Machine Learning and Intelligent Systems

Introduction

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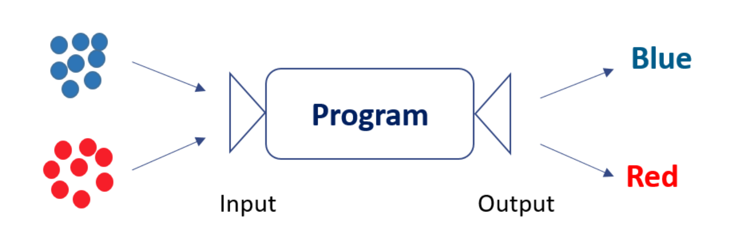
EURECOM - Data Science Department

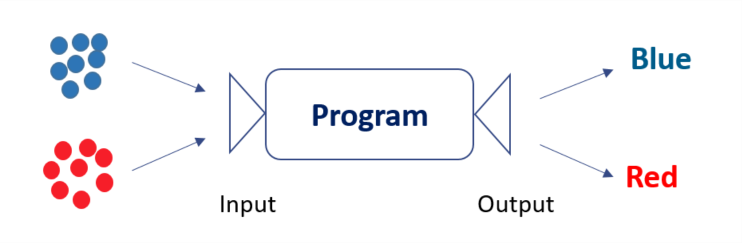
Introduction to Machine Learning

Traditional Computer Science vs. Machine Learning

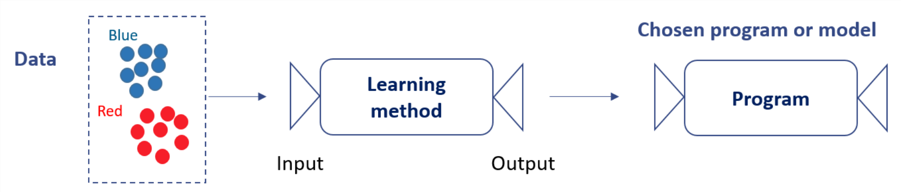


Traditional Way

Traditional Computer Science vs. Machine Learning



Traditional Way



Machine Learning

Machine Learning: Definition

- Term introduced in 1959 by Arthur L. Samuel [1]

Arthur Samuel (1901-1990)

Tom M. Mitchell
Computer Scientist and
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  A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E.

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  A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E.
- In simple words: Algorithms that improve on a task with experience

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[1] A. Samuel. Some studies in machine learning using the game of Checkers. IBM Journal of Research and Development (1959)

[2] T.M. Mitchel. Machine Learning (1997)

Machine Learning: Learning from Data

An example: Spam filtering

- Task (T):
- Experience (E):
- Performance measure (P):

Machine Learning: Learning from Data

An example: Spam filtering

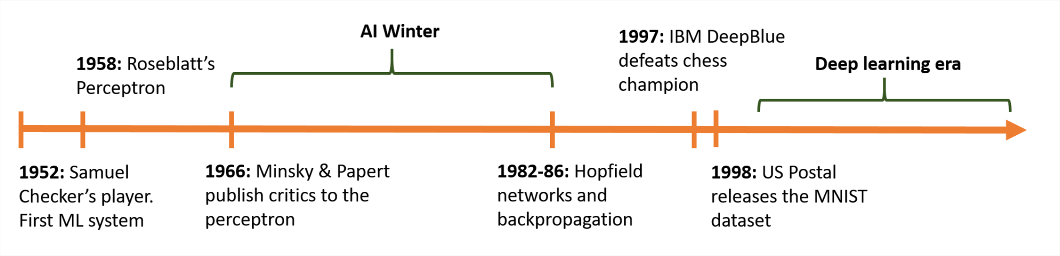
- Task (T):
- Experience (E):
- Performance measure (P):

Learning from experience (i.e. data) to be able to:

- Make predictions
- Find similarities
- Find patterns
- Discover knowledge

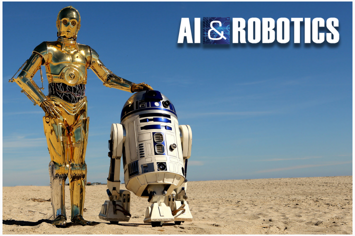
Example adapted from: T. Mitchell `http://www.cs.cmu.edu/afs/cs.cmu.edu/project/theo-20/www/mlbook/ch1.pdf`

Some history



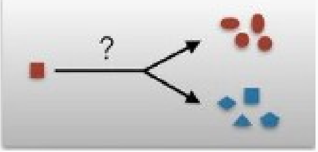
AI vs. Machine Learning

AI (before AI winter)



- Top-down approach
- Based on logic

Machine Learning



- Firstly, a way to get funding
- Bottom-up approach: Starts from smaller goals
- Based on statistics and optimization

AI in the DL era

- Term's rebirth: useful for funding
- Result of last decades success

Adapted from K. Weinberg course @CMU

Key Issues in Machine Learning

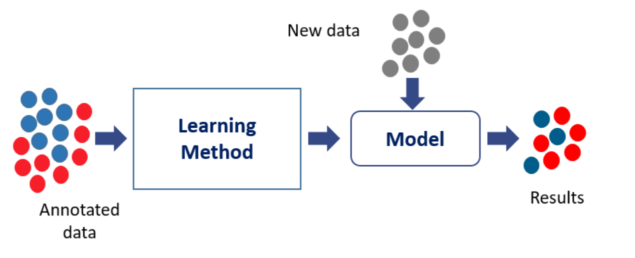
- What data (E) to use?
- How to represent it?
- Which algorithm should be used to learn?
- How to pick the best model?
- Can we be confident in the results?
- How to model a problem as a Machine Learning problem?

The Course

What you will learn

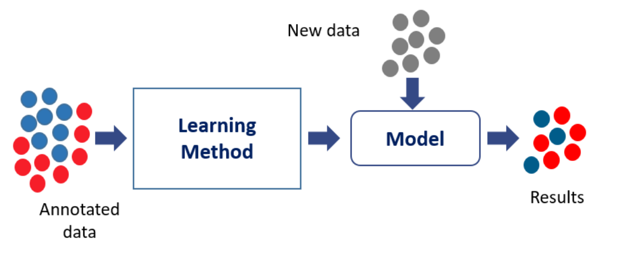
- Fundamental concepts underlying the mechanism of learning from data
- Several common algorithms to learn from data
- How to well-define a learning problem
- How to properly solve problems using these techniques

Types of Learning

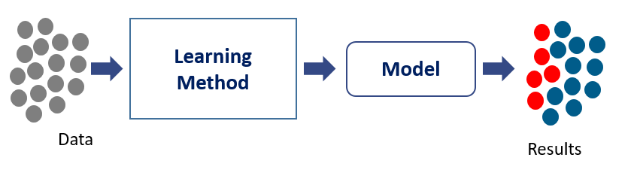


Supervised Learning (80%)

Types of Learning



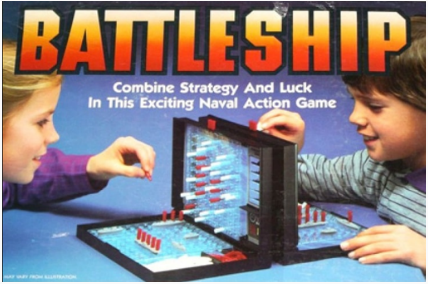
Supervised Learning (80%)



Unsupervised Learning (20%)

Types of Learning: Reinforcement Learning

- Learning what to do how to map situations to actions to maximize a numerical reward.
- The learner is not told which actions to take, but must discover which yield the most reward.
- Examples: Alpha GO, Robotics, Autonomous vehicles, resource management in computer clusters



Not covered in this course

The Project

This year the project's grade will be the average from 4 small projects to be delivered during the term

First Assignment:

Visit `https://malis-course.github.io/project` and read the detailed description

Logistics

Expected Previous Knowledge

Basic knowledge of:

- Probability
- Linear algebra
- Calculus

For the labs, basic knowledge of:

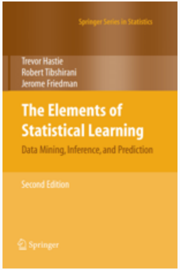
- Programming
- Python - Labs run in Python

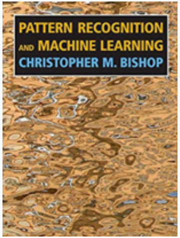
Bibliography

No official textbook followed.

Two suggested readings:

- The Elements of Statistical Learning Hastie, Tibshirani, Friedman
- Pattern Recognition and Machine Learning Bishop





Other resources (with links)

Machine Learning:

- Bayesian reasoning and Machine Learning Barber
- Understanding Machine Learning: From Theory to Algorithms Shalev-Shwartz & Ben-David
- Machine Learning a probabilistic perspective - Murphy

Linear algebra:

- Review notes from Stanfords ML course Kolter & Do
- Introduction to Linear Applied Linear Algebra Boyd & Vandenberghe

Probability: Review notes from Stanfords ML course Maleki & Do

Calculus: Review notes from University of Maryland Daum III

Python: Python cheat sheet Pointal

Modus Operandi

10 lectures

- Slides will be made available the Friday before the lecture in Moodle
- Slides with annotations will be available the next Friday following the lecture
- Some lectures will have accompanying code with exercises for you to complete (optional)

4 labs:

- Groups of 2

Assessment

- Labs : 10%
- Project : 30%
- Final exam : 60%

Important

To pass the course, every item grade needs to be greater or equal than 8.5

ChatGPT Policy

It can be used for the project, as long as it is documented

Communication & Contact

In order

1. Moodle: Forum and chat
2. Mail: `maria.zuluaga@eurecom.fr`
3. Office hours: Thursdays 13.00 - 14.00 (Office 427)
   An email should be send before to book a slot

Important
The main communication channel is the weekly lecture. If you fail to attend, it is your responsibility to find out about any announcement that has been made during the lecture.

Recommendation Letter Policy

Many students request a recommendation letter at the end of the term. I am fine with providing you a letter as long as the following two conditions are met:

1. Your final grade **at least** 15
2. I know who you are

Things I do not do:

1. Generic letters
2. Provide you the letter

Any questions?