Exercise 3
Gymnasium and PyTorch

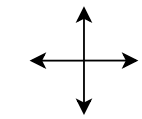
1 Gymnasium Gridworld

The Gymnasium/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 (stable-baselines3, Tianshou, RLlib, ...).

The documentation and further information can be found here:

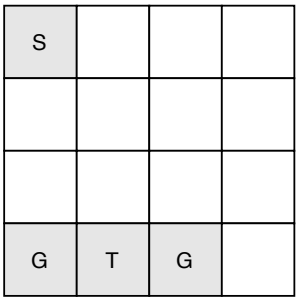
- `https://farama.org/Announcing-The-Farama-Foundation`
- `https://gymnasium.farama.org/`
- `https://github.com/Farama-Foundation/Gymnasium`

In this exercise, you will implement an environment based on the MDP definition. A simple grid world, similar to the last exercise, but with two different types of terminal states (two positives, **G**, and one negative **T**):



`action_space`

`self.map =`



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

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

3. `step(action)`. To simulate a one-time step, the method `step(action)` is called with the agent's action. 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, terminated, truncated, info)` that describes the transition. `observation` is the agent's perception of the new state. `reward` is the agent's reward in the new state. `terminal` is `True` if the next state is terminal, `False` otherwise. `truncated` can be neglegted for exercise an can be set to `False`. `info` is a list or dictionary that contains additional (debug) information about the environment – for this implementation, you can return an empty dictionary ({}).

4. `render()`. This helper method 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 frees 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.

Before continuing to the second exercise, we encourage you to test your implementation to find potential errors and problems. You can run the `env_test.py` file to execute random actions in your environment.

2 PyTorch

The deep learning framework PyTorch will form the basis of our implementations from this exercise onward. This week, we want you to get to know the framework on a simple supervised learning task. If you're already familiar with PyTorch, this exercise should be mostly familiar.

3 Setting up PyTorch

Install PyTorch to your local machine by following the instructions at `https://pytorch.org/get-started/locally/`. We recommend using Anaconda for the installation. You do not need to install CUDA, or use a GPU for this exercise.

Test your installation by creating a PyTorch `tensor` (equivalent to a numpy array) and printing it:

```
import torch
a = torch.arange(25)
a = a.reshape(5, 5)
print(a)
b = torch.tensor([1, 2, 3, 4, 5])

# Example 1
print(a * b)
# Example 2
print(a @ b)
```

What is the difference between examples 1 and 2?

4 Supervised Learning with Neural Networks in PyTorch

In this task, you will learn to train a simple classifier on the MNIST dataset. You can find documentation for the `torch.nn` module at `https://pytorch.org/docs/stable/nn.html`.

1. In the class 'Net', create a network with the following architecture:
   - Conv 2D (32 Channels, 3x3 Kernel, Stride 1)
   - ReLU
   - Conv 2D (64 Channels, 3x3 Kernel, Stride 1)
   - ReLU
   - Max Pool 2D (2x2 Kernel)
   - Fully Connected Layer ($9216 \Longrightarrow 128$)
   - ReLU
   - Fully Connected Layer ($128 \Longrightarrow 10$)
   - Softmax

   You'll need to create the appropriate members for your layers in `__init__` and perform the calculations in the `forward`-method. PyTorch will perform any needed gradient calculations for you.
2. Create an optimizer (e.g., `torch.optim.Adadelta`) for your model.
3. We already provide the basic outer training loop that will iterate over epochs and batches in `main`. Implement one step of prediction, loss computation (e.g. cross-entropy), gradient calculation, and optimization in the `train` and `test` methods.
4. Run the training. Your training and evaluation losses should decrease substantially.