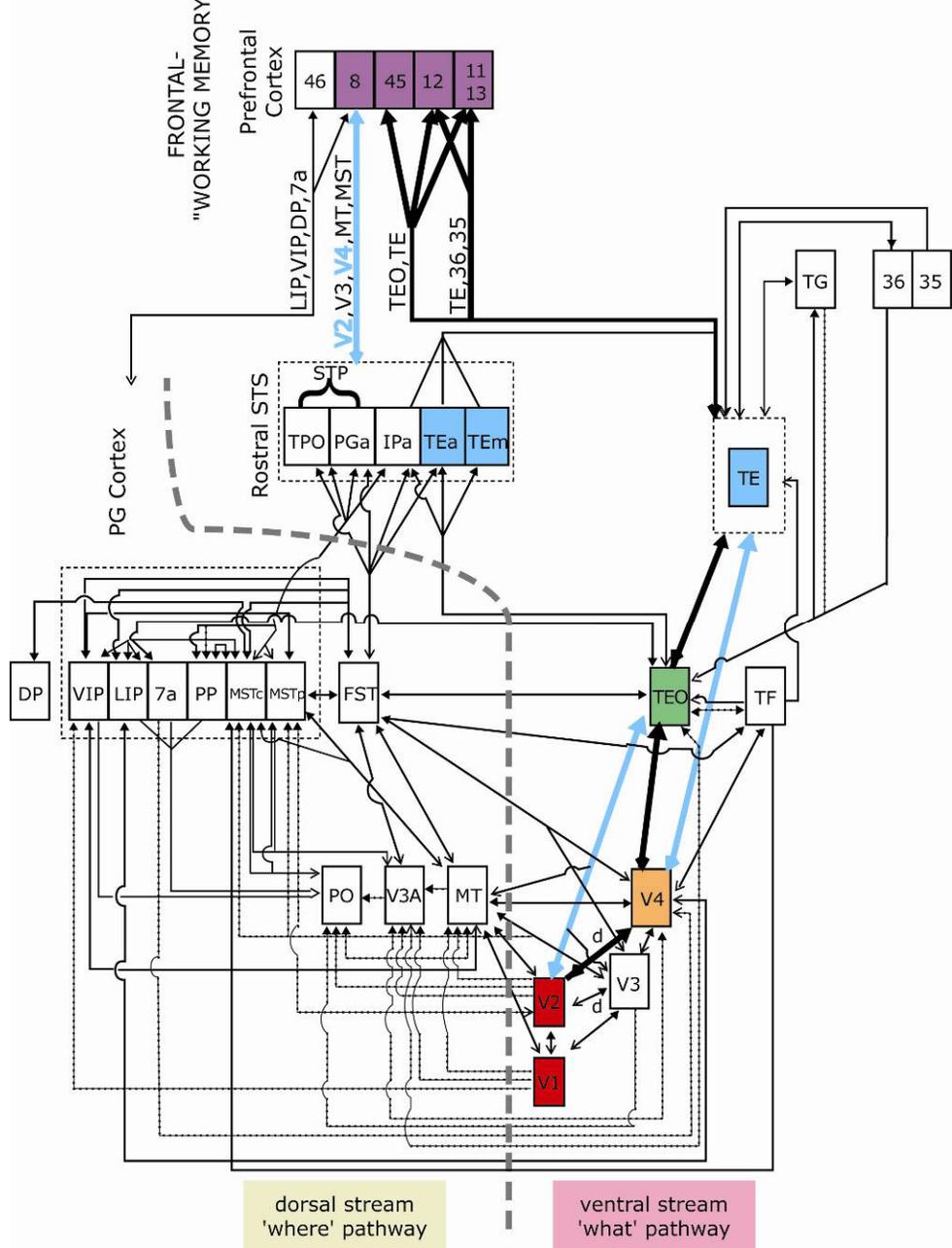


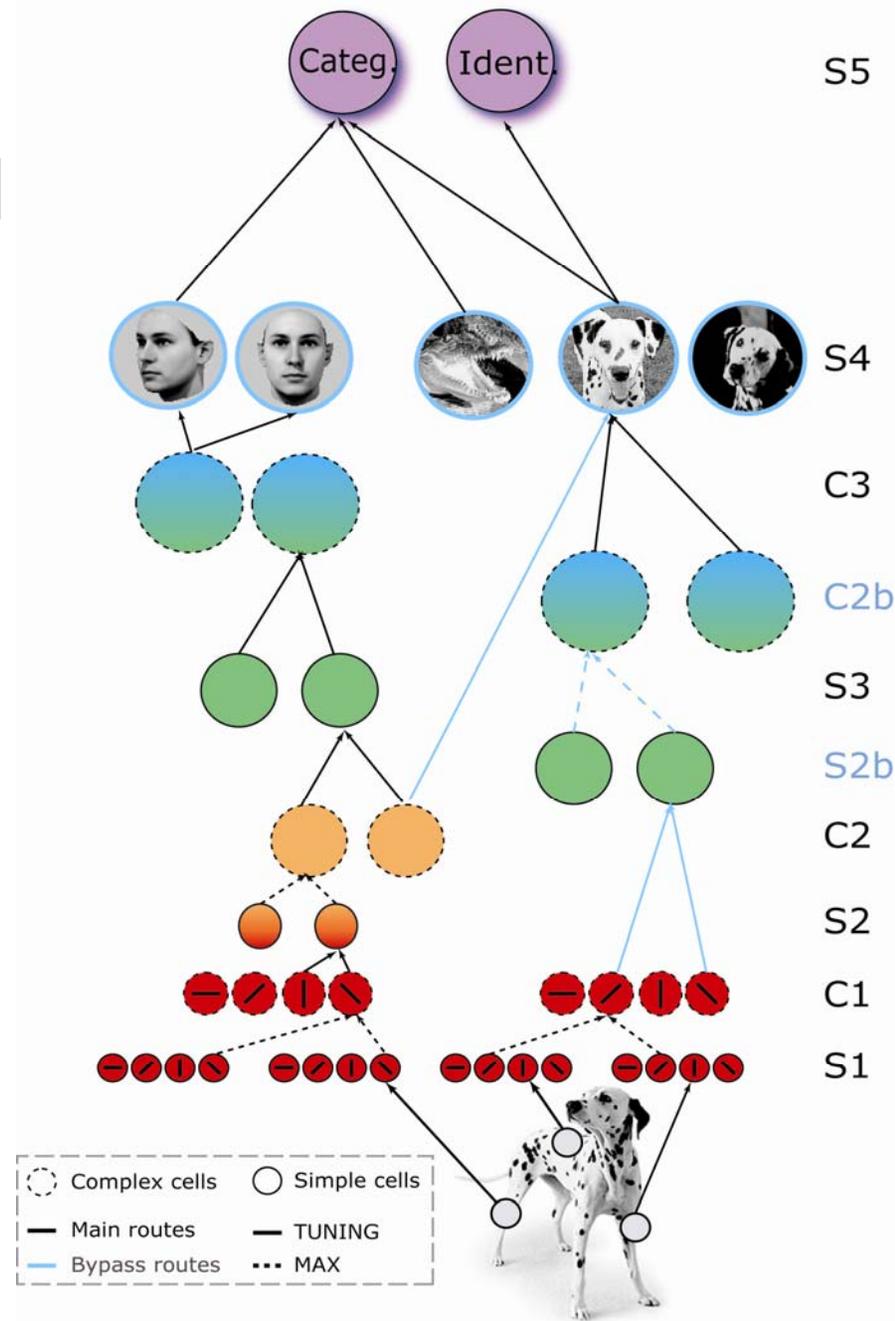
Feedforward theories of visual cortex predict human performance in rapid image categorization

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Modified from (Ungerleider & VanEssen)

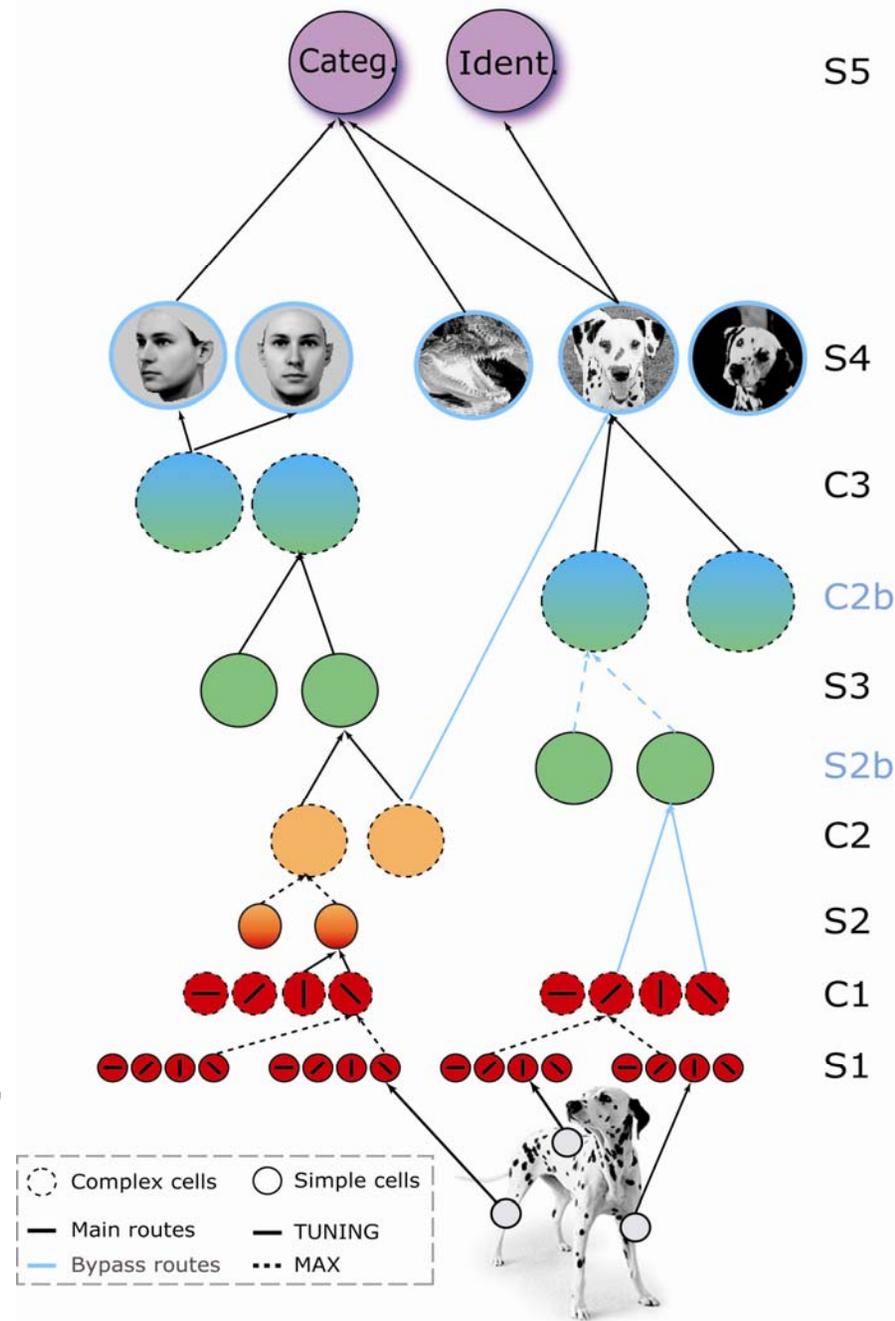


➤ Builds upon previous neurobiological models
 (Hubel & Wiesel, 1959; Fukushima, 1980; Oram & Perrett, 1993, Wallis & Rolls, 1997; Riesenhuber & Poggio, 1999)

➤ General class of feedforward hierarchical models of object recognition in cortex

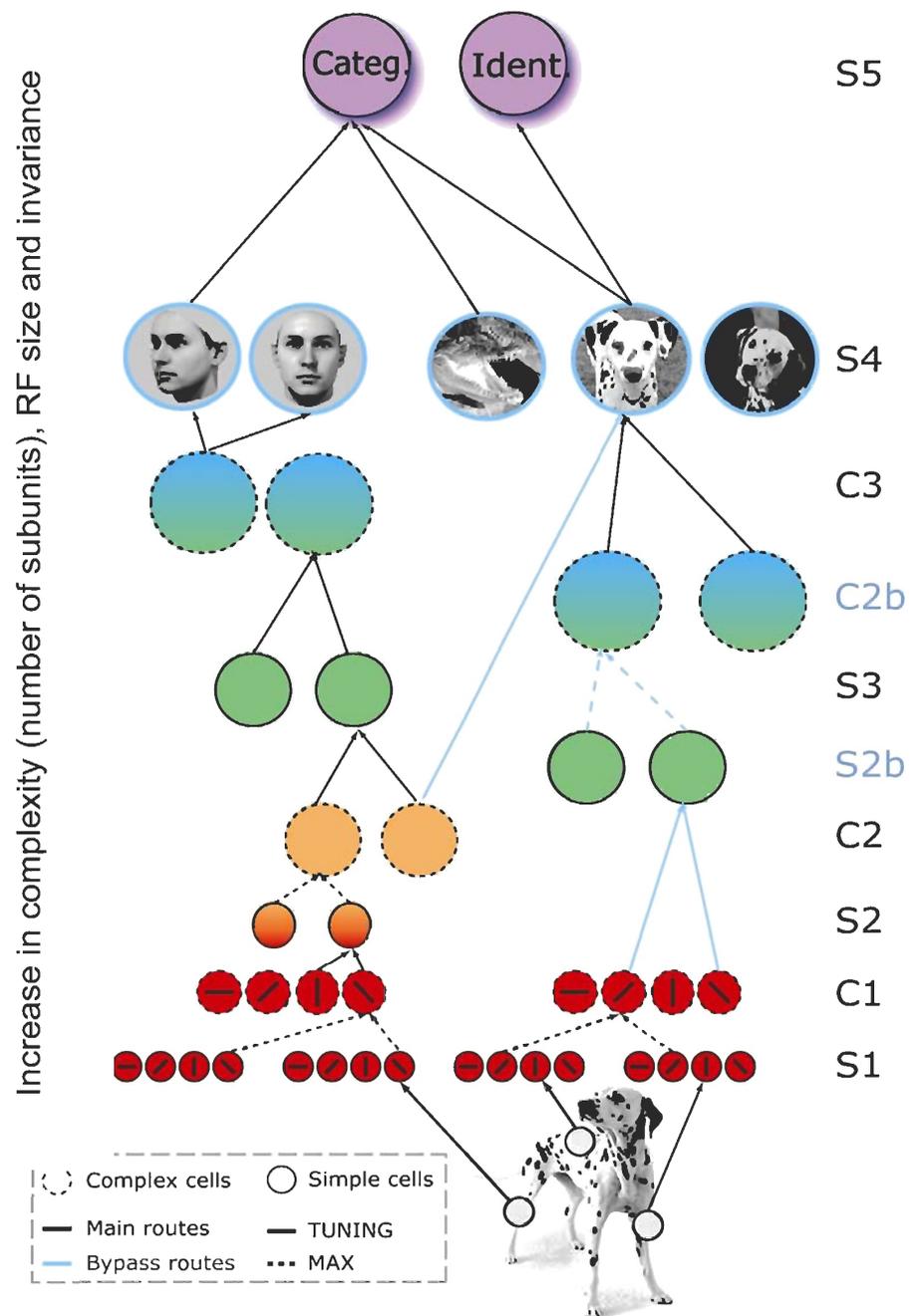
➤ Biophysically plausible operations

➤ Predicts several properties of cortical neurons
 (Serre, Kouh, Cadieu, Knoblich, Kreiman, Poggio, 2005)



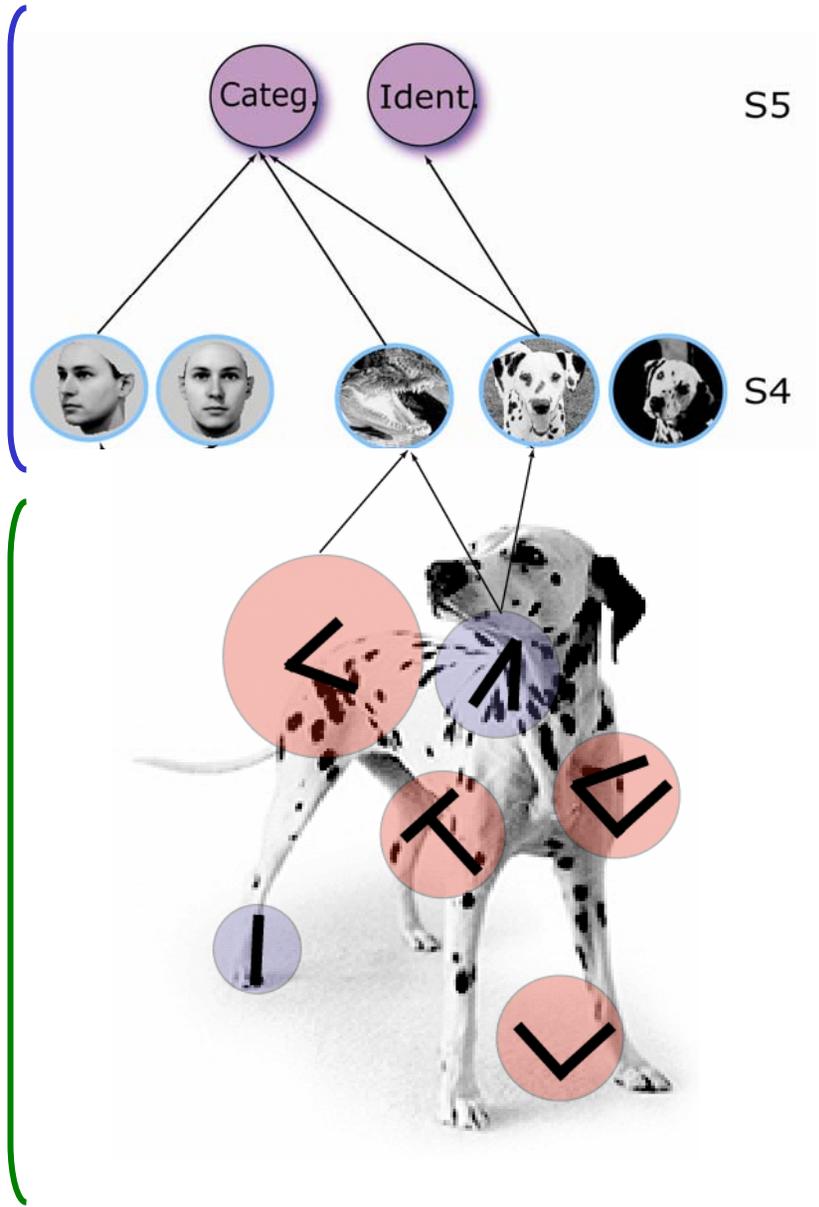
Model layers	Corresponding brain area (tentative)	RF sizes	Number units
classifier	PFC		$1.0 \cdot 10^0$
S4	AIT	 $>4.4^\circ$	$1.5 \cdot 10^2$ ~ 5,000 subunits
C3	PIT - AIT	 $>4.4^\circ$	$2.5 \cdot 10^3$
C2b	PIT	 $>4.4^\circ$	$2.5 \cdot 10^3$
S3	PIT	 $1.2^\circ - 3.2^\circ$	$7.4 \cdot 10^4$ ~ 100 subunits
S2b	V4 - PIT	 $0.9^\circ - 4.4^\circ$	$1.0 \cdot 10^7$ ~ 100 subunits
C2	V4	 $1.1^\circ - 3.0^\circ$	$2.8 \cdot 10^5$
S2	V2 - V4	 $0.6^\circ - 2.4^\circ$	$1.0 \cdot 10^7$ ~ 10 subunits
C1	V1 - V2	 $0.4^\circ - 1.6^\circ$	$1.2 \cdot 10^4$
S1	V1 - V2	 $0.2^\circ - 1.1^\circ$	$1.6 \cdot 10^6$

Supervised task-dependent learning
 Unsupervised task-independent learning

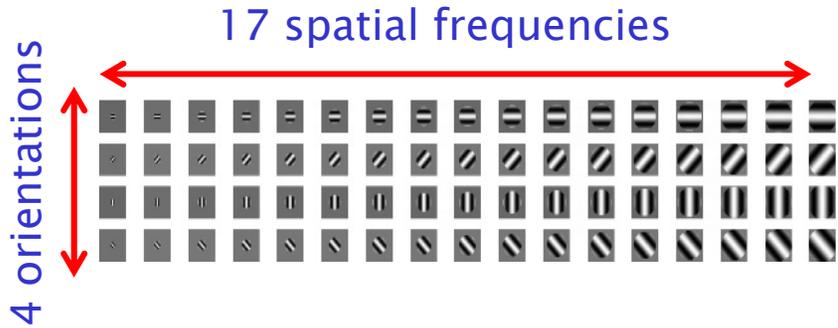


- **Task-specific circuits (from IT to PFC)**
 - ❑ Supervised learning
 - ❑ Linear classifier trained to minimize classification error on the training set (~ RBF net)

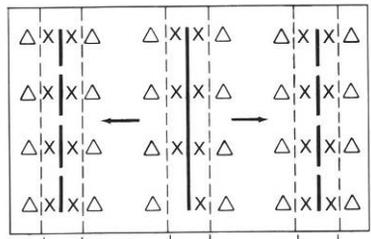
- **Generic dictionary of shape components (from V1 to IT)**
 - ❑ Unsupervised learning during developmental-like stage
 - ❑ From natural images unrelated to any categorization tasks



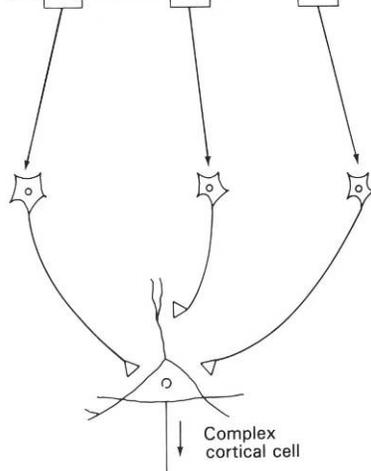
S1 and C1 units



S1

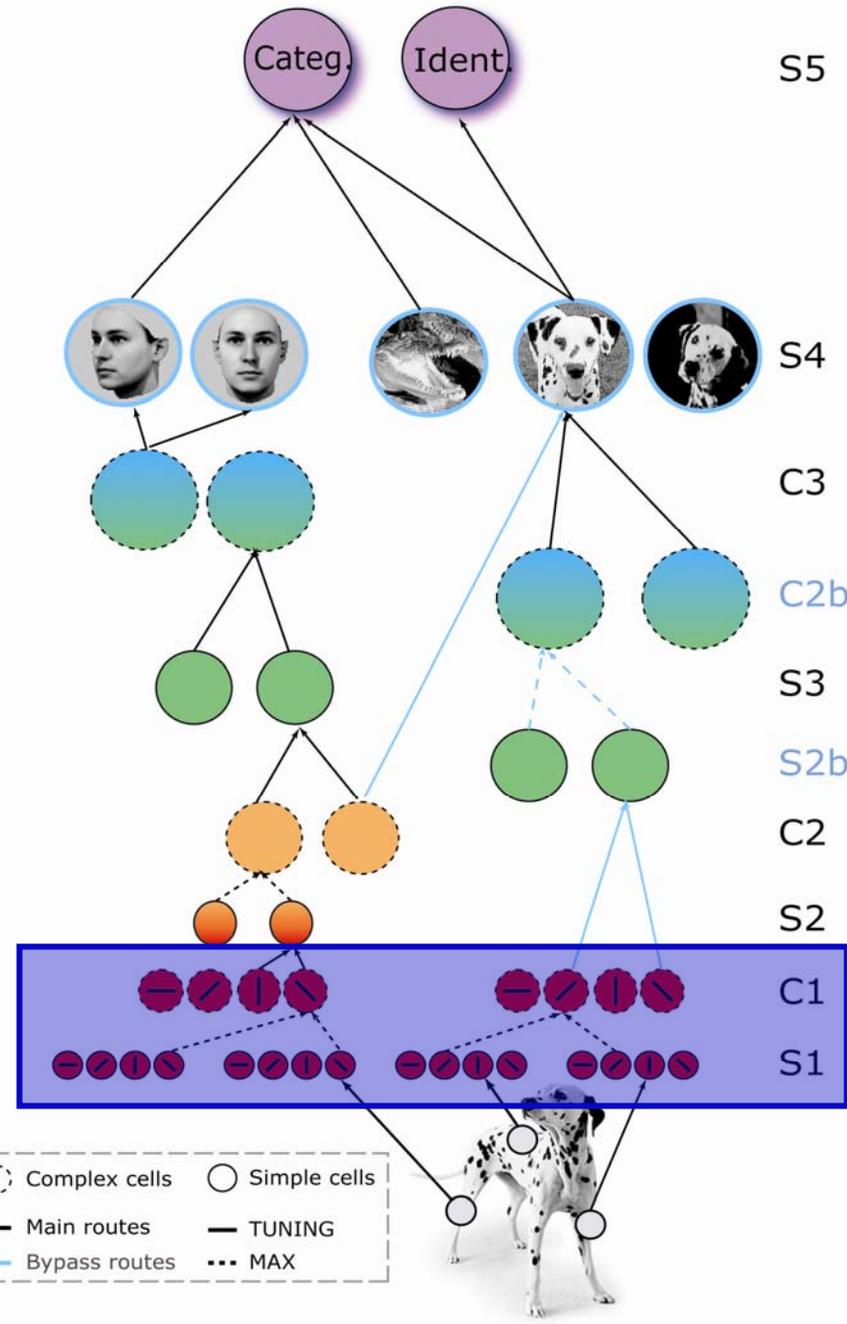


Simple cortical cells



(Hubel & Wiesel, 1959)

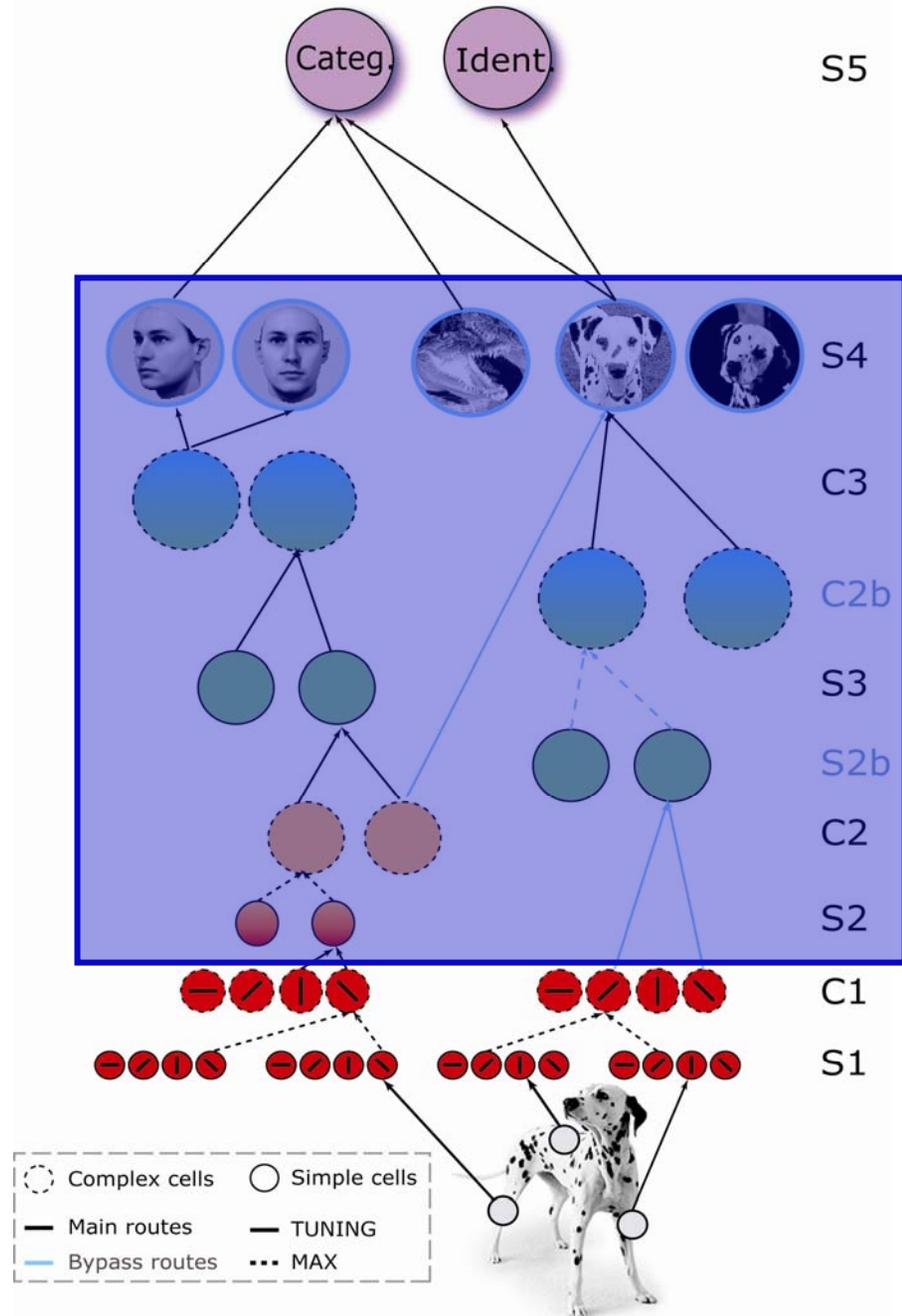
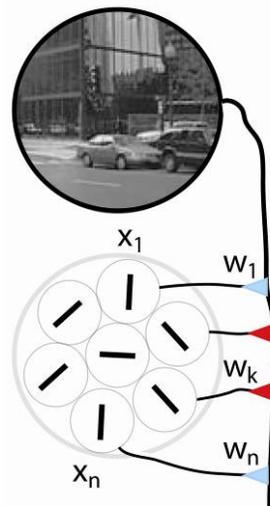
C1



From S2 to S4

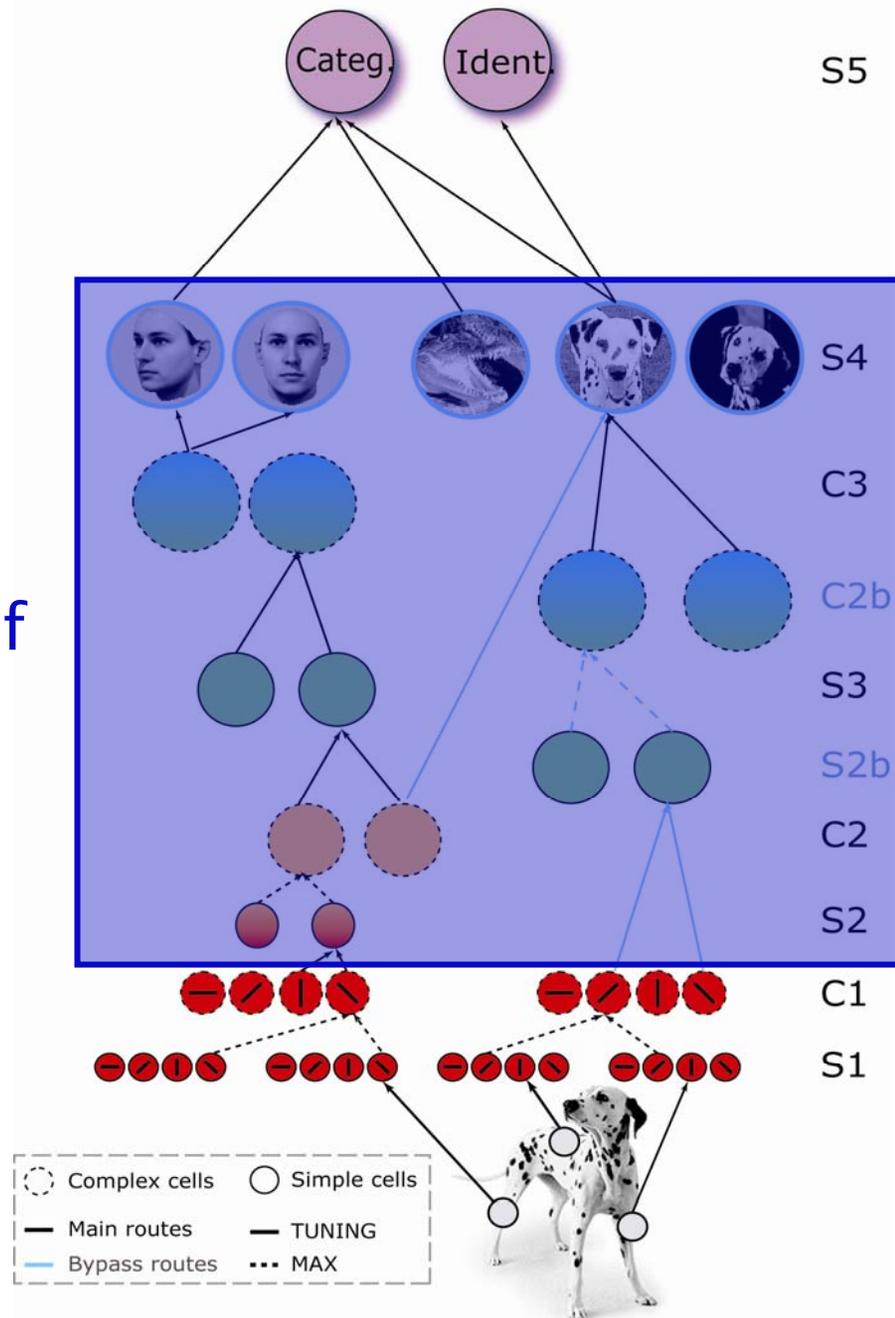
- Units are increasingly complex and invariant
- e.g, combination of V1-like complex units at different orientations

S2
unit



From C2 to S4

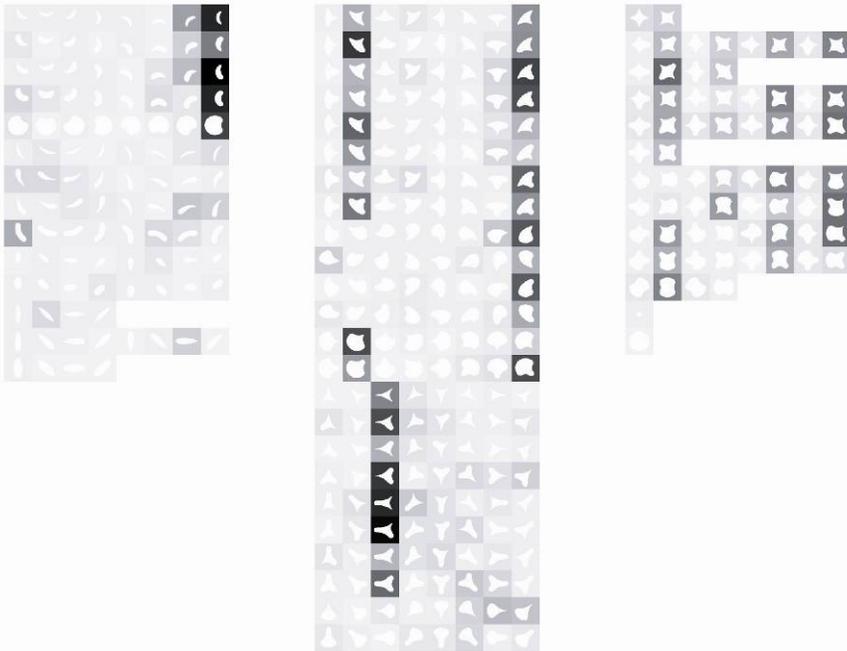
- 2,000 “features” at the C3 level ~ same number of feature columns in IT
(Fujita et al, 1992)
- Total ~6,000 types of features with various levels of complexity and invariance



The model predicts several properties of cortical neurons

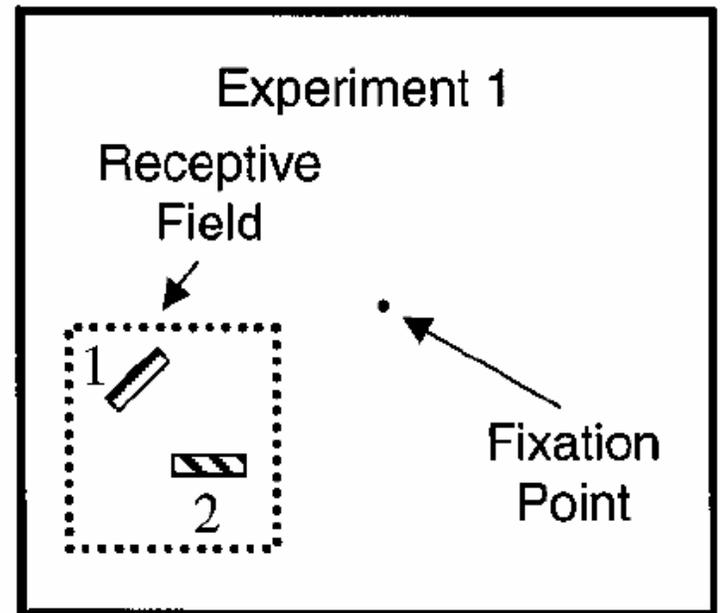
- In various cortical areas
- Examples from V4

Tuning for boundary conformation



(Pasupathy & Connor, 2001)

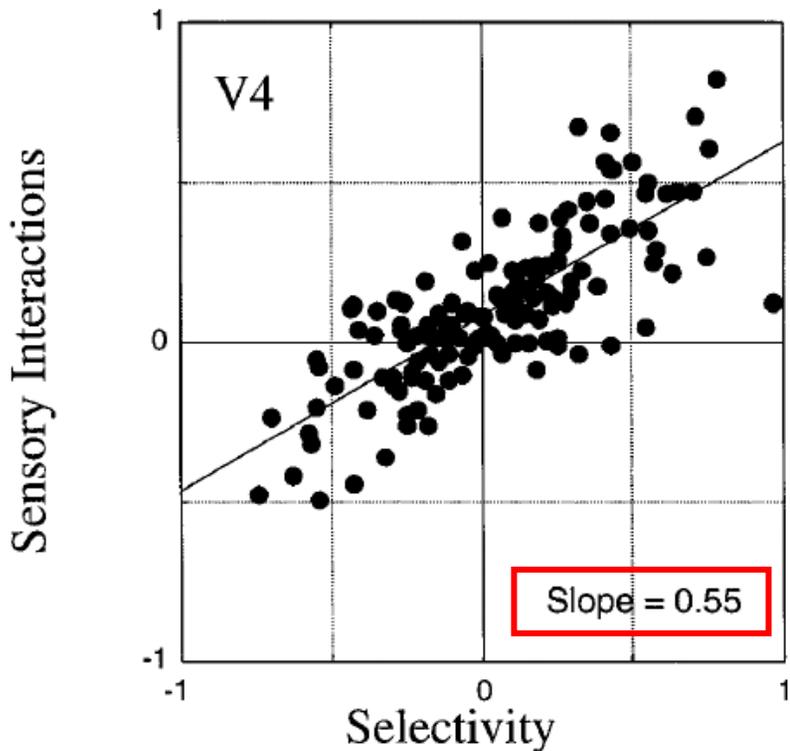
Tuning for two-bar stimuli



(Reynolds, Chelazzi and Desimone, 1999)

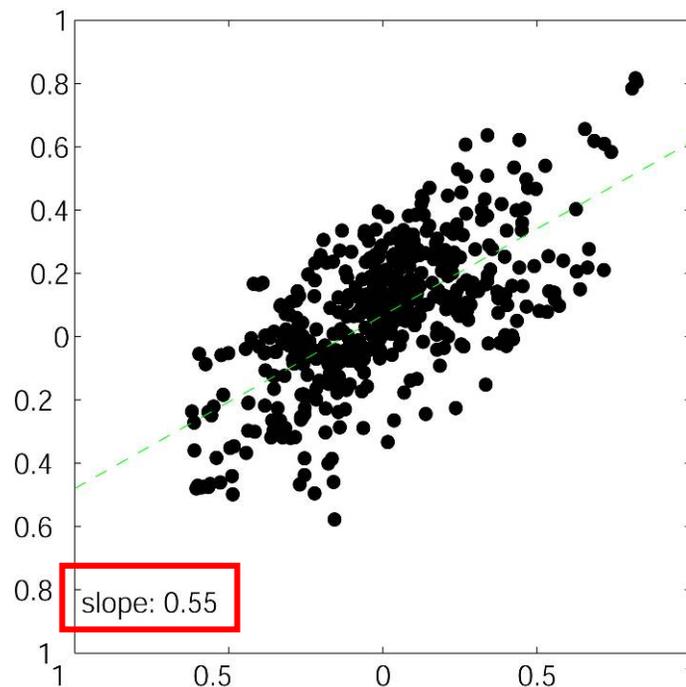
Prediction: Response of the pair is predicted to fall between the responses elicited by the stimuli alone

V4 neurons
(with attention directed away from receptive field)



(Reynolds , Chelazzi and Desimone, 1999)

C2 units



(Serre, Kouh, Cadieu, Knoblich, Kreiman and Poggio, 2005)

The model can perform complex recognition task very well

➤ At the level of some of the best computer vision systems

➤ e.g, constellation models

(Leung et al, 1995; Burl et al, 1998; Weber et al., 2000; Fergus et al, 2003; Li et al, 2004)

rear-car



airplane



frontal face



motorbike



leaf



Datasets			AI systems	Model
(CalTech)	Leaves	[Weber et al., 2000b]	84.0	97.0
(CalTech)	Cars	[Fergus et al., 2003]	84.8	99.7
(CalTech)	Faces	[Fergus et al., 2003]	96.4	98.2
(CalTech)	Airplanes	[Fergus et al., 2003]	94.0	96.7
(CalTech)	Motorcycles	[Fergus et al., 2003]	95.0	98.0

How does the model compare to
human observers?

Animal vs. non-animal categ.

- 1,200 stimuli (from Corel database)
- 600 animals in 4 categories:
 - ❑ Head
 - ❑ Close-body
 - ❑ Medium-body
 - ❑ Far-body and groups
- 600 matched distractors (½ art., ½ nat.)
to prevent reliance on low-level cues

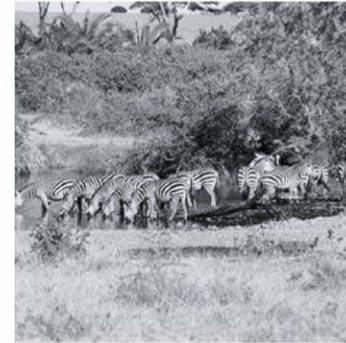
Head

Close-body

Medium-body

Far-body

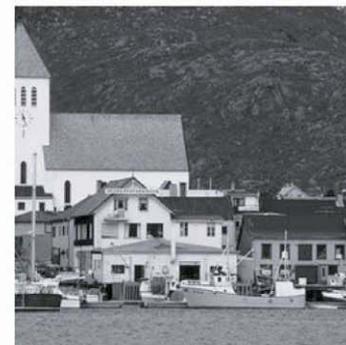
Animals



Natural
distractors

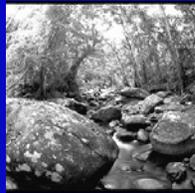


Artificial
distractors



Training and testing the model

- Random splits (good estimate of expected error)
- Split 1,200 stimuli into two sets

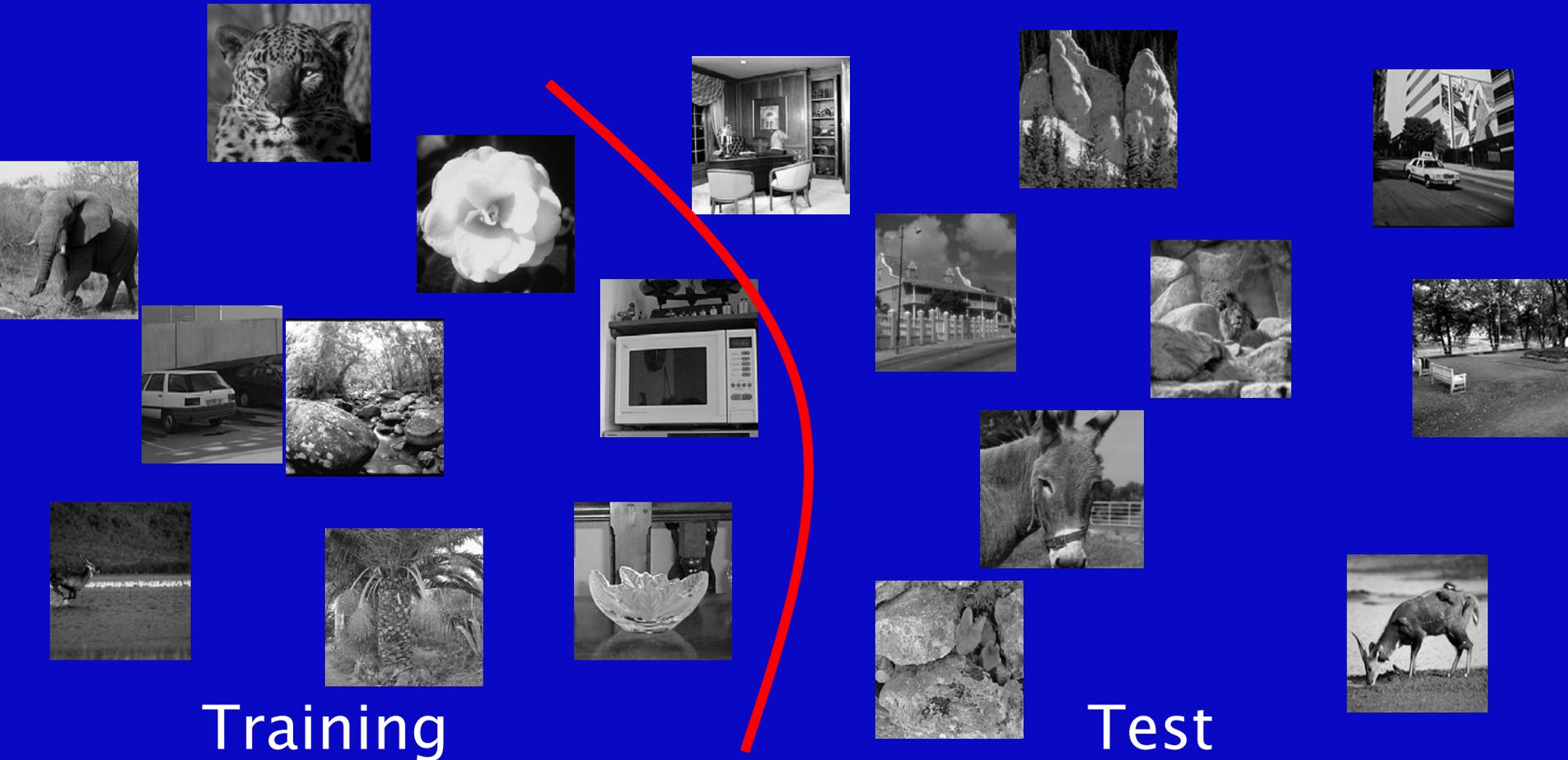


Training

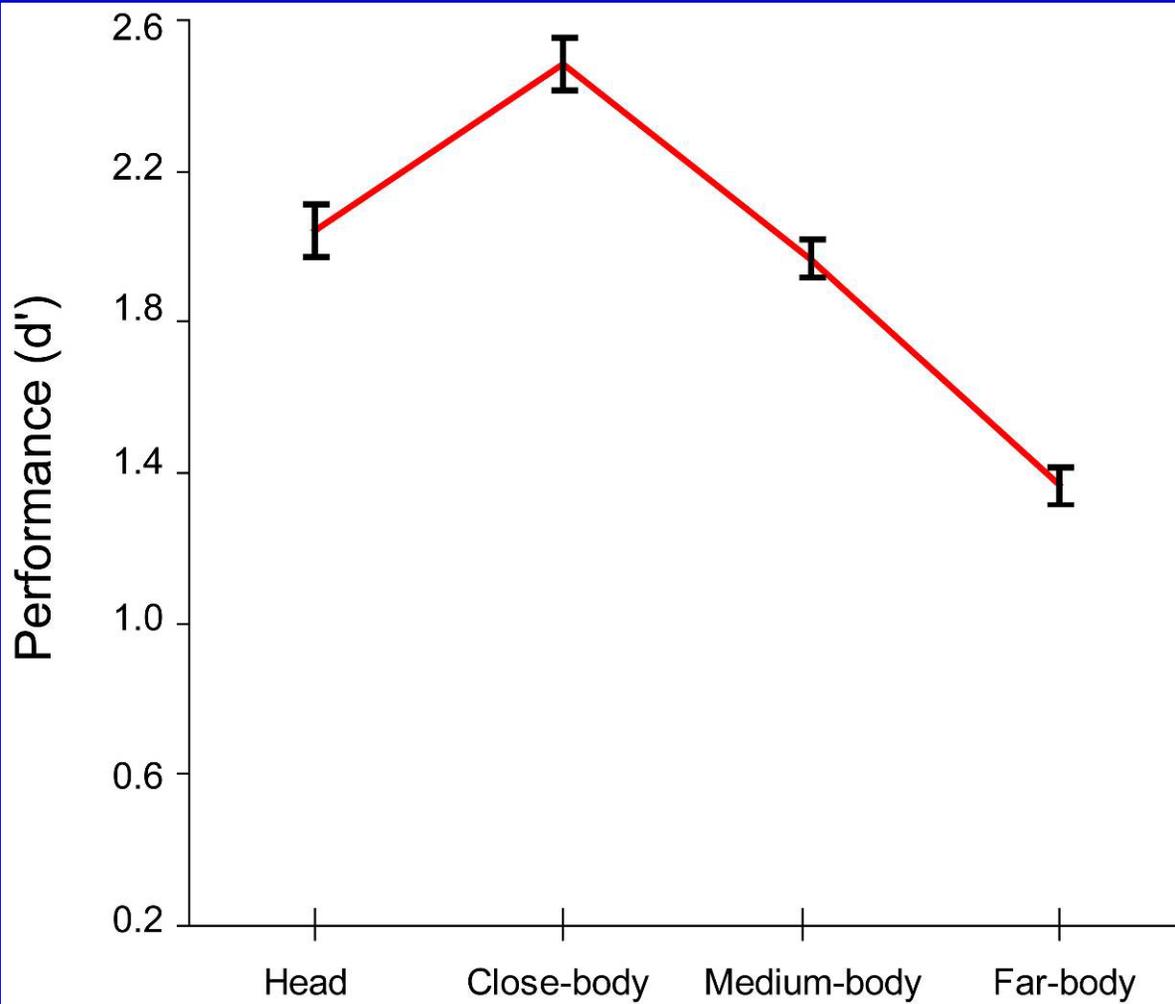
Test

Training the model

- Repeat 20 times
- Average model performance over all

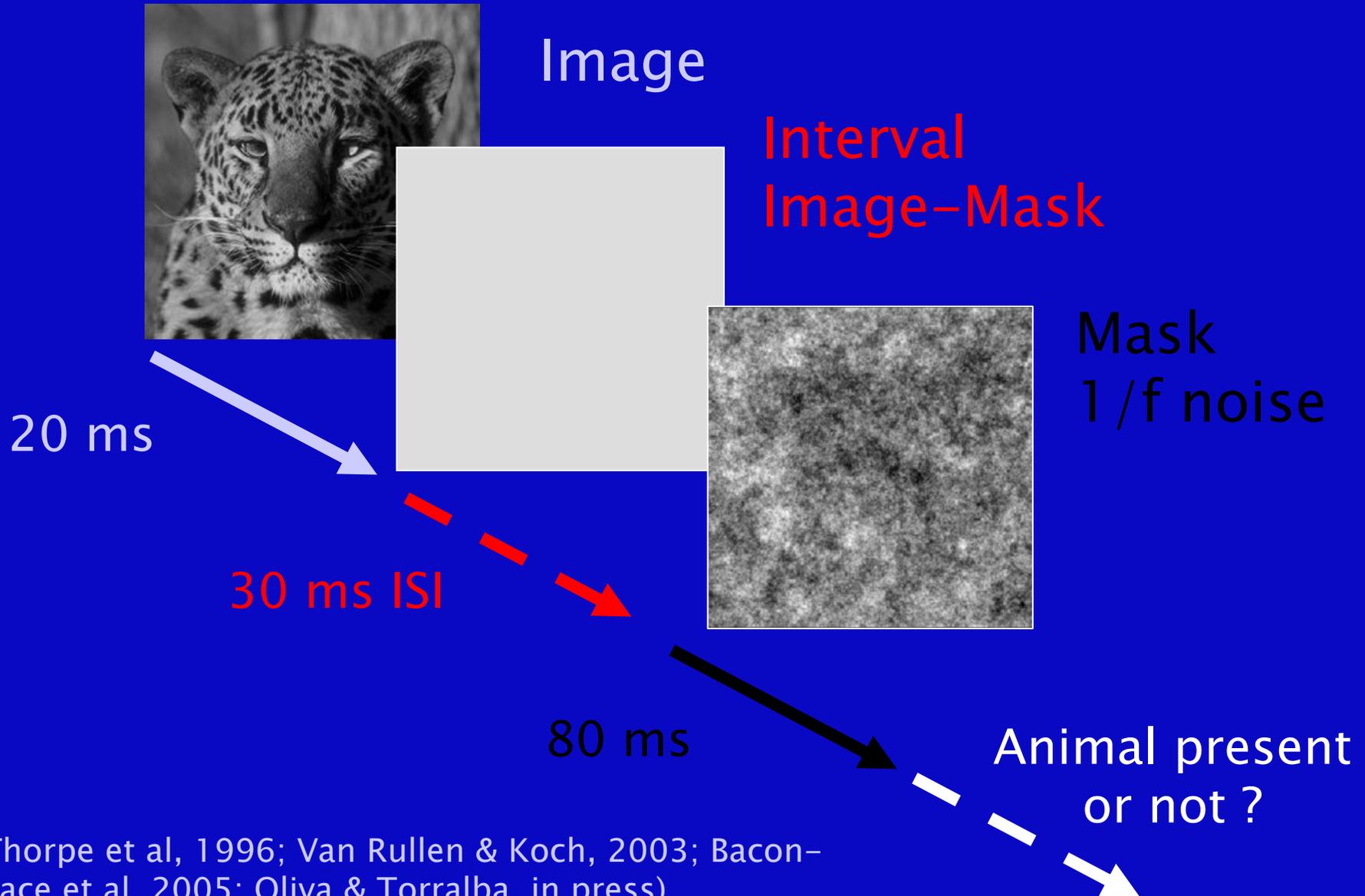


Results: Model

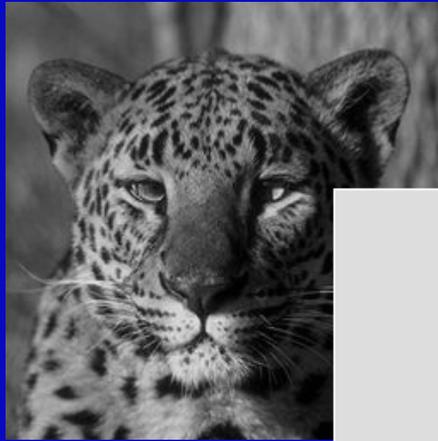


model

Rapid categorization task



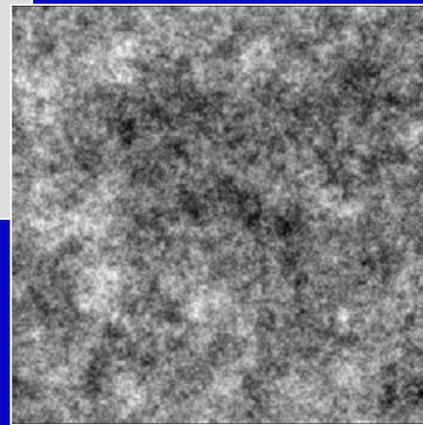
Rapid categorization task



Image



Interval
Image-Mask



Mask
1/f noise

~ 50 ms SOA

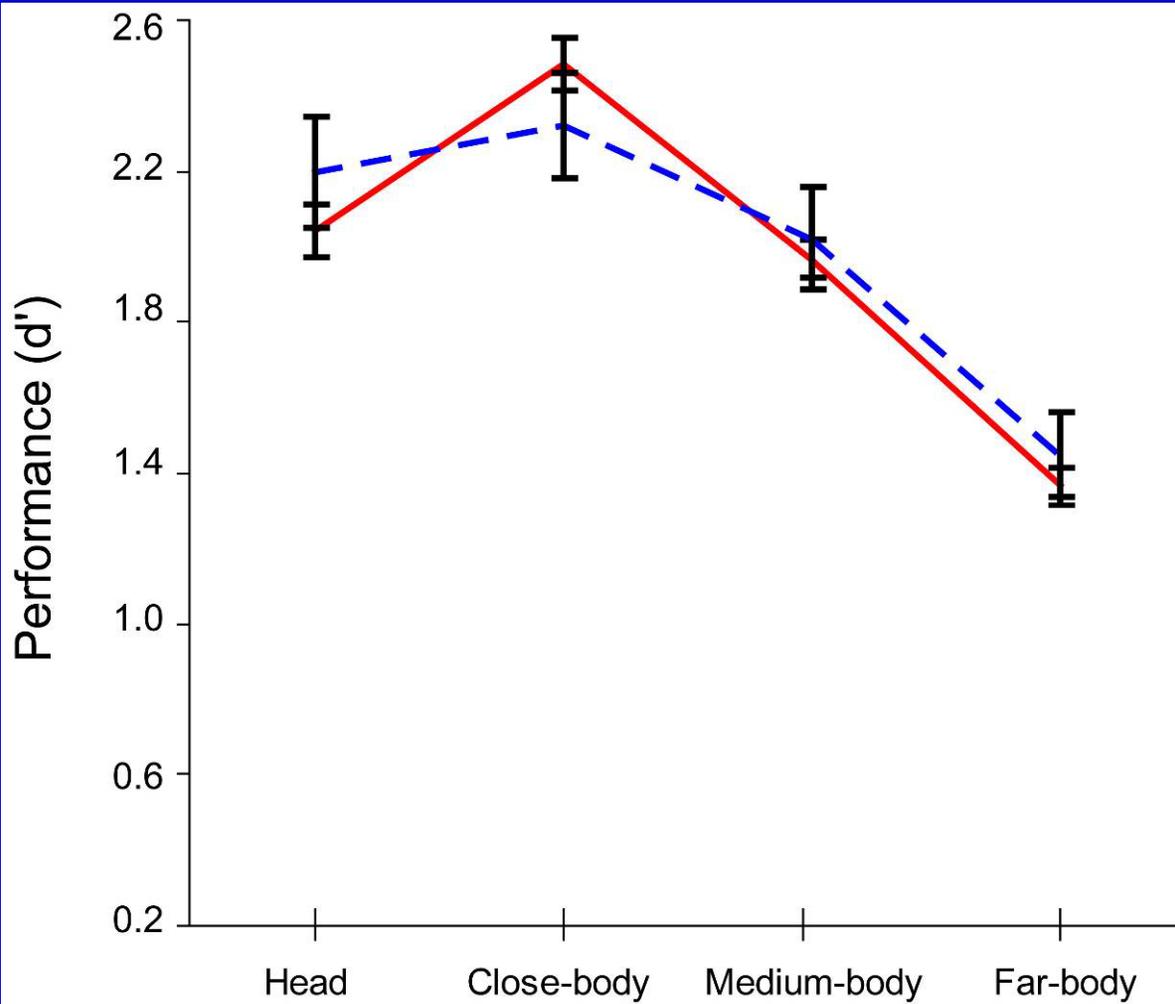
close to performance ceiling
in (Bacon-Mace et al, 2005)

80 msec

Animal present
or not ?

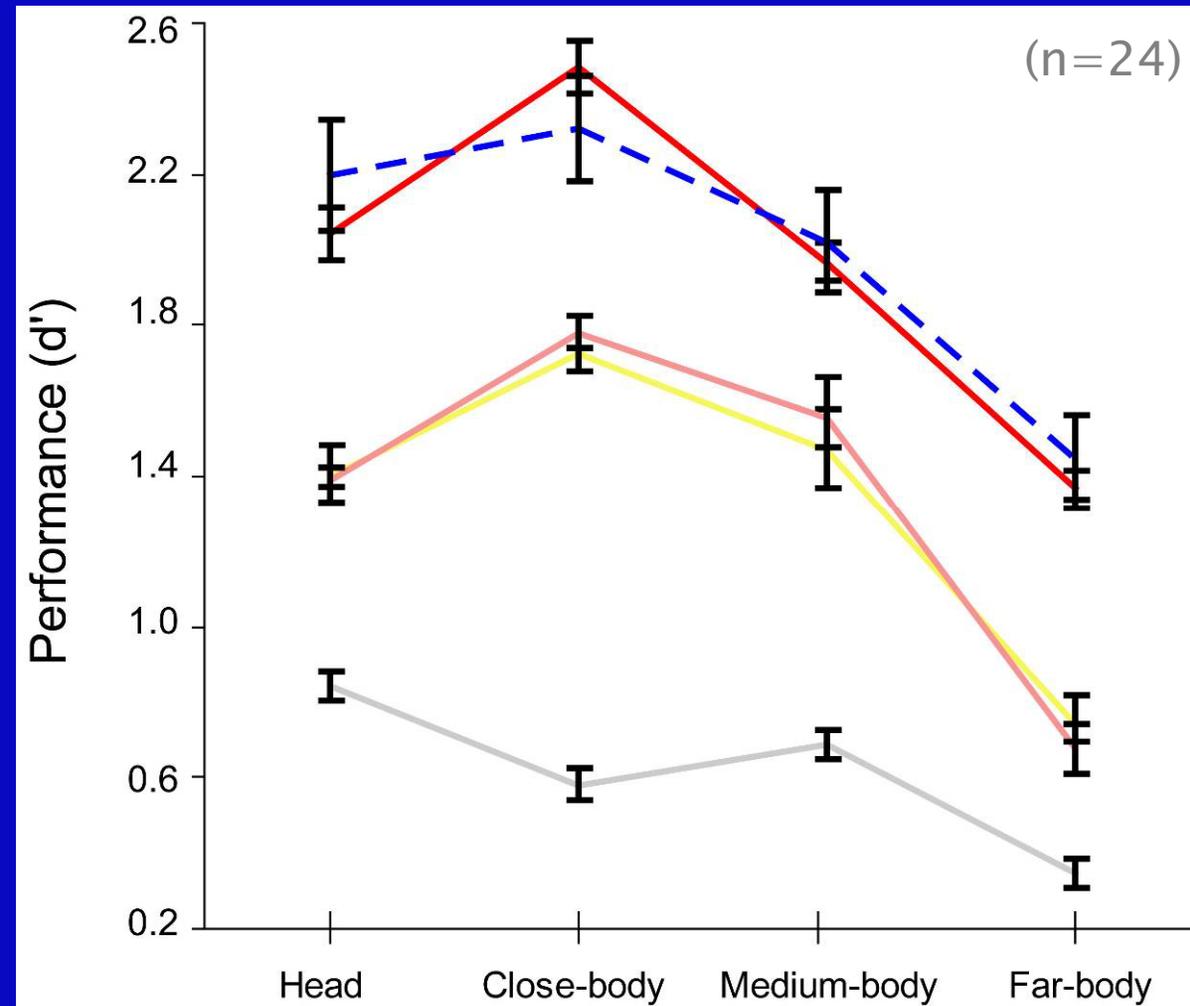
(Thorpe et al, 1996; VanRullen & Koch, 2003;
Bacon-Mace et al, 2005; Oliva & Torralba, in press)

Results: Human-observers



50 ms SOA (ISI=30 ms)
model

“Simpler” models cannot do the job



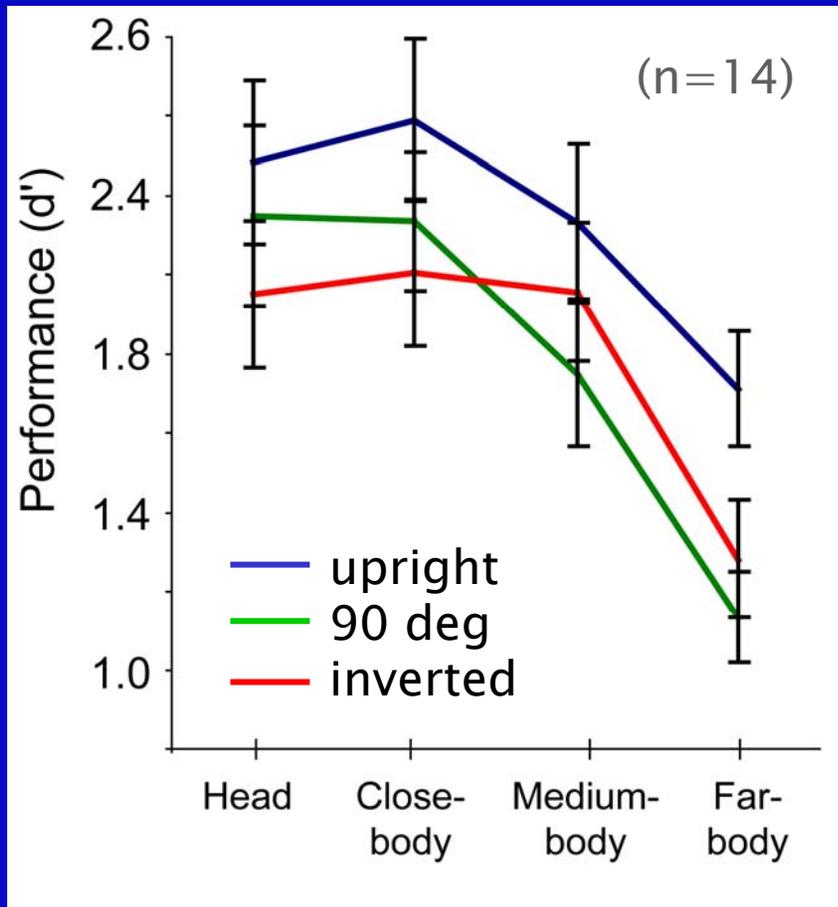
50 ms SOA (ISI=30 ms)
model

Model C1
(Torralba & Oliva, 2001)

(Renninger & Malik, 2004)

Results: Image orientation

Human observers



50 ms SOA (ISI=30 ms)

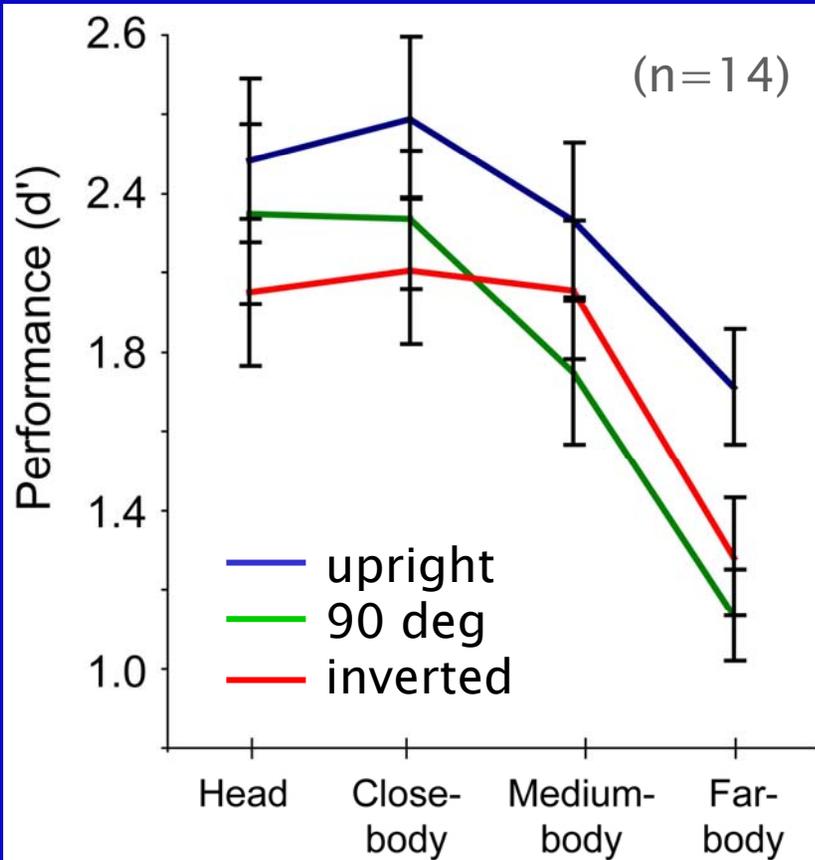
Robustness to image orientation is in agreement with previous results

(Rousselet et al, 2003; Guyonneau et al, ECVF 2005)

(Serre, Oliva and Poggio, in prep)

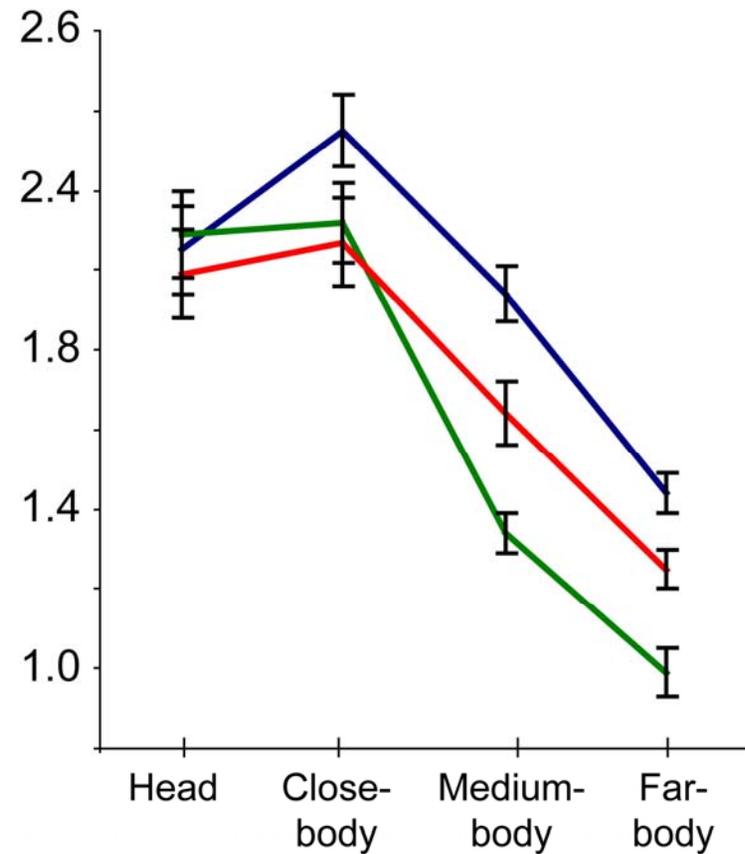
Results: Image orientation

Human observers



50 ms SOA (ISI=30 ms)

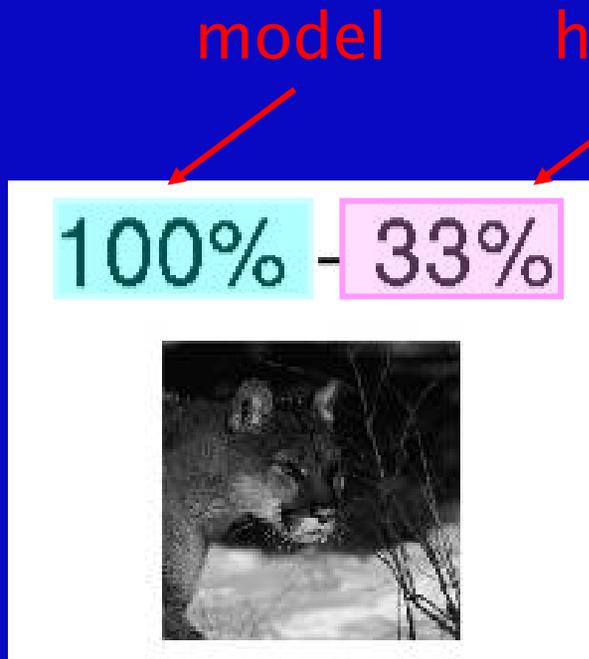
Model



(Serre, Oliva and Poggio, in prep)

Detailed comparison

- For each individual image
- How many times image classified as animal:
 - ❑ For humans: across subjects
 - ❑ For model: across 20 runs



- Heads: $\rho=0.71$
- Close-body: $\rho=0.84$
- Medium-body: $\rho=0.71$
- Far-body: $\rho=0.60$

Good agreement: Correctly rejections

0% 0%



0% 0%



0% 0%



0% 0%



0% 0%



0% 0%



0% 0%



0% 0%



29% 29%



30% 29%



22% 21%



18% 17%



18% 17%



40% 42%



10% 8%



14% 13%



Good agreement: Correct detections

100% 96%



100% 96%



100% 96%



100% 96%



100% 96%



100% 96%



100% 96%



100% 96%



100% 96%



100% 96%



100% 96%



100% 96%



100% 96%



100% 96%



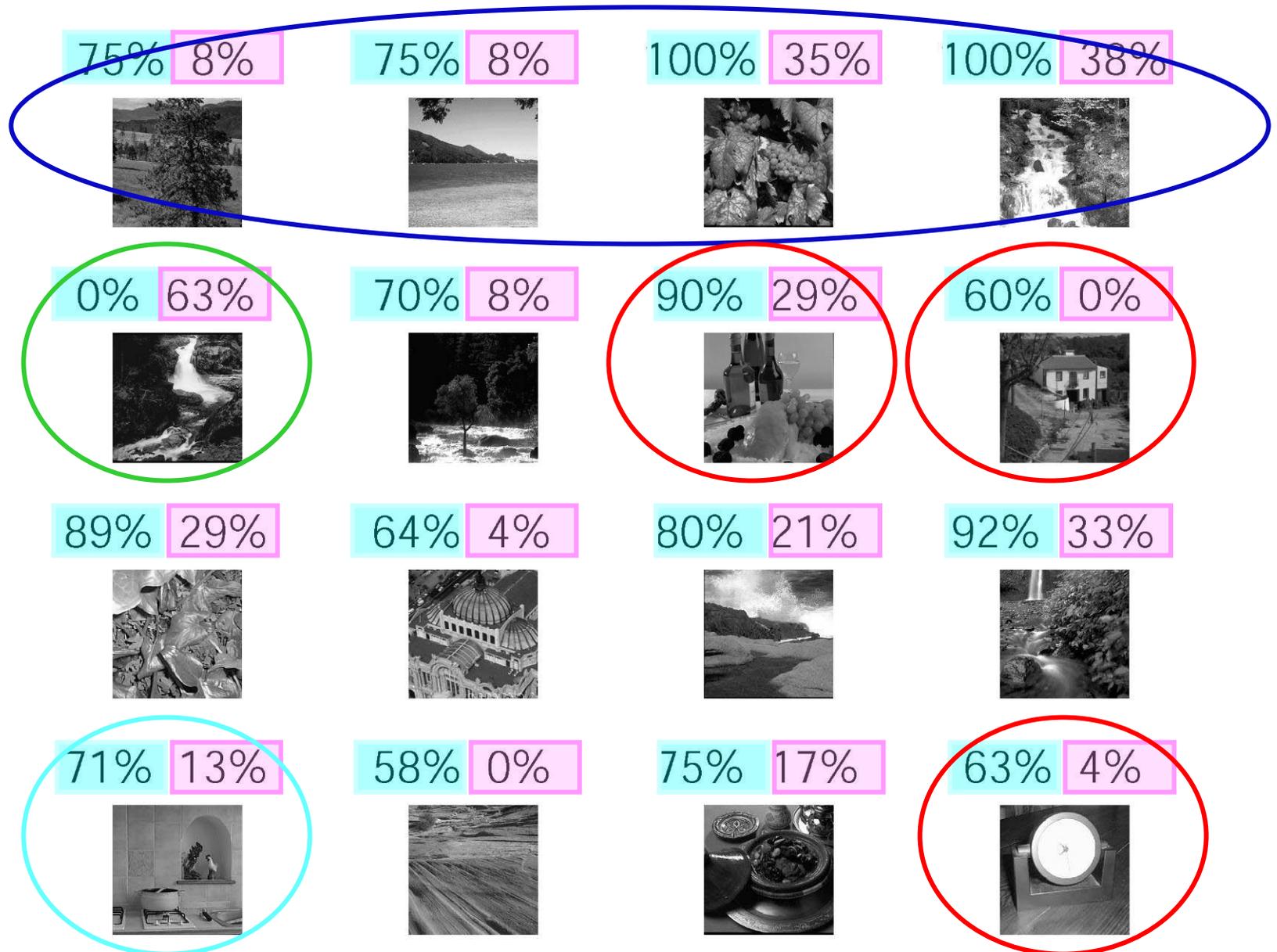
50% 54%



100% 96%



Disagreement



Disagreement

40% 100%



89% 29%



64% 4%



80% 21%



92% 33%



0% 58%



0% 58%



33% 92%



100% 42%



100% 42%



100% 42%



67% 8%



100% 42%



10% 67%



20% 75%



100% 46%

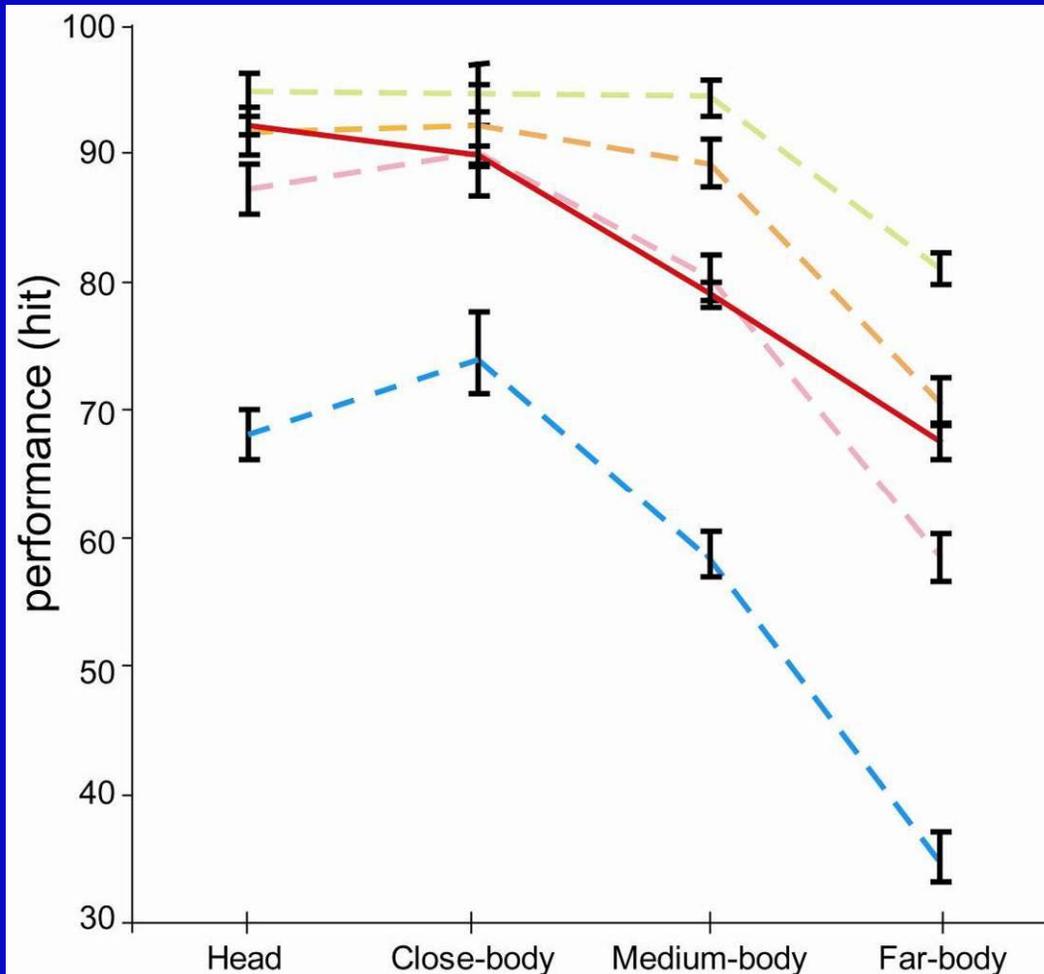


Discussion

- The model predicts human performance extremely well when the delay between the stimulus and the mask, i.e. the SOA is ~50 ms
- What happens for different SOAs?

Discussion

- Why should we expect the model to account for human performance around 50 ms SOA?



no mask condition

80 ms SOA (ISI=60 ms)

model

50 ms SOA (ISI=30 ms)

20 ms SOA (ISI=0 ms)

(Serre, Oliva and Poggio, in prep)

Discussion

- What is so special with 50 ms SOA?
 - Possible answer:
 - ✓ Nothing!!
 - ✓ Mask disrupts signal integration at the neural level
 - ✓ Model does not yet account for human level of performance

Discussion

➤ Alternative answer:

- 50 ms is a very long time!

- ✓ Within 50 ms most of the information has already been transmitted from one stage to the **next** (Rolls et al, 1999; Vogels et al, 1995, Keyser et al, 2001)

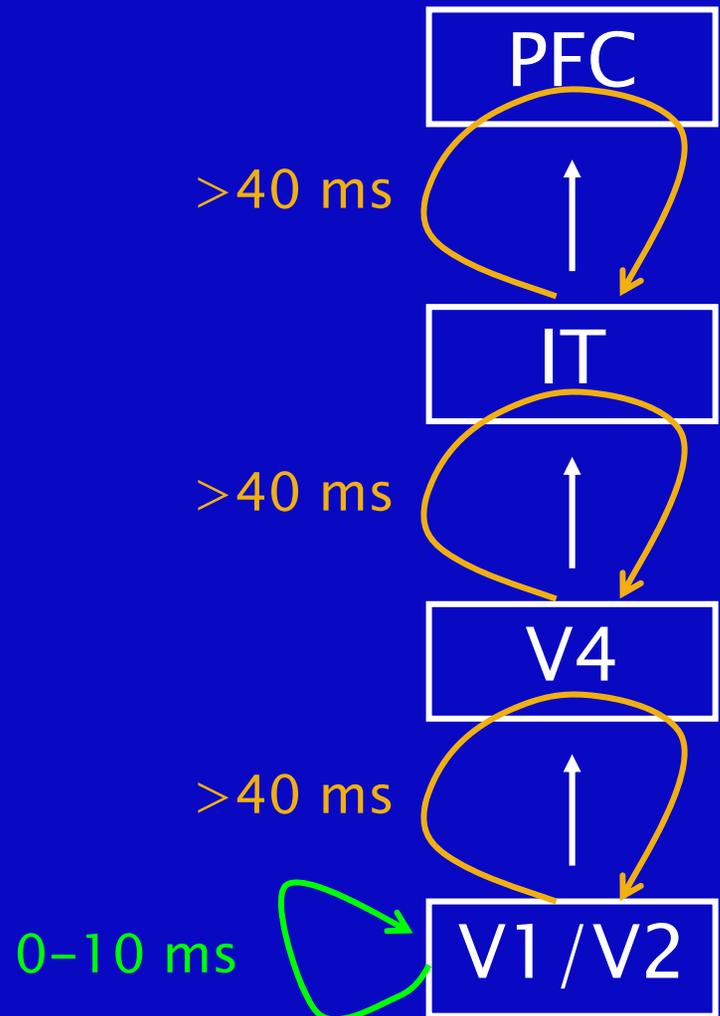
- ✓ Reading out from IT (~10–20ms):

- both object category and identity
- largely translation and scale invariant
(Hung, Kreiman, Poggio, DiCarlo, 2005)

➤ So what happened after the first 50 ms?

Speculation!!

- Our model is purely feedforward
 - ❑ Only local feedback loops
 - ❑ No feedback loops
- Feedback loops may already play a role for SOAs longer than 50 ms
- Discrepancy for longer SOAs may be due to the cortical back-projections



Timing estimates are for monkeys, based on (Thorpe & Fabre-Thorpe, 2001) and (Thorpe, Personal communication)

Summary

- I have described a model that is faithful to the anatomy and physiology of the ventral stream of visual cortex
- The model builds a dictionary of image features from V2 to IT which is compatible with the tuning of cortical neurons in several brain areas
- The model seems to be able to predict very well the level of performance of human observers in a rapid categorization task

Collaborators

➤ Aude Oliva

➤ Tomaso Poggio

➤ Other contributors

- ❑ S. Bileschi
- ❑ C. Cadieu
- ❑ U. Knoblich
- ❑ M. Kouh
- ❑ G. Kreiman
- ❑ M. Riesenhuber
- ❑ L. Wolf