Learning from suboptimal teachers

The role of compliance in the exploration-exploitation tradeoff

Final Presentation - Semester Project

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Under the supervision of :

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June 19, 2017

Outline

Introduction

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- Mapping state to action : *policy*
- Crucial problem in many robotics applications..

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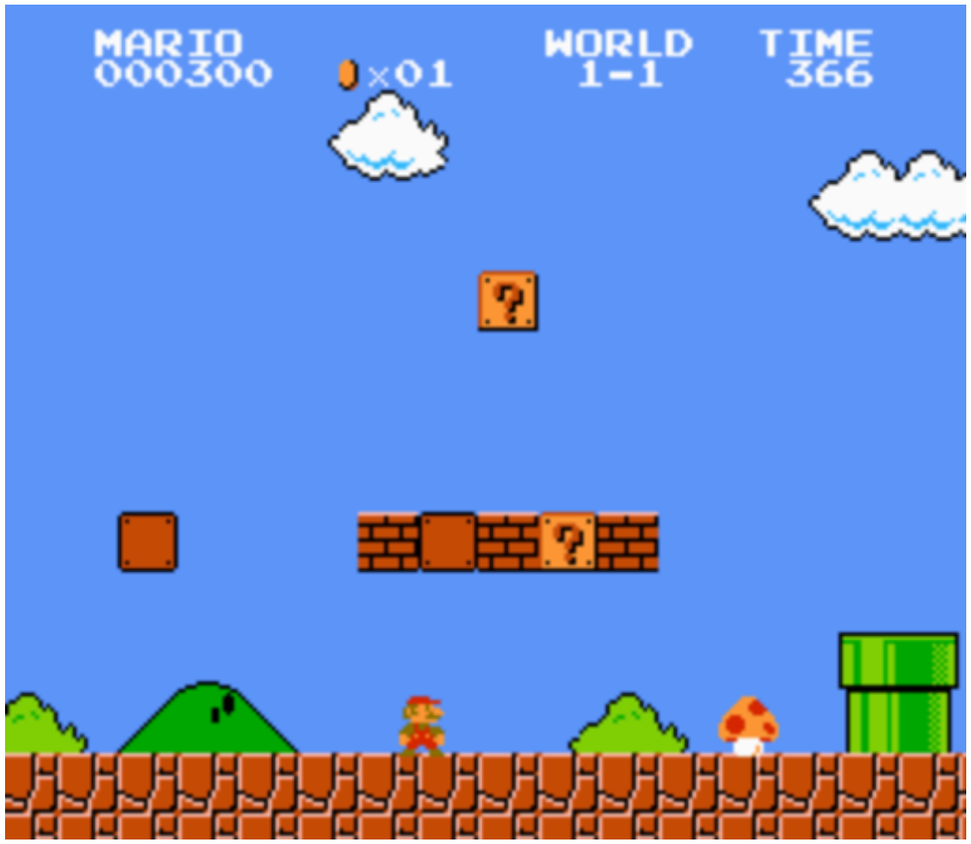

Super Mario Bros

REINFORCEMENT LEARNING[1]

[1] Richard S. Sutton and Andrew G. Barto. *Reinforcement Learning : An Introduction*

REINFORCEMENT LEARNING[1]

- Formulated for Markov Decision Process (MDP) :

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

with :

$\mathcal{S}$		state space
$\mathcal{A}$		state space
$\mathcal{P}^a_{ss'}$	$= \mathbb{P}(s_{t+1} = s' \mid s_t = s, a_t = a)$	Markovian dynamics
$\mathcal{R}^a_{ss'}$	$= \mathbb{E}\left(r_t \mid s_t = s, a_t = a, s_{t+1} = s'\right)$	Markovian reward

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\end{aligned}$$

- Objective : find the policy

$$\begin{aligned}
\pi : \quad & \mathcal{S} \to \mathcal{A}(s) \\
& s \to a
\end{aligned}$$

that maximizes the accumulated reward

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evaluate and improve the state-value function (static)

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Bootstrap, explore and backup (tabular RL)!

$$Q_\pi(s,a) \sim r_t + Q_\pi(s',a')$$

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	ON POLICY	OFF POLICY
TD(0)	Sampled from the exploratory policy (SARSA)	Sampled from the current greedy policy (QLearning)
TD(λ)	SARSA with eligibility traces	QLearning with eligibility traces

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- Help learning a policy by providing *good* examples of a task

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- Use reinforcement learning !

  - demonstrations counterbalance the greediness of RL
  - speed up the learning

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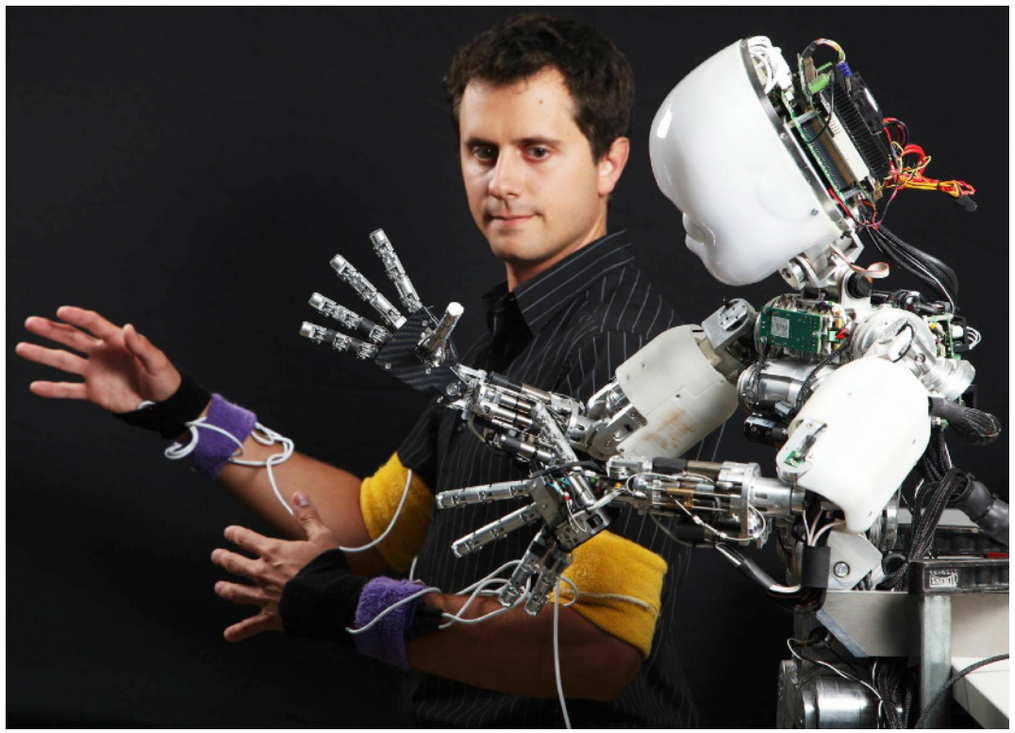
  - Ex : **Grasping objects**



Credits : Sylvain Calinon

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GOAL : - define a compliance-based approach for learning from suboptimal teachers
- experimentally evaluate its performances

INTUITION

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- Define : - $a_m(s)$ the mentor's action at state s
  - $p(s)$ the **compliance** at state s

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- Make the compliance vary throughout the learning

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Rather naive

Tuning might be delicate

No teacher evaluation

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- **β-IMPLICIT COMPLIANCE LEARNER**

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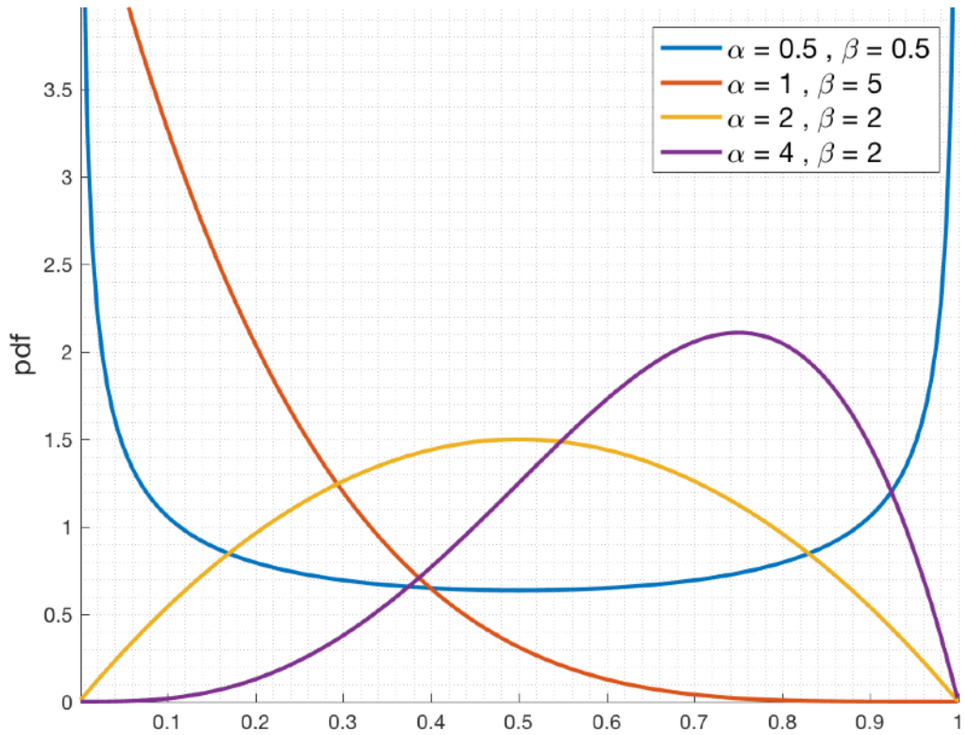
- Provide a Beta prior distribution for the compliance (initial bias)

$$\forall s \in \mathcal{S}, \quad p(s) \sim \boldsymbol{\beta}(\alpha(s), \beta(s))$$



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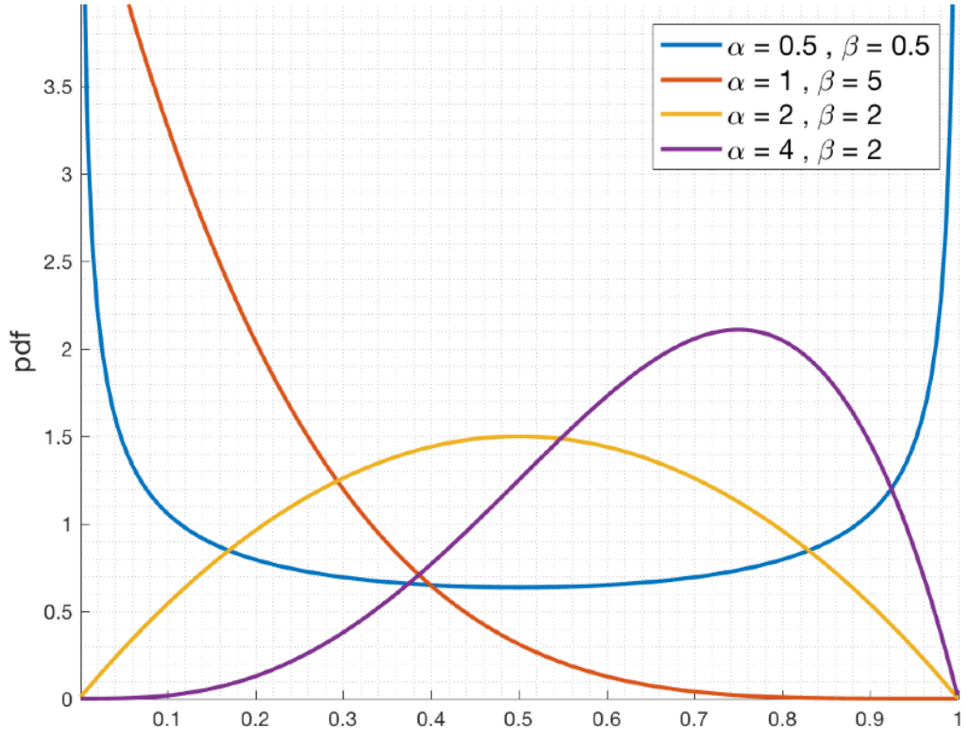

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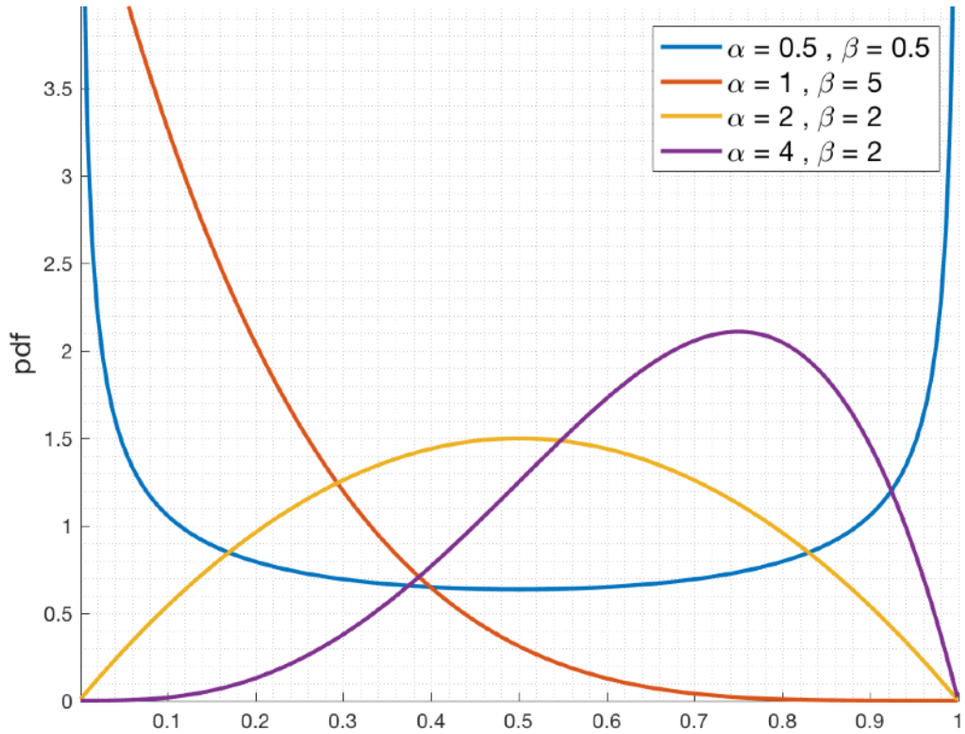

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- Update the p.d.f parameters accordingly

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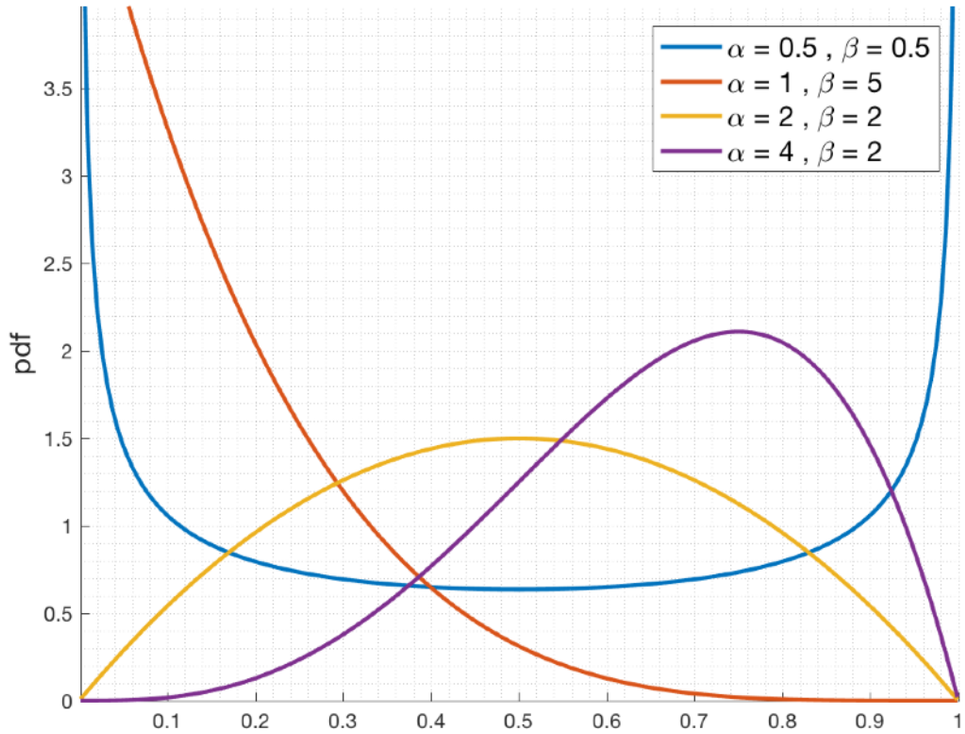

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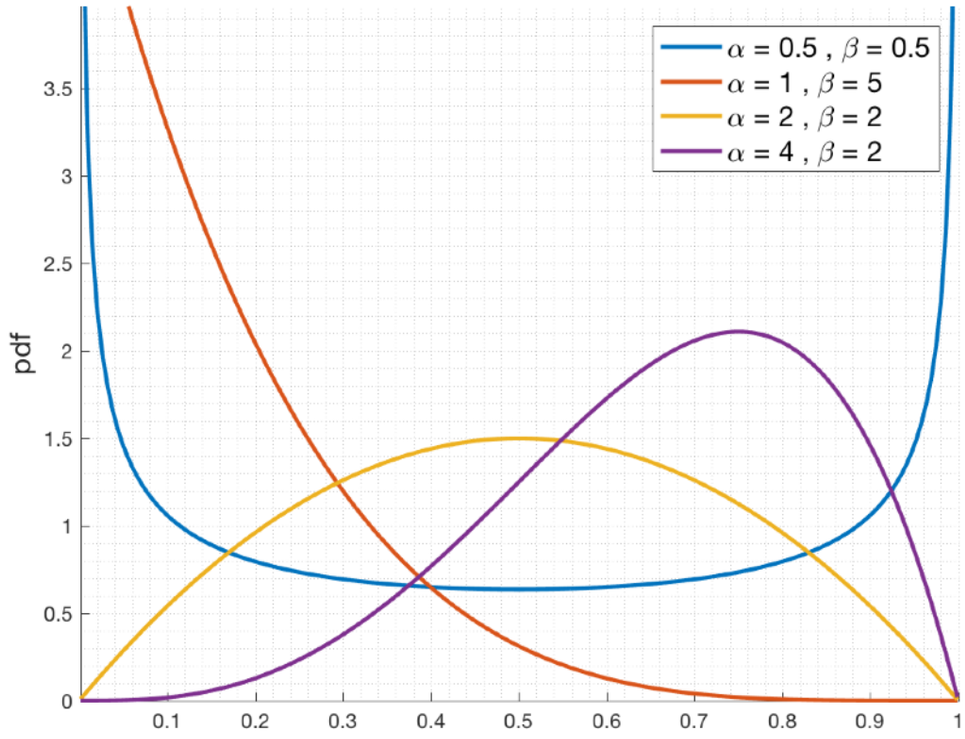
- Update Q-values



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- Learn the action-values of the MDP

$$\mathcal{A}_c(s) = \{'listen', 'discard'\}$$

- Gibbs sampling in this MDP drives the exploration of the initial MDP !

- Procedure :

Initialize (introduce bias):

$\{Q_c(s,l), Q_c(s,d)\}$ ← listen and discard Q-values

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Update initial MDP

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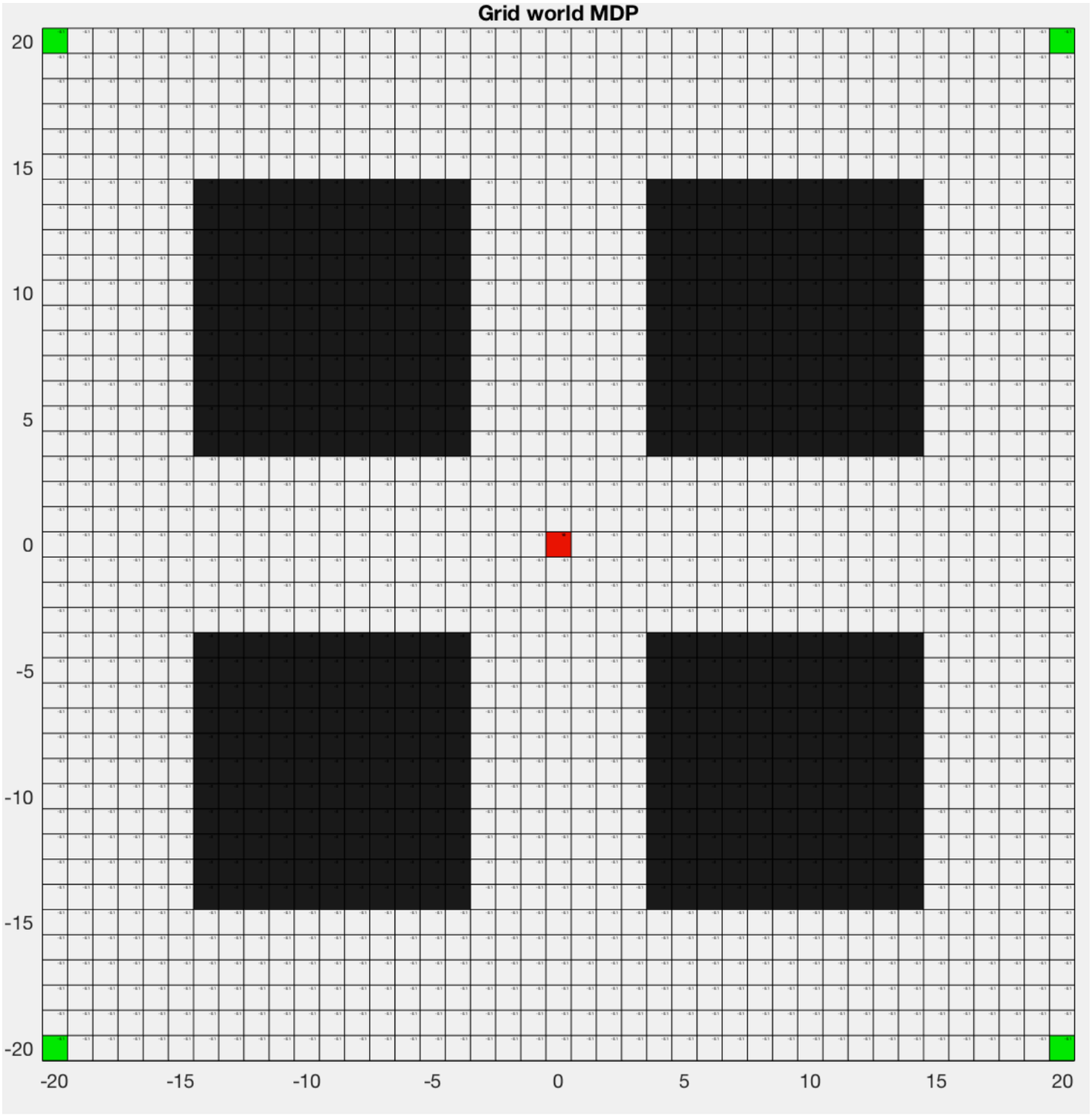
Update new MDP

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

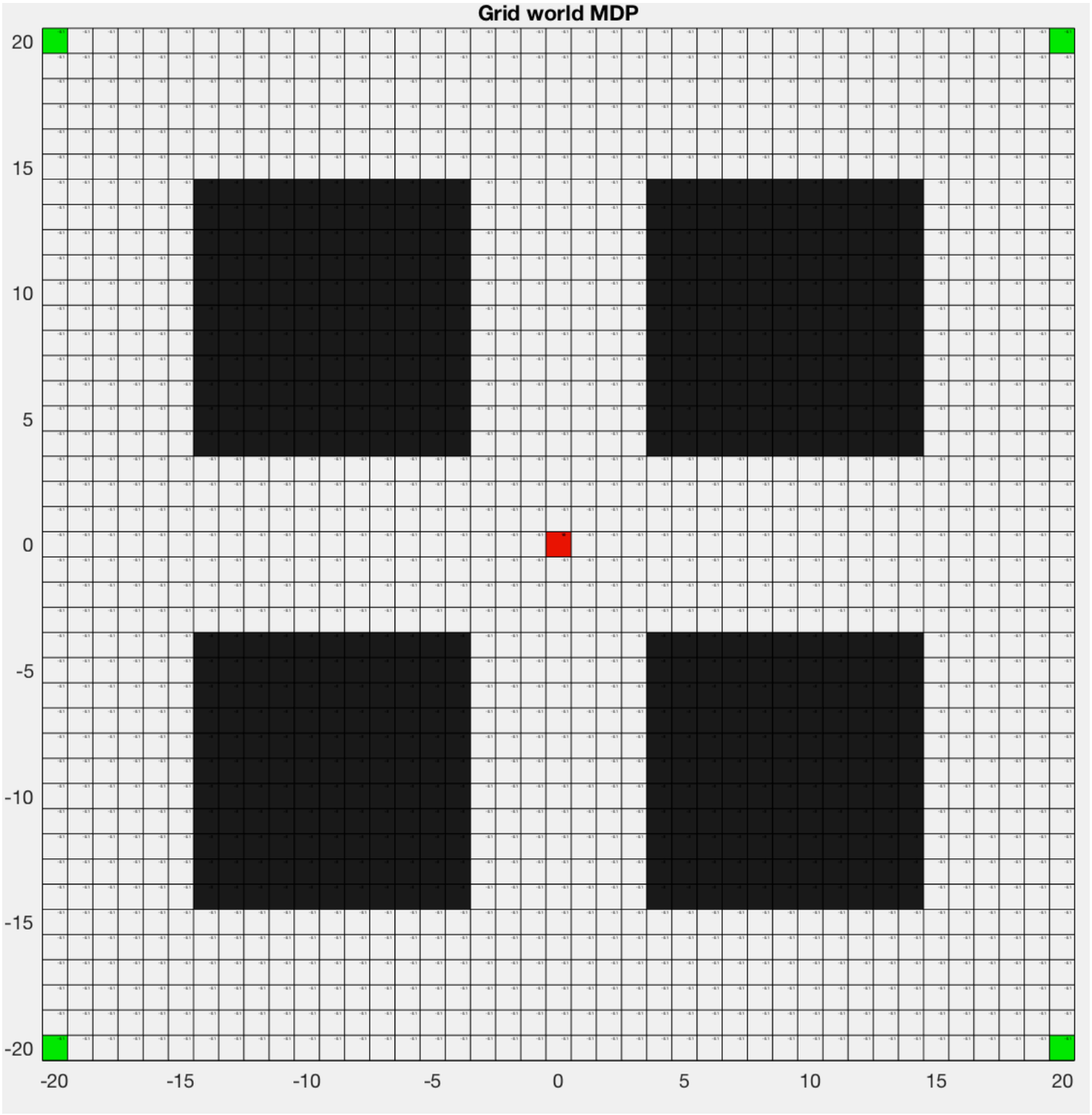
Results

- MDP



Results

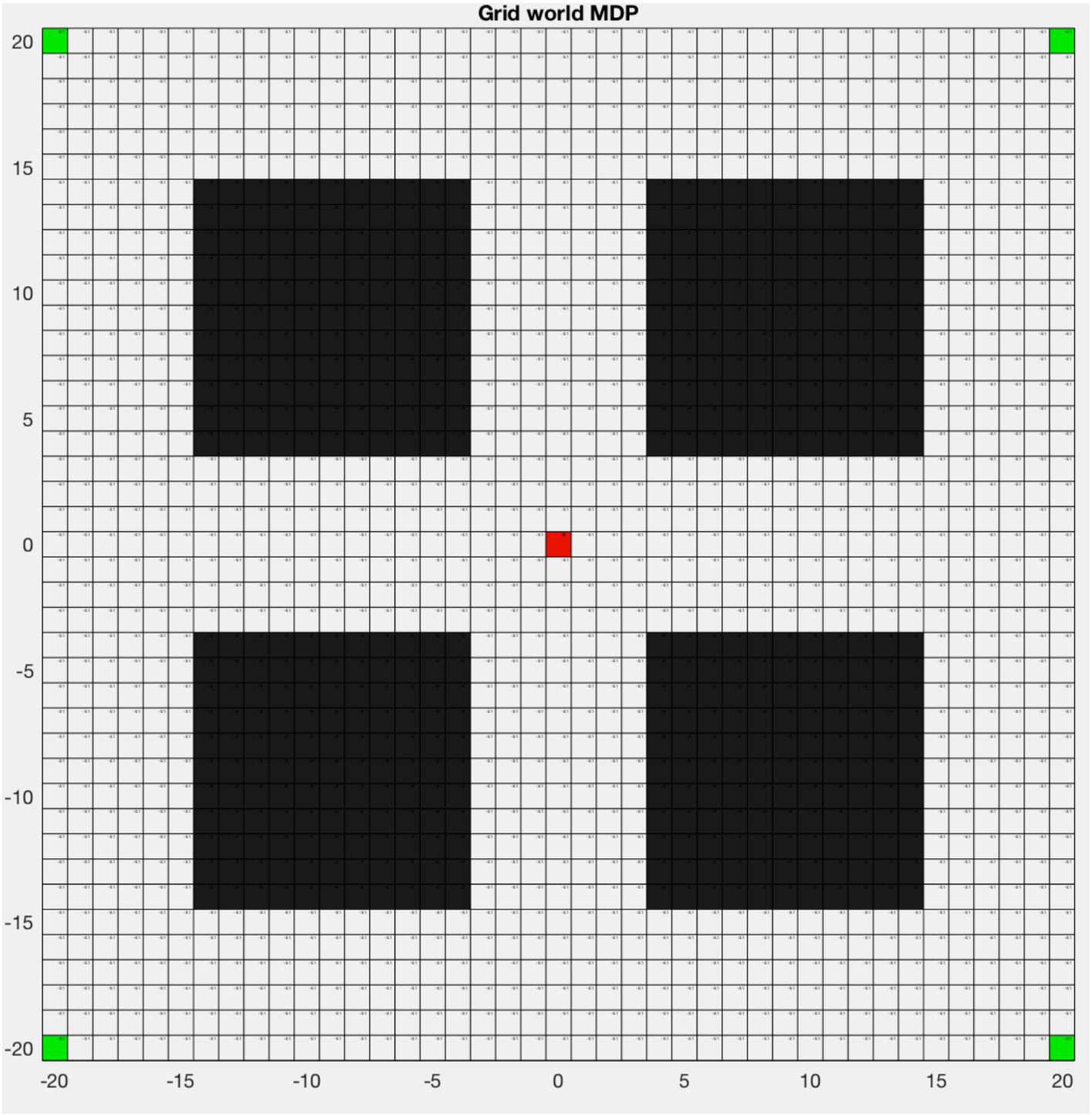
MDP



- Finite MDP

Results

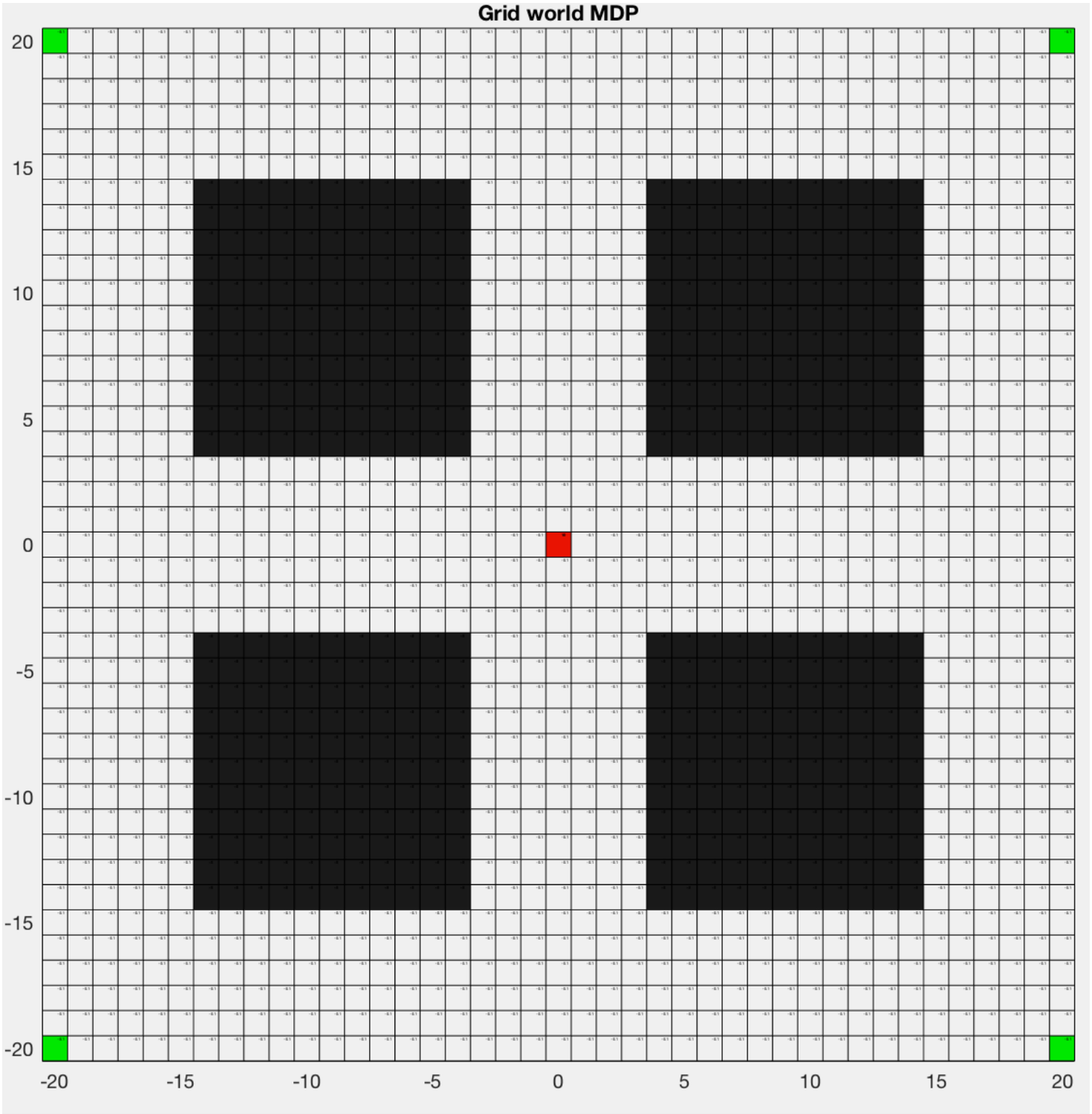
MDP



- Finite MDP
- From green cell to red cell as quickly as possible

Results

MDP



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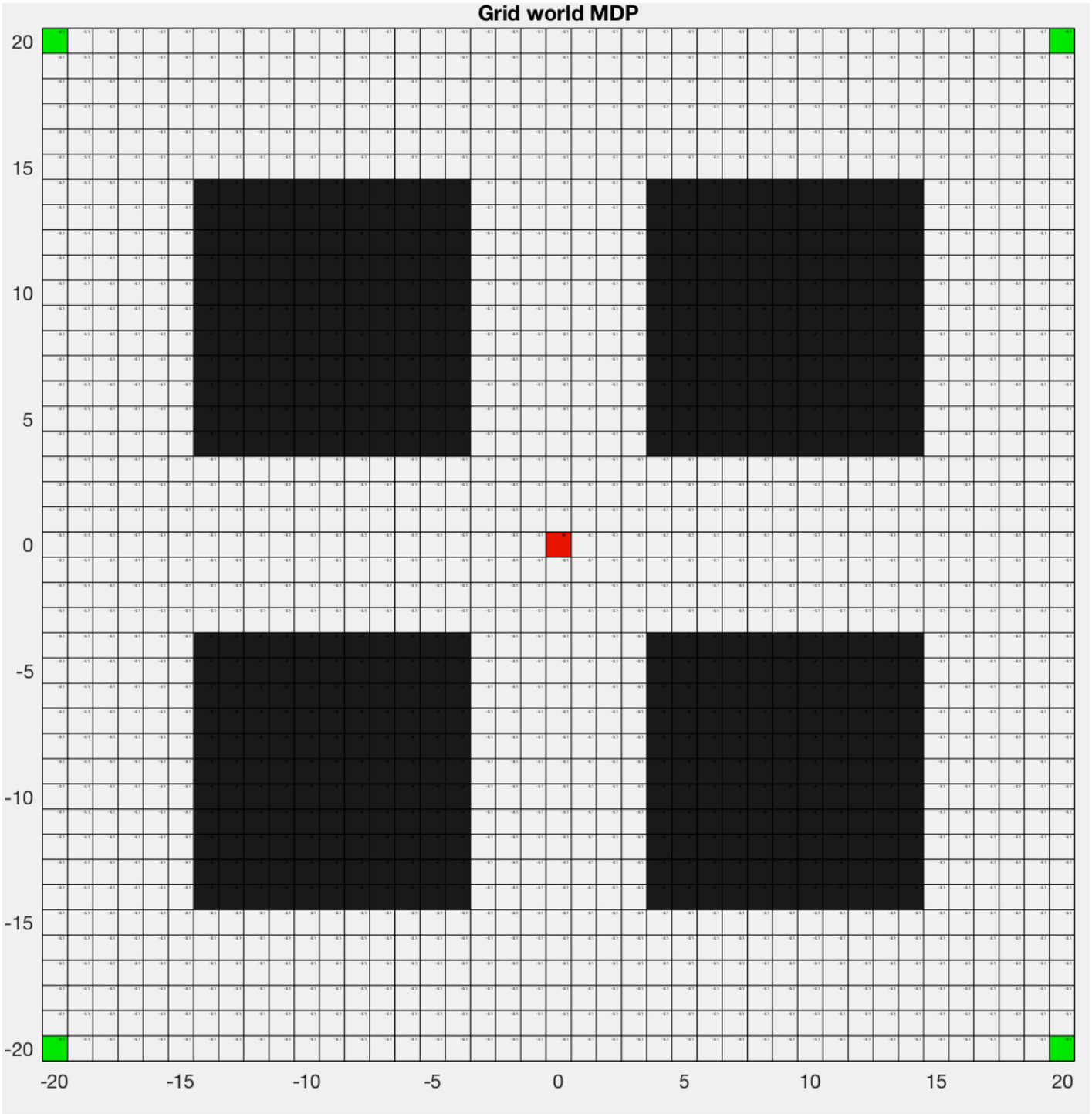
- Stochastic :

$$\mathcal{P}^{a}_{s,s'} = \begin{cases} 0.9 & \text{if } s' = a(s) \\ 0.1 & \text{otherwise} \end{cases}$$

Results

MDP



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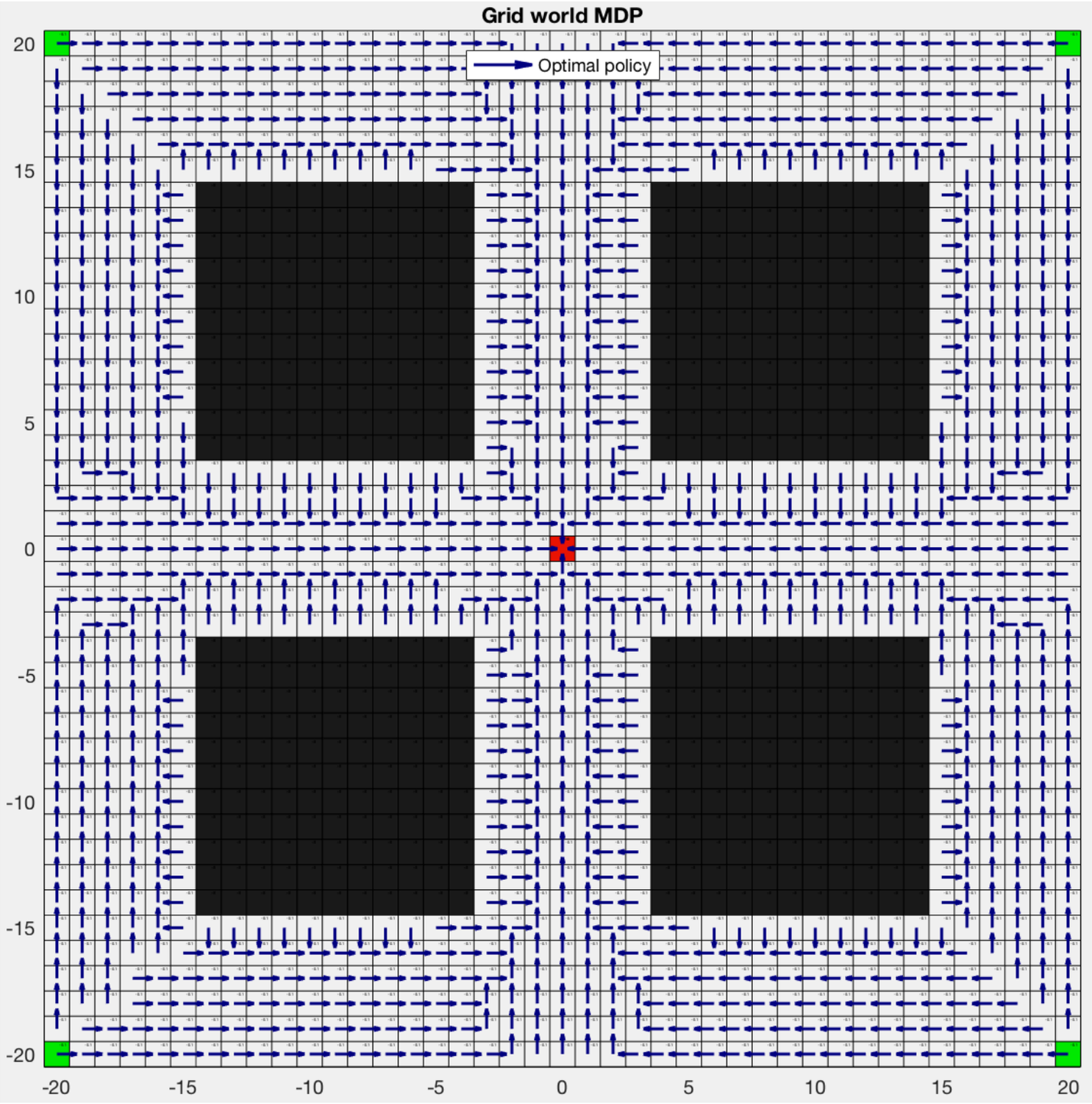
MDP



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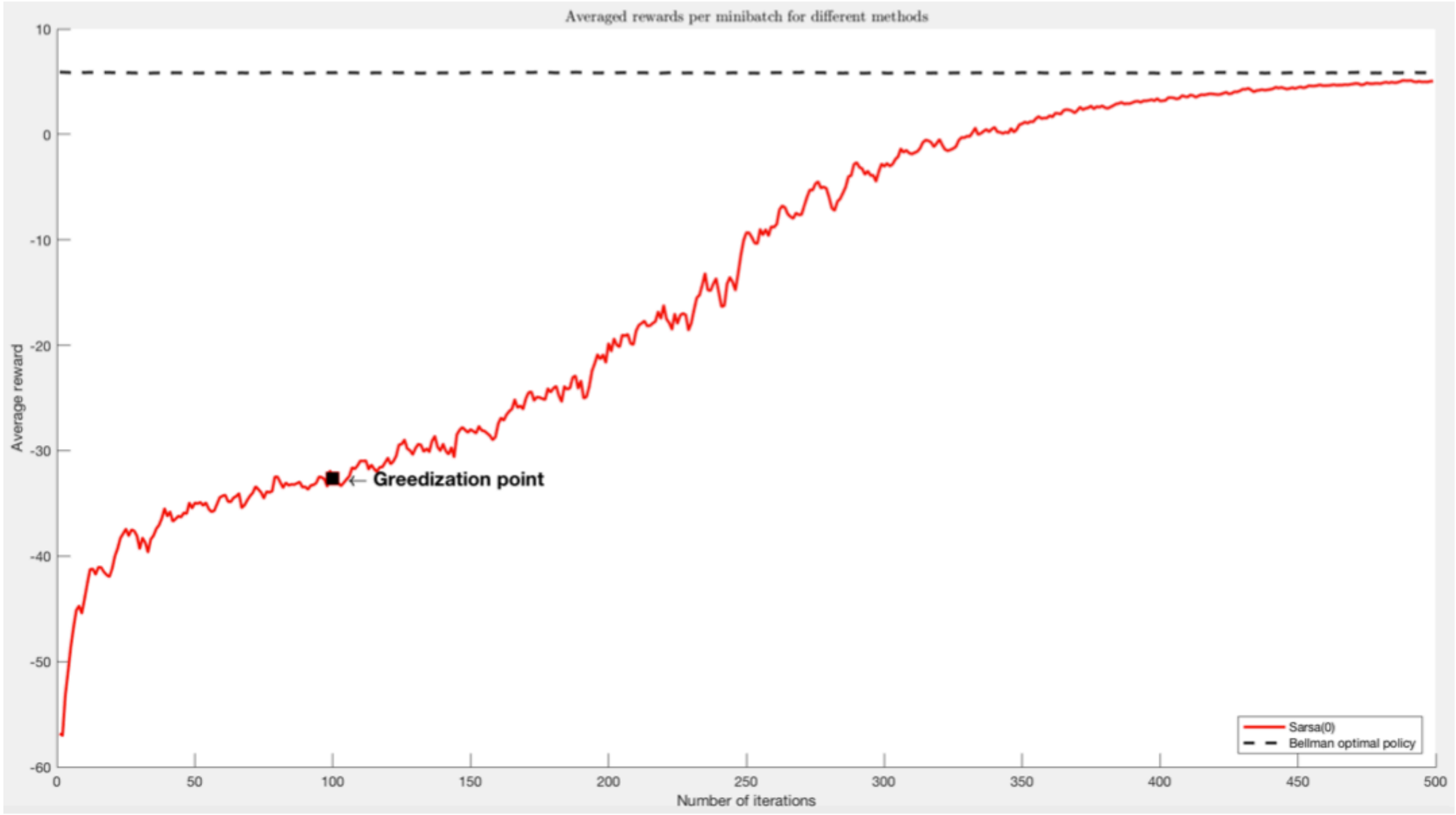
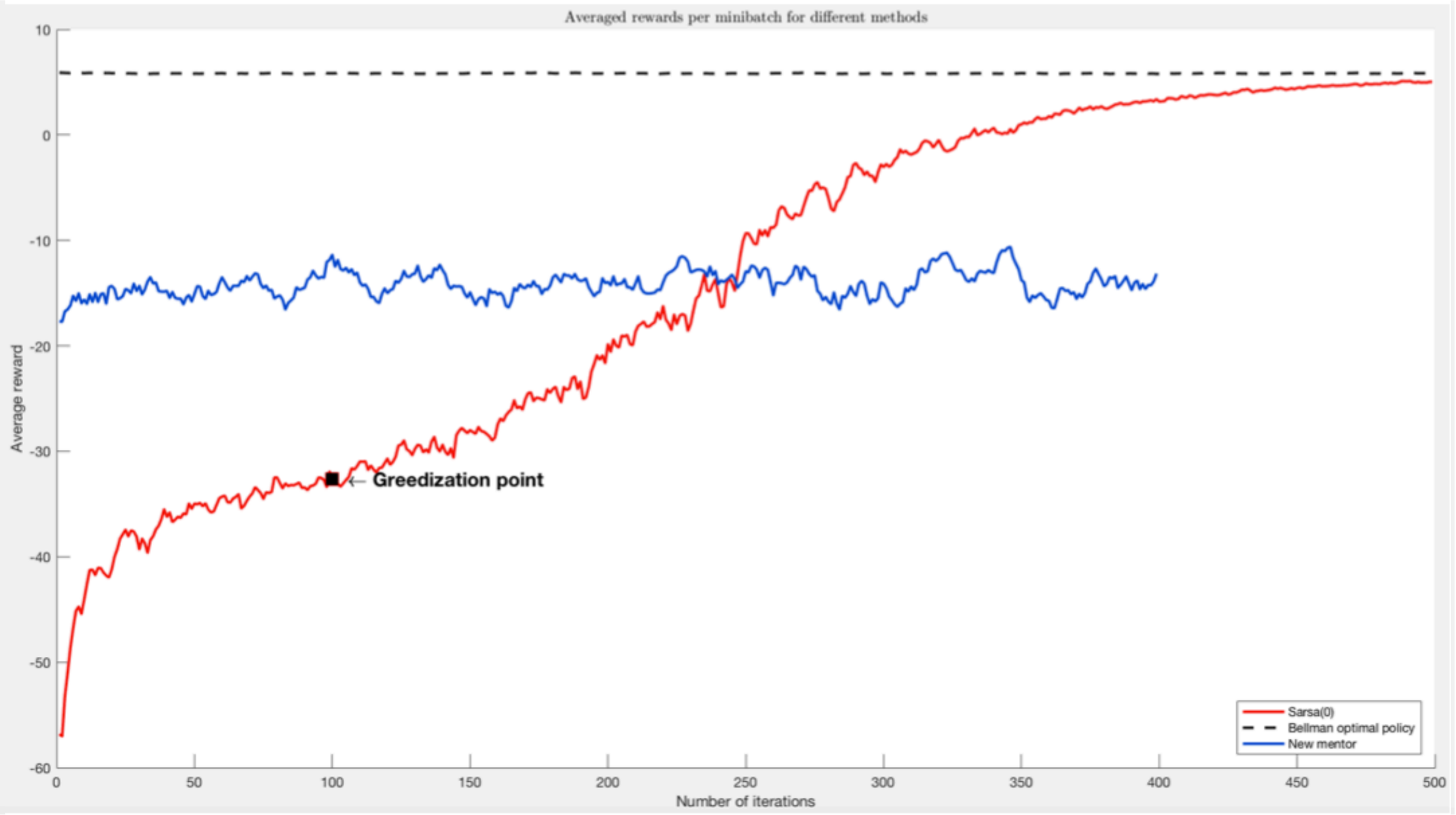
GENERATING MENTORS



Results

GENERATING MENTORS



Results

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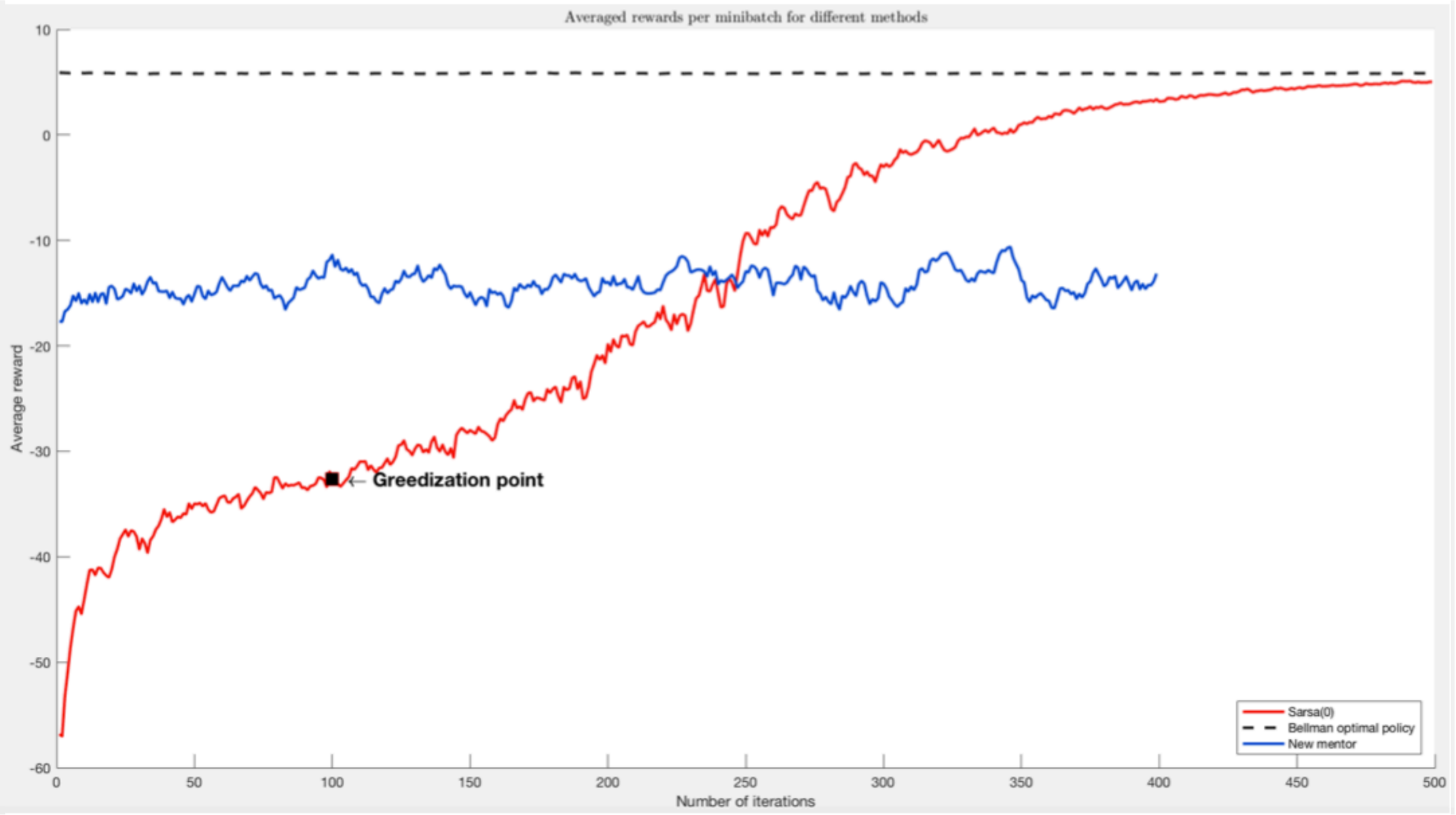

- Fairly strong hypothesis : **one mentor recommandation for every state**

Results

- **VANISHING COMPLIANCE** (The naive way)

Results

VANISHING COMPLIANCE (The naive way)

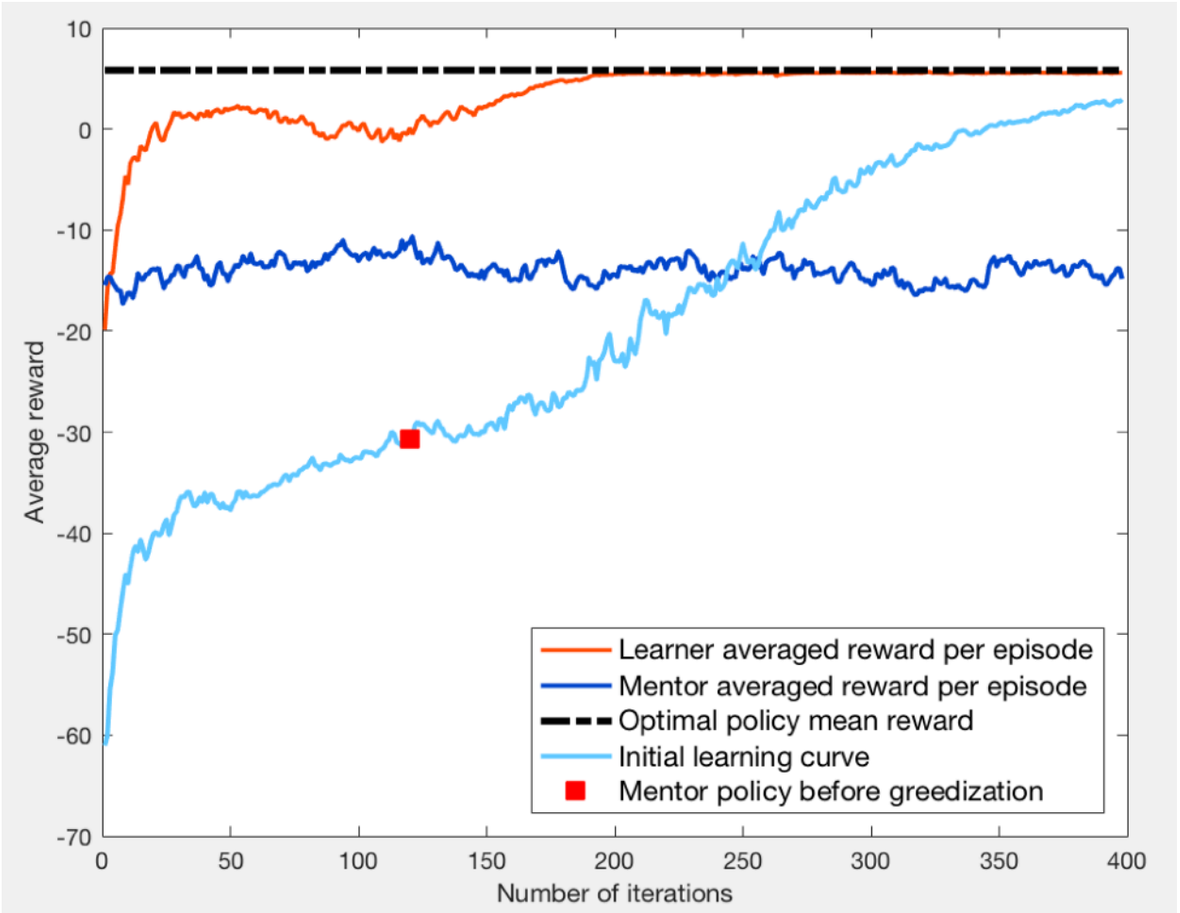

Figure : Learning Curve (Teacher 1)

Results

VANISHING COMPLIANCE (The naive way)

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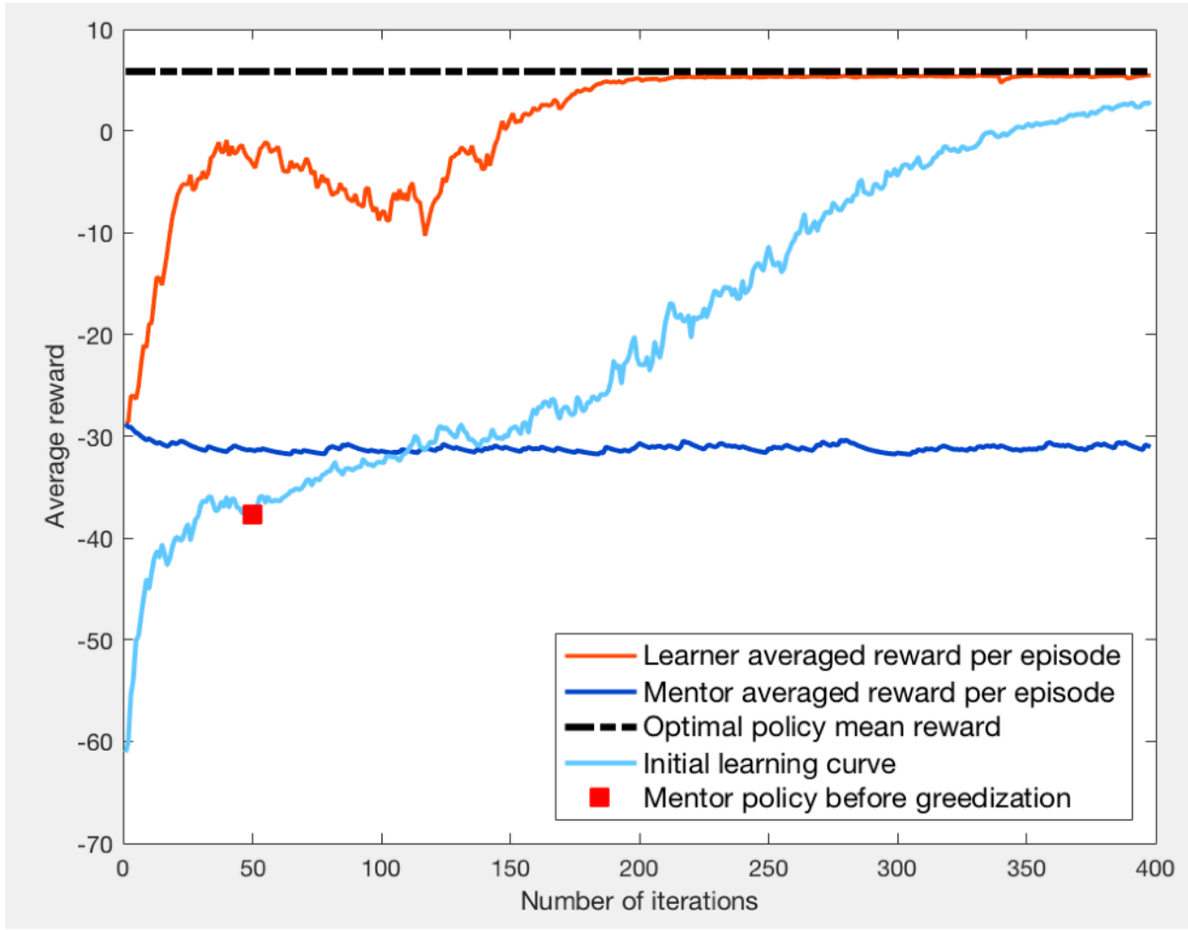
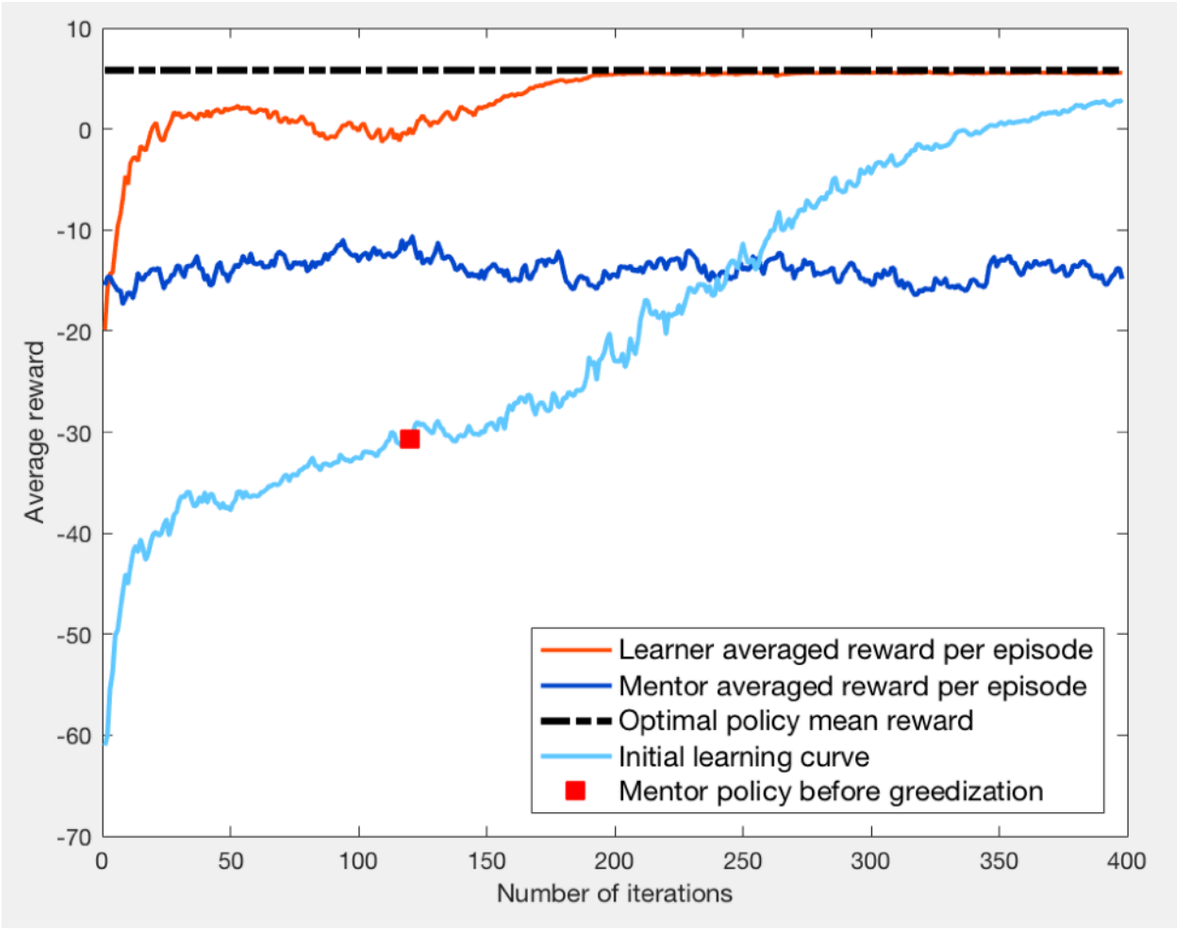


Figure : Learning Curve (Teacher 2)

Results

VANISHING COMPLIANCE (The naive way)



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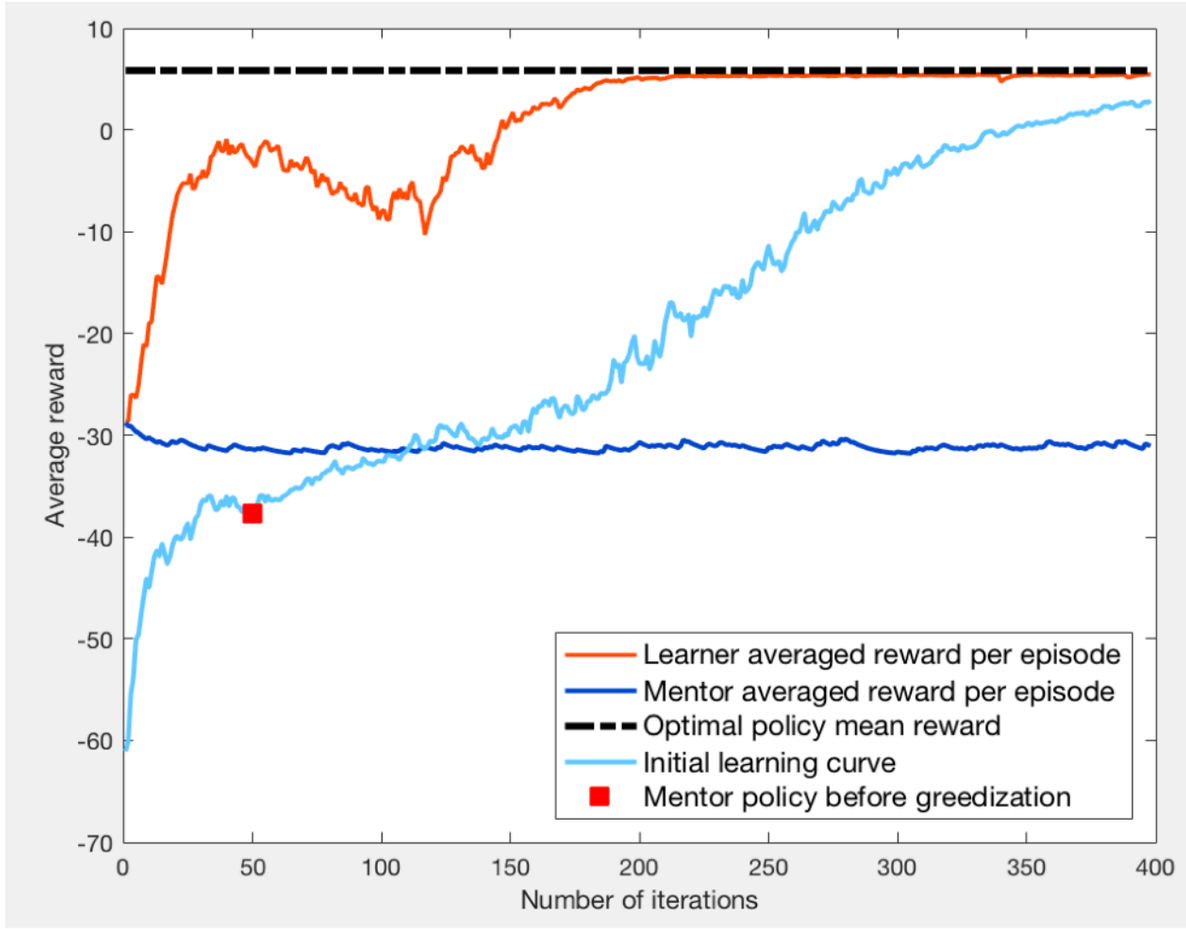


Figure : Learning Curve (Teacher 2)

- Too much time spent exploring around good solutions !

Results

ADAPTIVE LEARNERS

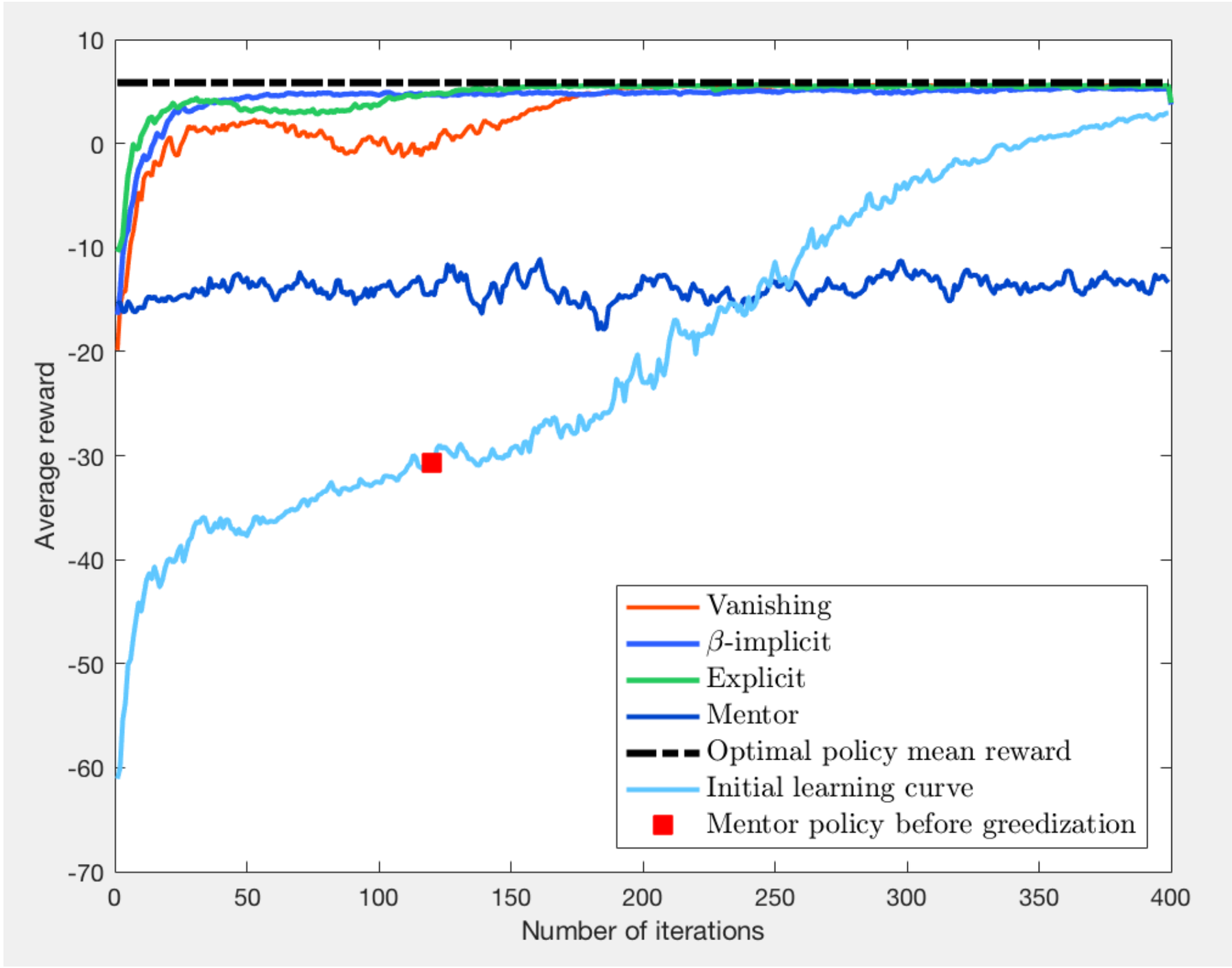


Figure : Learning Curves (Teacher 1)

Results

ADAPTIVE LEARNERS

Results

ADAPTIVE LEARNERS

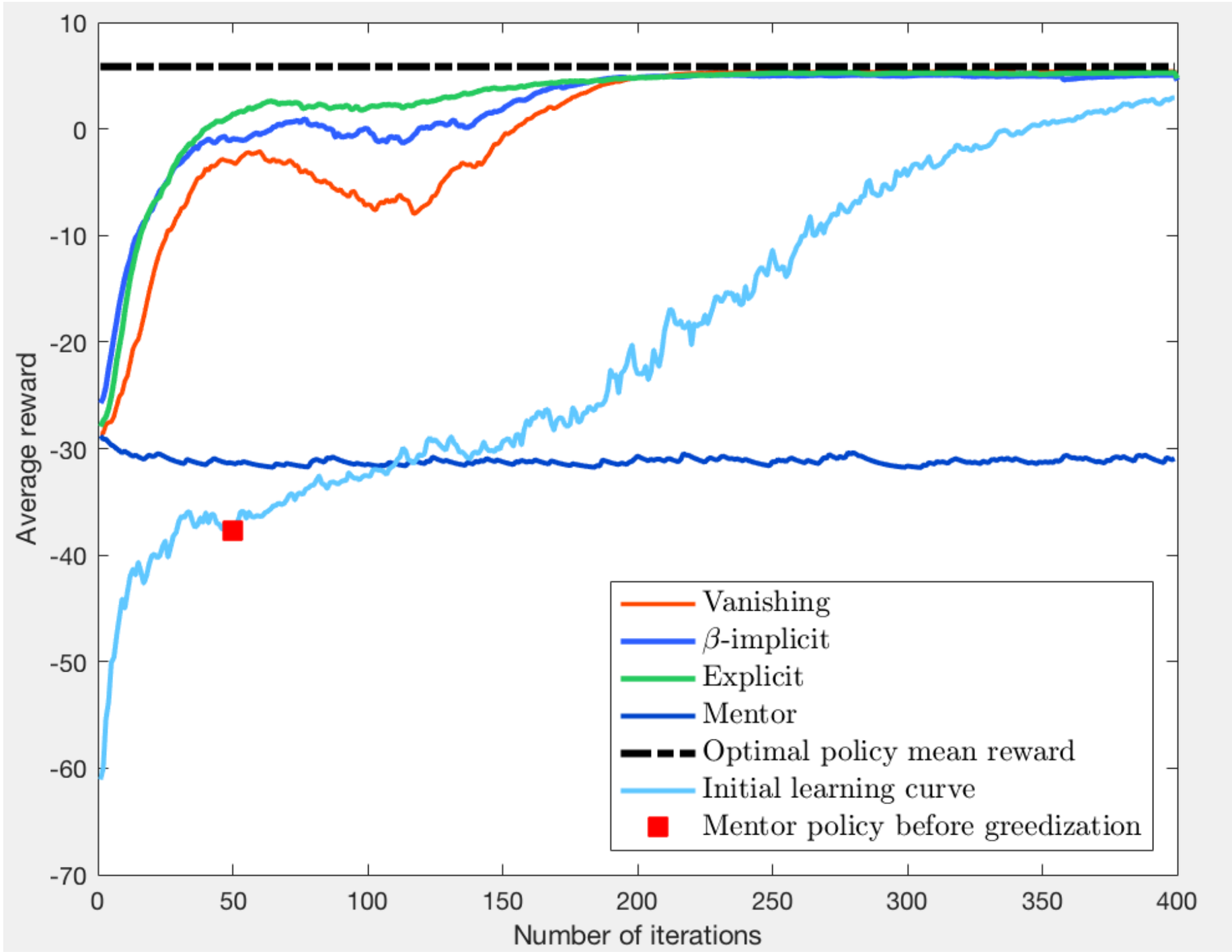


Figure : Learning Curves (Teacher 2)

Results

ADAPTIVE LEARNERS

- Mentor optimality : linear scaling between random policy and optimal policy reward

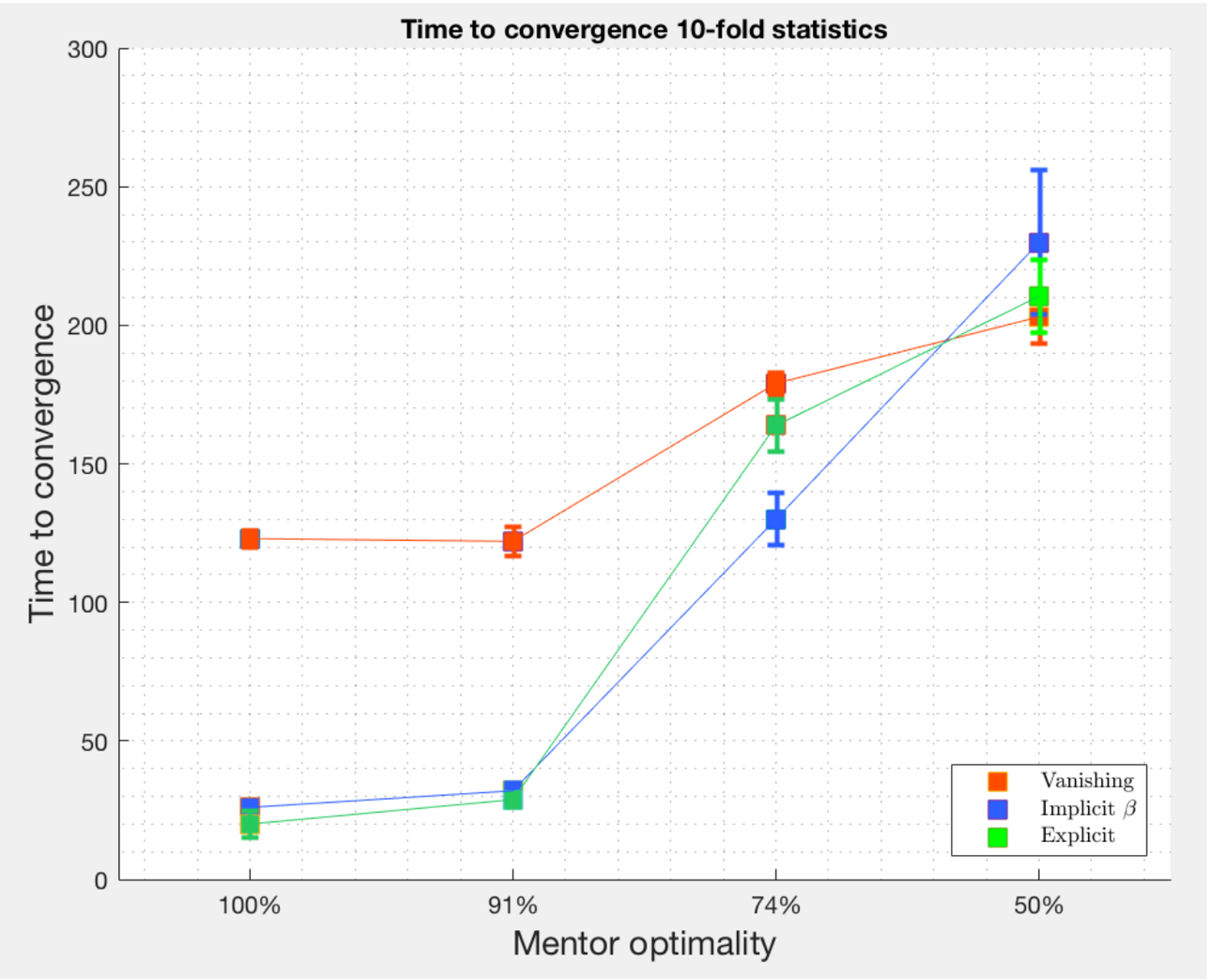


Figure : Time To Convergence

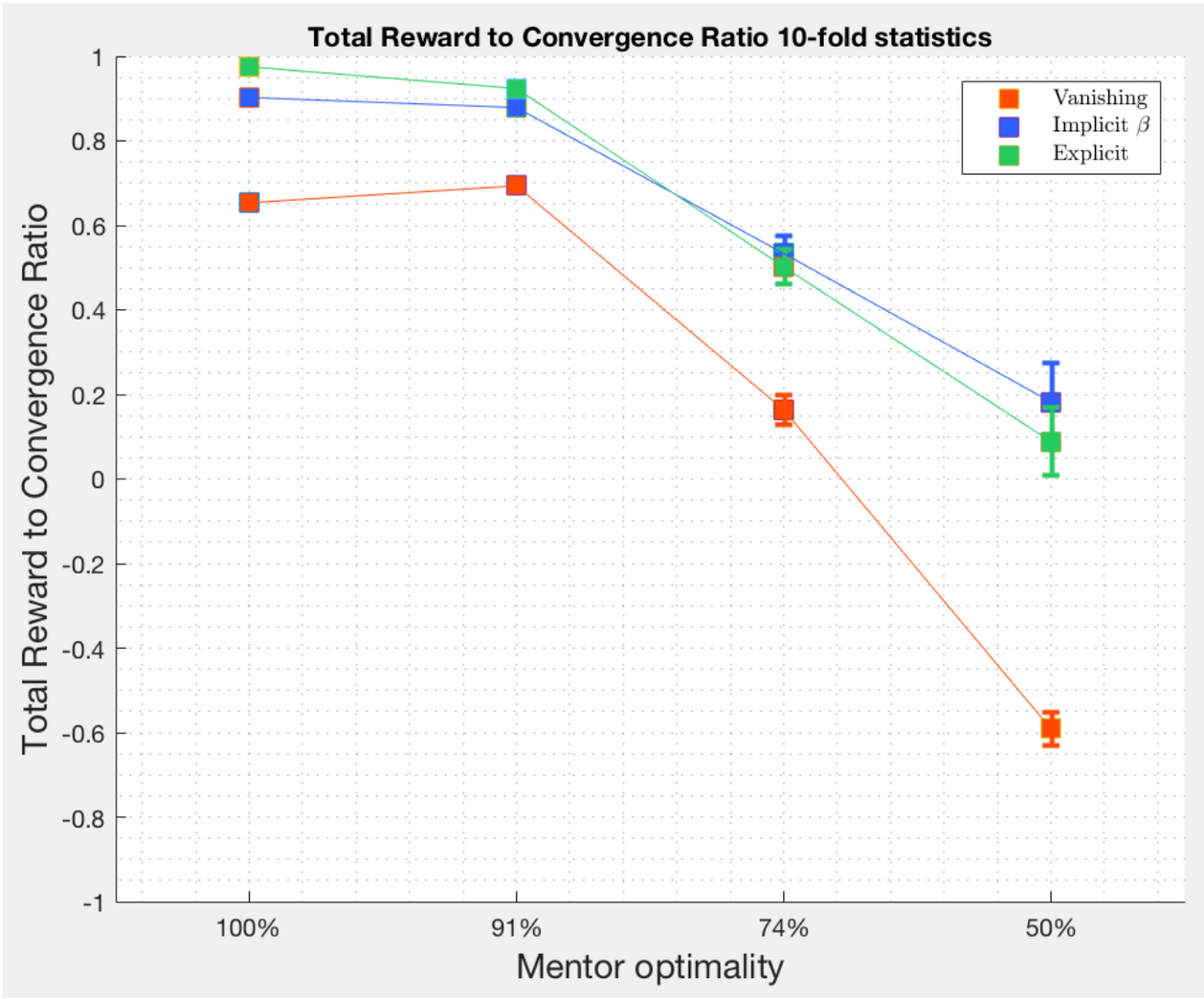
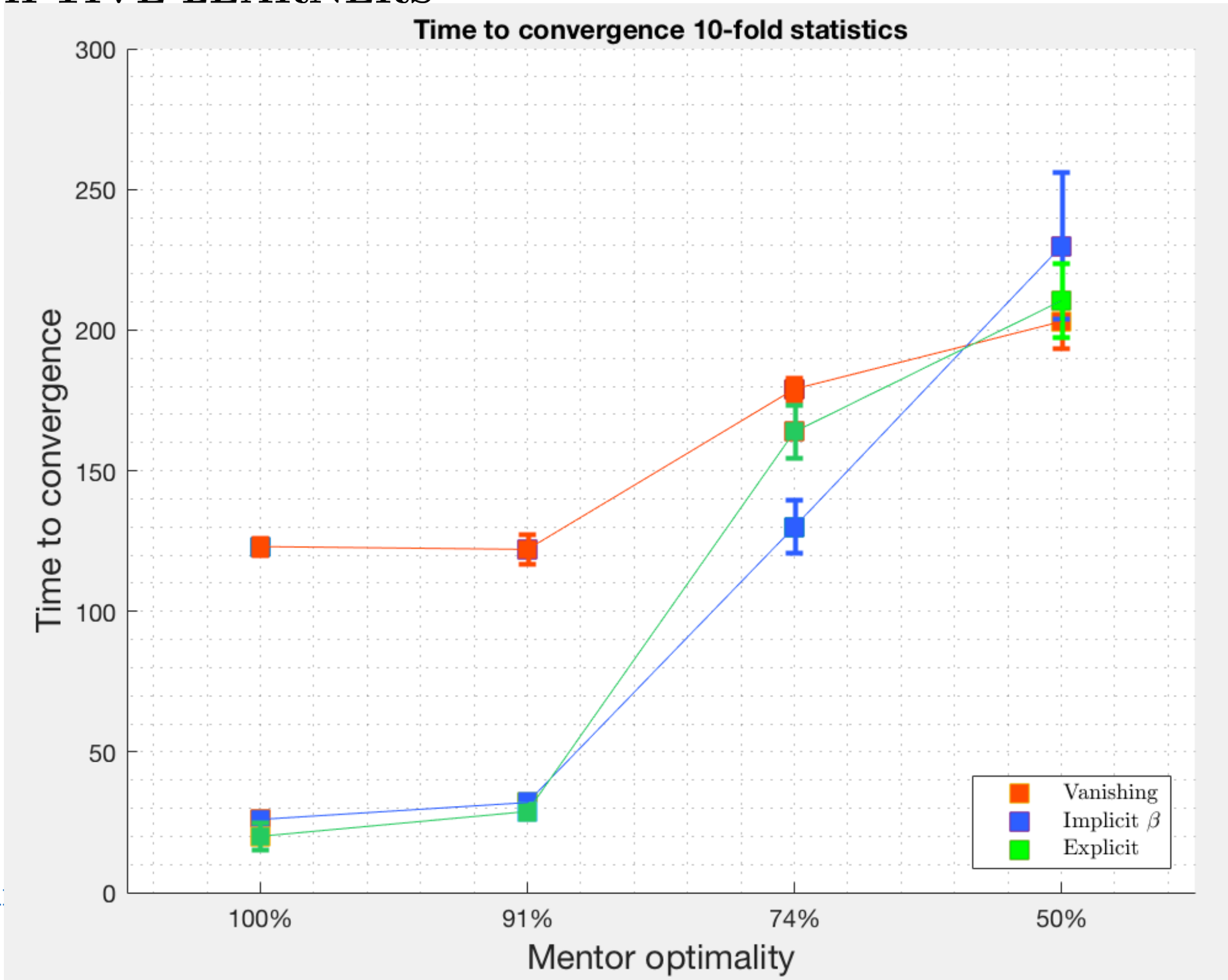


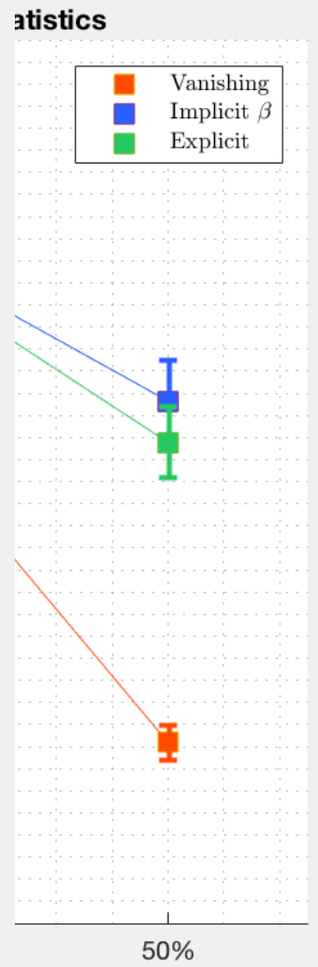
Figure : Reward Ratio to Convergence

Results

ADAPTIVE LEARNERS

- Mentor reward



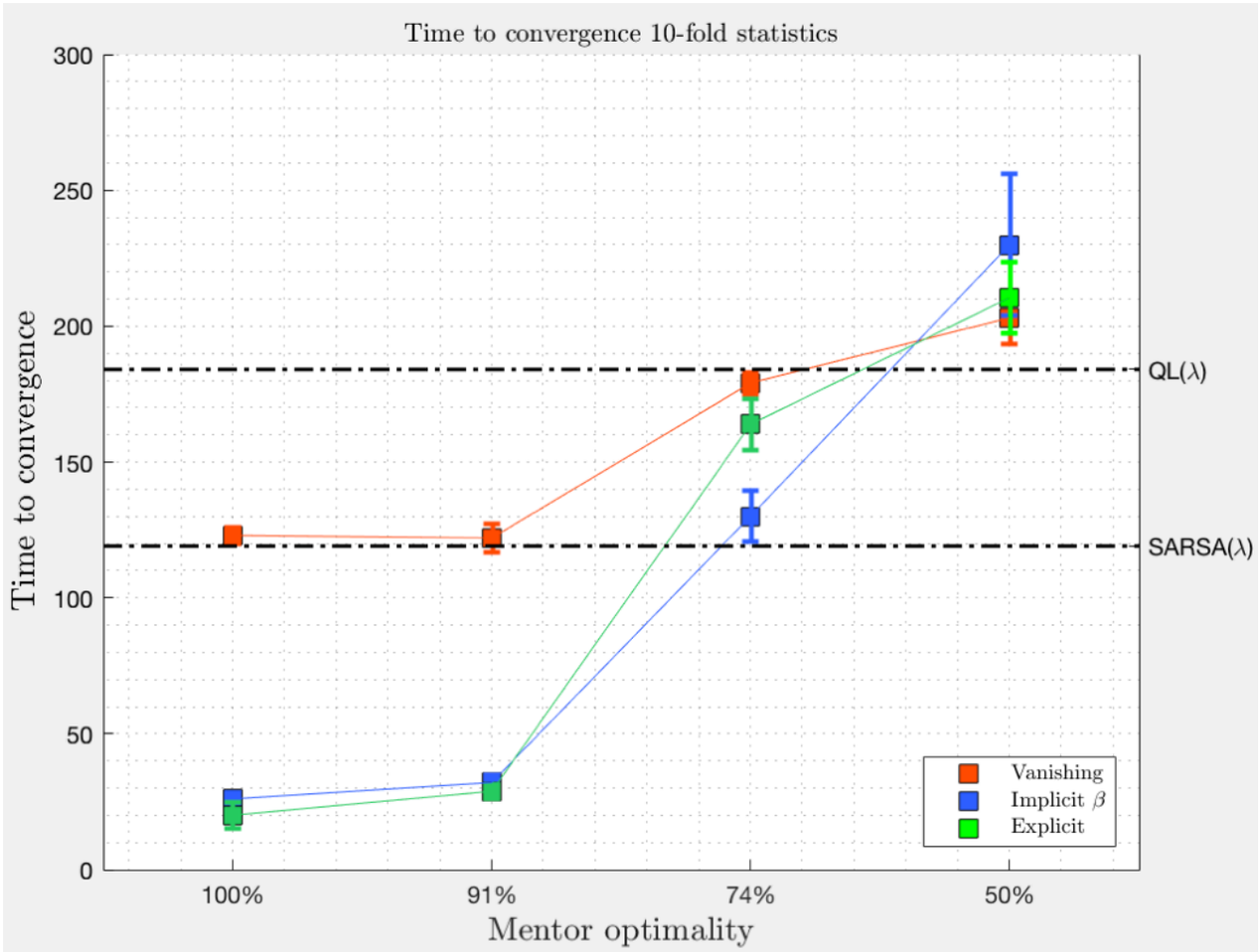


Figu vergence

Results

ADAPTIVE LEARNERS

- Compared to *classical learners*



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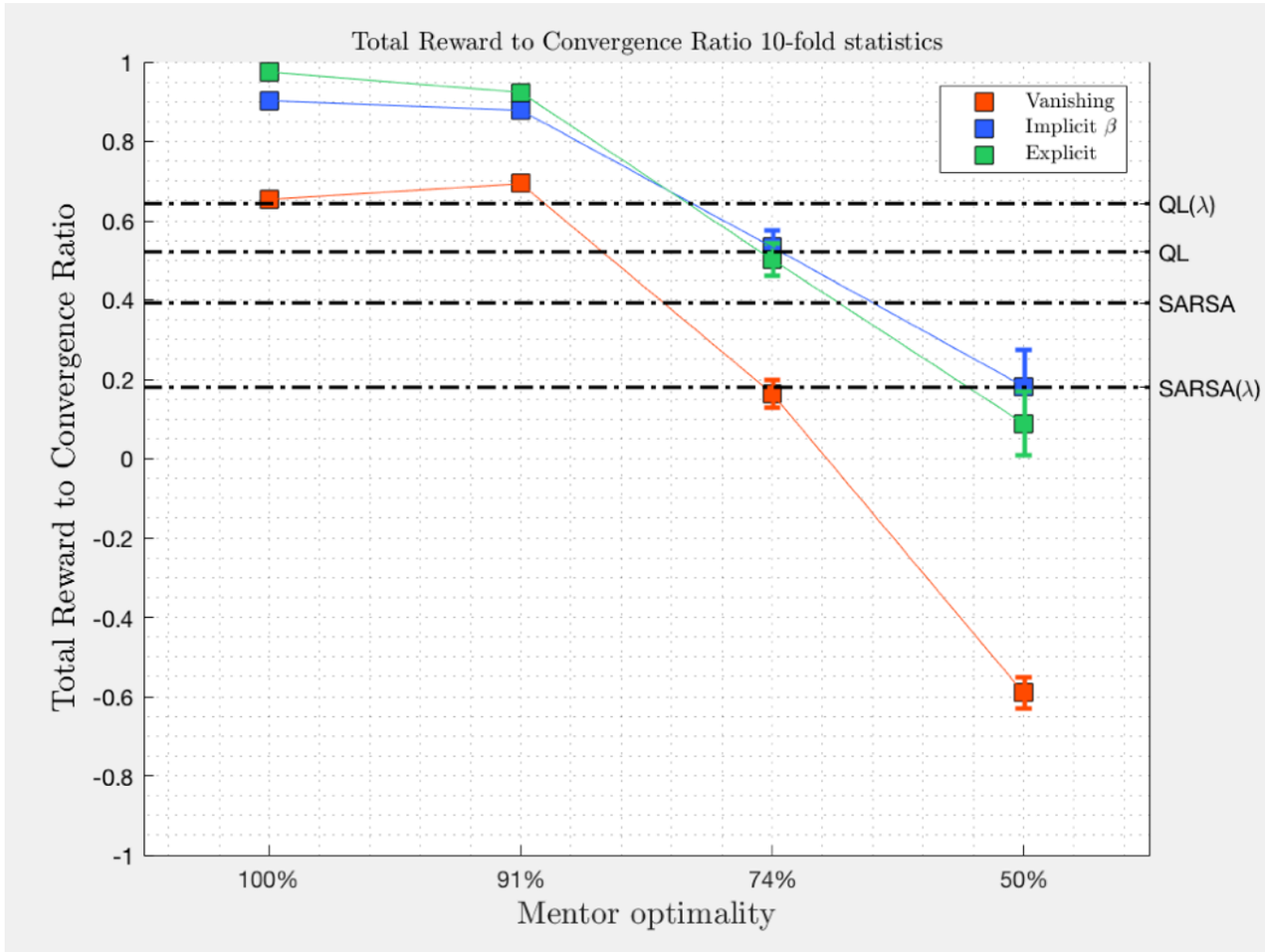
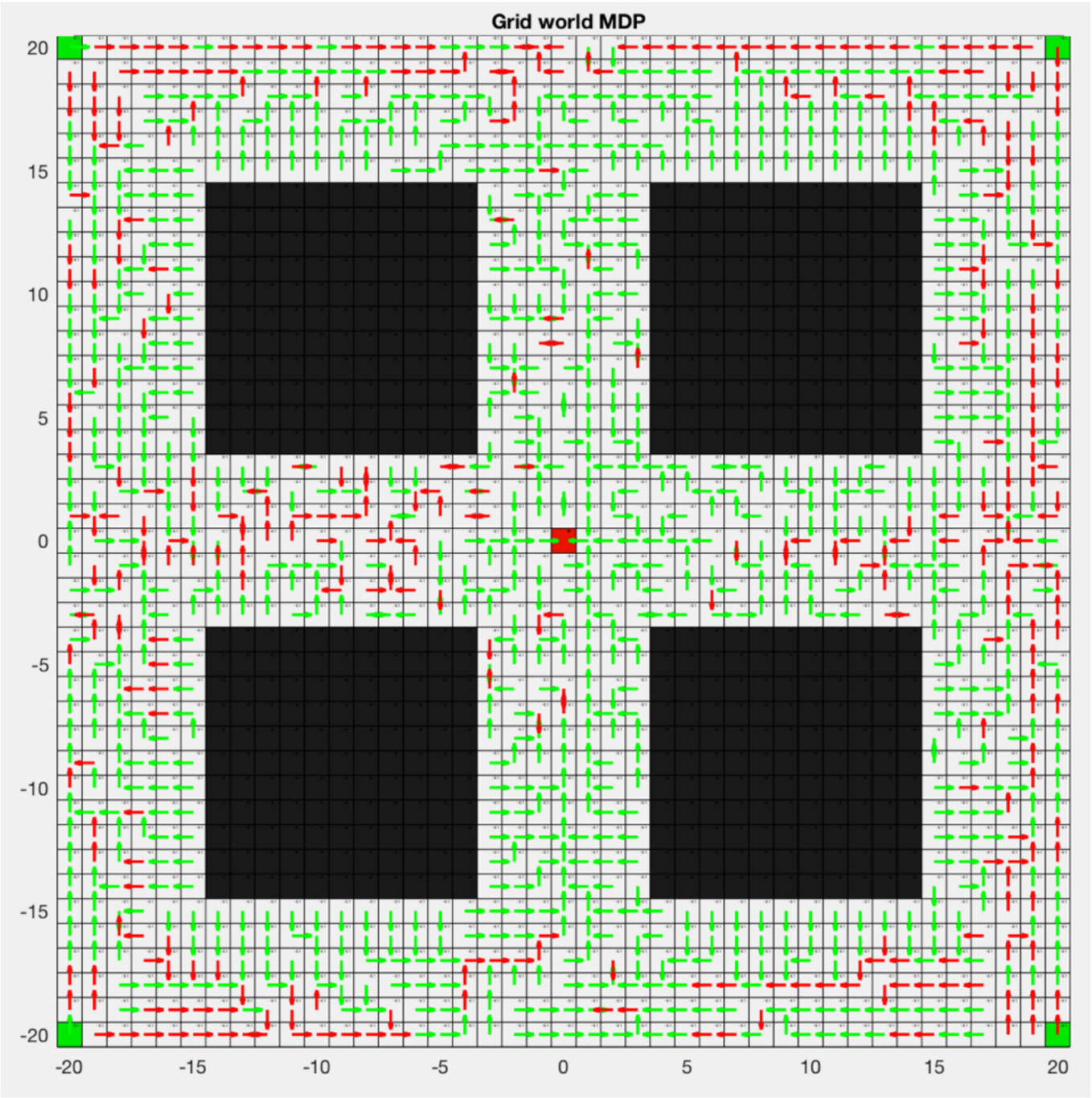


Figure : Reward Ratio to Convergence

Results

ADAPTIVE LEARNERS

- What is actually learnt ?



- Compliance heat-map

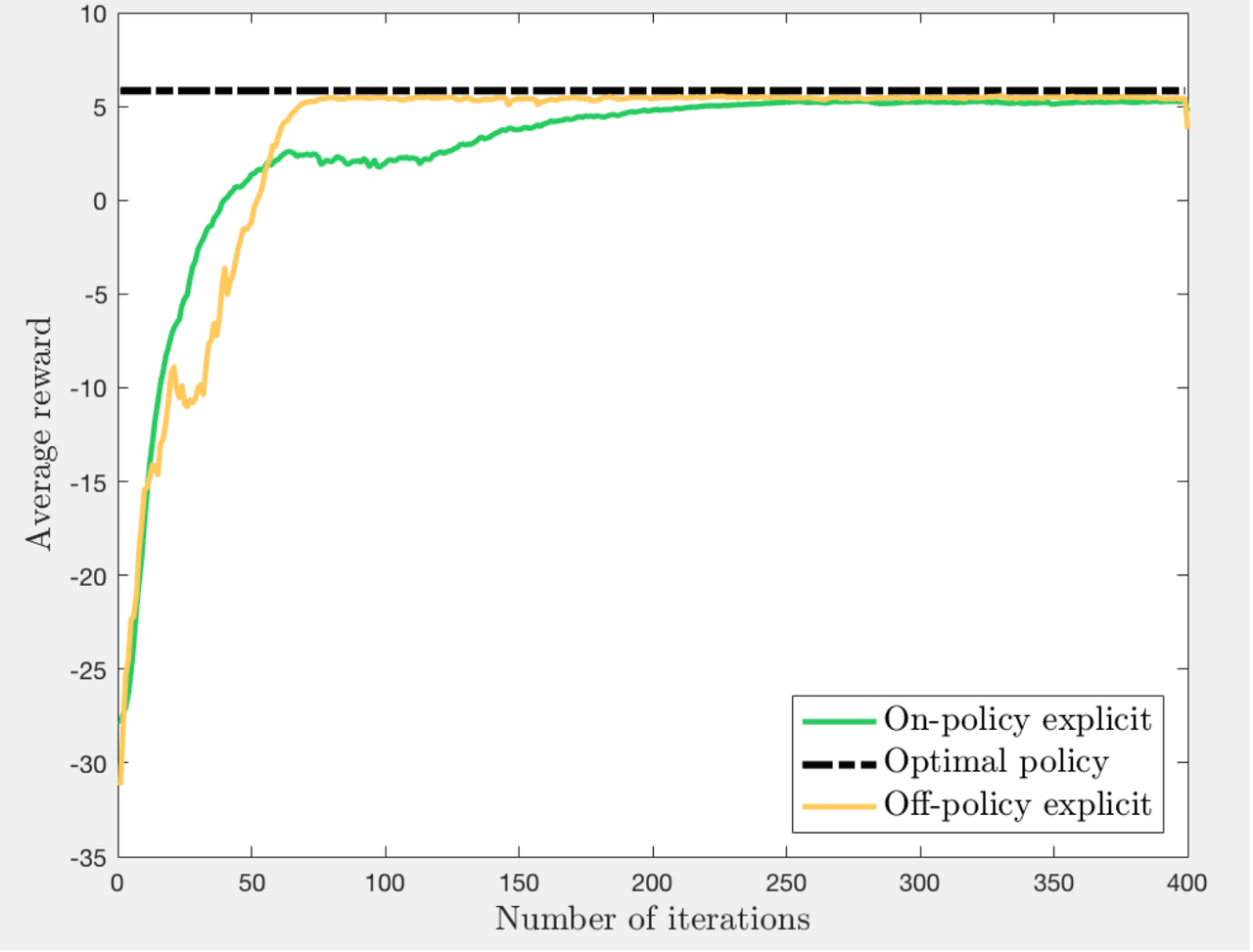
- Poor teacher recommandations back propagate too far

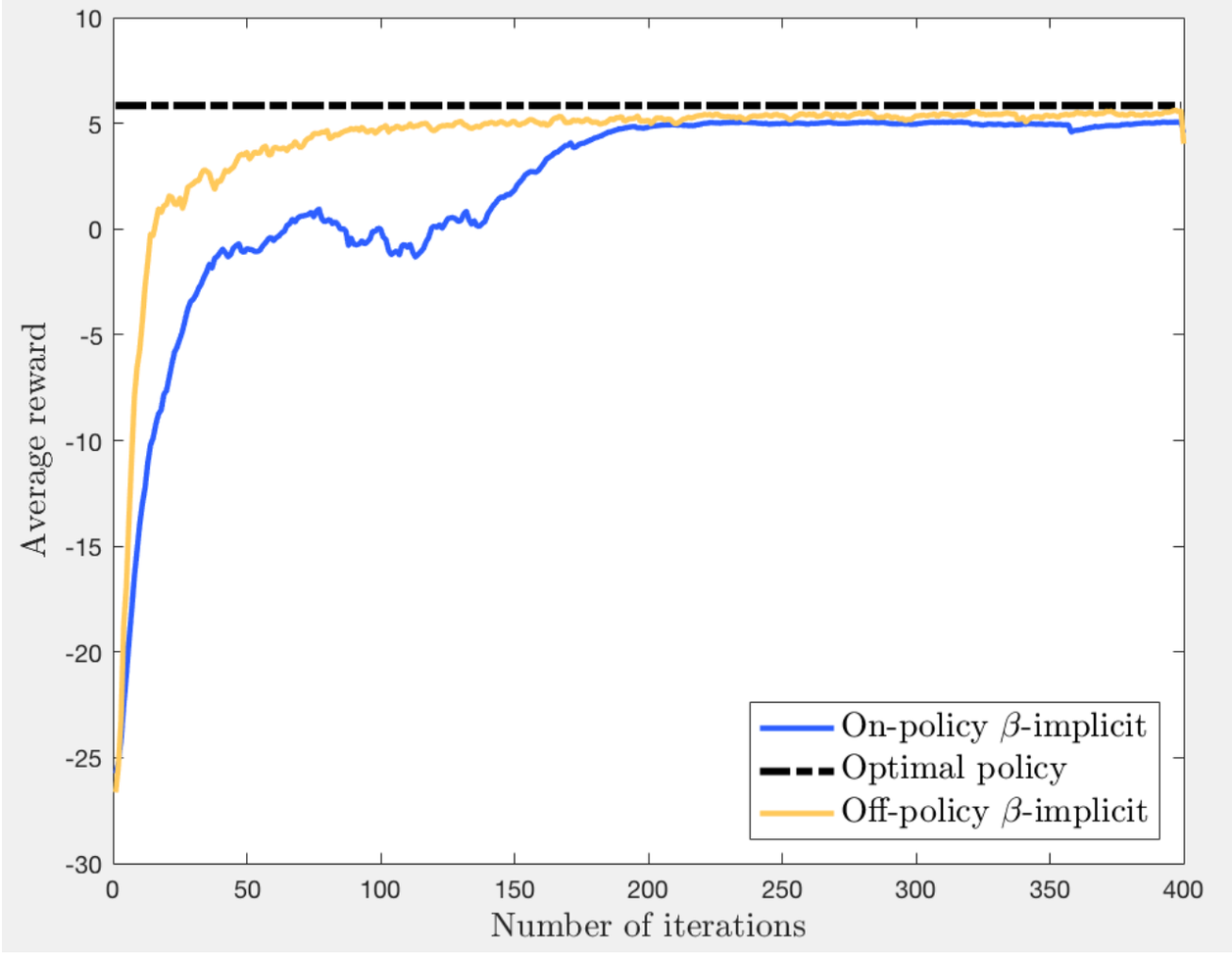
- The learner tries to circle the teacher instead of fixing it !

Results

IMPROVEMENTS

- Can off-policy learning improve this ?





- The learning now fixes the suboptimal regions !

Conclusion

WHAT WE DID :

- Provide **adaptive-compliant exploration policies**

WHAT'S NEXT :

Conclusion

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- Provide **adaptive-compliant exploration policies**
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  - Extract useful informations

WHAT'S NEXT :

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WHAT WE DID :

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  - Learn from suboptimal teachers
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  - Speed-up the learning

WHAT'S NEXT :

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WHAT WE DID :

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WHAT'S NEXT :

- Still some work to do !

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WHAT'S NEXT :

- Still some work to do !
  - Generalize to sparse recommandation

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WHAT'S NEXT :

- Still some work to do !
  - Generalize to sparse recommandation
  - Implement eligibility traces

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WHAT WE DID :

- Provide **adaptive-compliant exploration policies**
  - Learn from suboptimal teachers
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  - Speed-up the learning

WHAT'S NEXT :

- Still some work to do !
  - Generalize to sparse recommandation
  - Implement eligibility traces
  - Test in continuous MDP

Conclusion

THANK YOU FOR YOUR ATTENTION !