Theoretical and Computational Neuroscience

[PHYS 585 / BE 530: Syllabus: Spring 2020]

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Course Lecture: TR 9-10:30 in DRL A4
Instructor Office Hours: Wednesday, 9-10, Richards D402
TA Office Hours: Thursday, 3-5pm, Richards 4th Floor, Common Area
DRL = David Rittenhouse Laboratory

Course description: This course will develop theoretical and computational approaches to structural and functional organization in the brain. The course will cover: (i) the basic biophysics of neural responses, (ii) neural coding and decoding with an emphasis on sensory systems, (iii) approaches to the study of networks of neurons, (iv) models of adaptation, learning and memory, (v) models of decision making, and (vi) ideas that address *why* the brain is organized the way that it is. The course will be appropriate for advanced undergraduates and beginning graduate students. A knowledge of multi-variable calculus, linear algebra and differential equations is required (except by permission of the instructor). Prior exposure to neuroscience and/or Matlab programming will be helpful.

Pre-requisites: *Mathematics:* Knowledge of multi-variable calculus, some linear algebra and some differential equations is necessary for this course. The methods will be developed in class for the benefit of students without much exposure to this material. Students without some prior background must have the permission of the instructor to take this class. *Computation:* Prior knowledge of MATLAB will be useful, but students will go through programming exercises to develop their skills. *Neuroscience:* Basic knowledge of the architecture of the brain, and of the mechanisms of neural signaling will be very useful. However, for the benefit of students from physics and bioengineering without background in neuroscience, the necessary material will also be developed in class and in tutorial sessions.

Books: Required book is available for purchase at the Penn Book Store (corner of Walnut and 36th Street).
Required: P. Dayan and L.F. Abbott, "Theoretical Neuroscience: Computational and Mathematical Modeling of Neural Systems", MIT Press, 2001.
Optional:

1. F. Rieke, D. Warland, R. de Ruyter van Steveninck, and W. Bialek, "Spikes: Exploring the Neural Code", MIT Press, 1997. *Useful reference on the neural code and information theoretic methods.*
2. E. Kandel, "Principles of Neural Science", McGraw-Hill, 2000. *The standard neuroscience textbook, useful if you don't have prior exposure.*
3. P. Wallisch et al., "Matlab for neuroscientists: An introduction to scientific computing in Matlab", Academic Press, 2008. *An introduction to algorithms and*

computational methods that are useful in neuroscience. Useful if you don't have much programming experience.

4. M. Diamond and A. Scheibel, "The human brain coloring book", Collins Reference, 1985. *Coloring this book (get out your crayons) will teach you the basics of neuroanatomy.*

Handouts: The textbook may be supplemented with readings from the literature that will be posted on Canvas.

Matlab: Penn has a site license for MATLAB. You can buy a student copy for your own computer, or use it at: (1) SAS Computing Multi-Media Services (basement DRL), (2) Undergrad Data Analysis Lab (104/108 McNeil), (3) Weigle Information Commons (Van Pelt), (4) SEAS virtual PCs: http://www.seas.upenn.edu/cets/answers/virtualLab.html http://www.seas.upenn.edu/cets/answers/virtualLab.html, (3) More info at: http://www.sas.upenn.edu/computing/instructional/labs.html+ and http://www.upenn.edu/computing/view/labs/lablist.html+
A free, and mostly compatible alternative to MATLAB is Octave:
http://www.gnu.org/software/octave/

Final project: There will be a final project that students will carry out in small teams. Suggestions for possible final projects will be made, and a 1-2 page proposal for the final project will be due shortly afterwards. Projects will consist of two parts: (i) reading and summarizing the literature on a particular theoretical/computational problem in neuroscience and (ii) building and analyzing a theoretical or computational model in this domain. An interim report on the project of 1-2 pages will be due a few weeks before the end of term, and a 7-10 page final report will be due at the end of term.

Problem Sets: There will be regular problem sets that will be due in class on the Thursday after they are issued.

Grades: Problem sets: 65% (1 lowest homework grade dropped)
Final project proposal: 5%
Final project interim report: 5%
Final project report: 25%
Attendance: Attendance will be occasionally taken in class and included as a component of the problem set grade

Other Policies: We do not discuss grades over email. Late work will not be accepted unless there is a legitimate excuse (illness or a family crisis).

Topics Covered: Textbook chapters have been indicated where appropriate. Other material will be covered in class and in handouts.

1. Single Neurons
   a. Biophysics of spike generation and action potential propagation (Ch. 5 & 6)
   b. Neural coding and decoding – models of neural response, spike-triggered characterizations of response (Ch. 1 – 3)

c. Measuring neural information (Ch. 4)
d. Adaptation of neural responses
e. Normative models of function

2. Neural Populations
   a. Receptive field maps
   b. Parallel Channels
   c. Correlations and interactions
   d. Network structure and computation (Ch. 7)
3. Higher level functions
   a. Memory – the Hopfield model
   b. Decision making and Bayesian analysis

   If there is enough time (most likely not), we might address

   c. *Synaptic plasticity and learning (Ch. 8)*
   d. *Reinforcement Learning (Ch. 9)*
   e. *Representational learning (Ch. 10)*

Statistical Topics Covered

While going through the computational neuroscience topics described above, we will also cover many topics in probability theory and statistics. These include:

1. Essentials of probability theory
2. Bayesian statistics and probability
3. Correlation and covariance
4. Principal components analysis
5. Statistical inference of models and decision making
6. Bias-variance tradeoffs and Fisher Information
7. Elementary game theory
8. Simple stochastic processes
   a. Statistical independence and Poisson processes
   b. Tests of Poisson statistics
   c. Statistical dependence and Markov processes
9. Principal components analysis
10. Information theory
    a. Definition of entropy and mutual information
    b. Techniques for measuring information
    c. Efficient coding theory
11. Elements of statistical learning theory
    a. Learning from statistical correlations
    b. Elementary machine learning