南京大学
NANJING UNIVERSITY

人工智能导论

强化学习
(Reinforcement Learning)

郭兰哲

南京大学 智能科学与技术学院

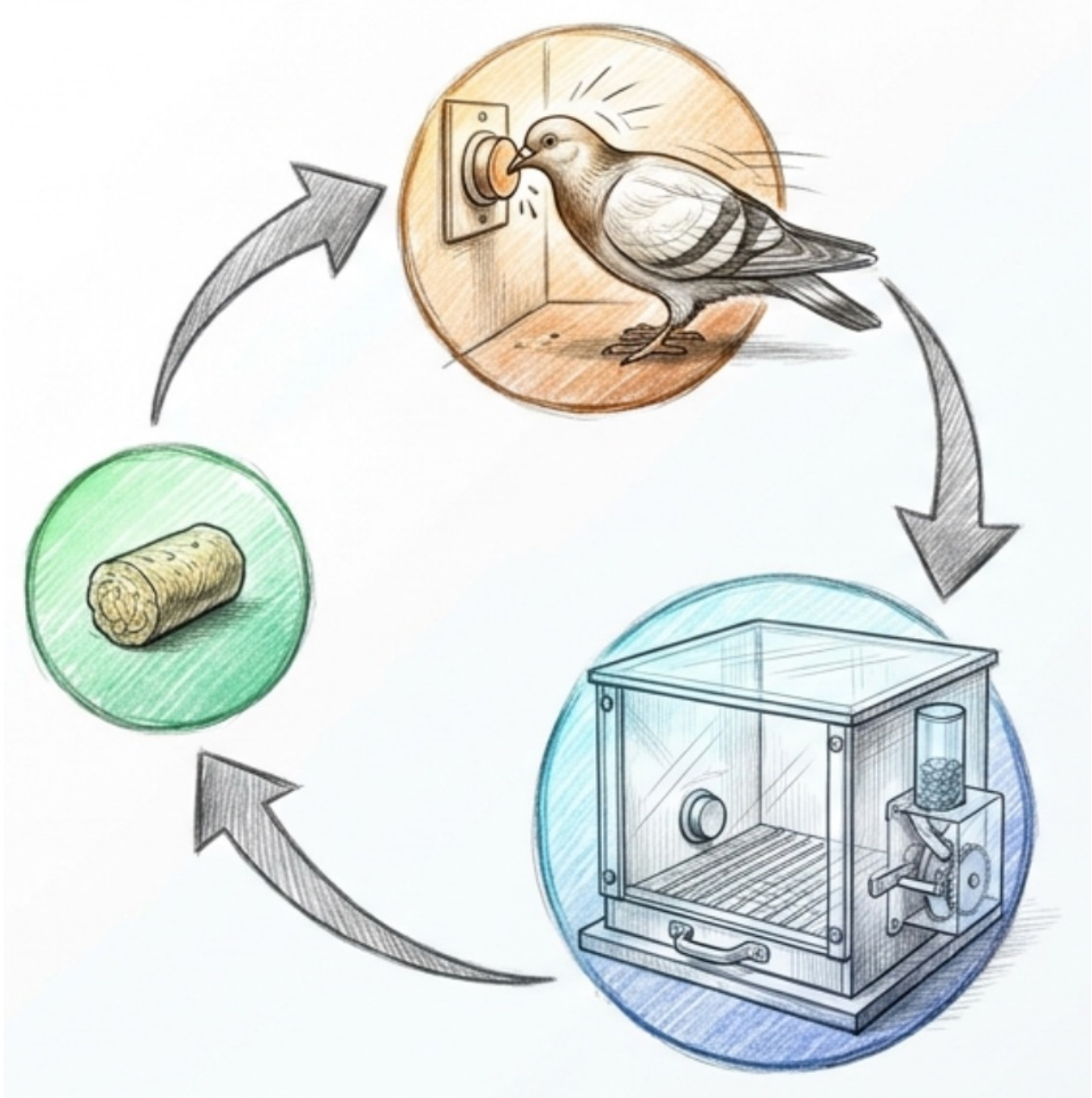
https://www.lamda.nju.edu.cn/guolz

Email: guolz@nju.edu.cn

作业

7	Monday Apr 13	7. Machine Learning Preliminary Slides 8. Statistical Machine Learning Slides	西瓜书对应章节	1. Sklearn 2. K-Means图像压缩代码演示 3. 西瓜数据集分类代码演示	Homework 2 Due: 05.20	-
8	Monday Apr 20	9. Neural Networks and Deep Learning Slides	动手学深度学习 3-4 章	人物 | Geoffrey Hinton的成功之路：从神经网络黑暗时代的坚守到今天的胜利		Project 3 Due: 05.15
9	Monday Apr 27	10. Convolutional Neural Network Slides	动手学深度学习 6-7 章	MNIST手写数字识别演示代码		
10	Monday May 04	五一劳动节停课一周~祝大家假期愉快！				
11	Monday May 11	11. Reinforcement Learning Slides	动手学强化学习 简介部分	Sutton播客		

斯金纳实验：行为与反馈的闭环 (1930s)

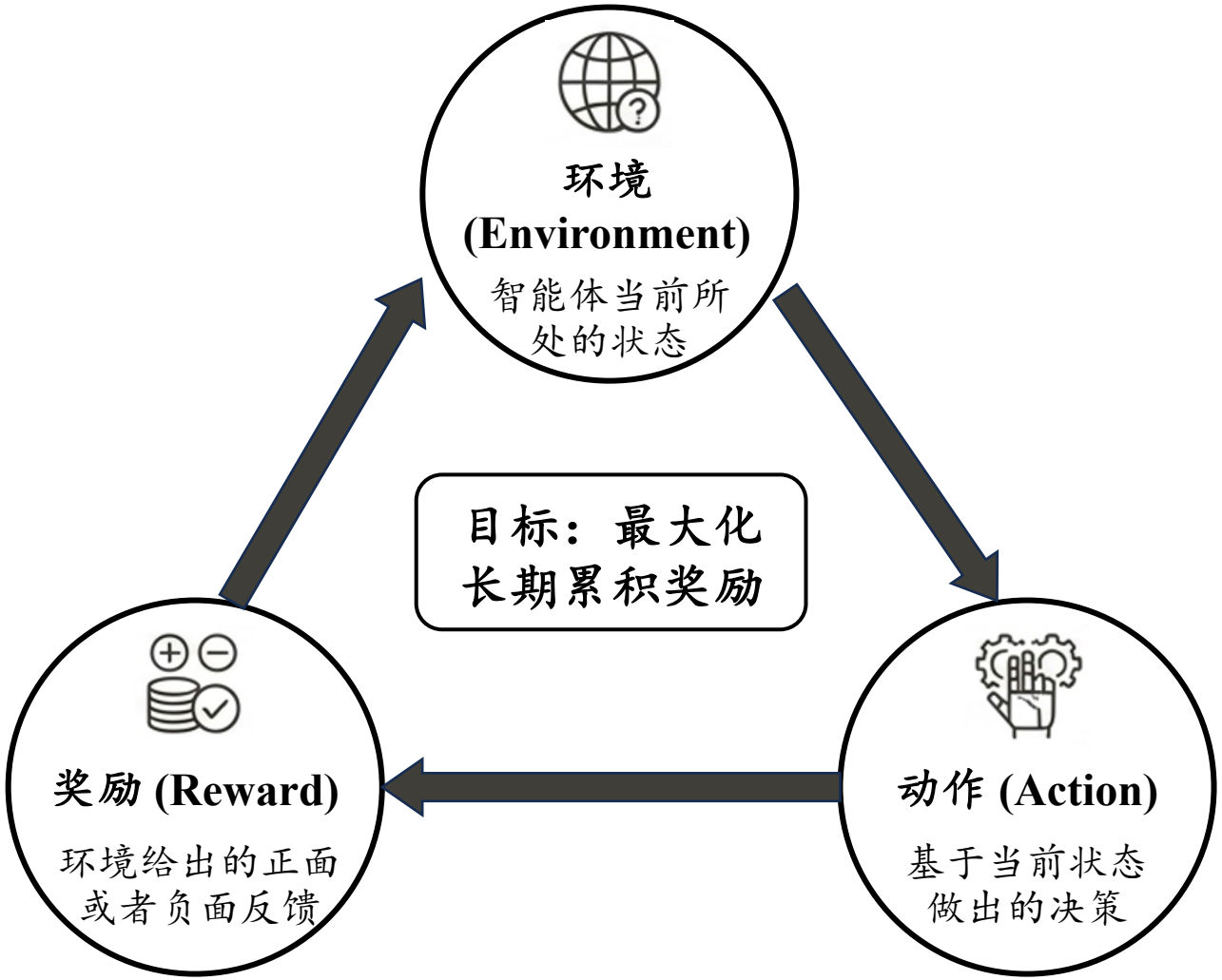


“被奖励的行为趋向于重复，被惩罚的行为趋向于消失。”

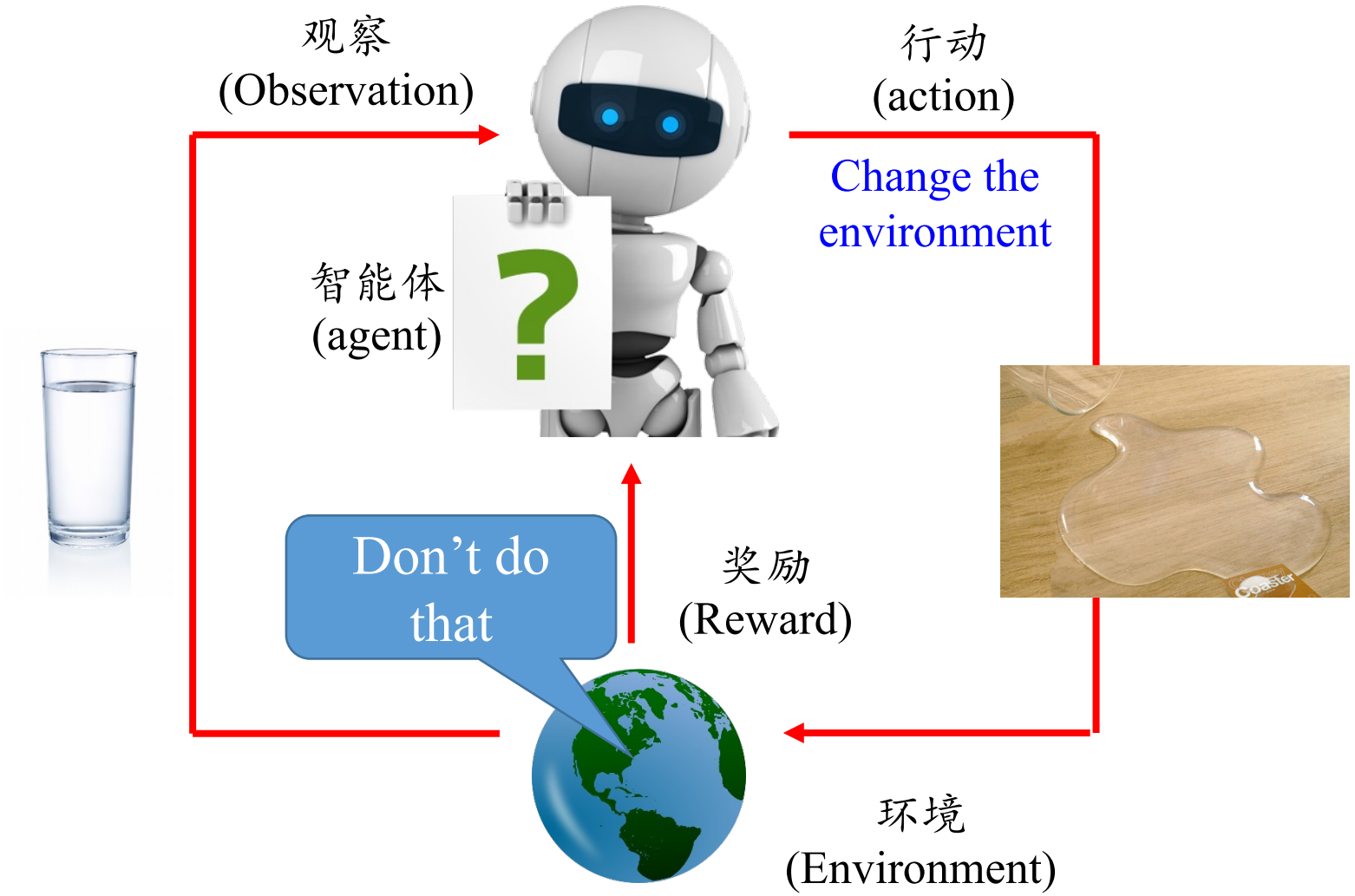
-- B.F. 斯金纳 《有机体的行为》，1938

斯金纳发现，鸽子通过“随机试错 + 获得反馈”学会了按压按钮，他将此命名为**操作性条件反射**

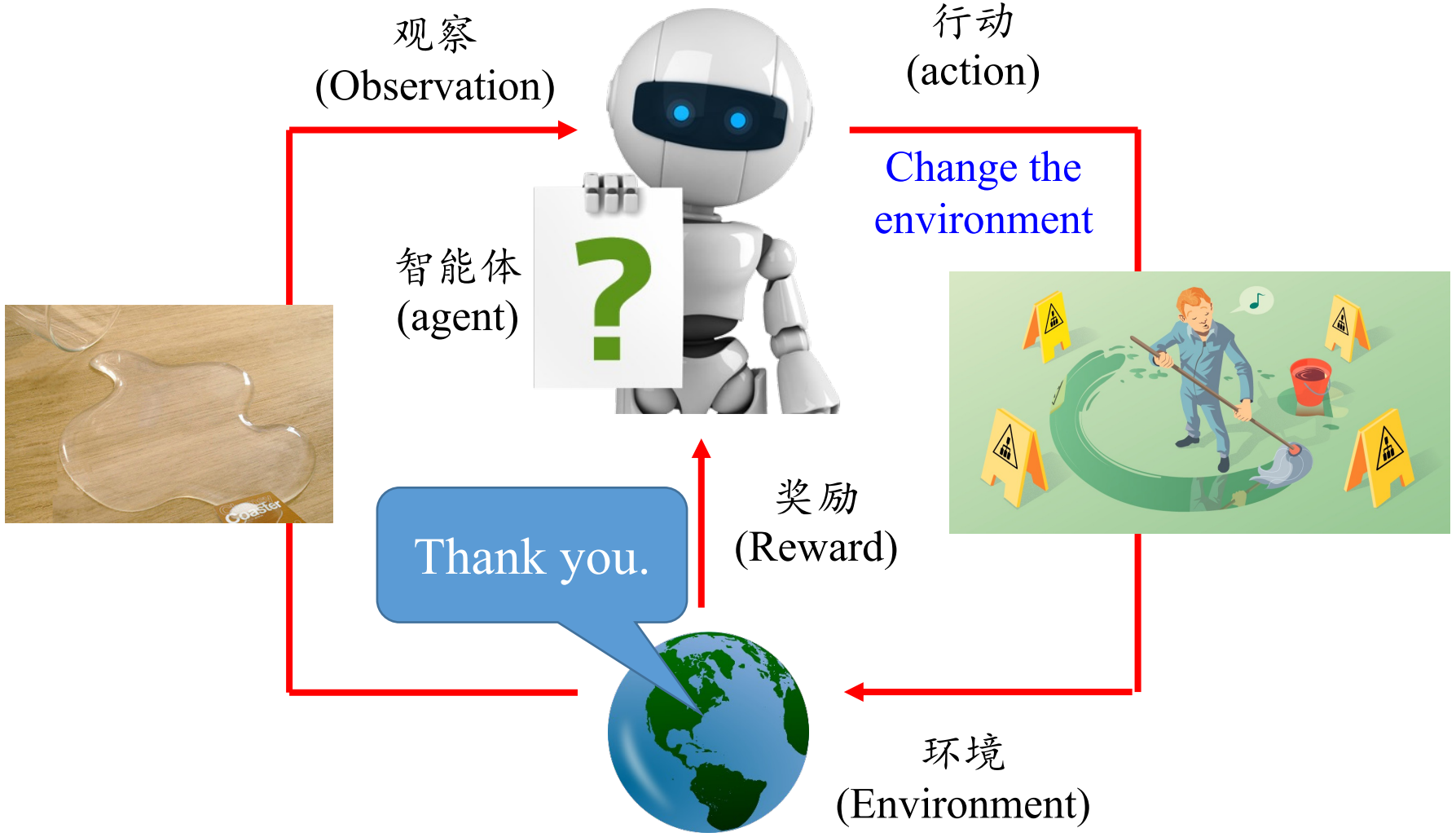
从生物学直接到计算框架：探索、反馈、强化



强化学习 (Reinforcement Learning)

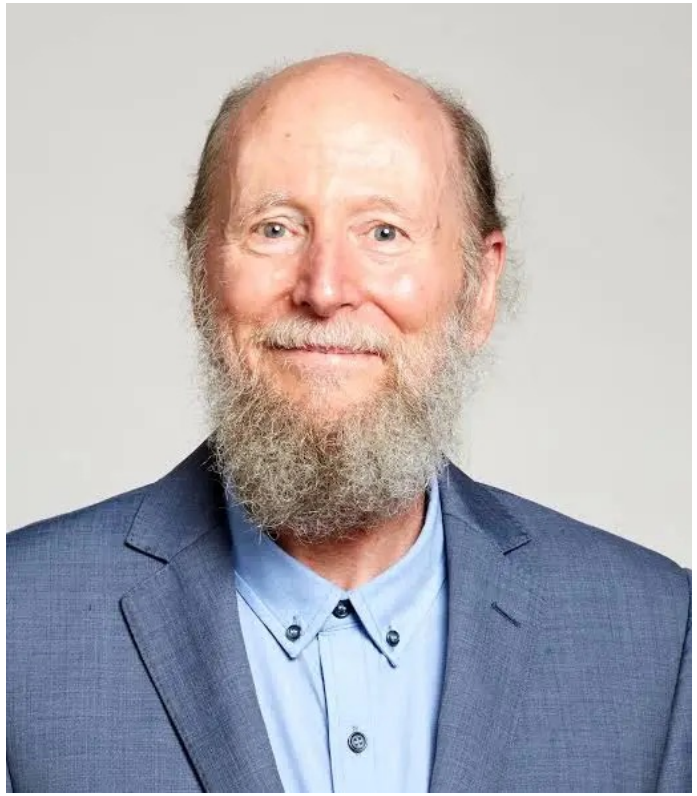


强化学习 (Reinforcement Learning)



智能体从交互中学习得到最大化累计奖励的行动

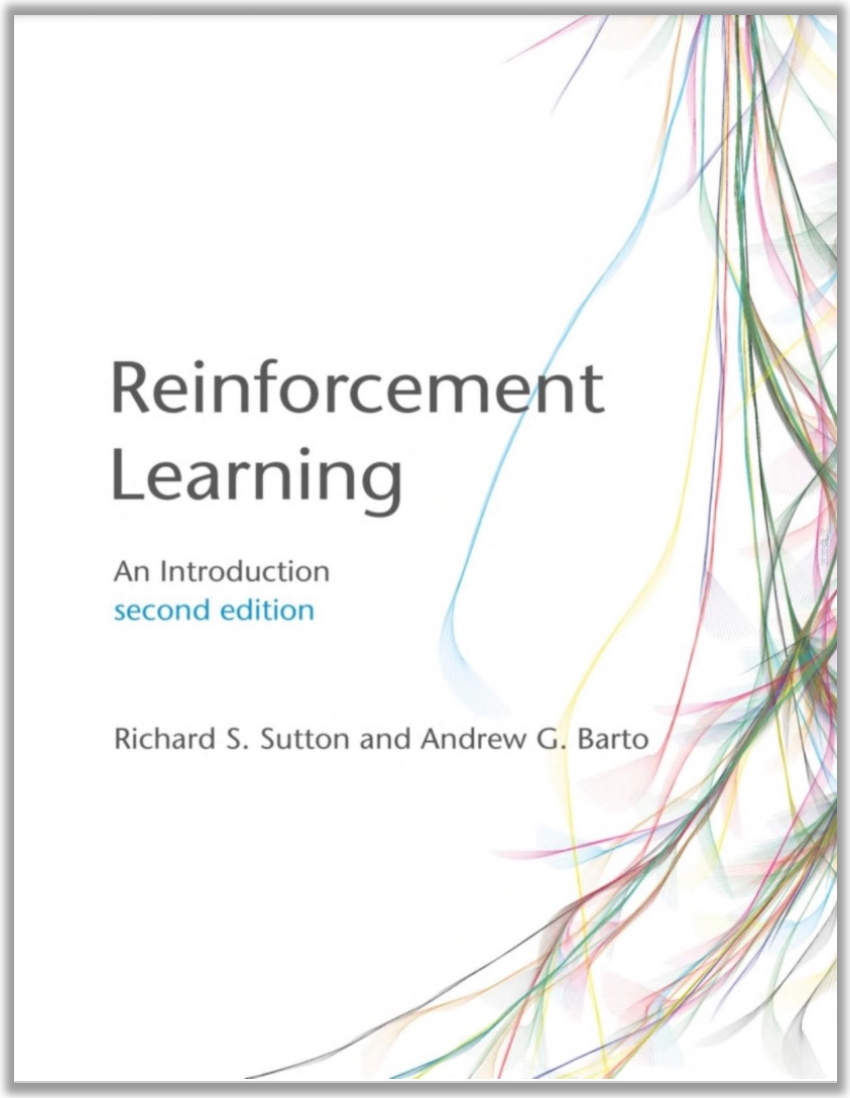
强化学习之父：理查德萨顿 (Richard Sutton)



Richard Sutton

2024年图灵奖得主

http://incompleteideas.net/



DeepMind的智力革命

2010年DeepMind在伦敦成立，愿景“解决智能，然后用它解决一切”

- 2010年DeepMind成立：Demis Hassabis，Shane Legg，Mustafa Suleyman
- 2013年发表DQN论文，在40款雅达利游戏中超越人类玩家
- 2014年被Google以6.5亿美元收购
- 2016年，AlphaGo，战胜世界围棋冠军李世石
- 2020年，AlphaFold，解决蛋白质预测问题
- 2024年，获诺贝尔化学奖

2008 年，姆尼赫在阿尔伯塔大学获得硕士学位后回到多伦多，加入了辛顿的团队，在一间改造过的储藏室里办公。[5] 在那里，他遇到了与塞佩斯瓦里相同的情况——深度学习研究者也不愿采用其他学派的方法。

“你想研究什么？”辛顿问他的新博士生。

姆尼赫回答说，他想将强化学习与深度学习结合起来。“我试过了，行不通。”辛顿劝告他。

姆尼赫又向其他几位同事提起了自己的抱负，但一位又一位深度学习研究者都劝他放弃。“一旦你成为强化学习研究者，就会进入一个独立的圈子，我们再也不会听到你的消息了。”有人明确地告诉他。

2012 年夏天，姆尼赫在苏格兰的一场 AI 会议上展示了他的博士研究成果。这场会议的主题多是像他的项目这样的严谨项目，打造 AGI 的未来主义方案并未出现在议程中。但在第一天晚上的招待会上，氛围突然发生了变化。两位参会者出现在派对上，宣布他们正在打造 AGI。他们在伦敦有一家初创公司，正在寻找认同这一使命的加入者。

DeepMind 的人问他：“你想研究什么？”姆尼赫给出了那个通常会让他遭到白眼的答案：“我想尝试将深度学习与强化学习结合起来。”

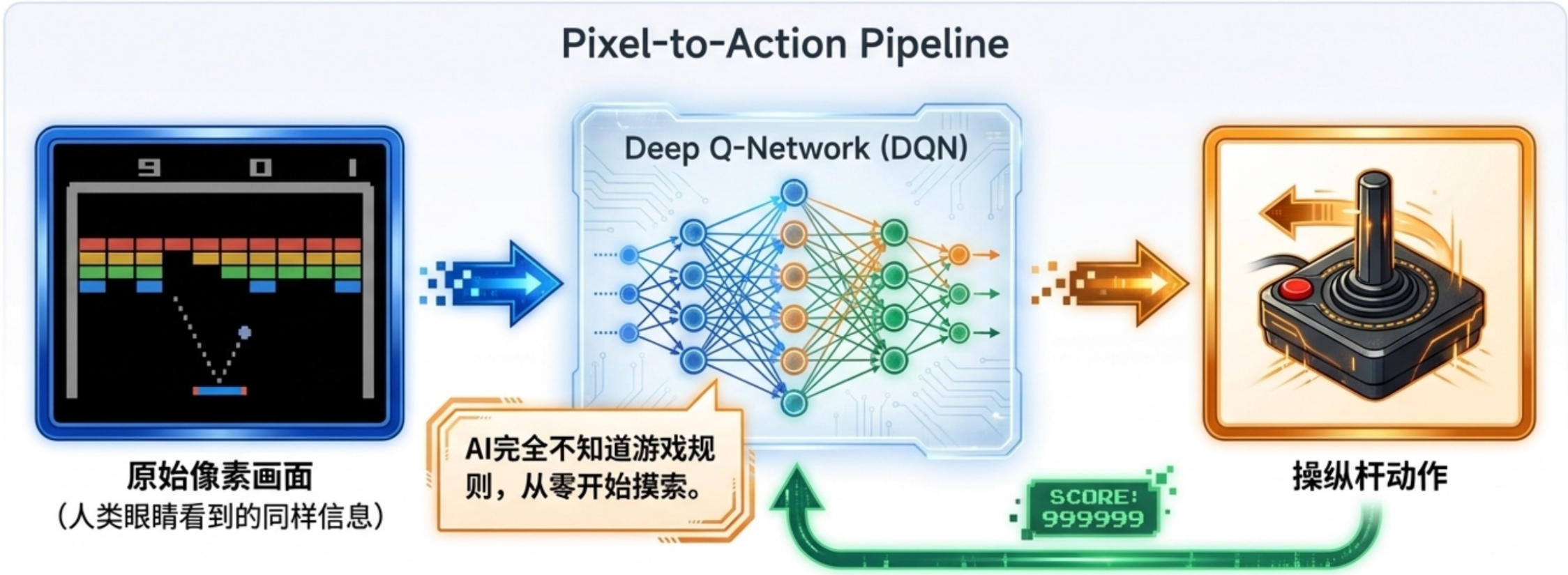
“我们正在做的就是这件事！”两人高兴地回答。在瑞士，这种跨领域结合的做法实际上是受到鼓励的。此外，神经科学也强烈表明，强化学习将是深度学习的必要补充。毕竟，强化学习中的奖励信号与人类大脑中的多巴胺信号非常相似。如果大脑是 AGI 的模板，那么强化学习对于打造 AGI 来说必不可少。[7]

姆尼赫开始觉得，这些“疯狂的家伙”可能真的知道些什么。他曾在多伦多和阿尔伯塔大学之间辗转，试图将自己对两大研究的热情结合起来。或许他应该把自己“转移”到伦敦去。

此外，姆尼赫意识到，打造 AGI 的抱负听起来可能有些狂妄，但它也有一个优势。根据他的经验，学术界的文化既枯燥保守又竞争激烈：枯燥是因为科学家们只追求渐进式进步，激烈是因为为了抢占首发权而互相倾轧。莱格和维尔斯特拉承诺会给他带来完全不同的体验——**追求巨大突破的激动人心的过程，以及几乎没有竞争对手的环境。**“他们说，是的，我们要做的事情没有竞争，因为没有人认为这是可能的，”姆尼赫回忆道，“而且如果成功了，它的影响将是巨大的。”[8]

第一声惊雷：仅凭像素学会玩雅达利游戏 (2013)

DeepMind两篇发表于NeurIPS和《Nature》的论文，提出了Deep Q-Network (DQN)算法，在49款经典雅达利游戏中，29款超越了人类顶尖水平



Playing Atari with Deep Reinforcement Learning

Volodymyr Mnih **Koray Kavukcuoglu** **David Silver** **Alex Graves** **Ioannis Antonoglou**

Daan Wierstra **Martin Riedmiller**

DeepMind Technologies

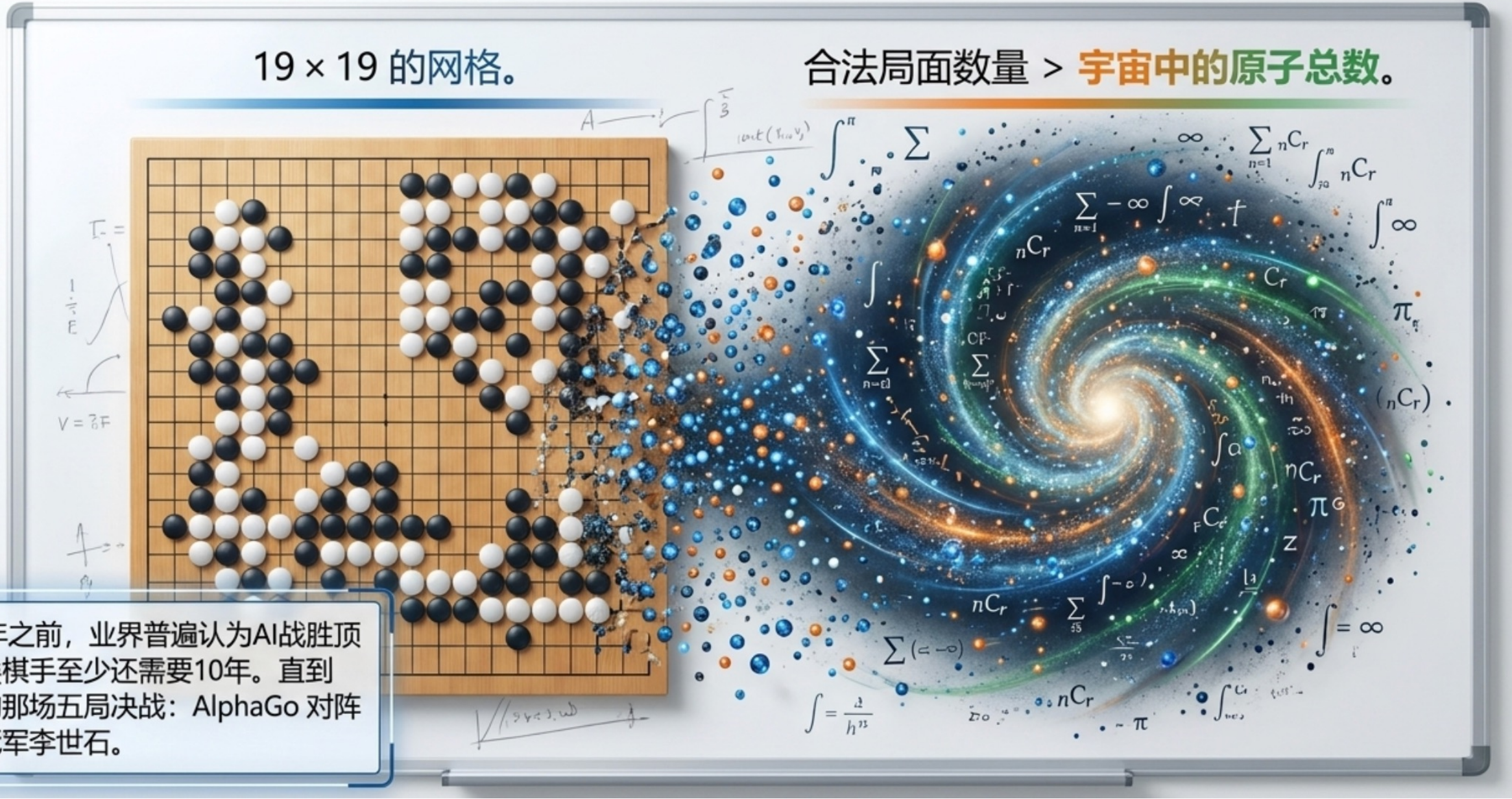
{vlad,koray,david,alex.graves,ioannis,daan,martin.riedmiller} @ deepmind.com

Abstract

We present the first deep learning model to successfully learn control policies directly from high-dimensional sensory input using reinforcement learning. The model is a convolutional neural network, trained with a variant of Q-learning, whose input is raw pixels and whose output is a value function estimating future rewards. We apply our method to seven Atari 2600 games from the Arcade Learning Environment, with no adjustment of the architecture or learning algorithm. We find that it outperforms all previous approaches on six of the games and surpasses a human expert on three of them.

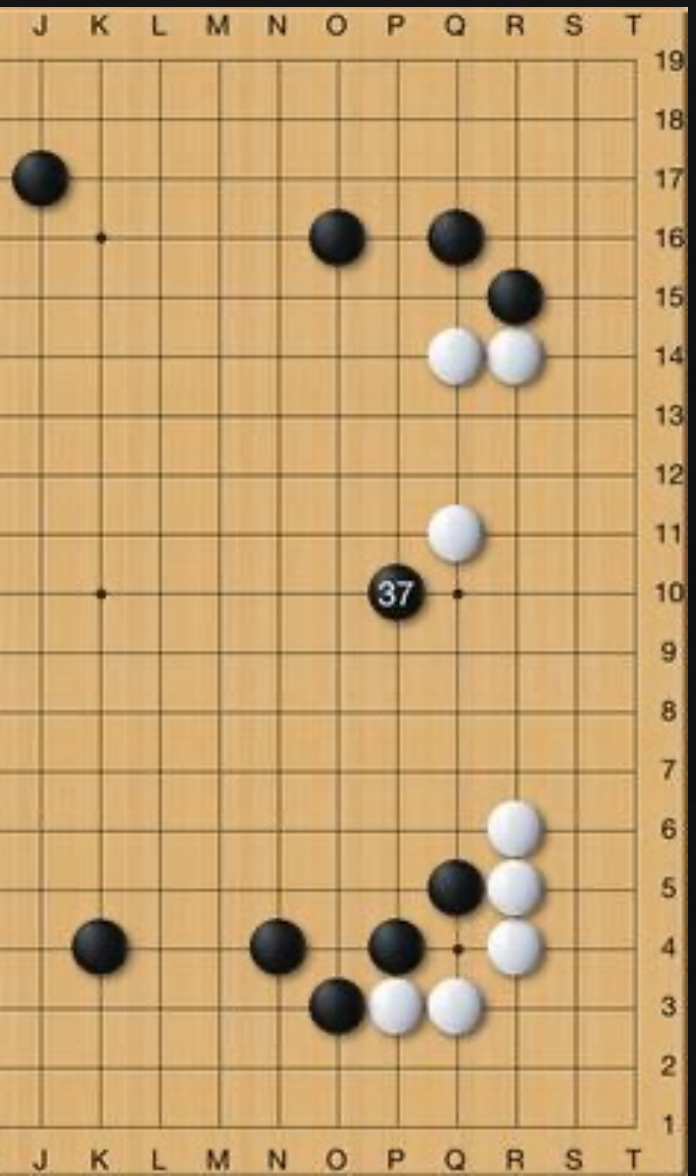
https://arxiv.org/pdf/1312.5602

挑战人类智力巅峰：围棋 (2016)



2016年之前，业界普遍认为AI战胜顶级人类棋手至少还需要10年。直到首尔的那场五局决战：AlphaGo 对阵世界冠军李世石。

AI的神之一手：不属于人类的、美丽的直觉



历史的涌现：神之一手（Move 37）

- 第二局，第37手。AlphaGo下出了一步极其罕见的“五线肩冲”。
- 当下：解说员与人类顶级棋手纷纷断言：“这步棋下错了，这是机器的Bug。”
- 思考：李世石震惊，起身离开棋盘，随后陷入长达11分钟的死寂沉思。
- 15分钟后：全世界的围棋大师突然醒悟——这是一步洞穿全局的天才之举。

这步棋不是人类会下的棋。但它是美丽的。
—— 职业棋手评价

最终比分 4:1。它不仅赢下了一盘棋，更粉碎了人类对于“机器无直觉”的傲慢。

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 game of Go has long been viewed as the most challenging of classic games for artificial intelligence owing to its enormous search space and the difficulty of evaluating board positions and moves. Here we introduce a new approach to computer Go that uses 'value networks' to evaluate board positions and 'policy networks' to select moves. These deep neural networks are trained by a novel combination of supervised learning from human expert games, and reinforcement learning from games of self-play. Without any lookahead search, the neural networks play Go at the level of state-of-the-art Monte Carlo tree search programs that simulate thousands of random games of self-play. We also introduce a new search algorithm that combines Monte Carlo simulation with value and policy networks. Using this search algorithm, our program AlphaGo achieved a 99.8% winning rate against other Go programs, and defeated the human European Go champion by 5 games to 0. This is the first time that a computer program has defeated a human professional player in the full-sized game of Go, a feat previously thought to be at least a decade away.

All games of perfect information have an optimal value function, $v^*(s)$, which determines the outcome of the game, from every board position or state s, under perfect play by all players. These games may be solved by recursively computing the optimal value function in a search tree containing approximately b^d possible sequences of moves, where b is the game's breadth (number of legal moves per position) and d is its depth (game length). In large games, such as chess ($b \approx 35$, $d \approx 80$)[1] and especially Go ($b \approx 250$, $d \approx 150$)[1], exhaustive search is infeasible[2,3], but the effective search space can be reduced by two general principles. First, the depth of the search may be reduced by position evaluation: truncating the search tree at state s and replacing the subtree below s by an approximate value function $v(s) \approx v^*(s)$ that predicts the outcome from state s. This approach has led to superhuman performance in chess[4], checkers[5] and othello[6], but it was believed to be intractable in Go due to the complexity of the game[7]. Second, the breadth of the search may be reduced by sampling actions from a policy $p(a|s)$ that is a probability distribution over possible moves a in position s. For example, Monte Carlo rollouts[8] search to maximum depth without branching at all, by sampling long sequences of actions for both players from a policy p. Averaging over such rollouts can provide an effective position evaluation, achieving superhuman performance in backgammon[8] and Scrabble[9], and weak amateur level play in Go[10].

Monte Carlo tree search (MCTS)[11,12] uses Monte Carlo rollouts to estimate the value of each state in a search tree. As more simulations are executed, the search tree grows larger and the relevant values become more accurate. The policy used to select actions during

policies[13–15] or value functions[16] based on a linear combination of input features.

Recently, deep convolutional neural networks have achieved unprecedented performance in visual domains: for example, image classification[17], face recognition[18], and playing Atari games[19]. They use many layers of neurons, each arranged in overlapping tiles, to construct increasingly abstract, localized representations of an image[20]. We employ a similar architecture for the game of Go. We pass in the board position as a 19×19 image and use convolutional layers to construct a representation of the position. We use these neural networks to reduce the effective depth and breadth of the search tree: evaluating positions using a value network, and sampling actions using a policy network.

We train the neural networks using a pipeline consisting of several stages of machine learning (Fig. 1). We begin by training a supervised learning (SL) policy network p_σ directly from expert human moves. This provides fast, efficient learning updates with immediate feedback and high-quality gradients. Similar to prior work[13,15], we also train a fast policy p_π that can rapidly sample actions during rollouts. Next, we train a reinforcement learning (RL) policy network p_ρ that improves the SL policy network by optimizing the final outcome of games of self-play. This adjusts the policy towards the correct goal of winning games, rather than maximizing predictive accuracy. Finally, we train a value network v_θ that predicts the winner of games played by the RL policy network against itself. Our program AlphaGo efficiently combines the policy and value networks with MCTS.

ARTICLE

doi:10.1038/nature24270

Mastering the game of Go without human knowledge

David Silver[1]*, Julian Schrittwieser[1]*, Karen Simonyan[1]*, Ioannis Antonoglou[1], Aja Huang[1], Arthur Guez[1], Thomas Hubert[1], Lucas Baker[1], Matthew Lai[1], Adrian Bolton[1], Yutian Chen[1], Timothy Lillicrap[1], Fan Hui[1], Laurent Sifre[1], George van den Driessche[1], Thore Graepel[1] & Demis Hassabis[1]

A long-standing goal of artificial intelligence is an algorithm that learns, *tabula rasa*, superhuman proficiency in challenging domains. Recently, AlphaGo became the first program to defeat a world champion in the game of Go. The tree search in AlphaGo evaluated positions and selected moves using deep neural networks. These neural networks were trained by supervised learning from human expert moves, and by reinforcement learning from self-play. Here we introduce an algorithm based solely on reinforcement learning, without human data, guidance or domain knowledge beyond game rules. AlphaGo becomes its own teacher: a neural network is trained to predict AlphaGo's own move selections and also the winner of AlphaGo's games. This neural network improves the strength of the tree search, resulting in higher quality move selection and stronger self-play in the next iteration. Starting *tabula rasa*, our new program AlphaGo Zero achieved superhuman performance, winning 100–0 against the previously published, champion-defeating AlphaGo.

Much progress towards artificial intelligence has been made using supervised learning systems that are trained to replicate the decisions of human experts[1–4]. However, expert data sets are often expensive, unreliable or simply unavailable. Even when reliable data sets are available, they may impose a ceiling on the performance of systems trained in this manner[5]. By contrast, reinforcement learning systems are trained from their own experience, in principle allowing them to exceed human capabilities, and to operate in domains where human expertise is lacking. Recently, there has been rapid progress towards this goal, using deep neural networks trained by reinforcement learning. These systems have outperformed humans in computer games, such as Atari[6,7] and 3D virtual environments[8–10]. However, the most challenging domains in terms of human intellect—such as the game of Go, widely viewed as a grand challenge for artificial intelligence[11]—require a precise and sophisticated lookahead in vast search spaces. Fully general methods have not previously achieved human-level performance in these domains.

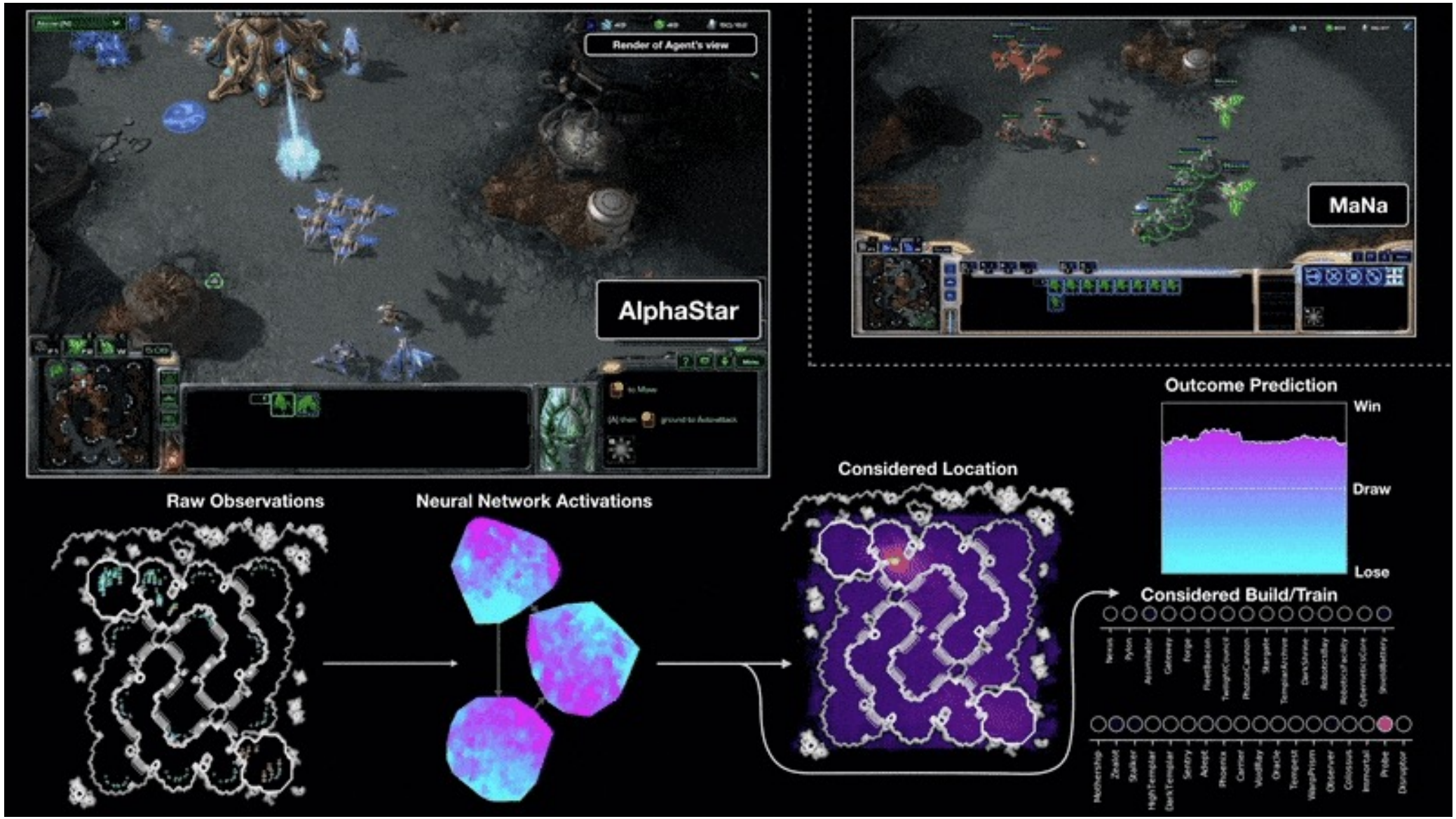
AlphaGo was the first program to achieve superhuman performance in Go. The published version[12], which we refer to as AlphaGo Fan, defeated the European champion Fan Hui in October 2015. AlphaGo Fan used two deep neural networks: a policy network that outputs move probabilities and a value network that outputs a position eval-

trained solely by self-play reinforcement learning, starting from random play, without any supervision or use of human data. Second, it uses only the black and white stones from the board as input features. Third, it uses a single neural network, rather than separate policy and value networks. Finally, it uses a simpler tree search that relies upon this single neural network to evaluate positions and sample moves, without performing any Monte Carlo rollouts. To achieve these results, we introduce a new reinforcement learning algorithm that incorporates lookahead search inside the training loop, resulting in rapid improvement and precise and stable learning. Further technical differences in the search algorithm, training procedure and network architecture are described in Methods.

Reinforcement learning in AlphaGo Zero

Our new method uses a deep neural network f_θ with parameters θ. This neural network takes as an input the raw board representation s of the position and its history, and outputs both move probabilities and a value, $(\boldsymbol{p}, v) = f_\theta(s)$. The vector of move probabilities $\boldsymbol{p}$ represents the probability of selecting each move a (including pass), $p_a = \Pr(a|s)$. The value v is a scalar evaluation, estimating the probability of the current player winning from position s. This neural network combines the roles of both policy network and value network[12] into a single architecture.

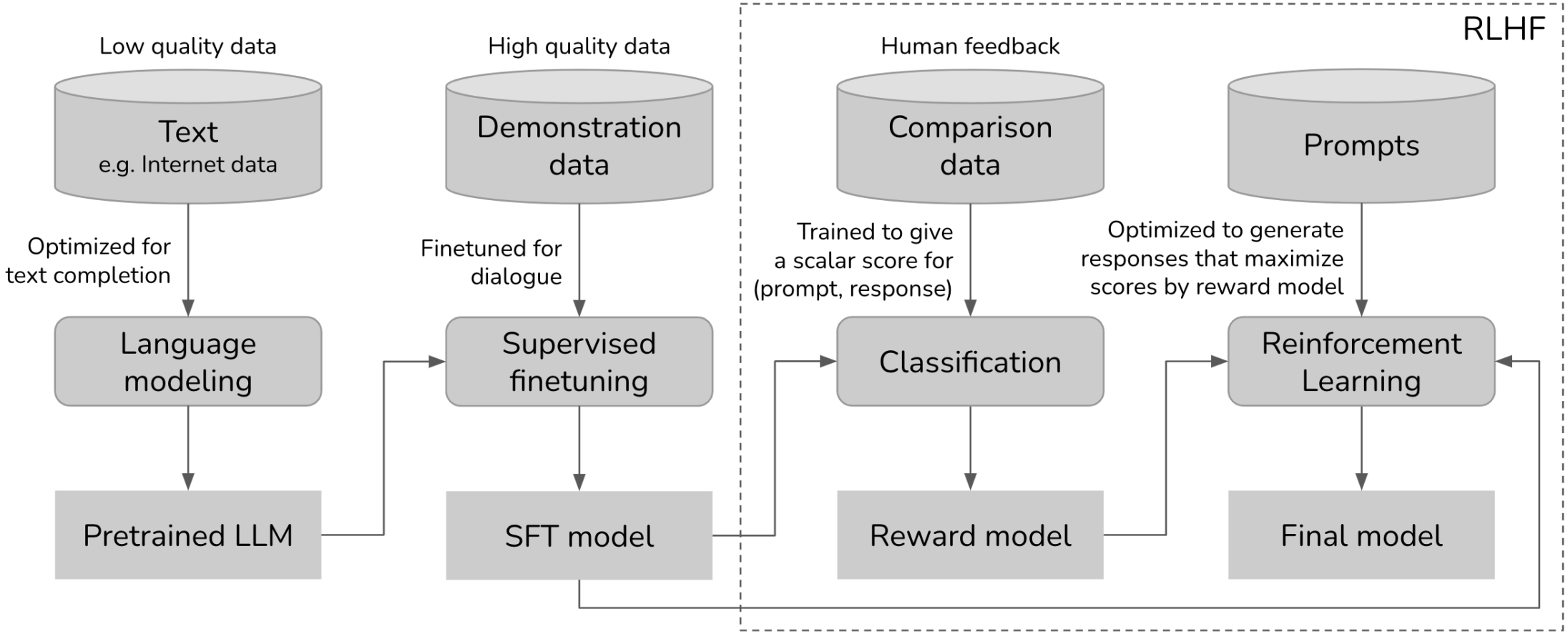
挑战星际争霸：AlphaStar (2019)



https://deepmind.google/blog/alphastar-mastering-the-real-time-strategy-game-starcraft-ii/

大模型时代的强化学习 - 2022

ChatGPT训练的三阶段：**预训练(Pre-Train)、有监督微调(Supervised Fine-Tuning)、基于人类反馈的强化学习(Reinforcement Learning from Human Feedback)**



DeepSeek-R1 (2025)

deepseek

DeepSeek-R1: Incentivizing Reasoning Capability in LLMs via Reinforcement Learning

DeepSeek-AI

research@deepseek.com

Abstract

General reasoning represents a long-standing and formidable challenge in artificial intelligence. Recent breakthroughs, exemplified by large language models (LLMs) (Brown et al., 2020; OpenAI, 2023) and chain-of-thought prompting (Wei et al., 2022b), have achieved considerable success on foundational reasoning tasks. However, this success is heavily contingent upon extensive human-annotated demonstrations, and models' capabilities are still insufficient for more complex problems. Here we show that the reasoning abilities of LLMs can be incentivized through pure reinforcement learning (RL), obviating the need for human-labeled reasoning trajectories. The proposed RL framework facilitates the emergent development of advanced reasoning patterns, such as self-reflection, verification, and dynamic strategy adaptation. Consequently, the trained model achieves superior performance on verifiable tasks such as mathematics, coding competitions, and STEM fields, surpassing its counterparts trained via conventional supervised learning on human demonstrations. Moreover, the emergent reasoning patterns exhibited by these large-scale models can be systematically harnessed to guide and enhance the reasoning capabilities of smaller models.

https://arxiv.org/abs/2501.12948

Article

DeepSeek-R1 incentivizes reasoning in LLMs through reinforcement learning

https://doi.org/10.1038/s41586-025-09422-z

Received: 14 February 2025

Accepted: 17 July 2025

Published online: 17 September 2025

Open access

Check for updates

General reasoning represents a long-standing and formidable challenge in artificial intelligence (AI). Recent breakthroughs, exemplified by large language models (LLMs)[1,2] and chain-of-thought (CoT) prompting[3], have achieved considerable success on foundational reasoning tasks. However, this success is heavily contingent on extensive human-annotated demonstrations and the capabilities of models are still insufficient for more complex problems. Here we show that the reasoning abilities of LLMs can be incentivized through pure reinforcement learning (RL), obviating the need for human-labelled reasoning trajectories. The proposed RL framework facilitates the emergent development of advanced reasoning patterns, such as self-reflection, verification and dynamic strategy adaptation. Consequently, the trained model achieves superior performance on verifiable tasks such as mathematics, coding competitions and STEM fields, surpassing its counterparts trained through conventional supervised learning on human demonstrations. Moreover, the emergent reasoning patterns exhibited by these large-scale models can be systematically used to guide and enhance the reasoning capabilities of smaller models.

Reasoning capability, the cornerstone of human intelligence, enables complex cognitive tasks ranging from mathematical problem-solving to logical deduction and programming. Recent advances in AI have demonstrated that LLMs can exhibit emergent behaviours, including reasoning abilities, when scaled to a sufficient size[4,5]. However, achieving such capabilities in pre-training typically demands substantial computational resources. In parallel, a complementary line of research has demonstrated that LLMs can be effectively augmented through CoT prompting. This technique, which involves either providing carefully designed few-shot examples or using minimalistic prompts such as "Let's think step by step"[3,6], enables models to produce intermediate reasoning steps, thereby substantially enhancing their performance on complex tasks. Similarly, further performance gains have been observed when models learn high-quality, multistep reasoning trajectories during the post-training phase[2,7]. Despite their effectiveness, these approaches exhibit notable limitations. Their dependence on human-annotated reasoning traces slows scalability and introduces cognitive biases. Furthermore, by constraining models to replicate human thought processes, their performance is inherently capped by the human-provided exemplars, which prevents the exploration of superior, non-human-like reasoning pathways.

To tackle these issues, we aim to explore the potential of LLMs for developing reasoning abilities through self-evolution in a RL framework, with minimal reliance on human labelling efforts. Specifically, we build on DeepSeek-V3 Base[8] and use Group Relative Policy Optimization (GRPO)[9] as our RL framework. The reward signal is only based on the correctness of final predictions against ground-truth answers, without imposing constraints on the reasoning process itself. Notably, we bypass the conventional supervised fine-tuning (SFT) phase before RL training. This design choice originates from our hypothesis that human-defined reasoning patterns may limit model exploration, whereas unrestricted RL training can better incentivize the emergence of new reasoning capabilities in LLMs. Through this process, detailed in the next section, our model (referred to as DeepSeek-R1-Zero) naturally developed diverse and sophisticated reasoning behaviours. To solve reasoning problems, the model exhibits a tendency to generate longer responses, incorporating verification, reflection and the exploration of alternative approaches within each response. Although we do not explicitly teach the model how to reason, it successfully learns improved reasoning strategies through RL.

Although DeepSeek-R1-Zero demonstrates excellent reasoning capabilities, it faces challenges such as poor readability and language mixing, occasionally combining English and Chinese in a single CoT response. Furthermore, the rule-based RL training stage of DeepSeek-R1-Zero is narrowly focused on reasoning tasks, resulting in limited performance in broader areas such as writing and open-domain question answering. To address these challenges, we introduce DeepSeek-R1, a model trained through a multistage learning framework that integrates rejection sampling, RL and supervised fine-tuning, detailed in the 'DeepSeek-R1' section. This training pipeline enables DeepSeek-R1 to inherit the reasoning capabilities of its predecessor, DeepSeek-R1-Zero, while aligning model behaviour with human preferences through further non-reasoning data.

To enable broader access to powerful AI at a lower energy cost, we have distilled several smaller models and made them publicly available. These distilled models exhibit strong reasoning capabilities, surpassing the performance of their original instruction-tuned counterparts. We believe that these instruction-tuned versions will also greatly contribute to the research community by providing a valuable resource for understanding the mechanisms underlying long CoT reasoning models and for promoting the development of more powerful reasoning models. We release DeepSeek-R1-Zero, DeepSeek-R1, data samples and distilled models to the public as described in the 'Code availability' section.

A list of authors and their affiliations appears at the end of the paper.

Agentic RL (2026)

The Landscape of Agentic Reinforcement Learning for LLMs: A Survey

Guibin Zhang[3†] Hejia Geng[1†] Xiaohang Yu[8†] Zhenfei Yin[1*] Zaibin Zhang[9,1]
Zelin Tan[7,2] Heng Zhou[7,2] Zhongzhi Li[10] Xiangyuan Xue[11,2] Yijiang Li[13]
Yifan Zhou[12] Yang Chen[2] Chen Zhang[7] Yutao Fan[2] Zihu Wang[14] Songtao Huang[6,2]
Piedrahita-Velez, Francisco[5] Yue Liao[3] Hongru Wang[11] Mengyue Yang[15]
Heng Ji[4] Jun Wang[6] Shuicheng Yan[3] Philip Torr[1] Lei Bai[2*]

[1]University of Oxford [2]Shanghai AI Laboratory [3]National University of Singapore
[4]University of Illinois Urbana-Champaign [5]Brown University [6]University College London
[7]University of Science and Technology of China [8]Imperial College London
[9]Dalian University of Technology [10]Chinese Academy of Sciences
[11]The Chinese University of Hong Kong [12]University of Georgia
[13]University of California, San Diego [14]University of California, Santa Barbara
[15]University of Bristol

† *Equal contribution,* * *Corresponding Author*

https://arxiv.org/pdf/2509.02547

关于大模型与强化学习的讨论与观点

Richard Sutton “The Bitter Lesson”

在人工智能的历史长河中，唯一被证明持续有效的方法，是利用无尽的计算力(Computation)进行通用的搜索(Search)和学习(Learning)，而不是依赖人类手工编码的领域知识(Domain Knowledge)

- 正面：大模型充分利用了人类的数据与算力进行学习
- 反面：语言本身是人类符号化的知识，动物智能并不依赖语言

关于大模型与强化学习的讨论与观点

【 Dwarkesh Patel播客 】强化学习之父 Richard Sutton， 大模型...

https://www.bilibili.com/video/BV1z4HczgE1m/?share_source=copy_web&vd_source=b19e968ea4fbdf0cb9dfd7fbc468280e

大家说 LLM很厉害，能写code、拿IMO/IOI金牌。

Richard Sutton的回答是：如果你觉得这很难，那你就这么觉得吧，我不这么觉得。我觉得**打造出一只松鼠的智能，才是真正难的问题**。一旦你能build松鼠的智能，让它在真实世界活下去，有自己的goal、有intrinsic reward、知道饥饿、有emotion和社群活动，那么写代码、上月球这些事都是再容易不过的。

如果抛下人类的自大，打造松鼠的智能其实是一个更难的问题。人类的智能不只是语言模型，有很多智能不能通过语言本身所决定。

站在宇宙和造物主的视角，重新造出一只松鼠，要比人类文明在5.3亿年进化史最后8秒创造的东西要伟大得多。

关于大模型与强化学习的讨论与观点

DeepMind强化学习掌门人David Silver离职创业！Alpha系列AI缔造者，哈萨比斯左膀右臂

关注前沿科技 量子位 2026年1月31日 09:34 北京 48人

https://www.bilibili.com/video/BV19SdiY6EsG/?share_source=copy_web&vd_source=b19e968ea4fbdf0cb9dfd7fbc468280e

要做“能永无止境学习”的超级智能

Silver为什么要出来单干?

据知情人士透露，他的动机是希望回归“解决AI领域最难题所带来的敬畏与奇迹”，并将超级智能视为当前最大的未解挑战。

> 构建一个能够自我发现所有知识基础、永无止境学习的超级智能。

他倡导AI进入一个全新的“经验时代”（Age of Experience），即AI系统通过强化学习从经验中自我学习，从而发现人类未知的新事物。

这一理念的经典例证，就是2016年AlphaGo与李世石比赛中著名的第37手棋，当时所有人类专家都认为这一步是失误，但事后证明它是AlphaGo获胜的关键。

Silver认为，要实现真正的超级智能，AI必须摆脱对人类知识和直觉的依赖，从第一性原理出发进行学习。

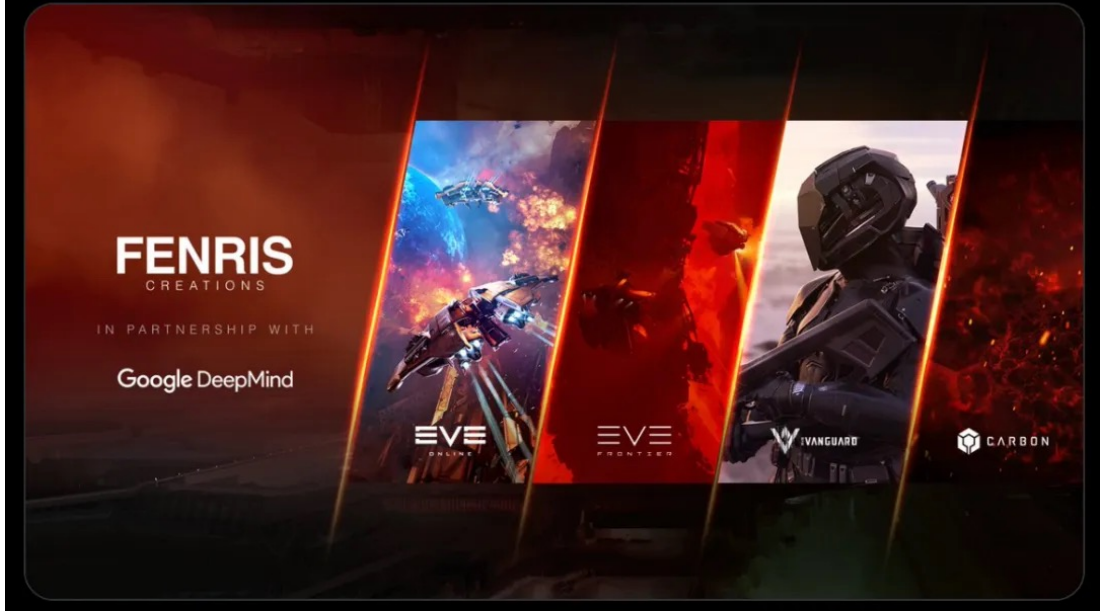
关于大模型与强化学习的讨论与观点

Demis Hassabis
@demishassabis

翻译自 英语 显示原文

我一直对游戏充满热情，它们在 @GoogleDeepMind 的历史中扮演了重要角色，作为 AI 的完美试验场。很高兴宣布与 @FenrisCreations 的这项研究合作——@EveOnline 是有史以来最非凡的游戏之一，拥有一个了不起的社区。非常期待与 @HilmarVeigar 和团队合作！

评价此翻译：



上午6:03 · 2026年5月7日 · **4.2万** 查看

FC Hellmar
@HilmarVeigar

Very excited to be working with @demishassabis and crew at @GoogleDeepMind as @FenrisCreations

In the progression of Atari DQN, AlphaGo, AlphaStar... then obviously @EveOnline is the final boss. It is multi-agent at scale, mixed-motive, persistent, imperfect information, real-time, and a metagame that bleeds.

But most importantly it has EVE Players, a hivemind of human cunning annealed by 23 years of drama into a collective intelligence. It does not lose 🧠

非常激动能与 @demishassabis 及其团队在 @GoogleDeepMind 合作，作为 @FenrisCreations

在 Atari DQN、AlphaGo、AlphaStar...的发展过程中， @EveOnline 显然是最终 BOSS。它具有多智能体、大规模、混合动机、持续性、信息不完整、实时性以及一个不断蔓延的元游戏。

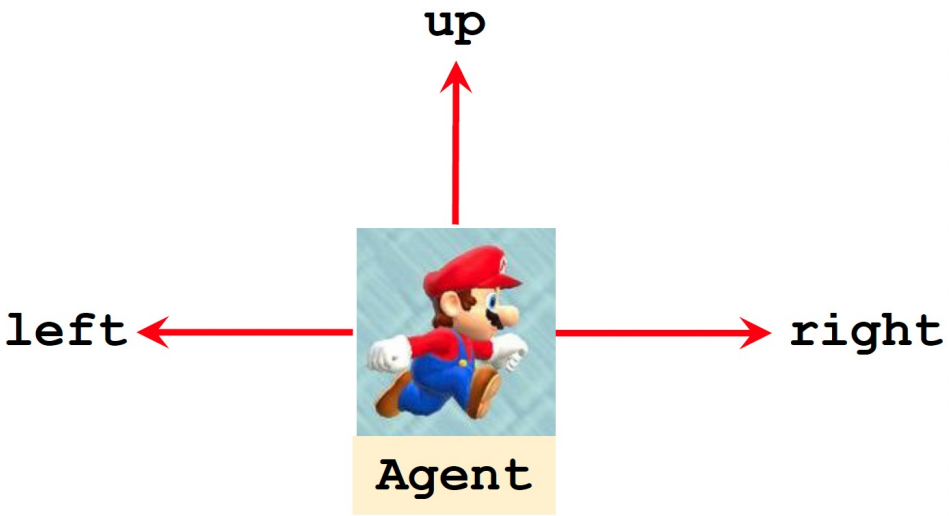
但最重要的是它有 EVE 玩家，一个由 23 年的戏剧磨练出的人类狡猾的集体智能。它不会输 🧠

强化学习的形式化定义

强化学习的关键要素

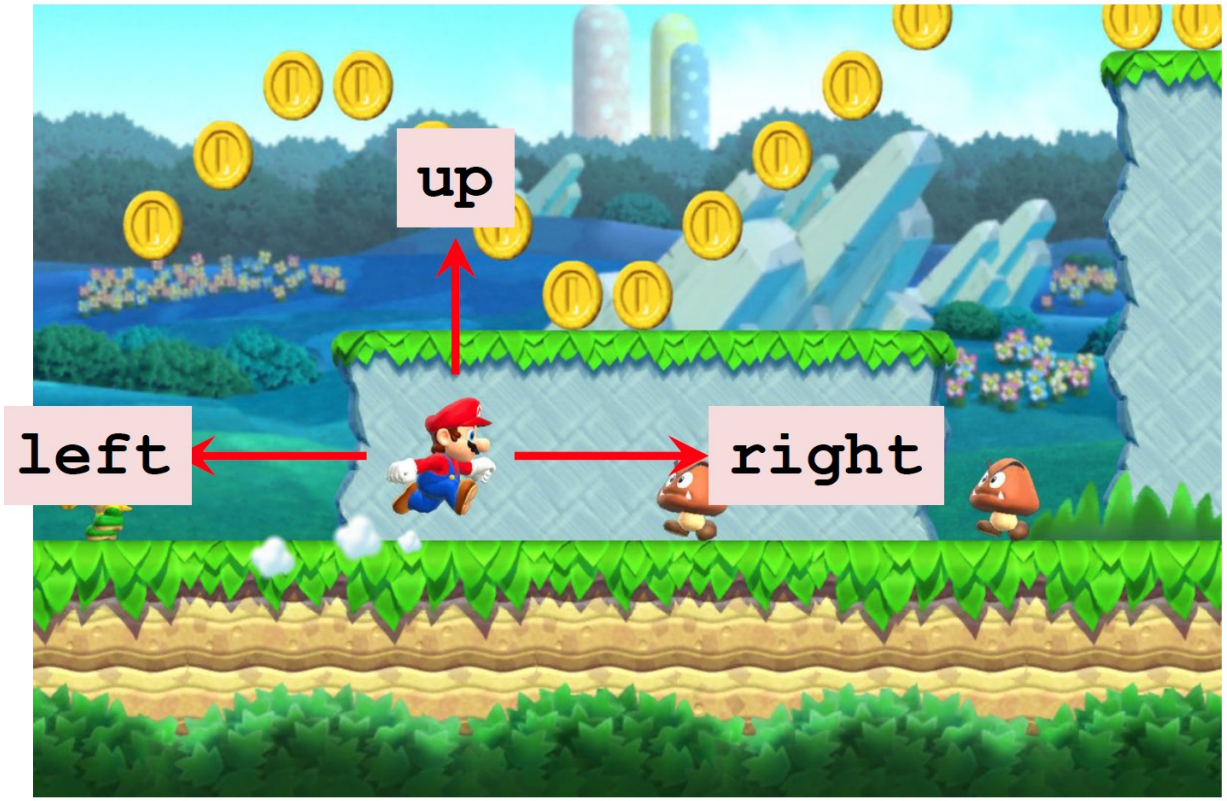
- 状态(State)：$s \in S$ 是对当前环境的描述
  - 围棋任务中，当前的局面
  - 超级马里奥中，当前的游戏画面
  - 网格世界中，当前的位置和状态
  - …

- 动作(Action)：$a \in A$对智能体采取的行动
  - 围棋任务中，选择一个位置落子
  - 超级马里奥中，向左、向右、向上
  - 网格世界中，选择一个方向移动
  - …



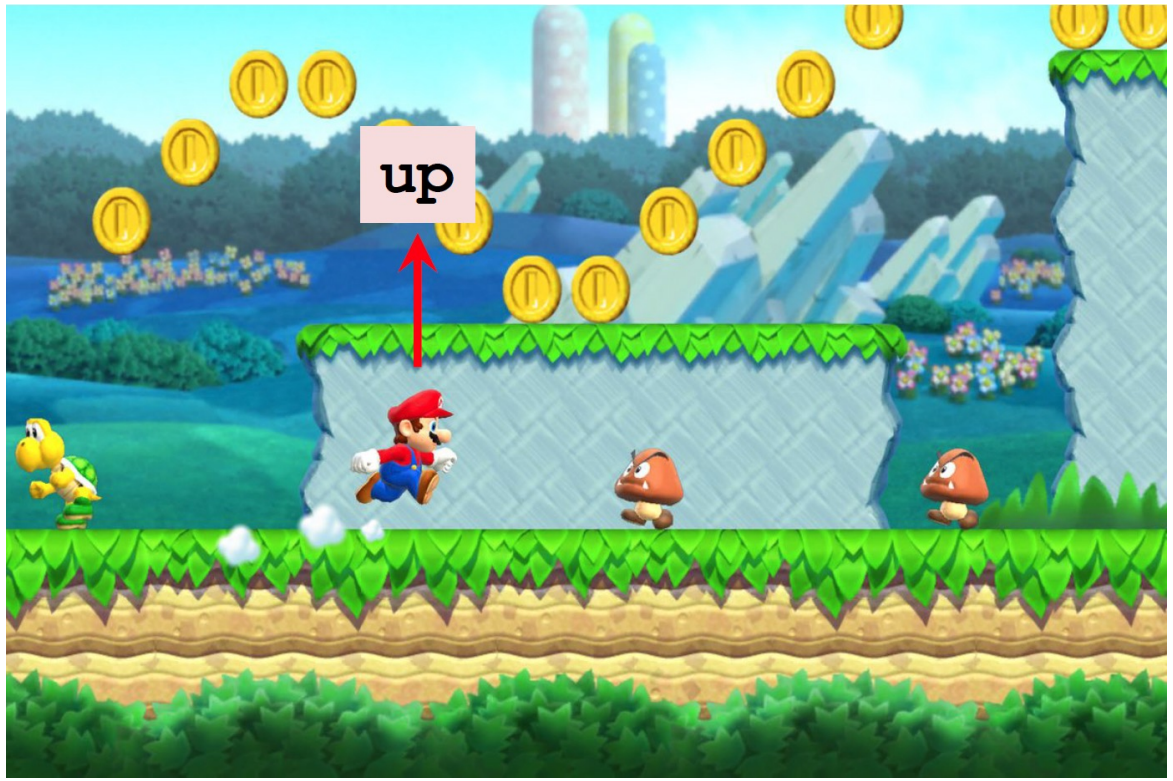
强化学习的关键要素

- 策略(Policy) π：智能体如何根据观察到的状态做决策，即从动作空间中选择一个动作
- **强化学习最终学得的就是一个策略函数**
- 确定性策略：π：$S \to A$
- 随机性策略：π：$S \times A \to \mathbb{R}$



强化学习的关键要素

- 状态转移(state transition)P：$S \times A \times S \to \mathbb{R}$
- 智能体从当前t时刻状态s_t转移到下一个时刻的状态s_{t+1}



强化学习的关键要素

- 状态转移(state transition)P：$S \times A \times S \to \mathbb{R}$
- 智能体从当前t时刻状态s_t转移到下一个时刻的状态s_{t+1}

考虑一般情况：非确定性环境
(Non-Deterministic Environment)

强化学习的关键要素

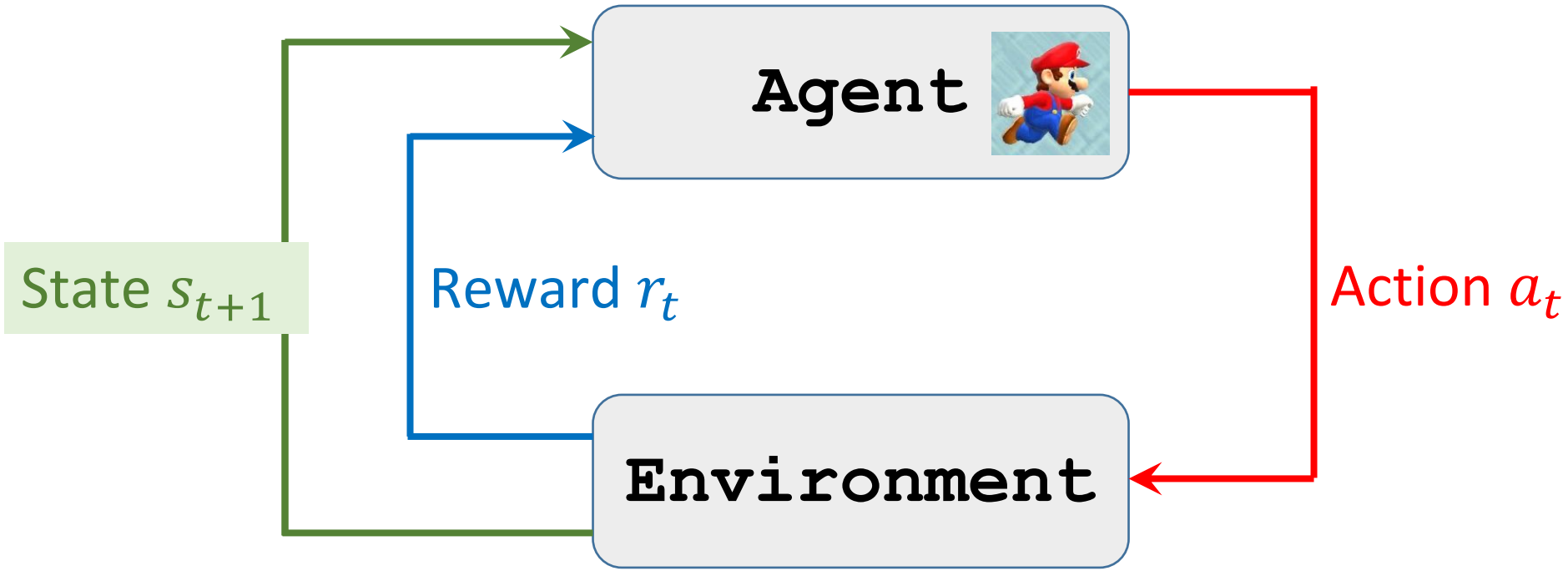
- 奖励(Reward)$R: S \times A \times S \longmapsto \mathbb{R}$ （或$R: S \times S \to \mathbb{R}$)
- 智能体执行一个动作之后，环境返回给智能体一个数值

- 通常需要人来定义

- 奖励函数的好坏影响强化学习的结果

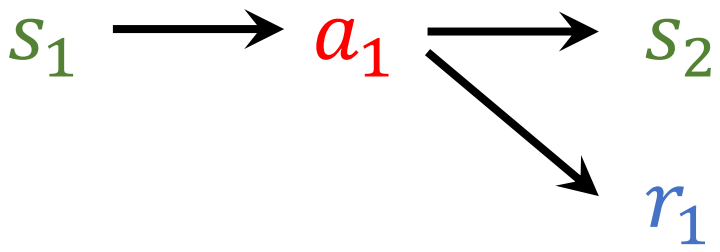
- 收集硬币：R=+1
- 被板栗仔撞到：R=-1000
- 通关：R=+1000
- 无事发生：R=0

强化学习的交互过程



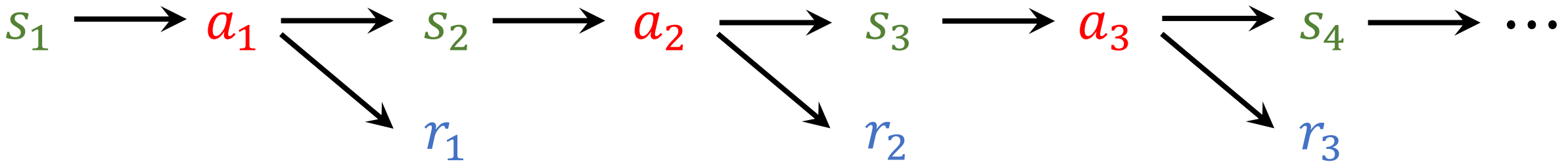
强化学习的交互过程

- 观察到状态s_t，根据策略$\pi(s_t)$选择动作a_t
- 执行动作a_t，状态转移至s_{t+1}，获得奖励r_t



强化学习的交互过程

- 观察到状态s_t，根据策略$\pi(s_t)$选择动作a_t
- 执行动作a_t，状态转移至s_{t+1}，获得奖励r_t



- 轨迹(trajectory)：智能体观测到的所有状态、动作、奖励的序列

$$s_1, a_1, r_1,\ s_2, a_2, r_2,\ \cdots\ ,\ s_n, a_n, r_n$$

什么是好的策略

- 回报(return)：从当前时刻开始到本回合结束的所有奖励总和

$$G_t = R_t + R_{t+1} + R_{t+2} + R_{t+3} + \cdots$$

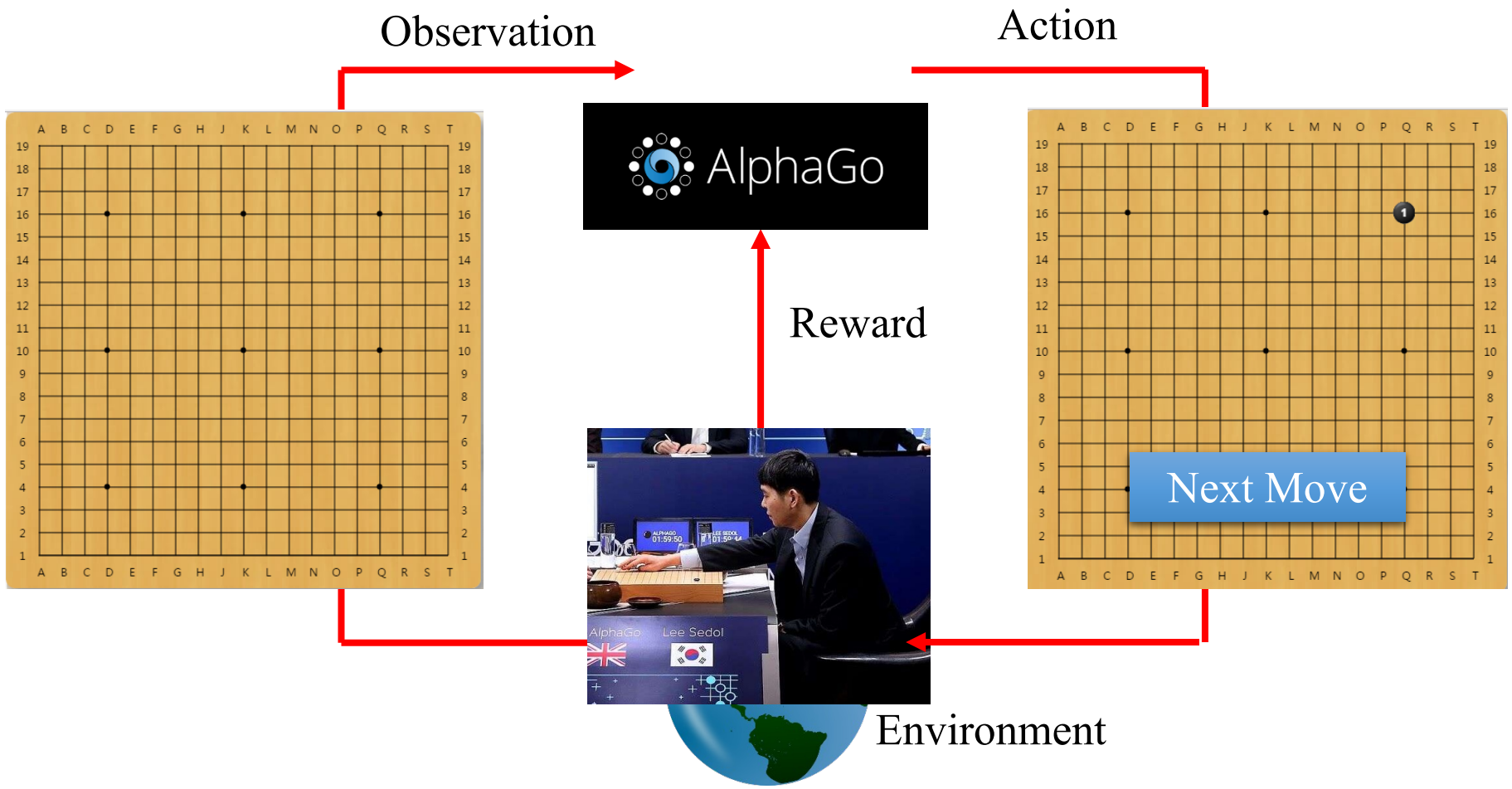
- **强化学习的目标是最大化回报，即累计奖励，而不是最大化当前奖励**（好比下棋的时候目标是赢得比赛，而不是吃掉对方的棋子）

- 通常考虑折扣汇报：$\gamma \in [0,1]$是未来奖励的折扣因子，使得和未来奖励相比起来智能体更重视即时奖励

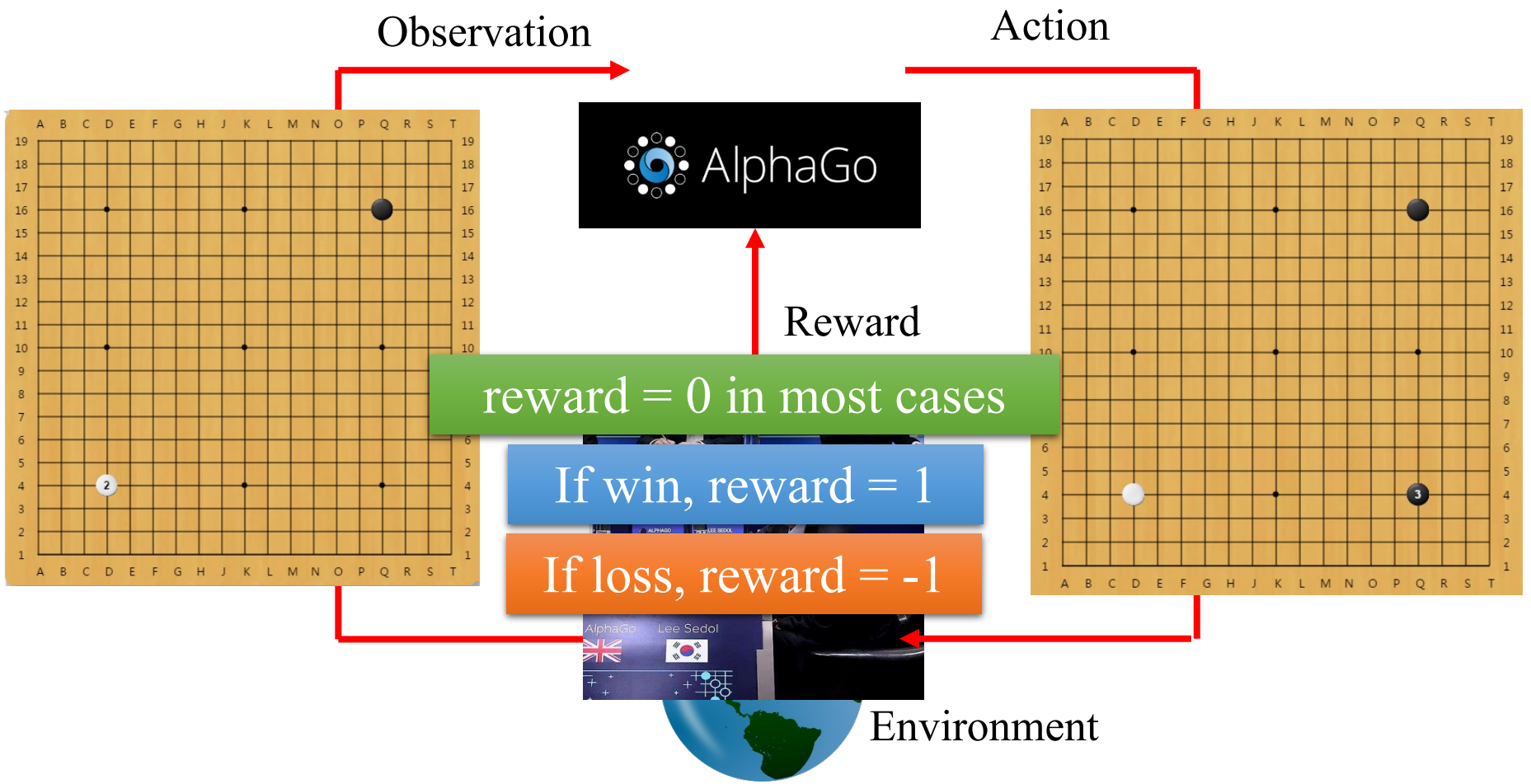
$$G_t = R_t + \gamma\, R_{t+1} + \gamma^2\, R_{t+2} + \gamma^3\, R_{t+3} + \cdots$$

- 以金融为例，今天的$1比明天的$1更有价值

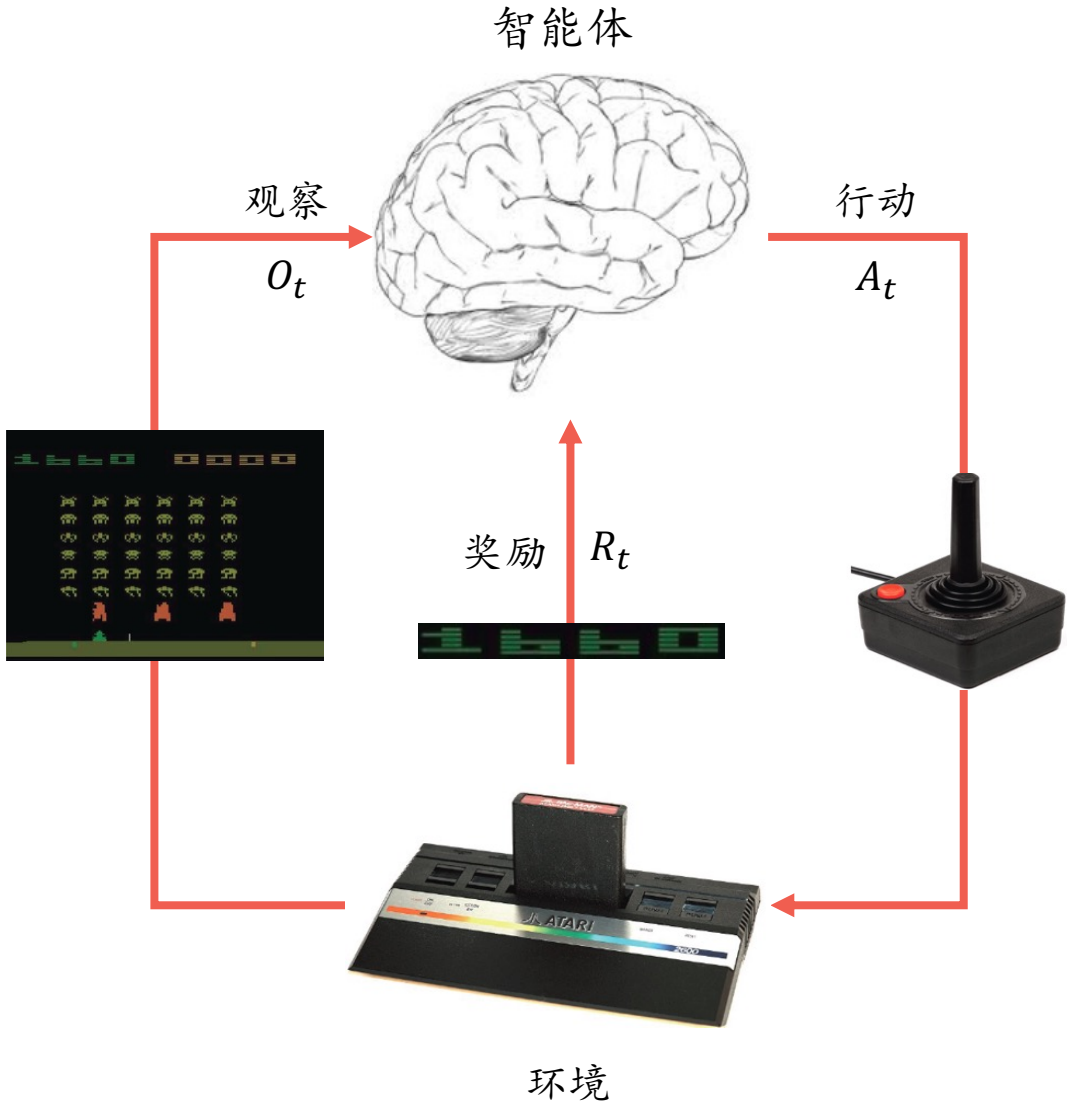
例子：围棋



例子：围棋


Observation
Action
AlphaGo
Reward
reward = 0 in most cases
If win, reward = 1
If loss, reward = -1
Environment

例子：游戏

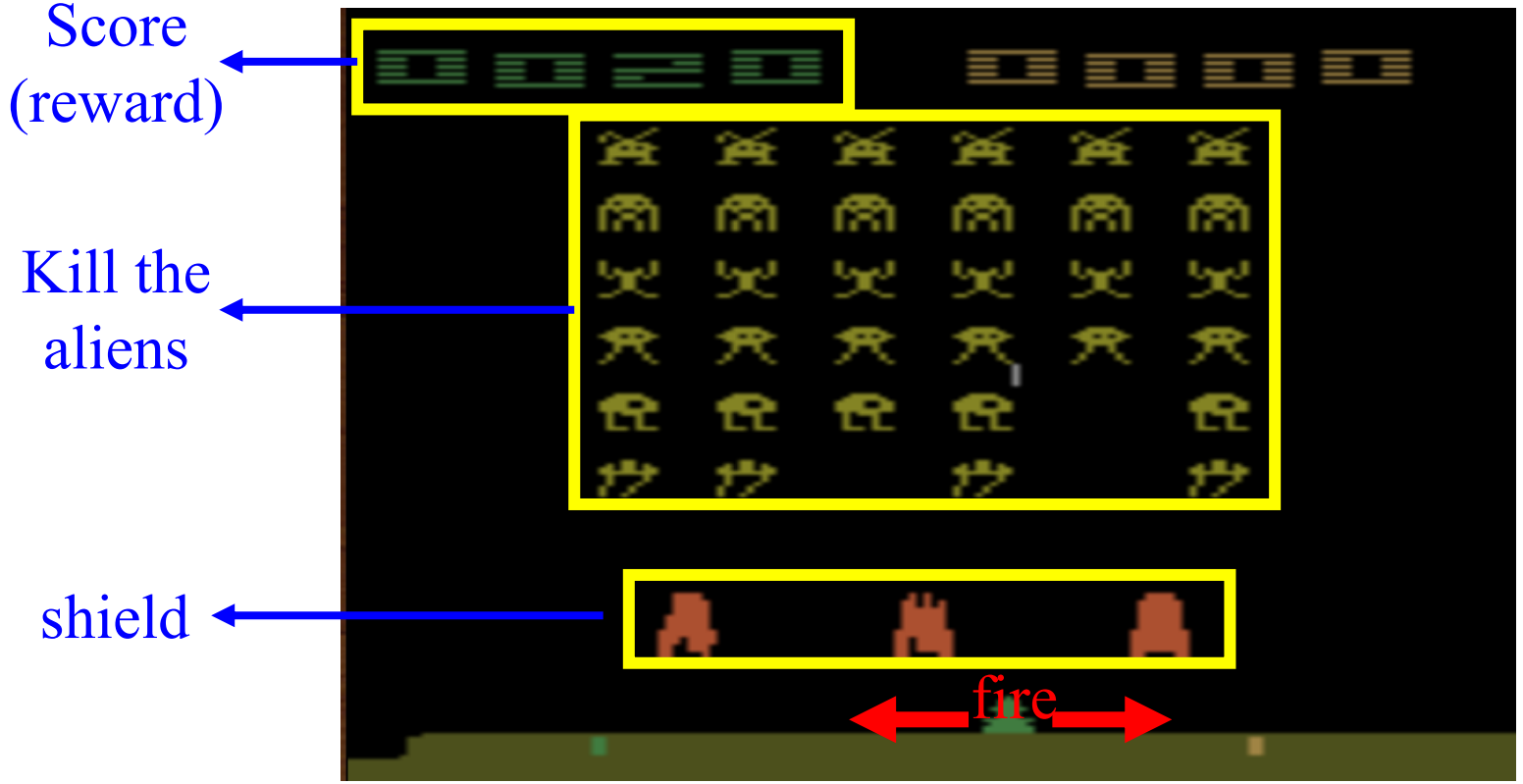


- 从交互游戏中进行学习
- 在操纵杆上选择行动并查看分数和像素画面

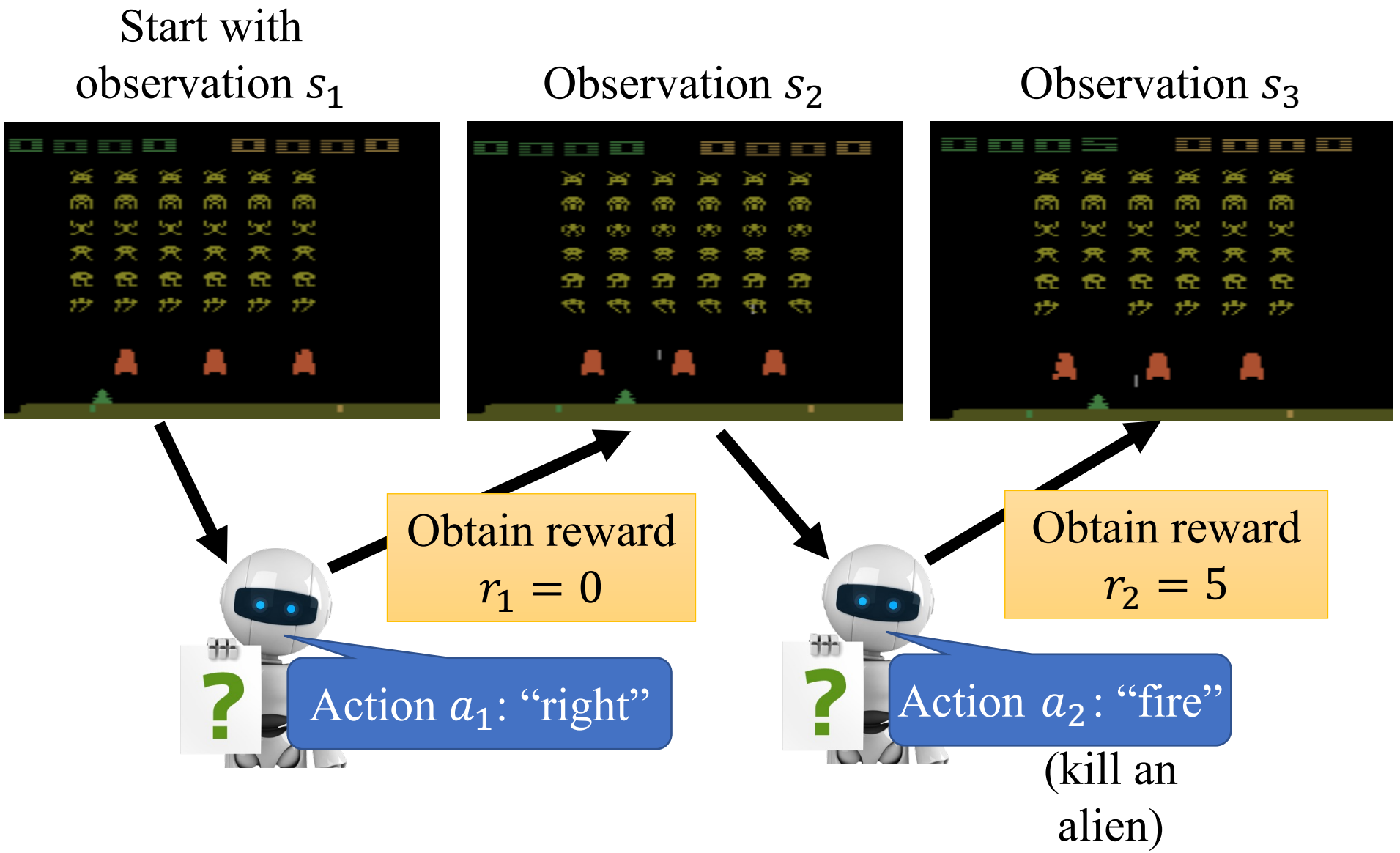
例子：游戏

- Space invader

Termination: all the aliens are killed, or your spaceship is destroyed.



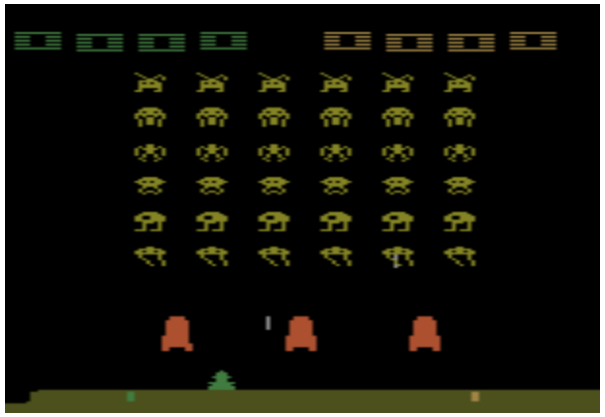
例子：游戏


Start with observation s_1
Observation s_2
Observation s_3
Obtain reward $r_1 = 0$
Action a_1: "right"
Obtain reward $r_2 = 5$
Action a_2: "fire" (kill an alien)

例子：游戏

Start with observation s_1

Observation s_2



Observation s_3

After many turns

This is an ***episode***.

Action a_T

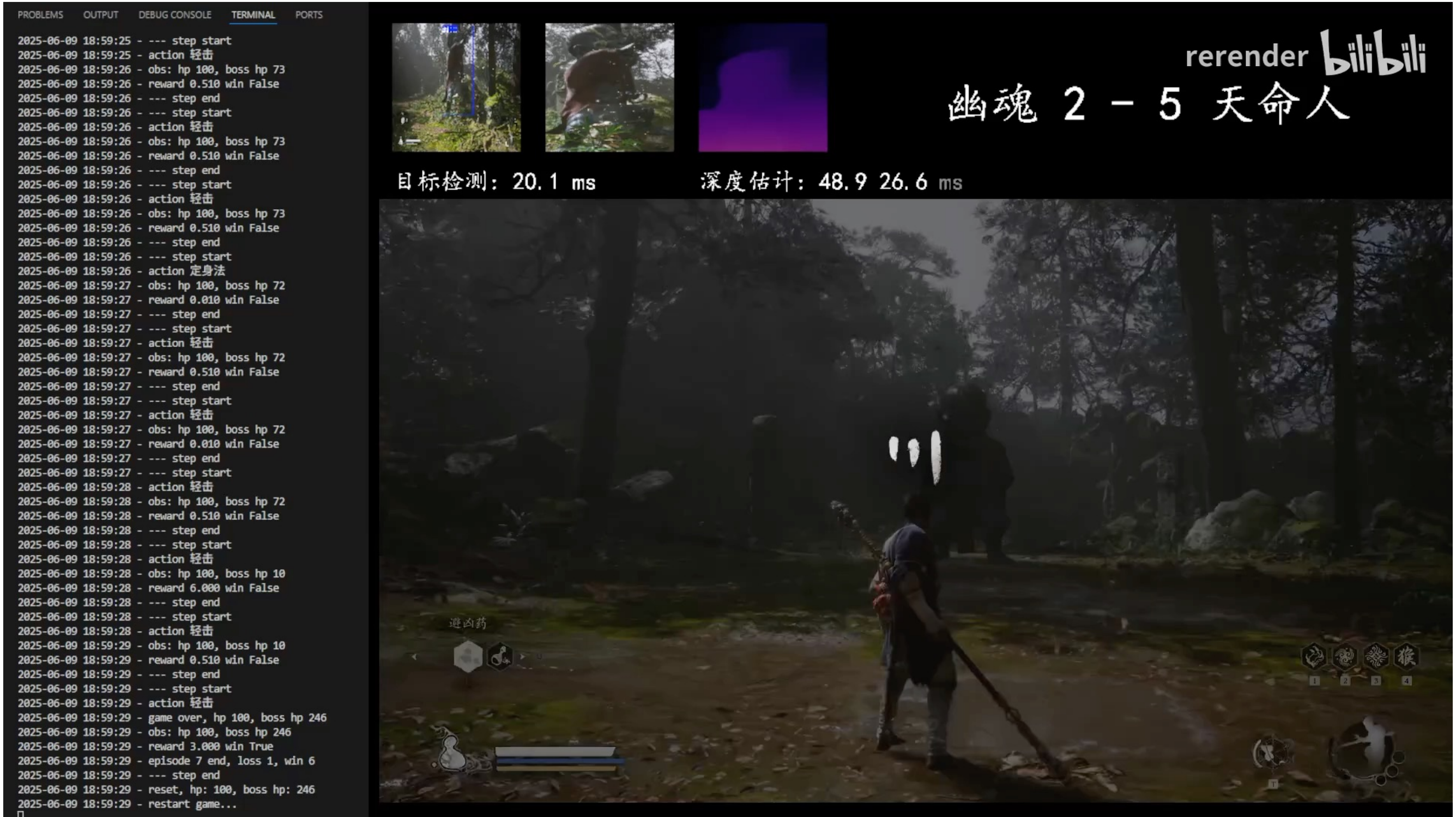
Obtain reward r_T

应用案例：机械臂操作

应用案例：无人驾驶小车

Alex Kendall et.al, Learning to Drive in a Day. ICRA 2019: 8248-8254
https://www.youtube.com/watch?v=eRwTbRtnT1I

应用案例：黑神话



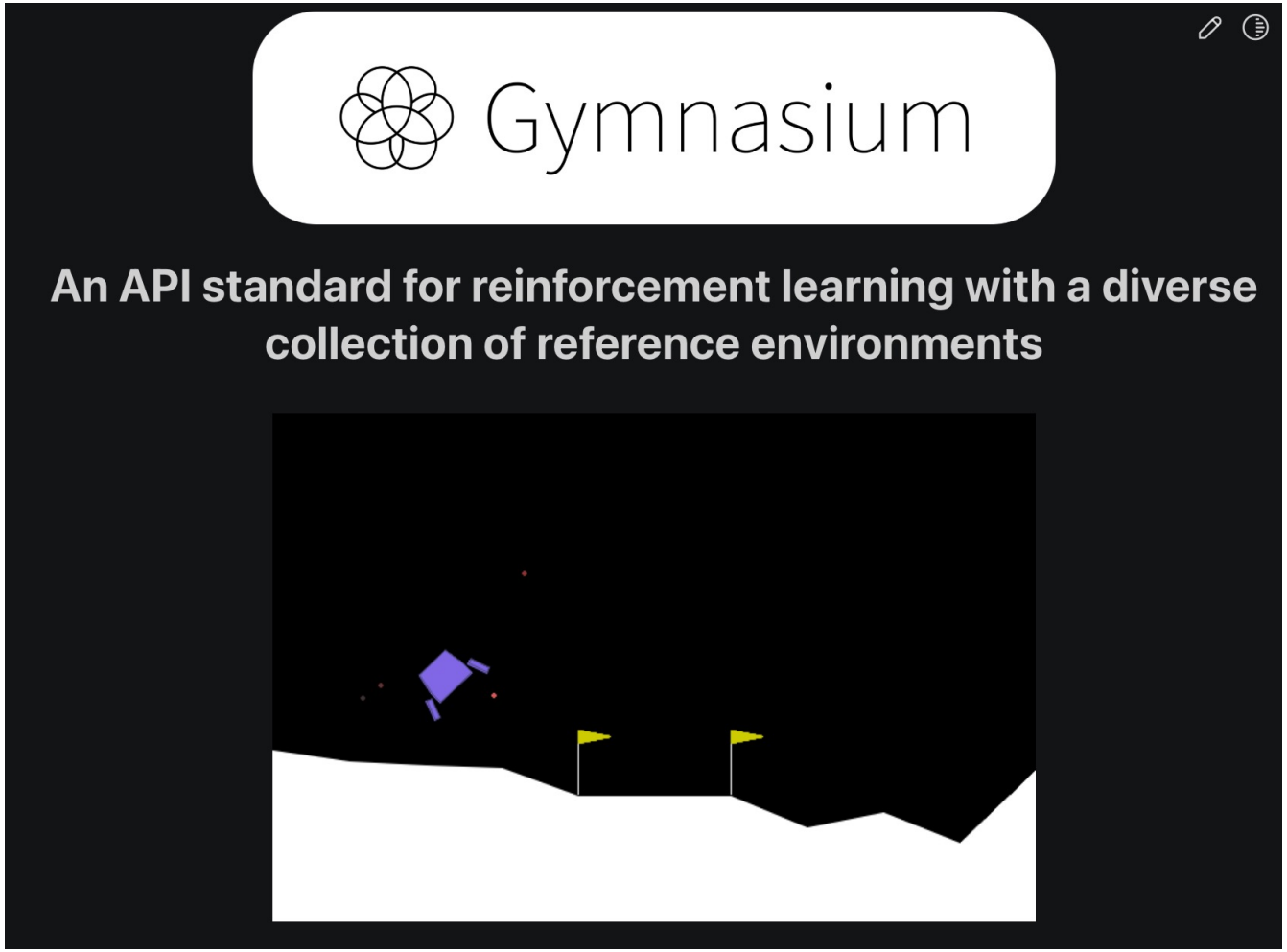
PROBLEMS
OUTPUT
DEBUG CONSOLE
TERMINAL
PORTS
2025-06-09 18:59:25 - --- step start
2025-06-09 18:59:25 - action 轻击
2025-06-09 18:59:26 - obs: hp 100, boss hp 73
2025-06-09 18:59:26 - reward 0.510 win False
2025-06-09 18:59:26 - --- step end
2025-06-09 18:59:26 - --- step start
2025-06-09 18:59:26 - action 轻击
2025-06-09 18:59:26 - obs: hp 100, boss hp 73
2025-06-09 18:59:26 - reward 0.510 win False
2025-06-09 18:59:26 - --- step end
2025-06-09 18:59:26 - --- step start
2025-06-09 18:59:26 - action 轻击
2025-06-09 18:59:26 - obs: hp 100, boss hp 73
2025-06-09 18:59:26 - reward 0.510 win False
2025-06-09 18:59:26 - --- step end
2025-06-09 18:59:26 - --- step start
2025-06-09 18:59:26 - action 定身法
2025-06-09 18:59:27 - obs: hp 100, boss hp 72
2025-06-09 18:59:27 - reward 0.010 win False
2025-06-09 18:59:27 - --- step end
2025-06-09 18:59:27 - --- step start
2025-06-09 18:59:27 - action 轻击
2025-06-09 18:59:27 - obs: hp 100, boss hp 72
2025-06-09 18:59:27 - reward 0.510 win False
2025-06-09 18:59:27 - --- step end
2025-06-09 18:59:27 - --- step start
2025-06-09 18:59:27 - action 轻击
2025-06-09 18:59:27 - obs: hp 100, boss hp 72
2025-06-09 18:59:27 - reward 0.010 win False
2025-06-09 18:59:27 - --- step end
2025-06-09 18:59:27 - --- step start
2025-06-09 18:59:28 - action 轻击
2025-06-09 18:59:28 - obs: hp 100, boss hp 72
2025-06-09 18:59:28 - reward 0.510 win False
2025-06-09 18:59:28 - --- step end
2025-06-09 18:59:28 - --- step start
2025-06-09 18:59:28 - action 轻击
2025-06-09 18:59:28 - obs: hp 100, boss hp 10
2025-06-09 18:59:28 - reward 6.000 win False
2025-06-09 18:59:28 - --- step end
2025-06-09 18:59:28 - --- step start
2025-06-09 18:59:28 - action 轻击
2025-06-09 18:59:29 - obs: hp 100, boss hp 10
2025-06-09 18:59:29 - reward 0.510 win False
2025-06-09 18:59:29 - --- step end
2025-06-09 18:59:29 - --- step start
2025-06-09 18:59:29 - action 轻击
2025-06-09 18:59:29 - game over, hp 100, boss hp 246
2025-06-09 18:59:29 - obs: hp 100, boss hp 246
2025-06-09 18:59:29 - reward 3.000 win True
2025-06-09 18:59:29 - episode 7 end, loss 1, win 6
2025-06-09 18:59:29 - --- step end
2025-06-09 18:59:29 - reset, hp: 100, boss hp: 246
2025-06-09 18:59:29 - restart game...
rerender bilibili
幽魂 2 - 5 天命人
目标检测：20.1 ms
深度估计：48.9 26.6 ms
避凶药

扩展材料

- Sutton’s book:
  - http://incompleteideas.net/sutton/book/the-book.html
- David Silver’s Lecture:
  - https://www.davidsilver.uk/teaching/
- Sergey Levine
  - https://rail.eecs.berkeley.edu/deeprlcourse/
- 动手学强化学习：
  - https://hrl.boyuai.com/chapter/intro

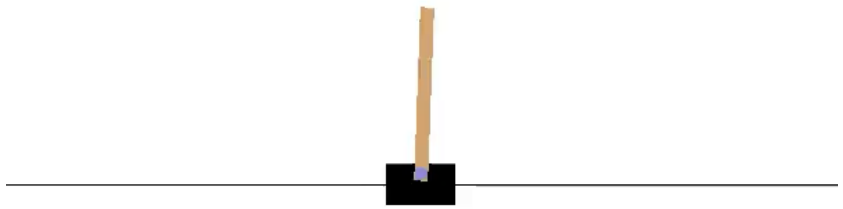
实验平台：OpenAI Gym

https://gymnasium.farama.org/

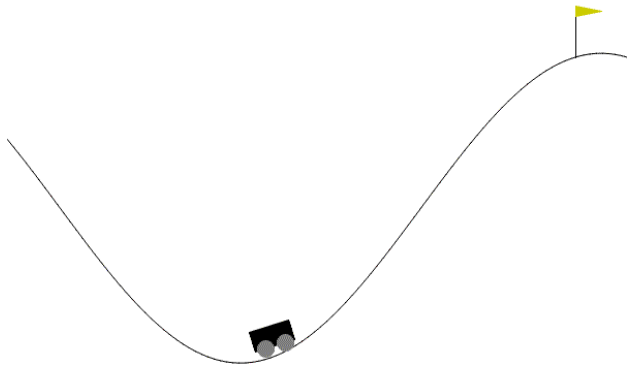


实验平台：OpenAI Gym

经典控制问题



Cart Pole



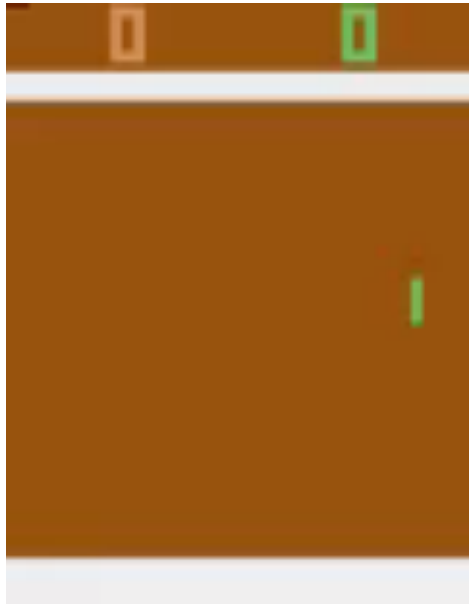
Mountain Car

Num	Observation	Min	Max
0	Cart Position	-4.8	4.8
1	Cart Velocity	-Inf	Inf
2	Pole Angle	~ -0.418 rad (-24°)	~ 0.418 rad (24°)
3	Pole Angular Velocity	-Inf	Inf

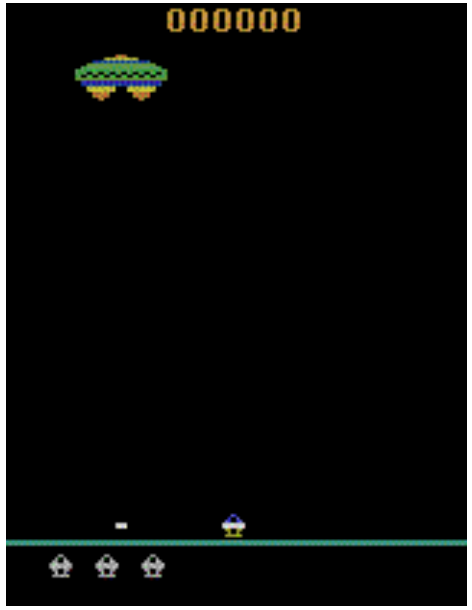
Num	Action
0	Push cart to the left
1	Push cart to the right

实验平台：OpenAI Gym

Atari游戏



Pong



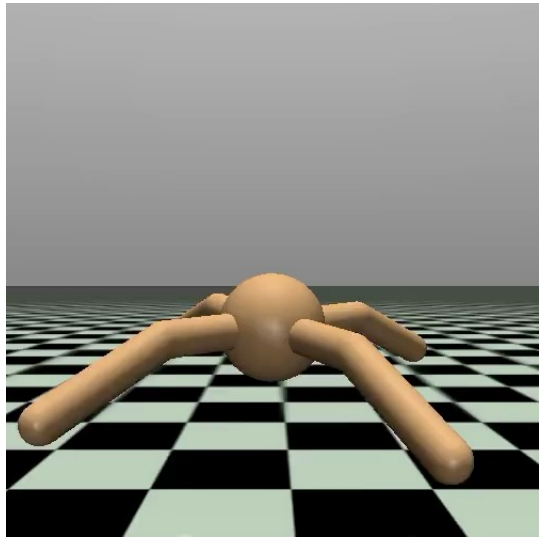
Assault

Space Invader

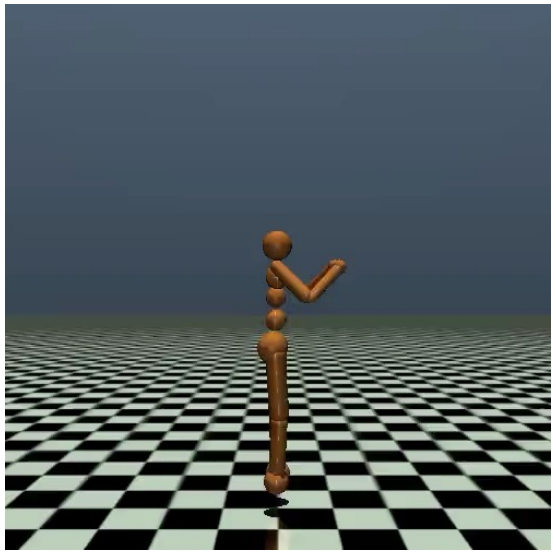
Breakout

实验平台：OpenAI Gym

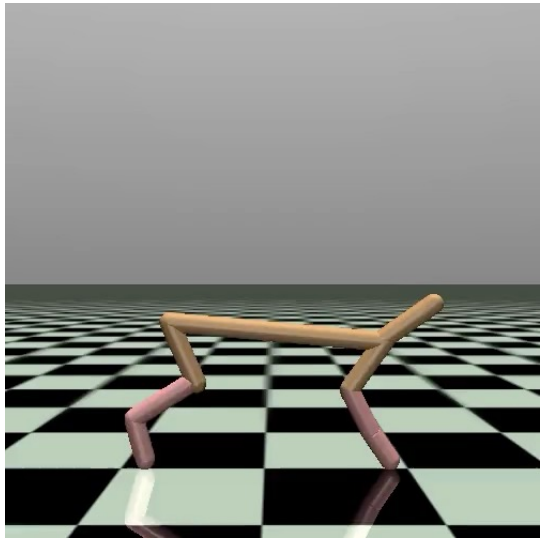
机器人的连续控制问题



Ant

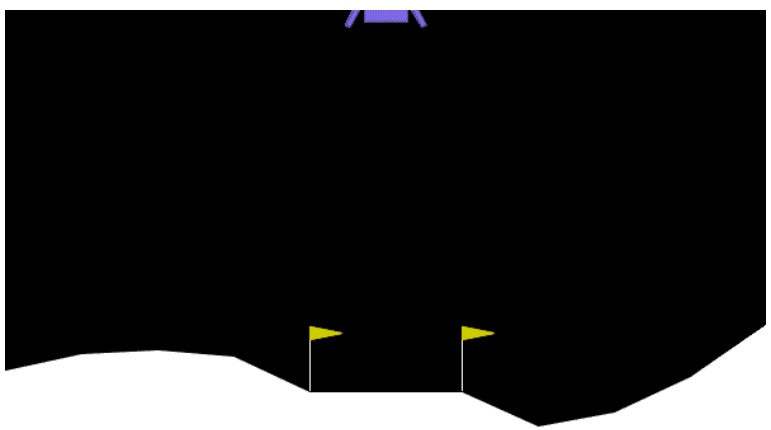


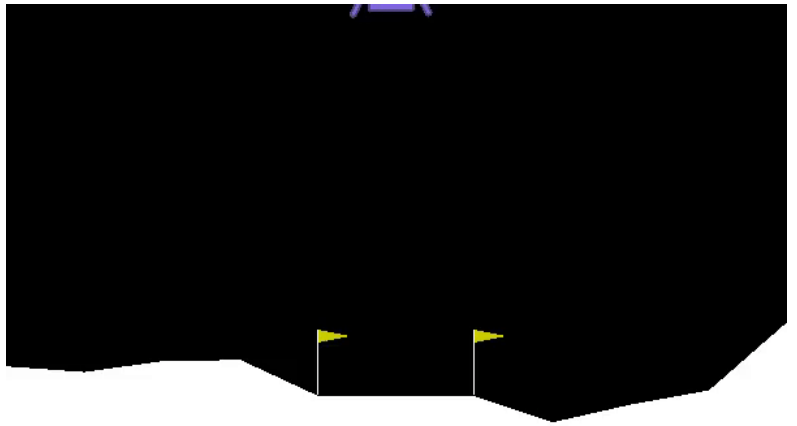
Humanoid



Half Cheetah

实验平台：OpenAI Gym



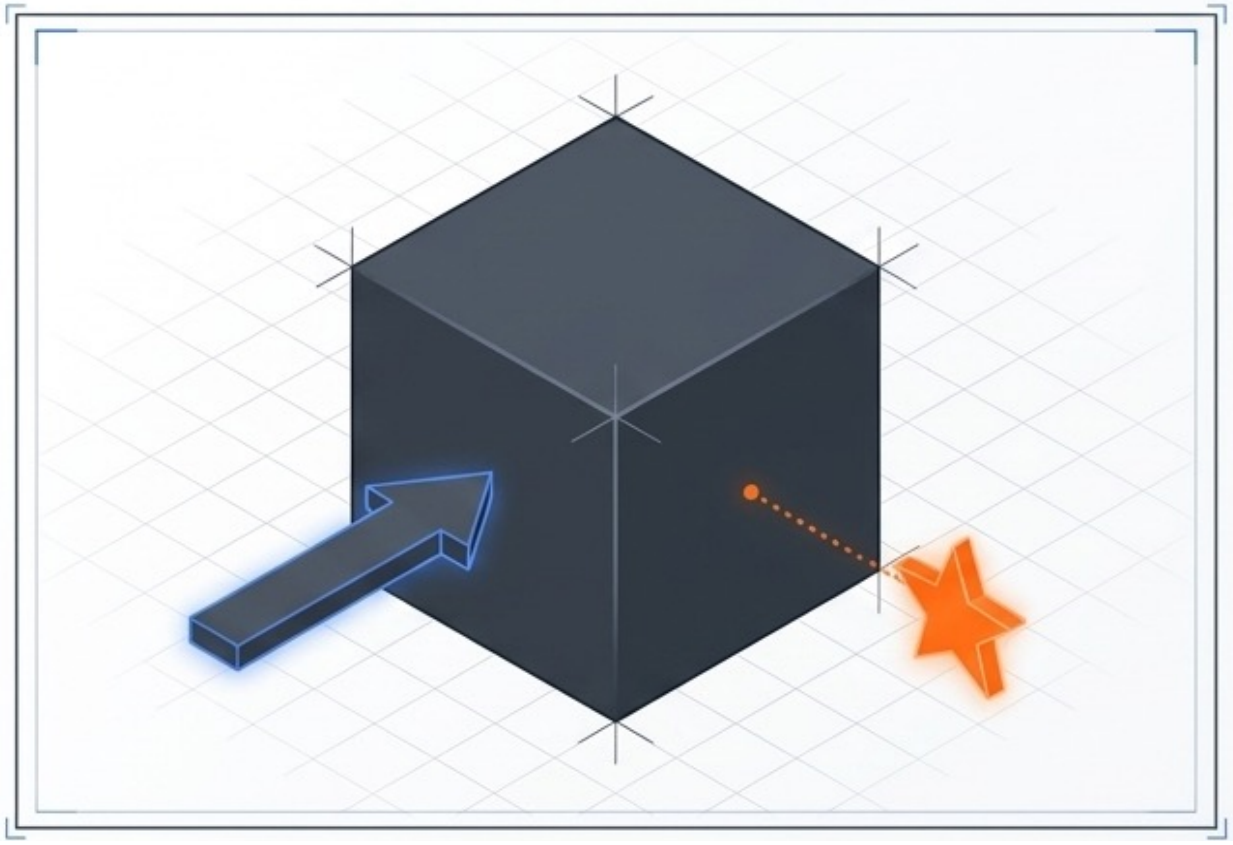


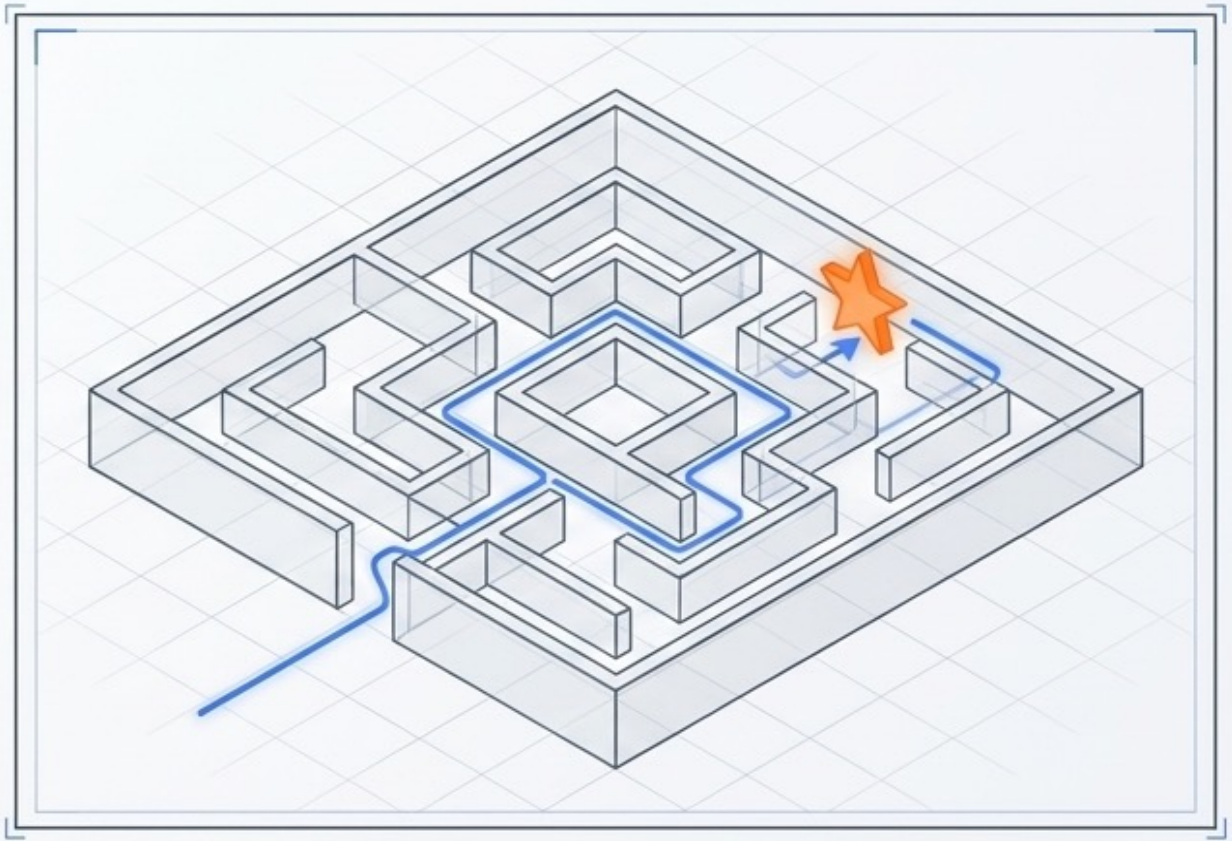
```python
import gym
env = gym.make("LunarLander-v2", render_mode="human")
env.action_space.seed(42)

observation, info = env.reset(seed=42)

for _ in range(1000):
    observation, reward, terminated, truncated, info = env.step(env.action_space.sample())

    if terminated or truncated:
        observation, info = env.reset()

env.close()
```

有模型学习(Model-based Learning)

有模型学习：世界的运行规则完全透明

假设：状态空间S 、动作空间A 、奖励函数R 、转移概率P 均已知





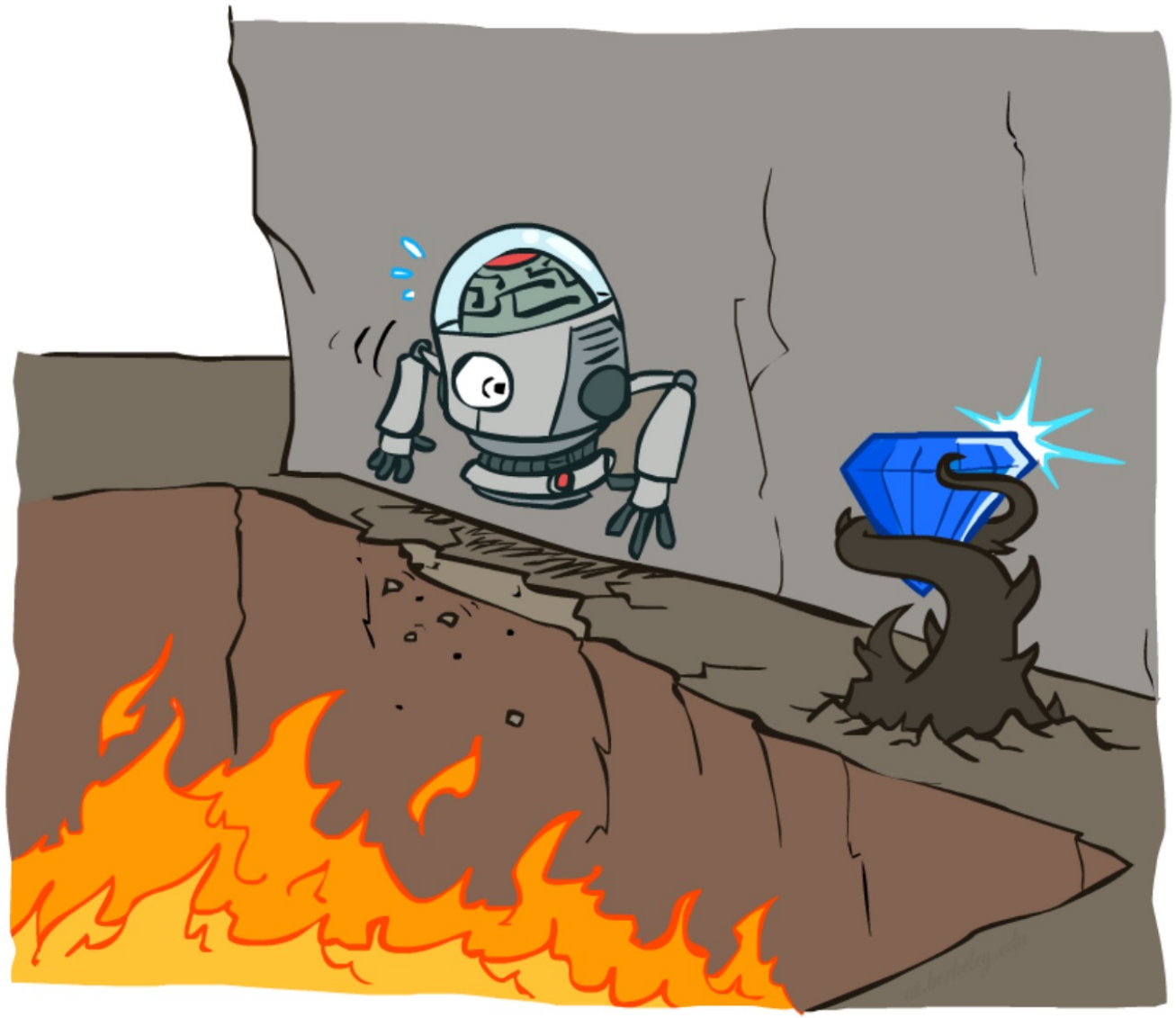
无模型(Model-Free)

规则未知，全靠探索

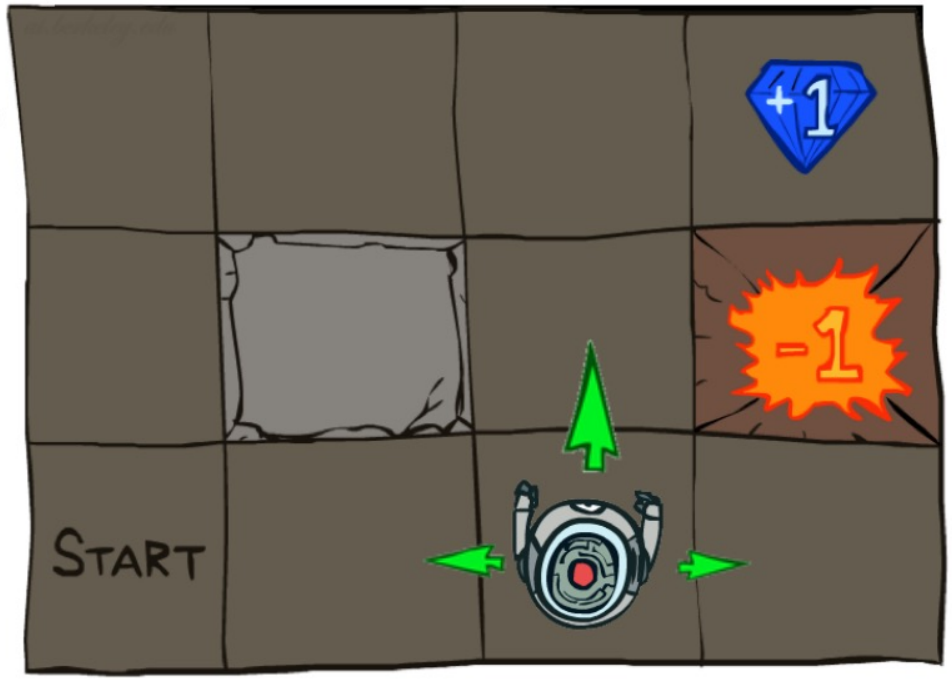
有模型学习(Model-based)

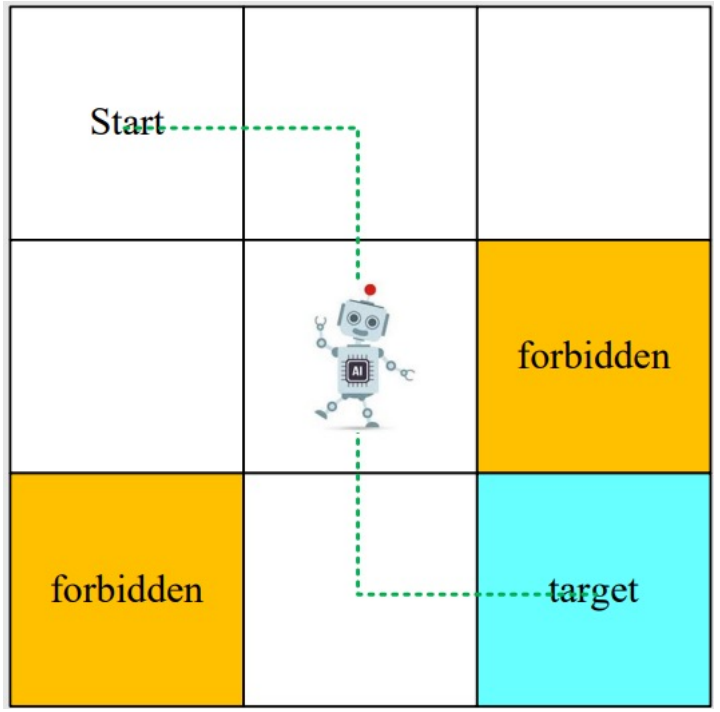
规则已知，只需数学计算

一个例子：网格世界(Grid World)



网格世界(Grid World)

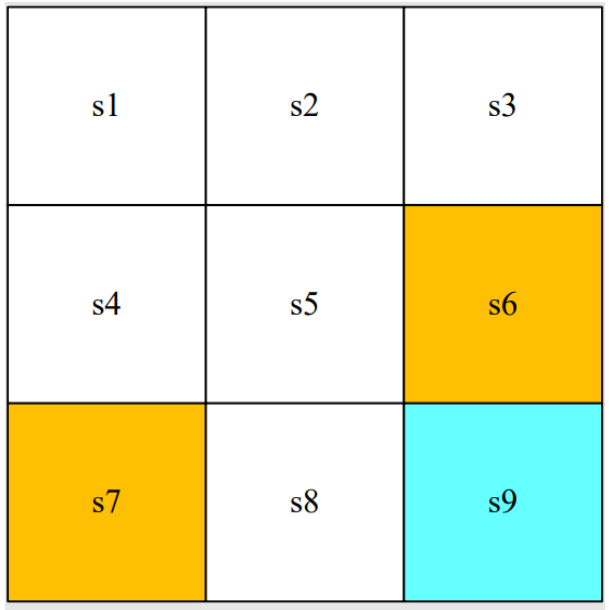




- 环境：由若干网格单元组成的网格世界
- 可通行单元 / 禁止进入单元 / 目标单元 / 边界
- 任务：给定任意起始位置，寻找一条通往目标的“较好”路径
- **如何定义“较好”？**

网格世界(Grid World)

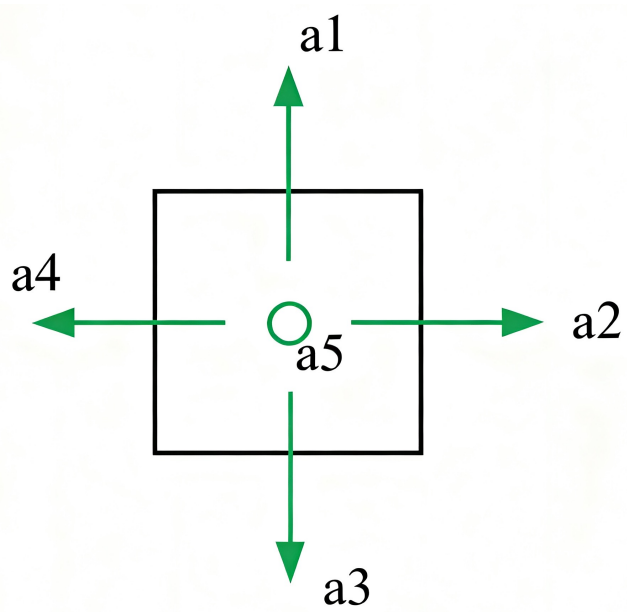
- **状态 (State)**： agent在环境中的状况
- 在grid-world中，状态就是agent所在的位置
- 共有 9 个可能的位置，那么就有 9 个状态 $S_1, S_2, \cdots, S_9$

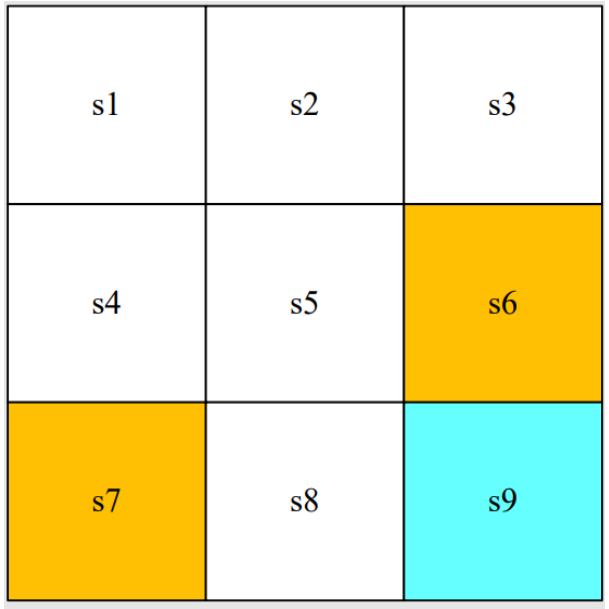


状态空间(State Space)：所有状态的集合 $\{S_1, S_2, \cdots, S_9\}$

网格世界(Grid World)

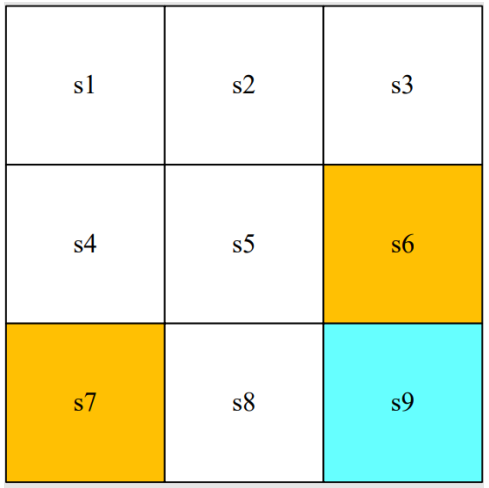
- **动作(Action)**： agent在每个状态可选的行动
- 向上、向右、向下、向左、保持不动





动作空间(Action Space)：所有可行动作的集合

网格世界(Grid World)



禁止区域（Forbidden area）：

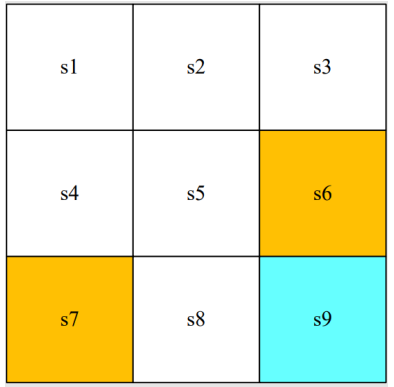
在状态S_5下，如果我们选择动作 a_2，下一个状态会是什么？存在两种情形：

- 情形 1（禁止区可进入但有惩罚）
- 情形 2（禁止区不可进入，例如被墙包围）

考虑第一种，让算法学会自己避免进入禁止区

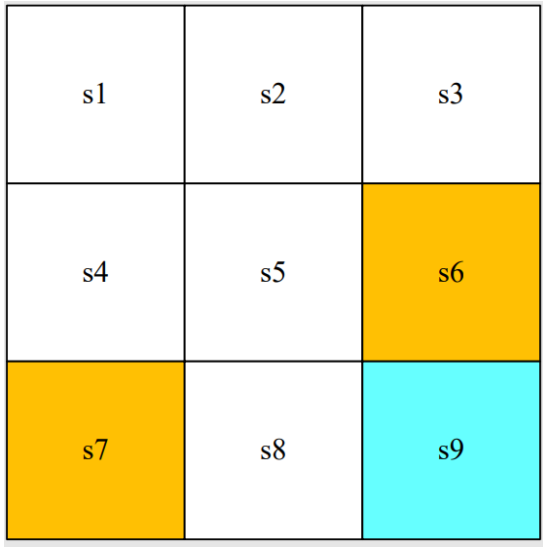
网格世界(Grid World)

- 表格表示(Tabular Representation)



	a_1 (upwards)	a_2 (rightwards)	a_3 (downwards)	a_4 (leftwards)	a_5 (unchanged)
s_1	s_1	s_2	s_4	s_1	s_1
s_2	s_2	s_3	s_5	s_1	s_2
s_3	s_3	s_3	s_6	s_2	s_3
s_4	s_1	s_5	s_7	s_4	s_4
s_5	s_2	s_6	s_8	s_4	s_5
s_6	s_3	s_6	s_9	s_5	s_6
s_7	s_4	s_8	s_7	s_7	s_7
s_8	s_5	s_9	s_8	s_7	s_8
s_9	s_6	s_9	s_9	s_8	s_9

网格世界(Grid World)



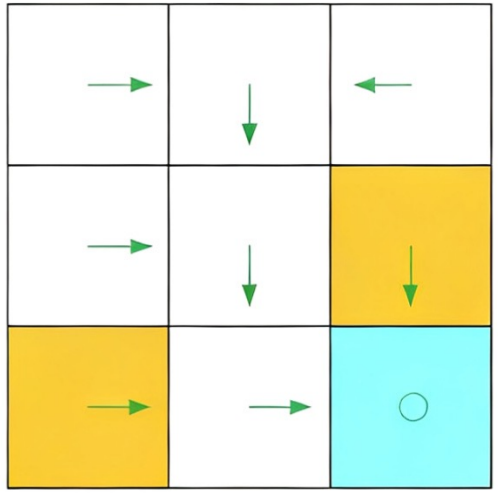
- 状态转移概率(State Transition Probability)
- Deterministic or Stochastic

$$P(S_2|S_1, a_2) = 1$$

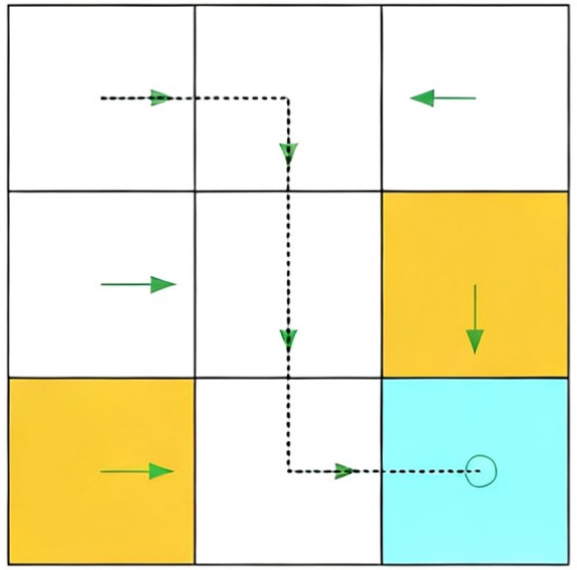
$$P(S_i|S_1, a_2) = 0, \forall i \neq 2$$

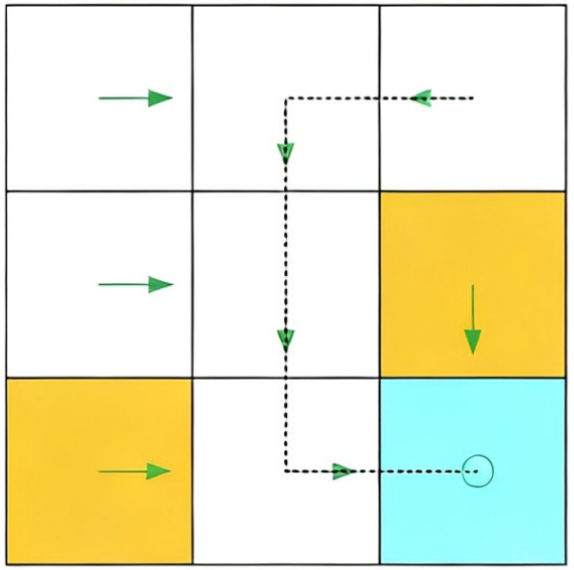
网格世界(Grid World)

Policy：告诉Agent每个状态下应该选择什么动作

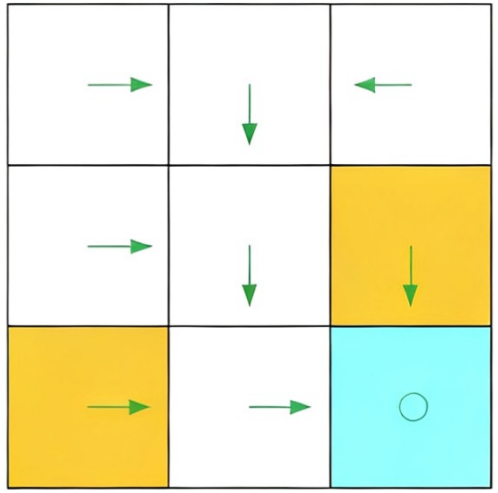


基于Policy可以得到任意起点出发的路径





网格世界(Grid World)



Deterministic Policy

$$\pi(a_1|s_1) = 0$$

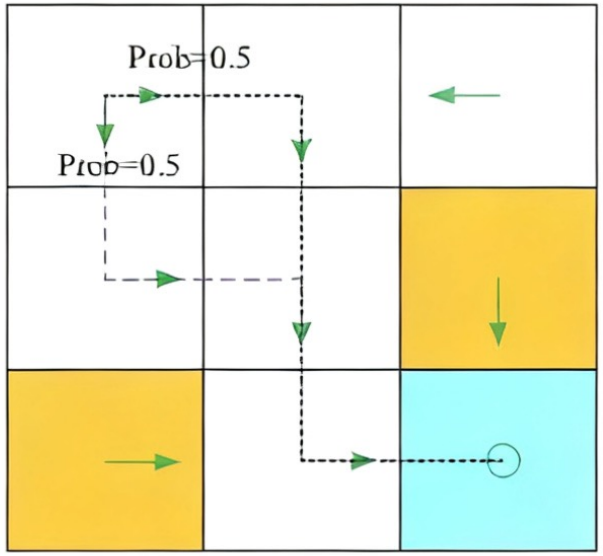
$$\pi(a_2|s_1) = 1$$

$$\pi(a_3|s_1) = 0$$

$$\pi(a_4|s_1) = 0$$

$$\pi(a_5|s_1) = 0$$

网格世界(Grid World)



Stochastic Policy

$$\pi(a_1|s_1) = 0$$

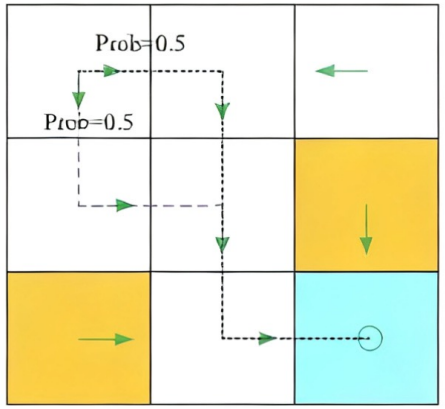
$$\pi(a_2|s_1) = 0.5$$

$$\pi(a_3|s_1) = 0.5$$

$$\pi(a_4|s_1) = 0$$

$$\pi(a_5|s_1) = 0$$

网格世界(Grid World)

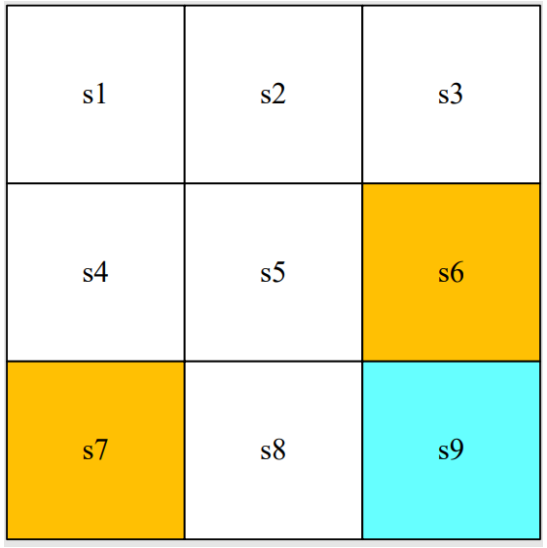


策略的表格表示

	a_1 (upwards)	a_2 (rightwards)	a_3 (downwards)	a_4 (leftwards)	a_5 (unchanged)
s_1	0	0.5	0.5	0	0
s_2	0	0	1	0	0
s_3	0	0	0	1	0
s_4	0	1	0	0	0
s_5	0	0	1	0	0
s_6	0	0	1	0	0
s_7	0	1	0	0	0
s_8	0	1	0	0	0
s_9	0	0	0	0	1

网格世界(Grid World)

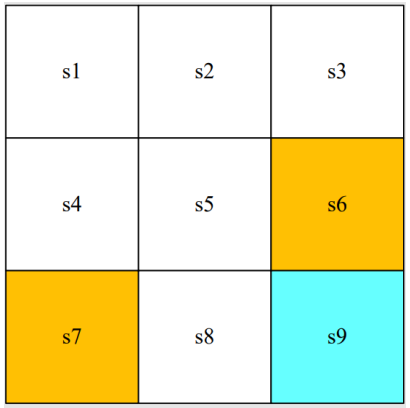
如何设计奖励函数？



在网格世界 (grid-world) 示例中，奖励函数的设计如下：

- 若Agent尝试越出边界，则奖励 $r_{bound} = -1$
- 若Agent尝试进入禁止单元，则奖励 $r_{forbid} = -1$
- 若Agent到达目标单元，则奖励 $r_{target} = 1$
- 其他情况下，奖励 $r = 0$

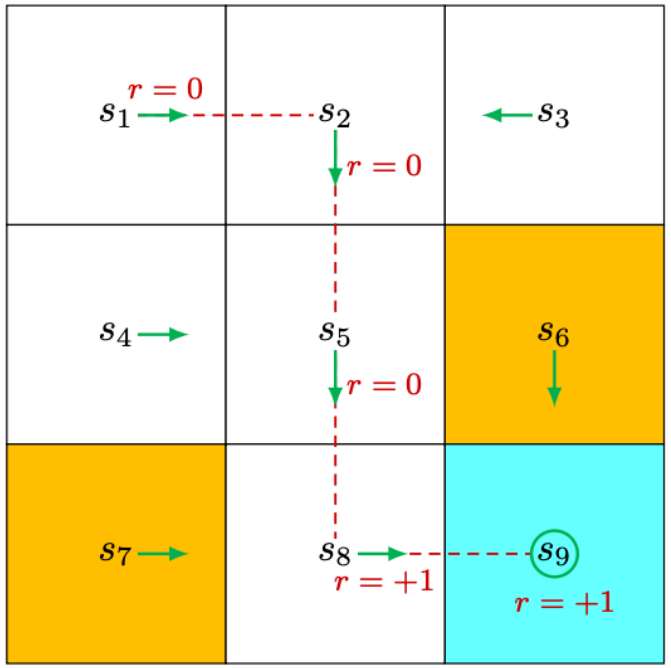
网格世界(Grid World)

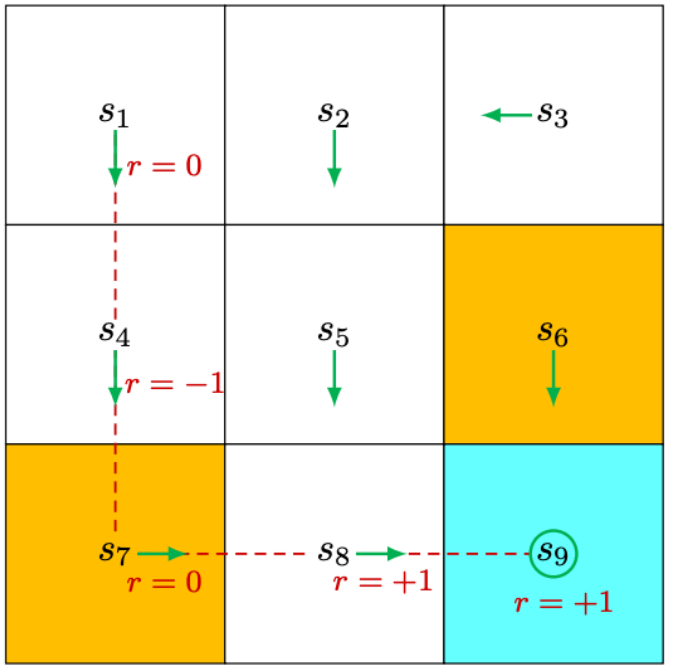


奖励的表格表示

	a_1 (upward)	a_2 (rightward)	a_3 (downward)	a_4 (leftward)	a_5 (still)
s_1	r_{boundary}	0	0	r_{boundary}	0
s_2	r_{boundary}	0	0	0	0
s_3	r_{boundary}	r_{boundary}	$r_{\text{forbidden}}$	0	0
s_4	0	0	$r_{\text{forbidden}}$	r_{boundary}	0
s_5	0	$r_{\text{forbidden}}$	0	0	0
s_6	0	r_{boundary}	r_{target}	0	$r_{\text{forbidden}}$
s_7	0	0	r_{boundary}	r_{boundary}	$r_{\text{forbidden}}$
s_8	0	r_{target}	r_{boundary}	$r_{\text{forbidden}}$	0
s_9	$r_{\text{forbidden}}$	r_{boundary}	r_{boundary}	0	r_{target}

Trajectory and Return





$$s_1 \xrightarrow[r=0]{a_2} s_2 \xrightarrow[r=0]{a_3} s_5 \xrightarrow[r=0]{a_3} s_8 \xrightarrow[r=1]{a_2} s_9$$

$$s_1 \xrightarrow[r=0]{a_3} s_4 \xrightarrow[r=-1]{a_3} s_7 \xrightarrow[r=0]{a_2} s_8 \xrightarrow[r=+1]{a_2} s_9$$

return = 0 + 0 + 0 + 1 = 1

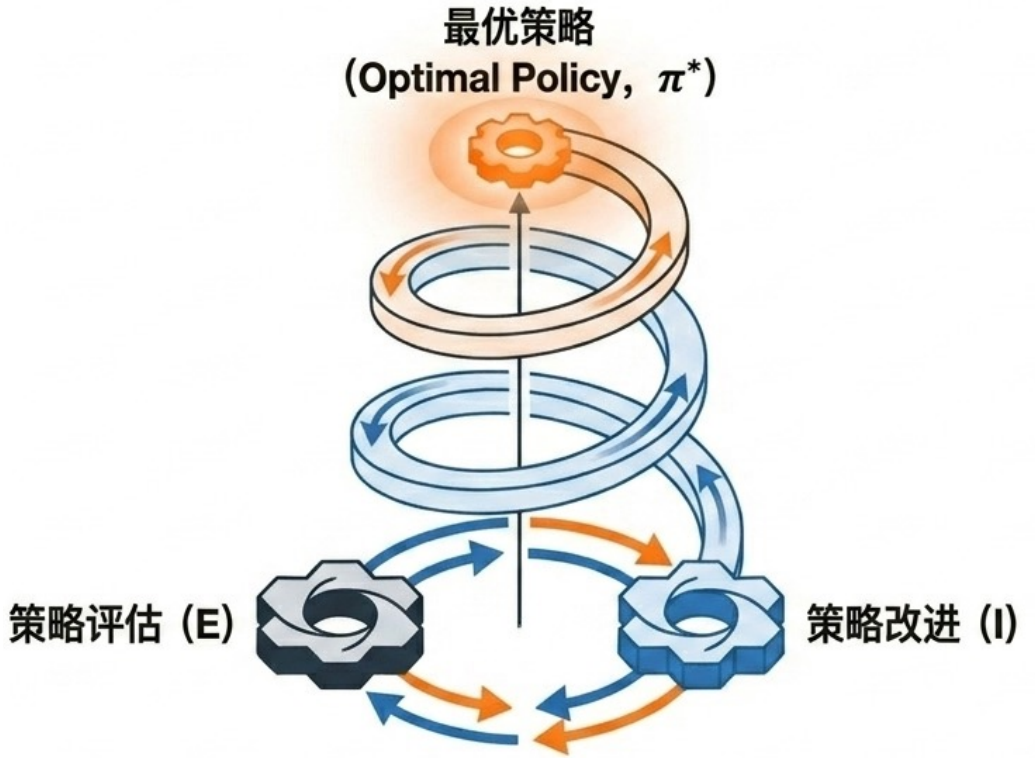
return = 0 - 1 + 0 + 1 = 0

有模型学习

- 目标：选择能够最大化累积奖励期望的策略$\pi(s): S \to A$

$$\mathbb{E}[r_0 + \gamma r_1 + \gamma^2 r_2 + \cdots]$$

- 三个步骤：
  - 策略评估
  - 策略改进
  - 策略迭代



策略评估：给定一个策略，如何评估好坏？

价值函数(Value Function)

- 给策略π定义价值函数，价值函数是状态（或状态-动作二元组）的函数，用来评估当前智能体在给定状态（获给定状态与动作）下有多好。这里的“好”是基于未来预期的回报（累计奖励）来定义的

- 状态值函数(State value function)

$$V^{\pi}(s_t) = \mathbb{E}[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \cdots | s = s_t]$$

- 状态-动作值函数(State-Action value function)

$$Q^{\pi}(s_t, a_t) = \mathbb{E}[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \cdots | s = s_t, a = a_t]$$

- 二者的关系：

$$V^{\pi}(s_t) = \sum_{a} \pi(s_t, a) \cdot Q^{\pi}(s_t, a)$$

贝尔曼与动态规划

1957年，贝尔曼提出**动态规划(Dynamic Programming)**理论

核心思想是将复杂的长期决策问题，分解为一系列简单的短期决策

贝尔曼方程(Bellman Equation)

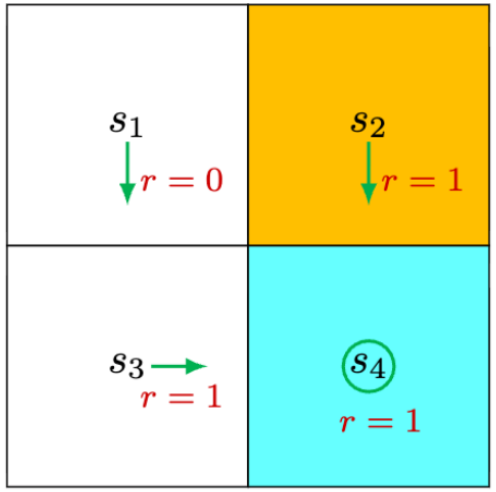
$$V^{\pi}(s) = \mathbb{E}[r_1 + \underbrace{\gamma r_2 + \gamma^2 r_3 + \cdots}_{\gamma V^{\pi}(s_{t+1})} | s_0 = s]$$

$$= \sum_{a} \boldsymbol{\pi(s,a)} \sum_{s' \in S} \boldsymbol{P_{sa}(s')\left(r_{sa}(s') + \gamma V^{\pi}(s')\right)}$$

Bellman等式

$$\boldsymbol{Q^{\pi}(s,a) = \sum_{s' \in S} P_{sa}(s')\left(r_{sa}(s') + \gamma V^{\pi}(s')\right)}$$

贝尔曼方程示例



贝尔曼方程：$V^{\pi}(s_t) = \sum_a \pi(s,a) \sum_{s' \in S} P_{sa}(s')\left(r_{sa}(s') + \gamma V^{\pi}(s')\right)$ **General Case**

$$V^{\pi}(s_1) = 0 + \gamma V^{\pi}(s_3)$$
$$V^{\pi}(s_2) = 1 + \gamma V^{\pi}(s_4)$$
$$V^{\pi}(s_3) = 1 + \gamma V^{\pi}(s_4)$$
$$V^{\pi}(S_4) = 1 + \gamma V^{\pi}(s_4)$$

贝尔曼方程示例

如何求解？

$$V^{\pi}(s_1) = 0 + \gamma V^{\pi}(s_3)$$
$$V^{\pi}(s_2) = 1 + \gamma V^{\pi}(s_4)$$
$$V^{\pi}(s_3) = 1 + \gamma V^{\pi}(s_4)$$
$$V^{\pi}(S_4) = 1 + \gamma V^{\pi}(s_4)$$

$$V^{\pi}(S_4) = \frac{1}{1-\gamma}$$
$$V^{\pi}(S_3) = \frac{1}{1-\gamma}$$
$$V^{\pi}(S_2) = \frac{1}{1-\gamma}$$
$$V^{\pi}(S_1) = \frac{\gamma}{1-\gamma}$$

贝尔曼方程示例

令$\gamma = 0.9$,

$$V^{\pi}(S_4) = \frac{1}{1-0.9} = 10$$

$$V^{\pi}(S_3) = \frac{1}{1-0.9} = 10$$

$$V^{\pi}(S_2) = \frac{1}{1-0.9} = 10$$

$$V^{\pi}(S_1) = \frac{0.9}{1-0.9} = 9$$

回顾：强化学习的关键要素

- Agent 
- Environment
- State s
- Action a
- Reward r
- Policy $\pi(s, a)$
- State transition $p_{sa}(s')$

- Return:

$$G_t = R_t + \gamma R_{t+1} + \gamma^2 R_{t+2} + \cdots$$

- Action-value function:

$$Q_\pi(s_t, a_t) = \mathbb{E}\left[G_t | s_t, a_t\right].$$

- State-value function:

$$V_\pi(s_t) = \mathbb{E}_{a\sim\pi}[Q_\pi(s_t, a)].$$

回顾：贝尔曼与动态规划

1957年，贝尔曼提出**动态规划(Dynamic Programming)**理论

核心思想是将复杂的长期决策问题，分解为一系列简单的短期决策

回顾：贝尔曼方程

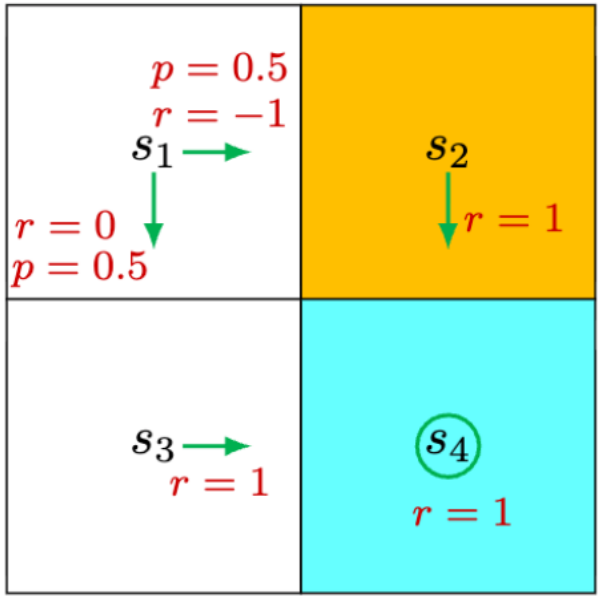
$$V^{\pi}(s) = \mathbb{E}[r_1 + \underbrace{\gamma r_2 + \gamma^2 r_3 + \cdots}_{\gamma V^{\pi}(s_{t+1})} | s_0 = s]$$

$$= \sum_{a} \boldsymbol{\pi(s,a)} \sum_{s' \in S} \boldsymbol{P_{sa}(s')\left(r_{sa}(s') + \gamma V^{\pi}(s')\right)}$$

Bellman等式

$$\boldsymbol{Q^{\pi}(s,a) = \sum_{s' \in S} P_{sa}(s')\left(r_{sa}(s') + \gamma V^{\pi}(s')\right)}$$

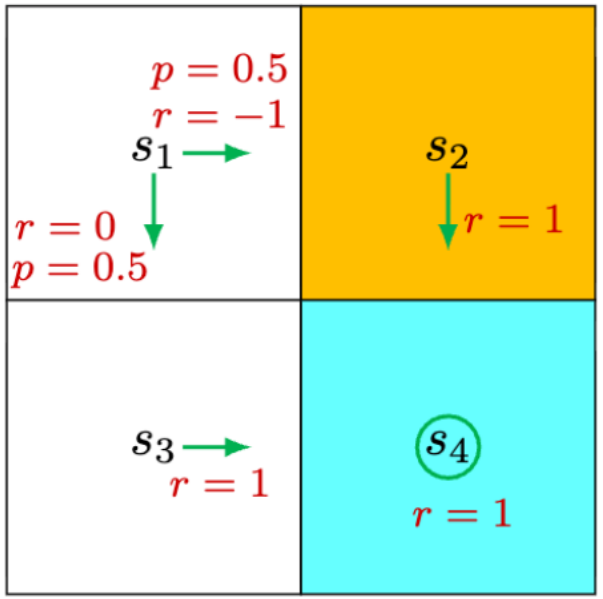
Exercise



贝尔曼方程：$V^{\pi}(s_t) = \sum_a \pi(s,a) \sum_{s' \in S} P_{sa}(s')\left(r_{sa}(s') + \gamma V^{\pi}(s')\right)$ **General Case**

- 写出每个状态的贝尔曼方程
- 计算状态值
- 该策略和上一例子中的策略相比如何？

Solution



$$V^{\pi}(s_1) = 0.5[0 + \gamma V^{\pi}(s_3)] + 0.5[-1 + \gamma V^{\pi}(s_2)]$$

$$V^{\pi}(s_2) = 1 + \gamma V^{\pi}(s_4)$$

$$V^{\pi}(s_3) = 1 + \gamma V^{\pi}(s_4)$$

$$V^{\pi}(S_4) = 1 + \gamma V^{\pi}(s_4)$$

求解上述方程可得：

$$V^{\pi}(S_2) = V^{\pi}(S_3) = V^{\pi}(S_4) = \frac{1}{1-\gamma}$$

$$V^{\pi}(S_1) = -0.5 + \frac{\gamma}{1-\gamma}$$

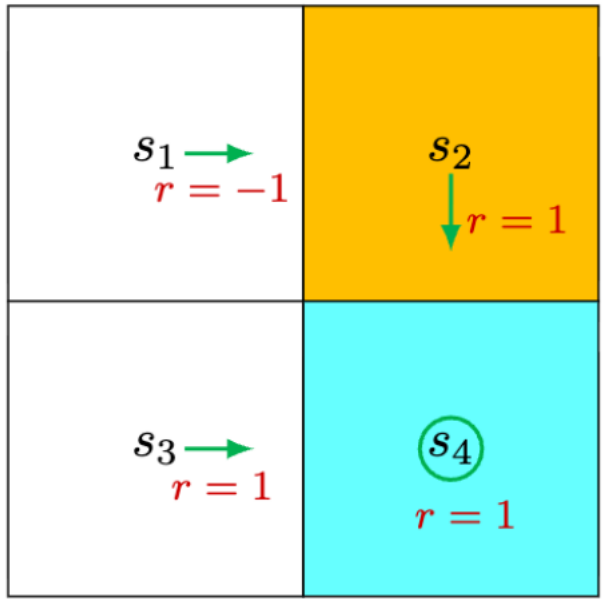
令γ=0.9可得

$$V^{\pi}(S_2) = V^{\pi}(S_3) = V^{\pi}(S_4) = 10$$

$$V^{\pi}(S_1) = -0.5 + 9 = 8.5$$

策略改进：如何改进一个策略？

示例

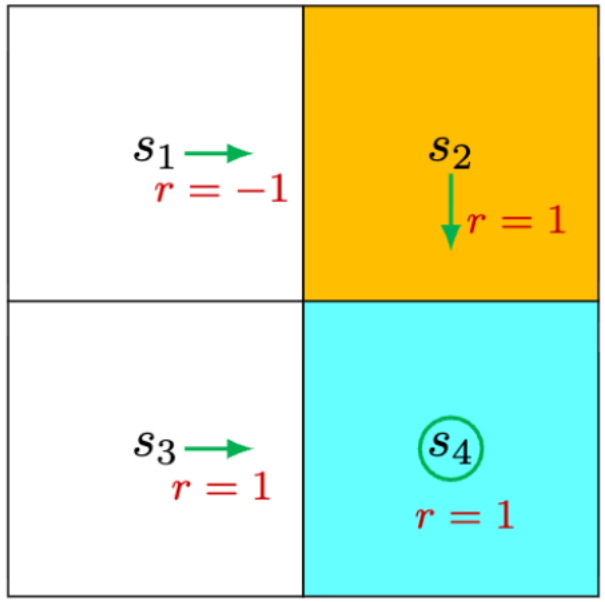


$$V^{\pi}(s_1) = -1 + \gamma V^{\pi}(s_2)$$
$$V^{\pi}(s_2) = 1 + \gamma V^{\pi}(s_4)$$
$$V^{\pi}(s_3) = 1 + \gamma V^{\pi}(s_4)$$
$$V^{\pi}(S_4) = 1 + \gamma V^{\pi}(s_4)$$

令$\gamma = 0.9$,

$V^{\pi}(s_1) = 8$, $V^{\pi}(s_2) = V^{\pi}(s_3) = V^{\pi}(4) = 10$

示例



令$\gamma = 0.9$,

$V^{\pi}(s_1) = 8$

$V^{\pi}(s_2) = V^{\pi}(s_3) = V^{\pi}(4) = 10$

$q^{\pi}(s_1, a_1) = -1 + \gamma V^{\pi}(s_1) = 6.2$

$q^{\pi}(s_1, a_2) = -1 + \gamma V^{\pi}(s_2) = 8$

$\boldsymbol{q^{\pi}(s_1, a_3) = 0 + \gamma V^{\pi}(s_3) = 9}$

$q^{\pi}(s_1, a_4) = -1 + \gamma V^{\pi}(s_1) = 6.2$

$q^{\pi}(s_1, a_5) = 0 + \gamma V^{\pi}(s_1) = 7.2$

如果我们更新策略，使之选择具有最大动作值的动作，就有望得到一个更好的策略

贝尔曼最优方程

- 最优策略对应的值函数称为最优值函数

$$V^*(s) = \max_{\pi} V^{\pi}(s)$$

- 最优价值函数的Bellman等式

$$V^*(s) = \max_{a} \sum_{s' \in S} P_{sa}(s')\left(r_{sa}(s') + \gamma V^{\pi}(s')\right) = \max_{a} Q^{\pi *}(s,a)$$

最优Bellman等式

- 非最优策略的改进方式：将策略选择的动作改为当前最优的动作

$$\pi'(s) = \arg\max_{a \in A} Q^{\pi}(s,a)$$

价值迭代 (Value Iteration)

- 对于一个动作空间和状态空间有限的MDP

$$|S| < \infty, |A| < \infty$$

- 价值迭代过程

1. 对每个状态s，初始化 $V(s)$=0

2. 重复以下过程直到收敛 {

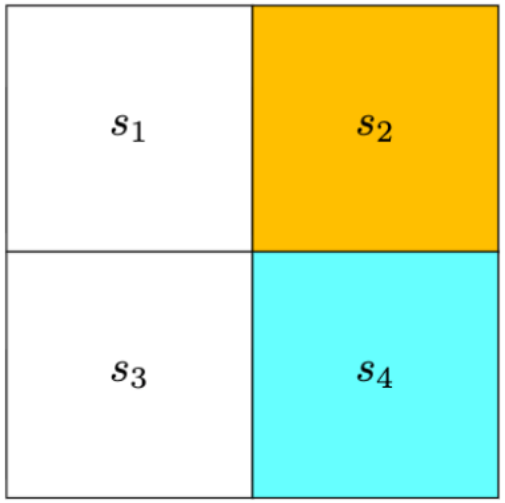
对每个状态，更新

$$V(s) = \max_a \sum_{s' \in S} P_{sa}(s')\left(r_{sa}(s') + \gamma V^{\pi}(s')\right) = \max Q^{\pi}(s,a)$$

}

价值迭代 (Value Iteration)

网格世界



Q表

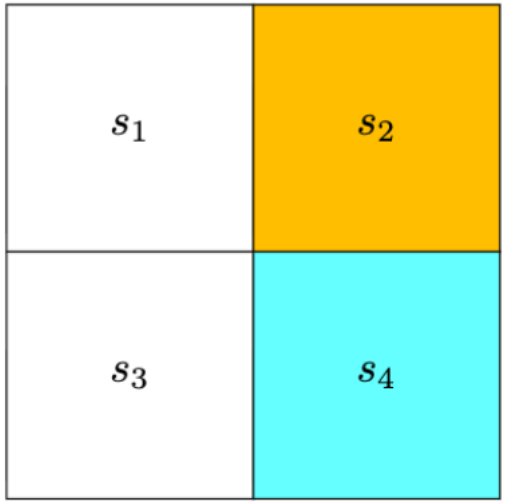
q-table	a_1	a_2	a_3	a_4	a_5
s_1	$-1+\gamma v(s_1)$	$-1+\gamma v(s_2)$	$0+\gamma v(s_3)$	$-1+\gamma v(s_1)$	$0+\gamma v(s_1)$
s_2	$-1+\gamma v(s_2)$	$-1+\gamma v(s_2)$	$1+\gamma v(s_4)$	$0+\gamma v(s_1)$	$-1+\gamma v(s_2)$
s_3	$0+\gamma v(s_1)$	$1+\gamma v(s_4)$	$-1+\gamma v(s_3)$	$-1+\gamma v(s_3)$	$0+\gamma v(s_3)$
s_4	$-1+\gamma v(s_2)$	$-1+\gamma v(s_4)$	$-1+\gamma v(s_4)$	$0+\gamma v(s_3)$	$1+\gamma v(s_4)$

价值迭代 (Value Iteration)

K=0：初始值v_0可任意选择，不失一般性，令

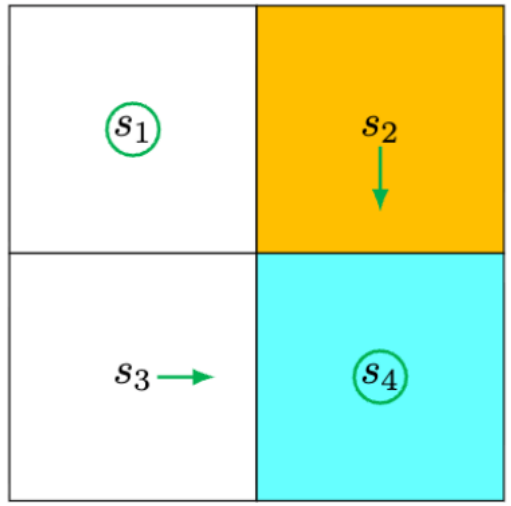
$$v_0(s_1) = v_0(s_2) = v_0(s_3) = v_0(s_4) = 0$$

q-table	a_1	a_2	a_3	a_4	a_5
s_1	-1	-1	0	-1	0
s_2	-1	-1	1	0	-1
s_3	0	1	-1	-1	0
s_4	-1	-1	-1	0	1



价值更新：

$$V(s) = \max_a \sum_{s' \in S} P_{sa}(s')\left(r_{sa}(s') + \gamma V^{\pi}(s')\right) = \max_a Q^{\pi}(s,a)$$

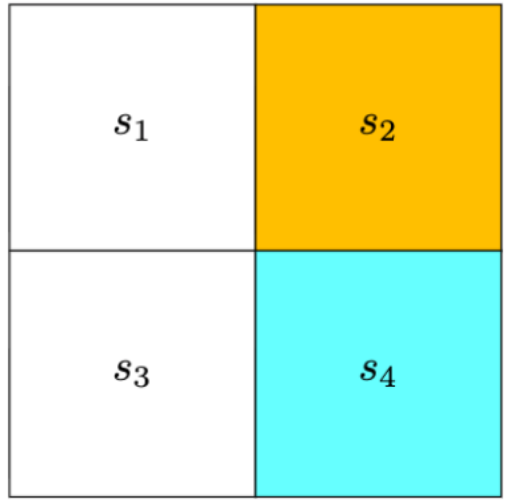


$$v_1(s_1) = 0, v_1(s_2) = 1, v_1(s_3) = 1, v_1(s_4) = 1$$

价值迭代 (Value Iteration)

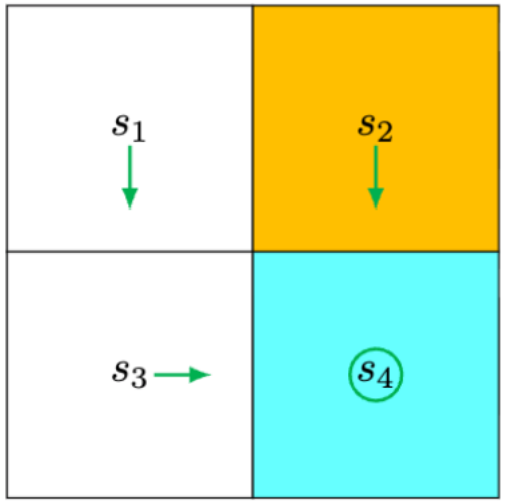
K=1： $v_1(s_1) = 0, v_1(s_2) = 1, v_1(s_3) = 1, v_1(s_4) = 1$

q-table	a_1	a_2	a_3	a_4	a_5
s_1	$-1+\gamma 0$	$-1+\gamma 1$	$0+\gamma 1$	$-1+\gamma 0$	$0+\gamma 0$
s_2	$-1+\gamma 1$	$-1+\gamma 1$	$1+\gamma 1$	$0+\gamma 0$	$-1+\gamma 1$
s_3	$0+\gamma 0$	$1+\gamma 1$	$-1+\gamma 1$	$-1+\gamma 1$	$0+\gamma 1$
s_4	$-1+\gamma 1$	$-1+\gamma 1$	$-1+\gamma 1$	$0+\gamma 1$	$1+\gamma 1$



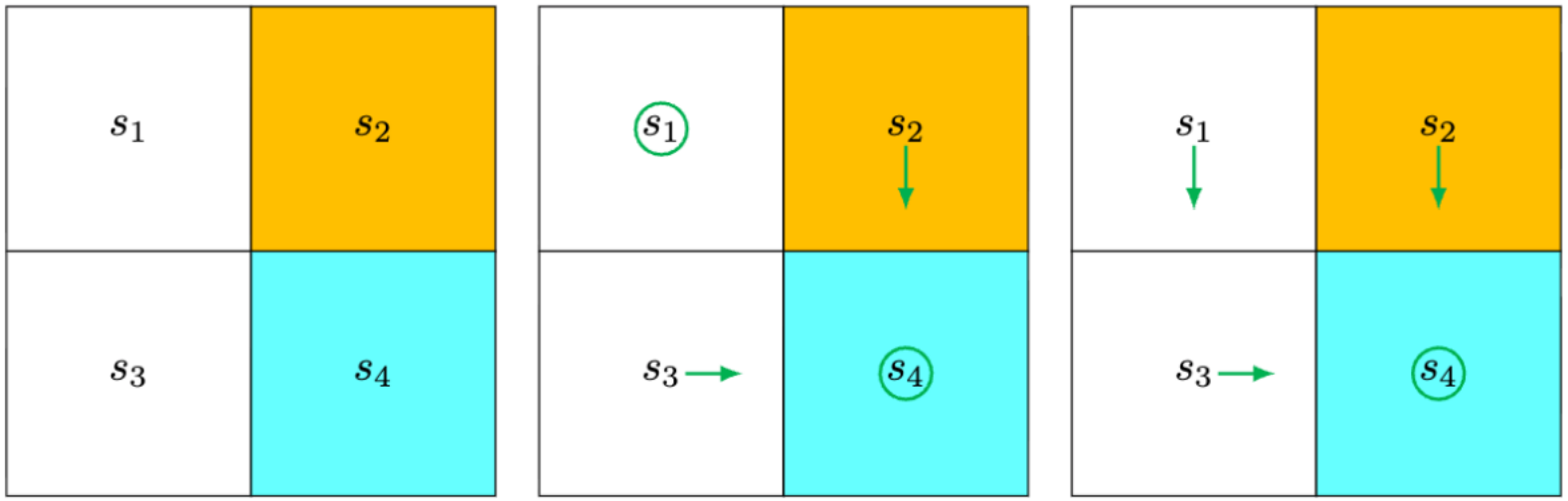
价值更新：

$$V(s) = \max_a \sum_{s' \in S} P_{sa}(s')\left(r_{sa}(s') + \gamma V^{\pi}(s')\right) = \max_a Q^{\pi}(s,a)$$



$v_2(s_1) = \gamma 1, v_2(s_2) = 1 + \gamma 1, v_2(s_3) = 1 + \gamma 1, v_2(s_4) = 1 + \gamma 1$

价值迭代 (Value Iteration)

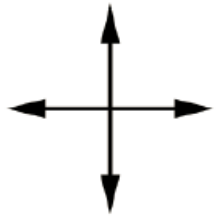


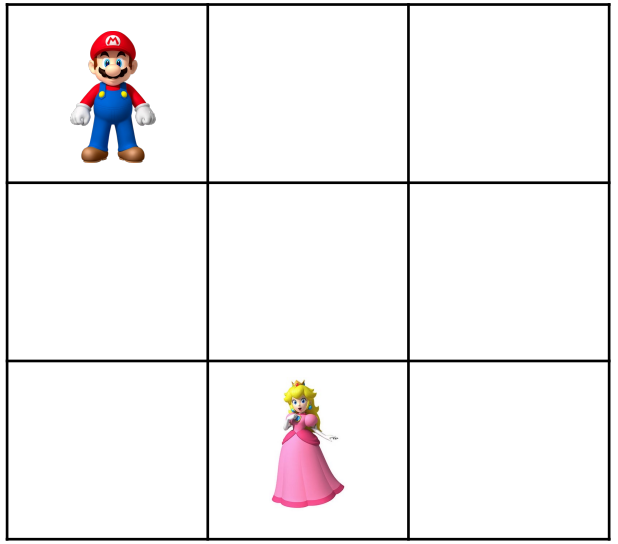
$$v_0(s_1) = v_0(s_2) = v_0(s_3) = v_0(s_4) = 0$$

$$v_1(s_1) = 0, v_1(s_2) = 1, v_1(s_3) = 1, v_1(s_4) = 1$$

$$v_2(s_1) = \gamma 1, v_2(s_2) = 1 + \gamma 1, v_2(s_3) = 1 + \gamma 1, v_2(s_4) = 1 + \gamma 1$$

Exercise: 价值迭代 – 公主营救





- 非折扣MDP $(\gamma = 1)$
- 每走一步，奖励为-1，直到到达终止状态
- 找到公主游戏结束
- 最小体力消耗找到公主
- 智能体的策略为均匀随机策略

$$\pi(n|\cdot) = \pi(e|\cdot) = \pi(s|\cdot) = \pi(w|\cdot) = 0.25$$

Exercise: 价值迭代 – 公主营救

 0	0	0
0	0	0
0	0 	0

Exercise: 价值迭代 – 公主营救

0	0	0
0	0	0
0	0	0

-1	-1	-1
-1	-1	-1
-1	0	-1

-2	-2	-2
-2	-1	-2
-1	0	-1

-3	-2	-3
-2	-1	-2
-1	0	-1

-3	-2	-3
-2	-1	-2
-1	0	-1

策略迭代 (Policy Iteration)

- 对于一个动作空间和状态空间有限的MDP

$$|S| < \infty, |A| < \infty$$

- 策略迭代过程

1. 随机初始化策略 π
2. 重复以下过程直到收敛 {

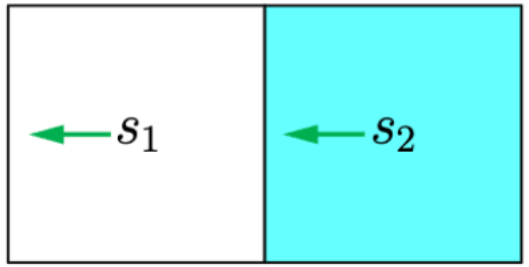
a) 策略评估：$\boldsymbol{V := V^{\pi} = \sum_{a} \pi(s,a) \sum_{s' \in S} P_{sa}(s') \left(r_{sa}(s') + \gamma V^{\pi}(s') \right)}$

b) 策略改进：对每个状态，更新

$$\boldsymbol{\pi(s) = arg \max_{a \in A} Q^{\pi}(s,a)}$$

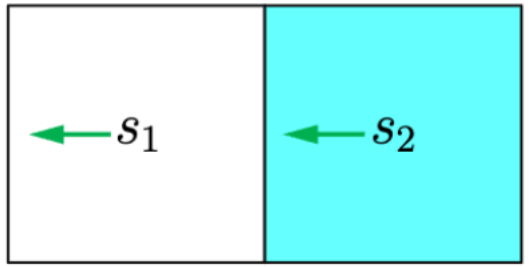
}

策略迭代 (Policy Iteration)



- 动作：向左、向右、不动
- $r_{boundary} = -1, r_{target} = 1$
- $\gamma = 0.9$

策略迭代 (Policy Iteration)



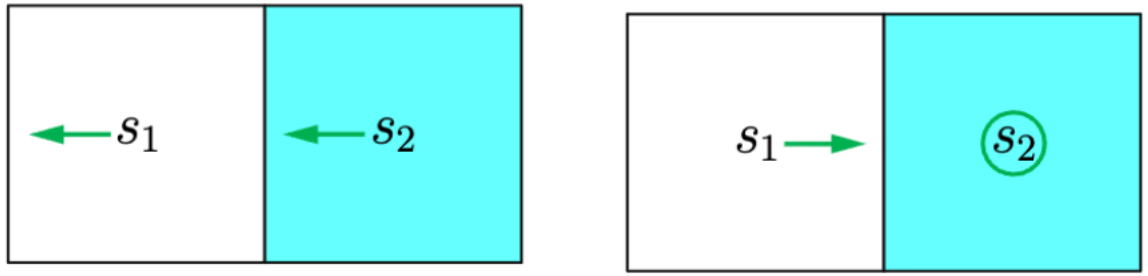
策略评估

$$V^{\pi_0}(s_1) = -1 + \gamma V^{\pi_0}(s_1)$$

$$V^{\pi_0}(s_2) = 0 + \gamma V^{\pi_0}(s_1)$$

$$V^{\pi_0}(s_1) = -10, \qquad V^{\pi_0}(s_2) = -9$$

策略迭代 (Policy Iteration)



策略改进

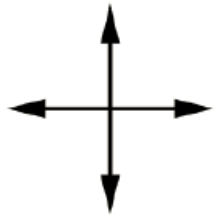
$q_{\pi_k}(s,a)$	a_ℓ	a_0	a_r
s_1	$-1+\gamma v_{\pi_k}(s_1)$	$0+\gamma v_{\pi_k}(s_1)$	$1+\gamma v_{\pi_k}(s_2)$
s_2	$0+\gamma v_{\pi_k}(s_1)$	$1+\gamma v_{\pi_k}(s_2)$	$-1+\gamma v_{\pi_k}(s_2)$

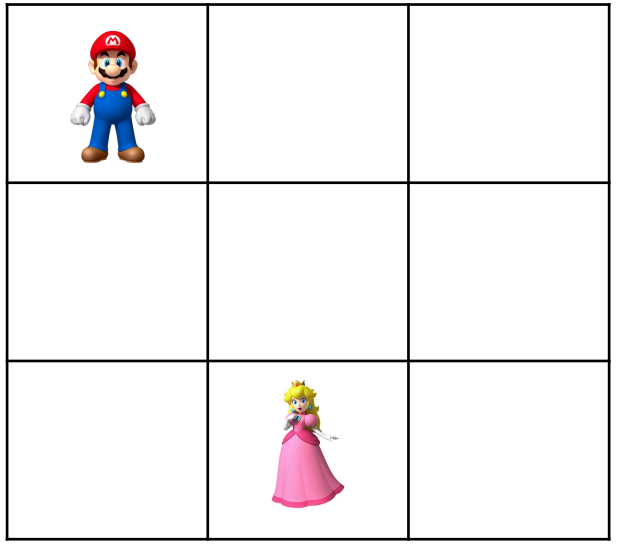
代入$V^{\pi_0}(s_1)=-10, V^{\pi_0}(s_2)=-9$，可得

$q_{\pi_0}(s,a)$	a_ℓ	a_0	a_r
s_1	-10	-9	-7.1
s_2	-9	-7.1	-9.1

在状态s_1应该选择向右，在状态s_2应该选择不动

Exercise：策略迭代之公主营救

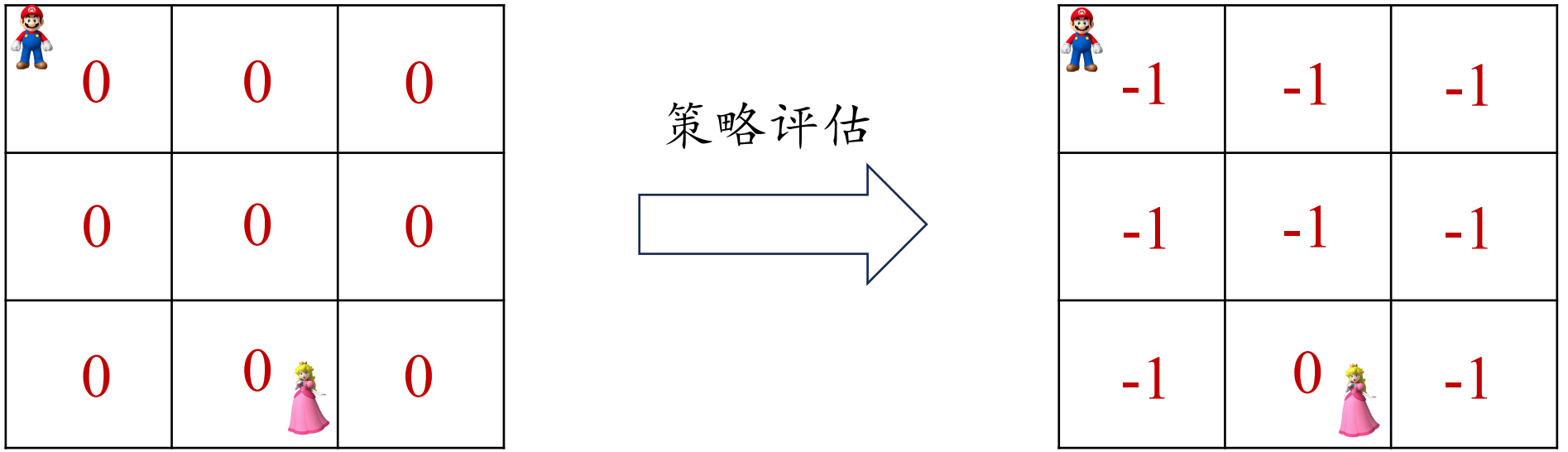




- 非折扣MDP $(\gamma = 1)$
- 每走一步，奖励为-1，直到到达终止状态
- 找到公主游戏结束
- 最小体力消耗找到公主
- 智能体的策略为均匀随机策略

$$\pi(n|\cdot) = \pi(e|\cdot) = \pi(s|\cdot) = \pi(w|\cdot) = 0.25$$

Exercise：策略迭代之公主营救



Exercise：策略迭代之公主营救

-1	-1	-1
-1	-1	-1
-1	0	-1

-2	-2	-2
-2	-1.75	-2
-2	0	-1.75

Exercise：策略迭代之公主营救

-2	-2	-2
-2	-1.75	-2
-2	0	-1.75

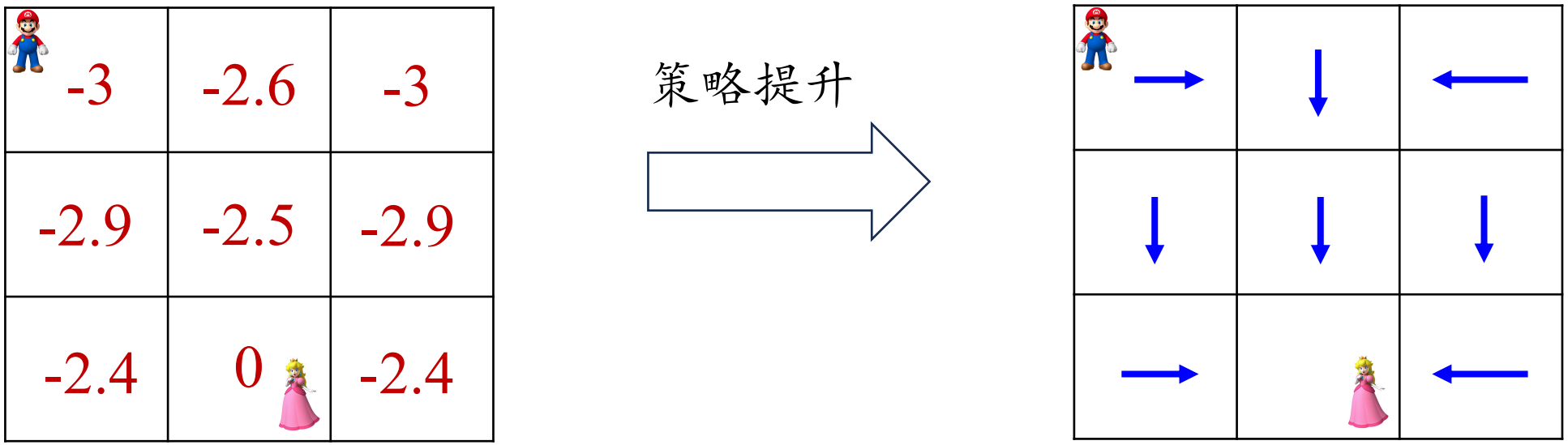
迭代至收敛

-3	-2.6	-3
-2.9	-2.5	-2.9
-2.4	0	-2.4

Exercise：策略迭代之公主营救

-3	-2.6	-3
-2.9	-2.5	-2.9
-2.4	0	-2.4

策略提升



价值迭代 vs. 策略迭代

- 价值迭代过程

  1. 对每个状态s，初始化 $V(s)$=0

  2. 重复以下过程直到收敛 {

     对每个状态，更新

$$V(s) = \max_a \sum_{s' \in S} P_{sa}(s')\left(r_{sa}(s') + \gamma V^{\pi}(s')\right)$$

  }

- 策略迭代过程

  1. 随机初始化策略 π

  2. 重复以下过程直到收敛 {

     a) 策略评估：$\boldsymbol{V} := \boldsymbol{V^{\pi}}$

     b) 策略改进：对每个状态，更新

$$\pi(s) = arg\max_{a \in A} Q^{\pi}(s,a)$$

  }

- ✓ 均可归结为基于动态规划的寻优算法
- ✓ 价值迭代是贪心更新法
- ✓ 策略迭代中，用Bellman等式更新价值函数代价很大
- ✓ 对于空间较小的MDP，策略迭代通常很快收敛
- ✓ 对于空间较大的MDP，价值迭代更实用（效率更高）

如果模型未知呢?

- 在模型未知的情形下，从目前我们关注在给出一个已知概率转移模型后：

  （也就是说，**状态转移**明确给定）

  - 计算最优价值函数
  - 学习最优策略

- 现实问题中，通常难以明确地给出状态转移和奖励函数,导致策略无法评估

  （模型未知导致无法做全概率展开）

学习一个环境模型

Episode1：$s_0^{(1)} \xrightarrow{a_0^{(1)},R(s_0)^{(1)}} s_1^{(1)} \xrightarrow{a_1^{(1)},R(s_1)^{(1)}} s_2^{(1)} \xrightarrow{a_2^{(1)},R(s_2)^{(1)}} s_3^{(1)} \cdots s_T^{(1)}$

Episode2：$s_0^{(2)} \xrightarrow{a_0^{(2)},R(s_0)^{(2)}} s_1^{(2)} \xrightarrow{a_1^{(2)},R(s_1)^{(2)}} s_2^{(2)} \xrightarrow{a_2^{(2)},R(s_2)^{(2)}} s_3^{(2)} \cdots s_T^{(2)}$

⋮ ⋮

- 从“经验”中学习一个环境模型：
  - 学习**状态转移概率**

$$P_{sa}(s') = \frac{\text{在}s\text{下采取动作}a\text{并转移到}s'\text{的次数}}{\text{在}s\text{下采取动作}a\text{的次数}}$$

世界模型 (World Model)

“所谓世界模型，就是世界在人脑或AI的神经网络中的内部表征（心理模型）。在大脑里对外部世界形成抽象表示，形成内部模拟，这可以用于理解、预测和规划外部环境的交互。

大脑构建了一个关于世界如何运作的、经过压缩的、可预测的内部模型。人知道苹果熟了会掉下来而不是飞上去，sora等视频生成AI知道人走在水面会沉下去而不是如履平地，这都是“世界模型”的作用

什么是world models/世界模型

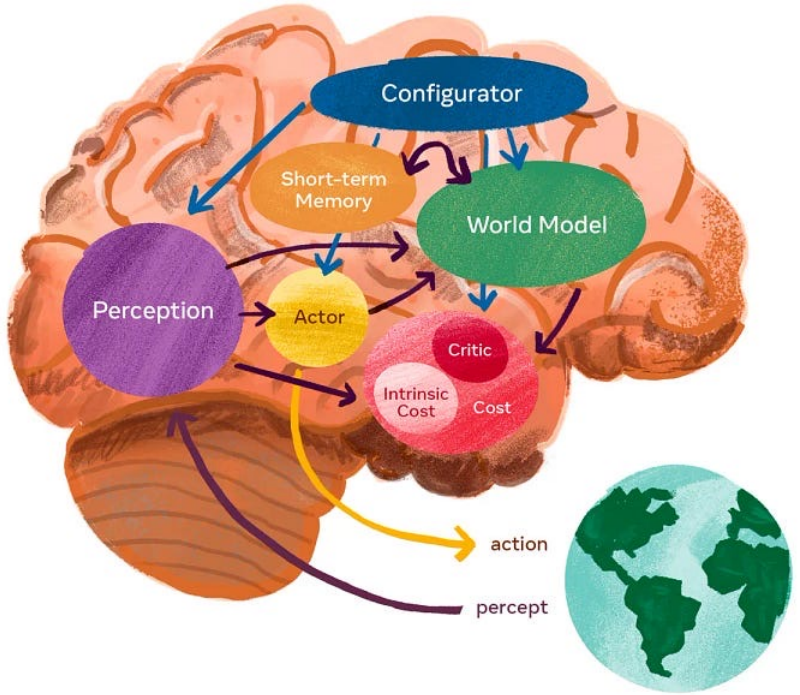
俞扬

新知答主

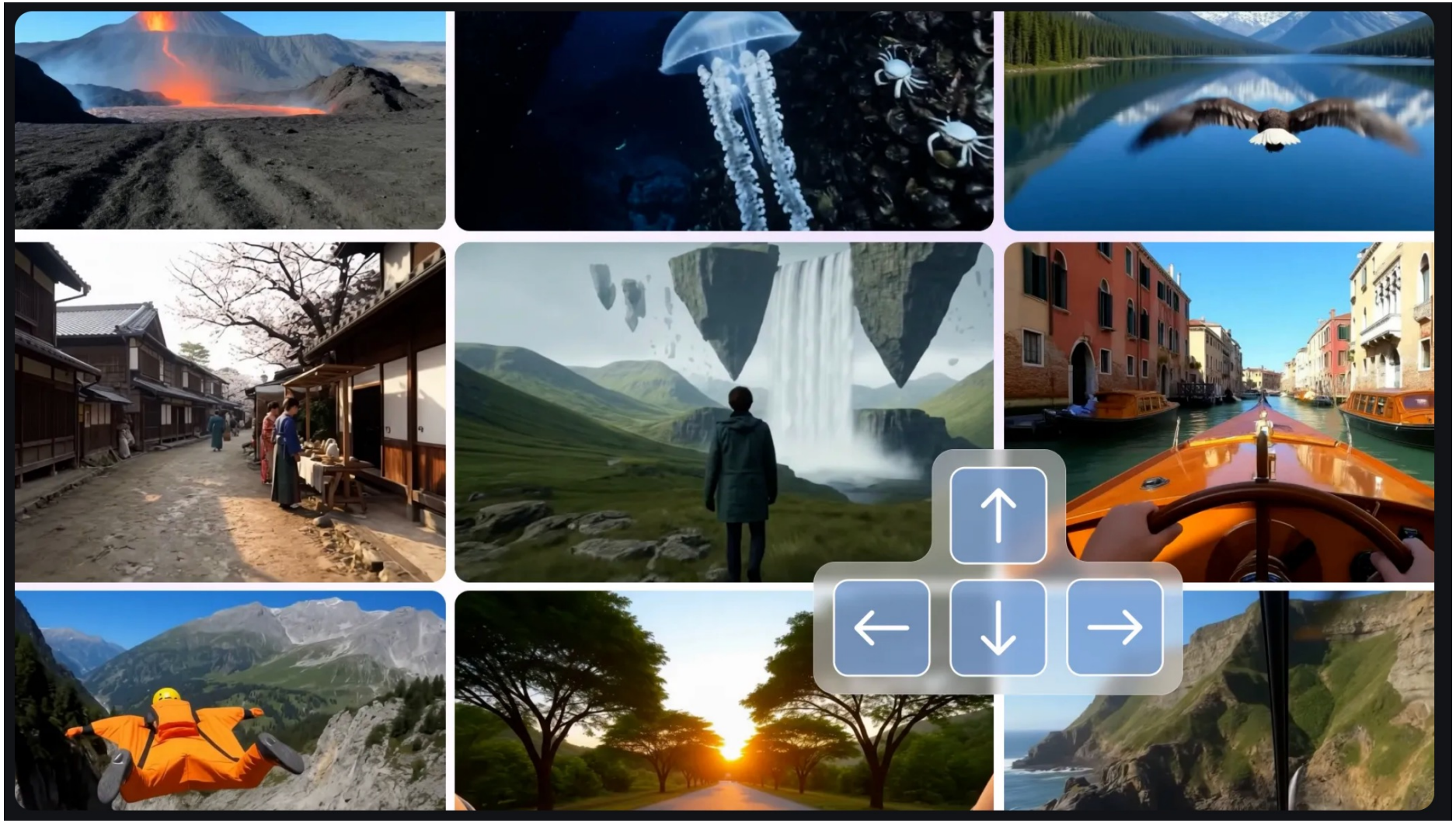
编辑推荐 等 2 项收录

收录于 · 超龄儿童的梦想 ›

https://zhuanlan.zhihu.com/p/661768957



Genie 3 - DeepMind

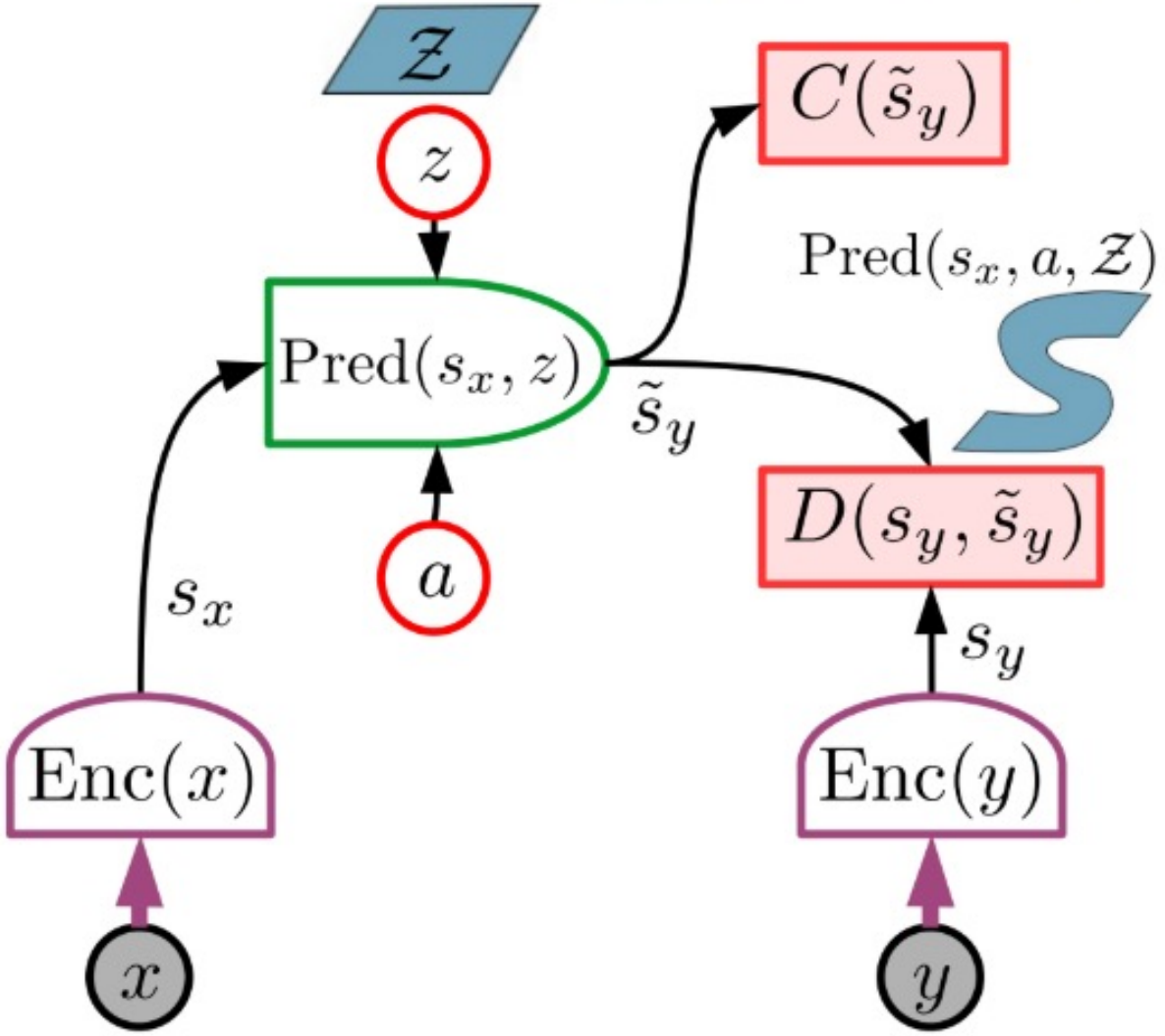


JEPA: Latent World Representation

Architecture for the world model: JEPA

Y. LeCun

- **JEPA: Joint Embedding Predictive Architecture.**
  - x: observed past and present
  - y: future
  - a: action
  - z: latent variable (unknown)
  - D( ): prediction cost
  - C( ): surrogate cost
  - JEPA predicts a representation of the future S_y from a representation of the past and present S_x



JEPA: Latent World Representation

- 大语言模型有用，但绝不是通往真正智能的道路
- 像素预测本质是死路
- LLM天生存在内生性缺陷
- 硅谷已经陷入羊群效应，所有人都挤在同一条战壕内卷
- VLA路线基本宣告失败，世界模型才是机器人、自动驾驶以及工业AI的唯一出路
- 到2027年初，整个行业都会明白，范式必须转变
- ……

五年内，JEPA全面统治！LeCun直言：我对Llama没有任何贡献！OpenAI是下一个Sun公司！LLM有内生缺陷！开源会追上闭源

原创 林芯 51CTO技术栈 2026年5月16日 18:28 北京 504人

有没有办法不学习MDP？

能不能从经验数据中直接学习价值函数和策略函数？

模型无关的强化学习

（Model-Free Reinforcement Learning)

价值学习与策略学习

- 价值学习（Value-based learning）通常是指学习最优价值函数$Q^*(s,a)$，假设我们有了Q^*，智能体就可以根据Q^*来做决策，选出最好的动作

- 例如，以超级马里奥为例，每次观测到一个状态s_t，让Q^*对所有动作做评价：

$$Q_\star(s_t, \text{左}) = 273, \qquad Q_\star(s_t, \text{右}) = -139, \qquad Q_\star(s_t, \text{上}) = 195$$

- 策略学习（Policy-based learning）通常是指学习最优策略函数$\pi^*(a|s)$，假设我们有了π^*，我们可以直接算出所有动作的概率值，然后去采样执行

$$\pi(\text{左} \,|\, s_t) = 0.6, \qquad \pi(\text{右} \,|\, s_t) = 0.1, \qquad \pi(\text{上} \,|\, s_t) = 0.3$$

蒙特卡洛强化学习

（Monte Carlo Reinforcement Learning)

蒙特卡洛强化学习

- 在模型未知的情形下，从起始状态出发，使用某个策略进行采样，获得轨迹
  - Episode 1：$s_1, a_1, r_1,\ s_2, a_2, r_2,\ \cdots,\ s_T, a_T, r_T$
  - …

- 对于轨迹中出现的每一对状态-动作，记录其奖赏之和，作为该状态-动作对的一次累计奖赏采样值
- 多次采样得到多条轨迹之后，将每个状态-动作对的累计奖赏采样值进行平均，得到状态-动作值函数Q的估计

蒙特卡洛强化学习

- 从某个状态-动作出发，执行策略得到一个回合的轨迹，基于该回合数据估计状态-动作的价值、

$$s_1 \xrightarrow{a_2} s_2 \xrightarrow{a_4} s_1 \xrightarrow{a_2} s_2 \xrightarrow{a_3} s_5 \xrightarrow{a_1} \dots$$

- 一个长的回合可以看做很多个从不同状态-动作出发的子回合，可以用于估计多个不同状态-动作的值；样本效率更高

$$\begin{aligned}
s_1 \xrightarrow{a_2} s_2 \xrightarrow{a_4} s_1 \xrightarrow{a_2} s_2 \xrightarrow{a_3} s_5 \xrightarrow{a_1} \dots \quad & [\text{original episode}] \\
s_2 \xrightarrow{a_4} s_1 \xrightarrow{a_2} s_2 \xrightarrow{a_3} s_5 \xrightarrow{a_1} \dots \quad & [\text{subepisode starting from } (s_2, a_4)] \\
s_1 \xrightarrow{a_2} s_2 \xrightarrow{a_3} s_5 \xrightarrow{a_1} \dots \quad & [\text{subepisode starting from } (s_1, a_2)] \\
s_2 \xrightarrow{a_3} s_5 \xrightarrow{a_1} \dots \quad & [\text{subepisode starting from } (s_2, a_3)] \\
s_5 \xrightarrow{a_1} \dots \quad & [\text{subepisode starting from } (s_5, a_1)]
\end{aligned}$$

蒙特卡洛强化学习

$$s_1 \xrightarrow{a_2} s_2 \xrightarrow{a_4} s_1 \xrightarrow{a_2} s_2 \xrightarrow{a_3} s_5 \xrightarrow{a_1} \dots$$

- 访问在一个回合中的每个时间步长t的状态s
  - 增量计数器 $N(s) \leftarrow N(s) + 1$
  - 增量总累计奖励 $S(s) \leftarrow S(s) + G_t$
  - 价值被估计为累计奖励的均值 $V(s) = S(s)/N(s)$

- 同理，可计算出$Q(s,a)$

增量蒙特卡洛强化学习

- 对于状态-动作对(s,a)，假定基于t个采样已经估计出 $Q_t^\pi(s,a)=\frac{1}{t}\sum_{i=1}^{t}G_i$
- 则在得到第$t+1$个采样时，有

$$Q_{t+1}^\pi(s,a)=Q_t^\pi(s,a)+\frac{1}{t+1}(G_{t+1}-Q_t^\pi(s,a))$$

- 更一般地，可以把$\frac{1}{t+1}$更换为系数a

$$Q_{t+1}^\pi(s,a)=Q_t^\pi(s,a)+\alpha\,(G_{t+1}-\ Q_t^\pi(s,a))$$

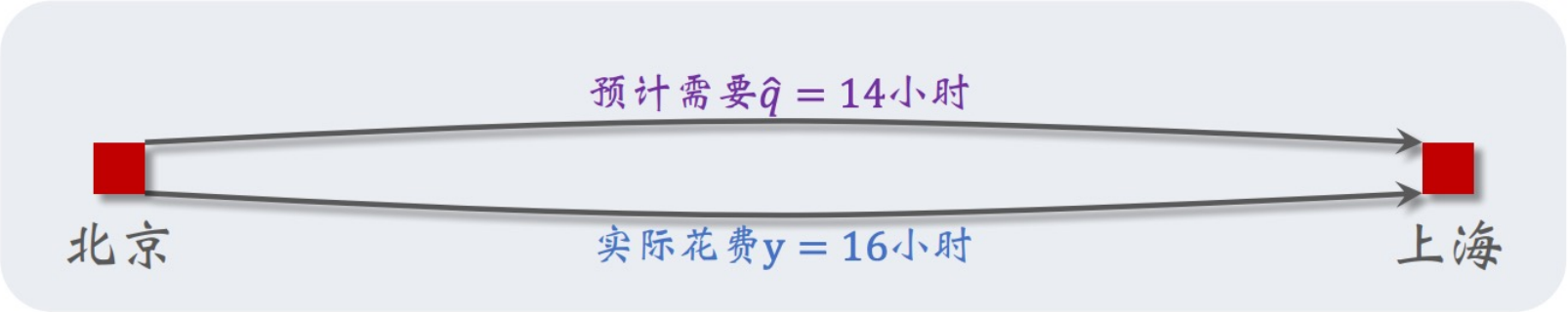
一个例子：驾车时间预测

- 假设我们有一个模型$Q(s,d)$，其中s是起点，d是终点，模型Q可以预测开车出行的时间开销，这个模型一开始不准确，但是得到更多数据之后，模型可以训练的越来越准

- 如何训练模型呢？在用户出发前，用户告诉模型起点和终点，模型做一个预测$\hat{q} = Q(s,d)$，当用户结束行程时，把实际用时y告诉模型，根据两者之差$y - \hat{q}$修正模型

一个例子：驾车时间预测

- 假设我要从北京开车去上海，出发前模型预测结果总车程为14小时，即$\hat{q} = 14$，到达上海时发现实际用时是16小时



- 基于两者之差（16-14）去更新模型，让模型预测更准

增量蒙特卡洛强化学习

- 蒙特卡罗强化学习通过考虑采样轨迹，克服了模型未知给策略估计造成的困难

  - 蒙特卡罗强化学习的缺点：低效
    - 求平均时以“批处理式”进行
    - 在一个完整的采样轨迹完成后才对状态-动作值函数进行更新

如何提升蒙特卡洛强化学习的效率呢？

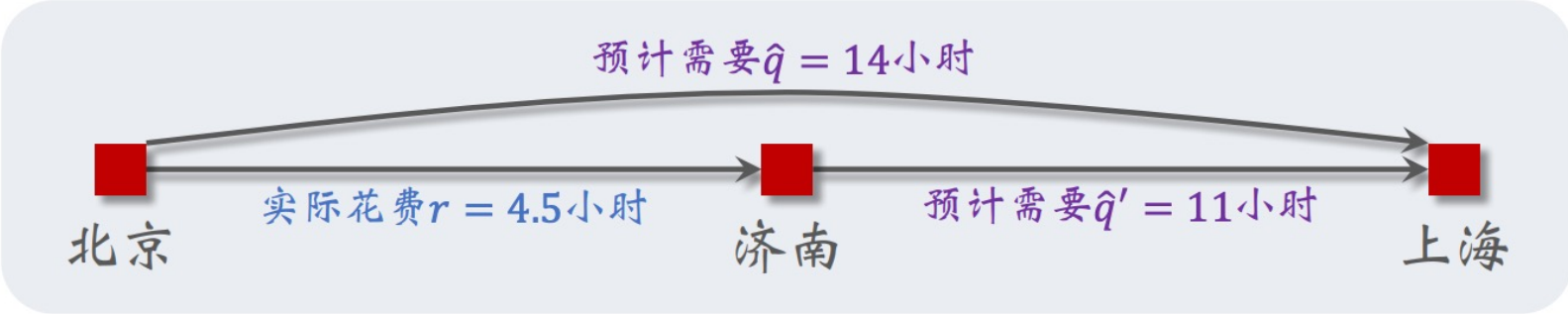
时序差分 (Temporal Difference，TD) 学习：

同时结合了动态规划和蒙特卡罗方法的思想

能做到更高效的免模型学习

一个例子：驾车时间预测

- 出发前模型预测总车程为14小时，假设我过了4.5小时到达济南，让模型再做一次预测，模型告诉我从济南到上海需要11小时



- 根据模型的最新估计，整个旅程的总时间是15.5小时，$\hat{y} = r + \hat{q}' = 4.5 + 11 = 15.5$

- TD算法将$\hat{y} = 15.5$称为TD目标，它比最初的预测$\hat{q} = 14$更可靠

一个例子：驾车时间预测

- 因此，可以用$\hat{y} = 15.5$去对模型做修正，希望估计值$\hat{q}$尽量接近TD目标$\hat{y}$
- 基于两者之差（15.5-14）去更新模型
- 模型估计从北京到上海全程需要14小时，模型还估计从济南到上海全程需要11小时。相当于模型估计从北京到济南需要的时间为3小时
- 而实际花费4.5小时，模型估计与真实观测之差$\delta = 3 - 4.5 = -1.5$（TD误差）

时序差分学习

- 蒙特卡洛强化学习

$$Q_{t+1}^{\pi}(s,a) = Q_t^{\pi}(s,a) + \alpha\left(\boldsymbol{G_{t+1} - Q_t^{\pi}(s,a)}\right)$$

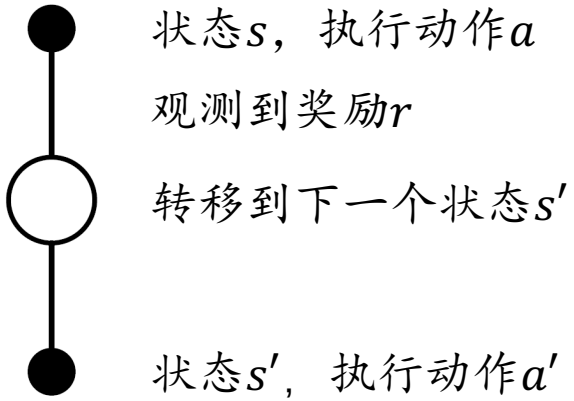
- 时序差分学习

$$Q_{t+1}^{\pi}(s,a) = Q_t^{\pi}(s,a) + \alpha\left(\boldsymbol{r_{sa}(s') + \gamma Q_t^{\pi}(s',a') - Q_t^{\pi}(s,a)}\right)$$

其中s'是前一次在状态s处执行动作a后转移到的状态， a'是策略π在s'选择的动作

SARSA

- 对于当前策略执行的每个（状态-动作-奖励-状态-动作）元组



- SARSA更新状态-动作值函数为

$$\boldsymbol{Q(s,a) \leftarrow Q(s,a) + \alpha(r_{sa}(s') + \gamma Q(s',a') - Q(s,a))}$$

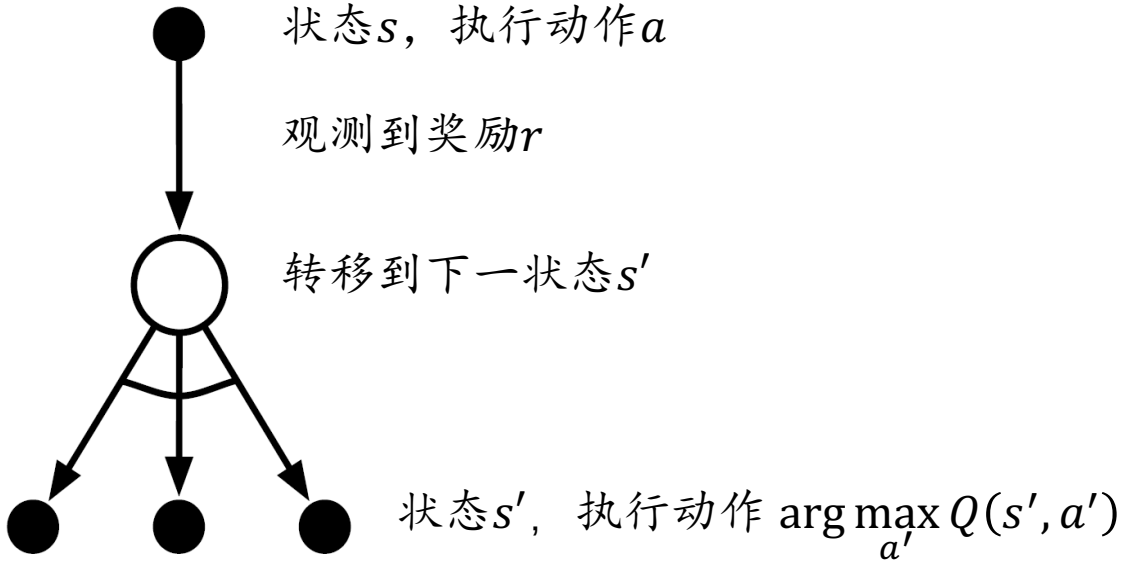
SARSA

Sarsa: An on-policy TD control algorithm

Initialize $Q(s,a), \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
  Initialize S
  Choose A from S using policy derived from Q (e.g., ϵ-greedy)
  Repeat (for each step of episode):
    Take action A, observe R, S'
    Choose A' from S' using policy derived from Q (e.g., ϵ-greedy)
    $Q(S,A) \leftarrow Q(S,A) + \alpha\big[R + \gamma Q(S',A') - Q(S,A)\big]$
    $S \leftarrow S'$; $A \leftarrow A'$;
  until S is terminal

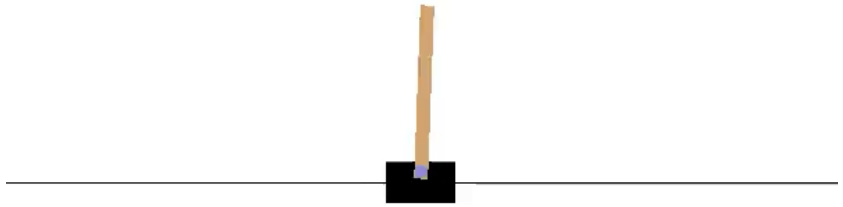
SARSA算法中的两个“A”都是由**当前策略**选择的

Q-Learning



- SARSA只能估计给定策略的动作值，必须结合策略改进步骤才能得到最优策略
- Q-Learning可以直接估计最优动作值进而找到最优策略

连续状态离散化



Num	Observation	Min	Max
0	Cart Position	-4.8	4.8
1	Cart Velocity	-Inf	Inf
2	Pole Angle	~ -0.418 rad (-24°)	~ 0.418 rad (24°)
3	Pole Angular Velocity	-Inf	Inf

Num	Action
0	Push cart to the left
1	Push cart to the right

从表格到函数

$Q_\theta(s,a)$

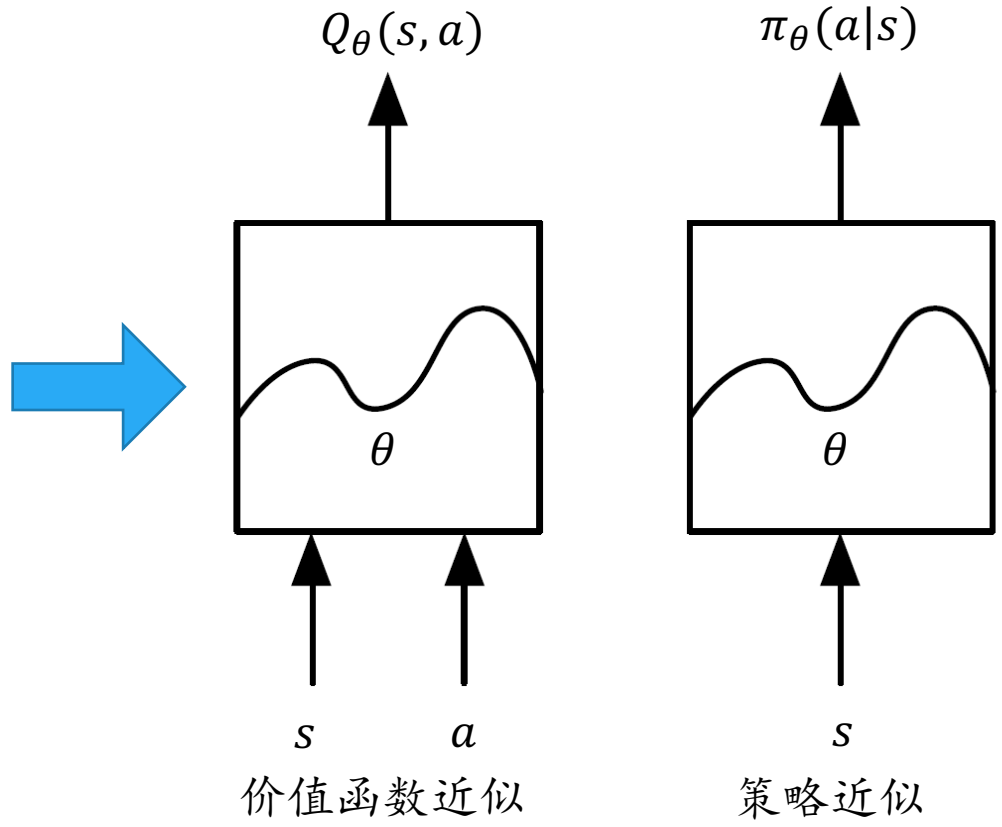
	a_1	a_2
s_1	3.2	4.1
s_2	0.8	1.2
s_3	2.3	-0.3

价值函数表格

$\pi_\theta(s,a)$

	a_1	a_2
s_1	0.2	0.8
s_2	0.4	0.6
s_3	0.9	0.1

策略表格



- 假如我们直接使用深度神经网络建立这些近似函数呢？
- **深度强化学习！**

深度强化学习

2013年12月，第一篇深度强化学习论文出自NIPS 2013 Reinforcement Learning Workshop

Playing Atari with Deep Reinforcement Learning

Volodymyr Mnih **Koray Kavukcuoglu** **David Silver** **Alex Graves** **Ioannis Antonoglou**

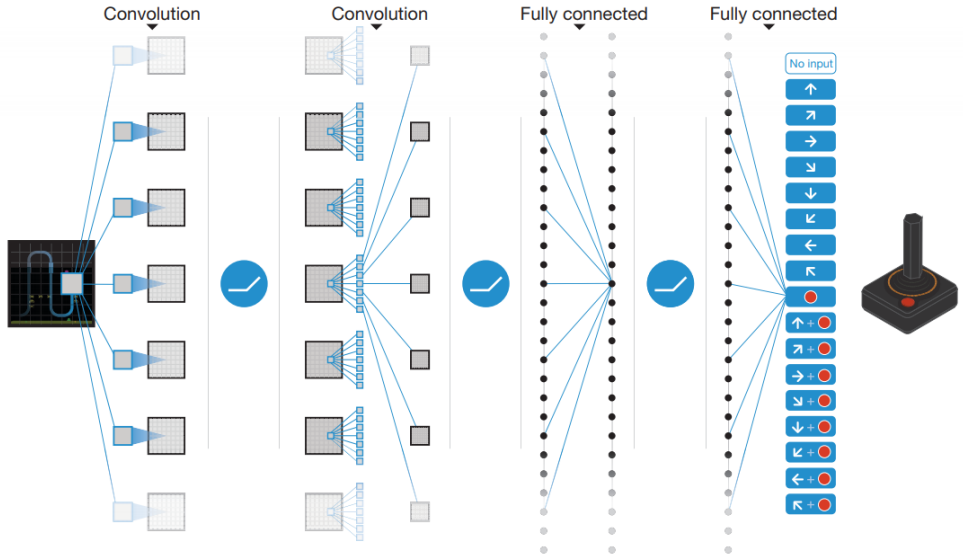
Daan Wierstra **Martin Riedmiller**

DeepMind Technologies

{vlad,koray,david,alex.graves,ioannis,daan,martin.riedmiller} @ deepmind.com

Volodymyr Mnih, Koray Kavukcuoglu, David Silver et al. Playing Atari with Deep Reinforcement Learning. NIPS 2013 workshop.

深度强化学习

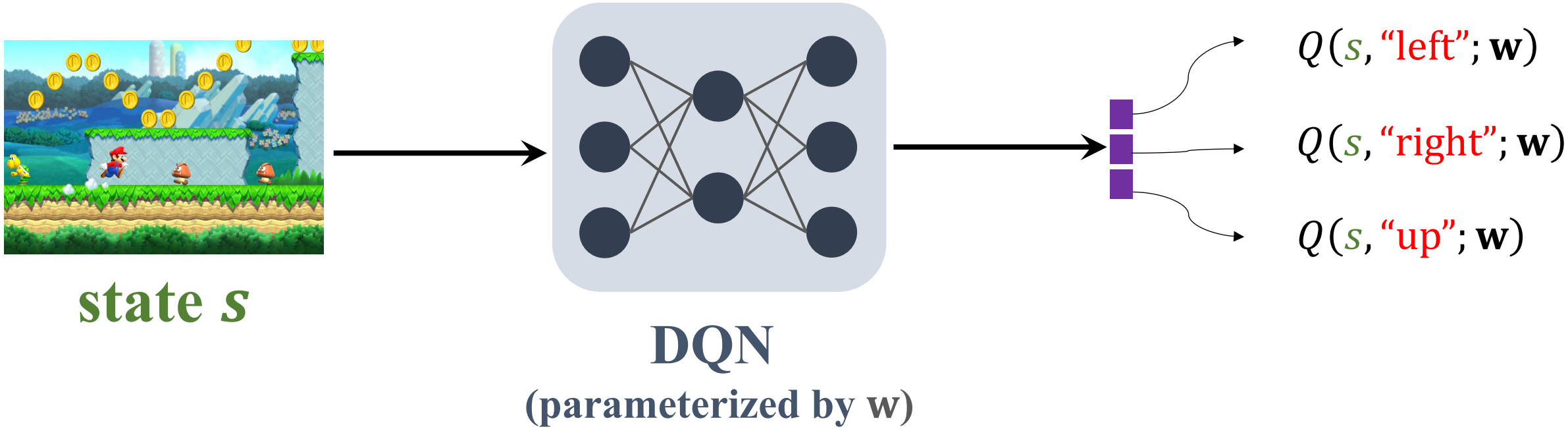


Q函数的参数通过神经网络反向传播学习

Volodymyr Mnih, Koray Kavukcuoglu, David Silver et al. Playing Atari with Deep Reinforcement Learning. NIPS 2013 workshop.

深度强化学习：DQN

DQN，$Q(s,a;\mathbf{w})$.是对最优动作价值函数 $Q^{\star}(s,a)$的近似



深度强化学习：DQN

DQN，$Q(s,a;\mathbf{w})$，是对最优动作价值函数 $Q^{\star}(s,a)$的近似

每次观察到一个transition：(s_t, a_t, r_t, s_{t+1})

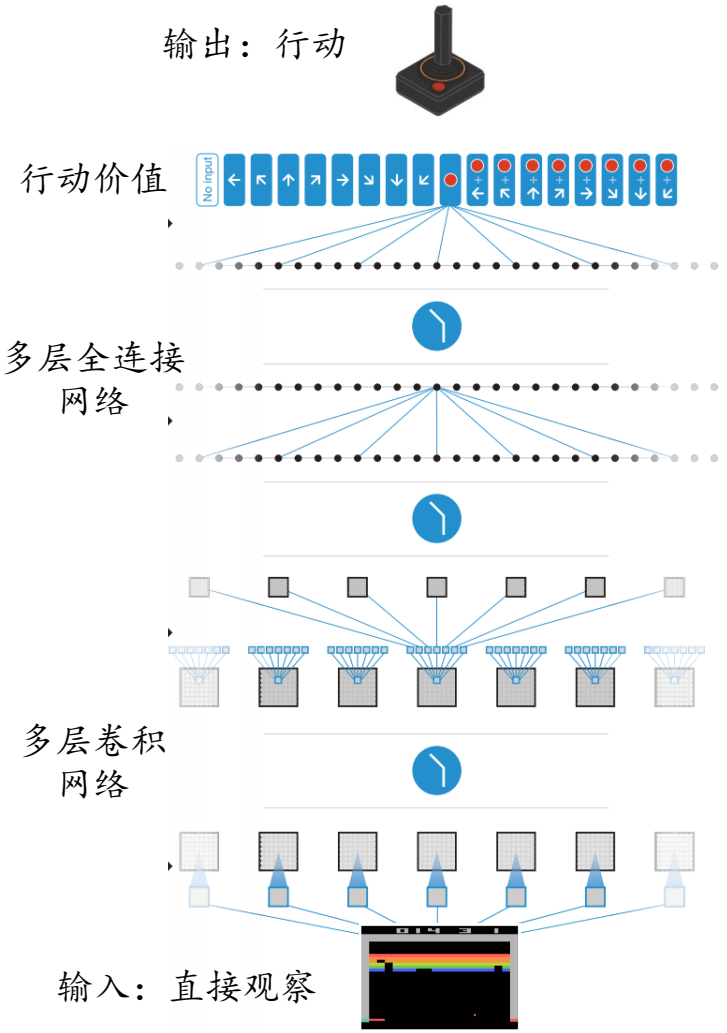
TD 目标：$y_t = r_t + \gamma \cdot \max_{a} Q(s_{t+1}, a; \mathbf{w})$

TD 误差：$\delta_t = Q(s_t, a_t; \mathbf{w}) - y_t$

参数更新：$\mathbf{w} \leftarrow \mathbf{w} - \alpha \cdot \delta_t \cdot \frac{\partial\, Q(s_t, a_t; \mathbf{w})}{\partial\, \mathbf{w}}$

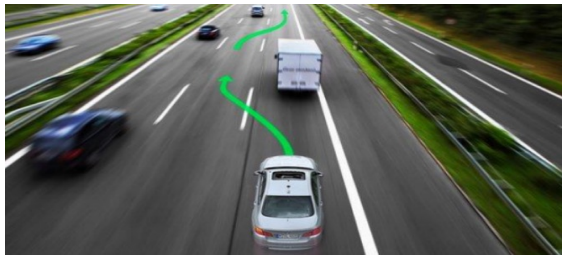
关于强化学习的热门话题

- 将深度学习（DL）和强化学习（RL）结合在一起会发生什么？
  - 价值函数和策略变成了深度神经网络
  - 相当高维的参数空间
  - 难以稳定地训练
  - 容易过拟合
  - 需要大量的数据
  - 需要高性能计算
  - CPU（用于收集经验数据）和GPU（用于训练神经网络）之间的平衡
  - …
- 这些新的问题促进着深度强化学习算法的创新

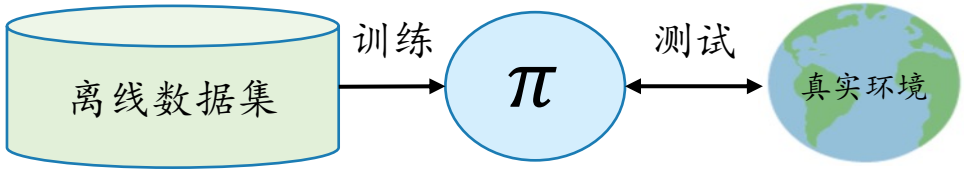


离线强化学习 (Offline RL)

- 动机：在真实环境中从零开始训练一个强化学习智能体往往不可取
  - 风险较高，例如无人驾驶归控、智能医疗等
  - 十分昂贵，例如机器人控制、推荐系统等

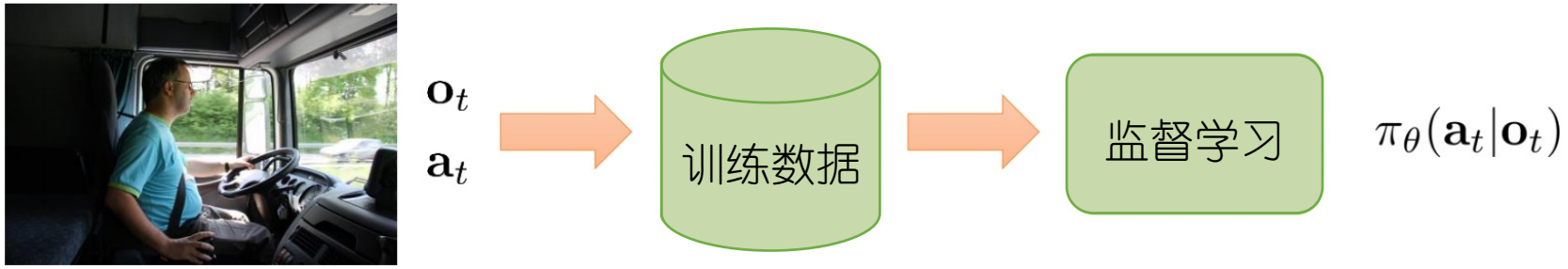


- 离线强化学习：在一个给定的离线数据集上直接训练出智能体策略，训练的过程中，智能体不得和环境做交互



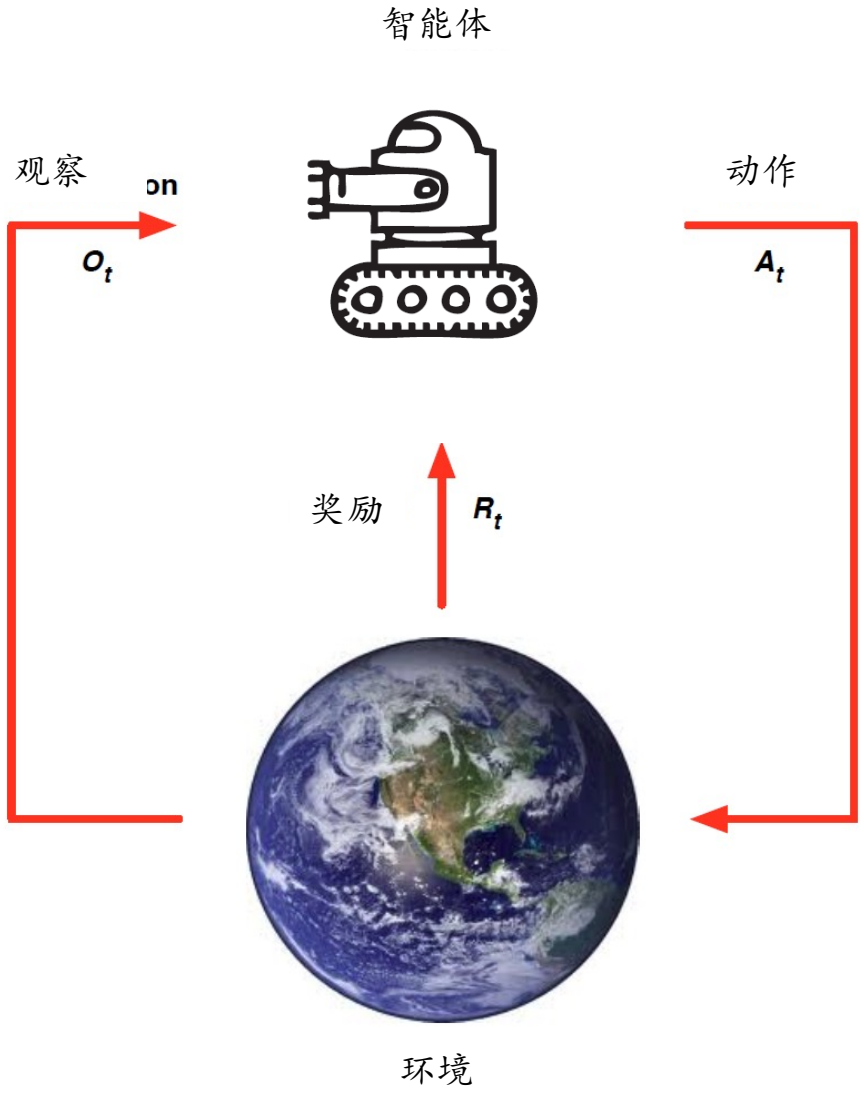
模仿学习 (Imitation Learning)

- 模仿学习：直接模仿人类专家的状态-动作对来学习策略
- 目的：都是学习策略，从而控制智能体
- 原理：
  - 强化学习利用环境反馈的奖励改进策略，目标是让累计奖励最大化
  - 模仿学习向人类专家学习，目标是让策略函数做出的决策与人类专家相同



多智能体强化学习(Multi-Agent Learning)

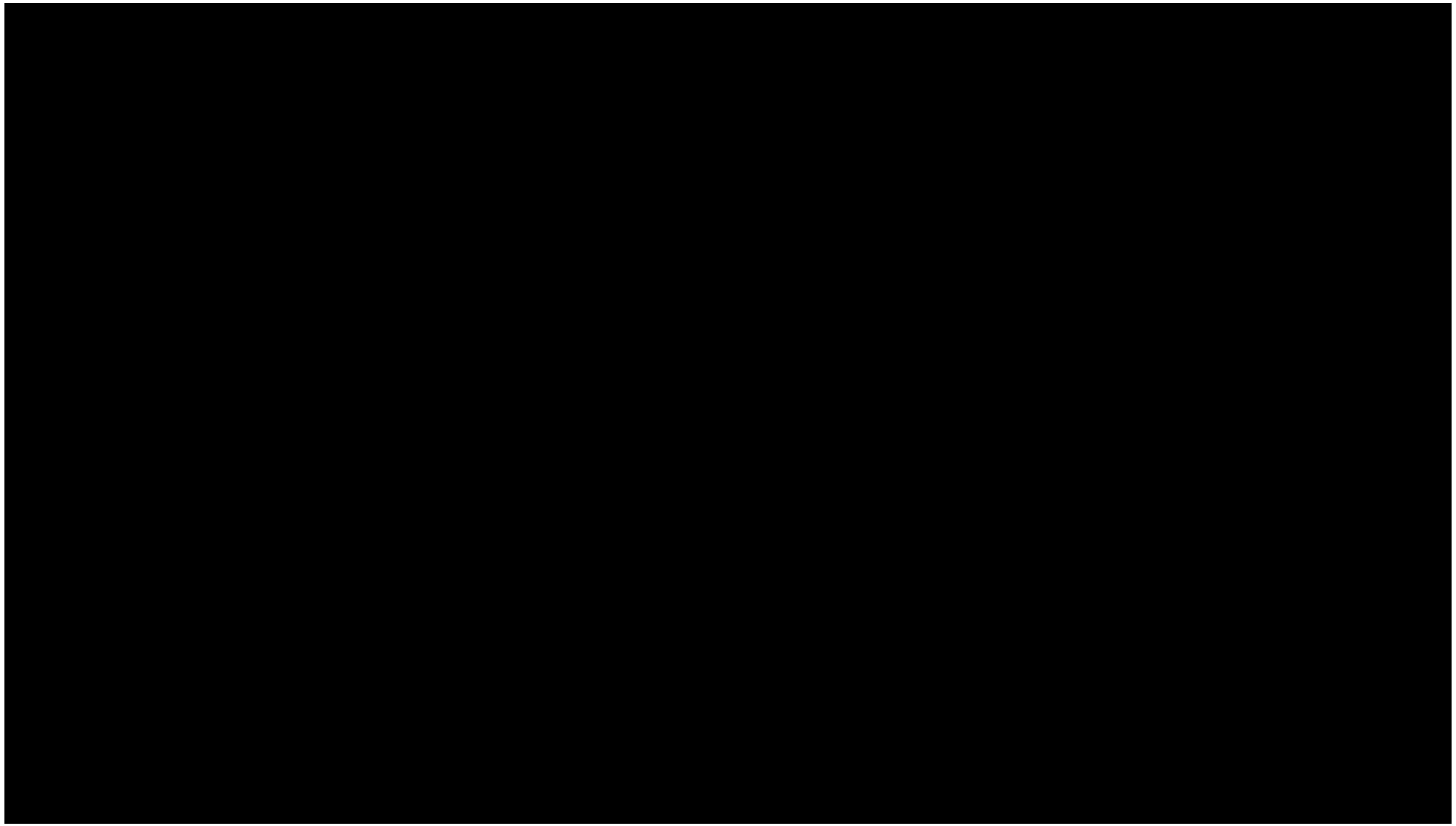
- 在与环境的交互过程中学习
- 环境包含有不断进行学习和更新的其他智能体
- 在任何一个智能体的视角下，环境是非稳态的（non-stationary）
  - 状态转移的概率分布会发生改变



多智能体强化学习(Multi-Agent Learning)

多智能体强化学习(Multi-Agent Learning)

多智能体强化学习(Multi-Agent Learning)



大模型时代的强化学习

- RLHF (Reinforcement Learning from Human Feedback)：让语言模型更符合人类偏好，例如回答更有帮助、更安全、更礼貌

- RLVR (Reinforcement Learning with Verifiable Reward)：可验证奖励强化学习，提升大模型推理能力，例如，数学、代码等

- Agentic RL：训练LLM工具调用与多步决策能力，例如，Web Agent、GUI Agent、Code Agent等

前往下一站


LLM
REASONING
PLANNING
Reasoning
Plaming
Plan
Tesk A
Task Bl
Goal
A→B