

COE206 – Principles of Artificial Intelligence

Mustafa MISIR

Istinye University, Department of Computer Engineering

mustafa.misir@istinye.edu.tr

<http://mustafamisir.github.io>

<http://memorylab.github.io>



L8: Learning Problem¹

¹ the content is adapted from the RPI - CSCI 4100/6100 course slides on the Learning from Data book's first chapter, made by Malik Magdon-Ismaïl – <https://www.cs.rpi.edu/~magdon/>

Let's Define a Tree



Let's Define a Tree

If you show a picture to a 3 year old kid and ask if there is a tree in it, you will probably get the right answer.



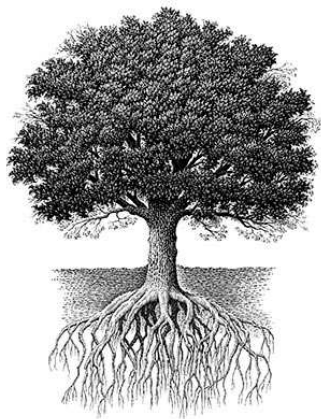
Let's Define a Tree

If you ask someone who is 30 years old the definition of the tree, you will probably get an inadequate answer

- ▶ We learn trees not from mathematical definitions, but by looking at them - that is, **learn from data**



Defining is Hard; Recognizing is Easy



Learning to Rate Movies

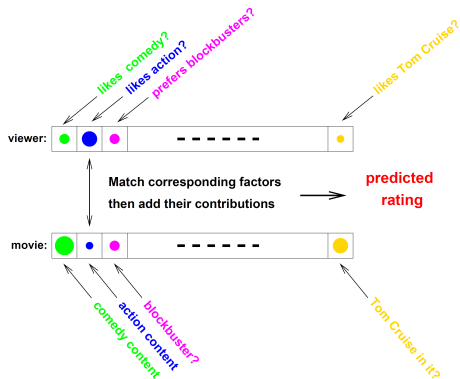
- ▶ Can we predict how a viewer would rate a movie?
- ▶ Why? So that Netflix can make better movie recommendations, and get more rentals
- ▶ **Netflix Prize**²: 1 million prize for a mere 10% improvement in their recommendation system

NETFLIX

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
Grand Prize - RMSE = 0.8567 - Winning Team: BellKor's Pragmatic Chaos				
1	BellKor's Pragmatic Chaos	0.8567	10.06	2009-07-26 18:18:28
2	The Ensemble	0.8567	10.06	2009-07-26 18:38:22
3	Grand Prize Team	0.8582	9.90	2009-07-10 21:24:40
4	Opera Solutions and Vandelay United	0.8588	9.84	2009-07-10 01:12:31

² <https://www.netflixprize.com/> - <https://www.wired.com/2009/09/how-the-netflix-prize-was-won/> - <https://www.thrillist.com/entertainment/nation/the-netflix-prize>

Learning to Rate Movies



- ▶ Viewer taste and movie content imply viewer rating
- ▶ No magical formula to predict viewer rating
- ▶ Netflix has data. We can learn to identify **movie categories** as well as **viewer preferences**

A pattern exists even though we don't know it yet. **We have data to learn it.**

Learning to Rate Movies

- ▶ **Movies:** Let's define each movie by a series of different **factors**; e.g. how much comedy is in it, etc.
- ▶ **Viewers:** Let's define each viewer by a series of different **factors**; e.g. how much he likes comedy, prefers simple or complex graphics, how important the appearance of the lead actor, etc.

Based on **factors** that can **explain the content of a movie** and the **taste of the viewer**, the **viewer's movie score** can be estimated

Credit Approval

Will the loan application of a bank customer be approved?

Age	32
Gender	Male
Salary	40.000 TL / year
Debt	26.000 TL
Work Duration	1 Year

Credit Approval – Learning

- ▶ Related factors: salary, debt, years in residence etc. – **input**
 $\mathbf{x} \in \mathbb{R}^d = \mathcal{X}$
- ▶ Approve credit or not – **output**
 $y \in \{-1, +1\} = \mathcal{Y}$
- ▶ True relationship between x and y – **target function**
 $f : \mathcal{X} \rightarrow \mathcal{Y}$
- ▶ Data on customers – **dataset**
 $\mathcal{D} = (\mathbf{x}_1, y_1), \dots, (\mathbf{x}_N, y_N)$ buradan $y_n = f(\mathbf{x}_n)$

\mathcal{X} , \mathcal{Y} and \mathcal{D} are given, yet the target function f is unknown

Learn f from the data \mathcal{D}

Credit Approval – Learning

Start with a set of candidate **hypotheses** \mathcal{H} which you think are likely to represent f

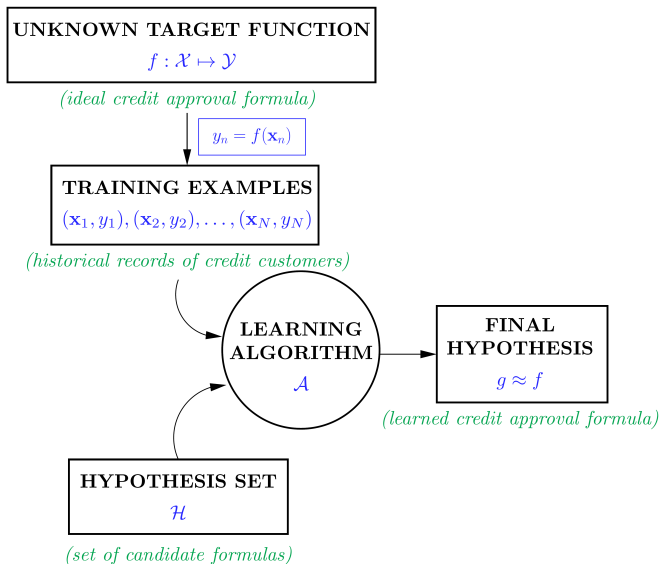
- ▶ **Hypotheses set** or **Model** : $\mathcal{H} = \{h_1, h_2, \dots, h_m\}$

Select a **hypothesis** g from \mathcal{H} . The way we do this is called a **learning algorithm**.

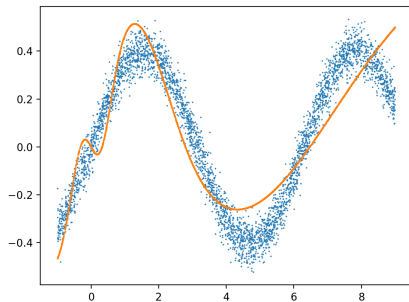
Use hypothesis g for new customers.

- ▶ The success of **hypothesis** g can be measured by the **similarity** between the selected **hypothesis** g and the **actual function** f : $g \approx f$

Summary of the Learning Setup



Learning – Function Approximation³



Learning can be seen as
function approximation

³

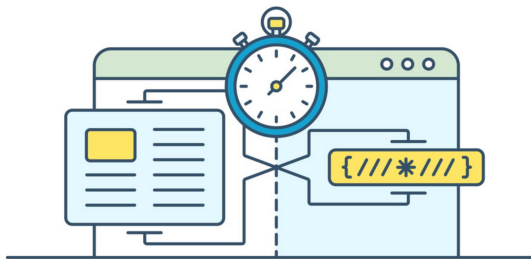
image source:

<https://stats.stackexchange.com/questions/320289/approximate-the-sine-function-with-shallow-neural-network>

Learning – Compression⁴

Learning performs **compression** by specifying a rule over the data, while getting a simpler explanation from the data, requiring less memory and computational resources

- ▶ e.g. when we learn the rules of addition, it is not necessary to remember the sum of every possible pair of numbers

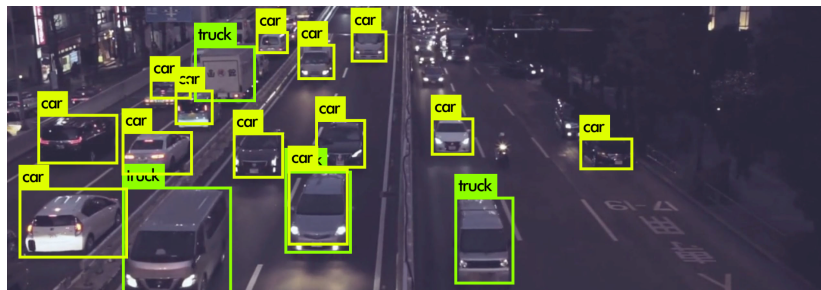


⁴

image source: <https://www.vectorstock.com/royalty-free-vector/data-compression-vector-19122120>

Learning – Labeling⁵

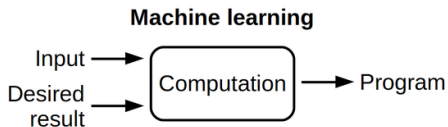
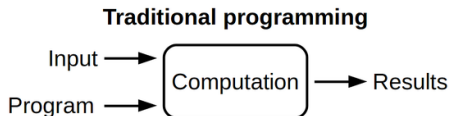
Learning can help to **label new, unlabeled data**



⁵ image source: <https://www.move-lab.com/blog/tracking-things-in-object-detection-videos>

Machine Learning (ML)⁷

Learning **without being explicitly programmed**⁶



⁶

image source: <https://www.futurice.com/blog/differences-between-machine-learning-and-software-engineering/>

⁷

https://en.wikipedia.org/wiki/Machine_learning

Why Machine Learning?⁸

Tasks That Are Too Complex to Program: tasks that can be performed by humans or animals

- ▶ As the tasks routinely performed by humans such as **driving**, **speech recognition** and **image understanding**, cannot be precisely described in detail, Machine Learning can be benefited to **learn from their experiences** (data)



⁸

Why Machine Learning?

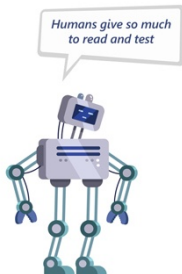
Tasks That Are Too Complex to Program: Tasks beyond human capabilities

- ▶ If the data is too much and extremely complex such that humans cannot make sense of them in practice, the increasing **speeds** and **memory** capabilities of the computing devices can be benefited with Machine Learning

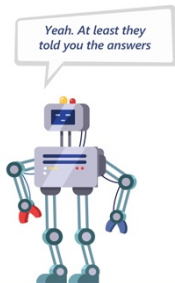


Types of Learning⁹

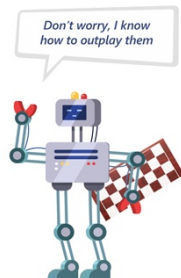
Supervised Learning



Unsupervised Learning



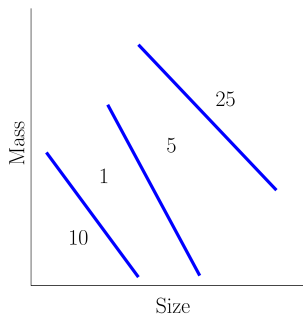
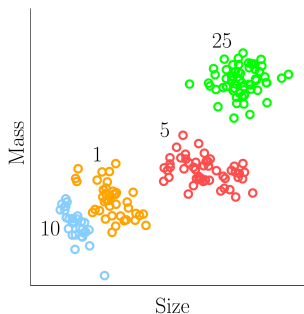
Reinforcement Learning



Types of Learning: Supervised Learning (SL)

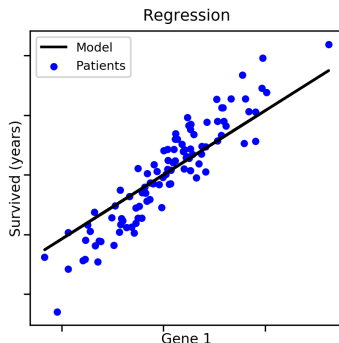
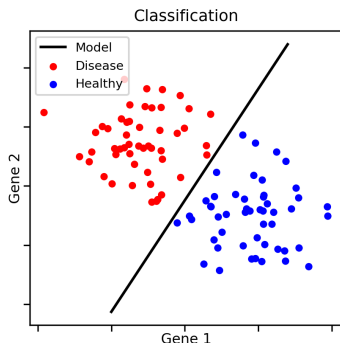
SL is concerned with the **labeled datasets** that can be used for **training** such that a resulting **model** or **function** can be applied to determine the **label** of any given, **unseen data**, e.g. coin classification

- ▶ The goal is to have a **model** that can generalize well on the **unseen datasets**



Types of Learning: Supervised Learning (SL)¹⁰

- ▶ **Classification** deals with predicting **categorical labels**
- ▶ **Regression** is a problem of predicting a **real-valued label** (target) given an **unlabeled** example

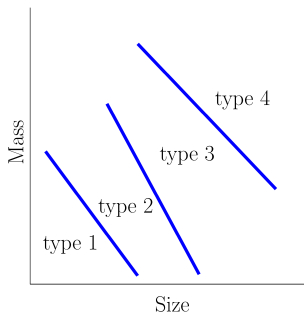
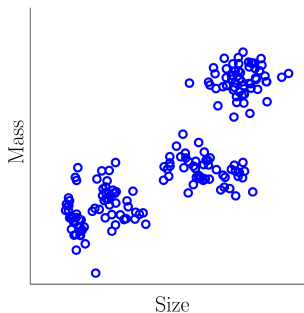


¹⁰

image source: <https://github.com/ramrathi/IECSE-ML-Winter18/wiki/Basic-Logistic-Regression>

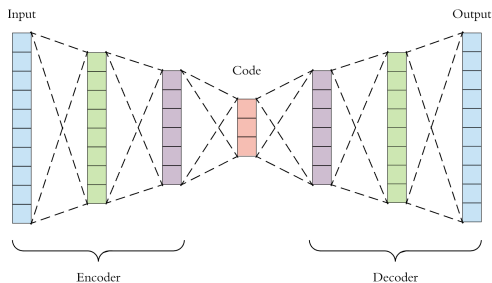
Types of Learning: Unsupervised Learning (UL)

A type of learning aim to **infer** using **unlabelled** datasets, e.g. coin grouping



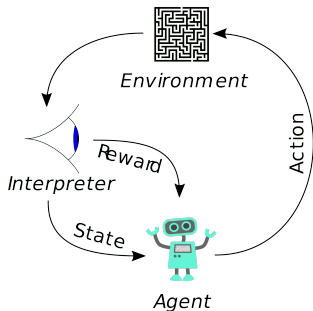
Types of Learning: Unsupervised Learning (UL)¹¹

- ▶ **Clustering:** differentiate data samples w.r.t. their attributes / features
- ▶ **Dimensionality Reduction:** reducing the data sample size by decreasing the number of attributes (or determining more inclusive features) without undermining the overall structure of the data



¹¹ image source: <https://ainews.spxbot.com/category/dimensionality-reduction/>

Types of Learning: Reinforcement Learning¹²



A **decision-making agent** aims at solving a given problem, in a certain **environment**, by performing successive **actions** under a **reward / penalty** scheme

After a series of **trial-and-error**, a **policy** is expected to be learned, deciding on which action to apply in which order (relying on the present **state**) for **maximizing** the total (long-term) **reward**

¹²

cart pole balancing : <https://www.youtube.com/watch?v=Lt-KLtkDlh8> – image source: <https://www.datahubbs.com/reinforcement-learning/>

