NEUROBIO 105A
Fundamentals of Computational Neuroscience

Syllabus in brief: The brain can be seen as an extremely complex computing device. The field of computational neuroscience seeks to understand brain function by constructing mathematical models of the nervous system to summarize our knowledge and gain new insights into how neurons perform basic tasks, e.g., encode stimuli, form memories, or generate movements. This course presents computational techniques for investigating, modeling, and understanding the function of neurons, neuronal networks, and systems.

Fall 2015 – Cellular learning

0 - Overview – Introduction to the structure of the tutorial plus introduction to MATLAB.

I – Single cell models

1. What do we want to model? Tuning curves, spike train statistics.
2. Overview over types of models (biophysically realistic to phenomenological)
3. Integrate and fire neuron, rate models and probabilistic models
4. Hodgkin-Huxley model
5. Models of synaptic transmission

II - Synaptic plasticity and cellular learning

1. Correlation based plasticity rules (Hebbian rules)
2. Constraints on synaptic plasticity – BCM rule, synaptic renormalization, homeostatic plasticity
3. Timing based learning rules: Spike timing dependent plasticity (STDP) and synaptic competition

Spring 2016 – Systems learning

III - Learning and memory storage by artificial neurons

1. Supervised learning – Perceptrons, Regression and learning rules: single and multi-layered networks. Backpropagation.
2. Hopfield networks, decision making and associative memory storage.

VI - Learning at the systems level

1. Sparse coding and overcomplete bases,
2. Reinforcement learning. Classical conditioning - Rescorla-Wagner model, temporal difference (TD) learning.
3. Supervised learning. Vestibular-ocular reflex and the cerebellum.

Learning objectives and method of instruction:

Through critical reading of journal articles and concisely conveying ideas in presentation, as well as by doing short programming exercises, the students will acquire skills of:

1. Familiarity with research in Computational Neuroscience
2. Learn to critically assess the scientific literature and communicate this effectively
3. Learn the basics of scientific computing (data analysis, implementing mathematical models)
4. Learn scientific concepts using a hands-on approach (programming/ assignments)

Sample description of a typical tutorial meeting

At the start of each meeting, we will spend a few minutes discussing the results of the students' weekly exercise, or coding problem.

The remainder of the class will comprise one or more of the following elements:

1. Short talks: We will give overview talks introducing key theoretical, numerical or biological concepts.
2. Paper presentation: A student will present a research paper that has been assigned to the class in the previous meeting. All students are expected to have read the paper and participate in its discussion. We will help stimulate discussion by posing questions to the paper presenters.
3. Coding exercises: The class will build computer models to understand important concepts in theoretical neuroscience, and in some instances, to reproduce specific results of assigned papers. For more complex models, we will provide supplementary code that the students can build on, or explore parameter space.

After this, we will give a brief introduction (~ 15 minutes) of the material for the next class – i.e. the research paper and/or assignments.

Typical weekly workload:

Less than four hours of preparation per week; up to 2h for the coding exercise and up to 2h for reading the article. A little more for the student who is presenting the paper (once per semester).

Presentations and written assignments:

Each student will give at least one 15-minute presentation per semester. The presentation will include background and selected results/figures, as well as a critical assessment. The student will also chair a discussion session of the presented paper (15-20 min). In addition, each student will post a question after reading the paper one day before the presentation, as well as work on a small programming exercise each week.

At the end of the semester each student will give a short presentation describing their coding project. This short project shall be an extension of one of the programming exercises/ computational models we learned in class and can be picked according to the interest of the student.

Grading:

Presentation of papers	25%
Participating in discussion	25%
Weekly assignments (coding + question)	30%
Semester coding project	20%

Selected bibliography:

Christopher R. DeCharms and Anthony Zador. Neural representation and the cortical code. Annu. Rev. Neurosci., 613–647, 2000.

Michael J Berry II and Markus Meister. Refractoriness and Neural Precision. Journal of Neuroscience, 18(6):2200-2211, 1998.

Michael J Berry II, Inman H. Brivanlou, Thomas A. Jordan and Markus Meister. Anticipation of moving stimuli by the retina. Nature, 398:334-338, 1999

Andreas VM Herz, Tim Gollisch, Christian K Machens, and Dieter Jaeger. Modeling Single-Neuron Dynamics Detail and Abstraction. Science 80., (October):80–85, 2006.

William R. Softky and Christof Koch. *The highly irregular firing of cortical cells is inconsistent with temporal integration of random EPSPs.* Journal of Neuroscience, 13(1):334-350, 1993

Simon Laughlin. *A simple coding procedure enhances a neuron's information capacity*. Z. Naturforsch., 36c:910-912, 1981

William Bialek, Fred Rieke, Rob R. De Ruyter van Steveninck, David Warland. *Reading a Neural Code.* Science, 252:1854-1857, 1991

Bienenstock, E.L., Cooper, L.N., and Munro, P.W. (1982). Theory for the development of neuron selectivity: orientation specificity and binocular interaction in visual cortex. J. Neurosci. 2, 32–48.

Gerstner, W., Kempter, R., van Hemmen, J.L., and Wagner, H. (1996). A neuronal learning rule for sub-millisecond temporal coding. Nature 383, 76–78.

Song, S., Miller, K.D., and Abbott, L.F. (2000). Competitive Hebbian learning through spike-timing-dependent synaptic plasticity. Nat Neurosci 3, 919–926.

Abbott, L.F., and Nelson, S.B. (2000). Synaptic plasticity: taming the beast. Nat Neurosci 3, 1178–1183.

Hopfield, J.J. (1982). Neural networks and physical systems with emergent collective computational abilities. PNAS 79, 2554–2558.

Olshausen, B.A., and Field, D.J. (1996). Emergence of simple-cell receptive field properties by learning a sparse code for natural images. Nature 381, 607–609.

Doya, K. (2000). Complementary roles of basal ganglia and cerebellum in learning and motor control. Current Opinion in Neurobiology 10, 732–739.

Montague, P.R., Hyman, S.E., and Cohen, J.D. (2004). Computational roles for dopamine in behavioural control. Nature 431, 760–767.

Knudsen, E.I. (1994). Supervised learning in the brain. J. Neurosci. 14, 3985–3997.

Houk, J.C., Adams, J.L., and Barto, A.G. (1995). A model of how the basal ganglia generate and use neural signals that predict reinforcement. In Models of Information Processing in the Basal Ganglia, J.C. Houk, J.L. Davis, and D.G. Beiser, eds. (Cambridge, MA, US: The MIT Press), pp. 249–270.

Useful books:

Fred Rieke, David Warland, Rob de Ruyter van Steveninck, and William Bialek. Spikes: Exploring the Neural Code. MIT Press, 1996.

Peter Dayan and Larry Abbott. Theoretical Neuroscience: Computational and Mathematical Modeling of Neural Systems. MIT Press, 2002.

Pascal Wallisch, Michael Lusignan, Marc Benayoun, Tanya I. Baker, Adam S. Dickey, Nicholas G. Hatsopoulos. MATLAB for Neuroscientists: An Introduction to Scientific Computing in MATLAB. Academic Press, 2009

Sutton, R.S., and Barto, A.G. (1998). Reinforcement Learning: An Introduction (MIT Press).

Example data sets:

V1 gratings and datasets & decoding code (Ecker et al. Decorrelated Neuronal Firing in Cortical Microcircuits. Science, 327(5965), 584-587, 2010 and Berens et al. A fast and simple population code for orientation in primate V1. Journal of Neuroscience, 32(31), 10618-10626, 2012.)
Online available at http://bethgelab.org/datasets/v1gratings/

Collaborative Research in Computational Neuroscience (Various data sets from multiple model systems and brain areas)
Online available at http://crcns.org/data-sets/

Exercises & data from the Dayan and Abbott book
Online available at http://neurotheory.columbia.edu/~larry/book/exercises.html