Neural computations: lessons from peeking inside the brain

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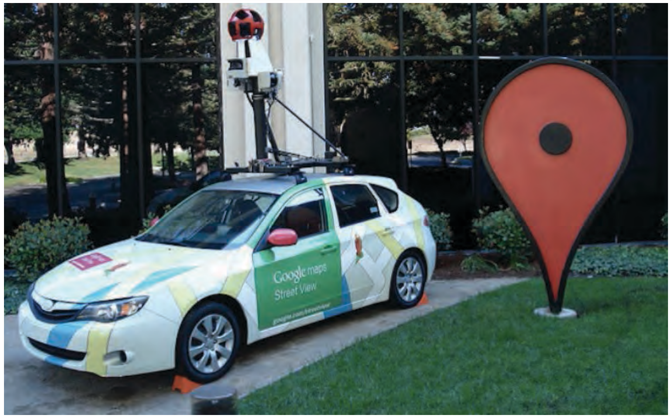
What computers can do [2014]



Humans vs. machines, 2014

Biologically-inspired computation

Claim:

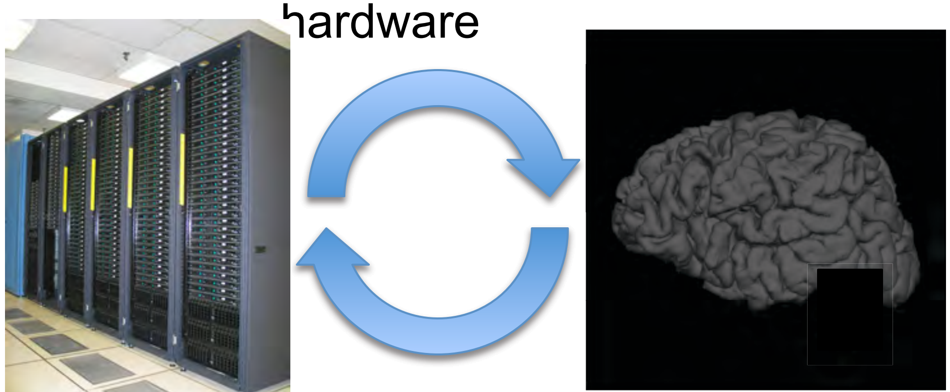
Interesting solutions to difficult problems have emerged through changes in neuronal circuits over millions of years of evolution

Massive computational power

Wireless data transmission

High-resolution, high-speed sensors (e.g. cameras)

Tools, models, hardware



Algorithms, solutions

Listening to neuronal circuits

Decoding activity in real time

Writing-in information

"… the great events of the world take place in the brain" (Oscar Wilde)

A flower, as seen by a computer

23	16	13	12	13	13	12	12	12	14	16	19	21	22	25	24	20	90	127	101
31	22	13	13	12	12	11	11	13	16	18	18	23	22	21	19	39	83	96	78
34	24	16	14	13	12	21	14	13	17	15	22	15	29	42	82	147	118	63	36
30	20	15	13	14	12	26	34	10	11	79	139	88	91	119	174	172	137	96	78
20	14	12	12	14	14	21	77	35	16	136	148	110	109	127	137	168	157	144	175
13	10	10	12	15	16	14	81	86	52	155	123	91	114	149	120	154	139	138	186
9	9	9	11	14	17	18	54	110	111	143	99	105	104	148	128	103	148	162	172
9	8	9	11	14	18	20	26	97	99	99	91	116	116	141	139	77	88	117	156
9	9	12	12	15	18	15	29	107	99	88	86	121	124	115	123	79	78	98	92
9	10	11	13	15	16	30	97	121	112	98	68	102	125	115	101	100	60	105	109
9	9	11	14	17	13	96	127	145	115	95	60	90	114	118	98	107	72	60	111
9	10	12	13	16	17	117	128	122	114	89	65	94	108	118	116	117	93	59	67
10	10	10	7	9	78	152	127	118	114	77	72	95	109	116	120	128	96	68	50
7	1	10	54	114	166	145	121	125	113	65	70	97	107	110	107	103	93	67	54
33	92	129	151	157	158	146	130	125	104	66	77	100	105	111	108	94	85	62	58
145	144	135	142	151	152	149	137	131	98	69	82	102	111	102	93	89	84	59	54
125	125	140	156	144	150	145	133	128	98	74	87	110	110	106	93	86	80	56	48
147	147	161	143	143	144	138	129	121	94	69	86	107	106	102	91	82	77	50	43
182	181	164	140	143	140	132	128	121	97	71	82	100	109	97	91	93	80	44	40
188	174	143	147	146	144	137	127	119	97	78	83	100	105	104	92	86	81	46	38

Vision as a summer project…

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

PROJECT MAC

Artificial Intelligence Group
Vision Memo. No. 100.

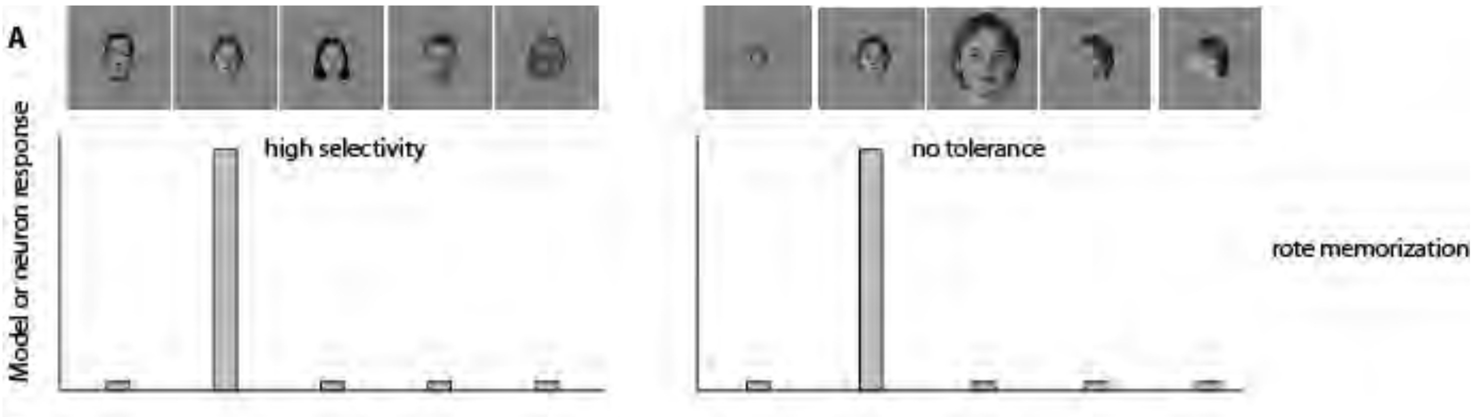
July 7, 1966

THE SUMMER VISION PROJECT

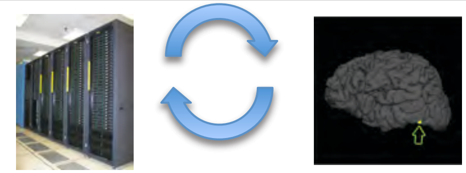
Seymour Papert

The summer vision project is an attempt to use our summer workers effectively in the construction of a significant part of a visual system. The particular task was chosen partly because it can be segmented into sub-problems which will allow individuals to work independently and yet participate in the construction of a system complex enough to be a real landmark in the development of "pattern recognition".

Why is vision difficult?

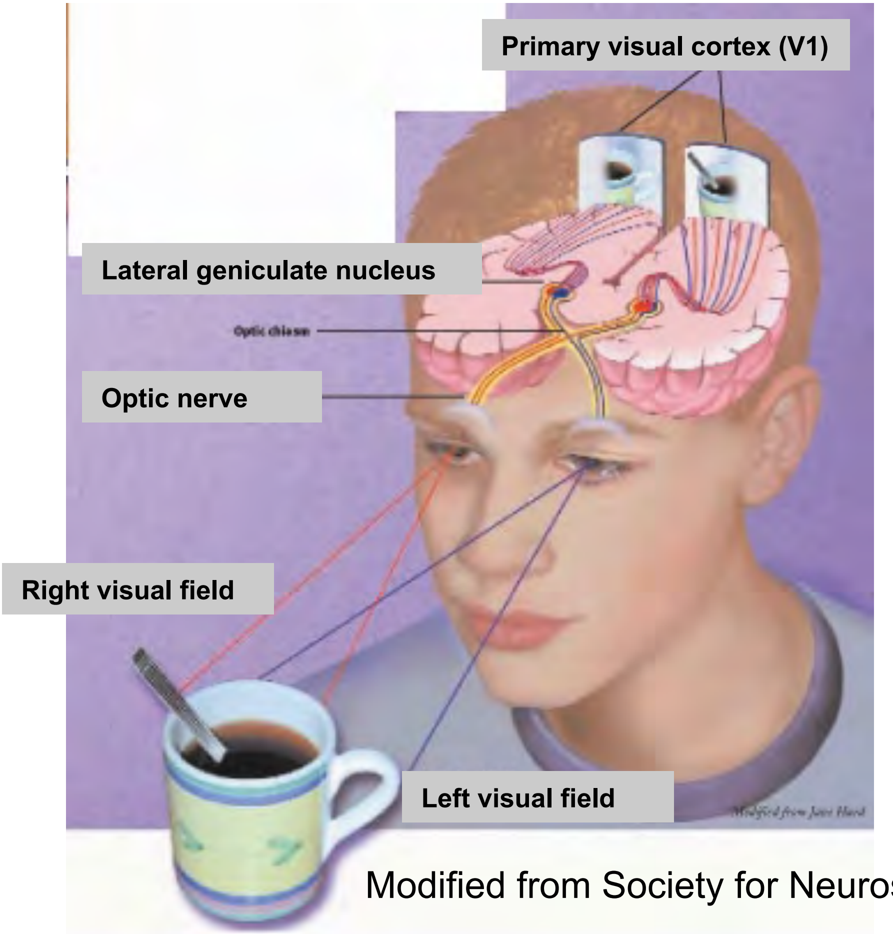


Partial Summary



1. Understanding neural circuits codes → Biologically-inspired algorithms underlying intelligent computations

Visual system circuitry

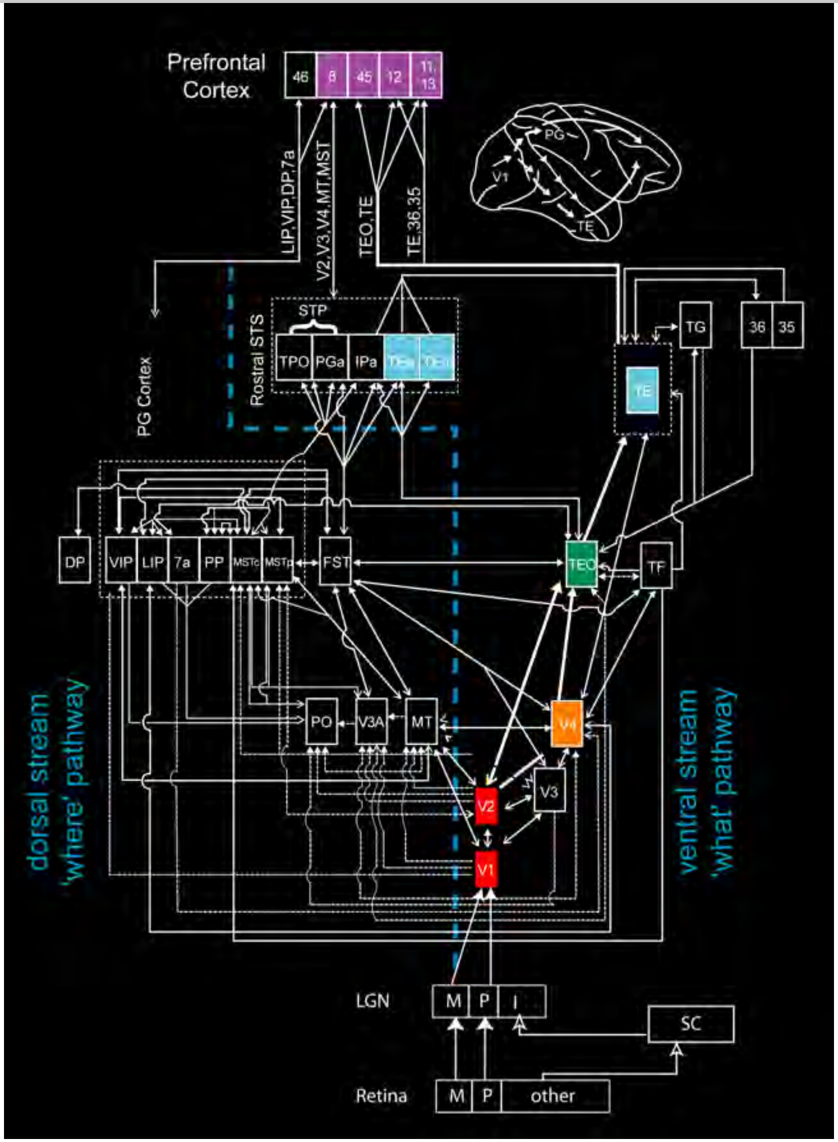


Modified from Society for Neuroscience Brain Facts

Magic in the brain: ventral visual cortex

NOTE:

- This is only a coarse description of the circuit
- Many (most?) connections are still probably missing
- We do not understand the functional role for most of the connections



Felleman and Van Essen. *Cerebral Cortex* 1991

Neocortical circuits can be quite specific

Table 1 Identity recognition and familiarity ratings for target and nontarget faces (patient E.H.)

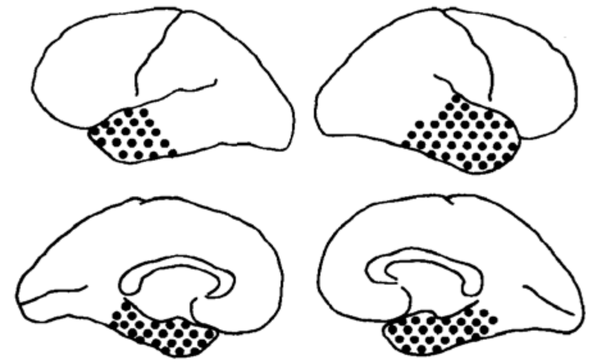
	N	Identity recognition (% correct)	Average familiarity rating (s.d. in parentheses)
Retrograde-family experiment			
Target	8	0	6.0 (0.0)
Nontarget	42	—	6.0 (0.0)
Retrograde-famous experiment			
Target	8	0	6.0 (0.0)
Nontarget	42	—	6.0 (0.0)

-Unable to visually recognize friends, famous people, relatives, even self

-Could not learn to recognize new faces (but could learn to recognize new people from voice and other cues)

-Normal language, memory, learning, non-face object recognition

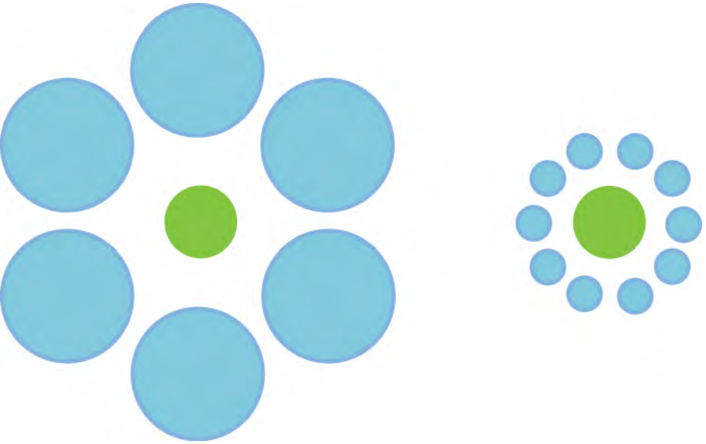
-Many normal visual functions



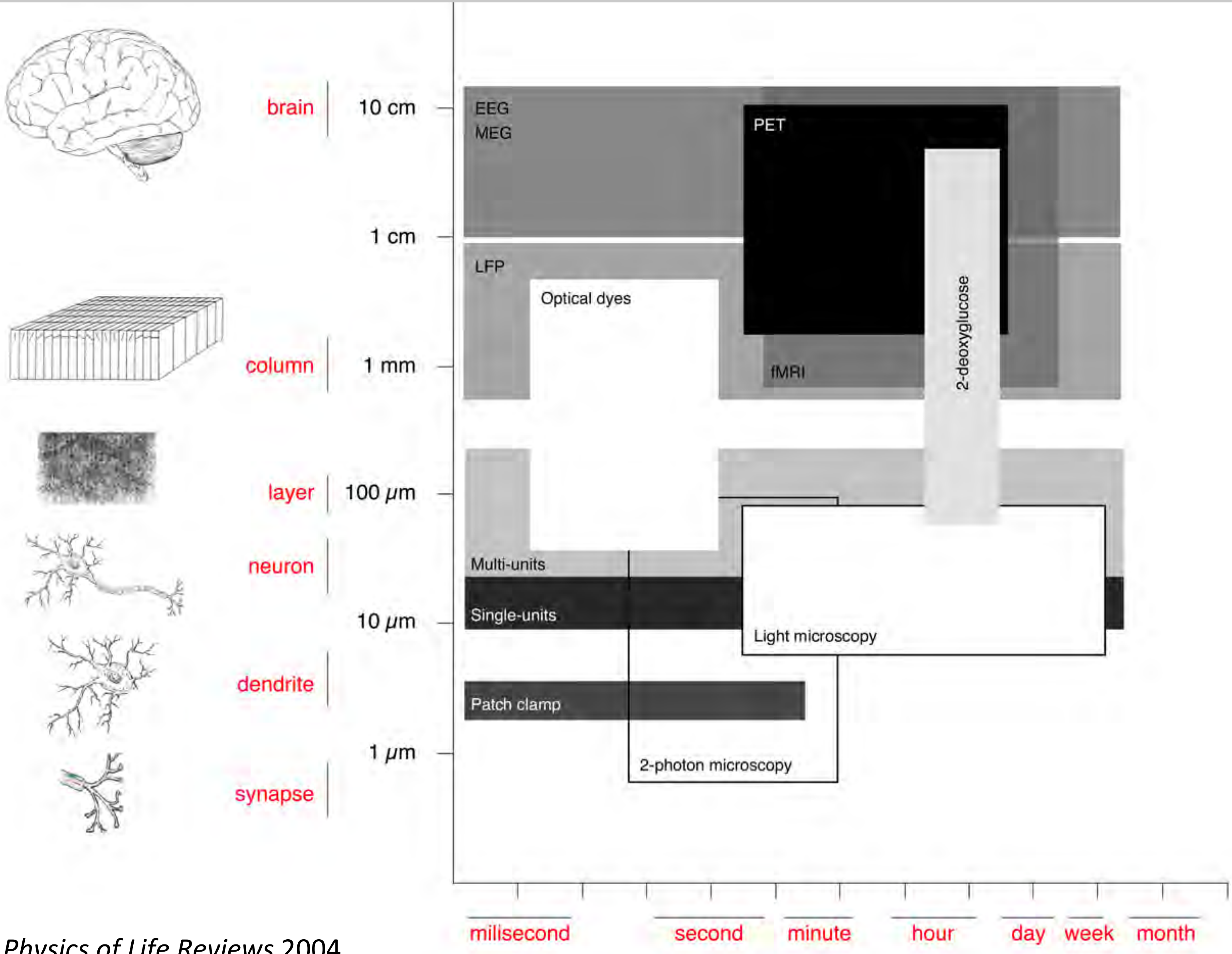
Distribution of lesion sites in cases of face agnosia

Damasio et al. *Face agnosia and the neural substrates of memory.* Annual Review of Neuroscience (1990). **13**:89-109

Vision is a constructive process



Methods to study the brain at different scales



Kreiman. *Physics of Life Reviews* 2004

Reading out the biological source code

23	16	13	12	13	13	12	12	12	14	16	19	21	22	25	24	20	90	127	101
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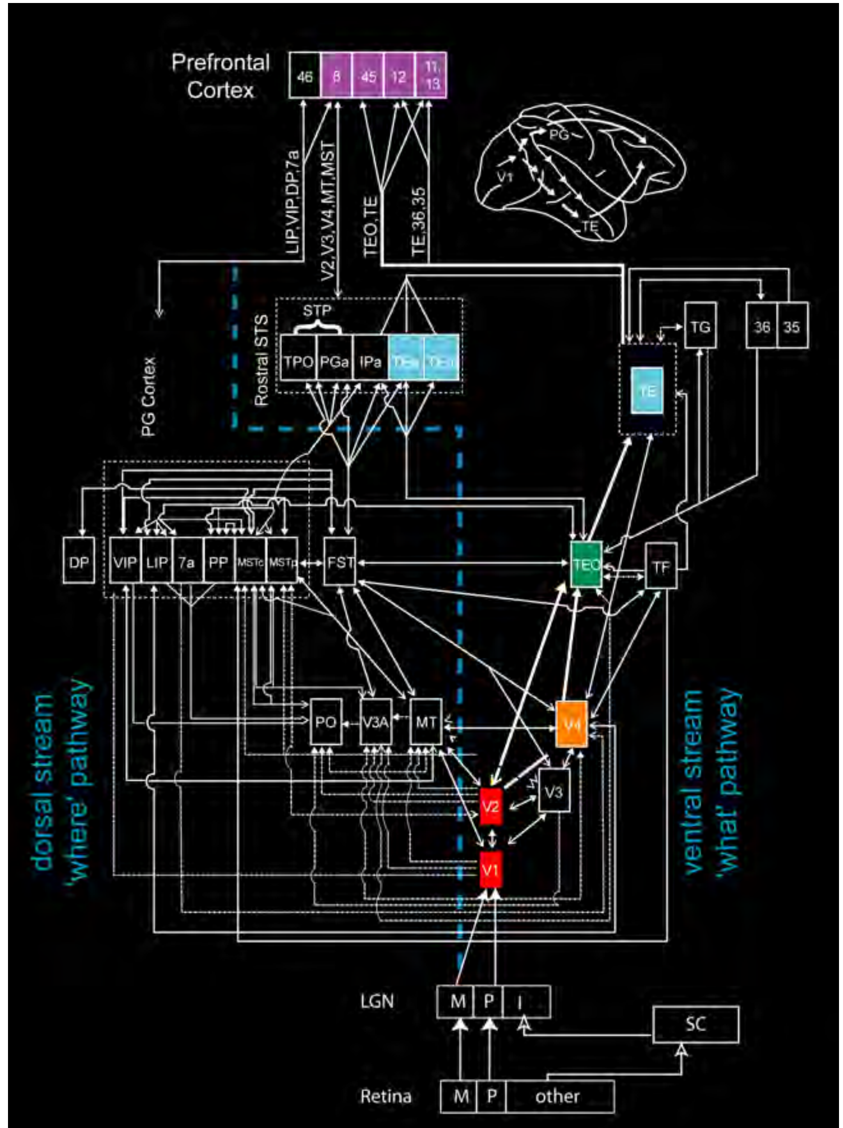
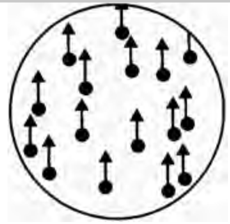
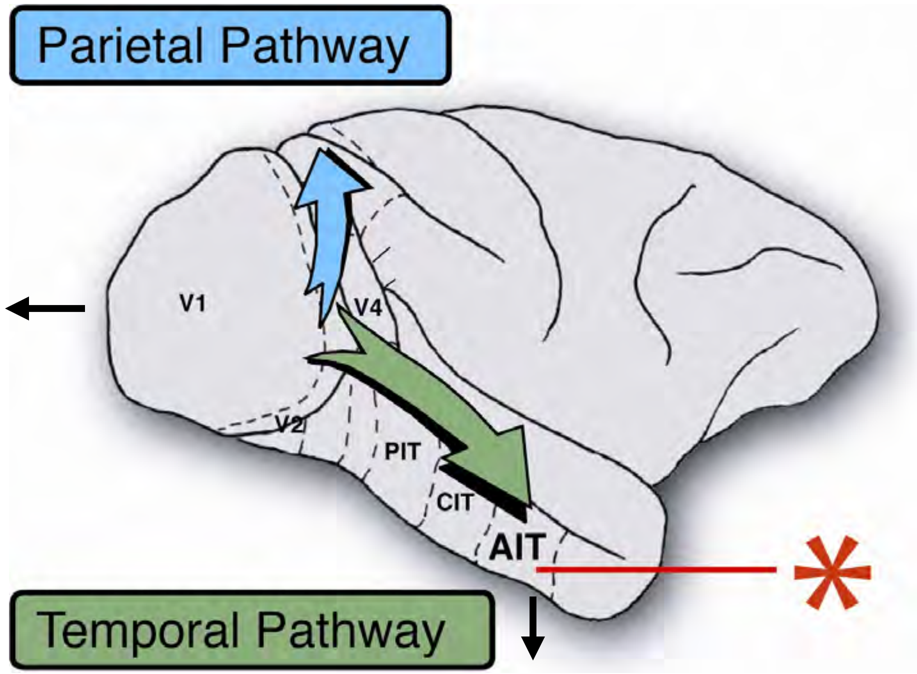
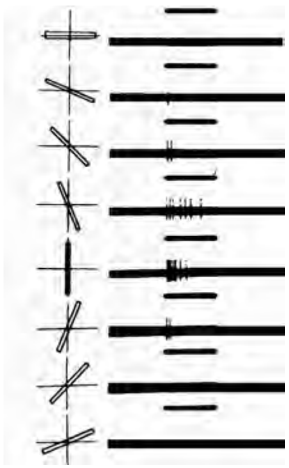


Neurons show sensitivity to special visual features

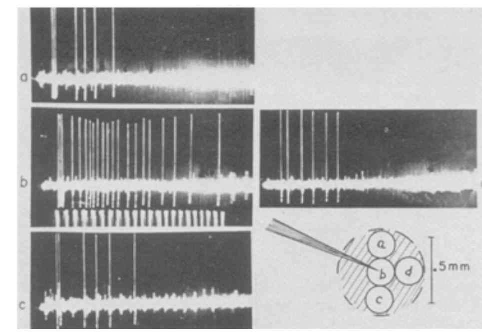


Newsome *et al* (1989)
Nature **341**:52-54

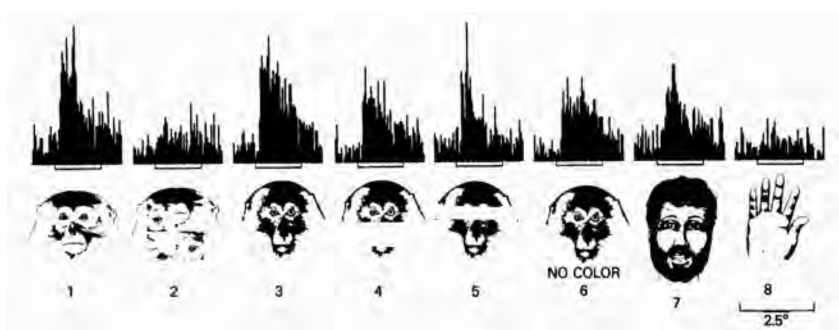




Hubel and Wiesel (1959) J. Physiol. **148**: 574-591

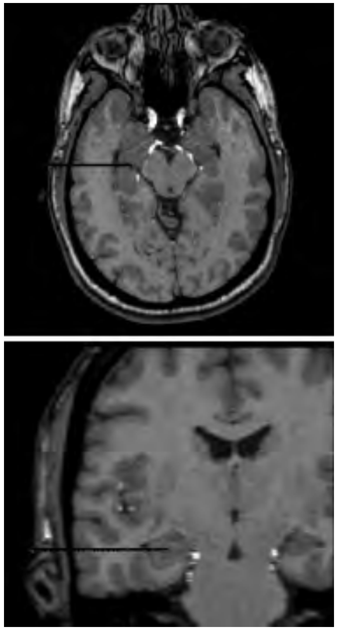


Kuffler, S. (1953)
J. Neurophys. **16**: 37-68



Desimone *et al* (1984)
*J. Neurosci. 4:*2051-2062

Invasive physiological recordings in the human brain

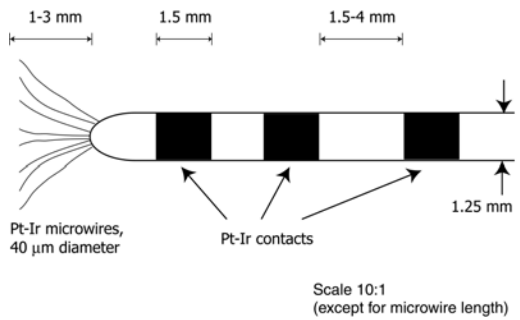


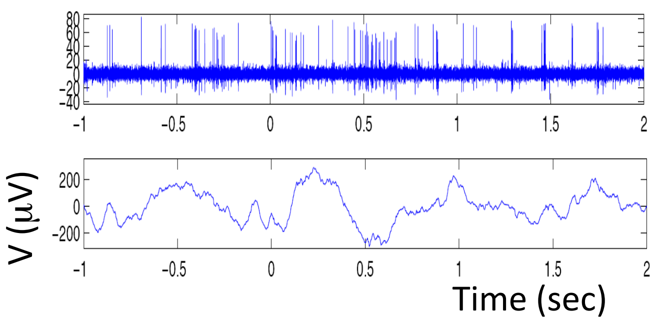
- Patients with pharmacologically intractable epilepsy
- Multiple electrodes implanted to localize seizure focus
- Targets typically include the temporal lobe (inferior temporal cortex, fusiform gyrus), medial temporal lobe (hippocampus, entorhinal cortex, amygdala and parahippocampal gyrus)
- Patients stay in the hospital for about 7-10 days

- Cannot choose type of electrodes
- Cannot choose number of electrodes
- Cannot choose electrode location
- Limits on recording time
- Many other limitations

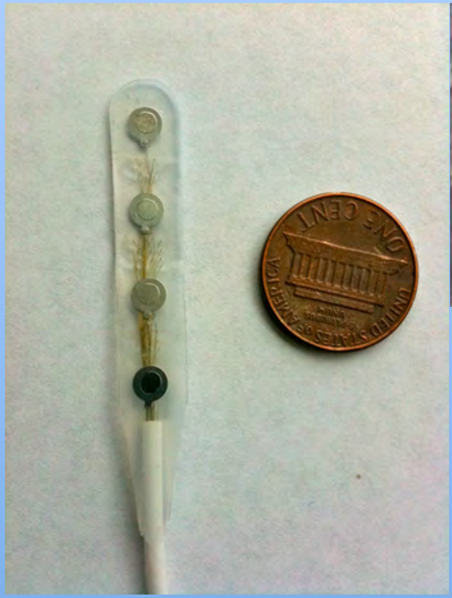
Itzhak Fried (UCLA)
Joseph Madsen (Harvard)
Alex Golby (Brigham and Women)
Stanley Anderson (J. Hopkins)

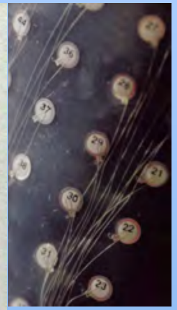
A panoply of different types of electrodes





- Targets typically include the medial temporal (hippocampus, entorhinal cortex, amygdala and parahippocampal gyrus)
- 40 micron diameter, impedance ~ 1 MOhm
- Action potentials, LFPs

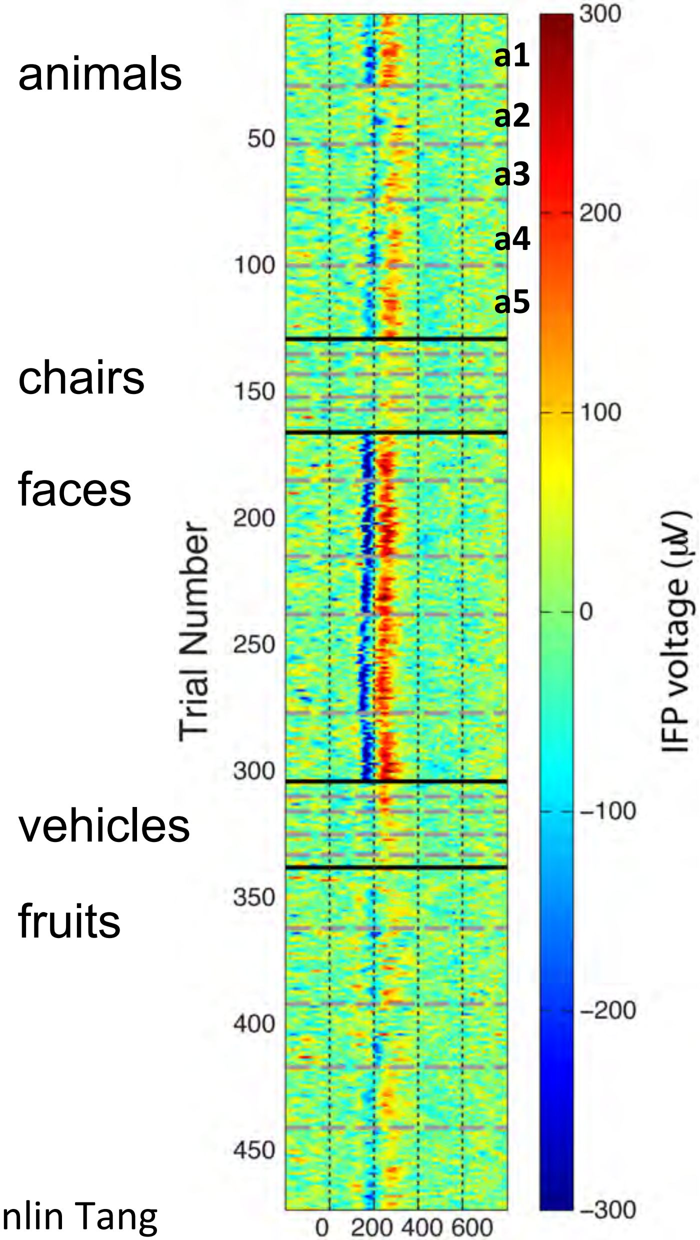


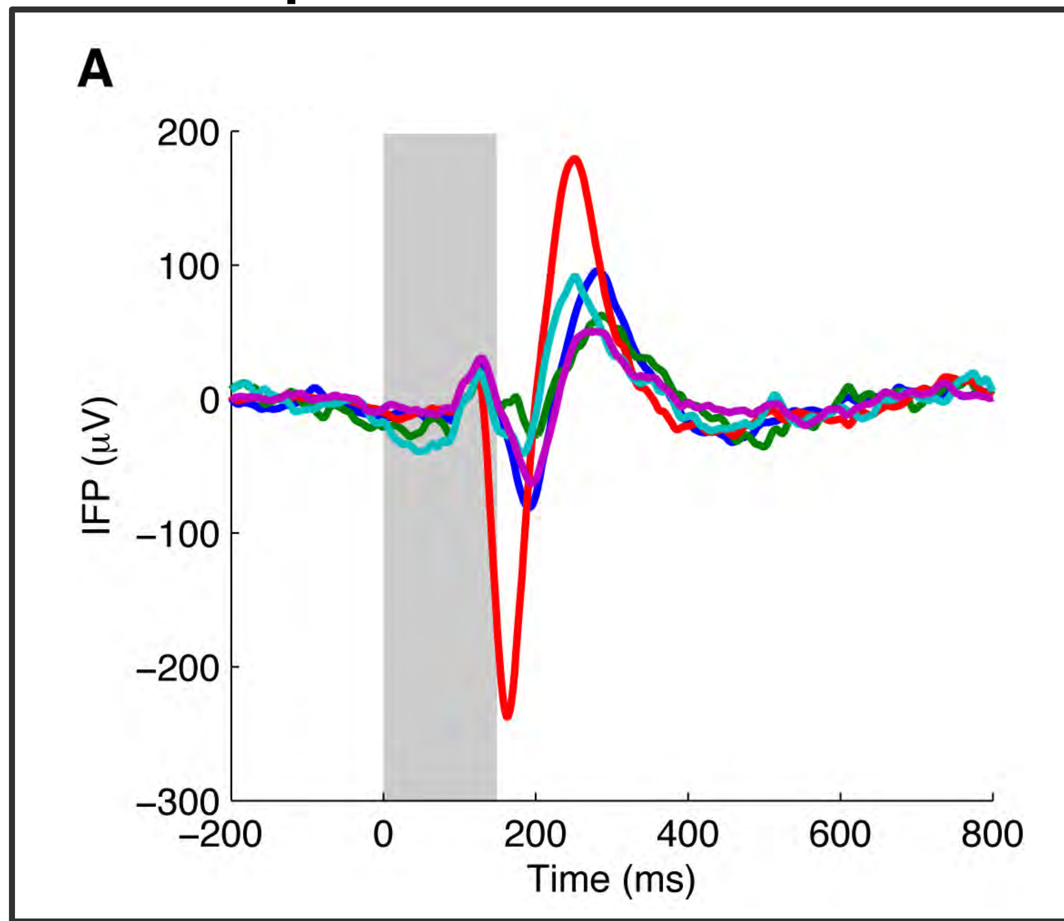


- Subdural (temporal cortex, frontal cortex)
- Low impedance macro contacts (<1 kOhm)
- High impedance microwires (~ 1MOhm)
- Large coverage

Itzhak Fried (UCLA), Joseph Madsen (Harvard), Alex Golby (Brigham and Women), Stanley Anderson (Hopkins)

Reliable, selective and rapid responses in human inferior temporal cortex



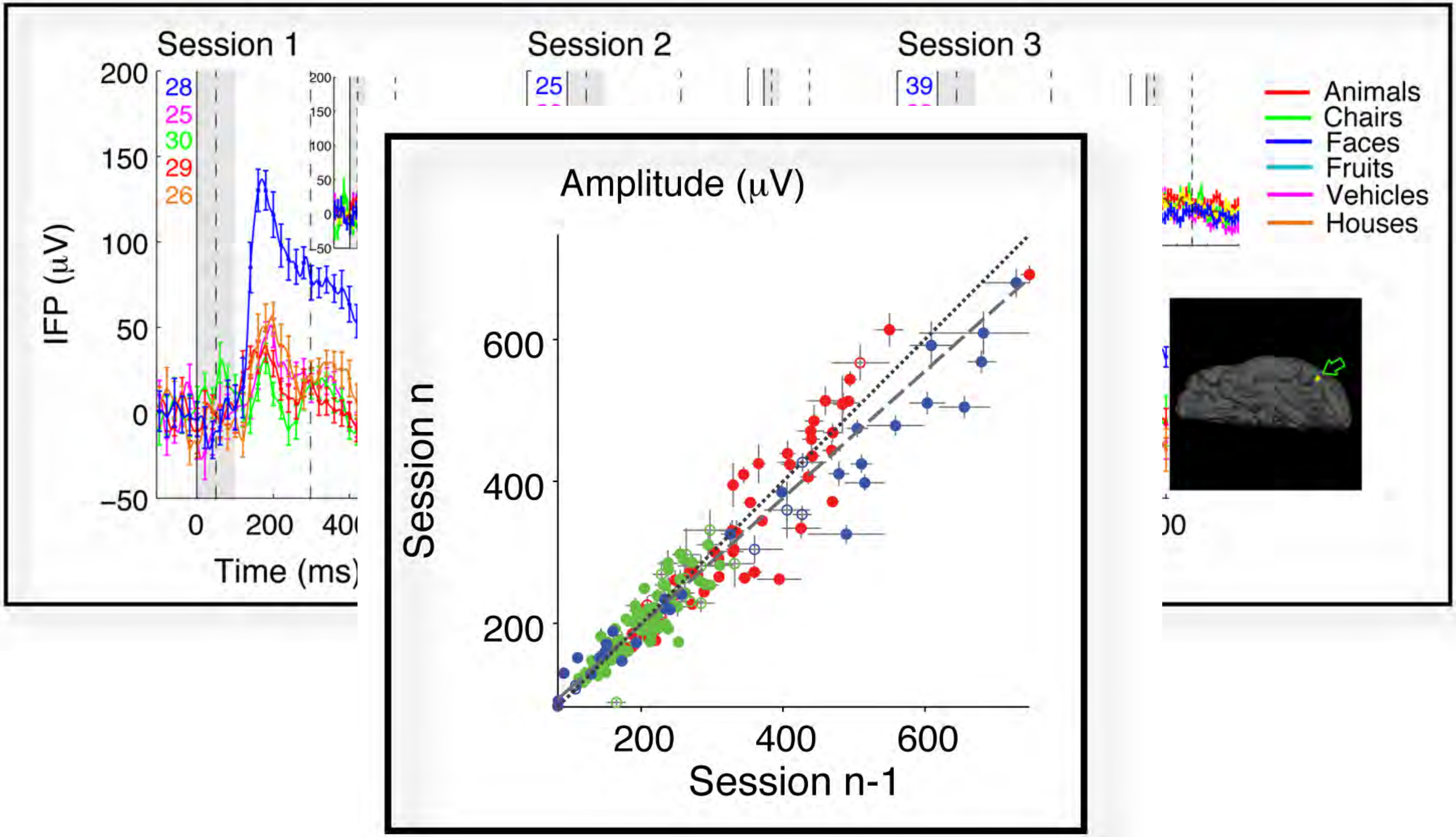


Inferior temporal gyrus

Hanlin Tang

Gross, Desimone, Logothetis, Richmond, Tanaka, Vogels, Rolls, Connors, Ito, Perret

Selective responses are stable over multiple days

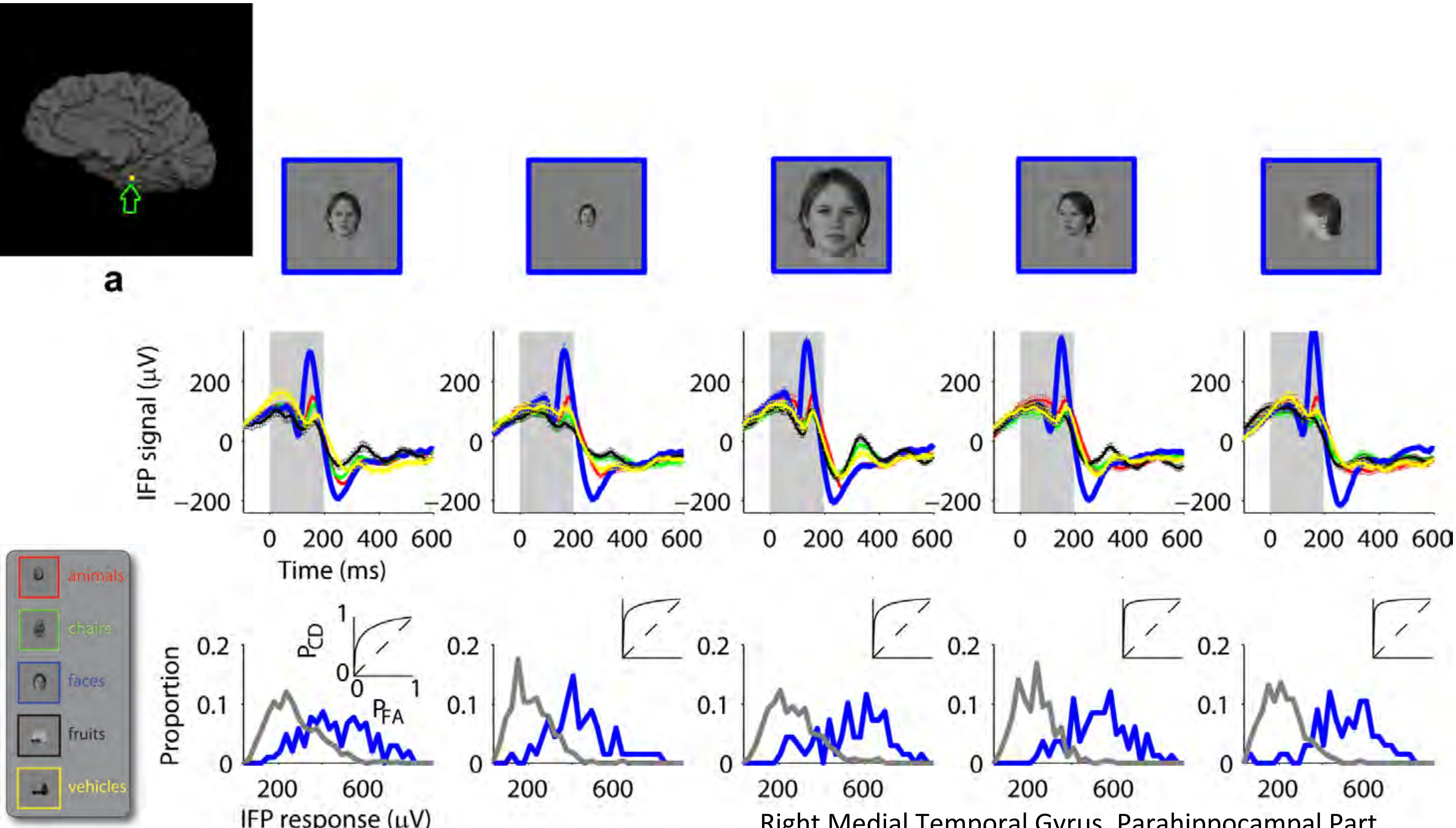


IFP = intracranial field potential

cf. Tolias, DiCarlo, Leopold

Bansal et al 2012

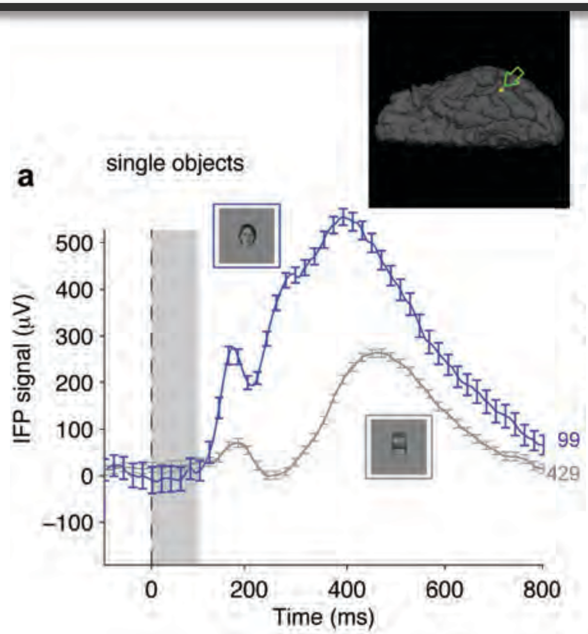
Tolerance to scale and rotation changes



Right Medial Temporal Gyrus, Parahippocampal Part (Talairach: [32,-34,-14])

Liu *et al* 2009

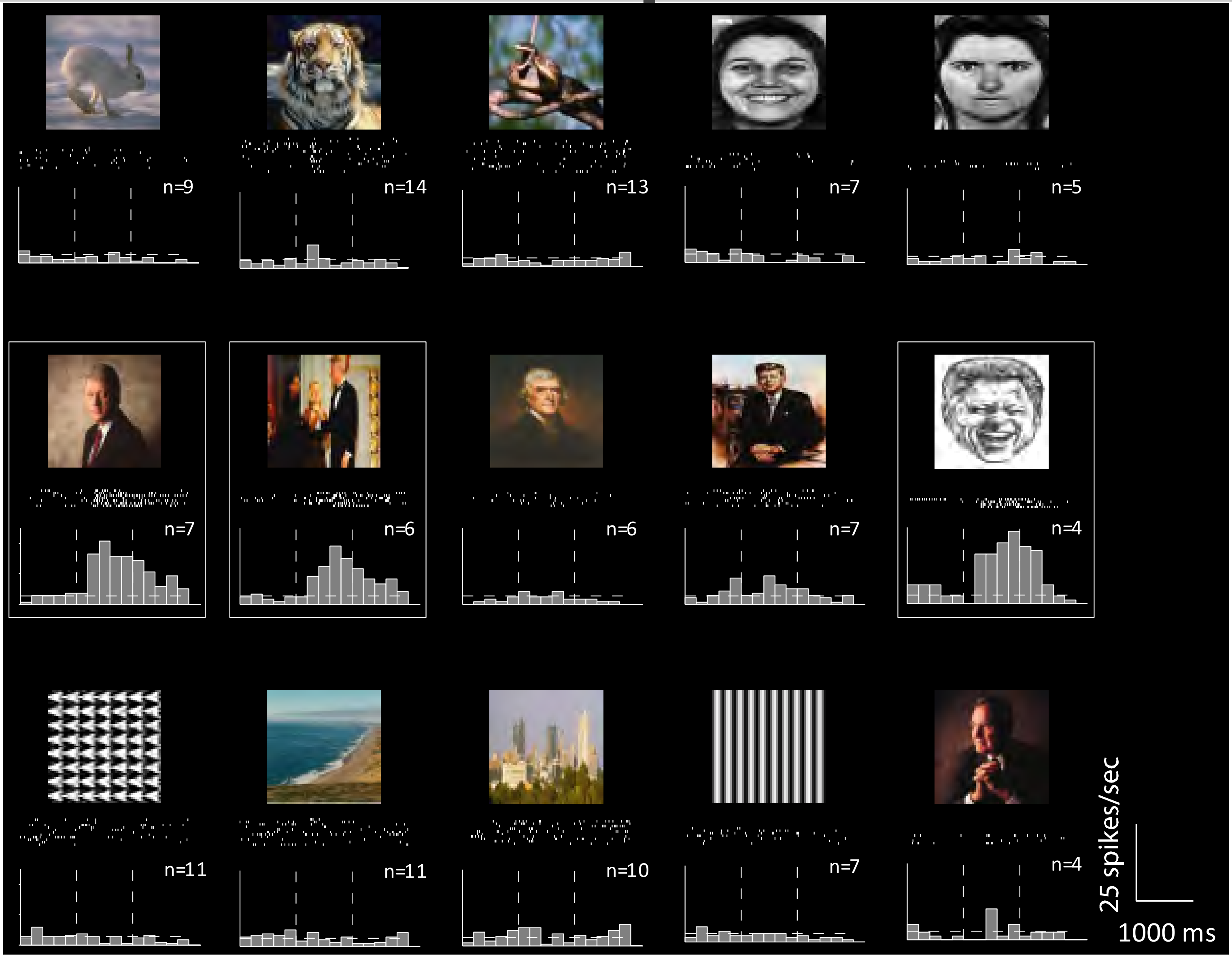
Responses are tolerant to small amounts of clutter



Left Occipito-Temporal Fusiform Gyrus [-42,-44,-24]

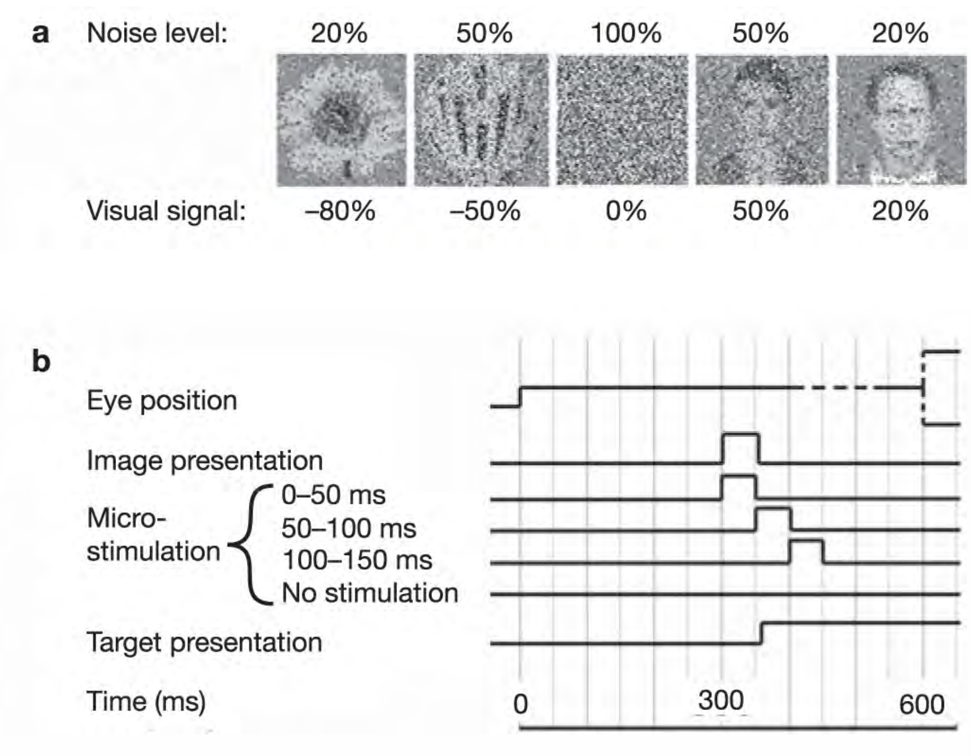
Agam *et al* 2010

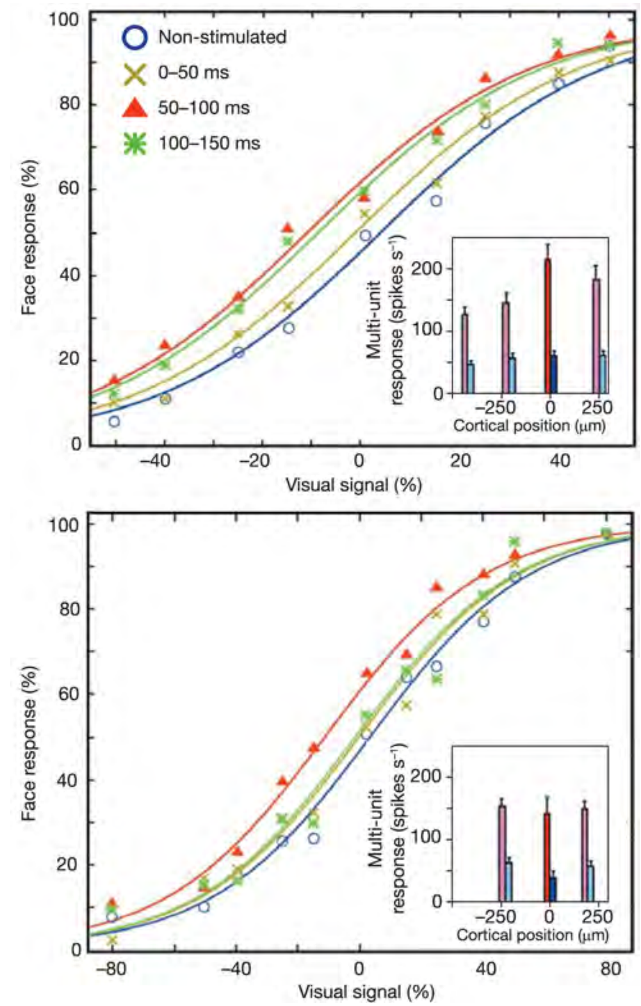
Highly selective and tolerant responses in the human medial temporal lobe



Quian Quiroga, Reddy, Kreiman, Koch, Fried. *Nature 2005*

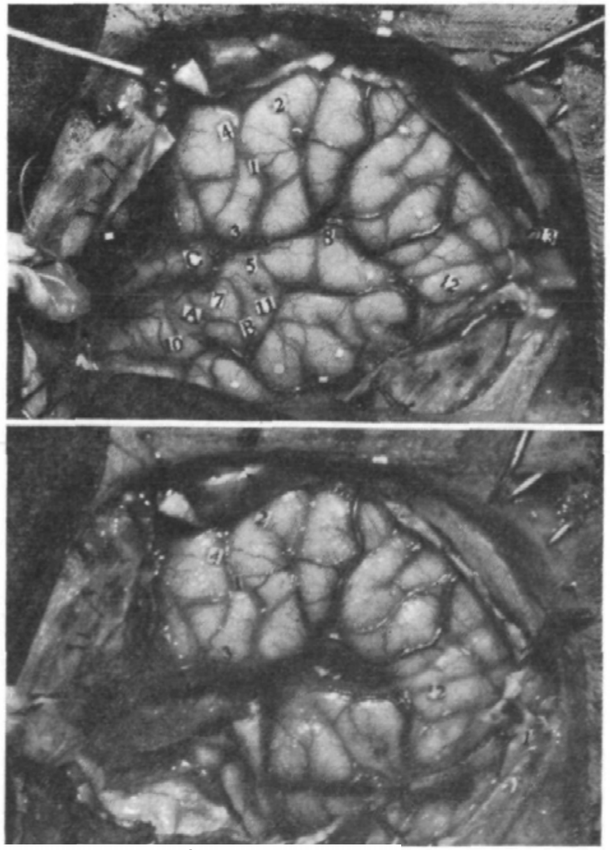
Electrical stimulation can bias visual perception

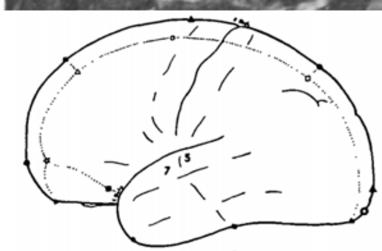




Afraz et al. *Microstimulation of inferotemporal cortex influences face categorization.* Nature (2006) **442**: 692-695.

Electrical stimulation in the human brain





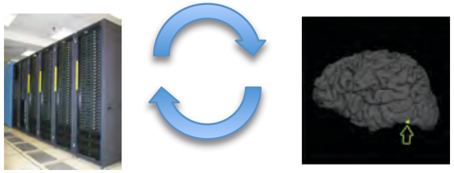
Case 2.—R. B.

Before the removal was carried out, stimulation at points 5 and 7 produced the following experiential responses.

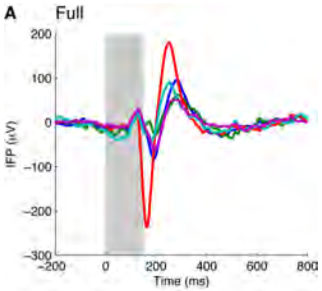
5. Patient did not reply.
5. Repeated. "Something."
5. Patient did not reply.
5. Repeated. "Something."
5. Repeated again. "People's voices talking." When asked, he said he could not tell what they were saying. They seemed to be far away.
5. Stimulation without warning. He said, "Now I hear them." Then he added, "A little like in a dream."
7. "Like footsteps walking—on the radio."
7. Repeated. "Like company in the room."
7. Repeated. He explained "it was like being in a dance hall, like standing in the doorway—in a gymnasium—like at the Kenwood Highschool." He added, "If I wanted to go there it would be similar to what I heard just now."
7. Repeated. Patient said, "Yes, yes, yes." After withdrawal of the stimulus, he said it was "like a lady was talking to a child. It seemed like it was in a room, but it seemed as though it was by the ocean—at the seashore."
7. Repeated. "I tried to think." When asked whether he saw something or heard something, he said, "I saw and heard. It seemed familiar, as though I had been there."
5. Repeated (20 minutes after last stimulation at 5). "People's voices." When asked, he said, "Relatives, my mother." When asked if it was over, he said, "I do not know." When asked if he also realized he was in the operating room, he said "Yes." He explained it seemed like a dream.
5. Repeated. Patient said, "I am trying." After withdrawal of the electrode he said, "It seemed as if my niece and nephew were visiting at my home. It happened like that many times. They were getting ready to go home, putting their things on—their coats and hats." When asked where, he said, "In the dining room—the front room—they were moving about. There were three of them and my mother was talking to them. She was rushed—in a hurry. I could not see them clearly or hear them clearly."

Penfield & Perot. *The brain's record of auditory and visual experience. A final summary and discussion. Brain* (1963) **86**:595-696

Partial Summary



1. Understanding neural circuits codes → Biologically-inspired algorithms underlying intelligent computations



2. Responses along the ventral visual stream

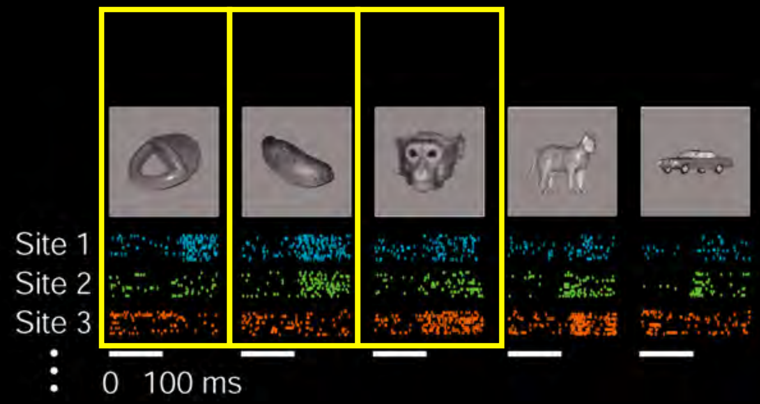
-- Increase in receptive field sizes

-- Selectivity to different shapes

-- Tolerance to transformations (scale, position, some rotation)

-- Rapid responses (100-150 ms)

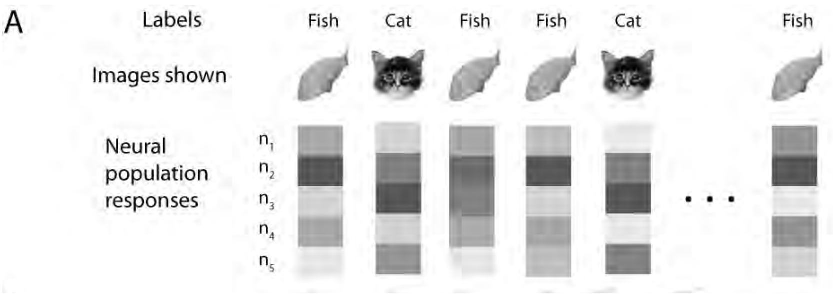
Deciphering the neural code



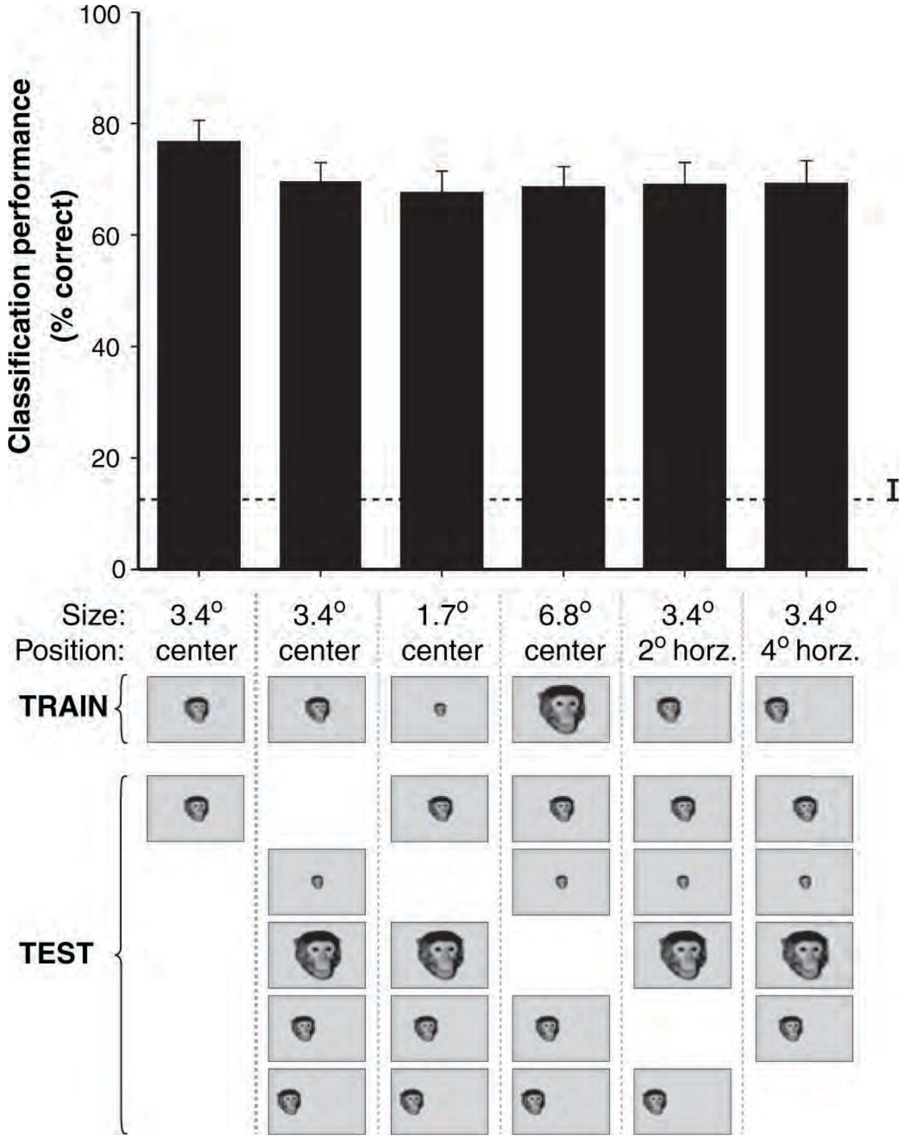
Neuron 1	Neuron 2	Neuron 3	Object
Yes	No	No	1
Yes	Yes	No	2
Yes	Yes	Yes	3

Hung et al, 2005

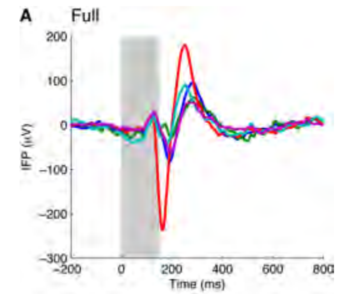
Machine learning approach to decode neural signals

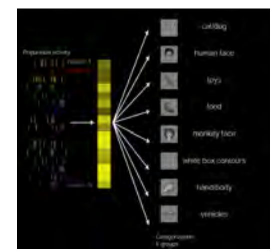


Decoding selective and transformation tolerant information



Partial Summary



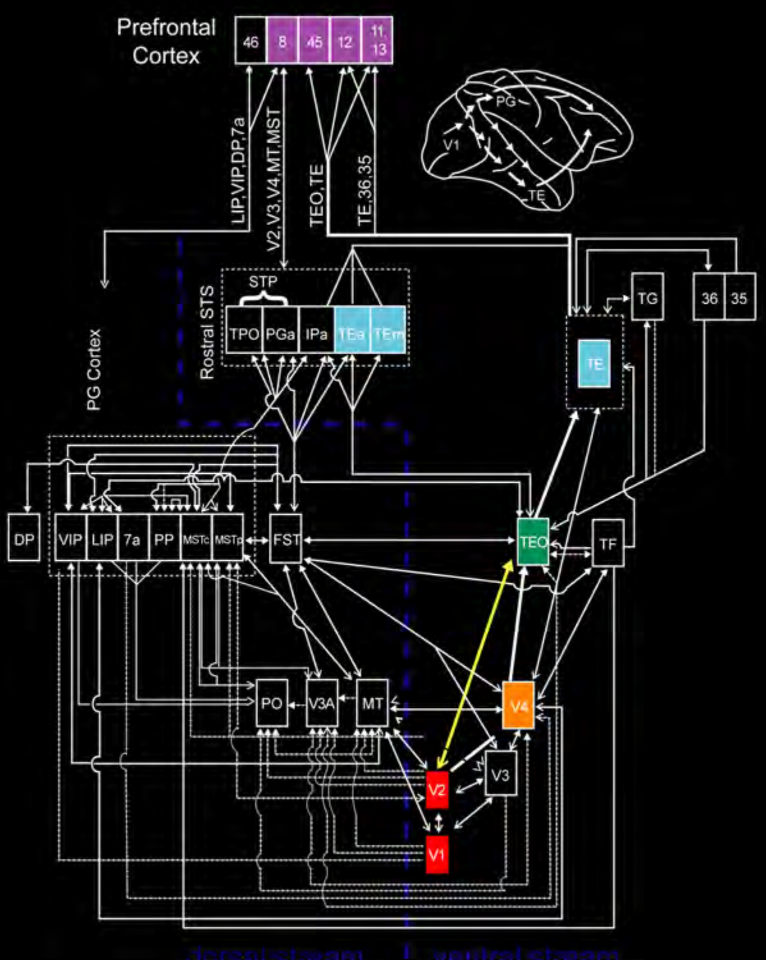


1. Understanding neural circuits codes → Biologically-inspired algorithms underlying intelligent computations

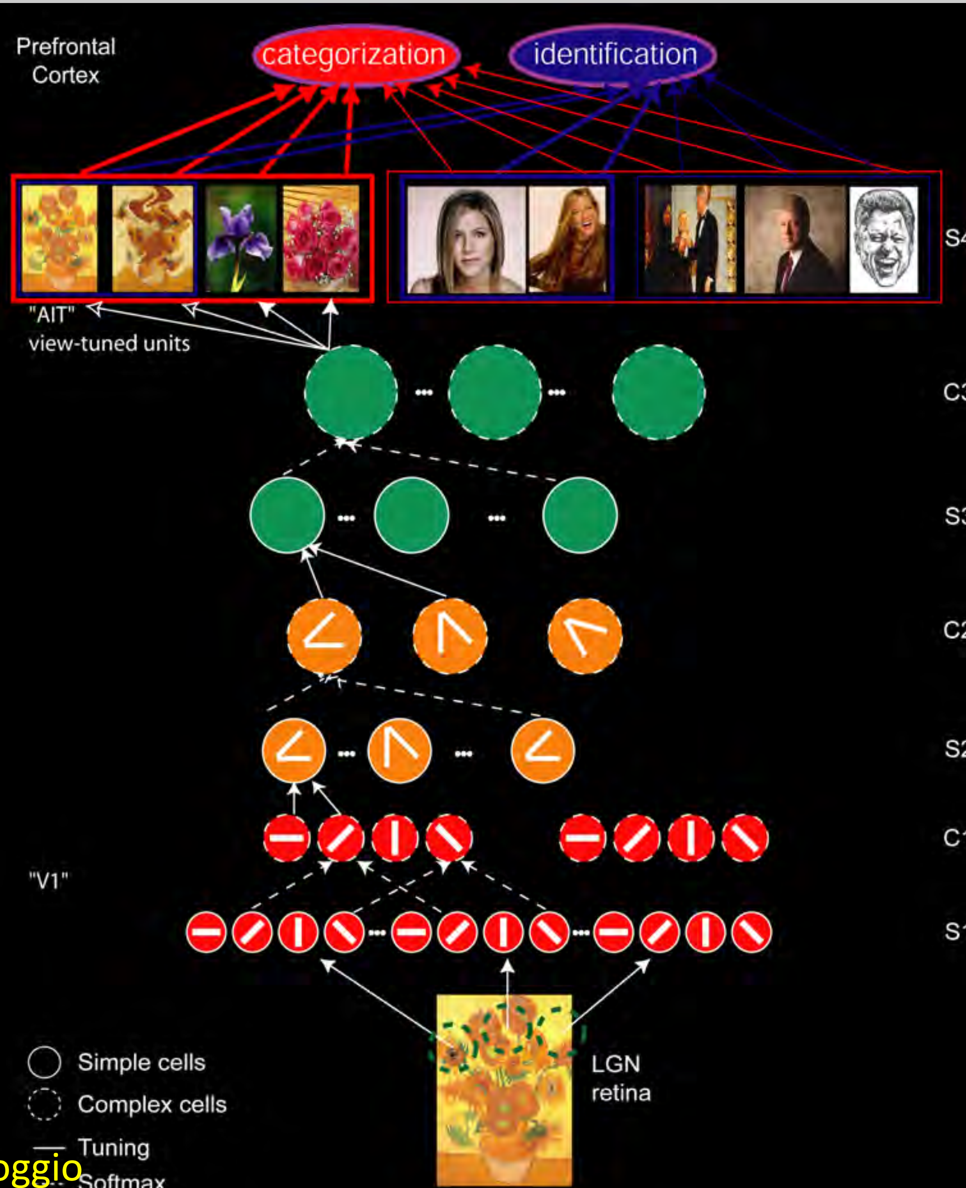
2. Responses along the ventral visual stream
   -- Increase in receptive field sizes
   -- Selectivity to different shapes
   -- Tolerance to transformations (scale, position, some rotation)
   -- Rapid responses (100-150 ms)

3. **We can use a machine learning approach to read out biological codes in single trials**

From biological code to computer code

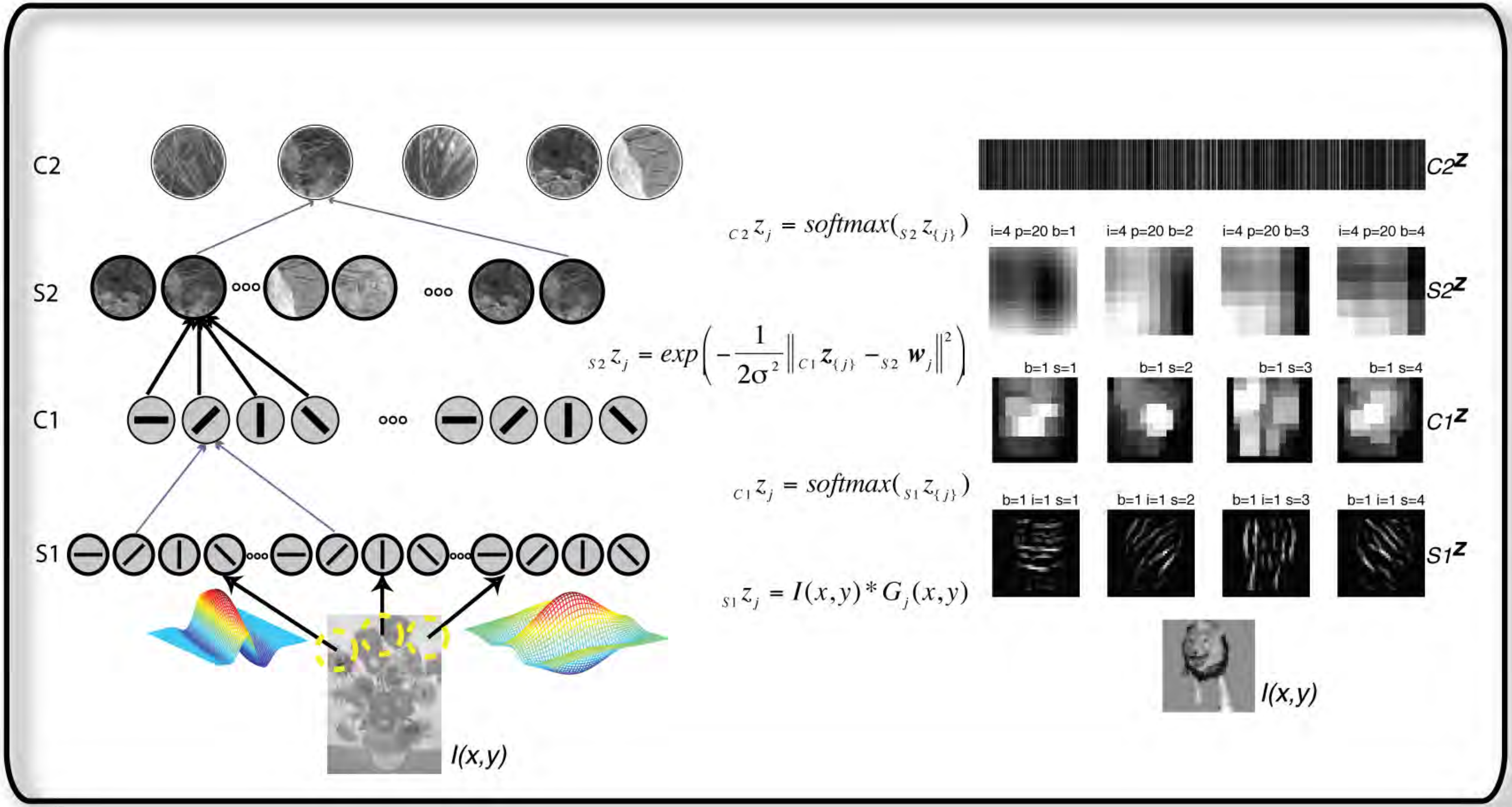


Felleman and Van Essen. *Cerebral Cortex* 1991



Fukushima, Rolls, LeCun, Wallis, Mel, Riesenhuber, Poggio
Riesenhuber&Poggio 1999; Serre et al 2007

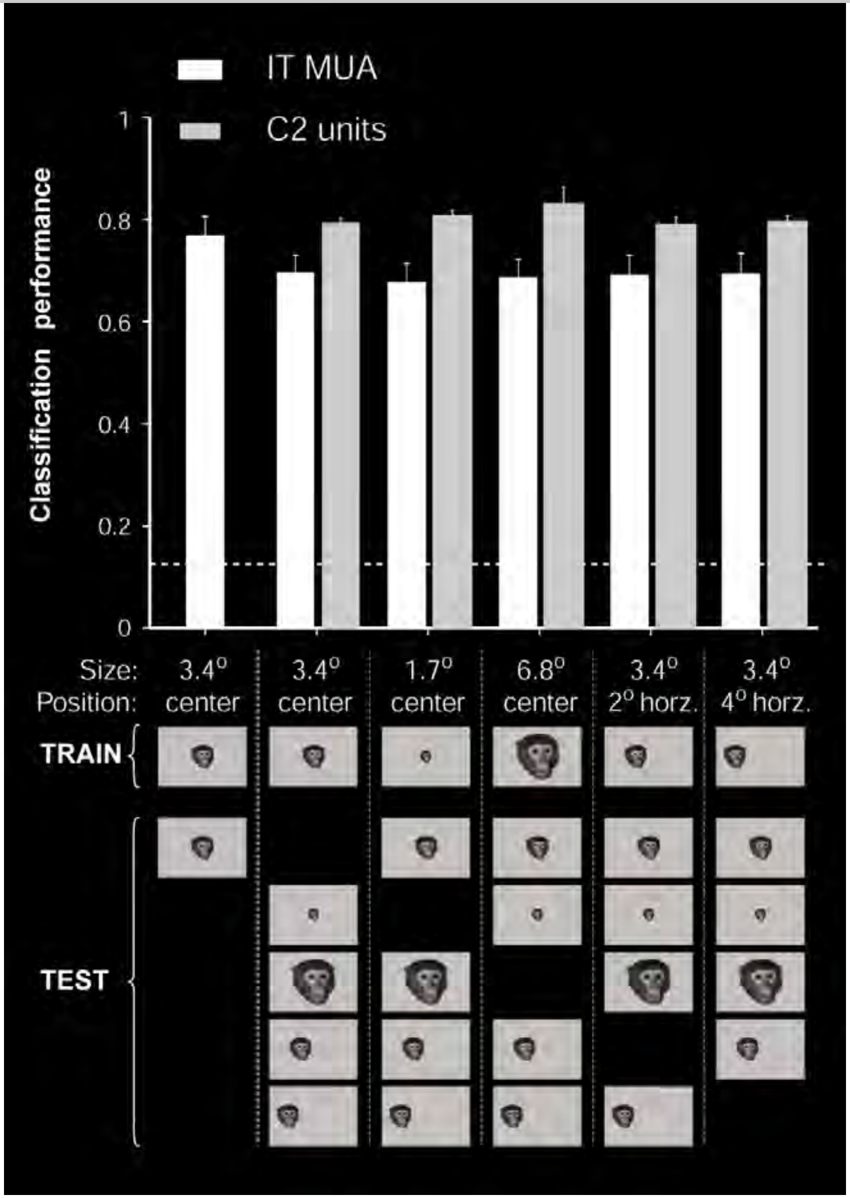
A biologically-inspired, bottom-up, hierarchical model of object recognition



Cadieu, Knoblich, Kouh, Mutch, Riesenhuber, Serre, Poggio

Scale and position tolerance when decoding from ITC and model units

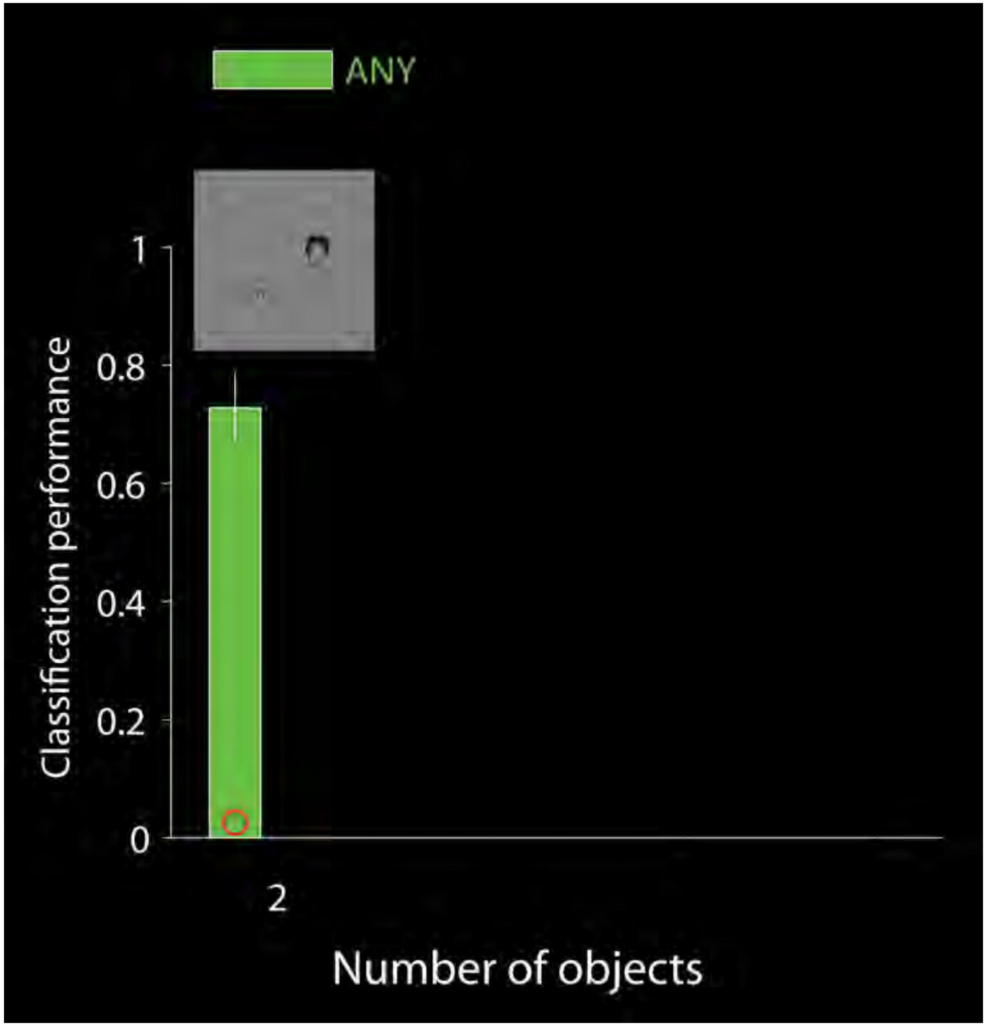
Support vector machine classifier
Linear kernel
Pseudo-population of 64 inferior tempora
cortex neurons [white]
Model: 64 random C2-level units
Categorization performance
Chance = 1/8
Cross-validation



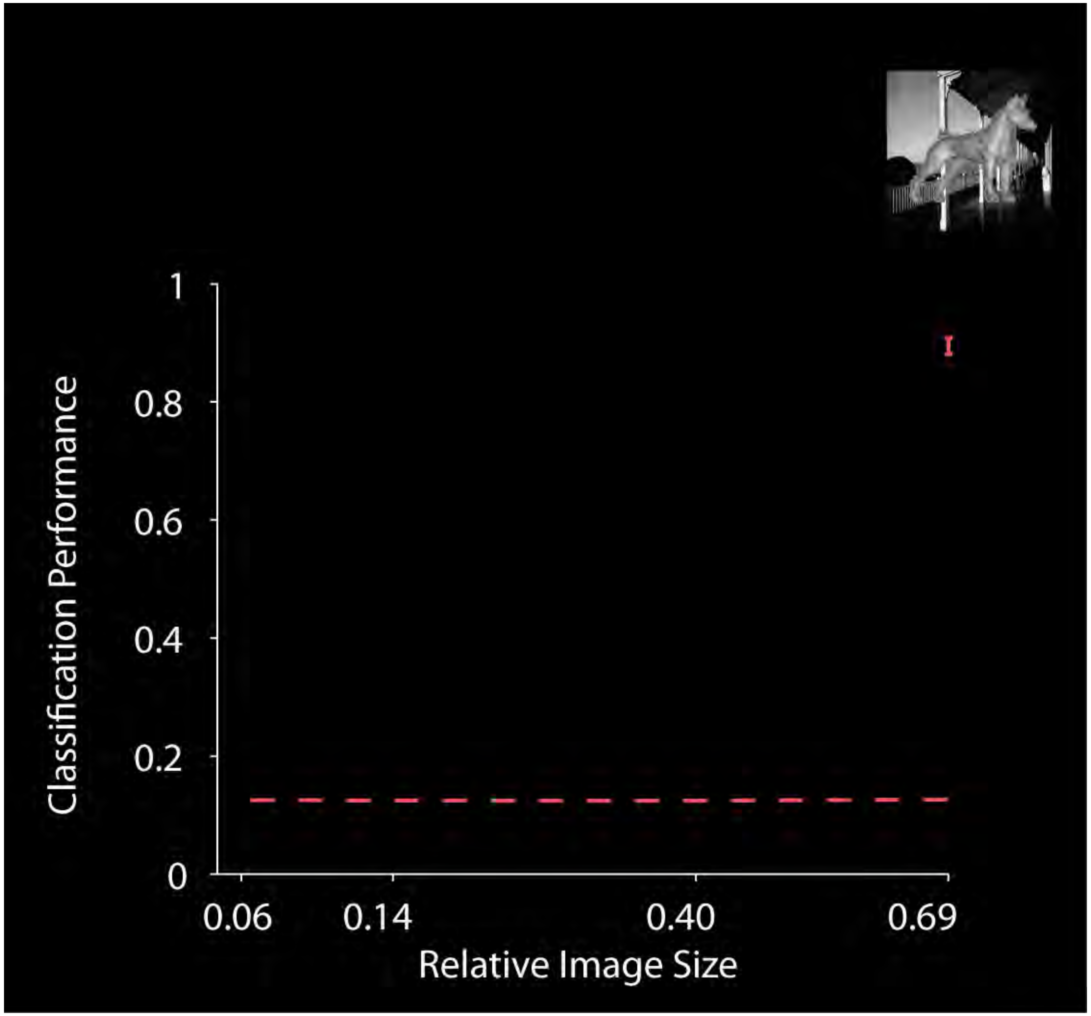
with Chou Hung, Jim DiCarlo, Tommy Poggio

Hung et al 2005

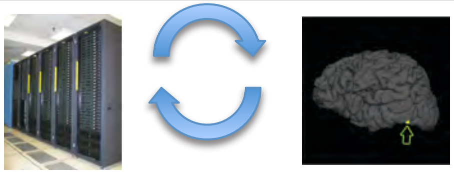
Model performance in the presence of clutter



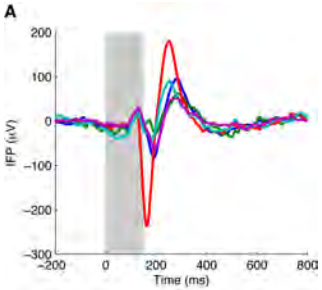
Towards understanding vision in real scenes



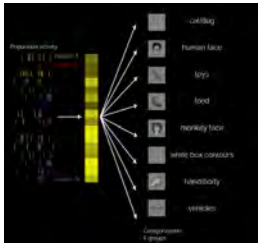
Partial Summary



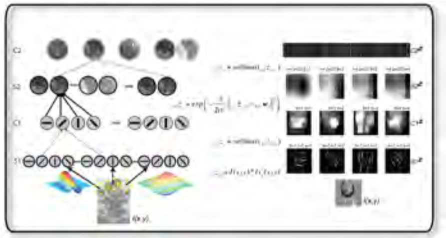
1. Understanding neural circuits codes → Biologically-inspired algorithms underlying intelligent computations



2. Responses along the ventral visual stream
   -- Increase in receptive field sizes
   -- Selectivity to different shapes
   -- Tolerance to transformations (scale, position, some rotation)
   -- Rapid responses (100-150 ms)

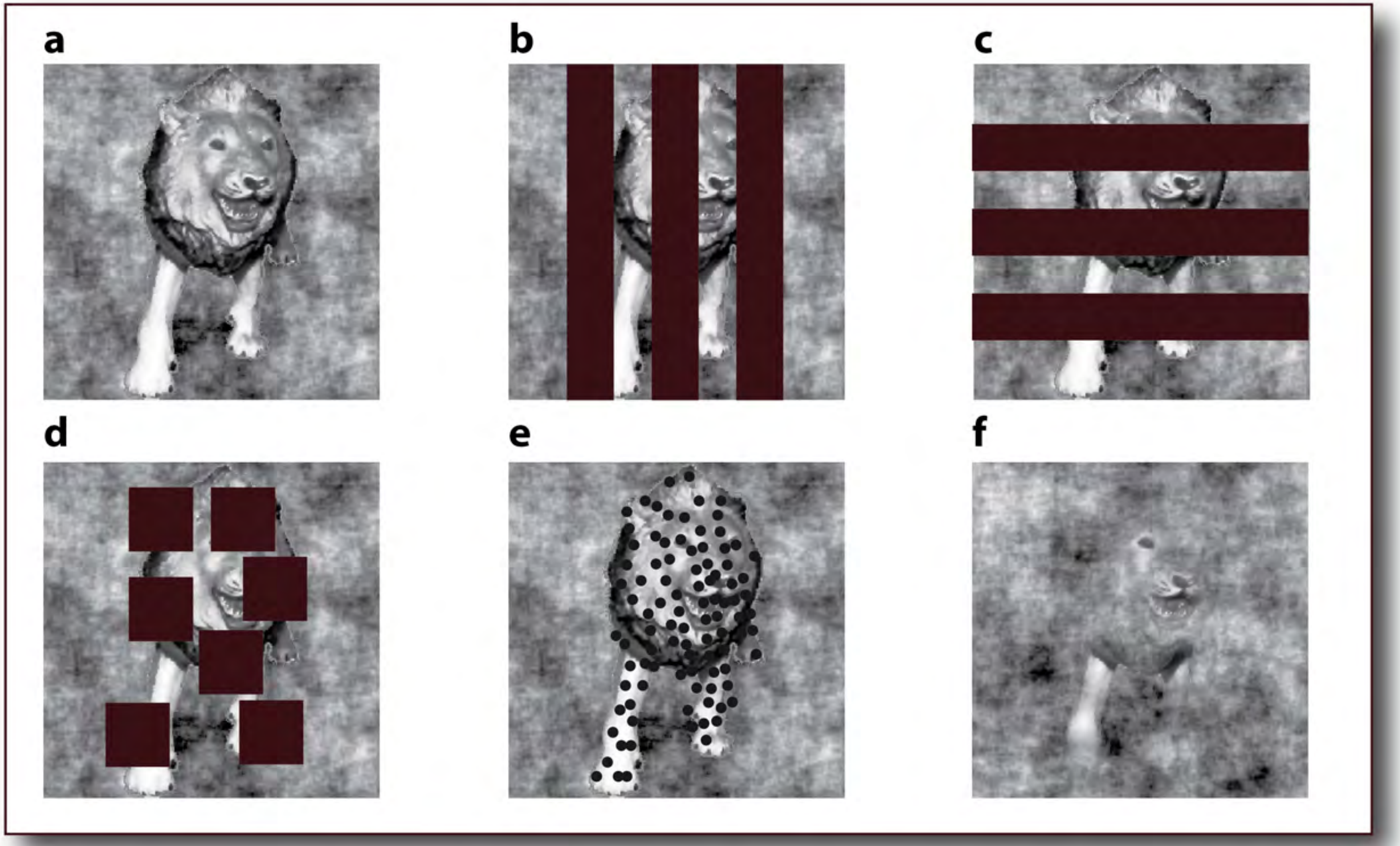


3. We can use a machine learning approach to read out biological codes in single trials

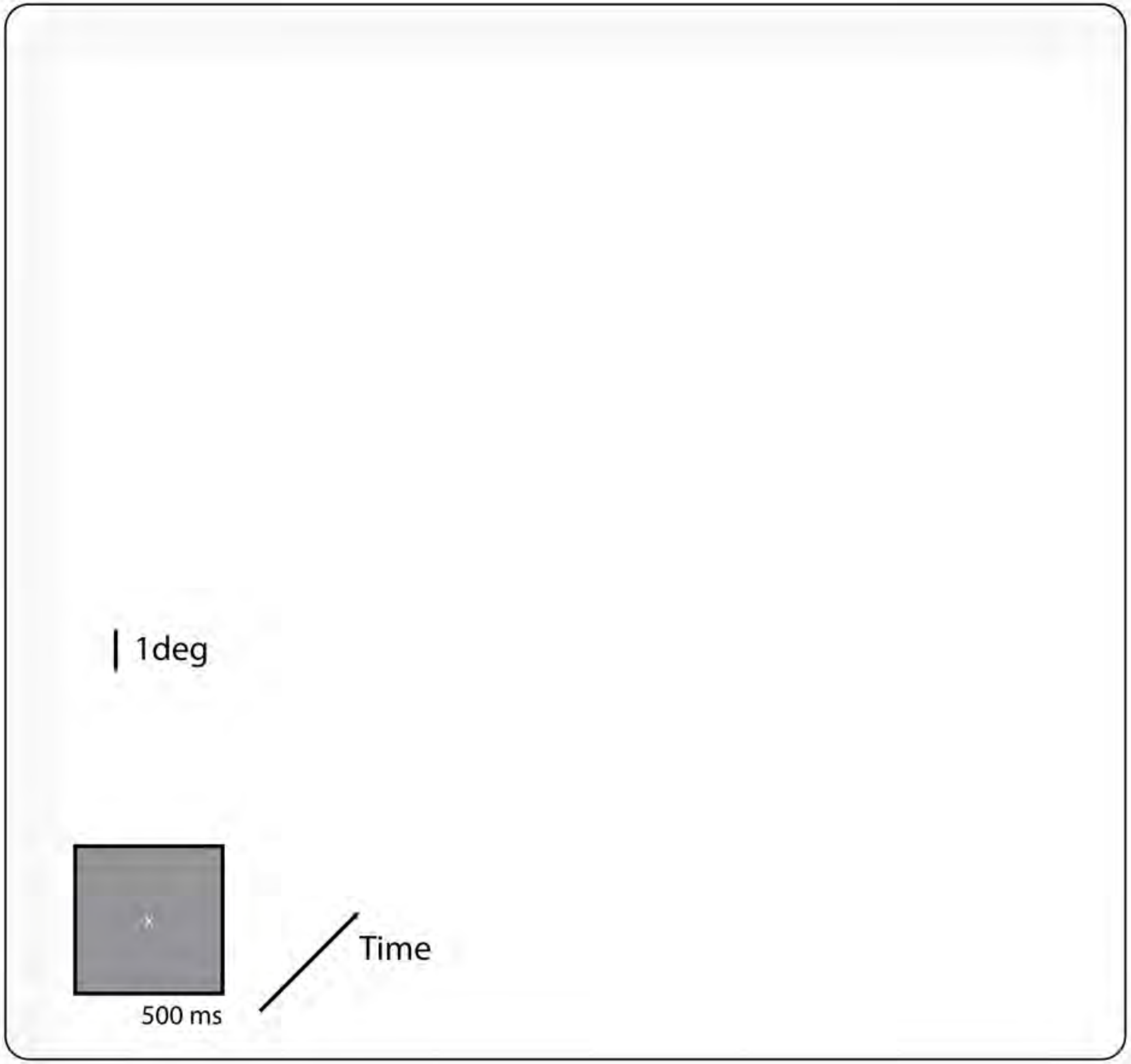


4. **Divide and conquer: a biologically inspired bottom-up hierarchical model can capture essentials aspects of object recognition**

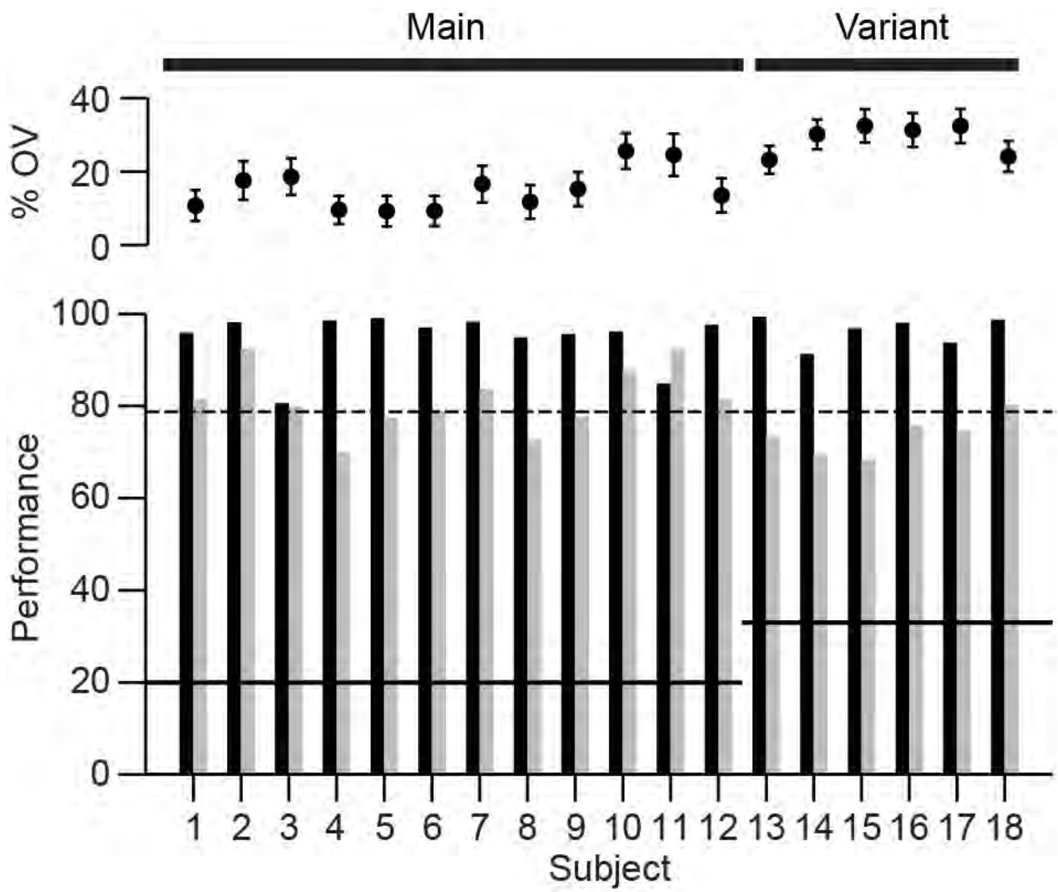
Objects can be recognized from partial information

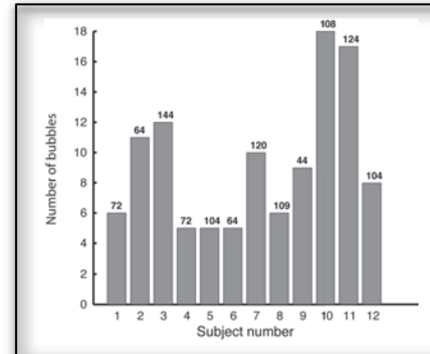


Object completion task

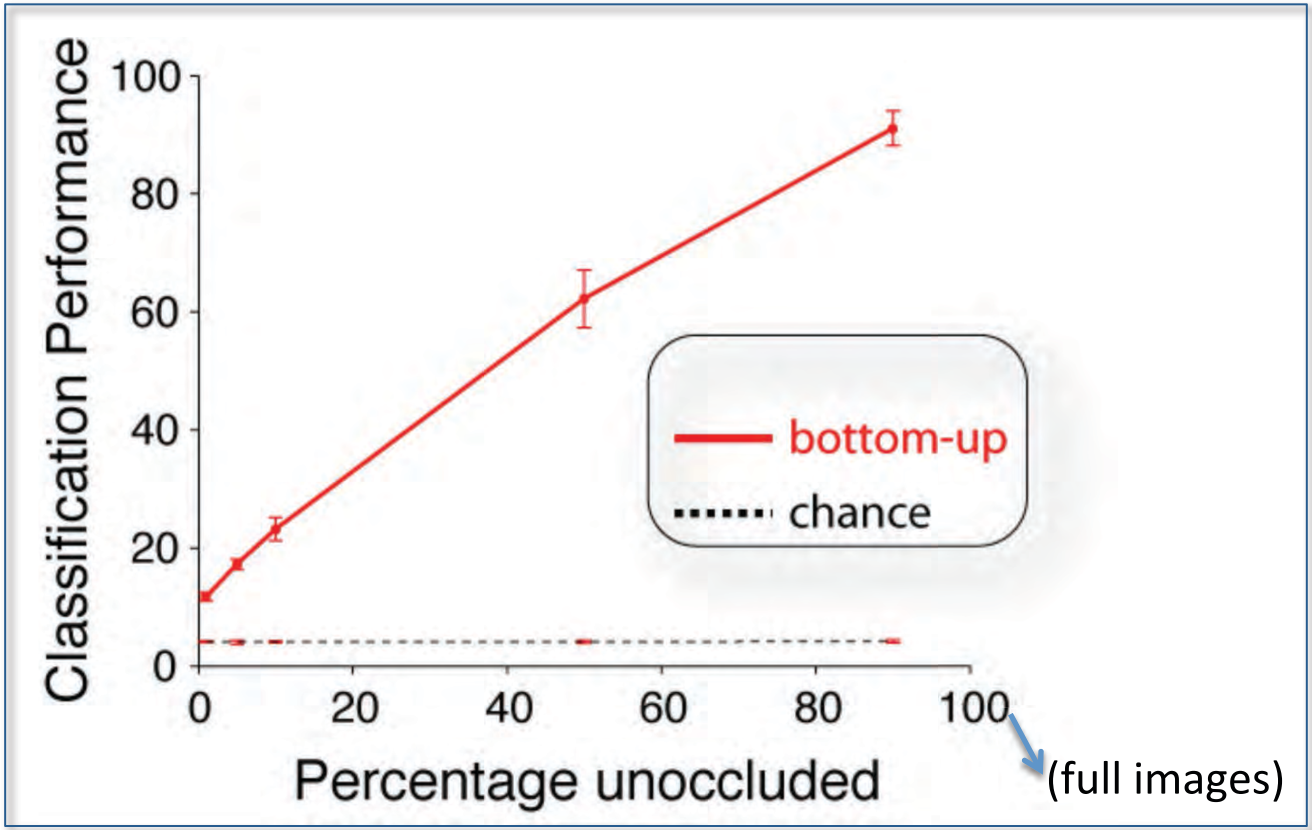


Performance in object completion task



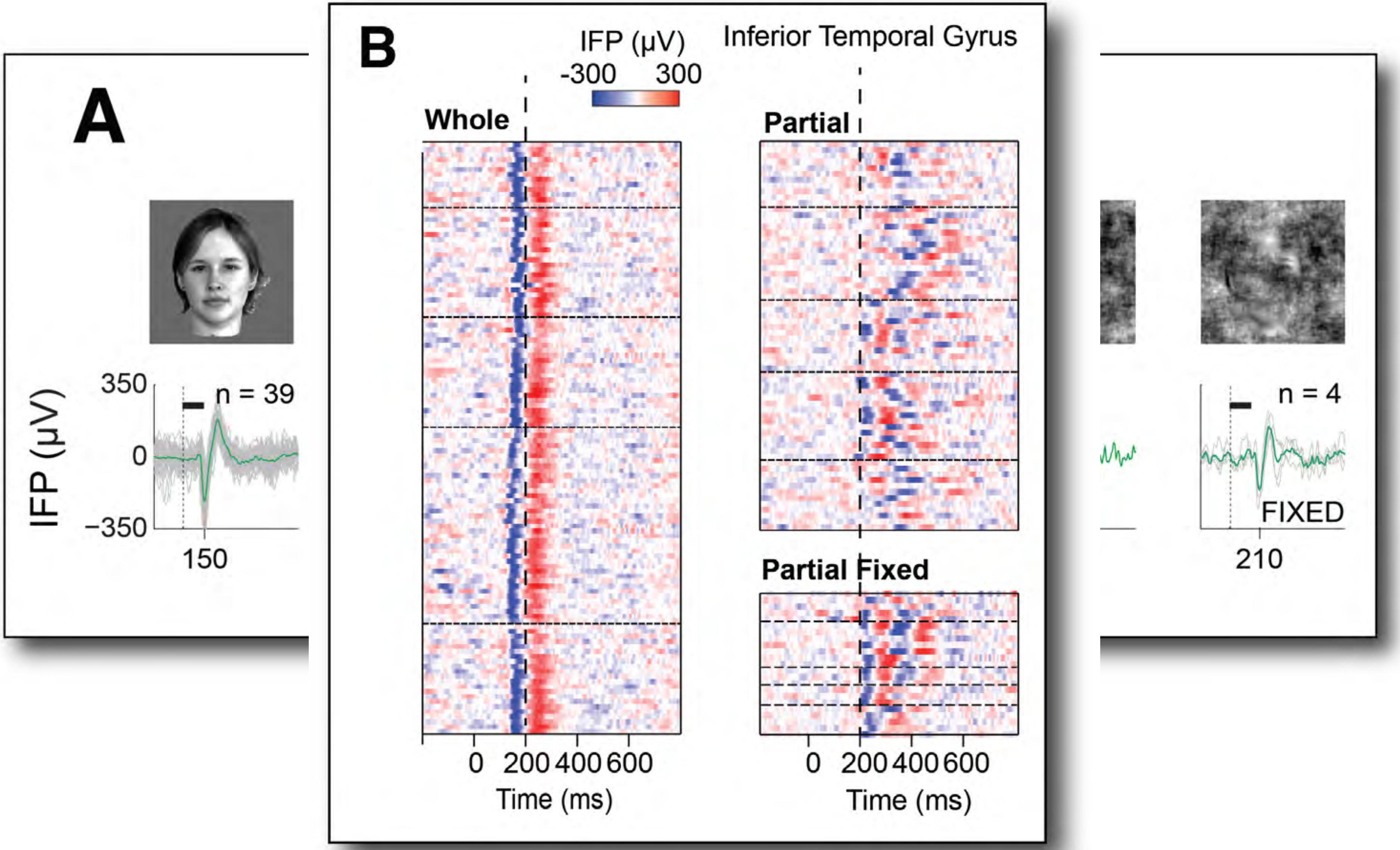


Limited object completion in feed-forward model



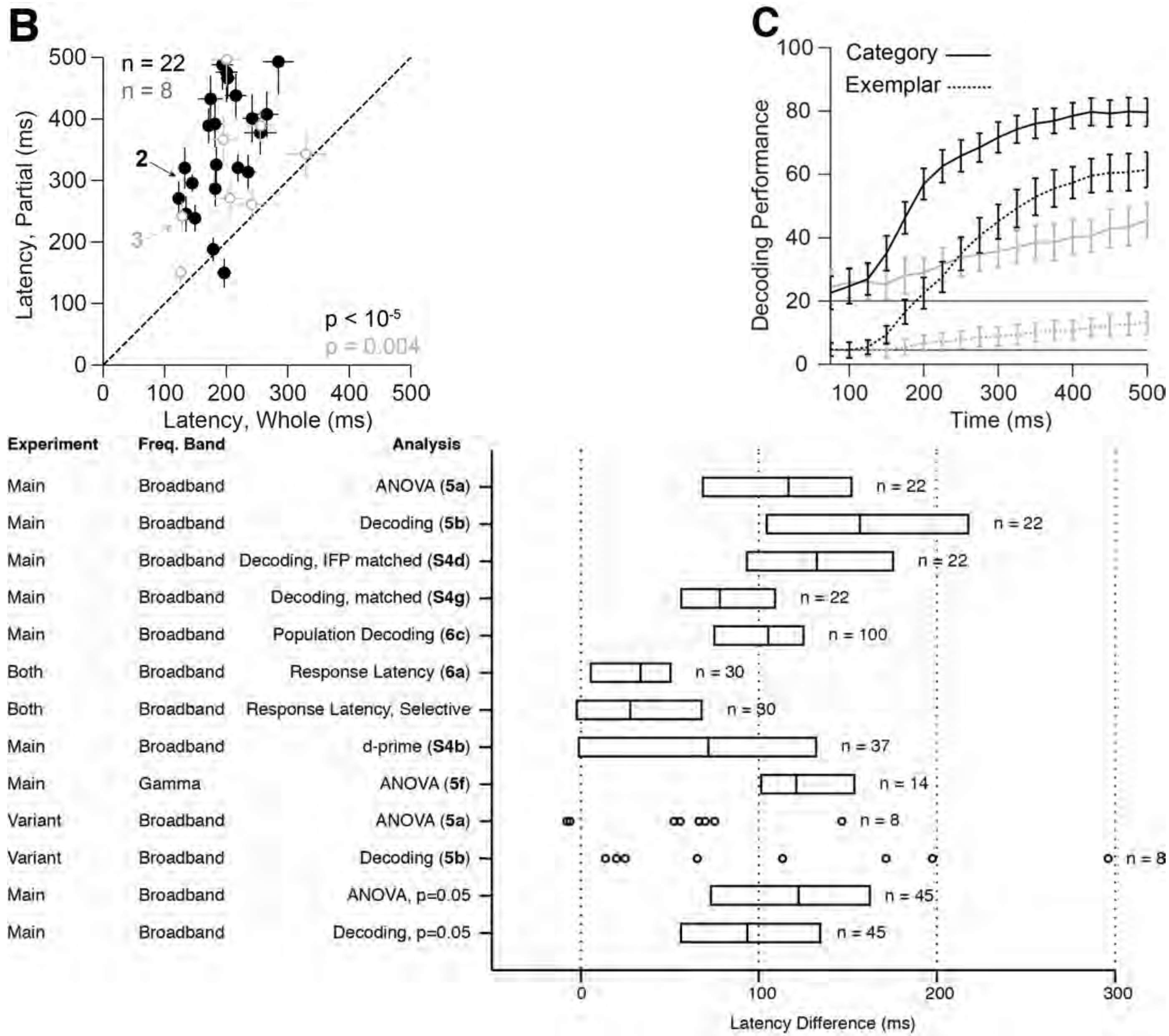
2000 “C2” units in the model
Model responses to 25 exemplar objects
Consider 20 units with high SNR (training data)
500 repetitions with different bubble locations
Train classifier with 70% of the repetitions
Test classifier on remaining 30% of the repetitions
Identification task (chance=4%)

Example responses during object completion



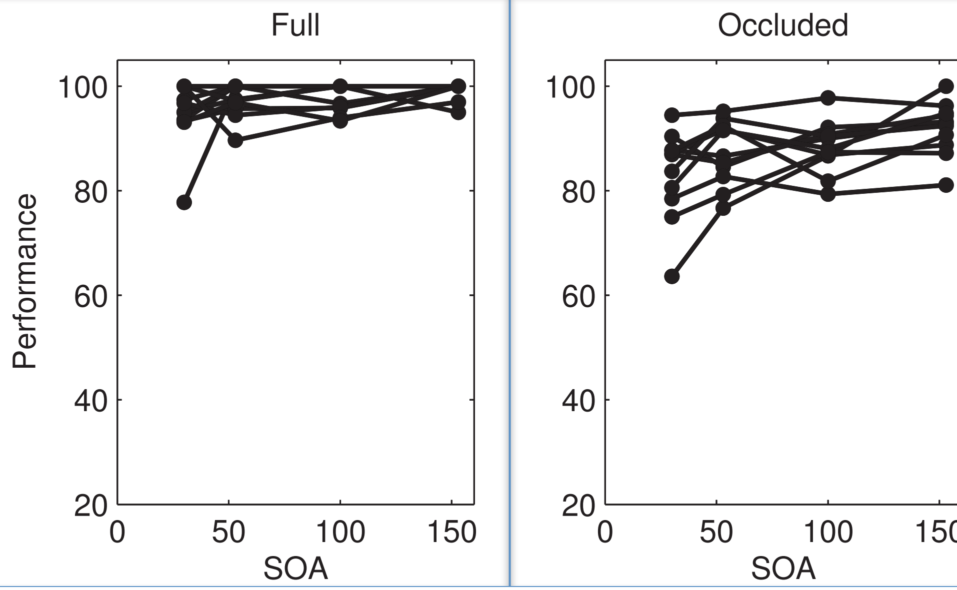
Inferior Temporal Gyrus

Delayed responses to partial objects



Object completion requires more time (behavior)

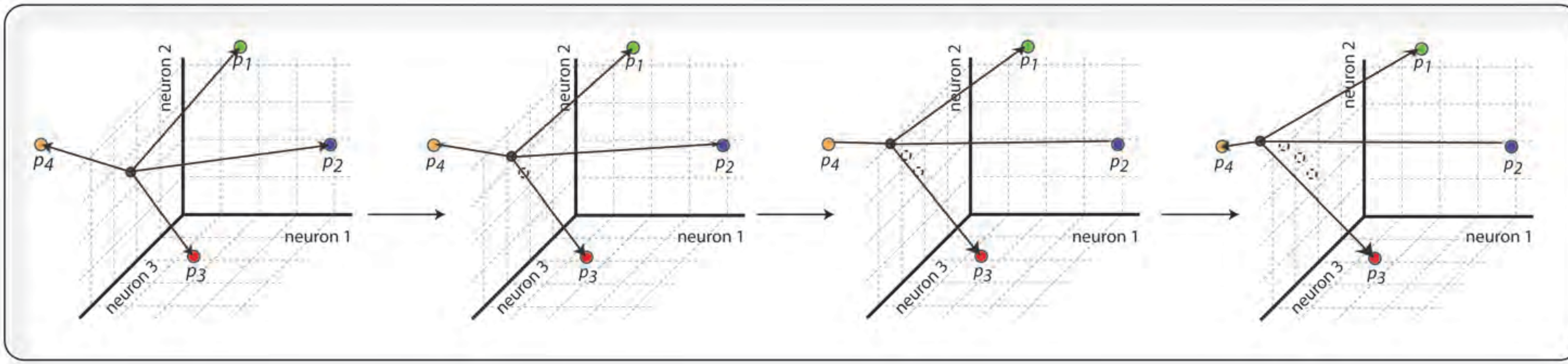
NO MASK



Walter Hardesty, Hanlin Tang

Top-down / recurrent signals may ameliorate the problem of missing information

Attractor networks can solve the problem of pattern completion (e.g. Hopfield)

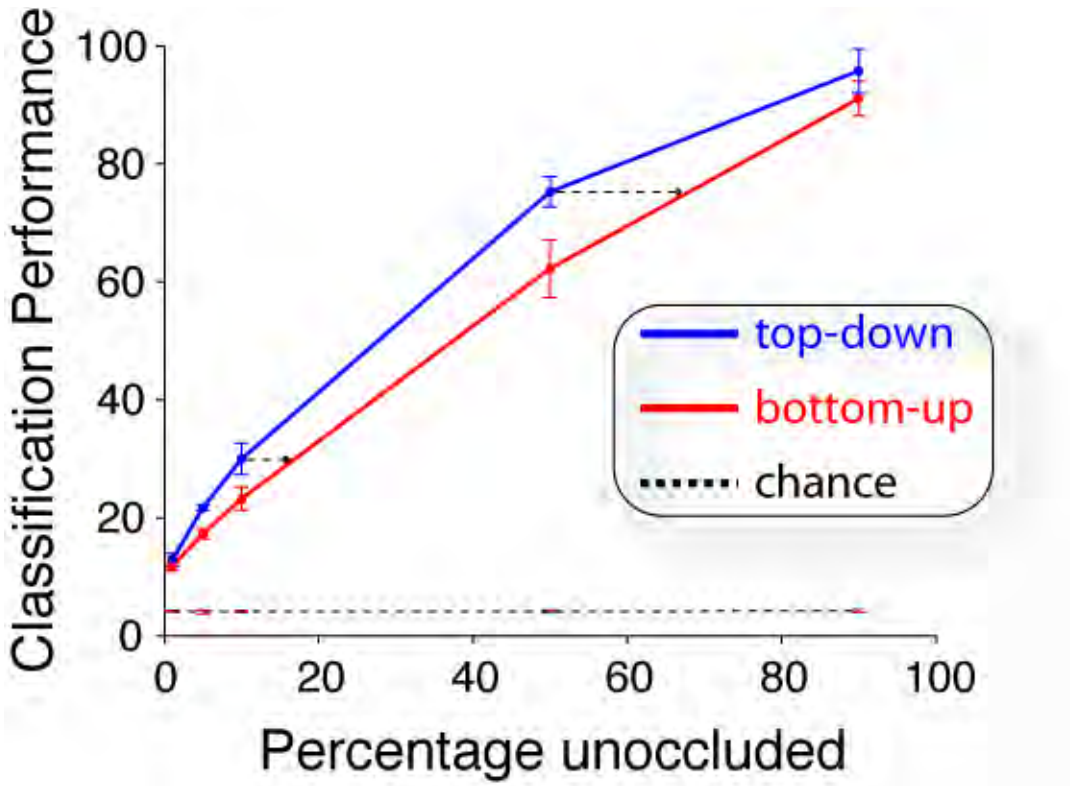


$$_{C2}z(t) = {}_{C2}z(t-1) + \sum_i \frac{\alpha(p_i - {}_{C2}z(t-1))}{d(z(t-1), p_i)^n}$$

p = prototypes (fixed)
i = 1,…,25
α, n = parameters
d = Euclidian distance

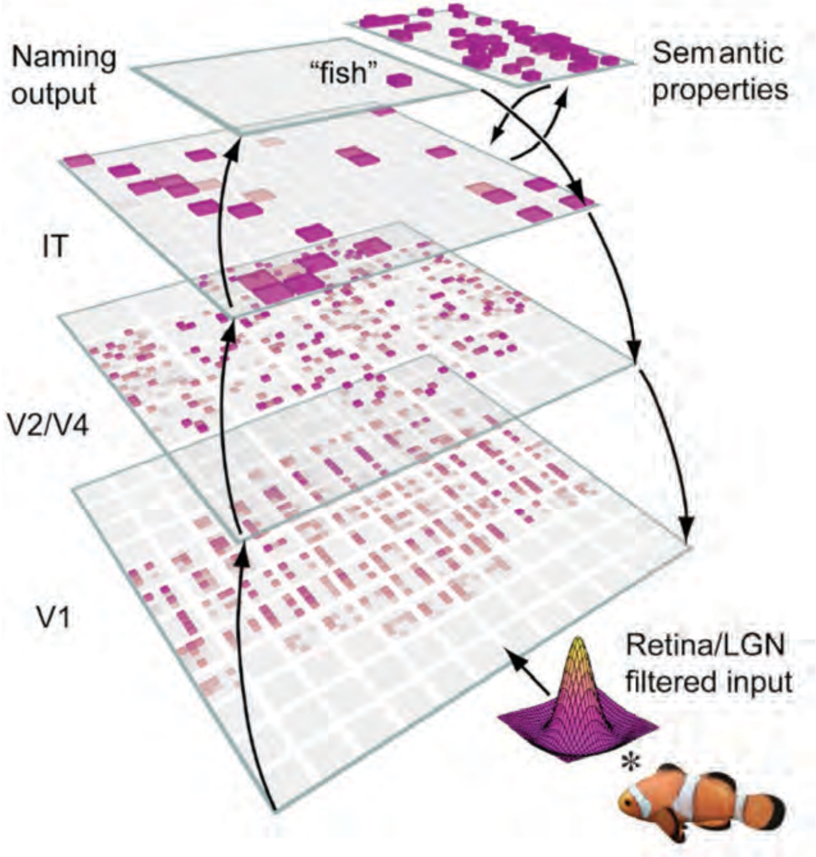
Calin Buia, Hanlin Tang

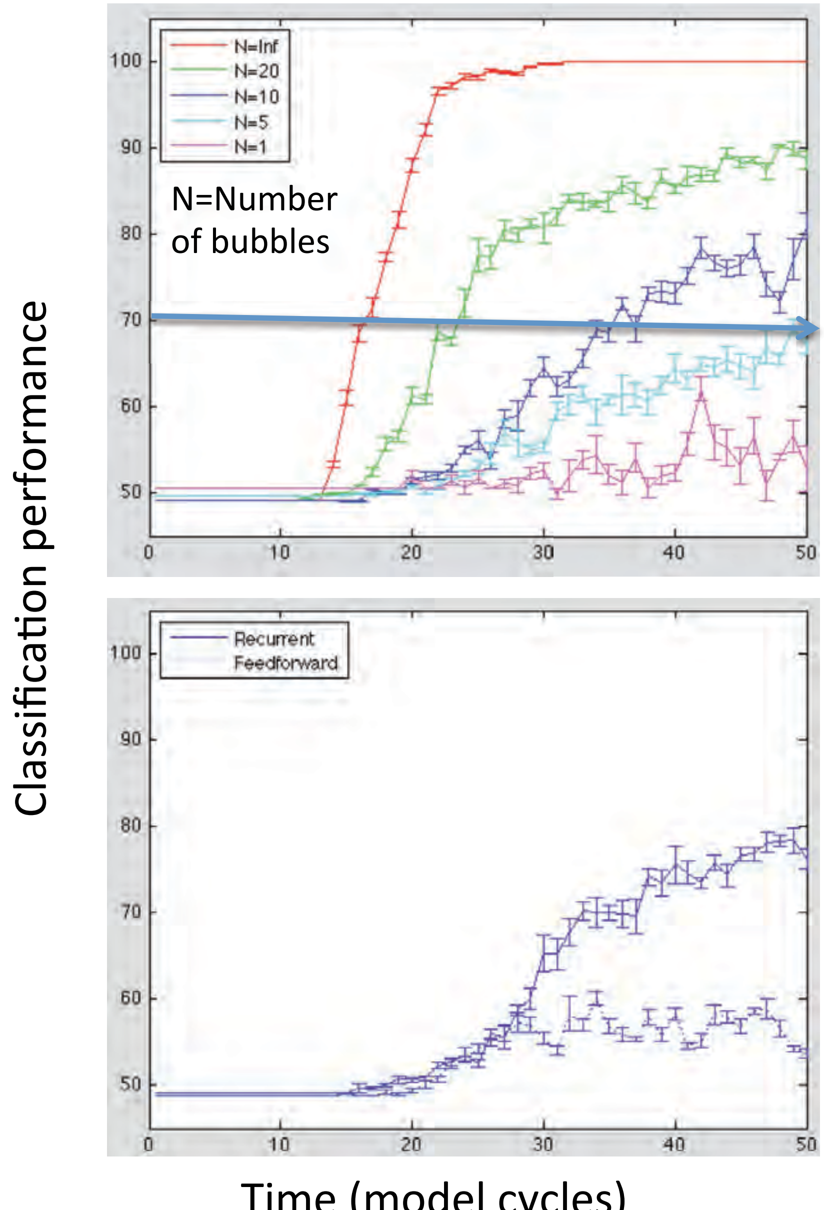
Proof-of-principle: Adding top-down signals improves recognition performance under occlusion



2000 “C2” units in the model
Model responses to 25 exemplar objects
Consider 20 units with high SNR (training data)
500 repetitions with different bubble locations
Train classifier with 70% of the repetitions
Test classifier on remaining 30% of the repetitions
Identification task (chance=4%)

Top-down connections help perform object completion

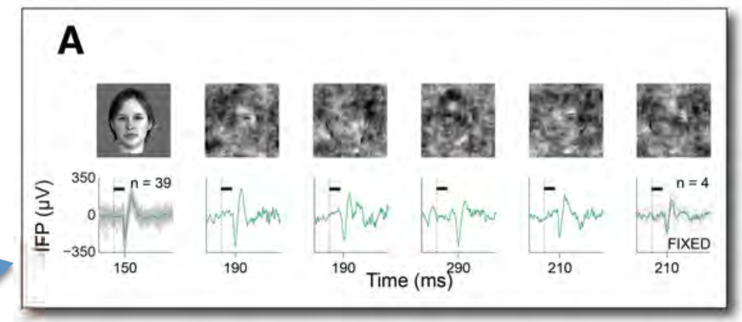


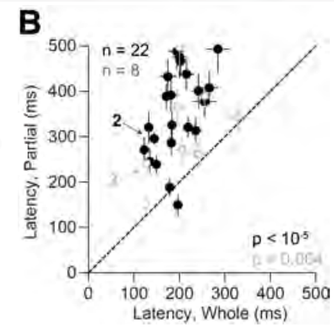


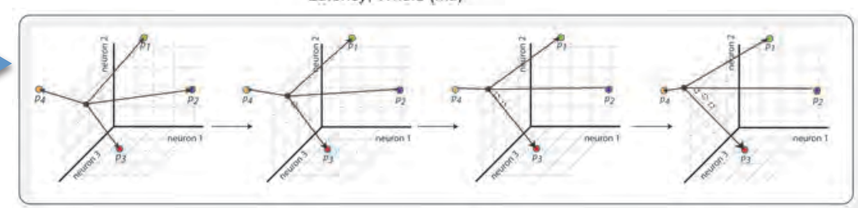
Dean Wyatte, Randall O'Reilly, Hanlin Tang

Summary (Object completion)

- Object completion presents a challenge for purely bottom-up architectures
- Neural signals in higher visual areas remain selective despite showing only a small fraction of an object
- Object completion requires additional computation (i.e. more time) (behavioral and physiological evidence)
- Recurrent and/or top-down connections can improve recognition of partial or occluded objects
- Top-down signals can enhance recognition under a variety of related roles (not shown)
    - Multiple fixations during target search tasks
    - Cluttered scenes



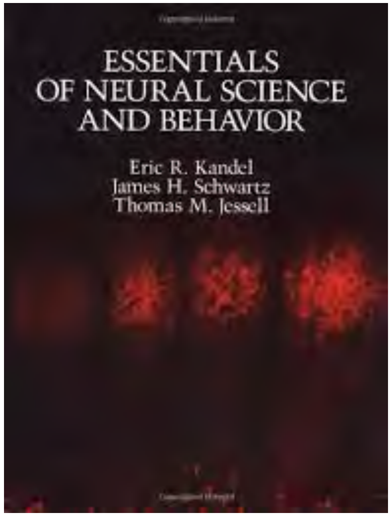


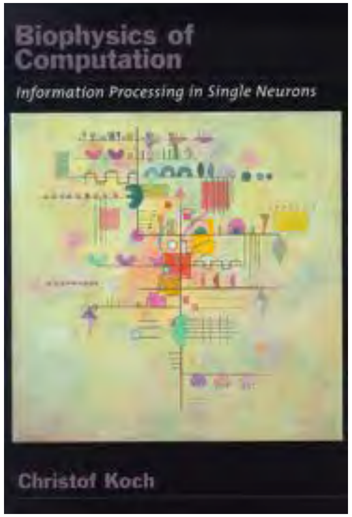


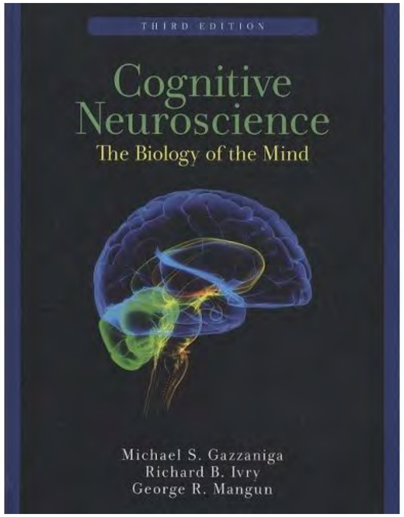
Acknowledgments

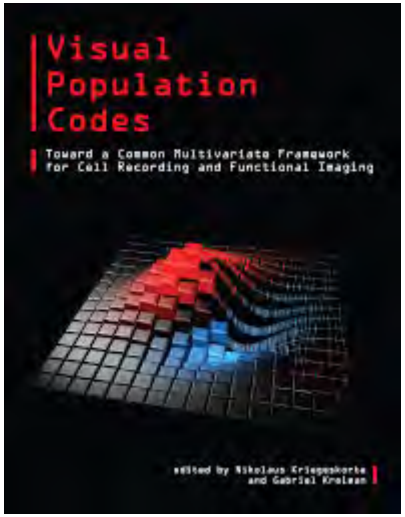
Hanlin Tang
Jed Singer
Hesheng Liu
Yigal Agam
Joseph Madsen
Stan Anderson
Thomas Serre
Tomaso Poggio
Thomas Miconi
Dean Wyatte

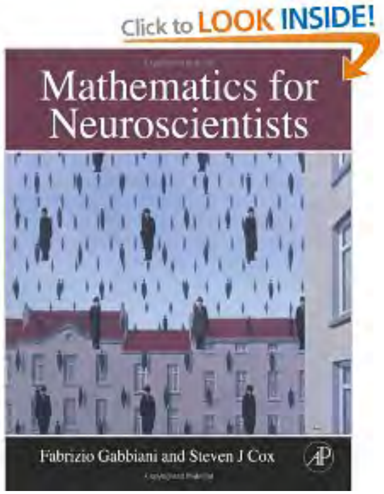
Recommended books

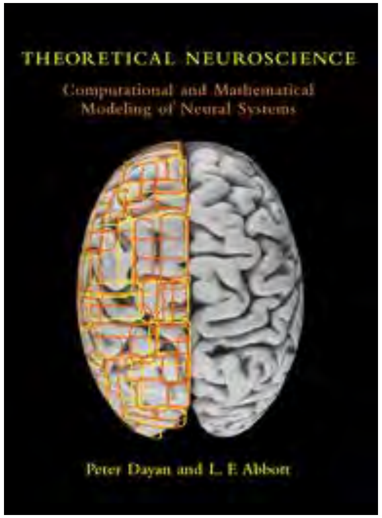


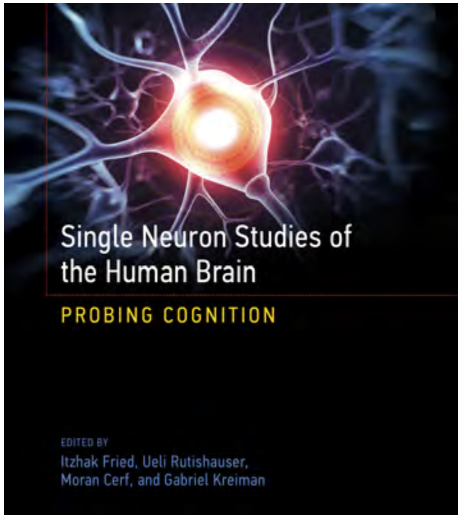


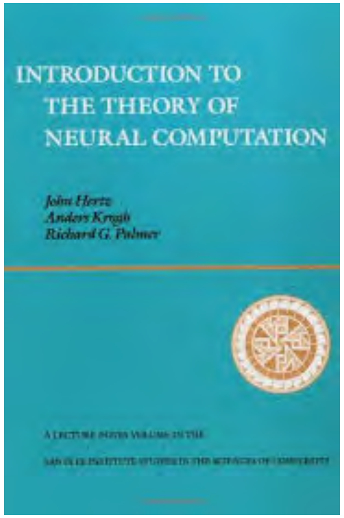












Neural computations: lessons from peeking inside the brain

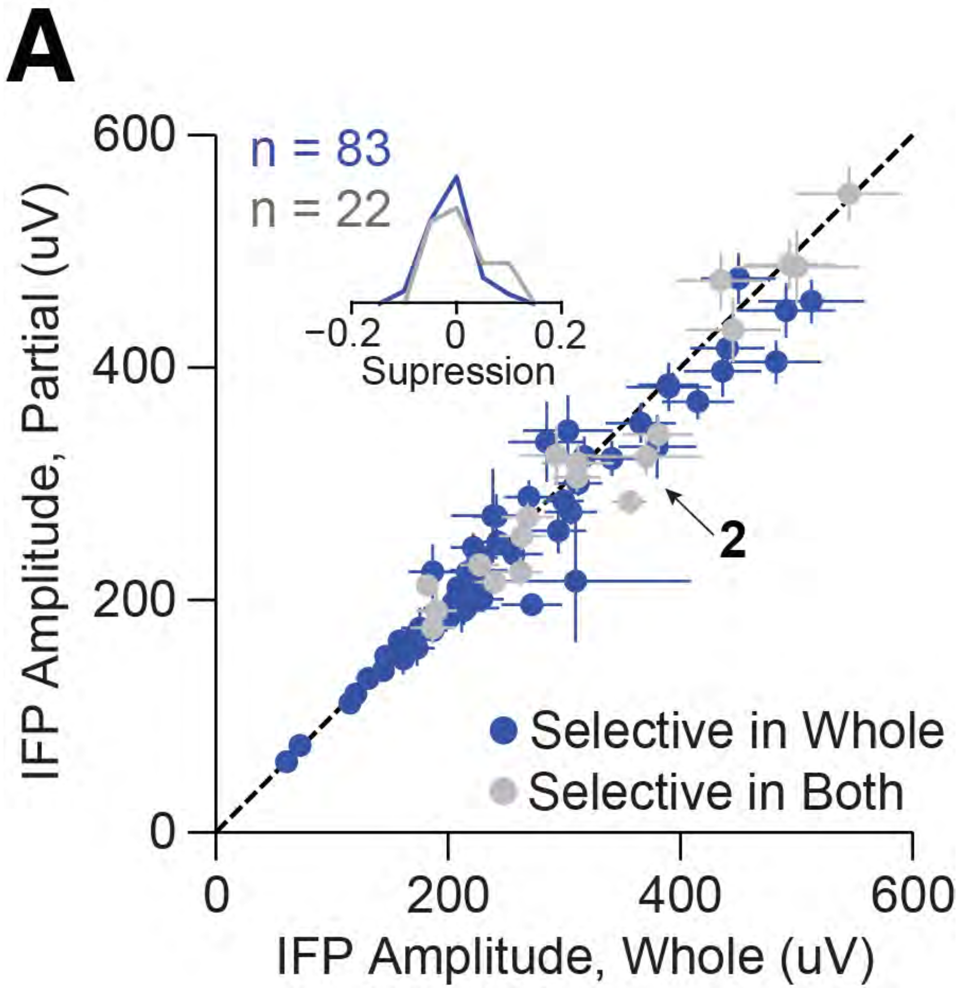
Gabriel Kreiman

Children's Hospital, Harvard Medical School

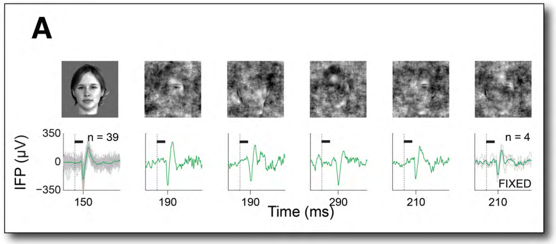
gabriel.kreiman@tch.harvard.edu

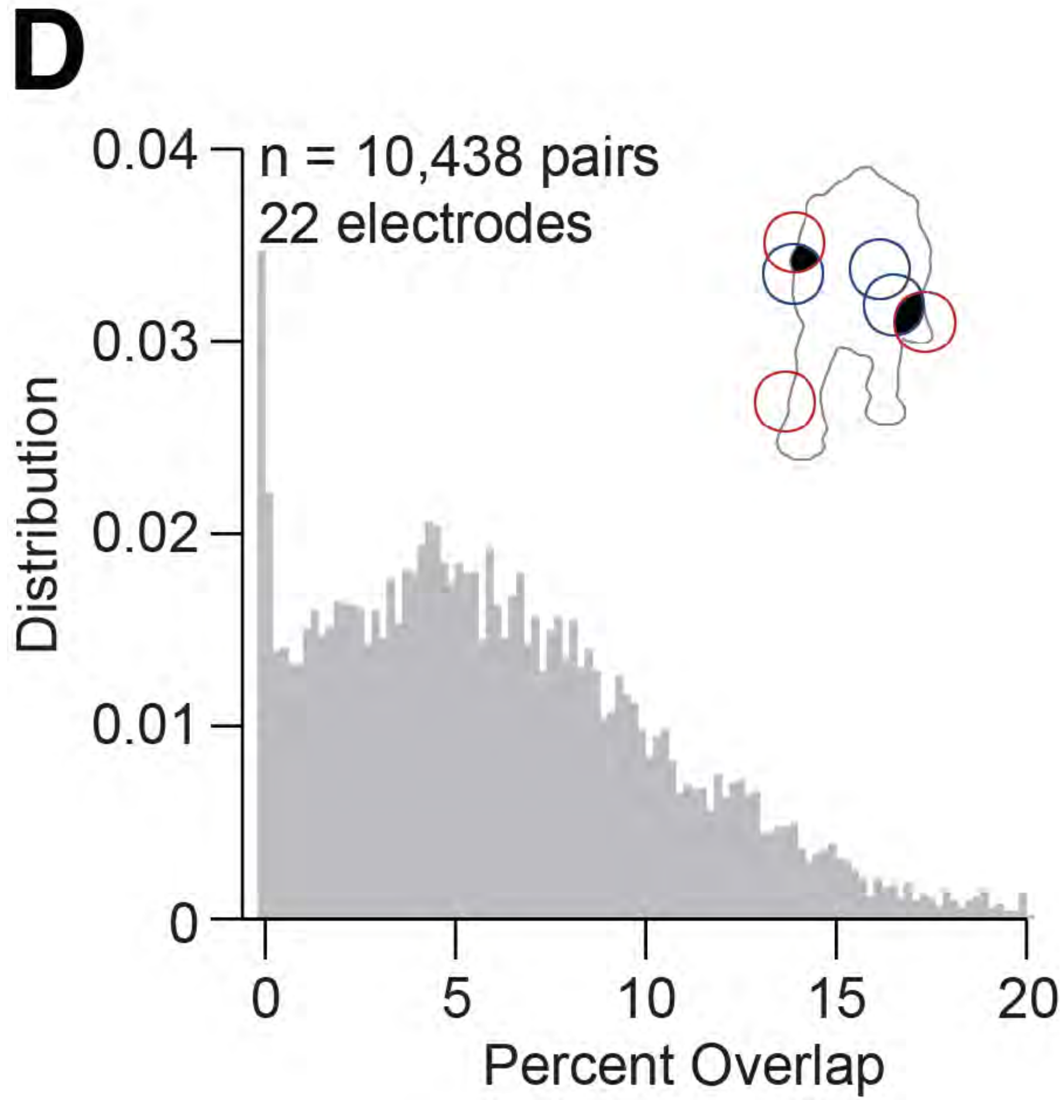
http://klab.tch.harvard.edu

No change in amplitude

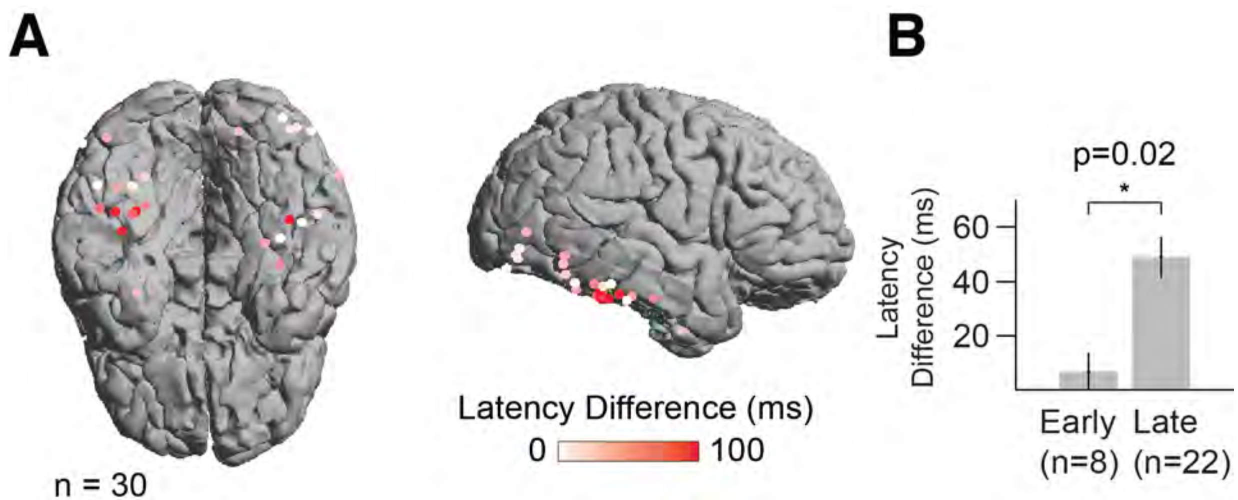


Holistic responses (?)

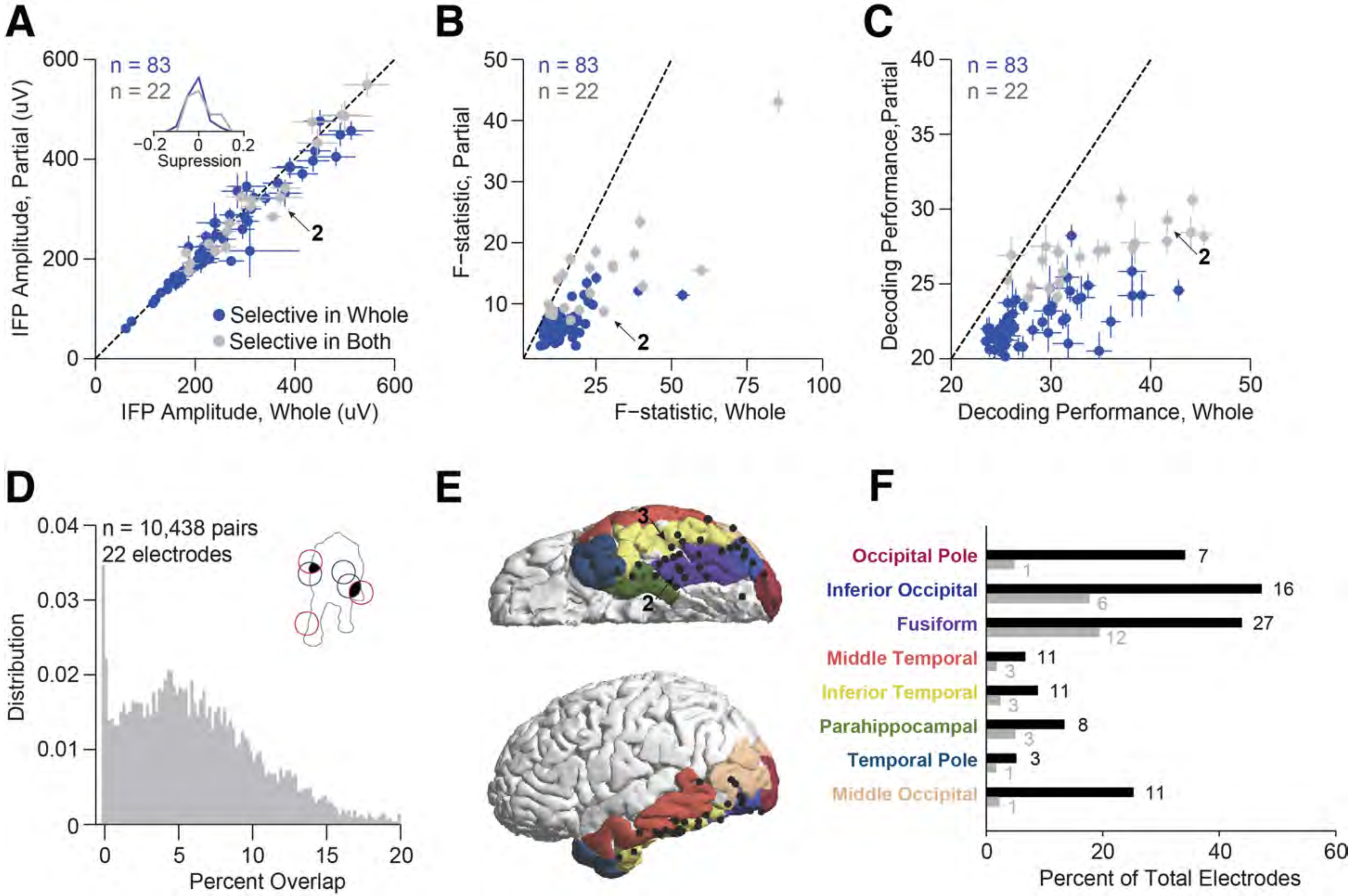




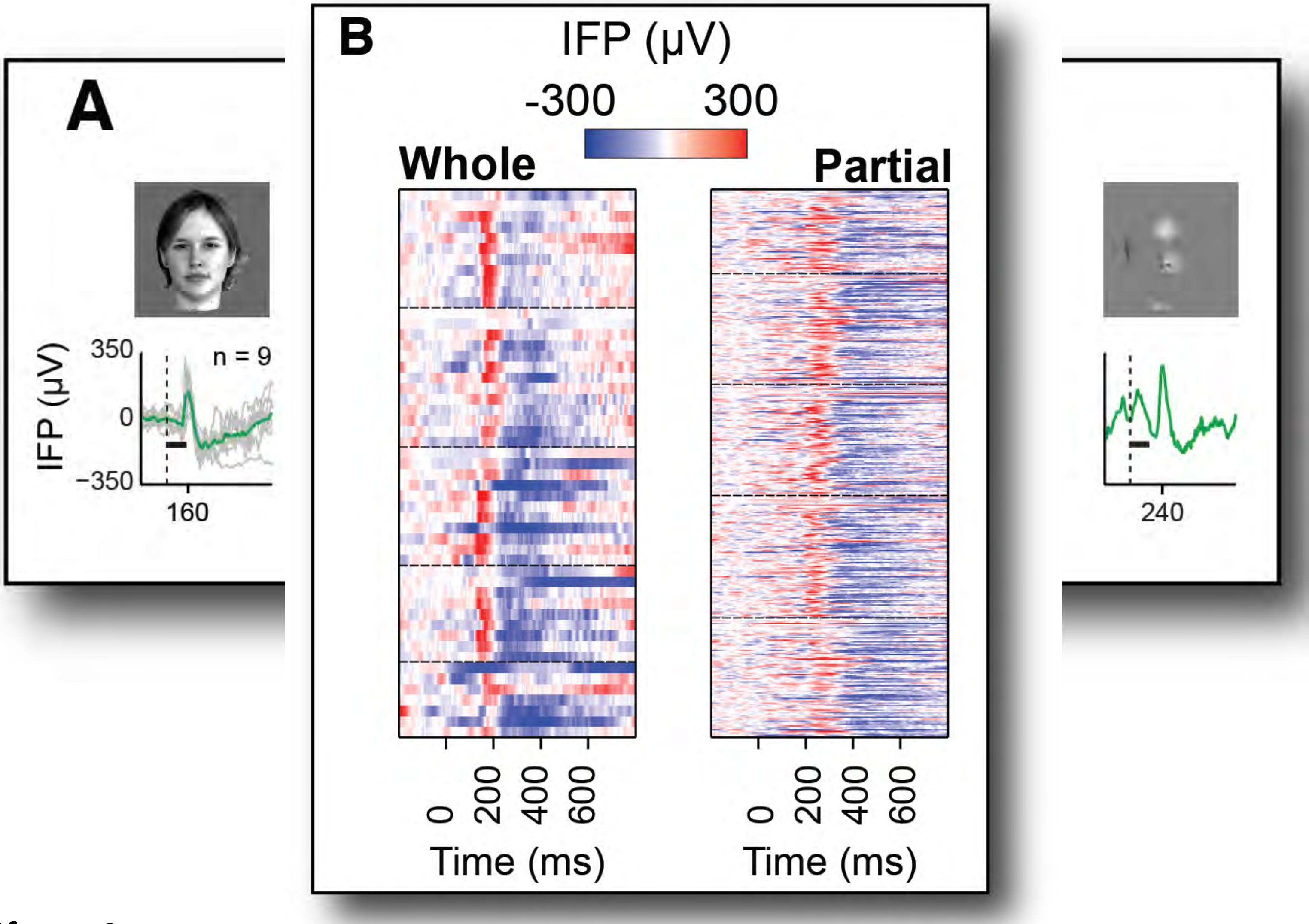
Increased latency differences in higher visual areas



No change in amplitude. Change in selectivity.

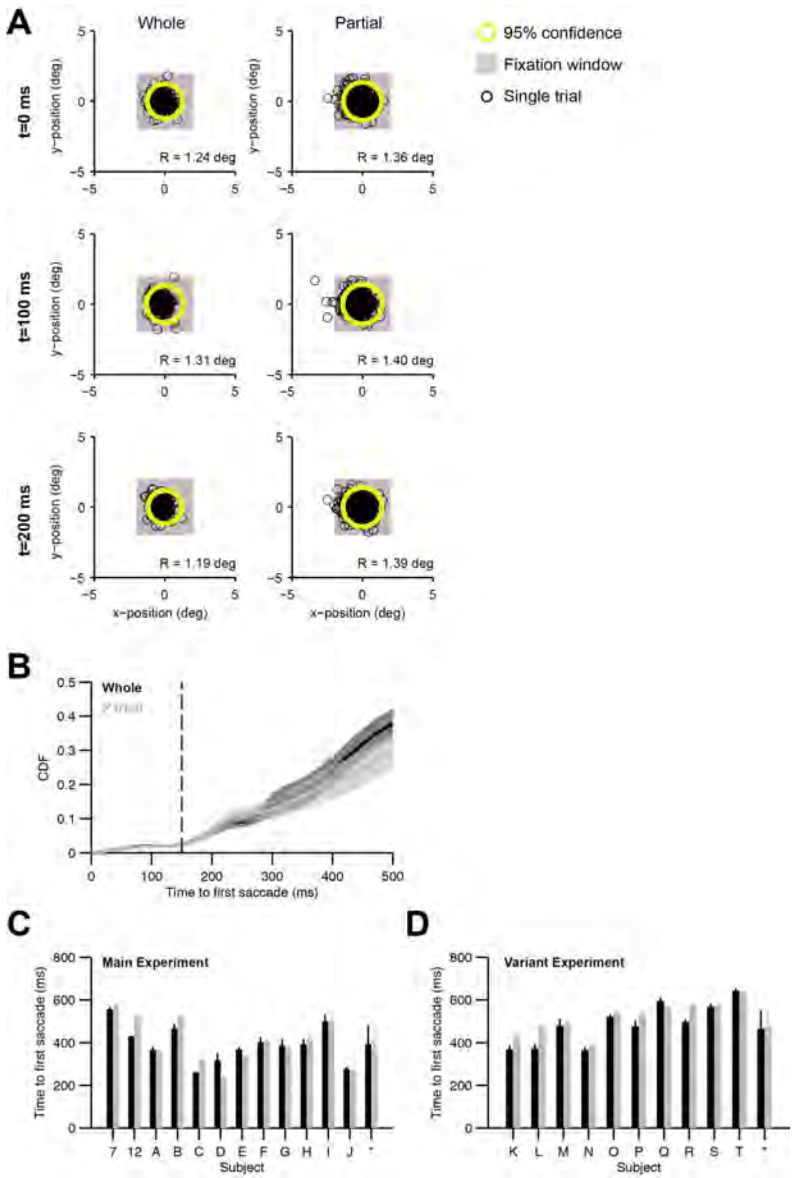


Example responses during object completion



Left Fusiform Gyrus

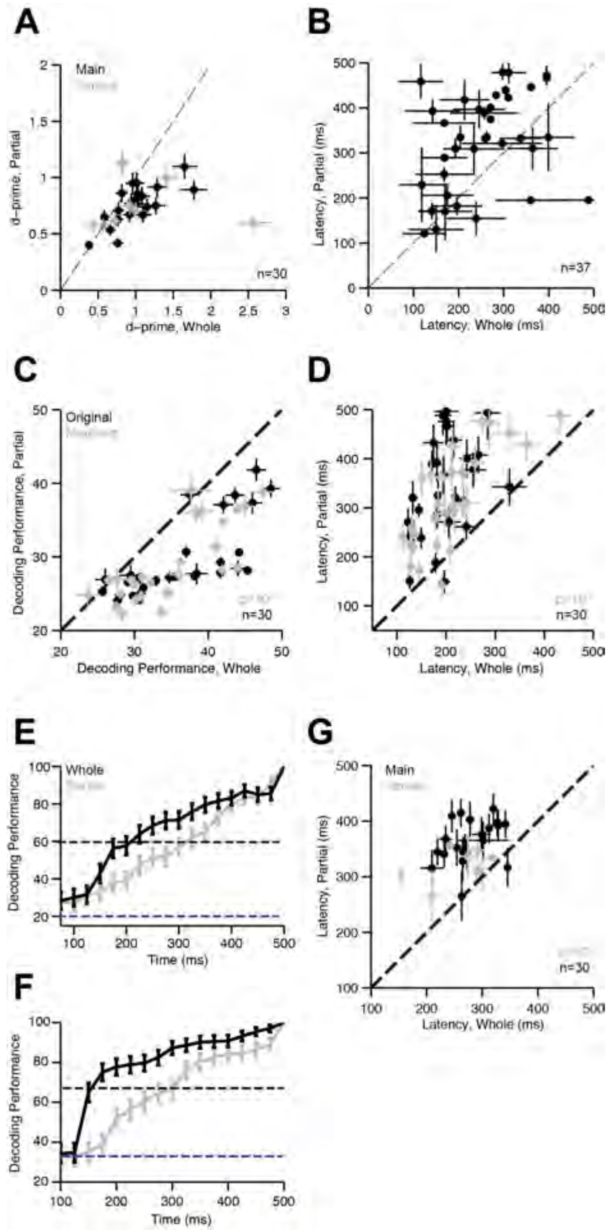
No changes in eye movements during object completion



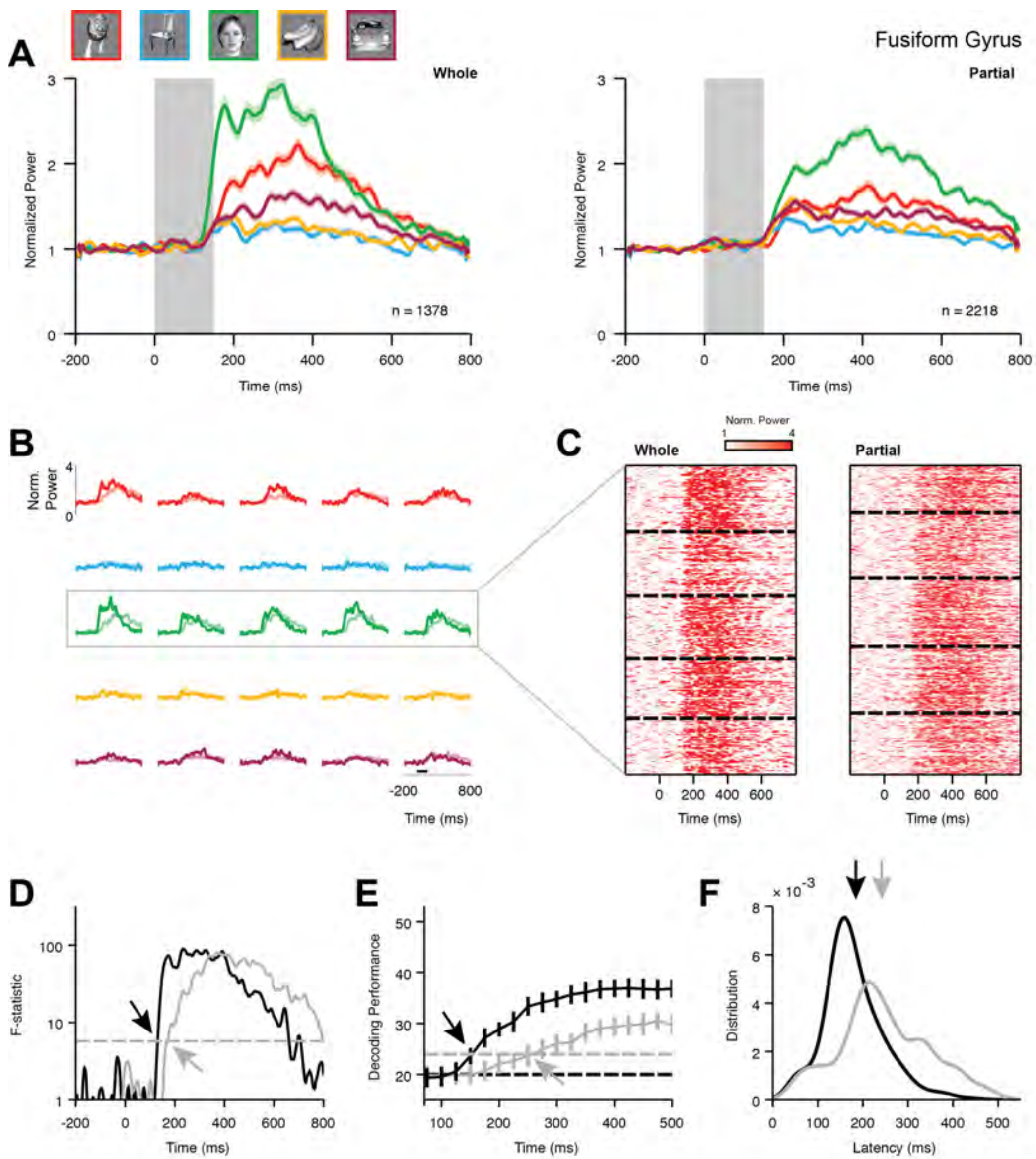
Matched amplitude and matched decoding comparisons

Response amplitudes matched

Decoding performance matched



Example responses in the gamma frequency band



70-100 Hz
Fusiform gyrus

Example responses during object completion

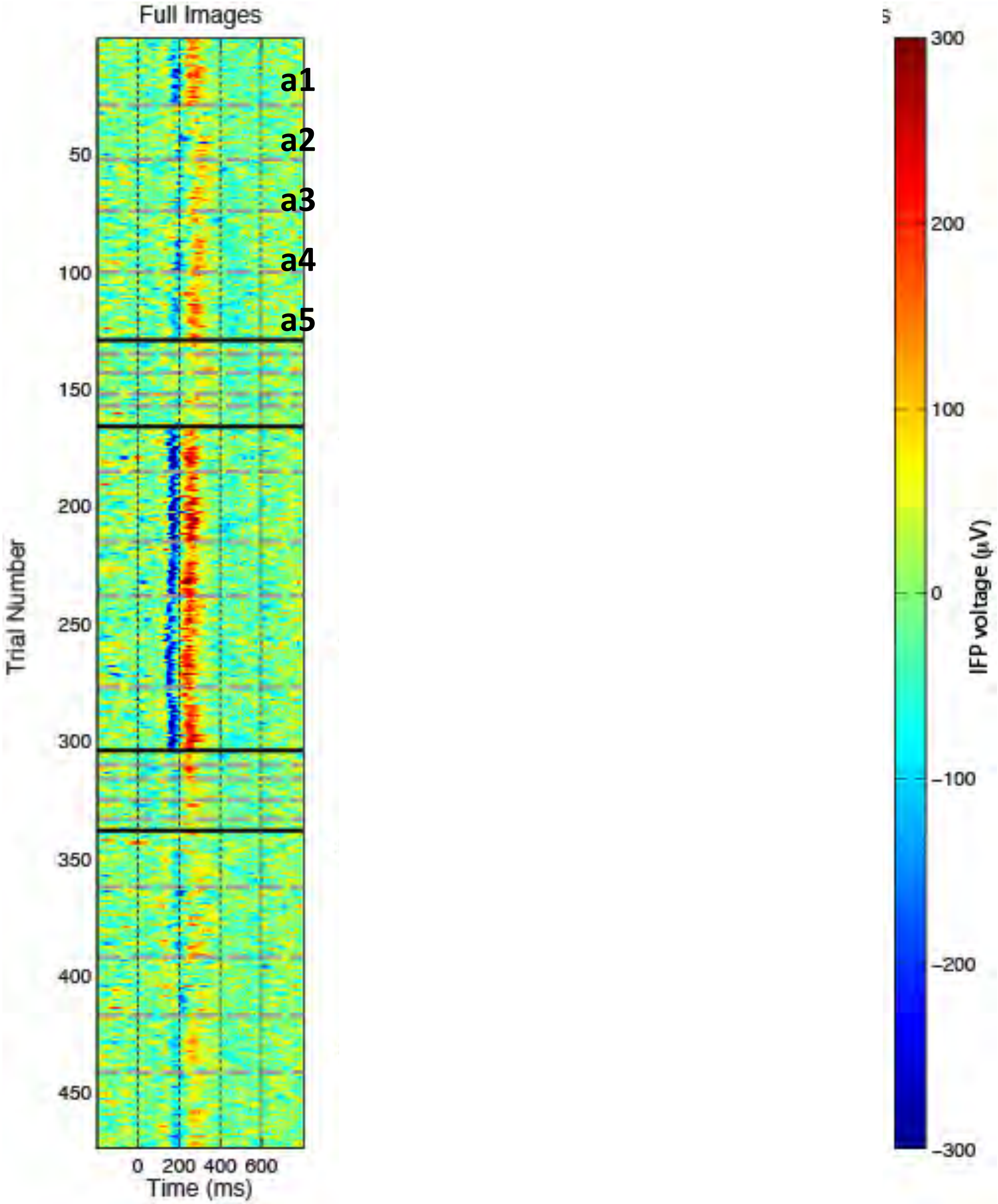
animals

chairs

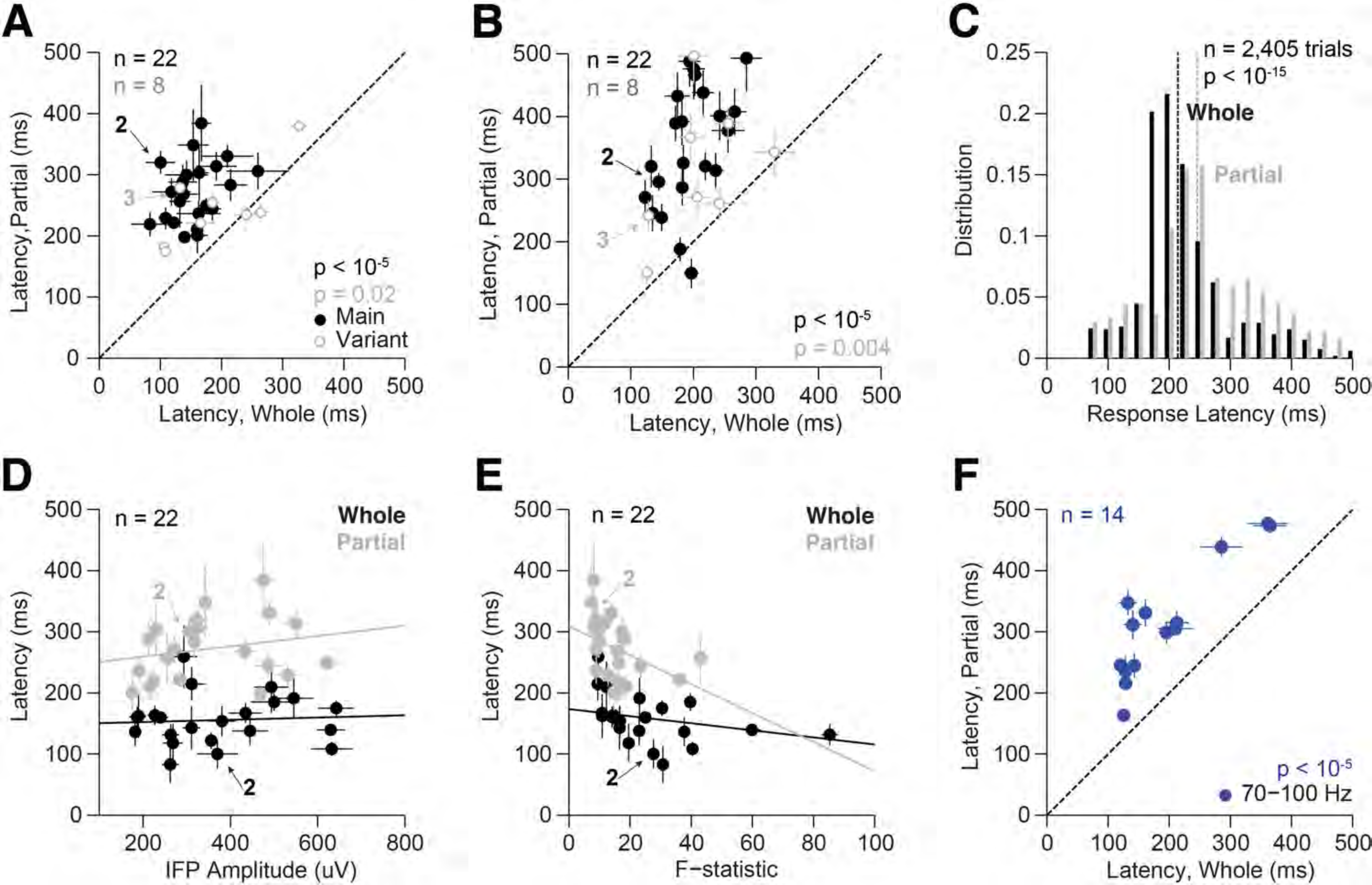
faces

vehicles

fruits

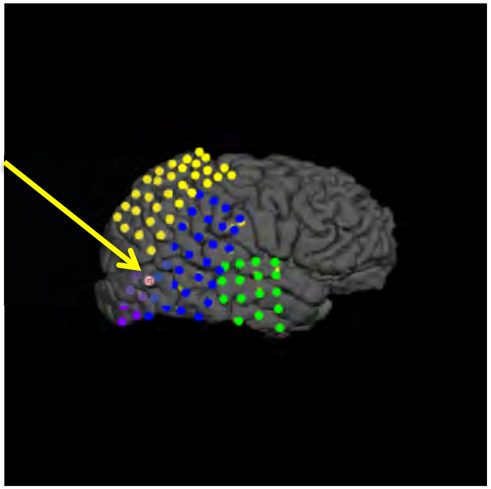


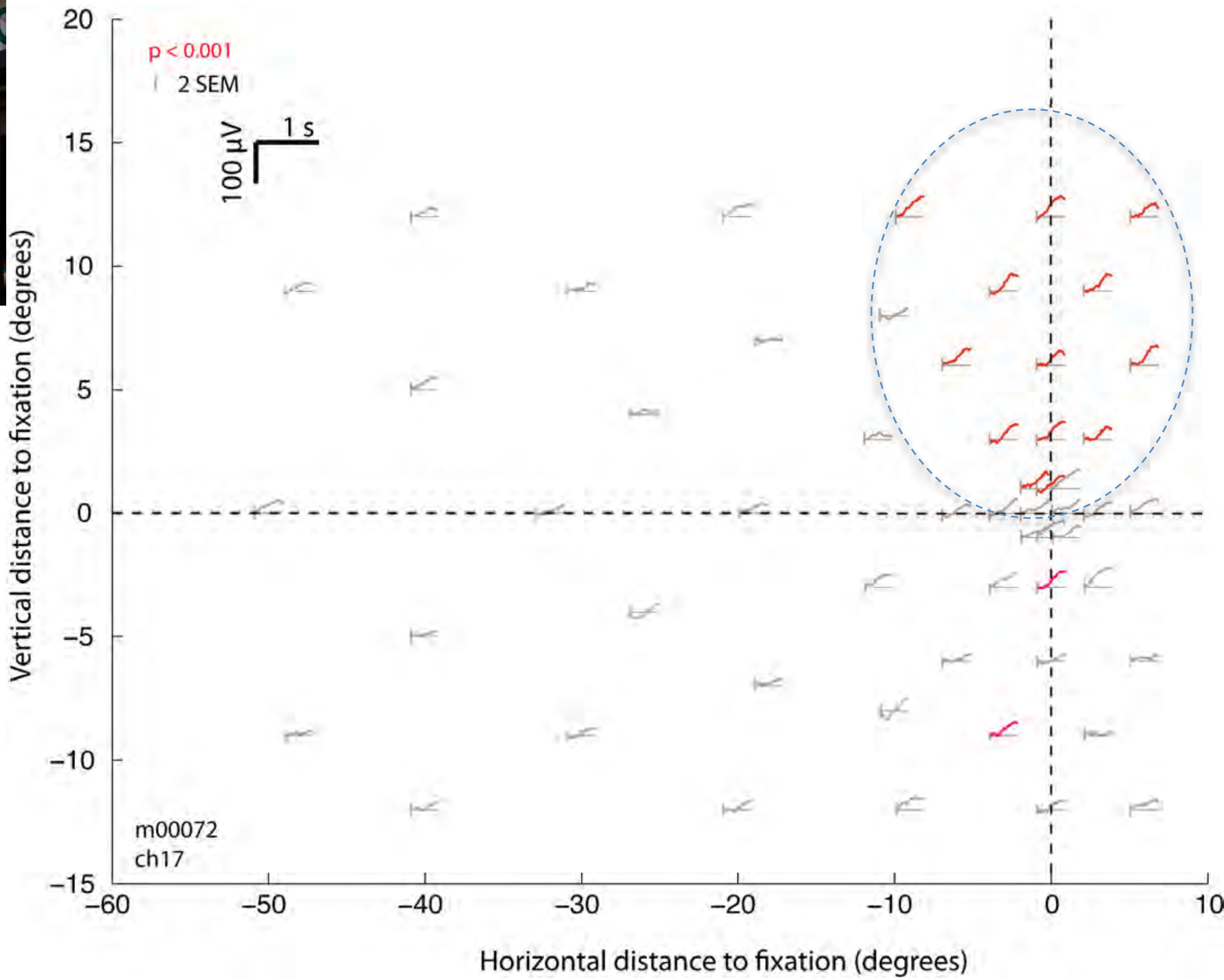
Delayed responses to partial objects



Tracking eye position and mapping receptive fields

EyeLink D1000 System
Temporal resolution: 2 ms
Spatial resolution: < 1 deg
Calibration time: ~ 20 secs
Can track one eye
Head movement tolerance
Real time feedback

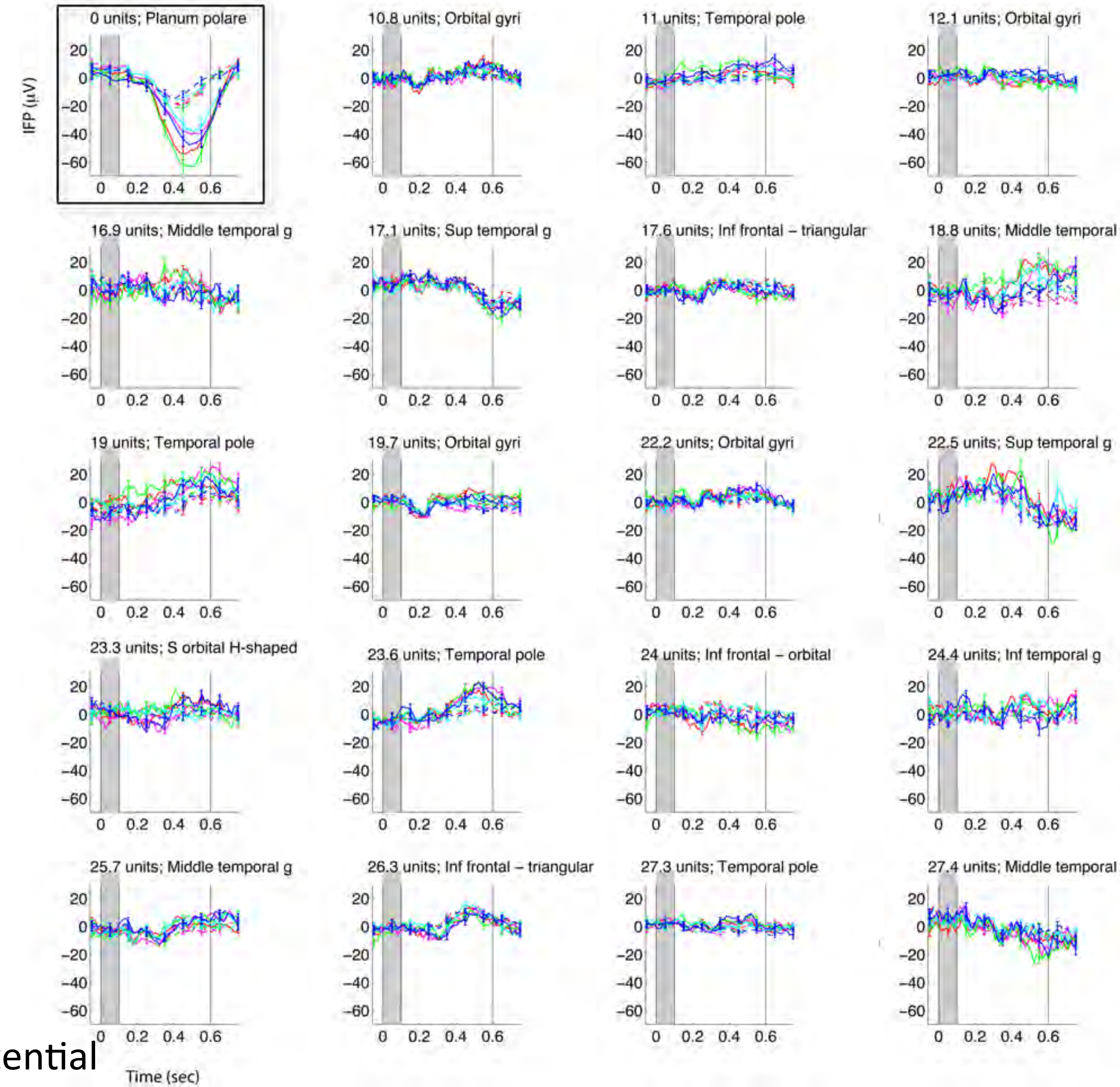




Jed Singer

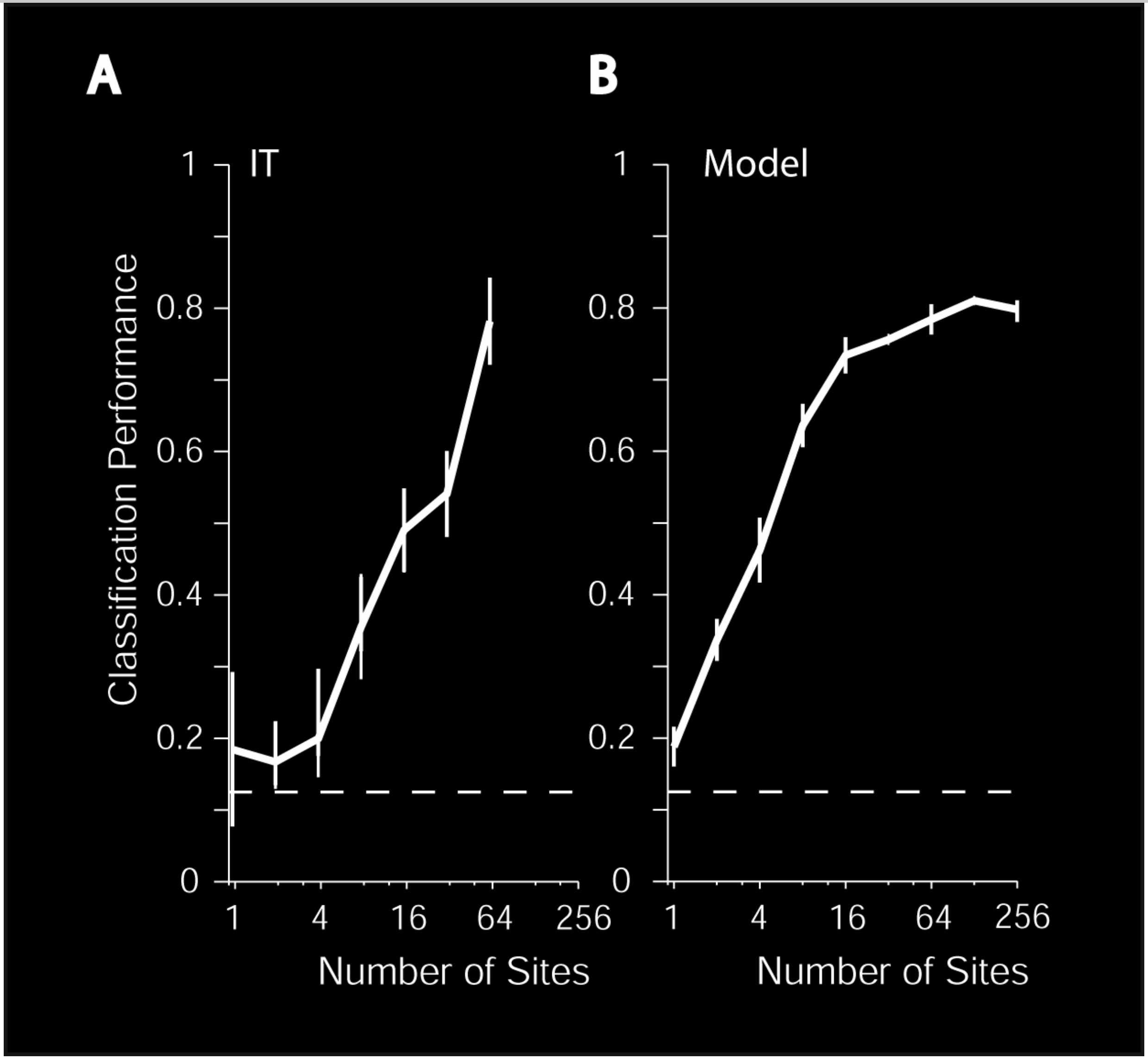
IFP signals are localized within ~10 mm

Units: < 200 μm
LFPs: 0.3 – 2 mm
IFPs: < 15 mm
EEG: ~10 cm



IFP = intracranial field potential

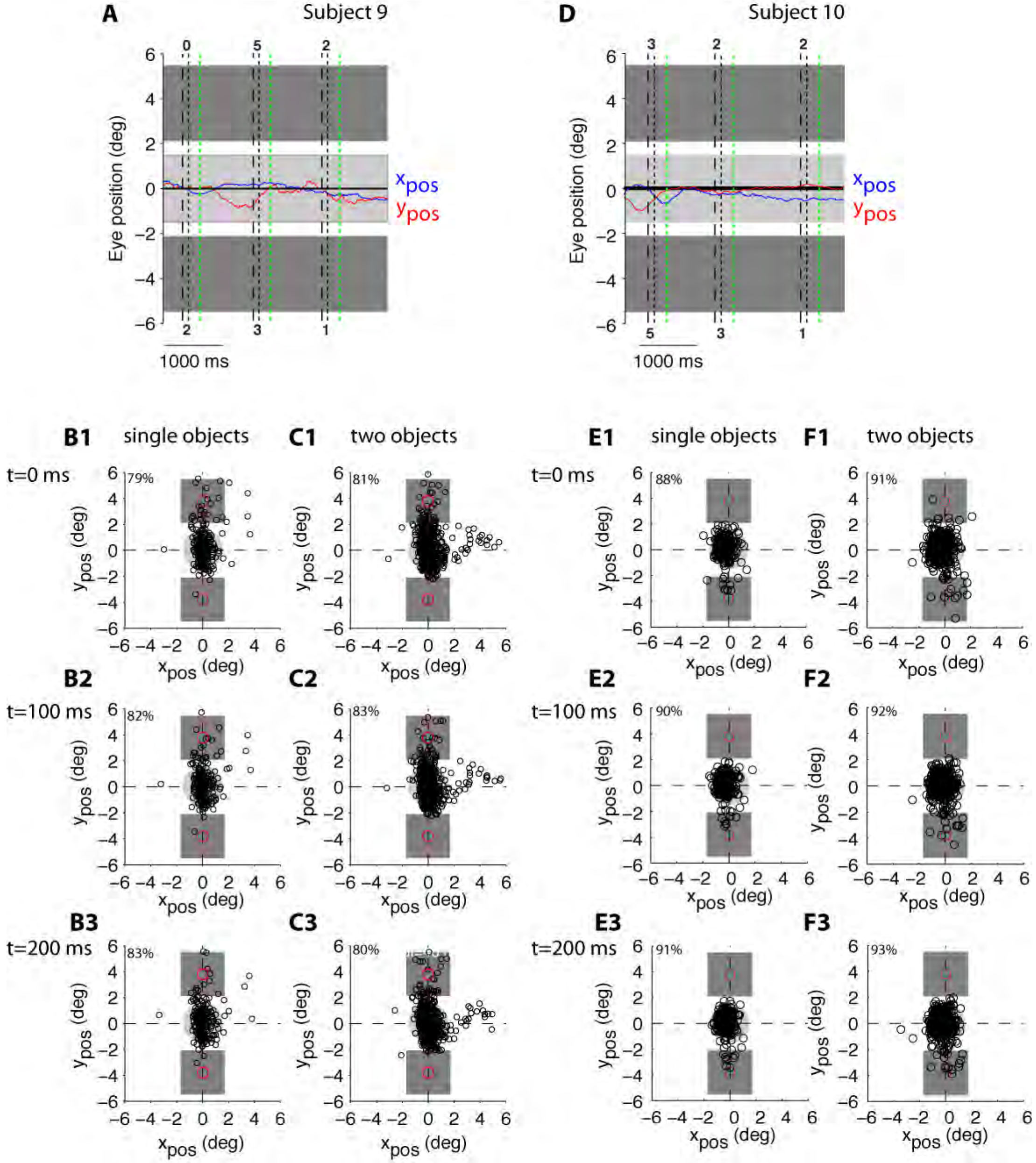
We can decode object information from the model units



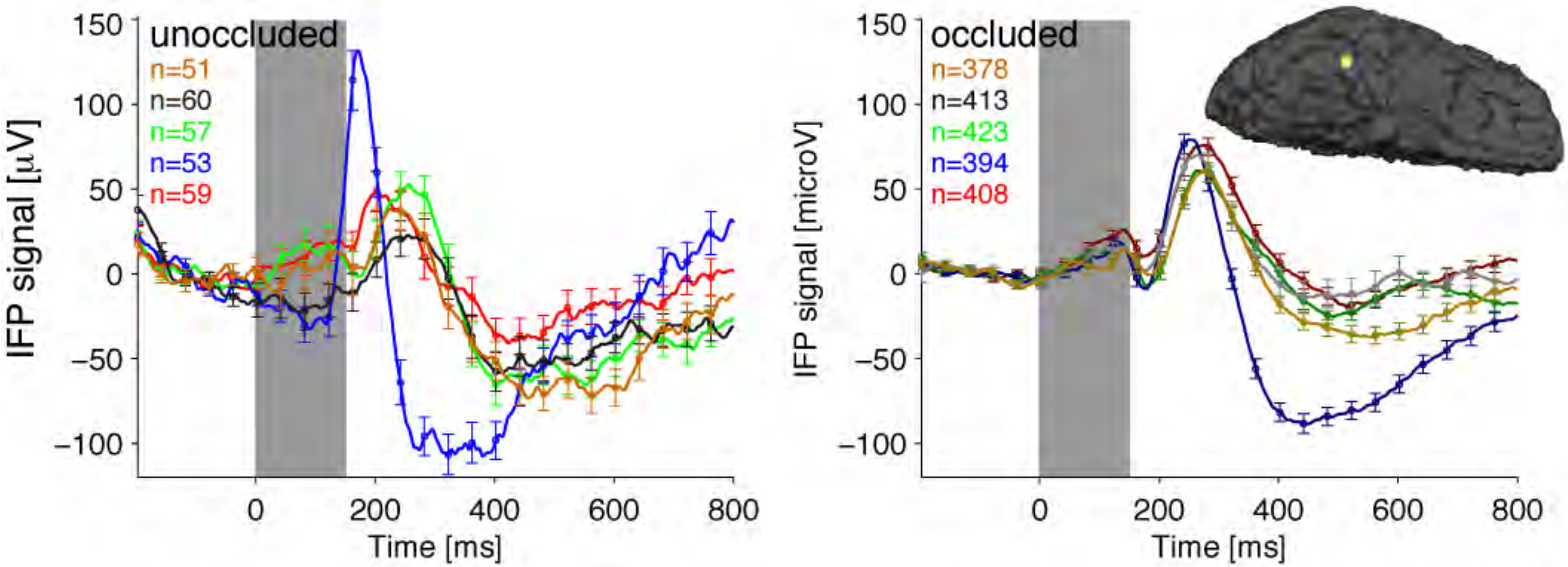
Chou Hung, Jim DiCarlo, Tommaso Poggio

Eye position was near the fixation point during the initial ~200 ms

Note: 2 subjects only

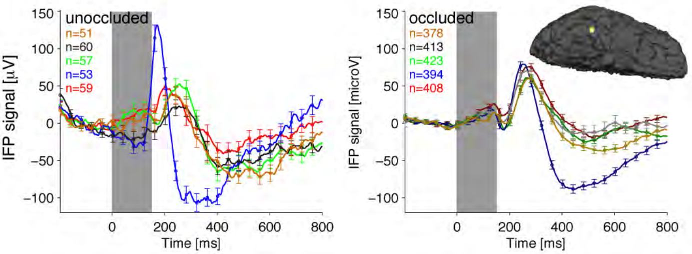


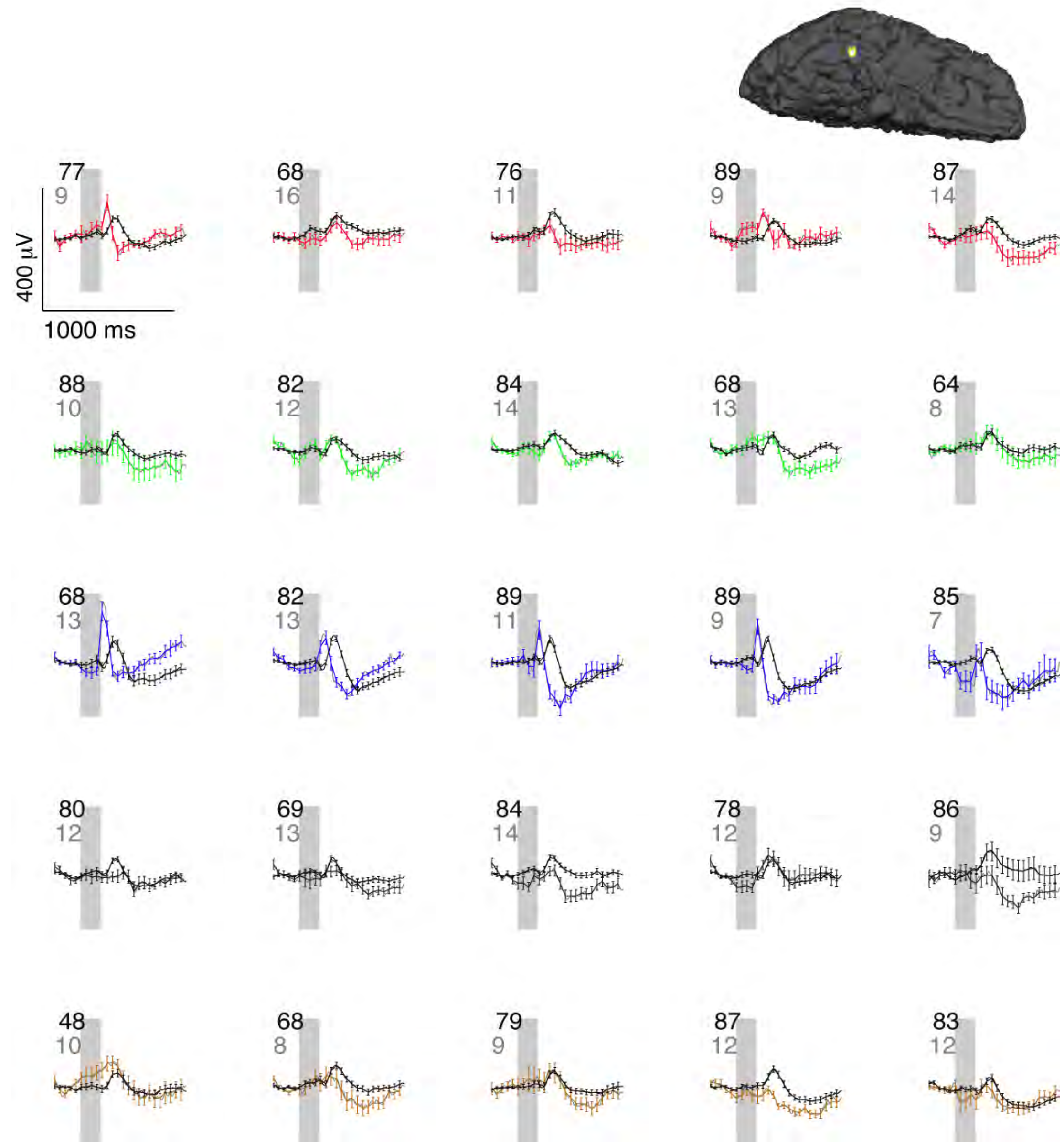
Example neurophysiological responses [1]



Subject m00026
Channel 49

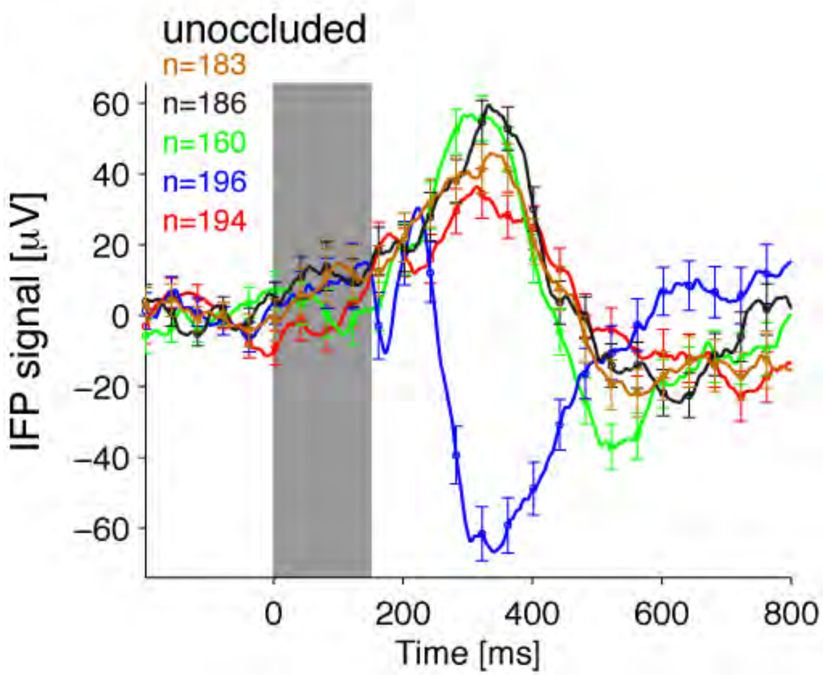
Example neurophysiological responses [1’]

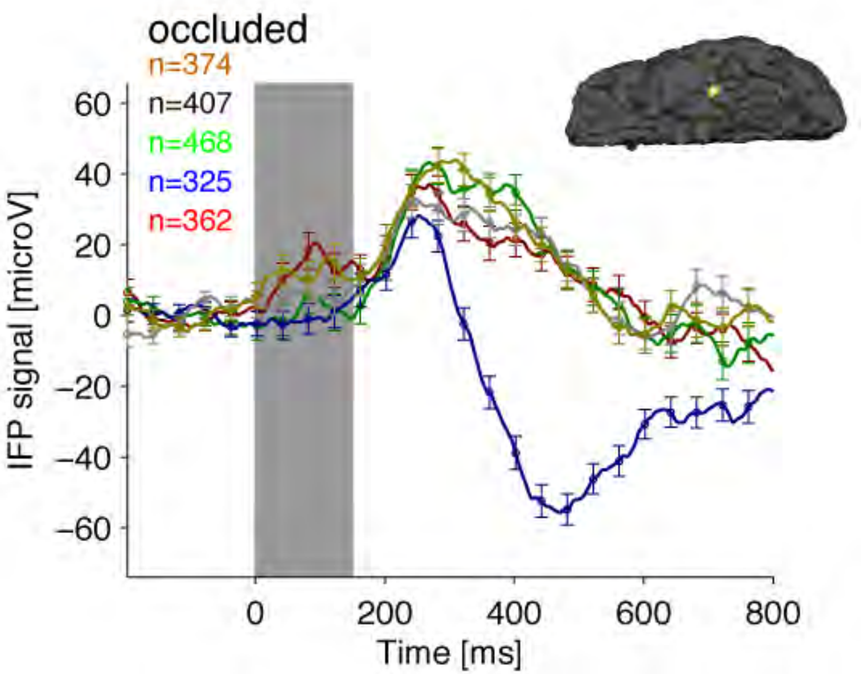




Subject m00026
Channel 49

Example neurophysiological responses [2]





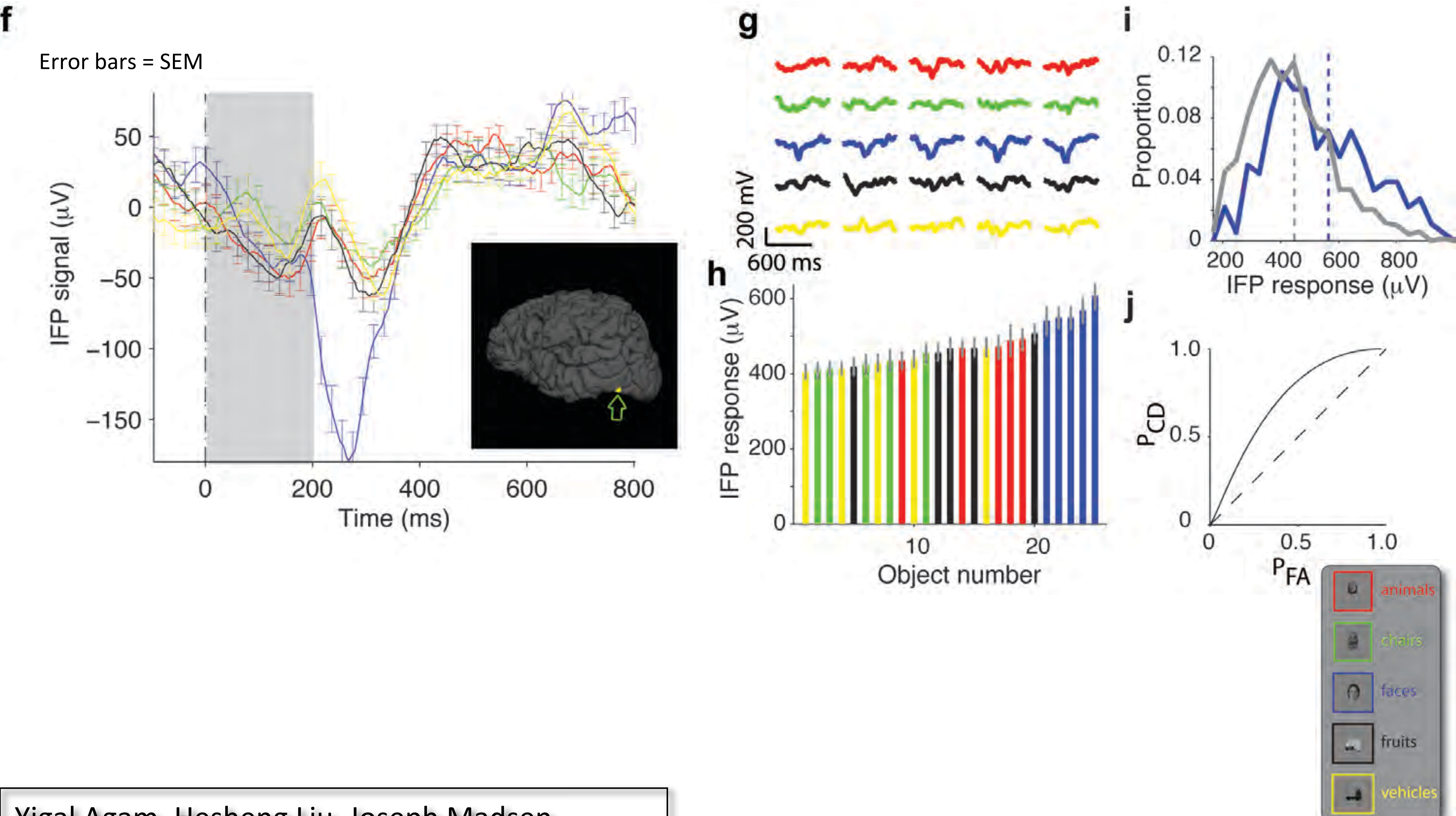
Subject m00032
Channel 21

OBJECT COMPLETION

Selectivity in human visual cortex - Example

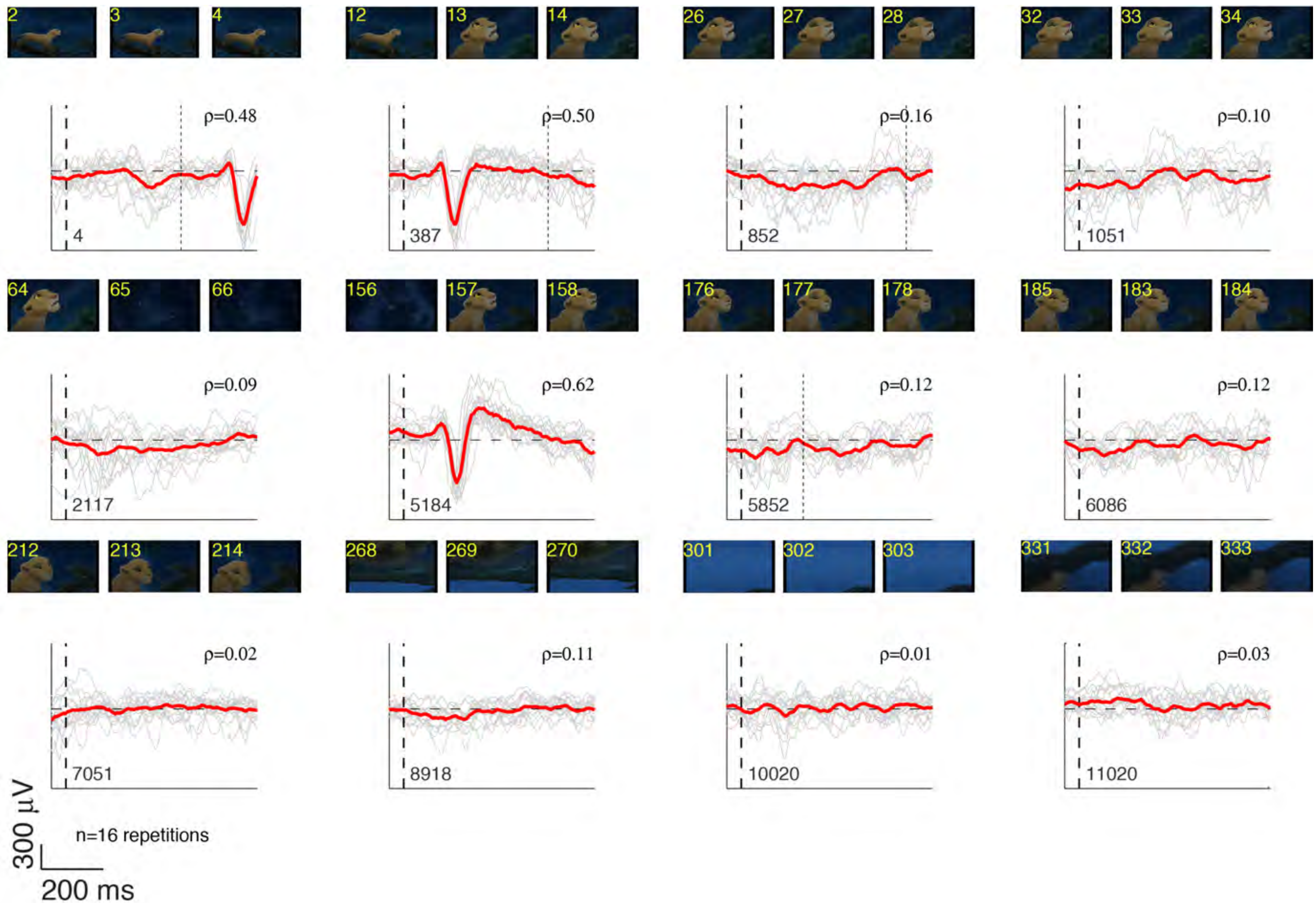
Left Inferior Occipital Gyrus and Sulcus
Talairach: [-48.8,-69.1,-11.8]

Classification performance = 65±5% (change=50%)



Yigal Agam, Hesheng Liu, Joseph Madsen

Example: Reliable and selective responses to a movie



Action potentials versus field potentials

Action potentials

Neurons communicate via action potentials

The biophysics underlying action potentials is relatively well understood

Typically, action potentials show stronger specificity than field potentials

Ultimately, our computational models are inspired by and neurons and synapses. The models in turn make predictions about neurons and synapses

Field potentials

We can examine areas currently not studied with action potentials in the human brain

We can sample a large number of brain areas

Spatial scale of ~0.5 to 20 mm

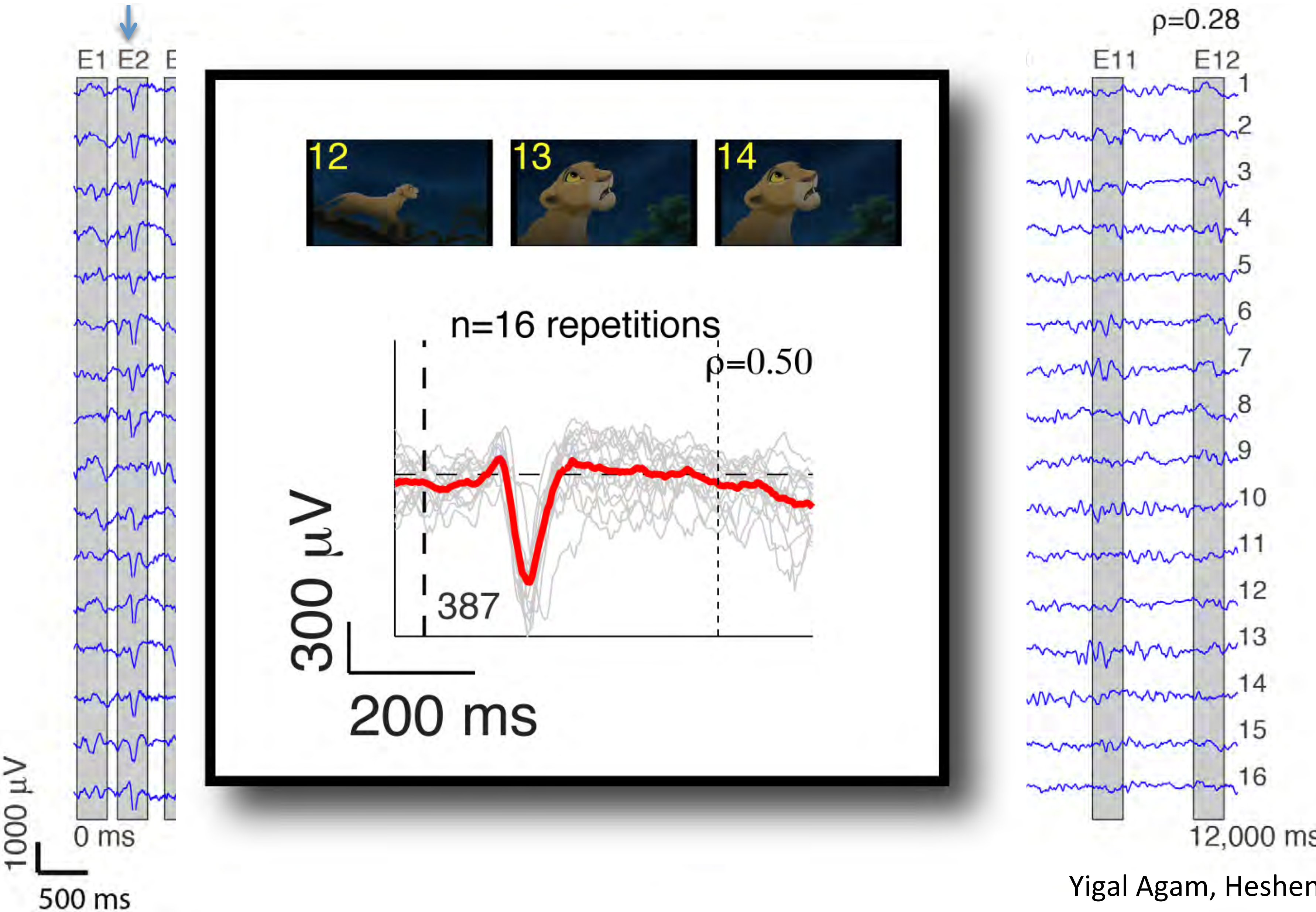
High signal-to-noise ratio

Strong temporal stability

Comparable trial-to-trial variability to action potentials

Biophysics less clearly understood

Reliable and selective responses to a movie



Yigal Agam, Hesheng Liu