# CS584 Machine Learning (Spring 2022)

## Instructor Contact

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**Lecture Hours:** MW 10:00AM --11:15 AM
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**Office Hours:** Wednesday 1:00PM - 3:00 PM or by appointment, zoom meeting (first 2 weeks, zoom link: https://iit-edu.zoom.us/j/8113748447 , for internal use only) / in-person
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## Teaching Assistant

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## Course Description

Introduce fundamental problems in machine learning. Provide understanding of mathematical concepts, and algorithms used in machine learning. Provide understanding of the limitations of various machine learning algorithms and the way to evaluate performance of learning algorithms.

Topics will include supervised learning, unsupervised learning, semi-supervised learning; Machine learning tasks will cover regression, classification (generative vs. discriminative), clustering, dimensionality reduction, linear models, nonlinear models, etc. Recent advanced topics such as sparse/low rank representation, graph neural networks, trustworthy learning, casual inference, machine learning for security, federated learning, is also covered.

**Topics NOT covered**: Reinforcement learning, Bayesian learning, Active learning, Sequential models, Sampling methods, Optimization theory, etc.

## Textbook (Free e-book)

- Pattern Recognition and Machine Learning, by Christopher M. Bishop
- Machine Learning: A Probabilistic Perspective, by Kevin P. Murphy

## Course Evaluation

- 5 assignments + 1 additional optional assignment (50%)
- Final project (presentation & report) (40%)
- Paper reading (10%)

## Course Objectives

- Know the specific machine learning task in real-world problems
- Know how to formulate a problem and specify its solution
- Good understanding of machine learning algorithms (key ideas, pros & cons, etc.)

## Prerequisites

Probability; Linear algebra; Optimization; Algorithms; Computer Programming (Python, Matlab, C)

## Grades

| *Assignments* | *Points Possible* | *Final Grade%* |
| --- | --- | --- |
| **Assignment 1** | *100 points* | *10%* |
| **Assignment 2** | *100 points* | *10%* |
| **Assignment 3** | *100 points* | *10%* |
| **Assignment 4** | *100 points* | *10%* |
| **Assignment 5** | *100 points* | *10%* |
| **Assignment 6 (optional)** | *100 points* | *10%* |
| **Final Project** | *100 points* | *40%* |
| **Paper reading** | *100 points* | *10%* |
| **Total** | | *100%* |

Notes: 1) About Assignment 6: It is an optional assignment that is used to replace the minimal grade in the first 5 required assignments. 2) About assignment submission: Please submit you solution to the Blackboard via a **single pdf** (either use word/latex or write down your solution and then scan it); If you also submit the source code, please upload the source files separately and **DO NOT** use a zip file; 3) About late submission: All assignments are due by Sunday at 11:59 PM. 50% of the grade will be deducted for that assignment if it is late within 1 day (24 hours). You will get a 0 grade if the assignment is late more than 1 day.

## Course Recordings

Synchronous (live) sessions in this course will be recorded for students enrolled in this class section to refer to throughout the semester. Class recordings are the intellectual property of the university or instructor and are reserved for use only by students in this class and only for educational purposes. Students may not post or otherwise share the recordings outside the class in any form.

## Initial & Final Project

Up to 3 students can form a group to collaboratively complete the final research project. An initial project topic (along with the group members) is due at the end of Spring Break. Please let me and TAs know as early as possible if you decide to change the research topic after the due date.

The final project includes a 5-min project representation (5%) and a final report (35%). The format of the final report should follow an academic paper (i.e., introduction, related work, problem, methods, results, conclusion). ALL group members should clearly clarify their contributions in the project. You can use the NeurIPS template (https://nips.cc/Conferences/2020/PaperInformation/StyleFiles) to organize the report.

## Academic Integrity

You are welcome to discuss assignments with classmates, but all final work must be your own. Academic dishonesty of any kind may result in a 0 grade on the assignment, a reduction in final grade, and/or referral to the Dean. The IIT code of Academic Honesty (https://www.iit.edu/student-affairs/student-handbook/fine-print/code-academic-honesty) can be found in the undergraduate handbook.

## Disability Accommodations

Reasonable accommodations will be made for students with documented disabilities. In order to receive accommodations, students must obtain a letter of accommodation from the Center for Disability Resources. The Center for Disability Resources (CDR) is located in Life Sciences Room 218, telephone 312 567.5744 or disabilities@iit.edu.

## (Tentative) Course Syllabus

CB = Christopher M. Bishop; KM = Kevin P. Murphy

| Week No. | Date | Content | Reading/Assignment |
|---|---|---|---|
| Week 1 | Jan 10 | Intro + Machine learning basics | Reading: Linear algebra & probability review |
| | Jan 12 | Regression: Linear regression, least square, geometric interpretation (KM Ch. 7.1-7.3, CB Ch. 3.1) | |
| Week 2 | Jan 17 | **No class (Martin Luther King Day)** | Reading: Elastic Net, group lasso |
| | Jan 19 | Regression (Regularization): Ridge regression, LASSO (CB Ch. 3.1.4, KM Ch. 7.4 13.3,13.4) | HW1: Regression |
| Week 3 | Jan 24 | Classification (discriminative models): Fisher Linear discriminative analysis, Perceptron & Convergence, MLP (CB Ch. 4.1) | Reading: MLP is a universal approximator |
| | Jan 26 | Classification (discriminative models): Support vector machines (SVM), kernels (CB Ch.7.1) | HW1 due: Sunday |
| Week 4 | Jan 31 | Classification (Prob. discriminative models): (Multi-class) Logistic regression, Iterative reweighted least square (CB Ch. 4.3, KM Ch. 8.28.3) | Reading: Sparse repres., Gaussian process |
| | Feb 2 | Classification (Prob. generative models): Gaussian discriminative analysis (GDA), Naïve bayes classifier (NB) (KM Ch. 4.2, 3.5, CB Ch. 4.2) | HW2: (Linear & nonlinear) classification |
| Week 5 | Feb 7 | Nonlinear classification: Deep neural networks/DBN + Back Propagation (Ch. 28.3) | Reading: ResNet, Locality preserving proj. |
| | Feb 9 | Nonlinear classification: (K) nearest neighborhood (?) / Machine learning theory basics? | HW2 due: Sunday |
| Week 6 | Feb 14 | Clustering: K-means; Mixture of Gaussians (EM) (CB Ch. 9) | Reading: Affinity propagation, DenPeak |
| | Feb 16 | Clustering: Graphs, Graph Laplacian, Spectral clustering (KM Ch. 25.4) | HW3: Clustering |
| Week 7 (Advanced topic) | Feb 21 | Clustering: sparse subspace clustering (SCC) | Reading: Low rank representation (LRR) |
| | Feb 23 | TA: HW answers | HW3 due: Sunday |
| Week 8 | Feb 28 | Dimensionality reduction (linear models): PCA/SVD, autoencoder, 2DPCA (KM Ch. 12.2, CB Ch. 12.1) | Reading: Robust PCA, Random projection |
| | Mar 2 | Dimensionality reduction (linear models): Nonnegative matrix factorization (NMF) & its variants | HW4: Dimensionality reduction |

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|---|---|---|---|
| Week 9 | Mar 7 | Dimensionality reduction (nonlinear models):<br>Manifold learning: LLE, LE | Reading: IsoMap or MVU & MFA |
| | Mar 9 | Dimensionality reduction (nonlinear models):<br>Deep neural network: Deep (denoising) autoencoder (KM Ch. 28.2), Deep Belief Net (Science, 2006) | HW4 due: Sunday |
| **Spring break** | Mar 14 | **No class** | |
| | Mar 16 | **No class** | **Initial project topic due: Sunday** |
| Week 10 | Mar 21 | (Graph-based) semi-supervised learning:<br>Recap: Graph basics; Random Walk | Reading: Manifold regularization |
| | Mar 23 | (Graph-based) semi-supervised learning:<br>Label propagation: Gaussian harmonic function (GHF), Local & global consistency (LGC) | HW5: Semi-supervised learning |
| Week 11 (Advanced topic) | Mar 28 | (Graph-based) Semi-supervised learning:<br>graphical models + belief propagation<br>(KM Ch. 10.1, 20.2, CB Ch.8) | Reading: Mixup & Mixmatch |
| | Mar 30 | (Graph-based) Semi-supervised learning:<br>Graph neural networks, e.g., GCN | HW5 due: Sunday |
| Week 12 (Advanced topic) | Apr 4 | Generative adversarial networks (GAN)<br>/ Contrastive learning | Reading: Contrastive learning/VAE |
| | Apr 6 | Guest lecture: Causal inference | HW6: (bonus) |
| Week 13 (Advanced topic) | Apr 11 | Trustworthy ML (Security of ML): Adversarial attacks (FGSM, PGD, CW, poisoning, backdoor, model inversion, model stealing, etc.) | Reading: False sense of security, Hyperpara. stealing |
| | Apr 13 | Trustworthy ML (Security of ML): Adversarial robustness (adversarial training, randomized smoothing, etc.) | HW6 due: Sunday |
| Week 14 (Advanced topic) | Apr 18 | Guest lecturer: ML for security | |
| | Apr 20 | Federated learning: FedAvg, FedProx /<br>Compressive sensing/dictionary learning/sparse coding | |
| Week 15 | Apr 25, 27 | Project presentation | |
| Week 16 | May 2, 4 | Final week: Project report | **Final report due: May 8** |