SYDE 556/750

Simulating Neurobiological Systems
Lecture 13: Conclusion

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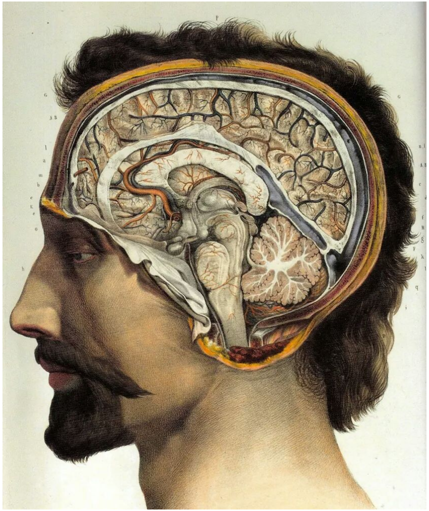

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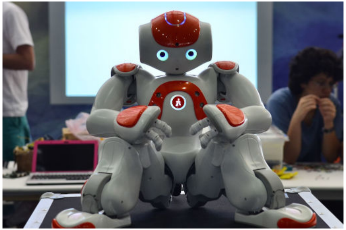
Goal of This Course

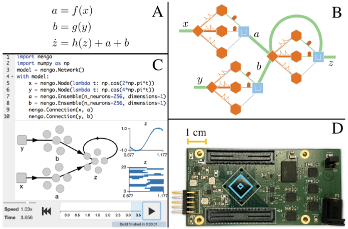
Building Large-Scale Brain Models

Why?

Understand how Brains Work



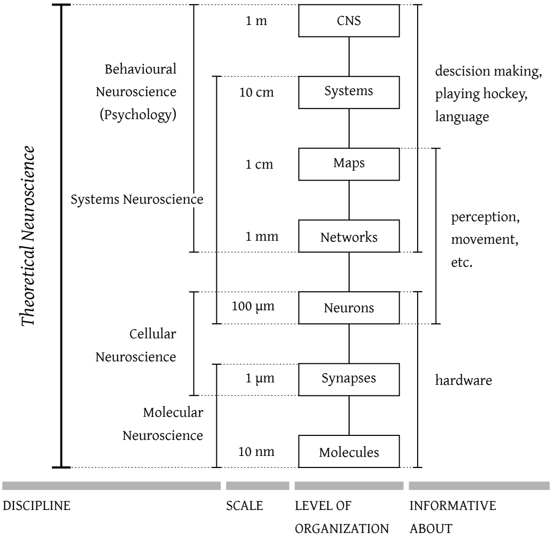
Build Better AI Systems



Program Neuromorphic Hardware

Image Sources. Left: "A chimpanzee brain at the Science Museum London", from Wikimedia. Centre: "Robot at a campus faire in São Paulo" from Wikimedia. Right: The Braindrop Neuromorphic hardware system, from "Braindrop: A Mixed-Signal Neuromorphic Architecture With a Dynamical Systems-Based Programming Model", Neckar et al., 2019.

Theoretical Neuroscience



The Brain – Some Statistics

- **Weight:**
  2 kg (2% of the body weight)
- **Power consumption:**
  20 W (25% of the body's total power consumption)
- **Surface area:**
  1500 cm^2 to 2000 cm^2 (roughly four A4/letter pages of paper)
- **Number of neurons:**
  100 billion (10^{11}, 150 000 mm^{-2})
- **Number of synapses:**
  100 trillion (10^{14}, about 1000 per neuron)

Neuromorphic Hardware

Goal: Brain-inspired hardware; lower power consumption; stream processing

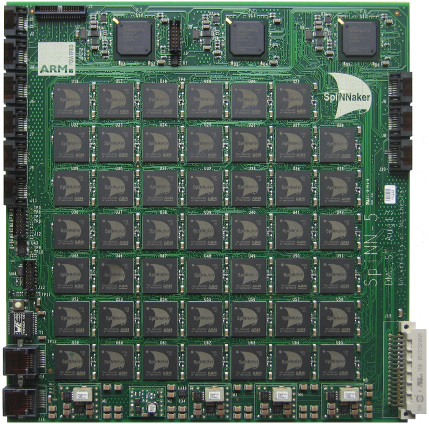
Digital

- Specialised digital hardware for simulating spiking neural networks
- Trivial weight-spike multiplication
- Often asynchronous (no central clock)
- ⊕ Deterministic
- ● Higher power consumption than analogue

Analogue/Mixed Signal

- Neuron models in analogue hardware (capacitors, resistors, ...)
- Digital interconnect and programming (weights, neuron parameters)
- ⊖ Not deterministic
- ⊖ Hard to program
- ⊕ Very low power consumption

Neuromorphic Hardware – SpiNNaker



- Manchester/Dresden collaboration; HBP
- Fully digital
- 18 ARM968 processors @ 180 MHz per chip
- 1000 current-based LIF neurons per core
- Toroidal, asynchronous interconnect mesh
- Up to $\approx 10^9$ neurons in one system
- ⊕ Easy to program, (outdated) Nengo interface
- ⊕ Public access via HBP
- ● Not very power efficient (version from 2013)
- ⊖ High setup times

Neuromorphic Hardware – Loihi

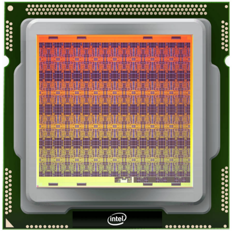


Image Sources. Intel Marketing Material

- Developed by Intel
- Digital, fully asynchronous architecture
- Circuits accelerating individual spiking neurons
- ⊕ Extremely low power consumption
- ⊕ Nengo Interface
- ⊖ Proprietary/no low level programming without signing an NDA

Neuromorphic Hardware – BrainDrop

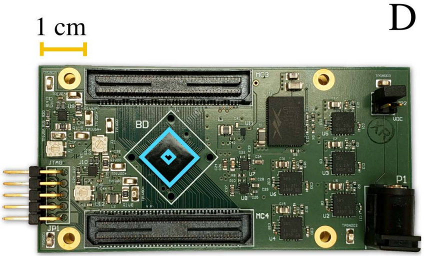
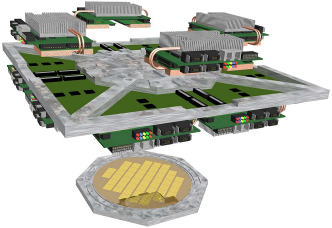
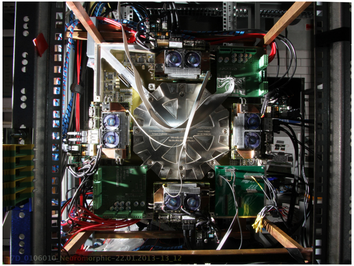


Image Sources. Braindrop: A Mixed-Signal Neuromorphic Architecture With a Dynamical Systems-Based Programming Model, Neckar et al. 2019

- Research project at Stanford
- Mixed signal, analogue neurons, synapse arrays
- Exploits process noise for diverse neural tuning
- Optimized for NEF networks
- (+) Extremely low power consumption
- (+) Nengo Interface
- (?) Availability/Documentation?
- (−) Small networks only

Neuromorphic Hardware – BrainScaleS





- Research Project in Heidelberg; HBP
- Mixed signal; above realtime
- Wafer-scale system; 384 x 256 neurons

- ⊕ Low power consumption
- ⊕ Public access via HBP
- ⊖ Complex; relatively low precision

Image Sources. Electronic Visions Group; Kirchhoff Institute for Physics; BrainScales/HBP Neuromorphics Project

Review: What Did We Learn? (I)

- **The Neural Engineering Framework**
  - Theory for theoretical neuroscience (**bridging laws**)
  - *Principle 1:*
    Populations of neurons represent values $\mathbf{x}$
  - *Principle 2:*
    Connections compute functions f
  - *Principle 3:*
    Values are states in a dynamical system
  - Model of how the brain computes. Is it wrong? Of course! But hopefully useful!

Review: What Did We Learn? (II)

- **Cognitive Architectures**
  - *Jackendoff's Challenges:*
    How to explain language in neural networks?
  - *Vector Symbolic Architectures:*
    Compressing symbolic information into vectors,
    circular convolution, word embeddings
  - *Semantic Pointer Architecture:*
    Combination of four ideas
    - VSAs
    - NEF
    - Deep Semantics: compression, decompression
    - Architecture: Basal Ganglia/Thalamus/Cortex Loop

Review: What Did We Learn? (III)

- **Methods & Techniques**
  - *The Delay Network:*
    Efficiently compress past history into a vector; optimal recurrent update rule
  - *Machine Learning:*
    Unsupervised, supervised learning, gradient descent,
    least squares, nonnegative least squares, delta learning rule (PES)
  - *Signal Processing:*
    Fourier, Laplace transformation; computing optimal filters
  - *Dimensionality Reduction:*
    PCA/SVD; function bases; Hebbian learning/Oja learning rule

Review: What Did We Learn? (IV)

- **“Meta-Level Skills”**
  - *Solving Problems by Building a Signal Flow Graph:*
    Applications to Hardware design, differentiable computing
  - *Programming with Python/Numpy*
  - *Building Neural Networks using Nengo:*
    Can be applied to neuromorphic hardware (see above)

Thank You!