Reinforcement Learning

Lecture 9: Model-based methods

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Lecture overview

Lecture covers chapter 8 in Sutton & Barto [1] and examples from David Silver [2]

1. **Model-based reinforcement learning**
   - taxonomy
   - overview
   - the simulation cycle
   - characteristics
2. **Integrated learning and planning**
   - Dyna-Q
   - characteristics
   - Monte Carlo tree search
3. **Model-based policy optimization**
   - Model ensembles
   - Model rollouts

Model-based RL taxonomy

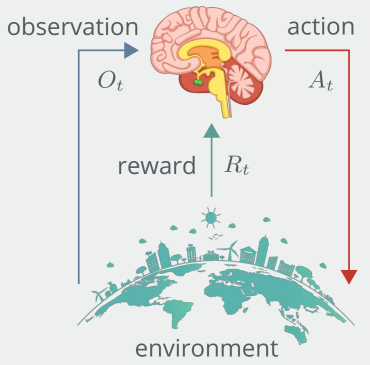
Taxonomy of reinforcement learning algorithms

- RL algorithms
  - Model-free
    - Policy optimisation
      - DPG
      - A3C
      - PPO
      - TD3
      - …
    - Q-learning
      - DQN
      - Double DQN
      - Noisy DQN
      - TRPO
      - …
  - Model-based
    - Learn model
      - World Models
      - I2A
      - MBMF
      - MBVE
      - …
    - Given model
      - AlphaZero
      - ExIt
      - …

This figure does not capture overlap, for example between policy optimsiation and Q-learning algorithms

Model-based RL overview

RL Agents



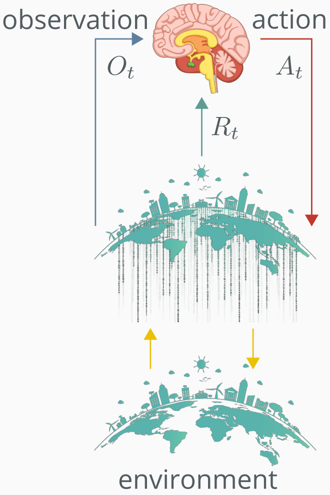
In **model-free** RL:

- No model
- **Learn** the value function $q(s, a)$ and/or the policy $\pi(a|s)$ from experience

In **model-based** RL:

- Learn the model from experience
- **Plan** the value function and/or the policy from the model

Figure based on [2, 1]



Model-based RL cycle:

- The agent experiences the real environment
- We learn a model to predict what the real environment does (when you take an action)
- We then use this simulated model to plan
- This allows us to estimate the value function and/or policy without directly interacting with the real environment
- But we use this policy to take real actions again

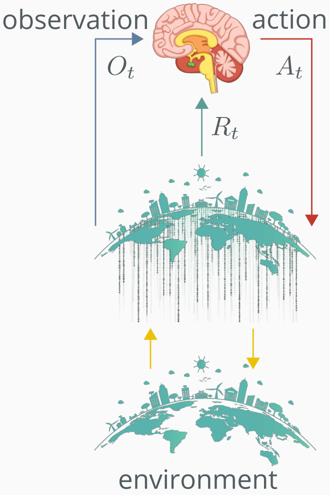
Model-based RL characteristics

Model-based RL advantages:

- The model can sometimes be a simpler and more useful representation of the environment than you can otherwise access by experience
- Can be learnt by supervised learning
- Can reason about model uncertainty

Model-based RL disadvantages:

- This is another component which introduces some approximation error
  - Value function and/or policy approximation and now model approximation
- We can only be as good as our model



Definition: model

A model $\mathcal{M} = \langle \mathcal{P}_\eta, \mathcal{R}_\eta \rangle$ is a parameterised η representation of an MDP: $\langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R} \rangle$. It approximates state transitions $\mathcal{P}_\eta \approx \mathcal{P}$ and rewards $\mathcal{R}_\eta \approx \mathcal{R}$, learning a distribution over the next states and rewards:

$$S_{t+1} \sim \mathcal{P}(S_{t+1} | S_t, A_t)$$
$$R_{t+1} = \mathcal{R}(R_{t+1} | S_t, A_t),$$

which typically are conditionally independent of each other:

$$P(S_{t+1}, R_{t+1} | S_t, A_t) = P(S_{t+1} | S_t, A_t) P(R_{t+1} | S_t, A_t)$$

Example: environment model

Learning the model

We learn the model $\mathcal{M}_\eta$ from experience $\{S_1, A_1, R_2, ..., S_T\}$ using **supervised learning**.

- We receive a stream of actual experiences
- This gives us a dataset:

$$S_1, A_1 \to R_2, S_2$$
$$S_2, A_2 \to R_3, S_3$$
$$\dots$$

- $s, a \to r$ is a regression problem
- $s, a \to s'$ is a density estimation problem

Integrated learning simulated and real experience

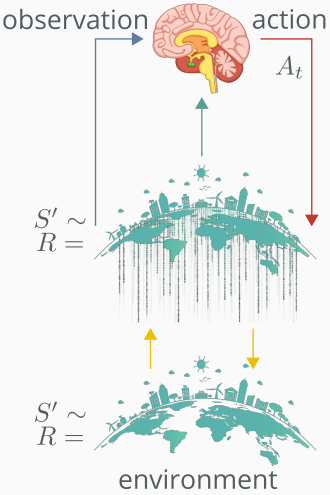
Experience can be simulated and real

Simulated experience sampled from $\mathcal{M}_\eta$

$$S' \sim \mathcal{P}_\eta(S'|S, A)$$
$$R = \mathcal{R}_\eta(R|S, A)$$

Real experience sampled from the true MDP

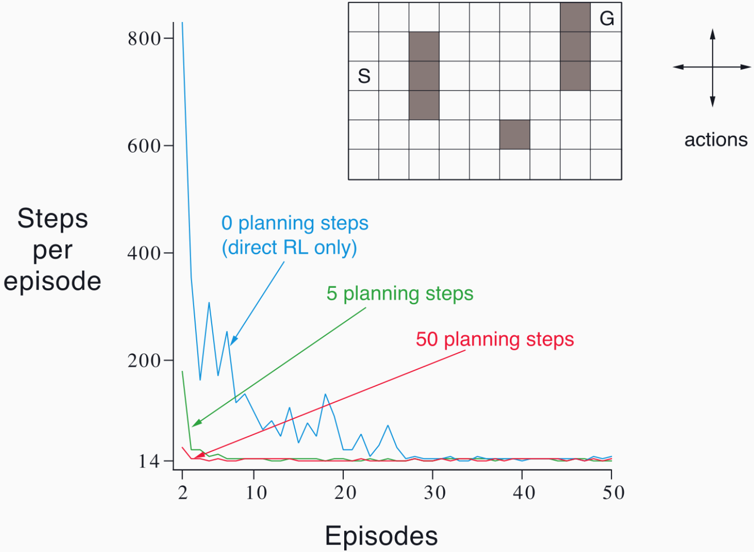
$$S' \sim \mathcal{P}^a_{s,s'}$$
$$R = \mathcal{R}^a_s$$

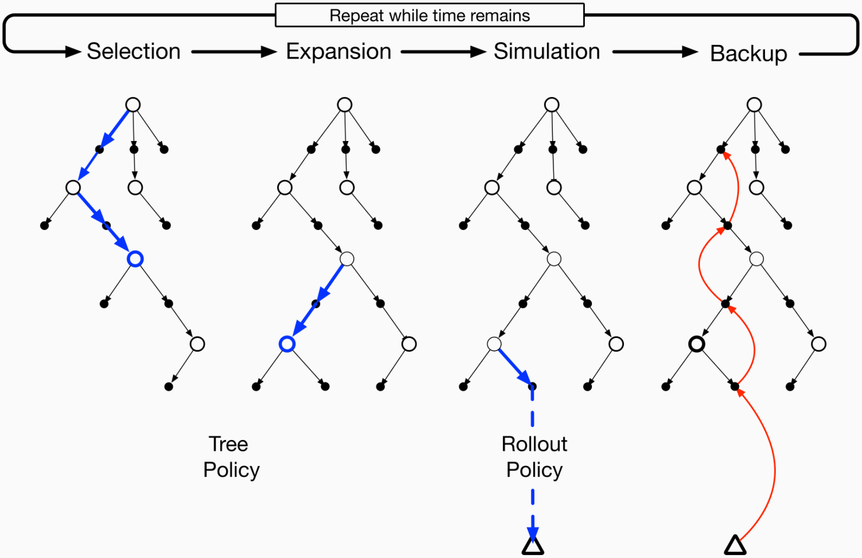


Algorithm: Dyna-Q [3, 4]

initialise $Q(s,a)$ and model $\mathcal{M}(s,a)$ **for** all $s \in \mathcal{S}$ and $a \in \mathcal{A}(s)$
while True:
  $s \leftarrow$ current (nonterminal) state
  $a \leftarrow \epsilon-$greedy(s, Q)
  $r, s' \leftarrow$ env.step(s, a)
  $Q(s,a) \leftarrow Q(s,a) + \alpha(r + \gamma \max_{\hat{a}} Q(s', \hat{a}) - Q(s,a))$
  $\mathcal{M}(s,a) \leftarrow r, s'$ (assuming deterministic environment)
  for i **in** range(n):
    $s \leftarrow$ random previously observed state
    $a \leftarrow$ random action previously taken in s
    $r, s' \leftarrow \mathcal{M}(s,a)$
    $Q(s,a) \leftarrow Q(s,a) + \alpha(r + \gamma \max_{\hat{a}} Q(s', \hat{a}) - Q(s,a))$

Model-based RL Dyna-Q characteristics




Repeat while time remains
Selection
Expansion
Simulation
Backup
Tree
Policy
Rollout
Policy

Algorithm Model-ensemble trust-region policy optimization (ME-TRPO) [5]

1: Initialize a policy π_θ and all models $\hat{f}_{\phi_1}, \hat{f}_{\phi_2}, ..., \hat{f}_{\phi_K}$.
2: Initialize an empty dataset $\mathcal{D}$.
3: **repeat**
4: Collect samples from the real system f using π_θ and add them to D.
5: Train all models using $\mathcal{D}$.
6: **repeat** ▷ Optimize π_θ using all models.
7: Collect fictitious samples from $\{\hat{f}_{\phi_i}\}_{i=1}^K$ using π_θ.
8: Update the policy on the fictitious samples.
9: Estimate the performances $\hat{\eta}(\theta; \phi_i)$ for $i = 1, ..., K$.
10: **until** the performances stop improving.
11: **until** the policy performs well in real environment f.

Model-based policy optimization rollouts

Algorithm Model-based policy optimization (MBPO) [6]

Initialize policy π_ϕ, predictive model p_θ, environment dataset $\mathcal{D}_{\text{env}}$, model dataset $\mathcal{D}_{\text{model}}$
for N epochs **do**
    Train model p_θ on $\mathcal{D}_{\text{env}}$ via maximum likelihood
    for E steps **do**
        Take action in environment according to π_ϕ; add to $\mathcal{D}_{\text{env}}$
        for M model rollouts **do**
            Sample s_t uniformly from $\mathcal{D}_{\text{env}}$
            Perform k-step model rollout starting from s_t using policy π_ϕ; add to $\mathcal{D}_{\text{model}}$
        for G gradient updates **do**
            Update policy parameters on model data: $\phi \leftarrow \phi - \lambda_\pi \hat{\nabla}_\phi J_\pi(\phi, \mathcal{D}_{\text{model}})$

Take Away Points

Summary

In summary, model-based methods:

- are easy to train with supervised learning
- allow for planning ahead
- can be very data efficient
- can be used to imagine situations without experiencing them
- but the value and policy learnt can only be as good as the model
- they can be combined with model-free methods

References I

[1] Richard S Sutton and Andrew G Barto. Reinforcement learning: An introduction (second edition). Available online. MIT press, 2018.

[2] David Silver. Reinforcement Learning lectures. https://www.davidsilver.uk/teaching/. 2015.

[3] Richard S Sutton. "Integrated architectures for learning, planning, and reacting based on approximating dynamic programming". In: Machine learning proceedings 1990. Elsevier, 1990, pp. 216–224.

[4] Baolin Peng et al. "Deep Dyna-Q: Integrating planning for task-completion dialogue policy learning". In: arXiv preprint arXiv:1801.06176 (2018).

[5] Thanard Kurutach et al. "Model-Ensemble Trust-Region Policy Optimization". In: International Conference on Learning Representations. 2018. URL: https://openreview.net/forum?id=SJJinbWRZ.

References II

[6] Michael Janner et al. "When to trust your model: Model-based policy optimization". In: arXiv preprint arXiv:1906.08253 (2019).