强化学习“探索与利用”方法研究

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背景知识

MDP

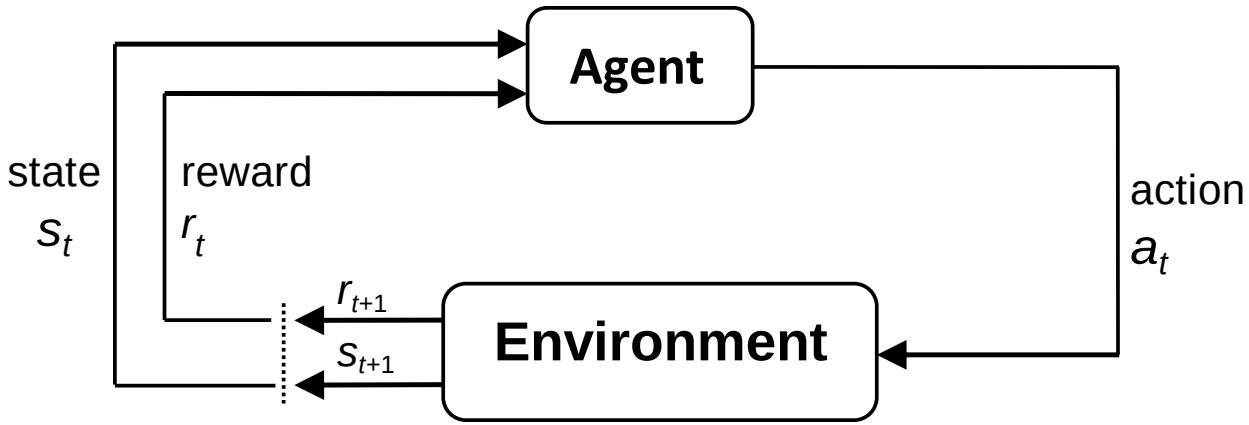


图 1: 智能体与环境交互示意

- MDP定义为$\langle S, A, P, R, \gamma \rangle$
- S和A分别为状态和动作集合
- $P(s, a, s')$是转移概率函数
- $R(s, a)$是即时收益函数
- γ为折扣因子$(0 < \gamma < 1)$
- 依据策略$\pi(s, a)$与环境交互

MDP

- 轨迹 $\boldsymbol{h} = [s_0, a_0, r_1, s_1, a_1, r_2, \ldots, s_t, a_t, r_{t+1}, \ldots]$
- 累计收益 $G_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}$
- 状态价值函数 $V^{\pi}(s) = \mathbb{E}_{\pi}[G_t | s_t = s]$
- 状态-动作价值函数 $Q^{\pi}(s, a) = \mathbb{E}_{\pi}[G_t | s_t = s, a_t = a]$
- 策略评估 评估策略π下的期望累积收益$\mathbb{E}[G_t]$
- 策略优化 找最优策略π^*以最大化期望累积收益$\mathbb{E}[G_t]$

$$\pi^* = \arg\max_{\pi} \mathbb{E}[G_t]$$

策略评估

- 贝尔曼期望等式

$$V^{\pi}(s) = \Sigma_a \pi(a|s) \Sigma_{s'} P\left(s, a, s'\right)\left(R\left(s, a, s'\right) + \gamma V^{\pi}\left(s'\right)\right)$$

$$Q^{\pi}(s, a) = \Sigma_{s'} P\left(s, a, s'\right)\left(R\left(s, a, s'\right) + \gamma \Sigma_{a'} \pi\left(a'|s'\right) Q^{\pi}\left(s', a'\right)\right)$$

- $R^{\pi}_{ave}(s) = \Sigma_a \pi(a|s) \Sigma_{s'} P\left(s, a, s'\right) R\left(s, a, s'\right)$
- $T^{\pi}(s \to s') = \Sigma_a \pi(a|s) P\left(s, a, s'\right)$

Theorem

基于$V^{\pi}(s) = \Sigma_a \pi(a|s) \Sigma_{s'} P\left(s, a, s'\right)\left(R\left(s, a, s'\right) + \gamma V^{\pi}\left(s'\right)\right)$定义算子$\mathcal{T}$，可证明$\mathcal{T}$为*Banach*空间中的压缩算子

$$\mathcal{T}V \equiv R^{\pi}_{ave} + \gamma T^{\pi} V$$

策略评估

Theorem

贝尔曼期望等式递推展开，得$V^{\pi}(\vec{S})$与$Q^{\pi}(s,a)$表达式

$$
\begin{aligned}
V^{\pi}(\vec{S}) &= R^{\pi}_{ave}(\vec{S}) + (\gamma T^{\pi})^{1} \cdot R^{\pi}_{ave}(\vec{S}) + (\gamma T^{\pi})^{2} \cdot R^{\pi}_{ave}(\vec{S}) + \dots \\
&= \sum_{k=0}^{\infty} (\gamma T^{\pi})^{k} \cdot R^{\pi}_{ave}(\vec{S}) \\
&= \sum_{k=0}^{\infty} (\gamma T^{\pi})^{(k)} \cdot R^{\pi}_{ave}(\vec{S}) \\
&= (\boldsymbol{I} - \gamma T^{\pi})^{-1} \cdot R^{\pi}_{ave}(\vec{S}) \\
Q^{\pi}(s,a) &= R(s,a) + \gamma P(s,a,\vec{S})(\boldsymbol{I} - \gamma T^{\pi})^{-1} R^{\pi}_{ave}(\vec{S})
\end{aligned}
$$

策略评估

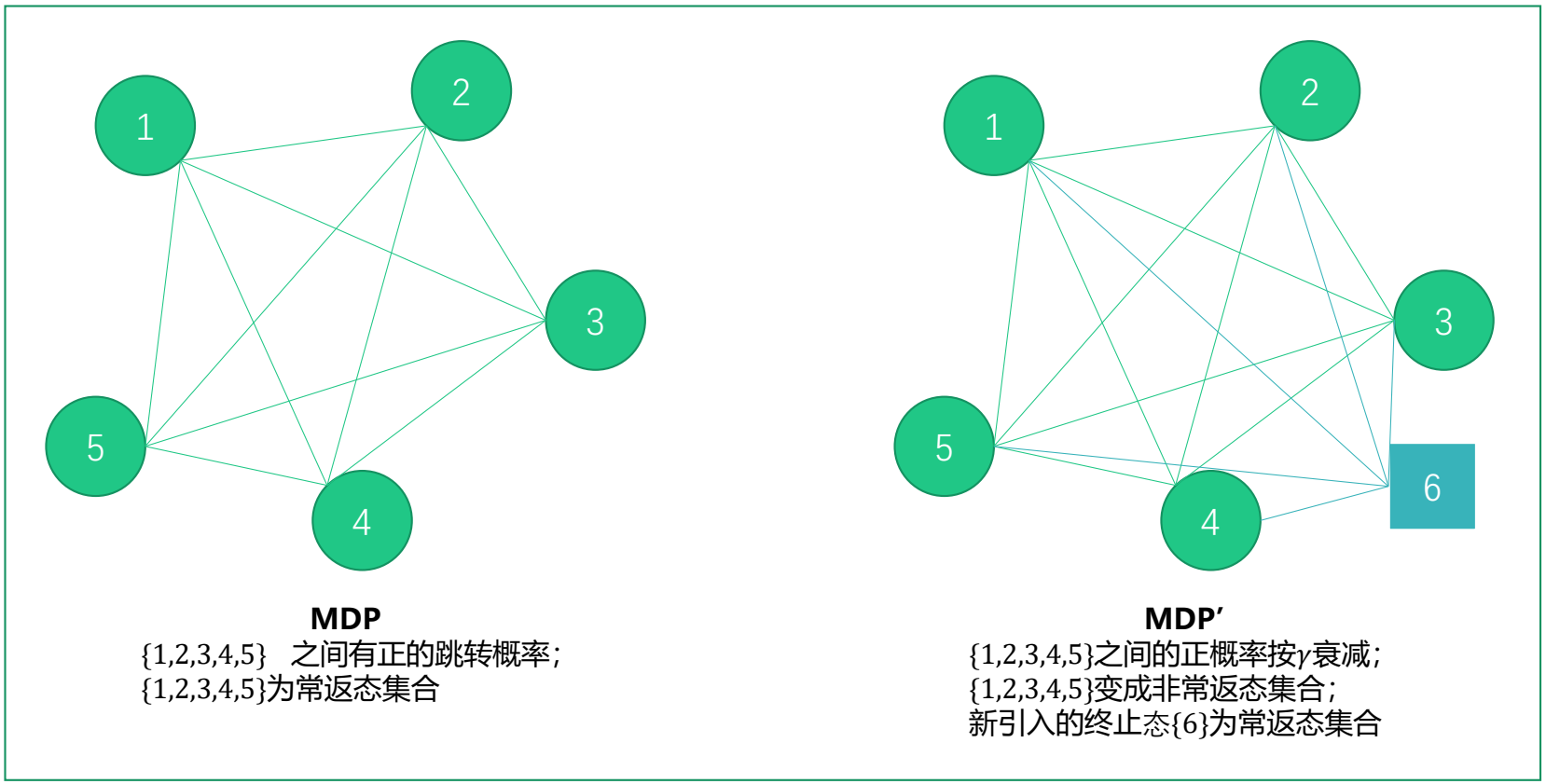


图 2: 引入$\gamma(0 < \gamma < 1)$可视作把MDP转换为MDP'的示例

策略优化

- 贝尔曼最优化等式

$$V^*(s) = \max_{\pi} V^{\pi}(s) = \max_{a} \Sigma_{s'} P(s,a,s')\left(R(s,a,s') + \gamma V^*(s')\right)$$

$$Q^*(s,a) = \max_{\pi} Q^{\pi}(s,a) = \Sigma_{s'} P(s,a,s')\left(R(s,a,s') + \gamma \max_{a'} Q^*(s',a')\right)$$

- 最优策略必为贪心选择动作导出的确定性策略，因此下式成立

$$V^*(s) = \max_{a} Q^*(s,a)$$

- 类似定义贝尔曼最优化算子具有压缩性以证明存在唯一不动点

策略优化

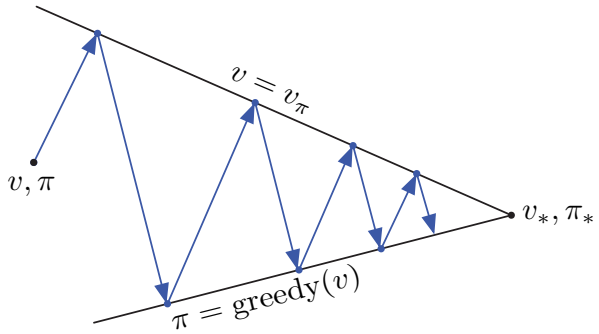


图 3: 广义策略提升框架GPI中策略评估与优化交替

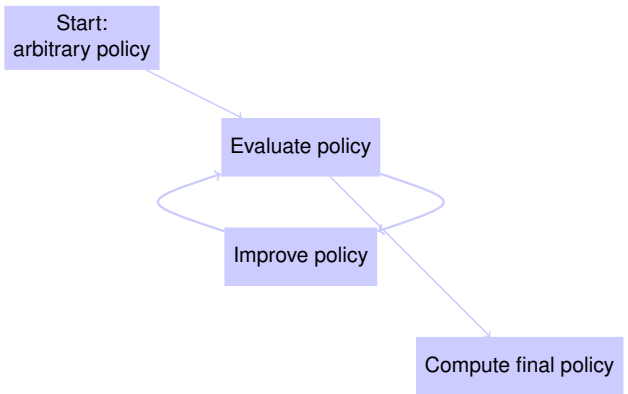


图 4: 策略迭代

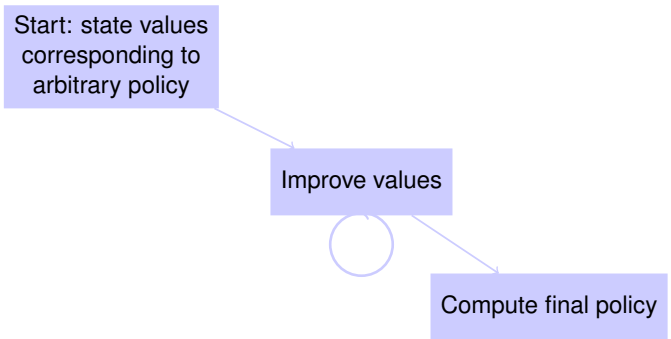


图 5: 值迭代

策略优化

策略从π提升到π'常采用greedy, $\epsilon-$greedy和softmax几种方式

- greedy

$$\pi'(a|s) = \begin{cases} 1 & a = \arg\max_a Q^\pi(s,a) \\ 0 & \text{otherwise} \end{cases}$$

- $\epsilon-$greedy

$$\pi'(a|s) = \begin{cases} \frac{\epsilon}{|A|} + 1 - \epsilon, & a = \arg\max_a Q^\pi(s,a) \\ \frac{\epsilon}{|A|}, & \text{otherwise} \end{cases}$$

- softmax

$$\pi'(a|s) = \frac{e^{\beta Q^\pi(s,a)}}{\sum_{a \in A} e^{\beta Q^\pi(s,a)}}$$

深度强化学习

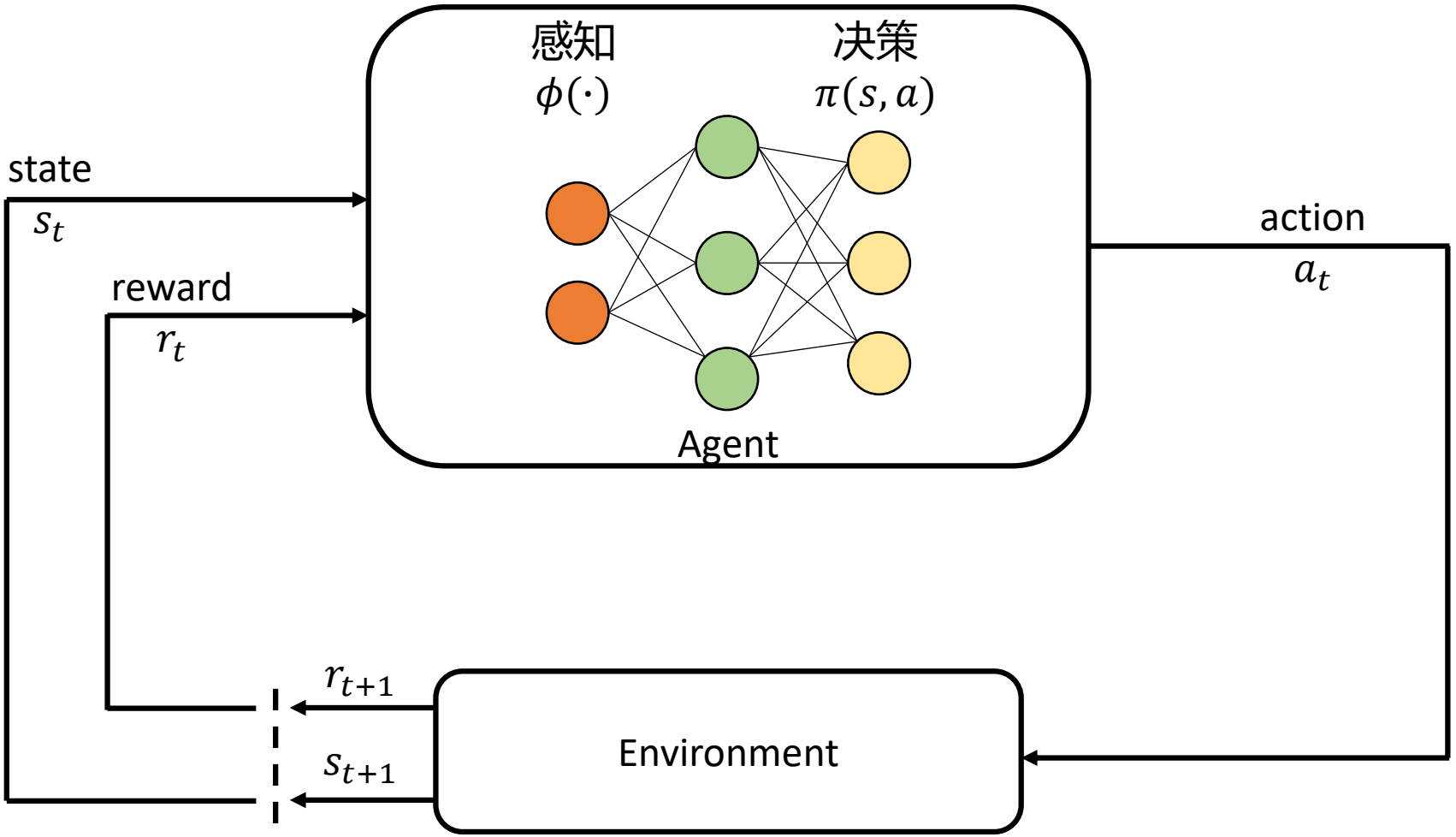
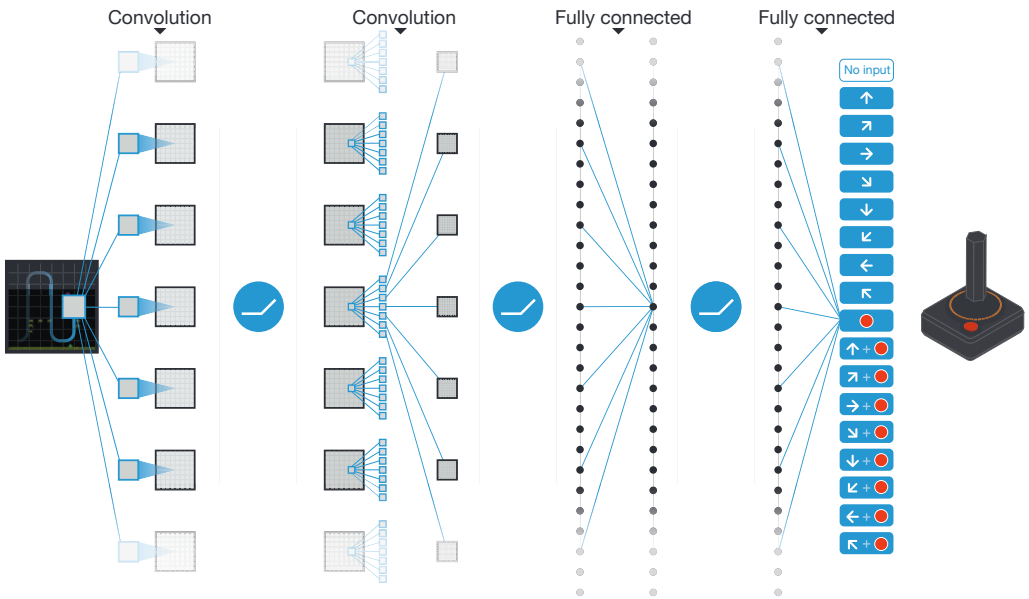


图 6: 深度强化学习智能体与环境交互示意

强化学习算法

DQN



- 深度卷积网络
- 经验回放
- 目标网络

图 7: DQN架构(Mnih et al., 2015)

$$L_i(\theta_i) = \mathbb{E}_{(s,a,r,s')\sim \mathrm{U}(D)}\left[\left(r + \gamma \max_{a'} Q\left(s', a'; \theta_i^-\right) - Q(s, a; \theta_i)\right)^2\right]$$

$$\nabla_{\theta_i} L(\theta_i) = \mathbb{E}_{s,a,r,s'}\left[\left(r + \gamma \max_{a'} Q\left(s', a'; \theta_i^-\right) - Q(s, a; \theta_i)\right) \nabla_{\theta_i} Q(s, a; \theta_i)\right]$$

DQN变种

表 1: DQN及其变种算法

算法	特点
DQN (Mnih et al., 2015)	CNN网络，卷积层感知，全连接层输出动作概率； 经验回放池机制； 目标网络以稳定训练； $Y^{DQN} \equiv r + \gamma \max_{a'} Q\left(s', a'; \theta_i^-\right)$
Double DQN (van Hasselt et al., 2016)	将选动作和评估值函数解耦，用两个网络 $Y^{DoubleDQN} \equiv r + \gamma Q\left(s', \arg\max_{a' \in A} Q(s', a', \theta_i); \theta_i^-\right)$
优先经验回放 (Schaul et al., 2016)	将相对更重要的记忆以更高频率被回放
Dueling DQN (Wang et al., 2016)	定义优势函数$A^{\pi}(s,a)$，将$Q^{\pi}(s,a)$拆解为$V^{\pi}(s)$与$A^{\pi}(s,a)$两部分
Rainbow (Hessel et al., 2018)	结合上述所有特点的方案，还包括多步、随机参数等技巧

随机策略梯度定理

$$
\begin{aligned}
\nabla V^{\pi}(s) &= \nabla\left[\sum_{a}\pi(s,a;\theta)Q^{\pi}(s,a)\right], \quad \text{对所有} s\in S \\
&= \sum_{a}\left[\nabla\pi(s,a;\theta)Q^{\pi}(s,a)+\pi(s,a;\theta)\nabla Q^{\pi}(s,a)\right] \\
&= \sum_{a}\left[\nabla\pi(s,a;\theta)Q^{\pi}(s,a)+\pi(s,a;\theta)\nabla\sum_{s'}P\left(s,a,s'\right)\left[r(s,a,s')+\gamma V^{\pi}\left(s'\right)\right]\right] \\
&= \sum_{a}\left[\nabla\pi(s,a;\theta)Q^{\pi}(s,a)+\gamma\pi(s,a;\theta)\sum_{s'}P\left(s,a,s'\right)\underbrace{\nabla V^{\pi}\left(s'\right)}_{\text{递推展开}}\right] \\
&= \sum_{a}\Bigg[\nabla\pi(s,a;\theta)Q^{\pi}(s,a)+\gamma\pi(s,a;\theta)\sum_{s'}P\left(s,a,s'\right)\times \\
&\quad \underbrace{\sum_{a'}\left[\nabla\pi(s',a';\theta)Q^{\pi}(s',a')+\gamma\pi(s',a';\theta)\sum_{s''}P(s',a',s'')\nabla V^{\pi}(s'')\right]}\Bigg] \\
&= \dots \\
&= \sum_{x}\sum_{k=0}(\gamma T^{\pi})^{(k)}_{s\to x}\sum_{a}\left[\nabla\pi(x,a;\theta)Q^{\pi}(x,a)\right] \\
&= \sum_{x}\sum_{k=0}(\gamma T^{\pi})^{(k)}_{s\to x}\sum_{a}\left[\frac{\nabla\pi(x,a;\theta)}{\pi(x,a;\theta)}\pi(x,a;\theta)Q^{\pi}(x,a)\right] \\
&= \sum_{x}\sum_{k=0}(\gamma T^{\pi})^{(k)}_{s\to x}\mathbb{E}_{\pi}\left[Q^{\pi}(x,a)\nabla\log\pi(x,a;\theta)\right]
\end{aligned}
$$

随机策略梯度定理

$$\sum_{k=0}(\gamma T^{\pi})^{(k)}_{s\to x} \approx \bar{\text{freq}}(x) = \frac{\sum_{k=0}\text{FREQ}^k(x)}{m}$$

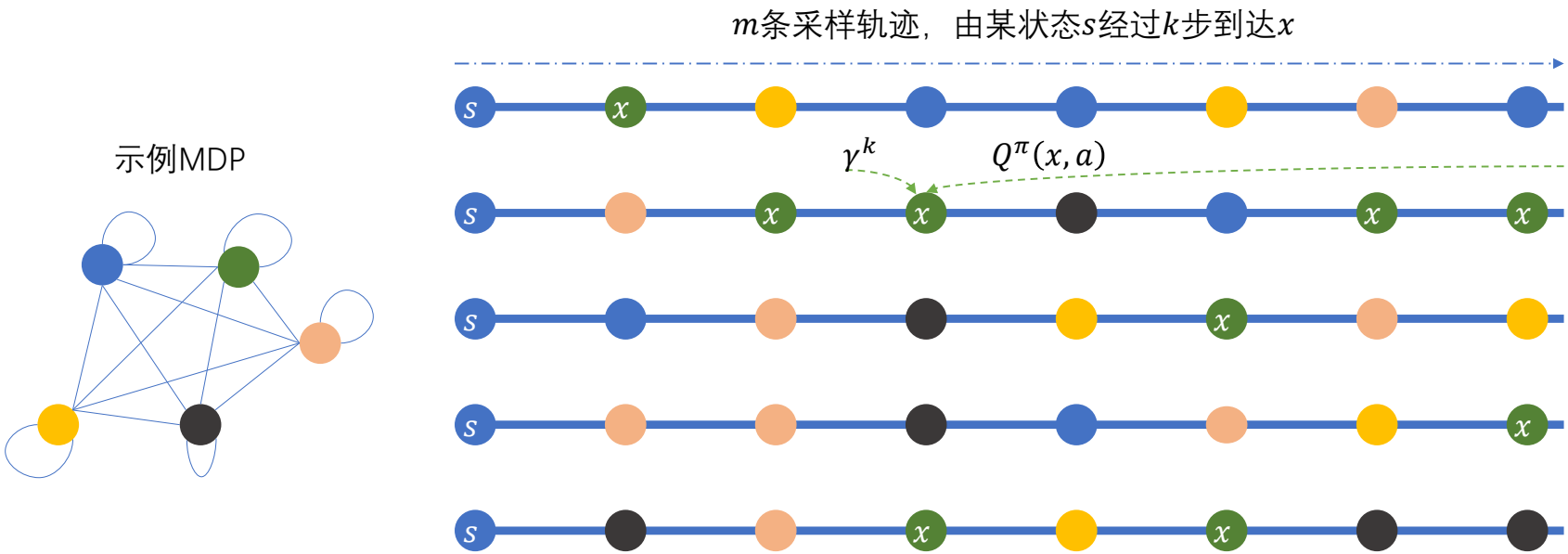


图 8: 从某一状态出发游走产生若干条轨迹

随机策略梯度定理

$$
\begin{aligned}
\nabla V^{\pi}(s) &= \sum_{x}\sum_{k=0}(\gamma T^{\pi})^{(k)}_{s\to x}\mathbb{E}_{\pi}\left[Q^{\pi}(x,a)\nabla\log\pi(x,a;\theta)\right] \\
&\approx \sum_{x}\underbrace{\bar{\text{freq}}(x)}_{\text{依据}\gamma T^{\pi}}\mathbb{E}_{\pi}\left[Q^{\pi}(x,a)\nabla\log\pi(x,a;\theta)\right] \\
&= \sum_{x}\underbrace{\frac{\sum_{k=0}\text{FREQ}^{k}(x)}{m}}_{\text{依据}\gamma T^{\pi}}\mathbb{E}_{\pi}\left[Q^{\pi}(x,a)\nabla\log\pi(x,a;\theta)\right] \\
&= \frac{1}{m}\sum_{x}\underbrace{\sum_{k=0}\text{FREQ}^{k}(x)}_{\text{依据}\gamma T^{\pi}}\mathbb{E}_{\pi}\left[Q^{\pi}(x,a)\nabla\log\pi(x,a;\theta)\right] \\
&= \frac{1}{m}\sum_{x}\sum_{k=0}\gamma^{k}\underbrace{\frac{1}{\gamma^{k}}\text{FREQ}^{k}(x)}_{\text{依据}T^{\pi}\text{从}s\text{出发经}k\text{步到}x\text{的频次}}\mathbb{E}_{\pi}\left[Q^{\pi}(x,a)\nabla\log\pi(x,a;\theta)\right] \\
&\approx \underbrace{\frac{1}{m}\sum_{i=1}^{m}\sum_{k=0}^{H_i}\left[\gamma^{k}Q(x,a)\nabla\log\pi(x,a;\theta)|s\xrightarrow{(k)}x\right]}_{\text{依据}T^{\pi}\text{且从}s\text{出发}}
\end{aligned}
$$

随机策略梯度定理

- 初始状态分布

$$
\begin{aligned}
\nabla J(\theta) &= \nabla V^{\pi}(x_0) \\
&= \sum_{x}\sum_{k=0}(\gamma T^{\pi})^{(k)}_{x_0\to x}\mathbb{E}_{\pi}\left[Q^{\pi}(x,a)\nabla \log \pi(x,a;\theta)\right] \\
&\approx \dots \\
&\approx \underbrace{\frac{1}{m}\sum_{i=1}^{m}\sum_{k=0}^{H_i}\left[\gamma^k Q(x,a)\nabla \log \pi(x,a;\theta)|x_0 \xrightarrow{(k)} x\right]}_{\text{依据}T^{\pi}\text{且}x_0\sim\text{uniform}(S)}
\end{aligned}
$$

- $\mathbb{E}_{x\sim\rho^{\pi_\theta},a\sim\pi}\left[Q^{\pi}(x,a)\nabla \log \pi(x,a;\theta)\right]$

REINFORCE等随机策略梯度算法

表 2: REINFORCE等随机策略梯度算法

算法	特点
REINFORCE	基于随机梯度定理，梯度为 $\sum_x \sum_{k=0} (\gamma T^\pi)^{(k)}_{s\to x} \mathbb{E}_\pi \left[Q^\pi(x,a) \nabla \log \pi(x,a;\theta) \right]$ 用蒙特卡洛方法估计梯度 $\frac{1}{m} \sum_{i=1}^{m} \sum_{k=0}^{H_i} \left[\gamma^k Q(x,a) \nabla \log \pi(x,a;\theta) \vert x_0 \xrightarrow{(k)} x \right]$
引入基线的REINFORCE	引入常数基数b有利于减小方差 且对策略梯度保持为无偏估计
Actor-Critic	策略函数拟合之外增加对状态-动作价值函数拟合
A2C	把Critic网络原始的累计收益替换成优势函数
A3C	多线程异步运行 全局有一套Actor神经网络参数 各环境中也存有一副本

确定性策略梯度定理

$$
\begin{aligned}
\nabla_\theta V^{\mu_\theta}(s) &= \nabla_\theta Q^{\mu_\theta}\left(s, \mu_\theta(s)\right) \\
&= \int_{\mathcal{S}} \sum_{t=0}^{\infty} \gamma^t p\left(s \to s', t, \mu_\theta\right) \nabla_\theta \mu_\theta\left(s'\right) \nabla_a Q^{\mu_\theta}\left(s', a\right)\Big|_{a=\mu_\theta(s')} \mathrm{d}s' \\
\nabla_\theta J\left(\mu_\theta\right) &= \nabla_\theta \int_{\mathcal{S}} p_1(s) V^{\mu_\theta}(s) \mathrm{d}s \\
&= \int_{\mathcal{S}} p_1(s) \nabla_\theta V^{\mu_\theta}(s) \mathrm{d}s \\
&= \int_{\mathcal{S}} \int_{\mathcal{S}} \sum_{t=0}^{\infty} \gamma^t p_1(s) p\left(s \to s', t, \mu_\theta\right) \nabla_\theta \mu_\theta\left(s'\right) \nabla_a Q^{\mu_\theta}\left(s', a\right)\Big|_{a=\mu_\theta(s')} \mathrm{d}s' \mathrm{d}s \\
&= \int_{\mathcal{S}} \rho^{\mu_\theta}(s) \nabla_\theta \mu_\theta(s) \nabla_a Q^{\mu_\theta}(s, a)\Big|_{a=\mu_\theta(s)} \mathrm{d}s
\end{aligned}
$$

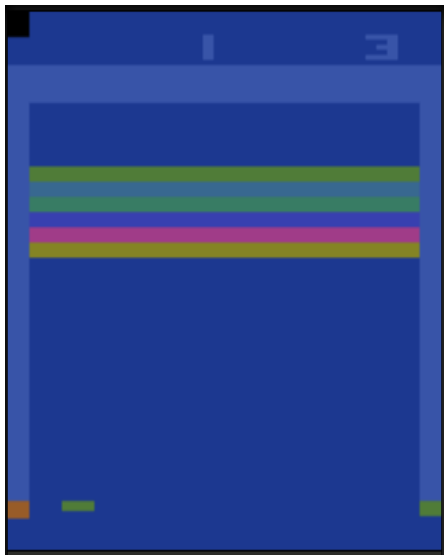
DDPG等确定性策略梯度算法

表 3: DDPG等确定性策略梯度算法

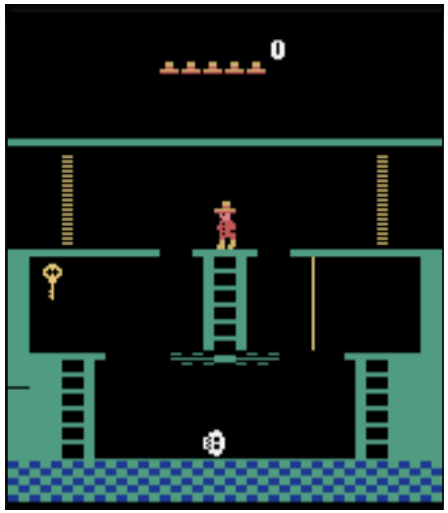
算法	特点
DPG	基于确定性策略梯度定理 状态映射到动作值而非动作概率分布$a = \mu_\theta(s)$ $\int_{\mathcal{S}} \rho^{\mu_\theta}(s) \nabla_\theta \mu_\theta(s) \nabla_a Q^{\mu_\theta}(s,a)\big\|_{a=\mu_\theta(s)} \mathrm{d}s$ $\theta^{k+1} = \theta^k + \alpha \mathbb{E}_{s\sim\rho^\mu}\left[\nabla_\theta \mu_\theta(s) \nabla_a Q^{\mu^k}(s,a)\big\|_{a=\mu_\theta(s)}\right]$
异策略DPG	利用行为策略的样本辅助训练 解决确定性策略探索性不足的问题
DDPG	借用DQN两个机制：经验回放和独立目标网络 目标网络的参数采用soft更新模式

研究动机

硬探索(Hard Exploration Problem)



Breakout



Montezuma's revenge

Pitfall

图 9: 三种Atari游戏

样本效率(Sample Inefficiency)

- 1000万游戏帧训练DQN

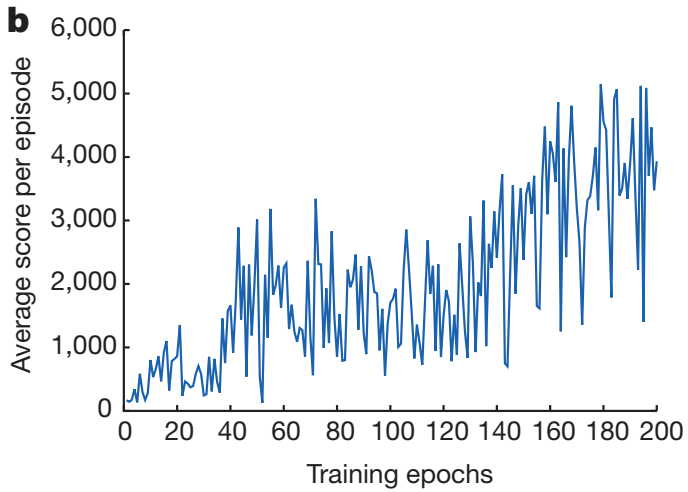


图 10: Seaquestc(Mnih et al., 2015)

- 490万局围棋对局

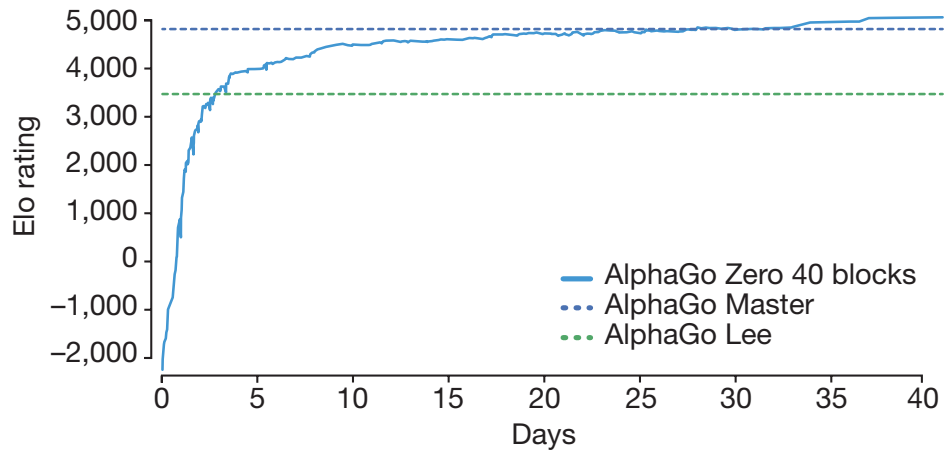
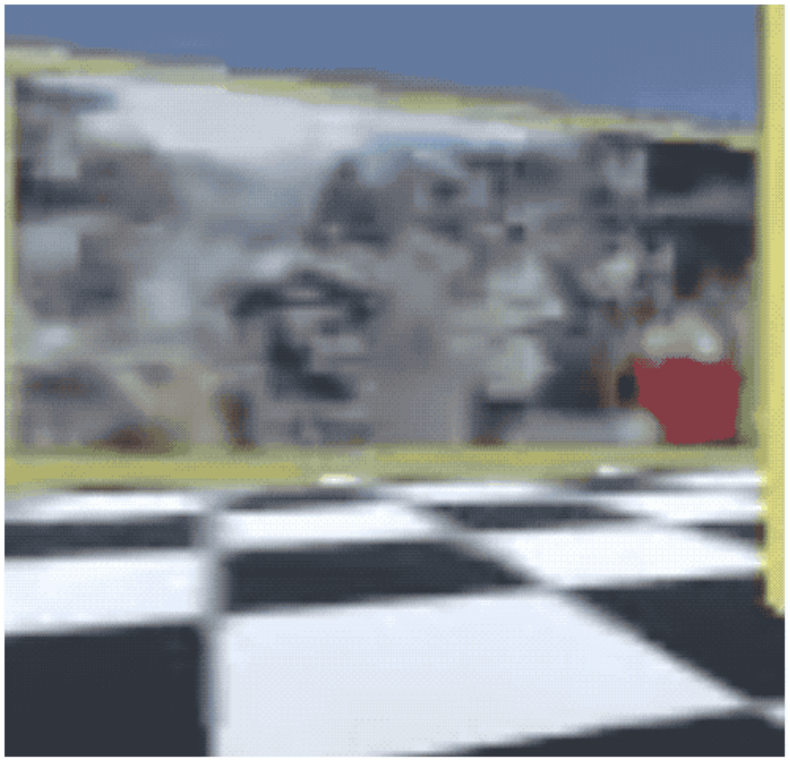
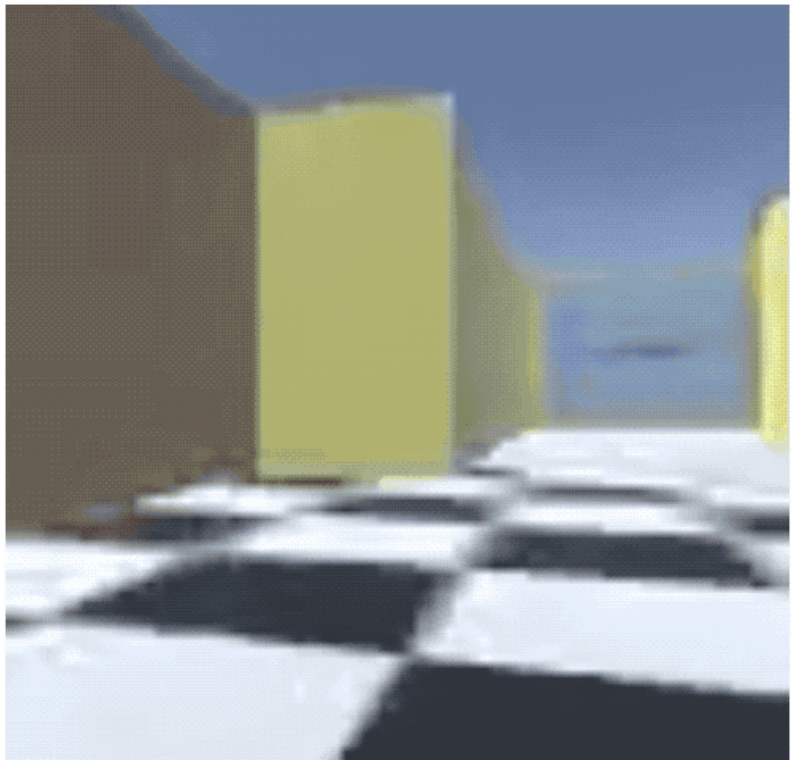


图 11: AlphaGo(Silver et al., 2017)

环境噪声(Noisy-TV Problem)



Agent in a maze with a noisy TV



Agent in a maze without a noisy TV

图 12: 迷宫墙面上的噪声电视(Noisy-TV Problem)(Burda et al., 2019)

“探索与利用”概述

探索与利用

- 探索问题
  - 智能体如何发现高收益策略，往往最优策略由时序上一系列复杂行动构成，且很可能单独考察每个行动并无正收益?
  - 智能体该如何决定：是该尝试新行动来发现更高收益，抑或用已知能够获取高收益的行动来继续应对?
- 两种权衡
  - 探索与利用困境(Exploration and Exploitation Dilemma)
  - 为将来利用而探索(Exploration for Future Exploitation)
- 探索策略
  - 随机探索
  - 系统性探索

多臂老虎机

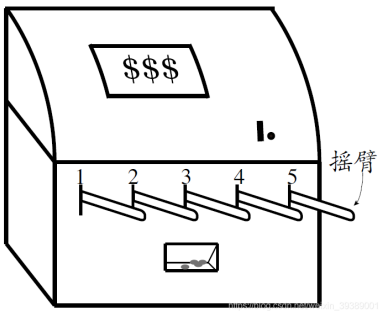


图 13: MAB

Algorithm 1: Multi-Armed Bandit (MAB) Learning

for $t = 1; \ldots; T$: **do**

Algorithm selects an arm $i_t \in [n]$;

Simultaneously, environment selects a reward vector $\mathbf{x}^t = (x_1^t, \ldots, x_n^t) \in [0, 1]^n$;

Algorithm observes reward $x_{i_t}^t$;

end

图 14: MAB Learning

基于乐观探索的方法

- 平均遗憾值函数$\mathrm{Reg}(T) = T\mu^* - \sum_{t=1}^{T} \mathbb{E}\left[\mu_{i_t}\right]$
- UCB1算法
  - $i_t \leftarrow \mathrm{argmax}_{i\in[n]} \left(\hat{\mu}_i^{t-1} + \sqrt{\frac{\alpha \ln t}{2N_i^{t-1}}} \right)$
  - $\mathrm{Reg}(T)$上界为$O(\log T)$

基于汤普森采样的方法

- 使用后验概率进行更有针对性的探索
- Beta分布为Bernoulli分布的共轭先验
  - 在先验分布为Beta分布而似然函数为Bernoulli分布时，后验概率分布仍是Beta分布

$$\theta_i \sim B(S_i + \alpha, F_i + \beta)$$

$$S_{\hat{i}} = S_{\hat{i}} + 1, \text{如果} r_{i \sim \text{Beta}} = 1$$

$$F_{\hat{i}} = F_{\hat{i}} + 1, \text{如果} r_{i \sim \text{Beta}} = 0$$

基于信息增益的方法

- 从信息增益角度提出探索策略IDS(Information Directed Sampling)

$$\begin{array}{ccccc} \mathscr{F}_t = (A_1, Y_{1,A_1}, \ldots, A_{t-1}, Y_{t-1,A_{t-1}}) \\ \downarrow \qquad \cdots \qquad \downarrow \\ R_{1,A_1} \qquad \cdots \qquad R_{t-1,A_{t-1}} \end{array}$$

- 信息增益$g_t(a) = \mathbb{E}\left[H(\alpha_t) - H(\alpha_{t+1}) \,|\mathscr{F}_t, A_t = a\right]$
  - $\alpha_t(a) = \mathbb{P}(A^* = a|\mathscr{F}_t)$为关于$A^*$的后验概率分布
- $\Delta_t(a) := \mathbb{E}\left[R_{t,A^*} - R_{t,a}|\mathscr{F}_t\right]$表示在$t$时选择$a$的即时遗憾期望
- $\Delta_t(\pi) = \sum_{a\in\mathscr{A}} \pi(a)\Delta_t(a)$
- 平均信息增益 $\pi \in \mathscr{D}(\mathscr{A}), g_t(\pi) := \Sigma_{a\in\mathscr{A}}\pi(a)g_t(a)$

基于信息增益的方法

$$\pi_t^{\mathrm{IDS}} \in \operatorname*{arg\,min}_{\pi \in \mathcal{D}(\mathscr{A})} \left\{ \Psi_t(\pi) := \frac{\Delta_t(\pi)^2}{g_t(\pi)} \right\}$$

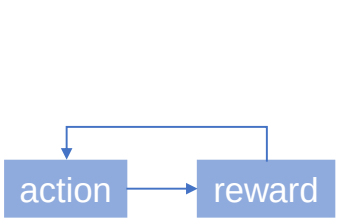
- 尽量避免那些几乎获取不到新信息的选择
- 且避免那些明显次优的选择。

探索方法的设计原则

- 在策略中增加随机扰动或考虑策略熵以增大探索性
- 对未知与不确定抱以乐观心态，选不确定性大的选项
- 认为“新”等同于“好”，给“好”状态赋以额外奖励
- 推断出概率分布，并依概率选最佳动作
- 选那些能带来新鲜感和惊讶，即能带来较大信息增益的选项等

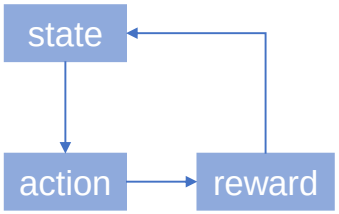
探索方法的理论分析

multi-armed bandits



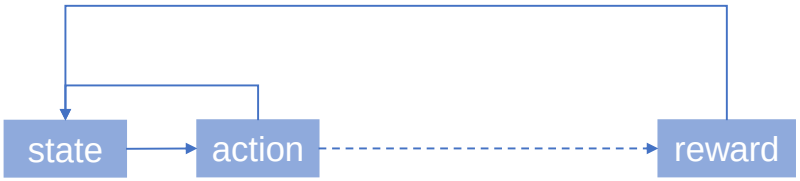
multi-armed bandits
(1-step stateless
RL problems)

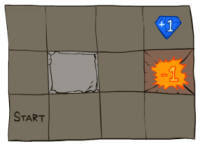
contextual bandits



contextual bandits
(1-step RL problems)

Full Reinforcement Learning Problems





small, finite MDPs
(e.g., tractable planning,
model-based RL setting)

large, infinite MDPs,
continuous spaces

theoretically tractable

theoretically intractable

图 15: 探索问题的理论分析难度随状态空间规模而变化(Levine, 2018)

强化学习中的“探索与利用”方法

强化学习中的“探索与利用”方法

- 基于好奇心驱动的探索
- 基于熵正则的探索
- 用带噪声神经网络实现探索
- 高效利用样本经验
- 其他方法及理论工作

Intrinsic Curiosity Module(ICM)

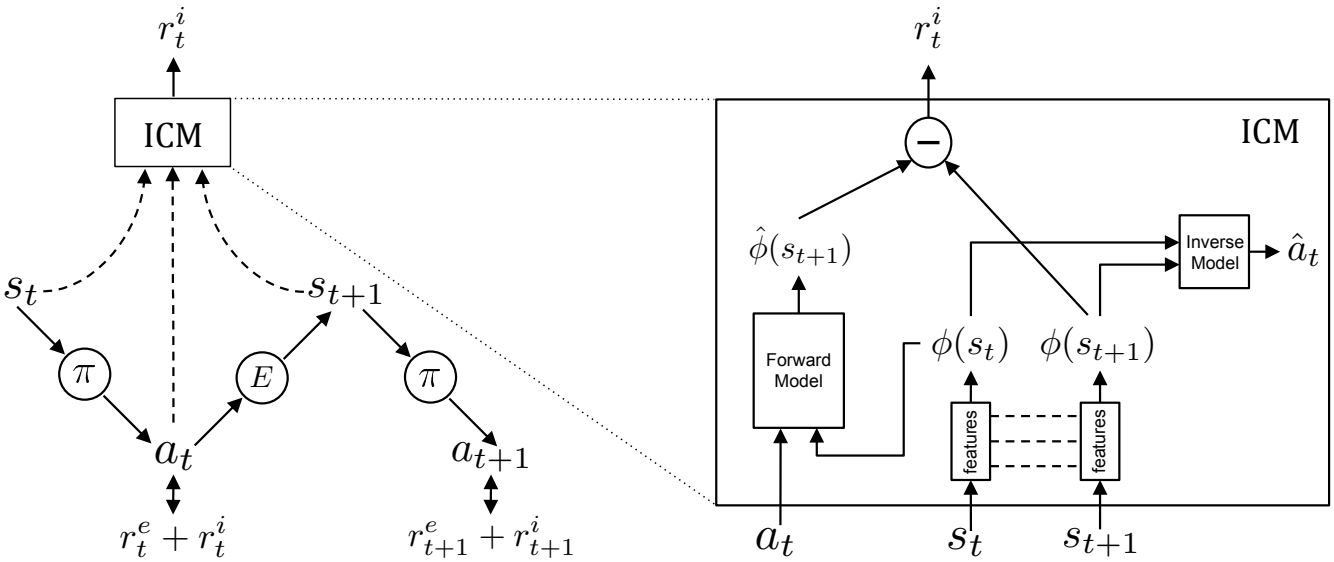


图 16: Intrinsic Curiosity Module(ICM)框架(Pathak et al., 2017)

$$L_F\left(\phi\left(s_t\right), \hat{\phi}\left(s_{t+1}\right)\right) = \frac{1}{2}\left\|f\left(\phi\left(s_t\right), a_t; \theta_F\right) - \phi\left(s_{t+1}\right)\right\|_2^2 \quad L_I\left(\hat{a}_t, a_t; \theta_I\right)$$

$$\min_{\theta_P, \theta_I, \theta_F}\left[-\lambda \mathbb{E}_{\pi\left(s_t; \theta_P\right)}\left[\Sigma_t r_t\right] + (1-\beta) L_I + \beta L_F\right]$$

Disagreement

- 多ICM集成，用模型间的不一致表达探索的额外收益

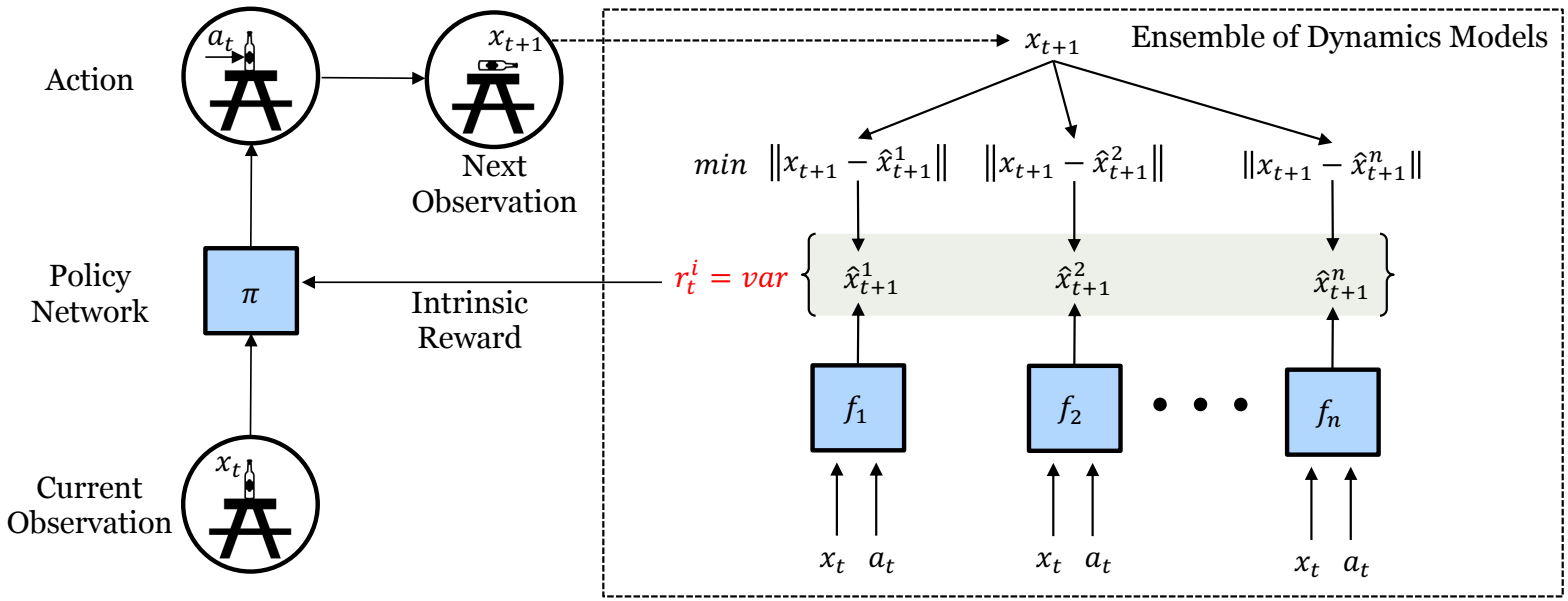


图 17: 基于不一致意见的探索模型框架(Pathak et al., 2019)

DORA

- 构造新MDP M'指引探索方向(Choshen et al., 2018)
  - 基于原MDP $M = (S, A, R, P, \gamma)$构造$M' = (S, A, 0, P, \gamma_E)$
  - 在M'上学习得到的Q值函数记做E值
  - 将M'中所有状态动作对的E值初始化为1，即$E(s, a) = 1$
  - 由于$E^*(s, a) = 0$，在训练过程中，状态动作对的$E(s, a)$将从1逐步变为0，接近真实的值函数

$$E(s, a) \leftarrow (1 - \alpha)E(s, a) + \alpha\left(0 + \gamma_E E\left(s', a'\right)\right)$$

  - 借助$\log_{1-\alpha} E$构造额外奖赏，指导动作选择

Episodic Curiosity

- 用可达性描述新颖度
- 用神经网络度量可达
- 基于可达定义增强奖赏

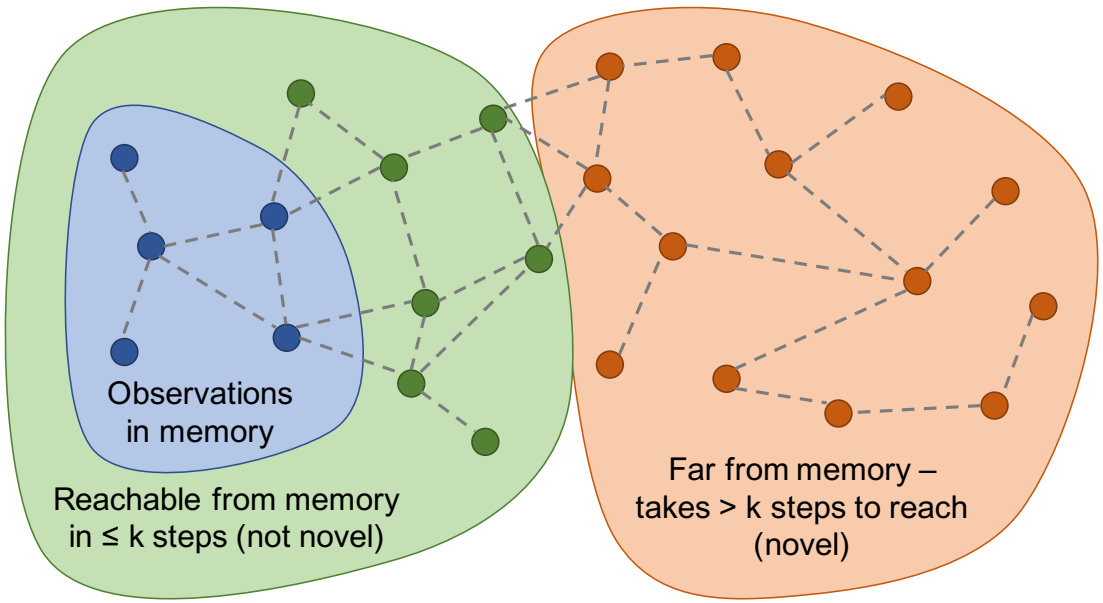


图 18: Episodic Curiosity中的新颖度(novelty)(Savinov et al., 2019)

Episodic Curiosity

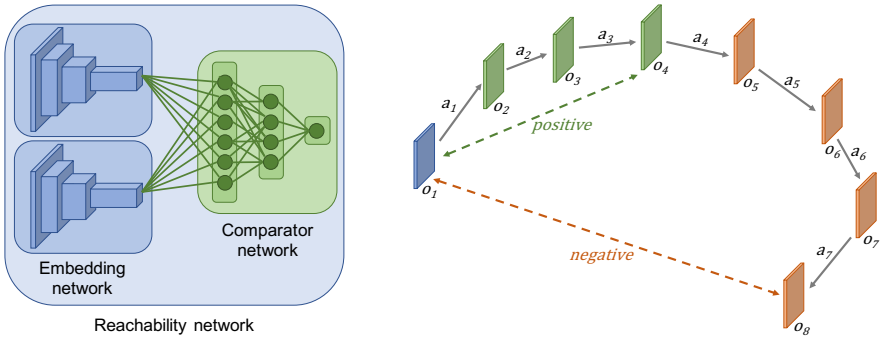


图 19: 可达性度量R-网络

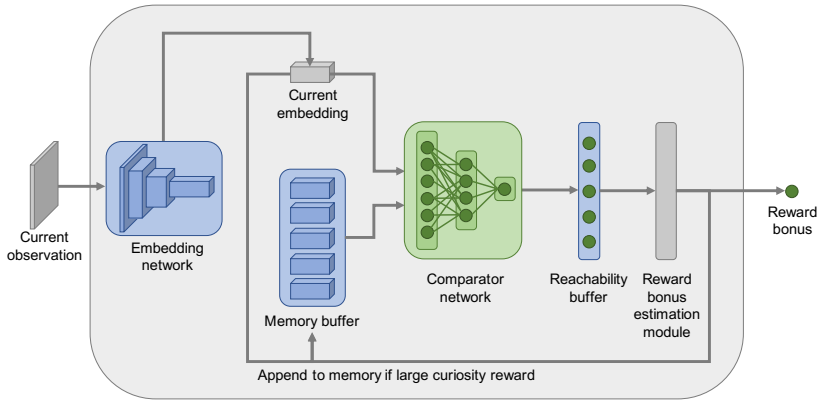


图 20: EC模型整体架构

$$\mathbf{e} = E(\mathbf{o}) \quad \text{embedding vector of } \mathbf{o}$$

$$\mathbf{M} = \langle \mathbf{e}_1, \ldots, \mathbf{e}_{|\mathbf{M}|} \rangle \quad \text{memory buffer stores } |\mathbf{M}| \text{ elements}$$

$$c_i = C(\mathbf{e}_i, \mathbf{e}), \quad i = 1, |\mathbf{M}| \quad \text{outputs of comparator network}$$

$$C(\mathbf{M}, \mathbf{e}) = F(c_1, \ldots, c_{|\mathbf{M}|}) \in [0, 1] \quad \text{aggregation function F, could be max}$$

$$b = B(\mathbf{M}, \mathbf{e}) = \alpha(\beta - C(\mathbf{M}, \mathbf{e})) \quad \text{bonus calculator}$$

Hash Based Pseudo-Counts

- 探索增强奖赏为$r^i : \mathcal{S} \mapsto \mathbb{R}$。

$$r^+(s) = \frac{\beta}{\sqrt{n(\phi(s))}}$$

- 通过$\phi(\mathbf{s})$将s压缩为k位编码，再计数$n(\phi(\mathbf{s}))$

$$\phi(s) = \text{sgn}(Ag(s)) \in \{-1, 1\}^k$$

- AutorEncoder编码更复杂或连续空间的观测

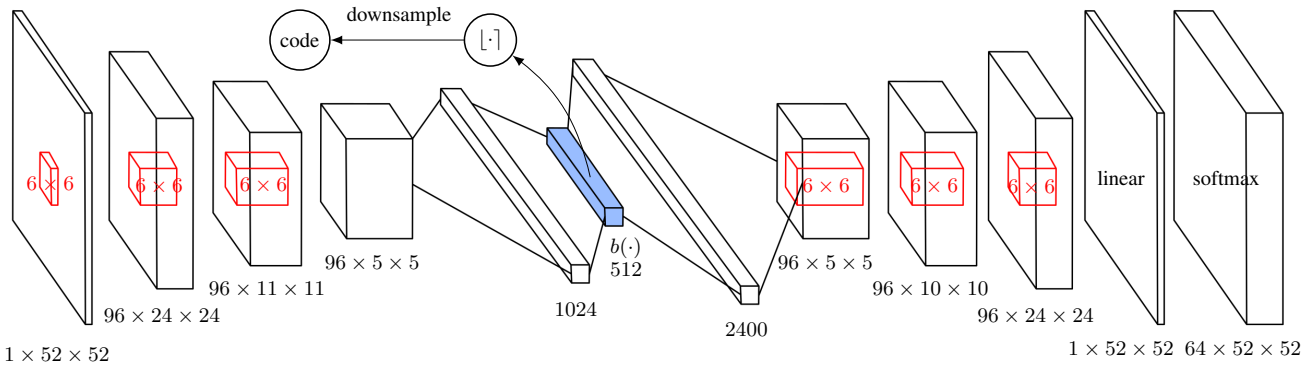


图 21: 基于自编码器的哈希编码计数方法架构(Tang et al., 2017)

Soft Q-Learning

- Q学习策略弊端
  - 连续状态、动作空间
  - 任务自适应性差

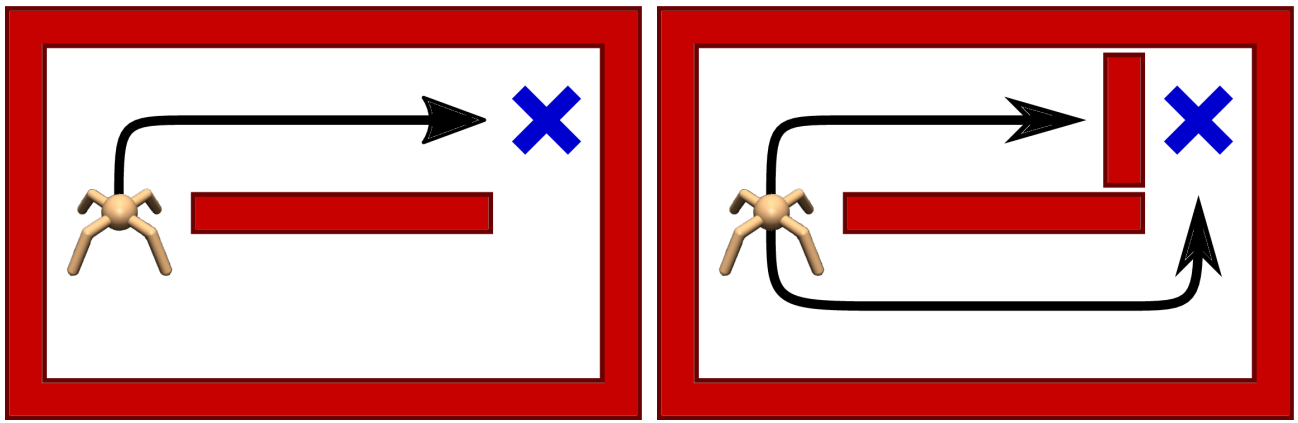


图 22: 巡航任务微调环境致最优策略彻底失效(Haarnoja et al., 2017)

Soft Q-Learning

- 引入熵正则化项并重构贝尔曼方程

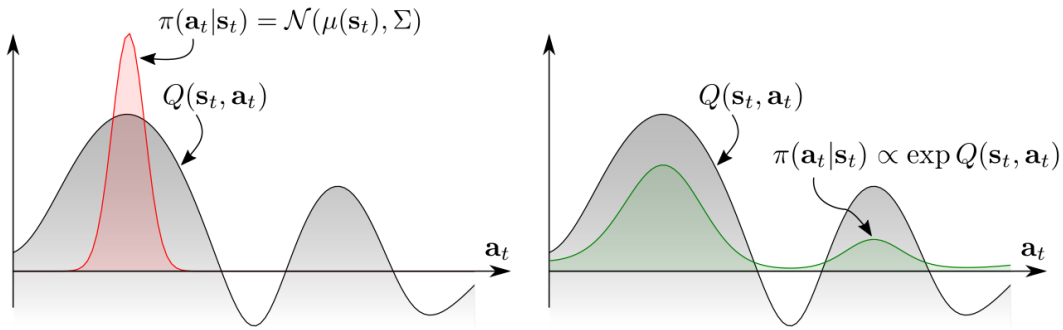


图 23: 将最优策略表达为玻尔兹曼分布

$$\pi^*_{\text{MaxEnt}} = \arg\max_{\pi} \sum_t \mathbb{E}_{(\mathbf{s}_t,\mathbf{a}_t)\sim\rho_\pi} \left[r\left(\mathbf{s}_t, \mathbf{a}_t\right) + \alpha \mathcal{H}\left(\pi\left(\cdot|\mathbf{s}_t\right)\right)\right]$$

$$Q^*_{\text{soft}}\left(\mathbf{s}_t, \mathbf{a}_t\right) = r_t + \mathbb{E}_{(\mathbf{s}_{t+1},\ldots)\sim\rho_\pi} \left[\sum_{l=1}^{\infty} \gamma^l \left(r_{t+l} + \alpha \mathcal{H}\left(\pi^*_{\text{MaxEnt}}\left(\cdot|\mathbf{s}_{t+l}\right)\right)\right)\right]$$

$$V^*_{\text{soft}}\left(\mathbf{s}_t\right) = \alpha \log \int_{\mathcal{A}} \exp\left(\frac{1}{\alpha} Q^*_{\text{soft}}\left(\mathbf{s}_t, \mathbf{a}'\right)\right) d\mathbf{a}'$$

Soft Actor-Critic

- (Haarnoja et al., 2018)引入熵正则项，重构造贝尔曼方程
  - **策略评估**

$$\mathcal{T}^{\pi} Q\left(\mathbf{s}_t, \mathbf{a}_t\right) = r\left(\mathbf{s}_t, \mathbf{a}_t\right) + \gamma \mathbb{E}_{\mathbf{s}_{t+1} \sim p}\left[V\left(\mathbf{s}_{t+1}\right)\right]$$

$$V\left(\mathbf{s}_t\right) = \mathbb{E}_{\mathbf{a}_t \sim \pi}\left[Q\left(\mathbf{s}_t, \mathbf{a}_t\right) - \log \pi\left(\mathbf{a}_t | \mathbf{s}_t\right)\right]$$

  - $Q^{k+1} = \mathcal{T}^{\pi} Q^{k}$反复迭代求得$Q$与$V$值收敛点
  - **策略提升**

$$\pi_{\text{new}} = \arg\min_{\pi' \in \Pi} \mathrm{D}_{\mathrm{KL}}\left(\pi'\left(\cdot | \mathbf{s}_t\right) \| \frac{\exp\left(Q^{\pi_{\text{old}}}\left(\mathbf{s}_t, \cdot\right)\right)}{Z^{\pi_{\text{old}}}\left(\mathbf{s}_t\right)}\right)$$

  - 引入V值目标网络、采用重参数化技巧处理梯度更新

NoisyNet

- NoisyNet(Fortunato et al., 2018)在神经网络参数中掺杂噪声以增强策略探索性

$$y = wx + b$$

$$y \overset{\text{def}}{=} \left(\mu^w + \sigma^w \odot \varepsilon^w\right) x + \mu^b + \sigma^b \odot \varepsilon^b$$

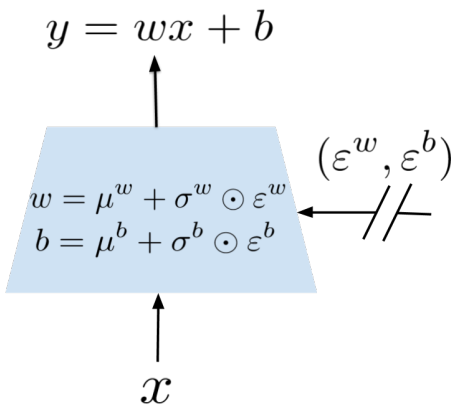


图 24: 引入随机噪声参数的线性层模型

Parameter Space Noise

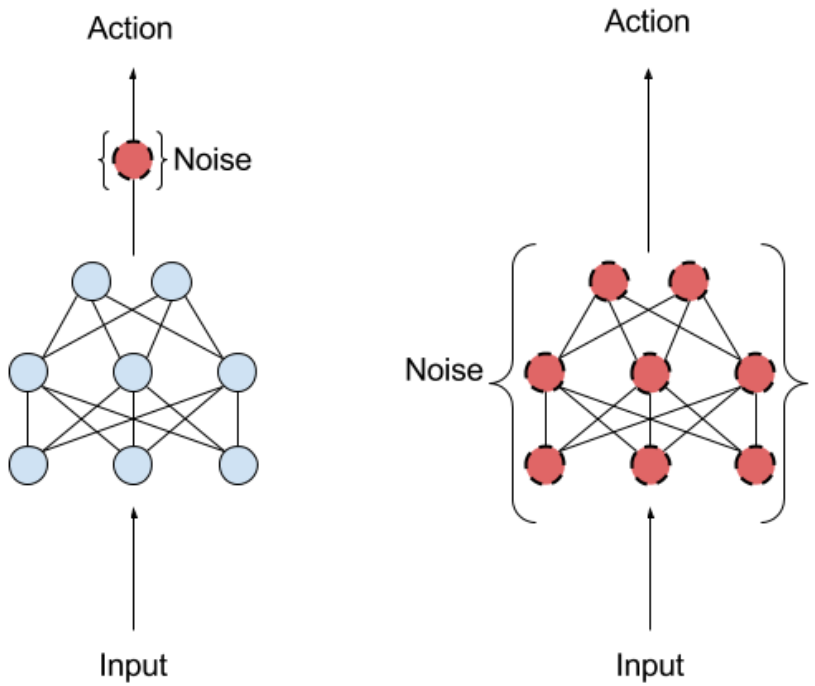


图 25: 动作空间和策略参数空间引入噪声对比(Plappert et al., 2017)

$$a_t = \pi(s_t) + \mathcal{N}\left(0, \sigma^2 I\right)$$

$$\widetilde{\theta} = \theta + \mathcal{N}\left(0, \sigma^2 I\right)$$

RND

- RND(Burda et al., 2019)引入网络蒸馏技术，Target Network有固定的随机初始化的权重，在训练中不改变，它能够为每一个状态观测输出一个特征表示
- Predictor Network将Target Network的输出结果作为label 并根据MSE损失更新参数θ

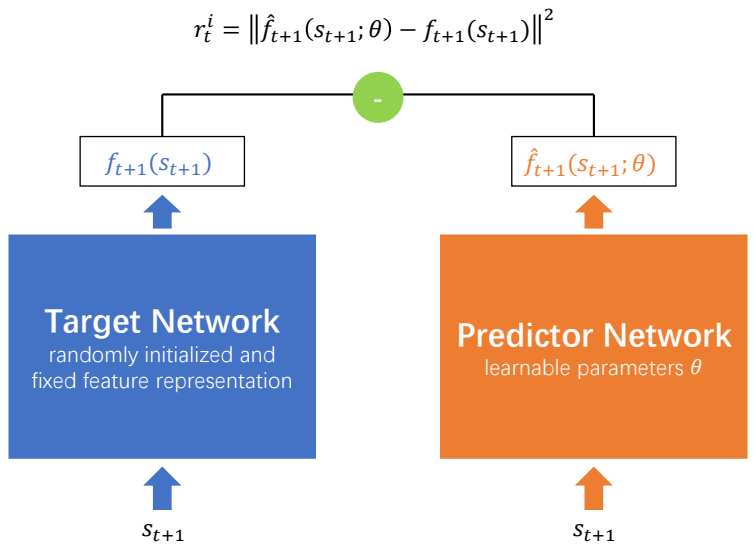


图 26: Random Network Distillation(RND)模型产生内在增强奖赏

RND

- 与ICM不同，RND框架中前向网络易于实现和计算，不以s_t,a_t作输入预测下一状态特征表示

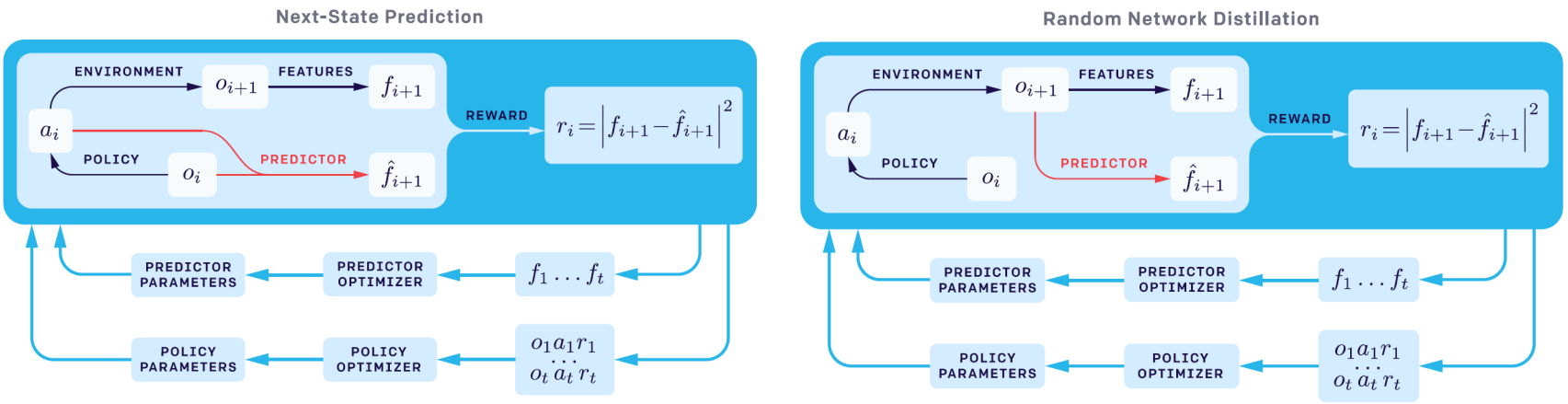


图 27: RND与ICM中前向预测模块对比

Hindsight Experience Replay

- HER(Andrychowicz et al., 2017)解决稀疏的二元奖赏任务
  - 预设目标g，轨迹序列为$s_0, s_1, s_2, \cdots, s_T \neq g$，将目标重设为$s_T$，未成功完成任务变为成功
  - 扩展目标集合$\mathcal{G}(g \in \mathcal{G})$，有利于扩充经验池中正例采样轨迹

$$a_t \leftarrow \pi_b\left(s_t \| g\right) \quad \|\text{意味着将}s_t\text{和}g\text{串接起来}$$

$$r_t := r\left(s_t, a_t, g\right) \quad g\text{随机取自}\mathcal{G}$$

$$\text{Replay Buffer} \leftarrow \left(s_t \| g, a_t, r_t, s_{t+1} \| g\right) \quad \text{串接}s_t\text{和}g\text{存入经验回放池}$$

- 课程学习(Curriculum Learning)(Bengio et al., 2009)

Go-Explore

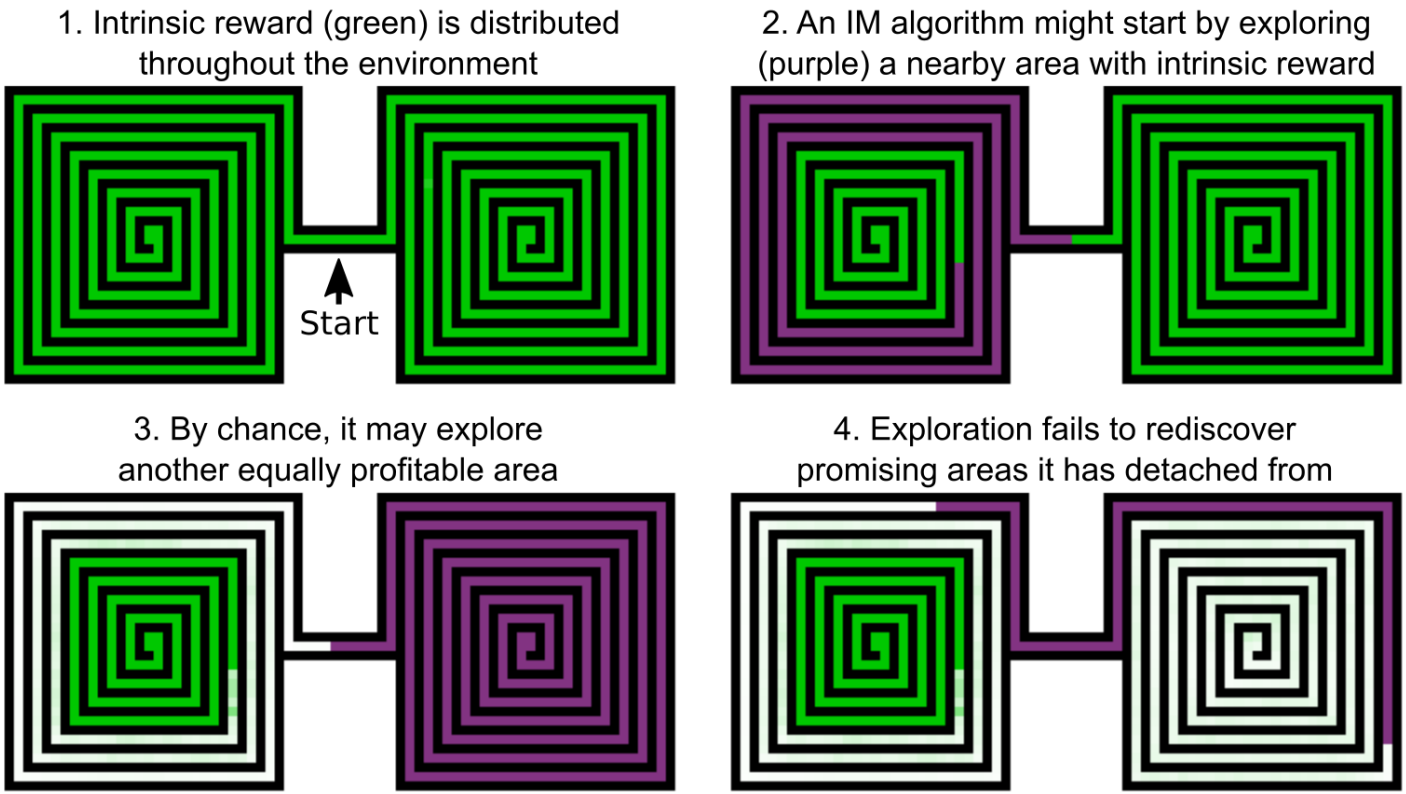


图 28: Intrinsic Motivation(IM)类方法存在的问题(Ecoffet et al., 2019)

Go-Explore

- Uber提出Go-Explore解决门特祖玛复仇问题
  - 存档探索过的路径
  - 如有必要对存档路径模仿学习
  - 图像粗粒化

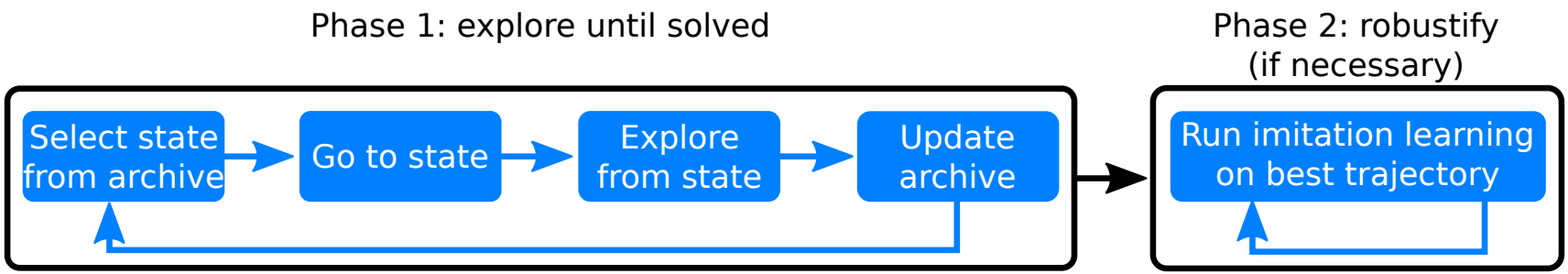
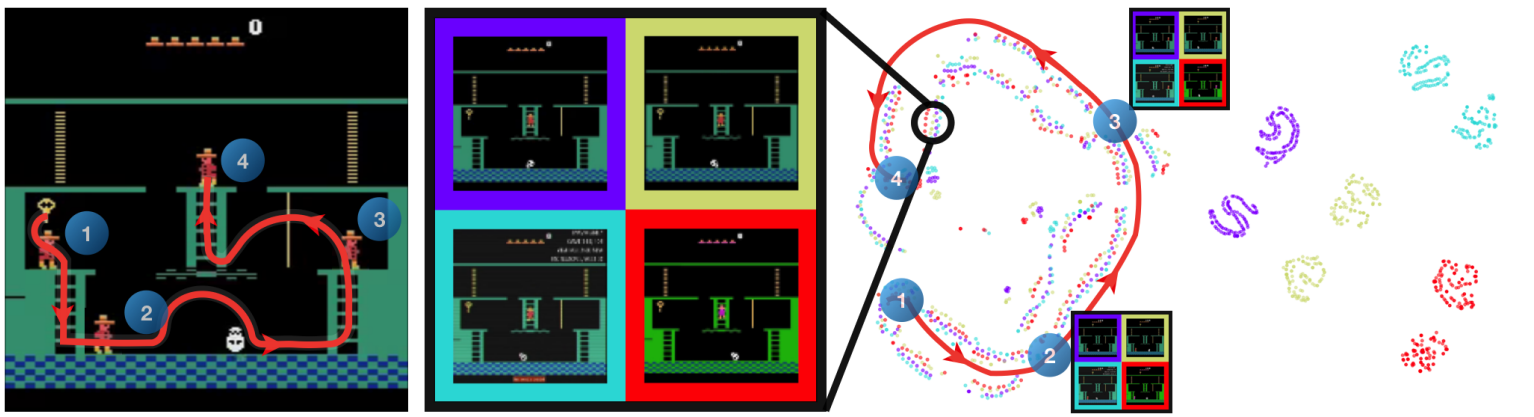


图 29: Go-Explore方法

TDC+CMC

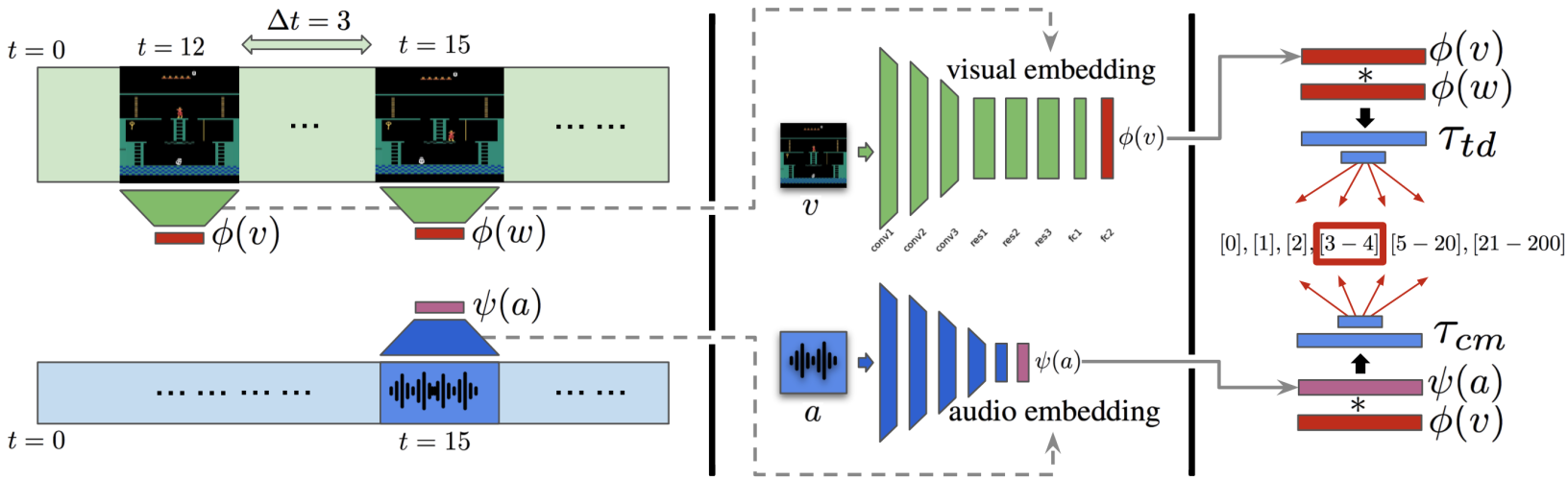
- Google团队利用人类玩家玩蒙特祖玛复仇的YouTube多版本在线录像来训练AI(Aytar et al., 2018)
  - 自监督学习方式对齐不同录像
  - TDC 画面时间差预测(**T**emporal **d**istance **c**lassification)
  - CMC 画面与声音对齐的跨模态时间差预测(**C**ross-**m**odal temporal distance **c**lassification)



(a) An example path (b) Aligned frames (c) Our embedding (d) Pixel embedding

图 30: 学习表征将不同画面在表征空间中对齐

TDC+CMC



(a) Temporal and cross-modal pair selection (b) Embedding networks (c) Classification networks

图 31: 基于YouTube示例录像的模仿学习神经网络模型

LfSD

- LfSD(Salimans and Chen, 2018)不断重新设置出发点，将长期规划任务拆分成多个子任务

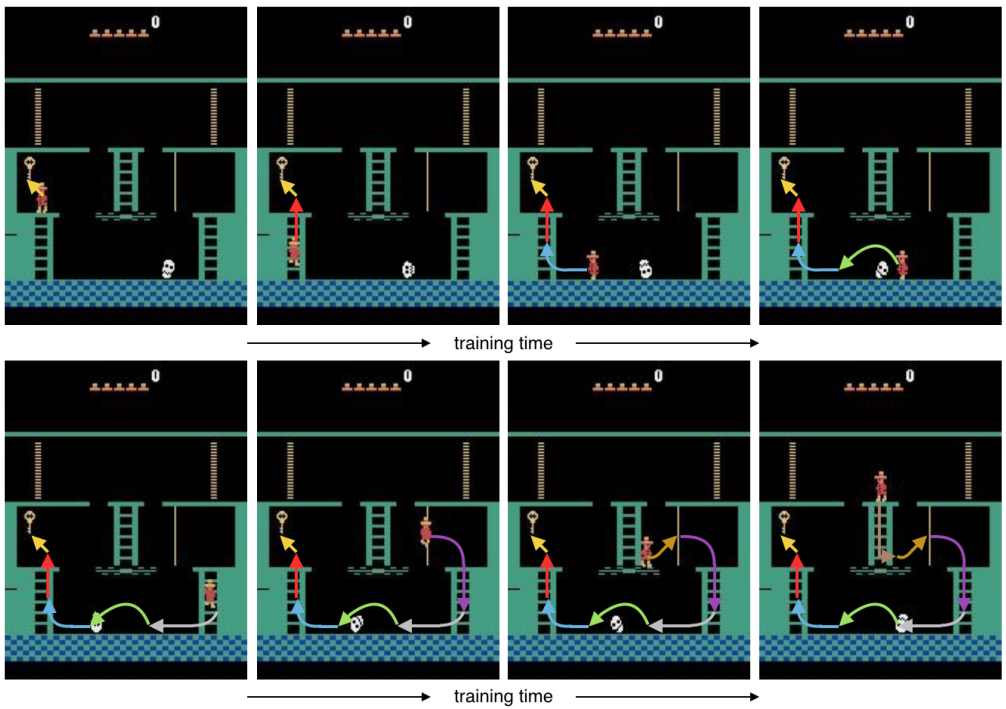


图 32: 逐步后置起始点从而引导智能体学习到更长的行动路径

R2D3

- R2D3(Paine et al., 2020)
  - 多个actor进程并行采样
  - 所有actor进程共享经验缓冲池
  - 全局learner运行Double DQN网络
  - 示例经验和actor采样经验按比例(ρ)混合

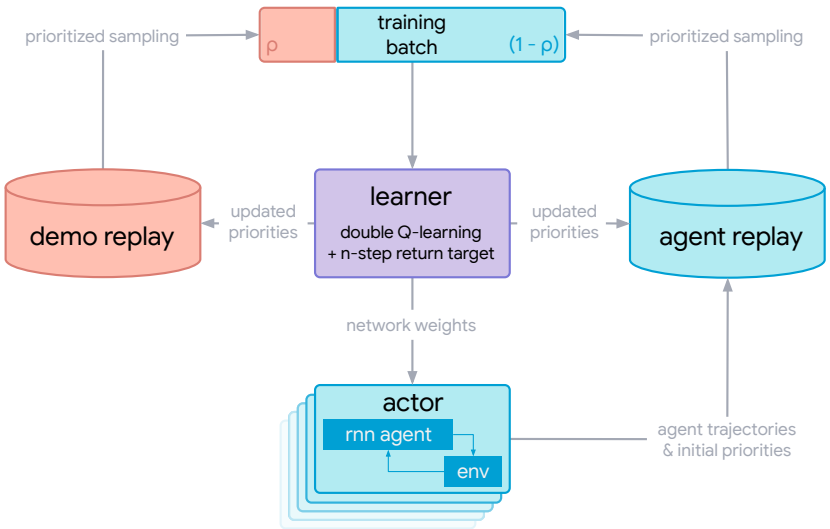


图 33: Recurrent Replay Distributed DQN from Demonstrations(R2D3)框架

Bootstrapped DQN

- Bootstrapped DQN(Osband et al., 2016)
  - 同时学习关于(s, a)的$K \in \mathbb{N}$个Q值来近似建模出Q值分布
  - 多个Q值网络共享一部分参数
  - 动作选取呈现出受Q值分布影响的探索效果

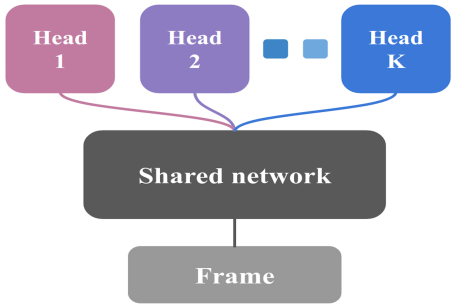


图 34: Bootstrapped DQN架构

VIME

- VIME(Houthooft et al., 2016)是基于变分信息最大化的探索方法
- 智能体连续决策并降低环境的不确定性，形式化为最大化在$\{a_t\}$上的累计熵减

$$\sum_t \left(H\left(\Theta|\xi_t, a_t\right) - H\left(\Theta|s_{t+1}, \xi_t, a_t\right)\right)$$

$$H\left(\Theta|\xi_t, a_t\right) - H\left(\Theta|s_{t+1}, \xi_t, a_t\right) = \mathbb{E}_{s_{t+1}\sim\mathcal{P}(.|\xi_t,a_t)}[D_{\mathrm{KL}}(p(\theta|\xi_t, a_t, s_{t+1})\|p$$

- 增强奖赏r^i

$$\eta D_{\mathrm{KL}}\left[p\left(\theta|\xi_t, a_t, s_{t+1}\right)\|p\left(\theta|\xi_t\right)\right]$$

总结与展望

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