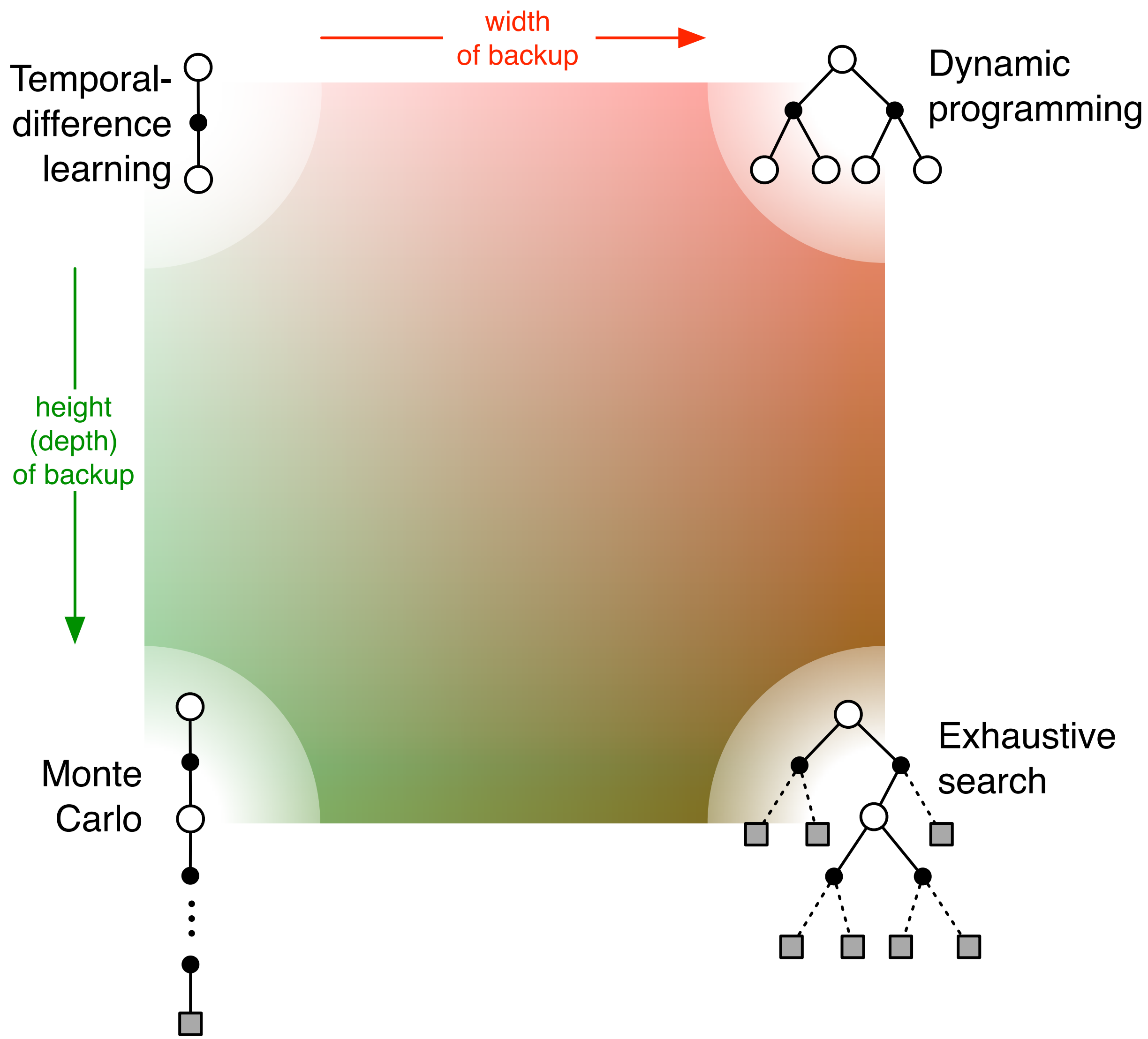
Unified View



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”

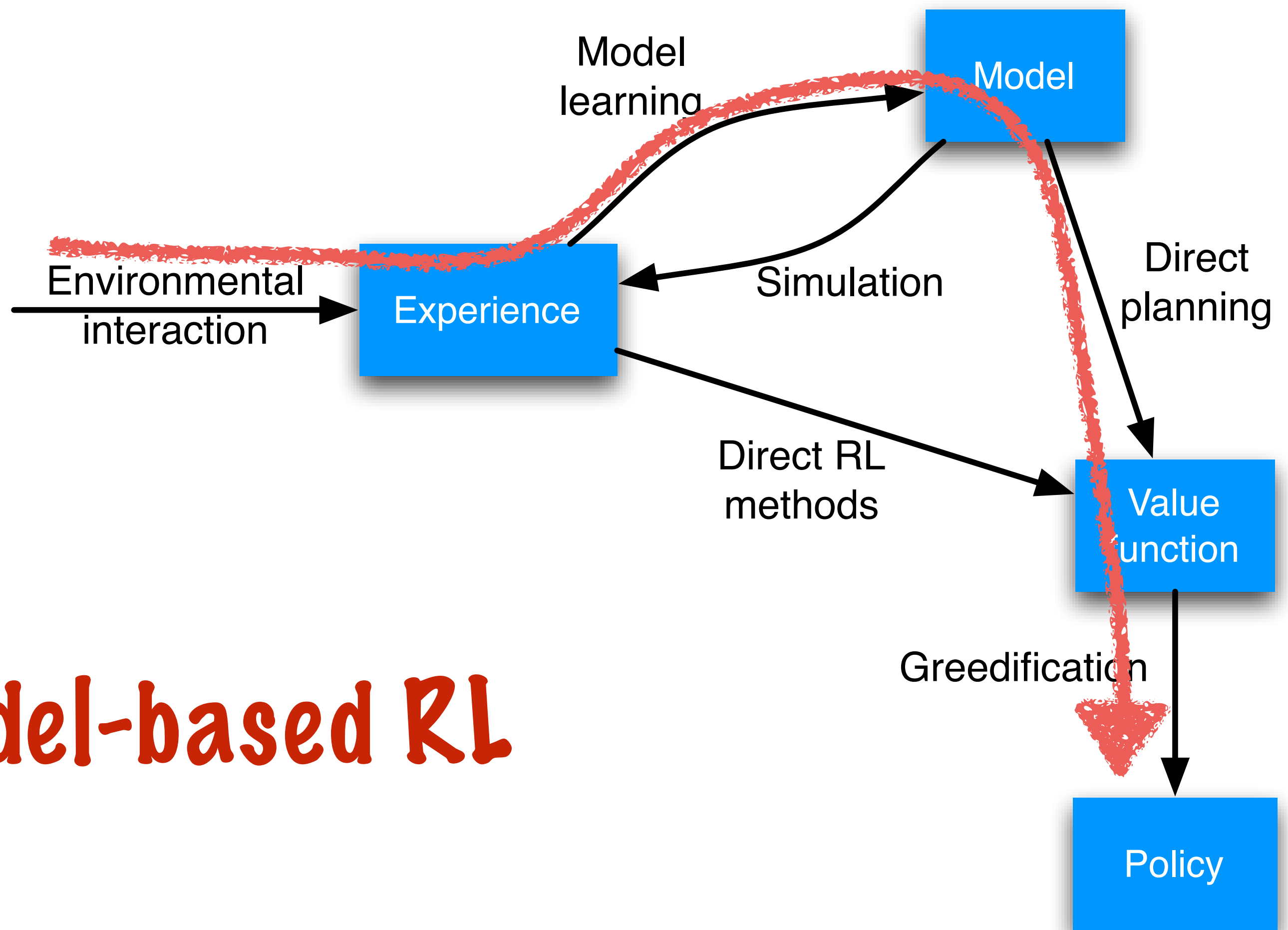
DP with Distribution models

- 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

Chapter 8: Planning and Learning

- Today we will learn about other ways to use models to compute policies
- … and learn about how those models can be learned

Paths to a policy



Model-based RL

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

model $\xrightarrow{\text{planning}}$ 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

model $\longrightarrow$ simulated experience $\xrightarrow{\text{updates}}$ values $\longrightarrow$ policy

Planning Cont.

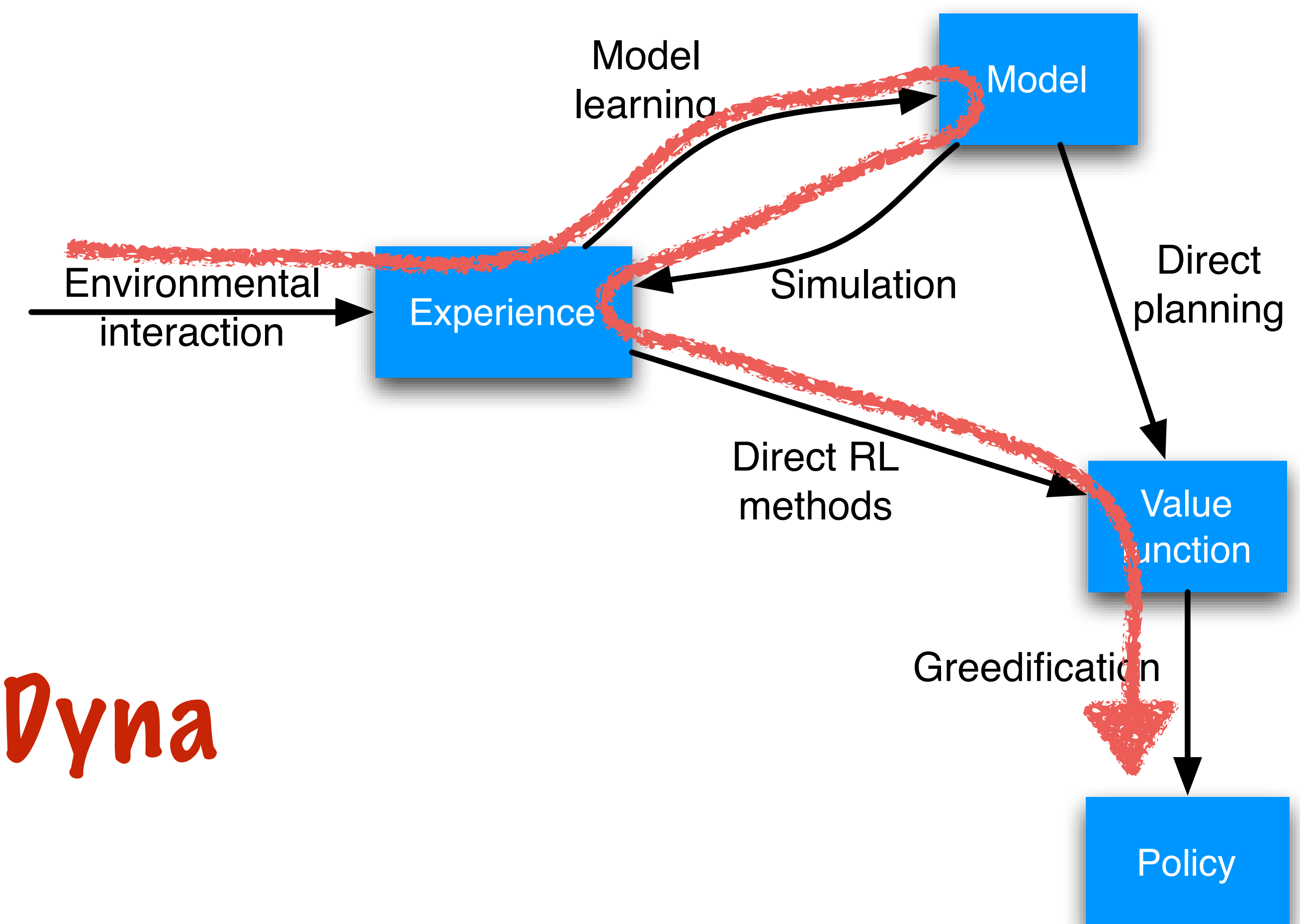
- Classical DP methods are state-space planning methods
- Heuristic search methods are state-space planning methods
- A planning method based on Q-learning:

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':
   $Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma \max_a Q(S', a) - Q(S, A)\big]$

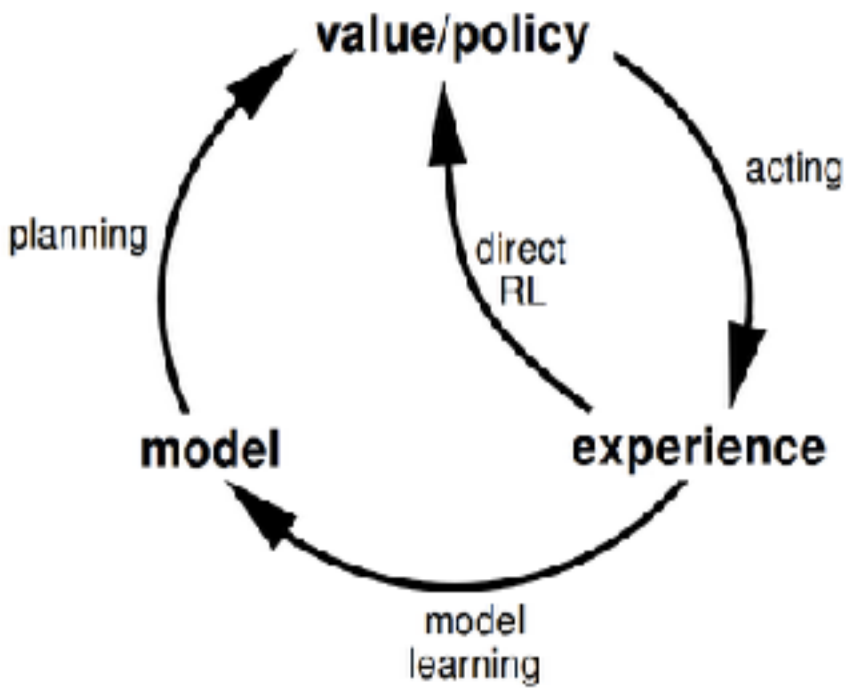
Environment program
Experiment program
Agent program

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.



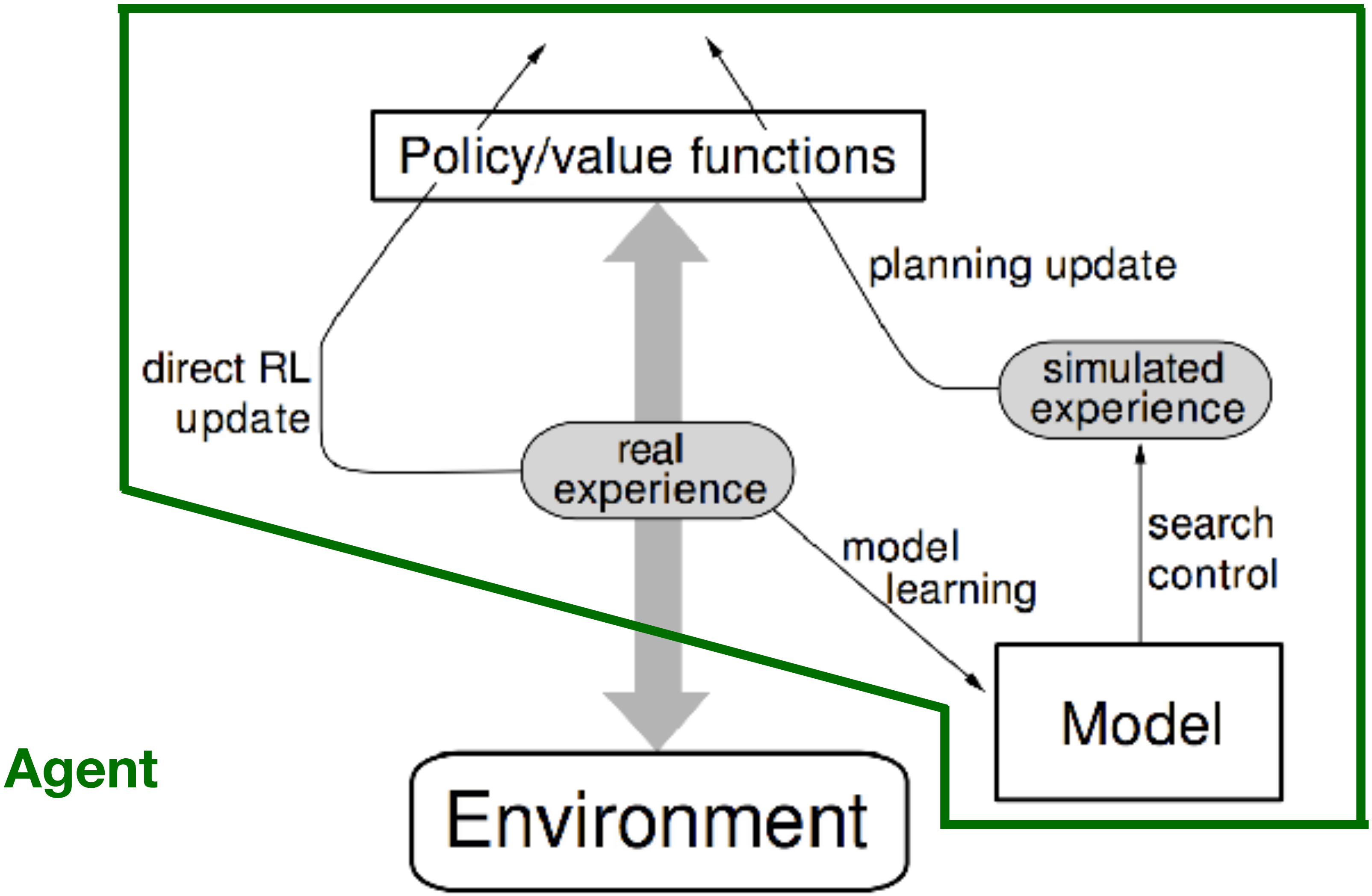
Direct (model-free) vs. Indirect (model-based) RL

- 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:
$S \leftarrow$ random previously observed state
$A \leftarrow$ random action previously taken in S **planning**
$R, S' \leftarrow Model(S,A)$
$Q(S,A) \leftarrow Q(S,A) + \alpha[R + \gamma \max_a Q(S', a) - Q(S,A)]$

Demo

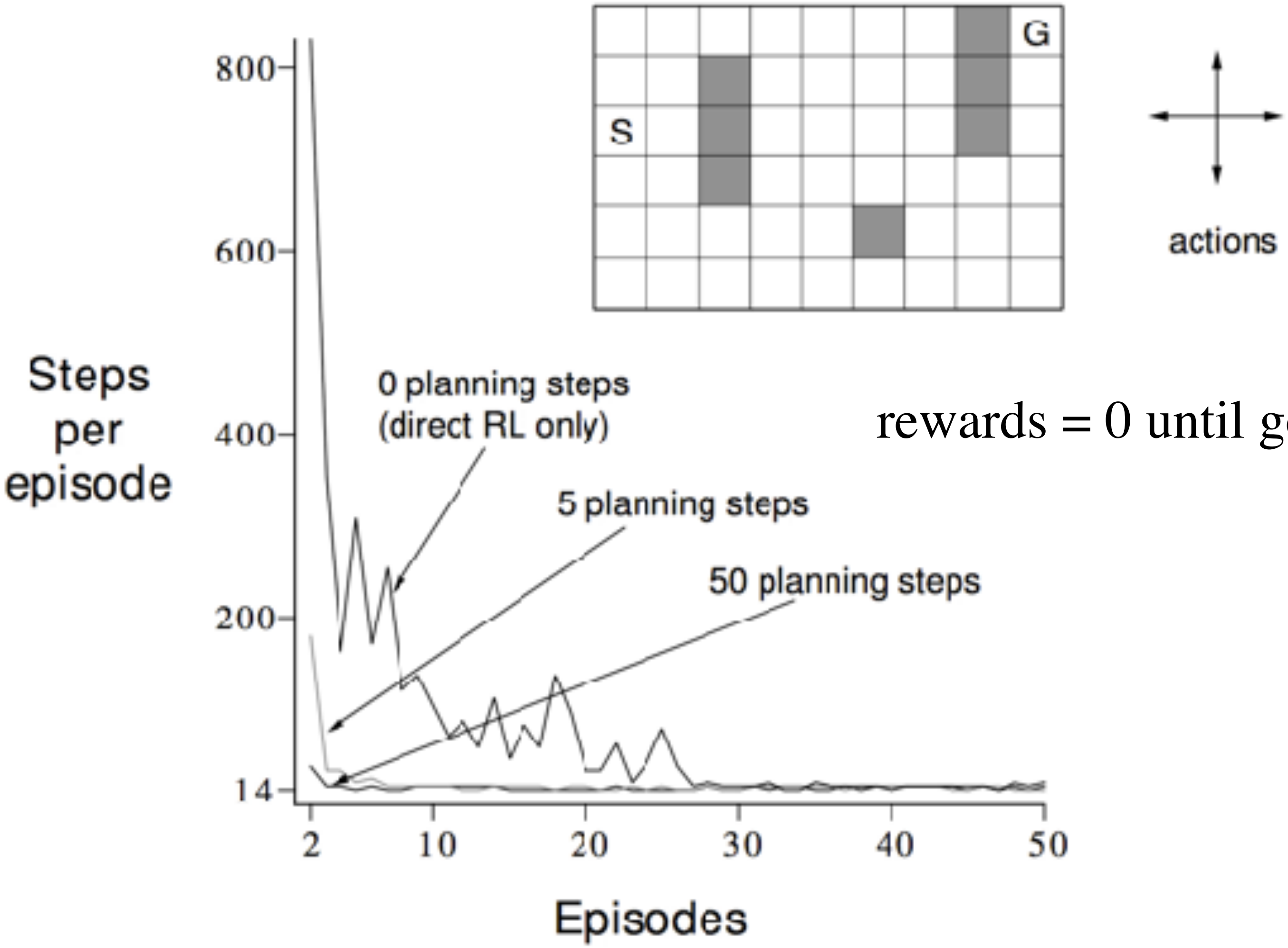
A simple maze: problem description

- 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

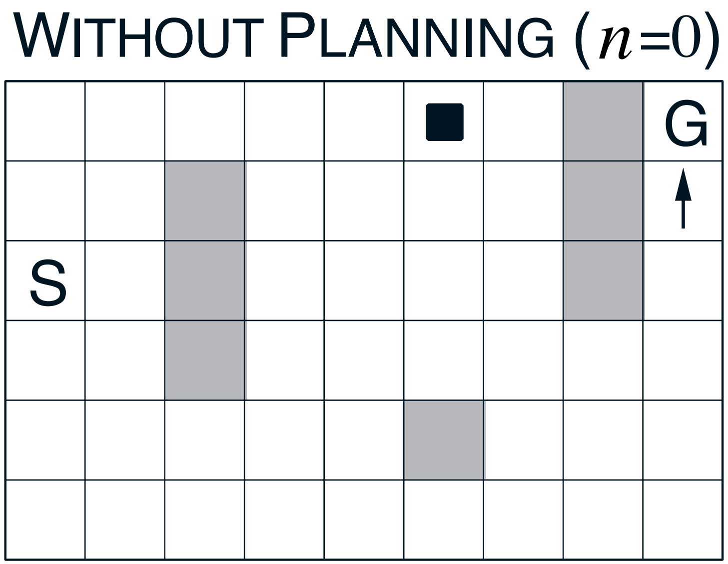
- Let's compare one-step tabular Q-learning and Dyna-Q with different values of n

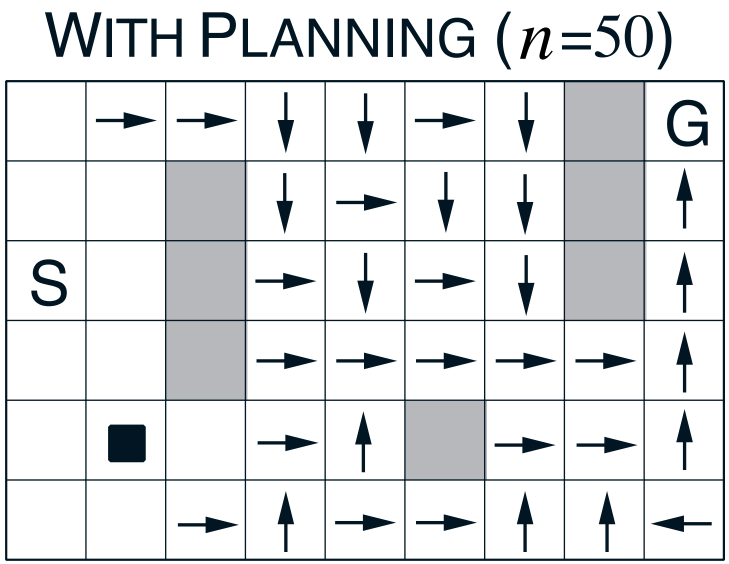
Dyna-Q on a Simple Maze



rewards = 0 until goal, when =1

Dyna-Q Snapshots: Midway in 2nd Episode





Implementation details

- Notice during the demo, that the one-step Q-learning agent and Dyna-Q agent appeared to be equally reactive
- Updating the value function and selecting a new action is very fast
  - Thus, there is usually some time left over
  - We can use that time to run a planning loop
    - Planning with n=5 helps a lot
- What are other ways we could integrate planning with learning and acting?
- Planning of this form is *anytime*

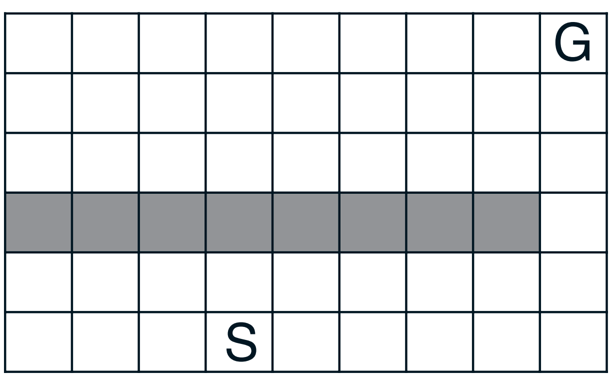
When the model is wrong

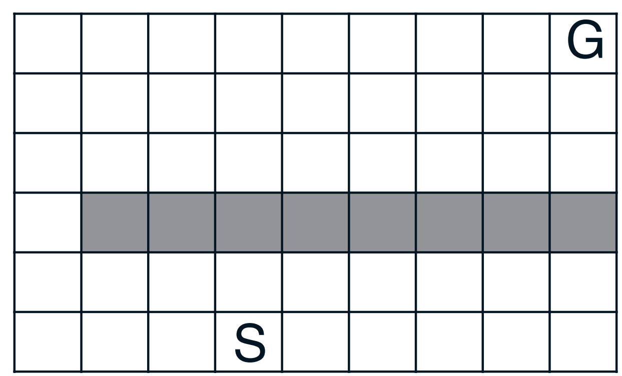
- So far we have considered models, that:
  - Start empty and are always updated with correct info.
- The model can be wrong! Because:
  - environment might be stochastic and we have only seen a few samples
  - the environment has changed
- Planning is likely to compute a suboptimal policy in this case

- Imagine the world changed, and:
  - The suboptimal policy leads to discovery and correction of the modeling error

Blocking Maze problem

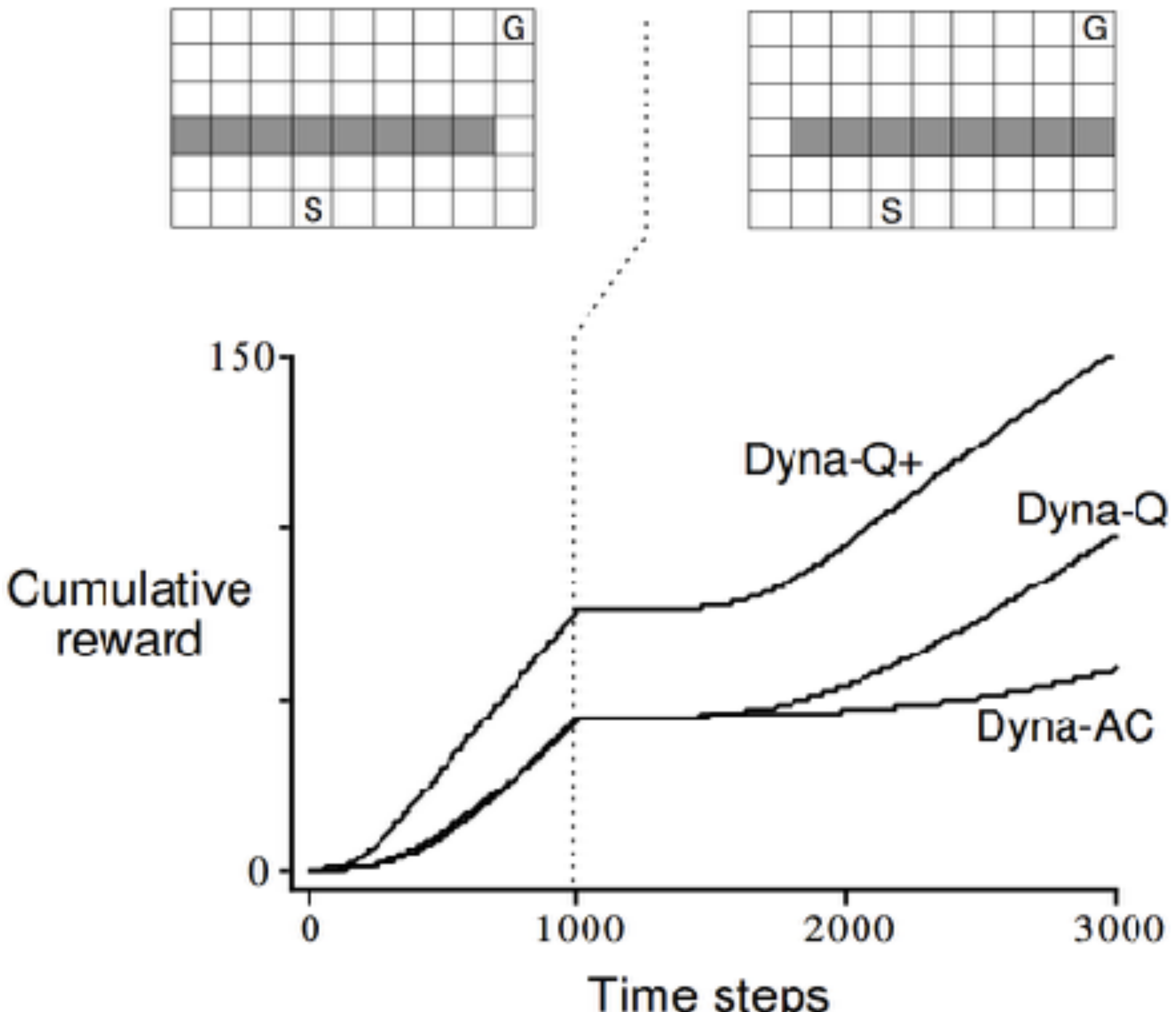
- Consider the Gridworld with a partition wall
- Dyna-Q can find the policy for reaching the goal state
- Then after 1000 time steps, we change the world:
  - we block the path of the existing planned policy
  - and open up a new path





When the Model is Wrong: Blocking Maze

The changed environment is harder

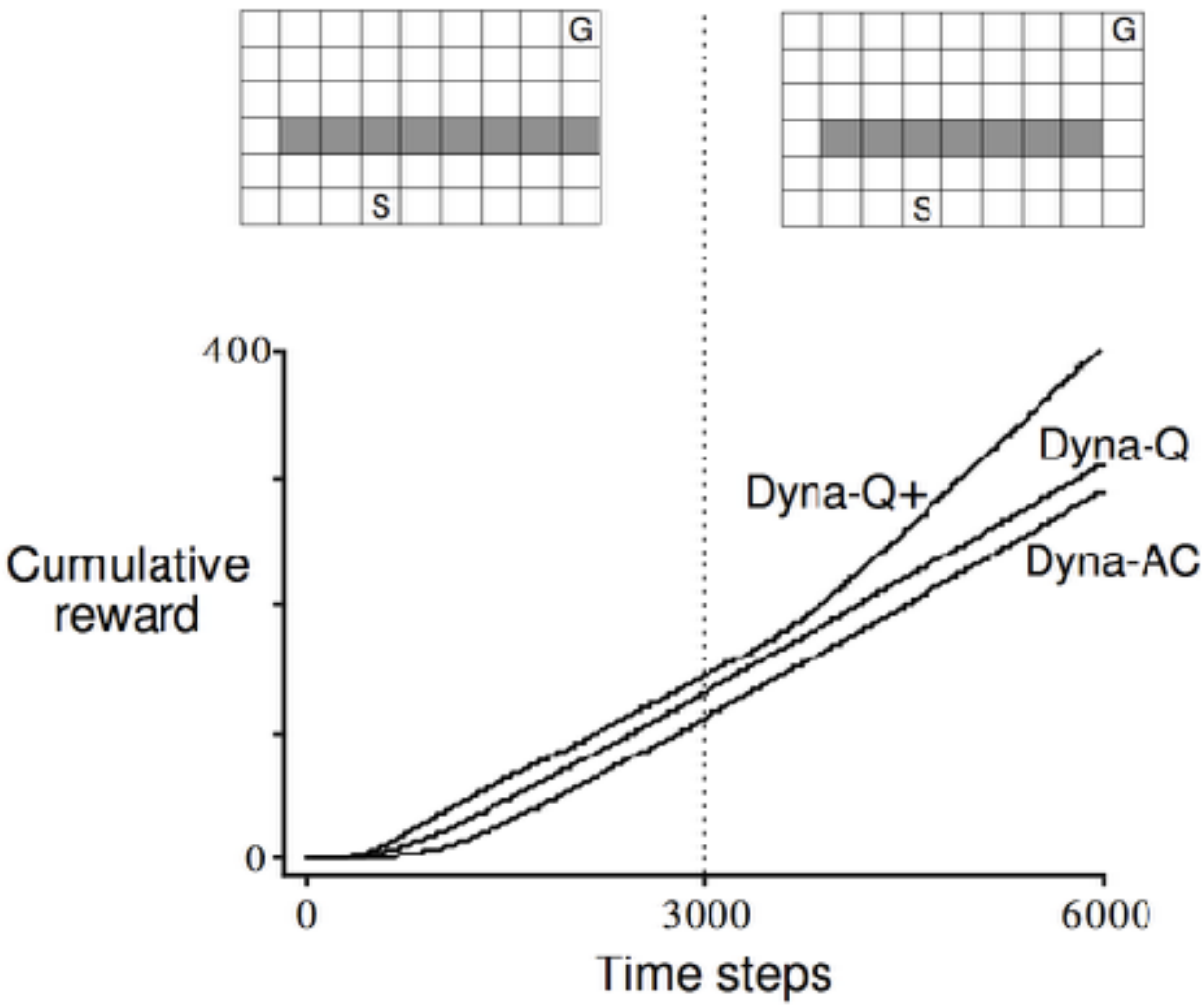


A change for the better

- If the world changes, such that a better path is possible:
  - the formerly correct policy will not reveal the improved situation
  - the modeling error may not be detected for a long time!

When the Model is Wrong: 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

$$R + \kappa\sqrt{\tau}$$

time since last visiting
the state-action pair

  - The agent actually “plans” how to visit long unvisited states

The conflict between exploration and exploitation

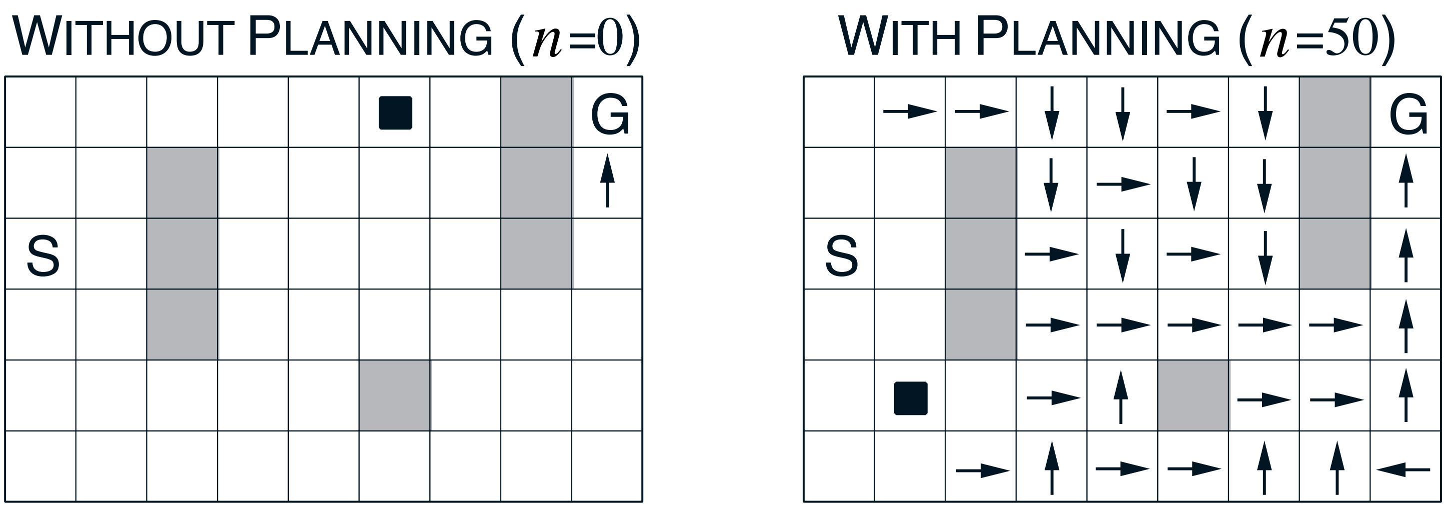
- Exploration in planning: trying actions that improve the model
  - Make it more accurate
  - Make it a better match with the environment
  - Proactively discover when the model is wrong

- Exploitation: behaving optimally with respect to the current model

- Simple heuristics can be effective

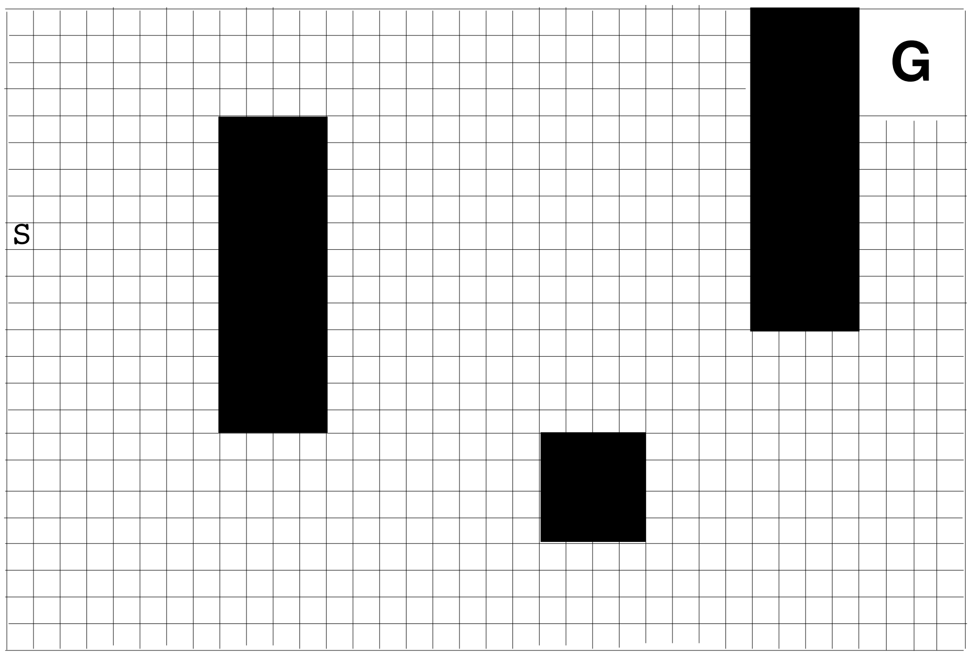
Prioritizing Search Control

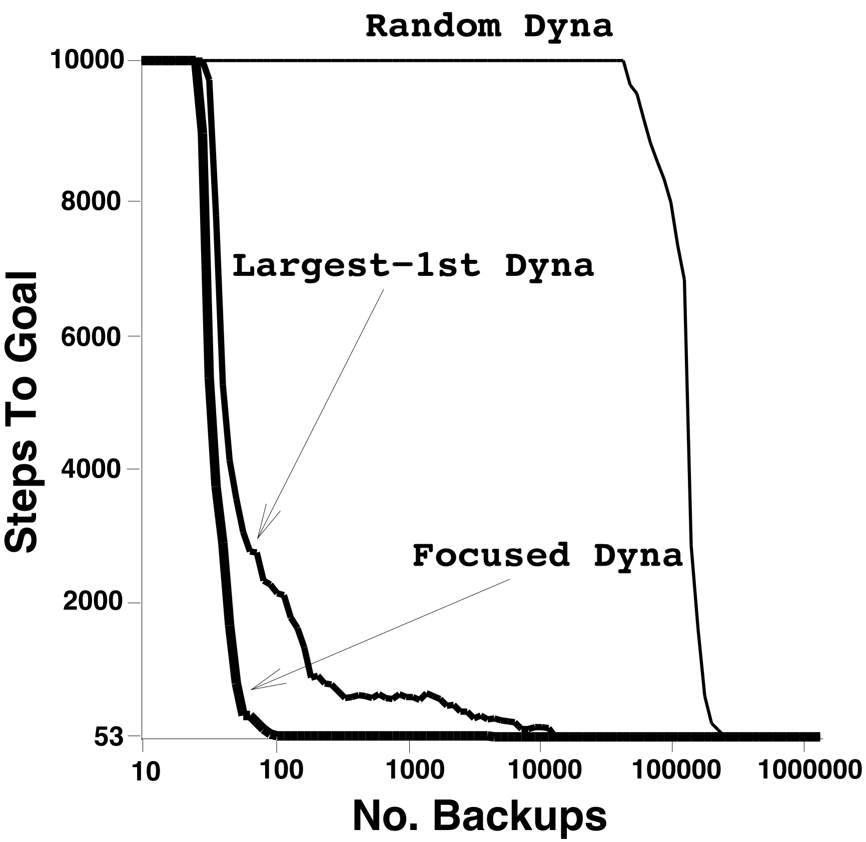
- Consider the second episode in the Dyna maze
  - The agent has successfully reached the goal once…



- 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)

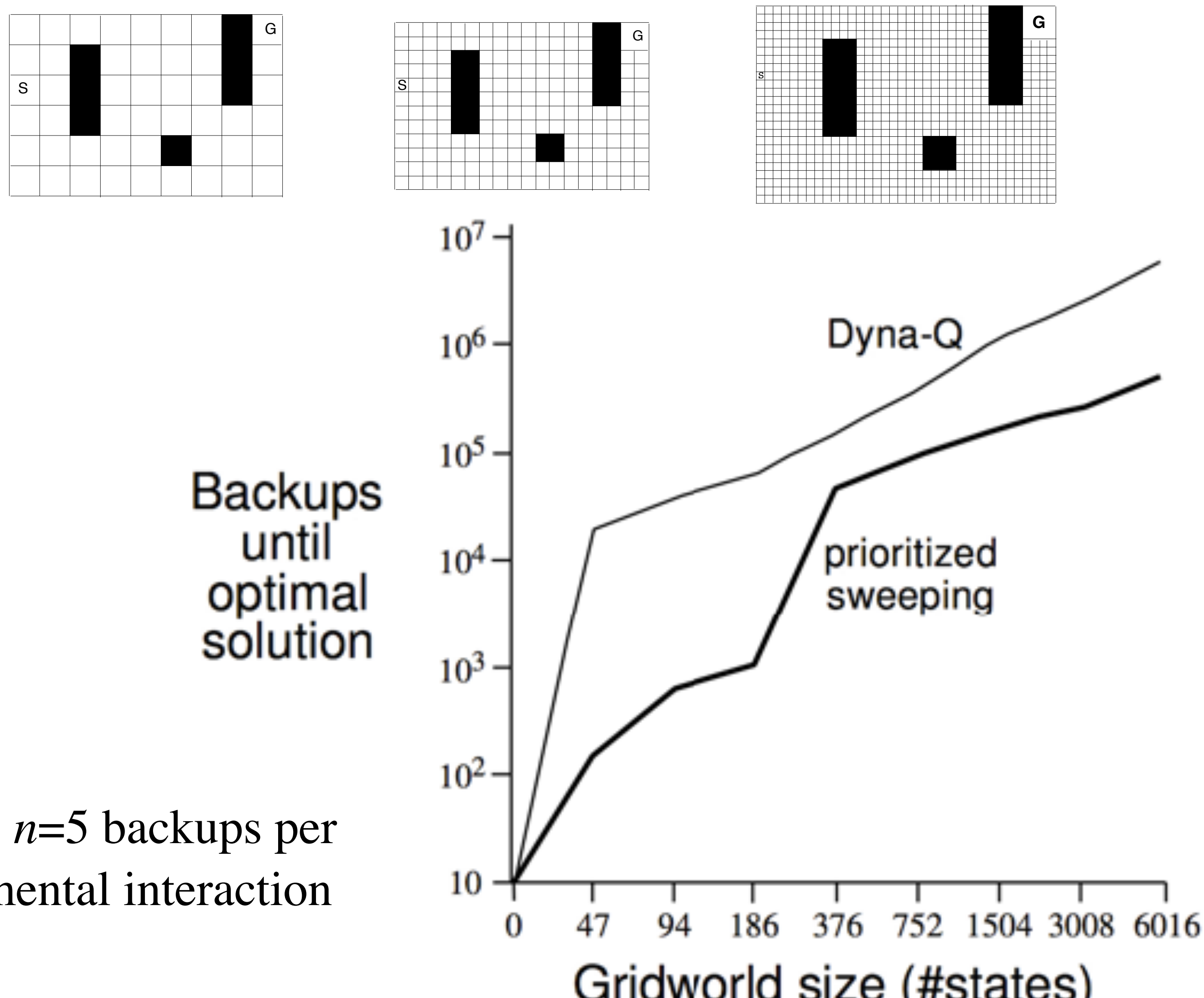
Prioritized Sweeping

- 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

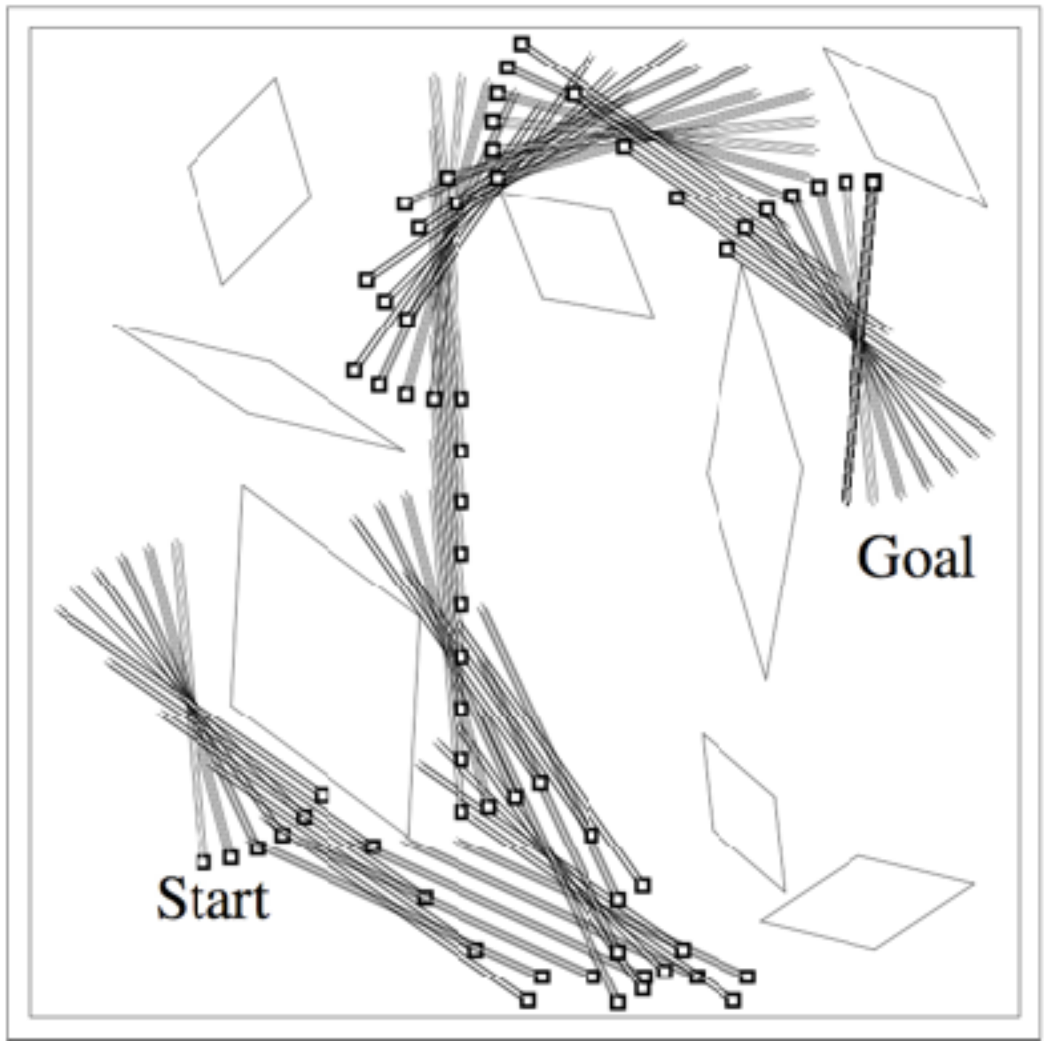
Initialize $Q(s,a)$, $Model(s,a)$, for all s, a, and $PQueue$ to empty
Do forever:
  (a) $S \leftarrow$ current (nonterminal) state
  (b) $A \leftarrow policy(S,Q)$
  (c) Execute action A; observe resultant reward, R, and state, S'
  (d) $Model(S,A) \leftarrow R, S'$
  (e) $P \leftarrow |R + \gamma \max_a Q(S',a) - Q(S,A)|$.
  (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

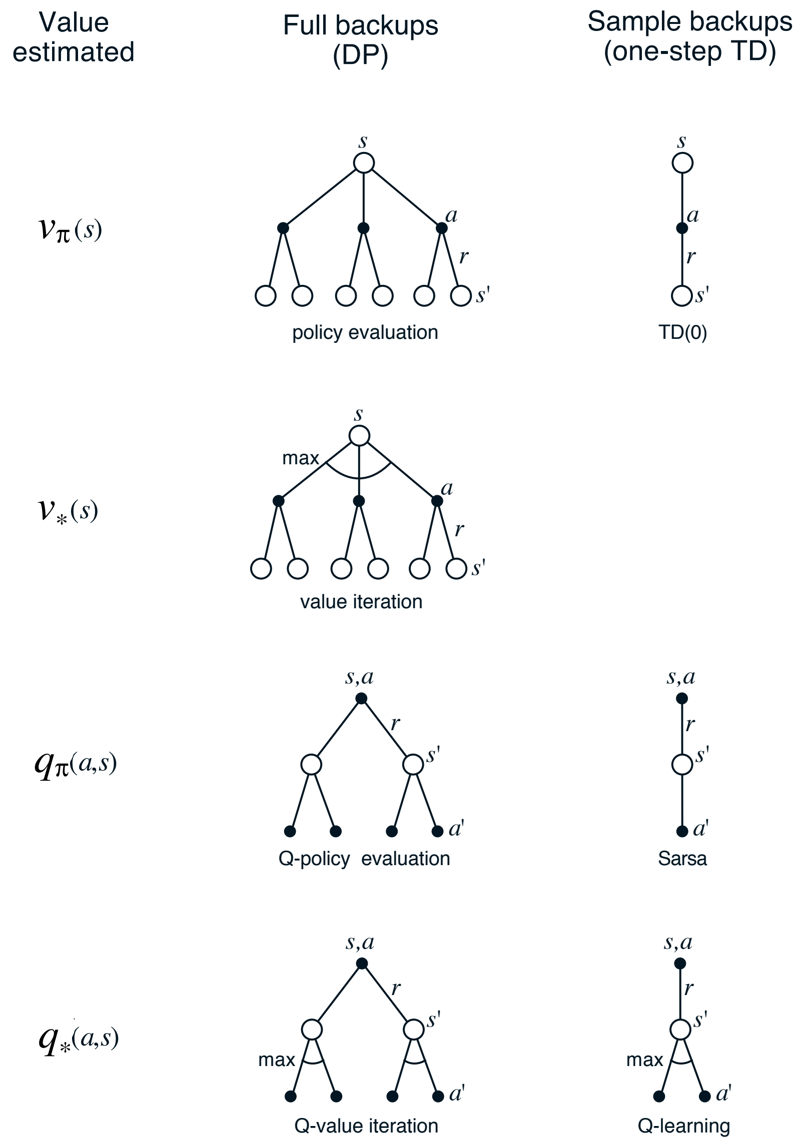
Rod Maneuvering (Moore and Atkeson 1993)



Improved Prioritized Sweeping with Small Backups

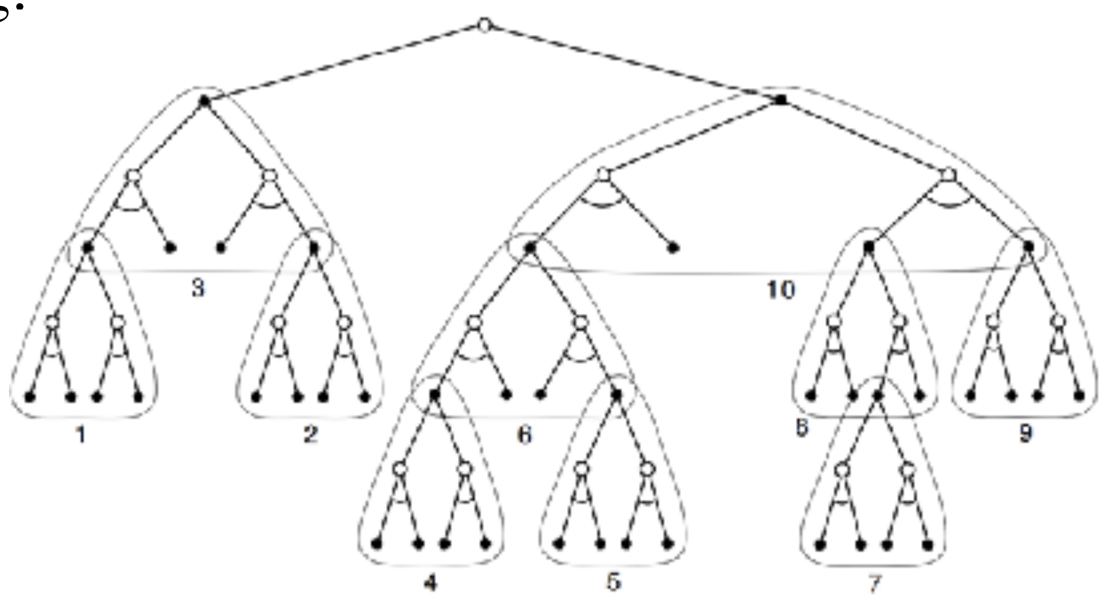
- Planning is a form of state-space search
  - a massive computation which we want to control to maximize its efficiency
- Prioritized sweeping is a form of search control
  - focusing the computation where it will do the most good
- But can we focus better?
- Can we focus more tightly?
- Small backups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

Full and Sample (One-Step) Backups



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