Intelligent Systems (AI-2)

Computer Science cpsc422, Lecture 7

Sep, 23, 2016

Course Announcements

Assignment 1 has been posted

- ValueOfInfo and ValueOfControl
- MDPs: Value Iteration
- POMDPs: Belief State Update

422 big picture

	Deterministic	Stochastic	_
Query	Logics First Order Logics Ontologies Temporal rep. • Full Resolution • SAT	Belief NetsApprox. : GibbsMarkov Chains and HMMsForward, Viterbi···.Approx. : Particle FilteringUndirected Graphical Models Conditional Random Fields	
Planning		Markov Decision Processes and Partially Observable MDP • Value Iteration • Approx. Inference	
		Reinforcement Learning	Representation
	Applicatio		Reasoning Technique

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Slide 3

Lecture Overview

- Start Reinforcement Learning
 - Start Q-learning
 - Estimate by Temporal Differences

MDP and Reinforcement Learning

Markov decision process

- Set of states S, set of actions A
- Transition probabilities to next states P(s' | s, a')
- **Reward** function R(s) or R(s, a) or R(s, a, s')

RL is based on MDPs, but

- Transition model is not known
- Reward model is not known

While for MDPs we can *compute* an optimal policy

RL *learns* an optimal policy

Search-Based Approaches to RL

Policy Search (stochastic local search)

- Start with an arbitrary policy
- To evaluate a policy, try it out in the world
- Generate some neighbours….

Problems with evolutionary algorithms

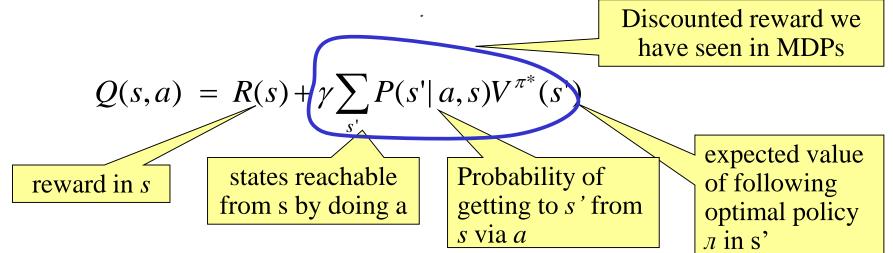
- Policy space can be huge: with n states and m actions there are mⁿ policies
- Policies are evaluated as a whole: cannot directly take into account locally good/bad behaviours

Q-learning

Contrary to search-based approaches, Q-learning learns after every action

Learns components of a policy, rather than the policy itself

Q(s,a) = expected value of doing action a in state s and then following the optimal policy



Q values



	s _o	<u>s</u>	•••	s _k
a ₀	$Q[s_0,a_0]$	$Q[s_1,a_0]$	• • • •	$Q[s_k,a_0]$
	$Q[s_0,a_1]$	$Q[s_1,a_1]$	•••	$Q[s_k,a_1]$
•••	•••	>	• • • •	•••
a _n	$Q[s_0,a_n]$	$Q[s_1,a_n]$	• • • •	$Q[s_k,a_n]$

If the agent had the **complete Q-function**, would it know how to act in every state?



But how to learn the Q-values?

Q values

	s _o	<u>S</u>	•••	s _k
a ₀	$Q[s_0,a_0]$	Q[s ₁ ,a ₀]	• • • •	$Q[s_k,a_0]$
	$Q[s_0,a_1]$	$Q[s_1,a_1]$	•••	$Q[s_k,a_1]$
•••	•••	>	• • • •	•••
a _n	$Q[s_0,a_n]$	$Q[s_1,a_n]$	• • • •	$Q[s_k,a_n]$

Once the agent has a **complete Q-function**, it knows how to act in every state

By learning what to do in each state, rather then the complete policy as in search based methods, learning becomes *linear* rather than *exponential* in the number of states

But how to learn the Q-values?

Q values

$$Q(s,a) = R(s) + \gamma \sum_{s'} P(s'|s,a) V^{\pi^*}(s')$$
(1)

Q(s,a) are known as Q-values, and are related to the utility of state s as follows

$$V^{\pi^*}(s) = \max_{a} Q(s, a)$$
 (2)

From (1) and (2) we obtain a constraint between the Q value in state s and the Q value of the states reachable from a

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



Learning the Q values

Can we exploit the relation between Q values in "adjacent" states?

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

A. Yes
B. No

No, because we don't know the transition probabilities P(s'|s,a) and the *reward function*

We'll use a different approach, that relies on the notion of Temporal Difference (TD)

Average Through Time

Suppose we have a sequence of values (your sample data):

$$V_1, V_2, ..., V_k$$

And want a running approximation of their expected value

- e.g., given sequence of grades, estimate expected value of next grade
- A reasonable estimate is the average of the first k values:

$$A_k = \frac{v_1 + v_2 + \dots + v_k}{k}$$

Average Through Time

$$A_{k} = \frac{v_{1} + v_{2} + \dots + v_{k}}{k}$$

$$kA_{k} = v_{1} + v_{2} + \dots + v_{k-1} + v_{k} \quad \text{and equivalently for } k-1:$$

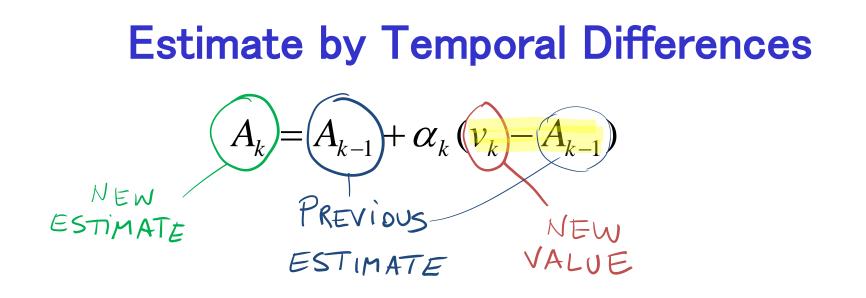
$$(k-1)A_{k-1} = v_{1} + v_{2} + \dots + v_{k-1} \quad \text{which replaced in the equation above gives}$$

$$kA_{k} = (k-1)A_{k-1} + v_{k} \quad \text{Dividing by } k \text{ we get }:$$

$$A_{k} = (1 - \frac{1}{k})A_{k-1} + \frac{v_{k}}{k} \quad \text{and if we set } \alpha_{k} = 1/k$$

$$\underline{A_{k}} = (1 - \alpha_{k})A_{k-1} + \alpha_{k}v_{k}$$

$$= A_{k-1} + \alpha_{k}(v_{k} - A_{k-1})$$
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- it specifies how different the new value v_k is from the prediction given by the previous running average A_{k-1}
- The new estimate (average) is obtained by updating the previous average by \mathcal{A}_k times the TD error

Q-learning: General Idea

Learn from the *history* of interaction with the environment, *i.e.*, a sequence of state-action-rewards

 $\langle s_0, a_0, r_1, s_1, a_1, r_2, s_2, a_2, r_3, \dots \rangle$

- History is seen as sequence of *experiences*, i.e., tuples
 - <s, a, r, s'>
 - agent doing action *a* in state *s*,
 - receiving reward r and ending up in s'
- These experiences are used to estimate the value of Q (s,a) expressed as

 $Q(s,a) = r + \chi \max_{d'} Q(s',d')$ CPSC 422 Lectu

But

$$Q-learning: General Idea$$

$$S \supset r \leq 5'$$

$$Q(s,a) = r + \gamma \max_{a'} Q[s',a']$$

Is an **approximation**.

The real link between Q(s,a) and Q(s',a') is

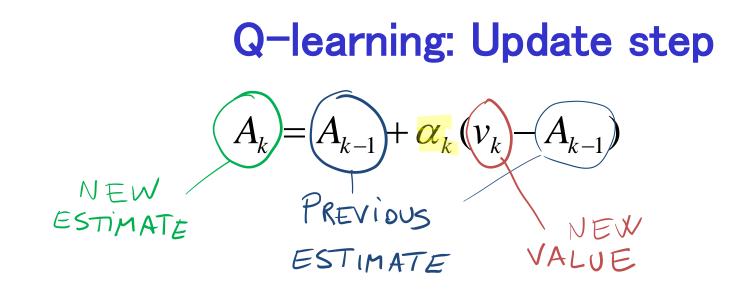
$$Q(s,a) = r + \gamma \sum_{s'} P(s'|s,a) \max_{a'} Q(s',a')$$

Q-learning: Main steps

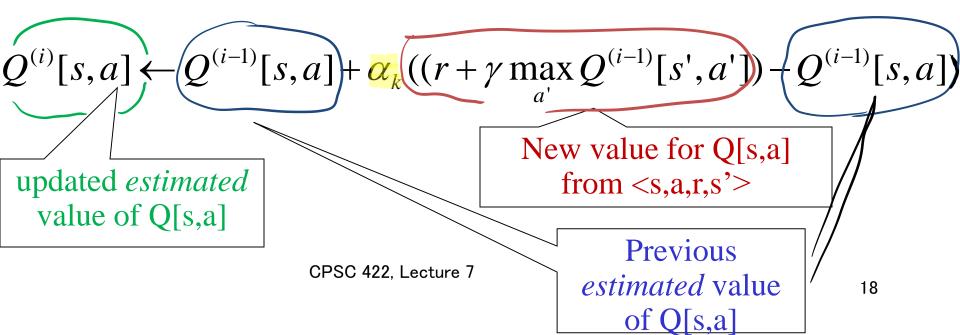
Store *Q[S, A]*, for every state *S* and action *A* in the world

Start with **arbitrary estimates** in $Q^{(0)}[S, A]$, Update them by using experiences

 Each experience <s, a, r, s'> provides one new data point on the actual value of Q[s, a]



 \succ *TD* formula applied to Q[s,a]



Q-learning: algorithm

controller Q-learning(S,A) inputs:

S is a set of states A is a set of actions γ the discount α is the step size internal state: real array Q[S,A]previous state s previous action a begin initialize Q[S,A] arbitrarily observe current state s

repeat forever:

select and carry out an action a

observe reward *r* and state *s'* $Q[s,a] \leftarrow Q[s,a] + \alpha (r + \gamma \max_{a'} Q[s',a']) - Q[s,a])$ $s \leftarrow s';$

end-repeat

end

Learning Goals for today's class

You can:

- Describe and criticize search-based approaches to RL
- Motivate Q-learning
- Justify Estimate by Temporal Differences
- Explain, trace and implement Q-learning

TODO for Mon

- Do Practice Ex. On Reinforcement Learning:
- Exercise 11.A: Q-learning
- •http://www.aispace.org/exercises.shtml