Computational Cognitive Neuroscience

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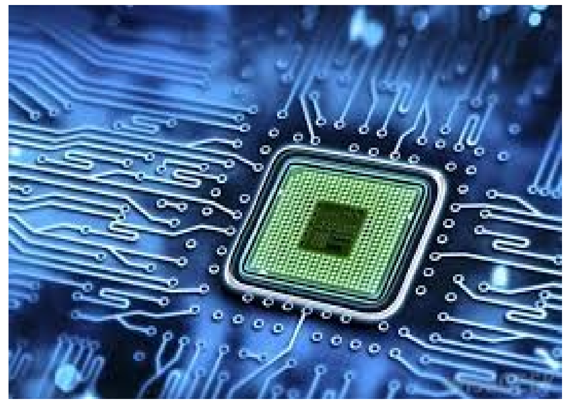

Computational Cognitive Neuroscience

*Computer vision,
*Pattern recognition,
*Classification,
*Picking the relevant information

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*Picking the relevant information,
*Learning from data/ from experience

*How information processing happens on the level of neurons?
*Is there basis in experimental neuroscience of learning and memory?
*What do the neurons react to?

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*Pattern recognition,
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*How does sensory data become perception?
*How does prior experience and knowledge influence Perception? (Subconscious inference)
*How are concepts and meanings grounded in sensory perception?

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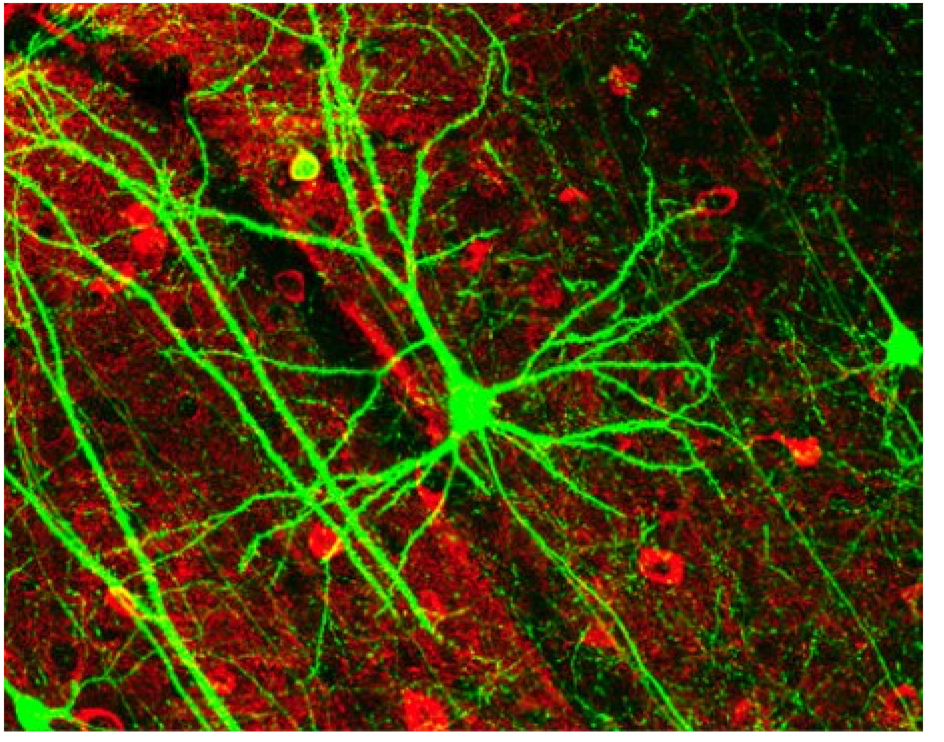
*What is the neurological basis of learning and memory?
*What do the neurons react to?

In this course we learn how neural networks and cognitive functions related to early vision can be modelled computationally with a focus on machine learning.

Neurons: First in Biology

In 1899 Ramon y Cajal discovered that the brain tissue is composed of individual cells which form a network.



Neuron Doctrine

The neuron is a basic structural and functional unit of the nervous system. Later adopted (in a sense) to cognitive science and artificial intelligence.

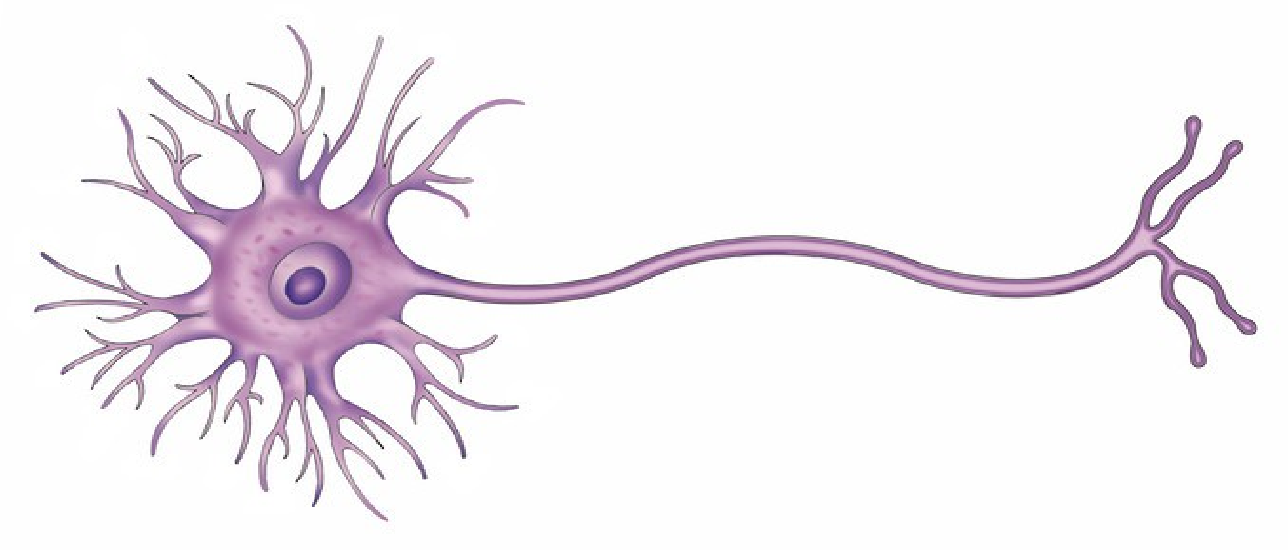
Cognitive Science: Connectionism vs. Computationalism

- Computationalism: Mental processes (language comprehension, meaning extraction, inference) are understood through formal symbol manipulation and symbol covariation.
- Connectionism: Mental processes emerge from interconnections of computing units, gathering information from all possible souces in a dynamic and adaptive way.

Grounding problem: Why symbols are meaningful?

- Computational neuroscience provides a connectionist approach to symbol grounding.
- In some of the project topics algorithms for visual and multi-modal meaning extraction will be explored.

Computational Neuroscience...



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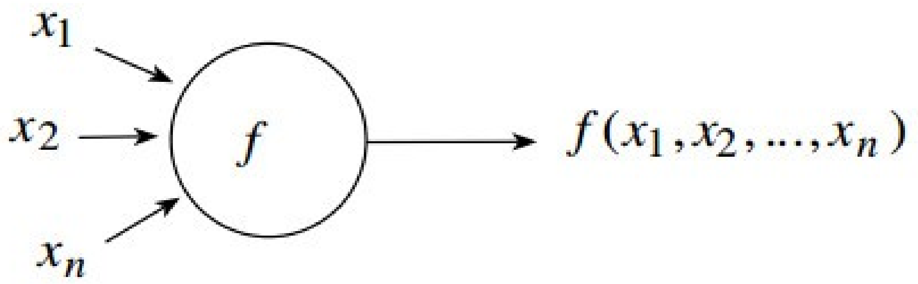
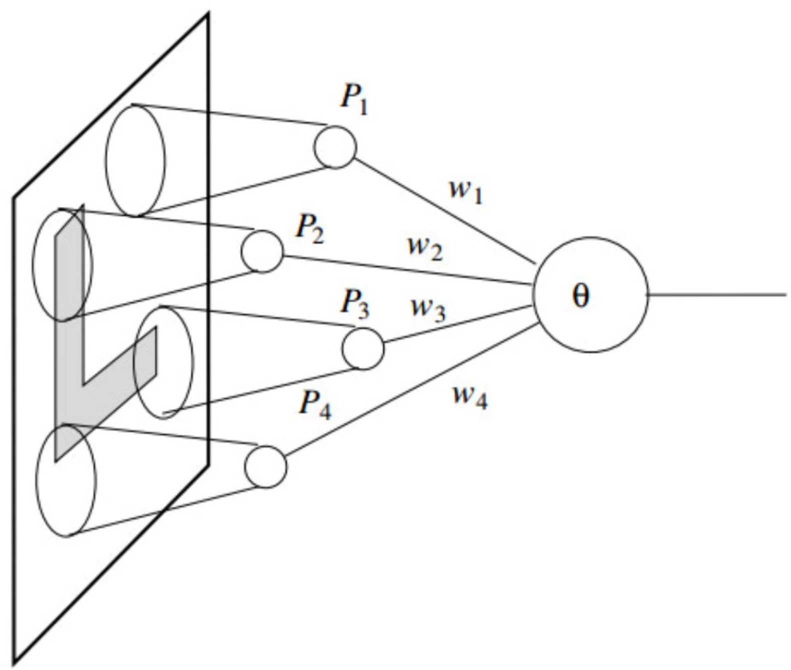


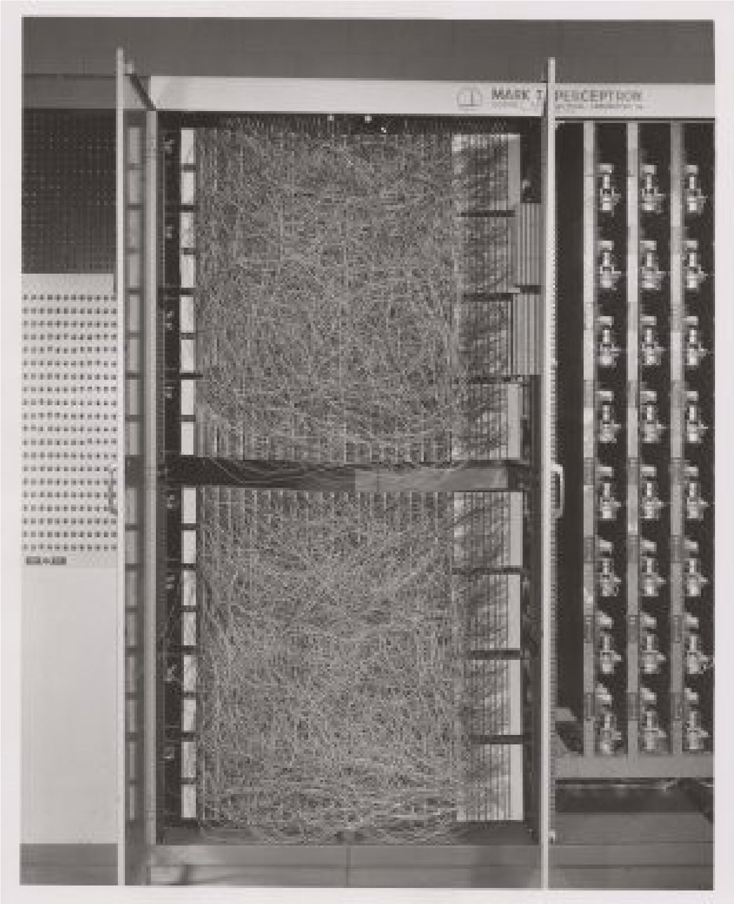
Neurons in Computer Science

- A simple model developed by logicians, computer scientists, cognitive scientists and neuroscientists: McCulloch-Pitts units and Perceptron.
- Very simplistic compared to true neurons in which e.g. signal integration is highly non-linear.



”The First” Perceptron

- Rosenblatt 1958. Perceptron designed to analyse 20x20 image patches.

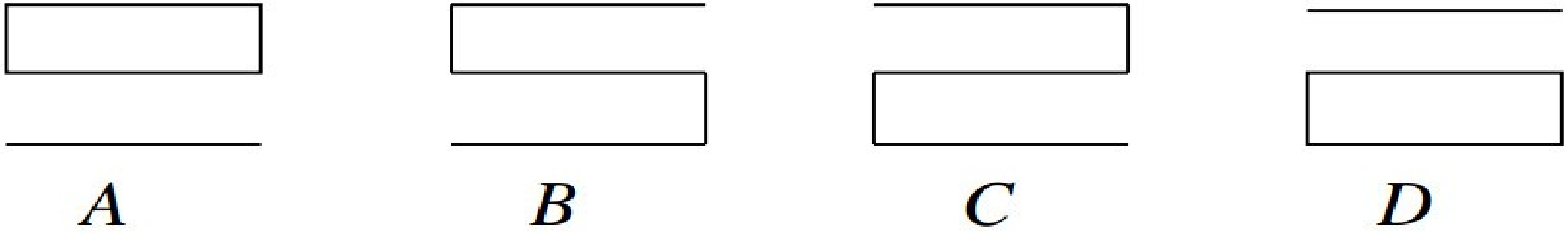


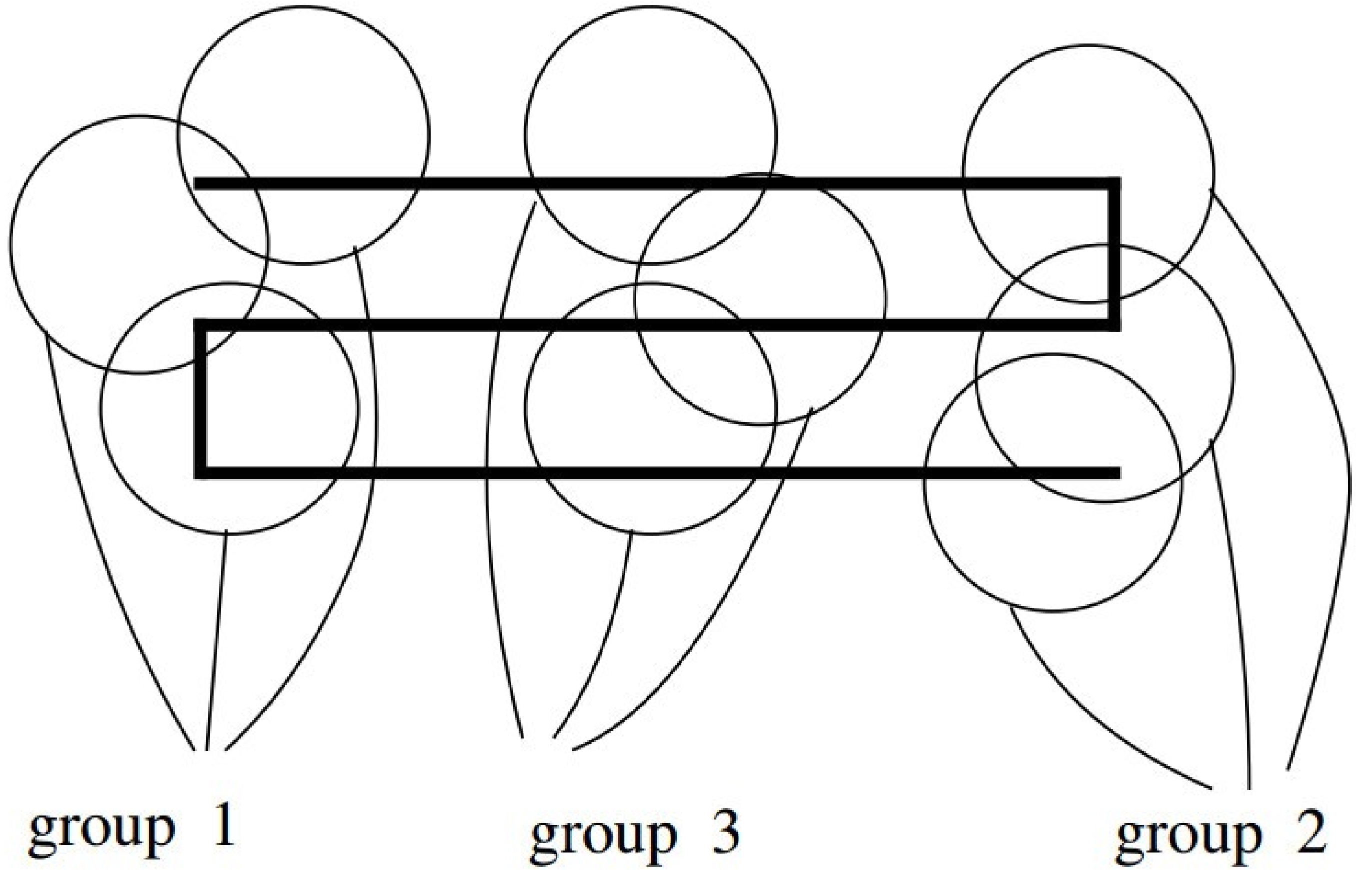
New York Times

Rosenblatt's Perceptron is "the embryo of an electronic computer that [the Navy] expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence."

Not so fast...

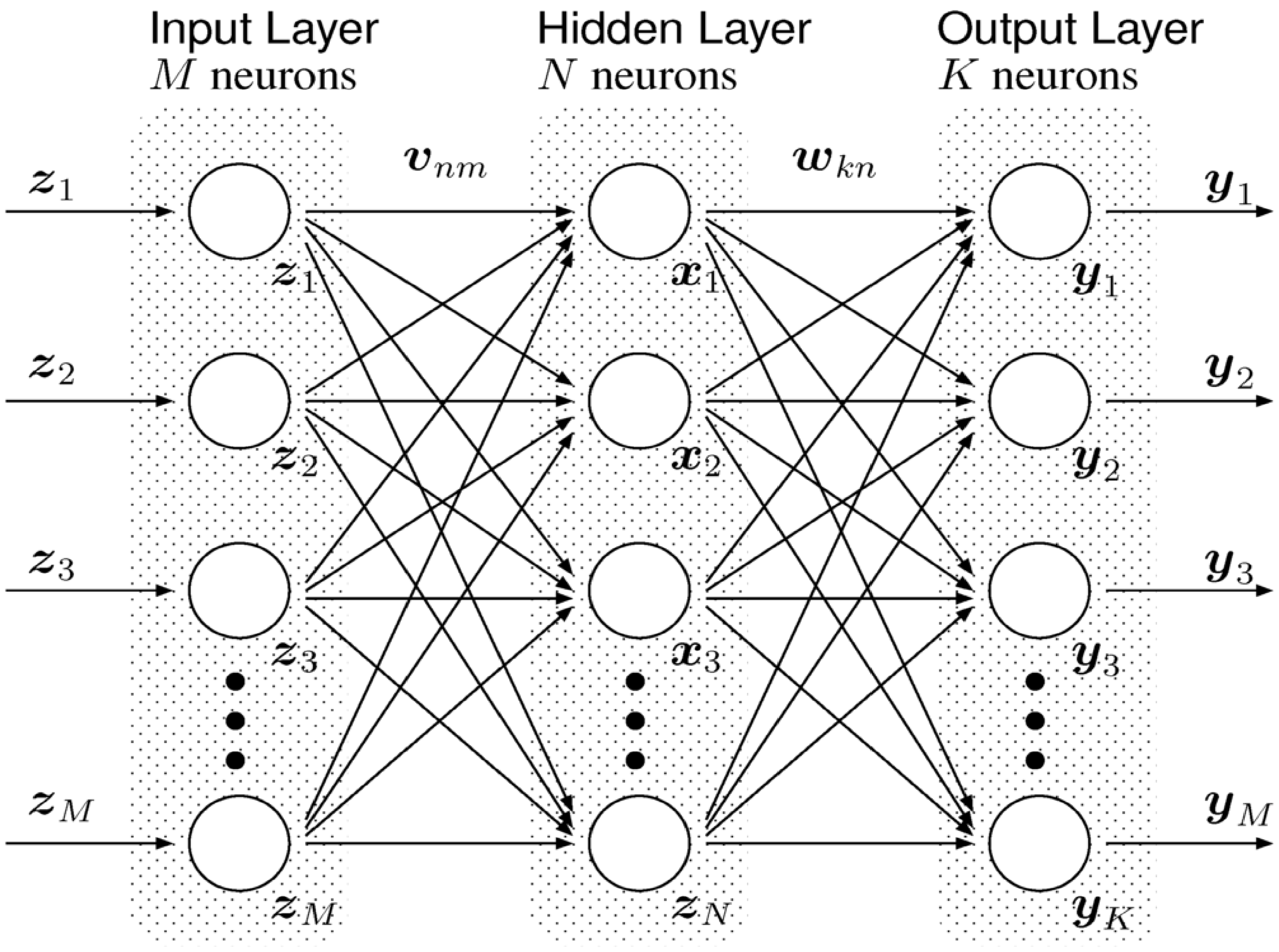
(Minsky, Papert 1969) A perceptron cannot distinguish connected from disconnected





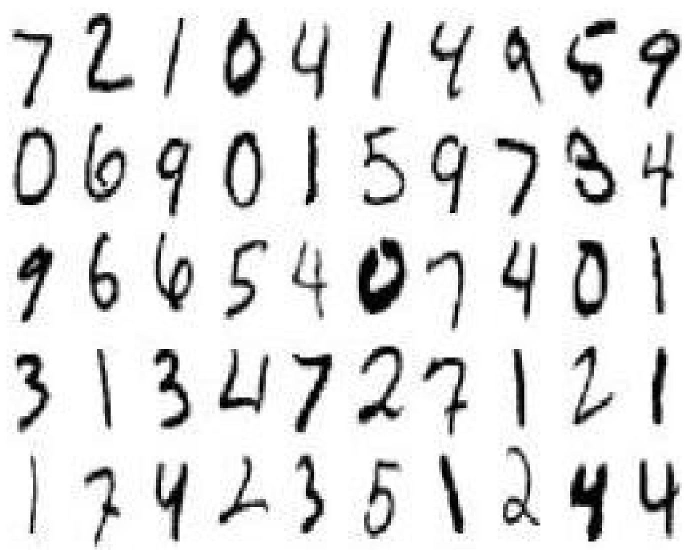
$$\sum_{i=1}^{n} w_i P_i \geq \theta$$

Multilayer Perceptron



Multilayer Perceptron

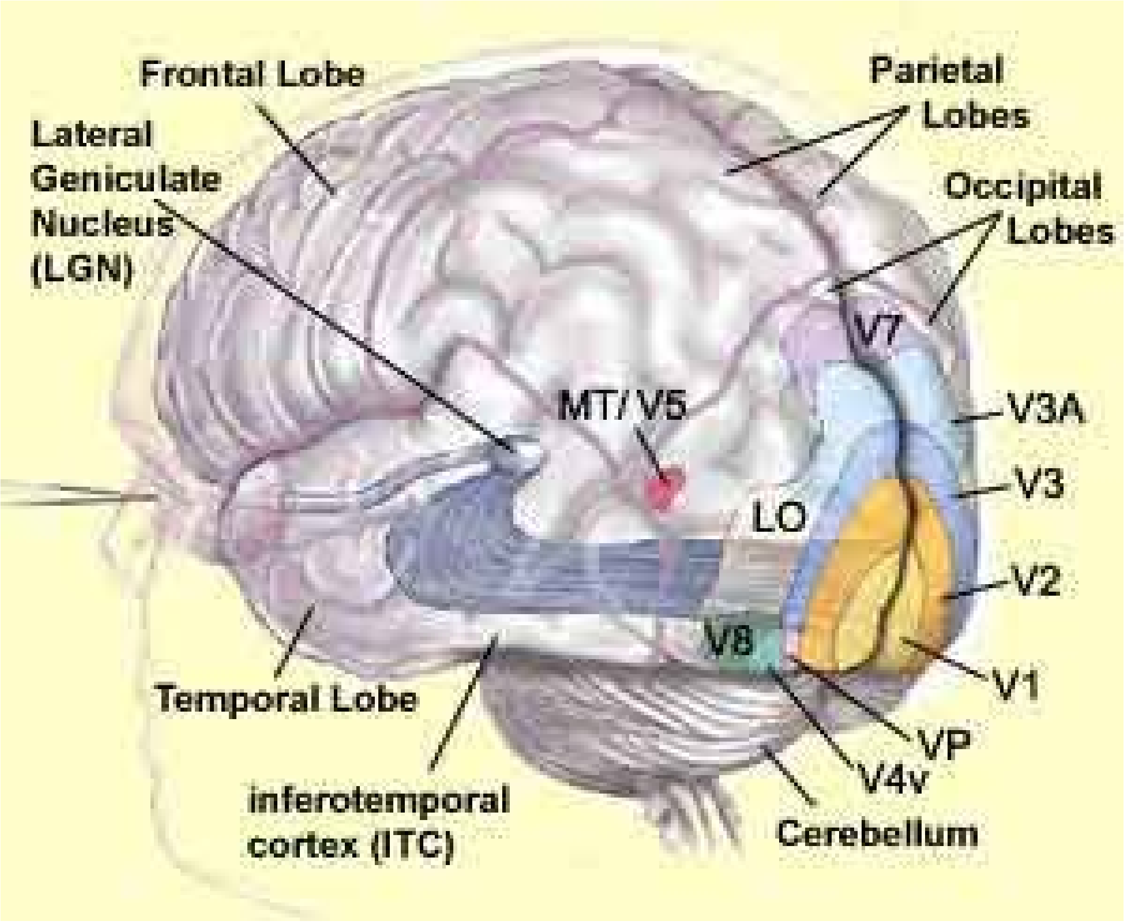
- For example, one of the project works for this course is to implement a 2-layer perceptron which learns to read hand-written digits



Deep learning

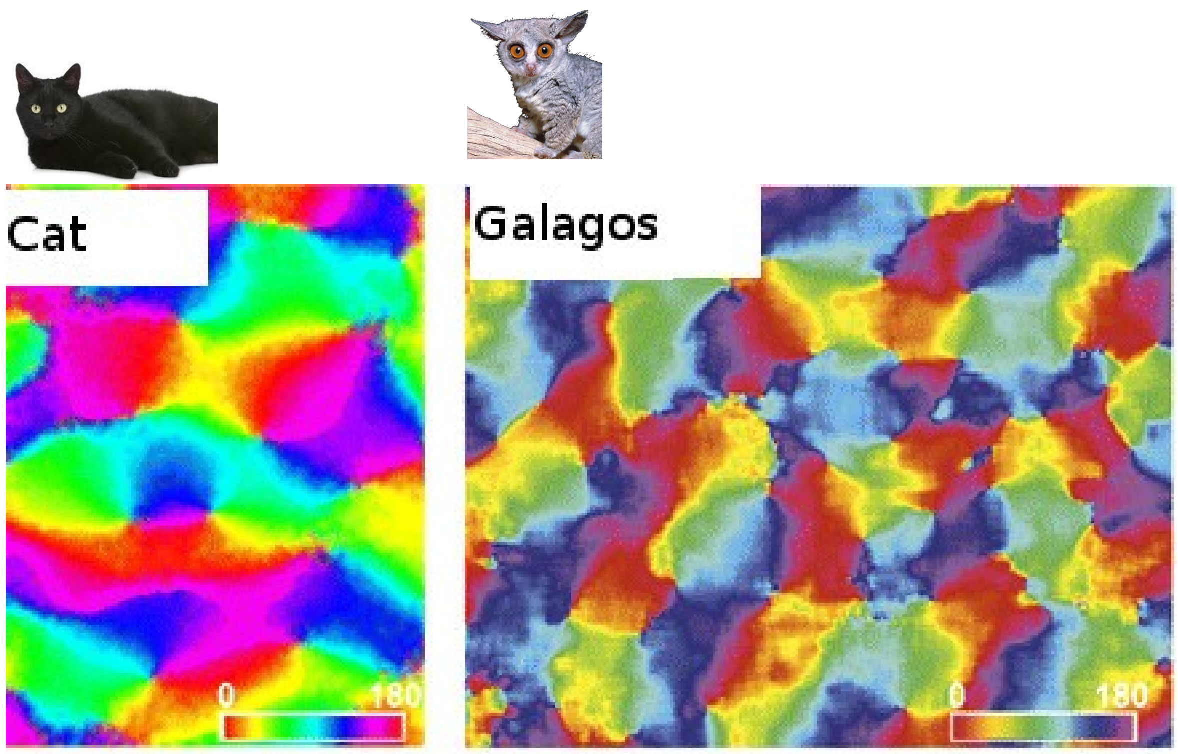
- Deep learning is not part of this course. However, there is a possibility to explore in one of the project works. The basic idea is to use many layered networks to code for increasingly abstract features.
- https://www.youtube.com/watch?v=SCE-QeDfXtA

Has basis in neuroscience...

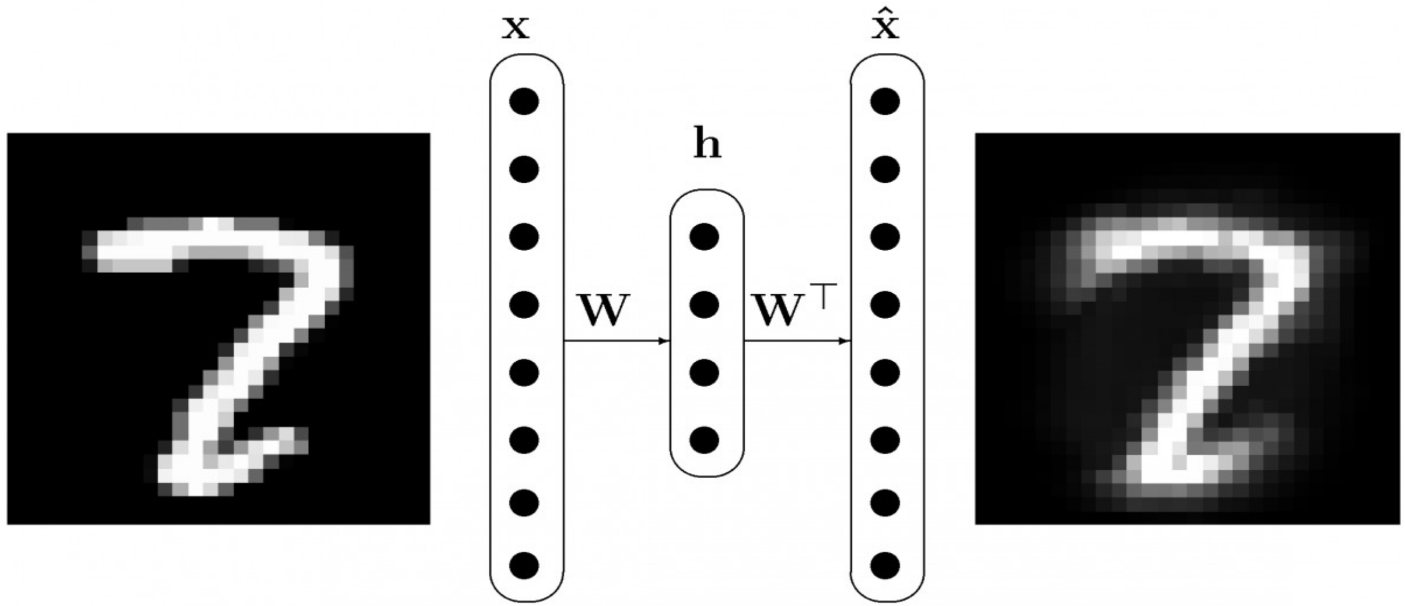


Early visual cortex

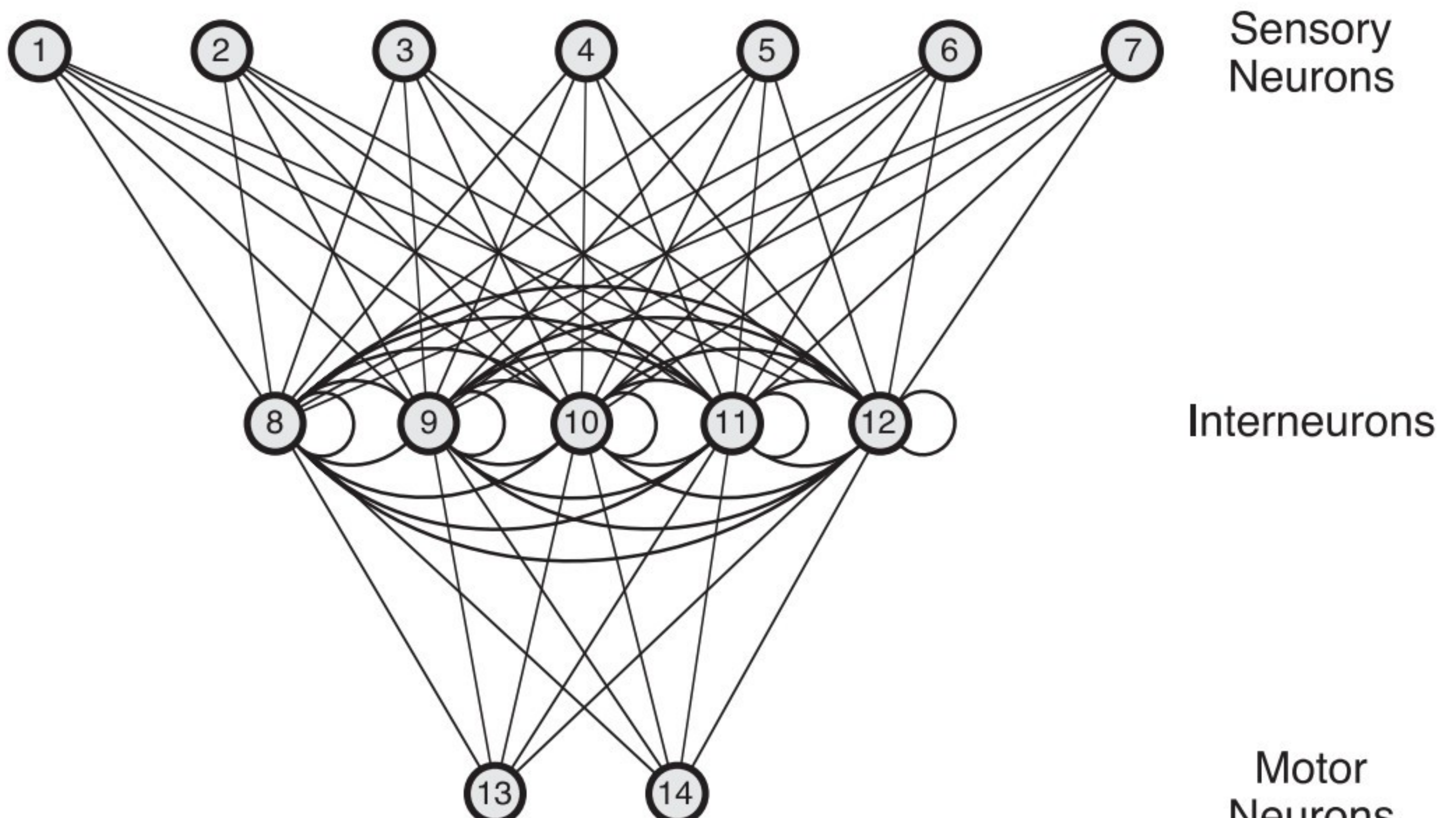
- https://www.youtube.com/watch?v=Cw5PKV9Rj3o



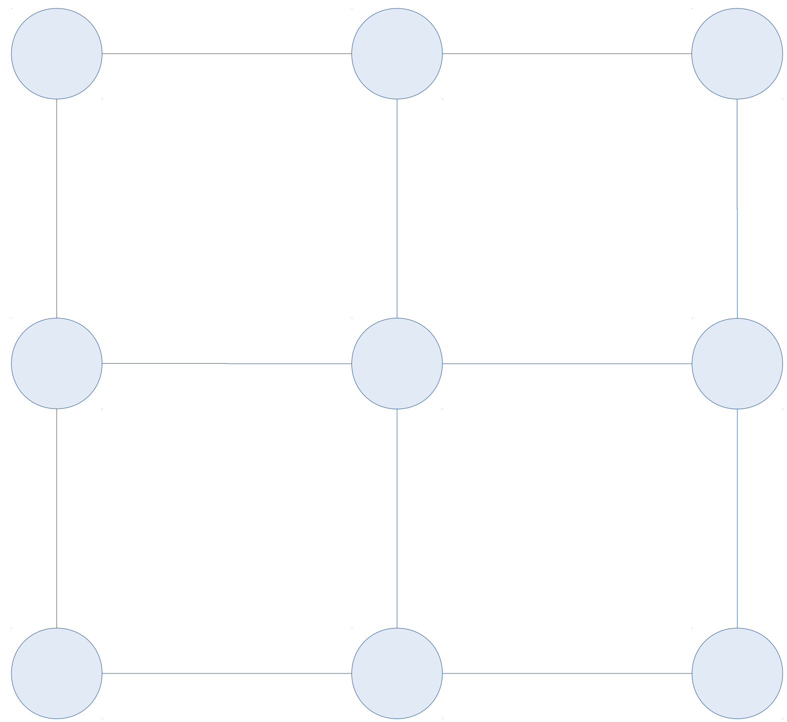
Another example: Autoencoder



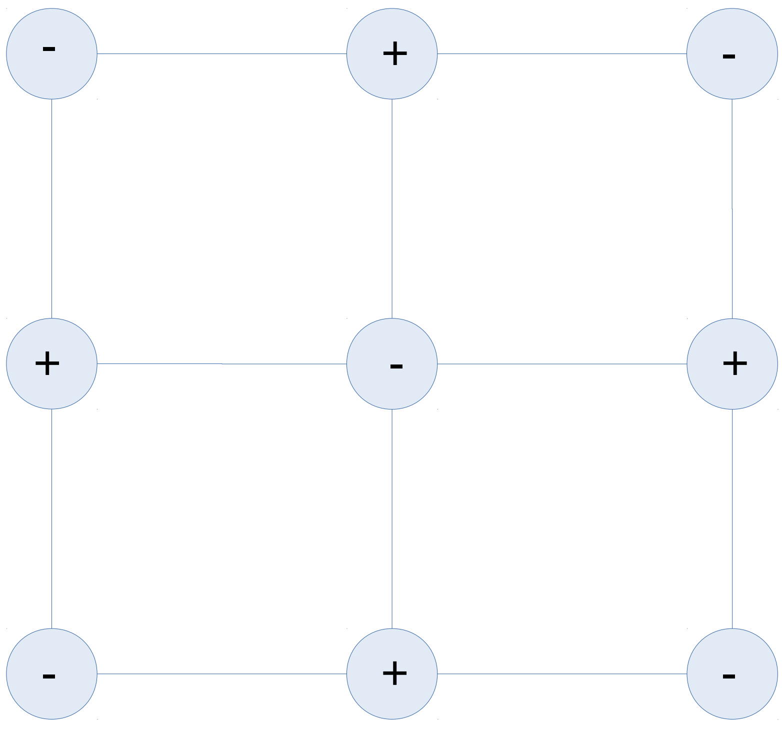
Recurrent Neural Networks



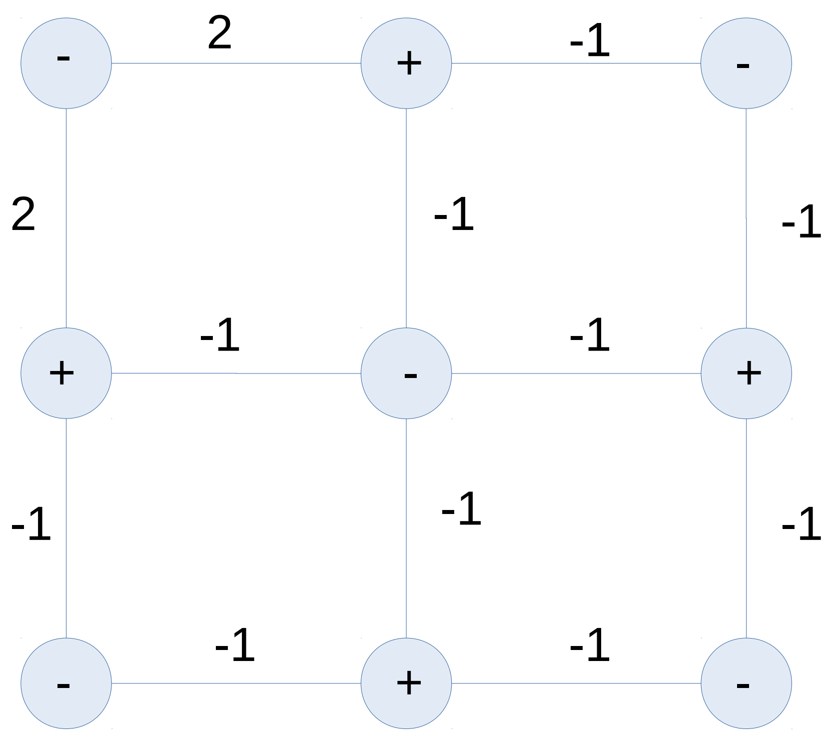
Hopfield Networks



Hopfield Networks



Hopfield Networks



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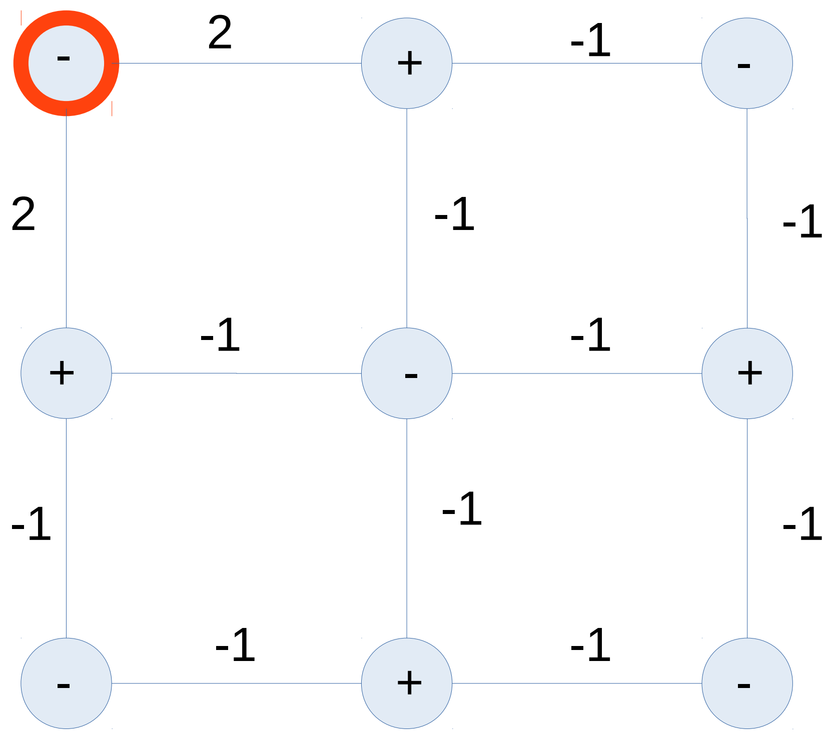
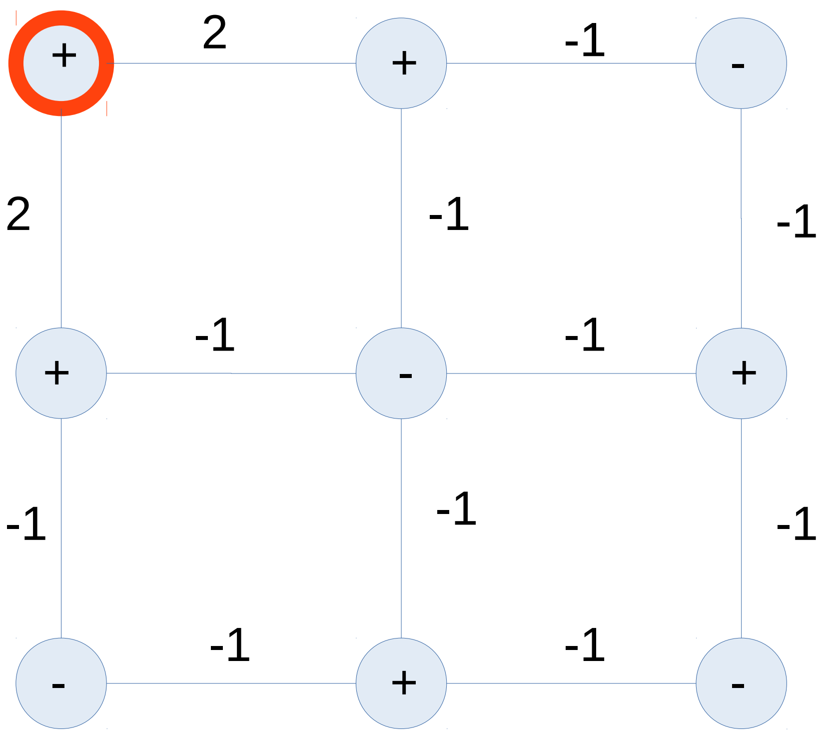


Hopfield Networks



Learning

- A neural network is useless if it is incapable of learning. Otherwise there are too many parameters to be programmed (or to be innate in an organism).
- Main focus of the course.
- **Supervised**

  - Perceptron, Back-propagation
- **Unsupervised**

  - Hebb (Hopfield), Associative, PCA, ICA
- **Reinforcement**

  - Evolution algorithms

EXAMPLES

Unsupervised: Hebbian Learning

- Hebb 1949: If a neuron A participates in exciting a neuron B towards firing, then the connection from A to B becomes stronger.
- (Keysers, Gazzola 2014) One way to explain mirror neurons is by referring to Hebbian learning.
- Adoption to ANN's: Correlation in firing increases the weight. Less realistic, but easier to deal with computationally.

Supervised: Backpropagation

- The algorithm is presented with a dataset of inputs and expected outputs. The learning algorithm tries to minimize the error by adjusting weights of the network. Gradient descent.
- Often used to train multilayer perceptrons, autoencoders.

Reinforcement learning (Probably not in this course)

- Evolutionary learning. The algorithm tries to maximize ”fitness”. Example:

  Research in Netherlands: https://www.youtube.com/watch?v=pgaEE27nsQw

Computational Cognitive Neuroscience: Vision modelling

Introduction to 2nd half

19th Jan 2015

Aapo Hyvärinen

Paradoxes in vision

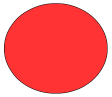
Vision seems
- effortless
- straightforward
- objective

Paradoxes in vision

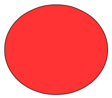
Vision seems
- effortless
- straightforward
- objective

In reality
- it cannot be easily programmed in a computer
- it seems to require complicated processing
- it can be fooled

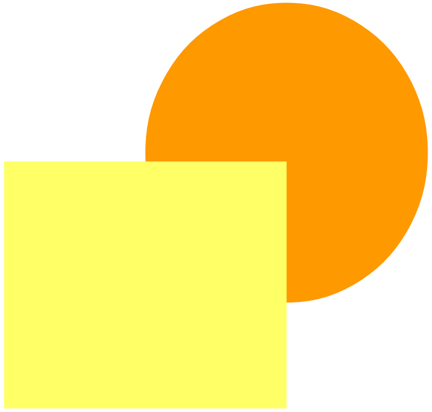
Example: Illusory motion



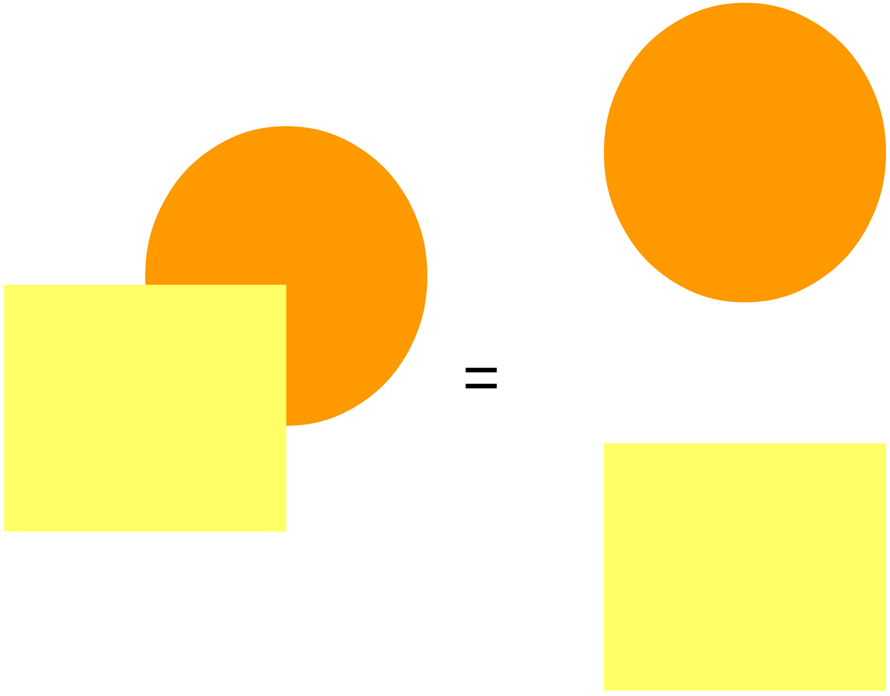
Example: Illusory motion



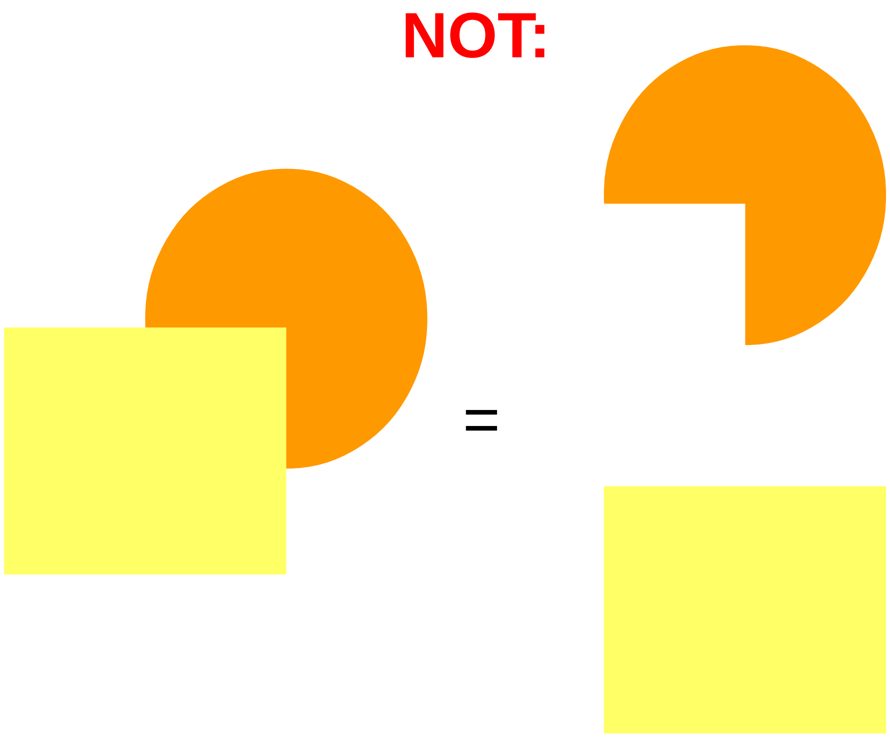
Example 2: completion



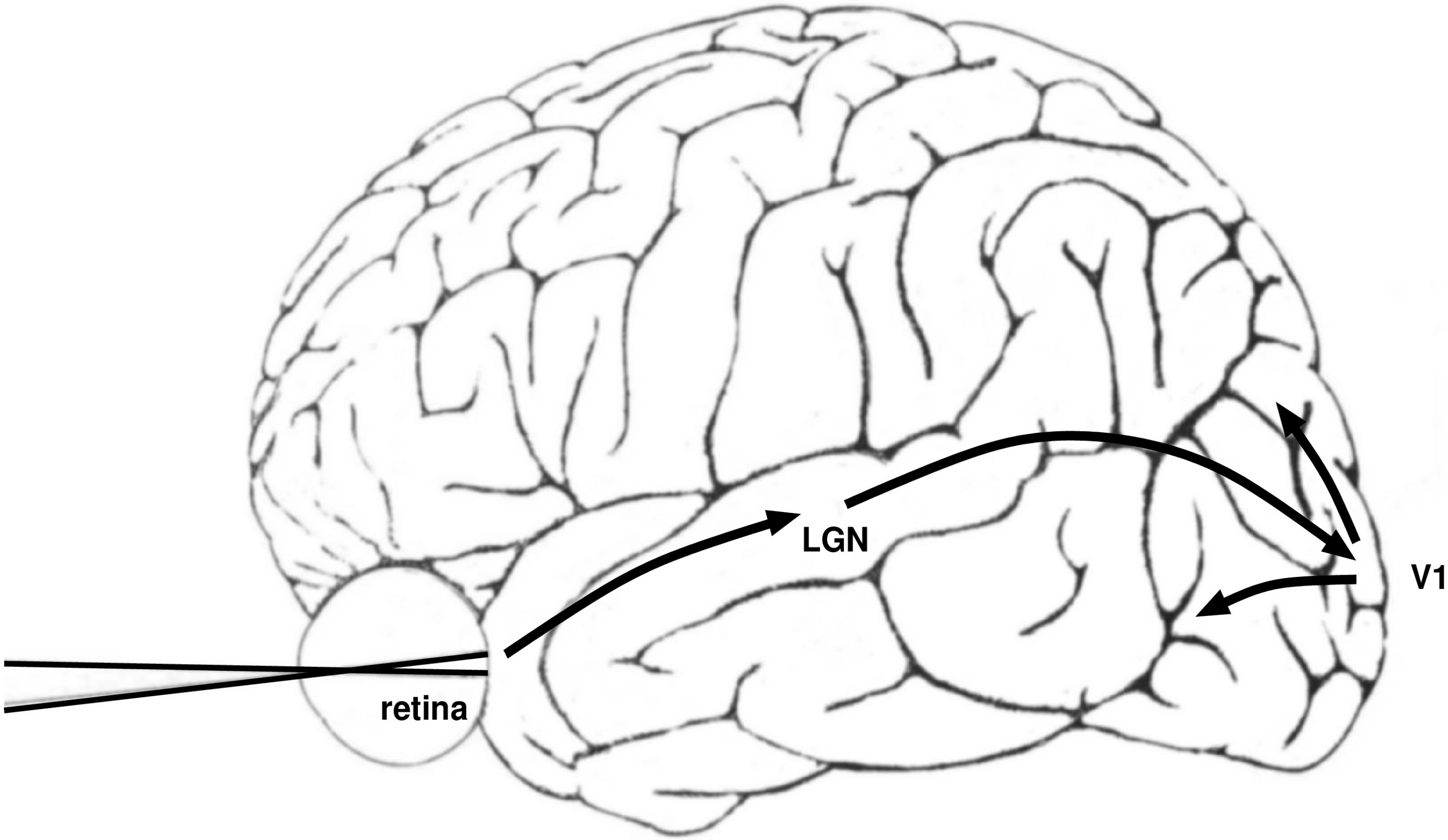
Example 2: completion



Example 2: completion

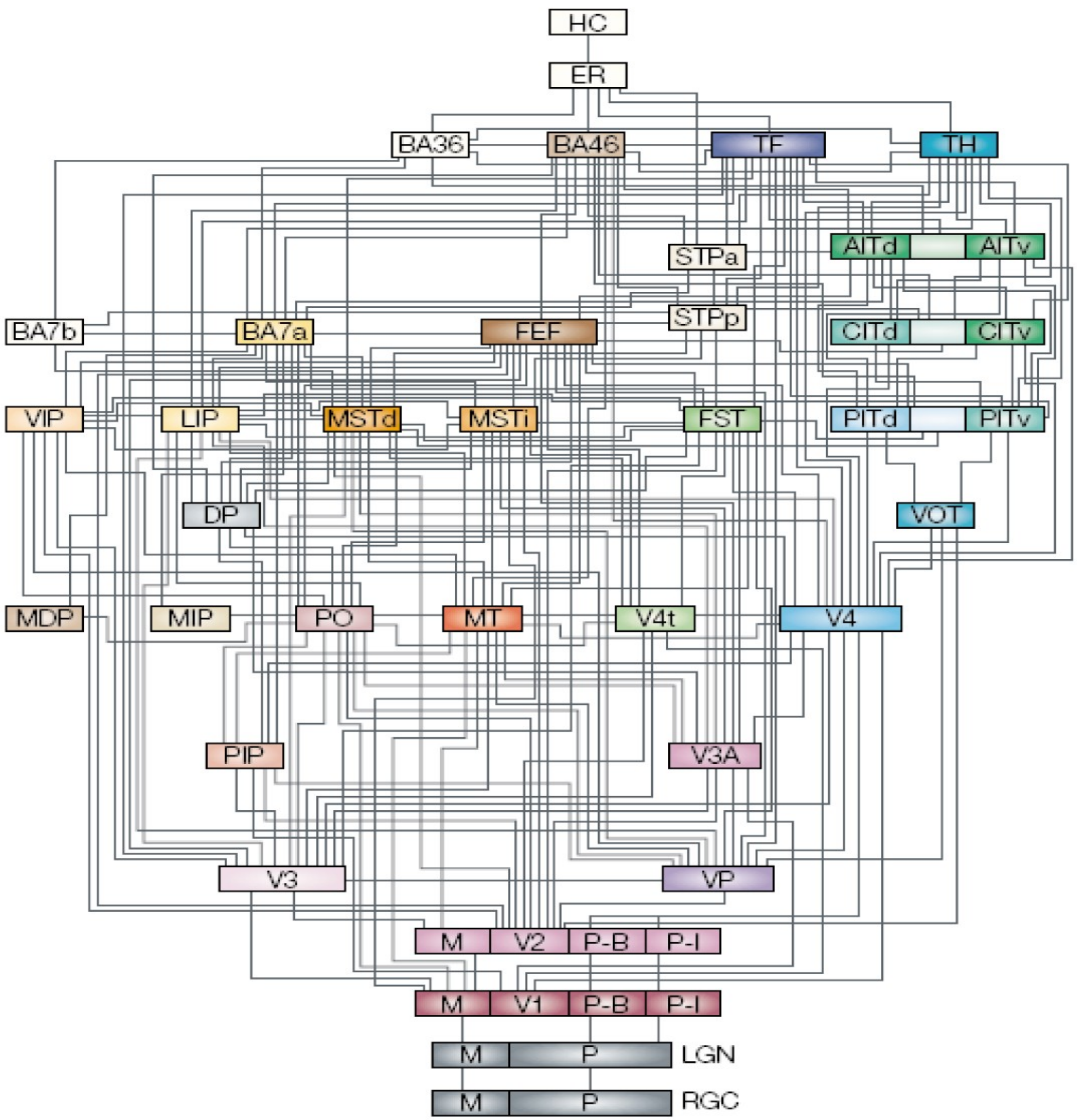


Visual system in the brain



V1 = primary visual cortex
Cortex = surface part of the brain
Brain = see figure

Visual system in the brain (2)



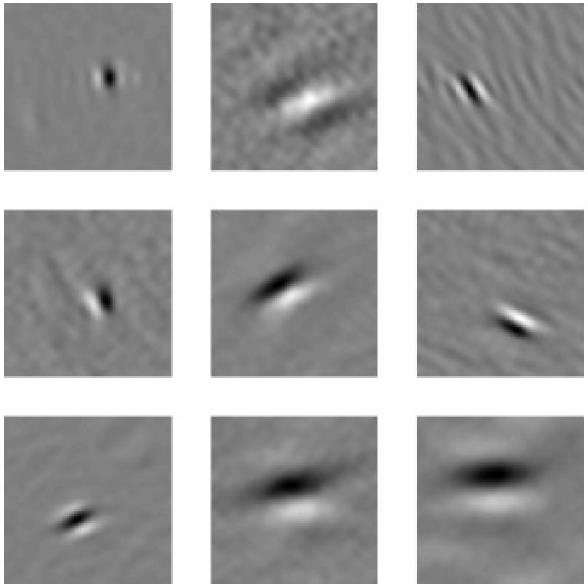
WHAT???

Why do we want to model the brain 1: the "What" question

What is really happening in the brain?

Quantitative description

Features coded by neurons
in the primary visual cortex



Courtesy of Dario Ringach, UCLA

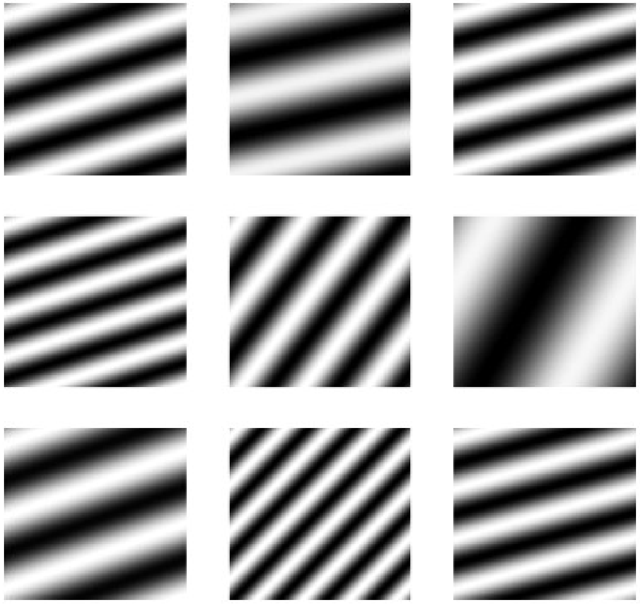
$$\exp(-\alpha^2 (x - x_0)^2) \cos(2\pi\beta(x - x_0) + \gamma)$$

$$\exp(-\alpha^2 (x - x_0)^2) \sin(2\pi\beta(x - x_0) + \gamma)$$

Fourier analysis

- Describe a function as a sum of oscillations

1D: $$f(x) = a_0 + \sum_{k \geq 1} a_k \cos(kx) + b_k \sin(kx)$$

2D: 

Gabor analysis

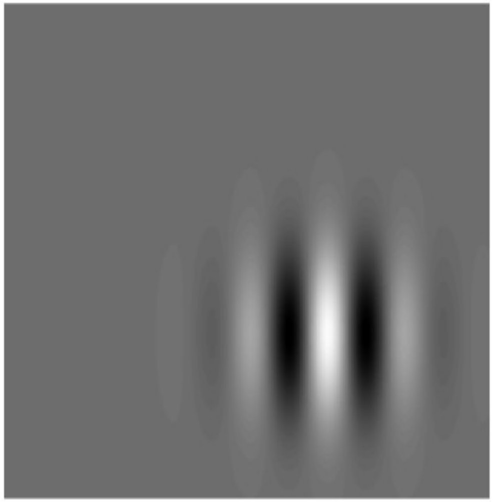
- Multiply oscillations by a windowing function

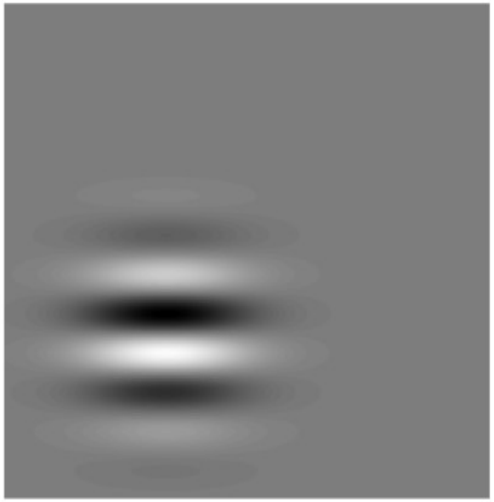
1D:

$$\exp(-\alpha^2(x-x_0)^2)\cos(2\pi\beta(x-x_0)+\gamma)$$

$$\exp(-\alpha^2(x-x_0)^2)\sin(2\pi\beta(x-x_0)+\gamma)$$

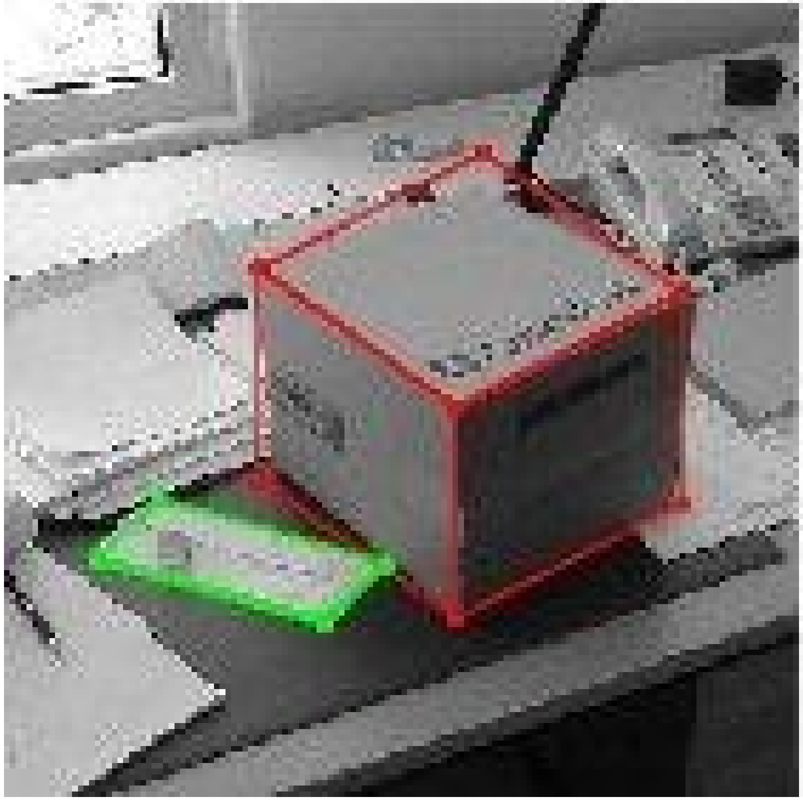
2D:





Why do we want to model the brain 2: Applications

Apply the same computations in machine vision

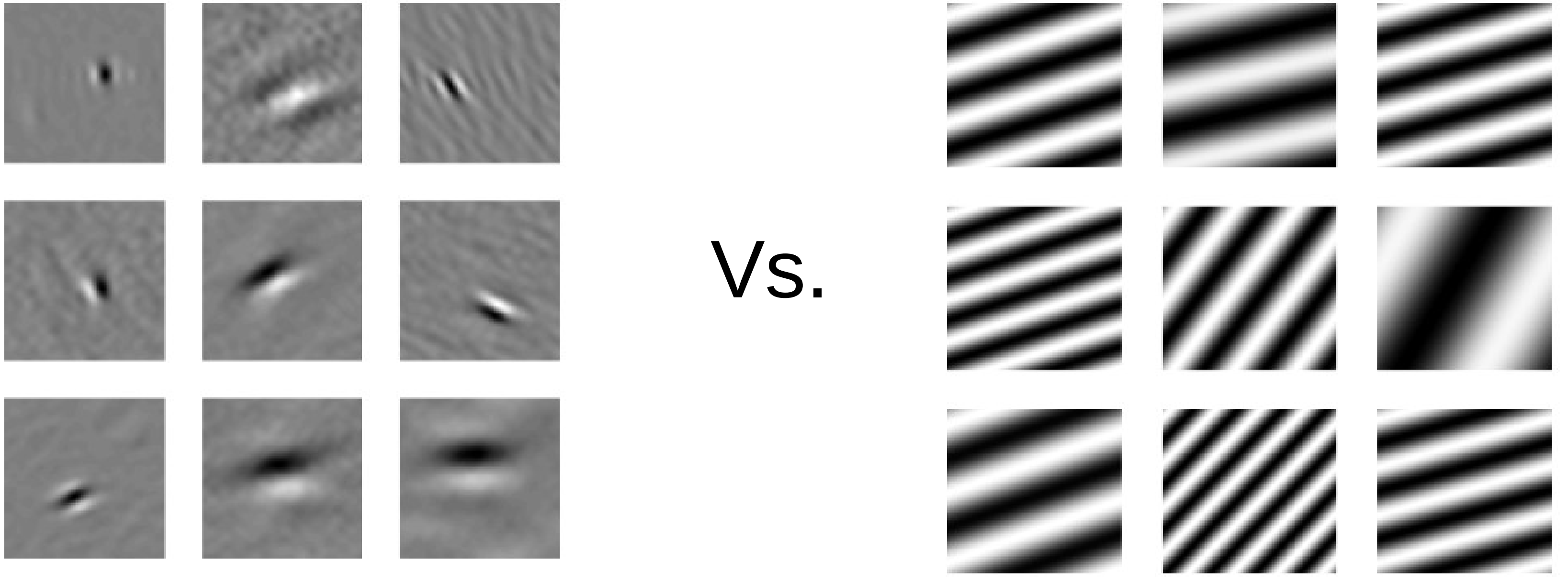


http://www.lce.hut.fi/publications/annual2001/node9.html

Why do we want to model the brain 3: the "Why" question

What are the computational goals of the brain?

Normative modelling: Given a computational goal, what should the brain be doing?



Two possible feature sets used in image analysis

Vision as learning and inference

Constructivism:

Perception is **unconscious inference**

Combine

a) Hidden assumptions (priors), e.g. internal models

b) Incoming sensory information

... in order to reach conclusions about the environment. (Helmholtz, late 19th century)

Formalized as Bayesian inference

Priors need to be learned

Bayesian inference

Basic formalism for combining prior information with incomplete observations

Assume we want to know the variable s (state of world) but only observe x (sensory input)

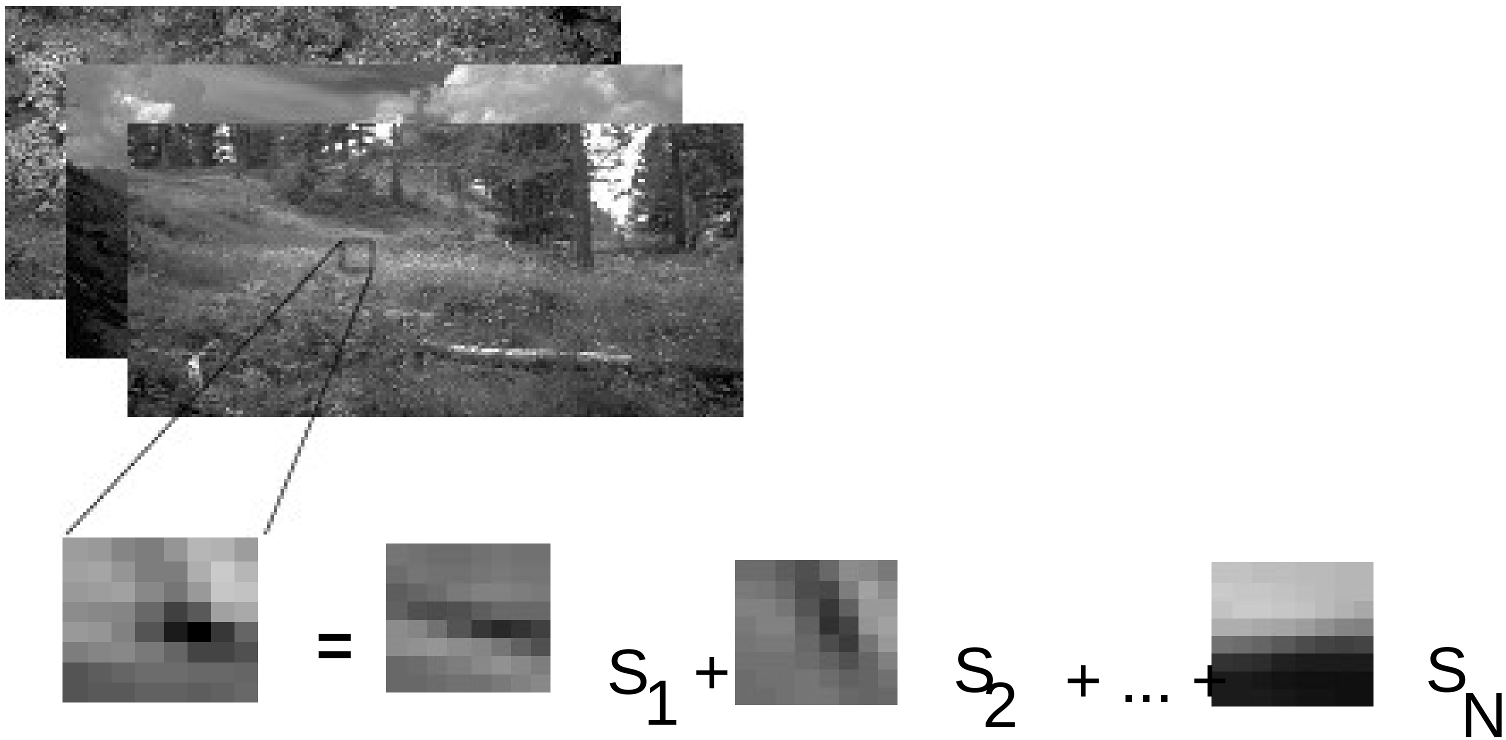
Bayes' formula: $p(s|x)=p(x|s)p(s)/p(x)$

$p(x|s)$ says how the state of the world produces sensory input

$p(s)$ is the prior distribution:
our knowledge of the structure of the world

($p(x)$ is not important)

Linear models of natural images



Learn best linear features for natural images

(Related viewpoint:)

Statistical-ecological approach to modelling/learning visual features

Ecology: What is important in a real environment?

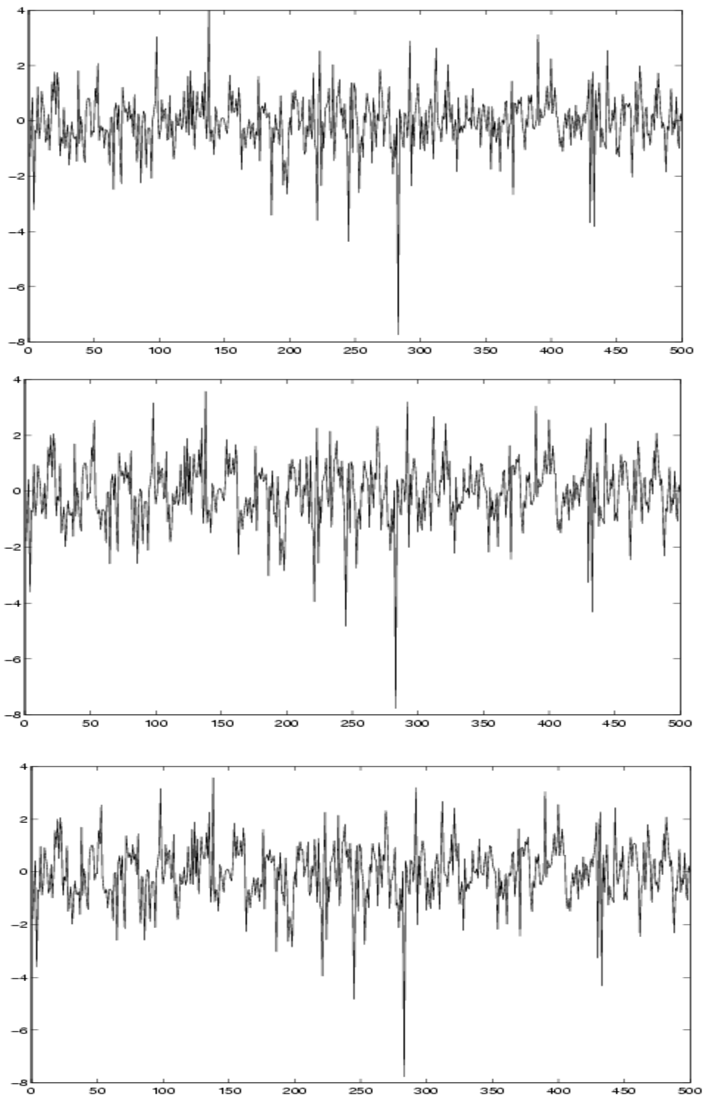
Consider natural images instead of some theoretical class

Statistics: Natural images have statistical regularities

Logic:

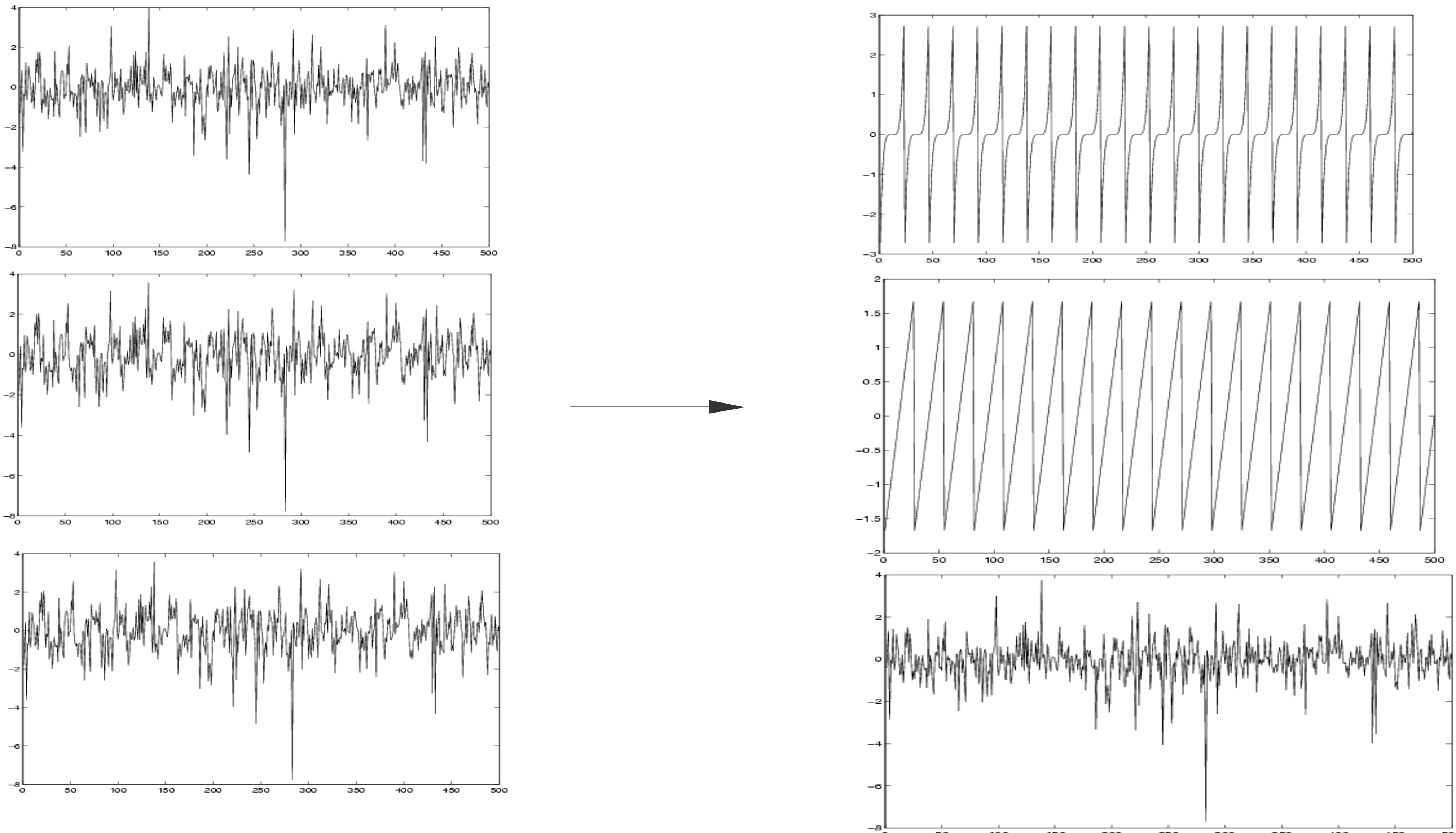
- different set of features are good for different kinds of data
- visual cortex uses/learns features which are good for natural images
- this enables optimal statistical signal processing and inference
- features embody the prior knowledge on the environment

Example: Independent component analysis



Linear mixtures of source signals: can we find the original ones?

Example:
Independent component analysis

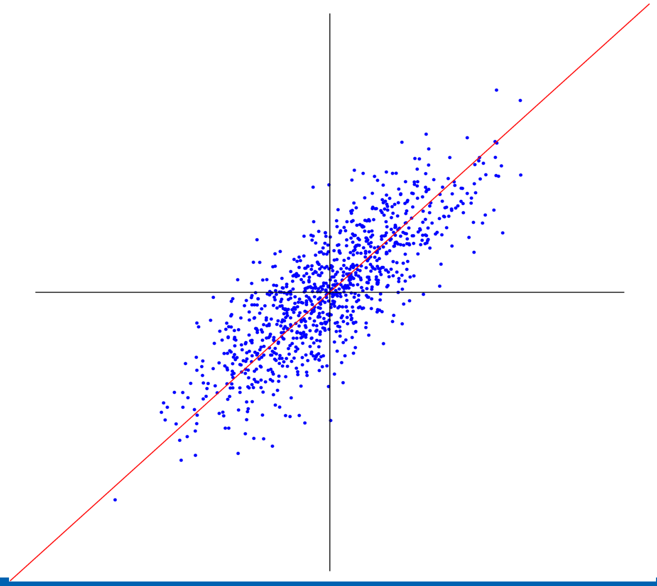


Independent Component Analysis

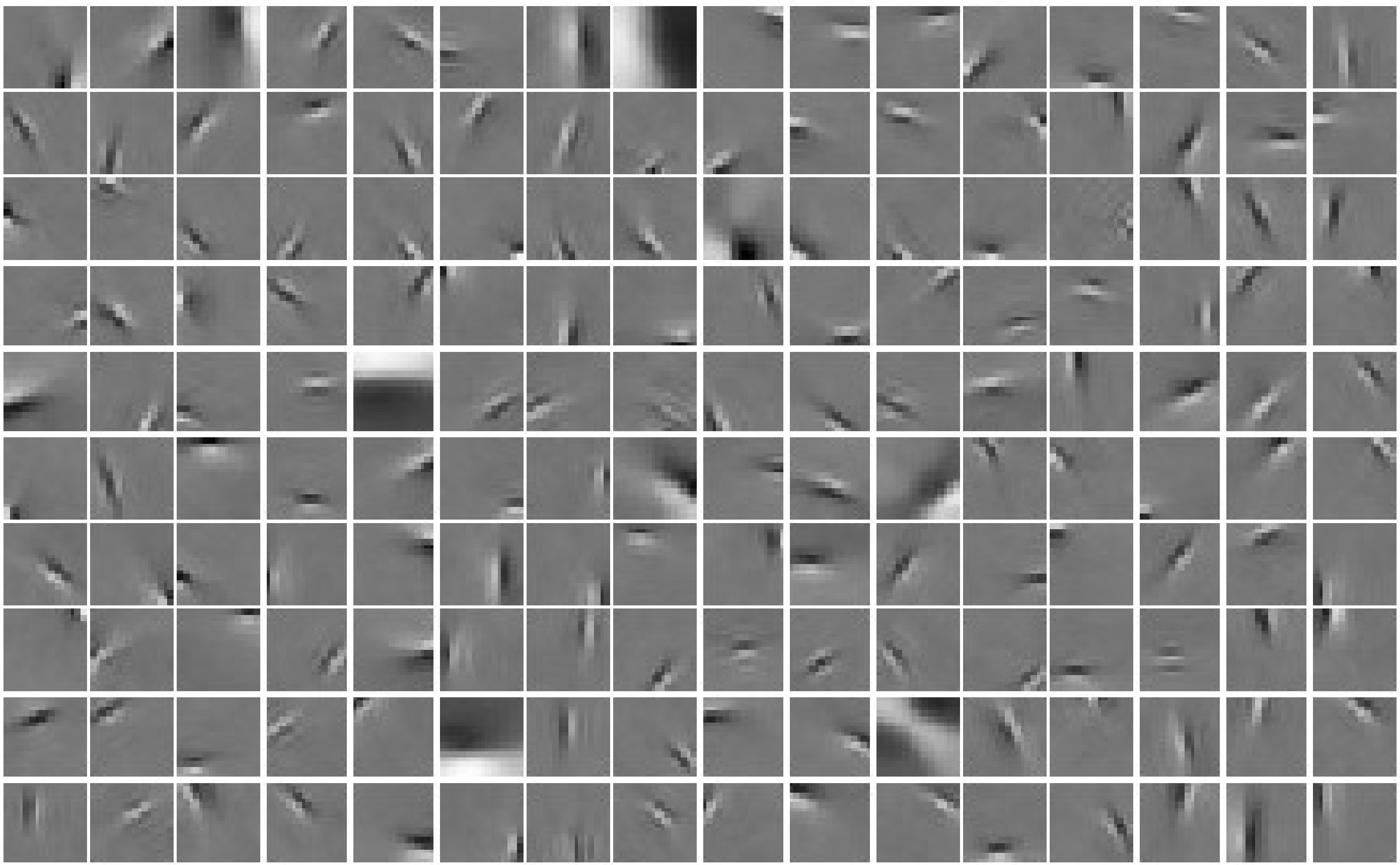
- Assume data is a linear superposition of independent "sources": $x_i = \Sigma_j a_{ij} s_j$
- Independent components are hopefully interesting in themselves, correspond to data generating process
- Must assume data is non-Gaussian, which makes it very different from PCA and factor analysis.

Principal component analysis & factor analysis

- Find projections / subspaces of data which have maximal variance (PCA) or explain most of the variance (FA)
- Main goal: Dimension reduction for
  - visualization
  - noise reduction
- Based on covariances

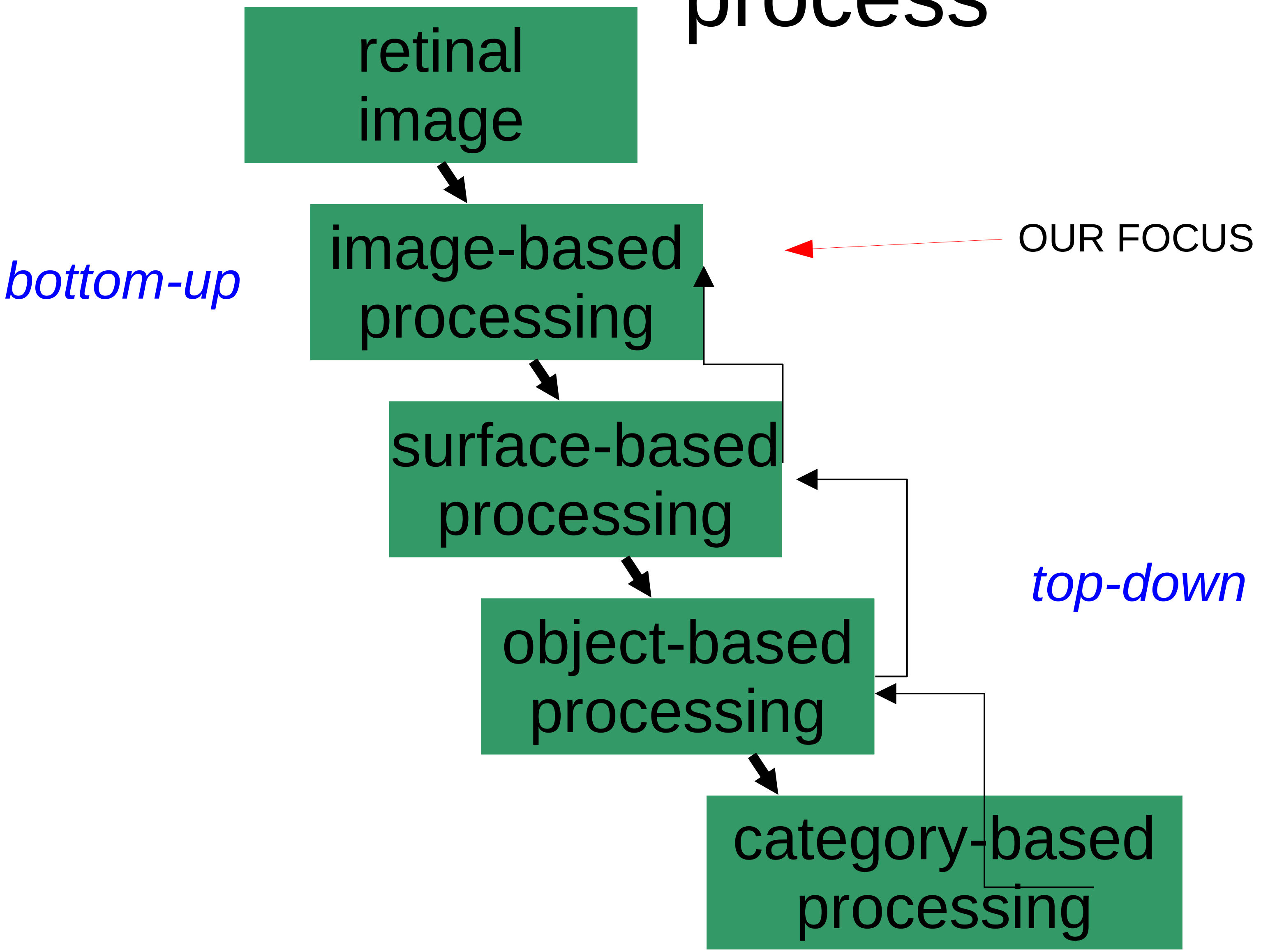


Independent component analysis of natural images



Low-level statistical prior
Similar to what is found in simple cells in primary visual cortex

Note: Perception is a long process



Outline of latter half of course

Background in Fourier analysis

Basic descripive models of visual features

  Gabor analysis

Statistical models of natural images:

  principal component analysis
  sparse coding
  independent component analysis

(Probably some further stuff TBA)