Theoretical Neuroscience: Learning, Perception and Cognition

NEUR 416 / CAAM 416 / ELEC 489

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:

Dr. Harel Shouval, University of Texas Medical School at Houston
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Dr. Xaq Pitkow, Baylor College of Medicine & Rice University
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Office hours by appointment.

3. Course Description

Tuesdays and Thursdays, 9:25-10:40 am
Location: Duncan Hall, Rice University

Audience: Graduate and undergraduate students with quantitative training and interests in theories of how the brain works.
Prerequisites: calculus, linear algebra, probability and statistics

3 credits Elective
Rice Spring semester, taught on Rice schedule.
Enrollment limitation: 25 students maximum

4. Grading Criteria: homework assignments, exams, and projects. The homework assignments will determine 50% of the final grade, the exams 40%, and the project 10%.

5. Topic outline:

Dr. Shouval's lectures (14) will cover the following topics:

1. Introduction. (January 12)
    - Fundamental questions of learning and memory.
    - Basic techniques
    - The synaptic hypothesis.

2. Formal Models of learning and memory (January 14- February 4)
    - Supervised learning – Perceptron learning, Linear separability, Credit assignment problem, Back Propagation.
    - Unsupervised learning and receptive field development – Hebb, PCA, BCM, ICA learning paradigms and how they can account for receptive field development in visual cortex.
    - Reinforcement learning – Temporal credit assignment, TD(λ) learning and experimental analogs of TD learning.
    - Associative memory – Matrix memory, Hopfield Networks, Capacity calculations.

3. The Biophysics of synaptic plasticity (February 9 – February 27)
    - Synaptic transmission – Neurotransmitter release, AMPA receptors, NMDA receptors.
    - Synaptic dynamics – models of paired pulse facilitation and depression.
    - Induction Protocols for LTP and LTD – rate-based and spike-timing-based protocols for inducing bidirectional synaptic plasticity.
    - What is altered during induction – presynaptic change of release, the silent synapse hypothesis and statistical methods for detecting the site of induction.
    - The Biophysical basis of induction – Calcium influx, NMDA receptors, Phosphatases and Kinases.
    - Biophysical modeling of signal transduction pathways – ODE methods for modeling signal transduction pathway and stochastic methods of modeling signal transduction pathways.
    - Calcium dependent learning models – Simplified calcium-based models for the induction of synaptic plasticity and how they can account for induction protocols and receptive field plasticity.
    - Stochastic considerations - How stochastic considerations affect calcium based models.

This period includes Spring Break March 3 - 7 and midterm March 11.

Dr. Pitkow's lectures (13) will cover the following topics:

1. Goals of neural computation (March 13 – 18)

    - Fitness and predictive information
    - Measures of good computation
    - Statistical structure of the natural environment
    - Invariance and ambiguity
2. Behaviors of neural networks (March 20 – April 1)
    - Linear networks: basic properties of recurrent networks
    - Nonlinear networks: dynamical systems and attractors
    - Stochastic networks: variability, statistics and information
3. Computation in neural networks (April 3 – April 24)
    - Feedforward networks: classifiers, population codes, invariances
    - Recurrent networks: integrators, liquid state machine, boltzmann machine, hopfield net
    - Probabilistic networks: generative and discriminative models, inference, evidence integration and marginalization, control theory