人工智能实践
Artificial Intelligence Practice

DCS3015 Autumn 2022

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Lecture 5：强化学习-1

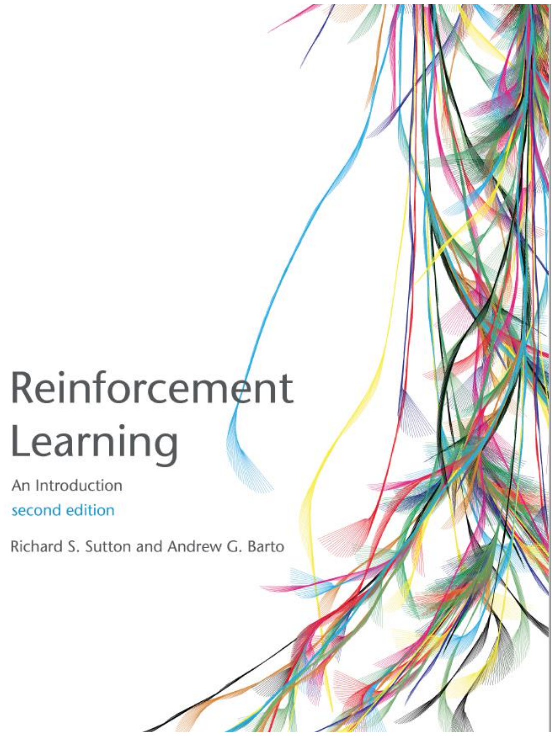
Textbook

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

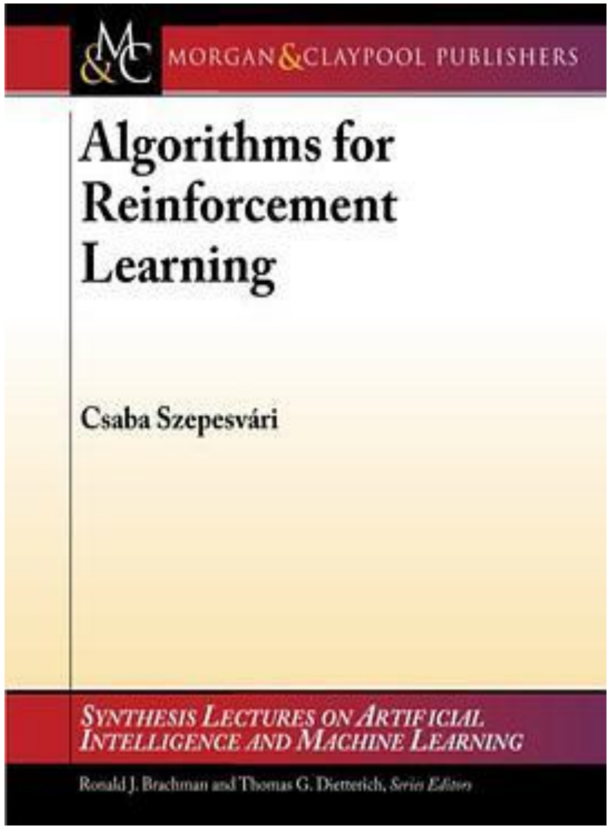
2nd Edition Website:
http://incompleteideas.net/sutton/book/the-book-2nd.html

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


MORGAN & CLAYPOOL PUBLISHERS
Algorithms for Reinforcement Learning
Csaba Szepesvári
SYNTHESIS LECTURES ON ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING
Ronald J. Brachman and Thomas G. Dietterich, Series Editors

Marco Wiering
Martijn van Otterlo (Eds.)
ADAPTATION, LEARNING, AND OPTIMIZATION Volume 12
Reinforcement Learning
State-of-the-Art
Springer

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.

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

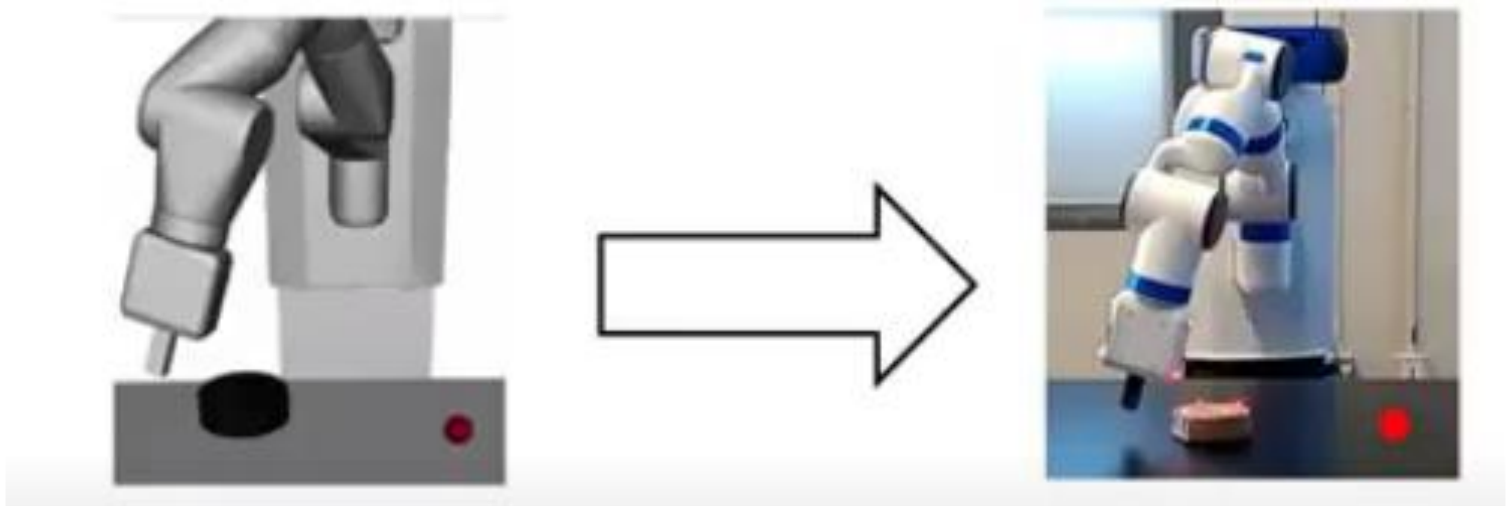
- Consequences of decisions can be much delayed
  - Actions will impact the input in the next step (data is not i.i.d.)
  - Should trade-off short-term and long-term outcome
- Cause the *credit assignment* problem
  - Different action sequences cause different outcomes
  - What caused later high or low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

Exploration

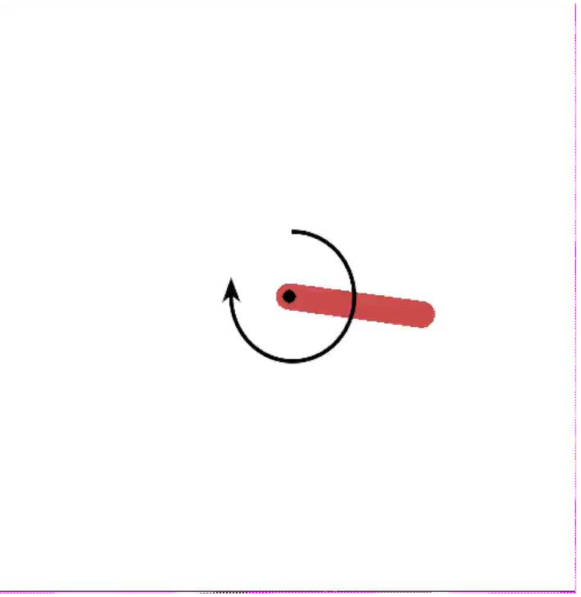
- RL is about learning from trail-and-error interactions
- Gain knowledge from the taken actions
  - *I know that restaurant A is good*
  - *I consider that the move of game playing is best*
- Trade-off between using the gained knowledge (exploitation) or try out new actions (exploration)
  - *Should 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*

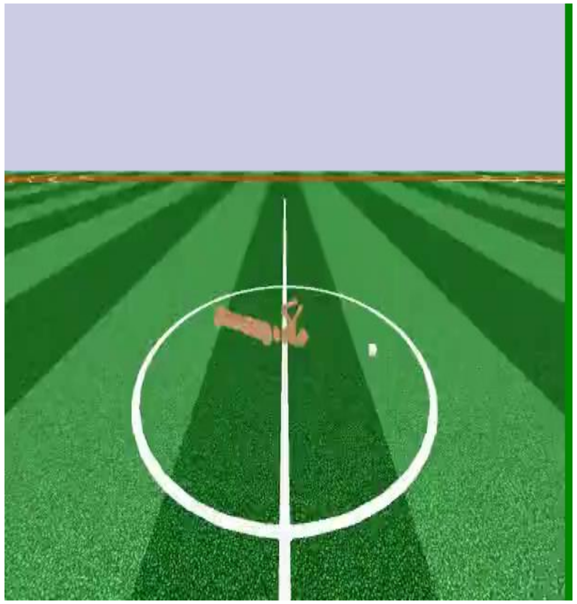
Generalization

- 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?

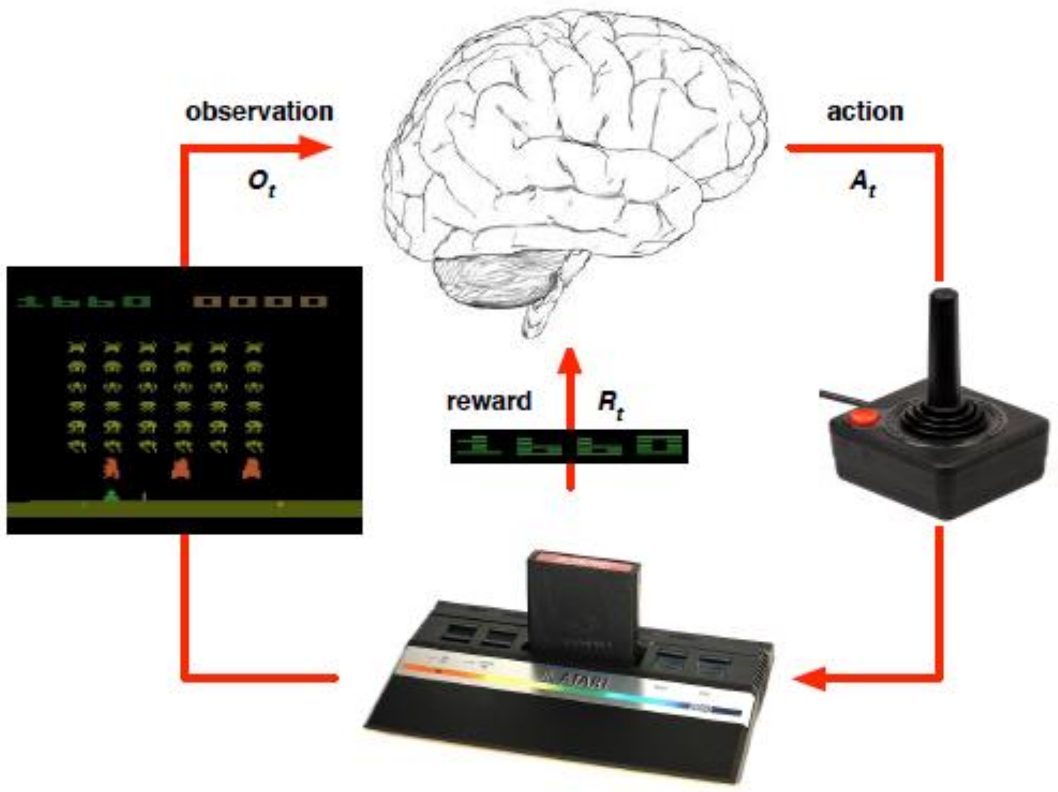
- Two fundamental problems in sequential decision making: learning *vs* planning
- Reinforcement Learning:
  - *The environment is initially unknown*
  - *The agent interacts with the environment*
  - *The agent improves its policy*
- Planning
  - *A model of the environment is known*
  - *The agent 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

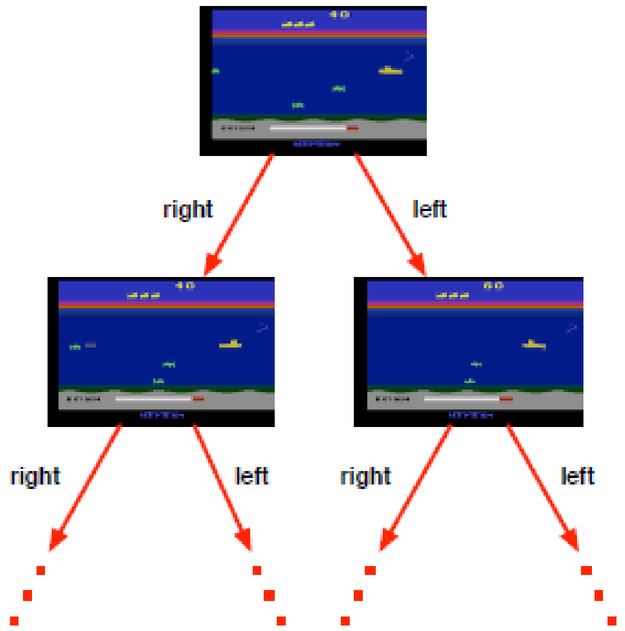
[from David Silver's course]

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

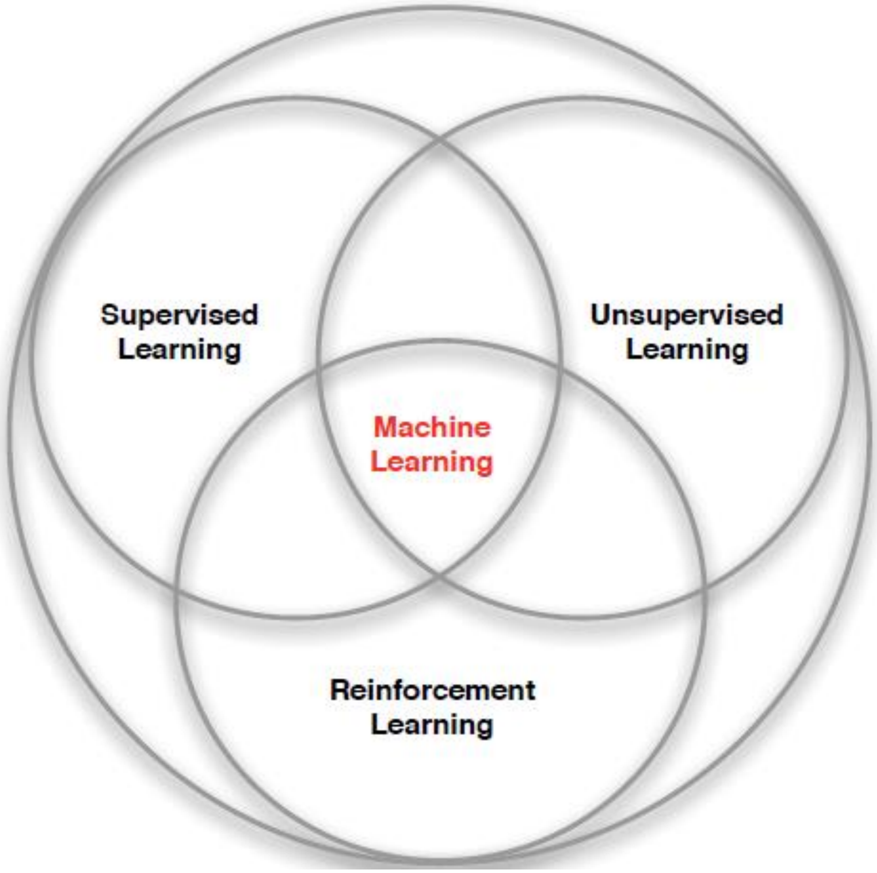


[from David Silver's course]

Characteristics of RL

What makes RL different from other related paradigms?

- Three fundamental problems in machine learning

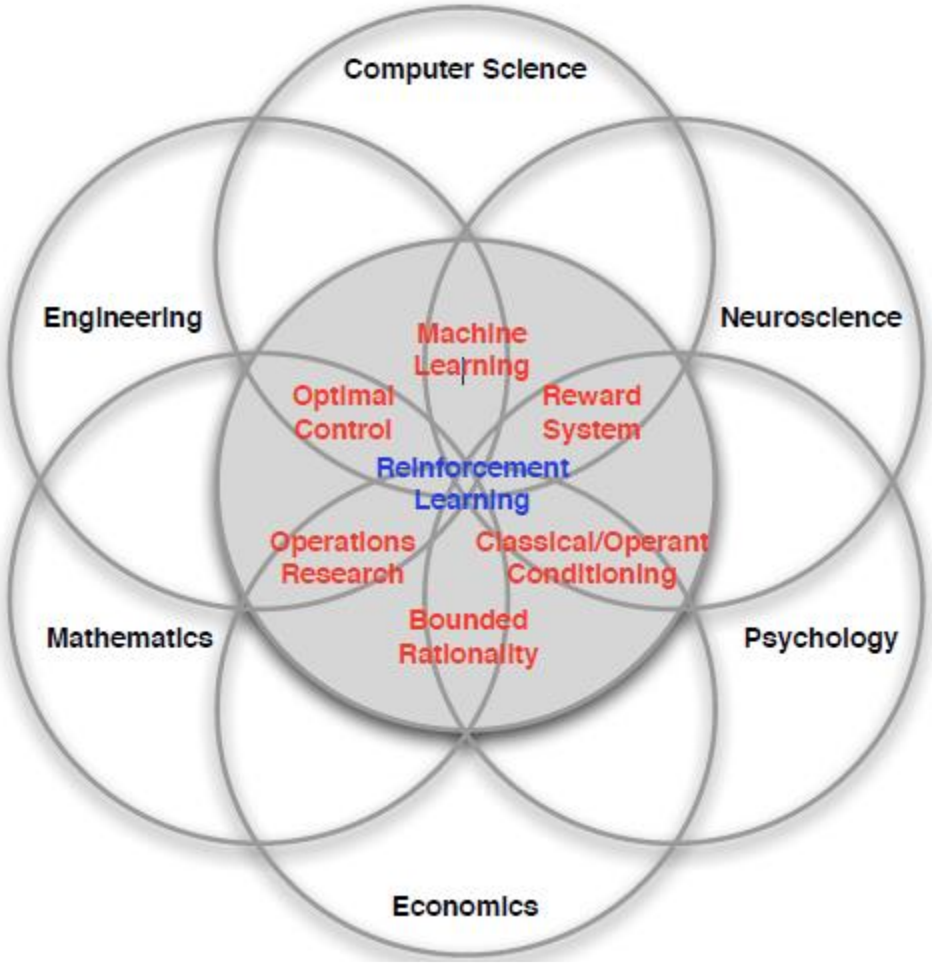


Characteristics of RL

What makes RL different from other related paradigms?

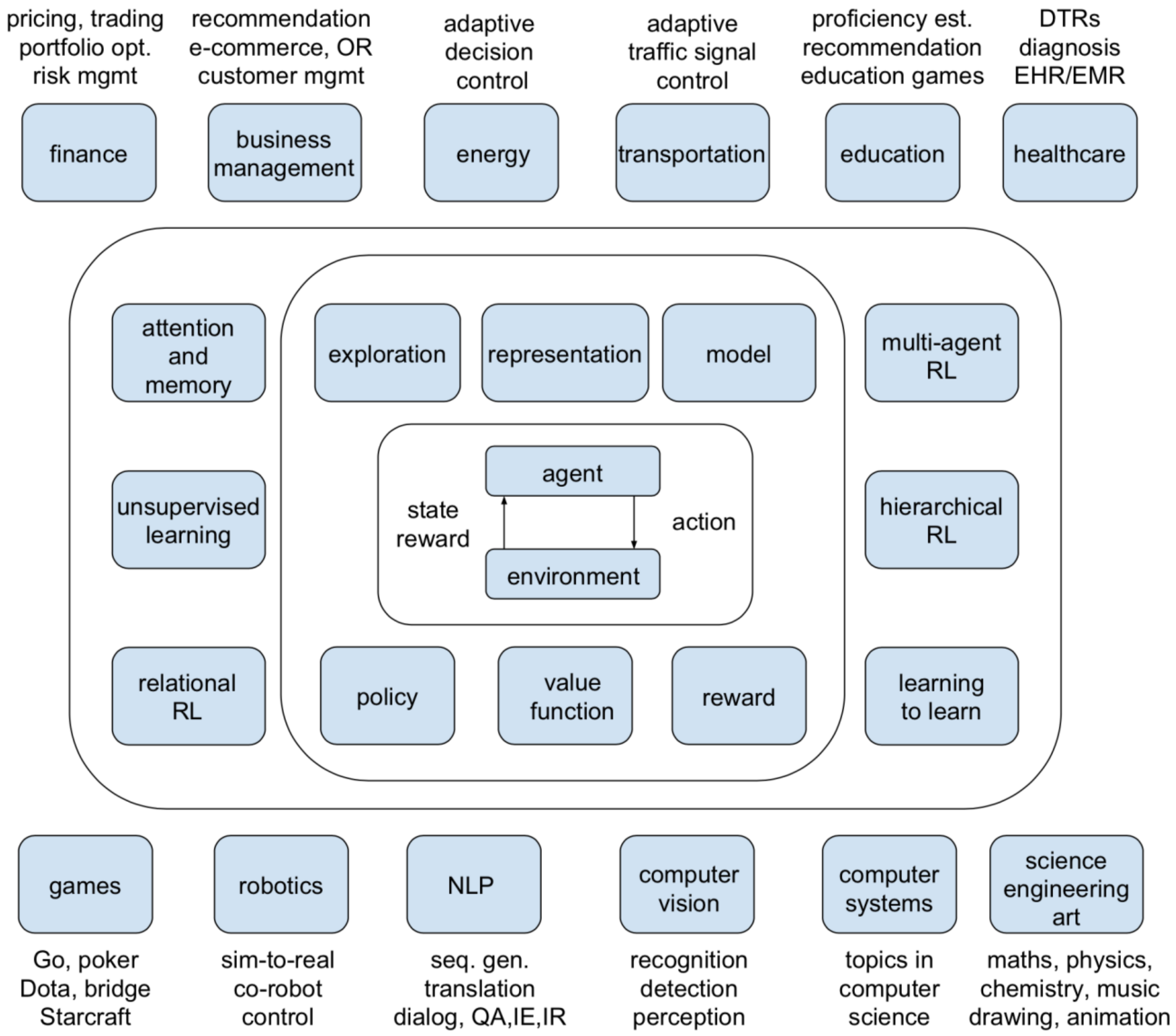
- Three fundamental problems in machine learning
- Supervised learning
  - *Classification or prediction from labeled (action,outcome) pairs*
  - *No interactions*
  - *No sequential decisions*
  - *No explorations*
- Unsupervised learning
  - *Discover inherent correlations among data*
  - *No interactions*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

Interdisciplinary RL



[from David Silver’s course]

Applications of RL



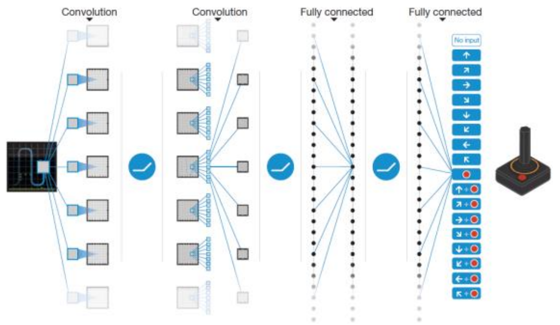
pricing, trading portfolio opt. risk mgmt
finance
recommendation e-commerce, OR customer mgmt
business management
adaptive decision control
energy
adaptive traffic signal control
transportation
proficiency est. recommendation education games
education
DTRs diagnosis EHR/EMR
healthcare
attention and memory
exploration
representation
model
multi-agent RL
unsupervised learning
agent
state reward
action
environment
hierarchical RL
relational RL
policy
value function
reward
learning to learn
games
Go, poker Dota, bridge Starcraft
robotics
sim-to-real co-robot control
NLP
seq. gen. translation dialog, QA,IE,IR
computer vision
recognition detection perception
computer systems
topics in computer science
science engineering art
maths, physics, chemistry, music drawing, animation

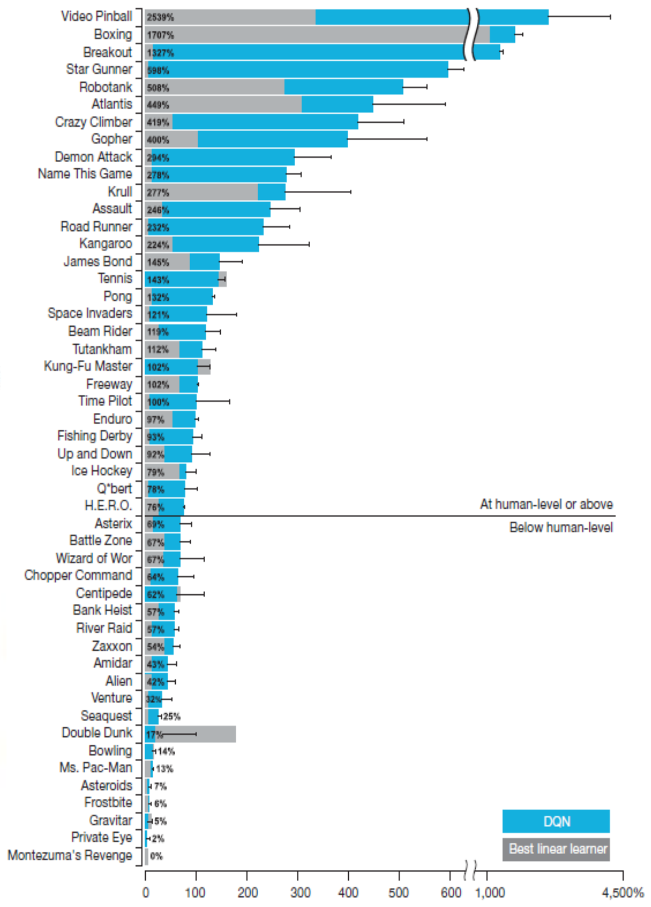
Yuxi Li, Deep Reinforcement Learning, https://arxiv.org/abs/1810.06339, 2018

Applications of RL–game playing

Human-level Atari agent (2015)

Human-level control through deep reinforcement learning

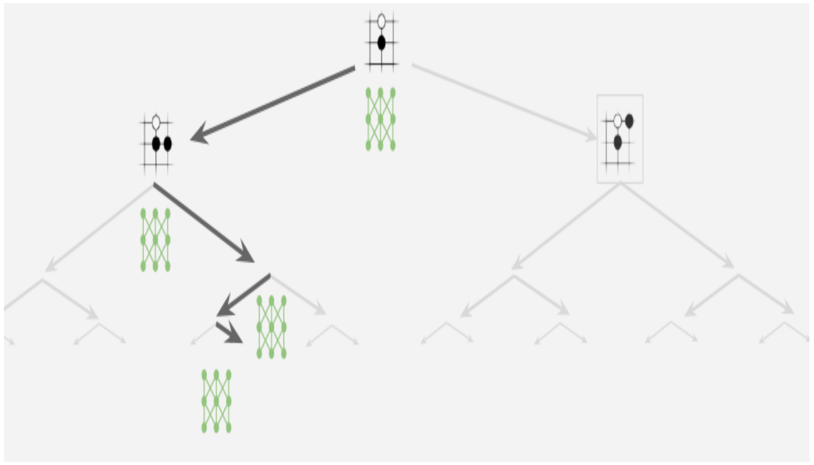


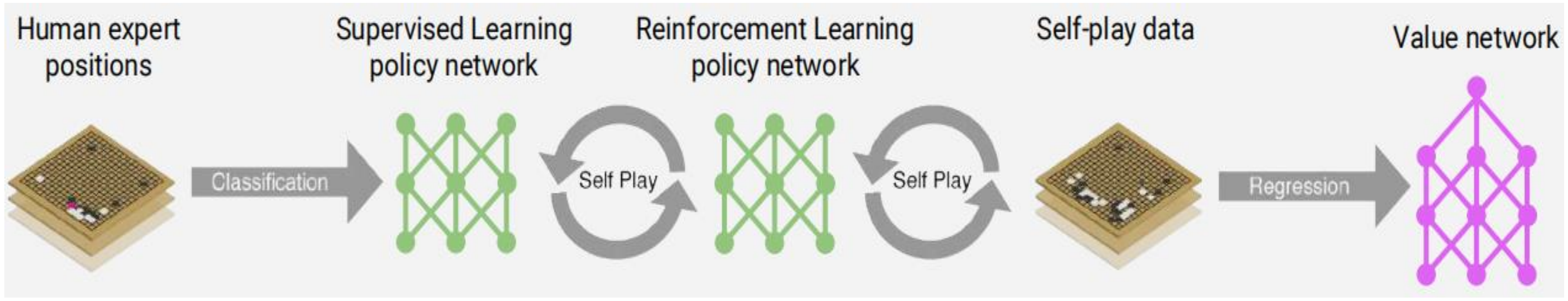


Mnih V, Kavukcuoglu K, Silver D, et al. Human-level control through deep reinforcement learning[J]. nature, 2015, 518(7540): 529-533.

Applications of RL–game playing

DeepMind's AlphaGo (2016)





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)

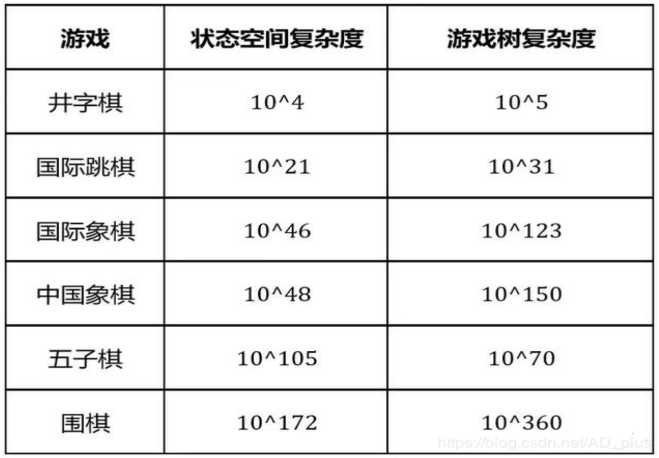
Defeat world champion

StarCraft AlphaStar
(DeepMind, 2019, Nature)

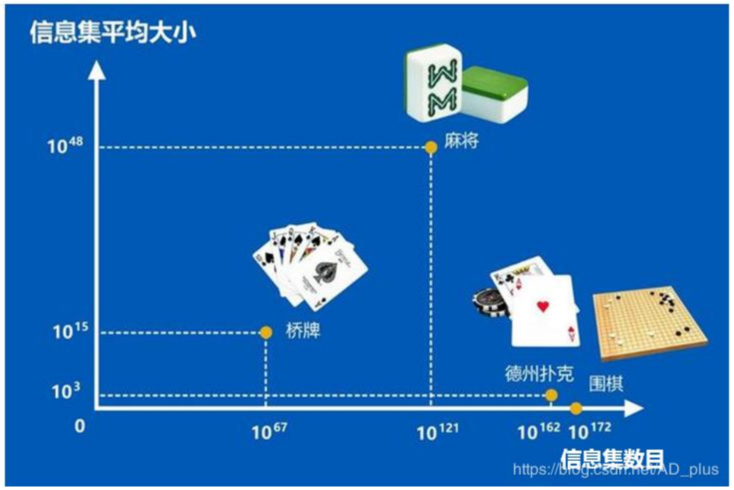
Win professionals （top 10）

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

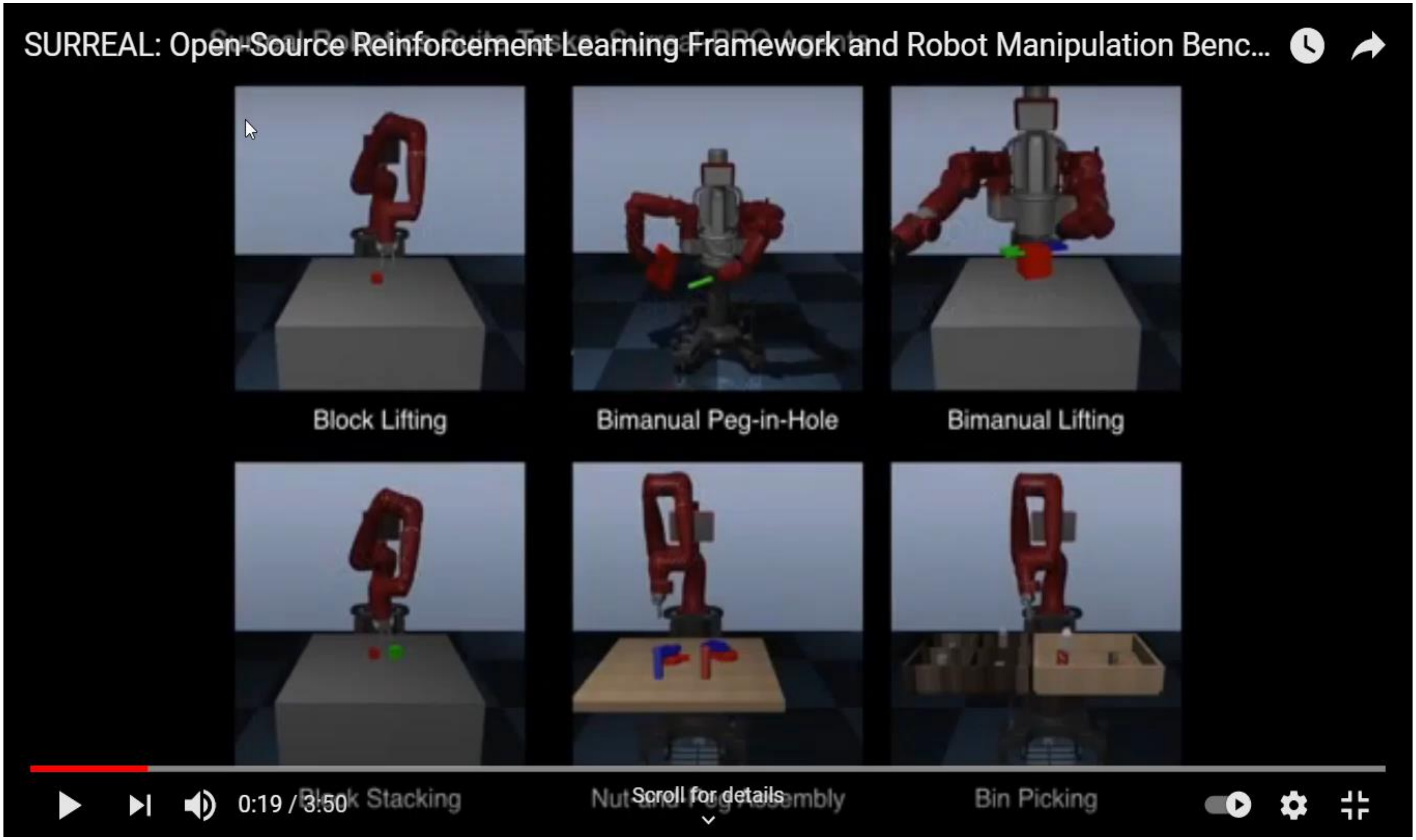


宇宙原子数

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

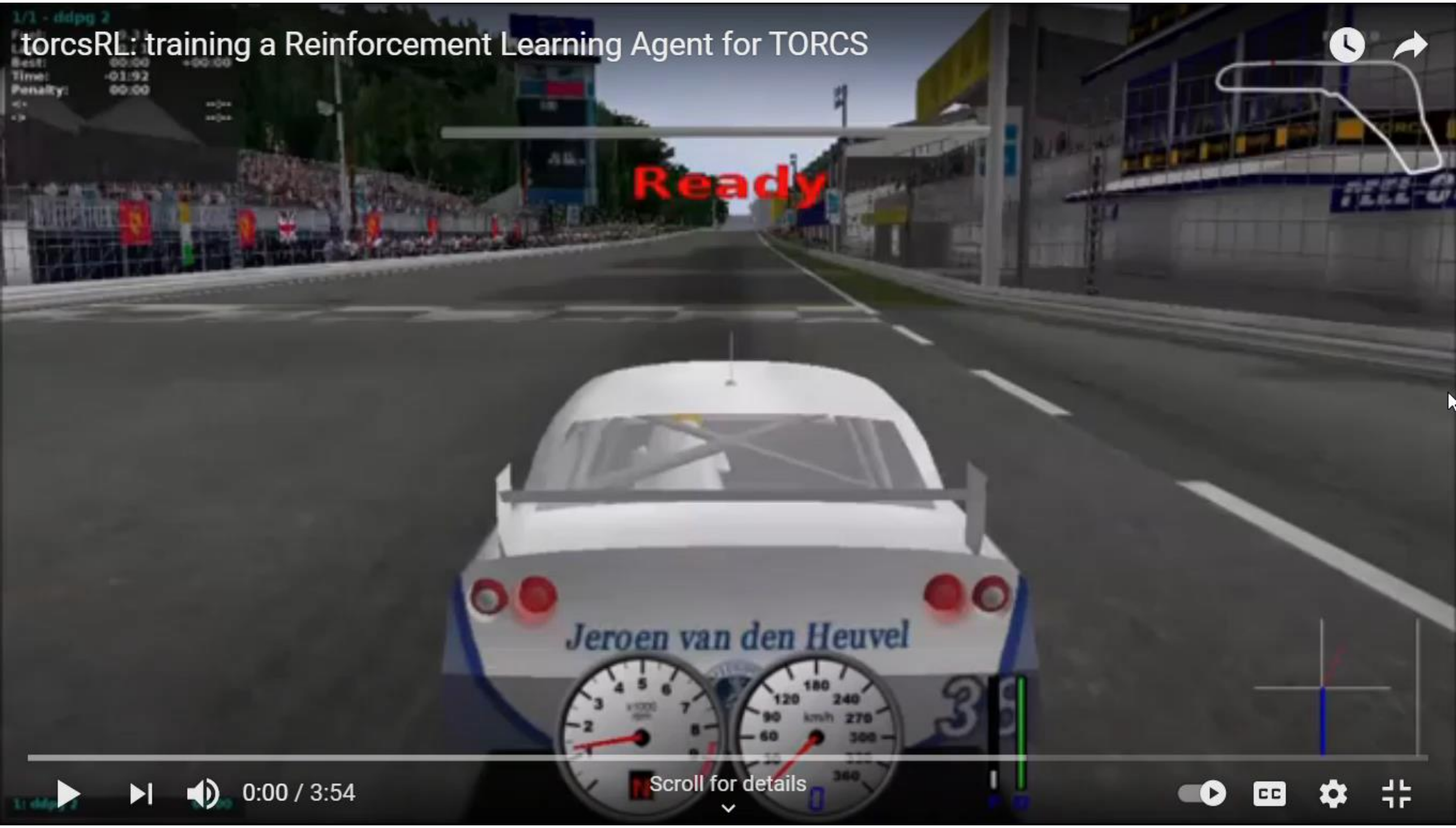
Applications of RL –robot manipulation control



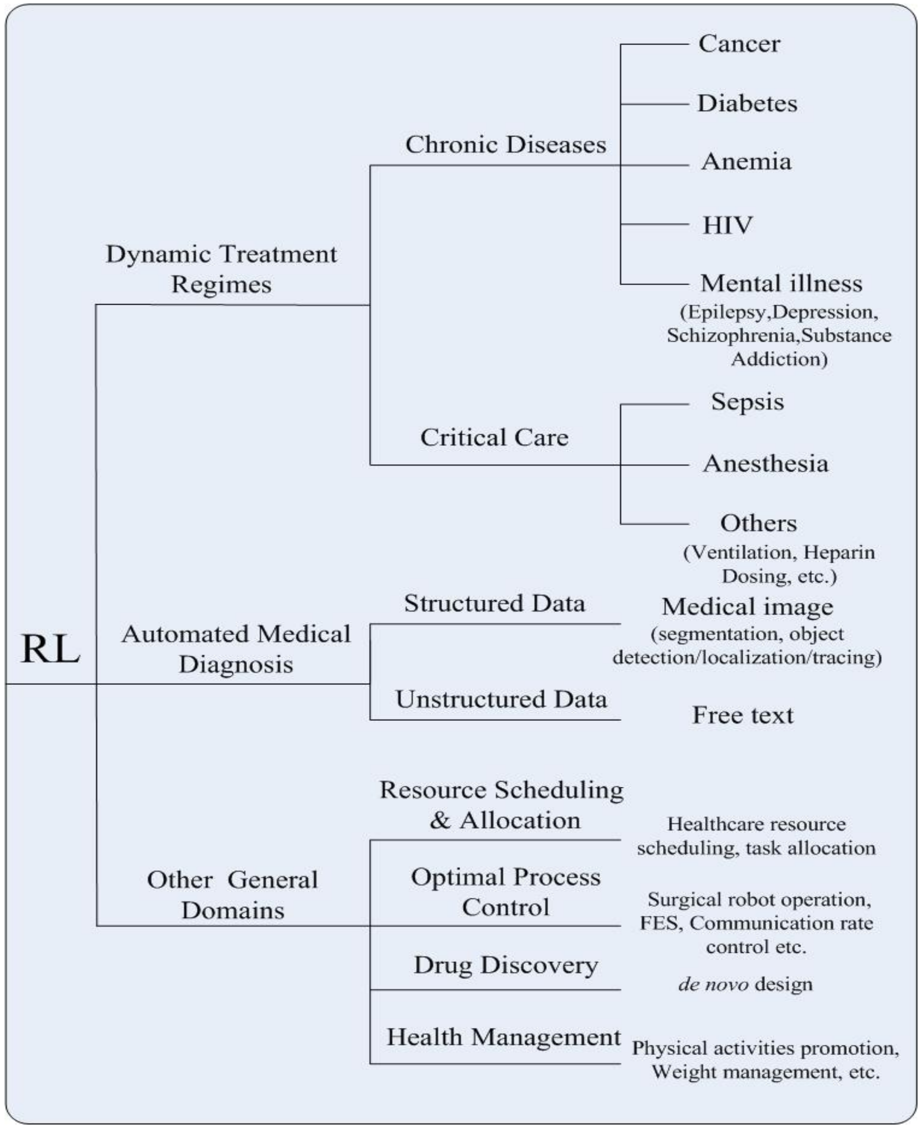
Applications of RL –traffic control

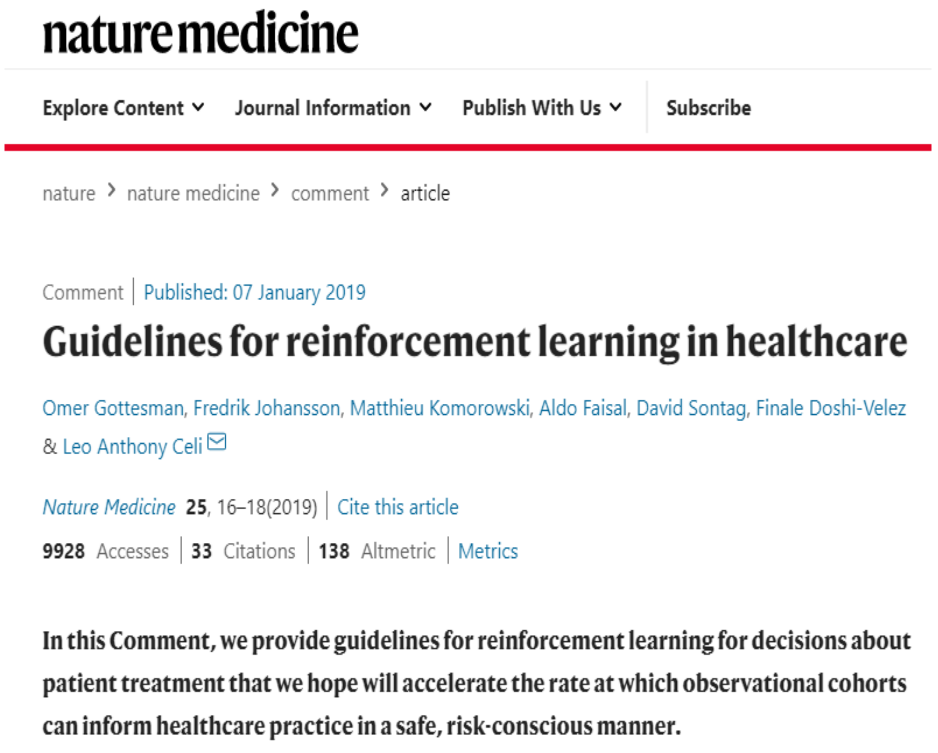
It only takes a tap on the brakes to start a traffic jam.

Applications of RL–autonomous driving



Applications of RL–healthcare


RL
Dynamic Treatment Regimes
Chronic Diseases
Cancer
Diabetes
Anemia
HIV
Mental illness (Epilepsy,Depression, Schizophrenia,Substance Addiction)
Critical Care
Sepsis
Anesthesia
Others (Ventilation, Heparin Dosing, etc.)
Automated Medical Diagnosis
Structured Data
Medical image (segmentation, object detection/localization/tracing)
Unstructured Data
Free text
Other General Domains
Resource Scheduling & Allocation
Healthcare resource scheduling, task allocation
Optimal Process Control
Surgical robot operation, FES, Communication rate control etc.
Drug Discovery
de novo design
Health Management
Physical activities promotion, Weight management, etc.



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

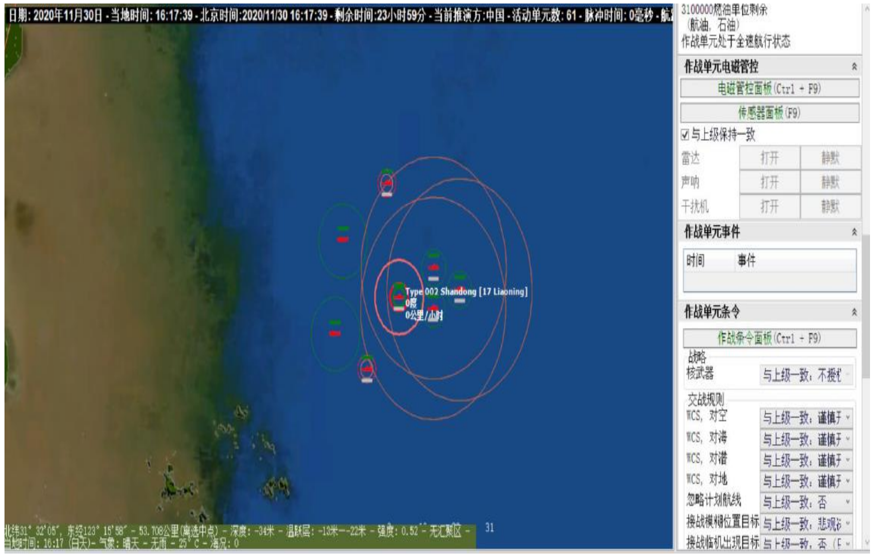
9928 Accesses | **33** Citations | **138** Altmetric | Metrics

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 C Yu, J Liu, S Nemati, G Yin ACM Computing Surveys (CSUR) 55 (1), 1-36	132	2021

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

Applications of RL–military



日期: 2020年11月30日 - 当地时间: 16:17:39 - 北京时间:2020/11/30 16:17:39 - 剩余时间:23小时59分 - 当前推演方:中国 - 活动单元数: 61 - 脉冲时间: 0毫秒 - 航

北纬31° 32′05″, 东经123° 15′58″ - 53.708公里(离选中点) - 深度: -34米 - 温跃层: -13米--22米 - 强度: 0.52 - 无汇聚区 -
当地时间: 16:17 (白天)- 气象: 晴天 - 无雨 - 25° C - 海况: 0

3100000燃油单位剩余
（航油，石油）
作战单元处于全速航行状态

作战单元电磁管控

电磁管控面板(Ctrl + F9)

传感器面板(F9)

☑ 与上级保持一致

雷达	打开	静默
声呐	打开	静默
干扰机	打开	静默

作战单元事件

时间	事件

作战单元条令

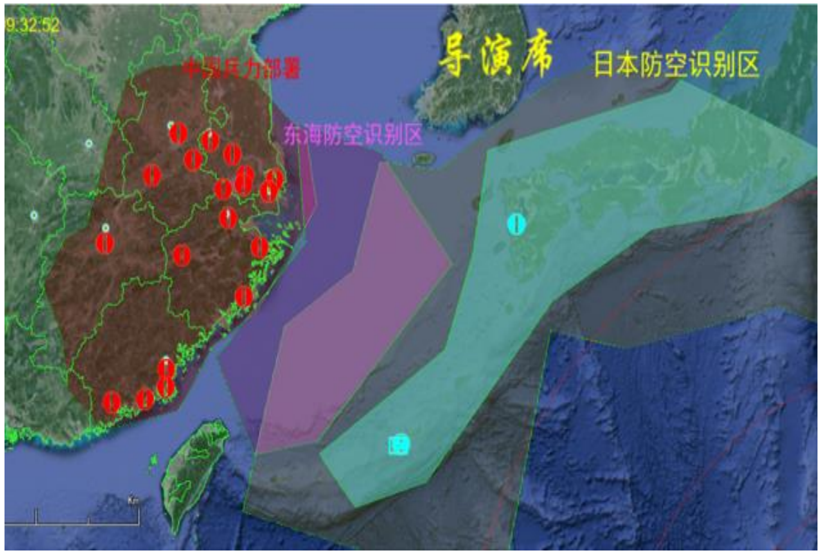
作战条令面板(Ctrl + F9)

战略

核武器	与上级一致：不授权

交战规则

WCS，对空	与上级一致：谨慎于
WCS，对海	与上级一致：谨慎于
WCS，对潜	与上级一致：谨慎于
WCS，对地	与上级一致：谨慎于
忽略计划航线	与上级一致：否
接战模糊位置目标	与上级一致：悲观
接战临机出现目标	与上级一致：否（F



War game

Applications of RL–military

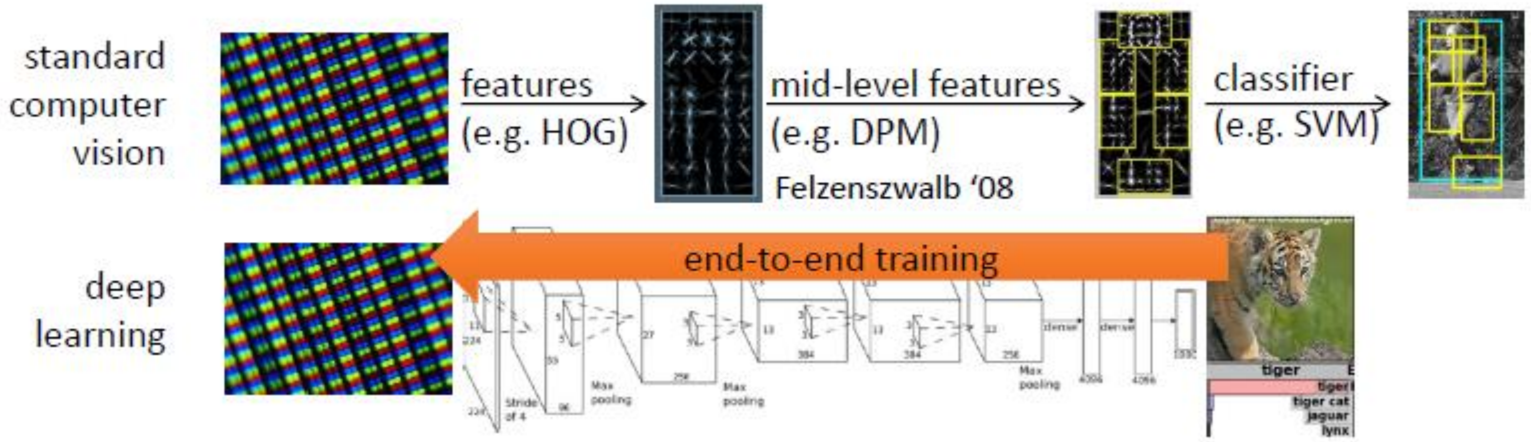
Near-distance Air Combat

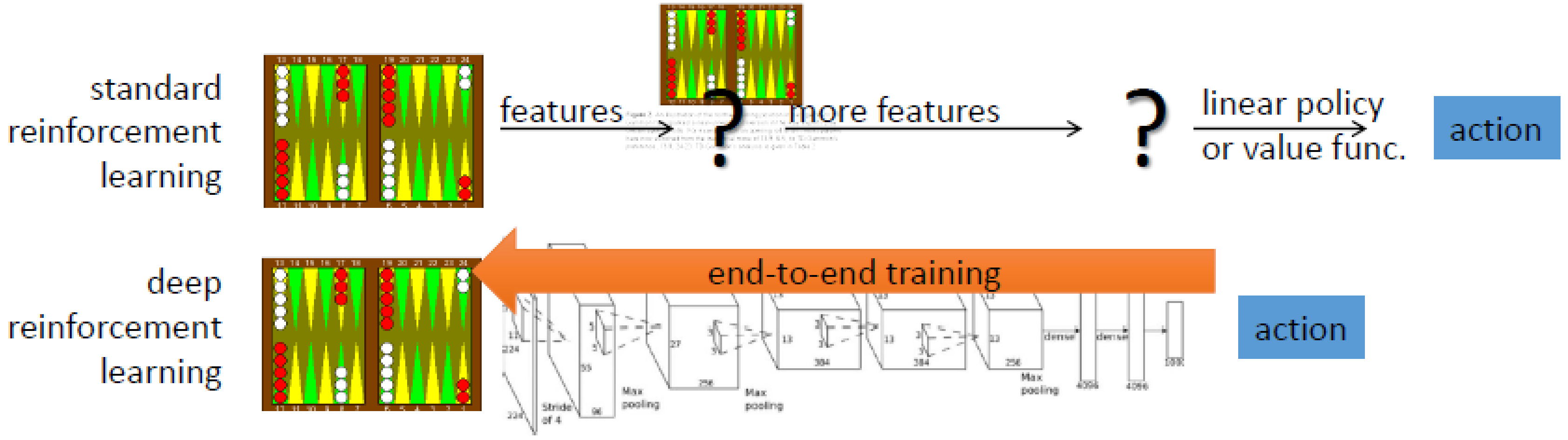
Why reinforcement learning?

Why RL is important?

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

Why RL is important?

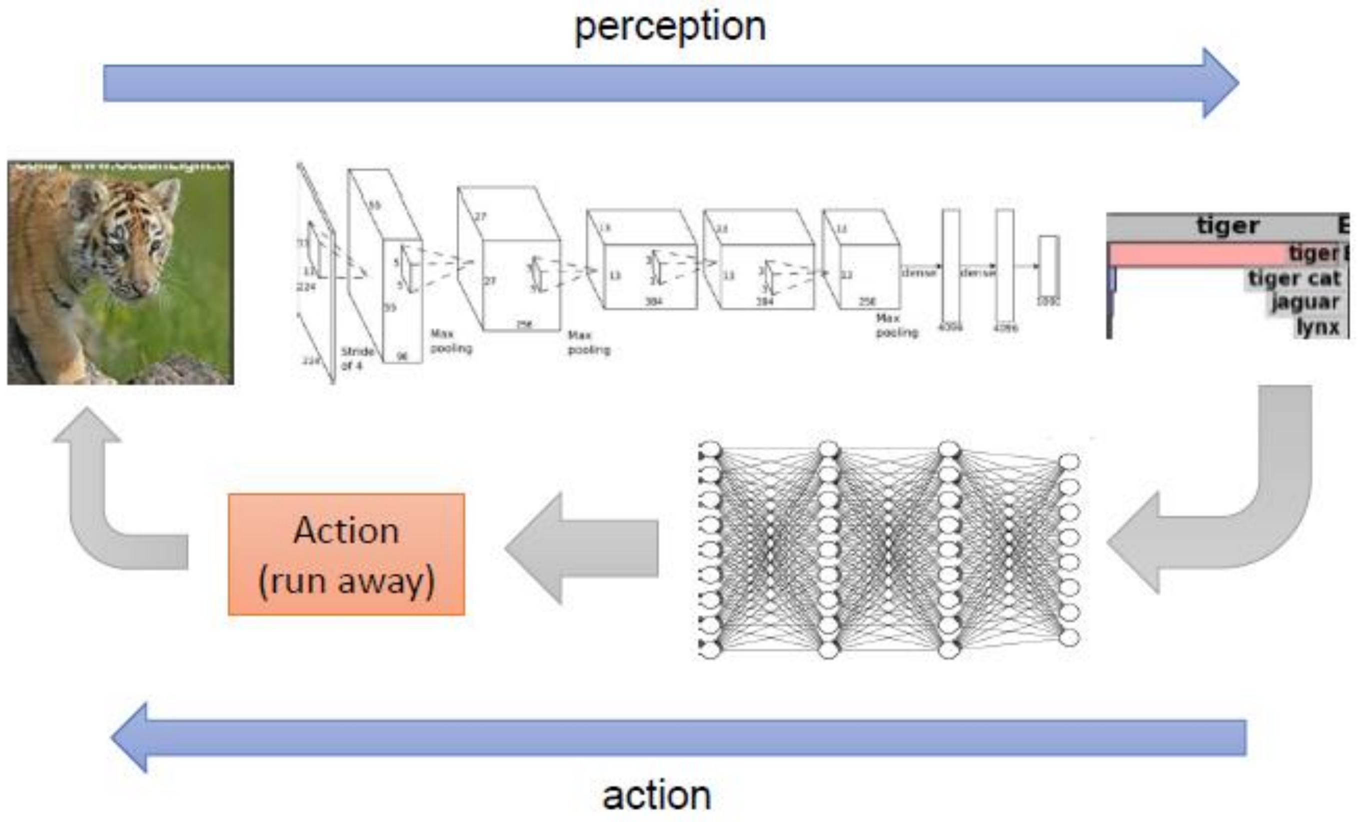



standard reinforcement learning
features
?
more features
?
linear policy or value func.
action
deep reinforcement learning
end-to-end training
action

[from Sergey Levine's course]

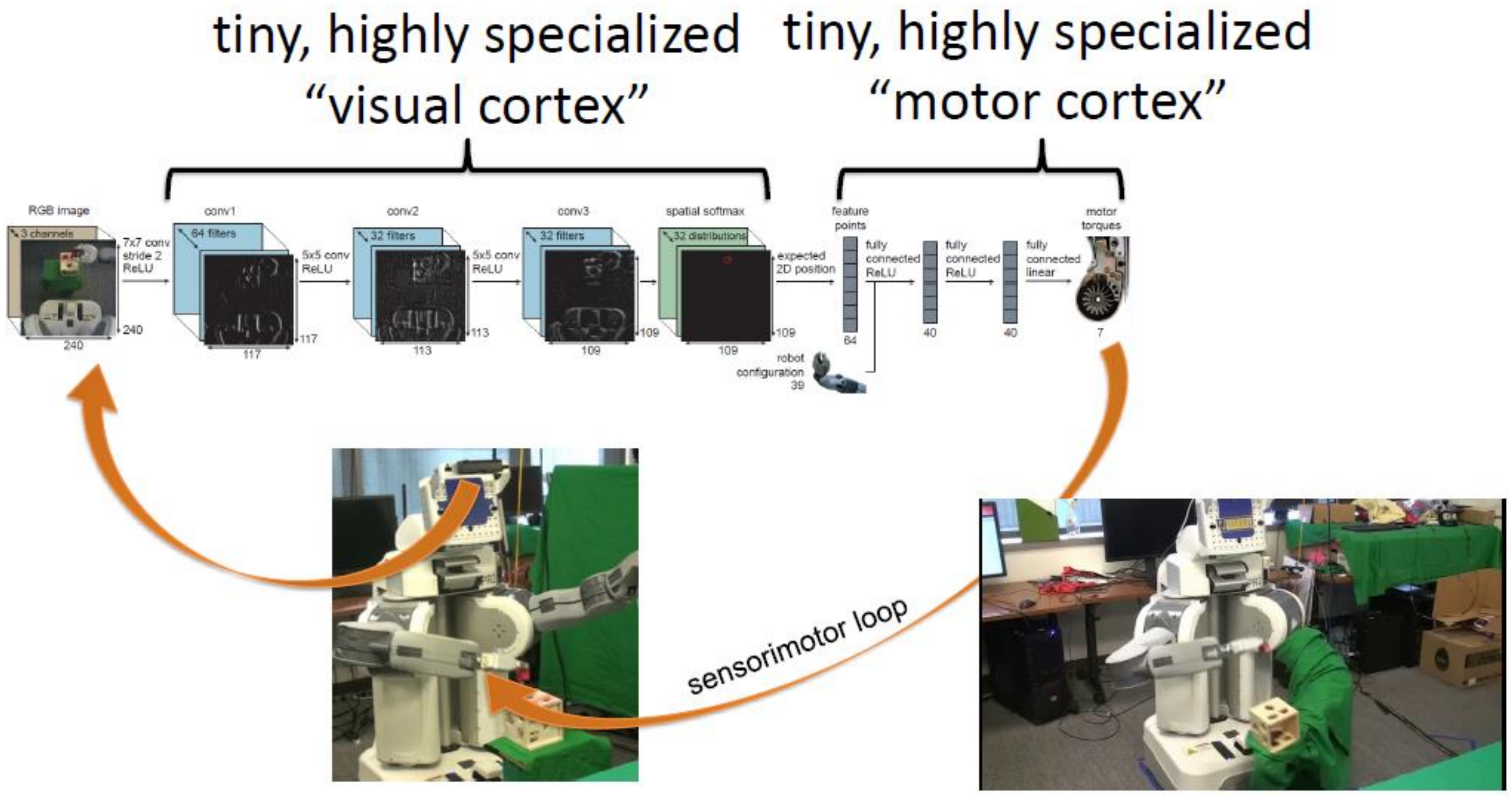
Why RL is important?

RL closes the loop of decision making from perception to control



[from Sergey Levine's course]

Why RL is important?



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

[from Sergey Levine’s course]

Why now?

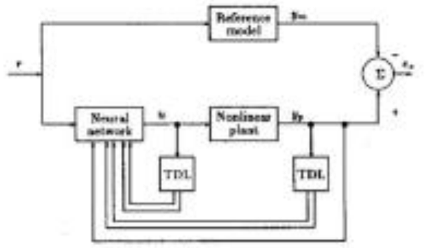
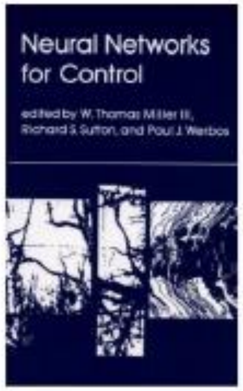
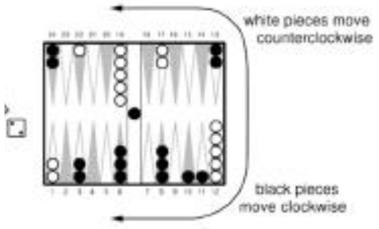


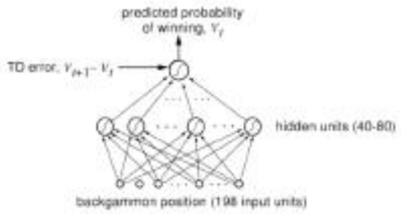
Fig. 21. Direct adaptive control of nonlinear plants using neural networks.



Neural Networks for Control
edited by W. Thomas Miller III, Richard S. Sutton, and Paul J. Werbos



white pieces move counterclockwise
black pieces move clockwise



predicted probability of winning, V_t
TD error, $V_{t+1} - V_t$
hidden units (40-80)
backgammon position (198 input units)

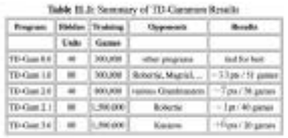


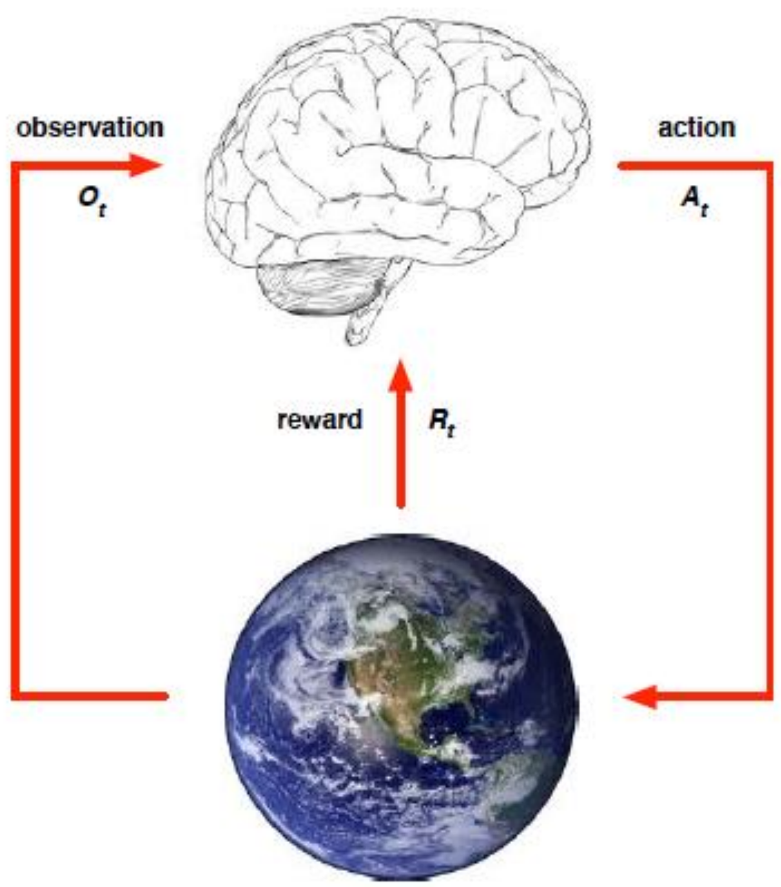
Table 11.1: Summary of TD-Gammon Results

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

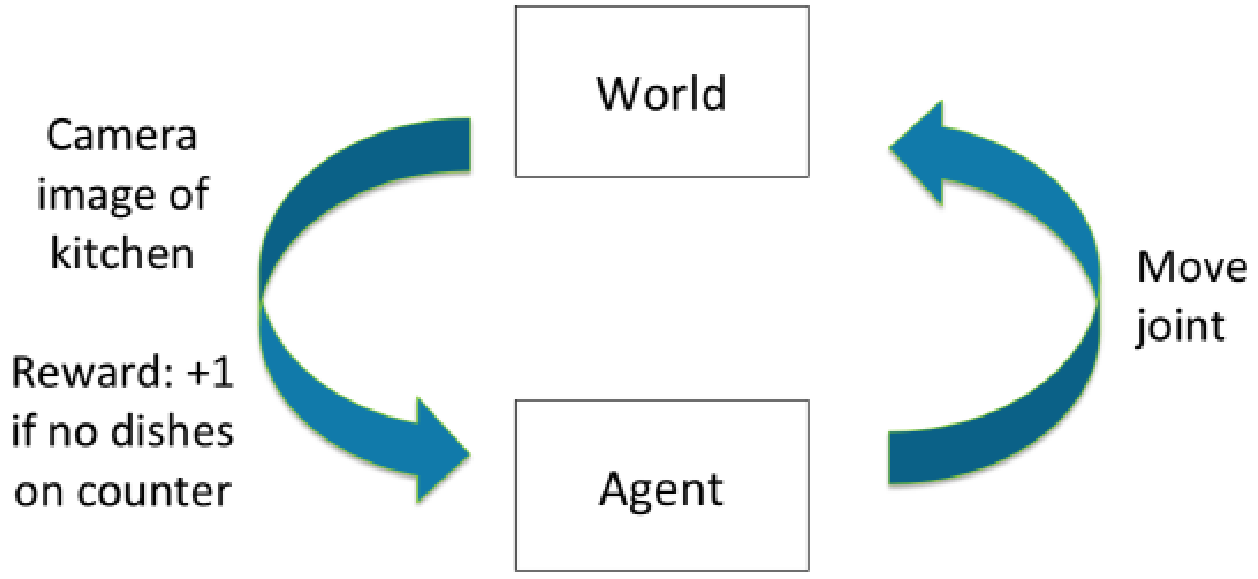


- At each step t the agent:
  - Executes action A_t
  - Receives observation O_t
  - Receives scalar reward R_t
- The environment:
  - Receives action A_t
  - Emits observation O_{t+1}
  - Emits scalar reward R_{t+1}

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

Example of RL Problems

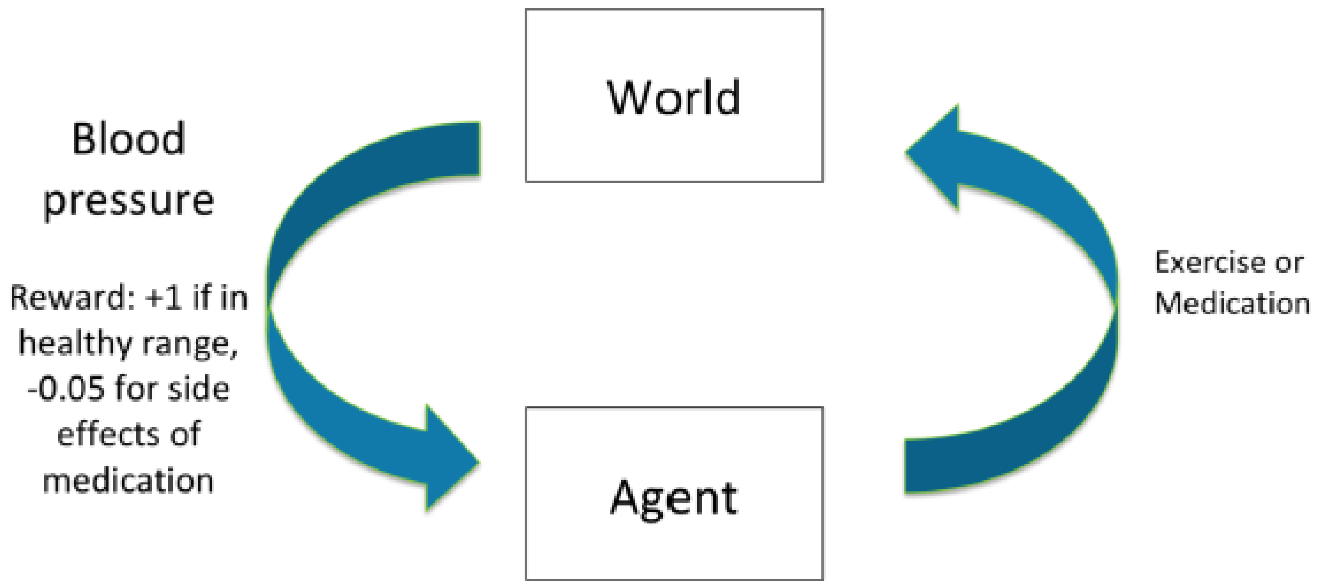
- Robot Unloading Dishwasher



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

Example of RL Problems

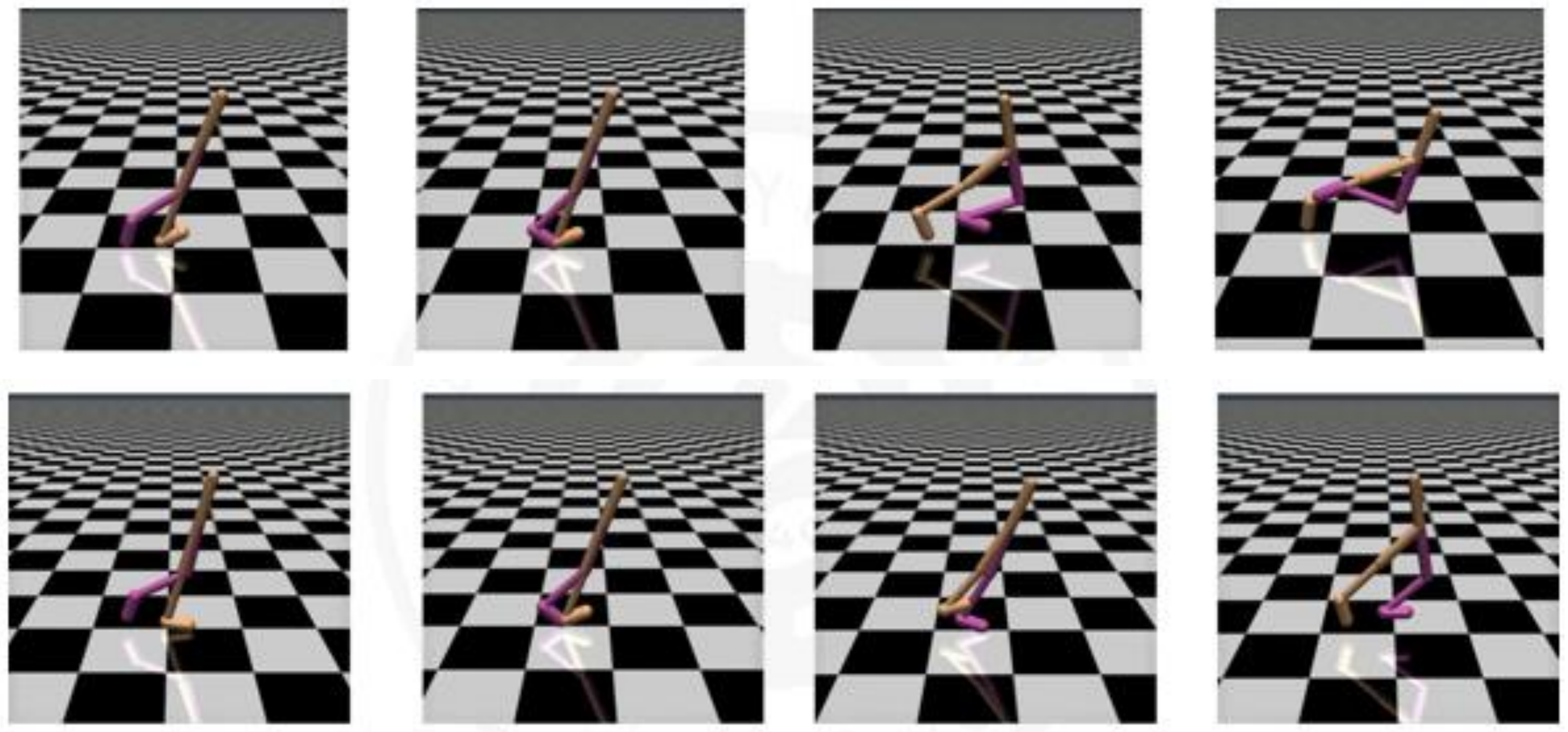
- Blood Pressure Control


World
Blood pressure
Reward: +1 if in healthy range, -0.05 for side effects of medication
Agent
Exercise or Medication

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

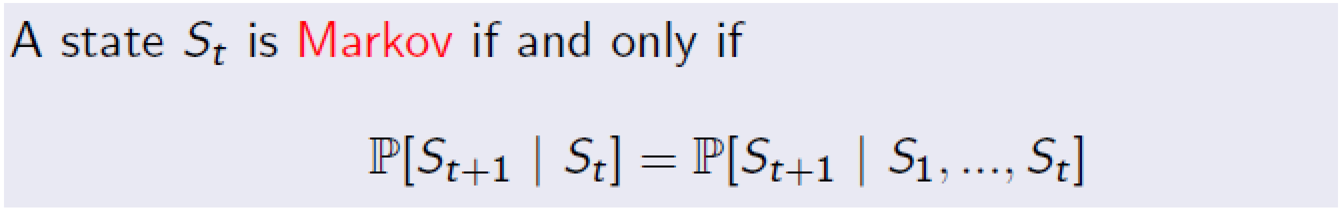
    +1 reward for forward motion

    -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

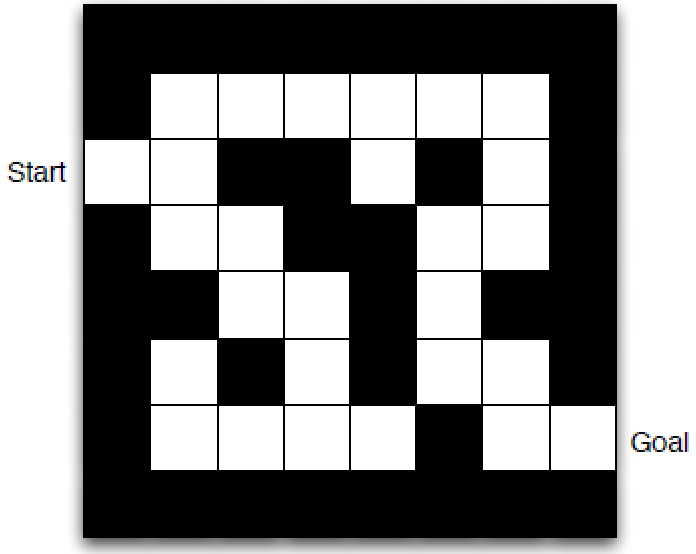
$$\mathbb{P}[S_{t+1} \mid S_t] = \mathbb{P}[S_{t+1} \mid S_1, ..., S_t]$$

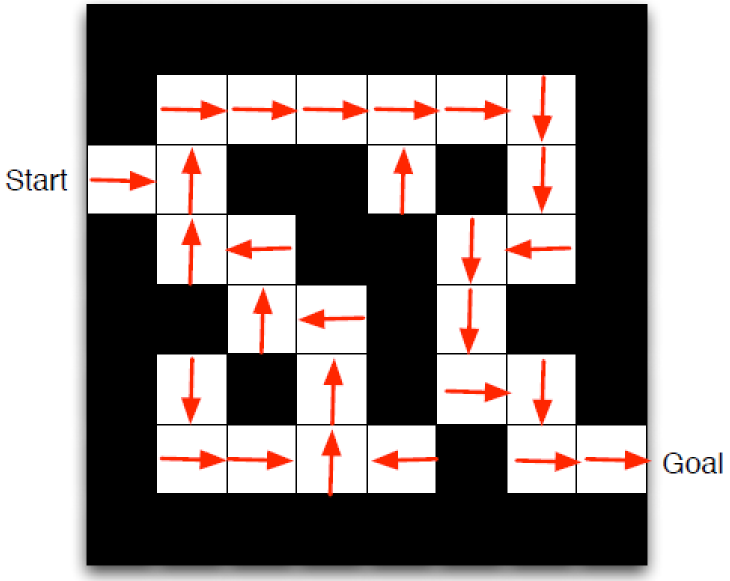
Elements of RL Problems - State

- 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: $\pi(a|s) = \mathbb{P}[A_t = a | S_t = s]$



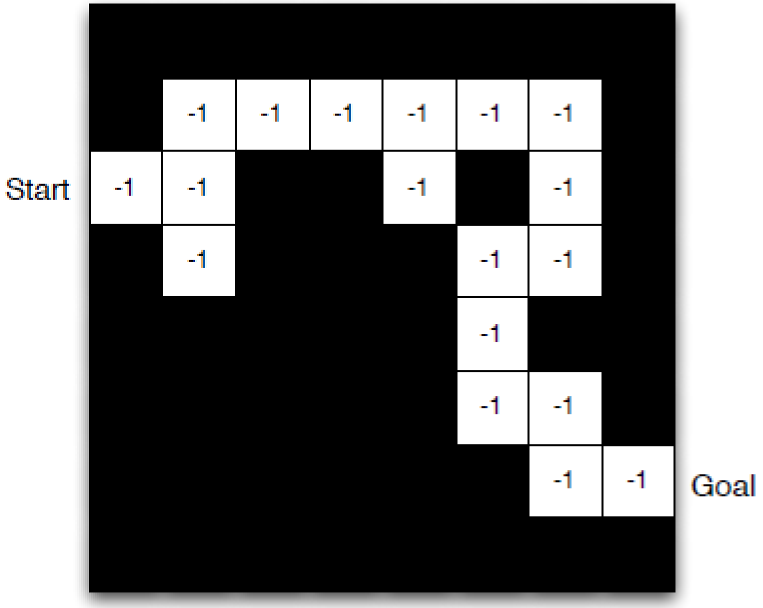


[from David Silver’s course]

Elements of RL Problems - Model

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

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

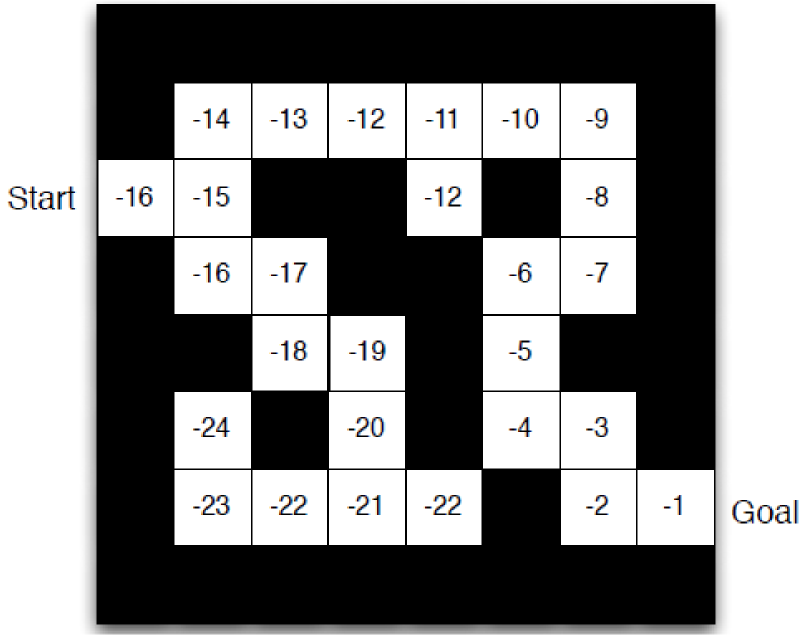


[from David Silver's course]

Elements of RL Problems – Value Function

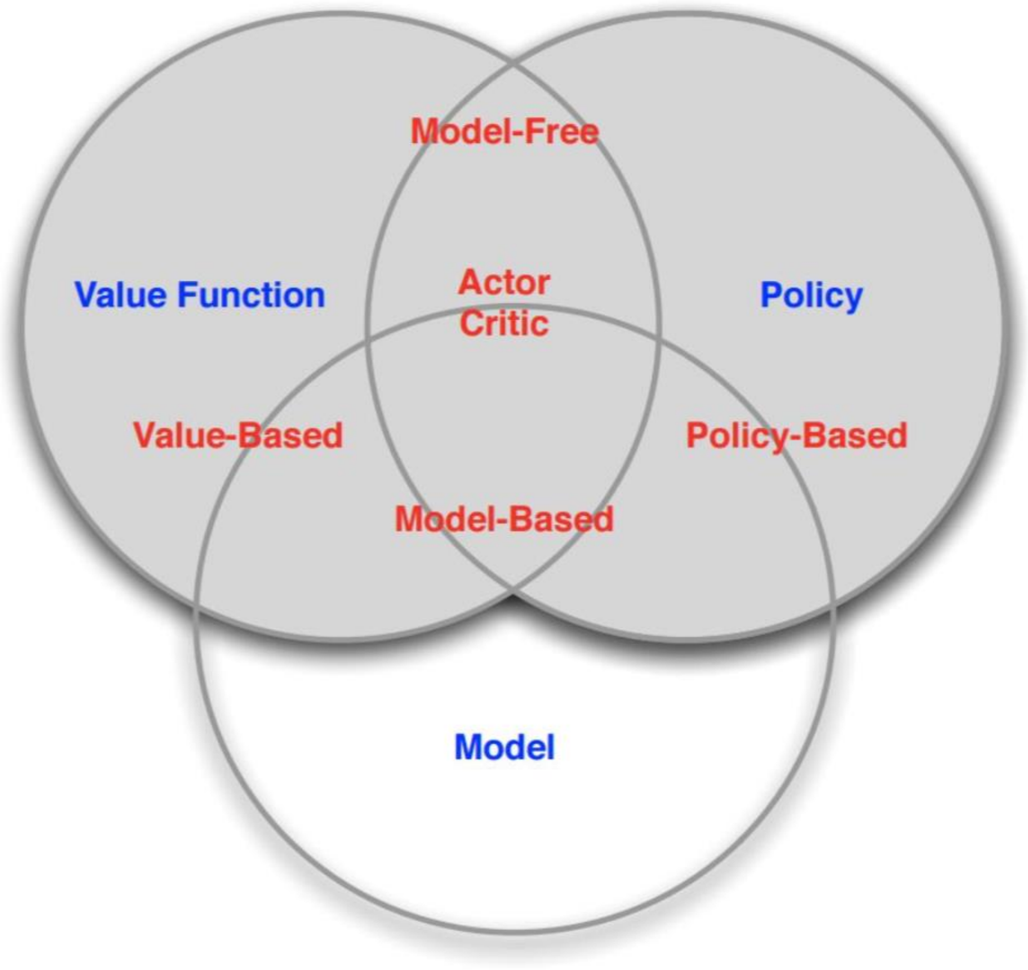
- Value functions: how good is each state and/or action
  - *Value function is a prediction of future reward*
  - *Used to evaluate the goodness/badness of states*
  - *And therefore used to select between actions*

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



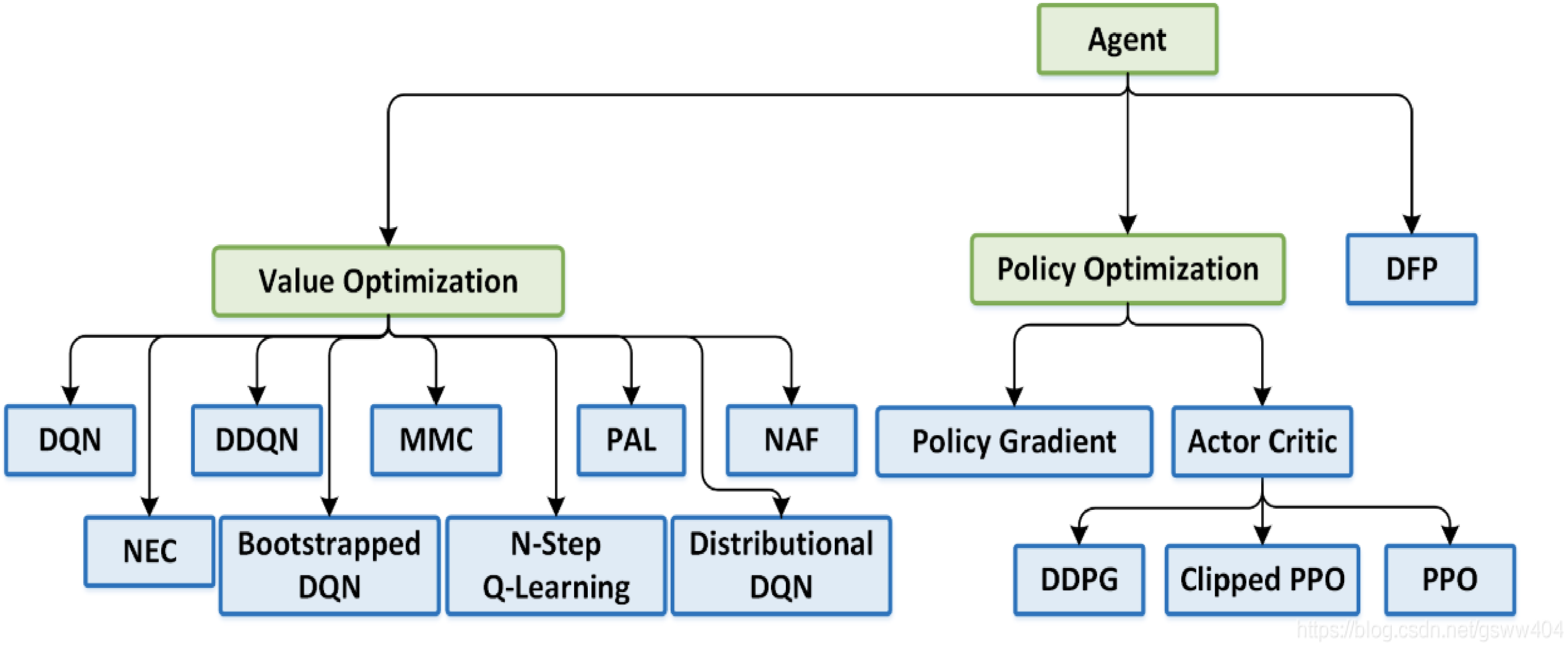
[from David Silver's course]

Categorizing RL Algorithms



[from David Silver's course]

Categorizing RL Algorithms



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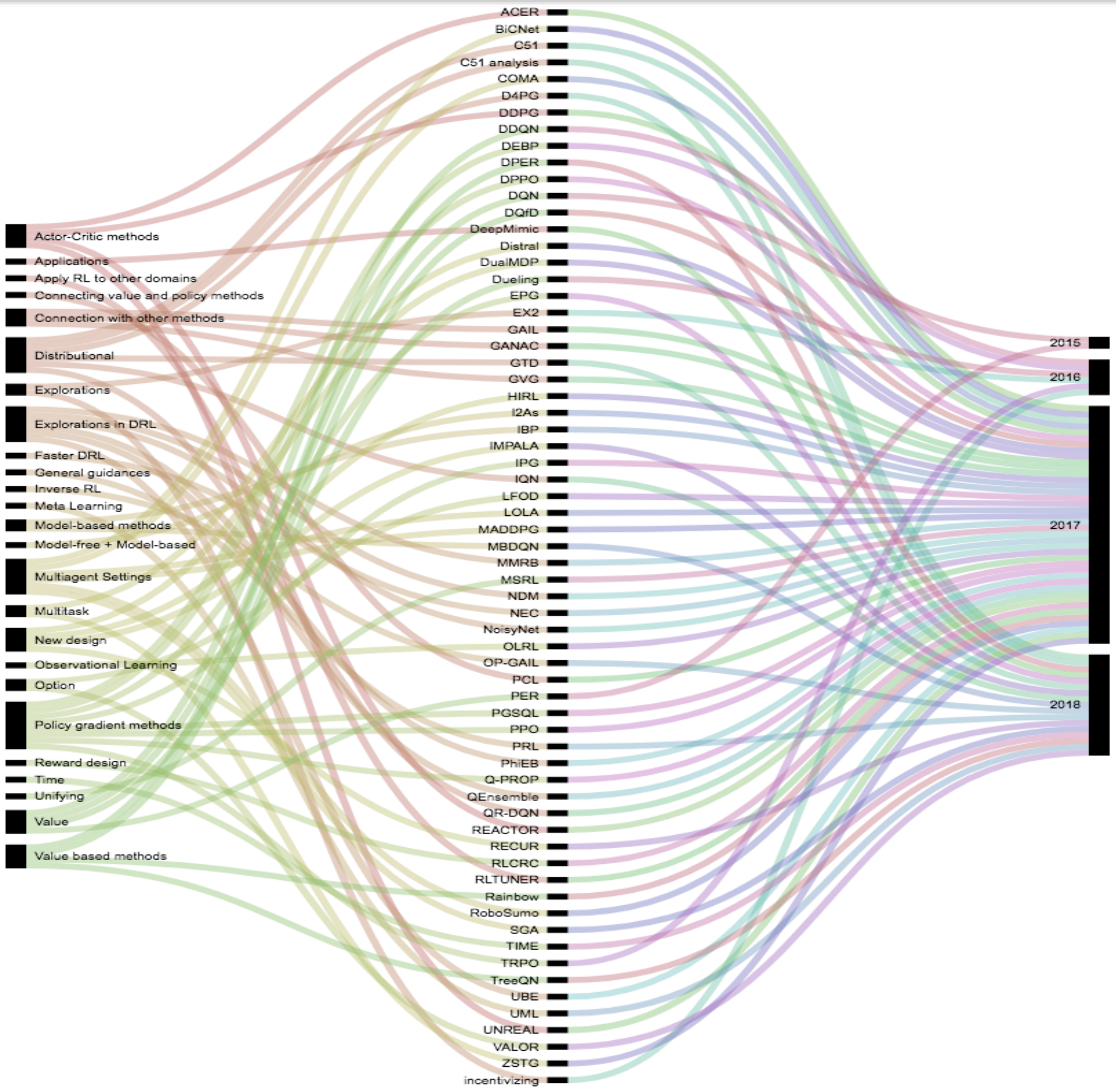
Categorizing RL Algorithms



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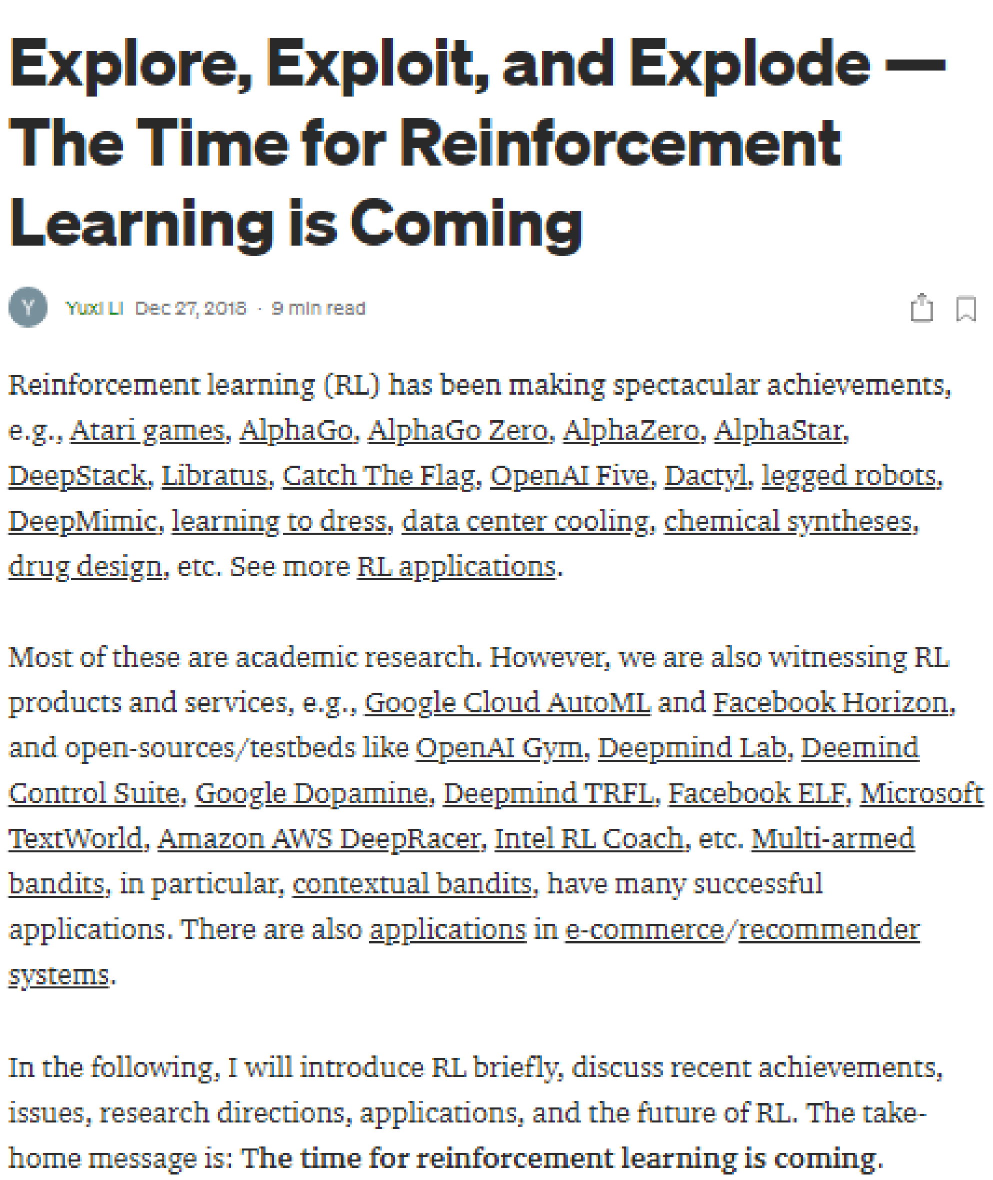
The New Era of AI



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

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.**