Reinforcement learning and robot navigation

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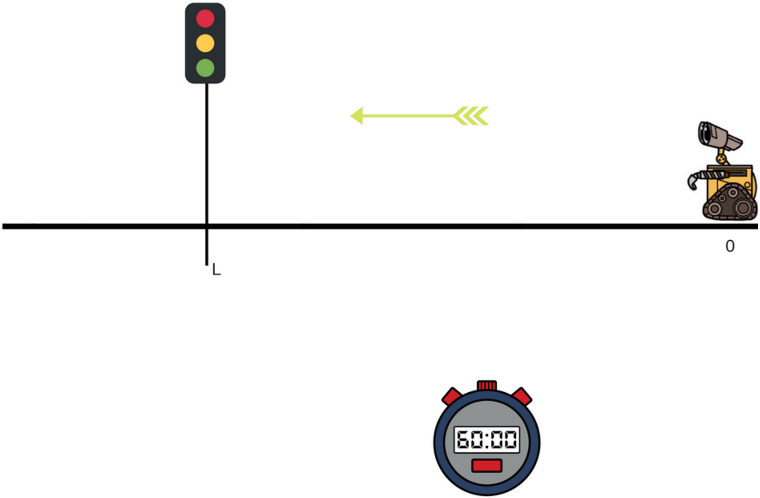
Introduction

The problem

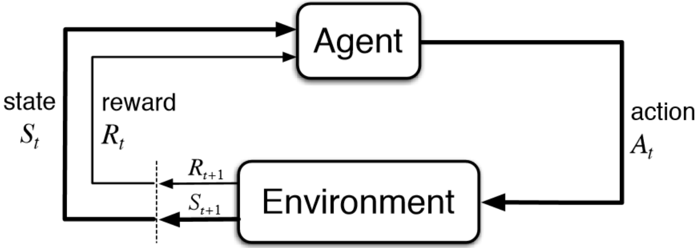
- Framework: a Raspberry Pi 3 robot which can follow lines
- The task: the robot should adapt its speed with respect to traffic lights
- How: using Reinforcement Learning (RL)

The task



Presentation

1. Reminders
2. Modeling
3. Simulation
4. Results



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

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 $R : \mathcal{S} \times \mathcal{A} \mapsto \mathbb{R}$
- A discount factor $0 \leq \gamma < 1$

Q-learning

Approximation $Q(s, a)$ (measure "how good is the action")
Action chosen: $\underset{a}{\operatorname{argmax}}\ Q(s, a)$

Modeling

States

States encode the following information:

- distance to the traffic light
- speed
- color of the traffic light
- time spent in current color
- previous action

Modeling

Actions

- slow down
- keep the same speed
- speed up

Possible speeds: $0, 20, 30, \ldots, 70$

Reward function: $\mathcal{R}(s, a)$

- positive reward if robot respects the traffic light
- negative reward for every step "far away" from the traffic light

Positive reward when the task is done and negative reward for every step along the way.

- how to compute the distance from the robot to the traffic light?
- how "fast" is speed $20, 30, \ldots$?
- how to simulate the traffic light?
- what are the exact parameters for the reward function?

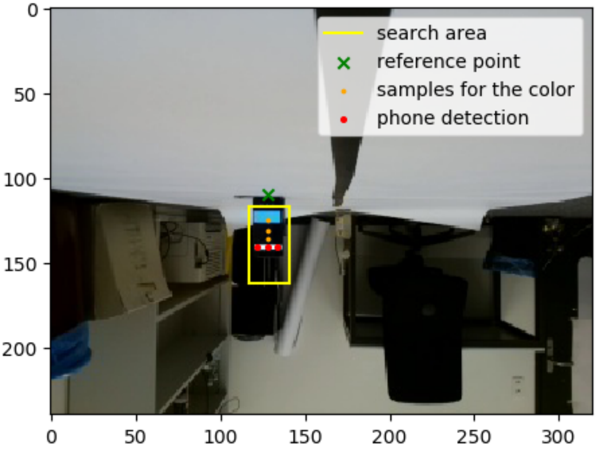


Figure: View from the robot camera

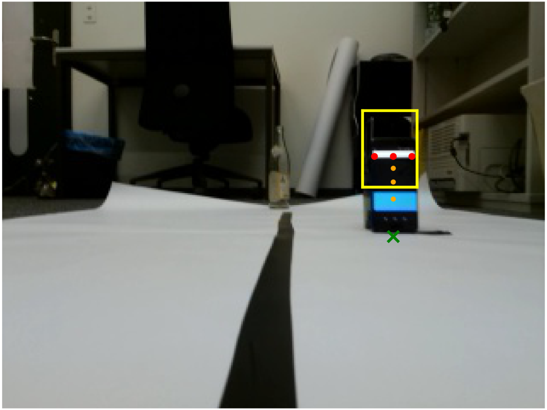
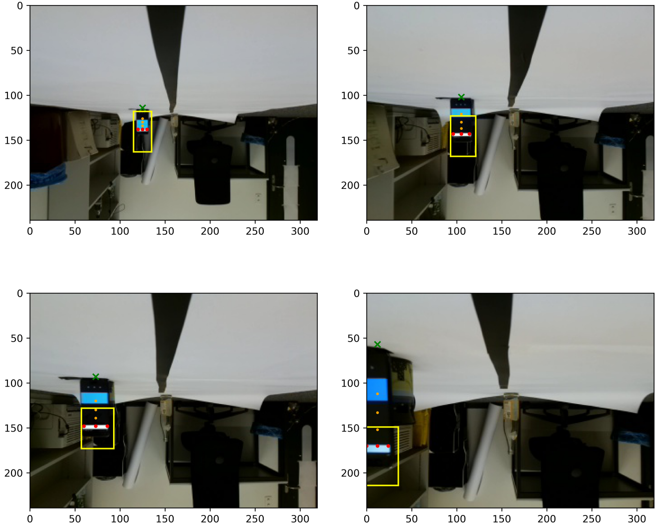


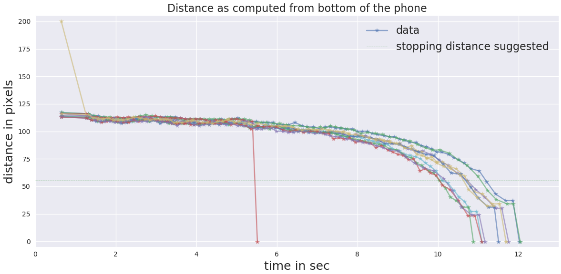
Figure: View from the robot camera

Simulation

measuring distance from the robot to the traffic light



How fast is fast? Graphs for speed 30 and 70



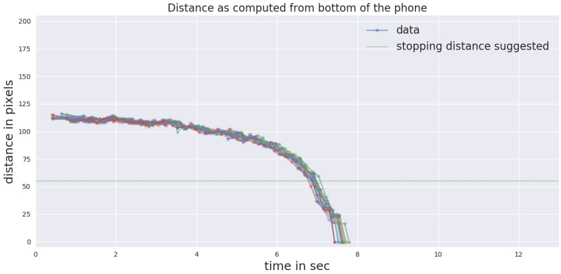


Table: Example of raw data obtained

position	outcomes		
80	75	74	73
81			
82	76	77	

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Mean of data from the surrounding points: 75

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Mean of data from the surrounding points: 75

Table: After imputation

position	outcomes		
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81	75	74	76
82	76	77	

Table: Example of data

position	outcomes				
80	75	74	74	73	75

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position	outcomes				
80	75	74	74	73	75

Table: Probabilities of transitions obtained from the data

from	to	probabilities
80	75	$0.4 = 2/5$
	74	$0.4 = 2/5$
	73	$0.2 = 1/5$

In the simulation, the time is defined in terms of number of interactions.

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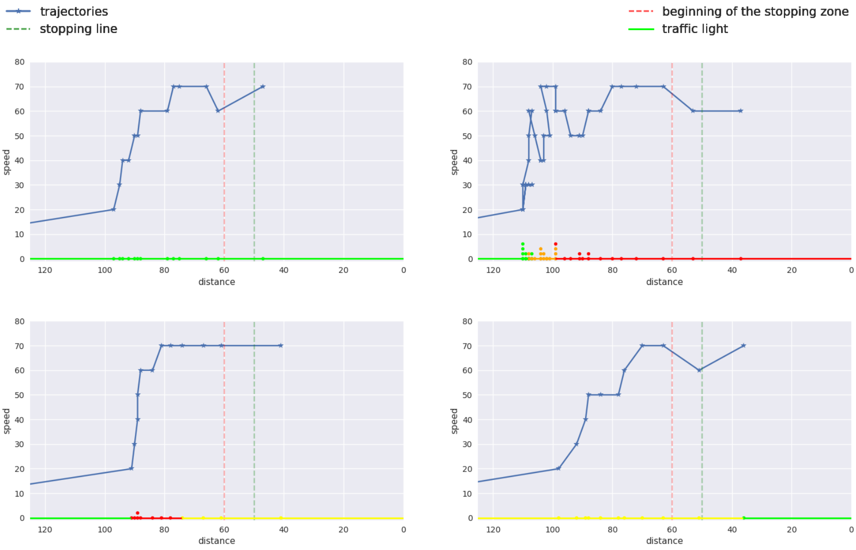
- We measured the number of pictures processed per second by the robot ($\sim$ 8 im/s)
- Learning for a specific traffic light
- Traffic light simulated to behave the same as in real life in terms of *time*

Issues with previous naive thinking

- The distance measurements are approximative, hence we cannot have a fixed distance to stop, so we use a *stopping zone*.
- Reward functions are not as simple as they seem. We had to test a lot of them, small changes have influence ...

Simulation

Reward function, naive approach 1 million episodes



Solutions

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- add great negative or positive reward for respecting or not red light ($\sim \pm 300$)
- try to bait the robot to learn what we want
- and try a lot of times different reward functions (maybe 20) with a lot of iterations ($\sim$ 10 millions, about half a day)

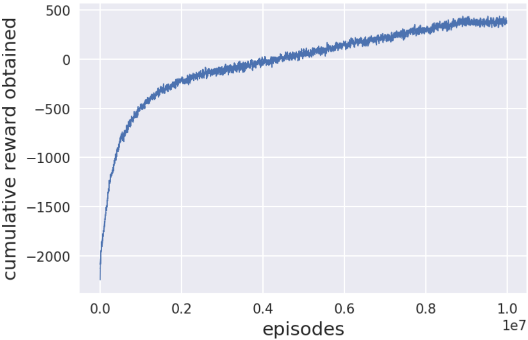
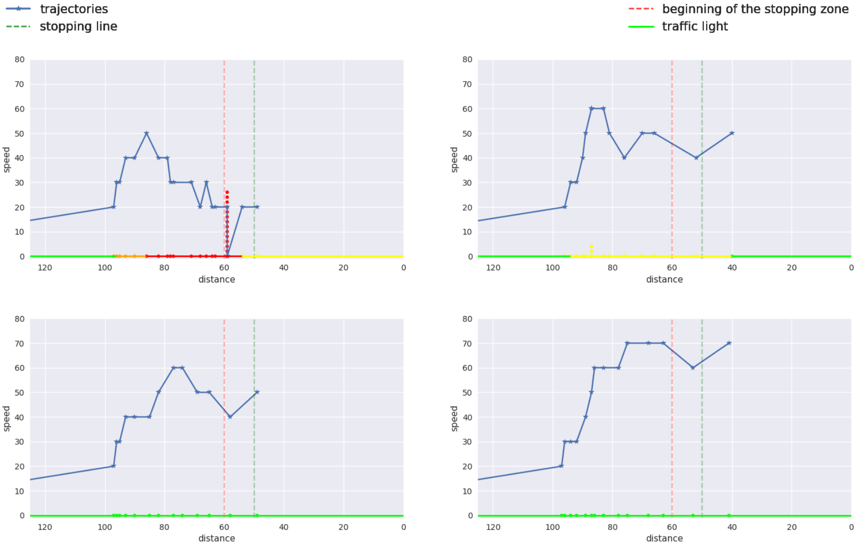


Figure: Q-learning curve (10 millions iterations)

Examples of trajectories obtained



What could be done next?

- we tried to learn with 50 millions iterations ($\geq$ 60 hours), but the results were not impressively better than with 10 millions iterations
- do grid search in order to find a better reward function
- generalize the learning to any traffic light
- Kalman filters to improve measurements
- ...

Thank you for your attention
Demo time !