1. Syllabus; Course website; Email list.

2. Motivation for Computational Neural Models of Cognition

   The Challenge: From Neurons to Behavior

   Enhanced visual processing of target presented to the attended location (70 - 90 ms after target onset).

Physical Reductionism

   Reductionism: explaining in terms of underlying mechanisms.
   Physical Reductionism: mechanism is the brain.
   Look to brain itself for language and principles upon which to explain cognition.
   These principles unlikely to map onto classical box and arrow depictions of the cognitive system.

Reconstructionism

   Complementary process to reductionism: Putting the reduced pieces back together.
   Critical when there are billions of such pieces (neurons).
   Computer simulations are essential.
   Complex processes in the brain are billions of such pieces (neurons).
   Neural networks for cognition (CPU & RAM & Logic & Lisp?)
   Reconstruction: explaining in terms of underlying mechanisms

3. Complexity and Levels of Analysis

   The brain is very complex: billions of neurons, 5,000 x billion synapses.
   Need to abstract away from this complexity!
   Is there some simpler, higher level for describing what the brain does during cognition?

Emergent Visual Illusion

4. Direct Extension to Perception...

   Emergent Visual Illusion

   Complexity and Levels of Analysis
Why should we care about computational models?

- The brain is a computing device
- Computational models can help us talk about brain functions in a precise way
- Abstract and formal theory can help us organize and interpret data

---

In a Computer Program

You can have three levels of abstraction (Marr, 1982):

1. Computational: what is overall goal?
   Example: program that sorts lists of numbers.
   (arrange numbers so that smallest is first in list, etc)

2. Algorithmic: what strategy?
   Different sorting strategies, speed/accuracy tradeoffs

3. Implementational: how to physically encode?
   How program written and executed using particular language

Can we focus only on the first two levels?
Only if you assume a particular implementation!

---

Neurobiological Mechanisms

- Neurons: serve as detectors, signal with activity
- Networks: link, coordinate, amplify, and select patterns of activity over neurons
- Learning: organizes networks to perform tasks & develop models of environment

---

Psychological Phenomena Captured by Models

- Visual encoding: a network learns normal scenes and develops principles of learning
- Spatial attention: a model focuses its attention in different locations in space and simulates performance under normal and some abnormal conditions
- Episodic encoding: a network learns normal scenes and develops principles of learning
- Working memory: a network maintains current information about the environment
- Spatial memory: a network retains spatial information about the environment
- Spatial encoding: a network learns normal scenes and develops principles of learning

---

Principles take constraints from, and are fundamentally shaped by, core levels of computation → not “privileged” as in Marr’s computational level

---

Alternative Levels

Cognitive Phenomena

- Neuropsychological Mechanisms

- Principles take constraints from, and are fundamentally shaped by, core levels of computation → not “privileged” as in Marr’s computational level

---

Neuropsychological Mechanisms and Principles

- Neurons: serve as detectors, signal with activity
- Networks: link, coordinate, amplify, and select patterns of activity
- Learning: organizes networks to perform tasks & develop models of environment

---

Psychological Phenomena Captured by Models

- Visual encoding: a network views natural scenes, and develops brain-like ways of encoding them using principles of learning
- Spatial attention: a model focuses its attention in different locations in space, and simulates performance under normal and some abnormal conditions
- Episodic memory: a network learns normal scenes and develops principles of learning
- Working memory: a network learns current information about the environment

---

Why should we care about computational models?

- Abstract and formal theory can help us organize and interpret data
- Computational models can help us think about brain functions
- The brain is a computational device

---

# pages in Principles of Neural Science

(Kandel, Schwartz and Jessel)

Our task is to make this book shorter!
Psychological Phenomena Captured by Models

Reinforcement learning: A network model of the basal ganglia / dopamine system learns to make decisions based on its experiences of positive and negative reinforcement, and reproduces patterns seen in Parkinsons patients.

Word reading: A network learns to read and pronounce nearly 3,000 English words, and generalizes to novel nonwords (e.g., "mave" or "nust") just like people do. Damaging a reading model simulates various forms of dyslexia.

Task directed behavior: A network simulates the "executive" part of the brain, the prefrontal cortex, which keeps us focused on performing the task at hand and protects us from distraction.

Advantages of Simulation Method

• Models help us understand phenomena: "If you really want to understand how something works, build it." – Can provide novel insights.
• Effects of brain damage/drugs.
• Models are explicit:
  – Deconstruct psychological constructs.
  – Make novel predictions.
  – Force accountability in simulating data.
• Enables complete control & understanding.
• Forces consistency & unity in framework.

Potential Traps/Problems

• Models are too simple.
• Models are too complex.
• Models can do anything.
• Models are reductionistic.

Multiple Levels of Computational Cognitive Models

Different levels of abstraction to account for data collected at different levels.

• Molecular modeling: details of neuron geometry, effects on dendritic integration, detailed ion channels
• Spiking "integrate and fire" models, less detail at single cell level, can study synchronization of firing across network of cells
• Firing rate models (Abstract connectionism); large networks of interacting neuron-like units; can approximate integrate and fire; brain is one big goop.
• Bayesian "optimal" approach: assumes brain performs optimal computation for any given task, usually without regard for implementation.
• Symbolic, production systems (if-then rules)

In practice these categories can blend to some degree.
Pros & Cons of Various Levels/Approaches

- No single one is a panacea! (as much as any researcher/lab wants/pretends for their method to be only important one..)
- Different potential for understanding cog systems vs brain
- Power for practical applications
- Biological plausibility
- Potential to inform about drugs and disease
- Number of parameters needed to fit data
- Ability to bridge gap between neurons and behavior

Detector Model

Each neuron detects some set of conditions (e.g., smoke detector). Neurons feed on each other's outputs — layers of ever more complicated detectors.

(Things can get very complex in terms of content, but each neuron is still carrying out basic detector function).

Networks

1. Compositional Selection: Putting it all together
2. Independent Component Extraction (transformation)
3. Independent Component Extraction (transformation) (Things can get very complex in terms of content, but each neuron)
4. Compositional Selection: Constructive interaction

Excitation (Unidirectional): Transformations

Input

• Detectors work in parallel to transform input activity pattern
• Emphasizes some distinctions, collapses across others.
• Function of what detectors detect (and what they ignore).

Networks

• Ability to bridge gap between neurons and behavior
• Number of parameters needed to fit data
• Relevant to known brain diseases and disorders
• Biological plausibility
• Power for practical applications
• Different potential for understanding cognitive systems vs brain

Detector Model

• How do they do it?

Application: NetTalk! (Sejnowski & Rosenberg, 1986)

• Learns to read & pronounce English text
• Inputs are one of 29 chars (26 letters + space, comma, full stop)
• 7 letter window (provides context) total = 29 * 7 = 203 inputs
• Hidden layer of 80 units
• Output generates one of 60 phonemes, represented by 21 articulation units and 5 units for stress/segmentation

Excitation: (transformation)
NetTalk: Results
• Learns regularities of English speech
• Generalizes to novel words not in training set with 78% accuracy

NetTalk: Results
• Knowledge is distributed: relearning after damage much faster than original training
• Distributed (spaced) practice more effective for long term retention than massed practice

NetTalk: Impressive, But...
• Solves reading and speaking at once (unlike people)
• Doesn’t address specialization of different brain areas in language processing
• Uses biologically implausible “error backpropagation” method for training weights
• Explicit “teacher” provides correct information on output articulatory units (instead of trial and error learning that we have to do)
• Requires many passes through exact same training set (rather than natural language experiences).

Conduction models
• Single or few neurons at high detail
• Branching points of dendrites, diameters lengths of different parts.
• Each compartment given active channels such as voltage-sensitive or synaptic channels.
• Ideal for explaining spikes, thresholds for initiating spikes, precise effects of synaptic input, bursting, spike adaptation, spikes that propagate backwards up dendritic tree.
• But: huge number of parameters, only few determined from experiments.
• Complex so difficult to analyze, and virtually impossible to use experimentally.

Integrate-and-fire models
• No active channels; approximation of spike generation coupled with leaky integrator model when voltage is below spike threshold.
• Simplified geometry, stereotyped time-course for synaptic input and spike-rate adaptation.
• Good for simulating large recurrently connected nets of neurons, synchronization and desynchronization across population, effects of noise, and other phenomena that we observe or can measure.
• flame propagation through population described, front appears at L configuration, steady state achieved.
• Flame propagation satisfies “front propagation” method.

Extra: (Students not responsible for material on following slides)
Firing rate models

• Most abstract, no spiking, outputs are continuous valued time-varying firing rates.
• Approximation to integrate and fire, with assumptions about time-constants of cells.
• Empirically and analytically tractable.
• Can be feedforward or recurrent.
• Coupled, non-linear differential equations show dynamical behaviors (attractance to one set of fixed points, oscillations). Regularities make them ideal as substrates for neural computation.
• Offer obvious way for large nets of simple units to perform sophisticated tasks without building knowledge in.
• Different levels of plausibility for learning rules (hypothesis).

Different levels of plausibility for learning rules (hypothesis):

• Empirically and analytically tractable
• Can be feedforward or recurrent
• Approximation to integrate and fire
• Various forms of variability in firing rates
• Various forms of variability in firing rates