Introduction to ML & DL

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Machine Learning

Outline

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1. What's Machine Learning?
2. What's Deep Learning?
3. About this Course...
4. FAQ

Prior vs. Posteriori Knowledge

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- Machine learning algorithms use the ***a posteriori knowledge*** to solve problems
  - Learnt from ***examples*** (as extra input)

Example Data $\mathbb{X}$ as Extra Input

- Unsupervised:
$$\mathbb{X} = \{\boldsymbol{x}^{(i)}\}_{i=1}^{N}, \text{ where } \boldsymbol{x}^{(i)} \in \mathbb{R}^{D}$$
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- Supervised:

$$\mathbb{X} = \{(\boldsymbol{x}^{(i)}, \boldsymbol{y}^{(i)})\}_{i=1}^{N}, \text{ where } \boldsymbol{x}^{(i)} \in \mathbb{R}^D \text{ and } \boldsymbol{y}^{(i)} \in \mathbb{R}^K,$$

  - E.g., $y^{(i)} \in \{0, 1\}$ a spam label

General Types of Learning (1/2)

- ***Supervised learning***: learn to predict the labels of future data points

$X \in \mathbb{R}^{N \times D}$: 

$\boldsymbol{y} \in \mathbb{R}^{N \times K}$: $[\boldsymbol{e}^{(6)}, \boldsymbol{e}^{(1)}, \boldsymbol{e}^{(9)}, \boldsymbol{e}^{(4)}, \boldsymbol{e}^{(2)}]$

$\boldsymbol{x}' \in \mathbb{R}^{D}$: 

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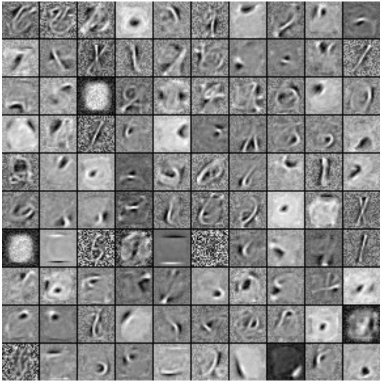
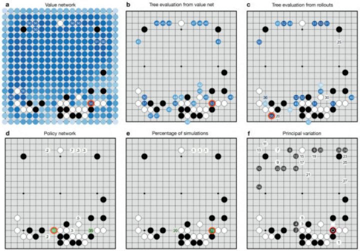
- ***Unsupervised learning***: learn patterns or latent factors in $\boldsymbol{X}$



General Types of Learning (2/2)

- ***Reinforcement learning***: learn from "good"/"bad" feedback of actions (instead of correct labels) to maximize the goal



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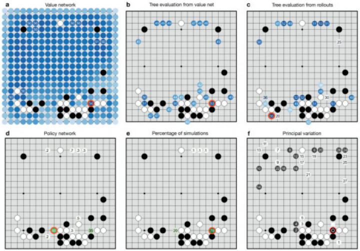

- AlphaGo [1] is a hybrid of reinforcement learning and supervised learning
  - Supervised learning from the game records
  - Then, reinforcement learning from self-play

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        1. f is assumed to be parametrized by $\boldsymbol{w}$

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5. Apply the model in the real world

Example for Spam Detection

1. Random split of your past emails and labels
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- See Notation

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Deep Learning

- ML where an $f(\cdot;\boldsymbol{w})$ has many (deep) layers

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- Pros:
  - Learns to pre-process data automatically
  - Learns a complex function (e.g., visual objects to labels)
- Cons:
  - Usually needs large data to train a model well
  - Higher computation costs (for both training and testing)

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Target Audience

- ***Senior undergraduate*** and ***graduate*** CS students
  - Easy-to-moderate level of theory
  - Coding and engineering (in Python)
  - Clean datasets (small & large)

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Topics Covered

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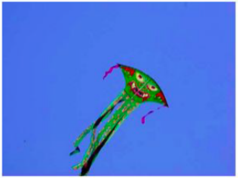
- with ***structural*** output:

A man holding a tennis racquet on a tennis court.

Two pizzas sitting on top of a stove top oven

A group of young people playing a game of Frisbee



A man flying through the air while riding a snowboard

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- Part 5: reinforcement learning (3 weeks)
  - Value/gradient policies, action/critics, reinforce RNNs

Grading (Tentative)

- Prerequisite quiz: ***15%***
  - ***In next Thu (9/22)***
  - ***You have to pass to be able to take this course: >70 or within top-70***
- Contests (x 4): ***40%***
  - At the end of each part
- Assignments: ***20%***
  - Come with the labs
- Final exam: ***25%***
- Bonus: ***6%***
  - Math labs (x 4)
  - Optional ML topics (x 2)

Classes Info

- Lectures on Tue (2 hours)
  - Concepts & theories
  - with companion videos
- Labs on Thu (1 hour)
  - Implementation (in Python) & engineering topics
- TA time: 4:20pm–5:30pm on Thu at Delta 724
- More info can be found in the course website

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Q: *Is this a light-loading course or heavy-loading one?*

A: Should be ***very heavy*** to most students. Please ***reserve your time***

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Q: *Why some sections are marked with "*" or "**" in the slides?*

A: The mark "*" means "can be skipped for the first time reader," and ""**" means "materials for reference only"

TODO

- Assigned reading:
  - Calculus
  - Get your feet wet with Python

Reference I

[1] D. Silver, A. Huang, C. J. Maddison, A. Guez, L. Sifre, G. Van Den Driessche, J. Schrittwieser, I. Antonoglou, V. Panneershelvam, M. Lanctot, et al.
Mastering the game of go with deep neural networks and tree search.
Nature, 529(7587):484–489, 2016.