

Learning from largely suboptimal teachers and the role of compliance

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Plan

1 Motivations

2 Background

- Reinforcement learning
- Imitation learning
- Transfer learning

3 Results

- Markov Decision Process
- Compliance-based learning
- Method comparison

4 Future work

Plan

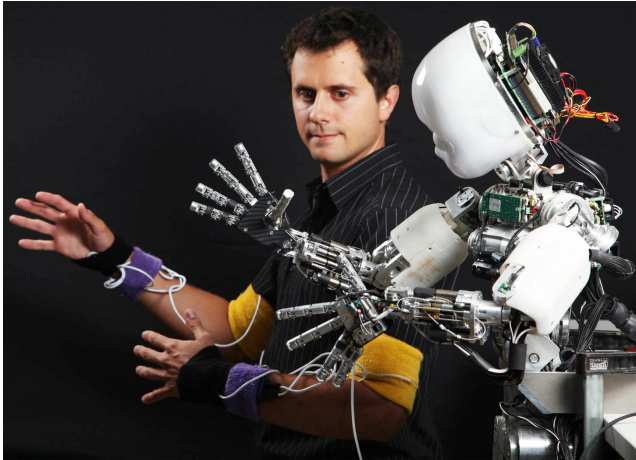
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■ An example :



Credits : Sylvain Calinon

- ▶ 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's demonstration as an exploration baseline**
- ▶ Child learning to dance : first follows its teacher's moves, before trying out new ones once he feels he has exploited the teacher's recommendations.
 - ⇒ notion of **compliance** w.r.t the teacher.

■ Goal :

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

in a **reinforcement learning framework**.

■ Method :

- ▶ Create a simple but generic Markov Decision Process
- ▶ Solve it using classical RL method
- ▶ Implement compliant-based learning methods

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■ RL :

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

Under a Markovian assumption, 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 functions under a policy (probabilistic decision rule) $\pi : \mathcal{S} \rightarrow \mathcal{A}$:

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

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

¹Richard S. Sutton and Andrew G. Barto. *Reinforcement Learning : An Introduction*. MIT Press, 1998. Print.

■ 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, ...

■ Imitation learning :

- ▶ For long and complex tasks : common machine learning algorithms 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)²

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

²Aude 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.

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

- ▶ Provide the learner with a mentor that is another learner
- ▶ In *homogeneous settings*³
- ▶ Study how convergence is affected

and eventually generalize to

- ▶ multiple teachers
- ▶ inhomogeneous settings

³Bob Price and Craig Boutilier. "Accelerating reinforcement learning through implicit imitation". *Journal of Artificial Intelligence Research* 19 (2003): 569–629. [Print.](#) 

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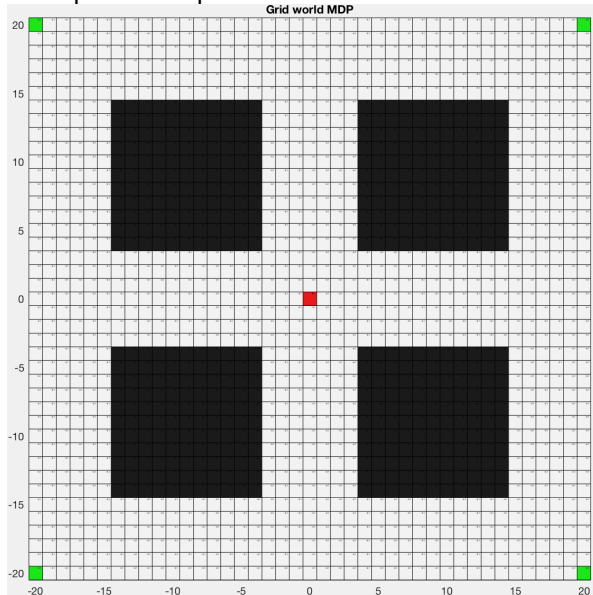
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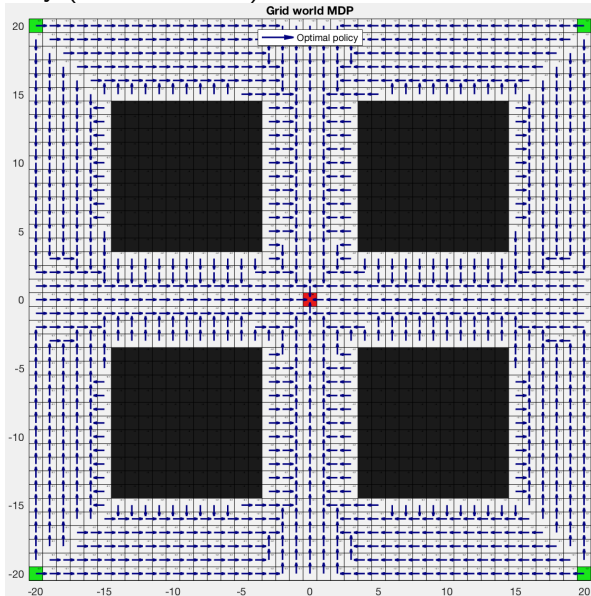
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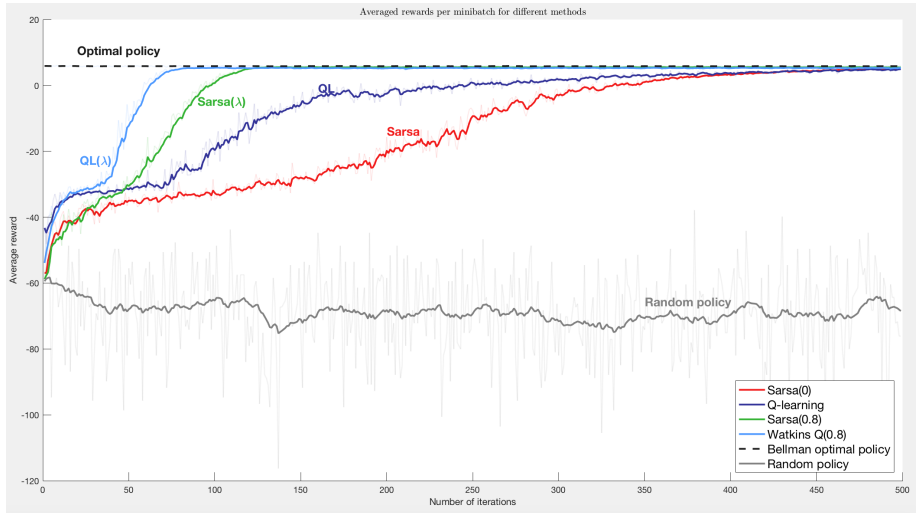
■ Generic and simple state space :



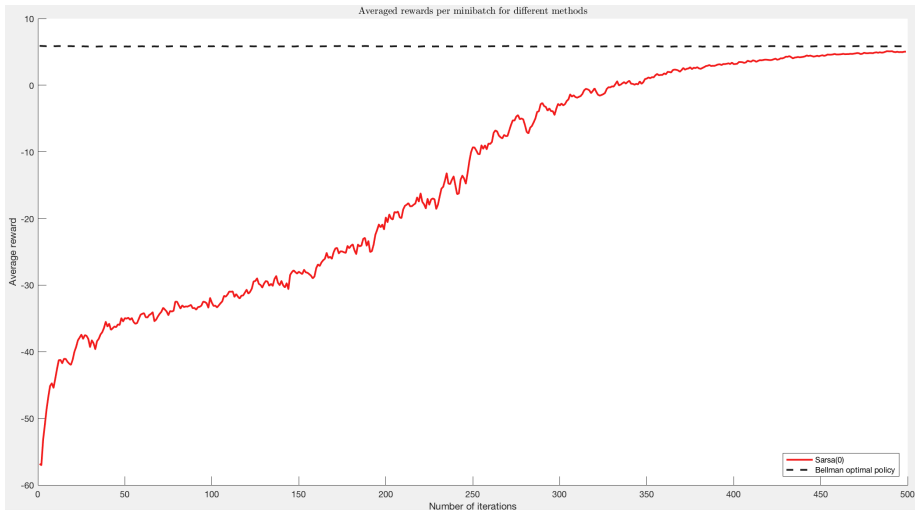
■ Optimal Policy (value iteration) :



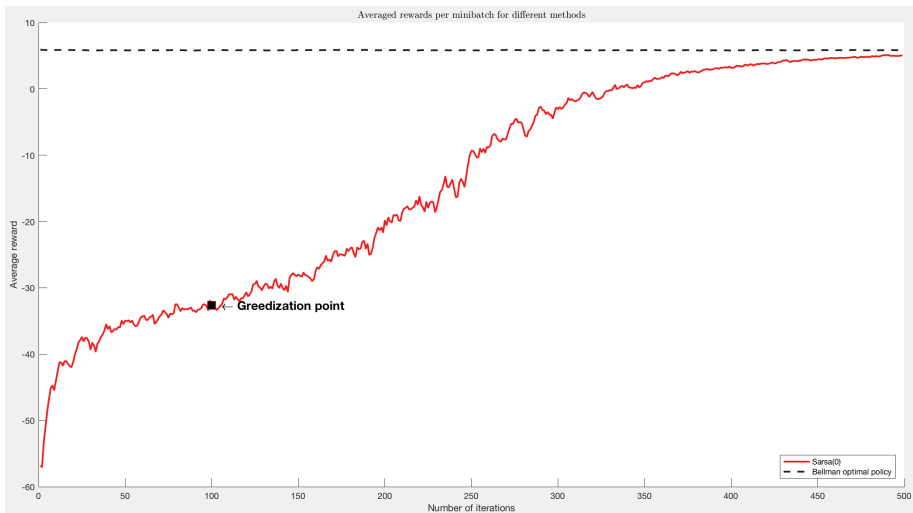
■ Learning the optimal policy



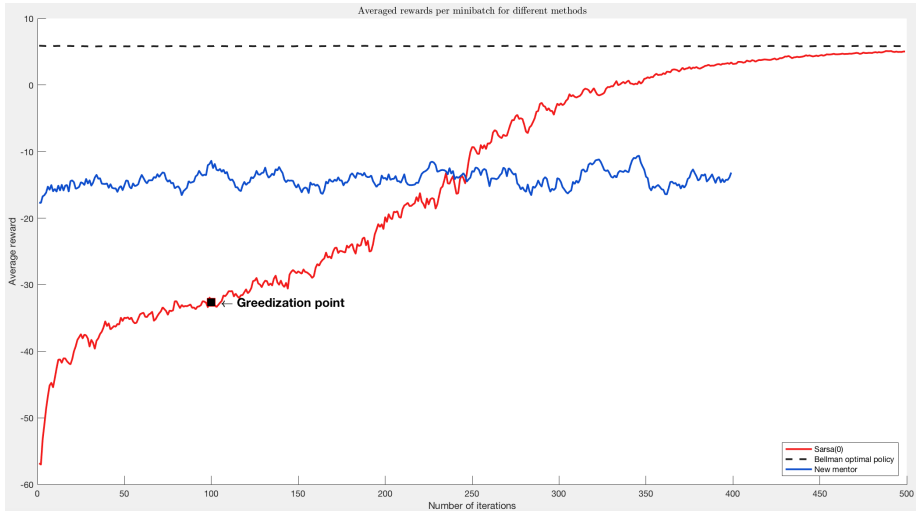
■ Generating a suboptimal mentor



■ Generating a suboptimal mentor



■ Generating a suboptimal mentor



■ Compliance learning

→ Intuitively :

- ▶ Follow the teacher
- ▶ Gain some knowledge about the environment and the task
- ▶ Take our own actions

→ The teacher should only influence our action selection:

- ▶ Global **compliance term** : $p \in [0, 1]$
- ▶ p -greedy action selection w.r.t the mentor's action a_m : $\forall s \in \mathcal{S}$

$$\pi(s) = \begin{cases} a_m \text{ with probability } p \\ a \in \mathcal{A}(s) \text{ (Gibbs softmax)} \end{cases} \quad (6)$$

■ Vanishing compliance :

► Constantly decreasing compliance :

$$\left| \begin{array}{l} p_0 \in [0, 1] \\ p_{t+1} = \beta p_t, \quad \beta < 1 \end{array} \right. \quad (7)$$

► Along with SARSA update :

$$Q(s, a) \leftarrow Q(s, a) + \alpha(r + \gamma Q(s', a') - Q(s, a)) \quad (8)$$

► Start with $p_0 \simeq 1$ (high confidence) and slowly decide to take your own decisions.

■ Constantly decreasing compliance :

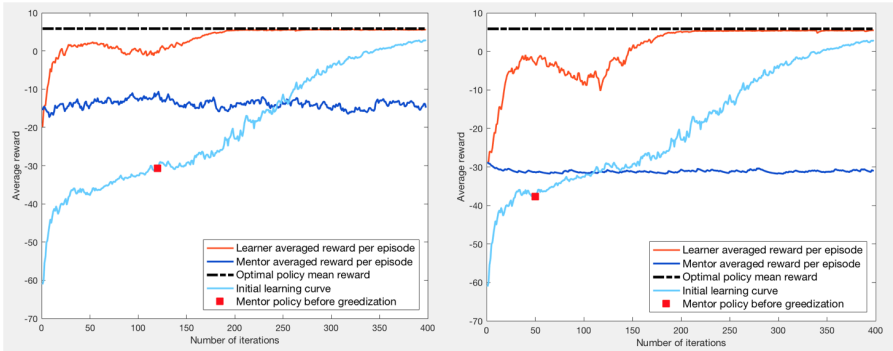


Figure: Average reward for two naive compliance learners

■ Learning the compliance term

$\forall s \in \mathcal{S}$, define $p(s)$ - compliance term that impact the action selection :

$$\pi(s) = \begin{cases} a_m \text{ with probability } p(s) \\ a \in \mathcal{A}(s) \setminus a_m \text{ with probability } 1-p(s) \end{cases} \quad (9)$$

Goal : learn $p(s)$, $\forall s \in \mathcal{S} \rightarrow$ measure how right the teacher seems to be

► **Implicit β -compliance :**

- $\forall s \in \mathcal{S}$, provide $p(s)$ with a Beta prior ($\alpha \gg \beta$)

$$p(s) \sim B(\alpha(s), \beta(s)) \quad (10)$$

- Given a (s, a, r, s', a') 5-tuple, compute the critic TD value :

$$\delta_t = r + \gamma Q(s', a') - Q(s, a_m) \quad \rightarrow \text{how good is the teacher ?} \quad (11)$$

- Compute **posterior distribution** over $p(s)$:

$$\begin{aligned} \alpha_t(s) &\leftarrow \alpha_t(s) + \mathbb{1}_{a=a_m} \delta_t \varepsilon_t \\ \beta_t(s) &\leftarrow \beta_t(s) + \mathbb{1}_{a \neq a_m} \delta_t \varepsilon_t \end{aligned} \quad (12)$$

► Implicit β -compliance :

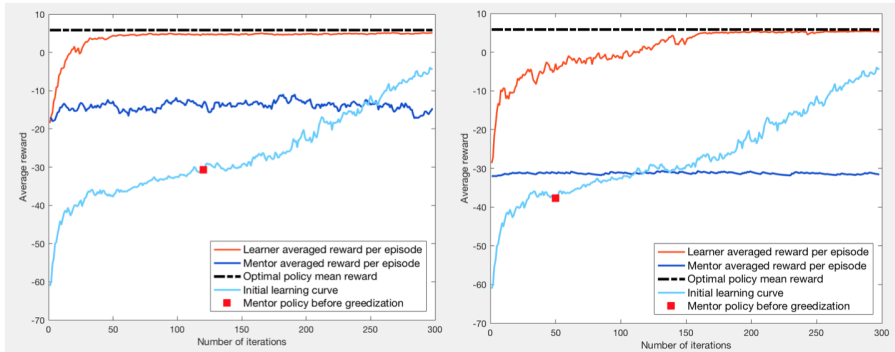
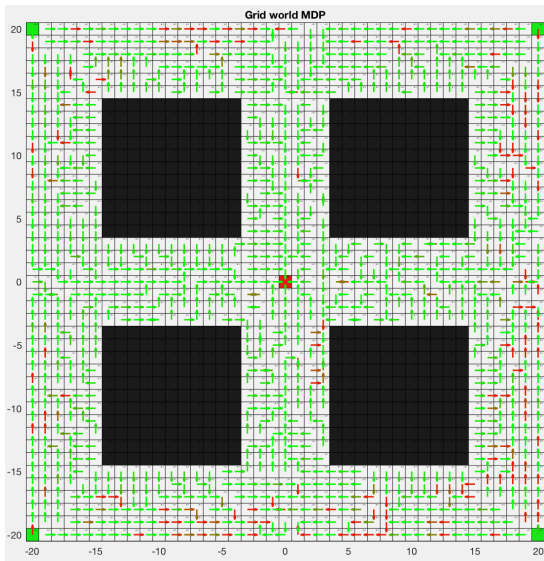


Figure: Average reward for two actor-critic compliance learners

- Faster convergence
- No undershoot + tuning is intuitive

► Implicit β -compliance :



► Explicit compliance :

- Adds a hierarchical MDP :

$$\forall s \in \mathcal{S}, \mathcal{A}_c(s) = \{ 'listen', 'discard' \} \quad (13)$$

- Define exploration based on $\{Q_c(s, l), Q_c(s, d)\}$:

$$\forall s \in \mathcal{S}, \quad \pi_c(s) = \begin{cases} 'l' & \text{with probability } p(s) = \sigma \left(\frac{Q_c(s, l) - Q_c(s, d)}{\tau} \right) \\ 'd' & \text{with probability } 1 - p(s) \end{cases} \quad (14)$$

- Perform SARSA update
- Update :

$$\begin{cases} Q_c(s, l) \leftarrow \beta Q_c(s, l) + (1 - \beta) Q(s, a_m) \\ Q_c(s, d) = \beta Q_c(s, d) + (1 - \beta) \max_{a \neq a_m} Q(s, a) \end{cases} \quad (15)$$

► Explicit compliance :

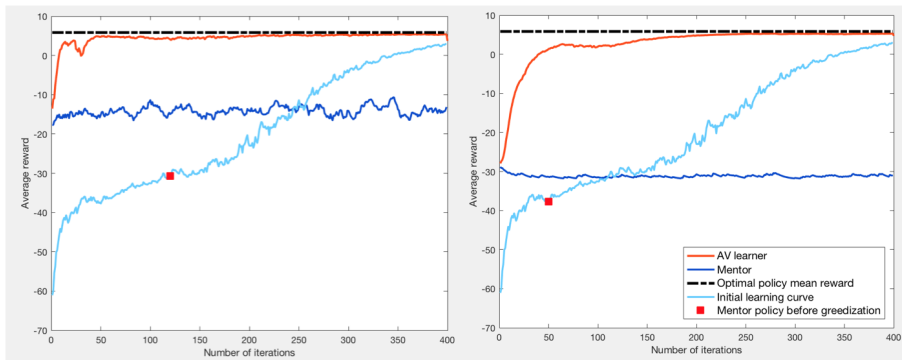
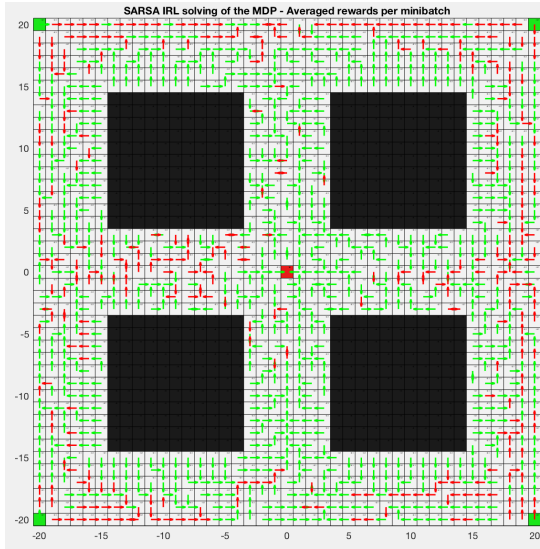
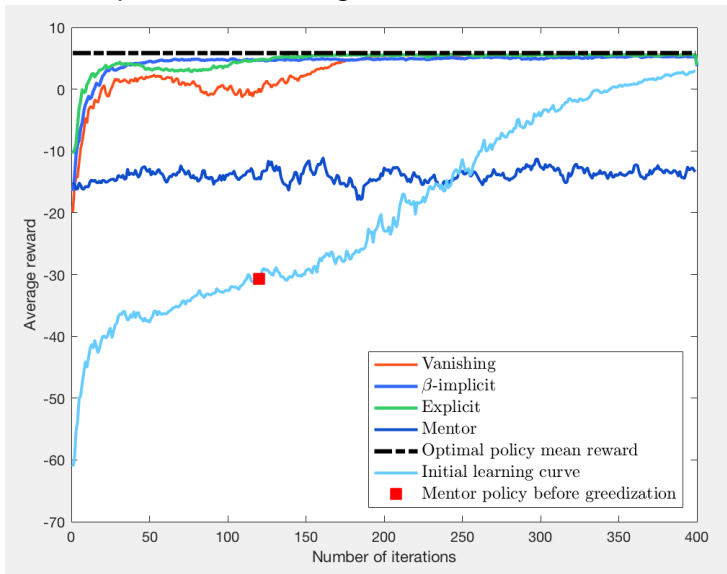


Figure: Average reward for two action-value compliance learners

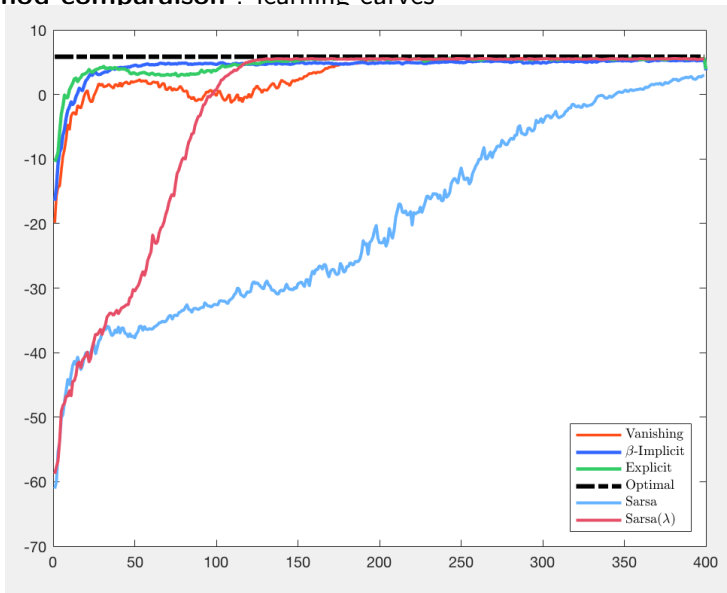
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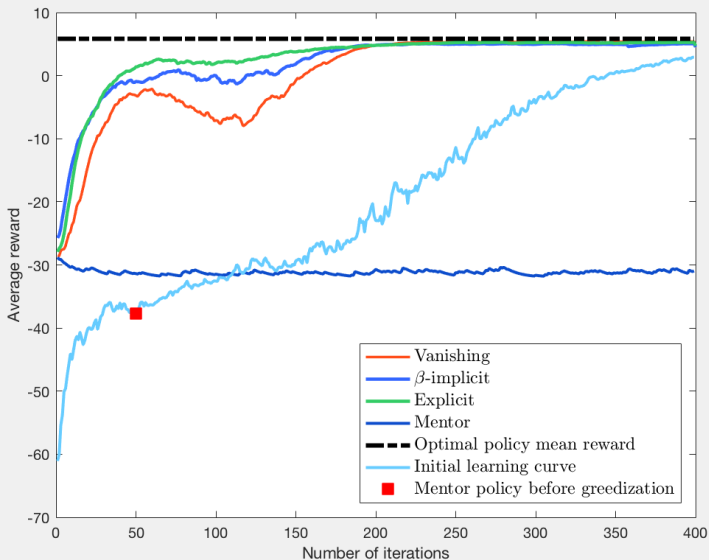
► Method comparison : learning curves



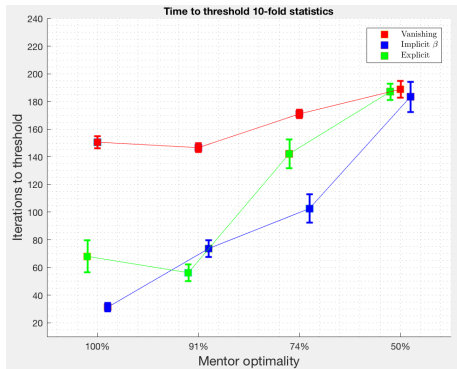
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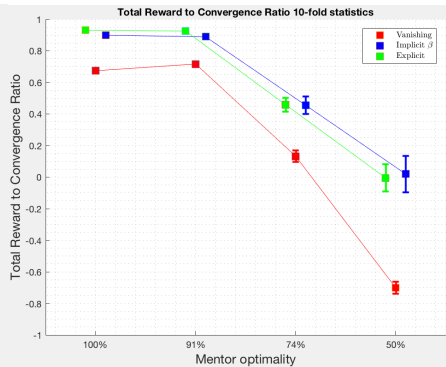
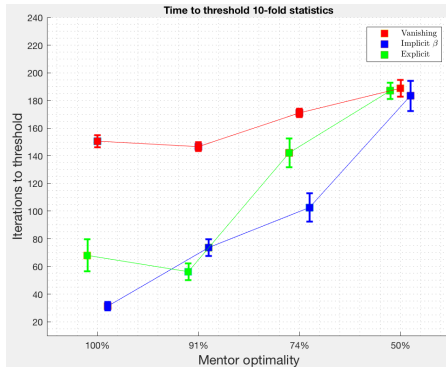
► Method comparison : learning curves



► Method comparison : f-fold metrics statistics



► Method comparison : f-fold metrics statistics



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► Future Work

- Convergence and final result is too much impacted by the mentor : **off-policy** generalization
- Eligibility-trace formulation
- Generalize to several mentors
- Generalize to sparse recommendations

Thank you for your attention !