

Learning from noisy demonstrations : a exploration/exploitation tradeoff

Louis Faury

Advisors : Mahdi Khoramshahi & Andrew Sutcliffe

Semester Project at LASA

April 20, 2017

Plan

1 Motivations

2 Background

- Reinforcement learning
- Transfer learning

3 Approach

- Sandbox state space
- Compliance-based learning
- Results

4 Future work

Plan

1 Motivations

2 Background

3 Approach

4 Future work

- ▶ For long and complex tasks : common machine learning algorithm are usually very slow to converge
- ▶ Accelerate learning via prior knowledge of the environment or task : provide a **demonstration** of the task
- ▶ Framework of *learning from demonstration* (LfD)¹

→ Ex. : robotic arm grabbing a cup
: maze solver

¹Aude G. Billard, Sylvain Calinon, and Rüdiger Dillmann. “Learning from Humans”. *Springer Handbook of Robotics*. Ed. Bruno Siciliano and Oussama Khatib. Cham: Springer International Publishing, 2016. 1995–2014. Web.

- ▶ How to take the teacher's demonstration into account?
 - ▶ Exactly reproduce the teacher's actions
 - ▶ Use demonstration data to build a representation of the environment's dynamics
 - ▶ **Use the teacher demonstration as an exploration baseline**
- ▶ Child learning to dance : first follow its dance teacher moves, before trying out new ones once he feels he has exploited the teacher's recommendation
 - ⇒ notion of **compliance** w.r.t the teacher.

■ Goal :

- ▶ Introduce a theoretical framework for compliance-based learning
- ▶ Grasp ideas and intuition about how such an approach can
 - ▶ Speed up the learning
 - ▶ Overcome some possible mentor's sub-optimality.
 - ▶ Generalize to *transfer learning*

in a **reinforcement learning framework**.

■ Approach :

- ▶ Create a simple but generic environment and task
- ▶ Solve it using classical RL method
- ▶ Implement compliant-based learning method
- ▶ Compare them with classical methods, evaluate their pros and cons

Plan

1 Motivations

2 Background

- Reinforcement learning
- Transfer learning

3 Approach

4 Future work

■ RL :

- ▶ Framework in which an agent (or a learner) learns its actions from interaction with its environment
- ▶ The environment generates scalar values called rewards, that the agent is seeking to maximize over time.

Under a Markovian assumption for the dynamics and reward system, the reinforcement learning problem can be formulated as a *Markov Decision Process* :

$$(\mathcal{S}, \mathcal{A}(\mathcal{S}), \mathcal{P}_{ss'}^a, \mathcal{R}_{ss'}^a) \quad (1)$$

where :

$$\begin{aligned} \mathcal{P}_{ss'}^a &= \underbrace{\mathbb{P}(s_{t+1} = s' \mid s_t = s, a_t = a)}_{\text{dynamics}} & \mathcal{S} : \text{state space} \\ \mathcal{R}_{ss'}^a &= \underbrace{\mathbb{E} [r_t \mid s_{t+1} = s', s_t = s, a_t = a]}_{\text{immediate reward}} & \mathcal{A}(\mathcal{S}) : \text{action space} \end{aligned} \quad (2)$$

■ RL :

- ▶ Define state value and action value function under a policy (probabilistic decision rule) $\pi : \mathcal{S} \rightarrow \mathcal{A}$:

$$\begin{aligned} V^\pi(s) &= \mathbb{E}_\pi \left[\sum_i \gamma^i r_{t+i+1} \mid s_t = s \right] \\ Q^\pi(s, a) &= \mathbb{E}_\pi \left[\sum_i \gamma^i r_{t+i+1} \mid s_t = s, a_t = a \right] \end{aligned} \tag{3}$$

- ▶ All algorithm computing optimal policies rely on various mix of a *Generalized Policy Iteration* :
 1. Evaluate the current policy (DP,...)
 2. Improve the current policy (greedization)
 3. Repeat

■ Solving RL : Two baseline methods :

- ▶ Model-based ($\mathcal{P}_{ss'}^a$ and $\mathcal{R}_{ss'}^a$ are known) : dynamic programming (value iteration algorithm, ...)
- ▶ Model-free : **exploitation vs exploration** paradigm for computing the optimal policy's Q-values :

$$\{Q(s, a)\}_{s \in \mathcal{S}, a \in \mathcal{A}(s)} \quad (4)$$

- ▶ Bootstrap from initial value
- ▶ Update in direction of the sampled expected return

$$Q(s, a) \leftarrow (1 - \alpha)Q(s, a) + \alpha \mathbb{E} [R_t | s, a] \quad (5)$$

- ▶ Many different variations : SARSA, Q-learning, R-learning, eligibility traces, ...

■ **Transfer learning** : speeding a learning process thanks to another learning experience.

- ▶ Provide the learner with a mentor that is another learner
- ▶ In *homogeneous settings*²
- ▶ Study how convergence is affected

and eventually generalize to

- ▶ multiple teacher
- ▶ inhomogeneous settings

²Bob Price and Craig Boutilier. "Accelerating reinforcement learning through implicit imitation". *Journal of Artificial Intelligence Research* 19 (2003): 569–629. [Print.](#) 

Plan

1 Motivations

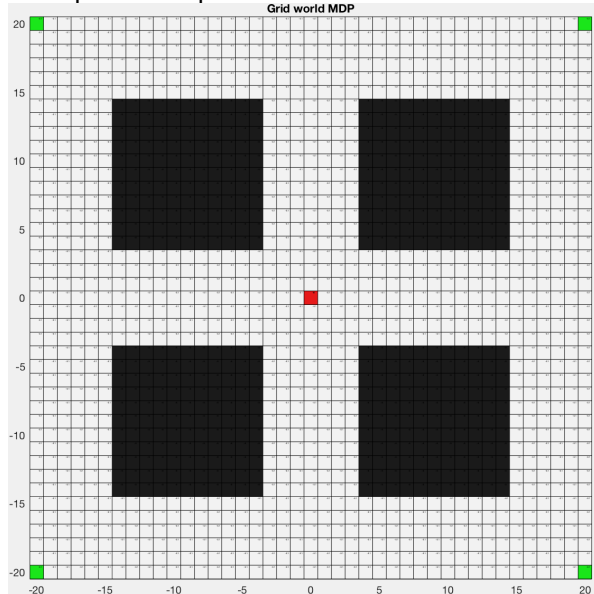
2 Background

3 Approach

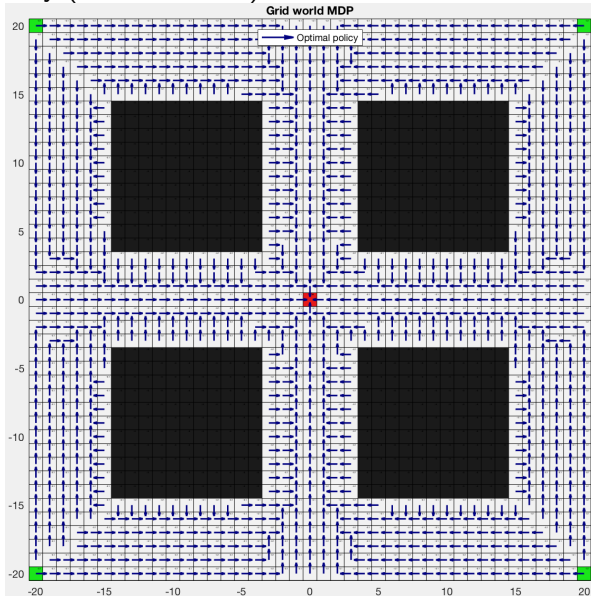
- Sandbox state space
- Compliance-based learning
- Results

4 Future work

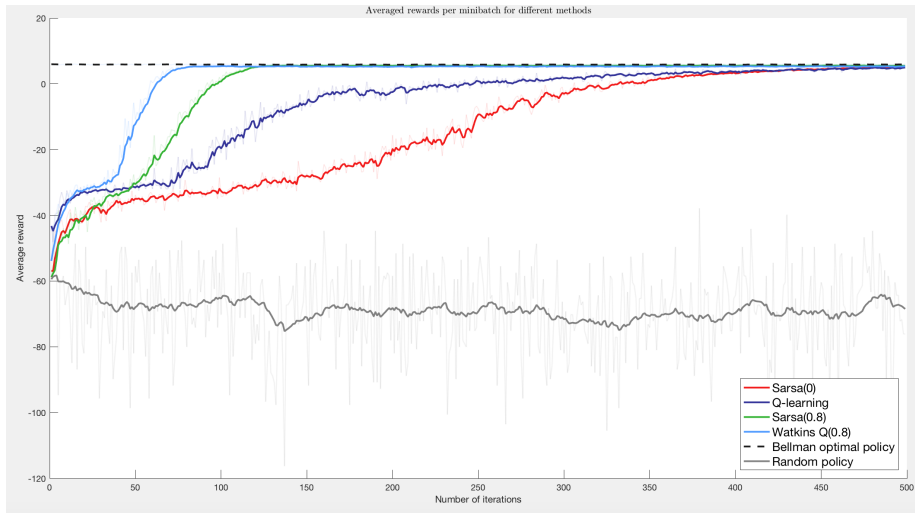
■ Generic and simple state space :



■ Optimal Policy (value iteration) :



■ Learning the optimal policy :



Plan

- 1 Motivations
- 2 Background
- 3 Approach
- 4 Future work