



Course title and number Machine Learning: CSCE 489
Term Spring 2019
Meeting times and location MWF 9:10 am - 10:00 am, H. R. Bright Building 113

Course Description and Prerequisites

Technical foundations of machine learning, pattern recognition, and generating predictive models/classifiers from data. Topics include methods for supervised and unsupervised learning (decision trees, linear discriminants, naïve Bayesian classifier, support vector machines and kernel methods, clustering, dimensionality reduction, neural networks and deep learning), optimization procedures, and statistical inference.

Prerequisites: MATH 304 and STAT 211, and (CSCE 221 or STAT 404)

Students are expected to have some familiarity with basic linear algebra, including vectors, matrices, matrix-vector computations, vector and matrix norms, linear independence, matrix rank, singularity, positive definiteness, eigenvalues/eigenvectors, matrix decomposition, orthogonality, multivariate calculus, including derivatives of univariate functions, derivatives of multivariate functions, chain rule, Taylor expansion, and basic probability and statistics, including discrete and continuous probability distributions, sum rule, product rule, marginal probability distributions, conditional probability distributions, joint probability distributions, independence and conditional independence, Bayes Theorem, variance and covariance, expectation.

Learning Outcomes or Course Objectives

The objective of this course is to teach fundamental methods of machine learning with focus on the theoretical underpinnings, practical implementations, and experimentation. Upon completion of the course students will:

1. Have a good understanding of the fundamental issues and challenges of machine learning: data, model selection, model complexity, etc.
2. Have an understanding of the strengths and weaknesses of many popular machine learning approaches.
3. Appreciate the underlying mathematical relationships within and across Machine Learning algorithms and the paradigms of supervised and un-supervised learning.
4. Be able to design and implement various machine learning algorithms in a range of real-world applications.

Instructor Information

Name Shuiwang Ji
Telephone number (979) 458-1547
Email address sji@tamu.edu
Office hours MW 10:00 am - 11:00 am, or by appointment
Office location HRBB 410C

TA Information

Name Yaochen Xie
Email address: ethanycx@tamu.edu
Office Hours: MWF 1-2pm
Office Location: HRBB 520

Textbook and/or Resource Material

- Learning from Data, by Yaser S. Abu-Mostafa, Malik Magdon-Ismael, and Hsuan-Tien Lin
- Machine Learning, McGraw Hill by Tom Mitchell
- Neural Networks and Deep Learning: A Textbook, Springer, by Charu Aggarwal

Assignments and Exams

1. Assignments (6). Most homework contains a written component and a programming component. Therefore, most homework submission should include a report and code. Submission instructions will be provided on each homework assignments. Most homework requires Python programming. Data and skeleton code will be provided in Python format.

2. Two exams (mid-term and final).

Grading Policies

1. Assignments: 60%
2. Exams: 40% (15% for mid-term and 25% for final), **Final exam will be Friday, May 3, 8:00-10:00 a.m.**

Attendance

All absences will be handled according to Texas A&M student rule 7 <http://student-rules.tamu.edu/rule07> It is *your* responsibility to keep up with the class, even when unexpected events interfere.

Missed Exams

Missed exams will only be rescheduled for university excused absences. Note that if advanced notice is not feasible, you have 2 business days to provide notification. A zero will be assigned for exams due to an unexcused absence. Documentation must be submitted prior to making up a missed exam or quiz.

Late Homework

Late homework assignments will be accepted up to 4 days late with a 5% penalty for each late day. No penalty for excused absences turned in up to four days after return to class. Please discuss unusual circumstances in advance with the instructor.

The midterm exam is scheduled for TBD, in class. The final exam is scheduled according to University Final Examination policy.

Grading Scale

A = 90-100
B = 80-89
C = 70-79
D = 60-69
F = <60

Course Topics (subject to change)

Week	Topic
1	Introduction, Linear algebra review
2	Linear regression
3	Logistic regression
4	Probability review
5	Basic probability and naïve Bayes classifier
6	Generalization and overfitting

- 7 Support vector machines and kernel methods
- 8 A unified view of supervised learning
- 9 Neural networks
- 10 Deep learning
- 11 Multi-class learning
- 12 Decision tree and random forests
- 13 Dimension reduction, principal component analysis
- 14 Unsupervised learning and K-means clustering, spectral clustering

Americans with Disabilities Act (ADA)

The Americans with Disabilities Act (ADA) is a federal anti-discrimination statute that provides comprehensive civil rights protection for persons with disabilities. Among other things, this legislation requires that all students with disabilities be guaranteed a learning environment that provides for reasonable accommodation of their disabilities. If you believe you have a disability requiring an accommodation, please contact Disability Services, currently located in the Disability Services building at the Student Services at White Creek complex on west campus or call 979-845-1637. For additional information, visit <http://disability.tamu.edu>.

Academic Integrity

For additional information please visit: <http://aggiehonor.tamu.edu>

"An Aggie does not lie, cheat, or steal, or tolerate those who do."