Reinforcement Learning

Chapter 21

TB Artificial Intelligence

INSTITUT Mines-Télécom

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Outline

Agents and Machine Learning (chap. 2)

Markov Decision Problems (chap. 18)

Passive Reinforcement Learning

Active Reinforcement Learning

Topic

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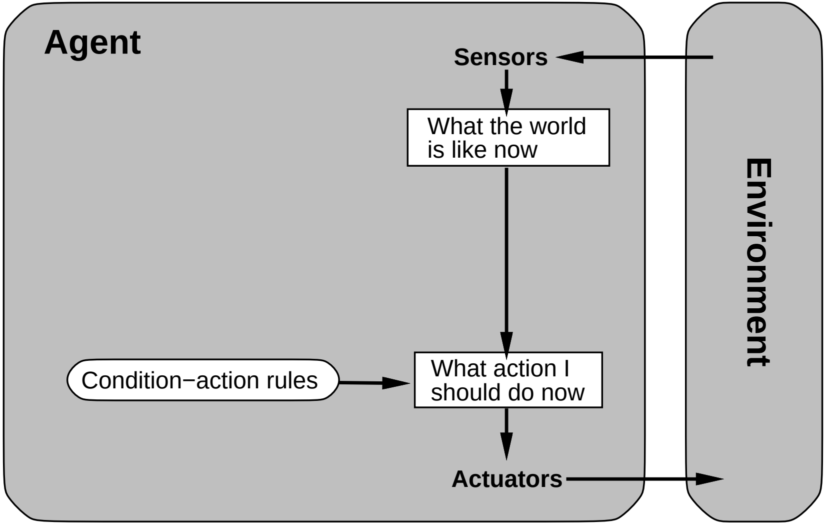
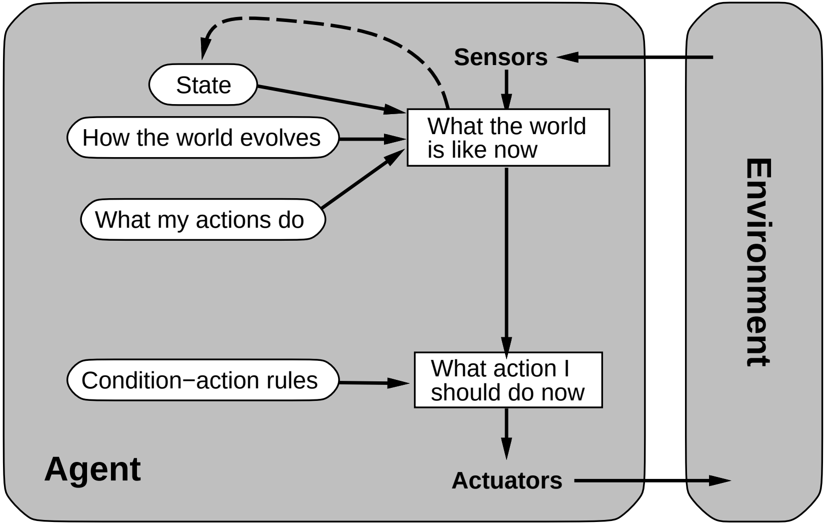
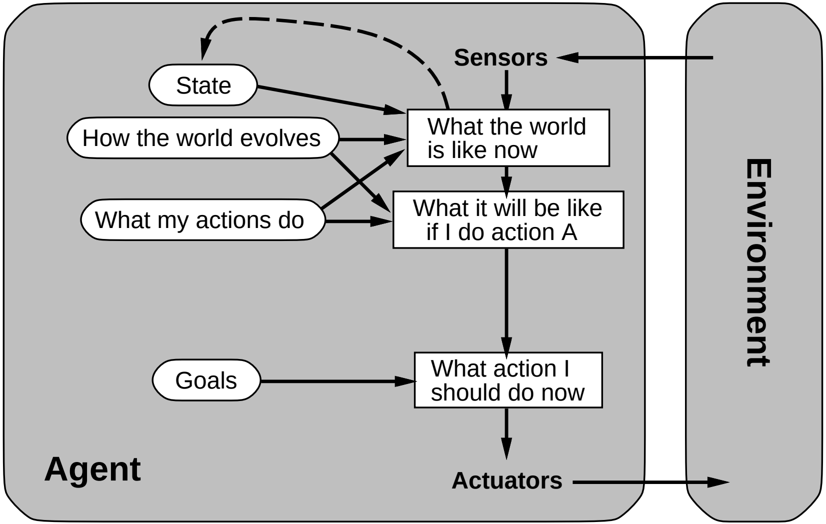
Simple Reflex Agent



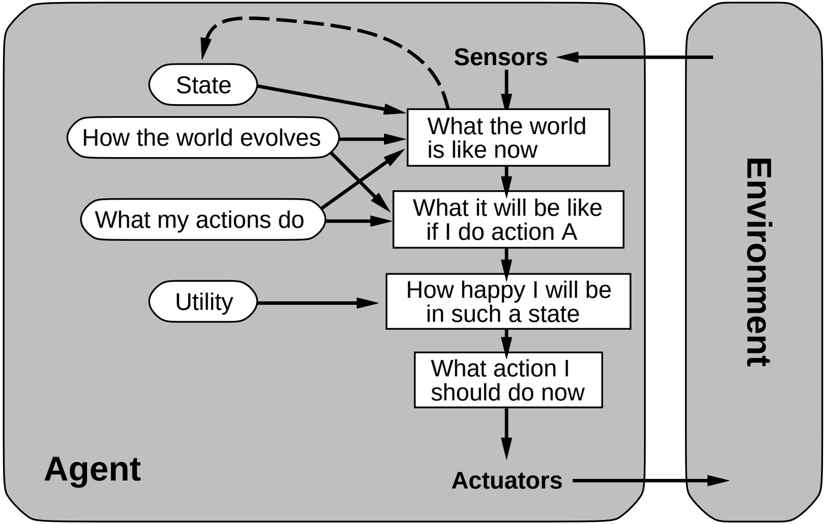
Model-based Reflex Agent



Goal-based Agent



Utility-based Agent



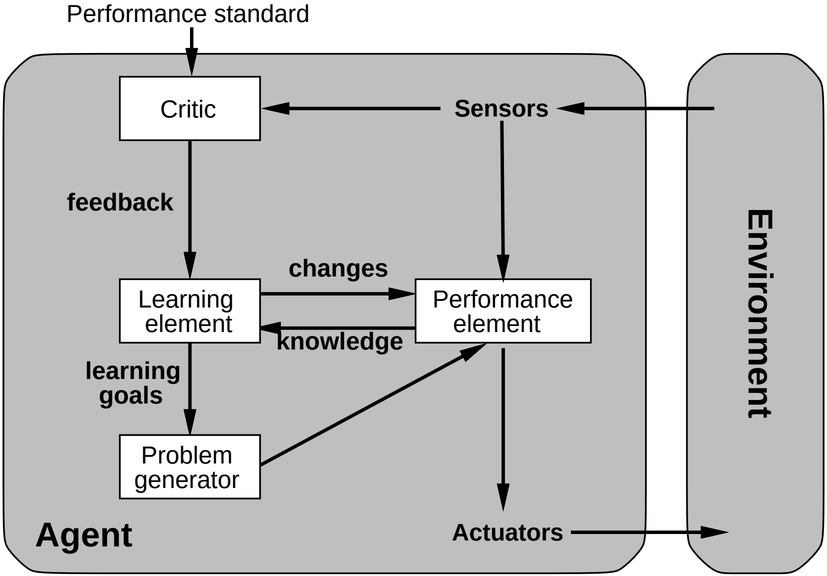
Learning Agent

4 basic kinds of intelligent agents (increasing order of complexity):

1. Simple Reflex agents
2. Model-based Reflex Agents
3. Goal-based Reflex Agents
4. Utility-based Reflex Agents

But it can be fastidious to program such agents...

Learning Agent (cont.)



Four Main Aspects

1. Which **feedback** from environnement is available?
   (supervised learning, unsupervised, reinforcement)
2. How knowledge is modeled?
   (algebraic expressions, production rules, graph, networks, sequences, . . .)
   Is there prior knowledge?
3. Which agent **components** must learn?
   - State $\rightarrow$ Action?
   - Environnement?
   - How the world evolves?
   - Predictable results of actions?
   - Desirability of actions ?
   - States which maximise utility ?
4. On-line or batch ?

Machine Learning

- Supervised Learning
  - Learning with labelled instances
  - Ex. : Decision Trees, Neural Networks, SVMS, ...
- Unsupervised Learning
  - Learning without labels
  - Ex. : K-means, clustering, ...
- Reinforcement Learning
  - Learning with rewards
  - App. : robots, autonomous vehicles, ...

Reinforcement Learning

- Supervised learning is simplest and best-studied type of learning
- Another type of learning tasks is learning behaviors when we don't have a teacher to tell us how
- The agent has a task to perform; it takes some actions in the world; at some later point gets feedback telling it how well it did on performing task
- The agent performs the same task over and over again
- The agent gets carrots for good behavior and sticks for bad behavior
- It's called reinforcement learning because the agent gets positive reinforcement for tasks done well and negative reinforcement for tasks done poorly

Reinforcement Learning (cont.)

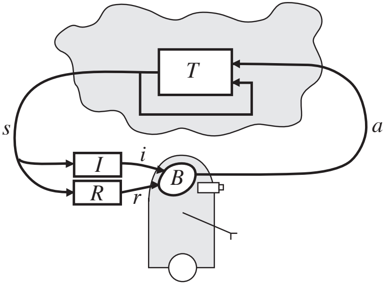
- The problem of getting an agent to act in the world so as to maximize its rewards
- Consider teaching a dog a new trick: you cannot tell it what to do, but you can reward/punish it if it does the right/wrong thing. It has to figure out what it did that made it get the reward/punishment, which is known as the credit assignment problem
- We can use a similar method to train computers to do many tasks, such as playing backgammon or chess, scheduling jobs, and controlling robot limbs

Example : SDyna for video games

Reinforcement Learning : Basic Model

[Kaelbling et al., 1996]

- i : input (some indications about s)
- s : state of the environment
- a : action
- r : reinforcement signal
- B : agent's behavior
- T : transition function
- I : input function (what is seen about the env.)



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Markov Decision Process

Definition (Markov Decision Process (MDP))

A sequential decision problem for a fully observable, stochastic environment with a Markovian transition function and additive reward is called a Markov Decision Problem, and defined by a tuple $\langle S, A, T, R \rangle$:

- A set of **states** $s \in S$
- A set of **actions** $a \in A$
- A stochastic **transition function** $T(s, a, s') = P(s'|s, a)$
- A **reward** function $R(s)$

Markov Decision Process (cont.)

-0.04	-0.04	-0.04	$\boxed{+1}$
-0.04		-0.04	$\boxed{-1}$
START	-0.04	-0.04	-0.04

with probability to go straight = 0.8, left = 0.1 and right = 0.1

- In a deterministic environment, a solution would be [$\uparrow$,$\uparrow$,$\rightarrow\rightarrow\rightarrow$]
- In our stochastic environment, the probability of reaching goal state +1 given this sequence of actions is only 0.33

Markov Decision Process: Policy

- A **policy** is a function $\pi : S \rightarrow A$ that specifies what action the agent should take in any given state
- Executing a policy can give rise to many action sequences!
- How can we determine the quality of a policy?

$\rightarrow$	$\rightarrow$	$\rightarrow$	$\boxed{+1}$
$\uparrow$		$\uparrow$	$\boxed{-1}$
$\uparrow$	$\leftarrow$	$\leftarrow$	$\leftarrow$

Markov Decision Process: Utility

- **Utility** is an internal measure of an agent's success
  - Agent's own internal **performance measure**
  - Surrogate for success and happiness
- The utility is a function of the rewards

$$
\begin{aligned}
U([s_0, s_1, s_2, \ldots]) &= \gamma^0 R(s_0) + \gamma^1 R(s_1) + \gamma^2 R(s_2) + \ldots \\
&= \sum_{t=0}^{\infty} \gamma^t R(s_t)
\end{aligned}
$$

with γ a discount factor

Markov Decision Process: Utility (cont.)

→	→	→	+1
↑		↑	-1
↑	←	←	←

Optimal Policy

0.812	0.868	0.918	+1
0.762		0.660	-1
0.705	0.655	0.611	0.388

Utilities

Value Iteration Algorithm

- Given an MDP, recursively formulate the utility of starting at state s

$$U(s) = R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s,a) U(s') \qquad \text{(Bellman Equation)}$$

- Suggest an iterative algorithm:

$$U_{i+1}(s) \leftarrow R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s,a) U_i(s')$$

- Once we have $U(s)$ for all states s, we can construct the optimal policy:

$$\pi^*(s) = \operatorname*{argmax}_{a \in A(s)} \sum_{s'} P(s'|s,a) U(s')$$

Policy Iteration Algorithm

- **Policy evaluation** : given π_i compute U_i

$$U_i(s) = U^{\pi_i}(s) = E\left[\sum_{t=0}^{\infty} {}^t R(S_t)\right]$$

- **Policy improvement** = given U_i compute π_{i+1}

$$\pi_{i+1}(s) = \operatorname*{argmax}_{a \in A(s)} \sum_{s'} P(s'|s,a) U_i(s')$$

- Repeat until stability

Why Reinforcement Learning?

- We could find an optimal policy for an MDP if we know the transition model $P(s'|s,a)$
- **But**, an agent in an unknown environment does not know the transition model nor in advance what rewards it will get in new states
- We want the agent to learn to behave rationally in an unsupervised process

The purpose of RL is to learn the optimal policy based only on received rewards

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Passive RL

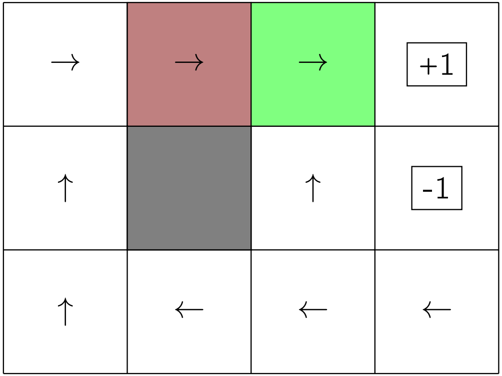
- In passive RL, the agents' policy π is fixed, it only needs to know how good it is
- Agent runs a number of trials, starting in (1,1) and continuing until it reaches a terminal state
- The utility of a state is the expected total remaining reward (reward-to-go)
- Each trial provides a sample of the reward-to-go for each visited state
- The agent keeps a running average for each state, which will converge to the true value
- This is a **direct utility estimation** method

Direct Utility Estimation

Trials

(1,1) $\uparrow$ -0.04
(1,2) $\uparrow$ -0.04
(1,3) $\rightarrow$ -0.04
(2,3) $\rightarrow$ -0.04
(3,3) $\rightarrow$ -0.04
(3,2) $\uparrow$ -0.04
(3,3) $\rightarrow$ -0.04
(4,3) exit +1
(done)

(1,1) -0.04
(1,2) $\uparrow$ -0.04
(1,3) $\rightarrow$ -0.04
(2,3) $\rightarrow$ -0.04
(3,3) $\rightarrow$ -0.04
(3,2) $\uparrow$ -0.04
(4,2) exit -1
(done)



$\gamma = 1,\ R = -0.04$

$V(2,3) \approx (0.840 - 1.12)/2 = -0.14$

$V(3,3) \approx (0.96 + 0.88 - 1.08)/3 = 0.86$

Problems with Direct Utility Estimation

- Direct utility fails to exploit the fact that states are dependent as shown in Bellman equations

$$U(s) = R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s,a) U(s')$$

- Learning can be speeded up by using these dependencies
- Direct utility can be seen as inductive learning search in a too large hypothesis space that contains many hypothesis violating Bellman equations

Adaptive Dynamic Programming

- An ADP agent uses dependencies between states to speed up value estimation
- It follows a policy π and can use observed transitions to incrementally built the transition model $P(s'|s, \pi(s))$
- It can then plug the learned transition model and observed rewards $R(s)$ into the Bellman equations to $U(s)$
  - The equations are linear because there is no $\max$ operator $\rightarrow$ easier to solve
- The result is $U(s)$ for the given policy π

Temporal-difference Learning

- TD is another passive utility value learning algorithm using Bellman equations
- Instead of solving the equations, TD uses the observed transitions to adjust the utilities of the observed states to agree with Bellman equations
- TD uses a **learning rate** parameter α to select the rate of change of utility adjustment
- TD does not need a trnasition model to perform its updates, only the observed transitions

Temporal-difference Learning (cont.)

- TD update rule for transition from s to s':

$$V^\pi(s) \leftarrow V^\pi(s) + \alpha(\boxed{R(s) + \gamma V^\pi(s')} - V^\pi(s))$$

(noisy) sample of value at s based on next state s'

- So the updates is maintaining a « mean » of the (noisy) value sample
- If the learning rate decreases appropriately with the number of samples (e.g. $1/n$) then the value estimates will converge to true values!

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

(Dan Klein, UC Berkeley)

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Active Reinforcement Learning

- While a passive RL agent executes a fixed policy π, an **active RL agent** has to decide which actions to take
- An active RL agent is an extension of a passive one, e.g. the passive ADP agent, and adds
  - Needs to learn a complete transition model for **all** actions (not just π), using passive ADP learning
  - Utilities need to reflect the optimal policy π^*, as expressed by the Bellman equations
  - Equations can be solved by VI or PI methods described before
  - Action to be selected as the optimal/maximizing one

(Roar Fjellheim, University of Oslo)

Exploitation vs. Exploration

- The active RL agent may select maximizing actions based on a faulty learned model, and fail to incorporate observations that might lead to a more correct model
- To avoid this, the agent design could include selecting actions that lead to more correct models at the cost of reduced immediate rewards
- This called **exploitation vs. exploration** tradeoff
- The issue of optimal exploration policy is studied in a subfield of statistical decision theory dealing with so-called bandit problems

(Roar Fjellheim, University of Oslo)

Q-Learning

- An action-utility function Q assigns an expected utility to taking a given action in a given state: $Q(a, s)$ is the value of doing action a in state s
- Q-values are related to utility values:

$$U(s) = \max_a Q(a, s)$$

- Q-values are sufficient for decision making without needing a transition model $P(s'|s, a)$
- Can be learned directly from rewards using a TD-method based on an update equation:

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

(Roar Fjellheim, University of Oslo)

Q-Learning

- Q-Learning: samplebased Q-value iteration
- Learn $Q^*(s,a)$ values
  - Receive a sample (s, a, s', r)
  - Consider your old estimate: $Q(s,a)$
  - Consider your new sample estimate:

$$Q^*(s,a) = \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma \max_{a'} Q^*(s', a,') \right]$$

$$sample = R(s,a,s') + \gamma \max_{a'} Q^*(s', a,')$$

  - Incorporate the new estimate into a running average:

$$Q(s,a) \leftarrow (1-\alpha) Q(s,a) + \alpha [sample]$$

(Dan Klein, UC Berkeley)

SARSA

- Updating the Q-value depends on the current state of the agent s_1, the action the agent chooses a_1, the reward r the agent gets for choosing this action, the state s_2 that the agent will now be in after taking that action, and finally the next action a_2 the agent will choose in its new state

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

- SARSA learns the Q values associated with taking **the policy it follows itself**, while Q-learning learns the Q values associated with taking the exploitation policy while following an exploration/exploitation policy

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

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

Generalization in RL

- In simple domains, U and Q can be represented by tables, indexed by state s
- However, for large state spaces the tables will be too large to be feasible, e.g. chess 10^{40} states
- Instead functional approximation can sometimes be used, e.g. $\widetilde{U}(s) = \sum parameter_i \times feature_i(s)$
- Instead of e.g. 10^{40} table entries, U can be estimated by e.g. 20 parameterized features
- Parameters can be found by supervised learning
- Problem: Such a function may not exist, and learning process may therefore fail to converge

(Roar Fjellheim, University of Oslo)

Summary

- Reinforcement learning (RL) examines how the agent can learn to act in an unknown environment just based on percepts and rewards
- Three RL designs are model-based, using a model P and utility function U, model-free, using action-utility function Q, and reflex, using a policy
- The utility of a state is the expected sum of rewards received up to the terminal state. Three methods are direct estimation, Adaptive dynamic programming (ADP), and Temporal-Difference (TD)
- Action-value function (Q-functions) can be learned by ADP or TD approaches
- In passive learning the agent just observes the environment, while an active learner must select actions to trade off immediate reward vs. exploration for improved model precision
- In domains with very large state spaces, utility tables U are replaced by approximate functions
- Policy search work directly on a representation of the policy, improving it in an iterative cycle
- Reinforcement learning is a very active research area, especially in robotics