Course Syllabus
STM 3915 – Special Topics: Mathematics of Machine Learning (4.5 credits)
Winter Term AY25–26

Instructor information

Alexander Kolpakov, akolpakov@uaustin.org
Office hours: as announced on Populi; otherwise by appointment

Course meeting schedule

2pm-3:15pm MWF

Required Text(s)

- Gareth James et al. An Introduction to Statistical Learning (with application in Python) https://www.statlearning.com/
- Trevor Hastie et al. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. https://hastie.su.domains/ElemStatLearn/
- Learn PyTorch for Deep Learning: Zero to Mastery Book. https://www.learnpytorch.io/

Course description

This course in quantitative reasoning aims to provide students with a foundation in key theoretical concepts of machine learning, while including practical programming projects. The course will be sufficiently advanced in its mathematical concepts, yet focus on hands-on implementations and real-world data analysis. Topics include linear regression, logistic regression, decision trees (with ensemble learning), and deep learning, with an emphasis on the theoretical understanding of models as well as practical implementation using Python/Scikit-learn. The main objective of the course is to provide the mathematical basics and the "big picture" of supervised machine learning, with practical exercises to stimulate students' interest. Additional literature will be provided for in-depth independent learning.

Course learning outcomes

Upon successful completion of this course, a student will be able to:

- Articulate the minimal theoretical background of most common ML techniques
- Understand the theoretical underpinnings of model development and training
- Able to use common ML libraries (PyTorch, Sklearn) in practice

Center learning outcomes

- Speak, read, and write in mathematical language
- Formulate and solve quantitative problems using appropriate technical language, models, and techniques
- Collect and analyze data using appropriate technology tools
- Communicate technical solutions clearly through writing, speaking, and visualization

Course Policies/Requirements

- Your instructor will specify all homework assignments, quizzes, projects, and examinations,
along with required completion dates. Daily assignments will be updated on Populi.

- Late assignments will not be accepted. The final course examination will be held during the university-wide exam week after Week 10.

- No makeup exams will be given unless you have a prior excusal or are sick in quarters. It is your responsibility to arrange for a makeup exam if required.

- Grading for this course will be consistent with university policy.

- Grade weighting will be:

1. *Weekly Projects and Problems: 25%*
2. *Quizzes: 20%*
3. *In-class solution presentation: 20%*
4. *Final Exam: 35%*

- You are expected to read/watch supporting material before the class session in order to be able to participate actively in discussion.

- Collaboration on homework is encouraged. Document any such collaboration.

- You may refer to outside sources to assist with homework. Document any such assistance.

- Cheating will not be tolerated. In particular, exchanging electronic files containing work you have done for a graded assignment is prohibited unless stated otherwise. Cheating also includes but is not limited to looking at another student's quiz or exam, copying someone else's homework, and using unauthorized material during a quiz or exam.

- You must have a laptop available for use outside of class. Laptops will be used periodically in class at the instructor's discretion. The use of computing technology is encouraged in support of all work outside of class unless otherwise stated.

- Please see the Student Handbook for policies regarding support for special needs or disabilities.

Attendance and Tardiness Policy

- Attendance is mandatory.

- Each student may miss 10% of classes for any reason, with no excuse needed, and without penalty, i.e., 1, 2, or 3 classes, respectively, in a 1.5, 3, or 4.5 credit course.

- After that, each additional absence (for any reason) will result in a 4% or 6% or 12% final grade penalty for a 4.5 or 3.0 or 1.5 credit course, respectively.

- Missing more than 25% of the classes in a course (without medical excuse), including "free" absences, will result in failing the course.

- Being more than 20 minutes late to a class counts as an unapproved absence.

Accessibility Statement
Please review the University Accessibility Statement in the student catalog. Students having special needs should contact the Polaris Center or email accomodations@uaustin.org
Disability Support Services: The university will make reasonable accommodations for students with disabilities in compliance with Section 504 of the Rehabilitation Act and the Americans with Disabilities Act. The purpose of accommodations is to provide equal access to educational opportunities for eligible students with academic and/or physical disabilities.

Academic Misconduct
Instructors at UATX have the authority to assess possible plagiarism, unauthorized use of artificial intelligence, and other forms of cheating in their courses. Normally, cheating will result in failing the assignment.

Course outline (subject to change)

Week	Dates	Topic
1	5-Jan	Introduction to Basic Concepts: necessary calculus and linear algebra
	7-Jan	Bias-Variance Tradeoff and Learning
	9-Jan	Computational Project | Problem session
2	12-Jan	Linear Regression Fundamentals
	14-Jan	Errors, residuals, goodness-of-fit (R2)
	16-Jan	Computational Project | Problem session
3	19-Jan	Applied Linear Regression with ML Libraries
	21-Jan	Training and evaluating models: training, test splits, cross-validation
	23-Jan	Computational Project | Problem session
4	26-Jan	Introduction to Logistic Regression
	28-Jan	DAGs, Confounding, and Causality
	30-Jan	Computational Project | Problem session
5	2-Feb	Applied Logistic Regression with ML Libraries
	4-Feb	Evaluation metrics: confusion matrix, accuracy, precision, recall, F1-score
	6-Feb	Computational Project | Problem session
6	9-Feb	Introduction to Decision Trees
	11-Feb	Criteria for splitting: Gini impurity, entropy, and mutual information
	13-Feb	Computational Project | Problem session
7	16-Feb	Tree Classifiers with ML Libraries
	18-Feb	Power of Ensemble Learning
	20-Feb	Computational Project | Problem session
8	23-Feb	Introduction to Deep Neural Networks
	25-Feb	Nonlinearity and Activation Functions
	27-Feb	Computational Project | Problem session
9	2-Mar	Backpropagation for Model Training
	4-Mar	Multi-Layer Perceptron (MLP)
	6-Mar	Computational Project | Problem session
10	9-Mar	Stochastic Gradient Descent
	11-Mar	Fine-Tuning and LoRA
	13-Nov	Computational Project | Problem session