BME 503

Computational Neuroengineering

BME 503

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- Office Hours- TBD
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BME 503

- WF 11:45-1:00 in Hudson 216
- End Date: Dec 7 (last day of ugrad classes)
- Final: Monday: Dec 17 (2-5PM) (not great!)
- Total Class Time: 33 Hrs, 45 minutes
- Expected out-of-class time: 140 hrs
- Total Time: 1.5 Person-Months of a full time Job
- Website: sakai.duke.edu – you should have a link to BME.503.01.F18

BME 503

- Should have background in electrobiology (Hodgkin Huxley Model, ion channels, etc. We will review quickly)
- Computer programming competency
- Will be using Brian 2- neural network simulator. Willingness to learn Python (and associated libraries). May also be using MATLAB. Will explore PyTorch- Tensorflow or equiv.

Questions for the Day

- What is Computational Neuroengineering?
- How are robots like Humans? How do robots and humans move? How could they be linked?
- How has Neuroscience Inspired the newest generation of artificial intelligence tools?
- What are our semester goal(s)?
- How do we learn?
- What should we learn?
- How should it be decided that we have learned?

What is Computational Neuroengineering?

- Development/Use of numerical models to simulate normal and abnormal brain activity.
- Developing computational analogs of the brain to perform processing or pattern recognition of complex data or to serve as controllers for external agents.
- Development/Use of computational/statistical/signal processing approaches to analyze brain-derived data or understand brain function.

7 Job Skills Of The Future (That AIs And Robots Can't Do Better Than Humans)

The Robots Are Coming! The Robots Are Coming!

Nvidia's Isaac shows the promise of speeding up robot training, bringing the future of work closer to reality.

Engineers Are Making Squishy, Bio-Inspired Robots, Here's How They Work

Scientists are looking to nature to inspire the next generation of robots. Here's what they have come up with.

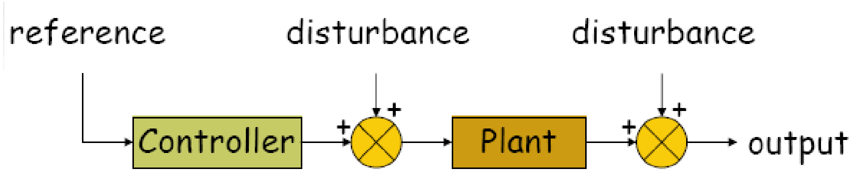
How are humans like robots?
How do robots move?
How do humans move?
How could robots and humans be linked?

Robots

- We would like robots to behave like autonomous, intelligent beings
- Biological nervous systems can be viewed as a control systems for living organisms
- To control a robot, we need to:
  - Define the state of the robot
  - Sense the state of the robot
  - Compare the state of the robot to a desired state
  - Decide what actions need to be taken to achieve the desired state optimally and issue the associated commands
  - Translate those command into physical action
  - Measure the effect of those physical actions

Open Loop Controller

- The Open Loop Controller (OLC) is the simplest kind
- Components:
  - Reference – Desired State
  - Controller – Issues Commands
  - Plant – Actuator
- The controller sends an input signal to the plant
- It does not compensate for disturbances that occur after the control stage
- No feedback to match actual to intended



http://quantum.esu.edu/faculty/rmarmelstein/

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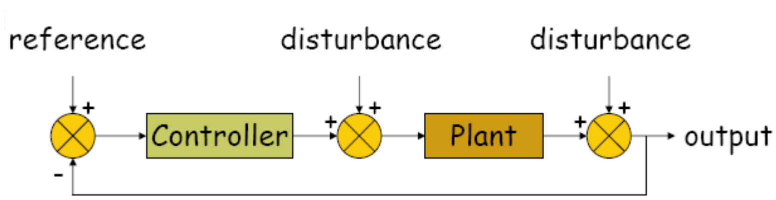
Closed Loop Controller

- In Closed-loop control, the output is sensed and compared with the reference. The resulting error signal is fed back to the controller [feedback].
- Components:
  - Reference – Desired State
  - Controller – Issues Commands
  - Plant – Actuator



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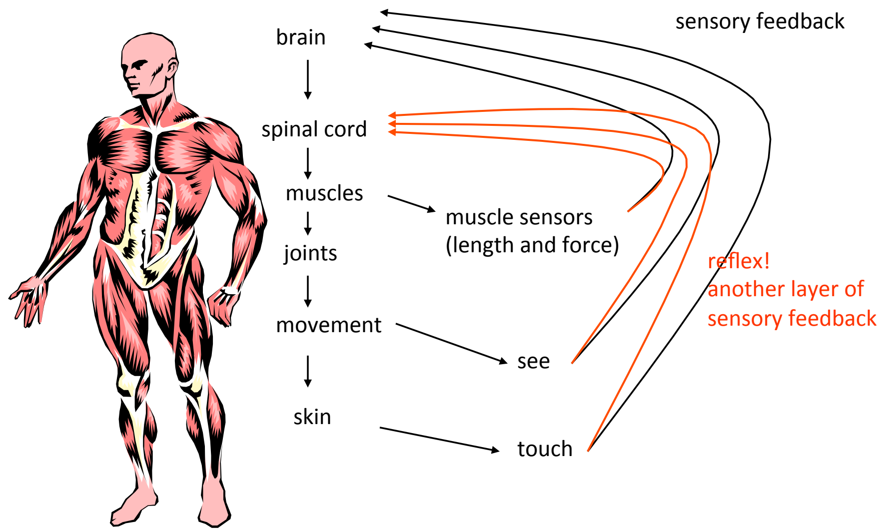
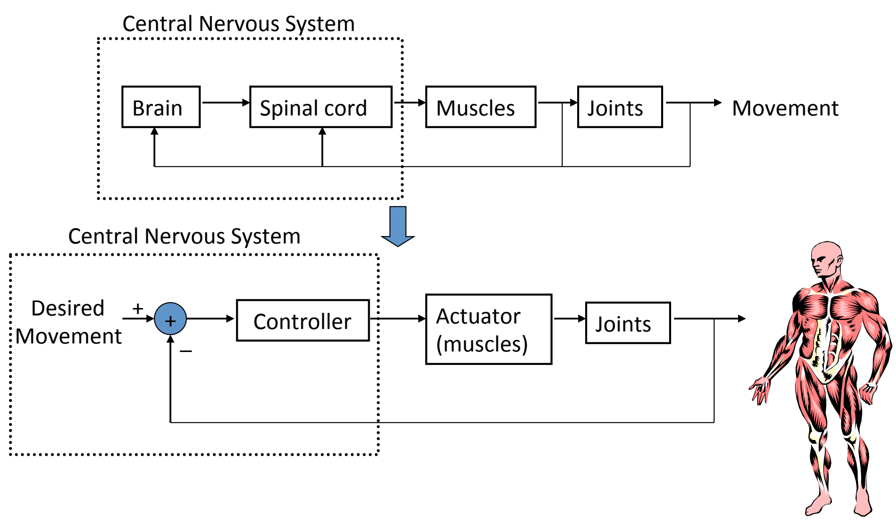
Nervous System as a Closed Loop System



http://courses.cs.washington.edu/courses/cse490i/07wi/lectures.html

Human Closed Loop System Box Diagram



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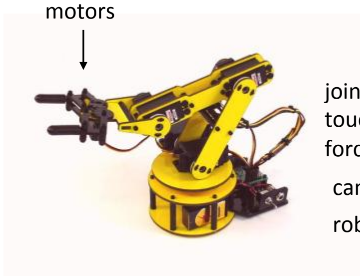
Robot Closed Loop System

computer

electronics (amplifiers, etc)

motors



joint angle sensors
touch sensors at gripper
force sensors

camera to see the position

robotics math gives gripper position
based on joint angles

sensory feedback

http://courses.cs.washington.edu/courses/cse490i/07wi/lectures.html

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Mini-biological ”robots” with a “simple” nervous system

First Project

- Using Brian, create a virtual creature/ neurorobot/insect that navigates inside a virtual world controlled by a virtual nervous system/brain/network inspired by one found nature.

- http://www.youtube.com/watch?v=YJAUJYLAm6I

ANIMATLAB – Virtual Hexapod

Where is Computational Neuroscience played a role in Artificial Intelligence?

By BRIAN MASTROIANNI | CBS NEWS | October 18, 2016, 3:56 PM

Microsoft says speech recognition technology reaches "human parity"

WHY DEEP LEARNING IS SUDDENLY CHANGING YOUR LIFE

Decades-old discoveries are now electrifying the computing industry and will soon transform corporate America.

A.I. MAKING A DIFFERENCE IN CANCER CARE

The artificial intelligence we see in daily life is just a fraction of its vast potential. Already it's making strides in cancer care

IBM Neuromorphic chip hits DARPA milestone and has been used to implement deep learning

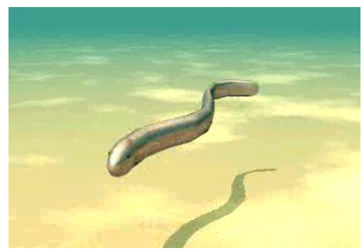
artificial intelligence, deep learning, machine learning, neuromorphic, science

How Analog and Neuromorphic Chips Will Rule the Robotic Age

By Shahin Farshchi
Posted 17 Oct 2016 | 19:45 GMT

Neural networks (applications)

- Face recognition
- Event recognition, tracking
- Time series prediction
- Process control
- Optical character recognition
- Handwriting recognition
- Robotics, movement
- Games: car control, etc
- Etc…



Types of Neural Networks

- Feed-forward neural networks
- Recurrent neural network
- Multi-layer perceptrons (MLP)
- Convolutional neural networks
- Recursive neural networks
- Deep learning networks
- Convolutional deep learning networks
- Self-Organizing Maps
- Deep Boltzmann machines
- Stacked de-noising auto-encoders

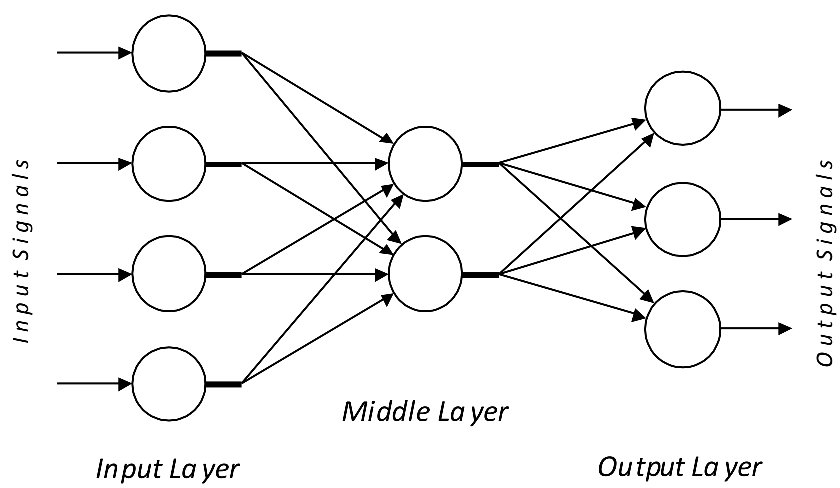
Neuron
Review

Neuroscience-Inspired Artificial Intelligence

Demis Hassabis,[1,2,*] Dharshan Kumaran,[1,3] Christopher Summerfield,[1,4] and Matthew Botvinick[1,2]
[1]DeepMind, 5 New Street Square, London, UK
[2]Gatsby Computational Neuroscience Unit, 25 Howland Street, London, UK
[3]Institute of Cognitive Neuroscience, University College London, 17 Queen Square, London, UK
[4]Department of Experimental Psychology, University of Oxford, Oxford, UK
*Correspondence: dhcontact@google.com
http://dx.doi.org/10.1016/j.neuron.2017.06.011

1. An artificial neural network consists of a number of very simple processors, also called **neurons**, which are analogous to the biological neurons in the brain.
2. The neurons are connected by weighted links passing signals from one neuron to another.
3. The output signal is transmitted through the neuron's outgoing connection. The outgoing connection splits into a number of branches that transmit the same signal. The outgoing branches terminate at the incoming connections of other neurons in the network.

Architecture of a typical artificial neural network

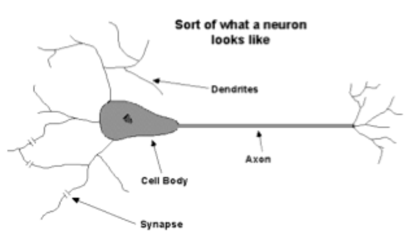


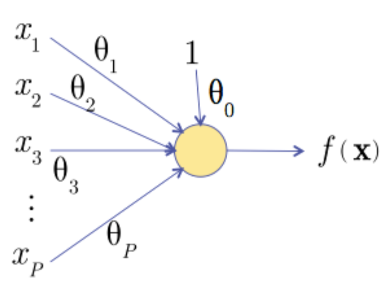
Analogy between biological and artificial neural networks

Biological Neural Network	***Artificial Neural Network***
Soma	Neuron
Dendrite	Input
Axon	Output
Synapse	Weight

The neuron metaphor

- Neurons
  - Accept information from multiple inputs
  - Transmit information to other neurons
  - Multiply inputs by weights along edges
  - Apply some function to the set of inputs at each node





Needed Topics

- Engineer's view of the the Brain
- Building Blocks for a Brain
  - Models of Neurons and Spiking
  - Models of Synapse- nature of connections
  - Models of Synaptic Plasticity
- Braitenberg Vehicles (simple model of an intelligent agent operating in the world)
- Neural Encoding and Population Response
- Building Networks of Neurons with Purpose
  - CPGs for movement
  - Role of inhibition in movement planning (new)
  - Feedforward/Recurrent Networks for visual processing
- ANNs
  - Learning (supervised, unsupervised), convergence

Student Outcomes

- Students can apply the principles of math and science to address a technical problem.
- Students will work effectively as a member of a team.
- Students will have the ability to engage in lifelong learning.
- Students will have effective communication skills.

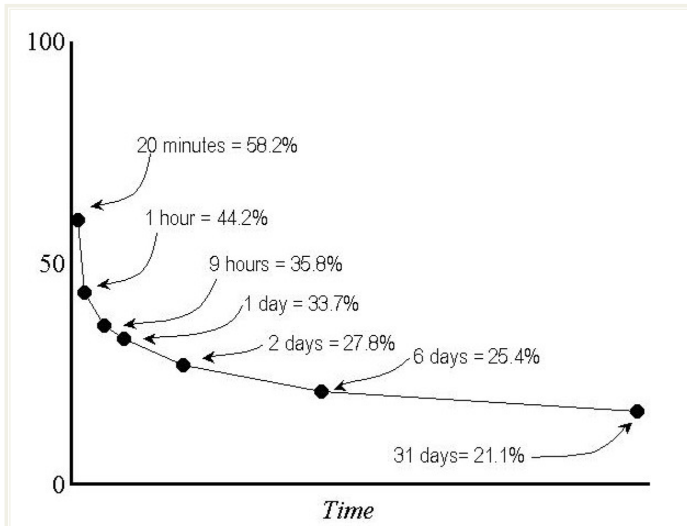
How to do we learn?

Why do we forget?

- Herman Ebbinghaus, 1885
- subject memorized a list of meaningless, three letter words
- tracked how quickly his subjects forgot the words
- became known as the Ebbinghaus or Forgetting Curve

Graphic Source: www.york.ac.uk/depts/maths/histstat/people/ebbinghaus.gif

Ebbinghaus Curve:

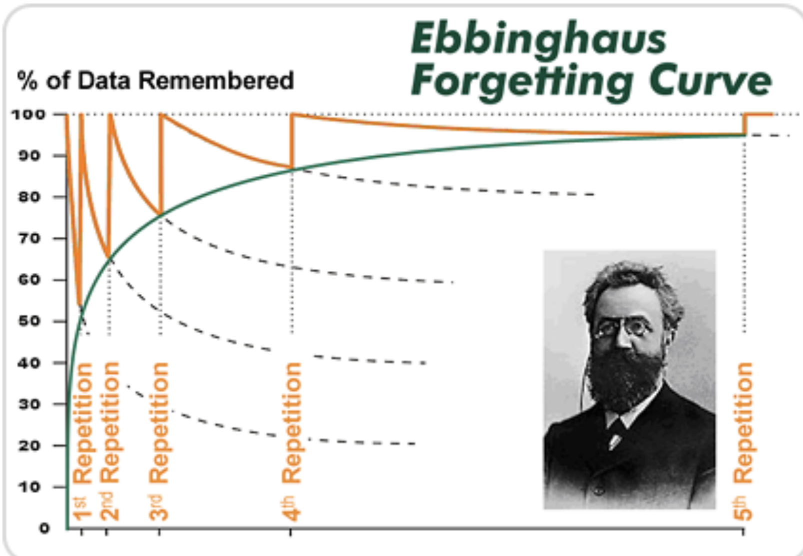


What can you do to improve your memory?

- Learn to connect new information with what you know already. Use memory hooks and other mnemonic devices to represent the new information in terms of already familiar concepts.
- Activate the information in regular, spaced intervals. It is important that the recall is active, that is, you should not just re-read the new information but reply to a question about the new information. Like that your brain will be forced to activate the memory and to deepen the neural connections.
- Use spaced repetitions. Spaced repetition (in particular spaced repetitions software) enables you to calculate the exact time when you profit most from a review: the time just before forgetting.

http://www.flashcardlearner.com/articles/hermann-ebbinghaus-a-pioneer-of-memory-research/

Reducing forgeting?



Approach to Class

- Mix of Lectures and Active Learning
- Short Quizzes to encourage review, reinforce learning and overcome forgetting
- Use of online materials (videos, articles)- neuroscience is HARD!
- Writing to demonstrate understanding
- Oral Presentations of technical material

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My expectations

- Be Curious!!
- Do not get behind.
- Work Hard but have fun with it.
- Help your classmates
- Let me know if you are struggling or confused

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Solving First Order ODEs

$$\frac{dy}{dt} = c_1(1 - y) - c_2 y$$

$$\dot{z} \equiv \frac{dz}{dt} = \frac{-z}{\tau} + g_{syn\max} u(t)$$

$$\dot{g} = \frac{-g}{\tau} + z(t)$$

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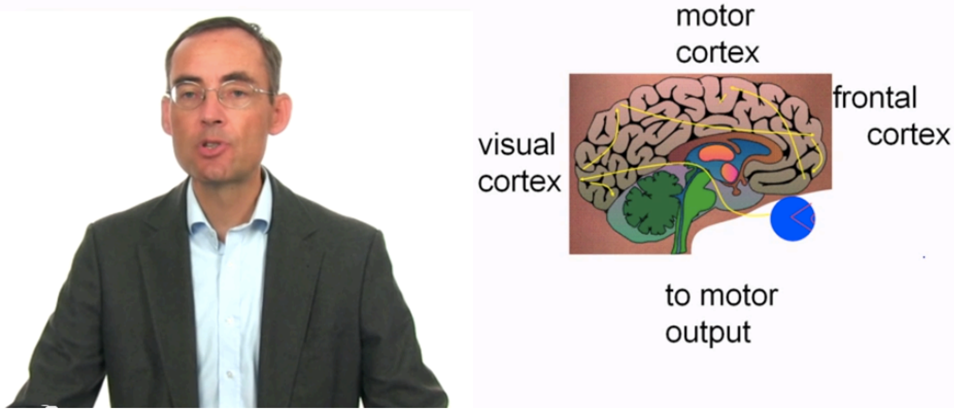
Neuronal Dynamics – 2.1. Introduction



http://lcn.epfl.ch/~gerstner/NeuronalDynamics-MOOC1.html

Wulfram Gerstner, Director of the Laboratory of Computational Neuroscience
EPFL, Lausanne Switzerland

Assessment

- 2 Written Reports with Check Points
  - Report 1 – Individual 45% (30% Final, 15% 4 Explorations)
  - Report 2 – Group 30% (18% Final, 12% Explorations)
- 1 Group Oral Presentation
  - Presentation Project 2 – Group 10%
- 6 short Quizzes (10 min)- (short answer, multiple choice) can drop 1. Excused quizzes require an oral exam. 15%

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Quizzes

- QUIZ 1: Linear ODEs, Neuroanatomy, (Sept 12)
  - See Enabling Math Videos on Sakai
- QUIZ 2: Neuron Models
- QUIZ 3: Synapses
- QUIZ 4: Neural Encoding
- QUIZ 5: Artificial Neural Networks
- QUIZ 6: Brain Inspired ANNs

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