<u>NEURL-GA 3042-001</u>
Modeling learning across scales: from single synapses to behavior

Instructor: Cristina Savin, csavin@nyu.edu
Location & time: Meyer 760, weekly course on Thursdays 12-2pm
Albert code: 2771
Office hours: by appointment
Target audience: graduate students in CNS, maximum 18.

Overview

This reading course is focused on mathematical models of learning across scales, from synaptic plasticity, to circuit models and behavior. Each class consists of a short lecture covering one classic model, followed by a round table discussion of related papers, showing state of the art, potential limitations of existing theories and explicit links to data. Topics include phenomenological and biophysically motivated models of synaptic (Hebb-type, STDP, discrete state, Ca-based biophysical model) and intrinsic plasticity, circuit-level models of memory and learning (e.g. Hopfield network and generalizations, models of hippocampus as center for episodic memory, neural models of reinforcement learning) and phenomenological models of learning and memory behavior. The goal is to provide a thorough review of classic mathematical models for learning and memory but also on building bridges across approaches and levels of description.

Course objectives

By the end of the course students will be able to:
1) explain the key features of classic models of learning
2) critically discuss different models, in particular in relation to the experimental data they are trying to explain
3) develop a mathematical understanding for the memory capacity of different memory models
4) discuss current state of the art, limitations, and possible ways forwards

Grading 30% presentations, 30% exercises, 20% written essay, 20% participation.

For essay: discuss in detail one paper that goes beyond what was covered in the course. Try to stretch beyond what is comfortable e.g. an experimentalist discussing theory; a theorist looking into recent experimental data that is not yet accounts for in current models; bonus points if explicitly linking information across scales.

NOTE: The detailed schedule is subject to change.

Detailed schedule

Date	Lecture title	Papers
Sept 6	1. Logistics. Intro	
Sept 13	2. Phenomenological models of synaptic plasticity: rate models	Gerstner, W., & Kistler, W. M. (2002). Mathematical formulations of Hebbian learning. *Biological Cybernetics*, *87*(5-6), 404–415. BCM rule
Sept 20	3. Phenomenological models of synaptic plasticity: spiking models	Clopath, C., Büsing, L., Vasilaki, E., & Gerstner, W. (2010). Connectivity reflects coding: a model of voltage-based STDP with homeostasis. *Nature Publishing Group*, *13*(3), 344–352. doi:10.1038/nn.2479 Graupner, Michael, and Nicolas Brunel. "Calcium-based plasticity model explains sensitivity of synaptic changes to spike pattern, rate, and dendritic location." *Proceedings of the National Academy of Sciences* 109.10 (2012): 3991-3996.
Sept 27	4. Other forms of plasticity	Vogels, T. P., Sprekeler, H., Zenke, F., Clopath, C., & Gerstner, W. (2011). Inhibitory plasticity balances excitation and inhibition in sensory pathways and memory networks. *Science*, *334*(6062), 1569–1573. doi:10.1126/science.1211095 Bono, J., Wilmes, K. A., & Clopath, C. (2017). Modelling plasticity in dendrites: from single cells to networks. *Current opinion in neurobiology*, *46*, 136–141. doi:10.1016/j.conb.2017.08.013

Oct 4	5. Unsupervised learning	Sparse coding models Savin, C., Joshi, P., & Triesch, J. (2010). Independent Component Analysis in Spiking Neurons. *PLoS Computational Biology*, *6*(4), e1000757. doi:10.1371/journal.pcbi.1000757 Bengio, Y., Fischer, A., & Mesnard, T. (2015). From STDP towards Biologically Plausible Deep Learning.
Oct 11	5. Reinforcement learning and 3-factor plasticity	Rescola Wagner, TD learning, Triplet STDP
Oct 18	6. Synaptic tag and capture, synaptic memory consolidation	Redondo, R. L., & Morris, R. G. M. (2011). Making memories last: the synaptic tagging and capture hypothesis. *Nature Reviews Neuroscience*, *12*(1), 17–30. doi:10.1038/nrn2963 Clopath, C., Ziegler, L., Vasilaki, E., Büsing, L., & Gerstner, W. (2008). Tag-trigger-consolidation: a model of early and late long-term-potentiation and depression. *PLoS Computational Biology*, *4*(12), e1000248. doi:10.1371/journal.pcbi.1000248
Oct 25	7. Multi-time scale synaptic changes and their contributions to memory	Fusi, S. (2017, June 15). Computational models of long term plasticity and memory. Benna, M. K., & Fusi, S. (2016). Computational principles of synaptic memory consolidation. *Nature Publishing Group*, *19*(12), 1697–1706. doi:10.1038/nn.4401 Fusi, S., & Abbott, L. F. (2007). Limits on the memory storage capacity of bounded synapses. *Nature Neuroscience*, *10*(4), 485–493. doi:doi:10.1038/nn1859

Nov 1	8. Memory: Hopfield	Hopfield, J. J. (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the National Academy of Sciences of the United States of America*, *79*(8), 2554–2558. Savin, C., Dayan, P., & Lengyel, M. (2014). Optimal Recall from Bounded Metaplastic Synapses: Predicting Functional Adaptations in Hippocampal Area CA3. *PLoS Computational Biology*, *10*(2), e1003489. doi:10.1371/journal.pcbi.1003489.s008
Nov 8	9. Memory: Hippocampus	Treves
Nov 15	10. Why have multiple memory systems?	Lengyel and Dayan
Nov 22	11. Recognition memory - behavior	Yonelinas, A. P. (2001). Components of episodic memory: the contribution of recollection and familiarity. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *356*(1413), 1363–1374. doi:10.1098/rstb.2001.0939 Brown, M. W., Warburton, E. C., & Aggleton, J. P. (2010). Recognition memory: material, processes, and substrates. *Hippocampus*, *20*(11), 1228–1244. doi:10.1002/hipo.20858
Nov 29	12. Recognition memory - networks	Norman, K., & O'Reilly, R. (2003). Modeling hippocampal and neocortical contributions to recognition memory: A complementary-learning-systems approach. *Psychological Review*.
Dec 6	13. Cognitive models	TBD
Dec. 13	Final reports discussion	