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 :
Mahdi Khoramshahi and Andrew Sutcliffe

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Outline

Introduction

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

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Super Mario Bros

Nao (SoftBank Robotics)

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

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- Objective : find the policy

$$\pi : \quad \mathcal{S} \to \mathcal{A}(s)$$
$$s \to a$$

that maximizes the accumulated reward

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- **REINFORCEMENT LEARNING**

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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

LEARNING FROM DEMONSTRATION[1,2]

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(2) Argall, Brenna D., et al. *"A survey of robot learning from demonstration."*

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- Use reinforcement learning !

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

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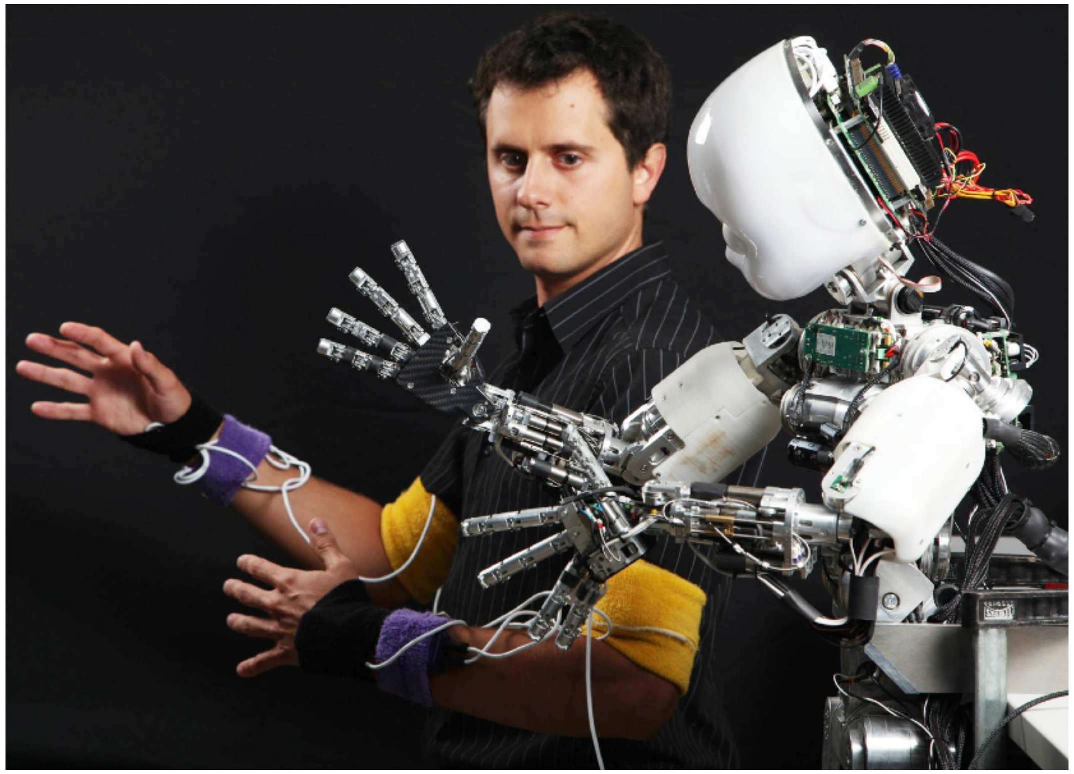
  - Ex : **Grasping objects**



Credits : Sylvain Calinon

Motivations

- **Find a way to learn from suboptimal teachers**

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  - Extend to non-expert teachers !
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GOAL : - define a compliance-based approach for learning from suboptimal teachers
- experimentally evaluate its performances

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

$$\forall s \in \mathcal{S}, \quad \pi_p(s) = \begin{cases} a_m(s) \text{ with probability } p(s) \\ a \in \mathcal{A}(s) \text{ with probability } (1 - p(s)) \end{cases}$$

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- **Make the compliance vary throughout the learning**

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- also, tuning might be difficult

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$\boldsymbol{\beta}$-IMPLICIT COMPLIANCE LEARNER

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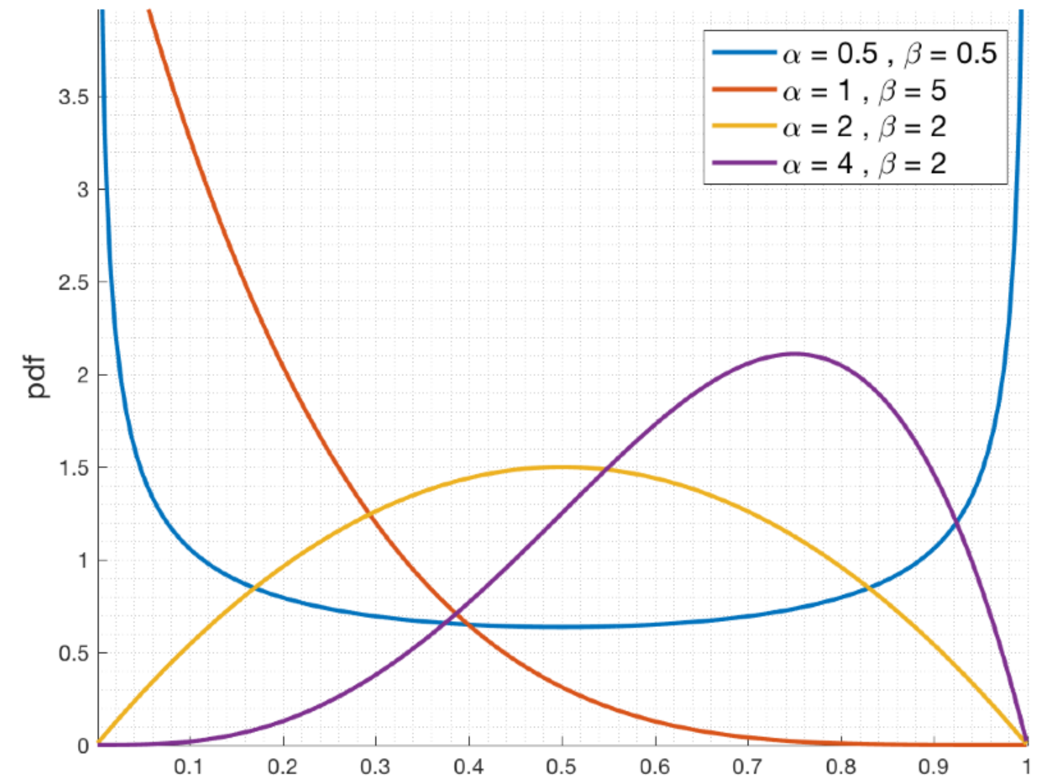

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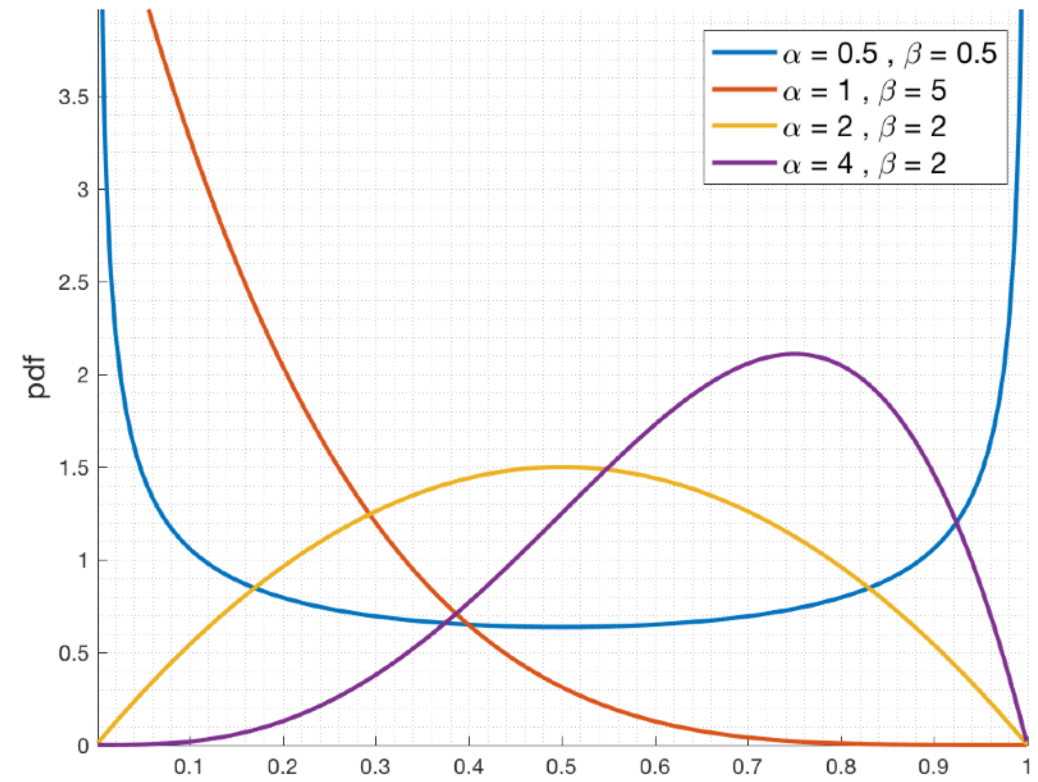

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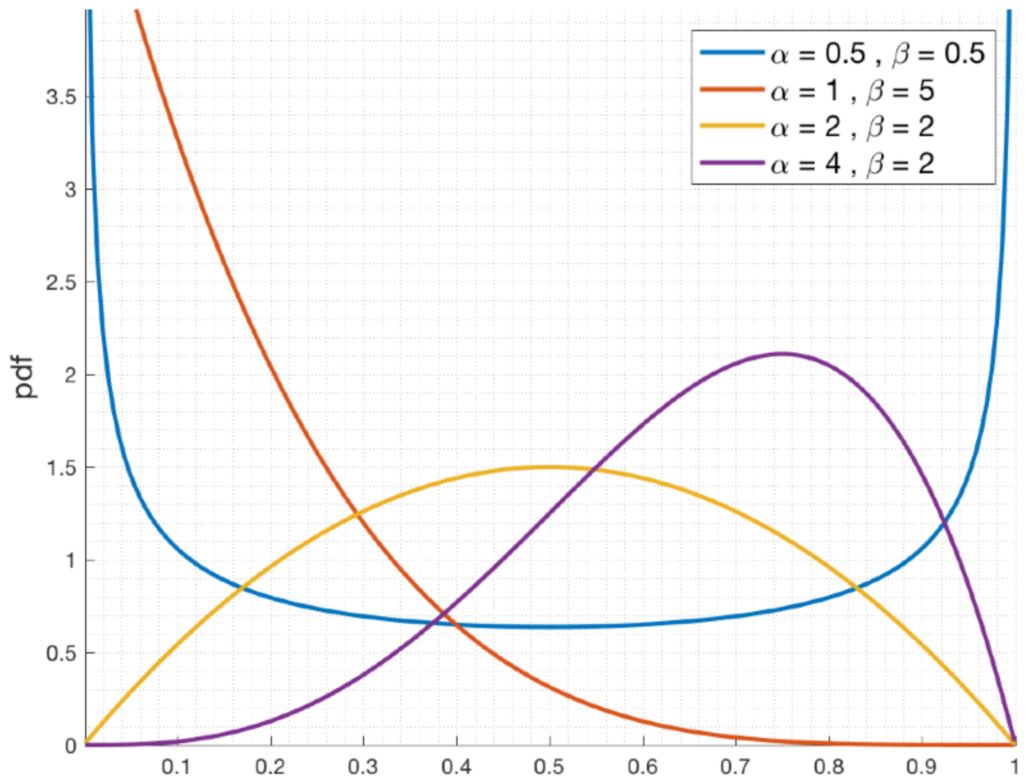

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- Update the p.d.f parameters accordingly

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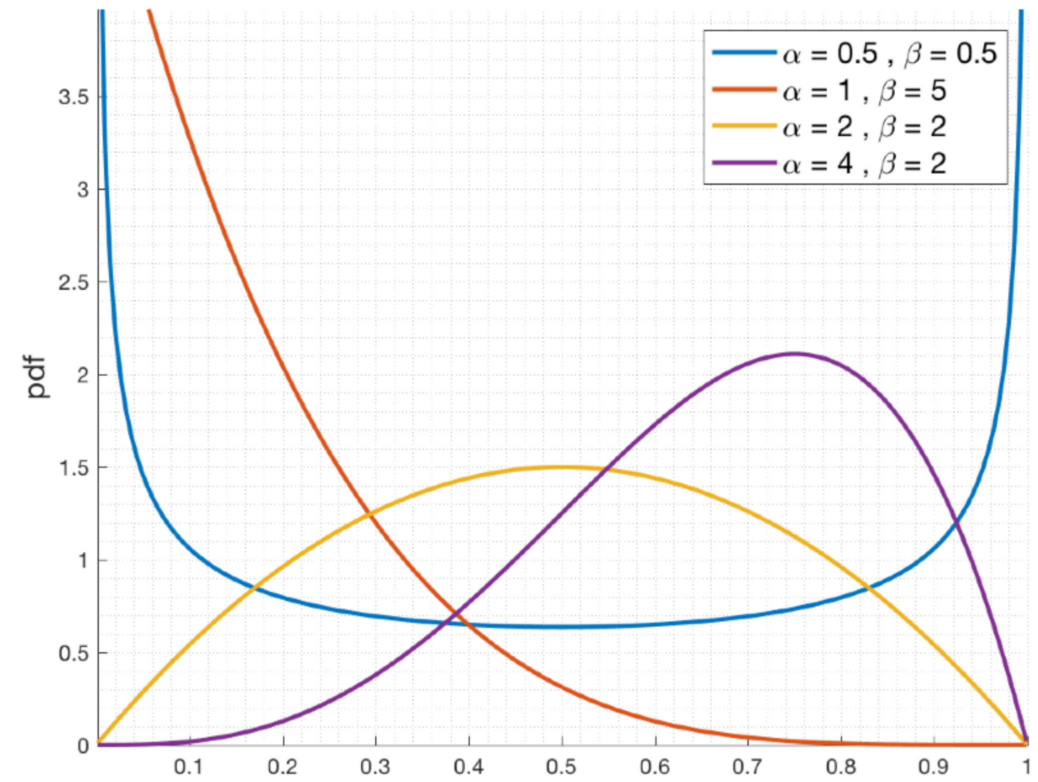

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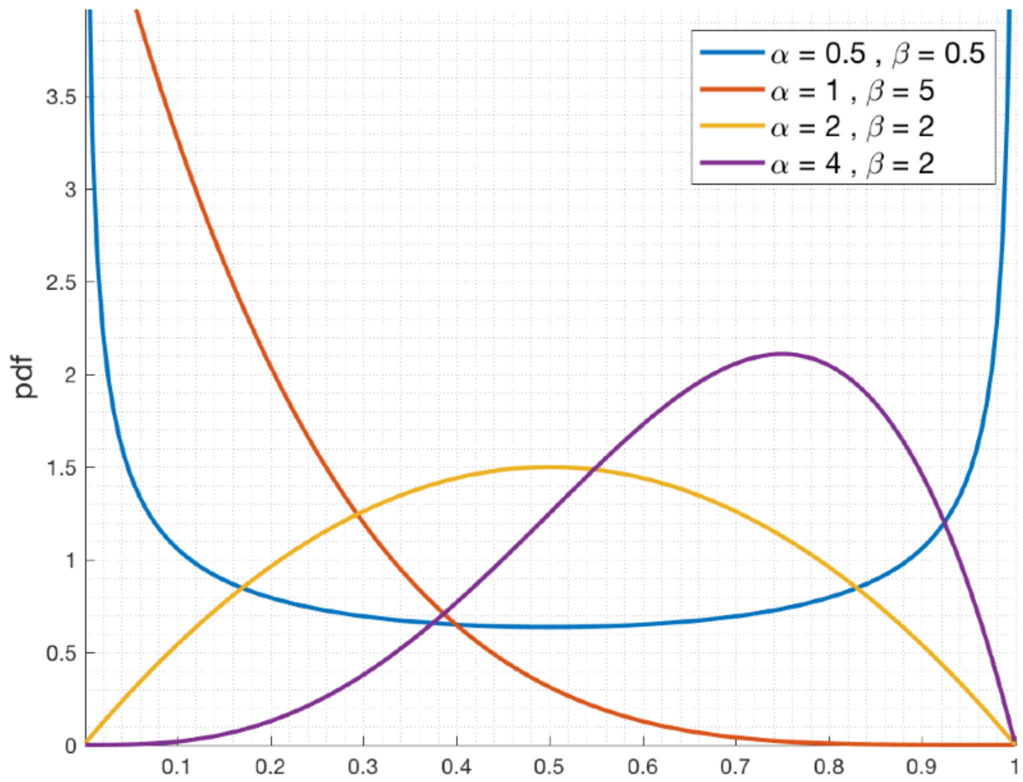

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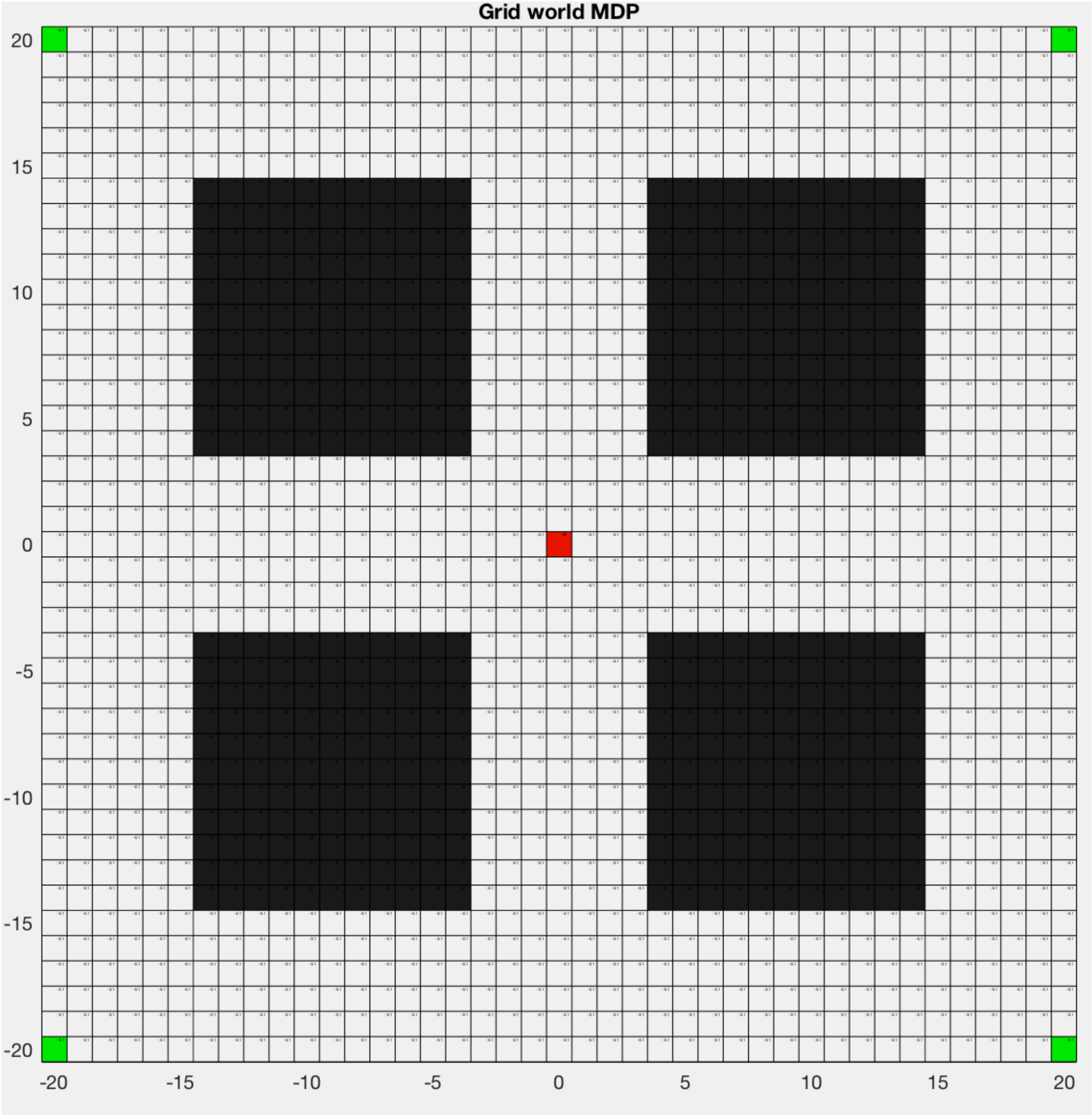
Update new MDP

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

Results

- MDP



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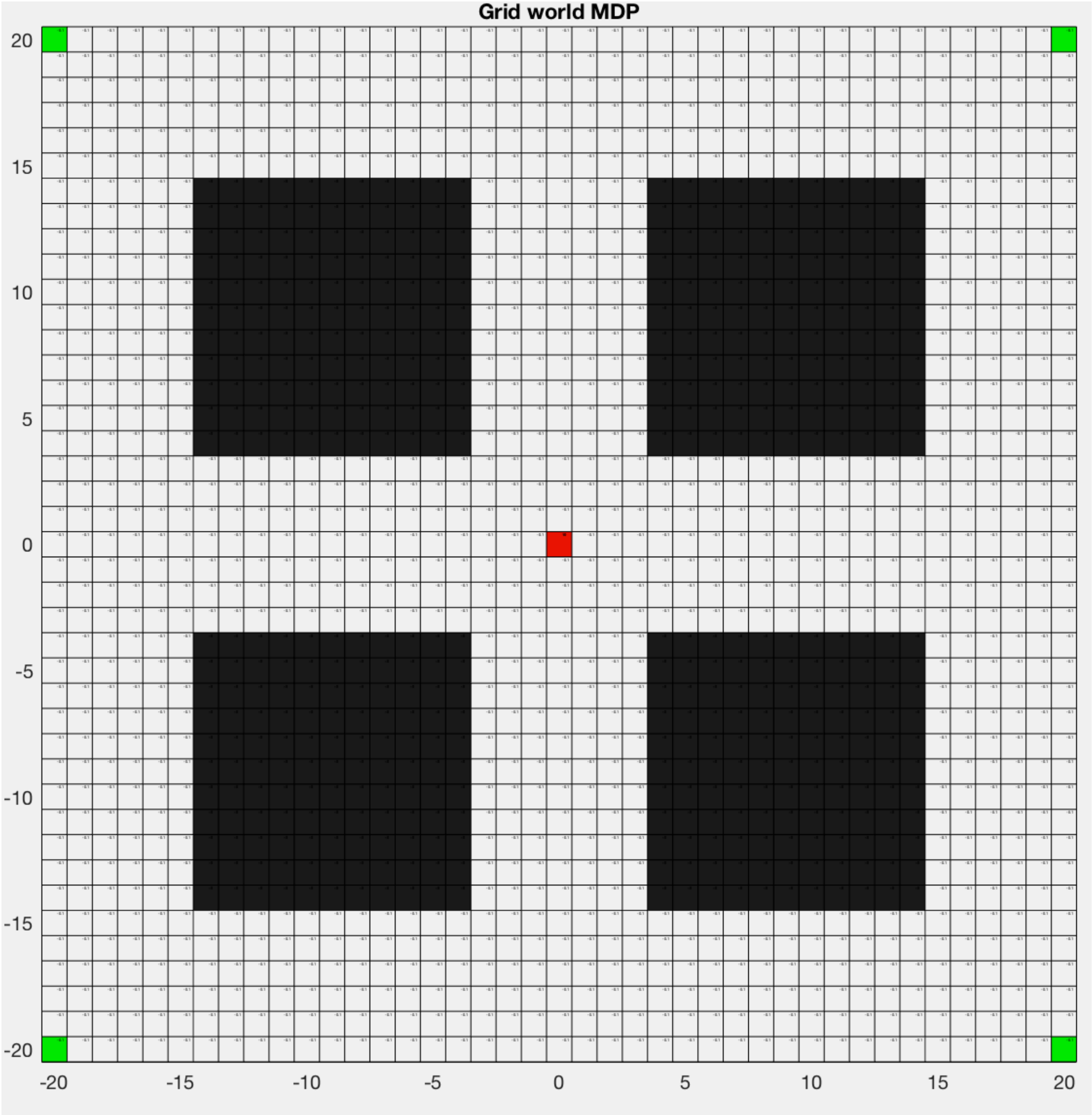

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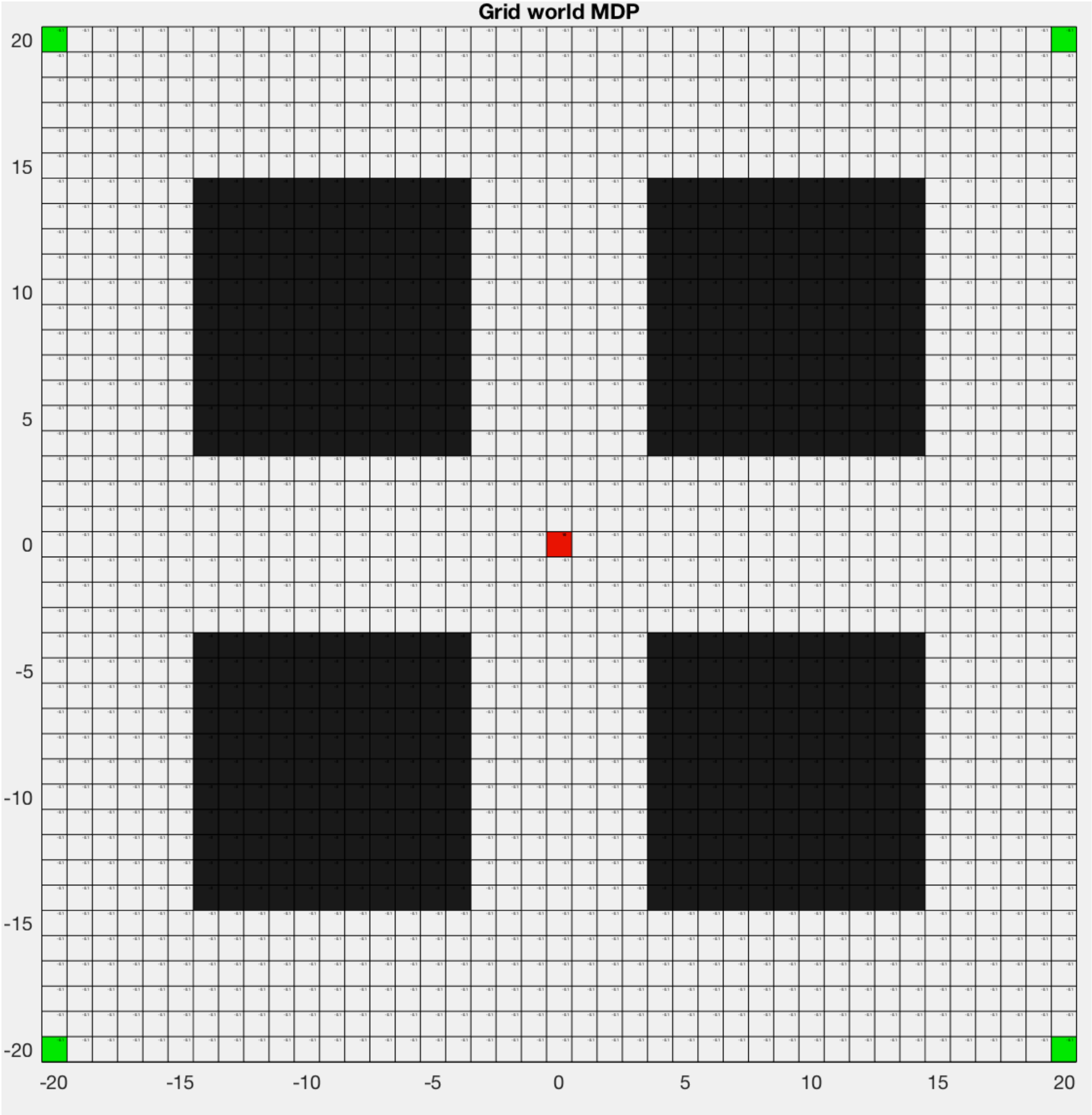

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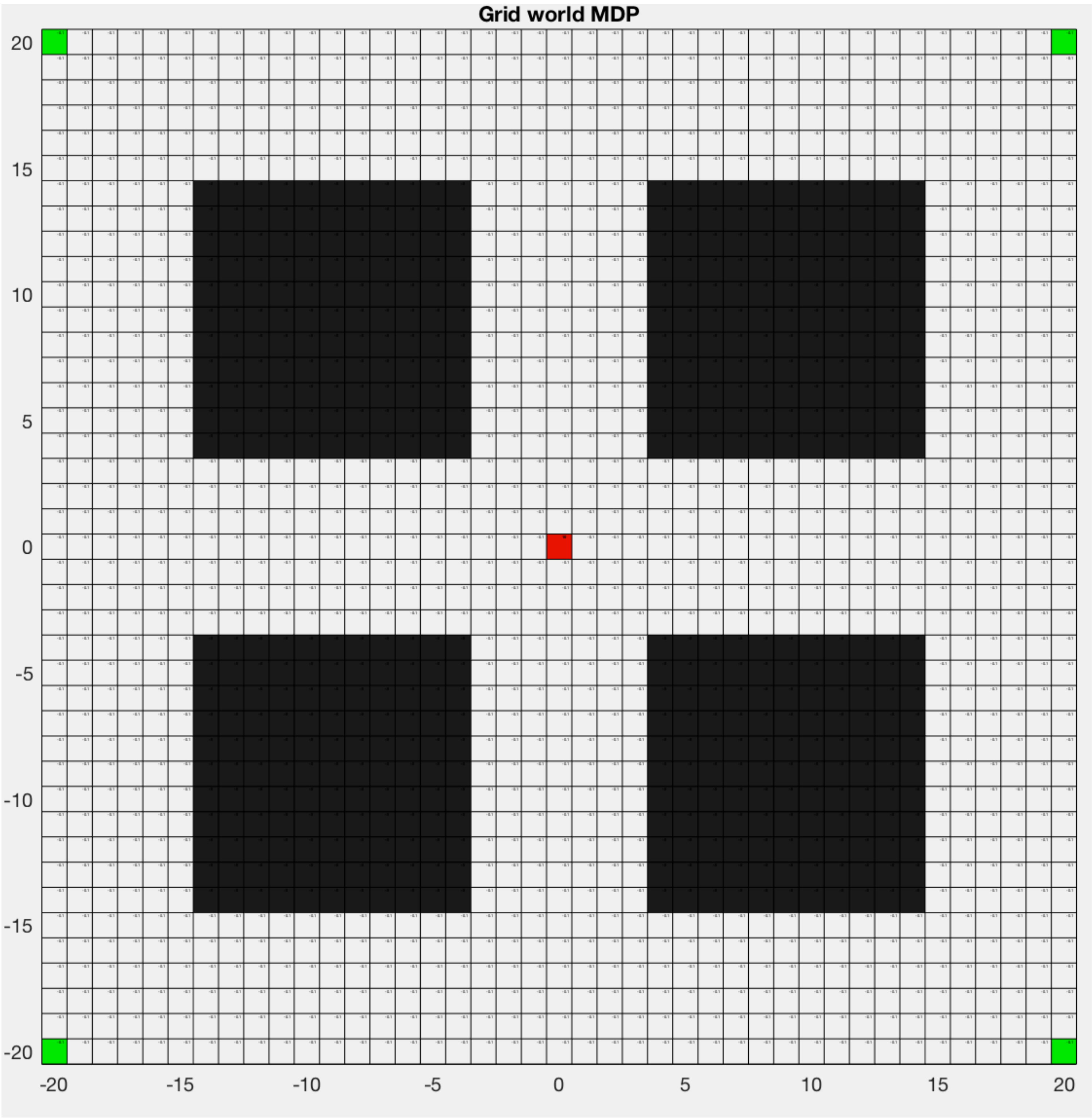

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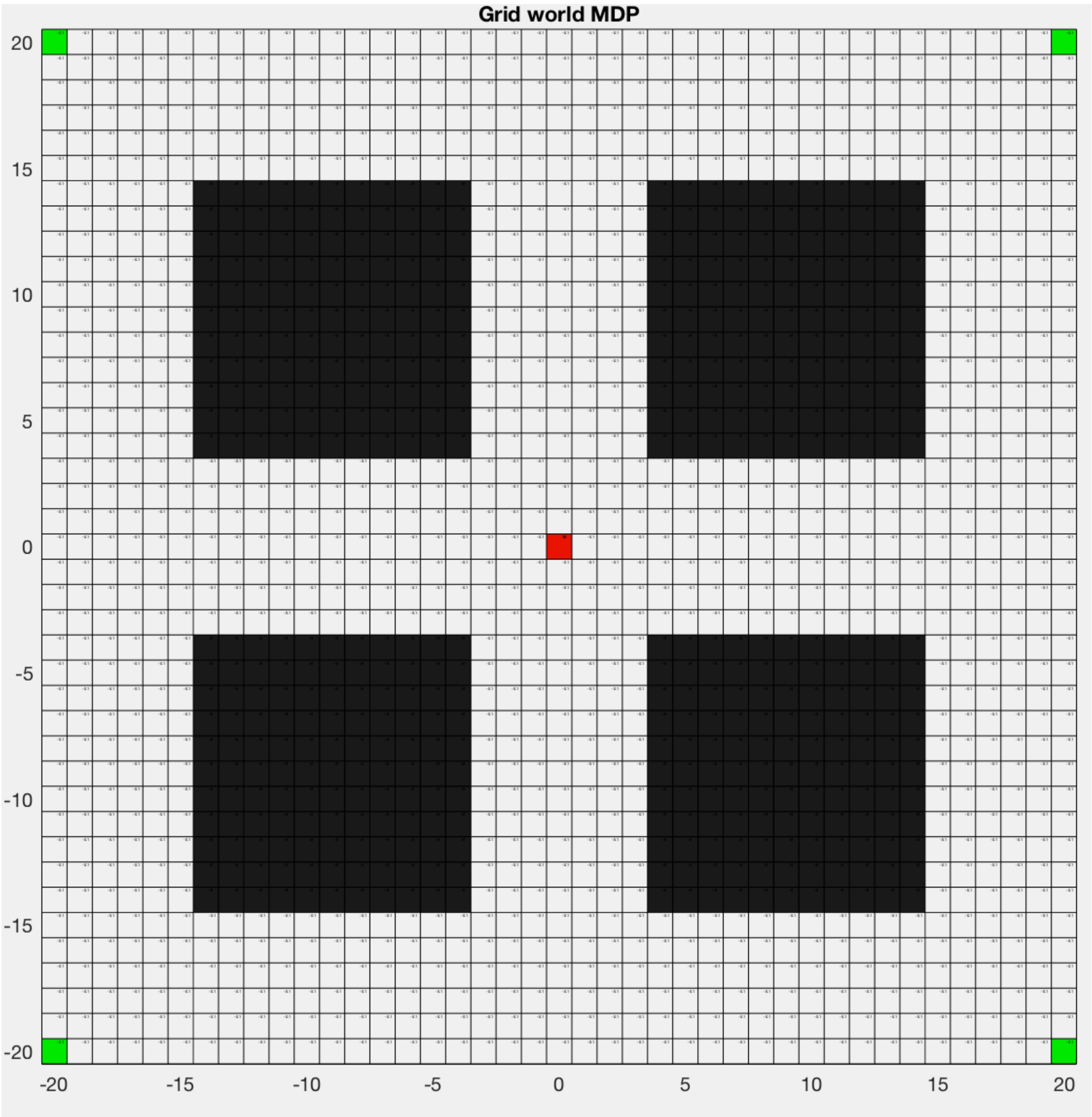

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- *Value iteration* for computing optimal policy (ground truth)

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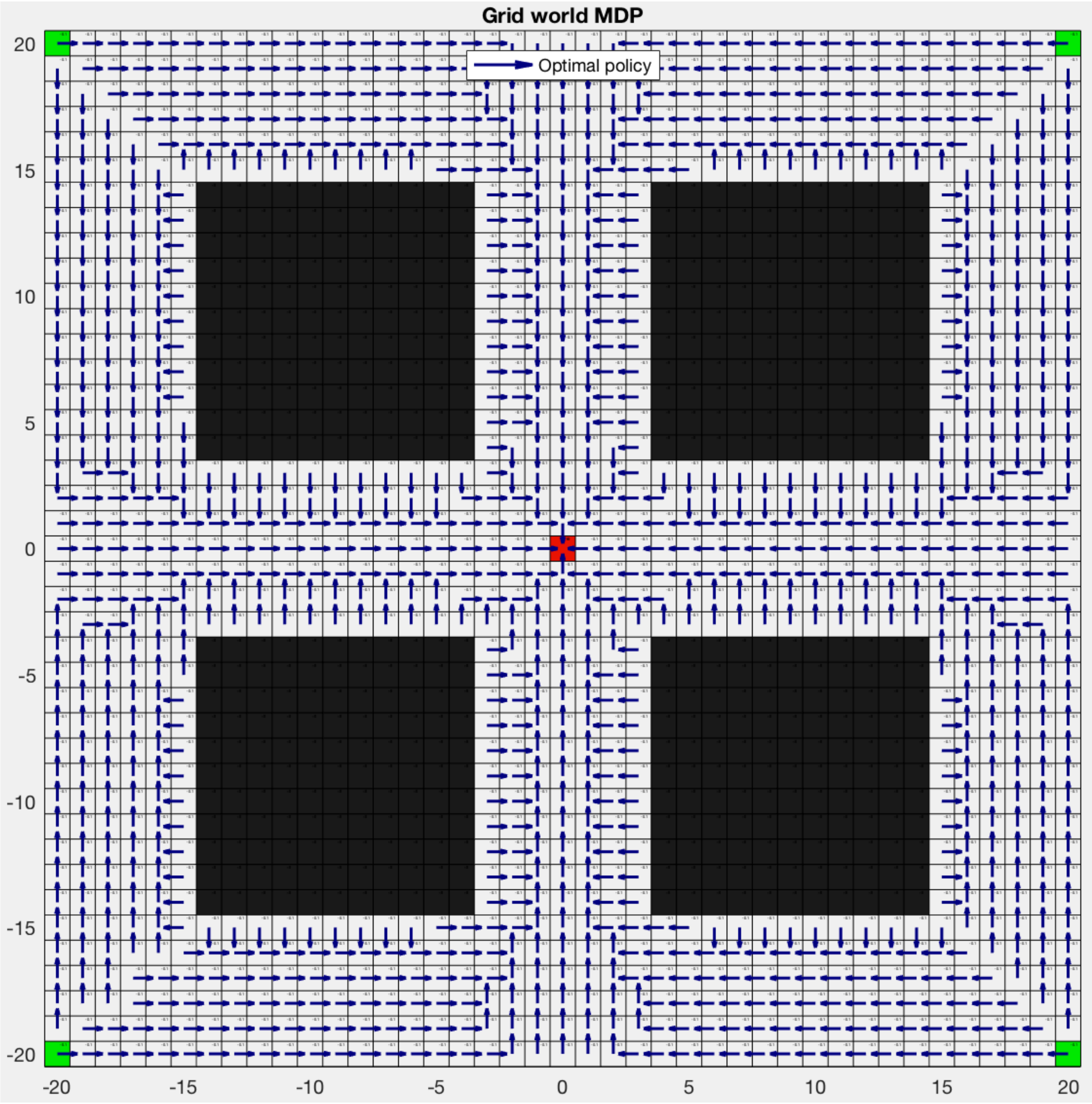
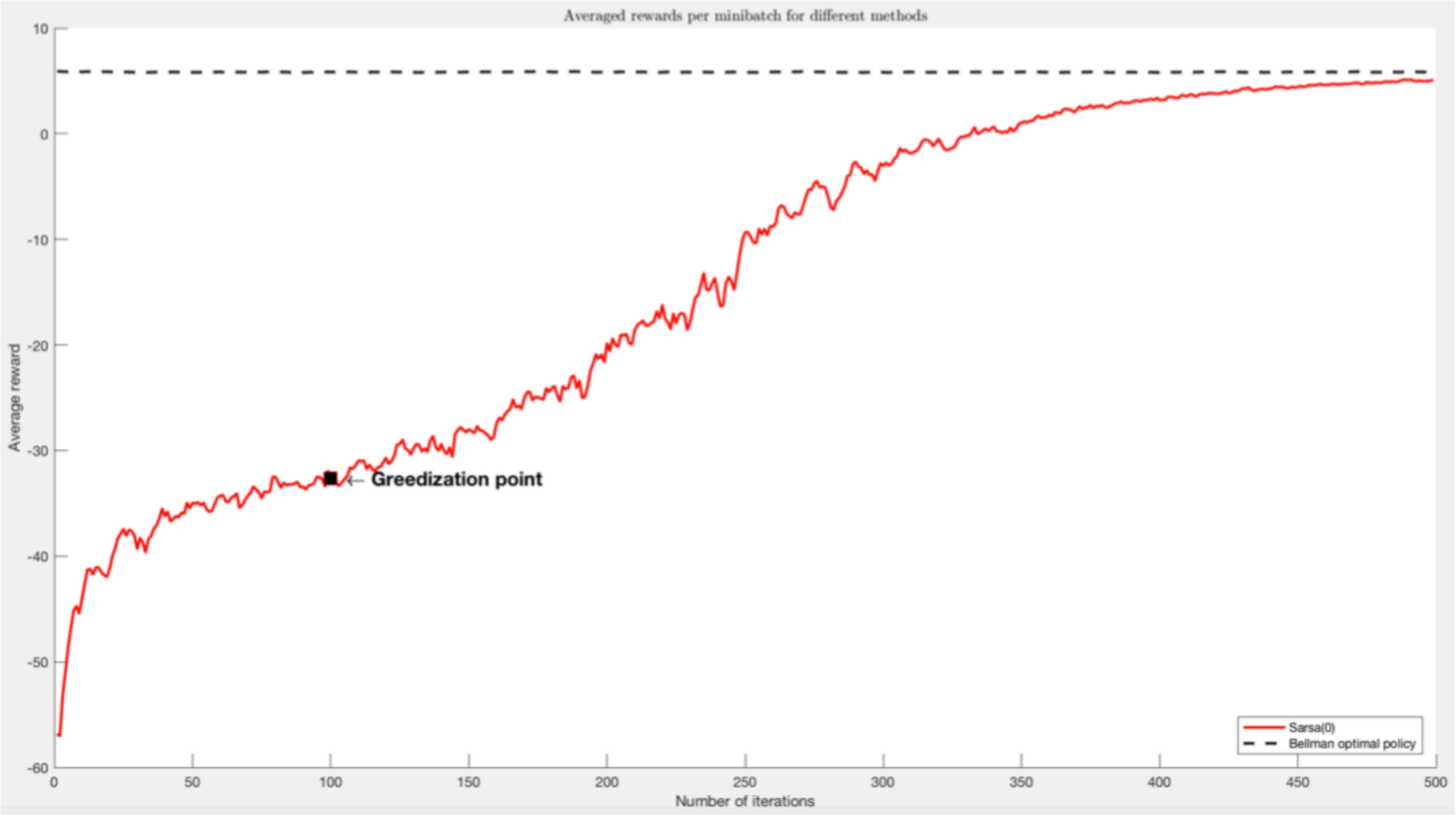


- Finite MDP
- From green cell to red cell as quickly as possible
- Stochastic :

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

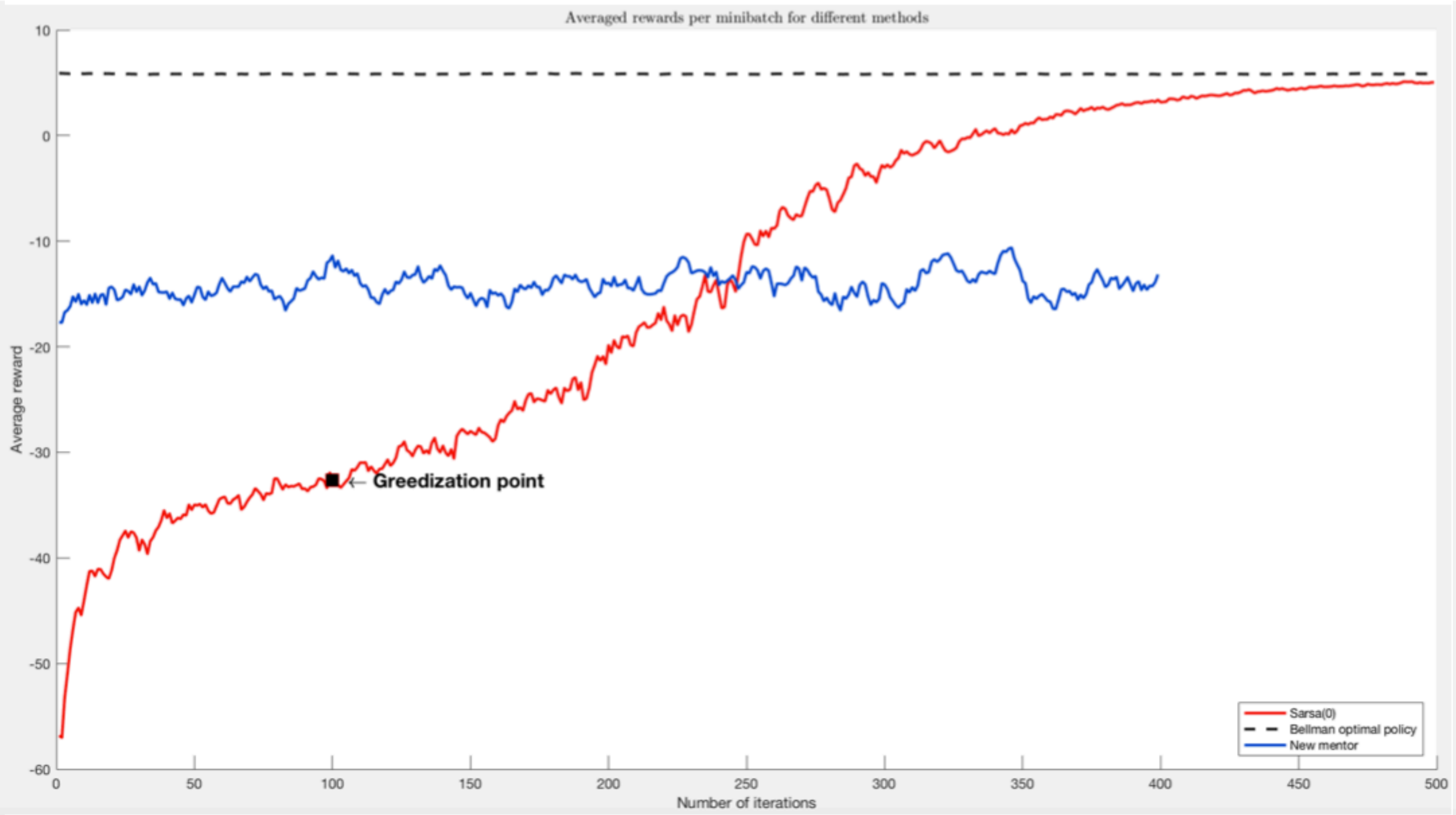
- *Value iteration* for computing optimal policy (ground truth)

GENERATING MENTORS



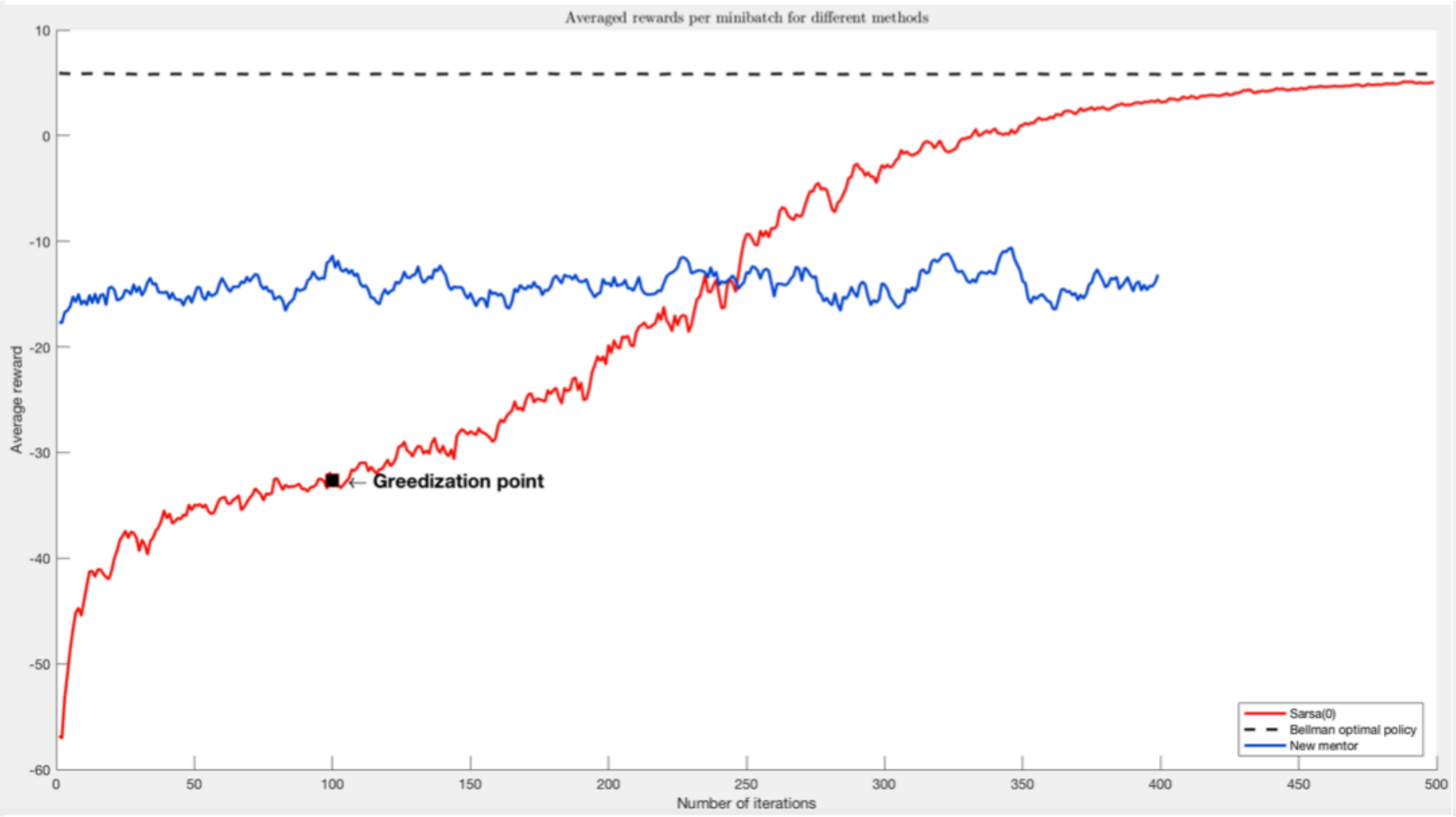
Results

GENERATING MENTORS



Results

GENERATING MENTORS



- 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

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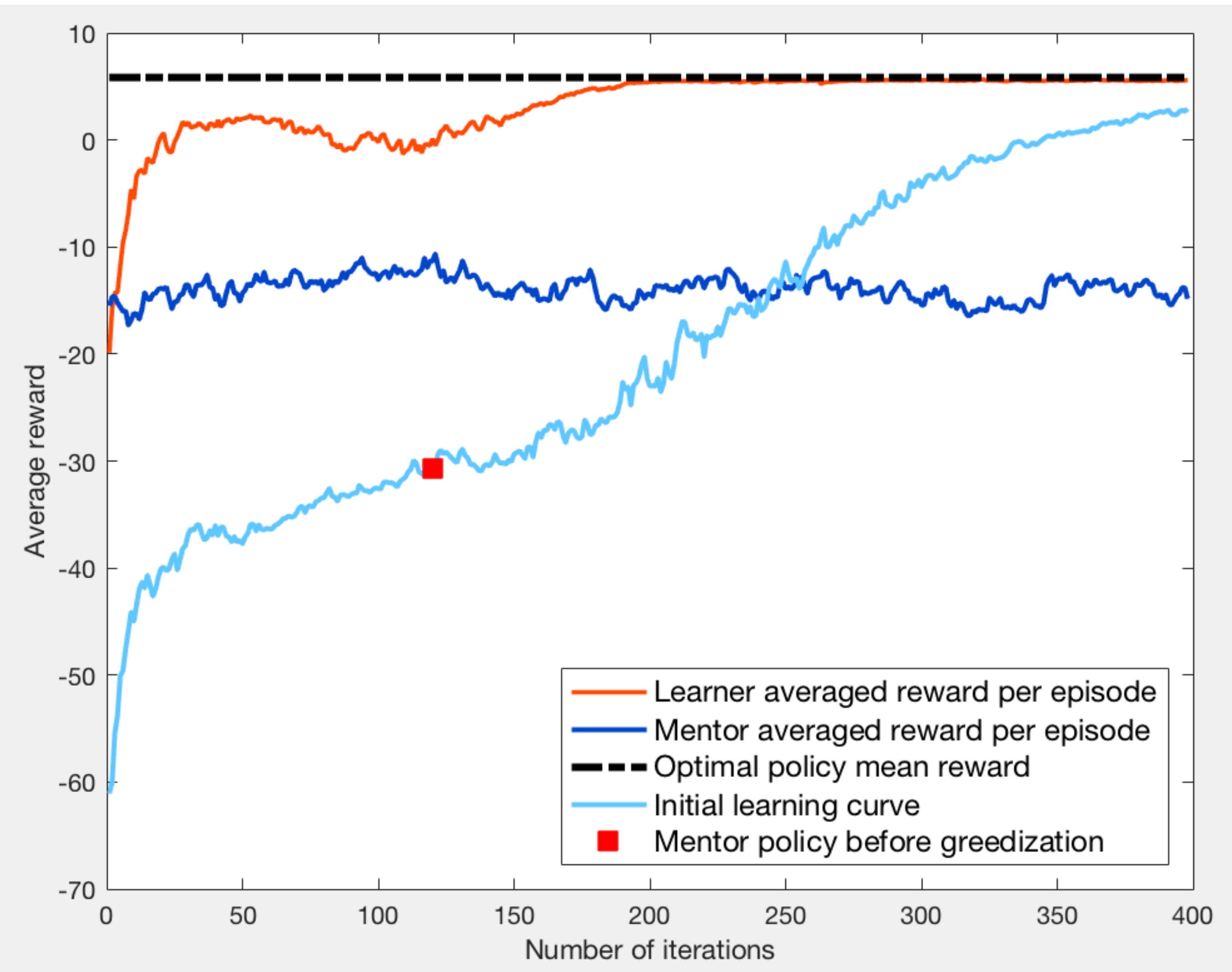

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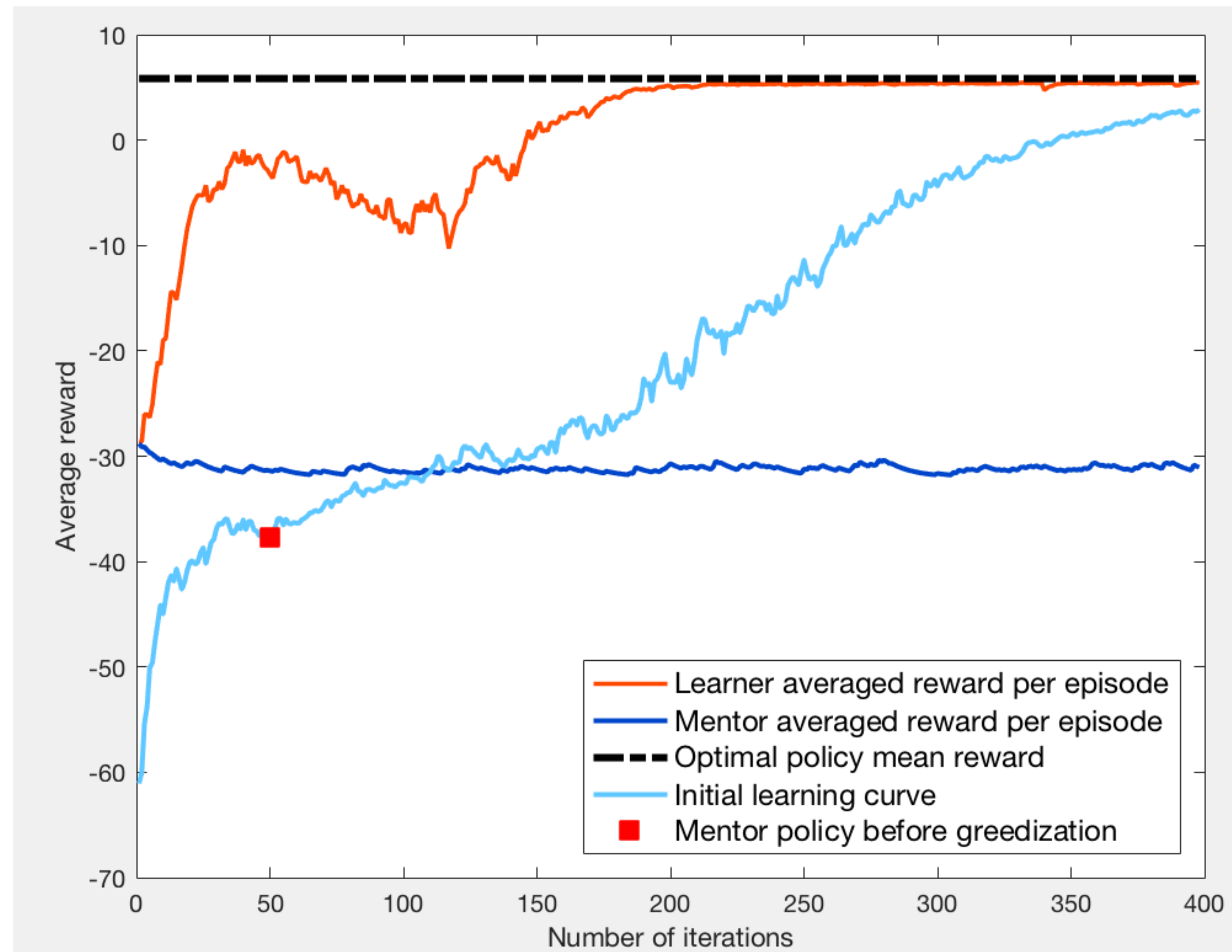


Figure : Learning Curve (Teacher 2)

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

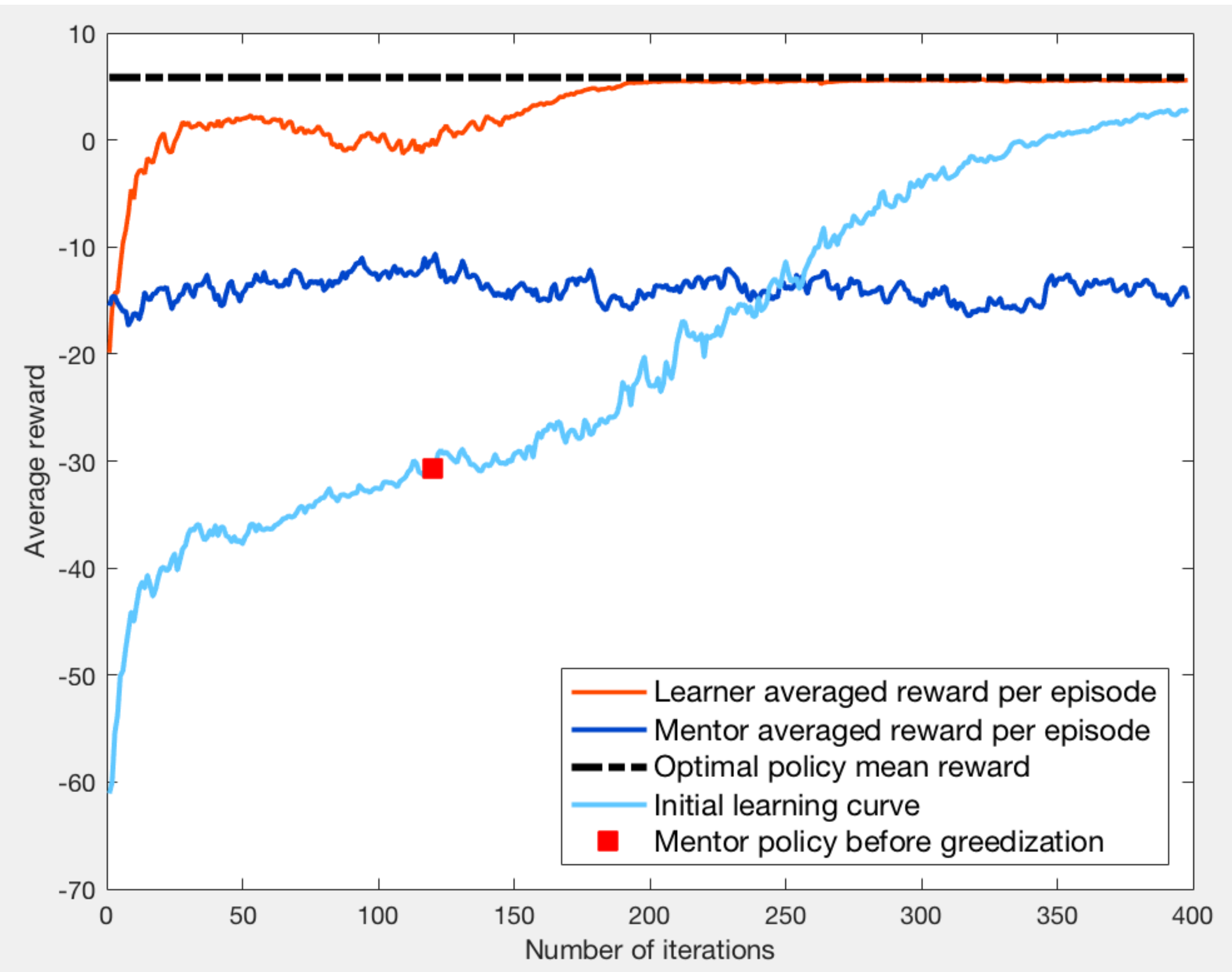


Figure : Learning Curve (Teacher 1)

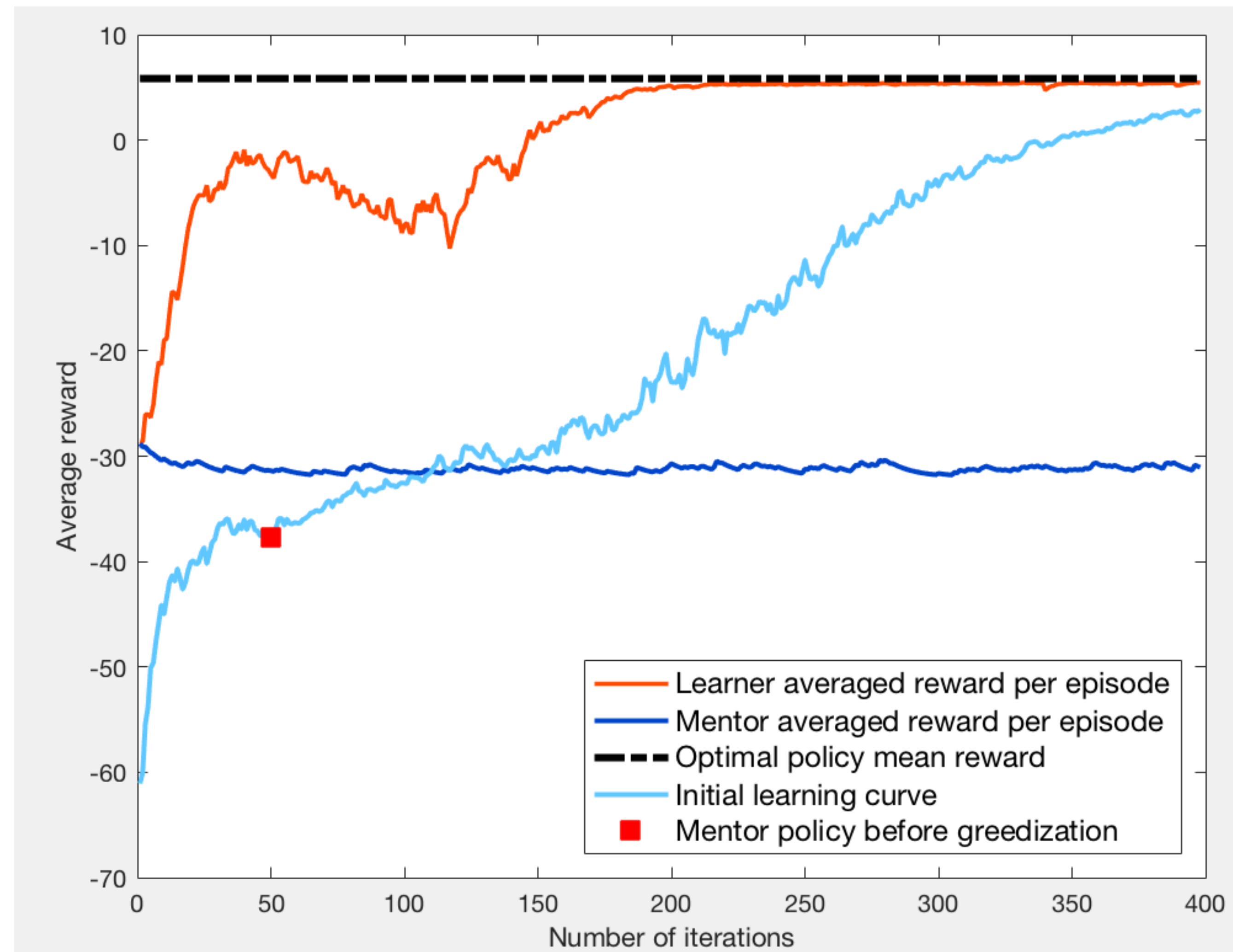


Figure : Learning Curve (Teacher 2)

- Too much time spent exploring around good solutions !

ADAPTIVE LEARNERS

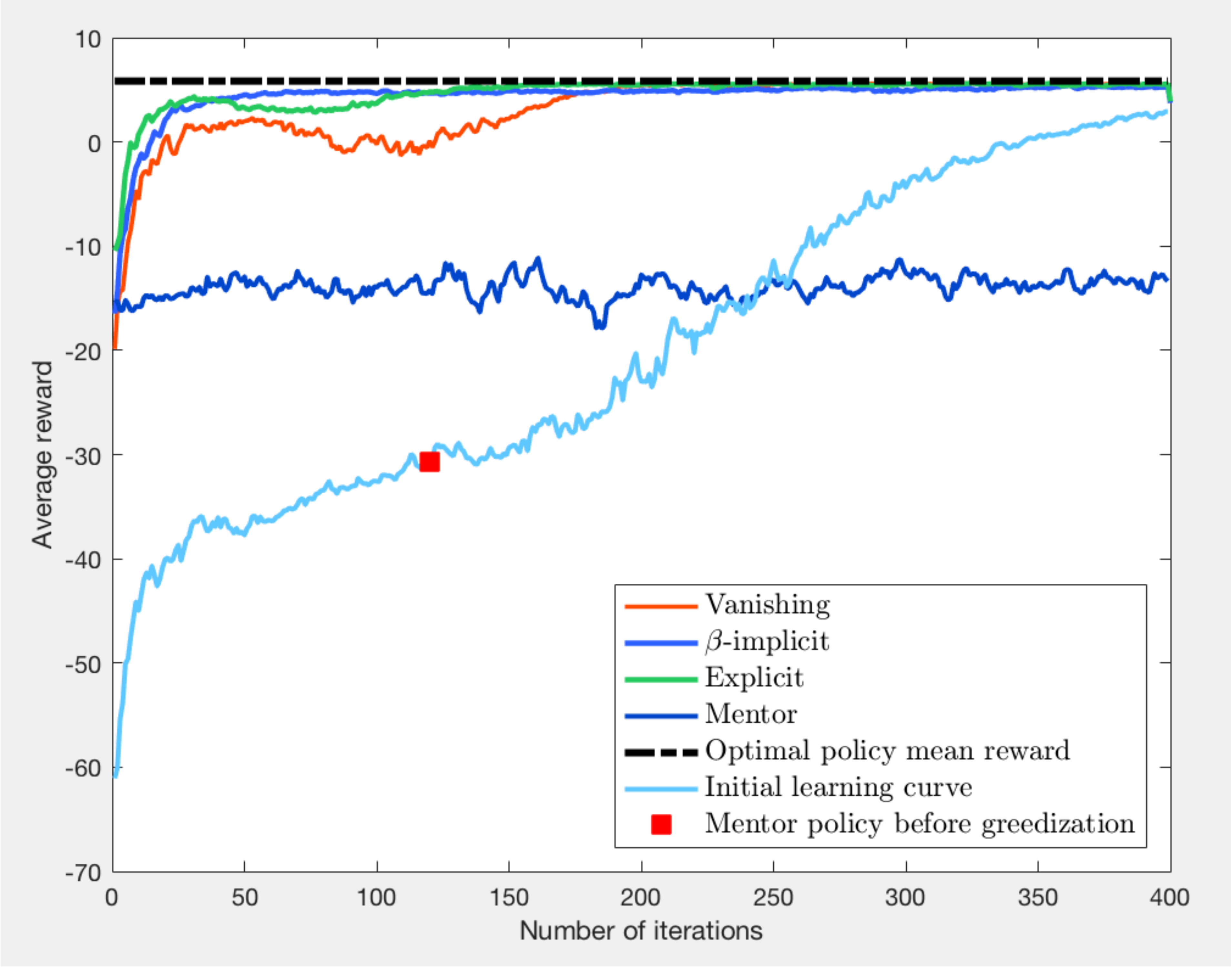


Figure : Learning Curves (Teacher 1)

Results

ADAPTIVE LEARNERS

ADAPTIVE LEARNERS

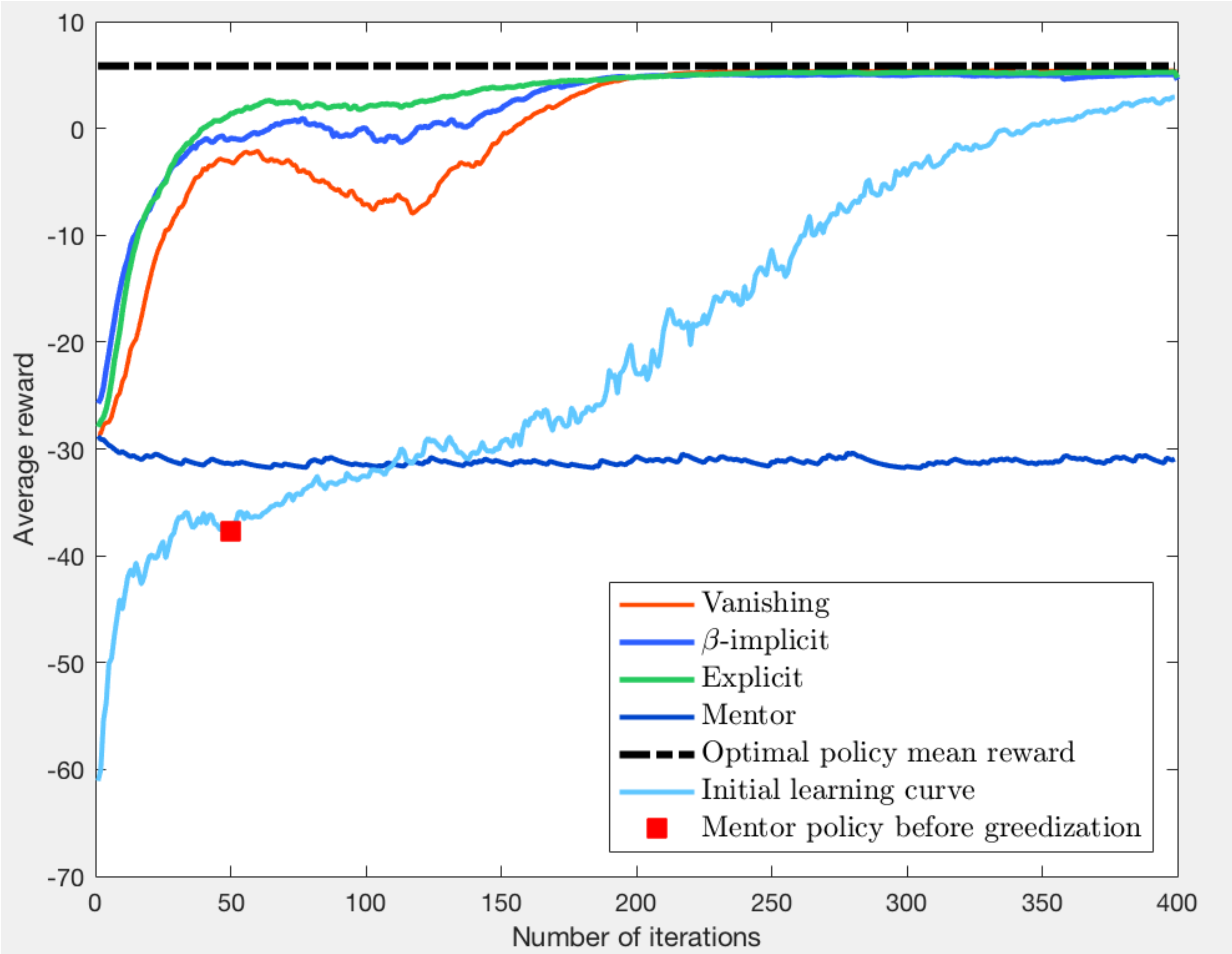


Figure : Learning Curves (Teacher 2)

ADAPTIVE LEARNERS

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

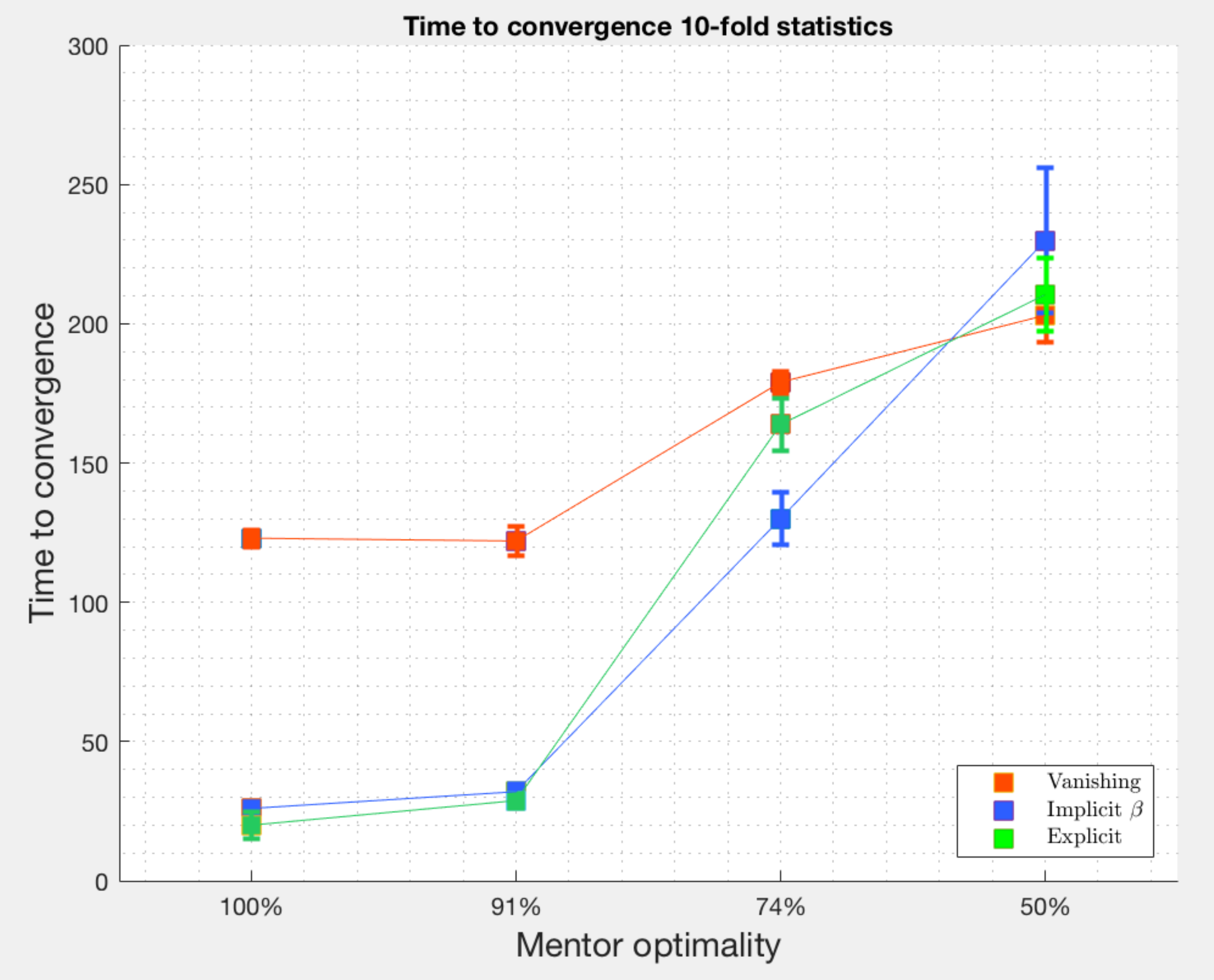
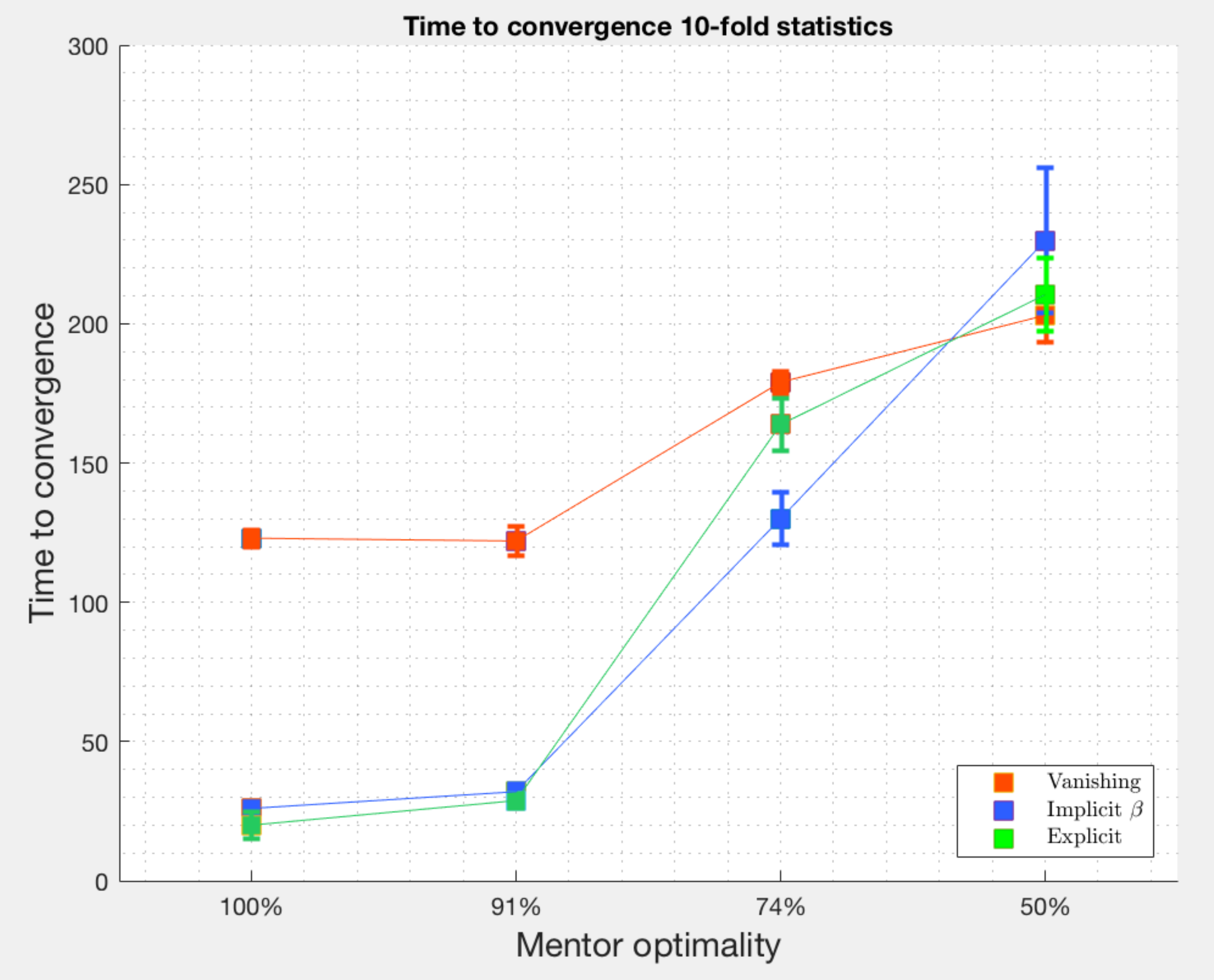


Figure : Time To Convergence

ADAPTIVE LEARNERS

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



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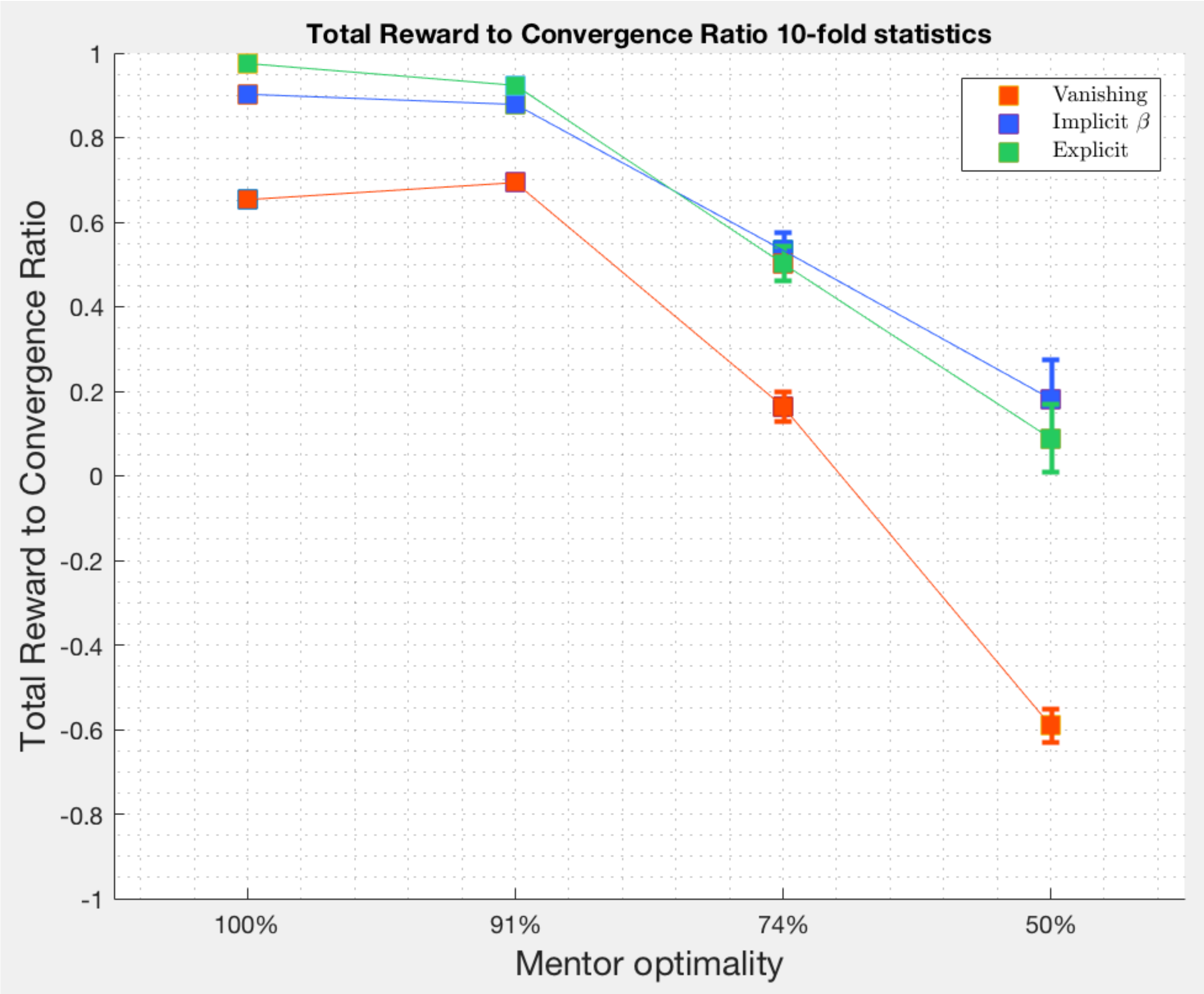


Figure : Reward Ratio to Convergence

ADAPTIVE LEARNERS

- Compared to *classical learners*

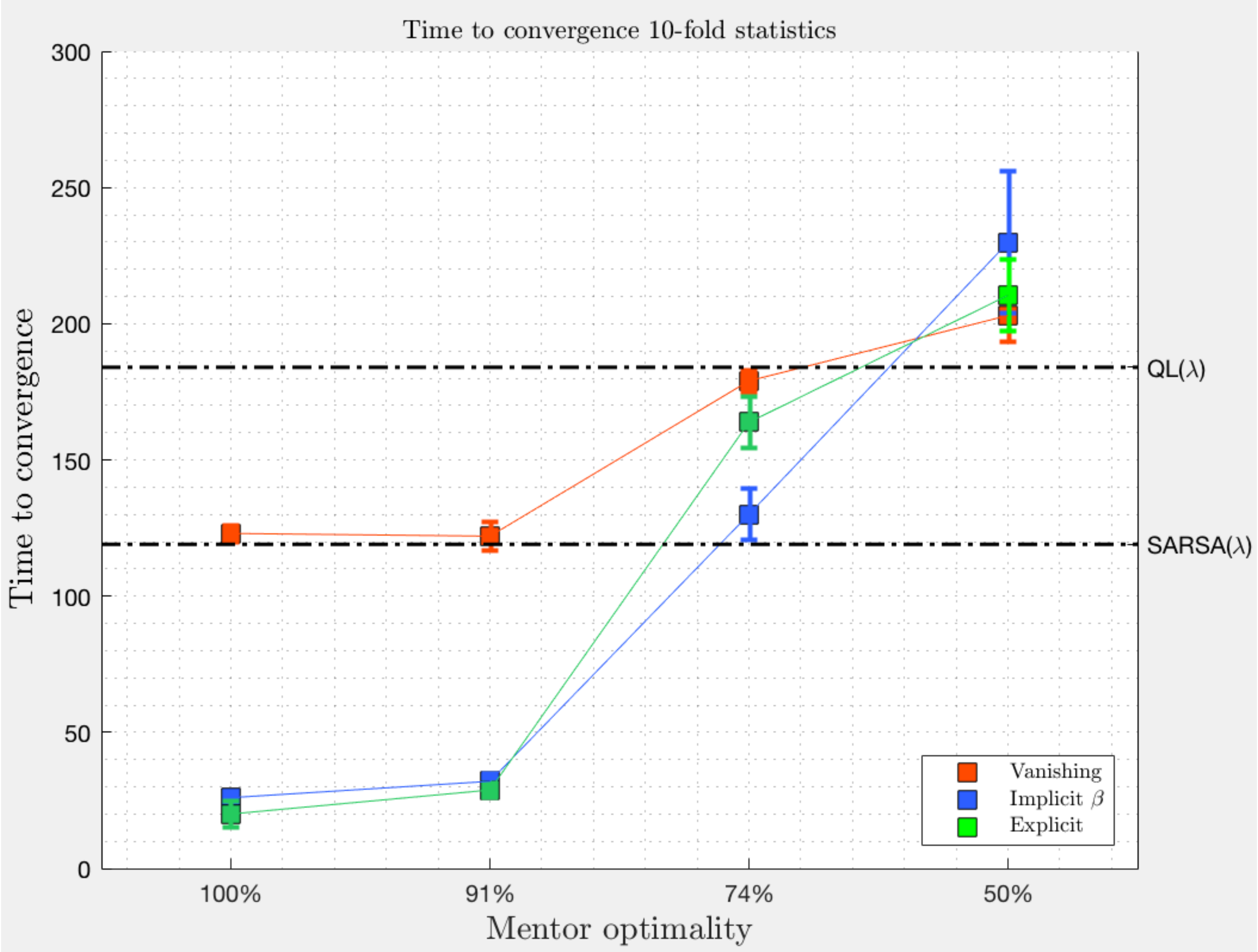
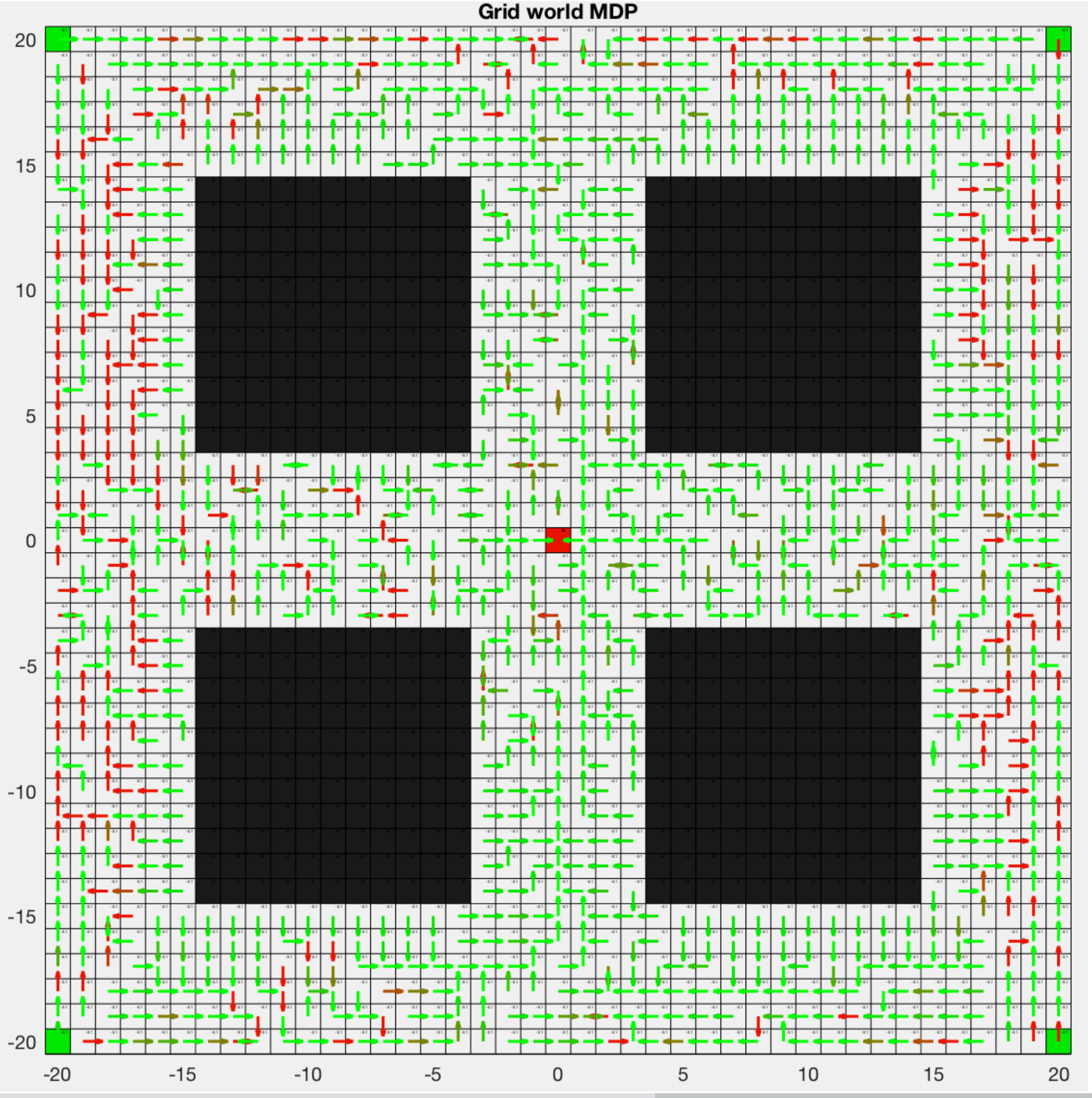


Figure : Time To Convergence

ADAPTIVE LEARNERS

- What is actually learnt ?

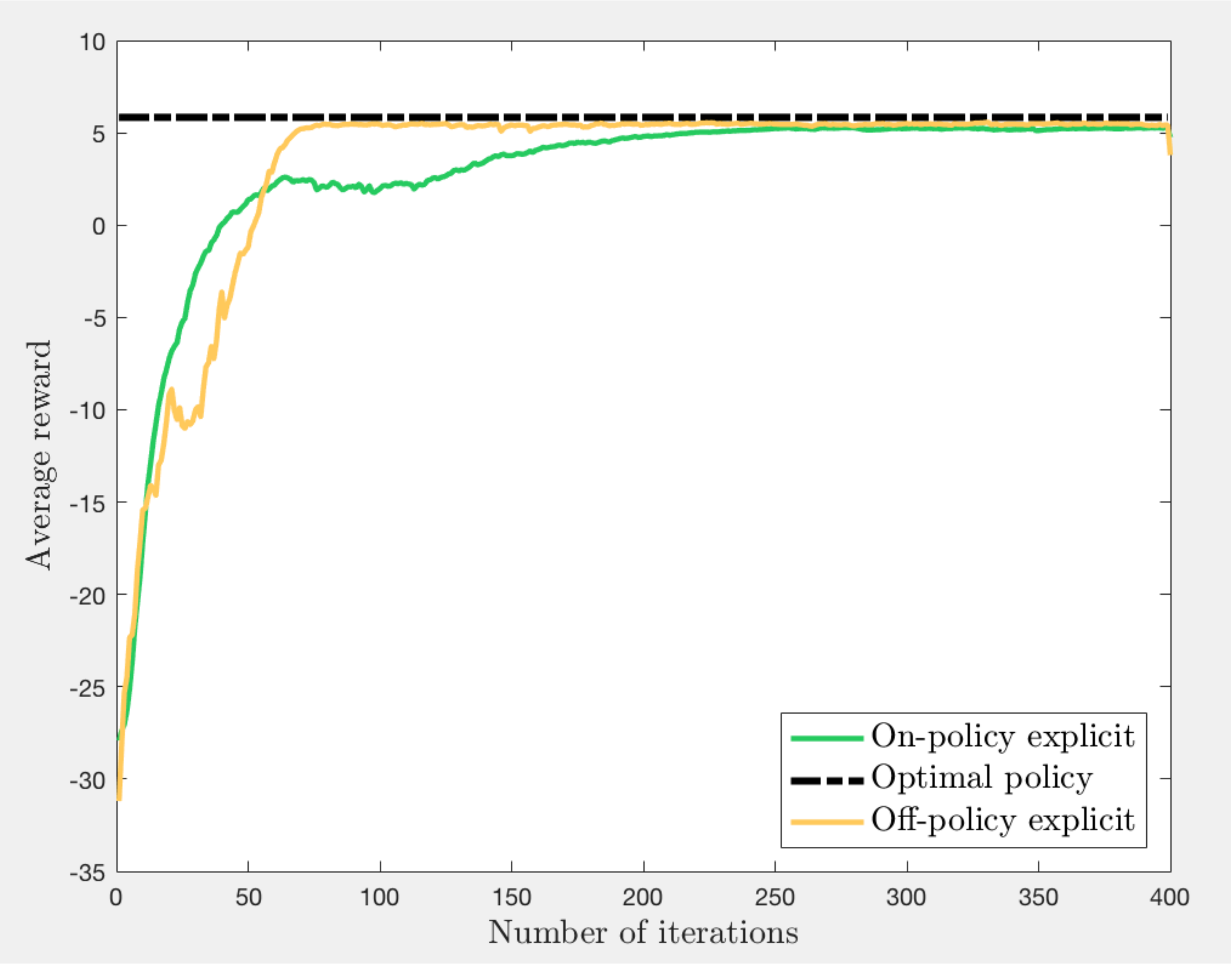


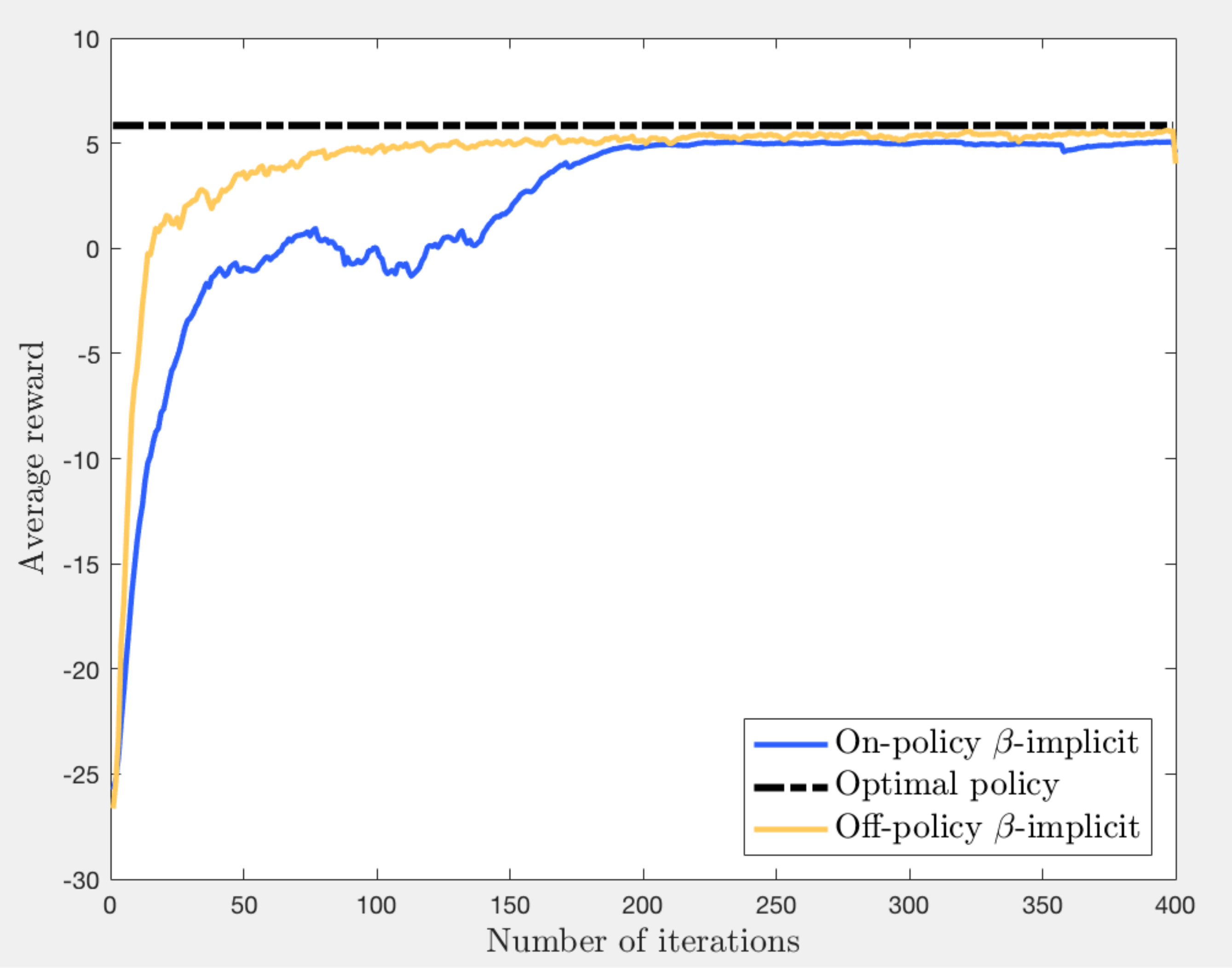
- Compliance heat-map
- Poor teacher recommandations back propagate too far
- The learner tries to circle the teacher instead of fixing it !

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**
  - Learn from suboptimal teachers

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  - Evaluate the optimality of a teacher

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WHAT WE DID :

- Provide **adaptive-compliant exploration policies**
  - Learn from suboptimal teachers
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WHAT'S NEXT :

- Still some work to do !

Conclusion

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- Provide **adaptive-compliant exploration policies**
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WHAT'S NEXT :

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

Conclusion

WHAT WE DID :

- Provide **adaptive-compliant exploration policies**
  - Learn from suboptimal teachers
  - Evaluate the optimality of a teacher
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WHAT'S NEXT :

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

Conclusion

WHAT WE DID :

- Provide **adaptive-compliant exploration policies**
    - Learn from suboptimal teachers
    - Evaluate the optimality of a teacher
    - Extract useful informations
    - Speed-up the learning

WHAT'S NEXT :

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

THANK YOU FOR YOUR ATTENTION !