An Introduction to Reinforcement Learning

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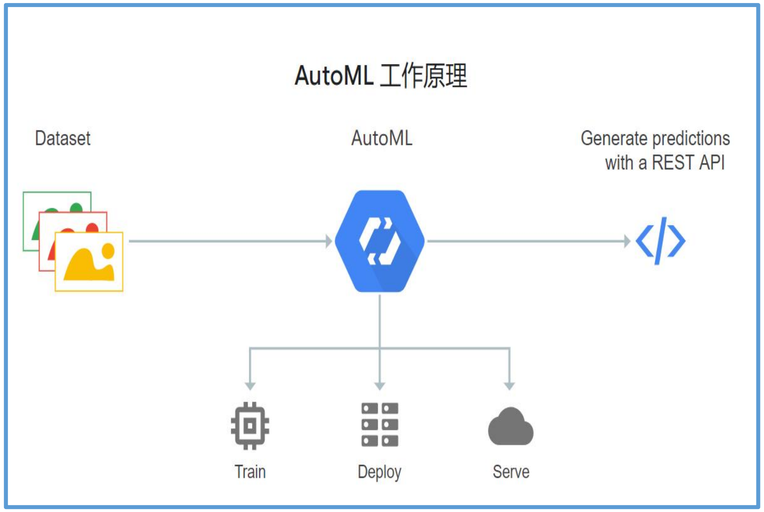
Reinforcement Learning Applications

AlphaGo, DeepMind

Dota 2 AI, OpenAI

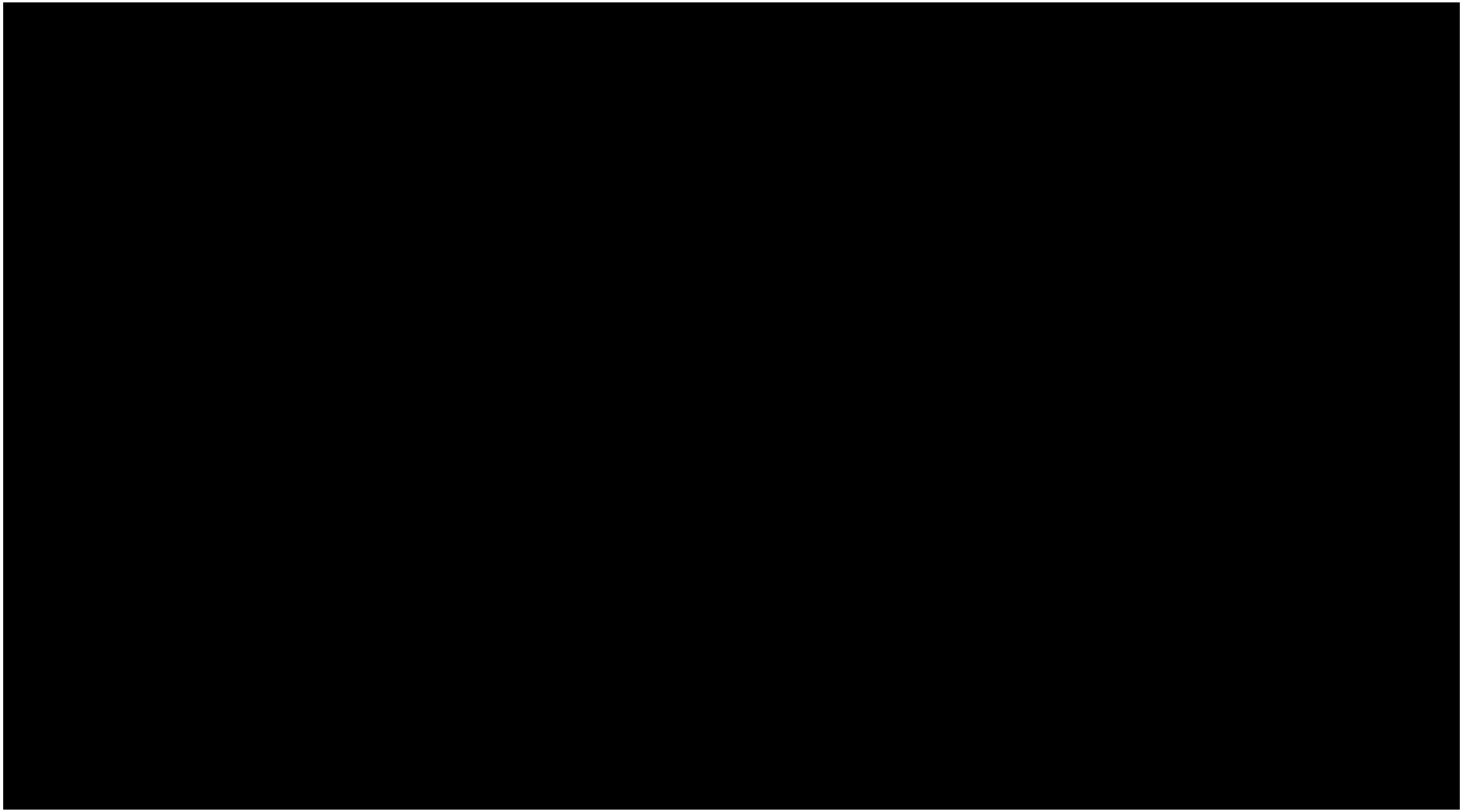
王者荣耀觉悟 AI，腾讯



自动化机器学习平台，Google

AI Taught Itself to Walk

AI Learns to Park



ChatGPT背后关键技术：人类反馈强化学习 (RLHF)

阶段1：监督训练

从数据集中采样问题

根据采样问题，人工给出高质量回答

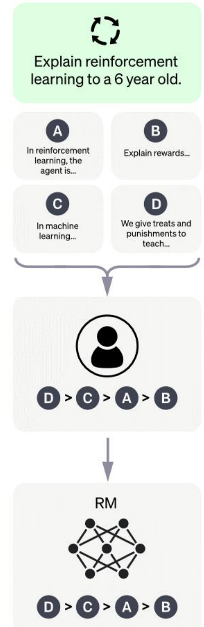
基于问题和回答，对GPT-3.5进行监督训练

阶段2：奖励模型训练（引入人类反馈）

从数据集采样问题并输入第一阶段训练的模型获取多条输出

人工对多个回答按照质量好坏排序

根据排序结果训练奖励模型



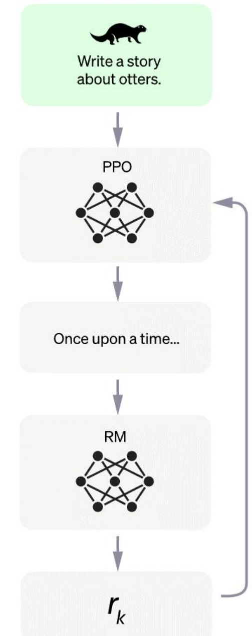
阶段3：基于强化学习的语言模型训练

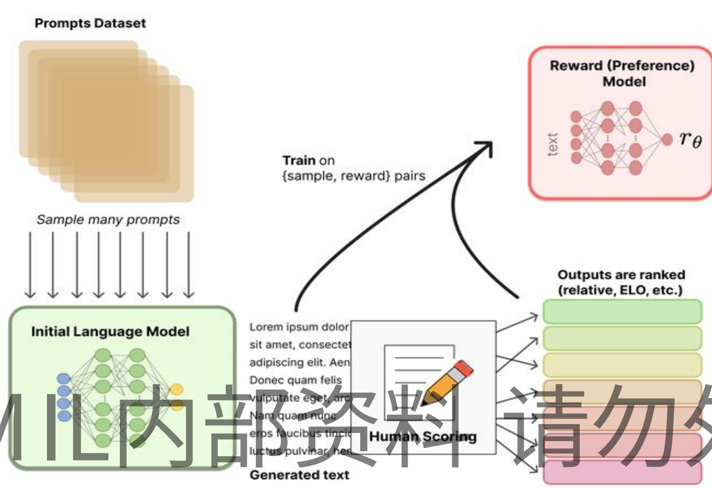
从数据集采样新的问题

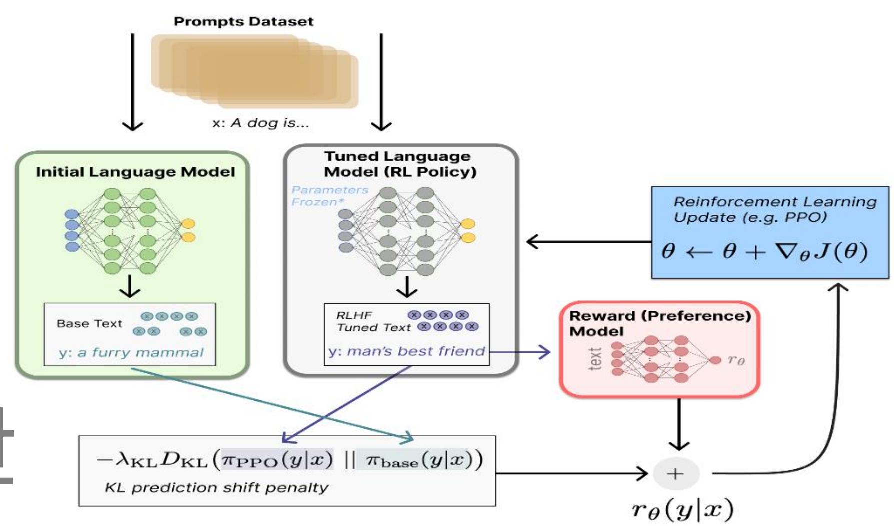
将问题输入第一阶段训练好的语言模型，根据输入生成文本

利用奖励模型给出人类价值判断，生成奖励值

使用强化学习算法，利用奖励值更新模型







Contents

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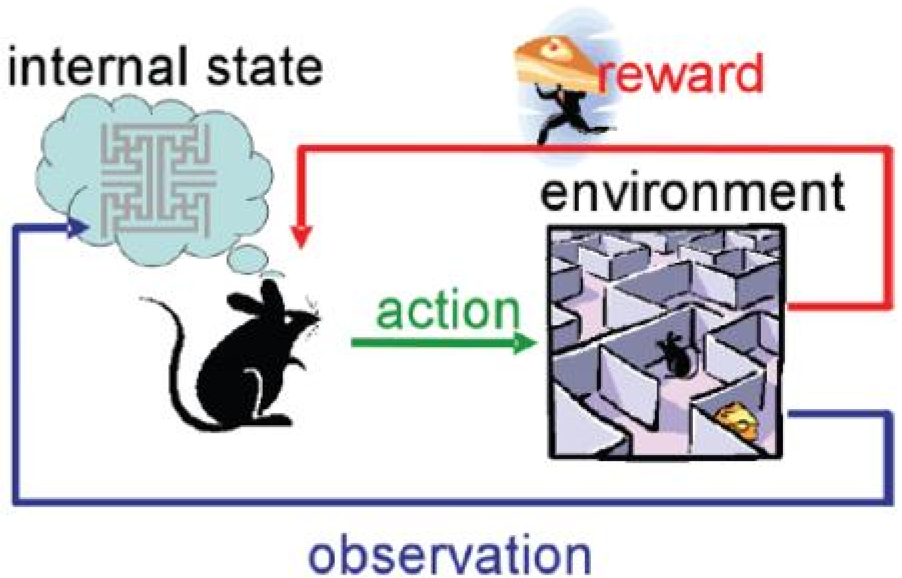
Reinforcement Learning

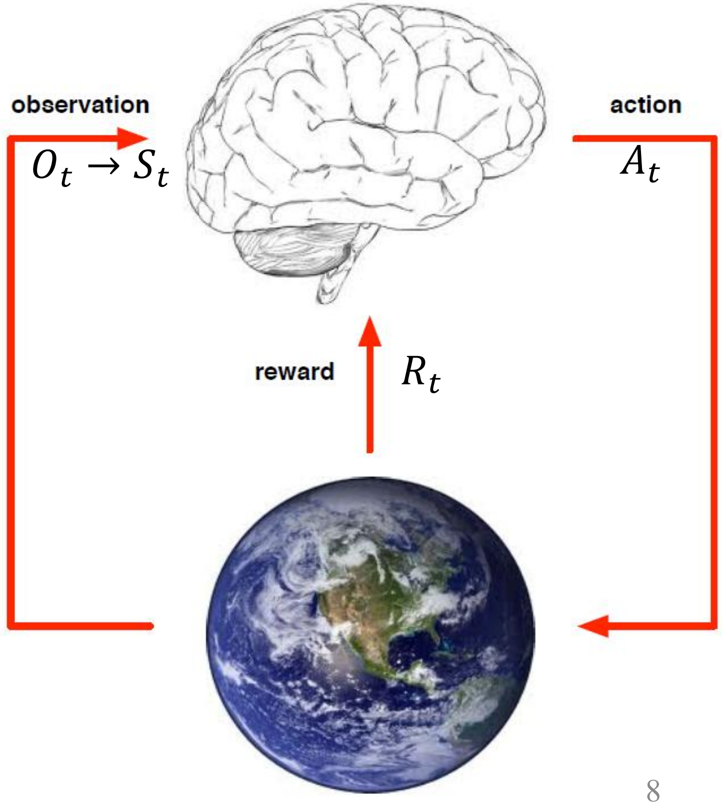
- **What is Reinforcement Learning?**

  Learning to solve sequential decision making problems

- **How it works?**

  Trial and error in a world that provides occasional rewards





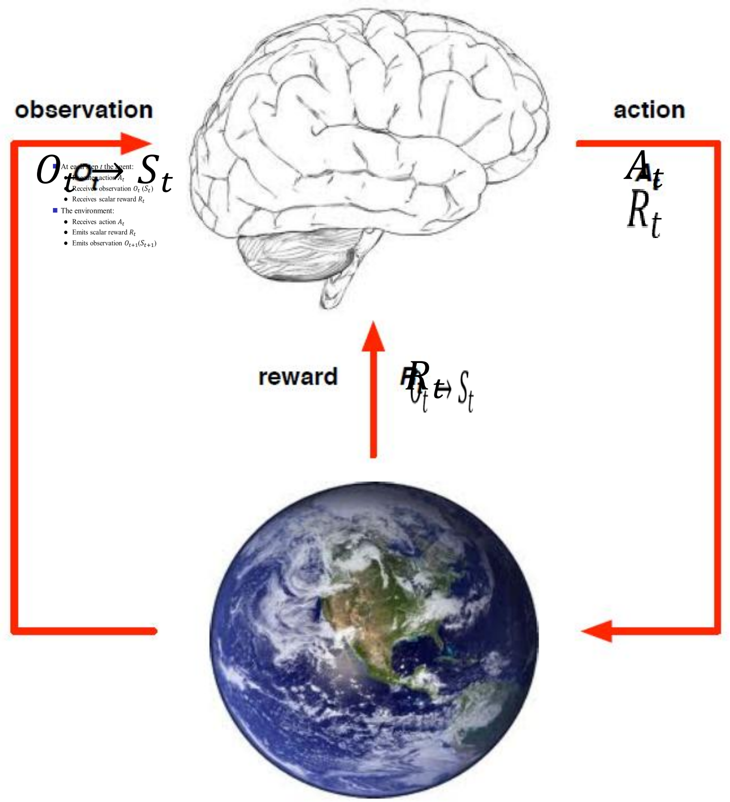
Characteristics of Reinforcement Learning

What makes reinforcement learning different from other machine learning paradigms?

- There is no supervisor, only a *reward* signal
- Feedback is delayed, not instantaneous
- Time really matters (sequential, non *i.i.d.* data)
- Agent's actions affect the subsequent data it receives

Agent and Environment

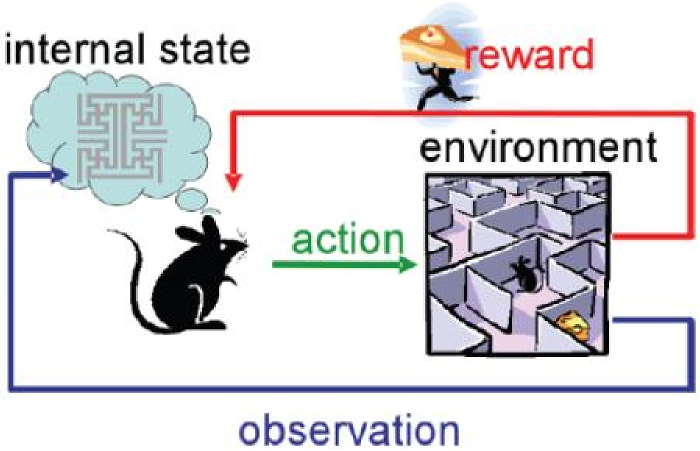
- At each step t the agent:
  - Executes action A_t
  - Receives observation O_t (S_t)
  - Receives scalar reward R_t
- The environment:
  - Receives action A_t
  - Emits scalar reward R_t
  - Emits observation $O_{t+1}(S_{t+1})$



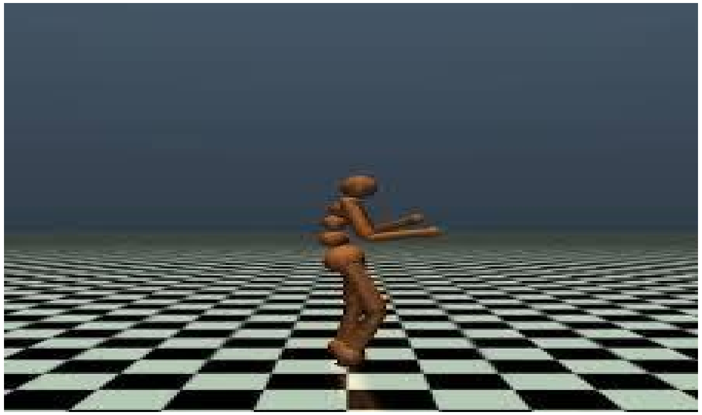
Reward

- A **reward** R_t is a scalar feedback signal at step t
- The agent's job is to **maximise cumulative reward**

$$G_t = R_{t+1} + \gamma R_{t+2} + \dots + \gamma^k R_{t+k+1} + \dots$$
$$= \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$$

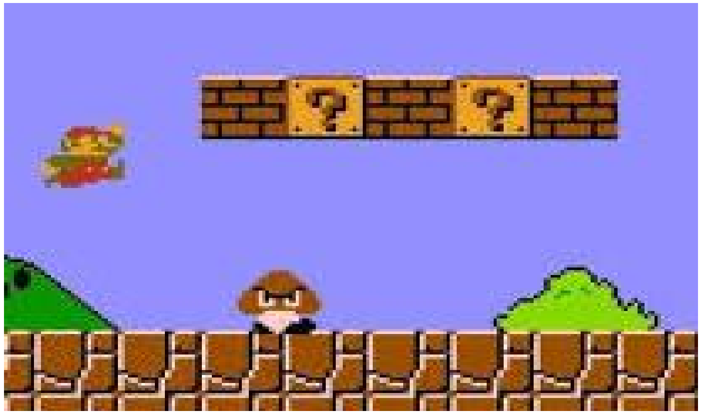


Make a humanoid robot walk



- positive R_t (+1) for moving forward
- negative R_t (-1) for falling down

Super Mario



- positive reward R_t (+1) for getting a gold coin

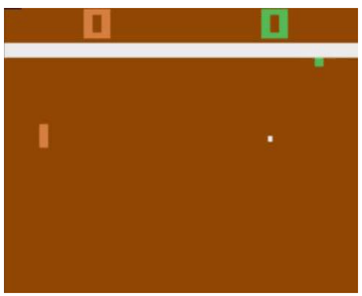
Sequential Decision Making

- Objective: Let an agent select **a series of actions** to **maximise total future rewards via** **some policy:**

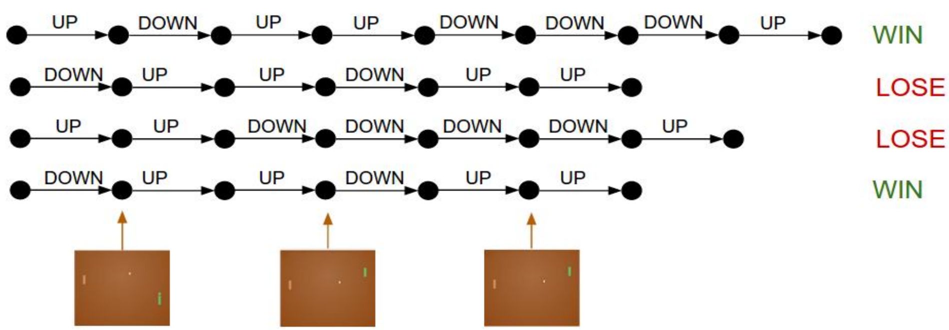
$$\pi(a|s) = P\,[a_t = a|s_t = s]$$

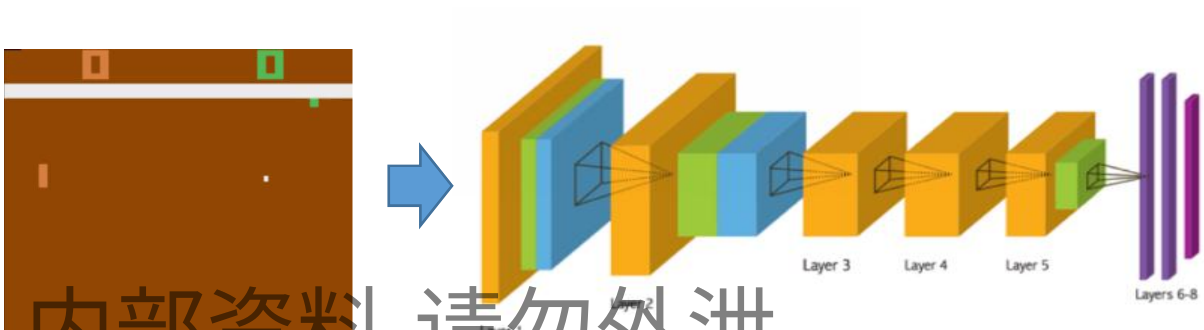
s: the current state

a: possible actions given current state: e.g., move UP or DOWN



Atari: Pong





Action: move UP or DOWN

Sequential Decision Making

- The **trajectory** is the sequence of observations, actions, rewards,

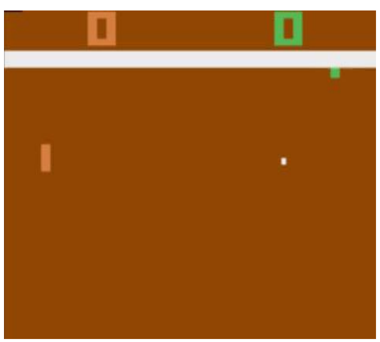
$$\tau =< S_0,\ A_0, R_1, S_1,\ A_1, R_2, \dots, S_{t-1}, A_{t-1}, R_t >$$

- **State** S_t is determined ***by previous trajectory*** **:**

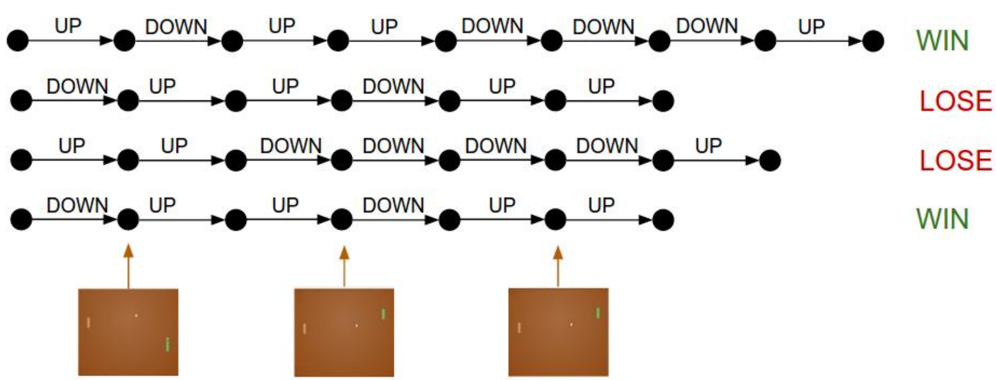
$$P(S_t) = P(S_t | S_0,\ A_0, R_1, S_1,\ A_1, R_2, \dots, S_{t-1}, A_{t-1}, R_t)$$

- The computation of the probability is much more complex!

Hypothesis: we introduce Markov Property to alleviate this issue!



Atari: Pong



Basic Tasks of Reinforcement Learning

- Prediction aka Evaluation

Policy/State Evaluation： Instant Reward

Difficulty: Sequential Decision Making; Agent's actions affect the subsequent data it receives

(Dynamic Programming)

$$v^{\pi}(s) = \sum_{a \in A} \pi(a|s)\left[R(s,a) + \gamma \sum_{s' \in S} P(s'|s,a) v^{\pi}(s')\right]$$

$$= \sum_{a} \pi(a|s) \sum_{s',r} p(s',r|s,a)\left[r + \gamma v^{\pi}(s')\right]$$

- Control： Making **Optimal** Decisions

1. 输入： MDP $< S, A, P, R, \gamma >$
2. 输出： 最佳价值函数 $v^*(s) = \max_{\pi} v^{\pi}(s)$

   以及最佳策略 $\pi^*(s) = \arg\max_{\pi} v^{\pi}(s)$

How to make an Agent to Predict and Control?

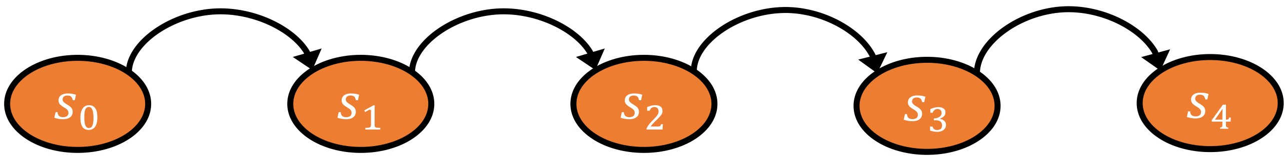
Contents

Markov Process

Given a sequence of random states $< \boldsymbol{s_0, s_1, \ldots, s_T} >$, it satisfies

Markov Property if and only if :

$$P(s_t|s_{t-1}) = P(s_t|s_0, \ldots, s_{t-2}, s_{t-1})$$



- Once the state is known, the history can be thrown away
- The state is a sufficient statistic of the future

Markov Process: The future is independent of the past given the present

A ***Markov Process*** (***or Markov Chain***) is a tuple $< \mathcal{S}, \mathcal{P} >$

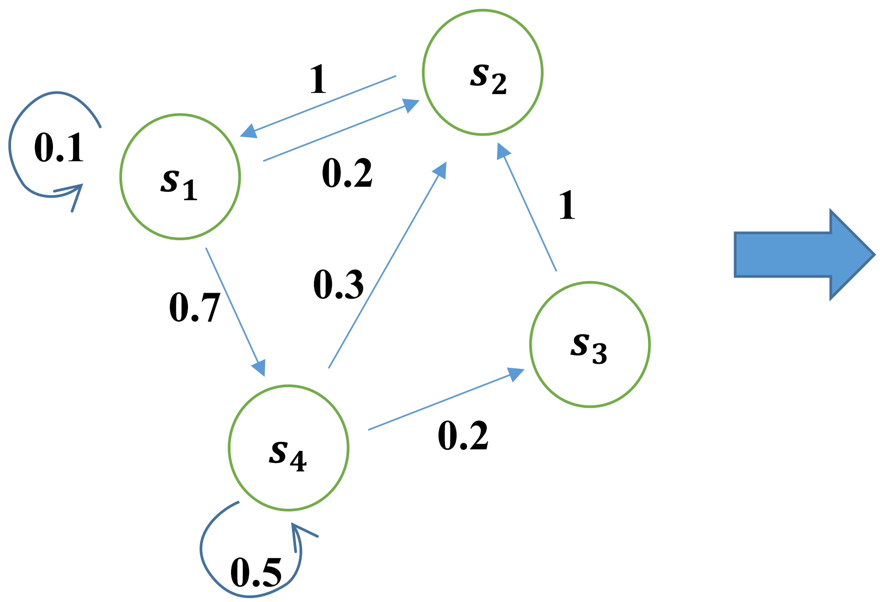
- $\mathcal{S}$ is a (finite) set of states $\mathcal{S} = \{\boldsymbol{s_0, s_1, \ldots, s_T}\}$
- $\mathcal{P}$ is a state transition probability matrix,

$$\mathcal{P}_{ss'} = P[s_{t+1} = s' | s_t = s]$$

State Transition Matrix

- State transition matrix $\mathcal{P}$ specifies $P(s_{t+1} = s' | s_t = s)$

$$\mathcal{P} = \begin{pmatrix} P(s_1|s_1) & \cdots & P(s_N|s_1) \\ \vdots & \ddots & \vdots \\ P(s_1|s_N) & \cdots & P(s_N|s_N) \end{pmatrix}$$

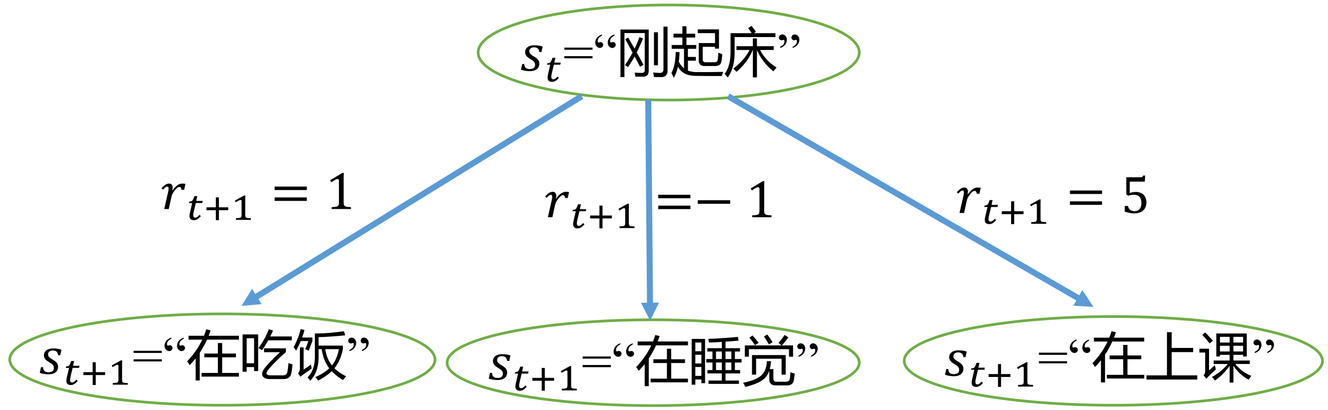


$\mathcal{S} = \{s_1, s_2, s_3, s_4\}$

$\mathcal{P} =$

	s_1	s_2	s_3	s_4
s_1	0.1	0.2	0	0.7
s_2	1	0	0	0
s_3	0	1	0	0
s_4	0	0.3	0.2	0.5

Markov Reward Process



- **Markov Reward Process** is a **Markov Chain** + **rewards**

Definition of *Markov Reward Process*

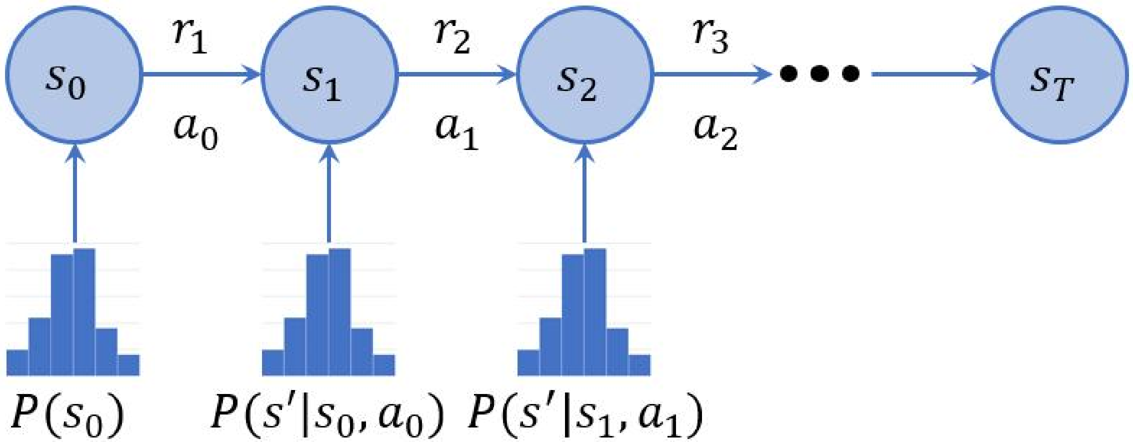
A ***Markov Reward Process*** is a tuple $< \mathcal{S}, \mathcal{P}, \mathcal{R}, \gamma >$

- $\mathcal{S}$ is a (finite) set of states
- $\mathcal{P}$ is a state transition probability matrix,

$$\mathcal{P}_{ss'} = P[s_{t+1} = s' | s_t = s]$$

- $\mathcal{R}$ is a reward function, $R(s_t = s) = \mathbb{E}[r_{t+1} | s_t = s]$
- γ is a discount factor, $\gamma \in [0,1]$

Markov **Decision** Process



- **Markov Decision Process** is a **Markov Reward Process** + **Actions**

Definition of ***Markov Decision Process***

A ***Markov Decision Process*** is a tuple $< \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma >$

- $\mathcal{S}$ is a finite set of states
- $\mathcal{A}$ is a finite set of actions
- $\mathcal{P}$ is a state transition probability matrix,

$$\mathcal{P}_{ss'}^{a} = P[s_{t+1} = s' | s_t = s, a_t = a]$$

- $\mathcal{R}$ is a reward function, $R(s_t = s, a_t = a) = \mathbb{E}[r_{t+1} | s_t = s, a_t = a]$
- γ is a discount factor, $\gamma \in [0,1]$

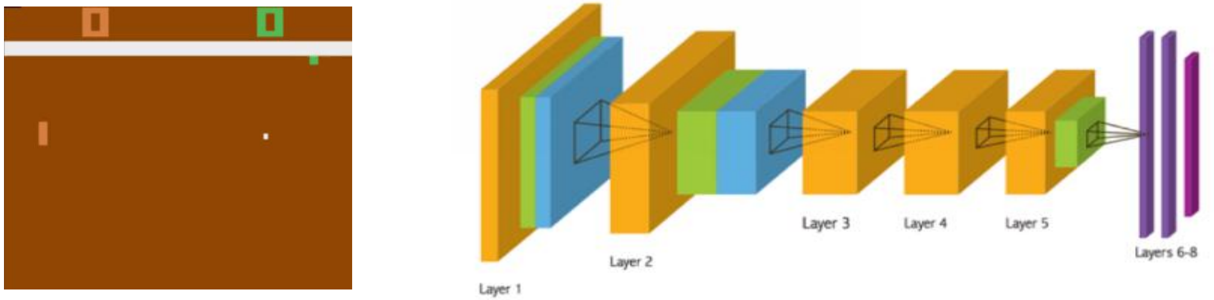
Policy

Definition of ***Policy***

A policy π is a distribution over actions given states：

$$\pi(a|s) = P\left[a_t = a | s_t = s\right]$$

- A policy $\pi(a|\, s)$: the agent's behavior model
- An MDP policy depend on the current state (not the history)
- $\pi(a|s)$ can be represented by neural networks



Action: move UP or DOWN

How to learn $\pi(a|s)$: **maximize total future rewards**!

Return

Definition of ***Return*** (*the* **total future rewards**)

The return $\boldsymbol{G_t}$ is the total discounted reward from time-step $\boldsymbol{t}$

$$G_t = R_{t+1} + \gamma\, R_{t+2} + \dots = \sum_{k=0}^{\infty} \gamma^k\, R_{t+k+1}$$

- $\gamma \in [0,1]$： discount factor for weighting the future rewards
- γ is used to trade off immediate reward and delayed reward
  - γ close to 0 leads to “short-term” evaluation
  - γ close to 1 leads to “long-term” evaluation

Why use discount factor?

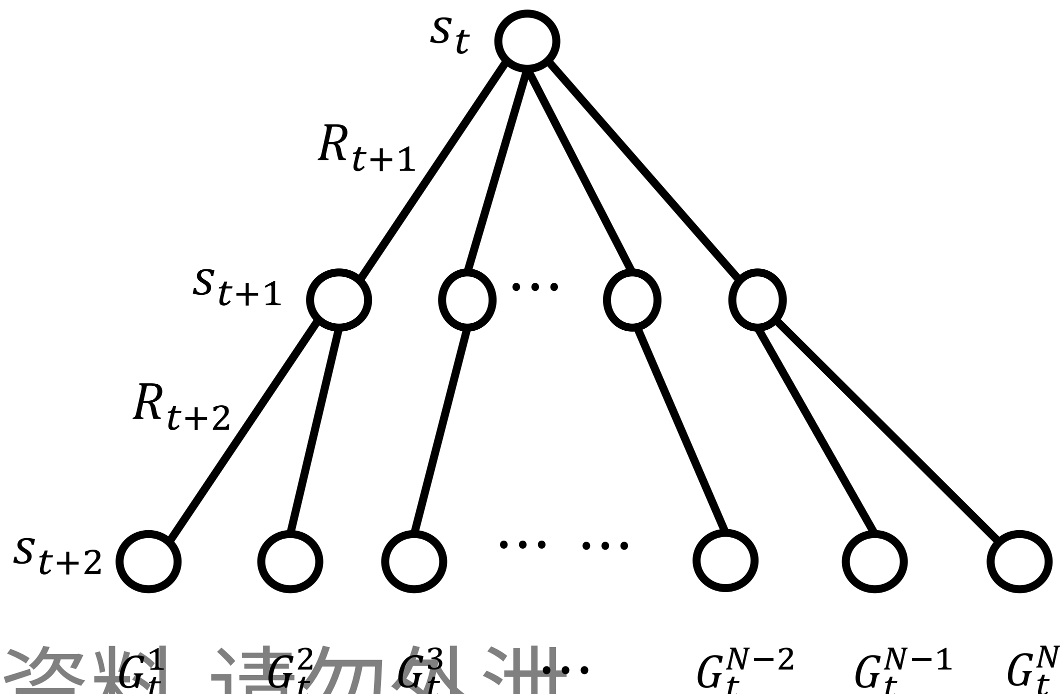
- Avoids infinite returns in cyclic Markov processes
- Ensures the convergence when solving an MDP by dynamic programming

State Value Function for MRP

Definition (State-value function)

The state-value function $V(s)$ is the expected return starting from state s:

$$V(s) = \mathbb{E}[G_t | s_t = s]$$



Bellman Equation for MRP

- The **state-value** function can be decomposed into immediate reward R_{t+1} and discounted value of successor state $\gamma V(s_{t+1})$

$$
\begin{aligned}
V(s) &= \mathbb{E}[G_t \mid s_t = s] \\
&= \mathbb{E}[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \ldots \mid s_t = s] \\
&= \mathbb{E}\left[R_{t+1} + \gamma (R_{t+2} + \gamma R_{t+3} + \ldots) \middle| s_t = s\right] \\
&= \mathbb{E}[R_{t+1} + \gamma G_{t+1} \mid s_t = s] \\
&= \mathbb{E}[R_{t+1} + \gamma V(s_{t+1}) \mid s_t = s]
\end{aligned}
$$

- Bellman equation describes the iterative relations of states

$$V(s) = R(s) + \gamma \sum_{s' \in S} P(s' \mid s) V(s')$$

$$\boxed{\text{The Bellman Equation indicates the value function of the current state can be evaluated by the next state}}$$

Bellman Equation in Matrix Form

$$\boxed{V(s) = R(s) + \gamma \sum_{s' \in \mathcal{S}} P(s'|s) V(s')}$$

- The Bellman equation can be expressed concisely using matrices

$$\begin{bmatrix} v(1) \\ \vdots \\ v(n) \end{bmatrix} = \begin{bmatrix} \mathcal{R}(1) \\ \vdots \\ \mathcal{R}(n) \end{bmatrix} + \gamma \begin{bmatrix} \mathcal{P}_{11} & \dots & \mathcal{P}_{1n} \\ \vdots & \vdots & \vdots \\ \mathcal{P}_{n1} & \dots & \mathcal{P}_{nn} \end{bmatrix} \begin{bmatrix} v(1) \\ \vdots \\ v(n) \end{bmatrix}$$

$$v = \mathcal{R} + \gamma \mathcal{P} v$$

$$(I - \gamma \mathcal{P}) v = \mathcal{R}$$

$$v = (I - \gamma \mathcal{P})^{-1} \mathcal{R}$$

Solution to MRP

- Solving MRP when the model $\mathcal{P}$ is known:

$$v = (I - \gamma\mathcal{P})^{-1}\mathcal{R}$$

  - Matrix inverse takes the **complexity $O(N^3)$** for N states
  - Only possible for small MRPs
  - The model $\mathcal{P}$ must be known

- **Iterative** methods for large MRPs:
  - Dynamic Programming
  - Monte-Carlo evaluation
  - Temporal-Difference learning

Contents

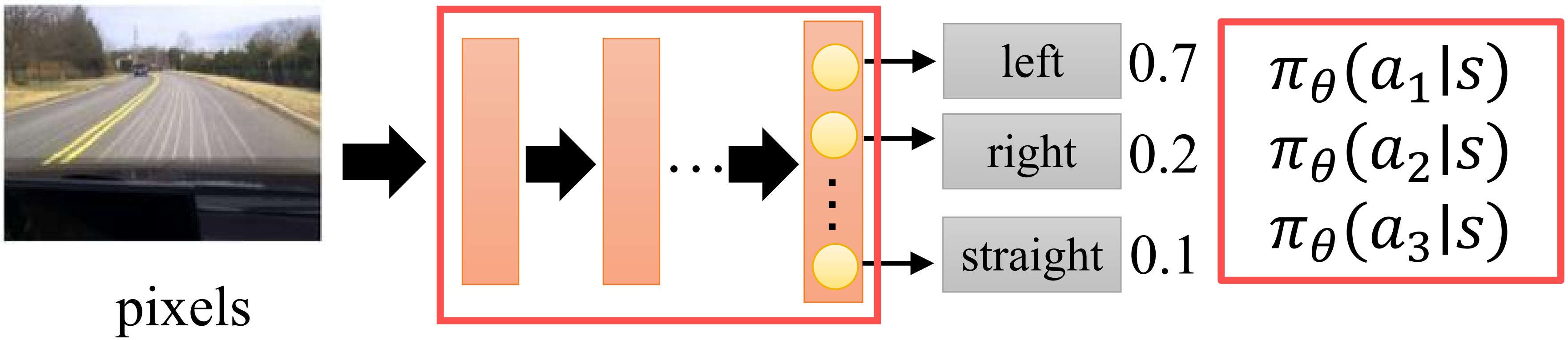
Policy of Agent

- Policy π can be represented by a network with parameter θ:

$$\pi_\theta(a|s) = P(a|s;\theta)$$

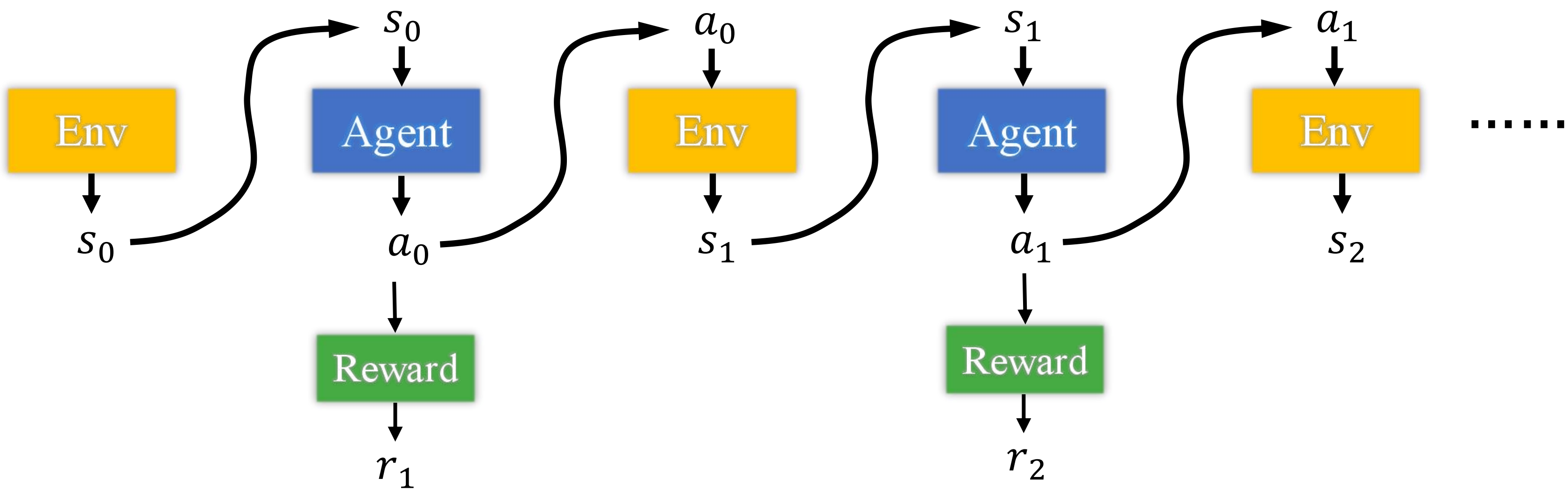
where $\pi_\theta(a_t|s)$ denotes the probability of taking an action a_t given state s

- **Input**: state s
- **Output**: each action a corresponds to a neuron in output layer
- Take the action based on the output probability



How to learn π_θ?

Objective Function



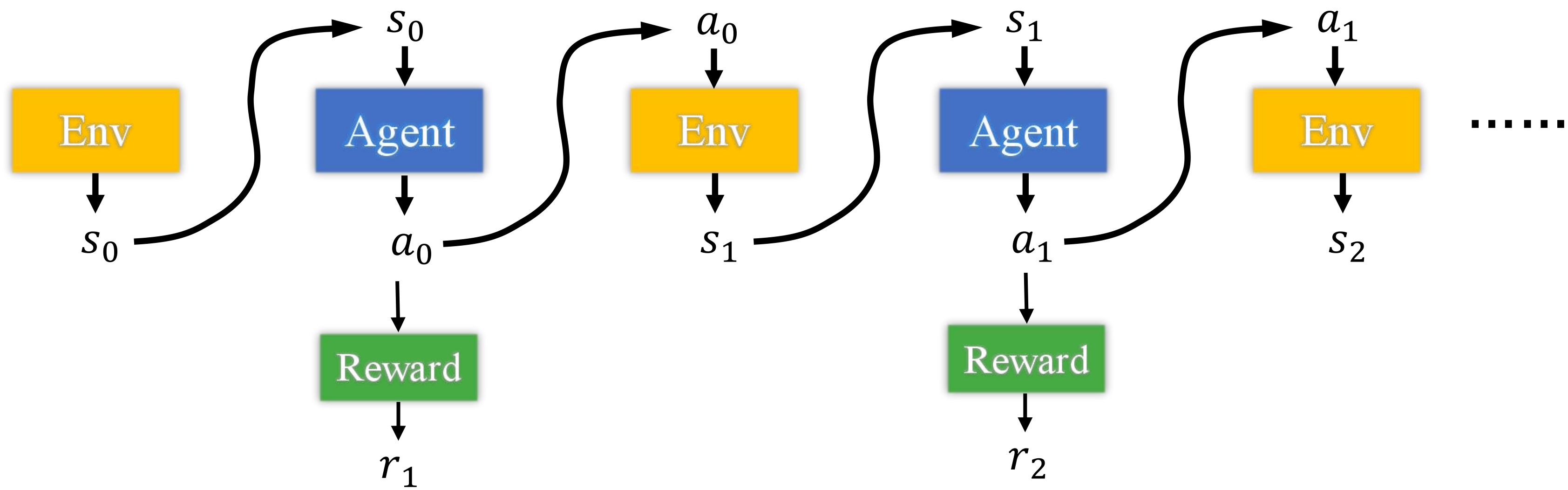
■ To measure the quality of a policy π_θ, we define the objective function

$$J(\theta) = E_{\tau\sim P(\tau\,;\theta)}[R(\tau)] = \sum_{\tau} P(\tau;\theta)R(\tau)$$

where $R(\tau)$ is a reward of τ: $R(\tau) = \sum_{t=0}^{T} \gamma^t r_{t+1}$

What is a trajectory τ ?

What is a Trajectory τ ?



- A trajectory τ is the sequence of state, action, and reward

$$\tau = (s_0, a_0, r_1, s_1, a_1, r_2 \ldots)$$

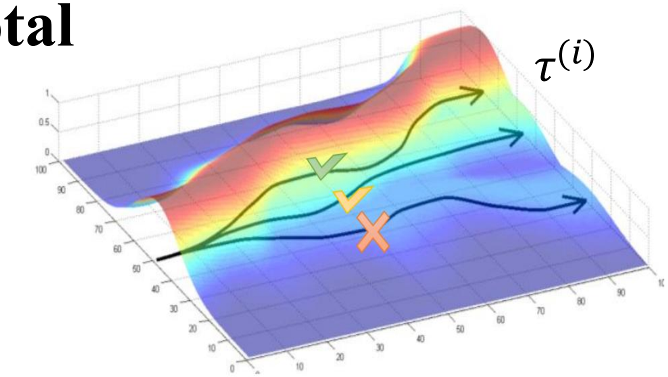
- Given θ, we can compute the probability of τ for each trajectory

$$P(\tau\,;\theta) = p(s_0)\pi_\theta(a_0|s_0)p(s_1|s_0,a_0)\,\pi_\theta(a_1|s_1)p(s_2|s_1,a_1)\ldots$$

$$= p(s_0)\prod_{t=0}^{T}\pi_\theta(a_t|s_t)p(s_{t+1}|s_t,a_t)$$

Policy Gradient

Learn the policy $\pi_\theta(a_t|s_t)$ by **maximizing total future rewards:**



$$\max_\theta \; J(\theta) = \sum_\tau P(\tau;\theta)R(\tau)$$

Policy Gradient algorithm:

Input: random initialized policy π_θ, max number of episodes N,
learning rate η

Output: π_θ

for $i = 1$ **to** N **do**

Sample a trajectory $\tau^{(i)} = \{s_0^{(i)}, a_0^{(i)}, r_1^{(i)}, \ldots, s_{T_i}^{(i)}, a_{T_i}^{(i)}, r_{T_i+1}^{(i)}\}$

for $t = 0$ **to** T_i **do**

$\mathrm{G} = \nabla_\theta J(\theta)$ *// calculate the gradient*

$\theta \leftarrow \theta + \eta G$ *// maximize the objective function by ascending the gradient*

end for

end for

How to comput $\nabla_\theta J(\theta)$?

Policy Gradient

How to compute $\nabla_\theta J(\theta)$?

Update Model

Given policy π_θ

τ^1: (s_0^1, a_0^1) $R(\tau^1)$

(s_1^1, a_1^1) $R(\tau^1)$

$\vdots$ $\vdots$

τ^2: (s_0^2, a_0^2) $R(\tau^2)$

(s_1^2, a_1^2) $R(\tau^2)$

$\vdots$ $\vdots$

$$\theta \leftarrow \theta + \eta \nabla_\theta J$$

$$\nabla_\theta J(\theta) = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=0}^{T_i} R\left(\tau^{(i)}\right) \nabla_\theta log\pi_\theta \left(a_t^{(i)} | s_t^{(i)}\right)$$

Data Collection

How to compute the Gradient $\nabla_\theta J(\theta)$?

The objective function is: $\max_\theta J(\theta) = \sum_\tau P(\tau;\theta)R(\tau)$

Taking the gradient w.r.t. θ gives

$$\nabla_\theta J(\theta) = \sum_\tau \nabla_\theta P(\tau;\theta)R(\tau)$$

$$= \sum_\tau P(\tau;\theta)\boxed{\frac{\nabla_\theta P(\tau;\theta)}{P(\tau;\theta)}}R(\tau)$$

$$= \sum_\tau P(\tau;\theta)\boxed{\nabla_\theta log P(\tau;\theta)}R(\tau)$$

$$\nabla f(x) = f(x)\nabla log f(x)$$

$$R(\tau) = \sum_t \gamma^t r(s_t, a_t)$$

$$P(\tau;\theta) = p(s_0)\prod_{t=0}^{T} \pi_\theta(a_t|s_t)p(s_{t+1}|s_t, a_t)$$

Approximate the gradient,

$$\nabla_\theta J(\theta) \approx \frac{1}{N}\sum_{i=1}^{N} \boxed{\nabla_\theta log P\left(\tau^{(i)};\theta\right)} R(\tau^{(i)})$$

How to compute $\nabla_\theta log P\left(\tau^{(i)};\theta\right)$?

How to compute $\nabla_\theta log P\left(\tau^{(i)};\theta\right)$?

$$\boxed{P(\tau\,;\theta) = p(s_0)\prod_{t=0}^{T}\pi_\theta(a_t|s_t)p(s_{t+1}|s_t,a_t)}$$

$$\nabla_\theta log P\left(\tau^{(i)};\theta\right) = \nabla_\theta \log\left[\prod_{t=0}^{T}\underbrace{p\left(s_{t+1}^{(i)}\middle|s_t^{(i)},a_t^{(i)}\right)}_{dynamics\ model}\cdot\underbrace{\pi_\theta\left(a_t^{(i)}|s_t^{(i)}\right)}_{\text{policy}}\right]$$

$$= \nabla_\theta\left[\sum_{t=0}^{T}\log p\left(s_{t+1}^{(i)}\middle|s_t^{(i)},a_t^{(i)}\right) + \sum_{t=0}^{T} log\pi_\theta\left(a_t^{(i)}|s_t^{(i)}\right)\right]$$

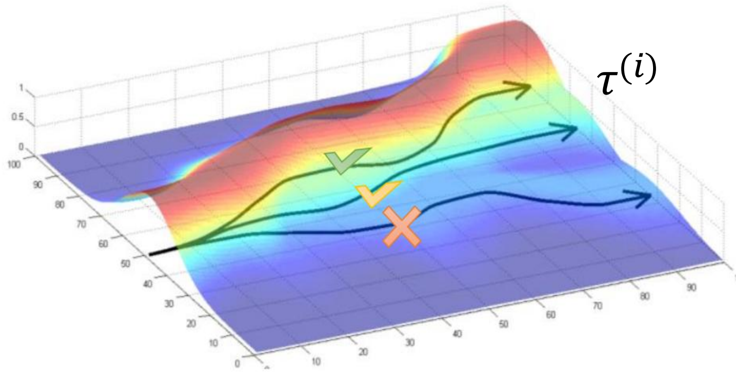
$$= \nabla_\theta\sum_{t=0}^{T} log\pi_\theta\left(a_t^{(i)}|s_t^{(i)}\right)$$

$$= \sum_{t=0}^{T}\underbrace{\nabla_\theta log\pi_\theta\left(a_t^{(i)}|s_t^{(i)}\right)}_{no\ dynamics\ model\ required}$$

Finally, we can obtain $\nabla_\theta J(\theta)$: $\quad \nabla_\theta J(\theta) \approx \frac{1}{N}\sum_{i=1}^{N} R\left(\tau^{(i)}\right)\sum_{t=0}^{T_i}\nabla_\theta log\pi_\theta\left(a_t^{(i)}|s_t^{(i)}\right)$

Policy Gradient

$$\max_{\theta} \; J(\theta) = \sum_{\tau} P(\tau;\theta)R(\tau)$$



Policy Gradient algorithm:

Input: random initialized policy π_θ, max number of episodes N, learning rate η

Output: π_θ

for $i = 1$ **to** N **do**

Sample a trajectory $\tau^{(i)} = \{s_0^{(i)}, a_0^{(i)}, r_1^{(i)}, \ldots, s_{T_i}^{(i)}, a_{T_i}^{(i)}, r_{T_i+1}^{(i)}\}$

for $t = 0$ **to** T_i **do**

$$\nabla_\theta J(\theta) = R\left(s_t^{(i)}, a_t^{(i)}, r_{t+1}^{(i)}, \ldots, r_{T_i+1}^{(i)}\right) \nabla_\theta log\pi_\theta\left(a_t^{(i)} | s_t^{(i)}\right)$$

$$\theta \leftarrow \theta + \eta \nabla_\theta J(\theta)$$

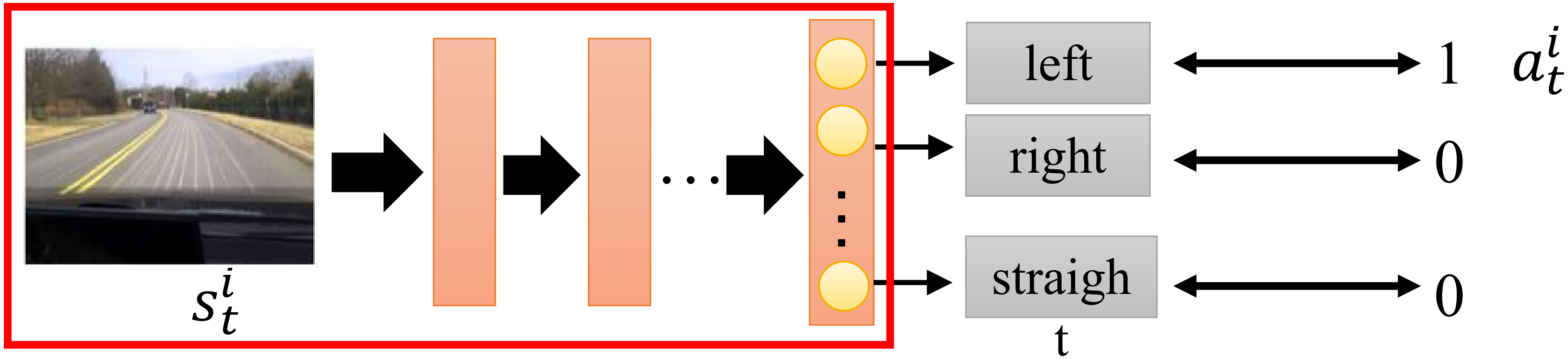
end for

end for

Differences from Gradient Descent

Consider as a classification problem

$s_t^i \quad a_t^i \quad R(\tau^i)$



Implementation for classification:

$$\frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T_i} logp_\theta(a_t^i|s_t^i) \xrightarrow[\text{TF, PyTorch …}]{} \frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T_i} \nabla logp_\theta(a_t^i|s_t^i)$$

Implementation for RL:

$$\frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T_i} R(\tau^i) logp_\theta(a_t^i|s_t^i) \xrightarrow[\text{TF, PyTorch …}]{} \frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T_i} R(\tau^i) \nabla logp_\theta(a_t^i|s_t^i)$$

Only difference

Tip : Add a Baseline

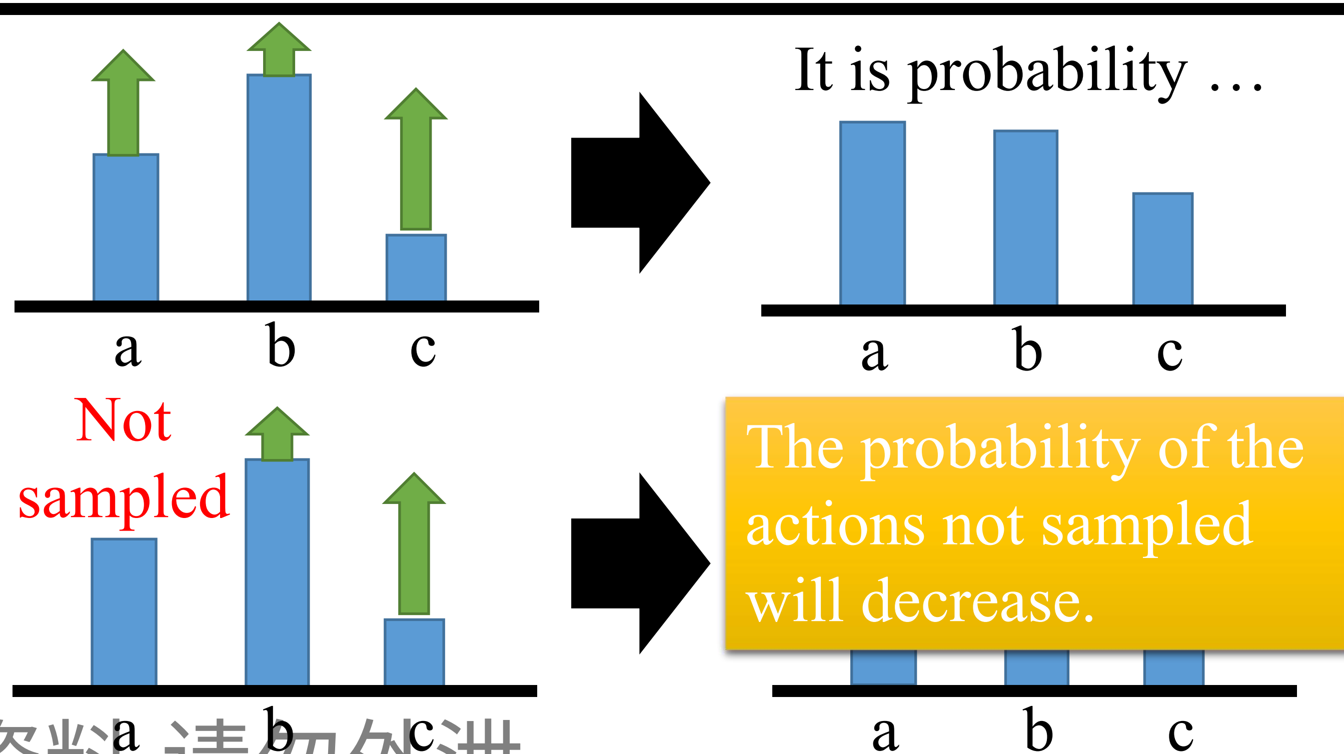
$$\theta \leftarrow \theta + \eta \nabla J_\theta$$

It is possible that $R(\tau^i)$ is always positive

$$\nabla_\theta J \approx \frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T_i}\left(R(\tau^i) - b\right)\nabla log p_\theta\left(a_t^i \mid s_t^i\right) \qquad b \approx E[R(\tau)]$$

Ideal case

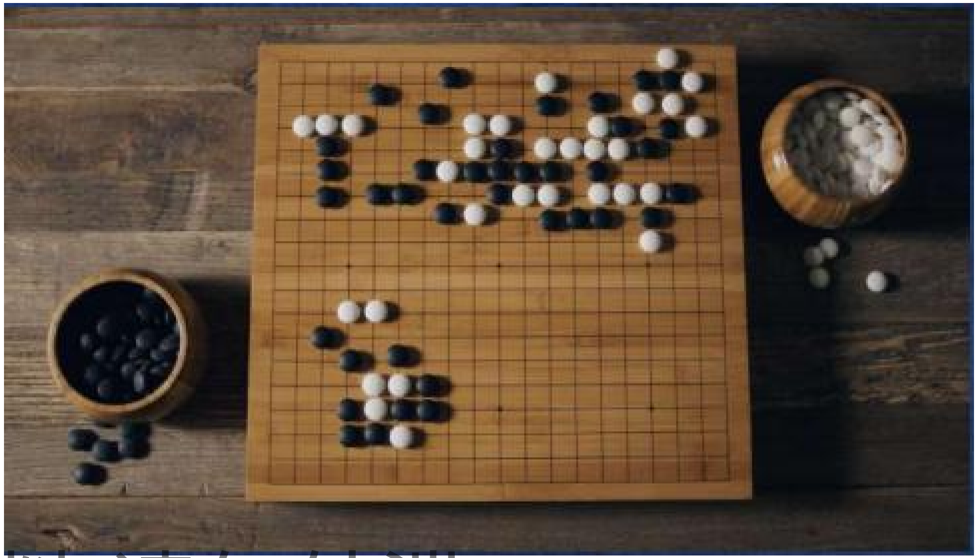
Sampling ……



Contents

What is Go?

- An abstract board game for two players
- Played on 19 x 19 board
- Playing pieces are black and white stones
- Stones placed on vacant intersections of board
- Player which surrounds more territory wins



Challenges for AI in Cracking Go

- Impossible to calculate every possible move on board
- Brute-force method used by most AIs clearly fails
  - Search space is **huge**
  - Impossible for computers to evaluate who is winning
- Go requires **more intuition and experience** than just logic
- Becomes necessary to mimic human mind

AlphaGo

- A computer program that plays Go game
- Developed by Google DeepMind in 2016
- Not a pre-programmed algorithm
- Can actually learn from itself
- Reduce search space
  - Reducing action candidates
  - Board Evaluation

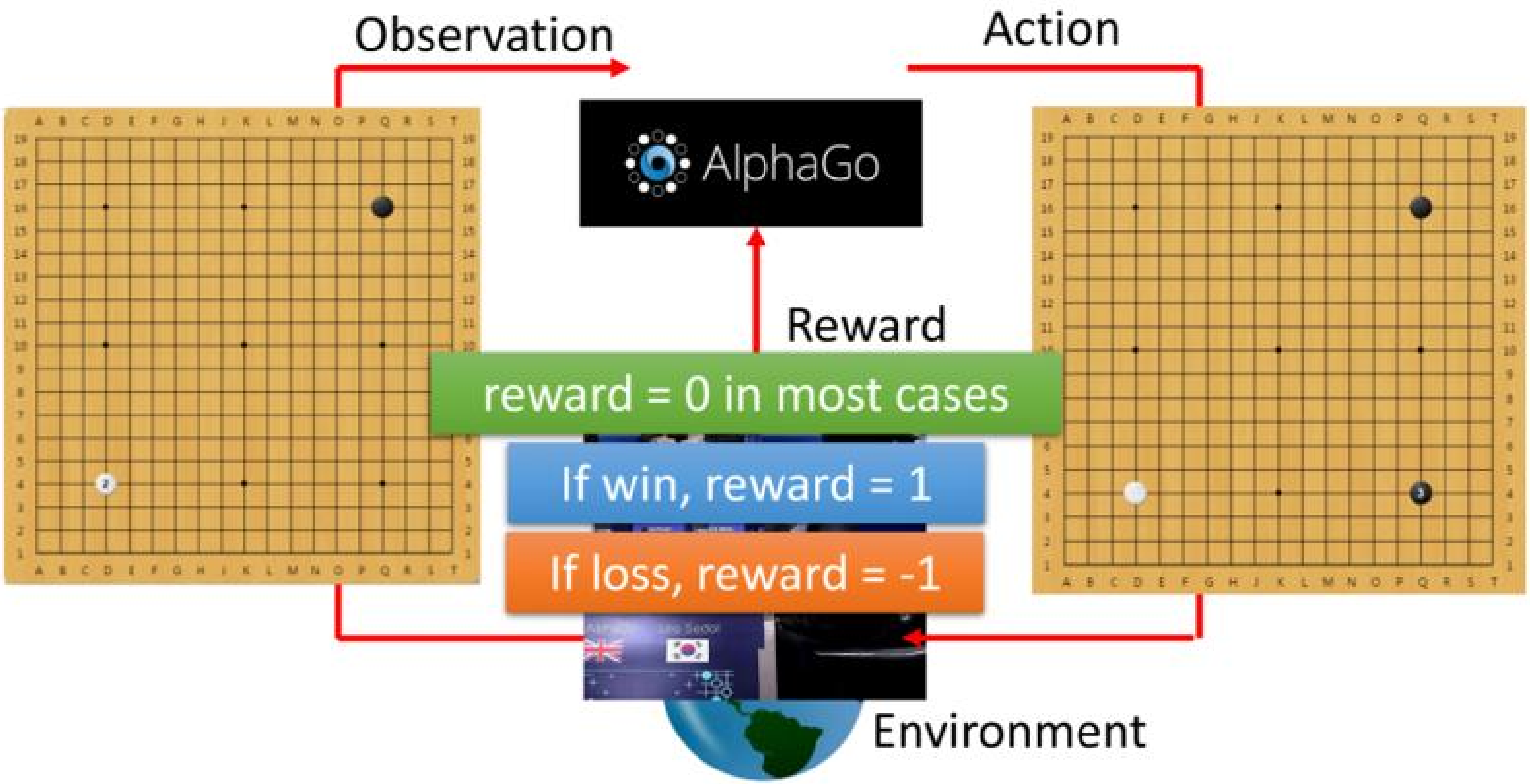
Reducing Action Candidates

- Imitating expert’s moves (supervised learning)

Training: $\Delta\sigma \propto \frac{\partial \log p_\sigma(a|s)}{\partial \sigma}$

Reducing Action Candidates

- Improving through self-plays (reinforcement learning)



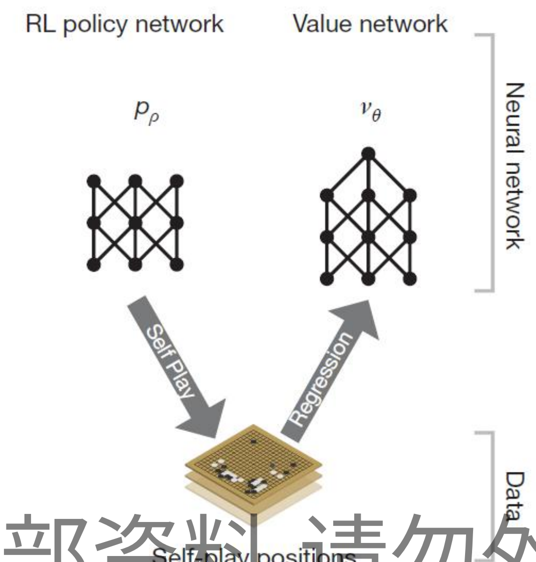
Reward

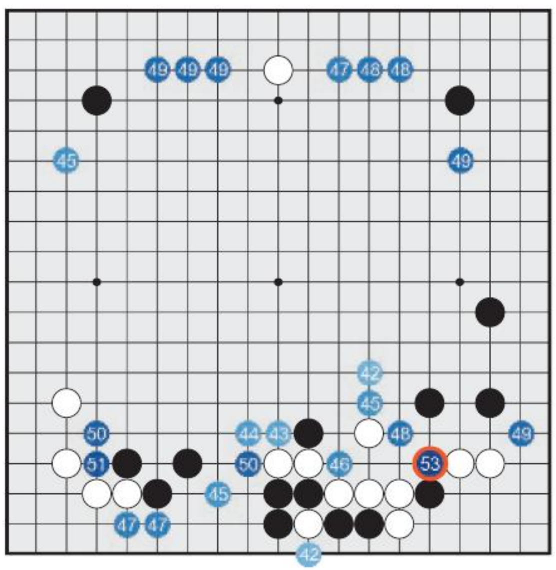
- The reward function $r(s)$ that is zero for all non-terminal state
- The reward signal is delayed
- The outcome $z_t = \pm\ r(s_T)$ is the terminal reward at the end of the game from the perspective of the current player at time step t
  - $+1$ for winning
  - -1 for losing
- Rollout is inefficient

Board Evaluation

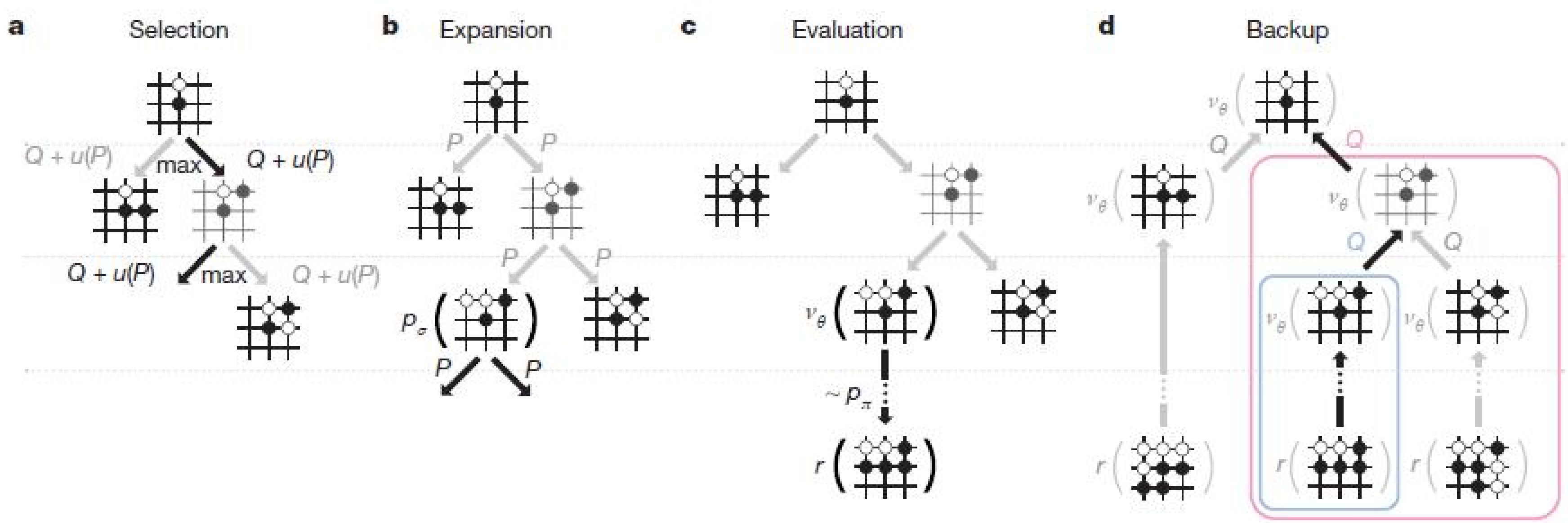
- Estimate a value function that predicts the outcome from the position
- Train the value network by regression on state-outcome pairs (s, z)
- Minimize the mean squared error (MSE) between the predicted value $v_\theta(s)$, and the corresponding outcome z

$$\Delta\theta \propto \frac{\partial v_\theta(s)}{\partial\theta}(z - v_\theta(s))$$





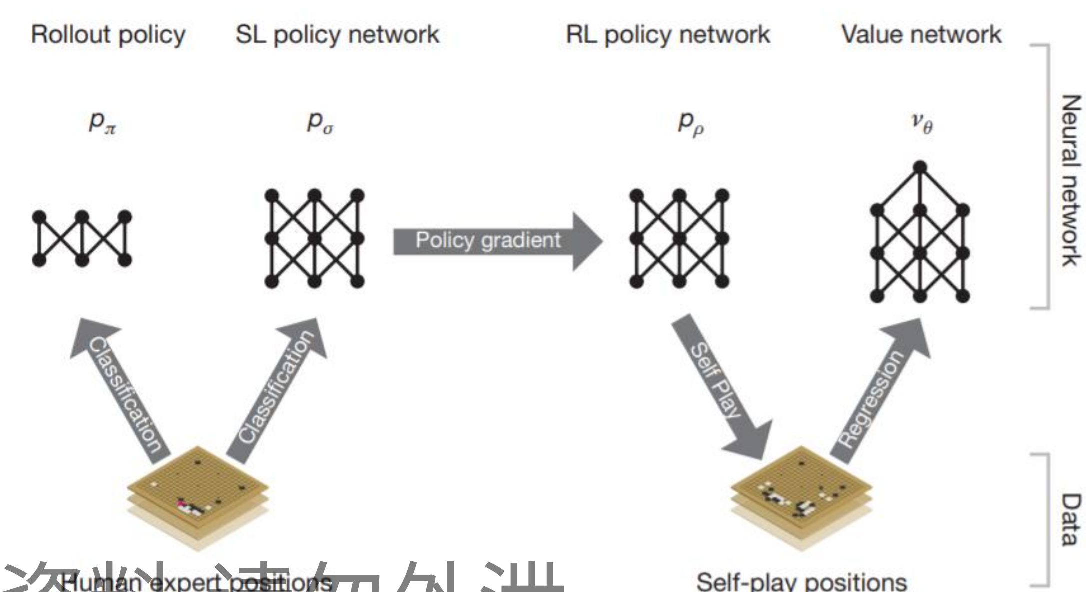
Monte Carlo Tree Search in AlphaGo



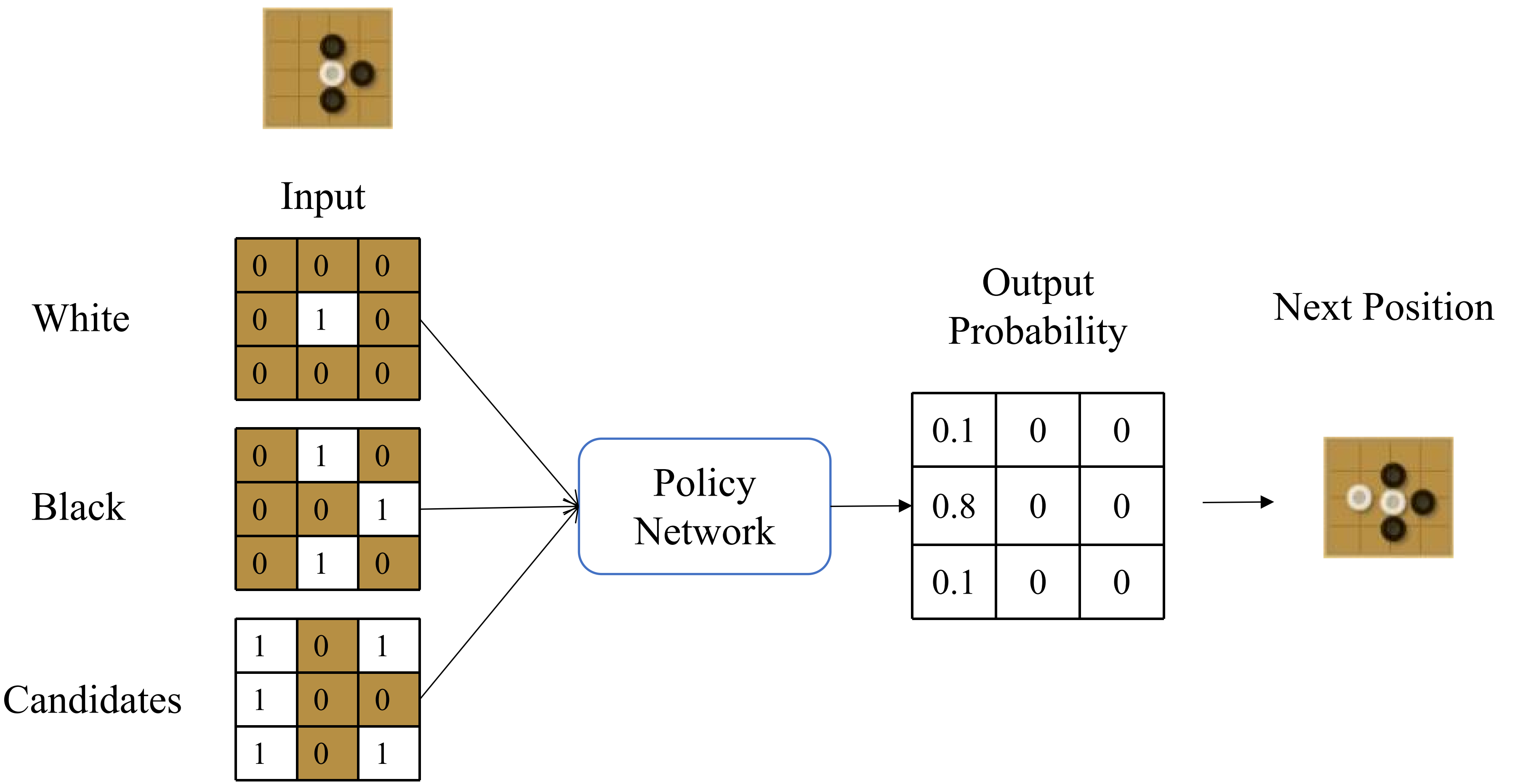
a. Selecting the edge with maximum action value Q
b. The leaf node may be expanded
c. At the end of a simulation, the leaf node is evaluated by value network
d. Action value Q are updated to track the mean value of all evaluations $r(\cdot)$ and $v_\theta(\cdot)$ in the subtree below that action

Learning Pipeline of AlphaGo

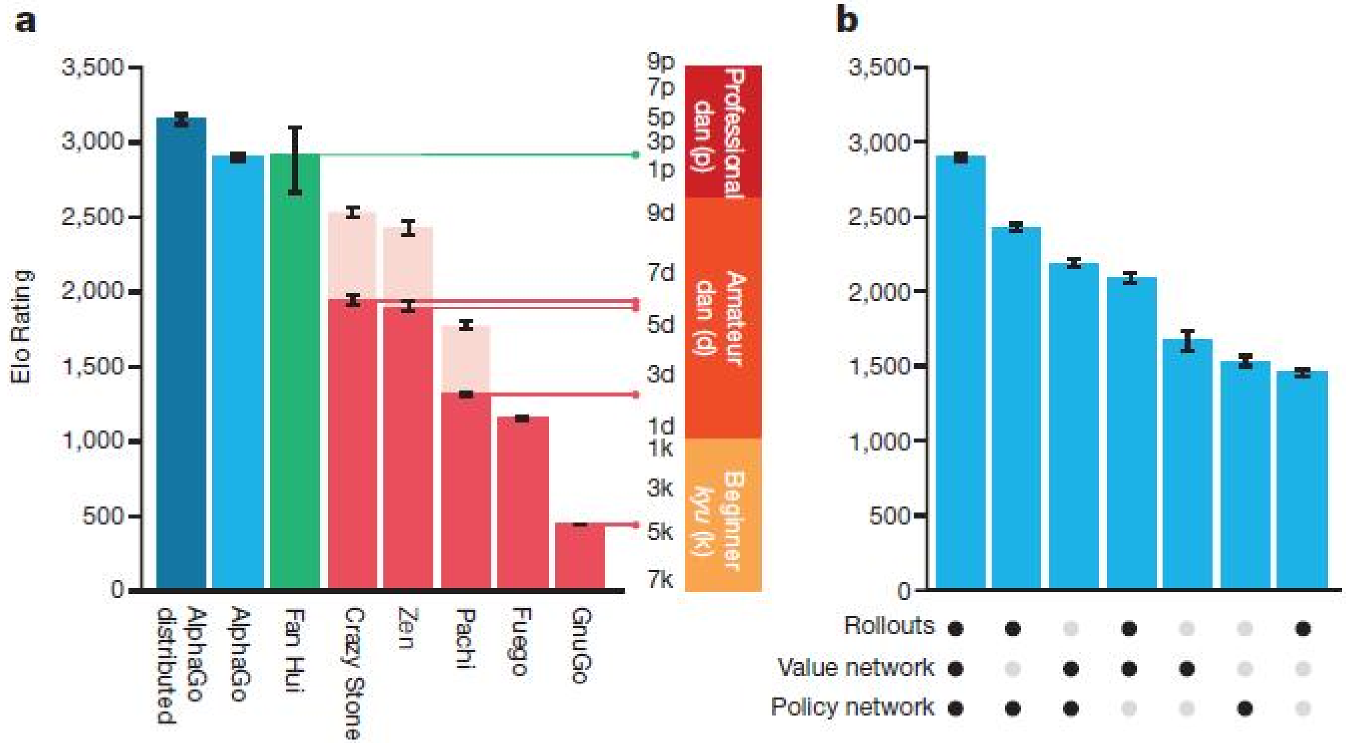
- A fast rollout policy p_π and supervised learning (SL) policy network p_σ are trained to predict human expert moves in a data set of positions.
- A reinforcement learning (RL) policy p_σ is initialized to the SL policy
- Then p_σ is improved by policy gradient learning to maximize the outcome (i.e., winning more game) against previous versions of the policy network.
- A new dataset is generated by playing games of self-play with the RL policy network.
- A value network v_θ is trained by regression to predict the expected outcome



Playing Go Using Learnt Policy



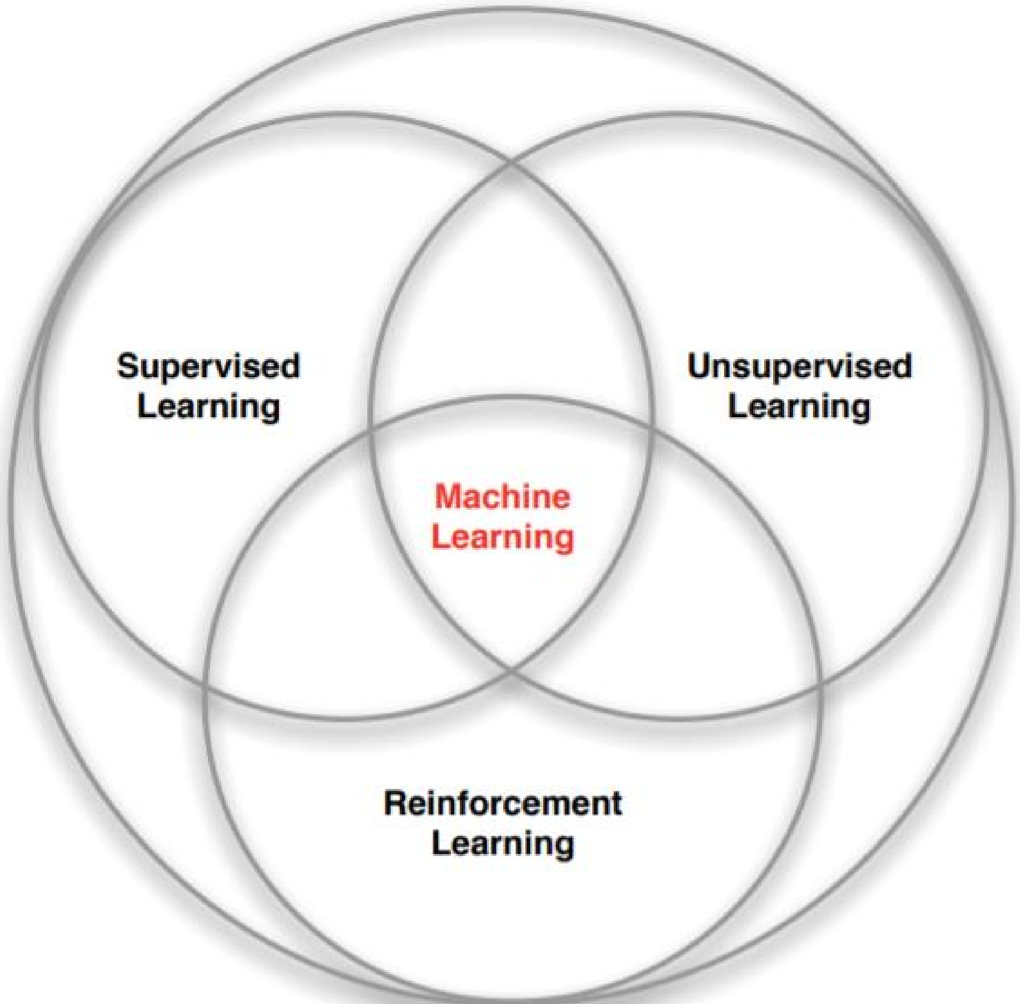
Performance



a. Results of a tournament between different Go programs. Each program used approximately 5s computation time per move.
b. Performance of AlphaGo for different combinations of components.

Contents

Branches of Machine Learning



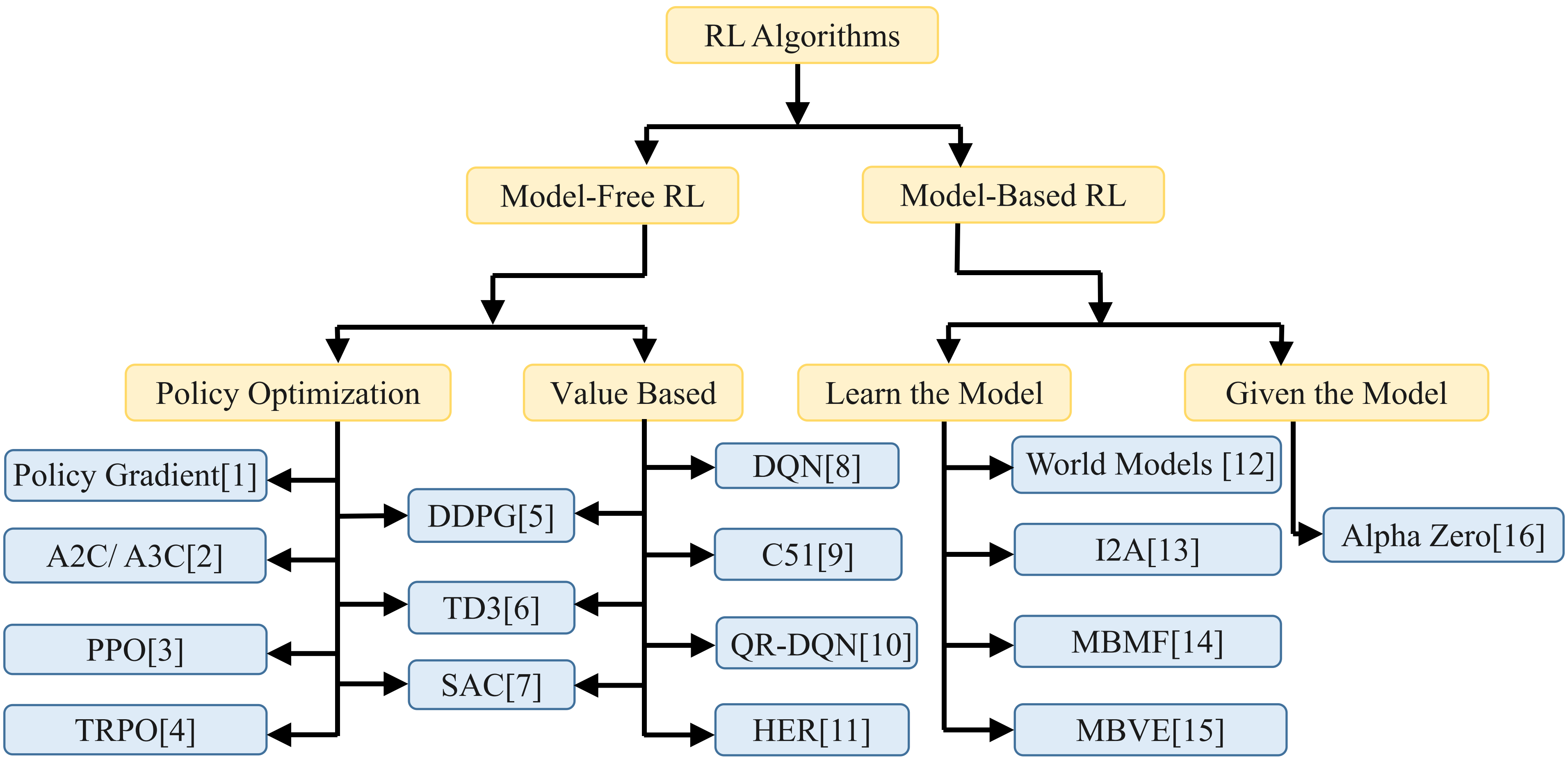
Categorizing of RL Agents (1)

- Value Based
  - No Policy (Implicit)
  - Value Function
- Policy Based
  - Policy
  - No Value Function
- Actor Critic
  - Policy
  - Value Function

Categorizing of RL Agents (2)

- Model Free
  - Policy and/or Value Function
  - No Model
- Model Based
  - Policy and/or Value Function
  - Model

Taxonomy of RL Algorithms



Types of RL algorithms

Model-based

- Learn the model of the world, then plan using the model
- Update model often
- Re-plan often

Value-based

- Learn the state or state-action value
- Act by choosing best action in state
- Exploration is a necessary add-on

Policy-based

- Learn the stochastic policy function that maps state to action
- Act by sampling policy
- Exploration is baked in

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Q&A