# Reinforcement learning (COMP-579)

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- Class web page: http://www.cs.mcgill.ca/~dprecup/courses/rl.html

# Outline

- Administrative issues
- What is reinforcement learning (RL)?
- Applications of RL
- If we have time: multi-arm bandits

# Prerequisites

- Knowledge of programming in Python
- Probability, calculus, linear algebra; general comfort with math
- Knowledge of machine learning (McGill courses: COMP-551, COMP-652)
- If in doubt about your background, contact Doina

# Course material

- Required textbook: Sutton & Barto, Reinforcement learning: An Introduction, Second edition, 2018 (available online)

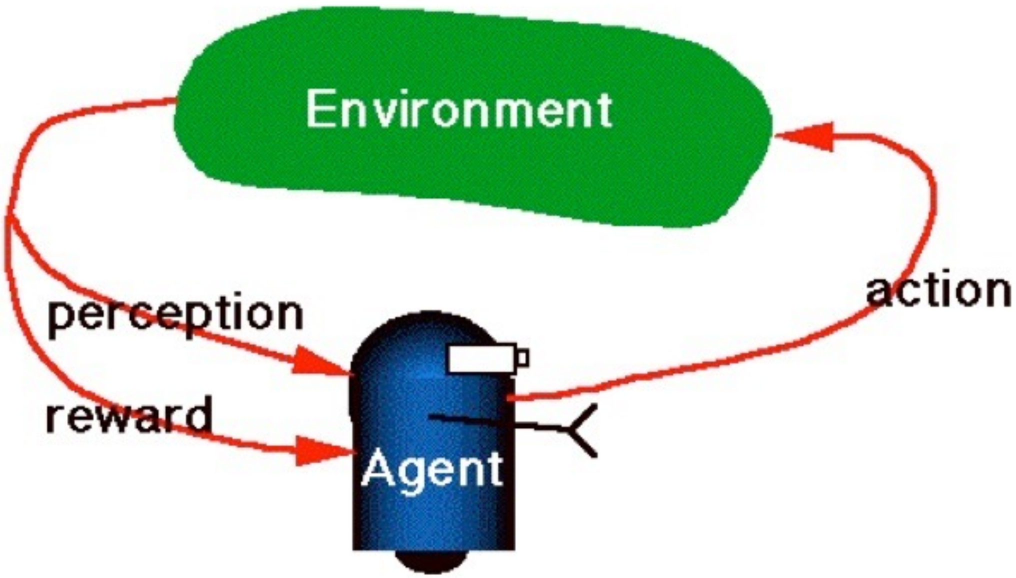
- Other required or suggested materials posted on the course web page

- Schedule posted on the web page; you MUST do the reading in order to really benefit from this course

# Evaluation

- Project (40%): individual or in groups of up to 3;
- Four assignments (60%, dates posted on course web page) individual or in groups of up to 3 (will be specified for each assignment)
- Assignments consist of a mix of theoretical and implementation/experimentation exercises. ALL members of a team are expected to be able to answer questions about ALL parts of the assignment

# Reinforcement Learning




Reward: Food or electric shock

Reward: Positive and negative numbers

- Learning by trial-and-error
- Numerical reward is often delayed

# A big success story: AlphaGo



ARTICLE

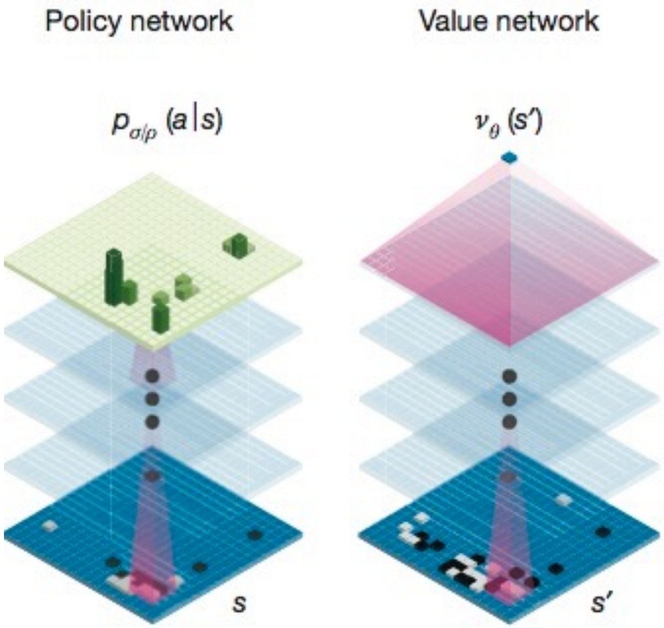
doi:10.1038/nature16961

## Mastering the game of Go with deep neural networks and tree search

David Silver[1]*, Aja Huang[1]*, Chris J. Maddison[1], Arthur Guez[1], Laurent Sifre[1], George van den Driessche[1], Julian Schrittwieser[1], Ioannis Antonoglou[1], Veda Panneershelvam[1], Marc Lanctot[1], Sander Dieleman[1], Dominik Grewe[1], John Nham[2], Nal Kalchbrenner[1], Ilya Sutskever[2], Timothy Lillicrap[1], Madeleine Leach[1], Koray Kavukcuoglu[1], Thore Graepel[1] & Demis Hassabis[1]

The first AI Go player to defeat a human (9 dan) champion

# Example: AlphaGo




- Perceptions: state of the board
- Actions: legal moves
- Reward: +1 or -1 at the end of the game
- Trained by playing games against itself
- Invented new ways of playing which seem superior

# Key Features of RL

- The learner is not told what actions to take, instead it find finds out what to do by *trial-and-error search*

  Eg. Players trained by playing thousands of simulated games, with no expert input on what are good or bad moves

- The environment is *stochastic*
- The *reward may be delayed*, so the learner may need to sacrifice short-term gains for greater long-term gains

  Eg. Player might get reward only at the end of the game, and needs to assign credit to moves along the way

- The learner has to balance the need to *explore* its environment and the need to *exploit* its current knowledge

  Eg. One has to try new strategies but also to win games

# Contrast: Supervised Learning

- Training experience: a set of *labeled examples* of the form $\langle x_1 x_2 \ldots x_n, y \rangle$, where $x_j$ are values for *input variables* and $y$ is the *desired output*
- This implies the existence of a "teacher" who knows the right answers
- What to learn: A *function* mapping inputs to outputs which optimizes an objective function
- E.g. Face detection and recognition:

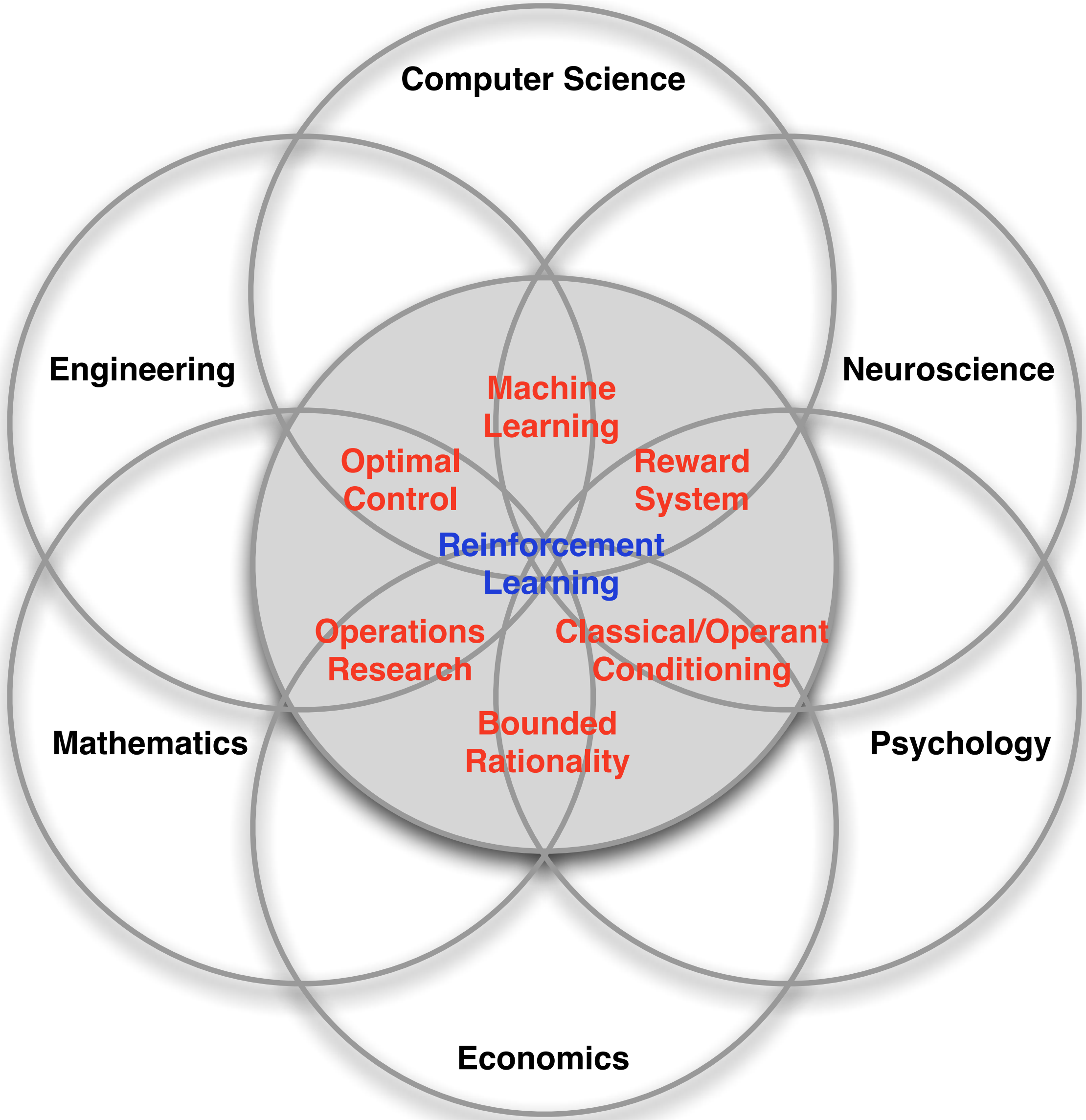
# Contrast: Unsupervised learning

- Training experience: unlabelled data
- What to learn: interesting associations in the data
- E.g., clustering, dimensionality reduction, density estimation
- Often there is no single correct answer
- Very necessary, but significantly more difficult that supervised learning

# Basic Principles of Reinforcement Learning

- *All machine learning is driven to minimize prediction errors*
- In reinforcement learning, the algorithm makes *predictions* about the *expected future cumulative reward*
- These predictions should be consistent, i.e. similar to each other over time
- *Errors* are computed *between predictions made at consecutive time steps*
- *If the situation improved since last time step, pick the last action more often*

# An Intersection Field!



# Initial successes: Games

- Learned the world's best player of Backgammon (Tesauro 1995)

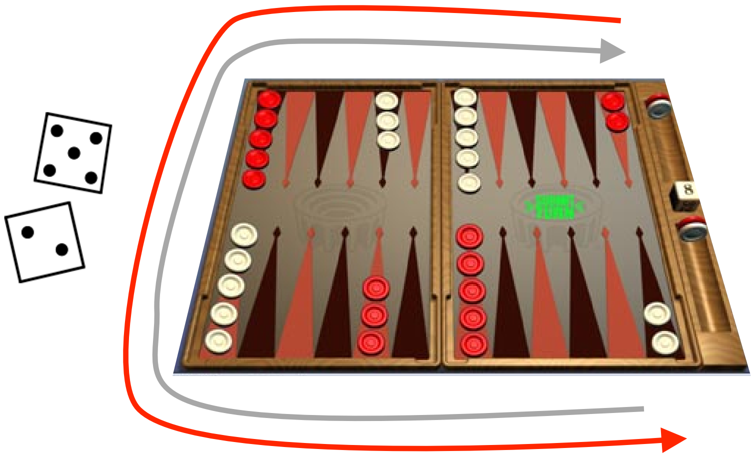
- Used to make strategic decisions in *Jeopardy!* (IBM's Watson 2011)

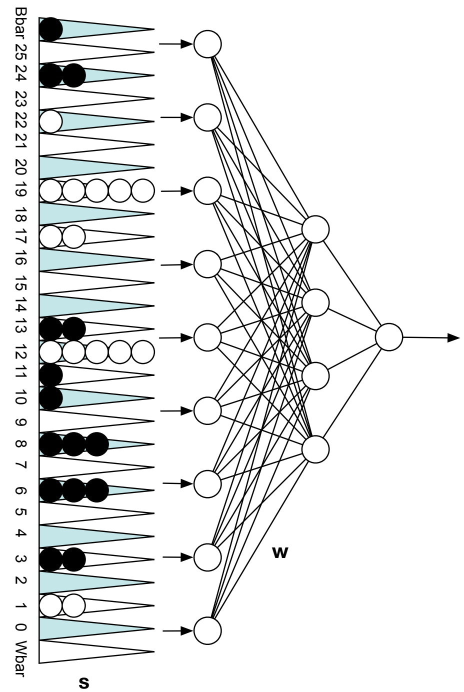
- Achieved human-level performance on Atari games from pixel-level visual input, in conjunction with deep learning (Google DeepMind 2015)

- In all these cases, performance was better than could be obtained by any other method, and was obtained without human instruction

# Example: TD-Gammon

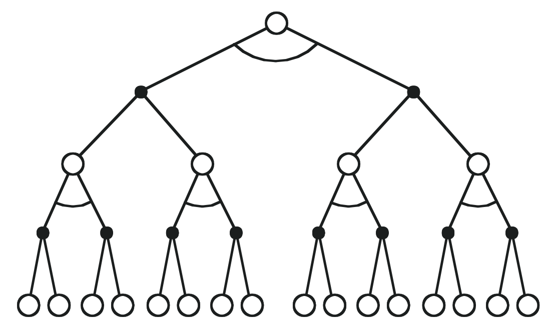
Tesauro, 1992-1995






estimated state value
(≈ prob of winning)

Action selection
by a shallow search



Start with a random Network

Play millions of games against itself

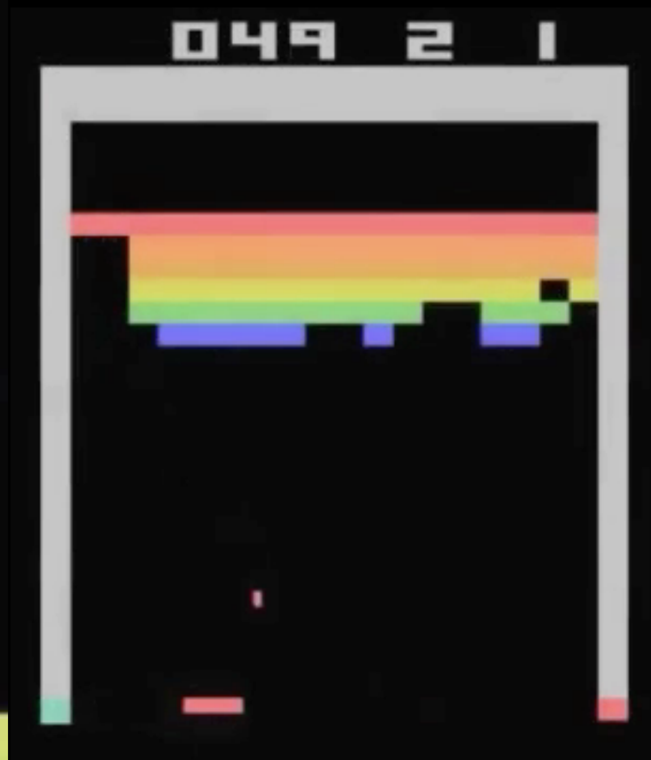
Learn a value function from this simulated experience

Six weeks later it's the best player of backgammon in the world

Originally used expert handcrafted features, later repeated with raw board positions

# RL + Deep Learing Performance on Atari Games


Space Invaders

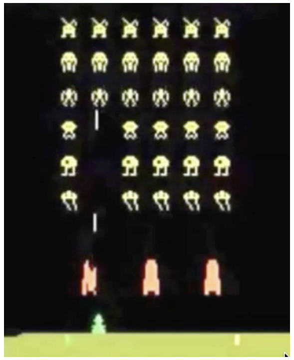



Breakout


Enduro

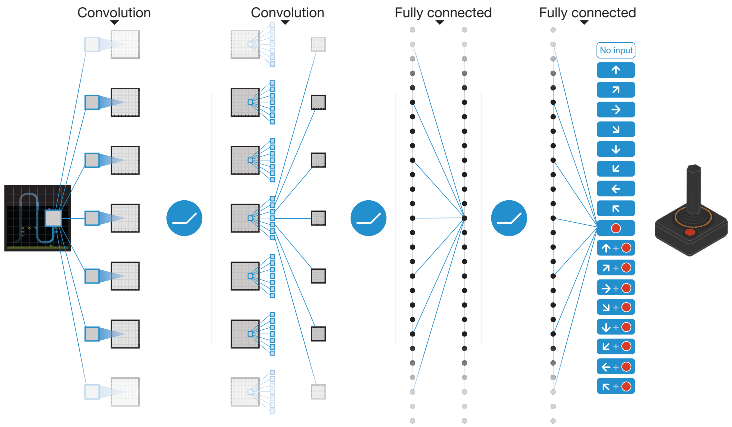
# RL + Deep Learning, applied to Classic Atari Games

Google Deepmind 2015, Bowling et al. 2012




- Learned to play 49 games for the Atari 2600 game console, without labels or human input, from self-play and the score alone

mapping raw screen pixels

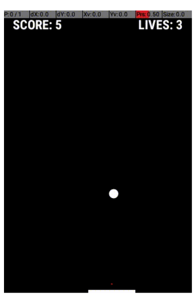


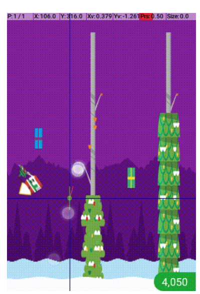

to predictions of final score for each of 18 joystick actions

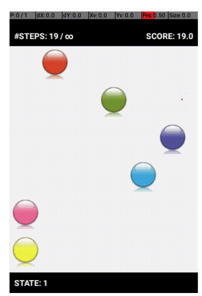
- Learned to play better than all previous algorithms and at human level for more than half the games

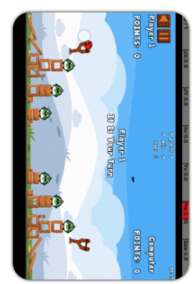
Same learning algorithm applied to all 49 games! w/o human tuning

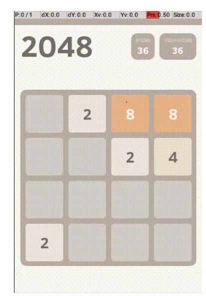
# RL can produce agents that play complex games!

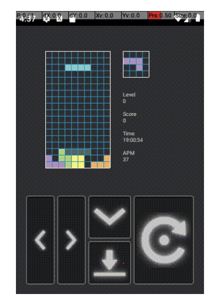


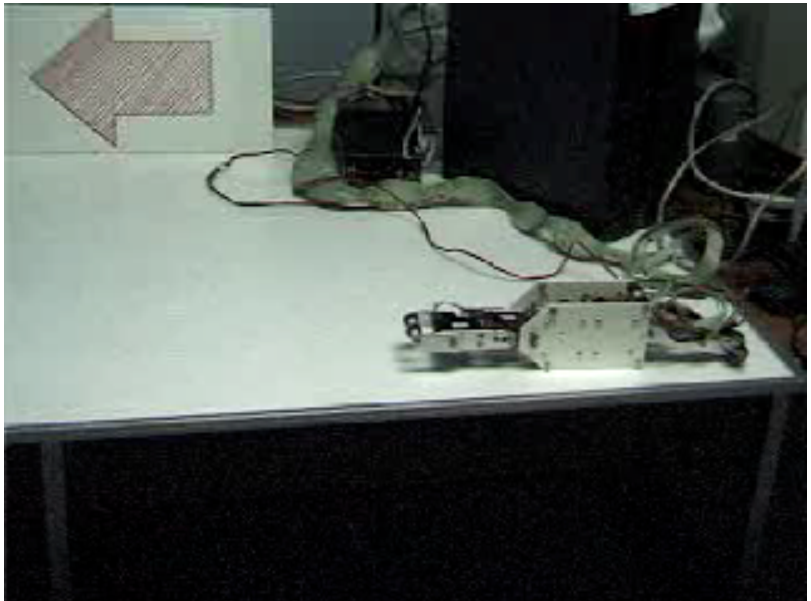


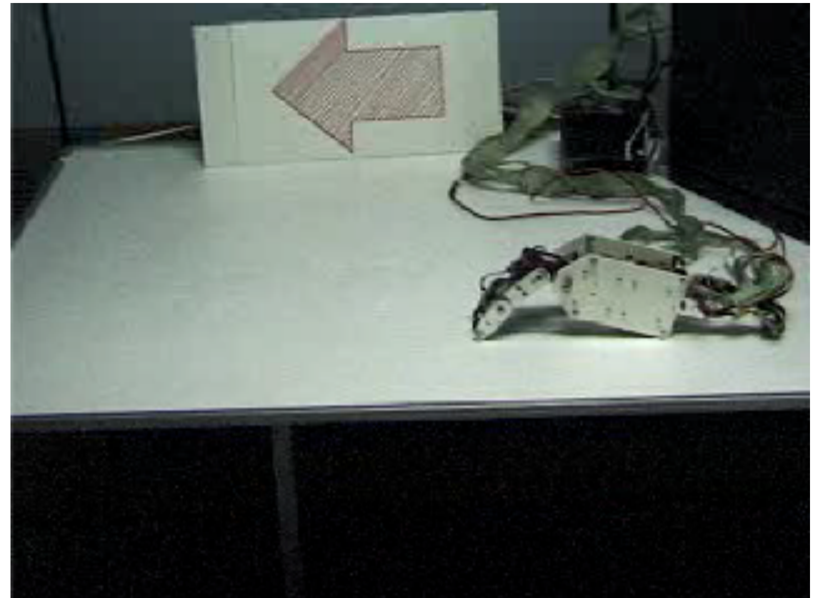
# More successes: Complex control tasks

- Learned acrobatic helicopter autopilots (Ng, Abbeel, Coates et al 2006+)
- Widely used in the placement and selection of advertisements and pages on the web (e.g., A-B tests)
- Control of tokamak plasma reactors
- In all these cases, performance was better than could be obtained by any other method, and was obtained without human instruction

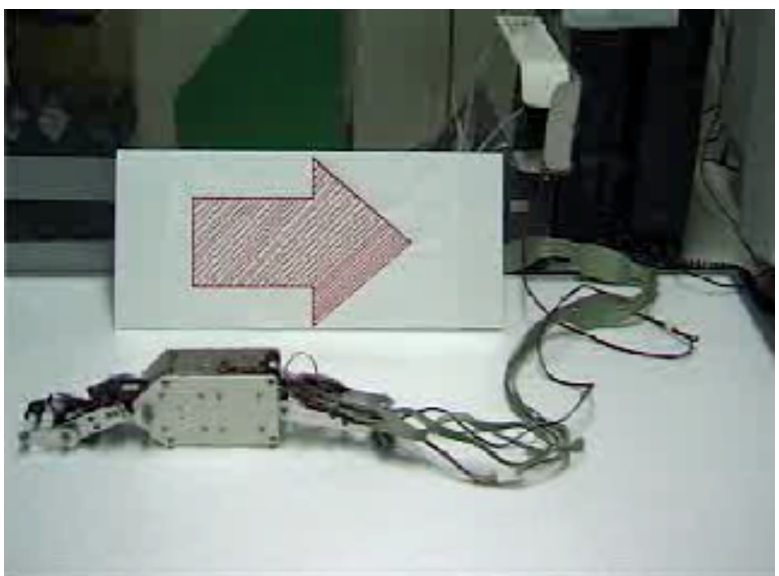
# Example: Hajime Kimura's RL Robots



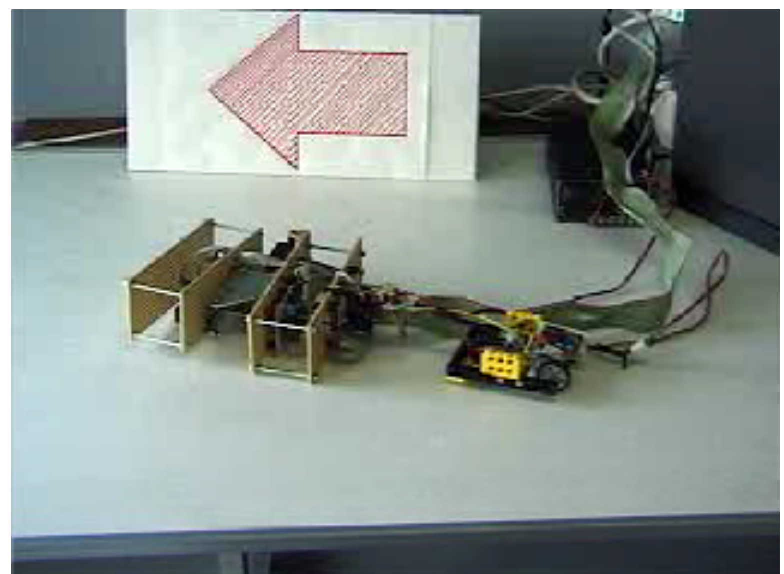
Before



After

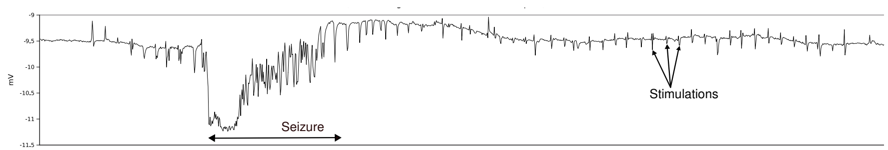


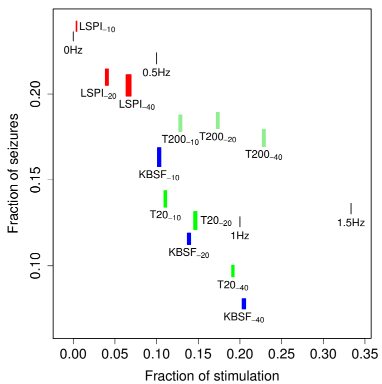
Backward



New Robot, Same algorithm

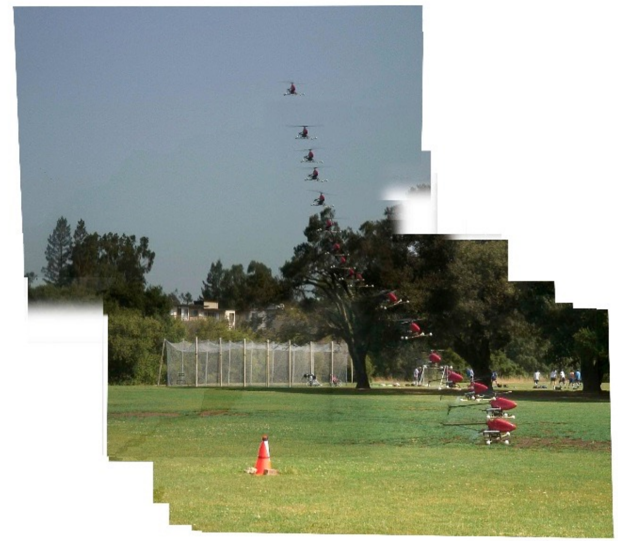
# RL can solve many problems!



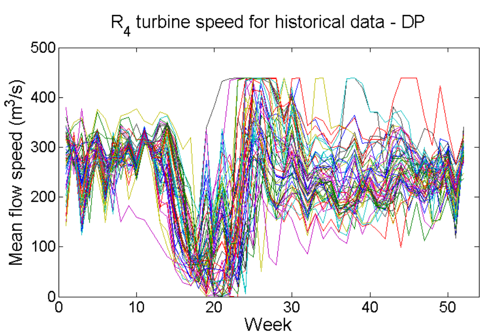



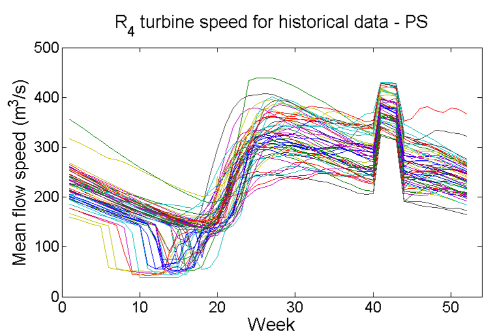

Epileptic seizure control

Guez et al, 2008
Barreto et al, 2011, 2012



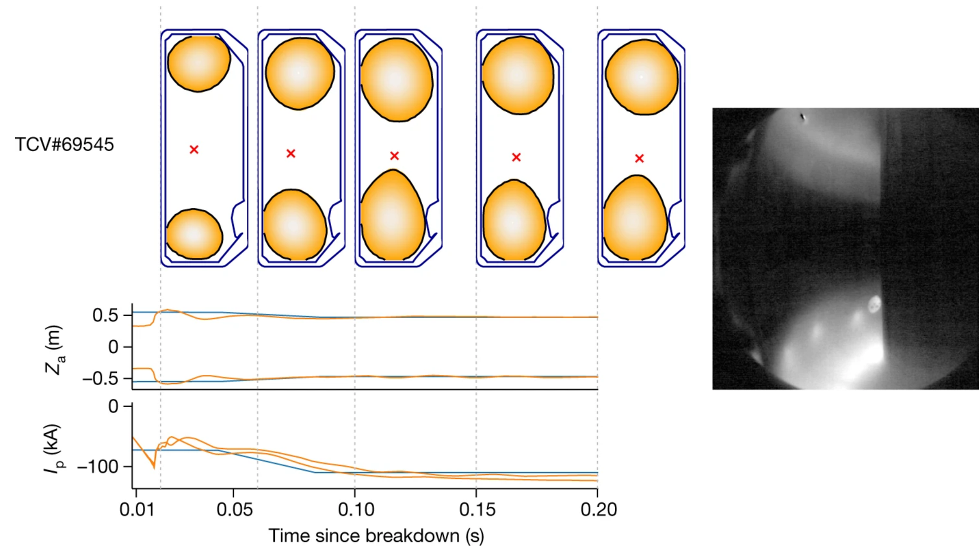
Helicopter control




Power plant optimization
Grinberg et al, 2014

# Recent Successes: Complex Control Tasks




Bellemare et al, Nature, 2020

Degrave et al, Nature, 2022

# Recent/Future Successes: Exa-Scale Search for Molecules

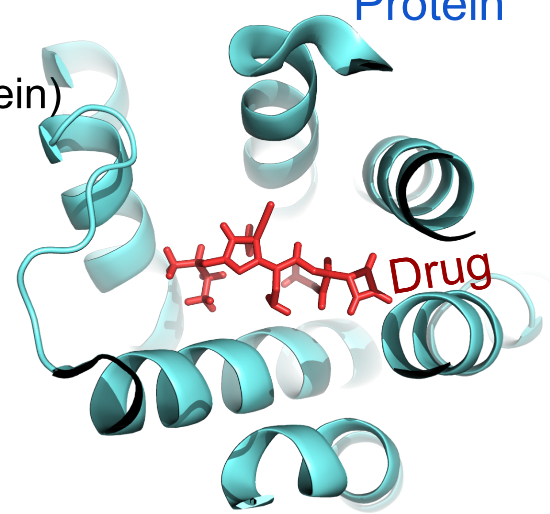
find drugs that bind to protein(s)

>$10^{16\sim20}$ space (simplified + for *one* protein)

most molecules are *bad*:

- not chemically feasible
- not binders
- toxic

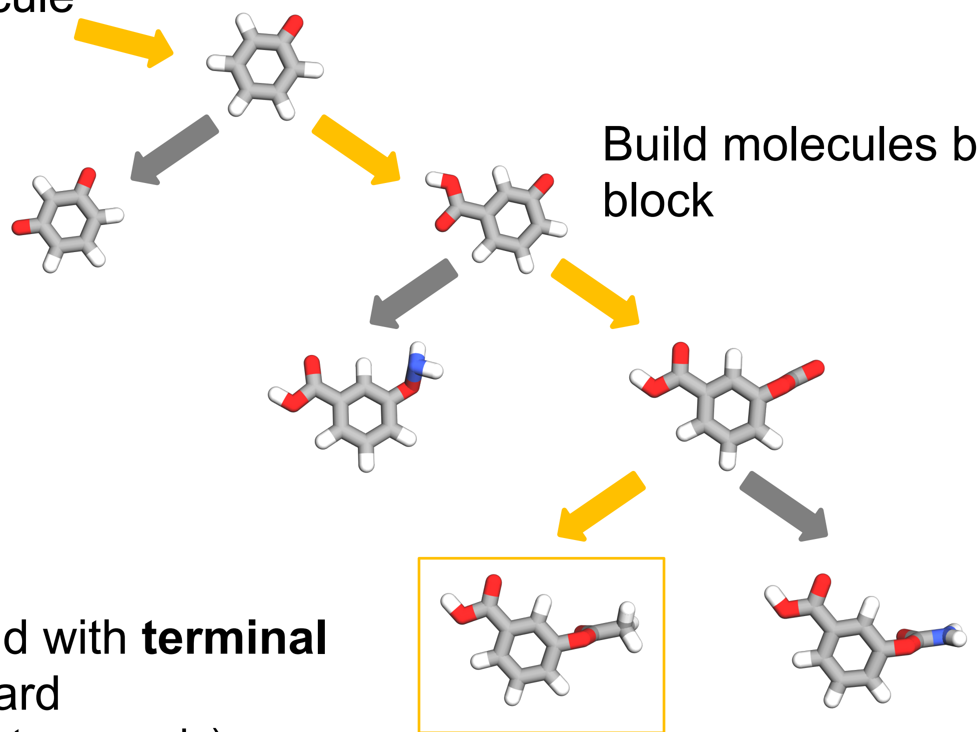
Needles in a haystack!




Mila

# Molecule Search as Reinforcement Learning

“empty molecule”



Build molecules block by block

Episodes end with **terminal** positive reward
(no intermediate rewards)

Bengio et al, NeurIPS’2021

Mila

# Recap: What is Reinforcement Learning?

- Agent-oriented learning—learning by interacting with an environment to achieve a goal
  - more realistic and ambitious than other kinds of machine learning
- Learning by trial and error, with only delayed evaluative feedback (reward)
  - the kind of machine learning most like natural learning
  - learning that can tell for itself when it is right or wrong
- The beginnings of a *science of mind*

# Signature challenges of RL

- Evaluative feedback (reward)
- Sequentiality, delayed consequences
- Need for trial and error, to explore as well as exploit
- Non-stationarity
- The fleeting nature of time and online data