

# CSC 480/580 Principles of Machine Learning Spring 2025

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# What is machine learning?

# What is machine learning?

- Tom Mitchell established Machine Learning Department at CMU (2006).

## Machine Learning, Tom Mitchell, McGraw Hill, 1997.



*Machine Learning is the study of computer algorithms that improve automatically through experience. Applications range from datamining programs that discover general rules in large data sets, to information filtering systems that automatically learn users' interests.*

*This book provides a single source introduction to the field. It is written for advanced undergraduate and graduate students, and for developers and researchers in the field. No prior background in artificial intelligence or statistics is assumed.*

- Algorithm that builds an algorithm through experience (=data)
- A subfield of Artificial Intelligence – algorithms to perform smart tasks. The difference from the traditional AI is “how” you build a computer program to do it.
- An outdated book but still has interesting discussion (and easy to read).

# AI Task 1: Image classification

- Predefined categories:  $C = \{\text{cat}, \text{dog}, \text{lion}, \dots\}$
- Given an image, classify it as one of the classes in  $C$  with the highest accuracy as possible.
- Use: sorting/searching images by category.
- Also: categorize types of stars/events in the Universe (images taken from large surveying telescopes)



# AI Task 2: Recommender systems

- Predict how user would rate a given movie (say 5-star rating)
- **Use**: For each user, pick an unwatched movie with the high predicted ratings.
- **Idea**: compute user-user similarity or movie-movie similarity, then compute a weighted average.

	User 1	User 2	User 3
Movie 1	1	2	1
Movie 2	?	3	1
Movie 3	2	5	2
Movie 4	4	?	5
Movie 5	?	4	2

- This particular approach is called 'collaborative filtering'

# AI Task 3: Machine translation

- No need to explain how useful it is.

English ↕ Chinese (Simplified) ↕

×

You can pay attention to the lecture.

您可以关注讲座。  
Nín kěyǐ guānzhù jiǎngzuò.

Chinese (Simplified) ↕ English ↕

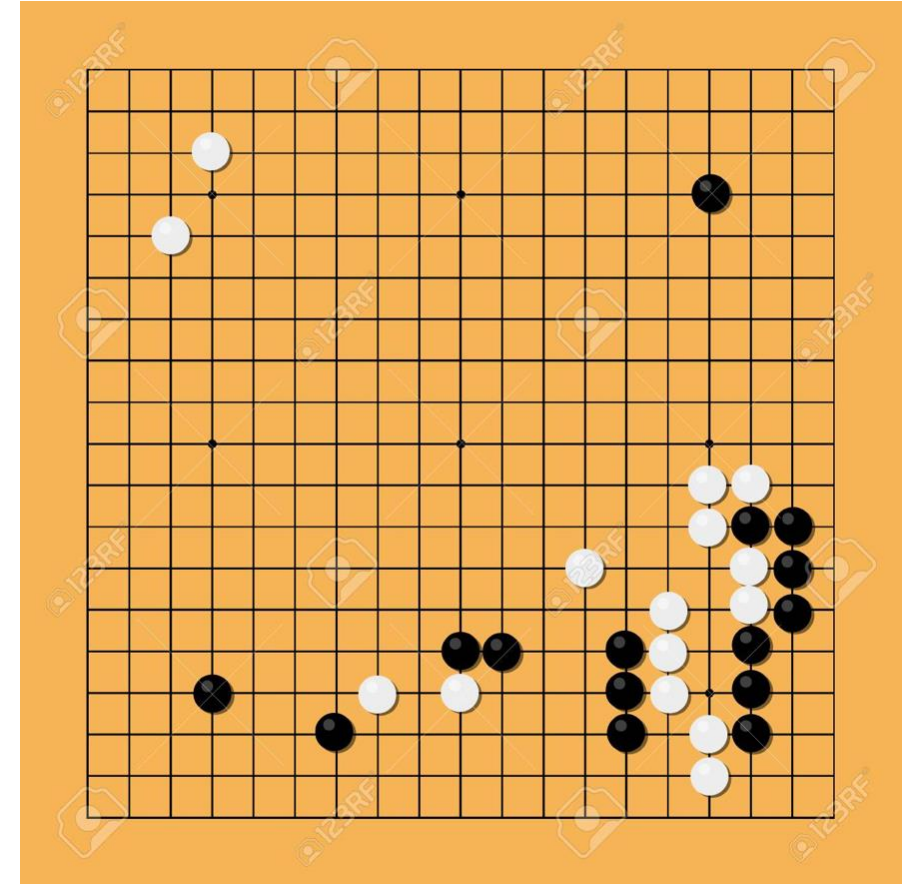
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您可以关注讲座。  
Nín kěyǐ guānzhù jiǎngzuò.

You can follow the lecture.

# AI Task 4: Board game

- Predict win probability of a move in a given game state (e.g., AlphaGo)
- Traditionally considered as a “very smart” task to perform.
- **Use**: From the AI Go player, you can do practice play or even learn from it.
  - These days, when people broadcast go game, they show the winning rate of each move!



# AI Task 5: ChatGPT

- No need to explain.
- Good at retrieving knowledge and presenting it in natural language.
- Not necessarily good at difficult tasks (e.g., reasoning).



# Traditional AI vs Machine Learning (ML)

- **Traditional AI:** you encode the knowledge (e.g., logic statements), and the machine executes it, with some more ‘inference’ like if  $a \rightarrow b$  and  $b \rightarrow c$ , then  $a \rightarrow c$ .
  - e.g., if you see some feather texture with two eyes and a beak, classify it as a bird.
- **ML:** I give you a number of input and output observations (e.g., animal picture + label), and you give me a **function (can be a set of logical statements or a neural network)** that maps the input to the output accurately.
  - As the “big data” era comes, data is abundant  $\Rightarrow$  far better to learn from data than to encode domain knowledge manually.
  - “statistical” approach // “data-driven” approach
  - *“Every time I fire a linguist, the performance of the speech recognizer goes up.” – 1988, Frederick Jelinek, a researcher who worked on speech recognition.*
- **Note:** ML approach to logic-based system: decision tree (simple rules) / inductive logic programming (complex rules)



# Work in ML

- The usual CS background is often not sufficient – especially mathematical side, beyond discrete math.
- Data scientists: may not necessarily use ML (e.g., find associations between age and disease)
- Applied ML
  - Collect/prepare data, build/train models, tune hyperparameters, measure performance.
- ML research
  - Design/analyze models and algorithms
  - Theory: Provide mathematical guarantees. E.g., If I were to achieve 90% accuracy, how many data points do we need? => generalization bound.

# Prereqs

- Math
  - Linear algebra, probability & statistics, multivariate calculus, reading and writing proofs.
  - Q: how many of you are familiar with eigen decomposition?
- Software/programming
  - Much ML work is implemented in python with libraries such as numpy and pytorch.
  - You need to be fluent at writing functions and using them efficiently.

# Overview of ML methods

supervised learning

unsupervised learning

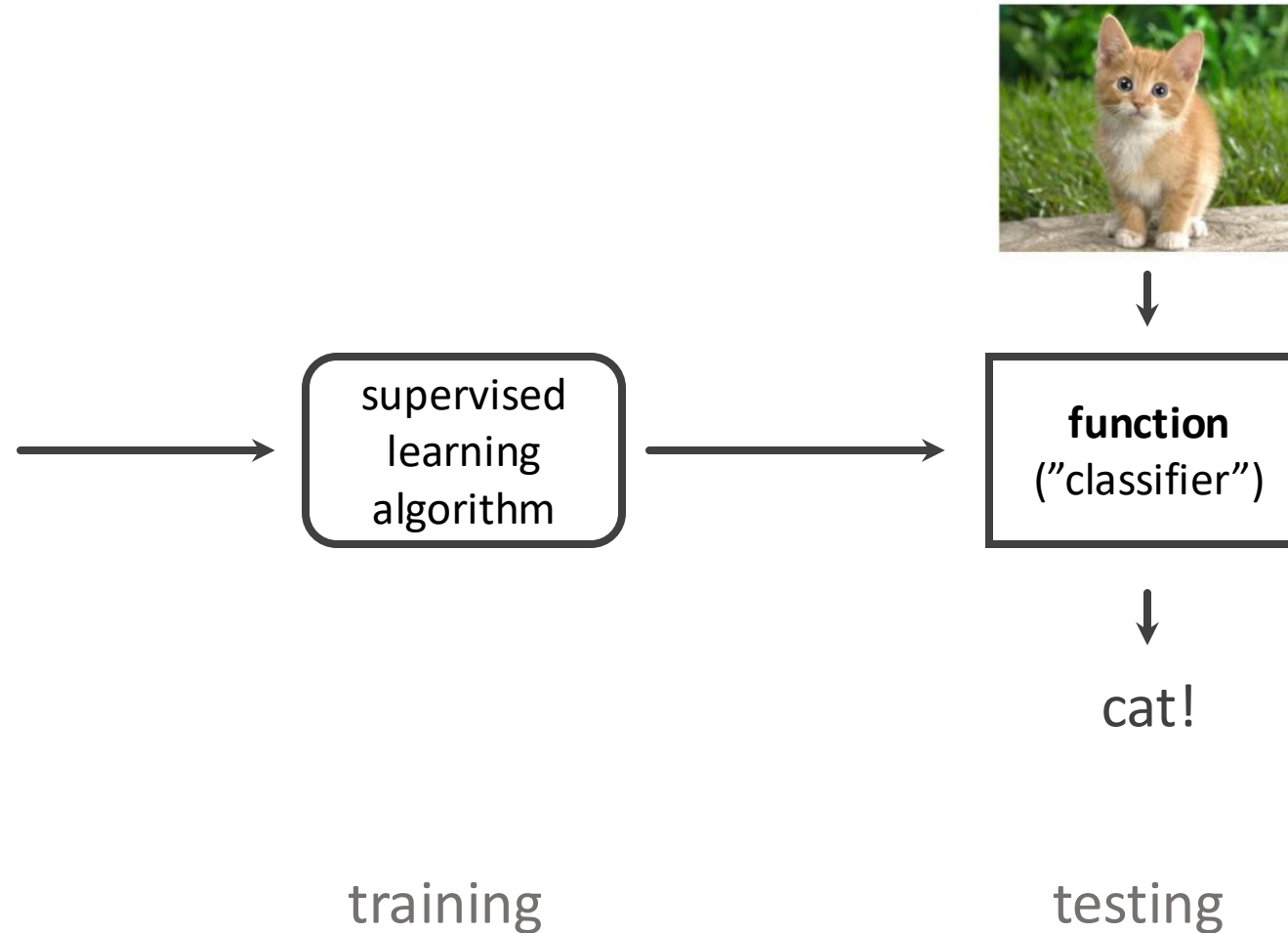
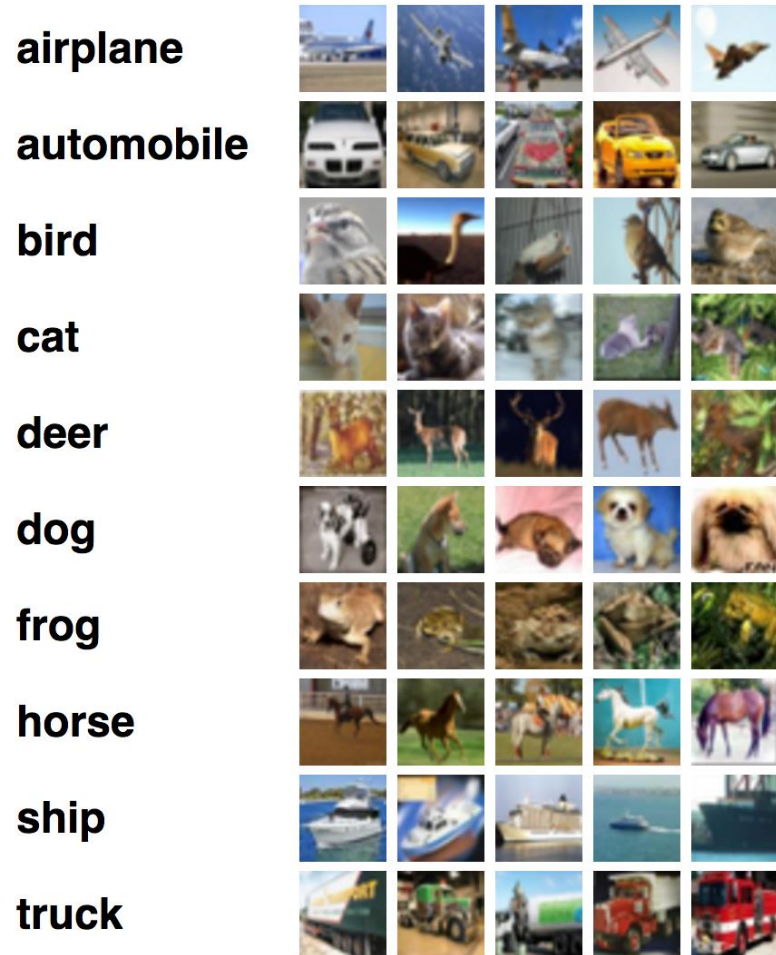
reinforcement learning  
(broadly, interactive learning)

# Supervised Learning

# Basic setting: Supervised learning

example = data point

- Training data: dataset comprised of labeled examples: a labeled example = a pair of (input, label)



# Examples function 1: Decision tree

- Task: predict the rating of a **movie** by a **user**
- If age  $\geq 40$  then
  - if genre = western then
    - return 4.3
  - else if release date  $> 1998$  then
    - return 2.5
  - else ..
    - ...
  - end if
- else if age  $< 40$  then
  - ...
- end if

can be deeply nested!

# Example function 2: Linear

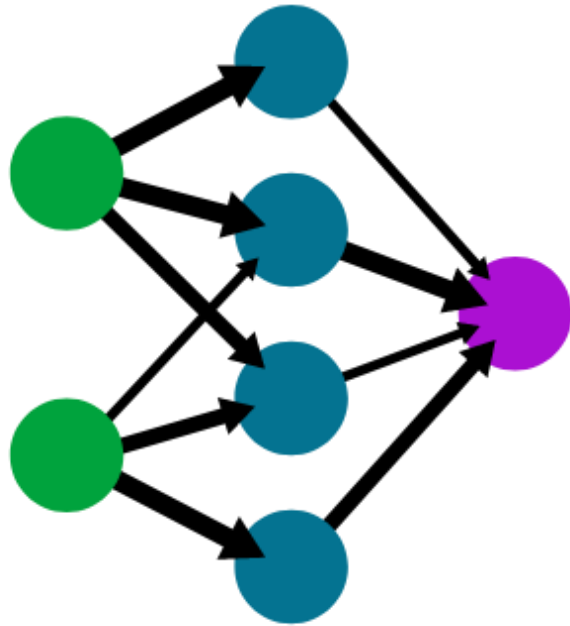
- E.g., Image classification
- Let  $x$  be a set of pixel values of a picture (30 by 30 pts) => 900 dimensional vector  $x \in [0,1]^{900}$ .
- If  $0.124 \cdot x_1 - 2.5 \cdot x_2 + \dots + 2.31 \cdot x_{900} > 2.12$  then
  - return cat
- else
  - return dog
- end
  
- Coefficients: signed “importance weights”

“linear combination”  
“inner product”



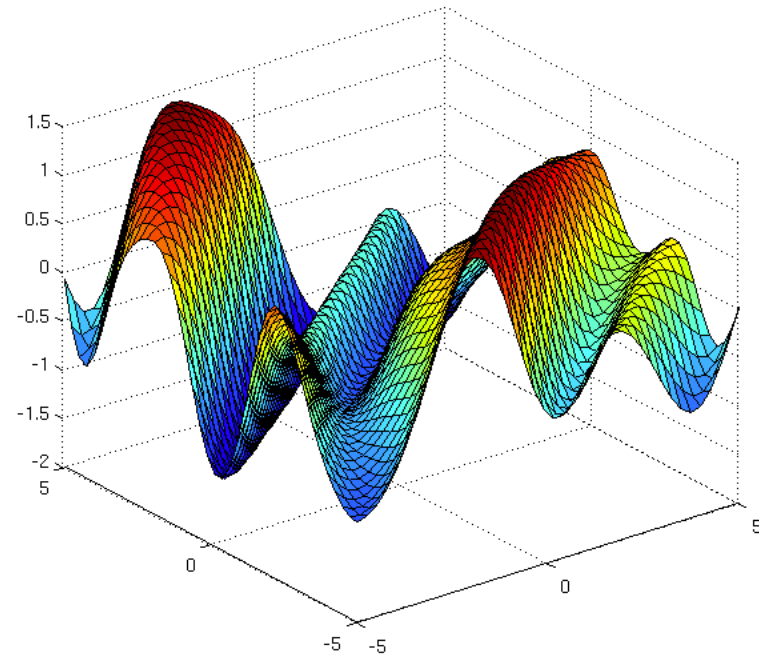
# Example function 3: Nonlinear

Neural network



(stacked **linear** models with nonlinear activation functions)

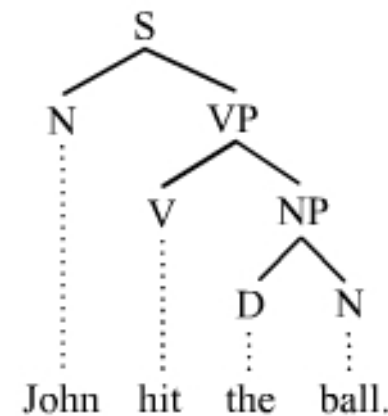
Gaussian process / Kernels



(**linear** in the induced feature space)

# Supervised learning: Types of prediction problems

- Binary classification
  - Given an email, is it spam or not? (or, the probability of it being spam)
- Multi-class classification
  - Image classification with 1000 categories.
- Regression: the label is real-valued (e.g., price)
  - Say I am going to visit Italy next month. Given the price trends in the past, what would be the price given (flight destination, the # of days before the departure, day of week)?
  - Pricing: predict the price that will maximize the profit.
- Structured output prediction: more than just a number
  - Given a sentence, what is its grammatical parse tree?

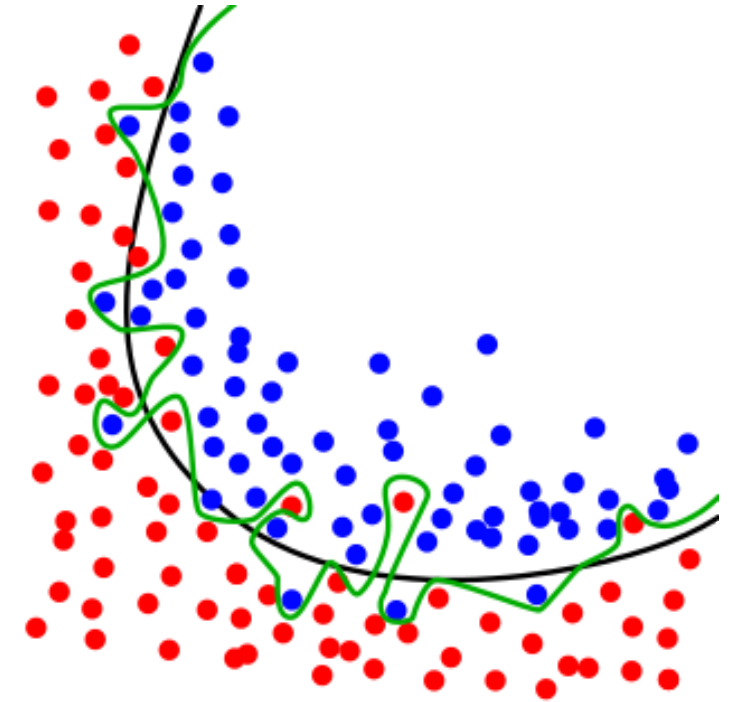


# Beyond supervised learning

- Online learning (opp. “batch learning”)
  - Immediate updates are needed (e.g., personalized product/content recommendation)
  - Sequential update for fast learning / adapt to changing environment
- Unsupervised learning
  - Finds patterns/representation in the data without the help of labels.
- Reinforcement learning
  - The environment interacts with your action, transferring you to different states.
  - It learns to take ‘actions’ as opposed to making ‘predictions’.
  - When there are no states: “**bandit**” feedback.
    - E.g., Amazon recommends you a pair of shoes. You did not click it. Amazon don’t know if you would’ve clicked had it recommended speakers or cookware.
    - The dataset is now dependent on the recommendation algorithm  $\Rightarrow$  biased data.
    - “bandit-logged” data.

# The challenge: How to learn a function

- Okay, we have a training data. Why not learn the most complex function that can work flawlessly for the training data and be done with it? (i.e., classifies every data point correctly)
- Extreme: let's memorize the data. To predict an unseen data, just follow the label of the closest memorized data.
- It does not work.
- You need to learn training dataset but don't "over-do" it.
- This is called "regularization" – an important notion.



**green:** memorization  
**black:** true decision boundary

# What to expect in the class

- ~~• How to use sklearn, pytorch, tensorflow, fine-tuning deep neural networks~~
- Algorithm and statistical principles
  - Well-studied models and methods.
  - Those that give you some “understanding”.
  - These are and will be referred/extended/revisited in the future.
- Programming and proofs
  - No need to be a guru.
  - But you must be familiar enough to (1) follow popular codes and proofs and (2) be able to adapt yourself to new programming tools and proofs in the future.

# Logistics

# Electronical Resources

**Course Webpage:** [http://pacheco.j.com/courses/csc480-580\\_spring25/](http://pacheco.j.com/courses/csc480-580_spring25/)

**Textbook:** [Daumé, Hal. "A Course in Machine Learning." 2017.](#)

**D2L 580:** <https://d2l.arizona.edu/d2l/home/1571901>

**D2L 480:** <https://d2l.arizona.edu/d2l/home/1571904>

**Piazza:** <https://piazza.com/arizona/spring2025/csc480580>

**Gradescope 480:** Register with code *G3Y8E2*

**Gradescope 580:** Register with code *WW84YW*

**Instructor Homepage:** <http://www.pacheco.j.com>

# Syllabus summary

- Basics of supervised learning
  - Basic supervised learning: decision tree, k-NN, perceptron
  - Practical issues: evaluation, feature selection, etc.
  - Bias-variance decomposition
- Learning methods
  - Linear models, kernels
  - Naïve Bayes, graphical models
  - Neural networks
- Other training methods: ensemble, stochastic gradient descent
- Other paradigms: unsupervised learning, reinforcement learning
- Learning theory
- Large language models



# Syllabus summary

- 01/16: HW0 (calibration) assigned
  - 01/28: HW1 assigned
  - 03/13: HW2 assigned
  - 03/06: Midterm exam (at the class meeting time)
  - 03/18: Project proposal due
  - 03/25: HW3 assigned
  - 04/08: HW4 assigned
  - 05/06: Final project due
  - 05/14: Final exam at 6:00pm – 8:00pm
  
  - **Due:** HW0 is due in 7 days. HW1-4 and is due in 10 days.
  - **NO LATE DAYS**
- Grading scheme
    - Assignments: 40%
    - Project Proposal: 5%
    - Project: 15%
    - Midterm Exam: 15%
    - Final Exam: 15%
    - Participation: 10%
  - Project
    - Pick a paper in recent ML venue and implement it
    - Pioneering new applications of ML (e.g., connect to your research)
    - Talk to me for other ideas.
    - Will explain 480 vs 580 later.

# 400- vs. 500-Level Credit

- This course will be co-convened CSC 480 / 580
- The same assignments will be issued to all students
- Assignments / Exams will have questions designated **only** for CSC 580 students
  - Undergraduates should not answer these questions
  - There won't be extra credit for answering them
- Expectations for the semester project will be higher for CSC 580 students
  - More emphasis on novelty
  - I.e. if you implement a paper you should explore ways to improve it
  - Undergrads may implement an algorithm as-is or apply it to a dataset of their choice.

# Office Hours

Office Hours are for:

- Clarification on lecture material
- Homework questions
- Other questions related to course logistics / material / ML

*I prefer “Jason” or “Professor”*

Me



Fridays @ 3:00 – 5:00pm  
Zoom

TA: Yinan Li



Office Hours TBA  
Undergraduates Only

# Participation

- Stop me at any point to ask questions! **There are no bad questions.**
- Any ideas to encourage participation?
- I **strongly** encourage off-class discussion in Piazza.
  - Students should also attempt to answer questions.
  - Sometimes answering questions helps us learn better (especially if we're wrong)
  - Online activities will be factored into the participation score.
- Lecture videos are for review -- you should attend lecture in-person.

# Academic Integrity Rules

- You **may** discuss assignments with other students
- You **may not** discuss or share assignment solutions
- You **may** consult any online or textbook resources
- You **may not** directly copy from external resources
- You **may not** upload solution material publicly accessible web
- You **may not** discuss exams with students in any capacity

**Good Rule** Cite any external resource you use that may be considered plagiarism without citation.

# HWO

- Calibration purpose; due on **01/23 @ 11:59pm**. NO LATE DAYS. Will not accept late submissions.
- Will not be part of the homework score.
- I require that you spend some time to figure out an answer to the homework.
- If you failed to figure out, please explain **what you have done to find an answer** and **where you get stuck**.
  - DON'T: "I googled it and nothing came up"
  - DO: "I read material A, and there is this statement B that seems to help, but when I tried to apply, C became an issue due to independence. ..."
- The participation score will be deducted (-2 out of 10pts) if ...
  - Empty answers
  - No nontrivial efforts to solve it.

# Useful Background Material

## Probability

- <http://cs229.stanford.edu/section/cs229-prob.pdf>
- Lecture notes: [http://www.cs.cmu.edu/~aarti/Class/10701/recitation/prob\\_review.pdf](http://www.cs.cmu.edu/~aarti/Class/10701/recitation/prob_review.pdf)

## Linear Algebra:

- <http://cs229.stanford.edu/section/cs229-linalg.pdf>
- Short video lectures by Prof. Zico Kolter: <http://www.cs.cmu.edu/~zkolter/course/linalg/outline.html>
- Handout associated with above video: [http://www.cs.cmu.edu/~zkolter/course/linalg/linalg\\_notes.pdf](http://www.cs.cmu.edu/~zkolter/course/linalg/linalg_notes.pdf)

## Big-O notation:

- <http://www.stat.cmu.edu/~cshalizi/uADA/13/lectures/app-b.pdf>
- <http://www.cs.cmu.edu/~avrim/451f13/recitation/rec0828.pdf>

## Other resources:

- The matrix cookbook: <https://www.math.uwaterloo.ca/~hwolkowi/matrixcookbook.pdf>
- The probability and statistics cookbook: <http://statistics.zone/>
- Calculus cheatsheet: [https://tutorial.math.lamar.edu/pdf/calculus\\_cheat\\_sheet\\_all.pdf](https://tutorial.math.lamar.edu/pdf/calculus_cheat_sheet_all.pdf)

I look forward to working with you!