Advanced Topics in Reinforcement Learning

Lecture 11: Models and Planning II

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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

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.

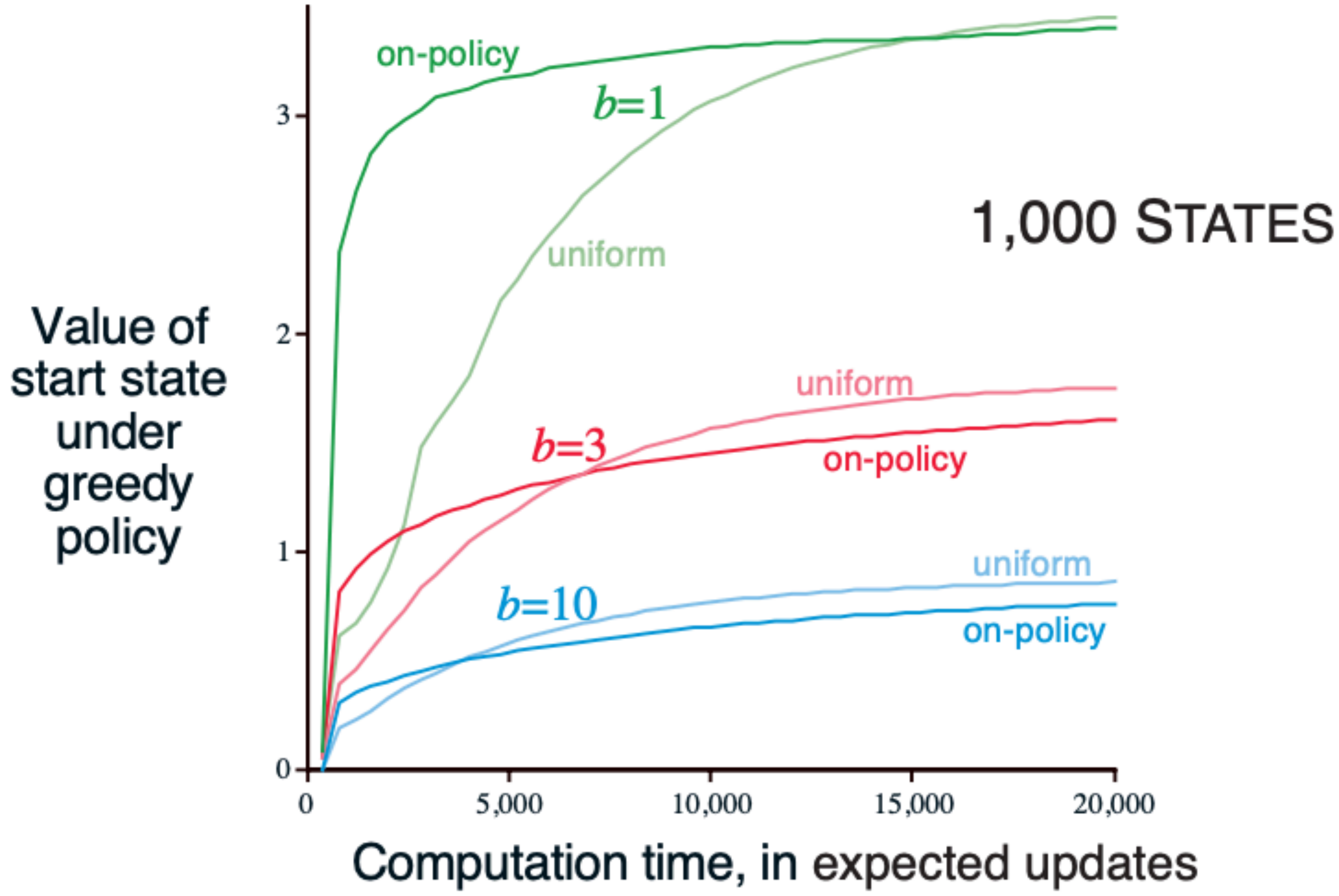
Today

- Finish RTDP
- Planning at decision-time:
    - Heuristic Search
    - Roll-out Algorithms
    - MCTS

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?
  - Initialize the agent in a start state and follow the current policy from there.
  - Simulate entire trajectories within the model or real world. Back-up the values for these states.

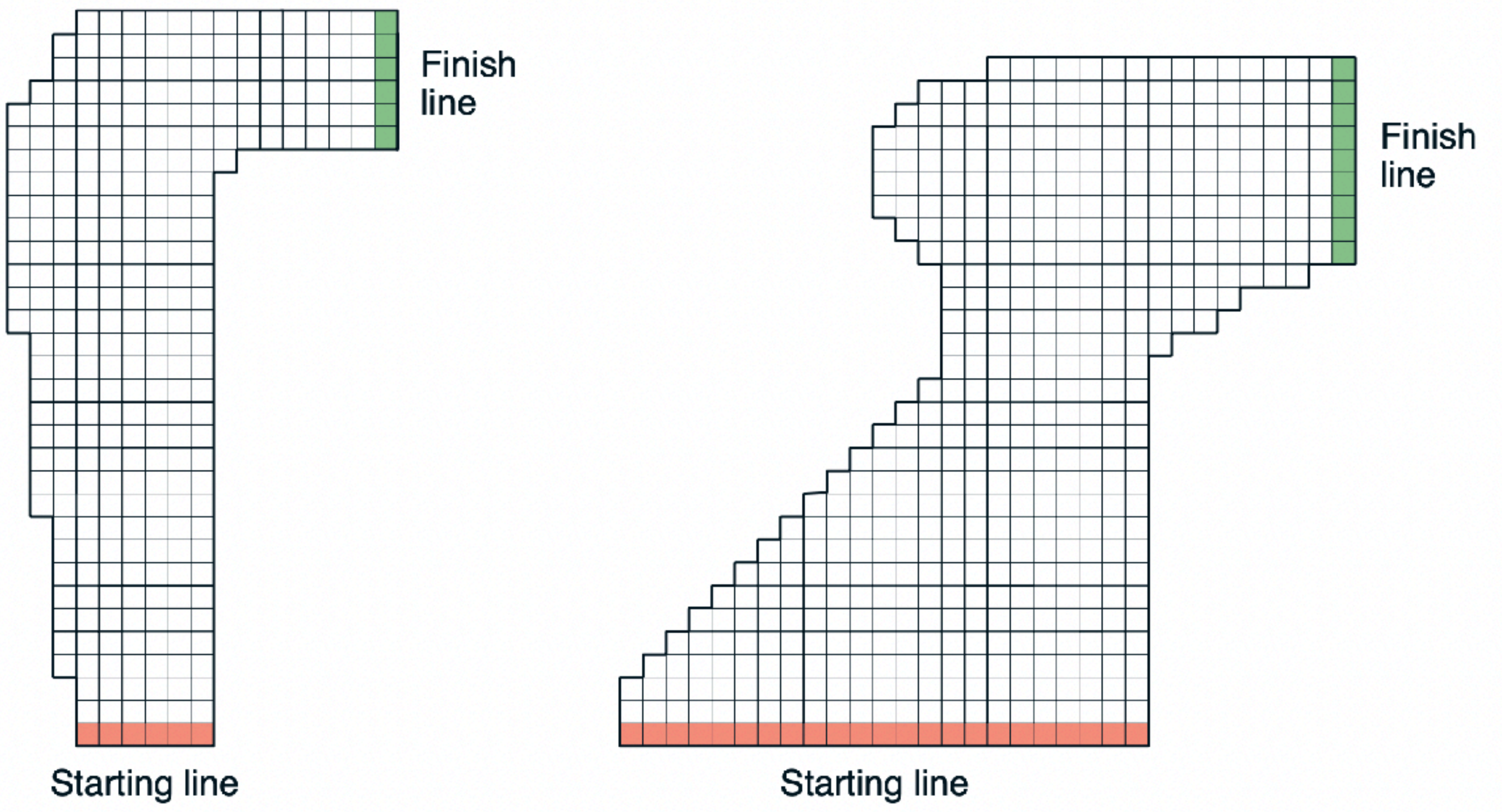
Trajectory Sampling



Real-time Dynamic Programming

- Key Idea: perform a value-iteration update on each state as it is visited.
- For n real episodes:
  - Start in initial state, S_0. Follow greedy policy until termination.
  - For each real step, run k simulations:
    - Repeat $A_t \sim \pi(A = a \mid S_t)$, $S', R \sim \texttt{Model}(S_t, A_t)$ where π is ϵ-greedy.
    - At each simulated step, t, apply the value iteration update to $Q(S_t, A_t)$:
    - $Q(S_t, A_t) \leftarrow \sum_{s',r} p(s', r \mid s, a)[r + \gamma \max_{a'} Q(s', a')]$

RTDP Example



Planning at Decision Time

- So far we considered using planning to improve the value-function and speed-up policy iteration.

- Now we consider using planning to immediately compute an action for a given state.

- $\pi(s) \leftarrow \arg\max_a \sum_{s',r} p(s', r \mid s, a)[r + \gamma v_\pi(s')]$

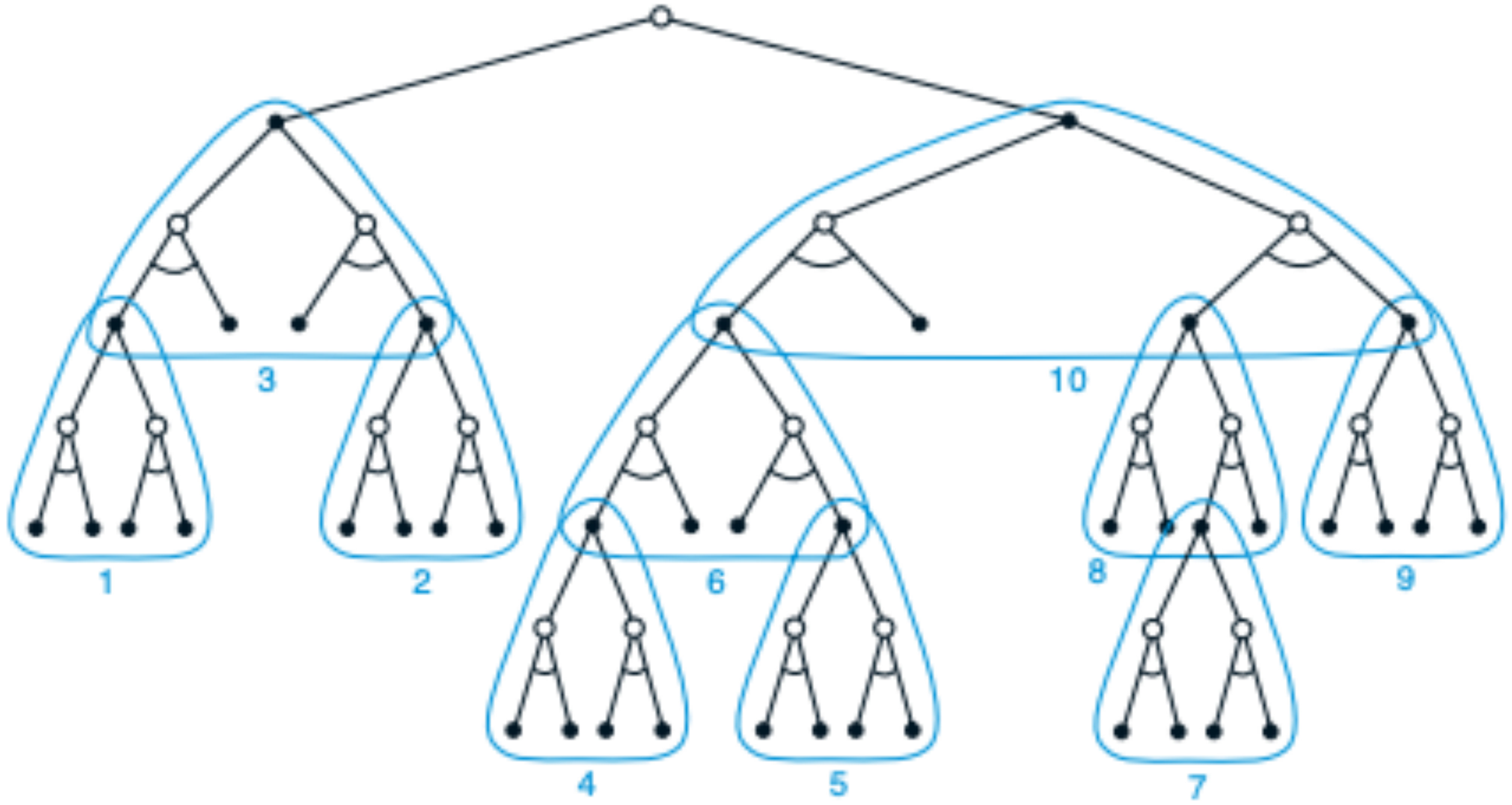
- $\pi(s) \leftarrow \arg\max_a \sum_{s',r} p(s', r \mid s, a)[r + \gamma \max_{a'} \sum_{s'',r'} p(s'', r' \mid s'', a')[r' + \gamma v_\pi(s'')]]$

- Slow deliberation before making a decision (System 2).

- Contrasts with immediate decision-making of model-free methods (System 1).

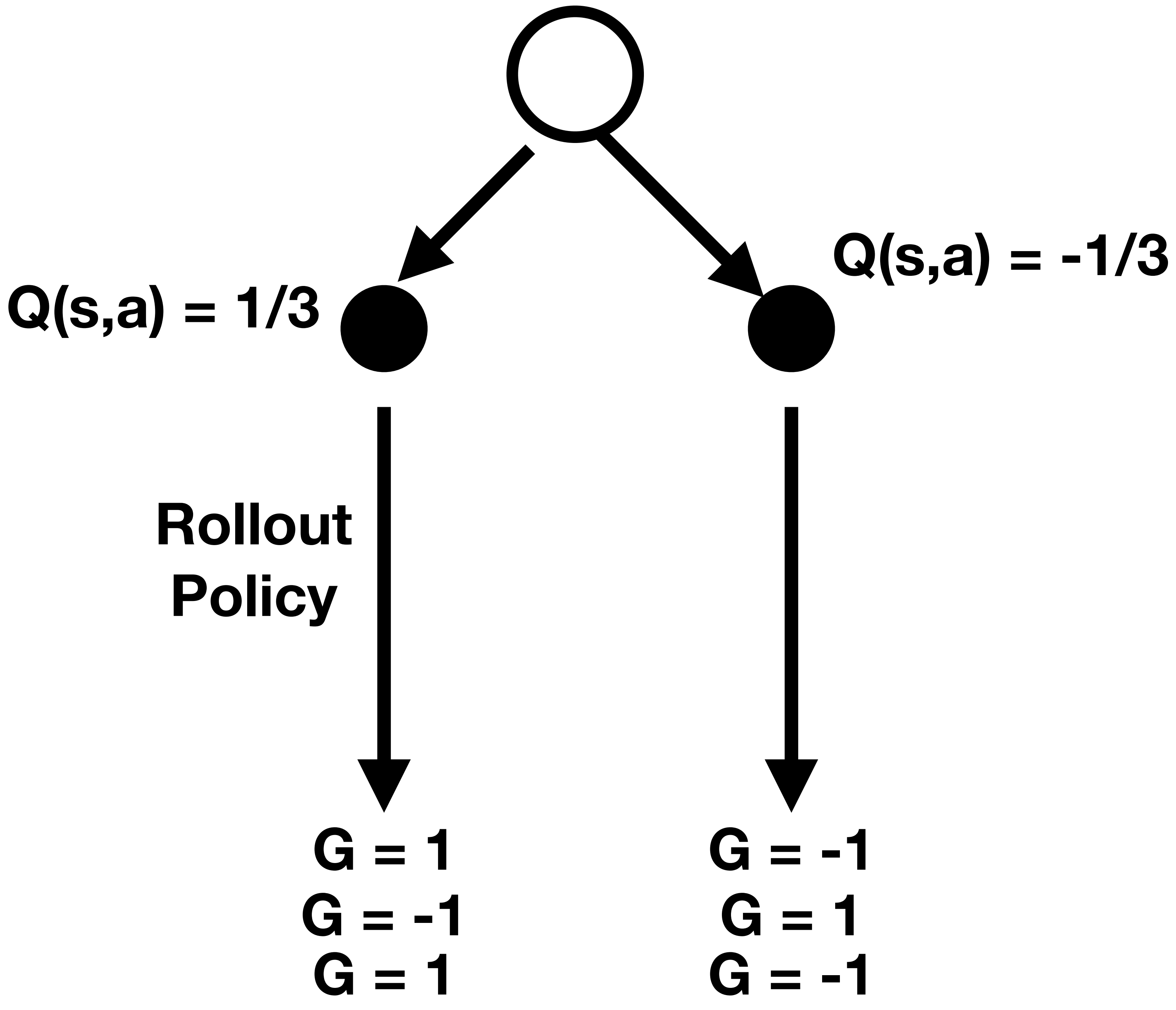
Heuristic Search

- Motivation: model is perfect and action-value function is imperfect.
- Focus memory and computation on immediate relevant state and next decision.
- Deeper search generally leads to a better action choice at expense of more computation.

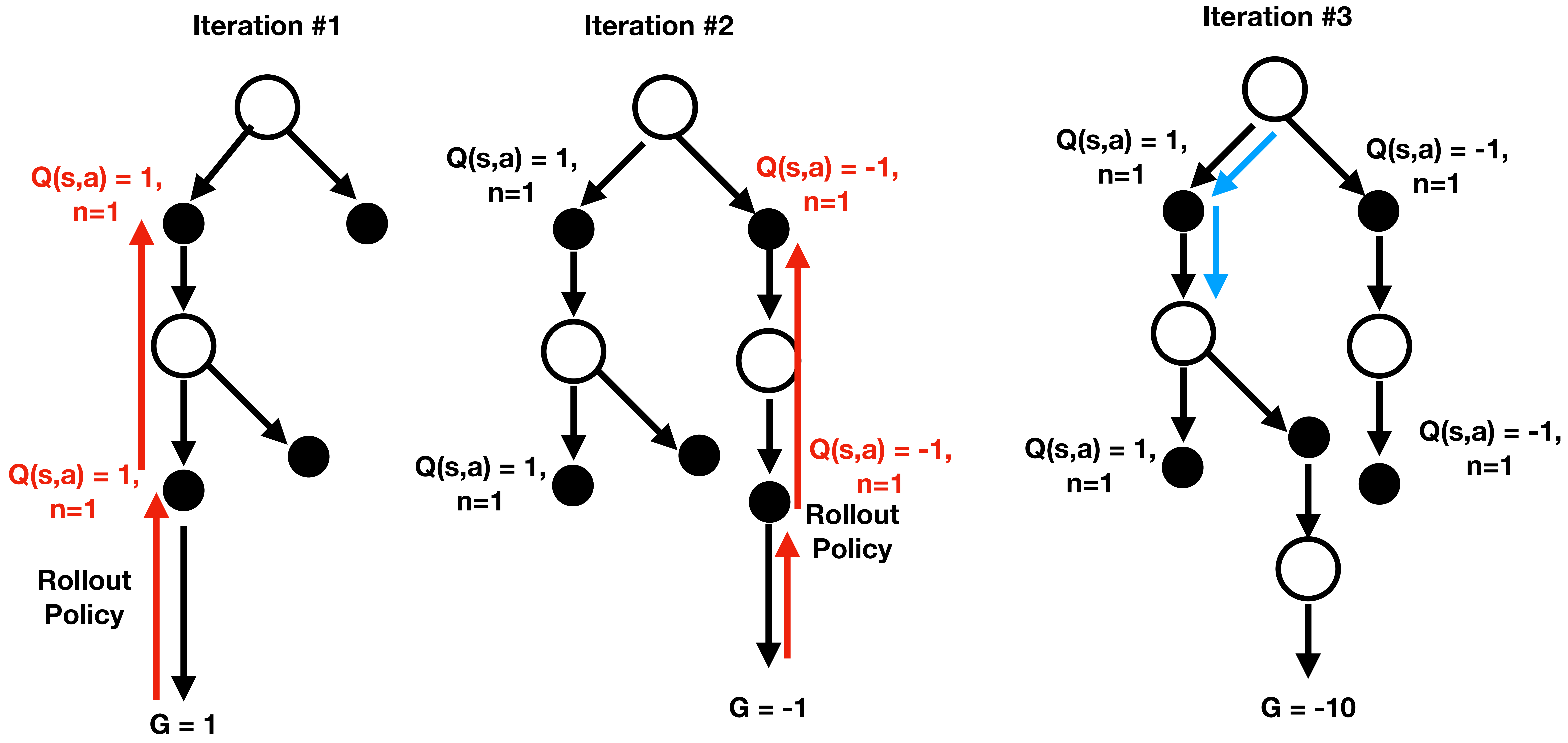


Roll-out Algorithms

- **Rollout:** following a policy until termination, i.e, rolling out the policy.
- Monte Carlo learning at decision-time; improve upon the roll-out policy.
- Rolling out the policy only requires a sample model.
- Computation time is a limiting factor. Roll-out algorithms computation affected by:
    - Speed to sample from model.
    - Speed to execute rollout policy.



Monte Carlo Tree Search



Dmitry’s Presentation

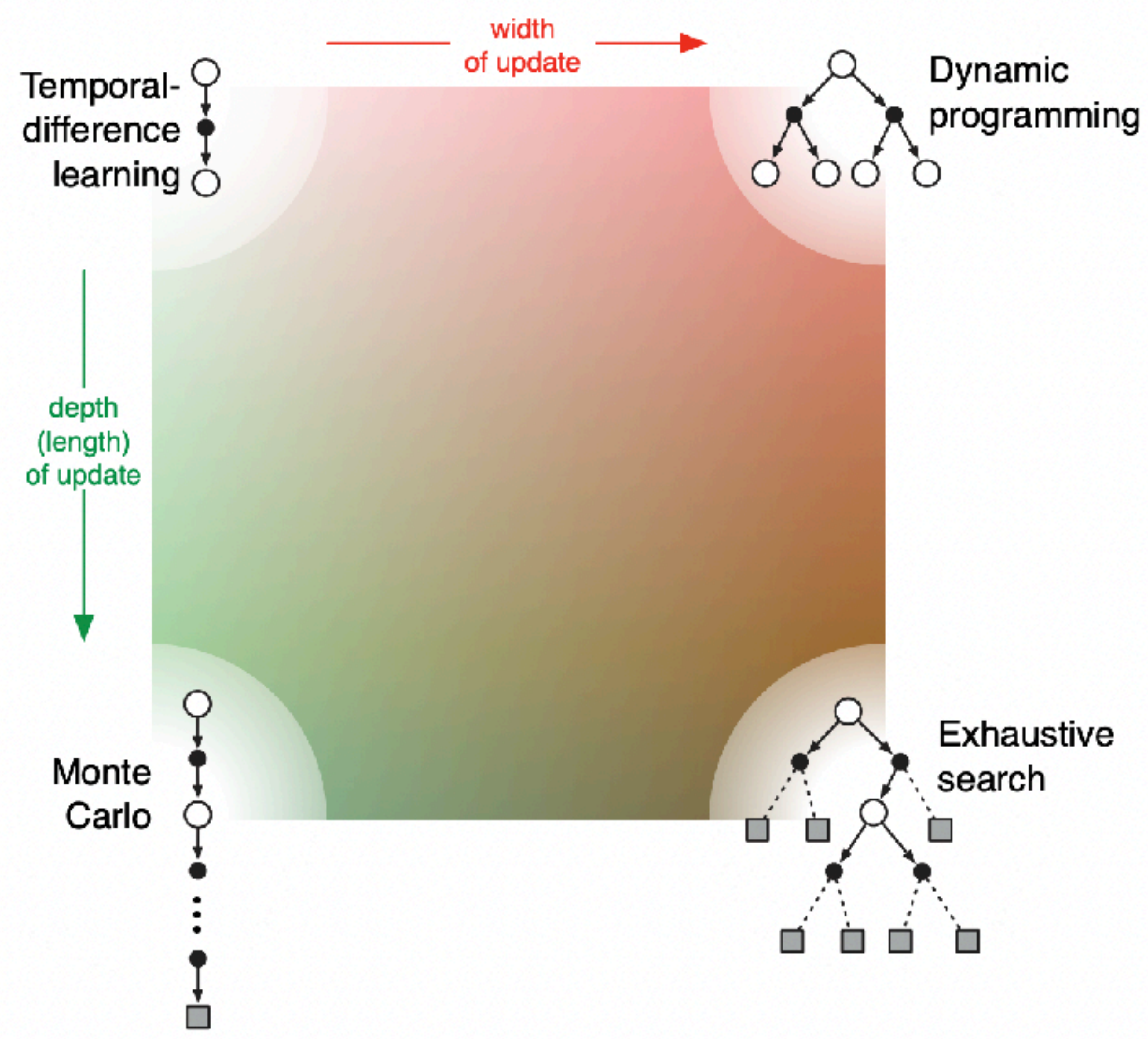
Mastering the game of Go with deep neural networks and tree search.

Silver et al. 2016

Slides

Part I Summary

- Functions (policies, value functions, and models) have been represented as look-up tables.
- We have seen 4 types of algorithms:
  - Dynamic programming methods.
  - Model-free Monte Carlo methods.
  - Model-free temporal difference learning methods.
  - Model-based learning and planning methods.
- All algorithms we have seen are instances of generalized policy iteration:
  - $\pi_0 \rightarrow q_0 \rightarrow \cdots \rightarrow \pi_k \rightarrow q_k \rightarrow \pi_{k+1} \rightarrow \cdots \rightarrow q_\star \rightarrow \pi_\star$



Part I Summary

- Much intuition and understanding carries forward as we move into Part II.
    - Returns and values defined similarly.
    - On-policy and off-policy methods.
    - Exploration vs. Exploitation trade-off.
- Looking ahead:
    - The learning agent has limited capacity to model $v_\pi(s)$ for all s.
    - The learning agent may never visit the same state twice.

Summary

- Models can be used to produce simulated experience to learn from.
    - Makes better use of finite data.
    - Distribution models permit *expected updates* such as those made by RTDP.
    - Sample models are generally easier to acquire and can be used with *sample* updates.
- Models can be used to compute a better decision than acting greedily w.r.t. an inaccurate action-value function.
    - Requires planning at decision time.
    - Computation is the bottleneck for making better decisions.

Action Items

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