Approximate information states for partially observable systems

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McGill University

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DataAI Seminar
11 Nov 2023

Recent successes of RL

Recent successes of RL

Alpha Go

Recent successes of RL

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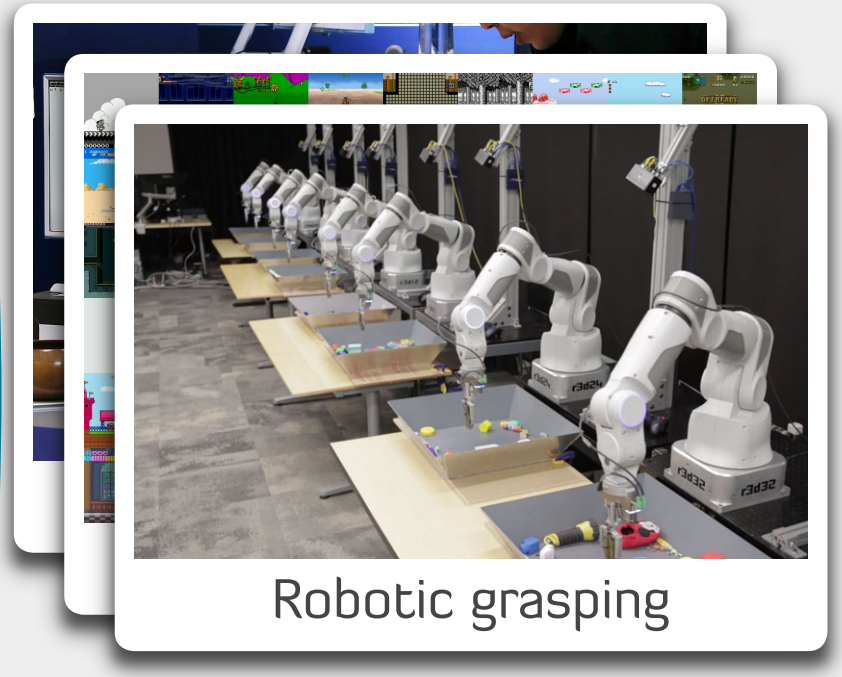
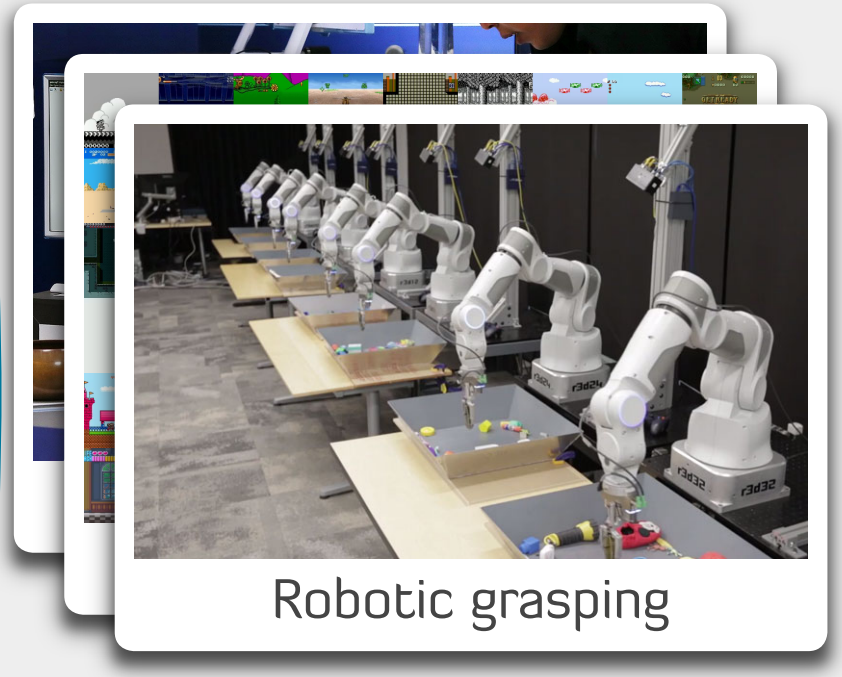
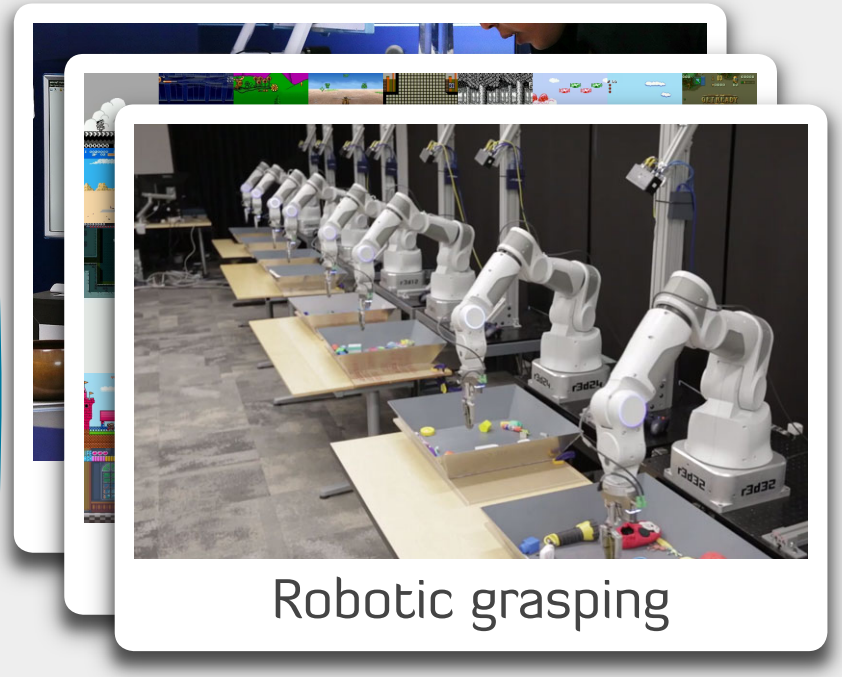


Robotic grasping



Recent successes of RL

- Algorithms based on comprehensive theory



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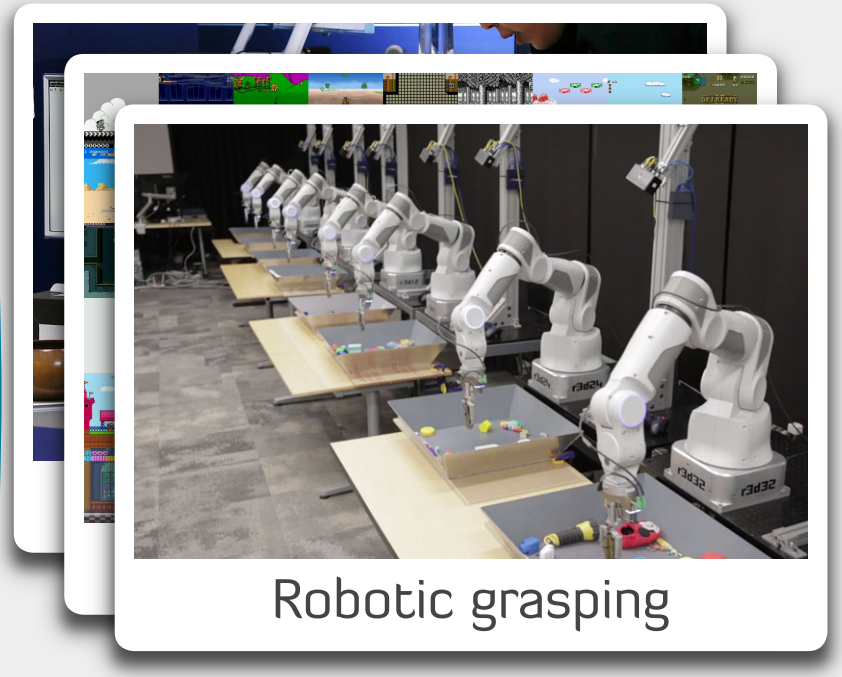
- Algorithms based on comprehensive theory
- The theory is restricted almost exclusively to systems with perfect state observations.



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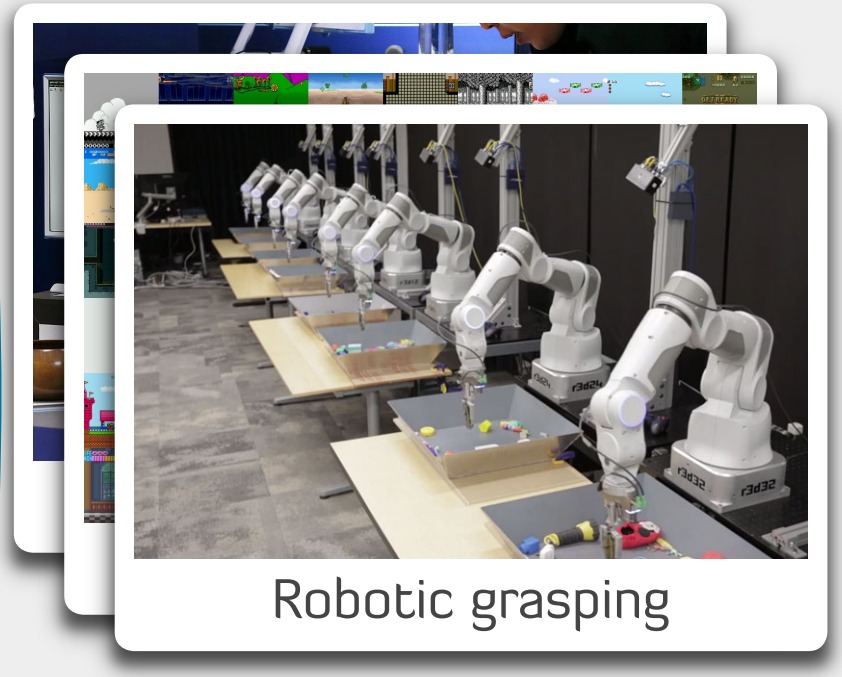
Many real-world applications are partially observed

- Healthcare
- Autonomous driving
- Finance (portfolio management)
- Retail and marketing



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How do we develop a theory for RL for partially observed systems?

Outline

Background

- Review of MDPs and RL
- Review of POMDPs
- Why is RL for POMDPs difficult?

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Approximate Planning for POMDPs

- Preliminaries on information state
- Approximate information state
- Approximation bounds

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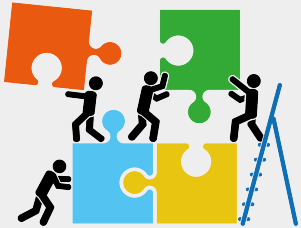

RL for POMDPs

- From approximation bounds to RL
- Numerical experiments

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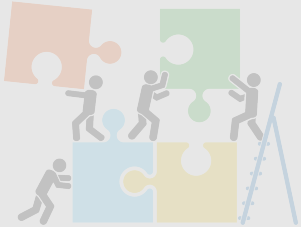

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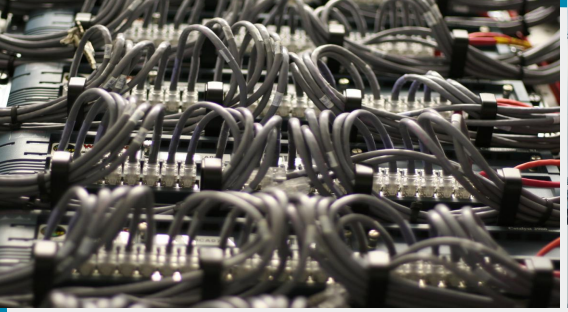
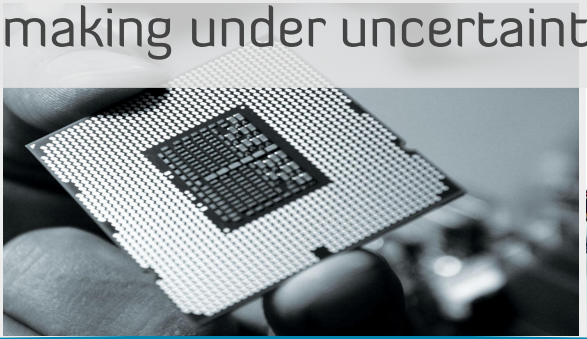
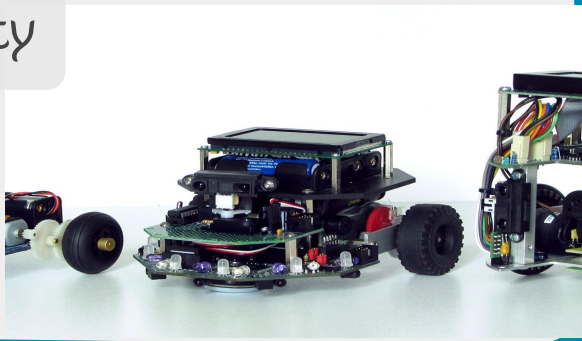
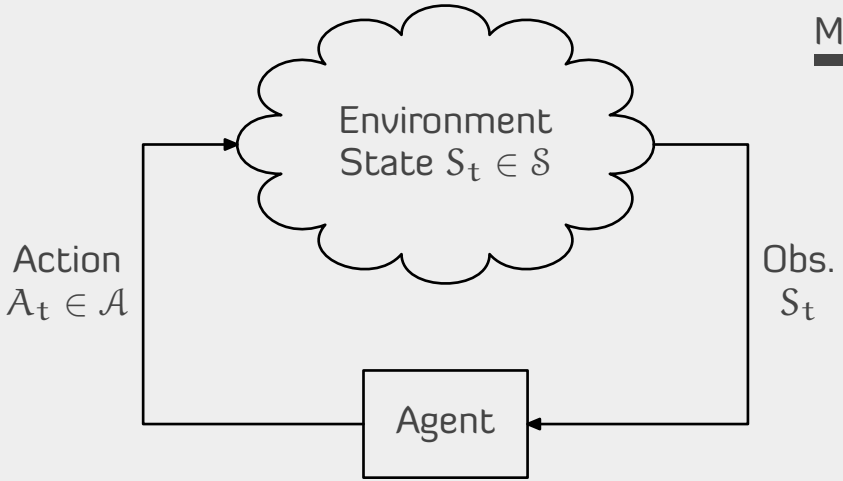





Common theme: multi-stage decision making under uncertainty

Review: Markov decision processes (MDPs)



MDP: MARKOV DECISION PROCESS

Dynamics: $\mathbb{P}(S_{t+1} \mid S_t, A_t)$

Observations: S_t

Reward $R_t = r(S_t, A_t)$.

Action: $A_t \sim \pi_t(S_{1:t}, A_{1:t-1})$.

$\pi = (\pi_t)_{t \geqslant 1}$ is called a policy.

The objective is to choose a policy π to maximize:

$$J(\pi) := \mathbb{E}^{\pi}\left[\sum_{t=1}^{\infty} \gamma^{t-1} R_t\right]$$

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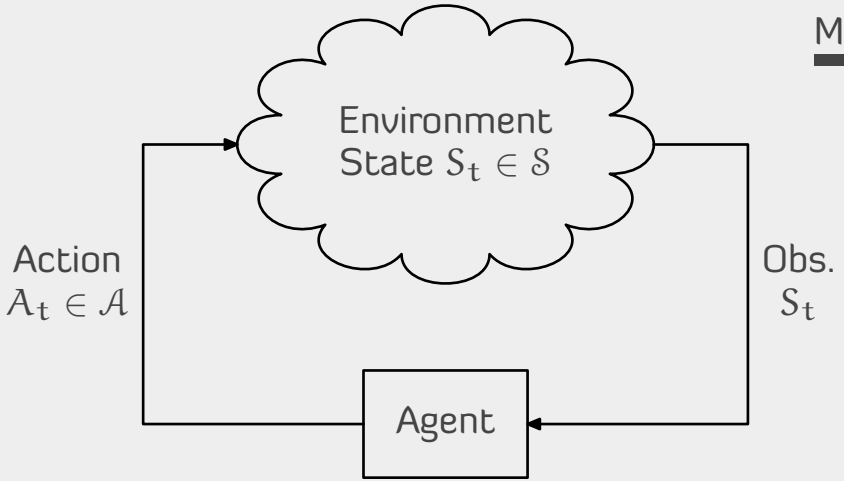

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$$\left[\sum_{t=1}^{\infty} \right]$$

Conceptual challenge

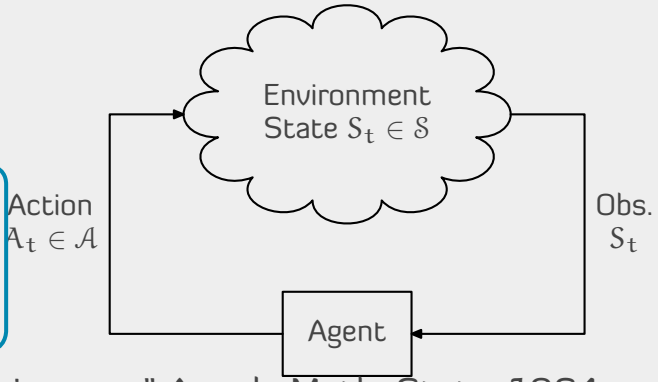
- Brute force search has an exponential complexity in time horizon.
- How to efficiently search an optimal policy?

Review: Markov decision processes (MDPs)

Key simplifying ideas

Principle of Irrelevant Information

Structure of optimal policy	There is no loss of optimality in choosing the action A_t as a function of the current state S_t



Blackwell, "Memoryless strategies in finite-stage dynamic prog.," Annals Math. Stats, 1964.

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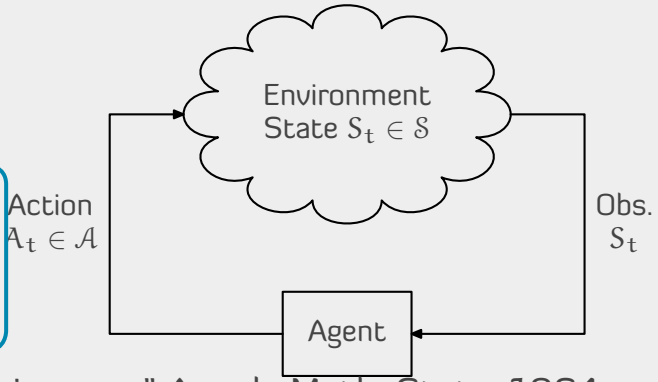

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Principle of Optimality

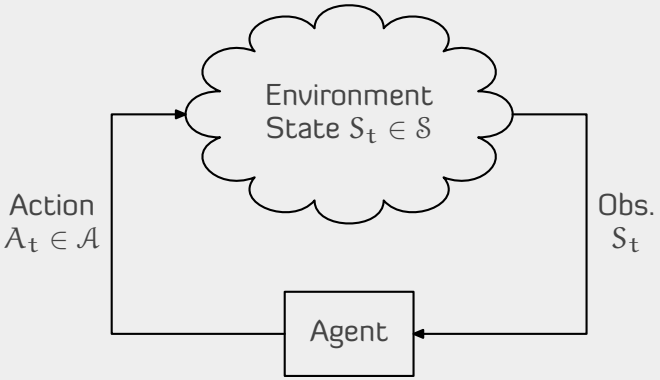
Dynamic Program	The optimal control policy is given a DP with state S_t: $V(s) = \max_{a \in \mathcal{A}} \left\{ r(s,a) + \gamma \int V(s') P(ds'|s,a) \right\}$

Bellman, "Dynamic Programming," 1957.

Review: Reinforcement Learning (RL)

The RL setting

- Dynamics and reward functions are unknown.
- Agent can interact with the environment and observe states and rewards.
- Design an algorithm that asymptotically identifies an optimal policy.



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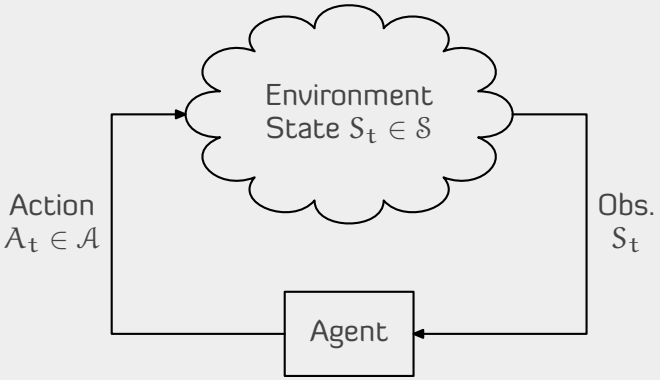


Value based methods

Estimate the Q-function $Q(s,a) = r(s,a) + \gamma \int V(s')P(ds'|s,a)$ using temporal difference learning (i.e., stochastic approximation).

[Watkins and Dayan, 1992; Tsitsiklis, 1994]

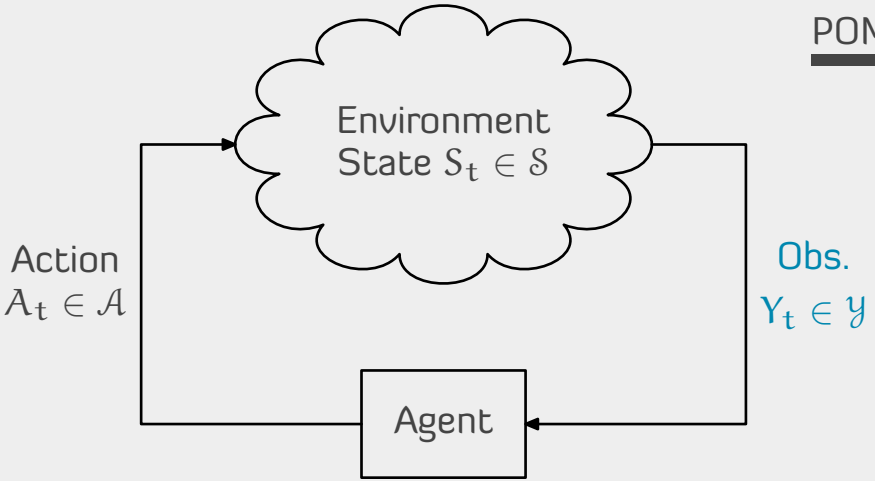
Policy-based methods

Use parameterized policies π_θ. Estimate $\nabla_\theta V_\theta(s)$ using single trajectory gradient estimates (i.e., infitesimal perturbation analysis).

[Sutton 2000, Marback and Tsitsiklis 2001], [Cao, 1985; Ho, 1987]

Why is learning difficult in partially observable environments?

Review: Planning in partially observable environments



POMDP: PARTIALLY OBSERVABLE MARKOV DECISION PROCESS

Dynamics: $\mathbb{P}(S_{t+1} \mid S_t, A_t)$

Observations: $\mathbb{P}(Y_t \mid S_t)$

Reward $R_t = r(S_t, A_t)$.

Action: $A_t \sim \pi_t(Y_{1:t}, A_{1:t-1})$.

$\pi = (\pi_t)_{t \geqslant 1}$ is called a policy.

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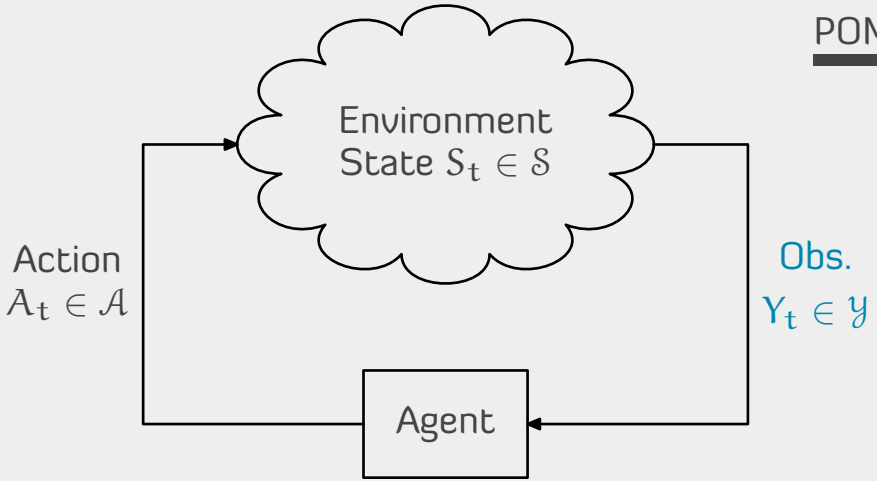

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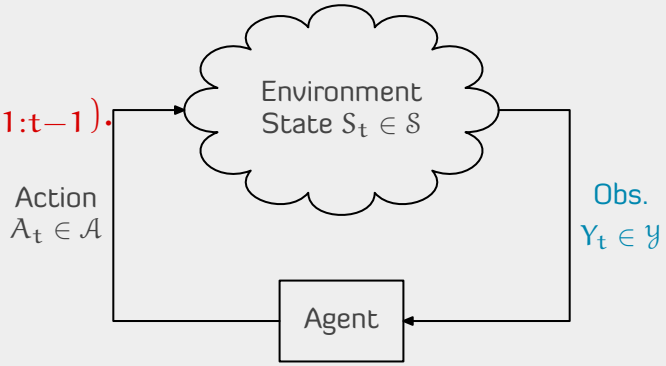
Conceptual challenge

- Action is a function of the history of observations and actions.
- The history is increasing in time. So, the search complexity increases exponentially in time.

Review: Planning in partially observable environments

Key simplifying idea

Define **belief state** $B_t \in \Delta(\mathcal{S})$ as $B_t(s) = \mathbb{P}(S_t = s \mid Y_{1:t}, A_{1:t-1})$.



- Belief state updates in a state-like manner

$$B_{t+1} = \text{function}(B_t, Y_{t+1}, A_t).$$

- Belief state is sufficient to evaluate rewards

$$\mathbb{E}[R_t \mid Y_{1:t}, A_{1:t}] = \hat{r}(B_t, A_t).$$

Thus, $\{B_t\}_{t \geqslant 1}$ is a perfectly observed controlled Markov process.

Astrom, "Optimal control of Markov processes with incomplete information," JMAA 1965.

Stratonovich, "Conditional Markov Processes," TVP 1960.

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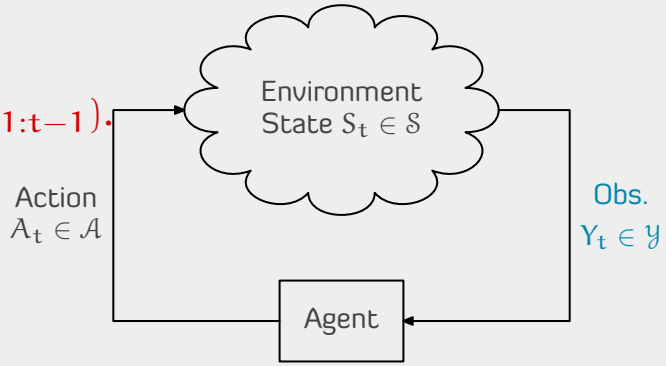

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Thus, $\{B_t\}_{t \geqslant 1}$ is a perfectly observed controlled Markov process. Therefore:

Structure of optimal policy	There is no loss of optimality in choosing the action A_t as a function of the belief state B_t
Dynamic Program	The optimal control policy is given a DP with belief B_t as state.

Implications of the POMDP modeling framework

Implications for planning

- Allows the use of the MDP machinery for partially observed systems.
- Various exact and approximate algorithms to efficiently solve the DP.

  Exact: incremental pruning, witness algorithm, linear support algo

  Approximate: QMDP, point based methods, SARSOP, DESPOT, . . .

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Implications for learning

- The construction of the belief state depends on the system model.
- So, when the system model is unknown, we cannot construct the belief state and therefore cannot use standard RL algorithms.

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- On the theoretical side:
  - Propose alternative methods: PSRs (predictive state representations), bisimulation metrics, . . .
  - Good theoretical guarantees, but difficult to scale.
- On the practical side:
  - Simply stack the previous k observations and treat it as a "state".
  - Instead of a CNN, use an RNN to model policy and action-value fn.
  - Can be made to work but lose theoretical guarantees and insights.

Our result: A theoretically grounded method for RL in partially observable models which has strong empirical performance for high-dimensional environments.

- paper 1: `JMLR, Feb 2022`
  co-authors: J. Subramanian, A. Sinha, and R. Seraj.
- paper 2: `arxiv:2306.05991, June 2024`
  co-authors: E. SeyedSalehi, N. Akbarzadeh, A. Sinha

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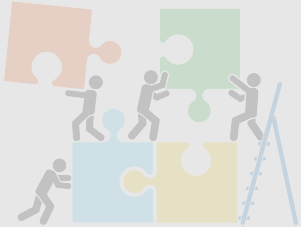

RL for POMDPs

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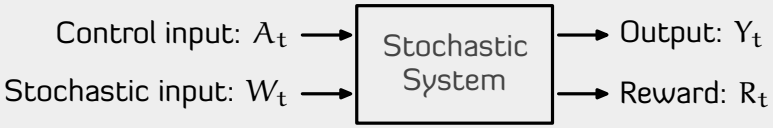
System model

- In RL, unobserved state space may not be known
- So, we work directly with input-output model

System model



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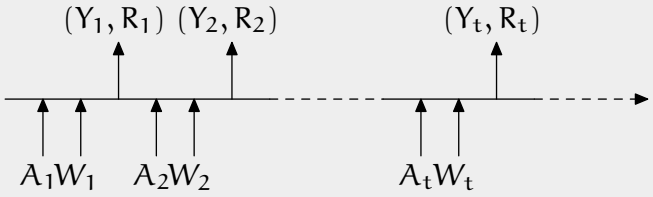

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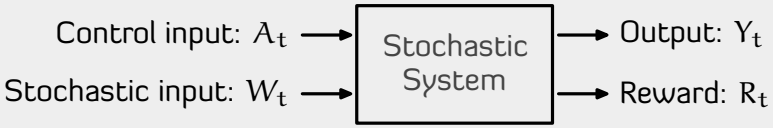

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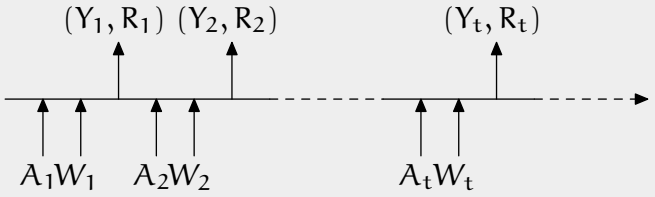
- $H_t = (Y_{1:t-1}, A_{1:t-1})$ denotes the history of all data available to the agent at time t.
- Agent chooses an $A_t \sim \pi_t(H_t)$.
- $\pi = (\pi_1, \pi_2, \ldots)$ denotes the control policy.



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Key solution concept: Information state

Informally, an information state is a compression of information which is sufficient for performance evaluation and predicting itself.

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Historical overview

- **Old concept**. May be viewed as as generalization of the notion of state (Nerode, 1958).
- Informal definitions given in Kwakernaak (1965), Bohlin (1970), Davis and Varaiya (1972), Kumar and Varaiya (1986) but no formal analysis.
- Related to but different from concepts such bisimulation, predictive state representations (PSR), and ε-machines.

Information state: Intuition

Sufficient Statistics

S State Y Obs. A Action $R = r(S, A)$ Reward

- Consider a compression of data $Z = \sigma(Y)$
- Z is a sufficient statistic for evaluating reward if

(P1) $\mathbb{E}[R \mid Y = y, A = a] = \mathbb{E}[R \mid Z = \sigma(y), A = a] =: \hat{r}(\sigma(y), a)$

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Self-predictive property

In a MDP/POMDP, a sequence of sufficient statistics $\{Z_t = \sigma(Y_t)\}$ where Z_t is sufficient for R_t is not sufficient for dynamic programming! We also need

(P2) $\mathbb{P}(Z_{t+1} = z_{t+1} | H_t = h_t, A_t = a_t)$
$= \mathbb{P}(Z_{t+1} = z_{t+1} | Z_t = \sigma_t(H_t), A_t = a_t)$

Information state: Definition

Given a state space $\mathcal{Z}$, an INFORMATION STATE GENERATOR is a tuple of

- history compression functions $\{\sigma_t : \mathcal{H}_t \to \mathcal{Z}\}_{t \geqslant 1}$
- reward function $\hat{r} : \mathcal{Z} \times \mathcal{A} \to \mathbb{R}$
- transition kernel $\hat{P} : \mathcal{Z} \times \mathcal{A} \to \Delta(\mathcal{Z})$

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(P2) The transition kernel $\hat{P}$ is sufficient for predicting the info state:

$$\mathbb{P}(Z_{t+1} \in B \mid H_t = h_t, A_t = a_t) = \hat{P}(B \mid \sigma_t(h_t), a_t).$$

Information state: Key result

An information state **always** leads to a dynamic programming decomposition.

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Let $\{Z_t\}_{t\geqslant 1}$ be any information state process. Let $\hat{V}$ be the fixed point of:

$$\hat{V}(z) = \max_{a\in\mathcal{A}} \Big\{ \hat{r}(z,a) + \gamma \int_{\mathcal{Z}} \hat{V}(z_+)\hat{P}(dz_+|z,a) \Big\}$$

Let $\pi^*(z)$ denote the arg max of the RHS.

Then, the policy $\pi = (\pi_t)_{t\geqslant 1}$ given by $\pi_t(h_t) = \pi^*(\sigma_t(h_t))$ is optimal.

Examples of information state

Markov decision processes (MDP)

Current state S_t is an info state

POMDP

Belief state is an info state

Examples of information state

Markov decision processes (MDP)

Current state S_t is an info state

MDP with delayed observations

$(S_{t-\delta+1}, A_{t-\delta+1:t-1})$ is an info state

POMDP

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$(\mathbb{P}(S_{t-\delta}|Y_{1:t-\delta}, A_{1:t-\delta}), A_{t-\delta+1:t-1})$
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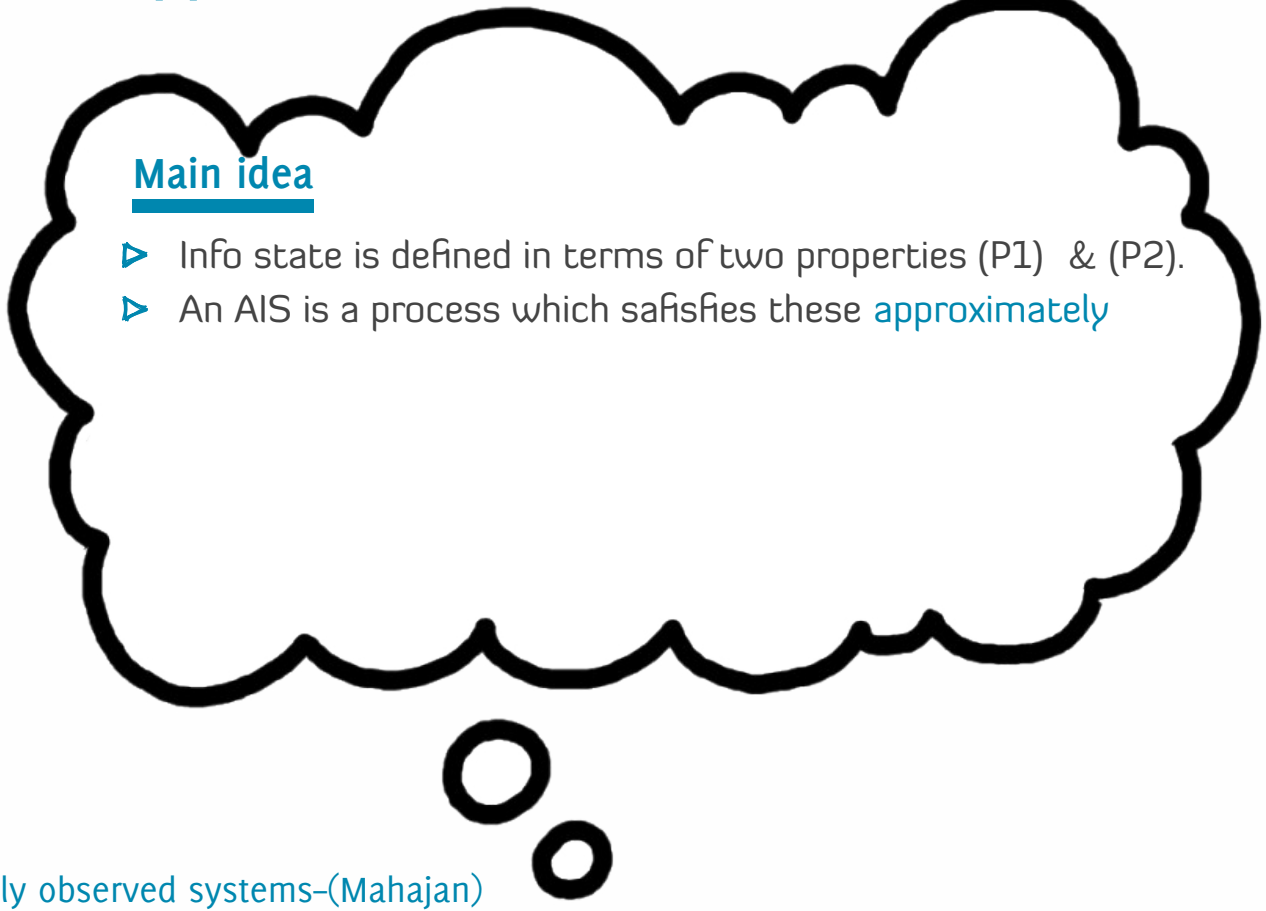
Linear Quadratic Gaussian (LQG)

The state estimate $\mathbb{E}[S_t|H_t]$ is an info state

Machine Maintenance

(τ, S^+_τ) is info state,
where τ is the time of last maintenance

And now to Approximate Information States . . .



Main idea

- Info state is defined in terms of two properties (P1) & (P2).
- An AIS is a process which safisfies these approximately

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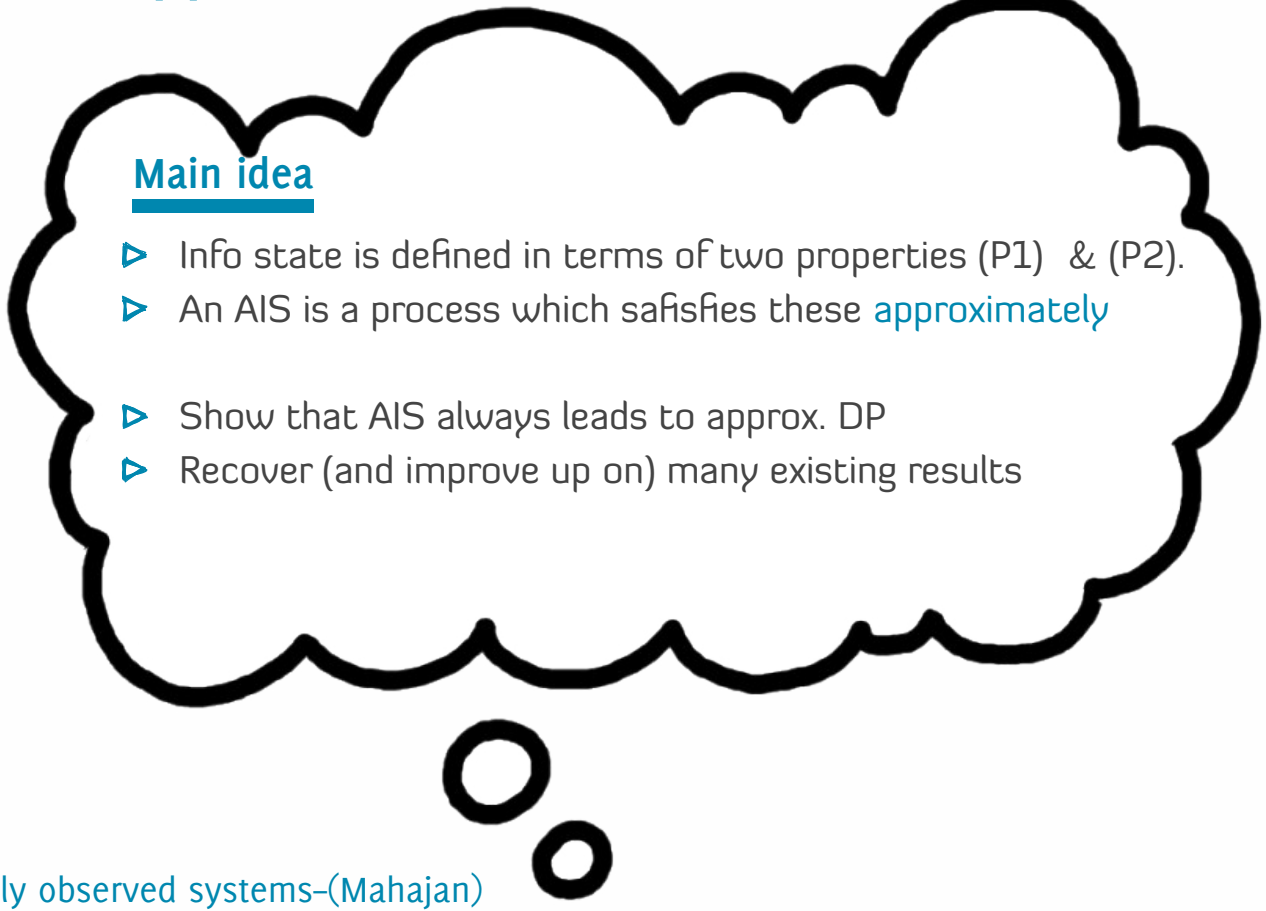

Main idea

- Info state is defined in terms of two properties (P1) & (P2).
- An AIS is a process which safisfies these approximately

- Show that AIS always leads to approx. DP
- Recover (and improve up on) many existing results

Approximate Information state: Definition

An (ε, δ)-APPROXIMATE INFORMATION STATE (AIS) generator is a tuple $(\sigma_t, \hat{r}, \hat{P})$ which approximately satisfies (P1) and (P2):

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$$\left|\mathbb{E}[R_t \mid H_t = h_t, A_t = a_t] - \hat{r}(\sigma_t(h_t), a_t)\right| \leqslant \varepsilon$$

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Results depend on the choice of **metric on probability spaces**

AIS based approximation bounds

Let V denote the optimal value and $\hat{V}$ denote the fixed point of the following equations:

$$\hat{V}(z) = \max_{a \in \mathcal{A}} \left\{ \hat{r}(z, a) + \gamma \int_{\mathcal{Z}} \hat{V}(z_+) \hat{P}(dz_+ | z, a) \right\}$$

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Value function approximation

The value function $\hat{V}$ is approximately optimal, i.e.,

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Policy approximation

Let $\hat{\pi}^* : \mathcal{Z} \to \Delta(\mathcal{A})$ be an optimal policy for $\hat{V}$.
Then, the policy $\pi = (\pi_1, \pi_2, \ldots)$ where $\pi_t = \hat{\pi}^* \circ \sigma_t$ is approx. optimal:

$$V_t(h_t) - V_t^{\pi}(h_t) \leqslant 2\alpha.$$

Some remarks on AIS

- Two ways to interpret the results:
  - Given the information state space $\mathcal{Z}$, find the best compression $\sigma_t : \mathcal{H}_t \to \mathcal{Z}$
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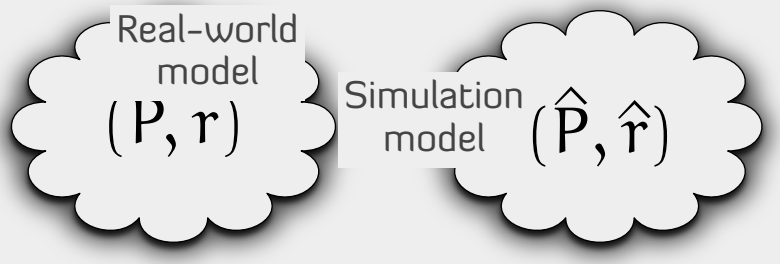
- Most of the existing literature on approximate DPs focuses on the first interpretation
- The second interpretation allows us to develop AIS-based RL algorithms

- Results depend on the choice of metric on probability spaces.
- The bounds use what are known as integral probability metrics (IPM), which include many commonly used metrics:
  - Total variation
  - Wasserstein distance
  - Maximum mean discrepancy (MMD)

Examples of AIS

Example 1: Robustness to model mismatch in MDPs



What is the loss in performance if we choose a policy using the simulation model and use it in the real world?

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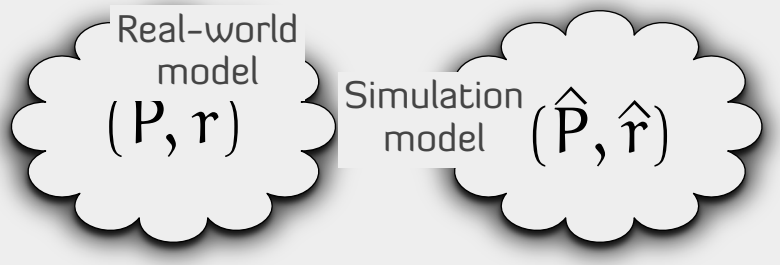

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Model mismatch as an AIS

- $(\text{Identity}, \hat{P}, \hat{r})$ is an (ε, δ)-AIS with $\varepsilon = \sup_{s,a} \left| r(s,a) - \hat{r}(s,a) \right|$ and $\delta_{\mathfrak{F}} = \sup_{s,a} d_{\mathfrak{F}}(P(\cdot|s,a), \hat{P}(\cdot|s,a))$.

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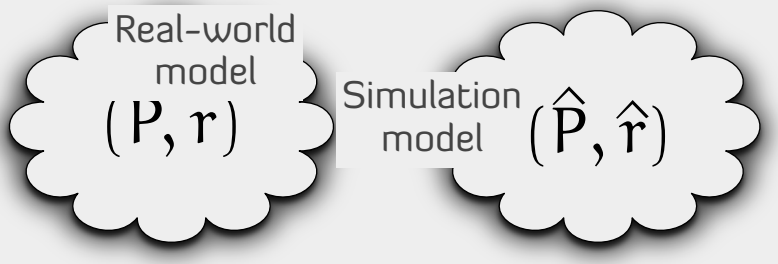

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$d_{\mathfrak{F}}$ is total variation

$$V(s) - V^{\pi}(s) \leqslant \frac{2\varepsilon}{1-\gamma} + \frac{\gamma\delta \operatorname{span}(r)}{(1-\gamma)^2}$$

Recover bounds of Müller (1997).

AIS for partially observed systems–(Mahajan)

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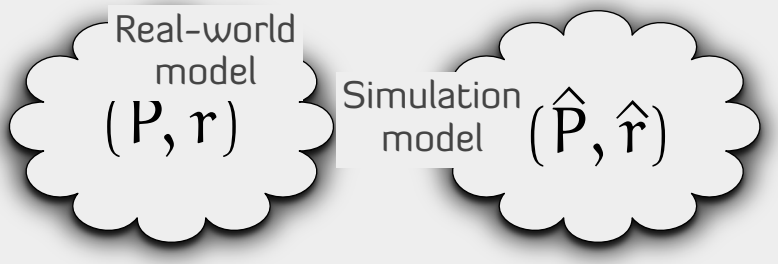

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Recover bounds of Asadi, Misra, Littman (2018).

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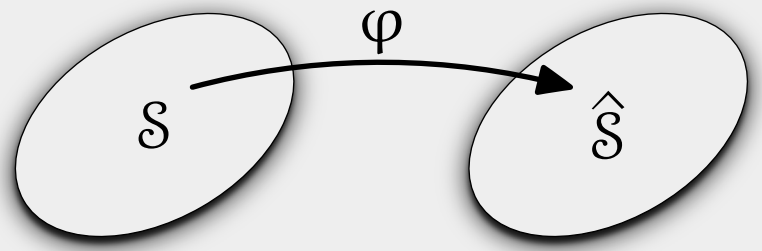
Example 2: Feature abstraction in MDPs



$(\hat{P}, \hat{r})$ is determined from (P, r) using φ

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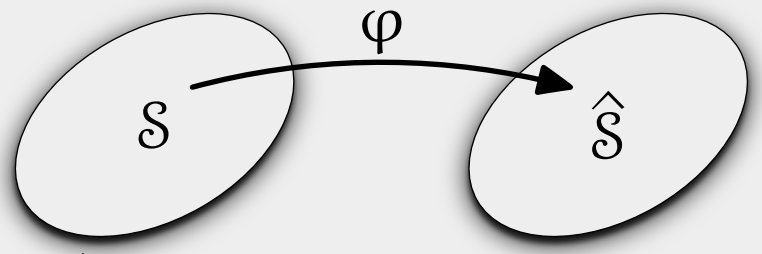

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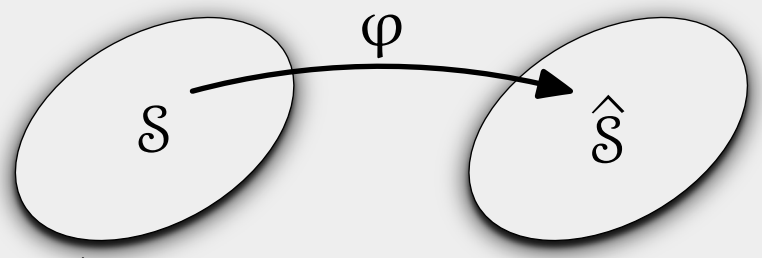

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Improve bounds of Abel et al. (2016)

AIS for partially observed systems–(Mahajan)

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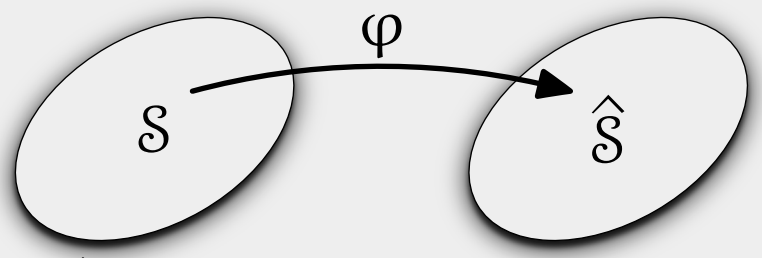

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Recover bounds of Gelada et al. (2019).

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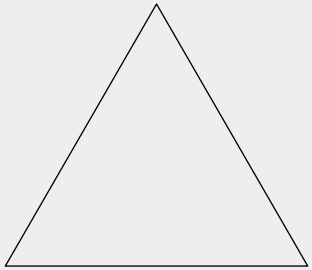
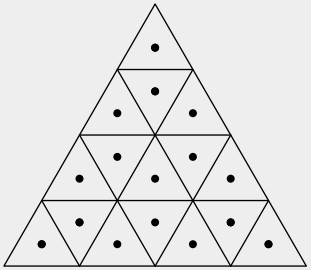
Example 3: Belief approximation in POMDPs



Belief space



Quantized beliefs

What is the loss in performance if we choose a policy using the approximate beliefs and use it in the original model?

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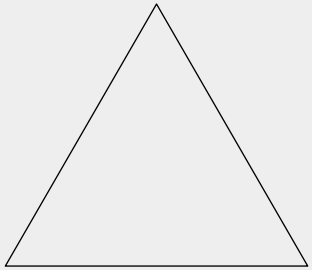

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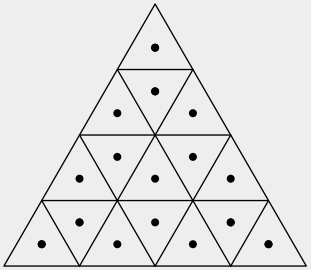

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Belief approximation in POMDPs

- Quantized cells of radius ε (in terms of total variation) are $(\varepsilon\|r\|_\infty, 3\varepsilon)$-AIS.

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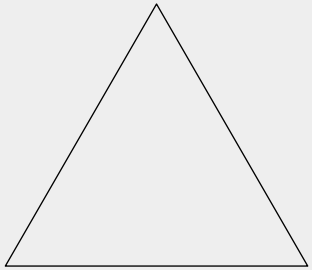

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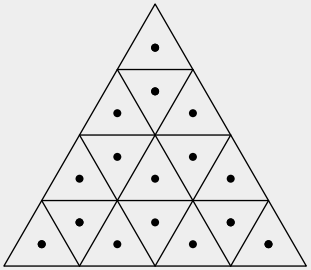

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Francois-Lavet, Rabusseau, Pineau, Ernst, Fonteneau, "On overfitting and asymptotic bias in batch reinforcement learning with partial observability," JAIR 2019.

Belief approximation in POMDPs

- Quantized cells of radius ε (in terms of total variation) are $(\varepsilon\|r\|_\infty, 3\varepsilon)$-AIS.

$$V(s) - V^\pi(s) \leqslant \frac{2\varepsilon\|r\|_\infty}{1-\gamma} + \frac{6\gamma\varepsilon\|r\|_\infty}{(1-\gamma)^2}$$

Improve bounds of Francois Lavet et al. (2019) by a factor of $1/(1-\gamma)$.

Thus, the notion of AIS unifies many of the approximation results in the literature, both for MDPs and POMDPs.

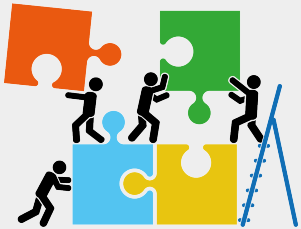
Outline

Background

- Review of MDPs and RL
- Review of POMDPs
- Why is RL for POMDPs difficult?

Approximate Planning for POMDPs

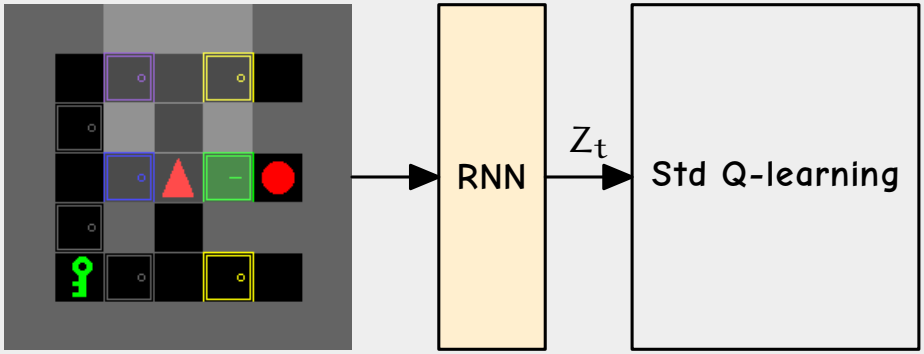
- Preliminaries on information state
- Approximate information state
- Approximation bounds



RL for POMDPs

- From approximation bounds to RL
- Numerical experiments

Q-learning for POMDPs



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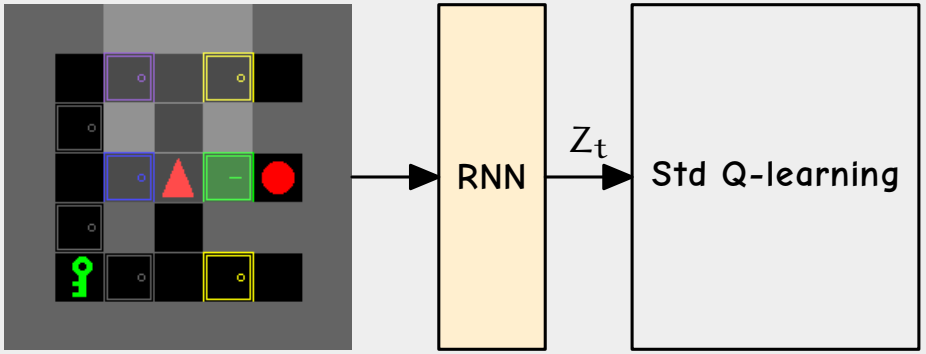
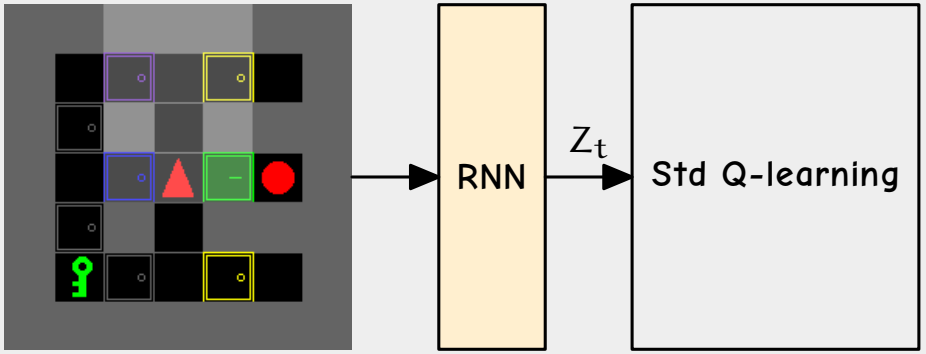


Agent state

$$Z_{t+1} = f(Z_t, Y_{t+1}, A_t).$$

Q-learning for POMDPs



Agent state

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Q-learning

$$\hat{Q}_{t+1}(z_t, a_t) = \hat{Q}_t(z_t, a_t) + \alpha_t(z_t, a_t)\left[R_t + \gamma \max_{a' \in \mathcal{A}} \hat{Q}_t(z_{t+1}, a') - \hat{Q}_t(z_t, a_t)\right]$$

What's the difficulty in analyzing Q-learning for POMDPs?

Review: How does Q-learning work in MDPs?

Dynamic programming decomposition

$$V(s) = \max_{a \in \mathcal{A}} Q(s, a)$$

$$Q(s, a) = r(s, a) + \gamma \sum_{s' \in \mathcal{S}} P(s'|s, a) V(s')$$

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Approximate via stochastic approximation

$$Q(s, a) \leftarrow Q(s, a) + \alpha \big[r(s, a) + \gamma \max_{a' \in \mathcal{A}} Q(s_+, a') - Q(s, a) \big]$$

Review: How does Q-learning work in MDPs?

Dynamic programming decomposition

$$V(s) = \max_{a \in \mathcal{A}} Q(s, a)$$

$$Q(s, a) = r(s, a) + \gamma \sum_{s' \in \mathcal{S}} P(s'|s, a) V(s')$$

Approximate via stochastic approximation

$$Q(s, a) \leftarrow Q(s, a) + \alpha \Big[r(s, a) + \gamma \max_{a' \in \mathcal{A}} Q(s_+, a') - Q(s, a) \Big]$$

unbiased sample

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unbiased sample

Why does Q-learning converge?

- Under approrpriate technical conditions, SA tracks an ODE (Borkar 1997).
- Since the Bellman operator is a contraction, the ODE has a unique equilibrium point which is globally asymptotically stable (Borkar and Soumyanatha, 1997).

Why is it difficult to analyze Q-learning for POMDPs?

Q-learning

$$\hat{Q}_{t+1}(z_t, a_t) = \hat{Q}_t(z_t, a_t) + \alpha_t(z_t, a_t)\Big[R_t + \gamma \max_{a' \in \mathcal{A}} \hat{Q}_t(z_{t+1}, a') - \hat{Q}_t(z_t, a_t)\Big]$$

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We cannot just write a DP:

$$Q(z, a) = \mathbb{E}[R_t | Z_t = z, A_t = a] + \gamma \sum_{z' \in \mathcal{S}} P(z' \mid s, a) V(z')$$

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Not time-homogeneous

Not-controlled Markov

Implication: Exploration policy matters!

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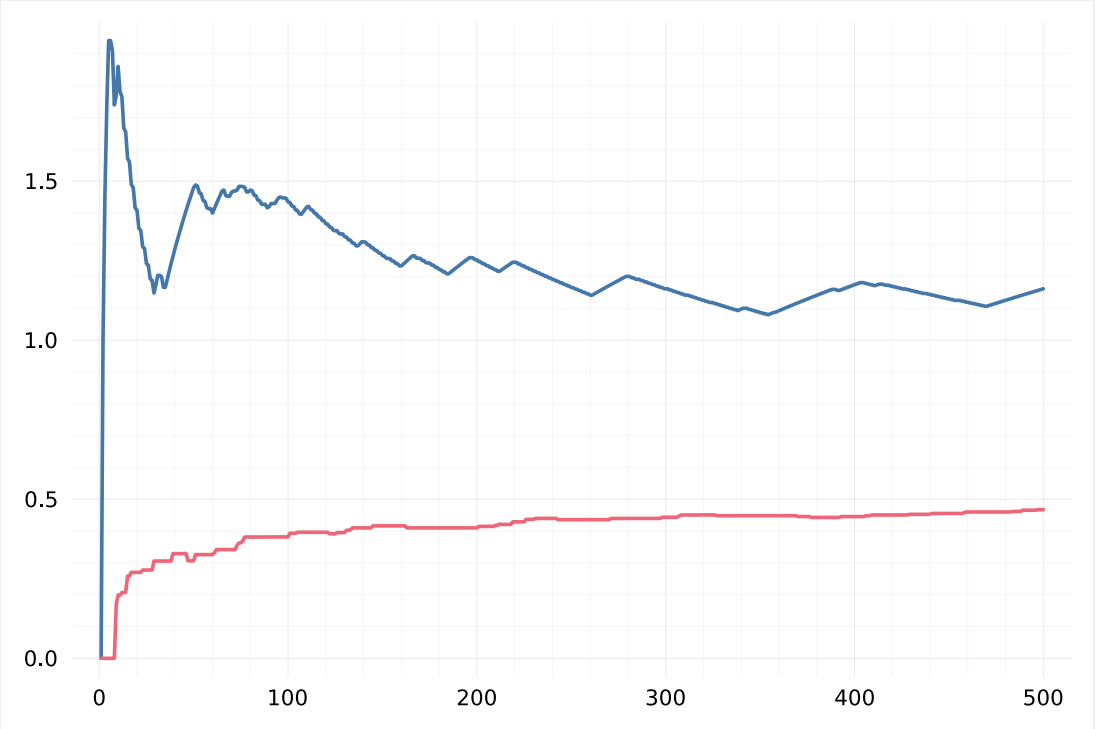

Characterizing convergence: Assumptions

Assumptions

(A1) Restrict to tabular setting

(A2) The exploration policy $\pi_{\text{exp}}: \mathcal{Z} \to \Delta(\mathcal{A})$ is such that the Markov chain $\{(S_t, Y_t, Z_t, A_t)\}_{t \geqslant 1}$ has a unique stationary distribution ξ. Plus, $\xi(s, y, z, a) > 0$.

(A3) $$\alpha_t(z, a) = \frac{\mathbb{1}\{Z_t = z, A_t = a\}}{\sum_{\tau=1}^{t} \mathbb{1}\{Z_\tau = z, A_\tau = a\}}$$

Characterizing convergence: Guarantees

Define:

- $r_\xi(z, a) = \sum_{s \in \mathcal{S}} \xi(s \mid z, a) r(s, a)$.
- $P_\xi(z' | z, a) = \sum_{s, s' \in \mathcal{S}} \sum_{y' \in \mathcal{Y}} \xi(s \mid z, a) P(s' | s, a) P(y' | s') \, \mathbb{1}\{z' = f(z, y', a)\}$.

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Let (V_ξ, Q_ξ) be the solution of the following DP:

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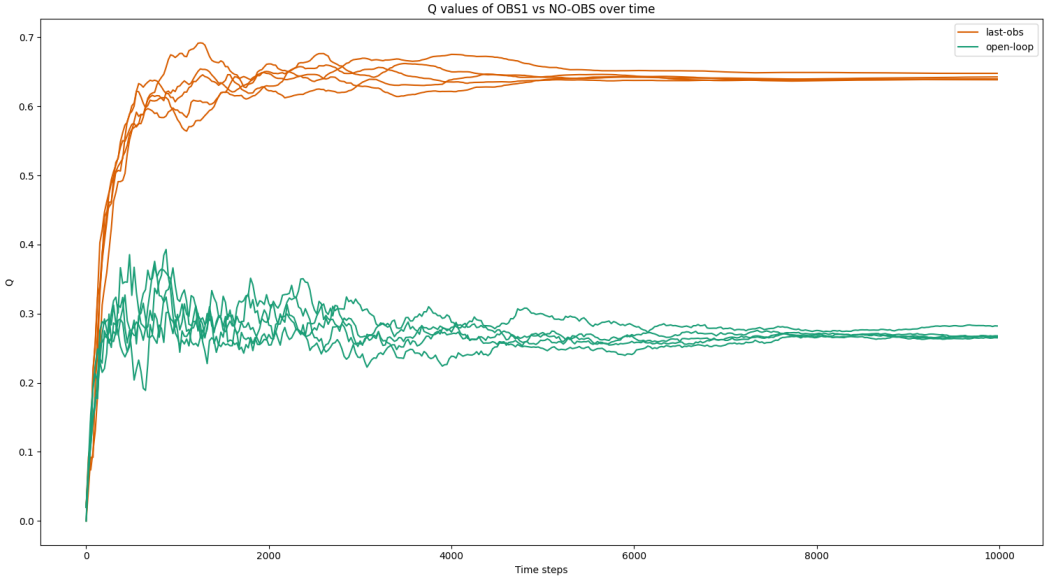
Under (A1)–(A3), $\hat{Q}_t \to Q_\xi$ a.s.

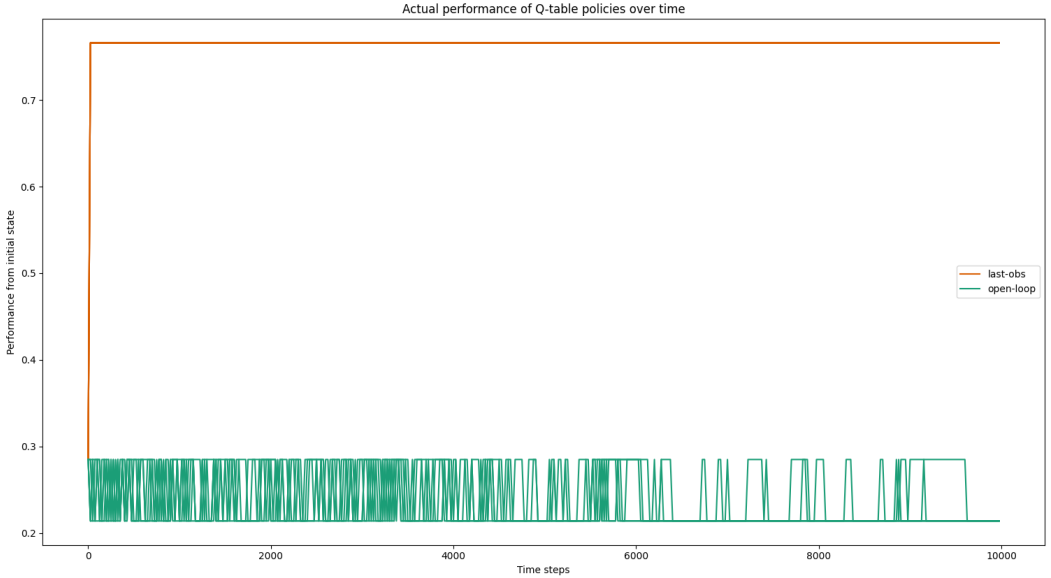
Characterizing convergence is not enough!

Convergence for two different update functions



Characterizing convergence is not enough!

Performance of greedy policy for two different update functions



Quality of converged solution

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(r_ξ, P_ξ) is an AIS!

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Approximation guarantee

For any history h_t

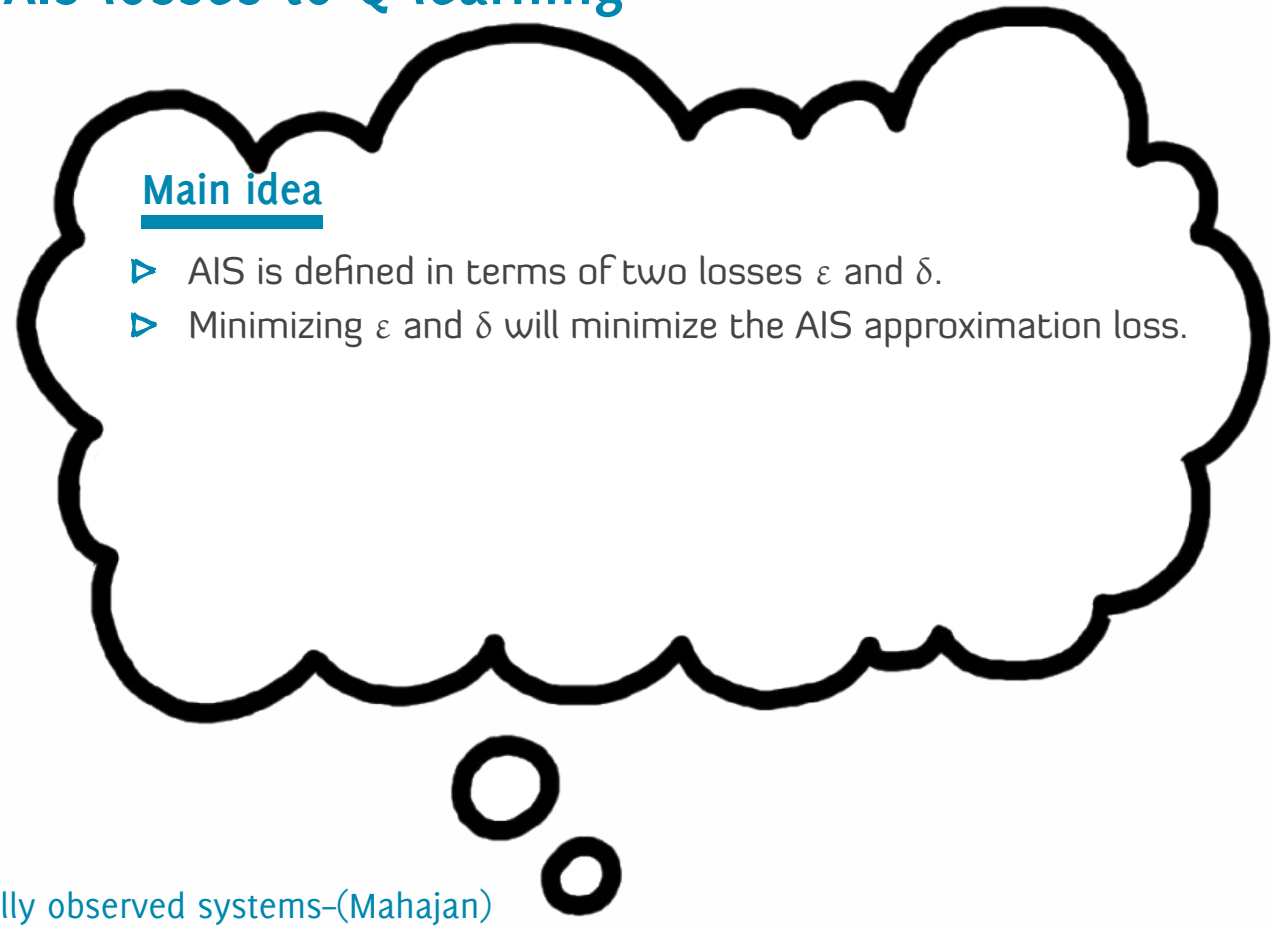
$$\left|V_t^*(h_t) - V_t^{\pi_\xi^* \circ \sigma_t}(h_t)\right| \quad \leqslant (1-\gamma)^{-1}\left[\varepsilon + \gamma \delta_{\mathfrak{F}} \rho_{\mathfrak{F}}(V_\xi)\right]$$

where

- $\varepsilon = \sup_{t \geqslant 1} \max_{h_t, a_t} \left|\mathbb{E}[r(S_t, a_t) \mid h_t, a_t] - r_\xi(\sigma_t(h_t), a_t)\right|$
- $\delta_{\mathfrak{F}} = \sup_{t \geqslant 1} \max_{h_t, a_t} d_{\mathfrak{F}}\Big(\mathbb{P}(Z_{t+1} = \cdot \mid h_t, a_t), P_\xi(\cdot \mid \sigma_t(h_t), a_t)\Big)$

Can we use this to improve Q-learning?

Adding AIS-losses to Q-learning



Main idea

- AIS is defined in terms of two losses ε and δ.
- Minimizing ε and δ will minimize the AIS approximation loss.

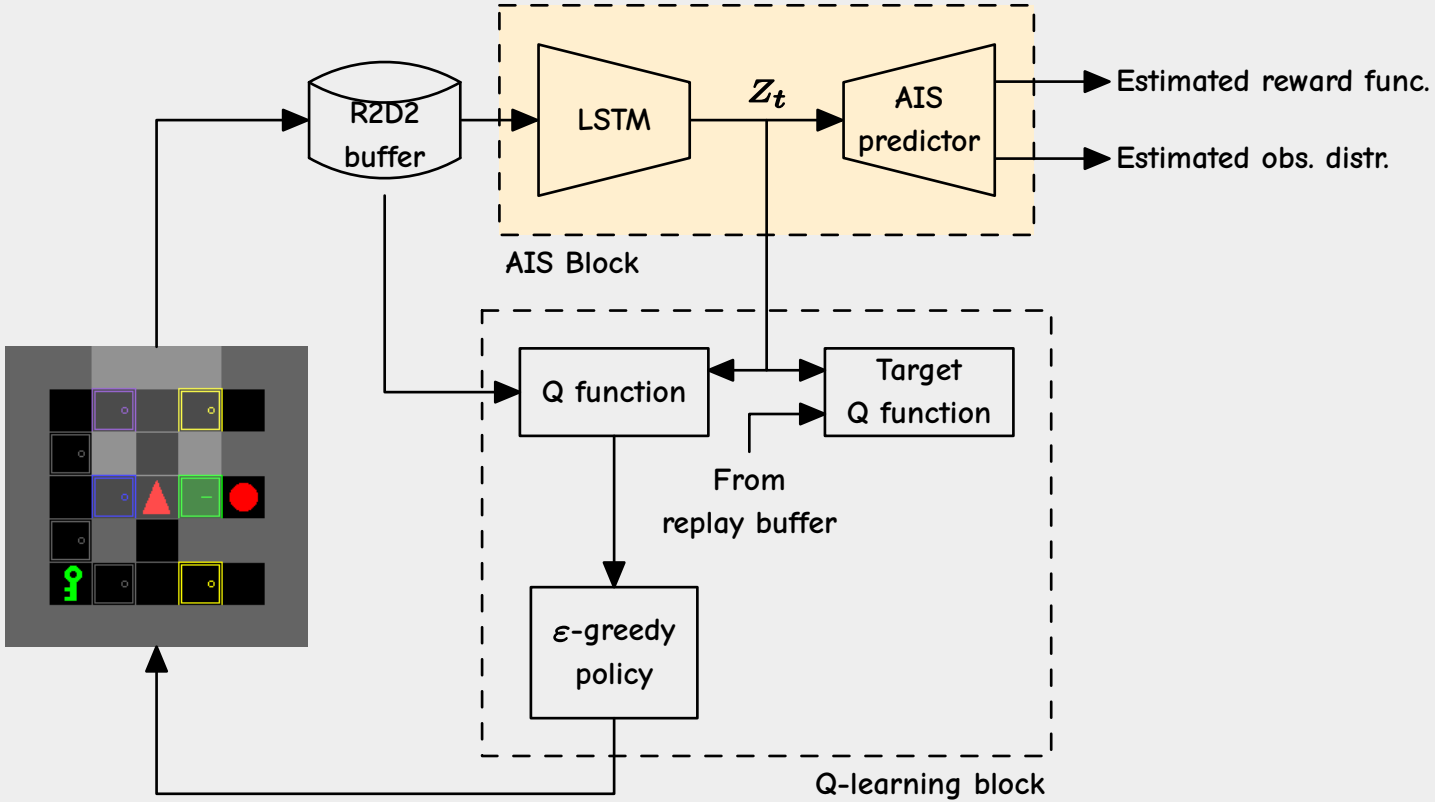
Adding AIS-losses to Q-learning

Main idea

- AIS is defined in terms of two losses ε and δ.
- Minimizing ε and δ will minimize the AIS approximation loss.

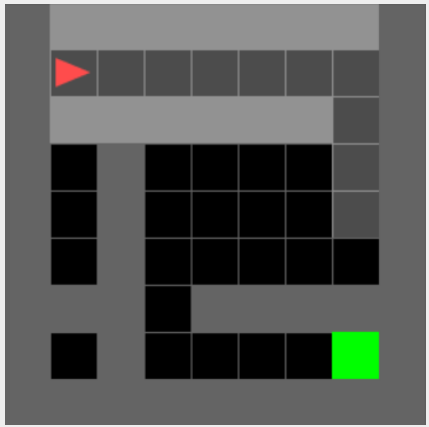
- Use $\lambda\varepsilon^2 + (1-\lambda)\delta^2$ as surrogate loss for the AIS generator
- . . . and combine it with standard Q-learning algorithm.

Recurrent Q-learning with AIS losses (RQL-AIS)

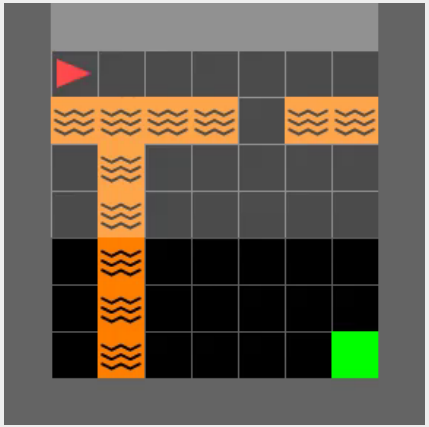


Numerical Experiments

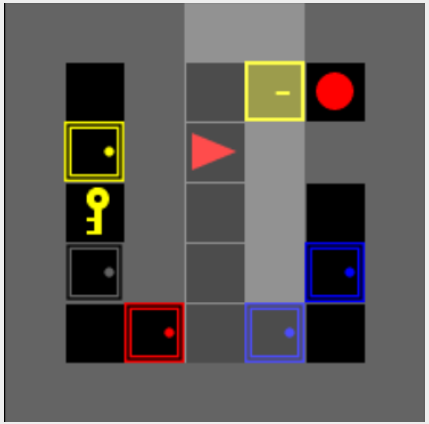
MiniGrid Environments



Simple Crossing



Lava Crossing

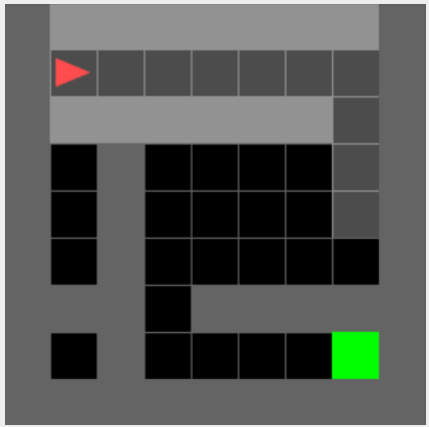


Key Corridor

Features

- Partially observable 2D grids. Agent has a view of a 7×7 field in front of it. Observations are obstructed by walls.
- Multiple entities (agents, walls, lava, boxes, doors, and keys)
- Multiple actions (Move Forward, Turn Left, Turn Right, Open Door/Box, . . .)

MiniGrid Environments



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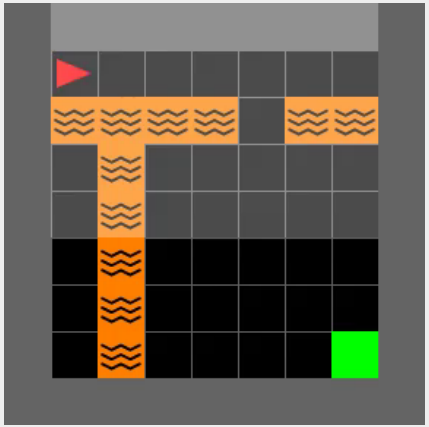

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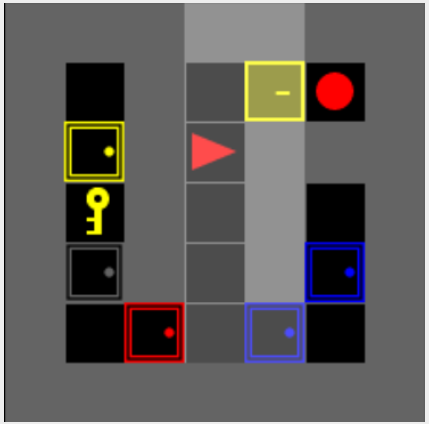


Key Corridor

Algorithms

R2D2

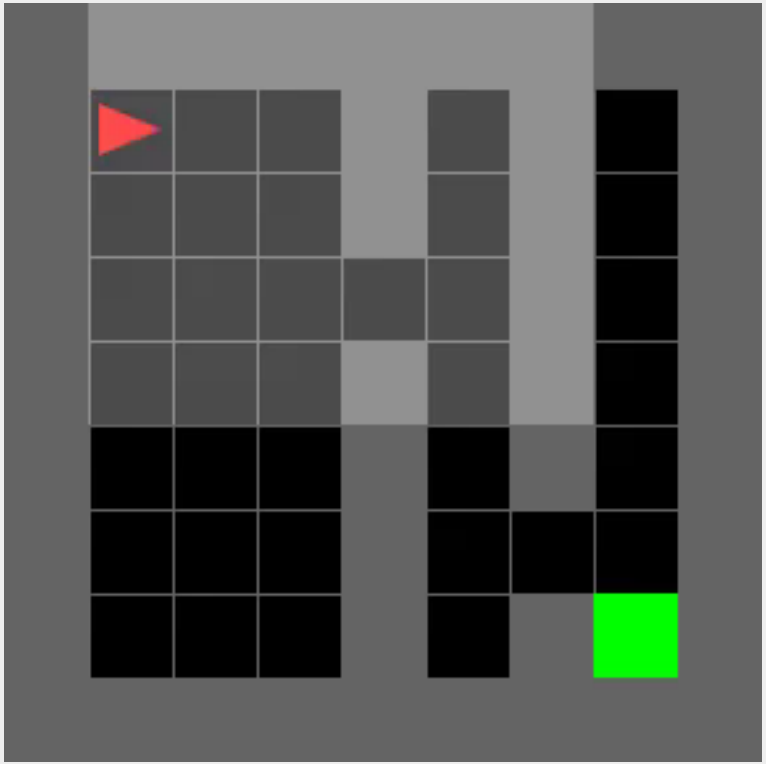
A competitive baseline for POMDPs

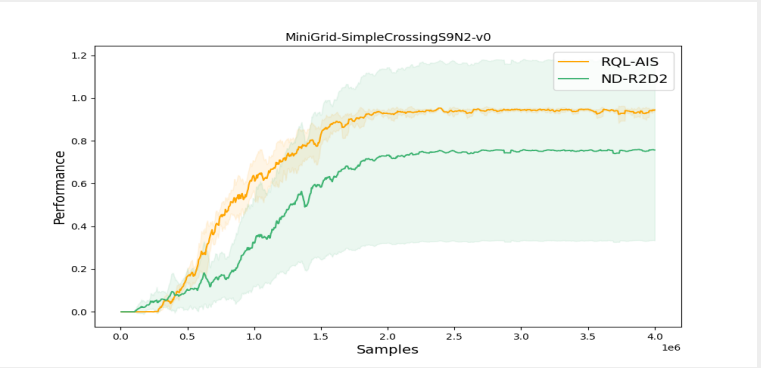
R2D2 + AIS

Add AIS losses to R2D2

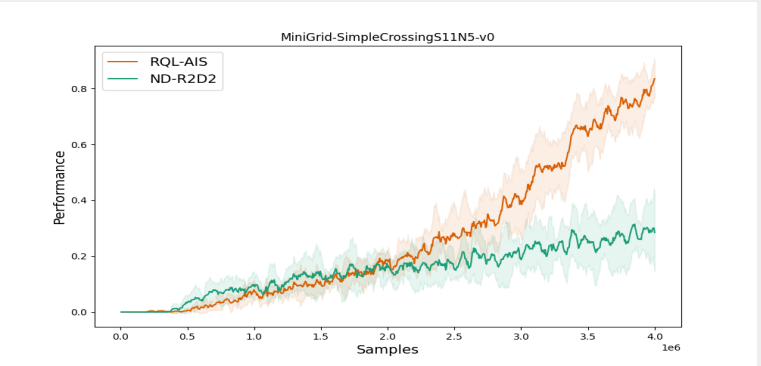
AIS for partially observed systems–(Mahajan)

Simple Crossing



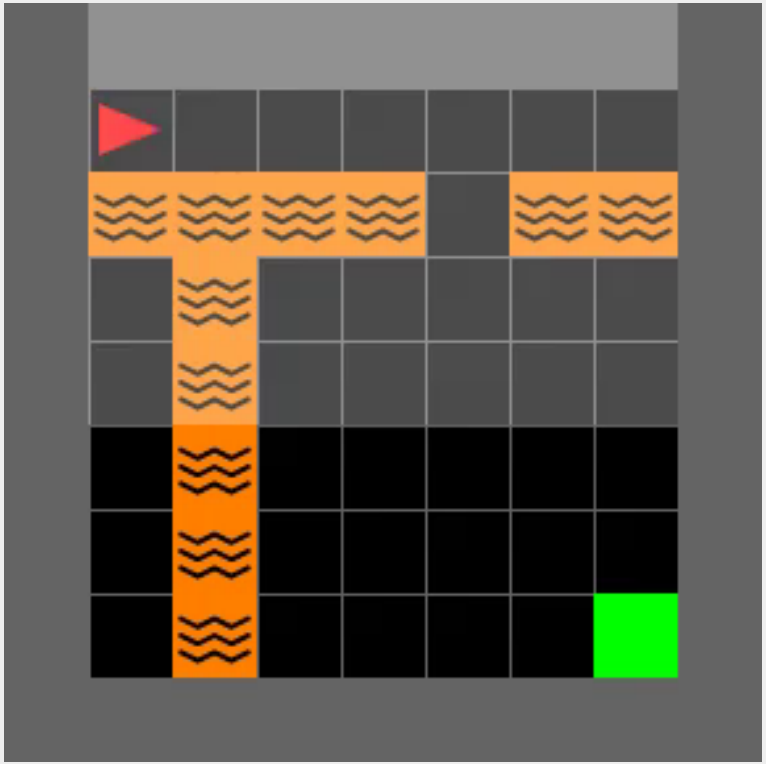


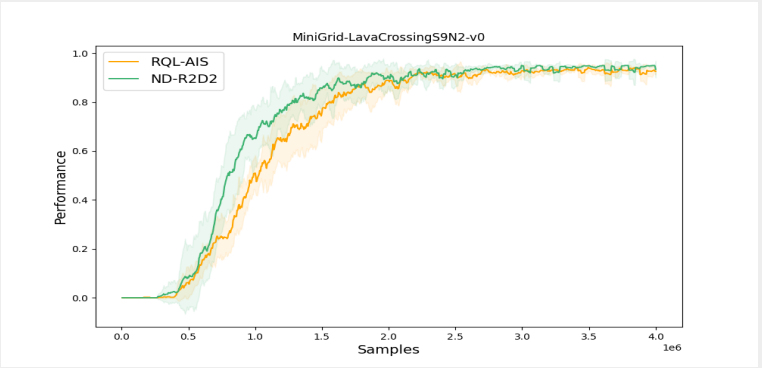
Simple Crossing S9N2



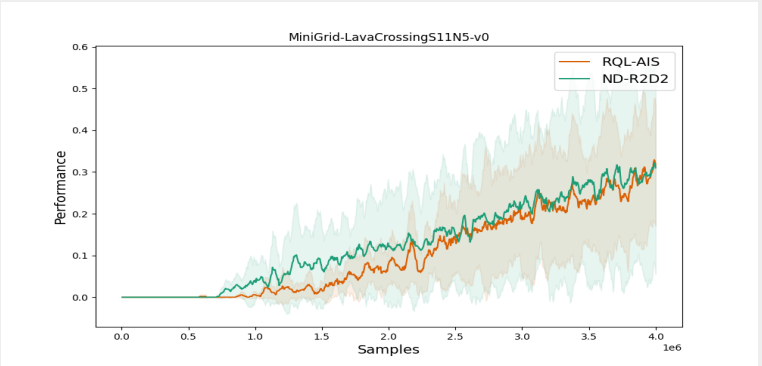
Simple Crossing S11N5

Lava Crossing



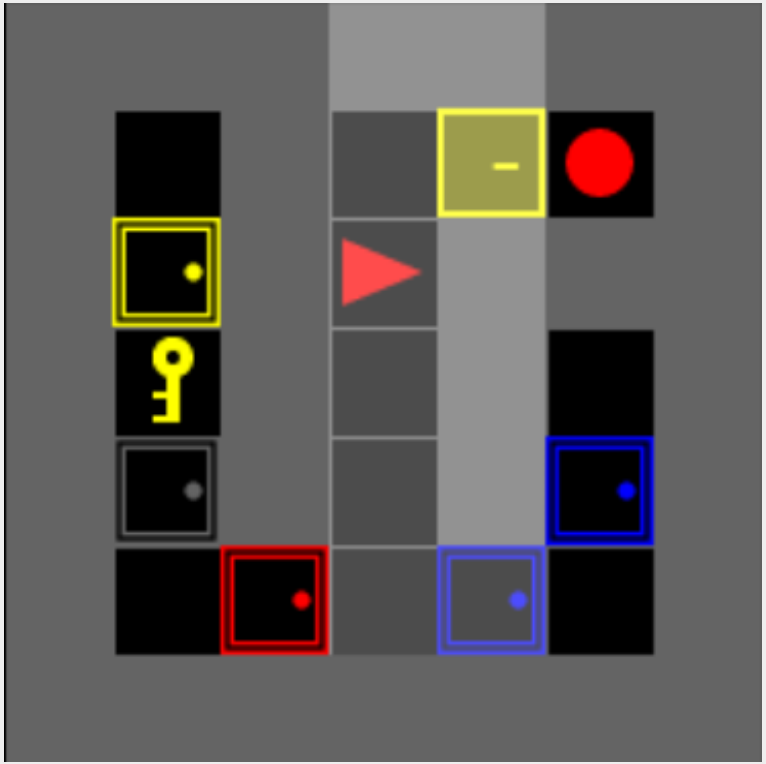


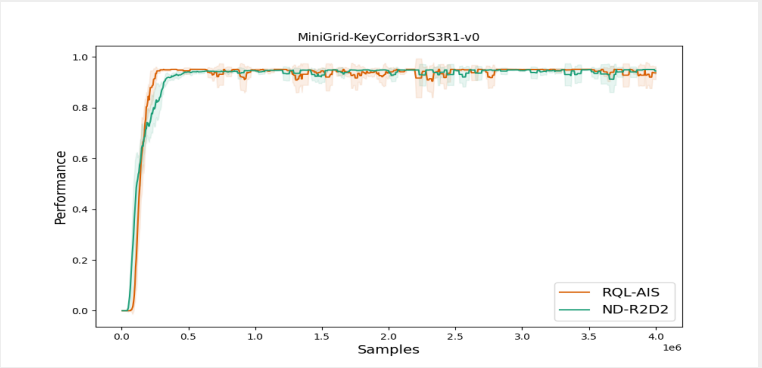
Lava Crossing S9N2



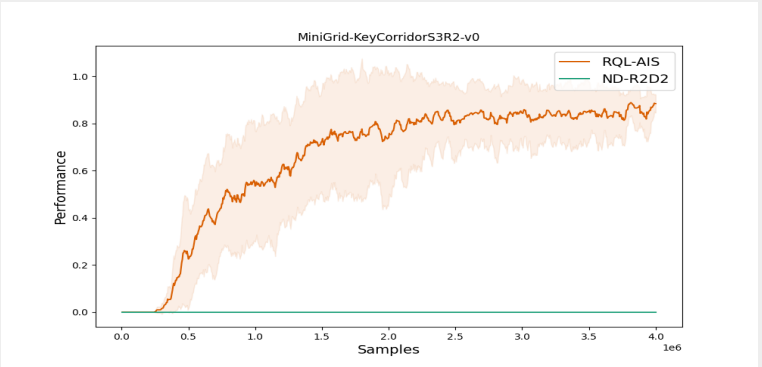
Lava Crossing S11N5

Key Corridor





Key Corridor S3R1



Key Corridor S3R2

Similar improvements for AIS-enhanced Q-learning

Environment	RQL-AIS	ND-R2D2
SimpleCrossingS9N2	0.944 ± 0.007	0.757 ± 0.423
LavaCrossingS9N2	0.926 ± 0.014	0.934 ± 0.034
RedBlueDoors-8x8	0.977 ± 0.009	0.962 ± 0.018
MultiRoom-N2-S4	0.790 ± 0.049	0.839 ± 0.010
DoorKey-8x8	0.942 ± 0.038	0.371 ± 0.508
ObstructedMaze-1Dl	0.916 ± 0.020	0.000 ± 0.000
KeyCorridorS3R2	0.885 ± 0.038	0.000 ± 0.000
UnlockPickup	0.517 ± 0.474	0.000 ± 0.000

Summary

A conceptually clean framework for approximate DP and online RL in partially observed systems

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Approximation results generalize to

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- action quantization
- lifelong learning
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- Markov games

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Ongoing work

- Other RL settings such as model based RL, offline RL, inverse RL.
- A building block for multi-agent RL.
- . . .

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- web: http://cim.mcgill.ca/~adityam

Thank you

- paper 1: JMLR, Feb 2022
  code: https://github.com/info-structures/ais
- paper 2: JMLR, Feb 2022
  code: https://github.com/info-structures/RQL-ais

Funding: NSERC, DND