Sapienza University of Rome

Master in Engineering in Computer Science

Artificial Intelligence & Machine Learning

A.Y. 2024/2025

Prof. Fabio Patrizi

1. Introduction

Fabio Patrizi

Info

- Teacher (ML): Fabio Patrizi
- 3CFU
- Personal webpage: `www.diag.uniroma1.it/patrizi`
- Course website: from "teaching" section in personal webpage
- Student hour: all info in personal webpage
- Textbooks:
  - [AIMA] S. Russel, P. Norvig, *Artificial Intelligence, a Modern Approach, 4th Ed.*
  - R.S. Sutton, A.G Barto. Reinforcement Learning 2nd Edition. (Available at: `incompleteideas.net/book/RLbook2020.pdf`)

Overview

- What is a Machine Learning problem
- ML problem classes
- Overview of ML
- Machine Learning issues

References

- [AIMA] 19.1, 19.2

Machine Learning

Machine Learning:

- *Programming computers to make them improve in a task using example data or past experience*

Useful when:

- No expertise available
- Humans are unable to explain how they carry out a task
- A general solution must be (fine-)tuned for specific cases
- No need to (fully) understand the solution (if it works, it's good)

INPUT	OUTPUT	$h_1(x)$	$h_1(x)$	$h_1(x)$
0	0	0	0	0
1	2	2	1,9	1.5
2	4	4	3,8	3
3	6	6	5,7	4.5
4	8	8	7,6	6
?	?			

$y = f(x)$

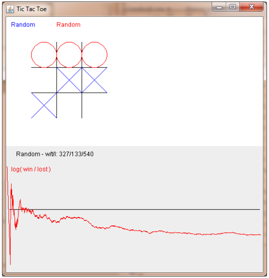
$x = 5 \rightarrow y = f(x) = 10$

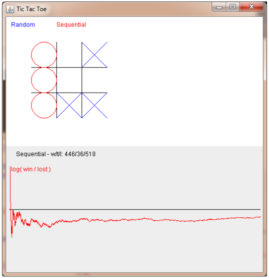
$h_1(x) = 2x$
$h_2(x) = 1.9x$
$h_3(x) = 1.5x$

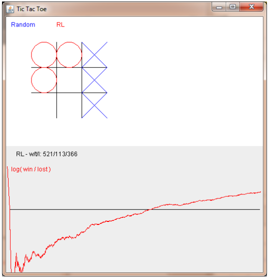
What is a Learning Problem?

- Task: what is to be done
- Performance measure: how well it is done
- Experience (data): examples of ideal performance or samples

Example: Tic Tac Toe







- Task: Tic Tac Toe
- Performance measure: win/loss
- Experience: Matches played so far

Example: Image Classification

- Task: Classify pictures as: *cat, horse, dog*
- Performance measure: # of correct classifications
- Experience: Classification examples

cat

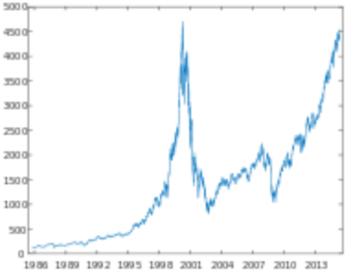
dog

horse

?

Example: Stock Price Prediction

- Task: Predict next stock price
- Performance measure: # predicted-vs-actual price difference
- Experience: Price chart



General Problem Formulation

Problem formulation:

- Find: function $f : X \rightarrow Y$ (X is the *instance space*)
- Given: *dataset* D providing *partial* information about f

Observe:

- D represents *experience* and its form depends on specific problem
- D does not allow for learning *exactly* f
- Need for *hypothesis* function (or *data model*) h approximating f: $h(x) \approx f(x)$
- h taken from *hypothesis space* H (*data model class*), e.g.:
  - linear, polynomial, exponential functions
  - boolean formulas, decision trees
  - ...

D

x	y
0	0
1	2
2	4
3	6
4	8

$D = \{\langle 0,0\rangle, \langle 1,2\rangle, \langle 2,4\rangle, \langle 3,6\rangle, \langle 4,8\rangle\}$

$f(x) =$

$f: N \to N$

Machine Learning Problems

Three classes of ML Problems:

1. **Supervised Learning**
   - Training data: input-output examples
   - Task: learn (approximate) function relating input to output
   - Two specific tasks:
     - Classification: given input data, return class (e.g., dog, cat, horse)
     - Regression: given input data, return (*real*) value (e.g., stock price)
2. **Unsupervised Learning**
   - Training data: input, no output
   - Task: Cluster similar data
3. **Reinforcement Learning**
   - Training data: state-action-reward sequences
   - Task: learn optimal *policy* π
     - mapping π : *states* $\rightarrow$ *actions*s that maximizes total (expected) reward

Supervised Learning

- Given a *training set* $D = \{(x_i, y_i = f(x_i))\}$ (*samples* from $f : X \rightarrow Y$)
- Learn function $h : X \rightarrow Y$ approximating f
  - **(Discrete input)**: $X = A_1 \times \ldots \times A_m$ (finite A_i)
  - **(Continuous input)**: $X = \mathbb{R}^n$
  - **(Classification)**: $Y = \{c_1, \ldots, c_k\}$
  - **(Regression)**: $Y = \mathbb{R}$

Supervised Learning: Classification

Learn $h : X \rightarrow Y$

- $Y = C = \{c_1, \ldots, c_k\}$ (each c_i is called *Class*)
- $D = \{(x_i, y_i)\} \subset X \times C$: classified instances
- $y_i = f(x_i) \in C$ (samples of f)

Examples:

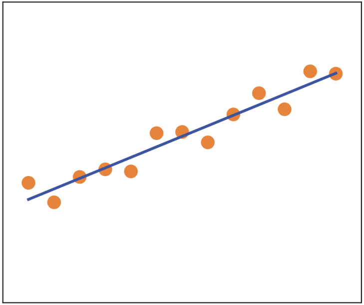
- Image classification:
  - X: images; $C = \{cat, dog, horse\}$; D: classified images
- Character recognition:
  - X: handwritten characters (different styles);
    $C = \{a, b, c, \ldots, 1, 2, 3, \ldots\}$;
    D: classified (images of) handwritten characters
- Speech recognition
- Medical diagnosis

Supervised Learning: Regression

Learn $h : X \to Y$

- $Y = \mathbb{R}$
- $D = \{(x_i, y_i)\} \subset X \times \mathbb{R}$: input-output examples (orange dots)
- $y_i = f(x_i) \in \mathbb{R}$ (samples of f)

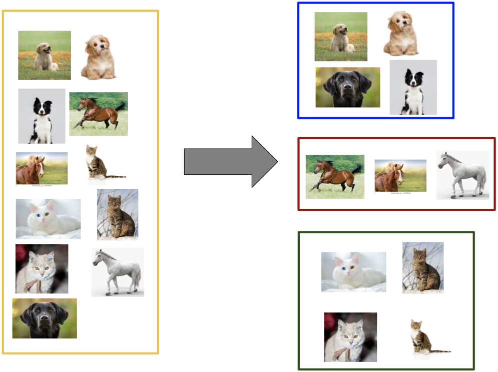
Example



Unsupervised Learning

Learn $h : X \rightarrow Y$

- $Y = 2^X$; $x_i \in h(x_i)$ (x_i belongs to its own cluster); *h partitions X*
- $D = \{x_i\} \subset X$: input samples (no output available)



Reinforcement Learning

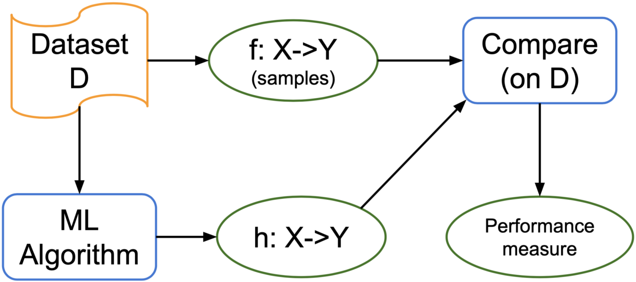
Learn $h : X \to Y$

- X: states; Y: actions;
- D: set of state-action-reward sequences $\langle s_0, a_0, r_0, \ldots, s_\ell, a_\ell, r_\ell \rangle$
- $r_i \in \mathbb{R}$
- D *is not* given, sequences must be generated by acting
- f must maximize (expected) sum of rewards along sequences

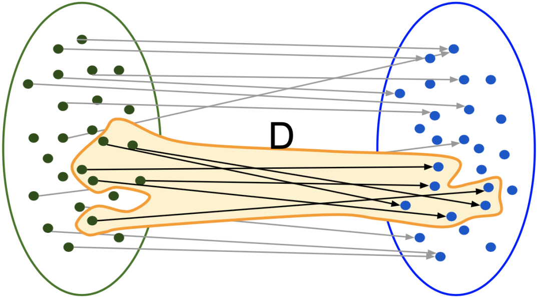
Example:

- Tic Tac Toe
  - X: board configurations
  - Y: possible moves
  - Reward: 1 if win; 0 if loss

Machine Learning Overview



Issues: Dataset Representativeness



- D provides only *partial* information about f:
  - Typically, X infinite (or extremely large): $|D| << |X|$
  - D not enough to *fully* characterize f
- We look for *generalization*: h learnt on D must work well on $X \setminus D$
- (Even if bad on D!)

Inductive Learning Hypothesis

Given:

- training set D
- hypothesis $h : X \to Y$ approximating target function f

Performance measure based on evaluating $h(x)$ vs $f(x)$ over all $x \in D$

Inductive learning hypothesis

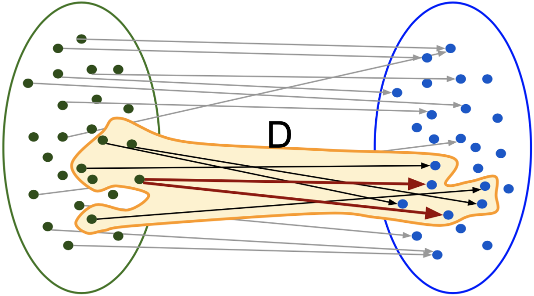
Any hypothesis h that approximates f *well* over a *sufficiently large* dataset D will also approximate f well over unobserved (new) instances $x \in X \setminus D$

Issues: Data Availability

- Data is the essence of ML
- Limited availability, cannot just get more data as needed
- Data collection is a major task
  - core business of many companies
- Must get the most out of available dataset D
  - training and testing

Issues: Noisy Data

Noisy data is normality



- D may be noisy, even inconsistent
  - sampling errors: $f(x) \neq y$, for $(x, y) \in D$
  - $f(x) = 3$ and $f(x) = 4$
  - No solution?

Statistical approaches needed to obtain noise-robust solutions

Summary

- Machine Learning amounts to approximating a function from samples
- Performance evaluated on dataset
- *Inductive Learning Hypothesis*
- Limited data availability
- Noisy/inconsistent data
- Statistical approaches needed