highway-env Documentation

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May 21, 2022

CONTENTS

This project gathers a collection of environment for *decision-making* in Autonomous Driving.

The purpose of this documentation is to provide:

1. a *quick start guide* describing the environments and their customization options;
2. a *detailed description* of the nuts and bolts of the project, and how *you* can contribute.

CHAPTER ONE

HOW TO CITE THIS WORK?

If you use this package, please consider citing it with this piece of BibTeX:

```
@misc{highway-env,
  author = {Leurent, Edouard},
  title = {An Environment for Autonomous Driving Decision-Making},
  year = {2018},
  publisher = {GitHub},
  journal = {GitHub repository},
  howpublished = {\url{https://github.com/eleurent/highway-env}},
}
```

CHAPTER

TWO

DOCUMENTATION CONTENTS

2.1 Installation

2.1.1 Prerequisites

This project requires python3 (>=3.5)

The graphics require the installation of pygame, which itself has dependencies that must be installed manually.

Ubuntu

```
sudo apt-get update -y
sudo apt-get install -y python-dev libsdl-image1.2-dev libsdl-mixer1.2-dev
    libsdl-ttf2.0-dev libsdl1.2-dev libsmpeg-dev python-numpy subversion libportmidi-dev
    ffmpeg libswscale-dev libavformat-dev libavcodec-dev libfreetype6-dev gcc
```

Windows 10

We recommend using Anaconda.

2.1.2 Stable release

To install the latest stable version:

```
pip install highway-env
```

2.1.3 Development version

To install the current development version:

```
pip install --user git+https://github.com/eleurent/highway-env
```

2.2 Getting Started

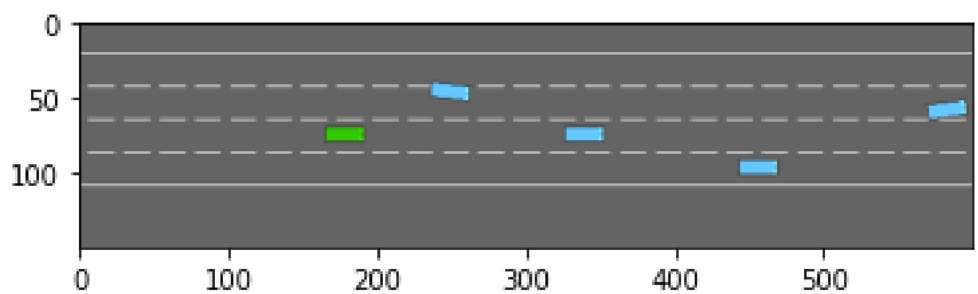
2.2.1 Making an environment

Here is a quick example of how to create an environment:

```
import gym
import highway_env
from matplotlib import pyplot as plt
%matplotlib inline

env = gym.make('highway-v0')
env.reset()
for _ in range(3):
    action = env.action_type.actions_indexes["IDLE"]
    obs, reward, done, info = env.step(action)
    env.render()

plt.imshow(env.render(mode="rgb_array"))
plt.show()
```



All the environments

Here is the list of all the environments available and their descriptions:

Highway

In this task, the ego-vehicle is driving on a multilane highway populated with other vehicles. The agent's objective is to reach a high speed while avoiding collisions with neighbouring vehicles. Driving on the right side of the road is also rewarded.

Usage

```
env = gym.make("highway-v0")
```

Default configuration

```
{
    "observation": {
        "type": "Kinematics"
    },
    "action": {
        "type": "DiscreteMetaAction",
    },
    "lanes_count": 4,
    "vehicles_count": 50,
    "duration": 40,  # [s]
    "initial_spacing": 2,
    "collision_reward": -1,  # The reward received when colliding with a vehicle.
    "reward_speed_range": [20, 30],  # [m/s] The reward for high speed is mapped␣
↪linearly from this range to [0, HighwayEnv.HIGH_SPEED_REWARD].
    "simulation_frequency": 15,  # [Hz]
    "policy_frequency": 1,  # [Hz]
    "other_vehicles_type": "highway_env.vehicle.behavior.IDMVehicle",
    "screen_width": 600,  # [px]
    "screen_height": 150,  # [px]
    "centering_position": [0.3, 0.5],
    "scaling": 5.5,
    "show_trajectories": False,
    "render_agent": True,
    "offscreen_rendering": False
}
```

More specifically, it is defined in:

classmethod HighwayEnv.**default_config**() → dict

Default environment configuration.

Can be overloaded in environment implementations, or by calling configure(). :return: a configuration dict

Faster variant

A faster (x15 speedup) variant is also available with:

```
env = gym.make("highway-fast-v0")
```

The details of this variant are described here.

API

class highway_env.envs.highway_env.**HighwayEnv**(*config: Optional[dict] = None*)

A highway driving environment.

The vehicle is driving on a straight highway with several lanes, and is rewarded for reaching a high speed, staying on the rightmost lanes and avoiding collisions.

classmethod default_config() → dict

Default environment configuration.

Can be overloaded in environment implementations, or by calling configure(). :return: a configuration dict

Merge

In this task, the ego-vehicle starts on a main highway but soon approaches a road junction with incoming vehicles on the access ramp. The agent's objective is now to maintain a high speed while making room for the vehicles so that they can safely merge in the traffic.

Usage

```
env = gym.make("merge-v0")
```

Default configuration

```
{
    "observation": {
        "type": "TimeToCollision"
    },
    "action": {
        "type": "DiscreteMetaAction"
    },
    "simulation_frequency": 15,  # [Hz]
    "policy_frequency": 1,  # [Hz]
    "other_vehicles_type": "highway_env.vehicle.behavior.IDMVehicle",
    "screen_width": 600,  # [px]
    "screen_height": 150,  # [px]
    "centering_position": [0.3, 0.5],
    "scaling": 5.5,
    "show_trajectories": False,
    "render_agent": True,
    "offscreen_rendering": False
}
```

More specifically, it is defined in:

classmethod MergeEnv.**default_config**() → dict

Default environment configuration.

Can be overloaded in environment implementations, or by calling configure(). :return: a configuration dict

API

class highway_env.envs.merge_env.**MergeEnv**(*config: Optional[dict] = None*)

A highway merge negotiation environment.

The ego-vehicle is driving on a highway and approached a merge, with some vehicles incoming on the access ramp. It is rewarded for maintaining a high speed and avoiding collisions, but also making room for merging vehicles.

classmethod default_config() → dict

Default environment configuration.

Can be overloaded in environment implementations, or by calling configure(). :return: a configuration dict

Roundabout

In this task, the ego-vehicle if approaching a roundabout with flowing traffic. It will follow its planned route automatically, but has to handle lane changes and longitudinal control to pass the roundabout as fast as possible while avoiding collisions.

Usage

```
env = gym.make("roundabout-v0")
```

Default configuration

```
{
    "observation": {
        "type": "TimeToCollision"
    },
    "action": {
        "type": "DiscreteMetaAction"
    },
    "incoming_vehicle_destination": None,
    "duration": 11
    "simulation_frequency": 15,  # [Hz]
    "policy_frequency": 1,  # [Hz]
    "other_vehicles_type": "highway_env.vehicle.behavior.IDMVehicle",
    "screen_width": 600,  # [px]
    "screen_height": 600,  # [px]
    "centering_position": [0.5, 0.6],
    "scaling": 5.5,
    "show_trajectories": False,
    "render_agent": True,
    "offscreen_rendering": False
}
```

More specifically, it is defined in:

classmethod RoundaboutEnv.**default_config**() → dict

Default environment configuration.

Can be overloaded in environment implementations, or by calling configure(). :return: a configuration dict

API

class highway_env.envs.roundabout_env.**RoundaboutEnv**(*config: Optional[dict] = None*)

classmethod default_config() → dict

Default environment configuration.

Can be overloaded in environment implementations, or by calling configure(). :return: a configuration dict

Parking

A goal-conditioned continuous control task in which the ego-vehicle must park in a given space with the appropriate heading.

Usage

```
env = gym.make("parking-v0")
```

Default configuration

```
{
    "observation": {
        "type": "KinematicsGoal",
        "features": ['x', 'y', 'vx', 'vy', 'cos_h', 'sin_h'],
        "scales": [100, 100, 5, 5, 1, 1],
        "normalize": False
    },
    "action": {
        "type": "ContinuousAction"
    },
    "simulation_frequency": 15,
    "policy_frequency": 5,
    "screen_width": 600,
    "screen_height": 300,
    "centering_position": [0.5, 0.5],
    "scaling": 7
    "show_trajectories": False,
    "render_agent": True,
    "offscreen_rendering": False
}
```

More specifically, it is defined in:

`classmethod ParkingEnv.default_config()` → dict

Default environment configuration.

Can be overloaded in environment implementations, or by calling configure(). :return: a configuration dict

API

`class highway_env.envs.parking_env.ParkingEnv`(*config: Optional[dict] = None*)

A continuous control environment.

It implements a reach-type task, where the agent observes their position and speed and must control their acceleration and steering so as to reach a given goal.

Credits to Munir Jojo-Verge for the idea and initial implementation.

`classmethod default_config()` → dict

Default environment configuration.

Can be overloaded in environment implementations, or by calling configure(). :return: a configuration dict

`define_spaces()` → None

Set the types and spaces of observation and action from config.

`compute_reward`(*achieved_goal: numpy.ndarray*, *desired_goal: numpy.ndarray*, *info: dict*, *p: float = 0.5*) → float

Proximity to the goal is rewarded

We use a weighted p-norm

Parameters

- **achieved_goal** – the goal that was achieved
- **desired_goal** – the goal that was desired
- **info** (*dict*) – any supplementary information
- **p** – the Lp^p norm used in the reward. Use p<1 to have high kurtosis for rewards in [0, 1]

Returns the corresponding reward

Intersection

An intersection negotiation task with dense traffic.

> **Warning:** It's quite hard to come up with good decentralized behaviors for other agents to avoid each other. Of course, this could be achieved by sophisticated centralized schedulers, or traffic lights, but to keep things simple a *rudimentary collision prediction* was added in the behaviour of other vehicles.
>
> This simple system sometime fails which results in collisions, blocking the way for the ego-vehicle. I figured it was fine for my own purpose, since it did not happen too often and it's reasonable to expect the ego-vehicle to simply wait the end of episode in these situations. But I agree that it is not ideal, and I welcome any contribution on that matter.

Usage

```
env = gym.make("intersection-v0")
```

Default configuration

```
{
    "observation": {
        "type": "Kinematics",
        "vehicles_count": 15,
        "features": ["presence", "x", "y", "vx", "vy", "cos_h", "sin_h"],
        "features_range": {
            "x": [-100, 100],
            "y": [-100, 100],
            "vx": [-20, 20],
            "vy": [-20, 20],
        },
        "absolute": True,
        "flatten": False,
        "observe_intentions": False
    },
    "action": {
        "type": "DiscreteMetaAction",
        "longitudinal": False,
        "lateral": True
    },
    "duration": 13,  # [s]
    "destination": "o1",
    "initial_vehicle_count": 10,
    "spawn_probability": 0.6,
    "screen_width": 600,
    "screen_height": 600,
    "centering_position": [0.5, 0.6],
    "scaling": 5.5 * 1.3,
    "collision_reward": IntersectionEnv.COLLISION_REWARD,
    "normalize_reward": False
}
```

More specifically, it is defined in:

classmethod `IntersectionEnv.default_config()` → dict

Default environment configuration.

Can be overloaded in environment implementations, or by calling configure(). :return: a configuration dict

API

class highway_env.envs.intersection_env.**IntersectionEnv**(*config: Optional[dict] = None*)

classmethod default_config() → dict

Default environment configuration.

Can be overloaded in environment implementations, or by calling configure(). :return: a configuration dict

step(*action: int*) → Tuple[numpy.ndarray, float, bool, dict]

Perform an action and step the environment dynamics.

The action is executed by the ego-vehicle, and all other vehicles on the road performs their default behaviour for several simulation timesteps until the next decision making step.

Parameters `action` – the action performed by the ego-vehicle

Returns a tuple (observation, reward, terminal, info)

Racetrack

A continuous control environment, where the he agent has to follow the tracks while avoiding collisions with other vehicles.

Credits and many thanks to @supperted825 for the idea and initial implementation.

Usage

```
env = gym.make("racetrack-v0")
```

Default configuration

```
{
    "observation": {
        "type": "OccupancyGrid",
        "features": ['presence', 'on_road'],
        "grid_size": [[-18, 18], [-18, 18]],
        "grid_step": [3, 3],
        "as_image": False,
        "align_to_vehicle_axes": True
    },
    "action": {
        "type": "ContinuousAction",
        "longitudinal": False,
        "lateral": True
    },
    "simulation_frequency": 15,
    "policy_frequency": 5,
    "duration": 300,
    "collision_reward": -1,
```

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```
    "lane_centering_cost": 4,
    "action_reward": -0.3,
    "controlled_vehicles": 1,
    "other_vehicles": 1,
    "screen_width": 600,
    "screen_height": 600,
    "centering_position": [0.5, 0.5],
    "scaling": 7
    "show_trajectories": False,
    "render_agent": True,
    "offscreen_rendering": False
}
```

More specifically, it is defined in:

classmethod RacetrackEnv.**default_config**() → dict

Default environment configuration.

Can be overloaded in environment implementations, or by calling configure(). :return: a configuration dict

API

class highway_env.envs.racetrack_env.**RacetrackEnv**(*config: Optional[dict] = None*)

A continuous control environment.

The agent needs to learn two skills: - follow the tracks - avoid collisions with other vehicles

Credits and many thanks to @supperted825 for the idea and initial implementation. See https://github.com/eleurent/highway-env/issues/231

classmethod default_config() → dict

Default environment configuration.

Can be overloaded in environment implementations, or by calling configure(). :return: a configuration dict

2.2.2 Configuring an environment

The *observations*, *actions*, *dynamics* and *rewards* of an environment are parametrized by a configuration, defined as a `config` dictionary. After environment creation, the configuration can be accessed using the `config` attribute.

```
import pprint

env = gym.make("highway-v0")
pprint.pprint(env.config)
```

```
{'action': {'type': 'DiscreteMetaAction'},
 'centering_position': [0.3, 0.5],
 'collision_reward': -1,
 'controlled_vehicles': 1,
 'duration': 40,
 'ego_spacing': 2,
 'high_speed_reward': 0.4,
```

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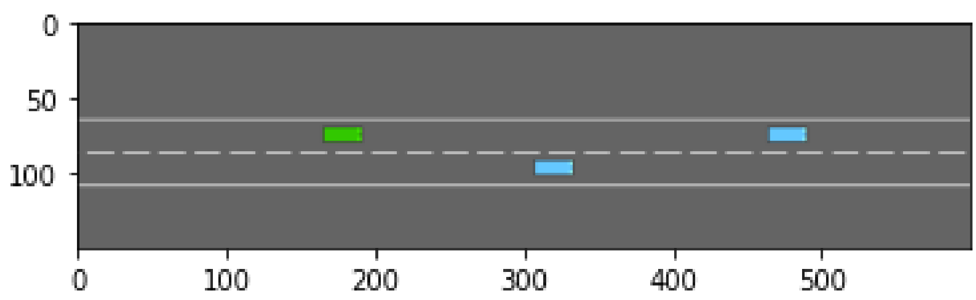
```
 'initial_lane_id': None,
 'lane_change_reward': 0,
 'lanes_count': 4,
 'manual_control': False,
 'observation': {'type': 'Kinematics'},
 'offroad_terminal': False,
 'offscreen_rendering': True,
 'other_vehicles_type': 'highway_env.vehicle.behavior.IDMVehicle',
 'policy_frequency': 1,
 'real_time_rendering': False,
 'render_agent': True,
 'reward_speed_range': [20, 30],
 'right_lane_reward': 0.1,
 'scaling': 5.5,
 'screen_height': 150,
 'screen_width': 600,
 'show_trajectories': False,
 'simulation_frequency': 15,
 'vehicles_count': 50,
 'vehicles_density': 1}
```

For example, the number of lanes can be changed with:

```
env.config["lanes_count"] = 2
env.reset()
plt.imshow(env.render(mode="rgb_array"))
plt.show()
```



Note: The environment must be *reset()* for the change of configuration to be effective.

2.2.3 Training an agent

Reinforcement Learning agents can be trained using libraries such as eleurent/rl-agents, openai/baselines or Stable Baselines3.

Here is an example of SB3's DQN implementation trained on `highway-fast-v0` with its default kinematics observation and an MLP model.

```
import gym
import highway_env
from stable_baselines3 import DQN

env = gym.make("highway-fast-v0")
model = DQN('MlpPolicy', env,
              policy_kwargs=dict(net_arch=[256, 256]),
              learning_rate=5e-4,
              buffer_size=15000,
              learning_starts=200,
              batch_size=32,
              gamma=0.8,
              train_freq=1,
              gradient_steps=1,
              target_update_interval=50,
              verbose=1,
              tensorboard_log="highway_dqn/")
model.learn(int(2e4))
model.save("highway_dqn/model")

# Load and test saved model
model = DQN.load("highway_dqn/model")
while True:
  done = False
  obs = env.reset()
  while not done:
    action, _states = model.predict(obs, deterministic=True)
    obs, reward, done, info = env.step(action)
    env.render()
```

A full run takes about 25mn on my laptop (fps=14). The following results are obtained:

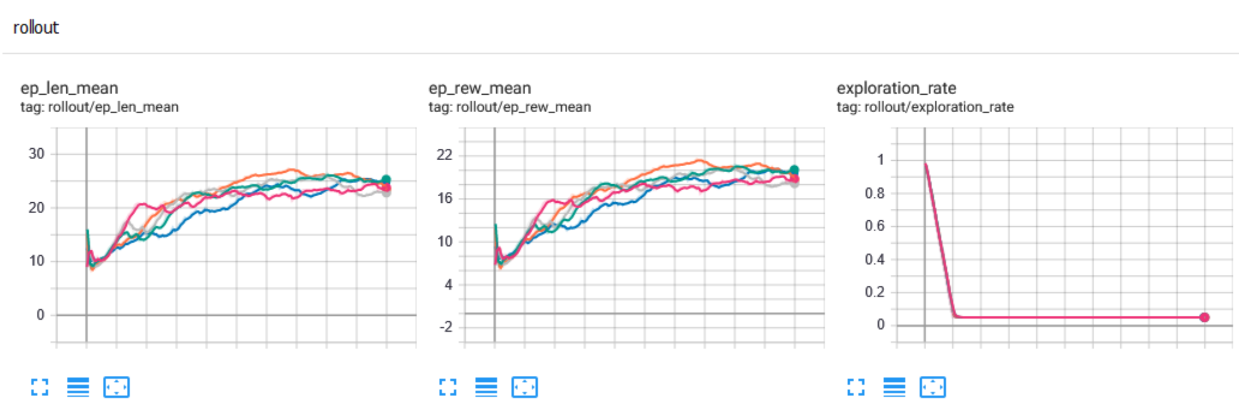


Fig. 1: Training curves, for 5 random seeds.

Fig. 2: Video of an episode run with the trained policy.

Note: There are several ways to get better performances. For instance, SB3 provides only vanilla Deep Q-Learning and has no extensions such as Double-DQN, Dueling-DQN and Prioritized Experience Replay. However, eleurent/rl-agents's implementation of DQN does provide those extensions, which yields better results. Improvements can also be obtained by changing the observation type or the model, see the *FAQ*.

2.2.4 Examples on Google Colab

Several scripts and notebooks to train driving policies on *highway-env* are available on this page. Here are a few of them:

- Highway with image observations and a CNN model
  Train SB3's DQN on *highway-fast-v0* , but using *image observations* and a CNN model for the value function.
- Trajectory Planning on Highway
  Plan a trajectory on *highway-v0* using the *OPD* [HM08] implementation from eleurent/rl-agents.
- A Model-based Reinforcement Learning tutorial on Parking
  A tutorial written for RLSS 2019 and demonstrating the principle of model-based reinforcement learning on the *parking-v0* task.
- Parking with Hindsight Experience Replay
  Train a goal-conditioned *parking-v0* policy using the *HER* [AWR+17] implementation from stable-baselines.
- Intersection with DQN and social attention
  Train an *intersection-v0* crossing policy using the social attention architecture [LM19] and the DQN implementation from eleurent/rl-agents.

2.3 User Guide

2.3.1 Observations

For all environments, **several types of observations** can be used. They are defined in the `observation` module. Each environment comes with a *default* observation, which can be changed or customised using *environment configurations*. For instance,

```python
import gym
import highway_env

env = gym.make('highway-v0')
env.configure({
    "observation": {
        "type": "OccupancyGrid",
        "vehicles_count": 15,
        "features": ["presence", "x", "y", "vx", "vy", "cos_h", "sin_h"],
        "features_range": {
            "x": [-100, 100],
            "y": [-100, 100],
            "vx": [-20, 20],
            "vy": [-20, 20]
        },
        "grid_size": [[-27.5, 27.5], [-27.5, 27.5]],
        "grid_step": [5, 5],
```

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```
        "absolute": False
    }
})
env.reset()
```

Note: The "type" field in the observation configuration takes values defined in `observation_factory()` (see source)

Kinematics

The *KinematicObservation* is a $V \times F$ array that describes a list of V nearby vehicles by a set of features of size F, listed in the "features" configuration field. For instance:

Vehicle	x	y	v_x	v_y
ego-vehicle	5.0	4.0	15.0	0
vehicle 1	-10.0	4.0	12.0	0
vehicle 2	13.0	8.0	13.5	0
...	...	...	...	...
vehicle V	22.2	10.5	18.0	0.5

Note: The ego-vehicle is always described in the first row

If configured with `normalize=True` (default), the observation is normalized within a fixed range, which gives for the range [100, 100, 20, 20]:

Vehicle	x	y	v_x	v_y
ego-vehicle	0.05	0.04	0.75	0
vehicle 1	-0.1	0.04	0.6	0
vehicle 2	0.13	0.08	0.675	0
...	...	...	...	...
vehicle V	0.222	0.105	0.9	0.025

If configured with `absolute=False`, the coordinates are relative to the ego-vehicle, except for the ego-vehicle which stays absolute.

Vehicle	x	y	v_x	v_y
ego-vehicle	0.05	0.04	0.75	0
vehicle 1	-0.15	0	-0.15	0
vehicle 2	0.08	0.04	-0.075	0
...	...	...	...	...
vehicle V	0.172	0.065	0.15	0.025

Note: The number V of vehicles is constant and configured by the `vehicles_count` field, so that the observation has a fixed size. If fewer vehicles than `vehicles_count` are observed, the last rows are placeholders filled with zeros. The `presence` feature can be used to detect such cases, since it is set to 1 for any observed vehicle and 0 for placeholders.

Feature	Description
$presence$	Disambiguate agents at 0 offset from non-existent agents.
x	World offset of ego vehicle or offset to ego vehicle on the x axis.
y	World offset of ego vehicle or offset to ego vehicle on the y axis.
vx	Velocity on the x axis of vehicle.
vy	Velocity on the y axis of vehicle.
$heading$	Heading of vehicle in radians.
cos_h	Trigonometric heading of vehicle.
sin_h	Trigonometric heading of vehicle.
cos_d	Trigonometric direction to the vehicle's destination.
sin_d	Trigonometric direction to the vehicle's destination.
$long_{off}$	Longitudinal offset to closest lane.
lat_{off}	Lateral offset to closest lane.
ang_{off}	Angular offset to closest lane.

Example configuration

```
import gym
import highway_env

config = {
    "observation": {
        "type": "Kinematics",
        "vehicles_count": 15,
        "features": ["presence", "x", "y", "vx", "vy", "cos_h", "sin_h"],
        "features_range": {
            "x": [-100, 100],
            "y": [-100, 100],
            "vx": [-20, 20],
            "vy": [-20, 20]
        },
        "absolute": False,
        "order": "sorted"
    }
}
env = gym.make('highway-v0')
env.configure(config)
obs = env.reset()
print(obs)
```

```
[[ 1.          1.          0.04        1.          0.          1.
   0.        ]
 [ 1.          0.18764801  0.08       -0.14044404  0.          1.
   0.        ]
 [ 1.          0.3872133   0.         -0.12662704  0.          1.
   0.        ]
 [ 1.          0.6224926   0.08       -0.0726107   0.          1.
   0.        ]
 [ 1.          0.8141772   0.04       -0.156732    0.          1.
   0.        ]
```

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```
[ 1.          1.          0.08        -0.14212266  0.          1.
  0.        ]
[ 1.          1.          0.08        -0.1410234   0.          1.
  0.        ]
[ 1.          1.         -0.04        -0.12309787  0.          1.
  0.        ]
[ 1.          1.          0.          -0.05738564  0.          1.
  0.        ]
[ 1.          1.          0.04        -0.06220595  0.          1.
  0.        ]
[ 0.          0.          0.           0.          0.          0.
  0.        ]
[ 0.          0.          0.           0.          0.          0.
  0.        ]
[ 0.          0.          0.           0.          0.          0.
  0.        ]
[ 0.          0.          0.           0.          0.          0.
  0.        ]
[ 0.          0.          0.           0.          0.          0.
  0.        ]]
```

Grayscale Image

The *GrayscaleObservation* is a $W \times H$ grayscale image of the scene, where W, H are set with the `observation_shape` parameter. The RGB to grayscale conversion is a weighted sum, configured by the `weights` parameter. Several images can be stacked with the `stack_size` parameter, as is customary with image observations.

Example configuration

```
   from matplotlib import pyplot as plt
   %matplotlib inline
config = {
       "observation": {
           "type": "GrayscaleObservation",
           "observation_shape": (128, 64),
           "stack_size": 4,
           "weights": [0.2989, 0.5870, 0.1140],  # weights for RGB conversion
           "scaling": 1.75,
       },
       "policy_frequency": 2
   }
   env.configure(config)
   obs = env.reset()

   _, axes = plt.subplots(ncols=4, figsize=(12, 5))
   for i, ax in enumerate(axes.flat):
       ax.imshow(obs[i, ...].T, cmap=plt.get_cmap('gray'))
   plt.show()
```

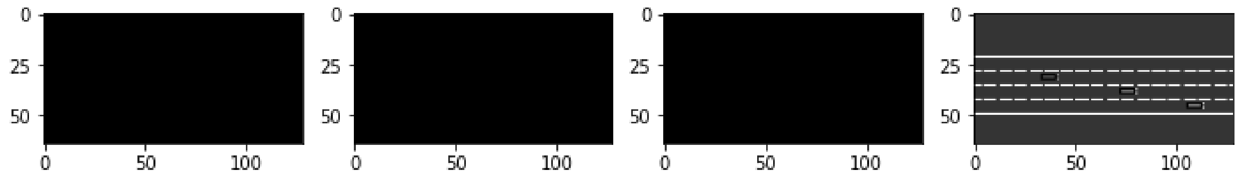
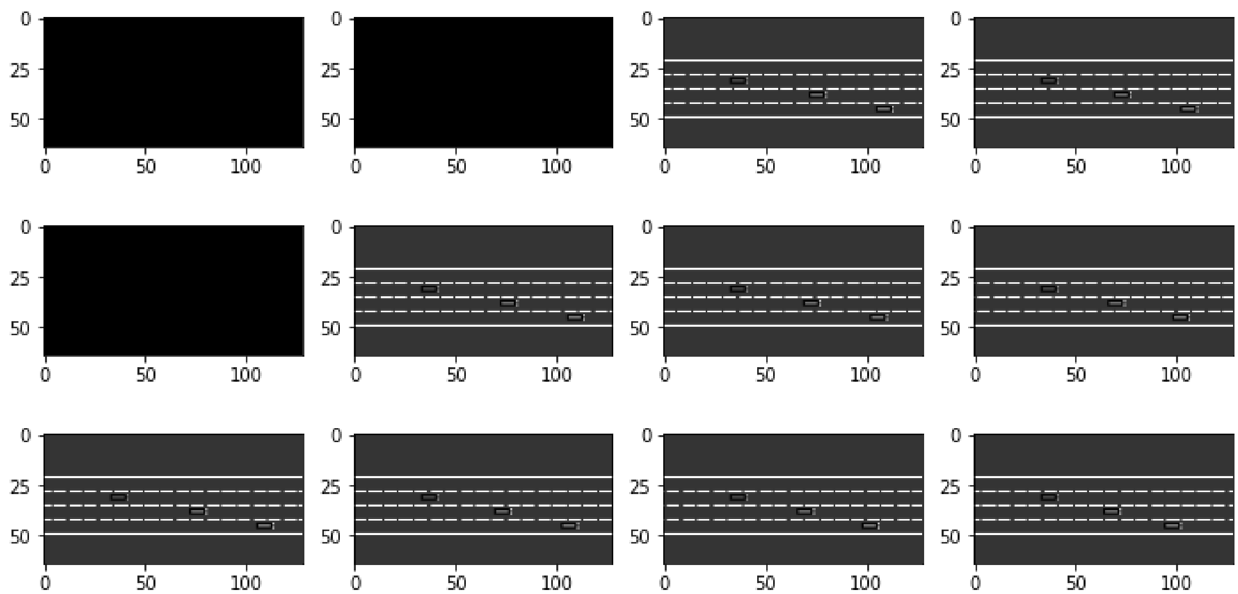


Illustration of the stack mechanism

We illustrate the stack update by performing three steps in the environment.

```python
for _ in range(3):
    obs, _, _, _ = env.step(env.action_type.actions_indexes["IDLE"])

    _, axes = plt.subplots(ncols=4, figsize=(12, 5))
    for i, ax in enumerate(axes.flat):
        ax.imshow(obs[i, ...].T, cmap=plt.get_cmap('gray'))
plt.show()
```



Occupancy grid

The *OccupancyGridObservation* is a $W \times H \times F$ array, that represents a grid of shape $W \times H$ discretising the space (X, Y) around the ego-vehicle in uniform rectangle cells. Each cell is described by F features, listed in the `"features"` configuration field. The grid size and resolution is defined by the `grid_size` and `grid_steps` configuration fields.

For instance, the channel corresponding to the `presence` feature may look like this:

Table 1: presence feature: one vehicle is close to the north, and one is farther to the east.

0	0	0	0	0
0	0	1	0	0
0	0	0	0	1
0	0	0	0	0
0	0	0	0	0

The corresponding v_x feature may look like this:

Table 2: v_x feature: the north vehicle drives at the same speed as the ego-vehicle, and the east vehicle a bit slower

0	0	0	0	0
0	0	0	0	0
0	0	0	0	-0.1
0	0	0	0	0
0	0	0	0	0

Example configuration

```
"observation": {
    "type": "OccupancyGrid",
    "vehicles_count": 15,
    "features": ["presence", "x", "y", "vx", "vy", "cos_h", "sin_h"],
    "features_range": {
        "x": [-100, 100],
        "y": [-100, 100],
        "vx": [-20, 20],
        "vy": [-20, 20]
    },
    "grid_size": [[-27.5, 27.5], [-27.5, 27.5]],
    "grid_step": [5, 5],
    "absolute": False
}
```

Time to collision

The `TimeToCollisionObservation` is a $V \times L \times H$ array, that represents the predicted time-to-collision of observed vehicles on the same road as the ego-vehicle. These predictions are performed for V different values of the ego-vehicle speed, L lanes on the road around the current lane, and represented as one-hot encodings over H discretised time values (bins), with 1s steps.

For instance, consider a vehicle at 25m on the right-lane of the ego-vehicle and driving at 15 m/s. Using $V = 3$, $L = 3\,H = 10$, with ego-speed of {15 m/s, 20 m/s and 25 m/s}, the predicted time-to-collisions are ∞, $5s$, $2.5s$ and the corresponding observation is

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0

Example configuration

```
"observation": {
    "type": "TimeToCollision"
    "horizon": 10
},
```

API

class highway_env.envs.common.observation.**GrayscaleObservation**(*env: AbstractEnv, observation_shape: Tuple[int, int], stack_size: int, weights: List[float], scaling: Optional[float] = None, centering_position: Optional[List[float]] = None, **kwargs*)

An observation class that collects directly what the simulator renders.

Also stacks the collected frames as in the nature DQN. The observation shape is C x W x H.

Specific keys are expected in the configuration dictionary passed. Example of observation dictionary in the environment config:

observation": { "type": "GrayscaleObservation", "observation_shape": (84, 84) "stack_size": 4, "weights": [0.2989, 0.5870, 0.1140], # weights for RGB conversion,

}

space() → gym.spaces.space.Space

Get the observation space.

observe() → numpy.ndarray

Get an observation of the environment state.

class highway_env.envs.common.observation.**KinematicObservation**(*env: AbstractEnv, features: List[str] = None, vehicles_count: int = 5, features_range: Dict[str, List[float]] = None, absolute: bool = False, order: str = 'sorted', normalize: bool = True, clip: bool = True, see_behind: bool = False, observe_intentions: bool = False, **kwargs: dict*)

Observe the kinematics of nearby vehicles.

space() → gym.spaces.space.Space

Get the observation space.

normalize_obs(*df: pandas.core.frame.DataFrame*) → pandas.core.frame.DataFrame

Normalize the observation values.

For now, assume that the road is straight along the x axis. :param Dataframe df: observation data

observe() → numpy.ndarray

Get an observation of the environment state.

class highway_env.envs.common.observation.**OccupancyGridObservation**(*env: AbstractEnv, features: Optional[List[str]] = None, grid_size: Optional[Tuple[Tuple[float, float], Tuple[float, float]]] = None, grid_step: Optional[Tuple[float, float]] = None, features_range: Dict[str, List[float]] = None, absolute: bool = False, align_to_vehicle_axes: bool = False, clip: bool = True, as_image: bool = False, **kwargs: dict*)

Observe an occupancy grid of nearby vehicles.

space() → gym.spaces.space.Space

Get the observation space.

normalize(*df: pandas.core.frame.DataFrame*) → pandas.core.frame.DataFrame

Normalize the observation values.

For now, assume that the road is straight along the x axis. :param Dataframe df: observation data

observe() → numpy.ndarray

Get an observation of the environment state.

pos_to_index(*position: Union[numpy.ndarray, Sequence[float]], relative: bool = False*) → Tuple[int, int]

Convert a world position to a grid cell index

If align_to_vehicle_axes the cells are in the vehicle's frame, otherwise in the world frame.

Parameters

- **position** – a world position
- **relative** – whether the position is already relative to the observer's position

Returns the pair (i,j) of the cell index

fill_road_layer_by_lanes(*layer_index: int, lane_perception_distance: float = 100*) → None

A layer to encode the onroad (1) / offroad (0) information

Here, we iterate over lanes and regularly placed waypoints on these lanes to fill the corresponding cells. This approach is faster if the grid is large and the road network is small.

Parameters

- **layer_index** – index of the layer in the grid
- **lane_perception_distance** – lanes are rendered +/- this distance from vehicle location

fill_road_layer_by_cell(*layer_index*) → None

A layer to encode the onroad (1) / offroad (0) information

In this implementation, we iterate the grid cells and check whether the corresponding world position at the center of the cell is onroad/offroad. This approach is faster if the grid is small and the road network large.

class highway_env.envs.common.observation.**KinematicsGoalObservation**(*env: AbstractEnv*, *scales: List[float]*, ***kwargs: dict*)

space() → gym.spaces.space.Space

Get the observation space.

observe() → Dict[str, numpy.ndarray]

Get an observation of the environment state.

class highway_env.envs.common.observation.**ExitObservation**(*env: AbstractEnv*, *features: List[str] = None*, *vehicles_count: int = 5*, *features_range: Dict[str, List[float]] = None*, *absolute: bool = False*, *order: str = 'sorted'*, *normalize: bool = True*, *clip: bool = True*, *see_behind: bool = False*, *observe_intentions: bool = False*, ***kwargs: dict*)

Specific to exit_env, observe the distance to the next exit lane as part of a KinematicObservation.

observe() → numpy.ndarray

Get an observation of the environment state.

2.3.2 Actions

Similarly to *observations*, **several types of actions** can be used in every environment. They are defined in the `action` module. Each environment comes with a *default* action type, which can be changed or customised using *environment configurations*. For instance,

```
import gym
import highway_env

env = gym.make('highway-v0')
env.configure({
    "action": {
        "type": "ContinuousAction"
    }
})
env.reset()
```

Continuous Actions

The `ContinuousAction` type allows the agent to directly set the low-level controls of the *vehicle kinematics*, namely the throttle a and steering angle δ.

Note: The control of throttle and steering can be enabled or disabled through the `longitudinal` and `lateral` configurations, respectively. Thus, the action space can be either 1D or 2D.

Discrete Actions

The `DiscreteAction` is a uniform quantization of the `ContinuousAction` above.

The `actions_per_axis` parameter allows to set the quantization step. Similarly to continuous actions, the longitudinal and lateral axis can be enabled or disabled separately.

Discrete Meta-Actions

The `DiscreteMetaAction` type adds a layer of *speed and steering controllers* on top of the continuous low-level control, so that the ego-vehicle can automatically follow the road at a desired velocity. Then, the available **meta-actions** consist in *changing the target lane and speed* that are used as setpoints for the low-level controllers.

The full corresponding action space is defined in `ACTIONS_ALL`

```
ACTIONS_ALL = {
        0: 'LANE_LEFT',
        1: 'IDLE',
        2: 'LANE_RIGHT',
        3: 'FASTER',
        4: 'SLOWER'
    }
```

Some of these actions might not be always available (lane changes at the edges of the roads, or accelerating/decelrating beyond the maximum/minimum velocity), and the list of available actions can be accessed with `get_available_actions()` method. Taking an unavailable action is equivalent to taking the `IDLE` action.

Similarly to continuous actions, the longitudinal (speed changes) and lateral (lane changes) actions can be disabled separately through the `longitudinal` and `lateral` parameters. For instance, in the default configuration of the *intersection* environment, only the speed is controlled by the agent, while the lateral control of the vehicle is automatically performed by a *steering controller* to track a desired lane.

Manual control

The environments can be used as a simulation:

```
env = gym.make("highway-v0")
env.configure({
    "manual_control": True
})
env.reset()
done = False
while not done:
    env.step(env.action_space.sample())  # with manual control, these actions are ignored
```

The ego-vehicle is controlled by directional arrows keys, as defined in `EventHandler`

API

class `highway_env.envs.common.action.`**`ActionType`**(*env: AbstractEnv*, ***kwargs*)

A type of action specifies its definition space, and how actions are executed in the environment

`space`() → gym.spaces.space.Space

The action space.

property vehicle_class: Callable

The class of a vehicle able to execute the action.

Must return a subclass of *`highway_env.vehicle.kinematics.Vehicle`*.

`act`(*action: Union[int, numpy.ndarray]*) → None

Execute the action on the ego-vehicle.

Most of the action mechanics are actually implemented in vehicle.act(action), where vehicle is an instance of the specified *`highway_env.envs.common.action.ActionType.vehicle_class`*. Must some pre-processing can be applied to the action based on the ActionType configurations.

Parameters **`action`** – the action to execute

property controlled_vehicle

The vehicle acted upon.

If not set, the first controlled vehicle is used by default.

class `highway_env.envs.common.action.`**`ContinuousAction`**(*env: AbstractEnv*, *acceleration_range: Optional[Tuple[float, float]] = None*, *steering_range: Optional[Tuple[float, float]] = None*, *speed_range: Optional[Tuple[float, float]] = None*, *longitudinal: bool = True*, *lateral: bool = True*, *dynamical: bool = False*, *clip: bool = True*, ***kwargs*)

An continuous action space for throttle and/or steering angle.

If both throttle and steering are enabled, they are set in this order: [throttle, steering]

The space intervals are always [-1, 1], but are mapped to throttle/steering intervals through configurations.

ACCELERATION_RANGE = (-5, 5.0)

Acceleration range: [-x, x], in m/s^2.

STEERING_RANGE = (-0.7853981633974483, 0.7853981633974483)

Steering angle range: [-x, x], in rad.

`space`() → gym.spaces.box.Box

The action space.

property vehicle_class: Callable

The class of a vehicle able to execute the action.

Must return a subclass of *`highway_env.vehicle.kinematics.Vehicle`*.

act(*action: numpy.ndarray*) → None

Execute the action on the ego-vehicle.

Most of the action mechanics are actually implemented in vehicle.act(action), where vehicle is an instance of the specified *highway_env.envs.common.action.ActionType.vehicle_class*. Must some pre-processing can be applied to the action based on the ActionType configurations.

Parameters **action** – the action to execute

class highway_env.envs.common.action.**DiscreteAction**(*env:* AbstractEnv, *acceleration_range: Optional[Tuple[float, float]] = None*, *steering_range: Optional[Tuple[float, float]] = None*, *longitudinal: bool = True*, *lateral: bool = True*, *dynamical: bool = False*, *clip: bool = True*, *actions_per_axis: int = 3*, ***kwargs*)

space() → gym.spaces.discrete.Discrete

The action space.

act(*action: int*) → None

Execute the action on the ego-vehicle.

Most of the action mechanics are actually implemented in vehicle.act(action), where vehicle is an instance of the specified *highway_env.envs.common.action.ActionType.vehicle_class*. Must some pre-processing can be applied to the action based on the ActionType configurations.

Parameters **action** – the action to execute

class highway_env.envs.common.action.**DiscreteMetaAction**(*env:* AbstractEnv, *longitudinal: bool = True*, *lateral: bool = True*, *target_speeds: Optional[Union[numpy.ndarray, Sequence[float]]] = None*, ***kwargs*)

An discrete action space of meta-actions: lane changes, and cruise control set-point.

ACTIONS_ALL = {0: 'LANE_LEFT', 1: 'IDLE', 2: 'LANE_RIGHT', 3: 'FASTER', 4: 'SLOWER'}

A mapping of action indexes to labels.

ACTIONS_LONGI = {0: 'SLOWER', 1: 'IDLE', 2: 'FASTER'}

A mapping of longitudinal action indexes to labels.

ACTIONS_LAT = {0: 'LANE_LEFT', 1: 'IDLE', 2: 'LANE_RIGHT'}

A mapping of lateral action indexes to labels.

space() → gym.spaces.space.Space

The action space.

property vehicle_class: Callable

The class of a vehicle able to execute the action.

Must return a subclass of *highway_env.vehicle.kinematics.Vehicle*.

act(*action: int*) → None

Execute the action on the ego-vehicle.

Most of the action mechanics are actually implemented in vehicle.act(action), where vehicle is an instance of the specified *highway_env.envs.common.action.ActionType.vehicle_class*. Must some pre-processing can be applied to the action based on the ActionType configurations.

Parameters **action** – the action to execute class highway_env.envs.common.action.**MultiAgentAction**(*env: AbstractEnv*, *action_config: dict*, ***kwargs*)

space() → gym.spaces.space.Space

The action space.

property vehicle_class: Callable

The class of a vehicle able to execute the action.

Must return a subclass of *highway_env.vehicle.kinematics.Vehicle*.

act(*action: Union[int, numpy.ndarray]*) → None

Execute the action on the ego-vehicle.

Most of the action mechanics are actually implemented in vehicle.act(action), where vehicle is an instance of the specified *highway_env.envs.common.action.ActionType.vehicle_class*. Must some pre-processing can be applied to the action based on the ActionType configurations.

Parameters **action** – the action to execute

2.3.3 Dynamics

The dynamics of every environment describes how vehicles move and behave through time. There are two important sections that affect these dynamics: the description of the roads, and the vehicle physics and behavioral models.

Roads

A *Road* is composed of a RoadNetwork and a list of *Vehicle*.

Lane

The geometry of lanes are described by *AbstractLane* objects, as a parametrized center line curve, providing a local coordinate system.

Conversions between the (longi, lat) coordinates in the Frenet frame and the global x, y coordinates are ensured by the *position()* and *local_coordinates()* methods.

The main implementations are:

- *StraightLane*
- *SineLane*
- *CircularLane*

API

class highway_env.road.lane.**AbstractLane**

A lane on the road, described by its central curve.

metaclass__

alias of abc.ABCMeta

abstract position(*longitudinal: float*, *lateral: float*) → numpy.ndarray

Convert local lane coordinates to a world position.

Parameters

- **longitudinal** – longitudinal lane coordinate [m]
- **lateral** – lateral lane coordinate [m]

Returns the corresponding world position [m]

abstract local_coordinates(*position: numpy.ndarray*) → Tuple[float, float]

Convert a world position to local lane coordinates.

Parameters **position** – a world position [m]

Returns the (longitudinal, lateral) lane coordinates [m]

abstract heading_at(*longitudinal: float*) → float

Get the lane heading at a given longitudinal lane coordinate.

Parameters **longitudinal** – longitudinal lane coordinate [m]

Returns the lane heading [rad]

abstract width_at(*longitudinal: float*) → float

Get the lane width at a given longitudinal lane coordinate.

Parameters **longitudinal** – longitudinal lane coordinate [m]

Returns the lane width [m]

classmethod from_config(*config: dict*)

Create lane instance from config

Parameters **config** – json dict with lane parameters

abstract to_config() → dict

Write lane parameters to dict which can be serialized to json

Returns dict of lane parameters

on_lane(*position: numpy.ndarray*, *longitudinal: Optional[float] = None*, *lateral: Optional[float] = None*, *margin: float = 0*) → bool

Whether a given world position is on the lane.

Parameters

- **position** – a world position [m]
- **longitudinal** – (optional) the corresponding longitudinal lane coordinate, if known [m]
- **lateral** – (optional) the corresponding lateral lane coordinate, if known [m]
- **margin** – (optional) a supplementary margin around the lane width

Returns is the position on the lane?

is_reachable_from(*position: numpy.ndarray*) → bool

Whether the lane is reachable from a given world position

Parameters **position** – the world position [m]

Returns is the lane reachable?

distance(*position: numpy.ndarray*)

Compute the L1 distance [m] from a position to the lane.

distance_with_heading(*position: numpy.ndarray*, *heading: Optional[float]*, *heading_weight: float = 1.0*)

Compute a weighted distance in position and heading to the lane.

local_angle(*heading: float*, *long_offset: float*)

Compute non-normalised angle of heading to the lane.

class highway_env.road.lane.**LineType**

A lane side line type.

class highway_env.road.lane.**StraightLane**(*start: Union[numpy.ndarray, Sequence[float]]*, *end: Union[numpy.ndarray, Sequence[float]]*, *width: float = 4*, *line_types: Optional[Tuple[highway_env.road.lane.LineType, highway_env.road.lane.LineType]] = None*, *forbidden: bool = False*, *speed_limit: float = 20*, *priority: int = 0*)

A lane going in straight line.

position(*longitudinal: float*, *lateral: float*) → numpy.ndarray

Convert local lane coordinates to a world position.

Parameters

- **longitudinal** – longitudinal lane coordinate [m]
- **lateral** – lateral lane coordinate [m]

Returns the corresponding world position [m]

heading_at(*longitudinal: float*) → float

Get the lane heading at a given longitudinal lane coordinate.

Parameters **longitudinal** – longitudinal lane coordinate [m]

Returns the lane heading [rad]

width_at(*longitudinal: float*) → float

Get the lane width at a given longitudinal lane coordinate.

Parameters **longitudinal** – longitudinal lane coordinate [m]

Returns the lane width [m]

local_coordinates(*position: numpy.ndarray*) → Tuple[float, float]

Convert a world position to local lane coordinates.

Parameters **position** – a world position [m]

Returns the (longitudinal, lateral) lane coordinates [m]

classmethod **from_config**(*config: dict*)

Create lane instance from config

Parameters **config** – json dict with lane parameters

to_config() → dict

Write lane parameters to dict which can be serialized to json

Returns dict of lane parameters

class highway_env.road.lane.**SineLane**(*start: Union[numpy.ndarray, Sequence[float]], end: Union[numpy.ndarray, Sequence[float]], amplitude: float, pulsation: float, phase: float, width: float = 4, line_types: Optional[List[*highway_env.road.lane.LineType*]] = None, forbidden: bool = False, speed_limit: float = 20, priority: int = 0*)

A sinusoidal lane.

position(*longitudinal: float, lateral: float*) → numpy.ndarray

Convert local lane coordinates to a world position.

Parameters

- **longitudinal** – longitudinal lane coordinate [m]
- **lateral** – lateral lane coordinate [m]

Returns the corresponding world position [m]

heading_at(*longitudinal: float*) → float

Get the lane heading at a given longitudinal lane coordinate.

Parameters **longitudinal** – longitudinal lane coordinate [m]

Returns the lane heading [rad]

local_coordinates(*position: numpy.ndarray*) → Tuple[float, float]

Convert a world position to local lane coordinates.

Parameters **position** – a world position [m]

Returns the (longitudinal, lateral) lane coordinates [m]

classmethod from_config(*config: dict*)

Create lane instance from config

Parameters **config** – json dict with lane parameters

to_config() → dict

Write lane parameters to dict which can be serialized to json

Returns dict of lane parameters

class highway_env.road.lane.**CircularLane**(*center: Union[numpy.ndarray, Sequence[float]], radius: float, start_phase: float, end_phase: float, clockwise: bool = True, width: float = 4, line_types: Optional[List[*highway_env.road.lane.LineType*]] = None, forbidden: bool = False, speed_limit: float = 20, priority: int = 0*)

A lane going in circle arc.

position(*longitudinal: float, lateral: float*) → numpy.ndarray

Convert local lane coordinates to a world position.

Parameters

- **longitudinal** – longitudinal lane coordinate [m]
- **lateral** – lateral lane coordinate [m]

Returns the corresponding world position [m]

heading_at(*longitudinal: float*) → float

Get the lane heading at a given longitudinal lane coordinate.

Parameters **longitudinal** – longitudinal lane coordinate [m]

Returns the lane heading [rad]

width_at(*longitudinal: float*) → float

Get the lane width at a given longitudinal lane coordinate.

Parameters **longitudinal** – longitudinal lane coordinate [m]

Returns the lane width [m]

local_coordinates(*position: numpy.ndarray*) → Tuple[float, float]

Convert a world position to local lane coordinates.

Parameters **position** – a world position [m]

Returns the (longitudinal, lateral) lane coordinates [m]

classmethod from_config(*config: dict*)

Create lane instance from config

Parameters **config** – json dict with lane parameters

to_config() → dict

Write lane parameters to dict which can be serialized to json

Returns dict of lane parameters

class highway_env.road.lane.**PolyLaneFixedWidth**(*lane_points: List[Tuple[float, float]]*, *width: float = 4*, *line_types: Optional[Tuple[highway_env.road.lane.LineType, highway_env.road.lane.LineType]] = None*, *forbidden: bool = False*, *speed_limit: float = 20*, *priority: int = 0*)

A fixed-width lane defined by a set of points and approximated with a 2D Hermite polynomial.

position(*longitudinal: float*, *lateral: float*) → numpy.ndarray

Convert local lane coordinates to a world position.

Parameters

- **longitudinal** – longitudinal lane coordinate [m]
- **lateral** – lateral lane coordinate [m]

Returns the corresponding world position [m]

local_coordinates(*position: numpy.ndarray*) → Tuple[float, float]

Convert a world position to local lane coordinates.

Parameters **position** – a world position [m]

Returns the (longitudinal, lateral) lane coordinates [m]

heading_at(*longitudinal: float*) → float

Get the lane heading at a given longitudinal lane coordinate.

Parameters **longitudinal** – longitudinal lane coordinate [m]

Returns the lane heading [rad]

width_at(*longitudinal: float*) → float

Get the lane width at a given longitudinal lane coordinate.

Parameters **longitudinal** – longitudinal lane coordinate [m]

Returns the lane width [m]

classmethod from_config(*config: dict*)

Create lane instance from config

Parameters **config** – json dict with lane parameters

to_config() → dict

Write lane parameters to dict which can be serialized to json

Returns dict of lane parameters

class highway_env.road.lane.**PolyLane**(*lane_points: List[Tuple[float, float]], left_boundary_points: List[Tuple[float, float]], right_boundary_points: List[Tuple[float, float]], line_types: Optional[Tuple[highway_env.road.lane.LineType, highway_env.road.lane.LineType]] = None, forbidden: bool = False, speed_limit: float = 20, priority: int = 0*)

A lane defined by a set of points and approximated with a 2D Hermite polynomial.

width_at(*longitudinal: float*) → float

Get the lane width at a given longitudinal lane coordinate.

Parameters **longitudinal** – longitudinal lane coordinate [m]

Returns the lane width [m]

to_config() → dict

Write lane parameters to dict which can be serialized to json

Returns dict of lane parameters

Road

A `Road` is composed of a `RoadNetwork` and a list of `Vehicle`.

The `RoadNetwork` describes the topology of the road infrastructure as a graph, where edges represent lanes and nodes represent intersections. It contains a `graph` dictionary which stores the `AbstractLane` geometries by their `LaneIndex`. A `LaneIndex` is a tuple containing:

- a string identifier of a starting position
- a string identifier of an ending position
- an integer giving the index of the described lane, in the (unique) road from the starting to the ending position

For instance, the geometry of the second lane in the road going from the `"lab"` to the `"pub"` can be obtained by:

```
lane = road.road_network.graph["lab"]["pub"][1]
```

The actual positions of the lab and the pub are defined in the ``lane```geometry object.

API

`class highway_env.road.road.Road`(*network: highway_env.road.road.RoadNetwork = None*, *vehicles: List[kinematics.Vehicle] = None*, *road_objects: List[objects.RoadObject] = None*, *np_random: numpy.random.mtrand.RandomState = None*, *record_history: bool = False*)

A road is a set of lanes, and a set of vehicles driving on these lanes.

act() → None

Decide the actions of each entity on the road.

step(*dt: float*) → None

Step the dynamics of each entity on the road.

Parameters **dt** – timestep [s]

neighbour_vehicles(*vehicle: kinematics.Vehicle*, *lane_index: Tuple[str, str, int] = None*) → Tuple[Optional[*kinematics.Vehicle*], Optional[*kinematics.Vehicle*]]

Find the preceding and following vehicles of a given vehicle.

Parameters

- **vehicle** – the vehicle whose neighbours must be found
- **lane_index** – the lane on which to look for preceding and following vehicles. It doesn't have to be the current vehicle lane but can also be another lane, in which case the vehicle is projected on it considering its local coordinates in the lane.

Returns its preceding vehicle, its following vehicle

Road regulation

A *RegulatedRoad* is a *Road* in which the behavior of vehicles take or give the right of way at an intersection based on the `priority` lane attribute.

On such a road, some rules are enforced:

- most of the time, vehicles behave as usual;
- however, they try to predict collisions with other vehicles through the `is_conflict_possible()` method;
- when it is the case, right of way is arbitrated through the *respect_priorities()* method, and the yielding vehicle target velocity is set to 0 until the conflict is resolved.

API

`class highway_env.road.regulation.RegulatedRoad`(*network: Optional[highway_env.road.road.RoadNetwork] = None*, *vehicles: Optional[List[highway_env.vehicle.kinematics.Vehicle]] = None*, *obstacles: Optional[List[highway_env.vehicle.objects.Obstacle]] = None*, *np_random: Optional[numpy.random.mtrand.RandomState] = None*, *record_history: bool = False*) `step`(*dt: float*) → None

Step the dynamics of each entity on the road.

Parameters `dt` – timestep [s]

`enforce_road_rules`() → None

Find conflicts and resolve them by assigning yielding vehicles and stopping them.

`static respect_priorities`(*v1:* highway_env.vehicle.kinematics.Vehicle, *v2:* highway_env.vehicle.kinematics.Vehicle) → *highway_env.vehicle.kinematics.Vehicle*

Resolve a conflict between two vehicles by determining who should yield

Parameters

- `v1` – first vehicle
- `v2` – second vehicle

Returns the yielding vehicle

Vehicles

Kinematics

The vehicles kinematics are represented in the `Vehicle` class by the *Kinematic Bicycle Model* [PAltcheDAndreaN17].

$$\begin{aligned}
\dot{x} &= v\cos(\psi+\beta) \\
\dot{y} &= v\sin(\psi+\beta) \\
\dot{v} &= a \\
\dot{\psi} &= \frac{v}{l}\sin\beta \\
\beta &= \tan^{-1}(1/2\tan\delta),
\end{aligned}$$

where

- (x, y) is the vehicle position;
- v its forward speed;
- ψ its heading;
- a is the acceleration command;
- β is the slip angle at the center of gravity;
- δ is the front wheel angle used as a steering command.

These calculations appear in the `step()` method.

API

class highway_env.vehicle.kinematics.**Vehicle**(*road: highway_env.road.road.Road*, *position: Union[numpy.ndarray, Sequence[float]]*, *heading: float = 0*, *speed: float = 0*, *predition_type: str = 'constant_steering'*)

A moving vehicle on a road, and its kinematics.

The vehicle is represented by a dynamical system: a modified bicycle model. It's state is propagated depending on its steering and acceleration actions.

LENGTH: float = 5.0

Vehicle length [m]

WIDTH: float = 2.0

Vehicle width [m]

DEFAULT_INITIAL_SPEEDS = [23, 25]

Range for random initial speeds [m/s]

MAX_SPEED = 40.0

Maximum reachable speed [m/s]

MIN_SPEED = -40.0

Minimum reachable speed [m/s]

HISTORY_SIZE = 30

Length of the vehicle state history, for trajectory display

classmethod create_random(*road: highway_env.road.road.Road*, *speed: Optional[float] = None*, *lane_from: Optional[str] = None*, *lane_to: Optional[str] = None*, *lane_id: Optional[int] = None*, *spacing: float = 1*) → *highway_env.vehicle.kinematics.Vehicle*

Create a random vehicle on the road.

The lane and /or speed are chosen randomly, while longitudinal position is chosen behind the last vehicle in the road with density based on the number of lanes.

Parameters

- **road** – the road where the vehicle is driving
- **speed** – initial speed in [m/s]. If None, will be chosen randomly
- **lane_from** – start node of the lane to spawn in
- **lane_to** – end node of the lane to spawn in
- **lane_id** – id of the lane to spawn in
- **spacing** – ratio of spacing to the front vehicle, 1 being the default

Returns A vehicle with random position and/or speed

classmethod create_from(*vehicle: highway_env.vehicle.kinematics.Vehicle*) → *highway_env.vehicle.kinematics.Vehicle*

Create a new vehicle from an existing one.

Only the vehicle dynamics are copied, other properties are default.

Parameters **vehicle** – a vehicle

Returns a new vehicle at the same dynamical state

`act`(*action: Optional[Union[dict, str]] = None*) → None

Store an action to be repeated.

Parameters **action** – the input action

`step`(*dt: float*) → None

Propagate the vehicle state given its actions.

Integrate a modified bicycle model with a 1st-order response on the steering wheel dynamics. If the vehicle is crashed, the actions are overridden with erratic steering and braking until complete stop. The vehicle's current lane is updated.

Parameters **dt** – timestep of integration of the model [s]

Control

The `ControlledVehicle` class implements a low-level controller on top of a `Vehicle`, allowing to track a given target speed and follow a target lane. The controls are computed when calling the `act()` method.

Longitudinal controller

The longitudinal controller is a simple proportional controller:

$$a = K_p(v_r - v),$$

where

- a is the vehicle acceleration (throttle);
- v is the vehicle velocity;
- v_r is the reference velocity;
- K_p is the controller proportional gain, implemented as `KP_A`.

It is implemented in the `speed_control()` method.

Lateral controller

The lateral controller is a simple proportional-derivative controller, combined with some non-linearities that invert those of the *kinematics model*.

Position control

$$\begin{aligned}
v_{\text{lat},r} &= -K_{p,\text{lat}} \Delta_{\text{lat}}, \\
\Delta \psi_r &= \arcsin\left(\frac{v_{\text{lat},r}}{v}\right),
\end{aligned}$$

Heading control

$$\begin{aligned}
\psi_r &= \psi_L + \Delta\psi_r, \\
\dot{\psi}_r &= K_{p,\psi}(\psi_r - \psi), \\
\delta &= \arcsin\left(\frac{1}{2}\frac{l}{v}\dot{\psi}_r\right),
\end{aligned}$$

where

- Δ_{lat} is the lateral position of the vehicle with respect to the lane center-line;
- $v_{\text{lat},r}$ is the lateral velocity command;
- $\Delta\psi_r$ is a heading variation to apply the lateral velocity command;
- ψ_L is the lane heading (at some lookahead position to anticipate turns);
- ψ_r is the target heading to follow the lane heading and position;
- $\dot{\psi}_r$ is the yaw rate command;
- δ is the front wheels angle control;
- $K_{p,\text{lat}}$ and $K_{p,\psi}$ are the position and heading control gains.

It is implemented in the `steering_control()` method.

API

`class highway_env.vehicle.controller.ControlledVehicle`(*road: highway_env.road.road.Road, position: Union[numpy.ndarray, Sequence[float]], heading: float = 0, speed: float = 0, target_lane_index: Optional[Tuple[str, str, int]] = None, target_speed: Optional[float] = None, route: Optional[List[Tuple[str, str, int]]] = None*)

A vehicle piloted by two low-level controller, allowing high-level actions such as cruise control and lane changes.

- The longitudinal controller is a speed controller;
- The lateral controller is a heading controller cascaded with a lateral position controller.

`target_speed: float`

Desired velocity.

`classmethod create_from`(*vehicle: highway_env.vehicle.controller.ControlledVehicle*) → *highway_env.vehicle.controller.ControlledVehicle*

Create a new vehicle from an existing one.

The vehicle dynamics and target dynamics are copied, other properties are default.

Parameters **`vehicle`** – a vehicle

Returns a new vehicle at the same dynamical state

`plan_route_to`(*destination: str*) → *highway_env.vehicle.controller.ControlledVehicle*

Plan a route to a destination in the road network

Parameters **`destination`** – a node in the road network

act(*action: Optional[Union[dict, str]] = None*) → None

Perform a high-level action to change the desired lane or speed.

- If a high-level action is provided, update the target speed and lane;
- then, perform longitudinal and lateral control.

Parameters `action` – a high-level action

follow_road() → None

At the end of a lane, automatically switch to a next one.

steering_control(*target_lane_index: Tuple[str, str, int]*) → float

Steer the vehicle to follow the center of an given lane.

1. Lateral position is controlled by a proportional controller yielding a lateral speed command
2. Lateral speed command is converted to a heading reference
3. Heading is controlled by a proportional controller yielding a heading rate command
4. Heading rate command is converted to a steering angle

Parameters `target_lane_index` – index of the lane to follow

Returns a steering wheel angle command [rad]

speed_control(*target_speed: float*) → float

Control the speed of the vehicle.

Using a simple proportional controller.

Parameters `target_speed` – the desired speed

Returns an acceleration command [m/s2]

get_routes_at_intersection() → List[List[Tuple[str, str, int]]]

Get the list of routes that can be followed at the next intersection.

set_route_at_intersection(*_to: int*) → None

Set the road to be followed at the next intersection.

Erase current planned route.

Parameters `_to` – index of the road to follow at next intersection, in the road network

predict_trajectory_constant_speed(*times: numpy.ndarray*) → Tuple[List[numpy.ndarray], List[float]]

Predict the future positions of the vehicle along its planned route, under constant speed

Parameters `times` – timesteps of prediction

Returns positions, headings

class highway_env.vehicle.controller.**MDPVehicle**(*road:* highway_env.road.road.Road, *position: List[float]*, *heading: float = 0*, *speed: float = 0*, *target_lane_index: Optional[Tuple[str, str, int]] = None*, *target_speed: Optional[float] = None*, *target_speeds: Optional[Union[numpy.ndarray, Sequence[float]]] = None*, *route: Optional[List[Tuple[str, str, int]]] = None*)

A controlled vehicle with a specified discrete range of allowed target speeds.

`act`(*action: Optional[Union[dict, str]] = None*) → None

Perform a high-level action.

- If the action is a speed change, choose speed from the allowed discrete range.
- Else, forward action to the ControlledVehicle handler.

Parameters **action** – a high-level action

`index_to_speed`(*index: int*) → float

Convert an index among allowed speeds to its corresponding speed

Parameters **index** – the speed index []

Returns the corresponding speed [m/s]

`speed_to_index`(*speed: float*) → int

Find the index of the closest speed allowed to a given speed.

Assumes a uniform list of target speeds to avoid searching for the closest target speed

Parameters **speed** – an input speed [m/s]

Returns the index of the closest speed allowed []

`classmethod speed_to_index_default`(*speed: float*) → int

Find the index of the closest speed allowed to a given speed.

Assumes a uniform list of target speeds to avoid searching for the closest target speed

Parameters **speed** – an input speed [m/s]

Returns the index of the closest speed allowed []

`predict_trajectory`(*actions: List*, *action_duration: float*, *trajectory_timestep: float*, *dt: float*) → List[*highway_env.vehicle.controller.ControlledVehicle*]

Predict the future trajectory of the vehicle given a sequence of actions.

Parameters

- **actions** – a sequence of future actions.
- **action_duration** – the duration of each action.
- **trajectory_timestep** – the duration between each save of the vehicle state.
- **dt** – the timestep of the simulation

Returns the sequence of future states

Behavior

Other simulated vehicles follow simple and realistic behaviors that dictate how they accelerate and steer on the road. They are implemented in the *IDMVehicle* class.

Longitudinal Behavior

The acceleration of the vehicle is given by the *Intelligent Driver Model* (IDM) from [THH00].

$$\dot{v} = a\left[1 - \left(\frac{v}{v_0}\right)^\delta - \left(\frac{d^*}{d}\right)^2\right]$$
$$d^* = d_0 + Tv + \frac{v\Delta v}{2\sqrt{ab}}$$

where v is the vehicle velocity, d is the distance to its front vehicle. The dynamics are parametrised by:

- v_0 the desired velocity, as `target_velocity`
- T the desired time gap, as *TIME_WANTED*
- d_0 the jam distance, as *DISTANCE_WANTED*
- a, b the maximum acceleration and deceleration, as *COMFORT_ACC_MAX* and *COMFORT_ACC_MIN*
- δ the velocity exponent, as *DELTA*

It is implemented in *acceleration()* method.

Lateral Behavior

The discrete lane change decisions are given by the *Minimizing Overall Braking Induced by Lane change* (MOBIL) model from [KTH07]. According to this model, a vehicle decides to change lane when:

- it is **safe** (do not cut-in):

$$\tilde{a}_n \geq -b_\text{safe};$$

- there is an **incentive** (for the ego-vehicle and possibly its followers):

$$\underbrace{\tilde{a}_c - a_c}_{\text{ego-vehicle}} + p\left(\underbrace{\tilde{a}_n - a_n}_{\text{new follower}} + \underbrace{\tilde{a}_o - a_o}_{\text{old follower}}\right) \geq \Delta a_\text{th},$$

where

- c is the center (ego-) vehicle, o is its old follower *before* the lane change, and n is its new follower *after* the lane change
- $a, \tilde{a}$ are the acceleration of the vehicles *before* and *after* the lane change, respectively.
- p is a politeness coefficient, implemented as `POLITENESS`
- Δa_th the acceleration gain required to trigger a lane change, implemented as `LANE_CHANGE_MIN_ACC_GAIN`
- b_safe the maximum braking imposed to a vehicle during a cut-in, implemented as `LANE_CHANGE_MAX_BRAKING_IMPOSED`

It is implemented in the *mobil()* method.

Note: In the *LinearVehicle* class, the longitudinal and lateral behaviours are approximated as linear weightings of several features, such as the distance and speed difference to the leading vehicle.

API

class `highway_env.vehicle.behavior.IDMVehicle`(*road: highway_env.road.road.Road, position: Union[numpy.ndarray, Sequence[float]], heading: float = 0, speed: float = 0, target_lane_index: Optional[int] = None, target_speed: Optional[float] = None, route: Optional[List[Tuple[str, str, int]]] = None, enable_lane_change: bool = True, timer: Optional[float] = None*)

A vehicle using both a longitudinal and a lateral decision policies.

- Longitudinal: the IDM model computes an acceleration given the preceding vehicle's distance and speed.
- Lateral: the MOBIL model decides when to change lane by maximizing the acceleration of nearby vehicles.

ACC_MAX = 6.0

Maximum acceleration.

COMFORT_ACC_MAX = 3.0

Desired maximum acceleration.

COMFORT_ACC_MIN = -5.0

Desired maximum deceleration.

DISTANCE_WANTED = 10.0

Desired jam distance to the front vehicle.

TIME_WANTED = 1.5

Desired time gap to the front vehicle.

DELTA = 4.0

Exponent of the velocity term.

DELTA_RANGE = [3.5, 4.5]

Range of delta when chosen randomly.

classmethod create_from(*vehicle: highway_env.vehicle.controller.ControlledVehicle*) → *highway_env.vehicle.behavior.IDMVehicle*

Create a new vehicle from an existing one.

The vehicle dynamics and target dynamics are copied, other properties are default.

Parameters `vehicle` – a vehicle

Returns a new vehicle at the same dynamical state

act(*action: Optional[Union[dict, str]] = None*)

Execute an action.

For now, no action is supported because the vehicle takes all decisions of acceleration and lane changes on its own, based on the IDM and MOBIL models.

Parameters `action` – the action

step(*dt: float*)

Step the simulation.

Increases a timer used for decision policies, and step the vehicle dynamics.

Parameters `dt` – timestep

acceleration(*ego_vehicle: highway_env.vehicle.controller.ControlledVehicle*, *front_vehicle: Optional[highway_env.vehicle.kinematics.Vehicle] = None*, *rear_vehicle: Optional[highway_env.vehicle.kinematics.Vehicle] = None*) → float

Compute an acceleration command with the Intelligent Driver Model.

The acceleration is chosen so as to: - reach a target speed; - maintain a minimum safety distance (and safety time) w.r.t the front vehicle.

Parameters

- **ego_vehicle** – the vehicle whose desired acceleration is to be computed. It does not have to be an IDM vehicle, which is why this method is a class method. This allows an IDM vehicle to reason about other vehicles behaviors even though they may not IDMs.
- **front_vehicle** – the vehicle preceding the ego-vehicle
- **rear_vehicle** – the vehicle following the ego-vehicle

Returns the acceleration command for the ego-vehicle [m/s2]

desired_gap(*ego_vehicle: highway_env.vehicle.kinematics.Vehicle*, *front_vehicle: Optional[highway_env.vehicle.kinematics.Vehicle] = None*, *projected: bool = True*) → float

Compute the desired distance between a vehicle and its leading vehicle.

Parameters

- **ego_vehicle** – the vehicle being controlled
- **front_vehicle** – its leading vehicle
- **projected** – project 2D velocities in 1D space

Returns the desired distance between the two [m]

change_lane_policy() → None

Decide when to change lane.

Based on: - frequency; - closeness of the target lane; - MOBIL model.

mobil(*lane_index: Tuple[str, str, int]*) → bool

MOBIL lane change model: Minimizing Overall Braking Induced by a Lane change

The vehicle should change lane only if: - after changing it (and/or following vehicles) can accelerate more; - it doesn't impose an unsafe braking on its new following vehicle.

Parameters **lane_index** – the candidate lane for the change

Returns whether the lane change should be performed

recover_from_stop(*acceleration: float*) → float

If stopped on the wrong lane, try a reversing maneuver.

Parameters **acceleration** – desired acceleration from IDM

Returns suggested acceleration to recover from being stuck

class highway_env.vehicle.behavior.**LinearVehicle**(*road: highway_env.road.road.Road*, *position: Union[numpy.ndarray, Sequence[float]]*, *heading: float = 0*, *speed: float = 0*, *target_lane_index: Optional[int] = None*, *target_speed: Optional[float] = None*, *route: Optional[List[Tuple[str, str, int]]] = None*, *enable_lane_change: bool = True*, *timer: Optional[float] = None*, *data: Optional[dict] = None*)

A Vehicle whose longitudinal and lateral controllers are linear with respect to parameters.

act(*action: Optional[Union[dict, str]] = None*)

Execute an action.

For now, no action is supported because the vehicle takes all decisions of acceleration and lane changes on its own, based on the IDM and MOBIL models.

Parameters **action** – the action

acceleration(*ego_vehicle:* highway_env.vehicle.controller.ControlledVehicle, *front_vehicle: Optional[*highway_env.vehicle.kinematics.Vehicle*] = None*, *rear_vehicle: Optional[*highway_env.vehicle.kinematics.Vehicle*] = None*) → float

Compute an acceleration command with a Linear Model.

The acceleration is chosen so as to: - reach a target speed; - reach the speed of the leading (resp following) vehicle, if it is lower (resp higher) than ego's; - maintain a minimum safety distance w.r.t the leading vehicle.

Parameters

- **ego_vehicle** – the vehicle whose desired acceleration is to be computed. It does not have to be an Linear vehicle, which is why this method is a class method. This allows a Linear vehicle to reason about other vehicles behaviors even though they may not Linear.
- **front_vehicle** – the vehicle preceding the ego-vehicle
- **rear_vehicle** – the vehicle following the ego-vehicle

Returns the acceleration command for the ego-vehicle [m/s2]

steering_control(*target_lane_index: Tuple[str, str, int]*) → float

Linear controller with respect to parameters.

Overrides the non-linear controller ControlledVehicle.steering_control()

Parameters **target_lane_index** – index of the lane to follow

Returns a steering wheel angle command [rad]

steering_features(*target_lane_index: Tuple[str, str, int]*) → numpy.ndarray

A collection of features used to follow a lane

Parameters **target_lane_index** – index of the lane to follow

Returns a array of features

collect_data()

Store features and outputs for parameter regression.

class highway_env.vehicle.behavior.**AggressiveVehicle**(*road:* highway_env.road.road.Road, *position: Union[numpy.ndarray, Sequence[float]]*, *heading: float = 0*, *speed: float = 0*, *target_lane_index: Optional[int] = None*, *target_speed: Optional[float] = None*, *route: Optional[List[Tuple[str, str, int]]] = None*, *enable_lane_change: bool = True*, *timer: Optional[float] = None*, *data: Optional[dict] = None*)

class highway_env.vehicle.behavior.**DefensiveVehicle**(*road:* highway_env.road.road.Road, *position: Union[numpy.ndarray, Sequence[float]]*, *heading: float = 0*, *speed: float = 0*, *target_lane_index: Optional[int] = None*, *target_speed: Optional[float] = None*, *route: Optional[List[Tuple[str, str, int]]] = None*, *enable_lane_change: bool = True*, *timer: Optional[float] = None*, *data: Optional[dict] = None*)

2.3.4 Rewards

The reward function is defined in the *_reward()* method, overloaded in every environment.

Note: The choice of an appropriate reward function that yields realistic optimal driving behaviour is a challenging problem, that we do not address in this project. In particular, we do not wish to specify every single aspect of the expected driving behaviour inside the reward function, such as keeping a safe distance to the front vehicle. Instead, we would rather only specify a reward function as simple and straightforward as possible in order to see adequate behaviour emerge from learning. In this perspective, keeping a safe distance is optimal not for being directly rewarded but for robustness against the uncertain behaviour of the leading vehicle, which could brake at any time.

Most environments

We generally focus on two features: a vehicle should

- progress quickly on the road;
- avoid collisions.

Thus, the reward function is often composed of a velocity term and a collision term:

$$R(s,a) = a\frac{v - v_{\min}}{v_{\max} - v_{\min} - b\,\text{collision}}$$

where v, $v_{\min, v_{\max}}$ are the current, minimum and maximum speed of the ego-vehicle respectively, and a, b are two coefficients.

Note: Since the rewards must be bounded, and the optimal policy is invariant by scaling and shifting rewards, we choose to normalize them in the $[0, 1]$ range, by convention. Normalizing rewards has also been observed to be practically beneficial in deep reinforcement learning [MKS+15]. Note that we forbid negative rewards, since they may encourage the agent to prefer terminating an episode early (by causing a collision) rather than risking suffering a negative return if no satisfying trajectory can be found.

In some environments, the weight of the collision penalty can be configured through the *collision_penalty* parameter.

Goal environments

In the *Parking* environment, however, the reward function must also specify the desired goal destination. Thus, the velocity term is replaced by a weighted p-norm between the agent state and the goal state.

$$R(s, a) = -\|s - s_g\|_{W,p}^p - b\,\text{collision}$$

where $s = [x, y, v_x, v_y, \cos\psi, \sin\psi]$, $s_g = [x_g, y_g, 0, 0, \cos\psi_g, \sin\psi_g]$, and $\|x\|_{W,p} = (\sum_i |W_i x_i|^p)^{1/p}$. We use a p-norm rather than an Euclidean norm in order to have a narrower spike of rewards at the goal.

2.3.5 Graphics

Environment rendering is done with pygame, which must be *installed separately*.

A window is created at the first call of `env.render()`. Its dimensions can be configured:

```
env = gym.make("roundabout-v0")
env.configure({
    "screen_width": 640,
    "screen_height": 480
})
env.reset()
env.render()
```

World surface

The simulation is rendered in a `RoadSurface` pygame surface, which defines the location and zoom of the rendered location. By default, the rendered area is always centered on the ego-vehicle. Its initial scale and offset can be set with the `"scaling"` and `"centering_position"` configurations, and can also be updated during simulation using the O,L keys and K,M keys, respectively.

Scene graphics

- Roads are rendered in the *`RoadGraphics`* class.
- Vehicles are rendered in the `VehicleGraphics` class.

API

class `highway_env.envs.common.graphics.`**`EnvViewer`**(*env: AbstractEnv*, *config: Optional[dict] = None*)

A viewer to render a highway driving environment.

`set_agent_display`(*agent_display: Callable*) → None

Set a display callback provided by an agent

So that they can render their behaviour on a dedicated agent surface, or even on the simulation surface.

Parameters **`agent_display`** – a callback provided by the agent to display on surfaces

`set_agent_action_sequence`(*actions: List[Action]*) → None

Set the sequence of actions chosen by the agent, so that it can be displayed

Parameters **`actions`** – list of action, following the env's action space specification

handle_events() → None

Handle pygame events by forwarding them to the display and environment vehicle.

display() → None

Display the road and vehicles on a pygame window.

get_image() → numpy.ndarray

The rendered image as a rgb array.

OpenAI gym's channel convention is H x W x C

window_position() → numpy.ndarray

the world position of the center of the displayed window.

close() → None

Close the pygame window.

class highway_env.road.graphics.**WorldSurface**(*size: Tuple[int, int]*, *flags: object*, *surf: pygame.Surface*)

A pygame Surface implementing a local coordinate system so that we can move and zoom in the displayed area.

pix(*length: float*) → int

Convert a distance [m] to pixels [px].

Parameters **length** – the input distance [m]

Returns the corresponding size [px]

pos2pix(*x: float*, *y: float*) → Tuple[int, int]

Convert two world coordinates [m] into a position in the surface [px]

Parameters

- **x** – x world coordinate [m]
- **y** – y world coordinate [m]

Returns the coordinates of the corresponding pixel [px]

vec2pix(*vec: Union[Tuple[float, float], numpy.ndarray]*) → Tuple[int, int]

Convert a world position [m] into a position in the surface [px].

Parameters **vec** – a world position [m]

Returns the coordinates of the corresponding pixel [px]

is_visible(*vec: Union[Tuple[float, float], numpy.ndarray]*, *margin: int = 50*) → bool

Is a position visible in the surface? :param vec: a position :param margin: margins around the frame to test for visibility :return: whether the position is visible

move_display_window_to(*position: Union[Tuple[float, float], numpy.ndarray]*) → None

Set the origin of the displayed area to center on a given world position.

Parameters **position** – a world position [m]

handle_event(*event: Event*) → None

Handle pygame events for moving and zooming in the displayed area.

Parameters **event** – a pygame event

class highway_env.road.graphics.**LaneGraphics**

A visualization of a lane.

STRIPE_SPACING: float = 4.33

Offset between stripes [m]

STRIPE_LENGTH: float = 3

Length of a stripe [m]

STRIPE_WIDTH: float = 0.3

Width of a stripe [m]

classmethod display(*lane: highway_env.road.lane.AbstractLane*, *surface: highway_env.road.graphics.WorldSurface*) → None

Display a lane on a surface.

Parameters

- **lane** – the lane to be displayed
- **surface** – the pygame surface

classmethod striped_line(*lane: highway_env.road.lane.AbstractLane*, *surface: highway_env.road.graphics.WorldSurface*, *stripes_count: int*, *longitudinal: float*, *side: int*) → None

Draw a striped line on one side of a lane, on a surface.

Parameters

- **lane** – the lane
- **surface** – the pygame surface
- **stripes_count** – the number of stripes to draw
- **longitudinal** – the longitudinal position of the first stripe [m]
- **side** – which side of the road to draw [0:left, 1:right]

classmethod continuous_curve(*lane: highway_env.road.lane.AbstractLane*, *surface: highway_env.road.graphics.WorldSurface*, *stripes_count: int*, *longitudinal: float*, *side: int*) → None

Draw a striped line on one side of a lane, on a surface.

Parameters

- **lane** – the lane
- **surface** – the pygame surface
- **stripes_count** – the number of stripes to draw
- **longitudinal** – the longitudinal position of the first stripe [m]
- **side** – which side of the road to draw [0:left, 1:right]

classmethod continuous_line(*lane: highway_env.road.lane.AbstractLane*, *surface: highway_env.road.graphics.WorldSurface*, *stripes_count: int*, *longitudinal: float*, *side: int*) → None

Draw a continuous line on one side of a lane, on a surface.

Parameters

- **lane** – the lane
- **surface** – the pygame surface

- **stripes_count** – the number of stripes that would be drawn if the line was striped
- **longitudinal** – the longitudinal position of the start of the line [m]
- **side** – which side of the road to draw [0:left, 1:right]

`classmethod draw_stripes`(*lane: highway_env.road.lane.AbstractLane*, *surface: highway_env.road.graphics.WorldSurface*, *starts: List[float]*, *ends: List[float]*, *lats: List[float]*) → None

Draw a set of stripes along a lane.

Parameters

- **lane** – the lane
- **surface** – the surface to draw on
- **starts** – a list of starting longitudinal positions for each stripe [m]
- **ends** – a list of ending longitudinal positions for each stripe [m]
- **lats** – a list of lateral positions for each stripe [m]

`class highway_env.road.graphics.RoadGraphics`

A visualization of a road lanes and vehicles.

`static display`(*road: highway_env.road.road.Road*, *surface: highway_env.road.graphics.WorldSurface*) → None

Display the road lanes on a surface.

Parameters

- **road** – the road to be displayed
- **surface** – the pygame surface

`static display_traffic`(*road: highway_env.road.road.Road*, *surface: highway_env.road.graphics.WorldSurface*, *simulation_frequency: int = 15*, *offscreen: bool = False*) → None

Display the road vehicles on a surface.

Parameters

- **road** – the road to be displayed
- **surface** – the pygame surface
- **simulation_frequency** – simulation frequency
- **offscreen** – render without displaying on a screen

`static display_road_objects`(*road: highway_env.road.road.Road*, *surface: highway_env.road.graphics.WorldSurface*, *offscreen: bool = False*) → None

Display the road objects on a surface.

Parameters

- **road** – the road to be displayed
- **surface** – the pygame surface
- **offscreen** – whether the rendering should be done offscreen or not

class highway_env.road.graphics.**RoadObjectGraphics**

A visualization of objects on the road.

classmethod display(*object_: RoadObject*, *surface: highway_env.road.graphics.WorldSurface*, *transparent: bool = False*, *offscreen: bool = False*)

Display a road objects on a pygame surface.

The objects is represented as a colored rotated rectangle

Parameters

- **object** – the vehicle to be drawn
- **surface** – the surface to draw the object on
- **transparent** – whether the object should be drawn slightly transparent
- **offscreen** – whether the rendering should be done offscreen or not

static blit_rotate(*surf: pygame.Surface*, *image: pygame.Surface*, *pos: Union[numpy.ndarray, Sequence[float]]*, *angle: float*, *origin_pos: Optional[Union[numpy.ndarray, Sequence[float]]] = None*, *show_rect: bool = False*) → None

Many thanks to https://stackoverflow.com/a/54714144.

2.3.6 The Multi-Agent setting

Most environments can be configured to a multi-agent version. Here is how:

Increase the number of controlled vehicles

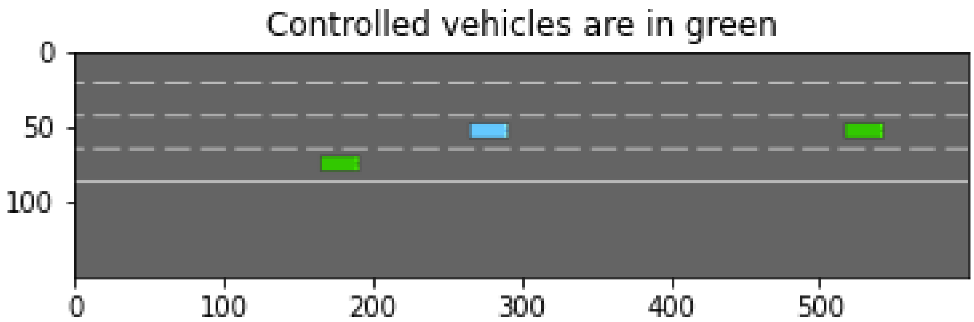
To that end, update the *environment configuration* to increase `controlled_vehicles`

```
import gym
import highway_env

env = gym.make('highway-v0')
env.seed(0)

env.configure({"controlled_vehicles": 2})  # Two controlled vehicles
env.configure({"vehicles_count": 1})  # A single other vehicle, for the sake of␣
↪visualisation
env.reset()

from matplotlib import pyplot as plt
%matplotlib inline
plt.imshow(env.render(mode="rgb_array"))
plt.title("Controlled vehicles are in green")
plt.show()
```



Change the action space

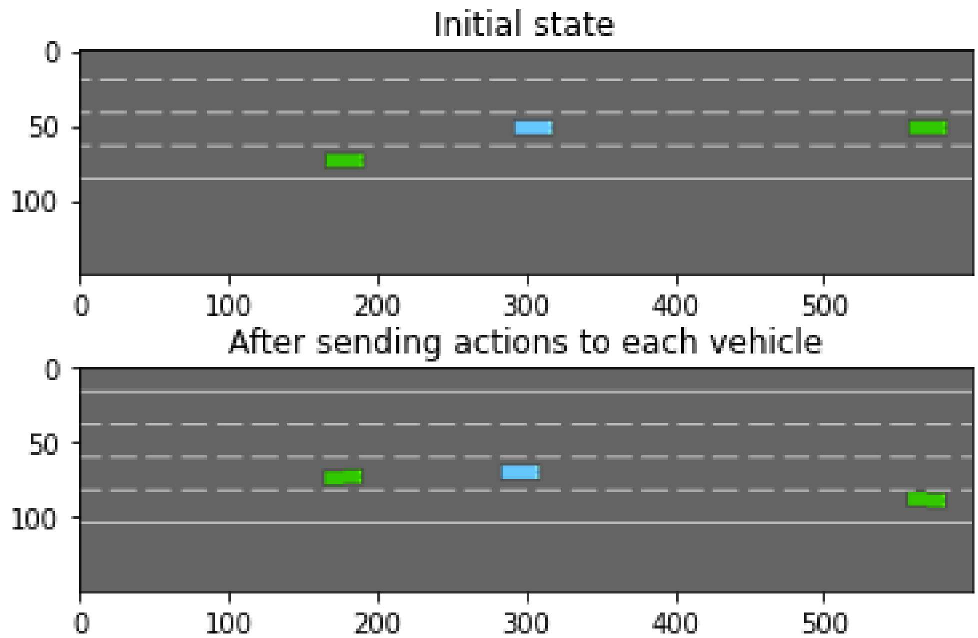
Right now, since the action space has not been changed, only the first vehicle is controlled by `env.step(action)`. In order for the environment to accept a tuple of actions, its action type must be set to *MultiAgentAction* The type of actions contained in the tuple must be described by a standard *action configuration* in the `action_config` field.

```
env.configure({
  "action": {
    "type": "MultiAgentAction",
    "action_config": {
      "type": "DiscreteMetaAction",
    }
  }
})
env.reset()

_, (ax1, ax2) = plt.subplots(nrows=2)
ax1.imshow(env.render(mode="rgb_array"))
ax1.set_title("Initial state")

# Make the first vehicle change to the left lane, and the second one to the right
action_1, action_2 = 0, 2  # See highway_env.envs.common.action.DiscreteMetaAction.
↪ACTIONS_ALL
env.step((action_1, action_2))

ax2.imshow(env.render(mode="rgb_array"))
ax2.set_title("After sending actions to each vehicle")
plt.show()
```



Change the observation space

In order to actually decide what `action_1` and `action_2` should be, both vehicles must generate their own observations. As before, since the observation space has not been changed no far, the observation only includes that of the first vehicle.

In order for the environment to return a tuple of observations – one for each agent –, its observation type must be set to `MultiAgentObservation` The type of observations contained in the tuple must be described by a standard *observation configuration* in the `observation_config` field.

```
env.configure({
  "observation": {
    "type": "MultiAgentObservation",
    "observation_config": {
      "type": "Kinematics",
    }
  }
})
obs = env.reset()

import pprint
pprint.pprint(obs)
```

```
(array([[ 1.        ,  0.90797305,  0.5       ,  0.3125    ,  0.        ],
       [ 1.        ,  0.10906096, -0.5       , -0.04341291,  0.        ],
       [ 1.        ,  0.33000726, -0.5       ,  0.        ,  0.        ],
       [ 0.        ,  0.        ,  0.        ,  0.        ,  0.        ],
       [ 0.        ,  0.        ,  0.        ,  0.        ,  0.        ]],
      dtype=float32),
 array([[1.    , 1.    , 0.    , 0.3125, 0.    ],
       [0.    , 0.    , 0.    , 0.    , 0.    ],
```

(continues on next page)

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```
       [0.    , 0.    , 0.    , 0.    , 0.    ],
       [0.    , 0.    , 0.    , 0.    , 0.    ],
       [0.    , 0.    , 0.    , 0.    , 0.    ]], dtype=float32))
```

Wrapping it up

Here is a pseudo-code example of how a centralized multi-agent policy could be trained:

```
# Multi-agent environment configuration
env.configure({
  "controlled_vehicles": 2,
  "observation": {
    "type": "MultiAgentObservation",
    "observation_config": {
      "type": "Kinematics",
    }
  },
  "action": {
    "type": "MultiAgentAction",
    "action_config": {
      "type": "DiscreteMetaAction",
    }
  }
})

# Dummy RL algorithm
class Model:
  """ Dummy code for an RL algorithm, which predicts an action from an observation,
  and update its model from observed transitions."""

  def predict(self, obs):
    return 0

  def update(self, obs, action, next_obs, reward, info, done):
    pass
model = Model()

# A training episode
obs = env.reset()
done = False
while not done:
  # Dispatch the observations to the model to get the tuple of actions
  action = tuple(model.predict(obs_i) for obs_i in obs)
  # Execute the actions
  next_obs, reward, info, done = env.step(action)
  # Update the model with the transitions observed by each agent
  for obs_i, action_i, next_obs_i in zip(obs, action, next_obs):
    model.update(obs_i, action_i, next_obs_i, reward, info, done)
  obs = next_obs
```

For example, this is supported by eleurent/rl-agents's DQN implementation, and can be run with

```
cd <path/to/rl-agents/scripts>
python experiments.py evaluate configs/IntersectionEnv/env_multi_agent.json \
                              configs/IntersectionEnv/agents/DQNAgent/ego_attention_2h.
↪json \
                              --train --episodes=3000
```

Fig. 3: Video of a multi-agent episode with the trained policy.

2.3.7 Make your own environment

Here are the steps required to create a new environment.

Note: Pull requests are welcome!

Set up files

1. Create a new `your_env.py` file in `highway_env/envs/`
2. Define a class YourEnv, that must inherit from *`AbstractEnv`*

This class provides several useful functions:

- A *`default_config()`* method, that provides a default configuration dictionary that can be overloaded.
- A *`define_spaces()`* method, that gives access to a choice of observation and action types, set from the environment configuration
- A *`step()`* method, which executes the desired actions (at policy frequency) and simulate the environment (at simulation frequency)
- A *`render()`* method, which renders the environment.

Create the scene

The first step is to create a `RoadNetwork` that describes the geometry and topology of roads and lanes in the scene. This should be achieved in a `YourEnv._make_road()` method, called from `YourEnv.reset()` to set the `self.road` field.

See *Roads* for reference, and existing environments as examples.

Create the vehicles

The second step is to populate your road network with vehicles. This should be achieved in a `YourEnv._make_road()` method, called from `YourEnv.reset()` to set the `self.road.vehicles` list of *`Vehicle`*.

First, define the controlled ego-vehicle by setting `self.vehicle`. The class of controlled vehicle depends on the choice of action type, and can be accessed as `self.action_type.vehicle_class`. Other vehicles can be created more freely, and added to the `self.road.vehicles` list.

See *vehicle behaviors* for reference, and existing environments as examples.

Make the environment configurable

To make a part of your environment configurable, overload the `default_config()` method to define new `{"config_key": value}` pairs with default values. These configurations then be accessed in your environment implementation with `self.config["config_key"]`, and once the environment is created, it can be configured with `env.configure({"config_key": other_value})` followed by `env.reset()`.

Register the environment

In `highway_env/envs/your_env.py`, add the following line:

```
register(
    id='your-env-v0',
    entry_point='highway_env.envs:YourEnv',
)
```

and import it from `highway_env/envs/__init__.py`:

```
from highway_env.envs.your_env import *
```

Profit

That's it! You should now be able to run the environment:

```
import gym
import highway_env

env = gym.make('your-env-v0')
obs = env.reset()
obs, reward, done, info = env.step(env.action_space.sample())
env.render()
```

API

class `highway_env.envs.common.abstract.`**`AbstractEnv`**(*config: Optional[dict] = None*)

A generic environment for various tasks involving a vehicle driving on a road.

The environment contains a road populated with vehicles, and a controlled ego-vehicle that can change lane and speed. The action space is fixed, but the observation space and reward function must be defined in the environment implementations.

PERCEPTION_DISTANCE = 200.0

The maximum distance of any vehicle present in the observation [m]

property vehicle: *`highway_env.vehicle.kinematics.Vehicle`*

First (default) controlled vehicle.

classmethod default_config() → dict

Default environment configuration.

Can be overloaded in environment implementations, or by calling configure(). :return: a configuration dict

seed(*seed: Optional[int] = None*) → List[int]

Sets the seed for this env's random number generator(s).

Note: Some environments use multiple pseudorandom number generators. We want to capture all such seeds used in order to ensure that there aren't accidental correlations between multiple generators.

Returns:

list<bigint>: Returns the list of seeds used in this env's random number generators. The first value in the list should be the "main" seed, or the value which a reproducer should pass to 'seed'. Often, the main seed equals the provided 'seed', but this won't be true if seed=None, for example.

define_spaces() → None

Set the types and spaces of observation and action from config.

_reward(*action: Union[int, numpy.ndarray]*) → float

Return the reward associated with performing a given action and ending up in the current state.

Parameters `action` – the last action performed

Returns the reward

_is_terminal() → bool

Check whether the current state is a terminal state

:return:is the state terminal

_info(*obs: numpy.ndarray*, *action: Union[int, numpy.ndarray]*) → dict

Return a dictionary of additional information

Parameters

- `obs` – current observation
- `action` – current action

Returns info dict

_cost(*action: Union[int, numpy.ndarray]*) → float

A constraint metric, for budgeted MDP.

If a constraint is defined, it must be used with an alternate reward that doesn't contain it as a penalty. :param action: the last action performed :return: the constraint signal, the alternate (constraint-free) reward

reset() → numpy.ndarray

Reset the environment to it's initial configuration

Returns the observation of the reset state

_reset() → None

Reset the scene: roads and vehicles.

This method must be overloaded by the environments.

step(*action: Union[int, numpy.ndarray]*) → Tuple[numpy.ndarray, float, bool, dict]

Perform an action and step the environment dynamics.

The action is executed by the ego-vehicle, and all other vehicles on the road performs their default behaviour for several simulation timesteps until the next decision making step.

Parameters `action` – the action performed by the ego-vehicle

Returns a tuple (observation, reward, terminal, info)

_simulate(*action: Optional[Union[int, numpy.ndarray]] = None*) → None

Perform several steps of simulation with constant action.

render(*mode: str = 'human'*) → Optional[numpy.ndarray]

Render the environment.

Create a viewer if none exists, and use it to render an image. :param mode: the rendering mode

close() → None

Close the environment.

Will close the environment viewer if it exists.

get_available_actions() → List[int]

Get the list of currently available actions.

Lane changes are not available on the boundary of the road, and speed changes are not available at maximal or minimal speed.

Returns the list of available actions

_automatic_rendering() → None

Automatically render the intermediate frames while an action is still ongoing.

This allows to render the whole video and not only single steps corresponding to agent decision-making. If a RecordVideo wrapper has been set, use it to capture intermediate frames.

simplify() → *highway_env.envs.common.abstract.AbstractEnv*

Return a simplified copy of the environment where distant vehicles have been removed from the road.

This is meant to lower the policy computational load while preserving the optimal actions set.

Returns a simplified environment state

change_vehicles(*vehicle_class_path: str*) → *highway_env.envs.common.abstract.AbstractEnv*

Change the type of all vehicles on the road

Parameters **vehicle_class_path** – The path of the class of behavior for other vehicles Example: "highway_env.vehicle.behavior.IDMVehicle"

Returns a new environment with modified behavior model for other vehicles

class highway_env.envs.common.abstract.**MultiAgentWrapper**(*env: gym.core.Env*)

step(*action*)

Run one timestep of the environment's dynamics. When end of episode is reached, you are responsible for calling *reset()* to reset this environment's state.

Accepts an action and returns a tuple (observation, reward, done, info).

Args: action (object): an action provided by the agent

Returns: observation (object): agent's observation of the current environment reward (float) : amount of reward returned after previous action done (bool): whether the episode has ended, in which case further step() calls will return undefined results info (dict): contains auxiliary diagnostic information (helpful for debugging, logging, and sometimes learning)

2.4 Frequently Asked Questions

This is a list of Frequently Asked Questions about highway-env. Feel free to suggest new entries!

I try to train an agent using the Kinematics Observation and an MLP model, but the resulting policy is not optimal. Why?
I also tend to get reasonable but sub-optimal policies using this observation-model pair. In [LM19], we argued that a possible reason is that the MLP output depends on the order of vehicles in the observation. Indeed, if the agent revisits a given scene but observes vehicles described in a different order, it will see it as a novel state and will not be able to reuse past information. Thus, the agent struggles to make use of its observation.

This can be addressed in two ways:

- – Change the *model*, to use a permutation-invariant architecture which will not be sensitive to the vehicles order, such as *e.g.* [QSMG17] or [LM19].

This example is implemented here (DQN) or here (SB3's PPO).

- – Change the *observation*. For example, the *Grayscale Image* does not depend on an ordering. In this case, a CNN model is more suitable than an MLP model.

This example is implemented here (SB3's DQN).

My videos are too fast / have a low framerate. This is because in openai/gym, a single video frame is generated at each call of `env.step(action)`. However, in highway-env, the policy typically runs at a low-level frequency (e.g. 1 Hz) so that a long action (*e.g.* change lane) actually corresponds to several (typically, 15) simulation frames. In order to also render these intermediate simulation frames, the following should be done:

```
import gym
import highway_env

# Wrap the env by a RecordVideo wrapper
env = gym.make("highway-v0")
env = RecordVideo(env, video_folder="run",
              episode_trigger=lambda e: True)  # record all episodes

# Provide the video recorder to the wrapped environment
# so it can send it intermediate simulation frames.
env.unwrapped.set_record_video_wrapper(env)

# Record a video as usual
obs = env.reset()
done = False:
while not done:
    action = env.action_space.sample()
    obs, reward, done, info = env.step(action)
    env.render()
env.close()
```

2.5 Bibliography

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