# Chapter 9: Planning and Learning

Objectives of this chapter:

- Use of environment models
- Integration of planning and learning methods

# Models

- Model: anything the agent can use to predict how the environment will respond to its actions
- Distribution model: description of all possibilities and their probabilities
  - e.g., $P_{ss'}^{a}$ and $R_{ss'}^{a}$ for all $s,\ s',$ and $a \in A(s)$
- Sample model: produces sample experiences
  - e.g., a simulation model
- Both types of models can be used to produce simulated experience
- Often sample models are much easier to come by

# Planning

- Planning: any computational process that uses a model to create or improve a policy


- Planning in AI:
  - state-space planning
  - plan-space planning (e.g., partial-order planner)
- We take the following (unusual) view:
  - all state-space planning methods involve computing value functions, either explicitly or implicitly
  - they all apply backups to simulated experience

# Planning Cont.

- Classical DP methods are state-space planning methods
- Heuristic search methods are state-space planning methods
- A planning method based on Q-learning:

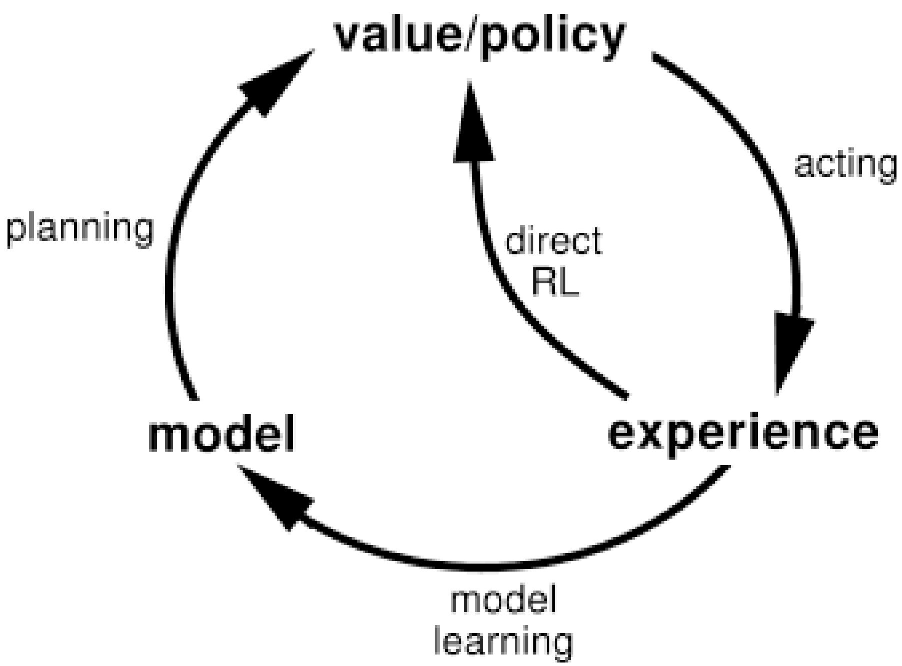
Do forever:

1. Select a state, $s \in \mathcal{S}$, and an action, $a \in \mathcal{A}(s)$, at random
2. Send $s, a$ to a sample model, and obtain a sample next state, $s'$, and a sample next reward, $r$
3. Apply one-step tabular Q-learning to $s, a, s', r$:
   $Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right]$

Random-Sample One-Step Tabular Q-Planning

# Learning, Planning, and Acting

- Two uses of real experience:
  - model learning: to improve the model
  - direct RL: to directly improve the value function and policy
- Improving value function and/or policy via a model is sometimes called indirect RL or model-based RL. Here, we call it planning.



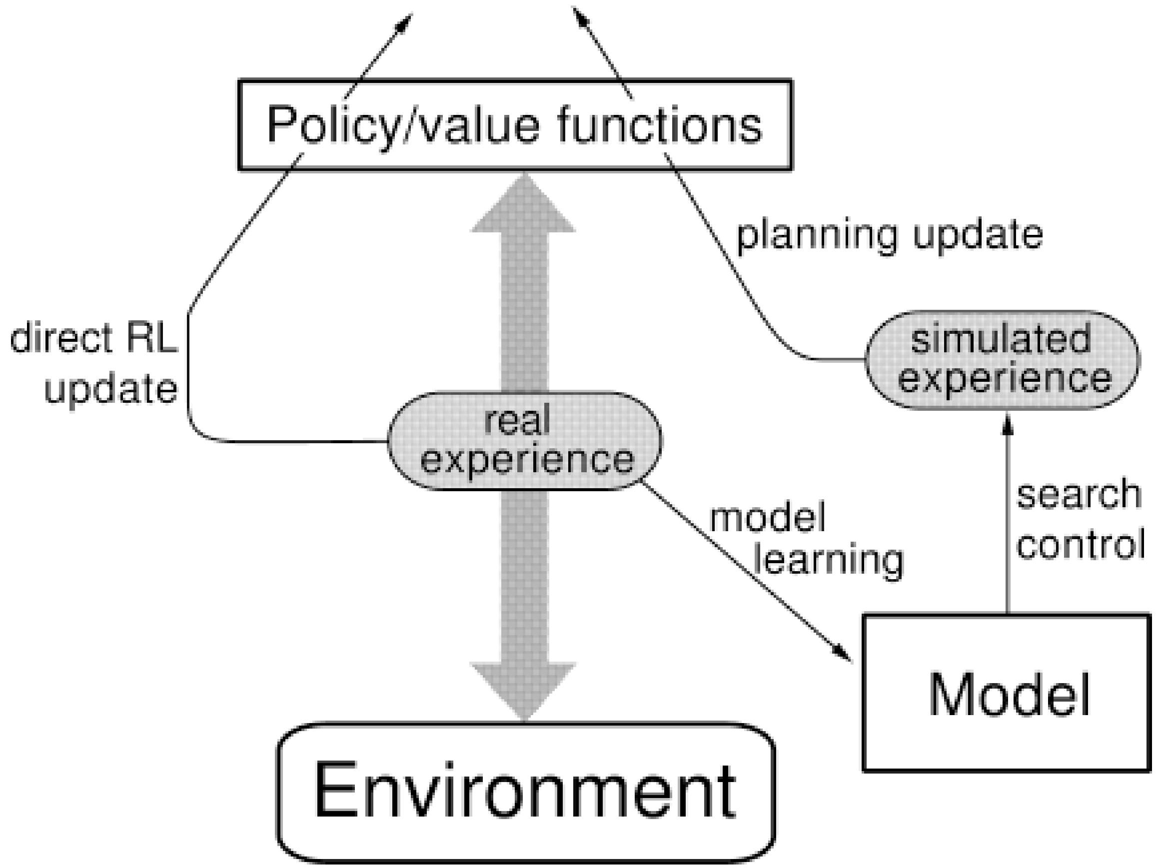
# Direct vs. Indirect RL

- Indirect (model-based) methods:
  - make fuller use of experience: get better policy with fewer environment interactions
- Direct methods
  - simpler
  - not affected by bad models

But they are very closely related and can be usefully combined:

planning, acting, model learning, and direct RL can occur simultaneously and in parallel

# The Dyna Architecture (Sutton 1990)



# The Dyna-Q Algorithm

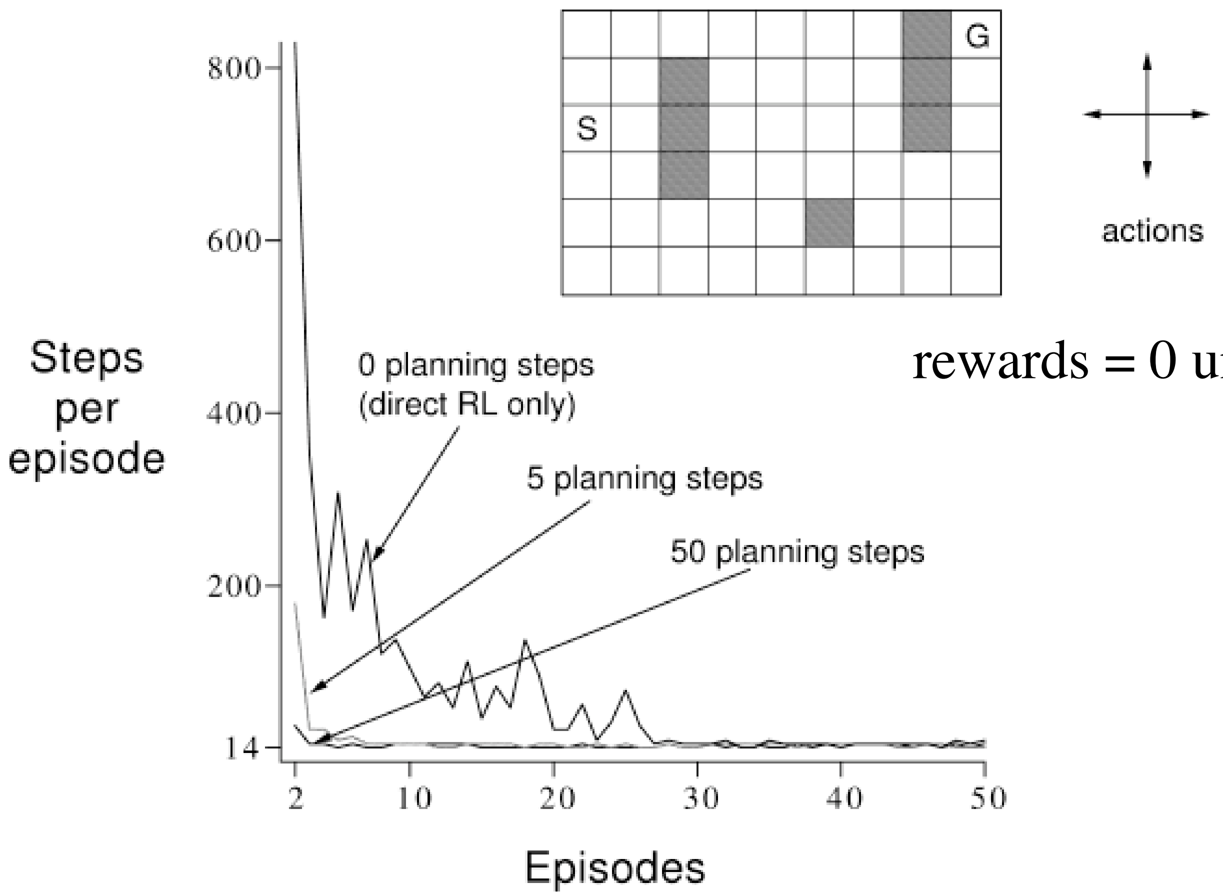
Initialize $Q(s,a)$ and $Model(s,a)$ for all $s \in \mathcal{S}$ and $a \in \mathcal{A}(s)$
Do forever:
(a) $s \leftarrow$ current (nonterminal) state
(b) $a \leftarrow \epsilon$-greedy$(s, Q)$
(c) Execute action $a$; observe resultant state, $s'$, and reward, $r$
(d) $Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right]$
(e) $Model(s,a) \leftarrow s', r$ (assuming deterministic environment)
(f) Repeat $N$ times:
$s \leftarrow$ random previously observed state
$a \leftarrow$ random action previously taken in $s$
$s', r \leftarrow Model(s,a)$
$Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right]$

direct RL

model learning

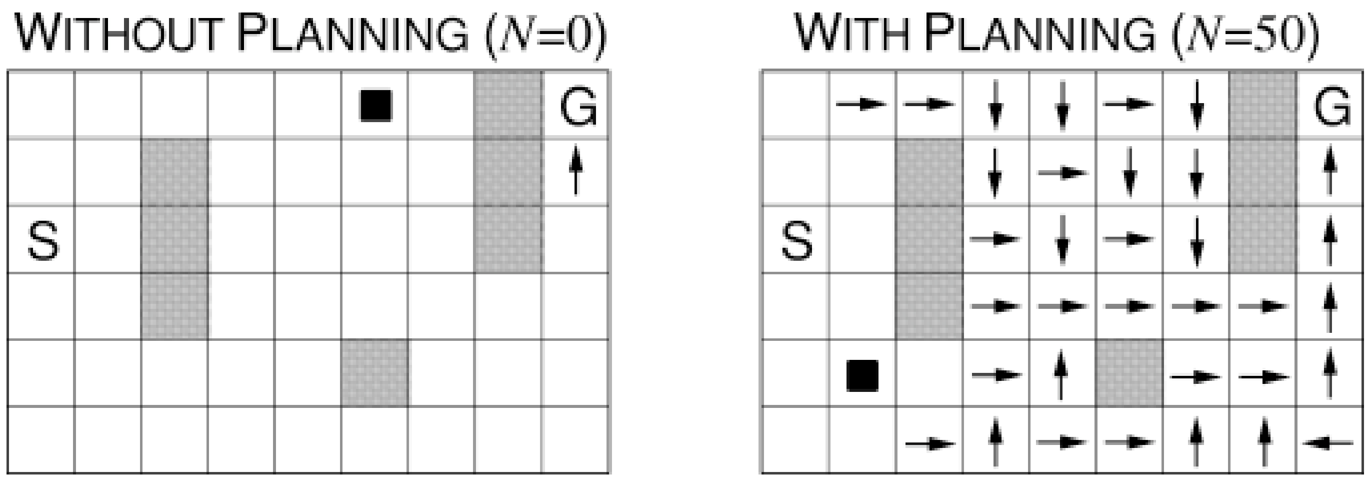
planning

# Dyna-Q on a Simple Maze



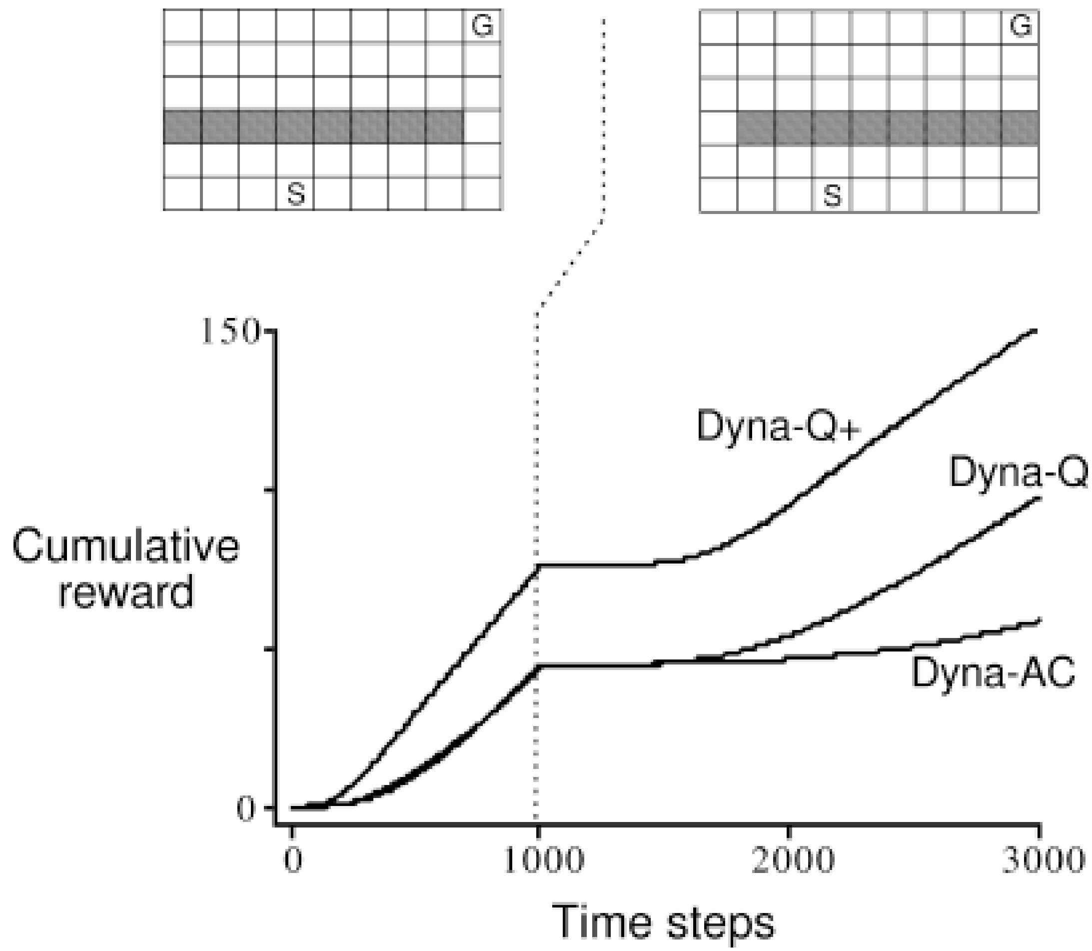

rewards = 0 until goal, when =1

# Dyna-Q Snapshots: Midway in 2nd Episode



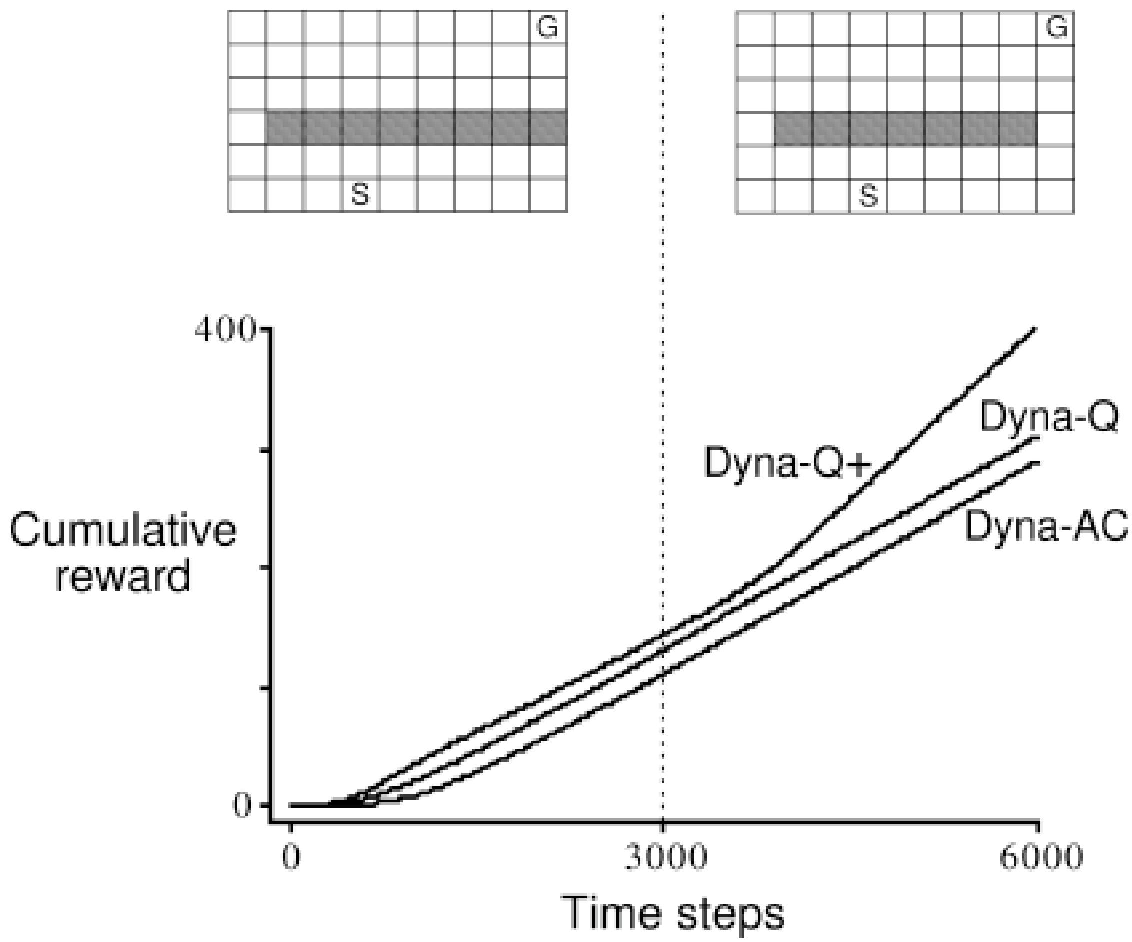
# When the Model is Wrong: Blocking Maze

The changed environment is harder



# Shortcut Maze

The changed environment is easier



# What is Dyna-Q$^+$?

- Uses an “exploration bonus”:
  - Keeps track of time since each state-action pair was tried for real
  - An extra reward is added for transitions caused by state-action pairs related to how long ago they were tried: the longer unvisited, the more reward for visiting
  - The agent actually “plans” how to visit long unvisited states

# Prioritized Sweeping

- Which states or state-action pairs should be generated during planning?
- Work backwards from states whose values have just changed:
  - Maintain a queue of state-action pairs whose values would change a lot if backed up, prioritized by the size of the change
  - When a new backup occurs, insert predecessors according to their priorities
  - Always perform backups from first in queue
- Moore and Atkeson 1993; Peng and Williams, 1993

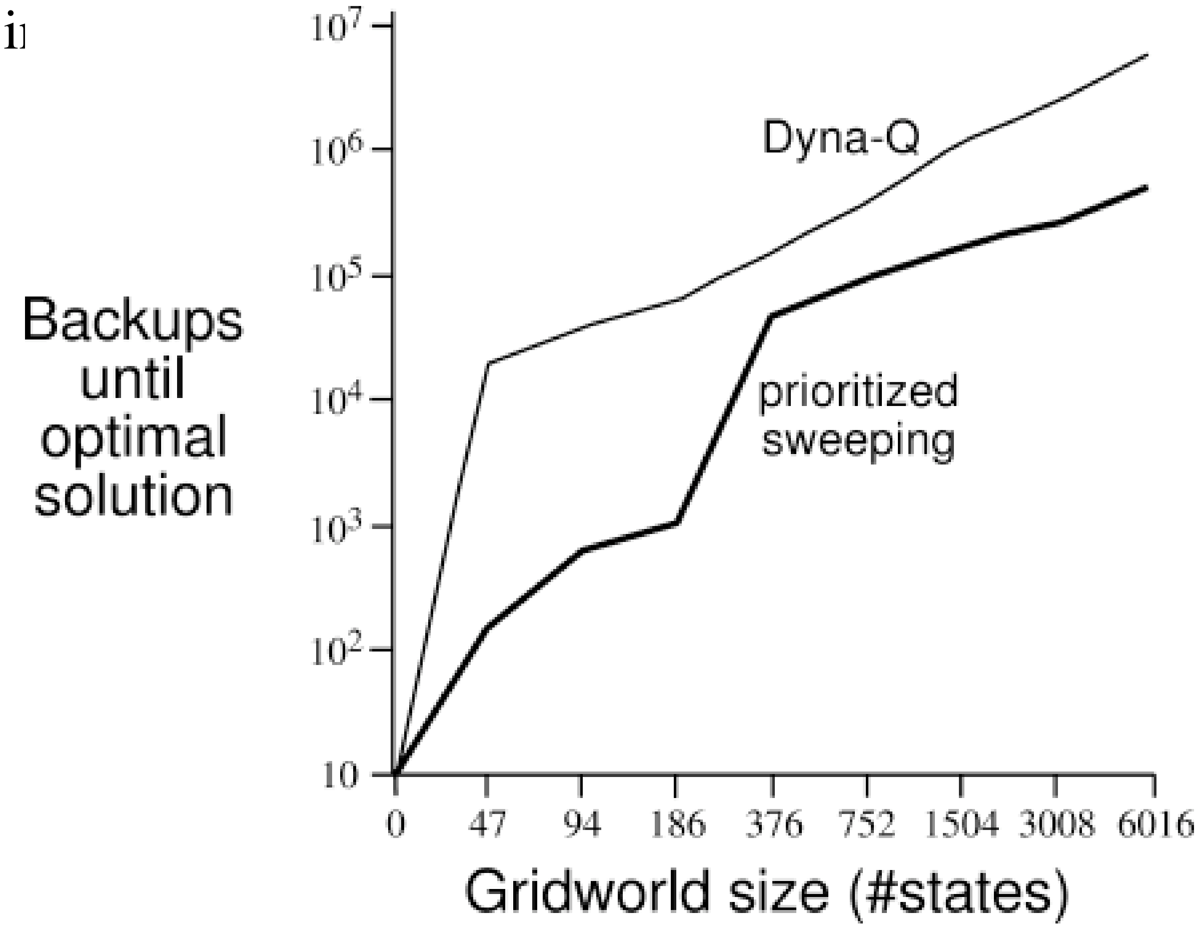
# Prioritized Sweeping

Initialize $Q(s,a)$, $Model(s,a)$, for all $s,a$, and $PQueue$ to empty
Do forever:

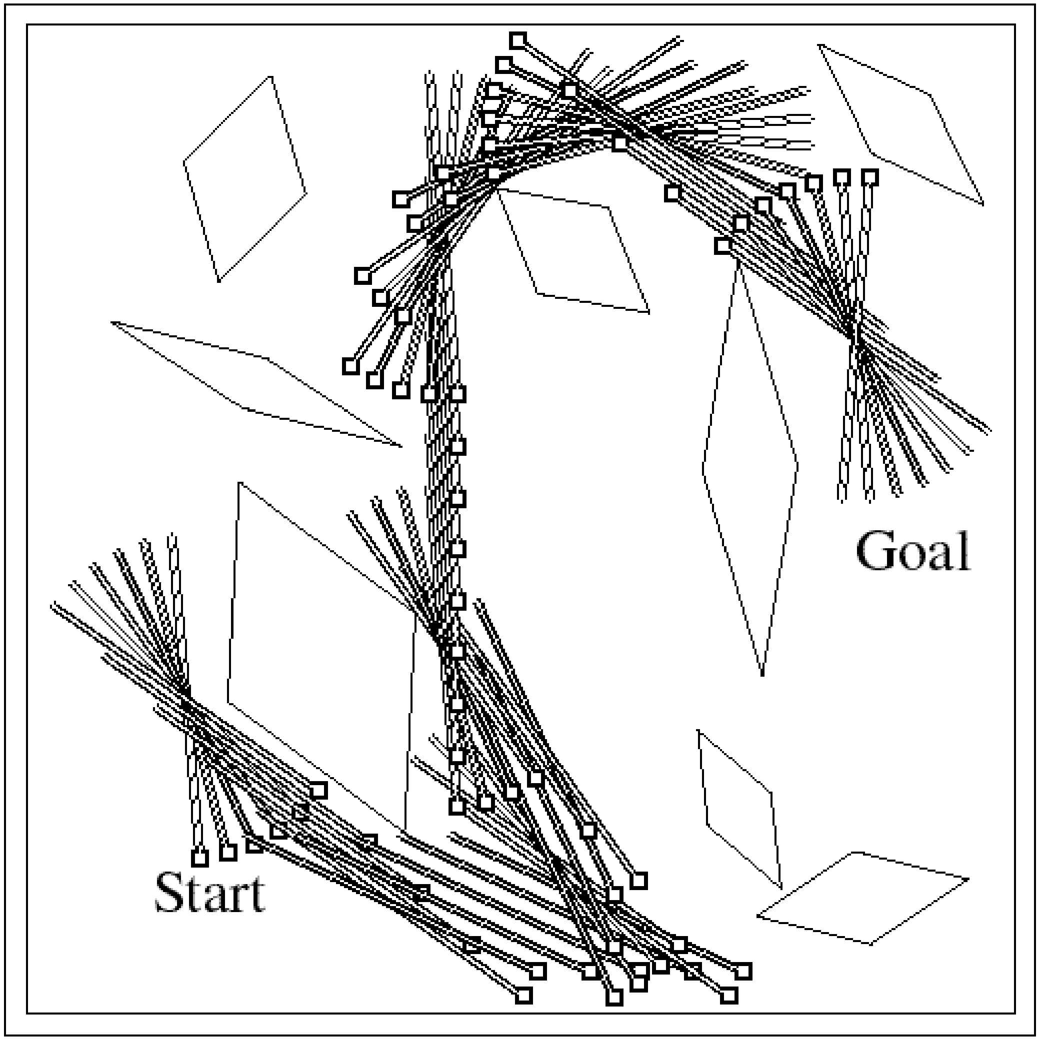
(a) $s \leftarrow$ current (nonterminal) state
(b) $a \leftarrow policy(s,Q)$
(c) Execute action $a$; observe resultant state, $s'$, and reward, $r$
(d) $Model(s,a) \leftarrow s', r$
(e) $p \leftarrow |r + \gamma \max_{a'} Q(s',a') - Q(s,a)|$.
(f) if $p > \theta$, then insert $s,a$ into $PQueue$ with priority $p$
(g) Repeat $N$ times, while $PQueue$ is not empty:
  $s,a \leftarrow first(PQueue)$
  $s',r \leftarrow Model(s,a)$
  $Q(s,a) \leftarrow Q(s,a) + \alpha\big[r + \gamma \max_{a'} Q(s',a') - Q(s,a)\big]$
  Repeat, for all $\bar{s},\bar{a}$ predicted to lead to $s$:
    $\bar{r} \leftarrow$ predicted reward
    $p \leftarrow |\bar{r} + \gamma \max_a Q(s,a) - Q(\bar{s},\bar{a})|$.
    if $p > \theta$ then insert $\bar{s},\bar{a}$ into $PQueue$ with priority $p$

# Prioritized Sweeping vs. Dyna-Q

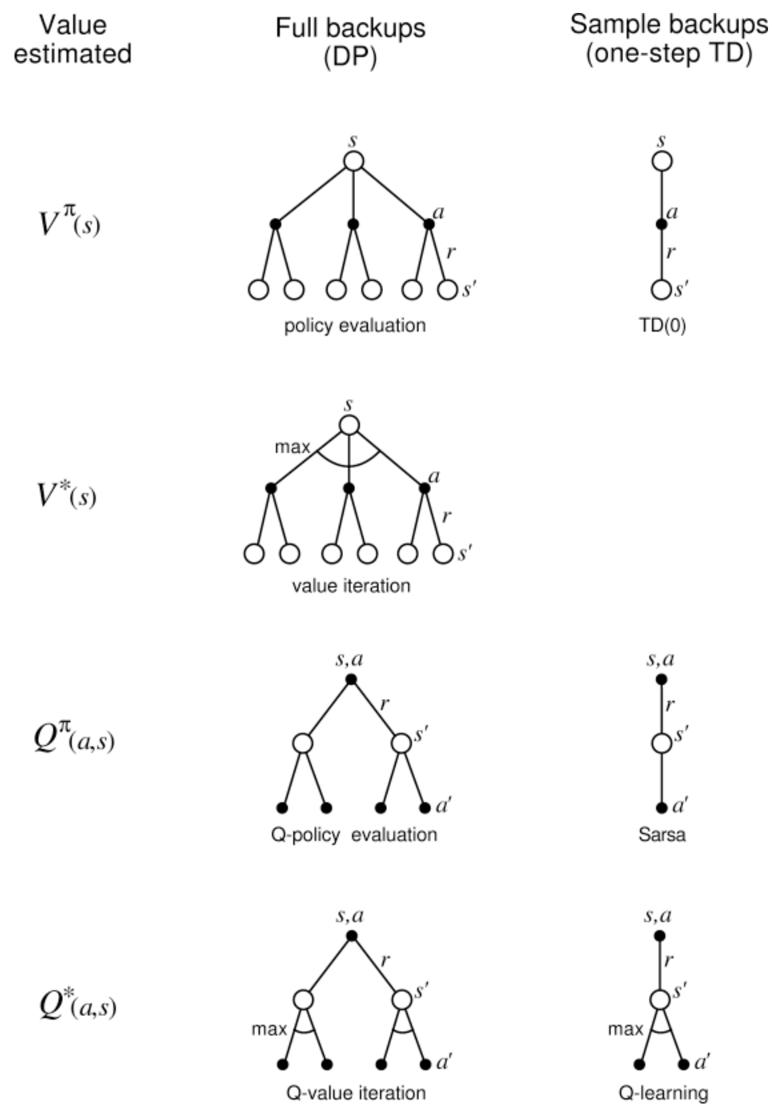
Both use N=5 backups per
environmental i



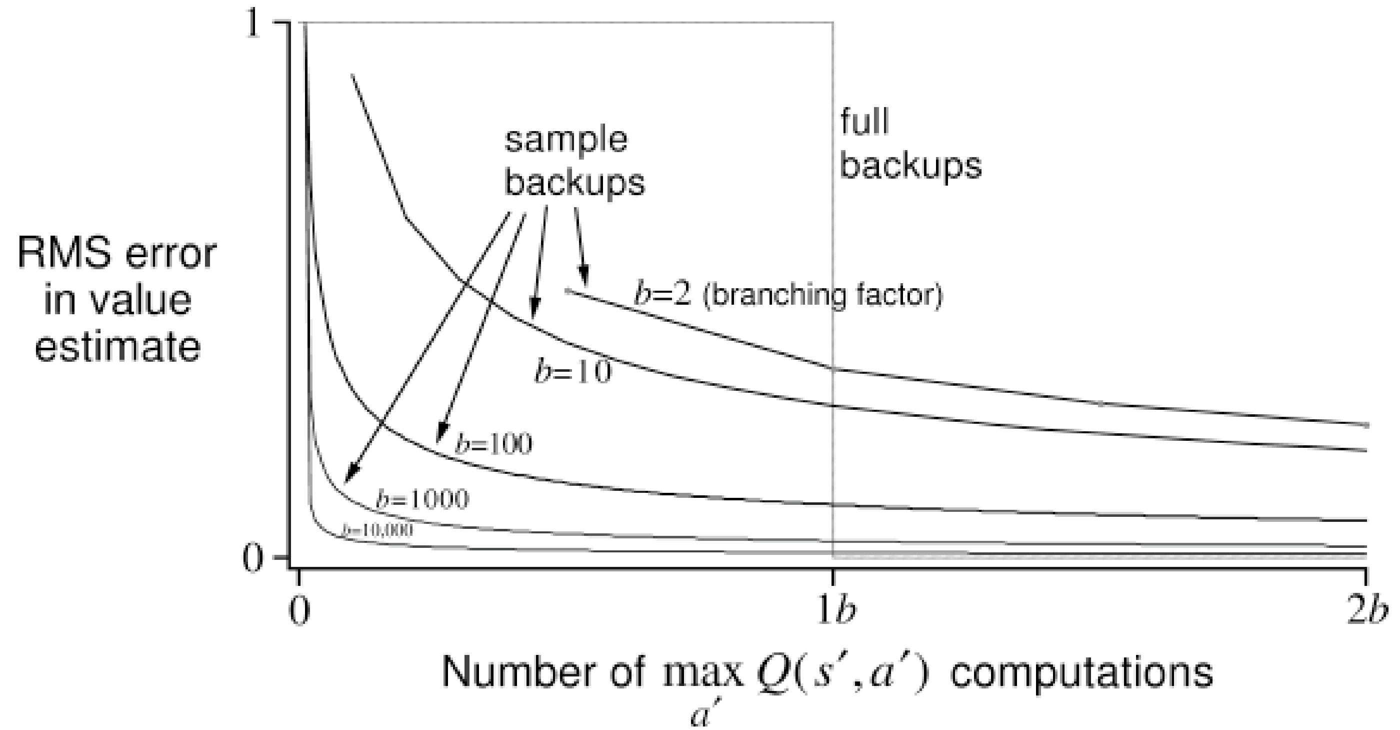
# Rod Maneuvering (Moore and Atkeson 1993)



# Full and Sample (One-Step) Backups



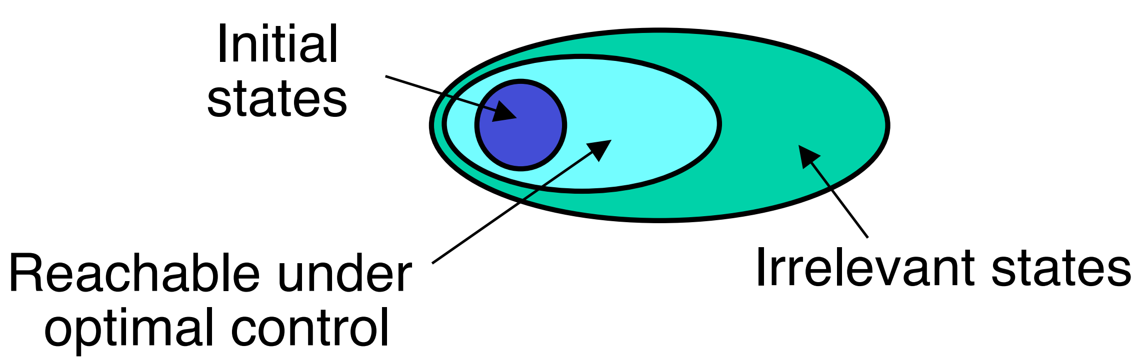
# Full vs. Sample Backups




b successor states, equally likely; initial error = 1;
assume all next states' values are correct

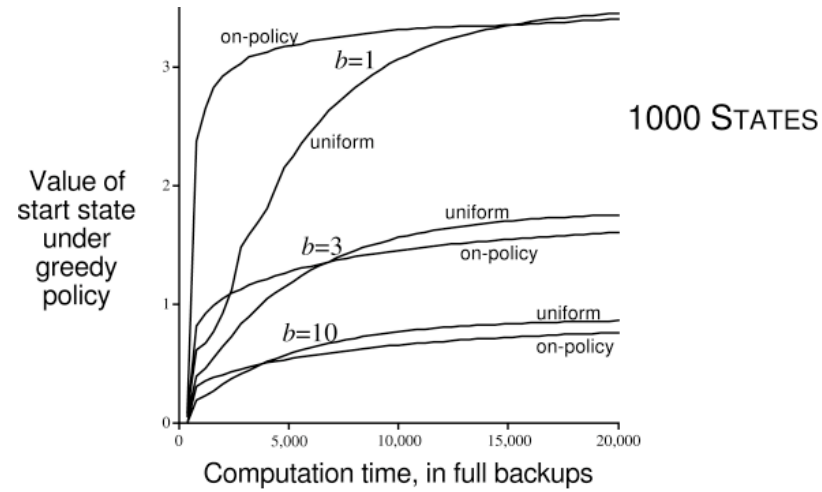
# Trajectory Sampling

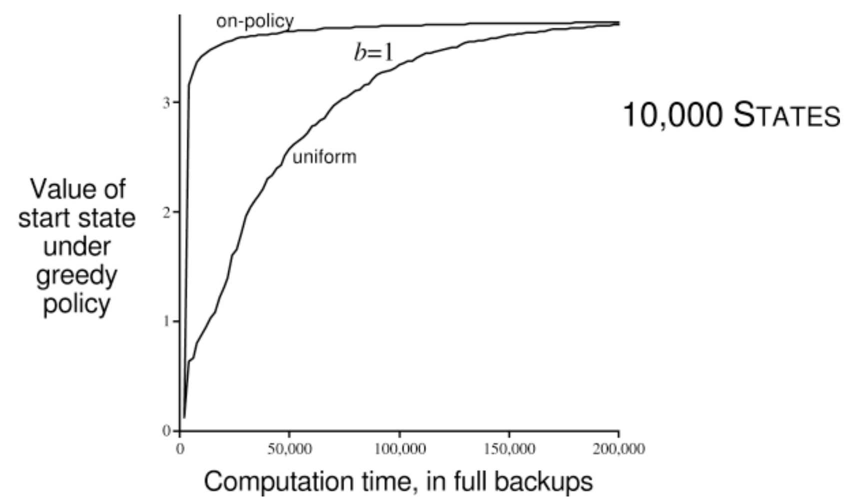
- Trajectory sampling: perform backups along simulated trajectories
- This samples from the on-policy distribution
- Advantages when function approximation is used
- Focusing of computation: can cause vast uninteresting parts of the state space to be (usefully) ignored:



# Trajectory Sampling Experiment

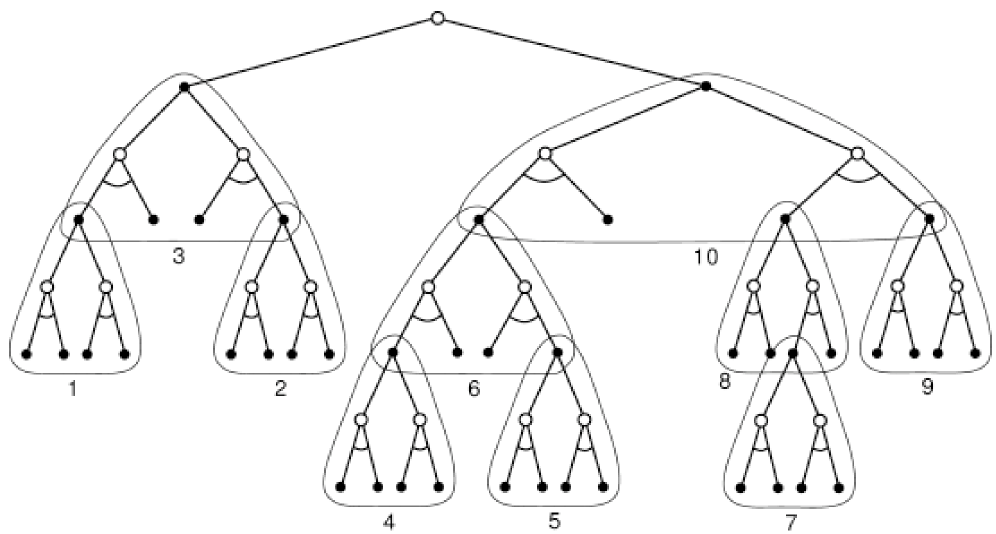
- one-step full tabular backups
- uniform: cycled through all state-action pairs
- on-policy: backed up along simulated trajectories
- 200 randomly generated undiscounted episodic tasks
- 2 actions for each state, each with b equally likely next states
- .1 prob of transition to terminal state
- expected reward on each transition selected from mean 0 variance 1 Gaussian



# Heuristic Search

- Used for action selection, not for changing a value function (=heuristic evaluation function)
- Backed-up values are computed, but typically discarded
- Extension of the idea of a greedy policy — only deeper
- Also suggests ways to select states to backup: smart focusing:



# Summary

- Emphasized close relationship between planning and learning
- Important distinction between distribution models and sample models
- Looked at some ways to integrate planning and learning
  - synergy among planning, acting, model learning
- Distribution of backups: focus of the computation
  - trajectory sampling: backup along trajectories
  - prioritized sweeping
  - heuristic search
- Size of backups: full vs. sample; deep vs. shallow