COS30018 – Week 4:
Introduction to Machine Learning (ML)

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Machine Learning (ML)

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Machine Learning is one of today's most exciting technologies:

- Powering a majority of AI systems
- Democratizing technologies & AI

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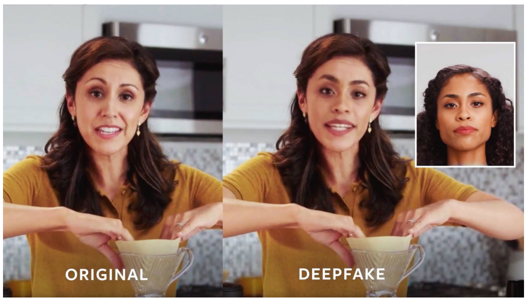
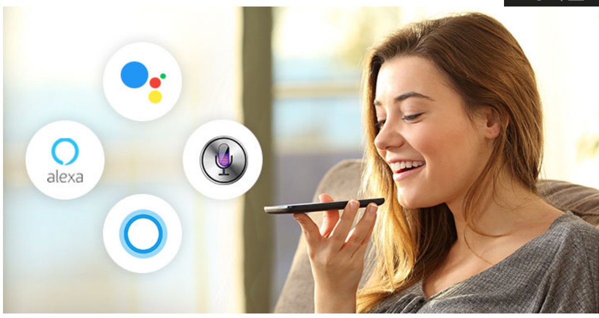
What is Machine Learning? Examples





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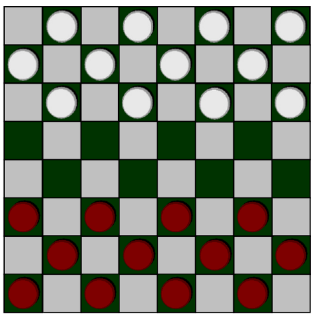
What is Machine Learning? Definition

Machine learning is a field of study that gives computers the ability to learn without being explicitly programmed.

(Arthur Samuel, 1959)



Samuel's Checkers program (approx. 1952 – 1956) uses a combination of:

- Rote learning ~ memorizing the game board positions and storing their values
- Generalization learning ~ updating the reward functions as more board positions are discovered and assigned a value (via self-playing)
- Self-playing ~ generating vast amount of training data

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Questions for AI researchers, developers & practitioners:

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Traditional programming

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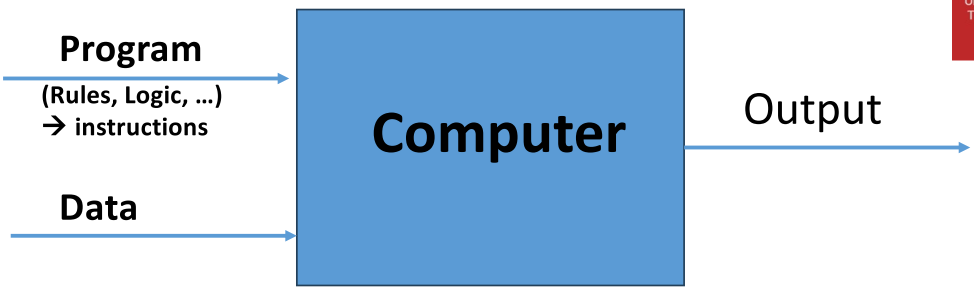

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Issues with traditional approach

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Issues with traditional approach

- What are the rules & logic you use to recognise your friend??

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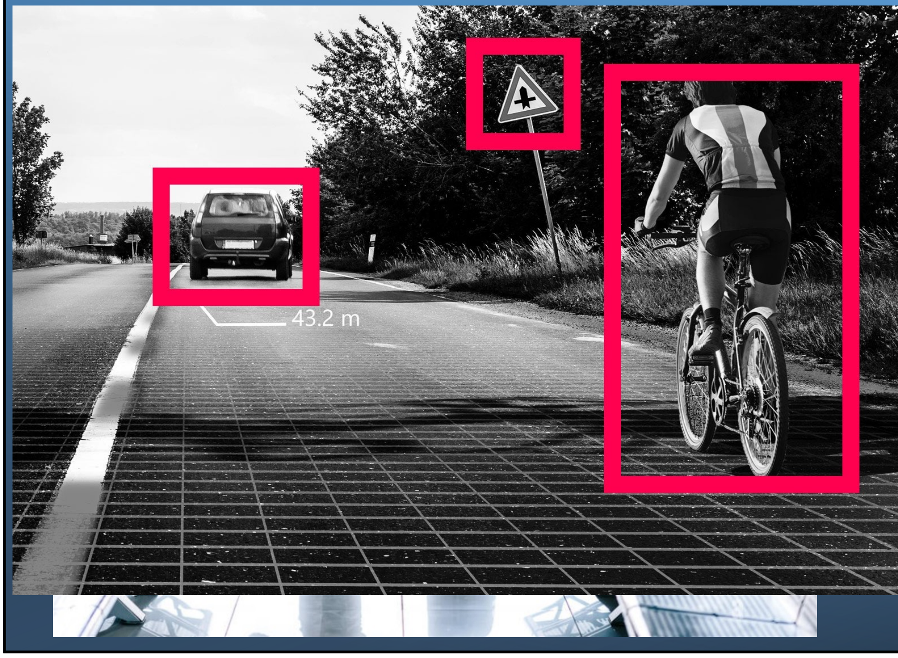

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Issues with traditional approach

- What are the rules & logic you use to recognise your friend??

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Machine Learning: Our hero??

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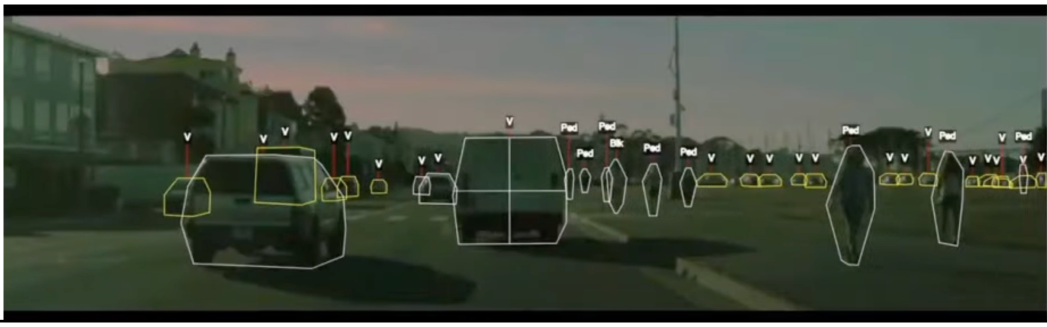
Data → **Computer** → "Program"

Output → **Computer**



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Machine Learning (ML):

Our hero??

Data

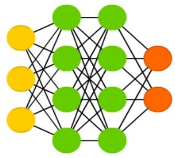
Output

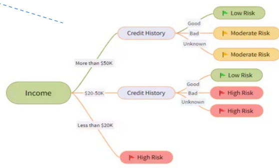
Computer

(ML Algorithm)

"Program"

(ML Model)





$$y = f(x_1, x_2, x_3, x_4) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \theta_4 x_4$$

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Machine Learning (ML) – How does the machine learn?

- A typical problem

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Leonardo DiCaprio
Ben Affleck
Taylor Swift
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Machine Learning (ML) – How does the machine learn?
• A typical problem

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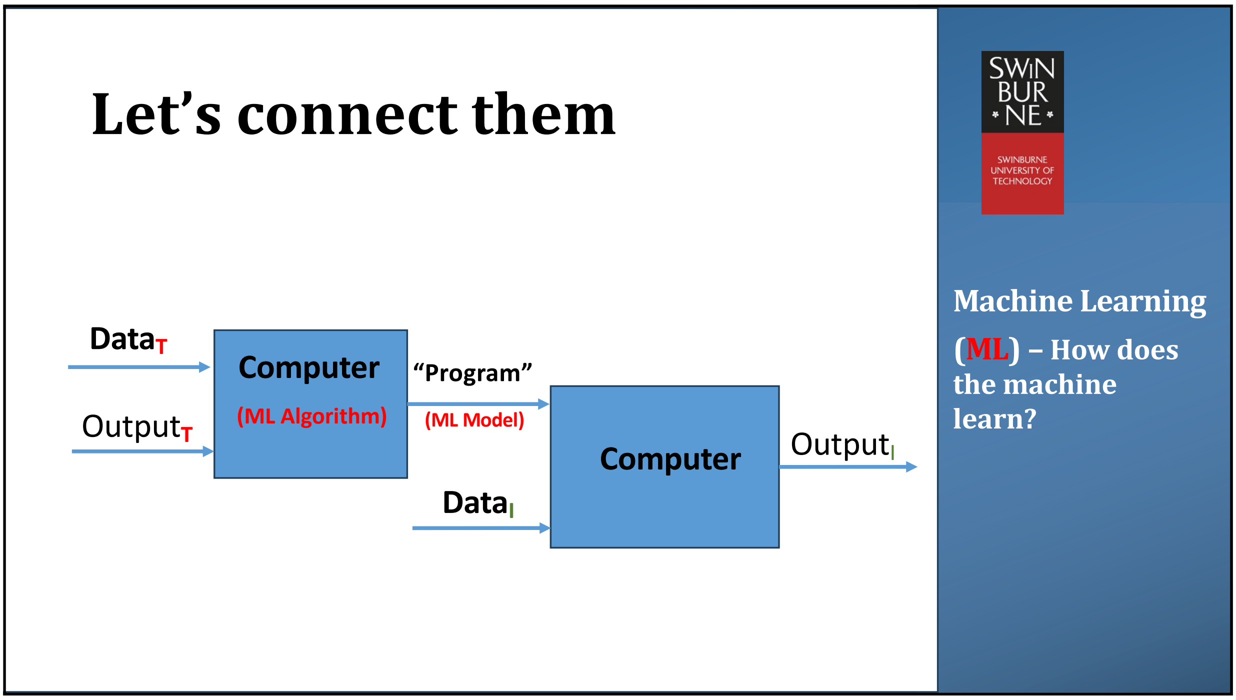
Let's connect them
$Data_T$
$Output_T$
Computer
(ML Algorithm)
"Program"
(ML Model)
Computer
$Data_I$
$Output_I$
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Machine Learning (ML) – How does the machine learn?

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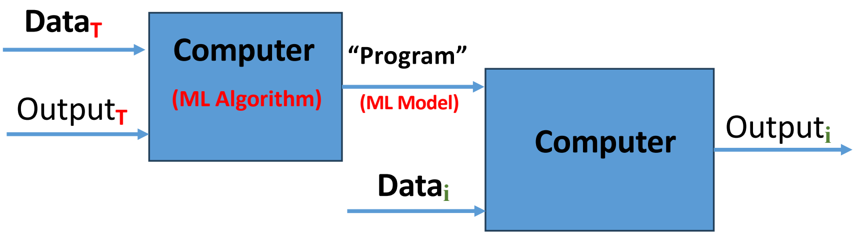
Let’s connect them



The most well-known models currently?
They are known as **Large Foundation Models**/**Large Language Models**, such as models from the **GPT**’s family, **Gemini**’s family, **Grok**’s family, **Llama**’s family

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Machine Learning (ML) – How does the machine learn?

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Machine Learning (ML) – How does the machine learn?

- From a dataset consisting of many examples
- From the experiences it gains from the direct interaction with environment

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Machine Learning (ML) – How does the machine learn?

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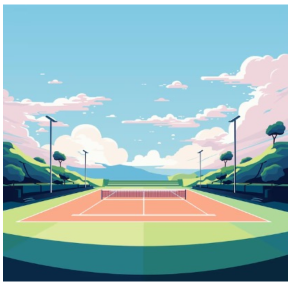

Machine Learning (ML) – Basic concepts

- A simple problem – When to play tennis??

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Source:
Tom Mitchell, 1997

Example	outlook	temp	humidity	windy	play
0	sunny	hot	high	False	no
1	sunny	hot	high	True	no
2	overcast	hot	high	False	yes
3	rainy	mild	high	False	yes
4	rainy	cool	normal	False	yes
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2				False	yes
3				False	yes
4				False	yes
5				True	no
6				True	yes
7				False	no
8				False	yes
9				False	yes
10				True	yes
11				True	yes
12				False	yes
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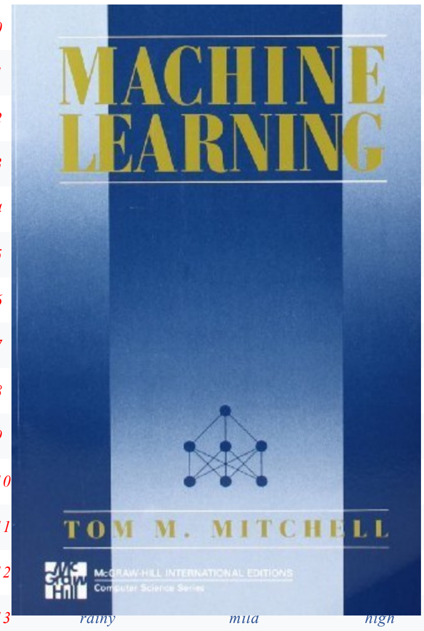

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Machine Learning (ML) – Basic concepts

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Features
(Attributes)

Example	outlook	temp	humidity	windy	play
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Machine Learning (ML) – Basic concepts

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Features
(Attributes)

Target
(Labels)

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Features (Attributes)

Target (Labels)

In ML lingua:

- Each example *i* is expressed as a pair (X^i, y^i), where $X^i = (X^i_1, ..., X^i_k)$ is also called ***Input*** and the Target y^i is also called ***Output.*** (Here k is the number of features)
- For example, in the "Play tennis" problem: Example 0 can be expressed as (X^0, y^0), where $X^0 = (X^0_{outlook}$ = sunny, X^0_{temp} = hot, $X^0_{humidity}$ = high, X^0_{windy} = False) and y^0 = no.

Source:
Tom Mitchell, 1997

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Machine Learning (ML) – Basic concepts

- **A simple problem – When to play tennis??**

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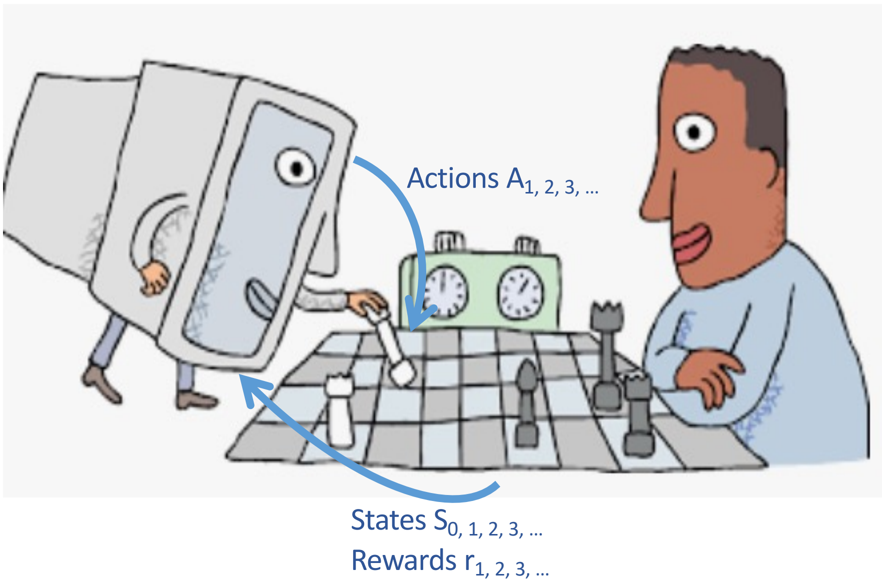

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Machine Learning (ML) – Basic concepts

- **A machine that plays chess**

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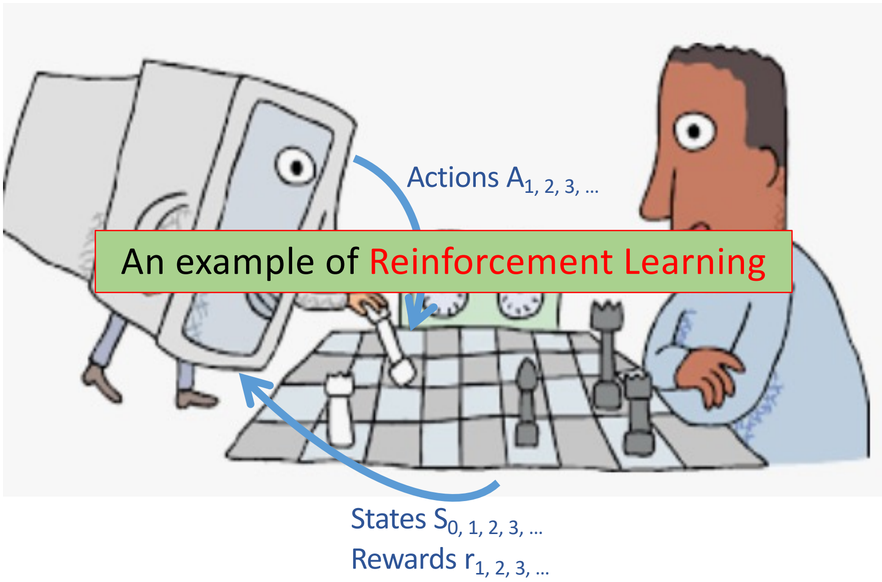

Machine Learning (ML) – Basic concepts

- **A machine that plays chess**

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Types of Learning

- Supervised (inductive) learning
  - Given: training data + desired outputs (labels)
- Unsupervised learning
  - Given: training data (without desired outputs)
- Semi-supervised learning
  - Given: training data + a few desired outputs
- Reinforcement learning
  - Rewards from sequence of actions

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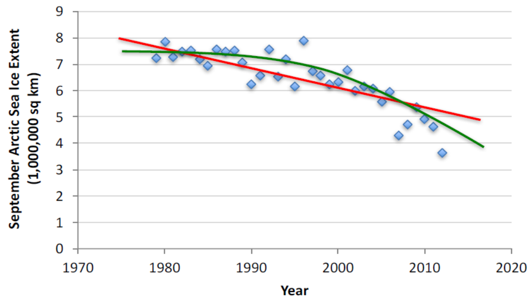
Supervised Learning: Regression and Classification

Given the dataset of observations $(x_1, t_1), (x_2, t_2), \ldots, (x_n, t_n)$

- Learn a function $f(x)$ to predict the target variable t given x



Data from G. Witt. Journal of Statistics Education, Volume 21, Number 1 (2013)

t is real-valued == regression

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t is categorical == classification

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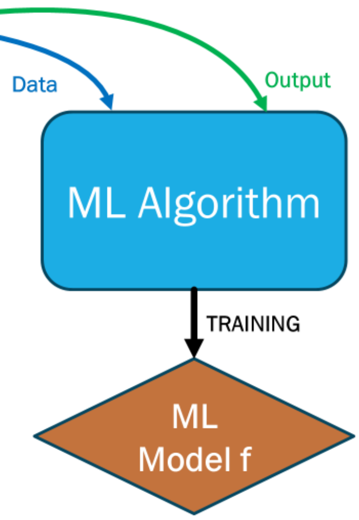
SUPERVISED LEARNING

	F_1	F_2	.....	F_k	T
Obs^1	Obs^1_1	Obs^1_2		Obs^1_k	t^1
Obs^2	Obs^2_1	Obs^2_2		Obs^2_k	t^2
...					...
...					...
Obs^i	Obs^i_1	Obs^i_2		Obs^i_k	t^i
...					
Obs^n	Obs^n_1	Obs^n_2		Obs^n_k	t^n



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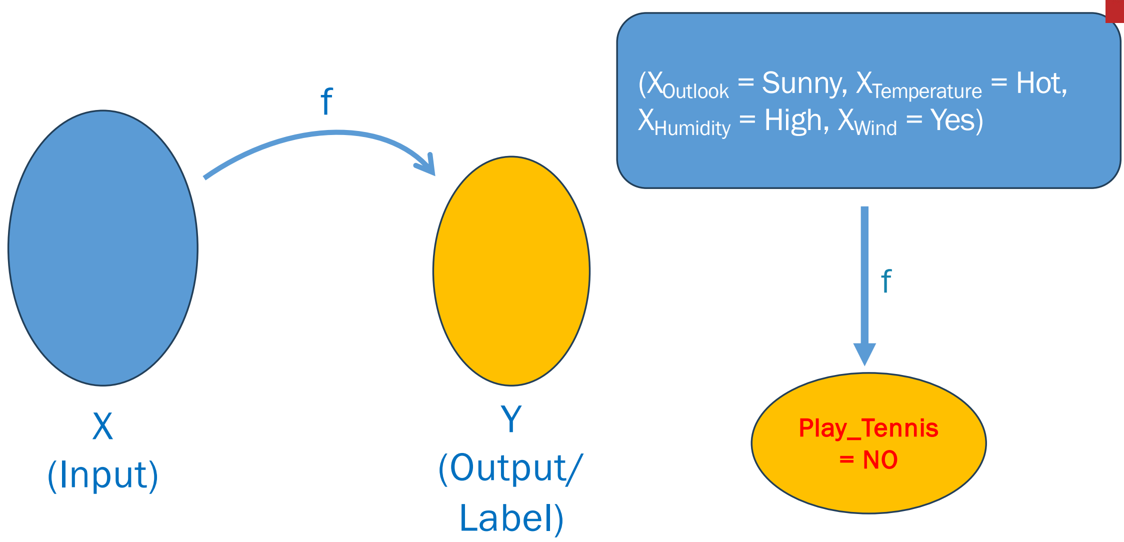
SUPERVISED LEARNING



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SUPERVISED LEARNING

Input (X)	Output (Y)	Application
email →	spam? (0/1)	spam filtering
audio →	text transcripts	speech recognition
English →	Spanish	machine translation
ad, user info →	click? (0/1)	online advertising
image, radar info →	position of other cars	self-driving car
image of phone →	defect? (0/1)	visual inspection

Source: Andrew Ng/Stanford Online

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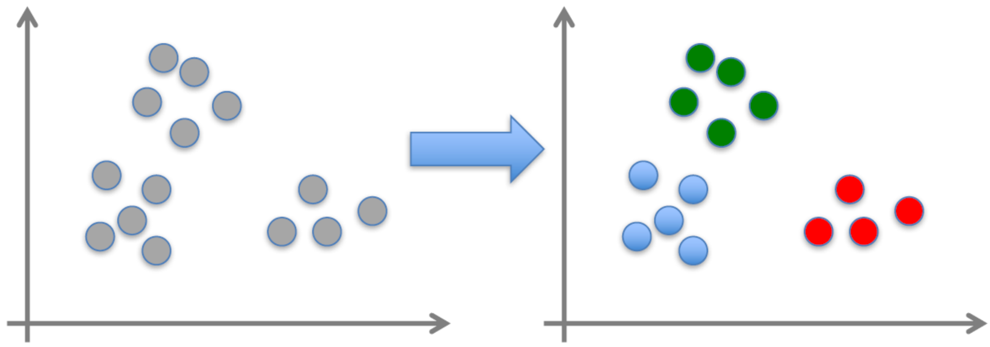
Unsupervised Learning

Given $x^1, x^2, \ldots, x^n$ (without labels)

- Output hidden structure behind the x's
  - E.g., clustering



E.g., https://news.google.com uses clustering

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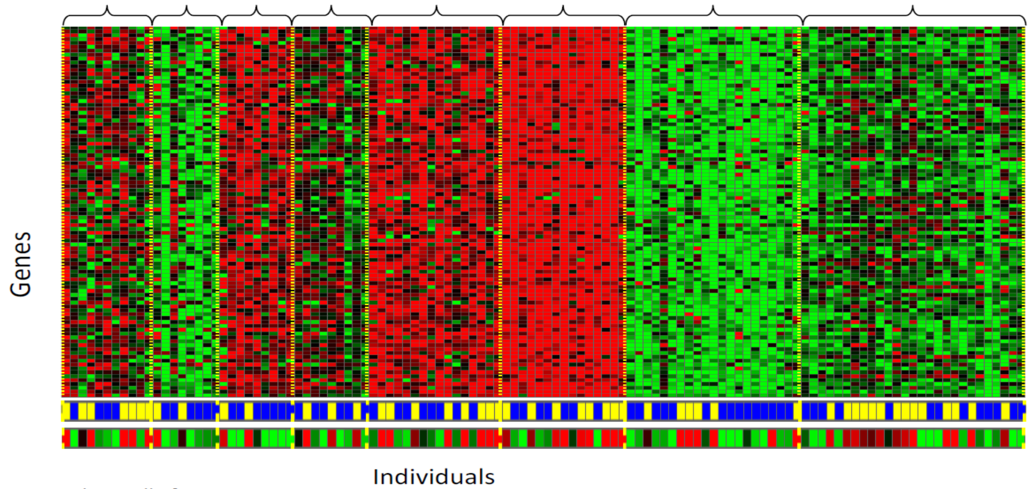
Unsupervised Learning

Genomics application: group individuals by genetic similarity



[Source: Daphne Koller]

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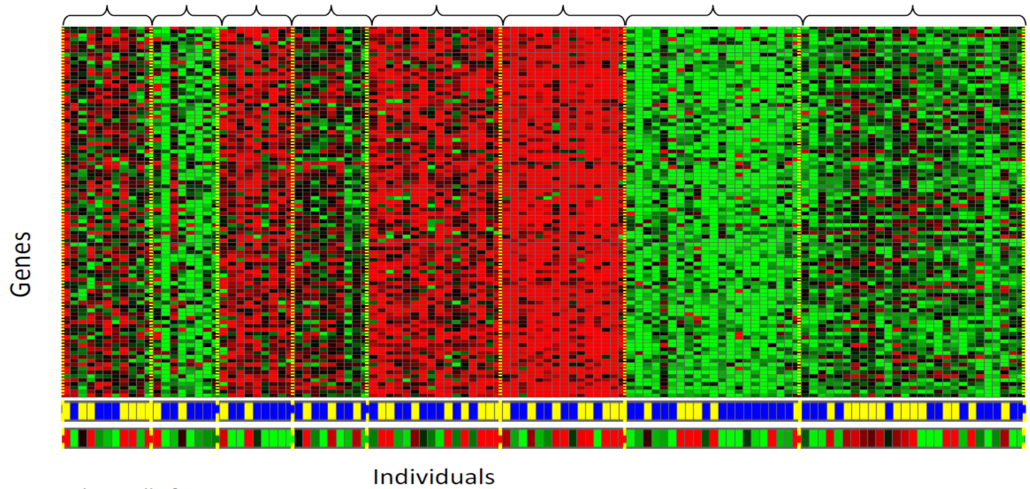
Unsup

Genomics

If members of a genomics group have a higher chance of getting a disease X then an individual from the same group should be monitored for X to ensure that the condition can be detected early.



[Source: Daphne Koller]

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Semi-supervised Learning

Can you build a spam filter for emails?

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Semi-supervised Learning

The given dataset does not have a label for every example

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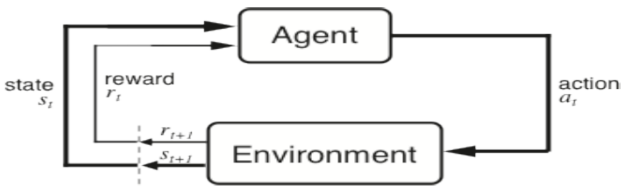
Reinforcement Learning: The Agent-Environment Interface



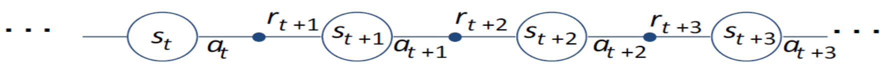
Agent and environment interact at discrete time steps : $t = 0, 1, 2, K$

Agent observes state at step t: $s_t \in S$

produces action at step t: $a_t \in A(s_t)$

gets resulting reward : $r_{t+1} \in \Re$

and resulting next state : s_{t+1}



Slide credit: Sutton & Barto

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Reinforcement Learning

Given a sequence of states and actions with (delayed) rewards, output a policy

– Policy is a mapping from states → actions that tells you what to do in a given state

Examples:

– Credit assignment problem
– Game playing
– Robot in a maze
– Balance a pole on your hand

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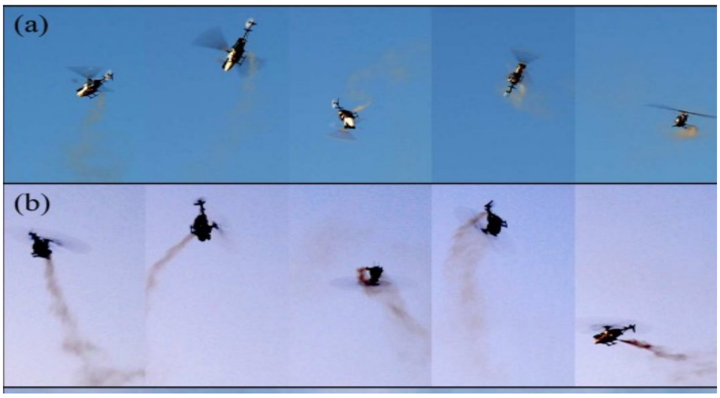
Reinforcement Learning

Learn policy from user demonstrations



Stanford Autonomous Helicopter
http://heli.stanford.edu/

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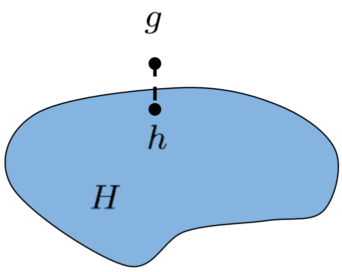
Learning from a Dataset of Examples: Inductive Learning

- Simplest form: learn a function from examples
  - A target function: g
  - Examples: input-output pairs $(x, g(x))$
  - E.g. x is an email and $g(x)$ is spam / ham
  - E.g. x is a house and $g(x)$ is its selling price
- Problem:
  - Given a hypothesis space H
  - Given a training set of examples x_i
  - Find a hypothesis $h(x)$ such that $h \sim g$
- Includes:
  - Classification (outputs = class labels)
  - Regression (outputs = real numbers)



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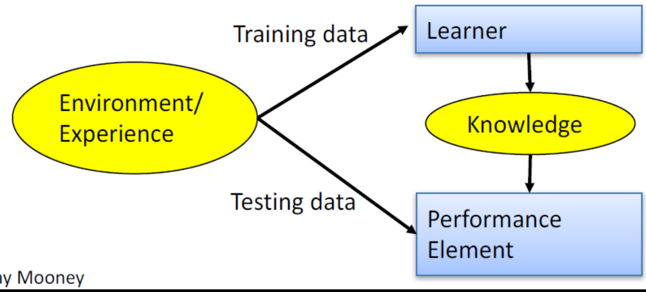
Designing a Learning System

- Choose the training experience
- Choose exactly what is to be learned – i.e. the ***target function***
- Choose how to represent the target function
- Choose a learning algorithm to infer the target function from the experience



Based on slide by Ray Mooney

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Training vs. Test Distribution

- We generally assume that the training and test examples are independently drawn from the same overall distribution of data
  - We call this "i.i.d" which stands for "independent and identically distributed"
- If examples are not independent, requires ***collective classification***
- If test distribution is different, requires ***transfer learning***

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ML in a Nutshell

- Tens of thousands of machine learning algorithms
  - Hundreds new every year
- Every ML algorithm has three components:
  - **Representation**
  - **Optimization**
  - **Evaluation**

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Various Function Representations

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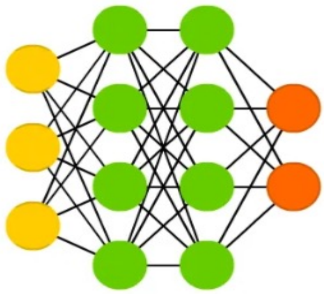
- Numerical functions
  - Linear regression
  - Neural networks
  - Support vector machines



$$y = f(x_1, x_2, x_3, x_4) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \theta_4 x_4$$

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Various Function Representations

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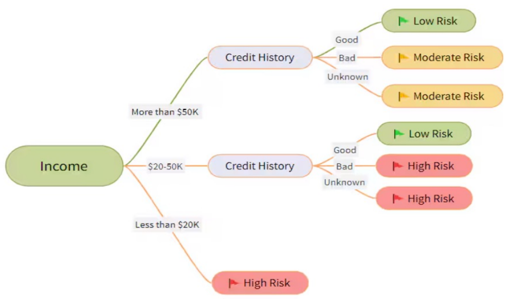
- Numerical functions
  - Linear regression
  - Neural networks
  - Support vector machines
- Symbolic functions
  - Decision trees
  - Rules in propositional logic
  - Rules in first-order predicate logic



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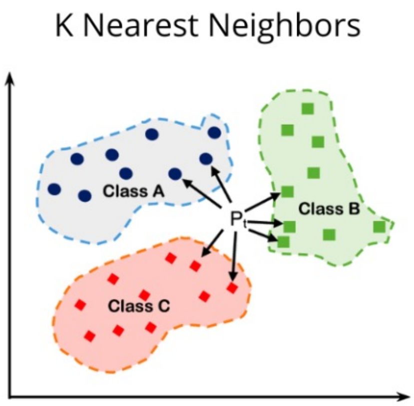
Various Function Representations



- Instance-based functions
  - Nearest-neighbor
  - Case-based
- Probabilistic Graphical Models
  - Naïve Bayes
  - Bayesian networks
  - Hidden-Markov Models (HMMs)
  - Probabilistic Context Free Grammars (PCFGs)
  - Markov networks

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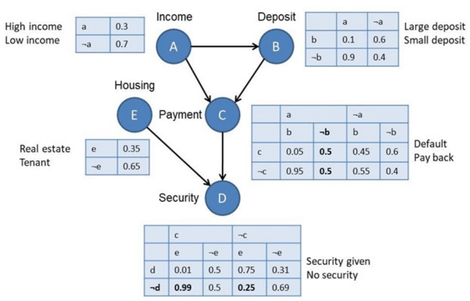
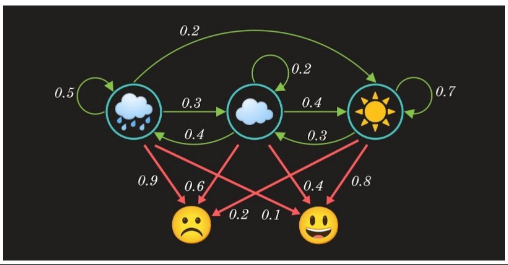
Various Function Representations





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Various Search/Optimization Algorithms

- Gradient descent
  - Perceptron
  - Backpropagation
- Dynamic Programming
  - HMM Learning
  - PCFG Learning
- Divide and Conquer
  - Decision tree induction
  - Rule learning
- Evolutionary Computation
  - Genetic Algorithms (GAs)
  - Genetic Programming (GP)
  - Neuro-evolution

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Evaluation

- Accuracy
- Precision and recall
- Squared error
- Likelihood
- Posterior probability
- Cost / Utility
- Margin
- Entropy
- K-L divergence
- etc.

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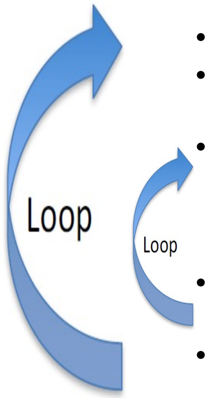
ML in Practice



- Understand domain, prior knowledge, and goals
- Data gathering, data integration, selection, cleaning, pre-processing, etc.
- Learn models
  - Model Selection
  - Model Training
  - Model Evaluation
- Interpret results
  - Hyperparameter tuning
- Consolidate and deploy discovered knowledge

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Summary

- Learning can be viewed as using direct or indirect experience to approximate a chosen target function.
- Function approximation can be viewed as a search through a space of hypotheses (representations of functions) for one that best fits a set of training data.
- Different learning methods assume different hypothesis spaces (representation languages) and/or employ different search techniques.

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