强化学习原理及应用
Reinforcement Learning (RL): Theories & Applications

DCS6289 Spring 2022

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School of Computer Science and Engineering
Sun Yat-Sen University

Lecture 1： Course Introduction

22th Feb. 2022

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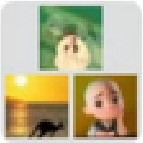
Class WeChat Group



2022强化学习研究生课程

该二维码7天内(2月28日前)有效，重新进入将更新

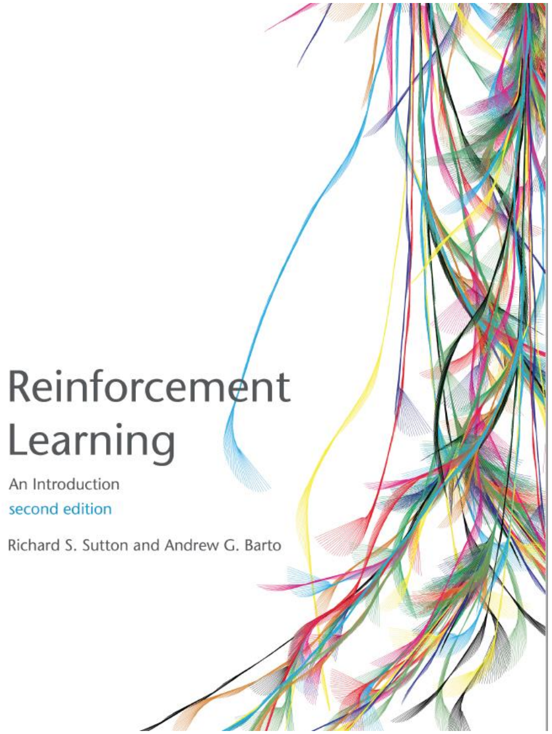
Textbook

- Reinforcement Learning: An Introduction (Second Edition), Richard S. Sutton and Andrew G. Barto, MIT Press, Cambridge, MA, 2018.

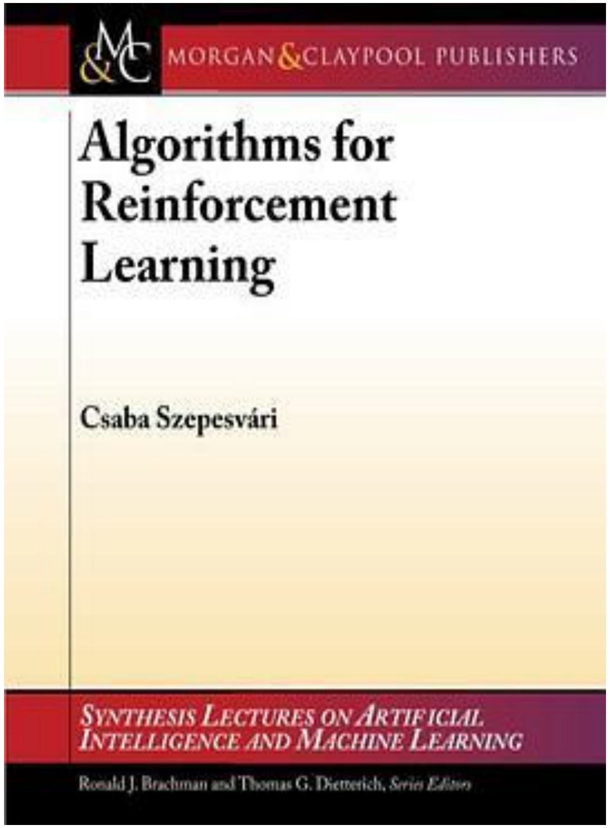
2nd Edition Website:
http://incompleteideas.net/sutton/book/the-book-2nd.html

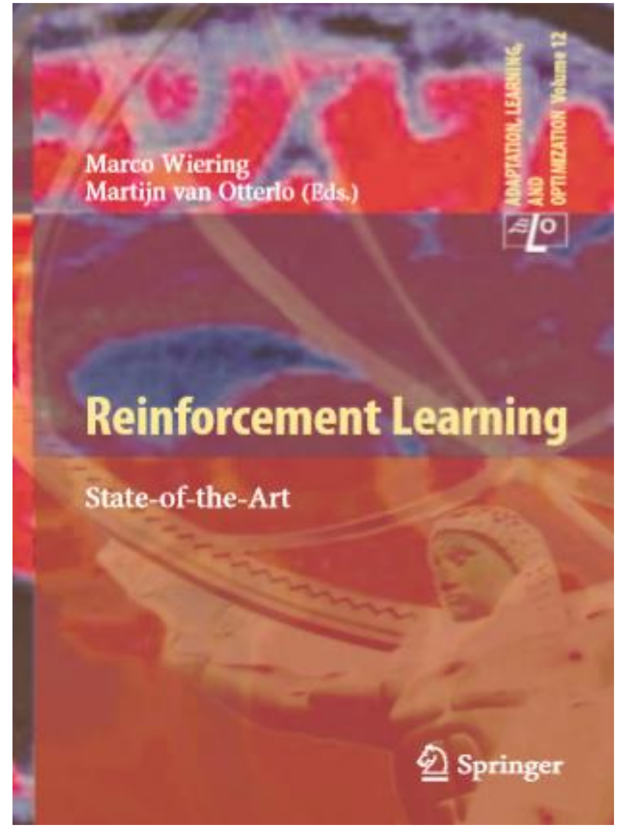
2nd Edition PDF version:
http://incompleteideas.net/sutton/book/RLbook2018.pdf

1st Edition html version:
http://incompleteideas.net/book/first/ebook/the-book.html



Textbook





Algorithms for Reinforcement Learning,
Csaba Szepesvári,
Morgan & Claypool Publishers, 2010.
https://sites.ualberta.ca/~szepesva/rlbook.html

Reinforcement Learning State-of-the-Art,
Wiering M.A.,
Springer, 2016.

Other Resources

https://medium.com/@yuxili/rl-applications-73ef685c07eb
https://blog.csdn.net/gsww404/article/details/103074046
https://github.com/ShangtongZhang/reinforcement-learning-an-introduction
https://github.com/MorvanZhou/Reinforcement-learning-with-tensorflow
http://www.mlss.cc/
http://videolectures.net/deeplearning2016_abbeel_deep_reinforcement/?q=robot%20reinforcement%20learning
https://www.cnblogs.com/steven-yang/p/6624253.html
https://blog.csdn.net/lqfarmer/article/details/72868471
https://sites.google.com/view/deeprl-symposium-nips2017/
https://www.youtube.com/watch?v=2pWv7GOvuf0&list=PLzuuYNsE1EZAXYR4FJ75jcJseBmo4KQ9-
https://zhuanlan.zhihu.com/p/78191585
https://arxiv.org/abs/1811.12560v2
https://arxiv.org/abs/1701.07274
https://www.jiqizhixin.com/articles/010902?from=timeline&isappinstalled=0
https://blog.csdn.net/Real_Myth/article/details/53414209

Make the best use of online resources!!!

Course Goal

- Have a deeper understanding of RL theories
  - Know the key features of RL
  - Master the principles of basic RL concepts and algorithms
  - Grasp the ideas of more advanced RL algorithms
  - Compare and contrast various RL algorithms on multiple criteria (e.g. *regret*, *sample complexity*, *computational complexity*, *empirical performance*, *convergence*, etc)
  - Possibly propose new powerful RL algorithms

- Improve the capabilities of RL applications
  - Implement in code common RL algorithms in toy domains
  - Determine if a real-life problem should be formulated as an RL problem, how to define it formally (in terms of the *state space*, *action space*, *dynamics and reward mode*l), and what algorithms are suited for addressing it.
  - Possibly intrigue new ideas and theoretical solutions from applications

Course Prerequisites

- Foundations of Math
  - Calculus, Linear Algebra, Basic Probability and Statistics
- Foundations of Machine Learning
  - Traditional supervised and unsupervised learning
  - Modern deep learning methods
  - Cost functions, derivatives and optimization with gradient descent
- Proficiency in Programing
  - Python is highly preferred. If you have a lot of programming experience but in a different language (e.g. C/ C++/ Matlab/ Javascript) you will probably be fine.

Grading Policies

- Final grade will be 60% coursework + 40% final project
- Coursework include 4 Assignments
  - Submitted with written report and zip source code
  - Report should be formal and academic (Latex preferred)
  - Code should provide basis comments
  - Evaluation criteria: correctness, formalization, etc.
  - Late policy: within 3 days after deadline
- Final project
  - May work in groups of up to three people
  - Each group will submit a report
  - A short paragraph to explain the role of each group member along with the final report

Collaboration and Misconduct

- For written assignments, you are welcome to discuss ideas with others, but expected to write up your own solutions independently (without referring to other's solutions).
- For coding, you may only share the input-output data of your programs. This encourages you to work separately but share ideas on how to test your implementation.
- If you share your solution with another student, even if you did not copy from another, you are still violating the honor code, and both receive 0 score.

Tentative Class Structure

Weeks 2-9	Lecture 1: Course introduction (2) Lecture 2: MDP and dynamic programming (3) Lecture 3: Model-free prediction (4) Lecture 4: Model-free control (TD) (5) Lecture 5: Function approximation (6) Lecture 6: Policy gradient (7-8) Lecture 7: Exploration (9)
Week 10	Mid-term Break
Weeks 11-19	Lecture 8: Deep RL (11-12) Lecture 9: Model-based methods (13) Lecture 10: Offline RL (14) Lecture 11: Distributed RL(15) Lecture 12: Multiagent RL (16-17) Lecture 13: Hierarchical RL (18) Lecture 14: Knowledge-based RL (19)
Week 20-21	Final Project

What is reinforcement learning?

About RL

"The idea that we learn by interacting with our environment is probably the first to occur to us when we think about the nature of learning. When an infant plays, waves its arms, or looks about, it has no explicit teacher, but it does have a direct sensori-motor connection to its environment. Exercising this connection produces a wealth of information about cause and effect, about the consequences of actions, and about what to do in order to achieve goals. Throughout our lives, such interactions are undoubtedly a major source of knowledge about our environment and ourselves. Whether we are learning to drive a car or to hold a conversation, we are all acutely aware of how our environment responds to what we do, and we seek to influence what happens through our behavior. Learning from interaction is a foundational idea underlying nearly all theories of learning and intelligence."

——Richard S. Sutton

About RL

"Reinforcement learning problems involve learning what to do --- how to map situations to actions --- so as to maximize a numerical reward signal. In an essential way these are closed-loop problems because the learning system's actions influence its later inputs. Moreover, the learner is not told which actions to take, as in many forms of machine learning, but instead must discover which actions yield the most reward by trying them out. In the most interesting and challenging cases, actions may affect not only the immediate reward but also the next situation and, through that, all subsequent rewards. These three characteristics --- being closed-loop in an essential way, not having direct instructions as to what actions to take, and where the consequences of actions, including reward signals, play out over extended time periods --- are the three most important distinguishing features of the reinforcement learning problem."

——Richard S. Sutton

About RL

RL, in a nutshell, is to "learn to *make good sequences of decisions through trail-and-errors*"

About RL

- Thus, there are four basic aspects in RL
  - Optimization *(good decisions*)
  - Delayed consequences (*sequential*)
  - Exploration (*trail-and-error*)
  - Generalization (*learn*)

Optimization

- The goal is to find an optimal (or near-optimal) way to make decisions
- The evaluation of optimality can be explicitly measured or provided in terms of utility functions, e.g.,
  - *the shortest path between two cities given a network of roads*
  - *the fast speed that a robot is able to run*
  - *the maximum area for a multi-robot system to cover*
  - *the most money a gambling agent can win*
  - *the least time for a group of vehicles to pass a crossroad*
  - *the highest possibility to win a war*
  - …

Delayed consequences

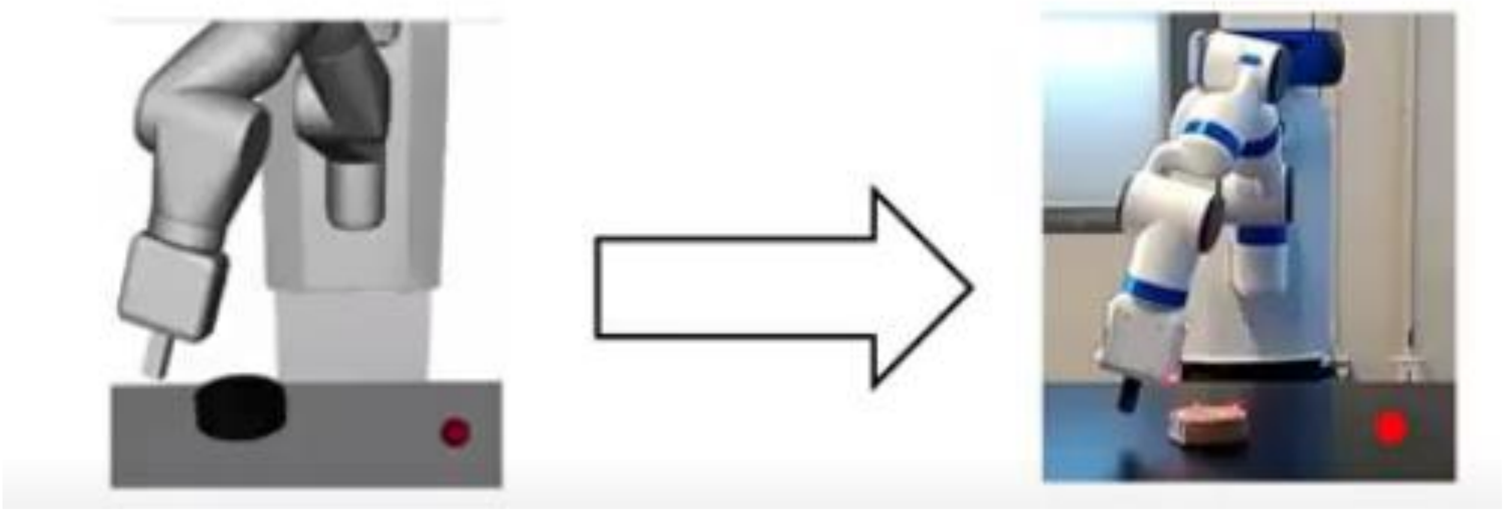
- Consequences of decisions can be much delayed
  - Actions will impact the input in the next step (data is not i.i.d.)
  - Should trade-off short-term and long-term outcome
- Cause the *credit assignment* problem
  - Different action sequences cause different outcomes
  - What caused later high or low rewards? Which action is responsible for the success or failure?

Exploration

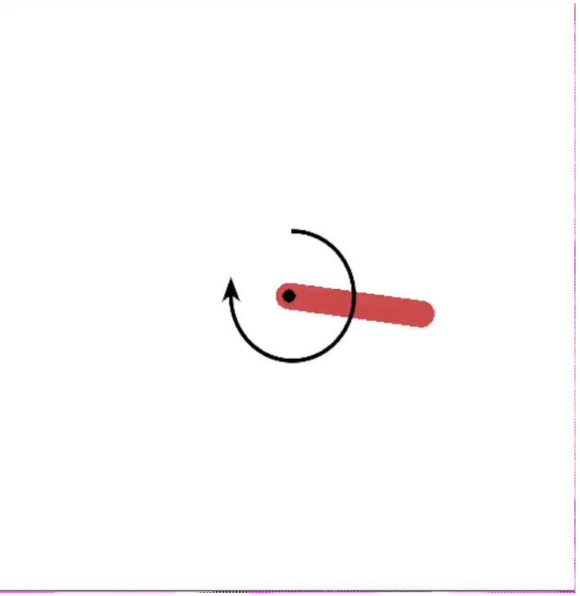
- RL is about learning from trail-and-error interactions
- Gain knowledge from the taken actions
  - *I know that restaurant A is good*
  - *I consider that the move of game playing is best*
- Trade-off between using the gained knowledge (exploitation) or try out new actions (exploration)
  - *Should I try other restaurant?*
  - *Should I try other moves?*
- Cause the *exploration-exploitation trade-off* problem
- Indicate sample efficiency and optimality of RL algorithms
  - *Use the least exploration to gain the optimal policies*
  - *Be able to jump out of local sub-optimal solution space*

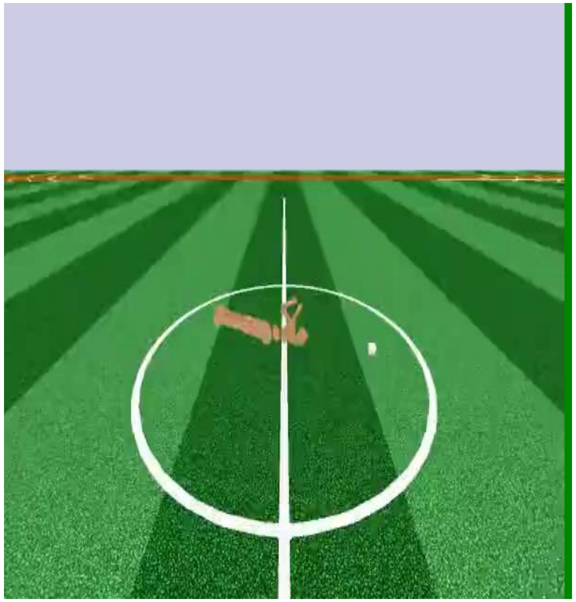
Generalization

- Why not just pre-program a policy?
  - No or limited knowledge of how the world functions
  - A policy that predesigned for a domain might not work in other related domains.



RL cases





Characteristics of RL

What makes RL different from other related paradigms?

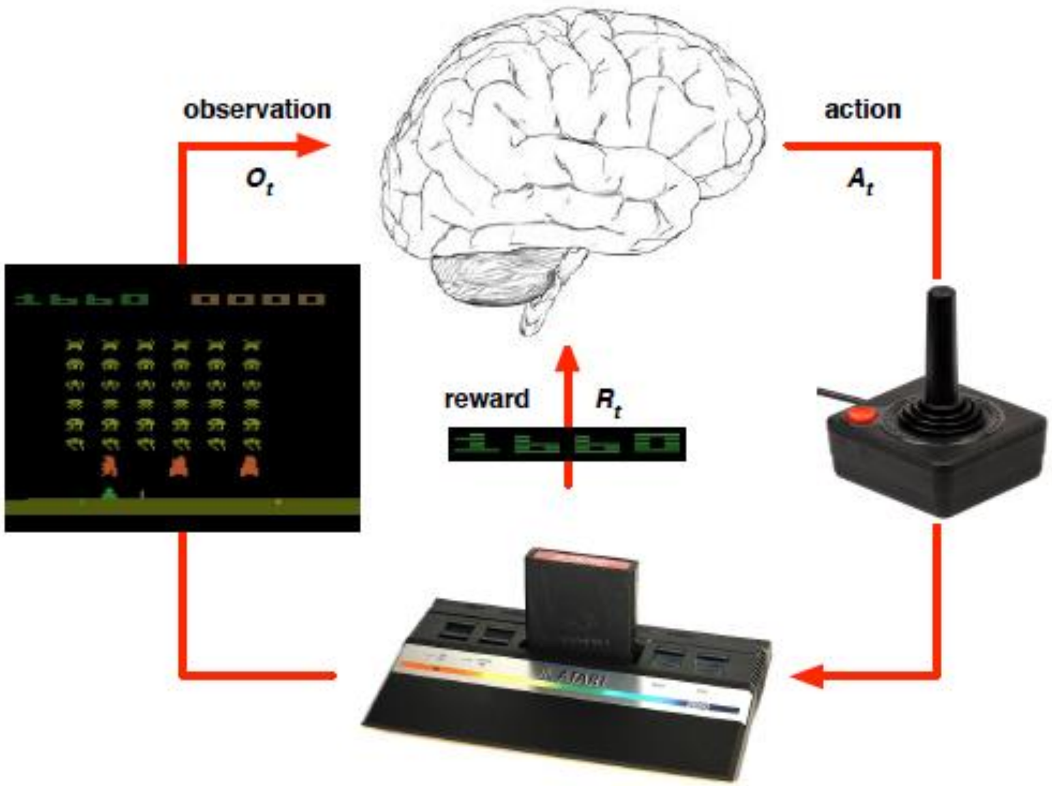
- Two fundamental problems in sequential decision making: learning *vs* planning
- Reinforcement Learning:
  - *The environment is initially unknown*
  - *The agent interacts with the environment*
  - *The agent improves its policy*
- Planning
  - *A model of the environment is known*
  - *The agent performs computations with its model (without any*
  - *external interaction)*
  - *The agent improves its policy*

  a.k.a. deliberation, reasoning, introspection, pondering, thought, search

Characteristics of RL

What makes RL different from other related paradigms?

- Atari Example: RL



- Rules of the game are unknown
- Learn directly from interactive game-play
- Pick actions on joystick, see pixels and scores

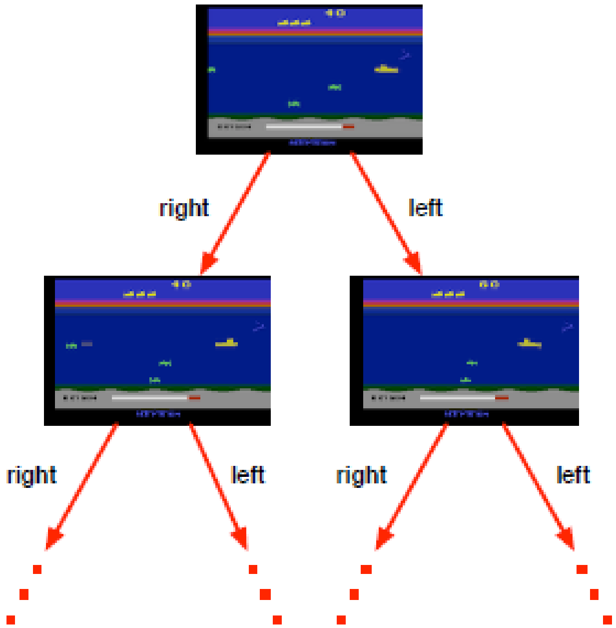
[from David Silver's course]

Characteristics of RL

What makes RL different from other related paradigms?

- Atari Example: Planning

  - Rules of the game are known
  - Can query emulator
    - perfect model inside agent's brain
  - If I take action *a* from state *s*:
    - what would the next state be?
    - what would the score be?
  - Plan ahead to find optimal policy
    - e.g. tree search

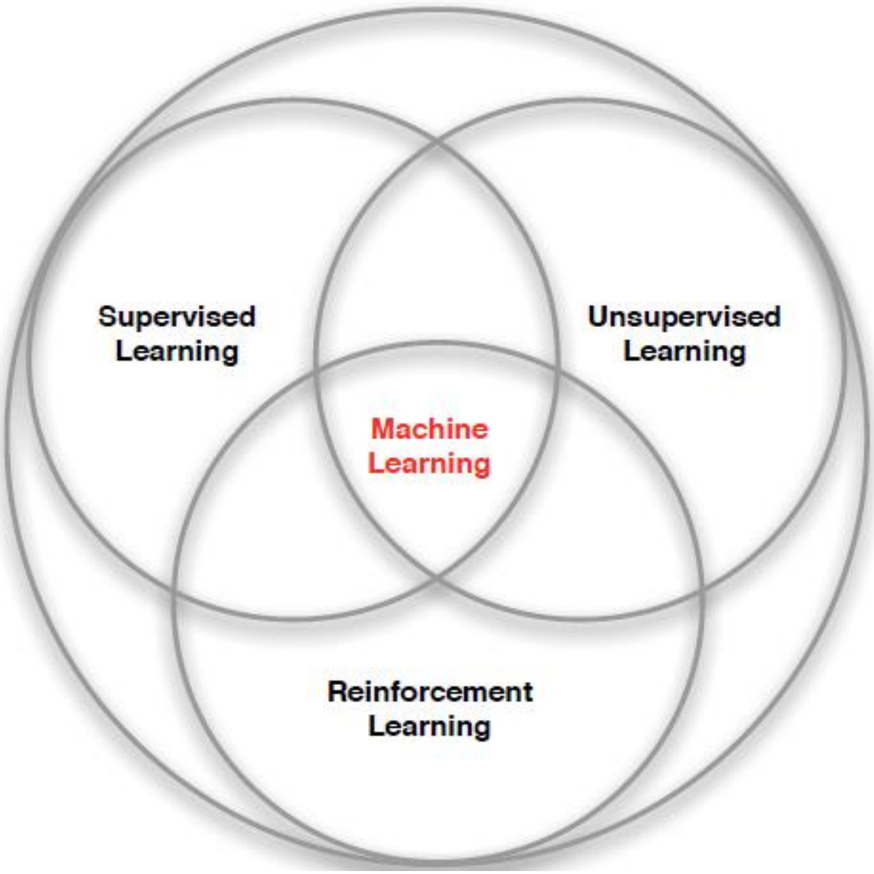


[from David Silver's course]

Characteristics of RL

What makes RL different from other related paradigms?

- Three fundamental problems in machine learning

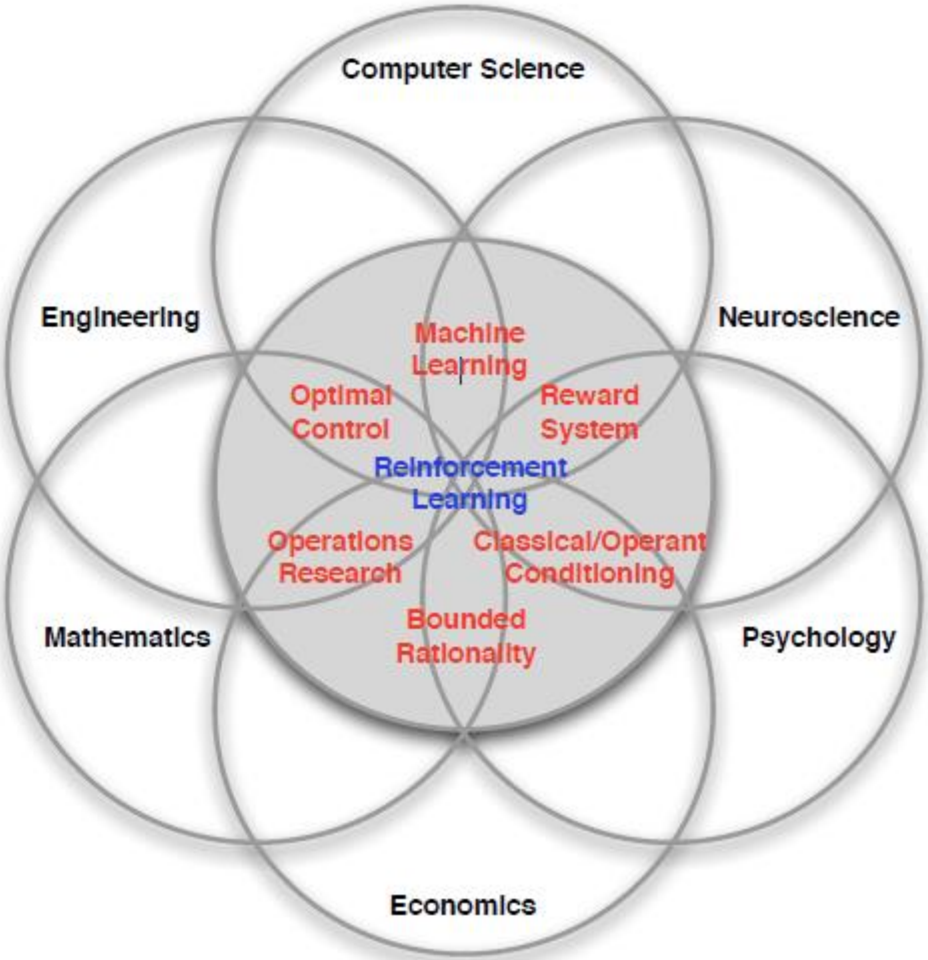


Characteristics of RL

What makes RL different from other related paradigms?

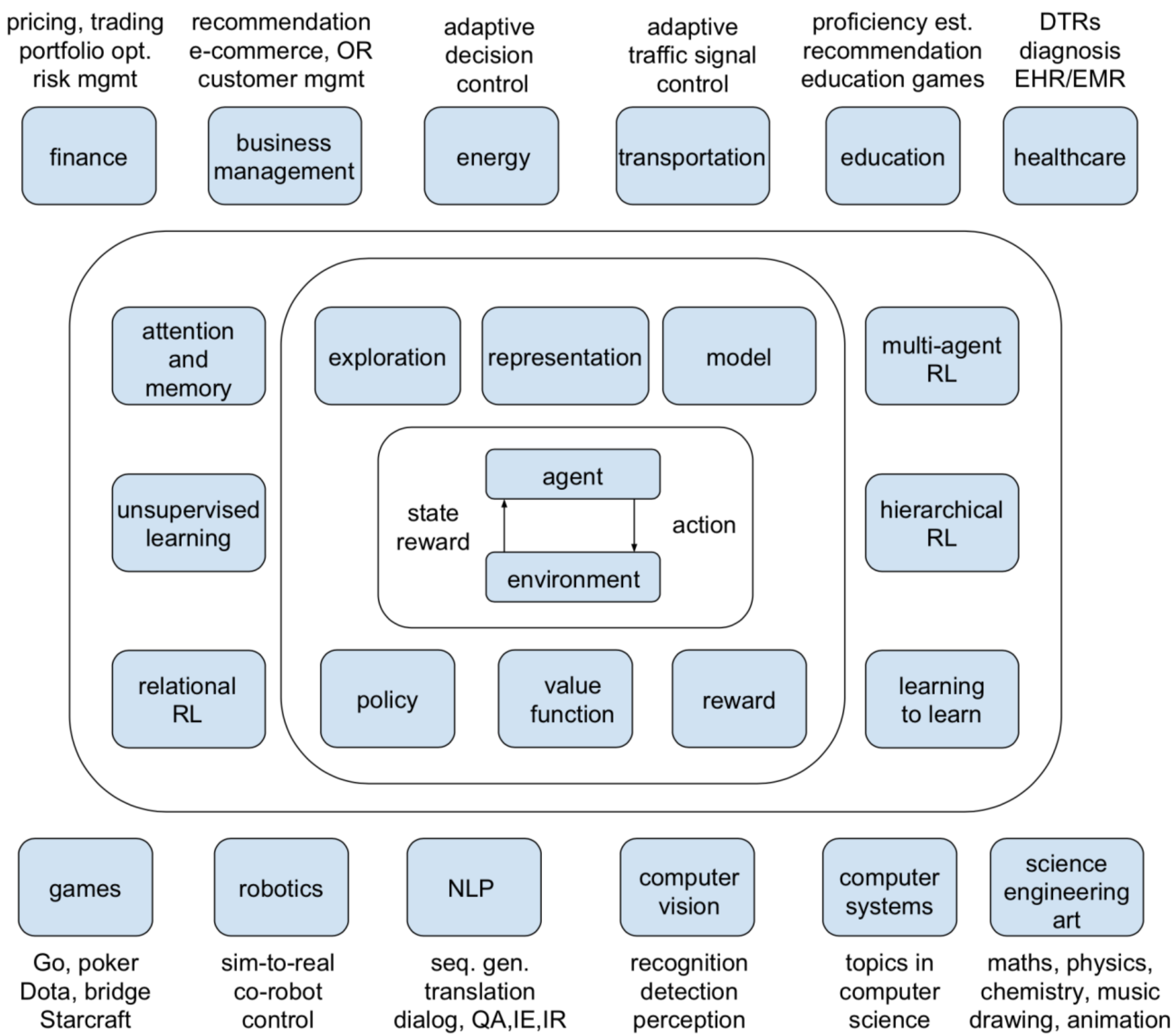
- Three fundamental problems in machine learning
- Supervised learning
  - *Classification or prediction from labeled (action,outcome) pairs*
  - *No interactions*
  - *No sequential decisions*
  - *No explorations*
- Unsupervised learning
  - *Discover inherent correlations among data*
  - *No interactions*
  - *No sequential decisions*
  - *No explorations*

Interdisciplinary RL



[from David Silver's course]

Applications of RL

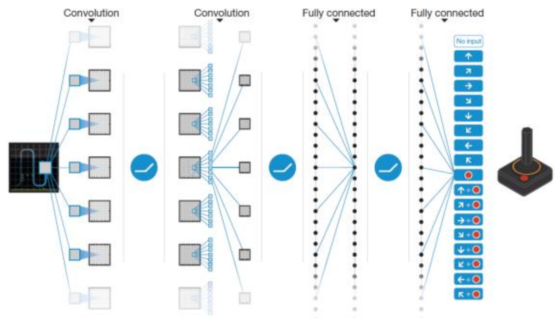


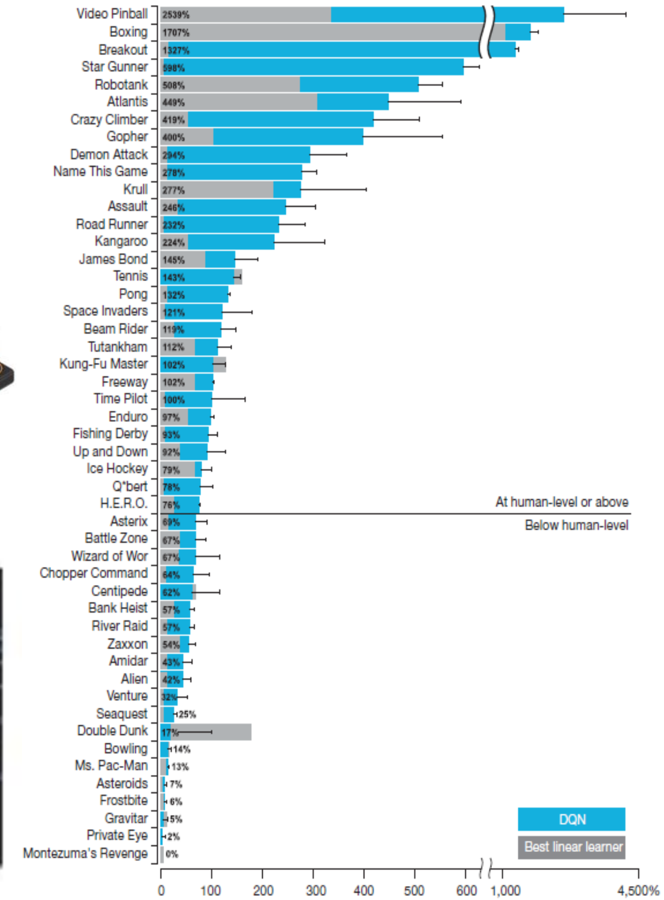
Yuxi Li, Deep Reinforcement Learning, https://arxiv.org/abs/1810.06339, 2018

Applications of RL–game playing

Human-level Atari agent (2015)

Human-level control through deep reinforcement learning



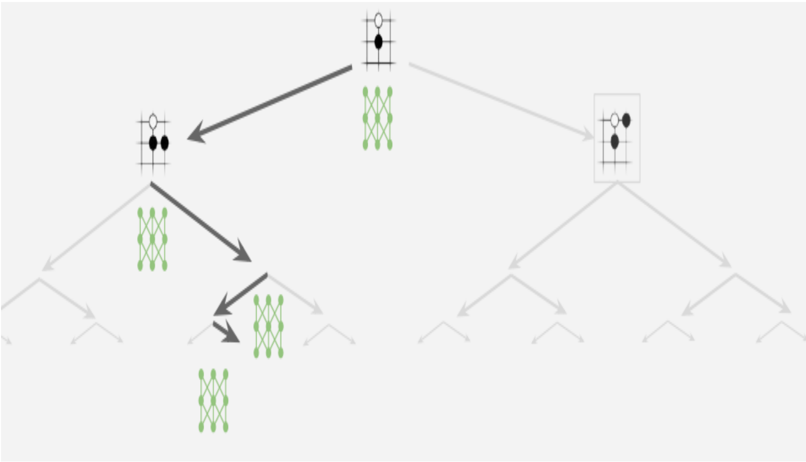


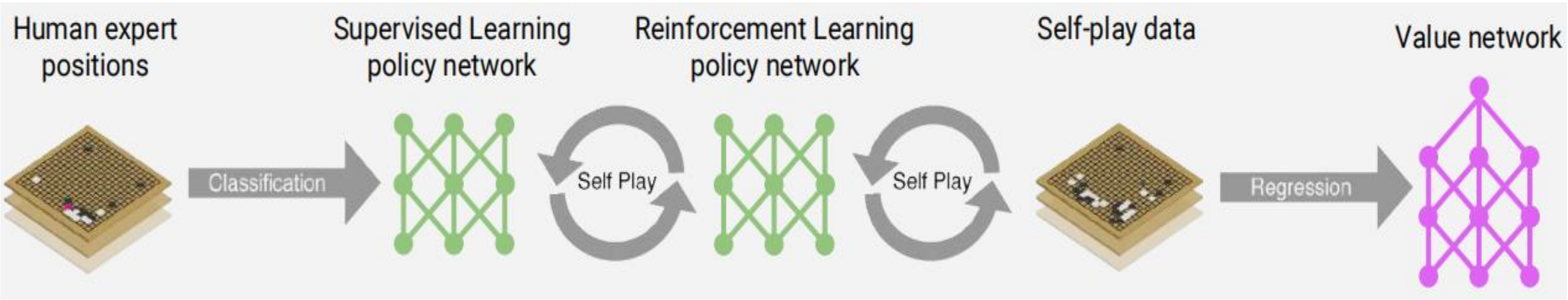
Mnih V, Kavukcuoglu K, Silver D, et al. Human-level control through deep reinforcement learning[J]. nature, 2015, 518(7540): 529-533.

Applications of RL–game playing

DeepMind’s AlphaGo (2016)

AlphaGo





Silver, David, et al. "Mastering the game of Go with deep neural networks and tree search." *nature* 529.7587 (2016): 484-489.

Applications of RL–game playing

Dota OpenAI Five
(OpenAI,2018)

Defeat world champion

StarCraft AlphaStar
(DeepMind, 2019, Nature)

Win professionals （top 10）

Texas Hold'em Pluribus
(Facebook&CMU, 2019, Science)

Win $1000/hour, i.e., $5/hand

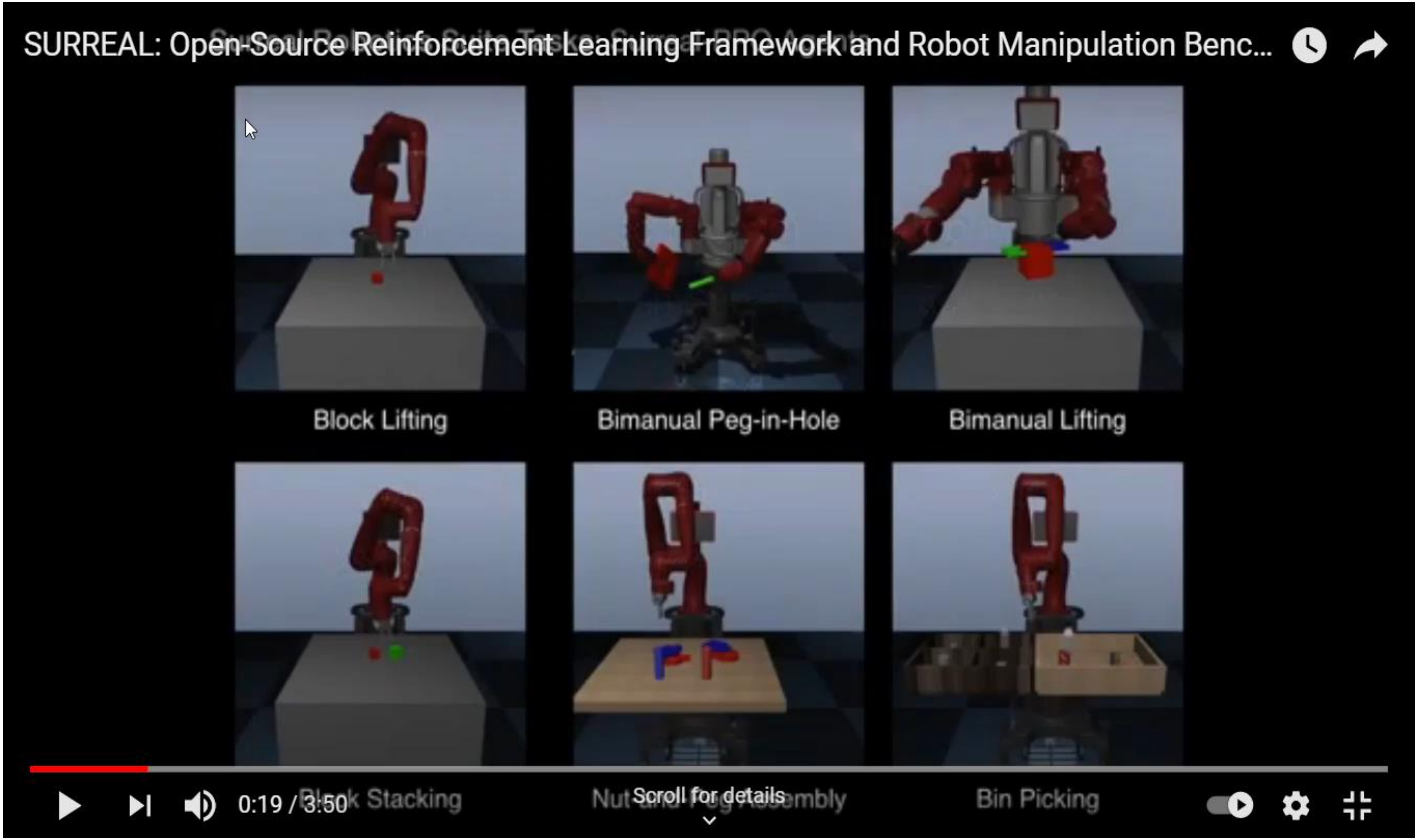
游戏	状态空间复杂度	游戏树复杂度
井字棋	10^4	10^5
国际跳棋	10^21	10^31
国际象棋	10^46	10^123
中国象棋	10^48	10^150
五子棋	10^105	10^70
围棋	10^172	10^360

宇宙原子数

8.64×10^-27×4/3×π×(4.3992×10^26)^3×0.049×0.75/(1.6735×10^-27)+8.64×10^-27×4/3×π×(4.3992×10^26)^3×0.049×0.24/(6.6465×10^-27)≈7.31×10^79个。

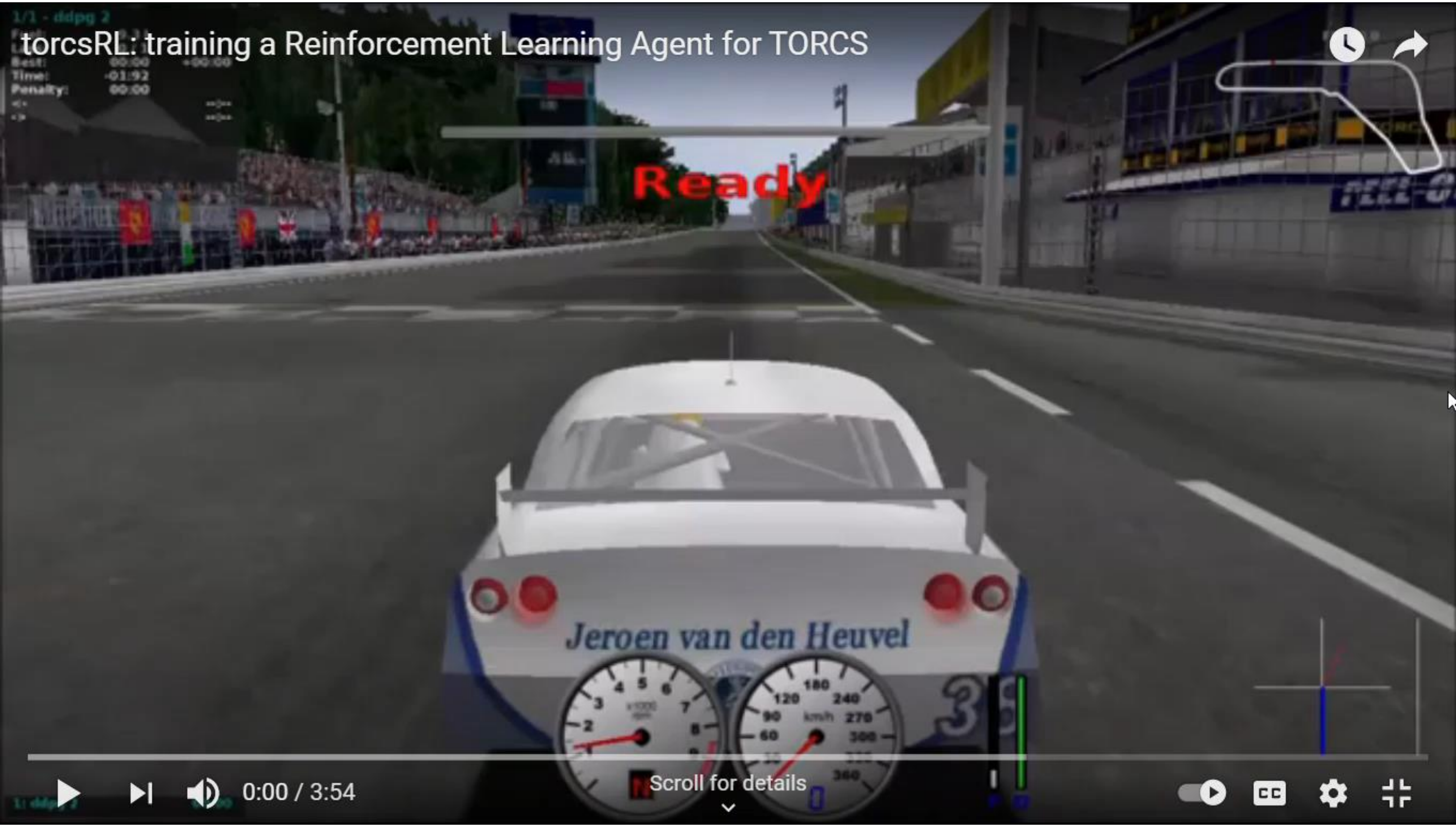
Applications of RL –robot locomotion control

Applications of RL –robot manipulation control

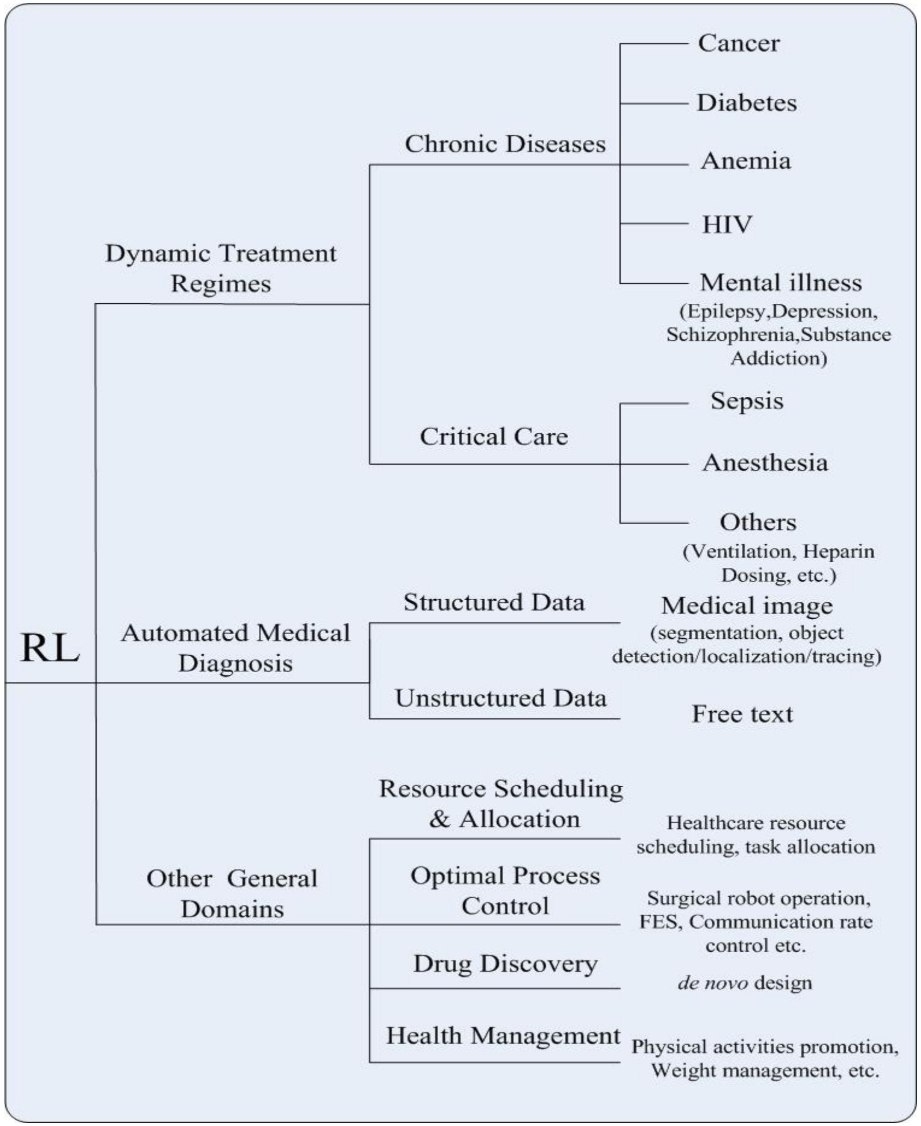


Applications of RL –traffic control

Applications of RL–autonomous driving



Applications of RL–healthcare



nature medicine

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Comment | Published: 07 January 2019

Guidelines for reinforcement learning in healthcare

Omer Gottesman, Fredrik Johansson, Matthieu Komorowski, Aldo Faisal, David Sontag, Finale Doshi-Velez & Leo Anthony Celi

Nature Medicine **25**, 16–18(2019) | Cite this article

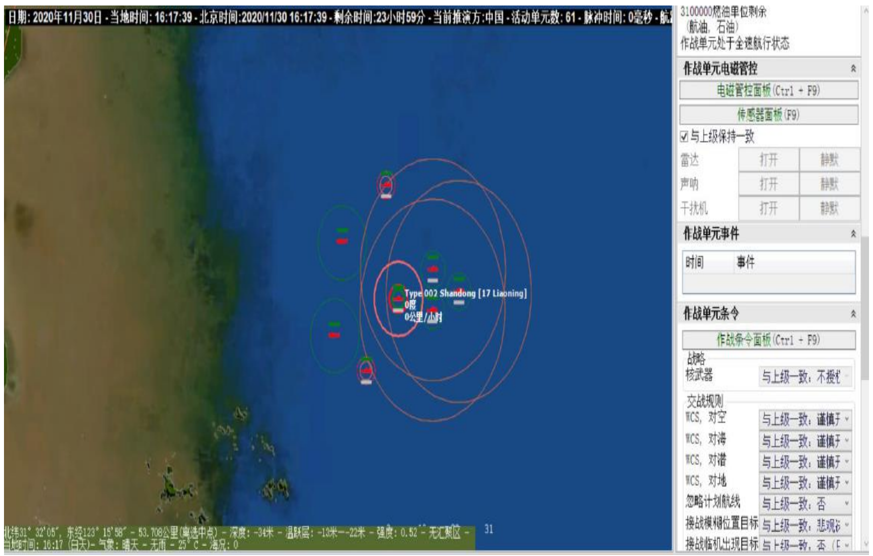
9928 Accesses | **33** Citations | **138** Altmetric | Metrics

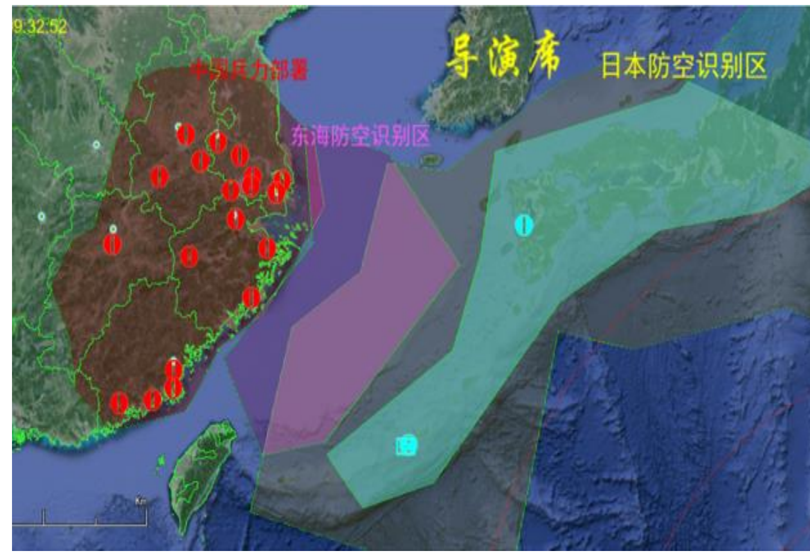
In this Comment, we provide guidelines for reinforcement learning for decisions about patient treatment that we hope will accelerate the rate at which observational cohorts can inform healthcare practice in a safe, risk-conscious manner.

Reinforcement learning in healthcare: A survey 132 2021
C Yu, J Liu, S Nemati, G Yin
ACM Computing Surveys (CSUR) 55 (1), 1-36

Yu C, Liu J, Nemati S. Reinforcement learning in healthcare: A survey[J]. ACM Computing Survey, 2021

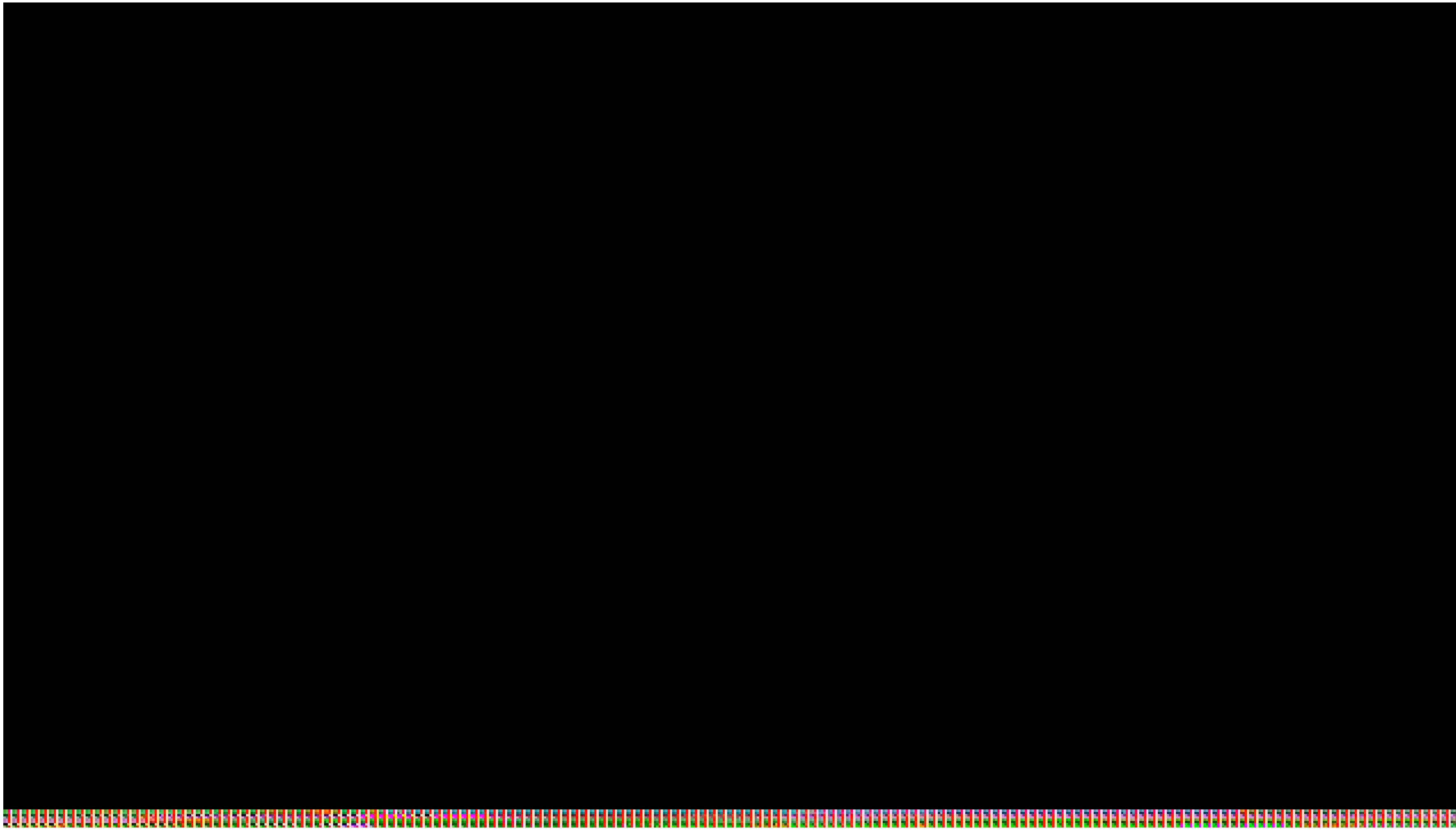
Applications of RL–military





War game

Applications of RL–military



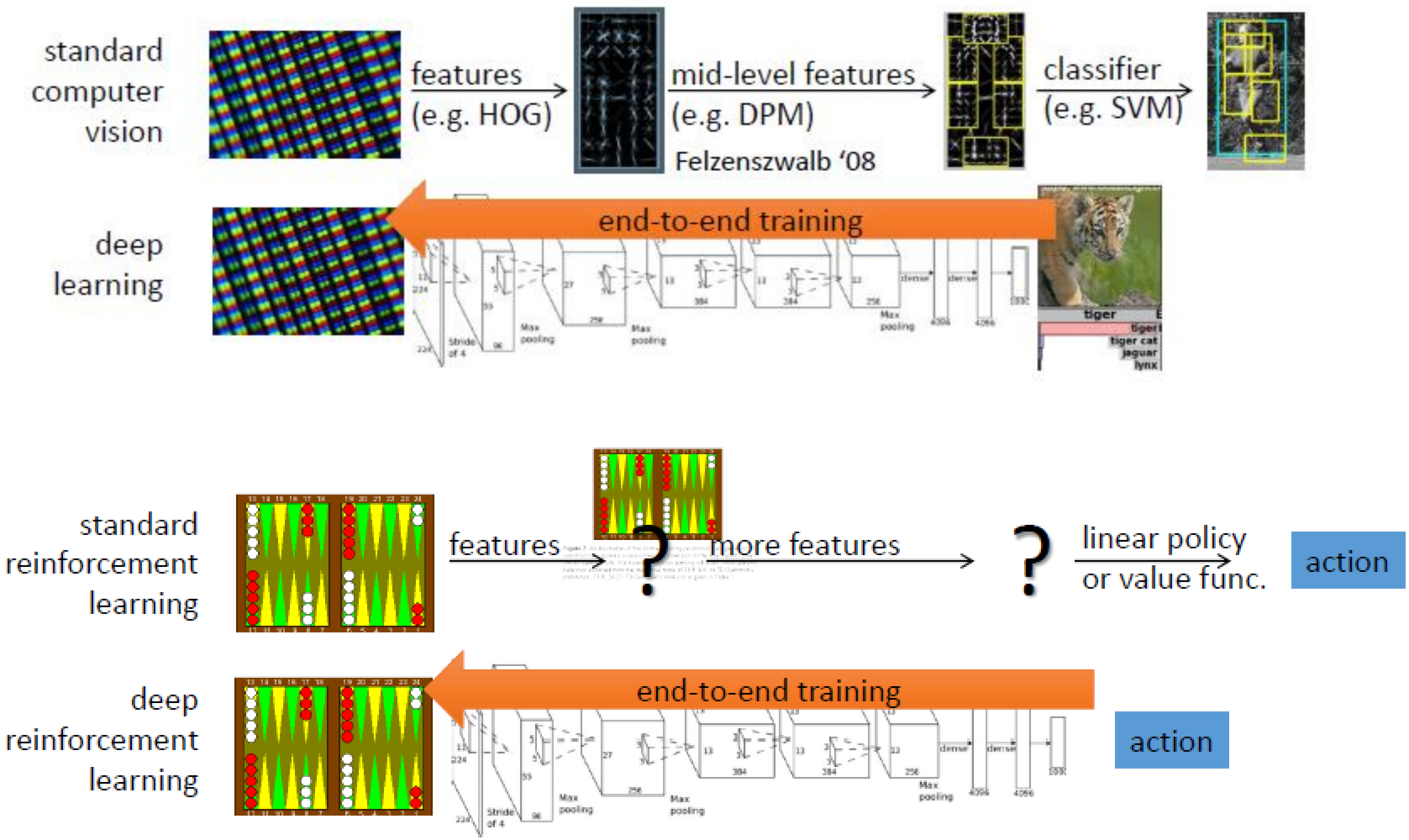
Near-distance Air Combat

Why reinforcement learning?

Why RL is important?

Fundamental challenge in artificial intelligence and machine learning is learning to make good decisions under uncertainty.

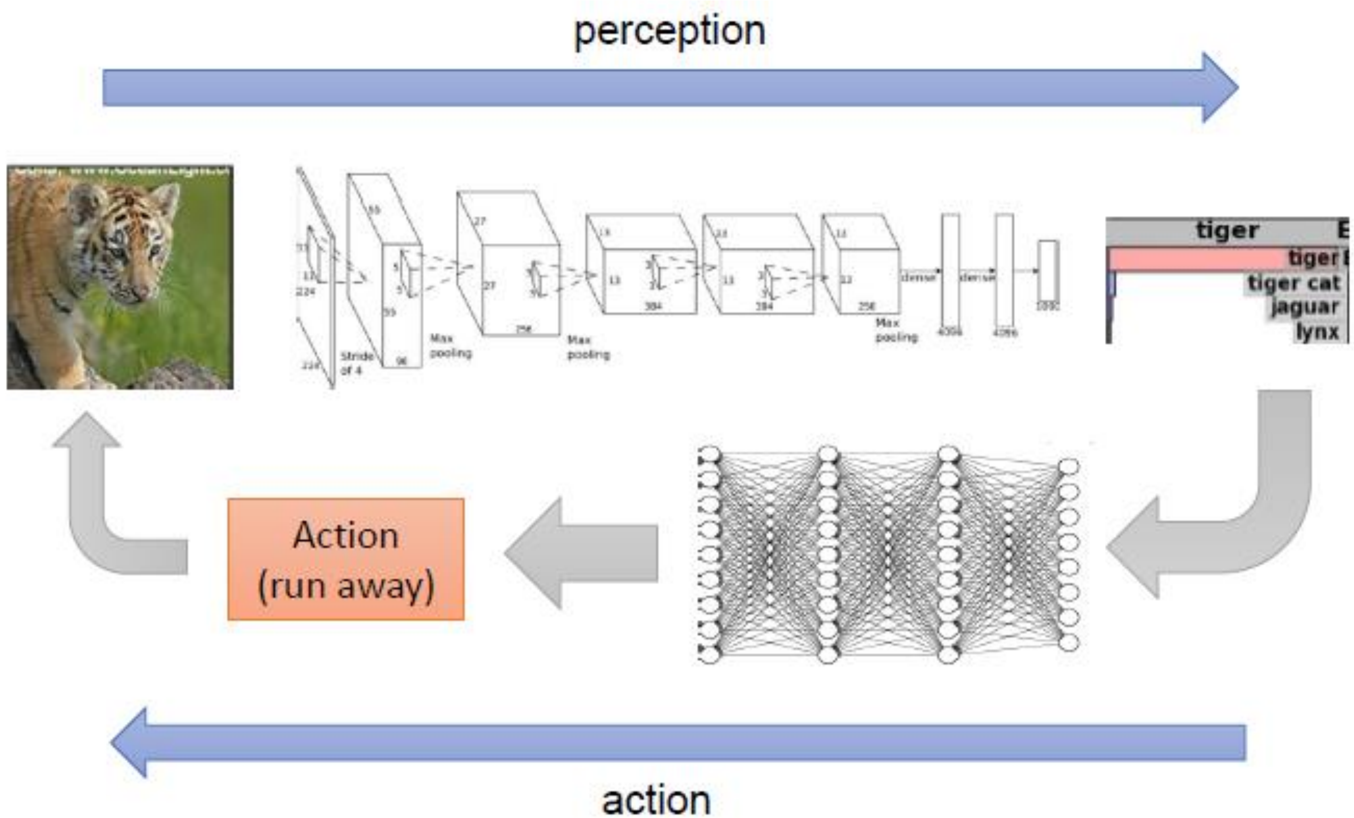
Why RL is important?



[from Sergey Levine's course]

Why RL is important?

RL closes the loop of decision making from perception to control

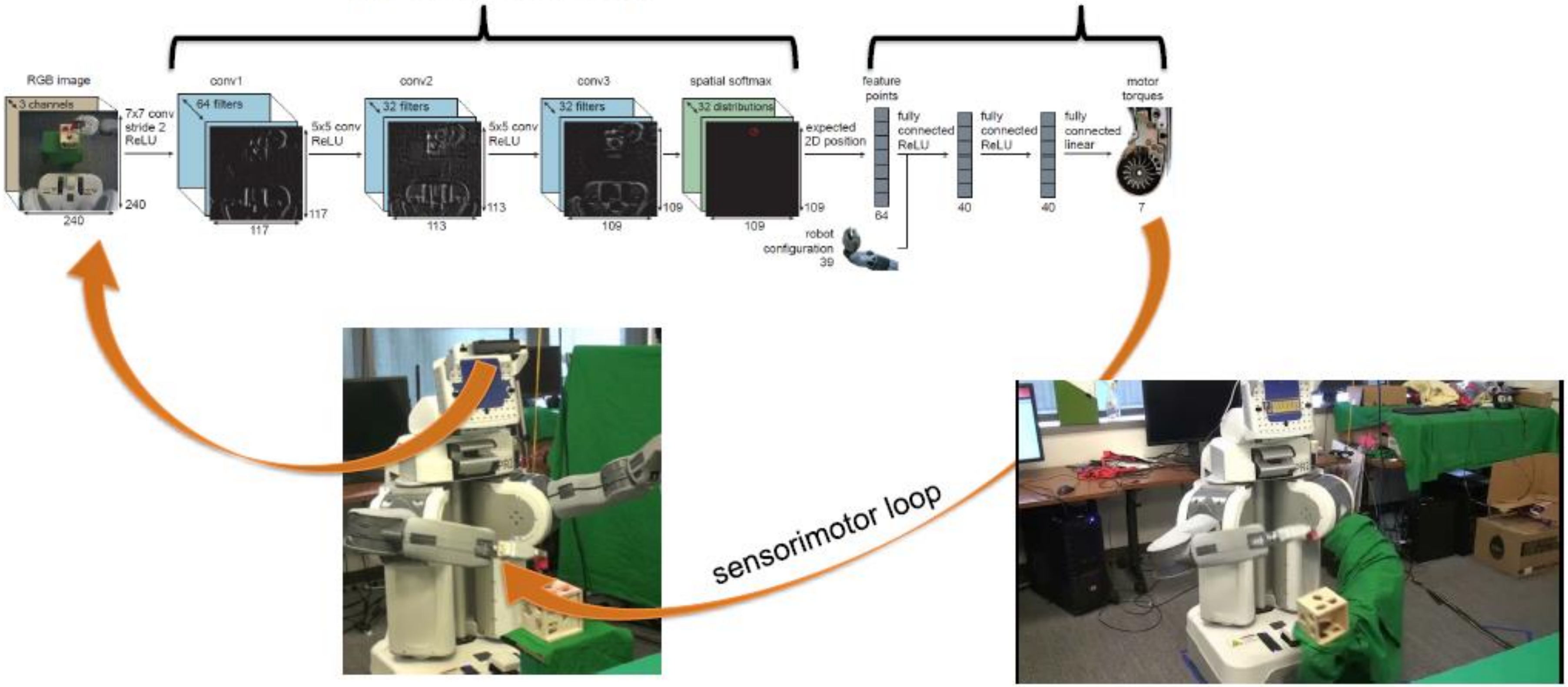


[from Sergey Levine's course]

Why RL is important?

tiny, highly specialized "visual cortex"

tiny, highly specialized "motor cortex"



The reinforcement learning problem **is** the AI problem!

[from Sergey Levine's course]

Why now?

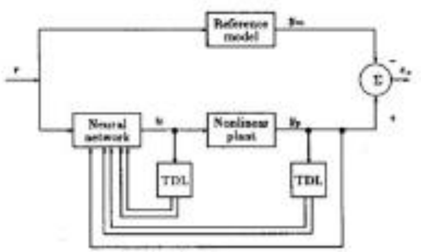
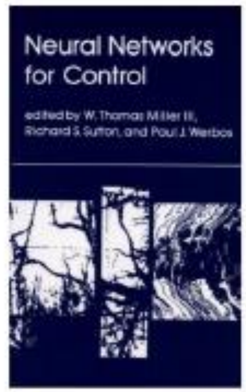
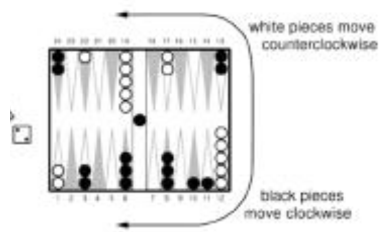


Fig. 21. Direct adaptive control of nonlinear plants using neural networks.





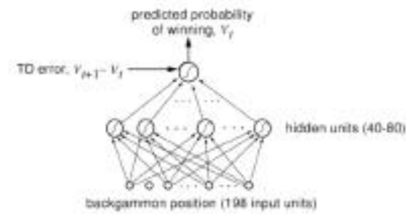


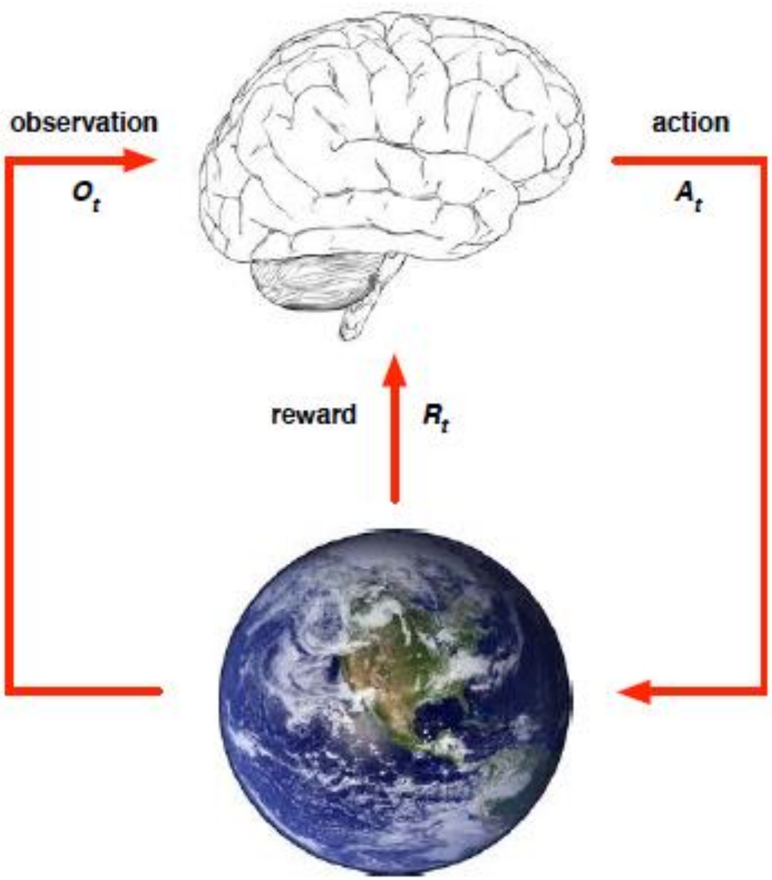
Table 11.1: Summary of TD-Gammon Results

Program	Hidden Units	Training Games	Opponents	Results
TD-Gam 0.0	40	300,000	other programs	tied for best
TD-Gam 1.0	80	300,000	Robertie, Magriel, ...	−13 pts / 51 games
TD-Gam 2.0	40	800,000	various Grandmasters	−7 pts / 38 games
TD-Gam 2.1	80	1,500,000	Robertie	−1 pt / 40 games
TD-Gam 3.0	80	1,500,000	Kazaros	+6 pts / 20 games

Tesauro, 1995

- Advances in deep learning
- Advances in reinforcement learning
- Advances in computational capability

The RL Problem

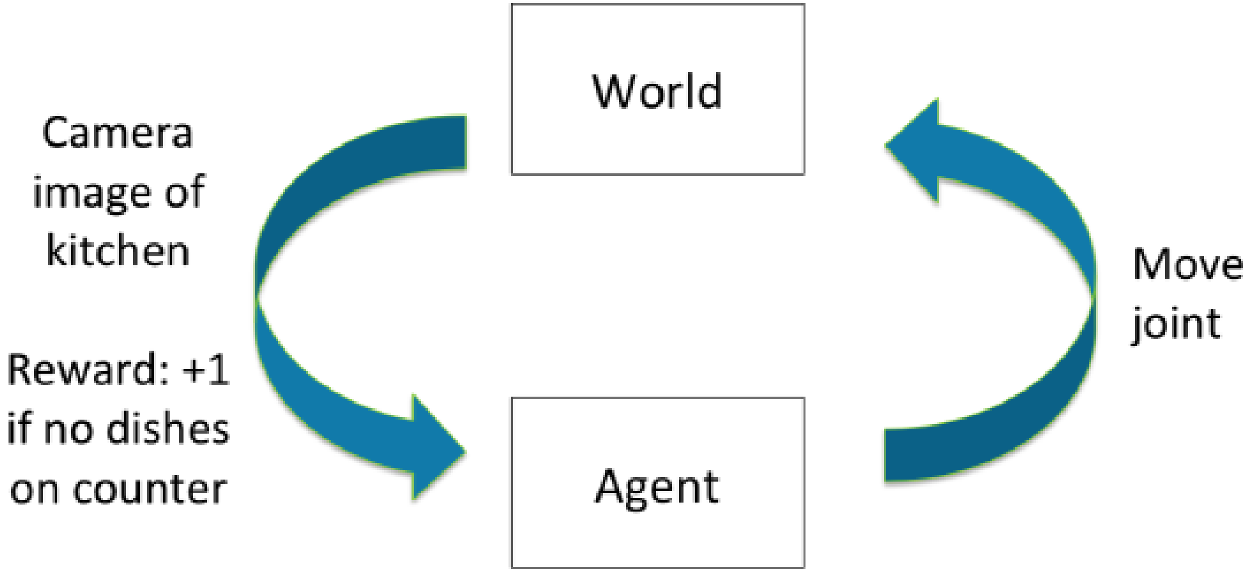


- At each step t the agent:
  - Executes action A_t
  - Receives observation O_t
  - Receives scalar reward R_t
- The environment:
  - Receives action A_t
  - Emits observation O_{t+1}
  - Emits scalar reward R_{t+1}

Goal: learn a policy (*i.e.*, a mapping from observations to actions) to maximise total future reward

Example of RL Problems

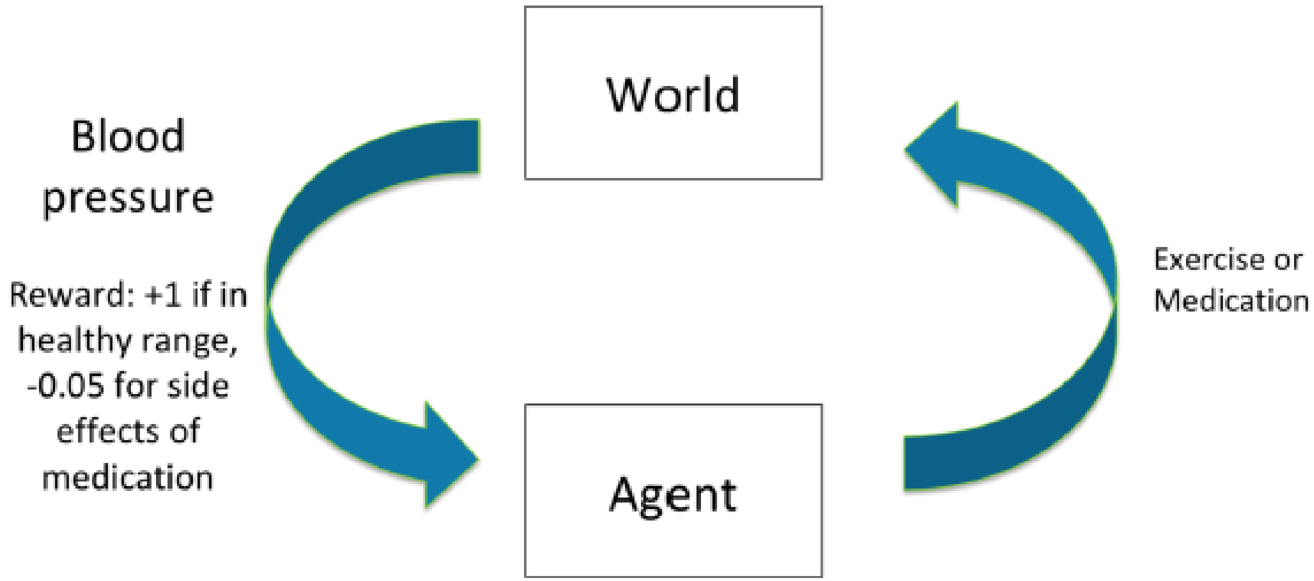
- Robot Unloading Dishwasher



Goal: learn a policy (*i.e.*, a mapping from observations to actions) to maximise total future reward

Example of RL Problems

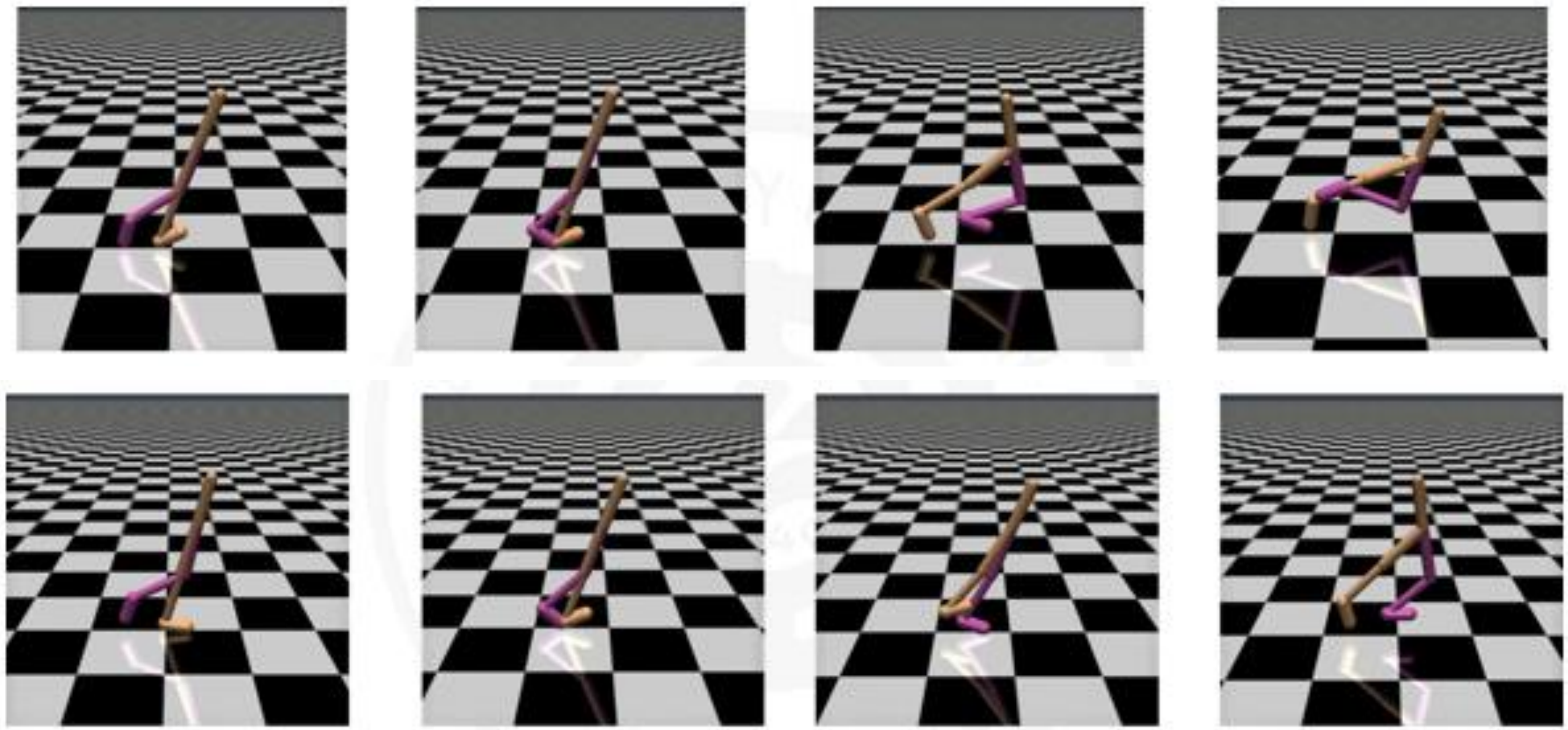
- Blood Pressure Control



Goal: learn a policy (*i.e.*, a mapping from observations to actions) to maximise total future reward

Example of RL Problems

- Robotic control



Goal: learn a policy (*i.e.*, a mapping from observations to actions) to maximise total future reward!

Elements of RL Problems - Reward

- A reward R_t is a scalar feedback signal
- Indicates how well agent is doing at step t
- The agent's job is to maximise cumulative reward
- The goal reward and the intermediate reward
  - defeat the world champion at Go
    +1/-1 reward for winning/losing a game
  - Make a humanoid robot walk
    +1 reward for forward motion
    -1 reward for falling over
  - Manage an investment portfolio
    +v reward for each $ in bank
- Reward is the most fundamental component in RL
  - Where is reward from? How to design the best reward? How to address sparse reward problems?
  - Inverse RL, Hierarchical RL, Transfer RL, Knowledge-driven RL, etc.

Elements of RL Problems - State

- The history is the sequence of observations, actions, rewards
  - *i.e. all observable variables up to time t*
  - *i.e. the sensorimotor stream of a robot or embodied agent*
- State is the information used to determine what happens next
- The environment state is its private representation
  - *whatever data to pick the next observation/reward*
  - *not usually visible to the agent*
  - *May contain irrelevant information*
- The agent state is the agent's internal representation
  - *whatever information the agent uses to pick the next action*
  - *it is the information used by RL algorithms*
- An Markov state contains all useful information from the history, i.e., future is independent of past given present

A state S_t is Markov if and only if

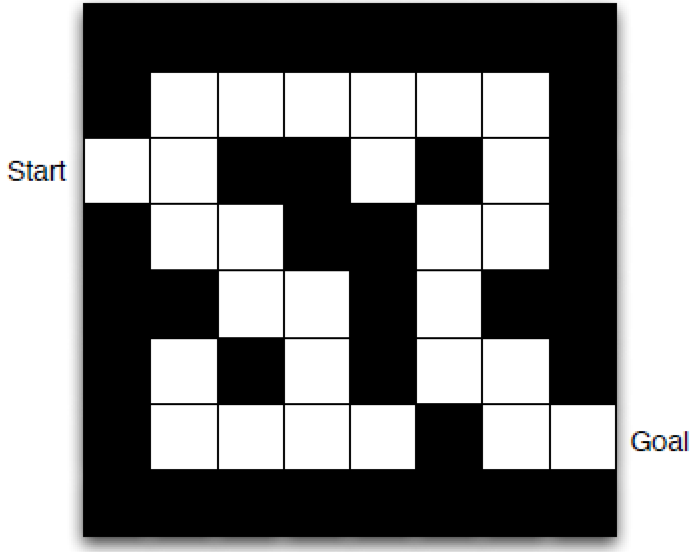
$$\mathbb{P}[S_{t+1} \mid S_t] = \mathbb{P}[S_{t+1} \mid S_1, ..., S_t]$$

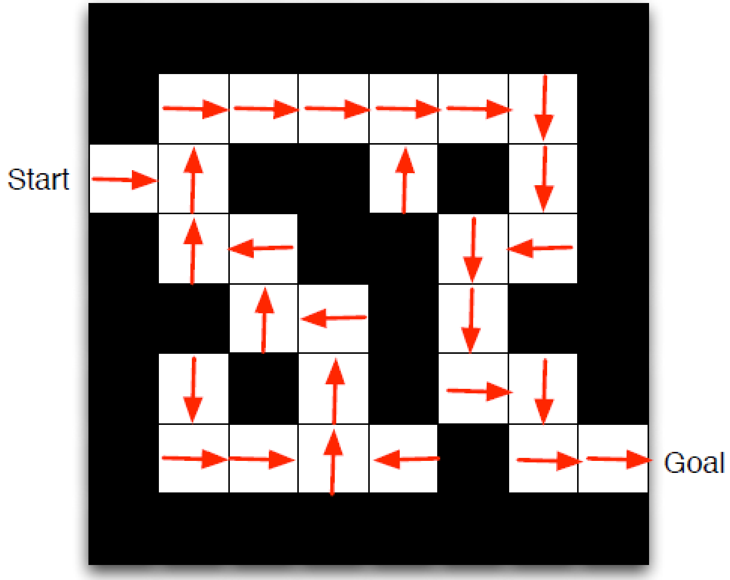
Elements of RL Problems - State

- Full observability: an agent directly observes environment state. Formally, this is a Markov decision process (MDP).
- Partial observability: an agent indirectly observes the environment, e.g.,:
  - *A robot with camera vision isn't told its absolute location*
  - *A trading agent only observes current prices*
  - *A poker playing agent only observes public cards*
  - *Formally, this is a partially observable Markov decision process (POMDP)*

Elements of RL Problems - Policy

- Policy: an agent's behaviour function, i.e., a mapping from state to action
  - Deterministic policy: $a = \pi(s)$
  - Stochastic policy: $\pi(a|s) = \mathbb{P}[A_t = a | S_t = s]$



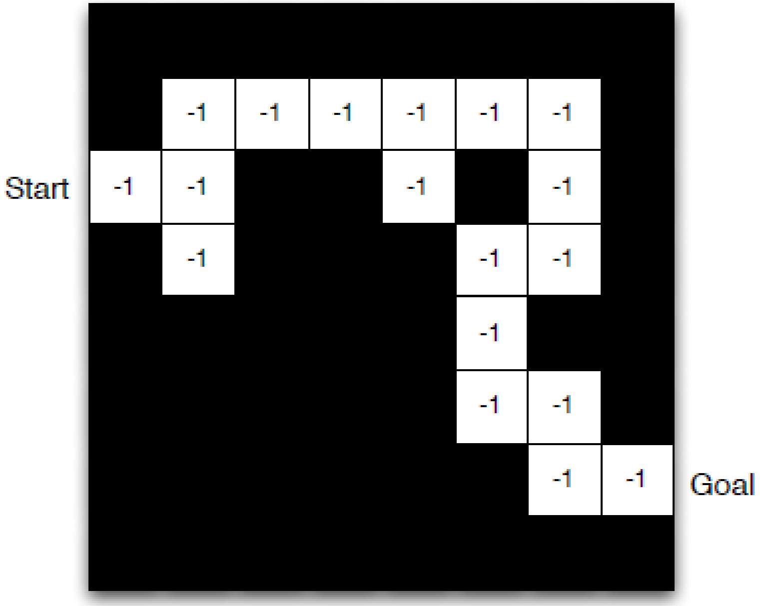


[from David Silver's course]

Elements of RL Problems - Model

- Model: A model predicts what the environment will do next, i.e., agent's representation of the environment
- $\mathcal{P}$ predicts the next state
- $\mathcal{R}$ predicts the next (immediate) reward

$$\mathcal{P}^a_{ss'} = \mathbb{P}[S_{t+1} = s' \mid S_t = s, A_t = a]$$
$$\mathcal{R}^a_s = \mathbb{E}[R_{t+1} \mid S_t = s, A_t = a]$$

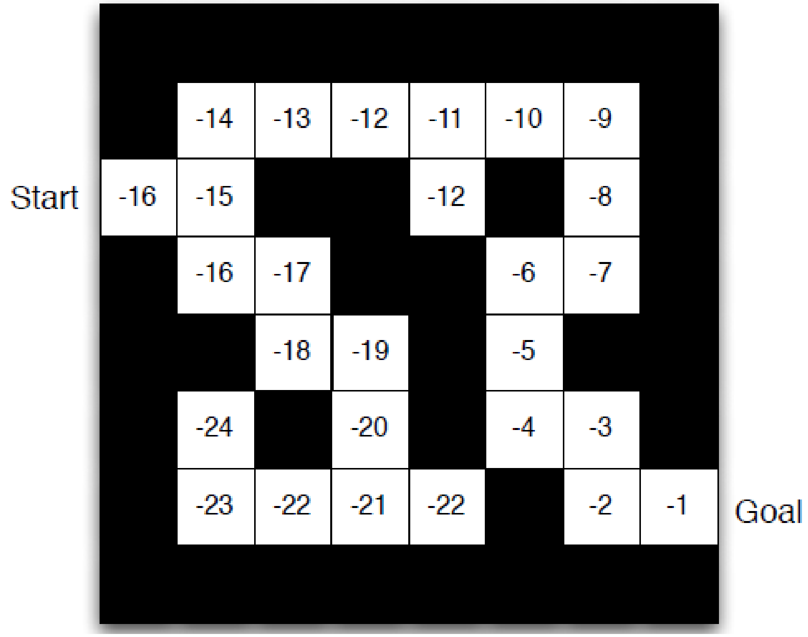


[from David Silver's course]

Elements of RL Problems – Value Function

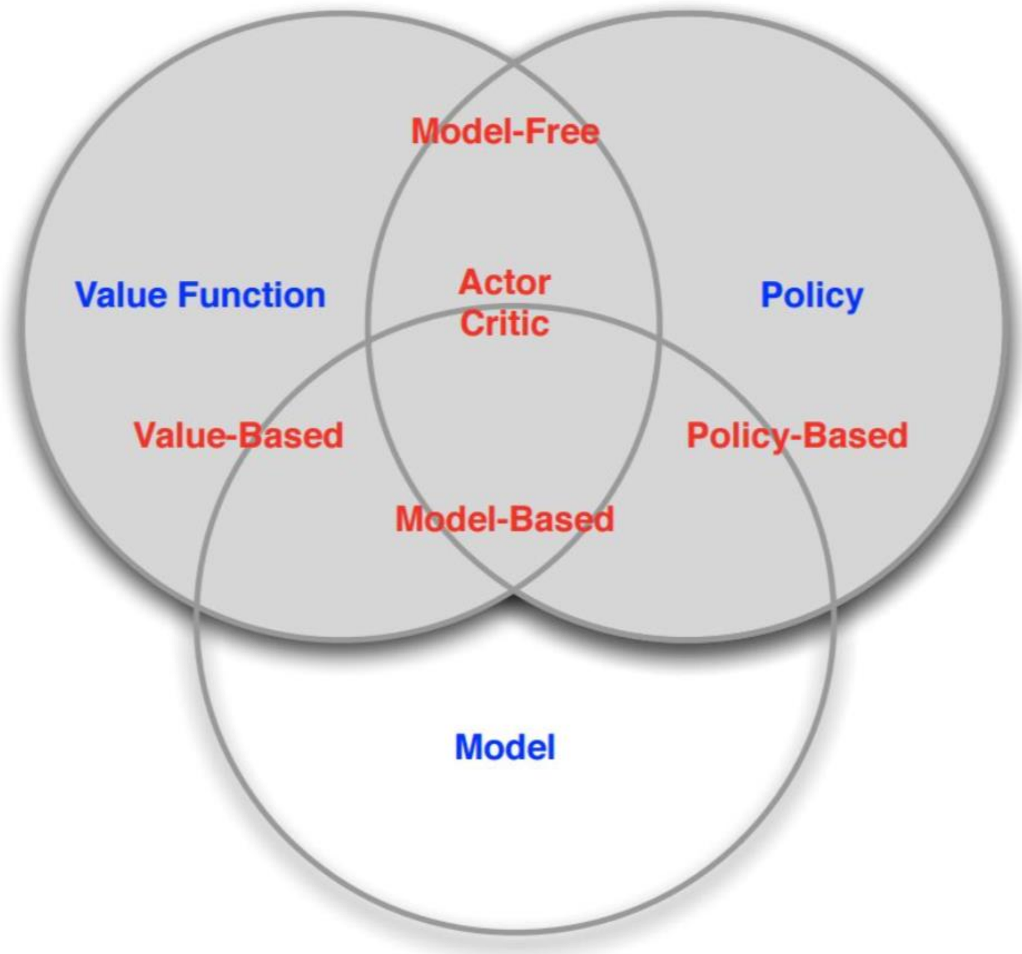
- Value functions: how good is each state and/or action
  - *Value function is a prediction of future reward*
  - *Used to evaluate the goodness/badness of states*
  - *And therefore used to select between actions*

$$v_\pi(s) = \mathbb{E}_\pi \left[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \dots \mid S_t = s \right]$$



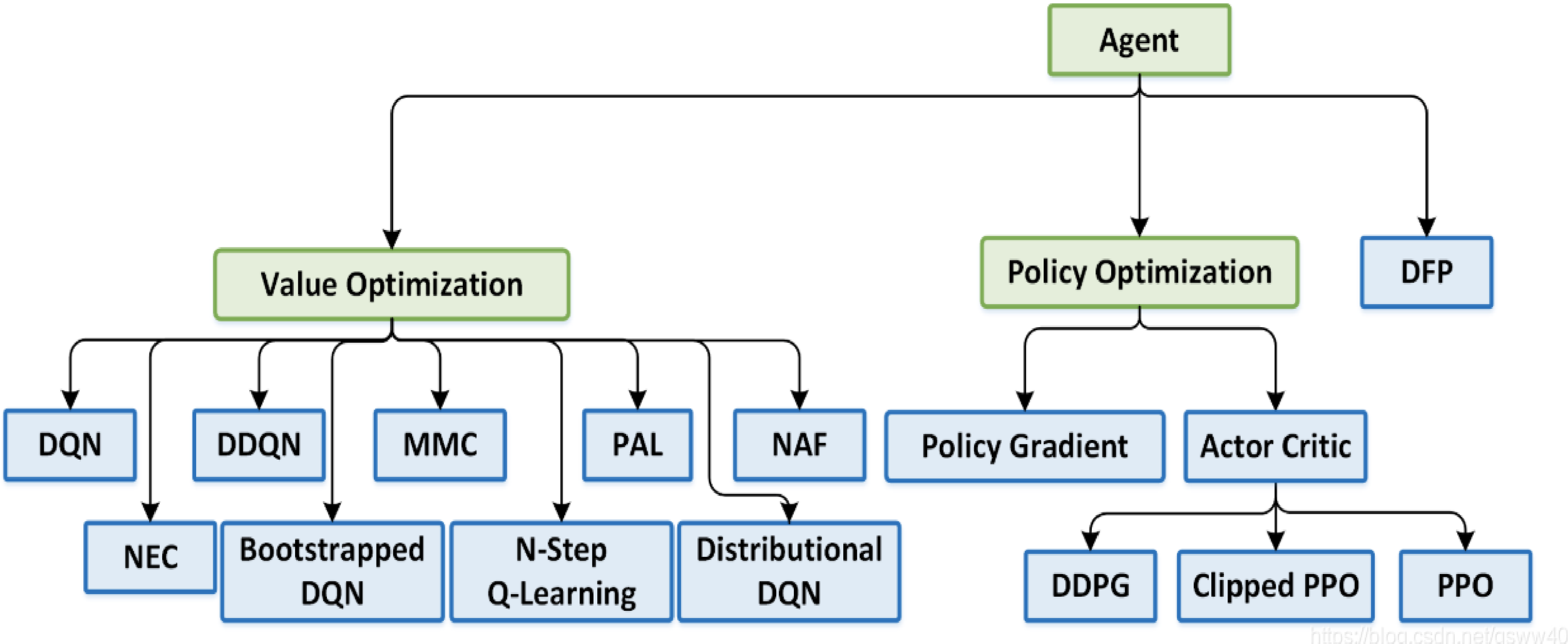
[from David Silver's course]

Categorizing RL Algorithms



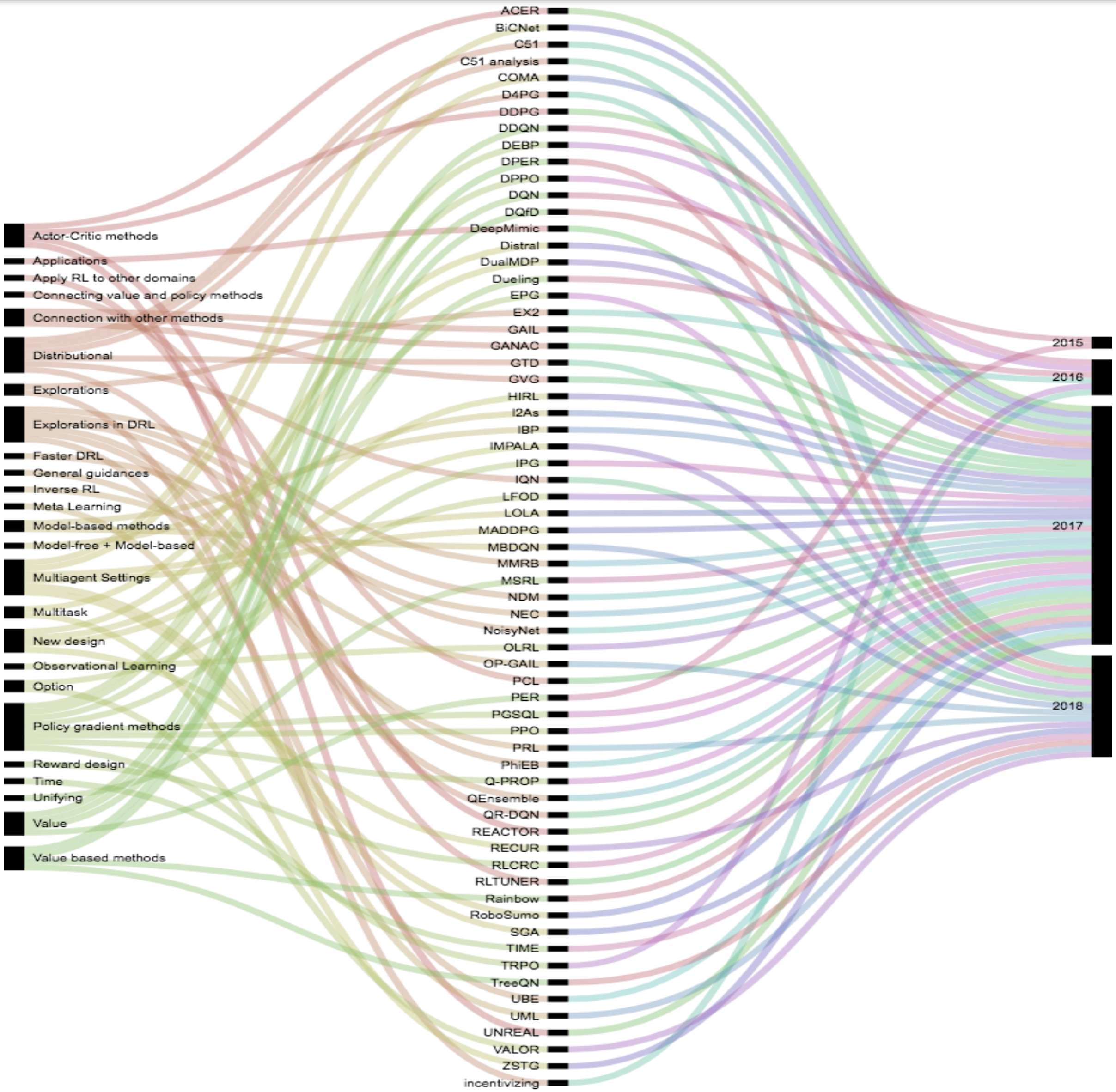
[from David Silver's course]

Categorizing RL Algorithms



[from https://blog.csdn.net/gsww404/article/details/103074046]

Categorizing RL Algorithms



[from https://blog.csdn.net/gsww404/article/details/103074046]

Explore, Exploit, and Explode — The Time for Reinforcement Learning is Coming

Y Yuxi Li Dec 27, 2018 · 9 min read

Reinforcement learning (RL) has been making spectacular achievements, e.g., Atari games, AlphaGo, AlphaGo Zero, AlphaZero, AlphaStar, DeepStack, Libratus, Catch The Flag, OpenAI Five, Dactyl, legged robots, DeepMimic, learning to dress, data center cooling, chemical syntheses, drug design, etc. See more RL applications.

Most of these are academic research. However, we are also witnessing RL products and services, e.g., Google Cloud AutoML and Facebook Horizon, and open-sources/testbeds like OpenAI Gym, Deepmind Lab, Deemind Control Suite, Google Dopamine, Deepmind TRFL, Facebook ELF, Microsoft TextWorld, Amazon AWS DeepRacer, Intel RL Coach, etc. Multi-armed bandits, in particular, contextual bandits, have many successful applications. There are also applications in e-commerce/recommender systems.

In the following, I will introduce RL briefly, discuss recent achievements, issues, research directions, applications, and the future of RL. The take-home message is: **The time for reinforcement learning is coming.**

Homework

- Check the homepage of main institutes, companies, universities, leading researchers in the area of RL
- Find out the application domains that you are most interested in