Reinforcement learning

Chapter 21, Sections 1–4

Outline

- ♢ Examples
- ♢ Learning a value function for a fixed policy
  – temporal difference learning
- ♢ Q-learning
- ♢ Function approximation
- ♢ Exploration

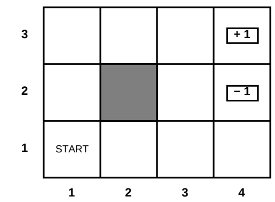
Reinforcement learning

Agent is in an MDP or POMDP environment

Only feedback for learning is percept + reward

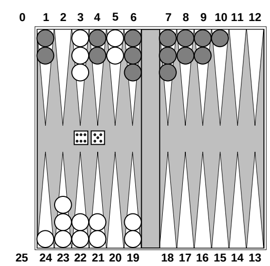
Agent must learn a policy in some form:
– transition model $T(s, a, s')$ plus value function $U(s)$
– $Q(a, s)$ = expected utility if we do a in s and then act optimally
– policy $\pi(s)$

Example: 4 × 3 world



$(1,1)_{-.04}\rightarrow(1,2)_{-.04}\rightarrow(1,3)_{-.04}\rightarrow(1,2)_{-.04}\rightarrow(1,3)_{-.04}\rightarrow\ \cdots\ (4,3)_{+1}$
$(1,1)_{-.04}\rightarrow(1,2)_{-.04}\rightarrow(1,3)_{-.04}\rightarrow(2,3)_{-.04}\rightarrow(3,3)_{-.04}\rightarrow\ \cdots\ (4,3)_{+1}$
$(1,1)_{-.04}\rightarrow(2,1)_{-.04}\rightarrow(3,1)_{-.04}\rightarrow(3,2)_{-.04}\rightarrow(4,2)_{-1}\ .$

Example: Backgammon



Reward for win/loss only in terminal states, otherwise zero

TDGammon learns $\hat{U}(s)$, represented as 3-layer neural network

Combined with depth 2 or 3 search, one of top three players in world

Example: Animal learning

RL studied experimentally for more than 60 years in psychology

Rewards: food, pain, hunger, recreational pharmaceuticals, etc.

Example: bees learn near-optimal foraging plan in field of artificial flowers with controlled nectar supplies

Bees have a direct neural connection from nectar intake measurement to motor planning area

Example: Autonomous helicopter

Reward = − squared deviation from desired state

Example: Autonomous helicopter

Temporal difference learning

Fix a policy π, execute it, learn $U^\pi(s)$

Bellman equation:

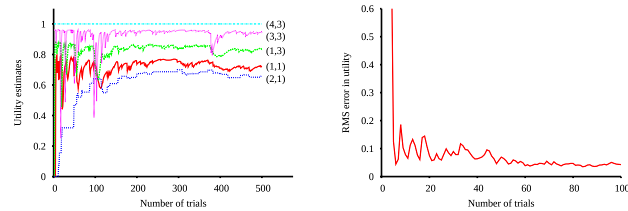
$$U^\pi(s) = R(s) + \gamma \sum_{s'} T(s, \pi(s), s') U^\pi(s')$$

TD update adjusts utility estimate to agree with Bellman equation:

$$U^\pi(s) \leftarrow U^\pi(s) + \alpha(R(s) + \gamma\, U^\pi(s') - U^\pi(s))$$

Essentially using sampling from the environment instead of exact summation

TD performance



Q-learning

One drawback of learning $U(s)$: still need $T(s,a,s')$ to make decisions

$Q(a,s)$ = expected utility if we do a in s and then act optimally

Bellman equation:

$$Q(a,s) = R(s) + \gamma \sum_{s'} T(s, \pi(s), s') \max_{a'} Q(a', s')$$

Q-learning update:

$$Q(a,s) \leftarrow Q(a,s) + \alpha(R(s) + \gamma \max_{a'} Q(a', s') - Q(a,s))$$

Q-learning is a **model-free** method for learning and decision making

Q-learning is a **model-free** method for learning and decision making (so cannot use model to constrain Q-values, do mental simulation, etc.)

Function approximation

For real problems, cannot represent U or Q as a table!!

Typically use linear function approximation:

$$\hat{U}_\theta(s) = \theta_1 f_1(s) + \theta_2 f_2(s) + \cdots + \theta_n f_n(s)\ .$$

Use a gradient step to modify θ parameters:

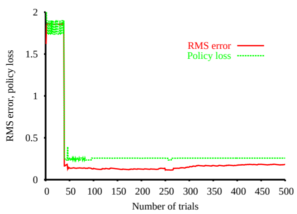
$$\theta_i \leftarrow \theta_i + \alpha\, [R(s) + \gamma\, \hat{U}_\theta(s') - \hat{U}_\theta(s)] \frac{\partial \hat{U}_\theta(s)}{\partial \theta_i}$$

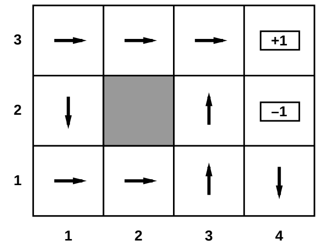
$$\theta_i \leftarrow \theta_i + \alpha\, [R(s) + \gamma \max_{a'} \hat{Q}_\theta(a', s') - \hat{Q}_\theta(a,s)] \frac{\partial \hat{Q}_\theta(a,s)}{\partial \theta_i}$$

Often very effective in practice, but convergence not guaranteed

Exploration

How should the agent behave? Choose action with highest expected utility?





Exploration vs. exploitation: occasionally try "suboptimal" actions!!

Summary

Reinforcement learning methods find approximate solutions to MDPs

Work directly from experience in the environment

Need not be given transition model *a priori*

Q-learning is completely model-free

Function approximation (e.g., linear combination of features) helps RL scale up to very large MDPs

Exploration is required for convergence to optimal solutions