Computational Neuroscience NBIO136b Spring 2017 (Tue & Fri 11am-12:20pm)

Instructor: Paul Miller Volen 252 tel: 6-2890 email pmiller@brandeis.edu Office hrs: Thu 11-noon
TA: Ryan Young Volen 317(B) tel: 781-296-6294 email ryoung@brandeis.edu Office hrs: Fri 3-5pm

Course website on Latte: also cf http://people.brandeis.edu/~pmiller/COMP_NEURO
Book: An Introductory Course in Computational Neuroscience (by P. Miller via NotaBene)
see also: Theoretical Neuroscience by Dayan and Abbott, for more in-depth material

Optional Tutorials: Date TBD (8-10:30pm) Matlab for those new to programming (Farber Computer Classroom).
Please do **download Matlab + practice the tutorial before class**! (Tutorial dates can be altered if need arises).

Jan 17	Intro to course, Matlab and differential equations. (Ch. 0, Section D)
Jan 20	Matlab Tutorial (Ch. 0 Sections D & E)
Jan 24	The leaky integrate-and-fire model (Tutorial 1.1, Ch. 1)
Jan 27	Modeling the refractory period (Tutorial 1.2, Ch. 1)
Jan 31	Extensions of the LIF model (Tutorial 1.3, Ch. 1)
Feb 3	Generating receptive fields with spike-triggered averages (Tutorial 2.1, Ch. 2)
Feb 7	Statistical properties of simulated spike trains (Tutorial 2.2, Ch. 2)
Feb 10	Receiver-operating characteristic of a noisy neuron (Tutorial 2.3, Ch. 2)
Feb 14	The Hodgkin-Huxley model (Tutorial 3.1, Ch. 3)
Feb 17	Post-inhibitory rebound (Tutorial 3.2, Ch. 3)
Feb 28	A two-compartment model of an intrinsically bursting neuron (Tutorial 3.3, Ch. 3)
Mar 3	Synaptic responses to changes in inputs (Tutorial 4.1, Ch. 4)
Mar 7	Detecting circuit structure and non-random features in a connectivity matrix (Tutorial 4.2, Ch. 4)
Mar 10	Bistability and oscillations from two LIF neurons (Tutorial 4.3, Ch.4)
Mar 14	Bistability and oscillations in a firing-rate model with feedback (Tutorial 5.1, Ch.5)
Mar 17	Dynamics of a decision making circuit with two modes of operation (Tutorial 5.2, Ch.5)
Mar 21	Frequency of excitatory-inhibitory coupled unit oscillator and PING (Tutorial 5.3, Ch.5)
Mar 24	Orientation selectivity in a ring model (Tutorial 5.4, Ch.5)
Mar 28	The inhibition-stabilized circuit (Tutorial 6.1, Ch.6)
Mar 31	Diverse dynamical systems from similar circuit architectures (Tutorial 6.2, Ch.6)
Apr 4	Pattern completion and pattern separation by Hebbian learning (Tutorial 7.1, Ch.7)
Apr 7	Competition via STDP (Tutorial 7.2, Ch.7)
Apr 21	Learning the weather-prediction task in a neural circuit (Tutorial 7.3, Ch.7)
Apr 25	A model of eye-blink conditioning (Tutorial 7.4, Ch.7)
Apr 28	Principle Component Analysis (Tutorial 8.1, Ch.8)
May 2	Revision class

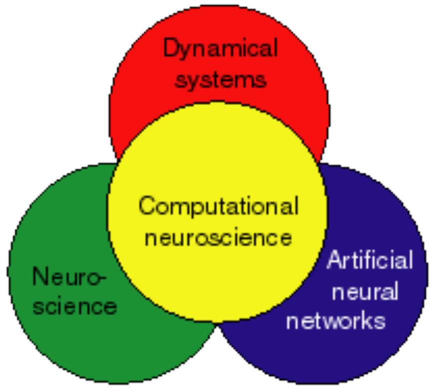
Grading: Tutorials 60%; Final exam 25%; NotaBene Comments 15%.
Tutorials: Each Tutorial scored out of 20, due by the next class. 2pts deducted per day late until a score of 10 is reached. Half of points lost for other than lateness can be regained by redoing the tutorial. **Only your best 12 Tutorials are kept! But 1% of grade subtracted for each unexcused absence/non-submission.**

If you are a student with a documented disability on record at Brandeis University and wish to have a reasonable accommodation made for you in this class, please see me immediately.
You are expected to be familiar with and to follow the University's policies on academic integrity (see http://www.brandeis.edu/studentlife/sdc/ai). Faculty may refer any suspected instances of alleged dishonesty to the Office of Student Development and Conduct. Instances of academic dishonesty may result in sanctions including but not limited to, failing grades being issued, educational programs, and other consequences.

Learning Goals

After taking this course you should be able to simulate model neurons and circuits and analyze basic spike train data. More generally you should gain the ability to produce a simple model of a dynamical biological system with appropriate differential equations, to write a computer code that will solve the model through time and interpret the meaning and relevance of the resulting outputs.

Computational Neuroscience: Overview



from http://www.scholarpedia.org/article/Encyclopedia_of_computational_neuroscience

Original definition of Computational Neuroscience:
"Computational neuroscience is the study of brain function in terms of the information processing properties of the structures that make up the nervous system"
Schwartz, Eric (1990). *Computational neuroscience*. Cambridge, Mass: MIT Press.

At the intersection of:
Neuroscience: The study of neurons, including their internal properties as well as their interconnected circuitry, and the associated biological processes that maintain the function of neural circuits. Some subfields of neuroscience: (1) neurogenetics, (2) cellular neuroscience, (3) systems neuroscience, (4) cognitive neuroscience.
At present computational neuroscience aims to link (2), (3) and (4).

Dynamical systems theory: A branch of mathematics, describing how a system changes over time in response to inputs as a function of its current state. Typically this can be the result of analyzing coupled differential equations.

Artificial Neural Networks: A field that studies how extremely simplified models, such as units of neural activity that are either "on" or "off", can lead to the solution of computational or cognitive problems. Solutions rely upon simple models of the connections between units so these models are sometimes called "Connectionist Models".

Within NBIO136:

Single cell models – how does a neuron work (and produce spikes) and how can we model it?
Models range in complexity as more channels or conductances are added to a neuron and/or more spatial complexity is added.

Small circuits – if 2 or more neurons are connected by a synapse, we model the synaptic interaction. The coordinated behavior of just 2 neurons can be qualitatively different from one alone. Small circuits are usually modeled with more realistic single-cell models and synapses.

Large circuits – tens to thousands of model cells, often aimed at producing behavior that matches either neural measurements in animals or can lead to intelligent behavior. Level of modeling can be from simple models of spiking neurons to "firing-rate" models similar to the "units" used in artificial neural networks.

Plasticity – the term used for changes in synapses connecting neurons, or the neurons themselves. Plasticity is essential for learning and long-term memory.

Spike train analysis – when spike times are recorded, what information can we derive from them?