FLATLAND CHALLENGE

Deep Learning Course - Final Project

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September 2020/21

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Flatland Improvements

Observator

The starting point for our observator is the tree observator from flatland.envs.observations.TreeObsForRailEnv.

We adapted it to the problem changing those main properties:

- the **node** structure
- the **search** strategy
- the number of **explored branches**

Custom Node

The default node is a NamedTuple.

To keep it clean and better organized we decided to introduce a custom Node class, with some methods for:

- listing numeric attributes
- convert tree into array
- normalize values

Search Strategy

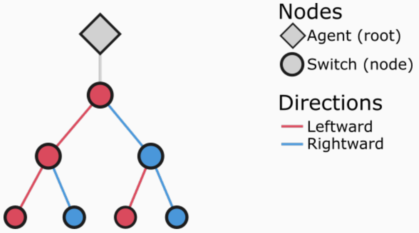
We preferred the **breath first** strategy with respect to the depth first strategy previously adopted for branch exploration.

Flatland switches often create railways which immediately merge again with the previous one. Those are really useful to avoid collision and traffic, but on the other hand we will have nodes explored twice during observation.

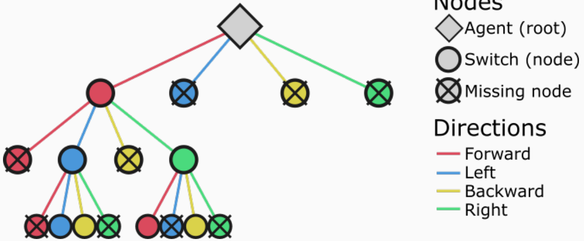
Explored Branches

Flatland switches allow only two possible directions and, as already set in the default tree observator, we save only nodes corresponding to switches.

The result of the observation is then a **binary tree**: only the leftward and the rightward child are created.



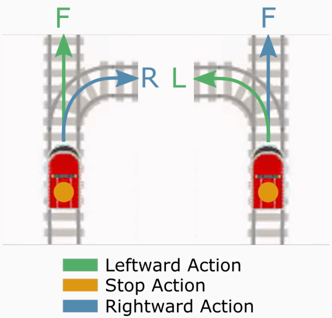
Explored Branches



Default Flatland Tree Observator

Actions

Considering the flatland environment, we have also optimized the set of possible actions, limiting them into: *`STOP, MOVE LEFTWARD, MOVE RIGHTWARD`*:



Example of custom actions, remapped to the Flatland's actions *`(Left, Forward, Right, Stop)`*

Reward

The flatland default reward is not enough to determine if a path could be a good one or not.

Therefore we introduced a positive and a negative reward. We call them **attractive force** and **repulsive force** because they refer to gravitational force. The first represents the attraction towards the target, while the second represents the repulsion from agents moving in opposite direction.

$$force_{attractive} = \frac{MASS_{TARGET}}{dist^2}$$
$$force_{repulsive} = \sum \frac{MASS_{AGENT} * N_{OPPOSITEAGENTS}}{dist^2}$$

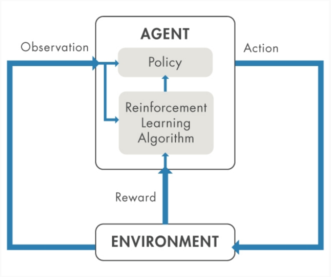
Reinforcement Learning

Reinforcement Learning

Reinforcement Learning is a technique in which agents interacting with an environment, learn the best actions given the observations from the environment, by *maximizing* a reward function.

Execution of a RL step:

1. Agent **observes** the environment
2. Agents chooses an **action**
3. Environment executes the action, advancing its **state**
4. A **reward** is provided to the agent, which is then used by the **RL Algorithm** to learn the best action



Q-Learning

The most simple RL algorithm is Q-Learning. It uses:

- A Q-Table that maps *state-action* pairs into numeric "quality" values

$$Q : S \times A \to \mathbb{R}$$

- Temporal Difference Learning, that accounts for the delayed future rewards as an effect of an action

$$Q^{new}(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \cdot [r_t + \gamma \cdot \max_a Q(s_{t+1}, a_t) - Q(s_t, a_t)]$$

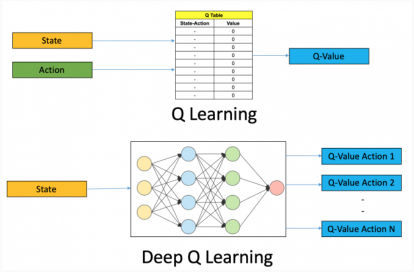
  where

  - s_t, a_t, r_t are the state, action and reward in the timestep t
  - α is the *learning rate*
  - γ is the *discount factor*

Deep-Q-Learning

Since traditional Q-Learning uses a table, it quickly becomes unfeasible as the observation space and action space increases. To solve this, **neural networks** are used to *approximate* the Q-Table.

The networks, instead of mapping state-action pairs into a single Q-Value, map states to **multiple Q-Values**, one for each action.



Deep-Q-Learning

To train the network, the loss function is defined as the *distance from the expected Q-Value and the prediction*:

$$L(\theta) = (\mathbb{E}_{s'}[r + \gamma \max_{a'} Q(s', a')] - Q(s, a, \theta))^2$$

The loss is computed using an experience memory that contains (s_i, a_i, r_i, s_{i+1}) tuples.

In this project the experiences stored inside the memory are sampled **randomly** with an uniform distribution.

Double Deep-Q-Learning

A variant of DQN, called Double Deep Q-Learning that reduces **bias overestimation** by:

- Using **two neural networks** with parameters θ and θ', alternating their roles
- A loss function using the second network to estimate the expected Q-Value

$$L(\theta) = (\mathbb{E}_{s'}[r + \gamma Q(s', \overline{a}|\theta')] - Q(s', a'|\theta))^2$$

$$\overline{a} = \arg\max_{a'} Q(s', a'|\theta)$$

- Periodically updating the first network with the parameters of the second, either with a full overwrite (hard update) or a weighted mean (soft update)

Policies

Policies are functions $\pi(a|s)$ that determine which actions to choose in a given state.

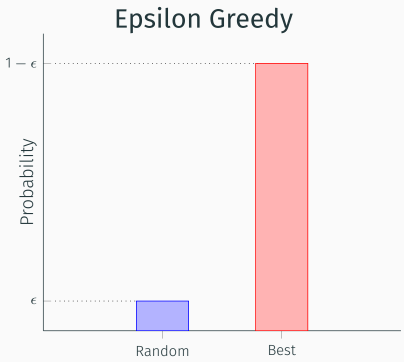
- **In testing** the action associated to the best Q-Value is always chosen
- **In training** the actions are chosen with a random probability, to explore novel strategies

Policies

We used three policies to test their performance in training speed:

- Epsilon Greedy Policy: selects a random with probability ϵ, otherwise the best action currently learnt
- Softmax: the Q-Values are normalized using the softmax-function and used as probabilities to select the action
- Boltzmann: a variation of softmax, which uses an hyper-parameter called *temperature* τ to modify the distribution.
    - Higher τ $\rightarrow$ more deviation (more spread)
    - Lower τ $\rightarrow$ less deviation (higher peaks)

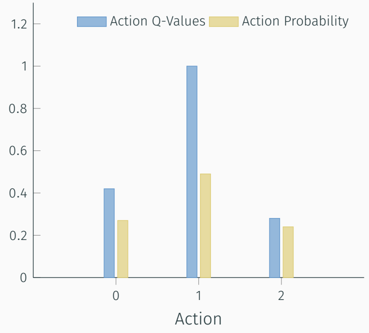
Policies



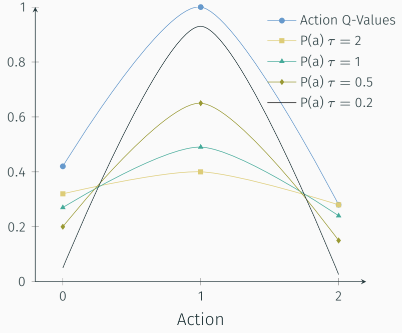
$$a = \begin{cases} \text{random action} & \text{if } r < \epsilon \\ \arg\max_a \; Q(s,a) & \text{if } r \geq \epsilon \end{cases}$$

Policies

Softmax



Boltzmann



$$P(a_i) = \frac{e^{Q(s,a_i)}}{\sum_a e^{Q(s,a)}}$$

$$P(a_i) = \frac{e^{Q(s,a_i)/\tau}}{\sum_a e^{Q(s,a)/\tau}}$$

Neural Networks

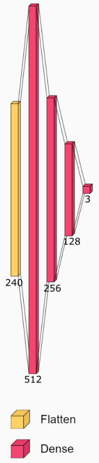
Sequential

In the project, all neural networks use a Sequential (Feed Forward) architecture.

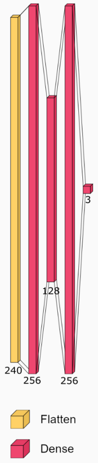
Three networks were designed, each with its own characteristics, to compare their performance:

Network	Parameters	Main Feature
seq1	288,003	Dense layers
seq2	128,387	Dense layers
conv1	7,551	Conv1D preprocessor + Dense layers

Dense

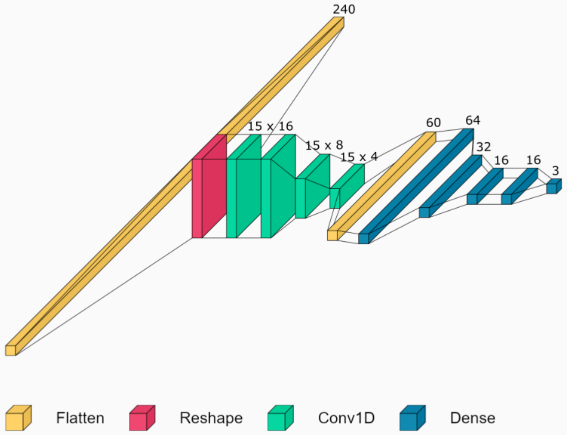


The *seq1* network structure



The *seq2* network structure

Convolutional 1D



The *conv1* network structure

Convolutional 1D

The main characteristics of the conv1 network are:

- The input is reshaped into a 15x16 matrix
- A series of 1D convolutional layers is used as a Preprocessor to reduce the dimension of the observation
- The reduced observations, representing the ”quality” of the network, are then used by a sequence of Dense layers to determine the final Q-Values

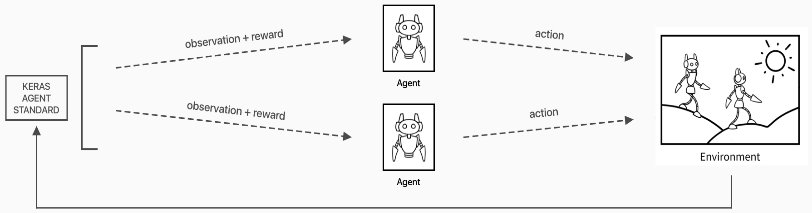
The advantage of this approach is a greatly reduced number of parameters, since the 1D convolution is parametrized only along one of its dimensions

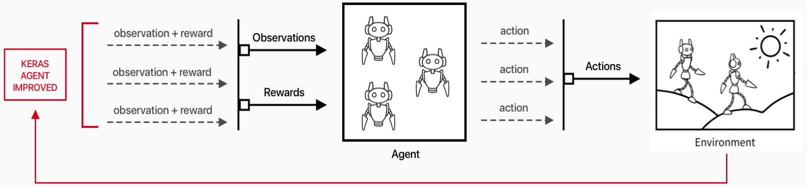
Implementation

Frameworks

	Keras-RL	TF-Agents	Tensorforce
custom-env	✓	✓	✓
custom-actions	✓	✓	✓
custom-memory	✓	-	-
framework-based	-	✓	✓
policies	✓	✓	-
callbacks	✓	-	-
DQN	✓	✓	✓
DDQN	✓	✓	✓
DDQN (dueling)	✓	-	✓
multi-actions	✓	-	-
multi-agents	-	-	-

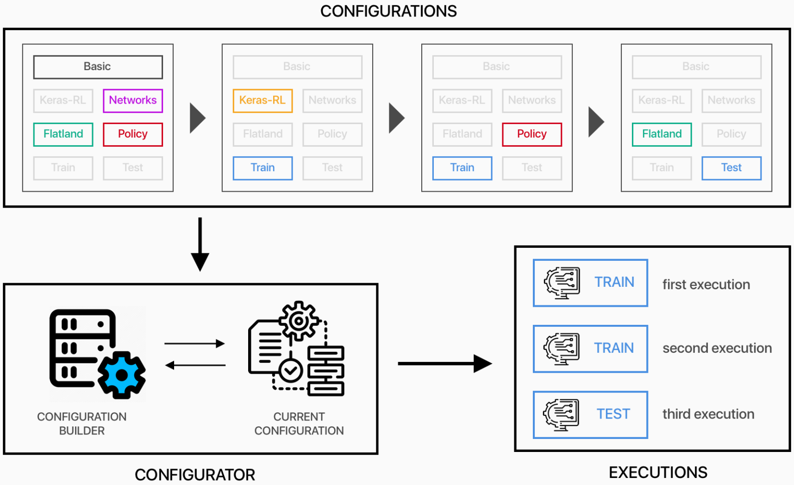
Keras-RL with Multi-Agent support





Configuration Of The Experiments

Baseline and Builder



Flatland

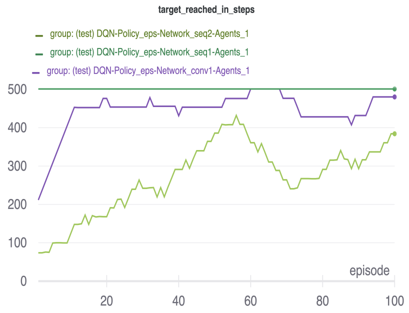
The static configuration of the Flatland environment used inside all the training/testing experiments is:

```
{
    "map_width": 28,
    "map_height": 21,
    "n_cities": 2,
    "max_rails_in_city": 4,
    "max_rails_between_cities": 4,
    "cities_grid_distribution": false,
    "malfunction_rate": 0.0001,
    "malfunction_min_duration": 1,
    "malfunction_max_duration": 5
}
```

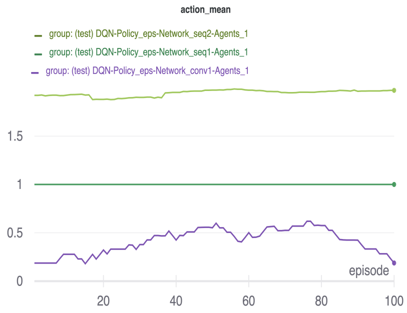
Analysis and Results

Networks

Evaluation of the three network **topologies**: seq1, seq2 and conv1, on 100 episodes of maximum 500 steps each.



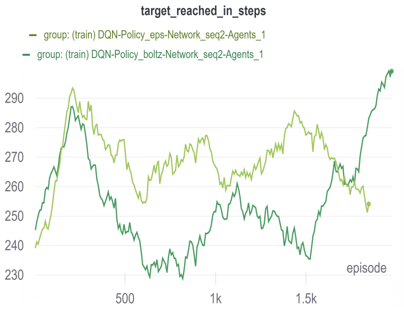
Number of steps to reach the target



Mean action value

Policies

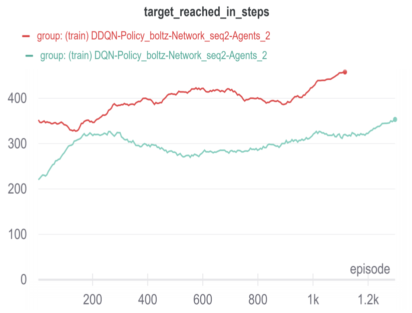
Training performance for the **policies**: Epsilon-Greedy and Boltzmann, using the *seq2* network, carried out over 500,000 training steps



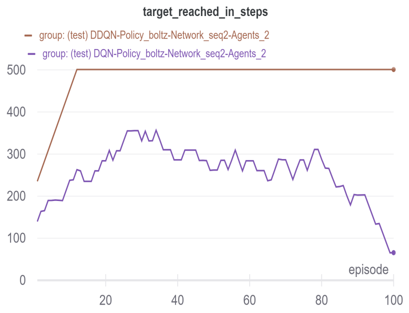
Number of steps to reach the target

RL Algorithms

Training and testing performance of DQN and DDQN, using the *seq2* network and *boltzmann* policy.
Training was carried out over 500,000 training steps and then tested on 100 episodes with 500 steps maximum each.



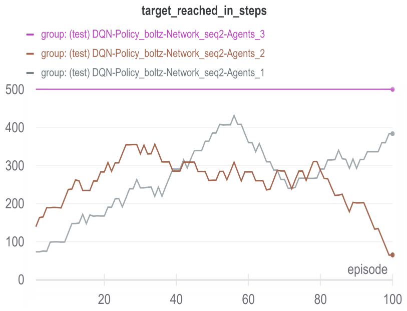
Training - Number of steps to reach the target



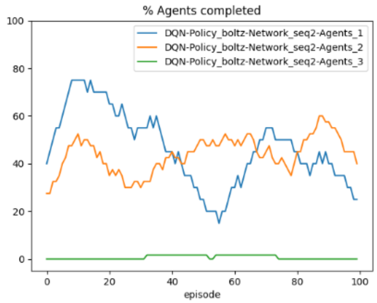
Testing - Number of steps to reach the target

Agents

Finally, to evaluate the performance in the multi-agent environment, a **DQN** with **seq2** network and **boltzmann** policy was tested in environment with one, two and three agents.
Testing was carried out over 100 episodes, of 500 steps each.



Number of steps (for each agent) to reach their target



Percentage of agents reaching their target

Conclusions

Improvements

Considering the power and ease of use of our custom JSON configurator, a number of improvements could be made using this project as a valid starting point:

- **Hyperparameter tuning** (learning rate, optimizer, policy parameters)
- **Policy annealing**
- Tuning the parameters and topology of the **1D Convolutional network**
- Using **prioritized experience** replay
- Different **environment** setup

Final Remarks

This project has been a wonderful opportunity to:

- Learn Reinforcement Learning and Deep Learning concepts in a first hands experience
- Understand that Deep Learning, particularly Reinforcement Learning, is a trial and error process that requires patience and perseverance
- Discover new libraries and resources
- Organize a team, making the best use of each of the member's strengths
- Think outside the box, to design and develop our own ideas to solve complex problems
- And many more!!

Thank you for your time and thanks for the opportunity!

- Davide, Manuel, Matteo