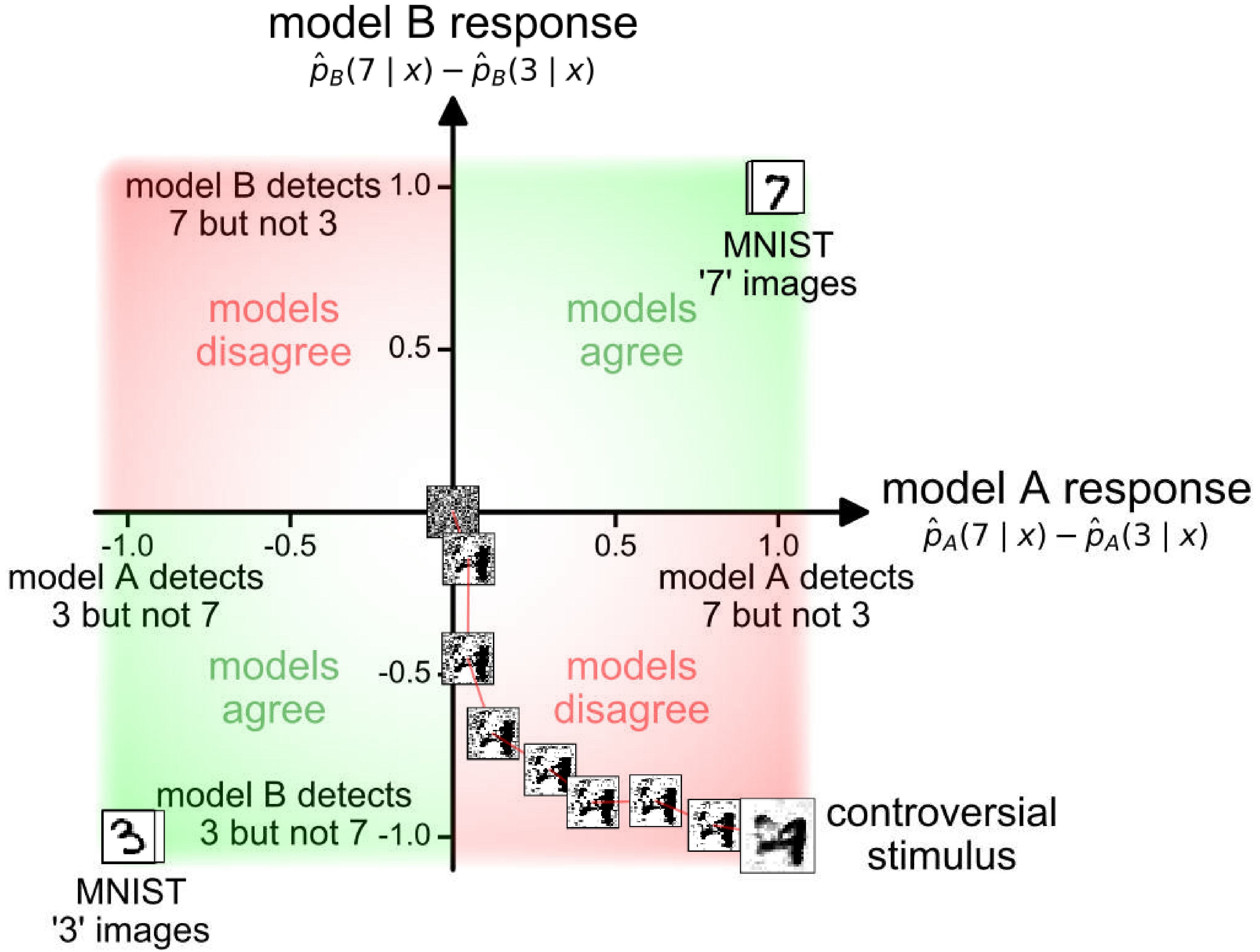
model pair

image

and model **B** detects digit **b**

and not digit **a**

Golan et al. 2020

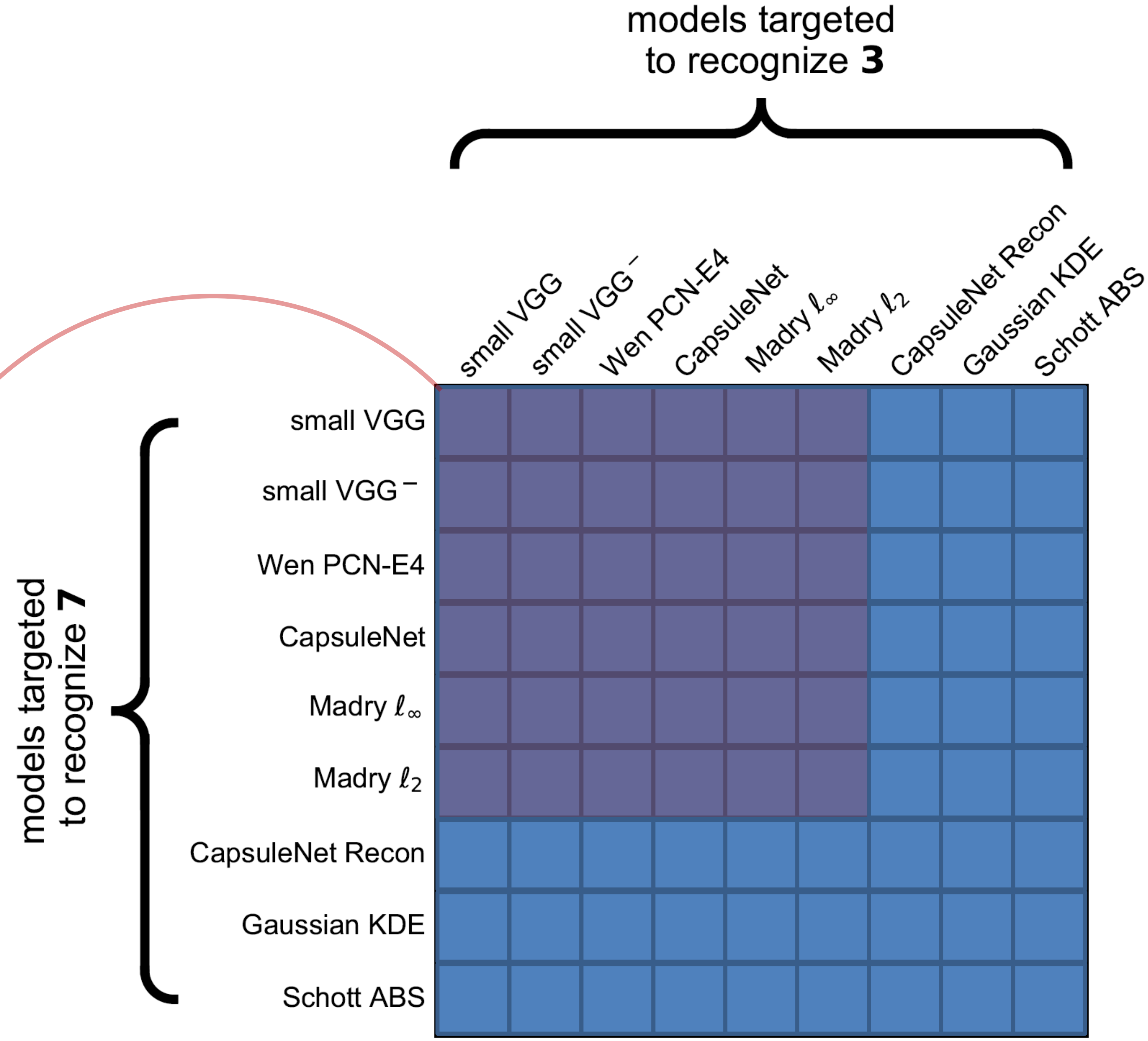


model B response
$\hat{p}_B(7 \mid x) - \hat{p}_B(3 \mid x)$
model B detects
7 but not 3
1.0
0.5
-0.5
-1.0
models
disagree
models
agree
MNIST
'7' images
model A response
$\hat{p}_A(7 \mid x) - \hat{p}_A(3 \mid x)$
-1.0
-0.5
0.5
1.0
model A detects
3 but not 7
model A detects
7 but not 3
models
agree
models
disagree
model B detects
3 but not 7
controversial
stimulus
MNIST
'3' images

Controversial stimuli

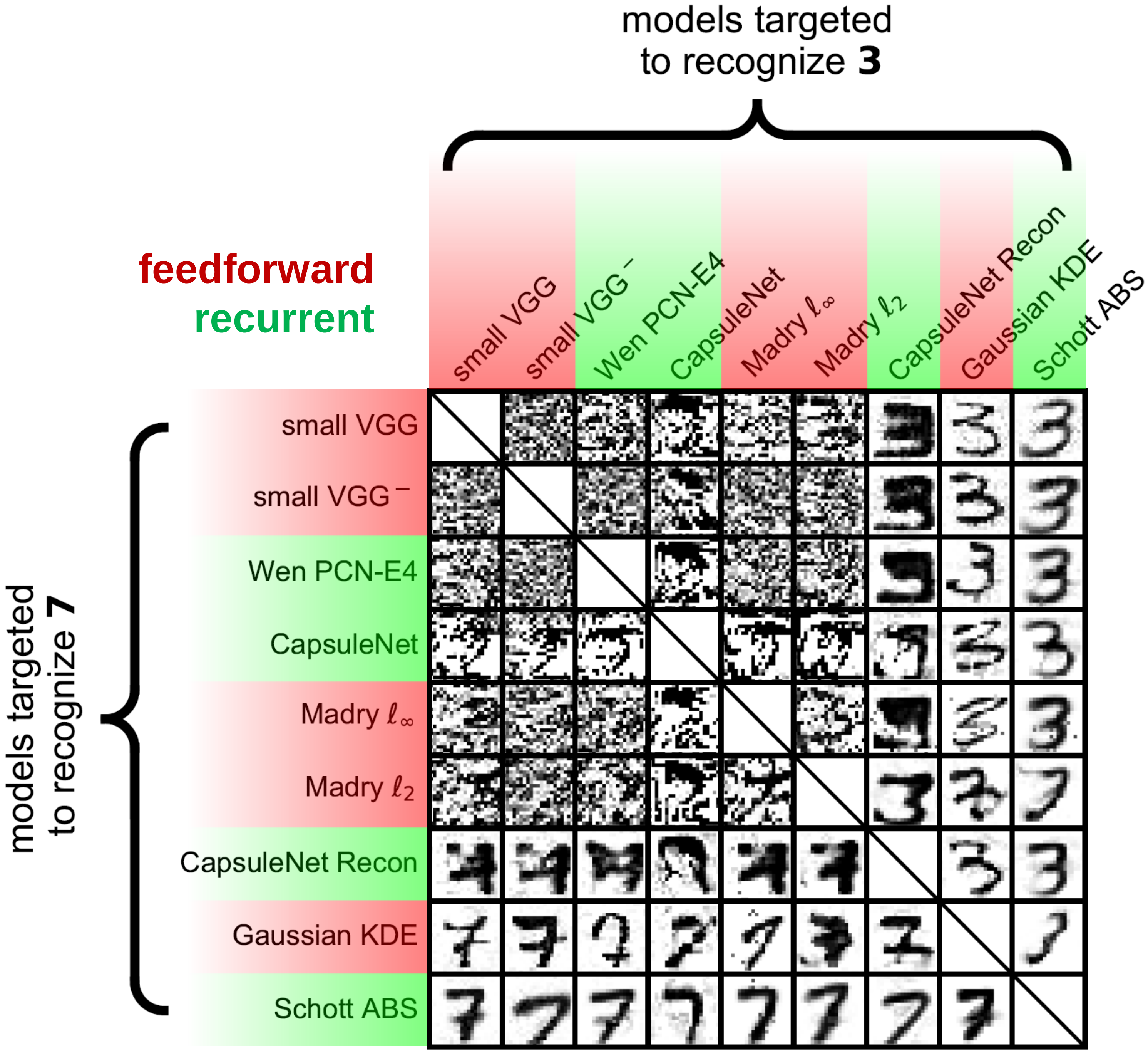
(optimized by gradient descent)

adversarial example
a stimulus that is controversial
between a model and ground truth



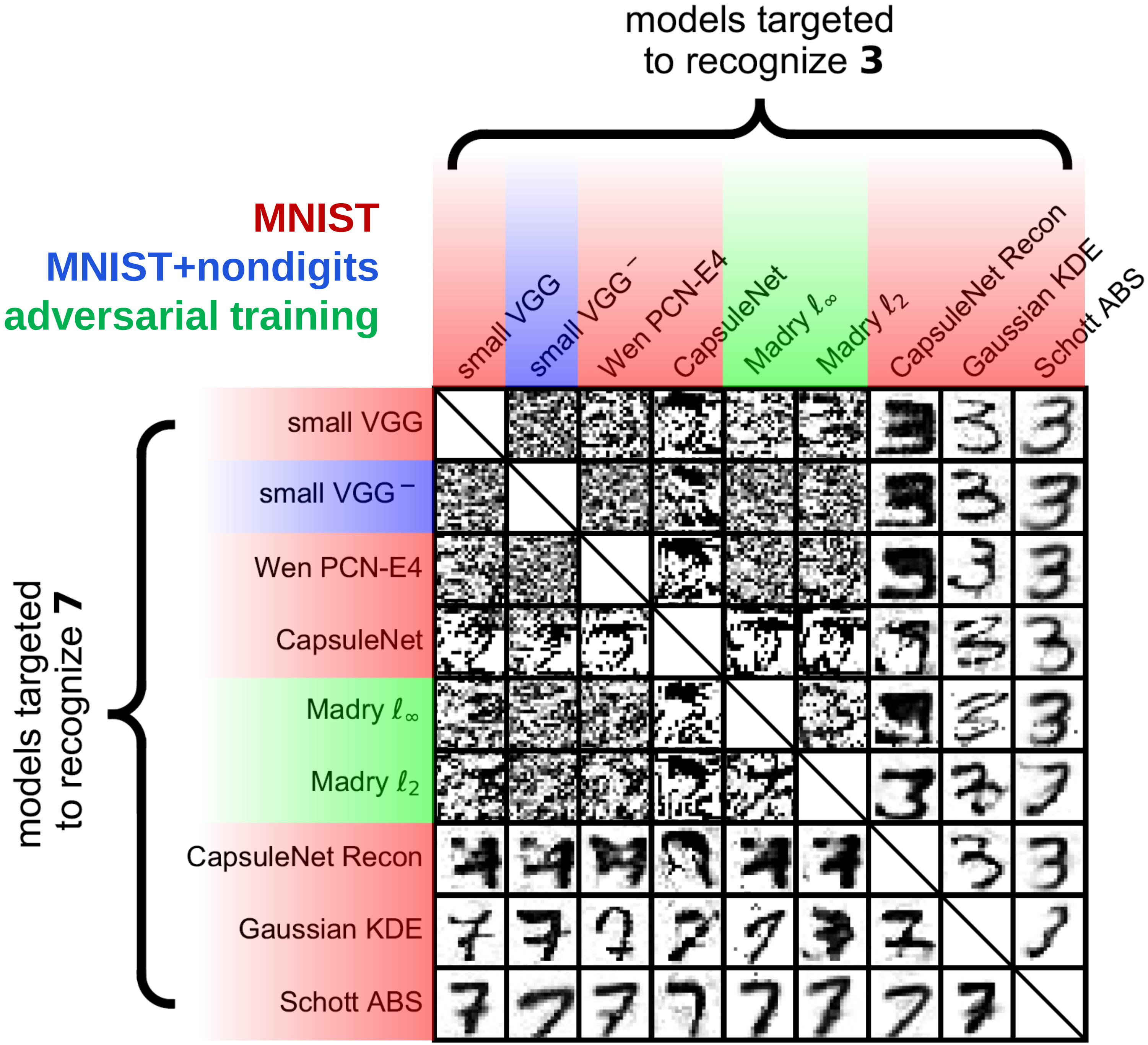
Golan et al. 2020

Controversial stimuli



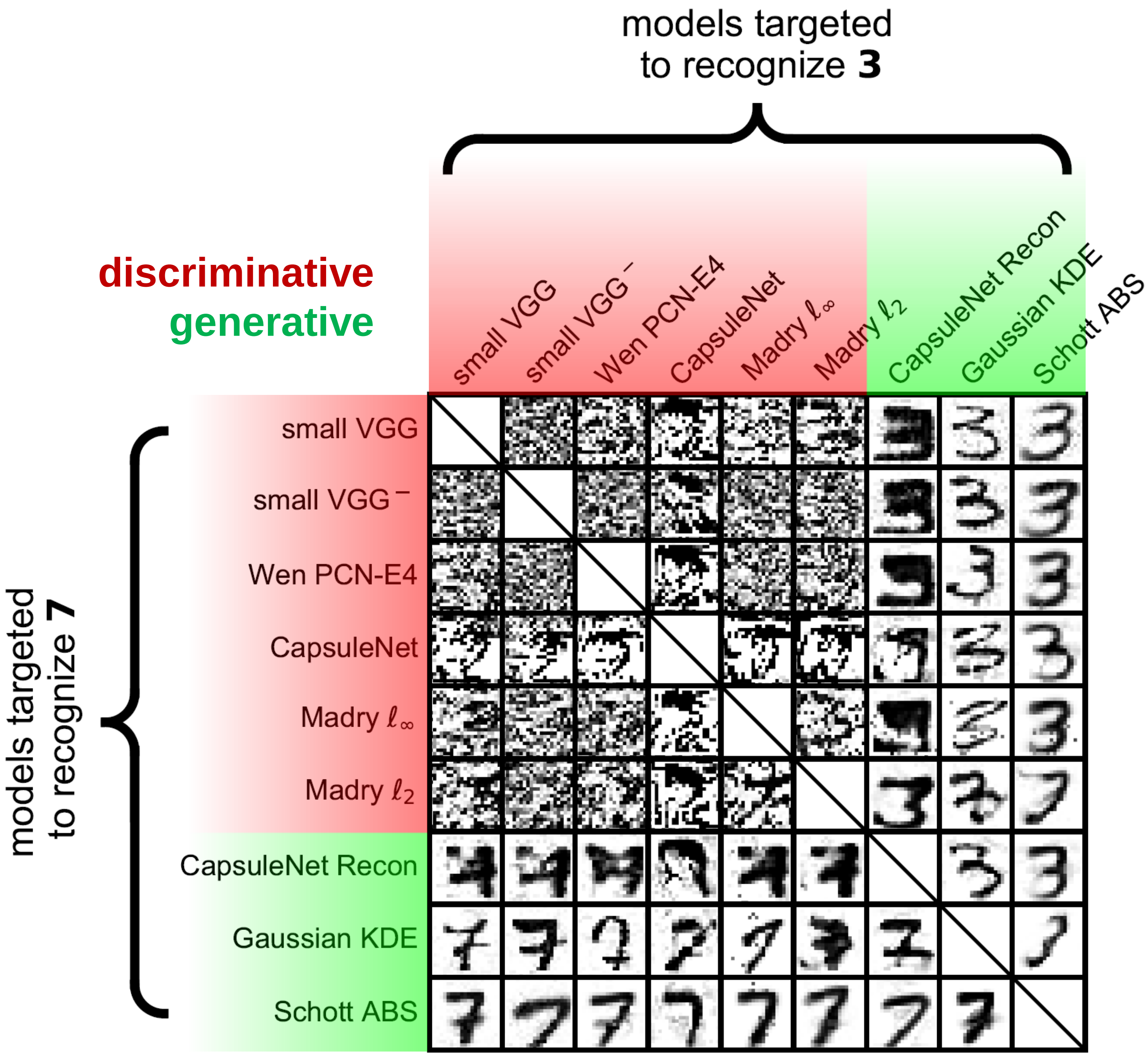
Golan et al. 2020

Controversial stimuli

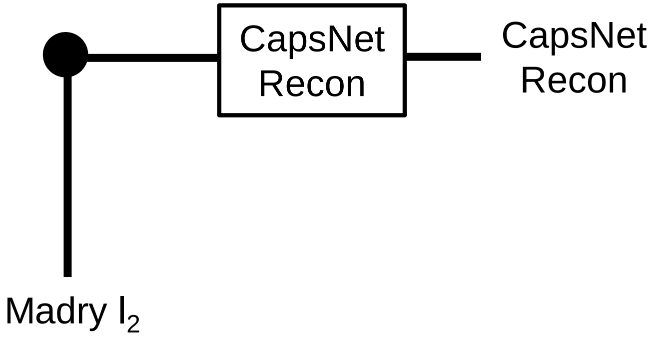


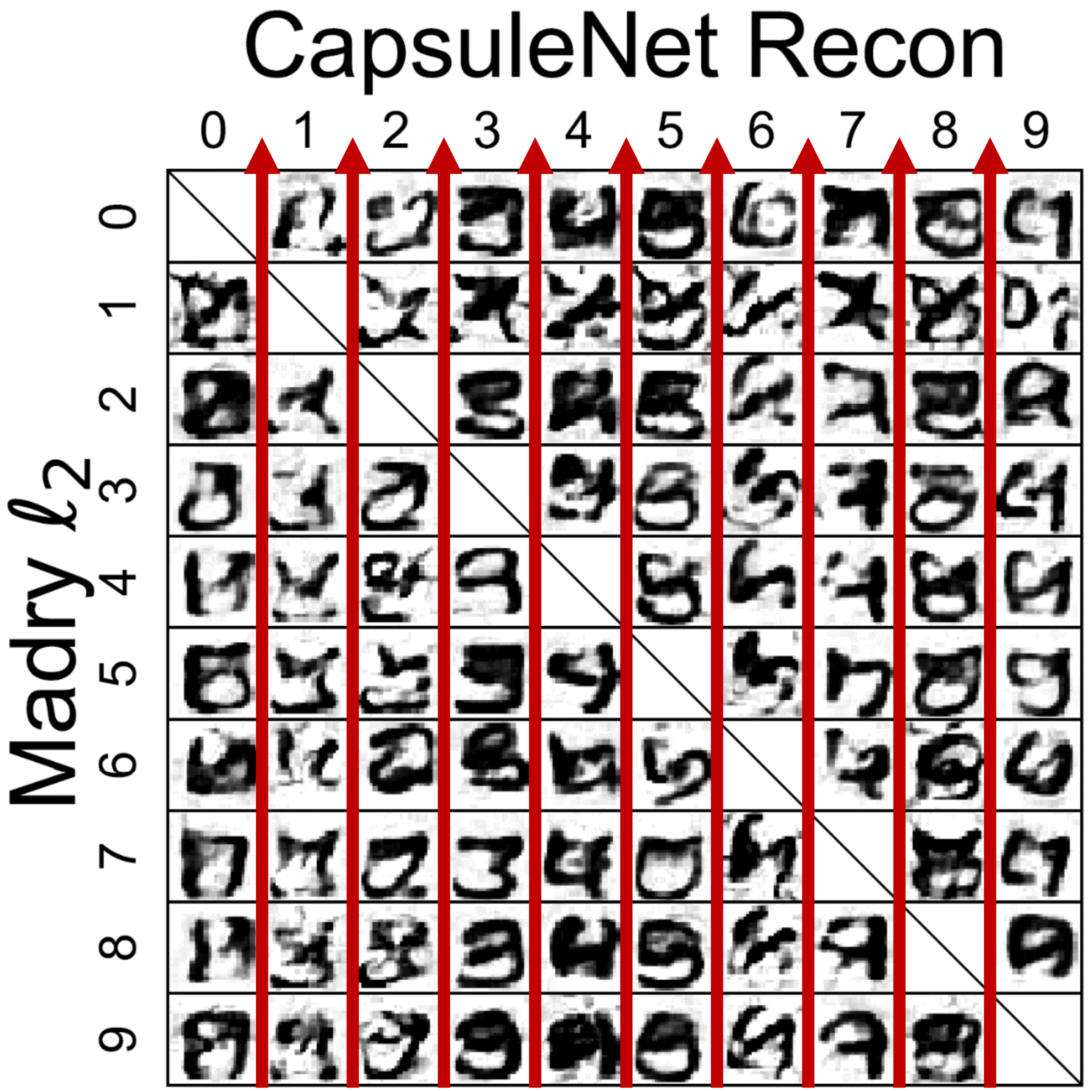
Golan et al. 2020

Controversial stimuli



Golan et al. 2020





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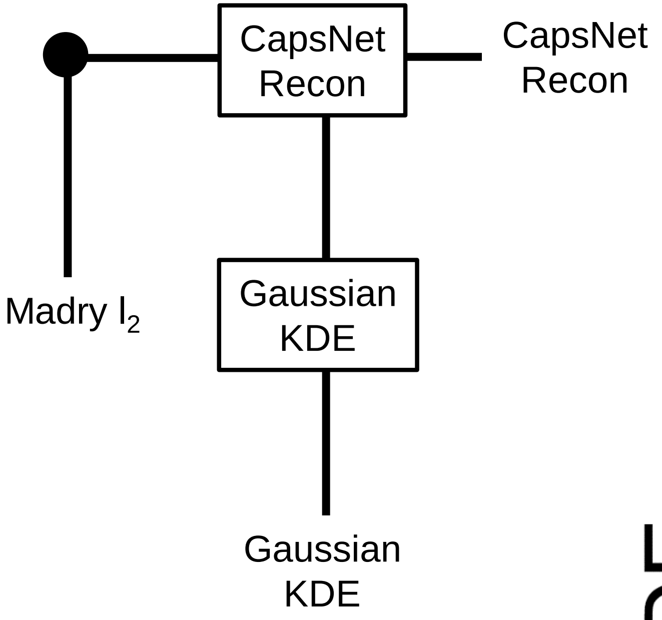

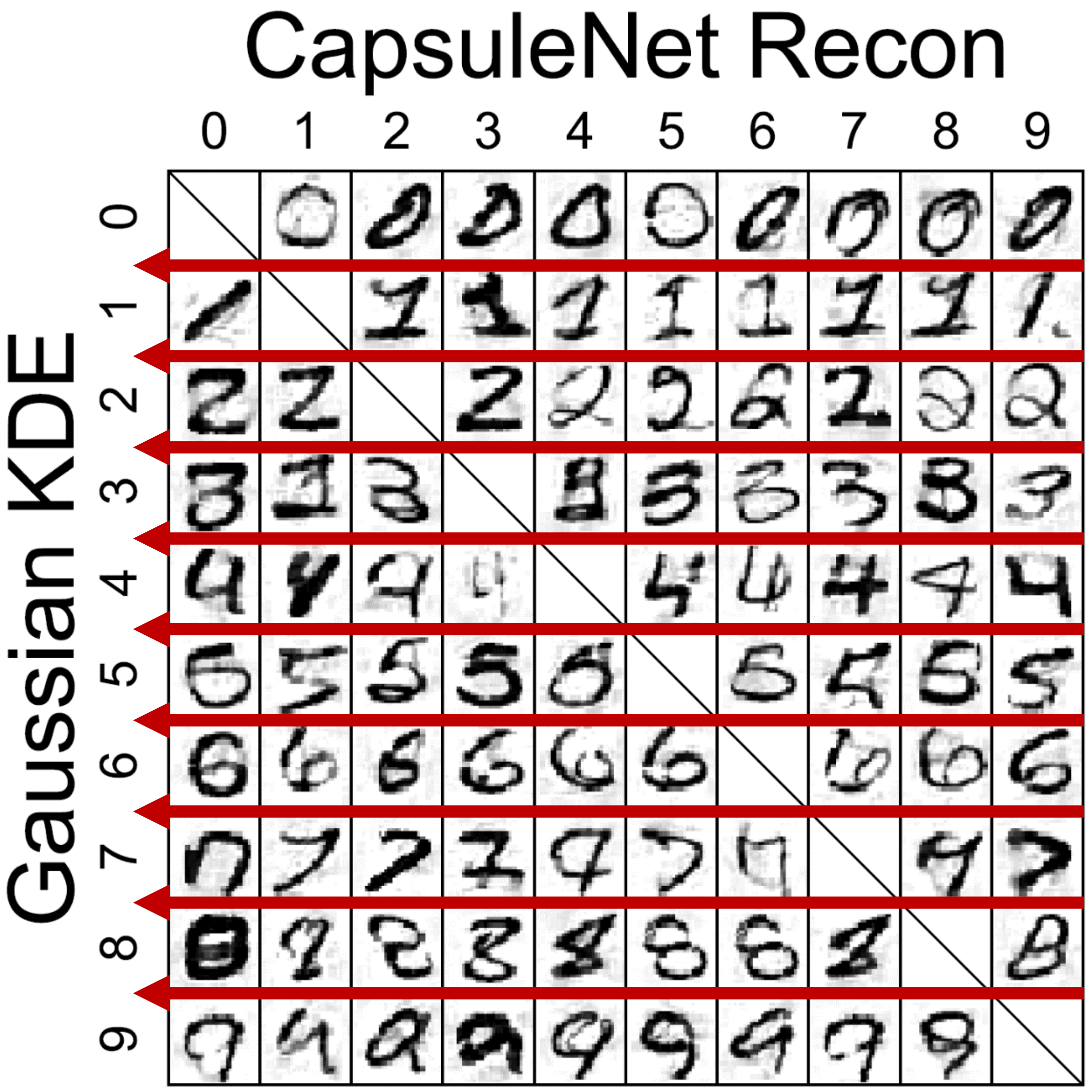

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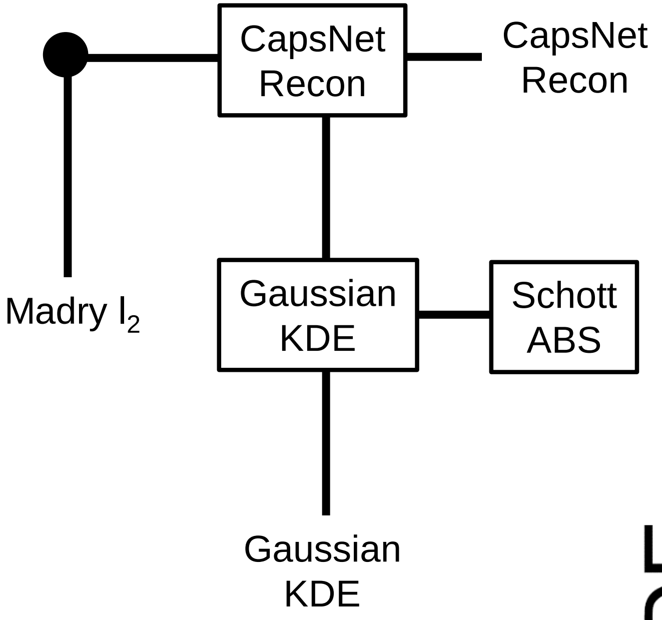

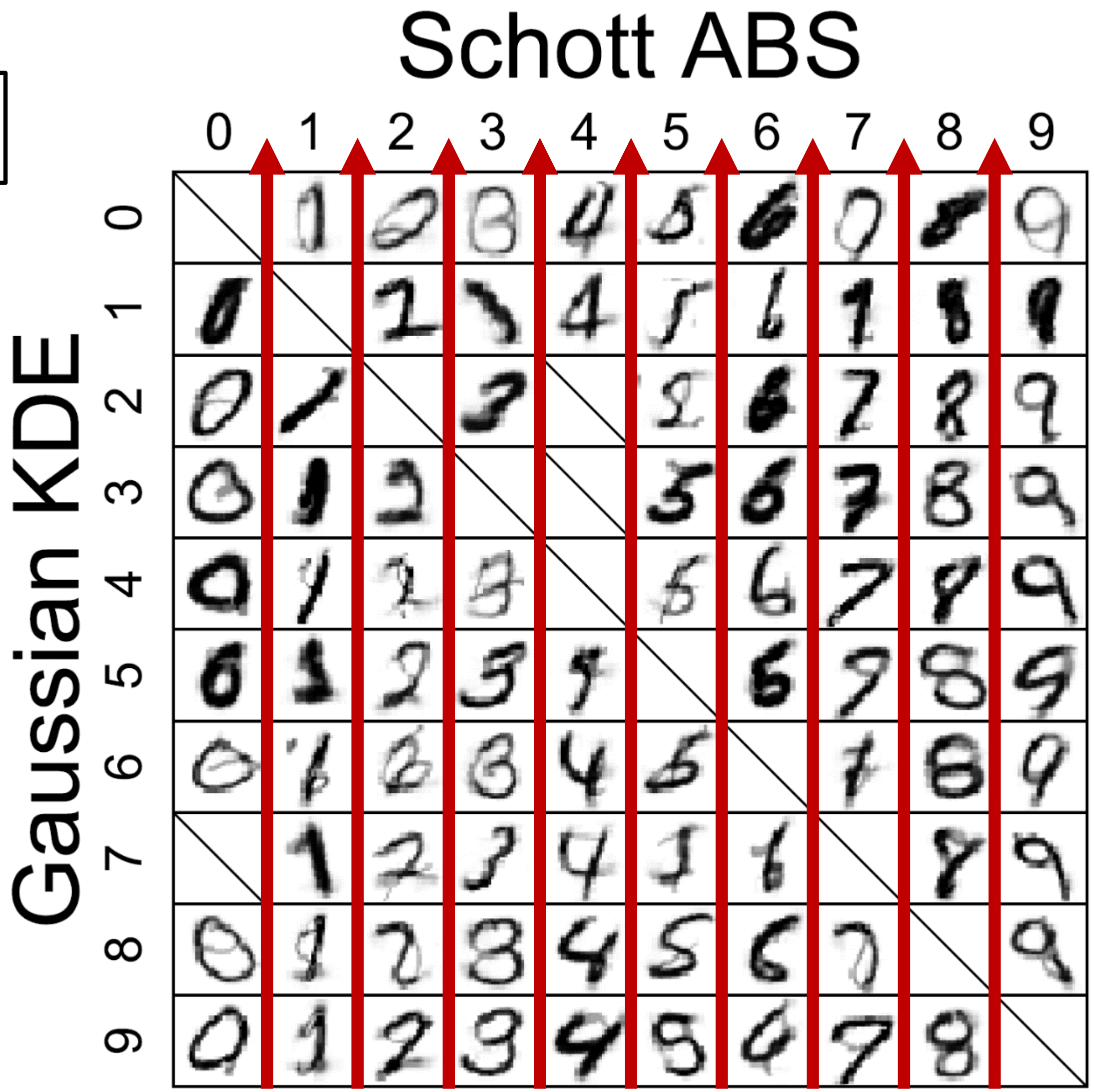

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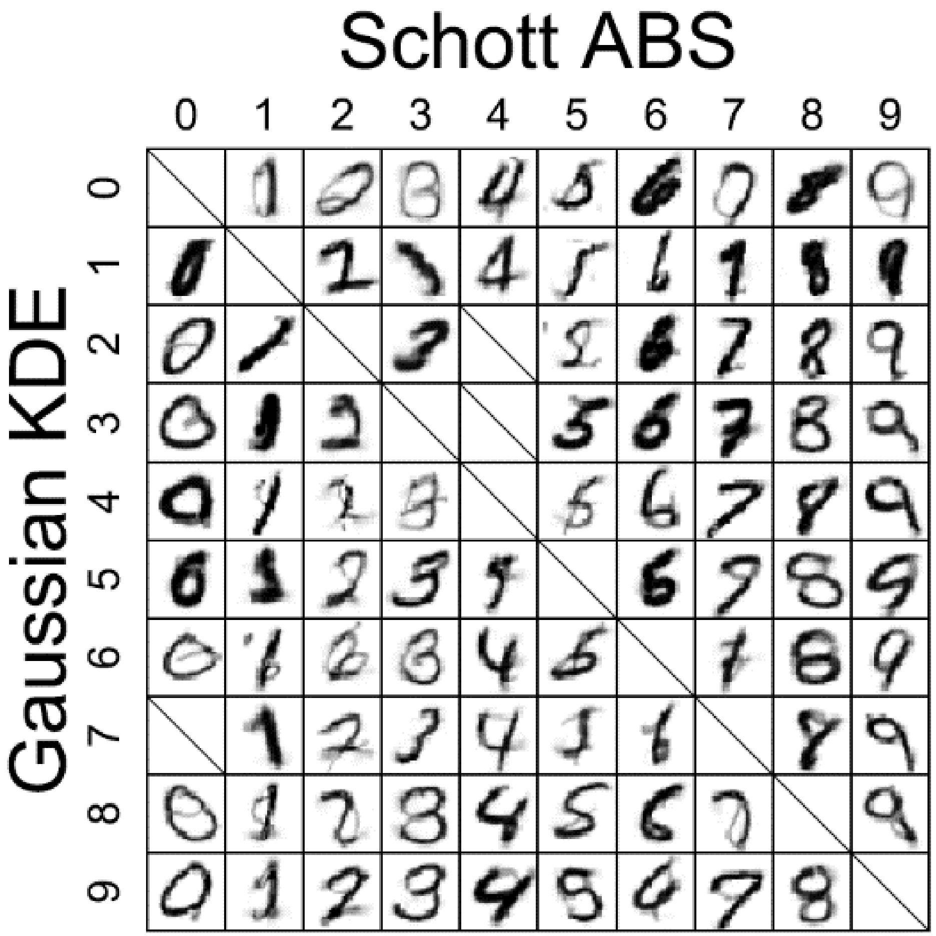

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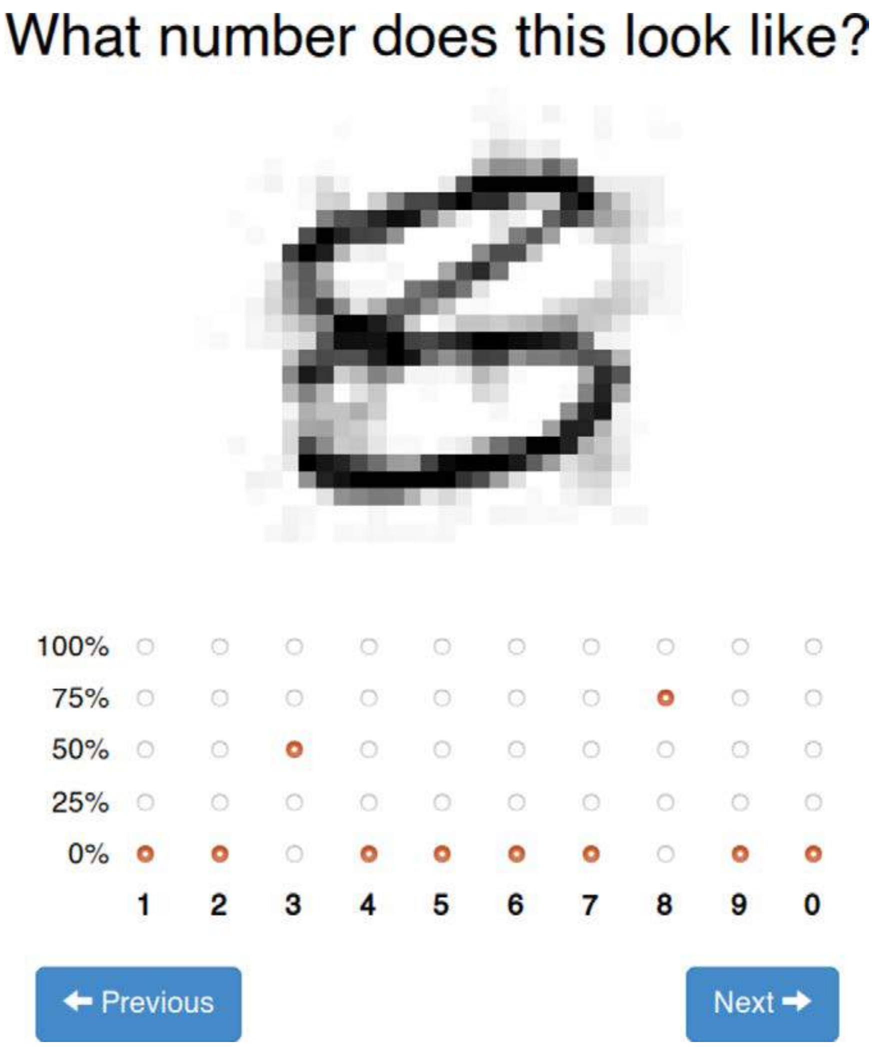
Behavioral experiment



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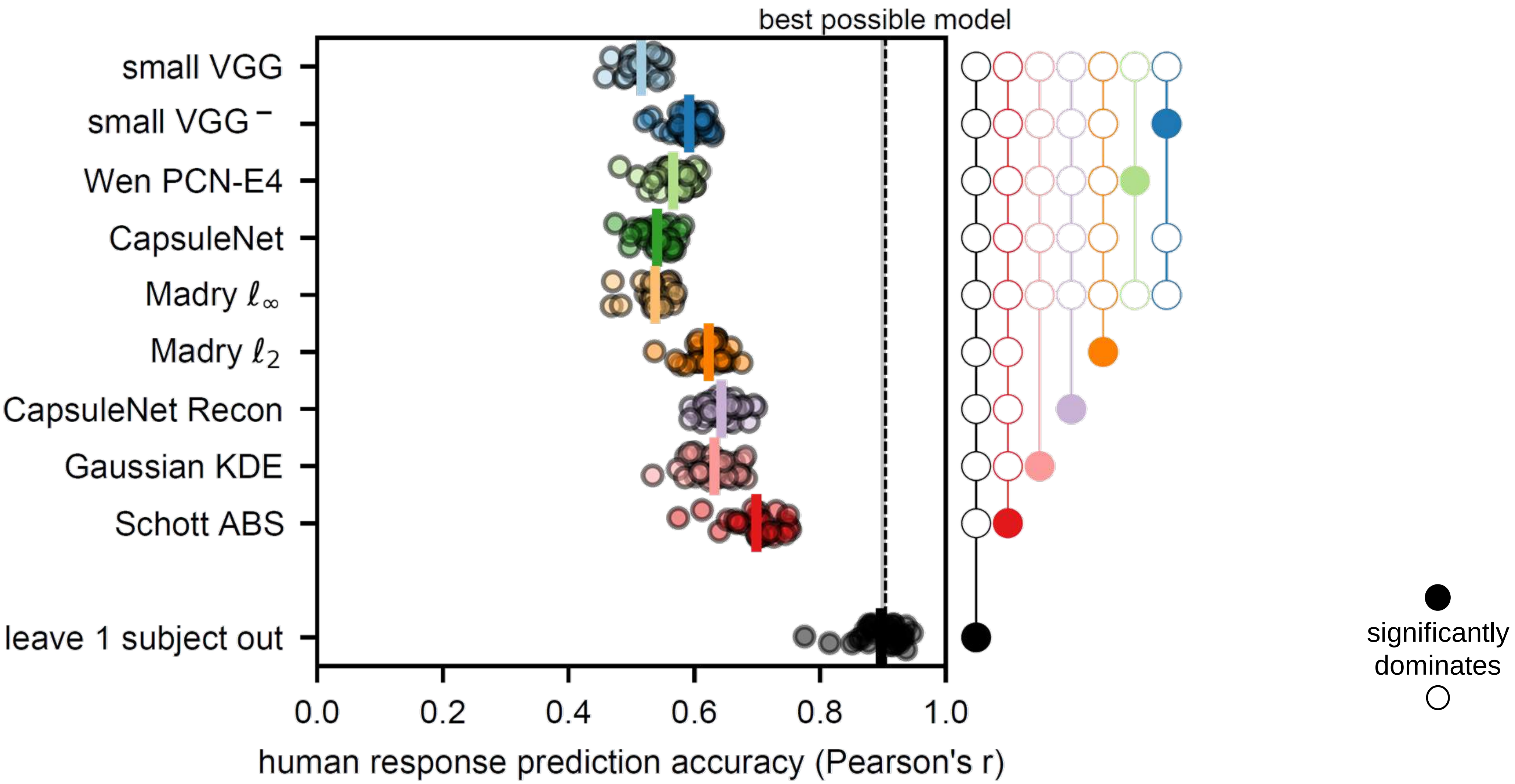
Behavioral experiment

- 30 subjects (tested via *Prolific*)
- stimuli included 20 controversial stimuli per model pair
  (36*20) + 100 MNIST images = 820 images per subject
- stimuli presented in a randomized order
- 820 stimuli x 10 scales x 30 subjects
  (246,000 data points)

Controversial stimuli



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Controversial stimuli

natural images
(CIFAR-10 set of small images)

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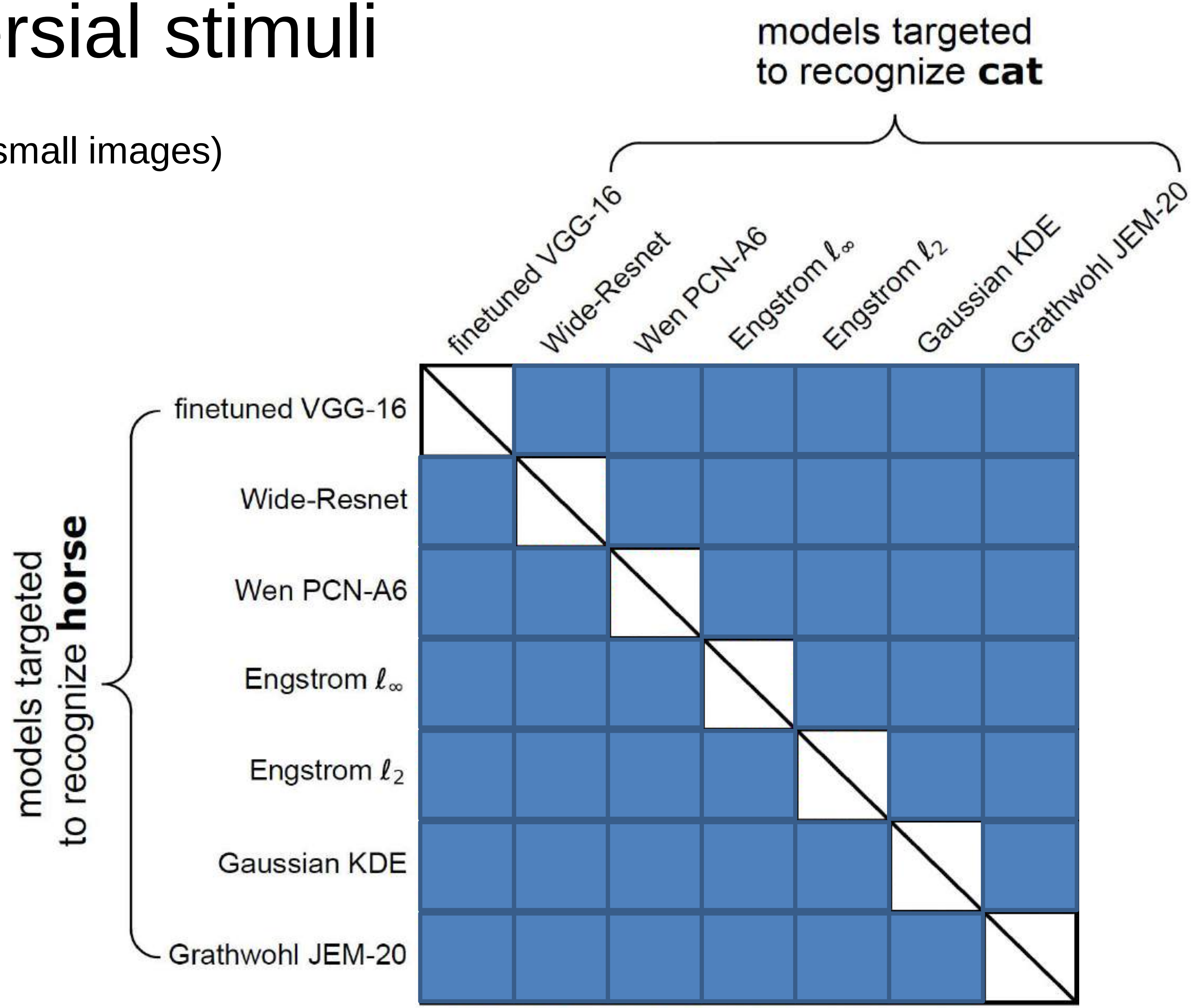
Controversial stimuli

natural images
(CIFAR-10 set of small images)



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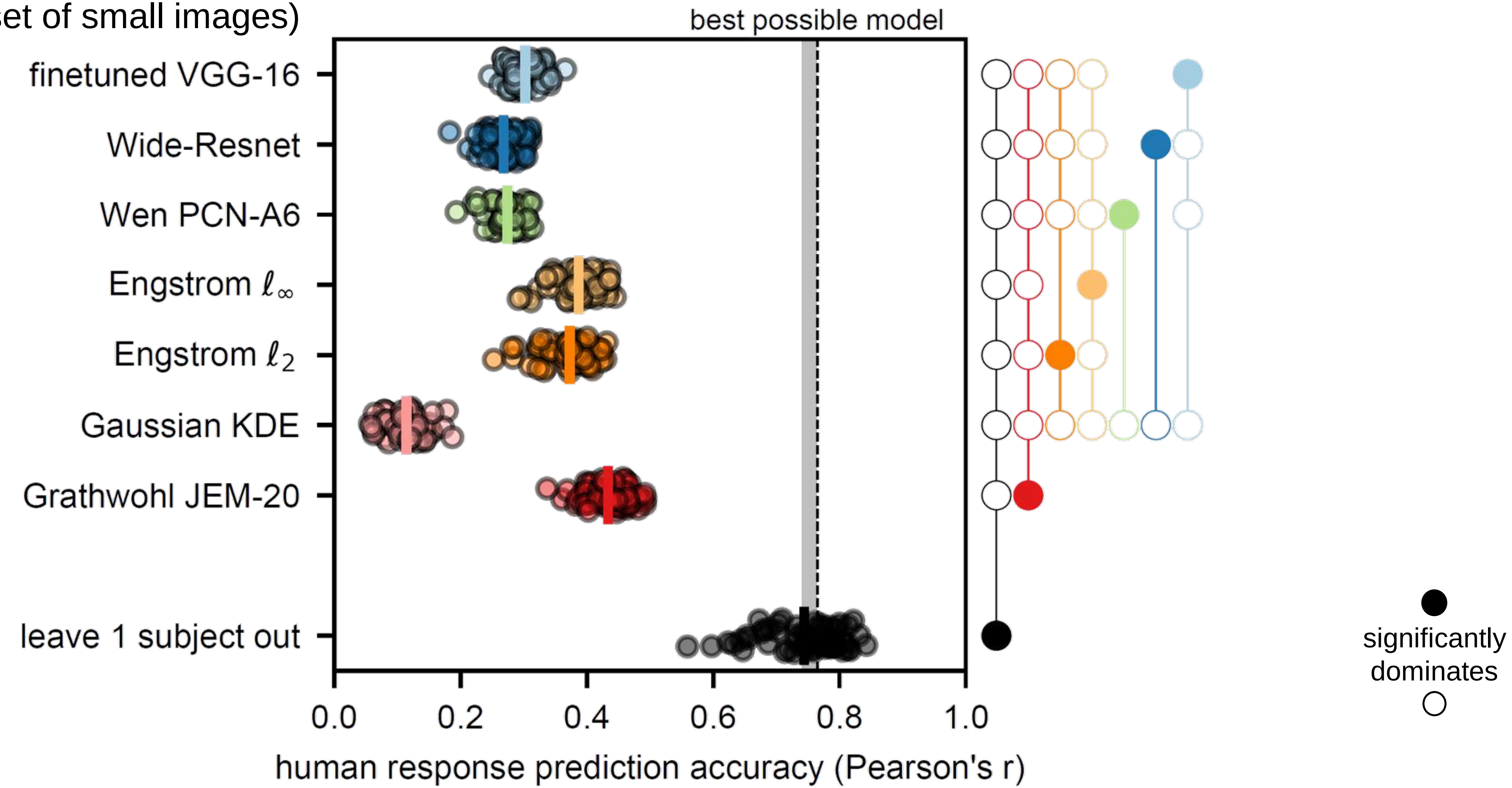
Controversial stimuli

natural images
(CIFAR-10 set of small images)



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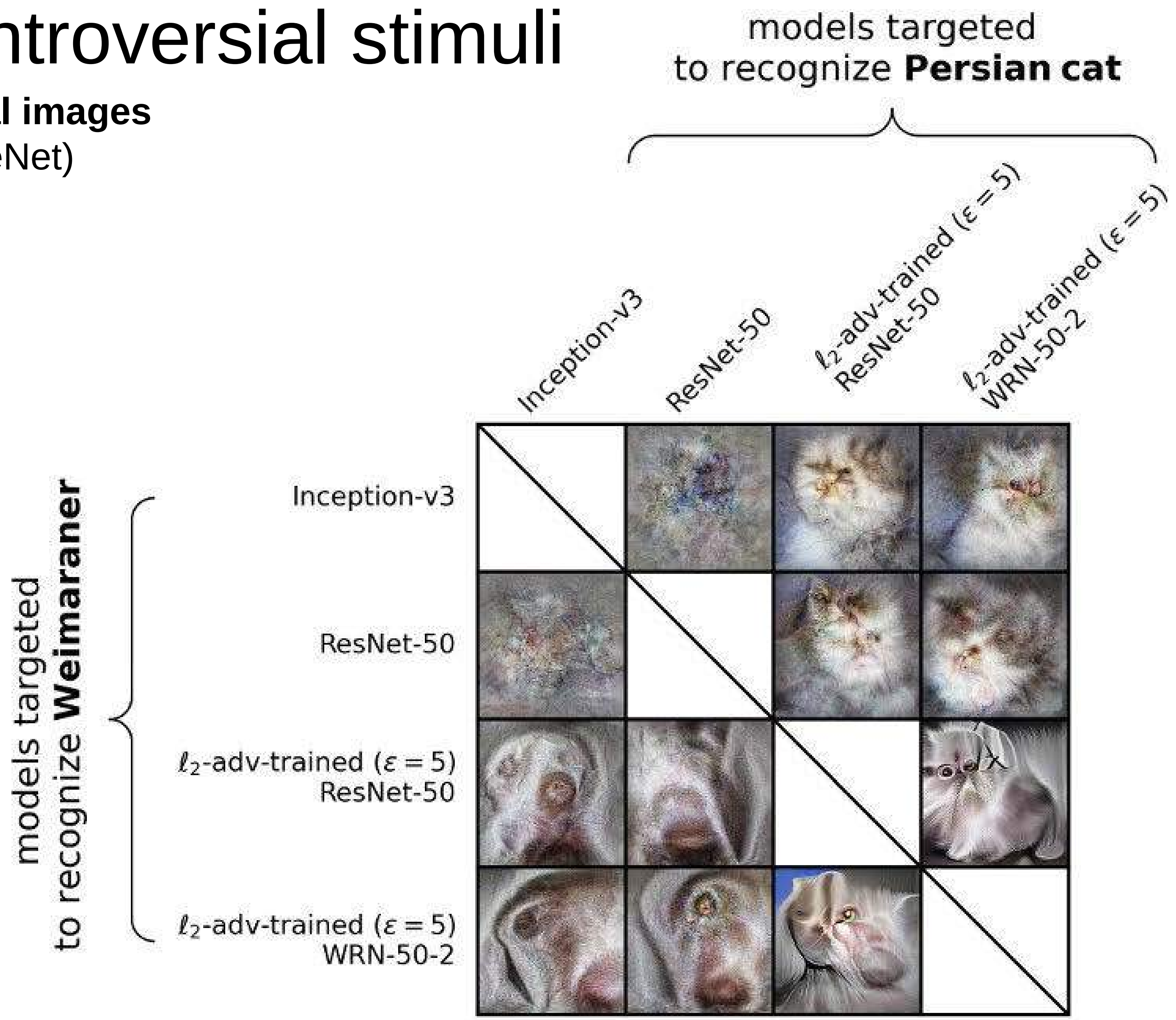
Controversial stimuli

natural images
(ImageNet)



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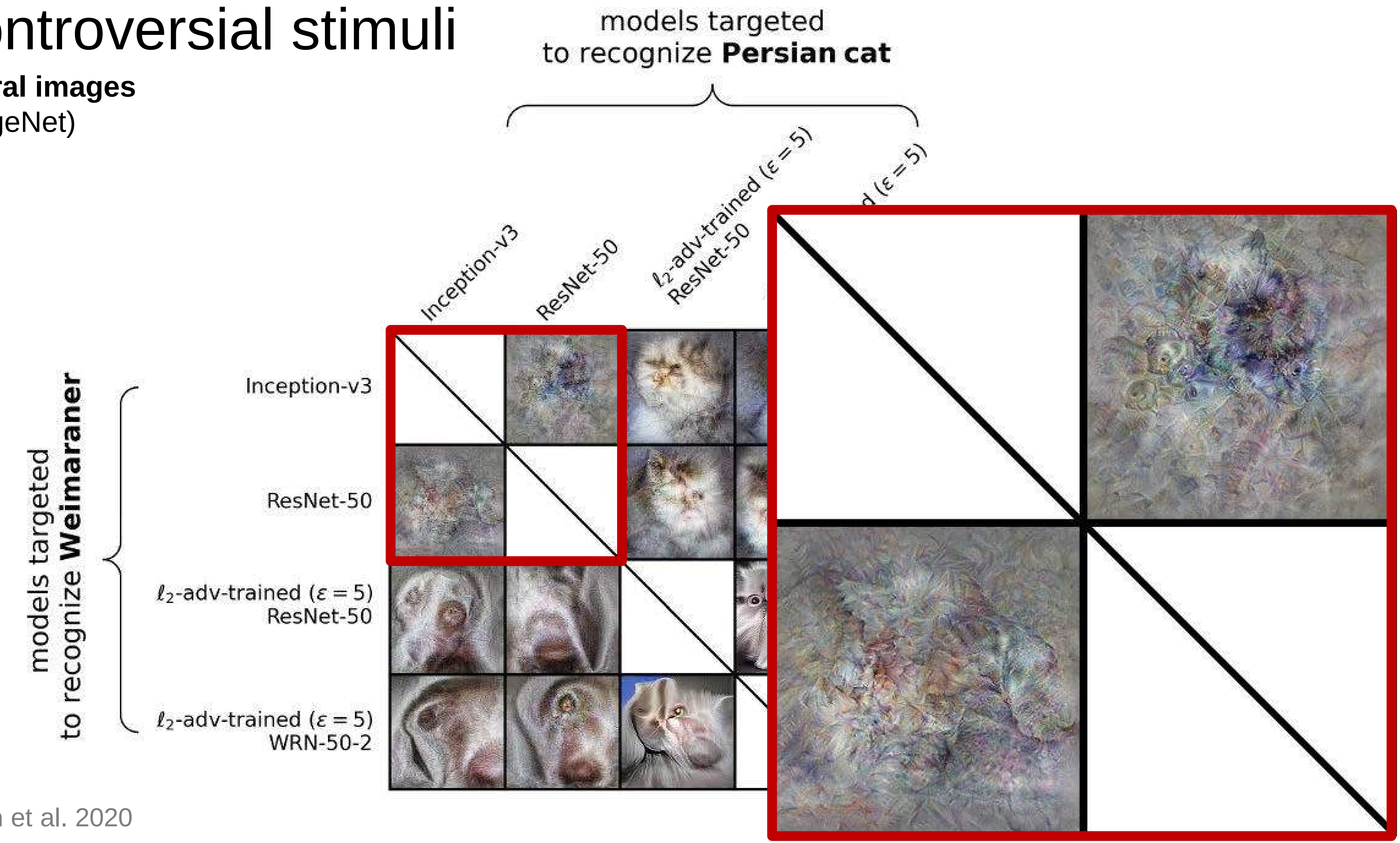
Controversial stimuli

natural images
(ImageNet)



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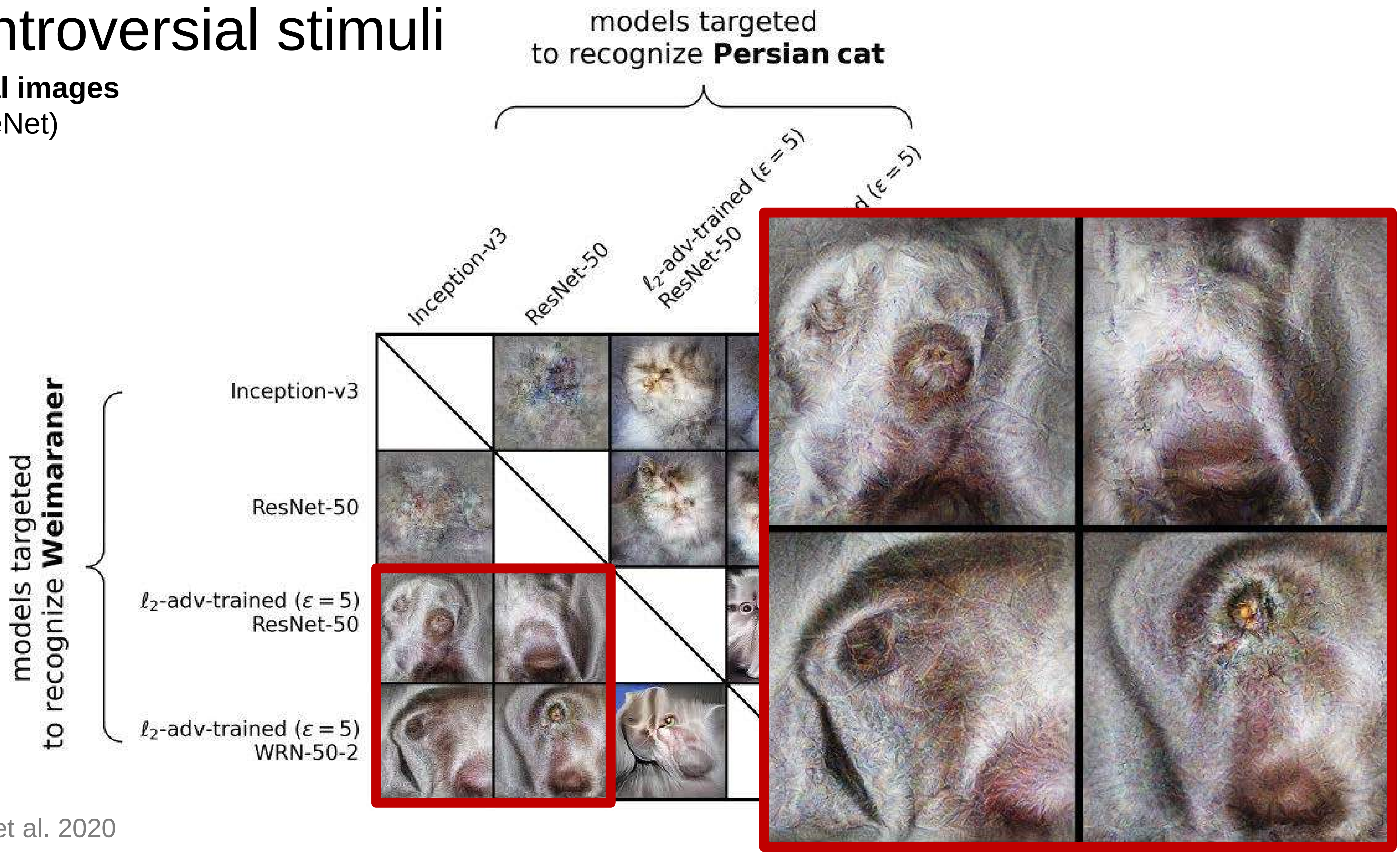
Controversial stimuli

natural images
(ImageNet)



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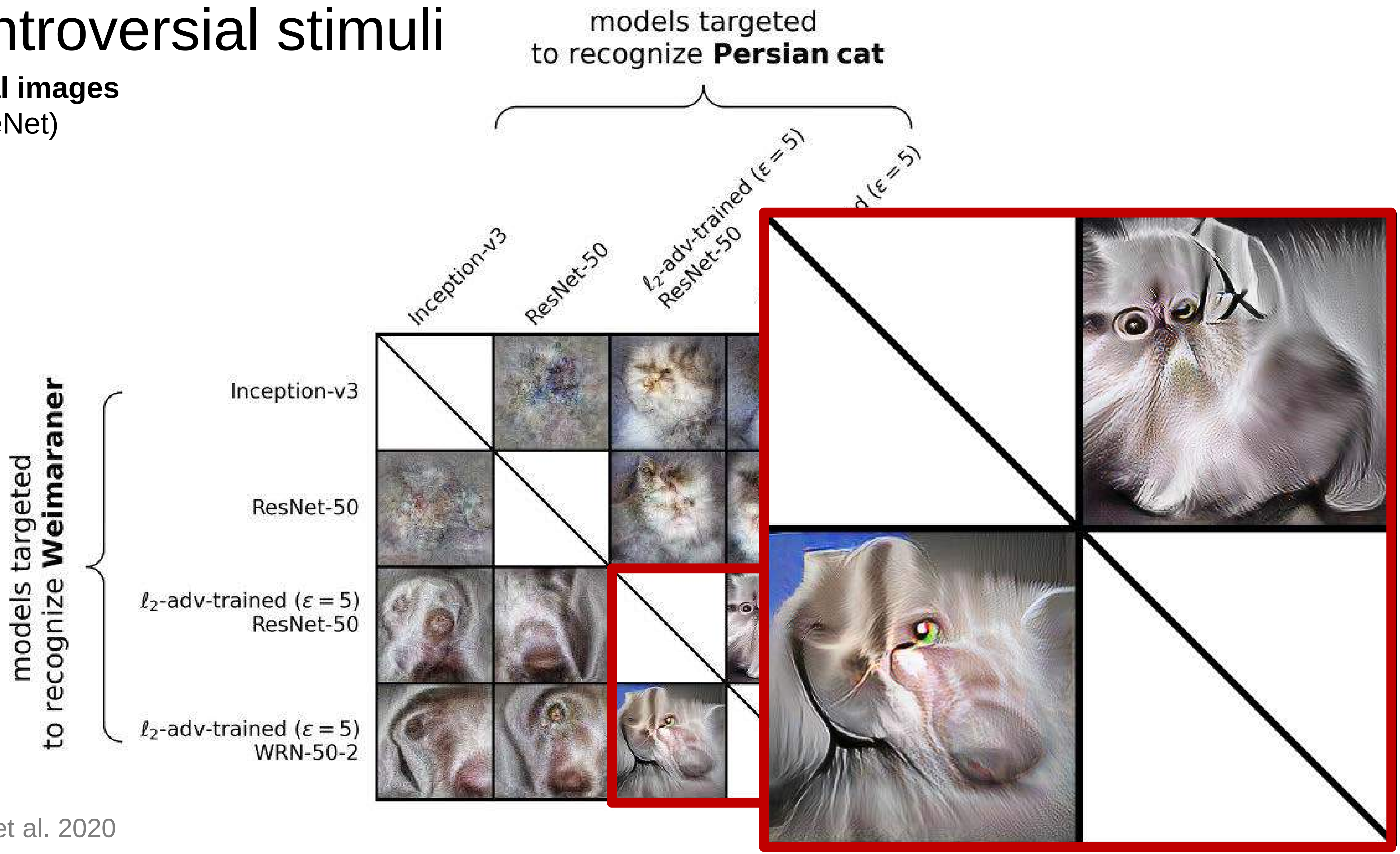
Controversial stimuli

natural images
(ImageNet)



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Overall conclusions

1. We can adjudicate among task-performing deep net models by inferentially comparing their representations to brain representations.
   Nili et al. 2014, **Kriegeskorte** & **Diedrichsen** 2019

2. Recurrent convolutional vision models better predict human ventral stream representational dynamics and reaction times
   Kietzmann et al. 2019, **Spoerer** et al. 2020

3. Controversial stimuli enable us to elicit differences in the inductive biases of deep net model.
   Golan et al. 2020

4. Human vision may rely on a computational mechanism that combines elements of discriminative and generative inference.
   Golan et al. 2020