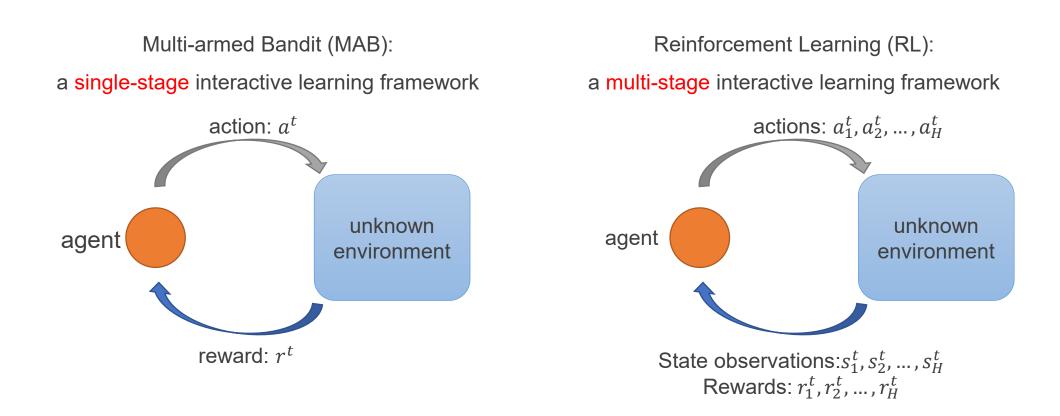




Learning in safety-critical, multi-agent, and lifelong systems: Bandits and RL approaches

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Background



Multi-armed Bandit

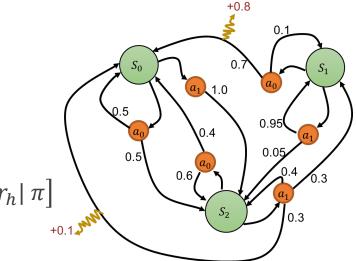
Multi-armed Bandit (MAB): a single-stage interactive learning framework

- Action set A
- Reward r(a).
- Goal (without knowledge of r): maximize r(a)

Reinforcement Learning

Reinforcement Learning (RL): a multi-stage interactive learning framework

- MDP: $M \coloneqq (S, A, H, P, r)$
- Transition kernel P(s'|s, a), reward r(s, a).
- Horizon H.
- A policy $\pi: S \to \Delta(A)$
- Goal (without knowledge of *P* and *r*): maximize $V^{\pi} \coloneqq E[\sum_{h=1}^{H} r_h | \pi]$



When the model is known, solve by dynamic programming.

Motivation 1

✤ Safety-critical systems:



- Challenges:
- Self-driving cars



- Medical trials
- > Playing unsafe actions/policies may result in catastrophic results
- Safety requirements are typically unknown and must be learned.

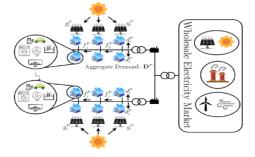
Our research goal: being safe while achieving good performance comparable to unsafe approaches

Motivation 2

Multi-Agent systems:







Smart energy grid

- ✤ Challenges:
 - > Certain systems are distributed inherently.
 - > Distributed solutions speed up the process.

Our research goal: improve communication and performance efficiency over prior work in muti-agent systems

Motivation 3

Lifelong learning systems:



Robotics



Self-driving cars

- ✤ Challenges:
 - > Learning a multi-task policy while solving a streaming sequence of arbitrary tasks.
 - Computationally efficient solutions

Our research goal: solutions that are provably computationally efficient while achieving good performance comparable to direct extensions of single-task approaches.

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Thank you very much!