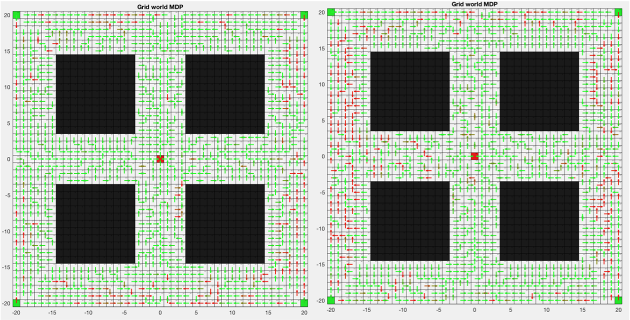

Learning from largely suboptimal teachers and the role of compliance

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Plan

1. Motivations
2. Background
   - Reinforcement learning
   - Imitation learning
   - Transfer learning
3. Results
   - Markov Decision Process
   - Compliance-based learning
   - Method comparaison
4. Future work

Plan

■ An example :

- A human teacher is showing the robot to reach for an object
- The teacher is not a robotic expert, and guides the robot along a trajectory near the edge of the robot's workspace, or very close to some obstacles
- Should the robot discard the demonstration ?
- There is still some valuable information in the demonstration (pose of the object, general direction of motion, ..)

- 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 recommandation

$\Rightarrow$ 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
  - 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

Plan

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

$$(\mathcal{S}, \mathcal{A}(\mathcal{S}), \mathcal{P}^a_{ss'}, \mathcal{R}^a_{ss'}) \tag{1}$$

where :

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

■ RL :

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

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

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

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

■ **Solving RL** : Two baseline methods :

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

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

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

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

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

■ Imitation learning :

- 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)[2]

$\longrightarrow$ Ex. : robotic arm grabbing a cup
: maze solver

[2] Aude 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

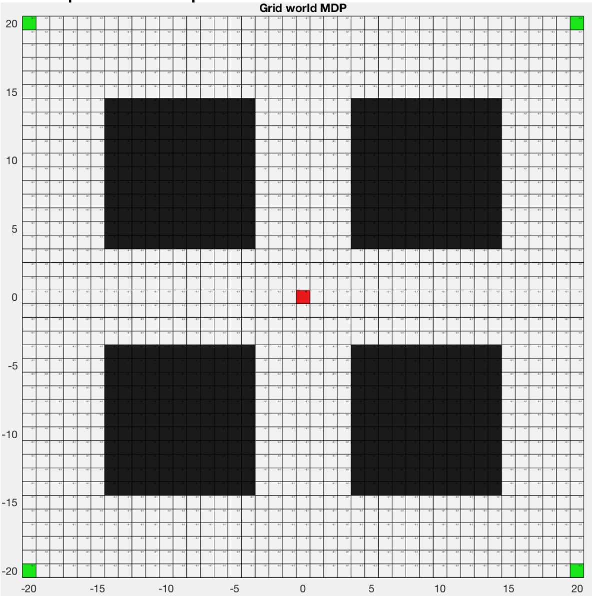
and eventually generalize to

- multiple teacher
- inhomogeneous settings

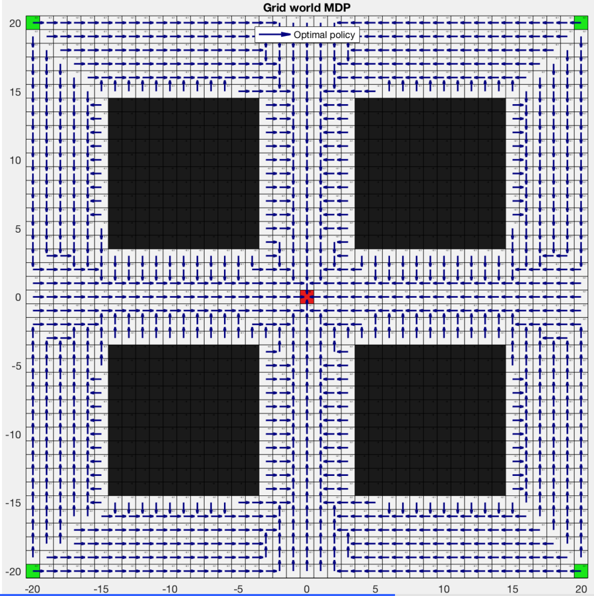
[3] Bob Price and Craig Boutilier. "Accelerating reinforcement learning through implicit imitation". *Journal of Artificial Intelligence Research* 19 (2003): 569–629. Print.

Plan

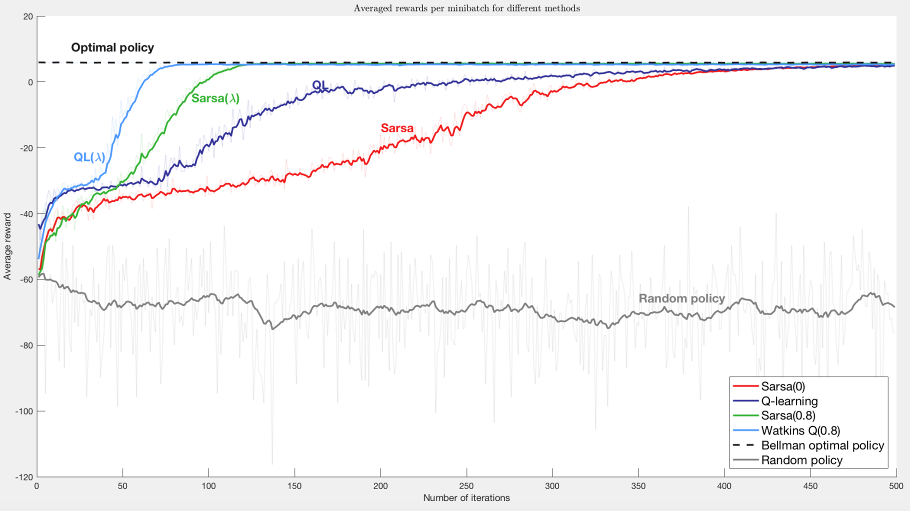
- Generic and simple state space :



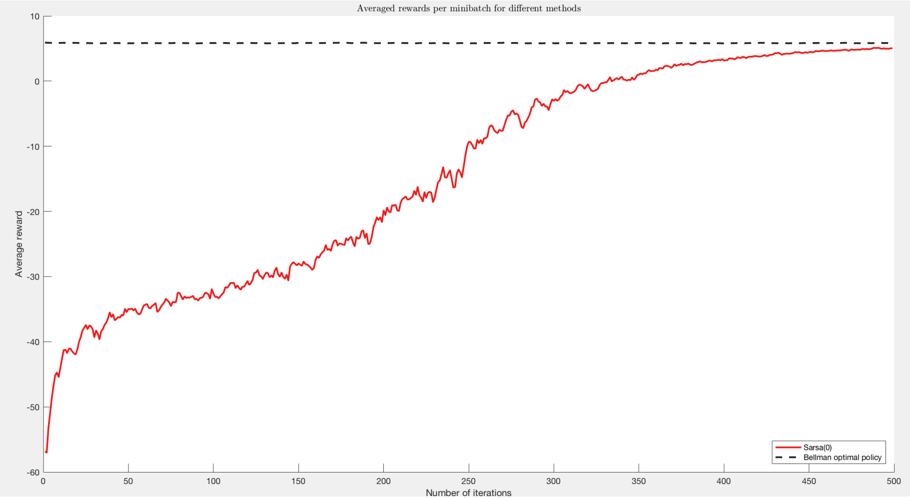
■ Optimal Policy (value iteration) :



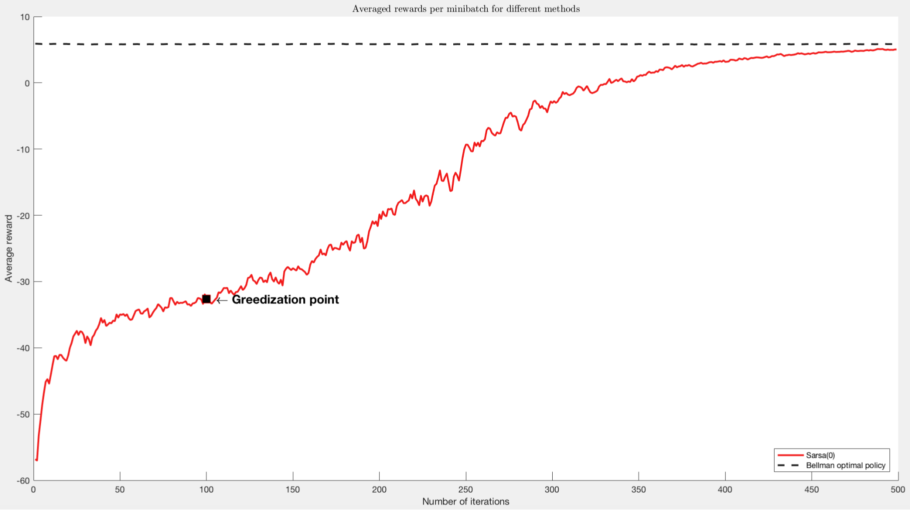
Learning the optimal policy



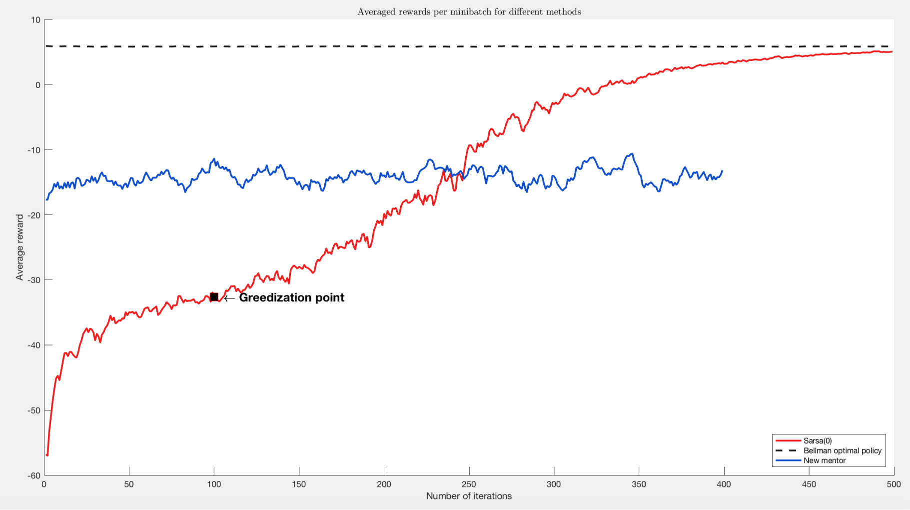
- Generating a suboptimal mentor



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** :

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

- Along with SARSA update :

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

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

■ Constantly decreasing compliance :

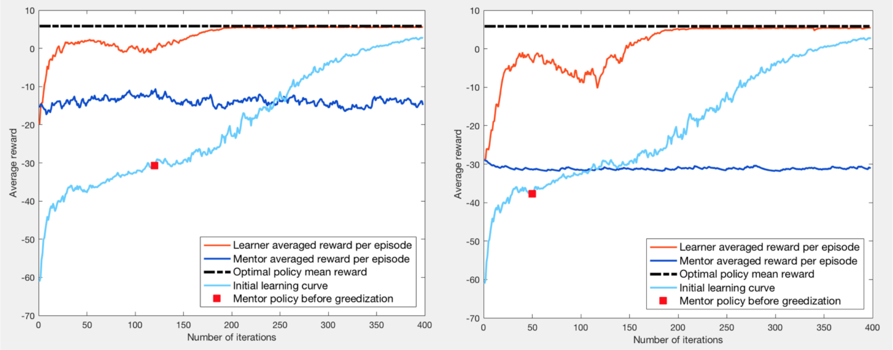


Figure: Average reward for two naive compliance learners

+	−
Easy to implement	Undershoot
Fast convergence (200 vs 500)	**Precise tuning**

■ Learning the compliance term

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

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

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 ($\alpha >> \beta$)

$$p(s) \sim B(\alpha(s), \beta(s)) \tag{10}$$

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

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

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

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

Implicit β-compliance :

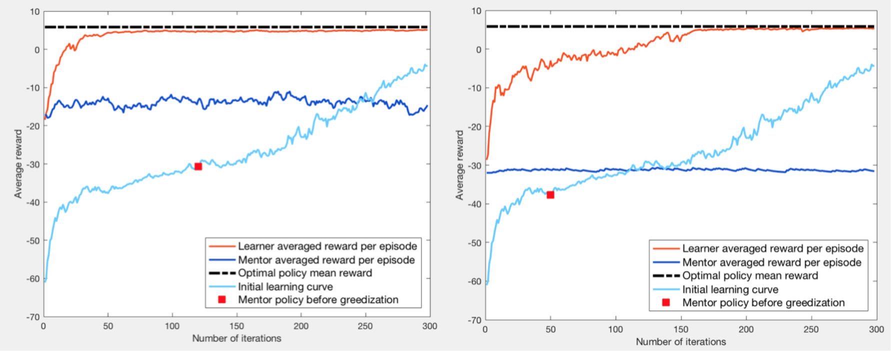
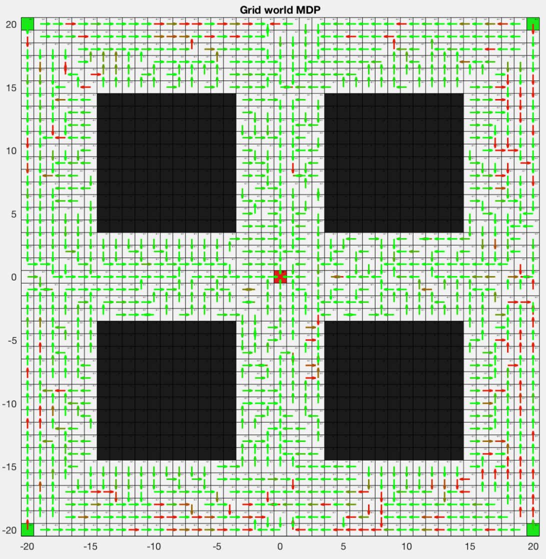


Figure: Average reward for two actor-critic compliance learners

- Faster convergence
- No undershoot + tuning is intuitive

- **Implicit β-compliance :**



- **Explicit compliance** :
  - Adds a hierarchical MDP :

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

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

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

  - Perform SARSA update
  - Update :

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

- **Action-value approach** :

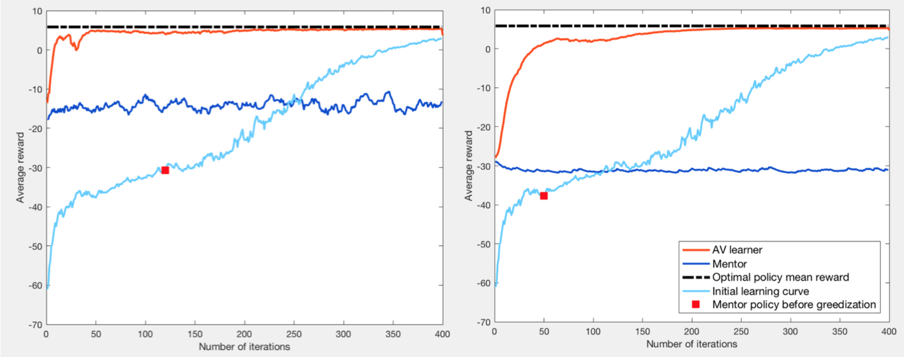
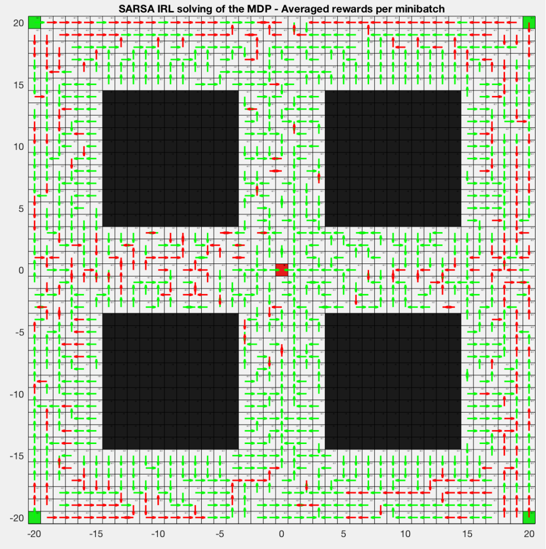
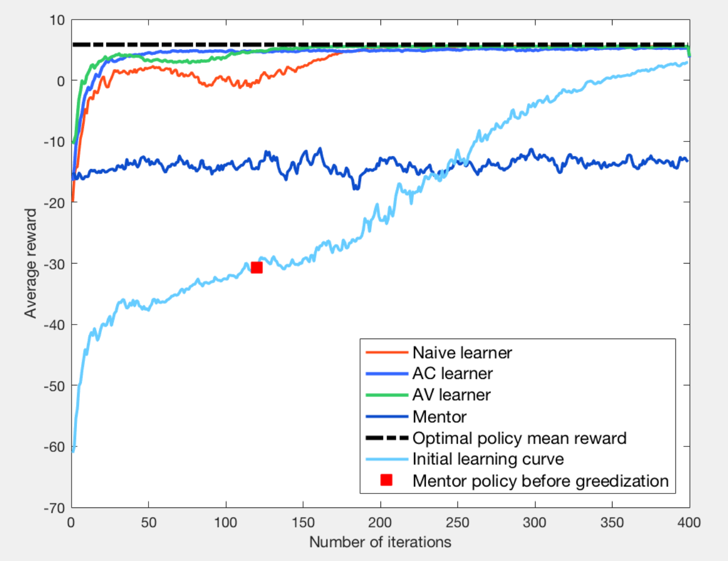


Figure: Average reward for two action-value compliance learners

- Action-value approach :



▶ Method comparaison : learning curves



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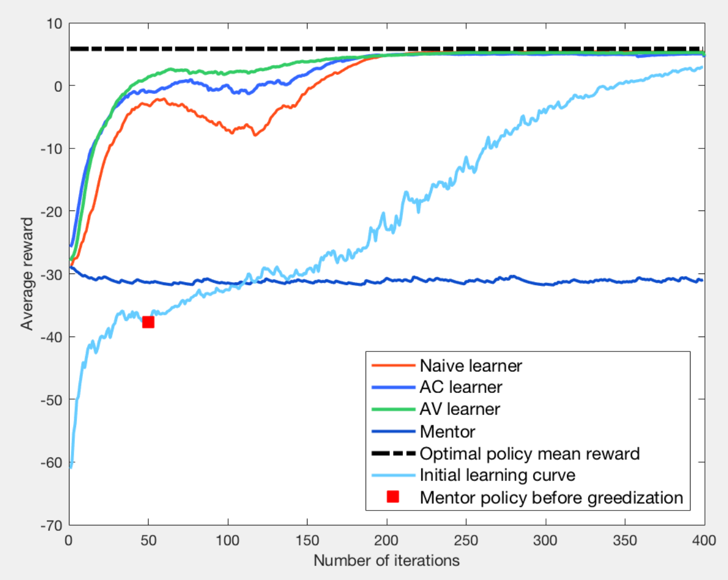

▶ **Method comparaison** : f-fold metrics statistics

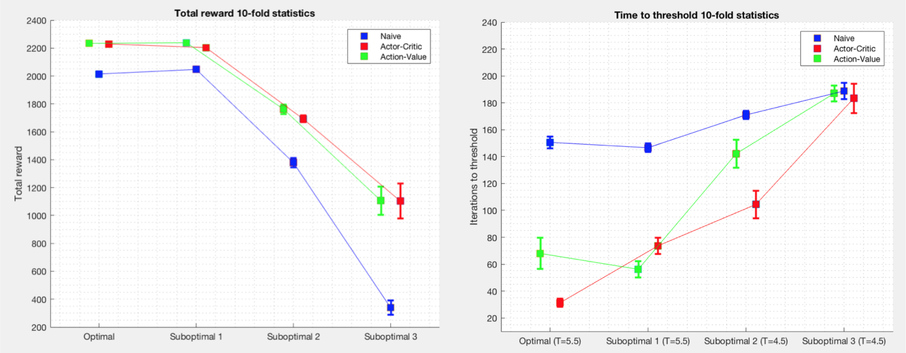

Figure: Metrics comparaison for imitation learning methods

Plan

- **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 recommandations