Advanced Topics in Reinforcement Learning

Lecture 10: Models and Planning I

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Announcements

- Homework released. Due: October 21 at 9:30AM (minute class starts)
- Read chapter 9 and 11 for next week. Function approximation!
- Upcoming dates:
  - Literature survey due: October 30
  - Exam: November 5

Project Literature Review

- The next phase of your project is a literature review.
- An essential element to any research project.
  - Minimum expectation is that each survey cites at least 20 relevant references.
  - For each surveyed source, *briefly describe* (1-2 sentences), say why it is relevant to your project, and then say how it is different from your project.
  - Survey should be submitted as a pdf on Gradescope.
- The survey is also a secondary check-in on project direction.
- See https://pages.cs.wisc.edu/~jphanna/teaching/2025fall_cs839/project.html for more details.

Learning Outcomes

After this week, you will be able to:

1. Explain the difference between background and decision-time planning in RL.

2. Implement Dyna, MCTS, and other model-based RL algorithms.

3. Understand how models can be integrated into RL agents.

But first, finish TD learning

Review

- Dynamic Programming Methods
  - Model is given.
- Monte Carlo methods.
  - Model-free but no bootstrapping.
- Temporal Difference Learning.
  - Model-free and bootstrapping.

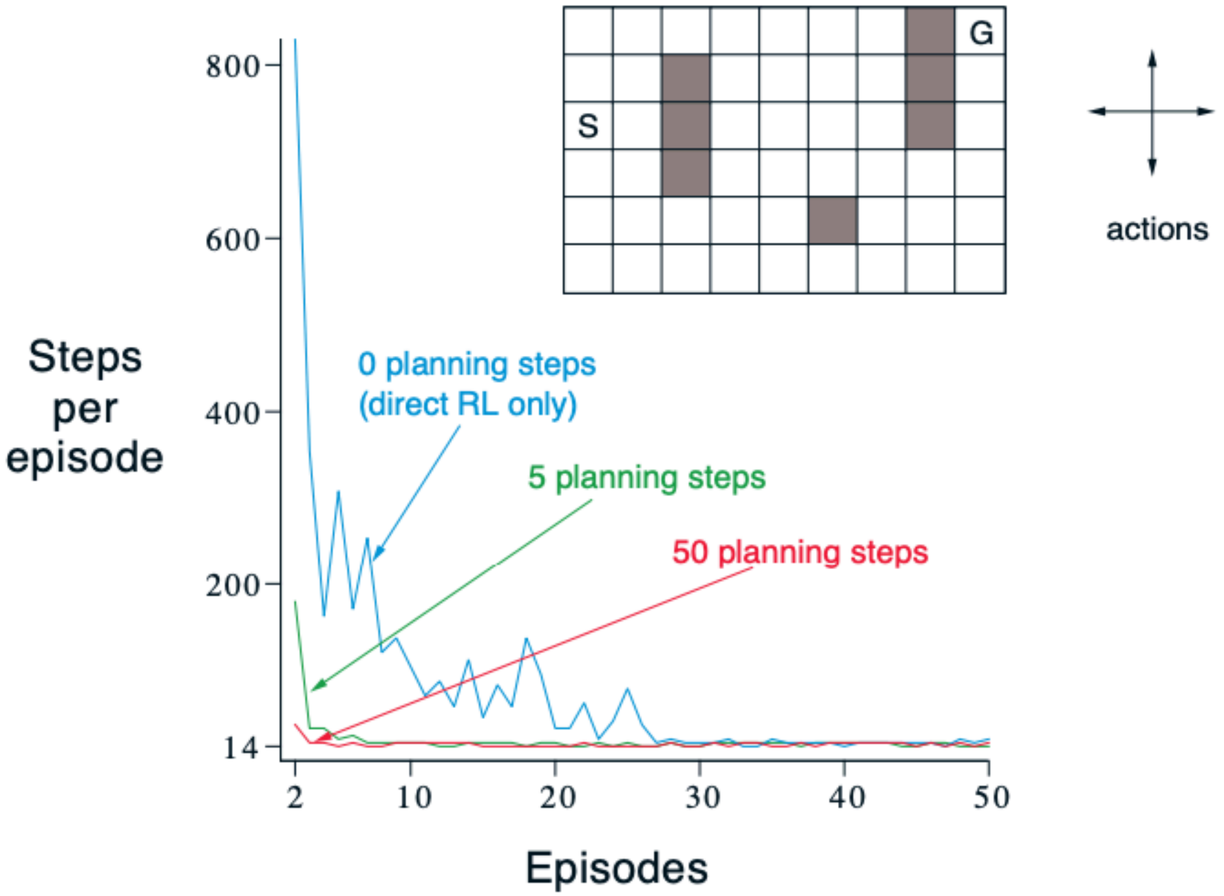
Plan-Space Search

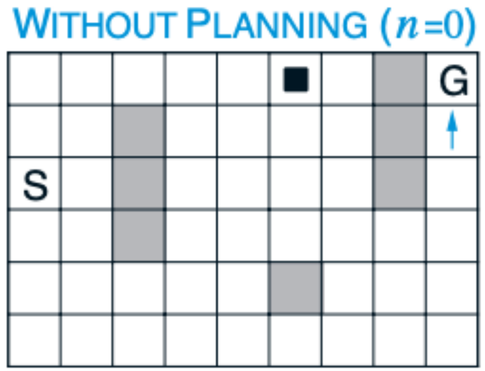
- The RL methods we will learn about in this class all follow the generalized policy iteration scheme.
  - $\pi_k \rightarrow q_k \rightarrow \pi_{k+1} \rightarrow q_{k+1} \rightarrow \cdots$
- Alternatively: search directly for a good policy without computing a value function.
  - Genetic algorithms, evolutionary strategies, random search, optimization, etc.
  - Define $f : \pi \rightarrow \mathbb{R}$ and then find π with maximal $f(\pi)$.
- (+) Robust to violations of MDP formalism.
- (+) Can be applied to almost any type of policy.
- (-) Size of policy space is exponential in the number of states and actions.
- (-) If interaction time is long and γ large, then learning methods may be preferred to static policies.

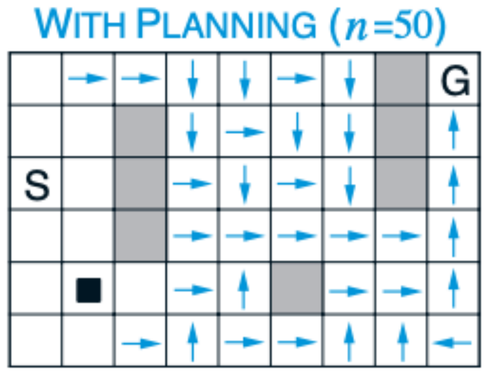
RL with a Learned Model

- Model-based learning and planning.
  - Use experience to model p. Then use planning methods to back-up values.
  - How to model p is a challenging question in practice!
  - Often more data-efficient (better policy with less interaction). Why?
  - Less computationally-efficient per time-step. Why?
- Access to a model provides much flexibility in how we back-up values.

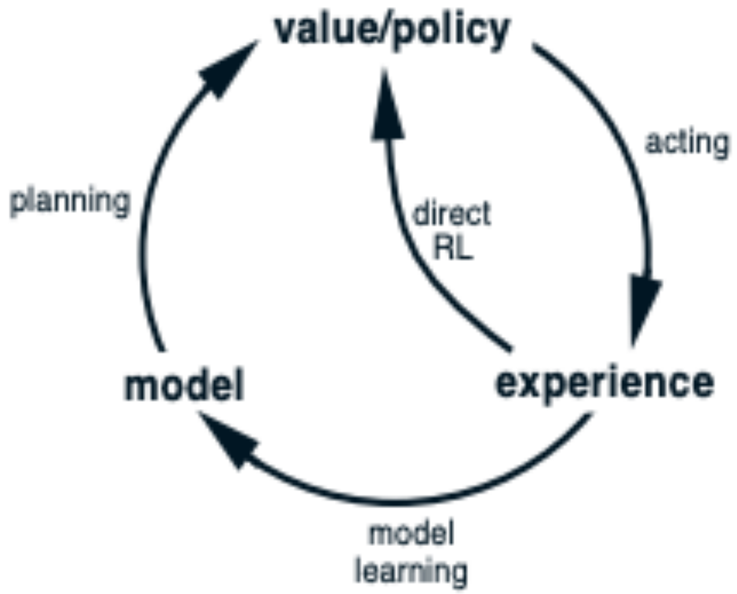
Model-based Data Efficiency







Dyna-style Model-based Learning



Dyna Agents

- In state S, take action A, observe R, and S'.
- Update model: Model$(S, A) \leftarrow R, S'$
- Repeat n times:
  - Sample random state-action pair, S, A.
  - $R, S' \leftarrow$ Model(S, A).
  - Apply q-learning update with S, A, R, S'.

Real Experience

Synthetic / Simulated Experience

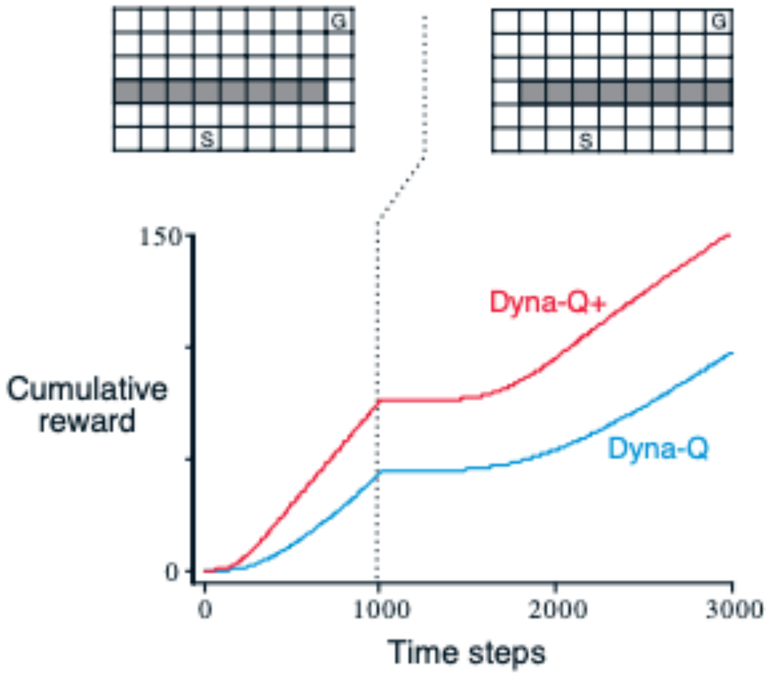
Yucheng’s Presentation

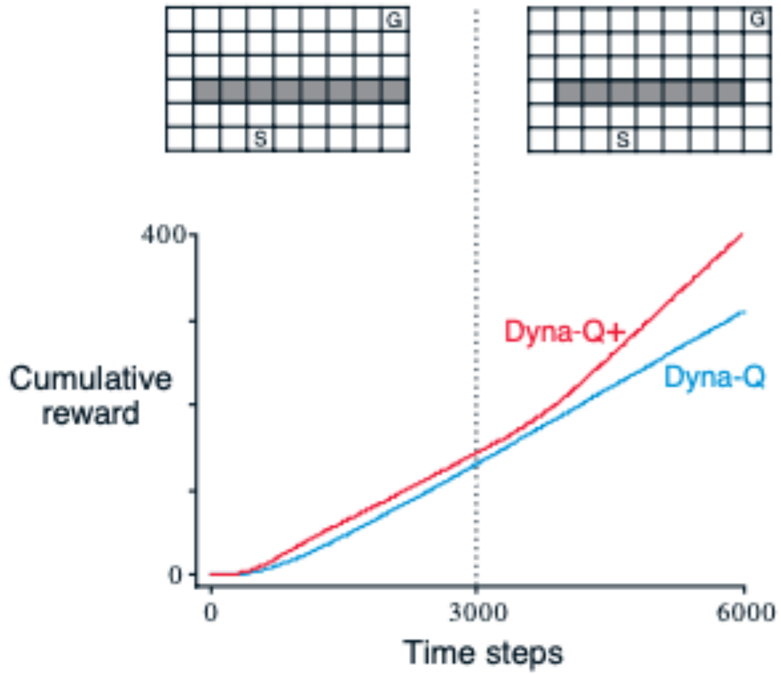
Mastering Diverse Domains through World Models
Hafner et al. 2023

Slides

When the Model is Wrong

- “All models are wrong but some are useful.” - George Box.
- In practice, models can be inaccurate for many reasons.
  - Partial observability, non-stationarity, function approximation, missing data, stochastic environment, etc.



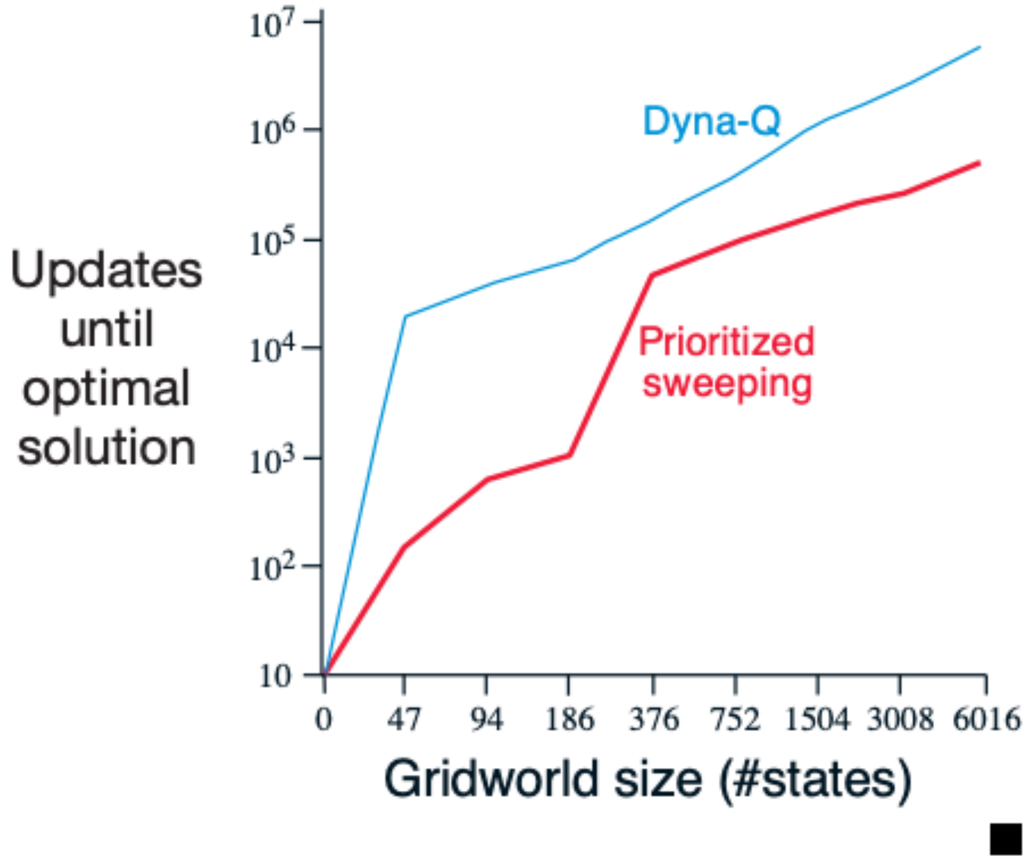


Prioritizing Updates

- Dyna-Q updates a random sub-set of states.
- What is one case where this is inefficient?
  - When many states won't have a value change.
- Prioritized sweeping: keep a priority queue of (S,A) pairs that are likely to have a large value change.
  - Can base this off of change to successor state, S', i.e., priority is:

$$|\bar{R} + \gamma \max_{a} Q(S', a) - Q(S, A)|$$

Prioritizing Updates



To Sample or Not?

- Dynamic programming typically uses *expected updates*.

$$Q(s,a) \leftarrow \sum_{s',r} \hat{p}(s', r \mid s, a)[r + \gamma \max_{a'} Q(s', a')]$$

- TD-method methods use *sample updates.*

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

- Can use either with simulated experience. How and which to choose?

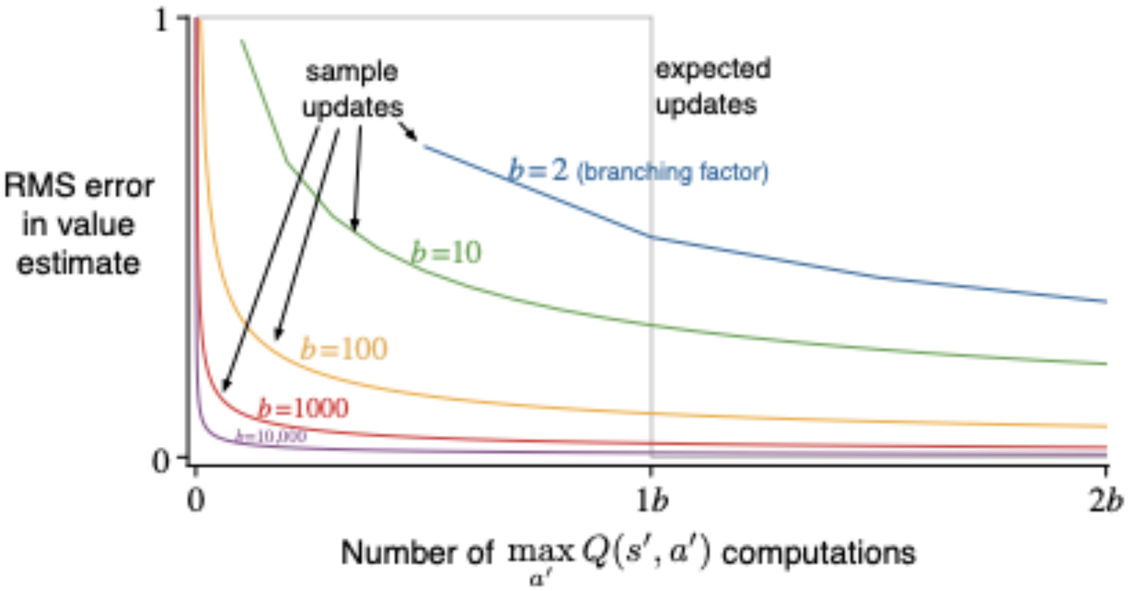


Figure 8.7: Comparison of efficiency of expected and sample updates.

Trajectory Sampling

- Uniform sampling of states can be inefficient.
- It may be more effective to focus value back-ups on states that the agent will visit often.
- How to know what states the agent will visit?
  - Simulate entire trajectories within the model. Back-up these states.
  - Initialize the agent in a start state and follow the current policy from there.

Real-time Dynamic Programming

- Key Idea: perform a value-iteration update on each state as it is visited.
- For n episodes of real experience:
  - Start in initial state, S_0.
  - Repeat $A_t \sim \pi(A = a \,|\, S_t)$, $S', R \sim \texttt{Model}(S_t, A_t)$ where π is ϵ-greedy.
  - At each step, t, apply the value iteration update to $Q(S_t, A_t)$.

Summary

- Building a model from experience can improve the efficiency of RL.
- Models can be used for:
  - Planning, i.e., dynamic programming updates.
  - Learning with synthetic experience.
- When coupling planning and interaction, we need to make efficient use of limited computational resources.

Action Items

- Complete homework.
- Begin literature review.
- Begin reading Chapter 9 and 11.