Tentative Syllabus:

Introduction
Computational Neuroscience: Contemporary Overview (Jan 22)

I. Principles of sensory processing: Efficient Neural Codes
Receptive fields, entropy, and the max-entropy principle (Jan 24-29)
Shannon Information and Principal Component Analysis (Jan 31)
Infomax principle and vision (Feb 5)
Independent Component Analysis and sparse coding (Feb 7)

II. Neuronal Circuits: Dynamics, Plasticity and Computation
Principles of neural circuit dynamics and linear networks (Feb 12)
Statistical mechanics of neural networks (Feb 14)
Associative memory (Feb 21)
Neural mechanisms of working memory, the line attractor (Feb 26)
Spatial navigation, the ring attractor (Feb 28)
Neural chaos and Excitation-Inhibition balance (March 4-6)

III. Supervised Learning in Neural Networks
Learning from Examples in linear systems (March 18)
The Perceptron (March 20)
Support Vector Machines (March 25)
Deep Networks â€“ expressivity and learning (March 27)
Deep Networks â€“ generalization and feature learning (April 1-3)

IV. Cognitive Functions
Object Manifolds and Concept Learning in Deep Networks and Visual Cortex (April 8-10)
Generative AI: Large Language Models, and brain language processing (April 15-17)
Generative AI: Diffusion models and neural dynamics (April 22)
From Brain to Mind (April 24)

Course format:

Mondays and Wednesdays 03:00-04:15 PM (in person), in Northwest B101

TA-led sections: Wednesdays 01:30-02:45 PM in Northwest B106.

Office hours: Alex - Mondays and Wednesdays after the lecture; Nathan - Thursdays 03:00-04:00 PM.

Assignments and grading:

Final grade will be based on homework (40%), a take-home final exam (40%), and active participation in classes (20%)

Prerequisites & Audience:

Prerequisites: Basic knowledge of multivariate calculus, differential equations, linear algebra, multivariate probability theory, and scientific programming.

Intended Audience: This course is aimed at graduate students and advanced undergraduates.

Sample reading list:

Neural Computation:

1. *Theoretical Neuroscience* by Peter Dayan and Larry Abbott
2. *Introduction to the Theory of Neural Computation* by John Hertz et al.
3. *Information theory, inference, and learning algorithms* by David MacKay. Free online: http://www.inference.org.uk/itprnn/book.html
4. *Deep learning* by Goodfellow et al. Free online: https://www.deeplearningbook.org/

Background material

1. *Neuroscience: Exploring the Brain* by Bear, Connors and Paradiso
2. *Probability and Random Processes* by R. Grimmett and D. Stirzaker
3. *Linear Algebra and Its Applications* by G. Strang
4. *Elements of Information Theory* by Cover and Thomas
5. *Nonlinear Dynamics and Chaos* by S. Strogatz
6. *Handbook of Stochastic Methods: for Physics, Chemistry and the Natural Sciences* by C.W. Gardiner