

COMPUTATIONAL COGNITIVE SCIENCE AND ENGINEERING

Yongqiang Ma

**IAIR Est.
1986**

Institute of
Artificial Intelligence
and Robotics

The Lecturer

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PhD, 2021, Xi'an Jiaotong University

- Cognitive Computing Models
- Spiking Neural Networks
- Neuromorphic Computing



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About This Class

Course Name: Computational Cognitive Science and Engineering

Credit: 2

Introduction: This course is an introduction to the study of intelligence, mind, brain from an interdisciplinary perspective.

- Brief overview of cognitive science (3hr)
- Visual perception (6hr)
- Attention (3hr)
- Memory (4hr)
- Language (2hr)
- Concept (2hr)
- Reasoning and decision making (4hr)
- Problem Solving (2hr)
- Cognitive and intention decoding (6hr)

Grading

Grading:

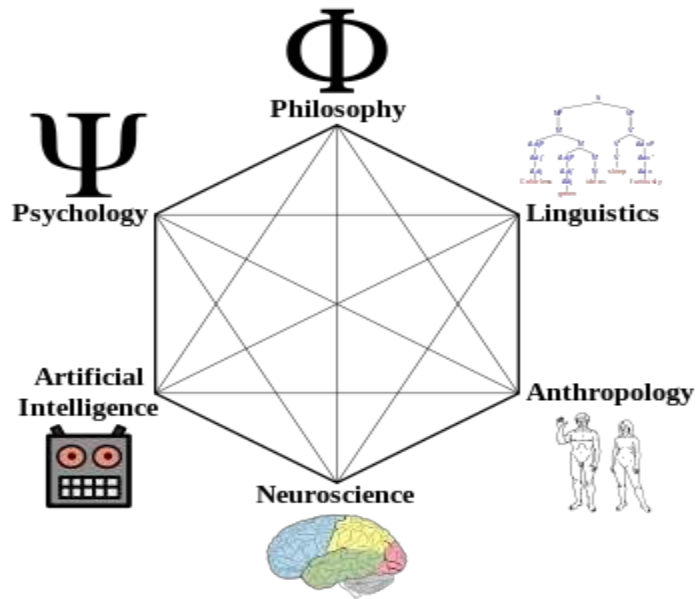
Attendance: 20%

Report: 80%

Course report:

The topic of the report should be related to cognitive science or engineering, or mathematical methods that can be applied in cognitive modeling or analysis. One may select a topic from the course lectures.

Cognitive Science



Interdisciplinary Nature

Cognitive science is the interdisciplinary study of mind and intelligence, operating at the intersection of psychology, philosophy, computer science, linguistics, anthropology, and neuroscience.

Cognitive Science



Levels of Analysis



A central tenet of cognitive science is that a complete understanding of the mind/brain cannot be attained by studying only a single level. An example would be the problem of remembering a phone number and recalling it later.

Scope

Cognitive science is a large field, and covers a wide array of topics on cognition. Below are some of the main topics that cognitive science is concerned with.

- Artificial Intelligence
- Attention
- Knowledge and Processing of Language
- Learning and Development
- Memory
- Perception and Action
- Consciousness

Research Methods

Many different methodologies can be used to study cognitive science.

- **Behavioral experiments**

- By measuring behavioral responses to different stimuli, one can understand something about how those stimuli are processed.

- **Brain imaging**

- Brain imaging involves analyzing activity within the brain while performing various tasks.

- **Computational modeling**

- [Computational models](#) require a mathematically and logically formal representation of a problem

- **Neurobiological methods**

- Research methods borrowed directly from [neuroscience](#) and [neuropsychology](#) can also help us to understand aspects of intelligence.

Research Centers

Abroad:

- MIT Computational Cognitive Science Group
- Berkeley Computational Cognitive Science Lab
- UIUC Cognitive Computation Group
-

China:

- 北京师范大学认知神经科学与学习国家重点实验室
- 中国科学院生物物理研究所脑与认知科学研究中心
-

Chinese Society for Cognitive Science



Members of the first session of the Council
Nov. 30, 2011

Related Journals

- Brain and Cognition
- Cognitive Computation
- Cognitive and Behavioral Neurology
- Cognitive Affective & Behavioral Neuroscience
- Cognitive Neurodynamics
- Cognitive Neuropsychology
- Cognitive Neuroscience
- Cognitive Psychology
- Cognitive System Research
- Journal of Cognitive Neuroscience
- Trends in Cognitive Sciences

Related Journals

- Journal of Neuroscience
- Neural Computation
- Human Brain Mapping
- Journal of Neural Engineering
- Brain
- Cerebral Cortex
- Neuroimage
- Brain Mind Magazine
- IEEE Trans. Cognitive Developmental Systems
- IEEE Trans. Biomedical Engineering

Recommended Bibliography

- Thomas J. Anastasio, *Tutorial on Neural Systems Modeling*, Sinauer Associates Inc. Publishers, 2010
- Bernard J. Baars and Nicole M. Gage, *Cognition, Brain, and Consciousness: Introduction to Cognitive Neuroscience*, 2nd ed., Academic Press, 2010
- Friedemann Pulvermuller, *The Neuroscience of Language*, Cambridge University Press, 2002
- Douglas Medin, Brian H. Ross, Arthur B. Markman, *Cognitive Psychology*, 4th ed., Wiley, 2004
- Patricia Churchland and Terrence J. Sejnowski, *The Computational Brain (Computational Neuroscience)*, MIT Press, 1994
- Jeff Hawkins, *On Intelligence*, Times Books, 2004

Recommended Bibliography

- *Theoretical Neuroscience: Computational and Mathematical Modeling of Neural Systems*, Peter Dayan and L. F. Abbott
- *Cognitive Science*, D. Kolak, W. Hirstein, P. Mandik, J. Waskan
- *Cognitive Dynamic Systems: Perception-action Cycle, Radar and Radio*, S. Haykin
- *Cortex and Mind: Unifying Cognition*, J. M. Fuster
- *Information Theoretic Learning: Renyi's Entropy and Kernel Perspectives*, J. C. Principe
- *Kernel Adaptive Filtering*, W. Liu, J. C. Principe, S. Haykin

Brain

- Cortex (part of forebrain) Divided into 2 hemispheres with some **lateralization**:

Usual functions:

- Left—analysis of information (reading, math problem-solving, linguistic)
- Right—synthesis of information (visual analysis, nonlinguistic)
- Each hemisphere receives info from and controls opposite side of body
- Myth—a person is NOT left or right brained—both used in complex functions



Image from morphnix.com

Brain

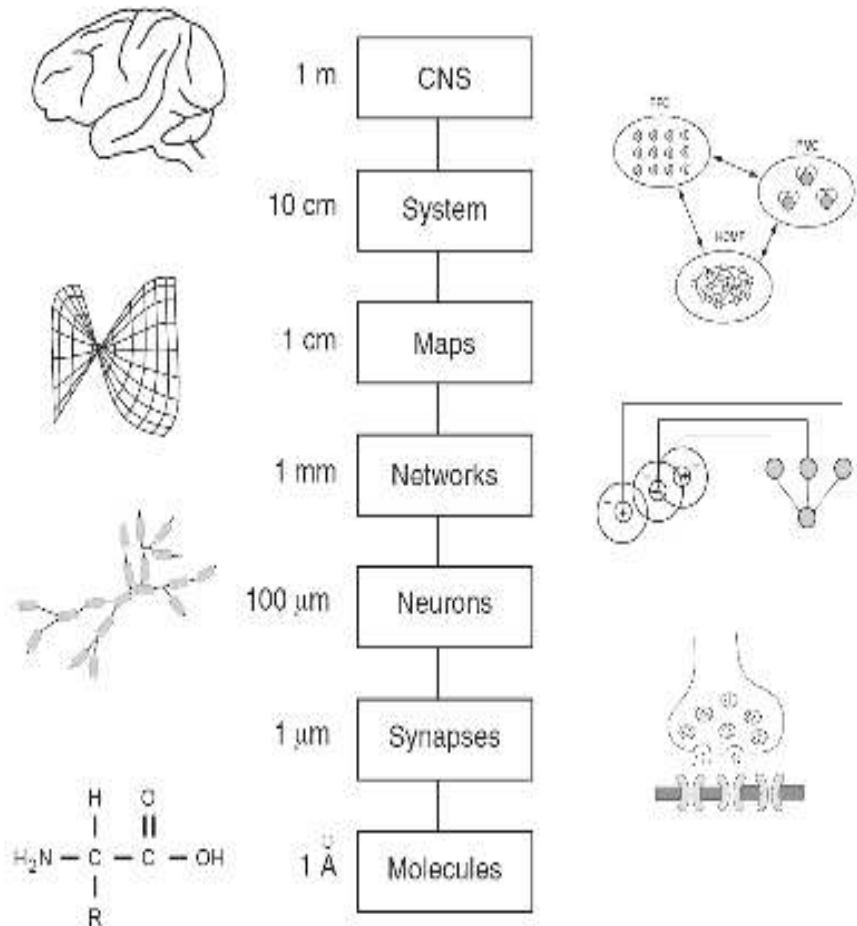


Brain is an extremely complex system



~100 billion neurons

~7000 synaptic connections per neuron



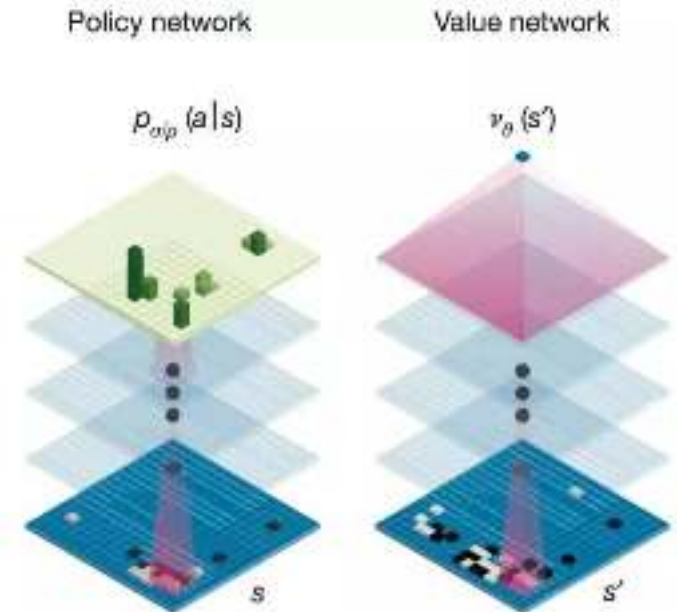
Artificial Intelligence

- Constructing artificial computer-based systems that produce intelligent outcomes
- Examples
 - Game Playing Programs
 - ✓ [Deep Blue](#)
 - Intelligent Robots
 - ✓ [Mars Rovers](#)
 - ✓ [DARPA Urban Challenge](#)
 - [Netflix Competition](#)
 - Large Language Models
 - ✓ [ChatGPT](#)
 - ✓ [DeepSeek](#)



Artificial Intelligence

AlphaGo is a computer program developed by [Google DeepMind](#) in London to play the board game [Go](#). In October 2015, it became the first [Computer Go](#) program to beat a professional human Go player without [handicaps](#) on a full-sized 19×19 board. In March 2016, it beat [Lee Sedol](#) in [a five-game match](#), the first time a computer Go program has beaten a [9-dan](#) professional without handicaps.



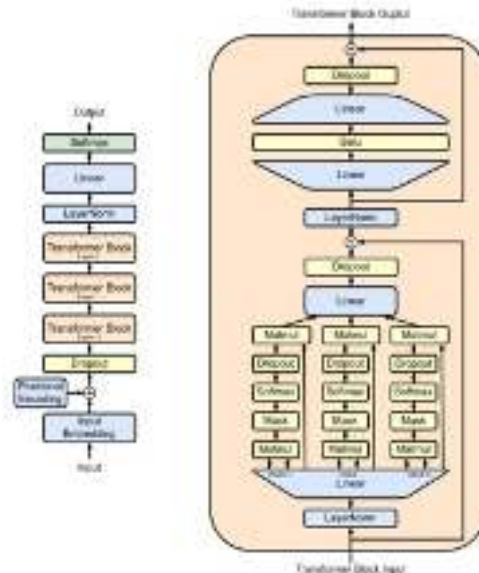
Artificial Intelligence

ChatGPT is an [artificial intelligence](#) (AI) [chatbot](#) developed by [OpenAI](#) and released in November 2022. It is built on top of OpenAI's [GPT-3.5](#) and [GPT-4](#) families of [large language models](#) (LLMs) and has been [fine-tuned](#) (an approach to [transfer learning](#)) using both [supervised](#) and [reinforcement learning](#) techniques.

Generative pre-trained transformers (GPT)



OpenAI CEO [Sam Altman](#)



The original GPT model



Weak vs. Strong AI

- **Weak AI** - using AI as a tool to understand human cognition
- **Strong AI** - a properly programmed computer has a “mind” capable of understanding

Strong AI makes the bold claim that computers can be made to think on a level (at least) equal to humans and possibly even be conscious of themselves. Weak AI simply states that some "thinking-like" features can be added to computers to make them more useful tools... and this has already started to happen (witness expert systems, drive-by-wire cars and speech recognition software). What does 'think' and 'thinking-like' mean? That's a matter of much debate.

Weak vs. Strong AI

STRONG AI
VS
WEAK AI

STRONG AI

VS

WEAK AI



Turing Test

- Can artificial intelligence be as good as human intelligence? How can we test this?
- **Turing test** (1950)
 - designed to test whether humans can distinguish between humans and computers based on conversations
 - A human interrogator could ask a respondent (either a computer or a human, whose identity was hidden) any question he or she wished, and based on either the computer's or the human's response, the interrogator had to decide if the answer was given by the computer or by the human.



Alan Turing (1912-1954)

Turing Test

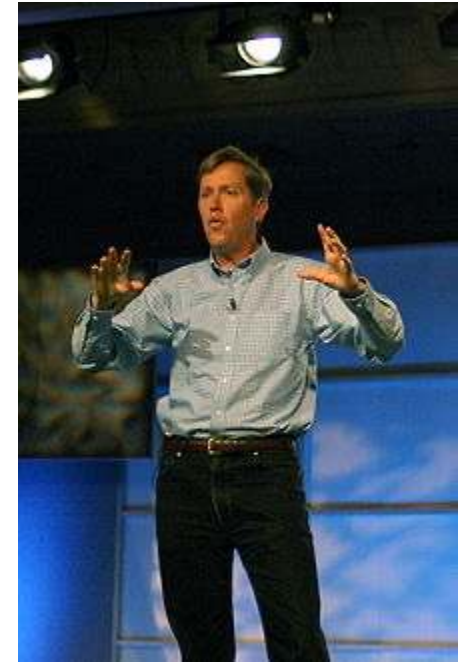


Turing Test



Jeff Hawkins' s Comments on AI

- AI defenders ... a program that produces outputs resembling (or surpassing) human performance on a task in some **narrow but useful way** really is just as good as the way our brains do it
- ...this kind of ends-justify-the-means interpretation of functionalism leads
- AI researchers astray



Jeff Hawkins

Jeff Hawkins' s Comments on ANN

- Connectionists intuitively felt the brain wasn't a computer and that its secrets lie in **how neurons behave when connected together**
- That was a good start, but the field barely moved on from its early successes
- Research on cortically realistic networks was, and remains, rare

Jeff Hawkins' s Comments on Intelligence

- Since **intelligence is an internal property** of a brain, we have to look inside the brain to understand what intelligence is
- To succeed, we will need to crib heavily from nature's engine of intelligence, the neocortex
- No other roads will get us there

Computational Modeling

- Most modeling in cognitive science targets natural intelligence
- Goal is to develop model or mimic some aspects of human cognitive functioning
 - produce the same errors as humans
- Simulations of aspects of human behavior

Why do we need computational models?

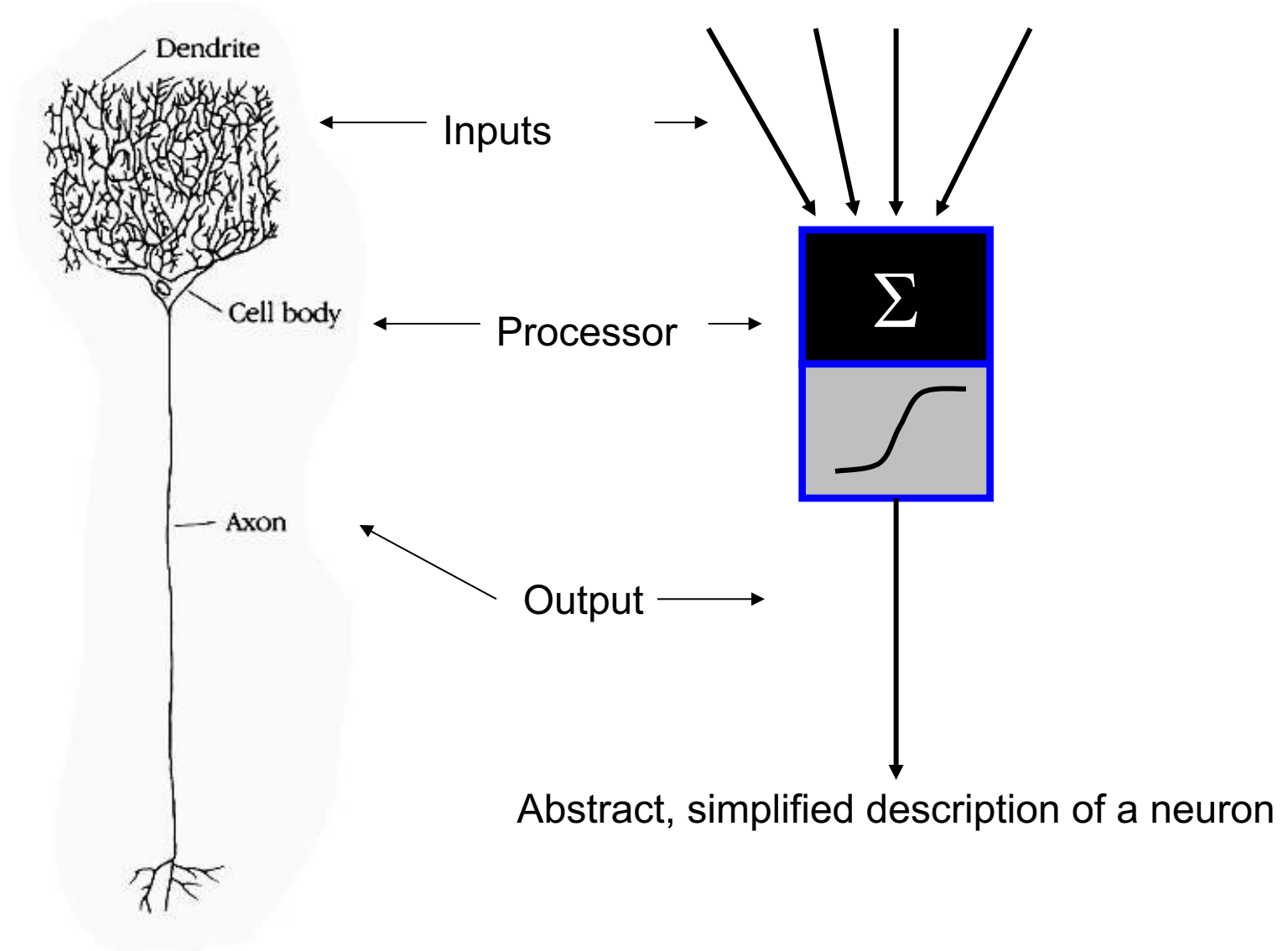
- Makes vague verbal terms specific
 - Provides **precision** needed to specify complex theories.
- Provides **explanations**
- Obtain quantitative **predictions**
 - just as meteorologists use computer models to predict *tomorrow's* weather, the goal of modeling human behavior is to predict performance in *novel* settings

Neural Networks

Neural Networks

- **Neural networks** are networks of simple processors that operate simultaneously
- Alternative to traditional information processing models
- Also known as:
 - **PDP** (parallel distributed processing approach)
 - **Connectionist** models
- Some biological plausibility

Idealized Neurons (Units)

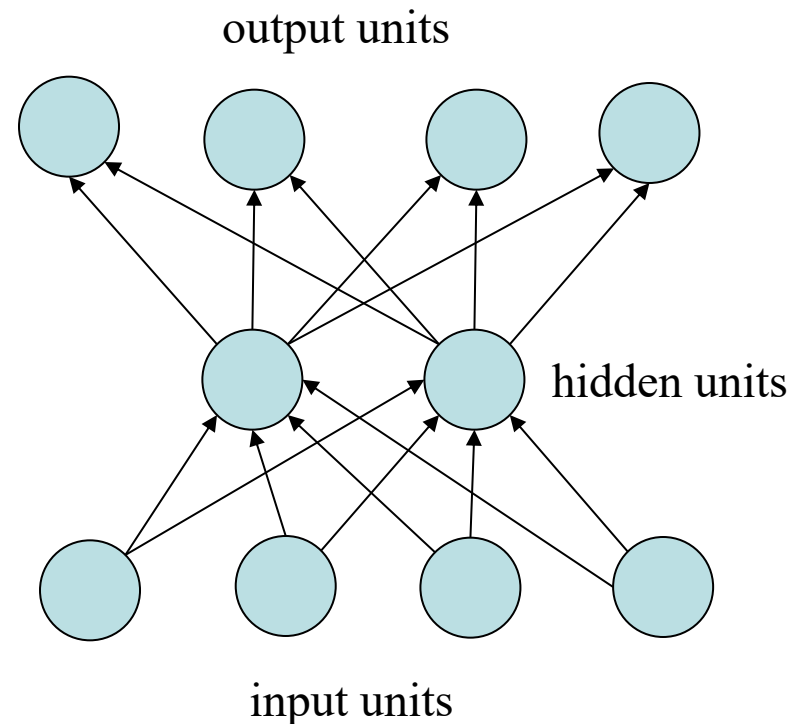


Neural Networks

- Units
 - **Activation** = Activity of unit
 - **Weight** = Strength of the connection between two units
- **Learning** = changing strength of connections between units
- **Excitatory** and **inhibitory** connections
 - correspond to positive and negative weights respectively

Multi-layered Networks

- Activation flows from a layer of **input units** through a set of **hidden units** to **output units**
- Weights determine how input patterns are mapped to output patterns
- Network can **learn** to **associate** output patterns with input patterns by **adjusting weights**
- Hidden units tend to develop **internal representations** of the input-output associations
- **Backpropagation** is a common weight-adjustment algorithm



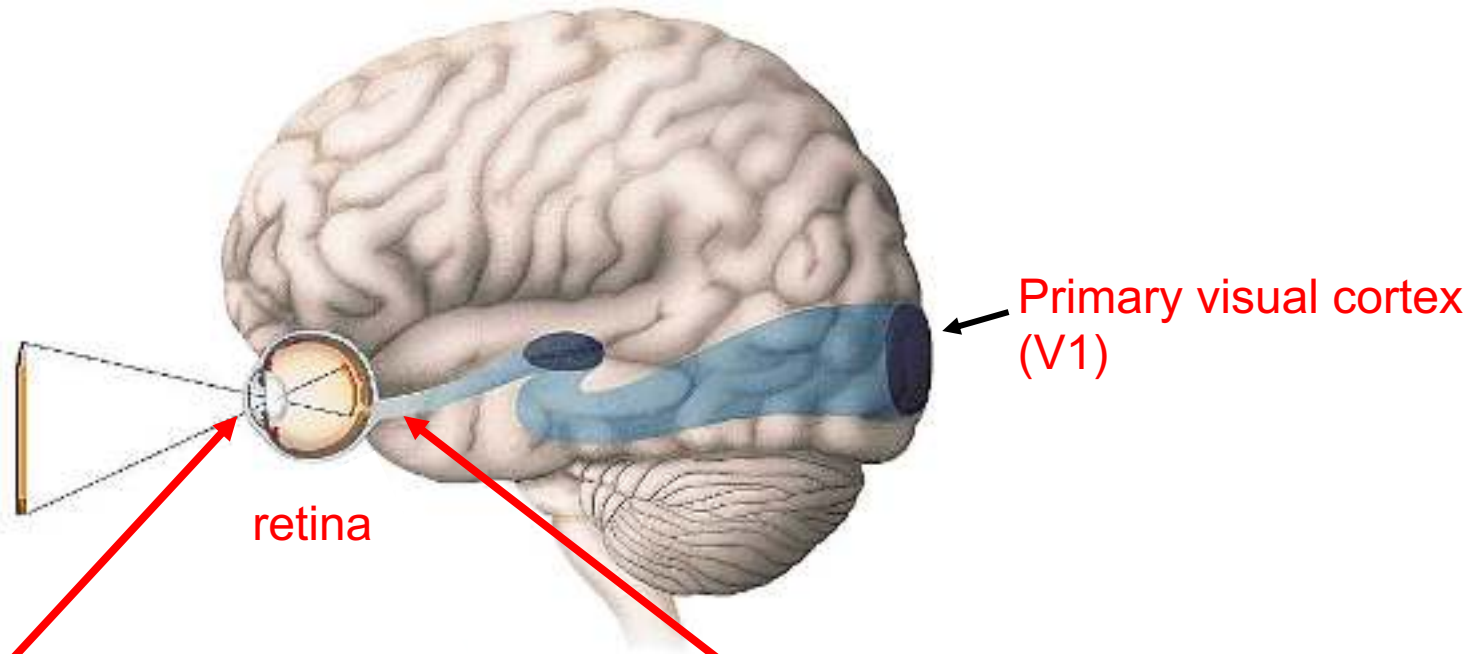
Neural Network Models

- Inspired by real neurons and brain organization but are **highly idealized**
- Can **spontaneously generalize** beyond information explicitly given to network
- Retrieve information even when network is damaged (**graceful degradation**)
- Networks can be taught: learning is possible by changing **weighted connections** between nodes

Information Theory

Information bottleneck in the visual pathway:

Optic nerve



retina

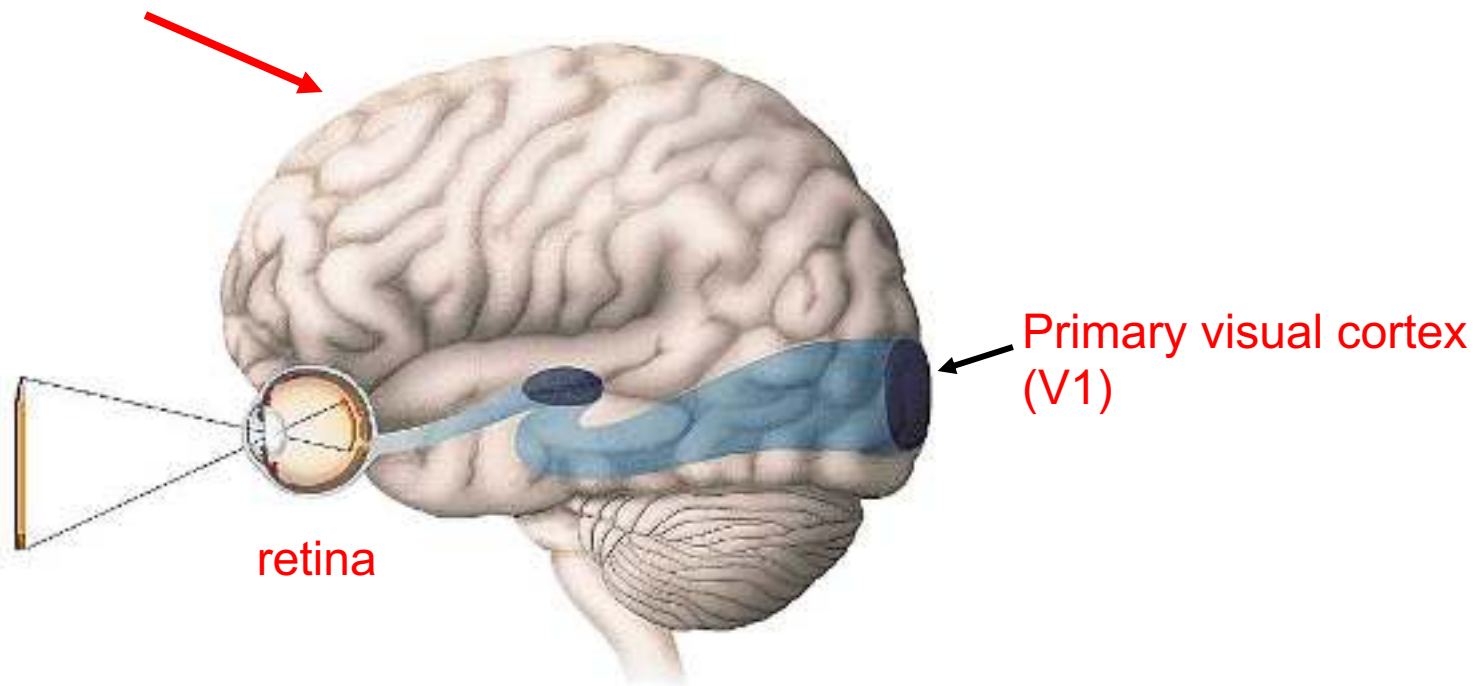
Primary visual cortex
(V1)

10^9 bits/second (Kelly 1962)
~ 25 frames/second, 2000x2000
pixels, 1 byte/pixel

10^7 bits/second
~ 10^6 neurons ,
~10 spikes/neuron
~1 spike/second

Information bottleneck in the visual pathway:

Attentional bottleneck ~ 40 bits/second

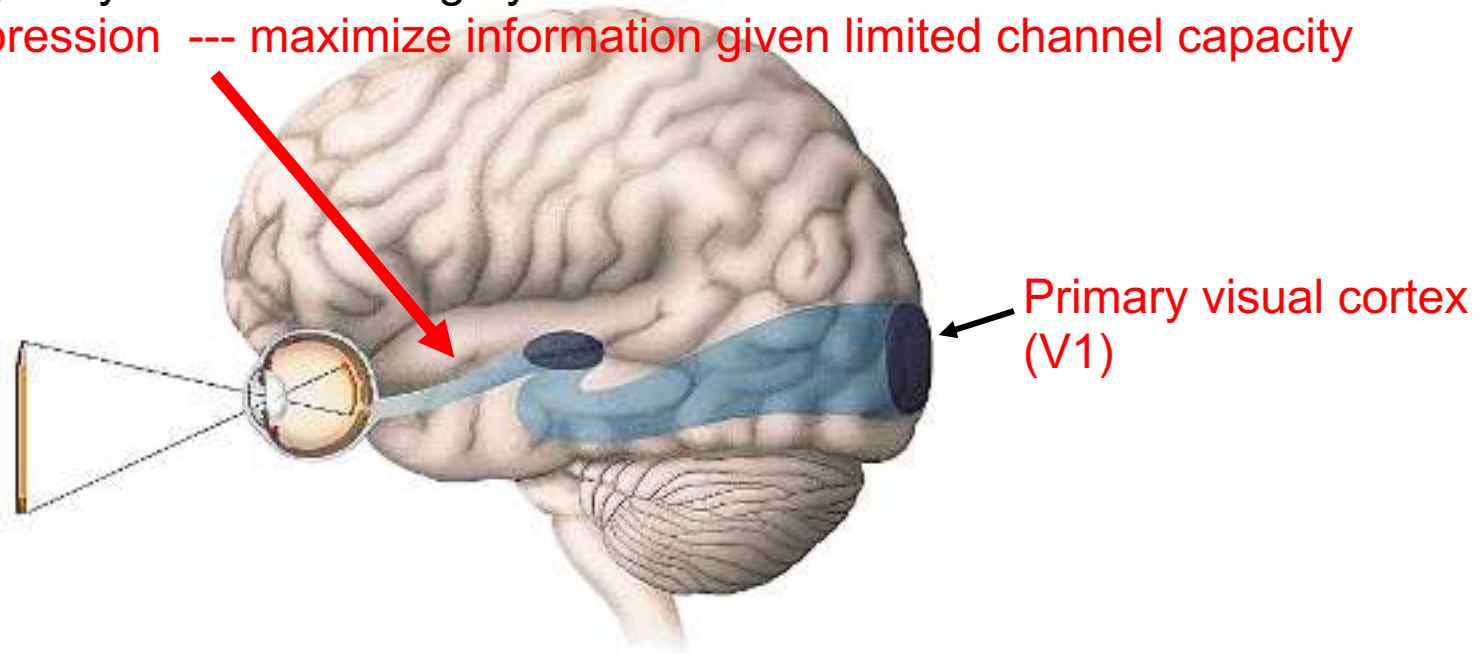


Information bottleneck in the visual pathway:

One hypothesis for early vision

Understanding early visual encoding by

data compression --- maximize information given limited channel capacity



See review paper: Zhaoping L. 2006,
Network: Computation in neural systems
(available from Zhaoping's webpage)

Barlow: 1950-60s --- redundancy reduction.

Laughlin, Linsker, Atick, Redlich, Li, van Hateran,
etc. 1980-90s mathematical (information theory)
formulation and derivation/prediction

Bell & Sejnowski, Olshausen & Field etc, 1990s,
computer simulations.

Information bottleneck in the visual pathway:

Formulation:

Input signal S ,

Input sampling noise N , hence $S' = S + N$

Neural encoding: from input S' to neural response (output) O

$O = K(S') + N_o$, where N_o is encoding noise

Information in O about S : $I(O; S)$, mutual information between O and S .

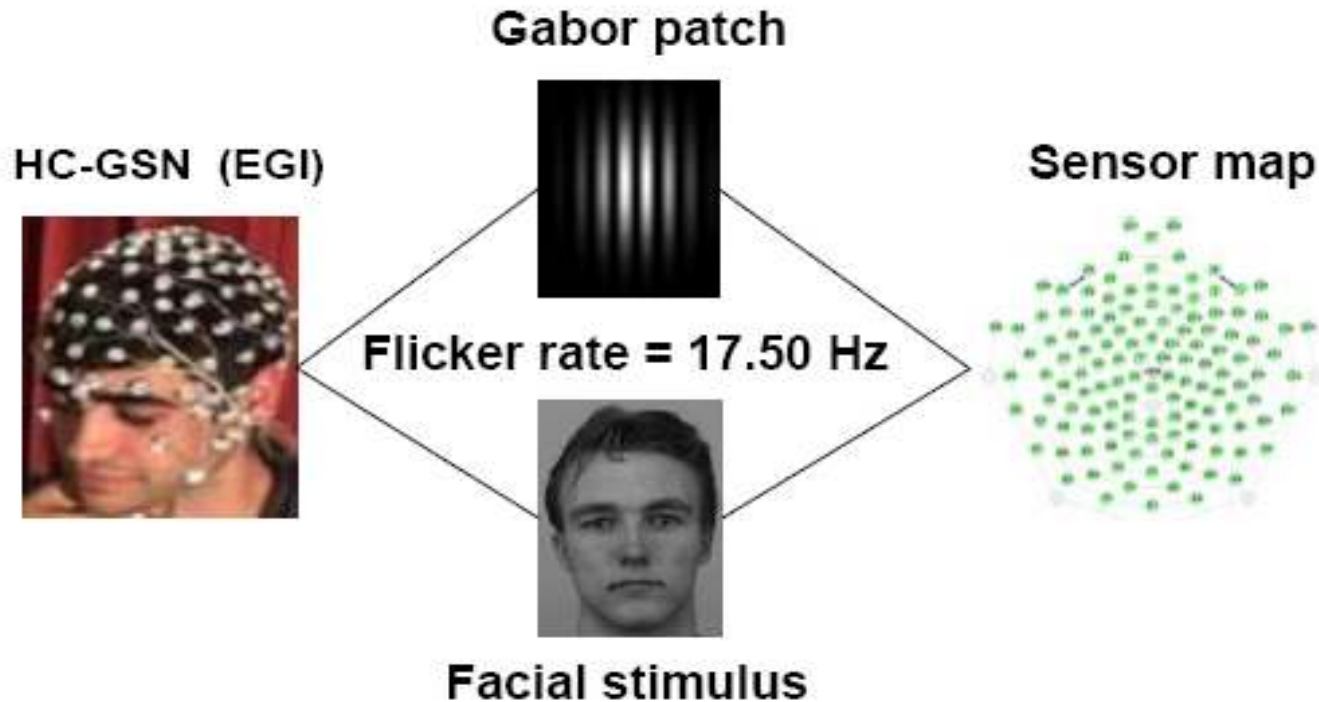
Should maximize $I(O; S)$ subject to a given neural cost, hence minimize:

$$E(K) = \text{neural cost} - \lambda \bullet I(O; S)$$

Solution, find the encoding K that satisfies $\partial E / \partial K = 0$.

Brain Signal Processing and Analysis

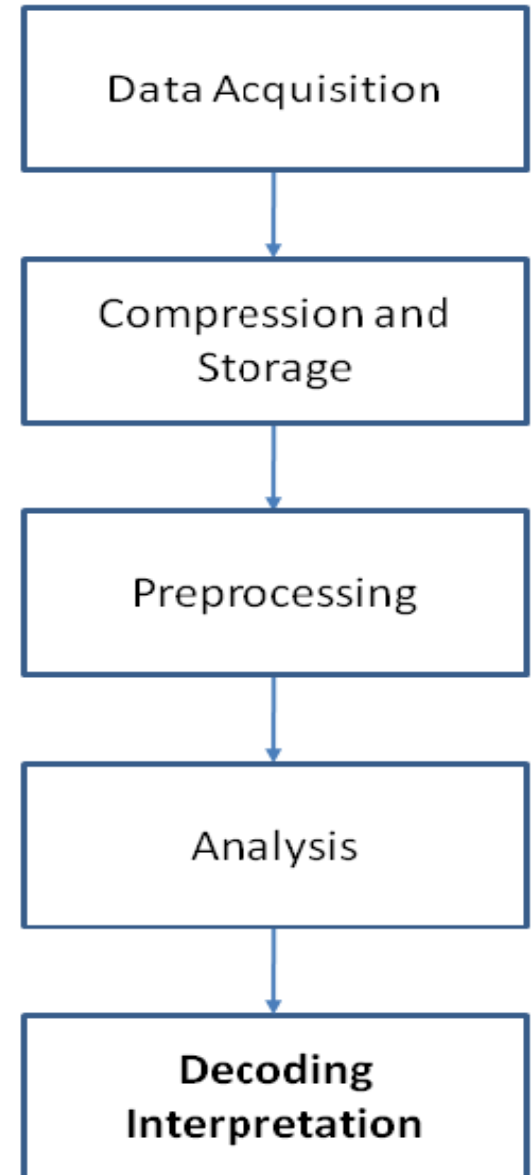
Brain Signals



- electroencephalograms (EEG)
- magnetoencephalograms (MEG)
- functional MRI (fMRI)
- spike trains,

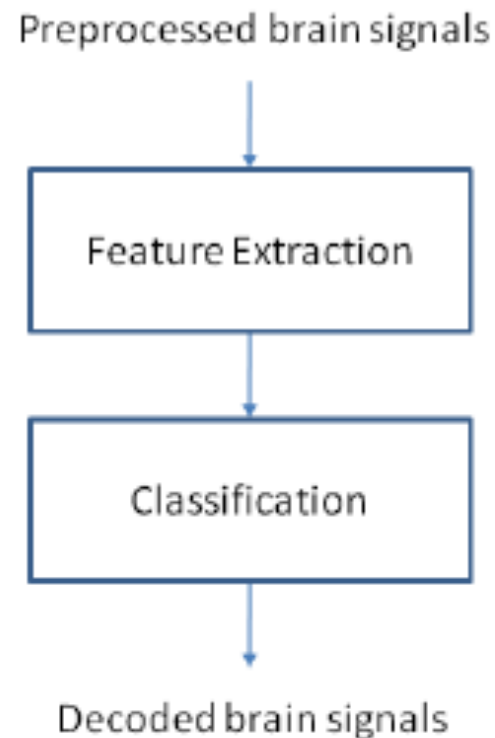
Brain Signal Processing and Analysis

- signal transformations
- filtering (basic, adaptive)
- blind source separation
- independent component analysis
- principal component analysis
- sparse component analysis
- quantization
- clustering
- feature extraction
- classification
- dependence and causality analysis

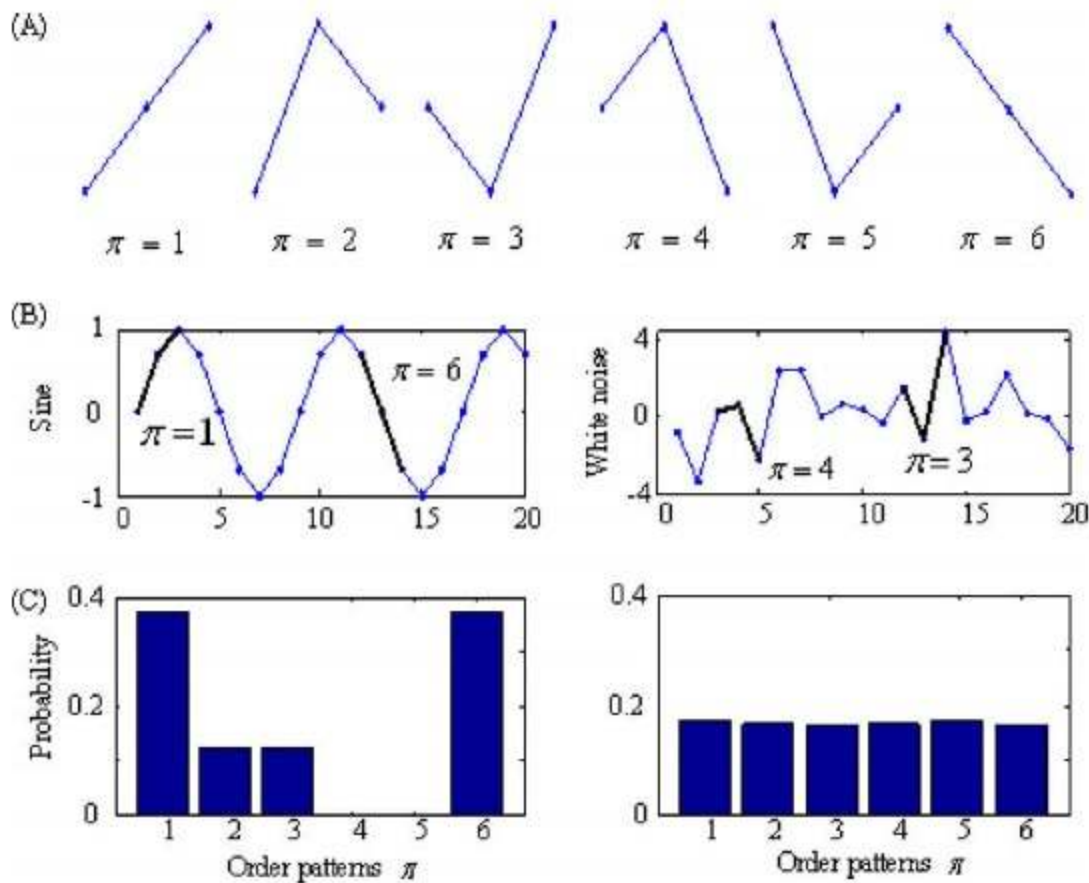


Decoding of Brain Signals

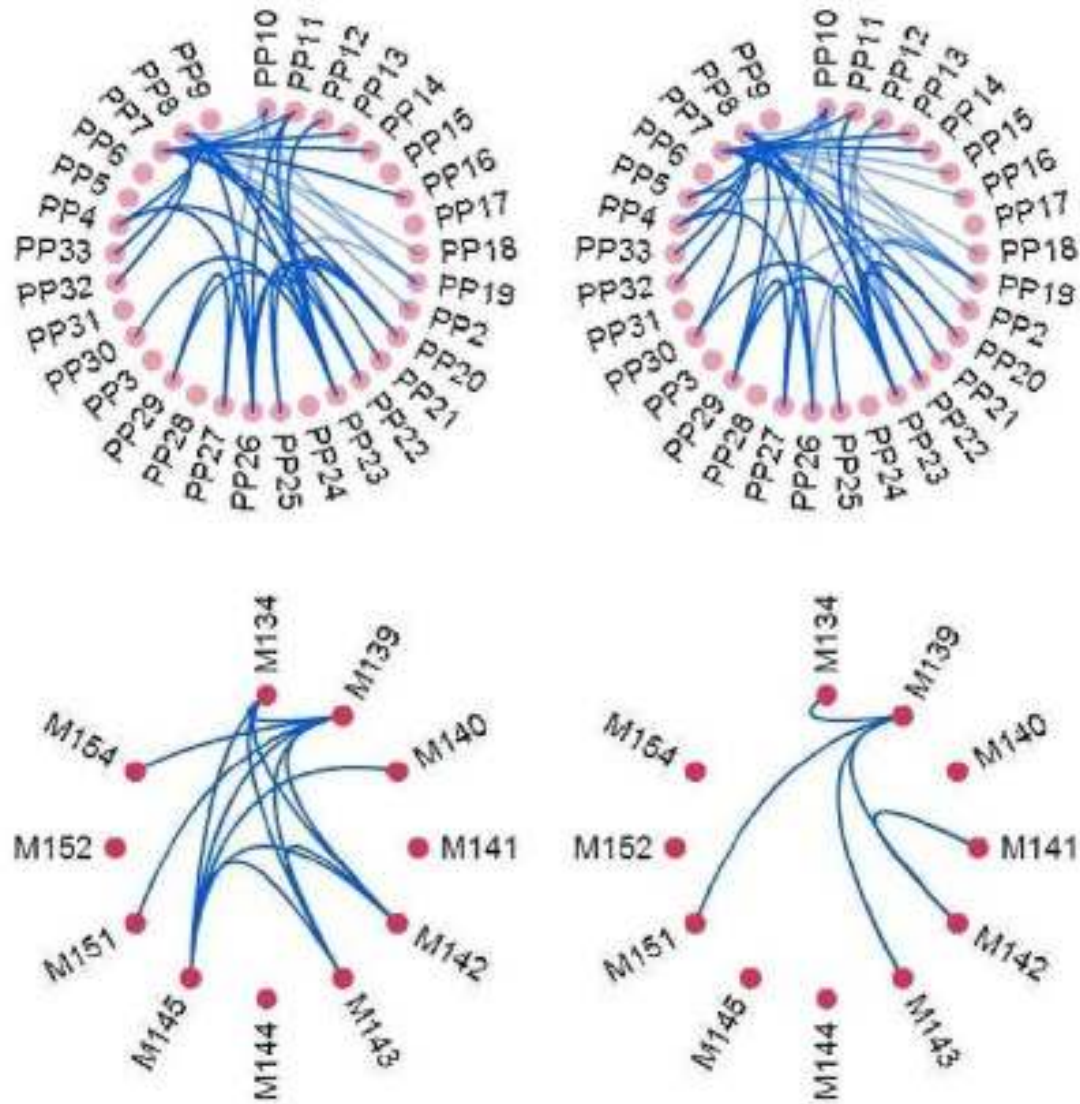
Decoding brain signals means mapping of brain signals to distinct stimuli (e.g., visual stimulation at particular frequency), mental states (e.g., asleep, awake, or drowsy), emotions (e.g., anger or fear), etc. A popular methodology is to extract a multitude of features from the brain signals (after suitable preprocessing). Those features are then used to train classifiers from labeled data; the output of the classifier (label) represents a particular stimulus, mental state, or emotion.



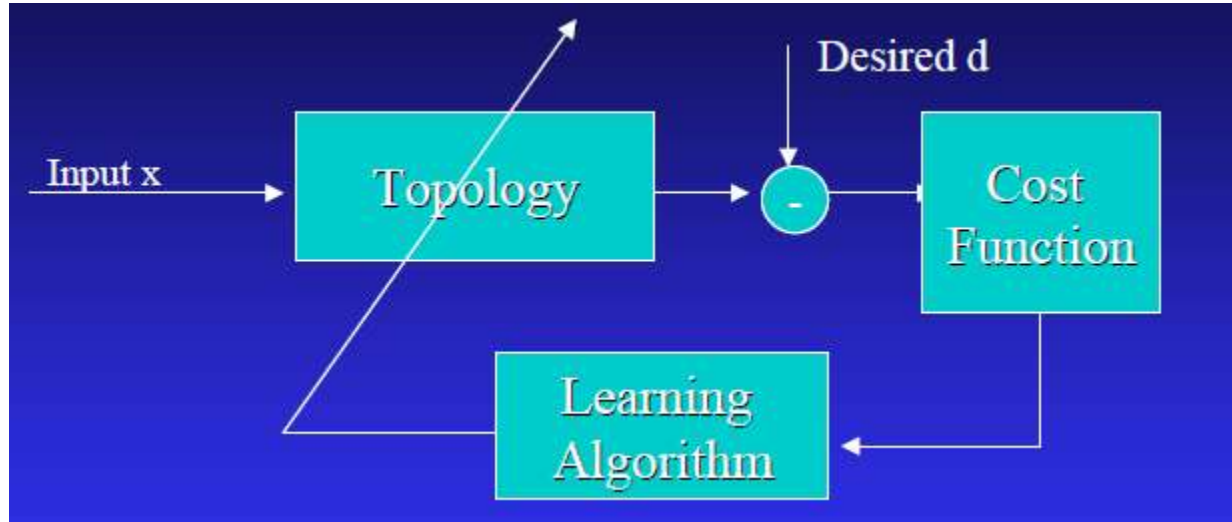
Complexity based Feature Extraction



Dependence and Causality Analysis

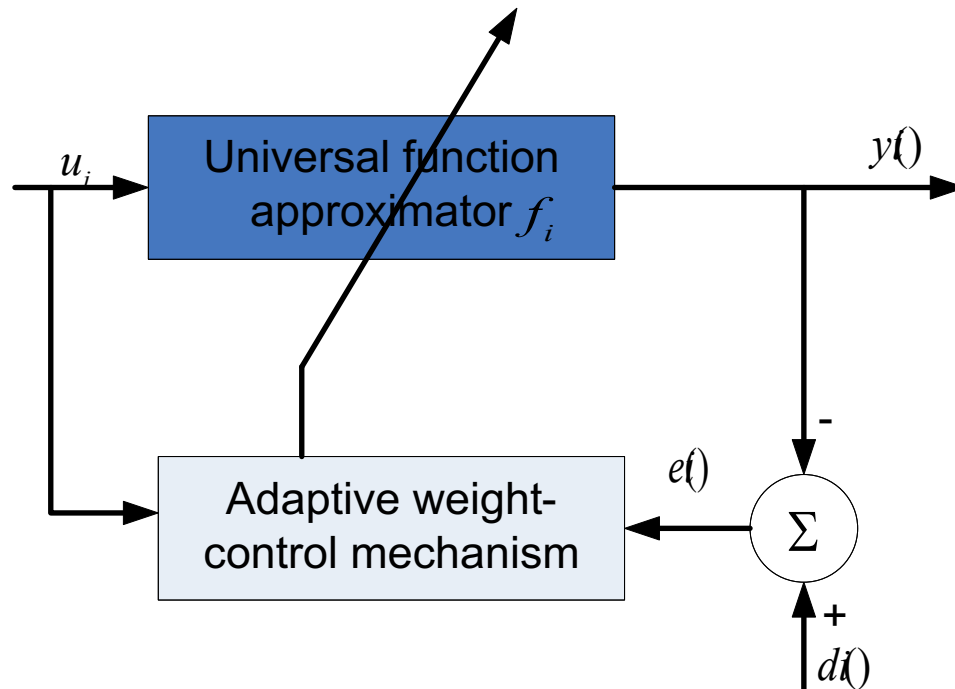
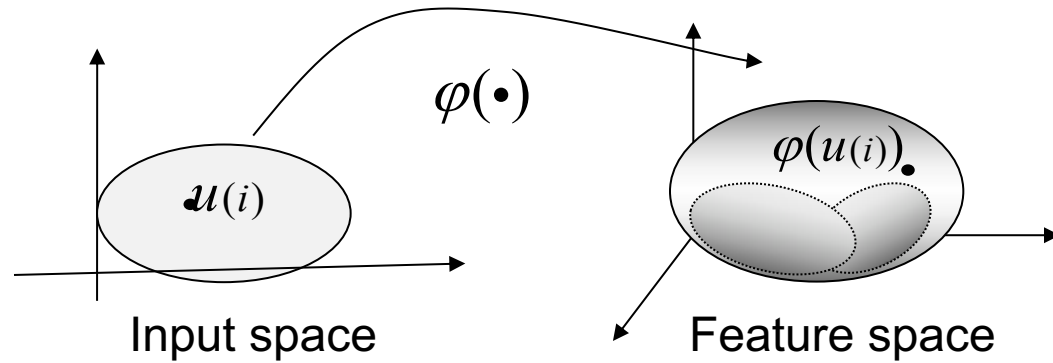


Information Theoretic Learning

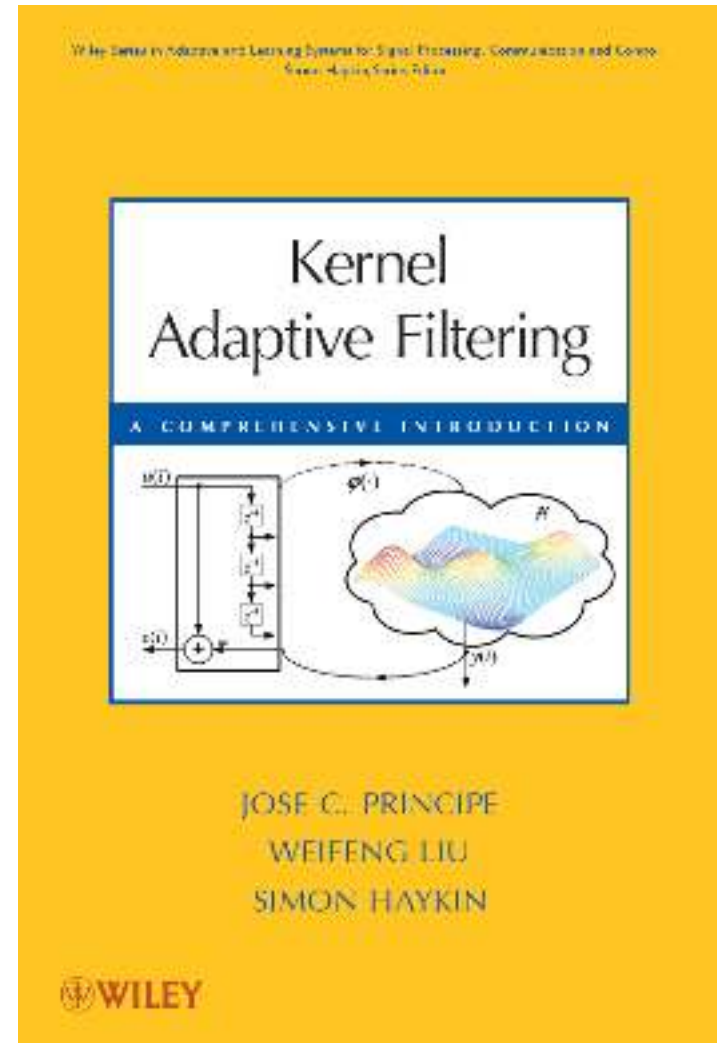
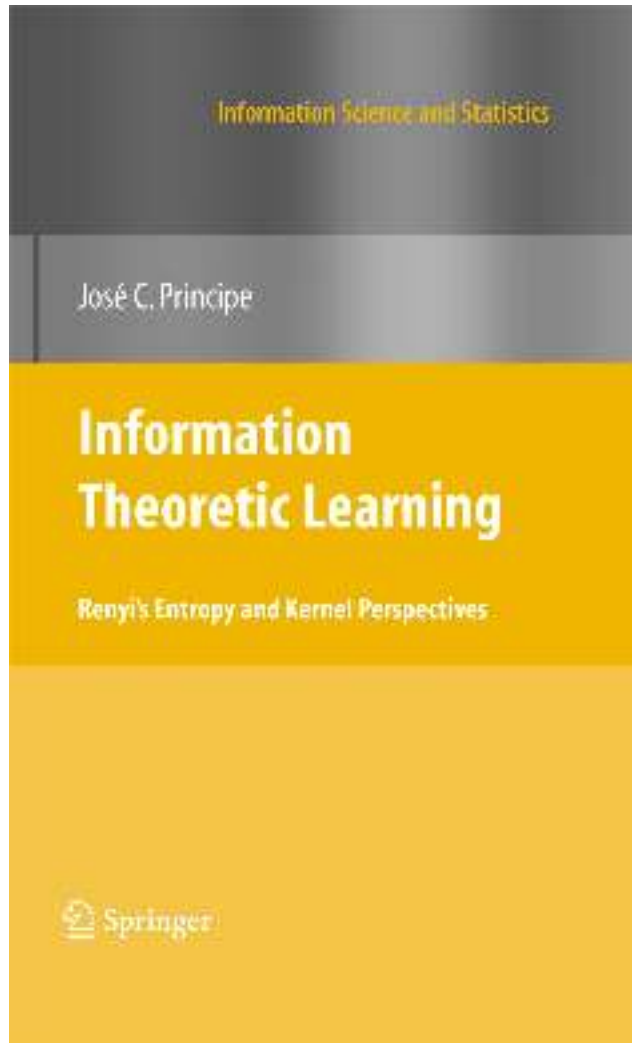


- **Training data:** (x, d)
- **Topology:** linear/nonlinear, or linear in RKHS
- **Cost:** MSE, higher-order statistics, information theoretic criteria (e.g. entropy, mutual information, KL divergence, etc.)
- **Algorithm:** gradient based, fixed point, evolutionary, etc.

Kernel Adaptive Filtering

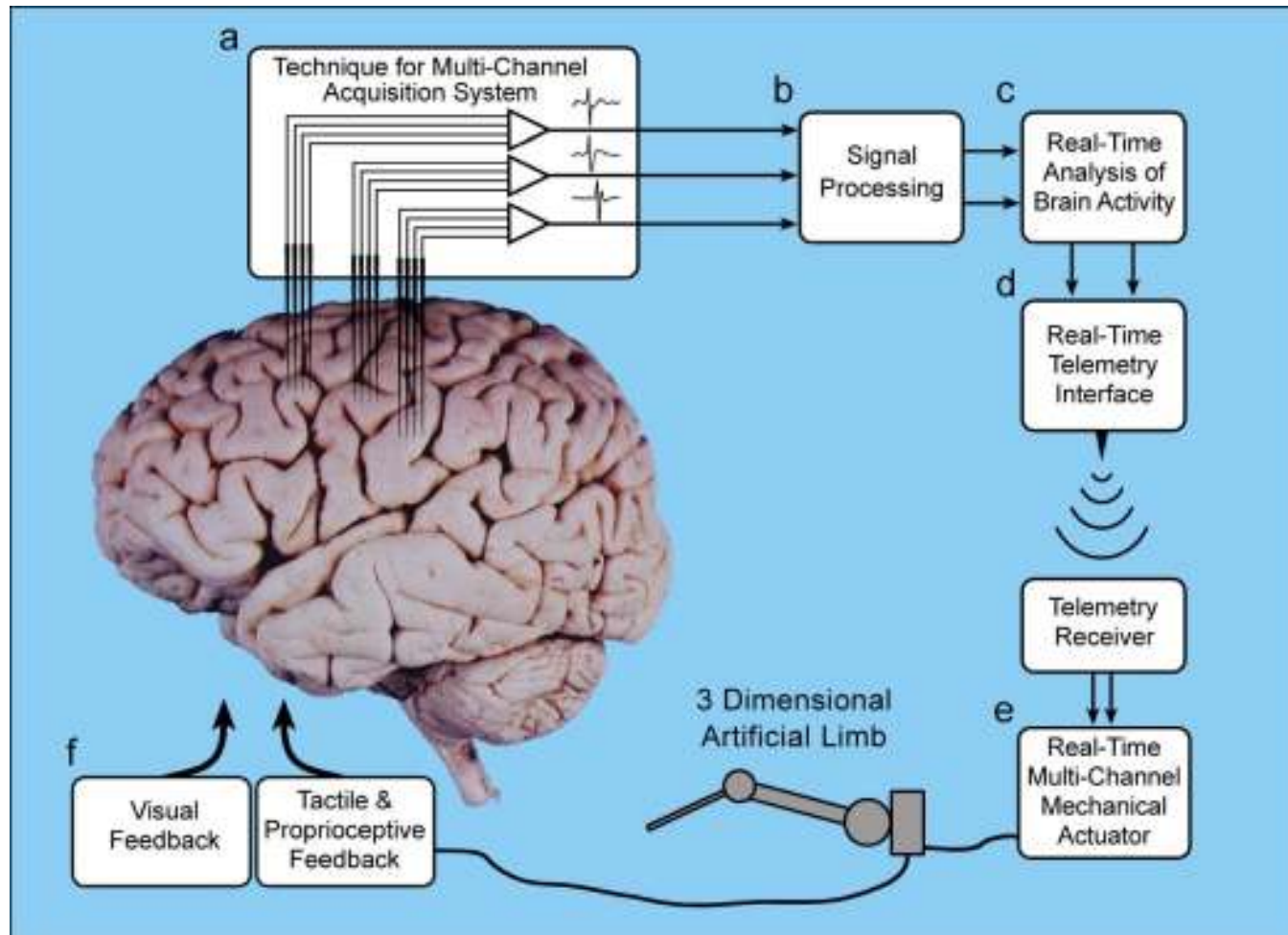


Advanced Adaptive Signal Processing



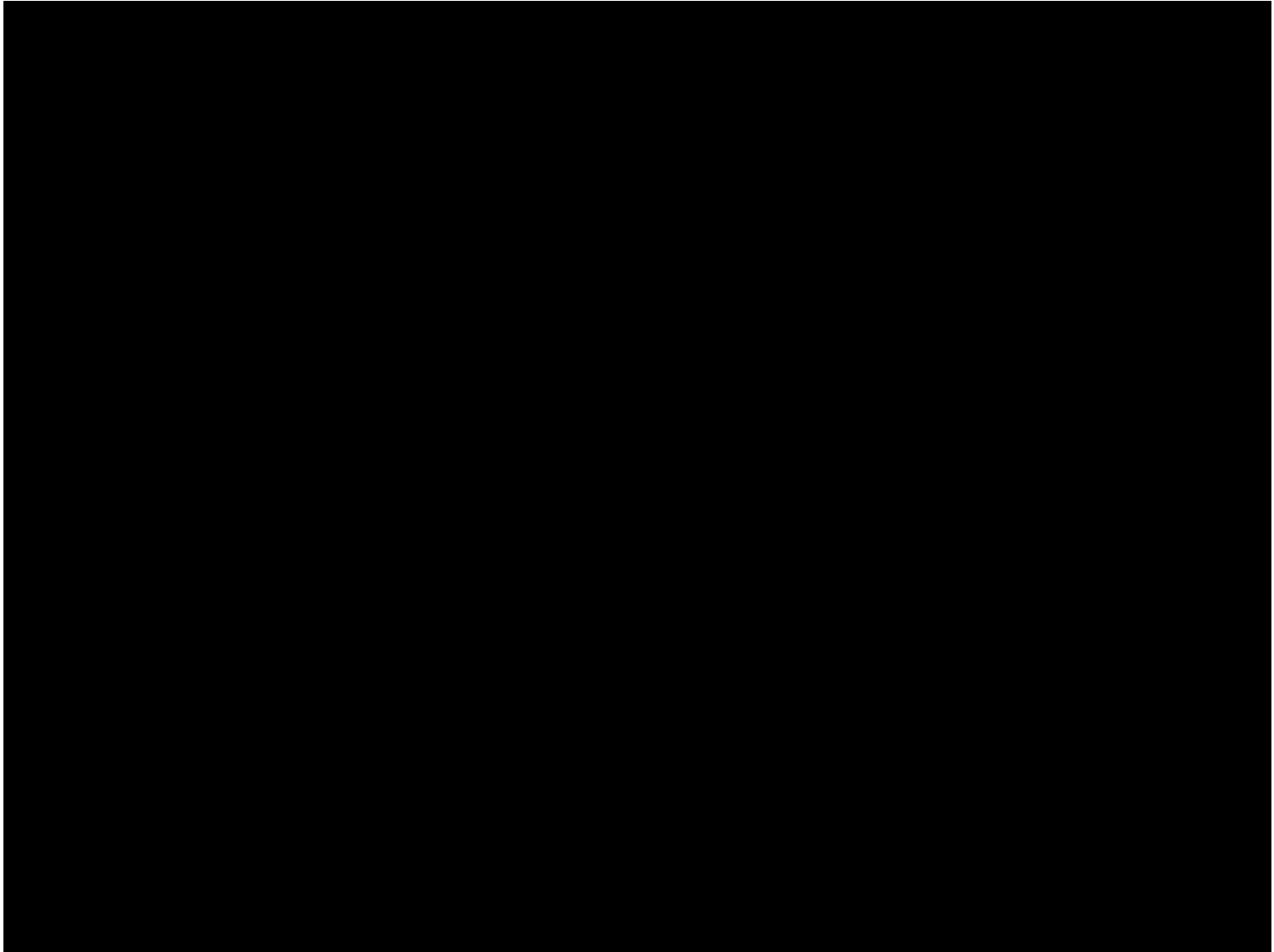
Brain Machine Interface

BMI (BCI)



BMI (BCI) bypasses the brain's normal pathways of peripheral nerves (and muscles)

BMI (BCI)



Types of BMIs

- **Sensory (Input BMI):** Providing sensory input to form percepts when natural systems are damaged.
 - Ex: Visual, Auditory Prosthesis
- **Motor (Output BMI):** Converting motor intent to a command output (physical device, damaged limbs)
 - Ex: Prosthetic Arm Control
- **Cognitive BMI:** Interpret internal neuronal state to deliver feedback to the neural population.
 - Ex: Epilepsy, DBS Prosthesis

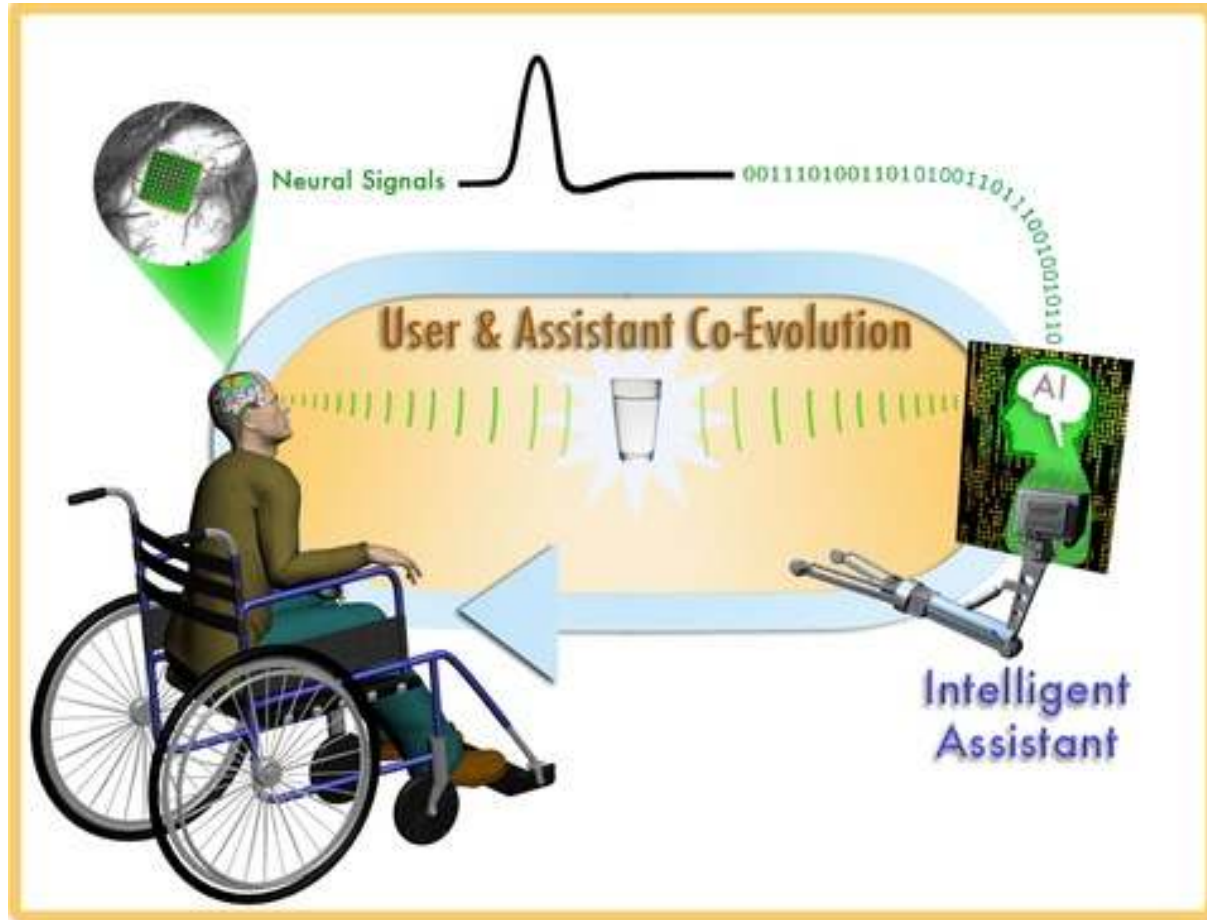
Computational Neuroscience and Technology developments are playing a larger role in the development of each of these areas.

Sensory BMIs



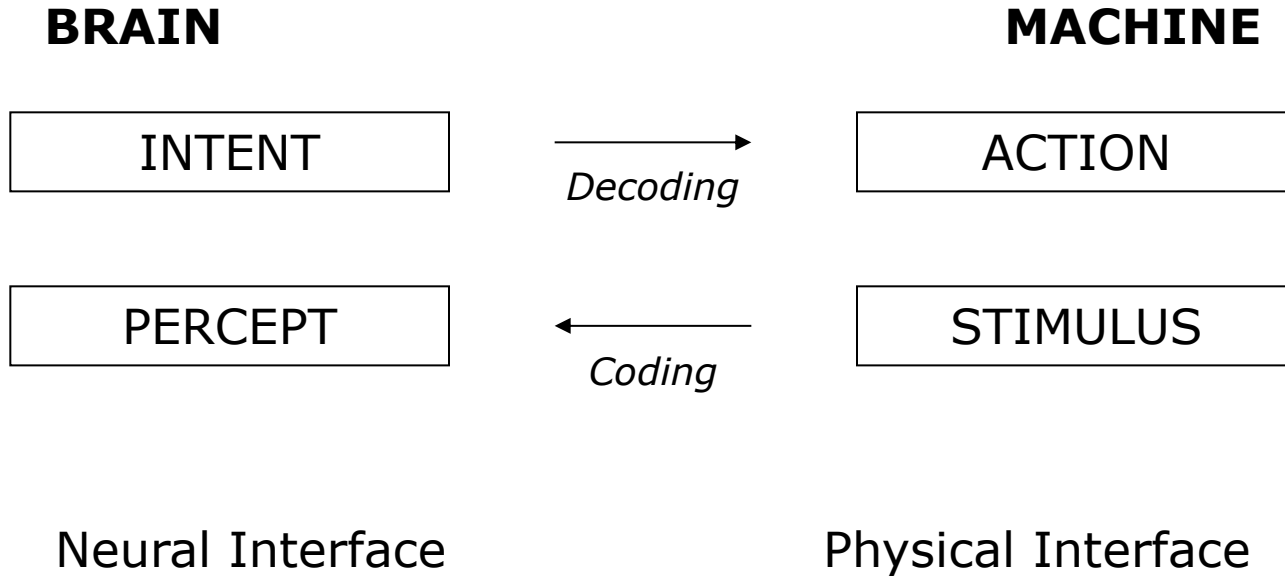
Providing a Sense of Touch through a BMI

Co-adaptive BMI



The approach is based on synergistic interaction between the user's neural modulations and an intelligent computational agent that are both seeking to maximize their own reward.

The Fundamental Concept



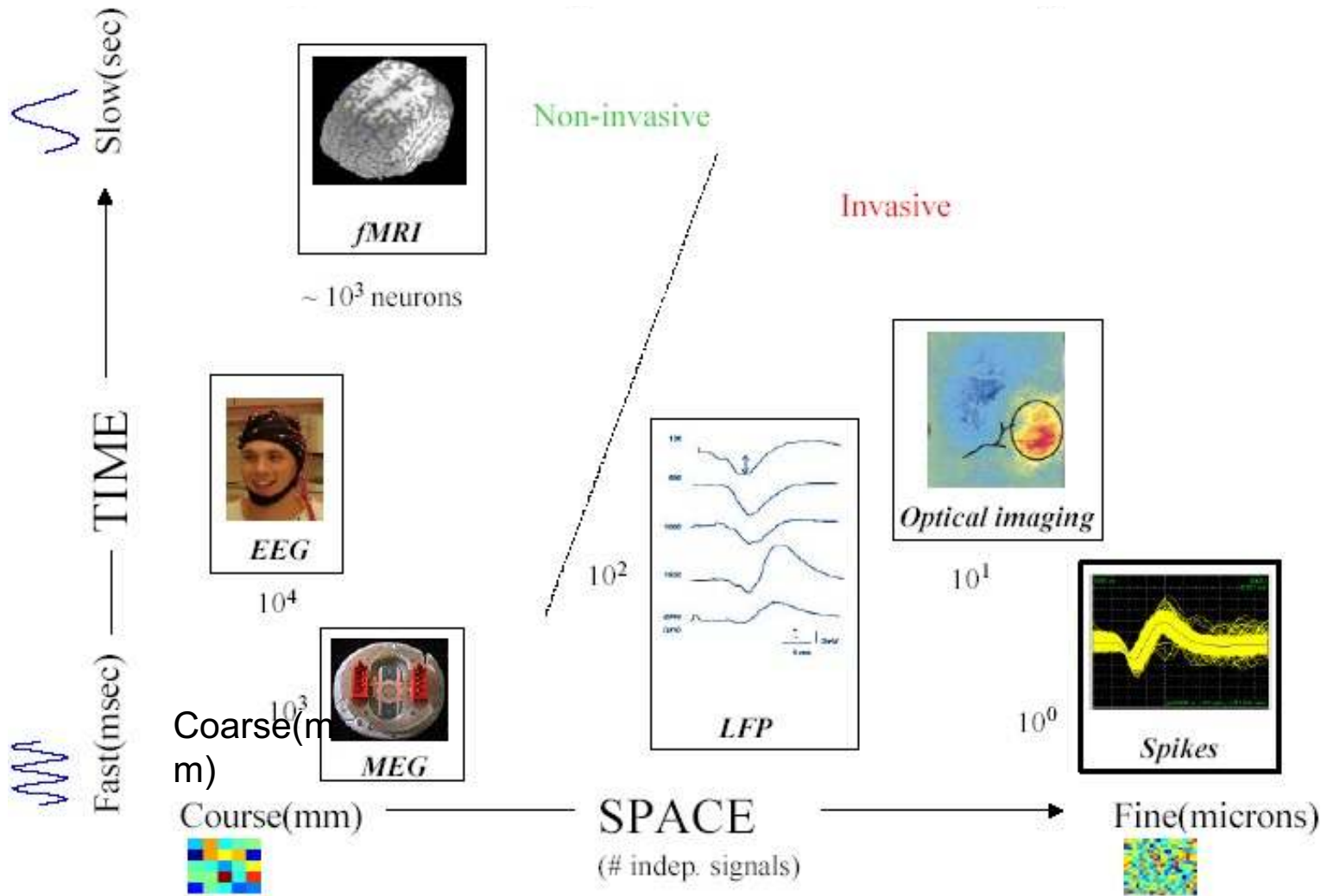
Need to understand how brain processes information.

| | <u>Stimulus</u> | <u>Neural Response</u> |
|----------|-----------------|------------------------|
| Coding | Given | To be inferred |
| Decoding | To be inferred | Given |

Tapping into the Nervous System

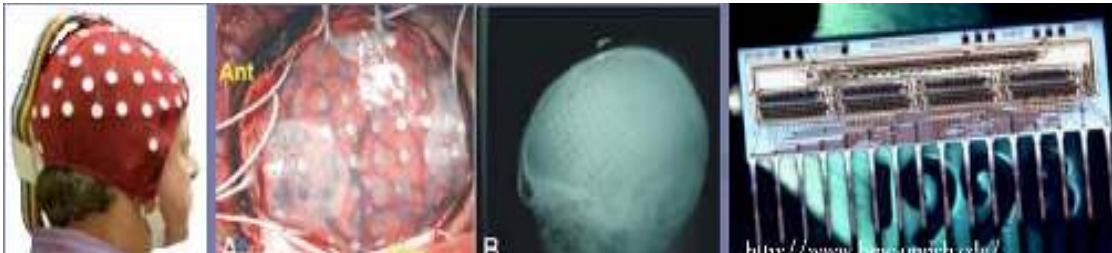
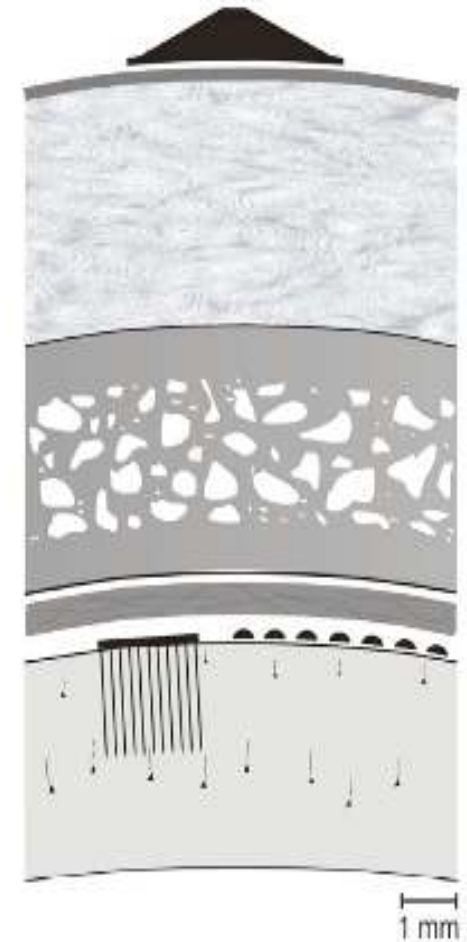
- The choice and availability of brain signals and recording methods can greatly influence the ultimate performance of the BMI.
- The level of BMI performance may be attributed to selection of **electrode** technology, choice of **model**, and methods for extracting **rate**, **frequency**, or **timing** codes.

Spatial and Temporal Scales of Neural Signals

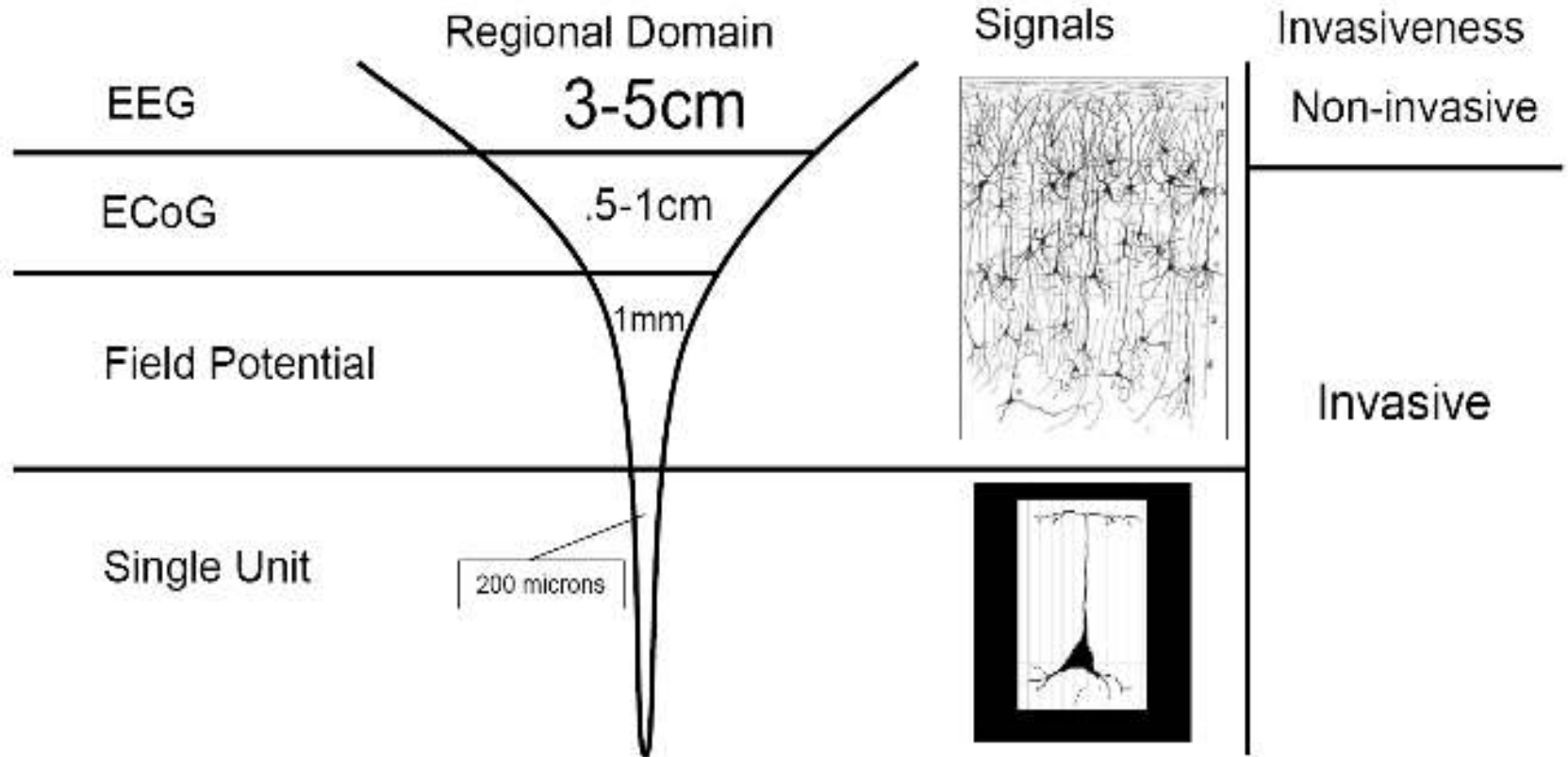


Choice of Scale for Neuroprosthetics

| | Bandwidth (approximate) | Localization |
|-----------------------------------|----------------------------|--|
| Scalp Electrodes | 0 ~ 80 Hz | Volume Conduction Cortical Surface |
| Electro- corticogram (ECoG) | 0 ~ 500Hz | Cortical Surface |
| Implanted Electrodes | 0 ~ 7kHz | Single Neuron |



Spatial Resolution of Recordings



Florida Multiscale Signal Acquisition

Develop a experimental paradigm with a nested hierarchy for studying neural population dynamics.

Least Invasive ↑

EEG

ECoG

Microelectrodes

↓ Highest Resolution



NRG IRB
Approval for
Human
Studies

NRG IACUC
Approval for
Animal
Studies

Common BMI-BCI Methods

- BMIs --- Invasive, work with intention of movement
 - Spike trains, field potentials, ECoG
 - Very specific, potentially better performance

- BCIs --- Noninvasive, subjects must learn how to control their brain activity
 - EEG
 - Very small bandwidth

Computational NeuroScience

- Integration of probabilistic models of information processing with the neurophysiological reality of brain anatomy, physiology and purpose.
- Need to abstract the details of the “wetware” and ask what is the purpose of the function. Then quantify it in mathematical terms.
- Difficult but very promising. One issue is that biological evolution is a **legacy system!**
- BMI research is an example of a computational neuroscience approach.

How to put it together?

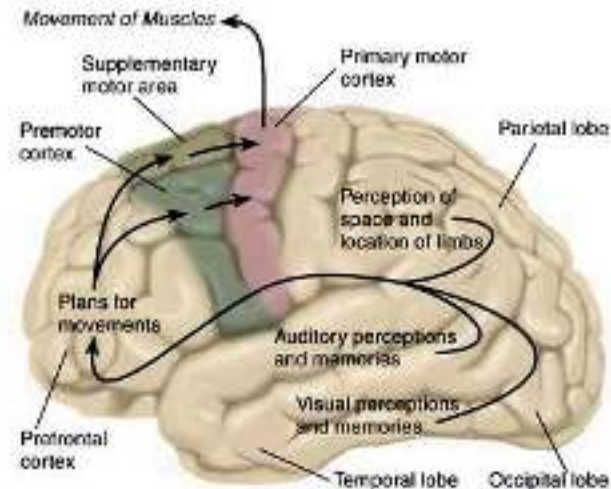
- NeoCortical Brain Areas Related to Movement

Posterior Parietal (PP) –
Visual to motor
transformation

Premotor (PM) and
Dorsal Premotor (PMD) -
Planning and guidance
(visual inputs)

Primary Motor (M1) –
Initiates muscle
contraction

► Cortical Control of Movement



Computational Models of Neural Intent

- Two different levels of neurophysiology realism
 - Black Box models – no realism, function relation between input desired response
 - Generative Models – minimal realism, state space models using neuroscience elements

Signal Processing Approaches with Black Box Modeling

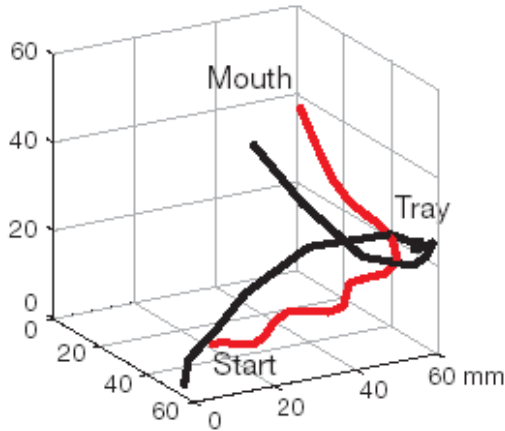
Accessing 2 types of signals (cortical activity and behavior) leads us to a general class of I/O models.

Data for these models are rate codes obtained by binning spikes on 100 msec windows.

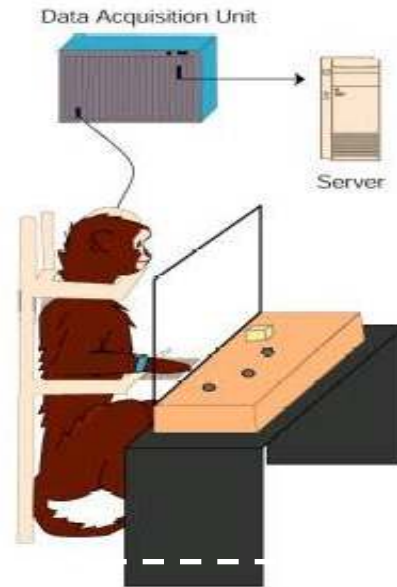
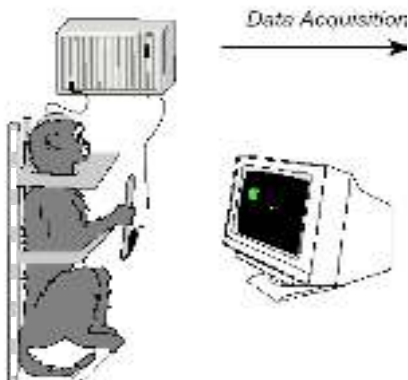
- Optimal FIR Filter – linear, feedforward
- TDNN – nonlinear, feedforward
- Multiple FIR filters – mixture of experts
- RMLP – nonlinear, dynamic

Motor Tasks Performed

Task 1

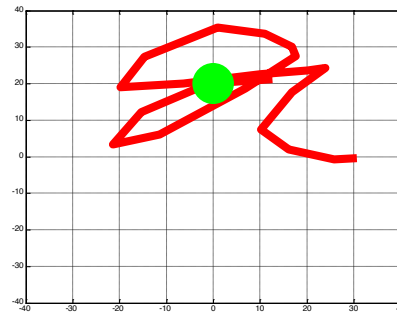


Task 2



Data

- 2 Owl monkeys – Belle, Carmen
- 2 Rhesus monkeys – Aurora, Ivy
- 54-192 sorted cells
- Cortices sampled: PP, M1, PMd, S1, SMA
- Neuronal activity **rate** and behavior is time synchronized and downsampled to 10Hz



Model Building Techniques

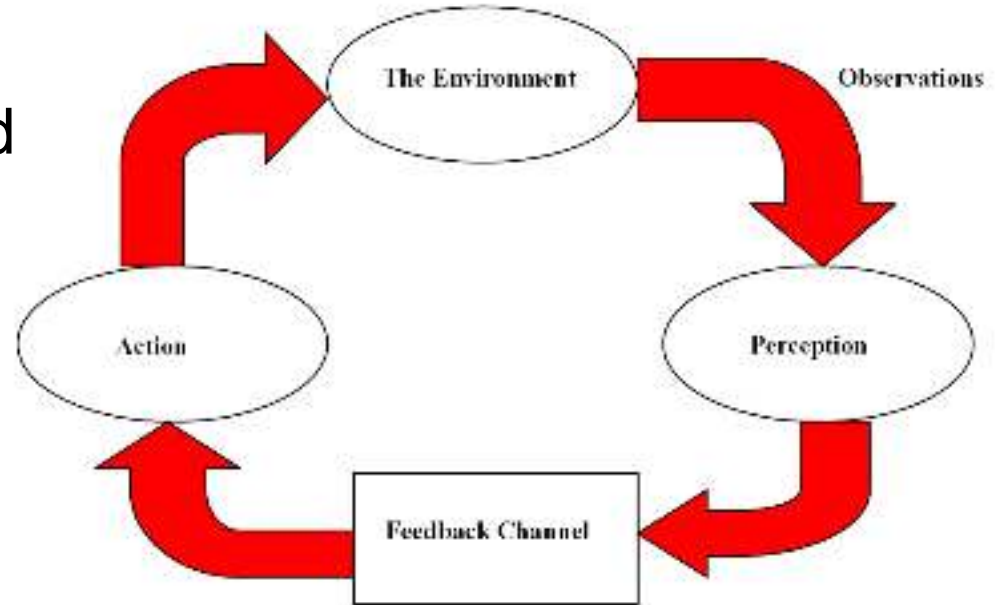
- Train the adaptive system with **neuronal firing rates** (100 msec) as the input and hand position as the desired signal.
- **Training** - 20,000 samples (~33 minutes of neuronal firing)
- Freeze weights and present novel neuronal data.
- **Testing** - 3,000 samples – (5 minutes of neuronal firing)

Cognitive Dynamic Systems

The perception-action cycle

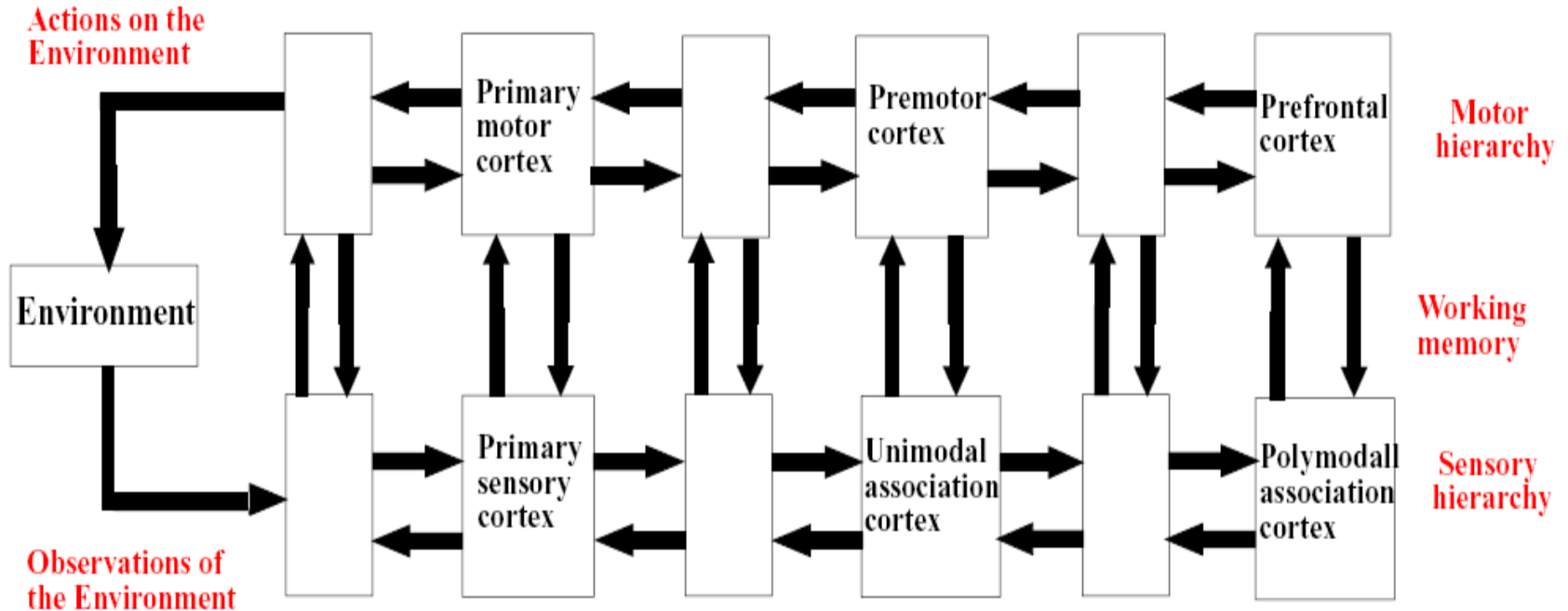
For an “*artificial*” dynamic system to assume the cognitive capabilities of the human brain, at the minimum it must have the capacity to perform the following tasks:

- learning and memory
- planning
- attention
- interaction with the world

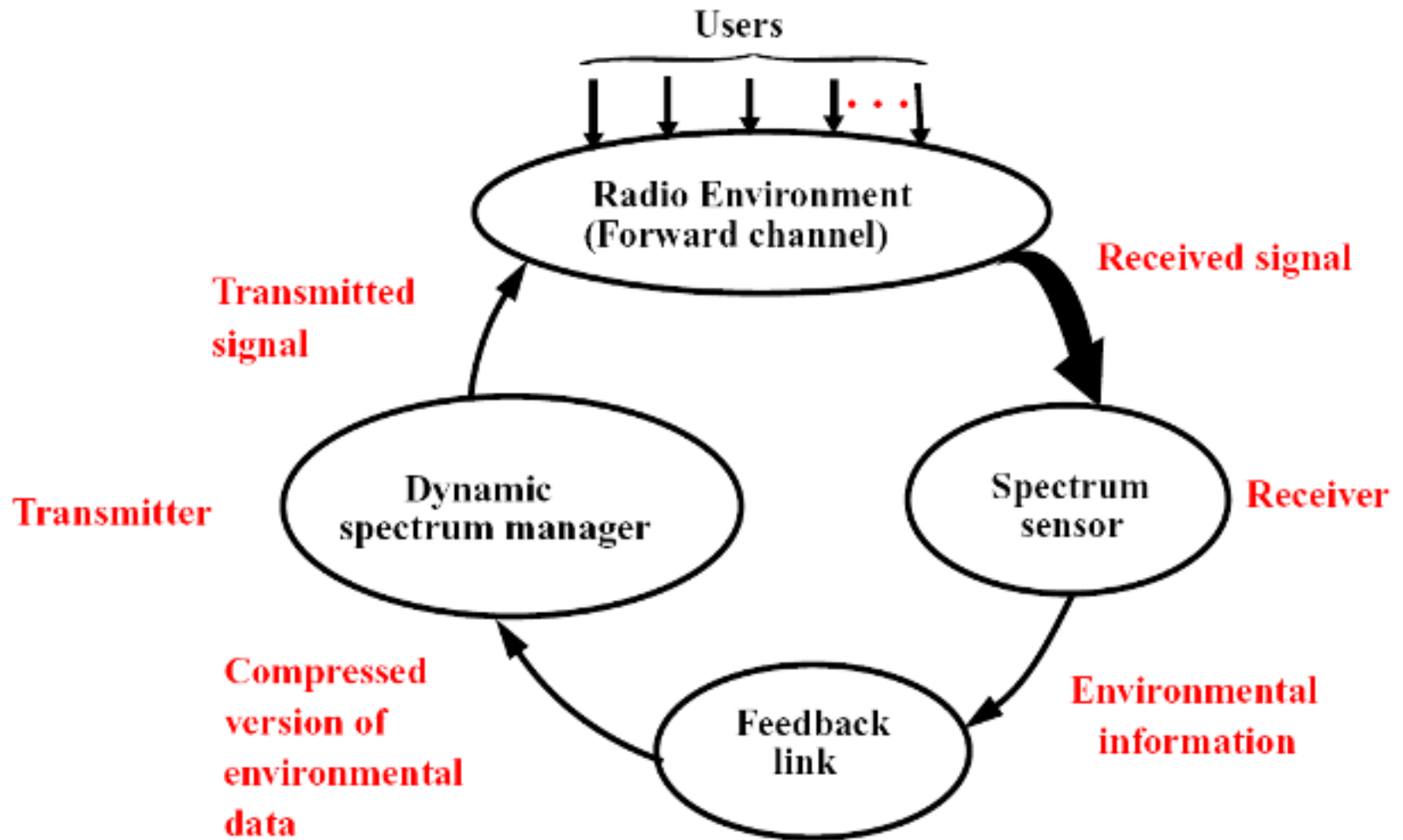


(Haykin, 2009)

Cybernetic cycle of the brain



Cognitive Radio Signal-processing Cycle



Visual Perception 1

Visual Perception 2



Attention

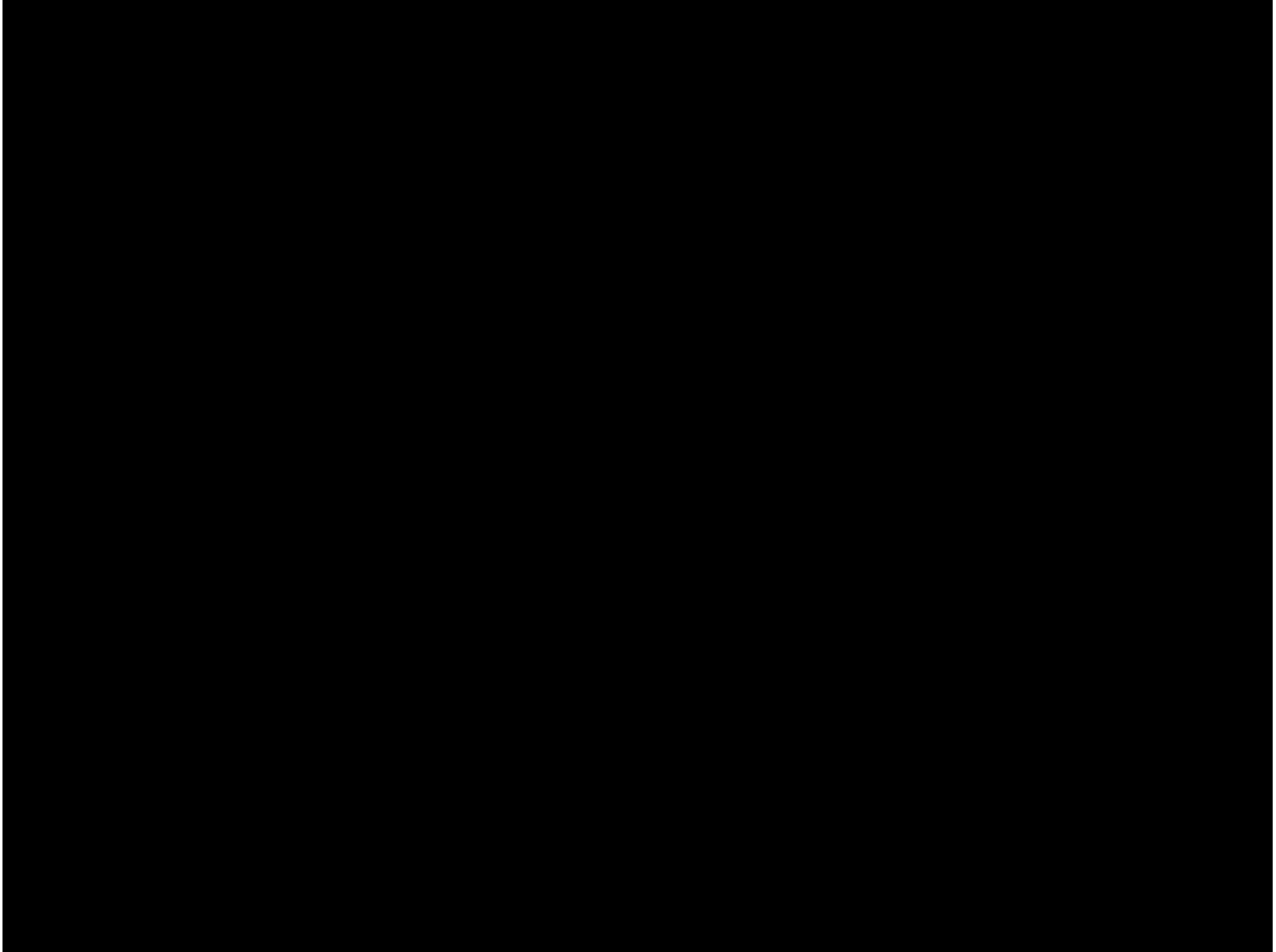


A video in collaboration between the Association of
American Medical Colleges and Khan Academy

www.khanacademy.org



Attention Test



Memory



Decision Making



Problem Solving

