Computational Neuroscience

Spring Semester, 2023
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Rutgers University Psychology Department

Course Information:
Course Number: The course is cross-listed under three designations:

Cognitive Science Graduate Course
Title: Seminar in Cognitive Science II: Computational Neuroscience
Rutgers Course Number: 16:185:601
Index Number: 11311

Psychology Graduate Course
Title: Advanced Studies in Psychology: Computational Neuroscience
Rutgers Course Number: 16:830:504
Index Number: 13678

Cognitive Science Undergraduate Course
Title: Advanced Topics II: Computational Neuroscience
Rutgers Course Number: 01:185:412
Index Number: 04462

Date and Time: Thursdays 10:00-12:30
Location: Psychology Department, Busch Campus Room 301.
Prerequisite Skills: Prior neurobiology coursework, facility with computer programming (Matlab preferred), basic statistics
Enrollment: Undergraduate enrollment is by permission of the instructor only

Instructor:
Dr. John P. McGann
Email: john.mcgann@rutgers.edu
Office: Psych 308 (Busch Campus)
Office Hours: TBD

Introduction and Goals for this Course: Neuroscience has a rich theoretical history, from Hodgkin and Huxley's account of the action potential to Hebb's learning rule to modern network simulations and coding models. The conceptual frameworks we use to interpret neural activity implicitly and explicitly guide our experimental designs and increasingly shape our data analysis and interpretations. The goal of this course is to provide an overview of modern theoretical neuroscience accompanied by hands-on training in related methods of analysis and simulation through demonstrations and individual in-class projects. This course will emphasize real-life challenges like framing of questions to be answered, scoping of simulations, and analysis and communication of results. Students are expected to be able to read sophisticated neuroscience texts independently so that class time may be reserved for discussion of the reading and in-class work on individual projects.

Topics to be covered:

- History, goals, and limits of theoretical neuroscience
- Representations of information in the nervous system
- Variance and "noise"
- Time and timing
- Neural plasticity: adaptive codes, learning & memory, physical substrates
- Questions of scale: molecular, synaptic, and circuit-level models, connectomics
- Degree of abstraction: how much detail do you really need?
- Simulation vs analysis
- Brains and statistics

Readings: Each week this course will include readings from the textbook and primary literature that relate to the subject for discussion. The papers can be downloaded from the class Canvas site under the Resources tab. This course assumes you have done the reading *before* each class meeting, so that you can bring questions and be prepared for discussion. You should read for both detail and understanding.

Principal Textbook:
Theoretical Neuroscience, by Dayan and Abbott (2005). This foundational text addresses most of the classic questions and approaches in computational neuroscience. We will not be using this textbook explicitly in class, but reading the relevant sections will provide valuable context for in class discussions.

Supplementary Textbooks:
MATLAB for Neuroscientists: A Introduction to Scientific Computing in MATLAB, by Pascal Wallisch, Lusignan, Benayoun, and Baker (2008). This text is just a useful guide to coding in Matlab with many helpful examples for beginner to intermediate programmers.

From Computer to Brain: Foundations of Computational Neuroscience, by William Lytton (2002). This is an introductory text in computational neuroscience that frames many of the principal issues in plain language. It may be helpful for students with limited background in math.

Primary Literature:
Each module of the course will include some readings from the primary literature, some of which are relatively accessible and some of which are fairly technical. In class guidance will be provided to help you prioritize your reading effort.

Canvas: The course has a dedicated Canvas site at canvas.rutgers.edu. All registered students should automatically be members of the site. The site includes downloadable readings for the course, this syllabus, a code bank, a chat room, and a venue for announcements to the class. This is the tool that will be used to email the entire class when necessary.

Evaluation (tentative): We may adjust the evaluation expectations depending on the mix of students who enroll in the class, but this is the initial plan:

> *Graduate enrollments:* The course will include an individual project for each student, including 1) an introductory in-class presentation framing the scientific question to be answered by the student's project, including a brief review of existing literature and an explanation of how theoretical methods will be used to explore the question (25% of course grade), 2) a final in-class presentation summarizing the outcome of the project (25%), and 3) a succinct final paper describing the project due on (25%). This work will be complemented by a take-home graduate-level conceptual exam (no computation) worth 25% of the course grade.
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> *Undergraduate enrollments:* The course will include participation in a group project, including an in-class presentation framing the scientific question to be answered by the student's project, including a brief review of existing literature and an explanation of how theoretical methods will be used to explore the question (20% of course grade) and final in-class presentation summarizing the outcome of the project (40%). This work will be complemented by a take-home undergraduate-level conceptual midterm exam (no computation) worth 15% of the course grade and a take-home undergraduate-level conceptual final exam worth 25% of the course grade.

In-class Work: Each class will include time to actively work on your theoretical neuroscience project, so please expect to bring a computer to class. During this time, you will be coached by the Instructor and will be tasked with working together in small groups to share ideas and methods.

Academic Integrity: All students are required to comply with the University's Academic Integrity Policy, as presented at http://academicintegrity.rutgers.edu.

Conduct: Students are expected to pay attention in class. Use of computers and other electronic devices for anything other than note-taking is distracting to fellow students and is not permitted. Should I perceive a student's behavior to be disruptive to fellow students in the class, I will ask the student to leave the classroom, and, if this occurs on a regular basis, I may judge the disruptive student to be unable to successfully complete the course with a passing grade.

Special Circumstances for Students with Disabilities: If you receive special accommodations for exams, you must provide your official Letters of Accommodation to Professor McGann at least one week prior to the conceptual exam. You must ALSO make appropriate arrangements with the Office of Disability Services for them to proctor your exam at the same day and time as the rest of the class. The ODS requires you to make these arrangements at least five business days ahead of each individual exam. If you fail to make arrangements through ODS, you will not receive special accommodations and will be required to take the exam with the rest of the class.

Course Schedule for Workshop in Computational Neuroscience

Each Unit will take approximately two weeks of class time. The exact schedule of which material is covered when may vary slightly.

NOTE: There will be no class on April 20.

Unit 1

What is theoretical neuroscience?

- Introduction to the course
- Theories of neural computation vs using computation to explore the brain
- Historical overview of theoretical neuroscience (e.g. Hodgkin-Huxley, Rall, Marr, Hubel & Wiesel, Hebb, Hopfield) and related theories and metaphors (information theory, learning theory, signal detection theory, signal processing)
- What theoretical neuroscience can and cannot do
- Formulating tractable questions
- Degree of abstraction: how much detail do you really need?
- Action potentials and firing rates
- Demonstration: Simulating and characterizing a spike train

Readings

- Marr, D. and Poggio, T. (1976) From understanding computation to understanding neural circuitry. MIT Artificial Intelligence Laboratory A.I. Memo 357.
- Abbott, L.F. (2008) Theoretical neuroscience rising. *Neuron* 60:489-495.
- Gordon, J. (2017) NIMH Director's Letter: Computational Neuroscience: Deciphering the Complex Brain. (https://www.nimh.nih.gov/about/director/messages/2017/computationalneurosciencedecipheringthecomplexbrain.shtml)
- Gerstner, W., Sprekeler, H., and Deco, G. (2012) Theory and simulation in neuroscience. *Science* 338:60-65.
- Gallistel, C.R. (2017) The coding question. *Trends in Cognitive Science* 21:498-508.
- Theoretical Neuroscience Chapter 1: Neural Encoding 1: Firing Rates and Spike Statistics

Unit 2

How to represent a neuron

- Integrate and fire (Lapicque) model
- Dendritic architecture, cable theory (Rall), and electrotonic structure
- Compartmental modeling
- Hodgkin-Huxley and conductance-based models, including conductance physiology
- Demonstration: Simulating single neurons and characterizing their behavior

Project work

- Group discussion and refinement of individual project ideas
- Scheduling of first talks

Readings

- Mainen, Z.F. and Sejnowski, T.J. (1996) Influence of dendritic structure on firing pattern in model neurons. *Nature* 382:363-6.
- Izhikevich, E.M. (2003) Simple model of spiking neurons. *IEEE Trans Neural Netw* 14:1569-72.
- Theoretical Neuroscience Chapter 5: Model neurons 1: Neuroelectronics
- Theoretical Neuroscience Chapter 6: Model neurons 2: Conductances and morphology

Unit 3

Network architectures and neuronal interactions

- Feedforward, lateral, and feedback connections
- Excitation/inhibition vs depolarization/hyperpolarization
- Divisive vs subtractive inhibition
- Presynaptic and postsynaptic kinetics and variance
- Axodendritic, axoaxonic, and presynaptic connectivity
- Demonstration: Simulating simple circuits and characterizing their behavior

Project work

- Project introductory talks by students

Readings

- Theoretical Neuroscience Chapter 7: Network models

Unit 4

Representation of information in brain: single neurons

- Introduction to information theory and Bayes rule
- Encoders and decoders
- Timing codes and (versus?) rate codes
- Mutual information between time-varying vectors
- Forward and reverse correlation to external stimuli
- Multiplexing in single neurons
- Demonstration: Reverse correlation analysis of neurons in simulated (“toy”) circuits

Project work

- Project updates and discussion

Readings

- Theoretical Neuroscience Chapter 2: Reverse correlation and visual receptive fields.
- Theoretical Neuroscience Chapter 3: Neural decoding
- Theoretical Neuroscience Chapter 4: Information Theory
- Chapter 2 of Spikes: Exploring the Neural Code, by Bialek et al.
- Rajan, K. and Bialek, W. (2013) Maximally informative “stimulus energies” in the analysis of neural responses to natural signals. *PLoS One* 8:e71959.

Unit 5

Representation of information in brain: network activity

- Local vs distributed representations
- Sparseness of coding and its quantification
- Linear decoding

- Network state analysis – state-space manifolds and Markov models
- Multiplexing in networks
- Demonstration: Analyzing and depicting network behavior

Project work

- Project updates and discussion

Readings

- Willmore, B. and Tolhurst, D.J. (2001) Characterizing the sparseness of neural codes. *Network* 12:255-70.
- Tkacik, G., Marre, O., Amodei, D., Schneidman, E., and Bialek, W. (2014) Searching for collective behavior in a large network of sensory neurons. *PLoS Comput Biol* 10:e1003408.
- Osborne, L.C., Palmer, S.E., Lisberger, S.G., and Bialek, W. (2008) The neural basis for combinatorial coding in a cortical population response. *J Neurosci* 28:13522-31.
- Stopfer, M., Jayaraman,V., and Laurent, G. (2003) Intensity versus identity coding in an olfactory system. *Neuron* 39:991-1004.
- Mazzucato, L., Fontanini, A., and La Camera, G. (2015) Dynamics of multistable states during ongoing and evoked cortical activity. *J Neurosci* 35:8214-31.

Unit 6

Plasticity and learning, a.k.a. information storage

- Content-addressable vs indexed memory
- Reading vs. writing – is there a meta-signal?
- Autoassociation and weight matrices
- Supervised vs unsupervised learning
- Error attribution and backpropagation
- Neuronal plasticity vs. synaptic plasticity (activity and timing dependent)
- Changing content vs changing code
- Demonstration: Simulating circuit-level plasticity

Project work

- Project updates and discussion

Readings

- Theoretical Neuroscience Chapter 8: Plasticity and learning
- Theoretical Neuroscience Chapter 9: Classical conditioning and Reinforcement Learning
- Moran, A. and Katz, D.B. (2014) Sensory cortical population dynamics uniquely track behavior across learning and extinction. *J Neurosci* 34:1248-57.
- Johansson, F., Hesslow, G., and Medina, J.F. (2016) Mechanisms for motor timing in the cerebellar cortex. *Curr Opin Behav Sci* 8:53-59.

Unit 7

Statistical learning & predictive coding

- Brains as statistical learners
- Predictive coding
- Variance and “noise”
- Expectations and timing

- Demonstration: Simulating anticipatory responding

Project work

- Student final presentations about their projects

Readings

- Theoretical Neuroscience Chapter 10: Representational Learning
- Shipp, S. (2016) Neural elements for predictive coding. *Front Psychol* 7:1792.
- Palmer, S.E., Marre, O., Berry, M.J., and Bialek, W. (2015) Predictive information in a sensory population. *PNAS* 112:6908-13.
- Zmarz, P. and Keller, G.B. (2016) Mismatch receptive fields in mouse visual cortex. *Neuron* 92:766-772
- Yildiz, I.B., Mesgarani, N., and Deneve, S. (2016) Predictive ensemble decoding of acoustical features explains context-dependent receptive fields. *J Neurosci* 36:12338-12350.