d3rlpy

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TUTORIALS

d3rlpy is a easy-to-use offline deep reinforcement learning library.

```
$ pip install d3rlpy
```

d3rlpy provides state-of-the-art offline deep reinforcement learning algorithms through out-of-the-box scikit-learn-style APIs. Unlike other RL libraries, the provided algorithms can achieve extremely powerful performance beyond their papers via several tweaks.

CHAPTER

ONE

TUTORIALS

1.1 Getting Started

This tutorial is also available on Google Colaboratory

1.1.1 Install

First of all, let's install `d3rlpy` on your machine:

```
$ pip install d3rlpy
```

See more information at *Installation*.

Note: If `core dump` error occurs in this tutorial, please try *Install from source*.

Note: `d3rlpy` supports Python 3.7+. Make sure which version you use.

Note: If you use GPU, please setup CUDA first.

1.1.2 Prepare Dataset

You can make your own dataset without any efforts. In this tutorial, let's use integrated datasets to start. If you want to make a new dataset, see *Replay Buffer*.

d3rlpy provides suites of datasets for testing algorithms and research. See more documents at *Datasets*.

```
from d3rlpy.datasets import get_cartpole # CartPole-v1 dataset
from d3rlpy.datasets import get_pendulum # Pendulum-v1 dataset
from d3rlpy.datasets import get_atari    # Atari 2600 task datasets
from d3rlpy.datasets import get_d4rl     # D4RL datasets
```

Here, we use the CartPole dataset to instantly check training results.

```
dataset, env = get_cartpole()
```

1.1.3 Setup Algorithm

There are many algorithms avaiable in d3rlpy. Since CartPole is the simple task, let's start from `DQN`, which is the Q-learnig algorithm proposed as the first deep reinforcement learning algorithm.

```
from d3rlpy.algos import DQNConfig

# if you don't use GPU, set device=None instead.
dqn = DQNConfig().create(device="cuda:0")

# initialize neural networks with the given observation shape and action size.
# this is not necessary when you directly call fit or fit_online method.
dqn.build_with_dataset(dataset)
```

See more algorithms and configurations at *Algorithms*.

1.1.4 Setup Metrics

Collecting evaluation metrics is important to train algorithms properly. d3rlpy provides `Evaluator` classes to compute evaluation metrics.

```
from d3rlpy.metrics import TDErrorEvaluator

# calculate metrics with training dataset
td_error_evaluator = TDErrorEvaluator(episodes=dataset.episodes)
```

Since evaluating algorithms without access to environment is still difficult, the algorithm can be directly evaluated with `EnvironmentEvaluator` if the environment is available to interact.

```
from d3rlpy.metrics import EnvironmentEvaluator

# set environment in scorer function
env_evaluator = EnvironmentEvaluator(env)

# evaluate algorithm on the environment
rewards = env_evaluator(dqn, dataset=None)
```

See more metrics and configurations at *Metrics*.

1.1.5 Start Training

Now, you have everything to start offline training.

```
dqn.fit(
    dataset,
    n_steps=10000,
    evaluators={
        'td_error': td_error_evaluator,
        'environment': env_evaluator,
    },
)
```

See more about logging at *Logging*.

Once the training is done, your algorithm is ready to make decisions.

```
observation, _ = env.reset()

# return actions based on the greedy-policy
action = dqn.predict(np.expand_dims(observation, axis=0))

# estimate action-values
value = dqn.predict_value(np.expand_dims(observation, axis=0), action)
```

1.1.6 Save and Load

d3rlpy provides several ways to save trained models.

```
import d3rlpy

# save full parameters and configurations in a single file.
dqn.save('dqn.d3')
# load full parameters and build algorithm
dqn2 = d3rlpy.load_learnable("dqn.d3")

# save full parameters only
dqn.save_model('dqn.pt')
# load full parameters with manual setup
dqn3 = DQN()
dqn3.build_with_dataset(dataset)
dqn3.load_model('dqn.pt')

# save the greedy-policy as TorchScript
dqn.save_policy('policy.pt')
# save the greedy-policy as ONNX
dqn.save_policy('policy.onnx')
```

See more information at *After Training Policies (Save and Load)*.

1.2 Data Collection

d3rlpy provides APIs to support data collection from environments. This feature is specifically useful if you want to build your own original datasets for research or practice purposes.

1.2.1 Prepare Environment

d3rlpy supports environments with OpenAI Gym interface. In this tutorial, let's use simple CartPole environment.

```
import gym

env = gym.make("CartPole-v1")
```

1.2.2 Data Collection with Random Policy

If you want to collect experiences with uniformly random policy, you can use `RandomPolicy` and `DiscreteRandomPolicy`. This procedure corresponds to `random` datasets in D4RL.

```
import d3rlpy

# setup algorithm
random_policy = d3rlpy.algos.DiscreteRandomPolicyConfig().create()

# prepare experience replay buffer
buffer = d3rlpy.dataset.create_fifo_replay_buffer(limit=100000, env=env)

# start data collection
random_policy.collect(env, buffer, n_steps=100000)

# save ReplayBuffer
with open("random_policy_dataset.h5", "w+b") as f:
    buffer.dump(f)
```

1.2.3 Data Collection with Trained Policy

If you want to collect experiences with previously trained policy, you can still use the same set of APIs. Here, let's say a DQN model is saved as `dqn_model.d3`. This procedure corresponds to `medium` datasets in D4RL.

```
# prepare pretrained algorithm
dqn = d3rlpy.load_learnable("dqn_model.d3")

# prepare experience replay buffer
buffer = d3rlpy.dataset.create_fifo_replay_buffer(limit=100000, env=env)

# start data collection
dqn.collect(env, buffer, n_steps=100000)

# save ReplayBuffer
with open("trained_policy_dataset.h5", "w+b") as f:
  buffer.dump(f)
```

1.2.4 Data Collection while Training Policy

If you want to use experiences collected during training to build a new dataset, you can simply use `fit_online` and save the dataset. This procedure corresponds to `replay` datasets in D4RL.

```
# setup algorithm
dqn = d3rlpy.algos.DQNConfig().create()

# prepare experience replay buffer
buffer = d3rlpy.dataset.create_fifo_replay_buffer(limit=100000, env=env)

# prepare exploration strategy if necessary
explorer = d3rlpy.algos.ConstantEpsilonGreedy(0.3)

# start data collection
dqn.fit_online(env, buffer, explorer, n_steps=100000)

# save ReplayBuffer
with open("replay_dataset.h5", "w+b") as f:
  buffer.dump(f)
```

1.3 Create Your Dataset

The data collection API is introduced in *Data Collection*. In this tutorial, you can learn how to build your dataset from logged data such as the user data collected in your web service.

1.3.1 Prepare Logged Data

First of all, you need to prepare your logged data. In this tutorial, let's use randomly generated data. `terminals` represents the last step of episodes. If `terminals[i] == 1.0`, i-th step is the terminal state. Otherwise you need to set zeros for non-terminal states.

```
import numpy as np

# vector observation
# 1000 steps of observations with shape of (100,)
observations = np.random.random((1000, 100))

# 1000 steps of actions with shape of (4,)
actions = np.random.random((1000, 4))

# 1000 steps of rewards
rewards = np.random.random(1000)

# 1000 steps of terminal flags
terminals = np.random.randint(2, size=1000)
```

1.3.2 Build MDPDataset

Once your logged data is ready, you can build `MDPDataset` object.

```
import d3rlpy

dataset = d3rlpy.dataset.MDPDataset(
    observations=observations,
    actions=actions,
    rewards=rewards,
    terminals=terminals,
)
```

1.3.3 Set Timeout Flags

In RL, there is the case where you want to stop an episode without a terminal state. For example, if you're collecting data of a 4-legged robot walking forward, the walking task basically never ends as long as the robot keeps walking while the logged episode must stop somewhere. In this case, you can use `timeouts` to represent this timeout states.

```
# terminal states
terminals = np.zeros(1000)

# timeout states
timeouts = np.random.randint(2, size=1000)

dataset = d3rlpy.dataset.MDPDataset(
    observations=observations,
    actions=actions,
    rewards=rewards,
    terminals=terminals,
    timeouts=timeouts,
)
```

1.4 Preprocess / Postprocess

In this tutorial, you can learn how to preprocess datasets and postprocess continuous action outputs. Please check *Preprocessing* for more information.

1.4.1 Preprocess Observations

If your dataset includes unnormalized observations, you can normalize or standardize the observations by specifying `observation_scaler` argument. In this case, the statistics of the dataset will be computed at the beginning of offline training.

```
import d3rlpy

dataset, _ = d3rlpy.datasets.get_dataset("pendulum-random")

# prepare scaler without initialization
```

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```
observation_scaler = d3rlpy.preprocessing.StandardObservationScaler()

sac = d3rlpy.algos.SACConfig(observation_scaler=observation_scaler).create()
```

Alternatively, you can manually instantiate preprocessing parameters.

```
# setup manually
observations = []
for episode in dataset.episodes:
    observations += episode.observations.tolist()
mean = np.mean(observations, axis=0)
std = np.std(observations, axis=0)
observation_scaler = d3rlpy.preprocessing.StandardObservationScaler(mean=mean, std=std)

# set as observation_scaler
sac = d3rlpy.algos.SACConfig(observation_scaler=observation_scaler).create()
```

Please check *Preprocessing* for the full list of available observation preprocessors.

1.4.2 Preprocess / Postprocess Actions

In training with continuous action-space, the actions must be in the range between `[-1.0, 1.0]` due to the underlying `tanh` activation at the policy functions. In d3rlpy, you can easily normalize inputs and denormalize outpus instead of normalizing datasets by yourself.

```
# prepare scaler without initialization
action_scaler = d3rlpy.preprocessing.MinMaxActionScaler()

# set as action scaler
sac = d3rlpy.algos.SACConfig(action_scaler=action_scaler).create()

# setup manually
actions = []
for episode in dataset.episodes:
    actions += episode.actions.tolist()
minimum_action = np.min(actions, axis=0)
maximum_action = np.max(actions, axis=0)
action_scaler = d3rlpy.preprocessing.MinMaxActionScaler(
    minimum=minimum_action,
    maximum=maximum_action,
)

# set as action scaler
sac = d3rlpy.algos.SACConfig(action_scaler=action_scaler).create()
```

Please check *Preprocessing* for the full list of available action preprocessors.

1.4.3 Preprocess Rewards

The effect of scaling rewards is not well studied yet in RL community, however, it's confirmed that the reward scale affects training performance.

```
# prepare scaler without initialization
reward_scaler = d3rlpy.preprocessing.StandardRewardScaler()

# set as reward scaler
sac = d3rlpy.algos.SACConfig(reward_scaler=reward_scaler).create()

# setup manuall
rewards = []
for episode in dataset.episodes:
    rewards += episode.rewards.tolist()
mean = np.mean(rewards)
std = np.std(rewards)
reward_scaler = StandardRewardScaler(mean=mean, std=std)

# set as reward scaler
sac = d3rlpy.algos.SACConfig(reward_scaler=reward_scaler).create()
```

Please check *Preprocessing* for the full list of available reward preprocessors.

1.5 Customize Neural Network

In this tutorial, you can learn how to integrate your own neural network models to d3rlpy. Please check *Network Architectures* for more information.

1.5.1 Prepare PyTorch Model

If you're familiar with PyTorch, this step should be easy for you.

```
import torch
import torch.nn as nn
import d3rlpy

class CustomEncoder(nn.Module):
    def __init__(self, observation_shape, feature_size):
        super().__init__()
        self.feature_size = feature_size
        self.fc1 = nn.Linear(observation_shape[0], feature_size)
        self.fc2 = nn.Linear(feature_size, feature_size)

    def forward(self, x):
        h = torch.relu(self.fc1(x))
        h = torch.relu(self.fc2(h))
        return h
```

1.5.2 Setup EncoderFactory

Once you setup your PyTorch model, you need to setup `EncoderFactory` as a dataclass class. In your `EncoderFactory` class, you need to define `create` and `get_type`. `get_type` method is used to serialize your customized neural network configuration.

```
import dataclasses

@dataclasses.dataclass()
class CustomEncoderFactory(d3rlpy.models.EncoderFactory):
    feature_size: int

    def create(self, observation_shape):
        return CustomEncoder(observation_shape, self.feature_size)

    @staticmethod
    def get_type() -> str:
        return "custom"
```

Now, you can use your model with d3rlpy.

```
# integrate your model into d3rlpy algorithm
dqn = d3rlpy.algos.DQNConfig(encoder_factory=CustomEncoderFactory(64)).create()
```

1.5.3 Support Q-function for Actor-Critic

In the above example, your original model is designed for the network that takes an observation as an input. However, if you customize a Q-function of actor-critic algorithm (e.g. SAC), you need to prepare an action-conditioned model.

```
class CustomEncoderWithAction(nn.Module):
    def __init__(self, observation_shape, action_size, feature_size):
        super().__init__()
        self.feature_size = feature_size
        self.fc1 = nn.Linear(observation_shape[0] + action_size, feature_size)
        self.fc2 = nn.Linear(feature_size, feature_size)

      def forward(self, x, action):
          h = torch.cat([x, action], dim=1)
          h = torch.relu(self.fc1(h))
          h = torch.relu(self.fc2(h))
          return h
```

Finally, you can update your `CustomEncoderFactory` as follows.

```
@dataclasses.dataclass()
class CustomEncoderFactory(d3rlpy.models.EncoderFactory):
    feature_size: int

    def create(self, observation_shape):
        return CustomEncoder(observation_shape, self.feature_size)

    def create_with_action(self, observation_shape, action_size, discrete_action):
        return CustomEncoderWithAction(observation_shape, action_size, self.feature_size)
```

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```
    @staticmethod
    def get_type() -> str:
        return "custom"
```

Now, you can customize actor-critic algorithms.

```
encoder_factory = CustomEncoderFactory(64)

sac = d3rlpy.algos.SACConfig(
    actor_encoder_factory=encoder_factory,
    critic_encoder_factory=encoder_factory,
).create()
```

1.6 Online RL

1.6.1 Prepare Environment

d3rlpy supports environments with OpenAI Gym interface. In this tutorial, let's use simple CartPole environment.

```
import gym

# for training
env = gym.make("CartPole-v1")

# for evaluation
eval_env = gym.make("CartPole-v1")
```

1.6.2 Setup Algorithm

Just like offline RL training, you can setup an algorithm object.

```
import d3rlpy

# if you don't use GPU, set use_gpu=False instead.
dqn = d3rlpy.algos.DQNConfig(
    batch_size=32,
    learning_rate=2.5e-4,
    target_update_interval=100,
).create(device="cuda:0")

# initialize neural networks with the given environment object.
# this is not necessary when you directly call fit or fit_online method.
dqn.build_with_env(env)
```

1.6.3 Setup Online RL Utilities

Unlike offline RL training, you'll need to setup an experience replay buffer and an exploration strategy.

```
# experience replay buffer
buffer = d3rlpy.dataset.create_fifo_replay_buffer(limit=100000, env=env)

# exploration strategy
# in this tutorial, epsilon-greedy policy with static epsilon=0.3
explorer = d3rlpy.algos.ConstantEpsilonGreedy(0.3)
```

1.6.4 Start Training

Now, you have everything you need to start online RL training. Let's put them together!

```
dqn.fit_online(
    env,
    buffer,
    explorer,
    n_steps=100000,  # train for 100K steps
    eval_env=eval_env,
    n_steps_per_epoch=1000,  # evaluation is performed every 1K steps
    update_start_step=1000,  # parameter update starts after 1K steps
)
```

1.6.5 Train with Stochastic Policy

If the algorithm uses a stochastic policy (e.g. SAC), you can train algorithms without setting an exploration strategy.

```
sac = d3rlpy.algos.DiscreteSACConfig().create()
sac.fit_online(
    env,
    buffer,
    n_steps=100000,
    eval_env=eval_env,
    n_steps_per_epoch=1000,
    update_start_step=1000,
)
```

1.7 Finetuning

d3rlpy supports smooth transition from offline training to online training.

1.7.1 Prepare Dataset and Environment

In this tutorial, let's use a built-in dataset for CartPole-v0 environment.

```
import d3rlpy

# setup random CartPole-v0 dataset and environment
dataset, env = d3rlpy.datasets.get_dataset("cartpole-random")
```

1.7.2 Pretrain with Dataset

```
# setup algorithm
dqn = d3rlpy.algos.DQNConfig().create()

# start offline training
dqn.fit(dataset, n_steps=100000)
```

1.7.3 Finetune with Environment

```
# setup experience replay buffer
buffer = d3rlpy.dataset.create_fifo_replay_buffer(limit=100000, env=env)

# setup exploration strategy if necessary
explorer = d3rlpy.algos.ConstantEpsilonGreedy(0.1)

# start finetuning
dqn.fit_online(env, buffer, explorer, n_steps=100000)
```

1.7.4 Finetune with Saved Policy

If you want to finetune the saved policy, that's also easy to do with d3rlpy.

```
# setup algorithm
dqn = d3rlpy.load_learnable("dqn_model.d3")

# start finetuning
dqn.fit_online(env, buffer, explorer, n_steps=100000)
```

1.7.5 Finetune with Different Algorithm

If you want to finetune the saved policy trained offline with online RL algorithms, you can do it in an out-of-the-box way.

```
# setup offline RL algorithm
cql = d3rlpy.algos.DiscreteCQLConfig().create()

# train offline
cql.fit(dataset, n_steps=100000)
```

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```
# transfer to DQN
dqn = d3rlpy.algos.DQNConfig().create()
dqn.build_with_env(env)
dqn.copy_q_function_from(cql)

# start finetuning
dqn.fit_online(env, buffer, explorer, n_steps=100000)
```

In actor-critic cases, you should also transfer the policy function.

```
# offline RL
cql = d3rlpy.algos.CQLConfig().create()
cql.fit(dataset, n_steps=100000)

# transfer to SAC
sac = d3rlpy.algos.SACConfig().create()
sac.build_with_env(env)
sac.copy_q_function_from(cql)
sac.copy_policy_from(cql)

# online RL
sac.fit_online(env, buffer, n_steps=100000)
```

1.8 Offline Policy Selection

d3rlpy supports offline policy selection by training Fitted Q Evaluation (FQE), which is an offline on-policy RL algorithm. The use of FQE for offline policy selection is proposed by Paine et al.. The concept is that FQE trains Q-function with the trained policy in on-policy manner so that the learned Q-function reflects the expected return of the trained policy. By using the Q-value estimation of FQE, the candidate trained policies can be ranked only with offline dataset. Check *Off-Policy Evaluation* for more information.

Note: Offline policy selection with FQE is confirmed that it usually works out with discrete action-space policies. However, it seems require some hyperparameter tuning for ranking continuous action-space policies. The more techniques will be supported along with the advancement of this research domain.

1.8.1 Prepare trained policies

In this tutorial, let's train DQN with the built-in CartPole-v0 dataset.

```
import d3rlpy

# setup replay CartPole-v0 dataset and environment
dataset, env = d3rlpy.datasets.get_dataset("cartpole-replay")

# setup algorithm
dqn = d3rlpy.algos.DQNConfig().create()
```

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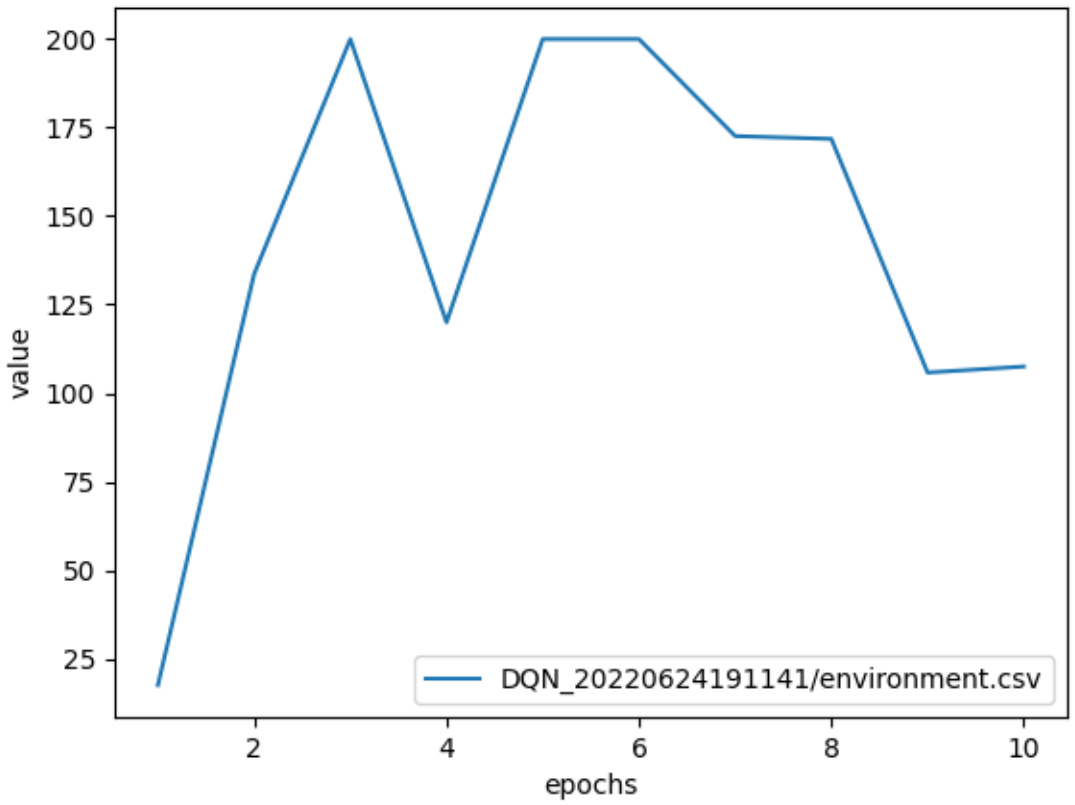
```
# start offline training
dqn.fit(
    dataset,
    n_steps=100000,
    n_steps_per_epoch=10000,
    scorers={
        "environment": d3rlpy.metrics.EnvironmentEvaluator(env),
    },
)
```

Here is the example result of online evaluation.

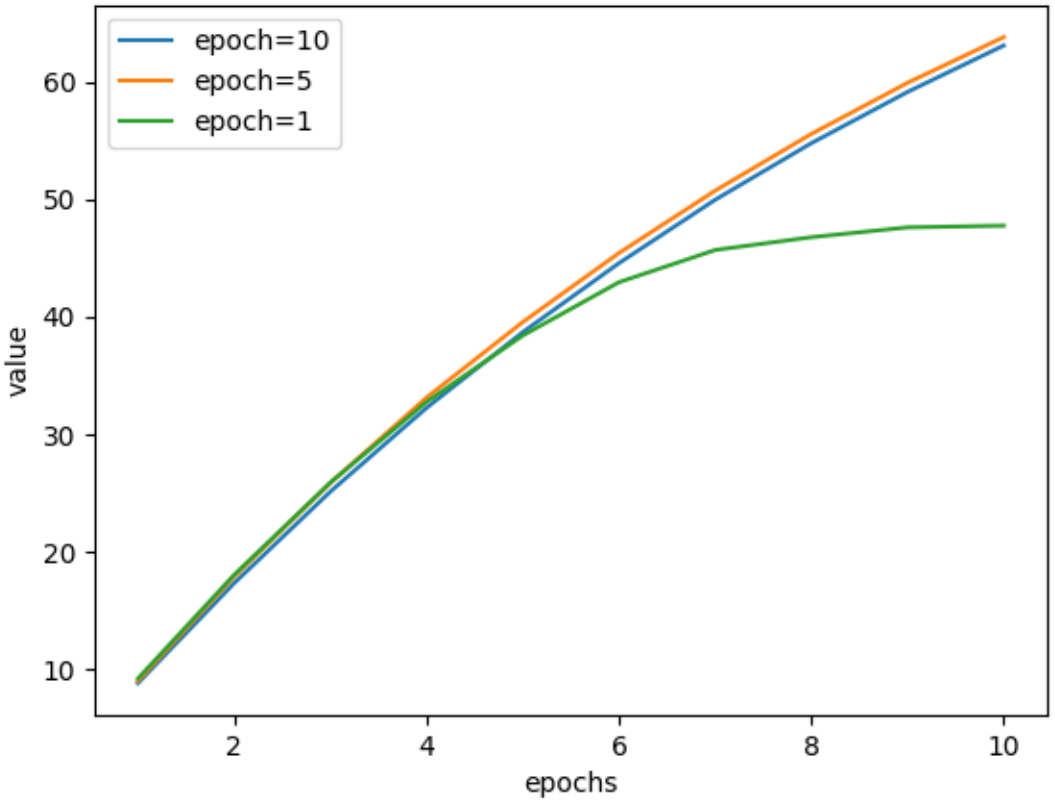


1.8.2 Train FQE with the trained policies

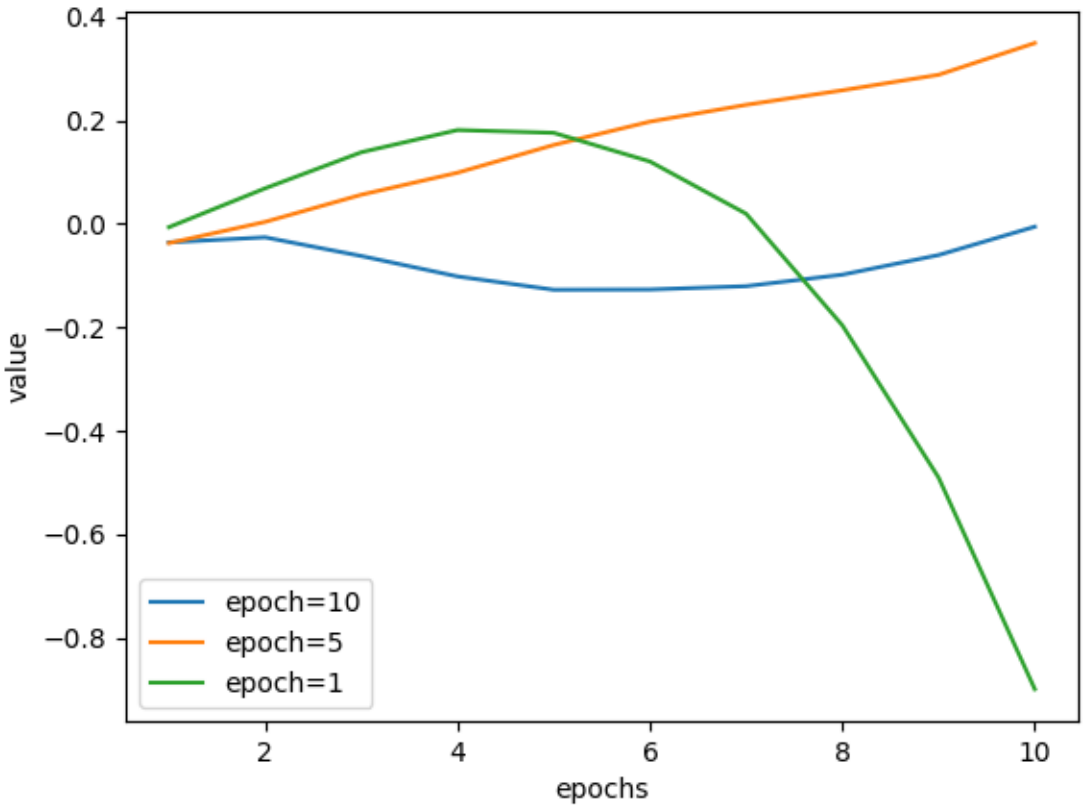
Next, we train FQE algorithm with the trained policies. Please note that we use `initial_state_value_estimation_scorer` and `soft_opc_scorer` proposed in Paine et al.. `initial_state_value_estimation_scorer` computes the mean action-value estimation at the initial states. Thus, if this value for a certain policy is bigger than others, the policy is expected to obtain the higher episode return. On the other hand, `soft_opc_scorer` computes the mean difference between the action-value estimation for the success episodes and the action-value estimation for the all episodes. If this value for a certain policy is bigger than others, the learned Q-function can clearly tell the difference between the success episodes and others.

```
import d3rlpy

# setup the same dataset used in policy training
dataset, _ = d3rlpy.datasets.get_dataset("cartpole-replay")

# load pretrained policy
dqn = d3rlpy.load_learnable("d3rlpy_logs/DQN_20220624191141/model_100000.d3")

# setup FQE algorithm
fqe = d3rlpy.ope.DiscreteFQE(algo=dqn, config=d3rlpy.ope.DiscreteFQEConfig())

# start FQE training
fqe.fit(
   dataset,
   n_steps=10000,
   n_steps_per_epoch=1000,
   scorers={
       "init_value": d3rlpy.metrics.InitialStateValueEstimationEvaluator(),
       "soft_opc": d3rlpy.metrics.SoftOPCEvaluator(180),  # set 180 for success return␣
↪threshold here
   },
)
```

In this example, the policies from epoch 10, epoch 5 and epoch 1 (evaluation episode returns of 107.5, 200.0 and 17.5 respectively) are compared. The first figure represents the `init_value` metrics during FQE training. As you can see here, the scale of `init_value` has correlation with the ranks of evaluation episode returns.



The second figure represents the `soft_opc` metrics during FQE training. These curves also have correlation with the ranks of evaluation episode returns.



Please note that there is usually no convergence in offline RL training due to the non-fixed bootstrapped target.

1.9 Use Distributional Q-Function

The one of the unique features in d3rlpy is to use distributional Q-functions with arbitrary d3rlpy algorithms. The distributional Q-functions are powerful and potentially capable of improving performance of any algorithms. In this tutorial, you can learn how to use them. Check *Q Functions* for more information.

```
# default standard Q-function
mean_q_function = d3rlpy.models.MeanQFunctionFactory()
sac = d3rlpy.algos.SACConfig(q_func_factory=mean_q_function).create()

# Quantile Regression Q-function
qr_q_function = d3rlpy.models.QRQFunctionFactory(n_quantiles=200)
sac = d3rlpy.algos.SACConfig(q_func_factory=qr_q_function).create()

# Implicit Quantile Network Q-function
iqn_q_function = d3rlpy.models.IQNQFunctionFactory(
    n_quantiles=32,
    n_greedy_quantiles=64,
    embed_size=64,
)
```

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```
sac = d3rlpy.algos.SACConfig(q_func_factory=iqn_q_function).create()
```

1.10 After Training Policies (Save and Load)

This page provides answers to frequently asked questions about how to use the trained policies with your environment.

1.10.1 Prepare Pretrained Policies

```
import d3rlpy

# prepare dataset and environment
dataset, env = d3rlpy.datasets.get_dataset('pendulum-random')

# setup algorithm
cql_old = d3rlpy.algos.CQLConfig().create(device="cuda:0")

# start offline training
cql_old.fit(dataset, n_steps=100000)
```

1.10.2 Load Trained Policies

```
# Option 1: Load d3 file

# save d3 file
cql_old.save("model.d3")
# reconstruct full setup from a d3 file
cql = d3rlpy.load_learnable("model.d3")


# Option 2: Load pt file

# save pt file
cql_old.save_model("model.pt")
# setup algorithm manually
cql = d3rlpy.algos.CQLConfig().create()

# choose one of three to build PyTorch models

# if you have MDPDataset object
cql.build_with_dataset(dataset)
# or if you have Gym-styled environment object
cql.build_with_env(env)
# or manually set observation shape and action size
cql.create_impl((3,), 1)

# load pretrained model
cql.load_model("model.pt")
```

1.10.3 Inference

Now, you can use `predict` method to infer the actions. Please note that the observation MUST have the batch dimension.

```
import numpy as np

# make sure that the observation has the batch dimension
observation = np.random.random((1, 3))

# infer the action
action = cql.predict(observation)
assert action.shape == (1, 1)
```

You can manually make the policy interact with the environment.

```
observation = env.reset()
while True:
   action = cql.predict([observation])[0]
   observation, reward, done, _ = env.step(action)
   if done:
       break
```

1.10.4 Export Policies as TorchScript

Q-learning

Alternatively, you can export the trained policy as TorchScript format. The advantage of the TorchScript format is that the exported policy can be used by not only Python programs, but also C++ programs, which would be useful for robotics integration. Another merit is that the trained policy depends only on PyTorch so that you don't need to install d3rlpy at production.

```
# export as TorchScript
cql.save_policy("policy.pt")


import torch

# load TorchScript policy
policy = torch.jit.load("policy.pt")

# infer the action
action = policy(torch.rand(1, 3))
assert action.shape == (1, 1)
```

If you train your policy with tuple observations, you can feed tuple observations as follows:

```
# load TorchScript policy
policy = torch.jit.load("tuple_policy.pt")

# infer the action
tuple_observation = [torch.rand(1, 3), torch.rand(1, 5)]
action = policy(tuple_observation[0], tuple_observation[1])
```

Decision Transformer

Decision Transformer-based algorithms also support TorchScript export.

```
# export as TorchScript
dt.save_policy("policy.pt")


import torch

# load TorchScript policy
policy = torch.jit.load("policy.pt")

# prepare sequence inputs
# context_size == 10, action_size=2
observations = torch.rand(10, 3)
actions = torch.rand(10, 2)
returns_to_go = torch.rand(10, 1)
timesteps = torch.zeros(10, dtype=torch.int32)

# infer the action
action = policy(observations, actions, returns_to_go, timesteps)
assert action.shape == (2,)
```

Tuple observations are also supported:

```
# load TorchScript policy
policy = torch.jit.load("tuple_policy.pt")

# prepare sequence inputs
# context_size == 10, action_size=2
observations1 = torch.rand(10, 3)
observations2 = torch.rand(10, 5)
actions = torch.rand(10, 2)
returns_to_go = torch.rand(10, 1)
timesteps = torch.zeros(10, dtype=torch.int32)

# infer the action
action = policy(observations1, observations2, actions, returns_to_go, timesteps)
assert action.shape == (2,)
```

1.10.5 Export Policies as ONNX

Q-learning

Alternatively, you can also export the trained policy as ONNX. ONNX is a widely used machine learning model format that is supported by numerous programming languages.

```
# export as ONNX
cql.save_policy("policy.onnx")
```

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```
import onnxruntime as ort

# load ONNX policy via onnxruntime
ort_session = ort.InferenceSession('policy.onnx', providers=["CPUExecutionProvider"])

# observation
observation = np.random.rand(1, 3).astype(np.float32)

# returns greedy action
action = ort_session.run(None, {'input_0': observation})[0]
assert action.shape == (1, 1)
```

If you train your policy with tuple observations, you can feed tuple observations as follows:

```
# load ONNX policy via onnxruntime
ort_session = ort.InferenceSession('tuple_policy.onnx', providers=["CPUExecutionProvider
↪"])

# infer the action
tuple_observation = [np.random.rand(1, 3).astype(np.float32), np.random.rand(1, 5).
↪astype(np.float32)]
action = ort_session.run(None, {'input_0': tuple_observation[0], 'input_1': tuple_
↪observation[1]})[0]
```

Decision Transformer

Decision Transformer-based algorithms also support ONNX export:

```
# export as ONNX
cql.save_policy("policy.onnx")


import onnxruntime as ort

# load ONNX policy via onnxruntime
ort_session = ort.InferenceSession('policy.onnx', providers=["CPUExecutionProvider"])

# prepare sequence inputs
# context_size == 10, action_size=2
observations = np.random.rand(10, 3).astype(np.float32)
actions = np.random.rand(10, 2).astype(np.float32)
returns_to_go = np.random.rand(10, 1).astype(np.float32)
timesteps = np.random.zeros(10, dtype=np.int32)

# returns greedy action
action = ort_session.run(
    None,
    {
        'observation_0': observations,
        'action': actions,
        'return_to_go': returns_to_go,
```

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```
        'timestep': timesteps,
    },
)
assert action.shape == (2,)
```

Tuple observations are also supported:

```
# load ONNX policy via onnxruntime
ort_session = ort.InferenceSession('tuple_policy.onnx', providers=["CPUExecutionProvider
↪"])

# prepare sequence inputs
# context_size == 10, action_size=2
observations1 = np.random.rand(10, 3).astype(np.float32)
observations2 = np.random.rand(10, 5).astype(np.float32)
actions = np.random.rand(10, 2).astype(np.float32)
returns_to_go = np.random.rand(10, 1).astype(np.float32)
timesteps = np.random.zeros(10, dtype=np.int32)

# returns greedy action
action = ort_session.run(
    None,
    {
        'observation_0': observations1,
        'observation_1': observations2,
        'action': actions,
        'return_to_go': returns_to_go,
        'timestep': timesteps,
    },
)
assert action.shape == (2,)
```

CHAPTER

TWO

JUPYTER NOTEBOOKS

- CartPole
- CartPole (online)
- Discrete Control with Atari
- TPU Example

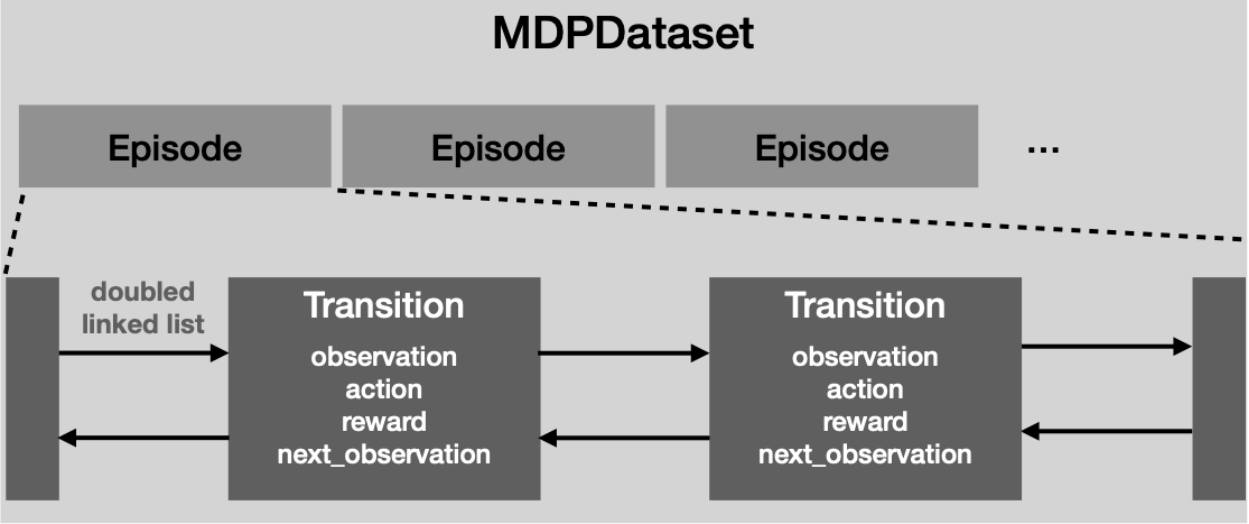
CHAPTER

THREE

SOFTWARE DESIGN

In this page, the software design of d3rlpy is explained.

3.1 MDPDataset



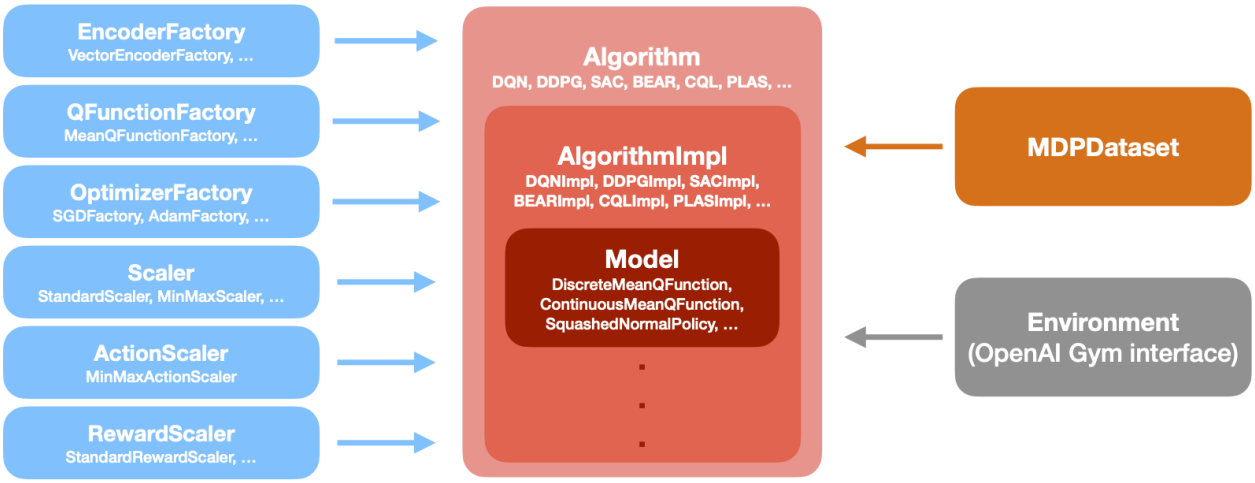
`MDPDataset` is a dedicated dataset structure for offline RL. `MDPDataset` automatically structures dataset based on `Episode` and `Transition`. `Episode` represents a single episode that includes multiple `Transition` objects collected in the episode. `Transition` represents a single tuple experience that consists of `observation`, `action`, `reward` and `next_observation`.

The advantage of this design is that you can split train and test datasets in an episode-wise manner. This feature is specifically useful for the offline RL training since holding out a continuous sequence of data is more making sense unlike a non-sequetial supervised training such as ImageNet classification models.

Regarding the engineering perspective, the underlying transition data is implemented by Cython, a Python-like language compiled to C language, to reduce the computational costs for the memory copies. This Cythonized implementation especially speeds up the cumulative returns for multi-step learning and frame-stacking for pixel observations.

Please check tutorials/play_with_mdp_dataset for the tutorial and *Replay Buffer* for the API reference.

3.2 Algorithm



The implemented algorithms are designed as above. The algorithm objects have a hierarchical structure where `Algorithm` provides the high-level API (e.g. `fit` and `fit_online`) for users and `AlgorithmImpl` provides the low-level API (e.g. `update_actor` and `update_critic`) used in the high-level API. The advantage of this design is to maximize the reusability of algorithm logics. For example, *delayed policy update* proposed in TD3 reduces the update frequency of the policy function. This mechanism can be implemented by changing the frequency of `update_actor` method calls in `Algorithm` layer without changing the underlying logics.

`Algorithm` class takes multiple components that configure the training. These are the links to the API reference.

Table 1: Algorithm Components

Name	Reference
Algorithm	*Algorithms*
EncoderFactory	*Network Architectures*
QFunctionFactory	*Q Functions*
OptimizerFactory	*Optimizers*
ObservationScaler	*Preprocessing*
ActionScaler	*Preprocessing*
RewardScaler	*Preprocessing*

CHAPTER

FOUR

API REFERENCE

4.1 Algorithms

d3rlpy provides state-of-the-art offline deep reinforcement learning algorithms as well as online algorithms for the base implementations.

Each algorithm provides its config class and you can instantiate it with specifying a device to use.

```
import d3rlpy

# instantiate algorithm with CPU
sac = d3rlpy.algos.SACConfig().create(device="cpu:0")
# instantiate algorithm with GPU
sac = d3rlpy.algos.SACConfig().create(device="cuda:0")
# instantiate algorithm with the 2nd GPU
sac = d3rlpy.algos.SACConfig().create(device="cuda:1")
```

You can also check advanced use cases at examples directory.

4.1.1 Base

LearnableBase

The base class of all algorithms.

class d3rlpy.base.**LearnableBase**(*config*, *device*, *impl=None*)

Bases: Generic[TImpl_co, TConfig_co]

property action_scaler: Optional[ActionScaler]

Preprocessing action scaler.

Returns
preprocessing action scaler.

Return type
Optional[ActionScaler]

property action_size: Optional[int]

Action size.

Returns
action size.

Return type
Optional[int]

property batch_size: int

Batch size to train.

Returns
batch size.

Return type
int

build_with_dataset(*dataset*)

Instantiate implementation object with ReplayBuffer object.

Parameters
dataset (ReplayBuffer) – dataset.

Return type
None

build_with_env(*env*)

Instantiate implementation object with OpenAI Gym object.

Parameters
env (*Union[Env[Any, Any], Env[Any, Any]]*) – gym-like environment.

Return type
None

property config: TConfig_co

Config.

Returns
config.

Return type
LearnableConfig

create_impl(*observation_shape*, *action_size*)

Instantiate implementation objects with the dataset shapes.

This method will be used internally when *fit* method is called.

Parameters

- **observation_shape** (*Union[Sequence[int], Sequence[Sequence[int]]]*) – observation shape.
- **action_size** (*int*) – dimension of action-space.

Return type
None

classmethod from_json(*fname*, *device=False*)

Construct algorithm from params.json file.

```
from d3rlpy.algos import CQL

cql = CQL.from_json("<path-to-json>", device='cuda:0')
```

Parameters

- **fname** (*str*) – path to params.json
- **device** (*Union[int, str, bool]*) – device option. If the value is boolean and True, `cuda:0` will be used. If the value is integer, `cuda:<device>` will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
Self

property gamma: float

Discount factor.

Returns
discount factor.

Return type
float

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

property grad_step: int

Total gradient step counter.

This value will keep counting after `fit` and `fit_online` methods finish.

Returns
total gradient step counter.

property impl: Optional[TImpl_co]

Implementation object.

Returns
implementation object.

Return type
Optional[ImplBase]

load_model(*fname*)

Load neural network parameters.

```
algo.load_model('model.pt')
```

Parameters
fname (*str*) – source file path.

Return type
None

property observation_scaler: Optional[ObservationScaler]

Preprocessing observation scaler.

Returns
preprocessing observation scaler.

Return type
Optional[ObservationScaler]

property observation_shape: Optional[Union[Sequence[int], Sequence[Sequence[int]]]]

Observation shape.

Returns
observation shape.

Return type
Optional[Sequence[int]]

property reward_scaler: Optional[RewardScaler]

Preprocessing reward scaler.

Returns
preprocessing reward scaler.

Return type
Optional[RewardScaler]

save(*fname*)

Saves paired data of neural network parameters and serialized config.

```
algo.save('model.d3')

# reconstruct everything
algo2 = d3rlpy.load_learnable("model.d3", device="cuda:0")
```

Parameters
fname (*str*) – destination file path.

Return type
None

save_model(*fname*)

Saves neural network parameters.

```
algo.save_model('model.pt')
```

Parameters
fname (*str*) – destination file path.

Return type
None

set_grad_step(*grad_step*)

Set total gradient step counter.

This method can be used to restart the middle of training with an arbitrary gradient step counter, which has effects on periodic functions such as the target update.

Parameters
grad_step (*int*) – total gradient step counter.

Return type
None

4.1.2 Q-learning

QLearningAlgoBase

The base class of Q-learning algorithms.

class d3rlpy.algos.**QLearningAlgoBase**(*config*, *device*, *impl=None*)

Bases: Generic[TQLearningImpl, TQLearningConfig], *LearnableBase*[TQLearningImpl, TQLearningConfig]

collect(*env*, *buffer=None*, *explorer=None*, *deterministic=False*, *n_steps=1000000*, *show_progress=True*)

Collects data via interaction with environment.

If `buffer` is not given, `ReplayBuffer` will be internally created.

Parameters

- **env** (*Union[Env[Any, Any], Env[Any, Any]]*) – Fym-like environment.
- **buffer** (*Optional[ReplayBufferBase]*) – Replay buffer.
- **explorer** (*Optional[Explorer]*) – Action explorer.
- **deterministic** (*bool*) – Flag to collect data with the greedy policy.
- **n_steps** (*int*) – Number of total steps to train.
- **show_progress** (*bool*) – Flag to show progress bar for iterations.

Returns
Replay buffer with the collected data.

Return type
ReplayBufferBase

copy_policy_from(*algo*)

Copies policy parameters from the given algorithm.

```
# pretrain with static dataset
cql = d3rlpy.algos.CQL()
cql.fit(dataset, n_steps=100000)

# transfer to online algorithm
sac = d3rlpy.algos.SAC()
sac.create_impl(cql.observation_shape, cql.action_size)
sac.copy_policy_from(cql)
```

Parameters
algo (*QLearningAlgoBase[QLearningAlgoImplBase, LearnableConfig]*) – Algorithm object.

Return type
None

copy_policy_optim_from(*algo*)

Copies policy optimizer states from the given algorithm.

```
# pretrain with static dataset
cql = d3rlpy.algos.CQL()
cql.fit(dataset, n_steps=100000)

# transfer to online algorithm
sac = d3rlpy.algos.SAC()
sac.create_impl(cql.observation_shape, cql.action_size)
sac.copy_policy_optim_from(cql)
```

Parameters

algo (QLearningAlgoBase[*QLearningAlgoImplBase*, *LearnableConfig*]) – Algorithm object.

Return type

None

copy_q_function_from(*algo*)

Copies Q-function parameters from the given algorithm.

```
# pretrain with static dataset
cql = d3rlpy.algos.CQL()
cql.fit(dataset, n_steps=100000)

# transfer to online algorithmn
sac = d3rlpy.algos.SAC()
sac.create_impl(cql.observation_shape, cql.action_size)
sac.copy_q_function_from(cql)
```

Parameters

algo (QLearningAlgoBase[*QLearningAlgoImplBase*, *LearnableConfig*]) – Algorithm object.

Return type

None

copy_q_function_optim_from(*algo*)

Copies Q-function optimizer states from the given algorithm.

```
# pretrain with static dataset
cql = d3rlpy.algos.CQL()
cql.fit(dataset, n_steps=100000)

# transfer to online algorithm
sac = d3rlpy.algos.SAC()
sac.create_impl(cql.observation_shape, cql.action_size)
sac.copy_policy_optim_from(cql)
```

Parameters

algo (QLearningAlgoBase[*QLearningAlgoImplBase*, *LearnableConfig*]) – Algorithm object.

Return type
None

fit(*dataset*, *n_steps*, *n_steps_per_epoch=10000*, *experiment_name=None*, *with_timestamp=True*, *logging_steps=500*, *logging_strategy=LoggingStrategy.EPOCH*, *logger_adapter=<d3rlpy.logging.file_adapter.FileAdapterFactory object>*, *show_progress=True*, *save_interval=1*, *evaluators=None*, *callback=None*, *epoch_callback=None*, *enable_ddp=False*)

Trains with given dataset.

```
algo.fit(episodes, n_steps=1000000)
```

Parameters

- **dataset** (ReplayBufferBase) – ReplayBuffer object.
- **n_steps** (*int*) – Number of steps to train.
- **n_steps_per_epoch** (*int*) – Number of steps per epoch. This value will be ignored when `n_steps` is `None`.
- **experiment_name** (*Optional[str]*) – Experiment name for logging. If not passed, the directory name will be *{class name}_{timestamp}*.
- **with_timestamp** (*bool*) – Flag to add timestamp string to the last of directory name.
- **logging_steps** (*int*) – Number of steps to log metrics. This will be ignored if logging_strategy is EPOCH.
- **logging_strategy** (*LoggingStrategy*) – Logging strategy to use.
- **logger_adapter** (LoggerAdapterFactory) – LoggerAdapterFactory object.
- **show_progress** (*bool*) – Flag to show progress bar for iterations.
- **save_interval** (*int*) – Interval to save parameters.
- **evaluators** (*Optional[Dict[str, EvaluatorProtocol]]*) – List of evaluators.
- **callback** (*Optional[Callable[[Self, int, int], None]]*) – Callable function that takes `(algo, epoch, total_step)` , which is called every step.
- **epoch_callback** (*Optional[Callable[[Self, int, int], None]]*) – Callable function that takes `(algo, epoch, total_step)`, which is called at the end of every epoch.
- **enable_ddp** (*bool*) – Flag to wrap models with DataDistributedParallel.

Returns
List of result tuples (epoch, metrics) per epoch.

Return type
List[*Tuple*[int, *Dict*[str, float]]]

fit_online(*env*, *buffer=None*, *explorer=None*, *n_steps=1000000*, *n_steps_per_epoch=10000*, *update_interval=1*, *n_updates=1*, *update_start_step=0*, *random_steps=0*, *eval_env=None*, *eval_epsilon=0.0*, *save_interval=1*, *experiment_name=None*, *with_timestamp=True*, *logging_steps=500*, *logging_strategy=LoggingStrategy.EPOCH*, *logger_adapter=<d3rlpy.logging.file_adapter.FileAdapterFactory object>*, *show_progress=True*, *callback=None*)

Start training loop of online deep reinforcement learning.

Parameters

- **env** (*Union[Env[Any, Any], Env[Any, Any]]*) – Gym-like environment.
- **buffer** (*Optional[ReplayBufferBase]*) – Replay buffer.
- **explorer** (*Optional[Explorer]*) – Action explorer.
- **n_steps** (*int*) – Number of total steps to train.
- **n_steps_per_epoch** (*int*) – Number of steps per epoch.
- **update_interval** (*int*) – Number of steps per update.
- **n_updates** (*int*) – Number of gradient steps at a time. The combination of `update_interval` and `n_updates` controls Update-To-Data (UTD) ratio.
- **update_start_step** (*int*) – Steps before starting updates.
- **random_steps** (*int*) – Steps for the initial random explortion.
- **eval_env** (*Optional[Union[Env[Any, Any], Env[Any, Any]]]*) – Gym-like environment. If None, evaluation is skipped.
- **eval_epsilon** (*float*) – ϵ-greedy factor during evaluation.
- **save_interval** (*int*) – Number of epochs before saving models.
- **experiment_name** (*Optional[str]*) – Experiment name for logging. If not passed, the directory name will be `{class name}_online_{timestamp}`.
- **with_timestamp** (*bool*) – Flag to add timestamp string to the last of directory name.
- **logging_steps** (*int*) – Number of steps to log metrics. This will be ignored if logging_strategy is EPOCH.
- **logging_strategy** (*LoggingStrategy*) – Logging strategy to use.
- **logger_adapter** (LoggerAdapterFactory) – LoggerAdapterFactory object.
- **show_progress** (*bool*) – Flag to show progress bar for iterations.
- **callback** (*Optional[Callable[[Self, int, int], None]]*) – Callable function that takes `(algo, epoch, total_step)` , which is called at the end of epochs.

Return type
None

fitter(*dataset*, *n_steps*, *n_steps_per_epoch=10000*, *logging_steps=500*, *logging_strategy=LoggingStrategy.EPOCH*, *experiment_name=None*, *with_timestamp=True*, *logger_adapter=<d3rlpy.logging.file_adapter.FileAdapterFactory object>*, *show_progress=True*, *save_interval=1*, *evaluators=None*, *callback=None*, *epoch_callback=None*, *enable_ddp=False*)

Iterate over epochs steps to train with the given dataset. At each iteration algo methods and properties can be changed or queried.

```
for epoch, metrics in algo.fitter(episodes):
    my_plot(metrics)
    algo.save_model(my_path)
```

Parameters

- **dataset** (ReplayBufferBase) – Offline dataset to train.
- **n_steps** (*int*) – Number of steps to train.

- **n_steps_per_epoch** (*int*) – Number of steps per epoch. This value will be ignored when `n_steps` is `None`.
- **experiment_name** (*Optional[str]*) – Experiment name for logging. If not passed, the directory name will be *{class name}_{timestamp}*.
- **with_timestamp** (*bool*) – Flag to add timestamp string to the last of directory name.
- **logging_steps** (*int*) – Number of steps to log metrics. This will be ignored if loggig_strategy is EPOCH.
- **logging_strategy** (*LoggingStrategy*) – Logging strategy to use.
- **logger_adapter** (LoggerAdapterFactory) – LoggerAdapterFactory object.
- **show_progress** (*bool*) – Flag to show progress bar for iterations.
- **save_interval** (*int*) – Interval to save parameters.
- **evaluators** (*Optional[Dict[str, EvaluatorProtocol]]*) – List of evaluators.
- **callback** (*Optional[Callable[[Self, int, int], None]]*) – Callable function that takes `(algo, epoch, total_step)` , which is called every step.
- **epoch_callback** (*Optional[Callable[[Self, int, int], None]]*) – Callable function that takes `(algo, epoch, total_step)`, which is called at the end of every epoch.
- **enable_ddp** (*bool*) – Flag to wrap models with DataDistributedParallel.

Returns
Iterator yielding current epoch and metrics dict.

Return type
Generator[*Tuple*[int, *Dict*[str, float]], None, None]

predict(*x*)

Returns greedy actions.

```
# 100 observations with shape of (10,)
x = np.random.random((100, 10))

actions = algo.predict(x)
# actions.shape == (100, action size) for continuous control
# actions.shape == (100,) for discrete control
```

Parameters
x (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observations

Returns
Greedy actions

Return type
ndarray[*Any*, *dtype*[*Any*]]

predict_value(*x*, *action*)

Returns predicted action-values.

```
# 100 observations with shape of (10,)
x = np.random.random((100, 10))

# for continuous control
# 100 actions with shape of (2,)
actions = np.random.random((100, 2))

# for discrete control
# 100 actions in integer values
actions = np.random.randint(2, size=100)

values = algo.predict_value(x, actions)
# values.shape == (100,)
```

Parameters

- **x** (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observations
- **action** (*ndarray[Any, dtype[Any]]*) – Actions

Returns
Predicted action-values

Return type
ndarray[*Any*, *dtype*[*Any*]]

reset_optimizer_states()

Resets optimizer states.

This is especially useful when fine-tuning policies with setting inital optimizer states.

Return type
None

sample_action(*x*)

Returns sampled actions.

The sampled actions are identical to the output of *predict* method if the policy is deterministic.

Parameters
x (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observations.

Returns
Sampled actions.

Return type
ndarray[*Any*, *dtype*[*Any*]]

save_policy(*fname*)

Save the greedy-policy computational graph as TorchScript or ONNX.

The format will be automatically detected by the file name.

```
# save as TorchScript
algo.save_policy('policy.pt')
```

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```
# save as ONNX
algo.save_policy('policy.onnx')
```

The artifacts saved with this method will work without d3rlpy. This method is especially useful to deploy the learned policy to production environments or embedding systems.

See also

- https://pytorch.org/tutorials/beginner/Intro_to_TorchScript_tutorial.html (for Python).
- https://pytorch.org/tutorials/advanced/cpp_export.html (for C++).
- https://onnx.ai (for ONNX)

Visit https://d3rlpy.readthedocs.io/en/stable/tutorials/after_training_policies.html#export-policies-as-torchscript for the further usage.

Parameters
fname (*str*) – Destination file path.

Return type
None

`update`(*batch*)

Update parameters with mini-batch of data.

Parameters
batch (*TransitionMiniBatch*) – Mini-batch data.

Returns
Dictionary of metrics.

Return type
Dict[str, float]

BC

`class d3rlpy.algos.BCConfig`(*batch_size=100*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *learning_rate=0.001*, *policy_type='deterministic'*, *optim_factory=<factory>*, *encoder_factory=<factory>*)

Bases: `LearnableConfig`

Config of Behavior Cloning algorithm.

Behavior Cloning (BC) is to imitate actions in the dataset via a supervised learning approach. Since BC is only imitating action distributions, the performance will be close to the mean of the dataset even though BC mostly works better than online RL algorithms.

$$L(\theta) = \mathbb{E}_{a_t, s_t \sim D}[(a_t - \pi_\theta(s_t))^2]$$

Parameters

- **learning_rate** (*float*) – Learing rate.
- **optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory.
- **encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory.
- **batch_size** (*int*) – Mini-batch size.

- **policy_type** (*str*) – the policy type. Available options are ['deterministic', 'stochastic'].
- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **action_scaler** (*d3rlpy.preprocessing.ActionScaler*) – Action preprocessor.
- **gamma** (*float*) –
- **reward_scaler** (*Optional[RewardScaler]*) –

create(*device=False*)

Returns algorithm object.

Parameters

device (*Union[int, str, bool]*) – device option. If the value is boolean and True, cuda:0 will be used. If the value is integer, cuda:<device> will be used. If the value is string in torch device style, the specified device will be used.

Returns

algorithm object.

Return type

BC

class d3rlpy.algos.**BC**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[BCBaseImpl, *BCConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns

action type.

Return type

ActionSpace

DiscreteBC

class d3rlpy.algos.**DiscreteBCConfig**(*batch_size=100*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *learning_rate=0.001*, *optim_factory=<factory>*, *encoder_factory=<factory>*, *beta=0.5*)

Bases: LearnableConfig

Config of Behavior Cloning algorithm for discrete control.

Behavior Cloning (BC) is to imitate actions in the dataset via a supervised learning approach. Since BC is only imitating action distributions, the performance will be close to the mean of the dataset even though BC mostly works better than online RL algorithms.

$$L(\theta) = \mathbb{E}_{a_t, s_t \sim D}[-\sum_a p(a|s_t) \log \pi_\theta(a|s_t)]$$

where $p(a|s_t)$ is implemented as a one-hot vector.

Parameters

- **learning_rate** (*float*) – Learing rate.
- **optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory.

- **encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory.
- **batch_size** (*int*) – Mini-batch size.
- **beta** (*float*) – Reguralization factor.
- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **gamma** (*float*) –
- **action_scaler** (*Optional[ActionScaler]*) –
- **reward_scaler** (*Optional[RewardScaler]*) –

create(*device=False*)

Returns algorithm object.

Parameters
device (*Union[int, str, bool]*) – device option. If the value is boolean and True, `cuda:0` will be used. If the value is integer, `cuda:<device>` will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
DiscreteBC

class d3rlpy.algos.**DiscreteBC**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[BCBaseImpl, *DiscreteBCConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

NFQ

class d3rlpy.algos.**NFQConfig**(*batch_size=32*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *learning_rate=6.25e-05*, *optim_factory=<factory>*, *encoder_factory=<factory>*, *q_func_factory=<factory>*, *n_critics=1*)

Bases: `LearnableConfig`

Config of Neural Fitted Q Iteration algorithm.

This NFQ implementation in d3rlpy is practically same as DQN, but excluding the target network mechanism.

$$L(\theta) = \mathbb{E}_{s_t, a_t, r_{t+1}, s_{t+1} \sim D}[(r_{t+1} + \gamma \max_a Q_{\theta'}(s_{t+1}, a) - Q_\theta(s_t, a_t))^2]$$

where θ' is the target network parameter. The target network parameter is synchronized every *target_update_interval* iterations.

References

- Riedmiller., Neural Fitted Q Iteration - first experiences with a data efficient neural reinforcement learning method.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **learning_rate** (*float*) – Learning rate.
- **optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory.
- **encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory.
- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **n_critics** (*int*) – Number of Q functions for ensemble.
- **action_scaler** (*Optional[ActionScaler]*) –

create(*device=False*)

Returns algorithm object.

Parameters

device (*Union[int, str, bool]*) – device option. If the value is boolean and True, cuda:0 will be used. If the value is integer, cuda:<device> will be used. If the value is string in torch device style, the specified device will be used.

Returns

algorithm object.

Return type

NFQ

class d3rlpy.algos.**NFQ**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[DQNImpl, *NFQConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns

action type.

Return type

ActionSpace

DQN

class d3rlpy.algos.**DQNConfig**(*batch_size=32*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *learning_rate=6.25e-05*, *optim_factory=<factory>*, *encoder_factory=<factory>*, *q_func_factory=<factory>*, *n_critics=1*, *target_update_interval=8000*)

Bases: `LearnableConfig`

Config of Deep Q-Network algorithm.

$$L(\theta) = \mathbb{E}_{s_t, a_t, r_{t+1}, s_{t+1} \sim D}[(r_{t+1} + \gamma \max_a Q_{\theta'}(s_{t+1}, a) - Q_\theta(s_t, a_t))^2]$$

where θ' is the target network parameter. The target network parameter is synchronized every *target_update_interval* iterations.

References

- Mnih et al., Human-level control through deep reinforcement learning.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **learning_rate** (*float*) – Learning rate.
- **optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory.
- **encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory.
- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **n_critics** (*int*) – Number of Q functions for ensemble.
- **target_update_interval** (*int*) – Interval to update the target network.
- **action_scaler** (*Optional[ActionScaler]*) –

create(*device=False*)

Returns algorithm object.

Parameters

device (*Union[int, str, bool]*) – device option. If the value is boolean and True, cuda:0 will be used. If the value is integer, cuda:<device> will be used. If the value is string in torch device style, the specified device will be used.

Returns

algorithm object.

Return type

DQN

class d3rlpy.algos.**DQN**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[DQNImpl, *DQNConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

DoubleDQN

class d3rlpy.algos.**DoubleDQNConfig**(*batch_size=32*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *learning_rate=6.25e-05*, *optim_factory=<factory>*, *encoder_factory=<factory>*, *q_func_factory=<factory>*, *n_critics=1*, *target_update_interval=8000*)

Bases: *DQNConfig*

Config of Double Deep Q-Network algorithm.

The difference from DQN is that the action is taken from the current Q function instead of the target Q function. This modification significantly decreases overestimation bias of TD learning.

$$L(\theta) = \mathbb{E}_{s_t,a_t,r_{t+1},s_{t+1} \sim D}[(r_{t+1} + \gamma Q_{\theta'}(s_{t+1}, \text{argmax}_a Q_\theta(s_{t+1}, a)) - Q_\theta(s_t, a_t))^2]$$

where θ' is the target network parameter. The target network parameter is synchronized every *target_update_interval* iterations.

References

- Hasselt et al., Deep reinforcement learning with double Q-learning.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **learning_rate** (*float*) – Learning rate.
- **optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory.
- **encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory.
- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **n_critics** (*int*) – Number of Q functions.
- **target_update_interval** (*int*) – Interval to synchronize the target network.

- **action_scaler** (*Optional[ActionScaler]*) –

create(*device=False*)

Returns algorithm object.

Parameters

device (*Union[int, str, bool]*) – device option. If the value is boolean and True, `cuda:0` will be used. If the value is integer, `cuda:<device>` will be used. If the value is string in torch device style, the specified device will be used.

Returns

algorithm object.

Return type

DoubleDQN

class d3rlpy.algos.**DoubleDQN**(*config*, *device*, *impl=None*)

Bases: *DQN*

DDPG

class d3rlpy.algos.**DDPGConfig**(*batch_size=256*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *actor_learning_rate=0.0003*, *critic_learning_rate=0.0003*, *actor_optim_factory=<factory>*, *critic_optim_factory=<factory>*, *actor_encoder_factory=<factory>*, *critic_encoder_factory=<factory>*, *q_func_factory=<factory>*, *tau=0.005*, *n_critics=1*)

Bases: `LearnableConfig`

Config of Deep Deterministic Policy Gradients algorithm.

DDPG is an actor-critic algorithm that trains a Q function parametrized with θ and a policy function parametrized with ϕ.

$$L(\theta) = \mathbb{E}_{s_t, a_t, r_{t+1}, s_{t+1} \sim D} \left[\left(r_{t+1} + \gamma Q_{\theta'} \left(s_{t+1}, \pi_{\phi'}(s_{t+1}) \right) - Q_\theta(s_t, a_t) \right)^2 \right]$$

$$J(\phi) = \mathbb{E}_{s_t \sim D} \left[Q_\theta \left(s_t, \pi_\phi(s_t) \right) \right]$$

where θ' and ϕ are the target network parameters. There target network parameters are updated every iteration.

$$\theta' \leftarrow \tau\theta + (1 - \tau)\theta'$$
$$\phi' \leftarrow \tau\phi + (1 - \tau)\phi'$$

References

- Silver et al., Deterministic policy gradient algorithms.
- Lillicrap et al., Continuous control with deep reinforcement learning.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **action_scaler** (*d3rlpy.preprocessing.ActionScaler*) – Action preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.

- **actor_learning_rate** (*float*) – Learning rate for policy function.
- **critic_learning_rate** (*float*) – Learning rate for Q function.
- **actor_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the actor.
- **critic_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the critic.
- **actor_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the actor.
- **critic_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the critic.
- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **tau** (*float*) – Target network synchronization coefficiency.
- **n_critics** (*int*) – Number of Q functions for ensemble.

create(*device=False*)

Returns algorithm object.

Parameters
device (*Union[int, str, bool]*) – device option. If the value is boolean and True, cuda:0 will be used. If the value is integer, cuda:<device> will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
DDPG

class d3rlpy.algos.**DDPG**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[DDPGImpl, *DDPGConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

TD3

class d3rlpy.algos.**TD3Config**(*batch_size=256*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *actor_learning_rate=0.0003*, *critic_learning_rate=0.0003*, *actor_optim_factory=<factory>*, *critic_optim_factory=<factory>*, *actor_encoder_factory=<factory>*, *critic_encoder_factory=<factory>*, *q_func_factory=<factory>*, *tau=0.005*, *n_critics=2*, *target_smoothing_sigma=0.2*, *target_smoothing_clip=0.5*, *update_actor_interval=2*)

Bases: `LearnableConfig`

Config of Twin Delayed Deep Deterministic Policy Gradients algorithm.

TD3 is an improved DDPG-based algorithm. Major differences from DDPG are as follows.

- TD3 has twin Q functions to reduce overestimation bias at TD learning. The number of Q functions can be designated by *n_critics*.
- TD3 adds noise to target value estimation to avoid overfitting with the deterministic policy.
- TD3 updates the policy function after several Q function updates in order to reduce variance of action-value estimation. The interval of the policy function update can be designated by *update_actor_interval*.

$$L(\theta_i) = \mathbb{E}_{s_t,a_t,r_{t+1},s_{t+1} \sim D}[(r_{t+1} + \gamma \min_j Q_{\theta'_j}(s_{t+1}, \pi_{\phi'}(s_{t+1}) + \epsilon) - Q_{\theta_i}(s_t, a_t))^2]$$

$$J(\phi) = \mathbb{E}_{s_t \sim D}[\min_i Q_{\theta_i}(s_t, \pi_\phi(s_t))]$$

where $\epsilon \sim clip(N(0, \sigma), -c, c)$

References

- Fujimoto et al., Addressing Function Approximation Error in Actor-Critic Methods.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **action_scaler** (*d3rlpy.preprocessing.ActionScaler*) – Action preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **actor_learning_rate** (*float*) – Learning rate for a policy function.
- **critic_learning_rate** (*float*) – Learning rate for Q functions.
- **actor_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the actor.
- **critic_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the critic.
- **actor_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the actor.
- **critic_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the critic.
- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.

- **gamma** (*float*) – Discount factor.
- **tau** (*float*) – Target network synchronization coefficiency.
- **n_critics** (*int*) – Number of Q functions for ensemble.
- **target_smoothing_sigma** (*float*) – Standard deviation for target noise.
- **target_smoothing_clip** (*float*) – Clipping range for target noise.
- **update_actor_interval** (*int*) – Interval to update policy function described as *delayed policy update* in the paper.

create(*device=False*)

Returns algorithm object.

Parameters
device (*Union[int, str, bool]*) – device option. If the value is boolean and True, `cuda:0` will be used. If the value is integer, `cuda:<device>` will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
TD3

class d3rlpy.algos.**TD3**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[TD3Impl, *TD3Config*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

SAC

class d3rlpy.algos.**SACConfig**(*batch_size=256*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *actor_learning_rate=0.0003*, *critic_learning_rate=0.0003*, *temp_learning_rate=0.0003*, *actor_optim_factory=<factory>*, *critic_optim_factory=<factory>*, *temp_optim_factory=<factory>*, *actor_encoder_factory=<factory>*, *critic_encoder_factory=<factory>*, *q_func_factory=<factory>*, *tau=0.005*, *n_critics=2*, *initial_temperature=1.0*)

Bases: LearnableConfig

Config Soft Actor-Critic algorithm.

SAC is a DDPG-based maximum entropy RL algorithm, which produces state-of-the-art performance in online RL settings. SAC leverages twin Q functions proposed in TD3. Additionally, *delayed policy update* in TD3 is also implemented, which is not done in the paper.

$$L(\theta_i) = \mathbb{E}_{s_t, a_t, r_{t+1}, s_{t+1} \sim D, a_{t+1} \sim \pi_\phi(\cdot|s_{t+1})} \Big[\big(y - Q_{\theta_i}(s_t, a_t) \big)^2 \Big]$$

$$y = r_{t+1} + \gamma \Big(\min_j Q_{\theta_j}(s_{t+1}, a_{t+1}) - \alpha \log \big(\pi_\phi(a_{t+1}|s_{t+1}) \big) \Big)$$

$$J(\phi) = \mathbb{E}_{s_t \sim D,\, a_t \sim \pi_\phi(\cdot|s_t)} \Big[\alpha \log(\pi_\phi(a_t|s_t)) - \min_i Q_{\theta_i}\big(s_t, \pi_\phi(a_t|s_t)\big) \Big]$$

The temperature parameter α is also automatically adjustable.

$$J(\alpha) = \mathbb{E}_{s_t \sim D,\, a_t \sim \pi_\phi(\cdot|s_t)} \Big[-\alpha \Big(\log\big(\pi_\phi(a_t|s_t)\big) + H \Big) \Big]$$

where H is a target entropy, which is defined as $\dim a$.

References

- Haarnoja et al., Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor.
- Haarnoja et al., Soft Actor-Critic Algorithms and Applications.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **action_scaler** (*d3rlpy.preprocessing.ActionScaler*) – Action preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **actor_learning_rate** (*float*) – Learning rate for policy function.
- **critic_learning_rate** (*float*) – Learning rate for Q functions.
- **temp_learning_rate** (*float*) – Learning rate for temperature parameter.
- **actor_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the actor.
- **critic_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the critic.
- **temp_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the temperature.
- **actor_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the actor.
- **critic_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the critic.
- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **tau** (*float*) – Target network synchronization coefficiency.
- **n_critics** (*int*) – Number of Q functions for ensemble.
- **initial_temperature** (*float*) – Initial temperature value.

create(*device=False*)

Returns algorithm object.

Parameters
device (*Union[int, str, bool]*) – device option. If the value is boolean and True, cuda:0 will be used. If the value is integer, cuda:<device> will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
SAC

class d3rlpy.algos.**SAC**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[SACImpl, *SACConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

DiscreteSAC

class d3rlpy.algos.**DiscreteSACConfig**(*batch_size=64*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *actor_learning_rate=0.0003*, *critic_learning_rate=0.0003*, *temp_learning_rate=0.0003*, *actor_optim_factory=<factory>*, *critic_optim_factory=<factory>*, *temp_optim_factory=<factory>*, *actor_encoder_factory=<factory>*, *critic_encoder_factory=<factory>*, *q_func_factory=<factory>*, *n_critics=2*, *initial_temperature=1.0*, *target_update_interval=8000*)

Bases: LearnableConfig

Config of Soft Actor-Critic algorithm for discrete action-space.

This discrete version of SAC is built based on continuous version of SAC with additional modifications.

The target state-value is calculated as expectation of all action-values.

$$V(s_t) = \pi_\phi(s_t)^T[Q_\theta(s_t) - \alpha \log(\pi_\phi(s_t))]$$

Similarly, the objective function for the temperature parameter is as follows.

$$J(\alpha) = \pi_\phi(s_t)^T[-\alpha(\log(\pi_\phi(s_t)) + H)]$$

Finally, the objective function for the policy function is as follows.

$$J(\phi) = \mathbb{E}_{s_t \sim D}[\pi_\phi(s_t)^T[\alpha \log(\pi_\phi(s_t)) - Q_\theta(s_t)]]$$

References

- Christodoulou, Soft Actor-Critic for Discrete Action Settings.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **actor_learning_rate** (*float*) – Learning rate for policy function.
- **critic_learning_rate** (*float*) – Learning rate for Q functions.
- **temp_learning_rate** (*float*) – Learning rate for temperature parameter.
- **actor_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the actor.
- **critic_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the critic.
- **temp_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the temperature.
- **actor_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the actor.
- **critic_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the critic.
- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **n_critics** (*int*) – Number of Q functions for ensemble.
- **initial_temperature** (*float*) – Initial temperature value.
- **action_scaler** (*Optional[ActionScaler]*) –
- **target_update_interval** (*int*) –

create(*device=False*)

Returns algorithm object.

Parameters

device (*Union[int, str, bool]*) – device option. If the value is boolean and True, `cuda:0` will be used. If the value is integer, `cuda:<device>` will be used. If the value is string in torch device style, the specified device will be used.

Returns

algorithm object.

Return type

DiscreteSAC

class d3rlpy.algos.**DiscreteSAC**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[DiscreteSACImpl, *DiscreteSACConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

BCQ

class d3rlpy.algos.**BCQConfig**(*batch_size=100*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *actor_learning_rate=0.001*, *critic_learning_rate=0.001*, *imitator_learning_rate=0.001*, *actor_optim_factory=<factory>*, *critic_optim_factory=<factory>*, *imitator_optim_factory=<factory>*, *actor_encoder_factory=<factory>*, *critic_encoder_factory=<factory>*, *imitator_encoder_factory=<factory>*, *q_func_factory=<factory>*, *tau=0.005*, *n_critics=2*, *update_actor_interval=1*, *lam=0.75*, *n_action_samples=100*, *action_flexibility=0.05*, *rl_start_step=0*, *beta=0.5*)

Bases: LearnableConfig

Config of Batch-Constrained Q-learning algorithm.

BCQ is the very first practical data-driven deep reinforcement learning lgorithm. The major difference from DDPG is that the policy function is represented as combination of conditional VAE and perturbation function in order to remedy extrapolation error emerging from target value estimation.

The encoder and the decoder of the conditional VAE is represented as E_ω and D_ω respectively.

$$L(\omega) = E_{s_t,a_t \sim D}[(a - \tilde{a})^2 + D_{KL}(N(\mu, \sigma)|N(0, 1))]$$

where $\mu, \sigma = E_\omega(s_t, a_t)$, $\tilde{a} = D_\omega(s_t, z)$ and $z \sim N(\mu, \sigma)$.

The policy function is represented as a residual function with the VAE and the perturbation function represented as $\xi_\phi(s, a)$.

$$\pi(s, a) = a + \Phi\xi_\phi(s, a)$$

where $a = D_\omega(s, z)$, $z \sim N(0, 0.5)$ and Φ is a perturbation scale designated by *action_flexibility*. Although the policy is learned closely to data distribution, the perturbation function can lead to more rewarded states.

BCQ also leverages twin Q functions and computes weighted average over maximum values and minimum values.

$$L(\theta_i) = \mathbb{E}_{s_t,a_t,r_{t+1},s_{t+1} \sim D}[(y - Q_{\theta_i}(s_t, a_t))^2]$$

$$y = r_{t+1} + \gamma \max_{a_i}[\lambda \min_j Q_{\theta'_j}(s_{t+1}, a_i) + (1 - \lambda) \max_j Q_{\theta'_j}(s_{t+1}, a_i)]$$

where $\{a_i \sim D(s_{t+1}, z), z \sim N(0, 0.5)\}_{i=1}^n$. The number of sampled actions is designated with *n_action_samples*.

Finally, the perturbation function is trained just like DDPG's policy function.

$$J(\phi) = \mathbb{E}_{s_t \sim D, a_t \sim D_\omega(s_t,z), z \sim N(0,0.5)}[Q_{\theta_1}(s_t, \pi(s_t, a_t))]$$

At inference time, action candidates are sampled as many as *n_action_samples*, and the action with highest value estimation is taken.

$$\pi'(s) = \text{argmax}_{\pi(s,a_i)} Q_{\theta_1}(s, \pi(s, a_i))$$

Note: The greedy action is not deterministic because the action candidates are always randomly sampled. This might affect *save_policy* method and the performance at production.

References

- Fujimoto et al., Off-Policy Deep Reinforcement Learning without Exploration.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **action_scaler** (*d3rlpy.preprocessing.ActionScaler*) – Action preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **actor_learning_rate** (*float*) – Learning rate for policy function.
- **critic_learning_rate** (*float*) – Learning rate for Q functions.
- **imitator_learning_rate** (*float*) – Learning rate for Conditional VAE.
- **actor_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the actor.
- **critic_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the critic.
- **imitator_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the conditional VAE.
- **actor_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the actor.
- **critic_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the critic.
- **imitator_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the conditional VAE.
- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **tau** (*float*) – Target network synchronization coefficiency.
- **n_critics** (*int*) – Number of Q functions for ensemble.
- **update_actor_interval** (*int*) – Interval to update policy function.
- **lam** (*float*) – Weight factor for critic ensemble.
- **n_action_samples** (*int*) – Number of action samples to estimate action-values.
- **action_flexibility** (*float*) – Output scale of perturbation function represented as Φ.
- **rl_start_step** (*int*) – Steps to start to update policy function and Q functions. If this is large, RL training would be more stabilized.
- **beta** (*float*) – KL reguralization term for Conditional VAE.

create(*device=False*)

Returns algorithm object.

Parameters
device (*Union[int, str, bool]*) – device option. If the value is boolean and True, cuda:0 will be used. If the value is integer, cuda:<device> will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
BCQ

class d3rlpy.algos.**BCQ**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[BCQImpl, *BCQConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

DiscreteBCQ

class d3rlpy.algos.**DiscreteBCQConfig**(*batch_size=32*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *learning_rate=6.25e-05*, *optim_factory=<factory>*, *encoder_factory=<factory>*, *q_func_factory=<factory>*, *n_critics=1*, *action_flexibility=0.3*, *beta=0.5*, *target_update_interval=8000*, *share_encoder=True*)

Bases: LearnableConfig

Config of Discrete version of Batch-Constrained Q-learning algorithm.

Discrete version takes theories from the continuous version, but the algorithm is much simpler than that. The imitation function $G_\omega(a|s)$ is trained as supervised learning just like Behavior Cloning.

$$L(\omega) = \mathbb{E}_{a_t,s_t \sim D}[-\sum_a p(a|s_t) \log G_\omega(a|s_t)]$$

With this imitation function, the greedy policy is defined as follows.

$$\pi(s_t) = \text{argmax}_{a|G_\omega(a|s_t)/\max_{\tilde{a}} G_\omega(\tilde{a}|s_t)>\tau} Q_\theta(s_t, a)$$

which eliminates actions with probabilities τ times smaller than the maximum one.

Finally, the loss function is computed in Double DQN style with the above constrained policy.

$$L(\theta) = \mathbb{E}_{s_t,a_t,r_{t+1},s_{t+1} \sim D}[(r_{t+1} + \gamma Q_{\theta'}(s_{t+1}, \pi(s_{t+1})) - Q_\theta(s_t, a_t))^2]$$

References

- Fujimoto et al., Off-Policy Deep Reinforcement Learning without Exploration.
- Fujimoto et al., Benchmarking Batch Deep Reinforcement Learning Algorithms.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **learning_rate** (*float*) – Learning rate.
- **optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory.
- **encoder_factory** (*d3rlpy.models.encoders.EncoderFactory or str*) – Encoder factory.
- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory or str*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **n_critics** (*int*) – Number of Q functions for ensemble.
- **action_flexibility** (*float*) – Probability threshold represented as τ.
- **beta** (*float*) – Reguralization term for imitation function.
- **target_update_interval** (*int*) – Interval to update the target network.
- **share_encoder** (*bool*) – Flag to share encoder between Q-function and imitation models.
- **action_scaler** (*Optional[ActionScaler]*) –

create(*device=False*)

Returns algorithm object.

Parameters
device (*Union[int, str, bool]*) – device option. If the value is boolean and True, cuda:0 will be used. If the value is integer, cuda:<device> will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
DiscreteBCQ

class d3rlpy.algos.**DiscreteBCQ**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[DiscreteBCQImpl, *DiscreteBCQConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

BEAR

class d3rlpy.algos.**BEARConfig**(*batch_size=256*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *actor_learning_rate=0.0001*, *critic_learning_rate=0.0003*, *imitator_learning_rate=0.0003*, *temp_learning_rate=0.0001*, *alpha_learning_rate=0.001*, *actor_optim_factory=<factory>*, *critic_optim_factory=<factory>*, *imitator_optim_factory=<factory>*, *temp_optim_factory=<factory>*, *alpha_optim_factory=<factory>*, *actor_encoder_factory=<factory>*, *critic_encoder_factory=<factory>*, *imitator_encoder_factory=<factory>*, *q_func_factory=<factory>*, *tau=0.005*, *n_critics=2*, *initial_temperature=1.0*, *initial_alpha=1.0*, *alpha_threshold=0.05*, *lam=0.75*, *n_action_samples=100*, *n_target_samples=10*, *n_mmd_action_samples=4*, *mmd_kernel='laplacian'*, *mmd_sigma=20.0*, *vae_kl_weight=0.5*, *warmup_steps=40000*)

Bases: `LearnableConfig`

Config of Bootstrapping Error Accumulation Reduction algorithm.

BEAR is a SAC-based data-driven deep reinforcement learning algorithm.

BEAR constrains the support of the policy function within data distribution by minimizing Maximum Mean Discreptancy (MMD) between the policy function and the approximated beahvior policy function $\pi_\beta(a|s)$ which is optimized through L2 loss.

$$L(\beta) = \mathbb{E}_{s_t, a_t \sim D, a \sim \pi_\beta(\cdot|s_t)}[(a - a_t)^2]$$

The policy objective is a combination of SAC's objective and MMD penalty.

$$J(\phi) = J_{SAC}(\phi) - \mathbb{E}_{s_t \sim D}\alpha(\text{MMD}(\pi_\beta(\cdot|s_t), \pi_\phi(\cdot|s_t)) - \epsilon)$$

where MMD is computed as follows.

$$\text{MMD}(x, y) = \frac{1}{N^2}\sum_{i,i'} k(x_i, x_{i'}) - \frac{2}{NM}\sum_{i,j} k(x_i, y_j) + \frac{1}{M^2}\sum_{j,j'} k(y_j, y_{j'})$$

where $k(x, y)$ is a gaussian kernel $k(x, y) = \exp\left((x - y)^2/(2\sigma^2)\right)$.

α is also adjustable through dual gradient decsent where α becomes smaller if MMD is smaller than the threshold ϵ.

References

- Kumar et al., Stabilizing Off-Policy Q-Learning via Bootstrapping Error Reduction.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **action_scaler** (*d3rlpy.preprocessing.ActionScaler*) – Action preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **actor_learning_rate** (*float*) – Learning rate for policy function.

- **critic_learning_rate** (*float*) – Learning rate for Q functions.
- **imitator_learning_rate** (*float*) – Learning rate for behavior policy function.
- **temp_learning_rate** (*float*) – Learning rate for temperature parameter.
- **alpha_learning_rate** (*float*) – Learning rate for α.
- **actor_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the actor.
- **critic_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the critic.
- **imitator_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the behavior policy.
- **temp_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the temperature.
- **alpha_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for α.
- **actor_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the actor.
- **critic_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the critic.
- **imitator_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the behavior policy.
- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **tau** (*float*) – Target network synchronization coefficiency.
- **n_critics** (*int*) – Number of Q functions for ensemble.
- **initial_temperature** (*float*) – Initial temperature value.
- **initial_alpha** (*float*) – Initial α value.
- **alpha_threshold** (*float*) – Threshold value described as ϵ.
- **lam** (*float*) – Weight for critic ensemble.
- **n_action_samples** (*int*) – Number of action samples to compute the best action.
- **n_target_samples** (*int*) – Number of action samples to compute BCQ-like target value.
- **n_mmd_action_samples** (*int*) – Number of action samples to compute MMD.
- **mmd_kernel** (*str*) – MMD kernel function. The available options are `['gaussian', 'laplacian']`.
- **mmd_sigma** (*float*) – σ for gaussian kernel in MMD calculation.
- **vae_kl_weight** (*float*) – Constant weight to scale KL term for behavior policy training.
- **warmup_steps** (*int*) – Number of steps to warmup the policy function.

create(*device=False*)

Returns algorithm object.

Parameters
device (*Union[int, str, bool]*) – device option. If the value is boolean and True, cuda:0 will be used. If the value is integer, cuda:<device> will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
BEAR

class d3rlpy.algos.**BEAR**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[BEARImpl, *BEARConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

CRR

class d3rlpy.algos.**CRRConfig**(*batch_size=100*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *actor_learning_rate=0.0003*, *critic_learning_rate=0.0003*, *actor_optim_factory=<factory>*, *critic_optim_factory=<factory>*, *actor_encoder_factory=<factory>*, *critic_encoder_factory=<factory>*, *q_func_factory=<factory>*, *beta=1.0*, *n_action_samples=4*, *advantage_type='mean'*, *weight_type='exp'*, *max_weight=20.0*, *n_critics=1*, *target_update_type='hard'*, *tau=0.005*, *target_update_interval=100*, *update_actor_interval=1*)

Bases: LearnableConfig

Config of Critic Reguralized Regression algorithm.

CRR is a simple offline RL method similar to AWAC.

The policy is trained as a supervised regression.

$$J(\phi) = \mathbb{E}_{s_t, a_t \sim D}[\log \pi_\phi(a_t|s_t) f(Q_\theta, \pi_\phi, s_t, a_t)]$$

where f is a filter function which has several options. The first option is binary function.

$$f := \mathbb{1}[A_\theta(s, a) > 0]$$

The other is exp function.

$$f := \exp(A(s, a)/\beta)$$

The $A(s, a)$ is an average function which also has several options. The first option is mean.

$$A(s, a) = Q_\theta(s, a) - \frac{1}{m} \sum_j^m Q(s, a_j)$$

The other one is `max`.

$$A(s, a) = Q_\theta(s, a) - \max_j^m Q(s, a_j)$$

where $a_j \sim \pi_\phi(s)$.

In evaluation, the action is determined by Critic Weighted Policy (CWP). In CWP, the several actions are sampled from the policy function, and the final action is re-sampled from the estimated action-value distribution.

References

- Wang et al., Critic Reguralized Regression.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **action_scaler** (*d3rlpy.preprocessing.ActionScaler*) – Action preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **actor_learning_rate** (*float*) – Learning rate for policy function.
- **critic_learning_rate** (*float*) – Learning rate for Q functions.
- **actor_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the actor.
- **critic_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the critic.
- **actor_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the actor.
- **critic_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the critic.
- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **beta** (*float*) – Temperature value defined as β above.
- **n_action_samples** (*int*) – Number of sampled actions to calculate $A(s, a)$ and for CWP.
- **advantage_type** (*str*) – Advantage function type. The available options are `['mean', 'max']`.
- **weight_type** (*str*) – Filter function type. The available options are `['binary', 'exp']`.
- **max_weight** (*float*) – Maximum weight for cross-entropy loss.
- **n_critics** (*int*) – Number of Q functions for ensemble.
- **target_update_type** (*str*) – Target update type. The available options are `['hard', 'soft']`.
- **tau** (*float*) – Target network synchronization coefficiency used with `soft` target update.

- **update_actor_interval** (*int*) – Interval to update policy function used with hard target update.
- **target_update_interval** (*int*) –

create(*device=False*)

Returns algorithm object.

Parameters
device (*Union[int, str, bool]*) – device option. If the value is boolean and True, cuda:0 will be used. If the value is integer, cuda:<device> will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
CRR

class d3rlpy.algos.**CRR**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[CRRImpl, *CRRConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

CQL

class d3rlpy.algos.**CQLConfig**(*batch_size=256*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *actor_learning_rate=0.0001*, *critic_learning_rate=0.0003*, *temp_learning_rate=0.0001*, *alpha_learning_rate=0.0001*, *actor_optim_factory=<factory>*, *critic_optim_factory=<factory>*, *temp_optim_factory=<factory>*, *alpha_optim_factory=<factory>*, *actor_encoder_factory=<factory>*, *critic_encoder_factory=<factory>*, *q_func_factory=<factory>*, *tau=0.005*, *n_critics=2*, *initial_temperature=1.0*, *initial_alpha=1.0*, *alpha_threshold=10.0*, *conservative_weight=5.0*, *n_action_samples=10*, *soft_q_backup=False*, *max_q_backup=False*)

Bases: LearnableConfig

Config of Conservative Q-Learning algorithm.

CQL is a SAC-based data-driven deep reinforcement learning algorithm, which achieves state-of-the-art performance in offline RL problems.

CQL mitigates overestimation error by minimizing action-values under the current policy and maximizing values under data distribution for underestimation issue.

$$L(\theta_i) = \alpha \, \mathbb{E}_{s_t \sim D} \left[\log \sum_a \exp Q_{\theta_i}(s_t, a) - \mathbb{E}_{a \sim D} \left[Q_{\theta_i}(s_t, a) \right] - \tau \right] + L_{\mathrm{SAC}}(\theta_i)$$

where α is an automatically adjustable value via Lagrangian dual gradient descent and τ is a threshold value. If the action-value difference is smaller than τ, the α will become smaller. Otherwise, the α will become larger to aggressively penalize action-values.

In continuous control, $\log \sum_a \exp Q(s, a)$ is computed as follows.

$$\log \sum_a \exp Q(s, a) \approx \log \left(\frac{1}{2N} \sum_{a_i \sim \text{Unif}(a)}^{N} \left[\frac{\exp Q(s, a_i)}{\text{Unif}(a)} \right] + \frac{1}{2N} \sum_{a_i \sim \pi_\phi(a|s)}^{N} \left[\frac{\exp Q(s, a_i)}{\pi_\phi(a_i|s)} \right] \right)$$

where N is the number of sampled actions.

The rest of optimization is exactly same as *d3rlpy.algos.SAC*.

References

- Kumar et al., Conservative Q-Learning for Offline Reinforcement Learning.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **action_scaler** (*d3rlpy.preprocessing.ActionScaler*) – Action preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **actor_learning_rate** (*float*) – Learning rate for policy function.
- **critic_learning_rate** (*float*) – Learning rate for Q functions.
- **temp_learning_rate** (*float*) – Learning rate for temperature parameter of SAC.
- **alpha_learning_rate** (*float*) – Learning rate for α.
- **actor_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the actor.
- **critic_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the critic.
- **temp_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the temperature.
- **alpha_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for α.
- **actor_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the actor.
- **critic_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the critic.
- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **tau** (*float*) – Target network synchronization coefficiency.
- **n_critics** (*int*) – Number of Q functions for ensemble.
- **initial_temperature** (*float*) – Initial temperature value.
- **initial_alpha** (*float*) – Initial α value.
- **alpha_threshold** (*float*) – Threshold value described as τ.

- **conservative_weight** (*float*) – Constant weight to scale conservative loss.
- **n_action_samples** (*int*) – Number of sampled actions to compute $\log \sum_a \exp Q(s, a)$.
- **soft_q_backup** (*bool*) – Flag to use SAC-style backup.
- **max_q_backup** (*bool*) – Flag to sample max Q-values for target.

create(*device=False*)

Returns algorithm object.

Parameters
device (*Union[int, str, bool]*) – device option. If the value is boolean and True, `cuda:0` will be used. If the value is integer, `cuda:<device>` will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
CQL

class d3rlpy.algos.**CQL**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[CQLImpl, *CQLConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

DiscreteCQL

class d3rlpy.algos.**DiscreteCQLConfig**(*batch_size=32*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *learning_rate=6.25e-05*, *optim_factory=<factory>*, *encoder_factory=<factory>*, *q_func_factory=<factory>*, *n_critics=1*, *target_update_interval=8000*, *alpha=1.0*)

Bases: LearnableConfig

Config of Discrete version of Conservative Q-Learning algorithm.

Discrete version of CQL is a DoubleDQN-based data-driven deep reinforcement learning algorithm (the original paper uses DQN), which achieves state-of-the-art performance in offline RL problems.

CQL mitigates overestimation error by minimizing action-values under the current policy and maximizing values under data distribution for underestimation issue.

$$L(\theta) = \alpha \mathbb{E}_{s_t \sim D}[\log \sum_a \exp Q_\theta(s_t, a) - \mathbb{E}_{a \sim D}[Q_\theta(s, a)]] + L_{DoubleDQN}(\theta)$$

References

- Kumar et al., Conservative Q-Learning for Offline Reinforcement Learning.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **learning_rate** (*float*) – Learning rate.
- **optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory.
- **encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory.
- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **n_critics** (*int*) – Number of Q functions for ensemble.
- **target_update_interval** (*int*) – Interval to synchronize the target network.
- **alpha** (*float*) – math:*alpha* value above.
- **action_scaler** (*Optional[ActionScaler]*) –

create(*device=False*)

Returns algorithm object.

Parameters

device (*Union[int, str, bool]*) – device option. If the value is boolean and True, cuda:0 will be used. If the value is integer, cuda:<device> will be used. If the value is string in torch device style, the specified device will be used.

Returns

algorithm object.

Return type

DiscreteCQL

class d3rlpy.algos.**DiscreteCQL**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[DiscreteCQLImpl, *DiscreteCQLConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns

action type.

Return type

ActionSpace

CalQL

class d3rlpy.algos.**CalQLConfig**(*batch_size=256*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *actor_learning_rate=0.0001*, *critic_learning_rate=0.0003*, *temp_learning_rate=0.0001*, *alpha_learning_rate=0.0001*, *actor_optim_factory=<factory>*, *critic_optim_factory=<factory>*, *temp_optim_factory=<factory>*, *alpha_optim_factory=<factory>*, *actor_encoder_factory=<factory>*, *critic_encoder_factory=<factory>*, *q_func_factory=<factory>*, *tau=0.005*, *n_critics=2*, *initial_temperature=1.0*, *initial_alpha=1.0*, *alpha_threshold=10.0*, *conservative_weight=5.0*, *n_action_samples=10*, *soft_q_backup=False*, *max_q_backup=False*)

Bases: *CQLConfig*

Config of Calibrated Q-Learning algorithm.

Cal-QL is an extension to CQL to mitigate issues in offline-to-online fine-tuning.

The CQL regularizer is modified as follows:

$$\mathbb{E}_{s\sim D,a\sim\pi}[\max(Q(s,a),V(s))] - \mathbb{E}_{s,a\sim D}[Q(s,a)]$$

References

- Mitsuhiko et al., Cal-QL: Calibrated Offline RL Pre-Training for Efficient Online Fine-Tuning.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **action_scaler** (*d3rlpy.preprocessing.ActionScaler*) – Action preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **actor_learning_rate** (*float*) – Learning rate for policy function.
- **critic_learning_rate** (*float*) – Learning rate for Q functions.
- **temp_learning_rate** (*float*) – Learning rate for temperature parameter of SAC.
- **alpha_learning_rate** (*float*) – Learning rate for α.
- **actor_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the actor.
- **critic_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the critic.
- **temp_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the temperature.
- **alpha_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for α.
- **actor_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the actor.
- **critic_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the critic.

- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **tau** (*float*) – Target network synchronization coefficiency.
- **n_critics** (*int*) – Number of Q functions for ensemble.
- **initial_temperature** (*float*) – Initial temperature value.
- **initial_alpha** (*float*) – Initial α value.
- **alpha_threshold** (*float*) – Threshold value described as τ.
- **conservative_weight** (*float*) – Constant weight to scale conservative loss.
- **n_action_samples** (*int*) – Number of sampled actions to compute $\log \sum_a \exp Q(s, a)$.
- **soft_q_backup** (*bool*) – Flag to use SAC-style backup.
- **max_q_backup** (*bool*) – Flag to sample max Q-values for target.

create(*device=False*)

Returns algorithm object.

Parameters
device (*Union[int, str, bool]*) – device option. If the value is boolean and True, `cuda:0` will be used. If the value is integer, `cuda:<device>` will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
CalQL

class d3rlpy.algos.**CalQL**(*config*, *device*, *impl=None*)

Bases: *CQL*

AWAC

class d3rlpy.algos.**AWACConfig**(*batch_size=1024*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *actor_learning_rate=0.0003*, *critic_learning_rate=0.0003*, *actor_optim_factory=<factory>*, *critic_optim_factory=<factory>*, *actor_encoder_factory=<factory>*, *critic_encoder_factory=<factory>*, *q_func_factory=<factory>*, *tau=0.005*, *lam=1.0*, *n_action_samples=1*, *n_critics=2*)

Bases: `LearnableConfig`

Config of Advantage Weighted Actor-Critic algorithm.

AWAC is a TD3-based actor-critic algorithm that enables efficient fine-tuning where the policy is trained with offline datasets and is deployed to online training.

The policy is trained as a supervised regression.

$$J(\phi) = \mathbb{E}_{s_t, a_t \sim D}[\log \pi_\phi(a_t|s_t) \exp(\frac{1}{\lambda} A^\pi(s_t, a_t))]$$

where $A^\pi(s_t, a_t) = Q_\theta(s_t, a_t) - Q_\theta(s_t, a'_t)$ and $a'_t \sim \pi_\phi(\cdot|s_t)$

The key difference from AWR is that AWAC uses Q-function trained via TD learning for the better sample-efficiency.

References

- Nair et al., Accelerating Online Reinforcement Learning with Offline Datasets.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **action_scaler** (*d3rlpy.preprocessing.ActionScaler*) – Action preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **actor_learning_rate** (*float*) – Learning rate for policy function.
- **critic_learning_rate** (*float*) – Learning rate for Q functions.
- **actor_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the actor.
- **critic_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the critic.
- **actor_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the actor.
- **critic_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the critic.
- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **tau** (*float*) – Target network synchronization coefficiency.
- **lam** (*float*) – λ for weight calculation.
- **n_action_samples** (*int*) – Number of sampled actions to calculate $A^\pi(s_t, a_t)$.
- **n_critics** (*int*) – Number of Q functions for ensemble.

create(*device=False*)

Returns algorithm object.

Parameters

device (*Union[int, str, bool]*) – device option. If the value is boolean and True, cuda:0 will be used. If the value is integer, cuda:<device> will be used. If the value is string in torch device style, the specified device will be used.

Returns

algorithm object.

Return type

AWAC

class d3rlpy.algos.**AWAC**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[AWACImpl, *AWACConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

PLAS

class d3rlpy.algos.**PLASConfig**(*batch_size=100*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *actor_learning_rate=0.0001*, *critic_learning_rate=0.001*, *imitator_learning_rate=0.0001*, *actor_optim_factory=<factory>*, *critic_optim_factory=<factory>*, *imitator_optim_factory=<factory>*, *actor_encoder_factory=<factory>*, *critic_encoder_factory=<factory>*, *imitator_encoder_factory=<factory>*, *q_func_factory=<factory>*, *tau=0.005*, *n_critics=2*, *lam=0.75*, *warmup_steps=500000*, *beta=0.5*)

Bases: LearnableConfig

Config of Policy in Latent Action Space algorithm.

PLAS is an offline deep reinforcement learning algorithm whose policy function is trained in latent space of Conditional VAE. Unlike other algorithms, PLAS can achieve good performance by using its less constrained policy function.

$$a \sim p_\beta(a|s, z = \pi_\phi(s))$$

where β is a parameter of the decoder in Conditional VAE.

References

- Zhou et al., PLAS: latent action space for offline reinforcement learning.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **action_scaler** (*d3rlpy.preprocessing.ActionScaler*) – Action preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **actor_learning_rate** (*float*) – Learning rate for policy function.
- **critic_learning_rate** (*float*) – Learning rate for Q functions.
- **imitator_learning_rate** (*float*) – Learning rate for Conditional VAE.
- **actor_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the actor.
- **critic_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the critic.

- **imitator_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the conditional VAE.
- **actor_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the actor.
- **critic_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the critic.
- **imitator_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the conditional VAE.
- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **tau** (*float*) – Target network synchronization coefficiency.
- **n_critics** (*int*) – Number of Q functions for ensemble.
- **lam** (*float*) – Weight factor for critic ensemble.
- **warmup_steps** (*int*) – Number of steps to warmup the VAE.
- **beta** (*float*) – KL reguralization term for Conditional VAE.

create(*device=False*)

Returns algorithm object.

Parameters
device (*Union[int, str, bool]*) – device option. If the value is boolean and True, cuda:0 will be used. If the value is integer, cuda:<device> will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
PLAS

class d3rlpy.algos.**PLAS**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[PLASImpl, *PLASConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

PLAS+P

class d3rlpy.algos.**PLASWithPerturbationConfig**(*batch_size=100*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *actor_learning_rate=0.0001*, *critic_learning_rate=0.001*, *imitator_learning_rate=0.0001*, *actor_optim_factory=<factory>*, *critic_optim_factory=<factory>*, *imitator_optim_factory=<factory>*, *actor_encoder_factory=<factory>*, *critic_encoder_factory=<factory>*, *imitator_encoder_factory=<factory>*, *q_func_factory=<factory>*, *tau=0.005*, *n_critics=2*, *lam=0.75*, *warmup_steps=500000*, *beta=0.5*, *action_flexibility=0.05*)

Bases: *PLASConfig*

Config of Policy in Latent Action Space algorithm with perturbation layer.

PLAS with perturbation layer enables PLAS to output out-of-distribution action.

References

- Zhou et al., PLAS: latent action space for offline reinforcement learning.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **action_scaler** (*d3rlpy.preprocessing.ActionScaler*) – Action preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **actor_learning_rate** (*float*) – Learning rate for policy function.
- **critic_learning_rate** (*float*) – Learning rate for Q functions.
- **imitator_learning_rate** (*float*) – Learning rate for Conditional VAE.
- **actor_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the actor.
- **critic_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the critic.
- **imitator_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the conditional VAE.
- **actor_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the actor.
- **critic_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the critic.
- **imitator_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the conditional VAE.

- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **tau** (*float*) – Target network synchronization coefficiency.
- **n_critics** (*int*) – Number of Q functions for ensemble.
- **update_actor_interval** (*int*) – Interval to update policy function.
- **lam** (*float*) – Weight factor for critic ensemble.
- **action_flexibility** (*float*) – Output scale of perturbation layer.
- **warmup_steps** (*int*) – Number of steps to warmup the VAE.
- **beta** (*float*) – KL reguralization term for Conditional VAE.

create(*device=False*)

Returns algorithm object.

Parameters
device (*Union[int, str, bool]*) – device option. If the value is boolean and True, `cuda:0` will be used. If the value is integer, `cuda:<device>` will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
PLASWithPerturbation

class d3rlpy.algos.**PLASWithPerturbation**(*config*, *device*, *impl=None*)

Bases: *PLAS*

TD3+BC

class d3rlpy.algos.**TD3PlusBCConfig**(*batch_size=256*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *actor_learning_rate=0.0003*, *critic_learning_rate=0.0003*, *actor_optim_factory=<factory>*, *critic_optim_factory=<factory>*, *actor_encoder_factory=<factory>*, *critic_encoder_factory=<factory>*, *q_func_factory=<factory>*, *tau=0.005*, *n_critics=2*, *target_smoothing_sigma=0.2*, *target_smoothing_clip=0.5*, *alpha=2.5*, *update_actor_interval=2*)

Bases: `LearnableConfig`

Config of TD3+BC algorithm.

TD3+BC is an simple offline RL algorithm built on top of TD3. TD3+BC introduces BC-reguralized policy objective function.

$$J(\phi) = \mathbb{E}_{s,a \sim D}[\lambda Q(s, \pi(s)) - (a - \pi(s))^2]$$

where

$$\lambda = \frac{\alpha}{\frac{1}{N} \sum_{(} s_i, a_i) |Q(s_i, a_i)|}$$

References

- Fujimoto et al., A Minimalist Approach to Offline Reinforcement Learning.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **action_scaler** (*d3rlpy.preprocessing.ActionScaler*) – Action preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **actor_learning_rate** (*float*) – Learning rate for a policy function.
- **critic_learning_rate** (*float*) – Learning rate for Q functions.
- **actor_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the actor.
- **critic_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the critic.
- **actor_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the actor.
- **critic_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the critic.
- **q_func_factory** (*d3rlpy.models.q_functions.QFunctionFactory*) – Q function factory.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **tau** (*float*) – Target network synchronization coefficiency.
- **n_critics** (*int*) – Number of Q functions for ensemble.
- **target_smoothing_sigma** (*float*) – Standard deviation for target noise.
- **target_smoothing_clip** (*float*) – Clipping range for target noise.
- **alpha** (*float*) – α value.
- **update_actor_interval** (*int*) – Interval to update policy function described as *delayed policy update* in the paper.

create(*device=False*)

Returns algorithm object.

Parameters

device (*Union[int, str, bool]*) – device option. If the value is boolean and True, `cuda:0` will be used. If the value is integer, `cuda:<device>` will be used. If the value is string in torch device style, the specified device will be used.

Returns

algorithm object.

Return type

TD3PlusBC

class d3rlpy.algos.**TD3PlusBC**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[TD3PlusBCImpl, *TD3PlusBCConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

IQL

class d3rlpy.algos.**IQLConfig**(*batch_size=256*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *actor_learning_rate=0.0003*, *critic_learning_rate=0.0003*, *actor_optim_factory=<factory>*, *critic_optim_factory=<factory>*, *actor_encoder_factory=<factory>*, *critic_encoder_factory=<factory>*, *value_encoder_factory=<factory>*, *tau=0.005*, *n_critics=2*, *expectile=0.7*, *weight_temp=3.0*, *max_weight=100.0*)

Bases: LearnableConfig

Implicit Q-Learning algorithm.

IQL is the offline RL algorithm that avoids ever querying values of unseen actions while still being able to perform multi-step dynamic programming updates.

There are three functions to train in IQL. First the state-value function is trained via expectile regression.

$$L_V(\psi) = \mathbb{E}_{(s,a)\sim D}[L_2^\tau(Q_\theta(s,a) - V_\psi(s))]$$

where $L_2^\tau(u) = |\tau - \mathbb{1}(u < 0)|u^2$.

The Q-function is trained with the state-value function to avoid query the actions.

$$L_Q(\theta) = \mathbb{E}_{(s,a,r,s')\sim D}[(r + \gamma V_\psi(s') - Q_\theta(s,a))^2]$$

Finally, the policy function is trained by using advantage weighted regression.

$$L_\pi(\phi) = \mathbb{E}_{(s,a)\sim D}[\exp(\beta(Q_\theta - V_\psi(s)))\log \pi_\phi(a|s)]$$

References

- Kostrikov et al., Offline Reinforcement Learning with Implicit Q-Learning.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **action_scaler** (*d3rlpy.preprocessing.ActionScaler*) – Action preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **actor_learning_rate** (*float*) – Learning rate for policy function.
- **critic_learning_rate** (*float*) – Learning rate for Q functions.

- **actor_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the actor.
- **critic_optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory for the critic.
- **actor_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the actor.
- **critic_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the critic.
- **value_encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory for the value function.
- **batch_size** (*int*) – Mini-batch size.
- **gamma** (*float*) – Discount factor.
- **tau** (*float*) – Target network synchronization coefficiency.
- **n_critics** (*int*) – Number of Q functions for ensemble.
- **expectile** (*float*) – Expectile value for value function training.
- **weight_temp** (*float*) – Inverse temperature value represented as β.
- **max_weight** (*float*) – Maximum advantage weight value to clip.

create(*device=False*)

Returns algorithm object.

Parameters
device (*Union[int, str, bool]*) – device option. If the value is boolean and True, cuda:0 will be used. If the value is integer, cuda:<device> will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
IQL

class d3rlpy.algos.**IQL**(*config*, *device*, *impl=None*)

Bases: *QLearningAlgoBase*[IQLImpl, *IQLConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

RandomPolicy

class d3rlpy.algos.**RandomPolicyConfig**(*batch_size=256*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *distribution='uniform'*, *normal_std=1.0*)

Bases: `LearnableConfig`

Random Policy for continuous control algorithm.

This is designed for data collection and lightweight interaction tests. `fit` and `fit_online` methods will raise exceptions.

Parameters

- **action_scaler** (*d3rlpy.preprocessing.ActionScaler*) – Action preprocessor.
- **distribution** (*str*) – Random distribution. Available options are `['uniform', 'normal']`.
- **normal_std** (*float*) – Standard deviation of the normal distribution. This is only used when `distribution='normal'`.
- **batch_size** (*int*) –
- **gamma** (*float*) –
- **observation_scaler** (*Optional[ObservationScaler]*) –
- **reward_scaler** (*Optional[RewardScaler]*) –

create(*device=False*)

Returns algorithm object.

Parameters

device (*Union[int, str, bool]*) – device option. If the value is boolean and True, `cuda:0` will be used. If the value is integer, `cuda:<device>` will be used. If the value is string in torch device style, the specified device will be used.

Returns

algorithm object.

Return type

RandomPolicy

class d3rlpy.algos.**RandomPolicy**(*config*)

Bases: *QLearningAlgoBase*[None, *RandomPolicyConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns

action type.

Return type

ActionSpace

predict(*x*)

Returns greedy actions.

```
# 100 observations with shape of (10,)
x = np.random.random((100, 10))

actions = algo.predict(x)
# actions.shape == (100, action size) for continuous control
# actions.shape == (100,) for discrete control
```

Parameters
x (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observations

Returns
Greedy actions

Return type
ndarray[*Any*, *dtype*[*Any*]]

predict_value(*x*, *action*)

Returns predicted action-values.

```
# 100 observations with shape of (10,)
x = np.random.random((100, 10))

# for continuous control
# 100 actions with shape of (2,)
actions = np.random.random((100, 2))

# for discrete control
# 100 actions in integer values
actions = np.random.randint(2, size=100)

values = algo.predict_value(x, actions)
# values.shape == (100,)
```

Parameters

- **x** (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observations
- **action** (*ndarray[Any, dtype[Any]]*) – Actions

Returns
Predicted action-values

Return type
ndarray[*Any*, *dtype*[*Any*]]

sample_action(*x*)

Returns sampled actions.

The sampled actions are identical to the output of *predict* method if the policy is deterministic.

Parameters
x (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observations.

Returns
Sampled actions.

Return type
ndarray[*Any*, *dtype*[*Any*]]

DiscreteRandomPolicy

class d3rlpy.algos.**DiscreteRandomPolicyConfig**(*batch_size=256*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*)

Bases: `LearnableConfig`

Random Policy for discrete control algorithm.

This is designed for data collection and lightweight interaction tests. `fit` and `fit_online` methods will raise exceptions.

Parameters

- **batch_size** (*int*) –
- **gamma** (*float*) –
- **observation_scaler** (*Optional[ObservationScaler]*) –
- **action_scaler** (*Optional[ActionScaler]*) –
- **reward_scaler** (*Optional[RewardScaler]*) –

create(*device=False*)

Returns algorithm object.

Parameters
device (*Union[int, str, bool]*) – device option. If the value is boolean and True, `cuda:0` will be used. If the value is integer, `cuda:<device>` will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
DiscreteRandomPolicy

class d3rlpy.algos.**DiscreteRandomPolicy**(*config*)

Bases: *QLearningAlgoBase*[`None`, *DiscreteRandomPolicyConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

predict(*x*)

Returns greedy actions.

```
# 100 observations with shape of (10,)
x = np.random.random((100, 10))

actions = algo.predict(x)
# actions.shape == (100, action size) for continuous control
# actions.shape == (100,) for discrete control
```

Parameters
x (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observations

Returns
Greedy actions

Return type
ndarray[*Any*, *dtype*[*Any*]]

predict_value(*x*, *action*)

Returns predicted action-values.

```
# 100 observations with shape of (10,)
x = np.random.random((100, 10))

# for continuous control
# 100 actions with shape of (2,)
actions = np.random.random((100, 2))

# for discrete control
# 100 actions in integer values
actions = np.random.randint(2, size=100)

values = algo.predict_value(x, actions)
# values.shape == (100,)
```

Parameters

- **x** (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observations
- **action** (*ndarray[Any, dtype[Any]]*) – Actions

Returns
Predicted action-values

Return type
ndarray[*Any*, *dtype*[*Any*]]

sample_action(*x*)

Returns sampled actions.

The sampled actions are identical to the output of *predict* method if the policy is deterministic.

Parameters
x (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observations.

Returns
Sampled actions.

Return type
ndarray[*Any*, *dtype*[*Any*]]

4.1.3 Decision Transformer

Decision Transformer-based algorithms usually require tricky interaction codes for evaluation. In d3rlpy, those algorithms provide `as_stateful_wrapper` method to easily integrate the algorithm into your system.

```
import d3rlpy

dataset, env = d3rlpy.datasets.get_pendulum()

dt = d3rlpy.algos.DecisionTransformerConfig().create(device="cuda:0")

# offline training
dt.fit(
   dataset,
   n_steps=100000,
   n_steps_per_epoch=1000,
   eval_env=env,
   eval_target_return=0,  # specify target environment return
)

# wrap as stateful actor for interaction
actor = dt.as_stateful_wrapper(target_return=0)

# interaction
observation, reward = env.reset(), 0.0
while True:
    action = actor.predict(observation, reward)
    observation, reward, done, truncated, _ = env.step(action)
    if done or truncated:
        break

# reset history
actor.reset()
```

TransformerAlgoBase

class d3rlpy.algos.**TransformerAlgoBase**(*config*, *device*, *impl=None*)

Bases: Generic[TTransformerImpl, TTransformerConfig], *LearnableBase*[TTransformerImpl, TTransformerConfig]

as_stateful_wrapper(*target_return*, *action_sampler=None*)

Returns a wrapped Transformer algorithm for stateful decision making.

Parameters

- **target_return** (*float*) – Target environment return.
- **action_sampler** (*Optional[TransformerActionSampler]*) – Action sampler.

Returns
StatefulTransformerWrapper object.

Return type
StatefulTransformerWrapper[*TTransformerImpl*, *TTransformerConfig*]

fit(*dataset*, *n_steps*, *n_steps_per_epoch=10000*, *experiment_name=None*, *with_timestamp=True*, *logger_adapter=<d3rlpy.logging.file_adapter.FileAdapterFactory object>*, *show_progress=True*, *eval_env=None*, *eval_target_return=None*, *eval_action_sampler=None*, *save_interval=1*, *callback=None*, *enable_ddp=False*)

Trains with given dataset.

Parameters

- **dataset** (ReplayBuffer) – Offline dataset to train.
- **n_steps** (*int*) – Number of steps to train.
- **n_steps_per_epoch** (*int*) – Number of steps per epoch. This value will be ignored when `n_steps` is `None`.
- **experiment_name** (*Optional[str]*) – Experiment name for logging. If not passed, the directory name will be *{class name}_{timestamp}*.
- **with_timestamp** (*bool*) – Flag to add timestamp string to the last of directory name.
- **logger_adapter** (LoggerAdapterFactory) – LoggerAdapterFactory object.
- **show_progress** (*bool*) – Flag to show progress bar for iterations.
- **eval_env** (*Optional[Union[Env[Any, Any], Env[Any, Any]]]*) – Evaluation environment.
- **eval_target_return** (*Optional[float]*) – Evaluation return target.
- **eval_action_sampler** (*Optional[TransformerActionSampler]*) – Action sampler used in evaluation.
- **save_interval** (*int*) – Interval to save parameters.
- **callback** (*Optional[Callable[[Self, int, int], None]]*) – Callable function that takes `(algo, epoch, total_step)` , which is called every step.
- **enable_ddp** (*bool*) – Flag to wrap models with DataDistributedParallel.

Return type
None

predict(*inpt*)

Returns action.

This is for internal use. For evaluation, use `StatefulTransformerWrapper` instead.

Parameters
inpt (*TransformerInput*) – Sequence input.

Returns
Action.

Return type
ndarray[*Any*, *dtype*[*Any*]]

save_policy(*fname*)

Save the greedy-policy computational graph as TorchScript or ONNX.

The format will be automatically detected by the file name.

```
# save as TorchScript
algo.save_policy('policy.pt')

# save as ONNX
algo.save_policy('policy.onnx')
```

The artifacts saved with this method will work without d3rlpy. This method is especially useful to deploy the learned policy to production environments or embedding systems.

See also

- https://pytorch.org/tutorials/beginner/Intro_to_TorchScript_tutorial.html (for Python).
- https://pytorch.org/tutorials/advanced/cpp_export.html (for C++).
- https://onnx.ai (for ONNX)

Visit https://d3rlpy.readthedocs.io/en/stable/tutorials/after_training_policies.html#export-policies-as-torchscript for the further usage.

Parameters
fname (*str*) – Destination file path.

Return type
None

update(*batch*)

Update parameters with mini-batch of data.

Parameters
batch (*TrajectoryMiniBatch*) – Mini-batch data.

Returns
Dictionary of metrics.

Return type
Dict[str, float]

DecisionTransformer

class d3rlpy.algos.**DecisionTransformerConfig**(*batch_size=64*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *context_size=20*, *max_timestep=1000*, *learning_rate=0.0001*, *encoder_factory=<factory>*, *optim_factory=<factory>*, *num_heads=1*, *num_layers=3*, *attn_dropout=0.1*, *resid_dropout=0.1*, *embed_dropout=0.1*, *activation_type='relu'*, *position_encoding_type=PositionEncodingType.SIMPLE*, *warmup_steps=10000*, *clip_grad_norm=0.25*, *compile=False*)

Bases: TransformerConfig

Config of Decision Transformer.

Decision Transformer solves decision-making problems as a sequence modeling problem.

References

- Chen at el., Decision Transformer: Reinforcement Learning via Sequence Modeling.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **action_scaler** (*d3rlpy.preprocessing.ActionScaler*) – Action preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **context_size** (*int*) – Prior sequence length.
- **max_timestep** (*int*) – Maximum environmental timestep.
- **batch_size** (*int*) – Mini-batch size.
- **learning_rate** (*float*) – Learning rate.
- **encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory.
- **optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory.
- **num_heads** (*int*) – Number of attention heads.
- **num_layers** (*int*) – Number of attention blocks.
- **attn_dropout** (*float*) – Dropout probability for attentions.
- **resid_dropout** (*float*) – Dropout probability for residual connection.
- **embed_dropout** (*float*) – Dropout probability for embeddings.
- **activation_type** (*str*) – Type of activation function.
- **position_encoding_type** (*d3rlpy.PositionEncodingType*) – Type of positional encoding (SIMPLE or GLOBAL).
- **warmup_steps** (*int*) – Warmup steps for learning rate scheduler.
- **clip_grad_norm** (*float*) – Norm of gradient clipping.
- **compile** (*bool*) – (experimental) Flag to enable JIT compilation.
- **gamma** (*float*) –

create(*device=False*)

Returns algorithm object.

Parameters

device (*Union[int, str, bool]*) – device option. If the value is boolean and True, cuda:0 will be used. If the value is integer, cuda:<device> will be used. If the value is string in torch device style, the specified device will be used.

Returns

algorithm object.

Return type

DecisionTransformer

class d3rlpy.algos.**DecisionTransformer**(*config*, *device*, *impl=None*)

Bases: *TransformerAlgoBase*[DecisionTransformerImpl, *DecisionTransformerConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

DiscreteDecisionTransformer

class d3rlpy.algos.**DiscreteDecisionTransformerConfig**(*batch_size=128*, *gamma=0.99*, *observation_scaler=None*, *action_scaler=None*, *reward_scaler=None*, *context_size=20*, *max_timestep=1000*, *learning_rate=0.0006*, *encoder_factory=<factory>*, *optim_factory=<factory>*, *num_heads=8*, *num_layers=6*, *attn_dropout=0.1*, *resid_dropout=0.1*, *embed_dropout=0.1*, *activation_type='gelu'*, *embed_activation_type='tanh'*, *position_encoding_type=PositionEncodingType.GLOBAL*, *warmup_tokens=10240*, *final_tokens=30000000*, *clip_grad_norm=1.0*, *compile=False*)

Bases: TransformerConfig

Config of Decision Transformer for discrte action-space.

Decision Transformer solves decision-making problems as a sequence modeling problem.

References

- Chen at el., Decision Transformer: Reinforcement Learning via Sequence Modeling.

Parameters

- **observation_scaler** (*d3rlpy.preprocessing.ObservationScaler*) – Observation preprocessor.
- **reward_scaler** (*d3rlpy.preprocessing.RewardScaler*) – Reward preprocessor.
- **context_size** (*int*) – Prior sequence length.
- **max_timestep** (*int*) – Maximum environmental timestep.
- **batch_size** (*int*) – Mini-batch size.
- **learning_rate** (*float*) – Learning rate.
- **encoder_factory** (*d3rlpy.models.encoders.EncoderFactory*) – Encoder factory.
- **optim_factory** (d3rlpy.models.optimizers.OptimizerFactory) – Optimizer factory.
- **num_heads** (*int*) – Number of attention heads.
- **num_layers** (*int*) – Number of attention blocks.

- **attn_dropout** (*float*) – Dropout probability for attentions.
- **resid_dropout** (*float*) – Dropout probability for residual connection.
- **embed_dropout** (*float*) – Dropout probability for embeddings.
- **activation_type** (*str*) – Type of activation function.
- **embed_activation_type** (*str*) – Type of activation function applied to embeddings.
- **position_encoding_type** (*d3rlpy.PositionEncodingType*) – Type of positional encoding (SIMPLE or GLOBAL).
- **warmup_tokens** (*int*) – Number of tokens to warmup learning rate scheduler.
- **final_tokens** (*int*) – Final number of tokens for learning rate scheduler.
- **clip_grad_norm** (*float*) – Norm of gradient clipping.
- **compile** (*bool*) – (experimental) Flag to enable JIT compilation.
- **gamma** (*float*) –
- **action_scaler** (*Optional[ActionScaler]*) –

create(*device=False*)

Returns algorithm object.

Parameters
device (*Union[int, str, bool]*) – device option. If the value is boolean and True, cuda:0 will be used. If the value is integer, cuda:<device> will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
DiscreteDecisionTransformer

class d3rlpy.algos.**DiscreteDecisionTransformer**(*config*, *device*, *impl=None*)

Bases: *TransformerAlgoBase*[DiscreteDecisionTransformerImpl, *DiscreteDecisionTransformerConfig*]

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

TransformerActionSampler

TransformerActionSampler is an interface to sample actions from DecisionTransformer outputs. Basically, the default action-sampler will be used if you don't explicitly specify one.

```
import d3rlpy

dataset, env = d3rlpy.datasets.get_pendulum()

dt = d3rlpy.algos.DecisionTransformerConfig().create(device="cuda:0")

# offline training
dt.fit(
   dataset,
   n_steps=100000,
   n_steps_per_epoch=1000,
   eval_env=env,
   eval_target_return=0,
   # manually specify action-sampler
   eval_action_sampler=d3rlpy.algos.IdentityTransformerActionSampler(),
)

# wrap as stateful actor for interaction with manually specified action-sampler
actor = dt.as_stateful_wrapper(
    target_return=0,
    action_sampler=d3rlpy.algos.IdentityTransformerActionSampler(),
)
```

d3rlpy.algos.TransformerActionSampler	Interface of TransformerActionSampler.
d3rlpy.algos.SoftmaxTransformerActionSampler	Softmax action-sampler.
d3rlpy.algos.GreedyTransformerActionSampler	Greedy action-sampler.

d3rlpy.algos.TransformerActionSampler

class d3rlpy.algos.**TransformerActionSampler**(**args*, ***kwargs*)

Interface of TransformerActionSampler.

Methods

__call__(*transformer_output*)

Returns sampled action from Transformer output.

Parameters

transformer_output (*ndarray[Any, dtype[Any]]*) – Output of Transformer algorithms.

Returns

Sampled action.

Return type

Union[*ndarray*[*Any*, *dtype*[*Any*]], int]

d3rlpy.algos.SoftmaxTransformerActionSampler

class d3rlpy.algos.**SoftmaxTransformerActionSampler**(*temperature=1.0*)

Softmax action-sampler.

This class implements softmax function to sample action from discrete probability distribution.

Parameters
temperature (*int*) – Softmax temperature.

Methods

__call__(*transformer_output*)

Returns sampled action from Transformer output.

Parameters
transformer_output (*ndarray[Any, dtype[Any]]*) – Output of Transformer algorithms.

Returns
Sampled action.

Return type
Union[*ndarray*[*Any*, *dtype*[*Any*]], int]

d3rlpy.algos.GreedyTransformerActionSampler

class d3rlpy.algos.**GreedyTransformerActionSampler**(**args*, ***kwargs*)

Greedy action-sampler.

This class implements greedy function to determine action from discrte probability distribution.

Methods

__call__(*transformer_output*)

Returns sampled action from Transformer output.

Parameters
transformer_output (*ndarray[Any, dtype[Any]]*) – Output of Transformer algorithms.

Returns
Sampled action.

Return type
Union[*ndarray*[*Any*, *dtype*[*Any*]], int]

4.2 Q Functions

d3rlpy provides various Q functions including state-of-the-arts, which are internally used in algorithm objects. You can switch Q functions by passing `q_func_factory` argument at algorithm initialization.

```
import d3rlpy

cql = d3rlpy.algos.CQLConfig(q_func_factory=d3rlpy.models.QRQFunctionFactory())
```

Also you can change hyper parameters.

```
q_func = d3rlpy.models.QRQFunctionFactory(n_quantiles=32)

cql = d3rlpy.algos.CQLConfig(q_func_factory=q_func).create()
```

The default Q function is `mean` approximator, which estimates expected scalar action-values. However, in recent advancements of deep reinforcement learning, the new type of action-value approximators has been proposed, which is called *distributional* Q functions.

Unlike the `mean` approximator, the *distributional* Q functions estimate distribution of action-values. This *distributional* approaches have shown consistently much stronger performance than the `mean` approximator.

Here is a list of available Q functions in the order of performance ascendingly. Currently, as a trade-off between performance and computational complexity, the higher performance requires the more expensive computational costs.

d3rlpy.models.MeanQFunctionFactory	Standard Q function factory class.
d3rlpy.models.QRQFunctionFactory	Quantile Regression Q function factory class.
d3rlpy.models.IQNQFunctionFactory	Implicit Quantile Network Q function factory class.

4.2.1 d3rlpy.models.MeanQFunctionFactory

class d3rlpy.models.**MeanQFunctionFactory**(*share_encoder=False*)

Standard Q function factory class.

This is the standard Q function factory class.

References

- Mnih et al., Human-level control through deep reinforcement learning.
- Lillicrap et al., Continuous control with deep reinforcement learning.

Parameters

share_encoder (*bool*) – flag to share encoder over multiple Q functions.

Methods

create_continuous(*encoder*, *hidden_size*)

Returns PyTorch's Q function module.

Parameters

- **encoder** (*EncoderWithAction*) – Encoder module that processes the observation and action to obtain feature representations.
- **hidden_size** (*int*) – Dimension of encoder output.

Returns
Tuple of continuous Q function and its forwarder.

Return type
Tuple[*ContinuousMeanQFunction*, *ContinuousMeanQFunctionForwarder*]

create_discrete(*encoder*, *hidden_size*, *action_size*)

Returns PyTorch's Q function module.

Parameters

- **encoder** (*Encoder*) – Encoder that processes the observation to obtain feature representations.
- **hidden_size** (*int*) – Dimension of encoder output.
- **action_size** (*int*) – Dimension of discrete action-space.

Returns
Tuple of discrete Q function and its forwarder.

Return type
Tuple[*DiscreteMeanQFunction*, *DiscreteMeanQFunctionForwarder*]

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

static get_type()

Returns Q function type.

Returns
Q function type.

Return type
str

classmethod schema(***, *infer_missing=False*, *only=None*, *exclude=()*, *many=False*, *context=None*, *load_only=()*, *dump_only=()*, *partial=False*, *unknown=None*)

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

serialize()

Return type
str

serialize_to_dict()

Return type
Dict[str, *Any*]

to_dict(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(***, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –

- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

Attributes

share_encoder: bool = False

4.2.2 d3rlpy.models.QRQFunctionFactory

class d3rlpy.models.**QRQFunctionFactory**(*share_encoder=False*, *n_quantiles=32*)

Quantile Regression Q function factory class.

References

- Dabney et al., Distributional reinforcement learning with quantile regression.

Parameters

- **share_encoder** (*bool*) – flag to share encoder over multiple Q functions.
- **n_quantiles** (*int*) – the number of quantiles.

Methods

create_continuous(*encoder*, *hidden_size*)

Returns PyTorch's Q function module.

Parameters

- **encoder** (*EncoderWithAction*) – Encoder module that processes the observation and action to obtain feature representations.
- **hidden_size** (*int*) – Dimension of encoder output.

Returns
Tuple of continuous Q function and its forwarder.

Return type
Tuple[*ContinuousQRQFunction*, *ContinuousQRQFunctionForwarder*]

create_discrete(*encoder*, *hidden_size*, *action_size*)

Returns PyTorch's Q function module.

Parameters

- **encoder** (*Encoder*) – Encoder that processes the observation to obtain feature representations.
- **hidden_size** (*int*) – Dimension of encoder output.
- **action_size** (*int*) – Dimension of discrete action-space.

Returns
Tuple of discrete Q function and its forwarder.

Return type
Tuple[*DiscreteQRQFunction*, *DiscreteQRQFunctionForwarder*]

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

static get_type()
Returns Q function type.

Returns
Q function type.

Return type
str

classmethod schema(***, *infer_missing=False*, *only=None*, *exclude=()*, *many=False*, *context=None*, *load_only=()*, *dump_only=()*, *partial=False*, *unknown=None*)

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –

- **partial** (*bool*) –

Return type
SchemaF[*A*]

serialize()

Return type
str

serialize_to_dict()

Return type
Dict[str, *Any*]

to_dict(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(*, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

Attributes

n_quantiles: int = 32

share_encoder: bool = False

4.2.3 d3rlpy.models.IQNQFunctionFactory

class d3rlpy.models.**IQNQFunctionFactory**(*share_encoder=False*, *n_quantiles=64*, *n_greedy_quantiles=32*, *embed_size=64*)

Implicit Quantile Network Q function factory class.

References

- Dabney et al., Implicit quantile networks for distributional reinforcement learning.

Parameters

- **share_encoder** (*bool*) – flag to share encoder over multiple Q functions.
- **n_quantiles** (*int*) – the number of quantiles.
- **n_greedy_quantiles** (*int*) – the number of quantiles for inference.
- **embed_size** (*int*) – the embedding size.

Methods

create_continuous(*encoder*, *hidden_size*)

Returns PyTorch's Q function module.

Parameters

- **encoder** (*EncoderWithAction*) – Encoder module that processes the observation and action to obtain feature representations.
- **hidden_size** (*int*) – Dimension of encoder output.

Returns
Tuple of continuous Q function and its forwarder.

Return type
Tuple[*ContinuousIQNQFunction*, *ContinuousIQNQFunctionForwarder*]

create_discrete(*encoder*, *hidden_size*, *action_size*)

Returns PyTorch's Q function module.

Parameters

- **encoder** (*Encoder*) – Encoder that processes the observation to obtain feature representations.
- **hidden_size** (*int*) – Dimension of encoder output.
- **action_size** (*int*) – Dimension of discrete action-space.

Returns
Tuple of discrete Q function and its forwarder.

Return type
Tuple[*DiscreteIQNQFunction*, *DiscreteIQNQFunctionForwarder*]

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

static get_type()

Returns Q function type.

Returns
Q function type.

Return type
str

classmethod schema(***, *infer_missing=False*, *only=None*, *exclude=()*, *many=False*, *context=None*, *load_only=()*, *dump_only=()*, *partial=False*, *unknown=None*)

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

serialize()

Return type
str

serialize_to_dict()

Return type
Dict[str, *Any*]

to_dict(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(**, skipkeys=False, ensure_ascii=True, check_circular=True, allow_nan=True, indent=None, separators=None, default=None, sort_keys=False, **kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

Attributes

embed_size: int = 64

n_greedy_quantiles: int = 32

n_quantiles: int = 64

share_encoder: bool = False

4.3 Replay Buffer

You can also check advanced use cases at examples directory.

4.3.1 MDPDataset

d3rlpy provides useful dataset structure for data-driven deep reinforcement learning. In supervised learning, the training script iterates input data X and label data Y. However, in reinforcement learning, mini-batches consist with sets of (s_t, a_t, r_t, s_{t+1}) and episode terminal flags. Converting a set of observations, actions, rewards and terminal flags into this tuples is boring and requires some codings.

Therefore, d3rlpy provides `MDPDataset` class which enables you to handle reinforcement learning datasets without any efforts.

```
import d3rlpy

# 1000 steps of observations with shape of (100,)
observations = np.random.random((1000, 100))
# 1000 steps of actions with shape of (4,)
actions = np.random.random((1000, 4))
# 1000 steps of rewards
rewards = np.random.random(1000)
# 1000 steps of terminal flags
terminals = np.random.randint(2, size=1000)

dataset = d3rlpy.dataset.MDPDataset(observations, actions, rewards, terminals)

# save as HDF5
with open("dataset.h5", "w+b") as f:
    dataset.dump(f)

# load from HDF5
with open("dataset.h5", "rb") as f:
    new_dataset = d3rlpy.dataset.ReplayBuffer.load(f, d3rlpy.dataset.InfiniteBuffer())
```

Note that the `observations`, `actions`, `rewards` and `terminals` must be aligned with the same timestep.

```
observations = [s1, s2, s3, ...]
actions      = [a1, a2, a3, ...]
rewards      = [r1, r2, r3, ...]  # r1 = r(s1, a1)
terminals    = [t1, t2, t3, ...]  # t1 = t(s1, a1)
```

`MDPDataset` is actually a shortcut of `ReplayBuffer` class.

d3rlpy.dataset.MDPDataset	Backward-compability class of MDPDataset.

d3rlpy.dataset.MDPDataset

class d3rlpy.dataset.**MDPDataset**(*observations*, *actions*, *rewards*, *terminals*, *timeouts=None*, *transition_picker=None*, *trajectory_slicer=None*, *action_space=None*, *action_size=None*)

Backward-compability class of MDPDataset.

This is a wrapper class that has a backward-compatible constructor interface.

Parameters

- **observations** (*ObservationSequence*) – Observations.
- **actions** (*np.ndarray*) – Actions.
- **rewards** (*np.ndarray*) – Rewards.
- **terminals** (*np.ndarray*) – Environmental terminal flags.
- **timeouts** (*np.ndarray*) – Timeouts.
- **transition_picker** (*Optional[TransitionPickerProtocol]*) – Transition picker implementation for Q-learning-based algorithms. If `None` is given, `BasicTransitionPicker` is used by default.

- **trajectory_slicer** (*Optional[TrajectorySlicerProtocol]*) – Trajectory slicer implementation for Transformer-based algorithms. If `None` is given, `BasicTrajectorySlicer` is used by default.
- **action_space** (*Optional[d3rlpy.constants.ActionSpace]*) – Action-space type.
- **action_size** (*Optional[int]*) – Size of action-space. For continuous action-space, this represents dimension of action vectors. For discrete action-space, this represents the number of discrete actions.

Methods

append(*observation*, *action*, *reward*)

Appends observation, action and reward to buffer.

Parameters

- **observation** (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observation.
- **action** (*Union[int, ndarray[Any, dtype[Any]]]*) – Action.
- **reward** (*Union[float, ndarray[Any, dtype[Any]]]*) – Reward.

Return type
None

append_episode(*episode*)

Appends episode to buffer.

Parameters
episode (*EpisodeBase*) – Episode.

Return type
None

clip_episode(*terminated*)

Clips current episode.

Parameters
terminated (*bool*) – Flag to represent environmental termination. This flag should be `False` if the episode is terminated by timeout.

Return type
None

dump(*f*)

Dumps buffer data.

```
with open('dataset.h5', 'w+b') as f:
    replay_buffer.dump(f)
```

Parameters
f (*BinaryIO*) – IO object to write to.

Return type
None

classmethod from_episode_generator(*episode_generator*, *buffer*, *transition_picker=None*, *trajectory_slicer=None*, *writer_preprocessor=None*)

Builds ReplayBuffer from episode generator.

Parameters

- **episode_generator** (*EpisodeGeneratorProtocol*) – Episode generator implementation.
- **buffer** (BufferProtocol) – Buffer implementation.
- **transition_picker** (*Optional[TransitionPickerProtocol]*) – Transition picker implementation for Q-learning-based algorithms.
- **trajectory_slicer** (*Optional[TrajectorySlicerProtocol]*) – Trajectory slicer implementation for Transformer-based algorithms.
- **writer_preprocessor** (*Optional[WriterPreprocessProtocol]*) – Writer preprocessor implementation.

Returns
Replay buffer.

Return type
ReplayBuffer

classmethod load(*f*, *buffer*, *episode_cls=<class 'd3rlpy.dataset.components.Episode'>*, *transition_picker=None*, *trajectory_slicer=None*, *writer_preprocessor=None*)

Builds ReplayBuffer from dumped data.

This method reconstructs replay buffer dumped by dump method.

```
with open('dataset.h5', 'rb') as f:
    replay_buffer = ReplayBuffer.load(f, buffer)
```

Parameters

- **f** (*BinaryIO*) – IO object to read from.
- **buffer** (BufferProtocol) – Buffer implementation.
- **episode_cls** (*Type[EpisodeBase]*) – Eisode class used to reconstruct data.
- **transition_picker** (*Optional[TransitionPickerProtocol]*) – Transition picker implementation for Q-learning-based algorithms.
- **trajectory_slicer** (*Optional[TrajectorySlicerProtocol]*) – Trajectory slicer implementation for Transformer-based algorithms.
- **writer_preprocessor** (*Optional[WriterPreprocessProtocol]*) – Writer preprocessor implementation.

Returns
Replay buffer.

Return type
ReplayBuffer

sample_trajectory(*length*)

Samples a partial trajectory.

Parameters
length (*int*) – Length of partial trajectory.

Returns
Partial trajectory.

Return type
PartialTrajectory

sample_trajectory_batch(*batch_size*, *length*)

Samples a mini-batch of partial trajectories.

Parameters

- **batch_size** (*int*) – Mini-batch size.
- **length** (*int*) – Length of partial trajectories.

Returns
Mini-batch.

Return type
TrajectoryMiniBatch

sample_transition()

Samples a transition.

Returns
Transition.

Return type
Transition

sample_transition_batch(*batch_size*)

Samples a mini-batch of transitions.

Parameters
batch_size (*int*) – Mini-batch size.

Returns
Mini-batch.

Return type
TransitionMiniBatch

size()

Returns number of episodes.

Returns
Number of episodes.

Return type
int

Attributes

buffer

dataset_info

episodes

trajectory_slicer

transition_count

transition_picker

4.3.2 Replay Buffer

`ReplayBuffer` is a class that represents an experience replay buffer in d3rlpy. In d3rlpy, `ReplayBuffer` is a highly moduralized interface for flexibility. You can compose sub-components of `ReplayBuffer`, `Buffer`, `TransitionPicker`, *TrajectorySlicer* and `WriterPreprocess` to customize experiments.

```
import d3rlpy

# Buffer component
buffer = d3rlpy.dataset.FIFOBuffer(limit=100000)

# TransitionPicker component
transition_picker = d3rlpy.dataset.BasicTransitionPicker()

# TrajectorySlicer component
trajectory_slicer = d3rlpy.dataset.BasicTrajectorySlicer()

# WriterPreprocess component
writer_preprocessor = d3rlpy.dataset.BasicWriterPreprocess()

# Need to specify signatures of observations, actions and rewards

# Option 1: Initialize with Gym environment
import gym
env = gym.make("Pendulum-v1")
replay_buffer = d3rlpy.dataset.ReplayBuffer(
   buffer=buffer,
   transition_picker=transition_picker,
   trajectory_slicer=trajectory_slicer,
   writer_preprocessor=writer_preprocessor,
   env=env,
)

# Option 2: Initialize with pre-collected dataset
dataset, _ = d3rlpy.datasets.get_pendulum()
replay_buffer = d3rlpy.dataset.ReplayBuffer(
   buffer=buffer,
   transition_picker=transition_picker,
   trajectory_slicer=trajectory_slicer,
   writer_preprocessor=writer_preprocessor,
```

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```
    episodes=dataset.episodes,
)

# Option 3: Initialize with manually specified signatures
observation_signature = d3rlpy.dataset.Signature(shape=[(3,)], dtype=[np.float32])
action_signature = d3rlpy.dataset.Signature(shape=[(1,)], dtype=[np.float32])
reward_signature = d3rlpy.dataset.Signature(shape=[(1,)], dtype=[np.float32])
replay_buffer = d3rlpy.dataset.ReplayBuffer(
    buffer=buffer,
    transition_picker=transition_picker,
    trajectory_slicer=trajectory_slicer,
    writer_preprocessor=writer_preprocessor,
    observation_signature=observation_signature,
    action_signature=action_signature,
    reward_signature=reward_signature,
)

# shortcut
replay_buffer = d3rlpy.dataset.create_fifo_replay_buffer(limit=100000, env=env)
```

d3rlpy.dataset.ReplayBufferBase	An interface of ReplayBuffer.
d3rlpy.dataset.ReplayBuffer	Replay buffer for experience replay.
d3rlpy.dataset.MixedReplayBuffer	A class combining two replay buffer instances.
d3rlpy.dataset.create_infinite_replay_buffer	Builds infinite replay buffer.
d3rlpy.dataset.create_fifo_replay_buffer	Builds FIFO replay buffer.

d3rlpy.dataset.ReplayBufferBase

class d3rlpy.dataset.**ReplayBufferBase**

An interface of ReplayBuffer.

Methods

abstract append(*observation*, *action*, *reward*)

Appends observation, action and reward to buffer.

Parameters

- **observation** (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observation.
- **action** (*Union[int, ndarray[Any, dtype[Any]]]*) – Action.
- **reward** (*Union[float, ndarray[Any, dtype[Any]]]*) – Reward.

Return type
None

abstract append_episode(*episode*)

Appends episode to buffer.

Parameters
episode (*EpisodeBase*) – Episode.

Return type
None

abstract clip_episode(*terminated*)

Clips current episode.

Parameters
terminated (*bool*) – Flag to represent environmental termination. This flag should be `False` if the episode is terminated by timeout.

Return type
None

abstract dump(*f*)

Dumps buffer data.

```
with open('dataset.h5', 'w+b') as f:
    replay_buffer.dump(f)
```

Parameters
f (*BinaryIO*) – IO object to write to.

Return type
None

abstract classmethod from_episode_generator(*episode_generator*, *buffer*, *transition_picker=None*, *trajectory_slicer=None*, *writer_preprocessor=None*)

Builds ReplayBuffer from episode generator.

Parameters

- **episode_generator** (*EpisodeGeneratorProtocol*) – Episode generator implementation.
- **buffer** (BufferProtocol) – Buffer implementation.
- **transition_picker** (*Optional[TransitionPickerProtocol]*) – Transition picker implementation for Q-learning-based algorithms.
- **trajectory_slicer** (*Optional[TrajectorySlicerProtocol]*) – Trajectory slicer implementation for Transformer-based algorithms.
- **writer_preprocessor** (*Optional[WriterPreprocessProtocol]*) – Writer preprocessor implementation.

Returns
Replay buffer.

Return type
ReplayBuffer

abstract classmethod load(*f*, *buffer*, *episode_cls=<class 'd3rlpy.dataset.components.Episode'>*, *transition_picker=None*, *trajectory_slicer=None*, *writer_preprocessor=None*)

Builds ReplayBuffer from dumped data.

This method reconstructs replay buffer dumped by `dump` method.

```
with open('dataset.h5', 'rb') as f:
    replay_buffer = ReplayBuffer.load(f, buffer)
```

Parameters

- **f** (*BinaryIO*) – IO object to read from.
- **buffer** (BufferProtocol) – Buffer implementation.
- **episode_cls** (*Type[EpisodeBase]*) – Eisode class used to reconstruct data.
- **transition_picker** (*Optional[TransitionPickerProtocol]*) – Transition picker implementation for Q-learning-based algorithms.
- **trajectory_slicer** (*Optional[TrajectorySlicerProtocol]*) – Trajectory slicer implementation for Transformer-based algorithms.
- **writer_preprocessor** (*Optional[WriterPreprocessProtocol]*) – Writer preprocessor implementation.

Returns
Replay buffer.

Return type
ReplayBuffer

abstract sample_trajectory(*length*)

Samples a partial trajectory.

Parameters
length (*int*) – Length of partial trajectory.

Returns
Partial trajectory.

Return type
PartialTrajectory

abstract sample_trajectory_batch(*batch_size*, *length*)

Samples a mini-batch of partial trajectories.

Parameters

- **batch_size** (*int*) – Mini-batch size.
- **length** (*int*) – Length of partial trajectories.

Returns
Mini-batch.

Return type
TrajectoryMiniBatch

abstract sample_transition()

Samples a transition.

Returns
Transition.

Return type
Transition

abstract sample_transition_batch(*batch_size*)

Samples a mini-batch of transitions.

Parameters
batch_size (*int*) – Mini-batch size.

Returns
Mini-batch.

Return type
TransitionMiniBatch

`abstract size()`

Returns number of episodes.

Returns
Number of episodes.

Return type
int

Attributes

`buffer`

Returns buffer.

Returns
Buffer.

`dataset_info`

Returns dataset information.

Returns
Dataset information.

`episodes`

Returns sequence of episodes.

Returns
Sequence of episodes.

`trajectory_slicer`

Returns trajectory slicer.

Returns
Trajectory slicer.

`transition_count`

Returns number of transitions.

Returns
Number of transitions.

`transition_picker`

Returns transition picker.

Returns
Transition picker.

d3rlpy.dataset.ReplayBuffer

class d3rlpy.dataset.**ReplayBuffer**(*buffer*, *transition_picker=None*, *trajectory_slicer=None*, *writer_preprocessor=None*, *episodes=None*, *env=None*, *observation_signature=None*, *action_signature=None*, *reward_signature=None*, *action_space=None*, *action_size=None*, *cache_size=10000*, *write_at_termination=False*)

Replay buffer for experience replay.

This replay buffer implementation is used for both online and offline training in d3rlpy. To determine shapes of observations, actions and rewards, one of `episodes`, `env` and signatures must be provided.

```
from d3rlpy.dataset import FIFOBuffer, ReplayBuffer, Signature

buffer = FIFOBuffer(limit=1000000)

# initialize with pre-collected episodes
replay_buffer = ReplayBuffer(buffer=buffer, episodes=<episodes>)

# initialize with Gym
replay_buffer = ReplayBuffer(buffer=buffer, env=<env>)

# initialize with manually specified signatures
replay_buffer = ReplayBuffer(
    buffer=buffer,
    observation_signature=Signature(dtype=[<dtype>], shape=[<shape>]),
    action_signature=Signature(dtype=[<dtype>], shape=[<shape>]),
    reward_signature=Signature(dtype=[<dtype>], shape=[<shape>]),
)
```

Parameters

- **buffer** (d3rlpy.dataset.BufferProtocol) – Buffer implementation.
- **transition_picker** (*Optional[*d3rlpy.dataset.TransitionPickerProtocol*]*) – Transition picker implementation for Q-learning-based algorithms. If `None` is given, `BasicTransitionPicker` is used by default.
- **trajectory_slicer** (*Optional[*d3rlpy.dataset.TrajectorySlicerProtocol*]*) – Trajectory slicer implementation for Transformer-based algorithms. If `None` is given, `BasicTrajectorySlicer` is used by default.
- **writer_preprocessor** (*Optional[*d3rlpy.dataset.WriterPreprocessProtocol*]*) – Writer preprocessor implementation. If `None` is given, `BasicWriterPreprocess` is used by default.
- **episodes** (*Optional[Sequence[d3rlpy.dataset.EpisodeBase]]*) – List of episodes to initialize replay buffer.
- **env** (*Optional[GymEnv]*) – Gym environment to extract shapes of observations and action.
- **observation_signature** (*Optional[d3rlpy.dataset.Signature]*) – Signature of observation.
- **action_signature** (*Optional[d3rlpy.dataset.Signature]*) – Signature of action.
- **reward_signature** (*Optional[d3rlpy.dataset.Signature]*) – Signature of reward.
- **action_space** (*Optional[d3rlpy.constants.ActionSpace]*) – Action-space type.

- **action_size** (*Optional[int]*) – Size of action-space. For continuous action-space, this represents dimension of action vectors. For discrete action-space, this represents the number of discrete actions.
- **cache_size** (*int*) – Size of cache to record active episode history used for online training. `cache_size` needs to be greater than the maximum possible episode length.
- **write_at_termination** (*bool*) – Flag to write experiences to the buffer at the end of an episode all at once.

Methods

append(*observation*, *action*, *reward*)

Appends observation, action and reward to buffer.

Parameters

- **observation** (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observation.
- **action** (*Union[int, ndarray[Any, dtype[Any]]]*) – Action.
- **reward** (*Union[float, ndarray[Any, dtype[Any]]]*) – Reward.

Return type
None

append_episode(*episode*)

Appends episode to buffer.

Parameters
episode (*EpisodeBase*) – Episode.

Return type
None

clip_episode(*terminated*)

Clips current episode.

Parameters
terminated (*bool*) – Flag to represent environmental termination. This flag should be `False` if the episode is terminated by timeout.

Return type
None

dump(*f*)

Dumps buffer data.

```
with open('dataset.h5', 'w+b') as f:
    replay_buffer.dump(f)
```

Parameters
f (*BinaryIO*) – IO object to write to.

Return type
None

classmethod from_episode_generator(*episode_generator*, *buffer*, *transition_picker=None*, *trajectory_slicer=None*, *writer_preprocessor=None*)

Builds ReplayBuffer from episode generator.

Parameters

- **episode_generator** (*EpisodeGeneratorProtocol*) – Episode generator implementation.
- **buffer** (BufferProtocol) – Buffer implementation.
- **transition_picker** (*Optional[TransitionPickerProtocol]*) – Transition picker implementation for Q-learning-based algorithms.
- **trajectory_slicer** (*Optional[TrajectorySlicerProtocol]*) – Trajectory slicer implementation for Transformer-based algorithms.
- **writer_preprocessor** (*Optional[WriterPreprocessProtocol]*) – Writer preprocessor implementation.

Returns
Replay buffer.

Return type
ReplayBuffer

classmethod load(*f*, *buffer*, *episode_cls=<class 'd3rlpy.dataset.components.Episode'>*, *transition_picker=None*, *trajectory_slicer=None*, *writer_preprocessor=None*)

Builds ReplayBuffer from dumped data.

This method reconstructs replay buffer dumped by dump method.

```
with open('dataset.h5', 'rb') as f:
    replay_buffer = ReplayBuffer.load(f, buffer)
```

Parameters

- **f** (*BinaryIO*) – IO object to read from.
- **buffer** (BufferProtocol) – Buffer implementation.
- **episode_cls** (*Type[EpisodeBase]*) – Eisode class used to reconstruct data.
- **transition_picker** (*Optional[TransitionPickerProtocol]*) – Transition picker implementation for Q-learning-based algorithms.
- **trajectory_slicer** (*Optional[TrajectorySlicerProtocol]*) – Trajectory slicer implementation for Transformer-based algorithms.
- **writer_preprocessor** (*Optional[WriterPreprocessProtocol]*) – Writer preprocessor implementation.

Returns
Replay buffer.

Return type
ReplayBuffer

sample_trajectory(*length*)

Samples a partial trajectory.

Parameters
length (*int*) – Length of partial trajectory.

Returns
Partial trajectory.

Return type
PartialTrajectory

sample_trajectory_batch(*batch_size*, *length*)

Samples a mini-batch of partial trajectories.

Parameters

- **batch_size** (*int*) – Mini-batch size.
- **length** (*int*) – Length of partial trajectories.

Returns
Mini-batch.

Return type
TrajectoryMiniBatch

sample_transition()

Samples a transition.

Returns
Transition.

Return type
Transition

sample_transition_batch(*batch_size*)

Samples a mini-batch of transitions.

Parameters
batch_size (*int*) – Mini-batch size.

Returns
Mini-batch.

Return type
TransitionMiniBatch

size()

Returns number of episodes.

Returns
Number of episodes.

Return type
int

Attributes

buffer

dataset_info

episodes

trajectory_slicer

transition_count

transition_picker

d3rlpy.dataset.MixedReplayBuffer

class d3rlpy.dataset.**MixedReplayBuffer**(*primary_replay_buffer*, *secondary_replay_buffer*, *secondary_mix_ratio*)

A class combining two replay buffer instances.

This replay buffer implementation combines two replay buffers (e.g. offline buffer and online buffer). The primary replay buffer is exposed to methods such as append. Mini-batches are sampled from each replay buffer based on secondary_mix_ratio.

```
import d3rlpy

# offline dataset
dataset, env = d3rlpy.datasets.get_cartpole()

# online replay buffer
online_buffer = d3rlpy.dataset.create_fifo_replay_buffer(
    limit=100000,
    env=env,
)

# combine two replay buffers
replay_buffer = d3rlpy.dataset.MixedReplayBuffer(
    primary_replay_buffer=online_buffer,
    secondary_replay_buffer=dataset,
    secondary_mix_ratio=0.5,
)
```

Parameters

- **primary_replay_buffer** (d3rlpy.dataset.ReplayBufferBase) – Primary replay buffer.
- **secondary_replay_buffer** (d3rlpy.dataset.ReplayBufferBase) – Secondary replay buffer.
- **secondary_mix_ratio** (*float*) – Ratio to sample mini-batches from the secondary replay buffer.

Methods

append(*observation*, *action*, *reward*)

Appends observation, action and reward to buffer.

Parameters

- **observation** (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observation.
- **action** (*Union[int, ndarray[Any, dtype[Any]]]*) – Action.
- **reward** (*Union[float, ndarray[Any, dtype[Any]]]*) – Reward.

Return type
None

append_episode(*episode*)

Appends episode to buffer.

Parameters
episode (*EpisodeBase*) – Episode.

Return type
None

clip_episode(*terminated*)

Clips current episode.

Parameters
terminated (*bool*) – Flag to represent environmental termination. This flag should be `False` if the episode is terminated by timeout.

Return type
None

dump(*f*)

Dumps buffer data.

```
with open('dataset.h5', 'w+b') as f:
    replay_buffer.dump(f)
```

Parameters
f (*BinaryIO*) – IO object to write to.

Return type
None

classmethod from_episode_generator(*episode_generator*, *buffer*, *transition_picker=None*, *trajectory_slicer=None*, *writer_preprocessor=None*)

Builds ReplayBuffer from episode generator.

Parameters

- **episode_generator** (*EpisodeGeneratorProtocol*) – Episode generator implementation.
- **buffer** (*BufferProtocol*) – Buffer implementation.
- **transition_picker** (*Optional[TransitionPickerProtocol]*) – Transition picker implementation for Q-learning-based algorithms.

- **trajectory_slicer** (*Optional[TrajectorySlicerProtocol]*) – Trajectory slicer implementation for Transformer-based algorithms.
- **writer_preprocessor** (*Optional[WriterPreprocessProtocol]*) – Writer preprocessor implementation.

Returns
Replay buffer.

Return type
ReplayBuffer

classmethod load(*f*, *buffer*, *episode_cls=<class 'd3rlpy.dataset.components.Episode'>*, *transition_picker=None*, *trajectory_slicer=None*, *writer_preprocessor=None*)

Builds ReplayBuffer from dumped data.

This method reconstructs replay buffer dumped by `dump` method.

```
with open('dataset.h5', 'rb') as f:
    replay_buffer = ReplayBuffer.load(f, buffer)
```

Parameters

- **f** (*BinaryIO*) – IO object to read from.
- **buffer** (*BufferProtocol*) – Buffer implementation.
- **episode_cls** (*Type[EpisodeBase]*) – Eisode class used to reconstruct data.
- **transition_picker** (*Optional[TransitionPickerProtocol]*) – Transition picker implementation for Q-learning-based algorithms.
- **trajectory_slicer** (*Optional[TrajectorySlicerProtocol]*) – Trajectory slicer implementation for Transformer-based algorithms.
- **writer_preprocessor** (*Optional[WriterPreprocessProtocol]*) – Writer preprocessor implementation.

Returns
Replay buffer.

Return type
ReplayBuffer

sample_trajectory(*length*)

Samples a partial trajectory.

Parameters
length (*int*) – Length of partial trajectory.

Returns
Partial trajectory.

Return type
PartialTrajectory

sample_trajectory_batch(*batch_size*, *length*)

Samples a mini-batch of partial trajectories.

Parameters

- **batch_size** (*int*) – Mini-batch size.

- **length** (*int*) – Length of partial trajectories.

Returns
Mini-batch.

Return type
TrajectoryMiniBatch

sample_transition()

Samples a transition.

Returns
Transition.

Return type
Transition

sample_transition_batch(*batch_size*)

Samples a mini-batch of transitions.

Parameters
batch_size (*int*) – Mini-batch size.

Returns
Mini-batch.

Return type
TransitionMiniBatch

size()

Returns number of episodes.

Returns
Number of episodes.

Return type
int

Attributes

buffer

dataset_info

episodes

primary_replay_buffer

secondary_replay_buffer

trajectory_slicer

transition_count

transition_picker

d3rlpy.dataset.create_infinite_replay_buffer

d3rlpy.dataset.**create_infinite_replay_buffer**(*episodes=None*, *transition_picker=None*, *trajectory_slicer=None*, *writer_preprocessor=None*, *env=None*)

Builds infinite replay buffer.

This function is a shortcut alias to build replay buffer with `InfiniteBuffer`.

Parameters

- **episodes** (*Optional[Sequence[EpisodeBase]]*) – List of episodes to initialize replay buffer.
- **transition_picker** (*Optional[TransitionPickerProtocol]*) – Transition picker implementation for Q-learning-based algorithms. If `None` is given, `BasicTransitionPicker` is used by default.
- **trajectory_slicer** (*Optional[TrajectorySlicerProtocol]*) – Trajectory slicer implementation for Transformer-based algorithms. If `None` is given, `BasicTrajectorySlicer` is used by default.
- **writer_preprocessor** (*Optional[WriterPreprocessProtocol]*) – Writer preprocessor implementation. If `None` is given, `BasicWriterPreprocess` is used by default.
- **env** (*Optional[Union[Env[Any, Any], Env[Any, Any]]]*) – Gym environment to extract shapes of observations and action.

Returns
Replay buffer.

Return type
ReplayBuffer

d3rlpy.dataset.create_fifo_replay_buffer

d3rlpy.dataset.**create_fifo_replay_buffer**(*limit*, *episodes=None*, *transition_picker=None*, *trajectory_slicer=None*, *writer_preprocessor=None*, *env=None*)

Builds FIFO replay buffer.

This function is a shortcut alias to build replay buffer with `FIFOBuffer`.

Parameters

- **limit** (*int*) – Maximum capacity of FIFO buffer.
- **episodes** (*Optional[Sequence[EpisodeBase]]*) – List of episodes to initialize replay buffer.
- **transition_picker** (*Optional[TransitionPickerProtocol]*) – Transition picker implementation for Q-learning-based algorithms. If `None` is given, `BasicTransitionPicker` is used by default.
- **trajectory_slicer** (*Optional[TrajectorySlicerProtocol]*) – Trajectory slicer implementation for Transformer-based algorithms. If `None` is given, `BasicTrajectorySlicer` is used by default.
- **writer_preprocessor** (*Optional[WriterPreprocessProtocol]*) – Writer preprocessor implementation. If `None` is given, `BasicWriterPreprocess` is used by default.

- **env** (*Optional[Union[Env[Any, Any], Env[Any, Any]]]*) – Gym environment to extract shapes of observations and action.

Returns
Replay buffer.

Return type
ReplayBuffer

4.3.3 Buffer

`Buffer` is a list-like component that stores and drops transitions.

d3rlpy.dataset.BufferProtocol	Interface of Buffer.
d3rlpy.dataset.InfiniteBuffer	Buffer with unlimited capacity.
d3rlpy.dataset.FIFOBuffer	FIFO buffer.

d3rlpy.dataset.BufferProtocol

class d3rlpy.dataset.**BufferProtocol**(**args*, ***kwargs*)

Interface of Buffer.

Methods

__getitem__(*index*)

Parameters
index (*int*) –

Return type
Tuple[*EpisodeBase*, int]

append(*episode*, *index*)

Adds transition to buffer.

Parameters

- **episode** (*EpisodeBase*) – Episode object.
- **index** (*int*) – Transition index.

Return type
None

Attributes

episodes

Returns list of episodes.

Returns
List of saved episodes.

transition_count

Returns the number of transitions.

Returns
Number of transitions.

d3rlpy.dataset.InfiniteBuffer

class d3rlpy.dataset.**InfiniteBuffer**

Buffer with unlimited capacity.

Methods

__getitem__(*index*)

Parameters
index (*int*) –

Return type
Tuple[*EpisodeBase*, int]

__len__()

Return type
int

append(*episode*, *index*)

Adds transition to buffer.

Parameters

- **episode** (*EpisodeBase*) – Episode object.
- **index** (*int*) – Transition index.

Return type
None

Attributes

episodes

transition_count

d3rlpy.dataset.FIFOBuffer

class d3rlpy.dataset.**FIFOBuffer**(*limit*)

FIFO buffer.

Parameters
limit (*int*) – buffer capacity.

Methods

__getitem__(*index*)

Parameters
index (*int*) –

Return type
Tuple[*EpisodeBase*, int]

__len__()

Return type
int

append(*episode*, *index*)
Adds transition to buffer.

Parameters

- **episode** (*EpisodeBase*) – Episode object.
- **index** (*int*) – Transition index.

Return type
None

Attributes

episodes

transition_count

4.3.4 TransitionPicker

`TransitionPicker` is a component that defines how to pick transition data used for Q-learning-based algorithms. You can also implement your own `TransitionPicker` for custom experiments.

```
import d3rlpy

# Example TransitionPicker that simply picks transition
class CustomTransitionPicker(d3rlpy.dataset.TransitionPickerProtocol):
    def __call__(self, episode: d3rlpy.dataset.EpisodeBase, index: int) -> d3rlpy.
↪dataset.Transition:
        observation = episode.observations[index]
        is_terminal = episode.terminated and index == episode.size() - 1
        if is_terminal:
            next_observation = d3rlpy.dataset.create_zero_observation(observation)
        else:
            next_observation = episode.observations[index + 1]
        return d3rlpy.dataset.Transition(
            observation=observation,
            action=episode.actions[index],
            reward=episode.rewards[index],
            next_observation=next_observation,
            terminal=float(is_terminal),
```

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```
        interval=1,
    )
```

d3rlpy.dataset.TransitionPickerProtocol	Interface of TransitionPicker.
d3rlpy.dataset.BasicTransitionPicker	Standard transition picker.
d3rlpy.dataset.FrameStackTransitionPicker	Frame-stacking transition picker.
d3rlpy.dataset.MultiStepTransitionPicker	Multi-step transition picker.
d3rlpy.dataset.SparseRewardTransitionPicker	Sparse reward transition picker.

d3rlpy.dataset.TransitionPickerProtocol

class d3rlpy.dataset.**TransitionPickerProtocol**(**args*, ***kwargs*)

Interface of TransitionPicker.

Methods

__call__(*episode*, *index*)

Returns transition specified by `index`.

Parameters

- **episode** (*EpisodeBase*) – Episode.
- **index** (*int*) – Index at the target transition.

Returns
Transition.

Return type
Transition

d3rlpy.dataset.BasicTransitionPicker

class d3rlpy.dataset.**BasicTransitionPicker**(**args*, ***kwargs*)

Standard transition picker.

This class implements a basic transition picking.

Methods

__call__(*episode*, *index*)

Returns transition specified by `index`.

Parameters

- **episode** (*EpisodeBase*) – Episode.
- **index** (*int*) – Index at the target transition.

Returns
Transition.

Return type
Transition

d3rlpy.dataset.FrameStackTransitionPicker

class d3rlpy.dataset.**FrameStackTransitionPicker**(*n_frames*)

Frame-stacking transition picker.

This class implements the frame-stacking logic. The observations are stacked with the last `n_frames-1` frames. When `index` specifies timestep below `n_frames`, those frames are padded by zeros.

```
episode = Episode(
    observations=np.random.random((100, 1, 84, 84)),
    actions=np.random.random((100, 2)),
    rewards=np.random.random((100, 1)),
    terminated=False,
)

frame_stacking_picker = FrameStackTransitionPicker(n_frames=4)
transition = frame_stacking_picker(episode, 10)

transition.observation.shape == (4, 84, 84)
```

Parameters
n_frames (*int*) – Number of frames to stack.

Methods

__call__(*episode*, *index*)

Returns transition specified by `index`.

Parameters

- **episode** (*EpisodeBase*) – Episode.
- **index** (*int*) – Index at the target transition.

Returns
Transition.

Return type
Transition

d3rlpy.dataset.MultiStepTransitionPicker

class d3rlpy.dataset.**MultiStepTransitionPicker**(*n_steps*, *gamma*)

Multi-step transition picker.

This class implements transition picking for the multi-step TD error. `reward` is computed as a multi-step discounted return.

Parameters

- **n_steps** – Delta timestep between `observation` and `net_observation`.
- **gamma** – Discount factor to compute a multi-step return.

Methods

__call__(*episode*, *index*)

Returns transition specified by `index`.

Parameters

- **episode** (*EpisodeBase*) – Episode.
- **index** (*int*) – Index at the target transition.

Returns
Transition.

Return type
Transition

d3rlpy.dataset.SparseRewardTransitionPicker

class d3rlpy.dataset.**SparseRewardTransitionPicker**(*failure_return*, *step_reward=0.0*)

Sparse reward transition picker.

This class extends BasicTransitionPicker to handle special returns_to_go calculation mainly used in AntMaze environments.

For the failure trajectories, this class sets the constant return value to avoid inconsistent horizon due to time out.

Parameters

- **failure_return** (*int*) – Return value for failure trajectories.
- **step_reward** (*float*) – Immediate step reward value in sparse reward setting.

Methods

__call__(*episode*, *index*)

Returns transition specified by `index`.

Parameters

- **episode** (*EpisodeBase*) – Episode.
- **index** (*int*) – Index at the target transition.

Returns
Transition.

Return type
Transition

4.3.5 TrajectorySlicer

`TrajectorySlicer` is a component that defines how to slice trajectory data used for Decision Transformer-based algorithms. You can also implement your own `TrajectorySlicer` for custom experiments.

```
import d3rlpy

class CustomTrajectorySlicer(d3rlpy.dataset.TrajectorySlicerProtocol):
    def __call__(
        self, episode: d3rlpy.dataset.EpisodeBase, end_index: int, size: int
    ) -> d3rlpy.dataset.PartialTrajectory:
        end = end_index + 1
        start = max(end - size, 0)
        actual_size = end - start

        # prepare terminal flags
        terminals = np.zeros((actual_size, 1), dtype=np.float32)
        if episode.terminated and end_index == episode.size() - 1:
            terminals[-1][0] = 1.0

        # slice data
        observations = episode.observations[start:end]
        actions = episode.actions[start:end]
        rewards = episode.rewards[start:end]
        ret = np.sum(episode.rewards[start:])
        all_returns_to_go = ret - np.cumsum(episode.rewards[start:], axis=0)
        returns_to_go = all_returns_to_go[:actual_size].reshape((-1, 1))

        # prepare metadata
        timesteps = np.arange(start, end)
        masks = np.ones(end - start, dtype=np.float32)

        # compute backward padding size
        pad_size = size - actual_size

        if pad_size == 0:
            return d3rlpy.dataset.PartialTrajectory(
                observations=observations,
                actions=actions,
                rewards=rewards,
                returns_to_go=returns_to_go,
                terminals=terminals,
                timesteps=timesteps,
                masks=masks,
                length=size,
            )

        return d3rlpy.dataset.PartialTrajectory(
            observations=d3rlpy.dataset.batch_pad_observations(observations, pad_size),
            actions=d3rlpy.dataset.batch_pad_array(actions, pad_size),
            rewards=d3rlpy.dataset.batch_pad_array(rewards, pad_size),
            returns_to_go=d3rlpy.dataset.batch_pad_array(returns_to_go, pad_size),
            terminals=d3rlpy.dataset.batch_pad_array(terminals, pad_size),
```

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```
            timesteps=d3rlpy.dataset.batch_pad_array(timesteps, pad_size),
            masks=d3rlpy.dataset.batch_pad_array(masks, pad_size),
            length=size,
        )
```

d3rlpy.dataset.TrajectorySlicerProtocol	Interface of TrajectorySlicer.
d3rlpy.dataset.BasicTrajectorySlicer	Standard trajectory slicer.
d3rlpy.dataset.FrameStackTrajectorySlicer	Frame-stacking trajectory slicer.

d3rlpy.dataset.TrajectorySlicerProtocol

class d3rlpy.dataset.**TrajectorySlicerProtocol**(**args*, ***kwargs*)

Interface of TrajectorySlicer.

Methods

__call__(*episode*, *end_index*, *size*)

Slice trajectory.

This method returns a partial trajectory from `t=end_index-size` to `t=end_index`. If `end_index-size` is smaller than 0, those parts will be padded by zeros.

Parameters

- **episode** (*EpisodeBase*) – Episode.
- **end_index** (*int*) – Index at the end of the sliced trajectory.
- **size** (*int*) – Length of the sliced trajectory.

Returns
Sliced trajectory.

Return type
PartialTrajectory

d3rlpy.dataset.BasicTrajectorySlicer

class d3rlpy.dataset.**BasicTrajectorySlicer**(**args*, ***kwargs*)

Standard trajectory slicer.

This class implements a basic trajectory slicing.

Methods

__call__(*episode*, *end_index*, *size*)

Slice trajectory.

This method returns a partial trajectory from `t=end_index-size` to `t=end_index`. If `end_index-size` is smaller than 0, those parts will be padded by zeros.

Parameters

- **episode** (*EpisodeBase*) – Episode.
- **end_index** (*int*) – Index at the end of the sliced trajectory.
- **size** (*int*) – Length of the sliced trajectory.

Returns
Sliced trajectory.

Return type
PartialTrajectory

d3rlpy.dataset.FrameStackTrajectorySlicer

class d3rlpy.dataset.**FrameStackTrajectorySlicer**(*n_frames*)

Frame-stacking trajectory slicer.

This class implements the frame-stacking logic. The observations are stacked with the last `n_frames-1` frames. When `index` specifies timestep below `n_frames`, those frames are padded by zeros.

```
episode = Episode(
    observations=np.random.random((100, 1, 84, 84)),
    actions=np.random.random((100, 2)),
    rewards=np.random.random((100, 1)),
    terminated=False,
)

frame_stacking_slicer = FrameStackTrajectorySlicer(n_frames=4)
trajectory = frame_stacking_slicer(episode, 0, 10)

trajectory.observations.shape == (10, 4, 84, 84)
```

Parameters
n_frames – Number of frames to stack.

Methods

__call__(*episode*, *end_index*, *size*)

Slice trajectory.

This method returns a partial trajectory from `t=end_index-size` to `t=end_index`. If `end_index-size` is smaller than 0, those parts will be padded by zeros.

Parameters

- **episode** (*EpisodeBase*) – Episode.
- **end_index** (*int*) – Index at the end of the sliced trajectory.

- **size** (*int*) – Length of the sliced trajectory.

Returns
Sliced trajectory.

Return type
PartialTrajectory

4.3.6 WriterPreprocess

`WriterPreprocess` is a component that defines how to write experiences to an experience replay buffer. You can also implement your own `WriterPreprocess` for custom experiments.

```
import d3rlpy

class CustomWriterPreprocess(d3rlpy.dataset.WriterPreprocessProtocol):
    def process_observation(self, observation: d3rlpy.dataset.Observation) -> d3rlpy.
↪dataset.Observation:
        return observation

    def process_action(self, action: np.ndarray) -> np.ndarray:
        return action

    def process_reward(self, reward: np.ndarray) -> np.ndarray:
        return reward
```

d3rlpy.dataset.WriterPreprocessProtocol	Interface of WriterPreprocess.
d3rlpy.dataset.BasicWriterPreprocess	Stanard data writer.
d3rlpy.dataset.LastFrameWriterPreprocess	Data writer that writes the last channel of observation.

d3rlpy.dataset.WriterPreprocessProtocol

class d3rlpy.dataset.**WriterPreprocessProtocol**(**args*, ***kwargs*)

Interface of WriterPreprocess.

Methods

process_action(*action*)

Processes action.

Parameters
action (*ndarray[Any, dtype[Any]]*) – Action.

Returns
Processed action.

Return type
ndarray[*Any*, *dtype*[*Any*]]

process_observation(*observation*)

Processes observation.

Parameters
observation (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observation.

Returns
Processed observation.

Return type
Union[*ndarray*[*Any*, *dtype*[*Any*]], *Sequence*[*ndarray*[*Any*, *dtype*[*Any*]]]]

process_reward(*reward*)

Processes reward.

Parameters
reward (*ndarray[Any, dtype[Any]]*) – Reward.

Returns
Processed reward.

Return type
ndarray[*Any*, *dtype*[*Any*]]

d3rlpy.dataset.BasicWriterPreprocess

class d3rlpy.dataset.**BasicWriterPreprocess**(**args*, ***kwargs*)

Stanard data writer.

This class implements identity preprocess.

Methods

process_action(*action*)

Processes action.

Parameters
action (*ndarray[Any, dtype[Any]]*) – Action.

Returns
Processed action.

Return type
ndarray[*Any*, *dtype*[*Any*]]

process_observation(*observation*)

Processes observation.

Parameters
observation (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observation.

Returns
Processed observation.

Return type
Union[*ndarray*[*Any*, *dtype*[*Any*]], *Sequence*[*ndarray*[*Any*, *dtype*[*Any*]]]]

process_reward(*reward*)

Processes reward.

Parameters
reward (*ndarray[Any, dtype[Any]]*) – Reward.

Returns
Processed reward.

Return type
ndarray[*Any*, *dtype*[*Any*]]

d3rlpy.dataset.LastFrameWriterPreprocess

class d3rlpy.dataset.**LastFrameWriterPreprocess**(**args*, ***kwargs*)

Data writer that writes the last channel of observation.

This class is designed to be used with `FrameStackTransitionPicker`.

Methods

process_action(*action*)

Processes action.

Parameters
action (*ndarray[Any, dtype[Any]]*) – Action.

Returns
Processed action.

Return type
ndarray[*Any*, *dtype*[*Any*]]

process_observation(*observation*)

Processes observation.

Parameters
observation (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observation.

Returns
Processed observation.

Return type
Union[*ndarray*[*Any*, *dtype*[*Any*]], *Sequence*[*ndarray*[*Any*, *dtype*[*Any*]]]]

process_reward(*reward*)

Processes reward.

Parameters
reward (*ndarray[Any, dtype[Any]]*) – Reward.

Returns
Processed reward.

Return type
ndarray[*Any*, *dtype*[*Any*]]

4.4 Datasets

d3rlpy provides datasets for experimenting data-driven deep reinforcement learning algorithms.

d3rlpy.datasets.get_cartpole	Returns cartpole dataset and environment.
d3rlpy.datasets.get_pendulum	Returns pendulum dataset and environment.
d3rlpy.datasets.get_atari	Returns atari dataset and envrironment.
d3rlpy.datasets.get_atari_transitions	Returns atari dataset as a list of Transition objects and envrironment.
d3rlpy.datasets.get_d4rl	Returns d4rl dataset and envrironment.
d3rlpy.datasets.get_dataset	Returns dataset and envrironment by guessing from name.
d3rlpy.datasets.get_minari	Returns minari dataset and envrironment.

4.4.1 d3rlpy.datasets.get_cartpole

d3rlpy.datasets.**get_cartpole**(*dataset_type='replay'*, *transition_picker=None*, *trajectory_slicer=None*, *render_mode=None*)

Returns cartpole dataset and environment.

The dataset is automatically downloaded to `d3rlpy_data/cartpole.h5` if it does not exist.

Parameters

- **dataset_type** (*str*) – dataset type. Available options are `['replay', 'random']`.
- **transition_picker** (*Optional[TransitionPickerProtocol]*) – TransitionPickerProtocol object.
- **trajectory_slicer** (*Optional[TrajectorySlicerProtocol]*) – TrajectorySlicerProtocol object.
- **render_mode** (*Optional[str]*) – Mode of rendering (`human`, `rgb_array`).

Returns
tuple of *d3rlpy.dataset.ReplayBuffer* and gym environment.

Return type
Tuple[ReplayBuffer, *Env*[*ndarray*[*Any*, *dtype*[*Any*]], int]]

4.4.2 d3rlpy.datasets.get_pendulum

d3rlpy.datasets.**get_pendulum**(*dataset_type='replay'*, *transition_picker=None*, *trajectory_slicer=None*, *render_mode=None*)

Returns pendulum dataset and environment.

The dataset is automatically downloaded to `d3rlpy_data/pendulum.h5` if it does not exist.

Parameters

- **dataset_type** (*str*) – dataset type. Available options are `['replay', 'random']`.
- **transition_picker** (*Optional[TransitionPickerProtocol]*) – TransitionPickerProtocol object.
- **trajectory_slicer** (*Optional[TrajectorySlicerProtocol]*) – TrajectorySlicerProtocol object.

- **render_mode** (*Optional[str]*) – Mode of rendering (human, rgb_array).

Returns
tuple of *d3rlpy.dataset.ReplayBuffer* and gym environment.

Return type
Tuple[ReplayBuffer, *Env*[*ndarray*[*Any*, *dtype*[*Any*]], *ndarray*[*Any*, *dtype*[*Any*]]]]

4.4.3 d3rlpy.datasets.get_atari

d3rlpy.datasets.**get_atari**(*env_name*, *num_stack=None*, *sticky_action=True*, *pre_stack=False*, *render_mode=None*)

Returns atari dataset and envrironment.

The dataset is provided through d4rl-atari. See more details including available dataset from its GitHub page.

```
from d3rlpy.datasets import get_atari

dataset, env = get_atari('breakout-mixed-v0')
```

References

- https://github.com/takuseno/d4rl-atari

Parameters

- **env_name** (*str*) – environment id of d4rl-atari dataset.
- **num_stack** (*Optional[int]*) – the number of frames to stack (only applied to env).
- **sticky_action** (*bool*) – Flag to enable sticky action.
- **pre_stack** (*bool*) – Flag to pre-stack observations. If this is False, FrameStackTransitionPicker and FrameStackTrajectorySlicer will be used to stack observations at sampling-time.
- **render_mode** (*Optional[str]*) – Mode of rendering (human, rgb_array).

Returns
tuple of *d3rlpy.dataset.ReplayBuffer* and gym environment.

Return type
Tuple[ReplayBuffer, *Env*[*ndarray*[*Any*, *dtype*[*Any*]], int]]

4.4.4 d3rlpy.datasets.get_atari_transitions

d3rlpy.datasets.**get_atari_transitions**(*game_name*, *fraction=0.01*, *index=0*, *num_stack=None*, *sticky_action=True*, *pre_stack=False*, *render_mode=None*)

Returns atari dataset as a list of Transition objects and envrironment.

The dataset is provided through d4rl-atari. The difference from get_atari function is that this function will sample transitions from all epochs. This function is necessary for reproducing Atari experiments.

```
from d3rlpy.datasets import get_atari_transitions

# get 1% of transitions from all epochs (1M x 50 epoch x 1% = 0.5M)
dataset, env = get_atari_transitions('breakout', fraction=0.01)
```

References

- https://github.com/takuseno/d4rl-atari

Parameters

- **game_name** (*str*) – Atari 2600 game name in lower_snake_case.
- **fraction** (*float*) – fraction of sampled transitions.
- **index** (*int*) – index to specify which trial to load.
- **num_stack** (*Optional[int]*) – the number of frames to stack (only applied to env).
- **sticky_action** (*bool*) – Flag to enable sticky action.
- **pre_stack** (*bool*) – Flag to pre-stack observations. If this is `False`, `FrameStackTransitionPicker` and `FrameStackTrajectorySlicer` will be used to stack observations at sampling-time.
- **render_mode** (*Optional[str]*) – Mode of rendering (`human`, `rgb_array`).

Returns
tuple of a list of `d3rlpy.dataset.Transition` and gym environment.

Return type
Tuple[ReplayBuffer, *Env*[*ndarray*[*Any*, *dtype*[*Any*]], int]]

4.4.5 d3rlpy.datasets.get_d4rl

d3rlpy.datasets.**get_d4rl**(*env_name*, *transition_picker=None*, *trajectory_slicer=None*, *render_mode=None*, *max_episode_steps=1000*)

Returns d4rl dataset and envrironment.

The dataset is provided through d4rl.

```
from d3rlpy.datasets import get_d4rl

dataset, env = get_d4rl('hopper-medium-v0')
```

References

- Fu et al., D4RL: Datasets for Deep Data-Driven Reinforcement Learning.
- https://github.com/rail-berkeley/d4rl

Parameters

- **env_name** (*str*) – environment id of d4rl dataset.

- **transition_picker** (*Optional[TransitionPickerProtocol]*) – TransitionPicker-Protocol object.
- **trajectory_slicer** (*Optional[TrajectorySlicerProtocol]*) – TrajectorySlicer-Protocol object.
- **render_mode** (*Optional[str]*) – Mode of rendering (human, rgb_array).
- **max_episode_steps** (*int*) – Maximum episode environmental steps.

Returns
tuple of *d3rlpy.dataset.ReplayBuffer* and gym environment.

Return type
Tuple[ReplayBuffer, *Env*[*ndarray*[*Any*, *dtype*[*Any*]], *ndarray*[*Any*, *dtype*[*Any*]]]]

4.4.6 d3rlpy.datasets.get_dataset

d3rlpy.datasets.**get_dataset**(*env_name*, *transition_picker=None*, *trajectory_slicer=None*, *render_mode=None*)

Returns dataset and envrironment by guessing from name.

This function returns dataset by matching name with the following datasets.

- cartpole-replay
- cartpole-random
- pendulum-replay
- pendulum-random
- d4rl-pybullet
- d4rl-atari
- d4rl

```
import d3rlpy

# cartpole dataset
dataset, env = d3rlpy.datasets.get_dataset('cartpole')

# pendulum dataset
dataset, env = d3rlpy.datasets.get_dataset('pendulum')

# d4rl-atari dataset
dataset, env = d3rlpy.datasets.get_dataset('breakout-mixed-v0')

# d4rl dataset
dataset, env = d3rlpy.datasets.get_dataset('hopper-medium-v0')
```

Parameters

- **env_name** (*str*) – environment id of the dataset.
- **transition_picker** (*Optional[TransitionPickerProtocol]*) – TransitionPicker-Protocol object.

- **trajectory_slicer** (*Optional*[TrajectorySlicerProtocol]) – TrajectorySlicerProtocol object.
- **render_mode** (*Optional*[*str*]) – Mode of rendering (human, rgb_array).

Returns
tuple of *d3rlpy.dataset.ReplayBuffer* and gym environment.

Return type
Tuple[ReplayBuffer, *Env*[*Any*, *Any*]]

4.4.7 d3rlpy.datasets.get_minari

d3rlpy.datasets.**get_minari**(*env_name*, *transition_picker=None*, *trajectory_slicer=None*, *render_mode=None*, *tuple_observation=False*)

Returns minari dataset and envrironment.

The dataset is provided through minari.

Parameters

- **env_name** (*str*) – environment id of minari dataset.
- **transition_picker** (*Optional*[TransitionPickerProtocol]) – TransitionPickerProtocol object.
- **trajectory_slicer** (*Optional*[TrajectorySlicerProtocol]) – TrajectorySlicerProtocol object.
- **render_mode** (*Optional*[*str*]) – Mode of rendering (human, rgb_array).
- **tuple_observation** (*bool*) – Flag to include goals as tuple element.

Returns
tuple of *d3rlpy.dataset.ReplayBuffer* and gym environment.

Return type
Tuple[ReplayBuffer, *Env*[*Any*, *Any*]]

4.5 Preprocessing

4.5.1 Observation

d3rlpy provides several preprocessors tightly incorporated with algorithms. Each preprocessor is implemented with PyTorch operation, which will be included in the model exported by *save_policy* method.

```
from d3rlpy.datasets import get_pendulum
from d3rlpy.algos import CQLConfig
from d3rlpy.preprocesing import StandardObservationScaler

dataset, _ = get_pendulum()

# choose from ['pixel', 'min_max', 'standard'] or None
cql = CQLConfig(observation_scaler=StandardObservationScaler()).create()

# observation scaler is fitted from the given dataset
```

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```
cql.fit(dataset, n_steps=100000)

# preprocesing is included in TorchScript
cql.save_policy('policy.pt')

# you don't need to take care of preprocessing at production
policy = torch.jit.load('policy.pt')
action = policy(unpreprocessed_x)
```

You can also initialize observation scalers by yourself.

```
from d3rlpy.preprocessing import StandardObservationScaler

observation_scaler = StandardObservationScaler(mean=..., std=...)

cql = CQLConfig(observation_scaler=observation_scaler).create()
```

d3rlpy.preprocessing.PixelObservationScaler	Pixel normalization preprocessing.
d3rlpy.preprocessing.MinMaxObservationScaler	Min-Max normalization preprocessing.
d3rlpy.preprocessing.StandardObservationScaler	Standardization preprocessing.

d3rlpy.preprocessing.PixelObservationScaler

class d3rlpy.preprocessing.**PixelObservationScaler**

Pixel normalization preprocessing.

$$x' = x/255$$

```
from d3rlpy.preprocessing import PixelObservationScaler
from d3rlpy.algos import CQLConfig

cql = CQLConfig(observation_scaler=PixelObservationScaler()).create()
```

Methods

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

fit_with_env(*env*)

Gets scaling parameters from environment.

Parameters
env (*Union[Env[Any, Any], Env[Any, Any]]*) – Gym environment.

Return type
None

fit_with_trajectory_slicer(*episodes*, *trajectory_slicer*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **trajectory_slicer** (TrajectorySlicerProtocol) – Trajectory slicer to process mini-batch.

Return type
None

fit_with_transition_picker(*episodes*, *transition_picker*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **transition_picker** (TransitionPickerProtocol) – Transition picker to process mini-batch.

Return type
None

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

`static get_type()`

Return type
str

`reverse_transform(x)`

Returns reversely transformed output.

Parameters
x (*Tensor*) – input.

Returns
Inversely transformed output.

Return type
Tensor

`reverse_transform_numpy(x)`

Returns reversely transformed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Inversely transformed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

`classmethod schema(*, infer_missing=False, only=None, exclude=(), many=False, context=None, load_only=(), dump_only=(), partial=False, unknown=None)`

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

`serialize()`

Return type
str

`serialize_to_dict()`

Return type
Dict[str, *Any*]

`to_dict(encode_json=False)`

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(*, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

transform(*x*)

Returns processed output.

Parameters
x (*Tensor*) – Input.

Returns
Processed output.

Return type
Tensor

transform_numpy(*x*)

Returns processed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Processed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

Attributes

built

d3rlpy.preprocessing.MinMaxObservationScaler

class d3rlpy.preprocessing.**MinMaxObservationScaler**(*minimum=None*, *maximum=None*)

Min-Max normalization preprocessing.

Observations will be normalized in range `[-1.0, 1.0]`.

$$x' = (x - \min x)/(\max x - \min x) * 2 - 1$$

```
from d3rlpy.preprocessing import MinMaxObservationScaler
from d3rlpy.algos import CQLConfig

# normalize based on datasets or environments
cql = CQLConfig(observation_scaler=MinMaxObservationScaler()).create()

# manually initialize
minimum = observations.min(axis=0)
maximum = observations.max(axis=0)
observation_scaler = MinMaxObservationScaler(
    minimum=minimum,
    maximum=maximum,
)
cql = CQLConfig(observation_scaler=observation_scaler).create()
```

Parameters

- **minimum** (*numpy.ndarray*) – Minimum values at each entry.
- **maximum** (*numpy.ndarray*) – Maximum values at each entry.

Methods

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

fit_with_env(*env*)

Gets scaling parameters from environment.

Parameters
env (*Union[Env[Any, Any], Env[Any, Any]]*) – Gym environment.

Return type
None

fit_with_trajectory_slicer(*episodes*, *trajectory_slicer*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **trajectory_slicer** (TrajectorySlicerProtocol) – Trajectory slicer to process mini-batch.

Return type
None

fit_with_transition_picker(*episodes*, *transition_picker*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **transition_picker** (TransitionPickerProtocol) – Transition picker to process mini-batch.

Return type
None

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

static get_type()

Return type
str

reverse_transform(*x*)

Returns reversely transformed output.

Parameters
x (*Tensor*) – input.

Returns
Inversely transformed output.

Return type
Tensor

`reverse_transform_numpy`(*x*)

Returns reversely transformed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Inversely transformed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

`classmethod schema`(**, infer_missing=False, only=None, exclude=(), many=False, context=None, load_only=(), dump_only=(), partial=False, unknown=None*)

Parameters
- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

`serialize`()

Return type
str

`serialize_to_dict`()

Return type
Dict[str, *Any*]

`to_dict`(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

`to_json`(**, skipkeys=False, ensure_ascii=True, check_circular=True, allow_nan=True, indent=None, separators=None, default=None, sort_keys=False, **kw*)

Parameters
- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –

- **sort_keys** (*bool*) –

Return type
str

transform(*x*)

Returns processed output.

Parameters
x (*Tensor*) – Input.

Returns
Processed output.

Return type
Tensor

transform_numpy(*x*)

Returns processed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Processed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

Attributes

built

maximum: Optional[ndarray[Any, dtype[Any]]] = None

minimum: Optional[ndarray[Any, dtype[Any]]] = None

d3rlpy.preprocessing.StandardObservationScaler

class d3rlpy.preprocessing.**StandardObservationScaler**(*mean=None*, *std=None*, *eps=0.001*)

Standardization preprocessing.

$$x' = (x - \mu)/\sigma$$

```
from d3rlpy.preprocessing import StandardObservationScaler
from d3rlpy.algos import CQLConfig

# normalize based on datasets
cql = CQLConfig(observation_scaler=StandardObservationScaler()).create()

# manually initialize
mean = observations.mean(axis=0)
std = observations.std(axis=0)
observation_scaler = StandardObservationScaler(mean=mean, std=std)
cql = CQLConfig(observation_scaler=observation_scaler).create()
```

Parameters

- **mean** (*numpy.ndarray*) – Mean values at each entry.
- **std** (*numpy.ndarray*) – Standard deviation at each entry.
- **eps** (*float*) – Small constant value to avoid zero-division.

Methods

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

fit_with_env(*env*)

Gets scaling parameters from environment.

Parameters
env (*Union[Env[Any, Any], Env[Any, Any]]*) – Gym environment.

Return type
None

fit_with_trajectory_slicer(*episodes*, *trajectory_slicer*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **trajectory_slicer** (TrajectorySlicerProtocol) – Trajectory slicer to process mini-batch.

Return type
None

fit_with_transition_picker(*episodes*, *transition_picker*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.

- **transition_picker** (TransitionPickerProtocol) – Transition picker to process mini-batch.

Return type
None

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

static get_type()

Return type
str

reverse_transform(*x*)

Returns reversely transformed output.

Parameters
x (*Tensor*) – input.

Returns
Inversely transformed output.

Return type
Tensor

reverse_transform_numpy(*x*)

Returns reversely transformed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Inversely transformed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

classmethod schema(***, *infer_missing=False*, *only=None*, *exclude=()*, *many=False*, *context=None*, *load_only=()*, *dump_only=()*, *partial=False*, *unknown=None*)

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

`serialize`()

Return type
str

`serialize_to_dict`()

Return type
Dict[str, *Any*]

`to_dict`(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

`to_json`(*, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

`transform`(*x*)

Returns processed output.

Parameters
x (*Tensor*) – Input.

Returns
Processed output.

Return type
Tensor

`transform_numpy`(*x*)

Returns processed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Processed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

Attributes

built

eps: float = 0.001

mean: Optional[ndarray[Any, dtype[Any]]] = None

std: Optional[ndarray[Any, dtype[Any]]] = None

4.5.2 Action

d3rlpy also provides the feature that preprocesses continuous action. With this preprocessing, you don't need to normalize actions in advance or implement normalization in the environment side.

```
from d3rlpy.datasets import get_pendulum
from d3rlpy.algos import CQLConfig
from d3rlpy.preprocessing import MinMaxActionScaler

dataset, _ = get_pendulum()

cql = CQLConfig(action_scaler=MinMaxActionScaler()).create()

# action scaler is fitted from the given episodes
cql.fit(dataset, n_steps=100000)

# postprocessing is included in TorchScript
cql.save_policy('policy.pt')

# you don't need to take care of postprocessing at production
policy = torch.jit.load('policy.pt')
action = policy(x)
```

You can also initialize scalers by yourself.

```
from d3rlpy.preprocessing import MinMaxActionScaler

action_scaler = MinMaxActionScaler(minimum=..., maximum=...)

cql = CQLConfig(action_scaler=action_scaler).create()
```

d3rlpy.preprocessing.MinMaxActionScaler	Min-Max normalization action preprocessing.

d3rlpy.preprocessing.MinMaxActionScaler

class d3rlpy.preprocessing.**MinMaxActionScaler**(*minimum=None*, *maximum=None*)

Min-Max normalization action preprocessing.

Actions will be normalized in range `[-1.0, 1.0]`.

$$a' = (a - \min a)/(\max a - \min a) * 2 - 1$$

```
from d3rlpy.preprocessing import MinMaxActionScaler
from d3rlpy.algos import CQLConfig

# normalize based on datasets or environments
cql = CQLConfig(action_scaler=MinMaxActionScaler()).create()

# manually initialize
minimum = actions.min(axis=0)
maximum = actions.max(axis=0)
action_scaler = MinMaxActionScaler(minimum=minimum, maximum=maximum)
cql = CQLConfig(action_scaler=action_scaler).create()
```

Parameters

- **minimum** (*numpy.ndarray*) – Minimum values at each entry.
- **maximum** (*numpy.ndarray*) – Maximum values at each entry.

Methods

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

fit_with_env(*env*)

Gets scaling parameters from environment.

Parameters
env (*Union[Env[Any, Any], Env[Any, Any]]*) – Gym environment.

Return type
None

`fit_with_trajectory_slicer`(*episodes*, *trajectory_slicer*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **trajectory_slicer** (TrajectorySlicerProtocol) – Trajectory slicer to process mini-batch.

Return type
None

`fit_with_transition_picker`(*episodes*, *transition_picker*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **transition_picker** (TransitionPickerProtocol) – Transition picker to process mini-batch.

Return type
None

`classmethod from_dict`(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

`classmethod from_json`(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

`static get_type`()

Return type
str

`reverse_transform`(*x*)

Returns reversely transformed output.

Parameters
x (*Tensor*) – input.

Returns
Inversely transformed output.

Return type
Tensor

reverse_transform_numpy(*x*)

Returns reversely transformed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Inversely transformed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

classmethod schema(*, *infer_missing=False*, *only=None*, *exclude=()*, *many=False*, *context=None*, *load_only=()*, *dump_only=()*, *partial=False*, *unknown=None*)

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

serialize()

Return type
str

serialize_to_dict()

Return type
Dict[str, *Any*]

to_dict(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(*, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

transform(*x*)

Returns processed output.

Parameters
x (*Tensor*) – Input.

Returns
Processed output.

Return type
Tensor

transform_numpy(*x*)

Returns processed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Processed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

Attributes

built

maximum: Optional[ndarray[Any, dtype[Any]]] = None

minimum: Optional[ndarray[Any, dtype[Any]]] = None

4.5.3 Reward

d3rlpy also provides the feature that preprocesses rewards. With this preprocessing, you don't need to normalize rewards in advance. Note that this preprocessor should be fitted with the dataset. Afterwards you can use it with online training.

```
from d3rlpy.datasets import get_pendulum
from d3rlpy.algos import CQLConfig
from d3rlpy.preprocessing import StandardRewardScaler

dataset, _ = get_pendulum()

cql = CQLConfig(reward_scaler=StandardRewardScaler()).create()

# reward scaler is fitted from the given episodes
cql.fit(dataset)

# reward scaler is also available at finetuning.
cql.fit_online(env)
```

You can also initialize scalers by yourself.

```
from d3rlpy.preprocessing import MinMaxRewardScaler

reward_scaler = MinMaxRewardScaler(minimum=..., maximum=...)

cql = CQLConfig(reward_scaler=reward_scaler).create()
```

d3rlpy.preprocessing.MinMaxRewardScaler	Min-Max reward normalization preprocessing.
d3rlpy.preprocessing.StandardRewardScaler	Reward standardization preprocessing.
d3rlpy.preprocessing.ClipRewardScaler	Reward clipping preprocessing.
d3rlpy.preprocessing.MultiplyRewardScaler	Multiplication reward preprocessing.
d3rlpy.preprocessing.ReturnBasedRewardScaler	Reward normalization preprocessing based on return scale.
d3rlpy.preprocessing.ConstantShiftRewardScaler	Reward shift preprocessing.

d3rlpy.preprocessing.MinMaxRewardScaler

class d3rlpy.preprocessing.**MinMaxRewardScaler**(*minimum=None*, *maximum=None*, *multiplier=1.0*)

Min-Max reward normalization preprocessing.

Rewards will be normalized in range `[0.0, 1.0]`.

$$r' = (r - \min(r))/(\max(r) - \min(r))$$

```
from d3rlpy.preprocessing import MinMaxRewardScaler
from d3rlpy.algos import CQLConfig

# normalize based on datasets
cql = CQLConfig(reward_scaler=MinMaxRewardScaler()).create()

# initialize manually
reward_scaler = MinMaxRewardScaler(minimum=0.0, maximum=10.0)
cql = CQLConfig(reward_scaler=reward_scaler).create()
```

Parameters

- **minimum** (*float*) – Minimum value.
- **maximum** (*float*) – Maximum value.
- **multiplier** (*float*) – Constant multiplication value.

Methods

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

fit_with_env(*env*)

Gets scaling parameters from environment.

Parameters
env (*Union[Env[Any, Any], Env[Any, Any]]*) – Gym environment.

Return type
None

fit_with_trajectory_slicer(*episodes*, *trajectory_slicer*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **trajectory_slicer** (TrajectorySlicerProtocol) – Trajectory slicer to process mini-batch.

Return type
None

fit_with_transition_picker(*episodes*, *transition_picker*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **transition_picker** (TransitionPickerProtocol) – Transition picker to process mini-batch.

Return type
None

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

`static get_type()`

Return type
str

`reverse_transform(x)`

Returns reversely transformed output.

Parameters
x (*Tensor*) – input.

Returns
Inversely transformed output.

Return type
Tensor

`reverse_transform_numpy(x)`

Returns reversely transformed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Inversely transformed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

`classmethod schema(*, infer_missing=False, only=None, exclude=(), many=False, context=None, load_only=(), dump_only=(), partial=False, unknown=None)`

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

`serialize()`

Return type
str

`serialize_to_dict()`

Return type
Dict[str, *Any*]

`to_dict(encode_json=False)`

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(*, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

transform(*x*)

Returns processed output.

Parameters
x (*Tensor*) – Input.

Returns
Processed output.

Return type
Tensor

transform_numpy(*x*)

Returns processed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Processed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

Attributes

built

maximum: Optional[float] = None

minimum: Optional[float] = None

multiplier: float = 1.0

d3rlpy.preprocessing.StandardRewardScaler

class d3rlpy.preprocessing.**StandardRewardScaler**(*mean=None*, *std=None*, *eps=0.001*, *multiplier=1.0*)

Reward standardization preprocessing.

$$r' = (r - \mu) / \sigma$$

```
from d3rlpy.preprocessing import StandardRewardScaler
from d3rlpy.algos import CQLConfig

# normalize based on datasets
cql = CQLConfig(reward_scaler=StandardRewardScaler()).create()

# initialize manually
reward_scaler = StandardRewardScaler(mean=0.0, std=1.0)
cql = CQLConfig(reward_scaler=reward_scaler).create()
```

Parameters

- **mean** (*float*) – Mean value.
- **std** (*float*) – Standard deviation value.
- **eps** (*float*) – Constant value to avoid zero-division.
- **multiplier** (*float*) – Constant multiplication value

Methods

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

fit_with_env(*env*)

Gets scaling parameters from environment.

Parameters
env (*Union[Env[Any, Any], Env[Any, Any]]*) – Gym environment.

Return type
None

`fit_with_trajectory_slicer`(*episodes*, *trajectory_slicer*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **trajectory_slicer** (TrajectorySlicerProtocol) – Trajectory slicer to process mini-batch.

Return type
None

`fit_with_transition_picker`(*episodes*, *transition_picker*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **transition_picker** (TransitionPickerProtocol) – Transition picker to process mini-batch.

Return type
None

`classmethod from_dict`(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

`classmethod from_json`(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

`static get_type`()

Return type
str

`reverse_transform`(*x*)

Returns reversely transformed output.

Parameters
x (*Tensor*) – input.

Returns
Inversely transformed output.

Return type
Tensor

reverse_transform_numpy(*x*)

Returns reversely transformed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Inversely transformed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

classmethod schema(*, *infer_missing=False*, *only=None*, *exclude=()*, *many=False*, *context=None*, *load_only=()*, *dump_only=()*, *partial=False*, *unknown=None*)

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

serialize()

Return type
str

serialize_to_dict()

Return type
Dict[str, *Any*]

to_dict(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(*, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

transform(*x*)

Returns processed output.

Parameters
x (*Tensor*) – Input.

Returns
Processed output.

Return type
Tensor

transform_numpy(*x*)

Returns processed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Processed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

Attributes

built

eps: float = 0.001

mean: Optional[float] = None

multiplier: float = 1.0

std: Optional[float] = None

d3rlpy.preprocessing.ClipRewardScaler

class d3rlpy.preprocessing.**ClipRewardScaler**(*low=None*, *high=None*, *multiplier=1.0*)

Reward clipping preprocessing.

```
from d3rlpy.preprocessing import ClipRewardScaler
from d3rlpy.algos import CQLConfig

# clip rewards within [-1.0, 1.0]
reward_scaler = ClipRewardScaler(low=-1.0, high=1.0)
cql = CQLConfig(reward_scaler=reward_scaler).create()
```

Parameters

- **low** (*Optional[float]*) – Minimum value to clip.
- **high** (*Optional[float]*) – Maximum value to clip.
- **multiplier** (*float*) – Constant multiplication value.

Methods

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

fit_with_env(*env*)

Gets scaling parameters from environment.

Parameters
env (*Union[Env[Any, Any], Env[Any, Any]]*) – Gym environment.

Return type
None

fit_with_trajectory_slicer(*episodes*, *trajectory_slicer*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **trajectory_slicer** (TrajectorySlicerProtocol) – Trajectory slicer to process mini-batch.

Return type
None

fit_with_transition_picker(*episodes*, *transition_picker*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **transition_picker** (TransitionPickerProtocol) – Transition picker to process mini-batch.

Return type
None

classmethod from_dict(*kvs*, *, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, *, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

static get_type()

Return type
str

reverse_transform(*x*)

Returns reversely transformed output.

Parameters
x (*Tensor*) – input.

Returns
Inversely transformed output.

Return type
Tensor

reverse_transform_numpy(*x*)

Returns reversely transformed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Inversely transformed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

classmethod schema(*, *infer_missing=False*, *only=None*, *exclude=()*, *many=False*, *context=None*, *load_only=()*, *dump_only=()*, *partial=False*, *unknown=None*)

Parameters
- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

serialize()

Return type
str

serialize_to_dict()

Return type
Dict[str, *Any*]

to_dict(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(*, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

transform(*x*)

Returns processed output.

Parameters
x (*Tensor*) – Input.

Returns
Processed output.

Return type
Tensor

transform_numpy(*x*)

Returns processed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Processed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

Attributes

built

high: Optional[float] = None

low: Optional[float] = None

multiplier: float = 1.0

d3rlpy.preprocessing.MultiplyRewardScaler

class d3rlpy.preprocessing.**MultiplyRewardScaler**(*multiplier=1.0*)

Multiplication reward preprocessing.

This preprocessor multiplies rewards by a constant number.

```
from d3rlpy.preprocessing import MultiplyRewardScaler
from d3rlpy.algos import CQLConfig

# multiply rewards by 10
reward_scaler = MultiplyRewardScaler(10.0)
cql = CQLConfig(reward_scaler=reward_scaler).create()
```

Parameters
multiplier (*float*) – Constant multiplication value.

Methods

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

fit_with_env(*env*)

Gets scaling parameters from environment.

Parameters
env (*Union[Env[Any, Any], Env[Any, Any]]*) – Gym environment.

Return type
None

fit_with_trajectory_slicer(*episodes*, *trajectory_slicer*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **trajectory_slicer** (TrajectorySlicerProtocol) – Trajectory slicer to process mini-batch.

Return type
None

fit_with_transition_picker(*episodes*, *transition_picker*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **transition_picker** (TransitionPickerProtocol) – Transition picker to process mini-batch.

Return type
None

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

static get_type()

Return type
str

reverse_transform(*x*)

Returns reversely transformed output.

Parameters
x (*Tensor*) – input.

Returns
Inversely transformed output.

Return type
Tensor

reverse_transform_numpy(*x*)

Returns reversely transformed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Inversely transformed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

classmethod schema(**, infer_missing=False, only=None, exclude=(), many=False, context=None, load_only=(), dump_only=(), partial=False, unknown=None*)

Parameters
- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

serialize()

Return type
str

serialize_to_dict()

Return type
Dict[str, *Any*]

to_dict(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(**, skipkeys=False, ensure_ascii=True, check_circular=True, allow_nan=True, indent=None, separators=None, default=None, sort_keys=False, **kw*)

Parameters
- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –

- **sort_keys** (*bool*) –

Return type
str

transform(*x*)

Returns processed output.

Parameters
x (*Tensor*) – Input.

Returns
Processed output.

Return type
Tensor

transform_numpy(*x*)

Returns processed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Processed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

Attributes

built

multiplier: float = 1.0

d3rlpy.preprocessing.ReturnBasedRewardScaler

class d3rlpy.preprocessing.**ReturnBasedRewardScaler**(*return_max=None*, *return_min=None*, *multiplier=1.0*)

Reward normalization preprocessing based on return scale.

$$r' = r/(R_{max} - R_{min})$$

```
from d3rlpy.preprocessing import ReturnBasedRewardScaler
from d3rlpy.algos import CQLConfig

# normalize based on datasets
cql = CQLConfig(reward_scaler=ReturnBasedRewardScaler()).create()

# initialize manually
reward_scaler = ReturnBasedRewardScaler(
    return_max=100.0,
    return_min=1.0,
)
cql = CQLConfig(reward_scaler=reward_scaler).create()
```

References

- Kostrikov et al., Offline Reinforcement Learning with Implicit Q-Learning.

Parameters

- **return_max** (*float*) – Maximum return value.
- **return_min** (*float*) – Standard deviation value.
- **multiplier** (*float*) – Constant multiplication value

Methods

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

fit_with_env(*env*)

Gets scaling parameters from environment.

Parameters
env (*Union[Env[Any, Any], Env[Any, Any]]*) – Gym environment.

Return type
None

fit_with_trajectory_slicer(*episodes*, *trajectory_slicer*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **trajectory_slicer** (TrajectorySlicerProtocol) – Trajectory slicer to process mini-batch.

Return type
None

fit_with_transition_picker(*episodes*, *transition_picker*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **transition_picker** (TransitionPickerProtocol) – Transition picker to process mini-batch.

Return type
None

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

static get_type()

Return type
str

reverse_transform(*x*)

Returns reversely transformed output.

Parameters
x (*Tensor*) – input.

Returns
Inversely transformed output.

Return type
Tensor

reverse_transform_numpy(*x*)

Returns reversely transformed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Inversely transformed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

classmethod schema(***, *infer_missing=False*, *only=None*, *exclude=()*, *many=False*, *context=None*, *load_only=()*, *dump_only=()*, *partial=False*, *unknown=None*)

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

serialize()

Return type
str

serialize_to_dict()

Return type
Dict[str, *Any*]

to_dict(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(*, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters
- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

transform(*x*)

Returns processed output.

Parameters
x (*Tensor*) – Input.

Returns
Processed output.

Return type
Tensor

transform_numpy(*x*)

Returns processed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Processed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

Attributes

built

multiplier: `float = 1.0`

return_max: `Optional[float] = None`

return_min: `Optional[float] = None`

d3rlpy.preprocessing.ConstantShiftRewardScaler

class d3rlpy.preprocessing.**ConstantShiftRewardScaler**(*shift*, *multiplier=1.0*, *multiply_first=False*)

Reward shift preprocessing.

$$r' = r + c$$

You need to initialize manually.

```
from d3rlpy.preprocessing import ConstantShiftRewardScaler
from d3rlpy.algos import CQLConfig

reward_scaler = ConstantShiftRewardScaler(shift=-1.0)
cql = CQLConfig(reward_scaler=reward_scaler).create()
```

References

- Kostrikov et al., Offline Reinforcement Learning with Implicit Q-Learning.

Parameters

- **shift** (*float*) – Constant shift value
- **multiplier** (*float*) – Constant multiplication value.
- **multiply_first** (*bool*) – Flag to multiply rewards and then shift.

Methods

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

fit_with_env(*env*)

Gets scaling parameters from environment.

Parameters
env (*Union[Env[Any, Any], Env[Any, Any]]*) – Gym environment.

Return type
None

fit_with_trajectory_slicer(*episodes*, *trajectory_slicer*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **trajectory_slicer** (TrajectorySlicerProtocol) – Trajectory slicer to process mini-batch.

Return type
None

fit_with_transition_picker(*episodes*, *transition_picker*)

Estimates scaling parameters from dataset.

Parameters

- **episodes** (*Sequence[EpisodeBase]*) – List of episodes.
- **transition_picker** (TransitionPickerProtocol) – Transition picker to process mini-batch.

Return type
None

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

`static get_type()`

Return type
str

`reverse_transform(x)`

Returns reversely transformed output.

Parameters
x (*Tensor*) – input.

Returns
Inversely transformed output.

Return type
Tensor

`reverse_transform_numpy(x)`

Returns reversely transformed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Inversely transformed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

`classmethod schema(*, infer_missing=False, only=None, exclude=(), many=False, context=None, load_only=(), dump_only=(), partial=False, unknown=None)`

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

`serialize()`

Return type
str

`serialize_to_dict()`

Return type
Dict[str, *Any*]

`to_dict(encode_json=False)`

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(*, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

transform(*x*)

Returns processed output.

Parameters
x (*Tensor*) – Input.

Returns
Processed output.

Return type
Tensor

transform_numpy(*x*)

Returns processed output in numpy.

Parameters
x (*ndarray[Any, dtype[Any]]*) – Input.

Returns
Processed output.

Return type
ndarray[*Any*, *dtype*[*Any*]]

Attributes

built

multiplier: float = 1.0

multiply_first: bool = False

shift: float

4.6 Optimizers

d3rlpy provides `OptimizerFactory` that gives you flexible control over optimizers. `OptimizerFactory` takes PyTorch's optimizer class and its arguments to initialize, which you can check more here.

```
import d3rlpy
from torch.optim import Adam

# modify weight decay
optim_factory = d3rlpy.models.OptimizerFactory(Adam, weight_decay=1e-4)

# set OptimizerFactory
dqn = d3rlpy.algos.DQNConfig(optim_factory=optim_factory).create()
```

There are also convenient alises.

```
# alias for Adam optimizer
optim_factory = d3rlpy.models.AdamFactory(weight_decay=1e-4)

dqn = d3rlpy.algos.DQNConfig(optim_factory=optim_factory).create()
```

d3rlpy.models.OptimizerFactory	A factory class that creates an optimizer object in a lazy way.
d3rlpy.models.SGDFactory	An alias for SGD optimizer.
d3rlpy.models.AdamFactory	An alias for Adam optimizer.
d3rlpy.models.RMSpropFactory	An alias for RMSprop optimizer.
d3rlpy.models.GPTAdamWFactory	AdamW optimizer for Decision Transformer architectures.

4.6.1 d3rlpy.models.OptimizerFactory

class d3rlpy.models.**OptimizerFactory**

A factory class that creates an optimizer object in a lazy way.

The optimizers in algorithms can be configured through this factory class.

Methods

create(*named_modules*, *lr*)

Returns an optimizer object.

Parameters

- **named_modules** (*list*) – List of tuples of module names and modules.
- **lr** (*float*) – Learning rate.

Returns
an optimizer object.

Return type
torch.optim.Optimizer

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

static get_type()

Return type
str

classmethod schema(***, *infer_missing=False*, *only=None*, *exclude=()*, *many=False*, *context=None*, *load_only=()*, *dump_only=()*, *partial=False*, *unknown=None*)

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

serialize()

Return type
str

serialize_to_dict()

Return type
Dict[str, *Any*]

to_dict(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(*, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

4.6.2 d3rlpy.models.SGDFactory

class d3rlpy.models.**SGDFactory**(*momentum=0.0*, *dampening=0.0*, *weight_decay=0.0*, *nesterov=False*)

An alias for SGD optimizer.

```
from d3rlpy.optimizers import SGDFactory

factory = SGDFactory(weight_decay=1e-4)
```

Parameters

- **momentum** (*float*) – momentum factor.
- **dampening** (*float*) – dampening for momentum.
- **weight_decay** (*float*) – weight decay (L2 penalty).
- **nesterov** (*bool*) – flag to enable Nesterov momentum.

Methods

create(*named_modules*, *lr*)

Returns an optimizer object.

Parameters

- **named_modules** (*list*) – List of tuples of module names and modules.
- **lr** (*float*) – Learning rate.

Returns
an optimizer object.

Return type
torch.optim.Optimizer

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

static get_type()

Return type
str

classmethod schema(*, *infer_missing=False*, *only=None*, *exclude=()*, *many=False*, *context=None*, *load_only=()*, *dump_only=()*, *partial=False*, *unknown=None*)

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

serialize()

Return type
str

serialize_to_dict()

Return type
Dict[str, *Any*]

to_dict(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(*, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

Attributes

dampening: float = 0.0

momentum: float = 0.0

nesterov: bool = False

weight_decay: float = 0.0

4.6.3 d3rlpy.models.AdamFactory

class d3rlpy.models.**AdamFactory**(*betas=(0.9, 0.999)*, *eps=1e-08*, *weight_decay=0*, *amsgrad=False*)

An alias for Adam optimizer.

```
from d3rlpy.optimizers import AdamFactory

factory = AdamFactory(weight_decay=1e-4)
```

Parameters

- **betas** (*Tuple[float, float]*) – coefficients used for computing running averages of gradient and its square.
- **eps** (*float*) – term added to the denominator to improve numerical stability.
- **weight_decay** (*float*) – weight decay (L2 penalty).
- **amsgrad** (*bool*) – flag to use the AMSGrad variant of this algorithm.

Methods

create(*named_modules*, *lr*)

Returns an optimizer object.

Parameters

- **named_modules** (*list*) – List of tuples of module names and modules.
- **lr** (*float*) – Learning rate.

Returns
an optimizer object.

Return type
torch.optim.Optimizer

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

static get_type()

Return type
str

classmethod schema(***, *infer_missing=False*, *only=None*, *exclude=()*, *many=False*, *context=None*, *load_only=()*, *dump_only=()*, *partial=False*, *unknown=None*)

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

serialize()

Return type
str

serialize_to_dict()

Return type
Dict[str, *Any*]

to_dict(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(***, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –

- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

Attributes

amsgrad: bool = False

betas: Tuple[float, float] = (0.9, 0.999)

eps: float = 1e-08

weight_decay: float = 0

4.6.4 d3rlpy.models.RMSpropFactory

class d3rlpy.models.**RMSpropFactory**(*alpha=0.95*, *eps=0.01*, *weight_decay=0.0*, *momentum=0.0*, *centered=True*)

An alias for RMSprop optimizer.

```
from d3rlpy.optimizers import RMSpropFactory

factory = RMSpropFactory(weight_decay=1e-4)
```

Parameters

- **alpha** (*float*) – smoothing constant.
- **eps** (*float*) – term added to the denominator to improve numerical stability.
- **weight_decay** (*float*) – weight decay (L2 penalty).
- **momentum** (*float*) – momentum factor.
- **centered** (*bool*) – flag to compute the centered RMSProp, the gradient is normalized by an estimation of its variance.

Methods

create(*named_modules*, *lr*)

Returns an optimizer object.

Parameters

- **named_modules** (*list*) – List of tuples of module names and modules.
- **lr** (*float*) – Learning rate.

Returns
an optimizer object.

Return type
torch.optim.Optimizer

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

static get_type()

Return type
str

classmethod schema(***, *infer_missing=False*, *only=None*, *exclude=()*, *many=False*, *context=None*, *load_only=()*, *dump_only=()*, *partial=False*, *unknown=None*)

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

serialize()

Return type
str

serialize_to_dict()

Return type
Dict[str, *Any*]

to_dict(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(*, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

Attributes

alpha: *float* = **0.95**

centered: *bool* = **True**

eps: *float* = **0.01**

momentum: *float* = **0.0**

weight_decay: *float* = **0.0**

4.6.5 d3rlpy.models.GPTAdamWFactory

class d3rlpy.models.**GPTAdamWFactory**(*betas=(0.9, 0.999)*, *eps=1e-08*, *weight_decay=0*, *amsgrad=False*)

AdamW optimizer for Decision Transformer architectures.

```
from d3rlpy.optimizers import GPTAdamWFactory

factory = GPTAdamWFactory(weight_decay=1e-4)
```

Parameters

- **betas** (*Tuple[float, float]*) – coefficients used for computing running averages of gradient and its square.

- **eps** (*float*) – term added to the denominator to improve numerical stability.
- **weight_decay** (*float*) – weight decay (L2 penalty).
- **amsgrad** (*bool*) – flag to use the AMSGrad variant of this algorithm.

Methods

create(*named_modules*, *lr*)

Returns an optimizer object.

Parameters

- **named_modules** (*list*) – List of tuples of module names and modules.
- **lr** (*float*) – Learning rate.

Returns
an optimizer object.

Return type
torch.optim.Optimizer

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

static get_type()

Return type
str

classmethod schema(*, *infer_missing=False*, *only=None*, *exclude=()*, *many=False*, *context=None*, *load_only=()*, *dump_only=()*, *partial=False*, *unknown=None*)

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

serialize()

Return type
str

serialize_to_dict()

Return type
Dict[str, *Any*]

to_dict(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(*, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

Attributes

amsgrad: `bool = False`

betas: `Tuple[float, float] = (0.9, 0.999)`

eps: `float = 1e-08`

weight_decay: `float = 0`

4.7 Network Architectures

In d3rlpy, the neural network architecture is automatically selected based on observation shape. If the observation is image, the algorithm uses the `Nature` DQN-based encoder at each function. Otherwise, the standard MLP architecture that consists with two linear layers with `256` hidden units.

Furthermore, d3rlpy provides `EncoderFactory` that gives you flexible control over the neural network architectures.

```
import d3rlpy

# encoder factory
encoder_factory = d3rlpy.models.VectorEncoderFactory(
    hidden_units=[300, 400],
    activation='tanh',
)

# set EncoderFactory
dqn = d3rlpy.algos.DQNConfig(encoder_factory=encoder_factory).create()
```

You can also build your own encoder factory.

```
import dataclasses
import torch
import torch.nn as nn

from d3rlpy.models.encoders import EncoderFactory

# your own neural network
class CustomEncoder(nn.Module):
    def __init__(self, obsevation_shape, feature_size):
        self.feature_size = feature_size
        self.fc1 = nn.Linear(observation_shape[0], 64)
        self.fc2 = nn.Linear(64, feature_size)

    def forward(self, x):
        h = torch.relu(self.fc1(x))
        h = torch.relu(self.fc2(h))
        return h

# your own encoder factory
@dataclasses.dataclass()
class CustomEncoderFactory(EncoderFactory):
    feature_size: int
```

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```
    def create(self, observation_shape):
        return CustomEncoder(observation_shape, self.feature_size)

    @staticmethod
    def get_type() -> str:
        return "custom"

dqn = d3rlpy.algos.DQNConfig(
   encoder_factory=CustomEncoderFactory(feature_size=64),
).create()
```

You can also define action-conditioned networks such as Q-functions for continuous controls. `create` or `create_with_action` will be called depending on the function.

```
class CustomEncoderWithAction(nn.Module):
    def __init__(self, obsevation_shape, action_size, feature_size):
        self.feature_size = feature_size
        self.fc1 = nn.Linear(observation_shape[0] + action_size, 64)
        self.fc2 = nn.Linear(64, feature_size)

    def forward(self, x, action): # action is also given
        h = torch.cat([x, action], dim=1)
        h = torch.relu(self.fc1(h))
        h = torch.relu(self.fc2(h))
        return h

@dataclasses.dataclass()
class CustomEncoderFactory(EncoderFactory):
    feature_size: int

    def create(self, observation_shape):
        return CustomEncoder(observation_shape, self.feature_size)

    def create_with_action(observation_shape, action_size, discrete_action):
        return CustomEncoderWithAction(observation_shape, action_size, self.feature_size)

    @staticmethod
    def get_type() -> str:
        return "custom"


factory = CustomEncoderFactory(feature_size=64)

sac = d3rlpy.algos.SACConfig(
   actor_encoder_factory=factory,
   critic_encoder_factory=factory,
).create()
```

If you want `load_learnable` method to load the algorithm configuration including your encoder configuration, you need to register your encoder factory.

```
from d3rlpy.models.encoders import register_encoder_factory

# register your own encoder factory
register_encoder_factory(CustomEncoderFactory)

# load algorithm from d3
dqn = d3rlpy.load_learnable("model.d3")
```

d3rlpy.models.DefaultEncoderFactory	Default encoder factory class.
d3rlpy.models.PixelEncoderFactory	Pixel encoder factory class.
d3rlpy.models.VectorEncoderFactory	Vector encoder factory class.

4.7.1 d3rlpy.models.DefaultEncoderFactory

class d3rlpy.models.**DefaultEncoderFactory**(*activation='relu'*, *use_batch_norm=False*, *dropout_rate=None*)

Default encoder factory class.

This encoder factory returns an encoder based on observation shape.

Parameters

- **activation** (*str*) – activation function name.
- **use_batch_norm** (*bool*) – flag to insert batch normalization layers.
- **dropout_rate** (*float*) – dropout probability.

Methods

create(*observation_shape*)

Returns PyTorch's state enocder module.

Parameters
observation_shape (*Union[Sequence[int], Sequence[Sequence[int]]]*) – observation shape.

Returns
an enocder object.

Return type
Encoder

create_with_action(*observation_shape*, *action_size*, *discrete_action=False*)

Returns PyTorch's state-action enocder module.

Parameters

- **observation_shape** (*Union[Sequence[int], Sequence[Sequence[int]]]*) – observation shape.
- **action_size** (*int*) – action size. If None, the encoder does not take action as input.
- **discrete_action** (*bool*) – flag if action-space is discrete.

Returns
an enocder object.

Return type
EncoderWithAction

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

static get_type()

Return type
str

classmethod schema(***, *infer_missing=False*, *only=None*, *exclude=()*, *many=False*, *context=None*, *load_only=()*, *dump_only=()*, *partial=False*, *unknown=None*)

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

serialize()

Return type
str

serialize_to_dict()

Return type
Dict[str, *Any*]

to_dict(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(*, skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

Attributes

activation: str = 'relu'

dropout_rate: Optional[float] = None

use_batch_norm: bool = False

4.7.2 d3rlpy.models.PixelEncoderFactory

class d3rlpy.models.**PixelEncoderFactory**(*filters=<factory>*, *feature_size=512*, *activation='relu'*, *use_batch_norm=False*, *dropout_rate=None*, *exclude_last_activation=False*, *last_activation=None*)

Pixel encoder factory class.

This is the default encoder factory for image observation.

Parameters

- **filters** (*list*) – List of tuples consisting with `(filter_size, kernel_size, stride)`. If None, `Nature DQN`-based architecture is used.

- **feature_size** (*int*) – Last linear layer size.
- **activation** (*str*) – Activation function name.
- **use_batch_norm** (*bool*) – Flag to insert batch normalization layers.
- **dropout_rate** (*float*) – Dropout probability.
- **exclude_last_activation** (*bool*) – Flag to exclude activation function at the last layer.
- **last_activation** (*str*) – Activation function name for the last layer.

Methods

create(*observation_shape*)

Returns PyTorch's state enocder module.

Parameters
observation_shape (*Union[Sequence[int], Sequence[Sequence[int]]]*) – observation shape.

Returns
an enocder object.

Return type
PixelEncoder

create_with_action(*observation_shape*, *action_size*, *discrete_action=False*)

Returns PyTorch's state-action enocder module.

Parameters

- **observation_shape** (*Union[Sequence[int], Sequence[Sequence[int]]]*) – observation shape.
- **action_size** (*int*) – action size. If None, the encoder does not take action as input.
- **discrete_action** (*bool*) – flag if action-space is discrete.

Returns
an enocder object.

Return type
PixelEncoderWithAction

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

static get_type()

Return type
str

classmethod schema(***, *infer_missing=False*, *only=None*, *exclude=()*, *many=False*, *context=None*, *load_only=()*, *dump_only=()*, *partial=False*, *unknown=None*)

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

serialize()

Return type
str

serialize_to_dict()

Return type
Dict[str, *Any*]

to_dict(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(***, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

Attributes

activation: `str = 'relu'`

dropout_rate: `Optional[float] = None`

exclude_last_activation: `bool = False`

feature_size: `int = 512`

last_activation: `Optional[str] = None`

use_batch_norm: `bool = False`

filters: `List[List[int]]`

4.7.3 d3rlpy.models.VectorEncoderFactory

class d3rlpy.models.**VectorEncoderFactory**(*hidden_units=<factory>*, *activation='relu'*, *use_batch_norm=False*, *dropout_rate=None*, *exclude_last_activation=False*, *last_activation=None*)

Vector encoder factory class.

This is the default encoder factory for vector observation.

Parameters

- **hidden_units** (*list*) – List of hidden unit sizes. If `None`, the standard architecture with `[256, 256]` is used.
- **activation** (*str*) – activation function name.
- **use_batch_norm** (*bool*) – Flag to insert batch normalization layers.
- **dropout_rate** (*float*) – Dropout probability.
- **exclude_last_activation** (*bool*) – Flag to exclude activation function at the last layer.
- **last_activation** (*str*) – Activation function name for the last layer.

Methods

create(*observation_shape*)

Returns PyTorch's state enocder module.

Parameters
observation_shape (*Union[Sequence[int], Sequence[Sequence[int]]]*) – observation shape.

Returns
an enocder object.

Return type
VectorEncoder

create_with_action(*observation_shape*, *action_size*, *discrete_action=False*)

Returns PyTorch's state-action enocder module.

Parameters

- **observation_shape** (*Union[Sequence[int], Sequence[Sequence[int]]]*) – observation shape.
- **action_size** (*int*) – action size. If None, the encoder does not take action as input.
- **discrete_action** (*bool*) – flag if action-space is discrete.

Returns
an enocder object.

Return type
VectorEncoderWithAction

classmethod deserialize(*serialized_config*)

Parameters
serialized_config (*str*) –

Return type
TConfig

classmethod deserialize_from_dict(*dict_config*)

Parameters
dict_config (*Dict[str, Any]*) –

Return type
TConfig

classmethod deserialize_from_file(*path*)

Parameters
path (*str*) –

Return type
TConfig

classmethod from_dict(*kvs*, ***, *infer_missing=False*)

Parameters
kvs (*Optional[Union[dict, list, str, int, float, bool]]*) –

Return type
A

classmethod from_json(*s*, ***, *parse_float=None*, *parse_int=None*, *parse_constant=None*, *infer_missing=False*, ***kw*)

Parameters
s (*Union[str, bytes, bytearray]*) –

Return type
A

static get_type()

Return type
str

classmethod schema(***, *infer_missing=False*, *only=None*, *exclude=()*, *many=False*, *context=None*, *load_only=()*, *dump_only=()*, *partial=False*, *unknown=None*)

Parameters

- **infer_missing** (*bool*) –
- **many** (*bool*) –
- **partial** (*bool*) –

Return type
SchemaF[*A*]

serialize()

Return type
str

serialize_to_dict()

Return type
Dict[str, *Any*]

to_dict(*encode_json=False*)

Return type
Dict[str, *Optional*[*Union*[dict, list, str, int, float, bool]]]

to_json(***, *skipkeys=False*, *ensure_ascii=True*, *check_circular=True*, *allow_nan=True*, *indent=None*, *separators=None*, *default=None*, *sort_keys=False*, ***kw*)

Parameters

- **skipkeys** (*bool*) –
- **ensure_ascii** (*bool*) –
- **check_circular** (*bool*) –
- **allow_nan** (*bool*) –
- **indent** (*Optional[Union[int, str]]*) –
- **separators** (*Optional[Tuple[str, str]]*) –
- **default** (*Optional[Callable]*) –
- **sort_keys** (*bool*) –

Return type
str

Attributes

activation: str = 'relu'

dropout_rate: Optional[float] = None

exclude_last_activation: bool = False

last_activation: Optional[str] = None

use_batch_norm: bool = False

hidden_units: List[int]

4.8 Metrics

d3rlpy provides scoring functions for offline Q-learning-based training. You can also check *Logging* to understand how to write metrics to files.

```
import d3rlpy

dataset, env = d3rlpy.datasets.get_cartpole()
# use partial episodes as test data
test_episodes = dataset.episodes[:10]

dqn = d3rlpy.algos.DQNConfig().create()

dqn.fit(
    dataset,
    n_steps=100000,
    evaluators={
        'td_error': d3rlpy.metrics.TDErrorEvaluator(test_episodes),
        'value_scale': d3rlpy.metrics.AverageValueEstimationEvaluator(test_episodes),
        'environment': d3rlpy.metrics.EnvironmentEvaluator(env),
    },
)
```

You can also implement your own metrics.

```
class CustomEvaluator(d3rlpy.metrics.EvaluatorProtocol):
    def __call__(self, algo: d3rlpy.algos.QLearningAlgoBase, dataset: ReplayBuffer) ->␣
↪float:
        # do some evaluation
```

d3rlpy.metrics.TDErrorEvaluator	Returns average TD error.
d3rlpy.metrics.DiscountedSumOfAdvantageEvaluator	Returns average of discounted sum of advantage.
d3rlpy.metrics.AverageValueEstimationEvaluator	Returns average value estimation.
d3rlpy.metrics.InitialStateValueEstimationEvaluator	Returns mean estimated action-values at the initial states.
d3rlpy.metrics.SoftOPCEvaluator	Returns Soft Off-Policy Classification metrics.
d3rlpy.metrics.ContinuousActionDiffEvaluator	Returns squared difference of actions between algorithm and dataset.
d3rlpy.metrics.DiscreteActionMatchEvaluator	Returns percentage of identical actions between algorithm and dataset.
d3rlpy.metrics.EnvironmentEvaluator	Action matches between algorithms.
d3rlpy.metrics.CompareContinuousActionDiffEvaluator	Action difference between algorithms.
d3rlpy.metrics.CompareDiscreteActionMatchEvaluator	Action matches between algorithms.

4.8.1 d3rlpy.metrics.TDErrorEvaluator

class d3rlpy.metrics.**TDErrorEvaluator**(*episodes=None*)

Returns average TD error.

This metric suggests how Q functions overfit to training sets. If the TD error is large, the Q functions are overfitting.

$$\mathbb{E}_{s_t,a_t,r_{t+1},s_{t+1}\sim D}[(Q_\theta(s_t,a_t) - r_{t+1} - \gamma \max_a Q_\theta(s_{t+1},a))^2]$$

Parameters

episodes – Optional evaluation episodes. If it's not given, dataset used in training will be used.

Methods

__call__(*algo*, *dataset*)

Computes metrics.

Parameters

- **algo** (*QLearningAlgoProtocol*) – Q-learning algorithm.
- **dataset** (ReplayBufferBase) – ReplayBuffer.

Returns

Computed metrics.

Return type

float

4.8.2 d3rlpy.metrics.DiscountedSumOfAdvantageEvaluator

class d3rlpy.metrics.**DiscountedSumOfAdvantageEvaluator**(*episodes=None*)

Returns average of discounted sum of advantage.

This metric suggests how the greedy-policy selects different actions in action-value space. If the sum of advantage is small, the policy selects actions with larger estimated action-values.

$$\mathbb{E}_{s_t,a_t\sim D}[\sum_{t'=t} \gamma^{t'-t} A(s_{t'},a_{t'})]$$

where $A(s_t, a_t) = Q_\theta(s_t, a_t) - \mathbb{E}_{a \sim \pi}[Q_\theta(s_t, a)]$.

References

- Murphy., A generalization error for Q-Learning.

Parameters
episodes – Optional evaluation episodes. If it's not given, dataset used in training will be used.

Methods

__call__(*algo*, *dataset*)

Computes metrics.

Parameters

- **algo** (*QLearningAlgoProtocol*) – Q-learning algorithm.
- **dataset** (ReplayBufferBase) – ReplayBuffer.

Returns
Computed metrics.

Return type
float

4.8.3 d3rlpy.metrics.AverageValueEstimationEvaluator

class d3rlpy.metrics.**AverageValueEstimationEvaluator**(*episodes=None*)

Returns average value estimation.

This metric suggests the scale for estimation of Q functions. If average value estimation is too large, the Q functions overestimate action-values, which possibly makes training failed.

$$\mathbb{E}_{s_t \sim D}[\max_a Q_\theta(s_t, a)]$$

Parameters
episodes – Optional evaluation episodes. If it's not given, dataset used in training will be used.

Methods

__call__(*algo*, *dataset*)

Computes metrics.

Parameters

- **algo** (*QLearningAlgoProtocol*) – Q-learning algorithm.
- **dataset** (ReplayBufferBase) – ReplayBuffer.

Returns
Computed metrics.

Return type
float

4.8.4 d3rlpy.metrics.InitialStateValueEstimationEvaluator

class d3rlpy.metrics.**InitialStateValueEstimationEvaluator**(*episodes=None*)

Returns mean estimated action-values at the initial states.

This metric suggests how much return the trained policy would get from the initial states by deploying the policy to the states. If the estimated value is large, the trained policy is expected to get higher returns.

$$\mathbb{E}_{s_0 \sim D}[Q(s_0, \pi(s_0))]$$

References

- Paine et al., Hyperparameter Selection for Offline Reinforcement Learning

Parameters

episodes – Optional evaluation episodes. If it's not given, dataset used in training will be used.

Methods

__call__(*algo*, *dataset*)

Computes metrics.

Parameters

- **algo** (*QLearningAlgoProtocol*) – Q-learning algorithm.
- **dataset** (ReplayBufferBase) – ReplayBuffer.

Returns

Computed metrics.

Return type

float

4.8.5 d3rlpy.metrics.SoftOPCEvaluator

class d3rlpy.metrics.**SoftOPCEvaluator**(*return_threshold*, *episodes=None*)

Returns Soft Off-Policy Classification metrics.

The metric of the scorer funciton is evaluating gaps of action-value estimation between the success episodes and the all episodes. If the learned Q-function is optimal, action-values in success episodes are expected to be higher than the others. The success episode is defined as an episode with a return above the given threshold.

$$\mathbb{E}_{s,a \sim D_{success}}[Q(s,a)] - \mathbb{E}_{s,a \sim D}[Q(s,a)]$$

References

- Irpan et al., Off-Policy Evaluation via Off-Policy Classification.

Parameters

- **return_threshold** – Return threshold of success episodes.
- **episodes** – Optional evaluation episodes. If it's not given, dataset used in training will be used.

Methods

__call__(*algo*, *dataset*)

Computes metrics.

Parameters

- **algo** (*QLearningAlgoProtocol*) – Q-learning algorithm.
- **dataset** (ReplayBufferBase) – ReplayBuffer.

Returns

Computed metrics.

Return type

float

4.8.6 d3rlpy.metrics.ContinuousActionDiffEvaluator

class d3rlpy.metrics.**ContinuousActionDiffEvaluator**(*episodes=None*)

Returns squared difference of actions between algorithm and dataset.

This metric suggests how different the greedy-policy is from the given episodes in continuous action-space. If the given episodes are near-optimal, the small action difference would be better.

$$\mathbb{E}_{s_t, a_t \sim D}[(a_t - \pi_\phi(s_t))^2]$$

Parameters

episodes – Optional evaluation episodes. If it's not given, dataset used in training will be used.

Methods

__call__(*algo*, *dataset*)

Computes metrics.

Parameters

- **algo** (*QLearningAlgoProtocol*) – Q-learning algorithm.
- **dataset** (ReplayBufferBase) – ReplayBuffer.

Returns

Computed metrics.

Return type

float

4.8.7 d3rlpy.metrics.DiscreteActionMatchEvaluator

class d3rlpy.metrics.**DiscreteActionMatchEvaluator**(*episodes=None*)

Returns percentage of identical actions between algorithm and dataset.

This metric suggests how different the greedy-policy is from the given episodes in discrete action-space. If the given episdoes are near-optimal, the large percentage would be better.

$$\frac{1}{N}\sum^{N} \| \{a_t = \text{argmax}_a Q_\theta(s_t, a)\}$$

Parameters

episodes – Optional evaluation episodes. If it's not given, dataset used in training will be used.

Methods

__call__(*algo*, *dataset*)

Computes metrics.

Parameters

- **algo** (*QLearningAlgoProtocol*) – Q-learning algorithm.
- **dataset** (ReplayBufferBase) – ReplayBuffer.

Returns

Computed metrics.

Return type

float

4.8.8 d3rlpy.metrics.EnvironmentEvaluator

class d3rlpy.metrics.**EnvironmentEvaluator**(*env*, *n_trials=10*, *epsilon=0.0*)

Action matches between algorithms.

This metric suggests how different the two algorithms are in discrete action-space. If the algorithm to compare with is near-optimal, the small action difference would be better.

$$\mathbb{E}_{s_t \sim D}[\| \{\text{argmax}_a Q_{\theta_1}(s_t, a) = \text{argmax}_a Q_{\theta_2}(s_t, a)\}]$$

Parameters

- **env** – Gym environment.
- **n_trials** – Number of episodes to evaluate.
- **epsilon** – Probability of random action.

Methods

__call__(*algo*, *dataset*)

Computes metrics.

Parameters

- **algo** (*QLearningAlgoProtocol*) – Q-learning algorithm.
- **dataset** (ReplayBufferBase) – ReplayBuffer.

Returns
Computed metrics.

Return type
float

4.8.9 d3rlpy.metrics.CompareContinuousActionDiffEvaluator

class d3rlpy.metrics.**CompareContinuousActionDiffEvaluator**(*base_algo*, *episodes=None*)

Action difference between algorithms.

This metric suggests how different the two algorithms are in continuous action-space. If the algorithm to compare with is near-optimal, the small action difference would be better.

$$\mathbb{E}_{s_t \sim D}[(\pi_{\phi_1}(s_t) - \pi_{\phi_2}(s_t))^2]$$

Parameters

- **base_algo** – Target algorithm to comapre with.
- **episodes** – Optional evaluation episodes. If it's not given, dataset used in training will be used.

Methods

__call__(*algo*, *dataset*)

Computes metrics.

Parameters

- **algo** (*QLearningAlgoProtocol*) – Q-learning algorithm.
- **dataset** (ReplayBufferBase) – ReplayBuffer.

Returns
Computed metrics.

Return type
float

4.8.10 d3rlpy.metrics.CompareDiscreteActionMatchEvaluator

class d3rlpy.metrics.**CompareDiscreteActionMatchEvaluator**(*base_algo*, *episodes=None*)

Action matches between algorithms.

This metric suggests how different the two algorithms are in discrete action-space. If the algorithm to compare with is near-optimal, the small action difference would be better.

$$\mathbb{E}_{s_t \sim D}[|| \{\text{argmax}_a Q_{\theta_1}(s_t, a) = \text{argmax}_a Q_{\theta_2}(s_t, a)\}]$$

Parameters

- **base_algo** – Target algorithm to comapre with.
- **episodes** – Optional evaluation episodes. If it's not given, dataset used in training will be used.

Methods

__call__(*algo*, *dataset*)

Computes metrics.

Parameters

- **algo** (*QLearningAlgoProtocol*) – Q-learning algorithm.
- **dataset** (ReplayBufferBase) – ReplayBuffer.

Returns

Computed metrics.

Return type

float

4.9 Off-Policy Evaluation

The off-policy evaluation is a method to estimate the trained policy performance only with offline datasets.

```
import d3rlpy

# prepare the trained algorithm
cql = d3rlpy.load_learnable("model.d3")

# dataset to evaluate with
dataset, env = d3rlpy.datasets.get_pendulum()

# off-policy evaluation algorithm
fqe = d3rlpy.ope.FQE(algo=cql, config=d3rlpy.ope.FQEConfig())

# train estimators to evaluate the trained policy
fqe.fit(
   dataset,
   n_steps=100000,
   evaluators={
      'init_value': d3rlpy.metrics.InitialStateValueEstimationEvaluator(),
```

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```
        'soft_opc': d3rlpy.metrics.SoftOPCEvaluator(return_threshold=-300),
    },
)
```

The evaluation during fitting is evaluating the trained policy.

4.9.1 For continuous control algorithms

d3rlpy.ope.FQE	Fitted Q Evaluation.

d3rlpy.ope.FQE

class d3rlpy.ope.**FQE**(*algo*, *config*, *device=False*, *impl=None*)

Fitted Q Evaluation.

FQE is an off-policy evaluation method that approximates a Q function $Q_\theta(s, a)$ with the trained policy $\pi_\phi(s)$.

$$L(\theta) = \mathbb{E}_{s_t, a_t, r_{t+1} s_{t+1} \sim D}[(Q_\theta(s_t, a_t) - r_{t+1} - \gamma Q_{\theta'}(s_{t+1}, \pi_\phi(s_{t+1})))^2]$$

The trained Q function in FQE will estimate evaluation metrics more accurately than learned Q function during training.

References

- Le et al., Batch Policy Learning under Constraints.

Parameters

- **algo** (*d3rlpy.algos.base.AlgoBase*) – Algorithm to evaluate.
- **config** (*d3rlpy.ope.FQEConfig*) – FQE config.
- **device** (*bool, int or str*) – Flag to use GPU, device ID or PyTorch device identifier.
- **impl** (*d3rlpy.metrics.ope.torch.FQEImpl*) – Algorithm implementation.

Methods

build_with_dataset(*dataset*)

Instantiate implementation object with ReplayBuffer object.

Parameters
dataset (ReplayBuffer) – dataset.

Return type
None

build_with_env(*env*)

Instantiate implementation object with OpenAI Gym object.

Parameters
env (*Union[Env[Any, Any], Env[Any, Any]]*) – gym-like environment.

Return type
None

collect(*env*, *buffer=None*, *explorer=None*, *deterministic=False*, *n_steps=1000000*, *show_progress=True*)

Collects data via interaction with environment.

If `buffer` is not given, `ReplayBuffer` will be internally created.

Parameters

- **env** (*Union[Env[Any, Any], Env[Any, Any]]*) – Fym-like environment.
- **buffer** (*Optional[ReplayBufferBase]*) – Replay buffer.
- **explorer** (*Optional[Explorer]*) – Action explorer.
- **deterministic** (*bool*) – Flag to collect data with the greedy policy.
- **n_steps** (*int*) – Number of total steps to train.
- **show_progress** (*bool*) – Flag to show progress bar for iterations.

Returns
Replay buffer with the collected data.

Return type
ReplayBufferBase

copy_policy_from(*algo*)

Copies policy parameters from the given algorithm.

```
# pretrain with static dataset
cql = d3rlpy.algos.CQL()
cql.fit(dataset, n_steps=100000)

# transfer to online algorithm
sac = d3rlpy.algos.SAC()
sac.create_impl(cql.observation_shape, cql.action_size)
sac.copy_policy_from(cql)
```

Parameters
algo (*QLearningAlgoBase[QLearningAlgoImplBase, LearnableConfig]*) – Algorithm object.

Return type
None

copy_policy_optim_from(*algo*)

Copies policy optimizer states from the given algorithm.

```
# pretrain with static dataset
cql = d3rlpy.algos.CQL()
cql.fit(dataset, n_steps=100000)

# transfer to online algorithm
sac = d3rlpy.algos.SAC()
sac.create_impl(cql.observation_shape, cql.action_size)
sac.copy_policy_optim_from(cql)
```

Parameters
algo (QLearningAlgoBase[QLearningAlgoImplBase, LearnableConfig]) – Algorithm object.

Return type
None

copy_q_function_from(*algo*)

Copies Q-function parameters from the given algorithm.

```
# pretrain with static dataset
cql = d3rlpy.algos.CQL()
cql.fit(dataset, n_steps=100000)

# transfer to online algorithmn
sac = d3rlpy.algos.SAC()
sac.create_impl(cql.observation_shape, cql.action_size)
sac.copy_q_function_from(cql)
```

Parameters
algo (QLearningAlgoBase[QLearningAlgoImplBase, LearnableConfig]) – Algorithm object.

Return type
None

copy_q_function_optim_from(*algo*)

Copies Q-function optimizer states from the given algorithm.

```
# pretrain with static dataset
cql = d3rlpy.algos.CQL()
cql.fit(dataset, n_steps=100000)

# transfer to online algorithm
sac = d3rlpy.algos.SAC()
sac.create_impl(cql.observation_shape, cql.action_size)
sac.copy_policy_optim_from(cql)
```

Parameters
algo (QLearningAlgoBase[QLearningAlgoImplBase, LearnableConfig]) – Algorithm object.

Return type
None

create_impl(*observation_shape*, *action_size*)

Instantiate implementation objects with the dataset shapes.

This method will be used internally when *fit* method is called.

Parameters

- **observation_shape** (Union[Sequence[int], Sequence[Sequence[int]]]) – observation shape.
- **action_size** (int) – dimension of action-space.

Return type
None

fit(*dataset*, *n_steps*, *n_steps_per_epoch=10000*, *experiment_name=None*, *with_timestamp=True*, *logging_steps=500*, *logging_strategy=LoggingStrategy.EPOCH*, *logger_adapter=<d3rlpy.logging.file_adapter.FileAdapterFactory object>*, *show_progress=True*, *save_interval=1*, *evaluators=None*, *callback=None*, *epoch_callback=None*, *enable_ddp=False*)

Trains with given dataset.

```
algo.fit(episodes, n_steps=1000000)
```

Parameters

- **dataset** (ReplayBufferBase) – ReplayBuffer object.
- **n_steps** (*int*) – Number of steps to train.
- **n_steps_per_epoch** (*int*) – Number of steps per epoch. This value will be ignored when `n_steps` is `None`.
- **experiment_name** (*Optional[str]*) – Experiment name for logging. If not passed, the directory name will be *{class name}_{timestamp}*.
- **with_timestamp** (*bool*) – Flag to add timestamp string to the last of directory name.
- **logging_steps** (*int*) – Number of steps to log metrics. This will be ignored if logging_strategy is EPOCH.
- **logging_strategy** (*LoggingStrategy*) – Logging strategy to use.
- **logger_adapter** (LoggerAdapterFactory) – LoggerAdapterFactory object.
- **show_progress** (*bool*) – Flag to show progress bar for iterations.
- **save_interval** (*int*) – Interval to save parameters.
- **evaluators** (*Optional[Dict[str, EvaluatorProtocol]]*) – List of evaluators.
- **callback** (*Optional[Callable[[Self, int, int], None]]*) – Callable function that takes `(algo, epoch, total_step)` , which is called every step.
- **epoch_callback** (*Optional[Callable[[Self, int, int], None]]*) – Callable function that takes `(algo, epoch, total_step)`, which is called at the end of every epoch.
- **enable_ddp** (*bool*) – Flag to wrap models with DataDistributedParallel.

Returns
List of result tuples (epoch, metrics) per epoch.

Return type
List[*Tuple*[int, *Dict*[str, float]]]

fit_online(*env*, *buffer=None*, *explorer=None*, *n_steps=1000000*, *n_steps_per_epoch=10000*, *update_interval=1*, *n_updates=1*, *update_start_step=0*, *random_steps=0*, *eval_env=None*, *eval_epsilon=0.0*, *save_interval=1*, *experiment_name=None*, *with_timestamp=True*, *logging_steps=500*, *logging_strategy=LoggingStrategy.EPOCH*, *logger_adapter=<d3rlpy.logging.file_adapter.FileAdapterFactory object>*, *show_progress=True*, *callback=None*)

Start training loop of online deep reinforcement learning.

Parameters

- **env** (*Union[Env[Any, Any], Env[Any, Any]]*) – Gym-like environment.
- **buffer** (*Optional[ReplayBufferBase]*) – Replay buffer.
- **explorer** (*Optional[Explorer]*) – Action explorer.
- **n_steps** (*int*) – Number of total steps to train.
- **n_steps_per_epoch** (*int*) – Number of steps per epoch.
- **update_interval** (*int*) – Number of steps per update.
- **n_updates** (*int*) – Number of gradient steps at a time. The combination of `update_interval` and `n_updates` controls Update-To-Data (UTD) ratio.
- **update_start_step** (*int*) – Steps before starting updates.
- **random_steps** (*int*) – Steps for the initial random explortion.
- **eval_env** (*Optional[Union[Env[Any, Any], Env[Any, Any]]]*) – Gym-like environment. If None, evaluation is skipped.
- **eval_epsilon** (*float*) – ϵ-greedy factor during evaluation.
- **save_interval** (*int*) – Number of epochs before saving models.
- **experiment_name** (*Optional[str]*) – Experiment name for logging. If not passed, the directory name will be `{class name}_online_{timestamp}`.
- **with_timestamp** (*bool*) – Flag to add timestamp string to the last of directory name.
- **logging_steps** (*int*) – Number of steps to log metrics. This will be ignored if logging_strategy is EPOCH.
- **logging_strategy** (*LoggingStrategy*) – Logging strategy to use.
- **logger_adapter** (LoggerAdapterFactory) – LoggerAdapterFactory object.
- **show_progress** (*bool*) – Flag to show progress bar for iterations.
- **callback** (*Optional[Callable[[Self, int, int], None]]*) – Callable function that takes `(algo, epoch, total_step)` , which is called at the end of epochs.

Return type
None

fitter(*dataset*, *n_steps*, *n_steps_per_epoch=10000*, *logging_steps=500*, *logging_strategy=LoggingStrategy.EPOCH*, *experiment_name=None*, *with_timestamp=True*, *logger_adapter=<d3rlpy.logging.file_adapter.FileAdapterFactory object>*, *show_progress=True*, *save_interval=1*, *evaluators=None*, *callback=None*, *epoch_callback=None*, *enable_ddp=False*)

Iterate over epochs steps to train with the given dataset. At each iteration algo methods and properties can be changed or queried.

```
for epoch, metrics in algo.fitter(episodes):
    my_plot(metrics)
    algo.save_model(my_path)
```

Parameters

- **dataset** (ReplayBufferBase) – Offline dataset to train.
- **n_steps** (*int*) – Number of steps to train.
- **n_steps_per_epoch** (*int*) – Number of steps per epoch. This value will be ignored when `n_steps` is `None`.

- **experiment_name** (*Optional[str]*) – Experiment name for logging. If not passed, the directory name will be *{class name}_{timestamp}*.
- **with_timestamp** (*bool*) – Flag to add timestamp string to the last of directory name.
- **logging_steps** (*int*) – Number of steps to log metrics. This will be ignored if loggig_strategy is EPOCH.
- **logging_strategy** (*LoggingStrategy*) – Logging strategy to use.
- **logger_adapter** (LoggerAdapterFactory) – LoggerAdapterFactory object.
- **show_progress** (*bool*) – Flag to show progress bar for iterations.
- **save_interval** (*int*) – Interval to save parameters.
- **evaluators** (*Optional[Dict[str, EvaluatorProtocol]]*) – List of evaluators.
- **callback** (*Optional[Callable[[Self, int, int], None]]*) – Callable function that takes `(algo, epoch, total_step)` , which is called every step.
- **epoch_callback** (*Optional[Callable[[Self, int, int], None]]*) – Callable function that takes `(algo, epoch, total_step)`, which is called at the end of every epoch.
- **enable_ddp** (*bool*) – Flag to wrap models with DataDistributedParallel.

Returns
Iterator yielding current epoch and metrics dict.

Return type
Generator[*Tuple*[int, *Dict*[str, float]], None, None]

classmethod from_json(*fname*, *device=False*)

Construct algorithm from params.json file.

```
from d3rlpy.algos import CQL

cql = CQL.from_json("<path-to-json>", device='cuda:0')
```

Parameters

- **fname** (*str*) – path to params.json
- **device** (*Union[int, str, bool]*) – device option. If the value is boolean and True, `cuda:0` will be used. If the value is integer, `cuda:<device>` will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
Self

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

inner_create_impl(*observation_shape*, *action_size*)

Parameters

- **observation_shape** (*Union[Sequence[int], Sequence[Sequence[int]]]*) –
- **action_size** (*int*) –

Return type
None

load_model(*fname*)

Load neural network parameters.

```
algo.load_model('model.pt')
```

Parameters
fname (*str*) – source file path.

Return type
None

predict(*x*)

Returns greedy actions.

```
# 100 observations with shape of (10,)
x = np.random.random((100, 10))

actions = algo.predict(x)
# actions.shape == (100, action size) for continuous control
# actions.shape == (100,) for discrete control
```

Parameters
x (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observations

Returns
Greedy actions

Return type
ndarray[*Any*, *dtype*[*Any*]]

predict_value(*x*, *action*)

Returns predicted action-values.

```
# 100 observations with shape of (10,)
x = np.random.random((100, 10))

# for continuous control
# 100 actions with shape of (2,)
actions = np.random.random((100, 2))

# for discrete control
# 100 actions in integer values
actions = np.random.randint(2, size=100)

```

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```
values = algo.predict_value(x, actions)
# values.shape == (100,)
```

Parameters

- **x** (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observations
- **action** (*ndarray[Any, dtype[Any]]*) – Actions

Returns
Predicted action-values

Return type
ndarray[*Any*, *dtype*[*Any*]]

reset_optimizer_states()

Resets optimizer states.

This is especially useful when fine-tuning policies with setting inital optimizer states.

Return type
None

sample_action(*x*)

Returns sampled actions.

The sampled actions are identical to the output of *predict* method if the policy is deterministic.

Parameters
x (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observations.

Returns
Sampled actions.

Return type
ndarray[*Any*, *dtype*[*Any*]]

save(*fname*)

Saves paired data of neural network parameters and serialized config.

```
algo.save('model.d3')

# reconstruct everything
algo2 = d3rlpy.load_learnable("model.d3", device="cuda:0")
```

Parameters
fname (*str*) – destination file path.

Return type
None

save_model(*fname*)

Saves neural network parameters.

```
algo.save_model('model.pt')
```

Parameters
fname (*str*) – destination file path.

Return type
None

save_policy(*fname*)

Save the greedy-policy computational graph as TorchScript or ONNX.

The format will be automatically detected by the file name.

```
# save as TorchScript
algo.save_policy('policy.pt')

# save as ONNX
algo.save_policy('policy.onnx')
```

The artifacts saved with this method will work without d3rlpy. This method is especially useful to deploy the learned policy to production environments or embedding systems.

See also

- https://pytorch.org/tutorials/beginner/Intro_to_TorchScript_tutorial.html (for Python).
- https://pytorch.org/tutorials/advanced/cpp_export.html (for C++).
- https://onnx.ai (for ONNX)

Visit https://d3rlpy.readthedocs.io/en/stable/tutorials/after_training_policies.html#export-policies-as-torchscript for the further usage.

Parameters
fname (*str*) – Destination file path.

Return type
None

set_grad_step(*grad_step*)

Set total gradient step counter.

This method can be used to restart the middle of training with an arbitrary gradient step counter, which has effects on periodic functions such as the target update.

Parameters
grad_step (*int*) – total gradient step counter.

Return type
None

update(*batch*)

Update parameters with mini-batch of data.

Parameters
batch (*TransitionMiniBatch*) – Mini-batch data.

Returns
Dictionary of metrics.

Return type
Dict[str, float]

Attributes

action_scaler

Preprocessing action scaler.

Returns
preprocessing action scaler.

Return type
Optional[ActionScaler]

action_size

Action size.

Returns
action size.

Return type
Optional[int]

algo

batch_size

Batch size to train.

Returns
batch size.

Return type
int

config

Config.

Returns
config.

Return type
LearnableConfig

gamma

Discount factor.

Returns
discount factor.

Return type
float

grad_step

Total gradient step counter.

This value will keep counting after `fit` and `fit_online` methods finish.

Returns
total gradient step counter.

impl

Implementation object.

Returns
implementation object.

Return type
Optional[ImplBase]

need_returns_to_go

observation_scaler

Preprocessing observation scaler.

Returns
preprocessing observation scaler.

Return type
Optional[ObservationScaler]

observation_shape

Observation shape.

Returns
observation shape.

Return type
Optional[Sequence[int]]

reward_scaler

Preprocessing reward scaler.

Returns
preprocessing reward scaler.

Return type
Optional[RewardScaler]

4.9.2 For discrete control algorithms

d3rlpy.ope.DiscreteFQE	Fitted Q Evaluation for discrete action-space.

d3rlpy.ope.DiscreteFQE

class d3rlpy.ope.**DiscreteFQE**(*algo*, *config*, *device=False*, *impl=None*)

Fitted Q Evaluation for discrete action-space.

FQE is an off-policy evaluation method that approximates a Q function $Q_\theta(s, a)$ with the trained policy $\pi_\phi(s)$.

$$L(\theta) = \mathbb{E}_{s_t, a_t, r_{t+1} s_{t+1} \sim D}[(Q_\theta(s_t, a_t) - r_{t+1} - \gamma Q_{\theta'}(s_{t+1}, \pi_\phi(s_{t+1})))^2]$$

The trained Q function in FQE will estimate evaluation metrics more accurately than learned Q function during training.

References

- Le et al., Batch Policy Learning under Constraints.

Parameters

- **algo** (d3rlpy.algos.qlearning.base.QLearningAlgoBase) – Algorithm to evaluate.
- **config** (*d3rlpy.ope.FQEConfig*) – FQE config.
- **device** (*bool, int or str*) – Flag to use GPU, device ID or PyTorch device identifier.
- **impl** (*d3rlpy.metrics.ope.torch.DiscreteFQEImpl*) – Algorithm implementation.

Methods

build_with_dataset(*dataset*)

Instantiate implementation object with ReplayBuffer object.

Parameters
dataset (ReplayBuffer) – dataset.

Return type
None

build_with_env(*env*)

Instantiate implementation object with OpenAI Gym object.

Parameters
env (*Union[Env[Any, Any], Env[Any, Any]]*) – gym-like environment.

Return type
None

collect(*env*, *buffer=None*, *explorer=None*, *deterministic=False*, *n_steps=1000000*, *show_progress=True*)

Collects data via interaction with environment.

If `buffer` is not given, `ReplayBuffer` will be internally created.

Parameters

- **env** (*Union[Env[Any, Any], Env[Any, Any]]*) – Fym-like environment.
- **buffer** (*Optional[ReplayBufferBase]*) – Replay buffer.
- **explorer** (*Optional[Explorer]*) – Action explorer.
- **deterministic** (*bool*) – Flag to collect data with the greedy policy.
- **n_steps** (*int*) – Number of total steps to train.
- **show_progress** (*bool*) – Flag to show progress bar for iterations.

Returns
Replay buffer with the collected data.

Return type
ReplayBufferBase

copy_policy_from(*algo*)

Copies policy parameters from the given algorithm.

```
# pretrain with static dataset
cql = d3rlpy.algos.CQL()
cql.fit(dataset, n_steps=100000)

# transfer to online algorithm
sac = d3rlpy.algos.SAC()
sac.create_impl(cql.observation_shape, cql.action_size)
sac.copy_policy_from(cql)
```

Parameters
algo (QLearningAlgoBase[*QLearningAlgoImplBase*, *LearnableConfig*]) – Algorithm object.

Return type
None

copy_policy_optim_from(*algo*)

Copies policy optimizer states from the given algorithm.

```
# pretrain with static dataset
cql = d3rlpy.algos.CQL()
cql.fit(dataset, n_steps=100000)

# transfer to online algorithm
sac = d3rlpy.algos.SAC()
sac.create_impl(cql.observation_shape, cql.action_size)
sac.copy_policy_optim_from(cql)
```

Parameters
algo (QLearningAlgoBase[*QLearningAlgoImplBase*, *LearnableConfig*]) – Algorithm object.

Return type
None

copy_q_function_from(*algo*)

Copies Q-function parameters from the given algorithm.

```
# pretrain with static dataset
cql = d3rlpy.algos.CQL()
cql.fit(dataset, n_steps=100000)

# transfer to online algorithmn
sac = d3rlpy.algos.SAC()
sac.create_impl(cql.observation_shape, cql.action_size)
sac.copy_q_function_from(cql)
```

Parameters
algo (QLearningAlgoBase[*QLearningAlgoImplBase*, *LearnableConfig*]) – Algorithm object.

Return type
None

copy_q_function_optim_from(*algo*)

Copies Q-function optimizer states from the given algorithm.

```
# pretrain with static dataset
cql = d3rlpy.algos.CQL()
cql.fit(dataset, n_steps=100000)

# transfer to online algorithm
sac = d3rlpy.algos.SAC()
sac.create_impl(cql.observation_shape, cql.action_size)
sac.copy_policy_optim_from(cql)
```

Parameters

algo (QLearningAlgoBase[*QLearningAlgoImplBase, LearnableConfig*]) – Algorithm object.

Return type

None

create_impl(*observation_shape*, *action_size*)

Instantiate implementation objects with the dataset shapes.

This method will be used internally when *fit* method is called.

Parameters

- **observation_shape** (*Union[Sequence[int], Sequence[Sequence[int]]]*) – observation shape.
- **action_size** (*int*) – dimension of action-space.

Return type

None

fit(*dataset*, *n_steps*, *n_steps_per_epoch=10000*, *experiment_name=None*, *with_timestamp=True*, *logging_steps=500*, *logging_strategy=LoggingStrategy.EPOCH*, *logger_adapter=<d3rlpy.logging.file_adapter.FileAdapterFactory object>*, *show_progress=True*, *save_interval=1*, *evaluators=None*, *callback=None*, *epoch_callback=None*, *enable_ddp=False*)

Trains with given dataset.

```
algo.fit(episodes, n_steps=1000000)
```

Parameters

- **dataset** (ReplayBufferBase) – ReplayBuffer object.
- **n_steps** (*int*) – Number of steps to train.
- **n_steps_per_epoch** (*int*) – Number of steps per epoch. This value will be ignored when `n_steps` is `None`.
- **experiment_name** (*Optional[str]*) – Experiment name for logging. If not passed, the directory name will be *{class name}_{timestamp}*.
- **with_timestamp** (*bool*) – Flag to add timestamp string to the last of directory name.
- **logging_steps** (*int*) – Number of steps to log metrics. This will be ignored if logging_strategy is EPOCH.
- **logging_strategy** (*LoggingStrategy*) – Logging strategy to use.

- **logger_adapter** (LoggerAdapterFactory) – LoggerAdapterFactory object.
- **show_progress** (*bool*) – Flag to show progress bar for iterations.
- **save_interval** (*int*) – Interval to save parameters.
- **evaluators** (*Optional[Dict[str, EvaluatorProtocol]]*) – List of evaluators.
- **callback** (*Optional[Callable[[Self, int, int], None]]*) – Callable function that takes `(algo, epoch, total_step)` , which is called every step.
- **epoch_callback** (*Optional[Callable[[Self, int, int], None]]*) – Callable function that takes `(algo, epoch, total_step)`, which is called at the end of every epoch.
- **enable_ddp** (*bool*) – Flag to wrap models with DataDistributedParallel.

Returns
List of result tuples (epoch, metrics) per epoch.

Return type
List[*Tuple*[int, *Dict*[str, float]]]

fit_online(*env*, *buffer=None*, *explorer=None*, *n_steps=1000000*, *n_steps_per_epoch=10000*, *update_interval=1*, *n_updates=1*, *update_start_step=0*, *random_steps=0*, *eval_env=None*, *eval_epsilon=0.0*, *save_interval=1*, *experiment_name=None*, *with_timestamp=True*, *logging_steps=500*, *logging_strategy=LoggingStrategy.EPOCH*, *logger_adapter=<d3rlpy.logging.file_adapter.FileAdapterFactory object>*, *show_progress=True*, *callback=None*)

Start training loop of online deep reinforcement learning.

Parameters

- **env** (*Union[Env[Any, Any], Env[Any, Any]]*) – Gym-like environment.
- **buffer** (*Optional[ReplayBufferBase]*) – Replay buffer.
- **explorer** (*Optional[Explorer]*) – Action explorer.
- **n_steps** (*int*) – Number of total steps to train.
- **n_steps_per_epoch** (*int*) – Number of steps per epoch.
- **update_interval** (*int*) – Number of steps per update.
- **n_updates** (*int*) – Number of gradient steps at a time. The combination of `update_interval` and `n_updates` controls Update-To-Data (UTD) ratio.
- **update_start_step** (*int*) – Steps before starting updates.
- **random_steps** (*int*) – Steps for the initial random explortion.
- **eval_env** (*Optional[Union[Env[Any, Any], Env[Any, Any]]]*) – Gym-like environment. If None, evaluation is skipped.
- **eval_epsilon** (*float*) – ϵ-greedy factor during evaluation.
- **save_interval** (*int*) – Number of epochs before saving models.
- **experiment_name** (*Optional[str]*) – Experiment name for logging. If not passed, the directory name will be `{class name}_online_{timestamp}`.
- **with_timestamp** (*bool*) – Flag to add timestamp string to the last of directory name.
- **logging_steps** (*int*) – Number of steps to log metrics. This will be ignored if logging_strategy is EPOCH.

- **logging_strategy** (*LoggingStrategy*) – Logging strategy to use.
- **logger_adapter** (LoggerAdapterFactory) – LoggerAdapterFactory object.
- **show_progress** (*bool*) – Flag to show progress bar for iterations.
- **callback** (*Optional[Callable[[Self, int, int], None]]*) – Callable function that takes `(algo, epoch, total_step)` , which is called at the end of epochs.

Return type
None

fitter(*dataset*, *n_steps*, *n_steps_per_epoch=10000*, *logging_steps=500*, *logging_strategy=LoggingStrategy.EPOCH*, *experiment_name=None*, *with_timestamp=True*, *logger_adapter=<d3rlpy.logging.file_adapter.FileAdapterFactory object>*, *show_progress=True*, *save_interval=1*, *evaluators=None*, *callback=None*, *epoch_callback=None*, *enable_ddp=False*)

Iterate over epochs steps to train with the given dataset. At each iteration algo methods and properties can be changed or queried.

```
for epoch, metrics in algo.fitter(episodes):
    my_plot(metrics)
    algo.save_model(my_path)
```

Parameters

- **dataset** (ReplayBufferBase) – Offline dataset to train.
- **n_steps** (*int*) – Number of steps to train.
- **n_steps_per_epoch** (*int*) – Number of steps per epoch. This value will be ignored when `n_steps` is `None`.
- **experiment_name** (*Optional[str]*) – Experiment name for logging. If not passed, the directory name will be *{class name}_{timestamp}*.
- **with_timestamp** (*bool*) – Flag to add timestamp string to the last of directory name.
- **logging_steps** (*int*) – Number of steps to log metrics. This will be ignored if loggig_strategy is EPOCH.
- **logging_strategy** (*LoggingStrategy*) – Logging strategy to use.
- **logger_adapter** (LoggerAdapterFactory) – LoggerAdapterFactory object.
- **show_progress** (*bool*) – Flag to show progress bar for iterations.
- **save_interval** (*int*) – Interval to save parameters.
- **evaluators** (*Optional[Dict[str, EvaluatorProtocol]]*) – List of evaluators.
- **callback** (*Optional[Callable[[Self, int, int], None]]*) – Callable function that takes `(algo, epoch, total_step)` , which is called every step.
- **epoch_callback** (*Optional[Callable[[Self, int, int], None]]*) – Callable function that takes `(algo, epoch, total_step)`, which is called at the end of every epoch.
- **enable_ddp** (*bool*) – Flag to wrap models with DataDistributedParallel.

Returns
Iterator yielding current epoch and metrics dict.

Return type
Generator[*Tuple*[int, *Dict*[str, float]], None, None]

classmethod from_json(*fname*, *device=False*)

Construct algorithm from params.json file.

```
from d3rlpy.algos import CQL

cql = CQL.from_json("<path-to-json>", device='cuda:0')
```

Parameters

- **fname** (*str*) – path to params.json
- **device** (*Union[int, str, bool]*) – device option. If the value is boolean and True, cuda:0 will be used. If the value is integer, cuda:<device> will be used. If the value is string in torch device style, the specified device will be used.

Returns
algorithm object.

Return type
Self

get_action_type()

Returns action type (continuous or discrete).

Returns
action type.

Return type
ActionSpace

inner_create_impl(*observation_shape*, *action_size*)

Parameters

- **observation_shape** (*Union[Sequence[int], Sequence[Sequence[int]]]*) –
- **action_size** (*int*) –

Return type
None

load_model(*fname*)

Load neural network parameters.

```
algo.load_model('model.pt')
```

Parameters
fname (*str*) – source file path.

Return type
None

predict(*x*)

Returns greedy actions.

```
# 100 observations with shape of (10,)
x = np.random.random((100, 10))
```

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```
actions = algo.predict(x)
# actions.shape == (100, action size) for continuous control
# actions.shape == (100,) for discrete control
```

Parameters
x (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observations

Returns
Greedy actions

Return type
ndarray[*Any*, *dtype*[*Any*]]

predict_value(*x*, *action*)

Returns predicted action-values.

```
# 100 observations with shape of (10,)
x = np.random.random((100, 10))

# for continuous control
# 100 actions with shape of (2,)
actions = np.random.random((100, 2))

# for discrete control
# 100 actions in integer values
actions = np.random.randint(2, size=100)

values = algo.predict_value(x, actions)
# values.shape == (100,)
```

Parameters

- **x** (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observations
- **action** (*ndarray[Any, dtype[Any]]*) – Actions

Returns
Predicted action-values

Return type
ndarray[*Any*, *dtype*[*Any*]]

reset_optimizer_states()

Resets optimizer states.

This is especially useful when fine-tuning policies with setting inital optimizer states.

Return type
None

sample_action(*x*)

Returns sampled actions.

The sampled actions are identical to the output of *predict* method if the policy is deterministic.

Parameters
x (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observations.

Returns
Sampled actions.

Return type
ndarray[*Any*, *dtype*[*Any*]]

save(*fname*)

Saves paired data of neural network parameters and serialized config.

```
algo.save('model.d3')

# reconstruct everything
algo2 = d3rlpy.load_learnable("model.d3", device="cuda:0")
```

Parameters
fname (*str*) – destination file path.

Return type
None

save_model(*fname*)

Saves neural network parameters.

```
algo.save_model('model.pt')
```

Parameters
fname (*str*) – destination file path.

Return type
None

save_policy(*fname*)

Save the greedy-policy computational graph as TorchScript or ONNX.

The format will be automatically detected by the file name.

```
# save as TorchScript
algo.save_policy('policy.pt')

# save as ONNX
algo.save_policy('policy.onnx')
```

The artifacts saved with this method will work without d3rlpy. This method is especially useful to deploy the learned policy to production environments or embedding systems.

See also

- https://pytorch.org/tutorials/beginner/Intro_to_TorchScript_tutorial.html (for Python).
- https://pytorch.org/tutorials/advanced/cpp_export.html (for C++).
- https://onnx.ai (for ONNX)

Visit https://d3rlpy.readthedocs.io/en/stable/tutorials/after_training_policies.html#export-policies-as-torchscript for the further usage.

Parameters
fname (*str*) – Destination file path.

Return type
None

`set_grad_step`(*grad_step*)

Set total gradient step counter.

This method can be used to restart the middle of training with an arbitrary gradient step counter, which has effects on periodic functions such as the target update.

Parameters
grad_step (*int*) – total gradient step counter.

Return type
None

`update`(*batch*)

Update parameters with mini-batch of data.

Parameters
batch (*TransitionMiniBatch*) – Mini-batch data.

Returns
Dictionary of metrics.

Return type
Dict[str, float]

Attributes

`action_scaler`

Preprocessing action scaler.

Returns
preprocessing action scaler.

Return type
Optional[ActionScaler]

`action_size`

Action size.

Returns
action size.

Return type
Optional[int]

`algo`

`batch_size`

Batch size to train.

Returns
batch size.

Return type
int

`config`

Config.

Returns
config.

Return type
LearnableConfig

`gamma`

Discount factor.

Returns
discount factor.

Return type
float

`grad_step`

Total gradient step counter.

This value will keep counting after `fit` and `fit_online` methods finish.

Returns
total gradient step counter.

`impl`

Implementation object.

Returns
implementation object.

Return type
Optional[ImplBase]

`need_returns_to_go`

`observation_scaler`

Preprocessing observation scaler.

Returns
preprocessing observation scaler.

Return type
Optional[ObservationScaler]

`observation_shape`

Observation shape.

Returns
observation shape.

Return type
Optional[Sequence[int]]

`reward_scaler`

Preprocessing reward scaler.

Returns
preprocessing reward scaler.

Return type
Optional[RewardScaler]

4.10 Logging

d3rlpy provides a customizable interface for logging metrics, `LoggerAdapter` and `LoggerAdapterFactory`.

```
import d3rlpy

dataset, env = d3rlpy.datasets.get_cartpole()

dqn = d3rlpy.algos.DQNConfig().create()

dqn.fit(
   dataset=dataset,
   n_steps=100000,
   # set FileAdapterFactory to save metrics as CSV files
   logger_adapter=d3rlpy.logging.FileAdapterFactory(root_dir="d3rlpy_logs"),
)
```

`LoggerAdapterFactory` is a parent interface that instantiates `LoggerAdapter` at the beginning of training. You can also use `CombineAdapter` to combine multiple `LoggerAdapter` in the same training.

```
# combine FileAdapterFactory and TensorboardAdapterFactory
logger_adapter = d3rlpy.logging.CombineAdapterFactory([
   d3rlpy.logging.FileAdapterFactory(root_dir="d3rlpy_logs"),
   d3rlpy.logging.TensorboardAdapterFactory(root_dir="tensorboard_logs"),
])

dqn.fit(dataset=dataset, n_steps=100000, logger_adapter=logger_adapter)
```

4.10.1 LoggerAdapter

`LoggerAdapter` is an inner interface of `LoggerAdapterFactory`. You can implement your own `LoggerAdapter` for 3rd-party visualizers.

```
import d3rlpy

class CustomAdapter(d3rlpy.logging.LoggerAdapter):
    def write_params(self, params: Dict[str, Any]) -> None:
        # save dictionary as json file
        with open("params.json", "w") as f:
            f.write(json.dumps(params, default=default_json_encoder, indent=2))

    def before_write_metric(self, epoch: int, step: int) -> None:
        pass

    def write_metric(
        self, epoch: int, step: int, name: str, value: float
    ) -> None:
        with open(f"{name}.csv", "a") as f:
```

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```
            print(f"{epoch},{step},{value}", file=f)

    def after_write_metric(self, epoch: int, step: int) -> None:
        pass

    def save_model(self, epoch: int, algo: Any) -> None:
        algo.save(f"model_{epoch}.d3")

    def close(self) -> None:
        pass
```

d3rlpy.logging.LoggerAdapter	Interface of LoggerAdapter.
d3rlpy.logging.FileAdapter	FileAdapter class.
d3rlpy.logging.TensorboardAdapter	TensorboardAdapter class.
d3rlpy.logging.WanDBAdapter	WandB Logger Adapter class.
d3rlpy.logging.NoopAdapter	NoopAdapter class.
d3rlpy.logging.CombineAdapter	CombineAdapter class.

d3rlpy.logging.LoggerAdapter

class d3rlpy.logging.**LoggerAdapter**(**args*, ***kwargs*)

Interface of LoggerAdapter.

Methods

after_write_metric(*epoch*, *step*)

Callback executed after write_metric method.

Parameters

- **epoch** (*int*) – Epoch.
- **step** (*int*) – Training step.

Return type
None

before_write_metric(*epoch*, *step*)

Callback executed before write_metric method.

Parameters

- **epoch** (*int*) – Epoch.
- **step** (*int*) – Training step.

Return type
None

close()

Closes this LoggerAdapter.

Return type
None

save_model(*epoch*, *algo*)

Saves models.

Parameters

- **epoch** (*int*) – Epoch.
- **algo** (*SaveProtocol*) – Algorithm that provides save method.

Return type
None

write_metric(*epoch*, *step*, *name*, *value*)

Writes metric.

Parameters

- **epoch** (*int*) – Epoch.
- **step** (*int*) – Training step.
- **name** (*str*) – Metric name.
- **value** (*float*) – Metric value.

Return type
None

write_params(*params*)

Writes hyperparameters.

Parameters
params (*Dict[str, Any]*) – Dictionary of hyperparameters.

Return type
None

d3rlpy.logging.FileAdapter

class d3rlpy.logging.**FileAdapter**(*logdir*)

FileAdapter class.

This class saves metrics as CSV files, hyperparameters as json file and models as d3 files.

Parameters
logdir (*str*) – Log directory.

Methods

after_write_metric(*epoch*, *step*)

Callback executed after write_metric method.

Parameters

- **epoch** (*int*) – Epoch.
- **step** (*int*) – Training step.

Return type
None

before_write_metric(*epoch*, *step*)

Callback executed before write_metric method.

Parameters

- **epoch** (*int*) – Epoch.
- **step** (*int*) – Training step.

Return type
None

close()

Closes this LoggerAdapter.

Return type
None

save_model(*epoch*, *algo*)

Saves models.

Parameters

- **epoch** (*int*) – Epoch.
- **algo** (*SaveProtocol*) – Algorithm that provides save method.

Return type
None

write_metric(*epoch*, *step*, *name*, *value*)

Writes metric.

Parameters

- **epoch** (*int*) – Epoch.
- **step** (*int*) – Training step.
- **name** (*str*) – Metric name.
- **value** (*float*) – Metric value.

Return type
None

write_params(*params*)

Writes hyperparameters.

Parameters
params (*Dict[str, Any]*) – Dictionary of hyperparameters.

Return type
None

Attributes

logdir

d3rlpy.logging.TensorboardAdapter

class d3rlpy.logging.**TensorboardAdapter**(*root_dir*, *experiment_name*)

TensorboardAdapter class.

This class saves metrics for Tensorboard visualization, powered by tensorboardX.

Note that this class does not save models. If you want to save models during training, consider `FileAdapter` as well.

Parameters

- **root_dir** (*str*) – Top-level log directory.
- **experiment_name** (*str*) – Experiment name.

Methods

after_write_metric(*epoch*, *step*)

Callback executed after write_metric method.

Parameters

- **epoch** (*int*) – Epoch.
- **step** (*int*) – Training step.

Return type
None

before_write_metric(*epoch*, *step*)

Callback executed before write_metric method.

Parameters

- **epoch** (*int*) – Epoch.
- **step** (*int*) – Training step.

Return type
None

close()

Closes this LoggerAdapter.

Return type
None

save_model(*epoch*, *algo*)

Saves models.

Parameters

- **epoch** (*int*) – Epoch.
- **algo** (*SaveProtocol*) – Algorithm that provides `save` method.

Return type
None

`write_metric`(*epoch*, *step*, *name*, *value*)

Writes metric.

Parameters

- **epoch** (*int*) – Epoch.
- **step** (*int*) – Training step.
- **name** (*str*) – Metric name.
- **value** (*float*) – Metric value.

Return type
None

`write_params`(*params*)

Writes hyperparameters.

Parameters
params (*Dict[str, Any]*) – Dictionary of hyperparameters.

Return type
None

d3rlpy.logging.WanDBAdapter

`class d3rlpy.logging.WanDBAdapter`(*experiment_name*, *project=None*)

WandB Logger Adapter class.

This class logs data to Weights & Biases (WandB) for experiment tracking.

Parameters
experiment_name (*str*) – Name of the experiment.

Methods

`after_write_metric`(*epoch*, *step*)

Callback executed after writing metric.

Parameters

- **epoch** (*int*) –
- **step** (*int*) –

Return type
None

`before_write_metric`(*epoch*, *step*)

Callback executed before writing metric.

Parameters

- **epoch** (*int*) –
- **step** (*int*) –

Return type
None

`close()`

Closes the logger and finishes the WandB run.

Return type
None

`save_model(epoch, algo)`

Saves models to Weights & Biases.

Not implemented for WandB.

Parameters

- **epoch** (*int*) –
- **algo** (*SaveProtocol*) –

Return type
None

`write_metric(epoch, step, name, value)`

Writes metric to WandB.

Parameters

- **epoch** (*int*) –
- **step** (*int*) –
- **name** (*str*) –
- **value** (*float*) –

Return type
None

`write_params(params)`

Writes hyperparameters to WandB config.

Parameters
params (*Dict[str, Any]*) –

Return type
None

d3rlpy.logging.NoopAdapter

`class d3rlpy.logging.NoopAdapter(*args, **kwargs)`

NoopAdapter class.

This class does not save anything. This can be used especially when programs are not allowed to write things to disks.

Methods

after_write_metric(*epoch*, *step*)

Callback executed after write_metric method.

Parameters

- **epoch** (*int*) – Epoch.
- **step** (*int*) – Training step.

Return type
None

before_write_metric(*epoch*, *step*)

Callback executed before write_metric method.

Parameters

- **epoch** (*int*) – Epoch.
- **step** (*int*) – Training step.

Return type
None

close()

Closes this LoggerAdapter.

Return type
None

save_model(*epoch*, *algo*)

Saves models.

Parameters

- **epoch** (*int*) – Epoch.
- **algo** (*SaveProtocol*) – Algorithm that provides `save` method.

Return type
None

write_metric(*epoch*, *step*, *name*, *value*)

Writes metric.

Parameters

- **epoch** (*int*) – Epoch.
- **step** (*int*) – Training step.
- **name** (*str*) – Metric name.
- **value** (*float*) – Metric value.

Return type
None

write_params(*params*)

Writes hyperparameters.

Parameters
params (*Dict[str, Any]*) – Dictionary of hyperparameters.

Return type
None

d3rlpy.logging.CombineAdapter

class d3rlpy.logging.**CombineAdapter**(*adapters*)

CombineAdapter class.

This class combines multiple LoggerAdapter to write metrics through different adapters at the same time.

Parameters
adapters (*Sequence[LoggerAdapter]*) – List of LoggerAdapter.

Methods

after_write_metric(*epoch*, *step*)

Callback executed after write_metric method.

Parameters

- **epoch** (*int*) – Epoch.
- **step** (*int*) – Training step.

Return type
None

before_write_metric(*epoch*, *step*)

Callback executed before write_metric method.

Parameters

- **epoch** (*int*) – Epoch.
- **step** (*int*) – Training step.

Return type
None

close()

Closes this LoggerAdapter.

Return type
None

save_model(*epoch*, *algo*)

Saves models.

Parameters

- **epoch** (*int*) – Epoch.
- **algo** (*SaveProtocol*) – Algorithm that provides `save` method.

Return type
None

write_metric(*epoch*, *step*, *name*, *value*)

Writes metric.

Parameters

- **epoch** (*int*) – Epoch.
- **step** (*int*) – Training step.
- **name** (*str*) – Metric name.
- **value** (*float*) – Metric value.

Return type
None

write_params(*params*)

Writes hyperparameters.

Parameters
params (*Dict[str, Any]*) – Dictionary of hyperparameters.

Return type
None

4.10.2 LoggerAdapterFactory

`LoggerAdapterFactory` is an interface that instantiates `LoggerAdapter` at the beginning of training. You can implement your own `LoggerAdapterFactory` for 3rd-party visualizers.

```
import d3rlpy

class CustomAdapterFactory(d3rlpy.logging.LoggerAdapterFactory):
    def create(self, experiment_name: str) -> d3rlpy.logging.FileAdapter:
        return CustomAdapter()
```

d3rlpy.logging.LoggerAdapterFactory	Interface of LoggerAdapterFactory.
d3rlpy.logging.FileAdapterFactory	FileAdapterFactory class.
d3rlpy.logging.TensorboardAdapterFactory	TensorboardAdapterFactory class.
d3rlpy.logging.WanDBAdapterFactory	WandB Logger Adapter Factory class.
d3rlpy.logging.NoopAdapterFactory	NoopAdapterFactory class.
d3rlpy.logging.CombineAdapterFactory	CombineAdapterFactory class.

d3rlpy.logging.LoggerAdapterFactory

class d3rlpy.logging.**LoggerAdapterFactory**(**args*, ***kwargs*)

Interface of LoggerAdapterFactory.

Methods

create(*experiment_name*)

Creates LoggerAdapter.

This method instantiates `LoggerAdapter` with a given `experiment_name`. This method is usually called at the beginning of training.

Parameters
experiment_name (*str*) – Experiment name.

Return type
LoggerAdapter

d3rlpy.logging.FileAdapterFactory

class d3rlpy.logging.**FileAdapterFactory**(*root_dir='d3rlpy_logs'*)

FileAdapterFactory class.

This class instantiates `FileAdapter` object. Log directory will be created at `<root_dir>/<experiment_name>`.

Parameters
root_dir (*str*) – Top-level log directory.

Methods

create(*experiment_name*)

Creates LoggerAdapter.

This method instantiates `LoggerAdapter` with a given `experiment_name`. This method is usually called at the beginning of training.

Parameters
experiment_name (*str*) – Experiment name.

Return type
FileAdapter

d3rlpy.logging.TensorboardAdapterFactory

class d3rlpy.logging.**TensorboardAdapterFactory**(*root_dir='tensorboard_logs'*)

TensorboardAdapterFactory class.

This class instantiates `TensorboardAdapter` object.

Parameters
root_dir (*str*) – Top-level log directory.

Methods

create(*experiment_name*)

Creates LoggerAdapter.

This method instantiates `LoggerAdapter` with a given `experiment_name`. This method is usually called at the beginning of training.

Parameters
experiment_name (*str*) – Experiment name.

Return type
TensorboardAdapter

d3rlpy.logging.WanDBAdapterFactory

class d3rlpy.logging.**WanDBAdapterFactory**(*project=None*)

WandB Logger Adapter Factory class.

This class creates instances of the WandB Logger Adapter for experiment tracking.

Methods

create(*experiment_name*)

Creates a WandB Logger Adapter instance.

Parameters
experiment_name (*str*) – Name of the experiment.

Returns
Instance of the WandB Logger Adapter.

Return type
LoggerAdapter

d3rlpy.logging.NoopAdapterFactory

class d3rlpy.logging.**NoopAdapterFactory**(**args*, ***kwargs*)

NoopAdapterFactory class.

This class instantiates `NoopAdapter` object.

Methods

create(*experiment_name*)

Creates LoggerAdapter.

This method instantiates `LoggerAdapter` with a given `experiment_name`. This method is usually called at the beginning of training.

Parameters
experiment_name (*str*) – Experiment name.

Return type
NoopAdapter

d3rlpy.logging.CombineAdapterFactory

class d3rlpy.logging.**CombineAdapterFactory**(*adapter_factories*)

CombineAdapterFactory class.

This class instantiates `CombineAdapter` object.

Parameters
adapter_factories (*Sequence[LoggerAdapterFactory]*) – List of LoggerAdapterFactory.

Methods

create(*experiment_name*)

Creates LoggerAdapter.

This method instantiates `LoggerAdapter` with a given `experiment_name`. This method is usually called at the beginning of training.

Parameters
experiment_name (*str*) – Experiment name.

Return type
CombineAdapter

4.11 Online Training

d3rlpy provides not only offline training, but also online training utilities. Despite being designed for offline training algorithms, d3rlpy is flexible enough to be trained in an online manner with a few more utilities.

```
import d3lpy
import gym

# setup environment
env = gym.make('CartPole-v1')
eval_env = gym.make('CartPole-v1')

# setup algorithm
dqn = d3rlpy.algos.DQN(
    batch_size=32,
    learning_rate=2.5e-4,
    target_update_interval=100,
).create(device="cuda:0")

# setup replay buffer
buffer = d3rlpy.dataset.create_fifo_replay_buffer(limit=100000, env=env)

# setup explorers
explorer = d3rlpy.algos.LinearDecayEpsilonGreedy(
    start_epsilon=1.0,
    end_epsilon=0.1,
    duration=10000,
)

# start training
dqn.fit_online(
    env,
    buffer,
    explorer=explorer, # you don't need this with probablistic policy algorithms
    eval_env=eval_env,
    n_steps=30000, # the number of total steps to train.
    n_steps_per_epoch=1000,
    update_interval=10, # update parameters every 10 steps.
)
```

4.11.1 Explorers

d3rlpy.algos.ConstantEpsilonGreedy	ϵ-greedy explorer with constant ϵ.
d3rlpy.algos.LinearDecayEpsilonGreedy	ϵ-greedy explorer with linear decay schedule.
d3rlpy.algos.NormalNoise	Normal noise explorer.

d3rlpy.algos.ConstantEpsilonGreedy

class d3rlpy.algos.**ConstantEpsilonGreedy**(*epsilon*)

ϵ-greedy explorer with constant ϵ.

Parameters
epsilon (*float*) – the constant ϵ.

Methods

sample(*algo*, *x*, *step*)

Parameters

- **algo** (*QLearningAlgoProtocol*) –
- **x** (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) –
- **step** (*int*) –

Return type
ndarray[*Any*, *dtype*[*Any*]]

d3rlpy.algos.LinearDecayEpsilonGreedy

class d3rlpy.algos.**LinearDecayEpsilonGreedy**(*start_epsilon=1.0*, *end_epsilon=0.1*, *duration=1000000*)

ϵ-greedy explorer with linear decay schedule.

Parameters

- **start_epsilon** (*float*) – Initial ϵ.
- **end_epsilon** (*float*) – Final ϵ.
- **duration** (*int*) – Scheduling duration.

Methods

compute_epsilon(*step*)

Returns decayed ϵ.

Returns
ϵ.

Parameters
step (*int*) –

Return type
float

sample(*algo*, *x*, *step*)

Returns ϵ-greedy action.

Parameters

- **algo** (*QLearningAlgoProtocol*) – Algorithm.
- **x** (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observation.
- **step** (*int*) – Current environment step.

Returns

ϵ-greedy action.

Return type

ndarray[*Any*, *dtype*[*Any*]]

d3rlpy.algos.NormalNoise

class d3rlpy.algos.**NormalNoise**(*mean=0.0*, *std=0.1*)

Normal noise explorer.

Parameters

- **mean** (*float*) – Mean.
- **std** (*float*) – Standard deviation.

Methods

sample(*algo*, *x*, *step*)

Returns action with noise injection.

Parameters

- **algo** (*QLearningAlgoProtocol*) – Algorithm.
- **x** (*Union[ndarray[Any, dtype[Any]], Sequence[ndarray[Any, dtype[Any]]]]*) – Observation.
- **step** (*int*) –

Returns

Action with noise injection.

Return type

ndarray[*Any*, *dtype*[*Any*]]

CHAPTER

FIVE

COMMAND LINE INTERFACE

d3rlpy provides the convenient CLI tool.

5.1 plot

Plot the saved metrics by specifying paths:

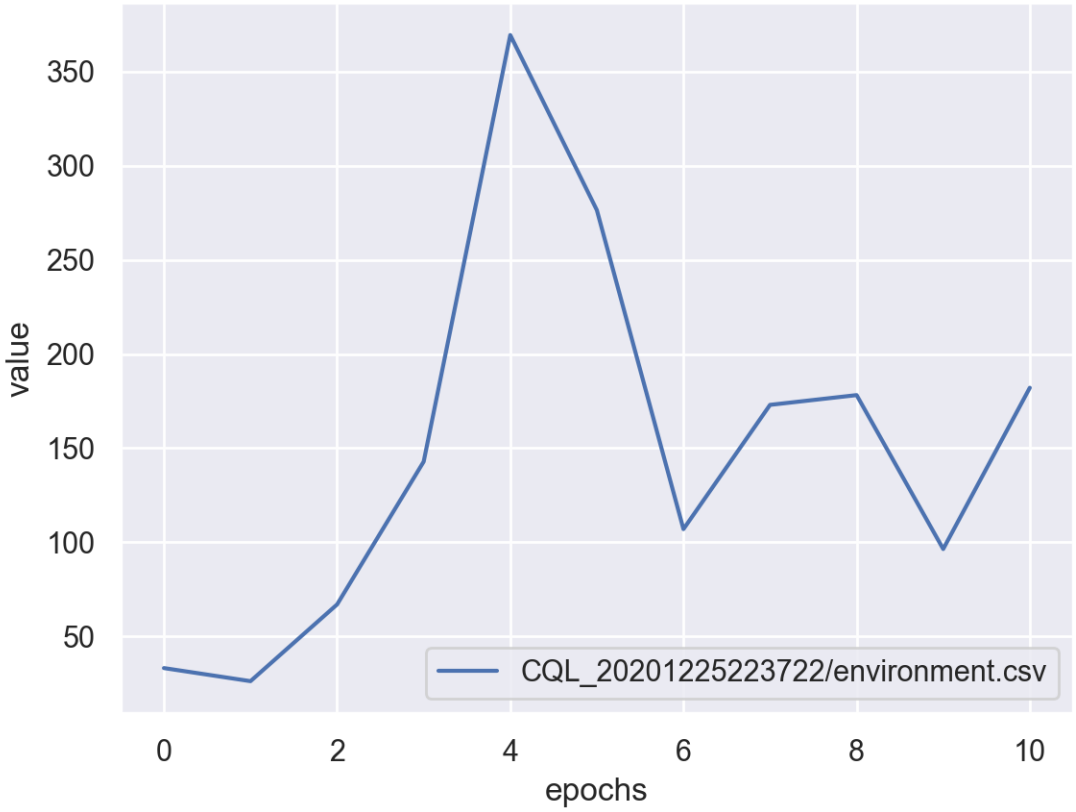
```
$ d3rlpy plot <path> [<path>...]
```

Table 1: options

option	description
`--window`	moving average window.
`--show-steps`	use iterations on x-axis.
`--show-max`	show maximum value.
`--label`	label in legend.
`--xlim`	limit on x-axis (tuple).
`--ylim`	limit on y-axis (tuple).
`--title`	title of the plot.
`--save`	flag to save the plot as an image.

example:

```
$ d3rlpy plot d3rlpy_logs/CQL_20201224224314/environment.csv
```



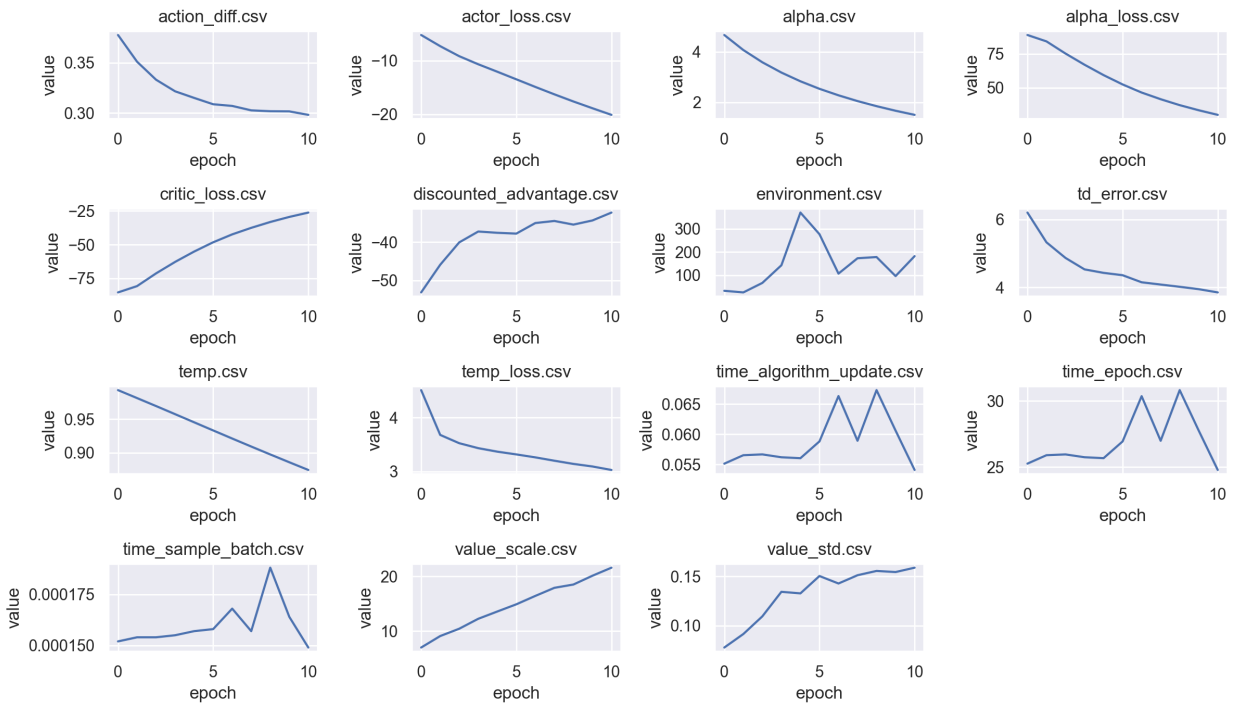
5.2 plot-all

Plot the all metrics saved in the directory:

```
$ d3rlpy plot-all <path>
```

example:

```
$ d3rlpy plot-all d3rlpy_logs/CQL_20201224224314
```



5.3 export

Export the saved model to the inference format, ONNX (`.onnx`) and TorchScript (`.pt`):

```
$ d3rlpy export <model_path> <out_path>
```

example:

```
$ d3rlpy export d3rlpy_logs/CQL_20201224224314/model_100.d3 policy.onnx
```

5.4 record

Record evaluation episodes as videos with the saved model:

```
$ d3rlpy record <path> --env-id <environment id>
```

Table 2: options

option	description
`--env-id`	Gym environment id.
`--env-header`	Arbitrary Python code to define environment to evaluate.
`--out`	Output directory.
`--n-episodes`	The number of episodes to record.
`--epsilon`	ϵ-greedy evaluation.
`--target-return`	The target environment return for Decision Transformer algorithms.

example:

```
# record simple environment
$ d3rlpy record d3rlpy_logs/CQL_20201224224314/model_100.d3 --env-id HopperBulletEnv-v0

# record wrapped environment
$ d3rlpy record d3rlpy_logs/Discrete_CQL_20201224224314/model_100.d3 \
    --env-header 'import gym; from d3rlpy.envs import Atari; env = Atari(gym.make(
↪"BreakoutNoFrameskip-v4", render_mode="rgb_array"), is_eval=True)'
```

5.5 play

Run evaluation episodes with rendering:

```
$ d3rlpy play <path> --env-id <environment id>
```

Table 3: options

option	description
`--env-id`	Gym environment id.
`--env-header`	Arbitrary Python code to define environment to evaluate.
`--n-episodes`	The number of episodes to run.
`--target-return`	The target environment return for Decision Transformer algorithms.

example:

```
# record simple environment
$ d3rlpy play d3rlpy_logs/CQL_20201224224314/model_100.d3 --env-id HopperBulletEnv-v0

# record wrapped environment
$ d3rlpy play d3rlpy_logs/Discrete_CQL_20201224224314/model_100.d3 \
    --env-header 'import gym; from d3rlpy.envs import Atari; env = Atari(gym.make(
↪"BreakoutNoFrameskip-v4", render_mode="human"), is_eval=True)'
```

5.6 install

Install additional packages:

```
$ d3rlpy install <name>
```

example:

```
# Install D4RL package
$ d3rlpy install d4rl
```

CHAPTER

SIX

INSTALLATION

6.1 Recommended Platforms

d3rlpy supports Linux, macOS and also Windows.

6.2 Install d3rlpy

6.2.1 Install via PyPI

pip is a recommended way to install d3rlpy:

```
$ pip install d3rlpy
```

6.2.2 Install via Anaconda

d3rlpy is also available on *conda-forge*:

```
$ conda install -c conda-forge d3rlpy
```

6.2.3 Install via Docker

d3rlpy is also available on Docker Hub:

```
$ docker run -it --gpus all --name d3rlpy takuseno/d3rlpy:latest bash
```

6.2.4 Install from source

You can also install via GitHub repository:

```
$ git clone https://github.com/takuseno/d3rlpy
$ cd d3rlpy
$ pip install -e .
```

CHAPTER

SEVEN

TIPS

7.1 Reproducibility

Reproducibility is one of the most important things when doing research activity. Here is a simple example in d3rlpy.

```
import d3rlpy
import gym

# set random seeds in random module, numpy module and PyTorch module.
d3rlpy.seed(313)

# set environment seed
env = gym.make('Hopper-v2')
d3rlpy.envs.seed_env(env, 313)
```

7.2 Learning from image observation

d3rlpy supports both vector observations and image observations. There are several things you need to care about if you want to train RL agents from image observations.

```
import d3rlpy

# observation MUST be uint8 array, and the channel-first images
observations = np.random.randint(256, size=(100000, 1, 84, 84), dtype=np.uint8)
actions = np.random.randomint(4, size=100000)
rewards = np.random.random(100000)
terminals = np.random.randint(2, size=100000)

dataset = d3rlpy.dataset.MDPDataset(
    observations=observations,
    actions=actions,
    rewards=rewards,
    terminals=terminals,
    # stack last 4 frames (stacked shape is [4, 84, 84])
    transition_picker=d3rlpy.dataset.FrameStackTransitionPicker(n_frames=4),
)

dqn = DQNConfig(
```

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```
    observation_scaler=d3rlpy.preprocessing.PixelObservationScaler(),  # pixels are␣
↪devided by 255
).create()
```

7.3 Improve performance beyond the original paper

d3rlpy provides many options that you can use to improve performance potentially beyond the original paper. All the options are powerful, but the best combinations and hyperparameters are always dependent on the tasks.

```
import d3rlpy

# use batch normalization
# this seems to improve performance with discrete action-spaces
encoder = d3rlpy.models.DefaultEncoderFactory(use_batch_norm=True)
# use distributional Q function leading to robust improvement
q_func = d3rlpy.models.QRQFunctionFactory()
dqn = d3rlpy.algos.DQNConfig(
    encoder_factory=encoder,
    q_func_factory=q_func,
).create()

# use dropout
# this could dramatically improve performance
encoder = d3rlpy.models.DefaultEncoderFactory(dropout_rate=0.2)
sac = d3rlpy.algos.SACConfig(actor_encoder_factory=encoder).create()

# multi-step transition sampling
transition_picker = d3rlpy.dataset.MultiStepTransitionPicker(
    n_steps=3,
    gamma=0.99,
)
# replay buffer for experience replay
buffer = d3rlpy.dataset.create_fifo_replay_buffer(
    limit=100000,
    env=env,
    transition_picker=transition_picker,
)
```

CHAPTER

EIGHT

PAPER REPRODUCTIONS

For the experiment code, please take a look at reproductions directory.

All the experimental results are available in d3rlpy-benchmarks repository.

CHAPTER

NINE

LICENSE

CHAPTER

TEN

INDICES AND TABLES

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PYTHON MODULE INDEX

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