Topics in Reinforcement Learning

Review of Multiagent Rollout

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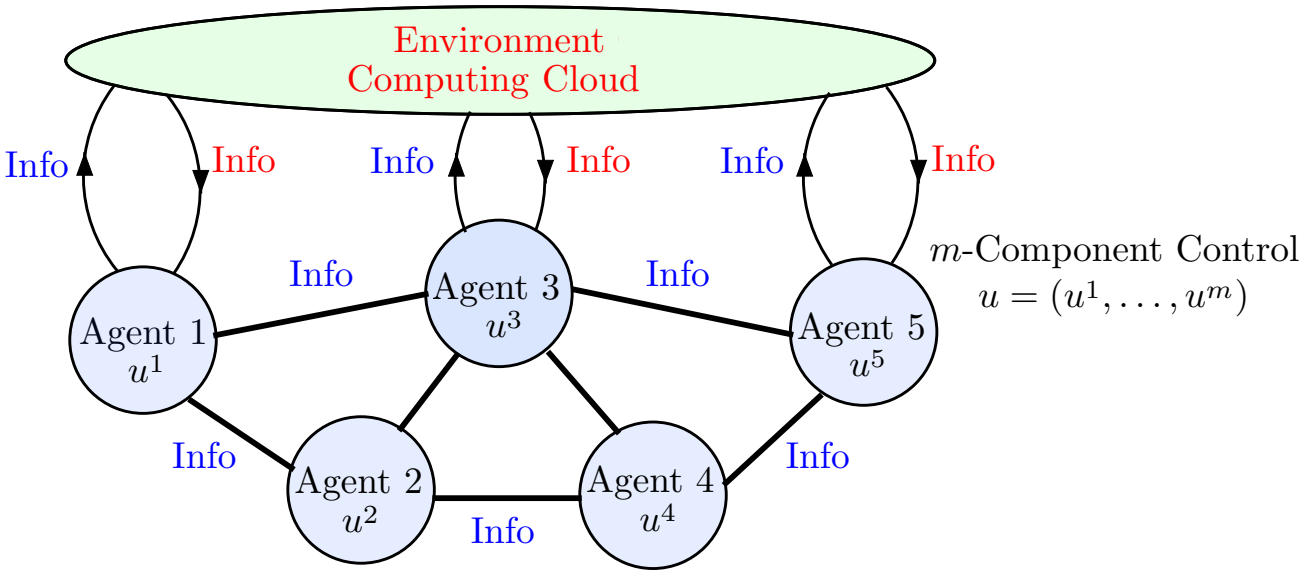
Multiagent Problems (1960s $\rightarrow$)

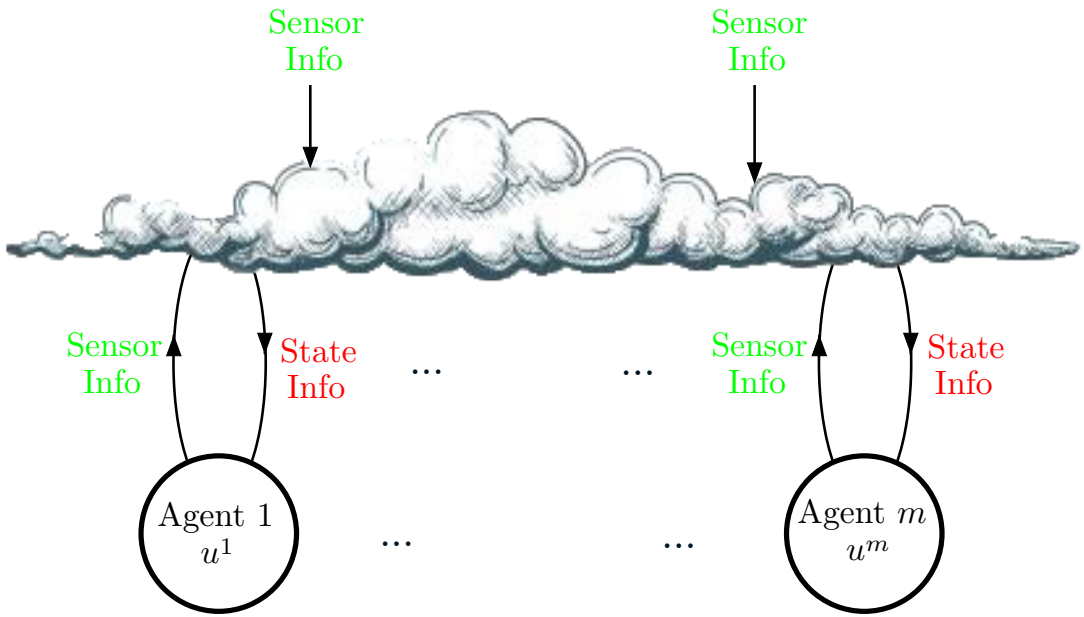


- Multiple agents collecting and sharing information selectively with each other and with an environment/computing cloud
- Agent i applies decision u^i sequentially in discrete time based on info received

The major mathematical distinction between problem structures

- The classical information pattern: Agents are fully cooperative, fully sharing and never forgetting information. Can be treated by DP
- The nonclassical information pattern: Agents are partially sharing information and may be antagonistic. HARD because it is hard to treat by DP

Starting Point: A Classical Information Pattern

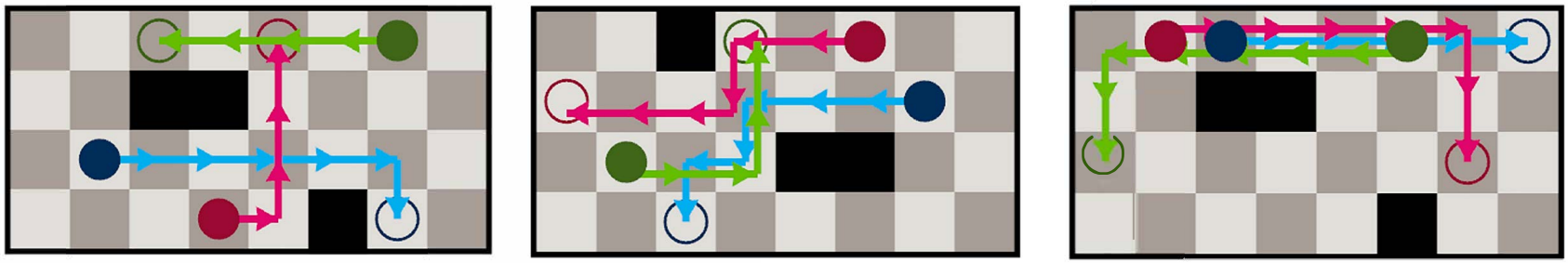


At each time: Agents have exact state info; choose their controls as function of state

Model: A discrete-time (possibly stochastic) system with state x and control u

- Decision/control has m components $u = (u^1, \ldots, u^m)$ corresponding to m "agents"
- "Agents" is just a metaphor - the important math structure is $u = (u^1, \ldots, u^m)$
- The theoretical framework is DP. We will reformulate for faster computation
  - We first aim to deal with the exponential size of the search/control space
  - Later we will discuss how to compute the agent controls in distributed fashion (in the process we will deal in part with nonclassical info pattern issues)

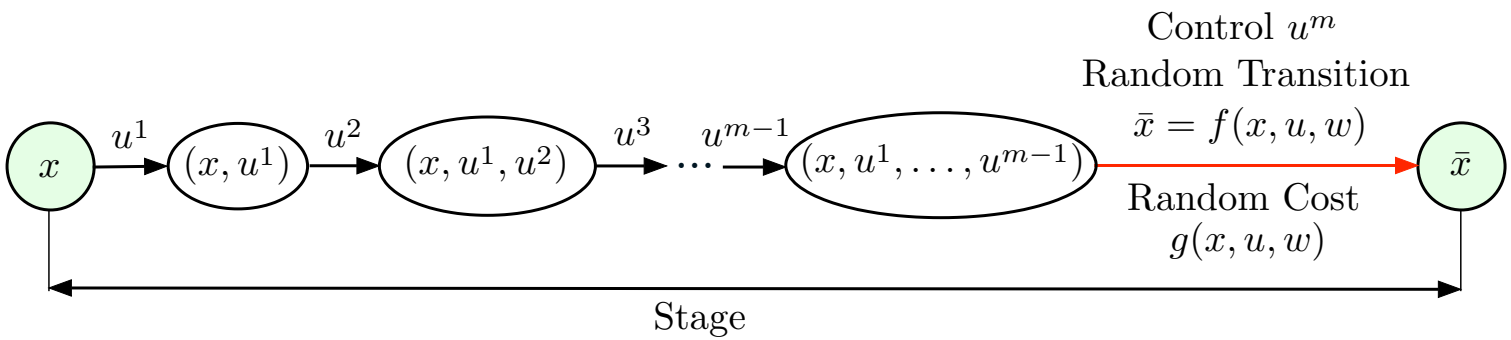
Multiagent Path Finding Example



3 agents move in 4 directions with perfect vision.
They have been assigned to some targets.
Objective is to reach their respective targets in minimum time
while avoiding collision with each other.

- At each time we must select one out of $\approx 5^m$ joint move choices
- We will reduce to $5 \cdot m$ (while maintaining good properties)
- Idea: Break down the control into a sequence of one-agent-at-a-time moves
- Scales well, up to $m = 200$ agents, with average computational time around 50 ms. Can also adapt to a changing environment through recomputation. See paper `https://arxiv.org/abs/2211.08201` as well as implementation in C++ `https://github.com/will-em/multi-agent-rollout`

Reformulation Ideas: Trading off Control and State Complexity



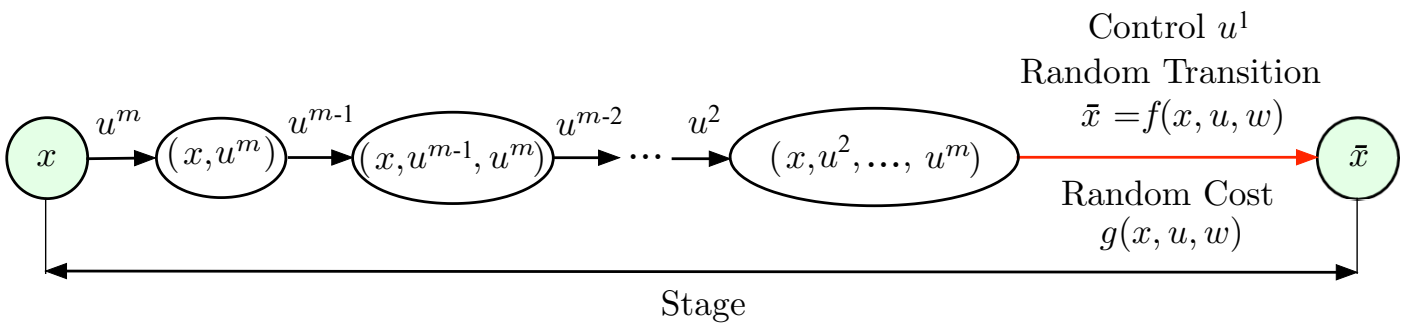
An equivalent reformulation - "Unfolding" the control action

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

$$J^1(x, u^1), J^2(x, u^1, u^2), \ldots, J^m(x, u^1, \ldots, u^m),$$

- Allows far more efficient rollout (one-agent-at-a-time). This is just standard rollout for the reformulated problem (so it involves a Newton step)
- The increase in size of the state space does not adversely affect rollout (only one state and its successors are looked at each stage during on-lin play)
- Complexity reduction: The one-step lookahead branching factor is reduced from n^m to $n \cdot m$, where n is the number of possible choices for each component u^i

Implementation Variants of Multiagent Rollout



- Reshuffling the order of agents results in a different, yet still equivalent problem.
- Multiagent rollout admits parallel implementation.
- Multiple base heuristics can be applied to enhance the performance further.
- All those ideas are independent of each other, and can be combined.