CMU 15-889e
Real Life Reinforcement Learning

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Fall 2015

Class Logistics

- Instructor: Emma Brunskill
- TA: Christoph Dann
- Time: Monday/Wednesday 1:30-2:50pm
- Website: http://www.cs.cmu.edu/~ebrun/15889e/index.html
- We will be using Piazza for class discussions and communication: please use this to pose all standard questions
- Office hours will be announced

Prerequisites

- Assume basic familiarity with probability, machine learning, sequential decision making under uncertainty and programming
- It is useful but not required to have taken one or more of: Machine Learning, Stat Techniques in Robotics, Graduate AI.
- Enthusiasm and creativity are required!

Class Requirements & Policy

- Grading
  - Homeworks (30%)
  - Midterm (20%)
  - Final project (40%)
  - Participation (10%)
- Late policy
  - 4 late days to use without penalty on homeworks only across the semester. See website for full details.
- Collaboration: unless otherwise specified, written homeworks can be discussed with others but must be written up individually. You must write the names of the other students you collaborated with on your homework.

Reinforcement Learning

Learn a behavior strategy (policy) that maximizes the long term sum of rewards in an unknown & stochastic environment

RL Examples: Intelligent Tutoring Systems

RL Examples: Robotics

RL Examples: Playing Atari

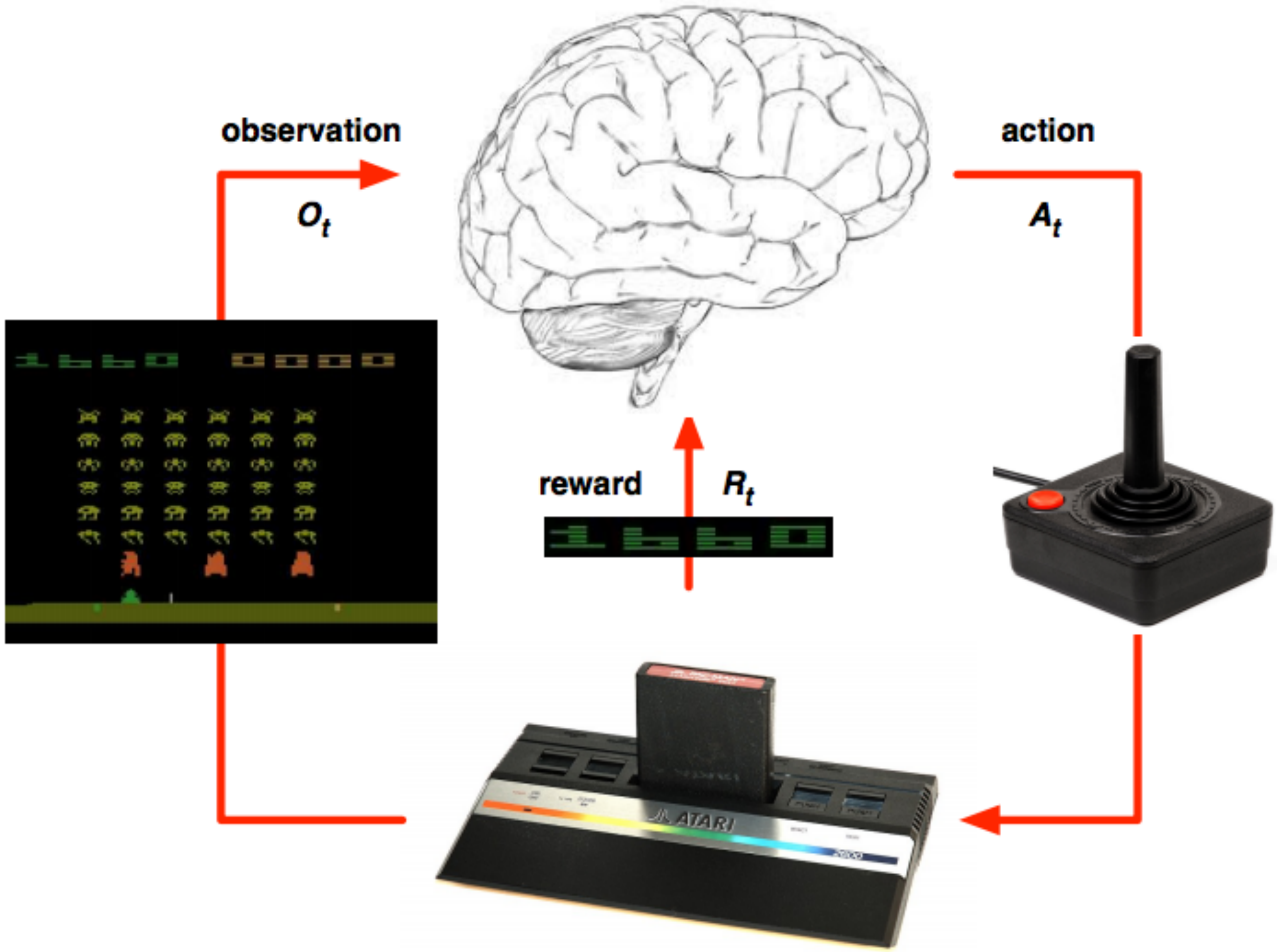


Image from David Silver

RL Examples: Healthcare decision support

Go through background knowledge check

Why is RL Different Than Other AI and Machine Learning?

optimization +

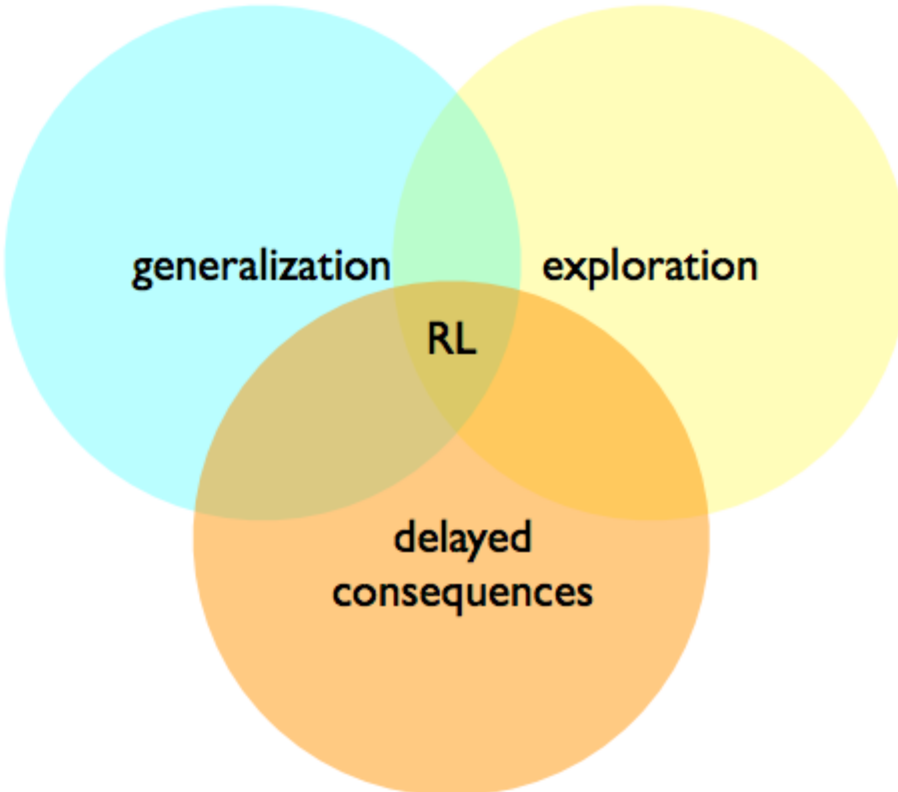


Image from Ben Van Roy

RL: Designer Choices

RL: Designer Choices

- Representation (how represent the world and the space of actions/interventions, and feedback signal/ reward)
- Algorithm for learning
- Objective function
- Evaluation

Common Restrictions / Constraints

- Computation time

Common Restrictions / Constraints

- Computation time
- Data available
- Restricted in way can act (policy class, constraints on which actions can take in states)
- Online vs offline
- Do we get to choose how to act or does someone else (an expert, semi-expert, offpolicy/onpolicy learning…)

Desirable Properties in a RL Algorithm?

Desirable Properties in a RL Algorithm?

Convergence
Consistency
Small generalization error
Small estimation error
Small approximation error
High learning speed
Safety

Broad Classes of RL Approaches

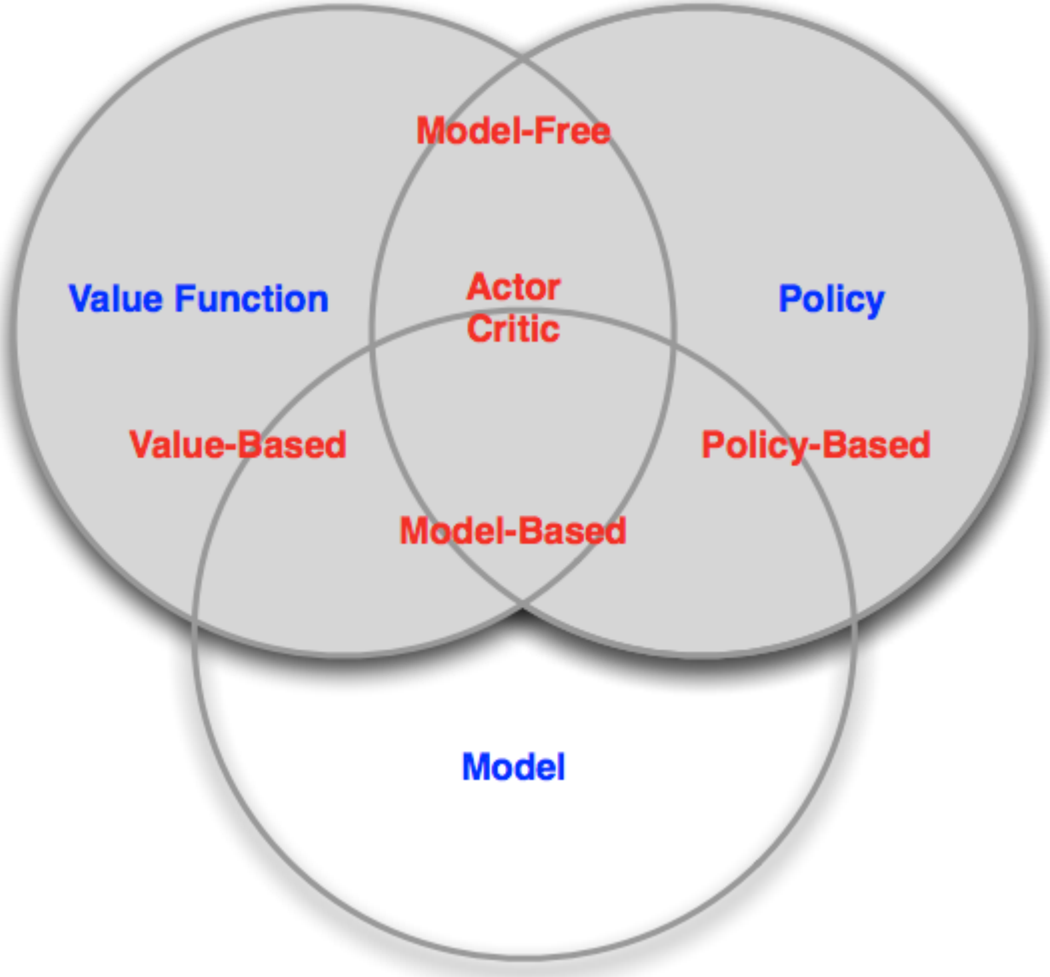


Image from David Silver

3 Important Challenges in Real Life RL

1. From Old Data to Future Decisions
2. Quickly Learning to Act Well: Highly Sample Efficient RL
3. Beyond Expectation: Safety & Risk Sensitive RL

→ Most of class will focus on these 3 topics

Reasoning Under Uncertainty

	Actions Don't Change State of the World	Actions Change State of the World
Learn model of outcomes	Multi-armed bandits	Reinforcement Learning
Given model of stochastic outcomes	Decision theory	Markov Decision Processes

Markov Decision Processes

MDP is a tuple (S, A, P, R, γ)

- Set of states S
- Start state s_0
- Set of actions A
- Transitions $P(s'|s,a)$ (or $T(s,a,s')$)
- Rewards $R(s,a,s')$ (or $R(s)$ or $R(s,a)$)
- Discount γ
- Policy = Choice of action for each state
- Utility / Value = sum of (discounted) rewards

- Value of a Policy
- $$V^{\pi}(s) = \sum_{s' \in S} p(s' \mid s, \pi(s)) \left[R(s, \pi(s), s') + \gamma V^{\pi}(s') \right]$$

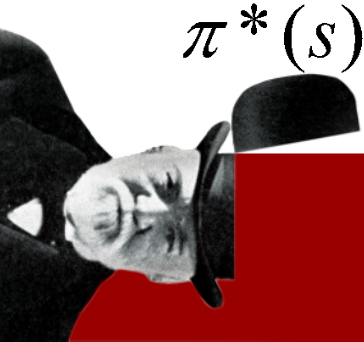
$$Q^{\pi}(s, a) = \sum_{s' \in S} p(s' \mid s, a) \left[R(s, a, s') + \gamma V^{\pi}(s') \right]$$

- Optimal Value & Optimal Policy

$$V^*(s_i) = \max_a \left(\sum_{s_j \in S} p(s_j \mid s_i, a) \left[R(s, \pi(s), s') + \gamma V^*(s_j) \right] \right)$$

$$= \max_a Q^*(s, a)$$

$$\pi^*(s) = \operatorname{argmax}_a Q^*(s, a)$$



Bellman Equation

$$V^*(s_i) = \max_a \left(\sum_{s_j \in S} p(s_j \mid s_i, a) \left[R(s, \pi(s), s') + \gamma V^*(s_j) \right] \right)$$

- Holds for V*
- Inspires an update rule

Value Iteration

1. Initialize $V_1(s_i)$ for all states s_i
2. k=2
3. While k < desired horizon or (if infinite horizon) values have converged
   - For all s,

$$V_k(s_i) = \max_a \left(\sum_{s_j \in S} p(s_j \mid s_i, a) \left[R(s, \pi(s), s') + \gamma V_{k-1}(s_j) \right] \right)$$

$$\pi_k(s_i) = \operatorname{argmax}_a \left(\sum_{s_j \in S} p(s_j \mid s_i, a) \left[R(s, \pi(s), s') + \gamma V_{k-1}(s_j) \right] \right)$$

Will Value Iteration Converge?

- Yes, if discount factor is < 1 or end up in a terminal state with probability 1

- Bellman equation is a contraction
- If apply it to two different value functions, distance between value functions shrinks after apply Bellman equation to each

Bellman Operator is a Contraction

|| V-V'|| = Infinity norm
(find max diff
Over all states)

$$\left\| BV - BV' \right\| = \left\| \begin{array}{l} \max_a \left[R(s,a) + \gamma \sum_{s_j \in S} p(s_j \mid s_i, a) V(s_j) \right] \\ - \max_{a'} \left[R(s,a') - \gamma \sum_{s_j \in S} p(s_j \mid s_i, a') V'(s_j) \right] \end{array} \right\|$$

$$\leq \left\| \max_a \left[R(s,a) + \gamma \sum_{s_j \in S} p(s_j \mid s_i, a) V(s_j) - R(s,a) + \gamma \sum_{s_j \in S} p(s_j \mid s_i, a) V'(s_j) \right] \right\|$$

$$\leq \gamma \left\| \max_a \left[\sum_{s_j \in S} p(s_j \mid s_i, a) V(s_j) - \sum_{s_j \in S} p(s_j \mid s_i, a) V'(s_j) \right] \right\|$$

$$= \gamma \max_a \left\| \left[\sum_{s_j \in S} p(s_j \mid s_i, a) (V(s_j) - V'(s_j)) \right] \right\|$$

$$\leq \gamma \max_{a, s_i} \sum_{s_j \in S} p(s_j \mid s_i, a) \left| V(s_j) - V'(s_j) \right|$$

$$\leq \gamma \max_{a, s_i} \sum_{s_j \in S} p(s_j \mid s_i, a) \left\| V - V' \right\|$$

$$= \gamma \left\| V - V' \right\|$$

Carnegie Mellon University

Properties of Contraction

- Only has 1 fixed point
  - If had two, then would not get closer when apply contraction function, violating definition of contraction
- When apply contraction function to any argument, value must get closer to fixed point
  - Fixed point doesn’t move
  - Repeated function applications yield fixed point

Value Iteration Converges

- If discount factor < 1
- Bellman is a contraction
- Value iteration converges to unique solution which is optimal value function