Rollout, Policy Iteration, and Distributed Reinforcement Learning

Current Course at ASU
(Research monograph to appear; partial draft at my website)

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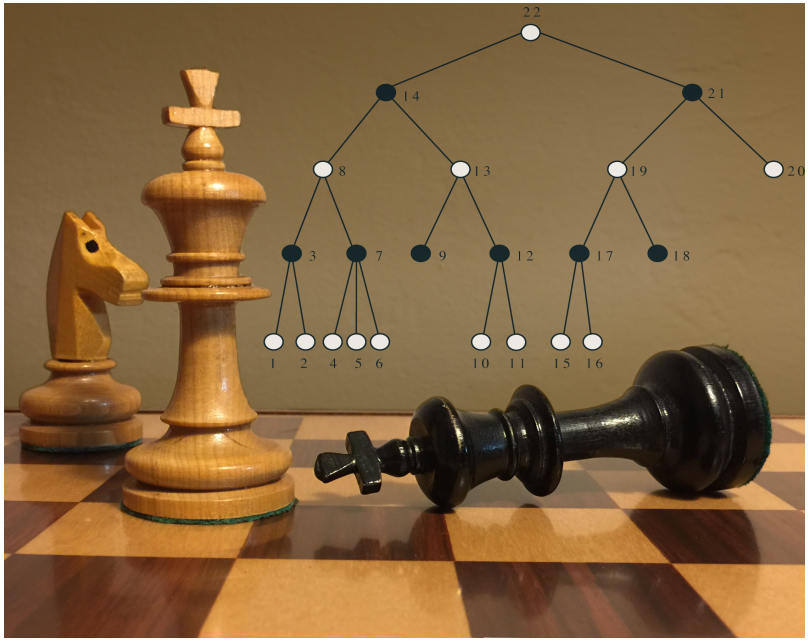
Outline

AlphaGo (2016) and AlphaZero (2017)



AlphaZero

Plays much better than all chess programs

Plays different!

Alphazero has discovered a new way to play!

Learned from scratch ... with 4 hours of training!

Same algorithm learned multiple games (Go, Shogi)

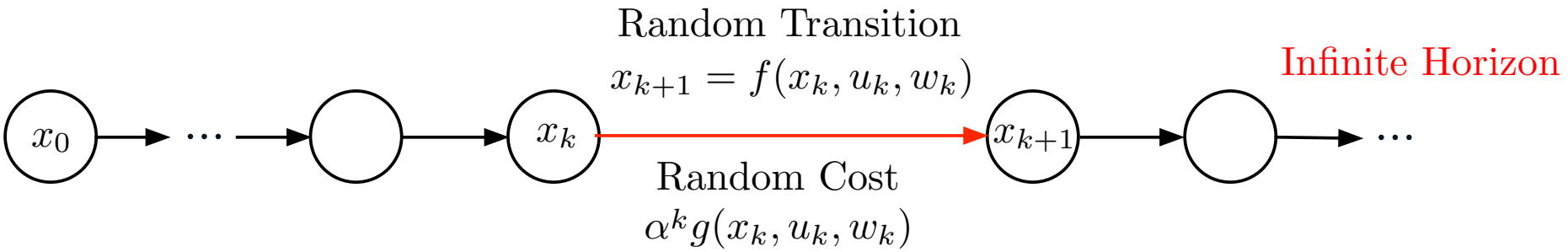
The AlphaZero methodology is based on several ideas:

- The fundamental DP idea of policy iteration/improvement.
- Approximations with value and policy neural net approximations.
- Massive parallel computation.
- Lookahead approximations: Monte Carlo Tree Search.

We will aim to:

Develop a methodology that relates to AlphaZero, but applies far more generally.

Recall the α-Discounted Markovian Decision Problem



Infinite number of stages, and stationary system and cost

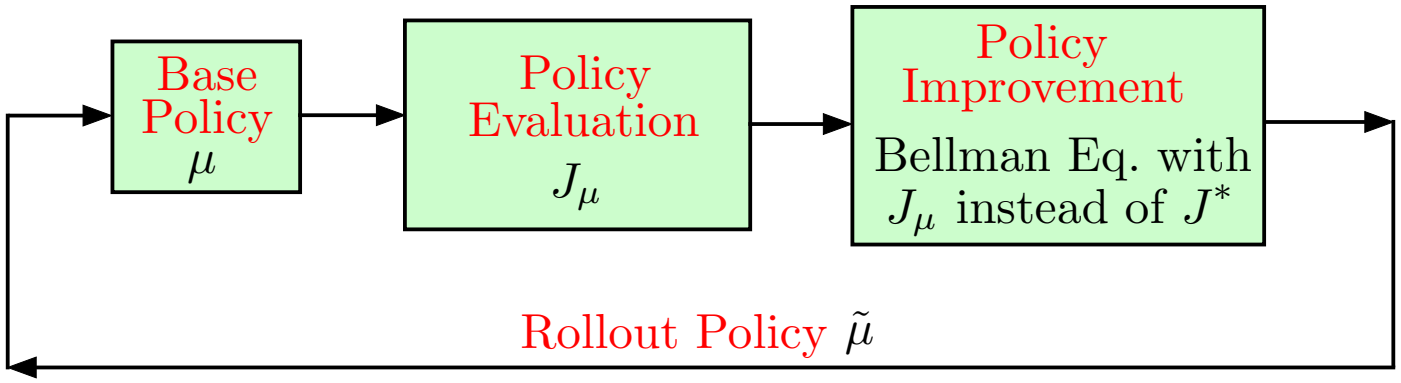
- System $x_{k+1} = f(x_k, u_k, w_k)$ with state, control, and random disturbance.
- Policies μ that map states to controls, with $\mu(x) \in U(x)$ for all x and k.
- Cost of stage k: $\alpha^k g\big(x_k, \mu(x_k), w_k\big)$; $\alpha \in (0, 1]$ is the discount factor.
- Cost of policy μ

$$J_\mu(x_0) = \lim_{N\to\infty} E_{w_k}\left\{\sum_{k=0}^{N-1} \alpha^k g\big(x_k, \mu(x_k), w_k\big)\right\}$$

- Optimal cost function $J^*(x_0) = \min_\mu J_\mu(x_0)$.
- Optimality condition: Minimize the RHS of Bellman's equation

$$\mu^*(x) \in \arg\min_{u\in U(x)} E\Big\{g(x, u, w) + J^*\big(f(x, u, w)\big)\Big\}$$

Policy Iteration Algorithm



Fundamental policy improvement property

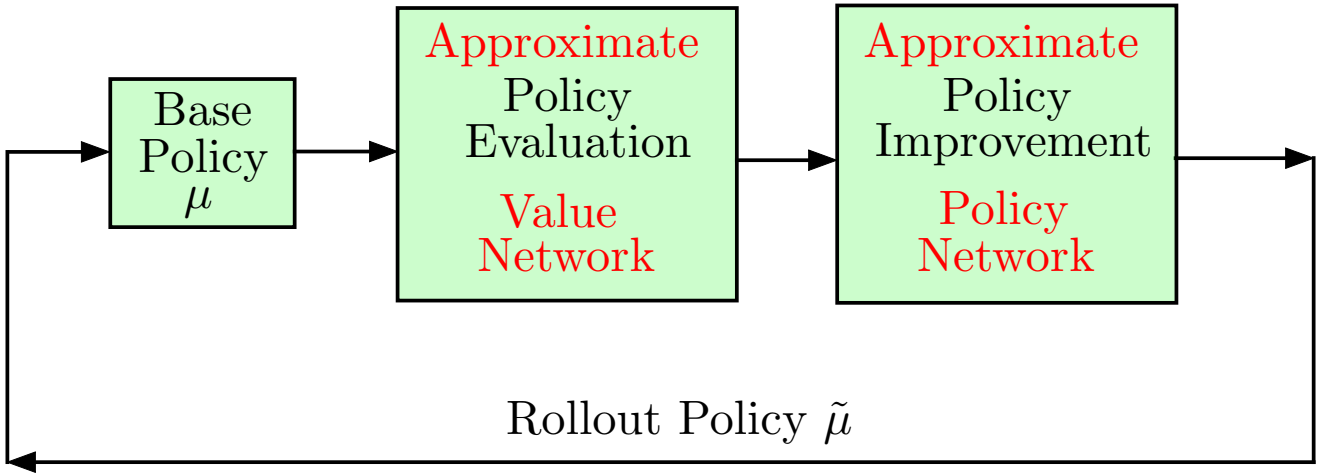
$$J_{\tilde{\mu}}(x) \leq J_\mu(x), \quad \text{for all } x$$

There are many variants of policy iteration

Optimistic, multistep, Q-learning versions, etc.

OUR FOCUS: APPROXIMATE VERSIONS

Approximate Policy Iteration



Policy improvement property holds approximately

Methodological issues to deal with for challenging large-scale problems

- Theoretical issues: Error bounds, convergence guarantees, sampling efficiency, etc.
- Implementation choices: What to approximate, how to sample, how to train, on-line vs off-line, model-free vs model-based, etc.
- No guarantee of success: We just try different schemes based on theoretical understanding, intuition, experience ... hopefully something will work.

OUR FOCUS: DISTRIBUTED (ASYNCHRONOUS) COMPUTATION

About this Talk

We will focus on two types of distributed computation schemes

- Multiagent parallelization: Deal with large control spaces, e.g., controls with multiple components

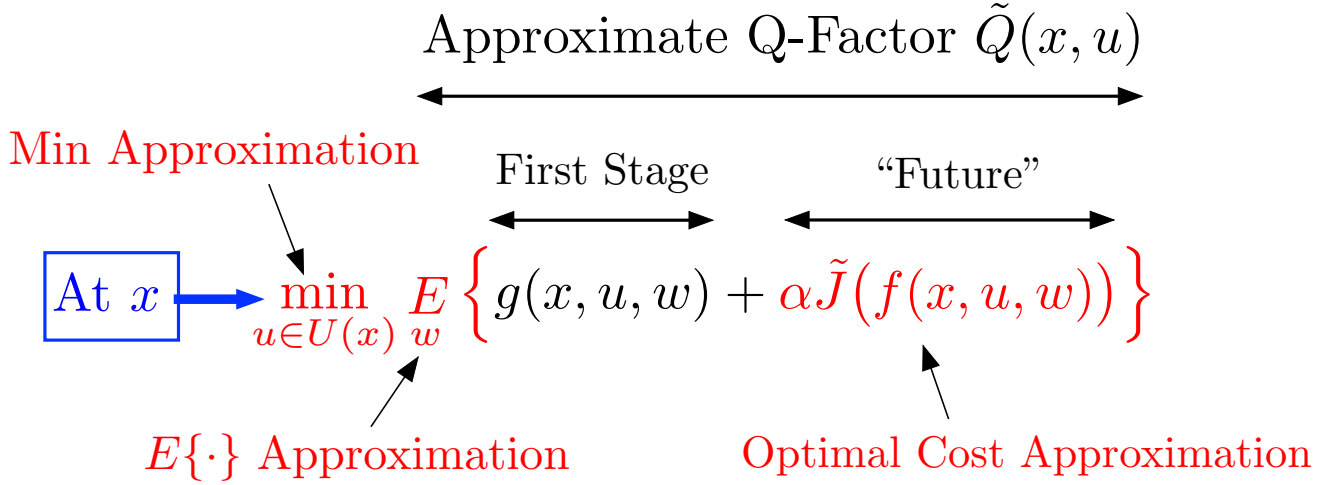
$$u = (u^1, \ldots, u^m)$$

- Multiprocessor parallelization: Deal with large state spaces through partitioning, and distributed training of multiple value and policy networks (one per set of the state space partition).

References

- Distributed asynchronous value iteration papers (DPB, 1982-83), Parallel and Distributed Computation book (DPB and Tsitsiklis, 1989).
- Distributed asynchronous policy iteration and Q-learning papers (Williams and Baird, 1993, DPB and Yu, 2010-14).
- Multiagent rollout paper (DPB, 2019).
- Partitioned rollout and policy iteration for POMDP paper (Bhattacharya, Badyal, Wheeler, Gil, DPB, 2020).

Approximation in Value Space: From Values $\tilde{J}(x)$ to a Policy $\tilde{\mu}(x)$



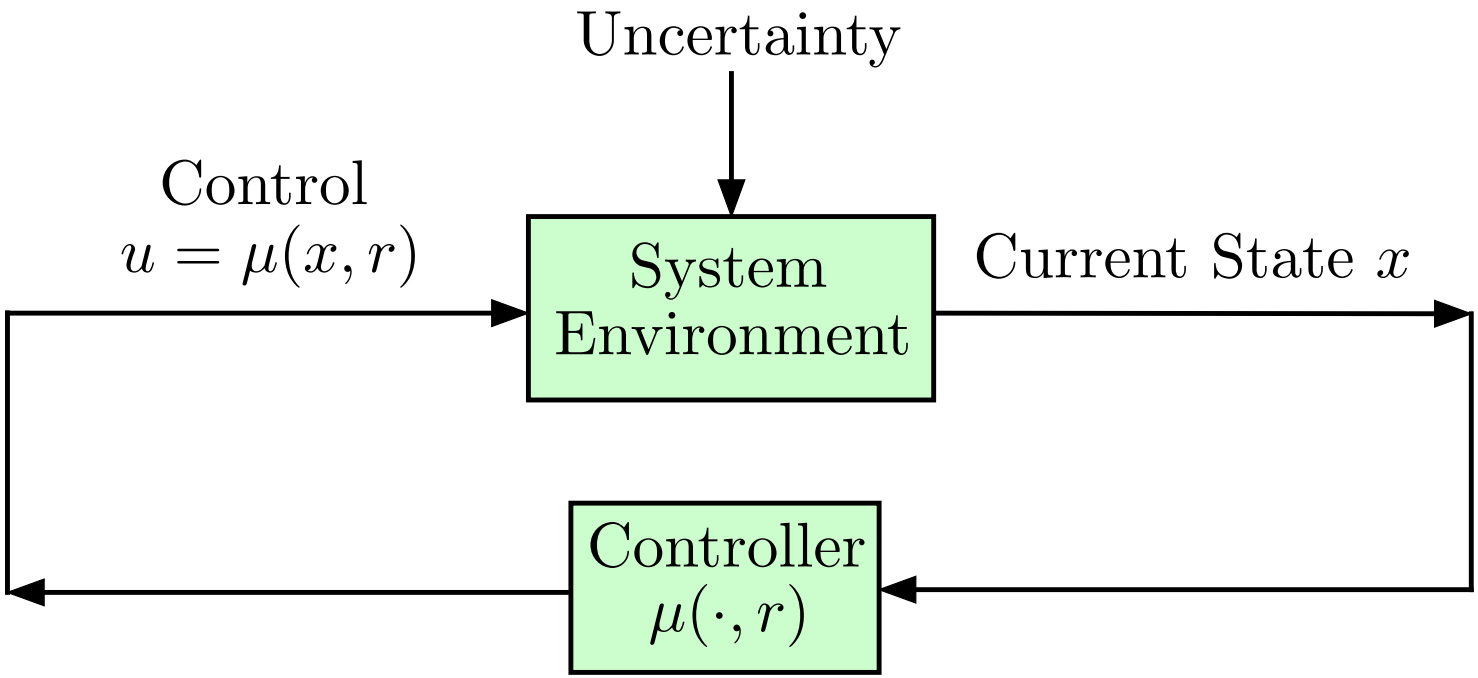
At state x, use $\tilde{J}$ (in place of J^*) in Bellman's Eq. to obtain a control $\tilde{u} = \tilde{\mu}(x)$.

THE THREE APPROXIMATIONS:

- How to construct $\tilde{J}$.
- How to simplify $E\{\cdot\}$ operation.
- How to simplify min operation.

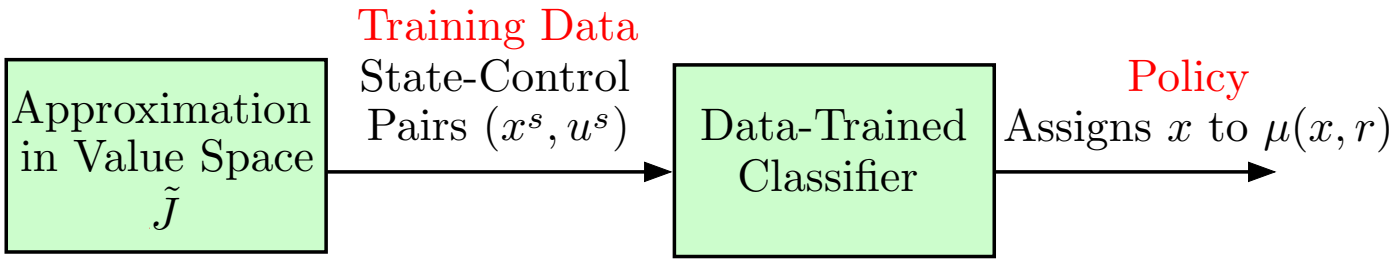
Each of the three approximations can be designed almost independently of the others, leading to a large variety of methods.

Parametric Approximation in Policy Space



Optimization and training over a parametric family of policies $\mu(x, r)$, where r is a parameter (e.g., a neural net).

From Value Approx. $\tilde{J}(x)$ to Policy $\mu(x, r)$



x is classified as type u $\iff$ at state x we apply control u

Training the rollout policy as a classifier:

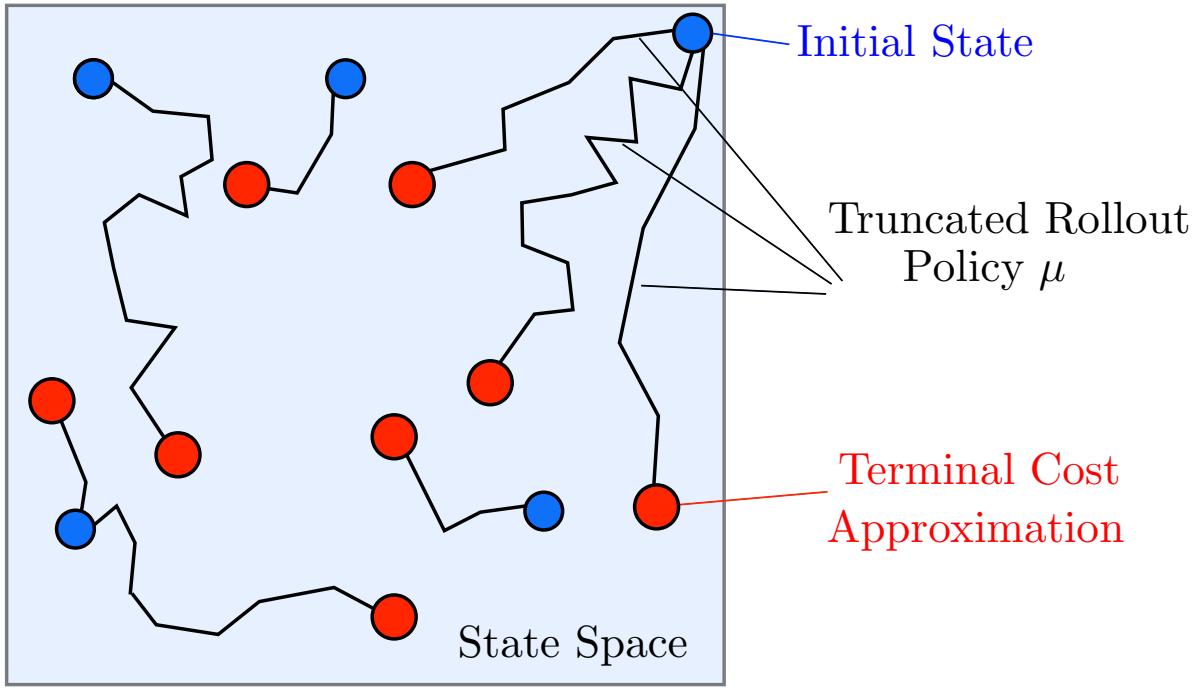
- We generate a training set of sample pairs (x^s, u^s), $s = 1, \ldots, q$, by one-step lookahead, i.e.,

$$u^s \in \arg \min_{u \in U(x)} E\Big\{ g(x^s, u, w) + \alpha \tilde{J}\big(f(x^s, u, w)\big) \Big\}$$

- Approximate the one-step lookahead policy using the training set.
- Example: Introduce a parametric family of policies $\mu(x, r)$ of some form (e.g., a neural net). Then estimate r by least squares fit

$$\min_r \sum_{s=1}^{q} \big\| u^s - \mu(x^s, r) \big\|^2$$

From Policy μ to Value Approx. $\tilde{J}$

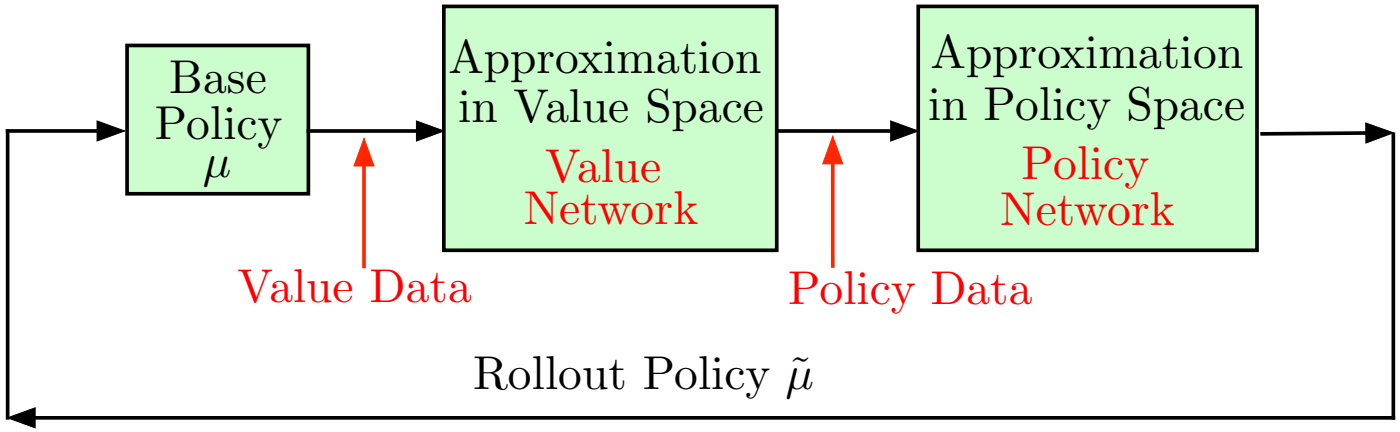


Policy μ defines a cost approximation $\tilde{J} \approx J_\mu$ through truncated simulation

How to approximate $J_\mu(x)$?

- For deterministic problems: Run μ from x once and accumulate stage costs.
- For stochastic problems: Run μ from x many times and Monte Carlo average.
- Use truncation: Simulate μ for a limited number of stages, and neglect the costs of the remaining stages or add some cost approximation at the end to compensate.

From Policy Approx. to Value Approx. to New Policy Approx.



- Policy improvement property: In the idealized case (no approximations),

$$J_{\tilde{\mu}}(x) \leq J_{\mu}(x), \qquad \text{for all } x$$

- With approximations, policy improvement is approximate (within an error bound).
- There are many variants of this scheme: Optimistic policy iteration, Q-learning, temporal differences, etc.
- Most RL algorithms, including Alphazero, use variants of the above scheme.
- Some variants are highly optimistic, i.e., use very little data between value updates and policy updates.

HOW DO WE USE PARALELLIZATION IN ROLLOUT AND APPROXIMATE PI?

Four Possible Types of Parallelization

Q-factor parallelization: At the current state x, one-step lookahead/rollout does a separate Q-factor calculation for each control $u \in U(x)$. These calculations are decoupled and can be executed in parallel.

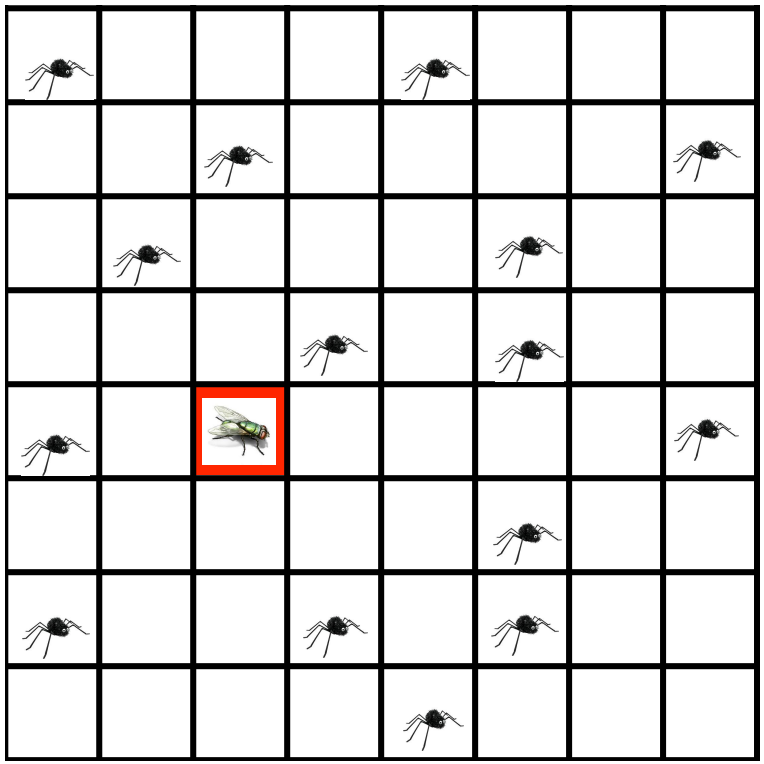
Monte Carlo parallelization: Each of the Q-factor calculations involves a Monte Carlo simulation when the problem is stochastic. Monte Carlo simulation can be parallelized.

Multiagent parallelization: When the control has m components, $u = (u^1, \ldots, u^m)$ the lookahead minimization at x involves the computation of as many as n^m Q-factors, where n is the max number of possible values of u^i. We will consider schemes that reduce the computation dramatically (to $n \cdot m$).

Multiprocessor parallelization: Use a state space partition, and execute separate (but coupled) value and policy approximations on each subset in parallel.

WE WILL FOCUS ON THE LAST TWO

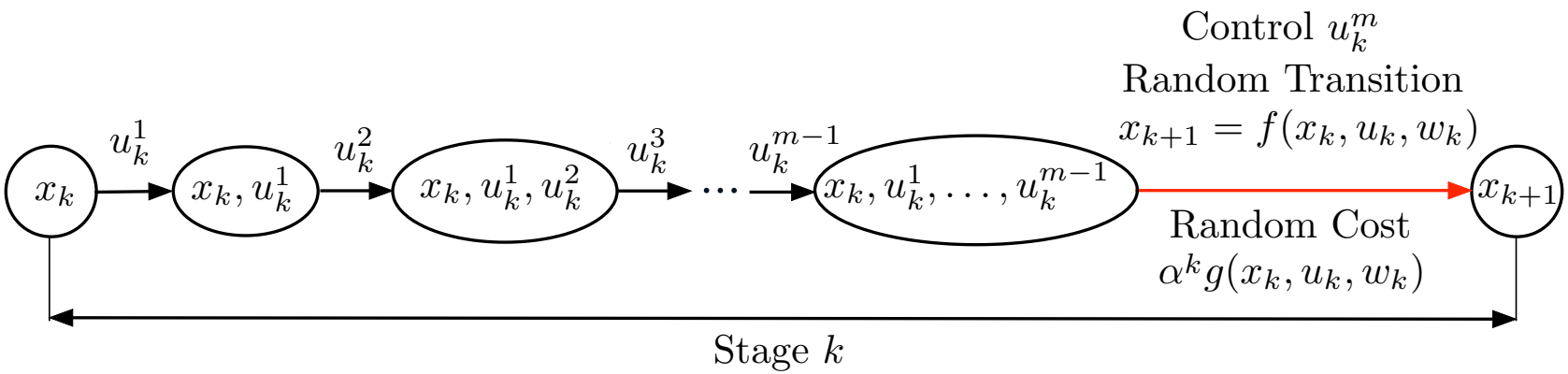
A Spiders-and-Fly Example (or Search-and-Rescue)



15 spiders move along 4 directions ($\leq$ 1 unit) w. perfect observation; fly moves randomly

- Objective is to catch the fly in minimum time.
- One-step lookahead and rollout are impossible: $\approx 5^{15}$ Q-factors.
- We reformulate one-step lookahead but maintain the cost improvement property:
  - Spiders move one-at-a-time with knowledge of other spiders' and fly's positions.
  - The control is broken down into a sequence of 15 spider moves ($5 \cdot 15 = 75$ Q-factors).

Trading off Control and State Complexity (NDP book, 1996)



An equivalent reformulation - “Unfolding" the control action

- The control space is simplified at the expense of $m-1$ additional layers of states, and corresponding $m-1$ cost functions

$$J^1(x_k, u_k^1), J^2(x_k, u_k^1, u_k^2), \ldots, J^{m-1}(x_k, u_k^1, \ldots, u_k^{m-1})$$

- Multiagent (one-component-at-a-time) rollout is just standard rollout for the reformulated problem.
- The increase in size of the state space does not adversely affect rollout.
- The cost improvement property is maintained.
- Complexity reduction: The one-step lookahead branching factor is reduced from n^m to nm, where n is the number of possible choices for each component u_k^i.

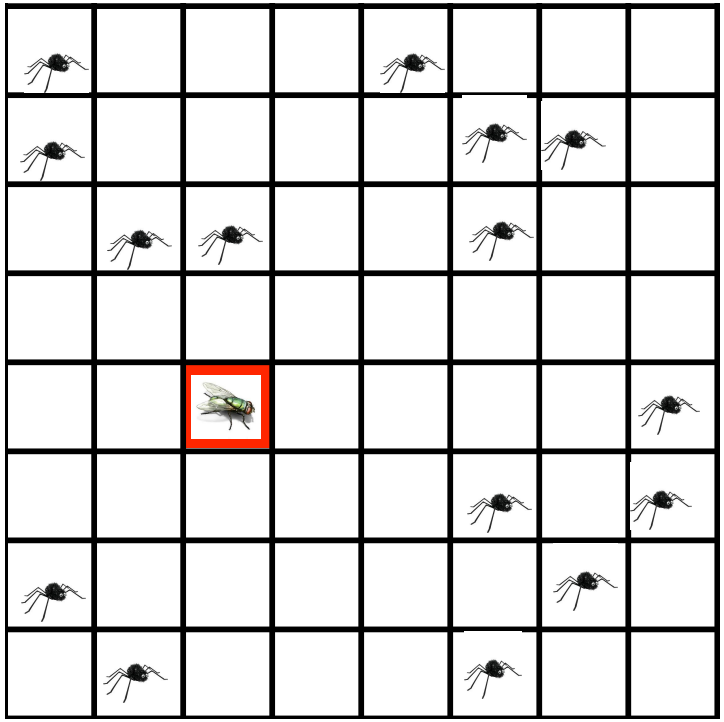
Demo 1

Shortest path All at once One at a time

Time to catch the flies

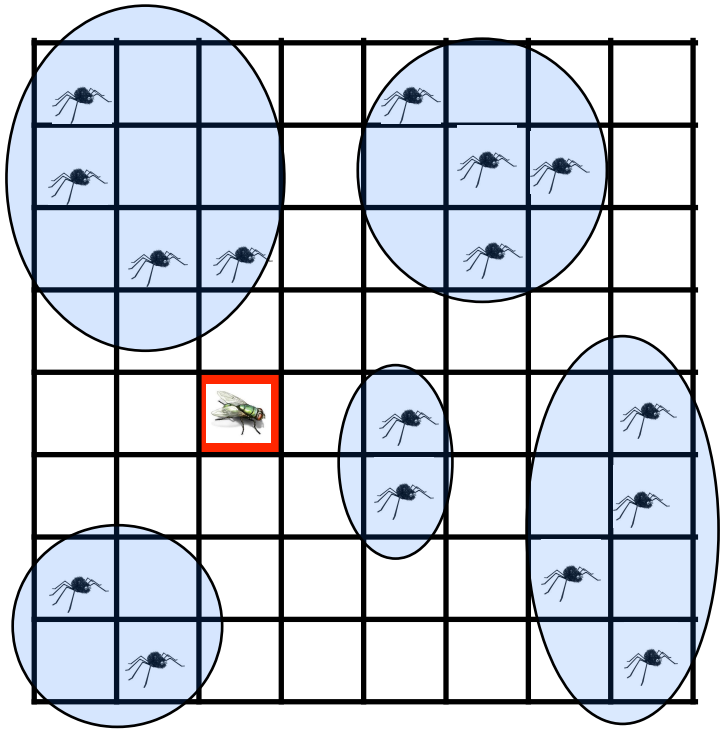
- Base policy (each spider follows the shortest path): 85
- All-at-once rollout (125 move choices): 34
- One-at-a-time rollout (15 move choices): 34

Multiagent Parallelization and Coordination Issues



- One-at-a-time rollout and all-at-once rollout produce different rollout policies. One may be better than the other.
- Exact policy iteration issues. One-at-a-time rollout used repeatedly (as in policy iteration) may stop short of the optimal.
- We speculate that in approximate policy iteration, one-at-a-time rollout will often perform about as well as all-at-once rollout.
- We can try to induce agent parallelization and asynchronism: Divide agents in "weakly coupled groups" ... Require little or no coordination among groups.

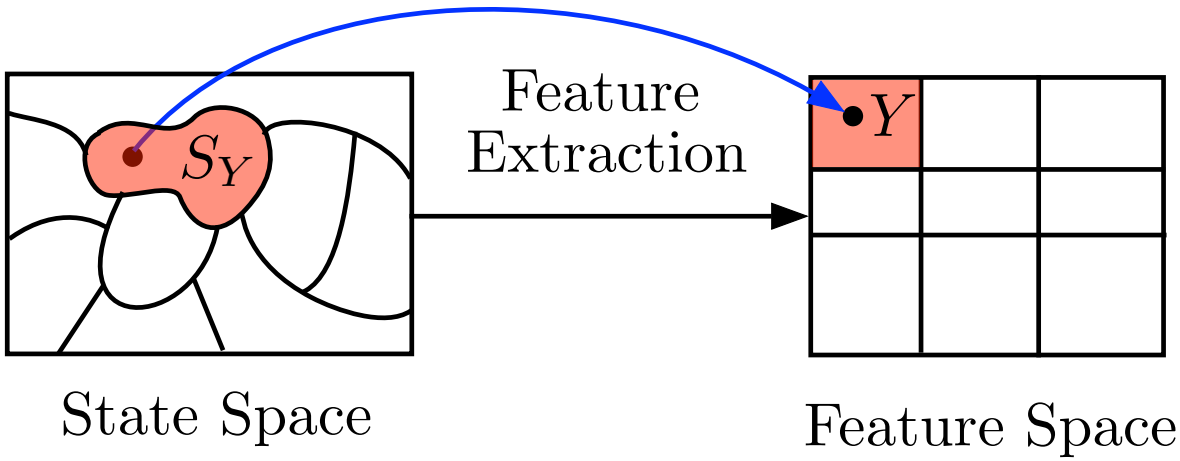
Group Coordination Issues



Several interesting theoretical and algorithmic issues remain to be resolved

- How do we form groups? Use feature-based groupings?
- Frequency of communication?
- Aggregated coordination between groups?
- Distributed info processing?

Multiprocessor Parallelization: State Space Partitioning



Partition the state space into several subsets and construct a separate policy and value approximation in each subset.

- Use features to generate the partition.
- How do we implement truncated rollout and policy iteration with partitioning?

Distributed Asynchronous Policy Iteration (Williams and Baird, 1993, Bertsekas and Yu, 2010)

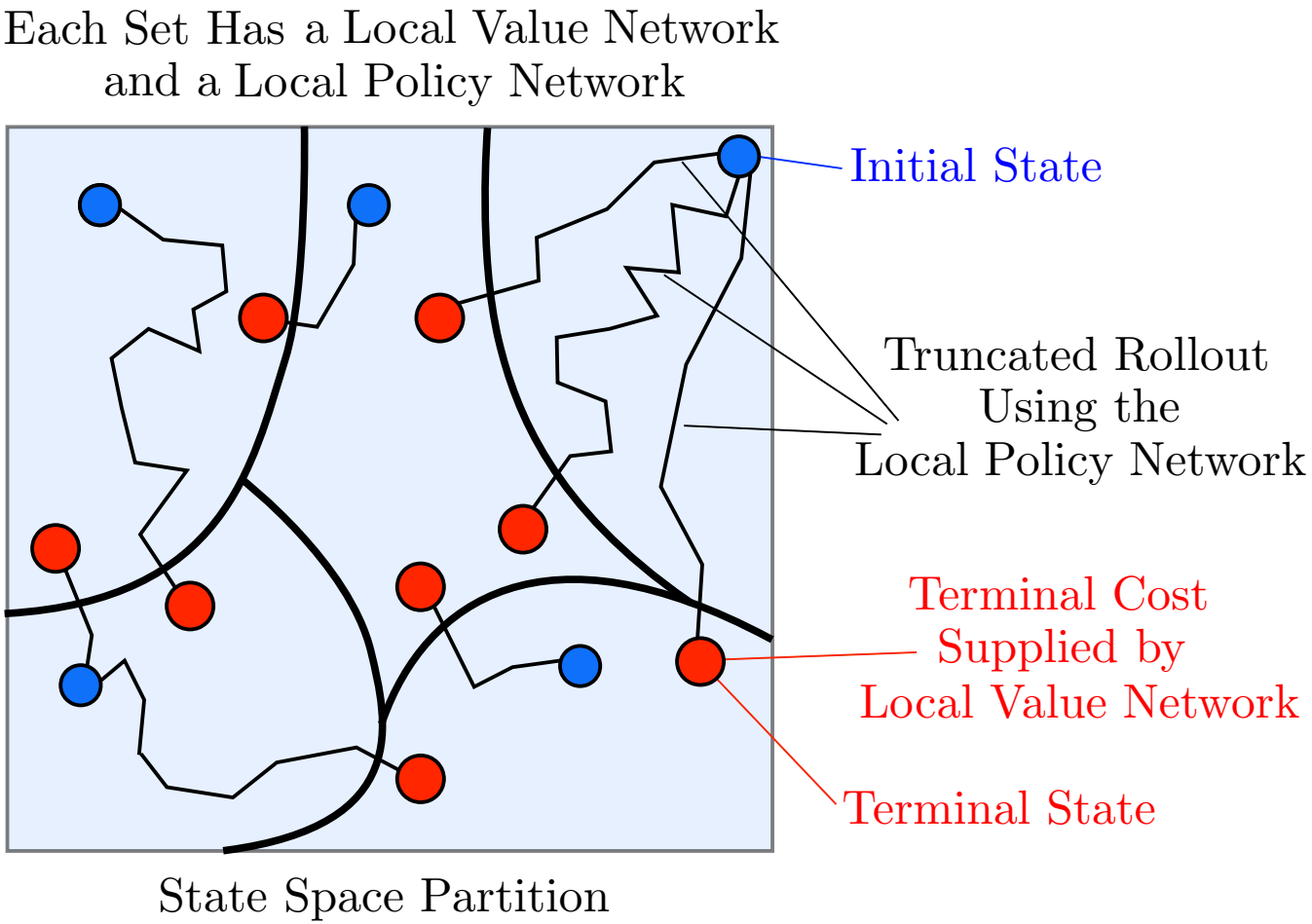
An old and fairly obvious training idea:

- Assign one processor to each subset of the partition.
- Each processor uses a local value and a local policy approximation, and maintains asynchronous communication to other processors.
- Update values locally on each subset (policy evaluation by value iteration).
- Update policies locally on each subset (policy improvement, possibly using multiagent parallelization).
- Communicate asynchronously local values and policies to other processors.

However:

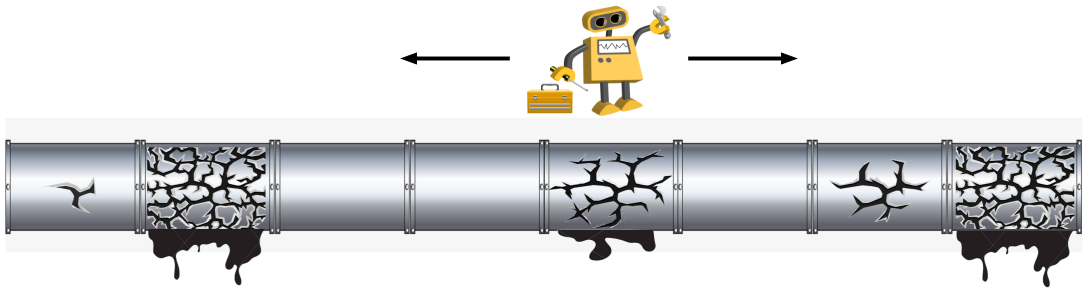
- The obvious algorithm fails (for the lookup table representation case - a counterexample by Williams and Baird, 1993).
- The DPB-HJY algorithm, 2010, corrects this difficulty and proves convergence (assuming a lookup table representation for policies and cost functions).
- Admits extension to neural net approximations (some error bounds available).

Approximate Policy Iteration with Local Value and Policy Networks

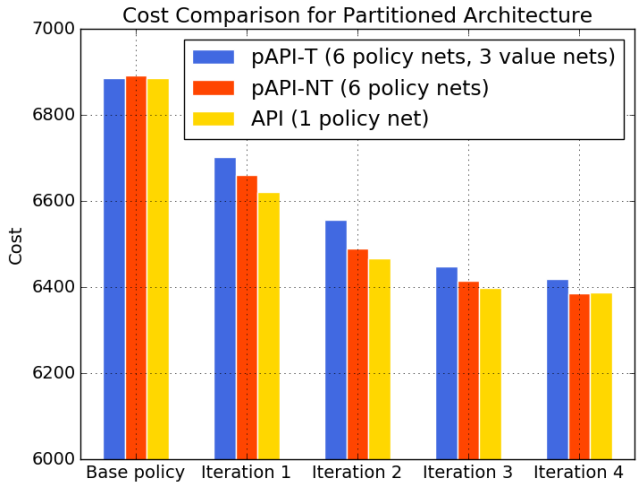


- Start with some base policy and a value network for each set.
- Obtain a policy and a value network for the truncated rollout policy. Repeat.
- Partitioning may be a good way to deal with adequate state space exploration.

Distributed RL for POMDP (BBWGB paper, 2020)



- 20 potentially damaged locations along a pipeline.
- Damage of each location is imperfectly known; evolves according to a Markov chain (5 levels of damage). Number of states: $\approx 10^{15}$
- Repair robot moves left or right, visits and repairs locations. May want to give preference to “urgent" repairs.
- Belief space partitioning with 6 policy networks and 3 value networks.



Concluding Remarks on Distributed RL

- RL is a VERY computationally intensive methodology.
- Parallel asynchronous computation is an obvious answer.
- It is important to identify methods that are amenable to distributed computation.
- One-time rollout with a base policy, multiagent parallelization, and/or local value and policy networks is well-suited. Often easy to implement, typically reliable.
- Repeated rollout (i.e, approximate policy iteration) with partitioned architecture and multiagent parallelization, and/or local value and policy networks is well-suited, but is more complicated and more ambitious.
- Rollout has close connections to model predictive control.
- Rollout has many applications to discrete/combinatorial optimization problems.
- There are many interesting analytical and implementation challenges.

Thank you!