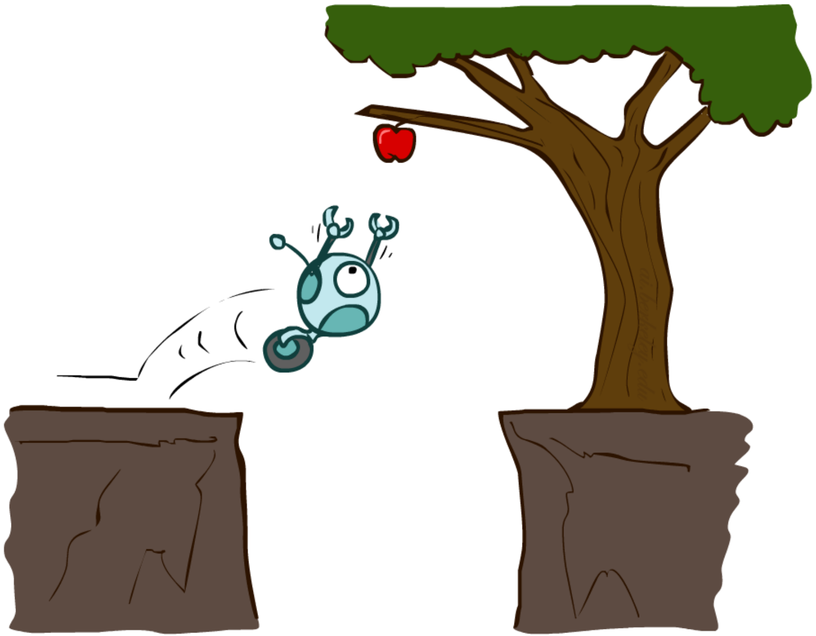
COMP1694

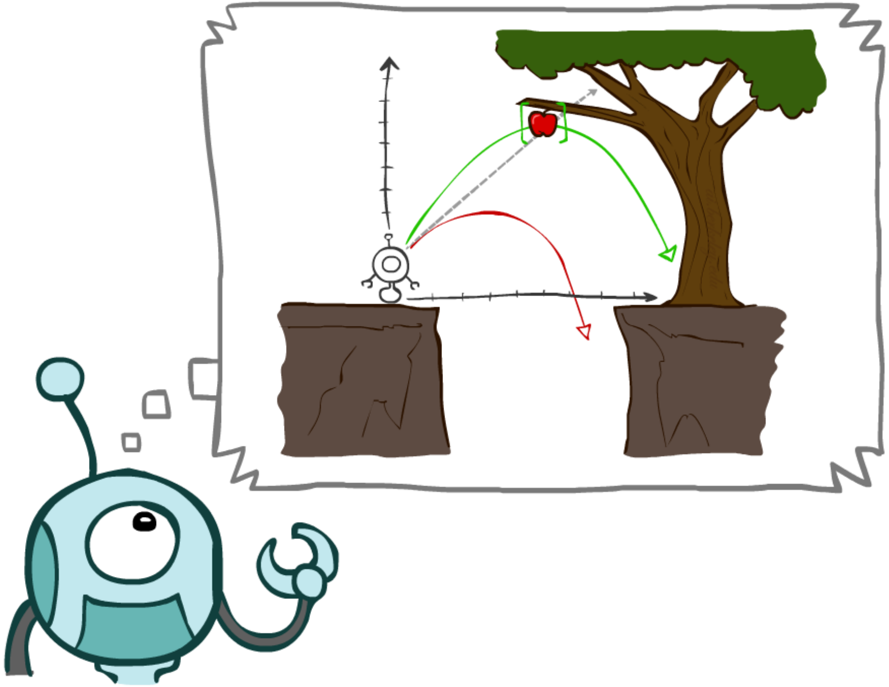
Artificial Intelligence

Lecture 9: Machine Learning

an introduction



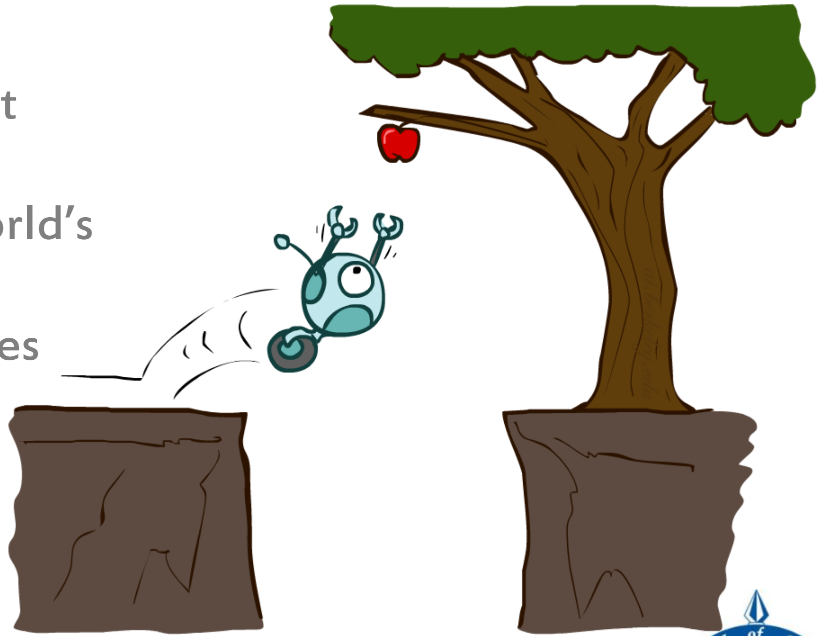
Agents that Plan



Reflex Agents

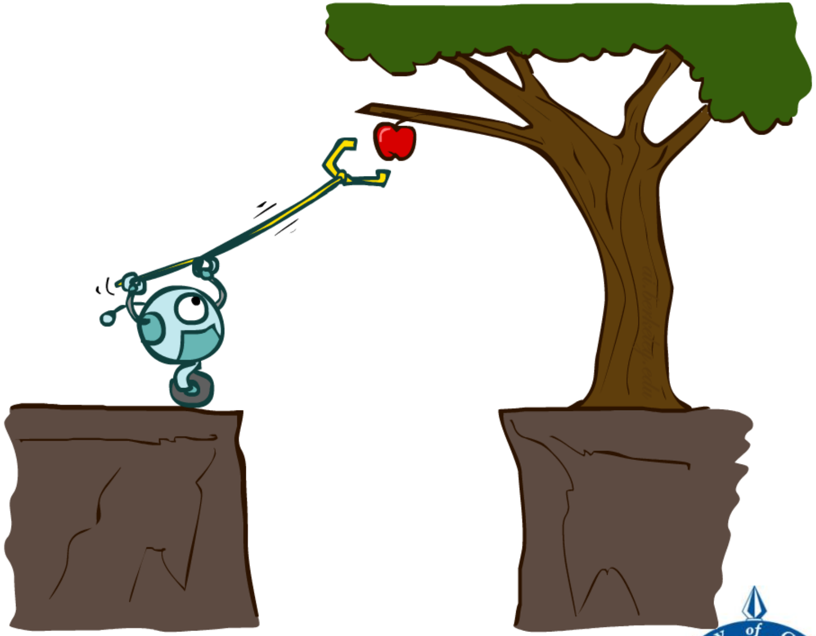
- Reflex agents:
  - Choose action based on current percept (and maybe memory)
  - May have memory or a model of the world's current state
  - Do not consider the future consequences of their actions
  - Consider how the world IS

- Can a reflex agent be rational?



Planning Agents

- Planning agents:
  - Ask “what if”
  - Decisions based on (hypothesised) consequences of actions
  - Must have a model of how the world evolves in response to actions
  - Must formulate a goal (test)
  - Consider how the world WOULD BE



- Optimal vs. complete planning
- Planning vs. replanning

Alone in the world!

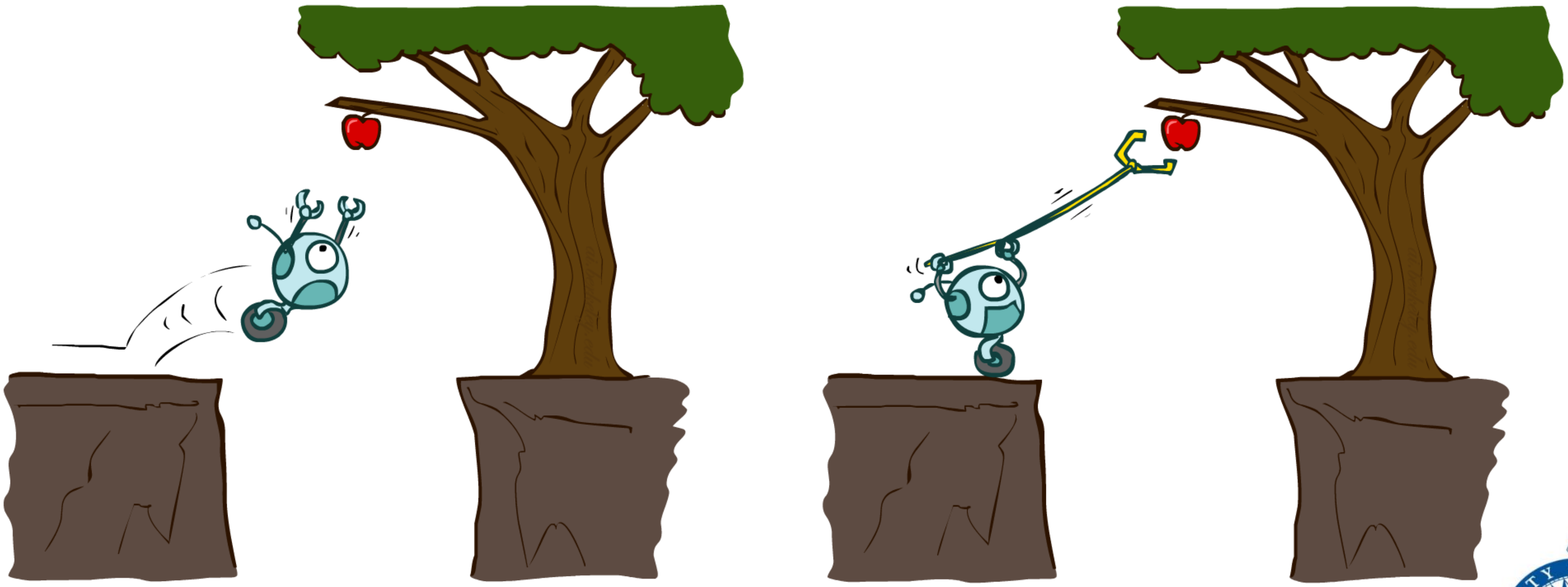


image ai.berkeley.edu

The Crawler!

Big Data

Data ≠ Knowledge

What is Machine Learning?

Machine Learning
principle

Study (design and analysis) of algorithms that

improve their performance ***P***

at some task ***T***

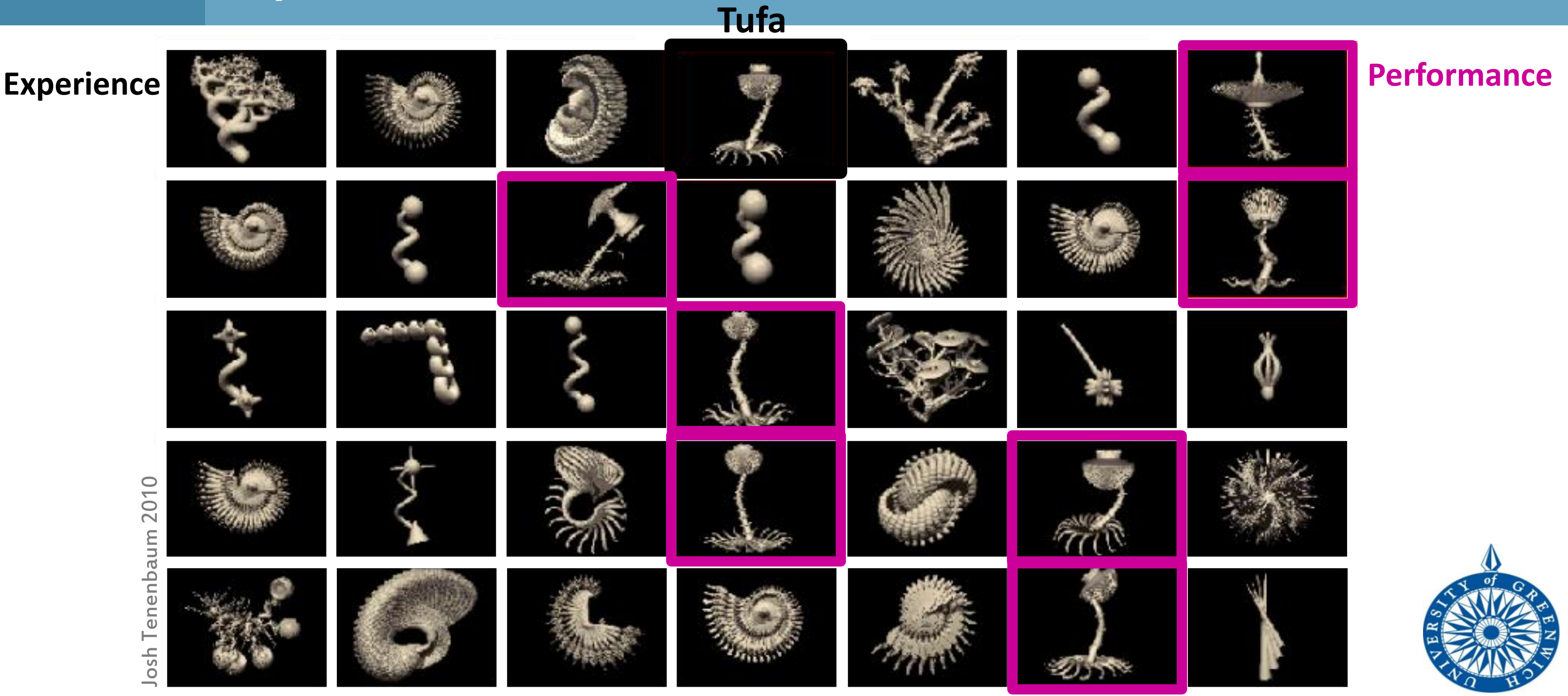
with experience ***E***

well-defined learning task: <P,T,E>

Data
experience → Learning Algorithm → Knowledge
Performance on task

Tom M. Mitchell, *Machine Learning*, McGraw Hill, 1997

Human Learning
spot the Tufas



Human Learning
what's the animal?

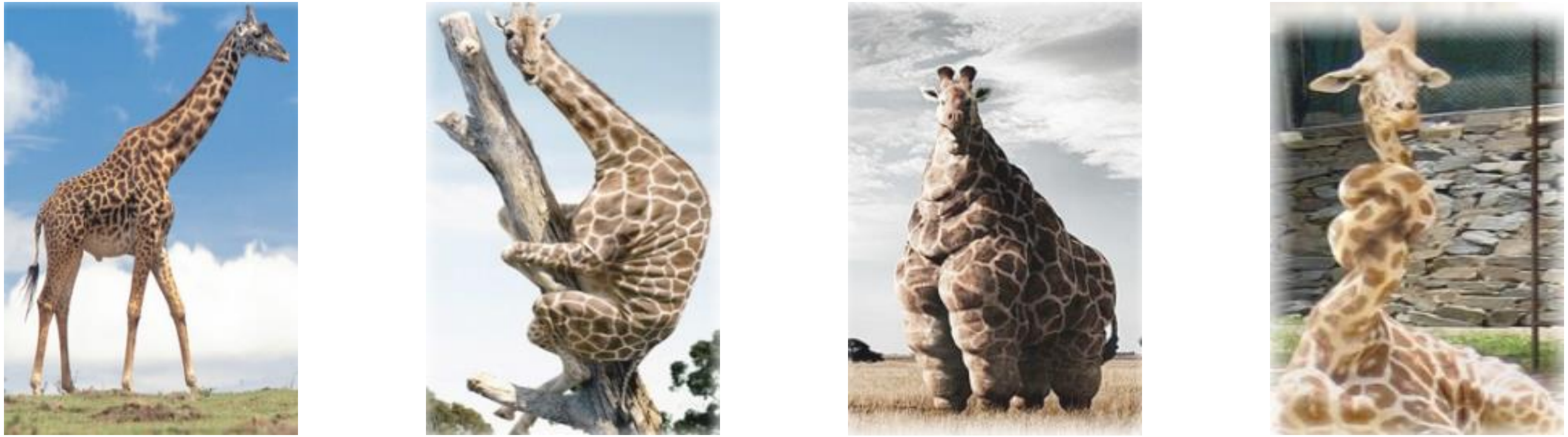


image Thomas Serre (2012), http://helper.ipam.ucla.edu/publications/gss2012/gss2012_10539.pdf

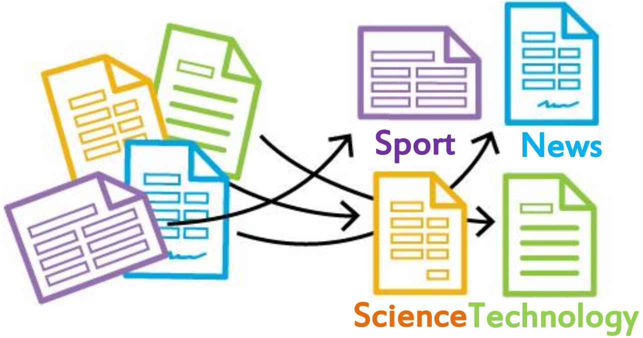
Learning is...

- Memorising something.
- Learning facts through observation and exploration.
- Improving motor and/or cognitive skills through practice.
- Organising new knowledge into general, effective representations

Learning denotes changes in a system that enable the system to do task(s) from the same projection more efficiently next time.

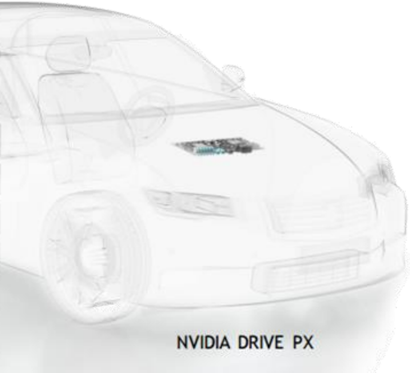
Herbert Simon, 1983

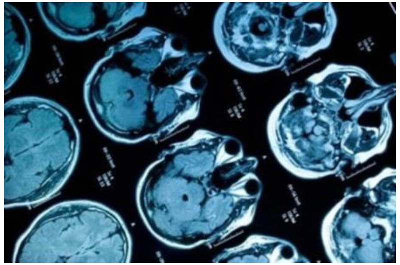
Machine Learning in Action



Google +

DeepMind
AlphaGo





Can criminal behaviour be predicted using brain scans?

University of New Mexico and Mind Research Network

Machine Learning
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well-defined learning task: <P,T,E>

Data
experience
→ Learning Algorithm →
Knowledge
Performance on task

Tom M. Mitchell, *Machine Learning*, McGraw Hill, 1997

Tasks – Experience – Performance

Kinds of Learning
popular examples...

- Supervised learning
  - given a set of example input/output pairs, find a rule that does a good job of predicting the output associated with a new input
  - training data includes both the input and desired results
- Unsupervised learning
  - given a set of examples, but no labelling of them, group them into clusters
  - no output datasets are provided, instead the data is clustered into different classes
- Reinforcement learning
  - agents interacting with the world make observations, take actions and are rewarded/punished – goal is to take actions to obtain maximum reward
  - learning from actions/reactions

Supervised Learning

Feature Space $\mathcal{X}$

Label Space $\mathcal{Y}$

Words in document

“Sports”
“News”
“Science”
“Technology”
…

Discrete Labels
Classification

Market Data up to time t

Share Price
“£ 28.4”

Continuous Labels
Regression

Task: Given $X \in \mathcal{X}$, predict $Y \in \mathcal{Y}$

Unsupervised Learning

AKA "learning without a teacher"

Feature Space $\mathcal{X}$

Words in document

Word distribution (probability of a word)

Task: Given $X \in \mathcal{X}$, learn $f(X)$

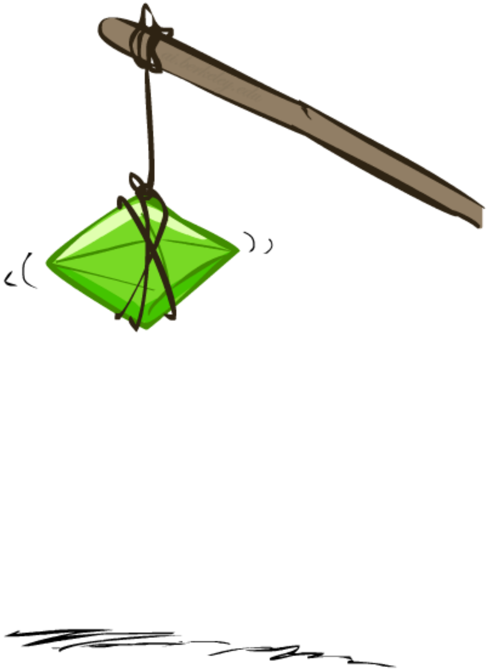
Unsupervised learning

- Clustering – group similar things eg. images [Gong, Y, et al (2015)]

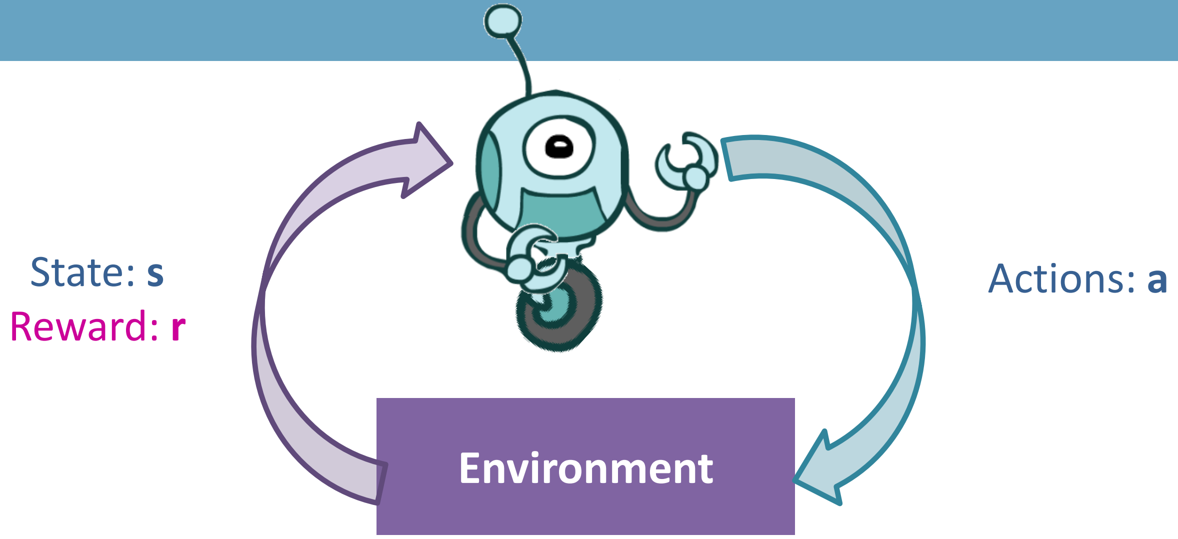
Unsupervised learning

- Dimensionality Reduction / Embedding

Reinforcement Learning



Reinforcement Learning



- **Basic idea:**
  - Receive feedback in the form of rewards
  - Agent's utility is defined by the reward function
  - Must (learn to) act so as to maximize expected rewards
  - All learning is based on observed samples of outcomes!

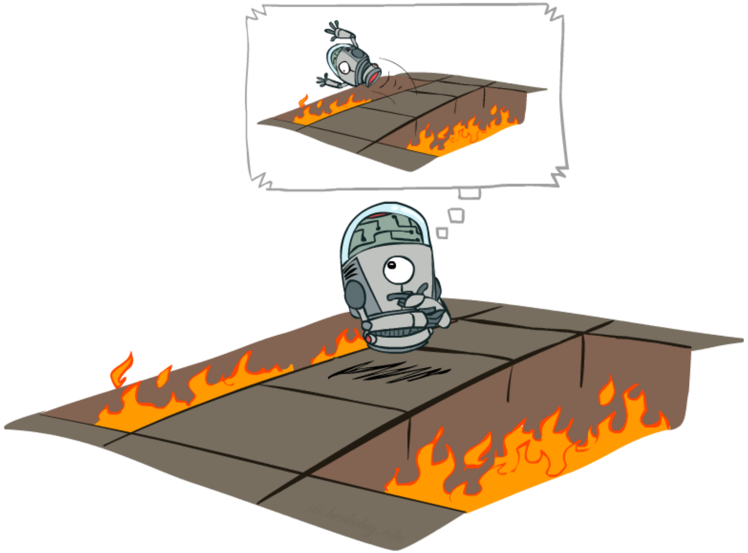
Reinforcement Learning

- Assume a Markov Decision Process (MDP):
  - A set of states $s \in S$
  - A set of actions (per state) A
  - A model T(s,a,s')
  - A reward function R(s,a,s')

- Still looking for a policy $\pi(s)$

- New twist: don't know T or R
  - I.e. we don't know which states are good or what the actions do
  - Must actually try actions and states out to learn

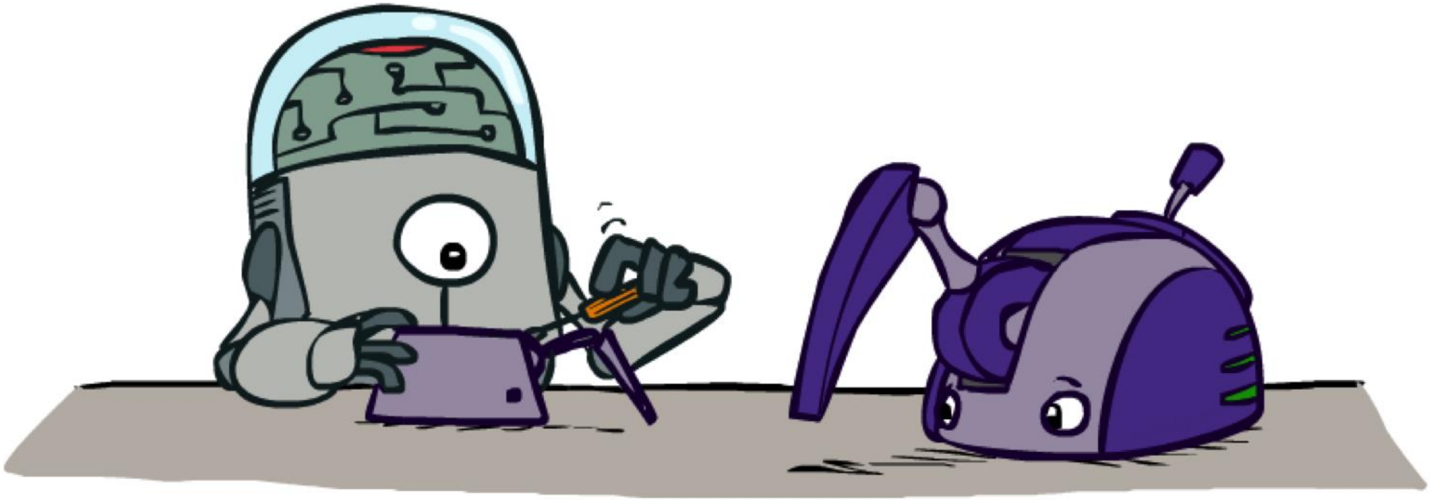
Offline (MDPs) vs. Online (RL)



Offline Solution

Online Learning

Model-Based Learning



Model-Based Learning

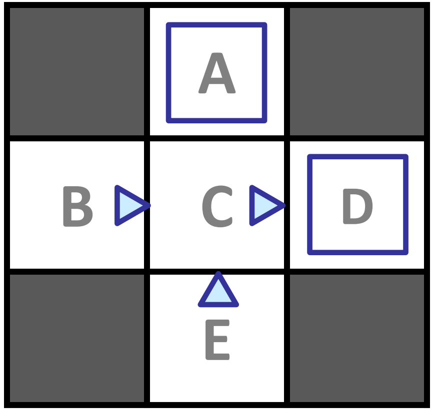
- Model-Based Idea:
  - Learn an approximate model based on experiences
  - Solve for values as if the learned model were correct

- Step 1: Learn empirical MDP model
  - Count outcomes s' for each s, a $\hat{T}(s, a, s')$
  - Normalize to give an estimate of
  - Discover each $\hat{R}(s, a, s')$ when we experience (s, a, s')

- Step 2: Solve the learned MDP
  - For example, use value iteration, as before

Example: Model-Based Learning

Input Policy π



Assume: $\gamma = 1$

Observed Episodes (Training)

Episode 1

B, east, C, -1
C, east, D, -1
D, exit, x, +10

Episode 2

B, east, C, -1
C, east, D, -1
D, exit, x, +10

Episode 3

E, north, C, -1
C, east, D, -1
D, exit, x, +10

Episode 4

E, north, C, -1
C, east, A, -1
A, exit, x, -10

Learned Model

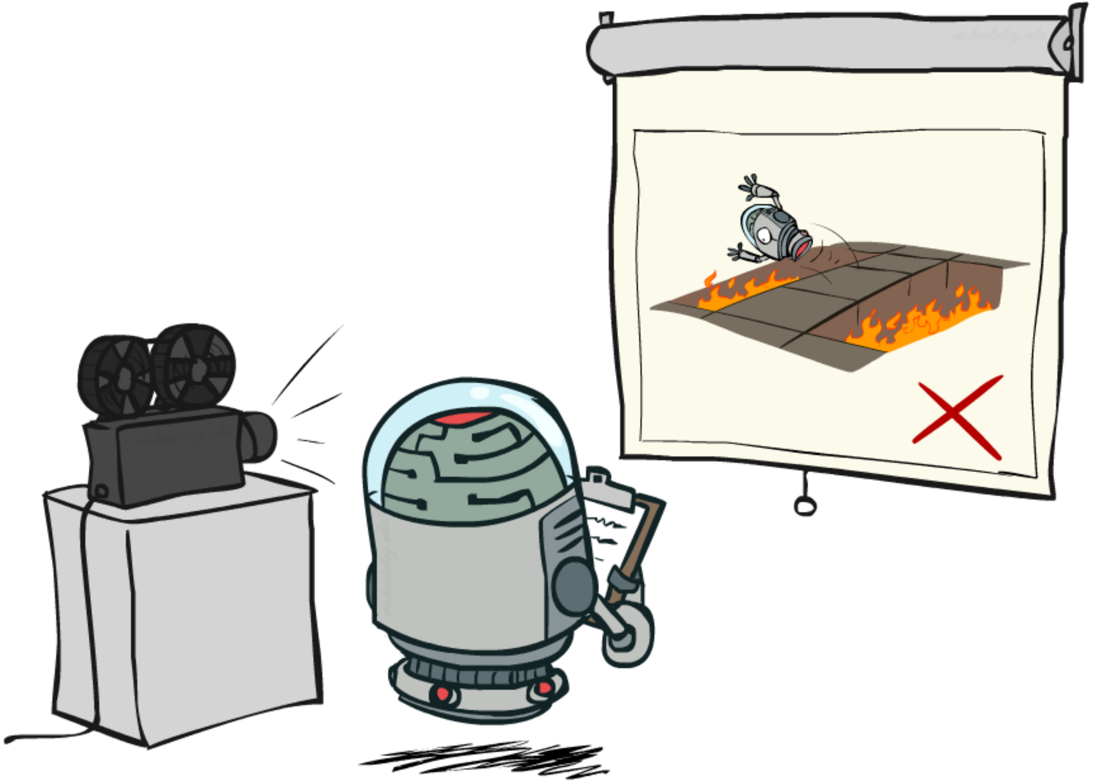
$\hat{T}(s, a, s')$

T(B, east, C) = 1.00
T(C, east, D) = 0.75
T(C, east, A) = 0.25
…

$\hat{R}(s, a, s')$

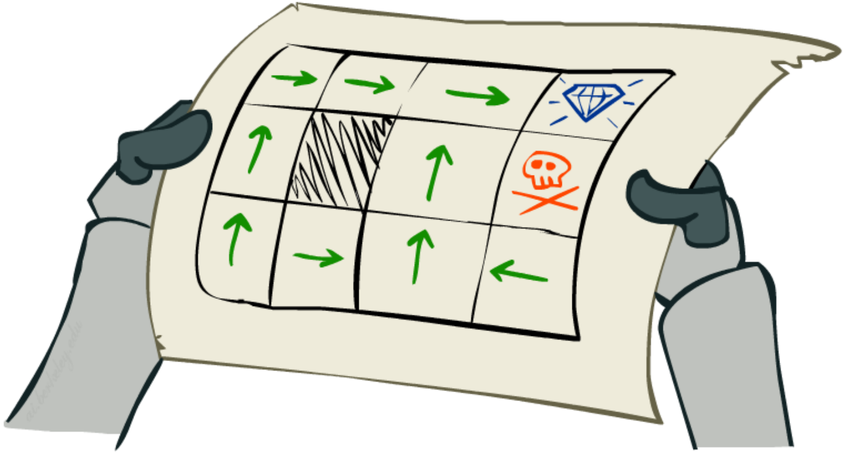
R(B, east, C) = -1
R(C, east, D) = -1
R(D, exit, x) = +10
…

Passive Reinforcement Learning



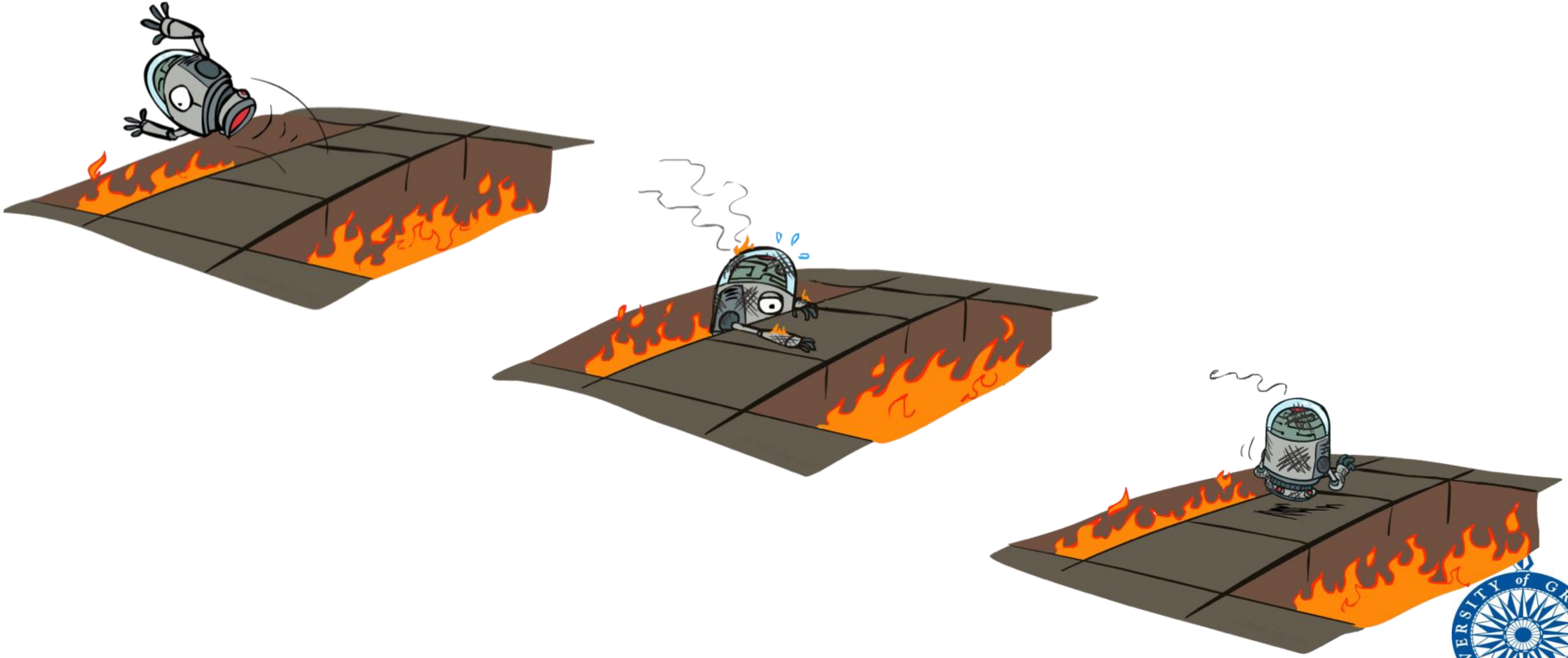
Passive Reinforcement Learning

- Simplified task: policy evaluation
  - Input: a fixed policy $\pi(s)$
  - You don't know the transitions T(s,a,s')
  - You don't know the rewards R(s,a,s')
  - Goal: learn the state values



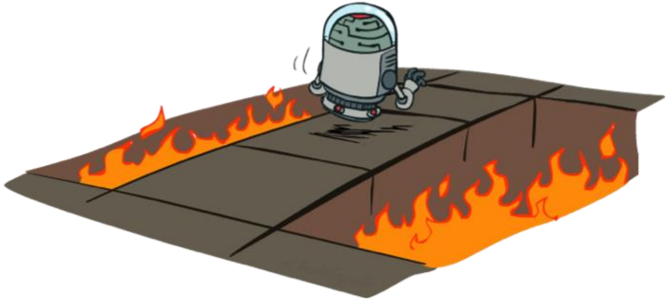
- In this case:
  - Learner is "along for the ride"
  - No choice about what actions to take
  - Just execute the policy and learn from experience
  - This is NOT offline planning! You actually take actions in the world.

Active Reinforcement Learning



Active Reinforcement Learning

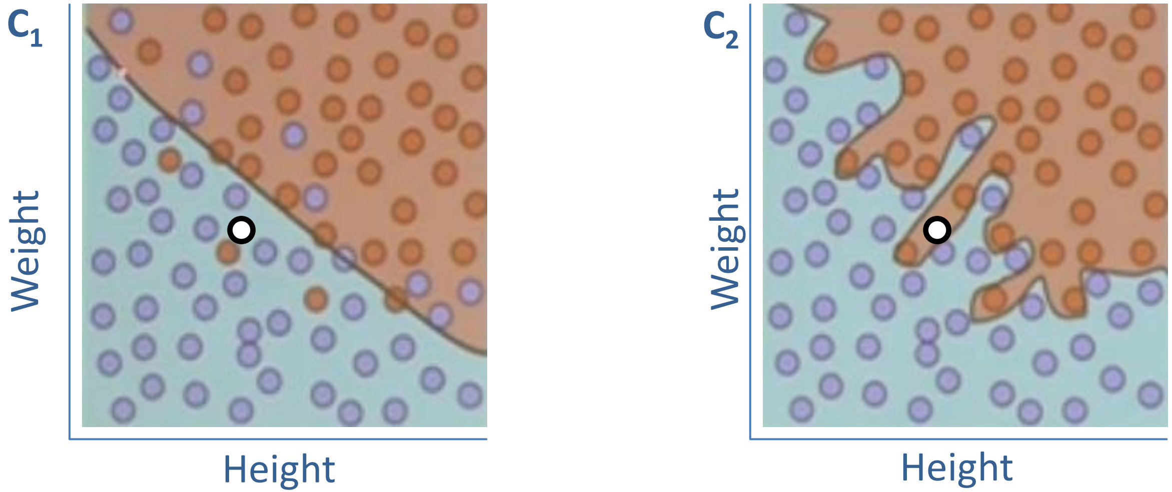
- Full reinforcement learning: optimal policies (like value iteration)
  - You don't know the transitions T(s,a,s')
  - You don't know the rewards R(s,a,s')
  - You choose the actions now
  - Goal: learn the optimal policy / values



- In this case:
  - Learner makes choices!
  - Fundamental tradeoff: exploration vs. exploitation
  - This is NOT offline planning! You actually take actions in the world and find out what happens…

Tasks – Experience – Performance

Training Data vs Test Data



Training Data

- Footballer
- Not

Test Data

- A good ML algorithm:
  - does not **overfit** training data (classifier2)
  - **generalises** well to test data

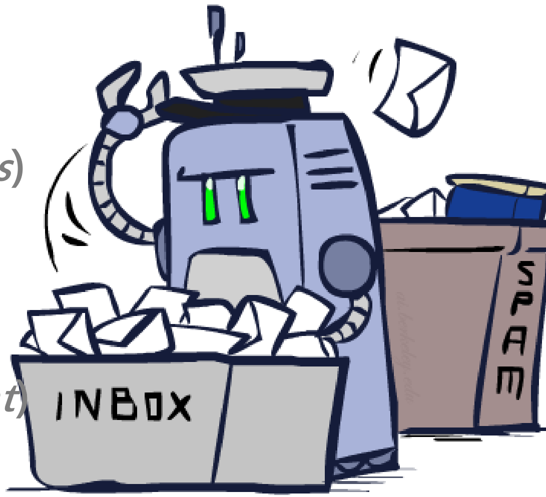
Tasks – Experience – Performance

Performance Measures

- For a random test data, measure the closeness between true label Y and prediction $f(X)$
  - Binary classification : $\text{Loss}(Y, f(X)) = 1_{\{f(X)) \neq Y\}}$ 0 or 1 loss
  - Regression: $\text{Loss}(Y, f(X)) = (f(X)) - Y)^2$ Square loss

Recap

- Machine learning deals with the problem of extracting ***features*** from data so as to solve many different ***predictive*** tasks:
  - Decision making (*e.g. robotics, games, compiler tuning, trading*)
  - Forecasting (*e.g. Energy demand prediction, finance*)
  - Imputing missing data (*e.g. Netflix recommendations*)
  - Detecting anomalies (*e.g. Security, fraud, virus mutations*)
  - Classifying (*e.g. Credit risk assessment, cancer diagnosis*)
  - Ranking (*e.g. Google search, personalization*)
  - Summarizing (*e.g. News zeitgeist, social media sentiment*)



When to apply machine learning

- Human expertise is absent (*e.g. Navigating on Mars*)
- Creating rational NPCs and agents (e.g. virtual reality games)
- Humans are unable to explain their expertise (*e.g. Speech recognition, vision, language*)
- Solution changes with time (*e.g. Tracking, temperature control, preferences*)
- Solution needs to be adapted to particular cases (*e.g. Biometrics, personalisation*)
- The problem size is to vast for our limited reasoning capabilities (*e.g. Calculating webpage ranks, matching ads to facebook pages*)

Further Reading
and interesting resources

- Learning
  - Artificial Intelligence: A Modern Approach by Stuart Russell and Peter Norvig, 3rd Edition, Chapter 5, Section 18
  - eBook available here: http://cessa.khu.ac.ir/wp-content/uploads/2015/12/Artificial-Intelligence-A-Modern-Approach-3rd-Edition.pdf
- Reinforcement learning
  - Russell and Norvig, Chapter 5 section 21
  - https://webdocs.cs.ualberta.ca/~sutton/book/ebook/the-book.html

Further Reading
and interesting resources

- Tom Mitchell's book on Machine Learning 1997
  - (things have moved on since then, but a good read) http://personal.disco.unimib.it/Vanneschi/McGrawHill_-_Machine_Learning_-Tom_Mitchell.pdf
- Machine learning in action
  - DeepMind: https://www.youtube.com/watch?v=TnUYcTuZJpM
  - AlphaGo, Mastering the game of Go with Deep Neural Networks & Tree Search: https://storage.googleapis.com/deepmind-media/alphago/AlphaGoNaturePaper.pdf
  - Google DeepMind playing Breakout, Pac-Man
- **AiGameDev - Community** of game developers focusing on AI http://aigamedev.com/

Further Reading
useful APIs

- WEKA
  - **Weka** is a collection of machine learning algorithms for data mining tasks
    http://www.cs.waikato.ac.nz/ml/weka/