NEUR 2110 – STATISTICAL NEUROSCIENCE – FALL 2026 – Tentative Syllabus

Instructor: Prof. Wilson Truccolo **E-mail:** Wilson_Truccolo@Brown.edu, Tel: x3.2161
Meeting time/location: WF 11:00 am – 12:30 pm, Sayles Hall, Room 105
Office hours: Monday 11:00 am – 12:00 pm, Sayles Hall, Room 105 (**appointments via email**)
Course website: Use Canvas (\Files) to access assigned readings, papers, homework assignments, etc
Organizational meeting: Friday, Sep 11 at 11:00 am, Sayles Hall, Room 105

DESCRIPTION: An introduction to the statistical modeling of multiscale neural dynamics in networks of neurons and large-scale brain networks with a focus on stochastic processes and random dynamical systems. Analysis of dynamical and statistical network properties: stationarity, directed transfer functions, stability and bifurcations, phase transitions. Related applications to prediction, control, low-dimensional representation, probabilistic neural population encoding and decoding are introduced as well. This is a course for senior undergraduate and graduate students with a background in systems/computational neuroscience and/or applied math/biomedical engineering. Lectures are accompanied by hands-on Python/Matlab-based applications to real and simulated neural data. Topics include (1) time and spectral domain models of network dynamics based on multivariate neural time series and point process observations with exogenous inputs; vector autoregressive processes, nonlinear Hawkes processes; stability, transfer functions; (2) identification of directed interactions in networks of neurons and brain inter-areal communication (Granger causality, transfer entropy, ODE networks); (3) collective dynamics and low-dimensional representations of network dynamics; (4) Prediction, neural population encoding and decoding for brain-computer interfaces: Bayesian probabilistic approaches based on linear/nonlinear state-space models, machine learning; (5) data assimilation for modeling neural network dynamics. Example datasets include neuronal spike trains, local field potentials, ECoG/SEEG. Instructor permission required.

LEVELS: Undergraduate/Graduate; **Grading:** Standard; Instructor permission required.

PREREQUISITES: Introduction to neuroscience and/or neuroengineering, systems neuroscience, introduction to statistics and probability, calculus and linear algebra, Python or Matlab programming; Familiarity with stochastic processes, difference/differential equations and related math background is a plus.

COURSE OUTCOMES: Upon successful completion of this course, students should be able to demonstrate:

(1) An understanding of the basic probability and statistical theory, concepts and principles underlying the current main approaches for modeling and analysis of time series and point processes obtained from neural measurements;

(2) An ability to implement and apply the presented modeling and analysis methods to simulated and actual neural data;

(3) An understanding of the main issues and caveats underlying the application of the introduced methods to neural data.

CREDIT HOURS: Over the fall term, students are expected to spend ~ 3 hours per week in class (36 hours total), 10 hours per week for reading and computational homework assignments (120 hours total). In addition, there is a final take-home exam for which approximately 30 hours of content review and work are anticipated.

ACCOMODATIONS: Brown University is committed to full inclusion of all students. Please inform me early in the term if you have a disability or other conditions that might require accommodations or modification of any of these course procedures. You may speak with me after class or during office hours. For more information, please contact Student and Employee Accessibility Services at 401-863-9588 or SEAS@brown.edu.

ASSIGNMENTS/ASSESSMENTS. Students will receive evaluation from two sources: (1) Homework assignments: 65% of grade. A computational homework will be assigned approximately every week / two lectures. (2) Final exam assignment: 35% of grade.

NEUR 2110 – STATISTICAL NEUROSCIENCE – FALL 2026 – TENTATIVE CLASS SCHEDULE

Lecture	Date	Topic
	09/11	Course overview and organizational meeting
		MODELING/ANALYSIS OF NEURAL TIME SERIES: NETWORK DYNAMICS
1	09/16	**Univariate stationary stochastic processes:** introduction
2	09/18	**Stationary processes**: univariate autoregressive processes AR(p)
3	09/23	**Spectral representation of stationary processes:** Fourier transform and power spectra
4	09/25	**Spectral estimation:** power spectra, multitaper method, nonstationarity and spectrograms, wavelet transforms
5	09/30	**Multivariate stationary processes and spectral estimation:** spectral matrix, cross-power, coherence, partial coherence
6	10/02	**Vector (Multivariate) AR(p):** stability, spectra, transfer functions, Wilson spectral factorization
7	10/07	**Directed neural network interactions:** Granger causality & transfer entropy
8	10/09	**Granger causality:** applications
9	10/14	**Cross-frequency amplitude-phase nonlinear coupling:** filtering & Hilbert transform
10	10/16	**Cross-frequency amplitude-phase nonlinear coupling:** statistical assessment
		MODELING STOCHASTIC NEURAL POINT PROCESSES: DYNAMICS / ENCODING
11	10/21	**Neural point process: basic theory** (a) General point processes, (b) conditional intensity function (CIF), (c) sample path pdfs, (d) homogeneous and inhomogeneous Poisson processes
12	10/23	**Neural point process: renewal processes** (a) Inter-Spike Interval (ISI) distributions and homogeneous renewal processes, e.g. Gamma and inverse Gaussian ISI distributions; (b) MLE and goodness-of-fit tests.
13	10/28	**Point process models based on CIF models: inference & statistical assessment** (a) MLE for CIF models within the Generalized Linear Model (GLM) framework, (b) Time rescaling theorem and goodness-of-fit tests, (c) predictive power.
14	10/30	**CIF models for single-neuron intrinsic dynamics:** (a) Univariate (auto-history) point process models, (b) nonlinear Hawkes processes with exogenous inputs, (c) basis functions for history temporal filters.
15	11/04	**Neuronal network dynamics:** multivariate (cross-history) point process models (a) Modeling stochastic dynamics in neuronal networks, (b) Multivariate nonlinear Hawkes process, (c) Examples: retina; human & non-human primate neocortex
16	11/06	**Analysis of neuronal circuits based on point process models:** (a) directed interactions; (b) algorithms for large-scale neuronal recordings.
17	11/11	**Neural point process spectra**
18	11/13	**Neural spike-field coherence & PP-GLMs**
		STATE-SPACE MODELS: NEURAL DECODING, CONTROL, COLLECTIVE DYNAMICS
19	11/18	**Stochastic state-space models for decoding:** Bayesian probabilistic decoding and linear Gaussian state-space models
20	11/20	**Stochastic nonlinear state-space models for decoding:** state-space models with point process nonlinear observations
	11/25 11/27	Final exam release; Thanksgiving break
21	12/02	**Latent state-space models:** system identification, prediction and control
22	12/04	**Latent state-space models:** low-dimensional collective (population) dynamics in neuronal networks, neural decoding and other applications
	12/12	Final exam due before midnight

Note: Weekly homework assignments will be assigned on Wednesdays and due on the following Tuesday before midnight.

Although collaboration is encouraged for exchanging ideas and clarifications, a student's name on any assignment report is regarded as assurance that the report is the result of the student's own efforts, thoughts and study, stated in his or her own words. If you use AI, you must document your usage (prompt history, etc.) with a footnote or appendix for more extensive uses. If asked, you must be able to explain your work in a verbal face-to-face conversation.

REFERENCES: Lecture handouts will be provided together with references to corresponding technical papers. Introductory background for about 1/3 of the content can be found in: (1) Kramer and Eden (2016) Case Studies in Neural Data Analysis; (2) Kass, Eden, Brown (2014) Analysis of Neural Data; (3) Gabbiani and Cox (2017) Mathematics for Neuroscientists. For the remaining content, references will consist mostly of journal articles.