Reinforcement learning and robot navigation

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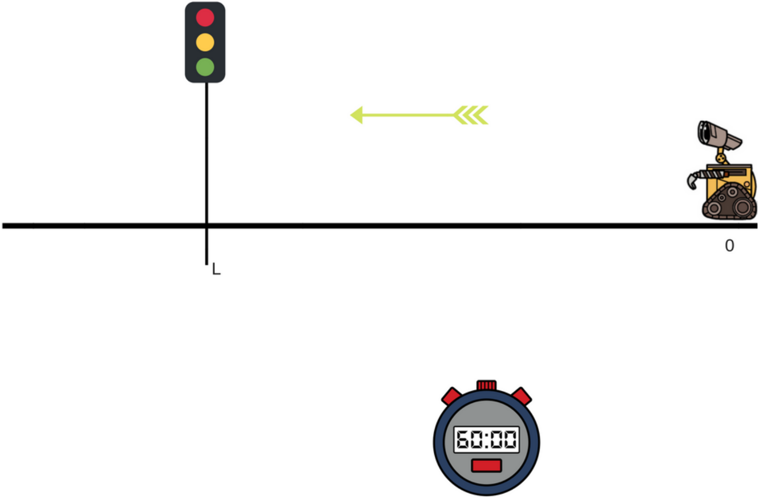
Introduction

The problem

- Framework: a raspberry pie 3 robot which can follow lines
- The task: the robot should adapt its speed with respect to traffic lights
- How: using Reinforcement Learning (RL) and Markov Decision Process (MDP)

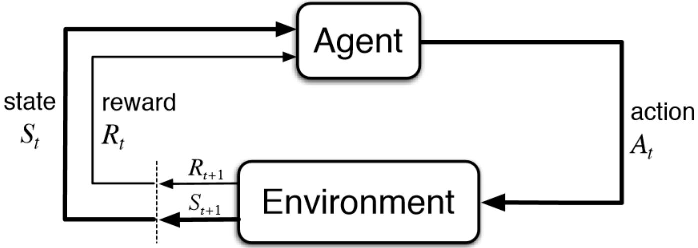
The task



Presentation

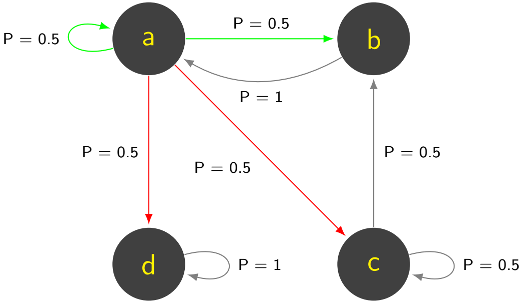
- Part I: theoretical background
- Part II: results from first implementations

Reinforcement learning



The agent's job is to find a behavior that maximizes the long-run sum of values of the rewards.

Markov Decision Process intuition



actions possible in state 0:

1. $\rightarrow$: action 1
2. $\rightarrow$: action 2

Episode : $s_0; a_1, s_1, r_1; a_2, s_2, r_2; \ldots; a_n, s_n, r_n$

Markov Decision Process

Definition: (MDP)

- A set of states $\mathcal{S} = \{s_0, s_1, s_2, \ldots, s_n\}$
- A set of actions $\mathcal{A} = \{a_1, a_2, a_3, \ldots, a_k\}$
- A transition function $T(a, s, s') = \mathbb{P}[s' \mid a, s]$
- A reward function $R : \mathcal{S} \mapsto \mathbb{R}$
- A discount factor $0 \leq \gamma < 1$

Markov property

The transitions only depends on the current state and the current action.

How to pick actions

Definition: (policy)

A *policy* π is a probabilistic mapping from the set of states to the set of actions :

$$\pi : \mathcal{A} x \mathcal{S} \mapsto [0, 1]$$

s.t. $\sum_a \pi(a \mid s) = 1 \quad \forall s \in \mathcal{S}$

Issue

How to

How to asses the quality of policies so we can find the best one?
What is the best policy?

How to asses the quality of policies

We are interested in maximizing the discounted return: G_t

$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} = R_{t+1} + \gamma G_{t+1}$$

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Action value while in a state s under π

$$q_\pi(s, a) = \mathbb{E}_\pi[G_t \mid S_t = s, A_t = a]$$

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State value under policy π

$$v_\pi(s) = \mathbb{E}_\pi[G_t \mid S_t = s]$$

Recursive definition of value functions

action value

$$q_\pi(s,a) = \sum_{s'} \mathbb{P}(s' \mid a, s)\left[R(s') + \gamma v_\pi(s')\right]$$

state value

$$v_\pi(s) = \sum_{a} \pi(a \mid s) \sum_{s'} \mathbb{P}(s' \mid a, s)\left[R(s') + \gamma v_\pi(s')\right]$$

How to asses the quality of policies

How to compare two policies

$$\pi \leq \pi' \iff v_\pi(s) \leq v_{\pi'}(s) \quad \forall s \in \mathcal{S}$$

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Optimal policy

$$\pi_* \quad s.t. \quad \forall \pi : \pi_* \geq \pi$$

Bellman optimality equations

We can associate the value function v_* and q_* to the optimal policy π_*

$$v_*(s) = \max_a q_*(s, a)$$

$$q_*(s, a) = \sum_{s'} \mathbb{P}(s' \mid s, a)[R(s') + \gamma \max_{a'} q_*(s', a')]$$

Finding optimal policy from value functions

$$\pi_*(s) = \underset{a}{\operatorname{argmax}}\; q_*(s, a)$$

Another issue

Computational issue

$|\mathcal{S}|$ linear equations to solve to evaluate policy

$|\mathcal{S}|$ non linear equations to solve the Bellman optimality equation

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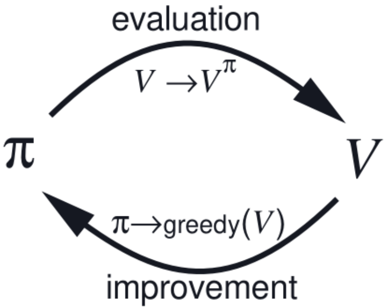
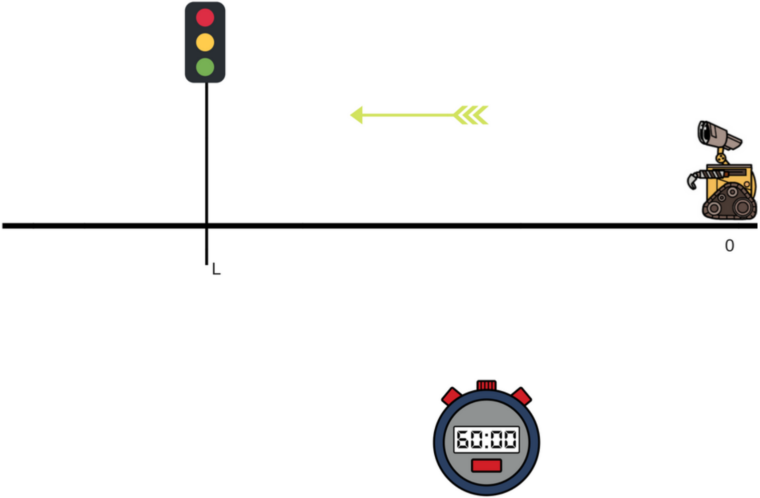
Approximation of value function
and
Policy iteration



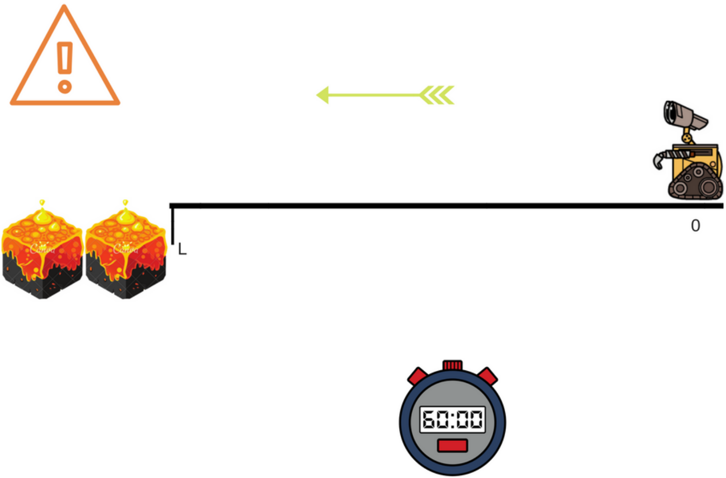
[1]

[1] From (Sutton & Barto, 1998)

Our problem



First a simpler problem



Modelization

states

- position {0,1,2,. . . ,L, Lava }
- speed {low, medium, high }

Modelization

states

- position $\{0,1,2,\ldots,L, \text{Lava}\}$
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actions

- slowing down
- maintaining speed
- speeding up

Modelization

states

- position $\{0,1,2,\ldots,L, \text{Lava}\}$
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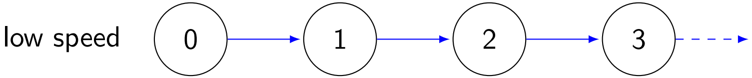
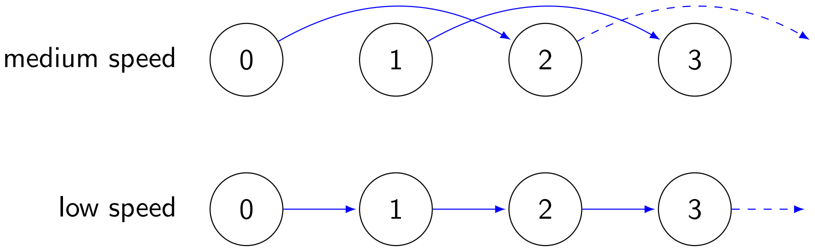
reward function

- Lava: reward of -L
- L in low speed: reward of $+$L
- any other state : reward of -1

Maintaining speed



Maintaining speed



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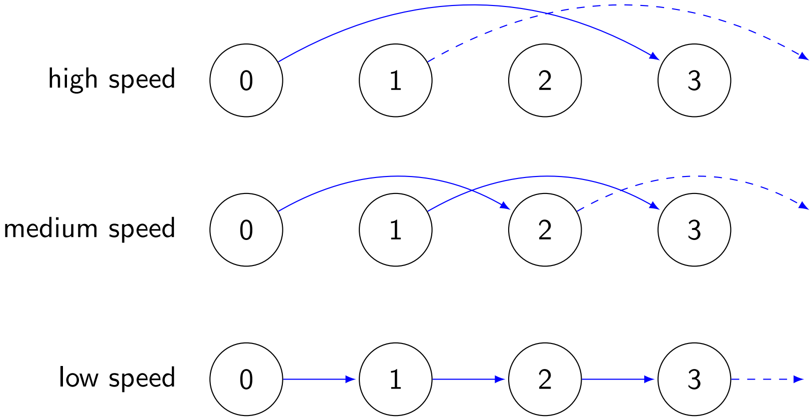
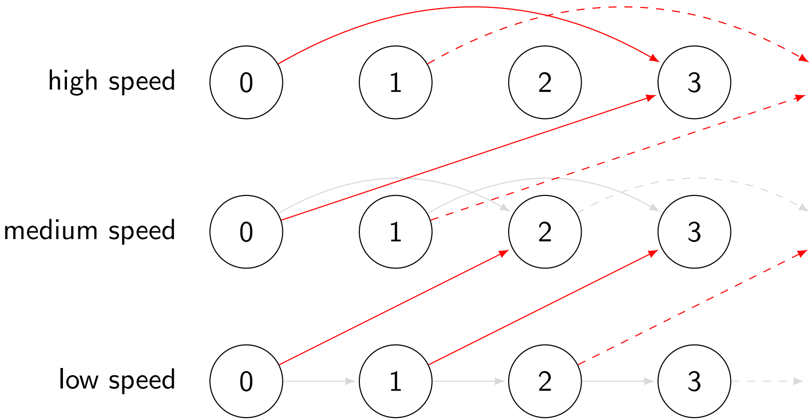
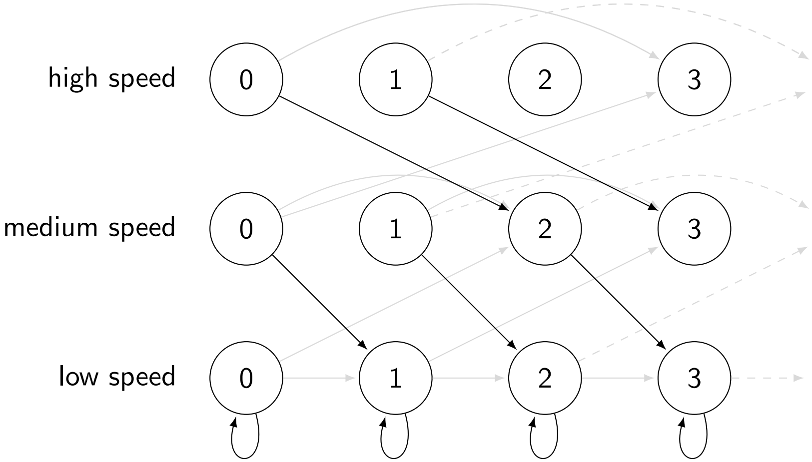


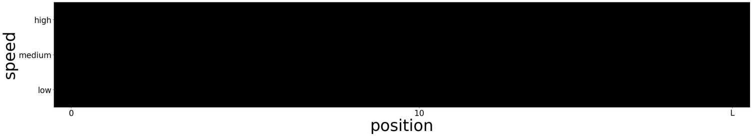
Speeding up



Slowing down



State value function at different iterations
the brighter the better the value



States values at iteration 0, all the state values are equal to 0

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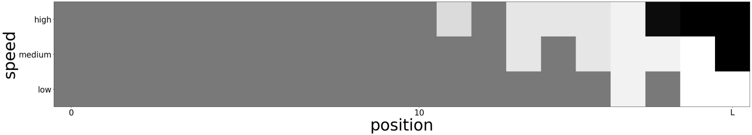
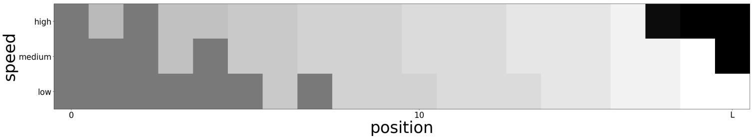


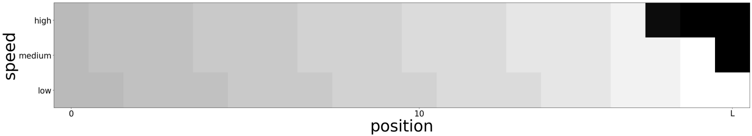
States values at iteration 2



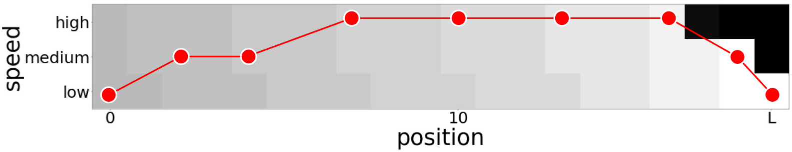
States values at iteration 4

State value function at different iterations

the brighter the better the value

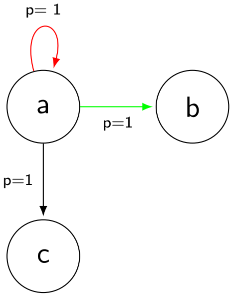


States values at iteration 6 (where stable policy is attained)



speed
high
medium
low
0
10
L
position

Deterministic actions are not really realistic



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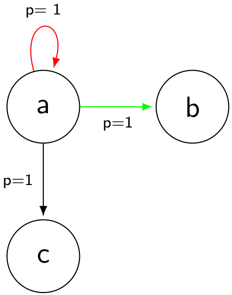

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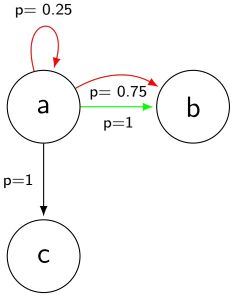
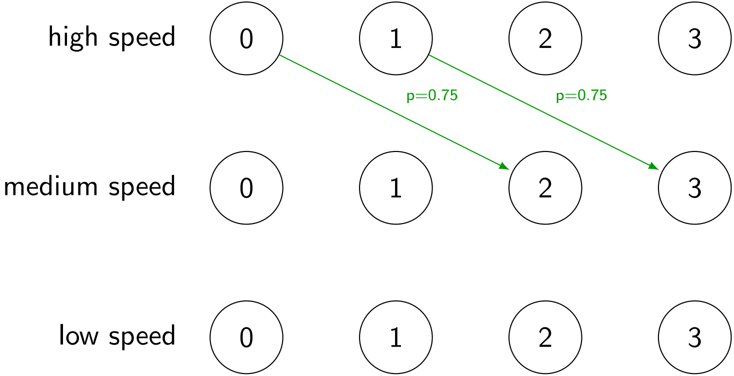


Stochastic actions

Decelerating for decelerating being a stochastic action



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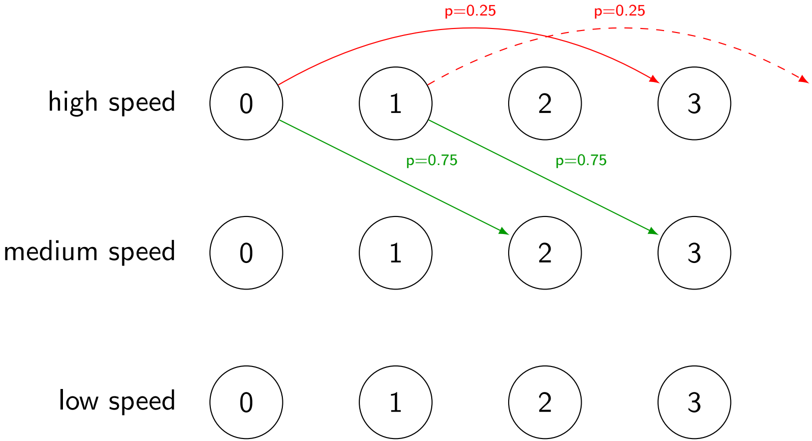
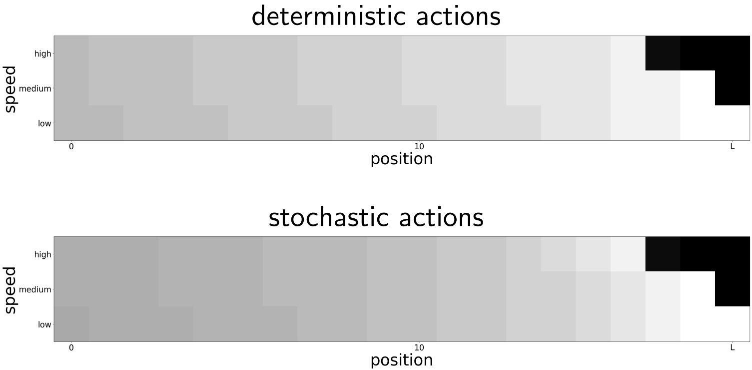


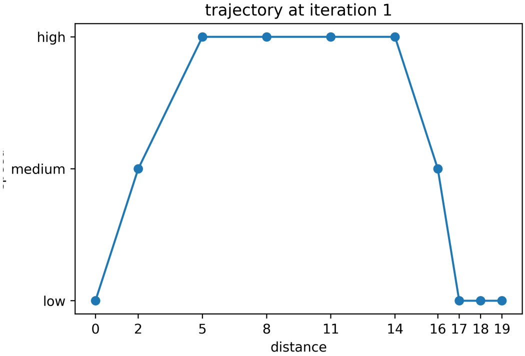
Results for stochastic actions

state-value function at the end of the iterations



Results for stochastic actions

decelerating results in keeping the same speed with probability 1/4



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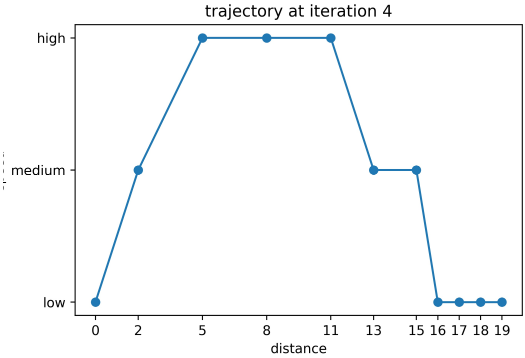

where stable policy is attained

Conclusion

- We introduced the theoretical framework: Reinforcement learning and Markov Decision Processes
- We solved a simple problem where we know the model (the transition function in particular)

What's next ?

already working on

- Add the traffic light into this setting
- Find the distance from the robot's camera to the traffic light
- getting data from the robot

In a not so distant future

- Explore other algorithms and compare them : Monte-Carlo methods, temporal difference learning, Q learning, Expected Sarsa...
- Neuro-dynamic programming ?

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Implement everything on the robot ... and pray that everything works well