Course Introduction

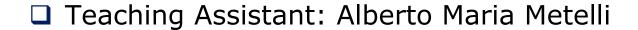
Machine Learning

Daniele Loiacono



Information

- ☐ Daniele Loiacono (Instructor)
 - ► Contact: daniele.loiacono@polimi.it +39 02 2399 **3615**
 - ▶ Office: DEIB, room 150



- Exam
 - Written test (closed-book)
 - Questions, exercises, code
 - See examples on WeBeep
 - Late enrollment is NEVER accepted
 - ► Check the remote exam policy on WeBeep







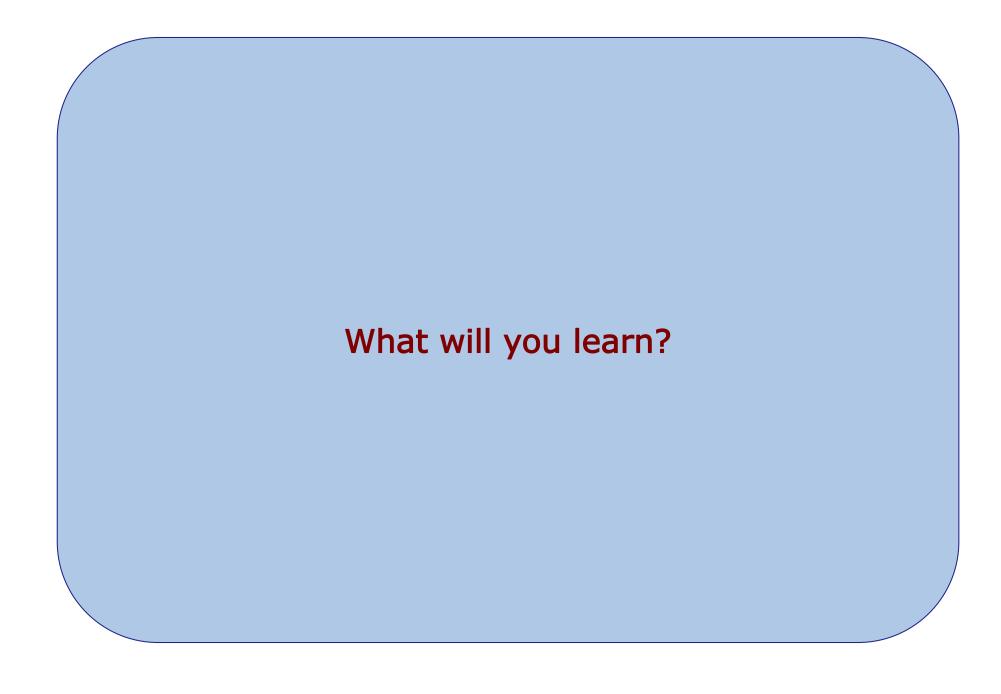
WeeBeep page

Information (2)

- Weekly schedule
 - ► Tue, 14.15 16.15, T11
 - ► Thu, 12.15 14.15, T21
- ☐ There is no streaming but lectures will be recorded
- ☐ Check the syllabus for (tentative) info about the topics of each lecture
- □ Practical classes
 - will cover exam-like exercises and practical examples
 - will present practical examples using Python (bring your laptop!)
- Interact
 - ► Feel free to ask questions
 - Use the forum of the course

References

- ☐ You will have access to all the materials used in classroom but slides are not an alternative to textbooks!
- Supervised Learning
 - Bishop, "Pattern Recognition and Machine Learning", Springer, 2006.
 - ► Hastie, Tibshirani, Friedman, "The Elements of Statistical Learning: Data Mining, Inference, and Prediction", Springer, 2009.
 - ▶ Mitchell, "Machine Learning", McGraw Hill, 1997.
 - ▶ Murphy, "Probabilistic Machine Learning: An Introduction", MIT Press, 2022
- Reinforcement Learning
 - ➤ Sutton and Barto, "Reinforcement Learning: an Introduction", MIT Press, 1998. New draft available at: http://www.incompleteideas.net/book/the-book-2nd.html



Goals

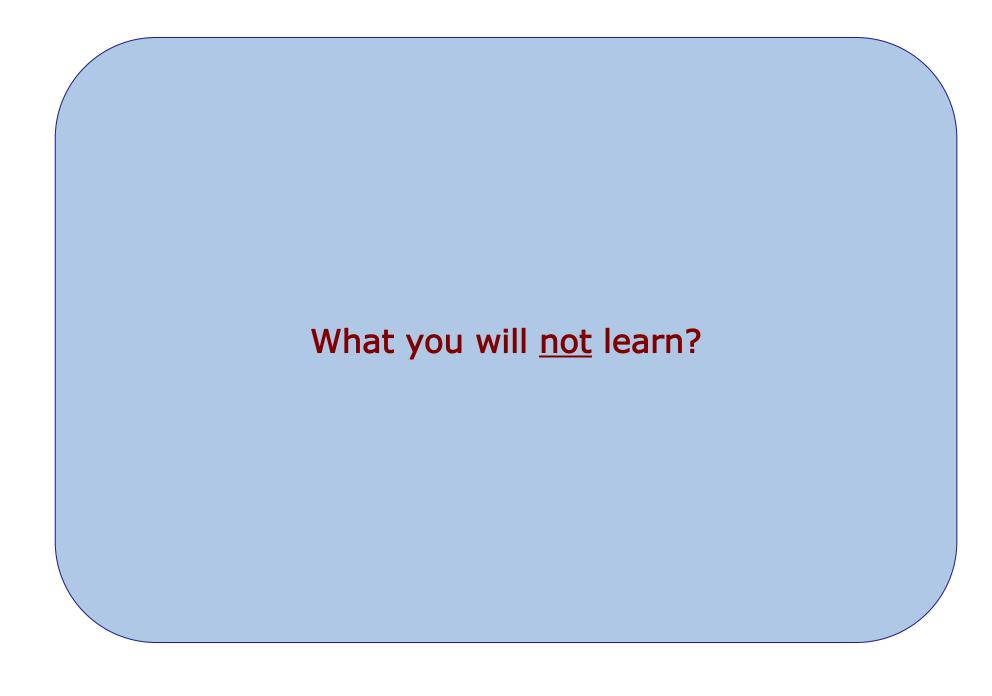
- ☐ Learn to correctly **model** machine learning problems
 - ► Can I apply machine learning to this problem?
 - ▶ What type of model is best suited for this task?
 - ► How do I define the inputs and outputs effectively?
- ☐ Learn the **principles** and the **main techniques** of ML
 - ► What are the main differences between supervised, unsupervised, and reinforcement learning?
 - ► How do domain constraints and data availability influence the choice of model?
 - ▶ What are the typical steps involved in an end-to-end machine learning workflow?
 - ▶ How models' parameters are optimized and how does it influence the outcome?

Goals (cont.)

- ☐ Learn how to **assess** the performances of ML models
 - ▶ Which performance metrics are suitable for classification, regression, or clustering tasks?
 - ▶ How do I accurately evaluate the performance of a model?
 - ► How do I detect and manage common issues such as overfitting or underfitting?
- ☐ Learn **limitations** of ML techniques and how to **choose** the most appropriate one for your problem
 - ▶ Under what circumstances might a simpler model outperform a more complex one?
 - ► How does data availability affect the choice of the model?
- Provide the basic background to understand the latest developments in this field
 - ► How do recent trends in machine learning fit into the broader field and build on existing foundations?
 - ► Which core principles drive these new developments, and what limitations or challenges might they face?

Topics

- Linear Regression
- Linear Classification
- Bias-Variance
- Model Selection
- PAC-Learning and VC dimension
- Kernel Methods
- Support Vector Machines
- Markov Decision Processes
- Dynamic Programming
- □ RL in finite MDPs
- Multi-armed bandit



Prerequisites

- ☐ Linear Algebra
 - Operations with matrix and vectors, eigenvalues, eigenvectors, etc.
- Probability and statistics
 - ▶ Distributions, confidence intervals, hypothesis test, bayesian statistics
- Optimization (basics)
- Basics understanding of Python (for practical classes)
- Where to find this?
 - Read Chapter 1-2 and Appendix B,C,E of textbook (Bishop, "Pattern Recognition and Machine Learning")
 - ▶ Check the recap lectures on Python, Linear Algebra and Probability
 - ► Chapter 1 of "Probabilistic Machine Learning: An Introduction"

Other courses

- ☐ A course of 5 credits is **not enough** to cover Machine Learning
- ☐ Fortunately, there are **other courses** that deal with other machine learning topics not covered in this course:
 - Data Mining
 - Uncertainty in Artificial Intelligence
 - Artificial Neural Networks and Deep Learning
 - Applied Statistics
 - Numerical Analysis for Machine Learning

> ...

What is Machine Learning? Why and when to apply it?

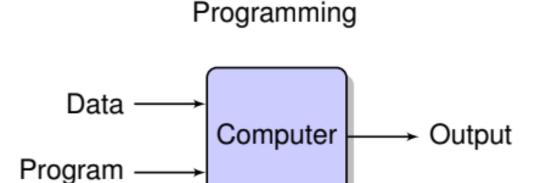
What is Machine Learning

"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, improves with experience E" Mitchell (1997)

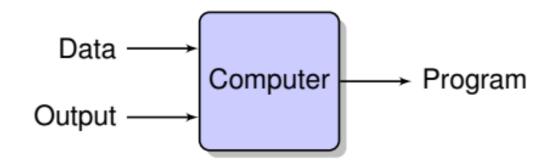
- ☐ ML is the sub-field of AI where the knowledge comes from:
 - Experience
 - ▶ Induction
- ☐ However, Machine learning is not magic!
 - You need to know how it works
 - You need to understand how to use it
 - ▶ It can extract information from data, not create information

Why Machine Learning?

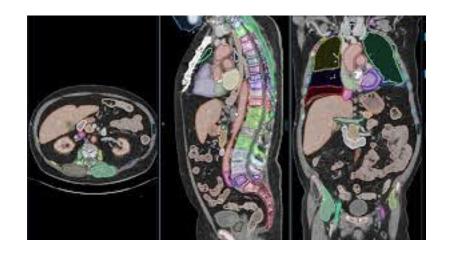
- We need computers to make informed decisions on new, unseen data
 - Often it is too difficult to design a set of meaningful rules
 - Machine learning allows to automatically extract relevant information from previous data and exploit it on new one
- ☐ Getting computers to **program** themselves (automating automation)
 - writing software is the bottleneck
 - let the data do the work instead

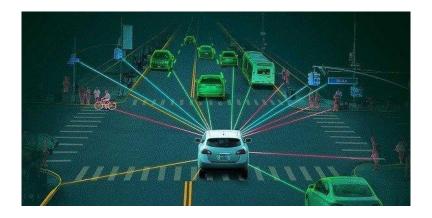


Machine Learning



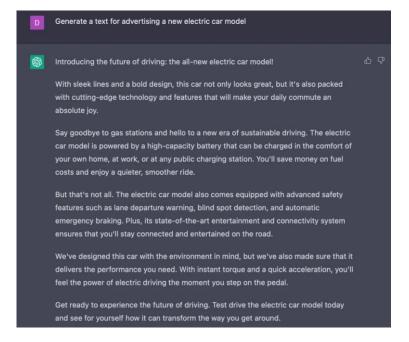
Machine Learning applications

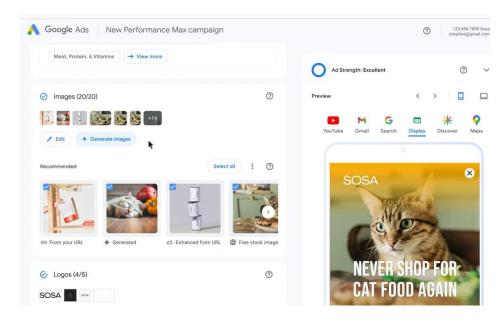




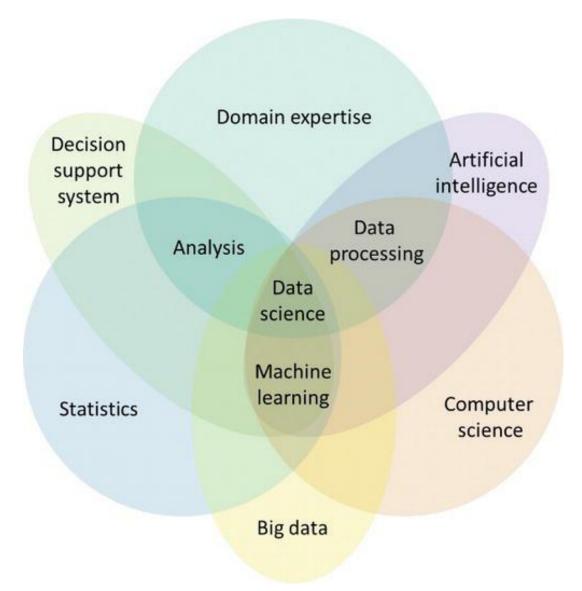








Machine Learning and other fields



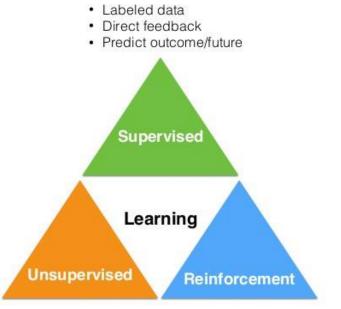
Artificial intelligence Natural language Visual perception processing Intelligent robot Automatic programming Knowledge Automatic Machine learning representation reasoning Linear/Logistic regression k-Means Support vector machine Principal component k-Nearest neighbor analysis Random Decision **Neural Networks** forest trees Boltzmann neural MLP networks. Deep Learning CNN DBN RNN Gen Al GPT VAE

Lee et al., 2018

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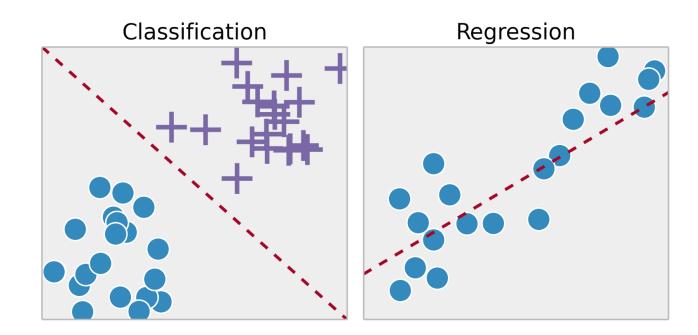
Learning Paradigms in ML

Supervised Learning

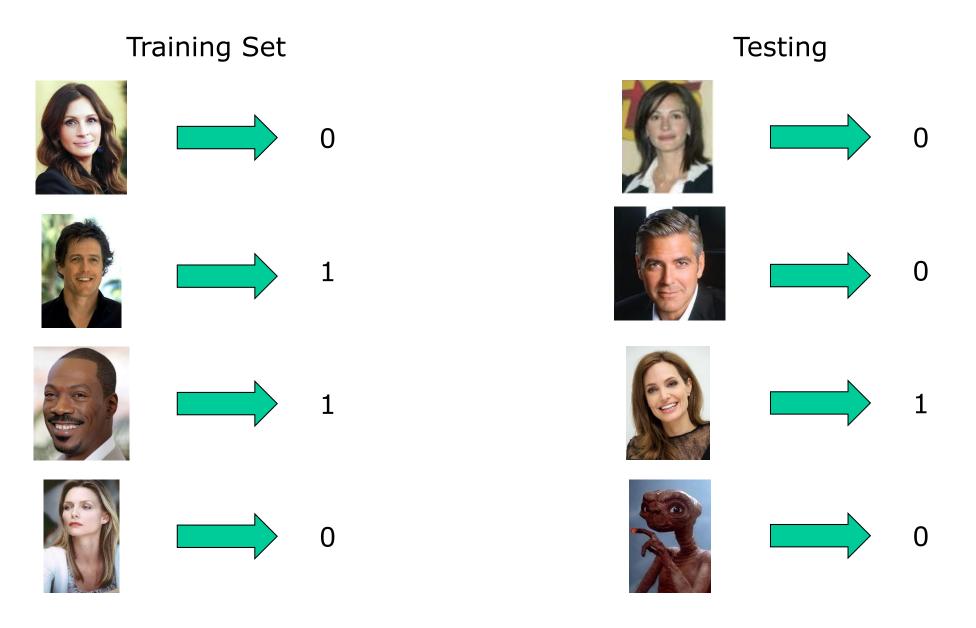


- No labels
- · No feedback
- · "Find hidden structure"

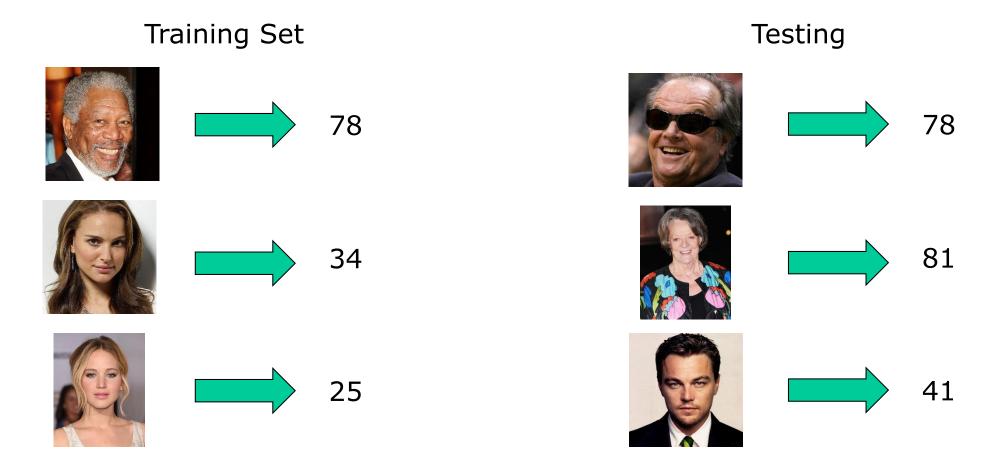
- · Decision process
- · Reward system
- · Learn series of actions



An example of classification



An example of regression

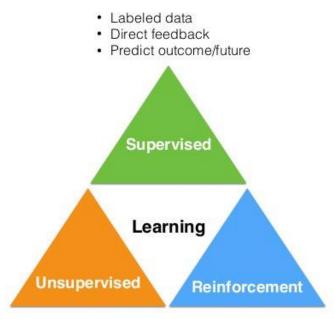


Supervised Learning

- □ Goal
 - ▶ Learn from data a model that maps known inputs to known outputs
 - ullet Training set: $\mathcal{D}=\{\langle x,t\rangle\}\Rightarrow t=f(x)$
- Tasks
 - Classification
 - ▶ Regression
 - Probability estimation
- Techniques
 - Linear Models
 - Artificial Neural Networks
 - Support Vector Machines
 - Decision trees
 - etc.

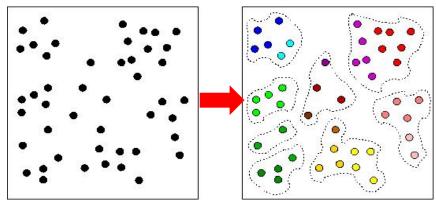
Learning Paradigms in ML

Unsupervised Learning

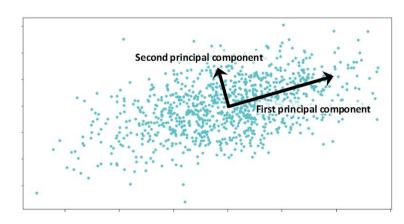


- · No labels
- · No feedback
- · "Find hidden structure"

- Decision process
- · Reward system
- · Learn series of actions

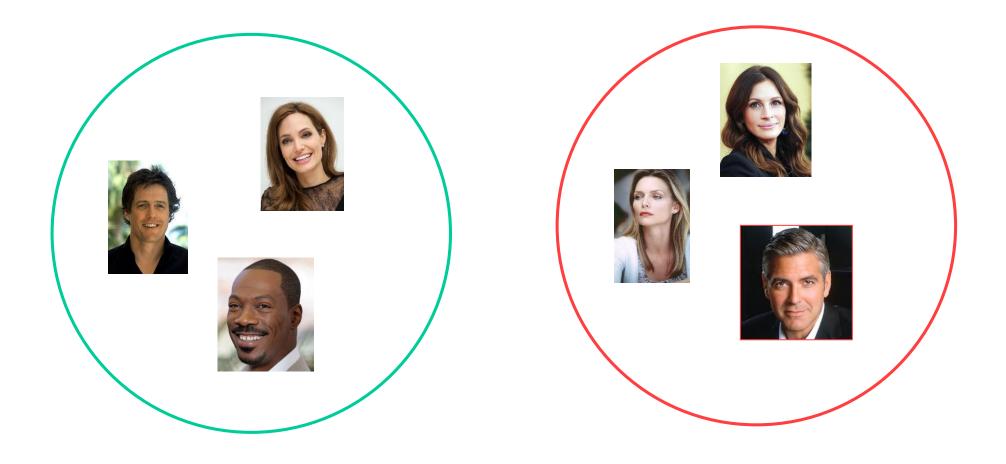


Clustering

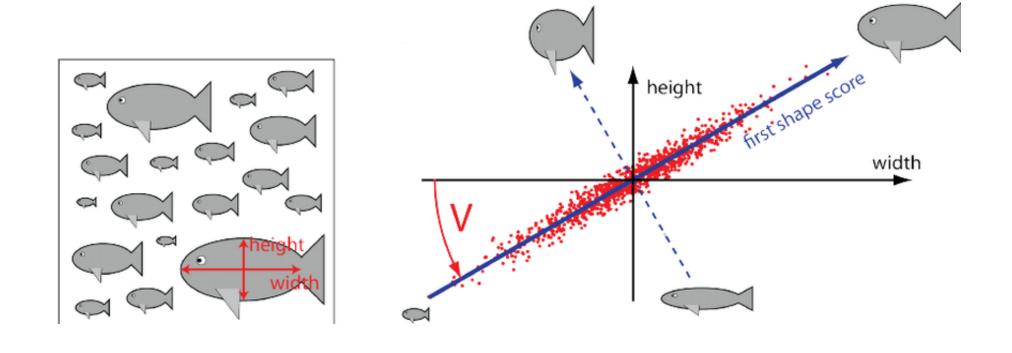


Dimensionality Reduction

An example of clustering



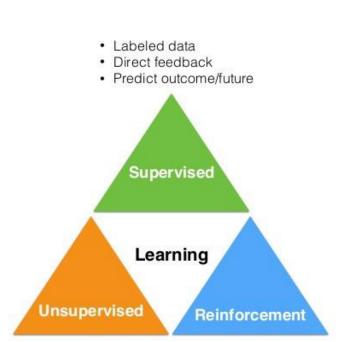
An example of dimensionality reduction



Unsupervised Learning

- ☐ Goal
 - ▶ Learn previously unknown patterns and efficient data representation
 - ▶ Training set: $\mathcal{D} = \{x\} \Rightarrow f(x)$
- Tasks
 - ▶ Dimensionality Reduction
 - Clustering
- Techniques
 - K-means
 - Self-organizing maps
 - Principal Component Analysis
 - etc.

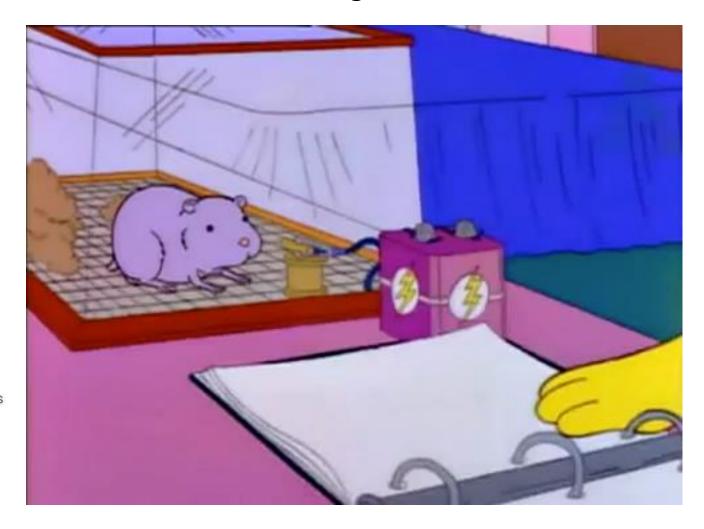
Learning Paradigms in ML



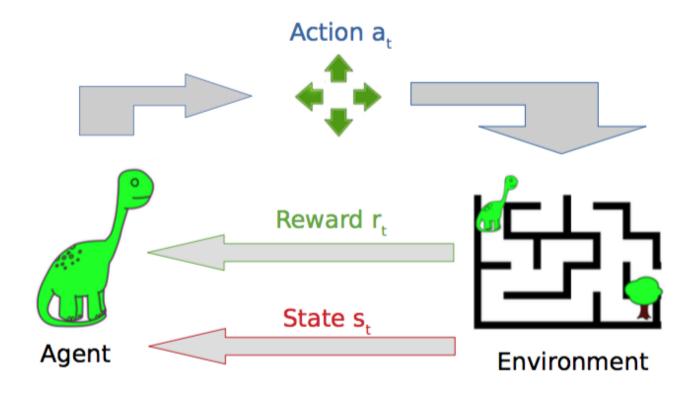
- No labels
- · No feedback
- · "Find hidden structure"

- Decision process
- · Reward system
- · Learn series of actions

■ Reinforcement Learning



An example of reinforcement learning



Reinforcement Learning

- Goal
 - ► Learning the optimal policy
 - ▶ Training set: $\mathcal{D} = \{\langle x, u, x', r \rangle\} \Rightarrow \pi^*(x) = arg \max_u \{Q^*(x, u)\}$

to estimate

- Problems
 - Markov Decision Process (MDP)
 - ► Partially Observable MDP (POMDP)
 - ▶ Stochastic Games (SG)
- Techniques
 - Q-learning
 - ► SARSA
 - ► Fitted Q-iteration
 - etc.