COGS500/CMPE489 Introduction to Cognitive Science Week III: 10.10.2017

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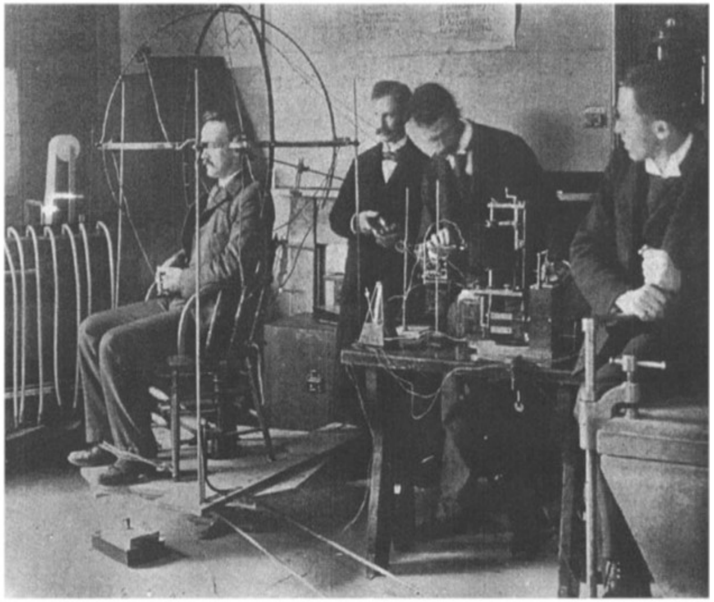
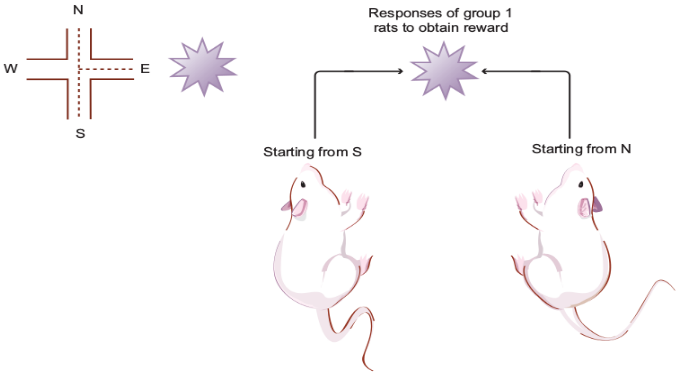
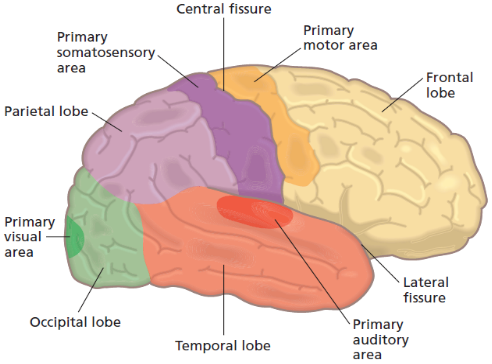
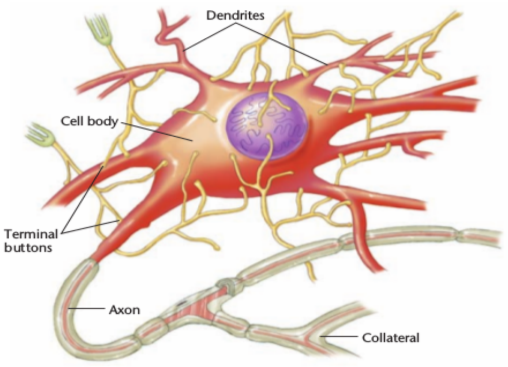
Previously

- Psychology
- Nervous system and brain
  - Nervous system
  - Cerebral cortex









Today

- Studying brain cont'd
- Computational models of neurons

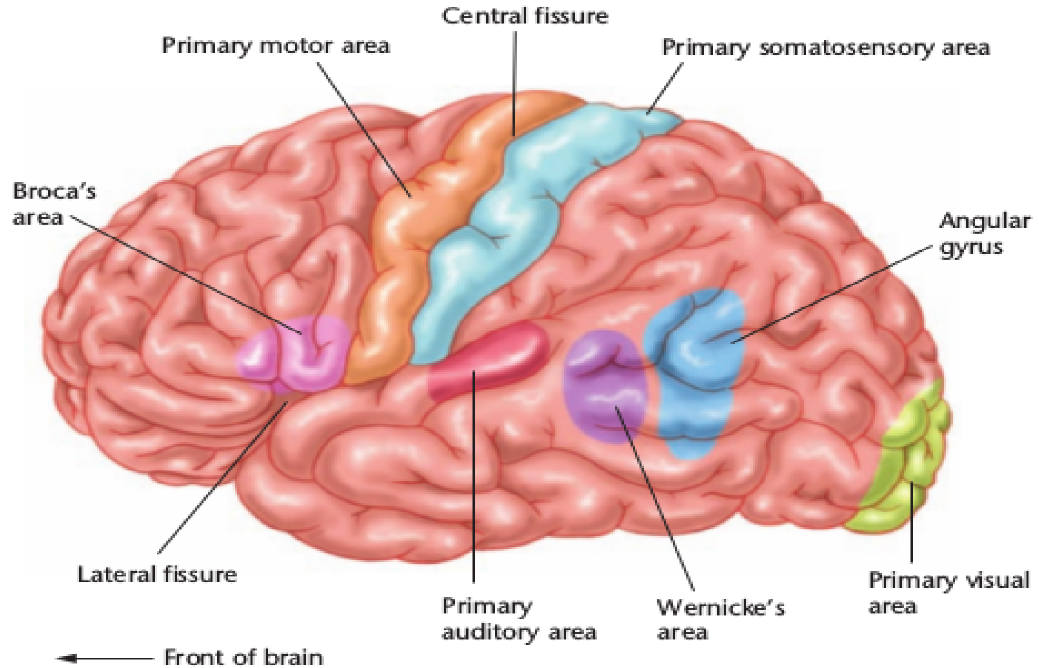
- Representation and integration of sensorimotor information
  - Guest lecture

Studying the brain: methods of inquiry

Name of method	*Procedure*	*Notes*
Selective lesioning	Studying the behavioral consequences of planned and selective lesioning (surgically removing or damaging a structure in the brain)	Only used in animal studies
Single-cell recordings	Studying the activity of single neurons, by probing them with small microelectrodes to discover what stimulus or behavior triggers the cell's activity	Only used in animal studies
Post mortem dissection	Examining patient's brain for lesions (damaged areas) after death	Behavioral consequences must have been studied prior to the death of the patient
Exploratory neurosurgery	Examining patient's brain by electrically stimulating certain areas of the exposed brain	
Event-related potentials (ERPs)	Recording the electrical activity of the brain at the scalp, using electroencephalograms (EEGs), as it occurs in response to a stimulus or preceding a motor response ('event-related')	Gives precise information on the timing of the brain activity, but less precise information on the location (since the recording occurs at the scalp only)
Computerized axial tomography (CAT or CT)	Mapping the brain using X-ray technique	Used to scan the brain for large structural abnormalities
Positron emission tomography (PET)	Measuring brain activity using a radioactive tracer mixed with glucose; active neurons require the most glucose and will be most radioactive	Gives precise information on the location of the brain activity, but less precise information on the timing (since glucose consumption is a relatively slow process)
Functional magnetic resonance imaging (fMRI)	Measuring brain activity by recording magnetic changes resulting from oxygen consumption	Gives precise temporal and spatial information; is relatively expensive
Transcranial magnetic stimulation (TMS)	Examining the consequences of (temporary) disruptions of normal brain functioning caused by magnetic stimulation of small areas	Used to study cognitive functioning
Magnetoencephalography (MEG)	Localizing brain activity by measuring magnetic changes	Precise method used in surgical applications, alongside electrical stimulation of the exposed brain

Language

- Much information comes from observations of patients with brain damage.. Rumor, penetrating head wound, rupture of blood vessels.
- Aphasia: language deficits caused by brain damage.
- 1861, Paul Broca, post-mortem dissection, found damage in an area of the left hemisphere above the lateral fissure in frontal lobe. Expressive aphasia. Broca's area involved in speech production.



- 1874, Carl Wernicke, left hemisphere, temporal lobe, receptive aphasia. Wernicke's area. Unable to comprehend words.

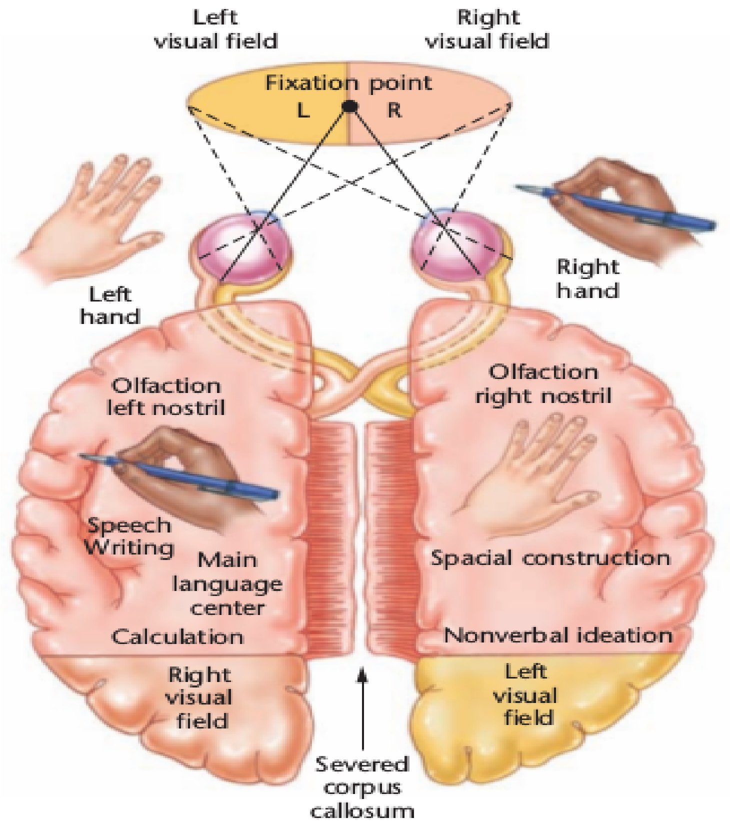
Language

- Wernicke-Geschwind model: Broca's area stores articulatory codes. Wernicke's area auditory codes and meanings of words

- Damage limited to Broca's area: speech production
- Damage to Wernicke's area: all aspects of language comprehension
- Damage to angular gyrus: cannot read, but can speak or comprehend spoken.
- Damage in auditory area: read and speak but cannot comprehend

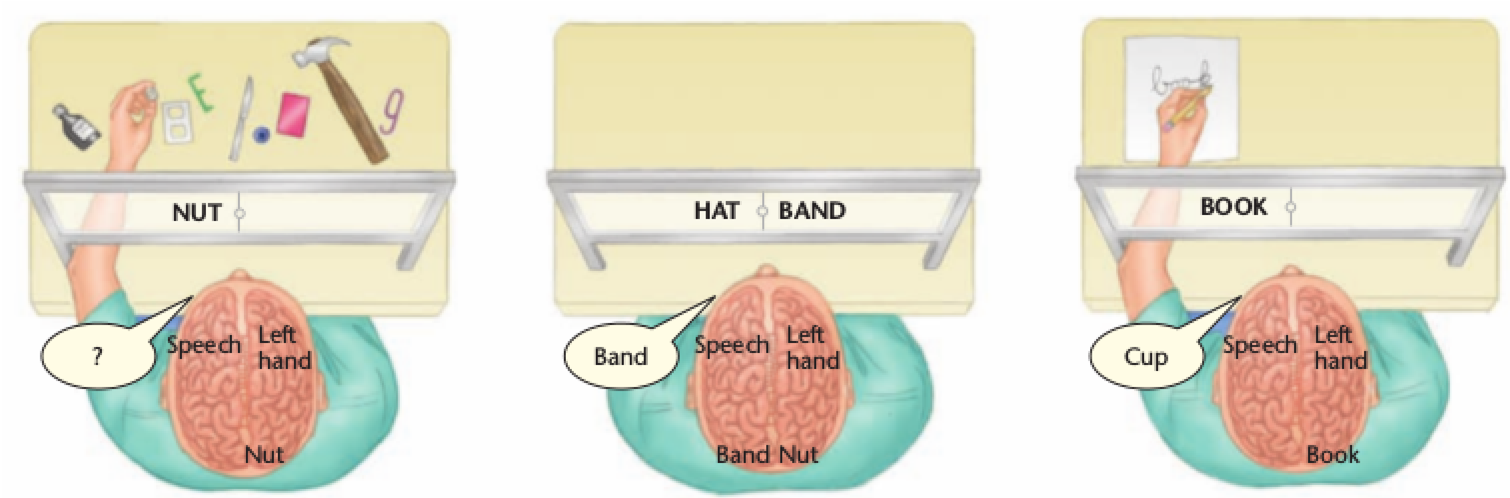
Split-brain research

- Epilepsy patients, seizure starting in one hemisphere may trigger massive response. Therefore, corpus collasum is distrupted.
- Roger Sperry, Nobel Prize in 1981.



Split-brain research

- Roger Sperry, Nobel Prize in 1981.
- 'nut' was not transferred. When questioned, seems unaware of what his left hand is doing.
- 10 seconds, otherwise eye moves and info goes to both sides.
- If blindfolded, some object is placed on left hand, can use.



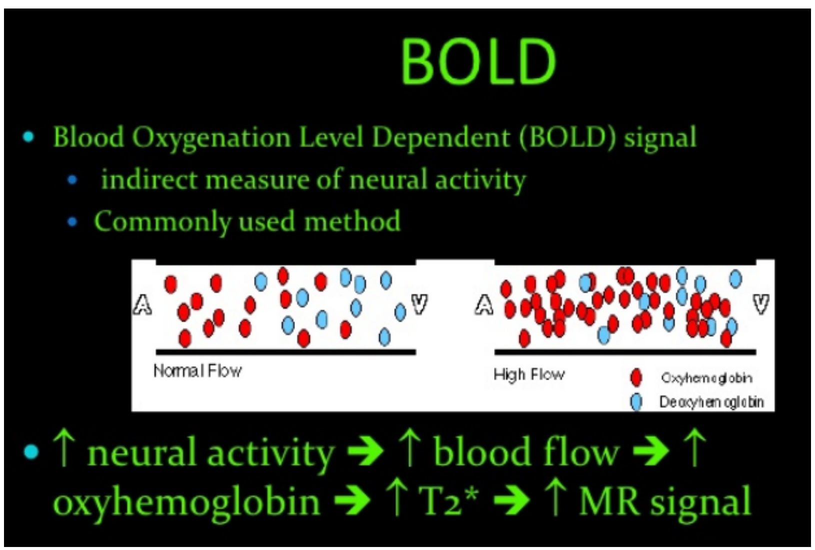
a) A split-brain patient correctly retrieves an object by touch with the left hand when its name is flashed to the right hemisphere, but he cannot name the object or describe what he has done.

b) The word 'hatband' is flashed so that 'hat' goes to the right cerebral hemisphere and 'band' goes to the left hemisphere. The patient reports that he sees the word 'band' but has no idea what kind of band.

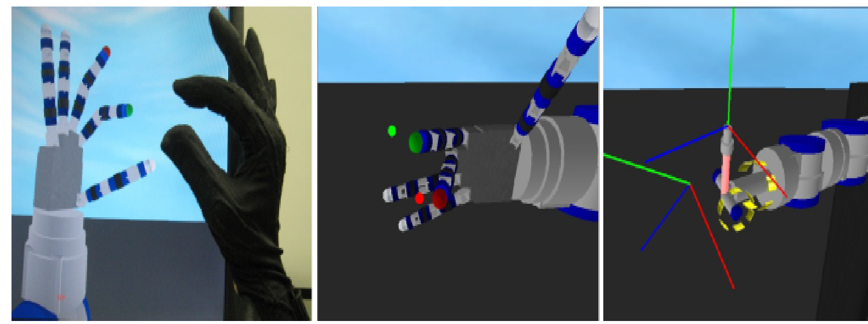
c) A list of common objects (including 'book' and 'cup') is initially shown to both hemispheres. One word from the list ('book') is then projected to the right hemisphere. When given the command to do so, the left hand begins writing the word 'book', but when questioned, the patient does not know what his left hand has written and guesses 'cup'.

Studying the brain: methods of inquiry

Functional magnetic resonance imaging (fMRI)	Measuring brain activity by recording magnetic changes resulting from oxygen consumption	Gives precise temporal and spatial information; is relatively expensive



https://www.slideshare.net/ricksw78/fmri-presentation



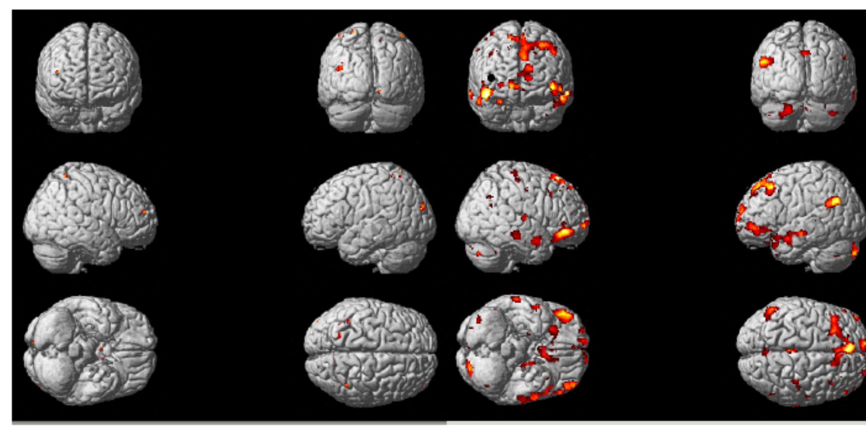


Figure 6. AN-NAN (left) and NAN-AN (right) contrasts for a single subject (p<0.005)

Humanoid Brain Science Erhan Oztop, Emre Ugur, Yu Shimizu, Hiroshi Imamizu, Humanoid Robotics and Neuroscience: Science, Engineering and Society, 29

Brain activity in use of anthropomorphically similar or dissimilar tools/agents

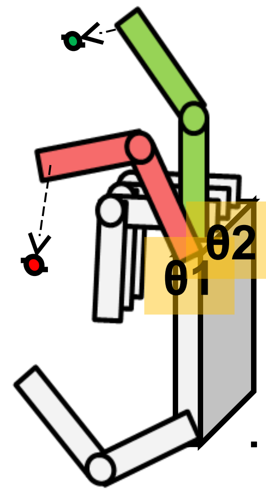
with

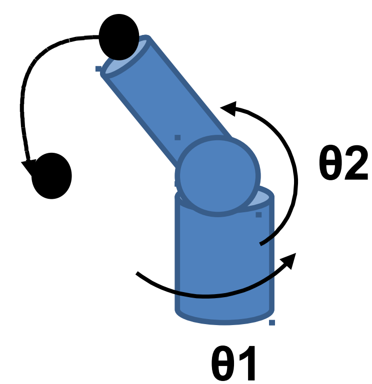
Erhan Oztop

Hiroshi Imamizu

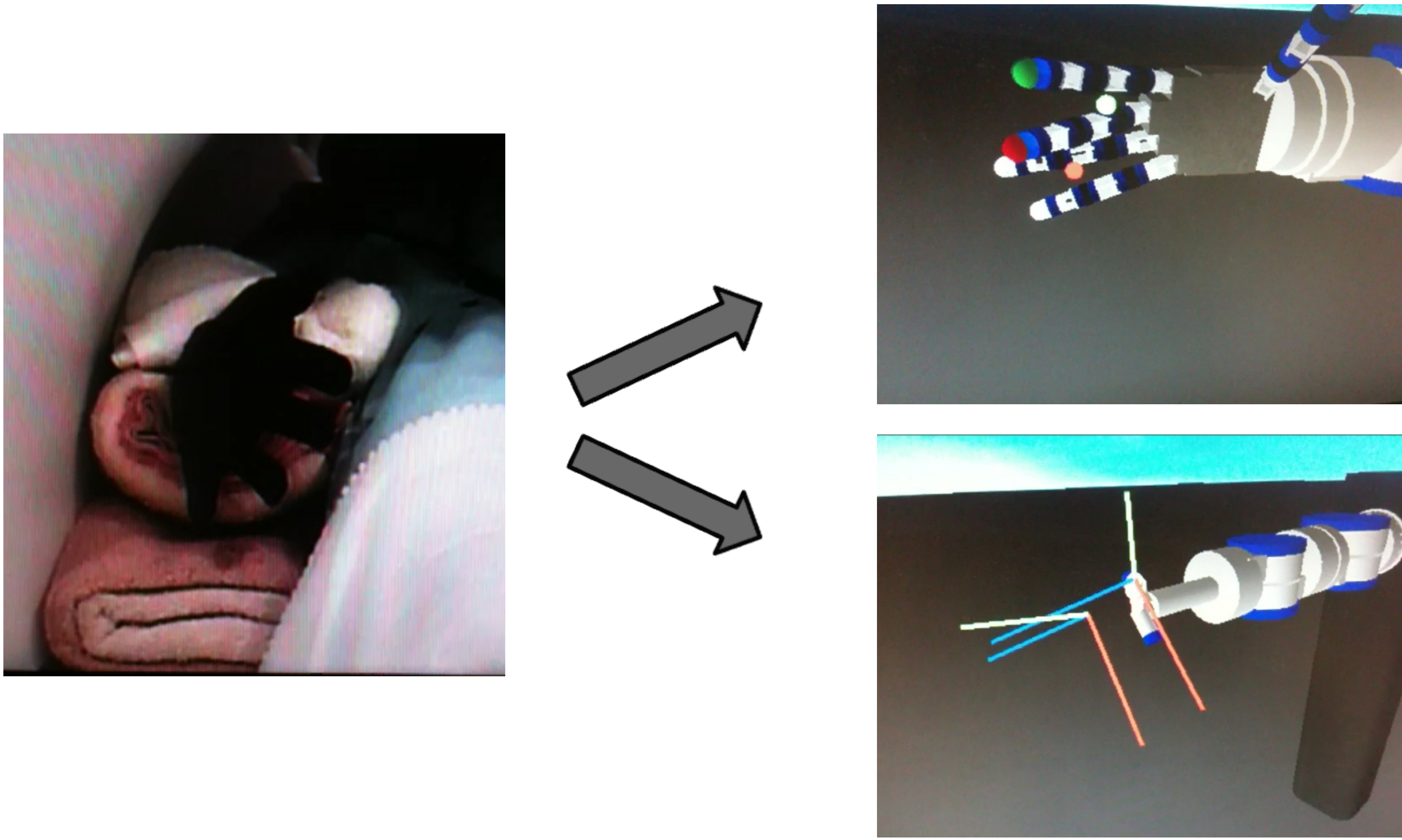
Tool use representation in body-schema?

- Neural representations of control of external agents and motor learning mechanisms of new tools.
- Robots anthropomorphically similar to human body became part of our body schema
- Whereas non-anthropomorphic robots induce internal model formation in other parts of the brain.
- Expect differences in fMRI activation.

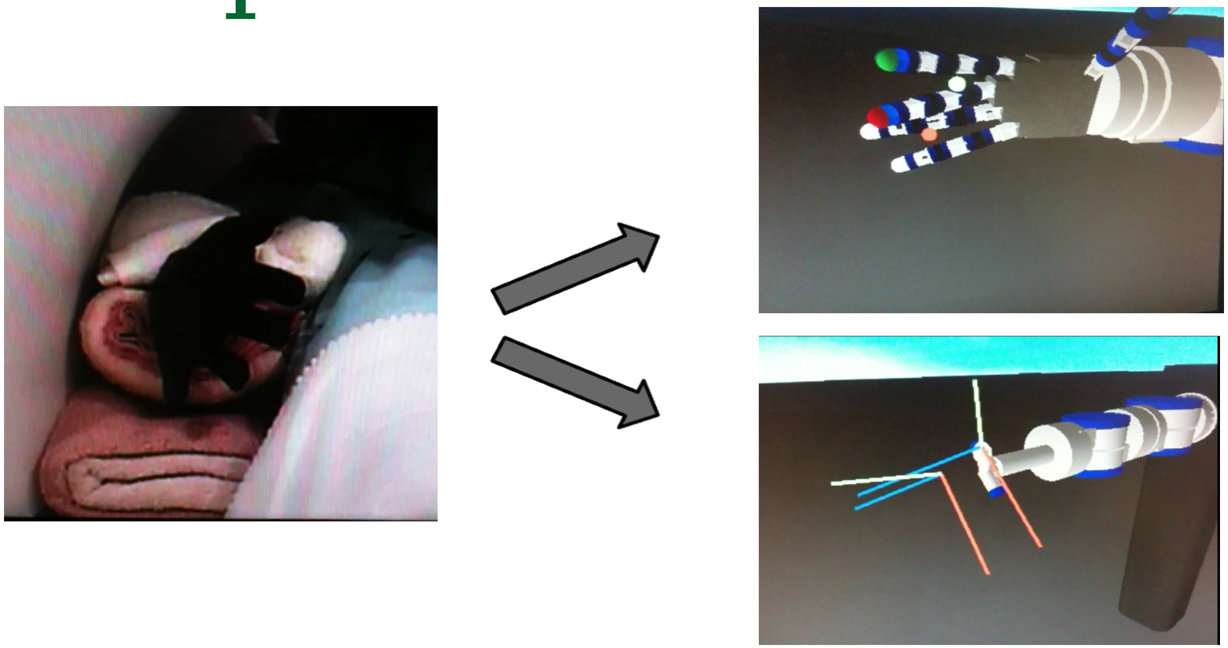




Anthropomorphic tools fMRI experiment



Anthropomorphic tools fMRI experiment



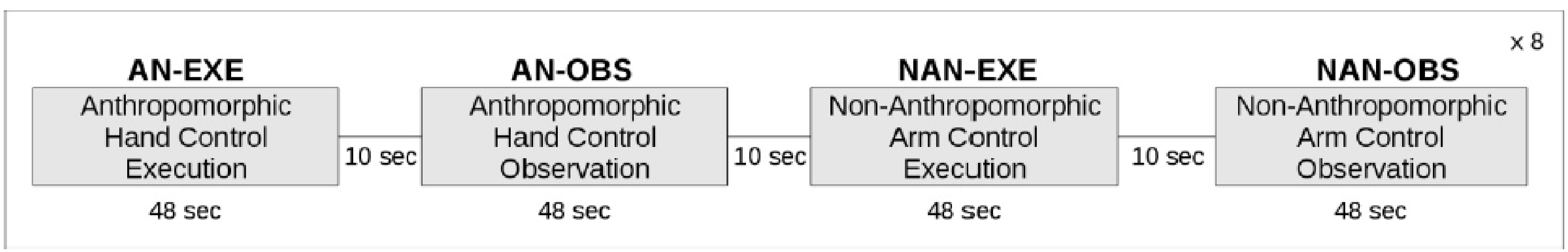


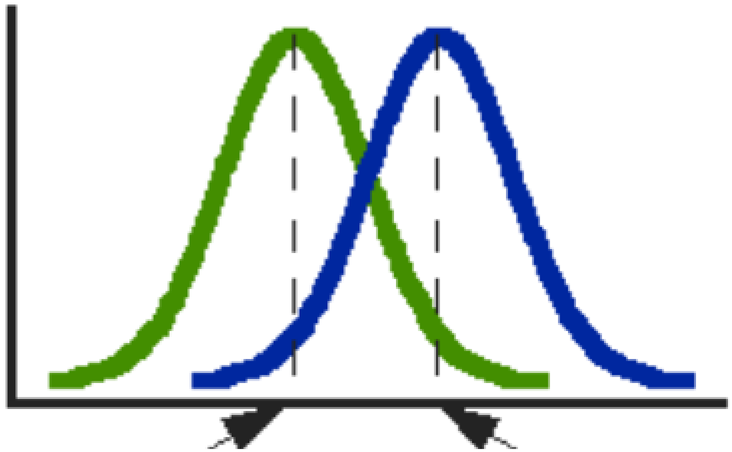
Figure 7. The experimental paradigm. Anthropomorphic and non-anthropomorphic control corresponds to hand and arm control, respectively. In the visual blocks, the subjects do not move, but watch a recording of the previous execution block including the robot movements.

Anthropomorphic (AN, hand) vs Non-anthropomorphic (NAN, arm)

- Question: What are the mechanism behind control and learning?
- Hypothesis: AN and NAN are represented in different regions
  - AN: becomes part of body schema – parietal cortex
  - NAN: external model – cerebellum
- Which control conditions should be kept fixed?

Significant difference in performance between hand and arm control?

- The t-test assesses whether the means of two groups are statistically different from each other.

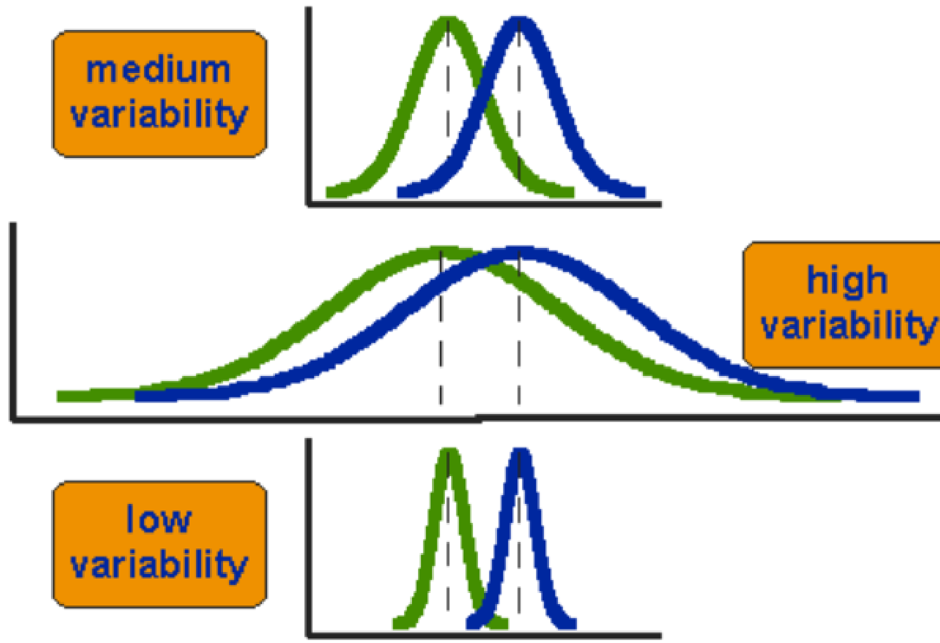


- Performance distributions of
  - Green: Robot control
  - Blue: Hand control

- From 2 executions?
- 2000 executions
- Number of sample counts!

Significant difference in performance between hand and arm control?

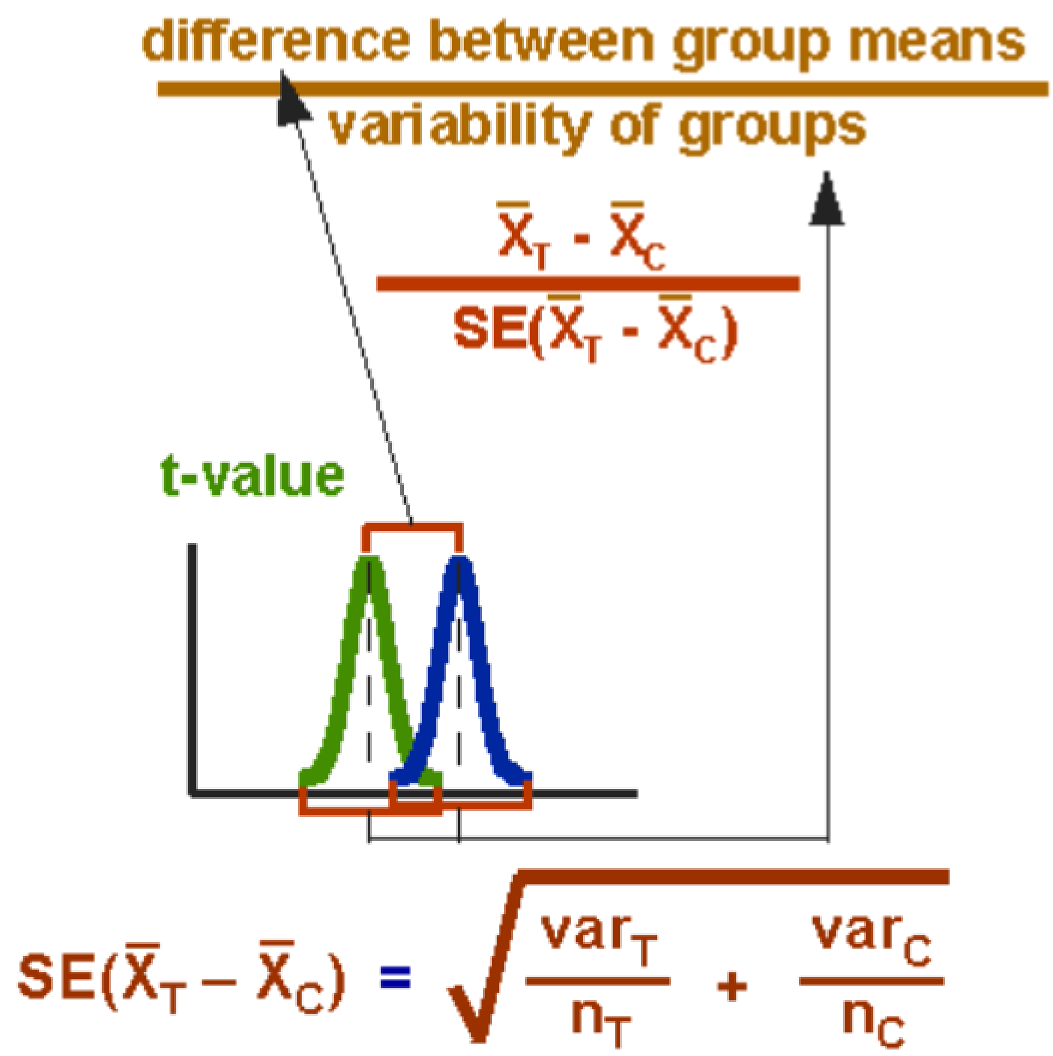
- The difference between the means is the same in all three.
- two groups appear most different or distinct
  - Where?
  - Why?



- Judge the difference between their means relative to the spread or variability of their scores.

Significant difference in performance between hand and arm control?

- t value boils down all of your sample data down to one value, the t-value
  - means, variances, number of samples
- Sign matters?
- look it up in a table of significance



Significant difference in performance between hand and arm control?

	a1	a2
	5	13
	3	9
	4	10
	4	8
	6	9
	1	12
	3	8
	4	12
	6	10
	4	9
Sum(A)	40	100
Sum of squares	180	1028

$$\sigma_{diff} = \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}} = \sqrt{\frac{2.22}{10} + \frac{3.11}{10}} = .73$$

$$t = \frac{\mu_{a1} - \mu_{a2}}{\sigma_{diff}} = \frac{-6}{.73} = -8.22$$

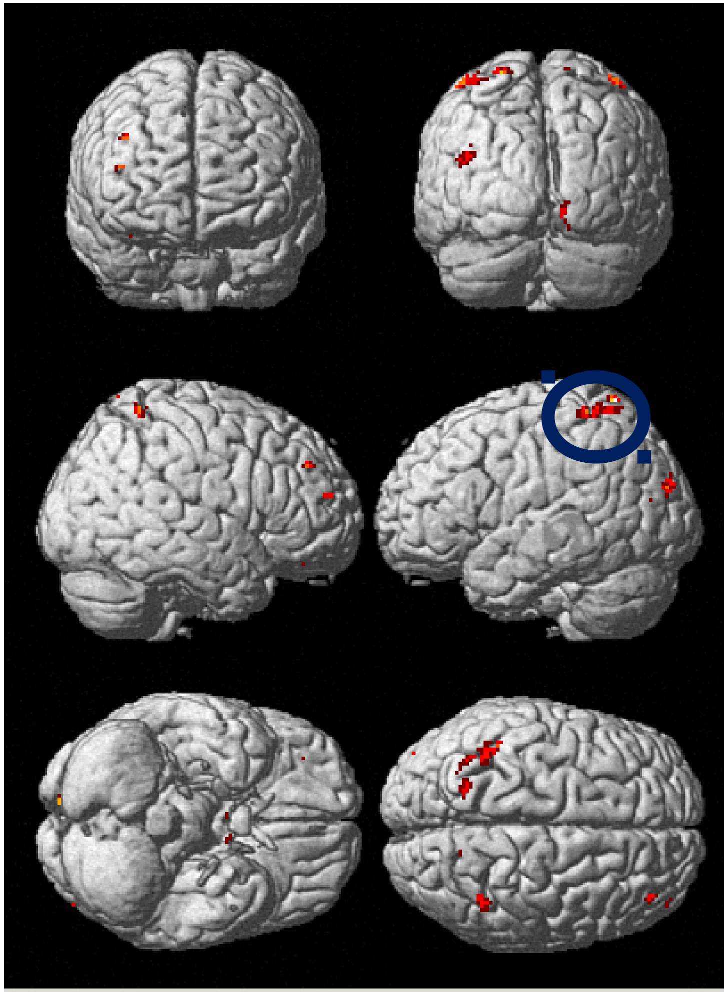
Significant difference in performance between hand and arm control?

- Critical values for t-test

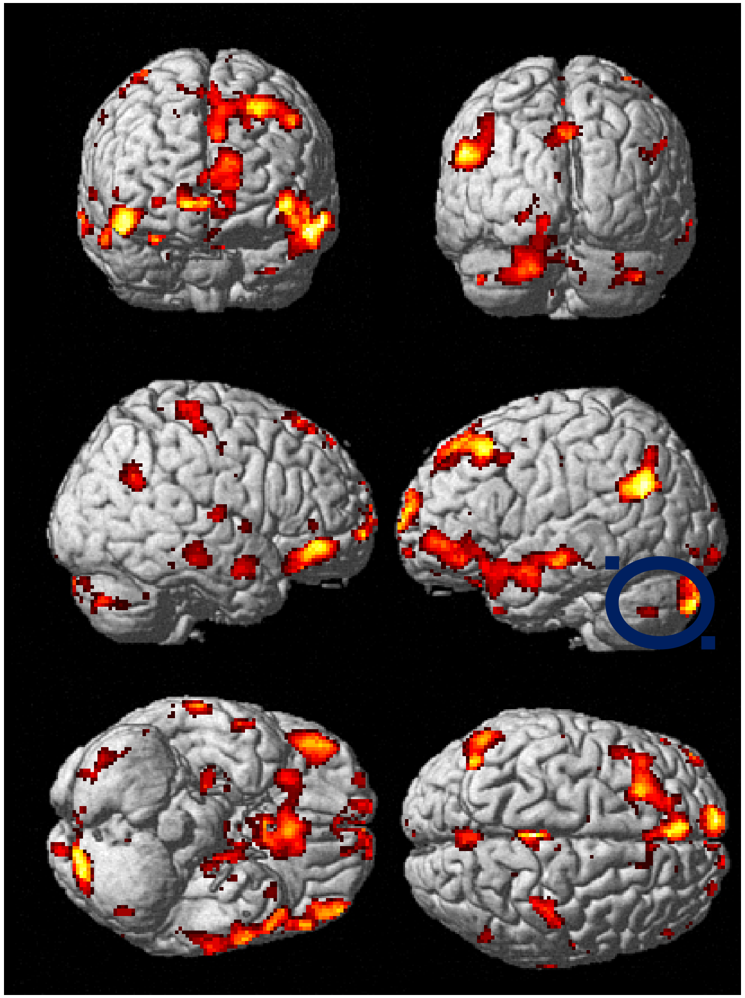
Probability less than the critical value ($t_{1-\alpha,\nu}$)

ν	0.90	0.95	0.975	0.99	0.995	0.999
1.	3.078	6.314	12.706	31.821	63.657	318.313
2.	1.886	2.920	4.303	6.965	9.925	22.327
3.	1.638	2.353	3.182	4.541	5.841	10.215
4.	1.533	2.132	2.776	3.747	4.604	7.173
5.	1.476	2.015	2.571	3.365	4.032	5.893
6.	1.440	1.943	2.447	3.143	3.707	5.208
7.	1.415	1.895	2.365	2.998	3.499	4.782
8.	1.397	1.860	2.306	2.896	3.355	4.499
9.	1.383	1.833	2.262	2.821	3.250	4.296
10.	1.372	1.812	2.228	2.764	3.169	4.143
11.	1.363	1.796	2.201	2.718	3.106	4.024
12.	1.356	1.782	2.179	2.681	3.055	3.929
13.	1.350	1.771	2.160	2.650	3.012	3.852
14.	1.345	1.761	2.145	2.624	2.977	3.787
15.	1.341	1.753	2.131	2.602	2.947	3.733
16.	1.337	1.746	2.120	2.583	2.921	3.686
17.	1.333	1.740	2.110	2.567	2.898	3.646
18.	1.330	1.734	2.101	2.552	2.878	3.610
19.	1.328	1.729	2.093	2.539	2.861	3.579
20.	1.325	1.725	2.086	2.528	2.845	3.552

Anthropomorphic tools fMRI results



AN > NAN



NAN > AN

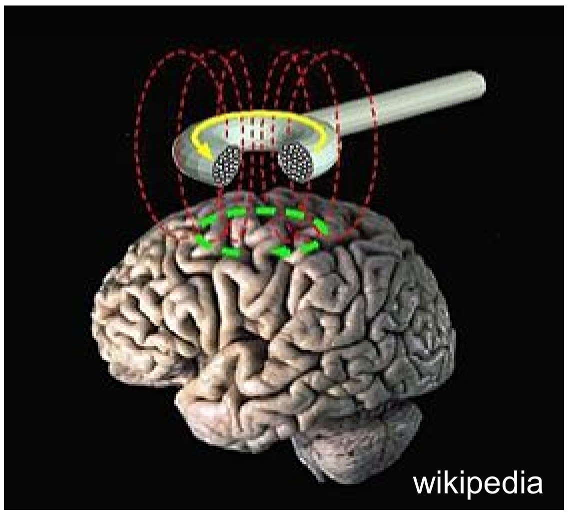
T-statistics were used for comparison of the estimated parameters of AN=(AN-EXE – AN-OBS) and NAN=(NAN-EXE – NAN-OBS). Two contrasts of AN –NAN and NAN – AN then yielded a t-value for each voxel. A threshold of P< 0.005 was used in obtaining the activation maps shown in this chapter.

Anthropomorphic tools fMRI results

- **High prefrontal activation** in the NAN-AN contrast indicates task difficulty in the NAN condition.
- NAN condition engaged the **angular gyrus**, which is involved in detection of mismatch between intended and actual movement leading to a loss of “action ownership” (agency)
- **Superior parietal regions** are involved in programming the movement according to extrinsic spatial information . The activation in this region suggests that the subject controlled the robot fingers as if they were the subject’s own fingers, thereby supporting the hypothesis that the hand robot was incorporated into the body schema
- The **occipital activity** in the AN-NAN contrasts may reflect the necessary fine control around the target points, which relies on detailed visual information

Studying the brain: methods of inquiry

Transcranial magnetic stimulation (TMS)	Examining the consequences of (temporary) disruptions of normal brain functioning caused by magnetic stimulation of small areas	Used to study cognitive functioning



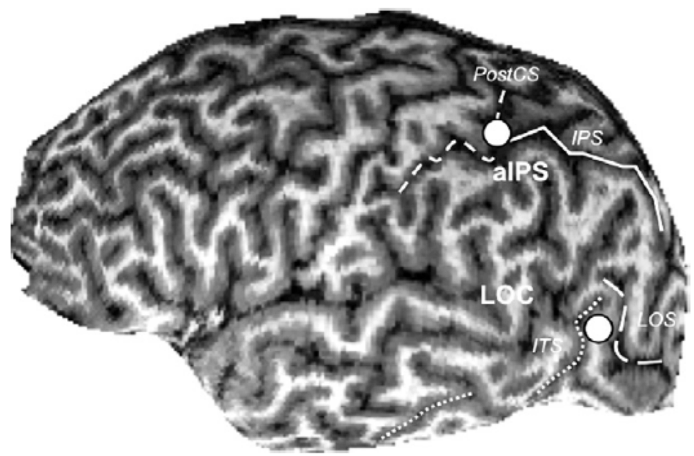
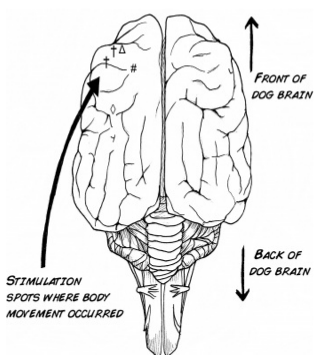


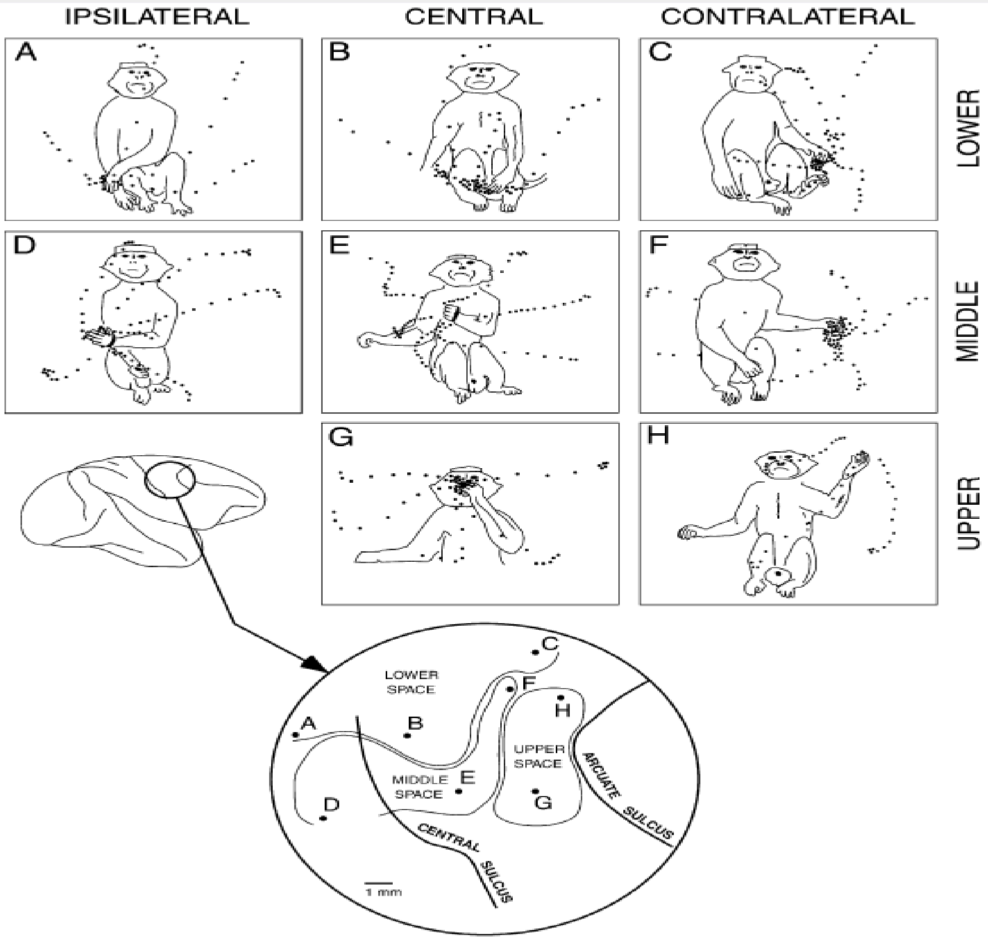
Fig. 2. Localization of brain sites for TMS. A three dimensional rendering of one subject's structural MRI in Brainsight, illustrating the cortical sites chosen for stimulation, as indicated by the white dots: (1) the anterior intraparietal sulcus, aIPS, site was located at the junction of the anterior intraparietal sulcus, (IPS, solid line), and the postcentral sulcus (PostCS, dashed line); (2) the lateral occipital, LO, site was near the junction of the inferior temporal sulcus (ITS, fine-dashed line) and lateral occipital sulcus (LOS, coarse-dashed line). Area MT+ lies at the junction of the two sulci (Dumoulin et al., 2000) and intersubject comparisons of MT+ and LO foci from an fMRI study (data provided by Tutis Vilis; see also Large, Aldcroft, & Vilis, 2005,

Ventral and dorsal stream contributions to the online control of immediate and delayed grasping: a TMS approach NR Cohen, ES Cross, E Tunik, ST Grafton, JC Culham - Neuropsychologia, 2009

Studying the brain: methods of inquiry

Microstimulation



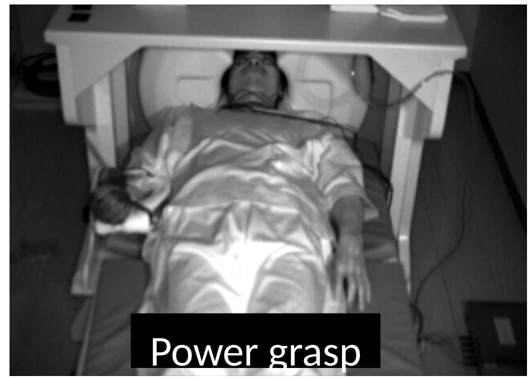


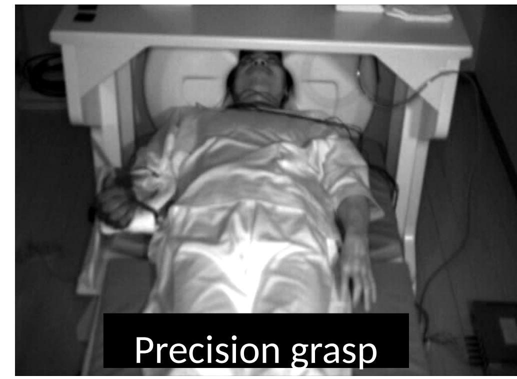
- Eduard Hitzig and Gustav Fritsch (1870)
  - the interaction between electric current and the brain.
  - electricity via a thin probe to the exposed cerebral cortex of a dog without anesthesia.
  - Identified the brain's "motor strip", a vertical strip of brain tissue on the cerebrum in the back of the frontal lobe

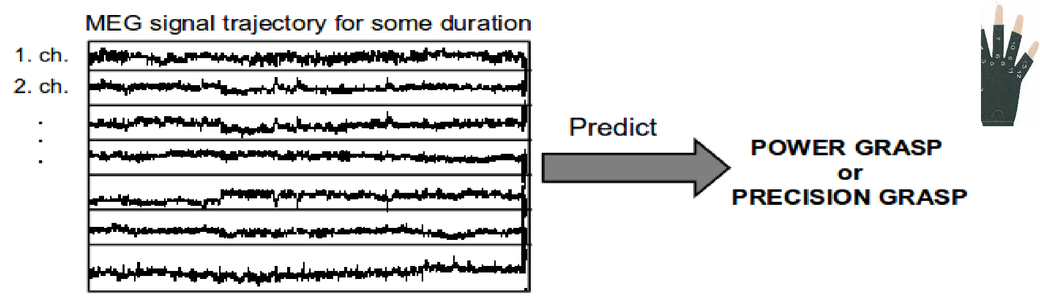
Complex movements evoked by microstimulation of precentral cortex MSA Graziano, CSR Taylor, T Moore - Neuron, 2002 - Elsevier

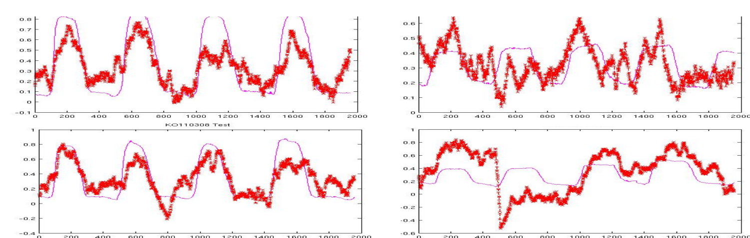
Studying the brain: methods of inquiry

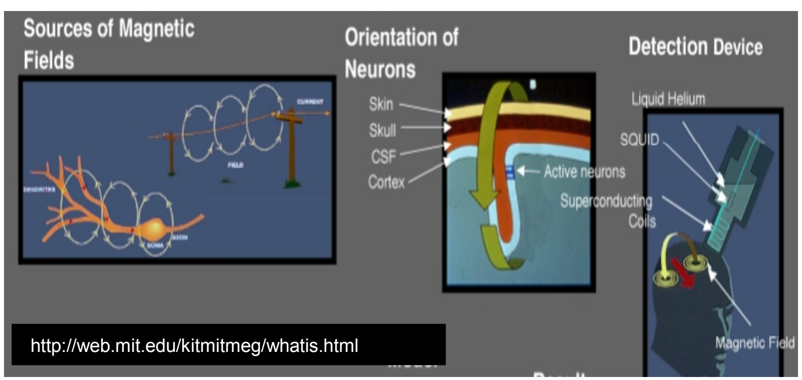
Magnetoencephalography (MEG)	Localizing brain activity by measuring magnetic changes	Precise method used in surgical applications, alongside electrical stimulation of the exposed brain











E. Ugur, Y. Shimizu, E. Oztop, and H. Imamizu, Reconstruction of Grasp Posture from MEG Brain Activity, The 34th Annual Meeting of the Japan Neuroscience Society, Yokohama, Japan, 2011.

Results on grasp decoding using MEG

In collaboration with

Yu Shimizu

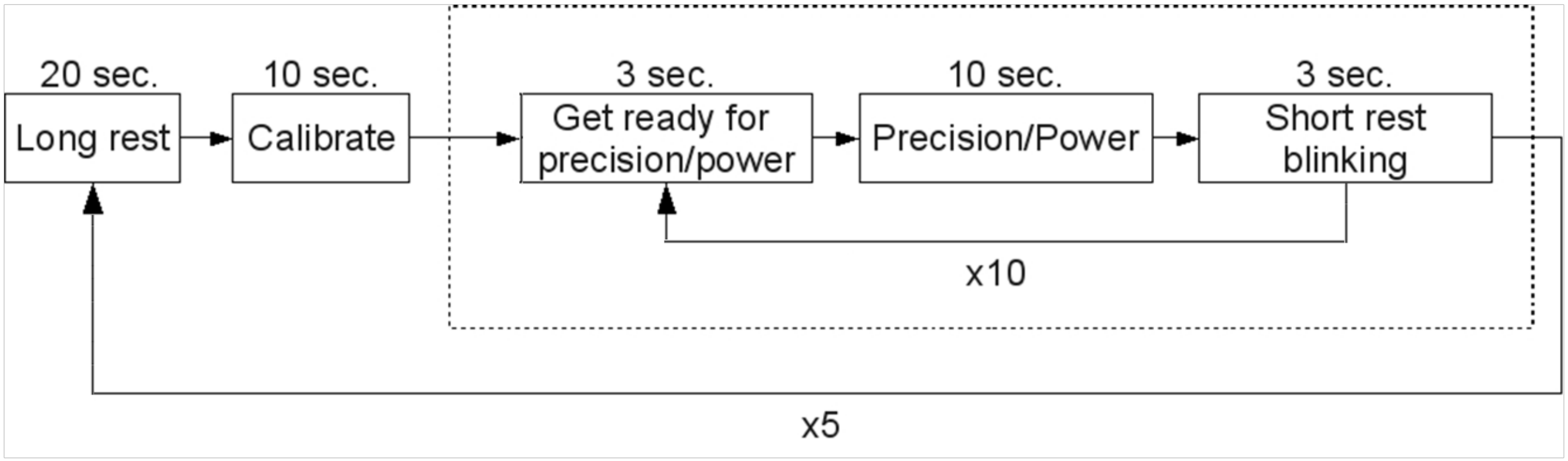
Erhan Oztop

Hiroshi Imamizu

Grasp decoding using MEG

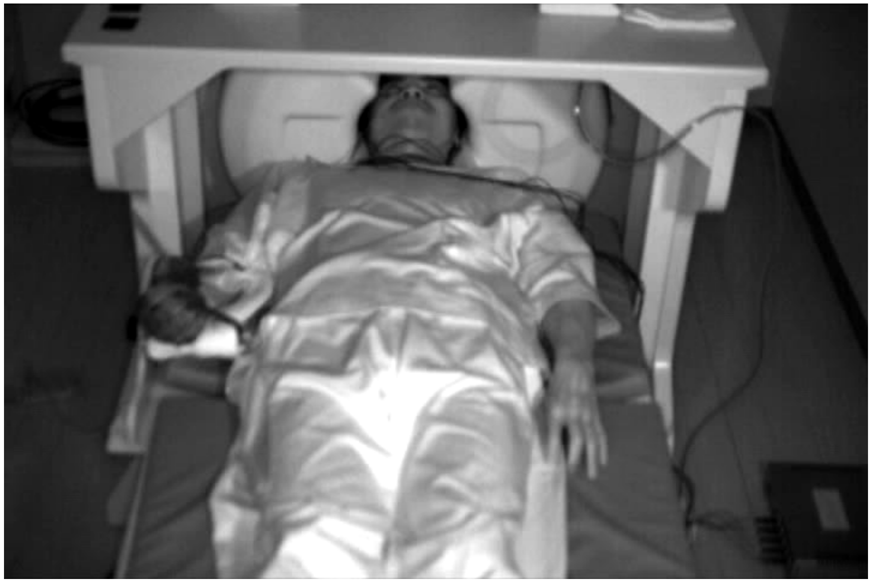
- We aim at both
  - decoding the grasp type (power or precision), and
  - reconstructing the aperture size based on MEG signals

Experimental Setup



- fMRI compatible data glove gets real joint angles
- Experiment details:
  - 1st and 2nd sessions: 5x10 blocks with usual hand orientation
  - 3rd session: 5x10 blocks with rotated hand orientation
- 200 Hz: 2000 data points in each block
- Only axial sensors are used

Experimental Setup



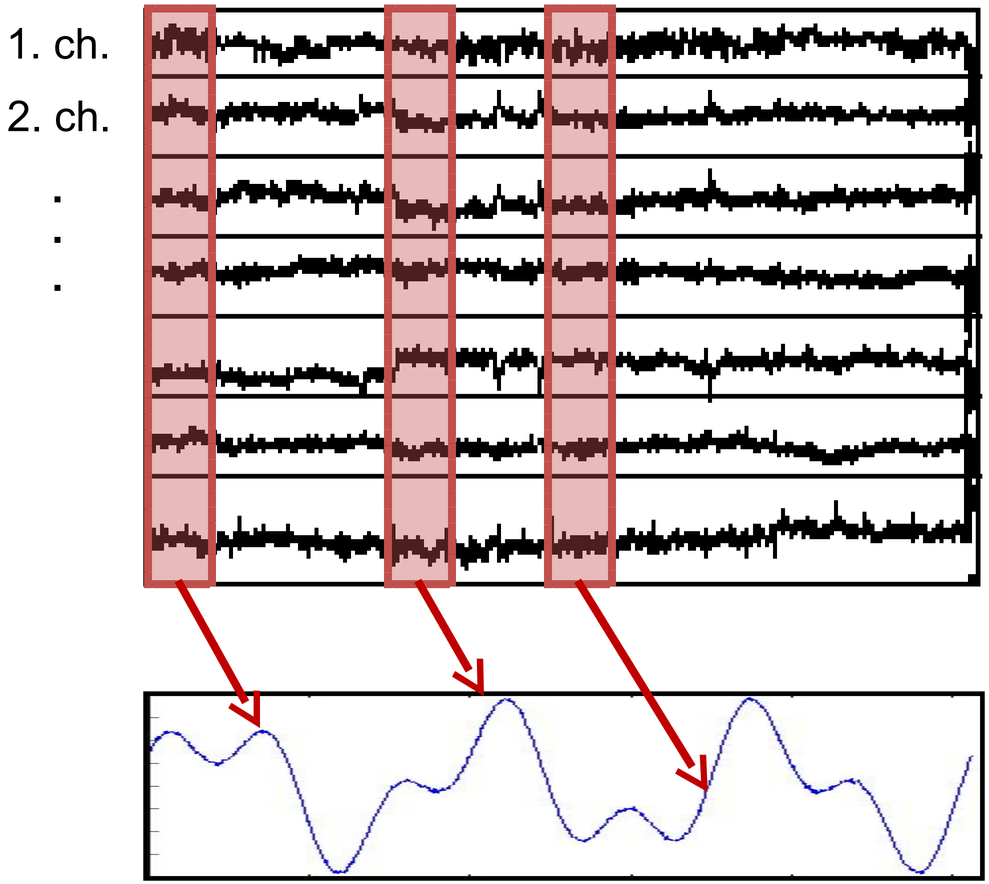
Power grasp

Precision grasp

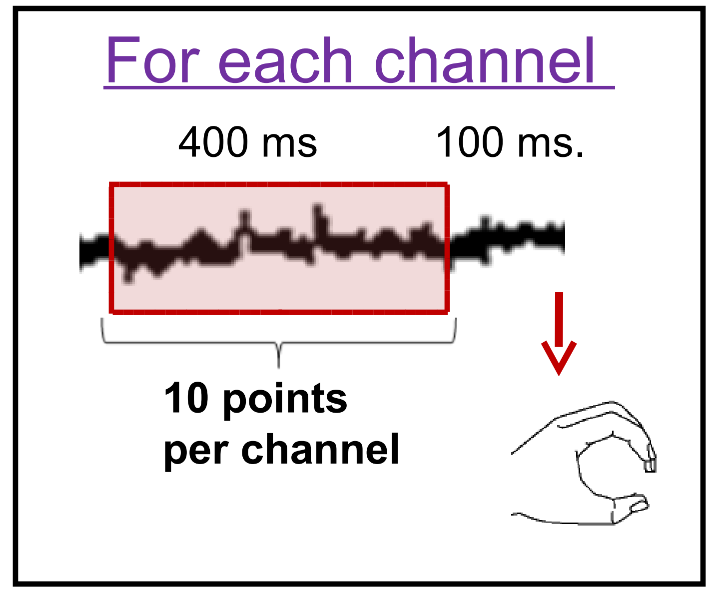
- Record joint angles using data glove
- Compute aperture size from joint angl
  - Power-grasp: mean(3,6,9,12)
  - Precision-grasp: mean (3,6)

Reconstruct aperture size

MEG signal trajectory for some duration



Grasp aperture or any joint angle

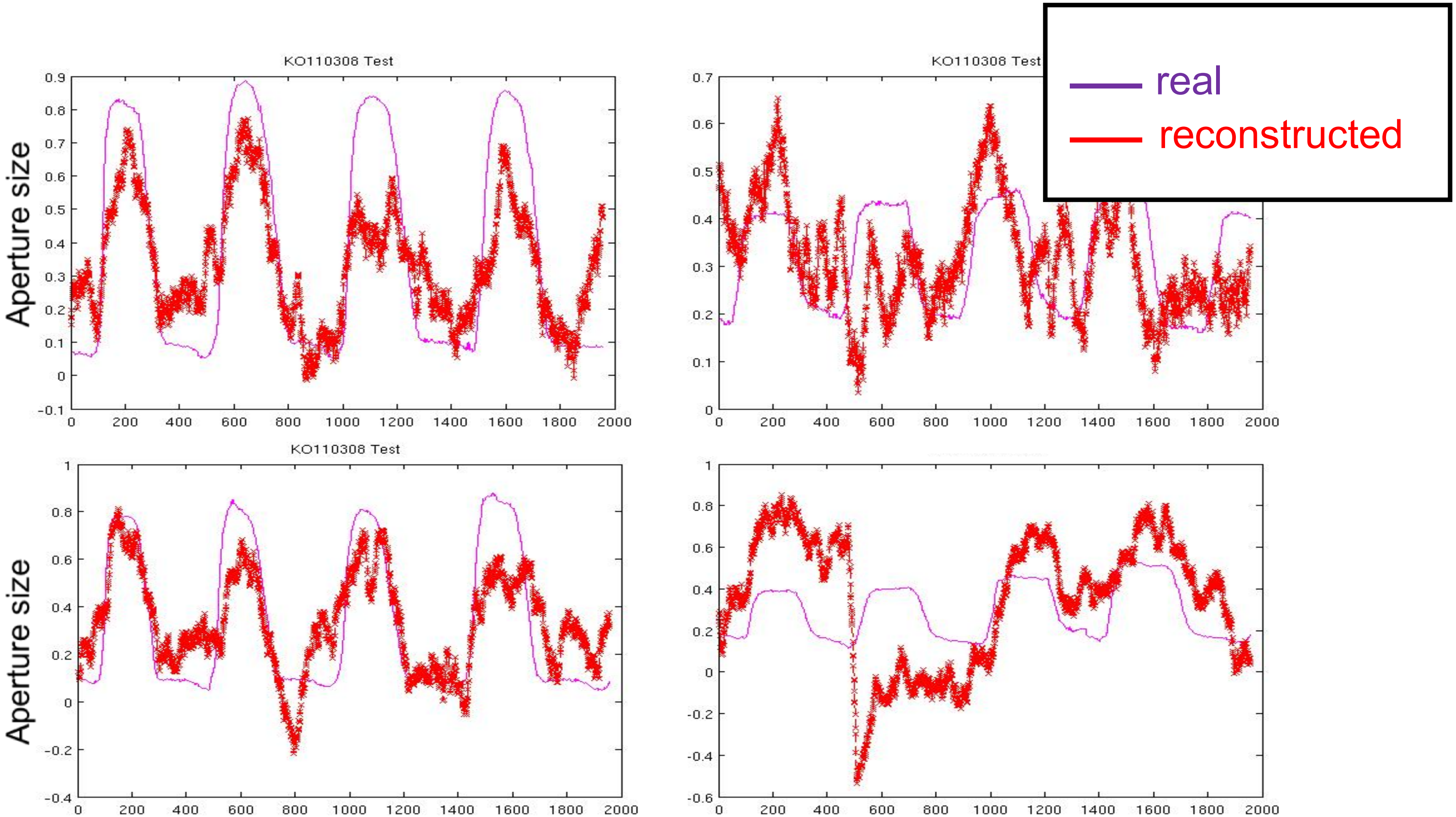


Sparse Linear Regression
(Sato et al. (2001) etc.)

\# of features = C x 10

where C is # of channels

Aperture reconstruction with power + precision combined



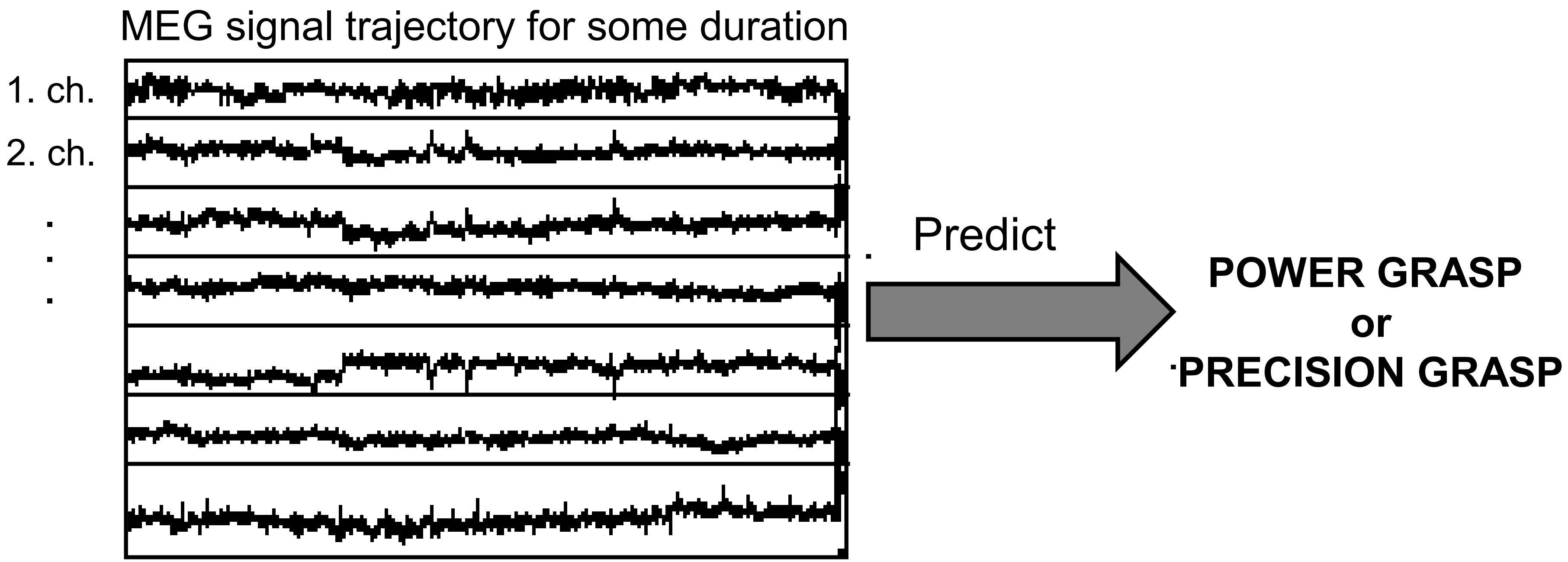
Sample power grasp trajectories

Sample precision grasp trajectories

Two step reconstruction

- Step 1: Make classification
  - Decide whether power or precision grasp in the beginning
- Step 2: Regress for each grasp type separately
  - Reconstruct based on its predicted grasp class

Step 1: Prediction of grasp type



Step 1: Prediction of grasp type

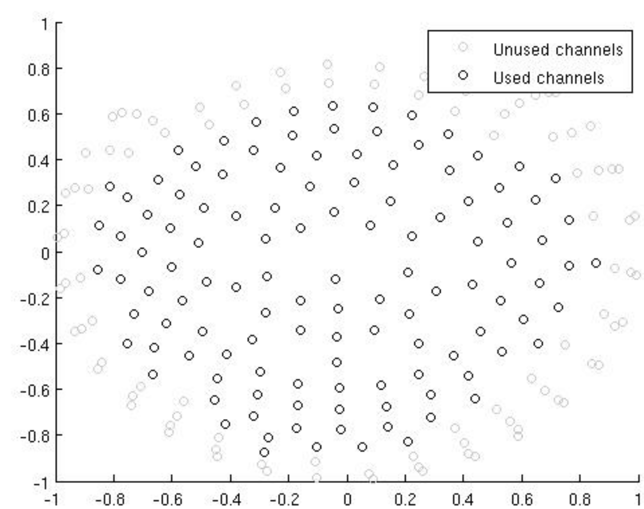
Features that represent statistics of MEG signal trajectory

1. ch.	(Mean, std. dev., coherence) in freq. band. X-Y (Mean, std. dev., coherence) in freq. band. Y-Z
2. ch.	(Mean, std. dev., coherence) in freq. band. X-Y (Mean, std. dev., coherence) in freq. band. Y-Z
119. ch.	(Mean, std. dev., coherence) in freq. band. X-Y (Mean, std. dev., coherence) in freq. band. Y-Z

Classify

POWER GRASP
or
PRECISION GRASP

- Train SVM
  - Feature number: (3 x 2 x 119)



Classification Results

Duration	SVM kernel	Same session	Different sessions Same hand orientation	Different sessions Different hand orientation
0-10 sec	RBF	78 %	62 %	
	Linear		68 %	
0-1 sec	RBF	76 %	70 %	76 %
	Linear		72 %	

Use several frequency bands and feature selection method

After grasp action started, it becomes rhythmic and automatic, so it may be difficult to classify in these stages.
→ FOCUS on 0-1 sec.

COGS500/CMPE489 Introduction to Cognitive Science Week III: 11.10.2017

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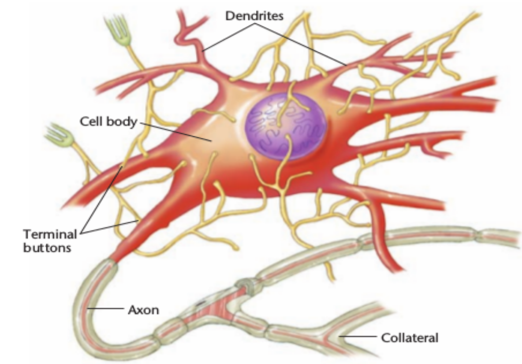
Mathematical models of the brain

- McCulloch & Pitts neuron
- Rosenblatt’s perceptron
- Multi-layer perceptron
- Hebbian learning
- Hodgkin-Huxley model
- Recurrent neural networks
- Hopfield network

McCulloch and Pitts neurons

- McCulloch and Pitts (1943) assumptions:
  - They are binary devices (Vi = [0,1])
  - Each neuron has a fixed threshold, theta
  - The neuron receives inputs from excitatory synapses, all having identical weights.
  - Inhibitory inputs have an absolute veto power over any excitatory inputs.
  - At each time step the neurons are simultaneously (synchronously) updated by summing the weighted excitatory inputs and setting the output (Vi) to 1 iff the sum is greater than or equal to the threshold AND if the neuron receives no inhibitory input.



McCulloch and Pitts neurons

A LOGICAL CALCULUS OF THE IDEAS IMMANENT IN NERVOUS ACTIVITY

WARREN S. MCCULLOCH and WALTER H. PITTS

Because of the "all-or-none" character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behavior of every net can be described in these terms, with the addition of more complicated logical means for nets containing circles; and that for any logical expression satisfying certain conditions, one can find a net behaving in the fashion it describes. It is shown that many particular choices among possible neurophysiological assumptions are equivalent, in the sense that for every net behaving under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time. Various applications of the calculus are discussed.

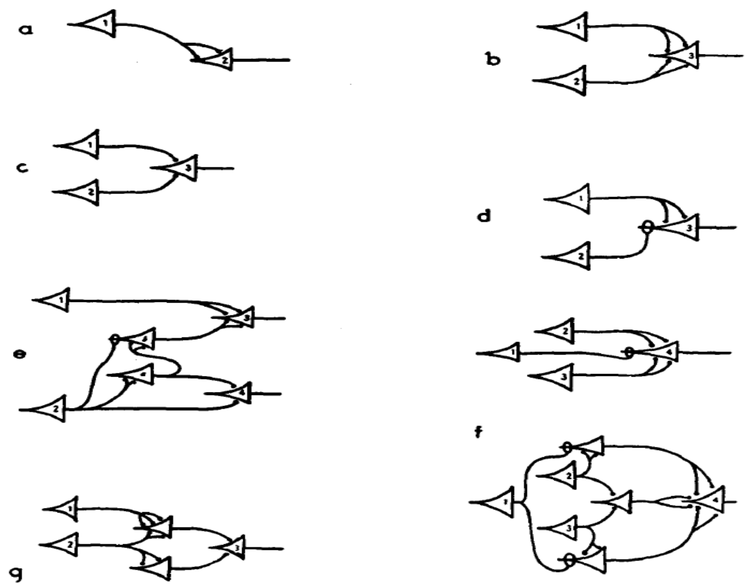


Figure 1a $N_2(t) . \equiv . N_1(t-1)$

Figure 1b $N_3(t) . \equiv . N_1(t-1) \vee N_2(t-1)$

Figure 1c $N_3(t) . \equiv . N_1(t-1) . N_2(t-1)$

Figure 1d $N_3(t) . \equiv . N_1(t-1) . \sim N_2(t-1)$

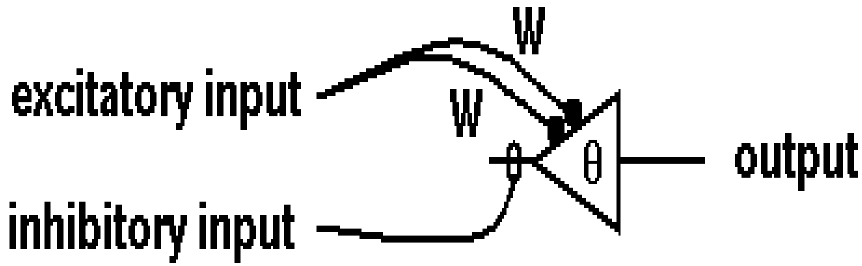
Figure 1e $N_3(t) : \equiv : N_1(t-1) . \vee . N_2(t-3) . \sim N_2(t-2)$

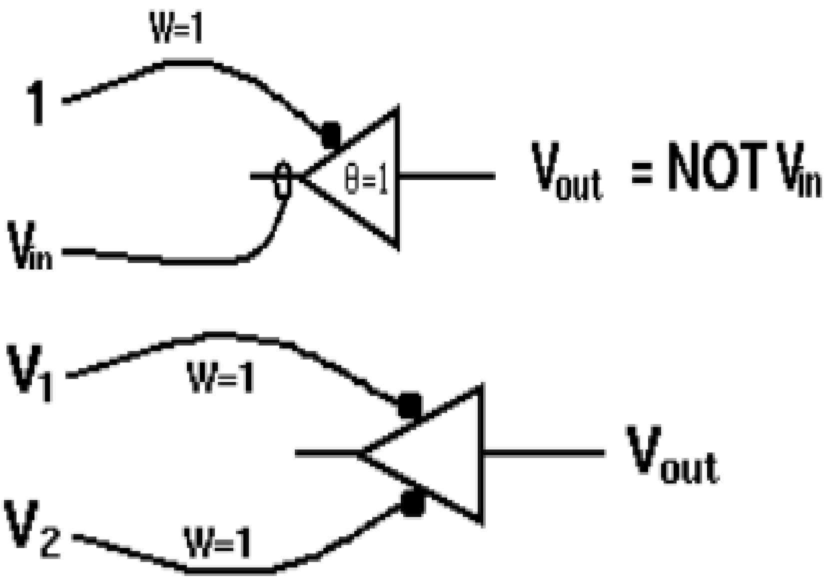
$N_4(t) . \equiv . N_2(t-2) . N_2(t-1)$

Figure 1f $N_4(t) : \equiv : \sim N_1(t-1) . N_2(t-1) \vee N_3(t-1) . \vee . N_1(t-1) . N_2(t-1) . N_3(t-1)$

$N_4(t) : \equiv : \sim N_1(t-2) . N_2(t-2) \vee N_3(t-2) . \vee . N_1(t-2) . N_2(t-2) . N_3(t-2)$

McCulloch and Pitts neurons





Quiz - NAND gate

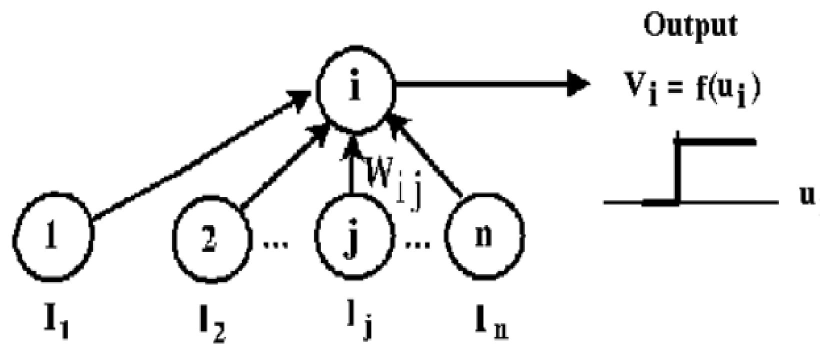
TRUTH TABLE

INPUTS			OUTPUT
W	X	Y	Z
0	0	0	0
0	0	1	1
0	1	0	1
0	1	1	1
1	0	0	1
1	0	1	1
1	1	0	1
1	1	1	1

http://ecee.colorado.edu/~ecen4831/lectures/NNet2.html

Rosenblatt’s simple perceptron

- The weights and thresholds were not all identical.
- Weights can be positive or negative.
- There is no absolute inhibitory synapse.
- Although the neurons were still two-state, the output function f(u) goes from [-1,1], not [0,1].
- Most importantly, there was a learning rule.



$$V_i = f(u_i) = \begin{cases} 0 & : \quad u_i < 0 \\ 1 & : \quad u_i \geq 0 \end{cases}$$

$$u_i = \sum_j W_{ij} I_j + \theta_i$$

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Learning with the perceptron

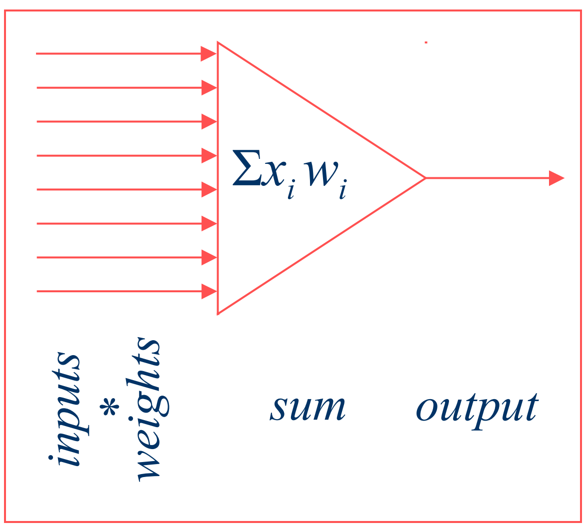
- $T = \{(\mathbf{x}_1, y_1), \ldots (\mathbf{x}_n, y_n)\}$ is a training set of n pairs of input $\mathbf{x}_i$ and desired output y_i
- To learn the correct weights **w**:
  - Initialize **w** randomly
  - For each sample j do:
    - Calculate the actual output $y'_j = \mathbf{w}\mathbf{x}_j$
    - Adapt the weights $\mathbf{w}_k' = \mathbf{w}_k + \alpha(y_j - y_j')\mathbf{x}_{jk}$ for each $\mathbf{w}_k$
  - Repeat until the error is sufficiently small

The Perceptron

Frank Rosenblatt (1962). *Principles of Neurodynamics*, Spartan, New York, NY.

Subsequent progress was inspired by the invention of *learning rules* inspired by ideas from neuroscience…

Rosenblatt's *Perceptron* could automatically learn to categorise or classify input vectors into types.



It obeyed the following rule:

If the sum of the weighted inputs exceeds a threshold, output 1, else output -1.

$$1 \text{ if } \Sigma\, input_i * weight_i > threshold$$

$$-1 \text{ if } \Sigma\, input_i * weight_i < threshold$$

https://www.cs.tau.ac.il/~nin/Courses/NC05/SingLayerPerc.ppt

Linear neurons

- The neuron has a real-valued output which is a weighted sum of its inputs

weight vector

$$\hat{y} = \sum_i w_i x_i = \mathbf{w}^T \mathbf{x}$$

Neuron’s estimate of the desired output

input vector

- The aim of learning is to minimize the discrepancy between the desired output and the actual output
  - How de we measure the discrepancies?
  - Do we update the weights after every training case?
  - Why don’t we solve it analytically?

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A motivating example

- Each day you get lunch at the cafeteria.
  - Your diet consists of fish, chips, and beer.
  - You get several portions of each
- The cashier only tells you the total price of the meal
  - After several days, you should be able to figure out the price of each portion.
- Each meal price gives a linear constraint on the prices of the portions:

$$price = x_{fish} w_{fish} + x_{chips} w_{chips} + x_{beer} w_{beer}$$

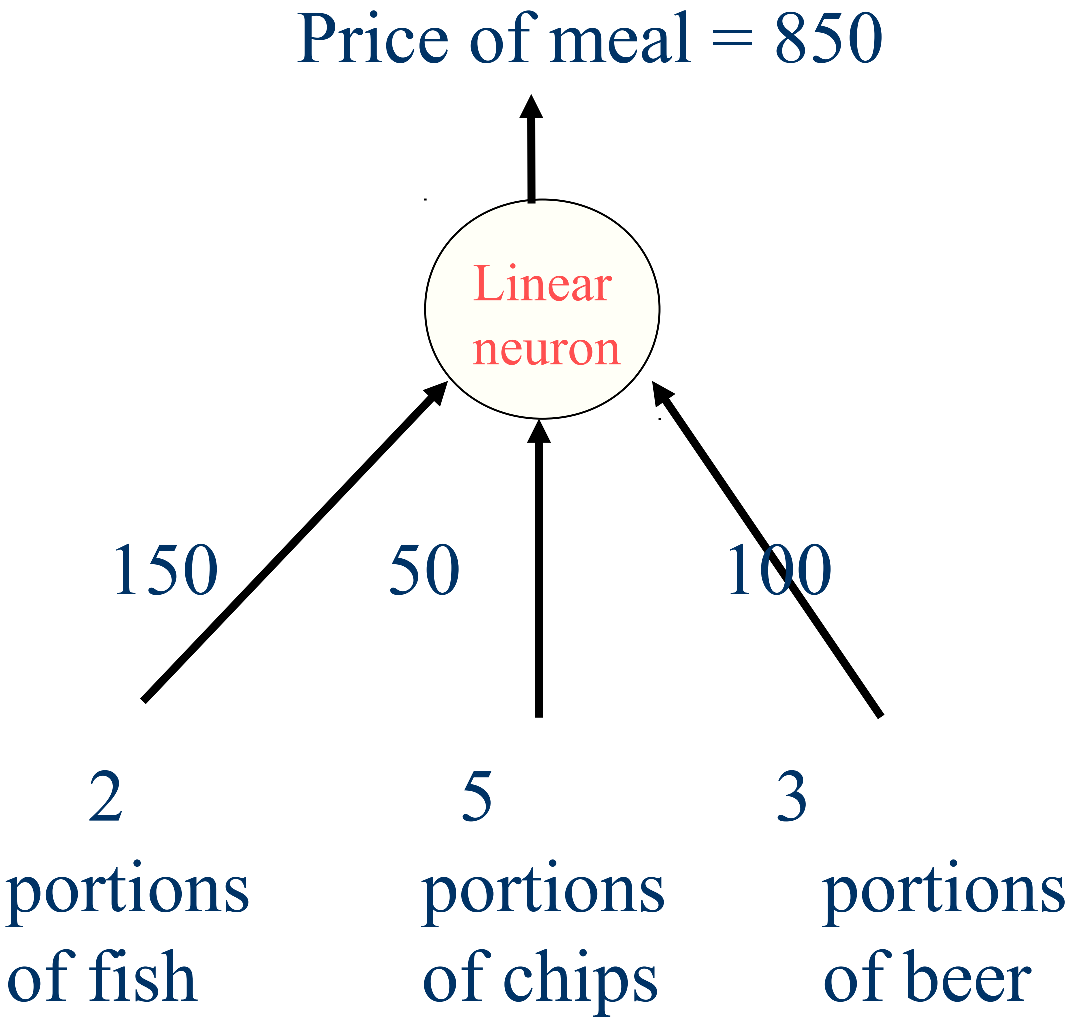
Two ways to solve the equations

- The obvious approach is just to solve a set of simultaneous linear equations, one per meal.
- But we want a method that could be implemented in a neural network.
- The prices of the portions are like the weights in of a linear neuron.

$$\mathbf{w} = (w_{fish}, w_{chips}, w_{beer})$$

- We will start with guesses for the weights and then adjust the guesses to give a better fit to the prices given by the cashier.

The cashier's brain



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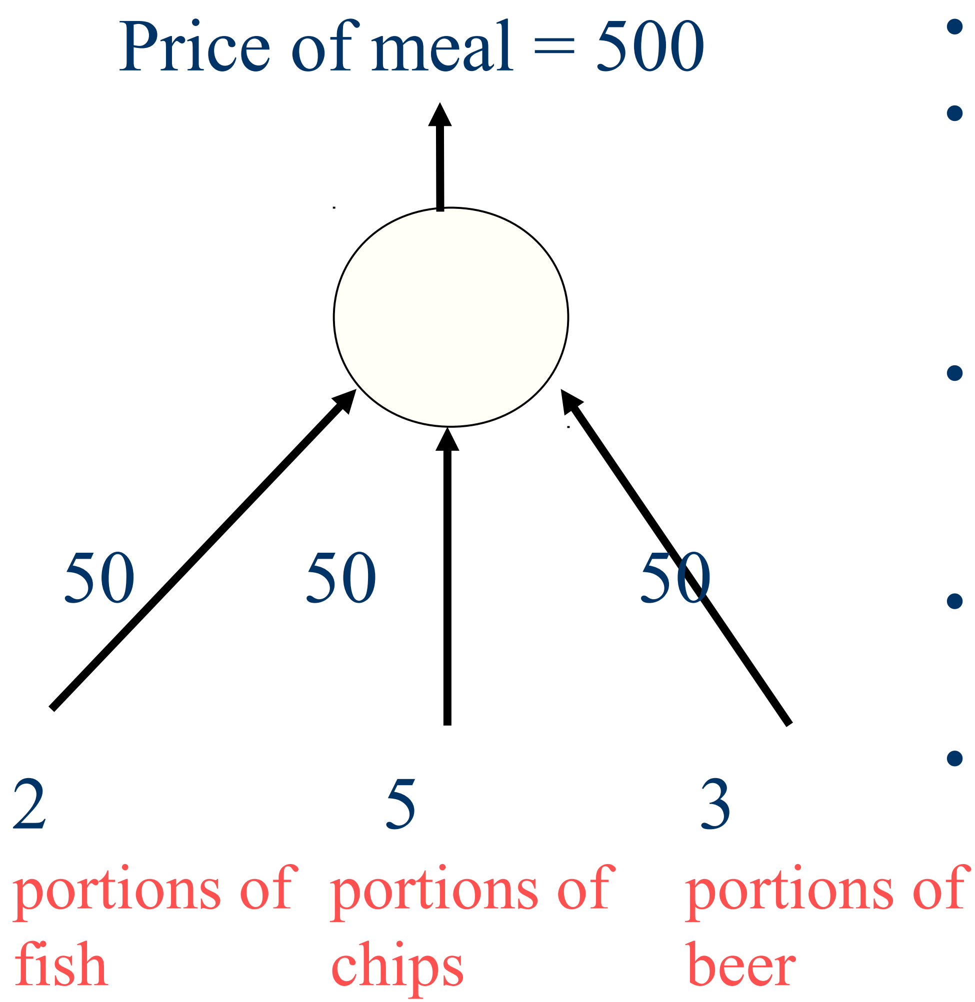
A model of the cashier's brain with arbitrary initial weights



- Residual error = 350
- The learning rule is:

$$\Delta w_i = \varepsilon \, x_i \, (y - \hat{y})$$

- With a learning rate ε of 1/35, the weight changes are +20, +50, +30
- This gives new weights of 70, 100, 80
- Notice that the weight for chips got worse!

https://www.cs.tau.ac.il/~nin/Courses/NC05/SingLayerPerc.ppt