Q-Learning Wrap-Up
Discussion: Bidirectional Search guaranteed to meet in the middle

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Announcements

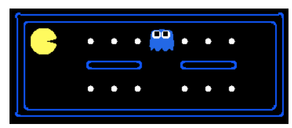
- Programming Assignment 2 code reviews today
- Turn in reading responses
- Midterm this week
  - Will find it in your CS mailbox by tomorrow at 10am (or in mine, if you don't have a mailbox)
  - Take it out when ready to do it; Complete by 4:30pm Friday
  - Mark start date/time and end date/time; Turn in immediately after end
  - Turn in "cheat sheet" with exam
- RL assignment now posted
  - **Confirm partners with me by Monday 9am**

Today

- Q-Learning Wrap-Up
- Discussion

Pacman

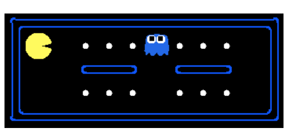
- States?
- Actions?
- Transition Model?
- Rewards?



Demo

Pacman

- States?
- Actions?
- Transition Model?
- Rewards?



Ability to generalize?

Q-Learning in the Real World

- In many cases, too many states
  - Might not be able to hold the Q-values in memory
  - Can't visit all during training
    - Or even if we can visit them, can't do so enough
- Want to make use of the power of generalization

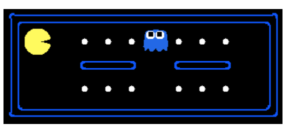
Feature-Based Representations

- Describe a state using a vector of features (properties)
  - Features are functions from states to real numbers (sometimes just 0/1)
  - Features capture important properties of the state
  - Pacman examples:
    - Distance to closest ghost [closest food, etc]
    - Number of ghosts [food, etc]
    - Is Pacman in a tunnel?
    - Is Pacman trapped?
- Can describe a Q state (i.e. Q(s, a)) with features, too

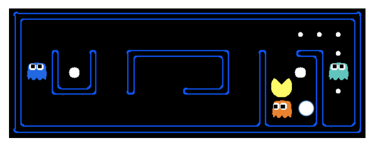
Values (utilities) as approximated by evaluation functions

- $V(s) = w_1f_1(s) + w_2f_2(s) + \ldots + w_nf_n(s)$
  - Recall your minimax evaluation functions!
- $Q(s, a) = w_1f_1(s,a) + w_2f_2(s,a) + \ldots + w_nf_n(s,a)$

- Learn values for the weights w_1, w_2, …, w_n, such that the evaluation function approximates the true value (utility)



- Say we have three features:
  - PowerPellet <= 1 (1=T,0=F)
  - ScaryGhost <= 1 (1=T,0=F)
  - Food <= 3 (1=T,0=F)
- Say $w_1 = 0.8$, $w_2 = 0.5$, $w_3 = 0.4$
- Then
  - $Q(s_{cur}, E) = .8(0) + .5(0) + .4(1) = .4$



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- Say $w_1 = 0.8$, $w_2 = 0.5$, $w_3 = 0.4$
- Then
  - $Q(s_{cur}, S) = .8(1) + .5(1) + .4(1) = 1.7$

Learning weights for linear Q-functions

Before:
sample = $R(s,a,s') + \gamma \max_{a'} Q(s', a')$
$Q(s, a) = (1-\alpha)\, Q(s, a) + \alpha(\textit{sample})$
$Q(s, a) = Q(s, a) + \alpha(\text{sample} - Q(s, a))$

$w_1 = w_1 + \alpha(\textit{sample} - \textit{current})(f_1(s,a))$
$w_2 = w_2 + \alpha(\textit{sample} - \textit{current})(f_2(s,a))$

$w_1 = 0.8 + 0.1(-10+ \gamma(0) - 1.7)1 = .8 + 0.1(-11.7) = -.37$
$w_2 = 0.5 + 0.1(-10+ \gamma(0) - 1.7)1 = .5 + 0.1(-11.7) = -.67$
$w_3 = 0.4 + 0.1(-10+ \gamma(0) - 1.7)1 = .4 + 0.1(-11.7) = -.77$

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Why?
Ordinary Least Squares

- Aim to minimize squared error:

  ½ (*current – obs total reward*)^2
- The rate of change of the error wrt each w parameter is the partial derivative:

  $(w_1 f_1(s,a) + w_2 f_2(s,a) - \textit{obs total reward}) f_1(s,a)$

  $(w_1 f_1(s,a) + w_2 f_2(s,a) - \textit{obs total reward}) f_2(s,a)$

Why?
Ordinary Least Squares

- The squared error defines a surface in (n+1)-dim space, where n is the number of parameters.
- To reach the minimum in an online fashion, we "step" along the surface in the direction opposite the gradient

  $w_1 = w_1 + \alpha(\textit{obs total reward} - \textit{current}) f_1(s,a)$

  $w_2 = w_2 + \alpha(\textit{obs total reward} - \textit{current}) f_2(s,a)$

Pros and Cons of Function Approximation

Pros
- Makes it practical to handle very large state spaces
- Allows the learner to generalize from states it has visited to states it has not yet seen

Cons
- There might not be a good function in the chosen hypothesis space (defined by the choice of features)
- Tradeoff between the size of the hypothesis space and the learning time
- As always, need to take care with learning rate parameter

Demo: RL Pacman