# Minimal Disclosure in Partially Observable Markov Decision Processes

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### Outline



2 Worst-case cost





Conclusion

## Markov Decision Processes (MDP)

States: Q; Actions: Act; Probabilistic transition function:  $\Delta$ 



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Strategy for the controller: based on actions and states

 $\sigma: Q \cdot (Act \cdot Q)^* \to Dist(Act)$ 

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States: Q; Actions: Act; Probabilistic transition function:  $\Delta$ 



Strategy for the controller: based on actions and states

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Memoryless pure strategy to reach Goal almost-surely:  $\sigma(1) = a, \ \sigma(2) = b, \ \sigma(3) = c$ 

Conclusion

## Partially Observable MDP (POMDP)

#### Partial observation: induced by partition O



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## Partially Observable MDP (POMDP)

#### Partial observation: induced by partition O



Strategy for the controller: based on actions and observations

 $\sigma: O \cdot (\mathsf{Act} \cdot O)^* \to \mathsf{Dist}(\mathsf{Act})$ 

No strategy to reach Goal almost-surely.

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## POMDP with disclosure

Additional request action to reveal the precise state of system. Observations: partition + individual states



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Strat. for the controller: based on extended actions and observations

 $\sigma: O' \cdot (\mathsf{Act}' \cdot O')^* \to \mathsf{Dist}(\mathsf{Act}')$ 

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## POMDP with disclosure

Additional request action to reveal the precise state of system. Observations: partition + individual states



Strat. for the controller: based on extended actions and observations

 $\sigma: O' \cdot (\mathsf{Act}' \cdot O')^* \to \mathsf{Dist}(\mathsf{Act}')$ 

Cheap strategy to reach Goal almost-surely?

### **Problem statement**

cost of a path = number of requests for disclosure cost of a strategy  $\sigma$  =

- worst-case cost along  $\sigma$ -paths (max number of requests)
- average cost along σ-paths (expected number of requests)

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### **Problem statement**

Finding almost-surely winning strategies that minimize:

- the worst-case cost, or
- the average cost

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## Belief

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#### Belief: (distribution over) states the system can be in



 $\{1\} (a, \bullet) \{1, 2\} (a, \bullet)$ 

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 $\{1\} (a, \bullet) \{1, 2\} (a, \bullet) \{3, 4\} (b, \bullet) \{5\}$  $\{1\} (a, \bullet) \{3, 4\} (req, \{4\}) \{4\} (b, \bullet) \{1\}$ 

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#### Belief: (distribution over) states the system can be in



#### up(S, a, O): belief update from S, after action a and observation O



#### Lose: beliefs that contain a state losing in the (fully-observable) MDP



*Lose*: beliefs that contain a state losing in the (fully-observable) MDP  $Win = \mathcal{B} \setminus Lose = W_{ok} \sqcup W_{reg} \sqcup W_{safe}$ 



Lose: beliefs that contain a state losing in the (fully-observable) MDP

- $Win = \mathcal{B} \setminus Lose = W_{ok} \sqcup W_{req} \sqcup W_{safe}$ 
  - ►  $W_{ok} = \{S \mid S \subseteq \text{Goal}\}$



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#### Canonical family of strategies $(\sigma_n)_{n \in \mathbb{N}}$ :

- In W<sub>req</sub>, play req, and
- in  $W_{safe}$ , play req with prob. 1/n and unif. prob. on safe actions.

a is safe from S if  $\forall O, up(S, a, O) \notin Lose$ 

#### Lemma

 $\sigma_n$  is almost-surely winning from *Win*.

#### Iterative computation of $S_k$ : set of beliefs where k req are sufficient.

 $S_0 \subseteq S_1 \subseteq S_2 \cdots \subseteq \textit{Win}$ 

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Computation of  $S_0$ :  $S_0 = \text{reach}_{=1}(W_{ok})$ almost-sure reachability question for the belief-MDP without requests

Optimized strategy: no request from  $S \in S_0$ 

Iterative computation of  $S_k$ : set of beliefs where k req are sufficient.

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Computation of S<sub>1</sub>

- ►  $L_1 = \{S \mid \forall s \in S, \{s\} \in S_0\}$
- $S_1 = \operatorname{reach}_{=1}(L_1 \cup S_0)$

Optimized Strategy:

request from  $S \in L_1 \setminus S_0$ 

uniform distribution on actions ensuring to stay in  $S_1$ , othw

Iterative computation of  $S_k$ : set of beliefs where k req are sufficient.

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Stabilisation for  $N \leq |\mathcal{B}|$ 

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Stabilisation for  $N \leq |\mathcal{B}|$ 

 $S_{\infty} = Win \setminus S_N$ 

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### Proposition

The minimum worst-case cost can be computed in EXPTIME, together with a finite-memory strategy.

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Undecidability

#### Value: infimum of average cost over almost-surely winning strategies

 $val(G) = inf\{av\_cost(\sigma) \mid \sigma \text{ almost-surely winning}\}$ 

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Not too surprising: optimizing cost functions for POMDP is undecidable

Skip proof

Proof idea

 $\mathcal{P}$  PFA s.t. either all words have probability  $\leq \varepsilon$ , or some word has probability  $> 1 - \varepsilon$ . Which holds is undecidable. [Madani Hanks Condon 03]

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 $(\Rightarrow) \sigma \text{ plays } (w \ \sharp \ req \ a|b)^* \text{ for } w \text{ with } \mathbb{P}(w) > 1 - \varepsilon \\ val(\sigma) < 0 \times (1 - \varepsilon) + 1 \times \varepsilon (1 - \varepsilon) + 2 \times \varepsilon^2 (1 - \varepsilon) \dots = \varepsilon / (1 - \varepsilon)$ 

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best approximation:  $|v - val(G)| = (\varepsilon/(1 - \varepsilon) + (1 - \varepsilon))/2$ 

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best approximation:  $|v - val(G)| = (\varepsilon/(1 - \varepsilon) + (1 - \varepsilon))/2$ approximation factor:  $\frac{|v - val(G)|}{val(G)} = \frac{(1 - \varepsilon)(1/(1 - \varepsilon) - \varepsilon)}{2\varepsilon} \xrightarrow{\varepsilon \to 0} \infty$ 

## Non-approximability

### Corollary: For every $\delta$ it is undecidable to approximate val(G) within $\delta$ . NB: bigger $\delta$ need bigger POMDP

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### NP-hardness of good approximations

Assuming  $P \neq NP$  there is a POMDP *G* with **few** reachable belief states (quadratic in *n*) s.t. any polynomial time algorithm  $\mathcal{A}$  returns for *G* a value *v* with approximation factor:  $\frac{|v-val(G)|}{val(G)} \ge 2^{n-1}/n^2$ , and absolute approximation error:  $|v - val(G)| \ge 2^{n-1}/n$ .

## Proof idea

 $\varphi$  3-SAT instance with *m* clauses and *k* variables; *n* = *mk* 

 $\varphi$  is satisfiable if for each clause  $C_i$ , one can choose a literal  $I_i$  and the choices do not conflict

POMDP behaviour:

- random choice of variable to monitor
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### Properties of the reduction

- $\varphi$  satisfiable  $\Rightarrow$  val(G) < n
- $\varphi$  not satisfiable  $\Rightarrow$   $val(G) > 2^n/n 2$



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### Contribution

Minimize requests for full-information in POMDP under an almost-sure reachability objective.

- Worst-case cost
  - computation in EXPTIME, together with an optimal strategy

#### Average cost

- computation undecidable
- approximation unfeasible
- large least approximation factors for polytime algorithms

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Minimize requests for full-information in POMDP under an almost-sure reachability objective.

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- Average cost
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#### Future work

- extend to several information levels
  - succesive partition refinement
- tradeoff between objective (reachability probability) and cost