Revision of Existing Graduate Course
Stevens Institute of Technology

School: **School of Engineering and Science**

Course Title: **Statistical Machine Learning**

Program(s): Computer Science

Proposed Course # or Level: CS560

Catalog Description:

Machine learning aims to extract useful information from the data, and to build an accurate model on top of the extracted information for future prediction. There are two important aspects that have to be taken into account for a machine learning problem: how can we develop computationally efficient algorithms to learn useful information, and what is the prediction performance of the algorithm on unseen data. More importantly, is it possible to achieve the best of the two worlds, or there has to be some trade-off. This course will introduce students to concepts relatingthe computational efficiency and the statistical accuracy for a broad range of problems, including regression, classification, clustering, adaptive learning, to name a few. It will cover popular numerical methods that carry out state-of-the-art performance on the computational side, and it will also discuss possible improvement in the price of estimation accuracy and memory usage. The goal of the course is to help students understand these trade-offs from atheoretical perspective and guide them to design near-optimal algorithms for real-world problems.

Course Objectives:

This course will lay solid theoretical foundation of machine learning. Students will learn a number of theoretical models, their developments, and the state-of-the-art results in the literature. Students will understand tradeoffs in machine learning algorithms, such as prediction accuracy, running time, and memory cost.

List of Course Outcomes:

1. Analyze complexity measures for machine learning models

2. Analyze sample complexity for linear models

3. Implement algorithms for learning from high-dimensional data

4. Analyze label complexity for linear models

5. Implement techniques to address practical concerns such as robustness and fairness

Prerequisites:[1] CS559

Cross-listing: None.

Grading Percentages: HW 20% Class work 0% Mid-term 40% Final 40% Project 0%

Other 0%

Credits: 3 credits

For Graduate Credit toward Degree or Certificate
Yes

Textbook(s) or References

Required: None.

Recommended:

S. Ben-David and S. Shalev-Shwartz, Understanding Machine Learning: From Theory to Algorithms, Cambridge University Press, 2014

Mode of Delivery Class

Program/Department Ownership: Computer Science

When first offered: 2019 Fall

Department Point of Contact and Title: Jie Shen, Assistant Professor

Date approved by individual school and/or department curriculum committee:

[1] You may provide a list of courses, competencies or other criteria (e.g., "Students must have taken CS 6XX" or "Students must have taken a course in thermodynamics," or "Students must be part of a certain cohort.")

Sample Syllabus: This syllabus should be sufficiently detailed to allow the Graduate Curriculum Committee to understand and discuss the scope of the course, its aims and assignments. The homework and reading sections should provide sufficient detail for the Committee to judge the amount and kind of work required of students. The Committee understands that this syllabus is a sample of how a course might be organized, not a commitment to always offer the course exactly as described every time. Note that a syllabus is not merely a listing of topics or a restatement of the catalog description.

	Topic(s)	**Reading(s)**	**Class exercises (Optional)**	**HW**
Week 1	Review of linear algebra and probability theory, concentration bounds			
Week 2	PAC learning: uniform convergence	Chapter 2 & 3 of the recommended book		
Week 3	PAC learning: VC dimension	Chapter 4		HW1: calculating VC dimension
Week 4	Rademacher complexity	Chapter 26		
Week 5	Multiclass learnability (part 1)	A Characterization of Multiclass Learnability, by Brukhim et al. 2022		

Week 6	Multiclass learnability (part 2)	A Characterization of Multiclass Learnability, by Brukhim et al. 2022		
Week 7	High-dimensional statistics	Chapter 23		HW2: designing learning algorithms for high-dimensional data
Week 8	Linear models and algorithms	Chapter 15		
Week 9	Online learning	Chapter 21		
Week 10	Active learning	Margin-based active learning, by Balcan et al 2007		HW3: implement the margin-based active learning algorithm
Week 11	Noise-tolerant learning	The Power of Localization for Efficiently Learning Linear Separators with Noise, by Awasthi et al. 2017		
Week 12	Boosting (part 1)	Chapter 10		
Week 13	Boosting (part 2)	Chapter 10		HW4: implement boosting

Week 14	Crowdsourcing	Efficient PAC learning from the crowd, by Awasthi et al. 2017		