Action Refinement in Reinforcement Learning by Probability Smoothing

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Speaker: Kai Xu

Presentation Overview

- *Background*
- The Probability Smoothing Method
- Experimental Study of Action Refinement
- Conclusion

Background -- Model Based Reinforcement Learning (MBRL)

- Experience gained during exploring is employed to learn the models of the state-action transition function and the reward function
- From the learned model, the optimal policy can be computed by many good algorithms
- MBRL is appropriate when the state and action space and relatively small and finite, and each exploring action is expensive.

Background -- Methods To Reduce the Need For Training Data

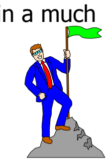
- By incorporate some kind of prior knowledge
- Previous Study: Abstraction knowledge across the states
  - So that the RL can generalize across states
- Abstraction knowledge across the actions (in this paper)
  - The RL assumes similar actions will have similar transition effects and rewards

Background -- Action Refinement

- Recall how human learns
  - Bad Kongfu Masters teach the students all the tricks at the beginning.
  - The students have to spend a long time to grasp all of them

Action Refinement

- Good Kongfu Masters teach the students only the basic actions at the beginning.
- After the students grasp the basic skills, he teach them the subtleties among different similar actions.
- The students grasp all the tricks in a much shorter time.



Action Refinement

- An RL algorithm initially treats a set of similar actions as a single abstraction
- Later, refines that abstraction action into individual actions.

The Probability Smoothing Method

- Background
- *The Probability Smoothing Method*
- Experimental Study of Action Refinement
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The Probability Smoothing Model

- Context:
  - The agent is interacting with an unknown but observable Markovian environment.
  - The environment contains a finite state set S, and a finite action set A.
  - The programmer groups set A into L disjoint action sets $A_1, A_2, \ldots, A_L$. Actions in the same subsets are 'similar'.

The Probability Smoothing Model

- Let $N_t(s,a)$ denote the # of times action a has been executed in state s.
- Let $N_t(s,a,s')$ denote the # of times this results in a transition to state s'.
- Let $W_t(s,a,s')$ denote the total rewards received when a caused a transition from s to s'.
- Define the probability smoothing model M_t such that

$$P_t(s'|s,a) = \frac{\sum_{a'\in A_l} \lambda_{a'} N_t(s,a',s')}{\sum_{a'\in A_l} \lambda_{a'} N_t(s,a')}$$

$$R_t(s,a,s') = \frac{\sum_{a'\in A_l} \lambda_{a'} W_t(s,a',s')}{\sum_{a'\in A_l} \lambda_{a'} N_t(s,a')}$$

Determine Smoothing Parameter λ

- Suppose the true transition probability from s to s' after executing action a is $P(s'|s,a)$, and the estimate to this probability is $P_t(s'|s,a)$
- We want to find a proper λ such that $P_t(s'|s,a)$ would be a consistent estimator for the true probability.
- To determine which estimator is more appropriate, we need to define the error measure as the following

$$J(s,a) = \sum_{s'} [P(s'|s,a) - P_t(s'|s,a)]^2$$

- So the problem is to find a λ which minimizes J(s,a)

Derivation of Optimal Smoothing Parameters in the simplest case

- Let's suppose there are only two similar actions, a_1 and a_2
- The current state is s
- There are only two possible resulting states, s' and s''
- Action a_1 has been applied on state s for N1 times.
- For H1 times it transit to state s'
- Action a_1 has been applied on state s for N2 times.
- For H2 times it transit to state s'

Derivation of Optimal Smoothing Parameters in the simplest case

- Suppose the true transition probability from s to s' after exe a_1 is p_1.
- Although H1/N1 is an estimator for p_1, it requires large number of trials.
- So we should use the smoothing model:

$$\hat{p}_1 = \frac{H_1 + \lambda H_2}{N_1 + \lambda N_2}$$

Derivation of Optimal Smoothing Parameters in the simplest case

- After calculation, we find the most appropriate smoothing parameter

$$\lambda = \frac{V_1}{N_2 \varepsilon^2 + V_2} \quad \text{where}$$

$$V_1 = p_1(1-p_1)\ ,\ V_2 = p_2(1-p_2)$$

$$\varepsilon = |p_1 - p_2|$$

- Properties of using this λ:

$$\lim_{N_1 \to \infty} \hat{p}_1 = p_1 \quad \text{and} \quad \lim_{N_1 \to \infty} \lim_{N_2 \to \infty} \hat{p}_1 = p_1$$

Derivation of Optimal Smoothing Parameters in the simplest case

- Therefore, the probability smoothing will converge to the optimal policy.
- This model can be expand to cases such as
  - there are more than 2 similar actions
  - there are more than 2 possible resulting states
- We can use the resulting λ to build good estimator for the reward.

Determine the Level of Smoothing in Practice

- Big problem: In most practical cases, we will never know the true value for p_1, p_2, or ε
- A naive approach for choosing λ would be estimate p_1 by H1/N1, estimate p_2 by H2/N2
- But when the trial number is small, the variance to these estimates are very high. The result is poor.
- So the paper proposed to use "default smoothing", in which we assume the default values of p_1, p_2, and ε, and plug in the value of N2 from the real data.

Determine the Level of Smoothing in Practice

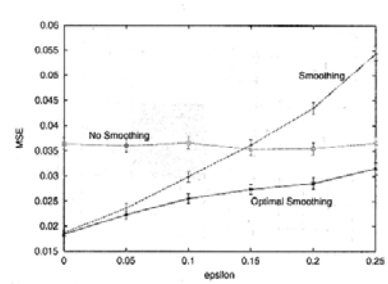
- The author proposed to use default values

$$p_1 = 0.1,\quad p_2 = 0.15,\quad \varepsilon = |p_1 - p_2| = 0.05$$

  for the simplest case.
- They work well when $\varepsilon < 0.15$ for all values of p_1
- For cases that there are more than 2 possible resulting states, the author proposed to use default values

$$V_1 = 0.09\ ,\quad V_2 = 0.1275\ ,\quad \varepsilon^2 = 0.0025$$

Determine the Level of Smoothing in Practice



Experimental Study of Action Refinement

- Background
- The Probability Smoothing Method
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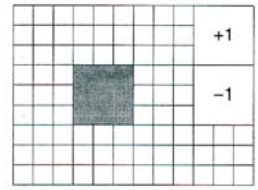
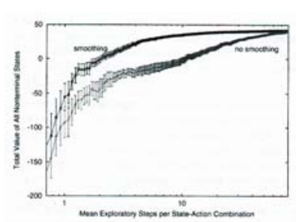
Experimental Study of Action Refinement -- Context

- A toy maze with 81 non-terminal states and 2 terminal states.
- 16 actions from the cross-product of the 4 compass directions with 4 modifiers.
- Actions are grouped into 4 sets.
- To measure the performance of a policy, we compute the value function V^{π} and sum the value of all 81 non-terminal states
- The optimal policy has total value of 43.37



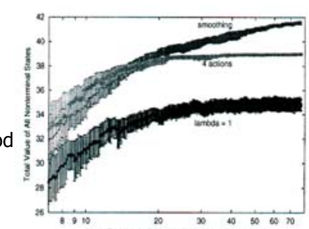
Experimental Study of Action Refinement -- Compare With No Smoothing Method

- Comparison of
  - probability smoothing, and
  - no smoothing ($\lambda = 0$)
- The probability smoothing model is much better



Experimental Study of Action Refinement -- Compare with fixed smoothing & four-action

- Comparison of
  - fixed smoothing ($\lambda = 1$)
  - four-action method
  - probability smoothing
- After 9.3 exploration steps, four-action method and probability smoothing method beat fixed smoothing.
- After 23 steps, probability smoothing method wins.

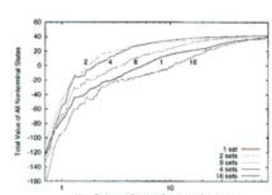


Experimental Study of Action Refinement -- Conclusion

- Conclusion for the previous experiment
  - The probability smoothing method is vastly superior to no-smoothing method.
  - If large training set is available, probability smoothing method is better than fix-smoothing and four-action method.

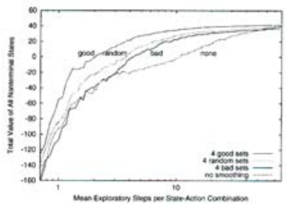
Experimental Study of Action Refinement -- Sensitivity To The Size of Action Sets

- Vary the # of action sets from 1, 2, 4, 8, and 16
- With similar actions be grouped together to the extent possible.
- 16 separate action sets gives high variance.
- One single action set gives high bias.
- 4 sets and 2 sets gave the best performance during the early part of the curve.



Experimental Study of Action Refinement -- Sensitivity To The Action Set Correctness

- At intermediate sample size (4), even random groupings give better performance than no smoothing.
- At large sample sizes, the bias in the random and bad groupings leads to worse performance than either no smoothing or well-chosen action sets.



Conclusions

- Probability Smoothing Method is introduced to action refinement to
  - speed up RL applications
  - by partition actions into sets of similar actions.
- It significantly eases the designing of a set of good actions in RL.
- Probability smoothing parameter is determined by “default smoothing” and the corresponding # of trials.
- Good prior action set partition is critical to the performance.

Action Refinement in Reinforcement Learning by Probability Smoothing

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Comments by : Sameer Apte

Action Refinement applied to the Robot Navigation Problem

- Robot navigates by finding visual landmarks
- Robot's camera has a viewing angle of 60 degrees
- The space around the robot was partitioned into six 60-degree sectors

Action Refinement applied to the Robot Navigation Problem

- An action called "Move While looking for Landmarks (MLL)" was defined
- Robot moves forward while aiming its camera in one of the six sectors to search for new visual landmarks
- Can define six MLL actions, one for each sector and let robot decide which sector to examine with the camera

Action Refinement applied to the Robot Navigation Problem

- Designers do not know which of these actions would be most useful
- Include all these actions in the MDP and let RL system determine which actions are useful
  - Problem : Large amount of exploration required to learn a good policy
- Train the robot several times ,each time with a different set of actions
  - Problem : Even more training experiences required

Action Refinement applied to the Robot Navigation Problem

- Solution : Action Refinement
- We know that different variants of the MLL action have similar behavior
- Initially treat these similar actions as a single abstract action
- Later allow the learning algorithm to refine abstract action into individual actions

Direct vs. Model-Based Reinforcement Learning

-- Commentary on Kai Xu's presentation

-- Commented by Ruinan Lu

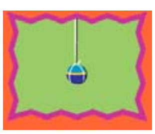
-- Reference: paper by C. Atkeson, et al.

Criteria

- Data efficiency
- Computing efficiency

Problem for comparison of the two approaches: single pendulum swing-up

- Make it swing!



Model-based RL

- Known reward function:

$$r(\theta,\tau) = ((\theta-\theta_d)^2 + \tau^2)\Delta$$

  - θ : angle of the pendulum
  - θ_d : desired angle for the inverted vertical state
  - τ : motor torque
  - Δ : time step

- Equation of motion: $\theta'' = \tau - 9.81\cos(\theta)$

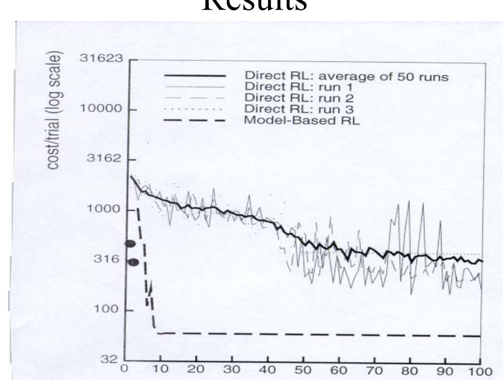
Q-learning

$$Q(x_k,u_k) = Q(x_k,u_k) + \alpha[r(x_k,u_k) + \gamma Q(x_{k+1},u_{k+1}) - Q(x_k,u_k)] * e(x_k,u_k)$$

- α : learning rate
- γ : discount factor
- x : state vector
- u : control vector

- Optimal action: $\arg\min_u Q(x_1,u)$

Results



Conclusions

- Simple Dynamics favor MRL
  - Exploratory action is expensive
  - Exploration is performed on a physical system
- Cases favor Direct RL
  - More training experiences
  - Learner interacts with an inexpensive simulator