Lab3 DQN for Highway Driving

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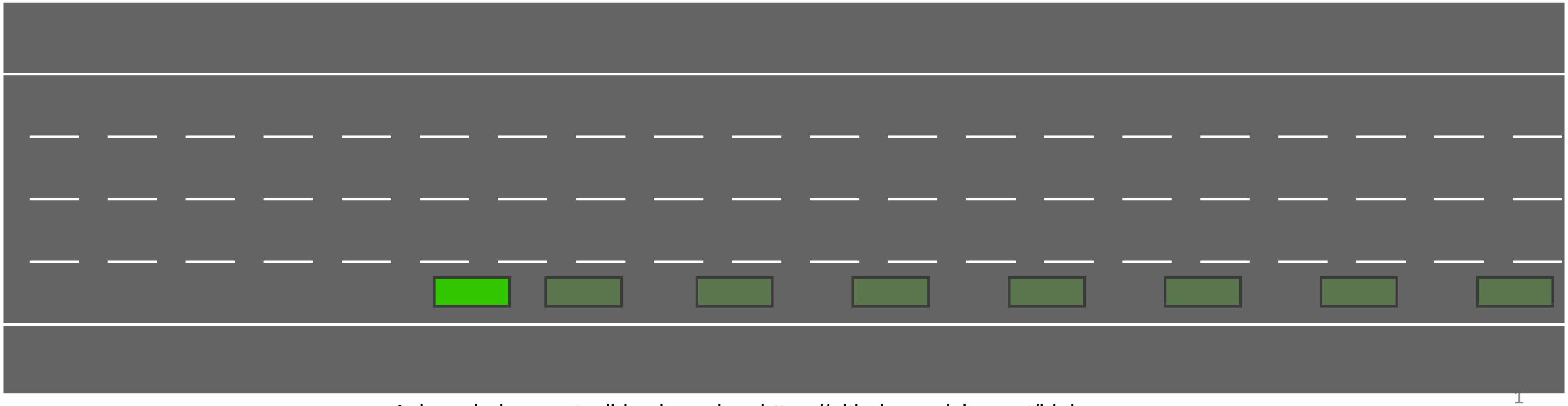


Acknowledgement: slides based on https://github.com/eleurent/highway-env

Highway Env

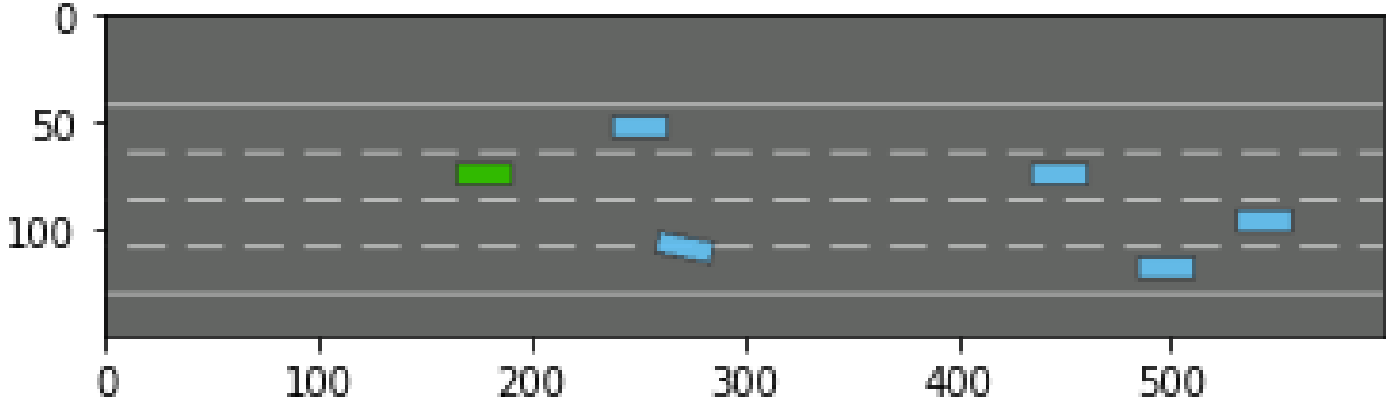
- A collection of environments for autonomous driving and tactical decision-making tasks, by Edouard Leurent
  - Source code: https://github.com/eleurent/highway-env
  - Documentation: https://eleurent.github.io/highway-env/

Making an env with gym.make()

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

- env = gym.make('highway-v0')
- # 5 environments: Highway, Merge, Roundabout, Parking, Intersection,
- 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()
- (Lab3 uses a different method env = load_environment(env_config))



Training an agent

- RL agents can be trained using libraries such as rl-agents (by Leurent), OpenAI baselines or stable-baselines3.

rl-agents

- A collection of RL agents authored by Leurent: https://github.com/eleurent/rl-agents
- Planning
  - Value Iteration
  - Cross-Entropy Method
  - Monte-Carlo Tree Search
    - Upper Confidence Trees
    - Deterministic Optimistic Planning
    - Open Loop Optimistic Planning
    - Trailblazer
    - PlaTyPOOS
- Safe planning
  - Robust Value Iteration
  - Discrete Robust Optimistic Planning
  - Interval-based Robust Planning
- Value-based
  - Deep Q-Network
  - Fitted-Q
- Safe value-based
  - Budgeted Fitted-Q

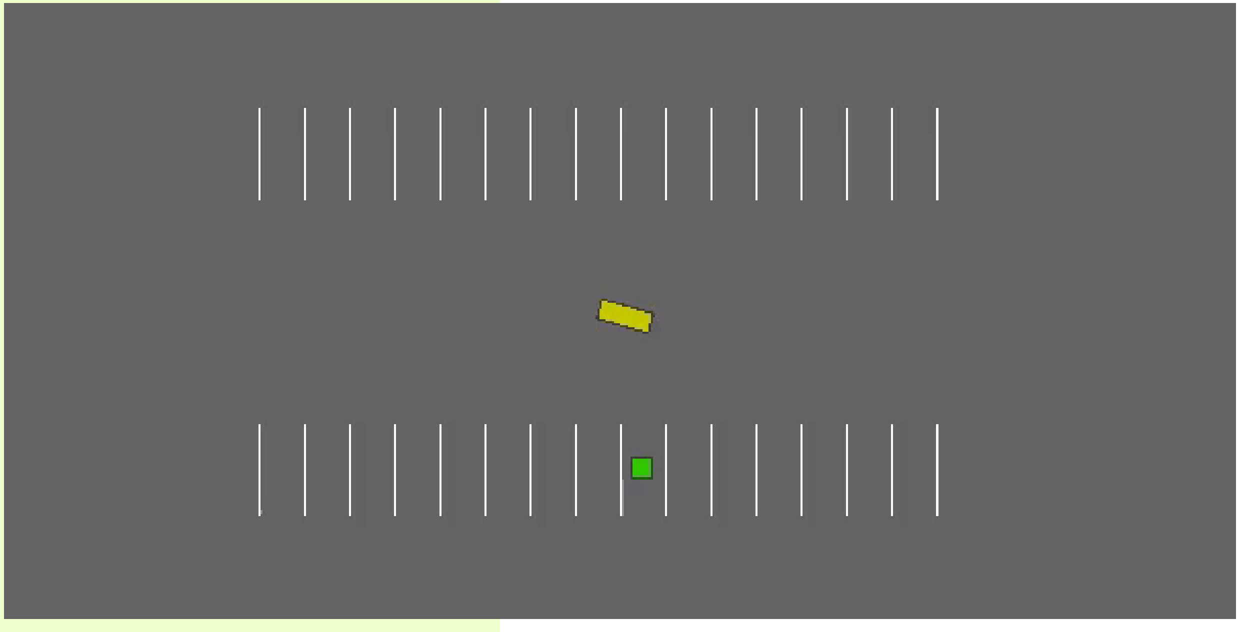
Stable Baselines

- A set of improved implementations of RL algorithms based on OpenAI Baselines: https://github.com/DLR-RM/stable-baselines3
- Training a PPO (Proximal Policy Gradient) agent with Stable Baselines:

```
import gym

from stable_baselines.common.policies import MlpPolicy
from stable_baselines import PPO2

env = gym.make('CartPole-v1')

model = PPO2(MlpPolicy, env, verbose=1)
# Train the agent
model.learn(total_timesteps=10000)

# Enjoy trained agent
obs = env.reset()
for i in range(1000):
    action, _states = model.predict(obs, deterministic=False)
    obs, reward, done, info = env.step(action)
    env.render()
    if done:
    obs = env.reset()
env.close()
```

highway-parking-v0 environment trained with HER (Hierarchical Experience replay).

```python
import gym
import highway_env
import numpy as np

from stable_baselines import HER, SAC, DDPG, TD3
from stable_baselines.ddpg import NormalActionNoise

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

# Create 4 artificial transitions per real transition
n_sampled_goal = 4

# SAC hyperparams:
model = HER('MlpPolicy', env, SAC, n_sampled_goal=n_sampled_goal,
            goal_selection_strategy='future',
            verbose=1, buffer_size=int(1e6),
            learning_rate=1e-3,
            gamma=0.95, batch_size=256,
            policy_kwargs=dict(layers=[256, 256, 256]))

model.learn(int(2e5))
model.save('her_sac_highway')

# Load saved model
model = HER.load('her_sac_highway', env=env)

obs = env.reset()

# Evaluate the agent
episode_reward = 0
for _ in range(100):
  action, _ = model.predict(obs)
  obs, reward, done, info = env.step(action)
  env.render()
  episode_reward += reward
  if done or info.get('is_success', False):
    print("Reward:", episode_reward, "Success?", info.get('is_success', False))
    episode_reward = 0.0
    obs = env.reset()
```



highway_env.py

- 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.
- 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. Here are the default config values:

observation.py

- GrayscaleObservation(ObservationType)
  - Observes the image rendered by the simulator (top-down view)
- KinematicObservation(ObservationType)
  - Observes the kinematics (position, speed, heading angle) of all nearby vehicles within PERCEPTION_DISTANCE=6.0*MDPVehicle.SPEED_MAX
- LidarObservation(ObservationType)
  - Observes direction and distance to obstacles within line of sight

```python
def observation_factory(env: 'AbstractEnv', config: dict) -> ObservationType:
    if config["type"] == "TimeToCollision":
        return TimeToCollisionObservation(env, **config)
    elif config["type"] == "Kinematics":
        return KinematicObservation(env, **config)
    elif config["type"] == "OccupancyGrid":
        return OccupancyGridObservation(env, **config)
    elif config["type"] == "KinematicsGoal":
        return KinematicsGoalObservation(env, **config)
    elif config["type"] == "GrayscaleObservation":
        return GrayscaleObservation(env, **config)
    elif config["type"] == "AttributesObservation":
        return AttributesObservation(env, **config)
    elif config["type"] == "MultiAgentObservation":
        return MultiAgentObservation(env, **config)
    elif config["type"] == "LidarObservation":
        return LidarObservation(env, **config)
    elif config["type"] == "ExitObservation":
        return ExitObservation(env, **config)
    else:
        raise ValueError("Unknown observation type")
```

action.py

- class ContinuousAction(ActionType)
  - 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)
    - [-x, x], in m/s²
  - STEERING_RANGE = (-np.pi / 4, np.pi / 4)
    - [-x, x], in rad
- class DiscreteMetaAction(ActionType)
  - 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.

```python
def action_factory(env: 'AbstractEnv', config: dict) -> ActionType:
    if config["type"] == "ContinuousAction":
        return ContinuousAction(env, **config)
    elif config["type"] == "DiscreteMetaAction":
        return DiscreteMetaAction(env, **config)
```

```python
:param env: the environment
:param longitudinal: include longitudinal actions
:param lateral: include lateral actions
"""
super().__init__(env)
self.longitudinal = longitudinal
self.lateral = lateral
self.actions = self.ACTIONS_ALL if longitudinal and lateral \
    else self.ACTIONS_LONGI if longitudinal \
    else self.ACTIONS_LAT if lateral \
    else None
```

Actions are controller targets

- The :py:class:`~highway_env.envs.common.action.DiscreteMetaAction` type adds a layer of :ref:`speed and steering controllers <vehicle_controller>` 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.

vehicle/controller.py

- A vehicle piloted by two low-level controllers, 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.
  - Control algorithm is Proportional control.
  - Vehicle model is dynamical bicycle model, with tire friction and slipping.

```python
def act(self, action: 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.

    :param action: a high-level action
    """
    self.follow_road()
    if action == "FASTER":
        self.target_speed += self.DELTA_SPEED
    elif action == "SLOWER":
        self.target_speed -= self.DELTA_SPEED
    elif action == "LANE_RIGHT":
        _from, _to, _id = self.target_lane_index
        target_lane_index = _from, _to, np.clip(_id + 1, 0, len(self.road.network.graph[_from][_to]) - 1)
        if self.road.network.get_lane(target_lane_index).is_reachable_from(self.position):
            self.target_lane_index = target_lane_index
    elif action == "LANE_LEFT":
        _from, _to, _id = self.target_lane_index
        target_lane_index = _from, _to, np.clip(_id - 1, 0, len(self.road.network.graph[_from][_to]) - 1)
        if self.road.network.get_lane(target_lane_index).is_reachable_from(self.position):
            self.target_lane_index = target_lane_index

    action = {"steering": self.steering_control(self.target_lane_index),
              "acceleration": self.speed_control(self.target_speed)}
    action['steering'] = np.clip(action['steering'], -self.MAX_STEERING_ANGLE, self.MAX_STEERING_ANGLE)
    super().act(action)
```

highway_env.py default_config

- In def default_config(cls) -> dict:
  - "collision_reward": -1,   # The reward received when colliding with a vehicle.
  - "right_lane_reward": 0.1, # The reward received when driving on the right-most lanes, linearly mapped to zero for other lanes.
  - "high_speed_reward": 0.4, # The reward received when driving at full speed, linearly mapped to zero for lower speeds according to config["reward_speed_range"].
  - "lane_change_reward": 0,   # The reward received at each lane change action.
  - "reward_speed_range": [20, 30],

highway_env.py _reward()

```python
def _reward(self, action: Action) -> float:
    """
    The reward is defined to foster driving at high speed, on the rightmost lanes, and to avoid collisions
    :param action: the last action performed
    :return: the corresponding reward
    """
    neighbours = self.road.network.all_side_lanes(self.vehicle.lane_index)
    lane = self.vehicle.target_lane_index[2] if isinstance(self.vehicle, ControlledVehicle) \
        else self.vehicle.lane_index[2]
    scaled_speed = utils.lmap(self.vehicle.speed, self.config["reward_speed_range"], [0, 1])
    reward = \
        + self.config["collision_reward"] * self.vehicle.crashed \
        + self.config["right_lane_reward"] * lane / max(len(neighbours) - 1, 1) \
        + self.config["high_speed_reward"] * np.clip(scaled_speed, 0, 1)
    reward = utils.lmap(reward,
                        [self.config["collision_reward"],
                         self.config["high_speed_reward"] + self.config["right_lane_reward"]],
                        [0, 1])
    reward = 0 if not self.vehicle.on_road else reward
    return reward
```

highway_env.py _reward() Explanations

- If crashed, add collision_reward (-1)
- Add right_lane_reward*Lane/max(nLanes-1,1)
  - lane_index has 3 elements (from, to, id), so lane_index[2] is the lane id. For self.vehicle, consider the target lane; for other vehicles, consider the current lane
  - neighbours contains all lanes in the same road.
  - Suppose nLanes=2, if Lane=0 (left lane), then $.1 * \frac{0}{1} = 0$; if Lane=1 (right lane), then $.1 * \frac{1}{1} = .1$
- utils.lmap(v: float, x: Interval, y: Interval) -> float
  - Linear map of value v within range x=$[x_0, x_1]$ to desired range y=$[y_0, y_1] = [0,1]$, returns $y_0 + \frac{(v-x_0)(y_1-y_0)}{(x_1-x_0)} \in [0,1]$
- Add high_speed_reward *scaled_speed=.4*np.clip(scaled_speed, 0, 1)
  - scaled_speed = utils.lmap(self.vehicle.speed, self.config["reward_speed_range"], [0, 1])
  - np.clip(scaled_speed, 0, 1) (if $v \notin [20,30]$, clip output to within $[0,1]$)
- reward = utils.lmap(reward, [-1, .5], [0,1])
  - Min reward=-1 (collision_reward); Max reward=.1+.4 (right_lane_reward+ high_speed_reward);

roundabout_env.py _reward(self, action: int)

- In def default_config(cls) -> dict: "collision_reward": -1, "high_speed_reward": 0.2, "right_lane_reward": 0, "lane_change_reward": -0.05
- If crashed, add collision_reward(-1)
- Add high_speed_reward*scaled speed index
- Add lane_change_reward*lane_change
- reward = utils.lmap(reward, [-1.05, .2], [0,1])

```python
def _reward(self, action: int) -> float:
    lane_change = action == 0 or action == 2
    reward = self.config["collision_reward"] * self.vehicle.crashed \
        + self.config["high_speed_reward"] * \
            MDPVehicle.get_speed_index(self.vehicle) / max(MDPVehicle.SPEED_COUNT - 1, 1) \
        + self.config["lane_change_reward"] * lane_change
    return utils.lmap(reward,
                      [self.config["collision_reward"] + self.config["lane_change_reward"],
                       self.config["high_speed_reward"]], [0, 1])
```

create_road(), create_vehicles()

```python
def _create_road(self) -> None:
    """Create a road composed of straight adjacent lanes."""
    self.road = Road(network=RoadNetwork.straight_road_network(self.config["lanes_count"], speed_limit=30),
                     np_random=self.np_random, record_history=self.config["show_trajectories"])

def _create_vehicles(self) -> None:
    """Create some new random vehicles of a given type, and add them on the road."""
    other_vehicles_type = utils.class_from_path(self.config["other_vehicles_type"])
    other_per_controlled = near_split(self.config["vehicles_count"], num_bins=self.config["controlled_vehicles"])

    self.controlled_vehicles = []
    for others in other_per_controlled:
        controlled_vehicle = self.action_type.vehicle_class.create_random(
            self.road,
            speed=25,
            lane_id=self.config["initial_lane_id"],
            spacing=self.config["ego_spacing"]
        )
        self.controlled_vehicles.append(controlled_vehicle)
        self.road.vehicles.append(controlled_vehicle)

        for _ in range(others):
            self.road.vehicles.append(
                other_vehicles_type.create_random(self.road, spacing=1 / self.config["vehicles_density"])
            )
```

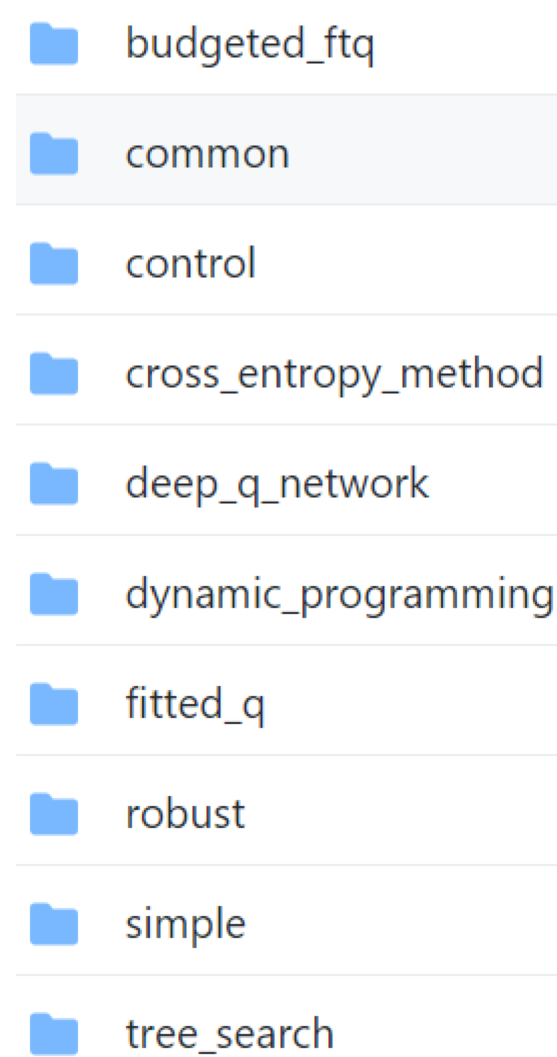
agents

- In random.py:
- def act(self, state):

```
  return
  self.env.action_space.sample()
```

- In deep_q_network/abstract.py:
- def act(self, state, step_exploration_time=True):

```
  if step_exploration_time:
      self.exploration_policy.step_time()
  values =
  self.get_state_action_values(state)
  self.exploration_policy.update(values)
  return self.exploration_policy.sample()
```



Env and Agent Configs

- `env_config = 'configs/HighwayEnv/env.json'`
- `agent_config = 'configs/HighwayEnv/agents/DQNAgent/dqn.json'`

```json
{
    "id": "highway-v0",
    "import_module": "highway_env"
}
```

env.json

(empty)

```json
{
    "__class__": "<class 'rl_agents.agents.deep_q_network.pytorch.DQNAgent'>",
    "model": {
        "type": "MultiLayerPerceptron",
        "layers": [256, 256]
    },
    "double": false,
    "gamma": 0.8,
    "n_steps": 1,
    "batch_size": 32,
    "memory_capacity": 15000,
    "target_update": 50,
    "exploration": {
        "method": "EpsilonGreedy",
        "tau": 6000,
        "temperature": 1.0,
        "final_temperature": 0.05
    },
    "loss_function": "l2"
}
```

dqn.json

abstract.py exploration_factory

```
def exploration_factory(exploration_config, action_space):
    """
        Handles creation of exploration policies
    :param exploration_config: configuration dictionary of the policy, must contain a "method" key
    :param action_space: the environment action space
    :return: a new exploration policy
    """
    from rl_agents.agents.common.exploration.boltzmann import Boltzmann
    from rl_agents.agents.common.exploration.epsilon_greedy import EpsilonGreedy
    from rl_agents.agents.common.exploration.greedy import Greedy

    if exploration_config['method'] == 'Greedy':
        return Greedy(action_space, exploration_config)
    elif exploration_config['method'] == 'EpsilonGreedy':
        return EpsilonGreedy(action_space, exploration_config)
    elif exploration_config['method'] == 'Boltzmann':
        return Boltzmann(action_space, exploration_config)
    else:
        raise ValueError("Unknown exploration method")
```

epsilon_greedy.py get_distribution()

- n: discrete action space size (# actions)
- For each action: $dist = \frac{\epsilon}{n}$
- For the optimal action: $dist = \frac{\epsilon}{n} + 1 - \epsilon$

```
def get_distribution(self):
    distribution = {action: self.epsilon / self.action_space.n for action in range(self.action_space.n)}
    distribution[self.optimal_action] += 1 - self.epsilon
    return distribution
```

epsilon_greedy.py update()

- $\epsilon = finalT + (T - finalT)e^{-\frac{time}{\tau}}$
- $\frac{time}{\tau} = 0 \Rightarrow \epsilon = T = 1.0$
- $\frac{time}{\tau} = \infty \Rightarrow \epsilon = finalT = .1$
- Hyperparam τ determines the speed of change of ϵ from T to $finalT$

```python
def default_config(cls):
    return dict(temperature=1.0,
                final_temperature=0.1,
                tau=5000)
```

```python
def update(self, values):
    """
        Update the action distribution parameters
    :param values: the state-action values
    :param step_time: whether to update epsilon schedule
    """
    self.optimal_action = np.argmax(values)
    self.epsilon = self.config['final_temperature'] + \
        (self.config['temperature'] - self.config['final_temperature']) * \
        np.exp(- self.time / self.config['tau'])
```