Course ID and Title: ECE 599 Data Science: Models and Systems Applications

Units: 4

Fall 2024 — Mondays and Wednesdays — Time: 2:00 – 3:50 pm

Location: KAP158

Instructor: Paul Bogdan

Office: EEB 304

Office Hours: EEB 304 Mondays and Wednesdays 4:00 – 5:30pm

Contact Info: pbogdan@usc.edu Phone number: 213-821-5720 (office). Timeline for replying to emails/calls: I usually respond to emails within 24 hours or as soon as I get to read them, in the event that I get sick or other emergencies, it may take longer to respond to emails. Responding to phone calls is harder because I do not have time to check my phone and spend most of my time with mathematical derivations.

Teaching Assistant: Xiong Ye Xiao

Office: EEB 351

Office Hours: Tuesdays and Thursdays 4:00 – 5:30pm

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IT Help: TBD

Hours of Service: TBD

Contact Info: [Email, phone number (office, cell), Skype]

Course Description

From system biology, network physiology, neuroscience, complex particle systems and complex cyber-physical systems (e.g., medical devices, bacteria engineered swarms for monitoring and drug delivery, power grids, smart transportation infrastructures) to social systems, data arises in all kinds of forms. Typically, the monitoring of physiological, biological and brain systems leads to time indexed data streams characterized by complex interdependencies, non-Gaussian statistics, non-Markovianity (long-range dependence) and non-ergodicity. Similarly, by observing socio-technical systems for characterizing how online and offline social networks interact and detect abnormalities contributes to complex weighted and hyperweighted graphs with nontrivial topology and geometry. For instance, by mining the intrinsic geometric characteristics of social media interaction characteristics enables accurate machine learning and artificial intelligence frameworks for early detection of fake news and combating strategies against misinformation events. Within this context, this course introduces and discusses a series of recent mathematical models and algorithmic strategies for describing various kinds of data from time series and event- (spike-) trains to weighted (hyperweighted), multi-layer and time varying graphs. A special emphasis will be on decoding and characterizing the (multifractal, differential, hyperbolic) geometry of data for developing mathematical models, analysis, forecasting and control. The mathematical models and related algorithms will be analyzed and discussed in the context of several real-world case studies including brain activity mining, single cell dynamics and cellular reprogramming, vaccine design, voltage blackout forecasting in power grids, and social media misinformation detection as well as complex software controlling autonomous systems and cyber-physical systems.
In this course, we will provide:

(1) a comprehensive overview of mathematical models for modeling shorth-range (Markovian) and long-range (non-Markovian) single-variable and multivariate processes, by considering several real-world case studies from complex particle systems (metamaterials) and cyber-physical systems;
(2) new mathematical concepts (e.g., graph multifractal spectrum, graph specific heat, graph curvature) and algorithmic tools for mining the complexity of data and graph data, as well as developing geometry-inspired machine learning (ML)/ artificial intelligence (AI) frameworks for mining complex data streams;
(3) review statistical machine learning concepts and discuss their statistical physics relations;
(4) new mathematical and algorithmic approaches for quantifying trustworthiness of deep learning architectures.
The course could be of interest to students interested in data science techniques for modeling, analyzing and controlling complex dynamic networks. To acquire deep knowledge in the mathematical concepts discussed, a semester long project will focus on tackling all issues from specification, to modeling / algorithmic development, to simulation / experimental investigation and validation.

Learning Objectives

The learning objectives of this course are:

- To learn and apply the mathematical definitions and concepts to various datasets from healthcare, biological systems, neuroscience, complex particle systems, transportation, power grids, social systems, self-driving cars and avionics;
- To generalize and develop new algorithms for specific data science problems (e.g., reconstructing networks from partial observations, identifying nodes responsible for observed dynamics);
- To apply theoretical concepts to concrete problems and to assess the performance and accuracy of various algorithms on specific datasets;
- To evaluate a proposed solution both analytically and experimentally (e.g., through computational thinking and simulation environments);
- To communicate research results and findings in a logical and persuasive manner

The lectures, project milestones and homework assignments are progressively following these learning objectives.

Prerequisite(s): Background in linear algebra, advanced calculus, probability theory and optimization.
Co-Requisite(s): None.
Concurrent Enrollment: None.
Recommended Preparation: Knowledge about linear algebra EE510 and probability theory EE503.

Course Notes

Lecture slides and additional readings marked as “highly recommended”, “recommended” or “optional” will be distributed in class and also posted on Blackboard before each lecture or the day of the lecture. In addition, homework assignments, laboratory description and supplementary materials will be also posted on Blackboard before each lecture it is assigned with a clearly indicated deadline and corresponding point credits. Although the main concepts will be discussed in detail throughout the course, students are expected to read the “highly recommended / recommended” papers (and may consult the “optional” papers) in order to acquire additional intuition and a strong foundation on the topics covered in this class. Evaluation will be based on homework assignments, in class participation via paper presentation, midterm and a semester-long project. Students should be prepared to put in enough effort to turn in a high-quality research project. Each project should start from a novel (unexplored topic) problem formulation and focus on developing the more appropriate and efficient solution strategy as well as thoroughly evaluate it on synthetic case studies and against the available real world datasets.

Technological Proficiency and Hardware/Software Required

Students are expected to have basic knowledge in at least one of the following high-level and general-purpose programming languages and environments: MATLAB, C/C++, Python. The basic knowledge refers to programming abilities to read and modify the provided codes in the project milestones. However, we will strive to help each student learn Python and corresponding programming environments which are crucial for statistical machine learning, statistical analysis and artificial intelligence based solution strategies evaluation.

Required Readings and Supplementary Materials

There is no single textbook containing all the concepts, topics and subjects to be discussed, reviewed and developed in this class. As highlighted earlier, the focus of this course is on reviewing and discussing very recent mathematical and algorithmic strategies (published in top ML/AI conferences and journals within the last 5 years), identify their benefits and drawbacks and, most importantly, initiate new mathematical modeling strategies based on the concepts discussed in this class. During each lecture, a number of scholarly articles or book chapters will be posted on USC Blackboard, marked as Highly Recommended / Recommended / Optional readings and covered to a large extent in the lecture materials. Some suggested readings are selected from the following books (but please note that the focus of the lecture is on current and forward-looking topics):

- V. Pipiras and M.S. Taqqu, *Long-Range Dependence and Self-Similarity*, Cambridge University Press, 2017.
- G.E.P. Box, et al. *Time series analysis: forecasting and control*. John Wiley & Sons, 2015.
- P. Abry, P. Goncalves and J.L. Vehel, *Scaling, Fractals, and Wavelets*, Wiley, 2013.
- G. Bianconi, *Multilayer Networks*, Oxford University Press, 2018
- S. N. Dorogovtsev and J.F.F. Mendes, Evolution of Networks From Biological Nets to the Internet and WWW, Oxford University Press, 2013.
- L. Wasserman, *All of Statistics: A Concise Course in Statistical Inference*, Springer, 2013.
- T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning Data Mining, Inference, and Prediction*, Springer 2013.
- M. Newman, *Networks*, Oxford University Press, 2018.
- A.-L. Barabási and M. Posfai, Network Science, Cambridge University Press, 2018.

However, the class material will be self-contained and I can help you with suggestions to which books, chapters and articles you should read if you are interested in a particular subject as class progresses.

Description and Assessment of Assignments

The learning objectives and outcomes will be assessed through homework assignments and a semester-long research project on an unexplored or poorly topic. The homework assignments assigned every two or three weeks will consist of questions and problem sets meant to test the understanding and assessment level of the knowledge discussed during the lectures. Every two or three weeks (depending on the difficulty of the homework assignment and the course workload such as upcoming project milestone) a homework assignment is returned, solutions are posted, and a new one is posted. The questions and problems sets in the homework assignments will include reading and researching the posted lecture materials and scholarly articles to assimilate the concepts discussed in class, as well as pencil-and-paper and programming exercises to achieve a comprehensive understanding. Mentoring and discussions of the homework assignment solutions will be provided during office hours.

The project is a major component of this course. Students can either choose their own project relevant to the course, pick one from the suggested topics or define their own problem formulation. In all such cases, the outcome of the project should be an original research inquiry and finding (simply implementing a strategy in a certain scholarly publication will not be accepted as project for this class), well documented with regard to related work, well-supported by either theoretical proofs or experimental investigation / validation. Students are encouraged to think big and develop out-of-the-box approaches that may lead to the development of significant solutions to problems in these areas of research. The project will count for 50% of the course grade. The project will consist of four milestones:

i) *Project definition*: Students are required to submit a 2 pages report stating the motivation for a specific project topic, discussing any prior work on solving related problem formulations or addressing challenges, outlining the problem statement, summarizing the main challenges, and formulating a tentative work plan to address the anticipated challenges. This milestone 1 will count for 5% of the course grade. The report must use the following template https://neurips.cc/Conferences/2023/PaperInformation/StyleFiles and written / developed throughout the course of the course in Overleaf to avoid losing previously obtained results and have a robust place where all approaches and results have been recorded.

ii) *Project updates*: There are two project updates consisting of: In milestone 2, students are required to submit a 4-page report (which builds on their previous write-up) summarizing the proposed solution, discuss the various candidate strategies to solve the formulated problem and receive feedback from faculty, TA and class participants. In milestone 3, students are required to submit a 6-page report discussing the improvements developed in the project based on the feedback received in milestone 2, modifying or justifying the pursued design methodology, and describing rigorous and verified preliminary results. A special emphasis will be put on understanding the concepts discussed in class and developing new algorithms and tools to solve the newly formulated problems in these projects. The milestones 2 and 3 will count for 10% and 15%, respectively, of the course grade.

iii) *Project evaluation*: Students are required to submit an 8-page report discussing the main results and contrasting the proposed solution with state-of-the-art solutions. The final milestone 4 will count for 20% of the course grade. The detailed requirements for each milestone reports and presentations will be posted on Blackboard before lecture 1. Final evaluation will consist on both the oral presentation of the project through an in class or poster presentation and the written report and submitted to faculty and TA as detailed in the disseminated project guidelines.

Project presentation: Students are required to present their main project findings in an interactive session. Students will have approximately three to four weeks to work on each project milestone. Project teams of up to two or three students will be allowed, but a statement will have to be included detailing each student's contribution and assigning an agreed upon percentage contribution. The final project grade will be weighted accordingly. The course includes an overview exam which will test the assimilation of theoretical concepts discussed during the lecture hours.

Participation

In-class participation will be randomly evaluated through unannounced quizzes. Participation will not exceed 5% of the total grade.

Grading Breakdown

All students are required to attend all lecture and laboratory hours. Participation will not contribute towards the final grade, but missing lecture and laboratory hours will likely affect your preparation for examination. The grading scheme is as follows:

Assignment	**Points**	**% of Grade**
Homework assignments (up to 4)	200	20%
Course Project (4 milestones)	500	50%
Course examination	200	20%
Paper presentation + quizzes	100	10%
Total	1000	100

Guidelines on preparing for each individual milestone of the project, as well as the homework and laboratory assignments will contain a clear description of the points breakdown for each topic / question / problem. Failing to address a specific item in the project milestones, homework and laboratory assignment will result in losing the assigned points.

Grading Scale
Course final grades will be determined using the following scale:

Letter grade	Corresponding numerical point range
A	95-100
A-	90-94
B+	87-89
B	83-86
B-	80-82
C+	77-79
C	73-76
C-	70-72
D+	67-69
D	63-66
D-	60-62
F	59 and below

Assignment Submission Policy
Assignments will be posted electronically on Blackboard.

Grading Timeline
All assignments will be graded within three days from the return date.

Course Specific Policies
No late homework or laboratory assignments will be allowed. Extensions can be granted for documented medical emergencies.

Attendance
Class attendance will be highly encouraged., Of note non-attendance can be the basis for lowering the grade, since some of the in-class activities will consist of discussing specific concepts or course project as clearly stated on the syllabus. Attendance policies will address student athletes with approved Travel Request Letters and students who give advance notice of religious observation.

Classroom norms
The classroom norms obey the guiding principle that our primary commitment is to learn from each other through a respectful discussion, expression of opinions and providing logical/scientific justification for each approach. We acknowledge differences among us in disciplines, experiences, interests, and values. Throughout the course we will encourage each student to build on one another's comments, work toward shared understanding, keep the tone and words respectful and productive, allow others a chance to participate as well as empower yourself to participate If you wish to challenge something that has been said, challenge the idea or the practice referred to, not the individual sharing this idea or practice. We will maintain one another's confidence and we want to create an atmosphere for open, honest exchange.

Zoom etiquette
No Zoom sessions, not applicable.

Academic Integrity
The University of Southern California is foremost a learning community committed to fostering successful scholars and researchers dedicated to the pursuit of knowledge and the transmission of ideas. Academic misconduct is in contrast to the university's mission to educate students through a broad array of first-rank academic, professional, and extracurricular programs and includes any act of dishonesty in the submission of academic work (either in draft or final form).

This course will follow the expectations for academic integrity as stated in the USC Student Handbook. All students are expected to submit assignments that are original work and prepared specifically for the course/section in this academic term. You may not submit work written by others or "recycle" work prepared for other courses without obtaining written permission from the instructor(s). Students suspected of engaging in academic misconduct will be reported to the Office of Academic Integrity.

Other violations of academic misconduct include, but are not limited to, cheating, plagiarism, fabrication (e.g., falsifying data), knowingly assisting others in acts of academic dishonesty, and any act that gains or is intended to gain an unfair academic advantage.

The impact of academic dishonesty is far-reaching and is considered a serious offense against the university and could result in outcomes such as failure on the assignment, failure in the course, suspension, or even expulsion from the university.

For more information about academic integrity see the student handbook or the Office of Academic Integrity's website, and university policies on Research and Scholarship Misconduct.

Course Content Distribution and Synchronous Session Recordings Policies

USC has policies that prohibit recording and distribution of any synchronous and asynchronous course content outside of the learning environment.

Recording a university class without the express permission of the instructor and announcement to the class, or unless conducted pursuant to an Office of Student Accessibility Services (OSAS) accommodation. Recording can inhibit free discussion in the future, and thus infringe on the academic freedom of other students as well as the instructor. (Living our Unifying Values: The USC Student Handbook, page 13).

Distribution or use of notes, recordings, exams, or other intellectual property, based on university classes or lectures without the express permission of the instructor for purposes other than individual or group study. This includes but is not limited to providing materials for distribution by services publishing course materials. This restriction on unauthorized use also applies to all information, which had been distributed to students or in any way had been displayed for use in relationship to the class, whether obtained in class, via email, on the internet, or via any other media. (Living our Unifying Values: The USC Student Handbook, page 13).

Course Evaluations

Course evaluation occurs at the end of the semester university-wide. We will request anonymous feedback through the mid-semester evaluation in order to improve and correct our course / instruction practice.

Course Schedule

Date			
August			
26, Mon	Introduction and overview of the course. Review basic probability concepts (e.g., random variable and stochastic process and characterization tools (e.g., auto-covariance, autocorrelation, spectral analysis).	V.V. Uchaikin and V.M. Zolotarev, *Chance and stability: stable distributions and their applications*. Walter de Gruyter, 2011.(Chapters 1 &2)	
28, Wed	Graph theory: introduction and definitions. Graph models: Erdos-Renyi, Strogatz-Watts, Barabasi-Albert. First order statistics: degree distribution. Second order statistics: assortativity distribution. Third order statistics: clustering coefficient distribution. Examples and implications for neuroscience, system biology and social systems.	N.A. Kiani, D. Gomez-Cabrero & G. Bianconi, *Networks of Networks in Biology: Concepts, Tools and Applications,* Cambridge Univ. Press, 2021. C. Yin, X. Xiao, V. Balaban, M.E. Kandel, Y.J. Lee, G. Popescu & P. Bogdan "Network science characteristics of brain-derived neuronal cultures deciphered from quantitative phase imaging data" *Scientific reports* 10, 2020	Homework 1 (assigned)
September			
2, Mon	**Labor Day** (university / federal holiday)		
4, Wed	Graph higher-order statistics: challenges and algorithms for multifractal analysis, node-based multifractal analysis, topological partition function, graph free energy, graph specific heat and phase transition detection.	R. Albert & A.-L. Barabási "Statistical mechanics of complex networks." *Reviews of modern physics*, 2002. S.N. Dorogovtsev & J.F.F. Mendes, Evolution of Networks, 2010. M. Gosak et al.,"Network science of biological systems at different scales: A review" *Physics of Life Reviews*, 2017.	HW 1
9, Mon	Graph distance and graph similarity analysis. Applications of multifractal analysis in network science, biological and chemical sciences, computer science and engineering.	X. Xiao, H. Chen & P. Bogdan. "Deciphering the generating rules and functionalities of complex networks." *Scientific reports* 11, 2021	
11, Wed	Differential geometry of networks: Ollivier-Ricci curvature, community detection, applications to material, chemical, physical and biological sciences, computer science and engineering. Community detection under partial information. Implications for automatic parallelization of software and hardware-soft-codesign, machine learning and artificial intelligence.	J. Sia, E. Jonckheere & P. Bogdan "Ollivier-Ricci curvature-based method to community detection in complex networks" *Scientific reports* 9, 2019 J. Sia, W. Zhang, E. Jonckheere, D. Cook & P.Bogdan "Inferring functional communities from partially observed biological networks exploiting geometric topology and side information" *Scientific Reports* 12, no. 1, 2022	
16, Mon	Detecting phase transitions in evolving graphs from partial information: Forman-Ricci curvature, phase transition detection algorithms, case studies and applications to material, chemical, physical and biological sciences, computer science and engineering. **Milestone 1:** Project definition, in class presentation & discussion	R. Forman "Bochner's method for cell complexes and combinatorial Ricci curvature." Discrete & Computational Geometry 29 (2003): 323-374. M.R. Znaidi, J. Sia, S. Ronquist, I. Rajapakse, E. Jonckheere & P. Bogdan, "A unified approach of detecting phase transition in time-varying complex networks" *Scientific Reports* 13, 2023	M1 in class presentation + written report (2 pages) submitted by end of day.
18, Wed	Graphon definitions & Multifractal graph generators: definitions, mathematical properties, controlling multifractality of weighted graphs / networks. Case studies in living (biological) neuronal networks from neuronal cultures and brain, chromatin conformation, material sciences. **Milestone 1:** Project definition, in class presentation & discussion	L. Lovász & S. Balázs. "Szemerédi's lemma for the analyst" *GAFA Geometric and Functional Analysis* 17 (2007): 252-270. D. Glasscock, "What is... a graphon" *Notices of the AMS* 62, no. 1 (2015): 46-48. R. Yang & P. Bogdan, "Controlling the multifractal generating measures of complex networks," *Scientific reports*, 10, 2020	
23, Mon	Multifractal network generators: inference algorithms and applications. Implications for neuroscience, synthetic & system biology	R. Yang, F. Sala, and P. Bogdan "Hidden network generating rules from partially observed complex networks." *Nature Communications Physics* 4, 2021	
25, Wed	Network reconstruction: problem definition, challenges and algorithms	Y.Xue & P. Bogdan, "Reconstructing missing complex networks against adversarial interventions," *Nature*	

		Communications, 10, 2019	
30, Mon	Hypergraphs and simplicial complexes. Higher-order interactions and learning.		
October			
2, Wed	Extracting graphs / networks from time series: Linear nonstationary models. Short-range memory / dependence vs. Long-range memory / dependence dynamics. Hurst exponent: stationary and nonstationary estimation methods of Hurst exponent. Applications to brain activity mining and power grid analysis.	Chapters 3 & 4, G.E.P. Box, et al. *Time series analysis: forecasting and control*. Wiley & Sons, 2015. A.Montanari, R.Rosso, & M.Taqqu, "Fractionally differenced ARIMA models applied to hydrologic time series: Identification, estimation, and simulation" Water Resources Research, 1997	
7, Mon	Fractional difference operators. Single variable autoregressive fractionally integrated moving average (ARFIMA) & multi-variate ARFIMA models. Applications to physiological processes modeling, brain activity mining and brain-machine-body interfaces. **Milestone 2 (M2):** Project update & discussion.	C.W.J. Granger & R. Joyeux, "An introduction to long-memory time series models and fractional differencing" Journal of Time Series Analysis. 1: 15–30, 1980. Yuankun Xue, Saul Rodriguez & Paul Bogdan "A spatio-temporal fractal model for a CPS approach to brain-machine-body interfaces." *Design, Automation & Test in Europe Conference & Exhibition* (DATE), 2016	M2 in-class presentation + report (4 pages) submitted by end of the day
9, Wed	Identification of multivariate ARFIMA models under unknown unknowns. Case studies concerning brain- machine interfaces, abnormality detection in physiological systems and system biology. **Milestone 2:** Project update & discussion	G. Gupta, S. Pequito and P. Bogdan, "Dealing with Unknown Unknowns: Identification and Selection of Minimal Sensing for Fractional Dynamics with Unknown Inputs," American Control Conference (ACC), 2018.	
14, Mon	Learning latent fractional dynamics with unknown unknowns. Case studies concerning brain- machine interfaces, abnormality detection in physiological systems and system biology.	Gaurav Gupta, Sérgio Pequito, & Paul Bogdan "Learning latent fractional dynamics with unknown unknowns." In 2019 American Control Conference (ACC), pp. 217-222. IEEE, 2019.	
16, Wed	Multi-fractal analysis. Applications to brain activity and gene expression mining. Multi- fractional spatiotemporal differencing. Non- Markovian master equations and non- Markovian partial differential equations. Mathematical modeling of multifractal processes.	Stéphane Jaffard, Bruno Lashermes, and Patrice Abry. "Wavelet leaders in multifractal analysis." In Wavelet analysis and applications, pp. 201-246, 2007. Mahboobeh Ghorbani, Edmond A. Jonckheere, and Paul Bogdan, "Gene expression is not random: scaling, long-range cross-dependence, and fractal characteristics of gene regulatory networks." Frontiers in physiology 9 (2018): 1446.	
21, Mon	Controlling Markovian and non-Markovian dynamical networks over predefined control horizons. Case studies on brain networks and large-scale technological networks.	Emily A. Reed, Guilherme Ramos, Paul Bogdan, and Sérgio Pequito. "The role of long-term power-law memory in controlling large-scale dynamical networks." Scientific Reports 13, no. 1 (2023): 19502.	
23, Wed	From sequences to models and analysis: data-driven approach to learn state generators for genomic sequences and applications in genomics, proteomics and virology	Siddharth Jain, Xiongye Xiao, Paul Bogdan, and Jehoshua Bruck. "Generator based approach to analyze mutations in genomic datasets." *Scientific Reports* 11, no. 1 (2021): 21084	
28, Mon	Physical networks: motivation, models, and opportunities for further development	Gábor Pete, Ádám Timár, Sigurdur Örn Stefánsson, Ivan Bonamassa, and Márton Pósfai. "Physical networks as network-of-networks." Nature Communications 15, no. 1 (2024): 4882.	
30, Wed	Statistics vs. machine learning. Maximum likelihood, Bayes, minmax, parametric vs. nonparametric methods.	Wasserman, Larry. All of nonparametric statistics. Springer Science & Business Media, 2006.	
November			
4, Mon	Artificial neural networks (ANNs), backpropagation, representation learning. Graph neural networks (GNNs). Distributed neural networks. Case studies to social systems, systems biology & computer systems research. **Milestone 3 (M3):** Project update, demo of most interesting results, & discussion.	A. Cheng, H. Ping, Z. Wang, X.Xiao, C. Yin, S. Nazarian, M. Cheng, & P. Bogdan. "Unlocking deep learning: A BP-free approach for parallel block-wise training of neural networks" *IEEE Intl. Conf. on Acoustics, Speech and Signal Processing* (ICASSP), pp. 4235-4239, 2024.	M3 in-class presentation + report submitted by end of the day
6,	CNNs, Recurrent NNs, LSTMs, Seq2seq,		

Wed	Transformer. Case studies to social systems, systems biology & computer systems research. **Milestone 3 (M3):** Project update, demo of most interesting results, & discussion.		
11, Mon	**Veterans Day**		
13, Wed	Causal inference. Minimax theory. Paper discussion.	J. Pearl, "Causal inference" Causality: objectives and assessment (2010): 39-58. P. Spirtes, "Introduction to causal inference." Journal of Machine Learning Research 11, no. 5 (2010).	
18, Mon	Distribution-free predictive inference: conformal prediction. High-dimensional statistics, concentration inequalities, Rademacher complexity, random matrices. Paper discussion.	M. Wainwright, *High-dimensional statistics: A non-asymptotic viewpoint*. Cambridge university press, 2019. C. Giraud, Introduction to high-dimensional statistics. Chapman and Hall/CRC, 2021. J. Lei and L. Wasserman. "Distribution-free prediction bands for non-parametric regression." Journal of the Royal Statistical Society Series B: Statistical Methodology 76, no. 1 (2014): 71-96.	
20, Wed	PCA and renormalization group. Paper discussion.	S. Braddeand W. Bialek. "Pca meets rg." Journal of statistical physics 167 (2017): 462-475.	
25, Mon	Markovian (model based) reinforcement learning vs Non-Markovian reinforcement learning. Paper discussion.	Thomas Moerland, Joost Broekens, Aske Plaat, & Catholijn M. Jonker. "Model-based reinforcement learning: A survey." Foundations and Trends® in Machine Learning 16, no. 1 (2023): 1-118. Gaurav Gupta, Chenzhong Yin, Jyotirmoy Deshmukh, and Paul Bogdan. "Non-markovian reinforcement learning using fractional dynamics." IEEE Conference on Decision and Control (CDC), pp. 1542-1547, 2021.	
27, Wed	**Thanksgiving Holiday**		
December			
2, Mon	Probabilistic reasoning & subjective logic, quality of data, trustworthiness. Paper discussion.	A. Josang, Ross Hayward, and Simon Pope. "Trust network analysis with subjective logic." *Proceedings of the Twenty-Ninth Australasian Computer Science Conference* (ACSW), pp. 85-94. 2006. Fabio Massimo Zennaro & Audun Jøsang. "Using subjective logic to estimate uncertainty in multi-armed bandit problems." arXiv:2008.07386 2020.	
4, Wed	Quantifying trust in deep learning and related machine learning architectures and case studies. Paper discussion.	M. Cheng et al. "There is hope after all: Quantifying opinion and trustworthiness in neural networks." Frontiers in artificial intelligence 3, 2020	
6, Fri	**Milestone 4 (M4):** Final project presentation and demo. M4 report (8 pages) electronically submitted by Dec. 10th 2024		Milestone 4

Statement on Academic Conduct and Support Systems

Academic Integrity:

The University of Southern California is a learning community committed to developing successful scholars and researchers dedicated to the pursuit of knowledge and the dissemination of ideas. Academic misconduct, which includes any act of dishonesty in the production or submission of academic work, comprises the integrity of the person who commits the act and can impugn the perceived integrity of the entire university community. It stands in opposition to the university's mission to research, educate, and contribute productively to our community and the world.

All students are expected to submit assignments that represent their own original work, and that have been prepared specifically for the course or section for which they have been submitted. You may not submit work written by others or "recycle" work prepared for other courses without obtaining written permission from the instructor(s).

Other violations of academic integrity include, but are not limited to, cheating, plagiarism, fabrication (e.g., falsifying data), collusion, knowingly assisting others in acts of academic dishonesty, and any act that gains or is intended to gain an unfair academic advantage.

The impact of academic dishonesty is far-reaching and is considered a serious offense against the university. All incidences of academic misconduct will be reported to the Office of Academic Integrity and could result in outcomes such as failure on the assignment, failure in the course, suspension, or even expulsion from the university.

For more information about academic integrity see the student handbook or the Office of Academic Integrity's website, and university policies on Research and Scholarship Misconduct.
Please ask your instructor if you are unsure what constitutes unauthorized assistance on an exam or assignment, or what information requires citation and/or attribution.

Students and Disability Accommodations:

USC welcomes students with disabilities into all of the University's educational programs. The Office of Student Accessibility Services (OSAS) is responsible for the determination of appropriate accommodations for students who encounter disability-related barriers. Once a student has completed the OSAS process (registration, initial appointment, and submitted documentation) and accommodations are determined to be reasonable and appropriate, a Letter of Accommodation (LOA) will be available to generate for each course. The LOA must be given to each course instructor by the student and followed up with a discussion. This should be done as early in the semester as possible as accommodations are not retroactive. More information can be found at osas.usc.edu. You may contact OSAS at (213) 740-0776 or via email at osasfrontdesk@usc.edu.

Support Systems:

Counseling and Mental Health - (213) 740-9355 – 24/7 on call
Free and confidential mental health treatment for students, including short-term psychotherapy, group counseling, stress fitness workshops, and crisis intervention.

988 Suicide and Crisis Lifeline - 988 for both calls and text messages – 24/7 on call
The 988 Suicide and Crisis Lifeline (formerly known as the National Suicide Prevention Lifeline) provides free and confidential emotional support to people in suicidal crisis or emotional distress 24 hours a day, 7 days a week, across the United States. The Lifeline is comprised of a national network of over 200 local crisis centers, combining custom local care and resources with national standards and best practices. The new, shorter phone number makes it easier for people to remember and access mental health crisis servic

(though the previous 1 (800) 273-8255 number will continue to function indefinitely) and represents a continued commitment to those in crisis.

Relationship and Sexual Violence Prevention Services (RSVP) - (213) 740-9355(WELL) – 24/7 on call
Free and confidential therapy services, workshops, and training for situations related to gender- and power-based harm (including sexual assault, intimate partner violence, and stalking).

Office for Equity, Equal Opportunity, and Title IX (EEO-TIX) - (213) 740-5086
Information about how to get help or help someone affected by harassment or discrimination, rights of protected classes, reporting options, and additional resources for students, faculty, staff, visitors, and applicants.

Reporting Incidents of Bias or Harassment - (213) 740-5086 or (213) 821-8298
Avenue to report incidents of bias, hate crimes, and microaggressions to the Office for Equity, Equal Opportunity, and Title for appropriate investigation, supportive measures, and response.

The Office of Student Accessibility Services (OSAS) - (213) 740-0776
OSAS ensures equal access for students with disabilities through providing academic accommodations and auxiliary aids in accordance with federal laws and university policy.

USC Campus Support and Intervention - (213) 740-0411
Assists students and families in resolving complex personal, financial, and academic issues adversely affecting their success as a student.

Diversity, Equity and Inclusion - (213) 740-2101
Information on events, programs and training, the Provost's Diversity and Inclusion Council, Diversity Liaisons for each academic school, chronology, participation, and various resources for students.

USC Emergency - UPC: (213) 740-4321, HSC: (323) 442-1000 – 24/7 on call
Emergency assistance and avenue to report a crime. Latest updates regarding safety, including ways in which instruction will be continued if an officially declared emergency makes travel to campus infeasible.

USC Department of Public Safety - UPC: (213) 740-6000, HSC: (323) 442-1200 – 24/7 on call
Non-emergency assistance or information.

Office of the Ombuds - (213) 821-9556 (UPC) / (323-442-0382 (HSC)
A safe and confidential place to share your USC-related issues with a University Ombuds who will work with you to explore options or paths to manage your concern.

Occupational Therapy Faculty Practice - (323) 442-2850 or otfp@med.usc.edu
Confidential Lifestyle Redesign services for USC students to support health promoting habits and routines that enhance quality of life and academic performance.