ECE595 / STAT598: Machine Learning I
Course Overview

Spring 2020

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Machine Learning: Your Interpretation?

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Machine Learning: Your Interpretation?

Elements of Learning?
Elements of Learning?

- Data
Elements of Learning?

- Data
- Computer
Elements of Learning?

- Data
- Computer
- Algorithm
What is Learning? What is NOT learning?
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You are given a bag of US coins.

Your task: Build a classifier.

Four classes: Penny, Nickel, Dime, Quarter.
What is Learning? What is NOT learning?

- You are given a bag of US coins.
- Your task: Build a classifier.
- Four classes: Penny, Nickel, Dime, Quarter.
Approach 1: Learning

You measure mass and size. Put each coin to its class. Plot a 2D histogram. Create the classifier.
Approach 1: Learning

You measure mass and size.
Approach 1: Learning

You measure mass and size.

Put each coin to its class. Plot a 2D histogram.
Approach 1: Learning

- You measure mass and size.
- Put each coin to its class. Plot a 2D histogram.
- Create the classifier.
Approach 2: Design

You go to United States Mint to ask for the ideal mass and size of the coins. You ask them to give you the measurement error. Plot the 2D distribution. Create the classifier.
Approach 2: Design

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Approach 2: Design

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- Create the classifier.
Which one fits learning? Which one fits design?

- Determining the age at which a particular medical test should be performed.
Which one fits learning? Which one fits design?

- Determining the age at which a particular medical test should be performed.
- Classifying numbers into primes and non-primes.
Which one fits learning? Which one fits design?

- Determining the age at which a particular medical test should be performed.
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- Detecting potential fraud in credit card charges.
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- Determining the time it would take a falling object to hit the ground.
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- Determining the age at which a particular medical test should be performed.
- Classifying numbers into primes and non-primes.
- Detecting potential fraud in credit card charges.
- Determining the time it would take a falling object to hit the ground.
- Determining the optimal cycle for traffic lights in a busy intersection.
Machine Learning Model

- Machine Learning Model
- Data points $x_1, \ldots, x_N$
- Labels $y_1, \ldots, y_N$
- Where does a data point $x_n$ come from?
- How is a label $y_n$ defined?
- What do we mean by a learning algorithm?
- What is a classifier?
- How to evaluate a classifier?
Machine Learning Model

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See Learning from Data (Chapter 1).
Learning Algorithm

1. Extract Feature
2. Prediction
3. Loss
4. Optimization Method
5. Ground Truth

Data $\rightarrow \phi(x) \rightarrow \text{prediction} \rightarrow g(\phi(x)) \rightarrow y \rightarrow L(g(\phi(x)), y)$
Types of Learning

- Supervised Learning: Labels available.
- Unsupervised Learning: No label.
Outline of ECE 595

Part 1: Mathematical Background
(2 weeks)
Linear Regression and Optimization
Please review linear algebra, probability, optimization in the Tutorial Note.

Part 2: Classification
(5 weeks)
Methods to train linear classifiers
Feature analysis, Geometry, Bayesian decision rule, logistic regression, perceptron algorithm, support vector machine

Part 3: Handling Uncertainty
(3 weeks)
Imperfect data: noisy label, unbalanced data, missing data, knowledge transfer
Robustness study: adversarial attack and defense

Part 4: Learning Theory
(5 weeks)
Evaluation of a classifier.
Feasibility of learning, VC dimension, bias-variance, validation
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Teaching Staff

Instructor: Prof. Stanley Chan
MSEE 338
By email appointment.

Teaching Assistants:
Guanzhe Hong, Tue 9-11am, EE 208/209
Tolunay Sefi, Thu 2-4pm, EE 208/209

Admin Assistants:
Camille Hamelman, MSEE 330
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Email: ece595chan@gmail.com
Please do not email our personal account.
You can specify whom you want to write to.

Piazza: https://piazza.com/class/k55p17bbatn2e0
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- Piazza: https://piazza.com/class/k55p17bbatn2e0
Textbook and References

- **Elements of Statistical Learning**, by Hastie, Tibshirani and Friedman, 2009.
Grades

- Homework Assignments (30%)

Late Homework:
- 20% off by 5pm. This includes printer failure, etc.
- 40% off by next business day 5pm.
- 100% off afterwards.

Acknowledge your friends. Write your own solution.

Coarse grading:
- 5 points. All correct / small typos.
- 4 points. Minor mistakes.
- 3 points. Some mistakes.
- 2 points. Major mistakes.
- 1 point. You hand in, but none of them is correct.
- 0 points. You do not hand in homework.

Put your class ID.

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Midterm (30%)

Probably before the Spring break. The exact date will be announced later.

Final (40%)

TBD

Letter Grade Option


Exact grade will be subject to class performance.

Pass / No Pass Option

Do everything. Pass if the overall score is above 50.

Audit

Welcome. Give me the audit form.
Grades

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Pre-Requisites

Linear Algebra:
- Matrix-vector multiplication $Ax$
- Transpose $A^T$
- Symmetric matrices $A = A^T$
- Norm $\|x\|$
- Trace $\text{Tr}(A)$
- Inverse $A^{-1}$
- Determinant $|A|$
- Eigenvalue and eigenvector $A = U\Lambda U^T$.


Probability:
- Random variable $X$
- Probability density function $p(x)$
- Cumulative distribution function $F(x)$
- Expectation $E[X]$
- Variance $\text{Var}[X]$
- Function of random variable $E[g(X)]$
- Joint Gaussian, Law of Large Number, Central Limit Theorem.


Optimization:
- Convex function, convex set, operations which preserve convexity
- Lagrange multiplier
- KKT conditions
- Primal optimal, dual optimal
- Complementary slackness
- Constrained optimization, duality theorem.

Pre-Requisites

- **Linear Algebra:**
  - Matrix-vector multiplication $Ax$, transpose $A^T$, symmetric matrices $A = A^T$, norm $\|x\|$, trace $\text{Tr}(A)$, inverse $A^{-1}$, determinant $|A|$, eigenvalue and eigenvector $A = U\Lambda U^T$.
  - Gilbert Strang, Linear Algebra and Its Applications, 5th Edition
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- **Optimization:**
  - Convex function, convex set, operations which preserve convexity, Lagrange multiplier, KKT conditions, primal optimal, dual optimal, complementary slackness, constrained optimization, duality theorem.
Pre-Requisites

Please do homework 0 at

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If you can comfortably do:

- 3-4 problems: You are ready for the course.
- 2 problems: You need to put extra effort if you take the course.
- 0-1 problem: Consider taking the course later.

“Comfortable” means

- You know the mainstream approach.
- No hacking.
Programming

- **Python**
  - Our primary programming language.
  - Convert your MATLAB code to Python.
  - [https://engineering.purdue.edu/ChanGroup/ECE595/python.html](https://engineering.purdue.edu/ChanGroup/ECE595/python.html)

- **CVX**
  - Optimization toolbox.
  - No need to write your own optimization.
  - [https://engineering.purdue.edu/ChanGroup/ECE595/cvx.html](https://engineering.purdue.edu/ChanGroup/ECE595/cvx.html)

- **LaTeX**
  - Typesetting your homework.
  - Recommended. Not required.
  - Template available
  - [https://engineering.purdue.edu/ChanGroup/ECE595/latex.html](https://engineering.purdue.edu/ChanGroup/ECE595/latex.html)
Quick Comparison

- Difference between ECE 595 and CS 578 Statistical ML:
  - Different offering units.
  - Different perspectives.

- Difference between ECE 595 and ECE 662 Pattern Recognition:
  - Part 2 of ECE 595 has some overlap with ECE 662.
  - Part 1, 3, 4 are different.

- Difference between ECE 595 and BME 595 Deep learning:
  - ECE 595 only touches briefly on deep learning.

- Difference between ECE 595 and ECE 570 Artificial Intelligence:
  - ECE 595 focuses on supervised learning.
  - ECE 570 has some coverage on unsupervised learning.

- Difference between ECE 595 and ECE 629 Neural Network:
  - We have some, but not a lot on neural networks.

- Difference between ML1 and ML2?
  - ECE 595 (ML1) focuses on foundation.
  - ECE 595 (ML2) focuses on deep learning.
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Tutorials

- Tutorial on Linear Algebra

- Tutorial on Probability
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