Introduction to Neural Networks

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Lecture 1-Introduction

Goals

Understand the functioning of the brain as a computational device. Theoretical and computational tools to explain the relationship between brain & behavior. Understand the relation to computational neuroscience, machine learning research, and cognitive science. Bridge mathematical levels of analysis from the activity of single neurons to large scale systems and behavior. Examples will mainly come from biological vision, learning and memory.

Relation to Cognitive Science and Psychology

Cognitive Science is the interdisciplinary study of the acquisition, storage, retrieval and utilization of knowledge. Many disciplines involved in cognitive science. Psychology is focused on understanding human behavior-- the primary motivation for the approach of this course. Problems studied: perception, learning, memory, decision making, reasoning, planning, action. Often, we don't know how to solve a problem even in principle. For others, we have solutions, but they don't resemble how a biological system might solve the problem. What kinds of problems can large interconnected systems of model neurons solve? What are the limitations? What are the strengths?
How do neural networks relate to the larger field of statistical inference, and pattern recognition?

Understanding the relation between brain and behavior requires...

A multidisciplinary approach
Multiple levels of abstraction and explanation.

Multidisciplinary approach

Three primary areas or disciplines influence current neural network research:

Behavioral sciences ⟶ psychology, behavioral neuroscience, ethology

Understand what subsystems are supposed to do as a functioning organism in the environment. Experimental studies of perception, cognition in animals and humans. Psychology & Computational theory =>The brain is NOT a general purpose computer.

Neuroscience ⟶ computational neuroscience

Understand the basic building blocks, the "hardware" or “wetware” of the nervous system.
These are: nerve cells or neurons, and their connections, the synapses

Explanations and models can be quite complex. Our emphasis is on: large scale neural networks. Requires great simplification in the model of the neuron...in order to compute and theorize about what large numbers of them can do.

Compare with other areas of Computational Neuroscience that emphasize the biology. Here we emphasize relating neural computation to behavior. We’ll see how statistical theories of inference, algorithms, help to provide the links from neurons to behavior. The models are often wrong in detail, but capture at a high-level how the complex processes of perception, and memory work.

So we will ask: What can these large scale neural systems do? That is, what can they compute? And how?

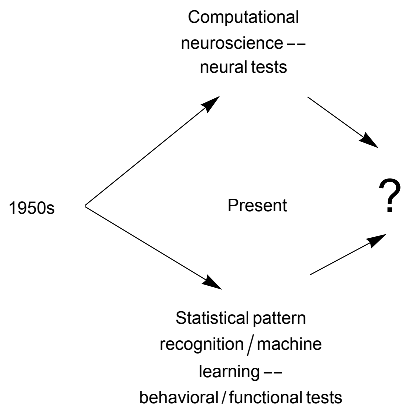
Computational theory ⟶ mathematics, statistical pattern recognition, machine learning

Statistical inference, engineering (information and communication theory), statistical physics, machine learning and artificial intelligence. Provides the tools and analogs to abstract and formalize complex behavioral systems for analysis and simulation.

One of the characteristics of this course is to try to relate the neural models to statistical methods of inference (classification, regression, hypothesis testing) in order to understand the computational principles and power behind a neural implementation. What are the ways in which information is represented? How can a system be designed to get from input to output representations?

When modeling complex behaviors, one may need to abstract out even more detail from large scale neural network models, to try to quantitatively describe with a manageable set of variables or dimensions.

How do different theoretical neural network approaches relate? A little history and future...



Multiple levels of analysis and explanation

Let's look in more detail at how different disciplines contribute to the theoretical analysis of the brain and behavior at different levels of abstract, often involving analysis over a range of spatial scales (further below).

Functional/Behavioral level

Psychology/Cognitive Science/Ethology tells us what problems are actually solved by functioning behaving organisms. What are we "designed" to do? Descriptions of behavior. E.g. the Necker Cube:

```
Manipulate[
 Graphics3D[{EdgeForm[{Thick, Blue}], FaceForm[{Pink, Opacity[0.0]}], Cuboid[]},
  ViewPoint → dist * {Pi, Pi / 2, 2}, ImageSize → Tiny,
  Boxed → False], {{dist, 2}, .5, 10}]
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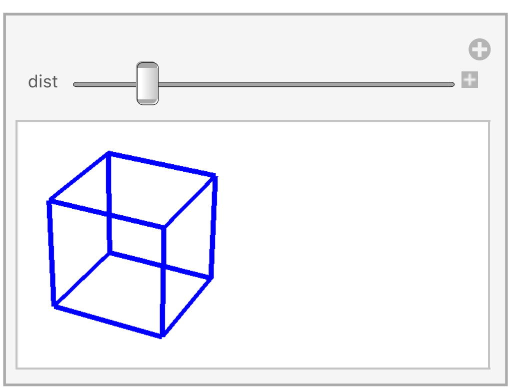


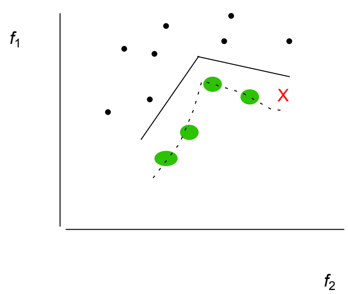
There is an infinite family of possible interpretations of the above shape, but human vision sees only two. This implies that vision constructs a interpretation of the 3D world from 2D image information, but not just any interpretation.

Statistical Inference level

Theories of pattern recognition, inference & estimation. Functionalities supported by neural network computing provide a useful way of categorizing models in terms of the computational tasks required:

1. Learning input/ouput mappings from examples (data)
(learning as finding regression parameters, or as classification boundaries given data)

Classification example: What features distinguish As from Bs? Discover or “learn” the features, $\{f_i\}$, from collections of {a, a,a,a...} and {b, b, b,..}, and find out how to classify any instance to one of two classes. Learning may mean finding the line that separates the features.



If the line is straight, this is linear discrimination.

Regression example: Another simple case is regression, where we fit a line (curve or surface) to some data. If the line is assumed to be straight, we estimate the slope and intercept. The line models the relationship between features. The model may not be linear, in which case it is called non-linear regression. The dotted line connecting the green circles models the non-linear relationship between the two features describing the class of b’s.

2. Inferring outputs from inputs (continuous estimation, discrete classification)

Once we’ve learned a model to classify the features, how can we use the model?

Classification: A vs. B. Given some data, X =$\mathcal{B}$, is it an instance of a A or a B? Does the instance fall on the “A” side of the discriminant line, or on the “B” side?

If we have learned the parameters for a straight line regression fit, and now we plug in a new “X value” to find out what the y value is.

memory recall, perceptual inference

3. **Modeling data.** Discovering (statistical) structure of a class of patterns from examples.

Here we don’t care about the line above, but how the instances (e.g. the black dots) are distributed in feature space.

Example: Instances of the letter A: A, A, A, A...

What model (think “explanation”) maps the "concept" A = A0 to all possible instances A?

$$A = s \times A0$$

In this case, the explanation of all the instances is that they are scaled versions of each other. Learning means finding that all the instances are linearly related via parameter s.

Another example would be to discover that all the instances tend to cluster around a prototype A0, and lie within a certain range. The emphasis is learning both “central tendencies” or “prototypes”, as well as the range of variation. A simple case is estimating the mean and standard deviation in a family of measurements.

We’ll see more complicated examples, for example, self-organization of sensory data into useful representations or classes (using e.g. principal components analysis, clustering). Learning input/output mappings can be treated as a special case.

Algorithms

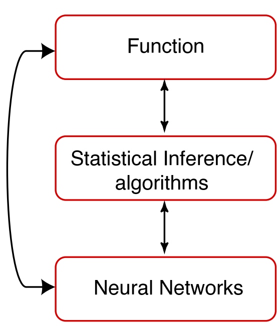
Mathematics of computation tells us what is computable, how to do it, and how efficiently. Input and output representation, and algorithms for getting from input to output. Programming rules, data structures. Some problems are just hard no matter regardless of the hardware or wetware available. Practical limits. E.g. parallel vs. serial.

Neural network level: implementation

Neurons have limited ways of integrating incoming information and passing that information on. Neuroscience, neurophysiology and anatomy tell us the adequacies and inadequacies of our modeling assumptions. Neuroscience, neurophysiology and anatomy tell us the adequacies and inadequacies of our modeling assumptions. And the implementation level is where we will start this course next time.

Summary of the emphasis in this course

Understand high-level functions such as perception, pattern recognition, learning, memory, inference and control. In the brain these functions involve large-scale systems each with many "modules" and 10s to 100s of thousands of neurons in each. Managing complexity through mathematical models aimed at understanding animal and human behavior requires higher degrees of abstraction. The interaction between levels of analysis considers a behavioral function (e.g. pattern recognition), the theory to understand the function (e.g. through statistical inference), and how the function may be realized in a neural system (neural networks):



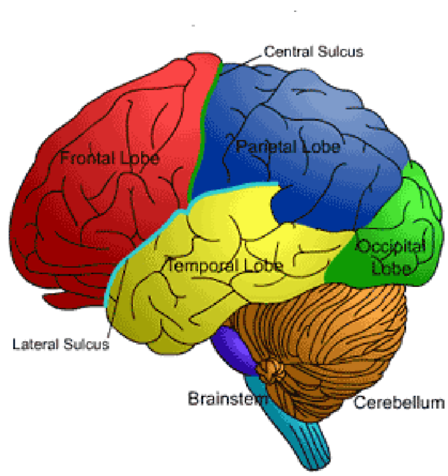
The Big Picture: Overview of the Brain

Before we look at models of neurons and their interactions, let us get an overview of the large scale context.

Understanding function means understanding how an organism's information processing is determined by the structure of its environmental inputs (e.g. natural images, objects to be avoided, places to go), and the nature of its outputs (e.g. remembering whether something is familiar or not, perceptual estimates, e.g. of shapes of objects, control parameter values to control object manipulation). The brain doesn't operate in isolation, these inputs and outputs are intimately tied to the sensory and motor neurons that make up the peripheral nervous system, as well as the physical make-up of the body itself.

The brain has both surface and interior structures. Surface structures that are visible in the side view below are: frontal, temporal, parietal and occipital lobes, and the cerebellum. But apart from the cerebellum, it isn't totally obvious where one part stops and another begins. Landmarks are the sulci (valleys) and gyri (bumps). E.g. the lateral fissure (sulcus) is perhaps the easiest to spot. It separates the temporal lobe from the frontal and parietal lobes. There are internal components too: Thalamus (sensory and motor relays), hypothalamus (control of endocrine activity, temperature, food intake, etc..), basal ganglia (motor behavior, habits), limbic system (emotion), medulla (part of lower brain stem, breathing, heart rate). We believe that much of what makes us interesting as humans, our thoughts, imaginations, words and actions, depends on having a large and complex cortex.

A common view shows the surface or cortex--the gray matter.



From: http://www.utdallas.edu/~kilgard/brain.jpg

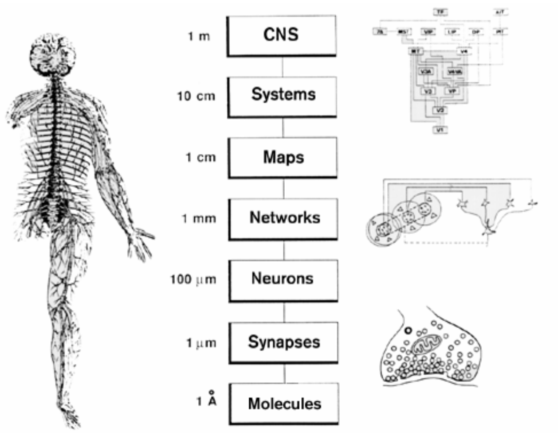
Check out: http://culhamlab.ssc.uwo.ca/fmri4newbies/

The anatomy provides an important, but static view of the brain. Progress in functional imaging provides dynamic pictures that illustrate relationships between human functions (seeing, imagining, etc.) are related to various cortical areas.

(For an early example from our own lab, see: http://gandalf.psych.umn.edu/users/kersten/kersten-lab/Perceptual.html)

Multiple spatial and temporal scales of organization of the brain and nervous system.

The brain, central and peripheral nervous system is organized at many different spatial and temporal scales.



From: Churchland & Sejnowski. (10,000 A to a micron)

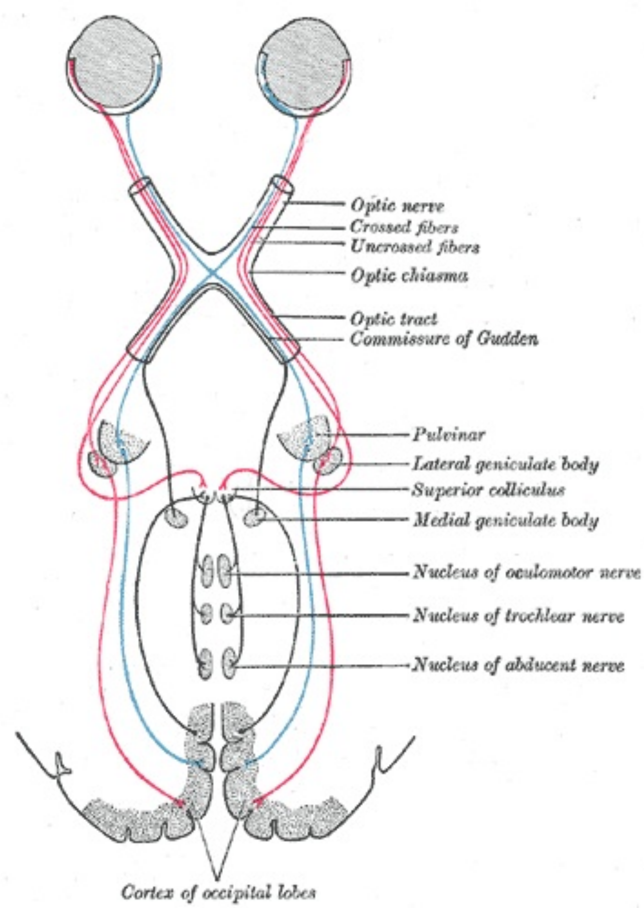
Overview of a sample subsystem of the brain

The visual system

Let's take a look from two points of view: 1) information flow through a specific system--the visual system; 2) levels of organization at successive stages.

At a very coarse spatial scale, we know that we have eyes and a portion of the brain that processes the incoming images. This system enables us to manipulate objects, to navigate, to recognize and think and talk about objects, their attributes and relations.

Anatomical view of a system

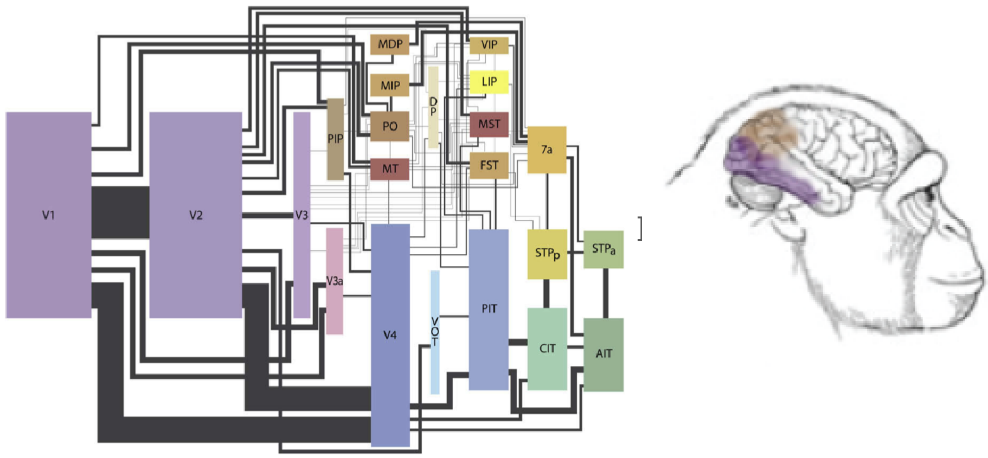


(From wikipedia entry for "Visual System")

The above picture ends at primary visual cortex (V1, area 17), but there are more than 30 other visual areas after that.

Spatial scales of the visual cortex: hierarchical organization (~ 10 cm scale), areas or “maps” (~ 1 cm scale),

Higher visual areas in cortex.

Image[]

From: Wallisch, P., & Movshon, J. A. (2008). Structure and Function Come Unglued in the Visual Cortex. *Neuron*, *60*(2), 194–197. doi:10.1016/j.neuron.2008.10.008

Monkeys and humans

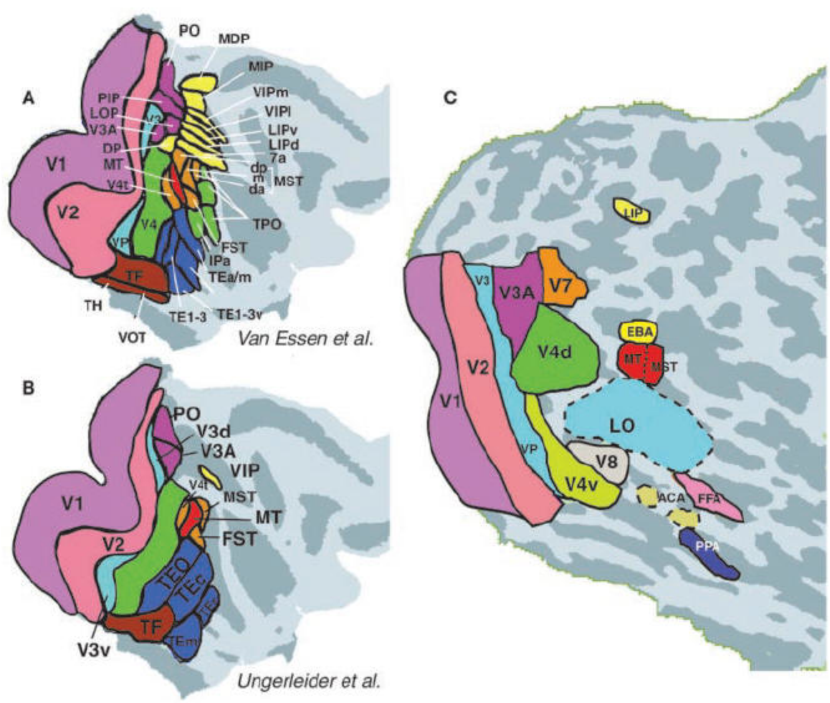
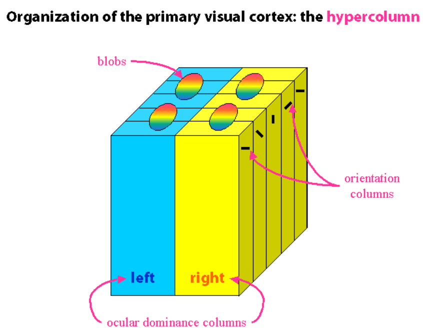


Figure 1. Maps of reported areas in primate visual cortex. Maps are shown on the flattened cortical surface from right hemisphere (light gray, gyri; dark gray, sulci). *A* shows areas in macaque reported by Van Essen and colleagues, and *B* shows the macaque areas reported by Ungerleider and collaborators (adapted from Van Essen et al., 2001). *C* shows areas in human visual cortex, as described in the text. Consensus is highest in lower-tier (generally, left-most) areas; such areas tend to be evolutionarily more conserved, and the retinotopy is more easily resolved.

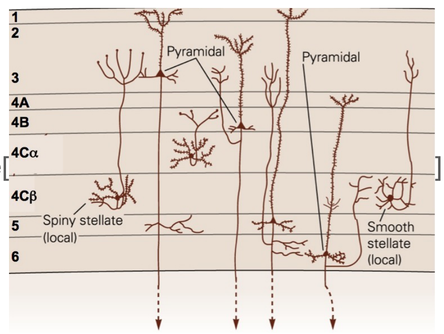
From: Tootell, R. B., Tsao, D., & Vanduffel, W. (2003). Neuroimaging weighs in: humans meet macaques in "primate" visual cortex. *J Neurosci, 23*(10), 3981-3989.

Cortical layers & circuits (~ 1 mm scale)

Structure within maps do not consist of randomly connected nerve cells. There is a medium-level organization into multiple functional groupings. The neocortex has 6 more or less distinguishable layers, there is a microorganization into vertical columns. In the primary visual cortical area (V1, see above figure), there are ocular dominance and orientation selectivity columns which are believed to form a functional unit called a hypercolumn (1 to 2 mm). Each hypercolumn takes into account local image intensities and colors to represent information or features for a single point of the visual field.



http://www.ualr.edu/~klwennstrom/hypercolumn.gif

Image[

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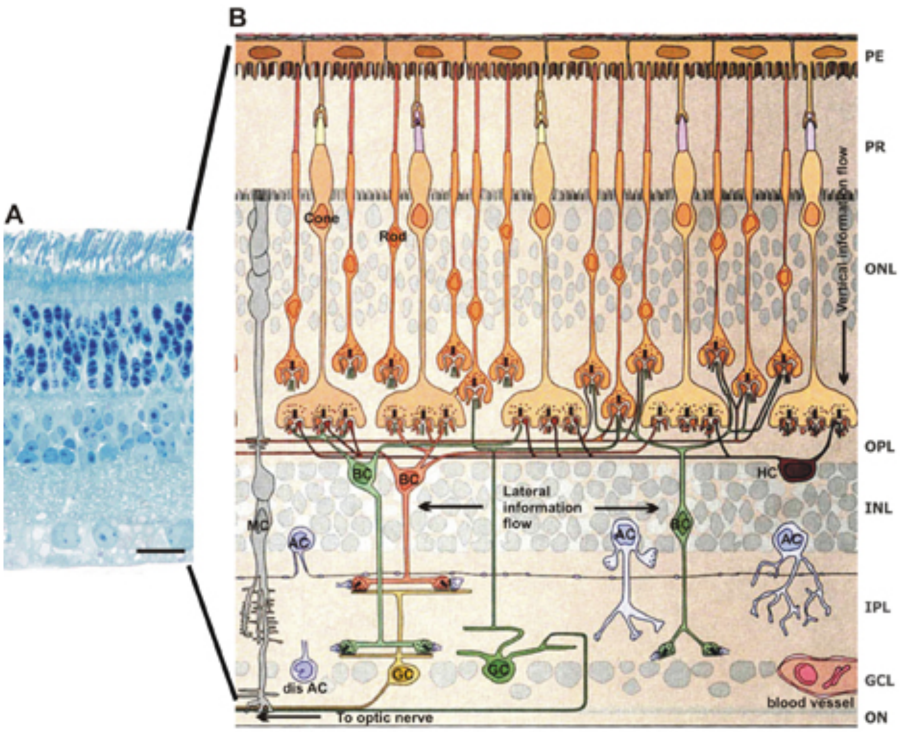
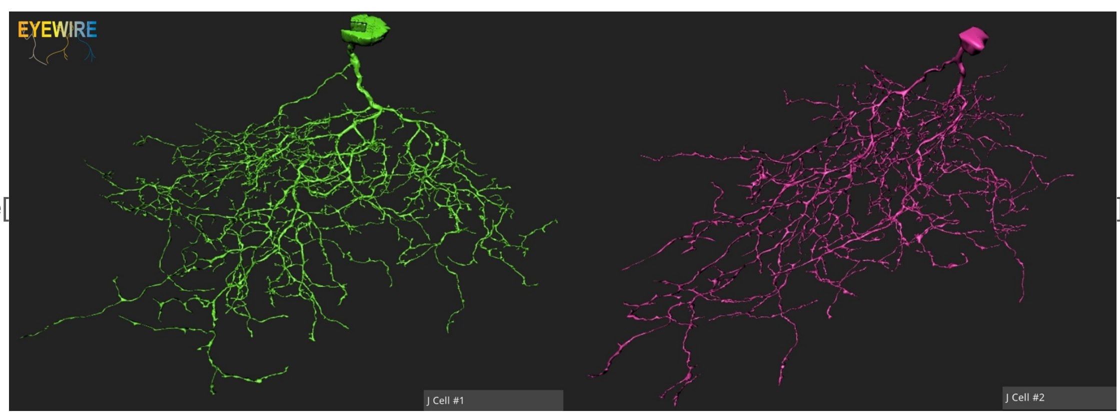
The above figure illustrates some cell types in layers of gray matter.

Cells and circuits: retina example (~100 microns)



Above Adapted from Rodieck 1998

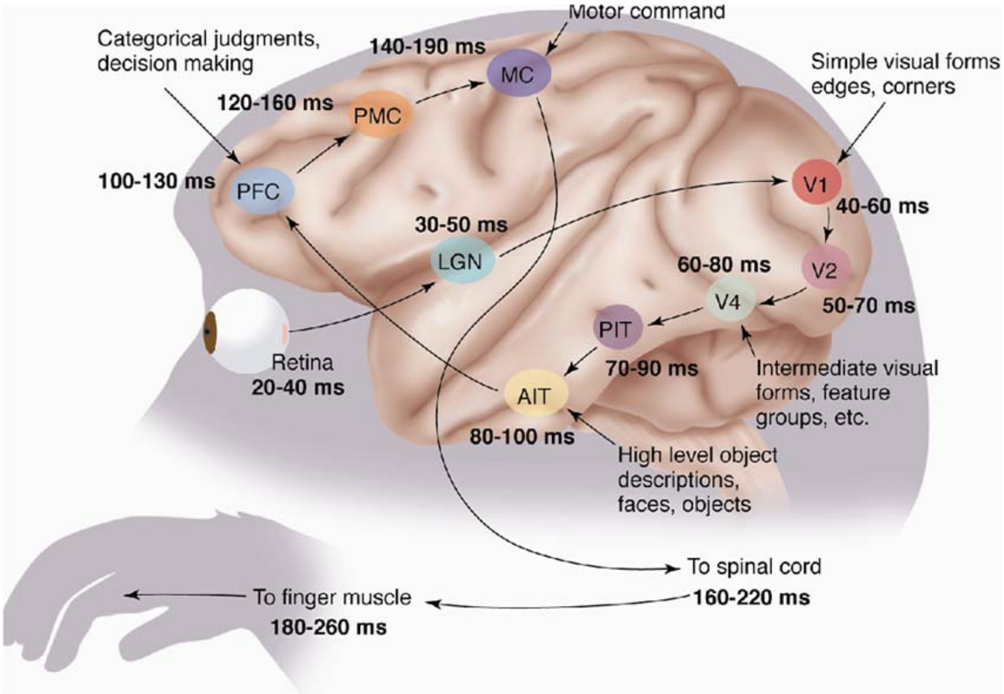
Rods, cones. Rods & rhodopsin molecules. Synapses. Different types of neurons: Spike-generating neurons, the ganglion cells.
Networks of neurons that behave as "image filters". M & P pathways.

Image[]

Retinal “J cell”: http://blog.eyewire.org/twos-company/

Temporal, functional view of a process

On the spatial scales of 1 to 10 to 50 cm, and time scale of a 1/4 of a second and less.

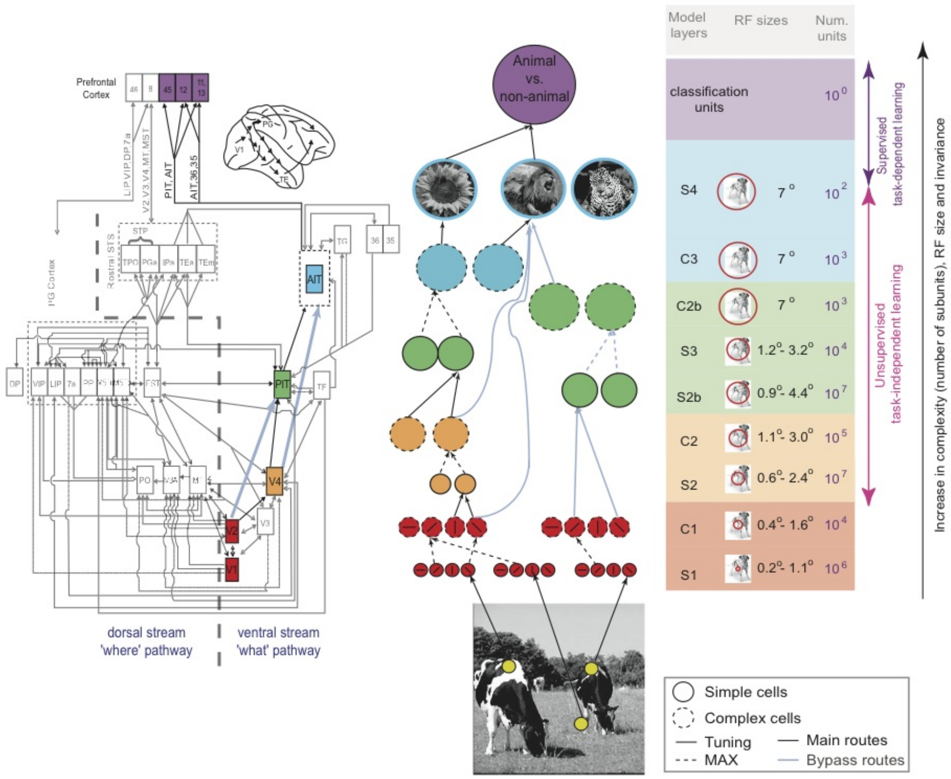


(example from Simon Thorpe's lab: http://www.cerco.ups-tlse.fr/Simon-THORPE?lang=en)

How to build a neural model?

Pick a problem and the scales of abstraction and space/time over which your model applies.

An example of a model based on the hierarchical structure of the ventral visual stream. On the order of 1 mm to 10 cm.



From Serre, T., Oliva, A., & Poggio, T. (2007). A feedforward architecture accounts for rapid categorization. *Proc Natl Acad Sci U S A, 104*(15), 6424-6429.

Mainly for fun: Some brain specs

The human brain is:: volume - 1.4 liters, Cortex 2 mm, volume 0.32 liters
Cortex: 1.6 x 10^10 neurons, with an average of about 4000 synapses/neuron, about 6x10^13 connections.

Area of cortex	1.60 E + 05	mm ^ 2		
Thickness of cortex	2.00 E + 00	mm		
Volume of cortex	3.20 E + 05	mm ^ 3	3.20 E - 01	liters
Cortex synapse density	4.00 E + 03	synapse / neuron		
Cortex connectivity	2.00 E + 08	synapses / mm ^ 3		
connectivity / neuron	5.00 E + 00	mm		
connection length / mm ^ 3	2.50 E + 04	mm		
neuron density in cortex	5.00 E + 04	neurons / mm ^ 3		
Total brain volume	1.40 E + 00	liters		
Total neurons in cortex	1.60 E + 10			
Total visual neurons	8.00 E + 09			

(50 % visual neurons is often quoted and used here, but is difficult to pin down)

Total visual connection lengths 4.00 E + 09 mm
4.00 E + 07 m or 24 874 miles of connections
(about the distance around the earth at the equator, 24, 901 miles)

Some reference numbers taken or inferred from those published by :

Cherniak, J. of Cog. Neurosc., 1990, vol 2., pp 58 – 68

Getting started with *Mathematica*

Mathematica vs. Matlab vs. Python vs. dedicated neural network simulation packages.

Front-end and Notebooks: Organize, outline, document. Program, evaluations, data all in one place
Kernel: Separate program does the calculations

To get an overview of *Mathematica* and its help resources:

The *Wolfram Documentation* window, under Help, and its search dialog box are useful to keep open for general code development

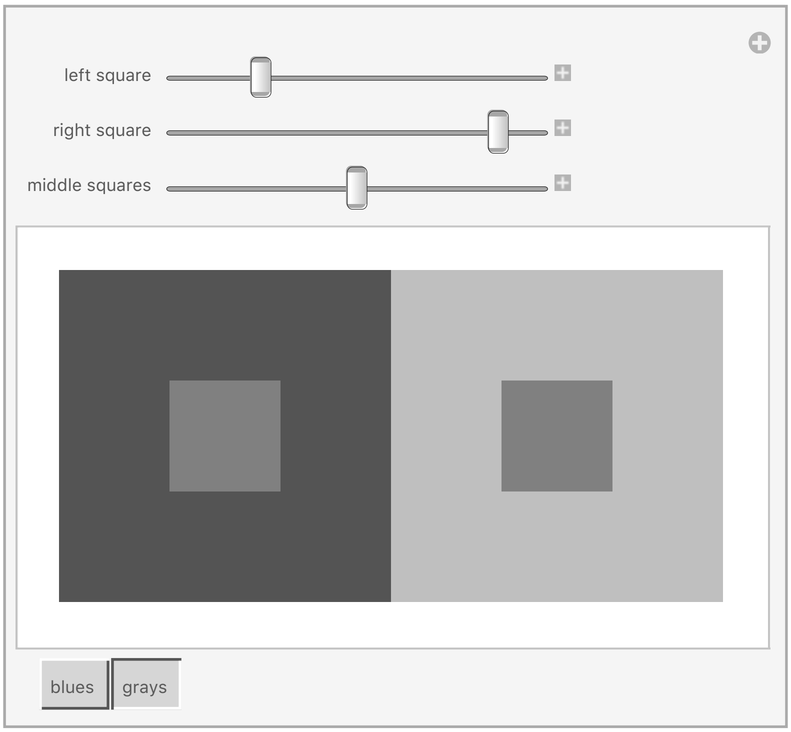
Homework: Exercise 1 (link)

Mathematica Demonstrations project

Check out the Demonstrations center at the Wolfram *Mathematica* site for some cool examples, such as:

```
Manipulate[Module[{bluecol, colfunc},
  bluecol[n_] := Blend[{Black, Blue, White}, n];
  If[usecol, colfunc = bluecol, colfunc = GrayLevel];

  Graphics[{colfunc[left], Rectangle[{0, 0}, {3, 3}],
    colfunc[right], Rectangle[{3, 0}, {6, 3}], colfunc[mid],
    Rectangle[{1, 1}, {2, 2}], Rectangle[{4, 1}, {5, 2}]}]],
 {{left, .35, "left square"}, .2, .8}, {{right, .75, "right square"}, .2, .8},
 {{mid, .5, "middle squares"}, .2, .8},
 {{usecol, True, ""}, {True → "blues", False → "grays"}, ControlPlacement → Bottom}]
```



"The Simultaneous Contrast Effect" from The Wolfram Demonstrations Project http://demonstrations.wolfram.com/TheSimultaneousContrastEffect/

Next time

Basic structure and function of a single neuron

References

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Rolls, E.T., & Treves, A. (1998). Neural networks and brain function. Oxford ; New York: Oxford University Press.
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Links

http://www.med.harvard.edu/AANLIB/cases/caseM/case.html
http://thalamus.wustl.edu/course/