Dodge falling objects game

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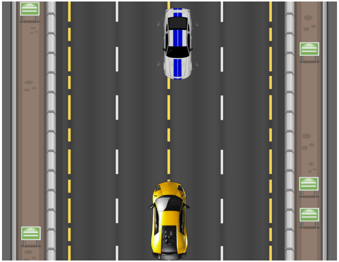

Introduction

What is the game about?

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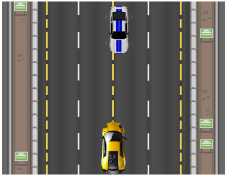
A simple example is Dodge Mania

Implementation

For the purposes of the project, a simple implementation has been chosen: you control a car moving along the horizontal axis along a road, you have to dodge another car moving towards you:



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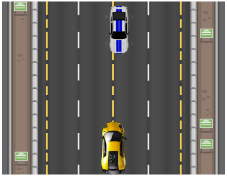

If your car crashes with the other car or with the side walls you lose:

Implementation

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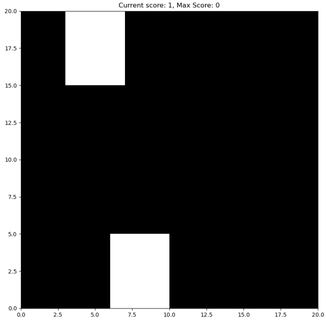
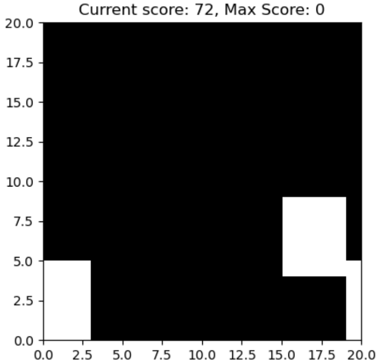
Playground class contains the functions to move the cars: at each iteration of the game, enemy car moves one step down, while your car can move one step left or right, or stand still.



Implementation

Also, a simpler variant with a continuous space has been tested. In this case, car cannot crash with the walls, but it will be able to exit from one side and re-enter from the other one:



Changing speed

Speed tells how many squares the cars will cross in a single step. It can be manually set, by default it is the same for both cars but some tests have also been done with increasing speed for enemy cars.

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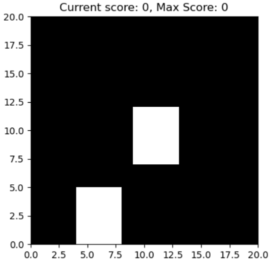

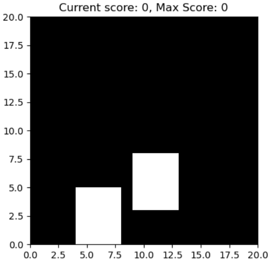

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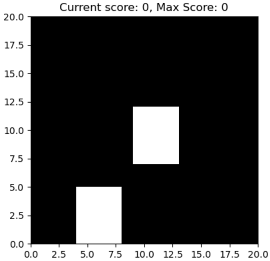

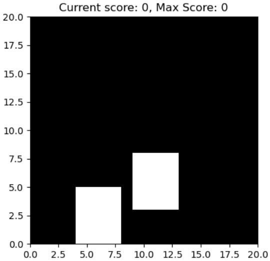

To help car to avoid enemies, boost can also be activated: the boosted car will move faster than usual, but this comes with a price...

Reinforcement Learning Framework

Actions Space

There are 5 possible actions:

1. stand still;
2. move right;
3. move left;
4. move right using boost (causes a negative reward);
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3. move left;
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They have been encoded using a variable `action` with values in `[0,4]`

States Space[1]

To encode the states, state binning has been used to reduce the space size:

- 2 attributes, with values in `[0,3]`, to monitor side obstacles (walls and car) distance;

[1]Note that these are actually observations of the environment, not states

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This gives us $4 \times 4 \times 2 \times 2 \times 5 = 320$ possible states.

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Rewards

Reward is -1000 in case of crash of whatever nature, else a complex reward is assigned at each step, composed by:

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- a term which rewards the car for being far from the enemy car
- a term which rewards the car for being far from the walls
- -100 if boost has been used
- -1 if car has moved (this encourages the car to stand still)

Solving technique

At each step, we are in a state S, we take an action A and we receive a reward R and a new state S':

```
# get the current state of the environment
state = Agent.get_state(env)

# get the action to be taken based on the state
action = Agent.get_action(state)

# play a step of the game and get the reward and the gameover status
reward, gameover = env.playstep(action, carspeed, policespeed)

# get the new state of the environment after the step
newstate = Agent.get_state(env)

# get the new action to be taken based on the new state
newaction = Agent.get_action(newstate)
```

Solving technique

We'll use Temporal Difference Learning algorithm to estimate and update the state-action value function $Q(s, a)$:

Algorithm 2 TD-Learning

Input Learning Rate $\alpha \in (0; 1]$, small $\epsilon > 0$

Initialize $\hat{Q}(s, a)\ \forall\ s \in S,\ a \in A$

loop for each episode:

  Initialize s

  loop Derive π from $\hat{Q}$ (with $\epsilon - greedy$)

    Choose a from A

    Take A, observe R, S'

    Compute TD-error δ

    Compute eligibility e

    $Q \leftarrow Q + +\alpha\delta e$

    $S \leftarrow S'$

Solving technique

Some notes:

- we have used $TD(0)$, hence the eligibility is the identity function:

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- we have used $TD(0)$, hence the eligibility is the identity function:

$$e = I(S_t = s, A_t = a)$$

- The learning rate used for the tests is fixed to $\alpha = 0.01$
- In order to balance exploration and exploitation, an ϵ-greedy policy has been followed, with $\epsilon = 0.5$ decreasing over time

Choosing δ

To compute temporal difference error δ we tested different algorithms:

- SARSA: $\delta = R + \gamma Q(S', A') - Q(S, A)$
- Q-learning: $\delta = R + \gamma \max_{a'} Q(S', a') - Q(S, A)$
- ExpectedSARSA: $\delta = R + \gamma \sum_{a'} \pi(a'|S') Q(S', a') - Q(S, A)$

where γ has been fixed to 1

Results

Training the model

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Anyway, learned model is quite flexible and can adapt to different rules (if they are not too restrictive).

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Base case: constant speed for both cars

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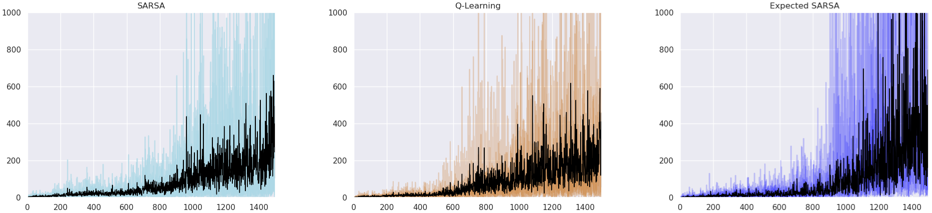
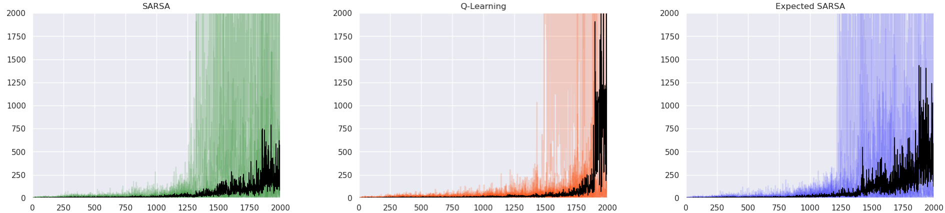


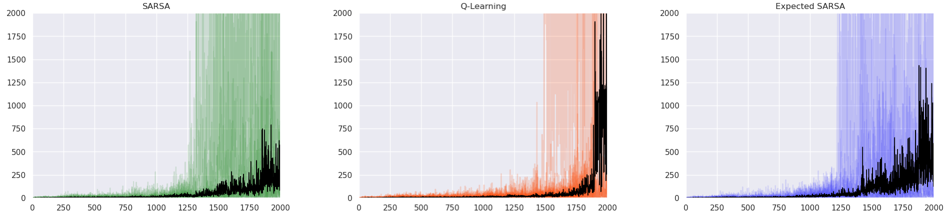
Boost activated

Standard environment



Test with a bigger car (6,5) and boost

Standard environment



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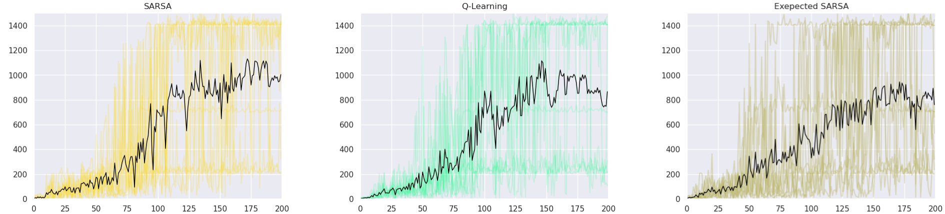

Test with a small car and enemy speed increasing every 100 points

Continuous environment

Base case: constant speed for both cars

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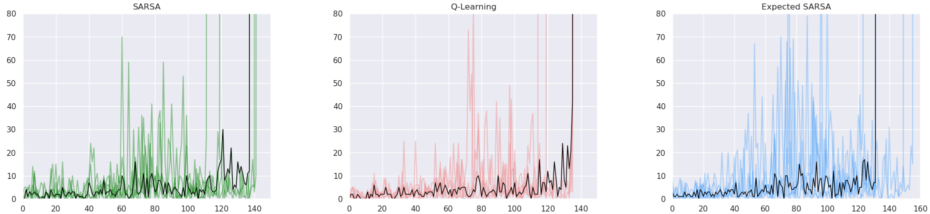

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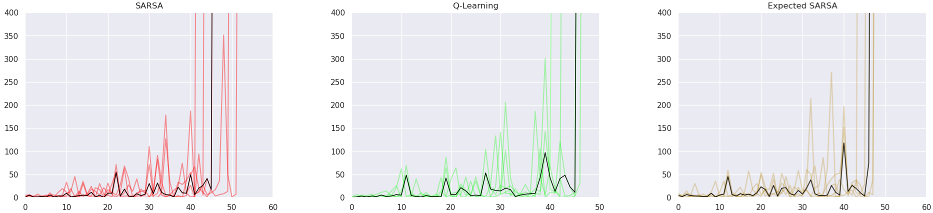

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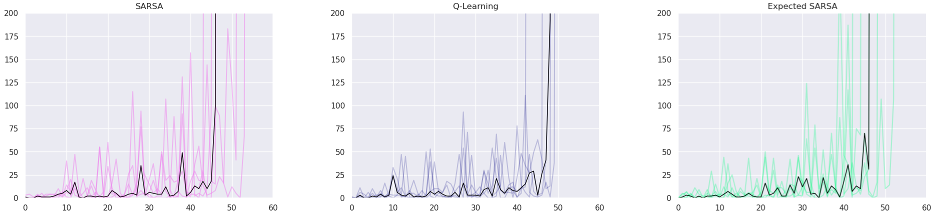

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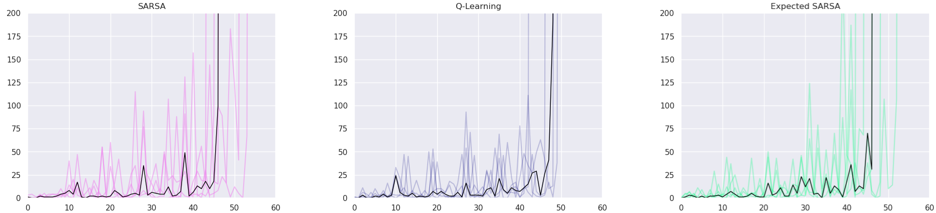

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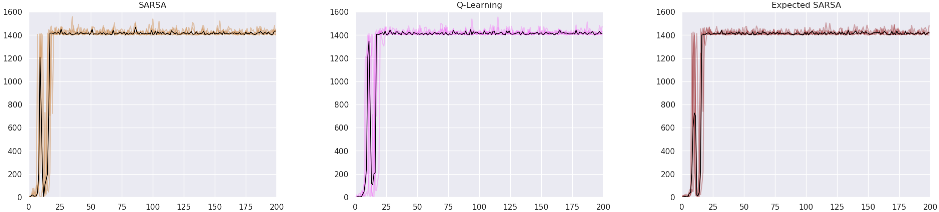

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- With Pacman rule, the agent is able to do a perfect score, if rules are not too restrictive (too big car, too fast enemy...)
- The learned agent is able to play also with different environment size (if the ratio between car size and environment size doesn't change too much)
- since we have a online learning, policies can be combined to improve performances

Possible improvements

Parameters

- Non constant learning rate α;

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- Bigger reward for being far from obstacles

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- Test different states, particularly in the case of vertical distance

End