Markov Decision Processes (MDPs) (cont.)

Machine Learning – 10701/15781
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November 29th, 2007

Markov Decision Process (MDP) Representation

- State space:
  - Joint state **x** of entire system
- Action space:
  - Joint action **a**= {a_1,…, a_n} for all agents
- Reward function:
  - Total reward R(**x**,**a**)
    - sometimes reward can depend on action
- Transition model:
  - Dynamics of the entire system P(**x**'|**x**,**a**)

Computing the value of a policy

linearity of expectations

$E[a+b] = E[a]+E[b]$

discounted

$$V_\pi(\mathbf{x_0}) = \mathbf{E}_\pi[R(\mathbf{x}_0) + \gamma\, R(\mathbf{x}_1) + \gamma^2\, R(\mathbf{x}_2) + \gamma^3\, R(\mathbf{x}_3) + \gamma^4\, R(\mathbf{x}_4) + \infty]$$

- Discounted value of a state:
  - value of starting from x_0 and continuing with policy π from then on

$$\begin{aligned} V_\pi(x_0) &= E_\pi[R(x_0) + \gamma R(x_1) + \gamma^2 R(x_2) + \gamma^3 R(x_3) + \cdots] \\ &= E_\pi[\sum_{t=0}^{\infty} \gamma^t R(x_t)] \end{aligned}$$

- A recursion!

$$V_\pi(x_0) = E_\pi[R(x_0) + \gamma R(x_1) + \gamma^2 R(x_2) + \cdots]$$

$$= \underbrace{E_\pi[R(x_0)]}_{R(x_0)} + \gamma\, \underbrace{E_\pi[R(x_1) + \gamma R(x_2) + \gamma^2 R(x_3) + \cdots]}_{E_{\pi, x_1}[V_\pi(x_1)]}$$

$$= R(x_0) + \gamma \sum_{x_1} P(x_1 \mid x_0, \pi(x_0))\, V_\pi(x_1)$$

Simple approach for computing the value of a policy: Iteratively

$$V_\pi(x) = R(x) + \gamma \sum_{x'} P(x' \mid x, a = \pi(x))V_\pi(x')$$

- Can solve using a simple convergent iterative approach: (a.k.a. dynamic programming)
  - Start with some guess V_0
  - Iteratively say:
    - $V_{t+1} = R + \gamma\, P_\pi\, V_t$
  - Stop when $\|V_{t+1}-V_t\|_\infty \leq \varepsilon$
    - means that $\|V_\pi-V_{t+1}\|_\infty \leq \varepsilon/(1-\gamma)$

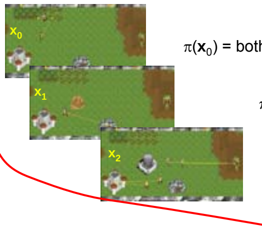
any guess works, but a good guess is $V_0(x) = R(x_0)$

$$V_{t+1}(x) = R(x) + \gamma \sum_{x'} P(x' \mid x, \pi(x))V_t(x')$$

But we want to learn a **Policy**

- So far, told you how good a policy is… $V_{\pi}(x)$
- But how can we choose the best policy???
- Suppose there was only one time step:
  - □ world is about to end!!!
  - □ select action that maximizes reward!

Policy: π(**x**) = **a** → At state **x**, action **a** for all agents



π($\mathbf{x}_0$) = both peasants get wood

π($\mathbf{x}_1$) = one peasant builds barrack, other gets gold

π($\mathbf{x}_2$) = peasants get gold, footmen attack

for state x

$$a^* = \arg\max_a R(x) + \underbrace{\sum_{x'} P(x'|x,a)}\, R(x')$$

Unrolling the recursion

- Choose actions that lead to best value in the long run
  - □ Optimal value policy achieves optimal value V*

$$V^*(x_0) = \max_{a_0} R(x_0,a_0) + \gamma E_{a_0}[\underbrace{\max_{a_1} R(x_1,a_1) + \gamma^2 E_{a_1}[\max_{a_2} R(x_2,a_2) + \cdots]]}_{V^*(x_1)}$$

OPT Value

$$\underbrace{V^*(x_0) = \max_{a_0} R(x_0,a_0) + \gamma \sum_{x_1} P(x_1|x_0,a_0)\, V^*(x_1)}_{\text{Bellman Eqn.}}$$

Bellman equation

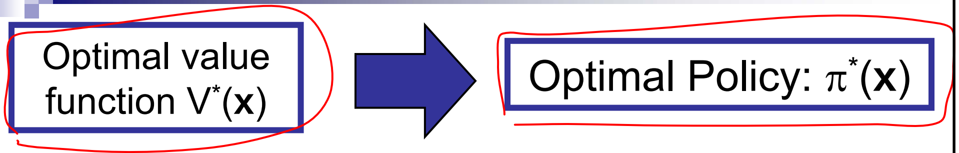
- Evaluating policy π:

$$\underline{V_\pi(x) \;=\; R(x) + \gamma \sum_{x'} P(x' \mid x, a = \pi(x)) V_\pi(x')}$$

- Computing the optimal value V* - Bellman equation

$$\underline{V^*(\mathbf{x}) = \max_{\mathbf{a}} R(\mathbf{x},\mathbf{a}) + \gamma \sum_{\mathbf{x}'} P(\mathbf{x}' \mid \mathbf{x},\mathbf{a}) V^*(\mathbf{x}')}$$

Optimal Long-term Plan



Optimal value function V*(**x**)

Optimal Policy: π*(**x**)

Optimal policy:

$$\boxed{\pi^*(\mathbf{x}) = \arg\max_{a} R(\mathbf{x},\mathbf{a}) + \gamma \sum_{\mathbf{x}'} P(\mathbf{x}' \mid \mathbf{x},\mathbf{a}) \underline{V^*}(\mathbf{x}')}$$

if I have V*, then OPT policy is Greedy, but Greedy wrt V*(x')

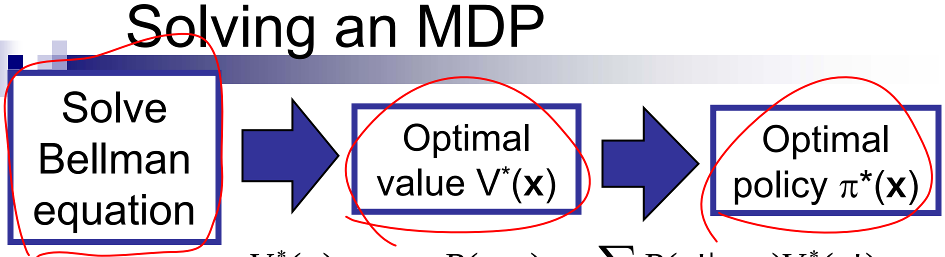
Interesting fact – Unique value

$$V^*(\mathbf{x}) = \max_{\mathbf{a}} R(\mathbf{x},\mathbf{a}) + \gamma \sum_{\mathbf{x}'} P(\mathbf{x}' \mid \mathbf{x},\mathbf{a}) V^*(\mathbf{x}')$$

- *Slightly surprising fact*: There is only one V^* that solves Bellman equation!
  - □ there may be many optimal policies that achieve V^*
- *Surprising fact*: optimal policies are good everywhere!!!

$$V_{\pi^*}(x) \geq V_\pi(x), \;\; \forall x, \;\; \forall \pi$$

Solving an MDP



Solve Bellman equation → Optimal value $V^*(\mathbf{x})$ → Optimal policy $\pi^*(\mathbf{x})$

$$V^*(\mathbf{x}) = \max_{\mathbf{a}} R(\mathbf{x},\mathbf{a}) + \gamma \sum_{\mathbf{x}'} P(\mathbf{x}' \mid \mathbf{x},\mathbf{a}) V^*(\mathbf{x}')$$

Bellman equation is non-linear!!!

Many algorithms solve the Bellman equations:

- Policy iteration [Howard '60, Bellman '57]
- Value iteration [Bellman '57]
- Linear programming [Manne '60]
- …

Value iteration (a.k.a. dynamic programming) – the simplest of all

$$V^*(\mathbf{x}) = \max_{\mathbf{a}} R(\mathbf{x},\mathbf{a}) + \gamma \sum_{\mathbf{x}'} P(\mathbf{x}'|\mathbf{x},\mathbf{a}) V^*(\mathbf{x}')$$

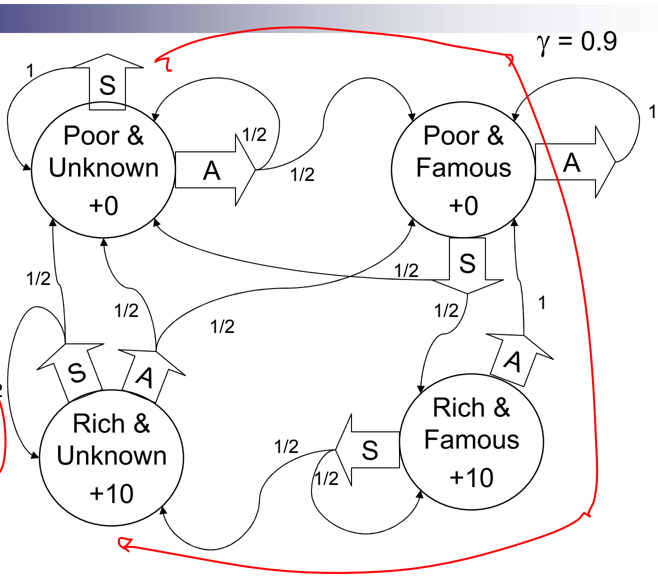
- Start with some guess V_0 ← eg., $V_0(x) = R(x)$
- Iteratively say:
  - $V_{t+1}(\mathbf{x}) = \underset{\text{then max } a}{\max_{\mathbf{a}}} \overbrace{R(\mathbf{x},\mathbf{a}) + \gamma \sum_{\mathbf{x}'} P(\mathbf{x}'|\mathbf{x},\mathbf{a}) V_t(\mathbf{x}')}^{\text{compute for each } a}$
- Stop when $\|V_{t+1}-V_t\|_\infty \leq \varepsilon$
  - □ means that $\|V^*-V_{t+1}\|_\infty \leq \varepsilon/(1-\gamma)$

A simple example

$\gamma = 0.9$

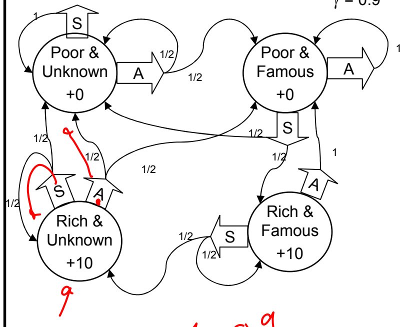
You run a startup company.

In every state you must choose between Saving money or Advertising.



Let's compute $V_t(x)$ for our example

$\gamma = 0.9$



$\gamma = 0.9$

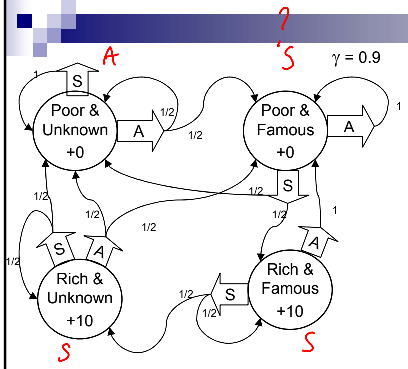
t	V_t(PU)	V_t(PF)	V_t(RU)	V_t(RF)
1	0	0	10	10
2			14.5	
3				
4				
5				
6				

$$V_2(RU) \overset{max}{=} \begin{cases} a=A = 10 + \gamma\left(0.5\, \overset{0}{V_1}(PU) + 0.5\, \overset{0}{V_1}(PF)\right) = 10 \\ a=S = 10 + \gamma\left(0.5\, \overset{10}{V_1}(RU) + 0.5\, \overset{0}{V_1}(PU)\right) = 10+5\gamma = 14.5 \end{cases}$$

$$V_{t+1}(\mathbf{x}) = \max_{\mathbf{a}} R(\mathbf{x},\mathbf{a}) + \gamma \sum_{\mathbf{x}'} P(\mathbf{x}' \mid \mathbf{x},\mathbf{a}) V_t(\mathbf{x}')$$

Let's compute $V_t(x)$ for our example

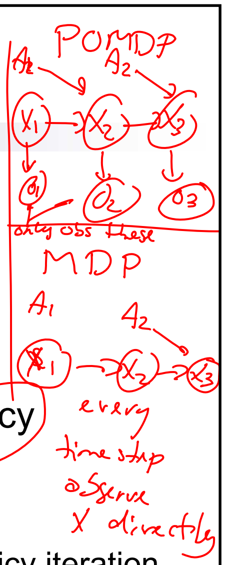
$\gamma = 0.9$



t	V_t(PU)	V_t(PF)	V_t(RU)	V_t(RF)
1	0	0	10	10
2	0	4.5	14.5	19
3	2.03	6.53	25.08	18.55 ?
4	3.852	12.20	29.63	19.26
5	7.22	15.07	32.00	20.40
6	10.03	17.65	33.58	22.43

$$V_{t+1}(\mathbf{x}) = \max_{\mathbf{a}} R(\mathbf{x},\mathbf{a}) + \gamma \sum_{\mathbf{x}'} P(\mathbf{x}' \mid \mathbf{x},\mathbf{a}) V_t(\mathbf{x}')$$

What you need to know



- What's a Markov decision process
  - □ state, actions, transitions, rewards
  - □ a policy
  - □ value function for a policy
    - computing V_π
- Optimal value function and optimal policy
  - □ Bellman equation
- Solving Bellman equation
  - □ with value iteration, (other possibilities: policy iteration and linear programming)

Acknowledgment

- This lecture contains some material from Andrew Moore's excellent collection of ML tutorials:
  - □ http://www.cs.cmu.edu/~awm/tutorials

Reinforcement Learning

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The Reinforcement Learning task

World: You are in state 34.
Your immediate reward is 3. You have possible 3 actions.

Robot: I'll take action 2.
World: You are in state 77.
Your immediate reward is -7. You have possible 2 actions.

Robot: I'll take action 1.
World: You're in state 34 (again).
Your immediate reward is 3. You have possible 3 actions.

$\langle x_1, r_1 \rangle$
$a_1 \downarrow$
$\langle x_2, r_2 \rangle$
$a_2 \downarrow$
$\vdots$

Formalizing the (online) reinforcement learning problem

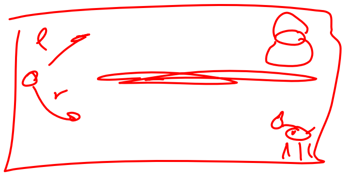
- Given a set of states **X** and actions **A**
  - □ in some versions of the problem size of **X** and **A** unknown
- Interact with world at each time step *t*:
  - □ world gives state $\mathbf{x}_t$ and reward r_t
  - □ you give next action $\mathbf{a}_t$
- **Goal**: (quickly) learn policy that (approximately) maximizes long-term expected discounted reward

time 1 <x=27, r=-3, a=2>
2 <x=33, r=7, a5>
3 <44, r=-1000, a=3>
4 <55, r=10, a=2>

could learn
$P(x'|x,a)$, $R(x,a)$ then use Value iteration

The “Credit Assignment” Problem

I’m in state	43,	reward = 0,	action = 2
“ “ “	39,	“ = 0,	“ = 4
“ “ “	22,	“ = 0,	“ = 1
“ “ “	21,	“ = 0,	“ = 1
“ “ “	21,	“ = 0,	“ = 1
“ “ “	13,	“ = 0,	“ = 2
“ “ “	54,	“ = 0,	“ = 2
“ “ “	26,	“ = 100,	

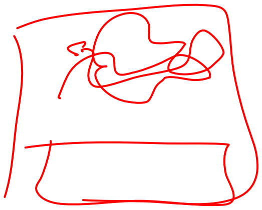


Yippee! I got to a state with a big reward! But which of my actions along the way actually helped me get there??

This is the Credit Assignment problem.

Exploration-Exploitation tradeoff

- You have visited part of the state space and found a reward of 100
  - □ is this the best I can hope for???



- **Exploitation**: should I stick with what I know and find a good policy w.r.t. this knowledge?
  - □ at the risk of missing out on some large reward somewhere
- **Exploration**: should I look for a region with more reward?
  - □ at the risk of wasting my time or collecting a lot of negative reward

Two main reinforcement learning approaches

- Model-based approaches:
  - □ explore environment, then learn model ($P(\mathbf{x}'|\mathbf{x},\mathbf{a})$ and $R(\mathbf{x},\mathbf{a})$) (almost) everywhere
  - □ use model to plan policy, MDP-style
  - □ approach leads to strongest theoretical results
  - □ works quite well in practice when state space is manageable
- Model-free approach:
  - □ don't learn a model, learn value function or policy directly
  - □ leads to weaker theoretical results
  - □ often works well when state space is large

Rmax – A model-based approach

Given a dataset – learn model

Given data, learn (MDP) Representation:

- Dataset: $\langle x_1, r_1, a_1, x_2\rangle$ ⋮
  $\langle x_2, r_2, a_2, x_3\rangle$
  ⋮
- Learn reward function:
  - □ R(**x**,**a**) $R : X, A \rightarrow \mathbb{R}$
- Learn transition model:
  - □ $P(\mathbf{x}'{=}1 \mid \mathbf{x}{=}2, \mathbf{a}{=}3)$ $= \dfrac{\text{Count}(X'=1, X=2, a=3)}{\text{Count}(X=2, a=3)}$

Some challenges in model-based RL 1: Planning with insufficient information

- Model-based approach:
  - □ estimate R(**x**,**a**) & P(**x**'|**x**,**a**)
  - □ obtain policy by value or policy iteration, or linear programming
  - □ No credit assignment problem ⇒ learning model, planning algorithm takes care of "assigning" credit
- What do you plug in when you don't have enough information about a state?
  - □ don't reward at a particular state
    - plug in smallest reward (R_{min})?
    - plug in largest reward (R_{max})?
  - □ don't know a particular transition probability?

$P(x'|x,a)$

Some challenges in model-based RL 2: Exploration-Exploitation tradeoff

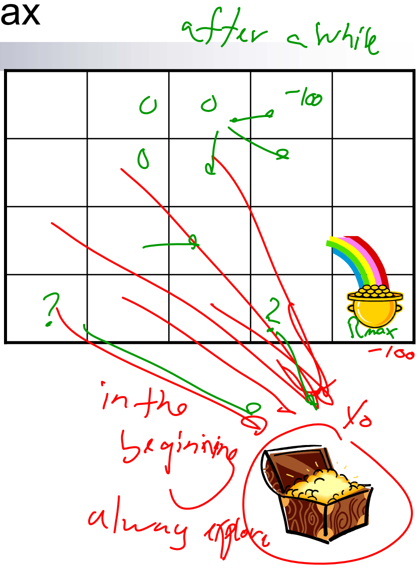
- A state may be very hard to reach
  - □ waste a lot of time trying to learn rewards and transitions for this state
  - □ after a much effort, state may be useless
- A strong advantage of a model-based approach:
  - □ you know which states estimate for rewards and transitions are bad
  - □ can (try) to plan to reach these states
  - □ have a good estimate of how long it takes to get there

A surprisingly simple approach for model based RL – The Rmax algorithm [Brafman & Tennenholtz]

- **Optimism in the face of uncertainty!!!!**
  - □ heuristic shown to be useful long before theory was done (e.g., Kaelbling '90)
- If you don't know reward for a particular state-action pair, set it to R_{max}!!! $R(x,a) = R_{max}$
- If you don't know the transition probabilities $P(\mathbf{x'}|\mathbf{x},\mathbf{a})$ from some some state action pair **x**,**a** assume you go to **a magic, fairytale** new state $\mathbf{x}_0$!!!
  - □ $R(\mathbf{x}_0,\mathbf{a}) = R_{max}$
  - □ $P(\mathbf{x}_0|\mathbf{x}_0,\mathbf{a}) = 1$

Understanding R_{max}

- With R_{max} you either:
  - □ **explore** – visit a state-action pair you don't know much about
    - because it seems to have lots of potential
  - □ **exploit** – spend all your time on known states
    - even if unknown states were amazingly good, it's not worth it
- Note: you never know if you are exploring or exploiting!!!



Implicit Exploration-Exploitation Lemma

- **Lemma**: every T time steps, either:
  - □ **Exploits**: achieves near-optimal reward for these T-steps, or
  - □ **Explores**: with high probability, the agent visits an unknown state-action pair
    - learns a little about an unknown state
  - □ T is related to *mixing time* of Markov chain defined by MDP
    - time it takes to (approximately) forget where you started

The Rmax algorithm

- **Initialization**:
  - □ Add state $\mathbf{x}_0$ to MDP
  - □ $R(\mathbf{x},\mathbf{a}) = R_{max}, \forall \mathbf{x},\mathbf{a}$
  - □ $P(\mathbf{x}_0|\mathbf{x},\mathbf{a}) = 1, \forall \mathbf{x},\mathbf{a}$
  - □ all states (except for $\mathbf{x}_0$) are **unknown**
- Repeat
  - □ obtain optimal policy for current MDP and Execute policy
  - □ for any visited state-action pair, set reward function to appropriate value
  - □ if visited some state-action pair **x**,**a** enough times to estimate $P(\mathbf{x}'|\mathbf{x},\mathbf{a})$
    - update transition probs. $P(\mathbf{x}'|\mathbf{x},\mathbf{a})$ for **x**,**a** using MLE
    - recompute policy

Visit enough times to estimate $P(\mathbf{x}'|\mathbf{x},\mathbf{a})$?

- How many times are enough?
  - □ use Chernoff Bound!
- **Chernoff Bound**:
  - □ $X_1,\ldots,X_n$ are i.i.d. Bernoulli trials with prob. θ
  - □ $P(|1/n \sum_i X_i - \theta| > \varepsilon) \leq \exp\{-2n\varepsilon^2\}$

Putting it all together

- **Theorem**: With prob. at least $1-\delta$, Rmax will reach a ε-optimal policy in time polynomial in: num. states, num. actions, T, $1/\varepsilon$, $1/\delta$
  - □ Every T steps:
    - achieve near optimal reward (great!), or
    - visit an unknown state-action pair → num. states and actions is finite, so can't take too long before all states are known

can only happen a poly number of times

Announcements

- University Course Assessments
  - □ Please, please, please, please, please, please, please, please, please, please, please, please, please, please, please, please…
- Project:
  - □ Poster session: Tomorrow 2-4:45pm, NSH Atrium
    - please arrive a 15mins early to set up
  - □ Paper: Friday December 14th by 2pm
    - electronic submission by email to instructors list
    - maximum of 8 pages, NIPS format
    - no late days allowed

no late minutes

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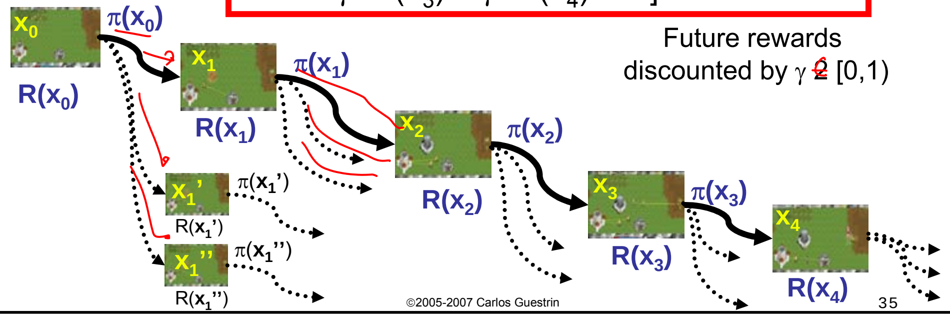
TD-Learning and Q-learning – Model-free approaches

Value of Policy

Value: $V_\pi(\mathbf{x})$ → Expected long-term reward starting from **x**

$$V_\pi(\mathbf{x_0}) = \mathbf{E}_\pi[R(\mathbf{x}_0) + \gamma\, R(\mathbf{x}_1) + \gamma^2\, R(\mathbf{x}_2) + \gamma^3\, R(\mathbf{x}_3) + \gamma^4\, R(\mathbf{x}_4) + \infty]$$

Start from $\mathbf{x_0}$



Future rewards discounted by $\gamma \in [0,1)$

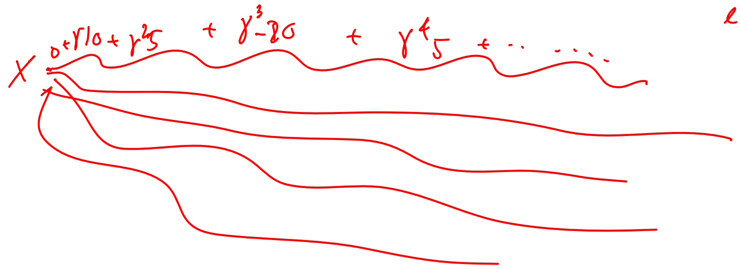
A simple monte-carlo policy evaluation

- Estimate $V_\pi(\mathbf{x})$, start several trajectories from **x** → $V_\pi(\mathbf{x})$ is average reward from these trajectories
  - □ Hoeffding's inequality tells you how many you need
  - □ discounted reward → don't have to run each trajectory forever to get reward estimate

$V_\pi(x)$

one estimate

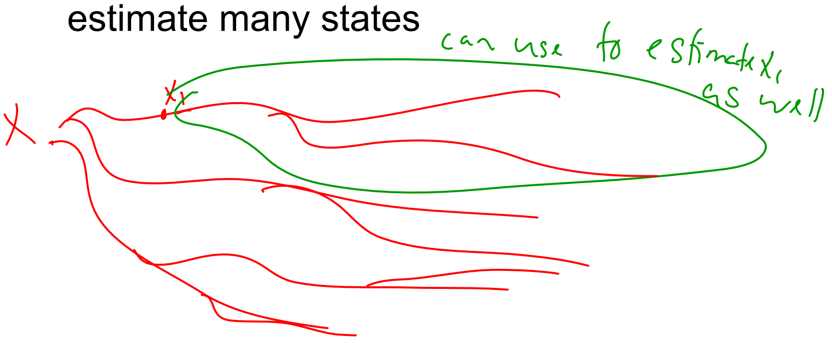
$V_\pi(x) \approx$ average of these estimates



x
$0 + \gamma 10 + \gamma^2 5 + \gamma^3 -20 + \gamma^4 5 + \ldots \ldots$

Problems with monte-carlo approach

- **Resets**: assumes you can restart process from same state many times
- **Wasteful**: same trajectory can be used to estimate many states



Reusing trajectories

- Value determination:

$$V_\pi(x) = R(x) + \gamma \sum_{x'} P(x' \mid x, a = \pi(x)) V_\pi(x')$$

- Expressed as an expectation over next states:

$$V_\pi(x) = R(x) + \gamma \underbrace{E\left[V_\pi(x') \mid x, a = \pi(x)\right]}_{\text{expected ~~[illegible]~~ value for next state}}$$

- Initialize value function (zeros, at random,…)

$V_\pi(x) = 0 \;\forall$

- Idea 1: Observe a transition: $\mathbf{x_t}$!$\mathbf{x_{t+1}}$,$\mathbf{r_{t+1}}$, approximate expec. with single sample:

$V(x_t) = r_{t+1} + \gamma V(x_{t+1})$

  - □ unbiased!!
  - □ but a very bad estimate!!!

$V_\pi(x_{t+1})$ is an unbiased estimate of $E[V_\pi(x') \mid x_t]$

Simple fix: Temporal Difference (TD) Learning [Sutton '84]

$$V_\pi(x) \;=\; R(x) + \gamma E\left[V_\pi(x') \mid x, a = \pi(x)\right]$$

- Idea 2: Observe a transition: $\mathbf{x_t} \to \mathbf{x_{t+1}}, \mathbf{r_{t+1}}$, approximate expectation by mixture of new sample with old estimate:

$$V_\pi(x_t) = (1-\alpha) \cdot V_\pi(x_t) + \alpha\left[r_{t+1} + \gamma V_\pi(x_{t+1})\right]$$

  - □ α>0 is learning rate

TD converges (can take a long time!!!)

$$V_\pi(x) \;=\; R(x) + \gamma \sum_{x'} P(x' \mid x, a = \pi(x)) V_\pi(x')$$

- **Theorem**: TD converges in the limit (with prob. 1), if:
  - □ every state is visited infinitely often
  - □ Learning rate decays just so:
    - $\sum_{i=1}^{\infty} \alpha_i = \infty$
    - $\sum_{i=1}^{\infty} \alpha_i^2 < \infty$

Another model-free RL approach: Q-learning [Watkins & Dayan '92]

- TD is just for one policy…
  - □ How do we find the optimal policy?
- Q-learning:
  - □ Simple modification to TD
  - □ Learns optimal value function (and policy), not just value of fixed policy
  - □ Solution (almost) independent of policy you execute!

Recall Value Iteration

- Value iteration: $V_{t+1}(\mathbf{x}) = \max_{\mathbf{a}} \overbrace{R(\mathbf{x},\mathbf{a}) + \gamma \sum_{\mathbf{x}'} P(\mathbf{x}' \mid \mathbf{x},\mathbf{a}) V_t(\mathbf{x}')}^{Q(x,a)}$

- Or: $Q_{t+1}(\mathbf{x},\mathbf{a}) = R(\mathbf{x},\mathbf{a}) + \gamma \sum_{\mathbf{x}'} P(\mathbf{x}' \mid \mathbf{x},\mathbf{a}) V_t(\mathbf{x}')$

  $V_{t+1}(\mathbf{x}) = \max_{\mathbf{a}} Q_{t+1}(\mathbf{x},\mathbf{a})$

if I know $Q^*(x,a)$

$\pi^*(x) = \arg\max_a Q^*(x,a)$

- Writing in terms of Q-function:

$$Q_{t+1}(\mathbf{x},\mathbf{a}) = R(\mathbf{x},\mathbf{a}) + \gamma \sum_{\mathbf{x}'} P(\mathbf{x}' \mid \mathbf{x},\mathbf{a}) \max_{\mathbf{a}'} Q_t(\mathbf{x}',\mathbf{a}')$$

Q-learning

$$Q_{t+1}(\mathbf{x},\mathbf{a}) = R(\mathbf{x},\mathbf{a}) + \gamma \sum_{\mathbf{x}'} P(\mathbf{x}' \mid \mathbf{x},\mathbf{a}) \max_{\mathbf{a}'} Q_t(\mathbf{x}',\mathbf{a}')$$

initialize $Q_0(x,a)$ to e.g. 0

- Observe a transition: $\mathbf{x_t,a_t}$! $\mathbf{x_{t+1},r_{t+1}}$, approximate expectation by mixture of new sample with old estimate:
  - □ transition now from state-action pair to next state and reward

$$Q(x_t,a_t) = (1-\alpha)\,Q(x_t,a_t) + \alpha\Big[r_{t+1} + \gamma \underbrace{\max_a Q(x_{t+1},a)}_{\approx V(x_{t+1})}\Big]$$

  - □ α>0 is learning rate

Q-learning convergence

- Under same conditions as TD, Q-learning converges to optimal value function Q*
- Can run any policy, as long as policy visits every state-action pair infinitely often
- Typical policies (non of these address ~~Exploration-Exploitation tradeoff~~)
  - □ ε-greedy: $\mathbf{a}_t = \arg\max_{\mathbf{a}} Q_t(\mathbf{x},\mathbf{a})$
    - with prob. (1-ε) take greedy action:
    - with prob. ε take an action at (uniformly) random

$t \leftarrow$ time step

  - □ Boltzmann (softmax) policy:
    - $P(\mathbf{a}_t \mid \mathbf{x}) \propto \exp\left\{\dfrac{Q_t(\mathbf{x},\mathbf{a})}{K}\right\}$
    - K – "temperature" parameter, ~~K!0, as t!1~~

$K \to 0$ as $t \to \infty$

The **curse of dimensionality**: A significant challenge in MDPs and RL

- MDPs and RL are polynomial in number of states and actions

in k position

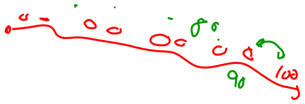
- Consider a game with n units (e.g., peasants, footmen, etc.)

  |A| actions

  - □ How many states? K^n
  - □ How many actions? $|A|^n$

- **Complexity is exponential in the number of variables used to define state!!!**

Addressing the curse!



- Some solutions for the curse of dimensionality:
  - □ **Learning the value function**: mapping from state-action pairs to values (real numbers) $Q : X, A \rightarrow \mathbb{R}$
    - **A regression problem!** , linear R., , DT, kNN, NNets, ...
  - □ **Learning a policy**: mapping from states to actions $\pi : X, \rightarrow A$
    - **A classification problem!**

- Use many of the ideas you learned this semester:
  - □ linear regression, SVMs, decision trees, neural networks, Bayes nets, etc.!!!

For example : TD Gammon : TD learning + Neural Net representation for V

What you need to know about RL

- A model-based approach:
  - □ address exploration-exploitation tradeoff and credit assignment problem
  - □ the R-max algorithm
- A model-free approach:
  - □ never needs to learn transition model and reward function
  - □ TD-learning
  - □ Q-learning

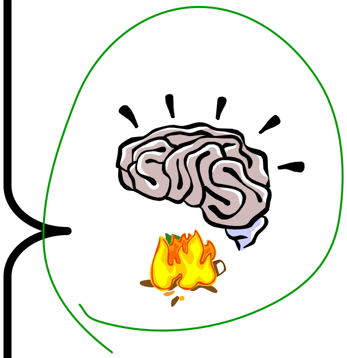
Closing….

Machine Learning – 10701/15781
Carlos Guestrin
Carnegie Mellon University

November 29th, 2007

What you have learned this semester

- Learning is function approximation
- Point estimation
- Regression
- Discriminative v. Generative learning
- Naïve Bayes
- Logistic regression
- Bias-Variance tradeoff
- Neural nets
- Decision trees
- Cross validation
- Boosting
- Instance-based learning
- SVMs
- Kernel trick
- PAC learning
- VC dimension
- Mistake bounds
- Bayes nets
  - □ representation, inference, parameter and structure learning
- HMMs
  - □ representation, inference, learning
- K-means
- EM
- Feature selection, dimensionality reduction, PCA
- MDPs
- Reinforcement learning



BIG PICTURE

- Improving the performance at some task though experience!!! ☺
  - □ before you start any learning task, remember the fundamental questions:

What is the learning problem?

From what experience?

What model?

What loss function are you optimizing?

With what optimization algorithm?

Which learning algorithm?

With what guarantees?

How will you evaluate it?

What next?

- Machine Learning Lunch talks: http://www.cs.cmu.edu/~learning/
- Intelligence Seminars: http://www.cs.cmu.edu/~iseminar/

- Journal:
  - □ JMLR – Journal of Machine Learning Research (free, on the web)

- Conferences:
  - □ ICML: International Conference on Machine Learning
  - □ NIPS: Neural Information Processing Systems
  - □ COLT: Computational Learning Theory
  - □ UAI: Uncertainty in AI
  - □ AIStats: intersection of Statistics and AI
  - □ Also AAAI, IJCAI and others

- Some MLD courses:
  - □ 10-708 Probabilistic Graphical Models (~~Fall~~) Spring 2009
  - □ 10-705 Intermediate Statistics (Fall)
  - □ 11-762 Language and Statistics II (Fall)
  - □ 10-702 Statistical Foundations of Machine Learning (Spring)
  - □ 10-7~~03~~25 Optimization (Spring)
  - □ …

You have done a lot!!!

- And (hopefully) learned a lot!!!
  - □ Implemented
    - NB
    - LR
    - Nearest Neighbors
    - Boosting
    - SVM
    - HMMs
    - PCA
    - EM and GMM
  - □ Answered hard questions and proved many interesting results
  - □ Completed (I am sure) an amazing ML project

Thank You for the Hard Work!!!