Cognitive Science and AI

Introduction

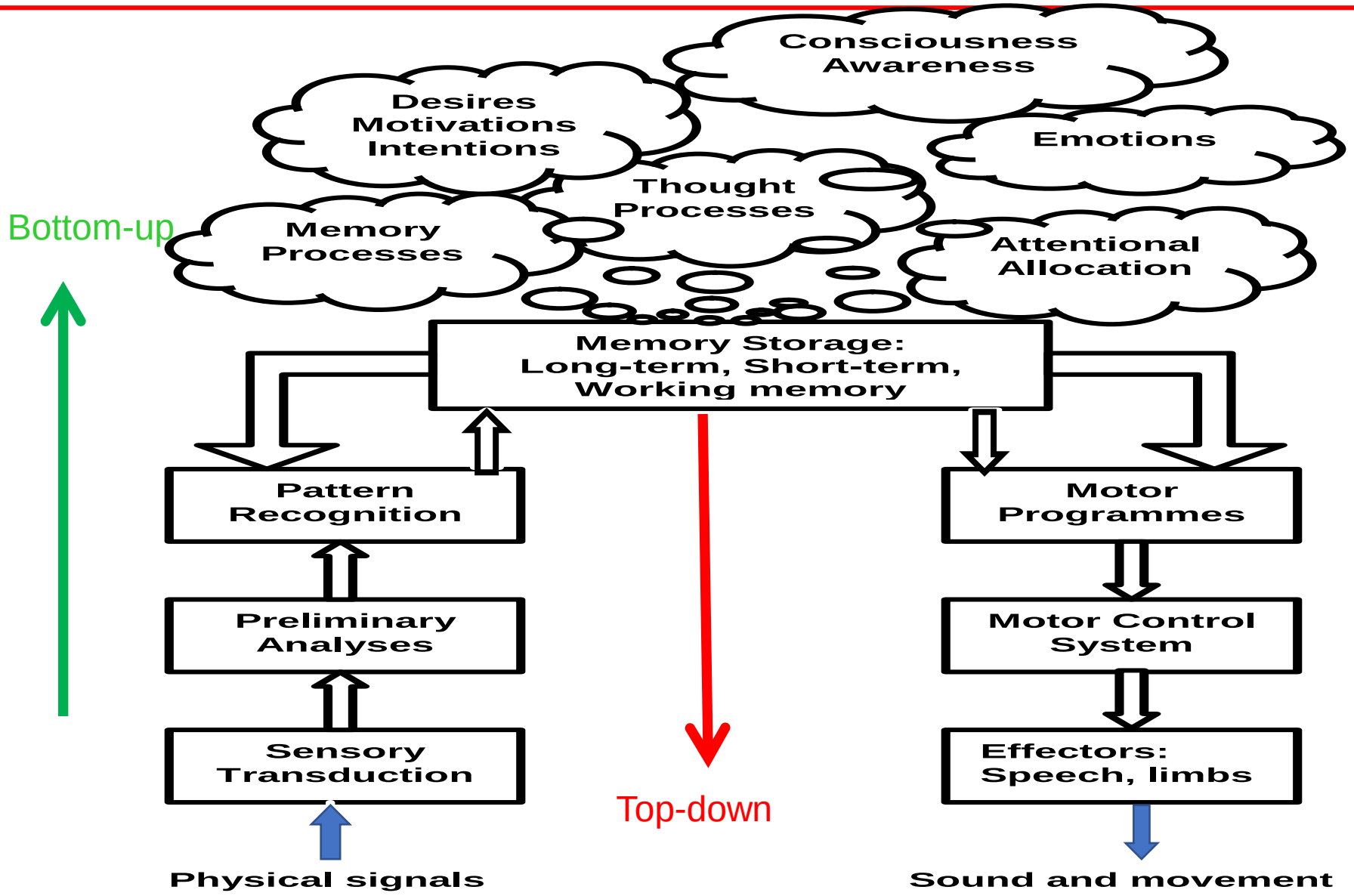
Preamble

- The goal of cognitive science is to understand the principles of intelligence with the hope that this will lead to a better comprehension of the mind and of learning and to develop intelligent devices. [Wikipedia: Cognitive Science]

- To elucidate the principles of organization in the brain and how they translate to algorithms for building intelligent systems

- Computational Representational Understanding of Mind (CRUM)
  - The central hypothesis of cognitive science is that thinking can best be understood in terms of representational structures in the mind and computational processes that operate on those structures. (Thagard)

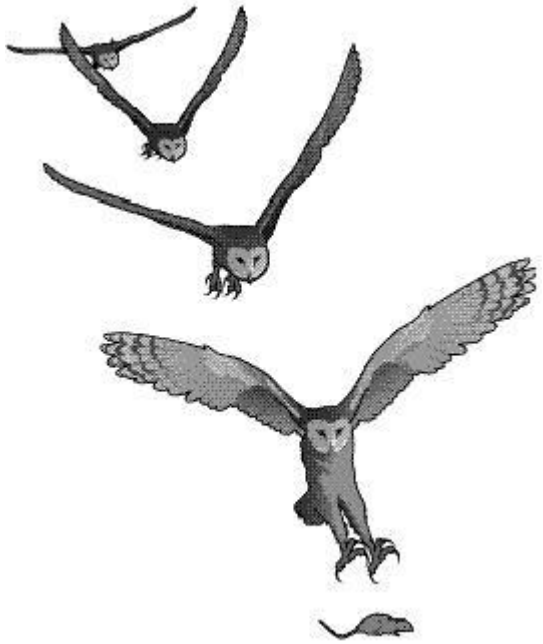
Human Information Processing System



What are the representations and computations that operate between the stimulus and the response?

Marr's Three Levels of Understanding

- Marr & Poggio program for understanding cognitive/computational systems (including brains).
- Example: sound localization in the barn owl (*Tyto alba*)



Example from: Shimon Edelman, Computing the Mind, 2008

The barn owl: hunting behavior

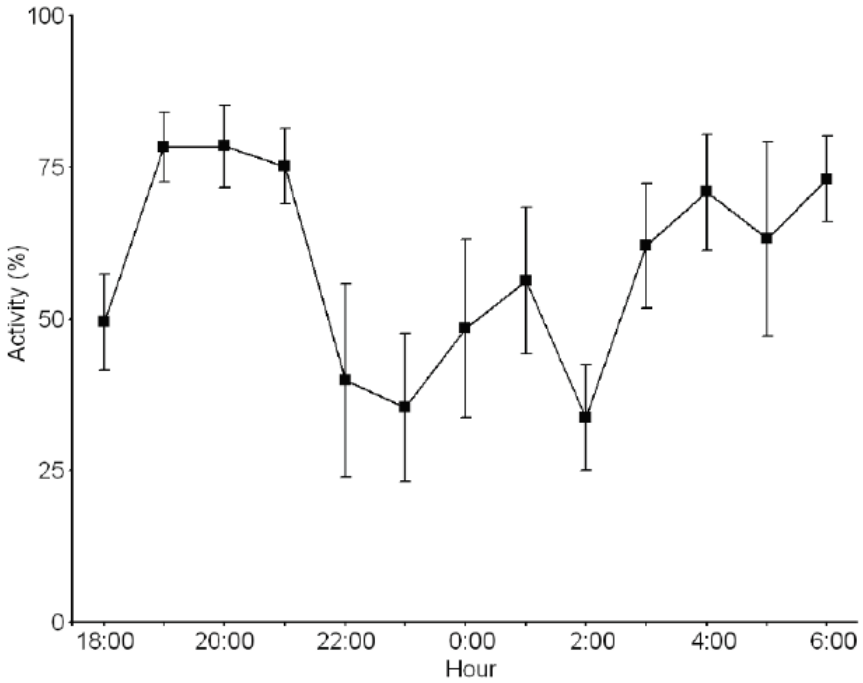


Figure 3. Mean (± SE) activity level of a Common Barn-owl (*Tyto alba*) instrumented with a GPS pet tracker device in an agroecosystem in Argentinean's rolling pampas during the period of data collection.

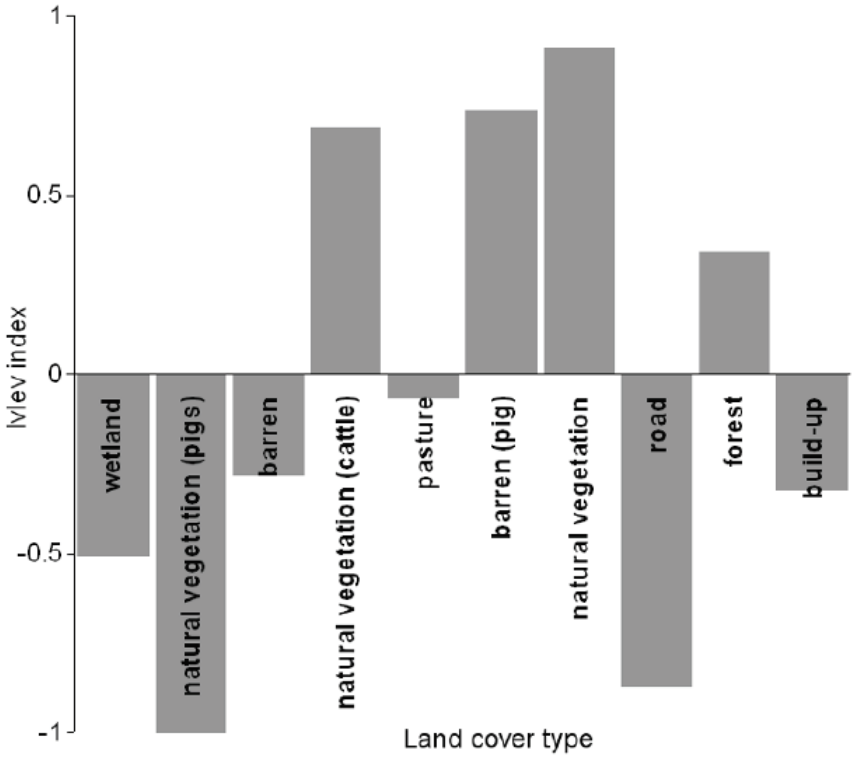


Figure 4. Values of the Ivlev's Electivity Index estimating land cover type selection by a Common Barn-owl (*Tyto alba*) instrumented with a GPS pet tracker device in an agroecosystem in Argentinean's rolling pampas.

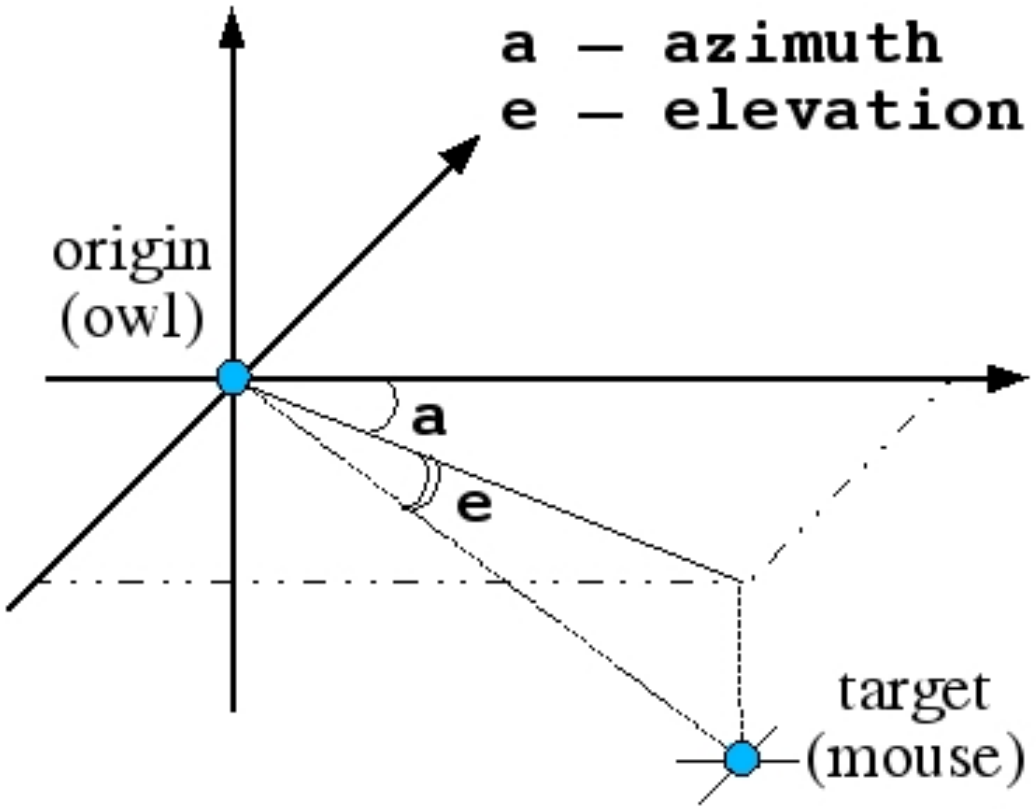
Tracking owls with GPS (Massa et al., 2015). Left: activity by time of night. Right: preferred terrain type.

The hunting owl

In the wild, the barn owl finds and catches mice in total darkness, presumably by homing in on the sound of their movement.

barn owl — posing the computational challenge

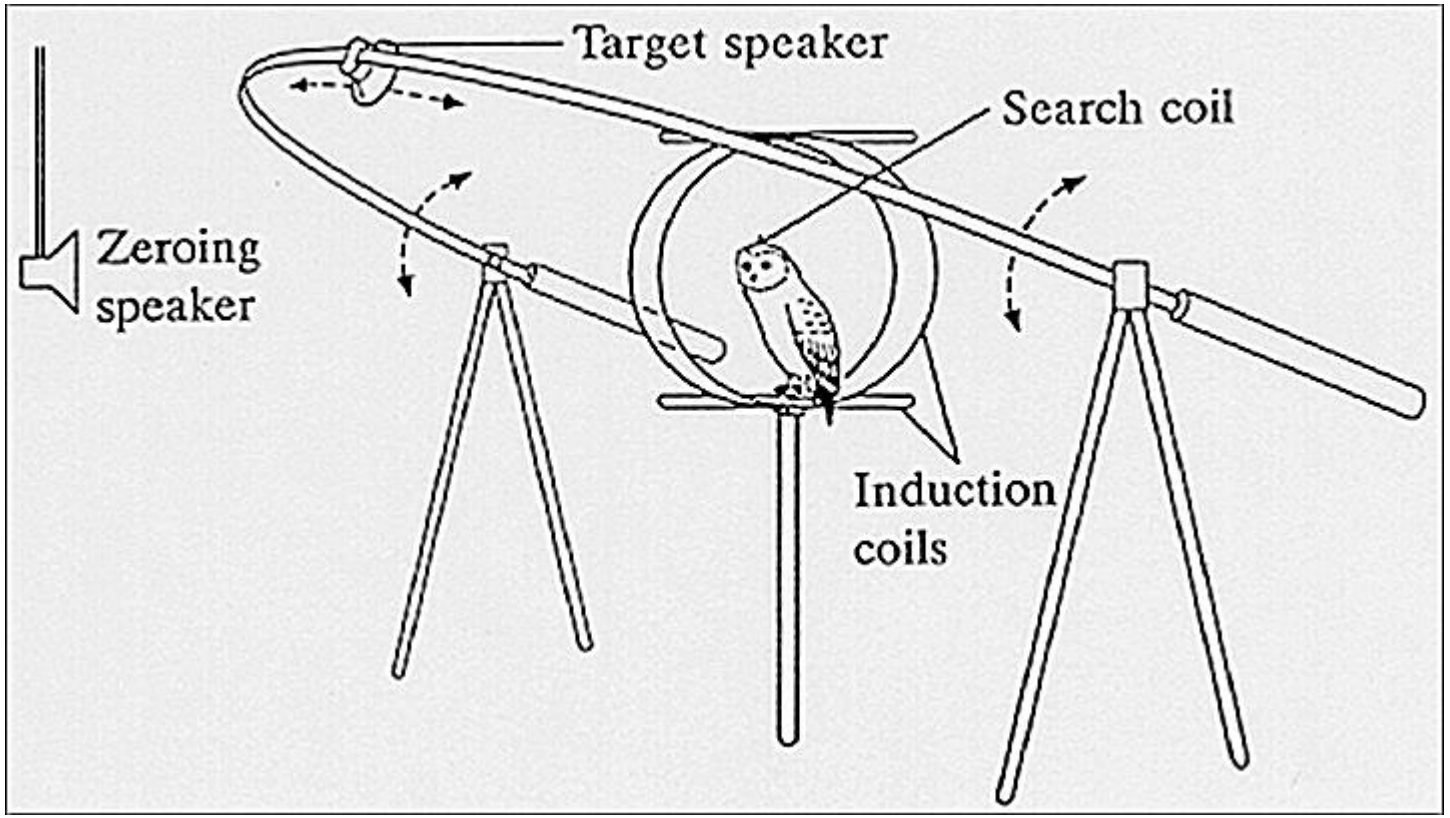
- Level 1 (the computational problem):
  - What is it that needs to be done for the hunting behavior to succeed?
    - **find target coordinates (azimuth, elevation)**



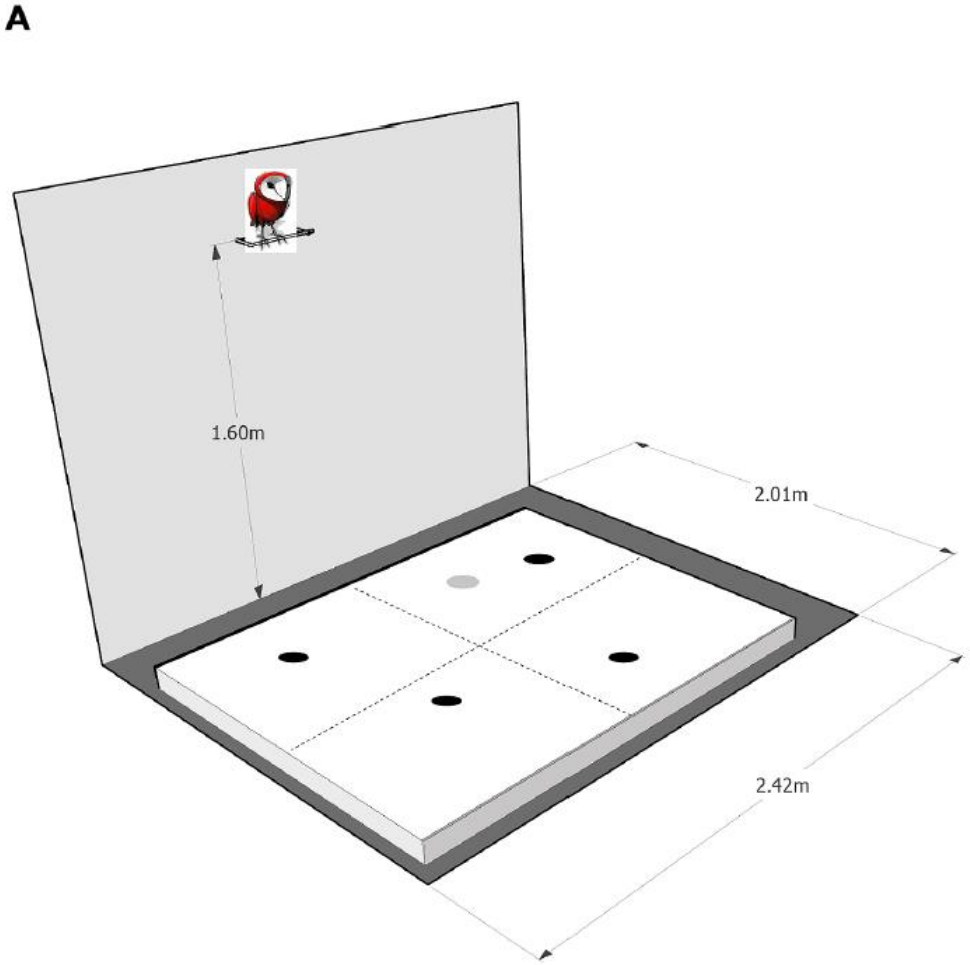
barn owl — a classical experimental setup for behavioural study of sound localization

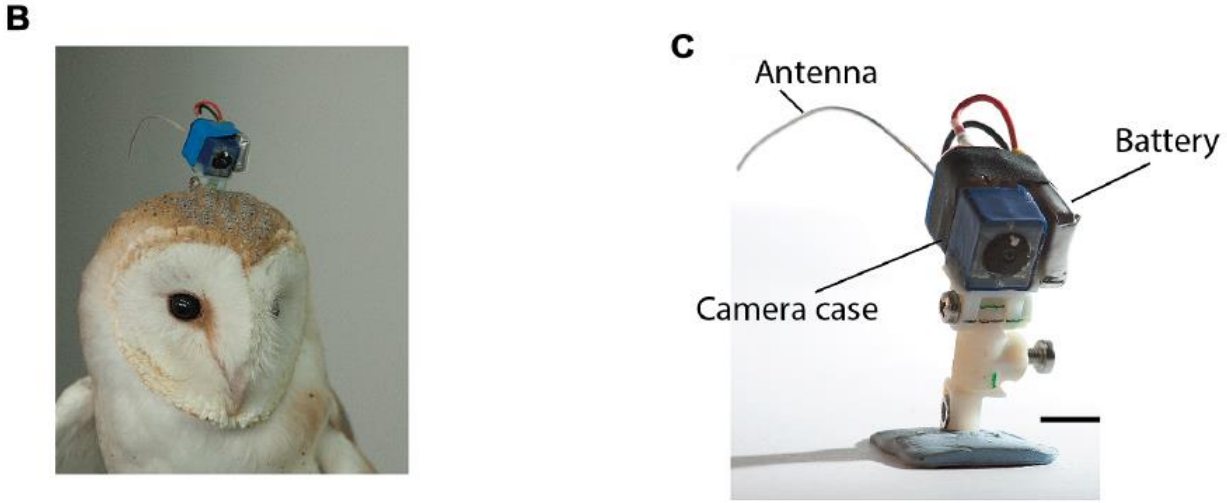
To address Levels 2 (representation and algorithm) and 3 (mechanism), controlled experimentation is required.

The diagram on the right illustrates the behavioral testing setup.



the barn owl: a recent behavioral study of sound+vision localization IN THE LAB





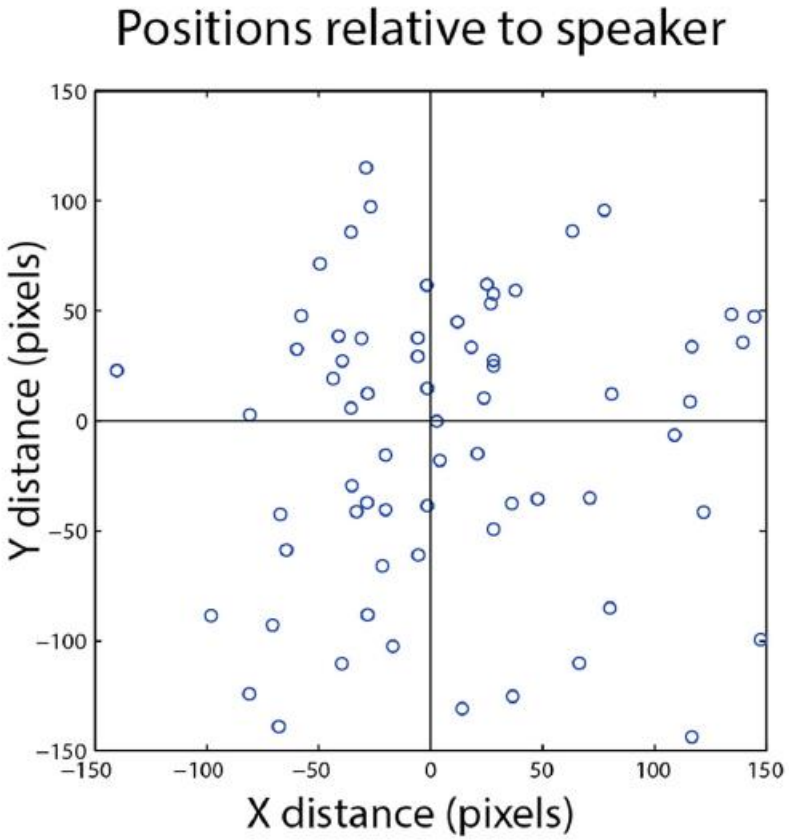
(B) An owl with the OwlCam attached to its head.

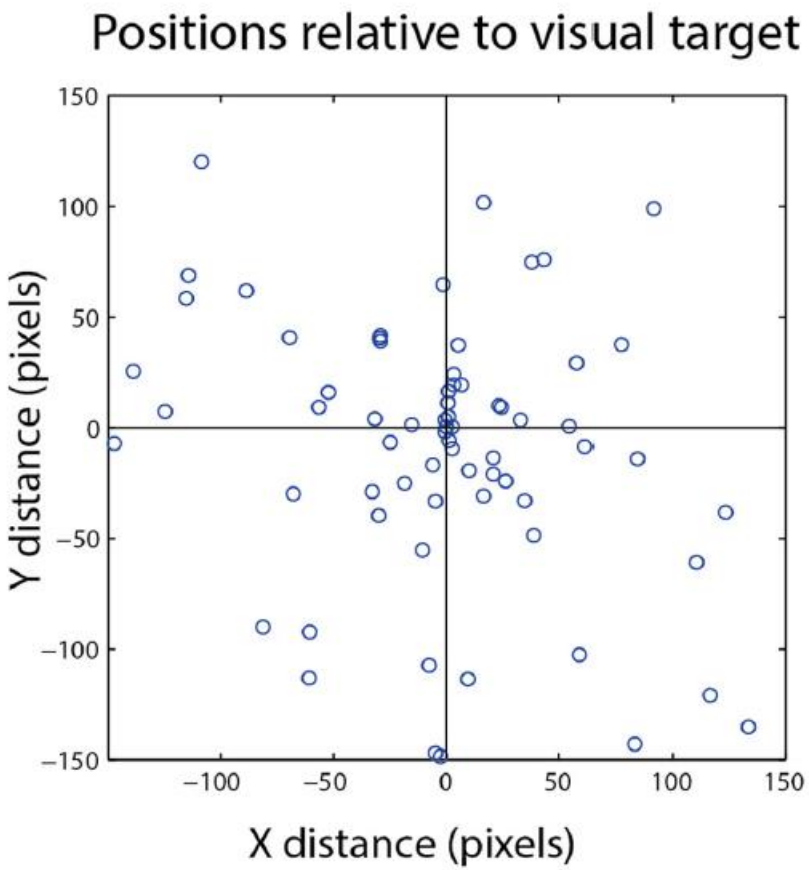
(C) A close view of the OwlCam with the attachment unit and the battery in place. The scale bar designates 10mm.

A) The dark spots on the arena designate possible positions of four food items. Items were spread so that each quadrant will contain one item. The gray spot on the arena designates a possible location of the loudspeaker.

Studying owl auditory-visual cue integration in the lab (Hazan et al., 2015)

the barn owl: a recent behavioral study of sound+vision localization IN THE LAB

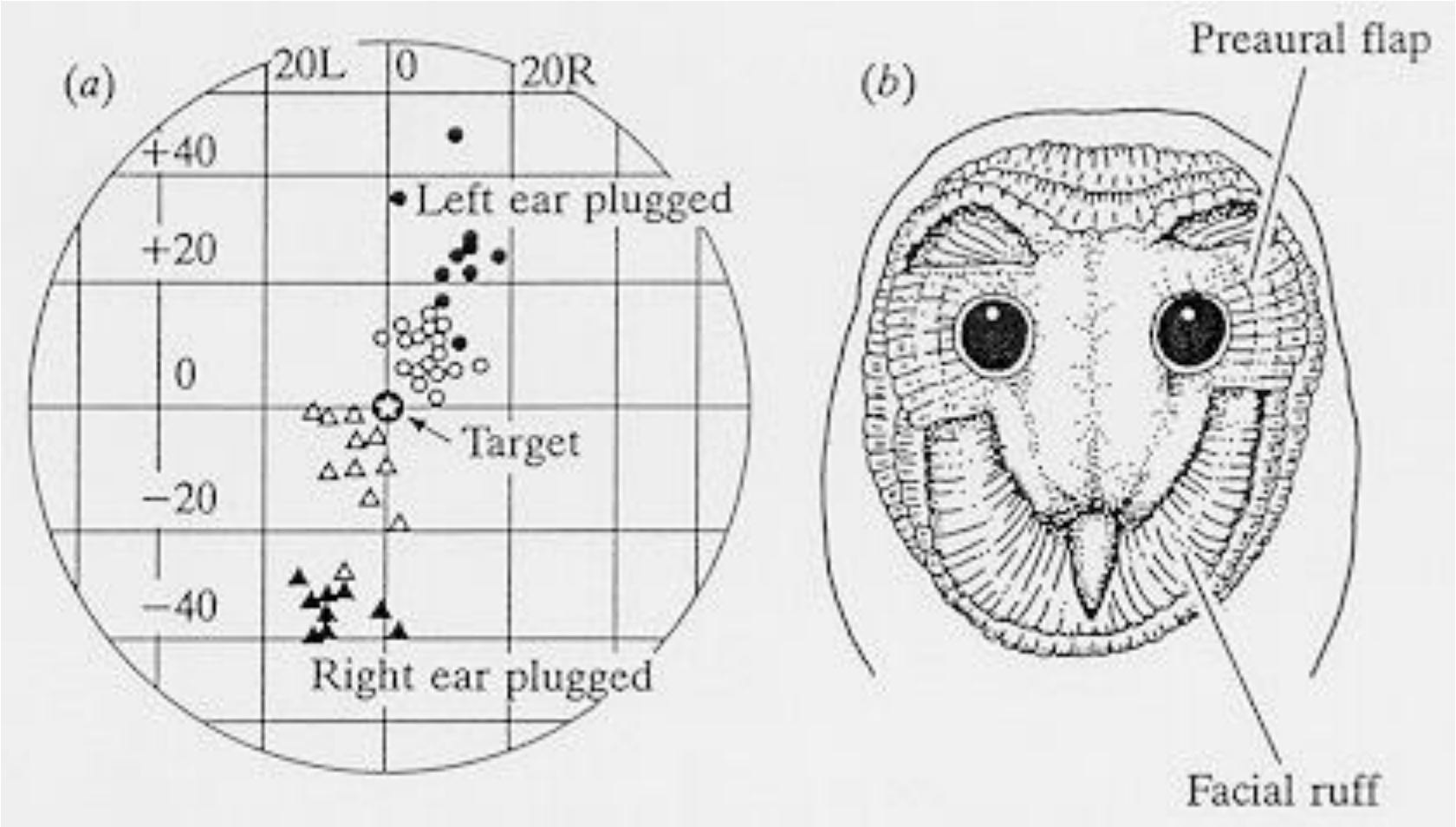




Note how bad auditory orienting (left) is, compared to visual (right)
Conducting the experiment in darkness approximates better (but not perfectly) the natural hunting conditions IN THE WILD!

Studying owl auditory-visual cue integration in the lab (Hazan et al., 2015)

Barn owl – Localization performance



Experiments in the wild showing how the owl uses binaural hearing

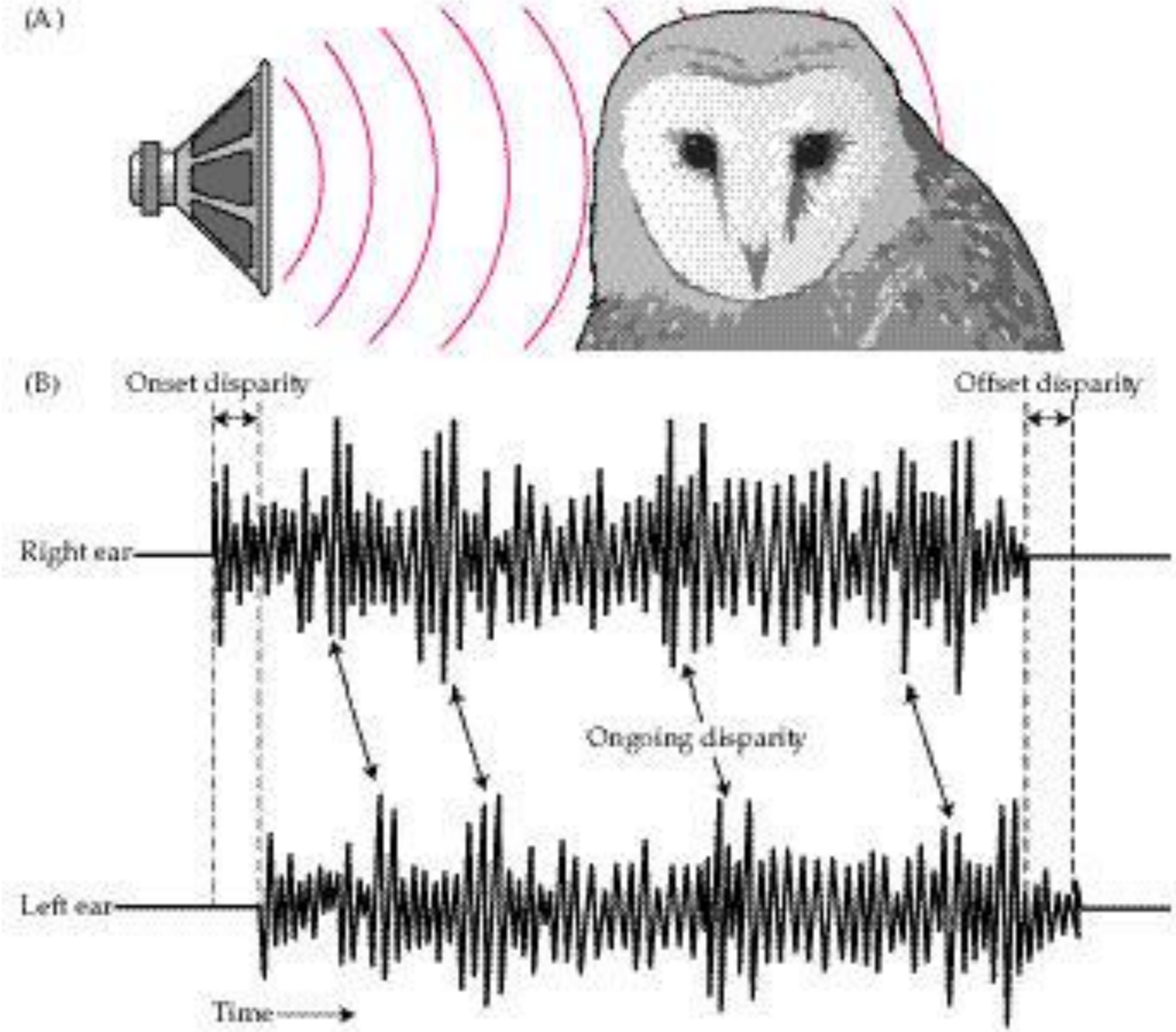
Barn owl — from problem to algorithm

How could binaural audio information be used to localize sound source?

Barn owl — from problem to algorithm

How could binaural audio information be used to localize sound source?

1. by noting **intensity difference** between the two ears;
2. by noting **timing difference** between the two ears.

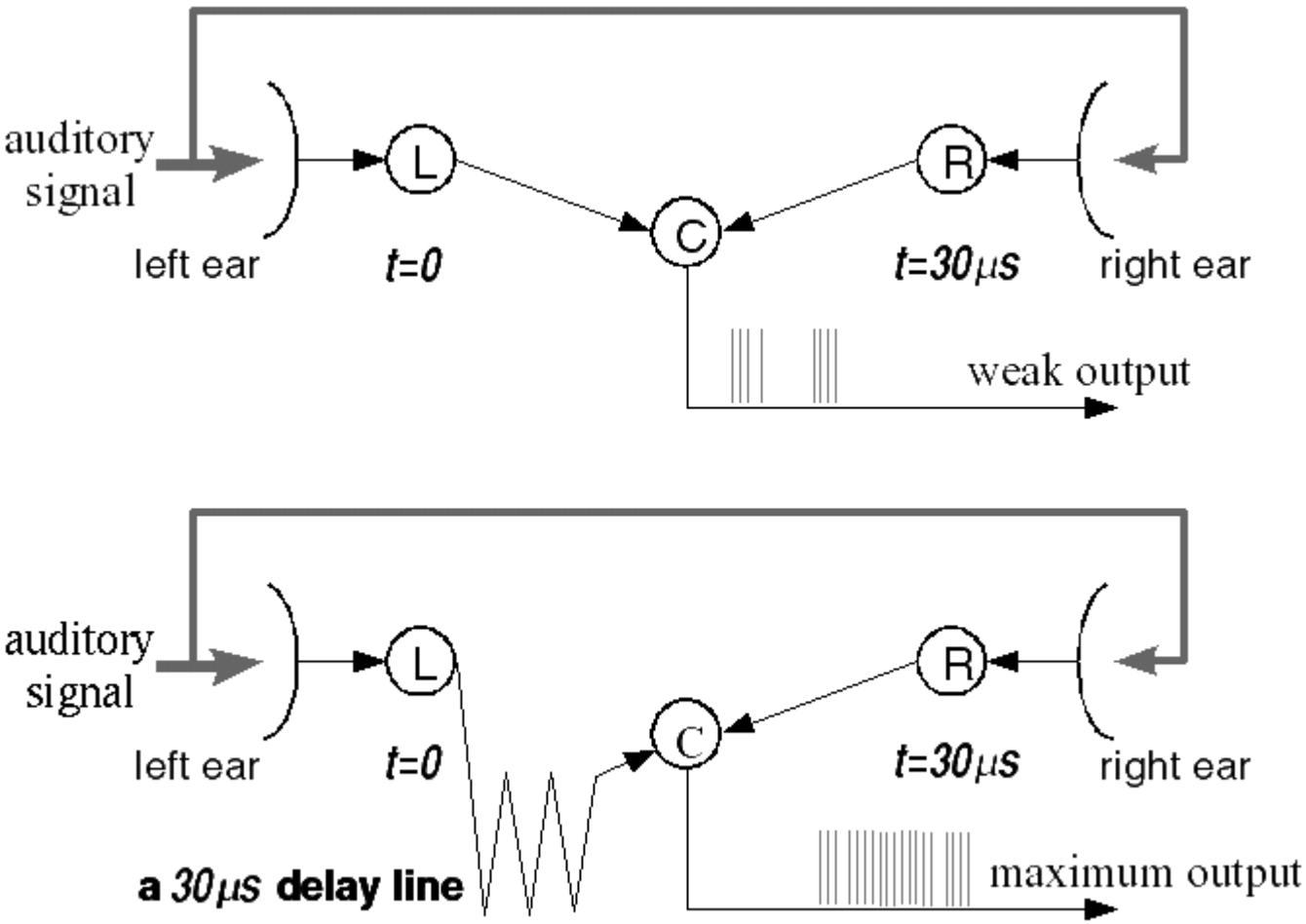


barn owl — algorithm, implementation (focusing on time difference)

A possible way of computing time difference (Jeffress, 1948) using:

a coincidence detector
and
a calibrated time delay line

(in air, a distance of 1 cm = 30 µs time delay).

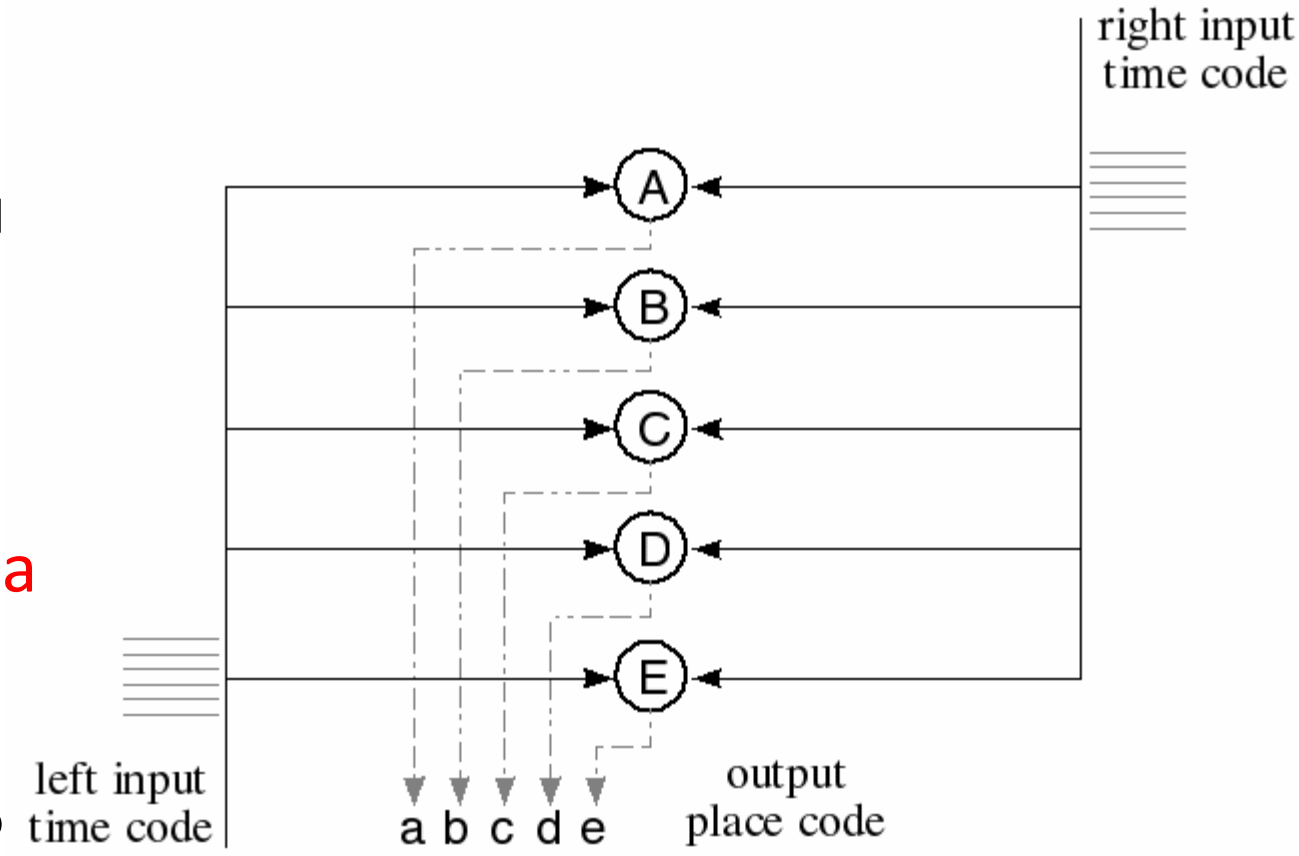


barn owl — implementation

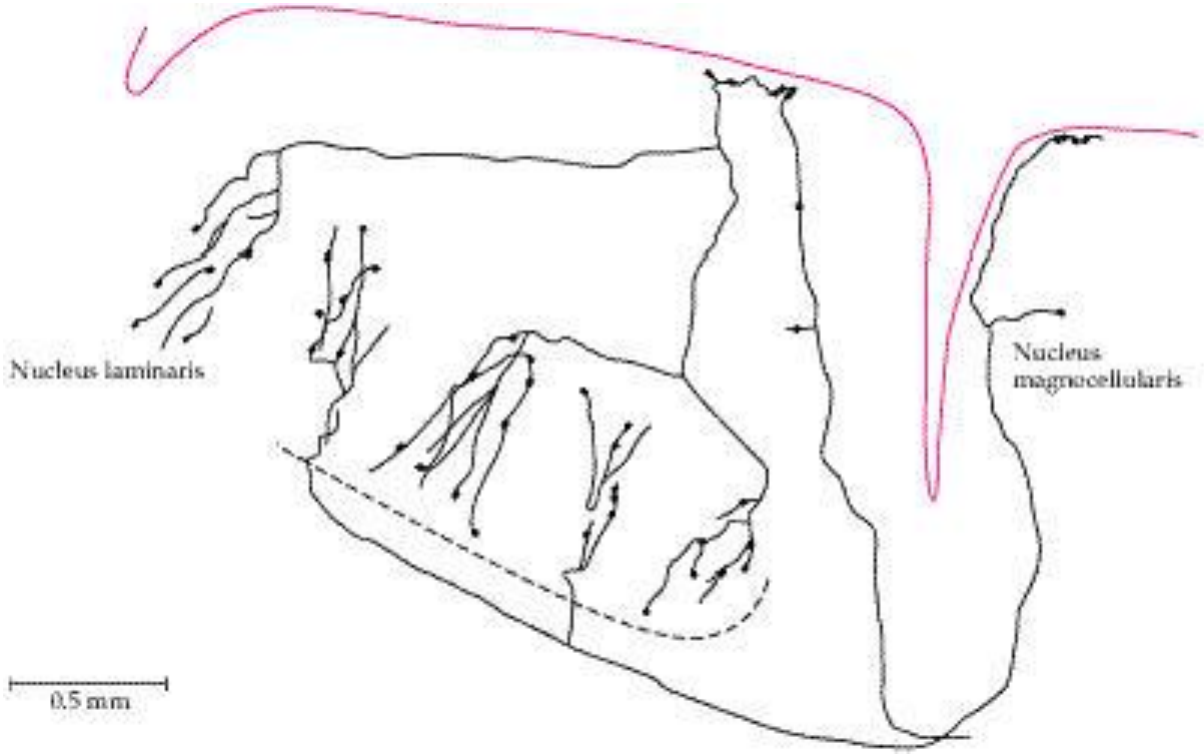
An elaboration of the coincidence + calibrated delay model by Masakazu Konishi —

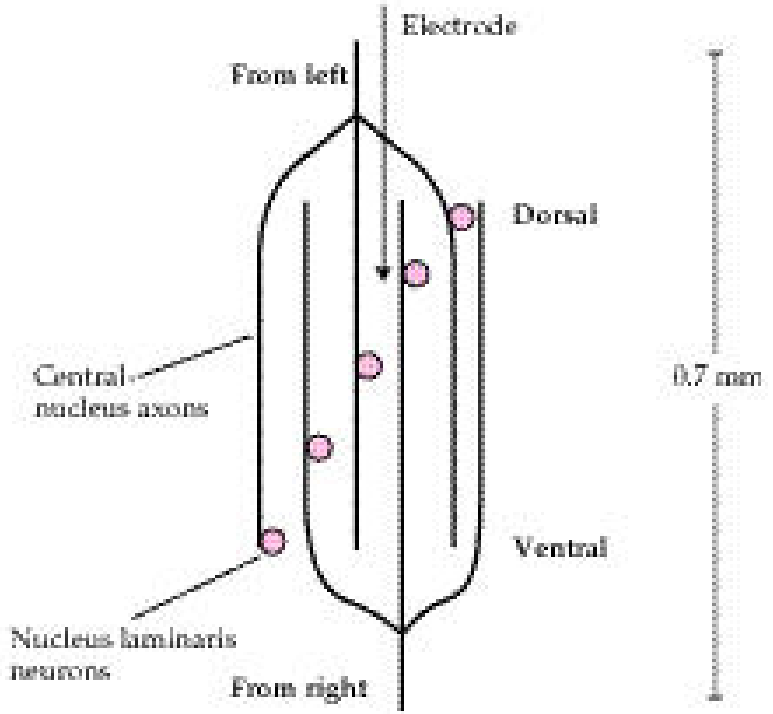
The key idea:
convert time delay information into a place code.

Does the barn owl use this method?
Yes!



barn owl — neural circuitry





anatomy: axons carrying information from the two ears enter the nucleus laminaris from opposite sides, and run parallel to each other.

Jeffress/Konishi model supported!!

physiology: neurons at the top of nucleus laminaris show response time LEAD to the ipsilateral ear, changing to LAG as the recording electrode descends into NL.

Update: on the algorithmic & evolutionary levels

B. J. Fischer and J. L. Peña (2011). Owl's behavior and neural representation predicted by Bayesian inference. Nature Neuroscience 14:1061-1067.

"Spatial hearing in birds and mammals is more alike than previously thought in its patterns of developmental plasticity, physiological responses, and the computations employed to interpret binaural cues and map the environment" (Shamma, 2015).

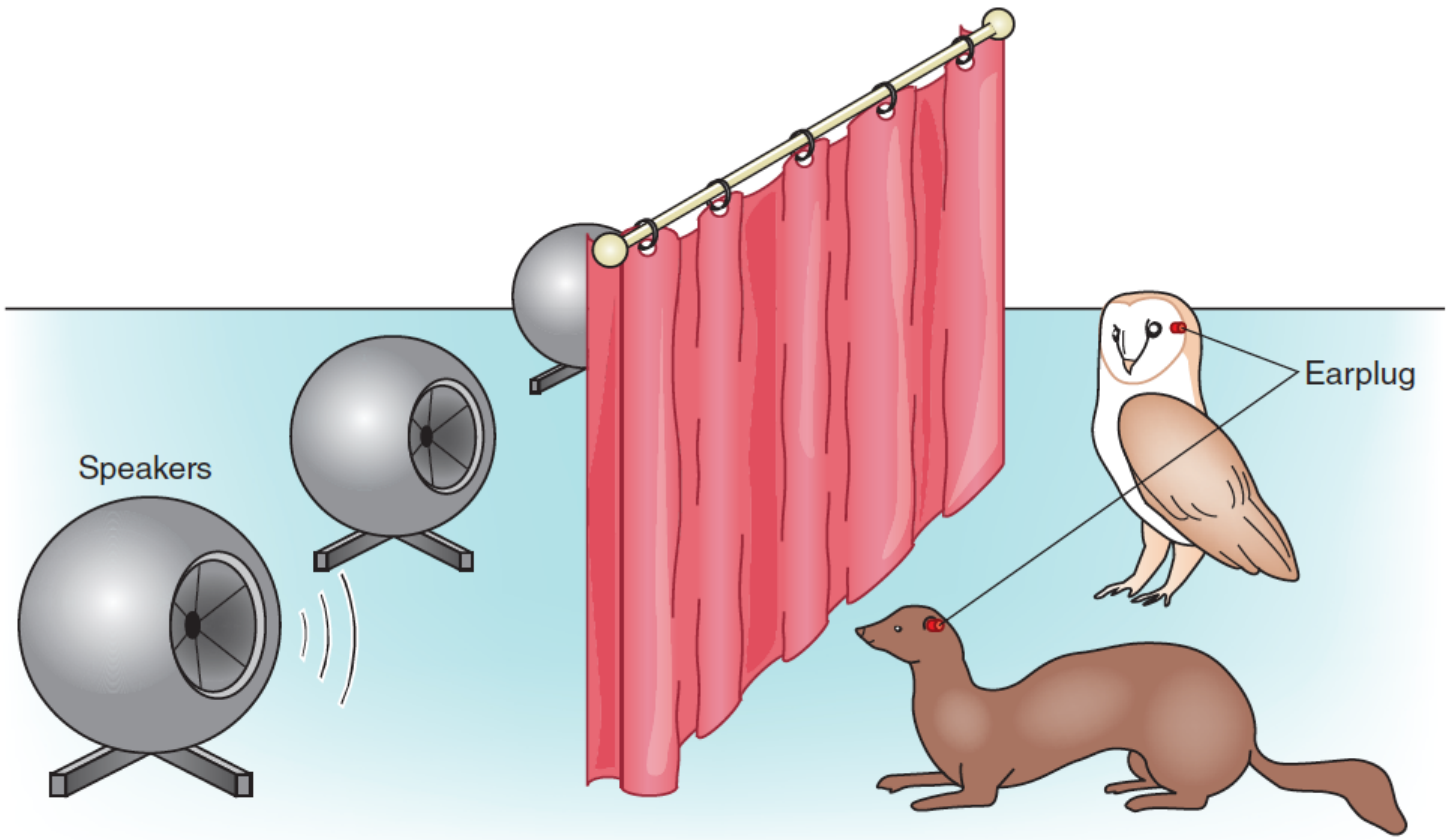


Figure 1 Sound localization with one ear plugged. Although once thought to employ different strategies, barn owls and ferrets utilize similar interaural level difference–based cues to localize a sound[5].

Summary of the Barn Owl Case Study

The multiple levels of analysis, applied to sound localization by the owl:

0. The evolutionary and behavioral context:
   - In the ecological niche they reside in, owls employ passive sound localization to pinpoint prey, by using interaural time (and intensity) differences.

1. The computational problem:
   - given timing (and intensity) differences measured at two locations, pinpoint the source of the sound.

2. Representation and algorithm:
   - use coincidence detection and delay lines to transform time difference into a place code in the brain.

3. The mechanism/implementation:
   - arrange the neurons and wire them up via delay lines to reflect the algorithmic solution.

Aim of the Course

- * What are the representations and computations that the brain/mind performs and
- ** how do they compare with AI solutions?
- *** What is the gap? Is there an opportunity?
- Course Goals:
  - Emphasis on understanding the current status on * (Lectures)
  - Open exploration and Reflection on ** and *** and debates thereof (Presentations, Project)
  - Give hands-on experience in addressing these questions on real brain data

Course Outline

- Sensation-Perception
- Vision
- Language and Speech
- Motor Systems
- Other topics:
  - Learning & Memory, Attention, Decision Making, Emotions, Consciousness
  - Compositionality, Causality, Learning-to-learn (Meta Learning)
  - Structure-to-Function, Development and Ageing
  - Representational Similarity Analysis (RSA)
  - Predictive Coding and Bayesian Brain

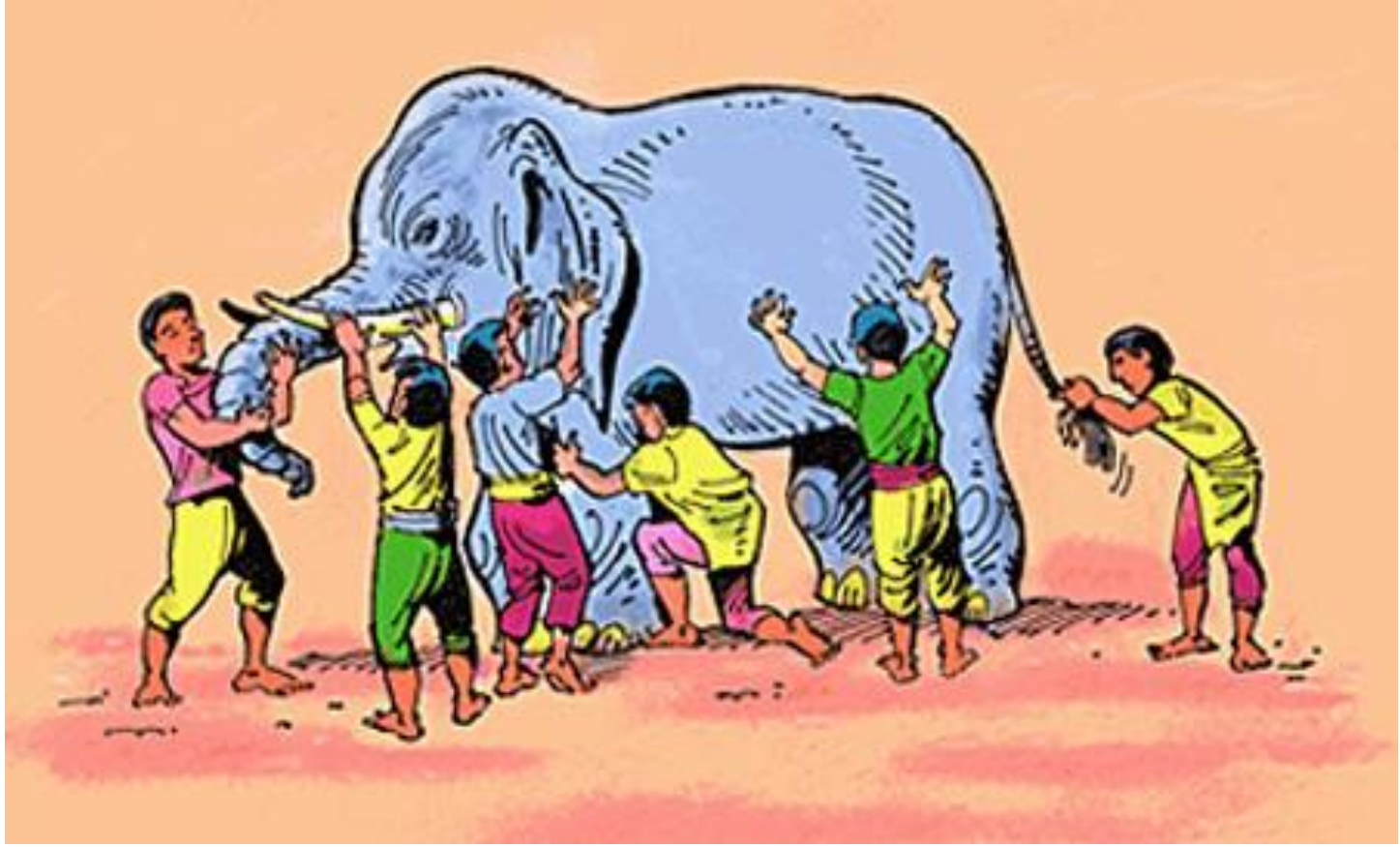
Course Logistics

- Assignments (6): 25%
  - ~3 using NILearn
  - ~3 on Brain Encoding and Decoding
- Presentations: 10% (Presentation + Summary Report)
  - 2 Presentations per class (starting from 18th Jan 2022)
  - 15 mins each presentation.
  - Groups of 2 per presentation.
- Project: (30%)
  - Groups of 3 per project
- Quizzes (2x10): 20%
- Mid-Sem: 15%

Cognitive Science and AI

Methods and Approaches

The Parable of blind men and an elephant



Methods, Approaches, and Limitations

- Four case studies — four approaches to understanding the brain, and their limitations:
  1. An ambitious broad-scope "computational" theory (J. R. Anderson. ACT: A simple theory of complex cognition. *American Psychologist*, 51:355-365, 1996).
  2. A single-cell electrophysiology study (C. D. Salzman, K. H. Britten, and W. T. Newsome. Cortical microstimulation influences perceptual judgements of motion direction. *Nature*, 346:174-177, 1990).
  3. An imaging study (J. V. Haxby, M. I. Gobbini, M. L. Furey, A. Ishai, J. L. Schouten, and P. Pietrini. Distributed and overlapping representations of faces and objects in ventral temporal cortex. *Science*, 293:2425-2430, 2001).
  4. A "deep learning" hack (V. Mnih et al., Human-level control through deep reinforcement learning. *Nature*, 518:529-518, 2015).

case study #1: ACT-R (John Anderson)

- The ACT-R (Adaptive Control of Thought, Rational) theory rests upon three important components:
  - rational [= "effective + adaptive"] analysis (Anderson, 1990),
  - the distinction between procedural and declarative memory (Anderson, 1976),
  - and a modular structure in which components communicate through buffers.

- The actual substrate of cognition is an interconnected network of neurons.

Taatgen, N.A. & Anderson, J.R. (2008). ACT-R. In R. Sun (ed.), Constraints in Cognitive Architectures. Cambridge University Press, 170-185.

ACT-R

- **A**daptive **C**ontrol of **T**hougt-**R**ational
- ACT-R is a cognitive architecture:
  - a theory for simulating and understanding human cognition.
  - To understand how people organize knowledge and produce intelligent behavior.
  - To build a system which can perform the full range of human cognitive tasks: capturing in great detail, the way we perceive, think about, and act on the world.
  - J. R. Anderson, CMU

Base system is coded in Lisp
and has a GUI for creating models.

http://act-r.psy.cmu.edu/

Ritter, F. E., Tehranchi, F., & Oury, J. D. (2018). ACT-R: A cognitive architecture for modeling cognition. Wiley Interdisciplinary Reviews: Cognitive Science, e1488.

ACT-R: a "simple theory of complex cognition"

- All that there is to intelligence is the simple accrual and tuning of many small units of knowledge that in total produce complex cognition.
  - The whole is no more than the sum of its parts, but it has a lot of parts.
- All this knowledge creates a serious problem.

How does one select the appropriate knowledge in a particular context?

- ACT-R has developed a two-pass solution for knowledge deployment. An initial parallel activation process identifies the knowledge structures (chunks and productions) that are most likely to be useful in the context, and then those knowledge structures determine performance.

J. R. Anderson (1996). ACT: A simple theory of complex cognition. American Psychologist, 51:355-365.

ACT-R: as a theory of cognition

- ACT-R is a hybrid architecture in the sense that it has both symbolic and subsymbolic aspects.
  - The symbolic aspects involve declarative chunks and procedural production rules. The declarative chunks are the knowledge-representation units that reside in declarative memory, and the production rules are responsible for the control of cognition.
  - Access to these symbolic structures is determined by a subsymbolic level of neural-like activation quantities.
  - ACT-R consists of two key memories — a declarative memory and a procedural memory. The system has separate memories for each different type of chunk — for example, addition facts are represented by one type memory, whereas integers are represented by a separate type memory.

Anderson, J. R., & C. Lebiere (2003). The Newell Test for a theory of cognition. *Behavioral and Brain Sciences* 26:587-640.

ACT-R: a "simple theory of complex cognition"

- Activation [of an item] in ACT-R theory reflects its log posterior odds of being appropriate in the current context. This is calculated as a sum of the log odds that the item has been useful in the past (log prior odds) plus an estimate that it will be useful given the current context (log likelihood ratio). [This is a Bayesian approach!]

- Thus, the ACT-R claim is that the mind keeps track of general usefulness and combines this with contextual appropriateness to make some inference about what knowledge to make available in the current context.
- The basic equation is
  - *Activation-Level = Base-level + Contextual-Priming*

J. R. Anderson (1996). ACT: A simple theory of complex cognition. American Psychologist, 51:355-365.

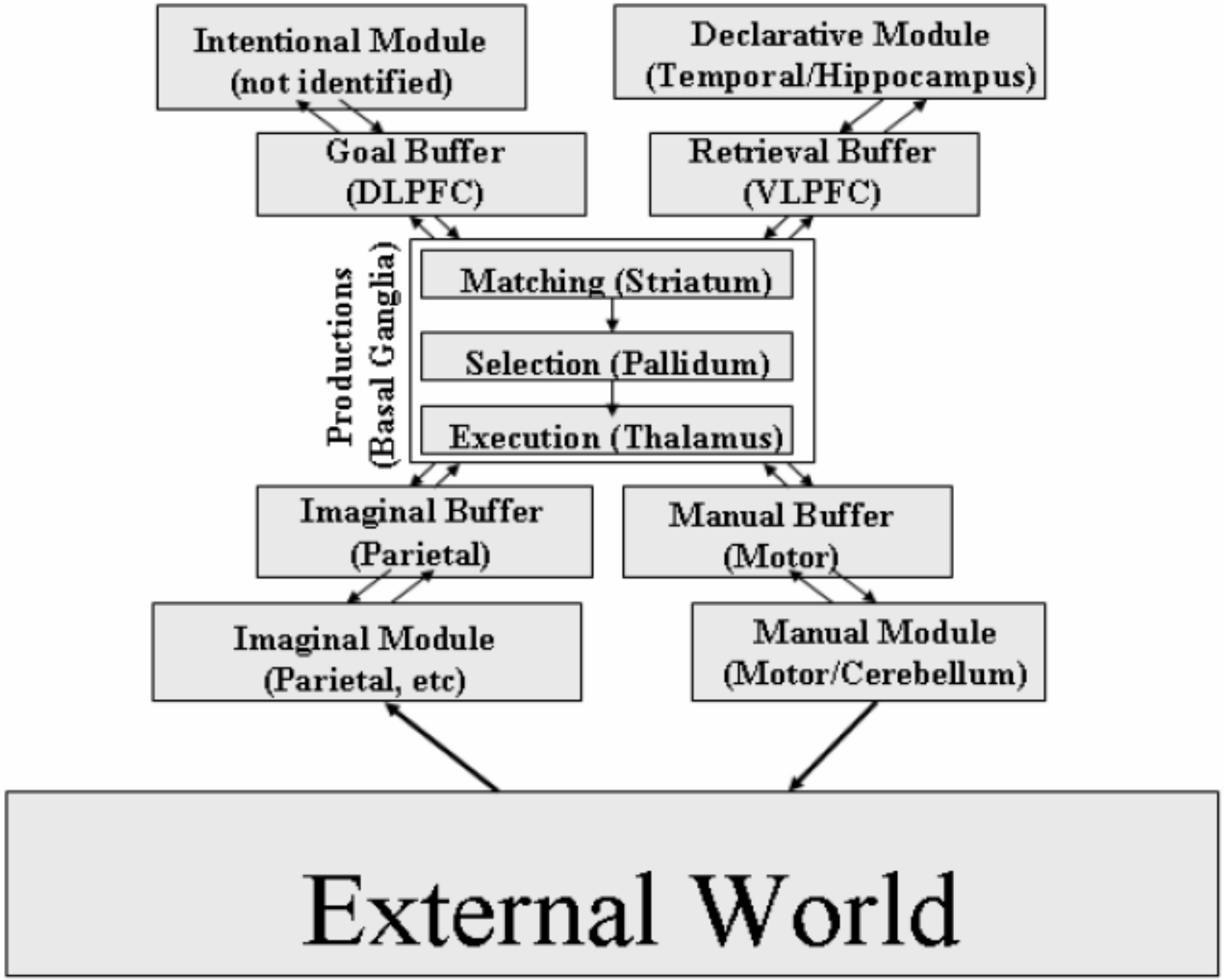
ACT-R: as a theory of cognition

- In addition to the learning mechanisms that update activation and expected outcome, ACT-R can also learn new chunks and production rules.
  - New chunks are learned automatically: Each time a goal is completed, or a new percept is encountered, it is added to declarative memory.
  - New production rules are learned by combining existing production rules.
  - The circumstance for learning a new production rule is that two rules fire one after another, with the first rule retrieving a chunk from memory.
  - A new production rule is formed that combines the two into a macro-rule but eliminates the retrieval.
  - Therefore, everything in an ACT-R model (chunks, productions, activations, and utilities) is learnable.

Anderson, J. R., & C. Lebiere (2003). The Newell Test for a theory of cognition. *Behavioral and Brain Sciences* 26:587-640.

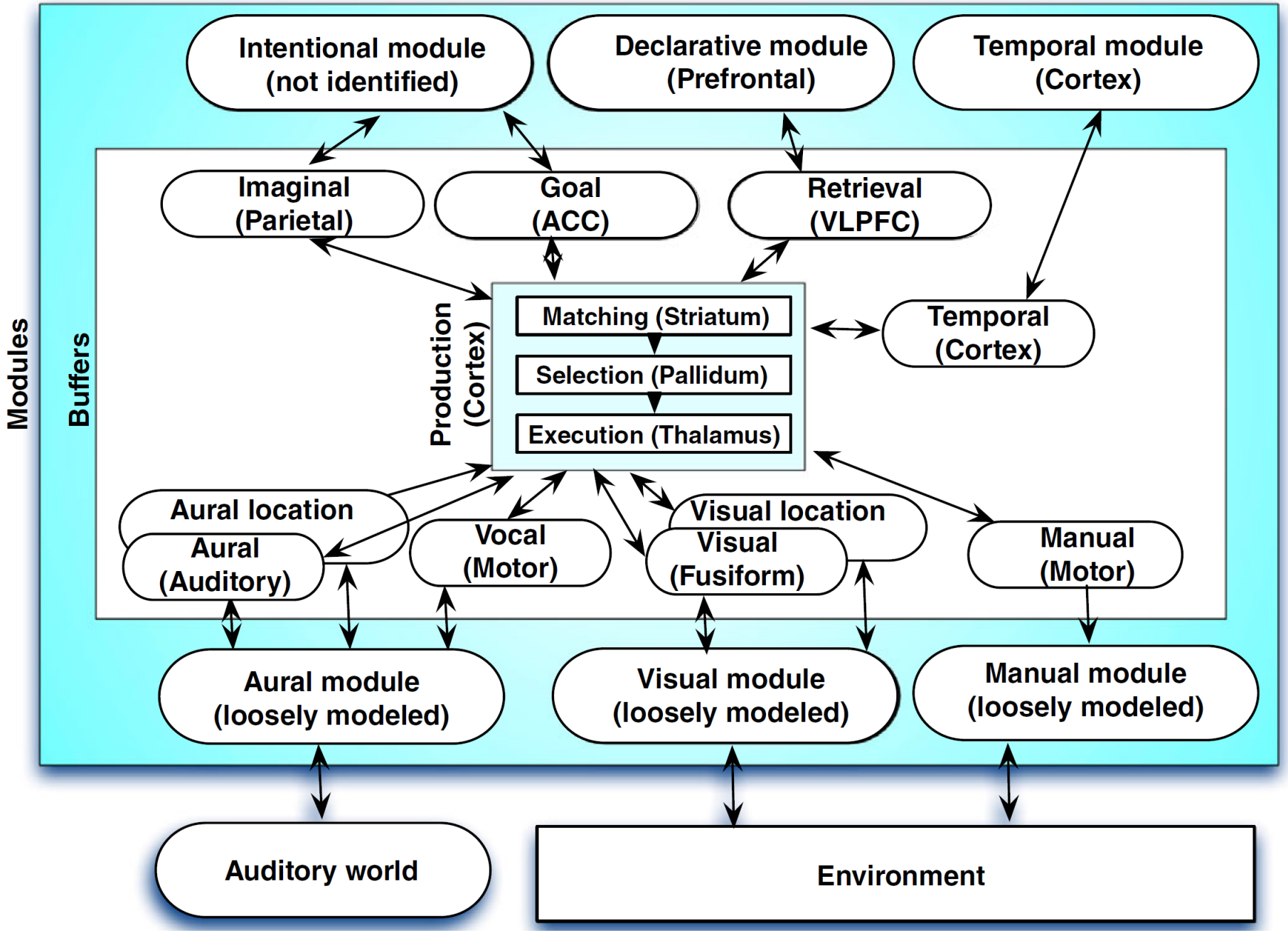
ACT-R architecture

- The symbolic structure of ACT-R emerges out of the structure of the brain.
- Information in the buffers associated with modules is responded to and changed by production rules.
  - *VLPFC*: ventrolateral prefrontal cortex.



Anderson, J. R., et al. (2004). An Integrated Theory of the Mind. *Psychological Review*, 111:1036-1060.

ACT-R arch



Ritter, F. E., Tehranchi, F., & Oury, J. D. (2018).

Applications of ACT-R

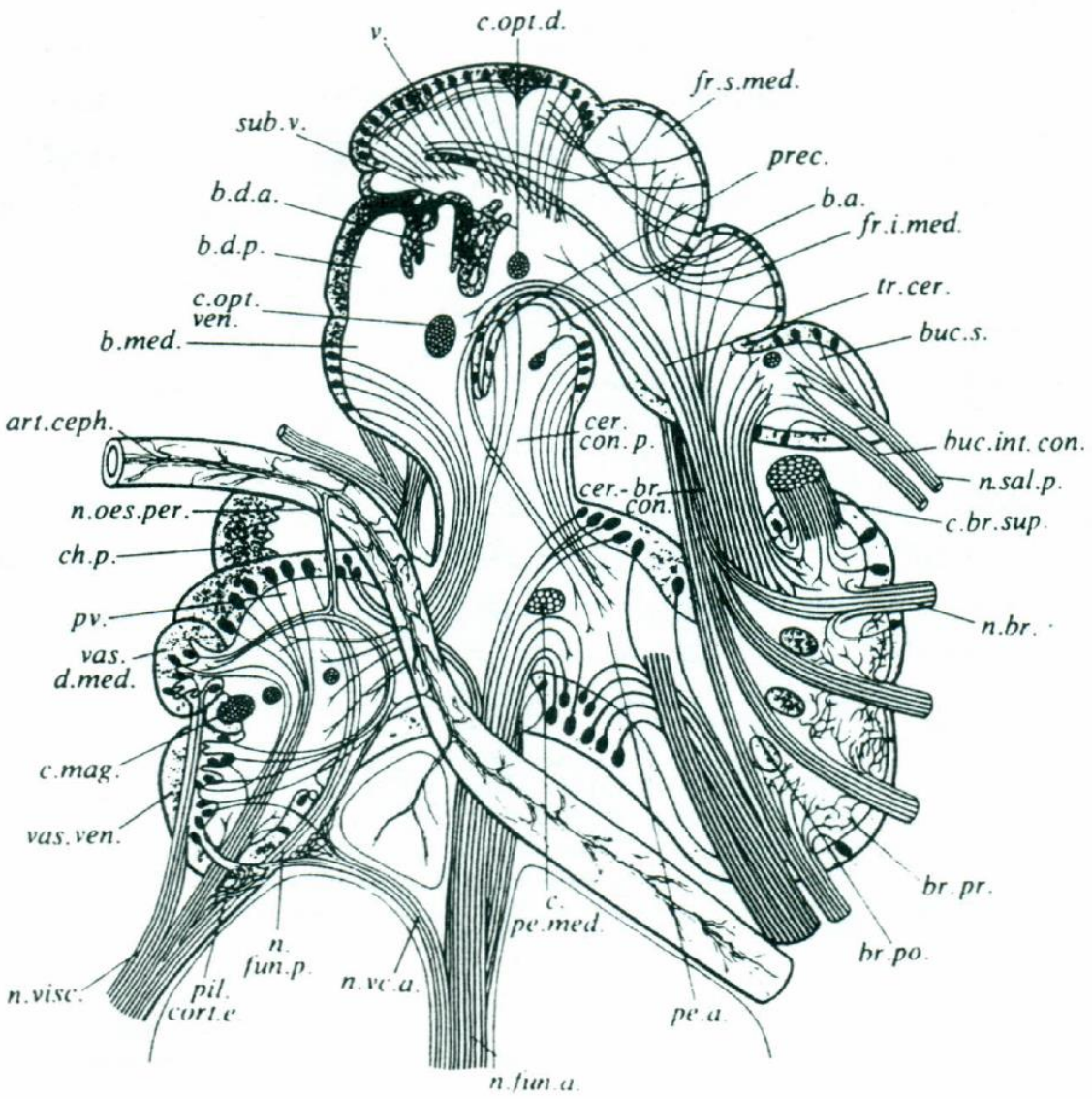
Model	Insights/implications
Models of memory effects, (e.g., fan effect, spreading activation, priming)	Shows how memory effects affect numerous aspects of behavior and provides a foundation for modeling
ACT-R/PM (perceptual-motor)	Shows how to incorporate a wide range of micro-theories about perception into a cognitive architecture as architectural components
Mapping of ACT-R to brain structures	Shows that the structures in ACT-R can be mapped to blood flow (activation) using fMRI and cognitive models that predict activation (blood flow) in the brain
Driving models	Shows how models can summarize behavior regularities in a complex real-time task
Taxiing at O'Hare Airport	Shows how to optimize large processes in large systems using ACT-R
Herbal/Dismal	Models novice to expert transition on a 20-min spreadsheet task using a model compiler
Synthetic teammate	Provides a comprehensive agent to live in a synthetic environment

Ritter, F. E., Tehranchi, F., & Oury, J. D. (2018).

ACT-R: Counterpoint!

https://www.youtube.com/watch?v=L2kFAjE_gyw&ab_channel=ImgnSpaces

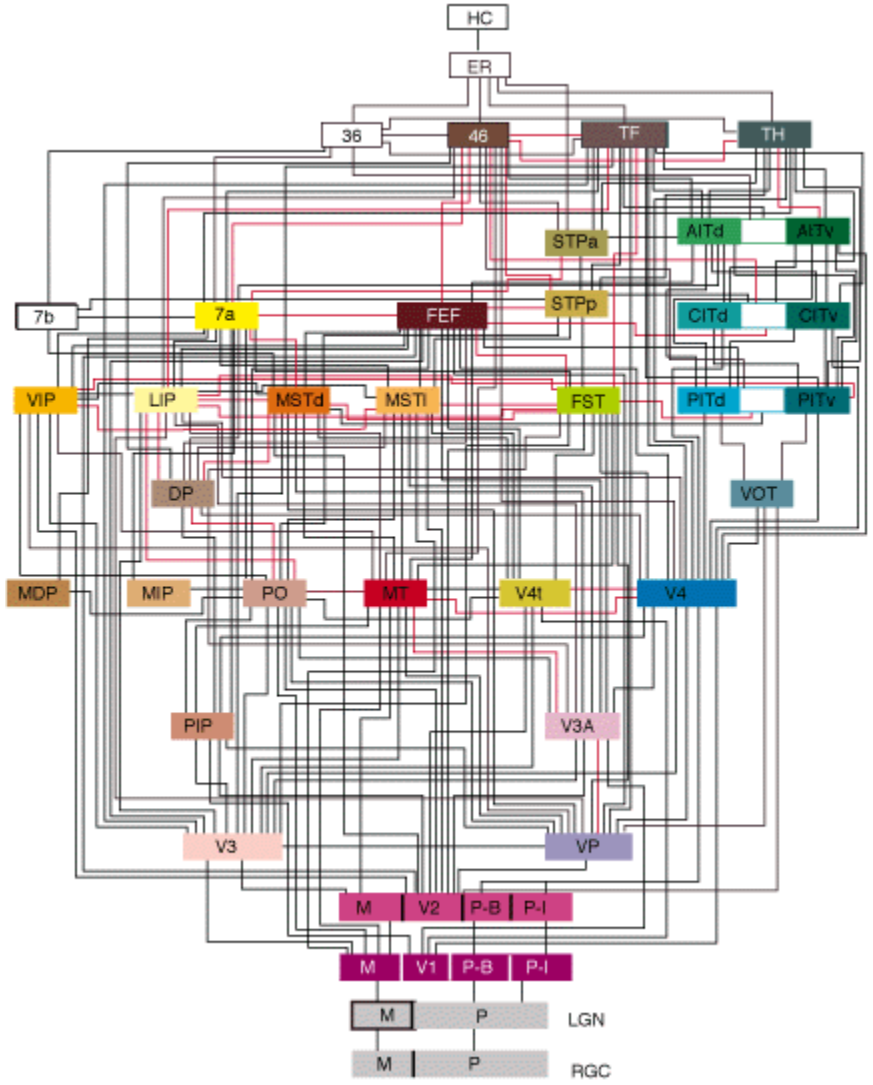
But consider this Octopus!!

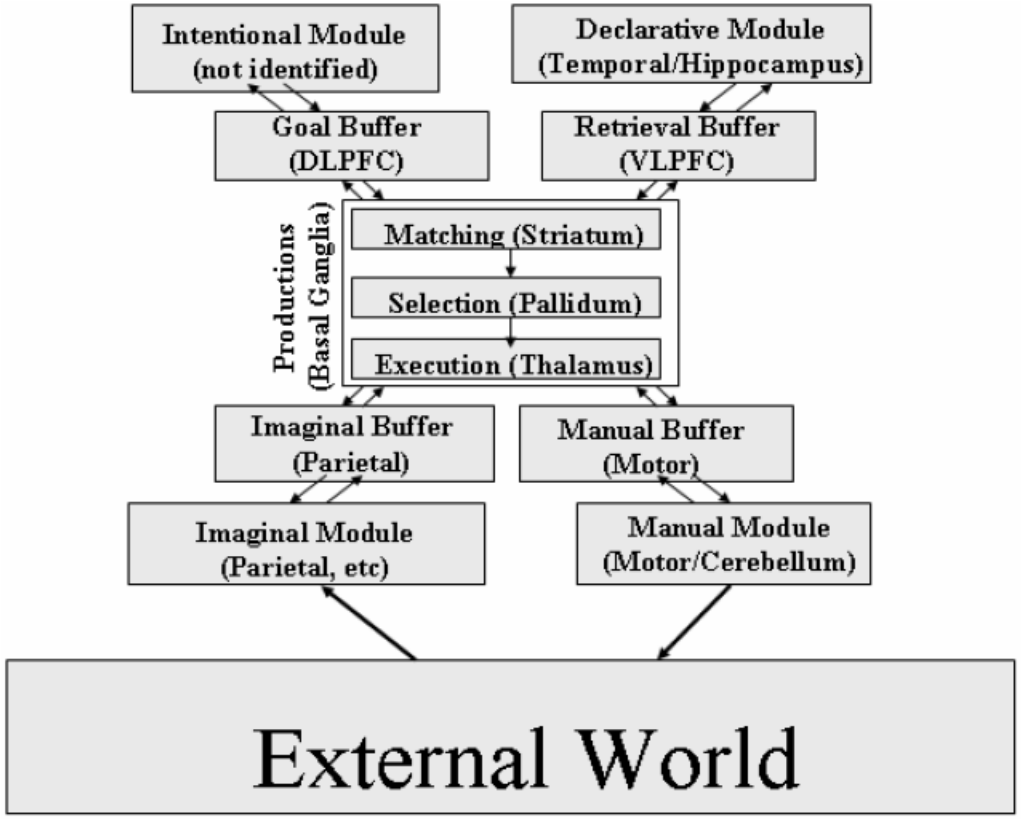


Octopus central nervous system (Fig. 6B from The cephalopod nervous system: What evolution has made of the molluscan design, B. U. Budelmann, 1995).

ACT-R: Counterpoint!

But consider the actual interconnection pattern of primate visual cortical areas





Felleman, D. J., and D. C. Van Essen (1991). Distributed hierarchical processing in the primate cerebral cortex. *Cerebral Cortex,* 1:1-47.

case study #2: single-cell physiology

Localized brain stimulation for diagnostic purposes, pioneered by Wilder Penfield

Wilder Penfield Video:
https://www.youtube.com/watch?v=aXKqoGuxS50&ab_channel=cdnmedhall

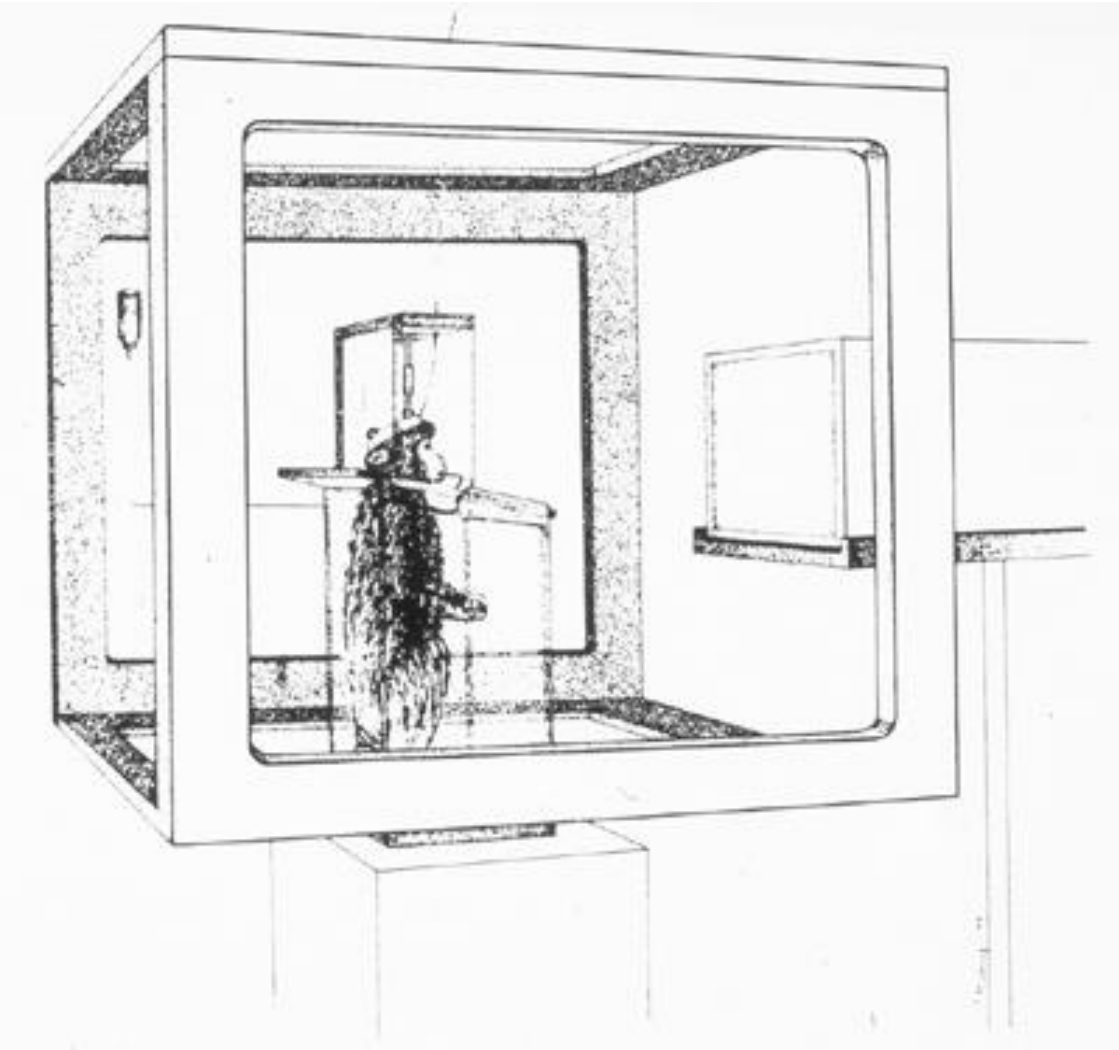
How to smell burnt toast that's not there!

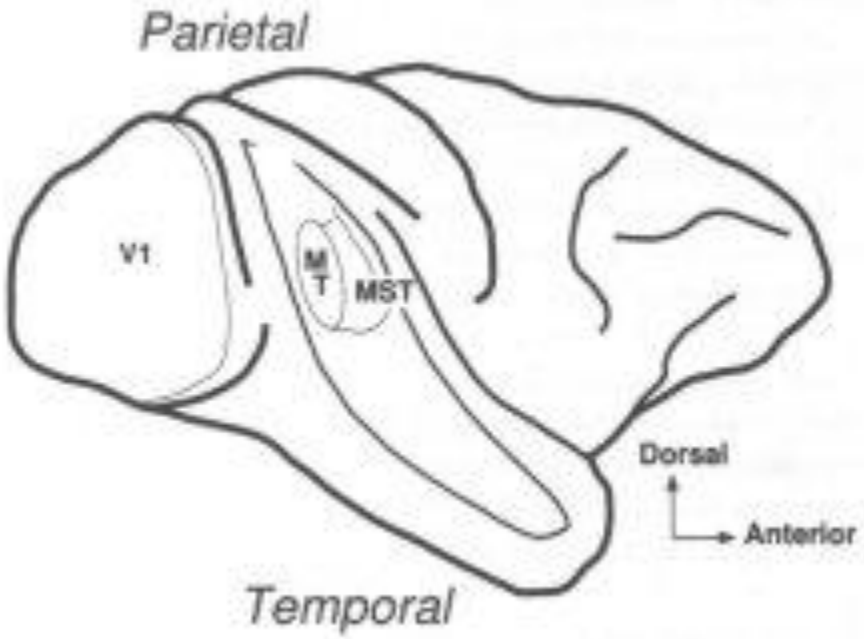
single-cell physiology (W. T. Newsome)

- The cue chosen for Newsome's study: visual motion
- Motion is a powerful cue to 3D structure and to "abstract" features of the moving object.

Motion videos: Dot Figures
https://www.youtube.com/watch?v=y8SEQ6l93lE&ab_channel=AdamPruden

inducing motion perception by microstimulation of cortical area MT

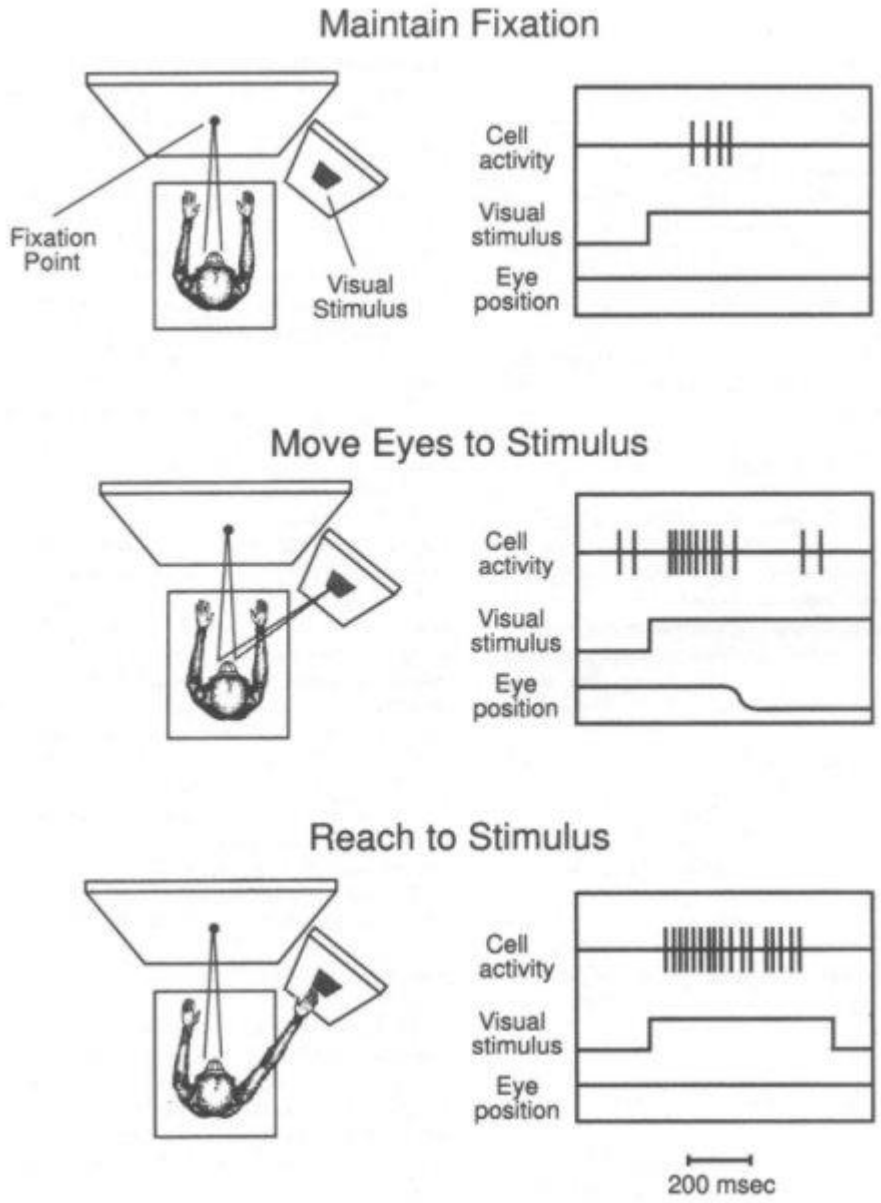




microstimulation of area MT: behavioral tasks and neural data

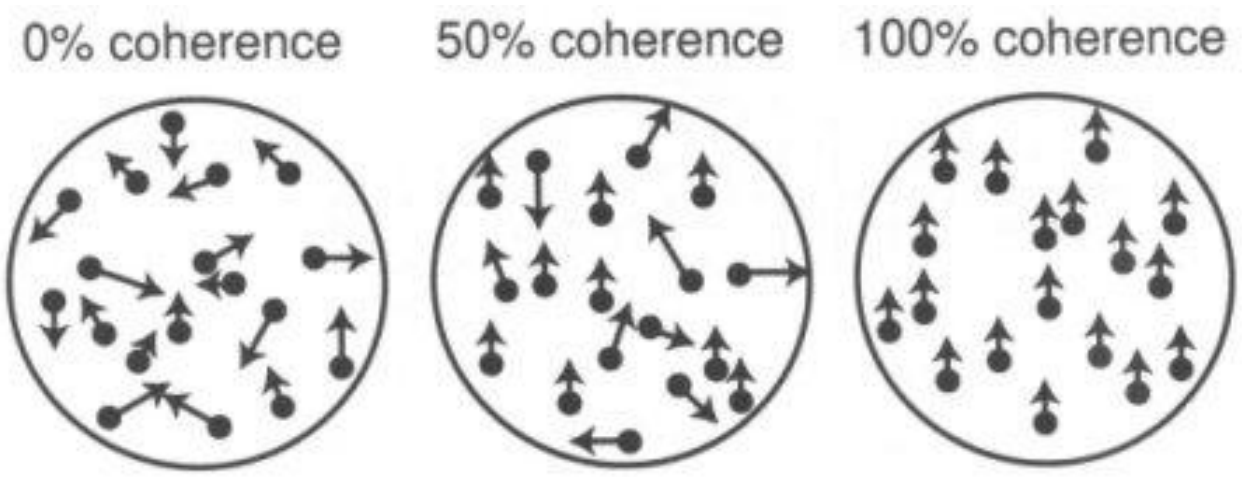
- Behavioral tasks:
  - fixation
  - saccade (gaze shift)
  - reaching

- The data: parallel recordings of —
  - cell activity
  - visual stimulus presence/absence
  - gaze direction



microstimulation of cortical area MT: stimulus properties

- Moving-dots stimuli at varying degrees of coherence:

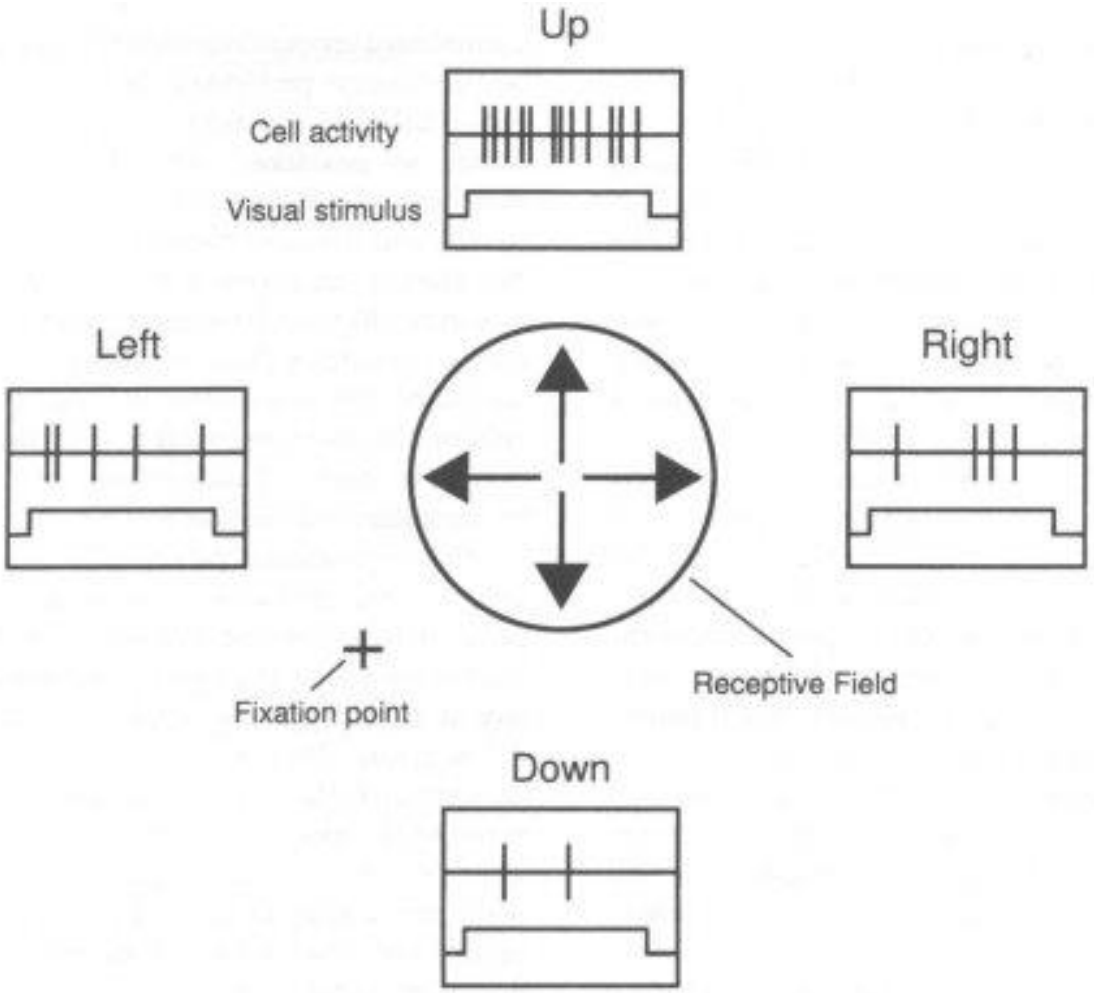


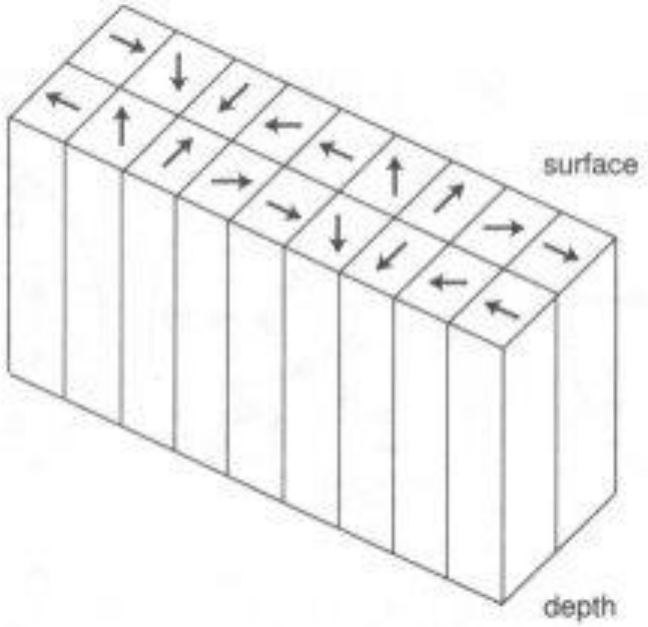
- The behavioral task is to detect and signal the direction of coherent motion. Its difficulty (and therefore the performance) depends on the degree of coherence.

degrees of motion coherence: examples

Example Videos: 0%, 5%, 30%, 100% Coherence

typical responses of an MT cell to motion stimuli





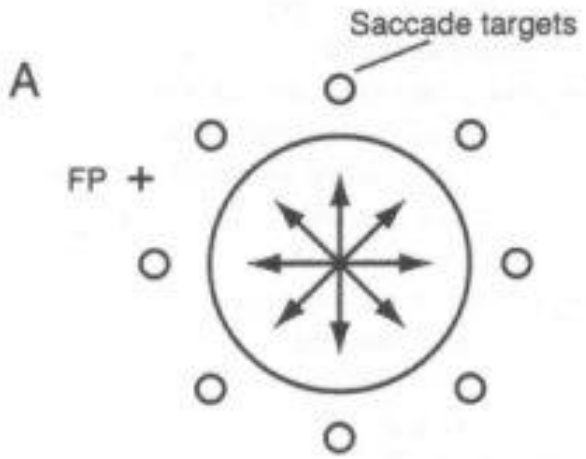
Area MT is organized in columns by the neurons' preferred direction of motion

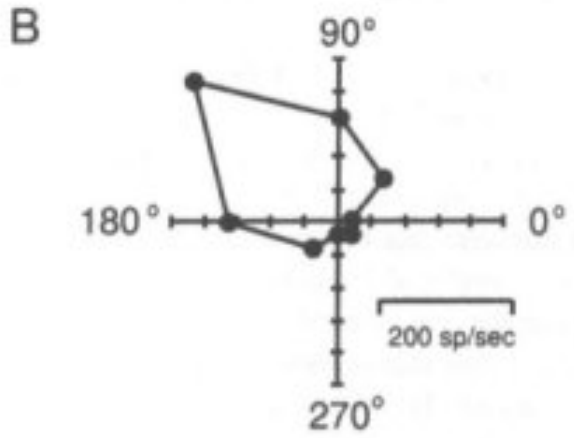
the typical response of a single neuron in area MT

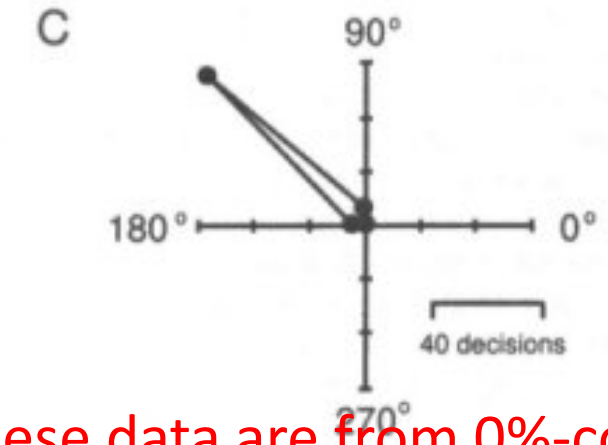
the outcome: inducing perception by cortical microstimulation

From William T. Newsome's lab (Stanford):

A. spatial layout of fixation point and eye movement targets
B. tuning curve illustrating collective responses of neurons in a single MT area column; data obtained from 100%-coherence trials
C. behavioral data obtained by electrically stimulating the column whose tuning is shown in B



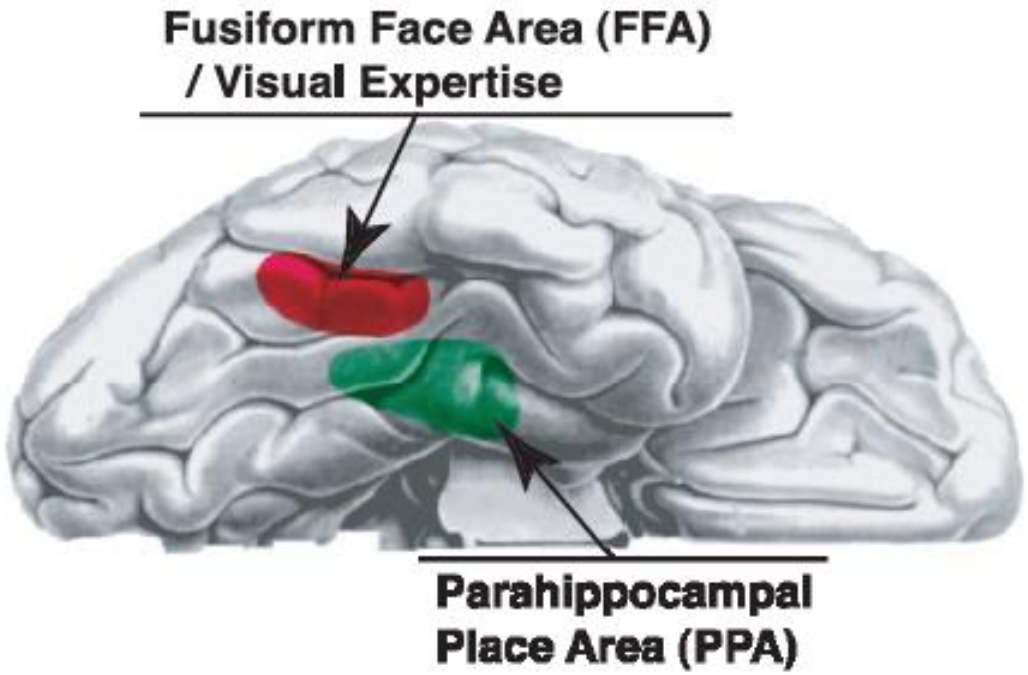




These data are from 0%-coherence trials!

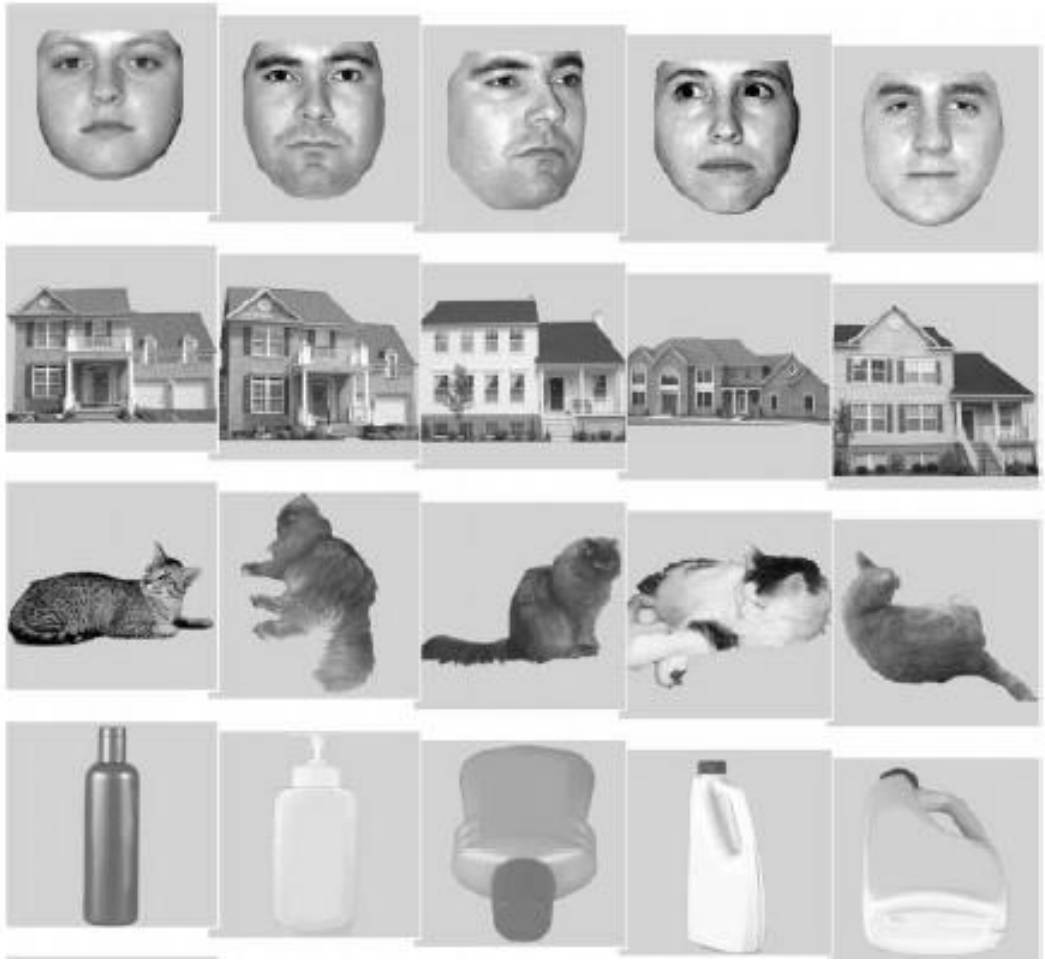
case study #3: fMRI (J. Haxby)

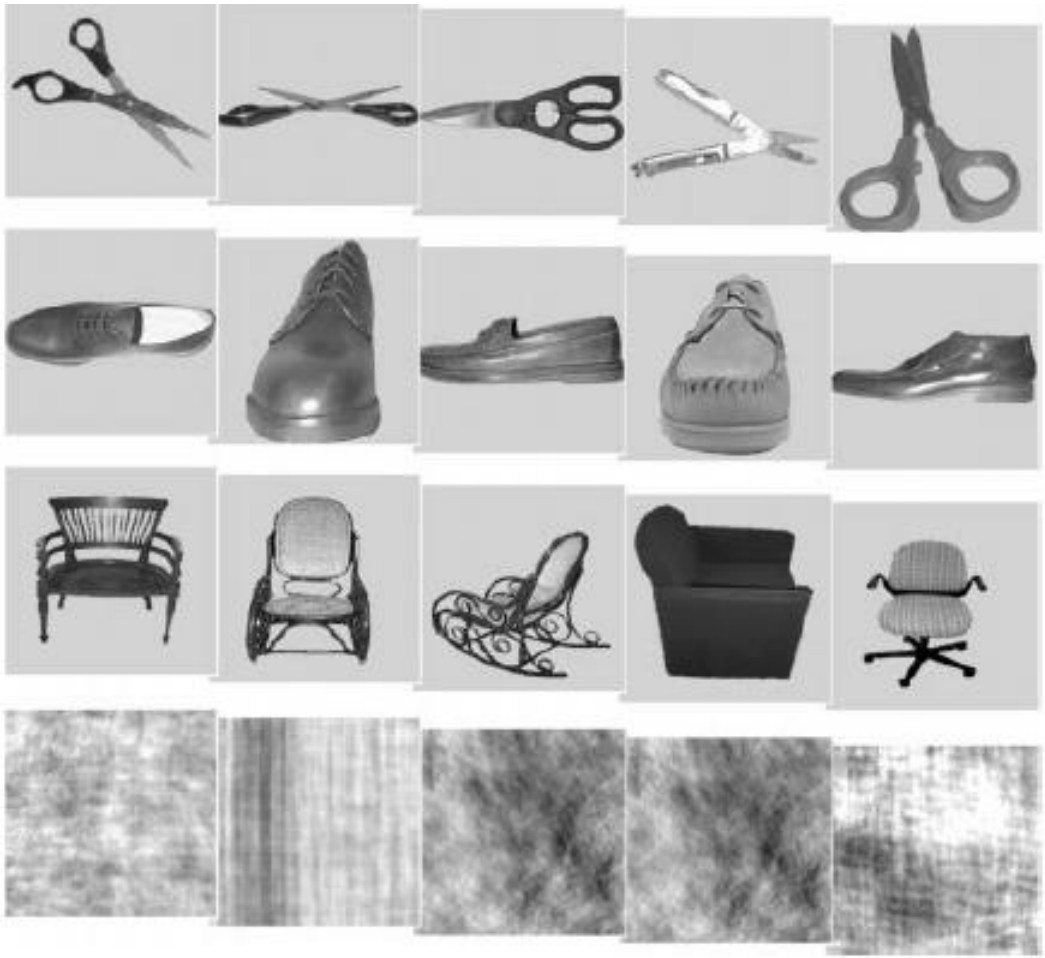
Schematic diagram illustrating the locations of the fusiform face area (FFA), which also has been implicated in expert visual recognition, and the parahippocampal place area (PPA) on the ventral surface of the right temporal lobe. In most brains, these areas are bilateral.



J. V. Haxby, M. I. Gobbini, M. L. Furey, A. Ishai, J. L. Schouten, and P. Pietrini (2001). Distributed and overlapping representations of faces and objects in ventral temporal cortex. *Science,* 293:2425-2430.

stimulus set





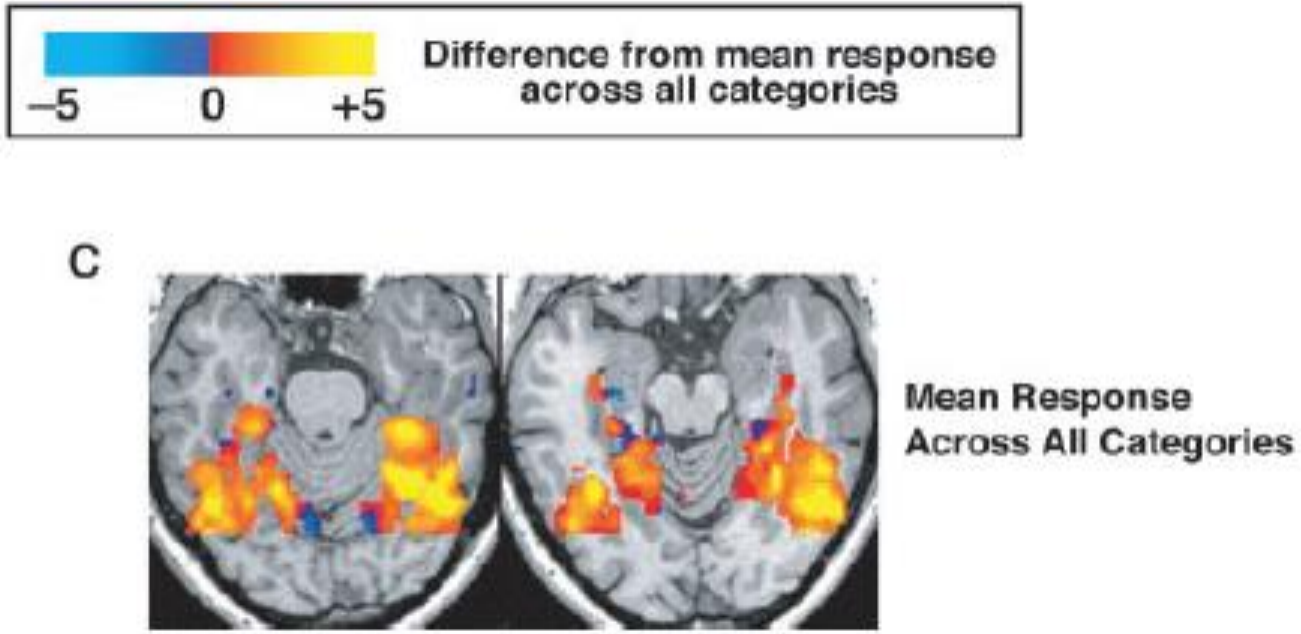
Subjects performed a one-back repetition detection task in which repetitions of meaningful pictures were different views of the same face or object.

brain response (average across categories)

The category specificity of patterns of response was analyzed with pairwise contrasts between within-category and between-category correlations. These patterns were normalized to a mean of zero in each voxel across categories by subtracting the mean response across all categories.

Brain images shown here are the normalized patterns of response in two axial slices in a single subject.

Responses in all object-selective voxels in ventral temporal cortex are shown.



Mean response across all categories relative to a resting baseline

classification based on multivoxel response

Table 1. Accuracy of identification of the category being viewed based on the patterns of response evoked in ventral temporal cortex. Accuracies are the percentage of comparisons between two categories that correctly identified which category was being viewed.

Region	Volume ($cm^3 \pm SE$)	Identification accuracy (%)							
		Faces	Houses	Cats	Bottles	Scissors	Shoes	Chairs	Scrambled
All ventral temporal object-selective cortex	22.9 ± 2.8	100***	100***	98 ± 2***	90 ± 6***	92 ± 6***	92 ± 7***	96 ± 2***	100***
Minus regions that were maximally responsive to categories being compared	15.4 ± 1.8	100***	100***	95 ± 2***	89 ± 6***	85 ± 9**	90 ± 8**	98 ± 1***	100***
Regions maximally responsive to:									
Faces	3.1 ± 0.9	94 ± 7***	99 ± 1***	76 ± 13*	81 ± 14*	77 ± 9*	70 ± 16	77 ± 11*	92 ± 7***
Houses	9.6 ± 1.8	100***	100***	88 ± 5***	85 ± 10**	81 ± 6**	96 ± 2***	94 ± 3***	100***
Cats	2.6 ± 0.4	96 ± 4***	96 ± 2***	82 ± 8**	65 ± 11	69 ± 5**	76 ± 9*	95 ± 4***	100***
Small objects	6.9 ± 1.1	100***	100***	95 ± 3***	83 ± 7**	92 ± 8**	94 ± 6***	90 ± 6***	96 ± 4***

Differs from chance (50%): *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$.

How reliably can the object that the participant is viewing be identified, given the activations (neural responses) in the regions listed on the left?!!

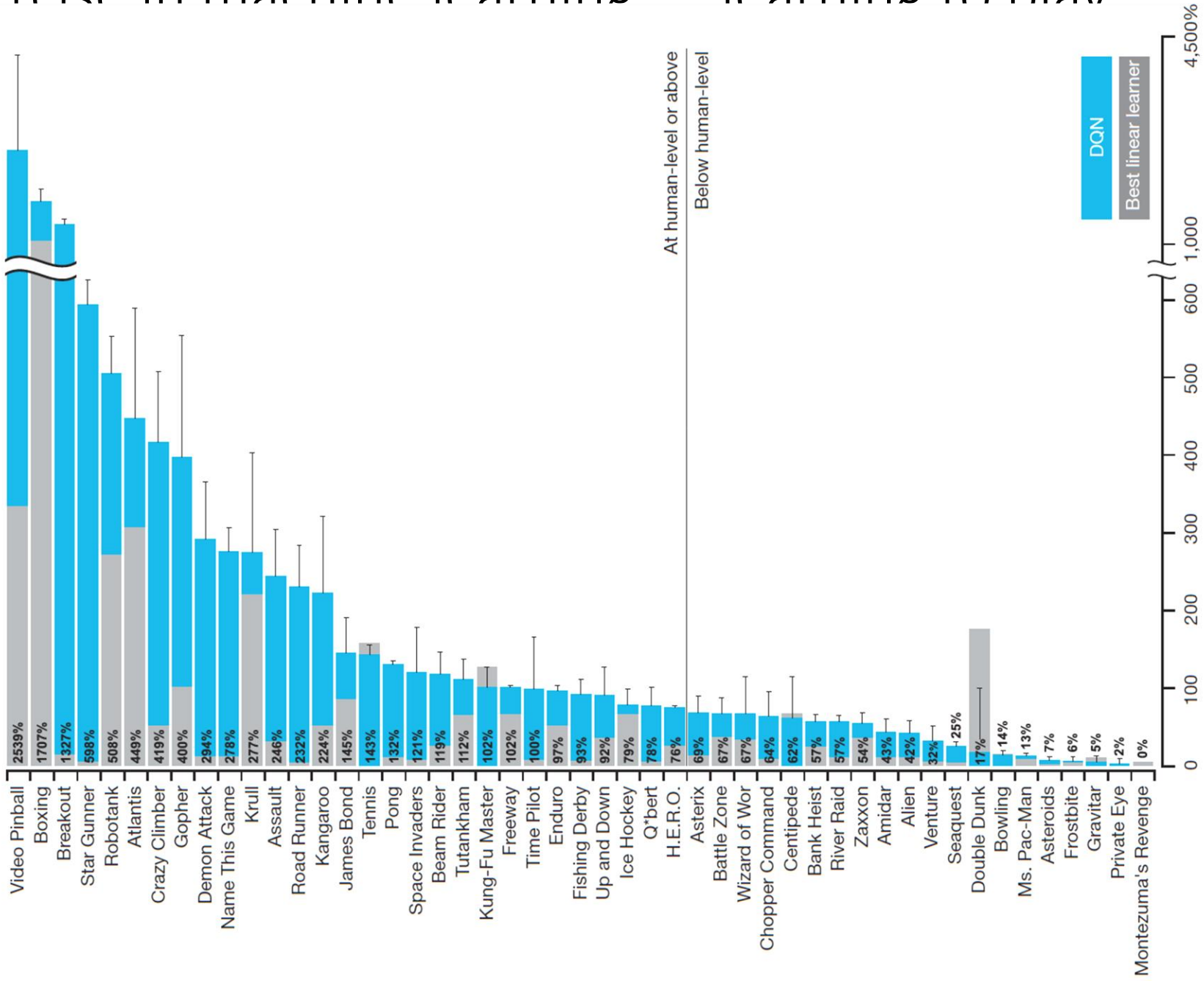
a more recent, related finding regarding multivoxel response

- All 66 [brain] regions were active in at least one [task] domain;
- 65 (98.5%) were active in two or more domains. [...]
- The 66 regions were active in an average of 9.09 (SD 2.27) different task domains.
- The 60 regions active in action tasks were also active in an average 7.38 (SD 0.98) non-action domains and 5.5 (SD 0.81) cognitive domains.
- The 64 regions active in perception tasks were also active in 7.39 (SD 1.87) non-perceptual domains and 5.34 cognitive domains.
- The 59 regions active in both perception and action tasks were also active in an average of 5.53 (SD 0.80) other domains,
- and the 7 regions not active in both perception and action tasks were active in an average of 3.00 (SD 1.41) of the cognitive domains.
- Only one region was active in only cognitive tasks, and that region was active only in memory.

Anderson, M. L. (2010). Neural reuse: A fundamental organizational principle of the brain. *Behavioral and Brain Sciences,* 33:245-266.

case study #4: an exercise in machine learning — learning to play Atari (V. Mnih et al.)

- games demanding more temporally extended planning strategies still constitute a major challenge for all existing agents [...] (for example, Montezuma's Revenge).

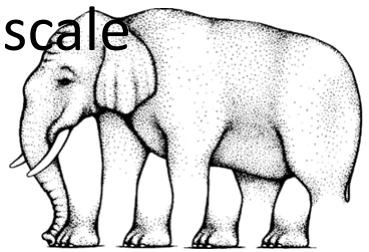


Mnih, V., et al. (2015). Human-level control through deep reinforcement learning. *Nature,* 518:529-533.

Summary:

- Four case studies — four approaches to understanding the brain, and their limitations:

  - An ambitious broad-scope "computational" theory (ACT-R): based on a single top-down assumption about the solution/mechanism — not about any of the problems that arise.
  - A single-cell electrophysiology study (microstimulation): neat, but leaves most questions unresolved.
  - An imaging study (fMRI): trying to pinpoint where in the brain particular operations happen is not only not informative; localization of function is a fool's hope, even if we're confident about what the function is.
  - Throwing machine learning at problems (Deep Learning etc.): even if the hack succeeds, it doesn't reveal much about how the brain works, or how to scale apps up.



Aim of the Course

- * What are the representations and computations that the brain/mind performs and
- ** how do they compare with AI solutions?
- *** What is the gap? Is there an opportunity?
- Course Goals:
  - Emphasis on understanding the current status on * (Lectures)
  - Open exploration and Reflection on ** and *** and debates thereof (Presentations, Project)
  - Give hands-on experience in addressing these questions on real brain data

Course Outline

- Sensation-Perception
- Vision
- Language and Speech
- Motor Systems
- Other topics:
  - Learning & Memory, Attention, Decision Making, Emotions, Consciousness
  - Compositionality, Causality, Learning-to-learn (Meta Learning)
  - Structure-to-Function, Development and Ageing
  - Representational Similarity Analysis (RSA)
  - Predictive Coding and Bayesian Brain

Course Logistics

- Assignments (6): 25%
  - ~3 using NILearn
  - ~3 on Brain Encoding and Decoding
- Presentations: 10% (Presentation + Summary Report)
  - 2 Presentations per class (starting from 18th Jan 2022)
  - 15 mins each presentation.
  - Groups of 2 per presentation.
- Project: (30%)
  - Groups of 3 per project
- Quizzes (2x10): 20%
- Mid-Sem: 15%

Cognitive Science and AI

Perception: Representation Spaces

Presentation from: Shimon Edelman, Computing the Mind, 2008 (Chapter 5: Perception)

Perception

- The phenomenal contents of perception — defy conceptualization – ineffable!
- To understand perception (as well as its relation to memory) we must, therefore, understand what the raw, phenomenal, pre-conceptual feel of sensing the world consists of, and how the sensory stimulation gets computed into that feel.

Ch 5: Perception: Shimon Edelman, Computing the Mind, 2008

Measurements and representation spaces

Perception is in the service of behaviour involves the brain performing many measurements on the outside world.

Think of this is as intelligence-gathering for the sake of the command-and-control processes that reside in the War Room.

No generals, though!
(British Cabinet War Room (WWII)

The War Room fight, from Stanley Kubrik's film `Dr. Strangelove'

Perceptual measurements and representations

- Perception in the service of behaviour involves the brain performing many measurements on the outside world:
- The measurements are structured in space and time, and they carry information about the space-time structure of the world.
  - Example: The use of Inter-aural time difference (ITD) in sound localization in Barn Owls (last lecture!)
  - Another one is shown in the next slide and also later.

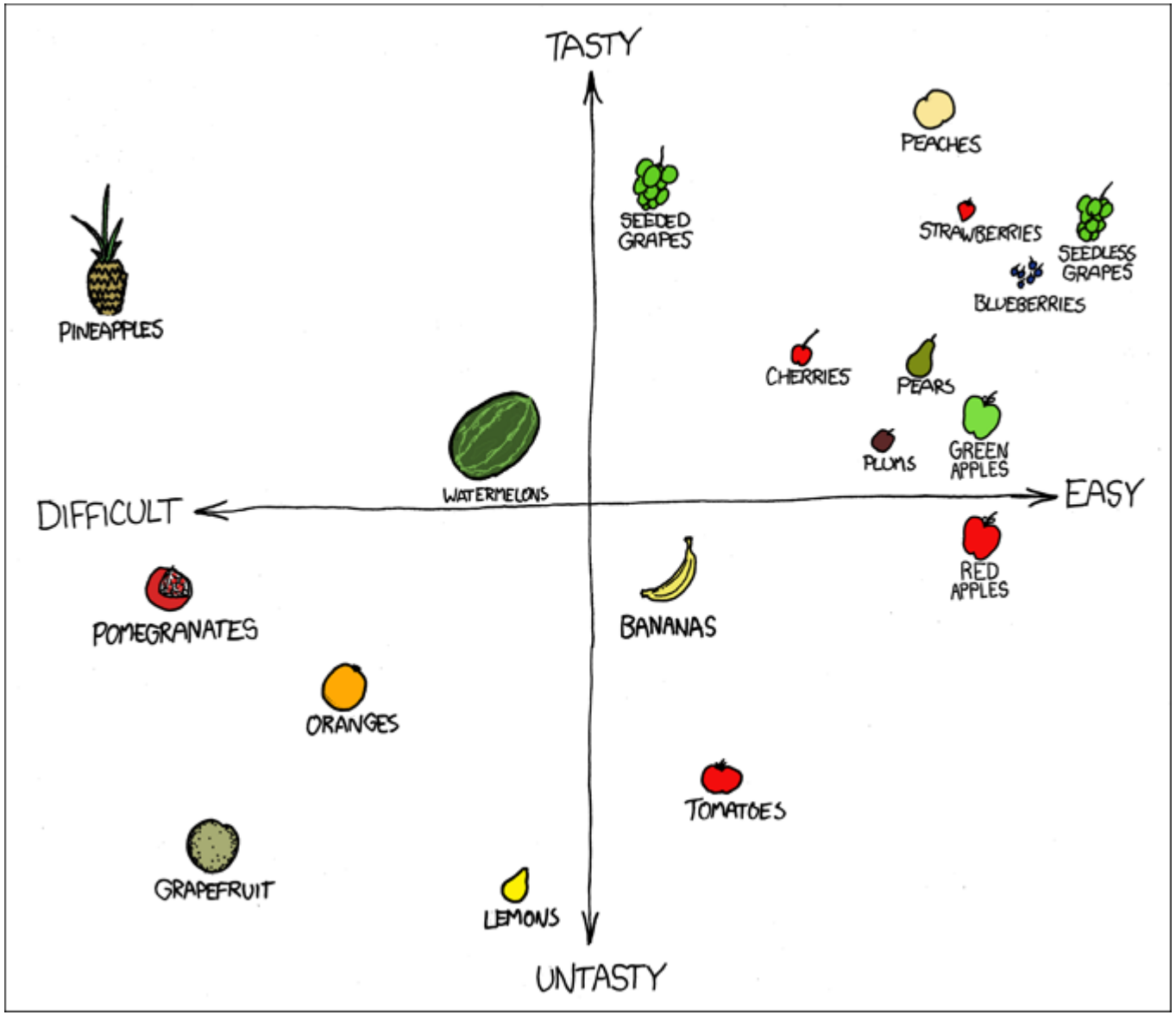
- The resulting representation spaces are also structured.

How many dimensions?

- Dimensionality of representation space

= # of measurements per point

- The measurements populate a representation space.
  - It's a topological SPACE (not merely a set) because intermediate points in it make sense too (like morphing).
  - Example: the "fruit space" has 2 dimensions – represented as 2 numbers per point.
  - Each point represents a single kind of item (apples, bananas, etc.).



How many measurements?

- Consider a skier skiing down a hill...

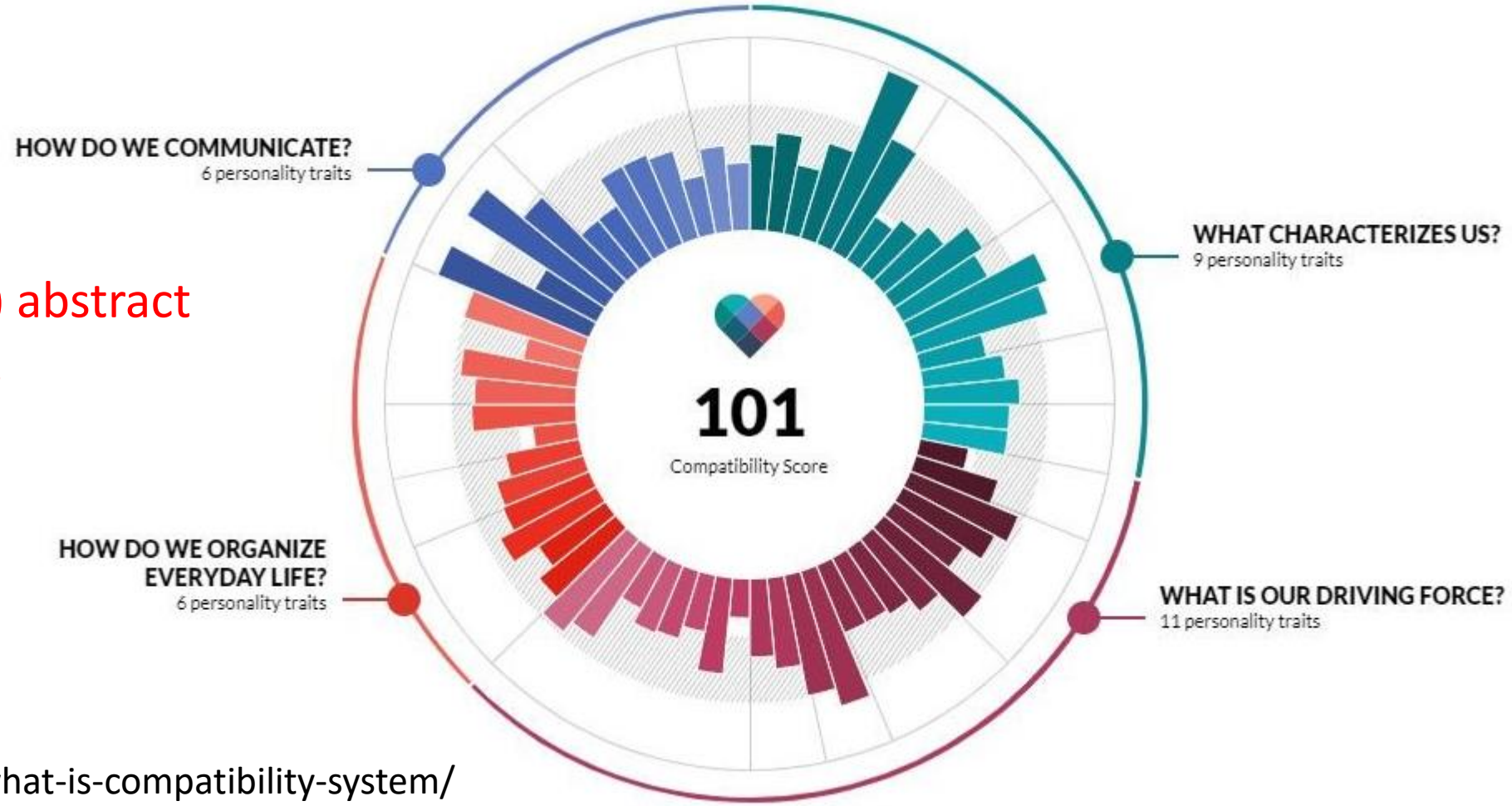
- To represent this process, one must represent a function that maps
  - Time [the domain of the function].
- to
  - the state of the skier [the range of the function].

- How many dimensions does this function's range possess?

[an abstract representation space]

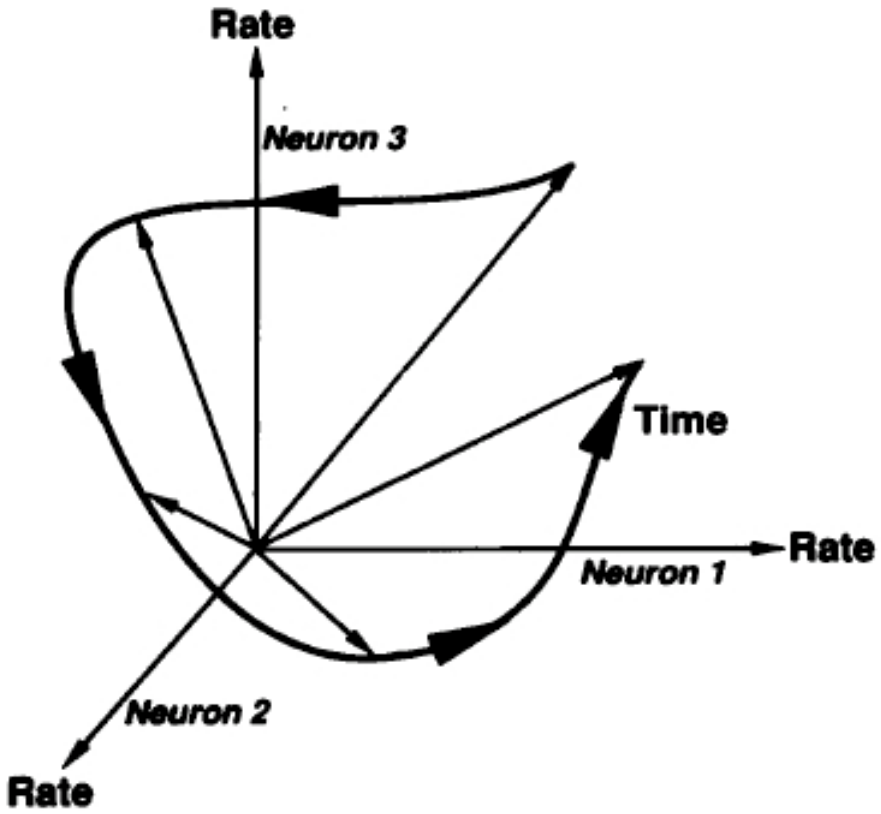
- *eharmony* member completes the Compatibility Quiz. This is a series of 70 questions that takes a deep dive into your personality, values and what's important to you in a relationship.

High dimensional (32) abstract representation space!



https://www.eharmony.com/tour/what-is-compatibility-system/

the state space of a 3-neuron brain



The trajectory — state plotted against time — of a three-neuron dynamical system through the space of its possible states.

Nominal and Effective dimensionality

- How many dimensions are there in the data that the eye sends to the brain?

- About 1,000,000!

- Luckily, throughout cognition,

  EFFECTIVE dimensionality << NOMINAL dimensionality

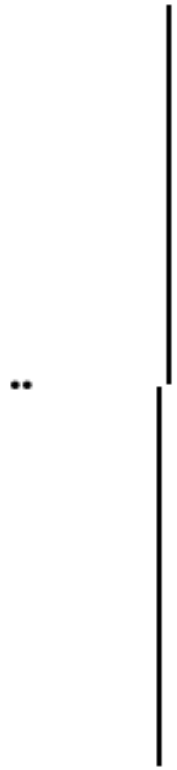
Importance of spatially structured measurements

- Dimensionality is about the number of measurements!
- Importance of spatially structured measurements: a visual task that illustrates this is acuity
- The spatial structure of the measurements is very important (as is their temporal structure).

  - Two spatial resolution tasks, illustrating two-dot and vernier acuity tasks —

    - The perception threshold for the two-dot task: about 30" (seconds of arc).

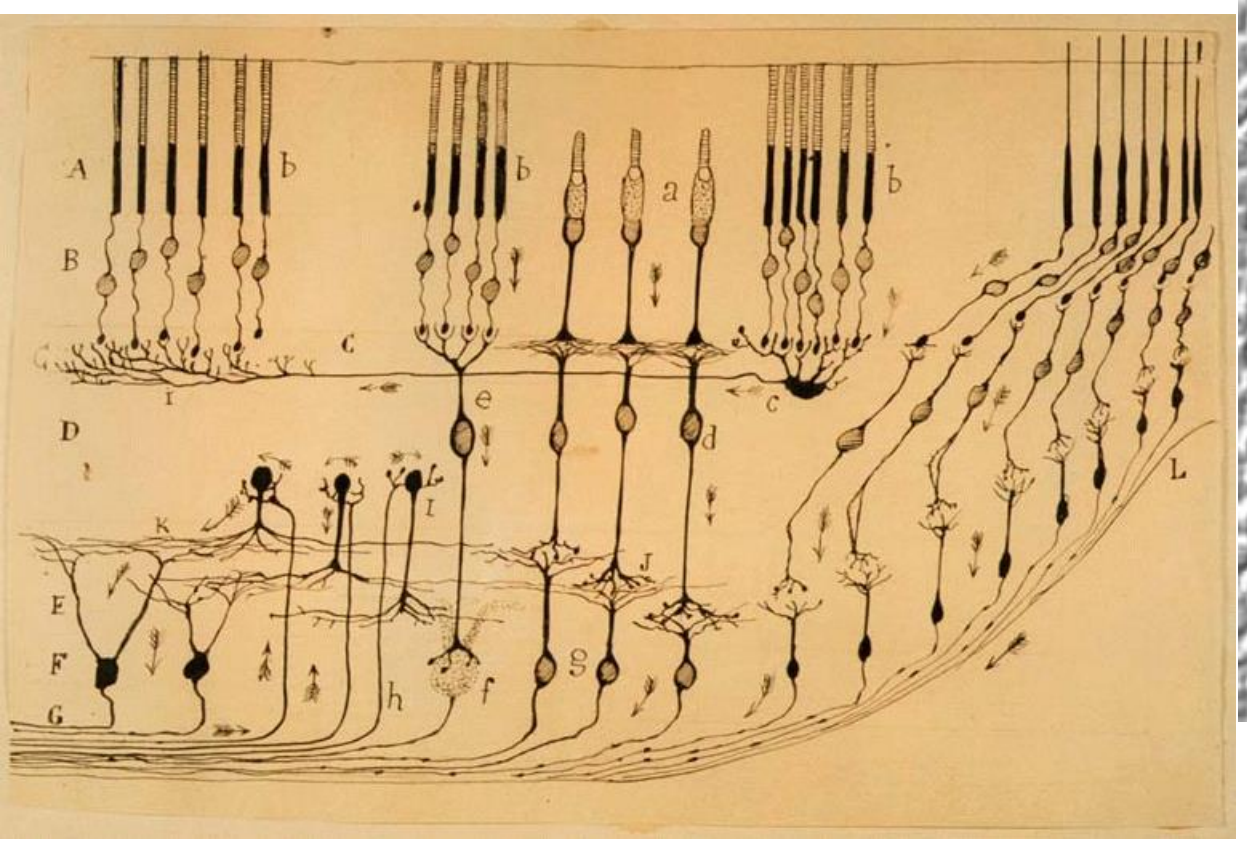
    - The perception threshold for the vernier task: can be as low as 5"!

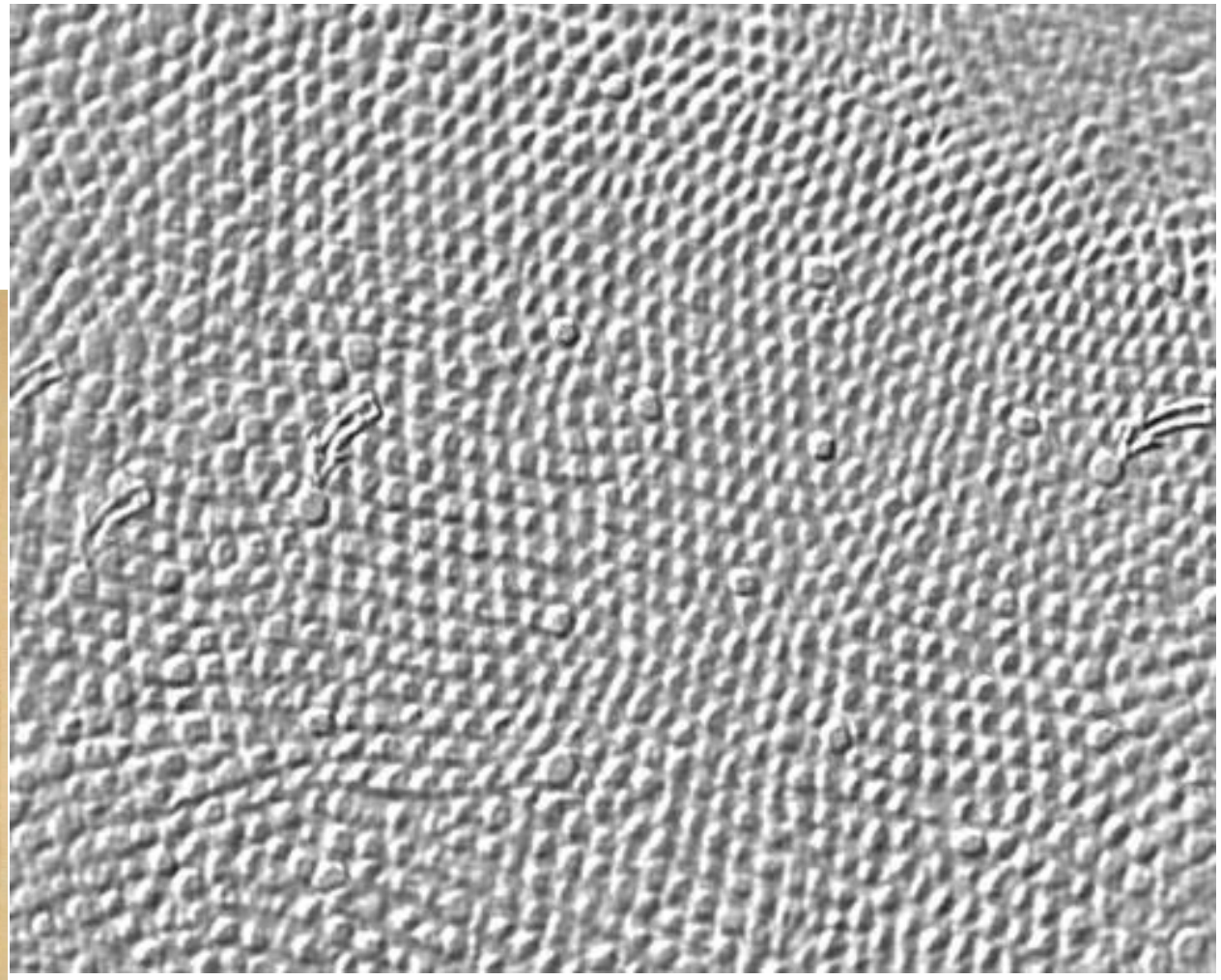


the measurement device

A magnified image of the retinal mosaic

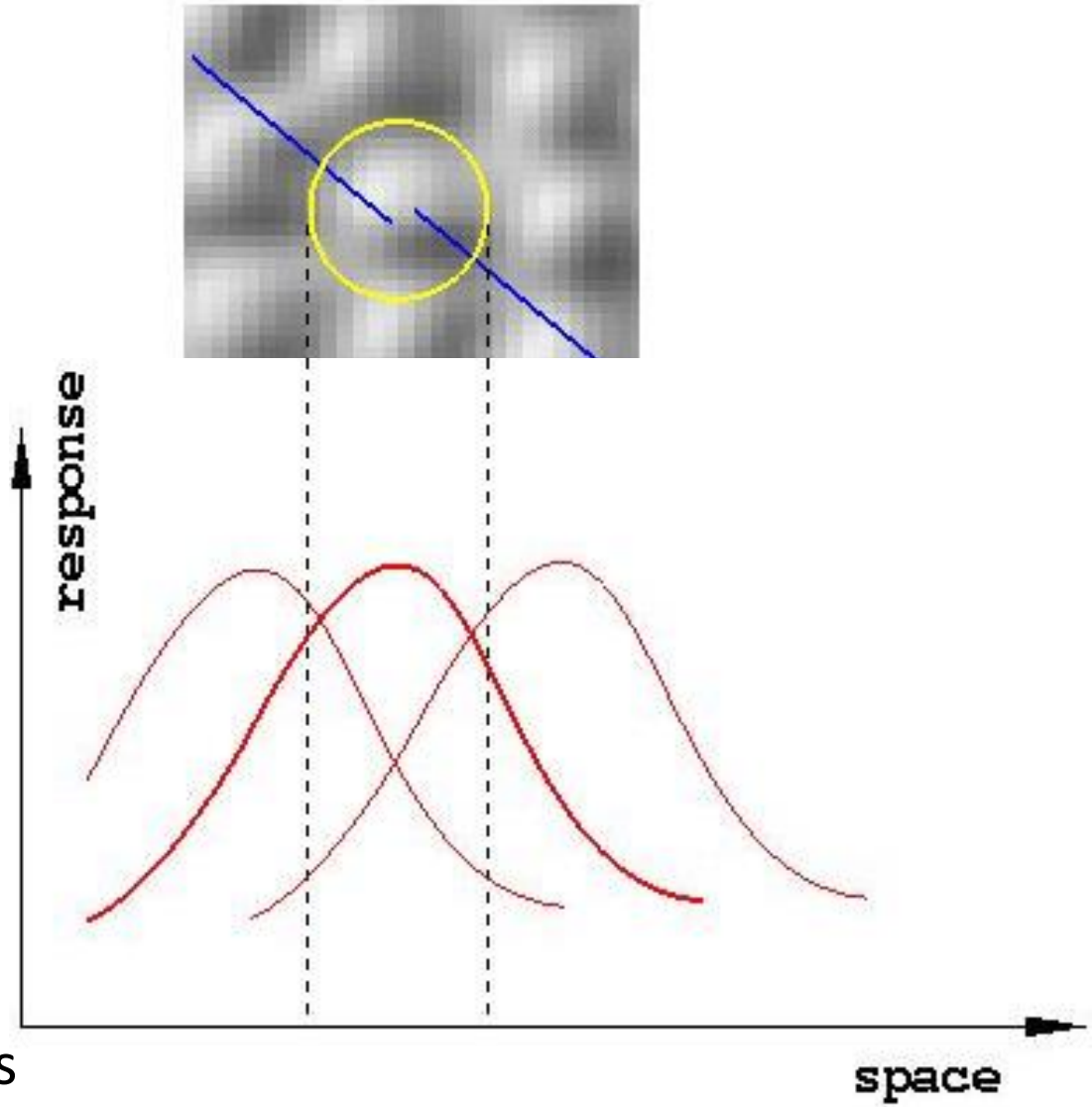
This is the fovea, hence no rods — only cones.





Hyperacuity

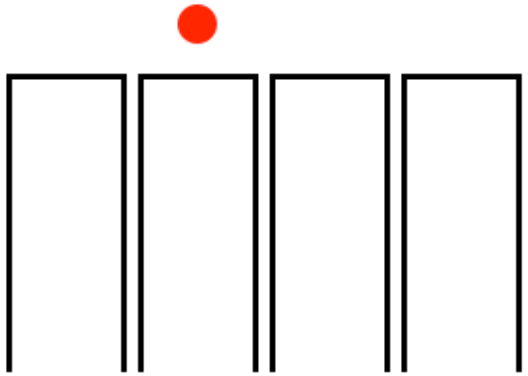
- The smallest discernible vernier, as it projects onto the retinal mosaic —
- Note that the vernier displacement is much smaller than photoreceptor size.
- This is an example of hyperacuity-level performance.
- This receptive field (RF) coding isn't very good
  - This measurement device is too **insensitive**: two close-by dots will likely fall under the same RF and their locations will be perceived as the same.



A cross-section of the receptive fields of three adjacent receptors.

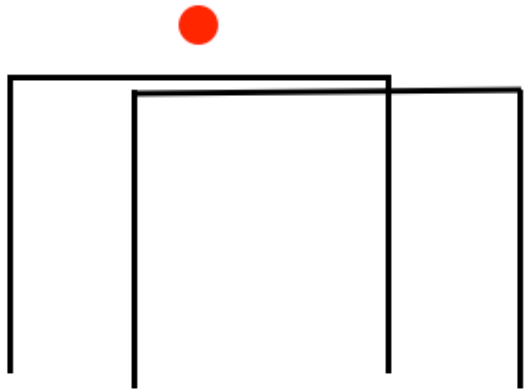
High-Resolution Coding?

- "high-resolution" coding isn't very good either
  - This measurement device is also suboptimal: dot locations get "digitized", but some information is still lost.



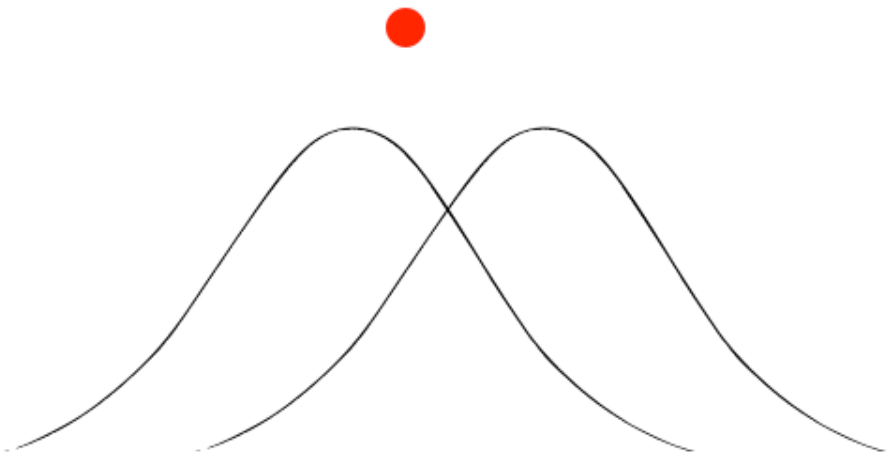
overlapping coding is better

- overlapping "tabletop" coding is better, why?

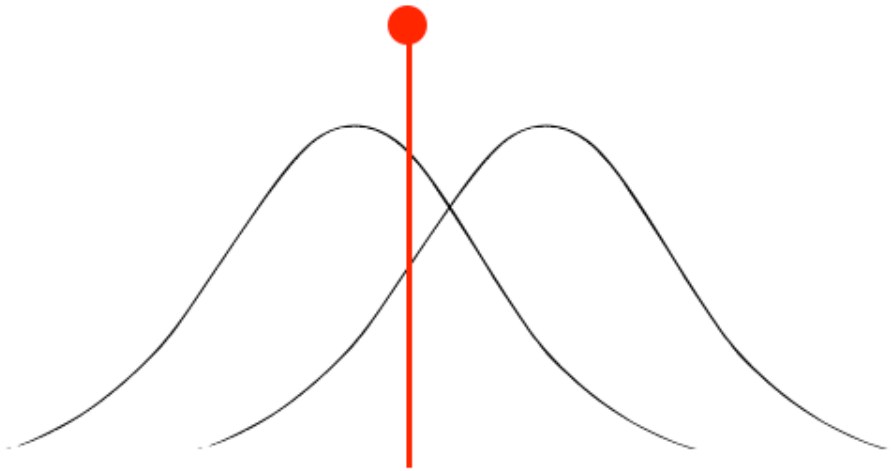


overlapping graded coding is better

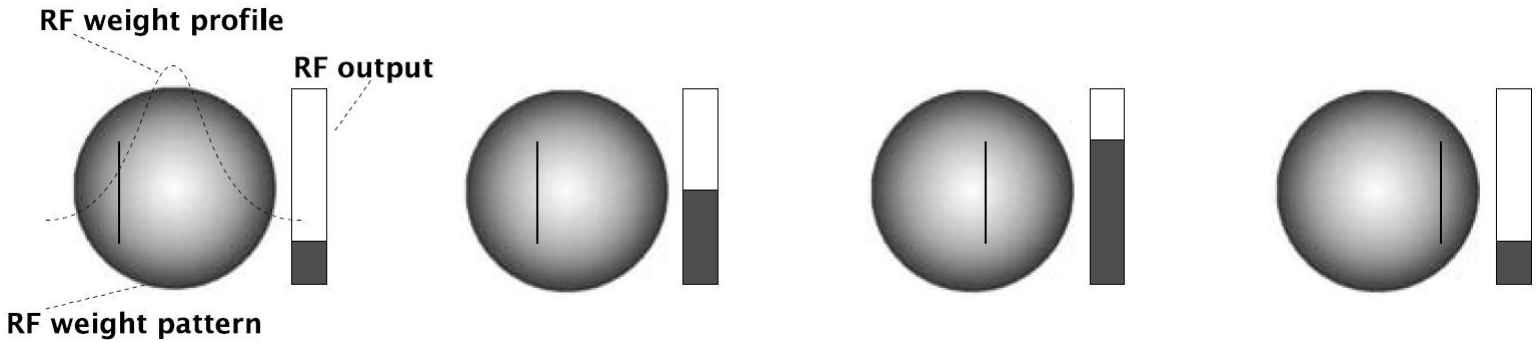
- overlapping, graded RF coding is even better, why?



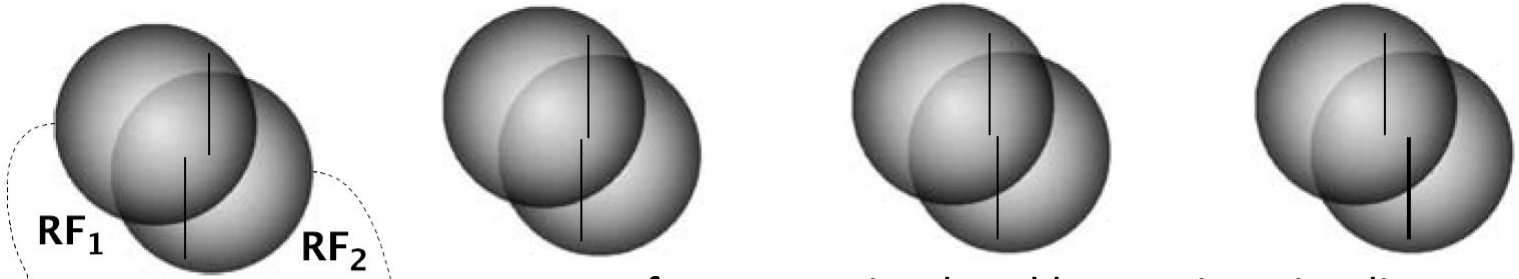
- Even small lateral displacements of the dot will not go unnoticed:
  - they get transduced into measurable changes in the outputs of the RFs.



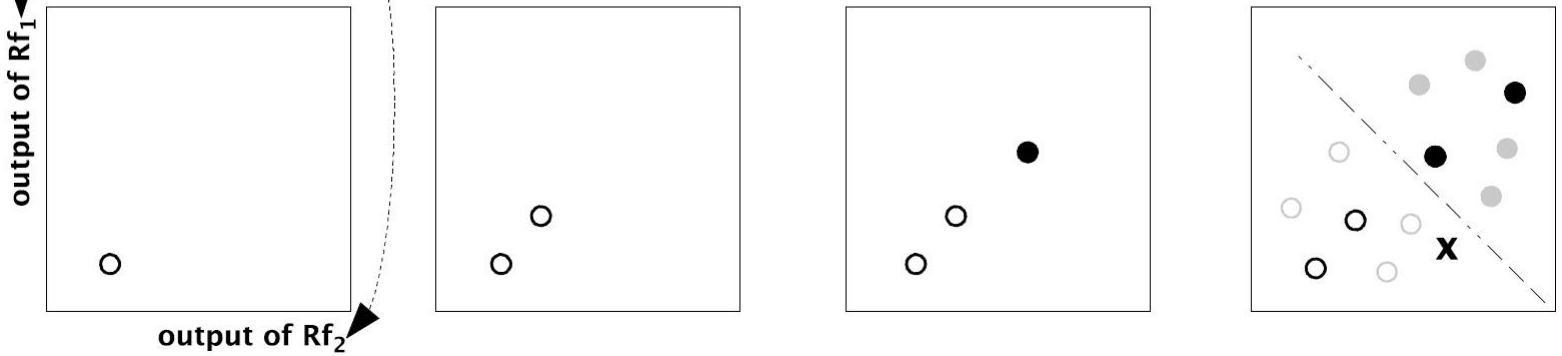
Computational Basis of Hyperacuity



Responses of a single receptive field (RF) stimulated with a vertical line



A system of two RFs stimulated by vernier stimuli



the activation states evoked by these stimuli. Open and filled circles represent sign flipping

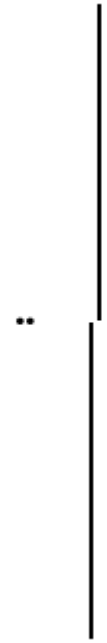
Poggio et al. (1992)

Broad, overlapping, graded receptive fields effective

Summary:

hyperacuity-level performance is possible because

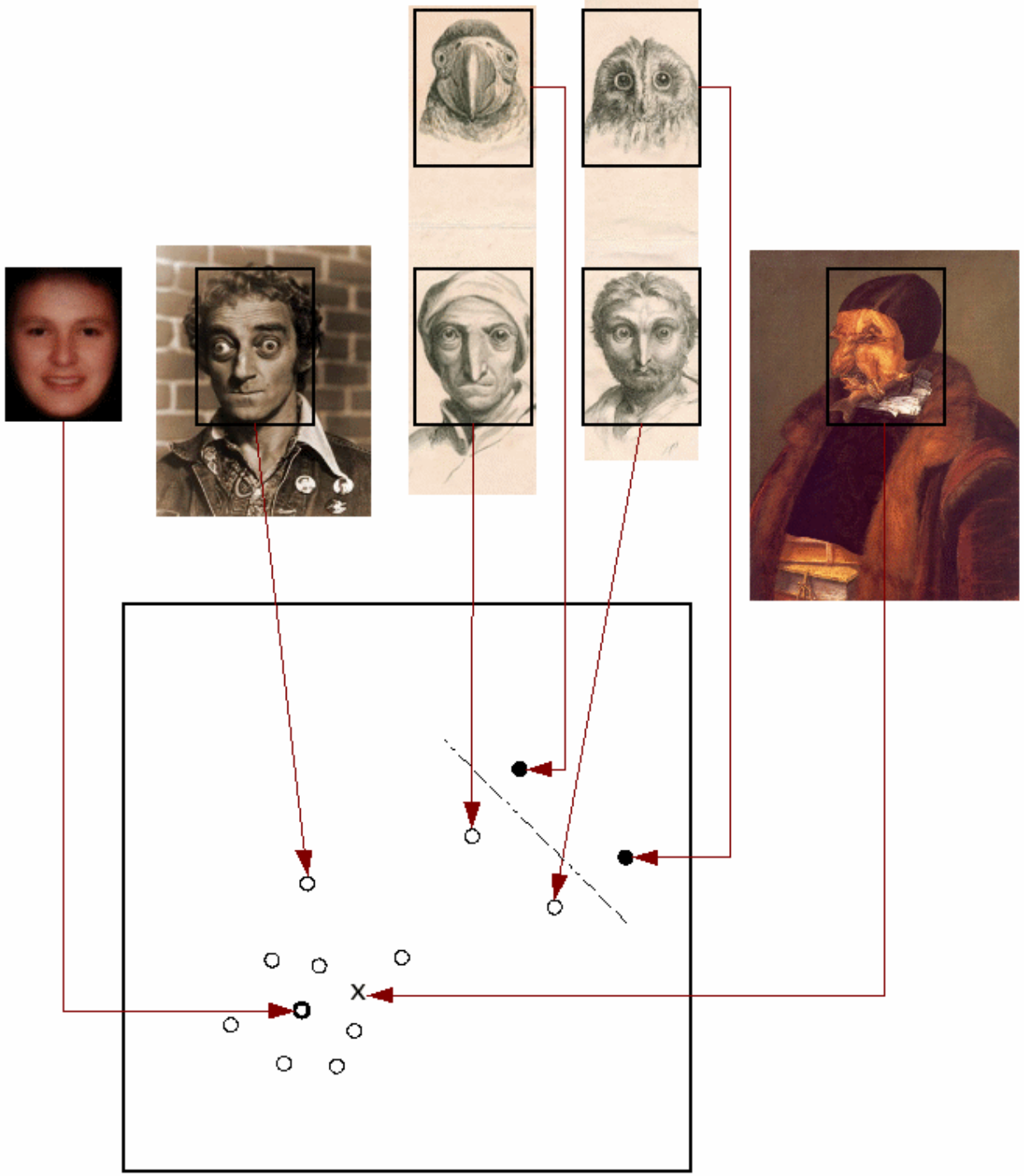
- the RFs are graded, and
- the RFs are broad and overlapping in space.



- Why is the performance for the vernier (two-line) stimulus is so much better than for the two-dot stimulus?

The structure of representation spaces

- A schematic diagram of a (high-dimensional) **face space**, illustrating the following concepts:
  - the average face
  - typical faces
  - atypical faces
  - novel faces



Let's Look at:

- Experimental evidence for the representation space being a space
- A powerful tool for studying representation spaces

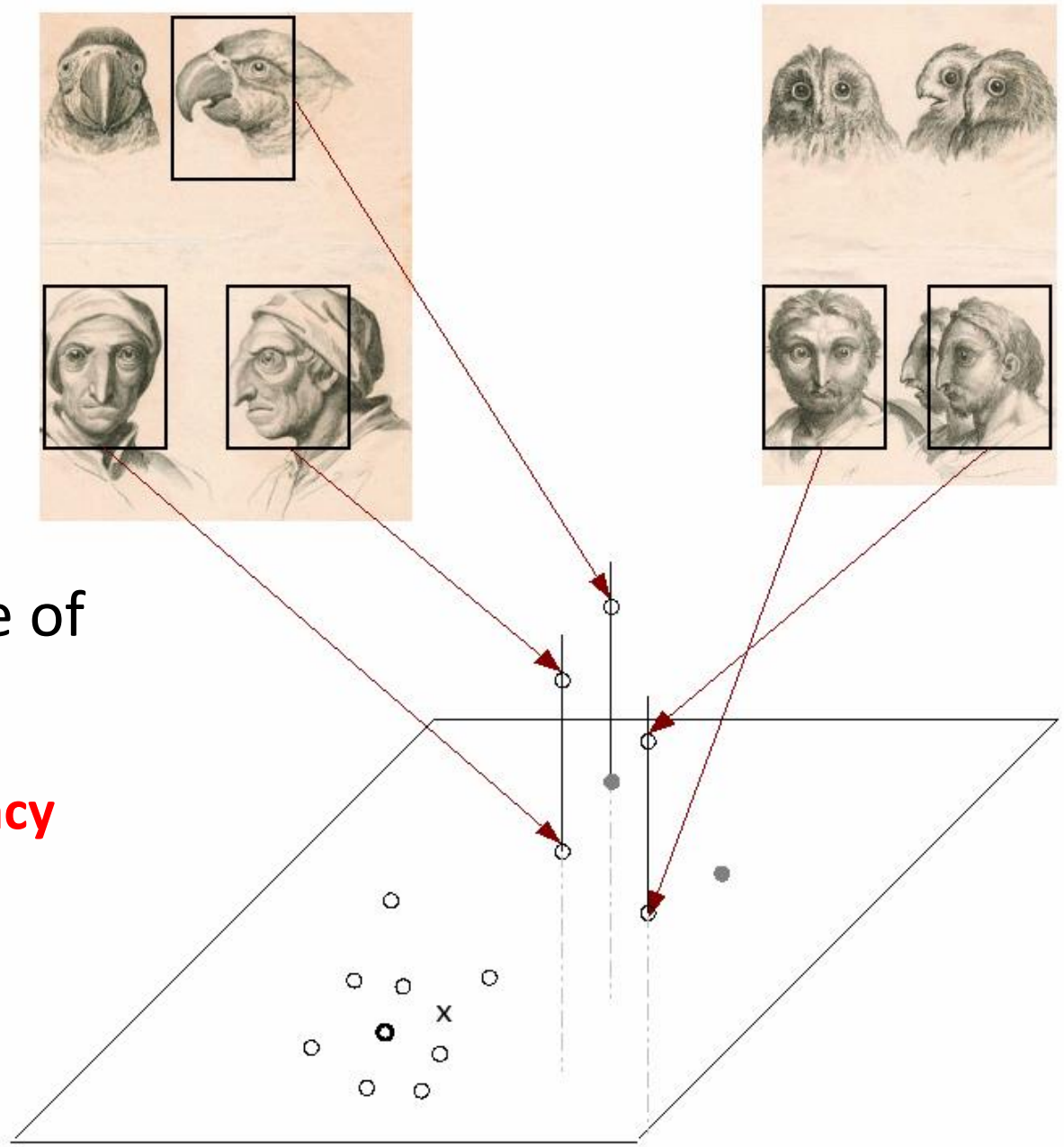
Perceptual Discrimination

FACE SPACE versus VIEW SPACE

In the plane:
the **face [shape] space**.

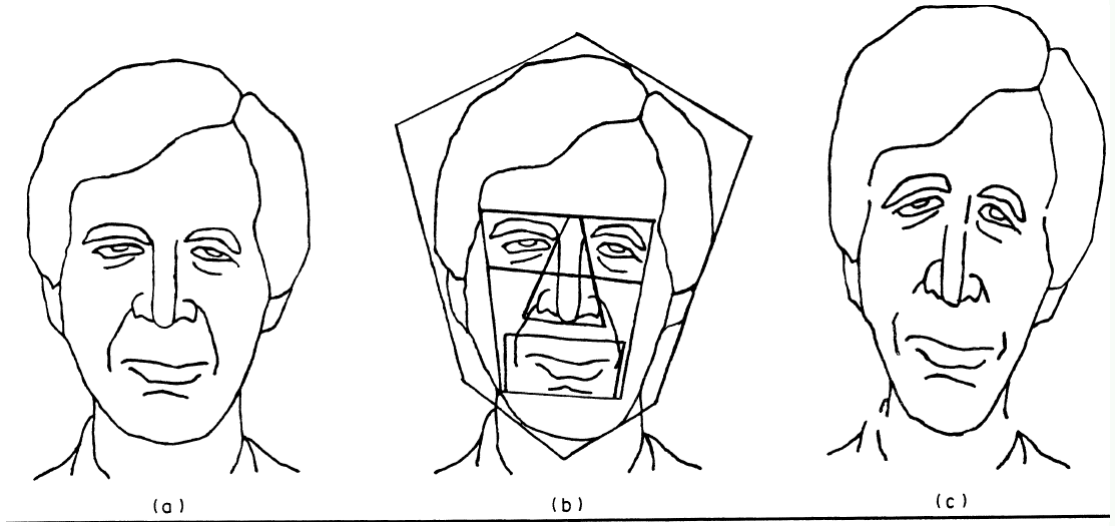
Perpendicular to it:
the **view [orientation] spaces** of some of the faces.

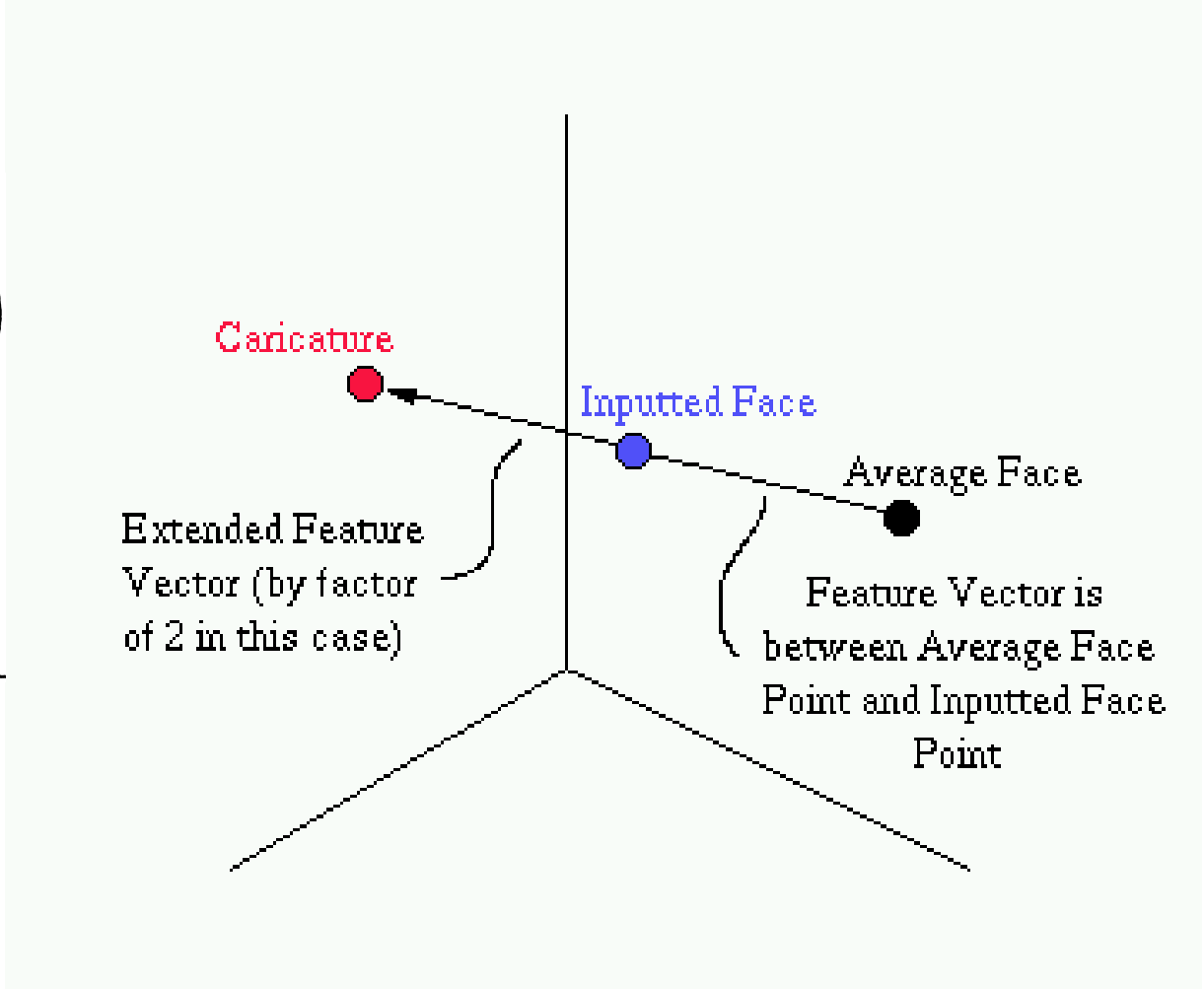
In computational terms, **Perceptual Constancy** corresponds to the ability to distill, out of all the dimensions of measurement performed on a stimulus, the few intrinsic variables of interest – Dimensionality Reduction



caricature as deviation from the mean in the face space

Caricatures and face morphing

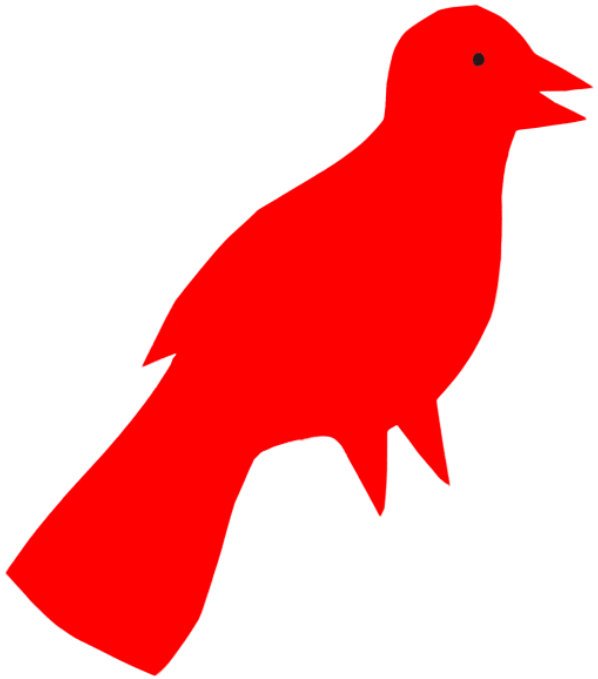




Caricature Generator: The Dynamic Exaggeration of Faces by Computer, Susan E. Brennan, *Leonardo* 18:170-178 (1985)

perceptual adaptation

- A quick demo of visual colour adaptation: Stare at the parrot for at least 30 seconds, then look at the center of the cage. What do you see?



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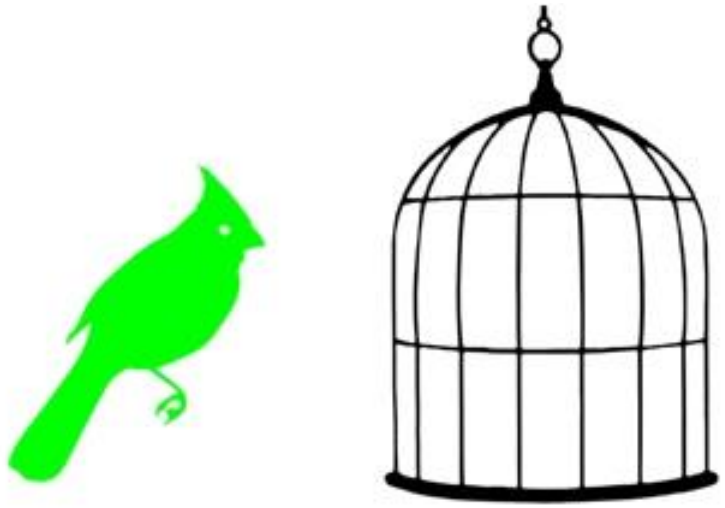
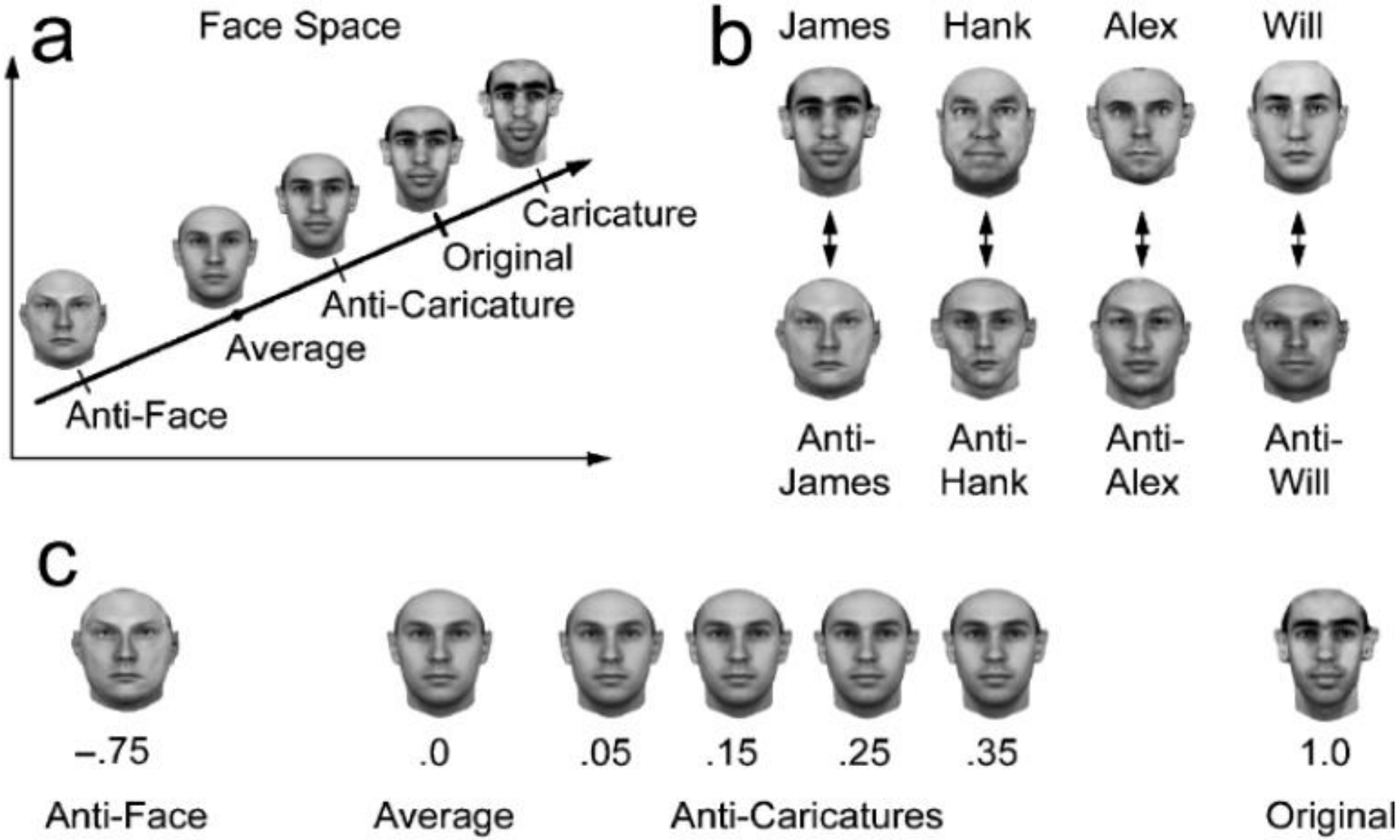


- Adaptation, to which all perceptual modalities are susceptible, reveals an important characteristic of neural coding:
- the brain uses Distributed Representations, so that when some of the units that participate in representing a particular stimulus get fatigued and respond less vigorously, the ones that have not been active "take over" and make the entire representation more like their own preferred features of the stimulus.

Perceptual adaptation reveals a general principle of representation in the brain

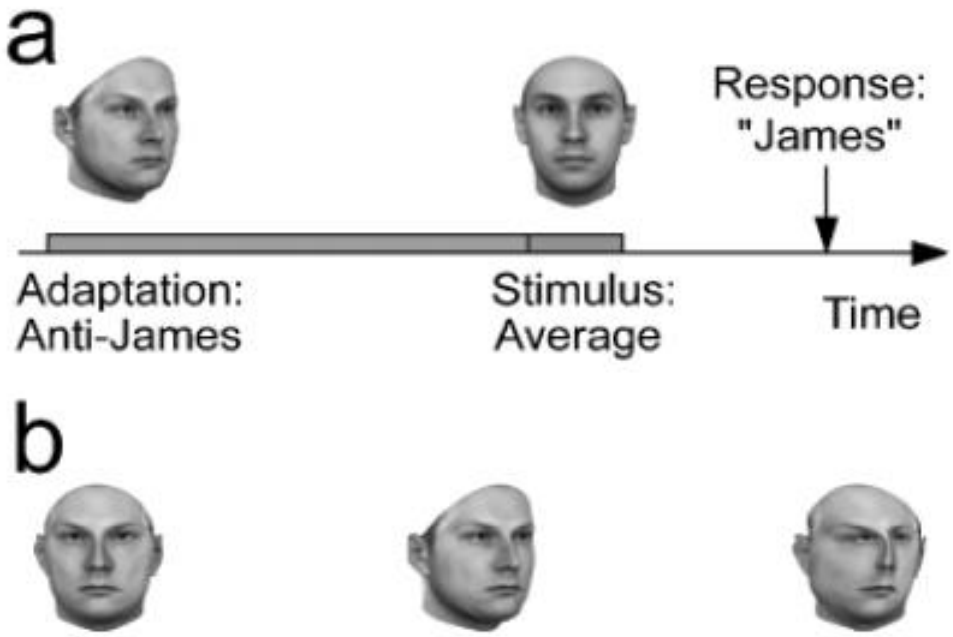
using morphing to study face space in the brain



Jiang, Blanz, and O'Toole (2006)

Experiment: Jiang et al (2006)

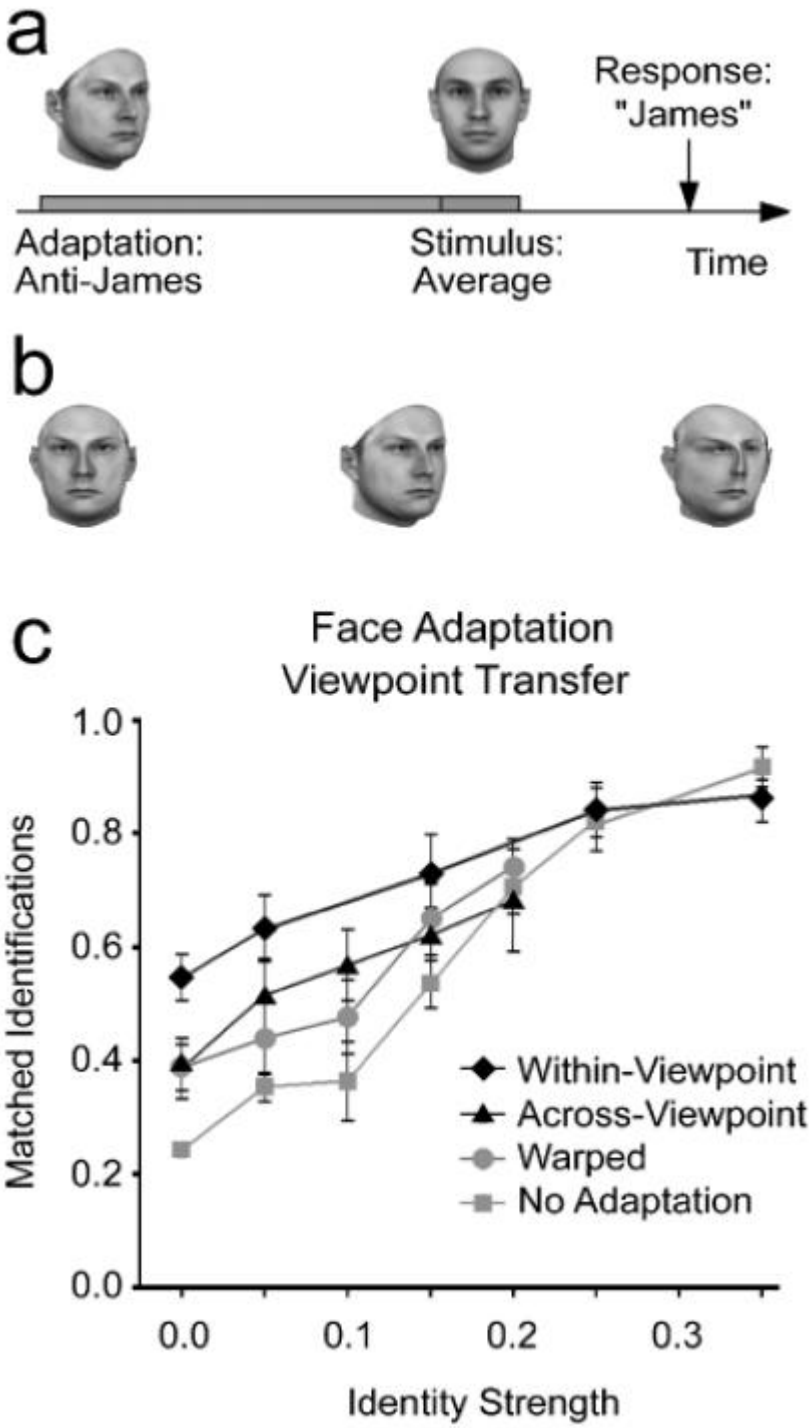
- (a) An example trial: across-viewpoint, neutral condition with 5 sec antiface adaptation.
- (b) Left: an antiface adapting stimulus as presented in the within-viewpoint condition; Middle: the corresponding antiface adapting stimulus in the view-changed condition; Right: the corresponding warped antiface.



Experiment: Jiang et al (2006)

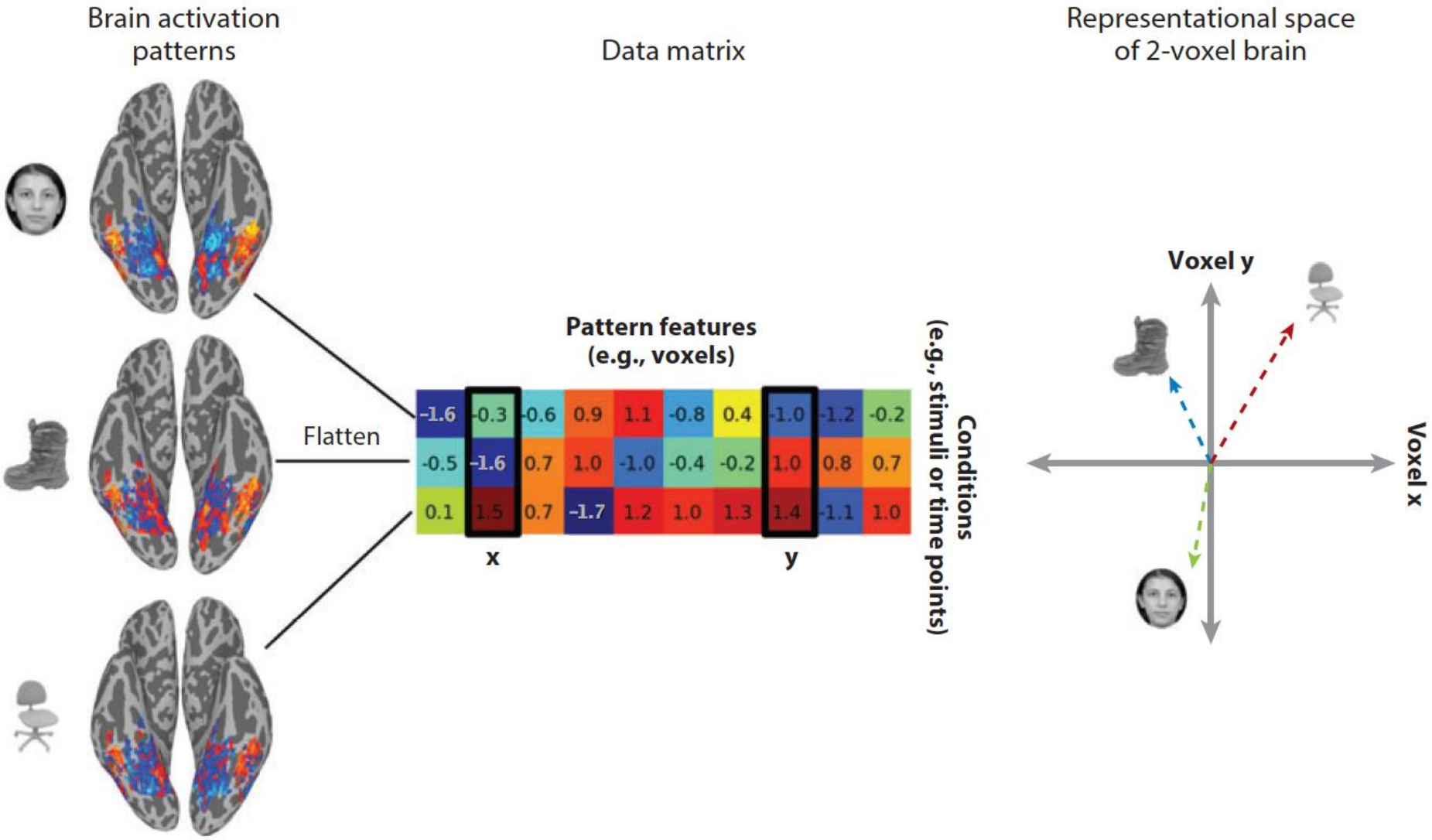
Findings:

- [within-viewpoint] The average face (identity strength = 0) was identified as the match to the antiface adapting stimulus on .55 of the trials, significantly more often than the .25 expected by chance.
- [across-viewpoint] The average face was identified as the match to the adapting stimulus on .39 of the trials, again significantly more often than expected by chance.
- Bottom line: the face space is not just a fanciful abstraction — subjects maintain representations of the face space and use those in processing face stimuli.



mapping representation spaces

- How can we visualize the face space as it is represented by the subject, from
- behavioral dat
- neural activity



mapping representation spaces

- PROBLEM: Unlike brain scans, behavioral data concerning internal representations do not include the coordinates for each point — only relational information.

- PROBLEM: Brain data typically reside in a high-dimensional space, which cannot be easily visualized (In this example, there are 10 dimensions).

- A particularly useful and theoretically interesting computational technique that can do that is multidimensional scaling (MDS).
- For both behavioral and neural cases, MDS can embed the data (1) faithfully and (2) in a space of much lower dimensionality.

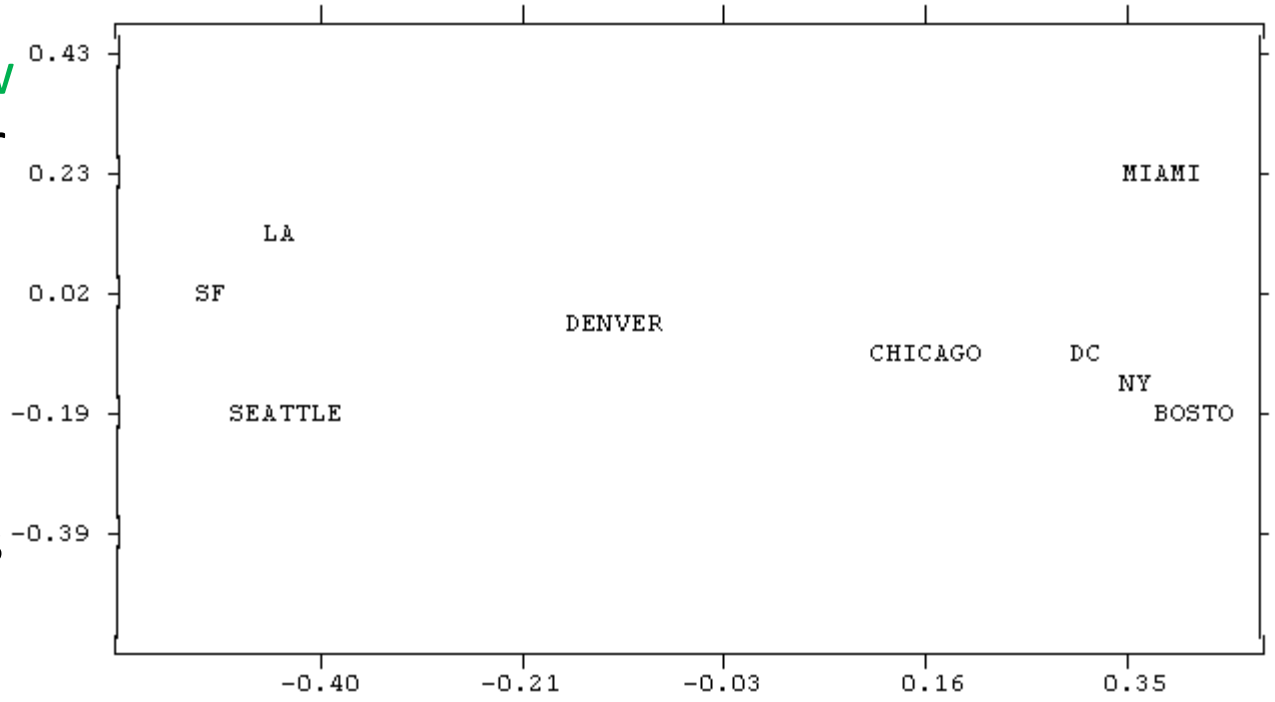
multidimensional scaling (MDS)

- Multidimensional scaling (MDS) is a procedure that takes
- a table of pairwise distances among points (which may come from a very high-dimensional space)

and turns it into

- a map of the points' layout in just a few dimensions (typically, 2 or 3, if used for visualization)
- while preserving the original absolute distances (in another version, original relative distances, or distance ranks) as much as possible.

		1	2	3	4	5	6	7	8	9
		BOST	NY	DC	MIAM	CHIC	SEAT	SF	LA	DENV
1	BOSTON	0	206	429	1504	963	2976	3095	2979	1949
2	NY	206	0	233	1308	802	2815	2934	2786	1771
3	DC	429	233	0	1075	671	2684	2799	2631	1616
4	MIAMI	1504	1308	1075	0	1329	3273	3053	2687	2037
5	CHICAGO	963	802	671	1329	0	2013	2142	2054	996
6	SEATTLE	2976	2815	2684	3273	2013	0	808	1131	1307
7	SF	3095	2934	2799	3053	2142	808	0	379	1235
8	LA	2979	2786	2631	2687	2054	1131	379	0	1059
9	DENVER	1949	1771	1616	2037	996	1307	1235	1059	0



two complementary conceptions of MDS

The conceptual underpinnings of MDS serve both the scientists who study the brain and the brain itself:

	Neuroscience	Cognition (Brain)
obtaining relational ("2nd-order") insight into a system	The **scientist** needs to know how brain representations are related to each other.	The **brain** needs to know how external objects and events are related to each other.
dimensionality reduction	The **scientist** needs to map the high-dimensional brain activity space into a few meaningful dimensions.	The **brain** needs to map the high-dimensional sensory measurement space into a few meaningful dimensions.

multidimensional scaling (MDS)

- MDS is uniquely suitable for bridging the gap between the brain and the world — in either direction — because it relates configurations of corresponding items in two spaces that are otherwise in principle absolutely unrelated to each other.
- Note that this is not the case for projection-based methods such as Principal Components Analysis or PCA.

- The key idea here is REPRESENTATION OF SIMILARITY.

Cognitive Science and AI

Perception: Learning and Generalization

Presentation from: Shimon Edelman, Computing the Mind, 2008 (Chapter 5: Perception)

perceptual constancies, categories, and generalization

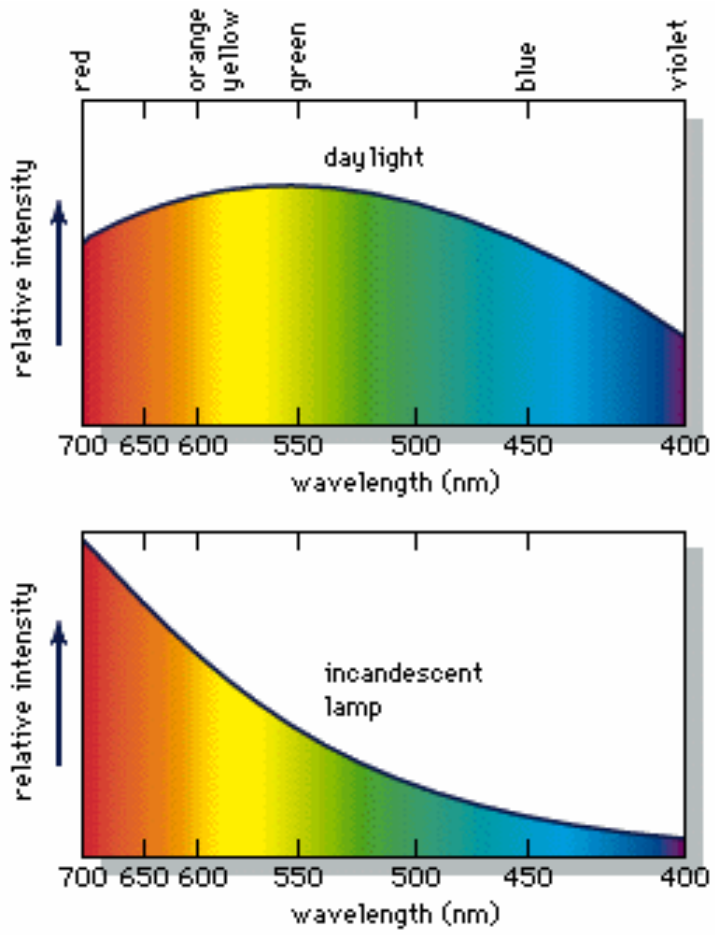
- The problem of dimensionality

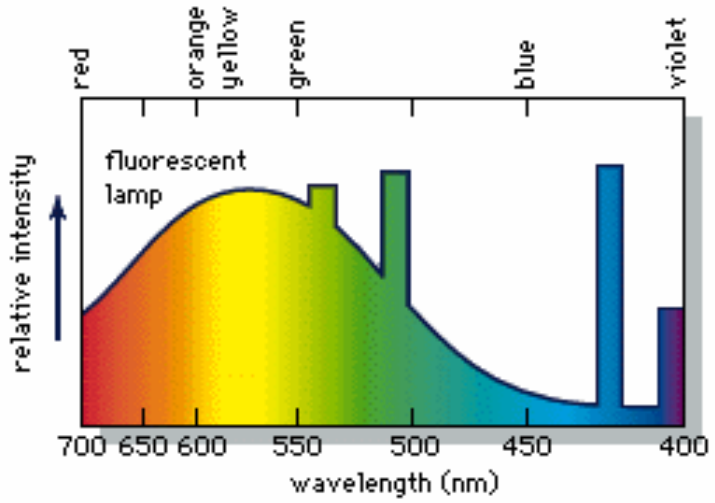
- The problem of indeterminacy

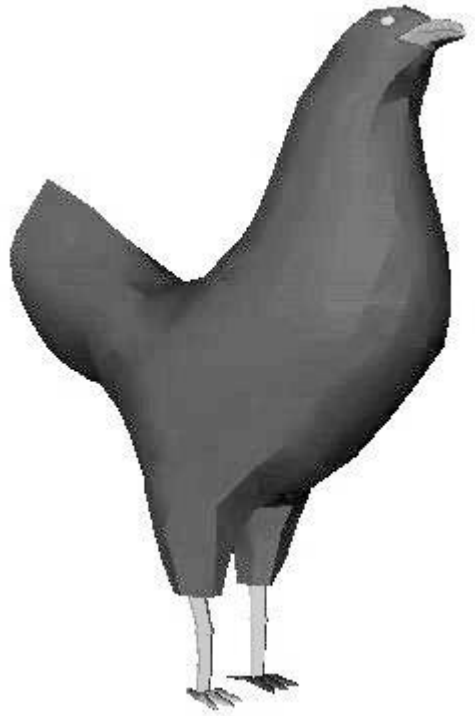
- A common solution:
  - assume the world to be well-behaved,
  - that is, characterized by statistical regularities
  - the technique known as regularization is a mathematical expression of these

Ch 5: Perception: Shimon Edelman, Computing the Mind, 2008

the problem of dimensionality







a multidimensional illumination space

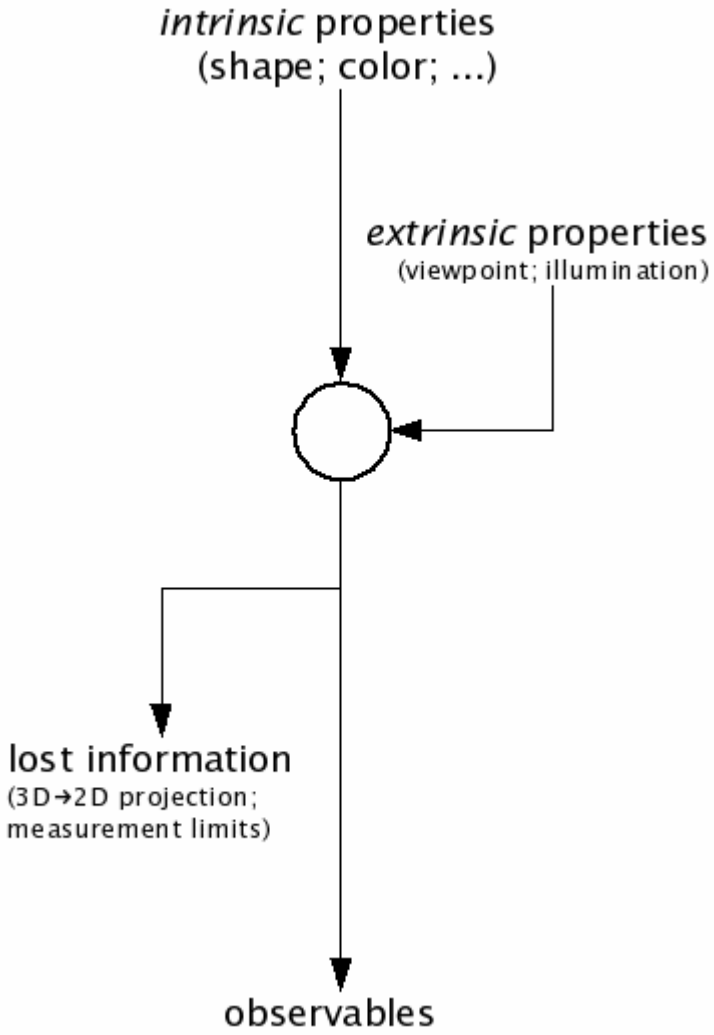
a multidimensional chicken

dimensionality reduction

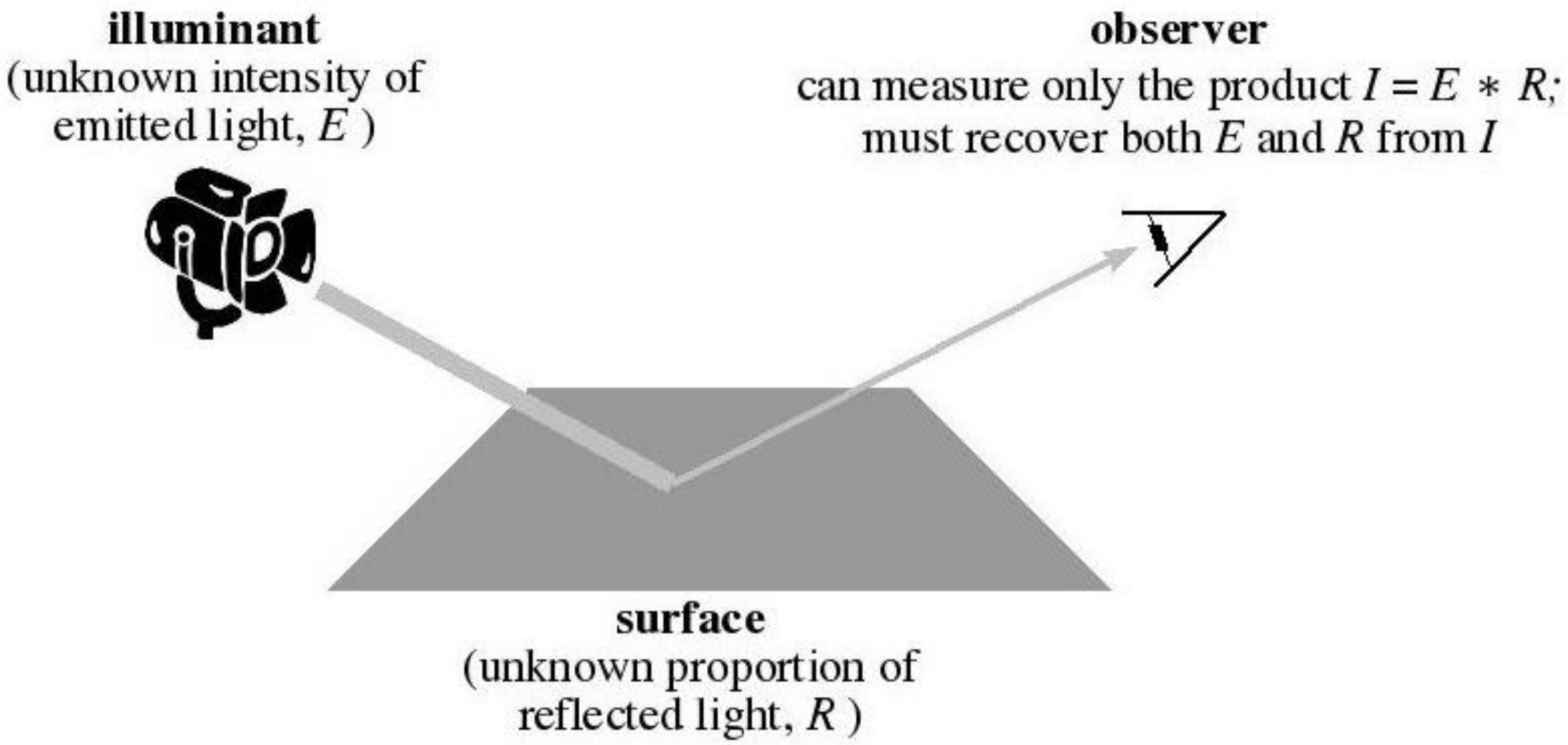
- Solution: assume that the world is statistically well-behaved —
  - a few dimensions suffice to characterize illumination;
  - a few dimensions suffice to distinguish between chickens and ducks, or between horses and donkeys.

causes of indeterminacy

- All perceptual problems share the same computational structure.
  - What is "intrinsic" and what is "extrinsic" depends on the task.



the problem of indeterminacy

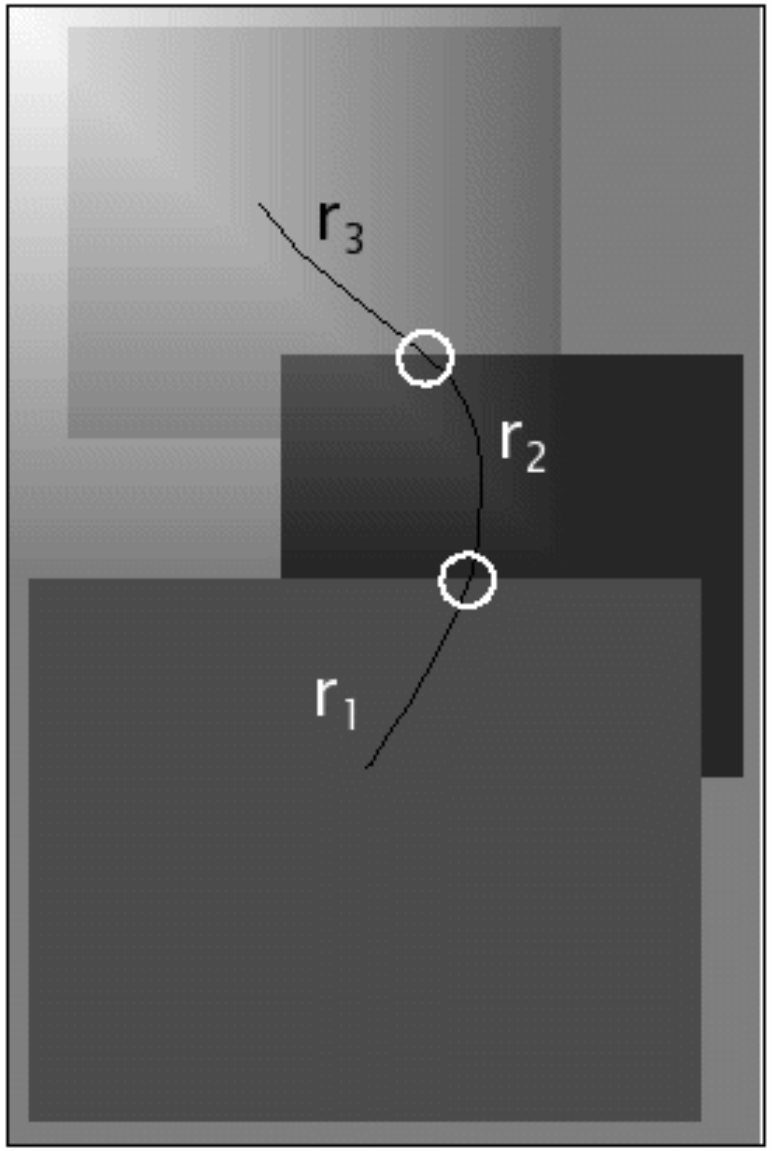


regularization

- Solution: assume that the world is statistically well-behaved —
  - illumination usually varies gradually over the scene;
  - surface lightness (reflectance) is piecewise constant over the scene, with occasional abrupt changes.

regularization

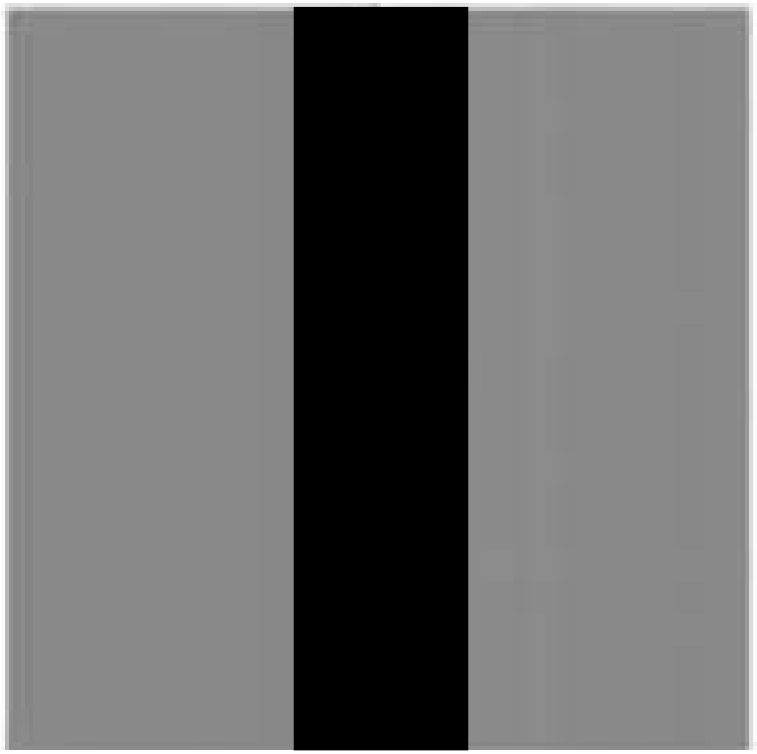
- The following algorithm for recovering lightness:
  - scan the image seeking abrupt jumps in intensity;
  - attribute every such jump to a change in lightness (as opposed to illumination);
  - at the end of this process, calibrate the extreme values ("black" and "white").

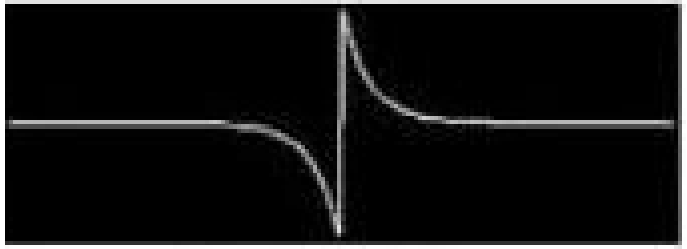


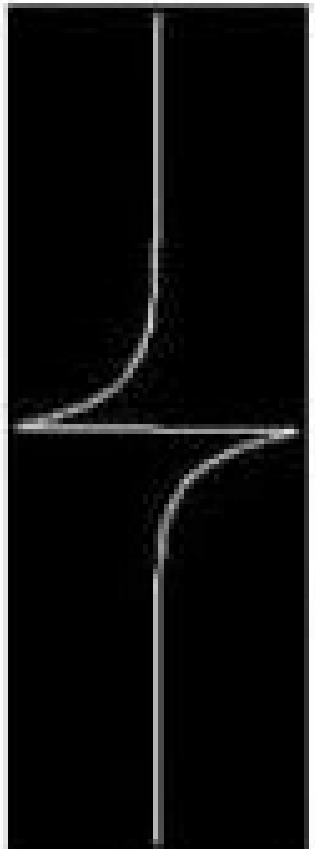
D. H. Brainard and B. A. Wandell (1986). Analysis of the Retinex theory of color vision, JOSA.

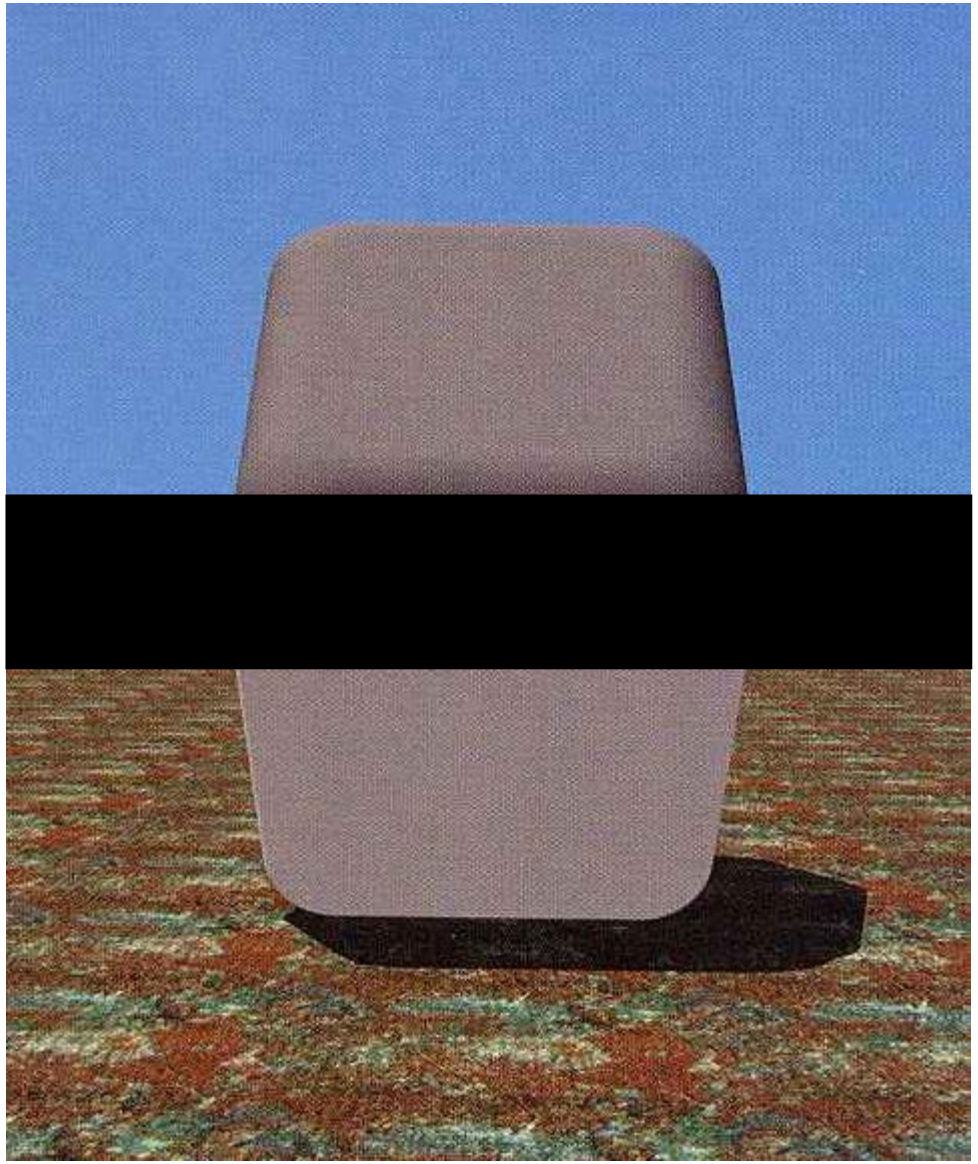
an example of a failure of lightness constancy

- The constancy computation fails when assumptions behind it are violated.

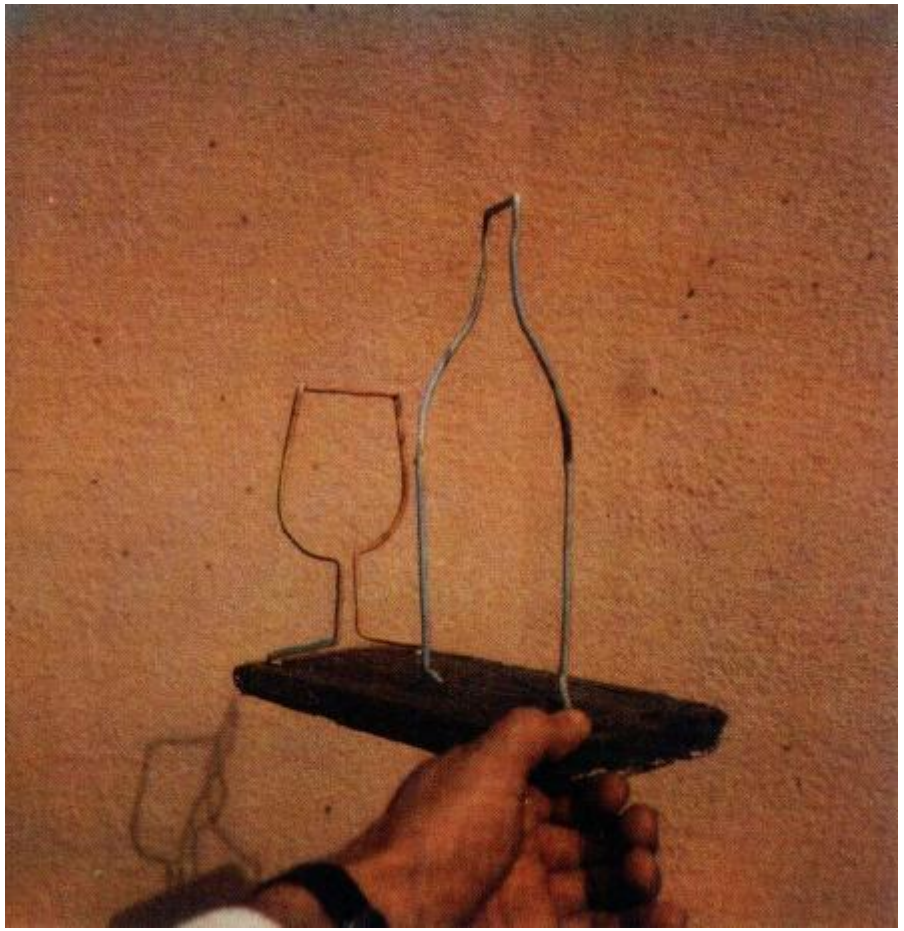








an example of a failure of shape constancy

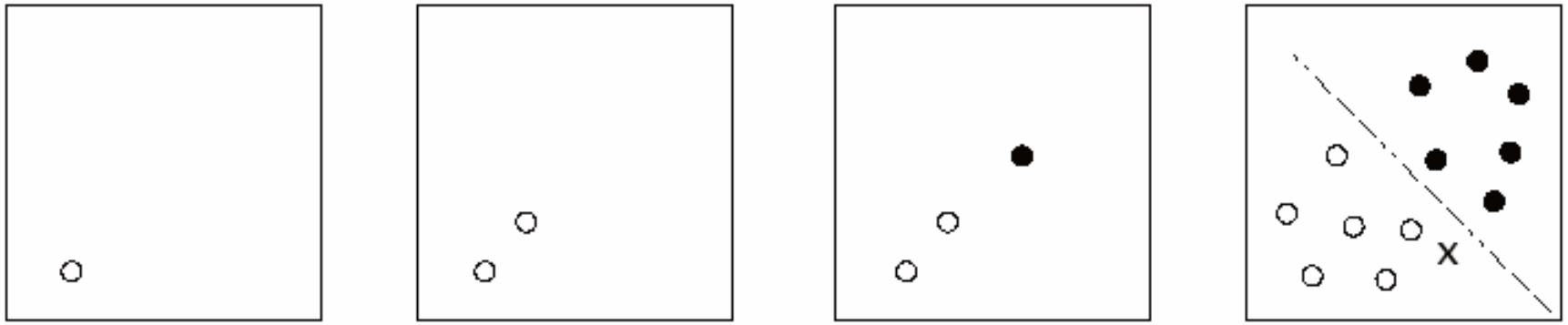


Markus Raetz: Das grosse Glass (1988) & Gross und Klein (1993)

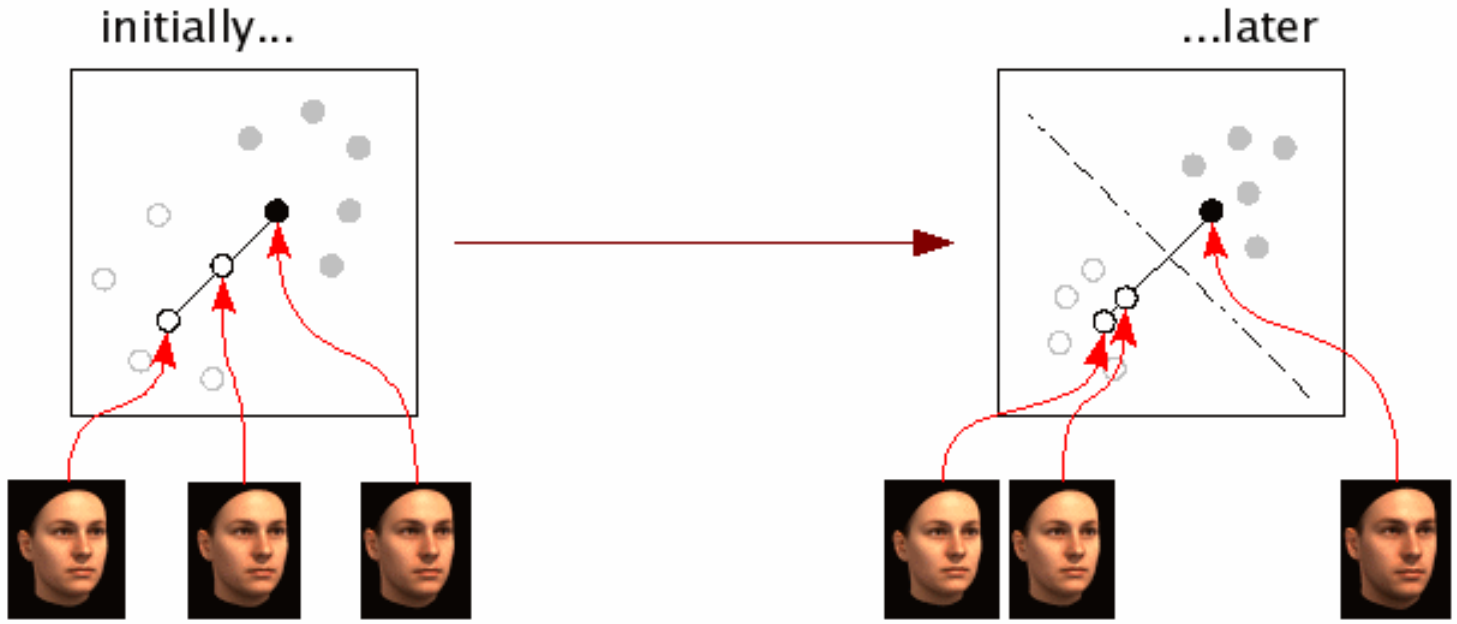
perceptual learning, categories, and generalization

- The emergence of perceptual categories
- Perceptual adaptation (vernier example, earlier)
- Shepard's Universal Law of Generalization

perceptual learning from examples



acquiring the examples and forming a decision boundary in the representation space

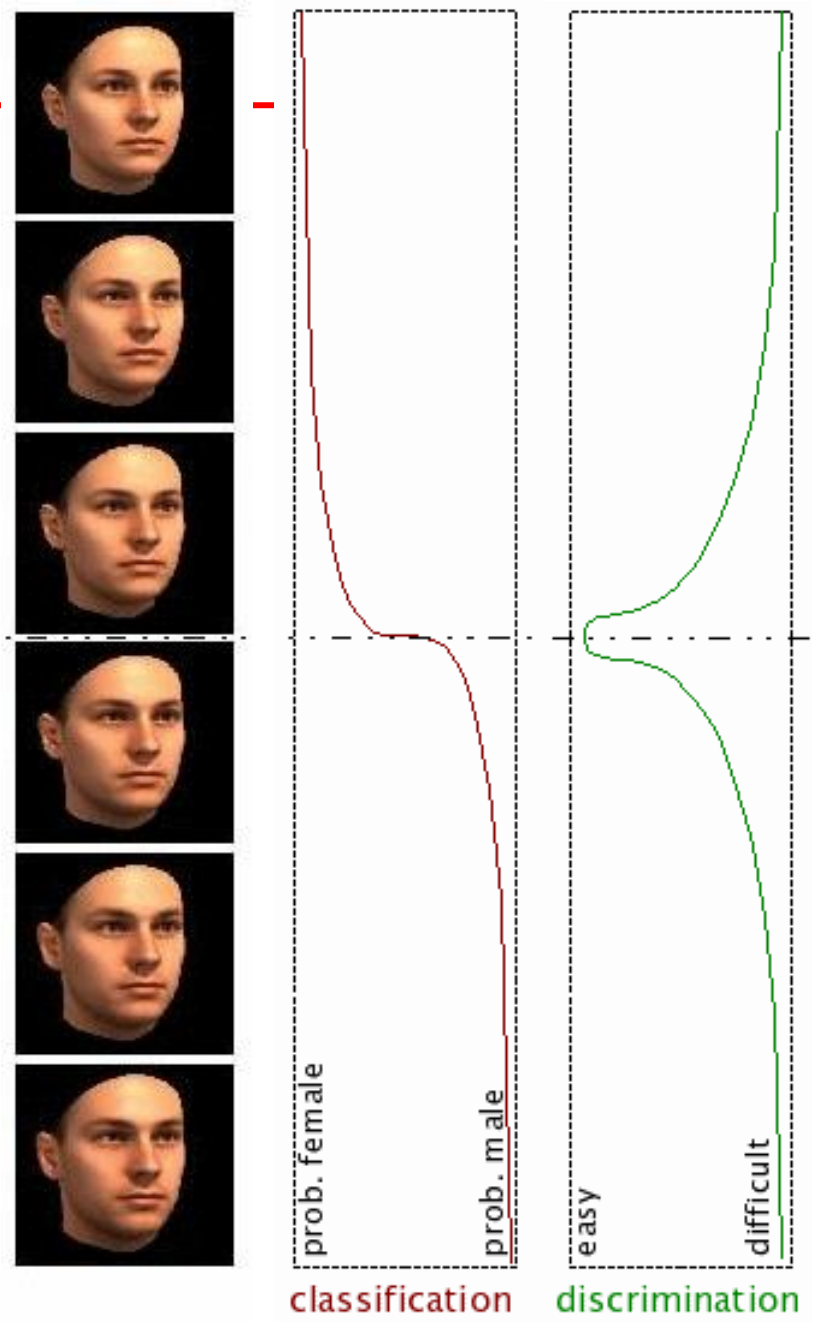


categorical perception through a warping of the representation space

Categorical perception

- A morph sequence of face images, and two revealing signs of categorical perception:
  - (i) sigmoidal response probability in a classification (for a single image, "which category is this?") task.
  - (ii) peaked performance (% correct) in a pairwise discrimination ("are these same or different?") task.

The inflection point of the sigmoid and the peak are both centered on the category boundary.

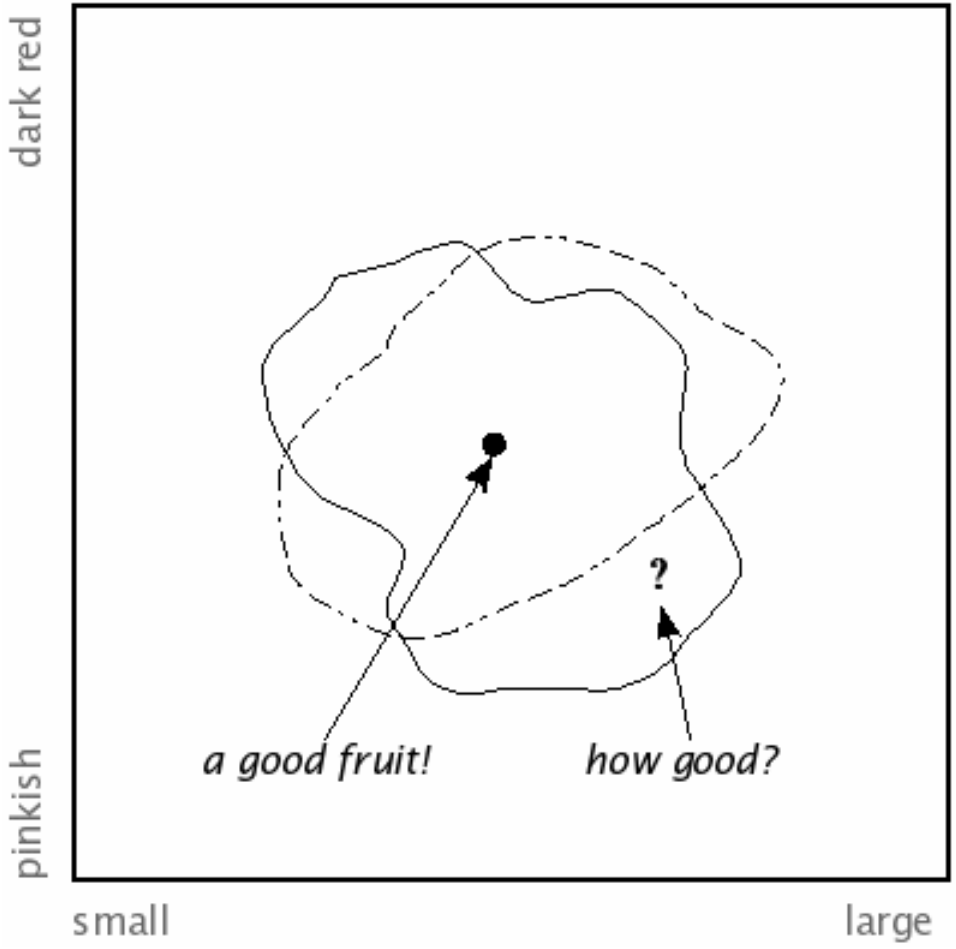


Bülthoff and Newell (2004)

categories and generalization

- Categories would be of little use if it were not possible to extend classification to new stimuli!
- Key Concept (Roger Shepard)
- consequential region: the set of points in the representation space, which stand for stimuli whose consequences are the same as those of the original stimulus (Roger Shepard).

- According to Shepard, a useful *a priori* assumption that could be made is that consequential regions are contiguous.



For generalization

- (dis)similarity = distance in a representation space

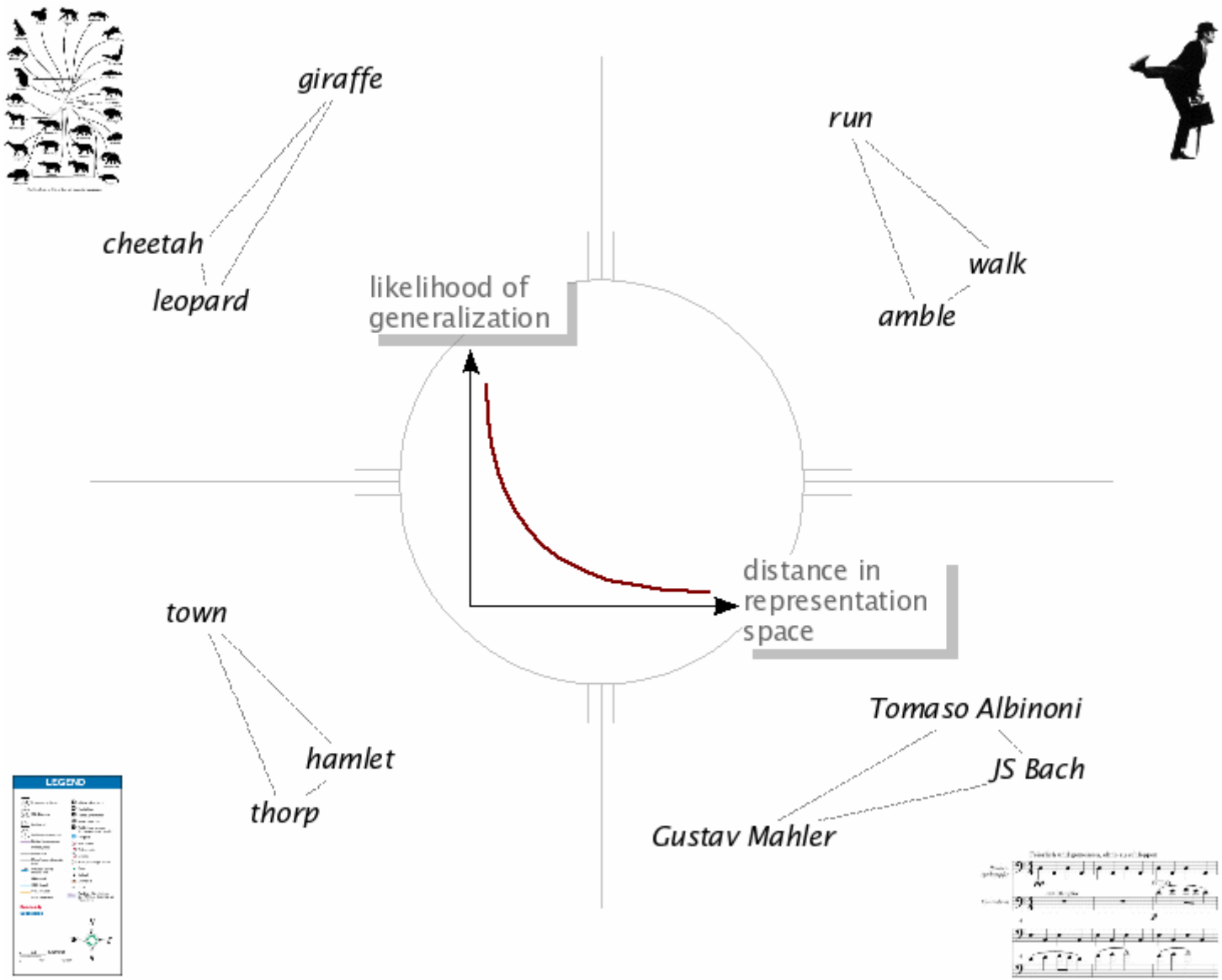
- Roger Shepard's universal law of generalization:

  - goal: explaining subjects' behavior towards a set of stimuli

  - a set of relatable stimuli can be arranged in a representation space [which Shepard calls "psychological space"]...

  - ... in such a manner that the likelihood that the subject will generalize the category label ["tasty"] from one stimulus [this apple] to another [that apple] diminishes exponentially with their distance in that space.

Shepard's law of generalization



Shepard's Law of Generalization: empirical support

- To study the perceptions of color in human vision (Ekman, 1954)
- 14 colors differing only in their hue (i.e., wavelengths from 434 µm to 674 µm)
- 31 people to rate on a five-point scale from 0 (no similarity at all) to 4 (identical) for each of $\binom{14}{2}$ pairs of colors.
- Average of 31 ratings for each pair (representing similarity) is then scaled and subtracted from 1 to represent dissimilarities

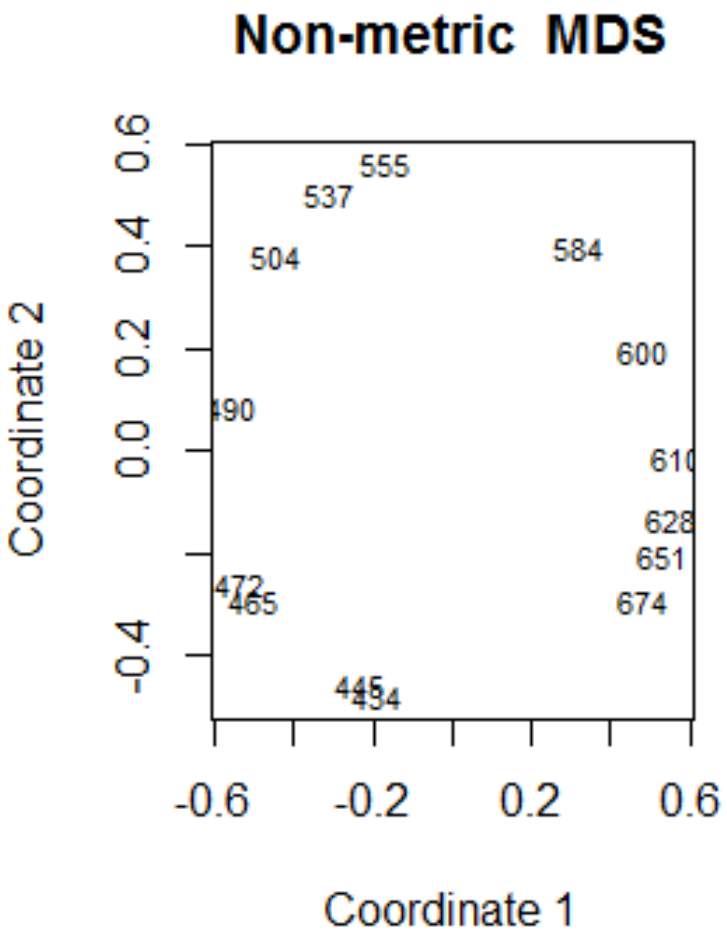
Shepard's Law of Generalization: empirical support

- The resulting 14 × 14 dissimilarity matrix is symmetric, and contains zeros in the diagonal. MDS seeks a 2D configuration to represent these colors.

	434	445	465	472	490	504	537	555	584	600	610	628	651
445	0.14												
465	0.58	0.50											
472	0.58	0.56	0.19										
490	0.82	0.78	0.53	0.46									
504	0.94	0.91	0.83	0.75	0.39								
537	0.93	0.93	0.90	0.90	0.69	0.38							
555	0.96	0.93	0.92	0.91	0.74	0.55	0.27						
584	0.98	0.98	0.98	0.98	0.93	0.86	0.78	0.67					
600	0.93	0.96	0.99	0.99	0.98	0.92	0.86	0.81	0.42				
610	0.91	0.93	0.98	1.00	0.98	0.98	0.95	0.96	0.63	0.26			
628	0.88	0.89	0.99	0.99	0.99	0.98	0.98	0.97	0.73	0.50	0.24		
651	0.87	0.87	0.95	0.98	0.98	0.98	0.98	0.98	0.80	0.59	0.38	0.15	
674	0.84	0.86	0.97	0.96	1.00	0.99	1.00	0.98	0.77	0.72	0.45	0.32	0.24

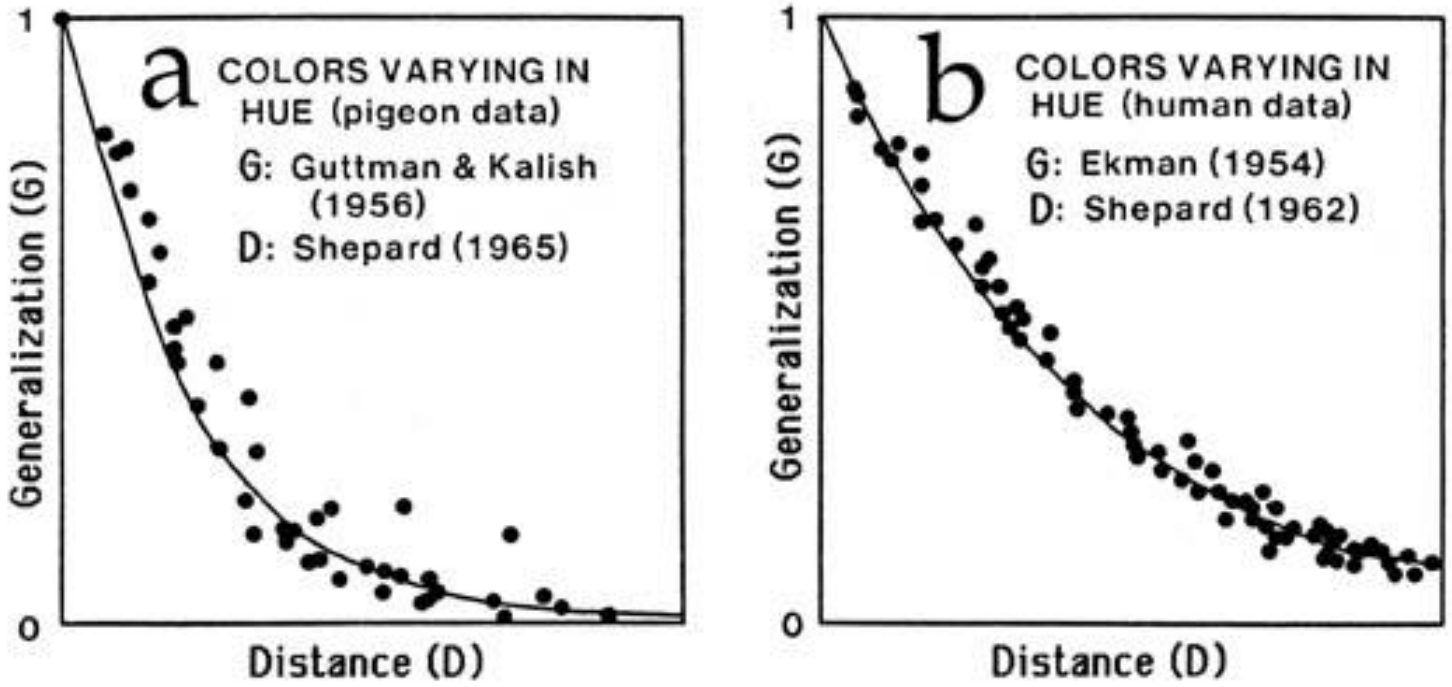
Shepard's Law of Generalization: empirical support

- MDS reproduces the well-known two-dimensional color circle.



Shepard's Law of Generalization: empirical support

- In this representation space, the probability of generalization from one stimulus to another falls exponentially with their distance.



This dependence of generalization on (dis)similarity is invariant across domains, tasks, and subjects.

Universal Laws!!

- Newton:
  - Every massive particle in the universe attracts every other massive particle with a force which is directly proportional to the product of their masses and inversely proportional to the square of the distance between them.
- Roger Shepard:
  - Every set of relatable stimuli can be arranged in a psychological space so that the likelihood of response generalization among them diminishes exponentially with their distance.

Cognitive Science and AI

Perception: Veridicality (Truth)

Presentation from: Shimon Edelman, Computing the Mind, 2008 (Chapter 5: Perception)

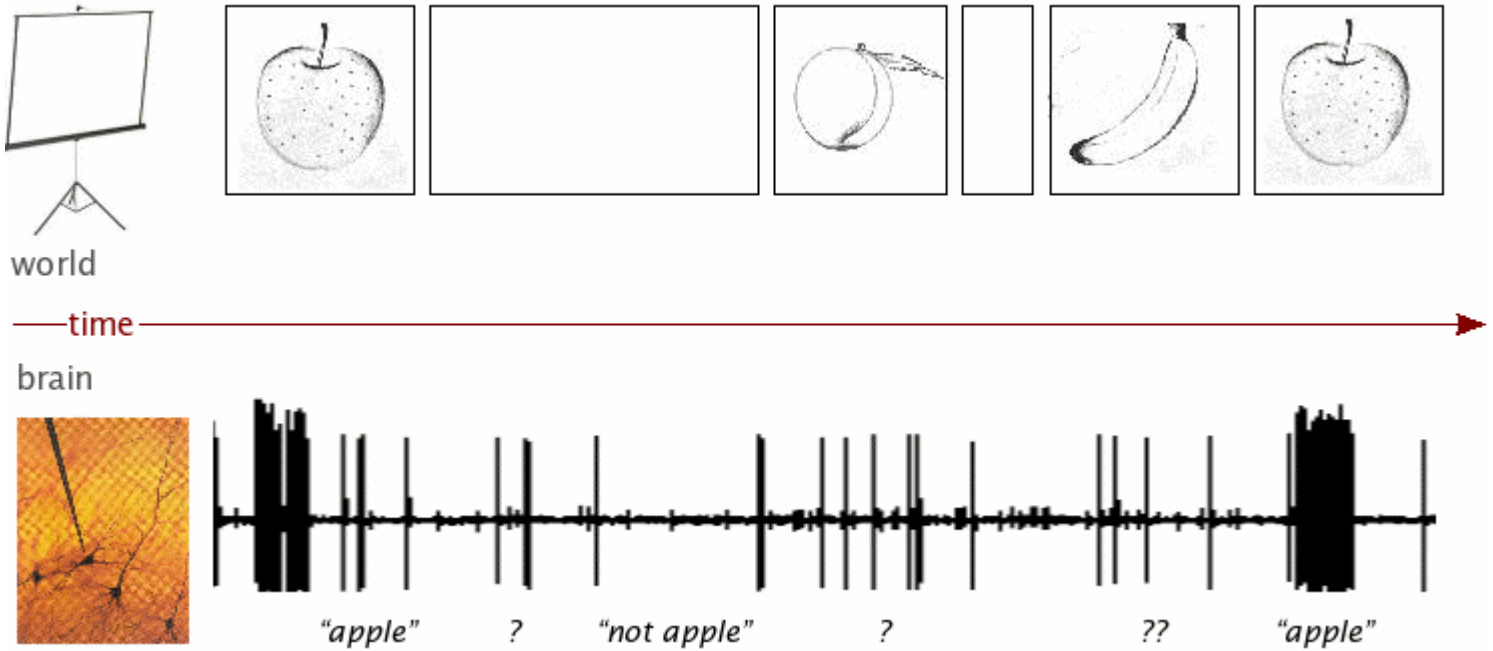
perceptual veridicality (truthfulness)

- How neurons can be truthful?
- Veridical representation: a computational definition
- Visualizing representational spaces with MDS (recap)
- Behavioral evidence for veridical perception of shape similarities
- Electrophysiological evidence for veridical representation of shape similarities
- Using fMRI to map the brain's shape representation space

Ch 5: Perception: Shimon Edelman, Computing the Mind, 2008

Veridicality?

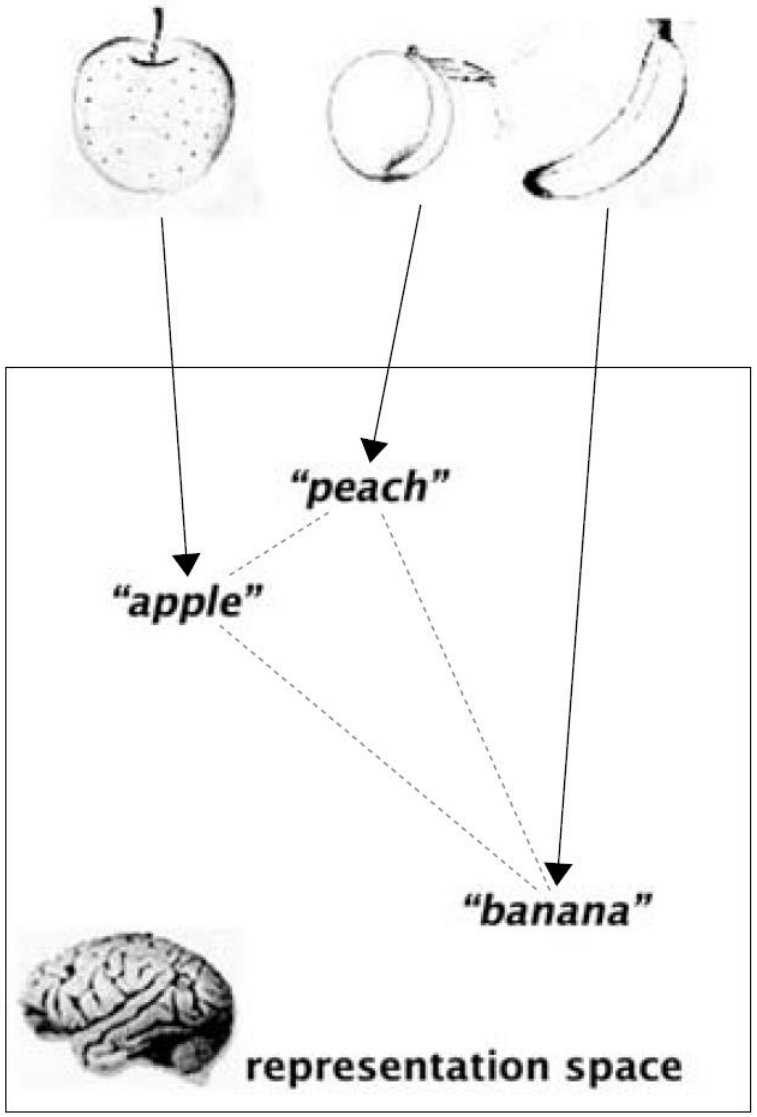
- Refers to the agreement of the representation of any object with the thing represented;
- or to the correspondence of the several parts of any arrangement with each other
- How can a neural representation be truthful?



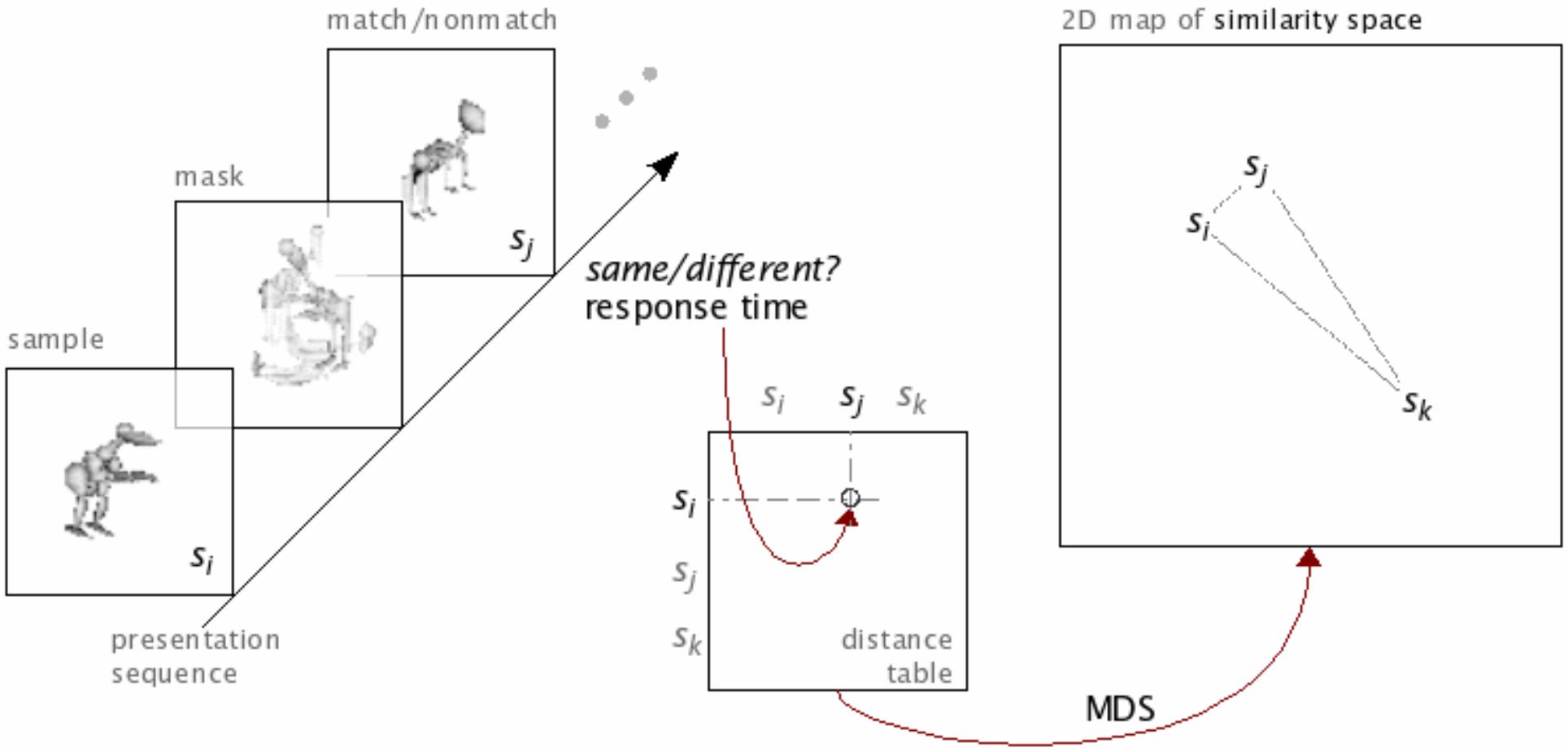
Conformity or Covariation Principle

Verdicality – operational definition

- by selectively responding to external ("distal") stimuli; (Conformity Principle)
- by being causally effective, as appropriate, towards other neurons (remember the Newsome's stimulation expt); and
- by veridically representing distal relationships (for instance, shape differences between objects "out there" in the world).

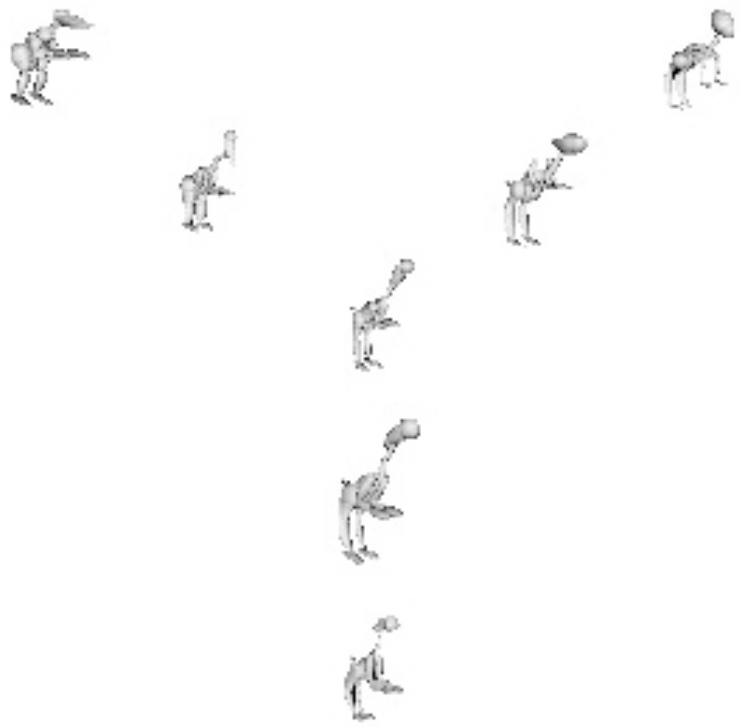


mapping the similarity space from behavioral data

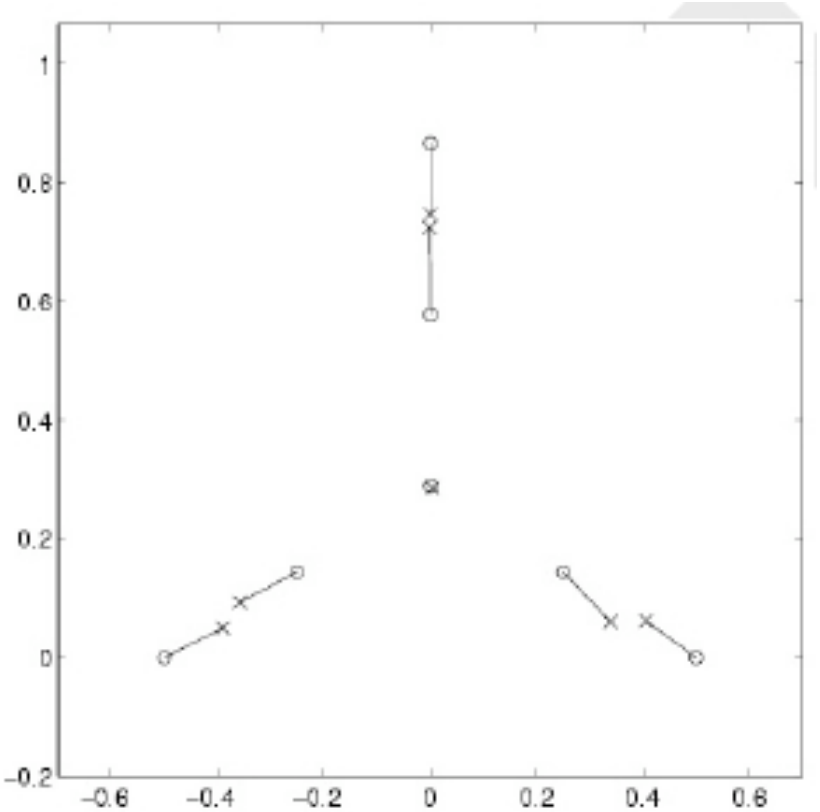


Cutzu, F., and S. Edelman (1996). Faithful representation of similarities among three-dimensional shapes in human vision, Proc. Natl. Acad. Sci. (USA) 93:12046-12050.

behavioral evidence for veridical perception of shape similarities



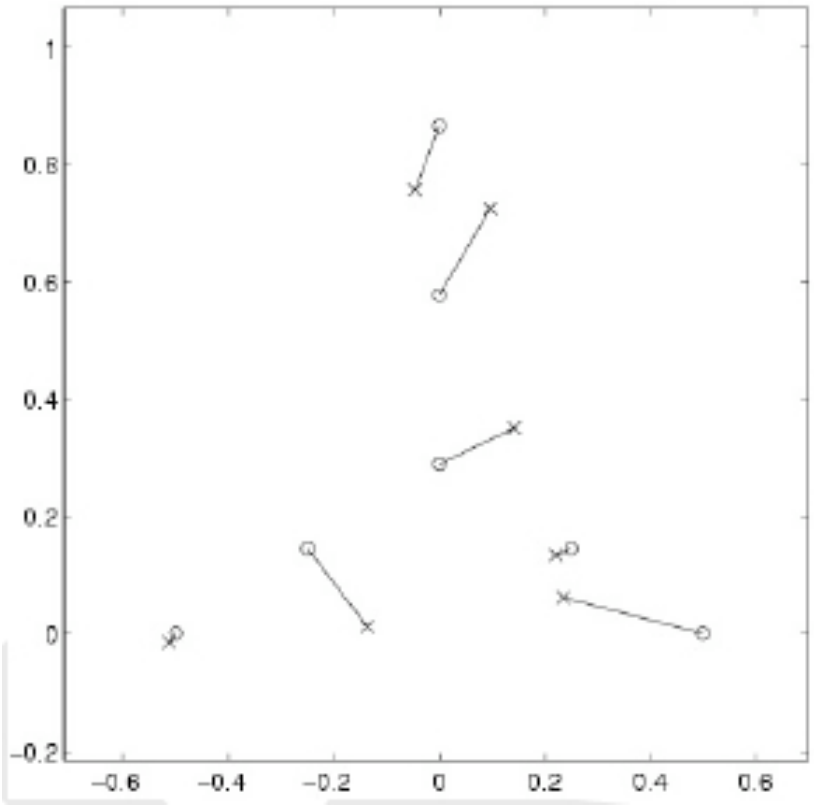
Seven computer-generated humanoid shapes used as stimuli, arranged so as to make explicit their similarity relationships.

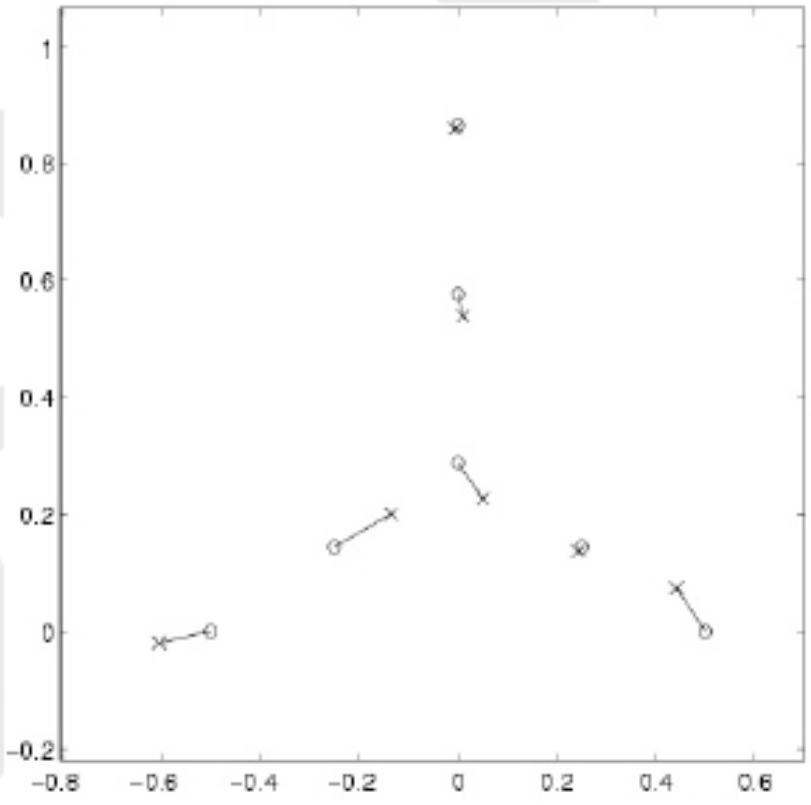


The star-shaped layout of the true similarity space is revealed in this MDS map of one of the subjects' **response** data. The fit between the true and actual configurations is highly significant

Cutzu, F., and S. Edelman (1996). Faithful representation of similarities among three-dimensional shapes in human vision, Proc. Natl. Acad. Sci. (USA) 93:12046-12050.

behavioral evidence for veridical perception of shape similarities





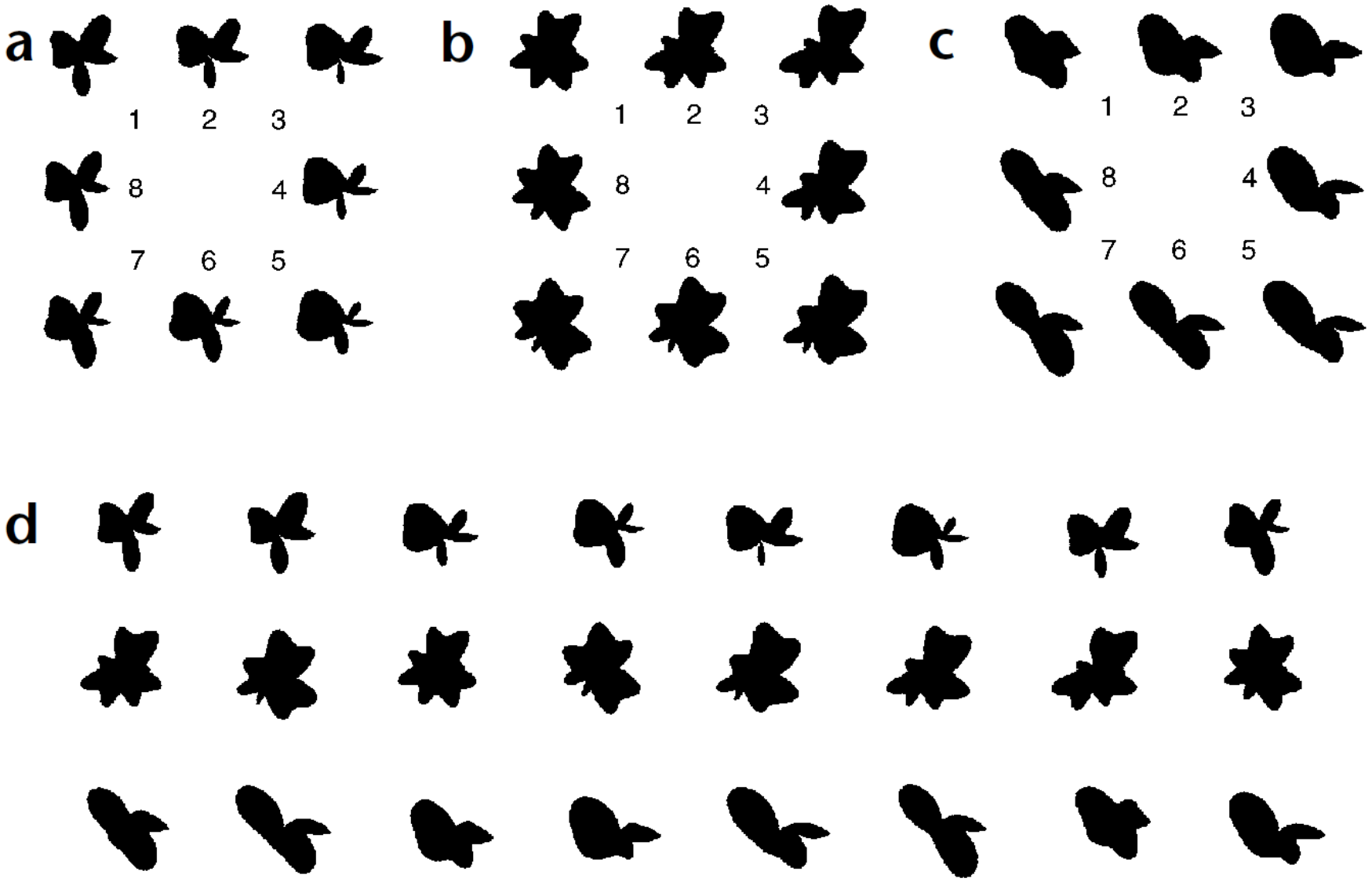
The same analysis, applied to data from a study in which subjects judged similarities among **memorized** shapes.

A computer model replicates perfectly the pattern of human performance.

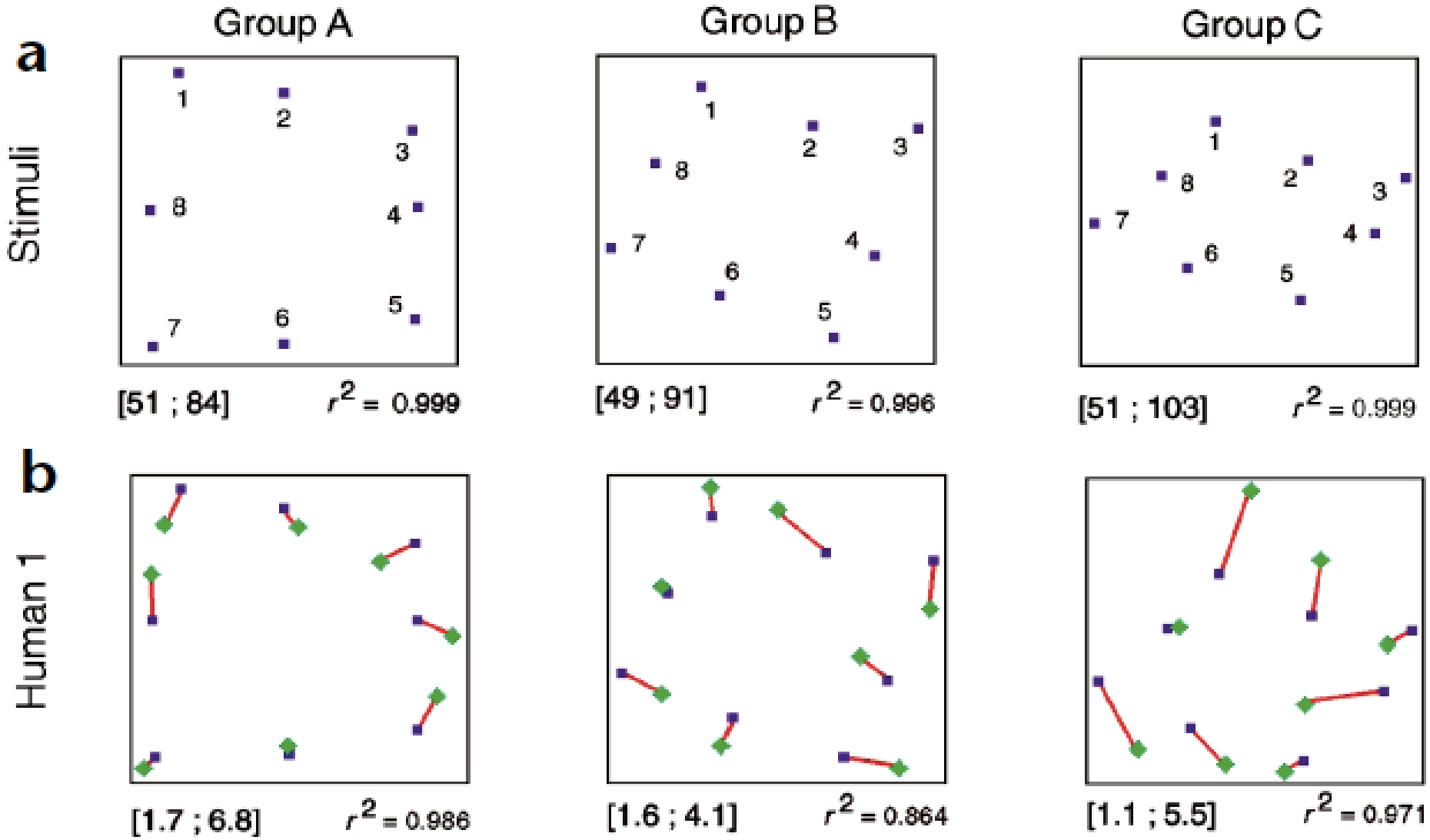
Cutzu, F., and S. Edelman (1996). Faithful representation of similarities among three-dimensional shapes in human vision, Proc. Natl. Acad. Sci. (USA) 93:12046-12050.

neuron-level veridicality in the monkey: the stimuli

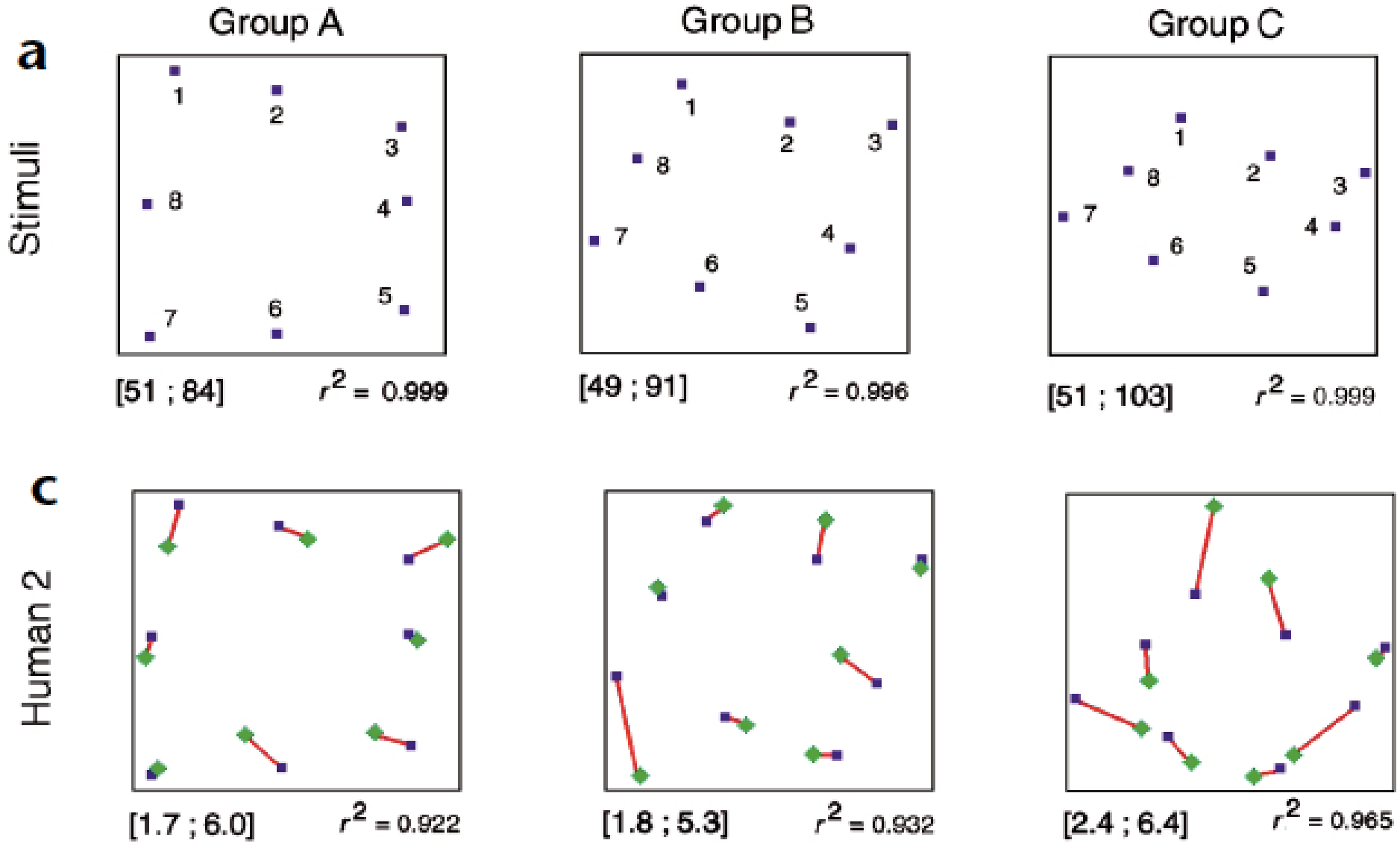
H. Op de Beeck, J. Wagemans, and R. Vogels, Inferotemporal neurons represent low-dimensional configurations of parameterized shapes, *Nature Neuroscience* 4:1244-1252 (2002).



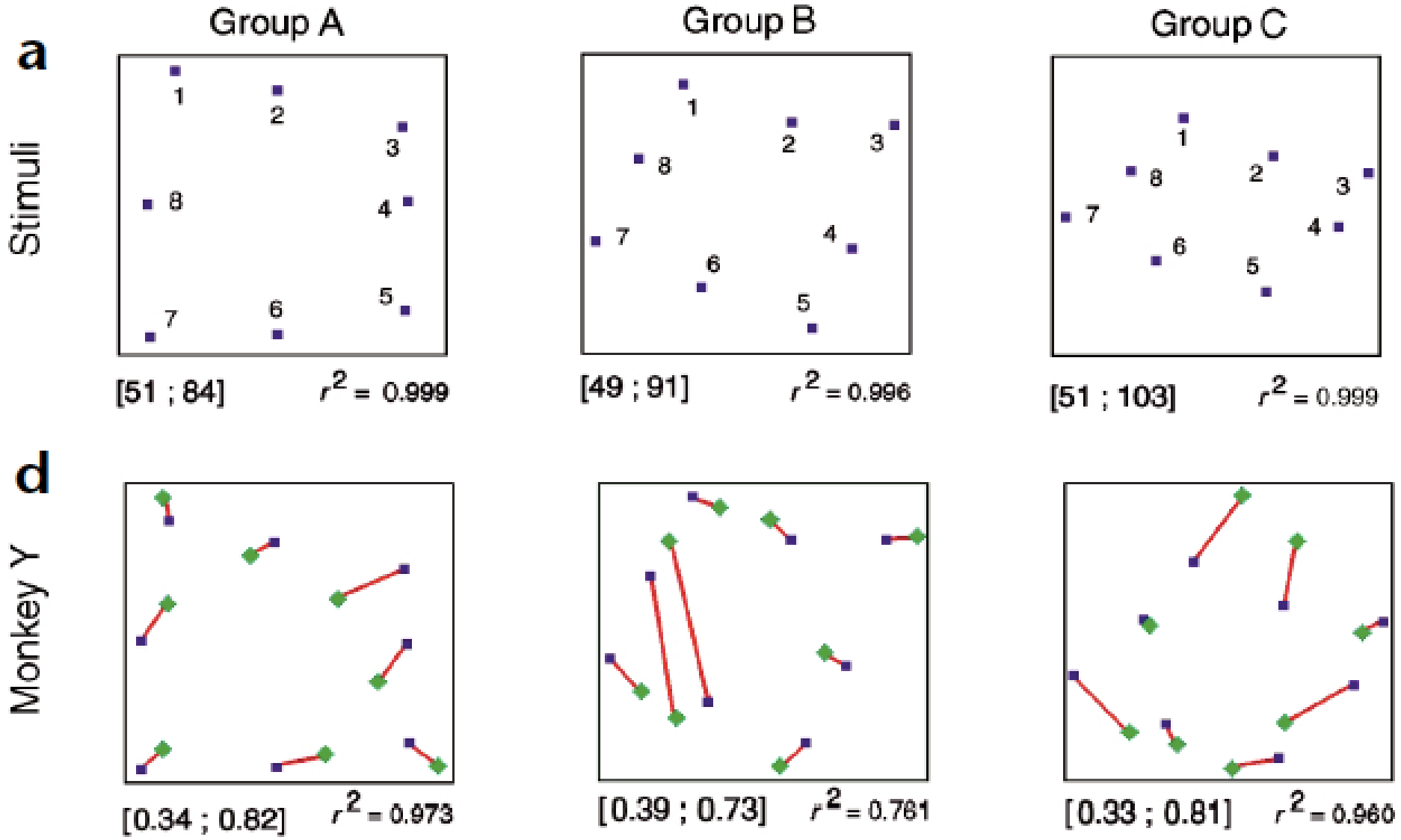
veridicality: stimuli configuration vs. human #1's behavioral data



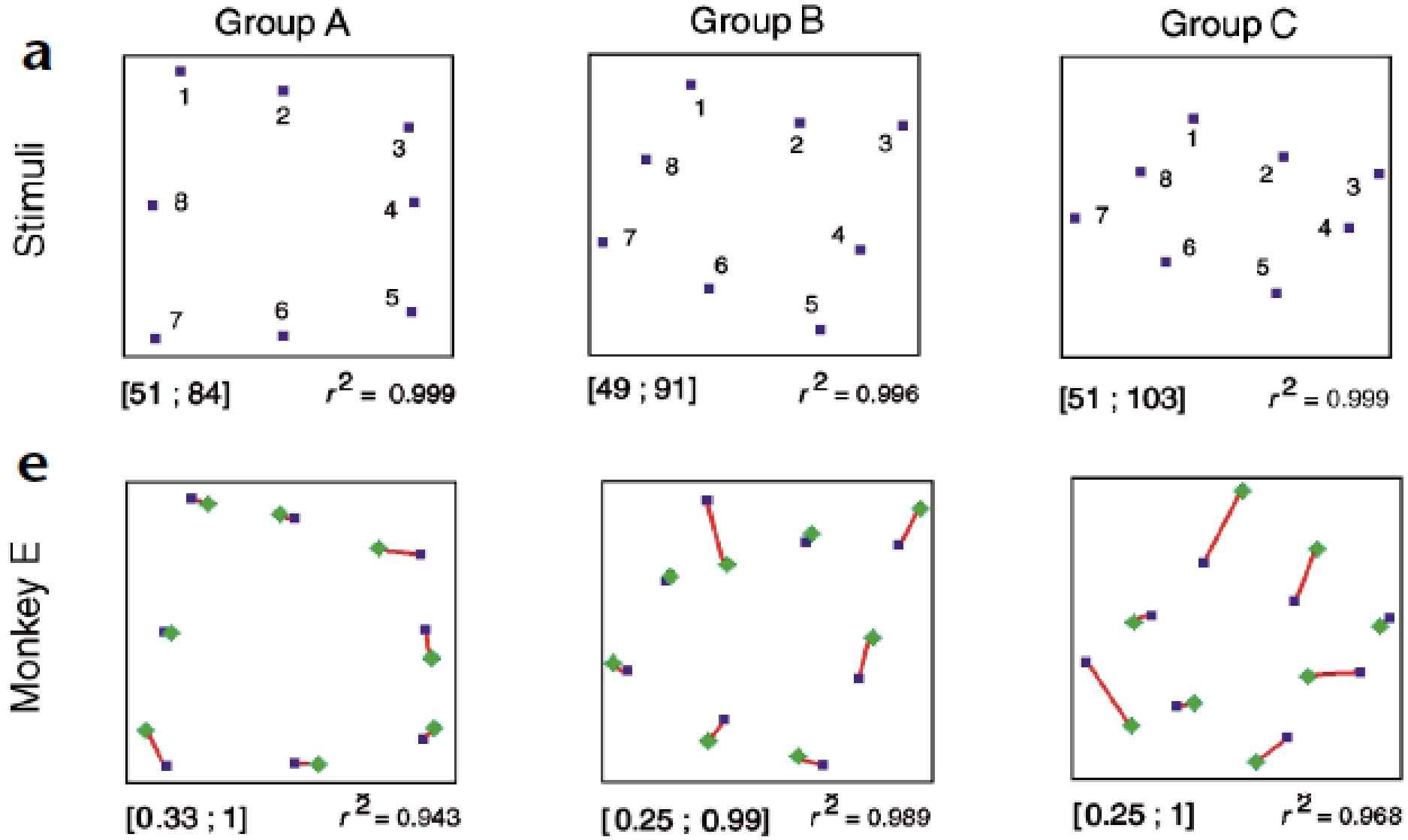
veridicality: stimuli configuration vs. human #2's behavioral data



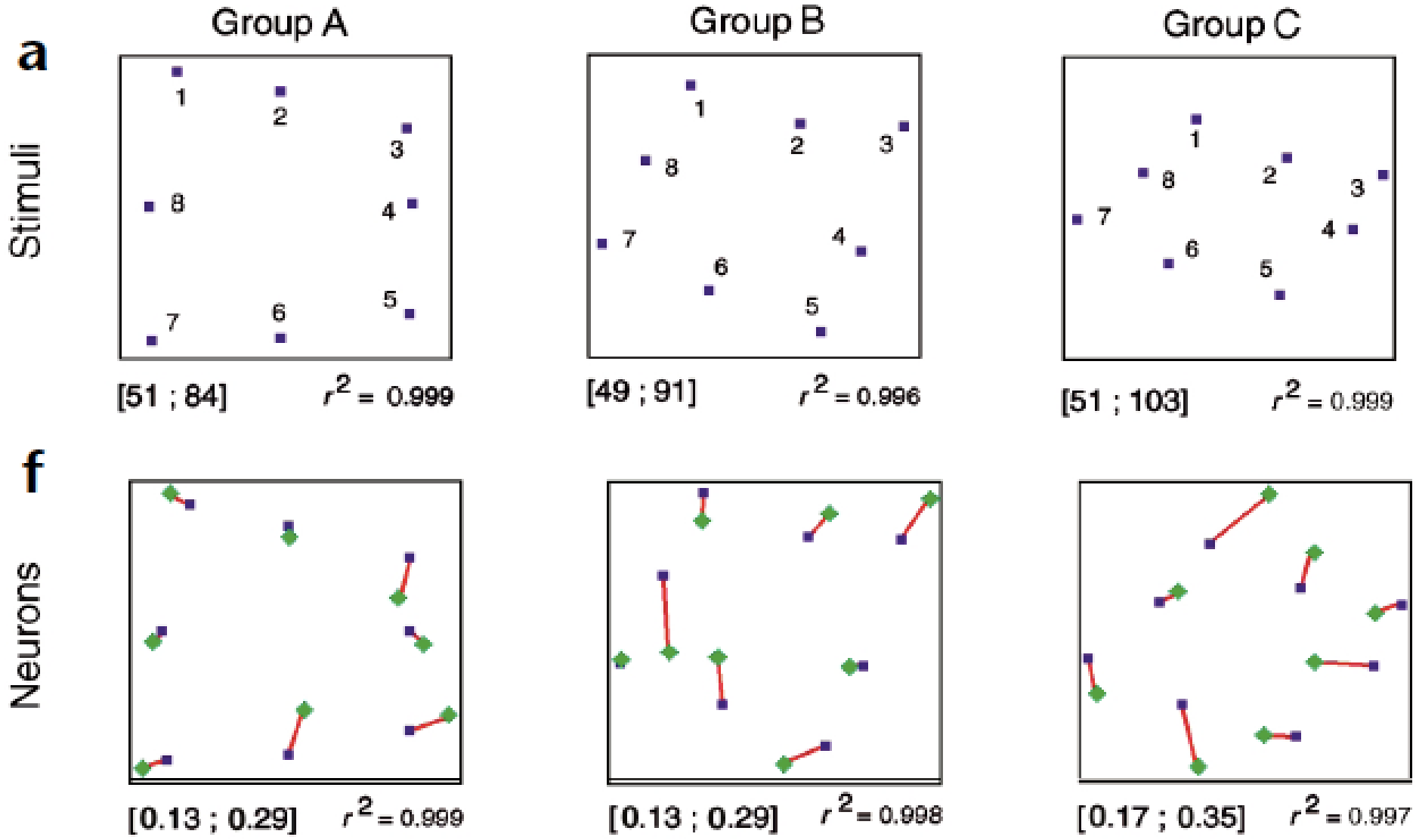
veridicality: stimuli configuration vs. monkeyY's behavioral data



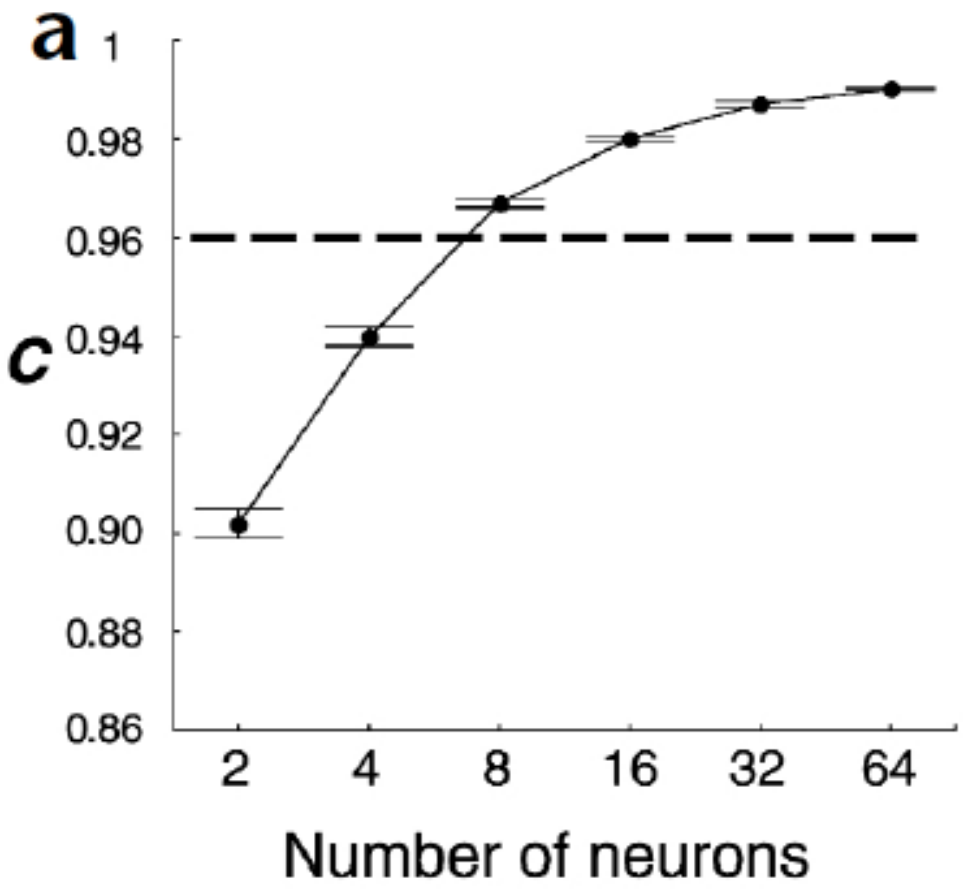
veridicality: stimuli configuration vs. monkey E's behavioral data



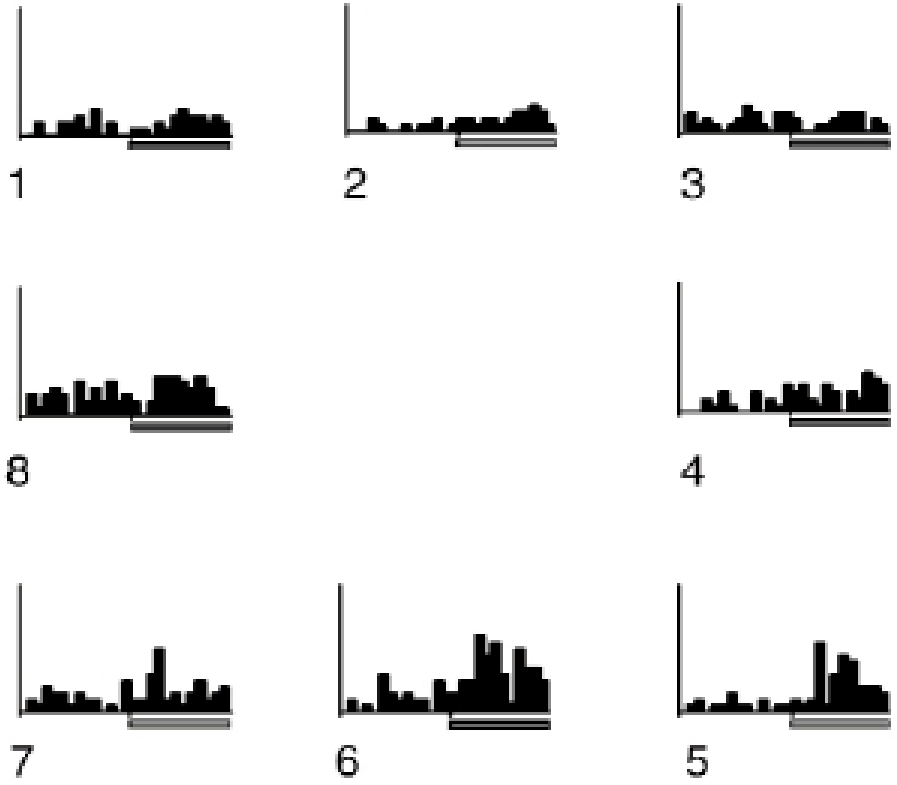
veridicality: stimuli configuration vs. neuron's response data



Veridicality: neuron's response data

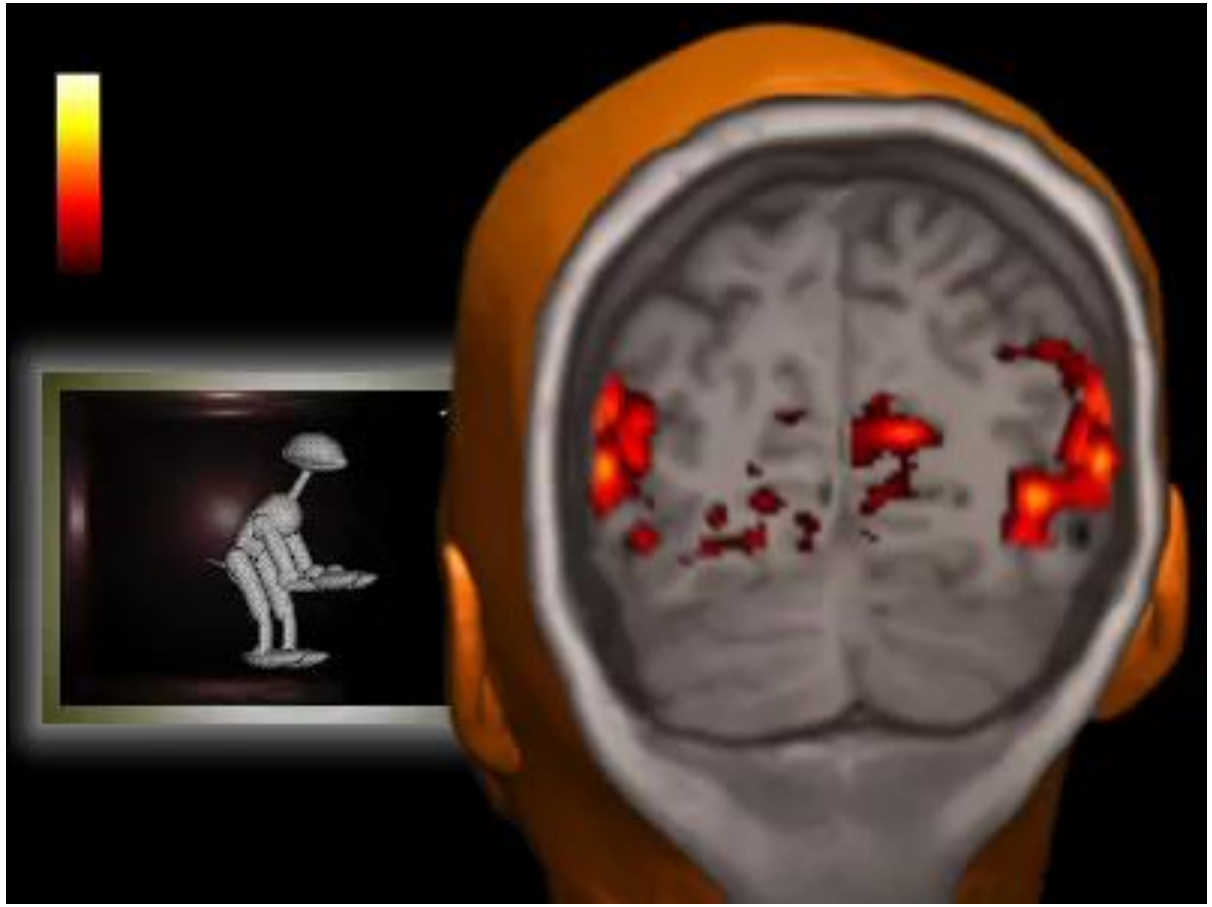


correlation ***c*** between the configuration recovered by MDS from neurons' responses and the real configuration, vs. the # of neurons (dashed line: threshold of significant difference from baseline)



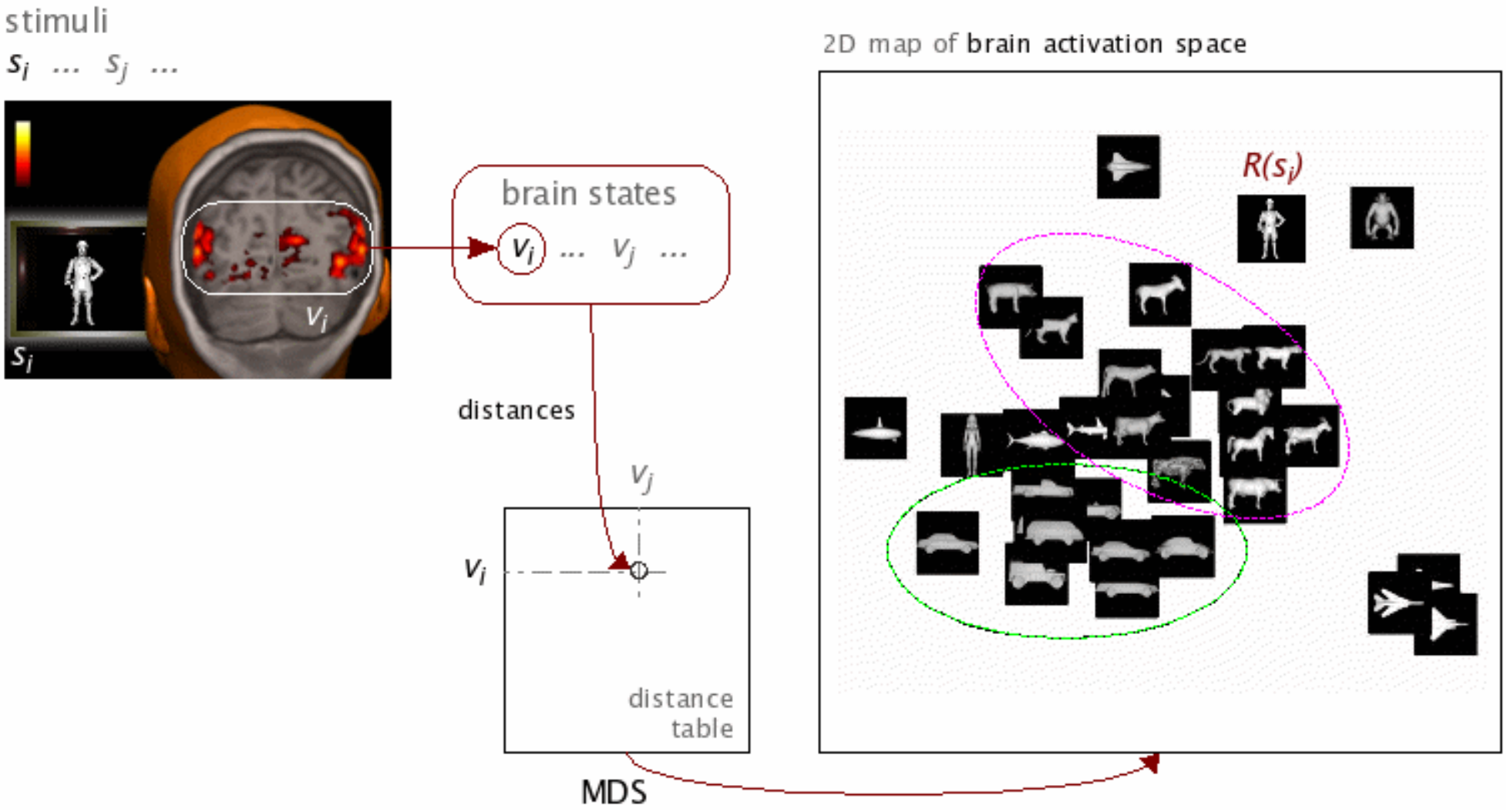
the responses of one of the neurons to the 8 stimuli (here tuned more to C6 and nearby C7 and C5.

visualizing the similarity space in the human brain



A sequence of fMRI snapshots of the brain activity of a subject watching a series of visual stimuli — [Grill-Spector et al., 1997]

visualizing the similarity space in the human brain



Towards direct visualization of the internal shape representation space by fMRI, S. Edelman, K. Grill-Spector, T. Kushnir, and R. Malach, *Psychobiology* 26:309-321 (1998).

Representation and Reality

- The perceptual representation of certain aspects of the world in the brain is veridical.

- Veridicality is ill-defined for a single stimulus. It can only be properly assessed for a set of stimuli (which makes it fundamentally **statistical** or **relational**).

Alon Hafri & Chaz Firestone (2021). The Perception of Relations: Review. Trends in Cognitive Sciences, Volume 25, Issue 6, June 2021, Pages 475-492. https://doi.org/10.1016/j.tics.2021.01.006

Neuroimaging for Cognitive Science

Kamalaker Dadi

IHuB-Data, IIIT Hyderabad

January 21, 2022

1. Principles of MRI

Cognitive Science and AI - Spring 2022

Neuroimaging and its use

Non-invasive or minimally invasive techniques that directly or indirectly image the structure or function of the brain in-vivo
e. g., fMRI, PET, etc.

Thousands of publications per year using these functional imaging techniques

Goals: Interdisclipinary science
e. g., Neurologists, Neuroscience, Psychologists, Psychiatrists, Physicists, Cognitive scientists and others

Neuroimaging techniques

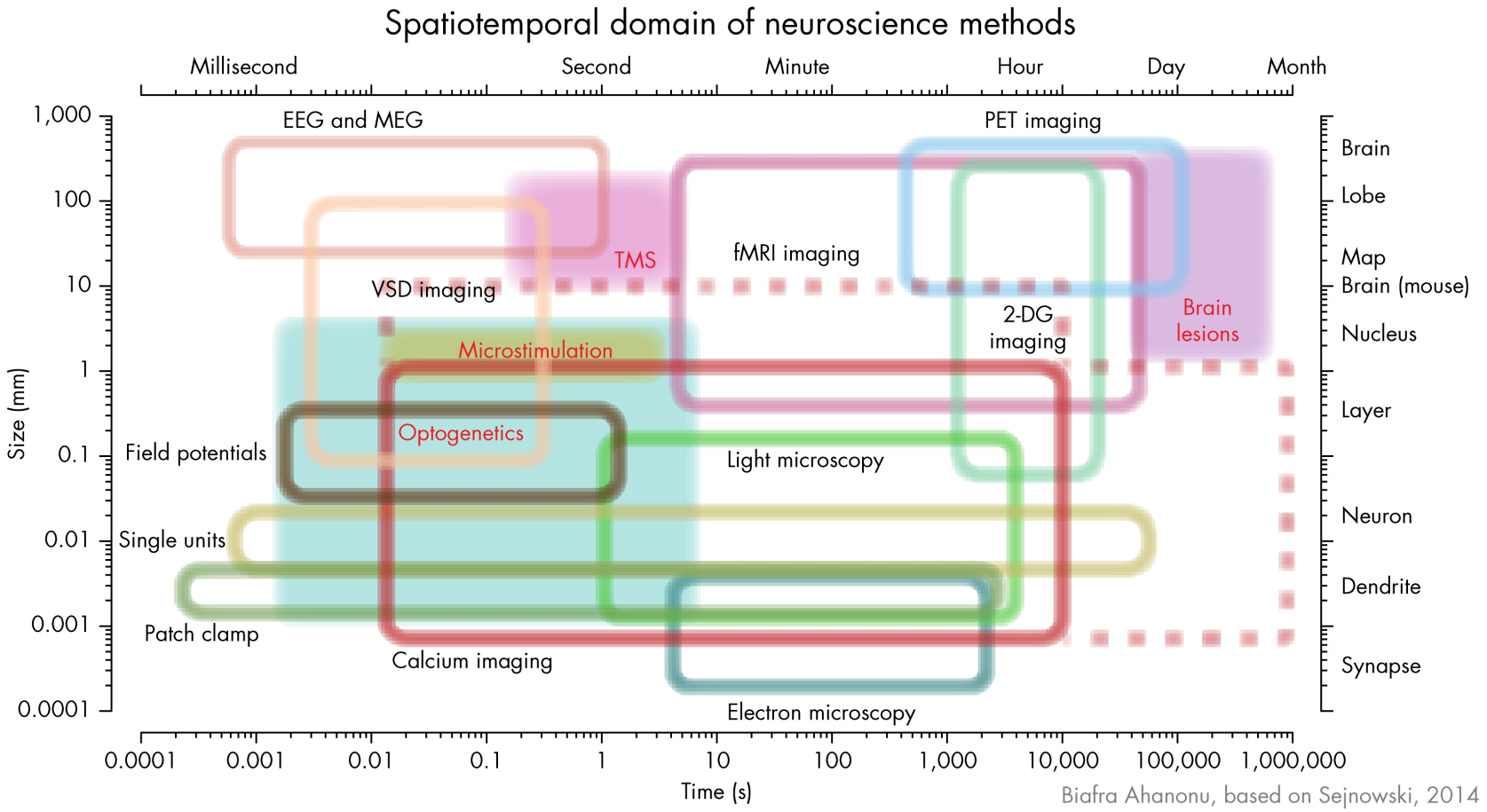


Image src: `https://bahanonu.com/syscarut/articles/212/` (Sejnowski *et al.* 2014)

MRI and Cognitive Science

Cognitive Science: The study of mind and its relatioships with the behavior

Mind

Sensation and Perception,
Attention, Memory control,
Decision making

$\longrightarrow$ Behavior

MRI and Cognitive Science

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Mind

Sensation and Perception,
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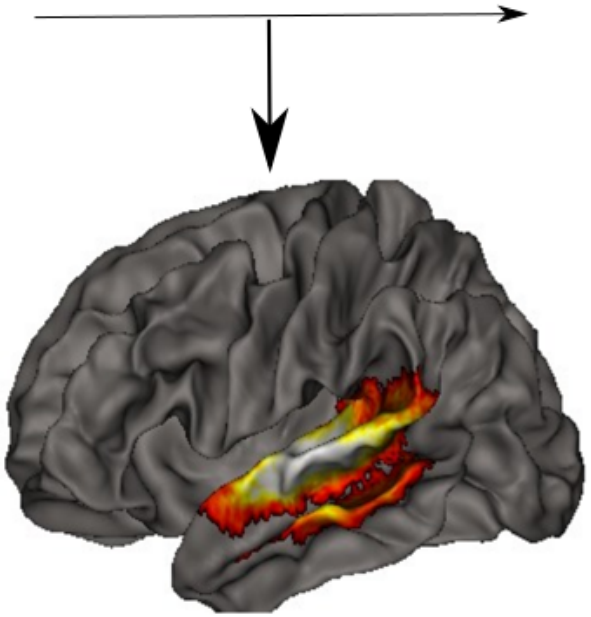
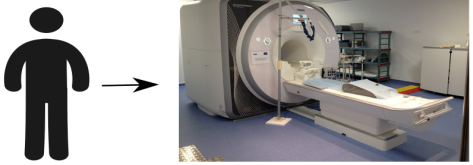


Behavior

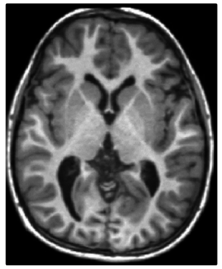
Brain representations

Multiple MRI measures

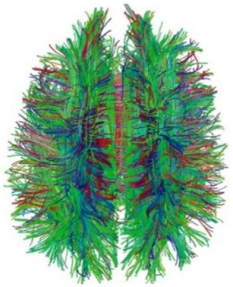
Two main categories: Structural and Functional brain imaging



Magnetic Resonance Imaging



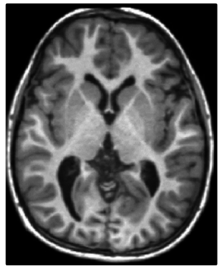
Brain structures



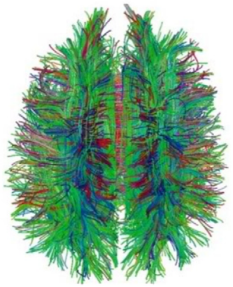
Structural Connectivity

Multiple MRI measures

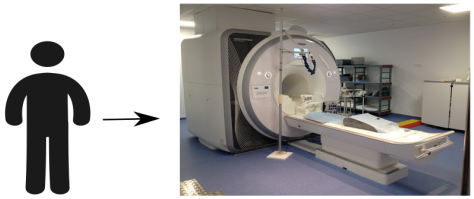
Two main categories: Structural and Functional brain imaging



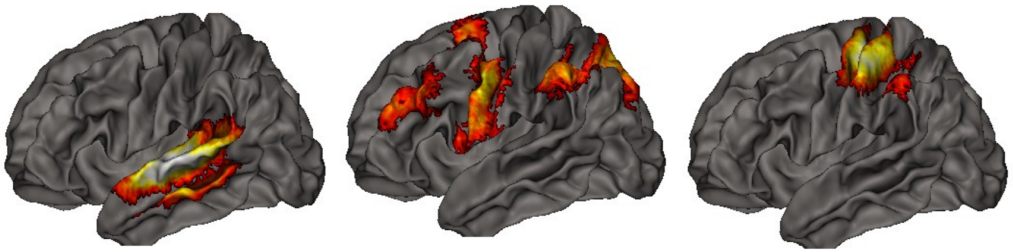
Brain structures

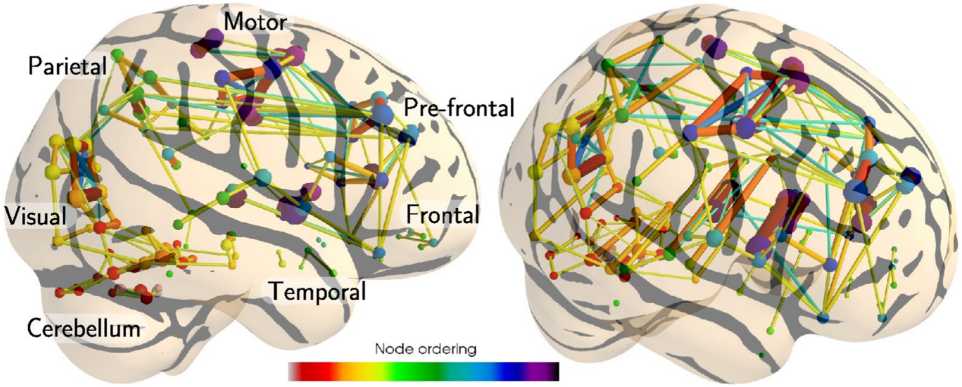


Structural Connectivity



Magnetic Resonance Imaging





Brain function

Brain function image src: `https://team.inria.fr/parietal/`

Outline

1. Basics of MRI Data acquisition: from scanner to images
2. Overview of Data preprocessing
3. Multiple MR measures: structural and functional images

This class

1. Basics of MRI Data acquisition: from scanner to images

Martin, A. L. & Tor, D. W. *Principles of functional Magnetic Resonance Imaging.* (2014)

MRI

The acronym stands for: Magnetic Resonance Imaging

M – Magnetic properties of hydrogen nuclei

R – Electromagnetic energy emission in response to an excitation

I – The process of converting signal in frequency domain to image domain

The MRI machine

MR scanner contains a electromagnet with a very strong magnetic field

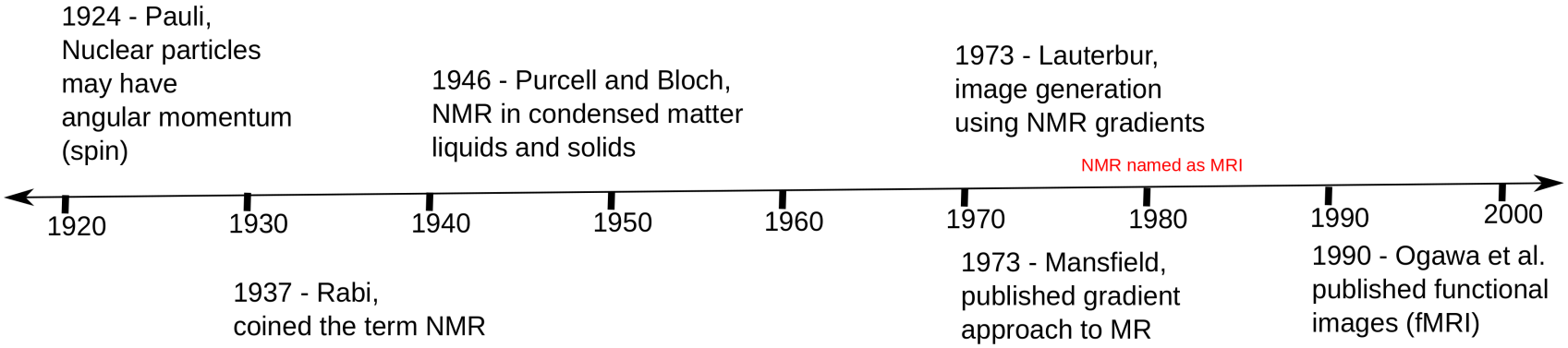
Siemens 3T Magnetom scanner

- 1.5 – 7 Tesla
- Earth's magnetic field = 0.00005 T
- 3T is 60,000 times stronger
- Very expensive

MRI measures human brain structure and function

Image src: `https://www.siemens-healthineers.com`

The evolution of MRI



(Raichle 1998)

The evolution of MRI

1924 - Pauli, Nuclear particles may have angular momentum (spin)

1946 - Purcell and Bloch, NMR in condensed matter liquids and solids

1973 - Lauterbur, image generation using NMR gradients

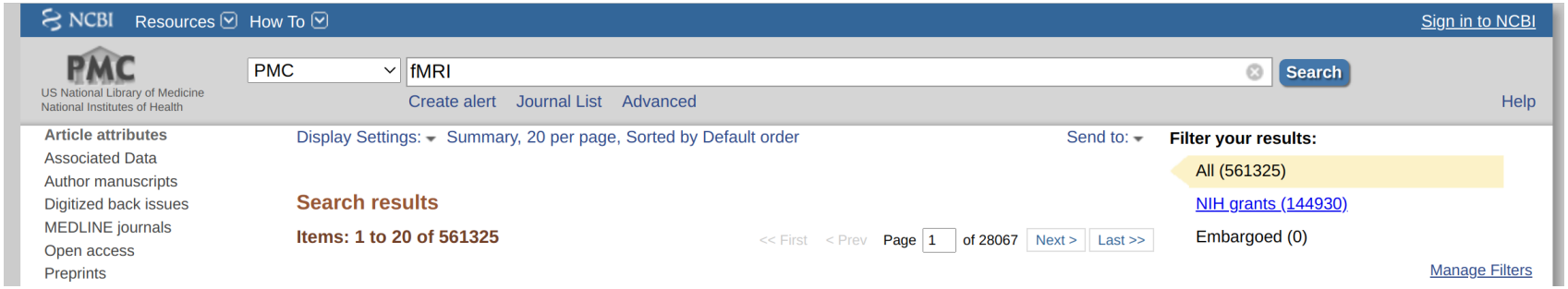
NMR named as MRI

1920 1930 1940 1950 1960 1970 1980 1990 2000

1937 - Rabi, coined the term NMR

1973 - Mansfield, published gradient approach to MR

1990 - Ogawa et al. published functional images (fMRI)

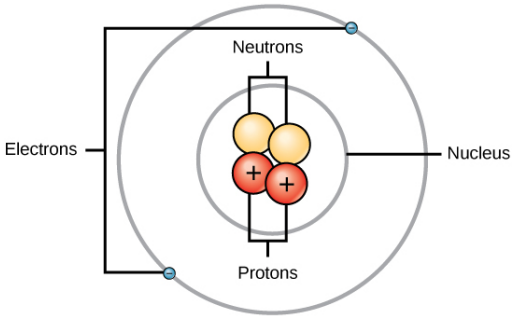


(Raichle 1998)

The principles of MRI

The atomic nuclei

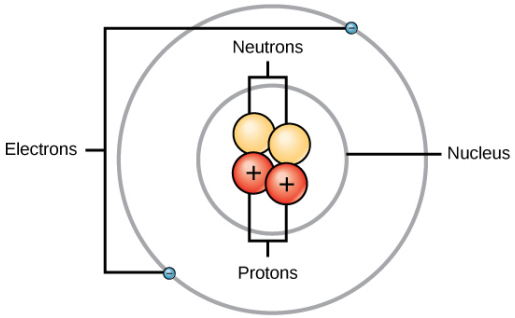
- Nucleus = Protons + Neutrons



Bohr's model

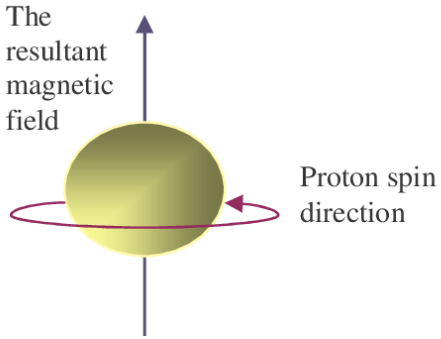
The atomic nuclei

- Nucleus = Protons + Neutrons



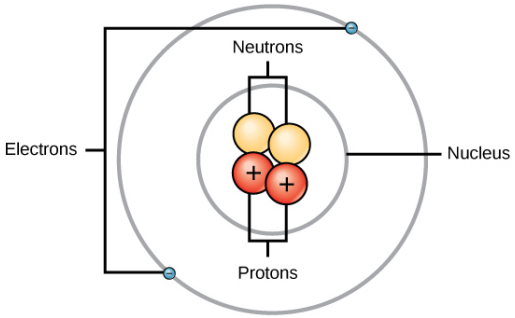
Bohr's model

- Magnetic property: Spin
- Net magnetic moment along the axis of the spin



The atomic nuclei

- Nucleus = Protons + Neutrons



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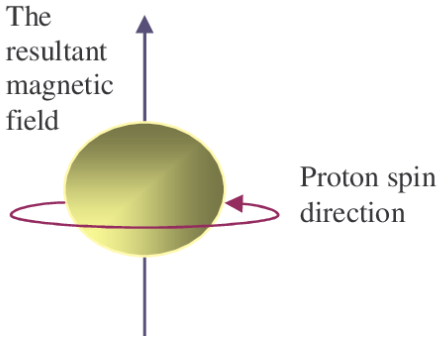
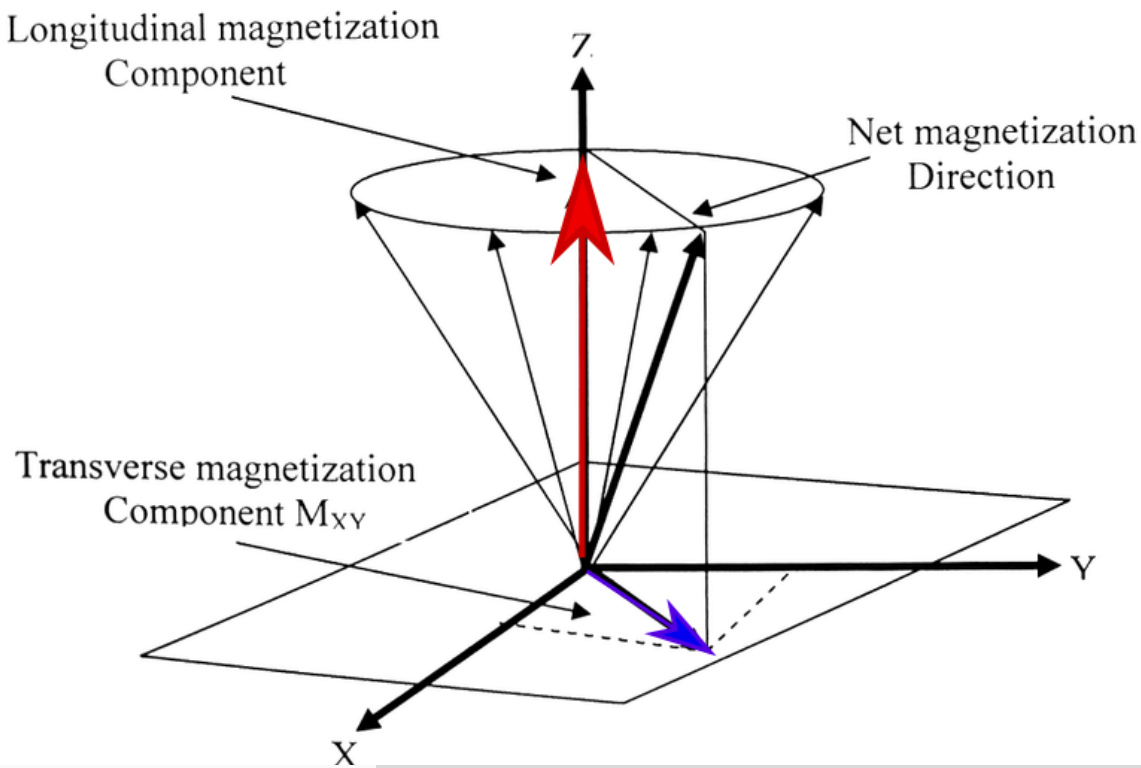


- Hydrogen (single proton)

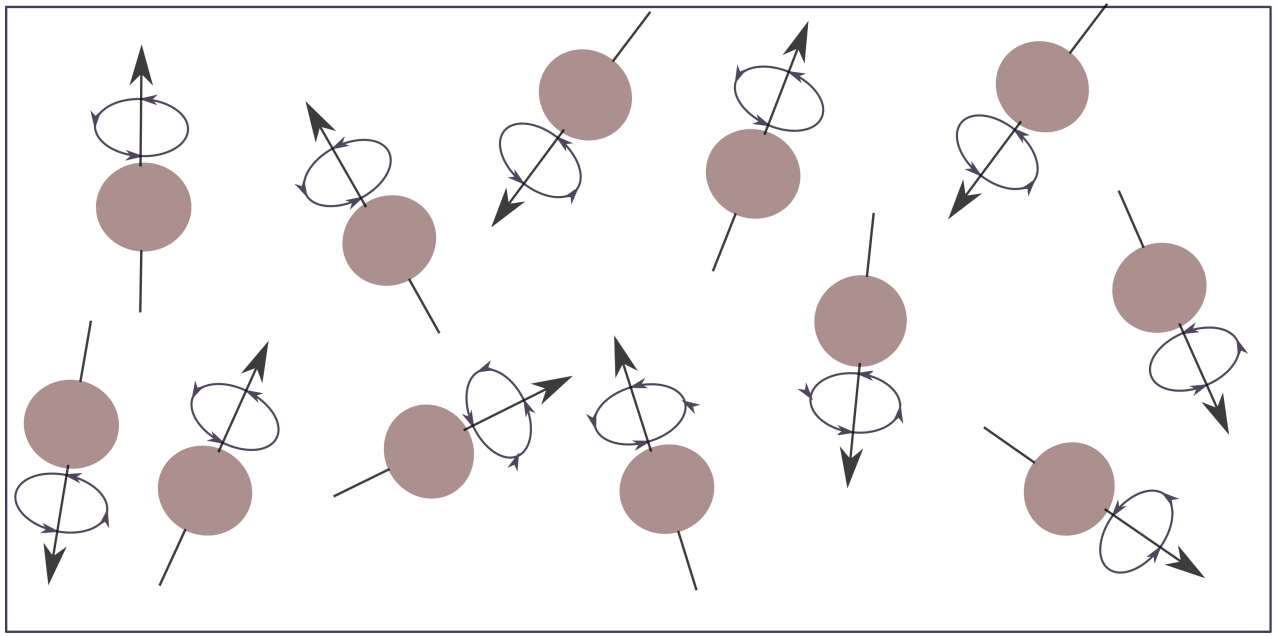
Net Magnetization

- Net magnetization is measured among several nuclei within a volume
- Magnetization vector $\boldsymbol{M}$ is a summary of two components
  - Longitudinal component $\parallel$ to the field
  - Transverse component $\perp$ to the field



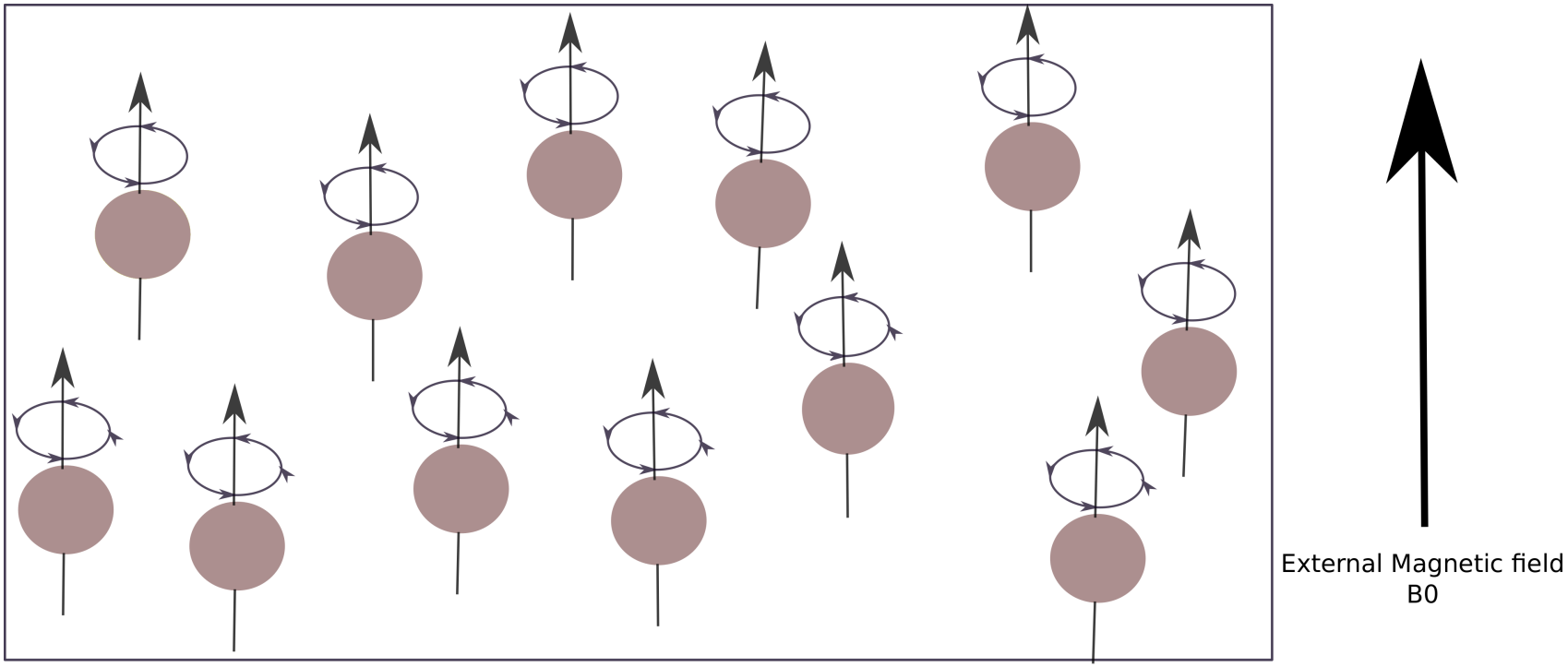
No net magnetization

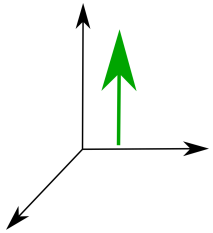
In the absence of strong magnetic field, the hydrogen $^{1}\mathbf{H}$ atoms are randomly oriented.



When strong magnetic field is applied

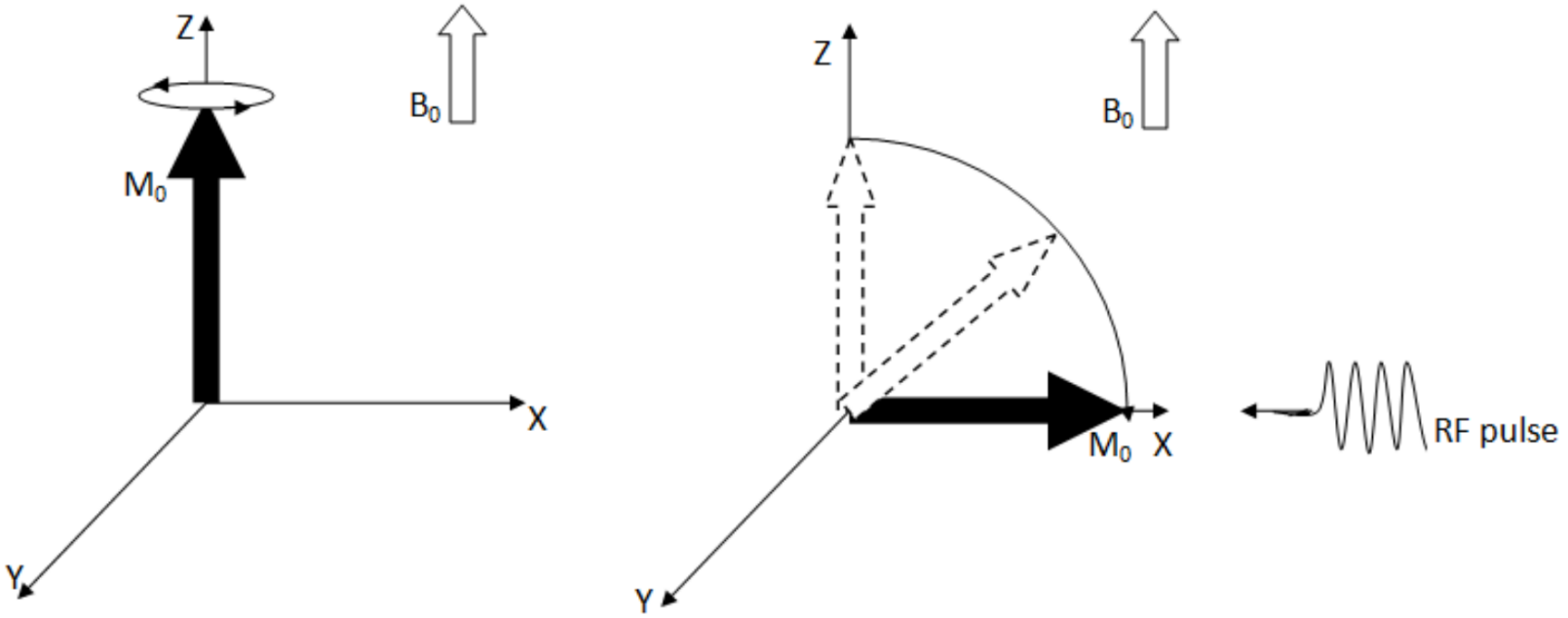
The nuclei aligns with the field which creates a net longitudinal magnetization in the direction of the field.





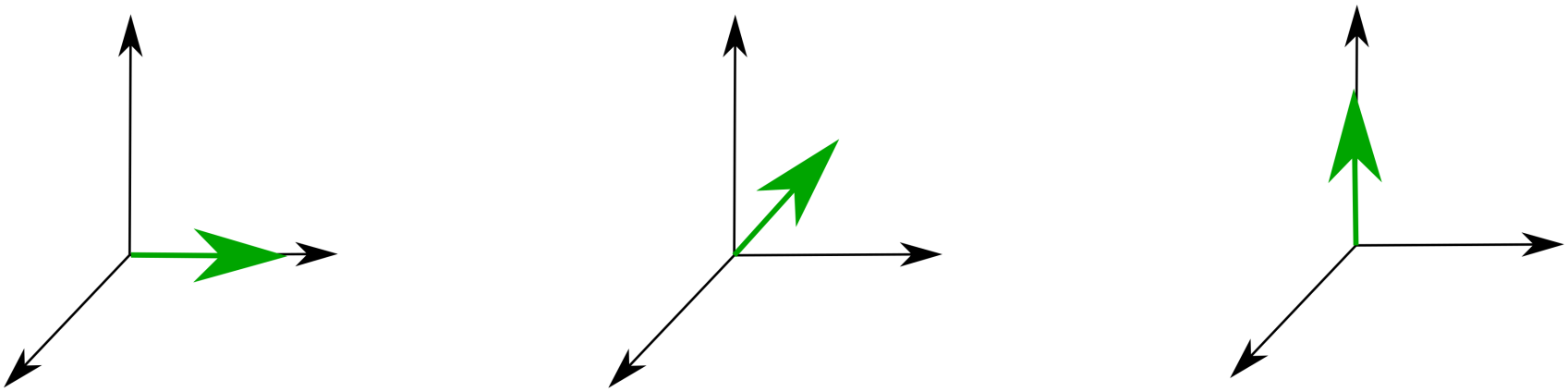
Resonance: RF pulse excitation for measuring the signal

- A radio frequency is applied that causes the spin to flip the net magnetization vector $\boldsymbol{M}_0$ to transverse magnetization $\boldsymbol{M}_{xy}$.



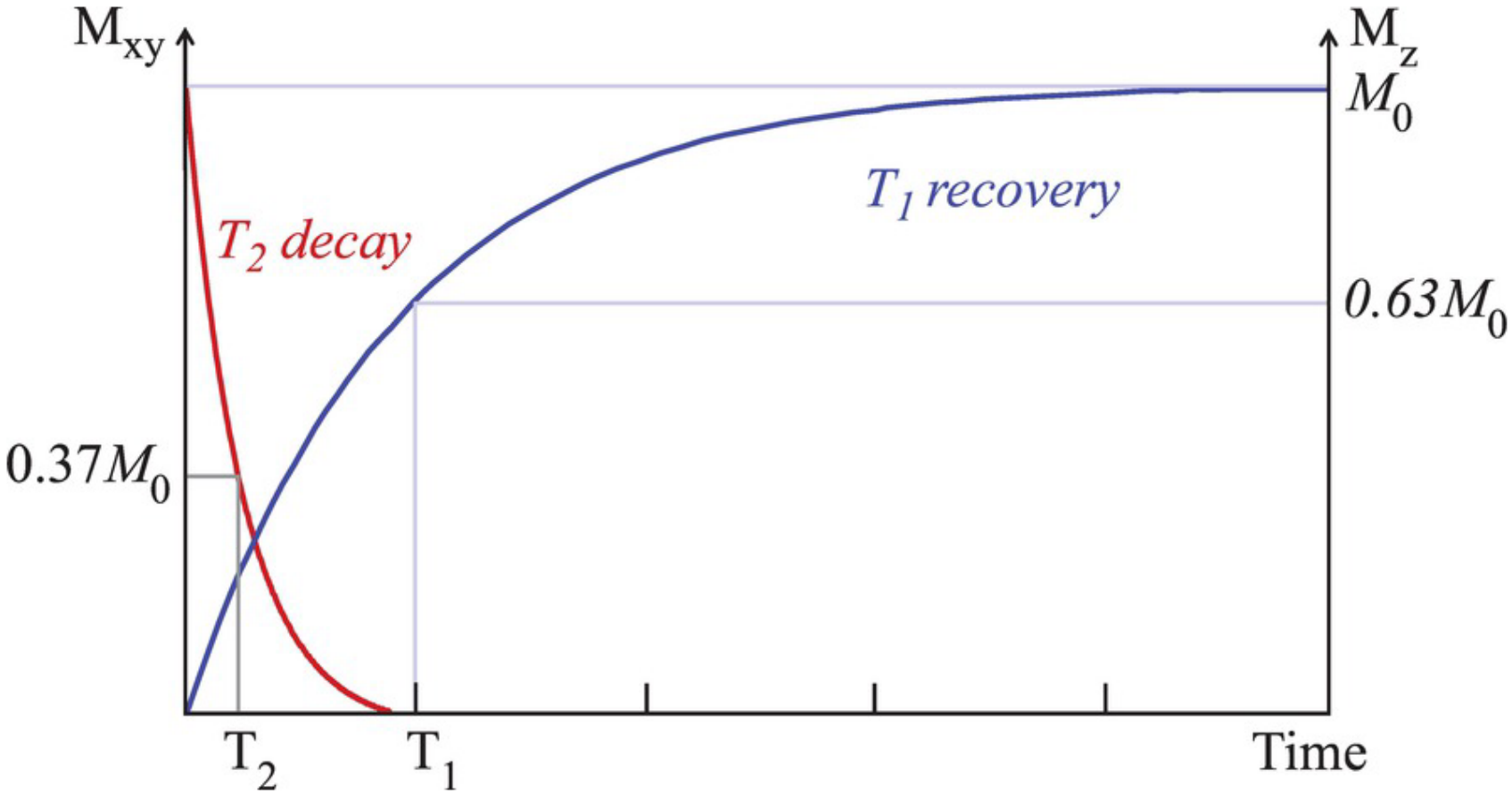
Relaxation

- After RF pulse is removed, the system returns back to the equilibrium to $\boldsymbol{M}_0$.
- Transverse magnetization disappears and longitudinal magnetization starts to reappear. This process is called as Relaxation.
- During this process, a signal is captured by the receiver coil.



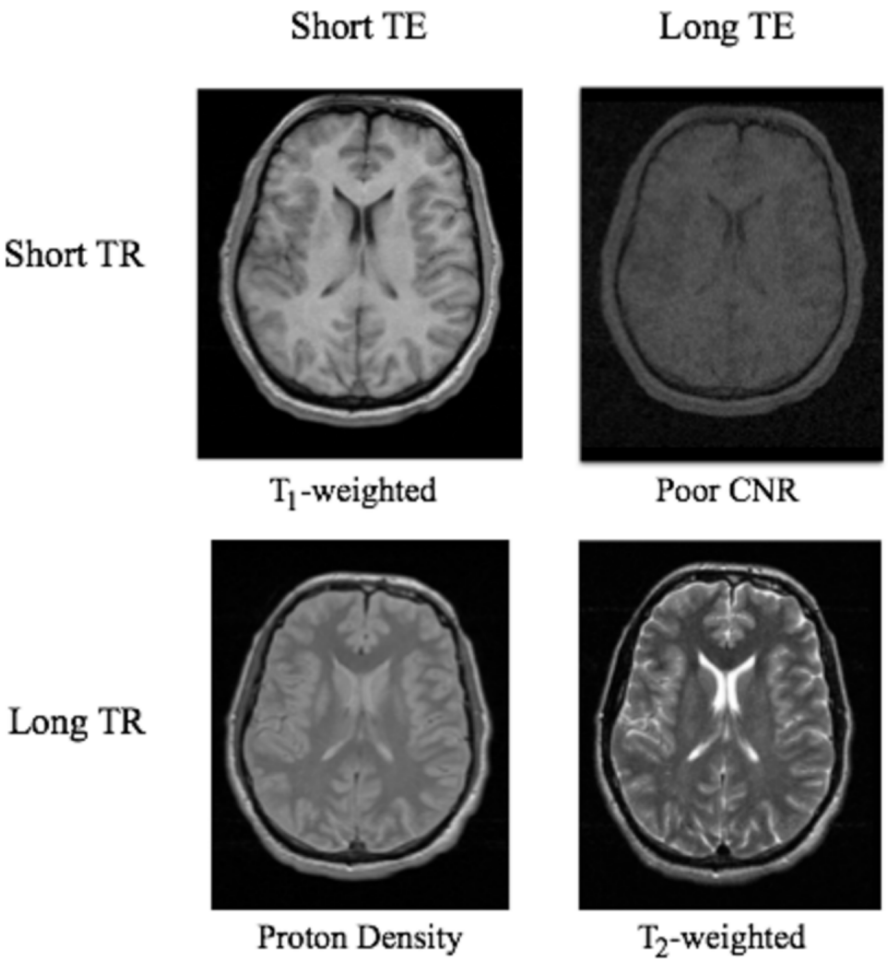
Relaxation times

The restoration of longitudinal magnetization is measured by time constant T1



The decay of transverse magnetization is described by time constant T2

Image contrast



The measured signal is approximated by:

$$M_0(1 - e^{-TR/T_1})e^{-TE/T_2}$$

TR - How often we excite the nuclei

TE - The time between excitation and data collection

https://www.fmrib.ox.ac.uk/primers/appendices/mri_physics.pdf

fMRI contrast

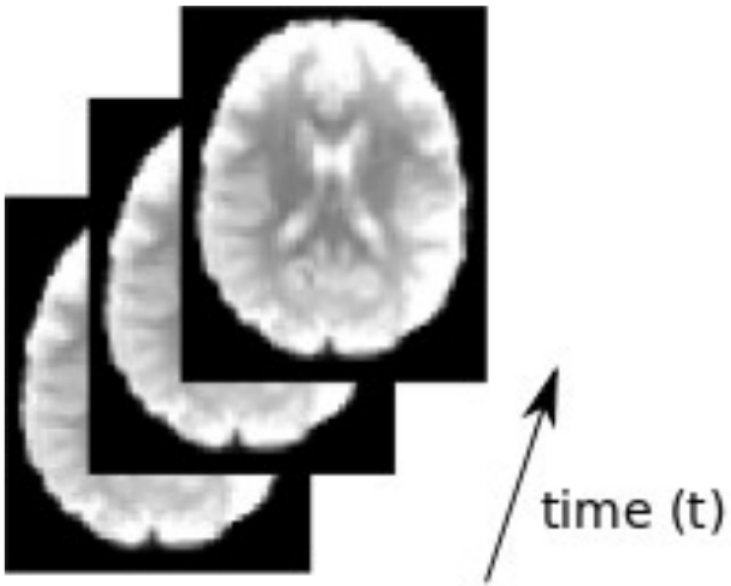
- T_2^* is the combined effect of T_2 and local inhomogeneities in the magnetic field
- This procedure forms the basis of the BOLD fMRI
- T_1, T_2 vary with tissue boundaries, helps in differentiating between gray and white matter
- T_2^* is sensitive to blood flow and oxygenation and it can be used to image brain function

What does MRI study?

- MRI studies brain anatomy
  - Structural T1 weighted images
  - High spatial resolution
  - Can easily distinguish between tissue types

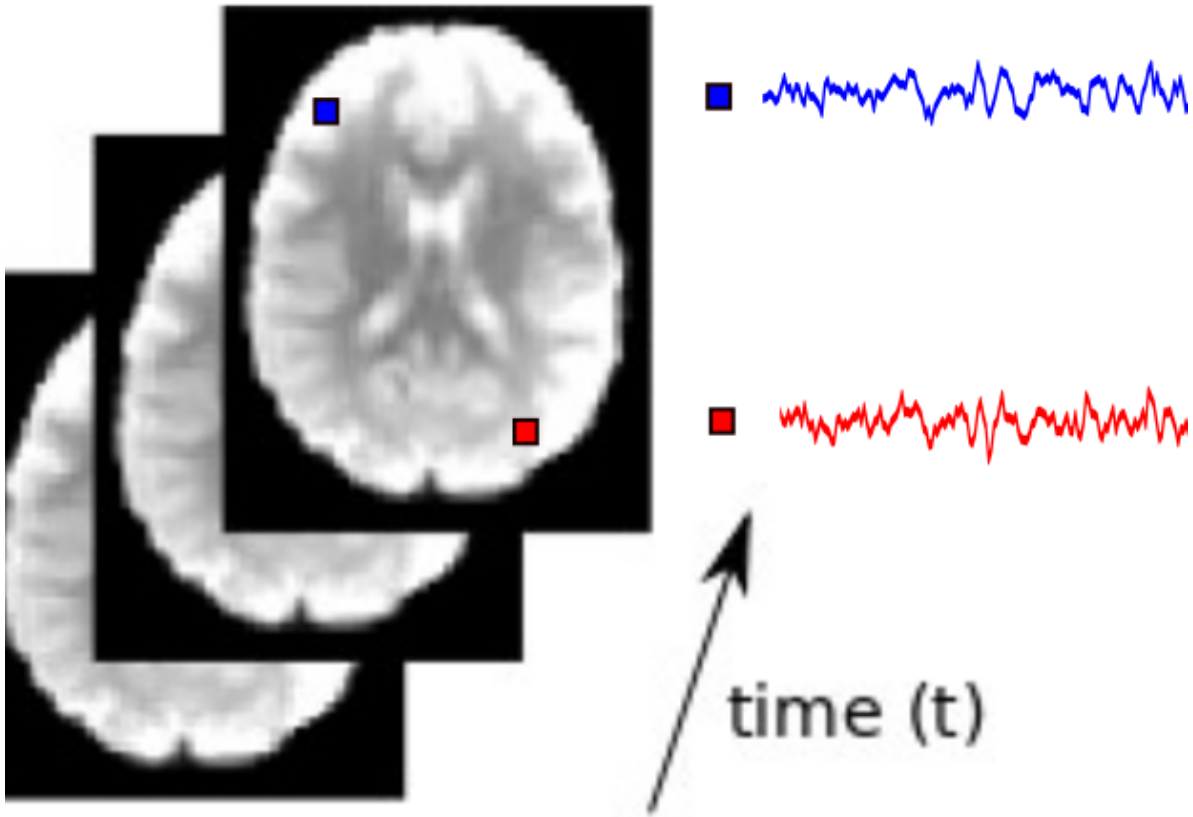
What does fMRI study?

- fMRI studies brain function
  - Functional (T_2^*) weighted images
  - Lower spatial resolution/high temporal resolution
  - Study changes in time series signal in relation to experimental manipulation



Functional MRI

An fMRI based experiment consists of a sequence of brain volumes where one can study blood oxygenation changes over time manipulated by an psychological condition.



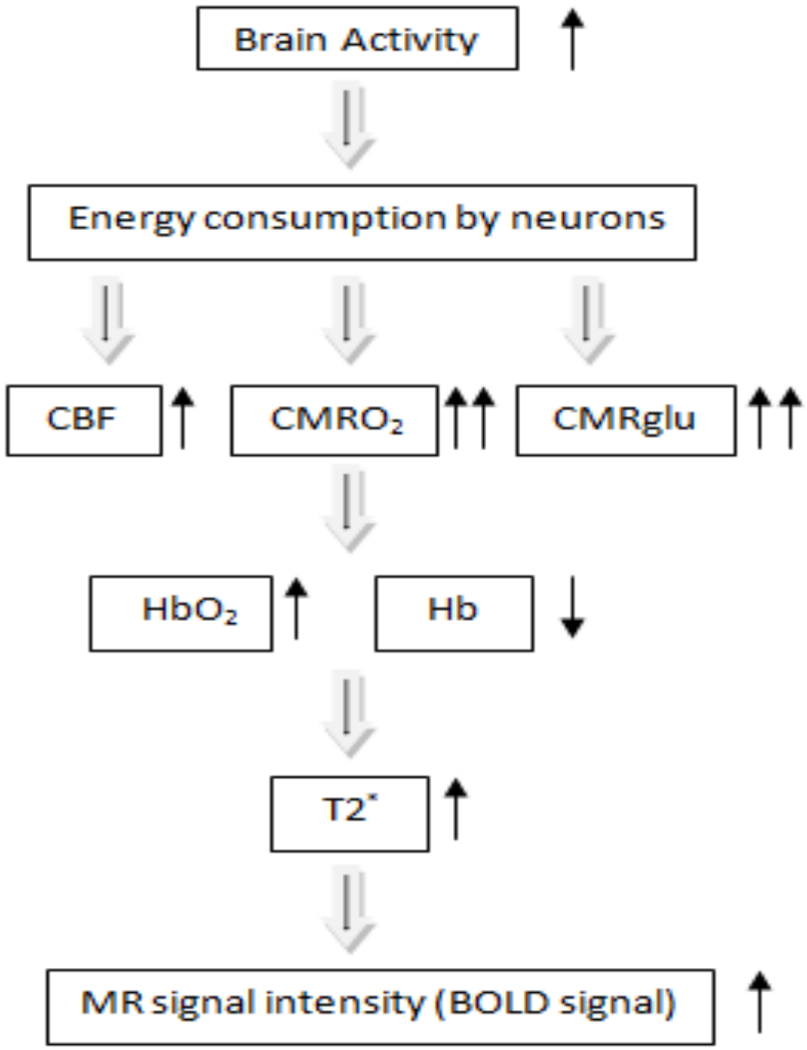
BOLD fMRI

BOLD - Blood Oxygenation Level Dependent contrast.

It depicts the changes in deoxyhemoglobin concentration as a response to certain tasks or spontaneous modulation of neural metabolism (oxygen consumption).

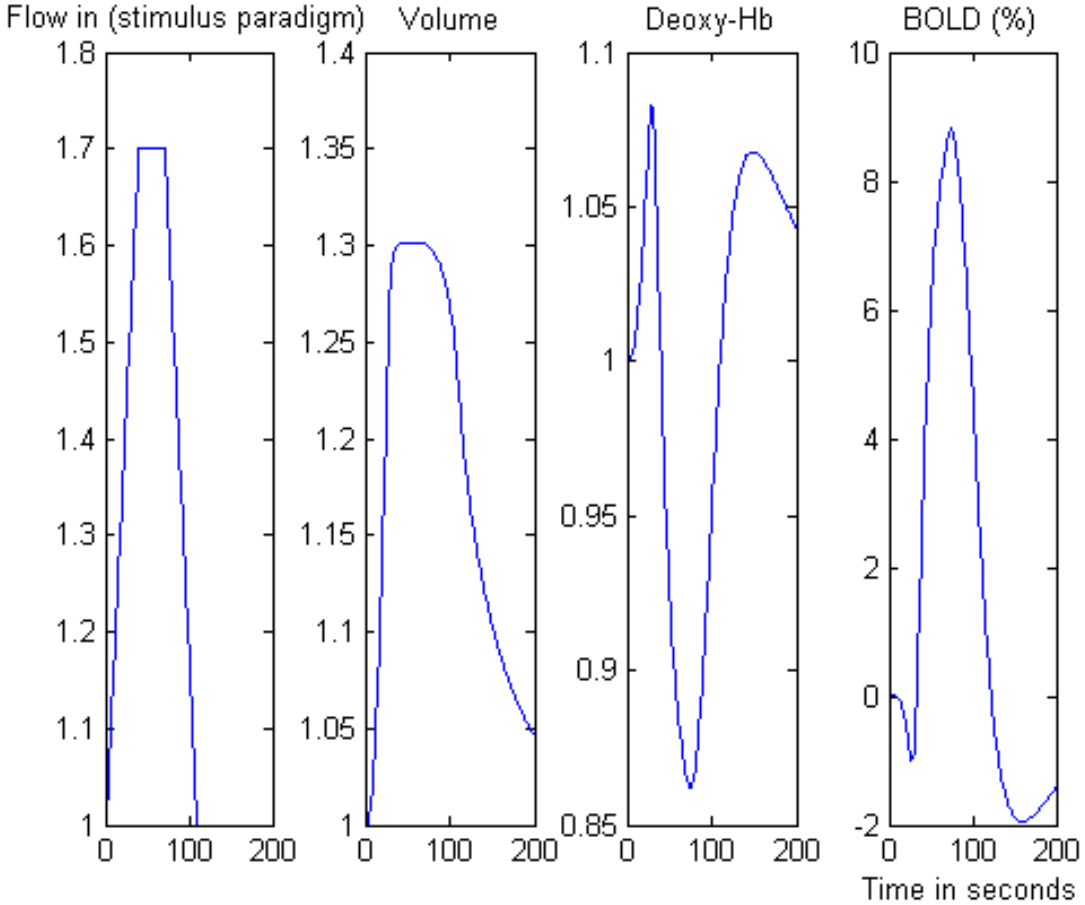
It is an indirect measure of neural activity.

Mechanism of BOLD signal acquisition



Hemodynamic Response Function

The change in magnetic signal instantiated by neural activity is known as the Hemodynamic Response Function.



https://liu.se/studieinfo/en/kurs/tbmt02/vt-2019/syllabus

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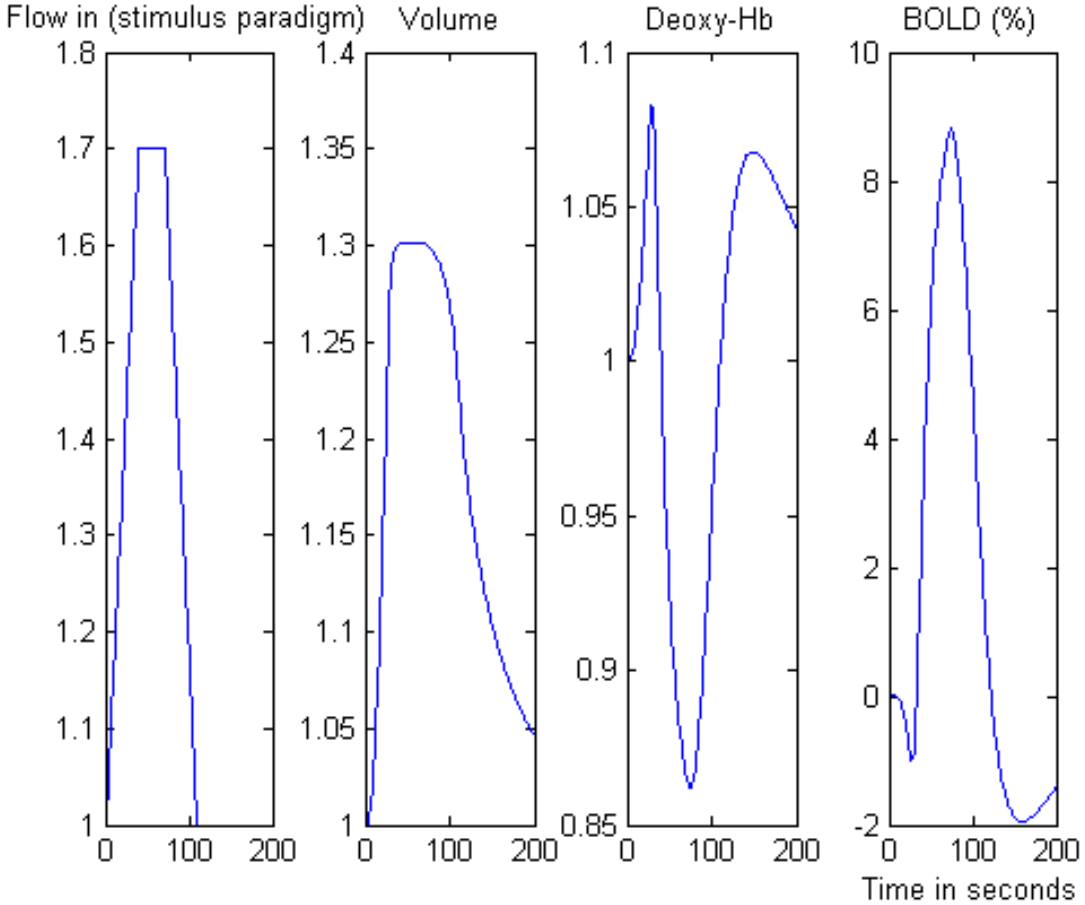
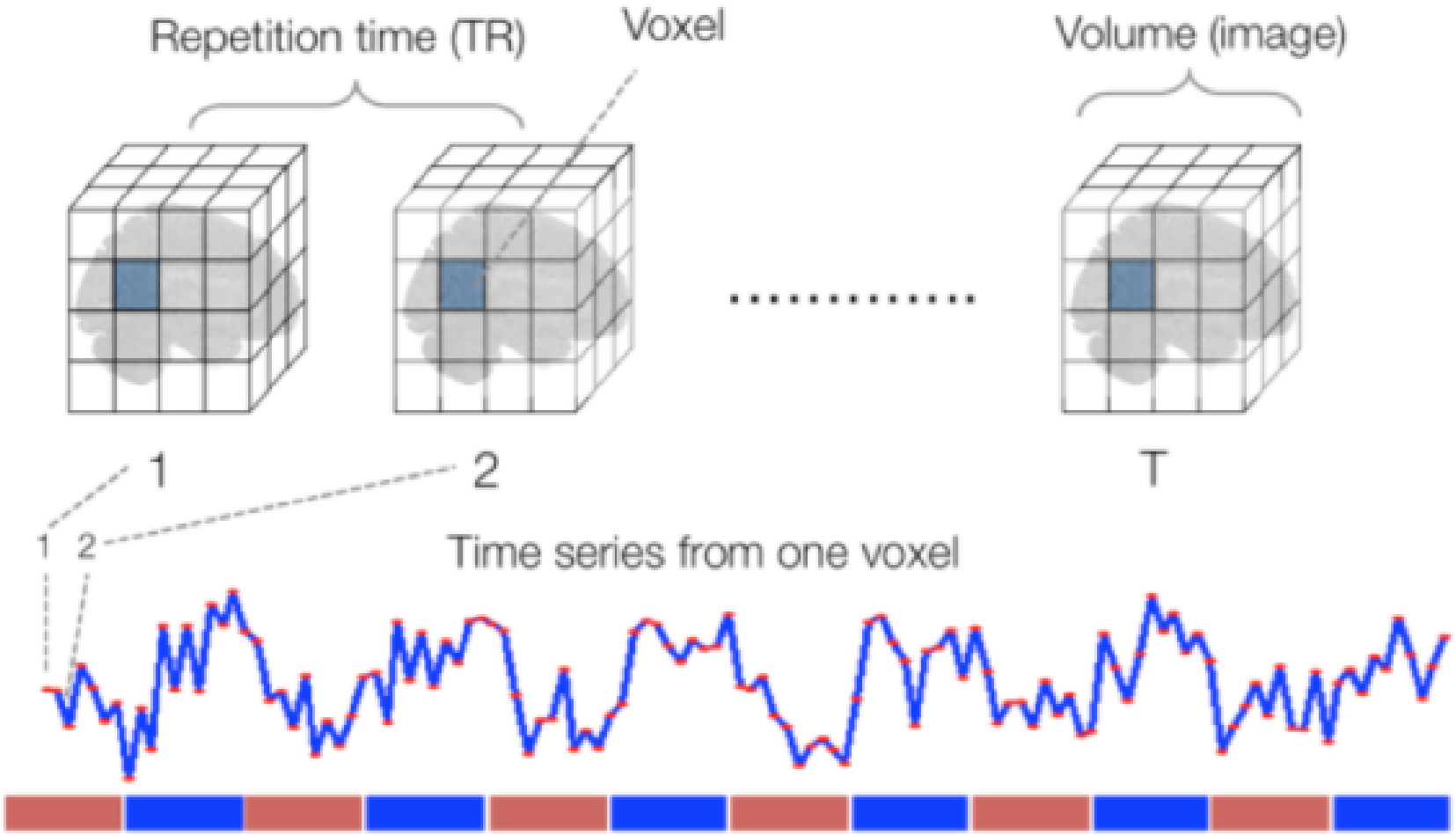


The strongest signal appears 5-6secs after activation

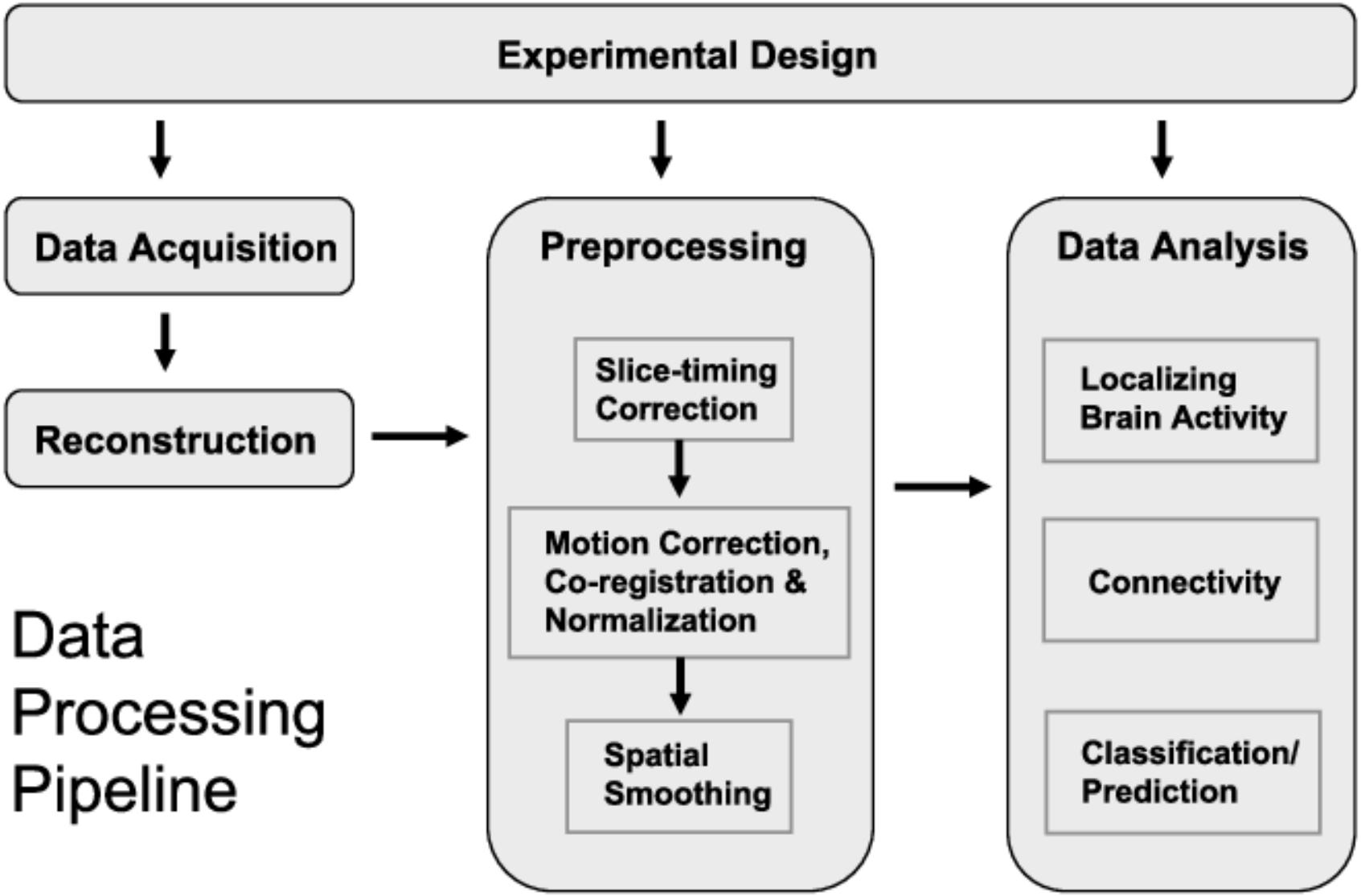
https://liu.se/studieinfo/en/kurs/tbmt02/vt-2019/syllabus

fMRI timeseries



https://www.imaios.com/en/e-Courses/e-MRI/Functional-MRI/introduction

Data processing pipeline



(Poldrack *et al.* 2011; Lindquist 2008)

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3. Raichle, M. E. Behind the scenes of functional brain imaging: A historical and physiological perspective. *Proceedings of the National Academy of Sciences* **95,** 765–772 (1998).
4. Poldrack, R. A., Mumford, J. A. & Nichols, T. E. *Handbook of Functional MRI Data Analysis.* (Cambridge University Press, 2011).
5. Lindquist, M. A. *The Statistical Analysis of FMRI Data..* (Statistical Science, 2008).

Bibliography II

Resource from FSL group:
https://www.fmrib.ox.ac.uk/primers/appendices/mri_physics.pdf

Videos

- http://www.brainmapping.org/NITP/Summer2015.php
- https://www.imaios.com/en/e-Courses/e-MRI/Functional-MRI/