Multiagent Reinforcement Learning: Rollout and Policy Iteration (Bertsekas, 2020)

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MARL Overview

Motivation

Multi-agent systems are ubiquitous

Eg. fleet of drones, factory robots, self-driving cars.

Recent advances in RL applications

Eg. AlphaGo/AlphaZero, playing Starcraft, robotic control.

Utilize modern computer architecture and software frameworks

Eg. cloud computing, stacks of graphics cards, TPUs; PyTorch, OpenAI gyms.

Benefits of modeling a problem as MARL

Scalability, robustness, faster learning through experience sharing, parallel computation.

Multi-Agent Reinforcement Learning Problem

Inherits Reinforcement Learning characteristics:

- Learning how to map situations into actions
- Trial-and-error search
- Delayed feedback
- Trade-off between exploration and exploitation
- Sequential decision making
- Agent's actions affect the subsequent data it receives

Adds multi-agent features:

- Actions of one agent influence other agents' rewards
- Communication problem
- Fully cooperative, fully info sharing (DP) vs. partial info sharing
- Curse of dimensionality (more severe than in RL)

"Bertsekas Dictionary"

Aligns optimal control definitions with the RL-world:

- Maximize value $\rightarrow$ minimize cost
- Agent $\rightarrow$ Decision maker or controller
- Action $\rightarrow$ Decision or control
- Environment $\rightarrow$ Dynamic system
- Learning $\rightarrow$ Solving a DP-related problem using simulation
- Self-learning (self-play) $\rightarrow$ Solving a DP problem using simulation-based policy iteration
- Planning vs Learning distinction $\rightarrow$ Solving a DP problem with model-based vs model-free simulation

Multi-Agent MDP

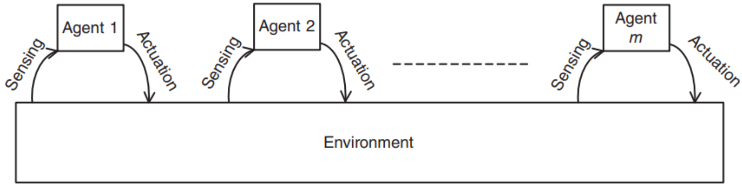


Figure: MARL Problem. Source: Sadhu, Konar (2020)

- All agents see the global state s
- Individual actions: $u^a \in U$
- State transitions: $P(s' \mid s, \mathbf{u}) : S \times \mathbf{U} \times S \to [0,1]$
- Shared team reward: $S \times \mathbf{U} \to \mathbb{R}$

Taxonomy

Cooperative

- The goal of cooperative agents is to achieve a common objective
- Coordination problem

Competitive

- Zero-sum games (eg. chess, tic-tac-toe)
- Minimax equilibria

Mixed

- General-sum games (win-win, lose-lose scenarios; eg. pollution model, "what movie to watch?")
- Nash equilibria

First Attempts to Solve MARL

Independent Q-Learning (Tan 93)

- Each agent learns its own Q-function
- Each agent treats the other agents as part of the environment
- Independent Q-learning update rule for agent a:

$$Q\left(s_t, u_t^a\right) \leftarrow Q\left(s_t, u_t^a\right) + \alpha \left[r_t + \gamma \max_u Q\left(s_{t+1}, u\right) - Q\left(s_t, u_t^a\right)\right]$$

Coordinated Q-Learning (Guestrin et al. 02)

- Stationary learning of joint value function $Q_{tot}(s, \mathbf{u})$
- Factorize to improve scalability:

$$Q_{tot}(s, \mathbf{u}) = \sum_{e=1}^{E} Q_e\left(s^e, \mathbf{u}^e\right)$$

Multiagent Rollout

Key Ideas

Deal with the exponential increase in the action space

$\rightarrow$ Introduce a form of sequential agent-by-agent one-step lookahead minimization – *multiagent rollout*

Compute the agent actions in parallel

$\rightarrow$ Decouple sequential agent-by-agent computation with *precomputed signaling policy* that embodies agent coordination

The Setting

- $P2_F$ – stochastic discrete-time optimal control problem over a finite horizon, with perfect information on the state
- Fully cooperative
- Tested in Spiders-And-Flies environment

$$x_{k+1} = f_k(x_k, u_k, w_k), \quad k = 0, 1, \dots, N-1$$

$$J_\pi(x_0) = E\left\{ g_N(x_N) + \sum_{k=0}^{N-1} g_k(x_k, \mu_k(x_k), w_k) \right\}$$

Policy Iteration and Rollout

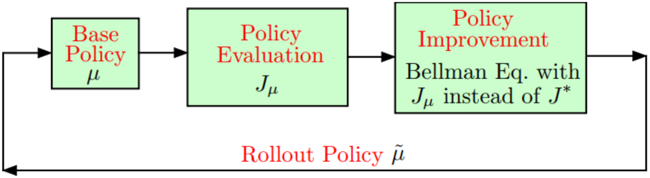


Figure: Policy Iteration Algorithm. Source: Bertsekas (2020)

- Fundamental property: policy improvement

$$J_{k,\tilde{\pi}}(x_k) \leq J_{k,\pi}(x_k), \quad \forall x_k, k$$

Standard Rollout Algorithm

- Rollout is one-time policy iteration
- Start with the initial state $x0$, and generate a trajectory:

$$\{x_0, \tilde{u}_0, x_1, \tilde{u}_1, \ldots, x_{N-1}, \tilde{u}_{N-1}, x_N\}$$

Where $\tilde{u}_k$ is

$$\tilde{u}_k \in \arg \min_{u_k \in U_k(x_k)} E\{g_k(x_k, u_k, w_k) + \\ + J_{k+1,\pi}(f_k(x_k, u_k, w_k))\}$$

- Defines rollout policy that possesses **cost improvement property** and **robustness property** (can adapt to changes in data distributions online)
- Works when argmin over small set of U!

Standard Rollout for MA Case (All-at-once Rollout)

- The control constraint set becomes the Cartesian product

$$U_k(x_k) = U_k^1(x_k) \times \cdots \times U_k^m(x_k)$$

- Argmin is now computed over q^m! (where q is an upper bound to the number of controls in U_k, m is the number of agents)
- Idea: trade-off control space complexity with state space complexity

One-at-a-time Rollout (Multiagent Rollout)

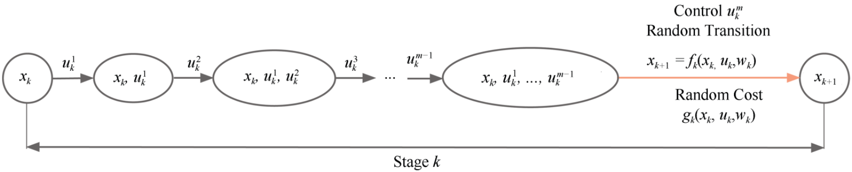


Figure: One-at-a-time action selection. Source: Bertsekas (2020)

1. Break down u_k into the sequence of m actions: $u_k^1, u_k^2, \ldots, u_k^m$
2. Introduce artificial states
$\left(x_k, u_k^1\right), \left(x_k, u_k^1, u_k^2\right), \ldots, \left(x_k, u_k^1, \ldots, u_k^{m-1}\right)$
3. u_k^m marks the transition to the new state $x_{k+1} = f(x_k, u_k, w_k)$ incurring cost $g_k(x_k, u_k, w_k)$

Benefits of the Multiagent Rollout Algorithm

Past controls determined by the rollout policy, and the future controls determined by the base policy!

- Reducing the action space by increasing the state space. Reasonable since Q-factor minimization is performed for just one state at each stage.
- We reduce the computation complexity from $O(q^m)$ to $O(qm)$, $q = |U|$
- In addition to that, solves coordination. problem.
- Preserves **cost improvement property** (see Bertsekas, part II.D for proof by induction for $m = 2$).

Multiagent Rollout Assumptions

1. All agents have access to the current state x_k;
2. There is an order in which agents compute and apply their local controls;
3. There is "intercommunication" between agents, so that agent l knows the local controls $u_k^1, u_k^2, ..., u_k^{l-1}$ computed by the predecessor agents $1, 2, ..., l-1$ in the given order.

Ordering of Agents

- Instead of predefined or random order, at each step k optimize over single agent's Q-factors.
- Simulate m sequences where each agent acts first, select the one with minimal Q-factor, "compete" for the second place with $m-1$ agents, etc.
- Total number of minimizations:

$$m + (m-1) + \cdots + 1 = \frac{m(m+1)}{2}$$

- Computations can be parallelized.

Extensions

Approximate Policy Iteration with Agent-by-Agent Policy Improvement

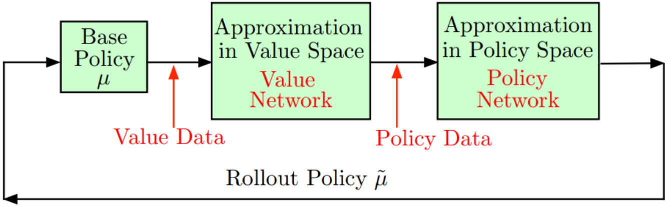


Figure: Approximate Policy Iteration. Source: Bertsekas (2020)

- Approximate policy improvement property: With approximations, policy improvement holds approximately
- If a single policy iteration is done (rollout), no need to train value and policy networks
- Multiple policy iterations can be done only with off-line training

Parallel Computation of Agents' Controls

- Reminder: parallel computation vs. action coordination.
- First Attempt: since the agent *l* does not know the rollout controls for the agents 1, ..., *l*1, uses the controls $\mu_k^1(x_k), \ldots, \mu_k^{\ell-1}(x_k)$ of the base policy in their place.
- Drawback: does not preserve cost improvement property.

Autonomous Multiagent Rollout

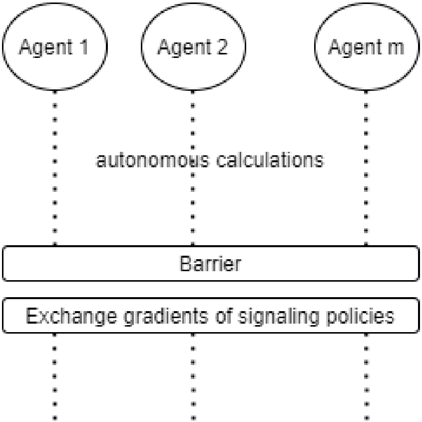
- Second Attempt: assume that once the agents know the state, they use precomputed approximations to the control components of the preceding agents, and compute their own control components in parallel and asynchronously – **autonomous multiagent rollout**.
- How to compute approximations? Train a neural network off-line training with training samples generated through the rollout policy – **signaling policy**.
- Use base and signaling policies to generate a rollout policy $\tilde{\pi} = \{\tilde{\mu}_0, \ldots, \tilde{\mu}_{N-1}\}$ autonomously in parallel.

Autonomous Multiagent Rollout Mechanics

$$
\begin{gathered}
\tilde{\mu}_k^1(x_k) \in \arg\min_{u_k^1 \in U_k^1(x_k)} E\Big\{g_k\Big(x_k, u_k^1, \mu_k^2(x_k), \\
\ldots, \mu_k^m(x_k), w_k\Big) \\
+ J_{k+1,\pi}\Big(f_k\Big(x_k, u_k^1, \mu_k^2(x_k) \\
\ldots, \mu_k^m(x_k), w_k\Big)\Big)\Big\} \\
\tilde{\mu}_k^2(x_k) \in \arg\min_{u_k^2 \in U_k^2(x_k)} E\Big\{g_k\Big(x_k, \widehat{\mu}_k^1(x_k), u_k^2 \\
\ldots, \mu_k^m(x_k), w_k\Big) \\
+ J_{k+1,\pi}\Big(f_k\Big(x_k, \widehat{\mu}_k^1(x_k), u_k^2 \\
\ldots, \mu_k^m(x_k), w_k\Big)\Big)\Big\} \\
\ldots \\
\ldots \\
\mu_k^m(x_k) \in \arg\min_{u_k^m \in U_k^m(x_k)} E\Big\{g_k\Big(x_k, \widehat{\mu}_k^1(x_k) \\
\ldots, \widehat{\mu}_k^{m-1}(x_k), u_k^m, w_k\Big) \\
+ J_{k+1,\pi}\Big(f_k\Big(x_k, \widehat{\mu}_k^1(x_k) \\
\ldots, \widehat{\mu}_k^{m-1}(x_k), u_k^m, w_k\Big)\Big)\Big\}
\end{gathered}
$$

Synchronized Autonomous Multiagent Rollout

- What if we allow periodic updates of the signaling policies?



Conclusion

Conclusion

- MARL problems are especially prone to the curse of the dimensionality problem;
- We could reduce the action space by allowin agent-be-agent updates;
- We could parallelize computations by adding a signaling policy (precalculated offline);
- Multi-agent rollout can be extended with approximate policy iteration;

References

Dimitri Bertsekas – Multiagent Reinforcement Learning: Rollout and Policy Iteration (2020). Web: https://web.mit.edu/dimitrib/www/Multiagent_Sinica_2020.pdf

Shimon Whiteson – Multi-Agent Reinforcement Learning Reinforcement (July 2019) [Eastern European Machine Learning Summer School Seminar].

Arup Kumar Sadhu, Amit Konar – Multi-Agent Coordination, A Reinforcement Learning Approach (2020).

Thanks for your attention!