# Abmarl

***Release 0.2.6***

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# CONTENTS

Abmarl is a package for developing Agent-Based Simulations and training them with MultiAgent Reinforcement Learning (MARL). We provide an intuitive command line interface for engaging with the full workflow of MARL experimentation: training, visualizing, and analyzing agent behavior. We define an *Agent-Based Simulation Interface* and *Simulation Manager*, which control which agents interact with the simulation at each step. We support *integration* with popular reinforcement learning simulation interfaces, including *gym.Env*, *MultiAgentEnv*, and *OpenSpiel*. We define our own *GridWorld Simulation Framework* for creating custom grid-based Agent Based Simulations.

Abmarl leverages RLlib's framework for reinforcement learning and extends it to more easily support custom simulations, algorithms, and policies. We enable researchers to rapidly prototype MARL experiments and simulation design and lower the barrier for pre-existing projects to prototype RL as a potential solution.

CHAPTER

# ONE

# WHAT'S NEW IN ABMARL

Abmarl version 0.2.6 features the new *Absolute Grid Observer*, which produces "top-down" observations of the grid "from the grid's perspective"; the *Maze Placement State* component for structuring the initial placement of agents within a grid while allowing for variation in each episode; and enhanced support for *buildling gridworld simulations*.

## 1.1 Absolute Grid Observer

The *Single and Multi Grid Observers* provide observations of the the grid centered on the observing agent, a view of the grid "from the agent's perspective". Abmarl's *Grid World Simulation Framework* now contains the *Absolute Grid Observer*, which produces observations of the grid "from the *grid's* perspective". The observation size matches the size of the grid, and the agent sees itself moving around the grid instead of seeing all the other agents positioned relative to itself.

Here we show the following state observations for the bottom-left red agent with a `view_range` of 2 via the *Single Grid Observer* and the new *Absolute Grid Observer*. The Single Grid Observation is sized by the agent's view range, the observing agent is in the very center, and all other cells are shown by their relative positions, including out of bounds cells. The Absolute Grid Observation is sized by the grid, all agents are shown in their actual grid positions, there are no out of bounds cells, and any cell that the agent cannot see is masked with a -2.

```
# Single Grid Observer, observing agent is shown here as *3
[ 0,  2,  2,  0,  2],
[ 0,  2,  0,  0,  0],
[ 0,  0, *3,  3,  0],
[ 0,  0,  0,  0,  0],
[-1, -1, -1, -1, -1],

# Absolute Grid Observer, observing agent is shown as -1
[-2, -2, -2, -2, -2, -2, -2],
[-2, -2, -2, -2, -2, -2, -2],
[-2, -2, -2, -2, -2, -2, -2],
[ 0,  2,  2,  0,  2, -2, -2],
[ 0,  2,  0,  0,  0, -2, -2],
[ 0,  0, -1,  3,  0, -2, -2],
[ 0,  0,  0,  0,  0, -2, -2]
```

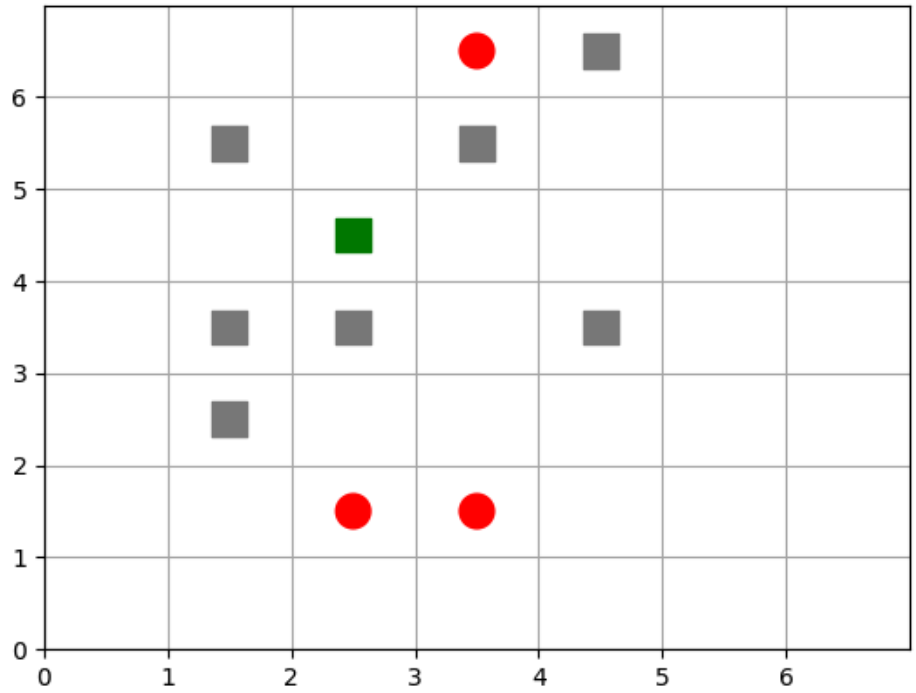


Fig. 1: Comparing observations for the bottom-left red agent with a `view_range` of 2. The green agent has an encoding of 1, the gray agents 2, and the red agents 3.

## 1.2 Maze Placement State

The *Position State* supports placing agents in the the grid either (1) according to their initial positions or (2) by randomly selecting an available cell. The new *Maze Placement State* supports more structure in initially placing agents. It starts by partitioning the grid into two types of cells, *free* or *barrier*, according to a maze that is generated starting at some *target agent's* position. Agents with *free encodings* and *barrier encodings* are then randomly placed in *free* cells and *barrier* cells, respectively. The Maze Placement State component can be configured such that it clusters *barrier* agents near the target and scatters *free* agents away from the target. The clustering is such that all paths to the target are not blocked. In this way, the grid can be randomized at the start of each episode, while still maintaining some desired structure.

## 1.3 Building a Gridworld Simulation

Abmarl's *Gridworld Simulation Framework* now supports *building the simulation* in these ways:

1. Building the simulation by specifying the rows, columns, and agents;
2. Building the simulation from an existing *grid*;
3. Building the simulation from an array and an object registry; and
4. Building the simulation from a file and an object registry.

Additionally, when building the simulation from a grid, array, or file, you can specify additional agents to build that are not in those inputs. The builder will combine the content from the grid, array, or file with the extra agents.

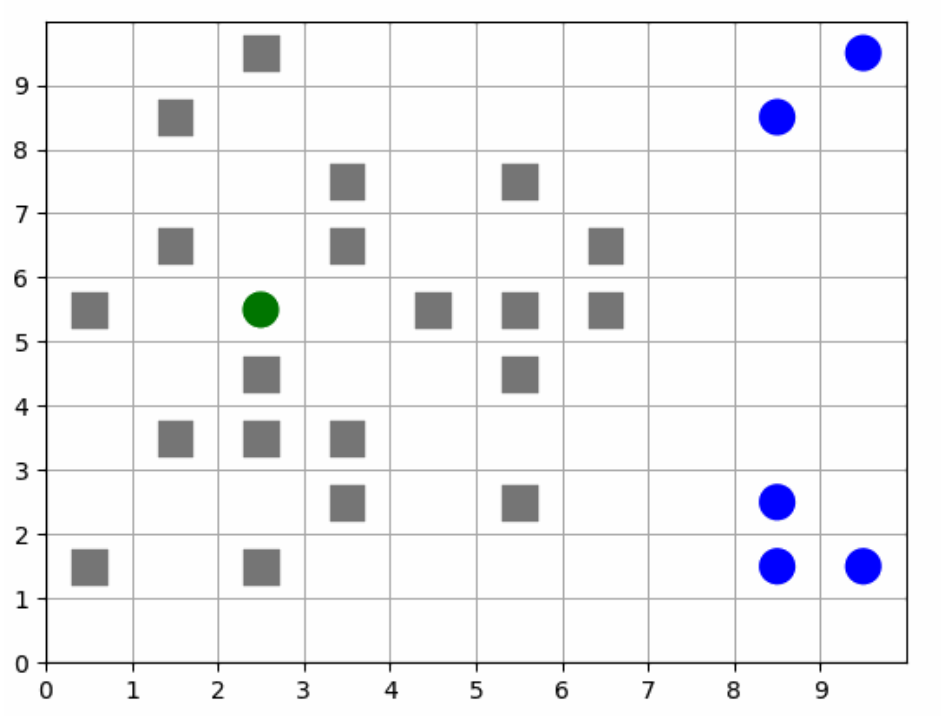


Fig. 2: Animation showing a target (green) starting at random positions at the beginning of each episode. Barriers (gray squares) are clustered near the target without blocking all paths to it. Free agents (blue) are scattered far from the target.

## 1.4 Miscellaneous

- New built-in *Target agent component* supports agents having a target agent with which they must overlap.
- New *Cross Move Actor* allows the agents to move up, down, left, right, or stay in place.
- The *All Step Manager* supports randomized ordering in the action dictionary.
- The *Position State* component supports ignoring the overlapping options during random placement. This results in agents being placed on unique cells.
- Abmarl's visualize component now supports the `--record-only` flag, which will save animations without displaying them on screen, useful for when running headless or processing in batch.
- Bugfix with the *Super Agent Wrapper* enables training with rllib 2.0.
- Abmarl now supports Python 3.9 and 3.10.
- Abmarl now supports gym 0.23.1.

CHAPTER

TWO

# DESIGN

A reinforcement learning experiment in Abmarl contains two interacting components: a Simulation and a Trainer.

The Simulation contains agent(s) who can observe the state (or a substate) of the Simulation and whose actions affect the state of the simulation. The simulation is discrete in time, and at each time step agents can provide actions. The simulation also produces rewards for each agent that the Trainer can use to train optimal behaviors. The Agent-Simulation interaction produces state-action-reward tuples (SARs), which can be collected in *rollout fragments* and used to optimize agent behaviors.

The Trainer contains policies that map agents' observations to actions. Policies are one-to-many with agents, meaning that there can be multiple agents using the same policy. Policies may be heuristic (i.e. coded by the researcher) or trainable by the RL algorithm.

In Abmarl, the Simulation and Trainer are specified in a single Python configuration file. Once these components are set up, they are passed as parameters to RLlib's tune command, which will launch the RLlib application and begin the training process. The training process will save checkpoints to an output directory, from which the user can visualize and analyze results. The following diagram demonstrates this workflow.

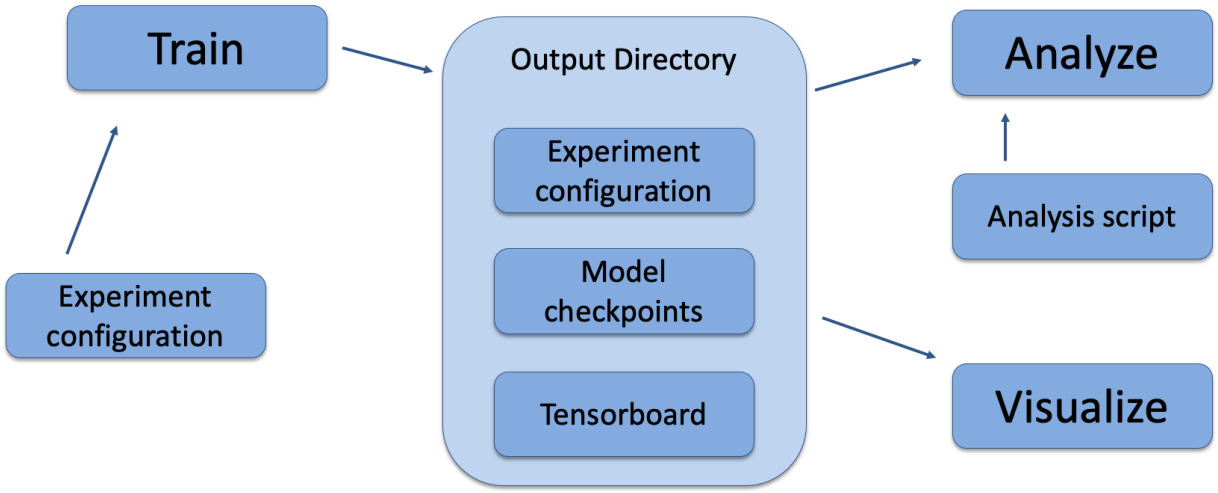


Fig. 1: Abmarl's usage workflow. An experiment configuration is used to train agents' behaviors. The policies and simulation are saved to an output directory. Behaviors can then be analyzed or visualized from the output directory.

## 2.1 Creating Agents and Simulations

Abmarl provides three interfaces for setting up agent-based simulations.

### 2.1.1 Agent

First, we have *Agents*. An agent is an object with an observation and action space. Many practitioners may be accustomed to *gym.Env's* interface, which defines the observation and action space for the *simulation*. However, in heterogeneous multiagent settings, each *agent* can have different spaces; thus we assign these spaces to the agents and not the simulation.

An agent can be created like so:

```
from gym.spaces import Discrete, Box
from abmarl.sim import Agent
agent = Agent(
    id='agent0',
    observation_space=Box(-1, 1, (2,)),
    action_space=Discrete(3),
    null_observation=[0, 0],
    null_action=0
)
```

At this level, the Agent is basically a dataclass. We have left it open for our users to extend its features as they see fit.

In Abmarl, agents who are *done* will be removed from the RL loop–they will no longer provide actions and no longer report observations and rewards. In some uses cases, such as when using the *SuperAgentWrapper* or running with *OpenSpiel*, agents continue in the loop even after they're done. To keep the training data from becoming contaminated, Abmarl provides the ability to specify a *null observation* and *null action* for each agent. These null points will be used in the rare case when a done agent is queried.

### 2.1.2 Agent Based Simulation

Next, we define an *Agent Based Simulation*, or ABS for short, with the ususal `reset` and `step` functions that we are used to seeing in RL simulations. These functions, however, do not return anything; the state information must be obtained from the getters: `get_obs`, `get_reward`, `get_done`, `get_all_done`, and `get_info`. The getters take an agent's id as input and return the respective information from the simulation's state. The ABS also contains a dictionary of agents that "live" in the simulation.

An Agent Based Simulation can be created and used like so:

```
from abmarl.sim import Agent, AgentBasedSimulation
class MySim(AgentBasedSimulation):
    def __init__(self, agents=None, **kwargs):
        self.agents = agents
     ... # Implement the ABS interface

# Create a dictionary of agents
agents = {f'agent{i}': Agent(id=f'agent{i}', ...) for i in range(10)}
# Create the ABS with the agents
sim = MySim(agents=agents)
sim.reset()
# Get the observations
```

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```
obs = {agent.id: sim.get_obs(agent.id) for agent in agents.values()}
# Take some random actions
sim.step({agent.id: agent.action_space.sample() for agent in agents.values()})
# See the reward for agent3
print(sim.get_reward('agent3'))
```

**Warning:** Implementations of AgentBasedSimulation should call `finalize` at the end of their `__init__`. Finalize ensures that all agents are configured and ready to be used for training.

**Note:** Instead of treating agents as dataclasses, we could have included the relevant information in the Agent Based Simulation with various dictionaries. For example, we could have `action_spaces` and `observation_spaces` that maps agents' ids to their action spaces and observation spaces, respectively. In Abmarl, we favor the dataclass approach and use it throughout the package and documentation.

### 2.1.3 Simulation Managers

The Agent Based Simulation interface does not specify an ordering for agents' interactions with the simulation. This is left open to give our users maximal flexibility. However, in order to interace with RLlib's learning library, we provide a *Simulation Manager* which specifies the output from `reset` and `step` as RLlib expects it. Specifically,

1. Agents that appear in the output dictionary will provide actions at the next step.
2. Agents that are done on this step will not provide actions on the next step.

Simulation managers are open-ended requiring only `reset` and `step` with output described above. For convenience, we have provided three managers: *Turn Based*, which implements turn-based games; *All Step*, which has every non-done agent provide actions at each step; and *Dynamic Order*, which allows the simulation to decide the agents' turns dynamically.

Simluation Managers "wrap" simulations, and they can be used like so:

```
from abmarl.managers import AllStepManager
from abmarl.sim import AgentBasedSimulation, Agent
class MySim(AgentBasedSimulation):
    ... # Define some simulation

# Instatiate the simulation
sim = MySim(agents=...)
# Wrap the simulation with the simulation manager
sim = AllStepManager(sim)
# Get the observations for all agents
obs = sim.reset()
# Get simulation state for all non-done agents, regardless of which agents
# actually contribute an action.
obs, rewards, dones, infos = sim.step({'agent0': 4, 'agent2': [-1, 1]})
```

**Warning:** The *Dynamic Order Manager* must be used with a *Dynamic Order Simulation*. This allows the simulation to dynamically choose the agents' turns, but it also requires the simulation to pay attention to the interface

rules. For example, a Dynamic Order Simulation must ensure that at every step there is at least one reported agent who is not done, unless it is the last turn, which the other managers handle automatically.

### 2.1.4 Wrappers

*Agent Based Simulations* can be *wrapped* to modify incoming and outgoing data. Abmarl's *Wrappers* are themselves *AgentBasedSimulations* and provide an additional *unwrapped* property that cascades through potentially many layers of wrapping to get the original, unwrapped simulation. Abmarl supports several built-in wrappers.

#### Ravel Discrete Wrapper

The *RavelDiscreteWrapper* converts observation and action spaces into Discrete spaces and automatically maps data to and from those spaces. It can convert Discrete, MultiBinary, MultiDiscrete, bounded integer Box, and any nesting of these observations and actions into Discrete observations and actions by *ravelling* their values according to numpy's *ravel_mult_index* function. Thus, observations and actions that are represented by (nested) arrays are converted into unique scalars. For example, see how the following nested space is ravelled to a Discrete space:

```
from gym.spaces import Dict, MultiBinary, MultiDiscrete, Discrete, Box, Tuple
import numpy as np
from abmarl.sim.wrappers.ravel_discrete_wrapper import ravel_space, ravel
my_space = Dict({
    'a': MultiDiscrete([5, 3]),
    'b': MultiBinary(4),
    'c': Box(np.array([[-2, 6, 3],[0, 0, 1]]), np.array([[2, 12, 5],[2, 4, 2]]),␣
↪dtype=int),
    'd': Dict({
        1: Discrete(3),
        2: Box(1, 3, (2,), int)
    }),
    'e': Tuple((
        MultiDiscrete([4, 1, 5]),
        MultiBinary(2),
        Dict({
            'my_dict': Discrete(11)
        })
    )),
    'f': Discrete(6),
})
point = {
    'a': [3, 1],
    'b': [0, 1, 1, 0],
    'c': np.array([[0, 7, 5],[1, 3, 1]]),
    'd': {1: 2, 2: np.array([1, 3])},
    'e': ([1,0,4], [1, 1], {'my_dict': 5}),
    'f': 1
}
ravel_space(my_space)
>>> Discrete(107775360000)
ravel(my_space, point)
>>> 74748022765
```

**Warning:** Some complex spaces have very high dimensionality. The *RavelDiscreteWrapper* was designed to work with tabular RL algorithms, and may not be the best choice for simulations with such complex spaces. Some RL libraries convert the Discrete space into a one-hot encoding layer, which is not possible for a very high-dimensional space. In these situations, it is better to either rely on the RL library's own processing or use Abmarl's *FlattenWrapper*.

### Flatten Wrapper

The *FlattenWrapper* flattens observation and action spaces into Box spaces and automatically maps data to and from it. The FlattenWrapper attempts to keep the *dtype* of the resulting Box space as integer if it can; otherwise it will cast up to float. See how the following nested space is flattened:

```
my_space = Dict({
    'a': MultiDiscrete([5, 3]),
    'b': MultiBinary(4),
    'c': Box(np.array([[-2, 6, 3],[0, 0, 1]]), np.array([[2, 12, 5],[2, 4, 2]]),␣
↪dtype=int),
    'd': Dict({
        1: Discrete(3),
        2: Box(1, 3, (2,), int)
    }),
    'e': Tuple((
        MultiDiscrete([4, 1, 5]),
        MultiBinary(2),
        Dict({
            'my_dict': Discrete(11)
        })
    )),
    'f': Discrete(6),
})
point = {
    'a': [3, 1],
    'b': [0, 1, 1, 0],
    'c': np.array([[0, 7, 5],[1, 3, 1]]),
    'd': {1: 2, 2: np.array([1, 3])},
    'e': ([1,0,4], [1, 1], {'my_dict': 5}),
    'f': 1
}
flatten_space(my_space)
>>> Box(low=[0, 0, 0, 0, 0, 0, -2, 6, 3, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0],
        high=[4, 2, 1, 1, 1, 1, 2, 12, 5, 2, 4, 2, 2, 3, 3, 3, 0, 4, 1, 1, 10, 5],
        (22,),
        int64) # We maintain the integer type instead of needlessly casting to float.
flatten(my_space, point)
>>> array([3, 1, 0, 1, 1, 0, 0, 7, 5, 1, 3, 1, 2, 1, 3, 1, 0, 4, 1, 1, 5, 1])
```

Because every subspace has integer type, the resulting Box space has dtype integer.

**Warning:** Sampling from the flattened space will not produce the same results as sampling from the original space and then flattening. There may be an issue with casting a float to an integer. Furthermore, the distribution of points

when sampling is not uniform in the original space, which may skew the learning process. It is best practice to first generate samples using the original space and then to flatten them as needed.

### Super Agent Wrapper

The *SuperAgentWrapper* creates *super* agents who *cover* and control multiple agents in the simulation. The super agents concatenate the observation and action spaces of all their covered agents. In addition, the observation space is given a *mask* channel to indicate which of their covered agents is done. This channel is important because the simulation dynamics change when a covered agent is done but the super agent may still be active. Without this mask, the super agent would experience completely different simulation dynamics for some of its covered agents with no indication as to why.

Unless handled carefully, the super agent will report observations for done covered agents. This may contaminate the training data with an unfair advantage. For example, a dead covered agent should not be able to provide the super agent with useful information. In order to correct this, the user may supply a *null observation* for an *ObservingAgent*. When a covered agent is done, the *SuperAgentWrapper* will try to use its null observation going forward.

A super agent's reward is the sum of its covered agents' rewards. This is also a point of concern because the simulation may continue generating rewards or penalties for done agents. Therefore when a covered agent is done, the *SuperAgentWrapper* will report a reward of zero for done agents so as to not contaminate the reward for the super agent.

Furthermore, super agents may still report actions for covered agents that are done. The *SuperAgentWrapper* filters out those actions before passing the action dict to the underlying sim.

Finally a super agent is considered done when *all* of its covered agents are done.

To use the *SuperAgentWrapper*, simply provide a *super_agent_mapping*, which maps the super agent's id to a list of covered agents, like so:

```
AllStepManager(
    SuperAgentWrapper(
        TeamBattleSim.build_sim(
            8, 8,
            agents=agents,
            overlapping=overlap_map,
            attack_mapping=attack_map
        ),
        super_agent_mapping = {
            'red': [agent.id for agent in agents.values() if agent.encoding == 1],
            'blue': [agent.id for agent in agents.values() if agent.encoding == 2],
            'green': [agent.id for agent in agents.values() if agent.encoding == 3],
            'gray': [agent.id for agent in agents.values() if agent.encoding == 4],
        }
    )
)
```

Check out the Super Agent Team Battle example for more details.

### 2.1.5 External Integration

Abmarl supports integration with several training libraries through its external wrappers. Each wrapper automatically handles the interaction between the external library and the underlying simulation.

#### OpenAI Gym

The *GymWrapper* can be used for simulations with a single *learning agent*. This wrapper allows integration with OpenAI's *gym.Env* class with which many RL practitioners are familiar, and many RL libraries support it. There are no restrictions on the number of entities in the simulation, but there can only be a *single* learning agent. The *observation space* and *action space* is then inferred from that agent. The *reset* and *step* functions operate on the values themselves as opposed to a dictionary mapping the agents' ids to the values.

#### RLlib MultiAgentEnv

The *MultiAgentWrapper* can be used for multi-agent simulations and connects with RLlib's *MultiAgentEnv* class. This interface is very similar to Abmarl's *Simulation Manager*, and the featureset and data format is the same between the two, so the wrapper is mostly boilerplate. It does explictly expose a set *agent_ids*, an *observation space* dictionary mapping the agent ids to their observation spaces, and an *action space* dictionary that does the same.

#### OpenSpiel Environment

The *OpenSpielWrapper* enables integration with OpenSpiel. OpenSpiel support turn-based and simultaneous simulations, which Abmarl provides through its *TurnBasedManager* and *AllStepManager*. OpenSpiel algorithms interact with the simulation through *TimeStep* objects, which include the observations, rewards, and step type. Among the observations, it expects a list of legal actions available to each agent. The OpenSpielWrapper converts output from the underlying simulation to the expected format. A TimeStep output typically looks like this:

```
TimeStpe(
    observations={
        info_state: {agent_id: agent_obs for agent_id in agents},
        legal_actions: {agent_id: agent_legal_actions for agent_id in agents},
        current_player: current_agent_id
    }
    rewards={
        {agent_id: agent_reward for agent_id in agents}
    }
    discounts={
        {agent_id: agent_discout for agent_id in agents}
    }
    step_type=StepType enum
)
```

Furthermore, OpenSpiel provides actions as a list. The *OpenSpielWrapper* converts those actions to a dict before forwarding it to the underlying simulation manager.

OpenSpiel does *not* support the ability for some agents in a simulation to finish before others. The simulation is either ongoing, in which all agents are providing actions, or else it is done for all agents. In contrast, Abmarl allows some agents to be done before others as the simulation progresses. Abmarl expects that done agents will not provide actions. OpenSpiel, however, will always provide actions for all agents. The *OpenSpielWrapper* removes the actions from agents that are already done before forwarding the action to the underlying simulation manager. Furthermore, OpenSpiel expects every agent to be present in the TimeStep outputs. Normally, Abmarl will not provide output for

agents that are done since they have finished generating data in the episode. In order to work with OpenSpiel, the OpenSpielWrapper forces output from all agents at every step, including those already done.

**Warning:** The *OpenSpielWrapper* only works with simulations in which the action and observation space of every agent is Discrete. Most simulations will need to be wrapped with the *RavelDiscreteWrapper*.

## 2.2 Training with an Experiment Configuration

In order to run experiments, we must define a configuration file that specifies Simulation and Trainer parameters. Here is the configuration file from the *Corridor tutorial* that demonstrates a simple corridor simulation with multiple agents.

```
# Import the MultiCorridor ABS, a simulation manager, and the multiagent
# wrapper needed to connect to RLlib's trainers
from abmarl.examples import MultiCorridor
from abmarl.managers import TurnBasedManager
from abmarl.external import MultiAgentWrapper

# Create and wrap the simulation
# NOTE: The agents in `MultiCorridor` are all homogeneous, so this simulation
# just creates and stores the agents itself.
sim = MultiAgentWrapper(TurnBasedManager(MultiCorridor()))

# Register the simulation with RLlib
sim_name = "MultiCorridor"
from ray.tune.registry import register_env
register_env(sim_name, lambda sim_config: sim)

# Set up the policies. In this experiment, all agents are homogeneous,
# so we just use a single shared policy.
ref_agent = sim.unwrapped.agents['agent0']
policies = {
    'corridor': (None, ref_agent.observation_space, ref_agent.action_space, {})
}
def policy_mapping_fn(agent_id):
    return 'corridor'

# Experiment parameters
params = {
    'experiment': {
        'title': f'{sim_name}',
        'sim_creator': lambda config=None: sim,
    },
    'ray_tune': {
        'run_or_experiment': 'PG',
        'checkpoint_freq': 50,
        'checkpoint_at_end': True,
        'stop': {
            'episodes_total': 2000,
        },
        'verbose': 2,
```

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```
        'local_dir': 'output_dir',
        'config': {
            # --- simulation ---
            'disable_env_checking': False,
            'env': sim_name,
            'horizon': 200,
            'env_config': {},
            # --- Multiagent ---
            'multiagent': {
                'policies': policies,
                'policy_mapping_fn': policy_mapping_fn,
            },
            # --- Parallelism ---
            "num_workers": 7,
            "num_envs_per_worker": 1,
        },
    }
}
```

**Warning:** The simulation must be a *Simulation Manager* or an *External Wrapper* as described above.

**Note:** This example has `num_workers` set to 7 for a computer with 8 CPU's. You may need to adjust this for your computer to be *<cpu count> - 1*.

### 2.2.1 Experiment Parameters

The strucutre of the parameters dictionary is very important. It *must* have an *experiment* key which contains both the *title* of the experiment and the *sim_creator* function. This function should receive a config and, if appropriate, pass it to the simulation constructor. In the example configuration above, we just return the already-configured simulation. Without the title and simulation creator, Abmarl may not behave as expected.

The experiment parameters also contains information that will be passed directly to RLlib via the *ray_tune* parameter. See RLlib's documentation for a list of common configuration parameters.

### 2.2.2 Command Line

With the configuration file complete, we can utilize the command line interface to train our agents. We simply type `abmarl train multi_corridor_example.py`, where *multi_corridor_example.py* is the name of our configuration file. This will launch Abmarl, which will process the file and launch RLlib according to the specified parameters. This particular example should take 1-10 minutes to train, depending on your compute capabilities. You can view the performance in real time in tensorboard with `tensorboard --logdir <local_dir>/abmarl_results`.

**Note:** By default, the "base" of the output directory is the home directory, and Abmarl will create the *abmarl_results* directory there. The base directory can by configured in the *params* under *ray_tune* using the *local_dir* parameter. This value can be a full path, like `'local_dir': '/usr/local/scratch'`, or it can be a relative path, like

`'local_dir': output_dir`, where the path is relative from the directory where Abmarl was launched, not from the configuration file. If a path is given, the output will be under `<local_dir>/abmarl_results`.

## 2.3 Debugging

It may be useful to trial run a simulation after setting up a configuration file to ensure that the simulation mechanics work as expected. Abmarl's `debug` command will run the simulation with random actions and create an output directory, wherein it will copy the configuration file and output the observations, actions, rewards, and done conditions for each step. The data from each episode will be logged to its own file in the output directory, where the output directory is configured as above. For example, the command

```
abmarl debug multi_corridor_example.py -n 2 -s 20 --render
```

will run the *MultiCorridor* simulation with random actions and output log files to the directory it creates for 2 episodes and a horizon of 20, as well as render each step in each episode.

Check out the debugging example to see how to debug within a python script.

## 2.4 Visualizing

We can visualize the agents' learned behavior with the `visualize` command, which takes as argument the output directory from the training session stored in `~/abmarl_results`. For example, the command

```
abmarl visualize ~/abmarl_results/MultiCorridor-2020-08-25_09-30/ -n 5 --record
```

will load the experiment (notice that the directory name is the experiment title from the configuration file appended with a timestamp) and display an animation of 5 episodes. The `--record` flag will save the animations as *.gif* animations in the training directory.

By default, each episode has a *horizon* of 200 steps (i.e. it will run for up to 200 steps). It may end earlier depending on the *done* condition from the simulation. You can control the *horizon* with `-s` or `--steps-per-episode` when running the visualize command.

Using the `--record` flag will not only save the animations, but it will also play them live. The `--record-only` flag is useful when you only want to save the animations, such as if you're running headless or processing results in batch.

## 2.5 Analyzing

The simulation and trainer can also be loaded into an analysis script for post-processing via the `analyze` command. The analysis script must implement the following *run* function. Below is an example that can serve as a starting point.

```
# Load the simulation and the trainer from the experiment as objects
def run(sim, trainer):
    """
    Analyze the behavior of your trained policies using the simulation and trainer
    from your RL experiment.

    Args:
        sim:
```

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```
            Simulation Manager object from the experiment.
        trainer:
            Trainer that computes actions using the trained policies.
    """
    # Run the simulation with actions chosen from the trained policies
    policy_agent_mapping = trainer.config['multiagent']['policy_mapping_fn']
    for episode in range(100):
        print('Episode: {}'.format(episode))
        obs = sim.reset()
        done = {agent: False for agent in obs}
        while True: # Run until the episode ends
            # Get actions from policies
            joint_action = {}
            for agent_id, agent_obs in obs.items():
                if done[agent_id]: continue # Don't get actions for done agents
                policy_id = policy_agent_mapping(agent_id)
                action = trainer.compute_action(agent_obs, policy_id=policy_id)
                joint_action[agent_id] = action
            # Step the simulation
            obs, reward, done, info = sim.step(joint_action)
            if done['__all__']:
                break
```

Analysis can then be performed using the command line interface:

```
abmarl analyze ~/abmarl_results/MultiCorridor-2020-08-25_09-30/ my_analysis_script.py
```

## 2.6 Trainer Prototype

Abmarl provide an initial prototype of its own *Trainer* framework to support in-house algorithm development. Trainers manage the interaction between policies and agents in a simulation. Abmarl currently supports a *MultiPolicyTrainer*, which allows each agent to have its own policy, and a *SinglePolicyTrainer*, which allows for a single policy shared among multiple agents. The trainer abstracts the data generation process behind its *generate_episode* function. The simulation reports an initial observation, which the trainer feeds through its policies according to the *policy_mapping_fn*. These policies return actions, which the trainer uses to step the simulation forward. Derived trainers overwrite the *train* function to implement the RL algorithm. For example, a custom trainer would look something like this:

```
class MyCustomTrainer(SinglePolicyTrainer):
    def train(self, iterations=10, gamma=0.9, **kwargs):
        for _ in range(iterations):
            states, actions, rewards, _ = self.generate_episode(**kwargs)
            self.policy.update(states, actions, rewards)
            # Perform some kind of policy update ^
```

Abmarl currently supports a *Monte Carlo Trainer* and a *Debug Trainer*, which is used by `abmarl debug` command line interface.

**Note:** Abmarl's trainer framework is in its early design stages. Stay tuned for more developments.

CHAPTER

THREE

# GRIDWORLD SIMULATION FRAMEWORK

Abmarl provides a GridWorld Simulation Framework for setting up grid-based Agent Based Simulations, which can be connected to Reinforcement Learning algorithms through Abmarl's *AgentBasedSimulation* interface. The GridWorld Simulation Framework is a *gray box*: we assume users have working knowledge of Python and object-oriented programming. Using the *built in features* requires minimal knowledge, but extending them and creating new features requires more knowledge. In addition to the design documentation below, see the *GridWorld tutorials* for in-depth examples on using and extending the GridWorld Simulation Framework.

## 3.1 Framework Design

The GridWorld Simulation Framework utilizes a modular design that allows users to create new features and plug them in as components of the simulation. Every component inherits from the *GridWorldBaseComponent* class and has a reference to a *Grid* and a dictionary of *Agents*. These components make up a *GridWorldSimulation*, which extends the *AgentBasedSimulation* interface. For example, a simulation might look something like this:

```
from abmarl.sim.gridworld.base import GridWorldSimulation
from abmarl.sim.gridworld.state import PositionState
from abmarl.sim.gridworld.actor import MoveActor
from abmarl.sim.gridworld.observer import SingleGridObserver

class MyGridSim(GridWorldSimulation):
    def __init__(self, **kwargs):
        self.agents = kwargs['agents']
        self.position_state = PositionState(**kwargs)
        self.move_actor = MoveActor(**kwargs)
        self.observer = SingleGridObserver(**kwargs)

    def reset(self, **kwargs):
        self.position_state.reset(**kwargs)

    def step(self, action_dict):
        for agent_id, action in action_dict.items():
            self.move_actor.process_action(self.agents[agent_id], action)

    def get_obs(self, agent_id, **kwargs):
        return self.observer.get_obs(self.agents[agent_id])
    ...
```

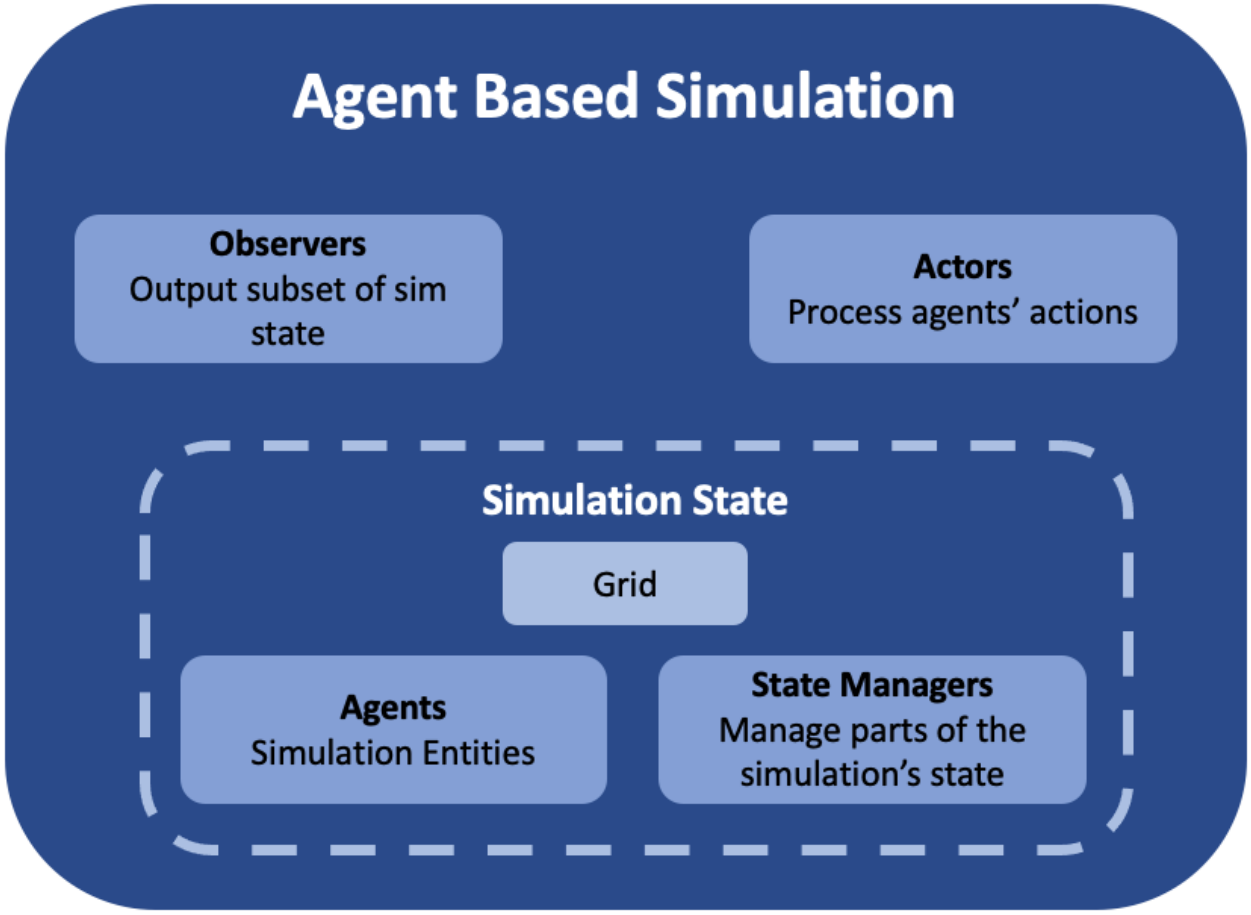


Fig. 1: Abmarl's GridWorld Simulation Framework. A simulation has a Grid, a dictionary of agents, and various components that manage the various features of the simulation. The componets shown in medium-blue are user-configurable and -creatable.

### 3.1.1 Agent

Every entity in the simulation is a *GridWorldAgent* (e.g. walls, foragers, resources, fighters, etc.). GridWorldAgents are *PrincipleAgents* with specific parameters that work with their respective components. Agents must be given an *encoding*, which is a positive integer that correlates to the type of agent and simplifies the logic for many components of the framework. GridWorldAgents can also be configured with an *initial position*, the ability to *block* other agents' abilities, and visualization parameters such as *shape* and *color*.

Following the dataclass model, additional agent classes can be defined that allow them to work with various components. For example, *GridObservingAgents* can work with *Observers*, and *MovingAgents* can work with the *MoveActor*. Any new agent class should inhert from *GridWorldAgent* and possibly from *ActingAgent* or *ObservingAgent* as needed. For example, one can define a new type of agent like so:

```
from abmarl.sim.gridworld.agent import GridWorldAgent
from abmarl.sim import ActingAgent

class CommunicatingAgent(GridWorldAgent, ActingAgent):
    def __init__(self, broadcast_range=None, **kwargs):
        super().__init__(**kwargs)
        self.broadcast_range = broadcast_range
        ...
```

**Warning:** Agents should follow the dataclass model, meaning that they should only be given parameters. All functionality should be written in the simulation components.

### 3.1.2 Grid

The *Grid* stores *Agents* in a two-dimensional numpy array. The Grid is configured to be a certain size (rows and columns) and to allow types of Agents to overlap (occupy the same cell). For example, you may want a ForagingAgent to be able to overlap with a ResourceAgent but not a WallAgent. The *overlapping* parameter is a dictionary that maps the Agent's *encoding* to a set of other Agents' *encodings* with which it can overlap. For example,

```
from abmarl.sim.gridworld.grid import Grid

overlapping = {
    1: {2},
    2: {1, 3},
    3: {2, 3}
}
grid = Grid(5, 6, overlapping=overlapping)
```

means that agents whose *encoding* is 1 can overlap with other agents whose *encoding* is 2; agents whose *encoding* is 2 can overlap with other agents whose *encoding* is 1 or 3; and agents whose *encoding* is 3 can overlap with other agents whose *encoding* is 2 or 3.

**Note:** If *overlapping* is not specified, then no agents will be able to occupy the same cell in the Grid.

Interaction between simulation components and the *Grid* is *data open*, which means that we allow components to access the internals of the Grid. Although this is possible and sometimes necessary, the Grid also provides an interface for safer interactions with components. Components can *query* the Grid to see if an agent can be placed at a specific position. Components can *place* agents at a specific position in the Grid, which will succeed if that cell is available

to the agent as per the *overlapping* configuration. And Components can *remove* agents from specific positions in the Grid.

### 3.1.3 State

*State Components* manage the state of the simulation alongside the *Grid*. At the bare minimum, each State resets the part of the simulation that it manages at the the start of each episode.

### 3.1.4 Actor

*Actor Components* are responsible for processing agent actions and producing changes to the state of the simulation. Actors assign supported agents with an appropriate action space and process agents' actions based on the Actor's key. The result of the action is a change in the simulation's state, and Actors should return that change in a reasonable form. For example, the *MoveActor* appends *MovingAgents'* action spaces with a 'move' channel and looks for the 'move' key in the agent's incoming action. After a move is processed, the MoveActor returns if the move was successful.

### 3.1.5 Observer

*Observer Components* are responsible for creating an agent's observation of the state of the simulation. Observers assign supported agents with an appropriate observation space and generate observations based on the Observer's key. For example, the *SingleGridObserver* generates an observation of the nearby grid and stores it in the 'grid' channel of the *ObservingAgent's* observation.

### 3.1.6 Done

*Done Components* manage the "done state" of each agent and of the simulation as a whole. Agents that are reported as done will cease sending actions to the simulation, and the episode will end when all the agents are done or when the simulation is done.

### 3.1.7 Component Wrappers

The GridWorld Simulation Framework also supports *Component Wrappers*. Wrapping a component can be useful when you don't want to add a completely new component and only need to make a modification to the way a component already works. A component wrapper is itself a component, and so it must implement the same interface as the wrapped component to ensure that it works within the framework. A component wrapper also defines additional functions for wrapping spaces and data to and from those spaces: `check_space` for ensuring the space can be transformed, `wrap_space` to perform the transformation, `wrap_point` to map data to the transformed space, and `unwrap_point` to map transformed data back to the original space.

As its name suggests, a *Component Wrapper* stands between the underlying component and other objects with which it exchanges data. As such, a wrapper typically modifies the incoming/outgoing data before leveraging the underlying component for the actual datda processing. The main difference among wrapper types is in the direction of data flow, which we detail below.

#### Actor Wrappers

*Actor Wrappers* receive actions in the *wrapped_space* through the `process_action` function. It can modify the data before sending it to the underlying Actor to process. An Actor Wrapper may need to modify the action spaces of corresponding agents to ensure that the action arrives in the correct format.

### 3.1.8 Building the Simulation

The *GridWorldSimluation* supports various methods of building a defined simulation. Each builder takes arguments specific to the builder. Additional arguments can be provided, and will be forwarded to the simulation for use in its components, for example.

#### Build Sim

Users can build a simulation by supplying the number of rows, columns, and a dictionary of agents. The grid is initialized to the specified size and populated using information contained in the agents dictionary in conjunction with the simulation's state components. For example, the following simulation is built using information just from the dictionary of agents:

```
import numpy as np
from abmarl.examples.sim import MultiAgentGridSim
from abmarl.sim.gridworld.agent import GridWorldAgent

agent = GridWorldAgent(id='agent0', encoding=1, initial_position=np.array([0, 0]))
sim = MultiAgentGridSim.build_sim(
    3, 4,
    agents={'agent0': agent}
)
sim.reset()
```

This simulation has a grid of size `(3 x 4)` with a single agent with encoding 1 placed at position `(0, 0)`.

#### Build Sim From Grid

Users can build a simulation by copying from an existing *grid*. The builder will use the state of the grid as the initial state for the new grid for the simulation. Particularly, agents will be assigned initial positions based on their positions within the input grid. Extra agents can be included in the simulation via the `extra_agents` argument. For example, the following simulation is built using a pre-defined grid and extra agents:

```
import numpy as np
from abmarl.examples.sim import MultiAgentGridSim
from abmarl.sim.gridworld.agent import GridWorldAgent
from abmarl.sim.gridworld.grid import Grid

grid = Grid(2, 2)
grid.reset()
agents = {
    'agent0': GridWorldAgent(id='agent0', encoding=1, initial_position=np.array([0, 0])),
    'agent1': GridWorldAgent(id='agent1', encoding=1, initial_position=np.array([0, 1])),
    'agent2': GridWorldAgent(id='agent2', encoding=1, initial_position=np.array([1, 0])),
}
```

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```
grid.place(agents['agent0'], (0, 0))
grid.place(agents['agent1'], (0, 1))
grid.place(agents['agent2'], (1, 0))

extra_agents = {
    'agent0': GridWorldAgent(id='agent0', encoding=2, initial_position=np.array([0, 1])),
    'agent3': GridWorldAgent(id='agent3', encoding=3, initial_position=np.array([0, 1])),
    'agent4': GridWorldAgent(id='agent4', encoding=4, initial_position=np.array([1, 0])),
    'agent5': GridWorldAgent(id='agent5', encoding=5),
}

sim = MultiAgentGridSim.build_sim_from_grid(
    grid,
    extra_agents=extra_agents,
    overlapping={1: {3, 4}, 3: {1}, 4: {1}}
)
sim.reset()
```

This simulation has a grid of size `(2 x 2)`. Agents 0-2 are positioned in the new grid according to their configuration in the original grid. Agents 3-5 are provided as extra agents, not from the original grid. Agent0 appears as both an extra agent and an agent in the original grid. If this happens, the builder prioritizes using the agent as it exist in the original grid.

---

**Note:** In the example above, the builder itself does not use the `overlapping` argument. That is passed on to the simulation.

---

---

**Note:** For consistency, the agents from the input grid should have their position in the grid as their `initial_position`.

---

**Caution:** The agents from the input grid are shallow-copied.

### Build Sim From Array

Users can build a simulation by populating a grid based on an array. The array must be 2-dimensional and contain alphanumeric characters corresponding to entries in an object registry. The object registry is a dictionary that maps those entries to agent-building functions, assigning each agent a unique id. Agents will be placed within the grid according to its position in the array. As above, extra agents can be included. The following simulation is built using an array, object registry, and extra agents:

```
import numpy as np
from abmarl.examples.sim import MultiAgentGridSim
from abmarl.sim.gridworld.agent import GridWorldAgent

array = np.array([
    ['A', '.', 'B', '0', ''],
    ['B', '_', '', 'C', 'A']
])
```

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```
obj_registry = {
    'A': lambda n: GridWorldAgent(
        id=f'A-class-barrier{n}',
        encoding=1,
    ),
    'B': lambda n: GridWorldAgent(
        id=f'B-class-barrier{n}',
        encoding=2,
    ),
    'C': lambda n: GridWorldAgent(
        id=f'C-class-barrier{n}',
        encoding=3,
    ),
}
extra_agents = {
    'B-class-barrier2': GridWorldAgent(
        id='B-class-barrier2',
        encoding=4,
        initial_position=np.array([1, 0])
    ),
    'extra_agent0': GridWorldAgent(
        id='extra_agent0',
        encoding=5,
        initial_position=np.array([0, 0])
    ),
    'extra_agent1': GridWorldAgent(
        id='extra_agent1',
        encoding=5,
        initial_position=np.array([0, 0])
    ),
    'extra_agent2': GridWorldAgent(
        id='extra_agent2',
        encoding=6,
        initial_position=np.array([0, 4])
    )
}
sim = MultiAgentGridSim.build_sim_from_array(
    array,
    obj_registry,
    extra_agents=extra_agents,
    overlapping={1: {5}, 5: {1, 5}}
)
sim.reset()
```

This simulation has a grid of size `(2 x 5)`, matching the input array. There are 3 types of agents in the object registry corresponding with the characters in the input array. `B-class-barrier2` appears in the extra agents, but it is also built from the input array. If this happens, the builder prioritizes using the agent as is built from the array.

**Note:** Dots, underscores, and zeros are reserved as empty space and cannot be used in the object registry.

### Build Sim From File

Building from a file works in the same way as building from an array. Here, the input is a file with alphanumeric characteres ordered in a grid-like fashion. An object registry is used to interpret those characters into agents, and they are placed in the grid. As above, extra agents can be included. The following shows an example of building a simulation from file:

```
A . B 0 _
B _ _ C A
```

This input file has two lines with 5 entries each, which will result in a `2 x 5` grid. Each entry is seperated by a space. Dots, underscores, and zeros are reserved for empty spaces.

```
import numpy as np
from abmarl.examples.sim import MultiAgentGridSim
from abmarl.sim.gridworld.agent import GridWorldAgent

file_name = 'grid_file.txt'
obj_registry = {
    'A': lambda n: GridWorldAgent(
        id=f'A-class-barrier{n}',
        encoding=1,
    ),
    'B': lambda n: GridWorldAgent(
        id=f'B-class-barrier{n}',
        encoding=2,
    ),
    'C': lambda n: GridWorldAgent(
        id=f'C-class-barrier{n}',
        encoding=3,
    ),
}
extra_agents = {
    'B-class-barrier2': GridWorldAgent(
        id='B-class-barrier2',
        encoding=4,
        initial_position=np.array([1, 0])
    ),
    'extra_agent0': GridWorldAgent(
        id='extra_agent0',
        encoding=5,
        initial_position=np.array([0, 0])
    ),
    'extra_agent1': GridWorldAgent(
        id='extra_agent1',
        encoding=5,
        initial_position=np.array([0, 0])
    ),
    'extra_agent2': GridWorldAgent(
        id='extra_agent2',
        encoding=6,
        initial_position=np.array([0, 4])
    )
}
```

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```
sim = MultiAgentGridSim.build_sim_from_file(
    file_name,
    obj_registry,
    extra_agents=extra_agents,
    overlapping={1: {5}, 5: {1, 5}}
)
sim.reset()
```

This simulation is the same as the one above that was built from the array.

## 3.2 Built-in Features

Below is a list of some features that are available to use out of the box. Rememeber, you can create your own features in the GridWorld Simulation Framework and use many combinations of components together to make up a simulation.

### 3.2.1 Position

*Agents* have *positions* in the *Grid* that are managed by the *PositionState*. Agents can be configured with an *initial position*, which is where they will start at the beginning of each episode. If they are not given an *initial position*, then they will start at a random cell in the grid. Agents can overlap according to the *Grid's overlapping* configuration. For example, consider the following setup:

```
import numpy as np
from abmarl.sim.gridworld.agent import GridWorldAgent
from abmarl.sim.gridworld.grid import Grid
from abmarl.sim.gridworld.state import PositionState

agent0 = GridWorldAgent(
    id='agent0',
    encoding=1,
    initial_position=np.array([2, 4])
)
agent1 = GridWorldAgent(
    id='agent1',
    encoding=1
)
position_state = PositionState(
    agents={'agent0': agent0, 'agent1': agent1},
    grid=Grid(4, 5)
)
position_state.reset()
```

*agent0* is configured with an *initial position* and *agent1* is not. At the start of each episode, *agent0* will be placed at (2, 4) and *agent1* will be placed anywhere in the grid (except for (2,4) because they cannot overlap).

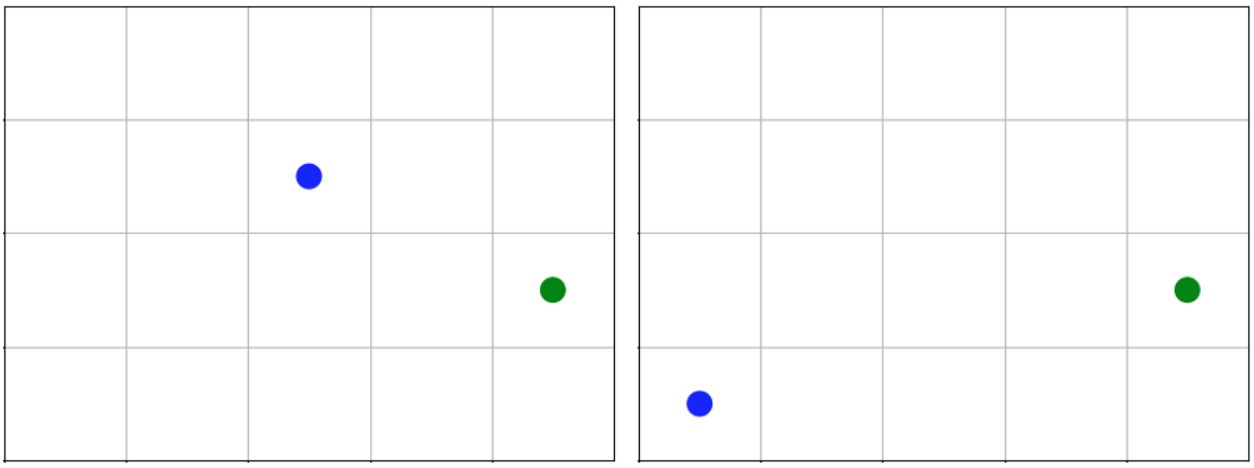

Fig. 2: agent0 in green starts at the same cell in every episode, and agent1 in blue starts at a random cell each time.

#### Maze Placement State

The *MazePlacementState* is a specialized state component used for positioning agents within mazes. The cells are partitioned into *free* and *barrier* cells. *Barrier-encoded* agents can be placed on *barrier* cells and *free-encoded* agents can be placed on *free* cells. There must be a *target agent*, which is used for clustering barriers and scattering free agents.

---

**Note:** Because the maze is randomly generated at the beginning of each episode and because the agents must be placed in either a free cell or barrier cell according to their encodings, it is highly recommended that none of your agents be given initial positions, except for the target agent.

---

The *MazePlacementState* is very useful for randomly placing agents at the beginning of each episode while maintaining a desired structure. In this case, we can use this state component to keep barriers clustered around a target and scatter free agents away from it, regardless of where that target is positioned at the beginning of each episode. The clustering is such that all paths to the target are not blocked.

### 3.2.2 Movement

*MovingAgents* can move around the *Grid* in conjunction with the *MoveActor*. MovingAgents require a *move range* parameter, indicating how many spaces away they can move in a single step. Agents cannot move out of bounds and can only move to the same cell as another agent if they are allowed to overlap. For example, in this setup

```
import numpy as np
from abmarl.sim.gridworld.agent import MovingAgent
from abmarl.sim.gridworld.grid import Grid
from abmarl.sim.gridworld.state import PositionState
from abmarl.sim.gridworld.actor import MoveActor

agents = {
    'agent0': MovingAgent(
        id='agent0', encoding=1, move_range=1, initial_position=np.array([2, 2])
    ),
    'agent1': MovingAgent(
        id='agent1', encoding=1, move_range=2, initial_position=np.array([0, 2])
```

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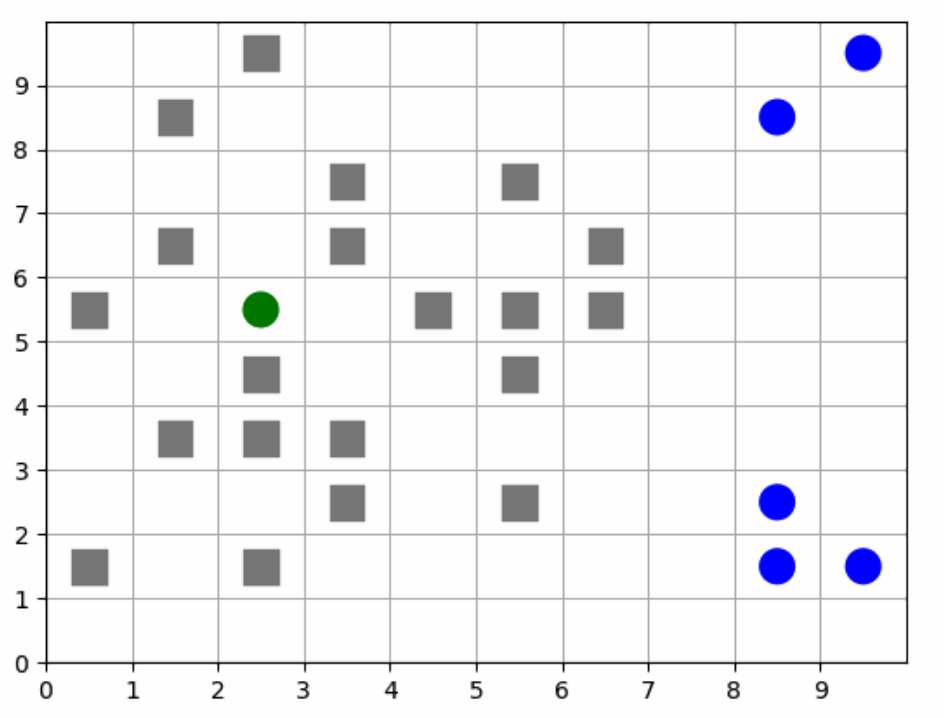


Fig. 3: Animation showing a target (green) starting at random positions at the beginning of each episode. Barriers (gray squares) are clustered near the target without blocking all paths to it. Free agents (blue) are scattered far from the target.

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```
    )
}
grid = Grid(5, 5, overlapping={1: {1}})
position_state = PositionState(agents=agents, grid=grid)
move_actor = MoveActor(agents=agents, grid=grid)

position_state.reset()
move_actor.process_action(agents['agent0'], {'move': np.array([0, 1])})
move_actor.process_action(agents['agent1'], {'move': np.array([2, 1])})
```

*agent0* starts at position (2, 2) and can move up to one cell away. *agent1* starts at (0, 2) and can move up to two cells away. The two agents can overlap each other, so when the move actor processes their actions, both agents will be at position (2, 3).

The *MoveActor* automatically assigns a *null action* of *[0, 0]*, indicating no move.

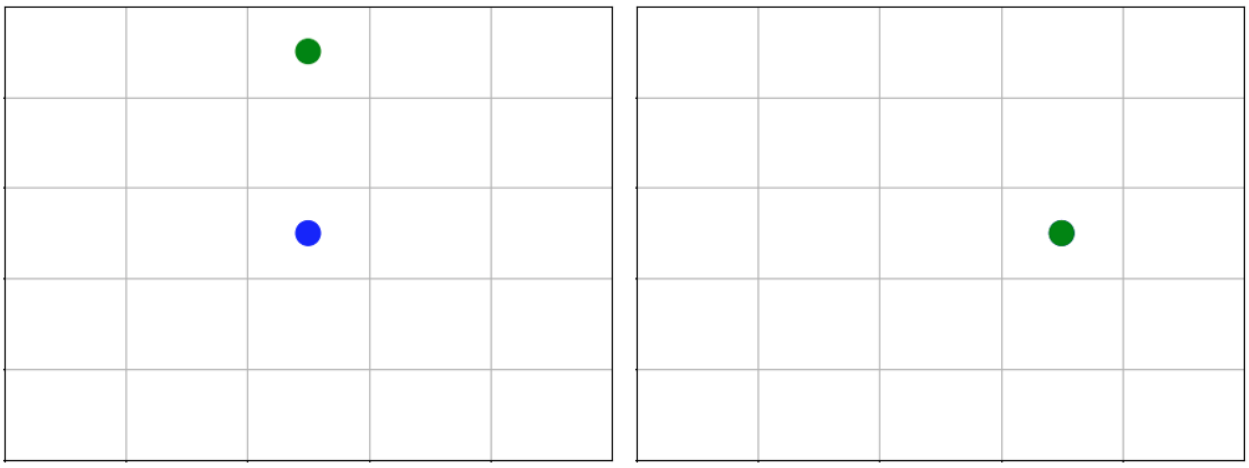

Fig. 4: agent0 and agent1 move to the same cell.

### 3.2.3 Cross Move Actor

The *CrossMoveActor* is very similar to the *MoveActor*. Rather than moving to any nearby squares based on some `move_range`, *MovingAgents* can move either up, down, left, right, or stay in place. The `move_range` parameter is ignored. The CrossMoveActor automatically assigns a *null_action* of 0, indicating the agent stays in place.

### 3.2.4 Absolute Position Observer

The *AbsolutePositionObserver* enables *ObservingAgents* to observe their own absolute position in the grid. The position is reported as a two-dimensional numpy array, whose lower bounds are `(0, 0)` and upper bounds are the size of the grid minus one. This observer does not provide information on any other agent in the grid.

### 3.2.5 Absolute Grid Observer

*AbsoluteGridObserver* means that the *GridObservingAgent* observes the grid as though it were looking at it from the top down, "from the grid's perspective", so to speak. As agents move around, the grid stays fixed and the observation shows each agent according to their actual positions. Agents are represented by their *encodings*, and in order for the observing agent to distinguish itself from other entities of the same *encoding*, it sees itself as a -1.

An agent's observation may be restricted by its own `view_range` and by other agents' *blocking*. This imposes a "fog of war" type masking on the observations. Cells that are not observable will be represented as a -2. For example, the following setup

```
import numpy as np
from abmarl.sim.gridworld.agent import GridObservingAgent, GridWorldAgent
from abmarl.sim.gridworld.grid import Grid
from abmarl.sim.gridworld.state import PositionState
from abmarl.sim.gridworld.observer import AbsoluteGridObserver

agents = {
    'agent0': GridObservingAgent(id='agent0', encoding=1, initial_position=np.array([2,␣
↪2]), view_range=2),
    'agent1': GridWorldAgent(id='agent1', encoding=2, initial_position=np.array([0, 1])),
    'agent2': GridWorldAgent(id='agent2', encoding=3, initial_position=np.array([1, 0])),
```

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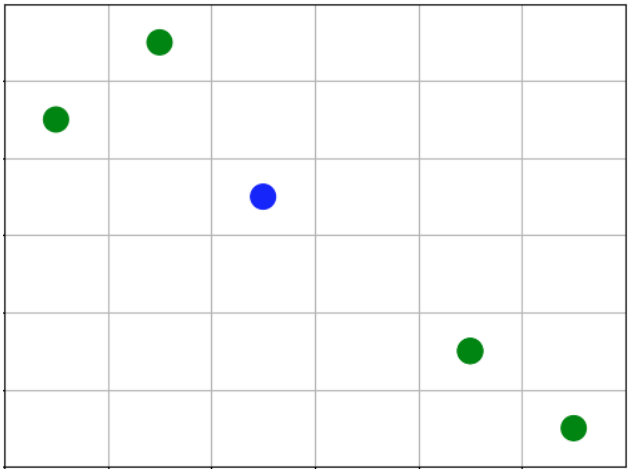
```
    'agent3': GridWorldAgent(id='agent3', encoding=4, initial_position=np.array([4, 4])),
    'agent4': GridWorldAgent(id='agent4', encoding=5, initial_position=np.array([4, 4])),
    'agent5': GridWorldAgent(id='agent5', encoding=6, initial_position=np.array([5, 5]))
}
grid = Grid(6, 6, overlapping={4: {5}, 5: {4}})
position_state = PositionState(agents=agents, grid=grid)
observer = AbsoluteGridObserver(agents=agents, grid=grid)

position_state.reset()
observer.get_obs(agents['agent0'])
```

will position agents as below and output an observation for *agent0* (blue) like so:



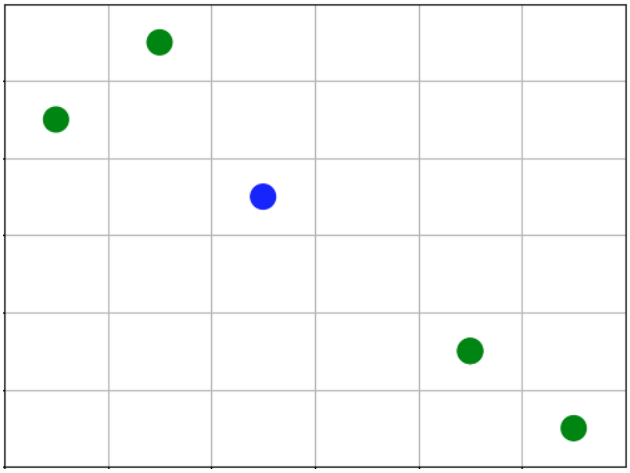
```
[ 0,  2,  0,  0,  0, -2],
[ 3,  0,  0,  0,  0, -2],
[ 0,  0, -1,  0,  0, -2],
[ 0,  0,  0,  0,  0, -2],
[ 0,  0,  0,  0, 3*, -2],
[-2, -2, -2, -2, -2, -2],
```

This is a `6 x 6` grid, so the observation is the same size. The observing agent is located at `(2, 2)` in the grid, just as its position indicates. Other agents appear in the grid represented as their encodings and appear according to their actual positions. Because the observing agent only has a `view_range` of 2, it cannot see the last row or column, so the observation masks those cells with the value of -2. There are two agents at position `(4, 4)`, one with encoding 3 and another with encoding 4. The *AbsoluteGridObserver* randomly chooses one from among those encodings.

The *AbsoluteGridObserver* automatically assigns a *null observation* as a matrix of all -2s, indicating that everything is masked.

### 3.2.6 Single Grid Observer

*GridObservingAgents* can observe the state of the *Grid* around them, namely which other agents are nearby, via the *SingleGridObserver*. The SingleGridObserver generates a two-dimensional matrix sized by the agent's *view range* with the observing agent located at the center of the matrix. While the *AbsoluteGridObserver* observes agents according to their actual positions, the SingleGridObserver observes agents according to their relative positions. All other agents within the *view range* will appear in the observation, shown as their *encoding*. For example, using the above setup with a `view_range` of 3 will output an observation for *agent0* (blue) like so:



```
[-1, -1, -1, -1, -1, -1, -1],
[-1,  0,  2,  0,  0,  0,  0],
[-1,  3,  0,  0,  0,  0,  0],
[-1,  0,  0,  1,  0,  0,  0],
[-1,  0,  0,  0,  0,  0,  0],
[-1,  0,  0,  0,  0, 4*,  0],
[-1,  0,  0,  0,  0,  0,  6]
```

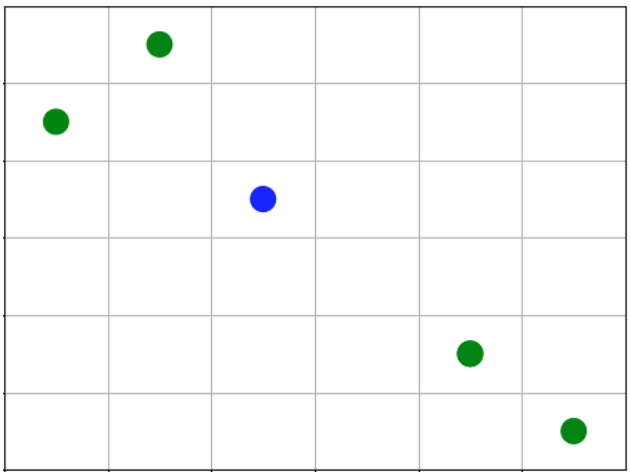
Since *view range* is the number of cells away that can be observed, the observation size is `(2 * view_range + 1) x (2 * view_range + 1)`. *agent0* is centered in the middle of this array, shown by its *encoding*: 1. All other agents appear in the observation relative to *agent0's* position and shown by their *encodings*. The agent observes some out of bounds cells, which appear as -1s. *agent3* and *agent4* occupy the same cell, and the *SingleGridObserver* will randomly select between their *encodings* for the observation.

By setting *observe_self* to False, the *SingleGridObserver* can be configured so that an agent doesn't observe itself and only observes other agents, which may be helpful if overlapping is an important part of the simulation.

The *SingleGridObserver* automatically assigns a *null observation* as a matrix of all -2s, indicating that everything is masked.

### 3.2.7 Multi Grid Observer

Similar to the *SingleGridObserver*, the *MultiGridObserver* observes the grid from the observing agent's perspective. It displays a separate matrix for every *encoding*. Each matrix shows the relative positions of the agents and the number of those agents that occupy each cell. Out of bounds indicators (-1) and masked cells (-2) are present in every matrix. For example, the above setup would show an observation like so:



```
# Encoding 1
[-1, -1, -1, -1, -1, -1, -1],
[-1,  0,  0,  0,  0,  0,  0],
[-1,  0,  0,  0,  0,  0,  0],
[-1,  0,  0,  1,  0,  0,  0],
[-1,  0,  0,  0,  0,  0,  0],
[-1,  0,  0,  0,  0,  0,  0],
[-1,  0,  0,  0,  0,  0,  0]

# Encoding 2
[-1, -1, -1, -1, -1, -1, -1],
[-1,  0,  1,  0,  0,  0,  0],
[-1,  0,  0,  0,  0,  0,  0],
[-1,  0,  0,  0,  0,  0,  0],
[-1,  0,  0,  0,  0,  0,  0],
[-1,  0,  0,  0,  0,  0,  0],
[-1,  0,  0,  0,  0,  0,  0]
...
```

*MultiGridObserver* may be preferable to *SingleGridObserver* in simulations where there are many overlapping agents.

The *MultiGridObserver* automatically assigns a *null observation* of a tensor of all -2s, indicating that everything is masked.

### Blocking

Agents can block other agents' abilities and characteristics, such as blocking them from view, which masks out parts of the observation. For example, if *agent4* above is configured with `blocking=True`, then the *SingleGridObserver* would produce an observation like this:

```
[-1, -1, -1, -1, -1, -1, -1],
[-1,  0,  2,  0,  0,  0,  0],
[-1,  3,  0,  0,  0,  0,  0],
[-1,  0,  0,  1,  0,  0,  0],
[-1,  0,  0,  0,  0,  0,  0],
[-1,  0,  0,  0,  0, 4*,  0],
[-1,  0,  0,  0,  0,  0, -2]
```

The -2 indicates that the cell is masked, and the choice of displaying *agent3* over *agent4* is still a random choice. Which cells get masked by blocking agents is determined by drawing two lines from the center of the observing agent's cell to the corners of the blocking agent's cell. Any cell whose center falls between those two lines will be masked, as shown below.

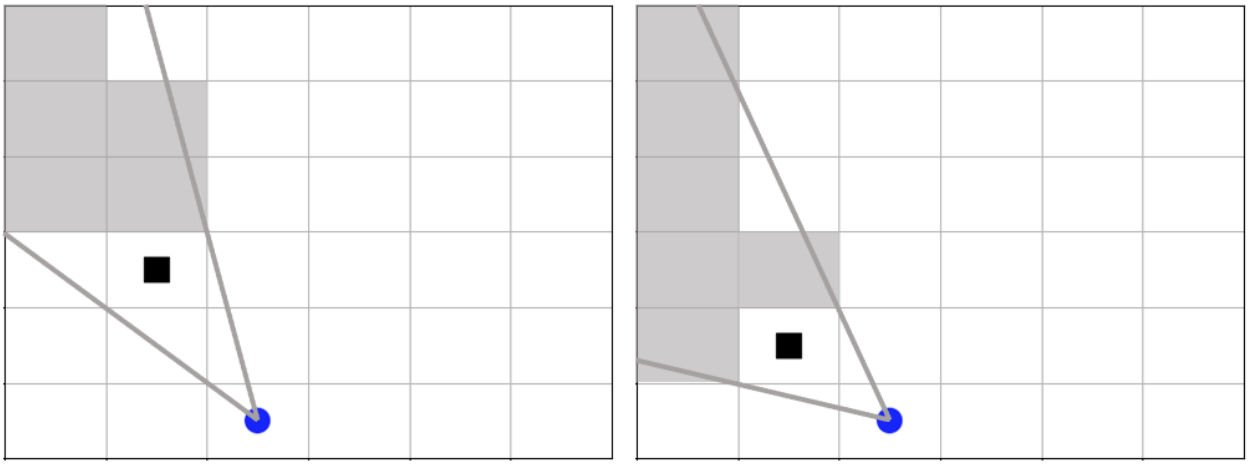


Fig. 5: The black agent is a wall agent that masks part of the grid from the blue agent. Cells whose centers fall betweent the lines are masked. Centers that fall directly on the line or outside of the lines are not masked. Two setups are shown to demonstrate how the masking may change based on the agents' positions.

Blocking works with any of the built-in grid observers.

## 3.2.8 Health

*HealthAgents* track their *health* throughout the simulation. *Health* is always bounded between 0 and 1. Agents whose *health* falls to 0 are marked as *inactive*. They can be given an *initial health*, which they start with at the beginning of the episode. Otherwise, their *health* will be a random number between 0 and 1, as managed by the *HealthState*. Consider the following setup:

```
from abmarl.sim.gridworld.agent import HealthAgent
from abmarl.sim.gridworld.grid import Grid
from abmarl.sim.gridworld.state import HealthState

agent0 = HealthAgent(id='agent0', encoding=1)
```

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```
grid = Grid(3, 3)
agents = {'agent0': agent0}
health_state = HealthState(agents=agents, grid=grid)
health_state.reset()
```

*agent0* will be assigned a random *health* value between 0 and 1.

### 3.2.9 Attacking

*Health* becomes more interesting when we let agents attack one another. *AttackingAgents* work in conjunction with an *AttackActor*. They have an *attack range*, which dictates the range of their attack; an *attack accuracy*, which dictates the chances of the attack being successful; an *attack strength*, which dictates how much *health* is depleted from the attacked agent, and an *attack count*, which dictates the number of attacks an agent can make per turn.

An *AttackActor* interprets these properties and processes the attacks according to its own internal design. In general, each AttackActor determines some set of attackable agents according to the following criteria:

1. The *attack mapping*, which is a dictionary that determines which *encodings* can attack other *encodings* (similar to the *overlapping* parameter for the *Grid*), must allow the attack.
2. The relative positions of the two agents must fall within the attacking agent's *attack range*.
3. The attackable agent must not be masked (e.g. hiding behind a wall). The masking is determined the same way as *blocking* described above.

Then, the *AttackActor* selects agents from that set based on the attacking agent's *attack count*. When an agent is successfully attacked, its health is depleted by the attacking agent's *attack strength*, which may result in the attacked agent's death. AttackActors can be configured to allow multiple attacks against a single agent per attacking agent and per turn via the *stacked attacks* property. The following four AttackActors are built into Abmarl:

#### Binary Attack Actor

With the *BinaryAttackActor*, *AttackingAgents* can choose to launch attacks up to its *attack count* or not to attack at all. For each attack, the BinaryAttackActor randomly searches the vicinity of the attacking agent for an attackble agent according to the *basic criteria listed above*. Consider the following setup:

```
import numpy as np
from abmarl.sim.gridworld.agent import AttackingAgent, HealthAgent
from abmarl.sim.gridworld.grid import Grid
from abmarl.sim.gridworld.state import PositionState, HealthState
from abmarl.sim.gridworld.actor import BinaryAttackActor

agents = {
    'agent0': AttackingAgent(
        id='agent0',
        encoding=1,
        initial_position=np.array([0, 0]),
        attack_range=1,
        attack_strength=0.4,
        attack_accuracy=1,
        attack_count=2
    ),
    'agent1': HealthAgent(id='agent1', encoding=2, initial_position=np.array([1, 0]),␣
```

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```
↪initial_health=1),
    'agent2': HealthAgent(id='agent2', encoding=2, initial_position=np.array([1, 1]),␣
↪initial_health=0.3),
    'agent3': HealthAgent(id='agent3', encoding=3, initial_position=np.array([0, 1]))
}
grid = Grid(2, 2)
position_state = PositionState(agents=agents, grid=grid)
health_state = HealthState(agents=agents, grid=grid)
attack_actor = BinaryAttackActor(agents=agents, grid=grid, attack_mapping={1: [2]},␣
↪stacked_attacks=False)

position_state.reset()
health_state.reset()
attack_actor.process_action(agents['agent0'], {'attack': 2})
assert not agents['agent2'].active
assert agents['agent1'].active
assert agents['agent3'].active
attack_actor.process_action(agents['agent0'], {'attack': 2})
assert agents['agent1'].active
assert agents['agent3'].active
```

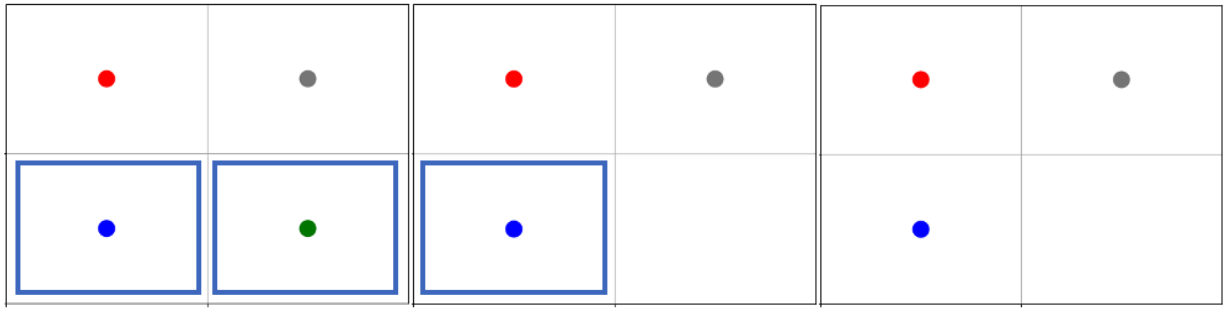

Fig. 6: *agent0* in red launches four attacks over two turns. *agent1* and *agent2*, blue and green respectively, are attackable. *agent2* dies because its health falls to zero, but *agent1* continues living even after two attacks.

As per the *attack mapping*, *agent0* can attack *agent1* or *agent2* but not *agent3*. It can make two attacks per turn, but because the *stacked attacks* property is False, it cannot attack the same agent twice in the same turn. Looking at the *attack strength* and *initial health* of the agents, we can see that *agent0* should be able to kill *agent2* with one attack but it will require three attacks to kill *agent1*. In each turn, *agent0* uses both of its attacks. In the first turn, both *agent1* and *agent2* are attacked and *agent2* dies. In the second turn, *agent0* attempts two attacks again, but because there is only one attackable agent in its vicinity and because *stacked attacks* are not allowed, only one of its attacks is successful: *agent1* is attacked, but it continues to live since it still has health. *agent3* was never attacked because although it is within *agent0*'s *attack range*, it is not in the *attack mapping*.

The *BinaryAttackActor* automatically assigns a *null action* of 0, indicating no attack.

### Encoding Based Attack Actor

The *EncodingBasedAttackActor* allows *AttackingAgents* to choose some number of attacks *per each encoding*. For each attack, the EncodingBasedAttackActor randomly searches the vicinity of the attacking agent for an attackble agent according to the *basic criteria listed above*. Contrast this actor with the *BinaryAttackActor* above, which does not allow agents to specify attack by encoding. Consider the following setup:

```
import numpy as np
from abmarl.sim.gridworld.agent import AttackingAgent, HealthAgent
from abmarl.sim.gridworld.grid import Grid
from abmarl.sim.gridworld.state import PositionState, HealthState
from abmarl.sim.gridworld.actor import EncodingBasedAttackActor

agents = {
    'agent0': AttackingAgent(
        id='agent0',
        encoding=1,
        initial_position=np.array([0, 0]),
        attack_range=1,
        attack_strength=0.4,
        attack_accuracy=1,
        attack_count=2
    ),
    'agent1': HealthAgent(id='agent1', encoding=2, initial_position=np.array([1, 0]),␣
↪initial_health=1),
    'agent2': HealthAgent(id='agent2', encoding=2, initial_position=np.array([1, 1]),␣
↪initial_health=1),
    'agent3': HealthAgent(id='agent3', encoding=3, initial_position=np.array([0, 1]),␣
↪initial_health=0.5)
}
grid = Grid(2, 2)
position_state = PositionState(agents=agents, grid=grid)
health_state = HealthState(agents=agents, grid=grid)
attack_actor = EncodingBasedAttackActor(agents=agents, grid=grid, attack_mapping={1: [2,␣
↪3]}, stacked_attacks=True)

position_state.reset()
health_state.reset()
attack_actor.process_action(agents['agent0'], {'attack': {2: 0, 3: 2}})
assert agents['agent1'].health == agents['agent1'].initial_health
assert agents['agent2'].health == agents['agent2'].initial_health
assert not agents['agent3'].active
```

As per the *attack mapping*, *agent0* can attack all the other agents. It can make up to two attacks per turn *per encoding* (e.g. two attacks on encoding 2 and two attacks on encoding 3 per turn), and because the *stacked attacks* property is True, it can attack the same agent twice in the same turn. Looking at the *attack strength* and *initial health* of the agents, we can see that *agent0* should be able to kill *agent3* with only two attacks. *agent0* launches no attacks on encoding 2 and two attacks on encoding 3. Because *agent3* is the only agent of encoding 3 and because *stacked attacks* are allowed, it gets attacked twice in one turn, resulting in its death. Even though *agent1* and *agent2* are in *agent0*'s *attack mapping* and *attack range*, neither of them is attacked because *agent0* specified zero attacks on encoding 2.

The *EncodingBasedAttackActor* automatically assigns a *null action* of 0 for each encoding, indicating no attack.

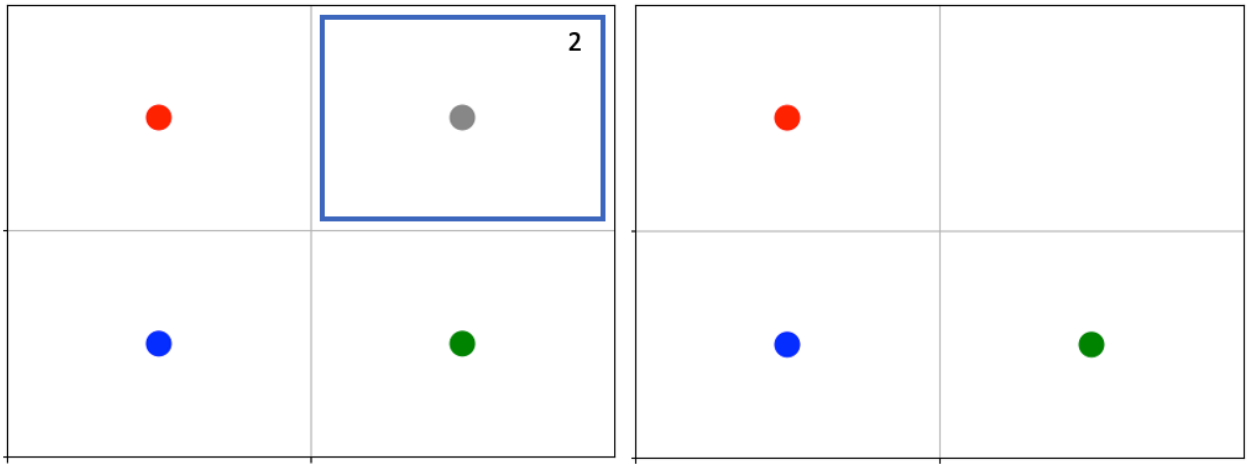


Fig. 7: *agent0* in red launches two attacks against encoding 3. Because stacked attacks are allowed, both attacks fall on *agent3* in the same turn, resulting in its death.

### Selective Attack Actor

The *SelectiveAttackActor* allows *AttackingAgents* to specify some number of attacks on each of the cells in some local grid defined by the agent's *attack range*. In contrast to the *BinaryAttackActor* and *EncodingBasedAttackActor* above, the SelectiveAttackActor does not randomly search for agents in the vicinity because it receives the attacked cells directly. The attacking agent can attack each cell up to its *attack count*. Attackable agents are defined according to the *basic criteria listed above*. If there are multiple attackable agents on the same cell, the actor randomly picks from among them based on the number of attacks on that cell and whether or not *stacked attacks* are allowed. Consider the following setup:

```
import numpy as np
from abmarl.sim.gridworld.agent import AttackingAgent, HealthAgent
from abmarl.sim.gridworld.grid import Grid
from abmarl.sim.gridworld.state import PositionState, HealthState
from abmarl.sim.gridworld.actor import SelectiveAttackActor

agents = {
    'agent0': AttackingAgent(
        id='agent0',
        encoding=1,
        initial_position=np.array([0, 0]),
        attack_range=1,
        attack_strength=1,
        attack_accuracy=1,
        attack_count=2
    ),
    'agent1': HealthAgent(id='agent1', encoding=2, initial_position=np.array([1, 0]),␣
↪initial_health=1),
    'agent2': HealthAgent(id='agent2', encoding=2, initial_position=np.array([0, 1]),␣
↪initial_health=1),
    'agent3': HealthAgent(id='agent3', encoding=3, initial_position=np.array([0, 1]))
}
grid = Grid(2, 2, overlapping={2: {3}, 3: {2}})
position_state = PositionState(agents=agents, grid=grid)
```

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```
health_state = HealthState(agents=agents, grid=grid)
attack_actor = SelectiveAttackActor(agents=agents, grid=grid, attack_mapping={1: [2]},␣
↪stacked_attacks=False)

position_state.reset()
health_state.reset()
attack = np.array([
    [0, 1, 0],
    [0, 1, 2],
    [0, 1, 0]
])
attack_actor.process_action(agents['agent0'], {'attack': attack})
assert not agents['agent1'].active
assert not agents['agent2'].active
assert agents['agent3'].active
```

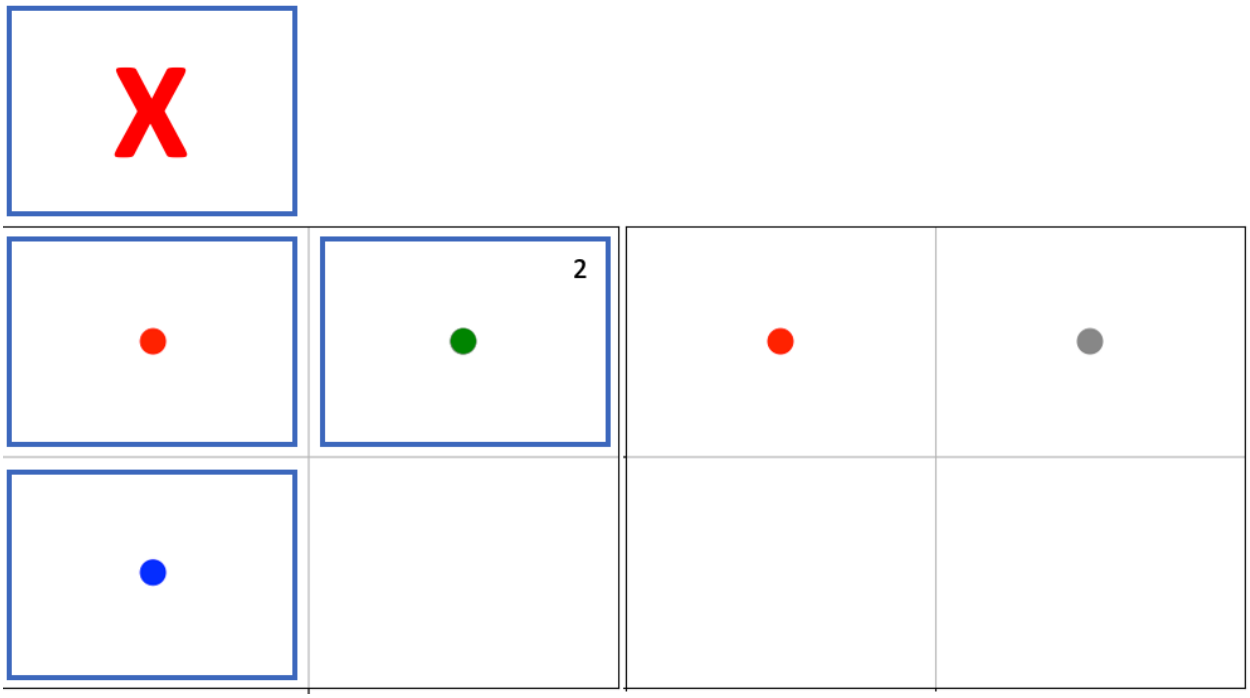


Fig. 8: *agent0* in red launches five attacks in the highlighted cells, resulting in *agent1* and *agent2* dying.

As per the *attack mapping*, *agent0* can attack *agent1* or *agent2* but not *agent3*. It can make two attacks per turn *per cell*, but because the *stacked attacks* property is False, it cannot attack the same agent twice in the same turn. Looking at the *attack strength* and *initial health* of the agents, we can see that *agent0* should be able to kill *agent1* and *agent2* with a single attack each. *agent0* launches 5 attacks: one on the cell above, one on its own cell, one on the cell below, and two on the cell to the right. The attack above is on a cell that is out of bounds, so this attack does nothing. The attack on its own cell fails because there are no attackable agents there. *agent1* is on the cell below, and that attack succeeds. *agent2* and *agent3* are both on the cell to the right, but only *agent2* is attackable per the attack mapping and *stacked attacks* are not allowed, so only one of the launched attacks is successful.

The *SelectiveAttackActor* automatically assigns a grid of 0s as the *null action*, indicating no attack on any cell.

### Restricted Selective Attack Actor

The *RestrictedSelectiveAttackActor* allows *AttackingAgents* to specify some number of attacks in some local grid defined by the attacking agent's *attack range*. This actor is more *restricted* than its counterpart, the *SelectiveAttackActor*, because rather than issuing attacks up to its *attack count per cell*, the attacking agent can only issue that many attacks in the *whole local grid*. Attackable agents are defined according to the *basic criteria listed above*. If there are multiple attackable agents on a the same cell, the actor randomly picks from among them based on the number of attacks on that cell and whether or not *stacked attacks* are allowed. Consider the following setup:

```
import numpy as np
from abmarl.sim.gridworld.agent import AttackingAgent, HealthAgent
from abmarl.sim.gridworld.grid import Grid
from abmarl.sim.gridworld.state import PositionState, HealthState
from abmarl.sim.gridworld.actor import RestrictedSelectiveAttackActor

agents = {
    'agent0': AttackingAgent(
        id='agent0',
        encoding=1,
        initial_position=np.array([0, 0]),
        attack_range=1,
        attack_strength=0.6,
        attack_accuracy=1,
        attack_count=3
    ),
    'agent1': HealthAgent(id='agent1', encoding=2, initial_position=np.array([1, 0]),␣
↪initial_health=0.1),
    'agent2': HealthAgent(id='agent2', encoding=2, initial_position=np.array([0, 1]),␣
↪initial_health=0.1),
    'agent3': HealthAgent(id='agent3', encoding=2, initial_position=np.array([1, 1]),␣
↪initial_health=1)
}
grid = Grid(2, 2)
position_state = PositionState(agents=agents, grid=grid)
health_state = HealthState(agents=agents, grid=grid)
attack_actor = RestrictedSelectiveAttackActor(agents=agents, grid=grid, attack_mapping=
↪{1: [2]}, stacked_attacks=False)

position_state.reset()
health_state.reset()
out = attack_actor.process_action(agents['agent0'], {'attack': [9, 9, 0]})
assert agents['agent3'].active
assert agents['agent3'].health == 0.4
out = attack_actor.process_action(agents['agent0'], {'attack': [9, 6, 8]})
assert not agents['agent1'].active
assert not agents['agent2'].active
assert not agents['agent3'].active
```

As per the *attack mapping*, *agent0* can attack all the other agents, and it can issue up to three attacks per turn. *stacked attacks* is False, so the same agent cannot be attacked twice in the same turn. Looking at the *attack strength* and *initial health* of the agents, we can see that *agent0* should be able to kill *agent1* and *agent2* with a single attack each but will need two attacks to kill *agent3*. In the first turn, *agent0* launches two attacks to the bottom right cell and chooses not to use its third attack. *agent3* is the only attackable agent on this cell, but because *stacked attacks* are not allowed, it only gets attacked once. In the next turn, *agent0* issues an attack on each of the three occupied cells, and each attack is

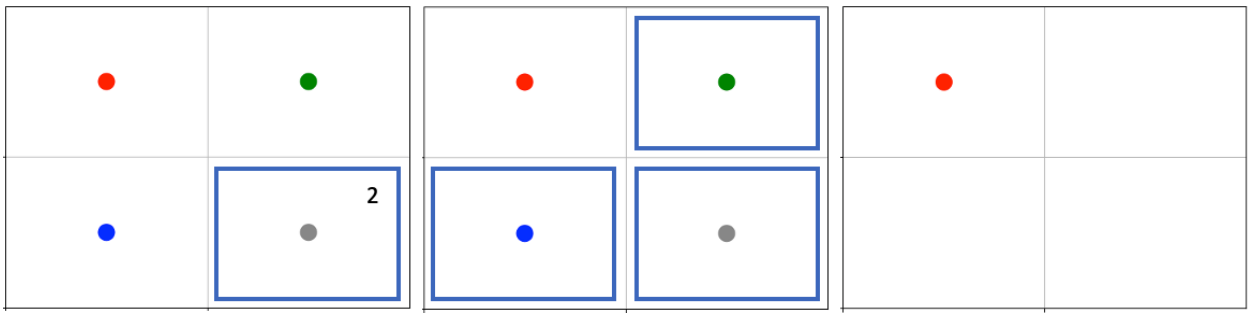


Fig. 9: *agent0* in red launches two attacks against the bottom right cell, catching *agent3* with one of them. Then it finishes off all the agents in the next turn.

succesful.

The *RestrictedSelectiveAttackActor* automatically assigns an array of 0s as the *null action*, indicating no attack on any cell.

---

**Note:** The form of the attack in the *RestrictedSelectiveAttackActor* is the most difficult for humans to interpret. The number of entries in the array reflects the agent's *attack count*. The attack appears as the cell's id, which is determined from ravelling the local grid, where 0 means no attack, 1 is the top left cell, 2 is to the right of that, and so on through the whole local grid.

---

### 3.2.10 Active Done

The *ActiveDone* component reports that agents are *done* based on their *active* property. If the agent is inactive, then it is done. If all the agents are inactive, then the entire simulation is done.

### 3.2.11 One Team Remaining Done

The *OneTeamRemainingDone* component reports that the simulation is done when there is only one "team" remaining; that is, when all the remaining active agents have the same encoding. This component does not report done for individual agents.

### 3.2.12 Target Agent Done

The *TargetAgentDone* component takes a `target_mapping`, which maps agents to their targets by id. If an agent overlaps its target, then that agent is done. If all of the agents have overlapped their targets, then the simulation is done.

### 3.2.13 RavelActionWrapper

The *RavelActionWrapper* transforms Discrete, MultiBinary, MultiDiscrete, bounded integer Box, and any nesting of those spaces into a Discrete space by "ravelling" their values according to numpy's `ravel_multi_index` function. Thus, actions that are represented by arrays are converted into unique Discrete numbers. For example, we can apply the RavelActionWrapper to the MoveActor, like so:

```
from abmarl.sim.gridworld.agent import MovingAgent
from abmarl.sim.gridworld.grid import Grid
from abmarl.sim.gridworld.state import PositionState
from abmarl.sim.gridworld.actor import MoveActor
from abmarl.sim.gridworld.wrapper import RavelActionWrapper

agents = {
    'agent0': MovingAgent(id='agent0', encoding=1, move_range=1),
    'agent1': MovingAgent(id='agent1', encoding=1, move_range=2)
}
grid = Grid(5, 5)
position_state = PositionState(agents=agents, grid=grid)
move_actor = MoveActor(agents=agents, grid=grid)
for agent in agents.values():
    agent.finalize()
position_state.reset()

# Move actor without wrapper
actions = {
    agent.id: agent.action_space.sample() for agent in agents.values()
}
print(actions)
# >>> {'agent0': OrderedDict([('move', array([1, 1]))]), 'agent1': OrderedDict([('move',␣
↪array([ 2, -1]))])}

# Wrapped move actor
```

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```
move_actor = RavelActionWrapper(move_actor)
actions = {
    agent.id: agent.action_space.sample() for agent in agents.values()
}
print(actions)
# >>> {'agent0': OrderedDict([('move', 1)]), 'agent1': OrderedDict([('move', 22)])}
```

The actions from the unwrapped actor are in the original *Box* space, whereas after we apply the wrapper, the actions from the wrapped actor are in the transformed *Discrete* space. The actor will receive move actions in the *Discrete* space and convert them to the *Box* space before passing them to the MoveActor.

### 3.2.14 Exclusive Channel Action Wrapper

The *ExclusiveChannelActionWrapper* works with *Dict* action spaces, where each subspace is to be ravelled independently and then combined so that that action channels are exclusive. The wrapping occurs in two steps. First, we use numpy's *ravel* capabilities to convert each subspace to a *Discrete* space. Second, we combine the *Discrete* spaces together in such a way that imposes exclusivity among the subspaces. The exclusion happens only on the top level, so a *Dict* nested within a *Dict* will be ravelled without exclusion.

We can apply the *ExclusiveChannelActionWrapper* with the *EncodingBasedAttackActor* to force the agent to only attack one encoding per turn, like so:

```
import numpy as np
from abmarl.sim.gridworld.agent import AttackingAgent, HealthAgent
from abmarl.sim.gridworld.grid import Grid
from abmarl.sim.gridworld.state import PositionState, HealthState
from abmarl.sim.gridworld.actor import EncodingBasedAttackActor
from abmarl.sim.gridworld.wrapper import ExclusiveChannelActionWrapper
from gym.spaces import Dict, Discrete

agents = {
    'agent0': AttackingAgent(
        id='agent0',
        encoding=1,
        initial_position=np.array([0, 0]),
        attack_range=1,
        attack_strength=0.4,
        attack_accuracy=1,
        attack_count=2
    ),
    'agent1': HealthAgent(id='agent1', encoding=2, initial_position=np.array([1, 0]),␣
↪initial_health=1),
    'agent2': HealthAgent(id='agent2', encoding=2, initial_position=np.array([1, 1]),␣
↪initial_health=1),
    'agent3': HealthAgent(id='agent3', encoding=3, initial_position=np.array([0, 1]),␣
↪initial_health=0.5)
}
grid = Grid(2, 2)
position_state = PositionState(agents=agents, grid=grid)
health_state = HealthState(agents=agents, grid=grid)
attack_actor = EncodingBasedAttackActor(agents=agents, grid=grid, attack_mapping={1: [2,␣
↪3]}, stacked_attacks=True)
```

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```
print(agents['agent0'].action_space)
>>> {'attack': Dict(2:Discrete(3), 3:Discrete(3))}

wrapped_attack_actor = ExclusiveChannelActionWrapper(attack_actor)
print(agents['agent0'].action_space)
>>> {'attack': Discrete(5)}

print(wrapped_attack_actor.wrap_point(Dict({2: Discrete(3), 3: Discrete(3)}), 0))
print(wrapped_attack_actor.wrap_point(Dict({2: Discrete(3), 3: Discrete(3)}), 1))
print(wrapped_attack_actor.wrap_point(Dict({2: Discrete(3), 3: Discrete(3)}), 2))
print(wrapped_attack_actor.wrap_point(Dict({2: Discrete(3), 3: Discrete(3)}), 3))
print(wrapped_attack_actor.wrap_point(Dict({2: Discrete(3), 3: Discrete(3)}), 4))
>>> {2: 0, 3: 0}
>>> {2: 1, 3: 0}
>>> {2: 2, 3: 0}
>>> {2: 0, 3: 1}
>>> {2: 0, 3: 2}
```

With just the *EncodingBasedAttackActor*, the agent's action space is `{'attack': Dict(2:Discrete(3), 3:Discrete(3))}` and there are 9 possible actions:

1. `{2: 0, 3: 0}`
2. `{2: 0, 3: 1}`
3. `{2: 0, 3: 2}`
4. `{2: 1, 3: 0}`
5. `{2: 1, 3: 1}`
6. `{2: 1, 3: 2}`
7. `{2: 2, 3: 0}`
8. `{2: 2, 3: 1}`
9. `{2: 2, 3: 2}`

When we apply the *ExclusiveChannelActionWrapper*, the action space becomes `{'attack': Discrete(5)}`, which is a result of the channel exlcusion and the ravelling. When unwrapped to the original space, the five possible actions become

1. `{2: 0, 3: 0}`
2. `{2: 1, 3: 0}`
3. `{2: 2, 3: 0}`
4. `{2: 0, 3: 1}`
5. `{2: 0, 3: 2}`

We can see that the channels are exclusive, so that the agent cannot attack both encodings in the same turn.

CHAPTER

FOUR

# FEATURED USE CASES

## 4.1 Emergent Collaborative and Competitive Behavior

In this experiment, we study how collaborative and competitive behaviors emerge among agents in a partially observable stochastic game. In our simulation, each agent occupies a square and can move around the map. Each agent can "attack" agents that are on a different "team"; the attacked agent loses its life and is removed from the simulation. Each agent can observe the state of the map in a region surrounding its location. It can see other agents and what team they're on as well as the edges of the map. The diagram below visuially depicts the agents' observation and action spaces.

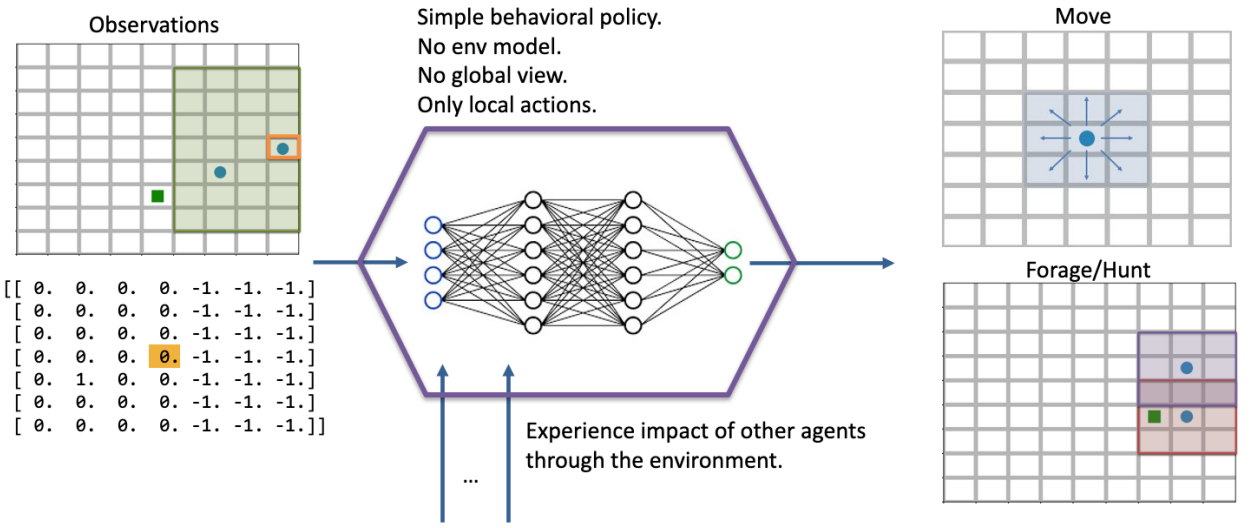



Fig. 1: Each agent has a partial observation of the map centered around its location. The green box shows the orange agent's observation of the map, and the matrix below it shows the actual observation. Each agent can choose to move or to "attack" another agent in one of the nearby squares. The policy is just a simple 2-layer MLP, each layer having 64 units. We don't apply any kind of specialized architecture that encourages collaboration or competition. Each agent is simple: they do not have a model of the simulation; they do not have a global view of the simulation; their actions are only local in both space and in agent interaction (they can only interact with one agent at a time). Yet, we will see efficient and complex strategies emerge, collaboration and competition from the common or conflicting interest among agents.

In the various examples below, each policy is a two-layer MLP, with 64 units in each layer. We use RLlib's A2C Trainer with default parameters and train for two million episodes on a compute node with 72 CPUs.

**Attention:** This page makes heavy use of animated graphics. It is best to read this content on our html site instead of our pdf manual.

### 4.1.1 Single Agent Foraging

We start by considering a single foraging agent whose objective is to move around the map collecting resource agents. The single forager can see up to three squares away, move up to one square away, and forage ("attack") resources up to one square away. The forager is rewarded for every resource it collects and given a small penalty for attempting to move off the map and an even smaller "entropy" penalty every time-step to encourage it to act quickly. At the beginning of every episode, the agents spawn at random locations in the map. Below is a video showing a typical full episode of the learned behavior and a brief analysis.

**Note:** From an Agent Based Modeling perspective, the resources are technically agents themselves. However, since they don't do or see anything, we tend not to call them agents in the text that follows.

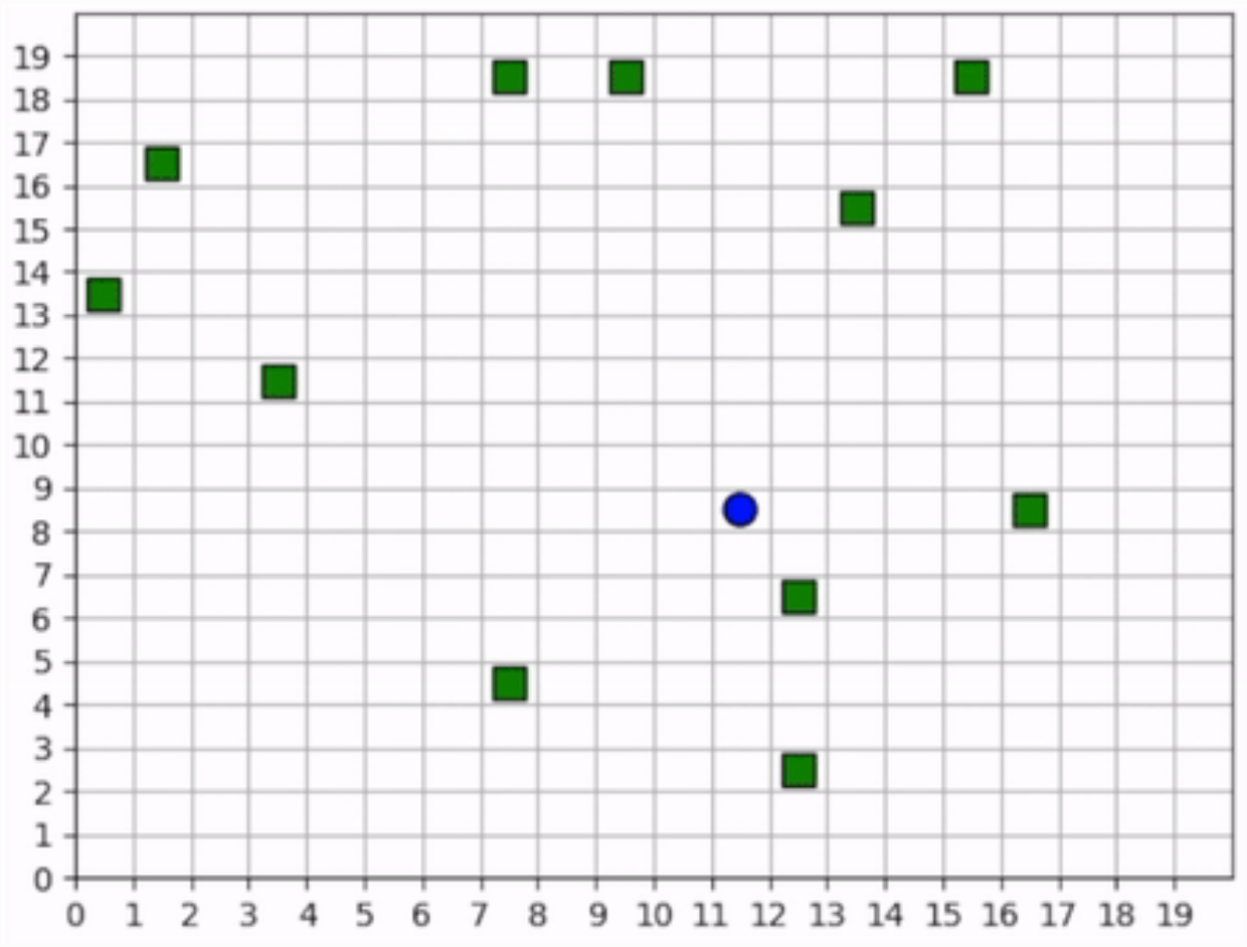



Fig. 2: A full episode showing the forager's learned strategy. The forager is the blue circle and the resources are the green squares. Notice how the forager bounces among resource clusters, greedily collecting all local resources before exploring the map for more.

### When it can see resources

The forager moves toward the closest resource that it observes and collects it. Note that the foraging range is 1 square: the forager rarely waits until it is directly over a resource; it usually forages as soon as it is within range. In some cases, the forager intelligently places itself in the middle of 2-3 resources in order to forage within the least number of moves. When the resources are near the edge of the map, it behaves with some inefficiency, likely due to the small penalty we give it for moving off the map, which results in an aversion towards the map edges. Below is a series of short video clips showing the foraging strategy.

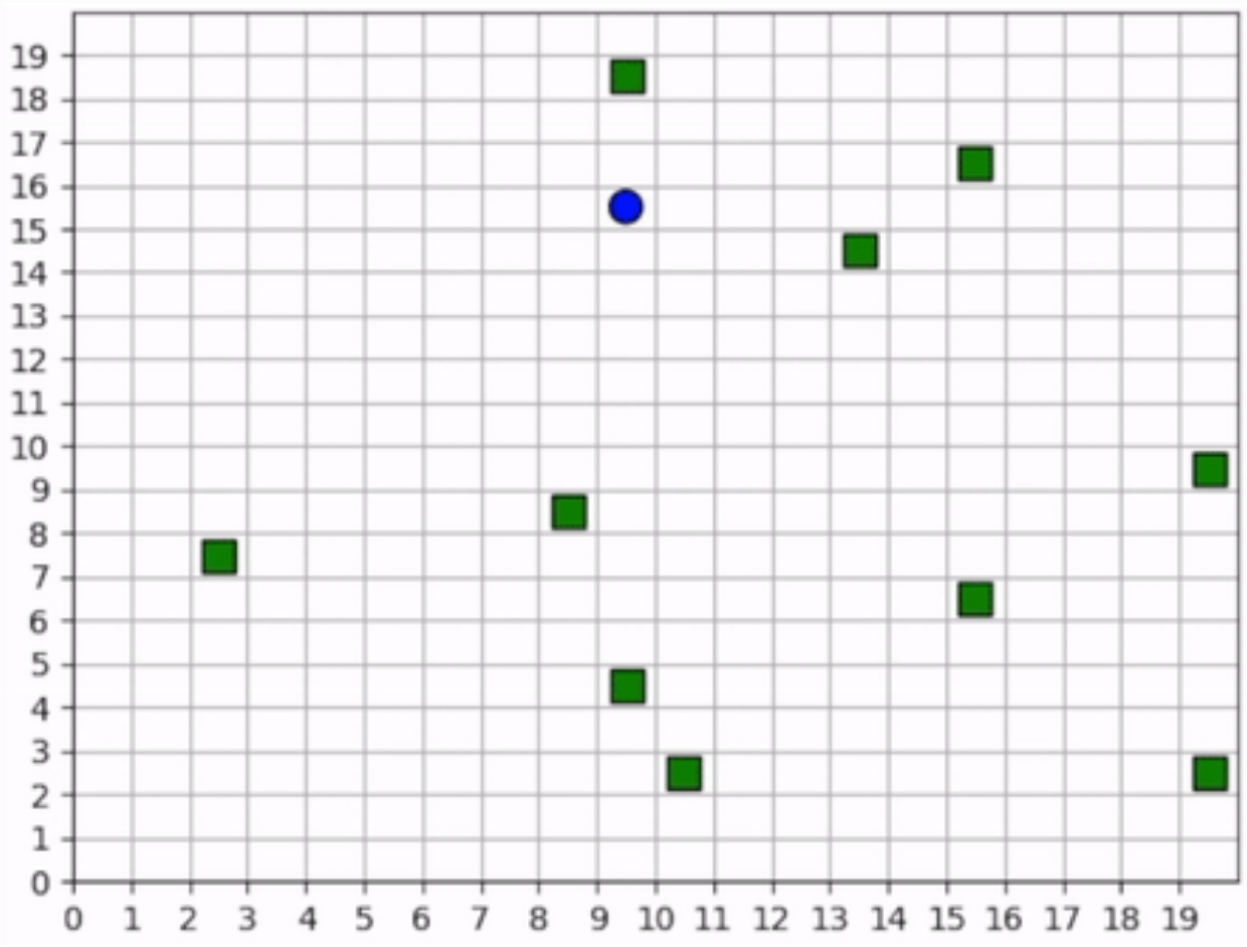



Fig. 3: The forager learns an effective foraging strategy, moving towards and collecting the nearest resources that it observes.

### When it cannot see resources

The forager's behavior when it is near resources is not surprising. But how does it behave when it cannot see any resources? The forager only sees that which is near it and does not have any information distinguishing one "deserted" area of the map from another. Recall, however, that it observes the edges of the map, and it uses this information to learn an effecive exploration strategy. In the video below, we can see that the forager learns to explore the map by moving along its edges in a clockwise direction, occasionally making random moves towards the middle of the map.

---

**Important:** We do not use any kind of heuristic or mixed policy. The exporation strategy *emerges* entirely from

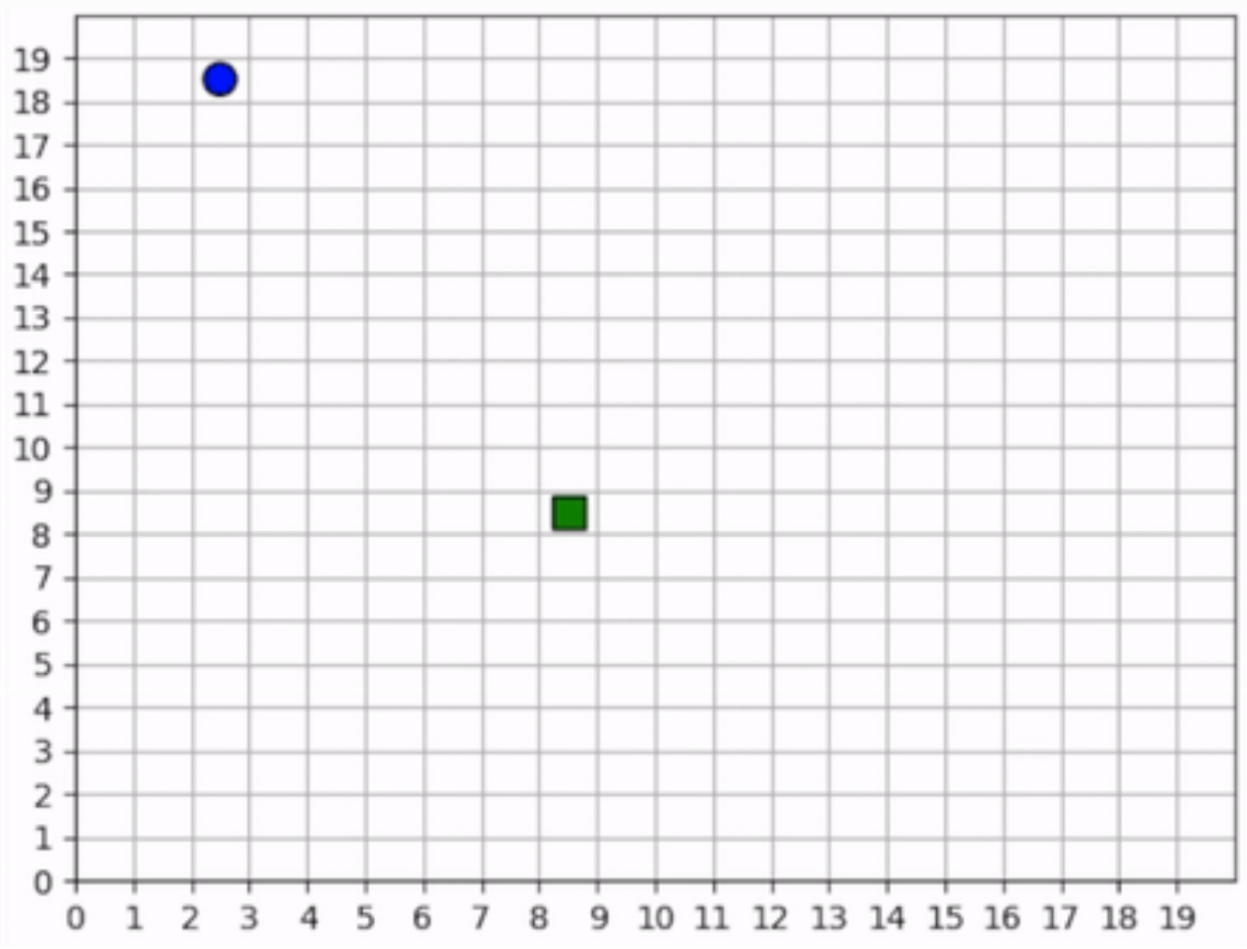



Fig. 4: The forager learns an effective exploration strategy, moving along the edge of the map in a clockwise direction.

reinforcement learning.

### 4.1.2 Multiple Agents Foraging

Having experimented with a single forager, let us now turn our attention to the strategies learned by multiple foragers interacting in the map at the same time. Each forager is homogeneous with each other as described above: they can all move up to one square away, observe up to three squares away, and are rewarded the same way. The observations include other foragers in addition to the resources and map edges. All agents share a single policy. Below is a brief analysis of the learned behaviors.

#### Cover and explore

Our reward schema implicitly encourages the foragers to collaborate because we give a small penalty to each one for taking too long. Thus, the faster they can collect all the resources, the less they are penalized. Furthermore, because each agent trains the same policy, there is no incentive for competitive behavior. An agent can afford to say, "I don't need to get the resource first. As long as one of us gets it quickly, then we all benefit". Therefore, the foragers learn to spread out to *cover* the map, maximizing the amount of squares that are observed.

In the video clips below, we see that the foragers avoid being within observation distance of one another. Typically, when two foragers get too close, they repel each other, each moving in opposite directions, ensuring that the space is *covered*. Furthermore, notice the dance-like exploration strategy. Similar to the single-agent case above, they learn to *explore* along the edges of the map in a clockwise direction. However, they're not as efficient as the single agent because they "repel" each other.

---

**Important:** We do not directly incentivize agents to keep their distance. No part of the reward schema directly deals with the agents' distances from each other. These strategies are *emergent*.

---

#### Breaking the pattern

When a forager observes a resource, it breaks its "cover and explore" strategy and moves directly for the resource. Even multiple foragers move towards the same resource. They have no reason to coordinate who will get it because, as we stated above, there is no incentive for competition, so no need to negotiate. If another forager gets there first, everyone benefits. The foragers learn to prioritize collecting the resources over keeping their distance from each other.

---

**Tip:** We should expect to see both of these strategies occuring at the same time within a simulation because while some agents are "covering and exploring", others are moving towards resources.

---

### 4.1.3 Introducing Hunters

So far, we have seen intelligent behaviors emerge in both single- and multi-forager scenarios; we even saw the emergence of collaborative behavior. In the following experiments, we explore competitive emergence by introducing hunters into the simulation. Like foragers, hunters can move up to one square away and observe other agents and map edges up to three squares away. Hunters, however, are more effective killers and can attack a forager up to two squares away. They are rewarded for successful kills, they are and penalized for bad moves and for taking too long, exactly the same way as foragers.

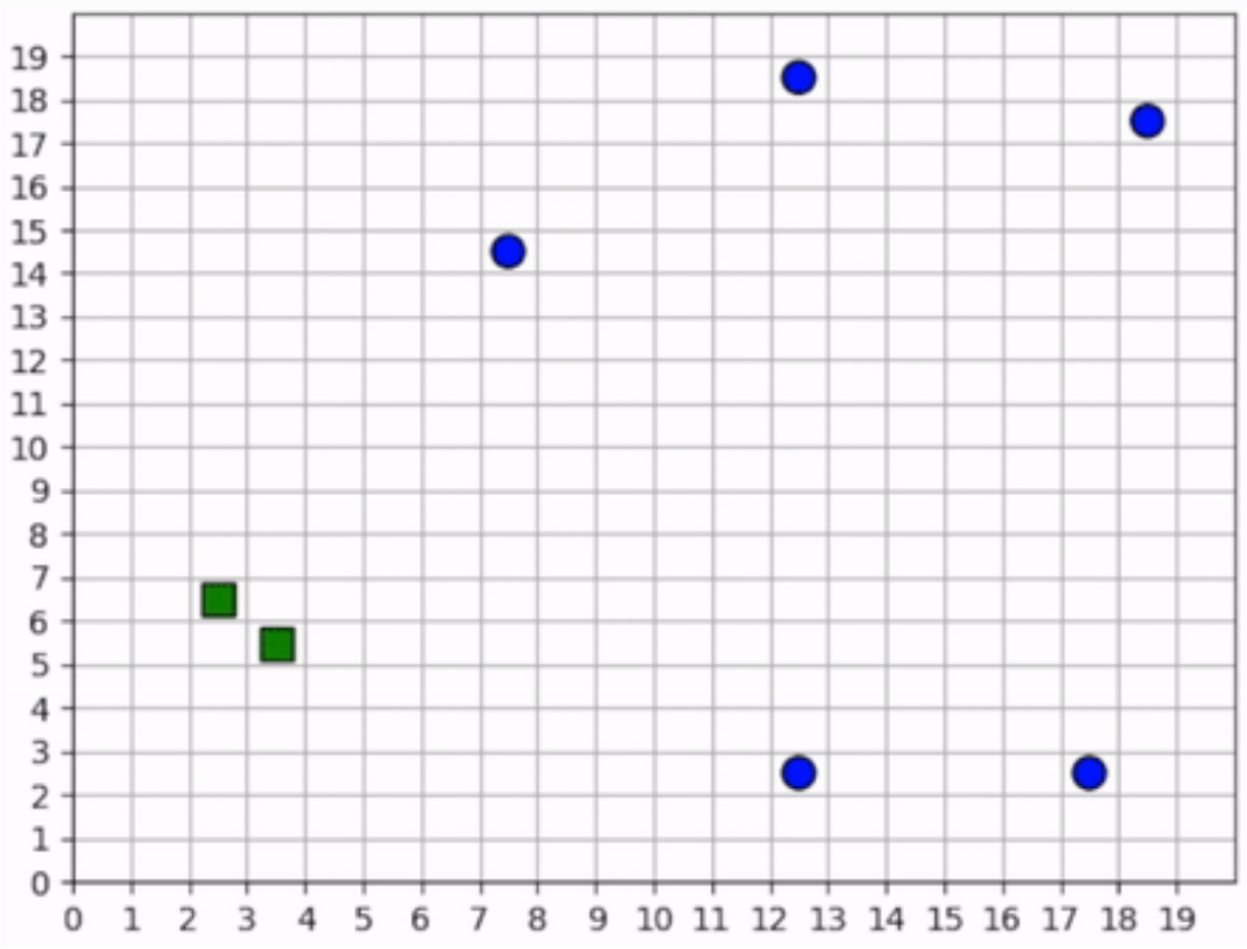



Fig. 5: The foragers cover the map by spreading out and explore it by traveling in a clockwise direction.

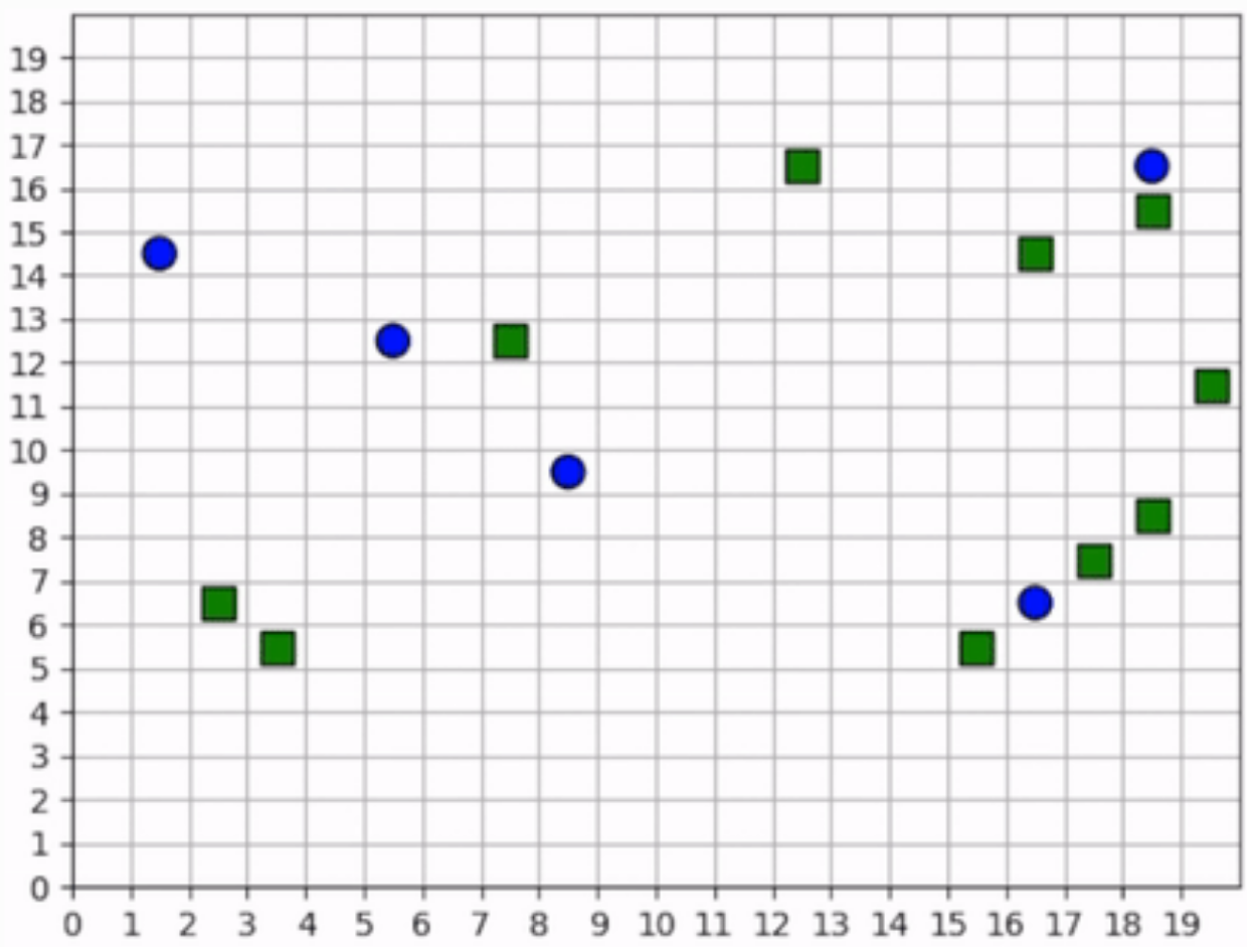
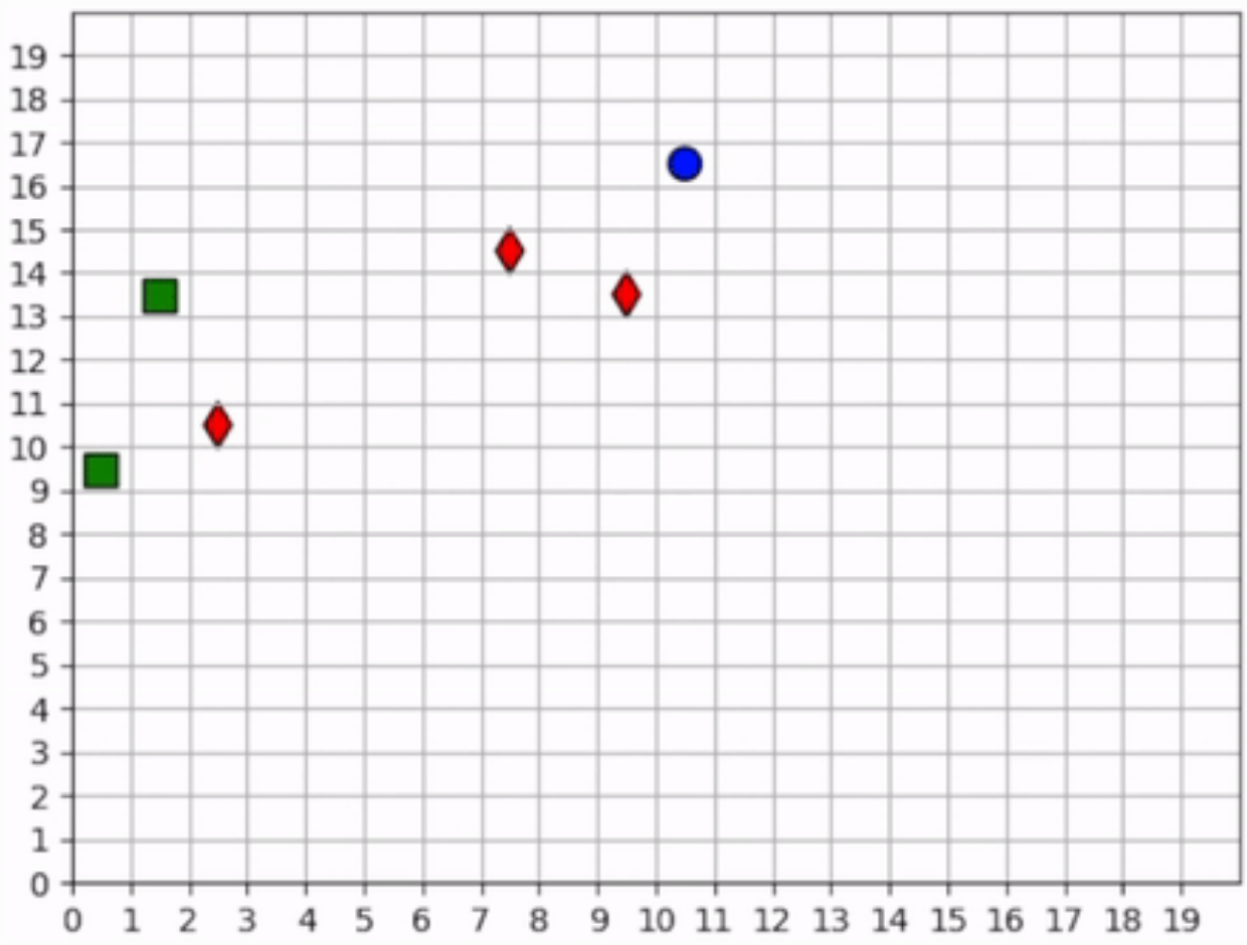



Fig. 6: The foragers move towards resources to forage, even when there are other foragers nearby.

However, the hunters and foragers have completely different objectives: a forager tries to clear the map of all *resources*, but a hunter tries to clear the map of all *foragers*. Therefore, we set up two policies. All the hunters will train the same policy, and all the foragers will train the same policy, and these policies will be distinct.

The learned behaviors among the two groups in this mixed collaborate-competitive simulation are tightly integrated, with multiple strategies appearing at the same time within a simulation. Therefore, in contrast to above, we will not show video clips that capture a single strategy; instead, we will show video clips that capture multiple strategies and attempt to describe them in detail.

### First Scenario



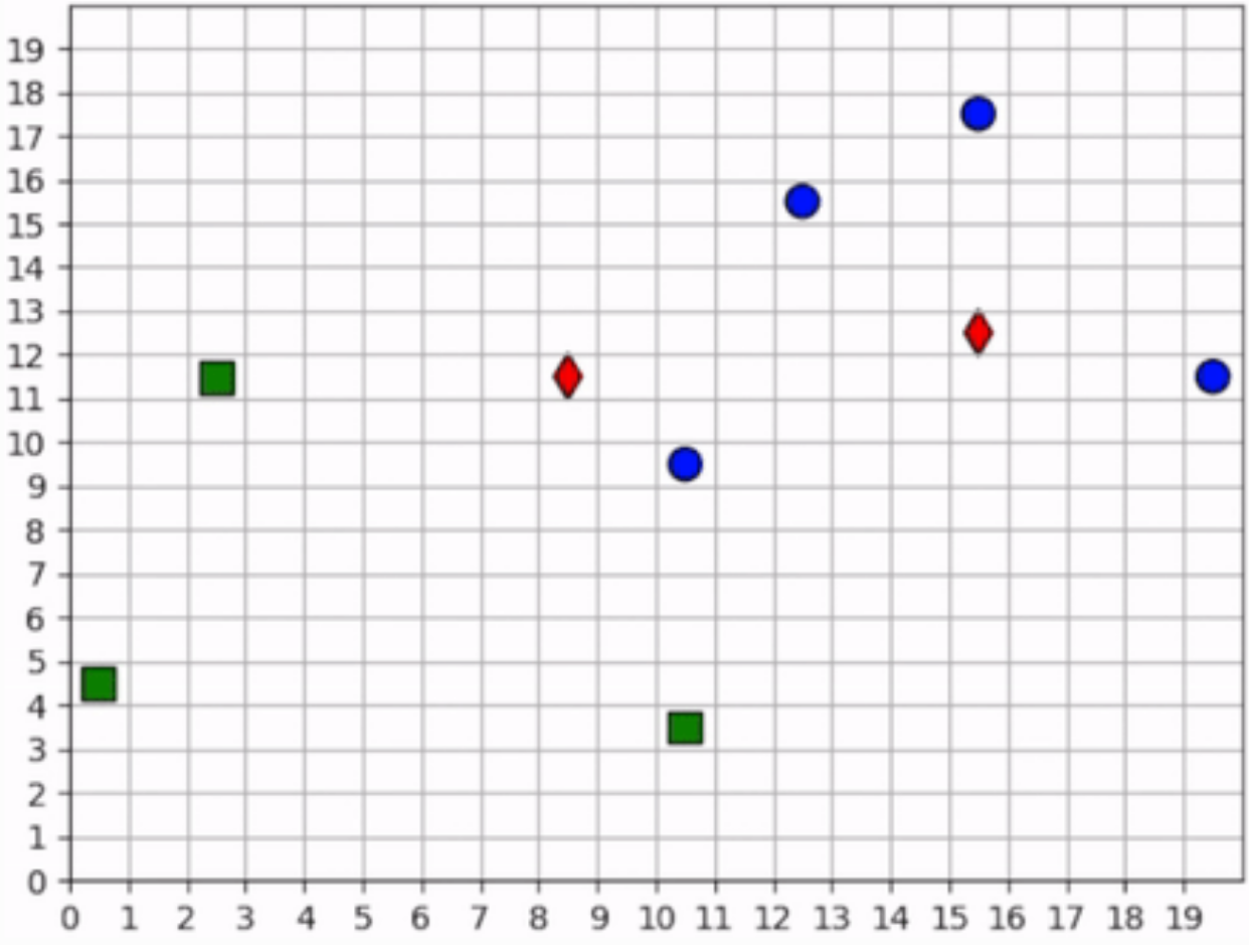

Two of the foragers spawn next to hunters and are killed immediately. Afterwards, the two hunters on the left do not observe any foragers for some time. They seem to have learned the *cover* strategy by spreading out, but they don't seem to have learned an effecient *explore* strategy since they mostly occupy the same region of the map for the duration of the simulation.

Three foragers remain at the bottom of the map. These foragers work together to collect all nearby resources. Just as they finish the resource cluster, a hunter moves within range and begins to chase them towards the bottom of the map. When they hit the edge, they split in two directions. The hunter kills one of them and then waits for one step, unsure about which forager to persue next. After one step, we see that it decides to persue the forager to the right.

Meanwhile, the forager to the left continues to run away, straight into the path of another hunter but also another resource. The forager could get away by running to the right, but it decides to collect the resource at the cost of its own life.

The last remaining forager has escaped the hunter and has conveniently found another cluster of resources, which it collects. A few frames later, it encounters the same hunter, and this time it is chased all the way across the map. It manages to evade the hunter and collect one final resource before encountering yet another hunter. At the end, we see both hunters chasing the forager to the top of the map, boxing it in and killing it.

### Second scenario




None of the foragers are under threat at the beginning of this scenario. They clear a cluster of resources before one of them wanders into the path of a hunter. The hunter gives chase, and the forager actually leads the hunter back to the group. This works to its benefit, however, as the hunter is repeatedly confused by the foragers exercising the *splitting* strategy. Meanwhile the second hunter has spotted a forager and joins the hunt. The two hunters together are able to split up the pack of foragers and systematically hunt them down. The last forager is chased into the corner and killed.

**Note:** Humorously, the first forager that was spotted is the one who manages to stay alive the longest.

CHAPTER

FIVE

# INSTALLATION

## 5.1 User Installation

You can install abmarl via *pip*:

```
pip install abmarl
```

## 5.2 Developer Installation

To install Abmarl for development, first clone the repository and then install via pip's development mode.

```
git clone git@github.com:LLNL/Abmarl.git
cd abmarl
pip install -r requirements.txt
pip install -e . --no-deps
```

**Warning:** If you are using *conda* to manage your virtual environment, then you must also install ffmpeg.

CHAPTER

SIX

# FULL TUTORIALS

We provide tutorials that demonstrate how to train, visualize, and analyze MARL policies. We also provide tutorials on the GridWorldSimulation framework.

## 6.1 MultiCorridor

MultiCorridor is a multi-agent-based simulation wherein agents must learn to move to the right in a one-dimensonal corridor to reach the end. Our implementation provides the ability to instantiate multiple agents in the simulation and restricts agents from occupying the same square. Every agent is homogeneous: they all have the same action space, observation space, and objective function.

Fig. 1: Animation of agents moving left and right in a corridor until they reach the end.

This tutorial uses the MultiCorridor simulation and the MultiCorridor configuration.

### 6.1.1 Creating the MultiCorridor Simulation

#### The Agents in the Simulation

It's helpful to start by thinking about what we want the agents to learn and what information they will need in order to learn it. In this tutorial, we want to train agents that can reach the end of a one-dimensional corridor without bumping into each other. Therefore, agents should be able to move left, move right, and stay still. In order to move to the end of the corridor without bumping into each other, they will need to see their own position and if the squares near them are occupied. Finally, we need to decide how to reward the agents. There are many ways we can do this, and we should at least capture the following:

- The agent should be rewarded for reaching the end of the corridor.
- The agent should be penalized for bumping into other agents.
- The agent should be penalized for taking too long.

Since all our agents are homogeneous, we can create them in the Agent Based Simulation itself, like so:

```
from enum import IntEnum

from gym.spaces import Box, Discrete, MultiBinary
import numpy as np

from abmarl.sim import Agent, AgentBasedSimulation

class MultiCorridor(AgentBasedSimulation):

    class Actions(IntEnum): # The three actions each agent can take
        LEFT = 0
        STAY = 1
        RIGHT = 2

    def __init__(self, end=10, num_agents=5):
        self.end = end
        agents = {}
        for i in range(num_agents):
            agents[f'agent{i}'] = Agent(
                id=f'agent{i}',
                action_space=Discrete(3), # Move left, stay still, or move right
                observation_space={
                    'position': Box(0, self.end-1, (1,), int), # Observe your own␣
↪position
                    'left': MultiBinary(1), # Observe if the left square is occupied
                    'right': MultiBinary(1) # Observe if the right square is occupied
                }
            )
        self.agents = agents

        self.finalize()
```

Here, notice how the agents' *observation_space* is a *dict* rather than a *gym.space.Dict*. That's okay because our *Agent* class can convert a *dict of gym spaces* into a *Dict* when `finalize` is called at the end of `__init__`.

### Resetting the Simulation

At the beginning of each episode, we want the agents to be randomly positioned throughout the corridor without occupying the same squares. We must give each agent a position attribute at reset. We will also create a data structure that captures which agent is in which cell so that we don't have to do a search for nearby agents but can directly index the space. Finally, we must track the agents' rewards.

```
def reset(self, **kwargs):
    location_sample = np.random.choice(self.end-1, len(self.agents), False)
    # Track the squares themselves
    self.corridor = np.empty(self.end, dtype=object)
    # Track the position of the agents
    for i, agent in enumerate(self.agents.values()):
        agent.position = location_sample[i]
        self.corridor[location_sample[i]] = agent

    # Track the agents' rewards over multiple steps.
```

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```
    self.reward = {agent_id: 0 for agent_id in self.agents}
```

### Stepping the Simulation

The simulation is driven by the agents' actions because there are no other dynamics. Thus, the MultiCorridor Simulation only concerns itself with processing the agents' actions at each step. For each agent, we'll capture the following cases:

- An agent attempts to move to a space that is unoccupied.
- An agent attempts to move to a space that is already occupied.
- An agent attempts to move to the right-most space (the end) of the corridor.

```
def step(self, action_dict, **kwargs):
    for agent_id, action in action_dict.items():
        agent = self.agents[agent_id]
        if action == self.Actions.LEFT:
            if agent.position != 0 and self.corridor[agent.position-1] is None:
                # Good move, no extra penalty
                self.corridor[agent.position] = None
                agent.position -= 1
                self.corridor[agent.position] = agent
                self.reward[agent_id] -= 1 # Entropy penalty
            elif agent.position == 0: # Tried to move left from left-most square
                # Bad move, only acting agent is involved and should be penalized.
                self.reward[agent_id] -= 5 # Bad move
            else: # There was another agent to the left of me that I bumped into
                # Bad move involving two agents. Both are penalized
                self.reward[agent_id] -= 5 # Penalty for offending agent
                # Penalty for offended agent
                self.reward[self.corridor[agent.position-1].id] -= 2
        elif action == self.Actions.RIGHT:
            if self.corridor[agent.position + 1] is None:
                # Good move, but is the agent done?
                self.corridor[agent.position] = None
                agent.position += 1
                if agent.position == self.end-1:
                    # Agent has reached the end of the corridor!
                    self.reward[agent_id] += self.end ** 2
                else:
                # Good move, no extra penalty
                    self.corridor[agent.position] = agent
                    self.reward[agent_id] -= 1 # Entropy penalty
            else: # There was another agent to the right of me that I bumped into
                # Bad move involving two agents. Both are penalized
                self.reward[agent_id] -= 5 # Penalty for offending agent
                # Penalty for offended agent
                self.reward[self.corridor[agent.position+1].id] -= 2
        elif action == self.Actions.STAY:
            self.reward[agent_id] -= 1 # Entropy penalty
```

**Attention:** Our reward schema reveals a training dynamic that is not present in single-agent simulations: an agent's reward does not entirely depend on its own interaction with the simulation but can be affected by other agents' actions. In this case, agents are slightly penalized for being "bumped into" when other agents attempt to move onto their square, even though the "offended" agent did not directly cause the collision. This is discussed in MARL literature and captured in the way we have designed our Simulation Managers. In Abmarl, we favor capturing the rewards as part of the simulation's state and only "flushing" them once they rewards are asked for in `get_reward`.

**Note:** We have not needed to consider the order in which the simulation processes actions. Our simulation simply provides the capabilities to process *any* agent's action, and we can use *Simulation Managers* to impose an order. This shows the flexibility of our design. In this tutorial, we will use the *TurnBasedManager*, but we can use any *SimulationManager*.

### Querying Simulation State

The trainer needs to see how agents' actions impact the simulation's state. They do so via getters, which we define below.

```
def get_obs(self, agent_id, **kwargs):
    agent_position = self.agents[agent_id].position
    if agent_position == 0 or self.corridor[agent_position-1] is None:
        left = False
    else:
        left = True
    if agent_position == self.end-1 or self.corridor[agent_position+1] is None:
        right = False
    else:
        right = True
    return {
        'position': [agent_position],
        'left': [left],
        'right': [right],
    }

def get_done(self, agent_id, **kwargs):
    return self.agents[agent_id].position == self.end - 1

def get_all_done(self, **kwargs):
    for agent in self.agents.values():
        if agent.position != self.end - 1:
            return False
    return True

def get_reward(self, agent_id, **kwargs):
    agent_reward = self.reward[agent_id]
    self.reward[agent_id] = 0
    return agent_reward

def get_info(self, agent_id, **kwargs):
    return {}
```

#### Rendering for Visualization

Finally, it's often useful to be able to visualize a simulation as it steps through an episode. We can do this via the render funciton.

```
def render(self, *args, fig=None, **kwargs):
    draw_now = fig is None
    if draw_now:
        from matplotlib import pyplot as plt
        fig = plt.gcf()

    fig.clear()
    ax = fig.gca()
    ax.set(xlim=(-0.5, self.end + 0.5), ylim=(-0.5, 0.5))
    ax.set_xticks(np.arange(-0.5, self.end + 0.5, 1.))
    ax.scatter(np.array(
        [agent.position for agent in self.agents.values()]),
        np.zeros(len(self.agents)),
        marker='s', s=200, c='g'
    )

    if draw_now:
        plt.plot()
        plt.pause(1e-17)
```

### 6.1.2 Training the MultiCorridor Simulation

Now that we have created the simulation and agents, we can create a configuration file for training.

#### Simulation Setup

We'll start by setting up the simulation we have just built. Then we'll choose a Simulation Manager. Abmarl comes with two built-In managers: *TurnBasedManager*, where only a single agent takes a turn per step, and *AllStepManager*, where all non-done agents take a turn per step. For this experiment, we'll use the *TurnBasedManager*. Then, we'll wrap the simulation with our *MultiAgentWrapper*, which enables us to connect with RLlib. Finally, we'll register the simulation with RLlib.

```
# MultiCorridor is the simulation we created above
from abmarl.examples import MultiCorridor
from abmarl.managers import TurnBasedManager
# MultiAgentWrapper needed to connect with RLlib
from abmarl.external import MultiAgentWrapper

# Create an instance of the simulation and register it
sim = MultiAgentWrapper(TurnBasedManager(MultiCorridor()))
sim_name = "MultiCorridor"
from ray.tune.registry import register_env
register_env(sim_name, lambda sim_config: sim)
```

### Policy Setup

Now we want to create the policies and the policy mapping function in our multiagent experiment. Each agent in our simulation is homogeneous: they all have the same observation space, action space, and objective function. Thus, we can create a single policy and map all agents to that policy.

```
ref_agent = sim.unwrapped.agents['agent0']
policies = {
    'corridor': (None, ref_agent.observation_space, ref_agent.action_space, {})
}
def policy_mapping_fn(agent_id):
    return 'corridor'
```

### Experiment Parameters

Having setup the simulation and policies, we can now bundle all that information into a parameters dictionary that will be read by Abmarl and used to launch RLlib.

```
params = {
    'experiment': {
        'title': f'{sim_name}',
        'sim_creator': lambda config=None: sim,
    },
    'ray_tune': {
        'run_or_experiment': 'PG',
        'checkpoint_freq': 50,
        'checkpoint_at_end': True,
        'stop': {
            'episodes_total': 2000,
        },
        'verbose': 2,
        'config': {
            # --- Simulation ---
            'disable_env_checking': False,
            'env': sim_name,
            'horizon': 200,
            'env_config': {},
            # --- Multiagent ---
            'multiagent': {
                'policies': policies,
                'policy_mapping_fn': policy_mapping_fn,
            },
            # --- Parallelism ---
            # Number of workers per experiment: int
            "num_workers": 7,
            # Number of simulations that each worker starts: int
            "num_envs_per_worker": 1, # This must be 1 because we are not "threadsafe"
        },
    }
}
```

#### Command Line interface

With the configuration file complete, we can utilize the command line interface to train our agents. We simply type `abmarl train multi_corridor_example.py`, where *multi_corridor_example.py* is the name of our configuration file. This will launch Abmarl, which will process the file and launch RLlib according to the specified parameters. This particular example should take 1-10 minutes to train, depending on your compute capabilities. You can view the performance in real time in tensorboard with `tensorboard --logdir ~/abmarl_results`.

#### Visualizing the Trained Behaviors

We can visualize the agents' learned behavior with the `visualize` command, which takes as argument the output directory from the training session stored in `~/abmarl_results`. For example, the command

```
abmarl visualize ~/abmarl_results/MultiCorridor-2020-08-25_09-30/ -n 5 --record
```

will load the experiment (notice that the directory name is the experiment title from the configuration file appended with a timestamp) and display an animation of 5 episodes. The `--record` flag will save the animations as *.mp4* videos in the training directory.

### 6.1.3 Extra Challenges

Having successfully trained a MARL experiment, we can further explore the agents' behaviors and the training process. Some ideas are:

- We could enhance the MultiCorridor Simulation so that the "target" cell is a different location in each episode.
- We could introduce heterogeneous agents with the ability to "jump over" other agents. With heterogeneous agents, we can nontrivially train multiple policies.
- We could study how the agents' behaviors differ if they are trained using the *AllStepManager*.
- We could create our own Simulation Manager so that if an agent causes a collision, it skips its next turn.
- We could do a parameter search over both simulation and algorithm parameters to study how the parameters affect the learned behaviors.
- We could analyze how often agents collide with one another and where those collisions most commonly occur.
- And much, much more!

As we attempt these extra challenges, we will experience one of Abmarl's strongest features: the ease with which we can modify our experiment file and launch another training job, going through the pipeline from experiment setup to behavior visualization and analysis!

## 6.2 GridWorld

The GridWorld Simulation Framework is composed of feature components that fit together to allow users to create a variety of simulations using the same pieces and to easily design their own features. We provide tutorials demonstrating the special features of this framework. First, we create a multi-team battle simulation using built-in features components. We then show how the exact same components can be reconfigured to create a maze-navigation simulation. Finally, we show how easy it is to add custom features as components and plug them into the simulation framework.

### 6.2.1 Team Battle

The Team Battle scenario involves multiple teams of agents fighting against each other. The goal of each team is to be the last team alive, at which point the simulation will end. Each agent can move around the grid and attack agents from other teams. Each agent can observe the grid around its position. We will reward each agent for successful kills and penalize them for bad moves. This tutorial can be found in full in our repo.

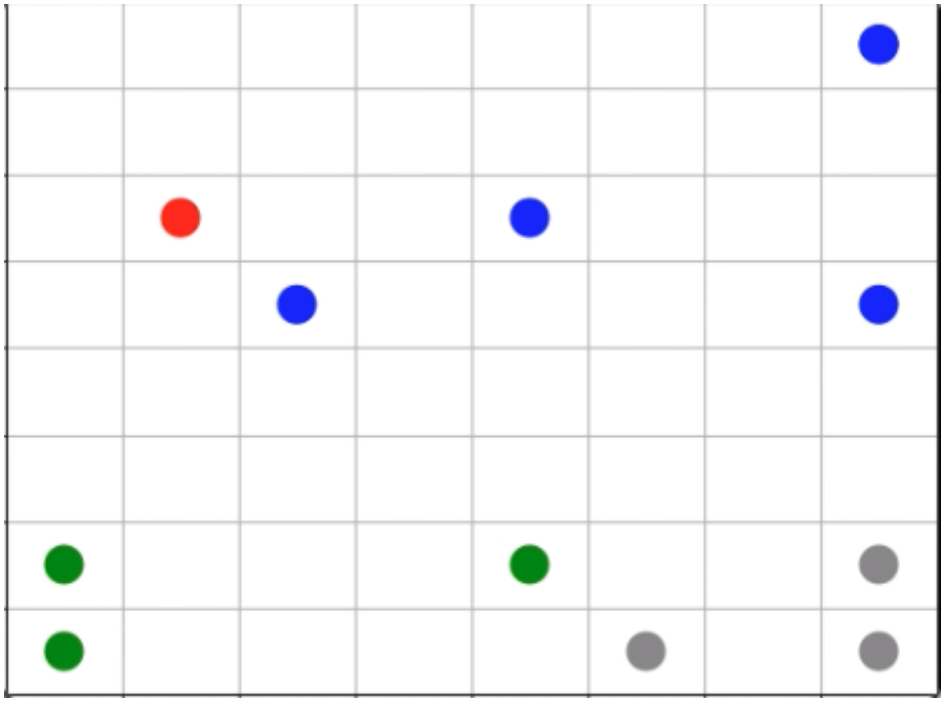

Fig. 2: Agents on four teams battling each other.

First, we import the components that we need. Each component is *already in Abmarl*, so we don't need to create anything new.

```
from matplotlib import pyplot as plt
import numpy as np

from abmarl.sim.gridworld.base import GridWorldSimulation
from abmarl.sim.gridworld.agent import GridObservingAgent, MovingAgent, AttackingAgent,␣
↪HealthAgent
from abmarl.sim.gridworld.state import HealthState, PositionState
from abmarl.sim.gridworld.actor import MoveActor, BinaryAttackActor
from abmarl.sim.gridworld.observer import SingleGridObserver
from abmarl.sim.gridworld.done import OneTeamRemainingDone
```

Then, we define our agent types. This simulation will only have a single type: the BattleAgent. Most of the agents' attributes will be the same, and we can preconfigure the class definition to save us time when we create the agents later on.

```
class BattleAgent(GridObservingAgent, MovingAgent, AttackingAgent, HealthAgent):
    def __init__(self, **kwargs):
        super().__init__(
            move_range=1,
```

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```
            attack_range=1,
            attack_strength=1,
            attack_accuracy=1,
            view_range=3,
            **kwargs
        )
```

Having defined the BattleAgent, we then put all the components together into a single simulation.

```
class TeamBattleSim(GridWorldSimulation):
    def __init__(self, **kwargs):
        self.agents = kwargs['agents']

        # State Components
        self.position_state = PositionState(**kwargs)
        self.health_state = HealthState(**kwargs)

        # Action Components
        self.move_actor = MoveActor(**kwargs)
        self.attack_actor = BinaryAttackActor(**kwargs)

        # Observation Components
        self.grid_observer = SingleGridObserver(**kwargs)

        # Done Compoennts
        self.done = OneTeamRemainingDone(**kwargs)

        self.finalize()
```

Next we define the start state of each simulation. We lean on the *State Components* to perform the reset. Note that we must track the rewards explicitly.

```
class TeamBattleSim(GridWorldSimulation):
    ...

    def reset(self, **kwargs):
        self.position_state.reset(**kwargs)
        self.health_state.reset(**kwargs)

        # Track the rewards
        self.rewards = {agent.id: 0 for agent in self.agents.values()}
```

Then we define how the simulation will step forward, leaning on the *Actors* to process their part of the action. The Actors' result determine the agents' rewards.

```
class TeamBattleSim(GridWorldSimulation):
    ...

    def step(self, action_dict, **kwargs):
        # Process attacks:
        for agent_id, action in action_dict.items():
            agent = self.agents[agent_id]
            if agent.active:
```

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```
                attack_status, attacked_agents = \
                    self.attack_actor.process_action(agent, action, **kwargs)
                if attack_status: # Attack was attempted
                    if not attacked_agents: # Attack failed
                        self.rewards[agent_id] -= 0.1
                    else:
                        for attacked_agent in attacked_agents:
                            if not attacked_agent.active: # Agent has died
                                self.rewards[attacked_agent.id] -= 1
                                self.rewards[agent_id] += 1

        # Process moves
        for agent_id, action in action_dict.items():
            agent = self.agents[agent_id]
            if agent.active:
                move_result = self.move_actor.process_action(agent, action, **kwargs)
                if not move_result:
                    self.rewards[agent.id] -= 0.1

        # Entropy penalty
        for agent_id in action_dict:
            self.rewards[agent_id] -= 0.01
```

Finally, we define each of the getters using the *Observers* and *Done components*.

```
class TeamBattleSim(GridWorldSimulation):
    ...

    def get_obs(self, agent_id, **kwargs):
        agent = self.agents[agent_id]
        return {
            **self.grid_observer.get_obs(agent, **kwargs)
        }

    def get_reward(self, agent_id, **kwargs):
        reward = self.rewards[agent_id]
        self.rewards[agent_id] = 0
        return reward

    def get_done(self, agent_id, **kwargs):
        return self.done.get_done(self.agents[agent_id])

    def get_all_done(self, **kwargs):
        return self.done.get_all_done(**kwargs)

    def get_info(self, agent_id, **kwargs):
        return {}
```

Now that we've defined our agents and simulation, let's create them and run it. First, we'll create the agents. There will be 4 teams, so we want to color the agent by team and start them at different corners of the grid. Besides that, all agent attributes will be the same, and here we benefit from preconfiguring the attributes in the class definition above.

```
colors = ['red', 'blue', 'green', 'gray'] # Team colors
positions = [np.array([1,1]), np.array([1,6]), np.array([6,1]), np.array([6,6])] # Grid corners
agents = {
    f'agent{i}': BattleAgent(
        id=f'agent{i}',
        encoding=i%4+1,
        render_color=colors[i%4],
        initial_position=positions[i%4]
    ) for i in range(24)
}
```

Having created the agents, we can now *build the simulation*. We will allow agents from the same team to occupy the same cell and allow agents to attack other agents if they are on different teams.

```
overlap_map = {
    1: {1},
    2: {2},
    3: {3},
    4: {4}
}
attack_map = {
    1: [2, 3, 4],
    2: [1, 3, 4],
    3: [1, 2, 4],
    4: [1, 2, 3]
}
sim = TeamBattleSim.build_sim(
    8, 8,
    agents=agents,
    overlapping=overlap_map,
    attack_mapping=attack_map
)
```

Finally, we can run the simulation with random actions and visualize it. The visualization produces an animation like the one at the top of this page.

```
sim.reset()
fig = plt.figure()
sim.render(fig=fig)

done_agents = set()
for i in range(50): # Run for at most 50 steps
    action = {
        agent.id: agent.action_space.sample() for agent in agents.values() if agent.id not in done_agents
    }
    sim.step(action)
    sim.render(fig=fig)

    if sim.get_all_done():
        break
    for agent in agents:
```

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```
        if sim.get_done(agent):
            done_agents.add(agent)
```

### Extra Challenges

Having successfully created and run a TeamBattle simulation, we can further explore the GridWorldSimulation framework. Some ideas are:

- Experiment with the number of agents and the impact that has on both the SingleGridObserver and the MultiGridObserver.
- Experiment with the number of agents per team as well as the capabilities of those agents. You might find that a super capable agent is still effective against a team of multiple agents.
- Create a Hunter-Forager simulation, where one team of agents act as immobile resources that can be foraged by another team, which can be hunted by a third team. Try using the same components here, although you may need to use a custom *done condition*.
- Connect this simulation with the Reinforcement Learning capabilities of Abmarl via a *Simulation Manager*. What kind of behaviors do the agents learn?
- And much, much more!

## 6.2.2 Maze Navigation

Using the same components as we did in the *Team Battle tutorial*, we can create a Maze Navigation Simulation that contains a single moving agent navigating a maze defined by wall agents in the grid. The moving agent's goal is to reach a target agent. We will construct the Grid by *reading a grid file*. This tutorial can be found in full in our repo.

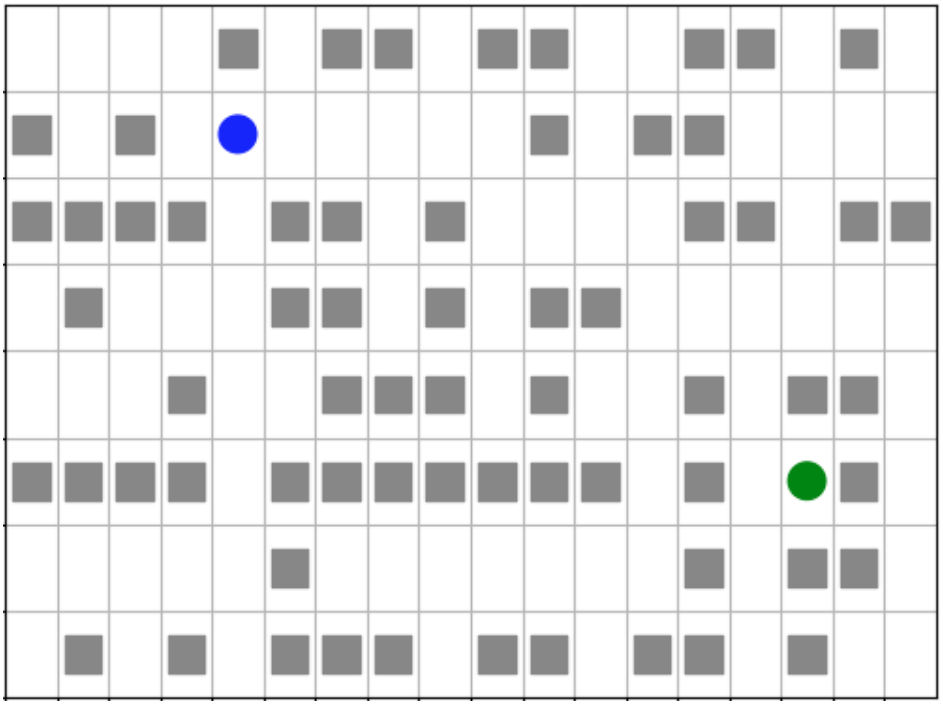

Fig. 3: Agent (blue) navigating a maze to the target (green).

**Note:** While we have multiple entities like walls and a target agent, the only agent that is actually doing something is the navigation agent. We will use some custom modifications to make this simulation easier, showing that we can easily use our components with custom modifications.

First we import the components that we need. Each feature is already in Abmarl, and they are the same features that we used in the *Team Battle tutorial*.

```
from matplotlib import pyplot as plt
import numpy as np

from abmarl.sim.gridworld.base import GridWorldSimulation
from abmarl.sim.gridworld.agent import GridObservingAgent, MovingAgent, GridWorldAgent
from abmarl.sim.gridworld.state import PositionState
from abmarl.sim.gridworld.actor import MoveActor
from abmarl.sim.gridworld.observer import SingleGridObserver
```

Then, we define our agent types. We need an MazeNavigationAgent, WallAgents to act as the barriers of the maze, and a TargetAgent to indicate the goal. Although we have these three types, we only need to define the MazeNavigationAgent because the WallAgent and the TargetAgent are the same as a generic *GridWorldAgent*.

```
class MazeNavigationAgent(GridObservingAgent, MovingAgent):
    def __init__(self, **kwargs):
        super().__init__(move_range=1, **kwargs)
```

Here we have preconfigured the agent with a *move range* of 1 becuase that makes the most sense for navigating mazes, but we have not preconfigured the *view range* since that is a parameter we may want to adjust, and it is easier to adjust it at the agent's initialization.

Then we define the simulation using the components and define all the necessary functions. We find it convient to explicitly store a reference to the navigation agent and the target agent. Rather than defining a new component for our simple done condition, we just write the condition itself in the function.

```
class MazeNaviationSim(GridWorldSimulation):
    def __init__(self, **kwargs):
        self.agents = kwargs['agents']

        # Store the navigation and target agents
        self.navigator = kwargs['agents']['navigator']
        self.target = kwargs['agents']['target']

        # State Components
        self.position_state = PositionState(**kwargs)

        # Action Components
        self.move_actor = MoveActor(**kwargs)

        # Observation Components
        self.grid_observer = SingleGridObserver(**kwargs)

        self.finalize()

    def reset(self, **kwargs):
        self.position_state.reset(**kwargs)
```

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```
        # Since there is only one agent that produces actions, there is only one reward.
        self.reward = 0

    def step(self, action_dict, **kwargs):
        # Only the navigation agent will send actions, so we pull that out
        action = action_dict['navigator']
        move_result = self.move_actor.process_action(self.navigator, action, **kwargs)
        if not move_result:
            self.reward -= 0.1

        # Entropy penalty
        self.reward -= 0.01

    def get_obs(self, agent_id, **kwargs):
        # pass the navigation agent itself to the observer becuase it is the only
        # agent that takes observations
        return {
            **self.grid_observer.get_obs(self.navigator, **kwargs)
        }

    def get_reward(self, agent_id, **kwargs):
        # Custom reward function
        if self.get_all_done():
            self.reward = 1
        reward = self.reward
        self.reward = 0
        return reward

    def get_done(self, agent_id, **kwargs):
        return self.get_all_done()

    def get_all_done(self, **kwargs):
        # We define the done condition here directly rather than creating a
        # separate component for it.
        return np.all(self.navigator.position == self.target.position)

    def get_info(self, agent_id, **kwargs):
        return {}
```

With everything defined, we're ready to create and run our simulation. We will create the simulation by reading a simulation file that shows the positions of each agent type in the grid. We will use *maze.txt*, which looks like this:

```
_ _ _ _ W _ W W _ W W _ _ W W _ W _
W _ W _ N _ _ _ _ _ W _ W W _ _ _ _
W W W W _ W W _ W _ _ _ _ W W _ W W
_ W _ _ _ W W _ W _ W W _ _ _ _ _ _
_ _ _ W _ _ W W W _ W _ _ W _ W W _
W W W W _ W W W W W W W _ W _ T W _
_ _ _ _ _ W _ _ _ _ _ _ _ W _ W W _
_ W _ W _ W W W _ W W _ W W _ W _ _
```

In order to assign meaning to the values in the grid file, we must create an *object registry* that maps the values in the

files to objects. We will use `W` for WallAgents, `N` for the NavigationAgent, and `T` for the TargetAgent. The values of the *object registry* must be lambda functions that take one argument and produce an agent.

```
object_registry = {
    'N': lambda n: MazeNavigationAgent(
        id=f'navigator',
        encoding=1,
        view_range=2, # Observation parameter that we can adjust as desired
        render_color='blue',
    ),
    'T': lambda n: GridWorldAgent(
        id=f'target',
        encoding=3,
        render_color='green'
    ),
    'W': lambda n: GridWorldAgent(
        id=f'wall{n}',
        encoding=2,
        blocking=True,
        render_shape='s'
    )
}
```

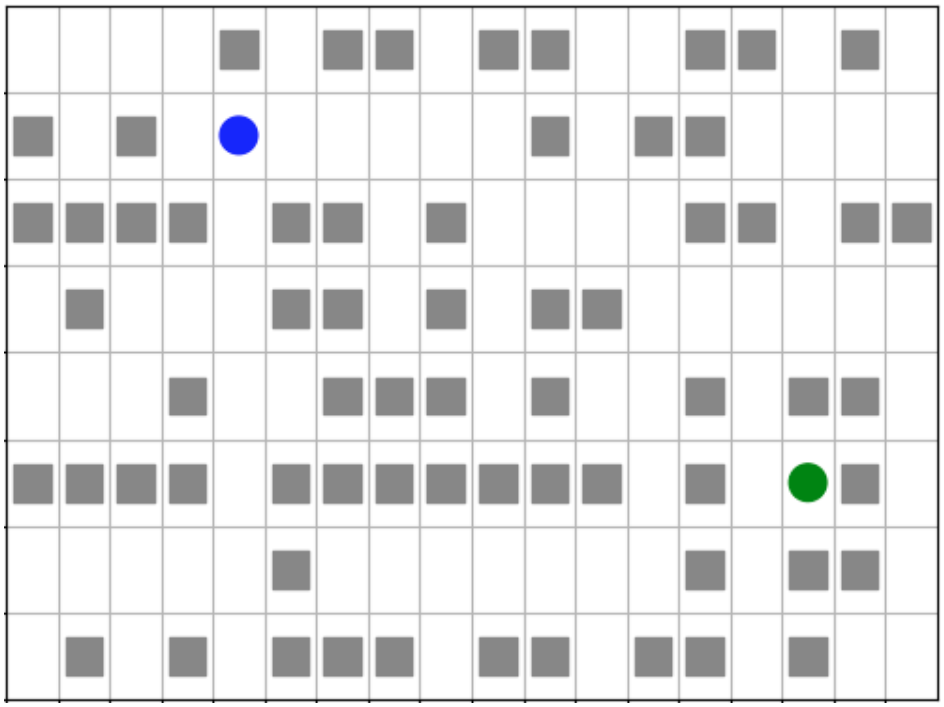
Now we can *build the simulation from the maze file* using the *object registry*. We must allow the navigation agent and the target agent to overlap since that is our done condition, and without it the simulation would never end. The visualization produces an animation like the one at the top of this page.

```
file_name = 'maze.txt'
sim = MazeNaviationSim.build_sim_from_file(
    file_name,
    object_registry,
    overlapping={1: {3}, 3: {1}}
)
sim.reset()
fig = plt.figure()
sim.render(fig=fig)

for i in range(100):
    action = {'navigator': sim.navigator.action_space.sample()}
    sim.step(action)
    sim.render(fig=fig)
    done = sim.get_all_done()
    if done:
        plt.pause(1)
        break
```

We can examine the observation to see how the walls effect what the navigation agent can observe. An example state and observation is given below.

```
-1 -2 -2 -2 -1
 0  0  2  0  2
 2  0  1  0  0
-2  2  0  2 -2
-2 -2  0 -2 -2
```



#### Extra Challenges

We've created a starkly different simulation using many of the same components as we did in the *TeamBattle tutorial*. We can further explore the capabilities of the GridWorld Simulation Framework, such as:

- Introduce additional navigating agents and modify the simulation so that the agents race to the target.
- Recreate pacman, frogger, and some of your favorite games from the Arcade Learning Environment. Not all games can be recreated with these components, and some cannot be recreated at all with the GridWorld Simulation Framework (because they are not grid-based).
- Connect this simulation with the Reinforcement Learning capabilities of Abmarl via a *Simulation Manager*. Does the agent learng how to solve mazes quickly?
- And much, much more!

### 6.2.3 Communication Blocking

Consider a simulation in which some agents send messages to each other in an attempt to reach consensus while another group of agents attempts to block these messages to impede consensus. Abmarl's GridWorld Simulation Framework already contains the features for the blocking agents; in this tutorial, we show how to create *new* components for the communication feature and connect them with the simulation framework. The tutorial can be found in full in our repo.

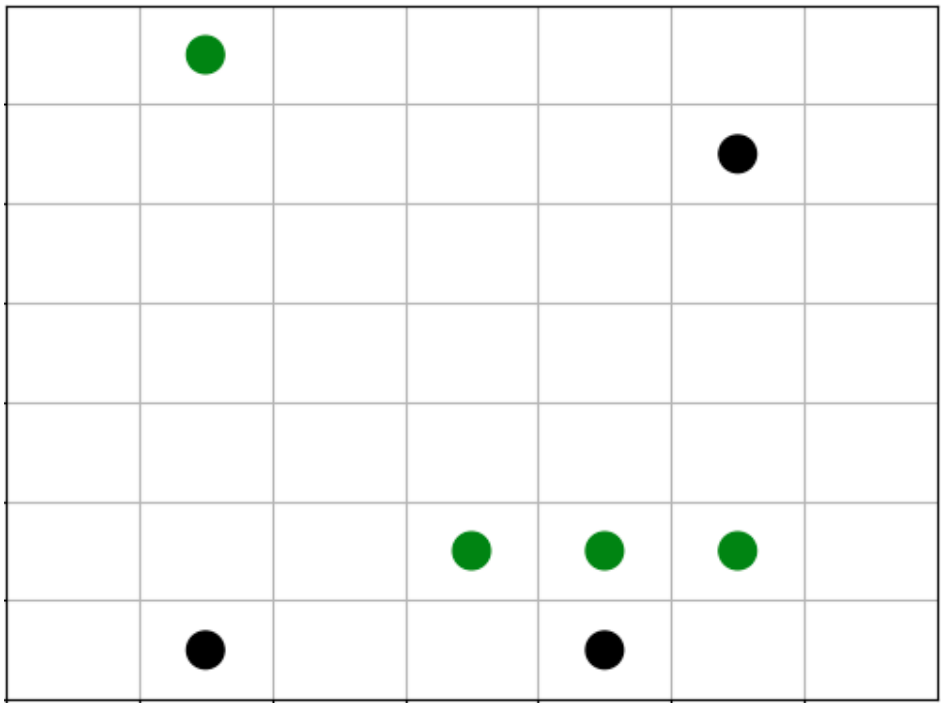


Fig. 4: Blockers (black) move around the maze blocking communications between broadcasters (green). The simulation ends when the broadcasters reach consensus.

### Using built-in features

Let's start by laying the groundwork using components already in Abmarl. We create a simulation with *position*, *movement*, and *observations*.

```
from matplotlib import pyplot as plt
import numpy as np

from abmarl.sim.gridworld.agent import MovingAgent, GridObservingAgent
from abmarl.sim.gridworld.base import GridWorldSimulation
from abmarl.sim.gridworld.state import PositionState
from abmarl.sim.gridworld.actor import MoveActor
from abmarl.sim.gridworld.observer import SingleGridObserver

class BlockingAgent(MovingAgent, GridObservingAgent):
    def __init__(self, **kwargs):
        super().__init__(blocking=True, **kwargs)

class BroadcastSim(GridWorldSimulation):
    def __init__(self, **kwargs):
        self.agents = kwargs['agents']
        self.position_state = PositionState(**kwargs)
        self.move_actor = MoveActor(**kwargs)
        self.grid_observer = SingleGridObserver(**kwargs)

        self.finalize()
```

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```
    def reset(self, **kwargs):
        self.position_state.reset(**kwargs)
        self.rewards = {agent.id: 0 for agent in self.agents.values()}

    def step(self, action_dict, **kwargs):
        # process moves
        for agent_id, action in action_dict.items():
            agent = self.agents[agent_id]
            move_result = self.move_actor.process_action(agent, action, **kwargs)
            if not move_result:
                self.rewards[agent.id] -= 0.1

        # Entropy penalty
        for agent_id in action_dict:
            self.rewards[agent_id] -= 0.01

    def get_obs(self, agent_id, **kwargs):
        agent = self.agents[agent_id]
        return {
            **self.grid_observer.get_obs(agent, **kwargs),
        }

    def get_reward(self, agent_id, **kwargs):
        reward = self.rewards[agent_id]
        self.rewards[agent_id] = 0
        return reward

    def get_done(self, agent_id, **kwargs):
        pass # Define this later

    def get_all_done(self, **kwargs):
        pass # Define this later

    def get_info(self, **kwargs):
        return {}
```

### Creating our own communication components

Next we build the communication components ourselves. We know that the GridWorld Simulation Framework is made up of *Agents*, *States*, *Actors*, *Observers*, and *Dones*, so we expect that we'll need to create each of these for our new communication feature. Let's start with the Agent component.

An agent communicates by broadcasting its message to other nearby agents. So we create a new agent with a *broadcast range* and an *initial message*. The *broadcast range* will be used by the BroadcastActor to determine successful broadcasting, and the *initial message*, an optional parameter, will be used by the BroadcastState to set its message.

```
from abmarl.sim import Agent
from abmarl.sim.gridworld.agent import GridWorldAgent

class BroadcastingAgent(Agent, GridWorldAgent):
    def __init__(self, broadcast_range=None, initial_message=None, **kwargs):
```

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```
        super().__init__(**kwargs)
        self.broadcast_range = broadcast_range
        self.initial_message = initial_message

    @property
    def broadcast_range(self):
        return self._broadcast_range

    @broadcast_range.setter
    def broadcast_range(self, value):
        assert type(value) is int and value >= 0, "Broadcast Range must be a nonnegative␣
↪integer."
        self._broadcast_range = value

    @property
    def initial_message(self):
        return self._initial_message

    @initial_message.setter
    def initial_message(self, value):
        if value is not None:
            assert -1 <= value <= 1, "Initial message must be a number between -1 and 1."
        self._initial_message = value

    @property
    def message(self):
        return self._message

    @message.setter
    def message(self, value):
        self._message = min(max(value, -1), 1)

    @property
    def configured(self):
        return super().configured and self.broadcast_range is not None
```

**Note:** We could have split the BroadcastingAgent into two agents types: one type of agent that has an internal message and another type that broadcasts. This is usually a better approach because it allows you to separate features and use them in greater combination with other features. We put them together in this tutorial for simplicity.

Next, we create the BroadcastState. This component manages the part of the simulation state that tracks which messages have been sent among the agents. It will be used by the BroadcastObserver to create the agent's observations. It also manages updates to each agent's message.

```
from abmarl.sim.gridworld.state import StateBaseComponent

class BroadcastingState(StateBaseComponent):
    def reset(self, **kwargs):
        for agent in self.agents.values():
            if isinstance(agent, BroadcastingAgent):
                if agent.initial_message is not None:
```

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```
                    agent.message = agent.initial_message
                else:
                    agent.message = np.random.uniform(-1, 1)

        # Tracks agents receiving messages from other agents
        self.receiving_state = {
            agent.id: [] for agent in self.agents.values() if isinstance(agent,␣
↪BroadcastingAgent)
        }

    def update_receipients(self, from_agent, to_agents):
        """
        Update messages received from other agents.
        """
        for agent in to_agents:
            self.receiving_state[agent.id].append((from_agent.id, from_agent.message))

    def update_message_and_reset_receiving(self, agent):
        """
        Update agent's internal message.

        The agent averages all the messages that it has received from other
        agents in this step.
        """
        receiving_from = self.receiving_state[agent.id]
        self.receiving_state[agent.id] = []

        messages = [message for _, message in receiving_from]
        messages.append(agent.message)
        agent.message = np.average(messages)

        return receiving_from
```

Then we define the BroadcastActor. Similar to the *BinaryAttackActor*, broadcasting will be a boolean action–either broadcast or don't broadcast. We provide a *broadcast mapping* for determining to which encodings each agent can broadcast. The message will be successfully sent to every agent that (1) is within the *broadcast range*, (2) has a compatible encoding, and (3) is not blocked.

```
from gym.spaces import Discrete
from abmarl.sim.gridworld.actor import ActorBaseComponent
import abmarl.sim.gridworld.utils as gu

class BroadcastingActor(ActorBaseComponent):
    """
    Process sending and receiving messages between agents.

    BroadcastingAgents can broadcast to compatible agents within their range
    according to the broadcast mapping and if the agent is not blocked.
    """
    def __init__(self, broadcast_mapping=None, **kwargs):
        super().__init__(**kwargs)
        self.broadcast_mapping = broadcast_mapping
```

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```
        for agent in self.agents.values():
            if isinstance(agent, self.supported_agent_type):
                agent.action_space[self.key] = Discrete(2)

    @property
    def key(self):
        return 'broadcast'

    @property
    def supported_agent_type(self):
        return BroadcastingAgent

    @property
    def broadcast_mapping(self):
        """
        Dict that dictates to which agents the broadcasting agent can broadcast.

        The dictionary maps the broadcasting agents' encodings to a list of encodings
        to which they can broadcast. For example, the folowing broadcast_mapping:
        {
            1: [3, 4, 5],
            3: [2, 3],
        }
        means that agents whose encoding is 1 can broadcast other agents whose encodings
        are 3, 4, or 5; and agents whose encoding is 3 can broadcast other agents whose
        encodings are 2 or 3.
        """
        return self._broadcast_mapping

    @broadcast_mapping.setter
    def broadcast_mapping(self, value):
        assert type(value) is dict, "Broadcast mapping must be dictionary."
        for k, v in value.items():
            assert type(k) is int, "All keys in broadcast mapping must be integer."
            assert type(v) is list, "All values in broadcast mapping must be list."
            for i in v:
                assert type(i) is int, \
                    "All elements in the broadcast mapping values must be integers."
        self._broadcast_mapping = value

    def process_action(self, broadcasting_agent, action_dict, **kwargs):
        """
        If the agent has chosen to broadcast, then we process their broadcast.

        The processing goes through a series of checks. The broadcast is successful
        if there is a receiving agent such that:
        1. The receiving agent is within range.
        2. The receiving agent is compatible according to the broadcast_mapping.
        3. The receiving agent is observable by the broadcasting agent.

        If the broadcast is successful, then the receiving agent receives the message
        in its observation.
```

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```
        """
        def determine_broadcast(agent):
            # Generate local grid and a broadcast mask.
            local_grid, mask = gu.create_grid_and_mask(
                agent, self.grid, agent.broadcast_range, self.agents
            )

            # Randomly scan the local grid for receiving agents.
            receiving_agents = []
            for r in range(2 * agent.broadcast_range + 1):
                for c in range(2 * agent.broadcast_range + 1):
                    if mask[r, c]: # We can see this cell
                        candidate_agents = local_grid[r, c]
                        if candidate_agents is not None:
                            for other in candidate_agents.values():
                                if other.id == agent.id: # Cannot broadcast to yourself
                                    continue
                                elif other.encoding not in self.broadcast_mapping[agent.
↪encoding]:
                                    # Cannot broadcast to this type of agent
                                    continue
                                else:
                                    receiving_agents.append(other)
            return receiving_agents

        if isinstance(broadcasting_agent, self.supported_agent_type):
            action = action_dict[self.key]
            if action: # Agent has chosen to attack
                return determine_broadcast(broadcasting_agent)
```

Now we define the BroadcastObserver. The observer enables agents to see all received messages, including their own current message. This observer is unique from all other components we have seen so far because it explicitly relies on the BroadcastingState component, which will have a small impact in how we initialize the simulation.

```
from gym.spaces import Dict, Box
from abmarl.sim.gridworld.observer import ObserverBaseComponent

class BroadcastObserver(ObserverBaseComponent):
    def __init__(self, broadcasting_state=None, **kwargs):
        super().__init__(**kwargs)

        assert isinstance(broadcasting_state, BroadcastingState), \
            "broadcasting_state must be an instance of BroadcastingState"
        self._broadcasting_state = broadcasting_state

        for agent in self.agents.values():
            if isinstance(agent, self.supported_agent_type):
                agent.observation_space[self.key] = Dict({
                    other.id: Box(-1, 1, (1,))
                    for other in self.agents.values() if isinstance(other, self.
↪supported_agent_type)
                })
```

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```
    @property
    def key(self):
        return 'message'

    @property
    def supported_agent_type(self):
        return BroadcastingAgent

    def get_obs(self, agent, **kwargs):
        if not isinstance(agent, self.supported_agent_type):
            return {}

        obs = {other: 0 for other in agent.observation_space[self.key]}
        receive_from = self._broadcasting_state.update_message_and_reset_receiving(agent)
        for agent_id, message in receive_from:
            obs[agent_id] = message
        obs[agent.id] = agent.message
        return obs
```

Finally, we can create a custom done condition. We want the broadcasting agents to finish when they've reached consensus; that is, when their internal message is within some tolerance of the average message.

```
from abmarl.sim.gridworld.done import DoneBaseComponent

class AverageMessageDone(DoneBaseComponent):
    def __init__(self, done_tolerance=None, **kwargs):
        super().__init__(**kwargs)
        self.done_tolerance = done_tolerance

    @property
    def done_tolerance(self):
        return self._done_tolerance

    @done_tolerance.setter
    def done_tolerance(self, value):
        assert type(value) in [int, float], "Done tolerance must be a number."
        assert value > 0, "Done tolerance must be positive."
        self._done_tolerance = value

    def get_done(self, agent, **kwargs):
        if isinstance(agent, BroadcastingAgent):
            average = np.average([
                other.message for other in self.agents.values()
                if isinstance(other, BroadcastingAgent)
            ])
            return np.abs(agent.message - average) <= self.done_tolerance
        else:
            return False

    def get_all_done(self, **kwargs):
        for agent in self.agents.values():
```

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```
            if isinstance(agent, BroadcastingAgent):
                if not self.get_done(agent):
                    return False
        return True
```

### Building and running the simulation

Now that all the components have been created, we can create the full simulation:

```
from abmarl.sim.gridworld.base import GridWorldSimulation

class BroadcastSim(GridWorldSimulation):
    def __init__(self, **kwargs):
        self.agents = kwargs['agents']

        self.position_state = PositionState(**kwargs)
        self.broadcasting_state = BroadcastingState(**kwargs)

        self.move_actor = MoveActor(**kwargs)
        self.broadcast_actor = BroadcastingActor(**kwargs)

        self.grid_observer = SingleGridObserver(**kwargs)
        self.broadcast_observer = BroadcastObserver(broadcasting_state=self.broadcasting_
↪state, **kwargs)

        self.done = AverageMessageDone(**kwargs)

        self.finalize()

    def reset(self, **kwargs):
        self.position_state.reset(**kwargs)
        self.broadcasting_state.reset(**kwargs)

        self.rewards = {agent.id: 0 for agent in self.agents.values()}

    def step(self, action_dict, **kwargs):
        # process broadcasts
        for agent_id, action in action_dict.items():
            agent = self.agents[agent_id]
            receiving_agents = self.broadcast_actor.process_action(agent, action,␣
↪**kwargs)
            if receiving_agents is not None:
                self.broadcasting_state.update_receipients(agent, receiving_agents)

        # process moves
        for agent_id, action in action_dict.items():
            agent = self.agents[agent_id]
            move_result = self.move_actor.process_action(agent, action, **kwargs)
            if not move_result:
                self.rewards[agent.id] -= 0.1
```

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```
        # Entropy penalty
        for agent_id in action_dict:
            self.rewards[agent_id] -= 0.01

    def render(self, **kwargs):
        super().render(**kwargs)
        for agent in self.agents.values():
            if isinstance(agent, BroadcastingAgent):
                print(f"{agent.id}: {agent.message}")
        print()

    def get_obs(self, agent_id, **kwargs):
        agent = self.agents[agent_id]
        return {
            **self.grid_observer.get_obs(agent, **kwargs),
            **self.broadcast_observer.get_obs(agent, **kwargs)
        }

    def get_reward(self, agent_id, **kwargs):
        reward = self.rewards[agent_id]
        self.rewards[agent_id] = 0
        return reward

    def get_done(self, agent_id, **kwargs):
        return self.done.get_done(agent_id, **kwargs)

    def get_all_done(self, **kwargs):
        return self.done.get_all_done(**kwargs)

    def get_info(self, **kwargs):
        return {}
```

Let's initialize our simulation and run it. We initialize some BroadcastingAgents and some BlockingAgents. Then we *initialize the simulation* with a *broadcast mapping* that specifies that broadcasts can only be made amongst agents with encoding 1, which are the BroadcastingAgents.

```
agents = {
    'broadcaster0': BroadcastingAgent(id='broadcaster0', encoding=1, broadcast_range=6,␣
↪render_color='green'),
    'broadcaster1': BroadcastingAgent(id='broadcaster1', encoding=1, broadcast_range=6,␣
↪render_color='green'),
    'broadcaster2': BroadcastingAgent(id='broadcaster2', encoding=1, broadcast_range=6,␣
↪render_color='green'),
    'broadcaster3': BroadcastingAgent(id='broadcaster3', encoding=1, broadcast_range=6,␣
↪render_color='green'),
    'blocker0': BlockingAgent(id='blocker0', encoding=2, move_range=2, view_range=3,␣
↪render_color='black'),
    'blocker1': BlockingAgent(id='blocker1', encoding=2, move_range=1, view_range=3,␣
↪render_color='black'),
    'blocker2': BlockingAgent(id='blocker2', encoding=2, move_range=1, view_range=3,␣
↪render_color='black'),
}
```

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```
sim = BroadcastSim.build_sim(
    7, 7,
    agents=agents,
    broadcast_mapping={1: [1]},
    done_tolerance=5e-10
)

sim.reset()
fig = plt.figure()
sim.render(fig=fig)

done_agents = set()
for i in range(50):
    action = {
        agent.id: agent.action_space.sample() for agent in agents.values() if agent.id
↪not in done_agents
    }
    sim.step(action)
    for agent in agents:
        if agent not in done_agents:
            obs = sim.get_obs(agent)
        if sim.get_done(agent):
            done_agents.add(agent)

    sim.render(fig=fig)
    if sim.get_all_done():
        break
```

The visualization produces an animation like the one at the top of this page. We can see the "path towards consensus" among the BroadcastingAgents in the output. Keep your eye open for the effects of blocking.

```
Step 1
broadcaster0: 0.5936447861764813
broadcaster1: -0.8344218389696239
broadcaster2: 0.09891331950679949
broadcaster3: 0.32590416873488093

Step 2
broadcaster0: 0.028375705313912796
broadcaster1: -0.25425883511737146
broadcaster2: -0.13653478357598114
broadcaster3: -0.25425883511737146

For steps 3-5, notice that Broadcaster3 is blocked. The other broadcasters
have reached a consensus, but the simulation does not end becaue they must all
agree.

Step 3
broadcaster0: -0.12080597112647994
broadcaster1: -0.12080597112647994
broadcaster2: -0.12080597112647995
broadcaster3: -0.15416918712420283
```

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```
Step 4
broadcaster0: -0.12080597112647994
broadcaster1: -0.12080597112647994
broadcaster2: -0.12080597112647995
broadcaster3: -0.15416918712420283

Step 5
broadcaster0: -0.12080597112647994
broadcaster1: -0.12080597112647994
broadcaster2: -0.12080597112647995
broadcaster3: -0.15416918712420283

Broadcaster3 is no longer blocked
Step 6
broadcaster0: -0.12080597112647995
broadcaster1: -0.12080597112647995
broadcaster2: -0.12080597112647995
broadcaster3: -0.1319270431257209

...

Step 16
broadcaster0: -0.1241744002450772
broadcaster1: -0.12417639653661512
broadcaster2: -0.12417523451616769
broadcaster3: -0.12417511533458334

Step 17
broadcaster0: -0.12417528665811084
broadcaster1: -0.12417528665811083
broadcaster2: -0.12417528665811083
broadcaster3: -0.12417528665811084
```

### Extra Challenges

Having successfully created new components and fit them into the GridWorld Simulation Framework, we can create a vast variety of different simulations, constrained primarily by our own imagination. We leave the extra challenges up to you and what you can think of.

CHAPTER

SEVEN

# ABMARL API SPECIFICATION

## 7.1 Abmarl Simulations

**class** abmarl.sim.**PrincipleAgent**(*id=None*, *seed=None*, ***kwargs*)

Principle Agent class for agents in a simulation.

**property active**

True if the agent is still active in the simulation.

Active means that the agent is in a valid state. For example, suppose agents in our Simulation can die. Then active is True if the agents are alive or False if they're dead.

**property configured**

All agents must have an id.

**finalize**(***kwargs*)

**property id**

The agent's unique identifier.

**property seed**

Seed for random number generation.

**class** abmarl.sim.**ObservingAgent**(*observation_space=None*, *null_observation=None*, ***kwargs*)

ObservingAgents can observe the state of the simulation.

The agent's observation must be *in* its observation space. The SimulationManager will send the observation to the Trainer, which will use it to produce actions.

**property configured**

Observing agents must have an observation space.

**finalize**(***kwargs*)

Wrap all the observation spaces with a Dict and seed it if the agent was created with a seed.

**property null_observation**

The null point in the observation space.

**property observation_space**

**class** abmarl.sim.**ActingAgent**(*action_space=None*, *null_action=None*, ***kwargs*)

ActingAgents can act in the simulation.

The Trainer will produce actions for the agents and send them to the SimulationManager, which will process those actions in its step function.

**property action_space**

**property configured**

Acting agents must have an action space.

**finalize**(***kwargs*)

Wrap all the action spaces with a Dict if applicable and seed it if the agent was created with a seed.

**property null_action**

The null point in the action space.

**class** abmarl.sim.**Agent**(*observation_space=None*, *null_observation=None*, ***kwargs*)

Bases: *ObservingAgent*, *ActingAgent*

An Agent that can both observe and act.

**class** abmarl.sim.**AgentBasedSimulation**

AgentBasedSimulation interface.

Under this design model the observations, rewards, and done conditions of the agents is treated as part of the simulations internal state instead of as output from reset and step. Thus, it is the simulations responsibility to manage rewards and dones as part of its state (e.g. via self.rewards dictionary).

This interface supports both single- and multi-agent simulations by treating the single-agent simulation as a special case of the multi-agent, where there is only a single agent in the agents dictionary.

**property agents**

A dict that maps the Agent's id to the Agent object. An Agent must be an instance of PrincipleAgent. A multi-agent simulation is expected to have multiple entries in the dictionary, whereas a single-agent simulation should only have a single entry in the dictionary.

**finalize**()

Finalize the initialization process. At this point, every agent should be configured with action and observation spaces, which we convert into Dict spaces for interfacing with the trainer.

**abstract get_all_done**(***kwargs*)

Return the simulation's done status.

**abstract get_done**(*agent_id*, ***kwargs*)

Return the agent's done status.

**abstract get_info**(*agent_id*, ***kwargs*)

Return the agent's info.

**abstract get_obs**(*agent_id*, ***kwargs*)

Return the agent's observation.

**abstract get_reward**(*agent_id*, ***kwargs*)

Return the agent's reward.

**abstract render**(***kwargs*)

Render the simulation for vizualization.

**abstract reset**(***kwargs*)

Reset the simulation simulation to a start state, which may be randomly generated.

**abstract step**(*action*, ***kwargs*)

Step the simulation forward one discrete time-step. The action is a dictionary that contains the action of each agent in this time-step.

**class** abmarl.sim.**DynamicOrderSimulation**

An AgentBasedSimulation where the simulation chooses the agents' turns dynamically.

**property next_agent**

The next agent(s) in the game.

## 7.2 Abmarl Simulation Managers

**class** abmarl.managers.**SimulationManager**(*sim*, ***kwargs*)

Control interaction between Trainer and AgentBasedSimulation.

A Manager implmenents the reset and step API, by which it calls the AgentBasedSimulation API, using the getters within reset and step to accomplish the desired control flow.

**sim**

The AgentBasedSimulation.

**agents**

The agents that are in the AgentBasedSimulation.

**done_agents**

Set of agents that are done.

**render**(***kwargs*)

**abstract reset**(***kwargs*)

Reset the simulation.

**Returns**
The first observation of the agent(s).

**abstract step**(*action_dict*, ***kwargs*)

Step the simulation forward one discrete time-step.

**Parameters**
**action_dict** – Dictionary mapping agent(s) to their actions in this time step.

**Returns**

The observations, rewards, done status, and info for the agent(s) whose actions we expect to receive next.

Note: We do not necessarily return anything for the agent whose actions we just received in this time-step. This behavior is defined by each Manager.

**class** abmarl.managers.**TurnBasedManager**(*sim*)

The TurnBasedManager allows agents to take turns. The order of the agents is stored and the obs of the first agent is returned at reset. Each step returns the info of the next agent "in line". Agents who are done are removed from this line. Once all the agents are done, the manager returns all done.

**reset**(***kwargs*)

Reset the simulation and return the observation of the first agent.

**step**(*action_dict*, ***kwargs*)

Assert that the incoming action does not come from an agent who is recorded as done. Step the simulation forward and return the observation, reward, done, and info of the next agent. If that next agent finished in this turn, then include the obs for the following agent, and so on until an agent is found that is not done. If all agents are done in this turn, then the wrapper returns all done.

class abmarl.managers.**AllStepManager**(*sim*, *randomize_action_input=False*, ***kwargs*)

The AllStepManager gets the observations of all agents at reset. At step, it gets the observations of all the agents that are not done. Once all the agents are done, the manager returns all done.

**property randomize_action_input**

Randomize the order of the action input at each step.

Multiple agents will report actions within a single step. Depending on how those actions are generated, the ordering within the action_dict may always be the same, which may result in unintended imposed-ordering in the simulation. For example, agent0's action may always come before agent1's. If randomize_action_input is set to True, then the agent ordering in the action dict is randomized each step.

**reset**(***kwargs*)

Reset the simulation and return the observation of all the agents.

**step**(*action_dict*, ***kwargs*)

Assert that the incoming action does not come from an agent who is recorded as done. Step the simulation forward and return the observation, reward, done, and info of all the non-done agents, including the agents that were done in this step. If all agents are done in this turn, then the manager returns all done.

class abmarl.managers.**DynamicOrderManager**(*sim*)

The DynamicOrderManager allows agents to take turns dynamically decided by the Simulation.

The order of the agents is dynamically decided by the simulation as it runs. The simulation must be a DynamicOrderSimulation. The agents reported at reset and step are those given in the sim's next_agent property.

**reset**(***kwargs*)

Reset the simulation and return the observation of the first agent.

**step**(*action_dict*, ***kwargs*)

Assert that the incoming action does not come from an agent who is recorded as done. Step the simulation forward and return the observation, reward, done, and info of the next agent. The simulation is responsible to ensure that there is at least one next_agent that did not finish in this turn, unless it is the last turn.

## 7.3 Abmarl Wrappers

class abmarl.sim.wrappers.**RavelDiscreteWrapper**(*sim*)

Convert observation and action spaces into a Discrete space.

Convert Discrete, MultiBinary, MultiDiscrete, bounded integer Box, and any nesting of these observations and actions into Discrete observations and actions by "ravelling" their values according to numpy's ravel_mult_index function. Thus, observations and actions that are represented by arrays are converted into unique numbers. This is useful for building Q tables where each observation and action is a row and column of the Q table, respectively.

If the agent has a null observation or a null action, that value is also ravelled into the new Discrete space.

**unwrap_action**(*from_agent*, *action*)

**unwrap_observation**(*from_agent*, *observation*)

**wrap_action**(*from_agent*, *action*)

**wrap_observation**(*from_agent*, *observation*)

class abmarl.sim.wrappers.**FlattenWrapper**(*sim*)

Flattens all agents' action and observation spaces into Boxes.

Nested spaces (e.g. Tuples and Dicts) are flattened element-wise, each element being concatentated onto the previous. A Discrete space is converted to a Box with a single element, whose bounds are 0 to `space.n` - 1. MultiBinary and MultiDiscrete are simply converted to Box with the corresponding bounds and integer dtype. A Box space is flattened to a one-dimensional array equivalent.

If the resulting Box can be made with dtype int, then it will be. Otherwise, it will cast up to float.

If the agent has a null observation or a null action, that value is also flattened into the new Box space.

NOTE: Sampling from the flattened space will not produce the same results as sampling from the original space and then flattening.

**unwrap_action**(*from_agent*, *action*)

**unwrap_observation**(*from_agent*, *observation*)

**wrap_action**(*from_agent*, *action*)

**wrap_observation**(*from_agent*, *observation*)

class abmarl.sim.wrappers.**SuperAgentWrapper**(*sim*, *super_agent_mapping=None*, ***kwargs*)

The SuperAgentWrapper creates "super" agents who cover and control multiple agents.

The super agents take the observation and action spaces of all their covered agents. In addition, the observation space is given a "mask" channel to indicate which of their covered agents is done. This channel is important because the simulation dynamics change when a covered agent is done but the super agent may still be active (see comments on get_done). Without this mask, the super agent would experience completely different simulation dynamcis for some of its covered agents with no indication as to why.

Unless handled carefully, the super agent will generate observations for done covered agents. This may contaminate the training data with an unfair advantage. For exmample, a dead covered agent should not be able to provide the super agent with useful information. In order to correct this, the user may supply the null observation for an ObservingAgent. When a covered agent is done, the SuperAgentWrapper will try to use its null observation going forward.

Furthermore, super agents may still report actions for covered agents that are done. This wrapper filters out those actions before passing them to the underlying sim. See step for more details.

**get_done**(*agent_id*, ***kwargs*)

Report the agent's done condition.

Because super agents are composed of multiple agents, it could be the case that some covered agents are done while other are not for the same super agent. Because we still want those non-done agents to interact with the simulation, the super agent only reports done when ALL of its covered agents report done.

**Parameters**

**agent_id** – The id of the agent for whom to report the done condition. Should not be a covered agent.

**Returns**

**The requested done conndition. Super agents are done when all their** covered agents are done.

**get_info**(*agent_id*, ***kwargs*)

Report the agent's additional info.

**Parameters**

**agent_id** – The id of the agent for whom to get info. Should not be a covered agent.

**Returns**
The requested info. Super agents info is collected from covered agents.

`get_obs`(*agent_id*, ***kwargs*)

Report observations from the simulation.

Super agent observations are collected from their covered agents. Super agents also have a "mask" channel that tells them which of their covered agent is done. This should assist the super agent in understanding the changing simulation dynamics for done agents (i.e. why actions from done agents don't do anything).

The super agent will report an observation for done covered agents. This may result in an unfair advantage during training (e.g. dead agent should not produce useful information), and Abmarl will issue a warning. To properly handle this, the user can supply the null observation for each covered agent. In that case, the super agent will use the null observation for any done covered agents.

**Parameters**
`agent_id` – The id of the agent for whom to produce an observation. Should not be a covered agent.

**Returns**
The requested observation. Super agent observations are collected from the covered agents.

`get_reward`(*agent_id*, ***kwargs*)

Report the agent's reward.

A super agent's reward is the sum of all its active covered agents' rewards.

**Parameters**
`agent_id` – The id of the agent for whom to report the reward. Should not be a covered agent.

**Returns**

**The requested reward. Super agent rewards are summed from the active covered** agents.

`reset`(***kwargs*)

Reset the simulation simulation to a start state, which may be randomly generated.

`step`(*action_dict*, ***kwargs*)

Give actions to the simulation.

Super agent actions are decomposed into the covered agent actions and then passed to the underlying sim. Because of the nature of this wrapper, the super agents may provide actions for covered agents that are already done. We filter out these actions.

**Parameters**
`action_dict` – Dictionary that maps agent ids to the actions. Covered agents should not be present.

`property super_agent_mapping`

A dictionary that maps from a super agent's id to a list of covered agent ids.

Suppose our simulation has 5 agents and we use the following super agent mapping: {'super0': ['agent0', 'agent1'], 'super1': ['agent3', 'agent4']} The resulting agents dict would have keys 'super0', 'super1', and 'agent2'; where 'agent0', 'agent1', 'agent3', and 'agent4' have been covered by the super agents and 'agent2' is left uncovered and therefore included in the dict of agents. If the super agent mapping is changed, then the dictionary of agents gets recreated immediately.

Super agents cannot have the same id as any of the agents in the simulation. Two super agents cannot cover the same agent. All covered agents must be learning agents.

## 7.4 Abmarl External Integration

**class** abmarl.external.**GymWrapper**(*sim*)

Wrap an AgentBasedSimulation object with only a single learning agent to the gym.Env interface. This wrapper exposes the single agent's observation and action space directly in the simulation.

**property action_space**

The agent's action space is the environment's action space.

**property observation_space**

The agent's observation space is the environment's observation space.

**render**(***kwargs*)

Forward render calls to the composed simulation.

**reset**(***kwargs*)

Return the observation from the single agent.

**step**(*action*, ***kwargs*)

Wrap the action by storing it in a dict that maps the agent's id to the action. Pass to sim.step. Return the observation, reward, done, and info from the single agent.

**property unwrapped**

Fall through all the wrappers and obtain the original, completely unwrapped simulation.

**class** abmarl.external.**MultiAgentWrapper**(*sim*)

Enable connection between SimulationManager and RLlib Trainer.

Wraps a SimulationManager and forwards all calls to the manager. This class is boilerplate and needed because RLlib checks that the simulation is an instance of MultiAgentEnv.

**sim**

The SimulationManager.

**render**(**args*, ***kwargs*)

See SimulationManager.

**reset**()

See SimulationManager.

**step**(*actions*)

See SimulationManager.

**class** abmarl.external.**OpenSpielWrapper**(*sim*, *discounts=1.0*, ***kwargs*)

Enable connection between Abmarl's SimulationManager and OpenSpiel agents.

OpenSpiel support turn-based and simultaneous simulations, which Abmarl provides through the TurnBasedManager and AllStepManager. OpenSpiel expects TimeStep objects as output, which include the observations, rewards, and step type. Among the observations, it expects a list of legal actions available to the agent. The OpenSpielWrapper converts output from the simulation manager to the expected format. Furthermore, OpenSpiel provides actions as a list. The OpenSpielWrapper converts those actions to a dict before forwarding it to the underlying simulation manager.

OpenSpiel does not support the ability for some agents in a simulation to finish before others. The simulation is either ongoing, in which all agents are providing actions, or else it is done for all agents. In contrast, Abmarl allows some agents to be done before others as the simulation progresses. Abmarl expects that done agents will not provide actions. OpenSpiel, however, will always provide actions for all agents. The OpenSpielWrapper removes the actions from agents that are already done before forwarding the action to the underlying simulation

manager. Furthermore, OpenSpiel expects every agent to be present in the TimeStep outputs. Normally, Abmarl will not provide output for agents that are done since they have finished generating data in the episode. In order to work with OpenSpiel, the OpenSpielWrapper forces output from all agents at every step, including those already done.

Currently, the OpenSpielWrapper only works with simulations in which the action and observation space of every agent is Discrete. Most simulations will need to be wrapped with the RavelDiscreteWrapper.

`action_spec()`

The agents' action spaces.

Abmarl uses gym spaces for the action space. The OpenSpielWrapper converts the gym space into a format that OpenSpiel expects.

`property current_player`

The agent that currently provides the action.

Current player is used in the observation part of the TimeStep output. If it is a turn based simulation, then the current player is the single agent who is providing an action. If it is a simultaneous simulation, then OpenSpiel does not use this property and the current player is just the first agent in the list of agents in the simulation.

`property discounts`

The learing discounts for each agent.

If provided as a number, then that value wil apply to all the agents. Make seperate discounts for each agent by providing a dictionary assigning each agent to its own discounted value.

`get_legal_actions`(*agent_id*)

Return the legal actions available to the agent.

By default, the OpenSpielWrapper uses the agent's entire action space as its legal actions in each time step. This function can be overwritten in a derived class to add logic for obtaining the actual legal actions available.

`property is_turn_based`

TurnBasedManager.

`property num_players`

The number of learning agents in the simulation.

`observation_spec()`

The agents' observations spaces.

Abmarl uses gym spaces for the observation space. The OpenSpielWrapper converts the gym space into a format that OpenSpiel expects.

`reset`(***kwargs*)

Reset the simulation.

**Returns**

**TimeStep object containing the initial observations. Uniquely at reset,**
the rewards and discounts are None and the step type is StepType.FIRST.

`step`(*action_list*, ***kwargs*)

Step the simulation forward using the reported actions.

OpenSpiel provides an action list of either (1) the agent whose turn it is in a turn-based simulation or (2) all the agents in a simultaneous simulation. The OpenSpielWrapper converts the list of actions to a dictionary before passing it to the underlying simulation.

OpenSpiel does not support the ability for some agents of a simulation to finish before others. As such, it may provide actions for agents that are already done. To work with Abmarl, the OpenSpielWrapper removes actions for agents that are already done.

**Parameters**
**action_list** – list of actions for the agents.

**Returns**
TimeStep object containing the observations of the new state, the rewards, and StepType.MID if the simulation is still progressing, otherwise StepType.LAST.

## 7.5 Abmarl GridWorld Simulation Framework

### 7.5.1 Base

**class** abmarl.sim.gridworld.base.**GridWorldSimulation**

GridWorldSimulation interface.

Extends the AgentBasedSimulation interface for the GridWorld. We provide builders for streamlining the building process.

**classmethod build_sim**(*rows*, *cols*, ***kwargs*)

Build a GridSimulation.

Specify the number of row, the number of cols, a dictionary of agents, and any additional parameters.

**Parameters**

- **rows** – The number of rows in the grid. Must be a positive integer.
- **cols** – The number of cols in the grid. Must be a positive integer.
- **agents** – The dictionary of agents in the grid.

**Returns**
A GridSimulation configured as specified.

**classmethod build_sim_from_array**(*array*, *object_registry*, *extra_agents=None*, ***kwargs*)

Build a GridSimulation from an array.

**Parameters**

- **array** – An array from which to build the initial grid. Each entry should be an alphanumeric character indicating which agent will be at that location. The agent will be given that initial position.
- **object_registry** – A dictionary that maps the characters in the array to a function that generates the agent with its unique id. Zeros, periods, and underscores are reserved for empty space.
- **extra_agents** – A dictionary of agents which are not in the input grid but which we want to be a part of the simulation. Note: if there is an agent in the array and in extra_agents, we will use the one from the array.

**Returns**
A GridSimulation built from the array along with any extra agents.

**classmethod build_sim_from_file**(*file_name*, *object_registry*, *extra_agents=None*, ***kwargs*)

Build a GridSimulation from a text file.

**Parameters**

- **file_name** – Name of the file that specifies the initial grid setup. In the file, each cell should be a single alphanumeric character indicating which agent will be at that position (from the perspective of looking down on the grid). That agent will be given that initial position.
- **object_registry** – A dictionary that maps characters from the file to a function that generates the agent. This must be a function because each agent must have unique id, which is generated here. Zeros, periods, and underscores are reserved for empty space.
- **extra_agents** – A dictionary of agents which are not in the input grid but which we want to be a part of the simulation. Note: if there is an agent in the file and in extra_agents, we will use the one from the file.

**Returns**

A GridSimulation built from the file along with any extra agents.

**classmethod build_sim_from_grid**(*grid*, *extra_agents=None*, ***kwargs*)

Build a GridSimluation from a Grid object.

**Parameters**

- **grid** – A Grid contains the all the agents index by location, so we can construct a simluation from it.
- **extra_agents** – A dictionary of agents which are not in the input grid but which we want to be a part of the simulation. Note: if there is an agent in the grid and in extra_agents, we will use the one from the grid.

**Returns**

A GridSimulation built from the grid along with any extra agents.

**render**(*fig=None*, ***kwargs*)

Draw the grid and all active agents in the grid.

Agents are drawn at their positions using their respective shape and color.

**Parameters**

**fig** – The figure on which to draw the grid. It's important to provide this figure because the same figure must be used when drawing each state of the simulation. Otherwise, a ton of figures will pop up, which is very annoying.

**class** abmarl.sim.gridworld.base.**GridWorldBaseComponent**(*agents=None*, *grid=None*, ***kwargs*)

Component base class from which all components will inherit.

Every component has access to the dictionary of agents and the grid.

**property agents**

A dict that maps the Agent's id to the Agent object. All agents must be GridWorldAgents.

**property cols**

The number of columns in the grid.

**property grid**

The grid indexes the agents by their position.

For example, an agent whose position is (3, 2) can be accessed through the grid with `self.grid[3, 2]`. Components are responsible for maintaining the connection between agent position and grid index.

property rows

The number of rows in the grid.

class abmarl.sim.gridworld.grid.Grid(*rows*, *cols*, *overlapping=None*, ***kwargs*)

A Grid stores the agents at indices in a numpy array.

Components can interface with the Grid. Each index in the grid is a dictionary that maps the agent id to the agent object itself. If agents can overlap, then there may be more than one agent per cell.

**Parameters**

- **rows** – The number of rows in the grid.
- **cols** – The number of columns in the grid.
- **overlapping** – Overlapping matrix tracks which agents can overlap based on their encodings.

property cols

The number of columns in the grid.

property overlapping

Overlapping matrix tracks which agents can overlap based on their encodings.

A dictionary that maps agents' encodings to a set of encodings with which they can overlap. If the overlapping matrix is not symmetrical, then we update it here to be symmetrical. That is, if 2 can overlap with 3, then 3 can overlap with 2.

place(*agent*, *ndx*)

Place an agent at an index.

If the cell is available, the agent will be placed at that index in the grid and the agent's position will be updated. The placement is successful if the new position is unoccupied or if the agent already occupying that position is overlappable AND this agent is overlappable.

**Parameters**

- **agent** – The agent to place.
- **ndx** – The new index for this agent.

**Returns**

The successfulness of the placement.

query(*agent*, *ndx*)

Query a cell in the grid to see if is available to this agent.

The cell is available for the agent if it is empty or if both the occupying agent and the querying agent are overlappable.

**Parameters**

- **agent** – The agent for which we are checking availabilty.
- **ndx** – The cell to query.

**Returns**

The availability of this cell.

remove(*agent*, *ndx*)

Remove an agent from an index.

**Parameters**

- **agent** – The agent to remove
- **ndx** – The old index for this agent

**reset**(***kwargs*)

Reset the grid to an empty state.

**property rows**

The number of rows in the grid.

### 7.5.2 Agents

**class** abmarl.sim.gridworld.agent.**GridWorldAgent**(*initial_position=None*, *blocking=False*, *encoding=None*, *render_shape='o'*, *render_color='gray'*, ***kwargs*)

The base agent in the GridWorld.

**property blocking**

Specify if this agent blocks other agent's observations and actions.

**property configured**

All agents must have an id.

**property encoding**

The numerical value that identifies the type of agent.

The value does not necessarily identify the agent itself. For example, other agents who observe this agent will see this value.

**property initial_position**

The agent's initial position at reset.

**property position**

The agent's position in the grid.

**property render_color**

The agent's color in the rendered grid.

**property render_shape**

The agent's shape in the rendered grid.

**class** abmarl.sim.gridworld.agent.**GridObservingAgent**(*view_range=None*, ***kwargs*)

Observe the grid up to view range cells away.

**property configured**

Observing agents must have an observation space.

**property view_range**

The number of cells away this agent can observe in each step.

**class** abmarl.sim.gridworld.agent.**MovingAgent**(*move_range=None*, ***kwargs*)

Move up to move_range cells.

**property configured**

Acting agents must have an action space.

**property move_range**

The maximum number of cells away that the agent can move.

**class** abmarl.sim.gridworld.agent.**HealthAgent**(*initial_health=None*, ***kwargs*)

Agents have health points and can die.

Health is bounded between 0 and 1. Agents become inactive when the health falls to 0.

**property health**

The agent's health throughout the simulation trajectory.

The health will always be between 0 and 1.

**property initial_health**

The agent's initial health between 0 and 1.

**class** abmarl.sim.gridworld.agent.**AttackingAgent**(*attack_range=None*, *attack_strength=None*, *attack_accuracy=None*, *attack_count=1*, ***kwargs*)

Agents that can attack other agents.

**property attack_accuracy**

The effective accuracy of the agent's attack.

Should be between 0 and 1. To make deterministic attacks, use 1.

**property attack_count**

The number of attacks the agent can make per turn.

This parameter is interpreted differently by each attack actor, but generally it specifies how many attacks this agent can carry out in a single step. See specific AttackActor documentation for more information.

**property attack_range**

The maximum range of the attack.

**property attack_strength**

The strength of the attack.

Should be between 0 and 1.

**property configured**

Acting agents must have an action space.

### 7.5.3 State

**class** abmarl.sim.gridworld.state.**StateBaseComponent**(*agents=None*, *grid=None*, ***kwargs*)

Abstract State Component base from which all state components will inherit.

**abstract reset**(***kwargs*)

Resets the part of the state for which it is responsible.

**class** abmarl.sim.gridworld.state.**PositionState**(*no_overlap_at_reset=False*, ***kwargs*)

Manage the agents' positions in the grid.

**property no_overlap_at_reset**

Attempt to place each agent on its own cell.

Agents with initial positions will override this property.

property ravelled_positions_available

A dictionary mapping the enodings to a list of positions available to agents of that encoding at reset. The list should contain cells represented in their ravelled form.

reset(**kwargs)

Give agents their starting positions.

We use the agent's initial position if it exists. Otherwise, we randomly place the agents in the grid.

class abmarl.sim.gridworld.state.MazePlacementState(*target_agent=None*, *barrier_encodings=None*, *free_encodings=None*, *cluster_barriers=False*, *scatter_free_agents=False*, ***kwargs*)

Place agents in the grid based on a maze generated around a target.

Partition the cells into two categories, either a free cell or a barrier, based on a maze, which is generated starting at a target agent's position. Specify available positions as follows: barrier-encoded agents will be placed at the maze barriers, free-encoded agents will be placed at free positions.

Note: Because the maze is randomly generated at the beginning of each episode and because the agents must be placed in either a free cell or barrier cell according to their encodings, it is highly recommended that none of your agents be given initial positions, except for the target agent.

**Parameters**

- **target_agent** – Start the maze generation at this agent's position and place the target agent here.
- **barrier_encodings** – A set of encodings corresponding to the maze's barrier cells.
- **free_encodings** – A set of encodigns corresponding to the maze's free cells.
- **cluster_barriers** – Prioritize the placement of barriers near the target.
- **scatter_free_agents** – Prioritize the placement of free agents away from the target.

property barrier_encodings

A set of encodings corresponding to the maze's barrier cells.

property cluster_barriers

If True, then prioritize placing barriers near the target agent.

property free_encodings

A set of encodings corresponding to the maze's free cells.

reset(**kwargs)

Give the agents their starting positions.

property scatter_free_agents

If True, then prioritize placing free agents away from the target agent.

property target_agent

The target agent is the place from which to start the maze generation.

class abmarl.sim.gridworld.state.HealthState(*agents=None*, *grid=None*, ***kwargs*)

Manage the state of the agents' healths.

Every HealthAgent has a health. If that health falls to zero, that agent dies and is remove from the grid.

reset(**kwargs)

Give HealthAgents their starting healths.

We use the agent's initial health if it exists. Otherwise, we randomly assign a value between 0 and 1.

### 7.5.4 Actors

class abmarl.sim.gridworld.actor.**ActorBaseComponent**(*agents=None*, *grid=None*, ***kwargs*)

Abstract Actor Component class from which all Actor Components will inherit.

**abstract property key**

The key in the action dictionary.

The action space of all acting agents in the gridworld framework is a dict. We can build up complex action spaces with multiple components by assigning each component an entry in the action dictionary. Actions will be a dictionary even if your simulation only has one Actor.

**abstract process_action**(*agent*, *action_dict*, ***kwargs*)

Process the agent's action.

**Parameters**

- **agent** – The acting agent.
- **action_dict** – The action dictionary for this agent in this step. The dictionary may have different entries, each of which will be processed by different Actors.

**abstract property supported_agent_type**

The type of Agent that this Actor works with.

If an agent is this type, the Actor will add its entry to the agent's action space and will process actions for this agent.

class abmarl.sim.gridworld.actor.**MoveActor**(***kwargs*)

Agents can move to nearby squares.

**property key**

This Actor's key is "move".

**process_action**(*agent*, *action_dict*, ***kwargs*)

The agent can move to nearby squares.

The agent's new position must be within the grid and the cell-occupation rules must be met.

**Parameters**

- **agent** – Move the agent if it is a MovingAgent.
- **action_dict** – The action dictionary for this agent in this step. If the agent is a MovingAgent, then the action dictionary will contain the "move" entry.

**Returns**

True if the move is successful, False otherwise.

**property supported_agent_type**

This Actor works with MovingAgents.

class abmarl.sim.gridworld.actor.**CrossMoveActor**(***kwargs*)

Agents can move up, down, left, right, or stay in place.

**grid_action**(*cross_action*)

Grid action converts the cross action to an action in the grid.

0: Stay 1: Move up 2: Move right 3; Move down 4: Move left

property key

This Actors key is "move".

process_action(*agent*, *action_dict*, ***kwargs*)

The agent can move up, down, left, right, or stay in place.

The agent's new position must be within the grid and the cell-occupation rules must be met.

**Parameters**

- **agent** – Move the agent if it is a MovingAgent.
- **action_dict** – The action dictionary for this agent in this step. If the agent is a MovingAgent, then the action dictionary will contain the "move" entry.

**Returns**

True if the move is successful, False otherwise.

property supported_agent_type

This Actor works with MovingAgent, but the move_range parameter is ignored.

class abmarl.sim.gridworld.actor.**AttackActorBaseComponent**(*attack_mapping=None*, *stacked_attacks=False*, ***kwargs*)

Abstract class that provides the properties and structure for attack actors.

The agent chooses to attack other agents within its surrounding grid. The derived attack actor interprets and implements the specific attack. Attacked agents have their health reduced by the attacking agent's strength and possibly become inactive if their health falls too low.

property attack_mapping

Dict that dictates which agents the attacking agent can attack.

The dictionary maps the attacking agents' encodings to a list of encodings that they can attack.

property key

This Actor's key is "attack".

process_action(*attacking_agent*, *action_dict*, ***kwargs*)

Process the agent's attack.

The derived attack actor interprets and implements the action. In general, an attack is successful if there are attackable agents such that:

1. The attackable agent is active.
2. The attackable agent is positioned at the attacked cell.
3. The attackable agent is valid according to the attack_mapping.
4. The attacking agent's accuracy is high enough.

Furthemore, a single agent may only be attacked once if stacked_attacks is False. Additional attacks will be applied on other agents or wasted.

If the attack is successful, then the attacked agent's health is depleted by the attacking agent's strength, possibly resulting in its death.

**Parameters**

- **attacking_agent** – The attacking agent.
- **action_dict** – The agent's action in this step.

**Returns**

Tuple of (bool, list). The first value is False if the agent is not an attacking agent or chose not to attack; otherwise it is True. The second value is a list of attacked agents, which will be empty if there was no attack or if the attack failed. Thus, there are three possible outcomes:

1. An attack was not attempted: False, []
2. An attack failed: True, []
3. An attack was successful: True, [non-empty]

**property stacked_attacks**

Allows an agent to attack the same agent multiple times per step.

When an agent has more than 1 attack per turn, this parameter allows them to use more than one attack on the same agent. Otherwise, the attacks will be applied to other agents, and if there are not enough attackable agents, then the extra attacks will be wasted.

**property supported_agent_type**

This Actor works with AttackingAgents.

**class** abmarl.sim.gridworld.actor.**BinaryAttackActor**(*attack_mapping=None*, *stacked_attacks=False*, ***kwargs*)

Launch attacks in a local grid.

Agents can choose to launch attacks up to their *attack count* or not to attack at all. For example, if an agent has an attack count of 3, then it can choose no attack, attack once, attack twice, or attack thrice. The BinaryAttackActor searches the nearby local grid defined by the agent's attack range for attackable agents, and randomly chooses from that set up to the number of attacks issued.

**class** abmarl.sim.gridworld.actor.**EncodingBasedAttackActor**(*attack_mapping=None*, *stacked_attacks=False*, ***kwargs*)

Launch attacks in a local grid based on encoding.

The attacking agent specifies how many attacks it would like to use per available encoding, based on its attack count and the attack mapping. For example, if the agent can attack encodings 1 and 2 and has up to 3 attacks available, then it may launch up to 3 attacks on encoding 1 and up to 3 attack on encoding 2. Agents with those encodings in the surrounding grid are liable to be attacked.

**class** abmarl.sim.gridworld.actor.**SelectiveAttackActor**(*attack_mapping=None*, *stacked_attacks=False*, ***kwargs*)

Launch attacks in a local grid by cell.

The attack is a local grid centered on the agent's position, and its size depends on the agent's attack range. Each cell in the grid has a nonnegative integer up to the agent's attack count, and it indicates how many attacks to use on that cell.

**class** abmarl.sim.gridworld.actor.**RestrictedSelectiveAttackActor**(*attack_mapping=None*, *stacked_attacks=False*, ***kwargs*)

Launch attacks in a local grid by cell.

Agents choose to attack specific cells in the surrounding grid. The agent can attack up to its attack count. It can choose to attack different cells or the same cell multiple times.

### 7.5.5 Observers

class abmarl.sim.gridworld.observer.**ObserverBaseComponent**(*agents=None*, *grid=None*, ***kwargs*)

Abstract Observer Component base from which all observer components will inherit.

**abstract get_obs**(*agent*, ***kwargs*)

Observe the state of the simulation.

**Parameters**
**agent** – The agent for which we return an observation.

**Returns**
This agent's observation.

**abstract property key**

The key in the observation dictionary.

The observation space of all observing agents in the gridworld framework is a dict. We can build up complex observation spaces with multiple components by assigning each component an entry in the observation dictionary. Observations will be a dictionary even if your simulation only has one Observer.

**abstract property supported_agent_type**

The type of Agent that this Observer works with.

If an agent is this type, the Observer will add its entry to the agent's observation space and will produce observations for this agent.

class abmarl.sim.gridworld.observer.**AbsolutePositionObserver**(***kwargs*)

Agents observe their absolute position.

**get_obs**(*agent*, ***kwargs*)

Agents observe their absolute position.

**property key**

This Observer's key is "position".

**property supported_agent_type**

This Observer works with ObservingAgents

class abmarl.sim.gridworld.observer.**AbsoluteGridObserver**(***kwargs*)

Observe the agents in the grid according to their actual positions.

This Observer represents agents by their encoding on cells according to their actual positions in the grid. If there are multiple agents on a single cell with different encodings, only a single randomly chosen encoding will be observed. To be consistent with other built-in observers, masked cells are indicated as -2. Typially, -1 is reserved for out of bounds encoding, but because this Observer only reports cells in the grid, we don't need an out of bounds distinction. Instead, in order for the observing agent to identify itself distinctly from other agents of the same encoding, it is reported as a -1.

**get_obs**(*agent*, ***kwargs*)

The agent observes the grid.

The observation may include the agent itself indicated by a -1, other agents indicated by their encodings, empty space indicated with a 0, and masked cells indicated as -2, which are masked either because they are too far away or because they are blocked from view by view-blocking agents.

**property key**

This Observer's key is "absolute_grid".

property supported_agent_type

This Observer work with GridObservingAgents

class abmarl.sim.gridworld.observer.SingleGridObserver(*observe_self=True*, ***kwargs*)

Observe a subset of the grid centered on the agent's position.

The observation is centered around the observing agent's position. Each agent in the "observation window" is recorded in the relative cell using its encoding. If there are multiple agents on a single cell with different encodings, the agent will observe only one of them chosen at random.

get_obs(*agent*, ***kwargs*)

The agent observes a sub-grid centered on its position.

The observation may include other agents, empty spaces, out of bounds, and masked cells, which can be blocked from view by other blocking agents.

**Returns**

The observation as a dictionary.

property key

This Observer's key is "grid".

property observe_self

Agents can observe themselves, which may hide important information if overlapping is important. This can be turned off by setting observe_self to False.

property supported_agent_type

This Observer works with GridObservingAgents.

class abmarl.sim.gridworld.observer.MultiGridObserver(***kwargs*)

Observe a subset of the grid centered on the agent's position.

The observation is centered around the observing agent's position. The observing agent sees a stack of observations, one for each positive encoding, where the number of agents of each encoding is given rather than the encoding itself. Out of bounds and masked indicators appear in every grid.

get_obs(*agent*, ***kwargs*)

The agent observes one or more sub-grids centered on its position.

The observation may include other agents, empty spaces, out of bounds, and masked cells, which can be blocked from view by other blocking agents. Each grid records the number of agents on a particular cell correlated to a specific encoding.

**Returns**

The observation as a dictionary.

property key

This Observer's key is "grid".

property supported_agent_type

This Observer works with GridObservingAgents.

### 7.5.6 Done

class abmarl.sim.gridworld.done.**DoneBaseComponent**(*agents=None*, *grid=None*, ***kwargs*)

Abstract Done Component class from which all Done Components will inherit.

**abstract get_all_done**(***kwargs*)

Determine if all the agents are done and/or if the simulation is done.

**Returns**
True if all agents are done or if the simulation is done. Otherwise False.

**abstract get_done**(*agent*, ***kwargs*)

Determine if an agent is done in this step.

**Parameters**
**agent** – The agent we are querying.

**Returns**
True if the agent is done, otherwise False.

class abmarl.sim.gridworld.done.**ActiveDone**(*agents=None*, *grid=None*, ***kwargs*)

Inactive agents are indicated as done.

**get_all_done**(***kwargs*)

Return True if all agents are inactive. Otherwise, return False.

**get_done**(*agent*, ***kwargs*)

Return True if the agent is inactive. Otherwise, return False.

class abmarl.sim.gridworld.done.**OneTeamRemainingDone**(*agents=None*, *grid=None*, ***kwargs*)

Inactive agents are indicated as done.

If the only active agents are those who are all of the same encoding, then the simulation ends.

**get_all_done**(***kwargs*)

Return true if all active agents have the same encoding. Otherwise, return false.

class abmarl.sim.gridworld.done.**TargetAgentDone**(*target_mapping=None*, ***kwargs*)

Agents are done when they overlap their target.

The target is prescribed per agent.

**get_all_done**(***kwargs*)

Determine if all the agents are done and/or if the simulation is done.

**Returns**
True if all agents are done or if the simulation is done. Otherwise False.

**get_done**(*agent*, ***kwarg*)

Determine if an agent is done in this step.

**Parameters**
**agent** – The agent we are querying.

**Returns**
True if the agent is done, otherwise False.

**property target_mapping**

Maps the agent to its respective target.

Mapping is done via the agents' ids.

### 7.5.7 Wrappers

**class** abmarl.sim.gridworld.wrapper.**ComponentWrapper**(*agents=None*, *grid=None*, ***kwargs*)

Wraps GridWorldBaseComponent.

Every wrapper must be able to wrap the respective space and points to/from that space. Agents and Grid are referenced directly from the wrapped component rather than received as initialization parameters.

**property agents**

The agent dictionary is directly taken from the wrapped component.

**abstract check_space**(*space*)

Verify that the space can be wrapped.

**property grid**

The grid is directly taken from the wrapped component.

**abstract unwrap_point**(*space*, *point*)

Unwrap a point using a reference space.

**Parameters**

- **space** – The reference space for unwrapping the point.
- **point** – The point to unwrap.

**property unwrapped**

Fall through all the wrappers and obtain the original, completely unwrapped component.

**abstract wrap_point**(*space*, *point*)

Wrap a point using a reference space.

**Parameters**

- **space** – The reference space for wrapping the point.
- **point** – The point to wrap.

**abstract wrap_space**(*space*)

Wrap the space.

**Parameters**
**space** – The space to wrap.

**abstract property wrapped_component**

Get the first-level wrapped component.

**class** abmarl.sim.gridworld.wrapper.**ActorWrapper**(*component*)

Wraps an ActorComponent.

Modify the action space of the agents involved with the Actor, namely the specific actor's channel. The actions recieved from the trainer are in the wrapped space, so we need to unwrap them to send them to the actor. This is the opposite from how we wrap and unwrap observations.

**property key**

The key is the same as the wrapped actor's key.

**process_action**(*agent*, *action_dict*, ***kwargs*)

Unwrap the action and pass it to the wrapped actor to process.

**Parameters**

- **agent** – The acting agent.
- **action_dict** – The action dictionary for this agent in this step. The action in this channel comes in the wrapped space.

**property supported_agent_type**

The supported agent type is the same as the wrapped actor's supported agent type.

**property wrapped_component**

Get the wrapped actor.

**class** abmarl.sim.gridworld.wrapper.**RavelActionWrapper**(*component*)

Use numpy's ravel capabilities to convert space and points to Discrete.

**check_space**(*space*)

Ensure that the space is of type that can be ravelled to discrete value.

**unwrap_point**(*space*, *point*)

Ravel point to a single discrete value.

**wrap_point**(*space*, *point*)

Unravel a single discrete point to a value in the space.

Recall that the action from the trainer arrives in the wrapped discrete space, so we need to unravel it so that it is in the unwrapped space before giving it to the actor.

**wrap_space**(*space*)

Convert the space into a Discrete space.

**class** abmarl.sim.gridworld.wrapper.**ExclusiveChannelActionWrapper**(*component*)

Ravel Dict space and points with top-level exclusion.

This wrapper works with Dict spaces, where each subspace is to be ravelled independently and then combined so that that actions are exclusive. The wrapping occurs in two steps. First, we use numpy's ravel capabilities to convert each subspace to a Discrete space. Second, we combine the Discrete spaces together in such a way that imposes exclusivity among the subspaces. The exclusion happens only on the top level, so a Dict nested within a Dict will be ravelled without exclusion.

**check_space**(*space*)

Top level must be Dict and subspaces must be ravel-able.

**unwrap_point**(*space*, *point*)

Ravel point to a single discrete value.

**wrap_point**(*space*, *point*)

Unravel a single discrete point to a value in the space.

Recall that the action from the trainer arrives in the wrapped discrete space, so we need to unravel it so that it is in the unwrapped space before giving it to the actor.

**wrap_space**(*space*)

Convert the space into a Discrete space.

The wrapping occurs in two steps. First, we use numpy's ravel capabilities to convert each subspace to a Discrete space. Second, we combine the Discrete spaces together, imposing that actions among the subspaces are exclusive.

## 7.6 Abmarl Trainers

class abmarl.trainers.**MultiPolicyTrainer**(*sim=None*, *policies=None*, *policy_mapping_fn=None*, ***kwargs*)

Train policies with data generated by agents interacting in a simulation.

**compute_actions**(*obs*)

Compute actions for agents in the observation.

Forwards the observations to the respective policy for each agent that reports an observation.

**Parameters**

**obs** – an observation dictionary, where the keys are the agents reporting from the sim and the values are the observations.

**Returns**

**An action dictionary where the keys are the agents from the observation**
and the values are the actions generated from each agent's policy.

**generate_episode**(*horizon=200*, *render=False*, ***kwargs*)

Generate an episode of data.

The fundamental data object is a SAR, a (state, action, reward) tuple. We restart the sim, generating initial observations (states) for agents reporting from the sim. Then we use the compute_action function to generate actions for agents who report an observation. Those actions are given to the sim, which steps forward and generates rewards and new observations for reporting agents. This loop continues until the simulation is done or we hit the horizon.

**Parameters**

- **horizon** – The maximum number of steps per epsidoe. The episode may finish early, but it will not progress further than this number of steps.
- **render** – Renders the simulation. This should be False when training, and can be True when debugging or evaluating in post-processing.

**Returns**

**Four dictionaries, one for observations, another for actions,**
another for rewards, and another for dones. This makes the SAR sequence and provides additional information on the done condition since some algorithms need this. The data is organized by agent_id, so you would call {observations, actions, rewards}[agent_id][i] in order to extract the ith SAR for an agent. NOTE: In multiagent simulations, the number of SARs may differ for each agent.

**property policies**

A dictionary that maps the policy id's to a policy object.

**property policy_mapping_fn**

A function that takes an agent's id as input and outputs its corresponding policy id.

**property sim**

The SimulationManager.

**abstract train**(*iterations=10000*, ***kwargs*)

Train the policy objects using generated data.

This function is abstract and should be implemented by the algorithm.

**Parameters**

- **iterations** – The number of training iterations.
- ****kwargs** – Any additional parameter your algorithm may need.

class abmarl.trainers.**SinglePolicyTrainer**(*sim=None*, *policy=None*, ***kwargs*)

Train a single policy with data generated by agents interacting in a simulation.

property **policies**

A dictionary that maps the policy id's to a policy object.

property **policy**

The policy to train.

property **policy_mapping_fn**

Return function always returns "policy", which is the name we give the policy.

class abmarl.trainers.monte_carlo.**OnPolicyMonteCarloTrainer**(*sim=None*, *policy=None*, ***kwargs*)

**train**(*iterations=10000*, *gamma=0.9*, ***kwargs*)

Implements on-policy monte carlo.

class abmarl.trainers.**DebugTrainer**(*policies=None*, *name=None*, *output_dir=None*, ***kwargs*)

Debug the training setup.

The DebugTrainer generates episodes using the simulation and policies. Rather than training those policies, The DebugTrainer simply dumps the observations, actions, rewards, and dones to disk.

The DebugTrainer can be run without policies. In this case, it generates a random policy for each agent. This effectively debug the simulation without having to debug the policy setup too.

property **name**

The name of the experiment.

If name is not specified, then we just use "DEBUG". We append the name with the date and time.

property **output_dir**

The directory for where to dump the episode data.

If the output dir is not specified, then we use "~/abmarl_results/". We append the experiment name to the end of the directory.

**train**(*iterations=5*, *render=False*, ***kwargs*)

Generate episodes and write write to disk.

Nothing is trained here. We just generate and dump the data and visualize the simulation if requested.

**Parameters**

- **iterations** – The number of episodes to generate.
- **render** – Set to True to visualize the simulation.

CHAPTER

# EIGHT

# CITATION

Abmarl has been published in the Journal of Open Source Software. It can be cited using the following bibtex entry:

```
@article{Rusu2021,
  doi = {10.21105/joss.03424},
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