

BS-CS Double major

2024 seminar, Lecture 2:  
Computational Neuroscience

Yocheved Loewenstern  
[yloewenstern@biu.ac.il](mailto:yloewenstern@biu.ac.il)  
Building 901 Room 418

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Computer Science and Neuroscience

- Computer science → Neuroscience  
*Modeling neuronal activity (classic computational neuroscience)*
- Neuroscience → Computer science  
*Inspiration for algorithms based on neural solutions*
- Analysis of neuroscience data (classic data science)

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Modeling – Why?

- Understand – gain new knowledge (e.g., attention)
- Emulate - develop new algorithms (e.g., learning algorithms)
- Heal – develop new therapies (e.g., deep brain stimulation)

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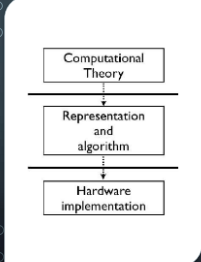
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### David Marr (1982) Tri-Level Hypothesis



- **Computational level:** what does the system do (e.g.: what problems does it solve or overcome) and similarly, why does it do these things
- **Algorithmic (representational) level:** how does the system do what it does, specifically, what representations does it use and what processes does it employ to build and manipulate the representations
- **Implementational (physical) level:** how is the system physically realized (in the case of biological vision, what neural structures and neuronal activities implement the visual system)

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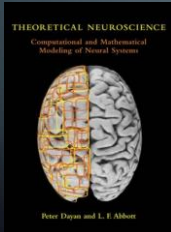
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### Dayan and Abbott



- **Mechanistic models** - how nervous systems operate based on known anatomy and physiology.
- **Descriptive models** - summarize large amounts of experimental data, accurately describing and quantifying the behavior of neurons and neural circuits.
- **Interpretive models** - explore the behavioral and cognitive significance of nervous system function, often connecting explaining experimental data in terms of certain theoretical principles.

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### Hierarchical multi-level approach

**COMPUTATIONAL NEUROSCIENCE**  
from single neuron to behavior

- (Sub-cellular models)
- Single neuron models – biophysical models
- Neural network models – connectionist models
- Behavioral models – cognitive models

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### Sub-cellular models

- Protein kinetics
- Vesicle kinetics
- Synapse growth/pruning
- ...

(Gabriel et al., JNS, 2011)

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### Single neurons

- A neuron is an electrically excitable cell consisting a cell body, dendrites and an axon.
- There is a large variety of neurons.

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### Single neuron models

- What is the amount of detail required for generating a useful model?
- A formal neuron
- Rate based neurons
- Leaky integrate and fire
- Hodgkin Huxley model
- Compartmental detailed neuron

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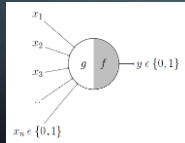
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### The formal neuron

- The McCulloch-Pitts model (1943) is an extremely simple artificial neuron. The inputs are  $\{0,1\}$  and so is the output.



$$g(x_1, x_2, x_3, \dots, x_n) = g(\mathbf{x}) = \sum_{i=1}^n x_i$$

$$y = f(g(\mathbf{x})) = \begin{cases} 1 & \text{if } g(\mathbf{x}) \geq \theta \\ 0 & \text{if } g(\mathbf{x}) < \theta \end{cases}$$

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### Rate based models

- The neurons are represented by their firing rate:

$$Y = f(WX+b)$$

- A common example is the perceptron:

$$f(\mathbf{x}) = \begin{cases} 1 & \text{if } \mathbf{w} \cdot \mathbf{x} + b > 0, \\ 0 & \text{otherwise} \end{cases}$$

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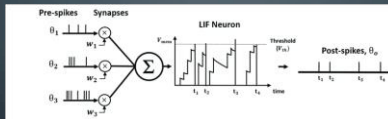
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### Leaky integrate and fire (LIF)



<p><b>Leaky integration</b></p> $\tau_m \frac{dv(t)}{dt} = -(v(t) - E_r) + Rf(t)$ $f(t) = \sum_i w_i \theta(t - t_i)$	<p><b>Fire (spike)</b></p> <p>If the potential reaches the threshold voltage: <math>v(t_i) = V_m</math></p> <p>then, add a spike and reset the potential to the reset voltage.</p> $v(t_i^+) = V_{reset}$
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[Implementation →](#)

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### LIFs are one example of threshold-based models

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### The Hodgkin & Huxley model (1952)

The empirical work lead to the development of a coupled set of differential equations describing the ionic basis of the action potential.

The ionic current is subdivided into three distinct components, a sodium current  $i_{Na}$ , a potassium current  $i_K$ , and a small leakage current  $i_L$  (chloride ions).

Based on the experiments, they were able to accurately estimate all parameters.

$$I = C_m \frac{dV_m}{dt} + \beta_{Na} \alpha^3(V_m - V_K) + \beta_{K} m^4 h(V_m - V_{K}) + \beta_L (V_m - V_L)$$

$$\frac{dV_m}{dt} = \alpha_{Na}(V_m)(1 - n) - \beta_{Na}(V_m)n$$

$$\frac{dm}{dt} = \alpha_m(V_m)(1 - m) - \beta_m(V_m)m$$

$$\frac{dh}{dt} = \alpha_h(V_m)(1 - h) - \beta_h(V_m)h$$


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### Biophysically detailed models (NEURON and others)

Large number of compartments (typically hundreds), each compartments has a few dozen free parameters.

$$I = C_m \frac{dV_m}{dt} + \beta_{Na} \alpha^3(V_m - V_K) + \beta_{K} m^4 h(V_m - V_{K}) + \beta_L (V_m - V_L)$$

$$\frac{dV_m}{dt} = \alpha_{Na}(V_m)(1 - n) - \beta_{Na}(V_m)n$$

$$\frac{dm}{dt} = \alpha_m(V_m)(1 - m) - \beta_m(V_m)m$$

$$\frac{dh}{dt} = \alpha_h(V_m)(1 - h) - \beta_h(V_m)h$$

Stamatiadis et al., 2016

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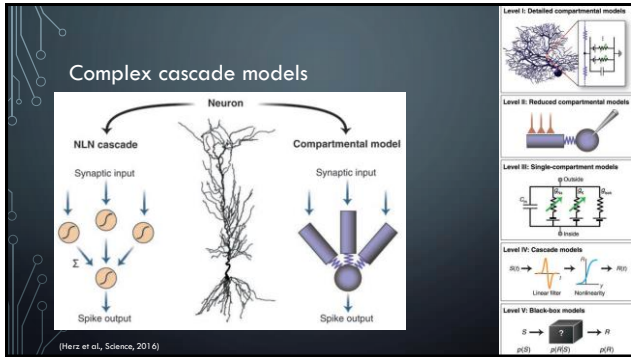
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### Model complexity

“A good theoretical model of a complex system should be like a good caricature: it should emphasize those features which are most important and should downplay the inessential details. Now the only snag with this advice is that one does not really know which are the inessential details until one has understood the phenomena under study” (M.E. Fisher, 1983)

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### SYSTEMS NEUROSCIENCE

- Neural circuits
- Distributed representations

Neurons never function in isolation; they are organized into ensembles or circuits that process specific kinds of information.

Afferent neurons, efferent neurons and interneurons are the basic constituents of all neural circuits.

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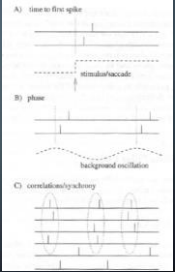
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### The neural code

- Rate coding
- Temporal Coding
  - Latency Coding
  - Phase Coding
  - Correlations and Synchrony
- Population Coding
- Local vs. Distributed Codes
- Synfire Chains



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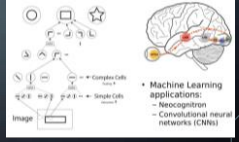
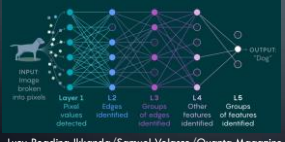
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### Neural networks (connectionist models)

Information is encoded by a network of neurons that collectively represent the object.



Lucy Reading-Ikkanda/Samuel Velasco/Quanta Magazine

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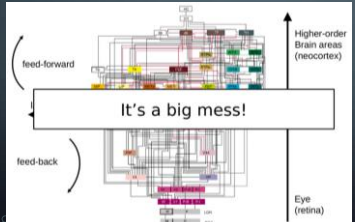
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### REAL networks - vision



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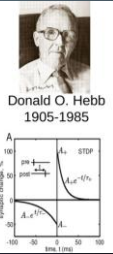
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## Plasticity and learning

- Hebb rule:
  - Neurons that fire together, wire together
- Short-term plasticity:
  - Weight changes depending on recent firing history of neurons
- Spike-timing dependent plasticity (STDP):
  - Weight changes depending on the degree of correlated firing
- Dopamine-modulated STDP:
  - Weight changes according to STDP only if dopamine present




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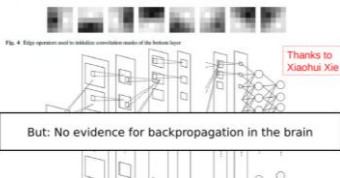
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## Neural network – machine learning

### Application: Convolutional Neural Networks




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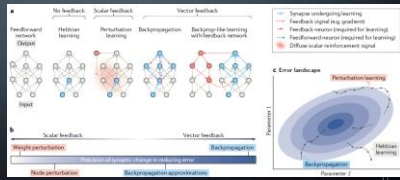
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## Neural network models

- Extremely active field in machine learning.
- Based upon “backpropagation” of errors – not realistic for the brain.

### Backpropagation and the brain

Faculty of Life Sciences, Allen Gardens, Julie Murray, Colin J. Alamean and Geoff Doherty




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### Behavioral models

- Addressing whole brain areas instead of individual elements (neurons) within it.

#### Brain, body & behavior

The human brain is made of ~88 billions neurons  
 Each neuron is connected to ~10,000 other neurons (average)  
 1mm<sup>2</sup> of cortex contains ~1 billion connections

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### Neurotransmitters and neuromodulation

phasic neuromodulation: threat, reward, surprise, effort

tonic neuromodulation

Exploitive/Decisive

Exploratory/Curious

(Kishida 2009)

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### Behavioral models

(a) Striatum, Frontal Cortex, SNc, STN, Thalamus, GPi, GPe, Go, NAc, y-IN

(b) Input, Output, Motor Cortex, Striatum, GP Ext, STN, Thalamus, SNc, GP Int

Legend: Blue arrow = Excitatory, Red arrow = Inhibitory, Green arrow = Modulatory

(Frank et al., 2007)

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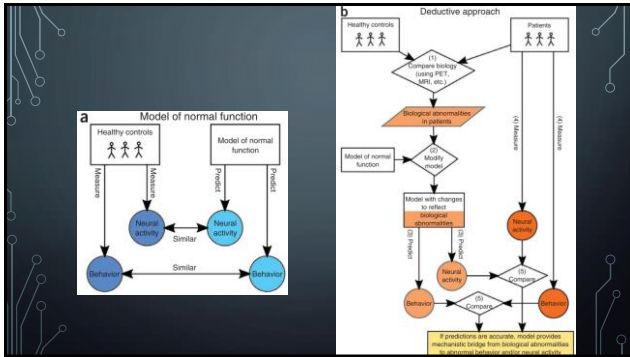
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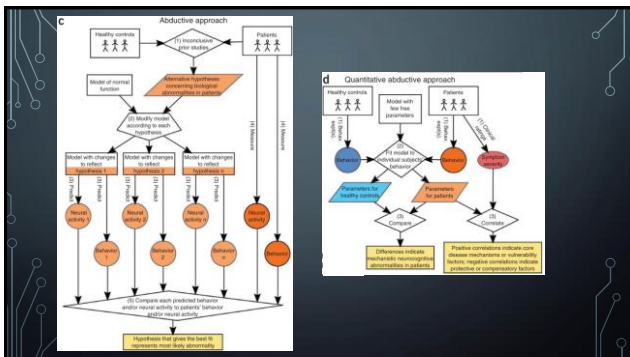
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### Summary

- Computational neuroscience focuses on modeling the brain.
- Modeling traverses multiple levels from sub-cellular activity to whole organisms.
- At each level, the complexity of representation varies greatly.
- Bridging between computational neuroscience and machine learning is a major field of research.

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