
Stable Baselines3 Documentation

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Stable Baselines3 Contributors

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USER GUIDE

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Stable Baselines3 (SB3) is a set of reliable implementations of reinforcement learning algorithms in PyTorch. It is the next major version of Stable Baselines.

Github repository: <https://github.com/DLR-RM/stable-baselines3>

Paper: <https://jmlr.org/papers/volume22/20-1364/20-1364.pdf>

RL Baselines3 Zoo (training framework for SB3): <https://github.com/DLR-RM/rl-baselines3-zoo>

RL Baselines3 Zoo provides a collection of pre-trained agents, scripts for training, evaluating agents, tuning hyperparameters, plotting results and recording videos.

SB3 Contrib (experimental RL code, latest algorithms): <https://github.com/Stable-Baselines-Team/stable-baselines3-contrib>

MAIN FEATURES

- Unified structure for all algorithms
- PEP8 compliant (unified code style)
- Documented functions and classes
- Tests, high code coverage and type hints
- Clean code
- Tensorboard support
- **The performance of each algorithm was tested** (see *Results* section in their respective page)

1.1 Installation

1.1.1 Prerequisites

Stable-Baselines3 requires python 3.7+ and PyTorch \geq 1.8.1.

Windows 10

We recommend using [Anaconda](#) for Windows users for easier installation of Python packages and required libraries. You need an environment with Python version 3.6 or above.

For a quick start you can move straight to installing Stable-Baselines3 in the next step.

Note: Trying to create Atari environments may result to vague errors related to missing DLL files and modules. This is an issue with atari-py package. [See this discussion for more information.](#)

Stable Release

To install Stable Baselines3 with pip, execute:

```
pip install stable-baselines3[extra]
```

Note: Some shells such as Zsh require quotation marks around brackets, i.e. `pip install 'stable-baselines3[extra]'` [More information](#).

This includes an optional dependencies like Tensorboard, OpenCV or `atari-py` to train on atari games. If you do not need those, you can use:

```
pip install stable-baselines3
```

Note: If you need to work with OpenCV on a machine without a X-server (for instance inside a docker image), you will need to install `opencv-python-headless`, see [issue #298](#).

1.1.2 Bleeding-edge version

```
pip install git+https://github.com/DLR-RM/stable-baselines3
```

1.1.3 Development version

To contribute to Stable-Baselines3, with support for running tests and building the documentation.

```
git clone https://github.com/DLR-RM/stable-baselines3 && cd stable-baselines3
pip install -e .[docs,tests,extra]
```

1.1.4 Using Docker Images

If you are looking for docker images with stable-baselines already installed in it, we recommend using images from [RL Baselines3 Zoo](#).

Otherwise, the following images contained all the dependencies for stable-baselines3 but not the stable-baselines3 package itself. They are made for development.

Use Built Images

GPU image (requires [nvidia-docker](#)):

```
docker pull stablebaselines/stable-baselines3
```

CPU only:

```
docker pull stablebaselines/stable-baselines3-cpu
```


Build the Docker Images

Build GPU image (with nvidia-docker):

```
make docker-gpu
```

Build CPU image:

```
make docker-cpu
```

Note: if you are using a proxy, you need to pass extra params during build and do some [tweaks](#):

```
--network=host --build-arg HTTP_PROXY=http://your.proxy.fr:8080/ --build-arg http_
↪proxy=http://your.proxy.fr:8080/ --build-arg HTTPS_PROXY=https://your.proxy.fr:8080/ --
↪build-arg https_proxy=https://your.proxy.fr:8080/
```

Run the images (CPU/GPU)

Run the nvidia-docker GPU image

```
docker run -it --runtime=nvidia --rm --network host --ipc=host --name test --mount src="
↪$(pwd)",target=/root/code/stable-baselines3,type=bind stablebaselines/stable-
↪baselines3 bash -c 'cd /root/code/stable-baselines3/ && pytest tests/'
```

Or, with the shell file:

```
./scripts/run_docker_gpu.sh pytest tests/
```

Run the docker CPU image

```
docker run -it --rm --network host --ipc=host --name test --mount src="$(pwd)",target=/
↪root/code/stable-baselines3,type=bind stablebaselines/stable-baselines3-cpu bash -c
↪'cd /root/code/stable-baselines3/ && pytest tests/'
```

Or, with the shell file:

```
./scripts/run_docker_cpu.sh pytest tests/
```

Explanation of the docker command:

- `docker run -it` create an instance of an image (=container), and run it interactively (so `ctrl+c` will work)
- `--rm` option means to remove the container once it exits/stops (otherwise, you will have to use `docker rm`)
- `--network host` don't use network isolation, this allow to use tensorboard/visdom on host machine
- `--ipc=host` Use the host system's IPC namespace. IPC (POSIX/SysV IPC) namespace provides separation of named shared memory segments, semaphores and message queues.
- `--name test` give explicitly the name `test` to the container, otherwise it will be assigned a random name
- `--mount src=...` give access of the local directory (`pwd` command) to the container (it will be map to `/root/code/stable-baselines`), so all the logs created in the container in this folder will be kept
- `bash -c '...'` Run command inside the docker image, here run the tests (`pytest tests/`)

1.2 Getting Started

Most of the library tries to follow a sklearn-like syntax for the Reinforcement Learning algorithms.

Here is a quick example of how to train and run A2C on a CartPole environment:

```
import gym

from stable_baselines3 import A2C

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

model = A2C('MlpPolicy', env, verbose=1)
model.learn(total_timesteps=10000)

obs = env.reset()
for i in range(1000):
    action, _state = model.predict(obs, deterministic=True)
    obs, reward, done, info = env.step(action)
    env.render()
    if done:
        obs = env.reset()
```

Note: You can find explanations about the logger output and names in the [Logger](#) section.

Or just train a model with a one liner if [the environment is registered in Gym](#) and if the policy is registered:

```
from stable_baselines3 import A2C

model = A2C('MlpPolicy', 'CartPole-v1').learn(10000)
```

1.3 Reinforcement Learning Tips and Tricks

The aim of this section is to help you doing reinforcement learning experiments. It covers general advice about RL (where to start, which algorithm to choose, how to evaluate an algorithm, ...), as well as tips and tricks when using a custom environment or implementing an RL algorithm.

Note: We have a [video on YouTube](#) that covers this section in more details. You can also find the [slides here](#).

1.3.1 General advice when using Reinforcement Learning

TL;DR

1. Read about RL and Stable Baselines3
2. Do quantitative experiments and hyperparameter tuning if needed
3. Evaluate the performance using a separate test environment (remember to check wrappers!)
4. For better performance, increase the training budget

Like any other subject, if you want to work with RL, you should first read about it (we have a dedicated [resource page](#) to get you started) to understand what you are using. We also recommend you read Stable Baselines3 (SB3) documentation and do the [tutorial](#). It covers basic usage and guide you towards more advanced concepts of the library (e.g. callbacks and wrappers).

Reinforcement Learning differs from other machine learning methods in several ways. The data used to train the agent is collected through interactions with the environment by the agent itself (compared to supervised learning where you have a fixed dataset for instance). This dependence can lead to vicious circle: if the agent collects poor quality data (e.g., trajectories with no rewards), then it will not improve and continue to amass bad trajectories.

This factor, among others, explains that results in RL may vary from one run to another (i.e., when only the seed of the pseudo-random generator changes). For this reason, you should always do several runs to have quantitative results.

Good results in RL are generally dependent on finding appropriate hyperparameters. Recent algorithms (PPO, SAC, TD3) normally require little hyperparameter tuning, however, *don't expect the default ones to work* on any environment.

Therefore, we *highly recommend* you to take a look at the [RL zoo](#) (or the original papers) for tuned hyperparameters. A best practice when you apply RL to a new problem is to do automatic hyperparameter optimization. Again, this is included in the [RL zoo](#).

When applying RL to a custom problem, you should always normalize the input to the agent (e.g. using VecNormalize for PPO/A2C) and look at common preprocessing done on other environments (e.g. for [Atari](#), frame-stack, ...). Please refer to *Tips and Tricks when creating a custom environment* paragraph below for more advice related to custom environments.

Current Limitations of RL

You have to be aware of the current [limitations](#) of reinforcement learning.

Model-free RL algorithms (i.e. all the algorithms implemented in SB) are usually *sample inefficient*. They require a lot of samples (sometimes millions of interactions) to learn something useful. That's why most of the successes in RL were achieved on games or in simulation only. For instance, in this [work](#) by ETH Zurich, the ANYmal robot was trained in simulation only, and then tested in the real world.

As a general advice, to obtain better performances, you should augment the budget of the agent (number of training timesteps).

In order to achieve the desired behavior, expert knowledge is often required to design an adequate reward function. This *reward engineering* (or *RewArt* as coined by [Freek Stulp](#)), necessitates several iterations. As a good example of reward shaping, you can take a look at [Deep Mimic paper](#) which combines imitation learning and reinforcement learning to do acrobatic moves.

One last limitation of RL is the instability of training. That is to say, you can observe during training a huge drop in performance. This behavior is particularly present in DDPG, that's why its extension TD3 tries to tackle that issue. Other method, like TRPO or PPO make use of a *trust region* to minimize that problem by avoiding too large update.

How to evaluate an RL algorithm?

Note: Pay attention to environment wrappers when evaluating your agent and comparing results to others' results. Modifications to episode rewards or lengths may also affect evaluation results which may not be desirable. Check `evaluate_policy` helper function in [Evaluation Helper](#) section.

Because most algorithms use exploration noise during training, you need a separate test environment to evaluate the performance of your agent at a given time. It is recommended to periodically evaluate your agent for n test episodes (n is usually between 5 and 20) and average the reward per episode to have a good estimate.

Note: We provide an `EvalCallback` for doing such evaluation. You can read more about it in the [Callbacks](#) section.

As some policy are stochastic by default (e.g. A2C or PPO), you should also try to set `deterministic=True` when calling the `.predict()` method, this frequently leads to better performance. Looking at the training curve (episode reward function of the timesteps) is a good proxy but underestimates the agent true performance.

We suggest you reading [Deep Reinforcement Learning that Matters](#) for a good discussion about RL evaluation.

You can also take a look at this [blog post](#) and this [issue](#) by Cédric Colas.

1.3.2 Which algorithm should I use?

There is no silver bullet in RL, depending on your needs and problem, you may choose one or the other. The first distinction comes from your action space, i.e., do you have discrete (e.g. LEFT, RIGHT, ...) or continuous actions (ex: go to a certain speed)?

Some algorithms are only tailored for one or the other domain: DQN only supports discrete actions, where SAC is restricted to continuous actions.

The second difference that will help you choose is whether you can parallelize your training or not. If what matters is the wall clock training time, then you should lean towards A2C and its derivatives (PPO, ...). Take a look at the [Vectorized Environments](#) to learn more about training with multiple workers.

To sum it up:

Discrete Actions

Note: This covers `Discrete`, `MultiDiscrete`, `Binary` and `MultiBinary` spaces

Discrete Actions - Single Process

DQN with extensions (double DQN, prioritized replay, ...) are the recommended algorithms. We notably provide QR-DQN in our [contrib repo](#). DQN is usually slower to train (regarding wall clock time) but is the most sample efficient (because of its replay buffer).

Discrete Actions - Multiprocessed

You should give a try to PPO or A2C.

Continuous Actions

Continuous Actions - Single Process

Current State Of The Art (SOTA) algorithms are SAC, TD3 and TQC (available in our [contrib repo](#)). Please use the hyperparameters in the [RL zoo](#) for best results.

Continuous Actions - Multiprocessed

Take a look at PPO, TRPO (available in our [contrib repo](#)) or A2C. Again, don't forget to take the hyperparameters from the [RL zoo](#) for continuous actions problems (cf *Bullet* envs).

Note: Normalization is critical for those algorithms

Goal Environment

If your environment follows the GoalEnv interface (cf [HER](#)), then you should use HER + (SAC/TD3/DDPG/DQN/QR-DQN/TQC) depending on the action space.

Note: The `batch_size` is an important hyperparameter for experiments with [HER](#)

1.3.3 Tips and Tricks when creating a custom environment

If you want to learn about how to create a custom environment, we recommend you read this [page](#). We also provide a [colab notebook](#) for a concrete example of creating a custom gym environment.

Some basic advice:

- always normalize your observation space when you can, i.e., when you know the boundaries
- normalize your action space and make it symmetric when continuous (cf potential issue below) A good practice is to rescale your actions to lie in $[-1, 1]$. This does not limit you as you can easily rescale the action inside the environment
- start with shaped reward (i.e. informative reward) and simplified version of your problem
- debug with random actions to check that your environment works and follows the gym interface:

We provide a helper to check that your environment runs without error:

```
from stable_baselines3.common.env_checker import check_env

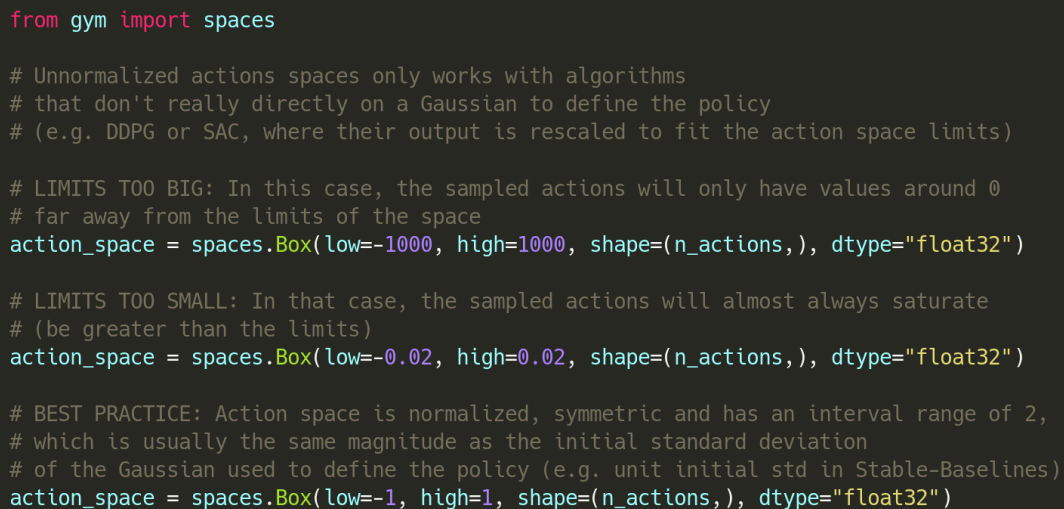
env = CustomEnv(arg1, ...)
# It will check your custom environment and output additional warnings if needed
check_env(env)
```

If you want to quickly try a random agent on your environment, you can also do:

```
env = YourEnv()
obs = env.reset()
n_steps = 10
for _ in range(n_steps):
    # Random action
    action = env.action_space.sample()
    obs, reward, done, info = env.step(action)
    if done:
        obs = env.reset()
```

Why should I normalize the action space?

Most reinforcement learning algorithms rely on a Gaussian distribution (initially centered at 0 with std 1) for continuous actions. So, if you forget to normalize the action space when using a custom environment, this can harm learning and be difficult to debug (cf attached image and [issue #473](#)).



```
from gym import spaces

# Unnormalized actions spaces only works with algorithms
# that don't really directly on a Gaussian to define the policy
# (e.g. DDPG or SAC, where their output is rescaled to fit the action space limits)

# LIMITS TOO BIG: In this case, the sampled actions will only have values around 0
# far away from the limits of the space
action_space = spaces.Box(low=-1000, high=1000, shape=(n_actions,), dtype="float32")

# LIMITS TOO SMALL: In that case, the sampled actions will almost always saturate
# (be greater than the limits)
action_space = spaces.Box(low=-0.02, high=0.02, shape=(n_actions,), dtype="float32")

# BEST PRACTICE: Action space is normalized, symmetric and has an interval range of 2,
# which is usually the same magnitude as the initial standard deviation
# of the Gaussian used to define the policy (e.g. unit initial std in Stable-Baselines)
action_space = spaces.Box(low=-1, high=1, shape=(n_actions,), dtype="float32")
```

Another consequence of using a Gaussian is that the action range is not bounded. That's why clipping is usually used as a bandage to stay in a valid interval. A better solution would be to use a squashing function (cf SAC) or a Beta distribution (cf [issue #112](#)).

Note: This statement is not true for DDPG or TD3 because they don't rely on any probability distribution.

1.3.4 Tips and Tricks when implementing an RL algorithm

When you try to reproduce a RL paper by implementing the algorithm, the [nuts and bolts of RL research](#) by John Schulman are quite useful ([video](#)).

We recommend following those steps to have a working RL algorithm:

1. Read the original paper several times
2. Read existing implementations (if available)
3. Try to have some “sign of life” on toy problems
4. **Validate the implementation by making it run on harder and harder envs (you can compare results against the RL zoo)**
You usually need to run hyperparameter optimization for that step.

You need to be particularly careful on the shape of the different objects you are manipulating (a broadcast mistake will fail silently cf [issue #75](#)) and when to stop the gradient propagation.

A personal pick (by @araffin) for environments with gradual difficulty in RL with continuous actions:

1. Pendulum (easy to solve)
2. HalfCheetahBullet (medium difficulty with local minima and shaped reward)
3. BipedalWalkerHardcore (if it works on that one, then you can have a cookie)

in RL with discrete actions:

1. CartPole-v1 (easy to be better than random agent, harder to achieve maximal performance)
2. LunarLander
3. Pong (one of the easiest Atari game)
4. other Atari games (e.g. Breakout)

1.4 Reinforcement Learning Resources

Stable-Baselines3 assumes that you already understand the basic concepts of Reinforcement Learning (RL).

However, if you want to learn about RL, there are several good resources to get started:

- [OpenAI Spinning Up](#)
- [David Silver’s course](#)
- [Lilian Weng’s blog](#)
- [Berkeley’s Deep RL Bootcamp](#)
- [Berkeley’s Deep Reinforcement Learning course](#)
- [More resources](#)

1.5 RL Algorithms

This table displays the rl algorithms that are implemented in the Stable Baselines3 project, along with some useful characteristics: support for discrete/continuous actions, multiprocessing.

Name	Box	Discrete	MultiDiscrete	MultiBinary	Multi Processing
ARS ¹	✓	✓			✓
A2C	✓	✓	✓	✓	✓
DDPG	✓				✓
DQN		✓			✓
HER	✓	✓			
PPO	✓	✓	✓	✓	✓
QR-DQN ¹		✓			✓
SAC	✓				✓
TD3	✓				✓
TQC ¹	✓				✓
TRPO ¹	✓	✓	✓	✓	✓
Maskable PPO ¹		✓	✓	✓	✓

Note: Tuple observation spaces are not supported by any environment however single-level Dict spaces are (cf. [Examples](#)).

Actions `gym.spaces`:

- **Box:** A N-dimensional box that contains every point in the action space.
- **Discrete:** A list of possible actions, where each timestep only one of the actions can be used.
- **MultiDiscrete:** A list of possible actions, where each timestep only one action of each discrete set can be used.
- **MultiBinary:** A list of possible actions, where each timestep any of the actions can be used in any combination.

Note: More algorithms (like QR-DQN or TQC) are implemented in our [contrib repo](#).

Note: Some logging values (like `ep_rew_mean`, `ep_len_mean`) are only available when using a `Monitor` wrapper. See [Issue #339](#) for more info.

Note: When using off-policy algorithms, [Time Limits](#) (aka timeouts) are handled properly (cf. [issue #284](#)). You can revert to SB3 < 2.1.0 behavior by passing `handle_timeout_termination=False` via the `replay_buffer_kwargs` argument.

¹ Implemented in [SB3 Contrib](#)

1.5.1 Reproducibility

Completely reproducible results are not guaranteed across PyTorch releases or different platforms. Furthermore, results need not be reproducible between CPU and GPU executions, even when using identical seeds.

In order to make computations deterministic, on your specific problem on one specific platform, you need to pass a seed argument at the creation of a model. If you pass an environment to the model using `set_env()`, then you also need to seed the environment first.

Credit: part of the *Reproducibility* section comes from [PyTorch Documentation](#)

1.6 Examples

Note: These examples are only to demonstrate the use of the library and its functions, and the trained agents may not solve the environments. Optimized hyperparameters can be found in the RL Zoo [repository](#).

1.6.1 Try it online with Colab Notebooks!

All the following examples can be executed online using Google colab notebooks:

- [Full Tutorial](#)
- [All Notebooks](#)
- [Getting Started](#)
- [Training, Saving, Loading](#)
- [Multiprocessing](#)
- [Monitor Training and Plotting](#)
- [Atari Games](#)
- [RL Baselines zoo](#)
- [PyBullet](#)
- [Hindsight Experience Replay](#)
- [Advanced Saving and Loading](#)

1.6.2 Basic Usage: Training, Saving, Loading

In the following example, we will train, save and load a DQN model on the Lunar Lander environment.

Fig. 1: Lunar Lander Environment

Note: LunarLander requires the python package `box2d`. You can install it using `apt install swig` and then `pip install box2d box2d-kengz`

Warning: `load` method re-creates the model from scratch and should be called on the Algorithm without instantiating it first, e.g. `model = DQN.load("dqn_lunar", env=env)` instead of `model = DQN(env=env)` followed by `model.load("dqn_lunar")`. The latter **will not work** as `load` is not an in-place operation. If you want to load parameters without re-creating the model, e.g. to evaluate the same model with multiple different sets of parameters, consider using `set_parameters` instead.

```
import gym

from stable_baselines3 import DQN
from stable_baselines3.common.evaluation import evaluate_policy

# Create environment
env = gym.make('LunarLander-v2')

# Instantiate the agent
model = DQN('MlpPolicy', env, verbose=1)
# Train the agent
model.learn(total_timesteps=int(2e5))
# Save the agent
model.save("dqn_lunar")
del model # delete trained model to demonstrate loading

# Load the trained agent
# NOTE: if you have loading issue, you can pass `print_system_info=True`
# to compare the system on which the model was trained vs the current one
# model = DQN.load("dqn_lunar", env=env, print_system_info=True)
model = DQN.load("dqn_lunar", env=env)

# Evaluate the agent
# NOTE: If you use wrappers with your environment that modify rewards,
#       this will be reflected here. To evaluate with original rewards,
#       wrap environment in a "Monitor" wrapper before other wrappers.
mean_reward, std_reward = evaluate_policy(model, model.get_env(), n_eval_episodes=10)

# Enjoy trained agent
obs = env.reset()
for i in range(1000):
    action, _states = model.predict(obs, deterministic=True)
    obs, rewards, dones, info = env.step(action)
    env.render()
```

1.6.3 Multiprocessing: Unleashing the Power of Vectorized Environments

Fig. 2: CartPole Environment

```
import gym
import numpy as np

from stable_baselines3 import PPO
from stable_baselines3.common.vec_env import DummyVecEnv, SubprocVecEnv
from stable_baselines3.common.env_util import make_vec_env
from stable_baselines3.common.utils import set_random_seed

def make_env(env_id, rank, seed=0):
    """
    Utility function for multiprocessed env.

    :param env_id: (str) the environment ID
    :param num_env: (int) the number of environments you wish to have in subprocesses
    :param seed: (int) the initial seed for RNG
    :param rank: (int) index of the subprocess
    """
    def _init():
        env = gym.make(env_id)
        env.seed(seed + rank)
        return env
    set_random_seed(seed)
    return _init

if __name__ == '__main__':
    env_id = "CartPole-v1"
    num_cpu = 4 # Number of processes to use
    # Create the vectorized environment
    env = SubprocVecEnv([make_env(env_id, i) for i in range(num_cpu)])

    # Stable Baselines provides you with make_vec_env() helper
    # which does exactly the previous steps for you.
    # You can choose between `DummyVecEnv` (usually faster) and `SubprocVecEnv`
    # env = make_vec_env(env_id, n_envs=num_cpu, seed=0, vec_env_cls=SubprocVecEnv)

    model = PPO('MlpPolicy', env, verbose=1)
    model.learn(total_timesteps=25_000)

    obs = env.reset()
    for _ in range(1000):
        action, _states = model.predict(obs)
        obs, rewards, dones, info = env.step(action)
        env.render()
```

1.6.4 Multiprocessing with off-policy algorithms

Warning: When using multiple environments with off-policy algorithms, you should update the `gradient_steps` parameter too. Set it to `gradient_steps=-1` to perform as many gradient steps as transitions collected. There is usually a compromise between wall-clock time and sample efficiency, see this [example in PR #439](#)

```
import gym

from stable_baselines3 import SAC
from stable_baselines3.common.env_util import make_vec_env

env = make_vec_env("Pendulum-v0", n_envs=4, seed=0)

# We collect 4 transitions per call to `env.step()`
# and performs 2 gradient steps per call to `env.step()`
# if gradient_steps=-1, then we would do 4 gradients steps per call to `env.step()`
model = SAC('MlpPolicy', env, train_freq=1, gradient_steps=2, verbose=1)
model.learn(total_timesteps=10_000)
```

1.6.5 Dict Observations

You can use environments with dictionary observation spaces. This is useful in the case where one can't directly concatenate observations such as an image from a camera combined with a vector of servo sensor data (e.g., rotation angles). Stable Baselines3 provides `SimpleMultiObsEnv` as an example of this kind of setting. The environment is a simple grid world but the observations for each cell come in the form of dictionaries. These dictionaries are randomly initialized on the creation of the environment and contain a vector observation and an image observation.

```
from stable_baselines3 import PPO
from stable_baselines3.common.envs import SimpleMultiObsEnv

# Stable Baselines provides SimpleMultiObsEnv as an example environment with Dict_
↳ observations
env = SimpleMultiObsEnv(random_start=False)

model = PPO("MultiInputPolicy", env, verbose=1)
model.learn(total_timesteps=100_000)
```

1.6.6 Using Callback: Monitoring Training

Note: We recommend reading the [Callback section](#)

You can define a custom callback function that will be called inside the agent. This could be useful when you want to monitor training, for instance display live learning curves in Tensorboard (or in Visdom) or save the best agent. If your callback returns `False`, training is aborted early.

```

import os

import gym
import numpy as np
import matplotlib.pyplot as plt

from stable_baselines3 import TD3
from stable_baselines3.common import results_plotter
from stable_baselines3.common.monitor import Monitor
from stable_baselines3.common.results_plotter import load_results, ts2xy, plot_results
from stable_baselines3.common.noise import NormalActionNoise
from stable_baselines3.common.callbacks import BaseCallback

class SaveOnBestTrainingRewardCallback(BaseCallback):
    """
    Callback for saving a model (the check is done every ``check_freq`` steps)
    based on the training reward (in practice, we recommend using ``EvalCallback``).

    :param check_freq:
    :param log_dir: Path to the folder where the model will be saved.
        It must contains the file created by the ``Monitor`` wrapper.
    :param verbose: Verbosity level.
    """
    def __init__(self, check_freq: int, log_dir: str, verbose: int = 1):
        super(SaveOnBestTrainingRewardCallback, self).__init__(verbose)
        self.check_freq = check_freq
        self.log_dir = log_dir
        self.save_path = os.path.join(log_dir, 'best_model')
        self.best_mean_reward = -np.inf

    def _init_callback(self) -> None:
        # Create folder if needed
        if self.save_path is not None:
            os.makedirs(self.save_path, exist_ok=True)

    def _on_step(self) -> bool:
        if self.n_calls % self.check_freq == 0:

            # Retrieve training reward
            x, y = ts2xy(load_results(self.log_dir), 'timesteps')
            if len(x) > 0:
                # Mean training reward over the last 100 episodes
                mean_reward = np.mean(y[-100:])
                if self.verbose > 0:
                    print(f"Num timesteps: {self.num_timesteps}")
                    print(f"Best mean reward: {self.best_mean_reward:.2f} - Last mean reward: {mean_reward:.2f}")
                # New best model, you could save the agent here
                if mean_reward > self.best_mean_reward:
                    self.best_mean_reward = mean_reward
                    # Example for saving best model

```

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```

        if self.verbose > 0:
            print(f"Saving new best model to {self.save_path}")
            self.model.save(self.save_path)

    return True

# Create log dir
log_dir = "tmp/"
os.makedirs(log_dir, exist_ok=True)

# Create and wrap the environment
env = gym.make('LunarLanderContinuous-v2')
env = Monitor(env, log_dir)

# Add some action noise for exploration
n_actions = env.action_space.shape[-1]
action_noise = NormalActionNoise(mean=np.zeros(n_actions), sigma=0.1 * np.ones(n_
    ↪actions))
# Because we use parameter noise, we should use a MlpPolicy with layer normalization
model = TD3('MlpPolicy', env, action_noise=action_noise, verbose=0)
# Create the callback: check every 1000 steps
callback = SaveOnBestTrainingRewardCallback(check_freq=1000, log_dir=log_dir)
# Train the agent
timesteps = 1e5
model.learn(total_timesteps=int(timesteps), callback=callback)

plot_results([log_dir], timesteps, results_plotter.X_TIMESTEPS, "TD3 LunarLander")
plt.show()

```

1.6.7 Atari Games

Fig. 3: Trained A2C agent on Breakout

Fig. 4: Pong Environment

Training a RL agent on Atari games is straightforward thanks to `make_atari_env` helper function. It will do all the preprocessing and multiprocessing for you. To install the Atari environments, run the command `pip install gym[atari, accept-rom-license]` to install the Atari environments and ROMs, or install Stable Baselines3 with `pip install stable-baselines3[extra]` to install this and other optional dependencies.

```

from stable_baselines3.common.env_util import make_atari_env
from stable_baselines3.common.vec_env import VecFrameStack
from stable_baselines3 import A2C

# There already exists an environment generator
# that will make and wrap atari environments correctly.

```

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```
# Here we are also multi-worker training (n_envs=4 => 4 environments)
env = make_atari_env('PongNoFrameskip-v4', n_envs=4, seed=0)
# Frame-stacking with 4 frames
env = VecFrameStack(env, n_stack=4)

model = A2C('CnnPolicy', env, verbose=1)
model.learn(total_timesteps=25_000)

obs = env.reset()
while True:
    action, _states = model.predict(obs)
    obs, rewards, dones, info = env.step(action)
    env.render()
```

1.6.8 PyBullet: Normalizing input features

Normalizing input features may be essential to successful training of an RL agent (by default, images are scaled but not other types of input), for instance when training on [PyBullet](#) environments. For that, a wrapper exists and will compute a running average and standard deviation of input features (it can do the same for rewards).

Note: you need to install pybullet with `pip install pybullet`

```
import os
import gym
import pybullet_envs

from stable_baselines3.common.vec_env import DummyVecEnv, VecNormalize
from stable_baselines3 import PPO

env = DummyVecEnv([lambda: gym.make("HalfCheetahBulletEnv-v0")])
# Automatically normalize the input features and reward
env = VecNormalize(env, norm_obs=True, norm_reward=True,
                  clip_obs=10.)

model = PPO('MlpPolicy', env)
model.learn(total_timesteps=2000)

# Don't forget to save the VecNormalize statistics when saving the agent
log_dir = "/tmp/"
model.save(log_dir + "ppo_halfcheetah")
stats_path = os.path.join(log_dir, "vec_normalize.pkl")
env.save(stats_path)

# To demonstrate loading
del model, env

# Load the saved statistics
env = DummyVecEnv([lambda: gym.make("HalfCheetahBulletEnv-v0")])
```

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```
env = VecNormalize.load(stats_path, env)
# do not update them at test time
env.training = False
# reward normalization is not needed at test time
env.norm_reward = False

# Load the agent
model = PPO.load(log_dir + "ppo_halfcheetah", env=env)
```

1.6.9 Hindsight Experience Replay (HER)

For this example, we are using [Highway-Env](#) by @eleurent.

Fig. 5: The highway-parking-v0 environment.

The parking env is a goal-conditioned continuous control task, in which the vehicle must park in a given space with the appropriate heading.

Note: The hyperparameters in the following example were optimized for that environment.

```
import gym
import highway_env
import numpy as np

from stable_baselines3 import HerReplayBuffer, SAC, DDPG, TD3
from stable_baselines3.common.noise import NormalActionNoise

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

# Create 4 artificial transitions per real transition
n_sampled_goal = 4

# SAC hyperparams:
model = SAC(
    "MultiInputPolicy",
    env,
    replay_buffer_class=HerReplayBuffer,
    replay_buffer_kwargs=dict(
        n_sampled_goal=n_sampled_goal,
        goal_selection_strategy="future",
        # IMPORTANT: because the env is not wrapped with a TimeLimit wrapper
        # we have to manually specify the max number of steps per episode
        max_episode_length=100,
        online_sampling=True,
    ),
    verbose=1,
    buffer_size=int(1e6),
```

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```

    learning_rate=1e-3,
    gamma=0.95,
    batch_size=256,
    policy_kwargs=dict(net_arch=[256, 256, 256]),
)

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

# Load saved model
# Because it needs access to `env.compute_reward()`
# HER must be loaded with the env
model = SAC.load("her_sac_highway", env=env)

obs = env.reset()

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

```

1.6.10 Learning Rate Schedule

All algorithms allow you to pass a learning rate schedule that takes as input the current progress remaining (from 1 to 0). PPO's `clip_range` parameter also accepts such schedule.

The RL Zoo already includes linear and constant schedules.

```

from typing import Callable

from stable_baselines3 import PPO

def linear_schedule(initial_value: float) -> Callable[[float], float]:
    """
    Linear learning rate schedule.

    :param initial_value: Initial learning rate.
    :return: schedule that computes
        current learning rate depending on remaining progress
    """
    def func(progress_remaining: float) -> float:
        """
        Progress will decrease from 1 (beginning) to 0.

```

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```

        :param progress_remaining:
        :return: current learning rate
        """
        return progress_remaining * initial_value

    return func

# Initial learning rate of 0.001
model = PPO("MlpPolicy", "CartPole-v1", learning_rate=linear_schedule(0.001), verbose=1)
model.learn(total_timesteps=20_000)
# By default, `reset_num_timesteps` is True, in which case the learning rate schedule
↪ resets.
# progress_remaining = 1.0 - (num_timesteps / total_timesteps)
model.learn(total_timesteps=10_000, reset_num_timesteps=True)

```

1.6.11 Advanced Saving and Loading

In this example, we show how to use some advanced features of Stable-Baselines3 (SB3): how to easily create a test environment to evaluate an agent periodically, use a policy independently from a model (and how to save it, load it) and save/load a replay buffer.

By default, the replay buffer is not saved when calling `model.save()`, in order to save space on the disk (a replay buffer can be up to several GB when using images). However, SB3 provides a `save_replay_buffer()` and `load_replay_buffer()` method to save it separately.

Stable-Baselines3 automatic creation of an environment for evaluation. For that, you only need to specify `create_eval_env=True` when passing the Gym ID of the environment while creating the agent. Behind the scene, SB3 uses an *EvalCallback*.

Note: For training model after loading it, we recommend loading the replay buffer to ensure stable learning (for off-policy algorithms). You also need to pass `reset_num_timesteps=True` to `learn` function which initializes the environment and agent for training if a new environment was created since saving the model.

```

from stable_baselines3 import SAC
from stable_baselines3.common.evaluation import evaluate_policy
from stable_baselines3.sac.policies import MlpPolicy

# Create the model, the training environment
# and the test environment (for evaluation)
model = SAC('MlpPolicy', 'Pendulum-v1', verbose=1,
            learning_rate=1e-3, create_eval_env=True)

# Evaluate the model every 1000 steps on 5 test episodes
# and save the evaluation to the "logs/" folder
model.learn(6000, eval_freq=1000, n_eval_episodes=5, eval_log_path="./logs/")

# save the model
model.save("sac_pendulum")

```

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```

# the saved model does not contain the replay buffer
loaded_model = SAC.load("sac_pendulum")
print(f"The loaded_model has {loaded_model.replay_buffer.size()} transitions in its_
↪buffer")

# now save the replay buffer too
model.save_replay_buffer("sac_replay_buffer")

# load it into the loaded_model
loaded_model.load_replay_buffer("sac_replay_buffer")

# now the loaded replay is not empty anymore
print(f"The loaded_model has {loaded_model.replay_buffer.size()} transitions in its_
↪buffer")

# Save the policy independently from the model
# Note: if you don't save the complete model with `model.save()`
# you cannot continue training afterward
policy = model.policy
policy.save("sac_policy_pendulum")

# Retrieve the environment
env = model.get_env()

# Evaluate the policy
mean_reward, std_reward = evaluate_policy(policy, env, n_eval_episodes=10,
↪deterministic=True)

print(f"mean_reward={mean_reward:.2f} +/- {std_reward}")

# Load the policy independently from the model
saved_policy = MlpPolicy.load("sac_policy_pendulum")

# Evaluate the loaded policy
mean_reward, std_reward = evaluate_policy(saved_policy, env, n_eval_episodes=10,
↪deterministic=True)

print(f"mean_reward={mean_reward:.2f} +/- {std_reward}")

```

1.6.12 Accessing and modifying model parameters

You can access model's parameters via `load_parameters` and `get_parameters` functions, or via `model.policy.state_dict()` (and `load_state_dict()`), which use dictionaries that map variable names to PyTorch tensors.

These functions are useful when you need to e.g. evaluate large set of models with same network structure, visualize different layers of the network or modify parameters manually.

Policies also offers a simple way to save/load weights as a NumPy vector, using `parameters_to_vector()` and `load_from_vector()` method.

Following example demonstrates reading parameters, modifying some of them and loading them to model by implementing [evolution strategy \(es\)](#) for solving the `CartPole-v1` environment. The initial guess for parameters is obtained

by running A2C policy gradient updates on the model.

```
from typing import Dict

import gym
import numpy as np
import torch as th

from stable_baselines3 import A2C
from stable_baselines3.common.evaluation import evaluate_policy

def mutate(params: Dict[str, th.Tensor]) -> Dict[str, th.Tensor]:
    """Mutate parameters by adding normal noise to them"""
    return dict((name, param + th.randn_like(param)) for name, param in params.items())

# Create policy with a small network
model = A2C(
    "MlpPolicy",
    "CartPole-v1",
    ent_coef=0.0,
    policy_kwargs={"net_arch": [32]},
    seed=0,
    learning_rate=0.05,
)

# Use traditional actor-critic policy gradient updates to
# find good initial parameters
model.learn(total_timesteps=10_000)

# Include only variables with "policy", "action" (policy) or "shared_net" (shared layers)
# in their name: only these ones affect the action.
# NOTE: you can retrieve those parameters using model.get_parameters() too
mean_params = dict(
    (key, value)
    for key, value in model.policy.state_dict().items()
    if ("policy" in key or "shared_net" in key or "action" in key)
)

# population size of 50 individuals
pop_size = 50
# Keep top 10%
n_elite = pop_size // 10
# Retrieve the environment
env = model.get_env()

for iteration in range(10):
    # Create population of candidates and evaluate them
    population = []
    for population_i in range(pop_size):
        candidate = mutate(mean_params)
        # Load new policy parameters to agent.
```

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```

    # Tell function that it should only update parameters
    # we give it (policy parameters)
    model.policy.load_state_dict(candidate, strict=False)
    # Evaluate the candidate
    fitness, _ = evaluate_policy(model, env)
    population.append((candidate, fitness))
    # Take top 10% and use average over their parameters as next mean parameter
    top_candidates = sorted(population, key=lambda x: x[1], reverse=True)[:n_elite]
    mean_params = dict(
        (
            name,
            th.stack([candidate[0][name] for candidate in top_candidates]).mean(dim=0),
        )
        for name in mean_params.keys()
    )
    mean_fitness = sum(top_candidate[1] for top_candidate in top_candidates) / n_elite
    print(f"Iteration {iteration + 1:<3} Mean top fitness: {mean_fitness:.2f}")
    print(f"Best fitness: {top_candidates[0][1]:.2f}")

```

1.6.13 SB3 and ProcgenEnv

Some environments like `Procgen` already produce a vectorized environment (see discussion in [issue #314](#)). In order to use it with SB3, you must wrap it in a `VecMonitor` wrapper which will also allow to keep track of the agent progress.

```

from procgen import ProcgenEnv

from stable_baselines3 import PPO
from stable_baselines3.common.vec_env import VecExtractDictObs, VecMonitor

# ProcgenEnv is already vectorized
venv = ProcgenEnv(num_envs=2, env_name='starpilot')

# To use only part of the observation:
# venv = VecExtractDictObs(venv, "rgb")

# Wrap with a VecMonitor to collect stats and avoid errors
venv = VecMonitor(venv=venv)

model = PPO("MultiInputPolicy", venv, verbose=1)
model.learn(10_000)

```

1.6.14 Record a Video

Record a mp4 video (here using a random agent).

Note: It requires `ffmpeg` or `avconv` to be installed on the machine.

```
import gym
from stable_baselines3.common.vec_env import VecVideoRecorder, DummyVecEnv

env_id = 'CartPole-v1'
video_folder = 'logs/videos/'
video_length = 100

env = DummyVecEnv([lambda: gym.make(env_id)])

obs = env.reset()

# Record the video starting at the first step
env = VecVideoRecorder(env, video_folder,
                      record_video_trigger=lambda x: x == 0, video_length=video_length,
                      name_prefix=f"random-agent-{env_id}")

env.reset()
for _ in range(video_length + 1):
    action = [env.action_space.sample()]
    obs, _, _, _ = env.step(action)
# Save the video
env.close()
```

1.6.15 Bonus: Make a GIF of a Trained Agent

Note: For Atari games, you need to use a screen recorder such as [Kazam](#). And then convert the video using `ffmpeg`

```
import imageio
import numpy as np

from stable_baselines3 import A2C

model = A2C("MlpPolicy", "LunarLander-v2").learn(100_000)

images = []
obs = model.env.reset()
img = model.env.render(mode='rgb_array')
for i in range(350):
    images.append(img)
    action, _ = model.predict(obs)
    obs, _, _, _ = model.env.step(action)
    img = model.env.render(mode='rgb_array')
```

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```
imageio.mimsave('lander_a2c.gif', [np.array(img) for i, img in enumerate(images) if i%2 == 0], fps=29)
```

1.7 Vectorized Environments

Vectorized Environments are a method for stacking multiple independent environments into a single environment. Instead of training an RL agent on 1 environment per step, it allows us to train it on n environments per step. Because of this, actions passed to the environment are now a vector (of dimension n). It is the same for observations, rewards and end of episode signals (dones). In the case of non-array observation spaces such as Dict or Tuple, where different sub-spaces may have different shapes, the sub-observations are vectors (of dimension n).

Name	Box	Discrete	Dict	Tuple	Multi Processing
DummyVecEnv	✓	✓	✓	✓	
SubprocVecEnv	✓	✓	✓	✓	✓

Note: Vectorized environments are required when using wrappers for frame-stacking or normalization.

Note: When using vectorized environments, the environments are automatically reset at the end of each episode. Thus, the observation returned for the i -th environment when `done[i]` is true will in fact be the first observation of the next episode, not the last observation of the episode that has just terminated. You can access the “real” final observation of the terminated episode—that is, the one that accompanied the done event provided by the underlying environment—using the `terminal_observation` keys in the info dicts returned by the VecEnv.

Warning: When defining a custom VecEnv (for instance, using `gym3 ProcgenEnv`), you should provide `terminal_observation` keys in the info dicts returned by the VecEnv (cf. note above).

Warning: When using `SubprocVecEnv`, users must wrap the code in an `if __name__ == "__main__":` if using the `forkserver` or `spawn` start method (default on Windows). On Linux, the default start method is `fork` which is not thread safe and can create deadlocks.

For more information, see Python’s [multiprocessing guidelines](#).

1.7.1 Vectorized Environments Wrappers

If you want to alter or augment a VecEnv without redefining it completely (e.g. stack multiple frames, monitor the VecEnv, normalize the observation, ...), you can use `VecEnvWrapper` for that. They are the vectorized equivalents (i.e., they act on multiple environments at the same time) of `gym.Wrapper`.

You can find below an example for extracting one key from the observation:

```
import numpy as np

from stable_baselines3.common.vec_env.base_vec_env import VecEnv, VecEnvStepReturn, \
↳VecEnvWrapper

class VecExtractDictObs(VecEnvWrapper):
    """
    A vectorized wrapper for filtering a specific key from dictionary observations.
    Similar to Gym's FilterObservation wrapper:
        https://github.com/openai/gym/blob/master/gym/wrappers/filter_observation.py

    :param venv: The vectorized environment
    :param key: The key of the dictionary observation
    """

    def __init__(self, venv: VecEnv, key: str):
        self.key = key
        super().__init__(venv=venv, observation_space=venv.observation_space.spaces[self.
↳key])

    def reset(self) -> np.ndarray:
        obs = self.venv.reset()
        return obs[self.key]

    def step_async(self, actions: np.ndarray) -> None:
        self.venv.step_async(actions)

    def step_wait(self) -> VecEnvStepReturn:
        obs, reward, done, info = self.venv.step_wait()
        return obs[self.key], reward, done, info

env = DummyVecEnv([lambda: gym.make("FetchReach-v1")])
# Wrap the VecEnv
env = VecExtractDictObs(env, key="observation")
```

1.7.2 VecEnv

class stable_baselines3.common.vec_env.**VecEnv**(num_envs, observation_space, action_space)

An abstract asynchronous, vectorized environment.

Parameters

- **num_envs** (int) – the number of environments
- **observation_space** (Space) – the observation space
- **action_space** (Space) – the action space

abstract close()

Clean up the environment's resources.

Return type None

abstract env_is_wrapped(*wrapper_class, indices=None*)

Check if environments are wrapped with a given wrapper.

Parameters

- **method_name** – The name of the environment method to invoke.
- **indices** (Union[None, int, Iterable[int]]) – Indices of envs whose method to call
- **method_args** – Any positional arguments to provide in the call
- **method_kwargs** – Any keyword arguments to provide in the call

Return type List[bool]

Returns True if the env is wrapped, False otherwise, for each env queried.

abstract env_method(*method_name, *method_args, indices=None, **method_kwargs*)

Call instance methods of vectorized environments.

Parameters

- **method_name** (str) – The name of the environment method to invoke.
- **indices** (Union[None, int, Iterable[int]]) – Indices of envs whose method to call
- **method_args** – Any positional arguments to provide in the call
- **method_kwargs** – Any keyword arguments to provide in the call

Return type List[Any]

Returns List of items returned by the environment's method call

abstract get_attr(*attr_name, indices=None*)

Return attribute from vectorized environment.

Parameters

- **attr_name** (str) – The name of the attribute whose value to return
- **indices** (Union[None, int, Iterable[int]]) – Indices of envs to get attribute from

Return type List[Any]

Returns List of values of 'attr_name' in all environments

get_images()

Return RGB images from each environment

Return type Sequence[ndarray]

getattr_depth_check(*name, already_found*)

Check if an attribute reference is being hidden in a recursive call to __getattr__

Parameters

- **name** (str) – name of attribute to check for
- **already_found** (bool) – whether this attribute has already been found in a wrapper

Return type Optional[str]

Returns name of module whose attribute is being shadowed, if any.

render(*mode='human'*)

Gym environment rendering

Parameters *mode* (str) – the rendering type

Return type Optional[ndarray]

abstract reset()

Reset all the environments and return an array of observations, or a tuple of observation arrays.

If `step_async` is still doing work, that work will be cancelled and `step_wait()` should not be called until `step_async()` is invoked again.

Return type Union[ndarray, Dict[str, ndarray], Tuple[ndarray, ...]]

Returns observation

abstract seed(*seed=None*)

Sets the random seeds for all environments, based on a given seed. Each individual environment will still get its own seed, by incrementing the given seed.

Parameters *seed* (Optional[int]) – The random seed. May be None for completely random seeding.

Return type List[Optional[int]]

Returns Returns a list containing the seeds for each individual env. Note that all list elements may be None, if the env does not return anything when being seeded.

abstract set_attr(*attr_name, value, indices=None*)

Set attribute inside vectorized environments.

Parameters

- **attr_name** (str) – The name of attribute to assign new value
- **value** (Any) – Value to assign to *attr_name*
- **indices** (Union[None, int, Iterable[int]]) – Indices of envs to assign value

Return type None

Returns

step(*actions*)

Step the environments with the given action

Parameters *actions* (ndarray) – the action

Return type Tuple[Union[ndarray, Dict[str, ndarray], Tuple[ndarray, ...]], ndarray, ndarray, List[Dict]]

Returns observation, reward, done, information

abstract step_async(*actions*)

Tell all the environments to start taking a step with the given actions. Call `step_wait()` to get the results of the step.

You should not call this if a `step_async` run is already pending.

Return type None

abstract step_wait()

Wait for the step taken with `step_async()`.

Return type Tuple[Union[ndarray, Dict[str, ndarray], Tuple[ndarray, ...], ndarray, ndarray, List[Dict]]]

Returns observation, reward, done, information

1.7.3 DummyVecEnv

class `stable_baselines3.common.vec_env.DummyVecEnv(env_fns)`

Creates a simple vectorized wrapper for multiple environments, calling each environment in sequence on the current Python process. This is useful for computationally simple environment such as `cartpole-v1`, as the overhead of multiprocessing or multithread outweighs the environment computation time. This can also be used for RL methods that require a vectorized environment, but that you want a single environments to train with.

Parameters `env_fns` (List[Callable[[], Env]]) – a list of functions that return environments to vectorize

close()

Clean up the environment's resources.

Return type None

env_is_wrapped(*wrapper_class, indices=None*)

Check if worker environments are wrapped with a given wrapper

Return type List[bool]

env_method(*method_name, *method_args, indices=None, **method_kwargs*)

Call instance methods of vectorized environments.

Return type List[Any]

get_attr(*attr_name, indices=None*)

Return attribute from vectorized environment (see base class).

Return type List[Any]

get_images()

Return RGB images from each environment

Return type Sequence[ndarray]

render(*mode='human'*)

Gym environment rendering. If there are multiple environments then they are tiled together in one image via `BaseVecEnv.render()`. Otherwise (if `self.num_envs == 1`), we pass the render call directly to the underlying environment.

Therefore, some arguments such as `mode` will have values that are valid only when `num_envs == 1`.

Parameters `mode` (str) – The rendering type.

Return type Optional[ndarray]

reset()

Reset all the environments and return an array of observations, or a tuple of observation arrays.

If `step_async` is still doing work, that work will be cancelled and `step_wait()` should not be called until `step_async()` is invoked again.

Return type Union[ndarray, Dict[str, ndarray], Tuple[ndarray, ...]]

Returns observation

seed(*seed=None*)

Sets the random seeds for all environments, based on a given seed. Each individual environment will still get its own seed, by incrementing the given seed.

Parameters **seed** (Optional[int]) – The random seed. May be None for completely random seeding.

Return type List[Optional[int]]

Returns Returns a list containing the seeds for each individual env. Note that all list elements may be None, if the env does not return anything when being seeded.

set_attr(*attr_name, value, indices=None*)

Set attribute inside vectorized environments (see base class).

Return type None

step_async(*actions*)

Tell all the environments to start taking a step with the given actions. Call `step_wait()` to get the results of the step.

You should not call this if a `step_async` run is already pending.

Return type None

step_wait()

Wait for the step taken with `step_async()`.

Return type Tuple[Union[ndarray, Dict[str, ndarray], Tuple[ndarray, ...]], ndarray, ndarray, List[Dict]]

Returns observation, reward, done, information

1.7.4 SubprocVecEnv

class `stable_baselines3.common.vec_env.SubprocVecEnv`(*env_fns, start_method=None*)

Creates a multiprocess vectorized wrapper for multiple environments, distributing each environment to its own process, allowing significant speed up when the environment is computationally complex.

For performance reasons, if your environment is not IO bound, the number of environments should not exceed the number of logical cores on your CPU.

Warning: Only ‘forkserver’ and ‘spawn’ start methods are thread-safe, which is important when TensorFlow sessions or other non thread-safe libraries are used in the parent (see issue #217). However, compared to ‘fork’ they incur a small start-up cost and have restrictions on global variables. With those methods, users must wrap the code in an `if __name__ == "__main__":` block. For more information, see the multiprocessing documentation.

Parameters

- **env_fns** (List[Callable[[], Env]]) – Environments to run in subprocesses
- **start_method** (Optional[str]) – method used to start the subprocesses. Must be one of the methods returned by `multiprocessing.get_all_start_methods()`. Defaults to ‘forkserver’ on available platforms, and ‘spawn’ otherwise.

close()

Clean up the environment's resources.

Return type None

env_is_wrapped(*wrapper_class, indices=None*)

Check if worker environments are wrapped with a given wrapper

Return type List[bool]

env_method(*method_name, *method_args, indices=None, **method_kwargs*)

Call instance methods of vectorized environments.

Return type List[Any]

get_attr(*attr_name, indices=None*)

Return attribute from vectorized environment (see base class).

Return type List[Any]

get_images()

Return RGB images from each environment

Return type Sequence[ndarray]

reset()

Reset all the environments and return an array of observations, or a tuple of observation arrays.

If `step_async` is still doing work, that work will be cancelled and `step_wait()` should not be called until `step_async()` is invoked again.

Return type Union[ndarray, Dict[str, ndarray], Tuple[ndarray, ...]]

Returns observation

seed(*seed=None*)

Sets the random seeds for all environments, based on a given seed. Each individual environment will still get its own seed, by incrementing the given seed.

Parameters `seed` (Optional[int]) – The random seed. May be None for completely random seeding.

Return type List[Optional[int]]

Returns Returns a list containing the seeds for each individual env. Note that all list elements may be None, if the env does not return anything when being seeded.

set_attr(*attr_name, value, indices=None*)

Set attribute inside vectorized environments (see base class).

Return type None

step_async(*actions*)

Tell all the environments to start taking a step with the given actions. Call `step_wait()` to get the results of the step.

You should not call this if a `step_async` run is already pending.

Return type None

step_wait()

Wait for the step taken with `step_async()`.

Return type Tuple[Union[ndarray, Dict[str, ndarray], Tuple[ndarray, ...]], ndarray, ndarray, List[Dict]]

Returns observation, reward, done, information

1.7.5 Wrappers

VecFrameStack

class `stable_baselines3.common.vec_env.VecFrameStack`(*venv, n_stack, channels_order=None*)

Frame stacking wrapper for vectorized environment. Designed for image observations.

Uses the `StackedObservations` class, or `StackedDictObservations` depending on the observations space

Parameters

- **venv** (*VecEnv*) – the vectorized environment to wrap
- **n_stack** (int) – Number of frames to stack
- **channels_order** (Union[str, Dict[str, str], None]) – If “first”, stack on first image dimension. If “last”, stack on last dimension. If None, automatically detect channel to stack over in case of image observation or default to “last” (default). Alternatively `channels_order` can be a dictionary which can be used with environments with Dict observation spaces

close()

Clean up the environment’s resources.

Return type None

reset()

Reset all environments

Return type Union[ndarray, Dict[str, ndarray]]

step_wait()

Wait for the step taken with `step_async()`.

Return type Tuple[Union[ndarray, Dict[str, ndarray]], ndarray, ndarray, List[Dict[str, Any]]]

Returns observation, reward, done, information

StackedObservations

class `stable_baselines3.common.vec_env.stacked_observations.StackedObservations`(*num_envs, n_stack, observation_space, channels_order=None*)

Frame stacking wrapper for data.

Dimension to stack over is either first (channels-first) or last (channels-last), which is detected automatically using `common.preprocessing.is_image_space_channels_first` if observation is an image space.

Parameters

- **num_envs** (int) – number of environments
- **n_stack** (int) – Number of frames to stack
- **observation_space** (Space) – Environment observation space.
- **channels_order** (Optional[str]) – If “first”, stack on first image dimension. If “last”, stack on last dimension. If None, automatically detect channel to stack over in case of image observation or default to “last” (default).

static compute_stacking(*num_envs, n_stack, observation_space, channels_order=None*)

Calculates the parameters in order to stack observations

Parameters

- **num_envs** (int) – Number of environments in the stack
- **n_stack** (int) – The number of observations to stack
- **observation_space** (Box) – The observation space
- **channels_order** (Optional[str]) – The order of the channels

Return type Tuple[bool, int, ndarray, int]

Returns tuple of channels_first, stack_dimension, stackedobs, repeat_axis

reset(*observation*)

Resets the stackedobs, adds the reset observation to the stack, and returns the stack

Parameters **observation** (ndarray) – Reset observation

Return type ndarray

Returns The stacked reset observation

stack_observation_space(*observation_space*)

Given an observation space, returns a new observation space with stacked observations

Return type Box

Returns New observation space with stacked dimensions

update(*observations, dones, infos*)

Adds the observations to the stack and uses the dones to update the infos.

Parameters

- **observations** (ndarray) – numpy array of observations
- **dones** (ndarray) – numpy array of done info
- **infos** (List[Dict[str, Any]]) – numpy array of info dicts

Return type Tuple[ndarray, List[Dict[str, Any]]]

Returns tuple of the stacked observations and the updated infos

StackedDictObservations

```
class stable_baselines3.common.vec_env.stacked_observations.StackedDictObservations(num_envs,  
                                                                                   n_stack,  
                                                                                   obser-  
                                                                                   va-  
                                                                                   tion_space,  
                                                                                   chan-  
                                                                                   nels_order=None)
```

Frame stacking wrapper for dictionary data.

Dimension to stack over is either first (channels-first) or last (channels-last), which is detected automatically using `common.preprocessing.is_image_space_channels_first` if observation is an image space.

Parameters

- **num_envs** (int) – number of environments
- **n_stack** (int) – Number of frames to stack
- **channels_order** (Union[str, Dict[str, str], None]) – If “first”, stack on first image dimension. If “last”, stack on last dimension. If None, automatically detect channel to stack over in case of image observation or default to “last” (default).

reset(*observation*)

Resets the stacked observations, adds the reset observation to the stack, and returns the stack

Parameters **observation** (Dict[str, ndarray]) – Reset observation

Return type Dict[str, ndarray]

Returns Stacked reset observations

stack_observation_space(*observation_space*)

Returns the stacked version of a Dict observation space

Parameters **observation_space** (Dict) – Dict observation space to stack

Return type Dict

Returns stacked observation space

update(*observations, dones, infos*)

Adds the observations to the stack and uses the dones to update the infos.

Parameters

- **observations** (Dict[str, ndarray]) – Dict of numpy arrays of observations
- **dones** (ndarray) – numpy array of dones
- **infos** (List[Dict[str, Any]]) – dict of infos

Return type Tuple[Dict[str, ndarray], List[Dict[str, Any]]]

Returns tuple of the stacked observations and the updated infos

VecNormalize

```
class stable_baselines3.common.vec_env.VecNormalize(venv, training=True, norm_obs=True,
                                                  norm_reward=True, clip_obs=10.0,
                                                  clip_reward=10.0, gamma=0.99, epsilon=1e-08,
                                                  norm_obs_keys=None)
```

A moving average, normalizing wrapper for vectorized environment. has support for saving/loading moving average,

Parameters

- **venv** (*VecEnv*) – the vectorized environment to wrap
- **training** (bool) – Whether to update or not the moving average
- **norm_obs** (bool) – Whether to normalize observation or not (default: True)
- **norm_reward** (bool) – Whether to normalize rewards or not (default: True)
- **clip_obs** (float) – Max absolute value for observation
- **clip_reward** (float) – Max value absolute for discounted reward
- **gamma** (float) – discount factor
- **epsilon** (float) – To avoid division by zero
- **norm_obs_keys** (Optional[List[str]]) – Which keys from observation dict to normalize. If not specified, all keys will be normalized.

get_original_obs()

Returns an unnormalized version of the observations from the most recent step or reset.

Return type Union[ndarray, Dict[str, ndarray]]

get_original_reward()

Returns an unnormalized version of the rewards from the most recent step.

Return type ndarray

static load(load_path, venv)

Loads a saved VecNormalize object.

Parameters

- **load_path** (str) – the path to load from.
- **venv** (*VecEnv*) – the VecEnv to wrap.

Return type *VecNormalize*

Returns

normalize_obs(obs)

Normalize observations using this VecNormalize's observations statistics. Calling this method does not update statistics.

Return type Union[ndarray, Dict[str, ndarray]]

normalize_reward(reward)

Normalize rewards using this VecNormalize's rewards statistics. Calling this method does not update statistics.

Return type ndarray

reset()

Reset all environments :rtype: Union[ndarray, Dict[str, ndarray]] :return: first observation of the episode

save(save_path)

Save current VecNormalize object with all running statistics and settings (e.g. clip_obs)

Parameters **save_path** (str) – The path to save to

Return type None

set_venv(venv)

Sets the vector environment to wrap to venv.

Also sets attributes derived from this such as *num_env*.

Parameters **venv** (*VecEnv*) –

Return type None

step_wait()

Apply sequence of actions to sequence of environments actions -> (observations, rewards, dones)

where dones is a boolean vector indicating whether each element is new.

Return type Tuple[Union[ndarray, Dict[str, ndarray], Tuple[ndarray, ...]], ndarray, ndarray, List[Dict]]

VecVideoRecorder

class stable_baselines3.common.vec_env.**VecVideoRecorder**(venv, video_folder, record_video_trigger, video_length=200, name_prefix='rl-video')

Wraps a VecEnv or VecEnvWrapper object to record rendered image as mp4 video. It requires ffmpeg or avconv to be installed on the machine.

Parameters

- **venv** (*VecEnv*) –
- **video_folder** (str) – Where to save videos
- **record_video_trigger** (Callable[[int], bool]) – Function that defines when to start recording. The function takes the current number of step, and returns whether we should start recording or not.
- **video_length** (int) – Length of recorded videos
- **name_prefix** (str) – Prefix to the video name

close()

Clean up the environment's resources.

Return type None

reset()

Reset all the environments and return an array of observations, or a tuple of observation arrays.

If step_async is still doing work, that work will be cancelled and step_wait() should not be called until step_async() is invoked again.

Return type Union[ndarray, Dict[str, ndarray], Tuple[ndarray, ...]]

Returns observation

step_wait()

Wait for the step taken with `step_async()`.

Return type Tuple[Union[ndarray, Dict[str, ndarray], Tuple[ndarray, ...]], ndarray, ndarray, List[Dict]]

Returns observation, reward, done, information

VecCheckNan

class `stable_baselines3.common.vec_env.VecCheckNan`(*venv*, *raise_exception=False*, *warn_once=True*, *check_inf=True*)

NaN and inf checking wrapper for vectorized environment, will raise a warning by default, allowing you to know from what the NaN or inf originated from.

Parameters

- **venv** ([VecEnv](#)) – the vectorized environment to wrap
- **raise_exception** (bool) – Whether or not to raise a ValueError, instead of a UserWarning
- **warn_once** (bool) – Whether or not to only warn once.
- **check_inf** (bool) – Whether or not to check for +inf or -inf as well

reset()

Reset all the environments and return an array of observations, or a tuple of observation arrays.

If `step_async` is still doing work, that work will be cancelled and `step_wait()` should not be called until `step_async()` is invoked again.

Return type Union[ndarray, Dict[str, ndarray], Tuple[ndarray, ...]]

Returns observation

step_async(actions)

Tell all the environments to start taking a step with the given actions. Call `step_wait()` to get the results of the step.

You should not call this if a `step_async` run is already pending.

Return type None

step_wait()

Wait for the step taken with `step_async()`.

Return type Tuple[Union[ndarray, Dict[str, ndarray], Tuple[ndarray, ...]], ndarray, ndarray, List[Dict]]

Returns observation, reward, done, information

VecTransposeImage

class `stable_baselines3.common.vec_env.VecTransposeImage`(*venv*, *skip=False*)

Re-order channels, from HxWxC to CxHxW. It is required for PyTorch convolution layers.

Parameters

- **venv** (*VecEnv*) –
- **skip** (bool) – Skip this wrapper if needed as we rely on heuristic to apply it or not, which may result in unwanted behavior, see GH issue #671.

`close()`

Clean up the environment's resources.

Return type `None`

`reset()`

Reset all environments

Return type `Union[ndarray, Dict]`

`step_wait()`

Wait for the step taken with `step_async()`.

Return type `Tuple[Union[ndarray, Dict[str, ndarray], Tuple[ndarray, ...]], ndarray, ndarray, List[Dict]]`

Returns observation, reward, done, information

static `transpose_image`(*image*)

Transpose an image or batch of images (re-order channels).

Parameters **image** (ndarray) –

Return type ndarray

Returns

transpose_observations(*observations*)

Transpose (if needed) and return new observations.

Parameters **observations** (Union[ndarray, Dict]) –

Return type Union[ndarray, Dict]

Returns Transposed observations

static `transpose_space`(*observation_space*, *key=""*)

Transpose an observation space (re-order channels).

Parameters

- **observation_space** (Box) –
- **key** (str) – In case of dictionary space, the key of the observation space.

Return type Box

Returns

VecMonitor

class stable_baselines3.common.vec_env.**VecMonitor**(*venv*, *filename=None*, *info_keywords=()*)

A vectorized monitor wrapper for *vectorized* Gym environments, it is used to record the episode reward, length, time and other data.

Some environments like [openai/procgen](#) or [gym3](#) directly initialize the vectorized environments, without giving us a chance to use the `Monitor` wrapper. So this class simply does the job of the `Monitor` wrapper on a vectorized level.

Parameters

- **venv** ([VecEnv](#)) – The vectorized environment
- **filename** (Optional[str]) – the location to save a log file, can be None for no log
- **info_keywords** (Tuple[str, ...]) – extra information to log, from the information return of `env.step()`

close()

Clean up the environment's resources.

Return type None

reset()

Reset all the environments and return an array of observations, or a tuple of observation arrays.

If `step_async` is still doing work, that work will be cancelled and `step_wait()` should not be called until `step_async()` is invoked again.

Return type Union[ndarray, Dict[str, ndarray], Tuple[ndarray, ...]]

Returns observation

step_wait()

Wait for the step taken with `step_async()`.

Return type Tuple[Union[ndarray, Dict[str, ndarray], Tuple[ndarray, ...]], ndarray, ndarray, List[Dict]]

Returns observation, reward, done, information

VecExtractDictObs

class stable_baselines3.common.vec_env.**VecExtractDictObs**(*venv*, *key*)

A vectorized wrapper for extracting dictionary observations.

Parameters

- **venv** ([VecEnv](#)) – The vectorized environment
- **key** (str) – The key of the dictionary observation

reset()

Reset all the environments and return an array of observations, or a tuple of observation arrays.

If `step_async` is still doing work, that work will be cancelled and `step_wait()` should not be called until `step_async()` is invoked again.

Return type ndarray

Returns observation

step_wait()

Wait for the step taken with `step_async()`.

Return type Tuple[Union[ndarray, Dict[str, ndarray], Tuple[ndarray, ...]], ndarray, ndarray, List[Dict]]

Returns observation, reward, done, information

1.8 Using Custom Environments

To use the RL baselines with custom environments, they just need to follow the *gym* interface. That is to say, your environment must implement the following methods (and inherits from OpenAI Gym Class):

Note: If you are using images as input, the observation must be of type `np.uint8` and be contained in `[0, 255]` is normalized (dividing by 255 to have values in `[0, 1]`) when using CNN policies. Images can be either channel-first or channel-last.

Note: Although SB3 supports both channel-last and channel-first images as input, we recommend using the channel-first convention when possible. Under the hood, when a channel-last image is passed, SB3 uses a `VecTransposeImage` wrapper to re-order the channels.

```
import gym
from gym import spaces

class CustomEnv(gym.Env):
    """Custom Environment that follows gym interface"""
    metadata = {'render.modes': ['human']}

    def __init__(self, arg1, arg2, ...):
        super(CustomEnv, self).__init__()
        # Define action and observation space
        # They must be gym.spaces objects
        # Example when using discrete actions:
        self.action_space = spaces.Discrete(N_DISCRETE_ACTIONS)
        # Example for using image as input (channel-first; channel-last also works):
        self.observation_space = spaces.Box(low=0, high=255,
                                             shape=(N_CHANNELS, HEIGHT, WIDTH), dtype=np.
↳ uint8)

    def step(self, action):
        ...
        return observation, reward, done, info
    def reset(self):
        ...
        return observation # reward, done, info can't be included
    def render(self, mode='human'):
        ...
    def close(self):
        ...
```

Then you can define and train a RL agent with:

```
# Instantiate the env
env = CustomEnv(arg1, ...)
# Define and Train the agent
model = A2C('CnnPolicy', env).learn(total_timesteps=1000)
```

To check that your environment follows the gym interface, please use:

```
from stable_baselines3.common.env_checker import check_env

env = CustomEnv(arg1, ...)
# It will check your custom environment and output additional warnings if needed
check_env(env)
```

We have created a [colab notebook](#) for a concrete example on creating a custom environment along with an example of using it with Stable-Baselines3 interface.

Alternatively, you may look at OpenAI Gym [built-in environments](#). However, the readers are cautioned as per OpenAI Gym [official wiki](#), its advised not to customize their built-in environments. It is better to copy and create new ones if you need to modify them.

Optionally, you can also register the environment with gym, that will allow you to create the RL agent in one line (and use `gym.make()` to instantiate the env):

```
from gym.envs.registration import register
# Example for the CartPole environment
register(
    # unique identifier for the env `name-version`
    id="CartPole-v1",
    # path to the class for creating the env
    # Note: entry_point also accept a class as input (and not only a string)
    entry_point="gym.envs.classic_control:CartPoleEnv",
    # Max number of steps per episode, using a `TimeLimitWrapper`
    max_episode_steps=500,
)
```

In the project, for testing purposes, we use a custom environment named `IdentityEnv` defined in [this file](#). An example of how to use it can be found [here](#).

1.9 Custom Policy Network

Stable Baselines3 provides policy networks for images (`CnnPolicies`), other type of input features (`MlpPolicies`) and multiple different inputs (`MultiInputPolicies`).

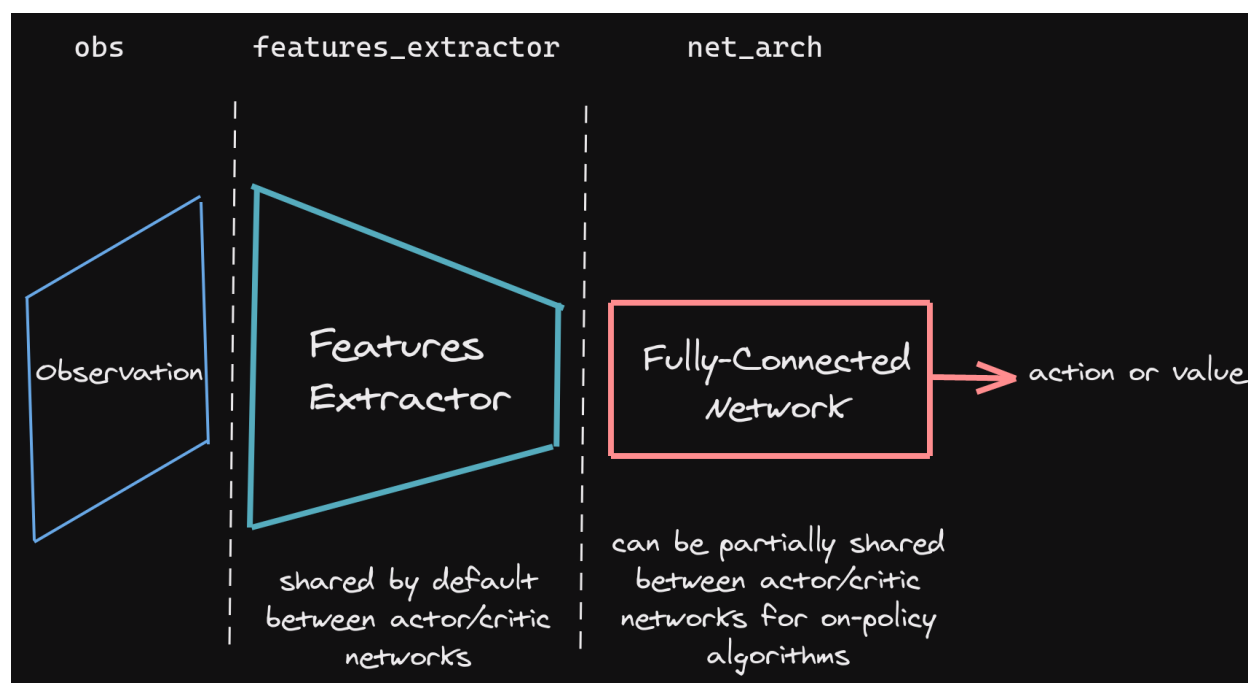
Warning: For A2C and PPO, continuous actions are clipped during training and testing (to avoid out of bound error). SAC, DDPG and TD3 squash the action, using a `tanh()` transformation, which handles bounds more correctly.

1.9.1 SB3 Policy

SB3 networks are separated into two main parts (see figure below):

- A features extractor (usually shared between actor and critic when applicable, to save computation) whose role is to extract features (i.e. convert to a feature vector) from high-dimensional observations, for instance, a CNN that extracts features from images. This is the `features_extractor_class` parameter. You can change the default parameters of that features extractor by passing a `features_extractor_kwargs` parameter.
- A (fully-connected) network that maps the features to actions/value. Its architecture is controlled by the `net_arch` parameter.

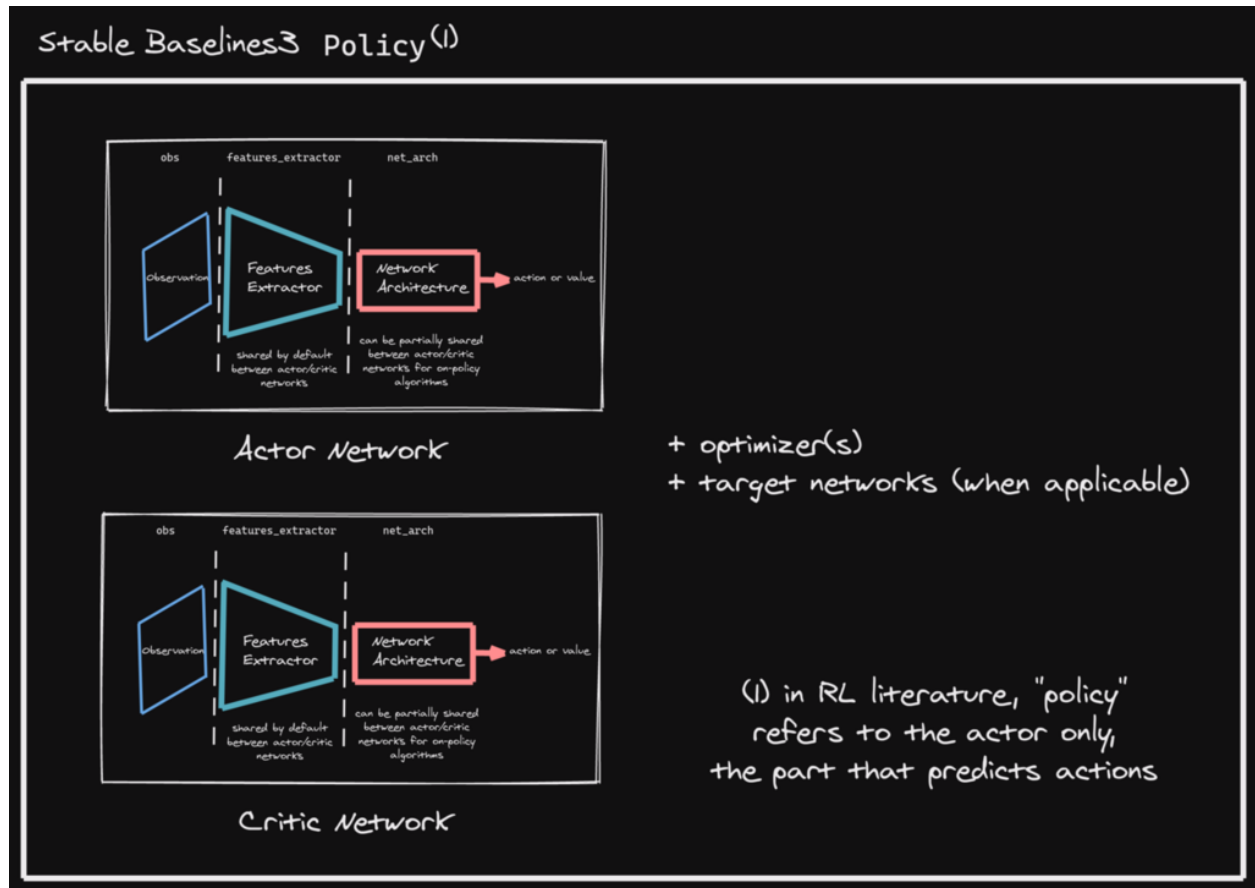
Note: All observations are first pre-processed (e.g. images are normalized, discrete obs are converted to one-hot vectors, ...) before being fed to the features extractor. In the case of vector observations, the features extractor is just a Flatten layer.



SB3 policies are usually composed of several networks (actor/critic networks + target networks when applicable) together with the associated optimizers.

Each of these network have a features extractor followed by a fully-connected network.

Note: When we refer to “policy” in Stable-Baselines3, this is usually an abuse of language compared to RL terminology. In SB3, “policy” refers to the class that handles all the networks useful for training, so not only the network used to predict actions (the “learned controller”).



1.9.2 Custom Network Architecture

One way of customising the policy network architecture is to pass arguments when creating the model, using `policy_kwargs` parameter:

```
import gym
import torch as th

from stable_baselines3 import PPO

# Custom actor (pi) and value function (vf) networks
# of two layers of size 32 each with Relu activation function
policy_kwargs = dict(activation_fn=th.nn.ReLU,
                      net_arch=[dict(pi=[32, 32], vf=[32, 32])])

# Create the agent
model = PPO("MlpPolicy", "CartPole-v1", policy_kwargs=policy_kwargs, verbose=1)
# Retrieve the environment
env = model.get_env()
# Train the agent
model.learn(total_timesteps=100000)
# Save the agent
model.save("ppo_cartpole")

del model
```

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```
# the policy_kwargs are automatically loaded
model = PPO.load("ppo_cartpole", env=env)
```

1.9.3 Custom Feature Extractor

If you want to have a custom feature extractor (e.g. custom CNN when using images), you can define class that derives from `BaseFeaturesExtractor` and then pass it to the model when training.

Note: By default the feature extractor is shared between the actor and the critic to save computation (when applicable). However, this can be changed by defining a custom policy for on-policy algorithms or setting `share_features_extractor=False` in the `policy_kwargs` for off-policy algorithms (and when applicable).

```
import gym
import torch as th
import torch.nn as nn

from stable_baselines3 import PPO
from stable_baselines3.common.torch_layers import BaseFeaturesExtractor

class CustomCNN(BaseFeaturesExtractor):
    """
    :param observation_space: (gym.Space)
    :param features_dim: (int) Number of features extracted.
        This corresponds to the number of unit for the last layer.
    """

    def __init__(self, observation_space: gym.spaces.Box, features_dim: int = 256):
        super(CustomCNN, self).__init__(observation_space, features_dim)
        # We assume CxHxW images (channels first)
        # Re-ordering will be done by pre-preprocessing or wrapper
        n_input_channels = observation_space.shape[0]
        self.cnn = nn.Sequential(
            nn.Conv2d(n_input_channels, 32, kernel_size=8, stride=4, padding=0),
            nn.ReLU(),
            nn.Conv2d(32, 64, kernel_size=4, stride=2, padding=0),
            nn.ReLU(),
            nn.Flatten(),
        )

        # Compute shape by doing one forward pass
        with th.no_grad():
            n_flatten = self.cnn(
                th.as_tensor(observation_space.sample()[None]).float()
            ).shape[1]

        self.linear = nn.Sequential(nn.Linear(n_flatten, features_dim), nn.ReLU())

    def forward(self, observations: th.Tensor) -> th.Tensor:
```

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```

        return self.linear(self.cnn(observations))

policy_kwargs = dict(
    features_extractor_class=CustomCNN,
    features_extractor_kwargs=dict(features_dim=128),
)
model = PPO("CnnPolicy", "BreakoutNoFrameskip-v4", policy_kwargs=policy_kwargs,
↳ verbose=1)
model.learn(1000)

```

1.9.4 Multiple Inputs and Dictionary Observations

Stable Baselines3 supports handling of multiple inputs by using Dict Gym space. This can be done using `MultiInputPolicy`, which by default uses the `CombinedExtractor` feature extractor to turn multiple inputs into a single vector, handled by the `net_arch` network.

By default, `CombinedExtractor` processes multiple inputs as follows:

1. If input is an image (automatically detected, see `common.preprocessing.is_image_space`), process image with Nature Atari CNN network and output a latent vector of size 256.
2. If input is not an image, flatten it (no layers).
3. Concatenate all previous vectors into one long vector and pass it to policy.

Much like above, you can define custom feature extractors. The following example assumes the environment has two keys in the observation space dictionary: “image” is a (1,H,W) image (channel first), and “vector” is a (D,) dimensional vector. We process “image” with a simple downsampling and “vector” with a single linear layer.

```

import gym
import torch as th
from torch import nn

from stable_baselines3.common.torch_layers import BaseFeaturesExtractor

class CustomCombinedExtractor(BaseFeaturesExtractor):
    def __init__(self, observation_space: gym.spaces.Dict):
        # We do not know features-dim here before going over all the items,
        # so put something dummy for now. PyTorch requires calling
        # nn.Module.__init__ before adding modules
        super(CustomCombinedExtractor, self).__init__(observation_space, features_dim=1)

        extractors = {}

        total_concat_size = 0
        # We need to know size of the output of this extractor,
        # so go over all the spaces and compute output feature sizes
        for key, subspace in observation_space.spaces.items():
            if key == "image":
                # We will just downsample one channel of the image by 4x4 and flatten.
                # Assume the image is single-channel (subspace.shape[0] == 0)
                extractors[key] = nn.Sequential(nn.MaxPool2d(4), nn.Flatten())
                total_concat_size += subspace.shape[1] // 4 * subspace.shape[2] // 4

```

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```

    elif key == "vector":
        # Run through a simple MLP
        extractors[key] = nn.Linear(subspace.shape[0], 16)
        total_concat_size += 16

    self.extractors = nn.ModuleDict(extractors)

    # Update the features dim manually
    self._features_dim = total_concat_size

    def forward(self, observations) -> th.Tensor:
        encoded_tensor_list = []

        # self.extractors contain nn.Modules that do all the processing.
        for key, extractor in self.extractors.items():
            encoded_tensor_list.append(extractor(observations[key]))
        # Return a (B, self._features_dim) PyTorch tensor, where B is batch dimension.
        return th.cat(encoded_tensor_list, dim=1)

```

1.9.5 On-Policy Algorithms

Shared Networks

The `net_arch` parameter of A2C and PPO policies allows to specify the amount and size of the hidden layers and how many of them are shared between the policy network and the value network. It is assumed to be a list with the following structure:

1. An arbitrary length (zero allowed) number of integers each specifying the number of units in a shared layer. If the number of ints is zero, there will be no shared layers.
2. An optional dict, to specify the following non-shared layers for the value network and the policy network. It is formatted like `dict(vf=[<value layer sizes>], pi=[<policy layer sizes>])`. If it is missing any of the keys (pi or vf), no non-shared layers (empty list) is assumed.

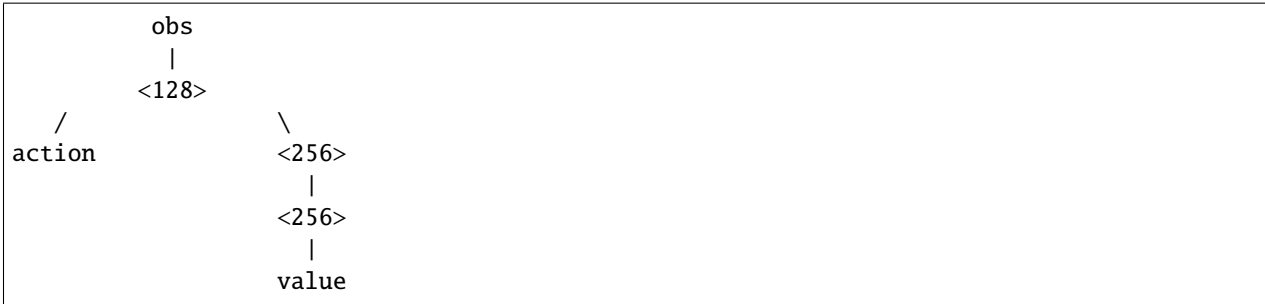
In short: `[<shared layers>, dict(vf=[<non-shared value network layers>], pi=[<non-shared policy network layers>])]`.

Examples

Two shared layers of size 128: `net_arch=[128, 128]`



Value network deeper than policy network, first layer shared: `net_arch=[128, dict(vf=[256, 256])]`



Initially shared then diverging: [128, dict(vf=[256], pi=[16])]



Advanced Example

If your task requires even more granular control over the policy/value architecture, you can redefine the policy directly:

```

from typing import Callable, Dict, List, Optional, Tuple, Type, Union

import gym
import torch as th
from torch import nn

from stable_baselines3 import PPO
from stable_baselines3.common.policies import ActorCriticPolicy

class CustomNetwork(nn.Module):
    """
    Custom network for policy and value function.
    It receives as input the features extracted by the feature extractor.

    :param feature_dim: dimension of the features extracted with the features_extractor
    ↪ (e.g. features from a CNN)
    :param last_layer_dim_pi: (int) number of units for the last layer of the policy
    ↪ network
    :param last_layer_dim_vf: (int) number of units for the last layer of the value
    ↪ network
    """

    def __init__(
        self,
        feature_dim: int,
        last_layer_dim_pi: int = 64,
        last_layer_dim_vf: int = 64,
    ):

```

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```

):
    super(CustomNetwork, self).__init__()

    # IMPORTANT:
    # Save output dimensions, used to create the distributions
    self.latent_dim_pi = last_layer_dim_pi
    self.latent_dim_vf = last_layer_dim_vf

    # Policy network
    self.policy_net = nn.Sequential(
        nn.Linear(feature_dim, last_layer_dim_pi), nn.ReLU()
    )
    # Value network
    self.value_net = nn.Sequential(
        nn.Linear(feature_dim, last_layer_dim_vf), nn.ReLU()
    )

    def forward(self, features: th.Tensor) -> Tuple[th.Tensor, th.Tensor]:
        """
        :return: (th.Tensor, th.Tensor) latent_policy, latent_value of the specified_
        ↪ network.
            If all layers are shared, then ``latent_policy == latent_value``
        """
        return self.policy_net(features), self.value_net(features)

    def forward_actor(self, features: th.Tensor) -> th.Tensor:
        return self.policy_net(features)

    def forward_critic(self, features: th.Tensor) -> th.Tensor:
        return self.value_net(features)

class CustomActorCriticPolicy(ActorCriticPolicy):
    def __init__(
        self,
        observation_space: gym.spaces.Space,
        action_space: gym.spaces.Space,
        lr_schedule: Callable[[float], float],
        net_arch: Optional[List[Union[int, Dict[str, List[int]]]]] = None,
        activation_fn: Type[nn.Module] = nn.Tanh,
        *args,
        **kwargs,
    ):
        super(CustomActorCriticPolicy, self).__init__(
            observation_space,
            action_space,
            lr_schedule,
            net_arch,
            activation_fn,
            # Pass remaining arguments to base class
            *args,

```

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```

        **kwargs,
    )
    # Disable orthogonal initialization
    self.ortho_init = False

    def _build_mlp_extractor(self) -> None:
        self.mlp_extractor = CustomNetwork(self.features_dim)

model = PPO(CustomActorCriticPolicy, "CartPole-v1", verbose=1)
model.learn(5000)

```

1.9.6 Off-Policy Algorithms

If you need a network architecture that is different for the actor and the critic when using SAC, DDPG or TD3, you can pass a dictionary of the following structure: `dict(qf=[<critic network architecture>], pi=[<actor network architecture>])`.

For example, if you want a different architecture for the actor (aka pi) and the critic (Q-function aka qf) networks, then you can specify `net_arch=dict(qf=[400, 300], pi=[64, 64])`.

Otherwise, to have actor and critic that share the same network architecture, you only need to specify `net_arch=[256, 256]` (here, two hidden layers of 256 units each).

Note: Compared to their on-policy counterparts, no shared layers (other than the feature extractor) between the actor and the critic are allowed (to prevent issues with target networks).

Note: For advanced customization of off-policy algorithms policies, please take a look at the code. A good understanding of the algorithm used is required, see discussion in [issue #425](#)

```

from stable_baselines3 import SAC

# Custom actor architecture with two layers of 64 units each
# Custom critic architecture with two layers of 400 and 300 units
policy_kwargs = dict(net_arch=dict(pi=[64, 64], qf=[400, 300]))
# Create the agent
model = SAC("MlpPolicy", "Pendulum-v1", policy_kwargs=policy_kwargs, verbose=1)
model.learn(5000)

```

1.10 Callbacks

A callback is a set of functions that will be called at given stages of the training procedure. You can use callbacks to access internal state of the RL model during training. It allows one to do monitoring, auto saving, model manipulation, progress bars, ...

1.10.1 Custom Callback

To build a custom callback, you need to create a class that derives from `BaseCallback`. This will give you access to events (`_on_training_start`, `_on_step`) and useful variables (like `self.model` for the RL model).

You can find two examples of custom callbacks in the documentation: one for saving the best model according to the training reward (see [Examples](#)), and one for logging additional values with Tensorboard (see [Tensorboard section](#)).

```
from stable_baselines3.common.callbacks import BaseCallback

class CustomCallback(BaseCallback):
    """
    A custom callback that derives from ``BaseCallback``.

    :param verbose: (int) Verbosity level 0: not output 1: info 2: debug
    """
    def __init__(self, verbose=0):
        super(CustomCallback, self).__init__(verbose)
        # Those variables will be accessible in the callback
        # (they are defined in the base class)
        # The RL model
        # self.model = None # type: BaseAlgorithm
        # An alias for self.model.get_env(), the environment used for training
        # self.training_env = None # type: Union[gym.Env, VecEnv, None]
        # Number of time the callback was called
        # self.n_calls = 0 # type: int
        # self.num_timesteps = 0 # type: int
        # local and global variables
        # self.locals = None # type: Dict[str, Any]
        # self.globals = None # type: Dict[str, Any]
        # The logger object, used to report things in the terminal
        # self.logger = None # stable_baselines3.common.logger
        # # Sometimes, for event callback, it is useful
        # # to have access to the parent object
        # self.parent = None # type: Optional[BaseCallback]

    def _on_training_start(self) -> None:
        """
        This method is called before the first rollout starts.
        """
        pass

    def _on_rollout_start(self) -> None:
        """
        A rollout is the collection of environment interaction

```

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```

    using the current policy.
    This event is triggered before collecting new samples.
    """
    pass

def _on_step(self) -> bool:
    """
    This method will be called by the model after each call to `env.step()`.

    For child callback (of an `EventCallback`), this will be called
    when the event is triggered.

    :return: (bool) If the callback returns False, training is aborted early.
    """
    return True

def _on_rollout_end(self) -> None:
    """
    This event is triggered before updating the policy.
    """
    pass

def _on_training_end(self) -> None:
    """
    This event is triggered before exiting the `learn()` method.
    """
    pass

```

Note: `self.num_timesteps` corresponds to the total number of steps taken in the environment, i.e., it is the number of environments multiplied by the number of time `env.step()` was called

For the other algorithms, `self.num_timesteps` is incremented by `n_envs` (number of environments) after each call to `env.step()`

Note: For off-policy algorithms like SAC, DDPG, TD3 or DQN, the notion of rollout corresponds to the steps taken in the environment between two updates.

1.10.2 Event Callback

Compared to Keras, Stable Baselines provides a second type of `BaseCallback`, named `EventCallback` that is meant to trigger events. When an event is triggered, then a child callback is called.

As an example, [EvalCallback](#) is an `EventCallback` that will trigger its child callback when there is a new best model. A child callback is for instance [StopTrainingOnRewardThreshold](#) that stops the training if the mean reward achieved by the RL model is above a threshold.

Note: We recommend to take a look at the source code of [EvalCallback](#) and [StopTrainingOnRewardThreshold](#) to have a better overview of what can be achieved with this kind of callbacks.

```
class EventCallback(BaseCallback):
    """
    Base class for triggering callback on event.

    :param callback: (Optional[BaseCallback]) Callback that will be called
        when an event is triggered.
    :param verbose: (int)
    """
    def __init__(self, callback: Optional[BaseCallback] = None, verbose: int = 0):
        super(EventCallback, self).__init__(verbose=verbose)
        self.callback = callback
        # Give access to the parent
        if callback is not None:
            self.callback.parent = self
        ...

    def _on_event(self) -> bool:
        if self.callback is not None:
            return self.callback()
        return True
```

1.10.3 Callback Collection

Stable Baselines provides you with a set of common callbacks for:

- saving the model periodically (*CheckpointCallback*)
- evaluating the model periodically and saving the best one (*EvalCallback*)
- chaining callbacks (*CallbackList*)
- triggering callback on events (*Event Callback*, *EveryNTimesteps*)
- stopping the training early based on a reward threshold (*StopTrainingOnRewardThreshold*)

CheckpointCallback

Callback for saving a model every `save_freq` calls to `env.step()`, you must specify a log folder (`save_path`) and optionally a prefix for the checkpoints (`rl_model` by default).

Warning: When using multiple environments, each call to `env.step()` will effectively correspond to `n_envs` steps. If you want the `save_freq` to be similar when using different number of environments, you need to account for it using `save_freq = max(save_freq // n_envs, 1)`. The same goes for the other callbacks.

```
from stable_baselines3 import SAC
from stable_baselines3.common.callbacks import CheckpointCallback
# Save a checkpoint every 1000 steps
checkpoint_callback = CheckpointCallback(save_freq=1000, save_path='./logs/',
                                         name_prefix='rl_model')

model = SAC('MlpPolicy', 'Pendulum-v1')
model.learn(2000, callback=checkpoint_callback)
```

EvalCallback

Evaluate periodically the performance of an agent, using a separate test environment. It will save the best model if `best_model_save_path` folder is specified and save the evaluations results in a numpy archive (`evaluations.npz`) if `log_path` folder is specified.

Note: You can pass child callbacks via `callback_after_eval` and `callback_on_new_best` arguments. `callback_after_eval` will be triggered after every evaluation, and `callback_on_new_best` will be triggered each time there is a new best model.

Warning: You need to make sure that `eval_env` is wrapped the same way as the training environment, for instance using the `VecTransposeImage` wrapper if you have a channel-last image as input. The `EvalCallback` class outputs a warning if it is not the case.

```
import gym

from stable_baselines3 import SAC
from stable_baselines3.common.callbacks import EvalCallback

# Separate evaluation env
eval_env = gym.make('Pendulum-v1')
# Use deterministic actions for evaluation
eval_callback = EvalCallback(eval_env, best_model_save_path='./logs/',
                             log_path='./logs/', eval_freq=500,
                             deterministic=True, render=False)

model = SAC('MlpPolicy', 'Pendulum-v1')
model.learn(5000, callback=eval_callback)
```

CallbackList

Class for chaining callbacks, they will be called sequentially. Alternatively, you can pass directly a list of callbacks to the `learn()` method, it will be converted automatically to a `CallbackList`.

```
import gym

from stable_baselines3 import SAC
from stable_baselines3.common.callbacks import CallbackList, CheckpointCallback, \
    EvalCallback

checkpoint_callback = CheckpointCallback(save_freq=1000, save_path='./logs/')
# Separate evaluation env
eval_env = gym.make('Pendulum-v1')
eval_callback = EvalCallback(eval_env, best_model_save_path='./logs/best_model',
                             log_path='./logs/results', eval_freq=500)

# Create the callback list
callback = CallbackList([checkpoint_callback, eval_callback])

model = SAC('MlpPolicy', 'Pendulum-v1')
```

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```
# Equivalent to:
# model.learn(5000, callback=[checkpoint_callback, eval_callback])
model.learn(5000, callback=callback)
```

StopTrainingOnRewardThreshold

Stop the training once a threshold in episodic reward (mean episode reward over the evaluations) has been reached (i.e., when the model is good enough). It must be used with the *EvalCallback* and use the event triggered by a new best model.

```
import gym

from stable_baselines3 import SAC
from stable_baselines3.common.callbacks import EvalCallback, \
    StopTrainingOnRewardThreshold

# Separate evaluation env
eval_env = gym.make('Pendulum-v1')
# Stop training when the model reaches the reward threshold
callback_on_best = StopTrainingOnRewardThreshold(reward_threshold=-200, verbose=1)
eval_callback = EvalCallback(eval_env, callback_on_new_best=callback_on_best, verbose=1)

model = SAC('MlpPolicy', 'Pendulum-v1', verbose=1)
# Almost infinite number of timesteps, but the training will stop
# early as soon as the reward threshold is reached
model.learn(int(1e10), callback=eval_callback)
```

EveryNTimesteps

An *Event Callback* that will trigger its child callback every `n_steps` timesteps.

Note: Because of the way PP01 and TRPO work (they rely on MPI), `n_steps` is a lower bound between two events.

```
import gym

from stable_baselines3 import PPO
from stable_baselines3.common.callbacks import CheckpointCallback, EveryNTimesteps

# this is equivalent to defining CheckpointCallback(save_freq=500)
# checkpoint_callback will be triggered every 500 steps
checkpoint_on_event = CheckpointCallback(save_freq=1, save_path='./logs/')
event_callback = EveryNTimesteps(n_steps=500, callback=checkpoint_on_event)

model = PPO('MlpPolicy', 'Pendulum-v1', verbose=1)

model.learn(int(2e4), callback=event_callback)
```

StopTrainingOnMaxEpisodes

Stop the training upon reaching the maximum number of episodes, regardless of the model's `total_timesteps` value. Also, presumes that, for multiple environments, the desired behavior is that the agent trains on each env for `max_episodes` and in total for `max_episodes * n_envs` episodes.

Note: For multiple environments, the agent will train for a total of `max_episodes * n_envs` episodes. However, it can't be guaranteed that this training will occur for an exact number of `max_episodes` per environment. Thus, there is an assumption that, on average, each environment ran for `max_episodes`.

```
from stable_baselines3 import A2C
from stable_baselines3.common.callbacks import StopTrainingOnMaxEpisodes

# Stops training when the model reaches the maximum number of episodes
callback_max_episodes = StopTrainingOnMaxEpisodes(max_episodes=5, verbose=1)

model = A2C('MlpPolicy', 'Pendulum-v1', verbose=1)
# Almost infinite number of timesteps, but the training will stop
# early as soon as the max number of episodes is reached
model.learn(int(1e10), callback=callback_max_episodes)
```

StopTrainingOnNoModelImprovement

Stop the training if there is no new best model (no new best mean reward) after more than a specific number of consecutive evaluations. The idea is to save time in experiments when you know that the learning curves are somehow well behaved and, therefore, after many evaluations without improvement the learning has probably stabilized. It must be used with the *EvalCallback* and use the event triggered after every evaluation.

```
import gym

from stable_baselines3 import SAC
from stable_baselines3.common.callbacks import EvalCallback,
↳ StopTrainingOnNoModelImprovement

# Separate evaluation env
eval_env = gym.make("Pendulum-v1")
# Stop training if there is no improvement after more than 3 evaluations
stop_train_callback = StopTrainingOnNoModelImprovement(max_no_improvement_evals=3, min_
↳ evals=5, verbose=1)
eval_callback = EvalCallback(eval_env, eval_freq=1000, callback_after_eval=stop_train_
↳ callback, verbose=1)

model = SAC("MlpPolicy", "Pendulum-v1", learning_rate=1e-3, verbose=1)
# Almost infinite number of timesteps, but the training will stop early
# as soon as the the number of consecutive evaluations without model
# improvement is greater than 3
model.learn(int(1e10), callback=eval_callback)
```

```
class stable_baselines3.common.callbacks.BaseCallback(verbose=0)
```

Base class for callback.

Parameters `verbose` (int) –

init_callback(*model*)

Initialize the callback by saving references to the RL model and the training environment for convenience.

Return type None

on_step()

This method will be called by the model after each call to `env.step()`.

For child callback (of an `EventCallback`), this will be called when the event is triggered.

Return type bool

Returns If the callback returns False, training is aborted early.

update_child_locals(*locals_*)

Update the references to the local variables on sub callbacks.

Parameters **locals** – the local variables during rollout collection

Return type None

update_locals(*locals_*)

Update the references to the local variables.

Parameters **locals** – the local variables during rollout collection

Return type None

class `stable_baselines3.common.callbacks.CallbackList`(*callbacks*)

Class for chaining callbacks.

Parameters **callbacks** (List[[BaseCallback](#)]) – A list of callbacks that will be called sequentially.

update_child_locals(*locals_*)

Update the references to the local variables.

Parameters **locals** – the local variables during rollout collection

Return type None

class `stable_baselines3.common.callbacks.CheckpointCallback`(*save_freq, save_path, name_prefix='rl_model', verbose=0*)

Callback for saving a model every `save_freq` calls to `env.step()`.

Warning: When using multiple environments, each call to `env.step()` will effectively correspond to `n_envs` steps. To account for that, you can use `save_freq = max(save_freq // n_envs, 1)`

Parameters

- **save_freq** (int) –
- **save_path** (str) – Path to the folder where the model will be saved.
- **name_prefix** (str) – Common prefix to the saved models
- **verbose** (int) –

class `stable_baselines3.common.callbacks.ConvertCallback`(*callback*, *verbose=0*)

Convert functional callback (old-style) to object.

Parameters

- **callback** (Callable[[Dict[str, Any], Dict[str, Any]], bool]) –
- **verbose** (int) –

class `stable_baselines3.common.callbacks.EvalCallback`(*eval_env*, *callback_on_new_best=None*,
callback_after_eval=None,
n_eval_episodes=5, *eval_freq=10000*,
log_path=None,
best_model_save_path=None,
deterministic=True, *render=False*,
verbose=1, *warn=True*)

Callback for evaluating an agent.

Warning: When using multiple environments, each call to `env.step()` will effectively correspond to `n_envs` steps. To account for that, you can use `eval_freq = max(eval_freq // n_envs, 1)`

Parameters

- **eval_env** (Union[Env, [VecEnv](#)]) – The environment used for initialization
- **callback_on_new_best** (Optional[[BaseCallback](#)]) – Callback to trigger when there is a new best model according to the `mean_reward`
- **callback_after_eval** (Optional[[BaseCallback](#)]) – Callback to trigger after every evaluation
- **n_eval_episodes** (int) – The number of episodes to test the agent
- **eval_freq** (int) – Evaluate the agent every `eval_freq` call of the callback.
- **log_path** (Optional[str]) – Path to a folder where the evaluations (`evaluations.npz`) will be saved. It will be updated at each evaluation.
- **best_model_save_path** (Optional[str]) – Path to a folder where the best model according to performance on the eval env will be saved.
- **deterministic** (bool) – Whether the evaluation should use a stochastic or deterministic actions.
- **render** (bool) – Whether to render or not the environment during evaluation
- **verbose** (int) –
- **warn** (bool) – Passed to `evaluate_policy` (warns if `eval_env` has not been wrapped with a Monitor wrapper)

update_child_locals(*locals_*)

Update the references to the local variables.

Parameters **locals** – the local variables during rollout collection

Return type None

class stable_baselines3.common.callbacks.**EventCallback**(*callback=None, verbose=0*)

Base class for triggering callback on event.

Parameters

- **callback** (Optional[[BaseCallback](#)]) – Callback that will be called when an event is triggered.
- **verbose** (int) –

init_callback(*model*)

Initialize the callback by saving references to the RL model and the training environment for convenience.

Return type None

update_child_locals(*locals_*)

Update the references to the local variables.

Parameters **locals** – the local variables during rollout collection

Return type None

class stable_baselines3.common.callbacks.**EveryNTimesteps**(*n_steps, callback*)

Trigger a callback every *n_steps* timesteps

Parameters

- **n_steps** (int) – Number of timesteps between two trigger.
- **callback** ([BaseCallback](#)) – Callback that will be called when the event is triggered.

class stable_baselines3.common.callbacks.**StopTrainingOnMaxEpisodes**(*max_episodes, verbose=0*)

Stop the training once a maximum number of episodes are played.

For multiple environments presumes that, the desired behavior is that the agent trains on each env for *max_episodes* and in total for *max_episodes* * *n_envs* episodes.

Parameters

- **max_episodes** (int) – Maximum number of episodes to stop training.
- **verbose** (int) – Select whether to print information about when training ended by reaching *max_episodes*

class stable_baselines3.common.callbacks.**StopTrainingOnNoModelImprovement**(*max_no_improvement_evals, min_evals=0, verbose=0*)

Stop the training early if there is no new best model (new best mean reward) after more than *N* consecutive evaluations.

It is possible to define a minimum number of evaluations before start to count evaluations without improvement.

It must be used with the `EvalCallback`.

Parameters

- **max_no_improvement_evals** (int) – Maximum number of consecutive evaluations without a new best model.
- **min_evals** (int) – Number of evaluations before start to count evaluations without improvements.
- **verbose** (int) – Verbosity of the output (set to 1 for info messages)


```
class stable_baselines3.common.callbacks.StopTrainingOnRewardThreshold(reward_threshold,  
                                                                    verbose=0)
```

Stop the training once a threshold in episodic reward has been reached (i.e. when the model is good enough).

It must be used with the EvalCallback.

Parameters

- **reward_threshold** (float) – Minimum expected reward per episode to stop training.
- **verbose** (int) –

1.11 Tensorboard Integration

1.11.1 Basic Usage

To use Tensorboard with stable baselines3, you simply need to pass the location of the log folder to the RL agent:

```
from stable_baselines3 import A2C

model = A2C('MlpPolicy', 'CartPole-v1', verbose=1, tensorboard_log="./a2c_cartpole_
↳tensorboard/")
model.learn(total_timesteps=10_000)
```

You can also define custom logging name when training (by default it is the algorithm name)

```
from stable_baselines3 import A2C

model = A2C('MlpPolicy', 'CartPole-v1', verbose=1, tensorboard_log="./a2c_cartpole_
↳tensorboard/")
model.learn(total_timesteps=10_000, tb_log_name="first_run")
# Pass reset_num_timesteps=False to continue the training curve in tensorboard
# By default, it will create a new curve
model.learn(total_timesteps=10_000, tb_log_name="second_run", reset_num_timesteps=False)
model.learn(total_timesteps=10_000, tb_log_name="third_run", reset_num_timesteps=False)
```

Once the learn function is called, you can monitor the RL agent during or after the training, with the following bash command:

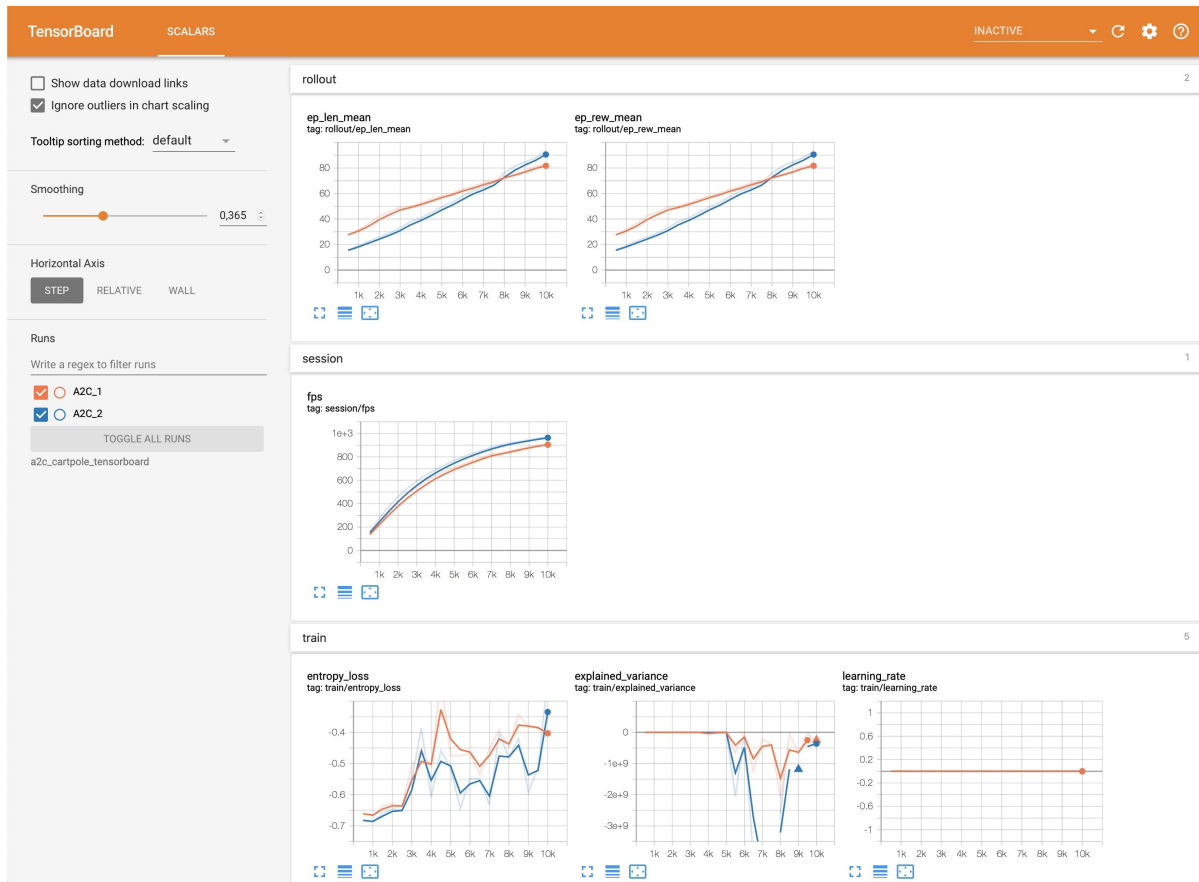
```
tensorboard --logdir ./a2c_cartpole_tensorboard/
```

Note: You can find explanations about the logger output and names in the [Logger](#) section.

you can also add past logging folders:

```
tensorboard --logdir ./a2c_cartpole_tensorboard/;./ppo2_cartpole_tensorboard/
```

It will display information such as the episode reward (when using a Monitor wrapper), the model losses and other parameter unique to some models.



1.11.2 Logging More Values

Using a callback, you can easily log more values with TensorBoard. Here is a simple example on how to log both additional tensor or arbitrary scalar value:

```
import numpy as np

from stable_baselines3 import SAC
from stable_baselines3.common.callbacks import BaseCallback

model = SAC("MlpPolicy", "Pendulum-v1", tensorboard_log="/tmp/sac/", verbose=1)

class TensorboardCallback(BaseCallback):
    """
    Custom callback for plotting additional values in tensorboard.
    """

    def __init__(self, verbose=0):
        super(TensorboardCallback, self).__init__(verbose)

    def _on_step(self) -> bool:
        # Log scalar value (here a random variable)
        value = np.random.random()
```

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```

        self.logger.record('random_value', value)
        return True

model.learn(50000, callback=TensorboardCallback())

```

Note: If you want to log values more often than the default to tensorboard, you manually call `self.logger.dump(self.num_timesteps)` in a callback (see [issue #506](#)).

1.11.3 Logging Images

TensorBoard supports periodic logging of image data, which helps evaluating agents at various stages during training.

Warning: To support image logging `pillow` must be installed otherwise, TensorBoard ignores the image and logs a warning.

Here is an example of how to render an image to TensorBoard at regular intervals:

```

from stable_baselines3 import SAC
from stable_baselines3.common.callbacks import BaseCallback
from stable_baselines3.common.logger import Image

model = SAC("MlpPolicy", "Pendulum-v1", tensorboard_log="/tmp/sac/", verbose=1)

class ImageRecorderCallback(BaseCallback):
    def __init__(self, verbose=0):
        super(ImageRecorderCallback, self).__init__(verbose)

    def _on_step(self):
        image = self.training_env.render(mode="rgb_array")
        # "HWC" specify the dataformat of the image, here channel last
        # (H for height, W for width, C for channel)
        # See https://pytorch.org/docs/stable/tensorboard.html
        # for supported formats
        self.logger.record("trajectory/image", Image(image, "HWC"), exclude=("stdout",
↪ "log", "json", "csv"))
        return True

model.learn(50000, callback=ImageRecorderCallback())

```

1.11.4 Logging Figures/Plots

TensorBoard supports periodic logging of figures/plots created with matplotlib, which helps evaluating agents at various stages during training.

Warning: To support figure logging `matplotlib` must be installed otherwise, TensorBoard ignores the figure and logs a warning.

Here is an example of how to store a plot in TensorBoard at regular intervals:

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

from stable_baselines3 import SAC
from stable_baselines3.common.callbacks import BaseCallback
from stable_baselines3.common.logger import Figure

model = SAC("MlpPolicy", "Pendulum-v1", tensorboard_log="/tmp/sac/", verbose=1)

class FigureRecorderCallback(BaseCallback):
    def __init__(self, verbose=0):
        super(FigureRecorderCallback, self).__init__(verbose)

    def _on_step(self):
        # Plot values (here a random variable)
        figure = plt.figure()
        figure.add_subplot().plot(np.random.random(3))
        # Close the figure after logging it
        self.logger.record("trajectory/figure", Figure(figure, close=True), exclude=(
            "stdout", "log", "json", "csv"))
        plt.close()
        return True

model.learn(50000, callback=FigureRecorderCallback())
```

1.11.5 Logging Videos

TensorBoard supports periodic logging of video data, which helps evaluating agents at various stages during training.

Warning: To support video logging `moviepy` must be installed otherwise, TensorBoard ignores the video and logs a warning.

Here is an example of how to render an episode and log the resulting video to TensorBoard at regular intervals:

```
from typing import Any, Dict

import gym
```

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```

import torch as th

from stable_baselines3 import A2C
from stable_baselines3.common.callbacks import BaseCallback
from stable_baselines3.common.evaluation import evaluate_policy
from stable_baselines3.common.logger import Video

class VideoRecorderCallback(BaseCallback):
    def __init__(self, eval_env: gym.Env, render_freq: int, n_eval_episodes: int = 1,
↳ deterministic: bool = True):
        """
        Records a video of an agent's trajectory traversing ``eval_env`` and logs it to
↳ TensorBoard

        :param eval_env: A gym environment from which the trajectory is recorded
        :param render_freq: Render the agent's trajectory every eval_freq call of the
↳ callback.
        :param n_eval_episodes: Number of episodes to render
        :param deterministic: Whether to use deterministic or stochastic policy
        """
        super().__init__()
        self._eval_env = eval_env
        self._render_freq = render_freq
        self._n_eval_episodes = n_eval_episodes
        self._deterministic = deterministic

    def _on_step(self) -> bool:
        if self.n_calls % self._render_freq == 0:
            screens = []

            def grab_screens(_locals: Dict[str, Any], _globals: Dict[str, Any]) -> None:
↳ """
        Renders the environment in its current state, recording the screen in
↳ the captured `screens` list

        :param _locals: A dictionary containing all local variables of the
↳ callback's scope
        :param _globals: A dictionary containing all global variables of the
↳ callback's scope
        """
            screen = self._eval_env.render(mode="rgb_array")
            # PyTorch uses CxHxW vs HxWxC gym (and tensorflow) image convention
            screens.append(screen.transpose(2, 0, 1))

            evaluate_policy(
                self.model,
                self._eval_env,
                callback=grab_screens,
                n_eval_episodes=self._n_eval_episodes,
                deterministic=self._deterministic,
            )

```

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```

        self.logger.record(
            "trajectory/video",
            Video(th.ByteTensor([screens]), fps=40),
            exclude=("stdout", "log", "json", "csv"),
        )
    return True

model = A2C("MlpPolicy", "CartPole-v1", tensorboard_log="runs/", verbose=1)
video_recorder = VideoRecorderCallback(gym.make("CartPole-v1"), render_freq=5000)
model.learn(total_timesteps=int(5e4), callback=video_recorder)

```

1.11.6 Directly Accessing The Summary Writer

If you would like to log arbitrary data (in one of the formats supported by `pytorch`), you can get direct access to the underlying `SummaryWriter` in a callback:

Warning: This method is not recommended and should only be used by advanced users.

```

from stable_baselines3 import SAC
from stable_baselines3.common.callbacks import BaseCallback
from stable_baselines3.common.logger import TensorBoardOutputFormat

model = SAC("MlpPolicy", "Pendulum-v1", tensorboard_log="/tmp/sac/", verbose=1)

class SummaryWriterCallback(BaseCallback):
    def _on_training_start(self):
        self._log_freq = 1000  # log every 1000 calls

        output_formats = self.logger.output_formats
        # Save reference to tensorboard formatter object
        # note: the failure case (not formatter found) is not handled here, should be
        ↪ done with try/except.
        self.tb_formatter = next(formatter for formatter in output_formats if
        ↪ isinstance(formatter, TensorBoardOutputFormat))

    def _on_step(self) -> bool:
        if self.n_calls % self._log_freq == 0:
            self.tb_formatter.writer.add_text("direct_access", "this is a value", self.
            ↪ num_timesteps)
            self.tb_formatter.writer.flush()

model.learn(50000, callback=SummaryWriterCallback())

```

1.12 Integrations

1.12.1 Weights & Biases

Weights & Biases provides a callback for experiment tracking that allows to visualize and share results.

The full documentation is available here: <https://docs.wandb.ai/guides/integrations/other/stable-baselines-3>

```
import gym
import wandb
from wandb.integration.sb3 import WandbCallback

from stable_baselines3 import PPO

config = {
    "policy_type": "MlpPolicy",
    "total_timesteps": 25000,
    "env_name": "CartPole-v1",
}
run = wandb.init(
    project="sb3",
    config=config,
    sync_tensorboard=True, # auto-upload sb3's tensorboard metrics
    # monitor_gym=True, # auto-upload the videos of agents playing the game
    # save_code=True, # optional
)

model = PPO(config["policy_type"], config["env_name"], verbose=1, tensorboard_log=f"runs/
↪{run.id}")
model.learn(
    total_timesteps=config["total_timesteps"],
    callback=WandbCallback(
        model_save_path=f"models/{run.id}",
        verbose=2,
    ),
)
run.finish()
```

1.12.2 Hugging Face

The Hugging Face Hub is a central place where anyone can share and explore models. It allows you to host your saved models.

You can see the list of stable-baselines3 saved models here: <https://huggingface.co/models?other=stable-baselines3>

Official pre-trained models are saved in the SB3 organization on the hub: <https://huggingface.co/sb3>

We wrote a tutorial on how to use Hub and Stable-Baselines3 here: <https://colab.research.google.com/drive/1GI0WpThwRHbl-Fu2RHfczq6dci5GBDVE#scrollTo=q4cz-w9MdO7T>

Installation

```
pip install huggingface_hub
pip install huggingface_sb3
```

Download a model from the Hub

You need to copy the repo-id that contains your saved model. For instance `sb3/demo-hf-CartPole-v1`:

```
import gym

from huggingface_sb3 import load_from_hub
from stable_baselines3 import PPO
from stable_baselines3.common.evaluation import evaluate_policy

# Retrieve the model from the hub
## repo_id = id of the model repository from the Hugging Face Hub (repo_id =
# → {organization}/{repo_name})
## filename = name of the model zip file from the repository
checkpoint = load_from_hub(
    repo_id="sb3/demo-hf-CartPole-v1",
    filename="ppo-CartPole-v1",
)
model = PPO.load(checkpoint)

# Evaluate the agent and watch it
eval_env = gym.make("CartPole-v1")
mean_reward, std_reward = evaluate_policy(
    model, eval_env, render=True, n_eval_episodes=5, deterministic=True, warn=False
)
print(f"mean_reward={mean_reward:.2f} +/- {std_reward}")
```

Upload a model to the Hub

First, you need to be logged in to Hugging Face to upload a model:

- If you're using Colab/Jupyter Notebooks:

```
from huggingface_hub import notebook_login
notebook_login()
```

- Otherwise:

```
huggingface-cli login
```

Then, in this example, we train a PPO agent to play CartPole-v1 and push it to a new repo `sb3/demo-hf-CartPole-v1`

```
from huggingface_sb3 import push_to_hub
from stable_baselines3 import PPO

# Define a PPO model with MLP policy network
model = PPO("MlpPolicy", "CartPole-v1", verbose=1)
```

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```
# Train it for 10000 timesteps
model.learn(total_timesteps=10_000)

# Save the model
model.save("ppo-CartPole-v1")

# Push this saved model to the hf repo
# If this repo does not exists it will be created
## repo_id = id of the model repository from the Hugging Face Hub (repo_id =
# → {organization}/{repo_name})
## filename: the name of the file == "name" inside model.save("ppo-CartPole-v1")
push_to_hub(
    repo_id="sb3/demo-hf-CartPole-v1",
    filename="ppo-CartPole-v1",
    commit_message="Added Cartpole-v1 model trained with PPO",
)
```

1.13 RL Baselines3 Zoo

RL Baselines3 Zoo is a training framework for Reinforcement Learning (RL).

It provides scripts for training, evaluating agents, tuning hyperparameters, plotting results and recording videos.

In addition, it includes a collection of tuned hyperparameters for common environments and RL algorithms, and agents trained with those settings.

Goals of this repository:

1. Provide a simple interface to train and enjoy RL agents
2. Benchmark the different Reinforcement Learning algorithms
3. Provide tuned hyperparameters for each environment and RL algorithm
4. Have fun with the trained agents!

1.13.1 Installation

1. Clone the repository:

```
git clone --recursive https://github.com/DLR-RM/rl-baselines3-zoo
cd rl-baselines3-zoo/
```

Note: You can remove the `--recursive` option if you don't want to download the trained agents

2. Install dependencies

```
apt-get install swig cmake ffmpeg
pip install -r requirements.txt
```

1.13.2 Train an Agent

The hyperparameters for each environment are defined in `hyperparameters/algo_name.yml`.

If the environment exists in this file, then you can train an agent using:

```
python train.py --algo algo_name --env env_id
```

For example (with evaluation and checkpoints):

```
python train.py --algo ppo2 --env CartPole-v1 --eval-freq 10000 --save-freq 50000
```

Continue training (here, load pretrained agent for Breakout and continue training for 5000 steps):

```
python train.py --algo a2c --env BreakoutNoFrameskip-v4 -i trained_agents/a2c/  
↳BreakoutNoFrameskip-v4_1/BreakoutNoFrameskip-v4.zip -n 5000
```

1.13.3 Enjoy a Trained Agent

If the trained agent exists, then you can see it in action using:

```
python enjoy.py --algo algo_name --env env_id
```

For example, enjoy A2C on Breakout during 5000 timesteps:

```
python enjoy.py --algo a2c --env BreakoutNoFrameskip-v4 --folder rl-trained-agents/ -n  
↳5000
```

1.13.4 Hyperparameter Optimization

We use [Optuna](#) for optimizing the hyperparameters.

Tune the hyperparameters for PPO, using a random sampler and median pruner, 2 parallel jobs, with a budget of 1000 trials and a maximum of 50000 steps:

```
python train.py --algo ppo --env MountainCar-v0 -n 50000 -optimize --n-trials 1000 --n-  
↳jobs 2 \  
--sampler random --pruner median
```

1.13.5 Colab Notebook: Try it Online!

You can train agents online using Google [colab notebook](#).

Note: You can find more information about the rl baselines3 zoo in the repo [README](#). For instance, how to record a video of a trained agent.

1.14 SB3 Contrib

We implement experimental features in a separate contrib repository: [SB3-Contrib](#)

This allows Stable-Baselines3 (SB3) to maintain a stable and compact core, while still providing the latest features, like Truncated Quantile Critics (TQC), Augmented Random Search (ARS), Trust Region Policy Optimization (TRPO) or Quantile Regression DQN (QR-DQN).

1.14.1 Why create this repository?

Over the span of stable-baselines and stable-baselines3, the community has been eager to contribute in form of better logging utilities, environment wrappers, extended support (e.g. different action spaces) and learning algorithms.

However sometimes these utilities were too niche to be considered for stable-baselines or proved to be too difficult to integrate well into the existing code without creating a mess. sb3-contrib aims to fix this by not requiring the neatest code integration with existing code and not setting limits on what is too niche: almost everything remotely useful goes! We hope this allows us to provide reliable implementations following stable-baselines usual standards (consistent style, documentation, etc) beyond the relatively small scope of utilities in the main repository.

Features

See documentation for the full list of included features.

RL Algorithms:

- [Augmented Random Search \(ARS\)](#)
- [Quantile Regression DQN \(QR-DQN\)](#)
- [Truncated Quantile Critics \(TQC\)](#)
- [Trust Region Policy Optimization \(TRPO\)](#)
- [PPO with invalid action masking \(Maskable PPO\)](#)

Gym Wrappers:

- [Time Feature Wrapper](#)

Documentation

Documentation is available online: <https://sb3-contrib.readthedocs.io/>

Installation

To install Stable-Baselines3 contrib with pip, execute:

```
pip install sb3-contrib
```

We recommend to use the `master` version of Stable Baselines3 and SB3-Contrib.

To install Stable Baselines3 `master` version:

```
pip install git+https://github.com/DLR-RM/stable-baselines3
```

To install Stable Baselines3 contrib `master` version:

```
pip install git+https://github.com/Stable-Baselines-Team/stable-baselines3-contrib
```

Example

SB3-Contrib follows the SB3 API and folder structure. So, if you are familiar with SB3, using SB3-Contrib should be easy too.

Here is an example of training a Quantile Regression DQN (QR-DQN) agent on the CartPole environment.

```
from sb3_contrib import QRDQN

policy_kwargs = dict(n_quantiles=50)
model = QRDQN("MlpPolicy", "CartPole-v1", policy_kwargs=policy_kwargs, verbose=1)
model.learn(total_timesteps=10000, log_interval=4)
model.save("qrdqn_cartpole")
```

1.15 Imitation Learning

The `imitation` library implements imitation learning algorithms on top of Stable-Baselines3, including:

- Behavioral Cloning
- DAgger with synthetic examples
- Adversarial Inverse Reinforcement Learning (AIRL)
- Generative Adversarial Imitation Learning (GAIL)

It also provides *CLI scripts* for training and saving demonstrations from RL experts, and for training imitation learners on these demonstrations.

1.15.1 Installation

Installation requires Python 3.7+:

```
pip install imitation
```

1.15.2 CLI Quickstart

```
# Train PPO agent on cartpole and collect expert demonstrations
python -m imitation.scripts.expert_demos with fast cartpole log_dir=quickstart

# Train GAIL from demonstrations
python -m imitation.scripts.train_adversarial with fast gail cartpole rollout_
↪ path=quickstart/rollouts/final.pkl

# Train AIRL from demonstrations
python -m imitation.scripts.train_adversarial with fast airl cartpole rollout_
↪ path=quickstart/rollouts/final.pkl
```

Note: You can remove the `fast` option to run training to completion. For more CLI options and information on reading Tensorboard plots, see the [README](#).

1.15.3 Python Interface Quickstart

This [example script](#) uses the Python API to train BC, GAIL, and AIRL models on CartPole data.

1.16 Migrating from Stable-Baselines

This is a guide to migrate from Stable-Baselines (SB2) to Stable-Baselines3 (SB3).

It also references the main changes.

1.16.1 Overview

Overall Stable-Baselines3 (SB3) keeps the high-level API of Stable-Baselines (SB2). Most of the changes are to ensure more consistency and are internal ones. Because of the backend change, from Tensorflow to PyTorch, the internal code is much much readable and easy to debug at the cost of some speed (dynamic graph vs static graph., see [Issue #90](#)) However, the algorithms were extensively benchmarked on Atari games and continuous control PyBullet envs (see [Issue #48](#) and [Issue #49](#)) so you should not expect performance drop when switching from SB2 to SB3.

1.16.2 How to migrate?

In most cases, replacing `from stable_baselines` by `from stable_baselines3` will be sufficient. Some files were moved to the common folder (cf below) and could result to import errors. Some algorithms were removed because of their complexity to improve the maintainability of the project. We recommend reading this guide carefully to understand all the changes that were made. You can also take a look at the [rl-zoo3](#) and compare the imports to the `rl-zoo` of SB2 to have a concrete example of successful migration.

Note: If you experience massive slow-down switching to PyTorch, you may need to play with the number of threads used, using `torch.set_num_threads(1)` or `OMP_NUM_THREADS=1`, see [issue #122](#) and [issue #90](#).

1.16.3 Breaking Changes

- SB3 requires python 3.7+ (instead of python 3.5+ for SB2)
- Dropped MPI support
- Dropped layer normalized policies (`MlpLnLstmPolicy`, `CnnLnLstmPolicy`)
- LSTM policies (``MlpLstmPolicy``, ``CnnLstmPolicy``) are not supported for the time being (see [PR #53](#) for a recurrent PPO implementation)
- Dropped parameter noise for DDPG and DQN
- PPO is now closer to the original implementation (no clipping of the value function by default), cf PPO section below
- Orthogonal initialization is only used by A2C/PPO

- The features extractor (CNN extractor) is shared between policy and q-networks for DDPG/SAC/TD3 and only the policy loss used to update it (much faster)
- Tensorboard legacy logging was dropped in favor of having one logger for the terminal and Tensorboard (cf [Tensorboard integration](#))
- We dropped ACKTR/ACER support because of their complexity compared to simpler alternatives (PPO, SAC, TD3) performing as good.
- We dropped GAIL support as we are focusing on model-free RL only, you can however take a look at the [imitation project](#) which implements GAIL and other imitation learning algorithms on top of SB3.
- `action_probability` is currently not implemented in the base class
- `pretrain()` method for behavior cloning was removed (see [issue #27](#))

You can take a look at the [issue about SB3 implementation design](#) for more details.

Moved Files

- `bench/monitor.py` -> `common/monitor.py`
- `logger.py` -> `common/logger.py`
- `results_plotter.py` -> `common/results_plotter.py`
- `common/cmd_util.py` -> `common/env_util.py`

Utility functions are no longer exported from `common` module, you should import them with their absolute path, e.g.:

```
from stable_baselines3.common.env_util import make_atari_env, make_vec_env
from stable_baselines3.common.utils import set_random_seed
```

instead of `from stable_baselines3.common import make_atari_env`

Changes and renaming in parameters

Base-class (all algorithms)

- `load_parameters` -> `set_parameters`
 - `get/set_parameters` return a dictionary mapping object names to their respective PyTorch tensors and other objects representing their parameters, instead of simpler mapping of parameter name to a NumPy array. These functions also return PyTorch tensors rather than NumPy arrays.

Policies

- `cnn_extractor` -> `features_extractor`, as `features_extractor` is now used with `MlpPolicy` too

A2C

- `epsilon` -> `rms_prop_eps`
- `lr_schedule` is part of `learning_rate` (it can be a callable).
- `alpha`, `momentum` are modifiable through `policy_kwargs` key `optimizer_kwargs`.

Warning: PyTorch implementation of RMSprop differs from Tensorflow's, which leads to different and potentially more unstable results. Use `stable_baselines3.common.sb2_compat.rmsprop_tf_like.RMSpropTFLike` optimizer to match the results with TensorFlow's implementation. This can be done through `policy_kwargs`: `A2C(policy_kwargs=dict(optimizer_class=RMSpropTFLike, optimizer_kwargs=dict(eps=1e-5)))`

PPO

- `cliprange` -> `clip_range`
- `cliprange_vf` -> `clip_range_vf`
- `nminibatches` -> `batch_size`

Warning: `nminibatches` gave different batch size depending on the number of environments: `batch_size = (n_steps * n_envs) // nminibatches`

- `clip_range_vf` behavior for PPO is slightly different: Set it to `None` (default) to deactivate clipping (in SB2, you had to pass `-1`, `None` meant to use `clip_range` for the clipping)
- `lam` -> `gae_lambda`
- `noptepochs` -> `n_epochs`

PPO default hyperparameters are the one tuned for continuous control environment. We recommend taking a look at the [RL Zoo](#) for hyperparameters tuned for Atari games.

DQN

Only the vanilla DQN is implemented right now but extensions will follow. Default hyperparameters are taken from the nature paper, except for the optimizer and learning rate that were taken from Stable Baselines defaults.

DDPG

DDPG now follows the same interface as SAC/TD3. For state/reward normalization, you should use `VecNormalize` as for all other algorithms.

SAC/TD3

SAC/TD3 now accept any number of critics, e.g. `policy_kwargs=dict(n_critics=3)`, instead of only two before.

Note: SAC/TD3 default hyperparameters (including network architecture) now match the ones from the original papers. DDPG is using TD3 defaults.

SAC

SAC implementation matches the latest version of the original implementation: it uses two Q function networks and two target Q function networks instead of two Q function networks and one Value function network (SB2 implementation, first version of the original implementation). Despite this change, no change in performance should be expected.

Note: SAC `predict()` method has now `deterministic=False` by default for consistency. To match SB2 behavior, you need to explicitly pass `deterministic=True`

HER

The HER implementation now also supports online sampling of the new goals. This is done in a vectorized version. The goal selection strategy `RANDOM` is no longer supported. HER now supports `VecNormalize` wrapper but only when `online_sampling=True`. For performance reasons, the maximum number of steps per episodes must be specified (see [HER](#) documentation).

New logger API

- Methods were renamed in the logger:
 - `logkv` -> `record`, `writeln` -> `write`, `writeseq` -> `write_sequence`,
 - `logkvs` -> `record_dict`, `dumpkvs` -> `dump`,
 - `getkvs` -> `get_log_dict`, `logkv_mean` -> `record_mean`,

Internal Changes

Please read the [Developer Guide](#) section.

1.16.4 New Features (SB3 vs SB2)

- Much cleaner and consistent base code (and no more warnings =D!) and static type checks
- Independent saving/loading/predict for policies
- A2C now supports Generalized Advantage Estimation (GAE) and advantage normalization (both are deactivated by default)
- Generalized State-Dependent Exploration (gSDE) exploration is available for A2C/PPO/SAC. It allows to use RL directly on real robots (cf <https://arxiv.org/abs/2005.05719>)

- Proper evaluation (using separate env) is included in the base class (using EvalCallback), if you pass the environment as a string, you can pass `create_eval_env=True` to the algorithm constructor.
- Better saving/loading: optimizers are now included in the saved parameters and there is two new methods `save_replay_buffer` and `load_replay_buffer` for the replay buffer when using off-policy algorithms (DQN/DDPG/SAC/TD3)
- You can pass `optimizer_class` and `optimizer_kwargs` to `policy_kwargs` in order to easily customize optimizers
- Seeding now works properly to have deterministic results
- Replay buffer does not grow, allocate everything at build time (faster)
- We added a memory efficient replay buffer variant (pass `optimize_memory_usage=True` to the constructor), it reduces drastically the memory used especially when using images
- You can specify an arbitrary number of critics for SAC/TD3 (e.g. `policy_kwargs=dict(n_critics=3)`)

1.17 Dealing with NaNs and infs

During the training of a model on a given environment, it is possible that the RL model becomes completely corrupted when a NaN or an inf is given or returned from the RL model.

1.17.1 How and why?

The issue arises then NaNs or infs do not crash, but simply get propagated through the training, until all the floating point number converge to NaN or inf. This is in line with the [IEEE Standard for Floating-Point Arithmetic \(IEEE 754\)](#) standard, as it says:

Note:

Five possible exceptions can occur:

- Invalid operation ($\sqrt{-1}$, $\text{inf} \times 1$, $\text{NaN} \bmod 1$, ...) return NaN
 - **Division by zero:**
 - if the operand is not zero ($1/0$, $-2/0$, ...) returns $\pm \text{inf}$
 - if the operand is zero ($0/0$) returns signaling NaN
 - Overflow (exponent too high to represent) returns $\pm \text{inf}$
 - Underflow (exponent too low to represent) returns 0
 - Inexact (not representable exactly in base 2, eg: $1/5$) returns the rounded value (ex: `assert (1/5) * 3 == 0.6000000000000001`)
-

And of these, only `Division by zero` will signal an exception, the rest will propagate invalid values quietly.

In python, dividing by zero will indeed raise the exception: `ZeroDivisionError: float division by zero`, but ignores the rest.

The default in numpy, will warn: `RuntimeWarning: invalid value encountered` but will not halt the code.

1.17.2 Anomaly detection with PyTorch

To enable NaN detection in PyTorch you can do

```
import torch as th
th.autograd.set_detect_anomaly(True)
```

1.17.3 Numpy parameters

Numpy has a convenient way of dealing with invalid value: `numpy.seterr`, which defines for the python process, how it should handle floating point error.

```
import numpy as np

np.seterr(all='raise')  # define before your code.

print("numpy test:")

a = np.float64(1.0)
b = np.float64(0.0)
val = a / b  # this will now raise an exception instead of a warning.
print(val)
```

but this will also avoid overflow issues on floating point numbers:

```
import numpy as np

np.seterr(all='raise')  # define before your code.

print("numpy overflow test:")

a = np.float64(10)
b = np.float64(1000)
val = a ** b  # this will now raise an exception
print(val)
```

but will not avoid the propagation issues:

```
import numpy as np

np.seterr(all='raise')  # define before your code.

print("numpy propagation test:")

a = np.float64('NaN')
b = np.float64(1.0)
val = a + b  # this will neither warn nor raise anything
print(val)
```

1.17.4 VecCheckNan Wrapper

In order to find when and from where the invalid value originated from, stable-baselines3 comes with a VecCheckNan wrapper.

It will monitor the actions, observations, and rewards, indicating what action or observation caused it and from what.

```
import gym
from gym import spaces
import numpy as np

from stable_baselines3 import PPO
from stable_baselines3.common.vec_env import DummyVecEnv, VecCheckNan

class NanAndInfEnv(gym.Env):
    """Custom Environment that raised NaNs and Infs"""
    metadata = {'render.modes': ['human']}

    def __init__(self):
        super(NanAndInfEnv, self).__init__()
        self.action_space = spaces.Box(low=-np.inf, high=np.inf, shape=(1,), dtype=np.
↪float64)
        self.observation_space = spaces.Box(low=-np.inf, high=np.inf, shape=(1,),
↪dtype=np.float64)

    def step(self, _action):
        randf = np.random.rand()
        if randf > 0.99:
            obs = float('NaN')
        elif randf > 0.98:
            obs = float('inf')
        else:
            obs = randf
        return [obs], 0.0, False, {}

    def reset(self):
        return [0.0]

    def render(self, mode='human', close=False):
        pass

# Create environment
env = DummyVecEnv([lambda: NanAndInfEnv()])
env = VecCheckNan(env, raise_exception=True)

# Instantiate the agent
model = PPO('MlpPolicy', env)

# Train the agent
model.learn(total_timesteps=int(2e5)) # this will crash explaining that the invalid
↪value originated from the environment.
```

1.17.5 RL Model hyperparameters

Depending on your hyperparameters, NaN can occur much more often. A great example of this: <https://github.com/hill-a/stable-baselines/issues/340>

Be aware, the hyperparameters given by default seem to work in most cases, however your environment might not play nice with them. If this is the case, try to read up on the effect each hyperparameter has on the model, so that you can try and tune them to get a stable model. Alternatively, you can try automatic hyperparameter tuning (included in the rl zoo).

1.17.6 Missing values from datasets

If your environment is generated from an external dataset, do not forget to make sure your dataset does not contain NaNs. As some datasets will sometimes fill missing values with NaNs as a surrogate value.

Here is some reading material about finding NaNs: https://pandas.pydata.org/pandas-docs/stable/user_guide/missing_data.html

And filling the missing values with something else (imputation): <https://towardsdatascience.com/how-to-handle-missing-data-8646b18db0d4>

1.18 Developer Guide

This guide is meant for those who want to understand the internals and the design choices of Stable-Baselines3.

At first, you should read the two issues where the design choices were discussed:

- <https://github.com/hill-a/stable-baselines/issues/576>
- <https://github.com/hill-a/stable-baselines/issues/733>

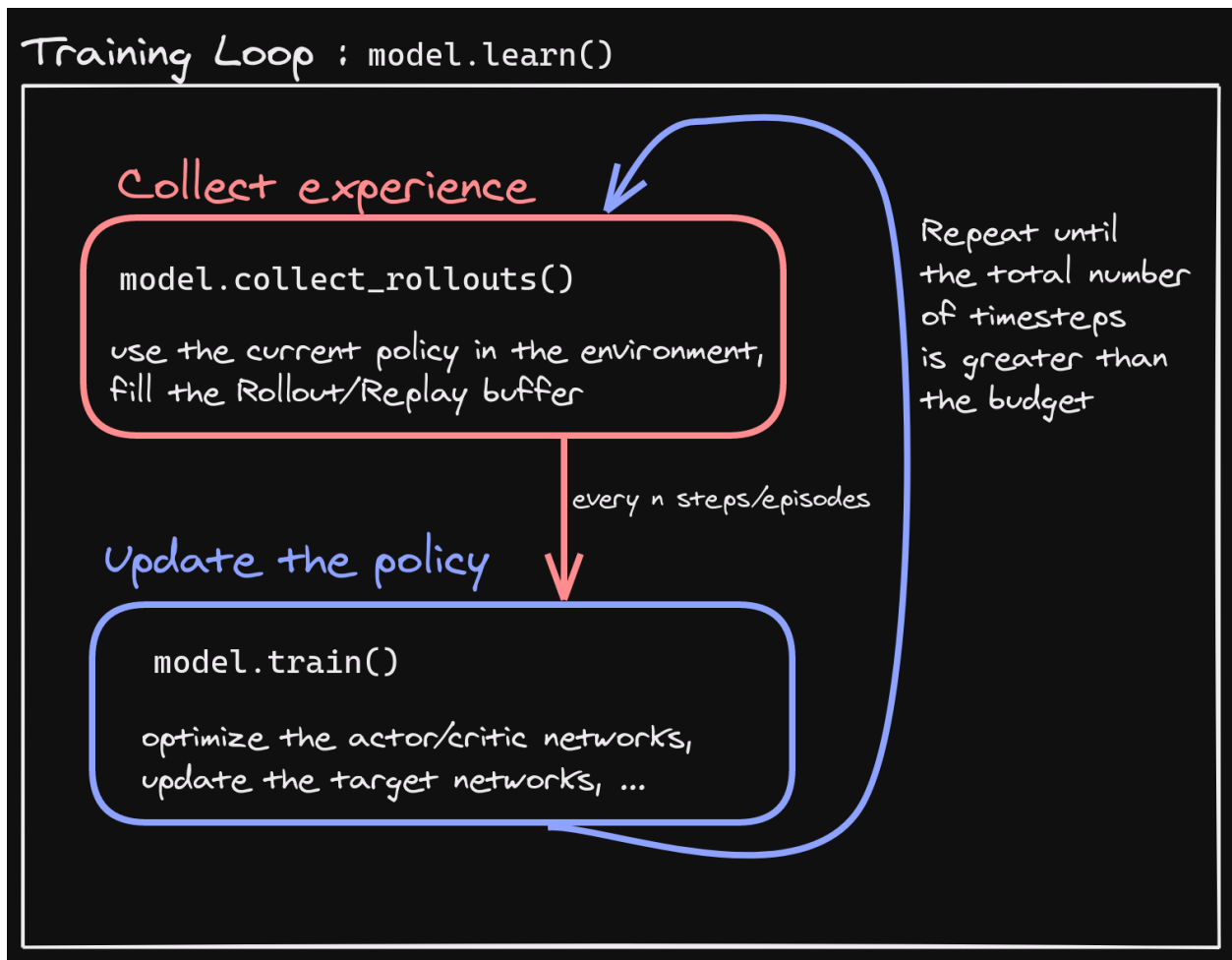
The library is not meant to be modular, although inheritance is used to reduce code duplication.

1.18.1 Algorithms Structure

Each algorithm (on-policy and off-policy ones) follows a common structure. Policy contains code for acting in the environment, and algorithm updates this policy. There is one folder per algorithm, and in that folder there is the algorithm and the policy definition (`policies.py`).

Each algorithm has two main methods:

- `.collect_rollouts()` which defines how new samples are collected, usually inherited from the base class. Those samples are then stored in a `RolloutBuffer` (discarded after the gradient update) or `ReplayBuffer`
- `.train()` which updates the parameters using samples from the buffer



1.18.2 Where to start?

The first thing you need to read and understand are the base classes in the `common/` folder:

- `BaseAlgorithm` in `base_class.py` which defines how an RL class should look like. It contains also all the “glue code” for saving/loading and the common operations (wrapping environments)
- `BasePolicy` in `policies.py` which defines how a policy class should look like. It contains also all the magic for the `.predict()` method, to handle as many spaces/cases as possible
- `OffPolicyAlgorithm` in `off_policy_algorithm.py` that contains the implementation of `collect_rollouts()` for the off-policy algorithms, and similarly `OnPolicyAlgorithm` in `on_policy_algorithm.py`.

All the environments handled internally are assumed to be `VecEnv` (`gym.Env` are automatically wrapped).

1.18.3 Pre-Processing

To handle different observation spaces, some pre-processing needs to be done (e.g. one-hot encoding for discrete observation). Most of the code for pre-processing is in `common/preprocessing.py` and `common/policies.py`.

For images, environment is automatically wrapped with `VecTransposeImage` if observations are detected to be images with channel-last convention to transform it to PyTorch's channel-first convention.

1.18.4 Policy Structure

When we refer to “policy” in Stable-Baselines3, this is usually an abuse of language compared to RL terminology. In SB3, “policy” refers to the class that handles all the networks useful for training, so not only the network used to predict actions (the “learned controller”). For instance, the TD3 policy contains the actor, the critic and the target networks.

To avoid the hassle of importing specific policy classes for specific algorithm (e.g. both A2C and PPO use `ActorCriticPolicy`), SB3 uses names like “`MlpPolicy`” and “`CnnPolicy`” to refer policies using small feed-forward networks or convolutional networks, respectively. Importing `[algorithm]/policies.py` registers an appropriate policy for that algorithm under those names.

1.18.5 Probability distributions

When needed, the policies handle the different probability distributions. All distributions are located in `common/distributions.py` and follow the same interface. Each distribution corresponds to a type of action space (e.g. `Categorical` is the one used for discrete actions. For continuous actions, we can use multiple distributions (“`DiagGaussian`”, “`SquashedGaussian`” or “`StateDependentDistribution`”))

1.18.6 State-Dependent Exploration

State-Dependent Exploration (SDE) is a type of exploration that allows to use RL directly on real robots, that was the starting point for the Stable-Baselines3 library. I (@araffin) published a paper about a generalized version of SDE (the one implemented in SB3): <https://arxiv.org/abs/2005.05719>

1.18.7 Misc

The rest of the `common/` is composed of helpers (e.g. evaluation helpers) or basic components (like the callbacks). The `type_aliases.py` file contains common type hint aliases like `GymStepReturn`.

Et voilà?

After reading this guide and the mentioned files, you should be now able to understand the design logic behind the library ;)

1.19 On saving and loading

Stable Baselines3 (SB3) stores both neural network parameters and algorithm-related parameters such as exploration schedule, number of environments and observation/action space. This allows continual learning and easy use of trained agents without training, but it is not without its issues. Following describes the format used to save agents in SB3 along with its pros and shortcomings.

Terminology used in this page:

- *parameters* refer to neural network parameters (also called “weights”). This is a dictionary mapping variable name to a PyTorch tensor.
- *data* refers to RL algorithm parameters, e.g. learning rate, exploration schedule, action/observation space. These depend on the algorithm used. This is a dictionary mapping classes variable names to their values.

1.19.1 Zip-archive

A zip-archived JSON dump, PyTorch state dictionaries and PyTorch variables. The data dictionary (class parameters) is stored as a JSON file, model parameters and optimizers are serialized with `torch.save()` function and these files are stored under a single .zip archive.

Any objects that are not JSON serializable are serialized with cloudpickle and stored as base64-encoded string in the JSON file, along with some information that was stored in the serialization. This allows inspecting stored objects without deserializing the object itself.

This format allows skipping elements in the file, i.e. we can skip deserializing objects that are broken/non-serializable. This can be done via `custom_objects` argument to load functions.

Note: If you encounter loading issue, for instance pickle issues or error after loading (see [#171](#) or [#573](#)), you can pass `print_system_info=True` to compare the system on which the model was trained vs the current one `model = PPO.load("ppo_saved", print_system_info=True)`

File structure:

```
saved_model.zip/
├── data                JSON file of class-parameters (dictionary)
├── *.optimizer.pth     PyTorch optimizers serialized
├── policy.pth          PyTorch state dictionary of the policy saved
├── pytorch_variables.pth Additional PyTorch variables
├── _stable_baselines3_version contains the SB3 version with which the model was saved
├── system_info.txt     contains system info (os, python version, ...) on which the model
└── was saved
```

Pros:

- More robust to unserializable objects (one bad object does not break everything).
- Saved files can be inspected/extracted with zip-archive explorers and by other languages.

Cons:

- More complex implementation.
- Still relies partly on cloudpickle for complex objects (e.g. custom functions) with can lead to [incompatibilities](#) between Python versions.

1.20 Exporting models

After training an agent, you may want to deploy/use it in another language or framework, like `tensorflowjs`. Stable Baselines3 does not include tools to export models to other frameworks, but this document aims to cover parts that are required for exporting along with more detailed stories from users of Stable Baselines3.

1.20.1 Background

In Stable Baselines3, the controller is stored inside policies which convert observations into actions. Each learning algorithm (e.g. DQN, A2C, SAC) contains a policy object which represents the currently learned behavior, accessible via `model.policy`.

Policies hold enough information to do the inference (i.e. predict actions), so it is enough to export these policies (cf *examples*) to do inference in another framework.

Warning: When using CNN policies, the observation is normalized during pre-preprocessing. This pre-processing is done *inside* the policy (dividing by 255 to have values in [0, 1])

1.20.2 Export to ONNX

As of June 2021, ONNX format *doesn't support* exporting models that use the `broadcast_tensors` functionality of `pytorch`. So in order to export the trained stable-baseline3 models in the ONNX format, we need to first remove the layers that use broadcasting. This can be done by creating a class that removes the unsupported layers.

The following examples are for `MlpPolicy` only, and are general examples. Note that you have to preprocess the observation the same way stable-baselines3 agent does (see `common.preprocessing.preprocess_obs`).

For PPO, assuming a shared feature extractor.

Warning: The following example is for continuous actions only. When using discrete or binary actions, you must do some *post-processing* to obtain the action (e.g., convert action logits to action).

```
from stable_baselines3 import PPO
import torch

class OnnxablePolicy(torch.nn.Module):
    def __init__(self, extractor, action_net, value_net):
        super(OnnxablePolicy, self).__init__()
        self.extractor = extractor
        self.action_net = action_net
        self.value_net = value_net

    def forward(self, observation):
        # NOTE: You may have to process (normalize) observation in the correct
        # way before using this. See `common.preprocessing.preprocess_obs`
        action_hidden, value_hidden = self.extractor(observation)
        return self.action_net(action_hidden), self.value_net(value_hidden)

# Example: model = PPO("MlpPolicy", "Pendulum-v1")
```

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```

model = PPO.load("PathToTrainedModel.zip")
model.policy.to("cpu")
onnxable_model = OnnxablePolicy(model.policy.mlp_extractor, model.policy.action_net,
    ↪model.policy.value_net)

dummy_input = torch.randn(1, observation_size)
torch.onnx.export(onnxable_model, dummy_input, "my_ppo_model.onnx", opset_version=9)

##### Load and test with onnx

import onnx
import onnxruntime as ort
import numpy as np

onnx_model = onnx.load(onnx_path)
onnx.checker.check_model(onnx_model)

observation = np.zeros((1, observation_size)).astype(np.float32)
ort_sess = ort.InferenceSession(onnx_path)
action, value = ort_sess.run(None, {'input.1': observation})

```

For SAC the procedure is similar. The example shown only exports the actor network as the actor is sufficient to roll out the trained policies.

```

from stable_baselines3 import SAC
import torch

class OnnxablePolicy(torch.nn.Module):
    def __init__(self, actor):
        super(OnnxablePolicy, self).__init__()

        # Removing the flatten layer because it can't be onnxed
        self.actor = torch.nn.Sequential(actor.latent_pi, actor.mu)

    def forward(self, observation):
        # NOTE: You may have to process (normalize) observation in the correct
        # way before using this. See `common.preprocessing.preprocess_obs`
        return self.actor(observation)

model = SAC.load("PathToTrainedModel.zip")
onnxable_model = OnnxablePolicy(model.policy.actor)

dummy_input = torch.randn(1, observation_size)
onnxable_model.policy.to("cpu")
torch.onnx.export(onnxable_model, dummy_input, "my_sac_actor.onnx", opset_version=9)

```

For more discussion around the topic refer to this [issue](#).

1.20.3 Export to C++

(using PyTorch JIT) TODO: help is welcomed!

1.20.4 Export to tensorflowjs / ONNX-JS

TODO: contributors help is welcomed! Probably a good starting point: <https://github.com/elliottwaite/pytorch-to-javascript-with-onnx-js>

1.20.5 Export to TFLite / Coral (Edge TPU)

Full example code: https://github.com/chunky/sb3_to_coral

Google created a chip called the “Coral” for deploying AI to the edge. It’s available in a variety of form factors, including USB (using the Coral on a Raspberry pi, with a SB3-developed model, was the original motivation for the code example above).

The Coral chip is fast, with very low power consumption, but only has limited on-device training abilities. More information is on the webpage here: <https://coral.ai>.

To deploy to a Coral, one must work via TFLite, and quantise the network to reflect the Coral’s capabilities. The full chain to go from SB3 to Coral is: SB3 (Torch) => ONNX => TensorFlow => TFLite => Coral.

The code linked above is a complete, minimal, example that:

1. Creates a model using SB3
2. Follows the path of exports all the way to TFLite and Google Coral
3. Demonstrates the forward pass for most exported variants

There are a number of pitfalls along the way to the complete conversion that this example covers, including:

- Making the Gym’s observation work with ONNX properly
- Quantising the TFLite model appropriately to align with Gym while still taking advantage of Coral
- Using OnnxablePolicy described as described in the above example

1.20.6 Manual export

You can also manually export required parameters (weights) and construct the network in your desired framework.

You can access parameters of the model via agents’ `get_parameters` function. As policies are also PyTorch modules, you can also access `model.policy.state_dict()` directly. To find the architecture of the networks for each algorithm, best is to check the `policies.py` file located in their respective folders.

Note: In most cases, we recommend using PyTorch methods `state_dict()` and `load_state_dict()` from the policy, unless you need to access the optimizers’ state dict too. In that case, you need to call `get_parameters()`.

Abstract base classes for RL algorithms.

1.21 Base RL Class

Common interface for all the RL algorithms

```
class stable_baselines3.common.base_class.BaseAlgorithm(policy, env, policy_base, learning_rate,
                                                    policy_kwargs=None,
                                                    tensorboard_log=None, verbose=0,
                                                    device='auto', support_multi_env=False,
                                                    create_eval_env=False,
                                                    monitor_wrapper=True, seed=None,
                                                    use_sde=False, sde_sample_freq=-1,
                                                    supported_action_spaces=None)
```

The base of RL algorithms

Parameters

- **policy** (Type[BasePolicy]) – Policy object
- **env** (Union[Env, [VecEnv](#), str, None]) – The environment to learn from (if registered in Gym, can be str. Can be None for loading trained models)
- **policy_base** (Type[BasePolicy]) – The base policy used by this method
- **learning_rate** (Union[float, Callable[[float], float]]) – learning rate for the optimizer, it can be a function of the current progress remaining (from 1 to 0)
- **policy_kwargs** (Optional[Dict[str, Any]]) – Additional arguments to be passed to the policy on creation
- **tensorboard_log** (Optional[str]) – the log location for tensorboard (if None, no logging)
- **verbose** (int) – The verbosity level: 0 none, 1 training information, 2 debug
- **device** (Union[device, str]) – Device on which the code should run. By default, it will try to use a Cuda compatible device and fallback to cpu if it is not possible.
- **support_multi_env** (bool) – Whether the algorithm supports training with multiple environments (as in A2C)
- **create_eval_env** (bool) – Whether to create a second environment that will be used for evaluating the agent periodically. (Only available when passing string for the environment)
- **monitor_wrapper** (bool) – When creating an environment, whether to wrap it or not in a Monitor wrapper.
- **seed** (Optional[int]) – Seed for the pseudo random generators
- **use_sde** (bool) – Whether to use generalized State Dependent Exploration (gSDE) instead of action noise exploration (default: False)
- **sde_sample_freq** (int) – Sample a new noise matrix every n steps when using gSDE Default: -1 (only sample at the beginning of the rollout)
- **supported_action_spaces** (Optional[Tuple[Space, ...]]) – The action spaces supported by the algorithm.

get_env()

Returns the current environment (can be None if not defined).

Return type Optional[[VecEnv](#)]

Returns The current environment

get_parameters()

Return the parameters of the agent. This includes parameters from different networks, e.g. critics (value functions) and policies (pi functions).

Return type Dict[str, Dict]

Returns Mapping of from names of the objects to PyTorch state-dicts.

get_vec_normalize_env()

Return the VecNormalize wrapper of the training env if it exists.

Return type Optional[VecNormalize]

Returns The VecNormalize env.

abstract learn(total_timesteps, callback=None, log_interval=100, tb_log_name='run', eval_env=None, eval_freq=-1, n_eval_episodes=5, eval_log_path=None, reset_num_timesteps=True)

Return a trained model.

Parameters

- **total_timesteps** (int) – The total number of samples (env steps) to train on
- **callback** (Union[None, Callable, List[BaseCallback], BaseCallback]) – callback(s) called at every step with state of the algorithm.
- **log_interval** (int) – The number of timesteps before logging.
- **tb_log_name** (str) – the name of the run for TensorBoard logging
- **eval_env** (Union[Env, VecEnv, None]) – Environment that will be used to evaluate the agent
- **eval_freq** (int) – Evaluate the agent every eval_freq timesteps (this may vary a little)
- **n_eval_episodes** (int) – Number of episode to evaluate the agent
- **eval_log_path** (Optional[str]) – Path to a folder where the evaluations will be saved
- **reset_num_timesteps** (bool) – whether or not to reset the current timestep number (used in logging)

Return type BaseAlgorithm

Returns the trained model

classmethod load(path, env=None, device='auto', custom_objects=None, print_system_info=False, force_reset=True, **kwargs)

Load the model from a zip-file. Warning: load re-creates the model from scratch, it does not update it in-place! For an in-place load use set_parameters instead.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – path to the file (or a file-like) where to load the agent from
- **env** (Union[Env, VecEnv, None]) – the new environment to run the loaded model on (can be None if you only need prediction from a trained model) has priority over any saved environment
- **device** (Union[device, str]) – Device on which the code should run.
- **custom_objects** (Optional[Dict[str, Any]]) – Dictionary of objects to replace upon loading. If a variable is present in this dictionary as a key, it will not be deserialized and

the corresponding item will be used instead. Similar to `custom_objects` in `keras.models.load_model`. Useful when you have an object in file that can not be deserialized.

- **print_system_info** (bool) – Whether to print system info from the saved model and the current system info (useful to debug loading issues)
- **force_reset** (bool) – Force call to `reset()` before training to avoid unexpected behavior. See <https://github.com/DLR-RM/stable-baselines3/issues/597>
- **kwargs** – extra arguments to change the model when loading

Return type `BaseAlgorithm`

Returns new model instance with loaded parameters

property logger: `stable_baselines3.common.logger.Logger`

Getter for the logger object.

Return type `Logger`

predict(*observation, state=None, episode_start=None, deterministic=False*)

Get the policy action from an observation (and optional hidden state). Includes sugar-coating to handle different observations (e.g. normalizing images).

Parameters

- **observation** (ndarray) – the input observation
- **state** (Optional[Tuple[ndarray, ...]]) – The last hidden states (can be None, used in recurrent policies)
- **episode_start** (Optional[ndarray]) – The last masks (can be None, used in recurrent policies) this correspond to beginning of episodes, where the hidden states of the RNN must be reset.
- **deterministic** (bool) – Whether or not to return deterministic actions.

Return type `Tuple[ndarray, Optional[Tuple[ndarray, ...]]]`

Returns the model's action and the next hidden state (used in recurrent policies)

save(*path, exclude=None, include=None*)

Save all the attributes of the object and the model parameters in a zip-file.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – path to the file where the rl agent should be saved
- **exclude** (Optional[Iterable[str]]) – name of parameters that should be excluded in addition to the default ones
- **include** (Optional[Iterable[str]]) – name of parameters that might be excluded but should be included anyway

Return type `None`

set_env(*env, force_reset=True*)

Checks the validity of the environment, and if it is coherent, set it as the current environment. Furthermore wrap any non vectorized env into a vectorized checked parameters: - `observation_space` - `action_space`

Parameters

- **env** (Union[Env, `VecEnv`]) – The environment for learning a policy

- **force_reset** (bool) – Force call to `reset()` before training to avoid unexpected behavior. See issue <https://github.com/DLR-RM/stable-baselines3/issues/597>

Return type None

set_logger(*logger*)

Setter for for logger object.

Warning: When passing a custom logger object, this will overwrite `tensorboard_log` and `verbose` settings passed to the constructor.

Return type None

set_parameters(*load_path_or_dict*, *exact_match=True*, *device='auto'*)

Load parameters from a given zip-file or a nested dictionary containing parameters for different modules (see `get_parameters`).

Parameters

- **load_path_or_iter** – Location of the saved data (path or file-like, see `save`), or a nested dictionary containing `nn.Module` parameters used by the policy. The dictionary maps object names to a state-dictionary returned by `torch.nn.Module.state_dict()`.
- **exact_match** (bool) – If True, the given parameters should include parameters for each module and each of their parameters, otherwise raises an Exception. If set to False, this can be used to update only specific parameters.
- **device** (Union[device, str]) – Device on which the code should run.

Return type None

set_random_seed(*seed=None*)

Set the seed of the pseudo-random generators (python, numpy, pytorch, gym, action_space)

Parameters *seed* (Optional[int]) –

Return type None

1.21.1 Base Off-Policy Class

The base RL algorithm for Off-Policy algorithm (ex: SAC/TD3)

```

class stable_baselines3.common.off_policy_algorithm.OffPolicyAlgorithm(policy, env,
                                                                    policy_base,
                                                                    learning_rate,
                                                                    buffer_size=1000000,
                                                                    learning_starts=100,
                                                                    batch_size=256,
                                                                    tau=0.005,
                                                                    gamma=0.99,
                                                                    train_freq=(1, 'step'),
                                                                    gradient_steps=1,
                                                                    action_noise=None, re-
                                                                    play_buffer_class=None, re-
                                                                    play_buffer_kwargs=None, opti-
                                                                    mize_memory_usage=False,
                                                                    policy_kwargs=None,
                                                                    tensorboard_log=None,
                                                                    verbose=0,
                                                                    device='auto', sup-
                                                                    port_multi_env=False,
                                                                    create_eval_env=False,
                                                                    moni-
                                                                    tor_wrapper=True,
                                                                    seed=None,
                                                                    use_sde=False,
                                                                    sde_sample_freq=-1,
                                                                    use_sde_at_warmup=False,
                                                                    sde_support=True, sup-
                                                                    ported_action_spaces=None)

```

The base for Off-Policy algorithms (ex: SAC/TD3)

Parameters

- **policy** (Type[BasePolicy]) – Policy object
- **env** (Union[Env, [VecEnv](#), str]) – The environment to learn from (if registered in Gym, can be str. Can be None for loading trained models)
- **policy_base** (Type[BasePolicy]) – The base policy used by this method
- **learning_rate** (Union[float, Callable[[float], float]]) – learning rate for the optimizer, it can be a function of the current progress remaining (from 1 to 0)
- **buffer_size** (int) – size of the replay buffer
- **learning_starts** (int) – how many steps of the model to collect transitions for before learning starts
- **batch_size** (int) – Minibatch size for each gradient update
- **tau** (float) – the soft update coefficient (“Polyak update”, between 0 and 1)
- **gamma** (float) – the discount factor
- **train_freq** (Union[int, Tuple[int, str]]) – Update the model every `train_freq` steps. Alternatively pass a tuple of frequency and unit like (5, "step") or (2, "episode").
- **gradient_steps** (int) – How many gradient steps to do after each rollout (see

`train_freq`) Set to -1 means to do as many gradient steps as steps done in the environment during the rollout.

- **action_noise** (Optional[[ActionNoise](#)]) – the action noise type (None by default), this can help for hard exploration problem. Cf `common.noise` for the different action noise type.
- **replay_buffer_class** (Optional[`ReplayBuffer`]) – Replay buffer class to use (for instance `HerReplayBuffer`). If None, it will be automatically selected.
- **replay_buffer_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the replay buffer on creation.
- **optimize_memory_usage** (bool) – Enable a memory efficient variant of the replay buffer at a cost of more complexity. See <https://github.com/DLR-RM/stable-baselines3/issues/37#issuecomment-637501195>
- **policy_kwargs** (Optional[Dict[str, Any]]) – Additional arguments to be passed to the policy on creation
- **tensorboard_log** (Optional[str]) – the log location for tensorboard (if None, no logging)
- **verbose** (int) – The verbosity level: 0 none, 1 training information, 2 debug
- **device** (Union[device, str]) – Device on which the code should run. By default, it will try to use a Cuda compatible device and fallback to cpu if it is not possible.
- **support_multi_env** (bool) – Whether the algorithm supports training with multiple environments (as in A2C)
- **create_eval_env** (bool) – Whether to create a second environment that will be used for evaluating the agent periodically. (Only available when passing string for the environment)
- **monitor_wrapper** (bool) – When creating an environment, whether to wrap it or not in a Monitor wrapper.
- **seed** (Optional[int]) – Seed for the pseudo random generators
- **use_sde** (bool) – Whether to use State Dependent Exploration (SDE) instead of action noise exploration (default: False)
- **sde_sample_freq** (int) – Sample a new noise matrix every n steps when using gSDE Default: -1 (only sample at the beginning of the rollout)
- **use_sde_at_warmup** (bool) – Whether to use gSDE instead of uniform sampling during the warm up phase (before learning starts)
- **sde_support** (bool) – Whether the model support gSDE or not
- **supported_action_spaces** (Optional[Tuple[Space, ...]]) – The action spaces supported by the algorithm.

collect_rollouts(*env, callback, train_freq, replay_buffer, action_noise=None, learning_starts=0, log_interval=None*)

Collect experiences and store them into a `ReplayBuffer`.

Parameters

- **env** ([VecEnv](#)) – The training environment
- **callback** ([BaseCallback](#)) – Callback that will be called at each step (and at the beginning and end of the rollout)

- **train_freq** (TrainFreq) – How much experience to collect by doing rollouts of current policy. Either TrainFreq(<n>, TrainFrequencyUnit.STEP) or TrainFreq(<n>, TrainFrequencyUnit.EPISODE) with <n> being an integer greater than 0.
- **action_noise** (Optional[ActionNoise]) – Action noise that will be used for exploration Required for deterministic policy (e.g. TD3). This can also be used in addition to the stochastic policy for SAC.
- **learning_starts** (int) – Number of steps before learning for the warm-up phase.
- **replay_buffer** (ReplayBuffer) –
- **log_interval** (Optional[int]) – Log data every log_interval episodes

Return type RolloutReturn

Returns

learn(total_timesteps, callback=None, log_interval=4, eval_env=None, eval_freq=-1, n_eval_episodes=5, tb_log_name='run', eval_log_path=None, reset_num_timesteps=True)

Return a trained model.

Parameters

- **total_timesteps** (int) – The total number of samples (env steps) to train on
- **callback** (Union[None, Callable, List[BaseCallback], BaseCallback]) – callback(s) called at every step with state of the algorithm.
- **log_interval** (int) – The number of timesteps before logging.
- **tb_log_name** (str) – the name of the run for TensorBoard logging
- **eval_env** (Union[Env, VecEnv, None]) – Environment that will be used to evaluate the agent
- **eval_freq** (int) – Evaluate the agent every eval_freq timesteps (this may vary a little)
- **n_eval_episodes** (int) – Number of episode to evaluate the agent
- **eval_log_path** (Optional[str]) – Path to a folder where the evaluations will be saved
- **reset_num_timesteps** (bool) – whether or not to reset the current timestep number (used in logging)

Return type OffPolicyAlgorithm

Returns the trained model

load_replay_buffer(path, truncate_last_traj=True)

Load a replay buffer from a pickle file.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – Path to the pickled replay buffer.
- **truncate_last_traj** (bool) – When using HerReplayBuffer with online sampling: If set to True, we assume that the last trajectory in the replay buffer was finished (and truncate it). If set to False, we assume that we continue the same trajectory (same episode).

Return type None

save_replay_buffer(path)

Save the replay buffer as a pickle file.

Parameters **path** (Union[str, Path, BufferedIOBase]) – Path to the file where the replay buffer should be saved. if path is a str or pathlib.Path, the path is automatically created if necessary.

Return type None

train(*gradient_steps*, *batch_size*)

Sample the replay buffer and do the updates (gradient descent and update target networks)

Return type None

1.21.2 Base On-Policy Class

The base RL algorithm for On-Policy algorithm (ex: A2C/PPO)

```
class stable_baselines3.common.on_policy_algorithm.OnPolicyAlgorithm(policy, env, learning_rate,
                                                                    n_steps, gamma,
                                                                    gae_lambda, ent_coef,
                                                                    vf_coef, max_grad_norm,
                                                                    use_sde, sde_sample_freq,
                                                                    policy_base=<class 'stable_baselines3.common.policies.ActorCriticPolicy'>,
                                                                    tensorboard_log=None,
                                                                    create_eval_env=False,
                                                                    monitor_wrapper=True,
                                                                    policy_kwargs=None,
                                                                    verbose=0, seed=None,
                                                                    device='auto',
                                                                    _init_setup_model=True,
                                                                    supported_action_spaces=None)
```

The base for On-Policy algorithms (ex: A2C/PPO).

Parameters

- **policy** (Union[str, Type[ActorCriticPolicy]]) – The policy model to use (MlpPolicy, CnnPolicy, ...)
- **env** (Union[Env, *VecEnv*, str]) – The environment to learn from (if registered in Gym, can be str)
- **learning_rate** (Union[float, Callable[[float], float]]) – The learning rate, it can be a function of the current progress remaining (from 1 to 0)
- **n_steps** (int) – The number of steps to run for each environment per update (i.e. batch size is n_steps * n_env where n_env is number of environment copies running in parallel)
- **gamma** (float) – Discount factor
- **gae_lambda** (float) – Factor for trade-off of bias vs variance for Generalized Advantage Estimator. Equivalent to classic advantage when set to 1.
- **ent_coef** (float) – Entropy coefficient for the loss calculation
- **vf_coef** (float) – Value function coefficient for the loss calculation
- **max_grad_norm** (float) – The maximum value for the gradient clipping
- **use_sde** (bool) – Whether to use generalized State Dependent Exploration (gSDE) instead of action noise exploration (default: False)

- **sde_sample_freq** (int) – Sample a new noise matrix every *n* steps when using gSDE
Default: -1 (only sample at the beginning of the rollout)
- **policy_base** (Type[BasePolicy]) – The base policy used by this method
- **tensorboard_log** (Optional[str]) – the log location for tensorboard (if None, no logging)
- **create_eval_env** (bool) – Whether to create a second environment that will be used for evaluating the agent periodically. (Only available when passing string for the environment)
- **monitor_wrapper** (bool) – When creating an environment, whether to wrap it or not in a Monitor wrapper.
- **policy_kwargs** (Optional[Dict[str, Any]]) – additional arguments to be passed to the policy on creation
- **verbose** (int) – the verbosity level: 0 no output, 1 info, 2 debug
- **seed** (Optional[int]) – Seed for the pseudo random generators
- **device** (Union[device, str]) – Device (cpu, cuda, ...) on which the code should be run. Setting it to auto, the code will be run on the GPU if possible.
- **_init_setup_model** (bool) – Whether or not to build the network at the creation of the instance
- **supported_action_spaces** (Optional[Tuple[Space, ...]]) – The action spaces supported by the algorithm.

collect_rollouts(*env, callback, rollout_buffer, n_rollout_steps*)

Collect experiences using the current policy and fill a `RolloutBuffer`. The term rollout here refers to the model-free notion and should not be used with the concept of rollout used in model-based RL or planning.

Parameters

- **env** (*VecEnv*) – The training environment
- **callback** (*BaseCallback*) – Callback that will be called at each step (and at the beginning and end of the rollout)
- **rollout_buffer** (*RolloutBuffer*) – Buffer to fill with rollouts
- **n_steps** – Number of experiences to collect per environment

Return type bool

Returns True if function returned with at least *n_rollout_steps* collected, False if callback terminated rollout prematurely.

learn(*total_timesteps, callback=None, log_interval=1, eval_env=None, eval_freq=-1, n_eval_episodes=5, tb_log_name='OnPolicyAlgorithm', eval_log_path=None, reset_num_timesteps=True*)

Return a trained model.

Parameters

- **total_timesteps** (int) – The total number of samples (env steps) to train on
- **callback** (Union[None, Callable, List[*BaseCallback*], *BaseCallback*]) – call-back(s) called at every step with state of the algorithm.
- **log_interval** (int) – The number of timesteps before logging.
- **tb_log_name** (str) – the name of the run for TensorBoard logging

- **eval_env** (Union[Env, [VecEnv](#), None]) – Environment that will be used to evaluate the agent
- **eval_freq** (int) – Evaluate the agent every eval_freq timesteps (this may vary a little)
- **n_eval_episodes** (int) – Number of episode to evaluate the agent
- **eval_log_path** (Optional[str]) – Path to a folder where the evaluations will be saved
- **reset_num_timesteps** (bool) – whether or not to reset the current timestep number (used in logging)

Return type [OnPolicyAlgorithm](#)

Returns the trained model

train()

Consume current rollout data and update policy parameters. Implemented by individual algorithms.

Return type None

1.22 A2C

A synchronous, deterministic variant of [Asynchronous Advantage Actor Critic \(A3C\)](#). It uses multiple workers to avoid the use of a replay buffer.

Warning: If you find training unstable or want to match performance of stable-baselines A2C, consider using `RMSpropTFLike` optimizer from `stable_baselines3.common.sb2_compat.rmsprop_tf_like`. You can change optimizer with `A2C(policy_kwargs=dict(optimizer_class=RMSpropTFLike, optimizer_kwargs=dict(eps=1e-5)))`. Read more [here](#).

1.22.1 Notes

- Original paper: <https://arxiv.org/abs/1602.01783>
- OpenAI blog post: <https://openai.com/blog/baselines-acktr-a2c/>

1.22.2 Can I use?

- Recurrent policies:
- Multi processing: ✓
- Gym spaces:

Space	Action	Observation
Discrete	✓	✓
Box	✓	✓
MultiDiscrete	✓	✓
MultiBinary	✓	✓
Dict		✓

1.22.3 Example

This example is only to demonstrate the use of the library and its functions, and the trained agents may not solve the environments. Optimized hyperparameters can be found in RL Zoo [repository](#).

Train a A2C agent on CartPole-v1 using 4 environments.

```
import gym

from stable_baselines3 import A2C
from stable_baselines3.common.env_util import make_vec_env

# Parallel environments
env = make_vec_env("CartPole-v1", n_envs=4)

model = A2C("MlpPolicy", env, verbose=1)
model.learn(total_timesteps=25000)
model.save("a2c_cartpole")

del model # remove to demonstrate saving and loading

model = A2C.load("a2c_cartpole")

obs = env.reset()
while True:
    action, _states = model.predict(obs)
    obs, rewards, dones, info = env.step(action)
    env.render()
```

1.22.4 Results

Atari Games

The complete learning curves are available in the [associated PR #110](#).

PyBullet Environments

Results on the PyBullet benchmark (2M steps) using 6 seeds. The complete learning curves are available in the [associated issue #48](#).

Note: Hyperparameters from the [gSDE paper](#) were used (as they are tuned for PyBullet envs).

Gaussian means that the unstructured Gaussian noise is used for exploration, *gSDE* (generalized State-Dependent Exploration) is used otherwise.

Environments	A2C	A2C	PPO	PPO
	Gaussian	gSDE	Gaussian	gSDE
HalfCheetah	2003 +/- 54	2032 +/- 122	1976 +/- 479	2826 +/- 45
Ant	2286 +/- 72	2443 +/- 89	2364 +/- 120	2782 +/- 76
Hopper	1627 +/- 158	1561 +/- 220	1567 +/- 339	2512 +/- 21
Walker2D	577 +/- 65	839 +/- 56	1230 +/- 147	2019 +/- 64

How to replicate the results?

Clone the `rl-zoo` repo:

```
git clone https://github.com/DLR-RM/rl-baselines3-zoo
cd rl-baselines3-zoo/
```

Run the benchmark (replace `$ENV_ID` by the envs mentioned above):

```
python train.py --algo a2c --env $ENV_ID --eval-episodes 10 --eval-freq 10000
```

Plot the results (here for PyBullet envs only):

```
python scripts/all_plots.py -a a2c -e HalfCheetah Ant Hopper Walker2D -f logs/ -o logs/
→ a2c_results
python scripts/plot_from_file.py -i logs/a2c_results.pkl -latex -l A2C
```

1.22.5 Parameters

```
class stable_baselines3.a2c.A2C(policy, env, learning_rate=0.0007, n_steps=5, gamma=0.99,
                                gae_lambda=1.0, ent_coef=0.0, vf_coef=0.5, max_grad_norm=0.5,
                                rms_prop_eps=1e-05, use_rms_prop=True, use_sde=False,
                                sde_sample_freq=-1, normalize_advantage=False,
                                tensorboard_log=None, create_eval_env=False, policy_kwargs=None,
                                verbose=0, seed=None, device='auto', _init_setup_model=True)
```

Advantage Actor Critic (A2C)

Paper: <https://arxiv.org/abs/1602.01783> Code: This implementation borrows code from <https://github.com/ikostrikov/pytorch-a2c-ppo-acktr-gail> and and Stable Baselines (<https://github.com/hill-a/stable-baselines>)

Introduction to A2C: <https://hackernoon.com/intuitive-rl-intro-to-advantage-actor-critic-a2c-4ff545978752>

Parameters

- **policy** (Union[str, Type[ActorCriticPolicy]]) – The policy model to use (MlpPolicy, CnnPolicy, ...)
- **env** (Union[Env, VecEnv, str]) – The environment to learn from (if registered in Gym, can be str)
- **learning_rate** (Union[float, Callable[[float], float]]) – The learning rate, it can be a function of the current progress remaining (from 1 to 0)
- **n_steps** (int) – The number of steps to run for each environment per update (i.e. batch size is `n_steps * n_env` where `n_env` is number of environment copies running in parallel)
- **gamma** (float) – Discount factor
- **gae_lambda** (float) – Factor for trade-off of bias vs variance for Generalized Advantage Estimator Equivalent to classic advantage when set to 1.
- **ent_coef** (float) – Entropy coefficient for the loss calculation
- **vf_coef** (float) – Value function coefficient for the loss calculation
- **max_grad_norm** (float) – The maximum value for the gradient clipping
- **rms_prop_eps** (float) – RMSProp epsilon. It stabilizes square root computation in denominator of RMSProp update

- **use_rms_prop** (bool) – Whether to use RMSprop (default) or Adam as optimizer
- **use_sde** (bool) – Whether to use generalized State Dependent Exploration (gSDE) instead of action noise exploration (default: False)
- **sde_sample_freq** (int) – Sample a new noise matrix every *n* steps when using gSDE
Default: -1 (only sample at the beginning of the rollout)
- **normalize_advantage** (bool) – Whether to normalize or not the advantage
- **tensorboard_log** (Optional[str]) – the log location for tensorboard (if None, no logging)
- **create_eval_env** (bool) – Whether to create a second environment that will be used for evaluating the agent periodically. (Only available when passing string for the environment)
- **policy_kwargs** (Optional[Dict[str, Any]]) – additional arguments to be passed to the policy on creation
- **verbose** (int) – the verbosity level: 0 no output, 1 info, 2 debug
- **seed** (Optional[int]) – Seed for the pseudo random generators
- **device** (Union[device, str]) – Device (cpu, cuda, ...) on which the code should be run. Setting it to auto, the code will be run on the GPU if possible.
- **_init_setup_model** (bool) – Whether or not to build the network at the creation of the instance

collect_rollouts(*env, callback, rollout_buffer, n_rollout_steps*)

Collect experiences using the current policy and fill a `RolloutBuffer`. The term rollout here refers to the model-free notion and should not be used with the concept of rollout used in model-based RL or planning.

Parameters

- **env** ([VecEnv](#)) – The training environment
- **callback** ([BaseCallback](#)) – Callback that will be called at each step (and at the beginning and end of the rollout)
- **rollout_buffer** (`RolloutBuffer`) – Buffer to fill with rollouts
- **n_steps** – Number of experiences to collect per environment

Return type bool

Returns True if function returned with at least *n_rollout_steps* collected, False if callback terminated rollout prematurely.

get_env()

Returns the current environment (can be None if not defined).

Return type Optional[[VecEnv](#)]

Returns The current environment

get_parameters()

Return the parameters of the agent. This includes parameters from different networks, e.g. critics (value functions) and policies (pi functions).

Return type Dict[str, Dict]

Returns Mapping of from names of the objects to PyTorch state-dicts.

get_vec_normalize_env()

Return the VecNormalize wrapper of the training env if it exists.

Return type Optional[VecNormalize]

Returns The VecNormalize env.

learn(total_timesteps, callback=None, log_interval=100, eval_env=None, eval_freq=-1, n_eval_episodes=5, tb_log_name='A2C', eval_log_path=None, reset_num_timesteps=True)

Return a trained model.

Parameters

- **total_timesteps** (int) – The total number of samples (env steps) to train on
- **callback** (Union[None, Callable, List[BaseCallback], BaseCallback]) – call-back(s) called at every step with state of the algorithm.
- **log_interval** (int) – The number of timesteps before logging.
- **tb_log_name** (str) – the name of the run for TensorBoard logging
- **eval_env** (Union[Env, VecEnv, None]) – Environment that will be used to evaluate the agent
- **eval_freq** (int) – Evaluate the agent every eval_freq timesteps (this may vary a little)
- **n_eval_episodes** (int) – Number of episode to evaluate the agent
- **eval_log_path** (Optional[str]) – Path to a folder where the evaluations will be saved
- **reset_num_timesteps** (bool) – whether or not to reset the current timestep number (used in logging)

Return type A2C

Returns the trained model

classmethod load(path, env=None, device='auto', custom_objects=None, print_system_info=False, force_reset=True, **kwargs)

Load the model from a zip-file. Warning: load re-creates the model from scratch, it does not update it in-place! For an in-place load use set_parameters instead.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – path to the file (or a file-like) where to load the agent from
- **env** (Union[Env, VecEnv, None]) – the new environment to run the loaded model on (can be None if you only need prediction from a trained model) has priority over any saved environment
- **device** (Union[device, str]) – Device on which the code should run.
- **custom_objects** (Optional[Dict[str, Any]]) – Dictionary of objects to replace upon loading. If a variable is present in this dictionary as a key, it will not be deserialized and the corresponding item will be used instead. Similar to custom_objects in keras.models.load_model. Useful when you have an object in file that can not be deserialized.
- **print_system_info** (bool) – Whether to print system info from the saved model and the current system info (useful to debug loading issues)
- **force_reset** (bool) – Force call to reset() before training to avoid unexpected behavior. See <https://github.com/DLR-RM/stable-baselines3/issues/597>

- **kwargs** – extra arguments to change the model when loading

Return type `BaseAlgorithm`

Returns new model instance with loaded parameters

property logger: `stable_baselines3.common.logger.Logger`

Getter for the logger object.

Return type `Logger`

predict(*observation, state=None, episode_start=None, deterministic=False*)

Get the policy action from an observation (and optional hidden state). Includes sugar-coating to handle different observations (e.g. normalizing images).

Parameters

- **observation** (ndarray) – the input observation
- **state** (Optional[Tuple[ndarray, ...]]) – The last hidden states (can be None, used in recurrent policies)
- **episode_start** (Optional[ndarray]) – The last masks (can be None, used in recurrent policies) this correspond to beginning of episodes, where the hidden states of the RNN must be reset.
- **deterministic** (bool) – Whether or not to return deterministic actions.

Return type Tuple[ndarray, Optional[Tuple[ndarray, ...]]]

Returns the model's action and the next hidden state (used in recurrent policies)

save(*path, exclude=None, include=None*)

Save all the attributes of the object and the model parameters in a zip-file.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – path to the file where the rl agent should be saved
- **exclude** (Optional[Iterable[str]]) – name of parameters that should be excluded in addition to the default ones
- **include** (Optional[Iterable[str]]) – name of parameters that might be excluded but should be included anyway

Return type None

set_env(*env, force_reset=True*)

Checks the validity of the environment, and if it is coherent, set it as the current environment. Furthermore wrap any non vectorized env into a vectorized checked parameters: - observation_space - action_space

Parameters

- **env** (Union[Env, `VecEnv`]) – The environment for learning a policy
- **force_reset** (bool) – Force call to `reset()` before training to avoid unexpected behavior. See issue <https://github.com/DLR-RM/stable-baselines3/issues/597>

Return type None

set_logger(*logger*)

Setter for for logger object.

Warning: When passing a custom logger object, this will overwrite `tensorboard_log` and `verbose` settings passed to the constructor.

Return type None

set_parameters(*load_path_or_dict*, *exact_match=True*, *device='auto'*)

Load parameters from a given zip-file or a nested dictionary containing parameters for different modules (see `get_parameters`).

Parameters

- **load_path_or_iter** – Location of the saved data (path or file-like, see `save`), or a nested dictionary containing `nn.Module` parameters used by the policy. The dictionary maps object names to a state-dictionary returned by `torch.nn.Module.state_dict()`.
- **exact_match** (bool) – If `True`, the given parameters should include parameters for each module and each of their parameters, otherwise raises an `Exception`. If set to `False`, this can be used to update only specific parameters.
- **device** (Union[device, str]) – Device on which the code should run.

Return type None

set_random_seed(*seed=None*)

Set the seed of the pseudo-random generators (python, numpy, pytorch, gym, action_space)

Parameters *seed* (Optional[int]) –

Return type None

train()

Update policy using the currently gathered rollout buffer (one gradient step over whole data).

Return type None

1.22.6 A2C Policies

stable_baselines3.a2c.MlpPolicy

alias of `stable_baselines3.common.policies.ActorCriticPolicy`

```
class stable_baselines3.common.policies.ActorCriticPolicy(observation_space, action_space,  
                                                    lr_schedule, net_arch=None,  
                                                    activation_fn=<class  
                                                    'torch.nn.modules.activation.Tanh'>,  
                                                    ortho_init=True, use_sde=False,  
                                                    log_std_init=0.0, full_std=True,  
                                                    sde_net_arch=None, use_expln=False,  
                                                    squash_output=False,  
                                                    features_extractor_class=<class 'sta-  
                                                    ble_baselines3.common.torch_layers.FlattenExtractor'>,  
                                                    features_extractor_kwargs=None,  
                                                    normalize_images=True,  
                                                    optimizer_class=<class  
                                                    'torch.optim.adam.Adam'>,  
                                                    optimizer_kwargs=None)
```

Policy class for actor-critic algorithms (has both policy and value prediction). Used by A2C, PPO and the likes.

Parameters

- **observation_space** (Space) – Observation space
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Optional[List[Union[int, Dict[str, List[int]]]]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **ortho_init** (bool) – Whether to use or not orthogonal initialization
- **use_sde** (bool) – Whether to use State Dependent Exploration or not
- **log_std_init** (float) – Initial value for the log standard deviation
- **full_std** (bool) – Whether to use (n_features x n_actions) parameters for the std instead of only (n_features,) when using gSDE
- **sde_net_arch** (Optional[List[int]]) – Network architecture for extracting features when using gSDE. If None, the latent features from the policy will be used. Pass an empty list to use the states as features.
- **use_expln** (bool) – Use `expln()` function instead of `exp()` to ensure a positive standard deviation (cf paper). It allows to keep variance above zero and prevent it from growing too fast. In practice, `exp()` is usually enough.
- **squash_output** (bool) – Whether to squash the output using a tanh function, this allows to ensure boundaries when using gSDE.
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Features extractor to use.
- **features_extractor_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the features extractor.
- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, `th.optim.Adam` by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer

evaluate_actions(*obs, actions*)

Evaluate actions according to the current policy, given the observations.

Parameters

- **obs** (Tensor) –
- **actions** (Tensor) –

Return type Tuple[Tensor, Tensor, Tensor]

Returns estimated value, log likelihood of taking those actions and entropy of the action distribution.

forward(*obs, deterministic=False*)

Forward pass in all the networks (actor and critic)

Parameters

- **obs** (Tensor) – Observation
- **deterministic** (bool) – Whether to sample or use deterministic actions

Return type Tuple[Tensor, Tensor, Tensor]

Returns action, value and log probability of the action

get_distribution(obs)

Get the current policy distribution given the observations.

Parameters obs (Tensor) –

Return type *Distribution*

Returns the action distribution.

predict_values(obs)

Get the estimated values according to the current policy given the observations.

Parameters obs (Tensor) –

Return type Tensor

Returns the estimated values.

reset_noise(n_envs=1)

Sample new weights for the exploration matrix.

Parameters n_envs (int) –

Return type None

stable_baselines3.a2c.**CnnPolicy**

alias of stable_baselines3.common.policies.ActorCriticCnnPolicy

```
class stable_baselines3.common.policies.ActorCriticCnnPolicy(observation_space, action_space,
                                                             lr_schedule, net_arch=None,
                                                             activation_fn=<class
                                                             'torch.nn.modules.activation.Tanh'>,
                                                             ortho_init=True, use_sde=False,
                                                             log_std_init=0.0, full_std=True,
                                                             sde_net_arch=None,
                                                             use_expln=False,
                                                             squash_output=False,
                                                             features_extractor_class=<class
                                                             'stable_baselines3.common.torch_layers.NatureCNN'>,
                                                             features_extractor_kwargs=None,
                                                             normalize_images=True,
                                                             optimizer_class=<class
                                                             'torch.optim.adam.Adam'>,
                                                             optimizer_kwargs=None)
```

CNN policy class for actor-critic algorithms (has both policy and value prediction). Used by A2C, PPO and the likes.

Parameters

- **observation_space** (Space) – Observation space
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)

- **net_arch** (Optional[List[Union[int, Dict[str, List[int]]]]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **ortho_init** (bool) – Whether to use or not orthogonal initialization
- **use_sde** (bool) – Whether to use State Dependent Exploration or not
- **log_std_init** (float) – Initial value for the log standard deviation
- **full_std** (bool) – Whether to use (n_features x n_actions) parameters for the std instead of only (n_features,) when using gSDE
- **sde_net_arch** (Optional[List[int]]) – Network architecture for extracting features when using gSDE. If None, the latent features from the policy will be used. Pass an empty list to use the states as features.
- **use_expln** (bool) – Use `expln()` function instead of `exp()` to ensure a positive standard deviation (cf paper). It allows to keep variance above zero and prevent it from growing too fast. In practice, `exp()` is usually enough.
- **squash_output** (bool) – Whether to squash the output using a tanh function, this allows to ensure boundaries when using gSDE.
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Features extractor to use.
- **features_extractor_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the features extractor.
- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, `th.optim.Adam` by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer

`stable_baselines3.a2c.MultiInputPolicy`

alias of `stable_baselines3.common.policies.MultiInputActorCriticPolicy`

```
class stable_baselines3.common.policies.MultiInputActorCriticPolicy(observation_space,
                                                                    action_space, lr_schedule,
                                                                    net_arch=None,
                                                                    activation_fn=<class
                                                                    'torch.nn.modules.activation.Tanh'>,
                                                                    ortho_init=True,
                                                                    use_sde=False,
                                                                    log_std_init=0.0,
                                                                    full_std=True,
                                                                    sde_net_arch=None,
                                                                    use_expln=False,
                                                                    squash_output=False, fea-
                                                                    tures_extractor_class=<class
                                                                    'sta-
                                                                    ble_baselines3.common.torch_layers.Combine
                                                                    fea-
                                                                    tures_extractor_kwards=None,
                                                                    normalize_images=True,
                                                                    optimizer_class=<class
                                                                    'torch.optim.adam.Adam'>,
                                                                    optimizer_kwards=None)
```

MultiInputActorClass policy class for actor-critic algorithms (has both policy and value prediction). Used by A2C, PPO and the likes.

Parameters

- **observation_space** (Dict) – Observation space (Tuple)
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Optional[List[Union[int, Dict[str, List[int]]]]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **ortho_init** (bool) – Whether to use or not orthogonal initialization
- **use_sde** (bool) – Whether to use State Dependent Exploration or not
- **log_std_init** (float) – Initial value for the log standard deviation
- **full_std** (bool) – Whether to use (n_features x n_actions) parameters for the std instead of only (n_features,) when using gSDE
- **sde_net_arch** (Optional[List[int]]) – Network architecture for extracting features when using gSDE. If None, the latent features from the policy will be used. Pass an empty list to use the states as features.
- **use_expln** (bool) – Use `expln()` function instead of `exp()` to ensure a positive standard deviation (cf paper). It allows to keep variance above zero and prevent it from growing too fast. In practice, `exp()` is usually enough.
- **squash_output** (bool) – Whether to squash the output using a tanh function, this allows to ensure boundaries when using gSDE.
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Uses the CombinedExtractor

- **features_extractor_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the feature extractor.
- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, `th.optim.Adam` by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer

1.23 DDPG

Deep Deterministic Policy Gradient (DDPG) combines the trick for DQN with the deterministic policy gradient, to obtain an algorithm for continuous actions.

Note: As DDPG can be seen as a special case of its successor *TD3*, they share the same policies and same implementation.

Available Policies

<i>MlpPolicy</i>	alias of <code>stable_baselines3.td3.policies.TD3Policy</code>
<code>CnnPolicy</code>	Policy class (with both actor and critic) for TD3.
<code>MultiInputPolicy</code>	Policy class (with both actor and critic) for TD3 to be used with Dict observation spaces.

1.23.1 Notes

- Deterministic Policy Gradient: <http://proceedings.mlr.press/v32/silver14.pdf>
- DDPG Paper: <https://arxiv.org/abs/1509.02971>
- OpenAI Spinning Guide for DDPG: <https://spinningup.openai.com/en/latest/algorithms/ddpg.html>

1.23.2 Can I use?

- Recurrent policies:
- Multi processing: ✓
- Gym spaces:

Space	Action	Observation
Discrete		✓
Box	✓	✓
MultiDiscrete		✓
MultiBinary		✓
Dict		✓

1.23.3 Example

This example is only to demonstrate the use of the library and its functions, and the trained agents may not solve the environments. Optimized hyperparameters can be found in RL Zoo [repository](#).

```
import gym
import numpy as np

from stable_baselines3 import DDPG
from stable_baselines3.common.noise import NormalActionNoise,
↳ OrnsteinUhlenbeckActionNoise

env = gym.make("Pendulum-v1")

# The noise objects for DDPG
n_actions = env.action_space.shape[-1]
action_noise = NormalActionNoise(mean=np.zeros(n_actions), sigma=0.1 * np.ones(n_
↳ actions))

model = DDPG("MlpPolicy", env, action_noise=action_noise, verbose=1)
model.learn(total_timesteps=100000, log_interval=10)
model.save("ddpg_pendulum")
env = model.get_env()

del model # remove to demonstrate saving and loading

model = DDPG.load("ddpg_pendulum")

obs = env.reset()
while True:
    action, _states = model.predict(obs)
    obs, rewards, dones, info = env.step(action)
    env.render()
```

1.23.4 Results

PyBullet Environments

Results on the PyBullet benchmark (1M steps) using 6 seeds. The complete learning curves are available in the [associated issue #48](#).

Note: Hyperparameters of *TD3* from the [gSDE paper](#) were used for DDPG.

Gaussian means that the unstructured Gaussian noise is used for exploration, *gSDE* (generalized State-Dependent Exploration) is used otherwise.

Environments	DDPG	TD3	SAC
	Gaussian	Gaussian	gSDE
HalfCheetah	2272 +/- 69	2774 +/- 35	2984 +/- 202
Ant	1651 +/- 407	3305 +/- 43	3102 +/- 37
Hopper	1201 +/- 211	2429 +/- 126	2262 +/- 1
Walker2D	882 +/- 186	2063 +/- 185	2136 +/- 67

How to replicate the results?

Clone the [rl-zoo](#) repo:

```
git clone https://github.com/DLR-RM/rl-baselines3-zoo
cd rl-baselines3-zoo/
```

Run the benchmark (replace \$ENV_ID by the envs mentioned above):

```
python train.py --algo ddpq --env $ENV_ID --eval-episodes 10 --eval-freq 10000
```

Plot the results:

```
python scripts/all_plots.py -a ddpq -e HalfCheetah Ant Hopper Walker2D -f logs/ -o logs/
  ↳ ddpq_results
python scripts/plot_from_file.py -i logs/ddpq_results.pkl -latex -l DDPG
```

1.23.5 Parameters

```
class stable_baselines3.ddpg.DDPG(policy, env, learning_rate=0.001, buffer_size=1000000,
    learning_starts=100, batch_size=100, tau=0.005, gamma=0.99,
    train_freq=(1, 'episode'), gradient_steps=-1, action_noise=None,
    replay_buffer_class=None, replay_buffer_kwargs=None,
    optimize_memory_usage=False, tensorboard_log=None,
    create_eval_env=False, policy_kwargs=None, verbose=0, seed=None,
    device='auto', _init_setup_model=True)
```

Deep Deterministic Policy Gradient (DDPG).

Deterministic Policy Gradient: <http://proceedings.mlr.press/v32/silver14.pdf> DDPG Paper: <https://arxiv.org/abs/1509.02971> Introduction to DDPG: <https://spinningup.openai.com/en/latest/algorithms/ddpg.html>

Note: we treat DDPG as a special case of its successor TD3.

Parameters

- **policy** (Union[str, Type[TD3Policy]]) – The policy model to use (MlpPolicy, CnnPolicy, ...)
- **env** (Union[Env, VecEnv, str]) – The environment to learn from (if registered in Gym, can be str)
- **learning_rate** (Union[float, Callable[[float], float]]) – learning rate for adam optimizer, the same learning rate will be used for all networks (Q-Values, Actor and Value function) it can be a function of the current progress remaining (from 1 to 0)
- **buffer_size** (int) – size of the replay buffer

- **learning_starts** (int) – how many steps of the model to collect transitions for before learning starts
- **batch_size** (int) – Minibatch size for each gradient update
- **tau** (float) – the soft update coefficient (“Polyak update”, between 0 and 1)
- **gamma** (float) – the discount factor
- **train_freq** (Union[int, Tuple[int, str]]) – Update the model every `train_freq` steps. Alternatively pass a tuple of frequency and unit like (5, "step") or (2, "episode").
- **gradient_steps** (int) – How many gradient steps to do after each rollout (see `train_freq`) Set to -1 means to do as many gradient steps as steps done in the environment during the rollout.
- **action_noise** (Optional[[ActionNoise](#)]) – the action noise type (None by default), this can help for hard exploration problem. Cf `common.noise` for the different action noise type.
- **replay_buffer_class** (Optional[ReplayBuffer]) – Replay buffer class to use (for instance `HerReplayBuffer`). If None, it will be automatically selected.
- **replay_buffer_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the replay buffer on creation.
- **optimize_memory_usage** (bool) – Enable a memory efficient variant of the replay buffer at a cost of more complexity. See <https://github.com/DLR-RM/stable-baselines3/issues/37#issuecomment-637501195>
- **create_eval_env** (bool) – Whether to create a second environment that will be used for evaluating the agent periodically. (Only available when passing string for the environment)
- **policy_kwargs** (Optional[Dict[str, Any]]) – additional arguments to be passed to the policy on creation
- **verbose** (int) – the verbosity level: 0 no output, 1 info, 2 debug
- **seed** (Optional[int]) – Seed for the pseudo random generators
- **device** (Union[device, str]) – Device (cpu, cuda, ...) on which the code should be run. Setting it to auto, the code will be run on the GPU if possible.
- **_init_setup_model** (bool) – Whether or not to build the network at the creation of the instance

collect_rollouts(*env, callback, train_freq, replay_buffer, action_noise=None, learning_starts=0, log_interval=None*)

Collect experiences and store them into a `ReplayBuffer`.

Parameters

- **env** ([VecEnv](#)) – The training environment
- **callback** ([BaseCallback](#)) – Callback that will be called at each step (and at the beginning and end of the rollout)
- **train_freq** (`TrainFreq`) – How much experience to collect by doing rollouts of current policy. Either `TrainFreq(<n>, TrainFrequencyUnit.STEP)` or `TrainFreq(<n>, TrainFrequencyUnit.EPISODE)` with `<n>` being an integer greater than 0.
- **action_noise** (Optional[[ActionNoise](#)]) – Action noise that will be used for exploration Required for deterministic policy (e.g. TD3). This can also be used in addition to the stochastic policy for SAC.
- **learning_starts** (int) – Number of steps before learning for the warm-up phase.

- **replay_buffer** (ReplayBuffer) –
- **log_interval** (Optional[int]) – Log data every log_interval episodes

Return type RolloutReturn

Returns

get_env()

Returns the current environment (can be None if not defined).

Return type Optional[VecEnv]

Returns The current environment

get_parameters()

Return the parameters of the agent. This includes parameters from different networks, e.g. critics (value functions) and policies (pi functions).

Return type Dict[str, Dict]

Returns Mapping of from names of the objects to PyTorch state-dicts.

get_vec_normalize_env()

Return the VecNormalize wrapper of the training env if it exists.

Return type Optional[VecNormalize]

Returns The VecNormalize env.

learn(total_timesteps, callback=None, log_interval=4, eval_env=None, eval_freq=1, n_eval_episodes=5, tb_log_name='DDPG', eval_log_path=None, reset_num_timesteps=True)

Return a trained model.

Parameters

- **total_timesteps** (int) – The total number of samples (env steps) to train on
- **callback** (Union[None, Callable, List[BaseCallback], BaseCallback]) – call-back(s) called at every step with state of the algorithm.
- **log_interval** (int) – The number of timesteps before logging.
- **tb_log_name** (str) – the name of the run for TensorBoard logging
- **eval_env** (Union[Env, VecEnv, None]) – Environment that will be used to evaluate the agent
- **eval_freq** (int) – Evaluate the agent every eval_freq timesteps (this may vary a little)
- **n_eval_episodes** (int) – Number of episode to evaluate the agent
- **eval_log_path** (Optional[str]) – Path to a folder where the evaluations will be saved
- **reset_num_timesteps** (bool) – whether or not to reset the current timestep number (used in logging)

Return type OffPolicyAlgorithm

Returns the trained model

classmethod load(path, env=None, device='auto', custom_objects=None, print_system_info=False, force_reset=True, **kwargs)

Load the model from a zip-file. Warning: load re-creates the model from scratch, it does not update it in-place! For an in-place load use set_parameters instead.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – path to the file (or a file-like) where to load the agent from
- **env** (Union[Env, *VecEnv*, None]) – the new environment to run the loaded model on (can be None if you only need prediction from a trained model) has priority over any saved environment
- **device** (Union[device, str]) – Device on which the code should run.
- **custom_objects** (Optional[Dict[str, Any]]) – Dictionary of objects to replace upon loading. If a variable is present in this dictionary as a key, it will not be deserialized and the corresponding item will be used instead. Similar to custom_objects in `keras.models.load_model`. Useful when you have an object in file that can not be deserialized.
- **print_system_info** (bool) – Whether to print system info from the saved model and the current system info (useful to debug loading issues)
- **force_reset** (bool) – Force call to `reset()` before training to avoid unexpected behavior. See <https://github.com/DLR-RM/stable-baselines3/issues/597>
- **kwargs** – extra arguments to change the model when loading

Return type *BaseAlgorithm***Returns** new model instance with loaded parameters**load_replay_buffer**(*path, truncate_last_traj=True*)

Load a replay buffer from a pickle file.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – Path to the pickled replay buffer.
- **truncate_last_traj** (bool) – When using `HerReplayBuffer` with online sampling: If set to `True`, we assume that the last trajectory in the replay buffer was finished (and truncate it). If set to `False`, we assume that we continue the same trajectory (same episode).

Return type None**property logger:** *stable_baselines3.common.logger.Logger*

Getter for the logger object.

Return type *Logger***predict**(*observation, state=None, episode_start=None, deterministic=False*)

Get the policy action from an observation (and optional hidden state). Includes sugar-coating to handle different observations (e.g. normalizing images).

Parameters

- **observation** (ndarray) – the input observation
- **state** (Optional[Tuple[ndarray, ...]]) – The last hidden states (can be None, used in recurrent policies)
- **episode_start** (Optional[ndarray]) – The last masks (can be None, used in recurrent policies) this correspond to beginning of episodes, where the hidden states of the RNN must be reset.
- **deterministic** (bool) – Whether or not to return deterministic actions.

Return type Tuple[ndarray, Optional[Tuple[ndarray, ...]]]

Returns the model's action and the next hidden state (used in recurrent policies)

save(*path*, *exclude=None*, *include=None*)

Save all the attributes of the object and the model parameters in a zip-file.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – path to the file where the rl agent should be saved
- **exclude** (Optional[Iterable[str]]) – name of parameters that should be excluded in addition to the default ones
- **include** (Optional[Iterable[str]]) – name of parameters that might be excluded but should be included anyway

Return type None

save_replay_buffer(*path*)

Save the replay buffer as a pickle file.

Parameters **path** (Union[str, Path, BufferedIOBase]) – Path to the file where the replay buffer should be saved. if path is a str or pathlib.Path, the path is automatically created if necessary.

Return type None

set_env(*env*, *force_reset=True*)

Checks the validity of the environment, and if it is coherent, set it as the current environment. Furthermore wrap any non vectorized env into a vectorized checked parameters: - observation_space - action_space

Parameters

- **env** (Union[Env, *VecEnv*]) – The environment for learning a policy
- **force_reset** (bool) – Force call to `reset()` before training to avoid unexpected behavior. See issue <https://github.com/DLR-RM/stable-baselines3/issues/597>

Return type None

set_logger(*logger*)

Setter for for logger object.

Warning: When passing a custom logger object, this will overwrite `tensorboard_log` and `verbose` settings passed to the constructor.

Return type None

set_parameters(*load_path_or_dict*, *exact_match=True*, *device='auto'*)

Load parameters from a given zip-file or a nested dictionary containing parameters for different modules (see `get_parameters`).

Parameters

- **load_path_or_iter** – Location of the saved data (path or file-like, see `save`), or a nested dictionary containing `nn.Module` parameters used by the policy. The dictionary maps object names to a state-dictionary returned by `torch.nn.Module.state_dict()`.

- **exact_match** (bool) – If True, the given parameters should include parameters for each module and each of their parameters, otherwise raises an Exception. If set to False, this can be used to update only specific parameters.
- **device** (Union[device, str]) – Device on which the code should run.

Return type None

set_random_seed(seed=None)

Set the seed of the pseudo-random generators (python, numpy, pytorch, gym, action_space)

Parameters **seed** (Optional[int]) –

Return type None

train(gradient_steps, batch_size=100)

Sample the replay buffer and do the updates (gradient descent and update target networks)

Return type None

1.23.6 DDPG Policies

stable_baselines3.ddpg.MlpPolicy

alias of stable_baselines3.td3.policies.TD3Policy

```
class stable_baselines3.td3.policies.TD3Policy(observation_space, action_space, lr_schedule,
                                              net_arch=None, activation_fn=<class
                                              'torch.nn.modules.activation.ReLU'>,
                                              features_extractor_class=<class 'stable_baselines3.common.torch_layers.FlattenExtractor'>,
                                              features_extractor_kwargs=None,
                                              normalize_images=True, optimizer_class=<class
                                              'torch.optim.adam.Adam'>, optimizer_kwargs=None,
                                              n_critics=2, share_features_extractor=True)
```

Policy class (with both actor and critic) for TD3.

Parameters

- **observation_space** (Space) – Observation space
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Union[List[int], Dict[str, List[int]], None]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Features extractor to use.
- **features_extractor_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the features extractor.
- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, th.optim.Adam by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer

- **n_critics** (int) – Number of critic networks to create.
- **share_features_extractor** (bool) – Whether to share or not the features extractor between the actor and the critic (this saves computation time)

forward(*observation*, *deterministic=False*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

Return type Tensor

set_training_mode(*mode*)

Put the policy in either training or evaluation mode.

This affects certain modules, such as batch normalisation and dropout.

Parameters *mode* (bool) – if true, set to training mode, else set to evaluation mode

Return type None

```
class stable_baselines3.ddpg.CnnPolicy(observation_space, action_space, lr_schedule, net_arch=None,
                                     activation_fn=<class 'torch.nn.modules.activation.ReLU'>,
                                     features_extractor_class=<class 'stable_baselines3.common.torch_layers.NatureCNN'>,
                                     features_extractor_kwargs=None, normalize_images=True,
                                     optimizer_class=<class 'torch.optim.adam.Adam'>,
                                     optimizer_kwargs=None, n_critics=2,
                                     share_features_extractor=True)
```

Policy class (with both actor and critic) for TD3.

Parameters

- **observation_space** (Space) – Observation space
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Union[List[int], Dict[str, List[int]], None]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Features extractor to use.
- **features_extractor_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the features extractor.
- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, `th.optim.Adam` by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer

- **n_critics** (int) – Number of critic networks to create.
- **share_features_extractor** (bool) – Whether to share or not the features extractor between the actor and the critic (this saves computation time)

```
class stable_baselines3.ddpg.MultiInputPolicy(observation_space, action_space, lr_schedule,
                                              net_arch=None, activation_fn=<class
                                              'torch.nn.modules.activation.ReLU'>,
                                              features_extractor_class=<class 'sta-
                                              ble_baselines3.common.torch_layers.CombinedExtractor'>,
                                              features_extractor_kwargs=None,
                                              normalize_images=True, optimizer_class=<class
                                              'torch.optim.adam.Adam'>, optimizer_kwargs=None,
                                              n_critics=2, share_features_extractor=True)
```

Policy class (with both actor and critic) for TD3 to be used with Dict observation spaces.

Parameters

- **observation_space** (Dict) – Observation space
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Union[List[int], Dict[str, List[int]], None]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Features extractor to use.
- **features_extractor_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the features extractor.
- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, `th.optim.Adam` by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer
- **n_critics** (int) – Number of critic networks to create.
- **share_features_extractor** (bool) – Whether to share or not the features extractor between the actor and the critic (this saves computation time)

1.24 DQN

Deep Q Network (DQN) builds on [Fitted Q-Iteration \(FQI\)](#) and make use of different tricks to stabilize the learning with neural networks: it uses a replay buffer, a target network and gradient clipping.

Available Policies

<i>MlpPolicy</i>	alias of <code>stable_baselines3.dqn.policies.DQNPoly</code>
<i>CnnPolicy</i>	Policy class for DQN when using images as input.
<i>MultiInputPolicy</i>	Policy class for DQN when using dict observations as input.

1.24.1 Notes

- Original paper: <https://arxiv.org/abs/1312.5602>
- Further reference: <https://www.nature.com/articles/nature14236>

Note: This implementation provides only vanilla Deep Q-Learning and has no extensions such as Double-DQN, Dueling-DQN and Prioritized Experience Replay.

1.24.2 Can I use?

- Recurrent policies:
- Multi processing: ✓
- Gym spaces:

Space	Action	Observation
Discrete	✓	✓
Box		✓
MultiDiscrete		✓
MultiBinary		✓
Dict		✓

1.24.3 Example

This example is only to demonstrate the use of the library and its functions, and the trained agents may not solve the environments. Optimized hyperparameters can be found in RL Zoo [repository](#).

```
import gym

from stable_baselines3 import DQN

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

model = DQN("MlpPolicy", env, verbose=1)
model.learn(total_timesteps=10000, log_interval=4)
model.save("dqn_cartpole")

del model # remove to demonstrate saving and loading
```

(continues on next page)

(continued from previous page)

```

model = DQN.load("dqn_cartpole")

obs = env.reset()
while True:
    action, _states = model.predict(obs, deterministic=True)
    obs, reward, done, info = env.step(action)
    env.render()
    if done:
        obs = env.reset()

```

1.24.4 Results

Atari Games

The complete learning curves are available in the [associated PR #110](#).

How to replicate the results?

Clone the [rl-zoo](#) repo:

```

git clone https://github.com/DLR-RM/rl-baselines3-zoo
cd rl-baselines3-zoo/

```

Run the benchmark (replace \$ENV_ID by the env id, for instance BreakoutNoFrameskip-v4):

```
python train.py --algo dqn --env $ENV_ID --eval-episodes 10 --eval-freq 10000
```

Plot the results:

```
python scripts/all_plots.py -a dqn -e Pong Breakout -f logs/ -o logs/dqn_results
python scripts/plot_from_file.py -i logs/dqn_results.pkl -latex -l DQN
```

1.24.5 Parameters

```

class stable_baselines3.dqn.DQN(policy, env, learning_rate=0.0001, buffer_size=1000000,
    learning_starts=50000, batch_size=32, tau=1.0, gamma=0.99,
    train_freq=4, gradient_steps=1, replay_buffer_class=None,
    replay_buffer_kwargs=None, optimize_memory_usage=False,
    target_update_interval=10000, exploration_fraction=0.1,
    exploration_initial_eps=1.0, exploration_final_eps=0.05,
    max_grad_norm=10, tensorboard_log=None, create_eval_env=False,
    policy_kwargs=None, verbose=0, seed=None, device='auto',
    _init_setup_model=True)

```

Deep Q-Network (DQN)

Paper: <https://arxiv.org/abs/1312.5602>, <https://www.nature.com/articles/nature14236> Default hyperparameters are taken from the nature paper, except for the optimizer and learning rate that were taken from Stable Baselines defaults.

Parameters

- **policy** (Union[str, Type[DQNPolicy]]) – The policy model to use (MlpPolicy, CnnPolicy, ...)
- **env** (Union[Env, *VecEnv*, str]) – The environment to learn from (if registered in Gym, can be str)
- **learning_rate** (Union[float, Callable[[float], float]]) – The learning rate, it can be a function of the current progress remaining (from 1 to 0)
- **buffer_size** (int) – size of the replay buffer
- **learning_starts** (int) – how many steps of the model to collect transitions for before learning starts
- **batch_size** (int) – Minibatch size for each gradient update
- **tau** (float) – the soft update coefficient (“Polyak update”, between 0 and 1) default 1 for hard update
- **gamma** (float) – the discount factor
- **train_freq** (Union[int, Tuple[int, str]]) – Update the model every train_freq steps. Alternatively pass a tuple of frequency and unit like (5, "step") or (2, "episode").
- **gradient_steps** (int) – How many gradient steps to do after each rollout (see train_freq) Set to -1 means to do as many gradient steps as steps done in the environment during the rollout.
- **replay_buffer_class** (Optional[ReplayBuffer]) – Replay buffer class to use (for instance HerReplayBuffer). If None, it will be automatically selected.
- **replay_buffer_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the replay buffer on creation.
- **optimize_memory_usage** (bool) – Enable a memory efficient variant of the replay buffer at a cost of more complexity. See <https://github.com/DLR-RM/stable-baselines3/issues/37#issuecomment-637501195>
- **target_update_interval** (int) – update the target network every target_update_interval environment steps.
- **exploration_fraction** (float) – fraction of entire training period over which the exploration rate is reduced
- **exploration_initial_eps** (float) – initial value of random action probability
- **exploration_final_eps** (float) – final value of random action probability
- **max_grad_norm** (float) – The maximum value for the gradient clipping
- **tensorboard_log** (Optional[str]) – the log location for tensorboard (if None, no logging)
- **create_eval_env** (bool) – Whether to create a second environment that will be used for evaluating the agent periodically. (Only available when passing string for the environment)
- **policy_kwargs** (Optional[Dict[str, Any]]) – additional arguments to be passed to the policy on creation
- **verbose** (int) – the verbosity level: 0 no output, 1 info, 2 debug
- **seed** (Optional[int]) – Seed for the pseudo random generators
- **device** (Union[device, str]) – Device (cpu, cuda, ...) on which the code should be run. Setting it to auto, the code will be run on the GPU if possible.

- **_init_setup_model** (bool) – Whether or not to build the network at the creation of the instance

collect_rollouts(*env, callback, train_freq, replay_buffer, action_noise=None, learning_starts=0, log_interval=None*)

Collect experiences and store them into a ReplayBuffer.

Parameters

- **env** (*VecEnv*) – The training environment
- **callback** (*BaseCallback*) – Callback that will be called at each step (and at the beginning and end of the rollout)
- **train_freq** (*TrainFreq*) – How much experience to collect by doing rollouts of current policy. Either *TrainFreq(<n>, TrainFrequencyUnit.STEP)* or *TrainFreq(<n>, TrainFrequencyUnit.EPISODE)* with <n> being an integer greater than 0.
- **action_noise** (*Optional[ActionNoise]*) – Action noise that will be used for exploration Required for deterministic policy (e.g. TD3). This can also be used in addition to the stochastic policy for SAC.
- **learning_starts** (int) – Number of steps before learning for the warm-up phase.
- **replay_buffer** (*ReplayBuffer*) –
- **log_interval** (*Optional[int]*) – Log data every log_interval episodes

Return type *RolloutReturn*

Returns

get_env()

Returns the current environment (can be None if not defined).

Return type *Optional[VecEnv]*

Returns The current environment

get_parameters()

Return the parameters of the agent. This includes parameters from different networks, e.g. critics (value functions) and policies (pi functions).

Return type *Dict[str, Dict]*

Returns Mapping of from names of the objects to PyTorch state-dicts.

get_vec_normalize_env()

Return the VecNormalize wrapper of the training env if it exists.

Return type *Optional[VecNormalize]*

Returns The VecNormalize env.

learn(*total_timesteps, callback=None, log_interval=4, eval_env=None, eval_freq=-1, n_eval_episodes=5, tb_log_name='DQN', eval_log_path=None, reset_num_timesteps=True*)

Return a trained model.

Parameters

- **total_timesteps** (int) – The total number of samples (env steps) to train on
- **callback** (*Union[None, Callable, List[BaseCallback], BaseCallback]*) – call-back(s) called at every step with state of the algorithm.

- **log_interval** (int) – The number of timesteps before logging.
- **tb_log_name** (str) – the name of the run for TensorBoard logging
- **eval_env** (Union[Env, [VecEnv](#), None]) – Environment that will be used to evaluate the agent
- **eval_freq** (int) – Evaluate the agent every eval_freq timesteps (this may vary a little)
- **n_eval_episodes** (int) – Number of episode to evaluate the agent
- **eval_log_path** (Optional[str]) – Path to a folder where the evaluations will be saved
- **reset_num_timesteps** (bool) – whether or not to reset the current timestep number (used in logging)

Return type [OffPolicyAlgorithm](#)

Returns the trained model

classmethod **load**(path, env=None, device='auto', custom_objects=None, print_system_info=False, force_reset=True, **kwargs)

Load the model from a zip-file. Warning: load re-creates the model from scratch, it does not update it in-place! For an in-place load use `set_parameters` instead.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – path to the file (or a file-like) where to load the agent from
- **env** (Union[Env, [VecEnv](#), None]) – the new environment to run the loaded model on (can be None if you only need prediction from a trained model) has priority over any saved environment
- **device** (Union[device, str]) – Device on which the code should run.
- **custom_objects** (Optional[Dict[str, Any]]) – Dictionary of objects to replace upon loading. If a variable is present in this dictionary as a key, it will not be deserialized and the corresponding item will be used instead. Similar to `custom_objects` in `keras.models.load_model`. Useful when you have an object in file that can not be deserialized.
- **print_system_info** (bool) – Whether to print system info from the saved model and the current system info (useful to debug loading issues)
- **force_reset** (bool) – Force call to `reset()` before training to avoid unexpected behavior. See <https://github.com/DLR-RM/stable-baselines3/issues/597>
- **kwargs** – extra arguments to change the model when loading

Return type [BaseAlgorithm](#)

Returns new model instance with loaded parameters

load_replay_buffer(path, truncate_last_traj=True)

Load a replay buffer from a pickle file.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – Path to the pickled replay buffer.
- **truncate_last_traj** (bool) – When using `HerReplayBuffer` with online sampling: If set to `True`, we assume that the last trajectory in the replay buffer was finished (and truncate it). If set to `False`, we assume that we continue the same trajectory (same episode).

Return type None

property logger: `stable_baselines3.common.logger.Logger`

Getter for the logger object.

Return type `Logger`

predict(*observation*, *state=None*, *episode_start=None*, *deterministic=False*)

Overrides the base_class predict function to include epsilon-greedy exploration.

Parameters

- **observation** (ndarray) – the input observation
- **state** (Optional[Tuple[ndarray, ...]]) – The last states (can be None, used in recurrent policies)
- **episode_start** (Optional[ndarray]) – The last masks (can be None, used in recurrent policies)
- **deterministic** (bool) – Whether or not to return deterministic actions.

Return type `Tuple[ndarray, Optional[Tuple[ndarray, ...]]]`

Returns the model's action and the next state (used in recurrent policies)

save(*path*, *exclude=None*, *include=None*)

Save all the attributes of the object and the model parameters in a zip-file.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – path to the file where the rl agent should be saved
- **exclude** (Optional[Iterable[str]]) – name of parameters that should be excluded in addition to the default ones
- **include** (Optional[Iterable[str]]) – name of parameters that might be excluded but should be included anyway

Return type `None`

save_replay_buffer(*path*)

Save the replay buffer as a pickle file.

Parameters **path** (Union[str, Path, BufferedIOBase]) – Path to the file where the replay buffer should be saved. if path is a str or pathlib.Path, the path is automatically created if necessary.

Return type `None`

set_env(*env*, *force_reset=True*)

Checks the validity of the environment, and if it is coherent, set it as the current environment. Furthermore wrap any non vectorized env into a vectorized checked parameters: - observation_space - action_space

Parameters

- **env** (Union[Env, `VecEnv`]) – The environment for learning a policy
- **force_reset** (bool) – Force call to `reset()` before training to avoid unexpected behavior. See issue <https://github.com/DLR-RM/stable-baselines3/issues/597>

Return type `None`

set_logger(*logger*)

Setter for for logger object.

Warning: When passing a custom logger object, this will overwrite `tensorboard_log` and `verbose` settings passed to the constructor.

Return type None

set_parameters(*load_path_or_dict*, *exact_match=True*, *device='auto'*)

Load parameters from a given zip-file or a nested dictionary containing parameters for different modules (see `get_parameters`).

Parameters

- **load_path_or_iter** – Location of the saved data (path or file-like, see `save`), or a nested dictionary containing `nn.Module` parameters used by the policy. The dictionary maps object names to a state-dictionary returned by `torch.nn.Module.state_dict()`.
- **exact_match** (bool) – If True, the given parameters should include parameters for each module and each of their parameters, otherwise raises an Exception. If set to False, this can be used to update only specific parameters.
- **device** (Union[device, str]) – Device on which the code should run.

Return type None

set_random_seed(*seed=None*)

Set the seed of the pseudo-random generators (python, numpy, pytorch, gym, action_space)

Parameters **seed** (Optional[int]) –

Return type None

train(*gradient_steps*, *batch_size=100*)

Sample the replay buffer and do the updates (gradient descent and update target networks)

Return type None

1.24.6 DQN Policies

`stable_baselines3.dqn.MlpPolicy`

alias of `stable_baselines3.dqn.policies.DQNPoly`

```
class stable_baselines3.dqn.policies.DQNPoly(observation_space, action_space, lr_schedule,
                                             net_arch=None, activation_fn=<class
                                             'torch.nn.modules.activation.ReLU'>,
                                             features_extractor_class=<class 'sta-
                                             ble_baselines3.common.torch_layers.FlattenExtractor'>,
                                             features_extractor_kwargs=None,
                                             normalize_images=True, optimizer_class=<class
                                             'torch.optim.adam.Adam'>, optimizer_kwargs=None)
```

Policy class with Q-Value Net and target net for DQN

Parameters

- **observation_space** (Space) – Observation space

- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Optional[List[int]]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Features extractor to use.
- **features_extractor_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the features extractor.
- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, `th.optim.Adam` by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer

forward(*obs*, *deterministic=True*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

Return type Tensor

set_training_mode(*mode*)

Put the policy in either training or evaluation mode.

This affects certain modules, such as batch normalisation and dropout.

Parameters *mode* (bool) – if true, set to training mode, else set to evaluation mode

Return type None

```
class stable_baselines3.dqn.CnnPolicy(observation_space, action_space, lr_schedule, net_arch=None,  
                                     activation_fn=<class 'torch.nn.modules.activation.ReLU'>,  
                                     features_extractor_class=<class  
                                     'stable_baselines3.common.torch_layers.NatureCNN'>,  
                                     features_extractor_kwargs=None, normalize_images=True,  
                                     optimizer_class=<class 'torch.optim.adam.Adam'>,  
                                     optimizer_kwargs=None)
```

Policy class for DQN when using images as input.

Parameters

- **observation_space** (Space) – Observation space
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Optional[List[int]]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function

- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Features extractor to use.
- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, `th.optim.Adam` by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer

```
class stable_baselines3.dqn.MultiInputPolicy(observation_space, action_space, lr_schedule,
                                           net_arch=None, activation_fn=<class
                                           'torch.nn.modules.activation.ReLU'>,
                                           features_extractor_class=<class 'sta-
                                           ble_baselines3.common.torch_layers.CombinedExtractor'>,
                                           features_extractor_kwargs=None,
                                           normalize_images=True, optimizer_class=<class
                                           'torch.optim.adam.Adam'>, optimizer_kwargs=None)
```

Policy class for DQN when using dict observations as input.

Parameters

- **observation_space** (Dict) – Observation space
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Optional[List[int]]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Features extractor to use.
- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, `th.optim.Adam` by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer

1.25 HER

Hindsight Experience Replay (HER)

HER is an algorithm that works with off-policy methods (DQN, SAC, TD3 and DDPG for example). HER uses the fact that even if a desired goal was not achieved, other goal may have been achieved during a rollout. It creates “virtual” transitions by relabeling transitions (changing the desired goal) from past episodes.

Warning: Starting from Stable Baselines3 v1.1.0, HER is no longer a separate algorithm but a replay buffer class `HerReplayBuffer` that must be passed to an off-policy algorithm when using `MultiInputPolicy` (to have Dict observation support).

Warning: HER requires the environment to inherit from `gym.GoalEnv`

Warning: For performance reasons, the maximum number of steps per episodes must be specified. In most cases, it will be inferred if you specify `max_episode_steps` when registering the environment or if you use a `gym.wrappers.TimeLimit` (and `env.spec` is not `None`). Otherwise, you can directly pass `max_episode_length` to the model constructor

Warning: Because it needs access to `env.compute_reward()` HER must be loaded with the env. If you just want to use the trained policy without instantiating the environment, we recommend saving the policy only.

1.25.1 Notes

- Original paper: <https://arxiv.org/abs/1707.01495>
- OpenAI paper: Plappert et al. (2018)
- OpenAI blog post: <https://openai.com/blog/ingredients-for-robotics-research/>

1.25.2 Can I use?

Please refer to the used model (DQN, QR-DQN, SAC, TQC, TD3, or DDPG) for that section.

1.25.3 Example

This example is only to demonstrate the use of the library and its functions, and the trained agents may not solve the environments. Optimized hyperparameters can be found in RL Zoo [repository](#).

```
from stable_baselines3 import HerReplayBuffer, DDPG, DQN, SAC, TD3
from stable_baselines3.her.goal_selection_strategy import GoalSelectionStrategy
from stable_baselines3.common.envs import BitFlippingEnv
from stable_baselines3.common.vec_env import DummyVecEnv

model_class = DQN # works also with SAC, DDPG and TD3
N_BITS = 15

env = BitFlippingEnv(n_bits=N_BITS, continuous=model_class in [DDPG, SAC, TD3], max_
↳ steps=N_BITS)

# Available strategies (cf paper): future, final, episode
goal_selection_strategy = 'future' # equivalent to GoalSelectionStrategy.FUTURE

# If True the HER transitions will get sampled online
online_sampling = True
# Time limit for the episodes
max_episode_length = N_BITS

# Initialize the model
```

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```

model = model_class(
    "MultiInputPolicy",
    env,
    replay_buffer_class=HerReplayBuffer,
    # Parameters for HER
    replay_buffer_kwargs=dict(
        n_sampled_goal=4,
        goal_selection_strategy=goal_selection_strategy,
        online_sampling=online_sampling,
        max_episode_length=max_episode_length,
    ),
    verbose=1,
)

# Train the model
model.learn(1000)

model.save("./her_bit_env")
# Because it needs access to `env.compute_reward()`
# HER must be loaded with the env
model = model_class.load('./her_bit_env', env=env)

obs = env.reset()
for _ in range(100):
    action, _ = model.predict(obs, deterministic=True)
    obs, reward, done, _ = env.step(action)

    if done:
        obs = env.reset()

```

1.25.4 Results

This implementation was tested on the `parking env` using 3 seeds.

The complete learning curves are available in the [associated PR #120](#).

How to replicate the results?

Clone the `rl-zoo` repo:

```

git clone https://github.com/DLR-RM/rl-baselines3-zoo
cd rl-baselines3-zoo/

```

Run the benchmark:

```
python train.py --algo tqc --env parking-v0 --eval-episodes 10 --eval-freq 10000
```

Plot the results:

```
python scripts/all_plots.py -a tqc -e parking-v0 -f logs/ --no-million
```

1.25.5 Parameters

1.25.6 HER Replay Buffer

```
class stable_baselines3.her.HerReplayBuffer(env, buffer_size, device='cpu', replay_buffer=None,
                                           max_episode_length=None, n_sampled_goal=4,
                                           goal_selection_strategy='future', online_sampling=True,
                                           handle_timeout_termination=True)
```

Hindsight Experience Replay (HER) buffer. Paper: <https://arxiv.org/abs/1707.01495>

Warning: For performance reasons, the maximum number of steps per episodes must be specified. In most cases, it will be inferred if you specify `max_episode_steps` when registering the environment or if you use a `gym.wrappers.TimeLimit` (and `env.spec` is not `None`). Otherwise, you can directly pass `max_episode_length` to the replay buffer constructor.

Replay buffer for sampling HER (Hindsight Experience Replay) transitions. In the online sampling case, these new transitions will not be saved in the replay buffer and will only be created at sampling time.

Parameters

- **env** (*VecEnv*) – The training environment
- **buffer_size** (int) – The size of the buffer measured in transitions.
- **max_episode_length** (Optional[int]) – The maximum length of an episode. If not specified, it will be automatically inferred if the environment uses a `gym.wrappers.TimeLimit` wrapper.
- **goal_selection_strategy** (Union[*GoalSelectionStrategy*, str]) – Strategy for sampling goals for replay. One of ['episode', 'final', 'future']
- **device** (Union[device, str]) – PyTorch device
- **n_sampled_goal** (int) – Number of virtual transitions to create per real transition, by sampling new goals.
- **handle_timeout_termination** (bool) – Handle timeout termination (due to time-limit) separately and treat the task as infinite horizon task. <https://github.com/DLR-RM/stable-baselines3/issues/284>

add(obs, next_obs, action, reward, done, infos)

Add elements to the buffer.

Return type None

extend(*args, **kwargs)

Add a new batch of transitions to the buffer

Return type None

reset()

Reset the buffer.

Return type None

sample(batch_size, env=None)

Sample function for online sampling of HER transition, this replaces the “regular” replay buffer `sample()` method in the `train()` function.

Parameters

- **batch_size** (int) – Number of element to sample
- **env** (Optional[[VecNormalize](#)]) – Associated gym VecEnv to normalize the observations/rewards when sampling

Return type DictReplayBufferSamples

Returns Samples.

sample_goals(*episode_indices, her_indices, transitions_indices*)

Sample goals based on goal_selection_strategy. This is a vectorized (fast) version.

Parameters

- **episode_indices** (ndarray) – Episode indices to use.
- **her_indices** (ndarray) – HER indices.
- **transitions_indices** (ndarray) – Transition indices to use.

Return type ndarray

Returns Return sampled goals.

set_env(*env*)

Sets the environment.

Parameters **env** ([VecEnv](#)) –

Return type None

size()

Return type int

Returns The current number of transitions in the buffer.

store_episode()

Increment episode counter and reset transition pointer.

Return type None

static swap_and_flatten(*arr*)

Swap and then flatten axes 0 (buffer_size) and 1 (n_envs) to convert shape from [n_steps, n_envs, ...] (when ... is the shape of the features) to [n_steps * n_envs, ...] (which maintain the order)

Parameters **arr** (ndarray) –

Return type ndarray

Returns

to_torch(*array, copy=True*)

Convert a numpy array to a PyTorch tensor. Note: it copies the data by default

Parameters

- **array** (ndarray) –
- **copy** (bool) – Whether to copy or not the data (may be useful to avoid changing things be reference)

Return type Tensor

Returns

truncate_last_trajectory()

Only for online sampling, called when loading the replay buffer. If called, we assume that the last trajectory in the replay buffer was finished (and truncate it). If not called, we assume that we continue the same trajectory (same episode).

Return type None

1.25.7 Goal Selection Strategies

class `stable_baselines3.her.GoalSelectionStrategy`(*value*)

The strategies for selecting new goals when creating artificial transitions.

1.26 PPO

The [Proximal Policy Optimization](#) algorithm combines ideas from A2C (having multiple workers) and TRPO (it uses a trust region to improve the actor).

The main idea is that after an update, the new policy should be not too far from the old policy. For that, ppo uses clipping to avoid too large update.

Note: PPO contains several modifications from the original algorithm not documented by OpenAI: advantages are normalized and value function can be also clipped .

1.26.1 Notes

- Original paper: <https://arxiv.org/abs/1707.06347>
- Clear explanation of PPO on Arxiv Insights channel: <https://www.youtube.com/watch?v=5P7I-xPq8u8>
- OpenAI blog post: <https://blog.openai.com/openai-baselines-ppo/>
- Spinning Up guide: <https://spinningup.openai.com/en/latest/algorithms/ppo.html>

1.26.2 Can I use?

- Recurrent policies:
- Multi processing: ✓
- Gym spaces:

Space	Action	Observation
Discrete	✓	✓
Box	✓	✓
MultiDiscrete	✓	✓
MultiBinary	✓	✓
Dict		✓

1.26.3 Example

This example is only to demonstrate the use of the library and its functions, and the trained agents may not solve the environments. Optimized hyperparameters can be found in RL Zoo [repository](#).

Train a PPO agent on CartPole-v1 using 4 environments.

```
import gym

from stable_baselines3 import PPO
from stable_baselines3.common.env_util import make_vec_env

# Parallel environments
env = make_vec_env("CartPole-v1", n_envs=4)

model = PPO("MlpPolicy", env, verbose=1)
model.learn(total_timesteps=25000)
model.save("ppo_cartpole")

del model # remove to demonstrate saving and loading

model = PPO.load("ppo_cartpole")

obs = env.reset()
while True:
    action, _states = model.predict(obs)
    obs, rewards, dones, info = env.step(action)
    env.render()
```

1.26.4 Results

Atari Games

The complete learning curves are available in the [associated PR #110](#).

PyBullet Environments

Results on the PyBullet benchmark (2M steps) using 6 seeds. The complete learning curves are available in the [associated issue #48](#).

Note: Hyperparameters from the [gSDE paper](#) were used (as they are tuned for PyBullet envs).

Gaussian means that the unstructured Gaussian noise is used for exploration, *gSDE* (generalized State-Dependent Exploration) is used otherwise.

Environments	A2C	A2C	PPO	PPO
	Gaussian	gSDE	Gaussian	gSDE
HalfCheetah	2003 +/- 54	2032 +/- 122	1976 +/- 479	2826 +/- 45
Ant	2286 +/- 72	2443 +/- 89	2364 +/- 120	2782 +/- 76
Hopper	1627 +/- 158	1561 +/- 220	1567 +/- 339	2512 +/- 21
Walker2D	577 +/- 65	839 +/- 56	1230 +/- 147	2019 +/- 64

How to replicate the results?

Clone the `rl-zoo` repo:

```
git clone https://github.com/DLR-RM/rl-baselines3-zoo
cd rl-baselines3-zoo/
```

Run the benchmark (replace `$ENV_ID` by the envs mentioned above):

```
python train.py --algo ppo --env $ENV_ID --eval-episodes 10 --eval-freq 10000
```

Plot the results (here for PyBullet envs only):

```
python scripts/all_plots.py -a ppo -e HalfCheetah Ant Hopper Walker2D -f logs/ -o logs/
→ ppo_results
python scripts/plot_from_file.py -i logs/ppo_results.pkl -latex -l PPO
```

1.26.5 Parameters

```
class stable_baselines3.ppo.PPO(policy, env, learning_rate=0.0003, n_steps=2048, batch_size=64,
                                n_epochs=10, gamma=0.99, gae_lambda=0.95, clip_range=0.2,
                                clip_range_vf=None, normalize_advantage=True, ent_coef=0.0,
                                vf_coef=0.5, max_grad_norm=0.5, use_sde=False, sde_sample_freq=-1,
                                target_kl=None, tensorboard_log=None, create_eval_env=False,
                                policy_kwargs=None, verbose=0, seed=None, device='auto',
                                _init_setup_model=True)
```

Proximal Policy Optimization algorithm (PPO) (clip version)

Paper: <https://arxiv.org/abs/1707.06347> Code: This implementation borrows code from OpenAI Spinning Up (<https://github.com/openai/spinningup/>) <https://github.com/ikostrikov/pytorch-a2c-ppo-acktr-gail> and and Stable Baselines (PPO2 from <https://github.com/hill-a/stable-baselines>)

Introduction to PPO: <https://spinningup.openai.com/en/latest/algorithms/ppo.html>

Parameters

- **policy** (Union[str, Type[ActorCriticPolicy]]) – The policy model to use (MlpPolicy, CnnPolicy, ...)
- **env** (Union[Env, VecEnv, str]) – The environment to learn from (if registered in Gym, can be str)
- **learning_rate** (Union[float, Callable[[float], float]]) – The learning rate, it can be a function of the current progress remaining (from 1 to 0)
- **n_steps** (int) – The number of steps to run for each environment per update (i.e. rollout buffer size is `n_steps * n_envs` where `n_envs` is number of environment copies running in parallel) NOTE: `n_steps * n_envs` must be greater than 1 (because of the advantage normalization) See <https://github.com/pytorch/pytorch/issues/29372>
- **batch_size** (int) – Minibatch size
- **n_epochs** (int) – Number of epoch when optimizing the surrogate loss
- **gamma** (float) – Discount factor
- **gae_lambda** (float) – Factor for trade-off of bias vs variance for Generalized Advantage Estimator

- **clip_range** (Union[float, Callable[[float], float]]) – Clipping parameter, it can be a function of the current progress remaining (from 1 to 0).
- **clip_range_vf** (Union[None, float, Callable[[float], float]]) – Clipping parameter for the value function, it can be a function of the current progress remaining (from 1 to 0). This is a parameter specific to the OpenAI implementation. If None is passed (default), no clipping will be done on the value function. IMPORTANT: this clipping depends on the reward scaling.
- **normalize_advantage** (bool) – Whether to normalize or not the advantage
- **ent_coef** (float) – Entropy coefficient for the loss calculation
- **vf_coef** (float) – Value function coefficient for the loss calculation
- **max_grad_norm** (float) – The maximum value for the gradient clipping
- **use_sde** (bool) – Whether to use generalized State Dependent Exploration (gSDE) instead of action noise exploration (default: False)
- **sde_sample_freq** (int) – Sample a new noise matrix every n steps when using gSDE Default: -1 (only sample at the beginning of the rollout)
- **target_kl** (Optional[float]) – Limit the KL divergence between updates, because the clipping is not enough to prevent large update see issue #213 (cf <https://github.com/hill-a/stable-baselines/issues/213>) By default, there is no limit on the kl div.
- **tensorboard_log** (Optional[str]) – the log location for tensorboard (if None, no logging)
- **create_eval_env** (bool) – Whether to create a second environment that will be used for evaluating the agent periodically. (Only available when passing string for the environment)
- **policy_kwargs** (Optional[Dict[str, Any]]) – additional arguments to be passed to the policy on creation
- **verbose** (int) – the verbosity level: 0 no output, 1 info, 2 debug
- **seed** (Optional[int]) – Seed for the pseudo random generators
- **device** (Union[device, str]) – Device (cpu, cuda, ...) on which the code should be run. Setting it to auto, the code will be run on the GPU if possible.
- **_init_setup_model** (bool) – Whether or not to build the network at the creation of the instance

collect_rollouts(*env, callback, rollout_buffer, n_rollout_steps*)

Collect experiences using the current policy and fill a `RolloutBuffer`. The term rollout here refers to the model-free notion and should not be used with the concept of rollout used in model-based RL or planning.

Parameters

- **env** ([VecEnv](#)) – The training environment
- **callback** ([BaseCallback](#)) – Callback that will be called at each step (and at the beginning and end of the rollout)
- **rollout_buffer** (`RolloutBuffer`) – Buffer to fill with rollouts
- **n_steps** – Number of experiences to collect per environment

Return type bool

Returns True if function returned with at least *n_rollout_steps* collected, False if callback terminated rollout prematurely.

get_env()

Returns the current environment (can be None if not defined).

Return type Optional[[VecEnv](#)]

Returns The current environment

get_parameters()

Return the parameters of the agent. This includes parameters from different networks, e.g. critics (value functions) and policies (pi functions).

Return type Dict[str, Dict]

Returns Mapping of from names of the objects to PyTorch state-dicts.

get_vec_normalize_env()

Return the VecNormalize wrapper of the training env if it exists.

Return type Optional[[VecNormalize](#)]

Returns The VecNormalize env.

learn(*total_timesteps*, *callback=None*, *log_interval=1*, *eval_env=None*, *eval_freq=- 1*, *n_eval_episodes=5*, *tb_log_name='PPO'*, *eval_log_path=None*, *reset_num_timesteps=True*)

Return a trained model.

Parameters

- **total_timesteps** (int) – The total number of samples (env steps) to train on
- **callback** (Union[None, Callable, List[[BaseCallback](#)], [BaseCallback](#)]) – call-back(s) called at every step with state of the algorithm.
- **log_interval** (int) – The number of timesteps before logging.
- **tb_log_name** (str) – the name of the run for TensorBoard logging
- **eval_env** (Union[Env, [VecEnv](#), None]) – Environment that will be used to evaluate the agent
- **eval_freq** (int) – Evaluate the agent every eval_freq timesteps (this may vary a little)
- **n_eval_episodes** (int) – Number of episode to evaluate the agent
- **eval_log_path** (Optional[str]) – Path to a folder where the evaluations will be saved
- **reset_num_timesteps** (bool) – whether or not to reset the current timestep number (used in logging)

Return type [PPO](#)

Returns the trained model

classmethod load(*path*, *env=None*, *device='auto'*, *custom_objects=None*, *print_system_info=False*, *force_reset=True*, ***kwargs*)

Load the model from a zip-file. Warning: load re-creates the model from scratch, it does not update it in-place! For an in-place load use `set_parameters` instead.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – path to the file (or a file-like) where to load the agent from

- **env** (Union[Env, *VecEnv*, None]) – the new environment to run the loaded model on (can be None if you only need prediction from a trained model) has priority over any saved environment
- **device** (Union[device, str]) – Device on which the code should run.
- **custom_objects** (Optional[Dict[str, Any]]) – Dictionary of objects to replace upon loading. If a variable is present in this dictionary as a key, it will not be deserialized and the corresponding item will be used instead. Similar to custom_objects in `keras.models.load_model`. Useful when you have an object in file that can not be deserialized.
- **print_system_info** (bool) – Whether to print system info from the saved model and the current system info (useful to debug loading issues)
- **force_reset** (bool) – Force call to `reset()` before training to avoid unexpected behavior. See <https://github.com/DLR-RM/stable-baselines3/issues/597>
- **kwargs** – extra arguments to change the model when loading

Return type *BaseAlgorithm*

Returns new model instance with loaded parameters

property logger: *stable_baselines3.common.logger.Logger*

Getter for the logger object.

Return type *Logger*

predict(*observation, state=None, episode_start=None, deterministic=False*)

Get the policy action from an observation (and optional hidden state). Includes sugar-coating to handle different observations (e.g. normalizing images).

Parameters

- **observation** (ndarray) – the input observation
- **state** (Optional[Tuple[ndarray, ...]]) – The last hidden states (can be None, used in recurrent policies)
- **episode_start** (Optional[ndarray]) – The last masks (can be None, used in recurrent policies) this correspond to beginning of episodes, where the hidden states of the RNN must be reset.
- **deterministic** (bool) – Whether or not to return deterministic actions.

Return type Tuple[ndarray, Optional[Tuple[ndarray, ...]]]

Returns the model's action and the next hidden state (used in recurrent policies)

save(*path, exclude=None, include=None*)

Save all the attributes of the object and the model parameters in a zip-file.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – path to the file where the rl agent should be saved
- **exclude** (Optional[Iterable[str]]) – name of parameters that should be excluded in addition to the default ones
- **include** (Optional[Iterable[str]]) – name of parameters that might be excluded but should be included anyway

Return type None

set_env(*env*, *force_reset=True*)

Checks the validity of the environment, and if it is coherent, set it as the current environment. Furthermore wrap any non vectorized env into a vectorized checked parameters: - observation_space - action_space

Parameters

- **env** (Union[Env, [VecEnv](#)]) – The environment for learning a policy
- **force_reset** (bool) – Force call to `reset()` before training to avoid unexpected behavior. See issue <https://github.com/DLR-RM/stable-baselines3/issues/597>

Return type None

set_logger(*logger*)

Setter for for logger object.

Warning: When passing a custom logger object, this will overwrite `tensorboard_log` and `verbose` settings passed to the constructor.

Return type None

set_parameters(*load_path_or_dict*, *exact_match=True*, *device='auto'*)

Load parameters from a given zip-file or a nested dictionary containing parameters for different modules (see `get_parameters`).

Parameters

- **load_path_or_iter** – Location of the saved data (path or file-like, see `save`), or a nested dictionary containing `nn.Module` parameters used by the policy. The dictionary maps object names to a state-dictionary returned by `torch.nn.Module.state_dict()`.
- **exact_match** (bool) – If True, the given parameters should include parameters for each module and each of their parameters, otherwise raises an Exception. If set to False, this can be used to update only specific parameters.
- **device** (Union[device, str]) – Device on which the code should run.

Return type None

set_random_seed(*seed=None*)

Set the seed of the pseudo-random generators (python, numpy, pytorch, gym, action_space)

Parameters **seed** (Optional[int]) –

Return type None

train()

Update policy using the currently gathered rollout buffer.

Return type None

1.26.6 PPO Policies

`stable_baselines3.ppo.MlpPolicy`

alias of `stable_baselines3.common.policies.ActorCriticPolicy`

```
class stable_baselines3.common.policies.ActorCriticPolicy(observation_space, action_space,
                                                         lr_schedule, net_arch=None,
                                                         activation_fn=<class
                                                         'torch.nn.modules.activation.Tanh'>,
                                                         ortho_init=True, use_sde=False,
                                                         log_std_init=0.0, full_std=True,
                                                         sde_net_arch=None, use_expln=False,
                                                         squash_output=False,
                                                         features_extractor_class=<class 'sta-
                                                         ble_baselines3.common.torch_layers.FlattenExtractor'>,
                                                         features_extractor_kwargs=None,
                                                         normalize_images=True,
                                                         optimizer_class=<class
                                                         'torch.optim.adam.Adam'>,
                                                         optimizer_kwargs=None)
```

Policy class for actor-critic algorithms (has both policy and value prediction). Used by A2C, PPO and the likes.

Parameters

- **observation_space** (Space) – Observation space
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Optional[List[Union[int, Dict[str, List[int]]]]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **ortho_init** (bool) – Whether to use or not orthogonal initialization
- **use_sde** (bool) – Whether to use State Dependent Exploration or not
- **log_std_init** (float) – Initial value for the log standard deviation
- **full_std** (bool) – Whether to use (n_features x n_actions) parameters for the std instead of only (n_features,) when using gSDE
- **sde_net_arch** (Optional[List[int]]) – Network architecture for extracting features when using gSDE. If None, the latent features from the policy will be used. Pass an empty list to use the states as features.
- **use_expln** (bool) – Use `expln()` function instead of `exp()` to ensure a positive standard deviation (cf paper). It allows to keep variance above zero and prevent it from growing too fast. In practice, `exp()` is usually enough.
- **squash_output** (bool) – Whether to squash the output using a tanh function, this allows to ensure boundaries when using gSDE.
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Features extractor to use.
- **features_extractor_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the features extractor.

- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, `th.optim.Adam` by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer

evaluate_actions(*obs, actions*)

Evaluate actions according to the current policy, given the observations.

Parameters

- **obs** (Tensor) –
- **actions** (Tensor) –

Return type Tuple[Tensor, Tensor, Tensor]

Returns estimated value, log likelihood of taking those actions and entropy of the action distribution.

forward(*obs, deterministic=False*)

Forward pass in all the networks (actor and critic)

Parameters

- **obs** (Tensor) – Observation
- **deterministic** (bool) – Whether to sample or use deterministic actions

Return type Tuple[Tensor, Tensor, Tensor]

Returns action, value and log probability of the action

get_distribution(*obs*)

Get the current policy distribution given the observations.

Parameters **obs** (Tensor) –

Return type *Distribution*

Returns the action distribution.

predict_values(*obs*)

Get the estimated values according to the current policy given the observations.

Parameters **obs** (Tensor) –

Return type Tensor

Returns the estimated values.

reset_noise(*n_envs=1*)

Sample new weights for the exploration matrix.

Parameters **n_envs** (int) –

Return type None

`stable_baselines3.ppo.CnnPolicy`

alias of `stable_baselines3.common.policies.ActorCriticCnnPolicy`

```

class stable_baselines3.common.policies.ActorCriticCnnPolicy(observation_space, action_space,
                                                            lr_schedule, net_arch=None,
                                                            activation_fn=<class
                                                                'torch.nn.modules.activation.Tanh'>,
                                                            ortho_init=True, use_sde=False,
                                                            log_std_init=0.0, full_std=True,
                                                            sde_net_arch=None,
                                                            use_expln=False,
                                                            squash_output=False,
                                                            features_extractor_class=<class
                                                                'stable_baselines3.common.torch_layers.NatureCNN'>,
                                                            features_extractor_kwargs=None,
                                                            normalize_images=True,
                                                            optimizer_class=<class
                                                                'torch.optim.adam.Adam'>,
                                                            optimizer_kwargs=None)

```

CNN policy class for actor-critic algorithms (has both policy and value prediction). Used by A2C, PPO and the likes.

Parameters

- **observation_space** (Space) – Observation space
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Optional[List[Union[int, Dict[str, List[int]]]]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **ortho_init** (bool) – Whether to use or not orthogonal initialization
- **use_sde** (bool) – Whether to use State Dependent Exploration or not
- **log_std_init** (float) – Initial value for the log standard deviation
- **full_std** (bool) – Whether to use (n_features x n_actions) parameters for the std instead of only (n_features,) when using gSDE
- **sde_net_arch** (Optional[List[int]]) – Network architecture for extracting features when using gSDE. If None, the latent features from the policy will be used. Pass an empty list to use the states as features.
- **use_expln** (bool) – Use `expln()` function instead of `exp()` to ensure a positive standard deviation (cf paper). It allows to keep variance above zero and prevent it from growing too fast. In practice, `exp()` is usually enough.
- **squash_output** (bool) – Whether to squash the output using a tanh function, this allows to ensure boundaries when using gSDE.
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Features extractor to use.
- **features_extractor_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the features extractor.
- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)

- **optimizer_class** (Type[Optimizer]) – The optimizer to use, th.optim.Adam by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer

stable_baselines3.ppo.**MultiInputPolicy**

alias of stable_baselines3.common.policies.MultiInputActorCriticPolicy

```
class stable_baselines3.common.policies.MultiInputActorCriticPolicy(observation_space,
                                                                    action_space, lr_schedule,
                                                                    net_arch=None,
                                                                    activation_fn=<class
                                                                    'torch.nn.modules.activation.Tanh'>,
                                                                    ortho_init=True,
                                                                    use_sde=False,
                                                                    log_std_init=0.0,
                                                                    full_std=True,
                                                                    sde_net_arch=None,
                                                                    use_expln=False,
                                                                    squash_output=False, fea-
                                                                    tures_extractor_class=<class
                                                                    'sta-
                                                                    ble_baselines3.common.torch_layers.Combine-
                                                                    fea-
                                                                    tures_extractor'>,
                                                                    normalize_images=True,
                                                                    optimizer_class=<class
                                                                    'torch.optim.adam.Adam'>,
                                                                    optimizer_kwargs=None)
```

MultiInputActorClass policy class for actor-critic algorithms (has both policy and value prediction). Used by A2C, PPO and the likes.

Parameters

- **observation_space** (Dict) – Observation space (Tuple)
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Optional[List[Union[int, Dict[str, List[int]]]]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **ortho_init** (bool) – Whether to use or not orthogonal initialization
- **use_sde** (bool) – Whether to use State Dependent Exploration or not
- **log_std_init** (float) – Initial value for the log standard deviation
- **full_std** (bool) – Whether to use (n_features x n_actions) parameters for the std instead of only (n_features,) when using gSDE
- **sde_net_arch** (Optional[List[int]]) – Network architecture for extracting features when using gSDE. If None, the latent features from the policy will be used. Pass an empty list to use the states as features.
- **use_expln** (bool) – Use `expln()` function instead of `exp()` to ensure a positive standard deviation (cf paper). It allows to keep variance above zero and prevent it from growing too fast. In practice, `exp()` is usually enough.

- **squash_output** (bool) – Whether to squash the output using a tanh function, this allows to ensure boundaries when using gSDE.
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Uses the CombinedExtractor
- **features_extractor_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the feature extractor.
- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, `th.optim.Adam` by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer

1.27 SAC

Soft Actor Critic (SAC) Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor.

SAC is the successor of [Soft Q-Learning SQL](#) and incorporates the double Q-learning trick from TD3. A key feature of SAC, and a major difference with common RL algorithms, is that it is trained to maximize a trade-off between expected return and entropy, a measure of randomness in the policy.

Available Policies

<i>MlpPolicy</i>	alias of <code>stable_baselines3.sac.policies.SACPolicy</code>
<i>CnnPolicy</i>	Policy class (with both actor and critic) for SAC.
<i>MultiInputPolicy</i>	Policy class (with both actor and critic) for SAC.

1.27.1 Notes

- Original paper: <https://arxiv.org/abs/1801.01290>
- OpenAI Spinning Guide for SAC: <https://spinningup.openai.com/en/latest/algorithms/sac.html>
- Original Implementation: <https://github.com/haarnoja/sac>
- Blog post on using SAC with real robots: <https://bair.berkeley.edu/blog/2018/12/14/sac/>

Note: In our implementation, we use an entropy coefficient (as in OpenAI Spinning or Facebook Horizon), which is the equivalent to the inverse of reward scale in the original SAC paper. The main reason is that it avoids having too high errors when updating the Q functions.

Note: The default policies for SAC differ a bit from others `MlpPolicy`: it uses ReLU instead of tanh activation, to match the original paper

1.27.2 Can I use?

- Recurrent policies:
- Multi processing: ✓
- Gym spaces:

Space	Action	Observation
Discrete		✓
Box	✓	✓
MultiDiscrete		✓
MultiBinary		✓
Dict		✓

1.27.3 Example

This example is only to demonstrate the use of the library and its functions, and the trained agents may not solve the environments. Optimized hyperparameters can be found in RL Zoo [repository](#).

```
import gym
import numpy as np

from stable_baselines3 import SAC

env = gym.make("Pendulum-v1")

model = SAC("MlpPolicy", env, verbose=1)
model.learn(total_timesteps=10000, log_interval=4)
model.save("sac_pendulum")

del model # remove to demonstrate saving and loading

model = SAC.load("sac_pendulum")

obs = env.reset()
while True:
    action, _states = model.predict(obs, deterministic=True)
    obs, reward, done, info = env.step(action)
    env.render()
    if done:
        obs = env.reset()
```

1.27.4 Results

PyBullet Environments

Results on the PyBullet benchmark (1M steps) using 3 seeds. The complete learning curves are available in the [associated issue #48](#).

Note: Hyperparameters from the [gSDE paper](#) were used (as they are tuned for PyBullet envs).

Gaussian means that the unstructured Gaussian noise is used for exploration, *gSDE* (generalized State-Dependent Exploration) is used otherwise.

Environments	SAC	SAC	TD3
	Gaussian	gSDE	Gaussian
HalfCheetah	2757 +/- 53	2984 +/- 202	2774 +/- 35
Ant	3146 +/- 35	3102 +/- 37	3305 +/- 43
Hopper	2422 +/- 168	2262 +/- 1	2429 +/- 126
Walker2D	2184 +/- 54	2136 +/- 67	2063 +/- 185

How to replicate the results?

Clone the [rl-zoo repo](#):

```
git clone https://github.com/DLR-RM/rl-baselines3-zoo
cd rl-baselines3-zoo/
```

Run the benchmark (replace \$ENV_ID by the envs mentioned above):

```
python train.py --algo sac --env $ENV_ID --eval-episodes 10 --eval-freq 10000
```

Plot the results:

```
python scripts/all_plots.py -a sac -e HalfCheetah Ant Hopper Walker2D -f logs/ -o logs/
→ sac_results
python scripts/plot_from_file.py -i logs/sac_results.pkl -latex -l SAC
```

1.27.5 Parameters

```
class stable_baselines3.sac.SAC(policy, env, learning_rate=0.0003, buffer_size=1000000,
                                learning_starts=100, batch_size=256, tau=0.005, gamma=0.99,
                                train_freq=1, gradient_steps=1, action_noise=None,
                                replay_buffer_class=None, replay_buffer_kwargs=None,
                                optimize_memory_usage=False, ent_coef='auto',
                                target_update_interval=1, target_entropy='auto', use_sde=False,
                                sde_sample_freq=-1, use_sde_at_warmup=False, tensorboard_log=None,
                                create_eval_env=False, policy_kwargs=None, verbose=0, seed=None,
                                device='auto', _init_setup_model=True)
```

Soft Actor-Critic (SAC) Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor, This implementation borrows code from original implementation (<https://github.com/haarnoja/sac>) from OpenAI Spinning Up (<https://github.com/openai/spinningup>), from the softlearning repo (<https://github.com/>

[rail-berkeley/softlearning/](#)) and from Stable Baselines (<https://github.com/hill-a/stable-baselines>) Paper: <https://arxiv.org/abs/1801.01290> Introduction to SAC: <https://spinningup.openai.com/en/latest/algorithms/sac.html>

Note: we use double q target and not value target as discussed in <https://github.com/hill-a/stable-baselines/issues/270>

Parameters

- **policy** (Union[str, Type[SACPolicy]]) – The policy model to use (MlpPolicy, CnnPolicy, ...)
- **env** (Union[Env, *VecEnv*, str]) – The environment to learn from (if registered in Gym, can be str)
- **learning_rate** (Union[float, Callable[[float], float]]) – learning rate for adam optimizer, the same learning rate will be used for all networks (Q-Values, Actor and Value function) it can be a function of the current progress remaining (from 1 to 0)
- **buffer_size** (int) – size of the replay buffer
- **learning_starts** (int) – how many steps of the model to collect transitions for before learning starts
- **batch_size** (int) – Minibatch size for each gradient update
- **tau** (float) – the soft update coefficient (“Polyak update”, between 0 and 1)
- **gamma** (float) – the discount factor
- **train_freq** (Union[int, Tuple[int, str]]) – Update the model every train_freq steps. Alternatively pass a tuple of frequency and unit like (5, "step") or (2, "episode").
- **gradient_steps** (int) – How many gradient steps to do after each rollout (see train_freq) Set to -1 means to do as many gradient steps as steps done in the environment during the rollout.
- **action_noise** (Optional[*ActionNoise*]) – the action noise type (None by default), this can help for hard exploration problem. Cf common.noise for the different action noise type.
- **replay_buffer_class** (Optional[ReplayBuffer]) – Replay buffer class to use (for instance HerReplayBuffer). If None, it will be automatically selected.
- **replay_buffer_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the replay buffer on creation.
- **optimize_memory_usage** (bool) – Enable a memory efficient variant of the replay buffer at a cost of more complexity. See <https://github.com/DLR-RM/stable-baselines3/issues/37#issuecomment-637501195>
- **ent_coef** (Union[str, float]) – Entropy regularization coefficient. (Equivalent to inverse of reward scale in the original SAC paper.) Controlling exploration/exploitation trade-off. Set it to ‘auto’ to learn it automatically (and ‘auto_0.1’ for using 0.1 as initial value)
- **target_update_interval** (int) – update the target network every target_network_update_freq gradient steps.
- **target_entropy** (Union[str, float]) – target entropy when learning ent_coef (ent_coef = ‘auto’)
- **use_sde** (bool) – Whether to use generalized State Dependent Exploration (gSDE) instead of action noise exploration (default: False)
- **sde_sample_freq** (int) – Sample a new noise matrix every n steps when using gSDE Default: -1 (only sample at the beginning of the rollout)

- **use_sde_at_warmup** (bool) – Whether to use gSDE instead of uniform sampling during the warm up phase (before learning starts)
- **create_eval_env** (bool) – Whether to create a second environment that will be used for evaluating the agent periodically. (Only available when passing string for the environment)
- **policy_kwargs** (Optional[Dict[str, Any]]) – additional arguments to be passed to the policy on creation
- **verbose** (int) – the verbosity level: 0 no output, 1 info, 2 debug
- **seed** (Optional[int]) – Seed for the pseudo random generators
- **device** (Union[device, str]) – Device (cpu, cuda, ...) on which the code should be run. Setting it to auto, the code will be run on the GPU if possible.
- **_init_setup_model** (bool) – Whether or not to build the network at the creation of the instance

collect_rollouts(*env, callback, train_freq, replay_buffer, action_noise=None, learning_starts=0, log_interval=None*)

Collect experiences and store them into a `ReplayBuffer`.

Parameters

- **env** ([VecEnv](#)) – The training environment
- **callback** ([BaseCallback](#)) – Callback that will be called at each step (and at the beginning and end of the rollout)
- **train_freq** (`TrainFreq`) – How much experience to collect by doing rollouts of current policy. Either `TrainFreq(<n>, TrainFrequencyUnit.STEP)` or `TrainFreq(<n>, TrainFrequencyUnit.EPISODE)` with <n> being an integer greater than 0.
- **action_noise** (Optional[[ActionNoise](#)]) – Action noise that will be used for exploration Required for deterministic policy (e.g. TD3). This can also be used in addition to the stochastic policy for SAC.
- **learning_starts** (int) – Number of steps before learning for the warm-up phase.
- **replay_buffer** (`ReplayBuffer`) –
- **log_interval** (Optional[int]) – Log data every `log_interval` episodes

Return type `RolloutReturn`

Returns

get_env()

Returns the current environment (can be None if not defined).

Return type Optional[[VecEnv](#)]

Returns The current environment

get_parameters()

Return the parameters of the agent. This includes parameters from different networks, e.g. critics (value functions) and policies (pi functions).

Return type Dict[str, Dict]

Returns Mapping of from names of the objects to PyTorch state-dicts.

get_vec_normalize_env()

Return the VecNormalize wrapper of the training env if it exists.

Return type Optional[VecNormalize]

Returns The VecNormalize env.

learn(total_timesteps, callback=None, log_interval=4, eval_env=None, eval_freq=-1, n_eval_episodes=5, tb_log_name='SAC', eval_log_path=None, reset_num_timesteps=True)

Return a trained model.

Parameters

- **total_timesteps** (int) – The total number of samples (env steps) to train on
- **callback** (Union[None, Callable, List[BaseCallback], BaseCallback]) – call-back(s) called at every step with state of the algorithm.
- **log_interval** (int) – The number of timesteps before logging.
- **tb_log_name** (str) – the name of the run for TensorBoard logging
- **eval_env** (Union[Env, VecEnv, None]) – Environment that will be used to evaluate the agent
- **eval_freq** (int) – Evaluate the agent every eval_freq timesteps (this may vary a little)
- **n_eval_episodes** (int) – Number of episode to evaluate the agent
- **eval_log_path** (Optional[str]) – Path to a folder where the evaluations will be saved
- **reset_num_timesteps** (bool) – whether or not to reset the current timestep number (used in logging)

Return type OffPolicyAlgorithm

Returns the trained model

classmethod load(path, env=None, device='auto', custom_objects=None, print_system_info=False, force_reset=True, **kwargs)

Load the model from a zip-file. Warning: load re-creates the model from scratch, it does not update it in-place! For an in-place load use set_parameters instead.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – path to the file (or a file-like) where to load the agent from
- **env** (Union[Env, VecEnv, None]) – the new environment to run the loaded model on (can be None if you only need prediction from a trained model) has priority over any saved environment
- **device** (Union[device, str]) – Device on which the code should run.
- **custom_objects** (Optional[Dict[str, Any]]) – Dictionary of objects to replace upon loading. If a variable is present in this dictionary as a key, it will not be deserialized and the corresponding item will be used instead. Similar to custom_objects in keras.models.load_model. Useful when you have an object in file that can not be deserialized.
- **print_system_info** (bool) – Whether to print system info from the saved model and the current system info (useful to debug loading issues)
- **force_reset** (bool) – Force call to reset() before training to avoid unexpected behavior. See <https://github.com/DLR-RM/stable-baselines3/issues/597>

- **kwargs** – extra arguments to change the model when loading

Return type *BaseAlgorithm*

Returns new model instance with loaded parameters

load_replay_buffer(*path, truncate_last_traj=True*)

Load a replay buffer from a pickle file.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – Path to the pickled replay buffer.
- **truncate_last_traj** (bool) – When using HerReplayBuffer with online sampling: If set to True, we assume that the last trajectory in the replay buffer was finished (and truncate it). If set to False, we assume that we continue the same trajectory (same episode).

Return type None

property logger: *stable_baselines3.common.logger.Logger*

Getter for the logger object.

Return type *Logger*

predict(*observation, state=None, episode_start=None, deterministic=False*)

Get the policy action from an observation (and optional hidden state). Includes sugar-coating to handle different observations (e.g. normalizing images).

Parameters

- **observation** (ndarray) – the input observation
- **state** (Optional[Tuple[ndarray, ...]]) – The last hidden states (can be None, used in recurrent policies)
- **episode_start** (Optional[ndarray]) – The last masks (can be None, used in recurrent policies) this correspond to beginning of episodes, where the hidden states of the RNN must be reset.
- **deterministic** (bool) – Whether or not to return deterministic actions.

Return type Tuple[ndarray, Optional[Tuple[ndarray, ...]]]

Returns the model's action and the next hidden state (used in recurrent policies)

save(*path, exclude=None, include=None*)

Save all the attributes of the object and the model parameters in a zip-file.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – path to the file where the rl agent should be saved
- **exclude** (Optional[Iterable[str]]) – name of parameters that should be excluded in addition to the default ones
- **include** (Optional[Iterable[str]]) – name of parameters that might be excluded but should be included anyway

Return type None

save_replay_buffer(*path*)

Save the replay buffer as a pickle file.

Parameters `path` (Union[str, Path, BufferedIOBase]) – Path to the file where the replay buffer should be saved. if path is a str or pathlib.Path, the path is automatically created if necessary.

Return type None

set_env(*env*, *force_reset=True*)

Checks the validity of the environment, and if it is coherent, set it as the current environment. Furthermore wrap any non vectorized env into a vectorized checked parameters: - observation_space - action_space

Parameters

- **env** (Union[Env, *VecEnv*]) – The environment for learning a policy
- **force_reset** (bool) – Force call to `reset()` before training to avoid unexpected behavior. See issue <https://github.com/DLR-RM/stable-baselines3/issues/597>

Return type None

set_logger(*logger*)

Setter for for logger object.

Warning: When passing a custom logger object, this will overwrite `tensorboard_log` and `verbose` settings passed to the constructor.

Return type None

set_parameters(*load_path_or_dict*, *exact_match=True*, *device='auto'*)

Load parameters from a given zip-file or a nested dictionary containing parameters for different modules (see `get_parameters`).

Parameters

- **load_path_or_iter** – Location of the saved data (path or file-like, see `save`), or a nested dictionary containing nn.Module parameters used by the policy. The dictionary maps object names to a state-dictionary returned by `torch.nn.Module.state_dict()`.
- **exact_match** (bool) – If True, the given parameters should include parameters for each module and each of their parameters, otherwise raises an Exception. If set to False, this can be used to update only specific parameters.
- **device** (Union[device, str]) – Device on which the code should run.

Return type None

set_random_seed(*seed=None*)

Set the seed of the pseudo-random generators (python, numpy, pytorch, gym, action_space)

Parameters `seed` (Optional[int]) –

Return type None

train(*gradient_steps*, *batch_size=64*)

Sample the replay buffer and do the updates (gradient descent and update target networks)

Return type None

1.27.6 SAC Policies

`stable_baselines3.sac.MlpPolicy`

alias of `stable_baselines3.sac.policies.SACPolicy`

```
class stable_baselines3.sac.policies.SACPolicy(observation_space, action_space, lr_schedule,
                                              net_arch=None, activation_fn=<class
                                              'torch.nn.modules.activation.ReLU'>, use_sde=False,
                                              log_std_init=-3, sde_net_arch=None,
                                              use_expln=False, clip_mean=2.0,
                                              features_extractor_class=<class 'sta-
                                              ble_baselines3.common.torch_layers.FlattenExtractor'>,
                                              features_extractor_kwargs=None,
                                              normalize_images=True, optimizer_class=<class
                                              'torch.optim.adam.Adam'>, optimizer_kwargs=None,
                                              n_critics=2, share_features_extractor=True)
```

Policy class (with both actor and critic) for SAC.

Parameters

- **observation_space** (Space) – Observation space
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Union[List[int], Dict[str, List[int]], None]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **use_sde** (bool) – Whether to use State Dependent Exploration or not
- **log_std_init** (float) – Initial value for the log standard deviation
- **sde_net_arch** (Optional[List[int]]) – Network architecture for extracting features when using gSDE. If None, the latent features from the policy will be used. Pass an empty list to use the states as features.
- **use_expln** (bool) – Use `expln()` function instead of `exp()` when using gSDE to ensure a positive standard deviation (cf paper). It allows to keep variance above zero and prevent it from growing too fast. In practice, `exp()` is usually enough.
- **clip_mean** (float) – Clip the mean output when using gSDE to avoid numerical instability.
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Features extractor to use.
- **features_extractor_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the features extractor.
- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, `th.optim.Adam` by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer
- **n_critics** (int) – Number of critic networks to create.
- **share_features_extractor** (bool) – Whether to share or not the features extractor between the actor and the critic (this saves computation time)

forward(*obs*, *deterministic=False*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

Return type Tensor

reset_noise(*batch_size=1*)

Sample new weights for the exploration matrix, when using gSDE.

Parameters *batch_size* (int) –

Return type None

set_training_mode(*mode*)

Put the policy in either training or evaluation mode.

This affects certain modules, such as batch normalisation and dropout.

Parameters *mode* (bool) – if true, set to training mode, else set to evaluation mode

Return type None

class `stable_baselines3.sac.CnnPolicy`(*observation_space*, *action_space*, *lr_schedule*, *net_arch=None*, *activation_fn=<class 'torch.nn.modules.activation.ReLU'>*, *use_sde=False*, *log_std_init=-3*, *sde_net_arch=None*, *use_expln=False*, *clip_mean=2.0*, *features_extractor_class=<class 'stable_baselines3.common.torch_layers.NatureCNN'>*, *features_extractor_kwargs=None*, *normalize_images=True*, *optimizer_class=<class 'torch.optim.adam.Adam'>*, *optimizer_kwargs=None*, *n_critics=2*, *share_features_extractor=True*)

Policy class (with both actor and critic) for SAC.

Parameters

- **observation_space** (Space) – Observation space
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Union[List[int], Dict[str, List[int]], None]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **use_sde** (bool) – Whether to use State Dependent Exploration or not
- **log_std_init** (float) – Initial value for the log standard deviation
- **sde_net_arch** (Optional[List[int]]) – Network architecture for extracting features when using gSDE. If None, the latent features from the policy will be used. Pass an empty list to use the states as features.

- **use_expln** (bool) – Use `expln()` function instead of `exp()` when using gSDE to ensure a positive standard deviation (cf paper). It allows to keep variance above zero and prevent it from growing too fast. In practice, `exp()` is usually enough.
- **clip_mean** (float) – Clip the mean output when using gSDE to avoid numerical instability.
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Features extractor to use.
- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, `th.optim.Adam` by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer
- **n_critics** (int) – Number of critic networks to create.
- **share_features_extractor** (bool) – Whether to share or not the features extractor between the actor and the critic (this saves computation time)

```
class stable_baselines3.sac.MultiInputPolicy(observation_space, action_space, lr_schedule,
                                           net_arch=None, activation_fn=<class
                                           'torch.nn.modules.activation.ReLU'>, use_sde=False,
                                           log_std_init=-3, sde_net_arch=None, use_expln=False,
                                           clip_mean=2.0, features_extractor_class=<class 'sta-
                                           ble_baselines3.common.torch_layers.CombinedExtractor'>,
                                           features_extractor_kwargs=None,
                                           normalize_images=True, optimizer_class=<class
                                           'torch.optim.adam.Adam'>, optimizer_kwargs=None,
                                           n_critics=2, share_features_extractor=True)
```

Policy class (with both actor and critic) for SAC.

Parameters

- **observation_space** (Space) – Observation space
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Union[List[int], Dict[str, List[int]], None]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **use_sde** (bool) – Whether to use State Dependent Exploration or not
- **log_std_init** (float) – Initial value for the log standard deviation
- **sde_net_arch** (Optional[List[int]]) – Network architecture for extracting features when using gSDE. If None, the latent features from the policy will be used. Pass an empty list to use the states as features.
- **use_expln** (bool) – Use `expln()` function instead of `exp()` when using gSDE to ensure a positive standard deviation (cf paper). It allows to keep variance above zero and prevent it from growing too fast. In practice, `exp()` is usually enough.
- **clip_mean** (float) – Clip the mean output when using gSDE to avoid numerical instability.
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Features extractor to use.

- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, `th.optim.Adam` by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer
- **n_critics** (int) – Number of critic networks to create.
- **share_features_extractor** (bool) – Whether to share or not the features extractor between the actor and the critic (this saves computation time)

1.28 TD3

Twin Delayed DDPG (TD3) Addressing Function Approximation Error in Actor-Critic Methods.

TD3 is a direct successor of *DDPG* and improves it using three major tricks: clipped double Q-Learning, delayed policy update and target policy smoothing. We recommend reading [OpenAI Spinning guide on TD3](#) to learn more about those.

Available Policies

<i>MlpPolicy</i>	alias of <code>stable_baselines3.td3.policies.TD3Policy</code>
<i>CnnPolicy</i>	Policy class (with both actor and critic) for TD3.
<i>MultiInputPolicy</i>	Policy class (with both actor and critic) for TD3 to be used with Dict observation spaces.

1.28.1 Notes

- Original paper: <https://arxiv.org/pdf/1802.09477.pdf>
- OpenAI Spinning Guide for TD3: <https://spinningup.openai.com/en/latest/algorithms/td3.html>
- Original Implementation: <https://github.com/sfujim/TD3>

Note: The default policies for TD3 differ a bit from others *MlpPolicy*: it uses ReLU instead of tanh activation, to match the original paper

1.28.2 Can I use?

- Recurrent policies:
- Multi processing: ✓
- Gym spaces:

Space	Action	Observation
Discrete		✓
Box	✓	✓
MultiDiscrete		✓
MultiBinary		✓
Dict		✓

1.28.3 Example

This example is only to demonstrate the use of the library and its functions, and the trained agents may not solve the environments. Optimized hyperparameters can be found in RL Zoo [repository](#).

```
import gym
import numpy as np

from stable_baselines3 import TD3
from stable_baselines3.common.noise import NormalActionNoise,
↳ OrnsteinUhlenbeckActionNoise

env = gym.make("Pendulum-v1")

# The noise objects for TD3
n_actions = env.action_space.shape[-1]
action_noise = NormalActionNoise(mean=np.zeros(n_actions), sigma=0.1 * np.ones(n_
↳ actions))

model = TD3("MlpPolicy", env, action_noise=action_noise, verbose=1)
model.learn(total_timesteps=10000, log_interval=10)
model.save("td3_pendulum")
env = model.get_env()

del model # remove to demonstrate saving and loading

model = TD3.load("td3_pendulum")

obs = env.reset()
while True:
    action, _states = model.predict(obs)
    obs, rewards, dones, info = env.step(action)
    env.render()
```

1.28.4 Results

PyBullet Environments

Results on the PyBullet benchmark (1M steps) using 3 seeds. The complete learning curves are available in the [associated issue #48](#).

Note: Hyperparameters from the [gSDE](#) paper were used (as they are tuned for PyBullet envs).

Gaussian means that the unstructured Gaussian noise is used for exploration, *gSDE* (generalized State-Dependent Exploration) is used otherwise.

Environments	SAC	SAC	TD3
	Gaussian	gSDE	Gaussian
HalfCheetah	2757 +/- 53	2984 +/- 202	2774 +/- 35
Ant	3146 +/- 35	3102 +/- 37	3305 +/- 43
Hopper	2422 +/- 168	2262 +/- 1	2429 +/- 126
Walker2D	2184 +/- 54	2136 +/- 67	2063 +/- 185

How to replicate the results?

Clone the [rl-zoo](#) repo:

```
git clone https://github.com/DLR-RM/rl-baselines3-zoo
cd rl-baselines3-zoo/
```

Run the benchmark (replace `$ENV_ID` by the envs mentioned above):

```
python train.py --algo td3 --env $ENV_ID --eval-episodes 10 --eval-freq 10000
```

Plot the results:

```
python scripts/all_plots.py -a td3 -e HalfCheetah Ant Hopper Walker2D -f logs/ -o logs/
  ↳ td3_results
python scripts/plot_from_file.py -i logs/td3_results.pkl -latex -l TD3
```

1.28.5 Parameters

```
class stable_baselines3.td3.TD3(policy, env, learning_rate=0.001, buffer_size=1000000,
                                learning_starts=100, batch_size=100, tau=0.005, gamma=0.99,
                                train_freq=(1, 'episode'), gradient_steps=-1, action_noise=None,
                                replay_buffer_class=None, replay_buffer_kwargs=None,
                                optimize_memory_usage=False, policy_delay=2, target_policy_noise=0.2,
                                target_noise_clip=0.5, tensorboard_log=None, create_eval_env=False,
                                policy_kwargs=None, verbose=0, seed=None, device='auto',
                                _init_setup_model=True)
```

Twin Delayed DDPG (TD3) Addressing Function Approximation Error in Actor-Critic Methods.

Original implementation: <https://github.com/sfujim/TD3> Paper: <https://arxiv.org/abs/1802.09477> Introduction to TD3: <https://spinningup.openai.com/en/latest/algorithms/td3.html>

Parameters

- **policy** (Union[str, Type[TD3Policy]]) – The policy model to use (MlpPolicy, CnnPolicy, ...)
- **env** (Union[Env, VecEnv, str]) – The environment to learn from (if registered in Gym, can be str)
- **learning_rate** (Union[float, Callable[[float], float]]) – learning rate for adam optimizer, the same learning rate will be used for all networks (Q-Values, Actor and Value function) it can be a function of the current progress remaining (from 1 to 0)

- **buffer_size** (int) – size of the replay buffer
- **learning_starts** (int) – how many steps of the model to collect transitions for before learning starts
- **batch_size** (int) – Minibatch size for each gradient update
- **tau** (float) – the soft update coefficient (“Polyak update”, between 0 and 1)
- **gamma** (float) – the discount factor
- **train_freq** (Union[int, Tuple[int, str]]) – Update the model every `train_freq` steps. Alternatively pass a tuple of frequency and unit like (5, "step") or (2, "episode").
- **gradient_steps** (int) – How many gradient steps to do after each rollout (see `train_freq`) Set to -1 means to do as many gradient steps as steps done in the environment during the rollout.
- **action_noise** (Optional[[ActionNoise](#)]) – the action noise type (None by default), this can help for hard exploration problem. Cf `common.noise` for the different action noise type.
- **replay_buffer_class** (Optional[ReplayBuffer]) – Replay buffer class to use (for instance `HerReplayBuffer`). If None, it will be automatically selected.
- **replay_buffer_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the replay buffer on creation.
- **optimize_memory_usage** (bool) – Enable a memory efficient variant of the replay buffer at a cost of more complexity. See <https://github.com/DLR-RM/stable-baselines3/issues/37#issuecomment-637501195>
- **policy_delay** (int) – Policy and target networks will only be updated once every `policy_delay` steps per training steps. The Q values will be updated `policy_delay` more often (update every training step).
- **target_policy_noise** (float) – Standard deviation of Gaussian noise added to target policy (smoothing noise)
- **target_noise_clip** (float) – Limit for absolute value of target policy smoothing noise.
- **create_eval_env** (bool) – Whether to create a second environment that will be used for evaluating the agent periodically. (Only available when passing string for the environment)
- **policy_kwargs** (Optional[Dict[str, Any]]) – additional arguments to be passed to the policy on creation
- **verbose** (int) – the verbosity level: 0 no output, 1 info, 2 debug
- **seed** (Optional[int]) – Seed for the pseudo random generators
- **device** (Union[device, str]) – Device (cpu, cuda, ...) on which the code should be run. Setting it to auto, the code will be run on the GPU if possible.
- **_init_setup_model** (bool) – Whether or not to build the network at the creation of the instance

collect_rollouts(*env, callback, train_freq, replay_buffer, action_noise=None, learning_starts=0, log_interval=None*)

Collect experiences and store them into a `ReplayBuffer`.

Parameters

- **env** ([VecEnv](#)) – The training environment

- **callback** ([BaseCallback](#)) – Callback that will be called at each step (and at the beginning and end of the rollout)
- **train_freq** ([TrainFreq](#)) – How much experience to collect by doing rollouts of current policy. Either `TrainFreq(<n>, TrainFrequencyUnit.STEP)` or `TrainFreq(<n>, TrainFrequencyUnit.EPISODE)` with `<n>` being an integer greater than 0.
- **action_noise** ([Optional\[ActionNoise\]](#)) – Action noise that will be used for exploration Required for deterministic policy (e.g. TD3). This can also be used in addition to the stochastic policy for SAC.
- **learning_starts** (`int`) – Number of steps before learning for the warm-up phase.
- **replay_buffer** ([ReplayBuffer](#)) –
- **log_interval** ([Optional\[int\]](#)) – Log data every `log_interval` episodes

Return type `RolloutReturn`

Returns

get_env()

Returns the current environment (can be `None` if not defined).

Return type `Optional[VecEnv]`

Returns The current environment

get_parameters()

Return the parameters of the agent. This includes parameters from different networks, e.g. critics (value functions) and policies (pi functions).

Return type `Dict[str, Dict]`

Returns Mapping of from names of the objects to PyTorch state-dicts.

get_vec_normalize_env()

Return the `VecNormalize` wrapper of the training env if it exists.

Return type `Optional[VecNormalize]`

Returns The `VecNormalize` env.

learn(`total_timesteps`, `callback=None`, `log_interval=4`, `eval_env=None`, `eval_freq=-1`, `n_eval_episodes=5`, `tb_log_name='TD3'`, `eval_log_path=None`, `reset_num_timesteps=True`)

Return a trained model.

Parameters

- **total_timesteps** (`int`) – The total number of samples (env steps) to train on
- **callback** (`Union[None, Callable, List[BaseCallback], BaseCallback]`) – call-back(s) called at every step with state of the algorithm.
- **log_interval** (`int`) – The number of timesteps before logging.
- **tb_log_name** (`str`) – the name of the run for TensorBoard logging
- **eval_env** (`Union[Env, VecEnv, None]`) – Environment that will be used to evaluate the agent
- **eval_freq** (`int`) – Evaluate the agent every `eval_freq` timesteps (this may vary a little)
- **n_eval_episodes** (`int`) – Number of episode to evaluate the agent
- **eval_log_path** (`Optional[str]`) – Path to a folder where the evaluations will be saved

- **reset_num_timesteps** (bool) – whether or not to reset the current timestep number (used in logging)

Return type *OffPolicyAlgorithm*

Returns the trained model

classmethod **load**(*path, env=None, device='auto', custom_objects=None, print_system_info=False, force_reset=True, **kwargs*)

Load the model from a zip-file. Warning: load re-creates the model from scratch, it does not update it in-place! For an in-place load use `set_parameters` instead.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – path to the file (or a file-like) where to load the agent from
- **env** (Union[Env, *VecEnv*, None]) – the new environment to run the loaded model on (can be None if you only need prediction from a trained model) has priority over any saved environment
- **device** (Union[device, str]) – Device on which the code should run.
- **custom_objects** (Optional[Dict[str, Any]]) – Dictionary of objects to replace upon loading. If a variable is present in this dictionary as a key, it will not be deserialized and the corresponding item will be used instead. Similar to `custom_objects` in `keras.models.load_model`. Useful when you have an object in file that can not be deserialized.
- **print_system_info** (bool) – Whether to print system info from the saved model and the current system info (useful to debug loading issues)
- **force_reset** (bool) – Force call to `reset()` before training to avoid unexpected behavior. See <https://github.com/DLR-RM/stable-baselines3/issues/597>
- **kwargs** – extra arguments to change the model when loading

Return type *BaseAlgorithm*

Returns new model instance with loaded parameters

load_replay_buffer(*path, truncate_last_traj=True*)

Load a replay buffer from a pickle file.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – Path to the pickled replay buffer.
- **truncate_last_traj** (bool) – When using `HerReplayBuffer` with online sampling: If set to `True`, we assume that the last trajectory in the replay buffer was finished (and truncate it). If set to `False`, we assume that we continue the same trajectory (same episode).

Return type `None`

property logger: *stable_baselines3.common.logger.Logger*

Getter for the logger object.

Return type *Logger*

predict(*observation, state=None, episode_start=None, deterministic=False*)

Get the policy action from an observation (and optional hidden state). Includes sugar-coating to handle different observations (e.g. normalizing images).

Parameters

- **observation** (ndarray) – the input observation
- **state** (Optional[Tuple[ndarray, ...]]) – The last hidden states (can be None, used in recurrent policies)
- **episode_start** (Optional[ndarray]) – The last masks (can be None, used in recurrent policies) this correspond to beginning of episodes, where the hidden states of the RNN must be reset.
- **deterministic** (bool) – Whether or not to return deterministic actions.

Return type Tuple[ndarray, Optional[Tuple[ndarray, ...]]]

Returns the model's action and the next hidden state (used in recurrent policies)

save(*path*, *exclude=None*, *include=None*)

Save all the attributes of the object and the model parameters in a zip-file.

Parameters

- **path** (Union[str, Path, BufferedIOBase]) – path to the file where the rl agent should be saved
- **exclude** (Optional[Iterable[str]]) – name of parameters that should be excluded in addition to the default ones
- **include** (Optional[Iterable[str]]) – name of parameters that might be excluded but should be included anyway

Return type None

save_replay_buffer(*path*)

Save the replay buffer as a pickle file.

Parameters **path** (Union[str, Path, BufferedIOBase]) – Path to the file where the replay buffer should be saved. if path is a str or pathlib.Path, the path is automatically created if necessary.

Return type None

set_env(*env*, *force_reset=True*)

Checks the validity of the environment, and if it is coherent, set it as the current environment. Furthermore wrap any non vectorized env into a vectorized checked parameters: - observation_space - action_space

Parameters

- **env** (Union[Env, *VecEnv*]) – The environment for learning a policy
- **force_reset** (bool) – Force call to `reset()` before training to avoid unexpected behavior. See issue <https://github.com/DLR-RM/stable-baselines3/issues/597>

Return type None

set_logger(*logger*)

Setter for for logger object.

Warning: When passing a custom logger object, this will overwrite `tensorboard_log` and `verbose` settings passed to the constructor.

Return type None

set_parameters(*load_path_or_dict*, *exact_match=True*, *device='auto'*)

Load parameters from a given zip-file or a nested dictionary containing parameters for different modules (see `get_parameters`).

Parameters

- **load_path_or_iter** – Location of the saved data (path or file-like, see `save`), or a nested dictionary containing `nn.Module` parameters used by the policy. The dictionary maps object names to a state-dictionary returned by `torch.nn.Module.state_dict()`.
- **exact_match** (bool) – If True, the given parameters should include parameters for each module and each of their parameters, otherwise raises an Exception. If set to False, this can be used to update only specific parameters.
- **device** (Union[device, str]) – Device on which the code should run.

Return type None

set_random_seed(*seed=None*)

Set the seed of the pseudo-random generators (python, numpy, pytorch, gym, action_space)

Parameters *seed* (Optional[int]) –

Return type None

train(*gradient_steps*, *batch_size=100*)

Sample the replay buffer and do the updates (gradient descent and update target networks)

Return type None

1.28.6 TD3 Policies

`stable_baselines3.td3.MlpPolicy`

alias of `stable_baselines3.td3.policies.TD3Policy`

```
class stable_baselines3.td3.policies.TD3Policy(observation_space, action_space, lr_schedule,
                                             net_arch=None, activation_fn=<class
                                             'torch.nn.modules.activation.ReLU'>,
                                             features_extractor_class=<class 'sta-
                                             ble_baselines3.common.torch_layers.FlattenExtractor'>,
                                             features_extractor_kwargs=None,
                                             normalize_images=True, optimizer_class=<class
                                             'torch.optim.adam.Adam'>, optimizer_kwargs=None,
                                             n_critics=2, share_features_extractor=True)
```

Policy class (with both actor and critic) for TD3.

Parameters

- **observation_space** (Space) – Observation space
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Union[List[int], Dict[str, List[int]], None]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Features extractor to use.

- **features_extractor_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the features extractor.
- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, `th.optim.Adam` by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer
- **n_critics** (int) – Number of critic networks to create.
- **share_features_extractor** (bool) – Whether to share or not the features extractor between the actor and the critic (this saves computation time)

forward(*observation*, *deterministic=False*)

Defines the computation performed at every call.

Should be overridden by all subclasses.

Note: Although the recipe for forward pass needs to be defined within this function, one should call the `Module` instance afterwards instead of this since the former takes care of running the registered hooks while the latter silently ignores them.

Return type Tensor

set_training_mode(*mode*)

Put the policy in either training or evaluation mode.

This affects certain modules, such as batch normalisation and dropout.

Parameters *mode* (bool) – if true, set to training mode, else set to evaluation mode

Return type None

```
class stable_baselines3.td3.CnnPolicy(observation_space, action_space, lr_schedule, net_arch=None,  
                                     activation_fn=<class 'torch.nn.modules.activation.ReLU'>,  
                                     features_extractor_class=<class  
                                     'stable_baselines3.common.torch_layers.NatureCNN'>,  
                                     features_extractor_kwargs=None, normalize_images=True,  
                                     optimizer_class=<class 'torch.optim.adam.Adam'>,  
                                     optimizer_kwargs=None, n_critics=2,  
                                     share_features_extractor=True)
```

Policy class (with both actor and critic) for TD3.

Parameters

- **observation_space** (Space) – Observation space
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Union[List[int], Dict[str, List[int]], None]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Features extractor to use.

- **features_extractor_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the features extractor.
- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, `th.optim.Adam` by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer
- **n_critics** (int) – Number of critic networks to create.
- **share_features_extractor** (bool) – Whether to share or not the features extractor between the actor and the critic (this saves computation time)

```
class stable_baselines3.td3.MultiInputPolicy(observation_space, action_space, lr_schedule,
                                           net_arch=None, activation_fn=<class
                                           'torch.nn.modules.activation.ReLU'>,
                                           features_extractor_class=<class 'sta-
                                           ble_baselines3.common.torch_layers.CombinedExtractor'>,
                                           features_extractor_kwargs=None,
                                           normalize_images=True, optimizer_class=<class
                                           'torch.optim.adam.Adam'>, optimizer_kwargs=None,
                                           n_critics=2, share_features_extractor=True)
```

Policy class (with both actor and critic) for TD3 to be used with Dict observation spaces.

Parameters

- **observation_space** (Dict) – Observation space
- **action_space** (Space) – Action space
- **lr_schedule** (Callable[[float], float]) – Learning rate schedule (could be constant)
- **net_arch** (Union[List[int], Dict[str, List[int]], None]) – The specification of the policy and value networks.
- **activation_fn** (Type[Module]) – Activation function
- **features_extractor_class** (Type[BaseFeaturesExtractor]) – Features extractor to use.
- **features_extractor_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the features extractor.
- **normalize_images** (bool) – Whether to normalize images or not, dividing by 255.0 (True by default)
- **optimizer_class** (Type[Optimizer]) – The optimizer to use, `th.optim.Adam` by default
- **optimizer_kwargs** (Optional[Dict[str, Any]]) – Additional keyword arguments, excluding the learning rate, to pass to the optimizer
- **n_critics** (int) – Number of critic networks to create.
- **share_features_extractor** (bool) – Whether to share or not the features extractor between the actor and the critic (this saves computation time)

1.29 Atari Wrappers

```
class stable_baselines3.common.atari_wrappers.AtariWrapper(env, noop_max=30, frame_skip=4,  
                                                         screen_size=84,  
                                                         terminal_on_life_loss=True,  
                                                         clip_reward=True)
```

Atari 2600 preprocessings

Specifically:

- NoopReset: obtain initial state by taking random number of no-ops on reset.
- Frame skipping: 4 by default
- Max-pooling: most recent two observations
- Termination signal when a life is lost.
- Resize to a square image: 84x84 by default
- Grayscale observation
- Clip reward to {-1, 0, 1}

Parameters

- **env** (Env) – gym environment
- **noop_max** (int) – max number of no-ops
- **frame_skip** (int) – the frequency at which the agent experiences the game.
- **screen_size** (int) – resize Atari frame
- **terminal_on_life_loss** (bool) – if True, then step() returns done=True whenever a life is lost.
- **clip_reward** (bool) – If True (default), the reward is clip to {-1, 0, 1} depending on its sign.

```
class stable_baselines3.common.atari_wrappers.ClipRewardEnv(env)
```

Clips the reward to {+1, 0, -1} by its sign.

Parameters **env** (Env) – the environment

reward(reward)

Bin reward to {+1, 0, -1} by its sign.

Parameters **reward** (float) –

Return type float

Returns

```
class stable_baselines3.common.atari_wrappers.EpisodicLifeEnv(env)
```

Make end-of-life == end-of-episode, but only reset on true game over. Done by DeepMind for the DQN and co. since it helps value estimation.

Parameters **env** (Env) – the environment to wrap

reset(**kwargs)

Calls the Gym environment reset, only when lives are exhausted. This way all states are still reachable even though lives are episodic, and the learner need not know about any of this behind-the-scenes.

Parameters **kwargs** – Extra keywords passed to env.reset() call

Return type ndarray

Returns the first observation of the environment

step(action)

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

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

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

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

Return type Tuple[Union[Tuple, Dict[str, Any], ndarray, int], float, bool, Dict]

class stable_baselines3.common.atari_wrappers.**FireResetEnv**(env)

Take action on reset for environments that are fixed until firing.

Parameters **env** (Env) – the environment to wrap

reset(**kwargs)

Resets the environment to an initial state and returns an initial observation.

This method should also reset the environment's random number generator(s) if *seed* is an integer or if the environment has not yet initialized a random number generator. If the environment already has a random number generator and *reset* is called with *seed=None*, the RNG should not be reset. Moreover, *reset* should (in the typical use case) be called with an integer seed right after initialization and then never again.

Returns: observation (object): the initial observation.
info (optional dictionary): a dictionary containing extra information, this is only returned if return_info is set to true

Return type ndarray

class stable_baselines3.common.atari_wrappers.**MaxAndSkipEnv**(env, skip=4)

Return only every skip-th frame (frameskipping)

Parameters

- **env** (Env) – the environment
- **skip** (int) – number of skip-th frame

reset(**kwargs)

Resets the environment to an initial state and returns an initial observation.

This method should also reset the environment's random number generator(s) if *seed* is an integer or if the environment has not yet initialized a random number generator. If the environment already has a random number generator and *reset* is called with *seed=None*, the RNG should not be reset. Moreover, *reset* should (in the typical use case) be called with an integer seed right after initialization and then never again.

Returns: observation (object): the initial observation. info (optional dictionary): a dictionary containing extra information, this is only returned if return_info is set to true

Return type Union[Tuple, Dict[str, Any], ndarray, int]

step(*action*)

Step the environment with the given action Repeat action, sum reward, and max over last observations.

Parameters *action* (int) – the action

Return type Tuple[Union[Tuple, Dict[str, Any], ndarray, int], float, bool, Dict]

Returns observation, reward, done, information

class stable_baselines3.common.atari_wrappers.NoopResetEnv(*env*, *noop_max*=30)

Sample initial states by taking random number of no-ops on reset. No-op is assumed to be action 0.

Parameters

- **env** (Env) – the environment to wrap
- **noop_max** (int) – the maximum value of no-ops to run

reset(***kwargs*)

Resets the environment to an initial state and returns an initial observation.

This method should also reset the environment's random number generator(s) if *seed* is an integer or if the environment has not yet initialized a random number generator. If the environment already has a random number generator and *reset* is called with *seed*=None, the RNG should not be reset. Moreover, *reset* should (in the typical use case) be called with an integer seed right after initialization and then never again.

Returns: observation (object): the initial observation. info (optional dictionary): a dictionary containing extra information, this is only returned if return_info is set to true

Return type ndarray

class stable_baselines3.common.atari_wrappers.WarpFrame(*env*, *width*=84, *height*=84)

Convert to grayscale and warp frames to 84x84 (default) as done in the Nature paper and later work.

Parameters

- **env** (Env) – the environment
- **width** (int) –
- **height** (int) –

observation(*frame*)

returns the current observation from a frame

Parameters *frame* (ndarray) – environment frame

Return type ndarray

Returns the observation

1.30 Environments Utils

`stable_baselines3.common.env_util.is_wrapped(env, wrapper_class)`

Check if a given environment has been wrapped with a given wrapper.

Parameters

- **env** (Type[Env]) – Environment to check
- **wrapper_class** (Type[Wrapper]) – Wrapper class to look for

Return type bool

Returns True if environment has been wrapped with `wrapper_class`.

`stable_baselines3.common.env_util.make_atari_env(env_id, n_envs=1, seed=None, start_index=0, monitor_dir=None, wrapper_kwargs=None, env_kwargs=None, vec_env_cls=None, vec_env_kwargs=None, monitor_kwargs=None)`

Create a wrapped, monitored VecEnv for Atari. It is a wrapper around `make_vec_env` that includes common preprocessing for Atari games.

Parameters

- **env_id** (Union[str, Type[Env]]) – the environment ID or the environment class
- **n_envs** (int) – the number of environments you wish to have in parallel
- **seed** (Optional[int]) – the initial seed for the random number generator
- **start_index** (int) – start rank index
- **monitor_dir** (Optional[str]) – Path to a folder where the monitor files will be saved. If None, no file will be written, however, the env will still be wrapped in a Monitor wrapper to provide additional information about training.
- **wrapper_kwargs** (Optional[Dict[str, Any]]) – Optional keyword argument to pass to the AtariWrapper
- **env_kwargs** (Optional[Dict[str, Any]]) – Optional keyword argument to pass to the env constructor
- **vec_env_cls** (Union[DummyVecEnv, SubprocVecEnv, None]) – A custom VecEnv class constructor. Default: None.
- **vec_env_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the VecEnv class constructor.
- **monitor_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the Monitor class constructor.

Return type *VecEnv*

Returns The wrapped environment

`stable_baselines3.common.env_util.make_vec_env(env_id, n_envs=1, seed=None, start_index=0, monitor_dir=None, wrapper_class=None, env_kwargs=None, vec_env_cls=None, vec_env_kwargs=None, monitor_kwargs=None, wrapper_kwargs=None)`

Create a wrapped, monitored VecEnv. By default it uses a `DummyVecEnv` which is usually faster than a `SubprocVecEnv`.

Parameters

- **env_id** (Union[str, Type[Env]]) – the environment ID or the environment class
- **n_envs** (int) – the number of environments you wish to have in parallel
- **seed** (Optional[int]) – the initial seed for the random number generator
- **start_index** (int) – start rank index
- **monitor_dir** (Optional[str]) – Path to a folder where the monitor files will be saved. If None, no file will be written, however, the env will still be wrapped in a Monitor wrapper to provide additional information about training.
- **wrapper_class** (Optional[Callable[[Env], Env]]) – Additional wrapper to use on the environment. This can also be a function with single argument that wraps the environment in many things.
- **env_kwargs** (Optional[Dict[str, Any]]) – Optional keyword argument to pass to the env constructor
- **vec_env_cls** (Optional[Type[Union[DummyVecEnv, SubprocVecEnv]]]) – A custom VecEnv class constructor. Default: None.
- **vec_env_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the VecEnv class constructor.
- **monitor_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the Monitor class constructor.
- **wrapper_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the Wrapper class constructor.

Return type *VecEnv***Returns** The wrapped environment`stable_baselines3.common.env_util.unwrap_wrapper(env, wrapper_class)`

Retrieve a VecEnvWrapper object by recursively searching.

Parameters

- **env** (Env) – Environment to unwrap
- **wrapper_class** (Type[Wrapper]) – Wrapper to look for

Return type Optional[Wrapper]**Returns** Environment unwrapped till wrapper_class if it has been wrapped with it

1.31 Custom Environments

Those environments were created for testing purposes.

1.31.1 BitFlippingEnv

1.31.2 SimpleMultiObsEnv

1.32 Probability Distributions

Probability distributions used for the different action spaces:

- `CategoricalDistribution` -> Discrete
- `DiagGaussianDistribution` -> Box (continuous actions)
- `StateDependentNoiseDistribution` -> Box (continuous actions) when `use_sde=True`

The policy networks output parameters for the distributions (named `flat` in the methods). Actions are then sampled from those distributions.

For instance, in the case of discrete actions. The policy network outputs probability of taking each action. The `CategoricalDistribution` allows to sample from it, computes the entropy, the log probability (`log_prob`) and backpropagate the gradient.

In the case of continuous actions, a Gaussian distribution is used. The policy network outputs mean and (log) std of the distribution (assumed to be a `DiagGaussianDistribution`).

Probability distributions.

class `stable_baselines3.common.distributions.BernoulliDistribution(action_dims)`

Bernoulli distribution for MultiBinary action spaces.

Parameters `action_dim` – Number of binary actions

actions_from_params(*action_logits, deterministic=False*)

Returns samples from the probability distribution given its parameters.

Return type Tensor

Returns actions

entropy()

Returns Shannon's entropy of the probability

Return type Tensor

Returns the entropy, or None if no analytical form is known

log_prob(*actions*)

Returns the log likelihood

Parameters `x` – the taken action

Return type Tensor

Returns The log likelihood of the distribution

log_prob_from_params(*action_logits*)

Returns samples and the associated log probabilities from the probability distribution given its parameters.

Return type Tuple[Tensor, Tensor]

Returns actions and log prob

mode()

Returns the most likely action (deterministic output) from the probability distribution

Return type Tensor

Returns the stochastic action

proba_distribution(action_logits)

Set parameters of the distribution.

Return type *BernoulliDistribution*

Returns self

proba_distribution_net(latent_dim)

Create the layer that represents the distribution: it will be the logits of the Bernoulli distribution.

Parameters **latent_dim** (int) – Dimension of the last layer of the policy network (before the action layer)

Return type Module

Returns

sample()

Returns a sample from the probability distribution

Return type Tensor

Returns the stochastic action

class stable_baselines3.common.distributions.CategoricalDistribution(action_dim)

Categorical distribution for discrete actions.

Parameters **action_dim** (int) – Number of discrete actions

actions_from_params(action_logits, deterministic=False)

Returns samples from the probability distribution given its parameters.

Return type Tensor

Returns actions

entropy()

Returns Shannon's entropy of the probability

Return type Tensor

Returns the entropy, or None if no analytical form is known

log_prob(actions)

Returns the log likelihood

Parameters **x** – the taken action

Return type Tensor

Returns The log likelihood of the distribution

log_prob_from_params(action_logits)

Returns samples and the associated log probabilities from the probability distribution given its parameters.

Return type Tuple[Tensor, Tensor]

Returns actions and log prob

mode()

Returns the most likely action (deterministic output) from the probability distribution

Return type Tensor

Returns the stochastic action

proba_distribution(action_logits)

Set parameters of the distribution.

Return type *CategoricalDistribution*

Returns self

proba_distribution_net(latent_dim)

Create the layer that represents the distribution: it will be the logits of the Categorical distribution. You can then get probabilities using a softmax.

Parameters **latent_dim** (int) – Dimension of the last layer of the policy network (before the action layer)

Return type Module

Returns

sample()

Returns a sample from the probability distribution

Return type Tensor

Returns the stochastic action

class stable_baselines3.common.distributions.DiagGaussianDistribution(action_dim)

Gaussian distribution with diagonal covariance matrix, for continuous actions.

Parameters **action_dim** (int) – Dimension of the action space.

actions_from_params(mean_actions, log_std, deterministic=False)

Returns samples from the probability distribution given its parameters.

Return type Tensor

Returns actions

entropy()

Returns Shannon's entropy of the probability

Return type Tensor

Returns the entropy, or None if no analytical form is known

log_prob(actions)

Get the log probabilities of actions according to the distribution. Note that you must first call the `proba_distribution()` method.

Parameters **actions** (Tensor) –

Return type Tensor

Returns

log_prob_from_params(mean_actions, log_std)

Compute the log probability of taking an action given the distribution parameters.

Parameters

- **mean_actions** (Tensor) –
- **log_std** (Tensor) –

Return type Tuple[Tensor, Tensor]

Returns

mode()

Returns the most likely action (deterministic output) from the probability distribution

Return type Tensor

Returns the stochastic action

proba_distribution(*mean_actions*, *log_std*)

Create the distribution given its parameters (mean, std)

Parameters

- **mean_actions** (Tensor) –
- **log_std** (Tensor) –

Return type *DiagGaussianDistribution*

Returns

proba_distribution_net(*latent_dim*, *log_std_init*=0.0)

Create the layers and parameter that represent the distribution: one output will be the mean of the Gaussian, the other parameter will be the standard deviation (log std in fact to allow negative values)

Parameters

- **latent_dim** (int) – Dimension of the last layer of the policy (before the action layer)
- **log_std_init** (float) – Initial value for the log standard deviation

Return type Tuple[Module, Parameter]

Returns

sample()

Returns a sample from the probability distribution

Return type Tensor

Returns the stochastic action

class `stable_baselines3.common.distributions.Distribution`

Abstract base class for distributions.

abstract **actions_from_params**(*args, **kwargs)

Returns samples from the probability distribution given its parameters.

Return type Tensor

Returns actions

abstract **entropy**()

Returns Shannon's entropy of the probability

Return type Optional[Tensor]

Returns the entropy, or None if no analytical form is known

get_actions(*deterministic=False*)

Return actions according to the probability distribution.

Parameters **deterministic** (bool) –

Return type Tensor

Returns

abstract log_prob(*x*)

Returns the log likelihood

Parameters **x** (Tensor) – the taken action

Return type Tensor

Returns The log likelihood of the distribution

abstract log_prob_from_params(**args, **kwargs*)

Returns samples and the associated log probabilities from the probability distribution given its parameters.

Return type Tuple[Tensor, Tensor]

Returns actions and log prob

abstract mode()

Returns the most likely action (deterministic output) from the probability distribution

Return type Tensor

Returns the stochastic action

abstract proba_distribution(**args, **kwargs*)

Set parameters of the distribution.

Return type *Distribution*

Returns self

abstract proba_distribution_net(**args, **kwargs*)

Create the layers and parameters that represent the distribution.

Subclasses must define this, but the arguments and return type vary between concrete classes.

Return type Union[Module, Tuple[Module, Parameter]]

abstract sample()

Returns a sample from the probability distribution

Return type Tensor

Returns the stochastic action

class stable_baselines3.common.distributions.**MultiCategoricalDistribution**(*action_dims*)

MultiCategorical distribution for multi discrete actions.

Parameters **action_dims** (List[int]) – List of sizes of discrete action spaces

actions_from_params(*action_logits, deterministic=False*)

Returns samples from the probability distribution given its parameters.

Return type Tensor

Returns actions

entropy()

Returns Shannon's entropy of the probability

Return type Tensor

Returns the entropy, or None if no analytical form is known

log_prob(actions)

Returns the log likelihood

Parameters **x** – the taken action

Return type Tensor

Returns The log likelihood of the distribution

log_prob_from_params(action_logits)

Returns samples and the associated log probabilities from the probability distribution given its parameters.

Return type Tuple[Tensor, Tensor]

Returns actions and log prob

mode()

Returns the most likely action (deterministic output) from the probability distribution

Return type Tensor

Returns the stochastic action

proba_distribution(action_logits)

Set parameters of the distribution.

Return type *MultiCategoricalDistribution*

Returns self

proba_distribution_net(latent_dim)

Create the layer that represents the distribution: it will be the logits (flattened) of the MultiCategorical distribution. You can then get probabilities using a softmax on each sub-space.

Parameters **latent_dim** (int) – Dimension of the last layer of the policy network (before the action layer)

Return type Module

Returns

sample()

Returns a sample from the probability distribution

Return type Tensor

Returns the stochastic action

class stable_baselines3.common.distributions.**SquashedDiagGaussianDistribution**(*action_dim*,
epsilon=1e-06)

Gaussian distribution with diagonal covariance matrix, followed by a squashing function (tanh) to ensure bounds.

Parameters

- **action_dim** (int) – Dimension of the action space.
- **epsilon** (float) – small value to avoid NaN due to numerical imprecision.

entropy()

Returns Shannon's entropy of the probability

Return type Optional[Tensor]

Returns the entropy, or None if no analytical form is known

log_prob(actions, gaussian_actions=None)

Get the log probabilities of actions according to the distribution. Note that you must first call the `proba_distribution()` method.

Parameters actions (Tensor) –

Return type Tensor

Returns

log_prob_from_params(mean_actions, log_std)

Compute the log probability of taking an action given the distribution parameters.

Parameters

- mean_actions (Tensor) –
- log_std (Tensor) –

Return type Tuple[Tensor, Tensor]

Returns

mode()

Returns the most likely action (deterministic output) from the probability distribution

Return type Tensor

Returns the stochastic action

proba_distribution(mean_actions, log_std)

Create the distribution given its parameters (mean, std)

Parameters

- mean_actions (Tensor) –
- log_std (Tensor) –

Return type *SquashedDiagGaussianDistribution*

Returns

sample()

Returns a sample from the probability distribution

Return type Tensor

Returns the stochastic action

```
class stable_baselines3.common.distributions.StateDependentNoiseDistribution(action_dim,
                                                                            full_std=True,
                                                                            use_expln=False,
                                                                            squash_output=False,
                                                                            learn_features=False,
                                                                            epsilon=1e-06)
```

Distribution class for using generalized State Dependent Exploration (gSDE). Paper: <https://arxiv.org/abs/2005.05719>

It is used to create the noise exploration matrix and compute the log probability of an action with that noise.

Parameters

- **action_dim** (int) – Dimension of the action space.
- **full_std** (bool) – Whether to use (n_features x n_actions) parameters for the std instead of only (n_features,)
- **use_expln** (bool) – Use `expln()` function instead of `exp()` to ensure a positive standard deviation (cf paper). It allows to keep variance above zero and prevent it from growing too fast. In practice, `exp()` is usually enough.
- **squash_output** (bool) – Whether to squash the output using a tanh function, this ensures bounds are satisfied.
- **learn_features** (bool) – Whether to learn features for gSDE or not. This will enable gradients to be backpropagated through the features `latent_sde` in the code.
- **epsilon** (float) – small value to avoid NaN due to numerical imprecision.

actions_from_params(*mean_actions*, *log_std*, *latent_sde*, *deterministic=False*)

Returns samples from the probability distribution given its parameters.

Return type Tensor

Returns actions

entropy()

Returns Shannon's entropy of the probability

Return type Optional[Tensor]

Returns the entropy, or None if no analytical form is known

get_std(*log_std*)

Get the standard deviation from the learned parameter (log of it by default). This ensures that the std is positive.

Parameters **log_std** (Tensor) –

Return type Tensor

Returns

log_prob(*actions*)

Returns the log likelihood

Parameters **x** – the taken action

Return type Tensor

Returns The log likelihood of the distribution

log_prob_from_params(*mean_actions*, *log_std*, *latent_sde*)

Returns samples and the associated log probabilities from the probability distribution given its parameters.

Return type Tuple[Tensor, Tensor]

Returns actions and log prob

mode()

Returns the most likely action (deterministic output) from the probability distribution

Return type Tensor

Returns the stochastic action

proba_distribution(*mean_actions*, *log_std*, *latent_sde*)

Create the distribution given its parameters (mean, std)

Parameters

- **mean_actions** (Tensor) –
- **log_std** (Tensor) –
- **latent_sde** (Tensor) –

Return type *StateDependentNoiseDistribution*

Returns

proba_distribution_net(*latent_dim*, *log_std_init*=- 2.0, *latent_sde_dim*=None)

Create the layers and parameter that represent the distribution: one output will be the deterministic action, the other parameter will be the standard deviation of the distribution that control the weights of the noise matrix.

Parameters

- **latent_dim** (int) – Dimension of the last layer of the policy (before the action layer)
- **log_std_init** (float) – Initial value for the log standard deviation
- **latent_sde_dim** (Optional[int]) – Dimension of the last layer of the features extractor for gSDE. By default, it is shared with the policy network.

Return type Tuple[Module, Parameter]

Returns

sample()

Returns a sample from the probability distribution

Return type Tensor

Returns the stochastic action

sample_weights(*log_std*, *batch_size*=1)

Sample weights for the noise exploration matrix, using a centered Gaussian distribution.

Parameters

- **log_std** (Tensor) –
- **batch_size** (int) –

Return type None

class stable_baselines3.common.distributions.**TanhBijector**(*epsilon*=1e-06)

Bijection transformation of a probability distribution using a squashing function (tanh) TODO: use Pyro instead (<https://pyro.ai/>)

Parameters **epsilon** (float) – small value to avoid NaN due to numerical imprecision.

static `atanh(x)`

Inverse of Tanh

Taken from Pyro: <https://github.com/pyro-ppl/pyro> `0.5 * torch.log((1 + x) / (1 - x))`

Return type Tensor

static `inverse(y)`

Inverse tanh.

Parameters `y` (Tensor) –

Return type Tensor

Returns

`stable_baselines3.common.distributions.kl_divergence(dist_true, dist_pred)`

Wrapper for the PyTorch implementation of the full form KL Divergence

Parameters

- **dist_true** (*Distribution*) – the p distribution
- **dist_pred** (*Distribution*) – the q distribution

Return type Tensor

Returns `KL(dist_true||dist_pred)`

`stable_baselines3.common.distributions.make_proba_distribution(action_space, use_sde=False, dist_kwargs=None)`

Return an instance of Distribution for the correct type of action space

Parameters

- **action_space** (Space) – the input action space
- **use_sde** (bool) – Force the use of StateDependentNoiseDistribution instead of DiagGaussianDistribution
- **dist_kwargs** (Optional[Dict[str, Any]]) – Keyword arguments to pass to the probability distribution

Return type *Distribution*

Returns the appropriate Distribution object

`stable_baselines3.common.distributions.sum_independent_dims(tensor)`

Continuous actions are usually considered to be independent, so we can sum components of the `log_prob` or the entropy.

Parameters `tensor` (Tensor) – shape: (n_batch, n_actions) or (n_batch,)

Return type Tensor

Returns shape: (n_batch,)

1.33 Evaluation Helper

```
stable_baselines3.common.evaluation.evaluate_policy(model, env, n_eval_episodes=10,
                                                    deterministic=True, render=False,
                                                    callback=None, reward_threshold=None,
                                                    return_episode_rewards=False, warn=True)
```

Runs policy for `n_eval_episodes` episodes and returns average reward. If a vector env is passed in, this divides the episodes to evaluate onto the different elements of the vector env. This static division of work is done to remove bias. See <https://github.com/DLR-RM/stable-baselines3/issues/402> for more details and discussion.

Note: If environment has not been wrapped with `Monitor` wrapper, reward and episode lengths are counted as it appears with `env.step` calls. If the environment contains wrappers that modify rewards or episode lengths (e.g. reward scaling, early episode reset), these will affect the evaluation results as well. You can avoid this by wrapping environment with `Monitor` wrapper before anything else.

Parameters

- **model** (*BaseAlgorithm*) – The RL agent you want to evaluate.
- **env** (Union[Env, *VecEnv*]) – The gym environment or *VecEnv* environment.
- **n_eval_episodes** (int) – Number of episode to evaluate the agent
- **deterministic** (bool) – Whether to use deterministic or stochastic actions
- **render** (bool) – Whether to render the environment or not
- **callback** (Optional[Callable[[Dict[str, Any], Dict[str, Any]], None]]) – callback function to do additional checks, called after each step. Gets `locals()` and `globals()` passed as parameters.
- **reward_threshold** (Optional[float]) – Minimum expected reward per episode, this will raise an error if the performance is not met
- **return_episode_rewards** (bool) – If True, a list of rewards and episode lengths per episode will be returned instead of the mean.
- **warn** (bool) – If True (default), warns user about lack of a `Monitor` wrapper in the evaluation environment.

Return type Union[Tuple[float, float], Tuple[List[float], List[int]]]

Returns Mean reward per episode, std of reward per episode. Returns ([float], [int]) when `return_episode_rewards` is True, first list containing per-episode rewards and second containing per-episode lengths (in number of steps).

1.34 Gym Environment Checker

```
stable_baselines3.common.env_checker.check_env(env, warn=True, skip_render_check=True)
```

Check that an environment follows Gym API. This is particularly useful when using a custom environment. Please take a look at <https://github.com/openai/gym/blob/master/gym/core.py> for more information about the API.

It also optionally check that the environment is compatible with Stable-Baselines.

Parameters

- **env** (Env) – The Gym environment that will be checked
- **warn** (bool) – Whether to output additional warnings mainly related to the interaction with Stable Baselines
- **skip_render_check** (bool) – Whether to skip the checks for the render method. True by default (useful for the CI)

Return type None

1.35 Monitor Wrapper

```
class stable_baselines3.common.monitor.Monitor(env, filename=None, allow_early_resets=True,  
                                             reset_keywords=(), info_keywords=())
```

A monitor wrapper for Gym environments, it is used to know the episode reward, length, time and other data.

Parameters

- **env** (Env) – The environment
- **filename** (Optional[str]) – the location to save a log file, can be None for no log
- **allow_early_resets** (bool) – allows the reset of the environment before it is done
- **reset_keywords** (Tuple[str, ...]) – extra keywords for the reset call, if extra parameters are needed at reset
- **info_keywords** (Tuple[str, ...]) – extra information to log, from the information return of env.step()

close()

Closes the environment

Return type None

get_episode_lengths()

Returns the number of timesteps of all the episodes

Return type List[int]

Returns

get_episode_rewards()

Returns the rewards of all the episodes

Return type List[float]

Returns

get_episode_times()

Returns the runtime in seconds of all the episodes

Return type List[float]

Returns

get_total_steps()

Returns the total number of timesteps

Return type int

Returns

reset(kwargs)**

Calls the Gym environment reset. Can only be called if the environment is over, or if `allow_early_resets` is `True`

Parameters **kwargs** – Extra keywords saved for the next episode. only if defined by `reset_keywords`

Return type `Union[Tuple, Dict[str, Any], ndarray, int]`

Returns the first observation of the environment

step(action)

Step the environment with the given action

Parameters **action** (`Union[ndarray, int]`) – the action

Return type `Tuple[Union[Tuple, Dict[str, Any], ndarray, int], float, bool, Dict]`

Returns observation, reward, done, information

class `stable_baselines3.common.monitor.ResultsWriter(filename="", header=None, extra_keys=())`

A result writer that saves the data from the *Monitor* class

Parameters

- **filename** (`str`) – the location to save a log file, can be `None` for no log
- **header** (`Optional[Dict[str, Union[float, str]]]`) – the header dictionary object of the saved csv
- **reset_keywords** – the extra information to log, typically is composed of `reset_keywords` and `info_keywords`

close()

Close the file handler

Return type `None`

write_row(epinfo)

Close the file handler

Parameters **epinfo** (`Dict[str, Union[float, int]]`) – the information on episodic return, length, and time

Return type `None`

`stable_baselines3.common.monitor.get_monitor_files(path)`

get all the monitor files in the given path

Parameters **path** (`str`) – the logging folder

Return type `List[str]`

Returns the log files

`stable_baselines3.common.monitor.load_results(path)`

Load all Monitor logs from a given directory path matching `*monitor.csv`

Parameters **path** (`str`) – the directory path containing the log file(s)

Return type `DataFrame`

Returns the logged data

1.36 Logger

To overwrite the default logger, you can pass one to the algorithm. Available formats are ["stdout", "csv", "log", "tensorboard", "json"].

Warning: When passing a custom logger object, this will overwrite `tensorboard_log` and `verbose` settings passed to the constructor.

```
from stable_baselines3 import A2C
from stable_baselines3.common.logger import configure

tmp_path = "/tmp/sb3_log/"
# set up logger
new_logger = configure(tmp_path, ["stdout", "csv", "tensorboard"])

model = A2C("MlpPolicy", "CartPole-v1", verbose=1)
# Set new logger
model.set_logger(new_logger)
model.learn(10000)
```

1.36.1 Explanation of logger output

You can find below short explanations of the values logged in Stable-Baselines3 (SB3). Depending on the algorithm used and of the wrappers/callbacks applied, SB3 only logs a subset of those keys during training.

Below you can find an example of the logger output when training a PPO agent:

```
-----
| eval/                |          |
|   mean_ep_length     |    200   |
|   mean_reward        |   -157   |
| rollout/             |          |
|   ep_len_mean        |    200   |
|   ep_rew_mean        |   -227   |
| time/                |          |
|   fps                |    972   |
|   iterations         |     19   |
|   time_elapsed       |     80   |
|   total_timesteps    |   77824  |
| train/               |          |
|   approx_kl          | 0.037781604 |
|   clip_fraction      |    0.243  |
|   clip_range         |     0.2   |
|   entropy_loss       |   -1.06   |
|   explained_variance |    0.999  |
|   learning_rate      |    0.001  |
|   loss               |    0.245  |
|   n_updates          |    180   |
|   policy_gradient_loss | -0.00398  |
|   std                |    0.205  |
```

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	value_loss	0.226	

eval/

All `eval/` values are computed by the `EvalCallback`.

- `mean_ep_length`: Mean episode length
- `mean_reward`: Mean episodic reward (during evaluation)
- `success_rate`: Mean success rate during evaluation (1.0 means 100% success), the environment info dict must contain an `is_success` key to compute that value

rollout/

- `ep_len_mean`: Mean episode length (averaged over 100 episodes)
- `ep_rew_mean`: Mean episodic training reward (averaged over 100 episodes), a `Monitor` wrapper is required to compute that value (automatically added by `make_vec_env`).
- `exploration_rate`: Current value of the exploration rate when using DQN, it corresponds to the fraction of actions taken randomly (epsilon of the “epsilon-greedy” exploration)
- `success_rate`: Mean success rate during training (averaged over 100 episodes), you must pass an extra argument to the `Monitor` wrapper to log that value (`info_keywords=("is_success",)`) and provide `info["is_success"]=True/False` on the final step of the episode

time/

- `episodes`: Total number of episodes
- `fps`: Number of frames per seconds (includes time taken by gradient update)
- `iterations`: Number of iterations (data collection + policy update for A2C/PPO)
- `time_elapsed`: Time in seconds since the beginning of training
- `total_timesteps`: Total number of timesteps (steps in the environments)

train/

- `actor_loss`: Current value for the actor loss for off-policy algorithms
- `approx_kl`: approximate mean KL divergence between old and new policy (for PPO), it is an estimation of how much changes happened in the update
- `clip_fraction`: mean fraction of surrogate loss that was clipped (above `clip_range` threshold) for PPO.
- `clip_range`: Current value of the clipping factor for the surrogate loss of PPO
- `critic_loss`: Current value for the critic function loss for off-policy algorithms, usually error between value function output and TD(0), temporal difference estimate
- `ent_coef`: Current value of the entropy coefficient (when using SAC)
- `ent_coef_loss`: Current value of the entropy coefficient loss (when using SAC)

- **entropy_loss**: Mean value of the entropy loss (negative of the average policy entropy)
- **explained_variance**: Fraction of the return variance explained by the value function, see https://scikit-learn.org/stable/modules/model_evaluation.html#explained-variance-score (ev=0 => might as well have predicted zero, ev=1 => perfect prediction, ev<0 => worse than just predicting zero)
- **learning_rate**: Current learning rate value
- **loss**: Current total loss value
- **n_updates**: Number of gradient updates applied so far
- **policy_gradient_loss**: Current value of the policy gradient loss (its value does not have much meaning)
- **value_loss**: Current value for the value function loss for on-policy algorithms, usually error between value function output and Monte-Carle estimate (or TD(lambda) estimate)
- **std**: Current standard deviation of the noise when using generalized State-Dependent Exploration (gSDE)

class stable_baselines3.common.logger.**CSVOutputFormat**(*filename*)

close()

closes the file

Return type None

write(*key_values*, *key_excluded*, *step*=0)

Write a dictionary to file

Parameters

- **key_values** (Dict[str, Any]) –
- **key_excluded** (Dict[str, Union[str, Tuple[str, ...]]]) –
- **step** (int) –

Return type None

class stable_baselines3.common.logger.**Figure**(*figure*, *close*)

Figure data class storing a matplotlib figure and whether to close the figure after logging it

Parameters

- **figure** (figure) – figure to log
- **close** (bool) – if true, close the figure after logging it

exception stable_baselines3.common.logger.**FormatUnsupportedError**(*unsupported_formats*,
value_description)

Custom error to display informative message when a value is not supported by some formats.

Parameters

- **unsupported_formats** (Sequence[str]) – A sequence of unsupported formats, for instance ["stdout"].
- **value_description** (str) – Description of the value that cannot be logged by this format.

class stable_baselines3.common.logger.**HumanOutputFormat**(*filename_or_file*, *max_length*=36)

A human-readable output format producing ASCII tables of key-value pairs.

Set attribute `max_length` to change the maximum length of keys and values to write to output (or specify it when calling `__init__`).

Parameters

- **filename_or_file** (Union[str, TextIO]) – the file to write the log to
- **max_length** (int) – the maximum length of keys and values to write to output. Outputs longer than this will be truncated. An error will be raised if multiple keys are truncated to the same value. The maximum output width will be $2 * \text{max_length} + 7$. The default of 36 produces output no longer than 79 characters wide.

close()

closes the file

Return type None

write(key_values, key_excluded, step=0)

Write a dictionary to file

Parameters

- **key_values** (Dict) –
- **key_excluded** (Dict) –
- **step** (int) –

Return type None

write_sequence(sequence)

write_sequence an array to file

Parameters **sequence** (List) –

Return type None

class stable_baselines3.common.logger.**Image**(image, dataformats)

Image data class storing an image and data format

Parameters

- **image** (Union[Tensor, ndarray, str]) – image to log
- **dataformats** (str) – Image data format specification of the form NCHW, NHWC, CHW, HWC, HW, WH, etc. More info in add_image method doc at <https://pytorch.org/docs/stable/tensorboard.html> Gym envs normally use ‘HWC’ (channel last)

class stable_baselines3.common.logger.**JSONOutputFormat**(filename)

close()

closes the file

Return type None

write(key_values, key_excluded, step=0)

Write a dictionary to file

Parameters

- **key_values** (Dict[str, Any]) –
- **key_excluded** (Dict[str, Union[str, Tuple[str, ...]]]) –
- **step** (int) –

Return type None

class stable_baselines3.common.logger.**KVWriter**

Key Value writer

close()

Close owned resources

Return type None**write**(*key_values*, *key_excluded*, *step=0*)

Write a dictionary to file

Parameters

- **key_values** (Dict[str, Any]) –
- **key_excluded** (Dict[str, Union[str, Tuple[str, ...]]]) –
- **step** (int) –

Return type None**class** `stable_baselines3.common.logger.Logger`(*folder*, *output_formats*)

The logger class.

Parameters

- **folder** (Optional[str]) – the logging location
- **output_formats** (List[KVWriter]) – the list of output formats

close()

closes the file

Return type None**debug**(**args*)

Write the sequence of args, with no separators, to the console and output files (if you've configured an output file). Using the DEBUG level.

Parameters **args** – log the arguments**Return type** None**dump**(*step=0*)

Write all of the diagnostics from the current iteration

Return type None**error**(**args*)

Write the sequence of args, with no separators, to the console and output files (if you've configured an output file). Using the ERROR level.

Parameters **args** – log the arguments**Return type** None**get_dir**()

Get directory that log files are being written to. will be None if there is no output directory (i.e., if you didn't call start)

Return type str**Returns** the logging directory

info(*args)

Write the sequence of args, with no separators, to the console and output files (if you've configured an output file). Using the INFO level.

Parameters **args** – log the arguments

Return type None

log(*args, level=20)

Write the sequence of args, with no separators, to the console and output files (if you've configured an output file).

level: int. (see `logger.py` docs) **If the global logger level is higher than** the level argument here, don't print to stdout.

Parameters

- **args** – log the arguments
- **level** (int) – the logging level (can be DEBUG=10, INFO=20, WARN=30, ERROR=40, DISABLED=50)

Return type None

record(key, value, exclude=None)

Log a value of some diagnostic Call this once for each diagnostic quantity, each iteration If called many times, last value will be used.

Parameters

- **key** (str) – save to log this key
- **value** (Any) – save to log this value
- **exclude** (Union[str, Tuple[str, ...], None]) – outputs to be excluded

Return type None

record_mean(key, value, exclude=None)

The same as `record()`, but if called many times, values averaged.

Parameters

- **key** (str) – save to log this key
- **value** (Any) – save to log this value
- **exclude** (Union[str, Tuple[str, ...], None]) – outputs to be excluded

Return type None

set_level(level)

Set logging threshold on current logger.

Parameters **level** (int) – the logging level (can be DEBUG=10, INFO=20, WARN=30, ERROR=40, DISABLED=50)

Return type None

warn(*args)

Write the sequence of args, with no separators, to the console and output files (if you've configured an output file). Using the WARN level.

Parameters **args** – log the arguments

Return type None

class `stable_baselines3.common.logger.SeqWriter`

sequence writer

write_sequence(*sequence*)

write_sequence an array to file

Parameters **sequence** (List) –

Return type None

class `stable_baselines3.common.logger.TensorBoardOutputFormat`(*folder*)

close()

closes the file

Return type None

write(*key_values*, *key_excluded*, *step=0*)

Write a dictionary to file

Parameters

- **key_values** (Dict[str, Any]) –
- **key_excluded** (Dict[str, Union[str, Tuple[str, ...]]]) –
- **step** (int) –

Return type None

class `stable_baselines3.common.logger.Video`(*frames*, *fps*)

Video data class storing the video frames and the frame per seconds

Parameters

- **frames** (Tensor) – frames to create the video from
- **fps** (Union[float, int]) – frames per second

`stable_baselines3.common.logger.configure`(*folder=None*, *format_strings=None*)

Configure the current logger.

Parameters

- **folder** (Optional[str]) – the save location (if None, \$SB3_LOGDIR, if still None, tempdir/SB3-[date & time])
- **format_strings** (Optional[List[str]]) – the output logging format (if None, \$SB3_LOG_FORMAT, if still None, ['stdout', 'log', 'csv'])

Return type *Logger*

Returns The logger object.

`stable_baselines3.common.logger.filter_excluded_keys`(*key_values*, *key_excluded*, *_format*)

Filters the keys specified by `key_exclude` for the specified format

Parameters

- **key_values** (Dict[str, Any]) – log dictionary to be filtered
- **key_excluded** (Dict[str, Union[str, Tuple[str, ...]]]) – keys to be excluded per format

- **_format** (str) – format for which this filter is run

Return type Dict[str, Any]

Returns dict without the excluded keys

`stable_baselines3.common.logger.make_output_format(_format, log_dir, log_suffix="")`

return a logger for the requested format

Parameters

- **_format** (str) – the requested format to log to ('stdout', 'log', 'json' or 'csv' or 'tensor-board')
- **log_dir** (str) – the logging directory
- **log_suffix** (str) – the suffix for the log file

Return type *KVWriter*

Returns the logger

`stable_baselines3.common.logger.read_csv(filename)`

read a csv file using pandas

Parameters **filename** (str) – the file path to read

Return type DataFrame

Returns the data in the csv

`stable_baselines3.common.logger.read_json(filename)`

read a json file using pandas

Parameters **filename** (str) – the file path to read

Return type DataFrame

Returns the data in the json

1.37 Action Noise

class `stable_baselines3.common.noise.ActionNoise`

The action noise base class

reset()

call end of episode reset for the noise

Return type None

class `stable_baselines3.common.noise.NormalActionNoise(mean, sigma)`

A Gaussian action noise

Parameters

- **mean** (ndarray) – the mean value of the noise
- **sigma** (ndarray) – the scale of the noise (std here)

```
class stable_baselines3.common.noise.OrnsteinUhlenbeckActionNoise(mean, sigma, theta=0.15,
                                                                dt=0.01, initial_noise=None)
```

An Ornstein Uhlenbeck action noise, this is designed to approximate Brownian motion with friction.

Based on <http://math.stackexchange.com/questions/1287634/implementing-ornstein-uhlenbeck-in-matlab>

Parameters

- **mean** (ndarray) – the mean of the noise
- **sigma** (ndarray) – the scale of the noise
- **theta** (float) – the rate of mean reversion
- **dt** (float) – the timestep for the noise
- **initial_noise** (Optional[ndarray]) – the initial value for the noise output, (if None: 0)

reset()

reset the Ornstein Uhlenbeck noise, to the initial position

Return type None

```
class stable_baselines3.common.noise.VectorizedActionNoise(base_noise, n_envs)
```

A Vectorized action noise for parallel environments.

Parameters

- **base_noise** (*ActionNoise*) – ActionNoise The noise generator to use
- **n_envs** (int) – The number of parallel environments

reset(indices=None)

Reset all the noise processes, or those listed in indices

Parameters **indices** (Optional[Iterable[int]]) – Optional[Iterable[int]] The indices to reset. Default: None. If the parameter is None, then all processes are reset to their initial position.

Return type None

1.38 Utils

```
stable_baselines3.common.utils.check_for_correct_spaces(env, observation_space, action_space)
```

Checks that the environment has same spaces as provided ones. Used by BaseAlgorithm to check if spaces match after loading the model with given env. Checked parameters: - observation_space - action_space

Parameters

- **env** (Union[Env, *VecEnv*]) – Environment to check for valid spaces
- **observation_space** (Space) – Observation space to check against
- **action_space** (Space) – Action space to check against

Return type None

```
stable_baselines3.common.utils.configure_logger(verbose=0, tensorboard_log=None, tb_log_name="",
                                                reset_num_timesteps=True)
```

Configure the logger's outputs.

Parameters

- **verbose** (int) – the verbosity level: 0 no output, 1 info, 2 debug
- **tensorboard_log** (Optional[str]) – the log location for tensorboard (if None, no logging)
- **tb_log_name** (str) – tensorboard log
- **reset_num_timesteps** (bool) – Whether the `num_timesteps` attribute is reset or not. It allows to continue a previous learning curve (`reset_num_timesteps=False`) or start from `t=0` (`reset_num_timesteps=True`, the default).

Return type *Logger*

Returns The logger object

`stable_baselines3.common.utils.constant_fn(val)`

Create a function that returns a constant It is useful for learning rate schedule (to avoid code duplication)

Parameters `val` (float) –

Return type Callable[[float], float]

Returns

`stable_baselines3.common.utils.explained_variance(y_pred, y_true)`

Computes fraction of variance that `y_pred` explains about `y`. Returns $1 - \text{Var}[y - y_{\text{pred}}] / \text{Var}[y]$

interpretation: `ev=0` => might as well have predicted zero `ev=1` => perfect prediction `ev<0` => worse than just predicting zero

Parameters

- **y_pred** (ndarray) – the prediction
- **y_true** (ndarray) – the expected value

Return type ndarray

Returns explained variance of `y_pred` and `y`

`stable_baselines3.common.utils.get_device(device='auto')`

Retrieve PyTorch device. It checks that the requested device is available first. For now, it supports only `cpu` and `cuda`. By default, it tries to use the `gpu`.

Parameters `device` (Union[device, str]) – One for 'auto', 'cuda', 'cpu'

Return type device

Returns

`stable_baselines3.common.utils.get_latest_run_id(log_path=None, log_name='')`

Returns the latest run number for the given log name and log path, by finding the greatest number in the directories.

Return type int

Returns latest run number

`stable_baselines3.common.utils.get_linear_fn(start, end, end_fraction)`

Create a function that interpolates linearly between `start` and `end` between `progress_remaining = 1` and `progress_remaining = end_fraction`. This is used in DQN for linearly annealing the exploration fraction (epsilon for the epsilon-greedy strategy).

Params `start` value to start with if `progress_remaining = 1`

Params end value to end with if `progress_remaining = 0`

Params end_fraction fraction of `progress_remaining` where end is reached e.g 0.1 then end is reached after 10% of the complete training process.

Return type Callable[[float], float]

Returns

`stable_baselines3.common.utils.get_schedule_fn(value_schedule)`

Transform (if needed) learning rate and clip range (for PPO) to callable.

Parameters `value_schedule` (Union[Callable[[float], float], float, int]) –

Return type Callable[[float], float]

Returns

`stable_baselines3.common.utils.get_system_info(print_info=True)`

Retrieve system and python env info for the current system.

Parameters `print_info` (bool) – Whether to print or not those infos

Return type Tuple[Dict[str, str], str]

Returns Dictionary summing up the version for each relevant package and a formatted string.

`stable_baselines3.common.utils.is_vectorized_box_observation(observation, observation_space)`

For box observation type, detects and validates the shape, then returns whether or not the observation is vectorized.

Parameters

- **observation** (ndarray) – the input observation to validate
- **observation_space** (Box) – the observation space

Return type bool

Returns whether the given observation is vectorized or not

`stable_baselines3.common.utils.is_vectorized_dict_observation(observation, observation_space)`

For dict observation type, detects and validates the shape, then returns whether or not the observation is vectorized.

Parameters

- **observation** (ndarray) – the input observation to validate
- **observation_space** (Dict) – the observation space

Return type bool

Returns whether the given observation is vectorized or not

`stable_baselines3.common.utils.is_vectorized_discrete_observation(observation, observation_space)`

For discrete observation type, detects and validates the shape, then returns whether or not the observation is vectorized.

Parameters

- **observation** (Union[int, ndarray]) – the input observation to validate
- **observation_space** (Discrete) – the observation space

Return type bool

Returns whether the given observation is vectorized or not

`stable_baselines3.common.utils.is_vectorized_multibinary_observation(observation, observation_space)`

For multibinary observation type, detects and validates the shape, then returns whether or not the observation is vectorized.

Parameters

- **observation** (ndarray) – the input observation to validate
- **observation_space** (MultiBinary) – the observation space

Return type bool

Returns whether the given observation is vectorized or not

`stable_baselines3.common.utils.is_vectorized_multidiscrete_observation(observation, observation_space)`

For multidiscrete observation type, detects and validates the shape, then returns whether or not the observation is vectorized.

Parameters

- **observation** (ndarray) – the input observation to validate
- **observation_space** (MultiDiscrete) – the observation space

Return type bool

Returns whether the given observation is vectorized or not

`stable_baselines3.common.utils.is_vectorized_observation(observation, observation_space)`

For every observation type, detects and validates the shape, then returns whether or not the observation is vectorized.

Parameters

- **observation** (Union[int, ndarray]) – the input observation to validate
- **observation_space** (Space) – the observation space

Return type bool

Returns whether the given observation is vectorized or not

`stable_baselines3.common.utils.obs_as_tensor(obs, device)`

Moves the observation to the given device.

Parameters

- **obs** (Union[ndarray, Dict[Union[str, int], ndarray]]) –
- **device** (device) – PyTorch device

Return type Union[Tensor, Dict[Union[str, int], Tensor]]

Returns PyTorch tensor of the observation on a desired device.

`stable_baselines3.common.utils.polyak_update(params, target_params, tau)`

Perform a Polyak average update on `target_params` using `params`: target parameters are slowly updated towards the main parameters. `tau`, the soft update coefficient controls the interpolation: `tau=1` corresponds to copying the parameters to the target ones whereas nothing happens when `tau=0`. The Polyak update is done in place, with `no_grad`, and therefore does not create intermediate tensors, or a computation graph, reducing memory cost and improving performance. We scale the target params by `1-tau` (in-place), add

the new weights, scaled by tau and store the result of the sum in the target params (in place). See <https://github.com/DLR-RM/stable-baselines3/issues/93>

Parameters

- **params** (Iterable[Parameter]) – parameters to use to update the target params
- **target_params** (Iterable[Parameter]) – parameters to update
- **tau** (float) – the soft update coefficient (“Polyak update”, between 0 and 1)

Return type None

`stable_baselines3.common.utils.safe_mean(arr)`

Compute the mean of an array if there is at least one element. For empty array, return NaN. It is used for logging only.

Parameters **arr** (Union[ndarray, list, deque]) –

Return type ndarray

Returns

`stable_baselines3.common.utils.set_random_seed(seed, using_cuda=False)`

Seed the different random generators.

Parameters

- **seed** (int) –
- **using_cuda** (bool) –

Return type None

`stable_baselines3.common.utils.should_collect_more_steps(train_freq, num_collected_steps, num_collected_episodes)`

Helper used in `collect_rollouts()` of off-policy algorithms to determine the termination condition.

Parameters

- **train_freq** (TrainFreq) – How much experience should be collected before updating the policy.
- **num_collected_steps** (int) – The number of already collected steps.
- **num_collected_episodes** (int) – The number of already collected episodes.

Return type bool

Returns Whether to continue or not collecting experience by doing rollouts of the current policy.

`stable_baselines3.common.utils.update_learning_rate(optimizer, learning_rate)`

Update the learning rate for a given optimizer. Useful when doing linear schedule.

Parameters

- **optimizer** (Optimizer) –
- **learning_rate** (float) –

Return type None

`stable_baselines3.common.utils.zip_strict(*iterables)`

`zip()` function but enforces that iterables are of equal length. Raises `ValueError` if iterables not of equal length. Code inspired by Stackoverflow answer for question #32954486.

Parameters ***iterables** – iterables to `zip()`

Return type Iterable

1.39 Changelog

1.39.1 Release 1.5.1a0 (WIP)

Breaking Changes:

New Features:

SB3-Contrib

Bug Fixes:

- Fixed saving and loading large policies greater than 2GB (@jkterry1, @ycheng517)

Deprecations:

Others:

Documentation:

1.39.2 Release 1.5.0 (2022-03-25)

Bug fixes, early stopping callback

Breaking Changes:

- Switched minimum Gym version to 0.21.0.

New Features:

- Added `StopTrainingOnNoModelImprovement` to callback collection (@caburu)
- Makes the length of keys and values in `HumanOutputFormat` configurable, depending on desired maximum width of output.
- Allow PPO to turn of advantage normalization (see [PR #763](#)) @vwxyzjn

SB3-Contrib

- coming soon: Cross Entropy Method, see <https://github.com/Stable-Baselines-Team/stable-baselines3-contrib/pull/62>

Bug Fixes:

- Fixed a bug in `VecMonitor`. The monitor did not consider the `info_keywords` during stepping (@ScheiklP)
- Fixed a bug in `HumanOutputFormat`. Distinct keys truncated to the same prefix would overwrite each others value, resulting in only one being output. This now raises an error (this should only affect a small fraction of use cases with very long keys.)
- Routing all the `nn.Module` calls through `implicit` rather than `explicit` forward as per pytorch guidelines (@manuel-delverme)
- Fixed a bug in `VecNormalize` where error occurs when `norm_obs` is set to `False` for environment with dictionary observation (@buoyancy99)
- Set default `env` argument to `None` in `HerReplayBuffer.sample` (@qgallouedec)
- Fix `batch_size` typing in DQN (@qgallouedec)
- Fixed sample normalization in `DictReplayBuffer` (@qgallouedec)

Deprecations:

Others:

- Fixed pytest warnings
- Removed parameter `remove_time_limit_termination` in off policy algorithms since it was dead code (@Gregwar)

Documentation:

- Added doc on Hugging Face integration (@simoninithomas)
- Added furuta pendulum project to project list (@armandpl)
- Fix indentation 2 spaces to 4 spaces in custom env documentation example (@Gautam-J)
- Update `MlpExtractor` docstring (@gianlucadecola)
- Added explanation of the logger output
- Update `Directly Accessing The Summary Writer` in tensorboard integration (@xy9485)

1.39.3 Release 1.4.0 (2022-01-18)

TRPO, ARS and multi env training for off-policy algorithms

Breaking Changes:

- Dropped python 3.6 support (as announced in previous release)
- Renamed `mask` argument of the `predict()` method to `episode_start` (used with RNN policies only)
- local variables `action`, `done` and `reward` were renamed to their plural form for offpolicy algorithms (`actions`, `done`s, `rewards`), this may affect custom callbacks.
- Removed `episode_reward` field from `RolloutReturn()` type

Warning: An update to the HER algorithm is planned to support multi-env training and remove the max episode length constrain. (see [PR #704](#)) This will be a backward incompatible change (model trained with previous version of HER won't work with the new version).

New Features:

- Added `norm_obs_keys` param for `VecNormalize` wrapper to configure which observation keys to normalize (@kachayev)
- Added experimental support to train off-policy algorithms with multiple envs (note: `HerReplayBuffer` currently not supported)
- Handle timeout termination properly for on-policy algorithms (when using `TimeLimit`)
- Added `skip` option to `VecTransposeImage` to skip transforming the channel order when the heuristic is wrong
- Added `copy()` and `combine()` methods to `RunningMeanStd`

SB3-Contrib

- Added Trust Region Policy Optimization (TRPO) (@cyprienc)
- Added Augmented Random Search (ARS) (@sgillen)
- Coming soon: PPO LSTM, see <https://github.com/Stable-Baselines-Team/stable-baselines3-contrib/pull/53>

Bug Fixes:

- Fixed a bug where `set_env()` with `VecNormalize` would result in an error with off-policy algorithms (thanks @cleveronahum)
- FPS calculation is now performed based on number of steps performed during last `learn` call, even when `reset_num_timesteps` is set to `False` (@kachayev)
- Fixed evaluation script for recurrent policies (experimental feature in SB3 contrib)
- Fixed a bug where the observation would be incorrectly detected as non-vectorized instead of throwing an error
- The env checker now properly checks and warns about potential issues for continuous action spaces when the boundaries are too small or when the dtype is not `float32`
- Fixed a bug in `VecFrameStack` with channel first image envs, where the terminal observation would be wrongly created.

Deprecations:

Others:

- Added a warning in the env checker when not using `np.float32` for continuous actions
- Improved test coverage and error message when checking shape of observation
- Added `newline="\n"` when opening CSV monitor files so that each line ends with `\r\n` instead of `\r\r\n` on Windows while Linux environments are not affected (@hsuehch)
- Fixed device argument inconsistency (@qgallouedec)

Documentation:

- Add drivergym to projects page (@theDebugger811)
- Add highway-env to projects page (@eleurent)
- Add tactile-gym to projects page (@ac-93)
- Fix indentation in the RL tips page (@cove9988)
- Update GAE computation docstring
- Add documentation on exporting to TFLite/Coral
- Added JMLR paper and updated citation
- Added link to RL Tips and Tricks video
- Updated `BaseAlgorithm.load` docstring (@Demetrio92)
- Added a note on load behavior in the examples (@Demetrio92)
- Updated SB3 Contrib doc
- Fixed A2C and migration guide guidance on how to set epsilon with `RMSpropTFLike` (@thomasgubler)
- Fixed custom policy documentation (@IperGiove)
- Added doc on Weights & Biases integration

1.39.4 Release 1.3.0 (2021-10-23)

Bug fixes and improvements for the user

<p>Warning: This version will be the last one supporting Python 3.6 (end of life in Dec 2021). We highly recommended you to upgrade to Python ≥ 3.7.</p>

Breaking Changes:

- `sde_net_arch` argument in policies is deprecated and will be removed in a future version.
- `_get_latent` (`ActorCriticPolicy`) was removed
- All logging keys now use underscores instead of spaces (@timokau). Concretely this changes:
 - `time/total timesteps` to `time/total_timesteps` for off-policy algorithms (PPO and A2C) and the `eval` callback (on-policy algorithms already used the underscored version),
 - `rollout/exploration rate` to `rollout/exploration_rate` and
 - `rollout/success rate` to `rollout/success_rate`.

New Features:

- Added methods `get_distribution` and `predict_values` for `ActorCriticPolicy` for A2C/PPO/TRPO (@cyprienc)
- Added methods `forward_actor` and `forward_critic` for `MlpExtractor`
- Added `sb3.get_system_info()` helper function to gather version information relevant to SB3 (e.g., Python and PyTorch version)
- Saved models now store system information where agent was trained, and load functions have `print_system_info` parameter to help debugging load issues

Bug Fixes:

- Fixed dtype of observations for `SimpleMultiObsEnv`
- Allow `VecNormalize` to wrap discrete-observation environments to normalize reward when observation normalization is disabled
- Fixed a bug where DQN would throw an error when using `Discrete` observation and stochastic actions
- Fixed a bug where sub-classed observation spaces could not be used
- Added `force_reset` argument to `load()` and `set_env()` in order to be able to call `learn(reset_num_timesteps=False)` with a new environment

Deprecations:

Others:

- Cap gym max version to 0.19 to avoid issues with atari-py and other breaking changes
- Improved error message when using dict observation with the wrong policy
- Improved error message when using `EvalCallback` with two envs not wrapped the same way.
- Added additional infos about supported python version for PyPi in `setup.py`

Documentation:

- Add Rocket League Gym to list of supported projects (@AechPro)
- Added gym-electric-motor to project page (@wkirgsn)
- Added policy-distillation-baselines to project page (@CUN-bjy)
- Added ONNX export instructions (@batu)
- Update read the doc env (fixed docutils issue)
- Fix PPO environment name (@IljaAvadiev)
- Fix custom env doc and add env registration example
- Update algorithms from SB3 Contrib
- Use underscores for numeric literals in examples to improve clarity

1.39.5 Release 1.2.0 (2021-09-03)

Hotfix for VecNormalize, training/eval mode support

Breaking Changes:

- SB3 now requires PyTorch $\geq 1.8.1$
- VecNormalize `ret` attribute was renamed to `returns`

New Features:

Bug Fixes:

- Hotfix for VecNormalize where the observation filter was not updated at reset (thanks @vwxyzjn)
- Fixed model predictions when using batch normalization and dropout layers by calling `train()` and `eval()` (@davidblom603)
- Fixed model training for DQN, TD3 and SAC so that their target nets always remain in evaluation mode (@ay-eright)
- Passing `gradient_steps=0` to an off-policy algorithm will result in no gradient steps being taken (vs as many gradient steps as steps done in the environment during the rollout in previous versions)

Deprecations:

Others:

- Enabled Python 3.9 in GitHub CI
- Fixed type annotations
- Refactored `predict()` by moving the preprocessing to `obs_to_tensor()` method

Documentation:

- Updated multiprocessing example
- Added example of `VecEnvWrapper`
- Added a note about logging to tensorboard more often
- Added warning about simplicity of examples and link to RL zoo (@MihaiAnca13)

1.39.6 Release 1.1.0 (2021-07-01)

Dict observation support, timeout handling and refactored HER buffer

Breaking Changes:

- All custom environments (e.g. the `BitFlippingEnv` or `IdentityEnv`) were moved to `stable_baselines3.common.envs` folder
- Refactored HER which is now the `HerReplayBuffer` class that can be passed to any off-policy algorithm
- Handle timeout termination properly for off-policy algorithms (when using `TimeLimit`)
- Renamed `_last_dones` and `dones` to `_last_episode_starts` and `episode_starts` in `RolloutBuffer`.
- Removed `ObsDictWrapper` as Dict observation spaces are now supported

```
her_kwargs = dict(n_sampled_goal=2, goal_selection_strategy="future", online_
↳sampling=True)
# SB3 < 1.1.0
# model = HER("MlpPolicy", env, model_class=SAC, **her_kwargs)
# SB3 >= 1.1.0:
model = SAC("MultiInputPolicy", env, replay_buffer_class=HerReplayBuffer, replay_buffer_
↳kwargs=her_kwargs)
```

- Updated the KL Divergence estimator in the PPO algorithm to be positive definite and have lower variance (@09tangriro)
- Updated the KL Divergence check in the PPO algorithm to be before the gradient update step rather than after end of epoch (@09tangriro)
- Removed parameter `channels_last` from `is_image_space` as it can be inferred.
- The logger object is now an attribute `model.logger` that be set by the user using `model.set_logger()`
- Changed the signature of `logger.configure` and `utils.configure_logger`, they now return a `Logger` object
- Removed `Logger.CURRENT` and `Logger.DEFAULT`
- Moved `warn()`, `debug()`, `log()`, `info()`, `dump()` methods to the `Logger` class
- `.learn()` now throws an import error when the user tries to log to tensorboard but the package is not installed

New Features:

- Added support for single-level Dict observation space (@JadenTravnik)
- Added `DictRolloutBuffer` `DictReplayBuffer` to support dictionary observations (@JadenTravnik)
- Added `StackedObservations` and `StackedDictObservations` that are used within `VecFrameStack`
- Added simple 4x4 room Dict test environments
- `HerReplayBuffer` now supports `VecNormalize` when `online_sampling=False`
- Added `VecMonitor` and `VecExtractDictObs` wrappers to handle gym3-style vectorized environments (@vwxyzjn)
- Ignored the terminal observation if it is not provided by the environment such as the gym3-style vectorized environments. (@vwxyzjn)
- Added `policy_base` as input to the `OnPolicyAlgorithm` for more flexibility (@09tangriro)
- Added support for image observation when using HER
- Added `replay_buffer_class` and `replay_buffer_kwargs` arguments to off-policy algorithms
- Added `kl_divergence` helper for `Distribution` classes (@09tangriro)

- Added support for vector environments with `num_envs > 1` (@benblack769)
- Added `wrapper_kwargs` argument to `make_vec_env` (@amy12xx)

Bug Fixes:

- Fixed potential issue when calling off-policy algorithms with default arguments multiple times (the size of the replay buffer would be the same)
- Fixed loading of `ent_coef` for SAC and TQC, it was not optimized anymore (thanks @Atlis)
- Fixed saving of A2C and PPO policy when using gSDE (thanks @liusida)
- Fixed a bug where no output would be shown even if `verbose>=1` after passing `verbose=0` once
- Fixed observation buffers dtype in DictReplayBuffer (@c-rizz)
- Fixed EvalCallback tensorboard logs being logged with the incorrect timestep. They are now written with the timestep at which they were recorded. (@skandermoalla)

Deprecations:

Others:

- Added flake8-bugbear to tests dependencies to find likely bugs
- Updated `env_checker` to reflect support of dict observation spaces
- Added Code of Conduct
- Added tests for GAE and lambda return computation
- Updated distribution entropy test (thanks @09tangriro)
- Added sanity check `batch_size > 1` in PPO to avoid NaN in advantage normalization

Documentation:

- Added gym pybullet drones project (@JacopoPan)
- Added link to SuperSuit in projects (@justinkterry)
- Fixed DQN example (thanks @ltbd78)
- Clarified channel-first/channel-last recommendation
- Update sphinx environment installation instructions (@tom-doerr)
- Clarified pip installation in Zsh (@tom-doerr)
- Clarified return computation for on-policy algorithms (TD(lambda) estimate was used)
- Added example for using `ProcgenEnv`
- Added note about advanced custom policy example for off-policy algorithms
- Fixed DQN unicode checkmarks
- Updated migration guide (@juancroldan)
- Pinned `docutils==0.16` to avoid issue with rtd theme
- Clarified callback `save_freq` definition

- Added doc on how to pass a custom logger
- Remove recurrent policies from A2C docs (@bstee615)

1.39.7 Release 1.0 (2021-03-15)

First Major Version

Breaking Changes:

- Removed `stable_baselines3.common.cmd_util` (already deprecated), please use `env_util` instead

Warning: A refactoring of the HER algorithm is planned together with support for dictionary observations (see [PR #243](#) and [#351](#)) This will be a backward incompatible change (model trained with previous version of HER won't work with the new version).

New Features:

- Added support for `custom_objects` when loading models

Bug Fixes:

- Fixed a bug with DQN predict method when using `deterministic=False` with image space

Documentation:

- Fixed examples
- Added new project using SB3: `rl_reach` (@PierreExeter)
- Added note about slow-down when switching to PyTorch
- Add a note on continual learning and resetting environment

Others:

- Updated RL-Zoo to reflect the fact that is it more than a collection of trained agents
- Added images to illustrate the training loop and custom policies (created with <https://excalidraw.com/>)
- Updated the custom policy section

1.39.8 Pre-Release 0.11.1 (2021-02-27)

Bug Fixes:

- Fixed a bug where `train_freq` was not properly converted when loading a saved model

1.39.9 Pre-Release 0.11.0 (2021-02-27)

Breaking Changes:

- `evaluate_policy` now returns rewards/episode lengths from a `Monitor` wrapper if one is present, this allows to return the unnormalized reward in the case of Atari games for instance.
- Renamed `common.vec_env.is_wrapped` to `common.vec_env.is_vecenv_wrapped` to avoid confusion with the new `is_wrapped()` helper
- Renamed `_get_data()` to `_get_constructor_parameters()` for policies (this affects independent saving/loading of policies)
- Removed `n_episodes_rollout` and merged it with `train_freq`, which now accepts a tuple (`frequency`, `unit`):
- `replay_buffer` in `collect_rollout` is no more optional

```
# SB3 < 0.11.0
# model = SAC("MlpPolicy", env, n_episodes_rollout=1, train_freq=-1)
# SB3 >= 0.11.0:
model = SAC("MlpPolicy", env, train_freq=(1, "episode"))
```

New Features:

- Add support for `VecFrameStack` to stack on first or last observation dimension, along with automatic check for image spaces.
- `VecFrameStack` now has a `channels_order` argument to tell if observations should be stacked on the first or last observation dimension (originally always stacked on last).
- Added `common.env_util.is_wrapped` and `common.env_util.unwrap_wrapper` functions for checking/unwrapping an environment for specific wrapper.
- Added `env_is_wrapped()` method for `VecEnv` to check if its environments are wrapped with given Gym wrappers.
- Added `monitor_kwargs` parameter to `make_vec_env` and `make_atari_env`
- Wrap the environments automatically with a `Monitor` wrapper when possible.
- `EvalCallback` now logs the success rate when available (`is_success` must be present in the info dict)
- Added new wrappers to log images and matplotlib figures to tensorboard. (@zampanteymedio)
- Add support for text records to `Logger`. (@lorenz-h)

Bug Fixes:

- Fixed bug where code added VecTranspose on channel-first image environments (thanks @qxcv)
- Fixed DQN predict method when using single `gym.Env` with `deterministic=False`
- Fixed bug that the arguments order of `explained_variance()` in `ppo.py` and `a2c.py` is not correct (@thisray)
- Fixed bug where full `HerReplayBuffer` leads to an index error. (@megan-klaiber)
- Fixed bug where replay buffer could not be saved if it was too big (> 4 Gb) for python<3.8 (thanks @hn2)
- Added informative PPO construction error in edge-case scenario where `n_steps * n_envs = 1` (size of rollout buffer), which otherwise causes downstream breaking errors in training (@decodyng)
- Fixed discrete observation space support when using multiple envs with A2C/PPO (thanks @ardabbour)
- Fixed a bug for TD3 delayed update (the update was off-by-one and not delayed when `train_freq=1`)
- Fixed numpy warning (replaced `np.bool` with `bool`)
- Fixed a bug where `VecNormalize` was not normalizing the terminal observation
- Fixed a bug where `VecTranspose` was not transposing the terminal observation
- Fixed a bug where the terminal observation stored in the replay buffer was not the right one for off-policy algorithms
- Fixed a bug where `action_noise` was not used when using HER (thanks @ShangqunYu)

Deprecations:

Others:

- Add more issue templates
- Add signatures to callable type annotations (@ernestum)
- Improve error message in NatureCNN
- Added checks for supported action spaces to improve clarity of error messages for the user
- Renamed variables in the `train()` method of SAC, TD3 and DQN to match SB3-Contrib.
- Updated docker base image to Ubuntu 18.04
- Set tensorboard min version to 2.2.0 (earlier version are apparently not working with PyTorch)
- Added warning for PPO when `n_steps * n_envs` is not a multiple of `batch_size` (last mini-batch truncated) (@decodyng)
- Removed some warnings in the tests

Documentation:

- Updated algorithm table
- Minor docstring improvements regarding rollout (@stheid)
- Fix migration doc for A2C (epsilon parameter)
- Fix clip_range docstring
- Fix duplicated parameter in EvalCallback docstring (thanks @tfederico)
- Added example of learning rate schedule
- Added SUMO-RL as example project (@LucasAlegre)
- Fix docstring of classes in atari_wrappers.py which were inside the constructor (@LucasAlegre)
- Added SB3-Contrib page
- Fix bug in the example code of DQN (@AptX395)
- Add example on how to access the tensorboard summary writer directly. (@lorenz-h)
- Updated migration guide
- Updated custom policy doc (separate policy architecture recommended)
- Added a note about OpenCV headless version
- Corrected typo on documentation (@mschweizer)
- Provide the environment when loading the model in the examples (@lorepieri8)

1.39.10 Pre-Release 0.10.0 (2020-10-28)

HER with online and offline sampling, bug fixes for features extraction

Breaking Changes:

- **Warning:** Renamed `common.cmd_util` to `common.env_util` for clarity (affects `make_vec_env` and `make_atari_env` functions)

New Features:

- Allow custom actor/critic network architectures using `net_arch=dict(qf=[400, 300], pi=[64, 64])` for off-policy algorithms (SAC, TD3, DDPG)
- Added Hindsight Experience Replay HER. (@megan-klaiber)
- `VecNormalize` now supports `gym.spaces.Dict` observation spaces
- Support logging videos to Tensorboard (@SwamyDev)
- Added `share_features_extractor` argument to SAC and TD3 policies

Bug Fixes:

- Fix GAE computation for on-policy algorithms (off-by one for the last value) (thanks @Wovchena)
- Fixed potential issue when loading a different environment
- Fix ignoring the exclude parameter when recording logs using json, csv or log as logging format (@SwamyDev)
- Make `make_vec_env` support the `env_kwargs` argument when using an env ID str (@ManifoldFR)
- Fix model creation initializing CUDA even when `device="cpu"` is provided
- Fix `check_env` not checking if the env has a Dict actionspace before calling `_check_nan` (@wmmmc88)
- Update the check for spaces unsupported by Stable Baselines 3 to include checks on the action space (@wmmmc88)
- Fixed feature extractor bug for target network where the same net was shared instead of being separate. This bug affects SAC, DDPG and TD3 when using `CnnPolicy` (or custom feature extractor)
- Fixed a bug when passing an environment when loading a saved model with a `CnnPolicy`, the passed env was not wrapped properly (the bug was introduced when implementing HER so it should not be present in previous versions)

Deprecations:

Others:

- Improved typing coverage
- Improved error messages for unsupported spaces
- Added `.vscode` to the gitignore

Documentation:

- Added first draft of migration guide
- Added intro to `imitation` library (@shwang)
- Enabled doc for `CnnPolicies`
- Added advanced saving and loading example
- Added base doc for exporting models
- Added example for getting and setting model parameters

1.39.11 Pre-Release 0.9.0 (2020-10-03)

Bug fixes, get/set parameters and improved docs

Breaking Changes:

- Removed device keyword argument of policies; use `policy.to(device)` instead. (@qxcv)
- Rename `BaseClass.get_torch_variables` -> `BaseClass._get_torch_save_params` and `BaseClass.excluded_save_params` -> `BaseClass._excluded_save_params`
- Renamed saved items tensors to `pytorch_variables` for clarity
- `make_atari_env`, `make_vec_env` and `set_random_seed` must be imported with (and not directly from `stable_baselines3.common`):

```
from stable_baselines3.common.cmd_util import make_atari_env, make_vec_env
from stable_baselines3.common.utils import set_random_seed
```

New Features:

- Added `unwrap_vec_wrapper()` to `common.vec_env` to extract `VecEnvWrapper` if needed
- Added `StopTrainingOnMaxEpisodes` to callback collection (@xicocaio)
- Added device keyword argument to `BaseAlgorithm.load()` (@liorcohen5)
- Callbacks have access to rollout collection locals as in SB2. (@PartiallyTyped)
- Added `get_parameters` and `set_parameters` for accessing/setting parameters of the agent
- Added actor/critic loss logging for TD3. (@mlloo3)

Bug Fixes:

- Added `unwrap_vec_wrapper()` to `common.vec_env` to extract `VecEnvWrapper` if needed
- Fixed a bug where the environment was reset twice when using `evaluate_policy`
- Fix logging of `clip_fraction` in PPO (@diditforlulz273)
- Fixed a bug where cuda support was wrongly checked when passing the GPU index, e.g., `device="cuda:0"` (@liorcohen5)
- Fixed a bug when the random seed was not properly set on cuda when passing the GPU index

Deprecations:

Others:

- Improve typing coverage of the `VecEnv`
- Fix type annotation of `make_vec_env` (@ManifoldFR)
- Removed `AlreadySteppingError` and `NotSteppingError` that were not used
- Fixed typos in SAC and TD3
- Reorganized functions for clarity in `BaseClass` (save/load functions close to each other, private functions at top)
- Clarified docstrings on what is saved and loaded to/from files
- Simplified `save_to_zip_file` function by removing duplicate code
- Store library version along with the saved models

- DQN loss is now logged

Documentation:

- Added `StopTrainingOnMaxEpisodes` details and example (@xicocaio)
- Updated custom policy section (added custom feature extractor example)
- Re-enable `sphinx_autodoc_typehints`
- Updated doc style for type hints and remove duplicated type hints

1.39.12 Pre-Release 0.8.0 (2020-08-03)

DQN, DDPG, bug fixes and performance matching for Atari games

Breaking Changes:

- `AtariWrapper` and other Atari wrappers were updated to match SB2 ones
- `save_replay_buffer` now receives as argument the file path instead of the folder path (@tirafesi)
- Refactored `Critic` class for TD3 and SAC, it is now called `ContinuousCritic` and has an additional parameter `n_critics`
- SAC and TD3 now accept an arbitrary number of critics (e.g. `policy_kwargs=dict(n_critics=3)`) instead of only 2 previously

New Features:

- Added DQN Algorithm (@Artemis-Skade)
- Buffer dtype is now set according to action and observation spaces for `ReplayBuffer`
- Added warning when allocation of a buffer may exceed the available memory of the system when `psutil` is available
- Saving models now automatically creates the necessary folders and raises appropriate warnings (@Partially-Typed)
- Refactored opening paths for saving and loading to use strings, `pathlib` or `io.BufferedIOBase` (@PartiallyTyped)
- Added DDPG algorithm as a special case of TD3.
- Introduced `BaseModel` abstract parent for `BasePolicy`, which critics inherit from.

Bug Fixes:

- Fixed a bug in the `close()` method of `SubprocVecEnv`, causing wrappers further down in the wrapper stack to not be closed. (@NeoExtended)
- Fix target for updating q values in SAC: the entropy term was not conditioned by terminals states
- Use `cloudpickle.load` instead of `pickle.load` in `CloudpickleWrapper`. (@shwang)
- Fixed a bug with orthogonal initialization when `bias=False` in custom policy (@rk37)
- Fixed approximate entropy calculation in PPO and A2C. (@andyshih12)

- Fixed DQN target network sharing feature extractor with the main network.
- Fixed storing correct `done`s in on-policy algorithm rollout collection. (@andyshih12)
- Fixed number of filters in final convolutional layer in NatureCNN to match original implementation.

Deprecations:

Others:

- Refactored off-policy algorithm to share the same `.learn()` method
- Split the `collect_rollout()` method for off-policy algorithms
- Added `_on_step()` for off-policy base class
- Optimized replay buffer size by removing the need of `next_observations` numpy array
- Optimized polyak updates (1.5-1.95 speedup) through inplace operations (@PartiallyTyped)
- Switch to `black` codestyle and added `make format`, `make check-codestyle` and `commit-checks`
- Ignored errors from newer `pytype` version
- Added a check when using `gSDE`
- Removed `codacy` dependency from Dockerfile
- Added `common.sb2_compat.RMSpropTFLike` optimizer, which corresponds closer to the implementation of `RMSprop` from Tensorflow.

Documentation:

- Updated notebook links
- Fixed a typo in the section of Enjoy a Trained Agent, in RL Baselines3 Zoo README. (@blurLake)
- Added Unity reacher to the projects page (@koulakis)
- Added PyBullet colab notebook
- Fixed typo in PPO example code (@joeljosephjin)
- Fixed typo in custom policy doc (@RaphaelWag)

1.39.13 Pre-Release 0.7.0 (2020-06-10)

Hotfix for PPO/A2C + gSDE, internal refactoring and bug fixes

Breaking Changes:

- `render()` method of `VecEnvs` now only accept one argument: `mode`
- Created new file `common/torch_layers.py`, similar to SB refactoring
 - Contains all PyTorch network layer definitions and feature extractors: `MlpExtractor`, `create_mlp`, `NatureCNN`
- Renamed `BaseRLModel` to `BaseAlgorithm` (along with `offpolicy` and `onpolicy` variants)

- Moved on-policy and off-policy base algorithms to `common/on_policy_algorithm.py` and `common/off_policy_algorithm.py`, respectively.
- Moved PPOPolicy to ActorCriticPolicy in `common/policies.py`
- Moved PPO (algorithm class) into OnPolicyAlgorithm (`common/on_policy_algorithm.py`), to be shared with A2C
- Moved following functions from BaseAlgorithm:
 - `_load_from_file` to `load_from_zip_file` (`save_util.py`)
 - `_save_to_file_zip` to `save_to_zip_file` (`save_util.py`)
 - `safe_mean` to `safe_mean` (`utils.py`)
 - `check_env` to `check_for_correct_spaces` (`utils.py`. Renamed to avoid confusion with environment checker tools)
- Moved static function `_is_vectorized_observation` from `common/policies.py` to `common/utils.py` under name `is_vectorized_observation`.
- Removed `{save,load}_running_average` functions of VecNormalize in favor of `load/save`.
- Removed `use_gae` parameter from `RolloutBuffer.compute_returns_and_advantage`.

New Features:

Bug Fixes:

- Fixed `render()` method for VecEnvs
- Fixed `seed()` method for SubprocVecEnv
- Fixed loading on GPU for testing when using gSDE and `deterministic=False`
- Fixed `register_policy` to allow re-registering same policy for same sub-class (i.e. assign same value to same key).
- Fixed a bug where the gradient was passed when using gSDE with PPO/A2C, this does not affect SAC

Deprecations:

Others:

- Re-enable unsafe `fork` start method in the tests (was causing a deadlock with tensorflow)
- Added a test for seeding SubprocVecEnv and rendering
- Fixed reference in NatureCNN (pointed to older version with different network architecture)
- Fixed comments saying “CxWxH” instead of “CxHxW” (same style as in torch docs / commonly used)
- Added bit further comments on register/getting policies (“MlpPolicy”, “CnnPolicy”).
- Renamed `progress` (value from 1 in start of training to 0 in end) to `progress_remaining`.
- Added `policies.py` files for A2C/PPO, which define MlpPolicy/CnnPolicy (renamed ActorCriticPolicies).
- Added some missing tests for VecNormalize, VecCheckNan and PPO.

Documentation:

- Added a paragraph on “MlpPolicy”/”CnnPolicy” and policy naming scheme under “Developer Guide”
- Fixed second-level listing in changelog

1.39.14 Pre-Release 0.6.0 (2020-06-01)

Tensorboard support, refactored logger

Breaking Changes:

- Remove State-Dependent Exploration (SDE) support for TD3
- Methods were renamed in the logger:
 - `logkv` -> `record`, `writetkvs` -> `write`, `writeseq` -> `write_sequence`,
 - `logkvs` -> `record_dict`, `dumpkvs` -> `dump`,
 - `getkvs` -> `get_log_dict`, `logkv_mean` -> `record_mean`,

New Features:

- Added env checker (Sync with Stable Baselines)
- Added `VecCheckNan` and `VecVideoRecorder` (Sync with Stable Baselines)
- Added determinism tests
- Added `cmd_util` and `atari_wrappers`
- Added support for `MultiDiscrete` and `MultiBinary` observation spaces (@rolandgvc)
- Added `MultiCategorical` and `Bernoulli` distributions for PPO/A2C (@rolandgvc)
- Added support for logging to tensorboard (@rolandgvc)
- Added `VectorizedActionNoise` for continuous vectorized environments (@PartiallyTyped)
- Log evaluation in the `EvalCallback` using the logger

Bug Fixes:

- Fixed a bug that prevented model trained on cpu to be loaded on gpu
- Fixed version number that had a new line included
- Fixed weird seg fault in docker image due to `FakeImageEnv` by reducing screen size
- Fixed `sde_sample_freq` that was not taken into account for SAC
- Pass logger module to `BaseCallback` otherwise they cannot write in the one used by the algorithms

Deprecations:**Others:**

- Renamed to Stable-Baseline3
- Added Dockerfile
- Sync VecEnvs with Stable-Baselines
- Update requirement: `gym>=0.17`
- Added `.readthedocs.yml` file
- Added `flake8` and `make lint` command
- Added Github workflow
- Added warning when passing both `train_freq` and `n_episodes_rollout` to Off-Policy Algorithms

Documentation:

- Added most documentation (adapted from Stable-Baselines)
- Added link to CONTRIBUTING.md in the README (@kinalmehta)
- Added gSDE project and update docstrings accordingly
- Fix TD3 example code block

1.39.15 Pre-Release 0.5.0 (2020-05-05)

CnnPolicy support for image observations, complete saving/loading for policies**Breaking Changes:**

- Previous loading of policy weights is broken and replace by the new saving/loading for policy

New Features:

- Added `optimizer_class` and `optimizer_kwargs` to `policy_kwargs` in order to easily customizer optimizers
- Complete independent save/load for policies
- Add `CnnPolicy` and `VecTransposeImage` to support images as input

Bug Fixes:

- Fixed `reset_num_timesteps` behavior, so `env.reset()` is not called if `reset_num_timesteps=True`
- Fixed `squashed_output` that was not pass to policy constructor for SAC and TD3 (would result in scaled actions for unscaled action spaces)

Deprecations:

Others:

- Cleanup rollout return
- Added `get_device` util to manage PyTorch devices
- Added type hints to logger + use f-strings

Documentation:

1.39.16 Pre-Release 0.4.0 (2020-02-14)

Proper pre-processing, independent save/load for policies

Breaking Changes:

- Removed CEMRL
- Model saved with previous versions cannot be loaded (because of the pre-preprocessing)

New Features:

- Add support for `Discrete` observation spaces
- Add saving/loading for policy weights, so the policy can be used without the model

Bug Fixes:

- Fix type hint for activation functions

Deprecations:

Others:

- Refactor handling of observation and action spaces
- Refactored features extraction to have proper preprocessing
- Refactored action distributions

1.39.17 Pre-Release 0.3.0 (2020-02-14)

Bug fixes, sync with Stable-Baselines, code cleanup

Breaking Changes:

- Removed default seed
- Bump dependencies (PyTorch and Gym)
- `predict()` now returns a tuple to match Stable-Baselines behavior

New Features:

- Better logging for SAC and PPO

Bug Fixes:

- Synced callbacks with Stable-Baselines
- Fixed colors in `results_plotter`
- Fix entropy computation (now summed over action dim)

Others:

- SAC with SDE now sample only one matrix
- Added `clip_mean` parameter to SAC policy
- Buffers now return `NamedTuple`
- More typing
- Add test for `expln`
- Renamed `learning_rate` to `lr_schedule`
- Add `version.txt`
- Add more tests for distribution

Documentation:

- Deactivated `sphinx_autodoc_typehints` extension

1.39.18 Pre-Release 0.2.0 (2020-02-14)

Python 3.6+ required, type checking, callbacks, doc build

Breaking Changes:

- Python 2 support was dropped, Stable Baselines3 now requires Python 3.6 or above
- Return type of `evaluation.evaluate_policy()` has been changed
- Refactored the replay buffer to avoid transformation between PyTorch and NumPy
- Created *OffPolicyRLModel* base class
- Remove deprecated JSON format for *Monitor*

New Features:

- Add `seed()` method to `VecEnv` class
- Add support for Callback (cf <https://github.com/hill-a/stable-baselines/pull/644>)
- Add methods for saving and loading replay buffer
- Add `extend()` method to the buffers
- Add `get_vec_normalize_env()` to `BaseRLModel` to retrieve `VecNormalize` wrapper when it exists
- Add `results_plotter` from Stable Baselines
- Improve `predict()` method to handle different type of observations (single, vectorized, ...)

Bug Fixes:

- Fix loading model on CPU that were trained on GPU
- Fix `reset_num_timesteps` that was not used
- Fix entropy computation for squashed Gaussian (approximate it now)
- Fix seeding when using multiple environments (different seed per env)

Others:

- Add type check
- Converted all format string to f-strings
- Add test for `OrnsteinUhlenbeckActionNoise`
- Add type aliases in `common.type_aliases`

Documentation:

- fix documentation build

1.39.19 Pre-Release 0.1.0 (2020-01-20)

First Release: base algorithms and state-dependent exploration

New Features:

- Initial release of A2C, CEM-RL, PPO, SAC and TD3, working only with Box input space
- State-Dependent Exploration (SDE) for A2C, PPO, SAC and TD3

1.39.20 Maintainers

Stable-Baselines3 is currently maintained by [Antonin Raffin](#) (aka [@araffin](#)), [Ashley Hill](#) (aka [@hill-a](#)), [Maximilian Ernestus](#) (aka [@ernestum](#)), [Adam Gleave](#) ([@AdamGleave](#)) and [Anssi Kanervisto](#) (aka [@Miffyli](#)).

1.39.21 Contributors:

In random order...

Thanks to the maintainers of V2: [@hill-a](#) [@enerijunior](#) [@AdamGleave](#) [@Miffyli](#)

And all the contributors: [@bjmuld](#) [@iambenzo](#) [@iandanforth](#) [@r7vme](#) [@brendenpetersen](#) [@huvar](#) [@abhiskk](#) [@JohannesAck](#) [@EliasHasle](#) [@mrakgr](#) [@Bleyddyn](#) [@antoine-galataud](#) [@junhyeokahn](#) [@AdamGleave](#) [@keshaviyen-gar](#) [@tperol](#) [@XMaster96](#) [@kantneel](#) [@Pastafarianist](#) [@GerardMaggiolino](#) [@PatrickWalter214](#) [@yutingsz](#) [@sc420](#) [@Aaahh](#) [@billtubbs](#) [@Miffyli](#) [@dwiel](#) [@miguelrass](#) [@qxcv](#) [@jaberkow](#) [@eavelarde](#) [@ruifeng96150](#) [@pedro-hbtp](#) [@srivatsankrishnan](#) [@evilsocket](#) [@MarvineGothic](#) [@jdossdollin](#) [@stheid](#) [@SyllogismRXS](#) [@rusu24edward](#) [@jbulow](#) [@Antymon](#) [@seheevic](#) [@justinkterry](#) [@edbeechnig](#) [@flodornier](#) [@KuKuXia](#) [@NeoExtended](#) [@Partially-Typed](#) [@mmcenta](#) [@richardwu](#) [@kinalmehta](#) [@rolandgvc](#) [@tkelestemur](#) [@mloo3](#) [@tirafesi](#) [@blurLake](#) [@koulakis](#) [@joeljosephjin](#) [@shwang](#) [@rk37](#) [@andyshih12](#) [@RaphaelWag](#) [@xicocao](#) [@diditforlulz273](#) [@liorcohen5](#) [@ManifoldFR](#) [@mloo3](#) [@SwamyDev](#) [@wmmc88](#) [@megan-klaiber](#) [@thisray](#) [@tfederico](#) [@hn2](#) [@LucasAlegre](#) [@AptX395](#) [@zampanteymedio](#) [@JadenTravnik](#) [@decodyng](#) [@ardabbour](#) [@lorenz-h](#) [@mschweizer](#) [@lorepieri8](#) [@vwxyzjn](#) [@ShangqunYu](#) [@PierreExeter](#) [@JacopoPan](#) [@ltbd78](#) [@tom-doerr](#) [@Atlis](#) [@liusida](#) [@09tangriro](#) [@amy12xx](#) [@juancroldan](#) [@benblack769](#) [@bstee615](#) [@c-rizz](#) [@skandermoalla](#) [@MihaiAnca13](#) [@davidblom603](#) [@ayeright](#) [@cyprienc](#) [@wkirgnsn](#) [@AechPro](#) [@CUN-bjy](#) [@batu](#) [@IljaAvadiev](#) [@timokau](#) [@kachayev](#) [@cleversonahum](#) [@eleurent](#) [@ac-93](#) [@cove9988](#) [@theDebugger811](#) [@hsuehch](#) [@Demetrio92](#) [@thomasgubler](#) [@IperGiovie](#) [@ScheikIP](#) [@simoninithomas](#) [@armandpl](#) [@manuel-delverme](#) [@Gautam-J](#) [@gianlucadecola](#) [@buoyancy99](#) [@caburu](#) [@xy9485](#) [@Gregwar](#) [@ycheng517](#)

1.40 Projects

This is a list of projects using stable-baselines3. Please tell us, if you want your project to appear on this page ;)

1.40.1 DriverGym

An open-source Gym-compatible environment specifically tailored for developing RL algorithms for autonomous driving. DriverGym provides access to more than 1000 hours of expert logged data and also supports reactive and data-driven agent behavior. The performance of an RL policy can be easily validated using an extensive and flexible closed-loop evaluation protocol. We also provide behavior cloning baselines using supervised learning and RL, trained in DriverGym.

Authors: Parth Kothari, Christian Perone, Luca Bergamini, Alexandre Alahi, Peter Ondruska

Github: <https://github.com/lyft/l5kit>

Paper: <https://arxiv.org/abs/2111.06889>

1.40.2 RL Reach

A platform for running reproducible reinforcement learning experiments for customisable robotic reaching tasks. This self-contained and straightforward toolbox allows its users to quickly investigate and identify optimal training configurations.

Authors: Pierre Aumjaud, David McAuliffe, Francisco Javier Rodríguez Lera, Philip Cardiff

Github: https://github.com/PierreExeter/rl_reach

Paper: <https://arxiv.org/abs/2102.04916>

1.40.3 Generalized State Dependent Exploration for Deep Reinforcement Learning in Robotics

An exploration method to train RL agent directly on real robots. It was the starting point of Stable-Baselines3.

Author: Antonin Raffin, Freek Stulp

Github: <https://github.com/DLR-RM/stable-baselines3/tree/sde>

Paper: <https://arxiv.org/abs/2005.05719>

1.40.4 Furuta Pendulum Robot

Everything you need to build and train a rotary inverted pendulum, also known as a furuta pendulum! This makes use of gSDE listed above. The Github repository contains code, CAD files and a bill of materials for you to build the robot. You can watch a [video overview of the project here](#).

Authors: Armand du Parc Locmaria, Pierre Fabre

Github: <https://github.com/Armandpl/furuta>

1.40.5 Reacher

A solution to the second project of the Udacity deep reinforcement learning course. It is an example of:

- wrapping single and multi-agent Unity environments to make them usable in Stable-Baselines3
- creating experimentation scripts which train and run A2C, PPO, TD3 and SAC models (a better choice for this one is <https://github.com/DLR-RM/rl-baselines3-zoo>)
- generating several pre-trained models which solve the reacher environment

Author: Marios Koulakis

Github: <https://github.com/koulakis/reacher-deep-reinforcement-learning>

1.40.6 SUMO-RL

A simple interface to instantiate RL environments with SUMO for Traffic Signal Control.

- Supports Multiagent RL
- Compatibility with `gym.Env` and popular RL libraries such as `stable-baselines3` and `RLlib`
- Easy customisation: state and reward definitions are easily modifiable

Author: Lucas Alegre

Github: <https://github.com/LucasAlegre/sumo-rl>

1.40.7 gym-pybullet-drones

PyBullet Gym environments for single and multi-agent reinforcement learning of quadcopter control.

- Physics-based simulation for the development and test of quadcopter control.
- Compatibility with `gym.Env`, `RLlib`'s `MultiAgentEnv`.
- Learning and testing script templates for `stable-baselines3` and `RLlib`.

Author: Jacopo Panerati

Github: <https://github.com/utiasDSL/gym-pybullet-drones/>

Paper: <https://arxiv.org/abs/2103.02142>

1.40.8 SuperSuit

SuperSuit contains easy to use wrappers for Gym (and multi-agent PettingZoo) environments to do all forms of common preprocessing (frame stacking, converting graphical observations to greyscale, max-and-skip for Atari, etc.). It also notably includes:

-Wrappers that apply lambda functions to observations, actions, or rewards with a single line of code. -All wrappers can be used natively on vector environments, wrappers exist to Gym environments to vectorized environments and concatenate multiple vector environments together -A wrapper is included that allows for using regular single agent RL libraries (e.g. `stable baselines`) to learn simple multi-agent PettingZoo environments, explained in this tutorial:

Author: Justin Terry

GitHub: <https://github.com/PettingZoo-Team/SuperSuit>

Tutorial on multi-agent support in stable baselines: <https://towardsdatascience.com/multi-agent-deep-reinforcement-learning-in-15-lines-of-code-using-pettingzoo-e0b963c0820b>

1.40.9 Rocket League Gym

A fully custom python API and C++ DLL to treat the popular game Rocket League like an OpenAI Gym environment.

- Dramatically increases the rate at which the game runs.
- Supports full configuration of initial states, observations, rewards, and terminal states.
- Supports multiple simultaneous game clients.
- Supports multi-agent training and self-play.
- Provides custom wrappers for easy use with stable-baselines3.

Authors: Lucas Emery, Matthew Allen

GitHub: <https://github.com/lucas-emery/rocket-league-gym>

Website: <https://rlgym.github.io>

1.40.10 gym-electric-motor

An OpenAI gym environment for the simulation and control of electric drive trains. Think of Matlab/Simulink for electric motors, inverters, and load profiles, but non-graphical and open-source in Python.

gym-electric-motor offers a rich interface for customization, including - plug-and-play of different control algorithms ranging from classical controllers (like field-oriented control) up to any RL agent you can find, - reward shaping, - load profiling, - finite-set or continuous-set control, - one-phase and three-phase motors such as induction machines and permanent magnet synchronous motors, among others.

SB3 is used as an example in one of many tutorials showcasing the easy usage of *gym-electric-motor*.

Author: Paderborn University, LEA department

GitHub: <https://github.com/upb-lea/gym-electric-motor>

SB3 Tutorial: [Colab Link](#)

Paper: [JOSS](#), [TNNLS](#), [ArXiv](#)

1.40.11 policy-distillation-baselines

A PyTorch implementation of Policy Distillation for control, which has well-trained teachers via Stable Baselines3.

- *policy-distillation-baselines* provides some good examples for policy distillation in various environment and using reliable algorithms.
- All well-trained models and algorithms are compatible with Stable Baselines3.

Authors: Junyeob Baek

GitHub: <https://github.com/CUN-bjy/policy-distillation-baselines>

Demo: [link](#)

1.40.12 highway-env

A minimalist environment for decision-making in Autonomous Driving.

Driving policies can be trained in different scenarios, and several notebooks using SB3 are provided as examples.

Author: [Edouard Leurent](#)

GitHub: <https://github.com/eleurent/highway-env>

Examples: [Colab Links](#)

1.40.13 tactile-gym

Suite of RL environments focussed on using a simulated tactile sensor as the primary source of observations. Sim-to-Real results across 4 out of 5 proposed envs.

Author: [Alex Church](#)

GitHub: https://github.com/ac-93/tactile_gym

Paper: <https://arxiv.org/abs/2106.08796>

Website: [tactile-gym website](#)

CITING STABLE BASELINES3

To cite this project in publications:

```
@article{stable-baselines3,  
  author = {Antonin Raffin and Ashley Hill and Adam Gleave and Anssi Kanervisto and ↵  
↵Maximilian Ernestus and Noah Dormann},  
  title  = {Stable-Baselines3: Reliable Reinforcement Learning Implementations},  
  journal = {Journal of Machine Learning Research},  
  year   = {2021},  
  volume = {22},  
  number = {268},  
  pages  = {1-8},  
  url    = {http://jmlr.org/papers/v22/20-1364.html}  
}
```


CONTRIBUTING

To any interested in making the rl baselines better, there are still some improvements that need to be done. You can check issues in the [repo](#).

If you want to contribute, please read [CONTRIBUTING.md](#) first.

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- `modindex`

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