Exercise 3
OpenAI Gym

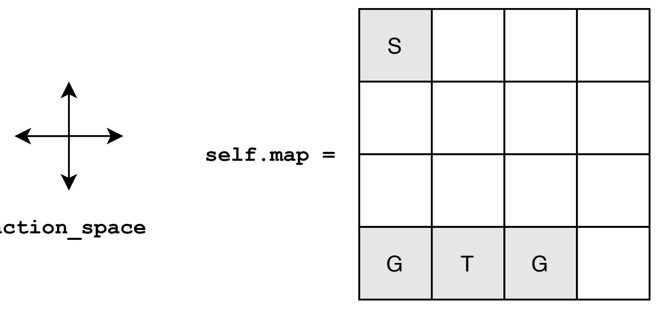
1 Gym Gridworld

The OpenAI Gym interface is a common standard for environments in reinforcement learning. It defines five methods that your environment has to implement. Providing the interface makes your environment compatible with nearly every RL framework out there (stable-baselines3, Tianshou, RLlib, ...).

The documentation can be found here:

- https://github.com/openai/gym
- https://gym.openai.com/docs

In this exercise you will implement an environment yourself based on the MDP definition that is stated below. a simple grid world, similar as in the last exercise:



$$R = \begin{cases} 1 & \text{if } s = G \\ -1 & \text{if } s = T \\ 0 & \text{else} \end{cases}$$

The agent starts in the cell marked **S**. At each time step the agent can step up, right, down, or left. If the agent reaches the goal (**G**), he receives a reward of 1, and the episode ends. If he falls into a trap (**T**), the episode ends with a reward of -1. Actions that would result in the agent leaving the board have no effect.

Programming Tasks:

1. `__init__()`. A `gym` environment has to define its action and state space via two members, `action_space` and `observation_space`. Define the appropriate spaces inside the constructor. Also, add a member for the current environment state and assign the start state to it.

2. `reset()`. To reset the environment it is required to implement a `reset()` method. This method should reset the environment state to a possible start state, and return the observation for this state.

3. `step(action)`. To simulate one time step, the method `step(action)` is called with the action of the agent. This method should simulate the environment dynamics and the agent's actions in one time step.

   `step(action)` should simulate one step in the environment and return a tuple `(observation, reward, done, info)` that describes the transition. `observation` is the information the agent perceives about the new state. `reward` is the reward that the agent is assigned in the new state. `done` is `True` if the next state is a terminal state, `False` otherwise. `info` is a list or dictionary that contains additional (debug) information about the environment – for this implementation, you can just return an empty dictionary ({}).

4. `render()`. This is a helper method that visualizes the current state in a human- or agent-readable way. In our case, this method should print an ascii-representation of the current map and agent.

5. `close()`. This method serves to free up any resources (file handles, sockets, ...) that your environment needs to operate. In our case, the provided implementation (`pass`) does not need to be adapted.

We encourage you to test your implementation to find potential errors and problems before continuing to the second exercise.

2 Temporal Difference Learning

TD-Learning is a technique that allows us to solve MDPs without access to the state transitions P. Your task is to implement a TD-Learning-Agent that solves the environment you implemented in Exercise 1. The file `td_agent.py` contains the skeleton code for this exercise. We supply testing code that deploys a random policy and visualizes the value function estimated through TD-learning implementation.

Programming Tasks

1. `learn(n_timesteps)`. This method currently implements `n_timesteps` of environment interaction via selecting a random action and deploying it in the environment. Implement TD-Learning and update the array `self.V` holding the current approximation at every time step. Run the script and examine the V-estimates.

2. **Policy** `action(s)`. Currently, this method implements a random policy. Manually implement a better policy (e.g., by mapping states to actions with a dictionary) and observe how the TD-estimate of V changes visually.