# Chapter 8: Planning and Learning

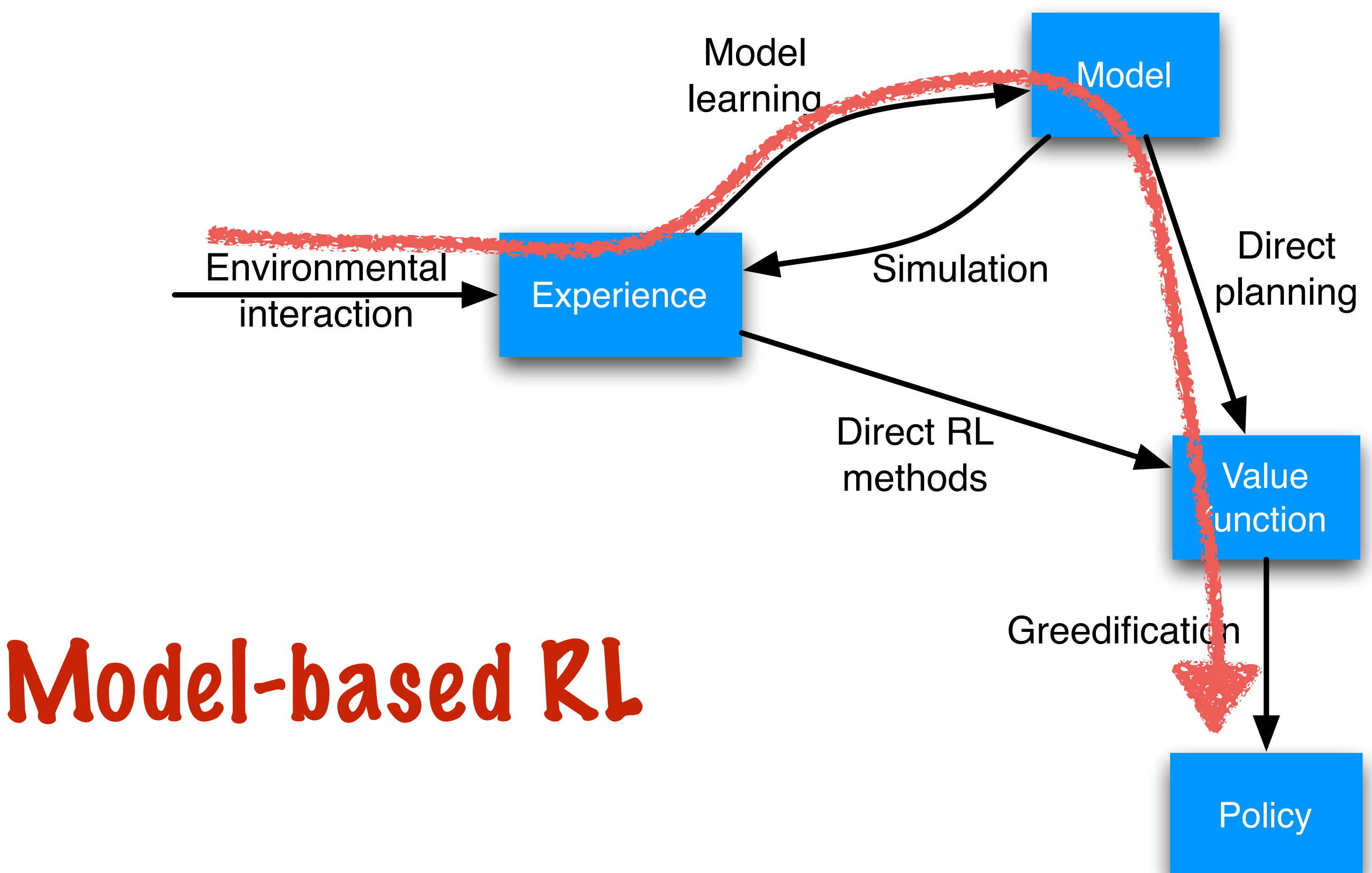
Objectives of this chapter:

- To think more generally about uses of environment models
- Integration of (unifying) planning, learning, and execution
- “Model-based reinforcement learning”

# DP with Distribution models

- In Chapter 4, we assumed access to a model of the world
  - These models describe all possibilities and their probabilities
  - We call them Distribution models
    - e.g., $p(s', r \mid s, a)$ for all $s, a, s', r$
- In Dynamic Programing we sweep the states:
  - in each state we consider all the possible rewards and next state values
  - the model describes the next states and rewards and their associated probabilities
  - using these values to update the value function
- In Policy Iteration, we then improve the policy using the computed value function

# Paths to a policy



# Sample Models

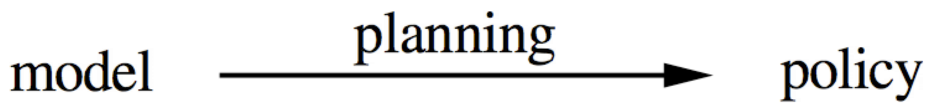
- Model: anything the agent can use to predict how the environment will respond to its actions
- Sample model, a.k.a. a simulation model
  - produces sample experiences for given *s*, *a*
    - – sampled according to the probabilities
  - allows reset, exploring starts
  - often much easier to come by
- Both types of models can be used mimic or simulate experience: to produce hypothetical experience

# Models

- Consider modeling the sum of two dice
  - A *distribution model* would produce all possible sums and their probabilities of occurring
  - A *sample model* would produce an individual sum drawn according to the correct probability distribution
- When we solved the Gambler's problem with value iteration, we used the distribution model
- When you solved the Gambler's problem with Monte-Carlo, you implemented a sample model in your environment code

# Planning

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




- We take the following (unusual) view:
  - update value functions using both real and simulated experience
  - all state-space planning methods involve computing value functions, either explicitly or implicitly
  - they all apply updates from simulated experience

# Planning Cont.

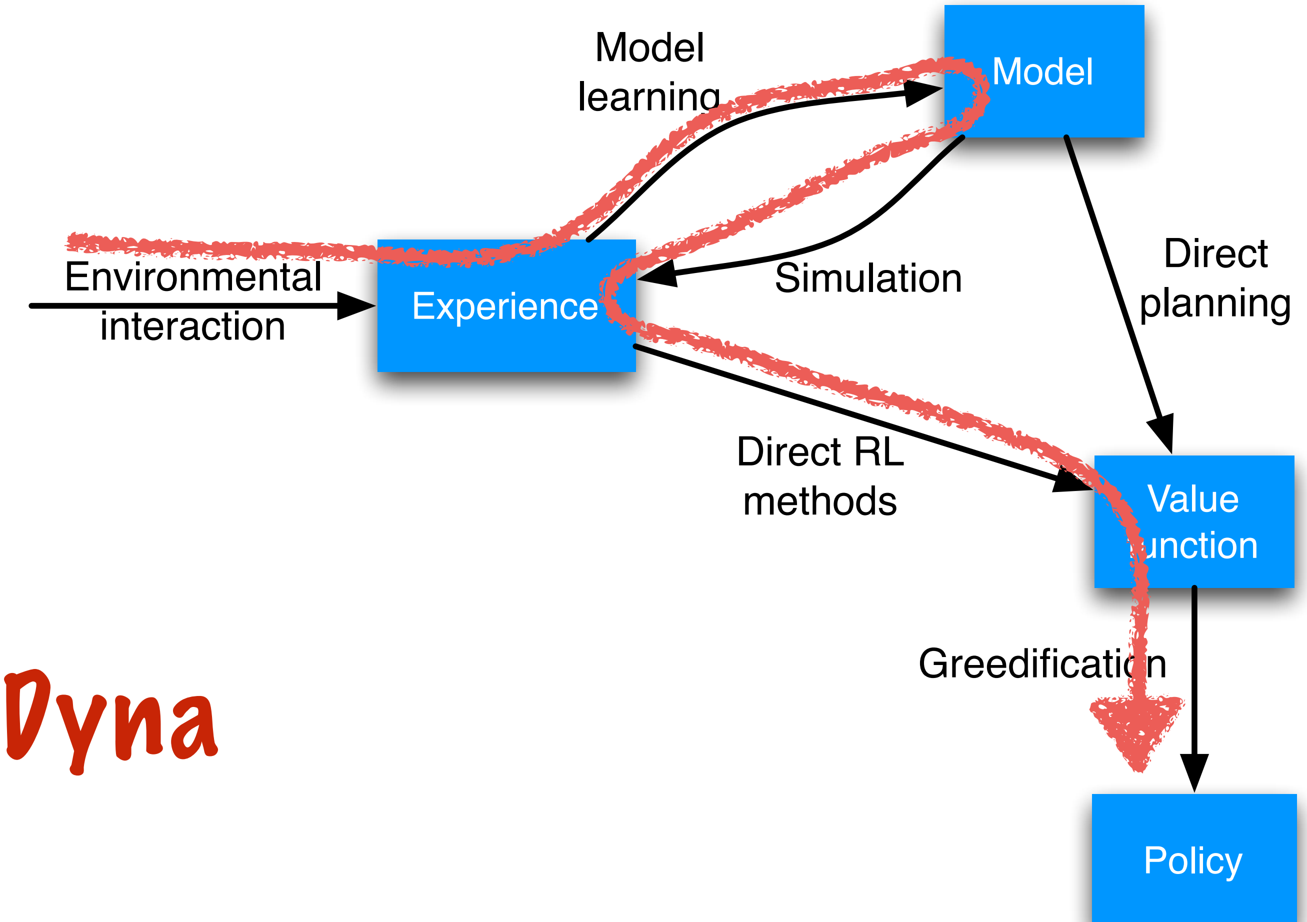
- Classical DP methods are state-space planning methods
- Heuristic search methods are state-space planning methods
- A planning method based on Q-learning:

**Random-sample one-step tabular Q-planning**

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 reward, $R$, and a sample next state, $S'$
3. Apply one-step tabular Q-learning to $S, A, R, S'$:
   $Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma \max_a Q(S', a) - Q(S, A)\big]$

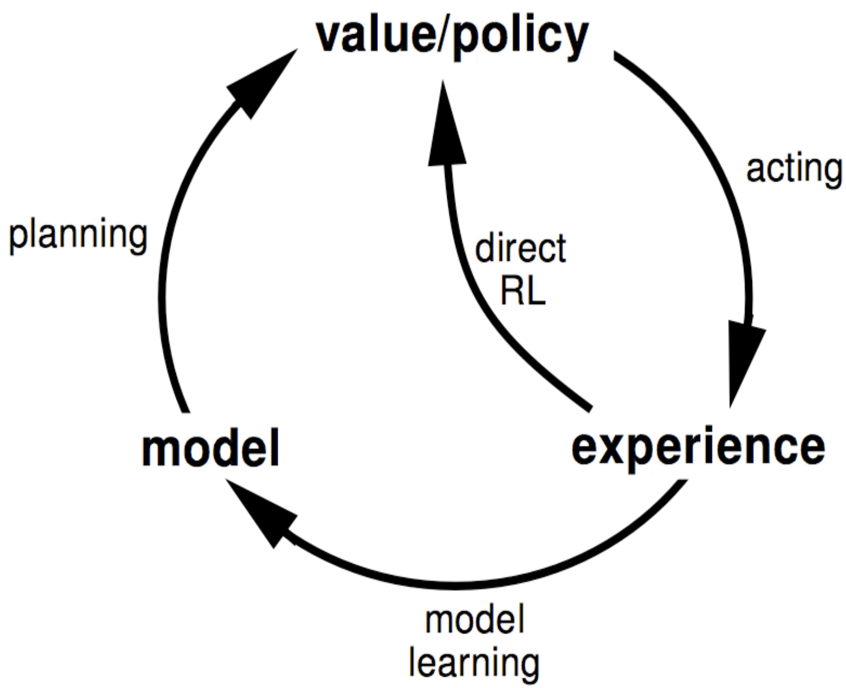
**Environment program**
**Experiment program**
**Agent program**

# Paths to a policy



# 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. Here, we call it planning.



# Direct (model-free) vs. Indirect (model-based) RL

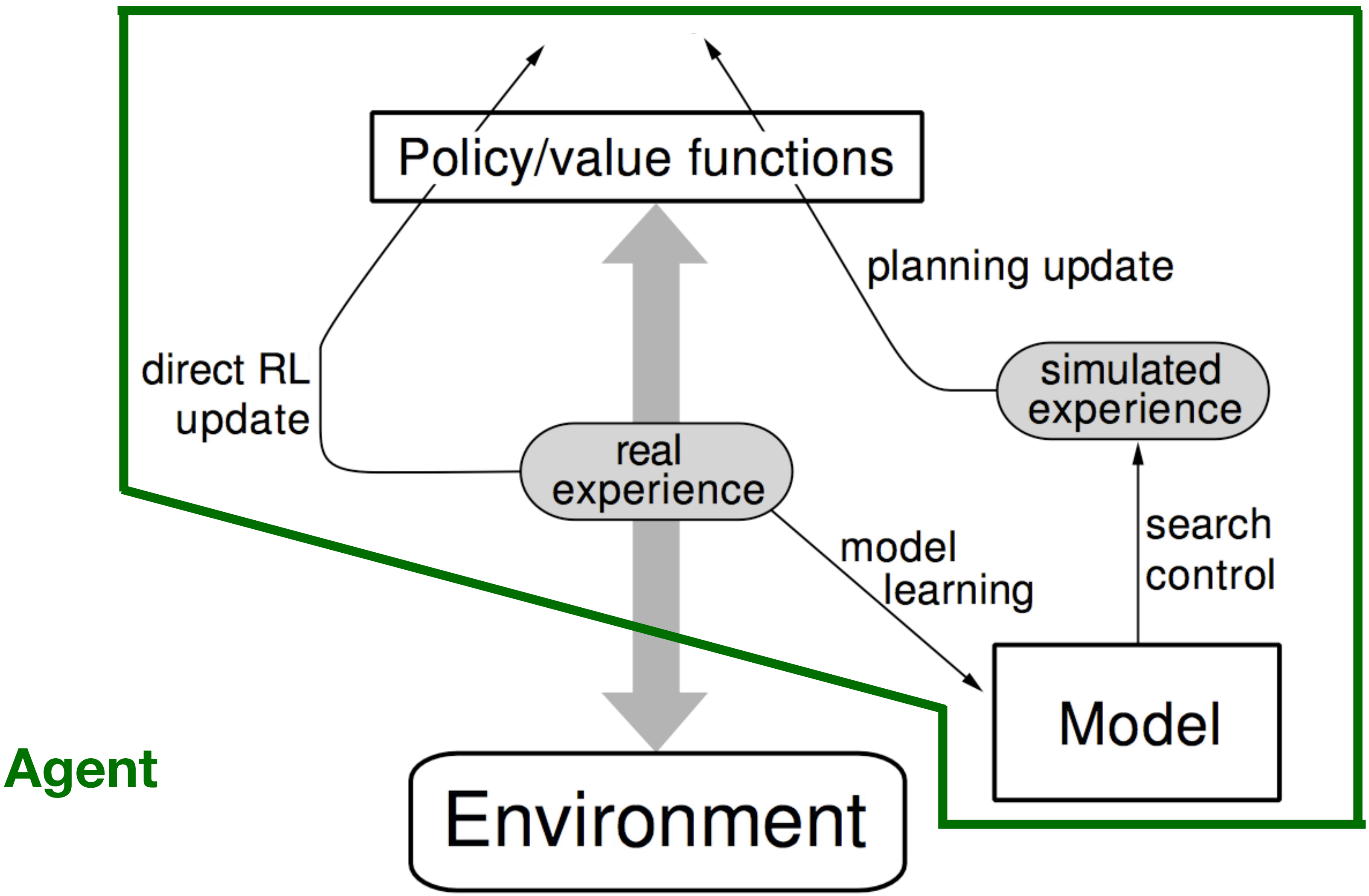
- Direct methods
  - simpler
  - not affected by bad models

- Indirect methods:
  - make fuller use of experience: get better policy with fewer environment interactions

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



# 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) $A \leftarrow \varepsilon$-greedy$(S, Q)$
(c) Execute action $A$; observe resultant reward, $R$, and state, $S'$
(d) $Q(S,A) \leftarrow Q(S,A) + \alpha[R + \gamma \max_a Q(S',a) - Q(S,A)]$ ← **direct RL**
(e) $Model(S,A) \leftarrow R, S'$ (assuming deterministic environment) ← **model learning**
(f) Repeat $n$ times: ← **planning**
$S \leftarrow$ random previously observed state
$A \leftarrow$ random action previously taken in $S$
$R, S' \leftarrow Model(S,A)$
$Q(S,A) \leftarrow Q(S,A) + \alpha[R + \gamma \max_a Q(S',a) - Q(S,A)]$

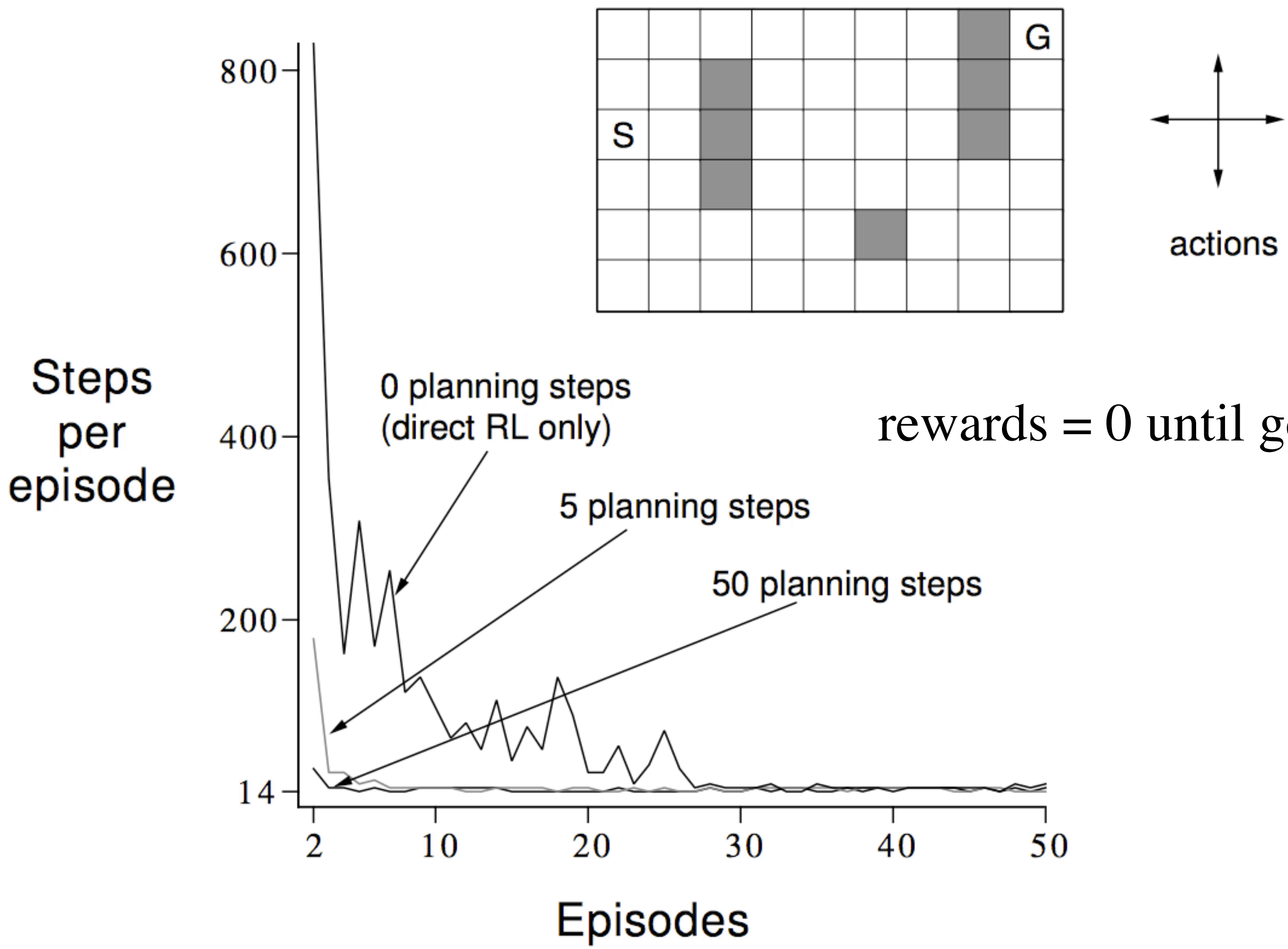
# A simple maze: problem description

- 47 states, 4 actions, deterministic dynamics
- Obstacles and walls
- Rewards are 0 except +1 for transition into goal state
- $\gamma = 0.95$, discounted episodic task

- Agent parameters:
  - $\alpha = 0.1$, $\epsilon = 0.1$
  - Initial action-values were all zero

- Let's compare one-step tabular Q-learning and Dyna-Q with different values of n

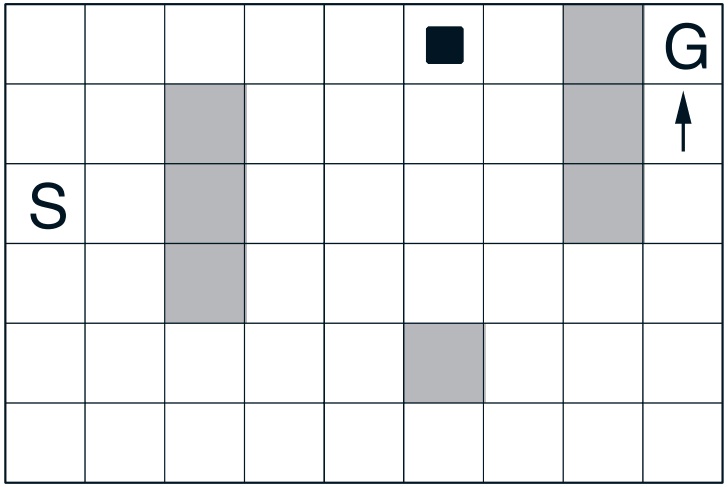
# Dyna-Q on a Simple Maze



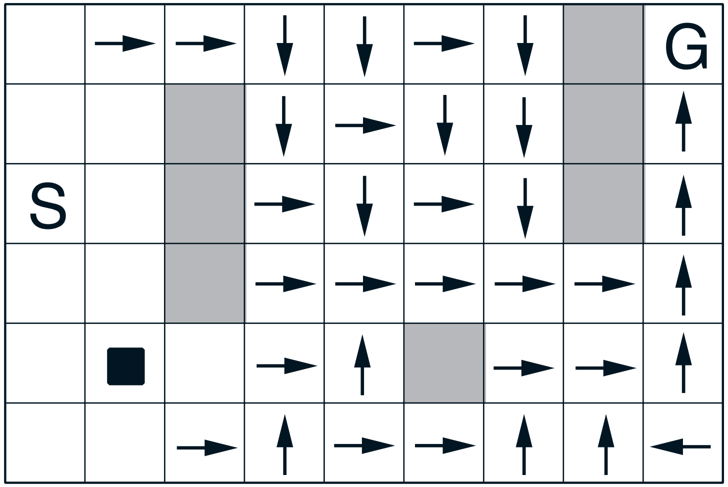

rewards = 0 until goal, when =1

# Dyna-Q Snapshots: Midway in 2nd Episode

WITHOUT PLANNING ($n$=0)




WITH PLANNING ($n$=50)

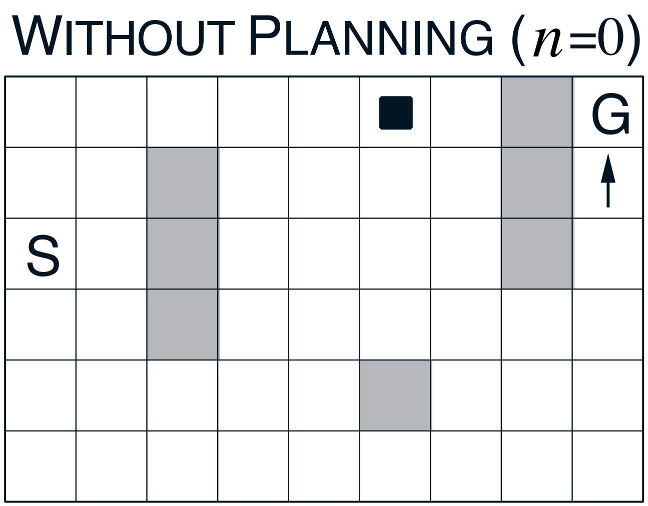


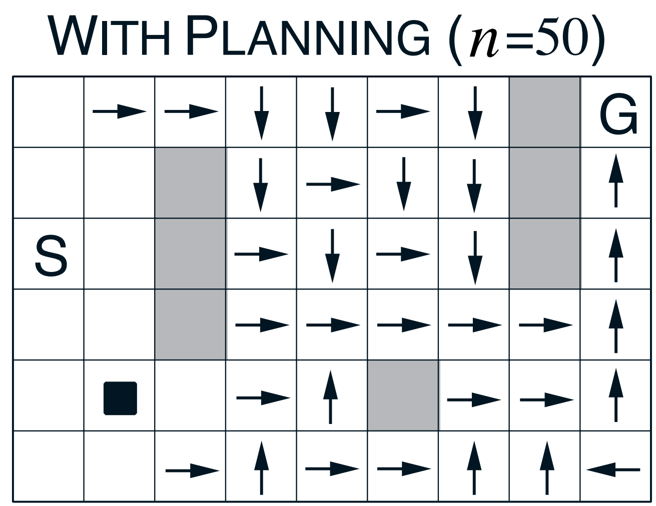
# The conflict between exploration and exploitation

- Exploration in planning: trying actions that improve the model
  - Make it more accurate
  - Make it a better match with the environment
  - Proactively discover when the model is wrong
- Exploitation: behaving optimally with respect to the current model
- Simple heuristics can be effective

# Prioritizing Search Control

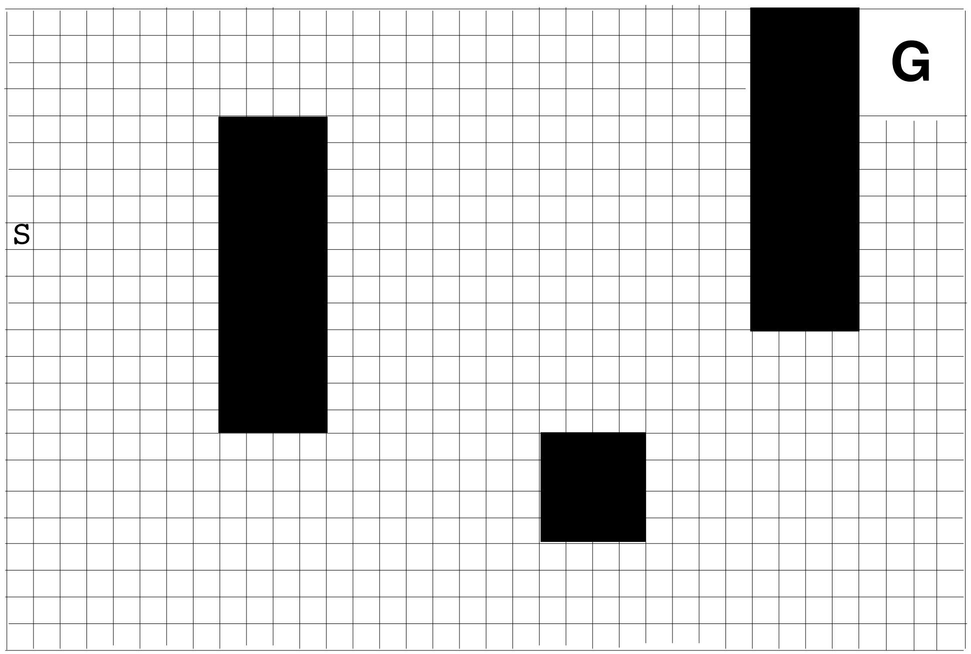
- Consider the second episode in the Dyna maze
  - The agent has successfully reached the goal once…

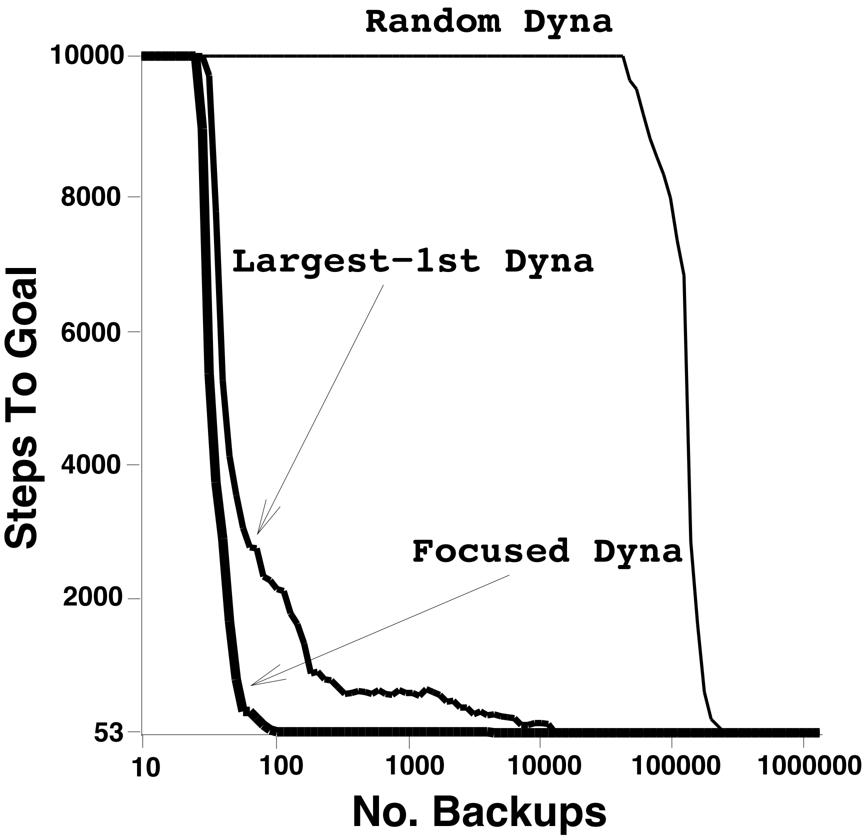



- In larger problems, the number of states is so large that unfocused planning would be extremely inefficient

# Large maze and random search control




(Peng and Williams, 1993)

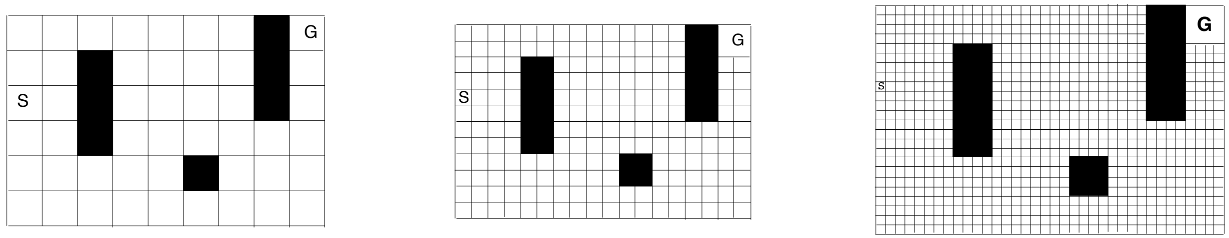
# Prioritized Sweeping

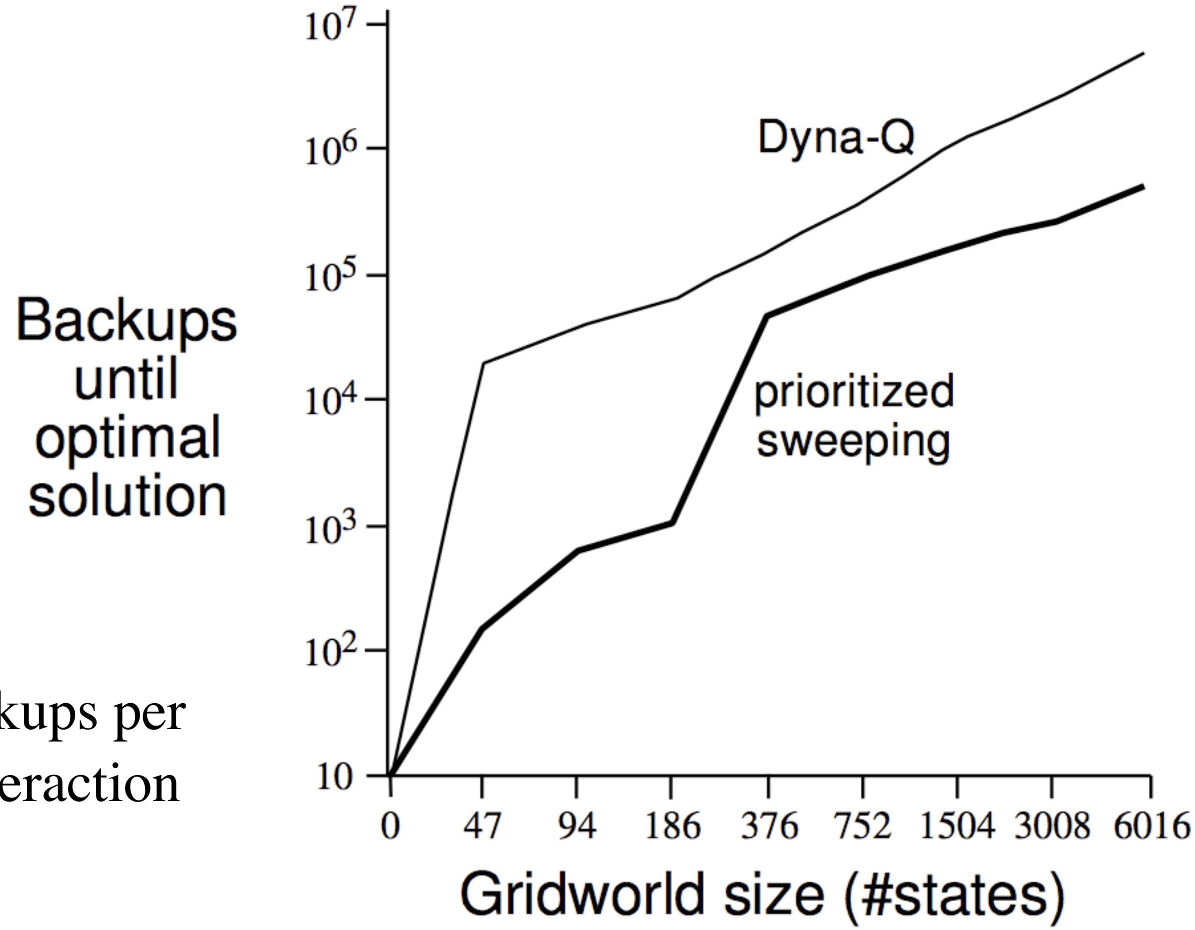
- Which states or state-action pairs should be generated during planning?
- Work backwards from states whose values have just changed:
  - Maintain a queue of state-action pairs whose values would change a lot if backed up, prioritized by the size of the change
  - When a new backup occurs, insert predecessors according to their priorities
  - Always perform backups from first in queue
- Moore & Atkeson 1993; Peng & Williams 1993
- improved by McMahan & Gordon 2005; Van Seijen 2013

# 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 reward, $R$, and state, $S'$
(d) $Model(S, A) \leftarrow R, S'$
(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:
$S, A \leftarrow first(PQueue)$
$R, S' \leftarrow Model(S, A)$
$Q(S, A) \leftarrow Q(S, A) + \alpha[R + \gamma \max_a Q(S', a) - Q(S, A)]$
Repeat, for all $\bar{S}, \bar{A}$ predicted to lead to $S$:
$\bar{R} \leftarrow$ predicted reward for $\bar{S}, \bar{A}, S$
$P \leftarrow |\bar{R} + \gamma \max_a Q(S, a) - Q(\bar{S}, \bar{A})|$.
if $P > \theta$ then insert $\bar{S}, \bar{A}$ into $PQueue$ with priority $P$

# Prioritized Sweeping vs. Dyna-Q



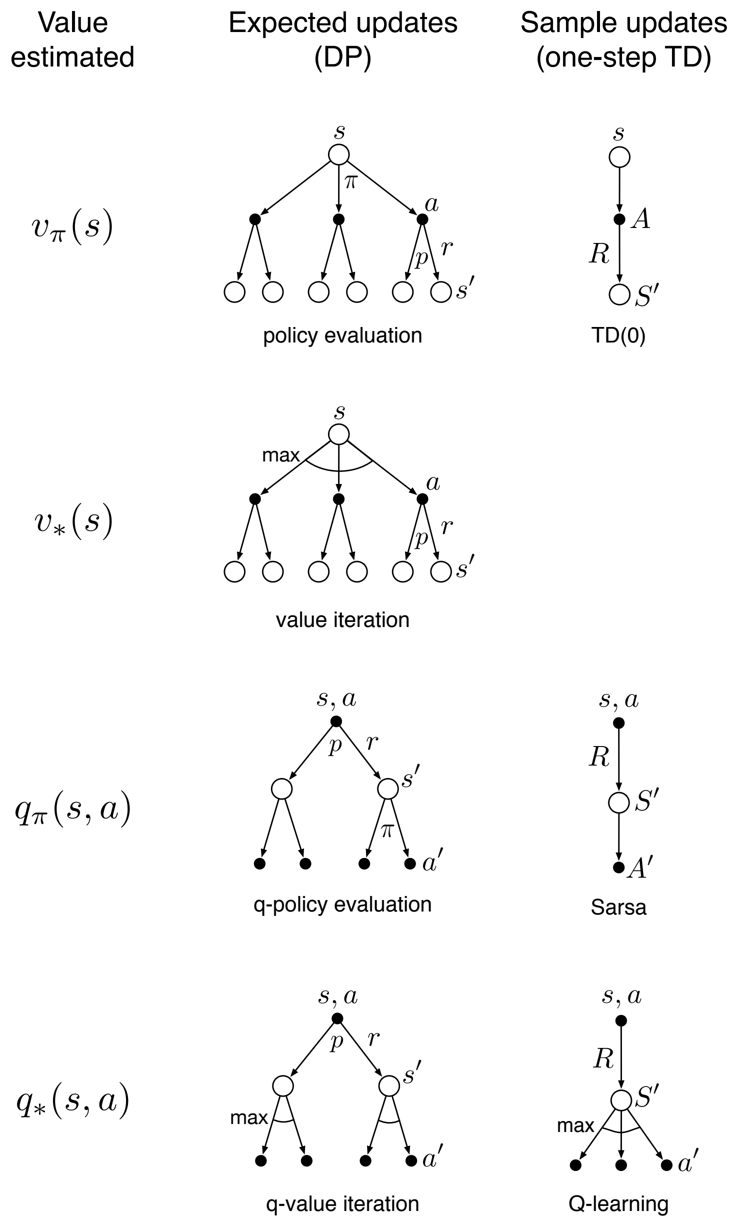




Both use $n$=5 backups per environmental interaction

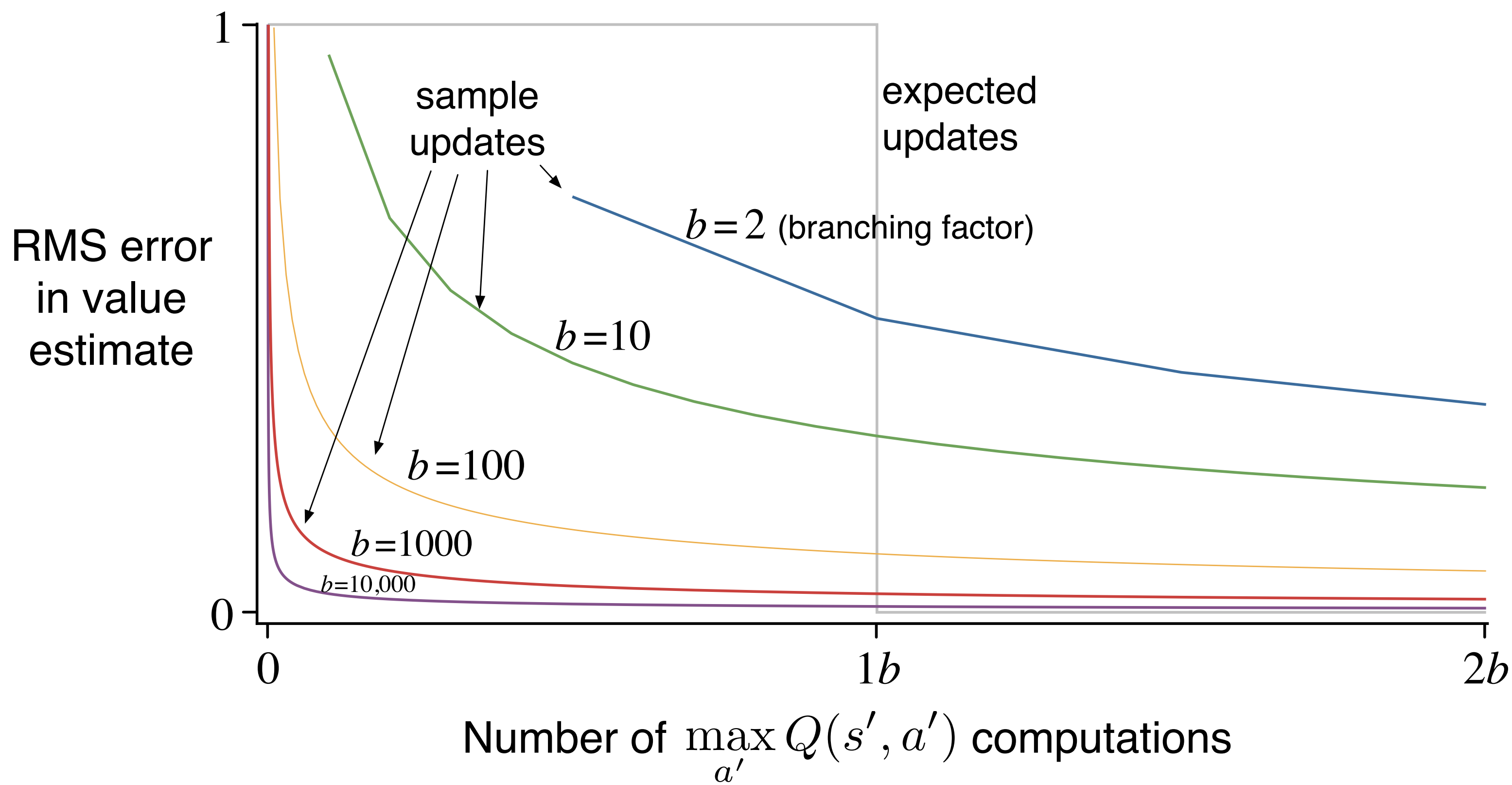
# Improved Prioritized Sweeping with Small Backups

- Planning is a form of state-space search
  - a massive computation which we want to control to maximize its efficiency
- Prioritized sweeping is a form of search control
  - focusing the computation where it will do the most good
- But can we focus better?
- Can we focus more tightly?
- Small backups are perhaps the smallest unit of search work
  - and thus permit the most flexible allocation of effort

# Expected and Sample Backups (One-Step)



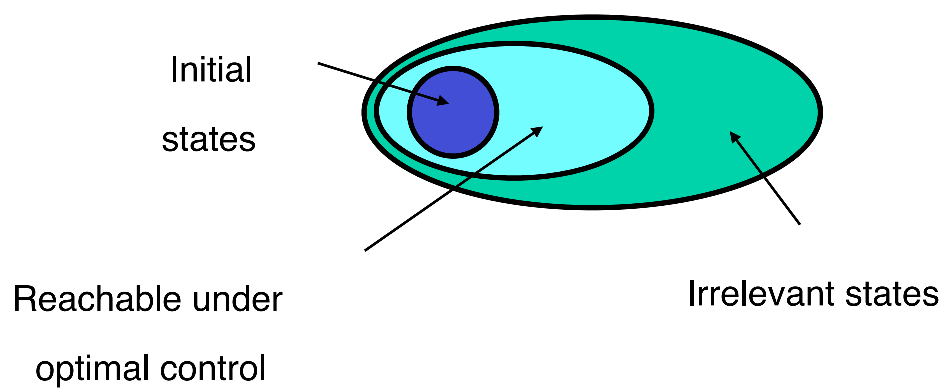
# Full vs. Sample Backups




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

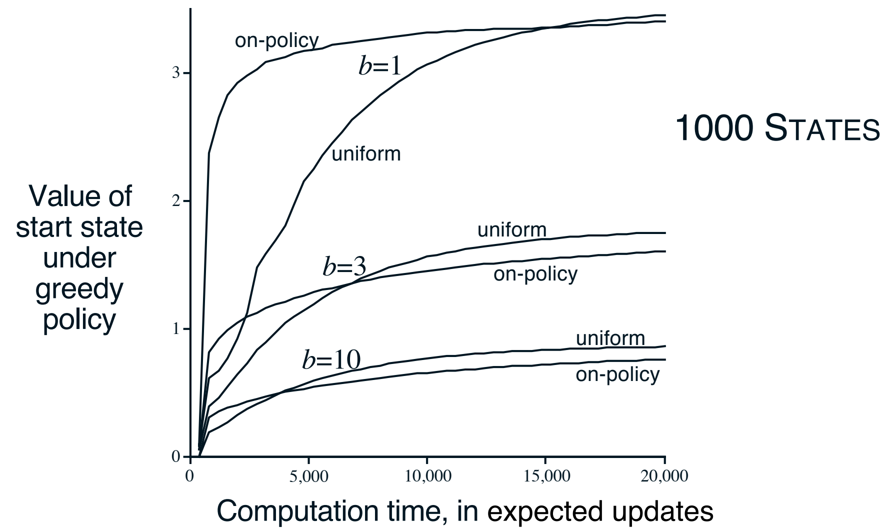
# Trajectory Sampling

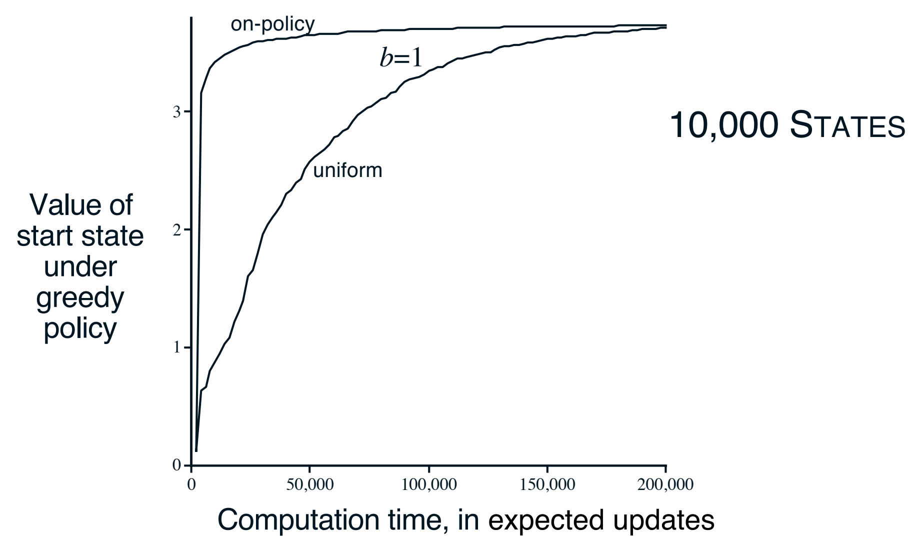
- Trajectory sampling: perform updates along simulated trajectories
- This samples from the on-policy distribution
- Advantages when function approximation is used (Part II)
- Focusing of computation:
  can cause vast uninteresting parts of the state space to be ignored:



# Trajectory Sampling Experiment

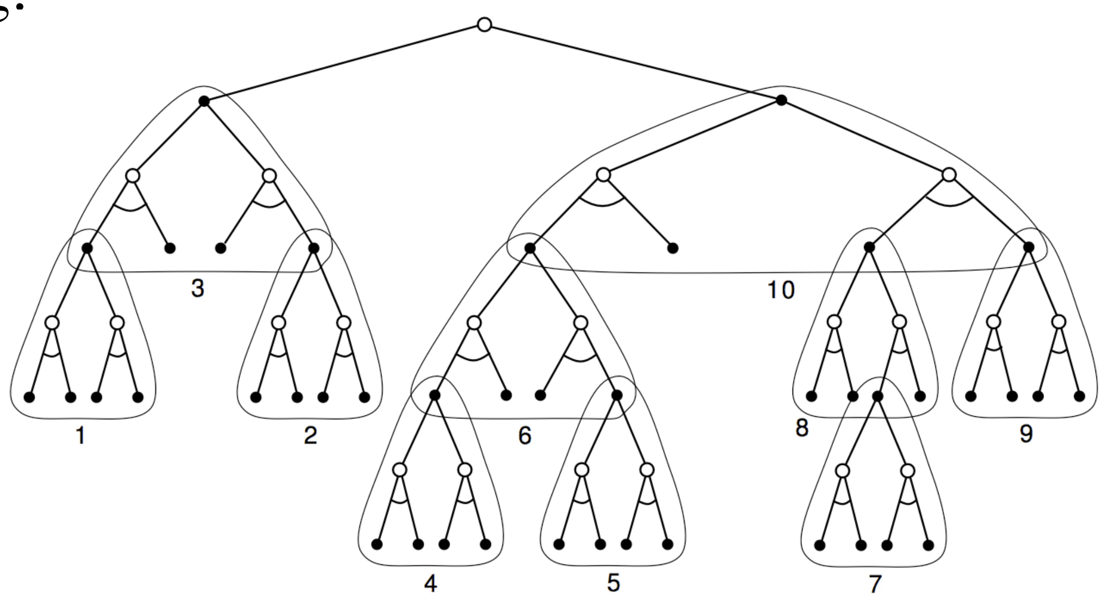
- one-step full tabular updates
- uniform: cycled through all state-action pairs
- on-policy: backed up along simulated trajectories
- 200 randomly generated undiscounted episodic tasks
- 2 actions for each state, each with $b$ equally likely next states
- 0.1 prob of transition to terminal state
- expected 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 of Chapter 8

- 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
  - prioritized sweeping
  - small backups
  - sample backups
  - trajectory sampling: backup along trajectories
  - heuristic search
- Size of backups: full/sample; deep/shallow