Neural Computation

NEUR 416 / CAAM 416 / ELEC 489 / ELEC 589

1. Course Summary

How does the brain work? Understanding the brain requires sophisticated theories to make sense of the collective actions of billions of neurons and trillions of synapses. Word theories are not enough; we need mathematical theories. The goal of this course is to provide an introduction to the mathematical theories of learning and computation by neural systems. These theories use concepts from dynamical systems (attractors, chaos) and concepts from statistics (information, uncertainty, inference) to relate the dynamics and function of neural networks. We will apply these theories to sensory computation, learning and memory, and motor control. Our learning objectives are for you to formalize and mathematically answer questions about neural computations including "what does a network compute?", "how does it compute?", and "why does it compute that way?"

2. Instructors:

Xaq Pitkow, Baylor College of Medicine & Rice University; xaq@rice.edu
Weekly office hours with TA to be determined. Office hours with Xaq by appointment.

3. Course Description

Tuesdays and Thursdays, 2:30-3:45 pm
Location: Keck 101, Rice University
Recommended textbook: *Theoretical Neuroscience*, by Dayan and Abbott

Audience: Graduate and undergraduate students with quantitative training and interests in theories of how the brain works.
Prerequisites: calculus, linear algebra, probability and statistics, some programming experience (MATLAB, Python, or similar)
3 credits Elective

4. Grading Criteria: homework (45%), quizzes (5%), two exams (15% each), and final project (20%).

Homeworks turned in late without pre-approved justification will lose 5% per day.

Several short quizzes (**Concept Questions**) must be completed before class, to get us started thinking about certain ideas. These do not require mathematical computation but rather emphasize conceptual reasoning.

Midterms will be 3-hour take-home exams. You may use your notes, lecture notes, and readings, but no internet.

Final projects will have a 15-minute in-class presentation (50%) and a written report (50%, ~6–10 pages). The topic of your final projects is flexible. Examples include:

- Reproducing and slightly extending results in a theory or modeling paper
- Analyzing real or simulated data in context of a theory
- Quantitatively contrasting or critiquing competing theories
- Interactive visualization of an interesting theoretical concept
- Historical review of a core theoretical idea

Undergraduates may work in pairs if desired. Individual contributions should be documented. Graduate students taking ELEC 589 are expected to work alone on projects, and to have more comprehensive results (~10 pages for grads, versus ~6 pages for undergrads).

Date	Content	Reading (DA = Dayan and Abbott)	Homework
8jan	Introduction Goals of neural computation		HW1: fun with gaussians and information (due 15jan)
10jan	Efficient coding 1		
15jan	Efficient coding 2	DA 4.1–4.2, appendix on Fourier Transforms van Hateren 1992	
17jan	Population codes: *encoding* (tuning curves, receptive fields)	DA 1.1–1.3 DA 3.1–3.3	HW2: efficient coding (due 22jan)
22jan	*decoding* (estimation, discrimination, action)		HW3: population codes (due 29 jan)
24jan	Feedforward networks (1 layer, perceptrons)	DiCarlo and Cox 2007	
29jan	Learning in networks: perceptron learning rule, Hebbian plasticity, backpropagation	DA 8.1–8.2, 8.4	HW4: feedforward nets (due 6 feb)
31jan	NeuroNex workshop, location = BRC 280, 9:00–5:00 Scott Linderman and John Cunningham speak on latent variable models from 3:00–5:00 *gulfcoastconsortia.org/events/neuronex-workshop-january-31-2019/*		
1feb (FRI)	Theoretical and Computational Neuroscience Symposium location = BRC, 9:00–5:00 *gulfcoastconsortia.org/events/16th-annual-gcc-conference-on-theoretical-and-computational-neuroscience-february-1-2019/*		
5feb	Multilayer nonlinear feedforward networks: *recoding* Object recognition by deep networks	Bishop 9.2	Project preparation
7feb	SPRING RECESS		
12feb	Linear recurrent networks (deterministic)	DA 7.4, up to linear recurrent networks. Appendix: Linear Algebra, Differential equations	
14feb	Univariate stochastic linear dynamics	Scholarpedia: Stochastic dynamical systems	HW5: linear recurrent networks (due 19feb)
19feb	Multivariate stochastic linear recurrent networks Kalman filter, line attractors, integrators	How a Kalman Filter works, in pictures. Gold and Shadlen 2001	Midterm (due 26feb)
21feb	Project check-in		
26feb	Nonlinear dynamics. Reduction techniques and stochastic nonlinear models (bursters, reduced line attractor models, Takens' theorem) Recurrent networks (continuous attractor, ring model)	Strogatz Ch 1 Wilson and Cowen 1972 DA 7.4 from Nonlinear recurrent networks, DA 7.5	HW6: nonlinear dynamics (due 5mar)
28feb	Nonlinear dynamics		
5mar	Microcircuitry		
7mar	Balanced networks	DA 7.5, 10.1–10.2	
	SPRING BREAK		
19mar	Associative memory: Hopfield network (discrete attractor)	DA 7.4: Associative Memory. Hopfield 1982	
21mar	Boltzmann machine (probabilistic computation, unsupervised learning)	DA 7.6; 8.4: "contrastive Hebbian learning" Ackley 1983	HW7: Hopfield net (due 26mar)

26mar	Probabilistic population codes	Ma et al 2006 Berkes et al 2007	
28mar	Causal inference Context dependent computation, gating	Bishop 8.2–8.3 Mante et al 2012	HW8: Boltzmann machine (due 2apr)
2apr	Motor control	Shenoy et al 2013	Midterm II (due 9apr)
4apr	Reinforcement learning	DA 9	
9apr	Deep thoughts: Integrated information, free will, practopoiesis		
11apr	Project preparation		
16apr	Project presentations		
18apr	Project presentations		Written projects (due 23 apr)