Reinforcement learning (COMP-767)

- Instructor: Doina Precup
- Email: dprecup@cs.mcgill.ca
- Class web page: http://www.cs.mcgill.ca/~dprecup/courses/rl.html

Outline

- Administrative issues
- What is reinforcement learning (RL)?
- 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)

- Supplementary textbooks: Alekh Agarwal, Nan Jiang and Sham Kakade, “Reinforcement Learning: Theory and Algorithms” (in preparation, draft available online); Csaba Szepesvari, “Algorithms for Reinforcement Learning” Morgan and Claypool, 2010, and Dimitri Bertsekas and John Tsitsiklis, “Neuro-dynamic programming”, Athena Scientific, 1997.

- 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 (30%): individual or in groups of 2; email a brief description to Doina by March 16; poster session April 8; report due by April 20
- Three assignments (45%, dates posted on course web page)
- Assignments (individual or in groups of 2) 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
- In-class midterm exam (25%) - March 11 (crib sheet allowed)

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* that is neither natural science nor applications technology

A big success story: AlphaGo

ARTICLE

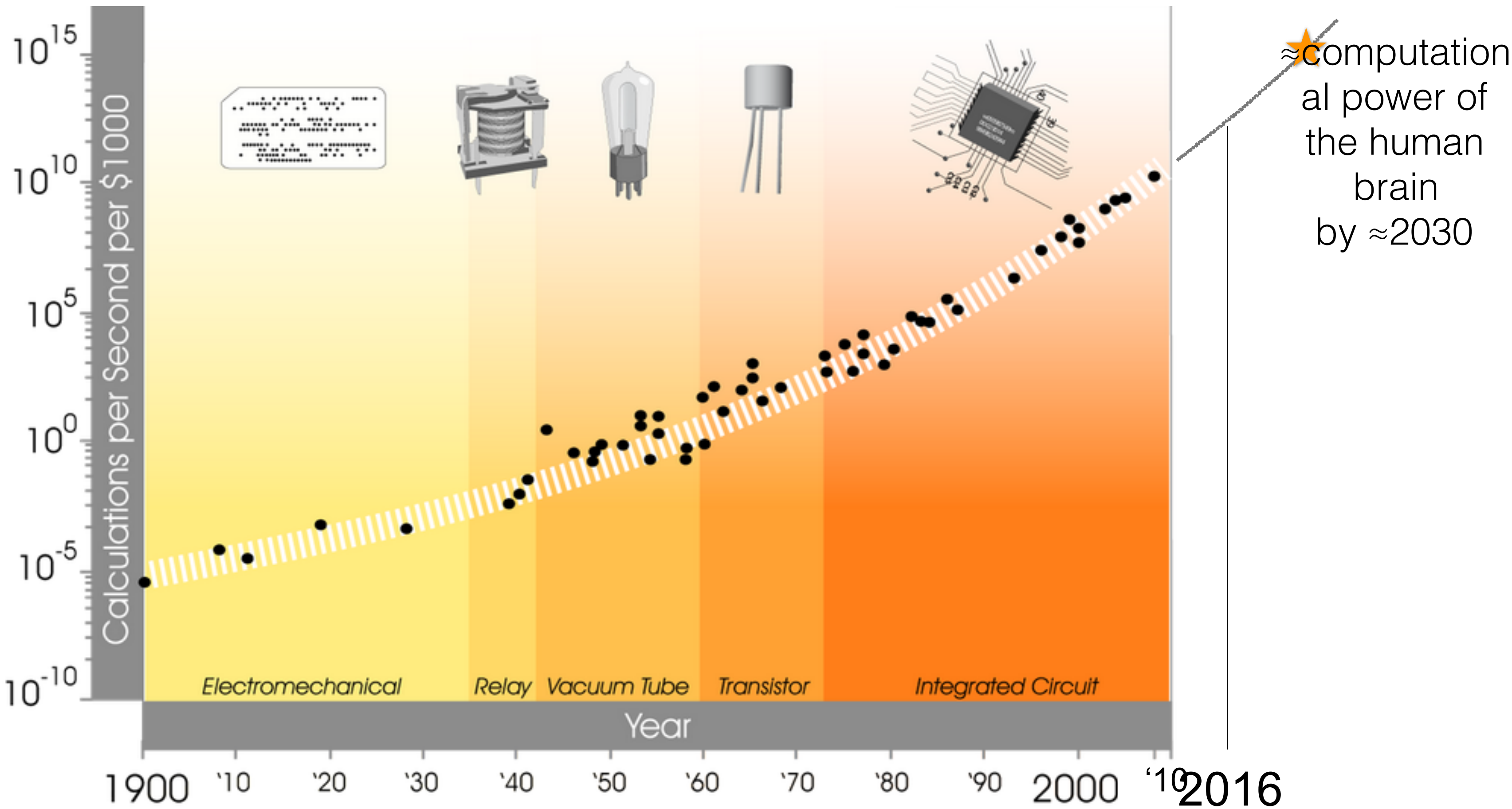
doi:10.1038/nature16961

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

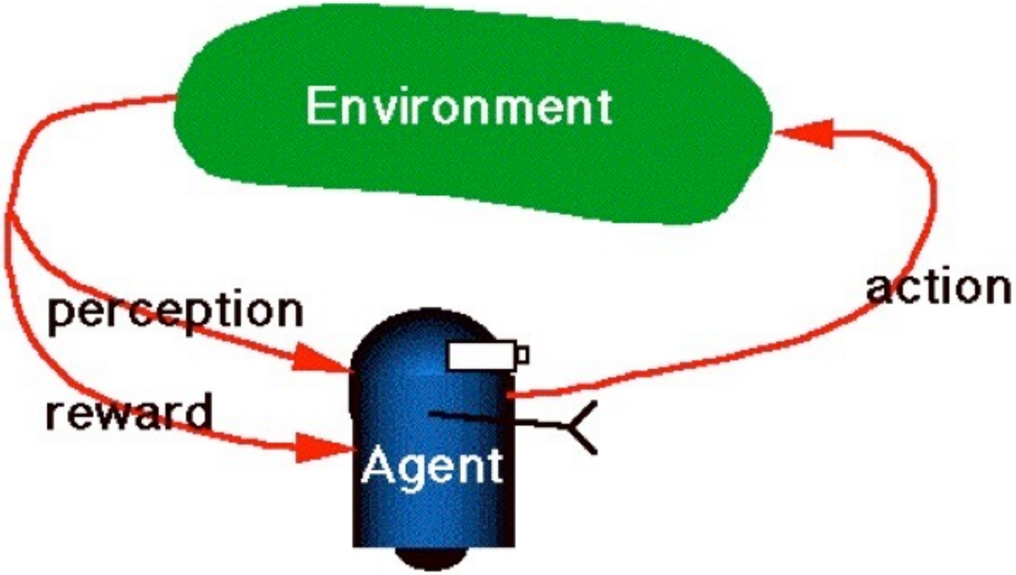
David Silver[1]*, Aja Huang[1]*, Chris J. Maddison[1], Arthur Guez[1], Laurent Sifre[1], George van den Driessche[1], Julian Schrittwieser[1], Ioannis Antonoglou[1], Veda Panneershelvam[1], Marc Lanctot[1], Sander Dieleman[1], Dominik Grewe[1], John Nham[2], Nal Kalchbrenner[1], Ilya Sutskever[2], Timothy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

The computational revolution



Reinforcement Learning



Reward: Food or electric shock

Reward: Positive and negative numbers

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

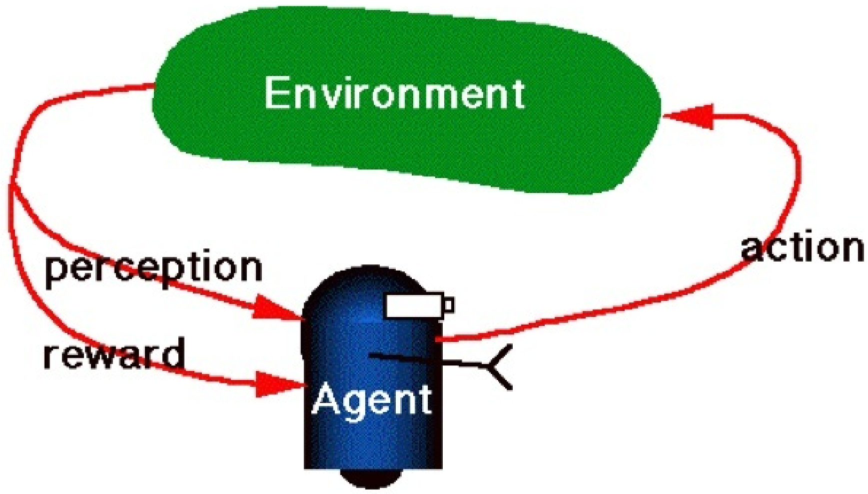
Contrast: Supervised Learning

- 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

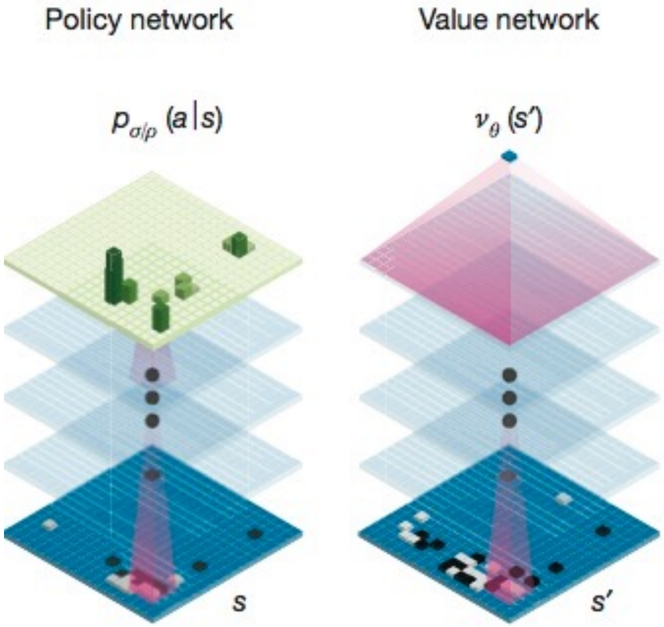
- Training experience: unlabelled data
- What to learn: interesting associations in the data
- E.g., clustering, dimensionality reduction, density estimation
- Often there is no single correct answer
- Very necessary, but significantly more difficult that supervised learning

Computational framework



- At every time step t, the agent perceives the *state* of the environment
- Based on this perception, it chooses an *action*
- The action causes the agent to receive a *numerical reward*
- Find a way of choosing actions, called a *policy* which *maximizes the agent's long-term expected return*

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*

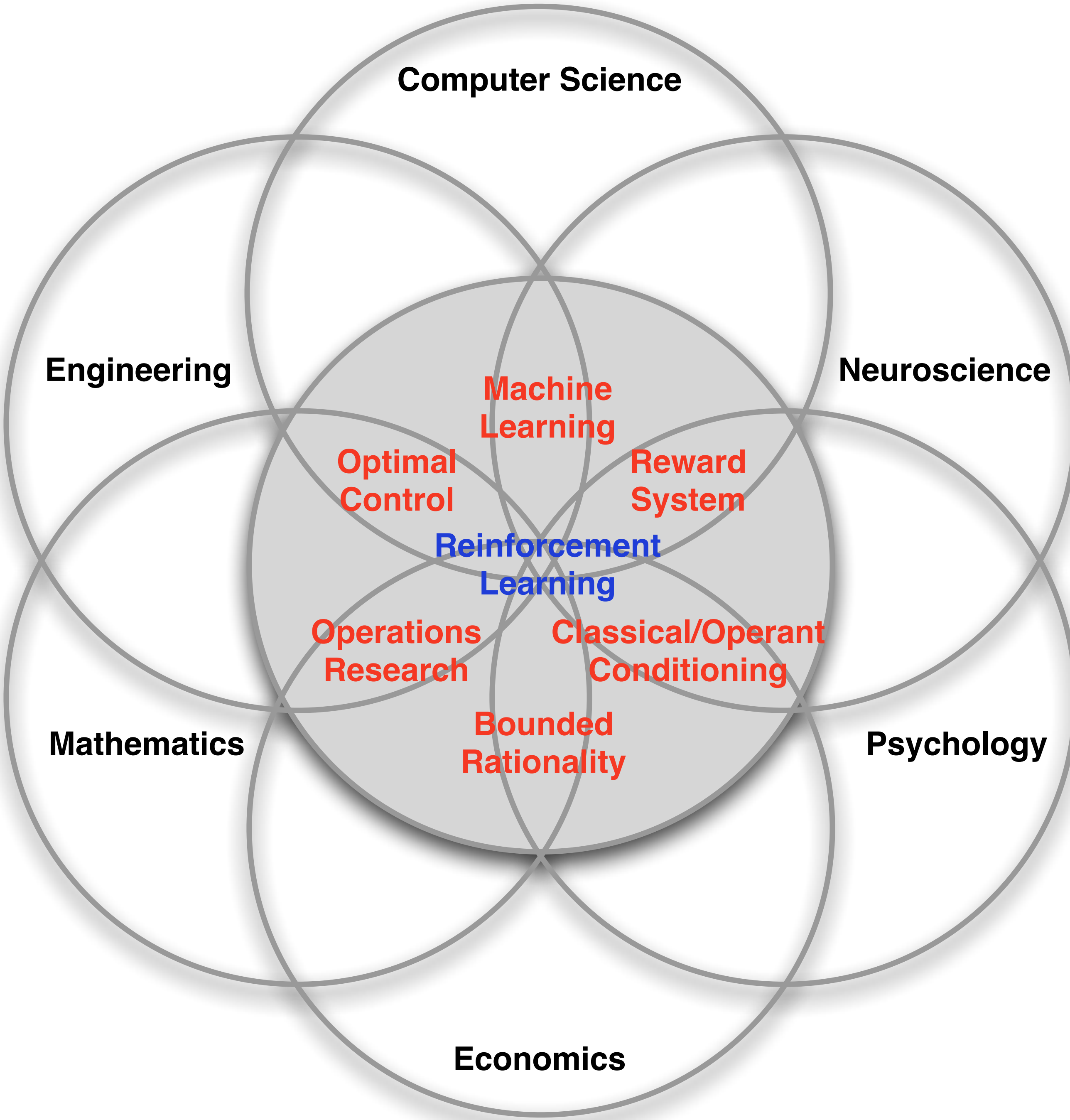
  Eg. Players trained by playing thousands of simulated games, with no expert input on what are good or bad moves

- 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



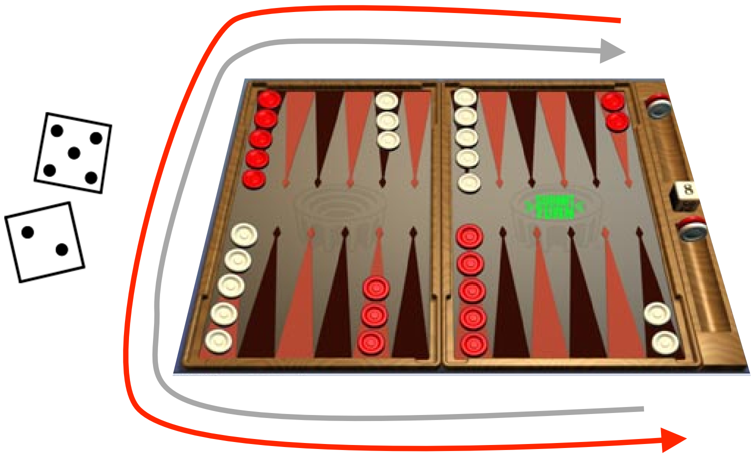
David Silver 2015

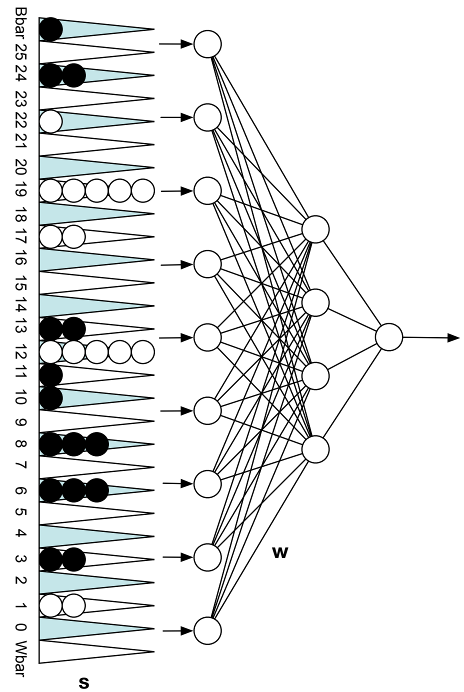
Some RL Successes

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

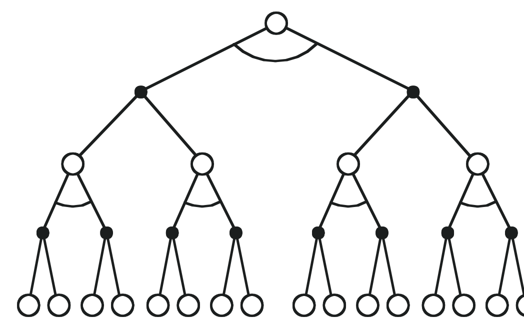
Tesauro, 1992-1995





estimated state value
(≈ prob of winning)

Action selection
by a shallow search



Start with a random Network

Play millions of games against itself

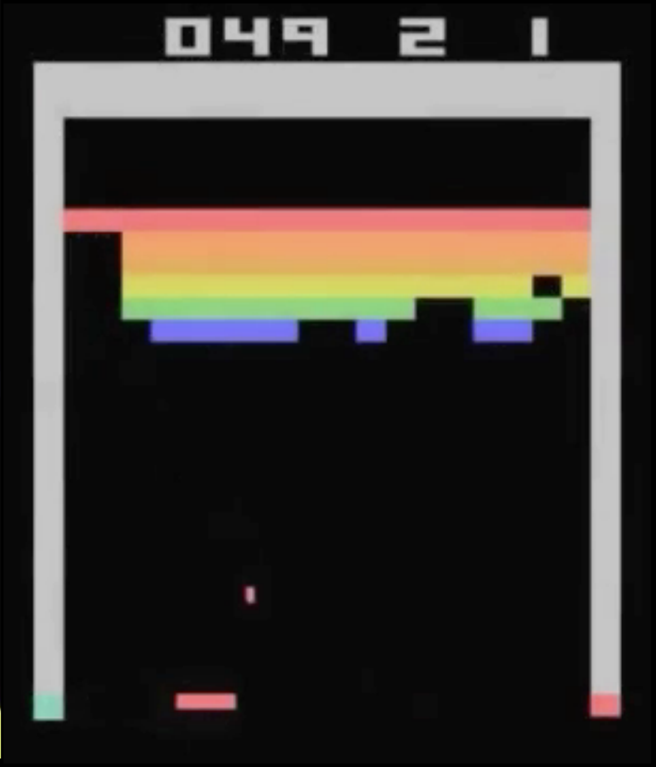
Learn a value function from this simulated experience

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

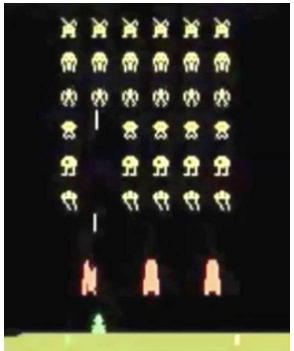


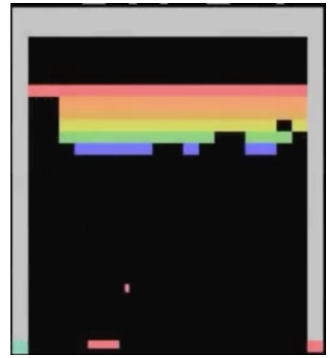
Breakout

Enduro

RL + Deep Learning, applied to Classic Atari Games

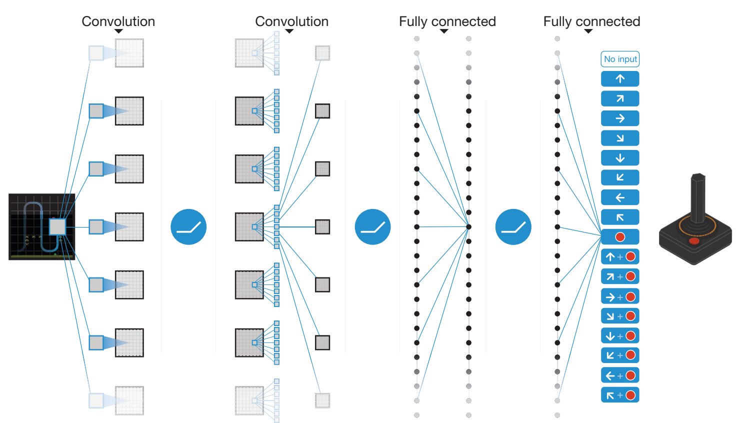
Google Deepmind 2015, Bowling et al. 2012





- 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

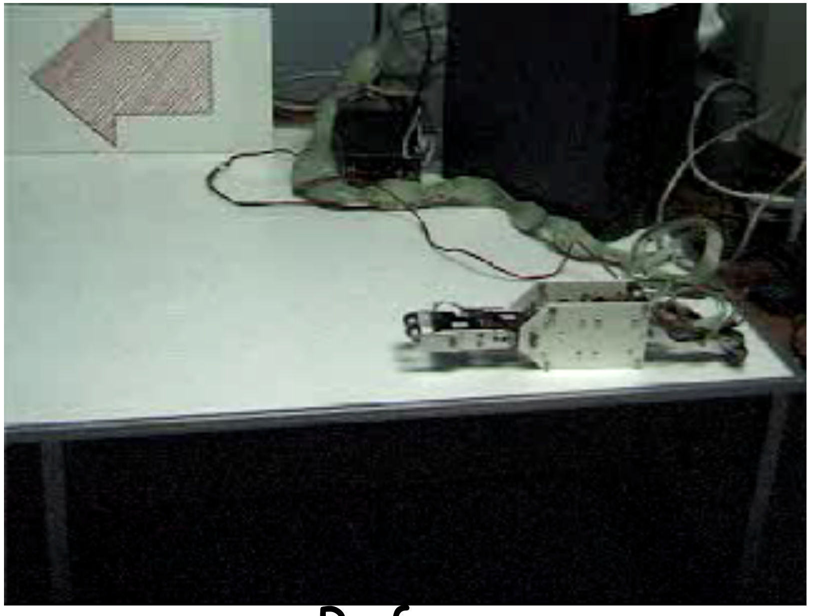


to predictions of final score for each of 18 joystick actions

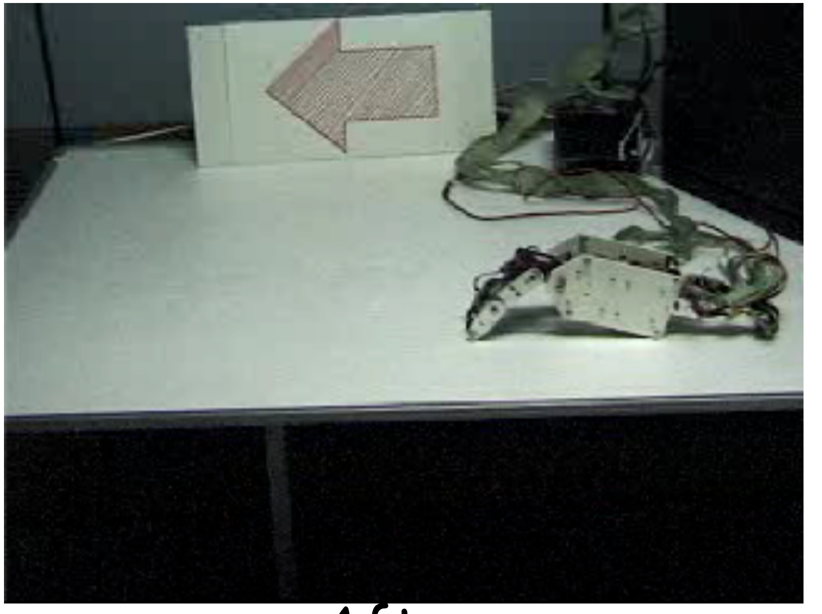
- Learned to play better than all previous algorithms and at human level for more than half the games

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

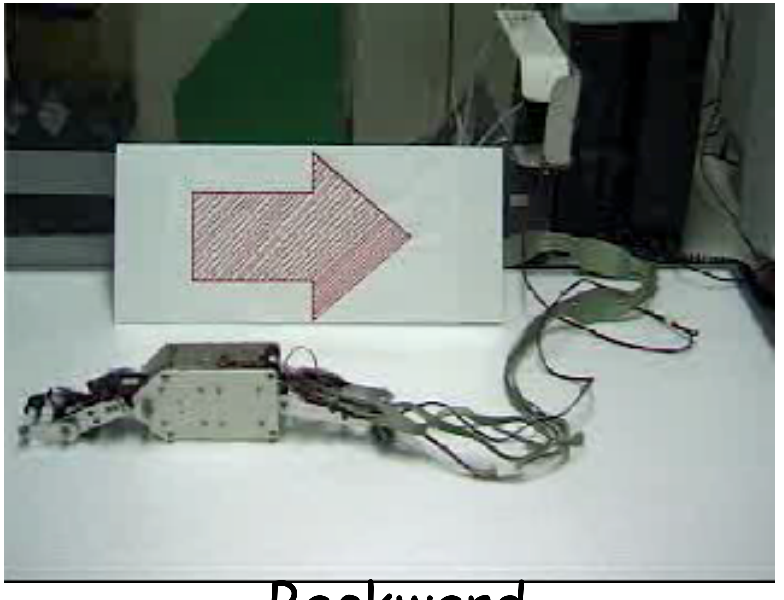
Example: Hajime Kimura's RL Robots



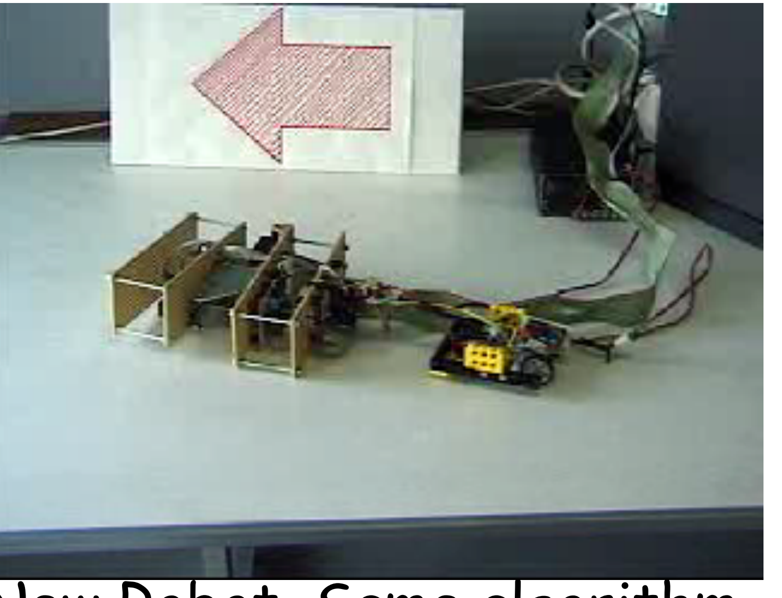
Before



After

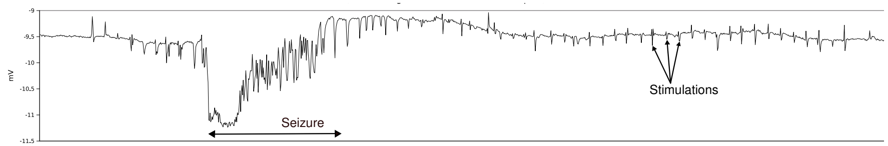


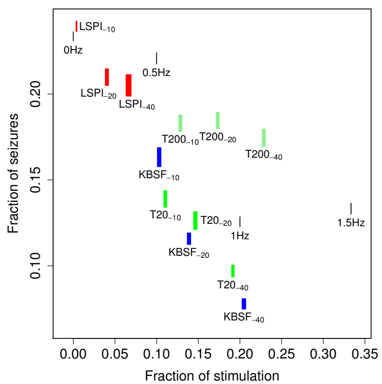
Backward



New Robot, Same algorithm

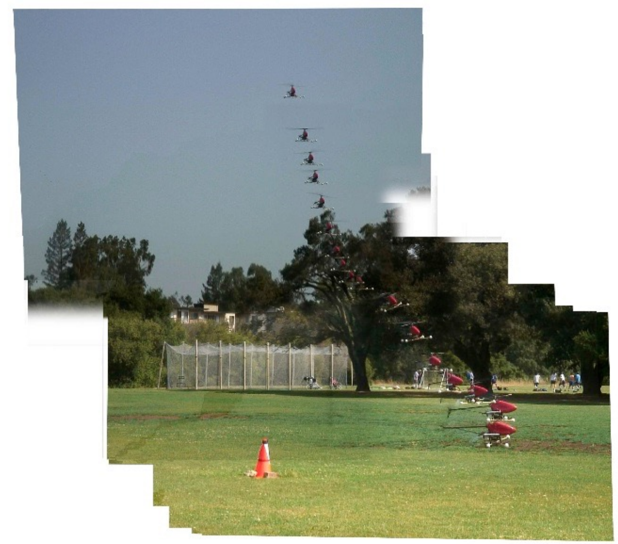
Applications: Few trajectories

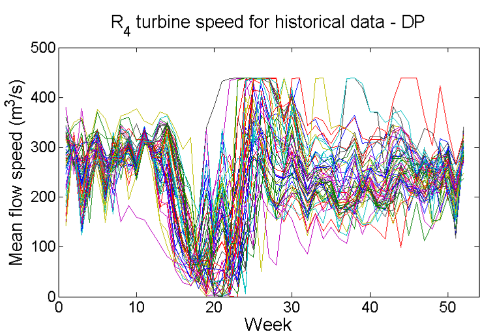


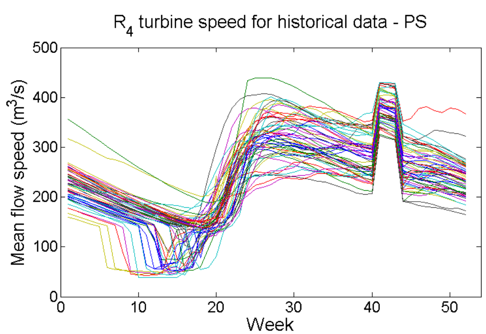


Epileptic seizure control

Our lab: Guez et al, 2008
Barreto et al, 2011, 2012







Helicopter control
; Our lab: Barreto, Gehring et al, 2013

Power plant optimization
Our lab: Grinberg et al, 2014

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