10701: Intro to Machine Learning

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Lectures: GHC 4401, Mondays and Wednesdays, 10:30 – 11:50 AM

Office Hours:

Pradeep Ravikumar: GHC 8111, Mondays 1:00 – 2:00 PM
Manuela Veloso: TBD

Course Description:
Machine learning is concerned with the study and development of automated systems that improve their performance through experience. Examples range from robots learning to better navigate based on experience gained by roaming their environments, medical decision aids that learn to predict which therapies work best for which diseases based on historical health records, and speech recognition systems that lean to better understand your speech based on experience listening to you.

Learning Objectives:
This course is designed to give a graduate-level student a thorough grounding in the methodologies, technologies, mathematics and algorithms currently needed by people who do research in machine learning, and related disciplines and applications.

Pre-requisites:
Students entering the class are expected to have a pre-existing working knowledge of probability, linear algebra, statistics and algorithms, though the class has been designed to allow students with a strong numerate background to catch up and fully participate. In addition, recitation sessions will be held to revise some basic concepts.

Outline of material:

- Foundations
  - Key Axes of ML: Data, Algorithms, Tasks
  - Data: Partially/Fully Observed, Interactive
  - Algorithms: Model-based, Model-Free
  - Tasks: Prediction, Description
  - Decision Theory, Generalization, Model Selection, Guarantees
- Regression
  - Linear, Polynomial
- Classification
  - Logistic Regression, Naïve Bayes, Support Vector Machines, Boosting, Surrogate Losses, Decision Trees
- Nonparametric Methods
  - K Nearest Neighbors, Kernel Regression and Density Estimation
  - Kernel Trick
- Unsupervised Learning
  - Graphical Models
  - Clustering
  - Latent Variables Models, Expectation Maximization
- Sequence Models
  - Hidden Markov Models
  - State Space Models
- Representation Learning
  - Random Features
  - Principal Component Analysis, Independent Component Analysis
  - Neural Networks, Deep Networks
- Reinforcement Learning
  - Markov Decision Processes
  - Value Iteration, Q Learning

Tentative Course Schedule:

Date	Instructor	Topic	Category	Readings	HW Out/Due
Jan 17	MV	Intro: Data, Algorithms, Tasks		KM Chap. 1	
Jan 22	PR	Prob. Models: Estimators, Guarantees, MLE	Foundations	KM Chap. 2, 6	
Jan 24	MV	Prob. Models: Bayesian Estimation, MAP		KM Chap. 5	
Jan 29	PR	Model-free Methods, Decision Theory		HTF Chap. 2	HW 1 out
Jan 31	MV	Regression: Linear Regression		CB Chap. 3	
Feb 5	MV	Regularized, Polynomial, Logistic Regression		CB Chap. 3, 4	
Feb 7	MV	Classification: Naive Bayes, Generative vs Discriminative	Prediction, Parametric Methods	CB Chap. 4	
Feb 12	PR	Classification: Support Vector Machines		KM Chap. 14	HW 1 due/ HW 2 out
Feb 14	Guest Lect.	Classification: Boosting, Surrogate Losses		HTF Chap. 10	
Feb 19	MV	Decision Trees		HTF Chap. 9	
Feb 21	PR	Foundations: Generalization, Model Selection		HTF Chap. 7	
Feb 26	MV	Neural Networks and Deep Learning		CB Chap. 5, KM Chap. 28	HW 2 due/ HW 3 out
Feb 28	PR	Non-parametric Models: K nearest neighbors, kernel density estimation		HTF Chap. 6, 13	
Mar 5	PR	Non-parametric Models: SVM, Lin Reg: primal + dual, Kernels, Kernel Trick	Non-parametric Methods	CB Chap. 6, 7	
Mar 7	PR	Non-parametric Models: Kernel Trick contd., possibly GPs		CB Chap. 6, 7	HW 3 due (Mar 9)
Mar 12		SPRING BREAK			
Mar 14		SPRING BREAK			
Mar 19	Guest Lect.	Unsupervised Learning: Clustering: Hierarchical, K Means		HTF Chap. 14.1-14.3	
Mar 21		Midterm			
Mar 26	PR	Unsupervised Learning: Clustering: Mixture of Gaussians, Expectation Maximization		CB Chap. 9	HW 4 out
Mar 28	PR	Unsupervised Learning: Latent Variable Models	Unsupervised Learning	CB Chap. 9	
Apr 2	PR	Unsupervised Learning: Graphical Models		KM Chap. 10, 19, 20	
Apr 4	PR	Unsupervised Learning: Graphical Models		KM Chap. 10, 19, 20	
Apr 9	MV	Sequence Models: Hidden Markov Models	Sequence Models	KM Chap. 17	HW 4 due/ HW 5 out
Apr 11	MV	Sequence Models: State Space Models, other time series models		KM Chap. 18	
Apr 16	TBD/PR	Representation Learning: Feature Transformation, Random Features, PCA	Representation Learning	HTF Chap. 14.5	
Apr 18	TBD/MV	Representation Learning: PCA Contd, ICA		HTF Chap. 14.7	
Apr 23	MV	RL: MDPs, Value Iteration, Q Learning	Reinforcement Learning		HW 5 due
Apr 25	MV	RL: Q learning in non-det domains, Deep RL			
Apr 30	PR	Foundations: Statistical Guarantees for Empirical Risk Minimization			
May 2	PR and MV	Final Project Presentations			

Books:
CB: Pattern Recognition and Machine Learning, Christopher Bishop
KM: Machine Learning: A probabilistic perspective, Kevin Murphy
HTF: The Elements of Statistical Learning: Data Mining, Inference and Prediction, Trevor Hastie, Robert Tibshirani, Jerome Friedman

Logistics:

Class Website:

http://www.cs.cmu.edu/~pradeepr/10701

The class schedule, logistics, and lecture materials will be posted there.

Discussion, Announcements:
We will use Piazza for announcements, as well as the discussion board for the class.

Textbooks:
Lectures are intended to be self-contained. For supplementary readings, with each lecture, we will have pointers to either online reference materials, or chapters from the following books:

- Pattern Recognition and Machine Learning, Christopher Bishop.
- Machine Learning: A probabilistic perspective, Kevin Murphy.
- The Elements of Statistical Learning: Data Mining, Inference and Prediction, Trevor Hastie, Robert Tibshirani, Jerome Friedman.

Homeworks:
There will be 5 homework assignments, approximately evenly spaced throughout the semester. The assignments will be posted on the course website, and on Piazza. We will use Gradescope for submitting, and grading assignments.

You will get a late day quota of TBD days, which you can distribute among the five homeworks as you wish. Homeworks submitted after your late day quota will not be accepted. We expect you to use the late day quota for conference deadlines and events of the like, so we cannot provide an additional extension for such cases. In the case of an emergency (sudden sickness, family problems, etc.), we can give you a reasonable extension. But we emphasize that this is reserved for true emergencies.

Collaboration Policy:
The homeworks are structured to give you experience in both written mathematical exercises and programming exercises. While it is completely acceptable for you to collaborate with other students in order to solve the problems, we assume that you will be taking full responsibility in terms of writing up your own solutions and implementing your own code. You must indicate on each homework the students with whom you collaborated.

Midterm:
There will be one midterm, scheduled to be about halfway through the semester. The precise date is on the course website. The exam will consist of multiple choice and true/false questions, as well as short-answer questions.

Class project:
There will be a class project. You can form groups of up to TBD students. Further details on the project can be found on the website.

Grading:

Homework	50%
Midterm	25%
Project	25%

Accommodations for Students with Disabilities:
If you have a disability and have an accommodations letter from the Disability Resources office, we encourage you to discuss your accommodations and needs with the instructors as early in the semester as possible. We will work with you to ensure that accommodations are provided as appropriate. If you suspect that you may have a disability and would benefit from accommodations but are not yet registered with the Office of Disability Resources, we encourage you to contact them at access@andrew.cmu.edu.

Take care of yourself:
Take care of yourself. Do your best to maintain a healthy lifestyle this semester by eating well, exercising, avoiding drugs and alcohol, getting enough sleep and taking some time to relax. This will help you achieve your goals and cope with stress.

All of us benefit from support during times of struggle. There are many helpful resources available on campus and an important part of the college experience is learning how to ask for help. Asking for support sooner rather than later is almost always helpful.

If you or anyone you know experiences any academic stress, difficult life events, or feelings like anxiety or depression, we strongly encourage you to seek support. Counseling and Psychological Services (CaPS) is here to help: call 412-268-2922 and visit their website athttp://www.cmu.edu/counseling/. Consider reaching out to a friend, faculty or family member you trust for help getting connected to the support that can help.

If you or someone you know is feeling suicidal or in danger of self-harm, call someone immediately, day or night:

- CaPS: 412-268-2922
- Re:solve Crisis Network: 888-796-8226

If the situation is life threatening, call the police

- On campus: CMU Police: 412-268-2323
- Off campus: 911

If you have questions about this or your coursework, please let me know. Thank you, and have a great semester.