Stable Baselines Documentation

Release 2.10.2a0

Stable Baselines Contributors

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User Guide

Stable Baselines is a set of improved implementations of Reinforcement Learning (RL) algorithms based on OpenAI Baselines.

Github repository: https://github.com/hill-a/stable-baselines

RL Baselines Zoo (collection of pre-trained agents): https://github.com/araffin/rl-baselines-zoo

RL Baselines zoo also offers a simple interface to train, evaluate agents and do hyperparameter tuning.

You can read a detailed presentation of Stable Baselines in the Medium article: link

Note: Stable-Baselines3 (PyTorch edition) beta is now online: https://github.com/DLR-RM/stable-baselines3

CHAPTER 1

Main differences with OpenAI Baselines

This toolset is a fork of OpenAI Baselines, with a major structural refactoring, and code cleanups:

- Unified structure for all algorithms
- PEP8 compliant (unified code style)
- Documented functions and classes
- More tests & more code coverage
- Additional algorithms: SAC and TD3 (+ HER support for DQN, DDPG, SAC and TD3)

1.1 Installation

1.1.1 Prerequisites

Baselines requires python3 (>=3.5) with the development headers. You'll also need system packages CMake, OpenMPI and zlib. Those can be installed as follows

Note: Stable-Baselines supports Tensorflow versions from 1.8.0 to 1.15.0, and does not work on Tensorflow versions 2.0.0 and above. PyTorch support is done in Stable-Baselines3

Ubuntu

```
sudo apt-get update && sudo apt-get install cmake libopenmpi-dev python3-dev zlib1g-
↪dev
```

Mac OS X

Installation of system packages on Mac requires Homebrew. With Homebrew installed, run the following:

```
brew install cmake openmpi
```

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 3.5 or above.

For a quick start you can move straight to installing Stable-Baselines in the next step (without MPI). This supports most but not all algorithms.

To support all algorithms, Install MPI for Windows (you need to download and install `msmpisetup.exe`) and follow the instructions on how to install Stable-Baselines with MPI support in following section.

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 with support for all algorithms, including those depending on OpenMPI, execute:

```
pip install stable-baselines[mpi]
```

GAIL, DDPG, TRPO, and PPO1 parallelize training using OpenMPI. OpenMPI has had weird interactions with Tensorflow in the past (see Issue #430) and so if you do not intend to use these algorithms we recommend installing without OpenMPI. To do this, execute:

```
pip install stable-baselines
```

If you have already installed with MPI support, you can disable MPI by uninstalling `mpi4py` with `pip uninstall mpi4py`.

Note: Unless you are using the bleeding-edge version, you need to install the correct Tensorflow version manually. See Issue #849

1.1.2 Bleeding-edge version

To install the latest master version:

```
pip install git+https://github.com/hill-a/stable-baselines
```

1.1.3 Development version

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

```
git clone https://github.com/hill-a/stable-baselines && cd stable-baselines
pip install -e .[docs,tests,mpi]
```

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 Baselines Zoo.

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

Use Built Images

GPU image (requires nvidia-docker):

```
docker pull stablebaselines/stable-baselines
```

CPU only:

```
docker pull stablebaselines/stable-baselines-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-baselines,type=bind stablebaselines/stable-
↪baselines bash -c 'cd /root/code/stable-baselines/ && 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-baselines,type=bind stablebaselines/stable-baselines-cpu␣
↪bash -c 'cd /root/code/stable-baselines/ && 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 PPO2 on a cartpole environment:

```
import gym

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

env = gym.make('CartPole-v1')
# Optional: PPO2 requires a vectorized environment to run
# the env is now wrapped automatically when passing it to the constructor
# env = DummyVecEnv([lambda: env])

model = PPO2(MlpPolicy, env, verbose=1)
model.learn(total_timesteps=10000)

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

Or just train a model with a one liner if the environment is registered in Gym and if the policy is registered:

```
from stable_baselines import PPO2

model = PPO2('MlpPolicy', 'CartPole-v1').learn(10000)
```

Fig. 1: Define and train a RL agent in one line of code!

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.

1.3.1 General advice when using Reinforcement Learning

TL;DR

1. Read about RL and Stable Baselines
2. Do quantitative experiments and hyperparameter tuning if needed
3. Evaluate the performance using a separate test environment
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 Baselines (SB) 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 PPO2/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?

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.

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.

Note: We provide an `EvalCallback` for doing such evaluation. You can read more about it in the *Callbacks* section.

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, and how you can do it (with or without MPI?). If what matters is the wall clock training time, then you should lean towards `A2C` and its derivatives (PPO, ACER, ACKTR, …). 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, . . .) and ACER are the recommended algorithms. 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 PPO2, A2C and its successors (ACKTR, ACER).

If you can multiprocess the training using MPI, then you should checkout PPO1 and TRPO.

Continuous Actions

Continuous Actions - Single Process

Current State Of The Art (SOTA) algorithms are `SAC` and `TD3`. Please use the hyperparameters in the RL zoo for best results.

Continuous Actions - Multiprocessed

Take a look at PPO2, TRPO 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

If you can use MPI, then you can choose between PPO1, TRPO and DDPG.

Goal Environment

If your environment follows the `GoalEnv` interface (cf HER), then you should use HER + (SAC/TD3/DDPG/DQN) depending on the action space.

Note: The number of workers is an important hyperparameters for experiments with HER. Currently, only HER+DDPG supports multiprocessing using MPI.

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_baselines.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)
```

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).

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-Baselines 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 baselines project, along with some useful characteristics: support for recurrent policies, discrete/continuous actions, multiprocessing.

Name	Refactored[1]	Recurrent	`Box`	`Discrete`	Multi Processing
A2C	✓	✓	✓	✓	✓
ACER	✓	✓	[4]	✓	✓
ACKTR	✓	✓	✓	✓	✓
DDPG	✓		✓		✓[3]
DQN	✓			✓	
HER	✓		✓	✓	
GAIL[2]	✓	✓	✓	✓	✓[3]
PPO1	✓		✓	✓	✓[3]
PPO2	✓	✓	✓	✓	✓
SAC	✓		✓		
TD3	✓		✓		
TRPO	✓		✓	✓	✓[3]

Note: Non-array spaces such as `Dict` or `Tuple` are not currently supported by any algorithm, except HER for dict when working with `gym.GoalEnv`

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: Some logging values (like `ep_rewmean`, `eplenmean`) are only available when using a Monitor wrapper See Issue #339 for more info.

1.5.1 Reproducibility

Completely reproducible results are not guaranteed across Tensorflow 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 CPU, on your specific problem on one specific platform, you need to pass a `seed` argument at the creation of a model and set *n_cpu_tf_sess=1* (number of cpu for Tensorflow session). If you pass an environment to the model using *set_env()*, then you also need to seed the environment first.

[1] Whether or not the algorithm has be refactored to fit the `BaseRLModel` class.
[4] TODO, in project scope.
[3] Multi Processing with MPI.
[2] Only implemented for TRPO.

Note: Because of the current limits of Tensorflow 1.x, we cannot ensure reproducible results on the GPU yet. This issue is solved in Stable-Baselines3 "PyTorch edition"

Note: TD3 sometimes fail to have reproducible results for obscure reasons, even when following the previous steps (cf PR #492). If you find the reason then please open an issue ;)

Credit: part of the *Reproducibility* section comes from PyTorch Documentation

1.6 Examples

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
- Breakout (trained agent included)
- Hindsight Experience Replay
- RL Baselines zoo

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. 2: 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`

Note: `load` function re-creates model from scratch on each call, which can be slow. If you need to e.g. evaluate same model with multiple different sets of parameters, consider using `load_parameters` instead.

```python
import gym

from stable_baselines import DQN
from stable_baselines.common.evaluation import evaluate_policy


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

# Instantiate the agent
model = DQN('MlpPolicy', env, learning_rate=1e-3, prioritized_replay=True, 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
model = DQN.load("dqn_lunar")

# Evaluate the agent
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)
    obs, rewards, dones, info = env.step(action)
    env.render()
```

1.6.3 Multiprocessing: Unleashing the Power of Vectorized Environments

Try it in a notebook

Fig. 3: CartPole Environment

```python
import gym
import numpy as np

from stable_baselines.common.policies import MlpPolicy
from stable_baselines.common.vec_env import SubprocVecEnv
from stable_baselines.common import set_global_seeds, make_vec_env
from stable_baselines import ACKTR

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 inital seed for RNG
```

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```
    :param rank: (int) index of the subprocess
    """
    def _init():
        env = gym.make(env_id)
        env.seed(seed + rank)
        return env
    set_global_seeds(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:
    # env = make_vec_env(env_id, n_envs=num_cpu, seed=0)

    model = ACKTR(MlpPolicy, env, verbose=1)
    model.learn(total_timesteps=25000)

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

1.6.4 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.

Try it in a CO notebook

```
import os

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

from stable_baselines import DDPG
from stable_baselines.ddpg.policies import LnMlpPolicy
from stable_baselines import results_plotter
from stable_baselines.bench import Monitor
from stable_baselines.results_plotter import load_results, ts2xy
from stable_baselines.common.noise import AdaptiveParamNoiseSpec
```

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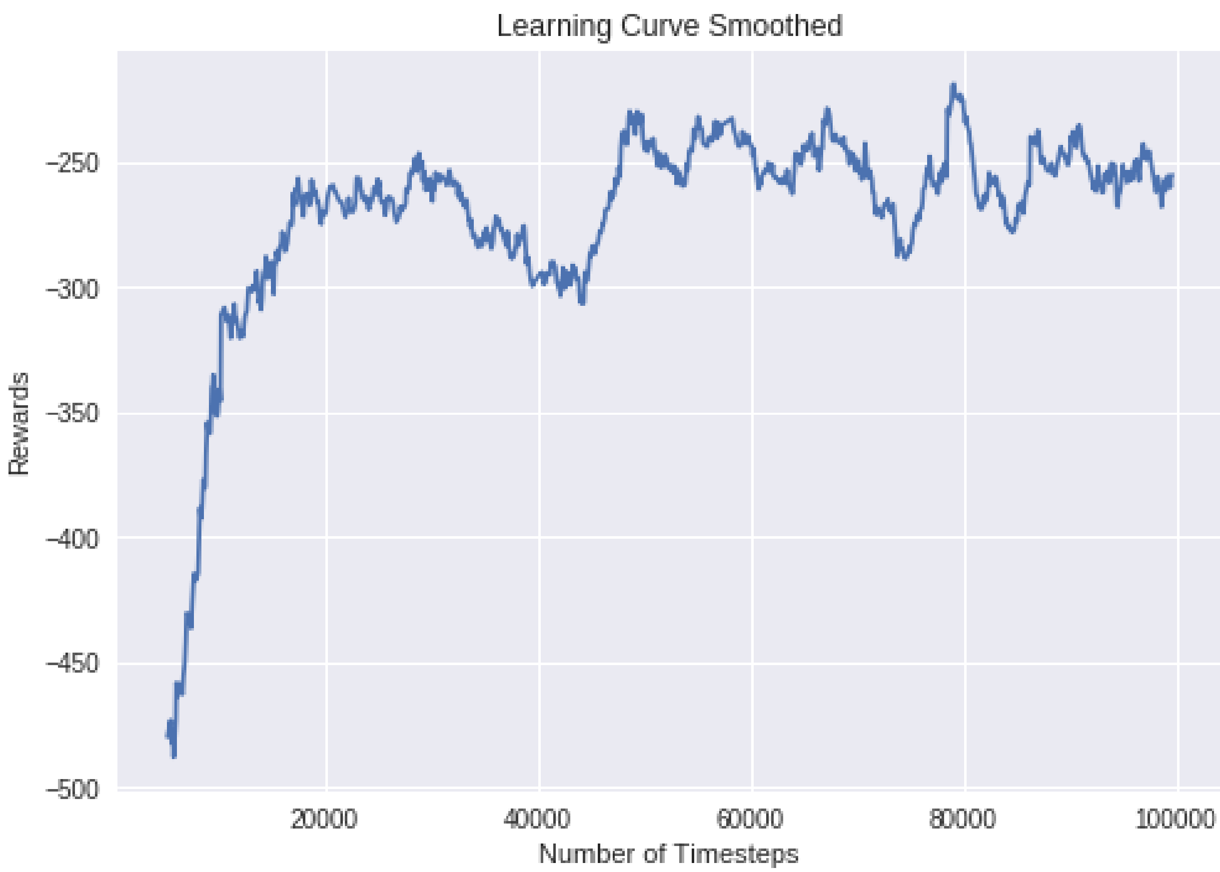

Fig. 4: Learning curve of DDPG on LunarLanderContinuous environment

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```
from stable_baselines.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: (int)
    :param log_dir: (str) Path to the folder where the model will be saved.
      It must contains the file created by the ``Monitor`` wrapper.
    :param verbose: (int)
    """
    def __init__(self, check_freq: int, log_dir: str, verbose=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("Num timesteps: {}".format(self.num_timesteps))
                print("Best mean reward: {:.2f} - Last mean reward per episode: {:.2f}
↪".format(self.best_mean_reward, mean_reward))

              # 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
                  if self.verbose > 0:
                    print("Saving new best model to {}".format(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 param noise for exploration
```

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```
param_noise = AdaptiveParamNoiseSpec(initial_stddev=0.1, desired_action_stddev=0.1)
# Because we use parameter noise, we should use a MlpPolicy with layer normalization
model = DDPG(LnMlpPolicy, env, param_noise=param_noise, verbose=0)
# Create the callback: check every 1000 steps
callback = SaveOnBestTrainingRewardCallback(check_freq=1000, log_dir=log_dir)
# Train the agent
time_steps = 1e5
model.learn(total_timesteps=int(time_steps), callback=callback)

results_plotter.plot_results([log_dir], time_steps, results_plotter.X_TIMESTEPS,
↪"DDPG LunarLander")
plt.show()
```

1.6.5 Atari Games

Fig. 5: Trained A2C agent on Breakout

Fig. 6: 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.

Try it in a notebook

```
from stable_baselines.common.cmd_util import make_atari_env
from stable_baselines.common.vec_env import VecFrameStack
from stable_baselines import ACER

# There already exists an environment generator
# that will make and wrap atari environments correctly.
# Here we are also multiprocessing training (num_env=4 => 4 processes)
env = make_atari_env('PongNoFrameskip-v4', num_env=4, seed=0)
# Frame-stacking with 4 frames
env = VecFrameStack(env, n_stack=4)

model = ACER('CnnPolicy', env, verbose=1)
model.learn(total_timesteps=25000)

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

1.6.6 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_baselines.common.vec_env import DummyVecEnv, VecNormalize
from stable_baselines import PPO2

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 = PPO2('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 agent
model = PPO2.load(log_dir + "ppo_halfcheetah")

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

1.6.7 Custom Policy Network

Stable baselines provides default policy networks for images (CNNPolicies) and other type of inputs (MlpPolicies). However, you can also easily define a custom architecture for the policy network (see custom policy section):

```
import gym

from stable_baselines.common.policies import FeedForwardPolicy
from stable_baselines.common.vec_env import DummyVecEnv
from stable_baselines import A2C

# Custom MLP policy of three layers of size 128 each
class CustomPolicy(FeedForwardPolicy):
    def __init__(self, *args, **kwargs):
```

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```
        super(CustomPolicy, self).__init__(*args, **kwargs,
                                           net_arch=[dict(pi=[128, 128, 128], vf=[128,
↪ 128, 128])],
                                           feature_extraction="mlp")

model = A2C(CustomPolicy, 'LunarLander-v2', verbose=1)
# Train the agent
model.learn(total_timesteps=100000)
```

1.6.8 Accessing and modifying model parameters

You can access model's parameters via `load_parameters` and `get_parameters` functions, which use dictionaries that map variable names to NumPy arrays.

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.

You can access original Tensorflow Variables with function `get_parameter_list`.

Following example demonstrates reading parameters, modifying some of them and loading them to model by implementing evolution strategy for solving `CartPole-v1` environment. The initial guess for parameters is obtained by running A2C policy gradient updates on the model.

```
import gym
import numpy as np

from stable_baselines import A2C

def mutate(params):
    """Mutate parameters by adding normal noise to them"""
    return dict((name, param + np.random.normal(size=param.shape))
                for name, param in params.items())

def evaluate(env, model):
    """Return mean fitness (sum of episodic rewards) for given model"""
    episode_rewards = []
    for _ in range(10):
        reward_sum = 0
        done = False
        obs = env.reset()
        while not done:
            action, _states = model.predict(obs)
            obs, reward, done, info = env.step(action)
            reward_sum += reward
        episode_rewards.append(reward_sum)
    return np.mean(episode_rewards)

# Create env
env = gym.make('CartPole-v1')
# Create policy with a small network
model = A2C('MlpPolicy', env, ent_coef=0.0, learning_rate=0.1,
            policy_kwargs={'net_arch': [8, ]})

# Use traditional actor-critic policy gradient updates to
# find good initial parameters
model.learn(total_timesteps=5000)
```

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```
# Get the parameters as the starting point for ES
mean_params = model.get_parameters()

# Include only variables with "/pi/" (policy) or "/shared" (shared layers)
# in their name: Only these ones affect the action.
mean_params = dict((key, value) for key, value in mean_params.items()
                   if ("/pi/" in key or "/shared" in key))

for iteration in range(10):
    # Create population of candidates and evaluate them
    population = []
    for population_i in range(100):
        candidate = mutate(mean_params)
        # Load new policy parameters to agent.
        # Tell function that it should only update parameters
        # we give it (policy parameters)
        model.load_parameters(candidate, exact_match=False)
        fitness = evaluate(env, model)
        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)[:10]
    mean_params = dict(
        (name, np.stack([top_candidate[0][name] for top_candidate in top_candidates]).
↪mean(0))
        for name in mean_params.keys()
    )
    mean_fitness = sum(top_candidate[1] for top_candidate in top_candidates) / 10.0
    print("Iteration {:<3} Mean top fitness: {:.2f}".format(iteration, mean_fitness))
```

1.6.9 Recurrent Policies

This example demonstrate how to train a recurrent policy and how to test it properly.

Warning: One current limitation of recurrent policies is that you must test them with the same number of environments they have been trained on.

```
from stable_baselines import PPO2

# For recurrent policies, with PPO2, the number of environments run in parallel
# should be a multiple of nminibatches.
model = PPO2('MlpLstmPolicy', 'CartPole-v1', nminibatches=1, verbose=1)
model.learn(50000)

# Retrieve the env
env = model.get_env()

obs = env.reset()
# Passing state=None to the predict function means
# it is the initial state
state = None
# When using VecEnv, done is a vector
done = [False for _ in range(env.num_envs)]
```

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```
for _ in range(1000):
    # We need to pass the previous state and a mask for recurrent policies
    # to reset lstm state when a new episode begin
    action, state = model.predict(obs, state=state, mask=done)
    obs, reward , done, _ = env.step(action)
    # Note: with VecEnv, env.reset() is automatically called

    # Show the env
    env.render()
```

1.6.10 Hindsight Experience Replay (HER)

For this example, we are using Highway-Env by @eleurent.

Try it in a notebook

Fig. 7: 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_baselines import HER, SAC, DDPG, TD3
from stable_baselines.ddpg import NormalActionNoise

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

# Create 4 artificial transitions per real transition
n_sampled_goal = 4

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

# DDPG Hyperparams:
# NOTE: it works even without action noise
# n_actions = env.action_space.shape[0]
# noise_std = 0.2
# action_noise = NormalActionNoise(mean=np.zeros(n_actions), sigma=noise_std * np.
↪ones(n_actions))
```

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```
# model = HER('MlpPolicy', env, DDPG, n_sampled_goal=n_sampled_goal,
#             goal_selection_strategy='future',
#             verbose=1, buffer_size=int(1e6),
#             actor_lr=1e-3, critic_lr=1e-3, action_noise=action_noise,
#             gamma=0.95, batch_size=256,
#             policy_kwargs=dict(layers=[256, 256, 256]))


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

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

obs = env.reset()

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

1.6.11 Continual Learning

You can also move from learning on one environment to another for continual learning (PPO2 on `DemonAttack-v0`, then transferred on `SpaceInvaders-v0`):

```
from stable_baselines.common.cmd_util import make_atari_env
from stable_baselines import PPO2

# There already exists an environment generator
# that will make and wrap atari environments correctly
env = make_atari_env('DemonAttackNoFrameskip-v4', num_env=8, seed=0)

model = PPO2('CnnPolicy', env, verbose=1)
model.learn(total_timesteps=10000)

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

# Close the processes
env.close()

# The number of environments must be identical when changing environments
env = make_atari_env('SpaceInvadersNoFrameskip-v4', num_env=8, seed=0)
```

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```
# change env
model.set_env(env)
model.learn(total_timesteps=10000)

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

1.6.12 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_baselines.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="random-agent-{}".format(env_id))

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

1.6.13 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_baselines import A2C
```

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```
model = A2C("MlpPolicy", "LunarLander-v2").learn(100000)

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')

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 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 VecEnv

class `stable_baselines.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** – (Gym Space) the observation space
- **action_space** – (Gym Space) the action space

close()
Clean up the environment's resources.

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** – (list,int) Indices of envs whose method to call
- **method_args** – (tuple) Any positional arguments to provide in the call
- **method_kwargs** – (dict) Any keyword arguments to provide in the call

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

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** – (list,int) Indices of envs to get attribute from

Returns (list) List of values of 'attr_name' in all environments

get_images() → Sequence[numpy.ndarray]
Return RGB images from each environment

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

Returns (str or None) name of module whose attribute is being shadowed, if any.

render(*mode: str = 'human'*)
Gym environment rendering

Parameters **mode** – the rendering type

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.

Returns ([int] or [float]) observation

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

Returns (List[Union[None, int]]) 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.

Parameters

- **attr_name** – (str) The name of attribute to assign new value
- **value** – (obj) Value to assign to *attr_name*
- **indices** – (list,int) Indices of envs to assign value

Returns (NoneType)

step (*actions*)
Step the environments with the given action

Parameters **actions** – ([int] or [float]) the action

Returns ([int] or [float], [float], [bool], dict) observation, reward, done, information

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.

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

Returns ([int] or [float], [float], [bool], dict) observation, reward, done, information

1.7.2 DummyVecEnv

class stable_baselines.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 multiprocess 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** – ([callable]) A list of functions that will create the environments (each callable returns a *Gym.Env* instance when called).

close ()
Clean up the environment's resources.

env_method (*method_name*, **method_args*, *indices=None*, ***method_kwargs*)
Call instance methods of vectorized environments.

get_attr (*attr_name*, *indices=None*)
Return attribute from vectorized environment (see base class).

get_images () → Sequence[numpy.ndarray]
Return RGB images from each environment

render (*mode: str = '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** – The rendering type.

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.

Returns ([int] or [float]) 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.

Returns (List[Union[None, int]]) 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).

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.

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

Returns ([int] or [float], [float], [bool], dict) observation, reward, done, information

1.7.3 SubprocVecEnv

class stable_baselines.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** – ([callable]) A list of functions that will create the environments (each callable returns a *Gym.Env* instance when called).
- **start_method** – (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.

env_method(*method_name*, **method_args*, *indices=None*, ***method_kwargs*)
Call instance methods of vectorized environments.

get_attr(*attr_name*, *indices=None*)
Return attribute from vectorized environment (see base class).

get_images() → Sequence[numpy.ndarray]
Return RGB images from each environment

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.

Returns ([int] or [float]) 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.

Returns (List[Union[None, int]]) 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).

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.

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

Returns ([int] or [float], [float], [bool], dict) observation, reward, done, information

1.7.4 Wrappers

VecFrameStack

class stable_baselines.common.vec_env.**VecFrameStack**(*venv*, *n_stack*)
Frame stacking wrapper for vectorized environment

Parameters

- **venv** – (VecEnv) the vectorized environment to wrap
- **n_stack** – (int) Number of frames to stack

close()
Clean up the environment's resources.

reset()
Reset all environments

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

Returns ([int] or [float], [float], [bool], dict) observation, reward, done, information

VecNormalize

class stable_baselines.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*)

A moving average, normalizing wrapper for vectorized environment.

It is pickleable which will save moving averages and configuration parameters. The wrapped environment *venv* is not saved, and must be restored manually with *set_venv* after being unpickled.

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

get_original_obs() → numpy.ndarray
Returns an unnormalized version of the observations from the most recent step or reset.

get_original_reward() → numpy.ndarray
Returns an unnormalized version of the rewards from the most recent step.

static load(*load_path*, *venv*)
Loads a saved VecNormalize object.

Parameters

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

Returns (VecNormalize)

load_running_average(*path*)

Parameters **path** – (str) path to log dir

Deprecated since version 2.9.0: This function will be removed in a future version

normalize_obs(*obs: numpy.ndarray*) → numpy.ndarray
Normalize observations using this VecNormalize's observations statistics. Calling this method does not update statistics.

normalize_reward(*reward: numpy.ndarray*) → numpy.ndarray
Normalize rewards using this VecNormalize's rewards statistics. Calling this method does not update statistics.

reset()
Reset all environments

save_running_average(*path*)

Parameters path – (str) path to log dir

Deprecated since version 2.9.0: This function will be removed in a future version

set_venv(*venv*)
Sets the vector environment to wrap to venv.

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

Parameters venv – (VecEnv)

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

where 'news' is a boolean vector indicating whether each element is new.

VecVideoRecorder

class stable_baselines.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 or VecEnvWrapper)
- **video_folder** – (str) Where to save videos
- **record_video_trigger** – (func) 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.

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.

Returns ([int] or [float]) observation

step_wait()

Wait for the step taken with step_async().

Returns ([int] or [float], [float], [bool], dict) observation, reward, done, information

VecCheckNan

class stable_baselines.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 of 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.

Returns ([int] or [float]) 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.

step_wait()

Wait for the step taken with step_async().

Returns ([int] or [float], [float], [bool], dict) 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 input values must be in [0, 255] as the observation is normalized (dividing by 255 to have values in [0, 1]) when using CNN policies.

```
import gym
from gym import spaces

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

```

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```
    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:
        self.observation_space = spaces.Box(low=0, high=255,
                                            shape=(HEIGHT, WIDTH, N_CHANNELS), 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_baselines.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 of creating a custom environment.

You can also find a complete guide online on creating a custom Gym environment.

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).

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 baselines provides default policy networks (see *Policies*) for images (CNNPolicies) and other type of input features (MlpPolicies).

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

```python
import gym
import tensorflow as tf

from stable_baselines import PPO2

# Custom MLP policy of two layers of size 32 each with tanh activation function
policy_kwargs = dict(act_fun=tf.nn.tanh, net_arch=[32, 32])
# Create the agent
model = PPO2("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("ppo2-cartpole")

del model
# the policy_kwargs are automatically loaded
model = PPO2.load("ppo2-cartpole")
```

You can also easily define a custom architecture for the policy (or value) network:

Note: Defining a custom policy class is equivalent to passing `policy_kwargs`. However, it lets you name the policy and so makes usually the code clearer. `policy_kwargs` should be rather used when doing hyperparameter search.

```python
import gym

from stable_baselines.common.policies import FeedForwardPolicy, register_policy
from stable_baselines.common.vec_env import DummyVecEnv
from stable_baselines import A2C

# Custom MLP policy of three layers of size 128 each
class CustomPolicy(FeedForwardPolicy):
    def __init__(self, *args, **kwargs):
        super(CustomPolicy, self).__init__(*args, **kwargs,
                                           net_arch=[dict(pi=[128, 128, 128],
                                                          vf=[128, 128, 128])],
                                           feature_extraction="mlp")

# Create and wrap the environment
env = gym.make('LunarLander-v2')
env = DummyVecEnv([lambda: env])

model = A2C(CustomPolicy, env, verbose=1)
# Train the agent
model.learn(total_timesteps=100000)
# Save the agent
model.save("a2c-lunar")

del model
# When loading a model with a custom policy
# you MUST pass explicitly the policy when loading the saved model
model = A2C.load("a2c-lunar", policy=CustomPolicy)
```

Warning: When loading a model with a custom policy, you must pass the custom policy explicitly when loading the model. (cf previous example)

You can also register your policy, to help with code simplicity: you can refer to your custom policy using a string.

```
import gym

from stable_baselines.common.policies import FeedForwardPolicy, register_policy
from stable_baselines.common.vec_env import DummyVecEnv
from stable_baselines import A2C

# Custom MLP policy of three layers of size 128 each
class CustomPolicy(FeedForwardPolicy):
    def __init__(self, *args, **kwargs):
        super(CustomPolicy, self).__init__(*args, **kwargs,
                                           net_arch=[dict(pi=[128, 128, 128],
                                                          vf=[128, 128, 128])],
                                           feature_extraction="mlp")

# Register the policy, it will check that the name is not already taken
register_policy('CustomPolicy', CustomPolicy)

# Because the policy is now registered, you can pass
# a string to the agent constructor instead of passing a class
model = A2C(policy='CustomPolicy', env='LunarLander-v2', verbose=1).learn(total_
↪timesteps=100000)
```

Deprecated since version 2.3.0: Use `net_arch` instead of `layers` parameter to define the network architecture. It allows to have a greater control.

The `net_arch` parameter of `FeedForwardPolicy` 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>])]`.

1.9.1 Examples

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

```
          obs
           |
         <128>
           |
         <128>
   /               \
action            value
```

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

```
          obs
           |
         <128>
   /               \
action             <256>
                     |
                   <256>
                     |
                   value
```

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

```
          obs
           |
         <128>
   /               \
 <16>             <256>
   |                |
action            value
```

The `LstmPolicy` can be used to construct recurrent policies in a similar way:

```
class CustomLSTMPolicy(LstmPolicy):
    def __init__(self, sess, ob_space, ac_space, n_env, n_steps, n_batch, n_lstm=64,␣
↪reuse=False, **_kwargs):
        super().__init__(sess, ob_space, ac_space, n_env, n_steps, n_batch, n_lstm,␣
↪reuse,
                         net_arch=[8, 'lstm', dict(vf=[5, 10], pi=[10])],
                         layer_norm=True, feature_extraction="mlp", **_kwargs)
```

Here the `net_arch` parameter takes an additional (mandatory) 'lstm' entry within the shared network section. The LSTM is shared between value network and policy network.

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

```
import gym
import tensorflow as tf

from stable_baselines.common.policies import ActorCriticPolicy, register_policy,␣
↪nature_cnn
from stable_baselines.common.vec_env import DummyVecEnv
from stable_baselines import A2C

# Custom MLP policy of three layers of size 128 each for the actor and 2 layers of 32␣
↪for the critic,
# with a nature_cnn feature extractor
class CustomPolicy(ActorCriticPolicy):
    def __init__(self, sess, ob_space, ac_space, n_env, n_steps, n_batch, reuse=False,
↪ **kwargs):
        super(CustomPolicy, self).__init__(sess, ob_space, ac_space, n_env, n_steps,␣
↪n_batch, reuse=reuse, scale=True)

        with tf.variable_scope("model", reuse=reuse):
            activ = tf.nn.relu

            extracted_features = nature_cnn(self.processed_obs, **kwargs)
            extracted_features = tf.layers.flatten(extracted_features)
```

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```
            pi_h = extracted_features
            for i, layer_size in enumerate([128, 128, 128]):
                pi_h = activ(tf.layers.dense(pi_h, layer_size, name='pi_fc' + str(i)))
            pi_latent = pi_h

            vf_h = extracted_features
            for i, layer_size in enumerate([32, 32]):
                vf_h = activ(tf.layers.dense(vf_h, layer_size, name='vf_fc' + str(i)))
            value_fn = tf.layers.dense(vf_h, 1, name='vf')
            vf_latent = vf_h

            self._proba_distribution, self._policy, self.q_value = \
                self.pdtype.proba_distribution_from_latent(pi_latent, vf_latent, init_
↪scale=0.01)

        self._value_fn = value_fn
        self._setup_init()

    def step(self, obs, state=None, mask=None, deterministic=False):
        if deterministic:
            action, value, neglogp = self.sess.run([self.deterministic_action, self.
↪value_flat, self.neglogp],
                                                   {self.obs_ph: obs})
        else:
            action, value, neglogp = self.sess.run([self.action, self.value_flat,␣
↪self.neglogp],
                                                   {self.obs_ph: obs})
        return action, value, self.initial_state, neglogp

    def proba_step(self, obs, state=None, mask=None):
        return self.sess.run(self.policy_proba, {self.obs_ph: obs})

    def value(self, obs, state=None, mask=None):
        return self.sess.run(self.value_flat, {self.obs_ph: obs})


# Create and wrap the environment
env = DummyVecEnv([lambda: gym.make('Breakout-v0')])

model = A2C(CustomPolicy, env, verbose=1)
# Train the agent
model.learn(total_timesteps=100000)
```

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_baselines.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: BaseRLModel
        # 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  # type: logger.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
        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:
```

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```
        """
        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

You should know that `PPO1` and `TRPO` update *self.num_timesteps* after each rollout (and not each step) because they rely on MPI.

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
    ...
```

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```
    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` steps, you must specify a log folder (`save_path`) and optionally a prefix for the checkpoints (`rl_model` by default).

```
from stable_baselines import SAC
from stable_baselines.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-v0')
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 a child callback via the `callback_on_new_best` argument. It will be triggered each time there is a new best model.

```
import gym

from stable_baselines import SAC
from stable_baselines.common.callbacks import EvalCallback

# Separate evaluation env
eval_env = gym.make('Pendulum-v0')
# Use deterministic actions for evaluation
eval_callback = EvalCallback(eval_env, best_model_save_path='./logs/',
```

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```
                             log_path='./logs/', eval_freq=500,
                             deterministic=True, render=False)

model = SAC('MlpPolicy', 'Pendulum-v0')
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_baselines import SAC
from stable_baselines.common.callbacks import CallbackList, CheckpointCallback,␣
↪EvalCallback

checkpoint_callback = CheckpointCallback(save_freq=1000, save_path='./logs/')
# Separate evaluation env
eval_env = gym.make('Pendulum-v0')
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-v0')
# 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_baselines import SAC
from stable_baselines.common.callbacks import EvalCallback,␣
↪StopTrainingOnRewardThreshold

# Separate evaluation env
eval_env = gym.make('Pendulum-v0')
# 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-v0', 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 `PPO1` and `TRPO` work (they rely on MPI), `n_steps` is a lower bound between two events.

```
import gym

from stable_baselines import PPO2
from stable_baselines.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 = PPO2('MlpPolicy', 'Pendulum-v0', verbose=1)

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

Legacy: A functional approach

Warning: This way of doing callbacks is deprecated in favor of the object oriented approach.

A callback function takes the `locals()` variables and the `globals()` variables from the model, then returns a boolean value for whether or not the training should continue.

Thanks to the access to the models variables, in particular `_locals["self"]`, we are able to even change the parameters of the model without halting the training, or changing the model's code.

```
from typing import Dict, Any

from stable_baselines import PPO2


def simple_callback(_locals: Dict[str, Any], _globals: Dict[str, Any]) -> bool:
    """
    Callback called at each step (for DQN and others) or after n steps (see ACER or␣
↪PPO2).
    This callback will save the model and stop the training after the first call.

    :param _locals: (Dict[str, Any])
    :param _globals: (Dict[str, Any])
    :return: (bool) If your callback returns False, training is aborted early.
    """
    print("callback called")
    # Save the model
    _locals["self"].save("saved_model")
    # If you want to continue training, the callback must return True.
    # return True # returns True, training continues.
    print("stop training")
    return False # returns False, training stops.
```

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```
model = PPO2('MlpPolicy', 'CartPole-v1')
model.learn(2000, callback=simple_callback)
```

class stable_baselines.common.callbacks.**BaseCallback**(*verbose: int = 0*)
Base class for callback.

Parameters verbose – (int)

init_callback(*model: BaseRLModel*) → None
Initialize the callback by saving references to the RL model and the training environment for convenience.

on_step() → 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.

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

update_locals(*locals_: Dict[str, Any]*) → None
Updates the local variables of the training process

For reference to which variables are accessible, check each individual algorithm's documentation :param *locals_*: (Dict[str, Any]) current local variables

class stable_baselines.common.callbacks.**CallbackList**(*callbacks: List[stable_baselines.common.callbacks.BaseCallback]*)
Class for chaining callbacks.

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

class stable_baselines.common.callbacks.**CheckpointCallback**(*save_freq: int, save_path: str, name_prefix='rl_model', verbose=0*)
Callback for saving a model every *save_freq* steps

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

class stable_baselines.common.callbacks.**ConvertCallback**(*callback, verbose=0*)
Convert functional callback (old-style) to object.

Parameters

- **callback** – (Callable)
- **verbose** – (int)

class stable_baselines.common.callbacks.**EvalCallback**(*eval_env: Union[gym.core.Env, stable_baselines.common.vec_env.base_vec_env.VecEnv], callback_on_new_best: Optional[stable_baselines.common.callbacks.BaseCallback] = None, n_eval_episodes: int = 5, eval_freq: int = 10000, log_path: str = None, best_model_save_path: str = None, deterministic: bool = True, render: bool = False, verbose: int = 1*)

Callback for evaluating an agent.

Parameters

- **eval_env** – (Union[gym.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*
- **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** – (str) Path to a folder where the evaluations (*evaluations.npz*) will be saved. It will be updated at each evaluation.
- **best_model_save_path** – (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)

class stable_baselines.common.callbacks.**EventCallback**(*callback: Optional[stable_baselines.common.callbacks.BaseCallback] = None, verbose: int = 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: BaseRLModel*) → None

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

class stable_baselines.common.callbacks.**EveryNTimesteps**(*n_steps: int, callback: stable_baselines.common.callbacks.BaseCallback*)

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_baselines.common.callbacks.**StopTrainingOnRewardThreshold**(*reward_threshold: float, verbose: int = 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 the rl baselines, you simply need to define a log location for the RL agent:

```
import gym

from stable_baselines import A2C

model = A2C('MlpPolicy', 'CartPole-v1', verbose=1, tensorboard_log="./a2c_cartpole_
↪tensorboard/")
model.learn(total_timesteps=10000)
```

Or after loading an existing model (by default the log path is not saved):

```
import gym

from stable_baselines.common.vec_env import DummyVecEnv
from stable_baselines import A2C

env = gym.make('CartPole-v1')
env = DummyVecEnv([lambda: env])  # The algorithms require a vectorized environment␣
↪to run

model = A2C.load("./a2c_cartpole.pkl", env=env, tensorboard_log="./a2c_cartpole_
↪tensorboard/")
model.learn(total_timesteps=10000)
```

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

```
import gym

from stable_baselines import A2C

model = A2C('MlpPolicy', 'CartPole-v1', verbose=1, tensorboard_log="./a2c_cartpole_
↪tensorboard/")
model.learn(total_timesteps=10000, 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
```

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```
model.learn(total_timesteps=10000, tb_log_name="second_run", reset_num_
↪timesteps=False)
model.learn(total_timesteps=10000, tb_log_name="thrid_run", reset_num_timesteps=False)
```

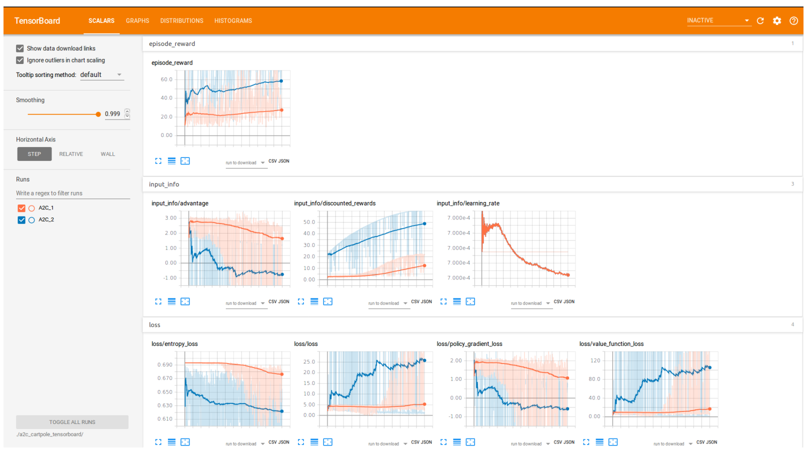
Once the learn function is called, you can monitor the RL agent during or after the training, with the following bash command:

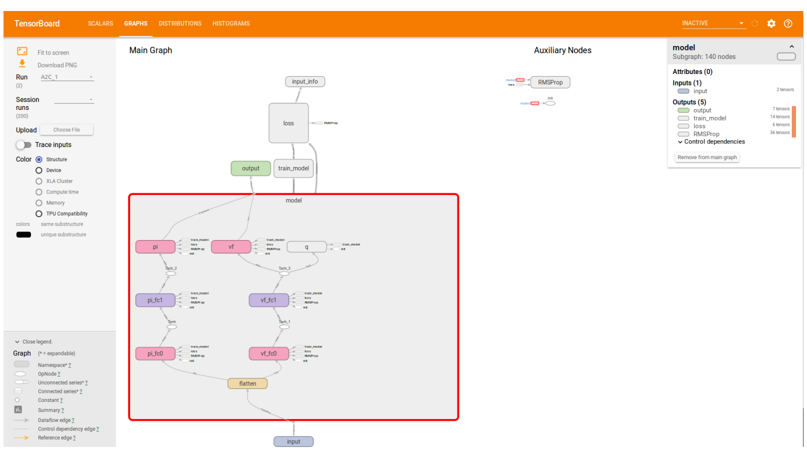
```
tensorboard --logdir ./a2c_cartpole_tensorboard/
```

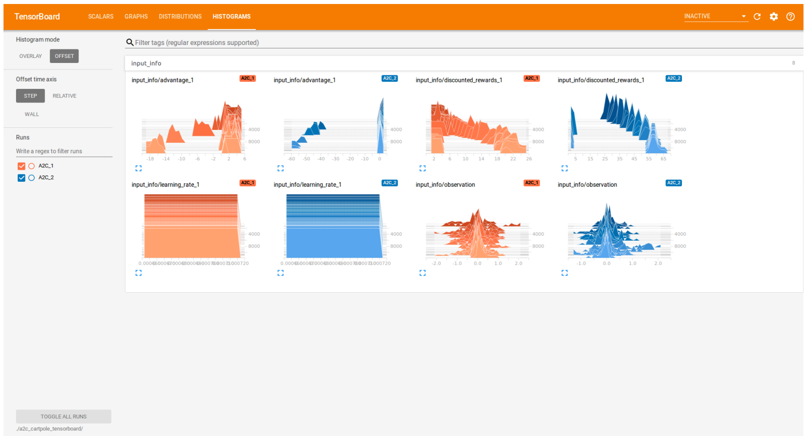
you can also add past logging folders:

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

It will display information such as the model graph, the episode reward, the model losses, the observation 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 tensorflow as tf
import numpy as np

from stable_baselines import SAC
from stable_baselines.common.callbacks import BaseCallback

model = SAC("MlpPolicy", "Pendulum-v0", tensorboard_log="/tmp/sac/", verbose=1)

class TensorboardCallback(BaseCallback):
    """
    Custom callback for plotting additional values in tensorboard.
    """
    def __init__(self, verbose=0):
        self.is_tb_set = False
        super(TensorboardCallback, self).__init__(verbose)

    def _on_step(self) -> bool:
        # Log additional tensor
        if not self.is_tb_set:
            with self.model.graph.as_default():
                tf.summary.scalar('value_target', tf.reduce_mean(self.model.value_
↪target))
                self.model.summary = tf.summary.merge_all()
            self.is_tb_set = True
        # Log scalar value (here a random variable)
        value = np.random.random()
        summary = tf.Summary(value=[tf.Summary.Value(tag='random_value', simple_
↪value=value)])
        self.locals['writer'].add_summary(summary, self.num_timesteps)
        return True


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

1.11.3 Legacy Integration

All the information displayed in the terminal (default logging) can be also logged in tensorboard. For that, you need to define several environment variables:

```
# formats are comma-separated, but for tensorboard you only need the last one
# stdout -> terminal
export OPENAI_LOG_FORMAT='stdout,log,csv,tensorboard'
export OPENAI_LOGDIR=path/to/tensorboard/data
```

and to configure the logger using:

```
from stable_baselines.logger import configure

configure()
```

Then start tensorboard with:

```
tensorboard --logdir=$OPENAI_LOGDIR
```

1.12 RL Baselines Zoo

RL Baselines Zoo. is a collection of pre-trained Reinforcement Learning agents using Stable-Baselines. It also provides basic scripts for training, evaluating agents, tuning hyperparameters and recording videos.

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!

1.12.1 Installation

1. Install dependencies

```
apt-get install swig cmake libopenmpi-dev zlib1g-dev ffmpeg
pip install stable-baselines box2d box2d-kengz pyyaml pybullet optuna pytablewriter
```

2. Clone the repository:

```
git clone https://github.com/araffin/rl-baselines-zoo
```

1.12.2 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 tensorboard support):

```
python train.py --algo ppo2 --env CartPole-v1 --tensorboard-log /tmp/stable-baselines/
```

Train for multiple environments (with one call) and with tensorboard logging:

```
python train.py --algo a2c --env MountainCar-v0 CartPole-v1 --tensorboard-log /tmp/
↪stable-baselines/
```

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.pkl -n 5000
```

1.12.3 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 trained_agents/ -n␣
↪5000
```

1.12.4 Hyperparameter Optimization

We use Optuna for optimizing the hyperparameters.

Tune the hyperparameters for PPO2, using a random sampler and median pruner, 2 parallels jobs, with a budget of 1000 trials and a maximum of 50000 steps:

```
python train.py --algo ppo2 --env MountainCar-v0 -n 50000 -optimize --n-trials 1000 --
↪n-jobs 2 \
  --sampler random --pruner median
```

1.12.5 Colab Notebook: Try it Online!

You can train agents online using Google colab notebook.

Note: You can find more information about the rl baselines zoo in the repo README. For instance, how to record a video of a trained agent.

1.13 Pre-Training (Behavior Cloning)

With the `.pretrain()` method, you can pre-train RL policies using trajectories from an expert, and therefore accelerate training.

Behavior Cloning (BC) treats the problem of imitation learning, i.e., using expert demonstrations, as a supervised learning problem. That is to say, given expert trajectories (observations-actions pairs), the policy network is trained to reproduce the expert behavior: for a given observation, the action taken by the policy must be the one taken by the expert.

Expert trajectories can be human demonstrations, trajectories from another controller (e.g. a PID controller) or trajectories from a trained RL agent.

Note: Only `Box` and `Discrete` spaces are supported for now for pre-training a model.

Note: Images datasets are treated a bit differently as other datasets to avoid memory issues. The images from the expert demonstrations must be located in a folder, not in the expert numpy archive.

1.13.1 Generate Expert Trajectories

Here, we are going to train a RL model and then generate expert trajectories using this agent.

Note that in practice, generating expert trajectories usually does not require training an RL agent.

The following example is only meant to demonstrate the `pretrain()` feature.

However, we recommend users to take a look at the code of the `generate_expert_traj()` function (located in `gail/dataset/` folder) to learn about the data structure of the expert dataset (see below for an overview) and how to record trajectories.

```
from stable_baselines import DQN
from stable_baselines.gail import generate_expert_traj

model = DQN('MlpPolicy', 'CartPole-v1', verbose=1)
      # Train a DQN agent for 1e5 timesteps and generate 10 trajectories
      # data will be saved in a numpy archive named `expert_cartpole.npz`
generate_expert_traj(model, 'expert_cartpole', n_timesteps=int(1e5), n_episodes=10)
```

Here is an additional example when the expert controller is a callable, that is passed to the function instead of a RL model. The idea is that this callable can be a PID controller, asking a human player, . . .

```
import gym

from stable_baselines.gail import generate_expert_traj

env = gym.make("CartPole-v1")
# Here the expert is a random agent
# but it can be any python function, e.g. a PID controller
def dummy_expert(_obs):
    """
    Random agent. It samples actions randomly
    from the action space of the environment.

    :param _obs: (np.ndarray) Current observation
    :return: (np.ndarray) action taken by the expert
    """
    return env.action_space.sample()
# Data will be saved in a numpy archive named `expert_cartpole.npz`
# when using something different than an RL expert,
# you must pass the environment object explicitly
generate_expert_traj(dummy_expert, 'dummy_expert_cartpole', env, n_episodes=10)
```

1.13.2 Pre-Train a Model using Behavior Cloning

Using the `expert_cartpole.npz` dataset generated with the previous script.

```
from stable_baselines import PPO2
from stable_baselines.gail import ExpertDataset
# Using only one expert trajectory
# you can specify `traj_limitation=-1` for using the whole dataset
dataset = ExpertDataset(expert_path='expert_cartpole.npz',
                        traj_limitation=1, batch_size=128)

model = PPO2('MlpPolicy', 'CartPole-v1', verbose=1)
# Pretrain the PPO2 model
model.pretrain(dataset, n_epochs=1000)

# As an option, you can train the RL agent
# model.learn(int(1e5))

# Test the pre-trained model
env = model.get_env()
obs = env.reset()

reward_sum = 0.0
for _ in range(1000):
        action, _ = model.predict(obs)
        obs, reward, done, _ = env.step(action)
        reward_sum += reward
        env.render()
        if done:
                print(reward_sum)
                reward_sum = 0.0
                obs = env.reset()

env.close()
```

1.13.3 Data Structure of the Expert Dataset

The expert dataset is a `.npz` archive. The data is saved in python dictionary format with keys: `actions`, `episode_returns`, `rewards`, `obs`, `episode_starts`.

In case of images, `obs` contains the relative path to the images.

obs, actions: shape (N * L,) + S

where N = # episodes, L = episode length and S is the environment observation/action space.

S = (1,) for discrete space

class `stable_baselines.gail.`**`ExpertDataset`**(*expert_path=None*, *traj_data=None*, *train_fraction=0.7*, *batch_size=64*, *traj_limitation=-1*, *randomize=True*, *verbose=1*, *sequential_preprocessing=False*)

Dataset for using behavior cloning or GAIL.

The structure of the expert dataset is a dict, saved as an ".npz" archive. The dictionary contains the keys 'actions', 'episode_returns', 'rewards', 'obs' and 'episode_starts'. The corresponding values have data concatenated across episode: the first axis is the timestep, the remaining axes index into the data. In case of images, 'obs' contains the relative path to the images, to enable space saving from image compression.

Parameters

- **expert_path** – (str) The path to trajectory data (.npz file). Mutually exclusive with traj_data.
- **traj_data** – (dict) Trajectory data, in format described above. Mutually exclusive with expert_path.
- **train_fraction** – (float) the train validation split (0 to 1) for pre-training using behavior cloning (BC)
- **batch_size** – (int) the minibatch size for behavior cloning
- **traj_limitation** – (int) the number of trajectory to use (if -1, load all)
- **randomize** – (bool) if the dataset should be shuffled
- **verbose** – (int) Verbosity
- **sequential_preprocessing** – (bool) Do not use subprocess to preprocess the data (slower but use less memory for the CI)

get_next_batch(*split=None*)

Get the batch from the dataset.

Parameters **split** – (str) the type of data split (can be None, 'train', 'val')

Returns (np.ndarray, np.ndarray) inputs and labels

init_dataloader(*batch_size*)

Initialize the dataloader used by GAIL.

Parameters **batch_size** – (int)

log_info()

Log the information of the dataset.

plot()

Show histogram plotting of the episode returns

class stable_baselines.gail.**DataLoader**(*indices, observations, actions, batch_size, n_workers=1, infinite_loop=True, max_queue_len=1, shuffle=False, start_process=True, backend='threading', sequential=False, partial_minibatch=True*)

A custom dataloader to preprocessing observations (including images) and feed them to the network.

Original code for the dataloader from https://github.com/araffin/robotics-rl-srl (MIT licence) Authors: Antonin Raffin, René Traoré, Ashley Hill

Parameters

- **indices** – ([int]) list of observations indices
- **observations** – (np.ndarray) observations or images path
- **actions** – (np.ndarray) actions
- **batch_size** – (int) Number of samples per minibatch
- **n_workers** – (int) number of preprocessing worker (for loading the images)
- **infinite_loop** – (bool) whether to have an iterator that can be reset
- **max_queue_len** – (int) Max number of minibatches that can be preprocessed at the same time

- **shuffle** – (bool) Shuffle the minibatch after each epoch
- **start_process** – (bool) Start the preprocessing process (default: True)
- **backend** – (str) joblib backend (one of 'multiprocessing', 'sequential', 'threading' or 'loky' in newest versions)
- **sequential** – (bool) Do not use subprocess to preprocess the data (slower but use less memory for the CI)
- **partial_minibatch** – (bool) Allow partial minibatches (minibatches with a number of element lesser than the batch_size)

sequential_next()
Sequential version of the pre-processing.

start_process()
Start preprocessing process

`stable_baselines.gail.`**generate_expert_traj**(*model*, *save_path=None*, *env=None*, *n_timesteps=0*, *n_episodes=100*, *image_folder='recorded_images'*)
Train expert controller (if needed) and record expert trajectories.

Note: only Box and Discrete spaces are supported for now.

Parameters

- **model** – (RL model or callable) The expert model, if it needs to be trained, then you need to pass `n_timesteps > 0`.
- **save_path** – (str) Path without the extension where the expert dataset will be saved (ex: 'expert_cartpole' -> creates 'expert_cartpole.npz'). If not specified, it will not save, and just return the generated expert trajectories. This parameter must be specified for image-based environments.
- **env** – (gym.Env) The environment, if not defined then it tries to use the model environment.
- **n_timesteps** – (int) Number of training timesteps
- **n_episodes** – (int) Number of trajectories (episodes) to record
- **image_folder** – (str) When using images, folder that will be used to record images.

Returns (dict) the generated expert trajectories.

1.14 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.

1.14.1 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 ($\sqrt{-1}$, inf $\times 1$, NaN mod 1, ...) return NaN
- **Division by zero:**
  - if the operand is not zero ($1/0$, $-2/0$, ...) returns $\pm$inf
  - if the operand is zero ($0/0$) returns signaling NaN
- Overflow (exponent too high to represent) returns $\pm$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.

And the worst of all, Tensorflow will not signal anything

```
import tensorflow as tf
import numpy as np

print("tensorflow test:")

a = tf.constant(1.0)
b = tf.constant(0.0)
c = a / b

sess = tf.Session()
val = sess.run(c)  # this will be quiet
print(val)
sess.close()

print("\r\nnumpy test:")

a = np.float64(1.0)
b = np.float64(0.0)
val = a / b  # this will warn
print(val)

print("\r\npure python test:")

a = 1.0
b = 0.0
val = a / b  # this will raise an exception and halt.
print(val)
```

Unfortunately, most of the floating point operations are handled by Tensorflow and numpy, meaning you might get little to no warning when a invalid value occurs.

1.14.2 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)
```

1.14.3 Tensorflow parameters

Tensorflow can add checks for detecting and dealing with invalid value: tf.add_check_numerics_ops and tf.check_numerics, however they will add operations to the Tensorflow graph and raise the computation time.

```
import tensorflow as tf

print("tensorflow test:")

a = tf.constant(1.0)
b = tf.constant(0.0)
c = a / b

check_nan = tf.add_check_numerics_ops()  # add after your graph definition.
```

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```
sess = tf.Session()
val, _ = sess.run([c, check_nan])  # this will now raise an exception
print(val)
sess.close()
```

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

```
import tensorflow as tf

print("tensorflow overflow test:")

check_nan = []  # the list of check_numerics operations

a = tf.constant(10)
b = tf.constant(1000)
c = a ** b

check_nan.append(tf.check_numerics(c, ""))  # check the 'c' operations

sess = tf.Session()
val, _ = sess.run([c] + check_nan)  # this will now raise an exception
print(val)
sess.close()
```

and catch propagation issues:

```
import tensorflow as tf

print("tensorflow propagation test:")

check_nan = []  # the list of check_numerics operations

a = tf.constant('NaN')
b = tf.constant(1.0)
c = a + b

check_nan.append(tf.check_numerics(c, ""))  # check the 'c' operations

sess = tf.Session()
val, _ = sess.run([c] + check_nan)  # this will now raise an exception
print(val)
sess.close()
```

1.14.4 VecCheckNan Wrapper

In order to find when and from where the invalid value originated from, stable-baselines 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
```

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```
from stable_baselines import PPO2
from stable_baselines.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 = PPO2('MlpPolicy', env)

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

1.14.5 RL Model hyperparameters

Depending on your hyperparameters, NaN can occurs 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 hyperparameters 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).

1.14.6 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

1.15 On saving and loading

Stable baselines 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 two formats used to save agents in stable baselines, their pros and shortcomings.

Terminology used in this page:

- *parameters* refer to neural network parameters (also called "weights"). This is a dictionary mapping Tensorflow variable name to a NumPy array.
- *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 their values.

1.15.1 Cloudpickle (stable-baselines<=2.7.0)

Original stable baselines save format. Data and parameters are bundled up into a tuple `(data, parameters)` and then serialized with `cloudpickle` library (essentially the same as `pickle`).

This save format is still available via an argument in model save function in stable-baselines versions above v2.7.0 for backwards compatibility reasons, but its usage is discouraged.

Pros:

- Easy to implement and use.
- Works with almost any type of Python object, including functions.

Cons:

- Pickle/Cloudpickle is not designed for long-term storage or sharing between Python version.
- If one object in file is not readable (e.g. wrong library version), then reading the rest of the file is difficult.
- Python-specific format, hard to read stored files from other languages.

If part of a saved model becomes unreadable for any reason (e.g. different Tensorflow versions), then it may be tricky to restore any of the model. For this reason another save format was designed.

1.15.2 Zip-archive (stable-baselines>2.7.0)

A zip-archived JSON dump and NumPy zip archive of the arrays. The data dictionary (class parameters) is stored as a JSON file, model parameters are serialized with `numpy.savez` function and these two 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.

This is the default save format in stable baselines versions after v2.7.0.

File structure:

```
saved_model.zip/
├── data              JSON file of class-parameters (dictionary)
├── parameter_list    JSON file of model parameters and their ordering (list)
├── parameters        Bytes from numpy.savez (a zip file of the numpy arrays). ...
    ├── ...           Being a zip-archive itself, this object can also be opened ...
        ├── ...       as a zip-archive and browsed.
```

Pros:

- More robust to unserializable objects (one bad object does not break everything).
- Saved file 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).

1.16 Exporting models

After training an agent, you may want to deploy/use it in an other language or framework, like PyTorch or tensorflowjs. Stable Baselines 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 Baselines.

1.16.1 Background

In Stable Baselines, the controller is stored inside *policies* which convert observations into actions. Each learning algorithm (e.g. DQN, A2C, SAC) contains one or more policies, some of which are only used for training. An easy way to find the policy is to check the code for the `predict` function of the agent: This function should only call one policy with simple arguments.

Policies hold the necessary Tensorflow placeholders and tensors to do the inference (i.e. predict actions), so it is enough to export these policies to do inference in an another framework.

Note: Learning algorithms also may contain other Tensorflow placeholders, that are used for training only and are not required for inference.

Warning: When using CNN policies, the observation is normalized internally (dividing by 255 to have values in [0, 1])

1.16.2 Export to PyTorch

A known working solution is to use *get_parameters* function to obtain model parameters, construct the network manually in PyTorch and assign parameters correctly.

> **Warning:** PyTorch and Tensorflow have internal differences with e.g. 2D convolutions (see discussion linked below).

See discussion #372 for details.

1.16.3 Export to C++

Tensorflow, which is the backbone of Stable Baselines, is fundamentally a C/C++ library despite being most commonly accessed through the Python frontend layer. This design choice means that the models created at Python level should generally be fully compliant with the respective C++ version of Tensorflow.

> **Warning:** It is advisable not to mix-and-match different versions of Tensorflow libraries, particularly in terms of the state. Moving computational graphs is generally more forgiving. As a matter of fact, mentioned below PPO_CPP project uses graphs generated with Python Tensorflow 1.x in C++ Tensorflow 2 version.

Stable Baselines comes very handily when hoping to migrate a computational graph and/or a state (weights) as the existing algorithms define most of the necessary computations for you so you don't need to recreate the core of the algorithms again. This is exactly the idea that has been used in the PPO_CPP project, which executes the training at the C++ level for the sake of computational efficiency. The graphs are exported from Stable Baselines' PPO2 implementation through `tf.train.export_meta_graph` function. Alternatively, and perhaps more commonly, you could use the C++ layer only for inference. That could be useful as a deployment step of server backends or optimization for more limited devices.

> **Warning:** As a word of caution, C++-level APIs are more imperative than their Python counterparts or more plainly speaking: cruder. This is particularly apparent in Tensorflow 2.0 where the declarativeness of Autograph exists only at Python level. The C++ counterpart still operates on Session objects' use, which are known from earlier versions of Tensorflow. In our use case, availability of graphs utilized by Session depends on the use of `tf.function` decorators. However, as of November 2019, Stable Baselines still uses Tensorflow 1.x in the main version which is slightly easier to use in the context of the C++ portability.

1.16.4 Export to tensorflowjs / tfjs

Can be done via Tensorflow's simple_save function and tensorflowjs_converter.

See discussion #474 for details.

1.16.5 Export to Java

Can be done via Tensorflow's simple_save function.

See this discussion for details.

1.16.6 Manual export

You can also manually export required parameters (weights) and construct the network in your desired framework, as done with the PyTorch example above.

You can access parameters of the model via agents' `get_parameters` function. If you use default policies, you can find the architecture of the networks in source for *policies*. Otherwise, for DQN/SAC/DDPG or TD3 you need to check the *policies.py* file located in their respective folders.

1.17 Base RL Class

Common interface for all the RL algorithms

class stable_baselines.common.base_class.**BaseRLModel**(*policy*, *env*, *verbose=0*, ***, *requires_vec_env*, *policy_base*, *policy_kwargs=None*, *seed=None*, *n_cpu_tf_sess=None*)

The base RL model

Parameters

- **policy** – (BasePolicy) Policy object
- **env** – (Gym environment) The environment to learn from (if registered in Gym, can be str. Can be None for loading trained models)
- **verbose** – (int) the verbosity level: 0 none, 1 training information, 2 tensorflow debug
- **requires_vec_env** – (bool) Does this model require a vectorized environment
- **policy_base** – (BasePolicy) the base policy used by this method
- **policy_kwargs** – (dict) additional arguments to be passed to the policy on creation
- **seed** – (int) Seed for the pseudo-random generators (python, numpy, tensorflow). If None (default), use random seed. Note that if you want completely deterministic results, you must set *n_cpu_tf_sess* to 1.
- **n_cpu_tf_sess** – (int) The number of threads for TensorFlow operations If None, the number of cpu of the current machine will be used.

action_probability(*observation*, *state=None*, *mask=None*, *actions=None*, *logp=False*)

If `actions` is `None`, then get the model's action probability distribution from a given observation.

Depending on the action space the output is:

- Discrete: probability for each possible action
- Box: mean and standard deviation of the action output

However if `actions` is not `None`, this function will return the probability that the given actions are taken with the given parameters (observation, state, ...) on this model. For discrete action spaces, it returns the probability mass; for continuous action spaces, the probability density. This is since the probability mass will always be zero in continuous spaces, see http://blog.christianperone.com/2019/01/ for a good explanation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)

- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **actions** – (np.ndarray) (OPTIONAL) For calculating the likelihood that the given actions are chosen by the model for each of the given parameters. Must have the same number of actions and observations. (set to None to return the complete action probability distribution)
- **logp** – (bool) (OPTIONAL) When specified with actions, returns probability in log-space. This has no effect if actions is None.

Returns (np.ndarray) the model's (log) action probability

get_env()
returns the current environment (can be None if not defined)

Returns (Gym Environment) The current environment

get_parameter_list()
Get tensorflow Variables of model's parameters

This includes all variables necessary for continuing training (saving / loading).

Returns (list) List of tensorflow Variables

get_parameters()
Get current model parameters as dictionary of variable name -> ndarray.

Returns (OrderedDict) Dictionary of variable name -> ndarray of model's parameters.

get_vec_normalize_env() → Optional[stable_baselines.common.vec_env.vec_normalize.VecNormalize]
Return the `VecNormalize` wrapper of the training env if it exists.

Returns Optional[VecNormalize] The `VecNormalize` env.

learn(*total_timesteps*, *callback=None*, *log_interval=100*, *tb_log_name='run'*, *reset_num_timesteps=True*)
Return a trained model.

Parameters

- **total_timesteps** – (int) The total number of samples to train on
- **callback** – (Union[callable, [callable], BaseCallback]) function called at every steps with state of the algorithm. It takes the local and global variables. If it returns False, training is aborted. When the callback inherits from BaseCallback, you will have access to additional stages of the training (training start/end), please read the documentation for more details.
- **log_interval** – (int) The number of timesteps before logging.
- **tb_log_name** – (str) the name of the run for tensorboard log
- **reset_num_timesteps** – (bool) whether or not to reset the current timestep number (used in logging)

Returns (BaseRLModel) the trained model

classmethod load(*load_path*, *env=None*, *custom_objects=None*, ***kwargs*)
Load the model from file

Parameters

- **load_path** – (str or file-like) the saved parameter location
- **env** – (Gym Environment) the new environment to run the loaded model on (can be None if you only need prediction from a trained model)

- **custom_objects** – (dict) 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.
- **kwargs** – extra arguments to change the model when loading

load_parameters(*load_path_or_dict*, *exact_match=True*)
Load model parameters from a file or a dictionary

Dictionary keys should be tensorflow variable names, which can be obtained with `get_parameters` function. If `exact_match` is True, dictionary should contain keys for all model's parameters, otherwise RunTimeError is raised. If False, only variables included in the dictionary will be updated.

This does not load agent's hyper-parameters.

> **Warning:** This function does not update trainer/optimizer variables (e.g. momentum). As such training after using this function may lead to less-than-optimal results.

Parameters

- **load_path_or_dict** – (str or file-like or dict) Save parameter location or dict of parameters as variable.name -> ndarrays to be loaded.
- **exact_match** – (bool) If True, expects load dictionary to contain keys for all variables in the model. If False, loads parameters only for variables mentioned in the dictionary. Defaults to True.

predict(*observation*, *state=None*, *mask=None*, *deterministic=False*)
Get the model's action from an observation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray, np.ndarray) the model's action and the next state (used in recurrent policies)

pretrain(*dataset*, *n_epochs=10*, *learning_rate=0.0001*, *adam_epsilon=1e-08*, *val_interval=None*)
Pretrain a model using behavior cloning: supervised learning given an expert dataset.

NOTE: only Box and Discrete spaces are supported for now.

Parameters

- **dataset** – (ExpertDataset) Dataset manager
- **n_epochs** – (int) Number of iterations on the training set
- **learning_rate** – (float) Learning rate
- **adam_epsilon** – (float) the epsilon value for the adam optimizer
- **val_interval** – (int) Report training and validation losses every n epochs. By default, every 10th of the maximum number of epochs.

Returns (BaseRLModel) the pretrained model

save (*save_path*, *cloudpickle=False*)
Save the current parameters to file

Parameters

- **save_path** – (str or file-like) The save location
- **cloudpickle** – (bool) Use older cloudpickle format instead of zip-archives.

set_env (*env*)
Checks the validity of the environment, and if it is coherent, set it as the current environment.

Parameters env – (Gym Environment) The environment for learning a policy

set_random_seed (*seed: Optional[int]*) → None

Parameters seed – (Optional[int]) Seed for the pseudo-random generators. If None, do not change the seeds.

setup_model ()
Create all the functions and tensorflow graphs necessary to train the model

1.18 Policy Networks

Stable-baselines provides a set of default policies, that can be used with most action spaces. To customize the default policies, you can specify the `policy_kwargs` parameter to the model class you use. Those kwargs are then passed to the policy on instantiation (see *Custom Policy Network* for an example). If you need more control on the policy architecture, you can also create a custom policy (see *Custom Policy Network*).

Note: CnnPolicies are for images only. MlpPolicies are made for other type of features (e.g. robot joints)

Warning: For all algorithms (except DDPG, TD3 and SAC), continuous actions are clipped during training and testing (to avoid out of bound error).

Available Policies

MlpPolicy	Policy object that implements actor critic, using a MLP (2 layers of 64)
MlpLstmPolicy	Policy object that implements actor critic, using LSTMs with a MLP feature extraction
MlpLnLstmPolicy	Policy object that implements actor critic, using a layer normalized LSTMs with a MLP feature extraction
CnnPolicy	Policy object that implements actor critic, using a CNN (the nature CNN)
CnnLstmPolicy	Policy object that implements actor critic, using LSTMs with a CNN feature extraction
CnnLnLstmPolicy	Policy object that implements actor critic, using a layer normalized LSTMs with a CNN feature extraction

1.18.1 Base Classes

class stable_baselines.common.policies.**BasePolicy**(*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *reuse=False*, *scale=False*, *obs_phs=None*, *add_action_ph=False*)

The base policy object

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batches to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **scale** – (bool) whether or not to scale the input
- **obs_phs** – (TensorFlow Tensor, TensorFlow Tensor) a tuple containing an override for observation placeholder and the processed observation placeholder respectively
- **add_action_ph** – (bool) whether or not to create an action placeholder

action_ph
tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state
The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete
bool: is action space discrete.

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step(*obs*, *state=None*, *mask=None*)
Returns the action probability for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) the action probability

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step(*obs*, *state=None*, *mask=None*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float], [float], [float], [float]) actions, values, states, neglogp

class stable_baselines.common.policies.**ActorCriticPolicy**(*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *reuse=False*, *scale=False*)

Policy object that implements actor critic

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **scale** – (bool) whether or not to scale the input

action
tf.Tensor: stochastic action, of shape (self.n_batch,) + self.ac_space.shape.

deterministic_action
tf.Tensor: deterministic action, of shape (self.n_batch,) + self.ac_space.shape.

neglogp
tf.Tensor: negative log likelihood of the action sampled by self.action.

pdtype
ProbabilityDistributionType: type of the distribution for stochastic actions.

policy
tf.Tensor: policy output, e.g. logits.

policy_proba
tf.Tensor: parameters of the probability distribution. Depends on pdtype.

proba_distribution
ProbabilityDistribution: distribution of stochastic actions.

step(*obs*, *state=None*, *mask=None*, *deterministic=False*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns ([float], [float], [float], [float]) actions, values, states, neglogp

value (*obs*, *state=None*, *mask=None*)
Returns the value for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) The associated value of the action

value_flat
tf.Tensor: value estimate, of shape (self.n_batch,)

value_fn
tf.Tensor: value estimate, of shape (self.n_batch, 1)

class stable_baselines.common.policies.**FeedForwardPolicy** (*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *reuse=False*, *layers=None*, *net_arch=None*, *act_fun=<MagicMock id='139640551970016'>*, *cnn_extractor=<function nature_cnn>*, *feature_extraction='cnn'*, ***kwargs*)
Policy object that implements actor critic, using a feed forward neural network.

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **layers** – ([int]) (deprecated, use net_arch instead) The size of the Neural network for the policy (if None, default to [64, 64])
- **net_arch** – (list) Specification of the actor-critic policy network architecture (see mlp_extractor documentation for details).
- **act_fun** – (tf.func) the activation function to use in the neural network.
- **cnn_extractor** – (function (TensorFlow Tensor, `**kwargs`): (TensorFlow Tensor)) the CNN feature extraction
- **feature_extraction** – (str) The feature extraction type ("cnn" or "mlp")
- **kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

proba_step (*obs*, *state=None*, *mask=None*)
Returns the action probability for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) the action probability

step(*obs*, *state=None*, *mask=None*, *deterministic=False*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns ([float], [float], [float], [float]) actions, values, states, neglogp

value(*obs*, *state=None*, *mask=None*)
Returns the value for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) The associated value of the action

class stable_baselines.common.policies.**LstmPolicy**(*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *n_lstm=256*, *reuse=False*, *layers=None*, *net_arch=None*, *act_fun=<MagicMock id='139640551928720'>*, *cnn_extractor=<function nature_cnn>*, *layer_norm=False*, *feature_extraction='cnn'*, ***kwargs*)

Policy object that implements actor critic, using LSTMs.

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **n_lstm** – (int) The number of LSTM cells (for recurrent policies)
- **reuse** – (bool) If the policy is reusable or not

- **layers** – ([int]) The size of the Neural network before the LSTM layer (if None, default to [64, 64])
- **net_arch** – (list) Specification of the actor-critic policy network architecture. Notation similar to the format described in mlp_extractor but with additional support for a 'lstm' entry in the shared network part.
- **act_fun** – (tf.func) the activation function to use in the neural network.
- **cnn_extractor** – (function (TensorFlow Tensor, `**kwargs`): (TensorFlow Tensor)) the CNN feature extraction
- **layer_norm** – (bool) Whether or not to use layer normalizing LSTMs
- **feature_extraction** – (str) The feature extraction type ("cnn" or "mlp")
- **kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

proba_step (*obs*, *state=None*, *mask=None*)
Returns the action probability for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) the action probability

step (*obs*, *state=None*, *mask=None*, *deterministic=False*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns ([float], [float], [float], [float]) actions, values, states, neglogp

value (*obs*, *state=None*, *mask=None*)
Cf base class doc.

1.18.2 MLP Policies

class stable_baselines.common.policies.**MlpPolicy** (*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *reuse=False*, ***_kwargs*)
Policy object that implements actor critic, using a MLP (2 layers of 64)

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run

- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

class stable_baselines.common.policies.**MlpLstmPolicy**(*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *n_lstm=256*, *reuse=False*, ***_kwargs*)

Policy object that implements actor critic, using LSTMs with a MLP feature extraction

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **n_lstm** – (int) The number of LSTM cells (for recurrent policies)
- **reuse** – (bool) If the policy is reusable or not
- **kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

class stable_baselines.common.policies.**MlpLnLstmPolicy**(*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *n_lstm=256*, *reuse=False*, ***_kwargs*)

Policy object that implements actor critic, using a layer normalized LSTMs with a MLP feature extraction

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **n_lstm** – (int) The number of LSTM cells (for recurrent policies)
- **reuse** – (bool) If the policy is reusable or not
- **kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

1.18.3 CNN Policies

class stable_baselines.common.policies.**CnnPolicy**(*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *reuse=False*, ***_kwargs*)

Policy object that implements actor critic, using a CNN (the nature CNN)

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

class stable_baselines.common.policies.**CnnLstmPolicy**(*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *n_lstm=256*, *reuse=False*, ***_kwargs*)

Policy object that implements actor critic, using LSTMs with a CNN feature extraction

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **n_lstm** – (int) The number of LSTM cells (for recurrent policies)
- **reuse** – (bool) If the policy is reusable or not
- **kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

class stable_baselines.common.policies.**CnnLnLstmPolicy**(*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *n_lstm=256*, *reuse=False*, ***_kwargs*)

Policy object that implements actor critic, using a layer normalized LSTMs with a CNN feature extraction

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **n_lstm** – (int) The number of LSTM cells (for recurrent policies)
- **reuse** – (bool) If the policy is reusable or not
- **kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

1.19 A2C

A synchronous, deterministic variant of Asynchronous Advantage Actor Critic (A3C). It uses multiple workers to avoid the use of a replay buffer.

1.19.1 Notes

- Original paper: https://arxiv.org/abs/1602.01783
- OpenAI blog post: https://openai.com/blog/baselines-acktr-a2c/
- `python -m stable_baselines.a2c.run_atari` runs the algorithm for 40M frames = 10M timesteps on an Atari game. See help (`-h`) for more options.
- `python -m stable_baselines.a2c.run_mujoco` runs the algorithm for 1M frames on a Mujoco environment.

1.19.2 Can I use?

- Recurrent policies: ✓
- Multi processing: ✓
- Gym spaces:

Space	Action	Observation
Discrete	✓	✓
Box	✓	✓
MultiDiscrete	✓	✓
MultiBinary	✓	✓

1.19.3 Example

Train a A2C agent on *CartPole-v1* using 4 processes.

```
import gym

from stable_baselines.common.policies import MlpPolicy
from stable_baselines.common import make_vec_env
from stable_baselines import A2C

# 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()
```

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

1.19.4 Parameters

class stable_baselines.a2c.**A2C**(*policy*, *env*, *gamma=0.99*, *n_steps=5*, *vf_coef=0.25*, *ent_coef=0.01*, *max_grad_norm=0.5*, *learning_rate=0.0007*, *alpha=0.99*, *momentum=0.0*, *epsilon=1e-05*, *lr_schedule='constant'*, *verbose=0*, *tensorboard_log=None*, *_init_setup_model=True*, *policy_kwargs=None*, *full_tensorboard_log=False*, *seed=None*, *n_cpu_tf_sess=None*)

The A2C (Advantage Actor Critic) model class, https://arxiv.org/abs/1602.01783

Parameters

- **policy** – (ActorCriticPolicy or str) The policy model to use (MlpPolicy, CnnPolicy, CnnLstmPolicy, . . .)
- **env** – (Gym environment or str) The environment to learn from (if registered in Gym, can be str)
- **gamma** – (float) Discount factor
- **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)
- **vf_coef** – (float) Value function coefficient for the loss calculation
- **ent_coef** – (float) Entropy coefficient for the loss calculation
- **max_grad_norm** – (float) The maximum value for the gradient clipping
- **learning_rate** – (float) The learning rate
- **alpha** – (float) RMSProp decay parameter (default: 0.99)
- **momentum** – (float) RMSProp momentum parameter (default: 0.0)
- **epsilon** – (float) RMSProp epsilon (stabilizes square root computation in denominator of RMSProp update) (default: 1e-5)
- **lr_schedule** – (str) The type of scheduler for the learning rate update ('linear', 'constant', 'double_linear_con', 'middle_drop' or 'double_middle_drop')
- **verbose** – (int) the verbosity level: 0 none, 1 training information, 2 tensorflow debug
- **tensorboard_log** – (str) the log location for tensorboard (if None, no logging)
- **_init_setup_model** – (bool) Whether or not to build the network at the creation of the instance (used only for loading)
- **policy_kwargs** – (dict) additional arguments to be passed to the policy on creation
- **full_tensorboard_log** – (bool) enable additional logging when using tensorboard WARNING: this logging can take a lot of space quickly
- **seed** – (int) Seed for the pseudo-random generators (python, numpy, tensorflow). If None (default), use random seed. Note that if you want completely deterministic results, you must set *n_cpu_tf_sess* to 1.

- **n_cpu_tf_sess** – (int) The number of threads for TensorFlow operations If None, the number of cpu of the current machine will be used.

action_probability (*observation*, *state=None*, *mask=None*, *actions=None*, *logp=False*)
If `actions` is `None`, then get the model's action probability distribution from a given observation.

Depending on the action space the output is:

- Discrete: probability for each possible action
- Box: mean and standard deviation of the action output

However if `actions` is not `None`, this function will return the probability that the given actions are taken with the given parameters (observation, state, ...) on this model. For discrete action spaces, it returns the probability mass; for continuous action spaces, the probability density. This is since the probability mass will always be zero in continuous spaces, see http://blog.christianperone.com/2019/01/ for a good explanation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **actions** – (np.ndarray) (OPTIONAL) For calculating the likelihood that the given actions are chosen by the model for each of the given parameters. Must have the same number of actions and observations. (set to None to return the complete action probability distribution)
- **logp** – (bool) (OPTIONAL) When specified with actions, returns probability in log-space. This has no effect if actions is None.

Returns (np.ndarray) the model's (log) action probability

get_env()
returns the current environment (can be None if not defined)

Returns (Gym Environment) The current environment

get_parameter_list()
Get tensorflow Variables of model's parameters

This includes all variables necessary for continuing training (saving / loading).

Returns (list) List of tensorflow Variables

get_parameters()
Get current model parameters as dictionary of variable name -> ndarray.

Returns (OrderedDict) Dictionary of variable name -> ndarray of model's parameters.

get_vec_normalize_env() → Optional[stable_baselines.common.vec_env.vec_normalize.VecNormalize]
Return the `VecNormalize` wrapper of the training env if it exists.

Returns Optional[VecNormalize] The `VecNormalize` env.

learn (*total_timesteps*, *callback=None*, *log_interval=100*, *tb_log_name='A2C'*, *reset_num_timesteps=True*)
Return a trained model.

Parameters

- **total_timesteps** – (int) The total number of samples to train on

- **callback** – (Union[callable, [callable], BaseCallback]) function called at every steps with state of the algorithm. It takes the local and global variables. If it returns False, training is aborted. When the callback inherits from BaseCallback, you will have access to additional stages of the training (training start/end), please read the documentation for more details.
- **log_interval** – (int) The number of timesteps before logging.
- **tb_log_name** – (str) the name of the run for tensorboard log
- **reset_num_timesteps** – (bool) whether or not to reset the current timestep number (used in logging)

Returns (BaseRLModel) the trained model

classmethod load(*load_path*, *env=None*, *custom_objects=None*, ***kwargs*)
Load the model from file

Parameters

- **load_path** – (str or file-like) the saved parameter location
- **env** – (Gym Environment) the new environment to run the loaded model on (can be None if you only need prediction from a trained model)
- **custom_objects** – (dict) 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.
- **kwargs** – extra arguments to change the model when loading

load_parameters(*load_path_or_dict*, *exact_match=True*)
Load model parameters from a file or a dictionary

Dictionary keys should be tensorflow variable names, which can be obtained with `get_parameters` function. If `exact_match` is True, dictionary should contain keys for all model's parameters, otherwise RunTimeError is raised. If False, only variables included in the dictionary will be updated.

This does not load agent's hyper-parameters.

> **Warning:** This function does not update trainer/optimizer variables (e.g. momentum). As such training after using this function may lead to less-than-optimal results.

Parameters

- **load_path_or_dict** – (str or file-like or dict) Save parameter location or dict of parameters as variable.name -> ndarrays to be loaded.
- **exact_match** – (bool) If True, expects load dictionary to contain keys for all variables in the model. If False, loads parameters only for variables mentioned in the dictionary. Defaults to True.

predict(*observation*, *state=None*, *mask=None*, *deterministic=False*)
Get the model's action from an observation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)

- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray, np.ndarray) the model's action and the next state (used in recurrent policies)

pretrain(*dataset*, *n_epochs=10*, *learning_rate=0.0001*, *adam_epsilon=1e-08*, *val_interval=None*)
Pretrain a model using behavior cloning: supervised learning given an expert dataset.

NOTE: only Box and Discrete spaces are supported for now.

Parameters

- **dataset** – (ExpertDataset) Dataset manager
- **n_epochs** – (int) Number of iterations on the training set
- **learning_rate** – (float) Learning rate
- **adam_epsilon** – (float) the epsilon value for the adam optimizer
- **val_interval** – (int) Report training and validation losses every n epochs. By default, every 10th of the maximum number of epochs.

Returns (BaseRLModel) the pretrained model

save(*save_path*, *cloudpickle=False*)
Save the current parameters to file

Parameters

- **save_path** – (str or file-like) The save location
- **cloudpickle** – (bool) Use older cloudpickle format instead of zip-archives.

set_env(*env*)
Checks the validity of the environment, and if it is coherent, set it as the current environment.

Parameters **env** – (Gym Environment) The environment for learning a policy

set_random_seed(*seed: Optional[int]*) → None

Parameters **seed** – (Optional[int]) Seed for the pseudo-random generators. If None, do not change the seeds.

setup_model()
Create all the functions and tensorflow graphs necessary to train the model

1.19.5 Callbacks - Accessible Variables

Depending on initialization parameters and timestep, different variables are accessible. Variables accessible "From timestep X" are variables that can be accessed when `self.timestep==X` in the `on_step` function.

Variable	Availability
• self • total_timesteps • callback • log_interval • tb_log_name • reset_num_timesteps • new_tb_log • writer • t_start • mb_obs • mb_rewards • mb_actions • mb_values • mb_dones • mb_states • ep_infos • actions • values • states • clipped_actions • obs • rewards • dones • infos	From timestep 1
• info • maybe_ep_info	From timestep 2
• update • rollout • masks • true_reward	From timestep `n_step+1`
• value_loss • policy_entropy • n_seconds • fps	From timestep `2 * n_step+1`

1.20 ACER

Sample Efficient Actor-Critic with Experience Replay (ACER) combines several ideas of previous algorithms: it uses multiple workers (as A2C), implements a replay buffer (as in DQN), uses Retrace for Q-value estimation, importance sampling and a trust region.

1.20.1 Notes

- Original paper: https://arxiv.org/abs/1611.01224
- `python -m stable_baselines.acer.run_atari` runs the algorithm for 40M frames = 10M timesteps on an Atari game. See help (`-h`) for more options.

1.20.2 Can I use?

- Recurrent policies: ✓
- Multi processing: ✓
- Gym spaces:

Space	Action	Observation
Discrete	✓	✓
Box		✓
MultiDiscrete		✓
MultiBinary		✓

1.20.3 Example

```
import gym

from stable_baselines.common.policies import MlpPolicy, MlpLstmPolicy, MlpLnLstmPolicy
from stable_baselines.common import make_vec_env
from stable_baselines import ACER

# multiprocess environment
env = make_vec_env('CartPole-v1', n_envs=4)

model = ACER(MlpPolicy, env, verbose=1)
model.learn(total_timesteps=25000)
model.save("acer_cartpole")

del model # remove to demonstrate saving and loading

model = ACER.load("acer_cartpole")

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

1.20.4 Parameters

class stable_baselines.acer.**ACER**(*policy*, *env*, *gamma=0.99*, *n_steps=20*, *num_procs=None*, *q_coef=0.5*, *ent_coef=0.01*, *max_grad_norm=10*, *learning_rate=0.0007*, *lr_schedule='linear'*, *rprop_alpha=0.99*, *rprop_epsilon=1e-05*, *buffer_size=5000*, *replay_ratio=4*, *replay_start=1000*, *correction_term=10.0*, *trust_region=True*, *alpha=0.99*, *delta=1*, *verbose=0*, *tensorboard_log=None*, *_init_setup_model=True*, *policy_kwargs=None*, *full_tensorboard_log=False*, *seed=None*, *n_cpu_tf_sess=1*)

The ACER (Actor-Critic with Experience Replay) model class, https://arxiv.org/abs/1611.01224

Parameters

- **policy** – (ActorCriticPolicy or str) The policy model to use (MlpPolicy, CnnPolicy, CnnLstmPolicy, . . .)
- **env** – (Gym environment or str) The environment to learn from (if registered in Gym, can be str)
- **gamma** – (float) The discount value
- **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)
- **num_procs** – (int) The number of threads for TensorFlow operations

  Deprecated since version 2.9.0: Use *n_cpu_tf_sess* instead.
- **q_coef** – (float) The weight for the loss on the Q value
- **ent_coef** – (float) The weight for the entropy loss
- **max_grad_norm** – (float) The clipping value for the maximum gradient
- **learning_rate** – (float) The initial learning rate for the RMS prop optimizer
- **lr_schedule** – (str) The type of scheduler for the learning rate update ('linear', 'constant', 'double_linear_con', 'middle_drop' or 'double_middle_drop')
- **rprop_epsilon** – (float) RMSProp epsilon (stabilizes square root computation in denominator of RMSProp update) (default: 1e-5)
- **rprop_alpha** – (float) RMSProp decay parameter (default: 0.99)
- **buffer_size** – (int) The buffer size in number of steps
- **replay_ratio** – (float) The number of replay learning per on policy learning on average, using a poisson distribution
- **replay_start** – (int) The minimum number of steps in the buffer, before learning replay
- **correction_term** – (float) Importance weight clipping factor (default: 10)
- **trust_region** – (bool) Whether or not algorithms estimates the gradient KL divergence between the old and updated policy and uses it to determine step size (default: True)
- **alpha** – (float) The decay rate for the Exponential moving average of the parameters
- **delta** – (float) max KL divergence between the old policy and updated policy (default: 1)
- **verbose** – (int) the verbosity level: 0 none, 1 training information, 2 tensorflow debug
- **tensorboard_log** – (str) the log location for tensorboard (if None, no logging)

- **_init_setup_model** – (bool) Whether or not to build the network at the creation of the instance
- **policy_kwargs** – (dict) additional arguments to be passed to the policy on creation
- **full_tensorboard_log** – (bool) enable additional logging when using tensorboard WARNING: this logging can take a lot of space quickly
- **seed** – (int) Seed for the pseudo-random generators (python, numpy, tensorflow). If None (default), use random seed. Note that if you want completely deterministic results, you must set *n_cpu_tf_sess* to 1.
- **n_cpu_tf_sess** – (int) The number of threads for TensorFlow operations If None, the number of cpu of the current machine will be used.

action_probability(*observation*, *state=None*, *mask=None*, *actions=None*, *logp=False*)

If `actions` is `None`, then get the model's action probability distribution from a given observation.

Depending on the action space the output is:

- Discrete: probability for each possible action
- Box: mean and standard deviation of the action output

However if `actions` is not `None`, this function will return the probability that the given actions are taken with the given parameters (observation, state, ...) on this model. For discrete action spaces, it returns the probability mass; for continuous action spaces, the probability density. This is since the probability mass will always be zero in continuous spaces, see http://blog.christianperone.com/2019/01/ for a good explanation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **actions** – (np.ndarray) (OPTIONAL) For calculating the likelihood that the given actions are chosen by the model for each of the given parameters. Must have the same number of actions and observations. (set to None to return the complete action probability distribution)
- **logp** – (bool) (OPTIONAL) When specified with actions, returns probability in log-space. This has no effect if actions is None.

Returns (np.ndarray) the model's (log) action probability

get_env()

returns the current environment (can be None if not defined)

Returns (Gym Environment) The current environment

get_parameter_list()

Get tensorflow Variables of model's parameters

This includes all variables necessary for continuing training (saving / loading).

Returns (list) List of tensorflow Variables

get_parameters()

Get current model parameters as dictionary of variable name -> ndarray.

Returns (OrderedDict) Dictionary of variable name -> ndarray of model's parameters.

get_vec_normalize_env() → Optional[stable_baselines.common.vec_env.vec_normalize.VecNormalize]
Return the `VecNormalize` wrapper of the training env if it exists.

Returns Optional[VecNormalize] The `VecNormalize` env.

learn(*total_timesteps*, *callback=None*, *log_interval=100*, *tb_log_name='ACER'*, *reset_num_timesteps=True*)
Return a trained model.

Parameters

- **total_timesteps** – (int) The total number of samples to train on
- **callback** – (Union[callable, [callable], BaseCallback]) function called at every steps with state of the algorithm. It takes the local and global variables. If it returns False, training is aborted. When the callback inherits from BaseCallback, you will have access to additional stages of the training (training start/end), please read the documentation for more details.
- **log_interval** – (int) The number of timesteps before logging.
- **tb_log_name** – (str) the name of the run for tensorboard log
- **reset_num_timesteps** – (bool) whether or not to reset the current timestep number (used in logging)

Returns (BaseRLModel) the trained model

classmethod load(*load_path*, *env=None*, *custom_objects=None*, ***kwargs*)
Load the model from file

Parameters

- **load_path** – (str or file-like) the saved parameter location
- **env** – (Gym Environment) the new environment to run the loaded model on (can be None if you only need prediction from a trained model)
- **custom_objects** – (dict) 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.
- **kwargs** – extra arguments to change the model when loading

load_parameters(*load_path_or_dict*, *exact_match=True*)
Load model parameters from a file or a dictionary

Dictionary keys should be tensorflow variable names, which can be obtained with `get_parameters` function. If `exact_match` is True, dictionary should contain keys for all model's parameters, otherwise RunTimeError is raised. If False, only variables included in the dictionary will be updated.

This does not load agent's hyper-parameters.

> **Warning:** This function does not update trainer/optimizer variables (e.g. momentum). As such training after using this function may lead to less-than-optimal results.

Parameters

- **load_path_or_dict** – (str or file-like or dict) Save parameter location or dict of parameters as variable.name -> ndarrays to be loaded.

- **exact_match** – (bool) If True, expects load dictionary to contain keys for all variables in the model. If False, loads parameters only for variables mentioned in the dictionary. Defaults to True.

predict (*observation*, *state=None*, *mask=None*, *deterministic=False*)
Get the model's action from an observation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray, np.ndarray) the model's action and the next state (used in recurrent policies)

pretrain (*dataset*, *n_epochs=10*, *learning_rate=0.0001*, *adam_epsilon=1e-08*, *val_interval=None*)
Pretrain a model using behavior cloning: supervised learning given an expert dataset.

NOTE: only Box and Discrete spaces are supported for now.

Parameters

- **dataset** – (ExpertDataset) Dataset manager
- **n_epochs** – (int) Number of iterations on the training set
- **learning_rate** – (float) Learning rate
- **adam_epsilon** – (float) the epsilon value for the adam optimizer
- **val_interval** – (int) Report training and validation losses every n epochs. By default, every 10th of the maximum number of epochs.

Returns (BaseRLModel) the pretrained model

save (*save_path*, *cloudpickle=False*)
Save the current parameters to file

Parameters

- **save_path** – (str or file-like) The save location
- **cloudpickle** – (bool) Use older cloudpickle format instead of zip-archives.

set_env (*env*)
Checks the validity of the environment, and if it is coherent, set it as the current environment.

Parameters **env** – (Gym Environment) The environment for learning a policy

set_random_seed (*seed: Optional[int]*) → None

Parameters **seed** – (Optional[int]) Seed for the pseudo-random generators. If None, do not change the seeds.

setup_model ()
Create all the functions and tensorflow graphs necessary to train the model

1.20.5 Callbacks - Accessible Variables

Depending on initialization parameters and timestep, different variables are accessible. Variables accessible from "timestep X" are variables that can be accessed when `self.timestep==X` from the `on_step` function.

Variable	Availability
• self • total_timesteps • callback • log_interval • tb_log_name • reset_num_timesteps • new_tb_log • writer • episode_stats • buffer • t_start • enc_obs • mb_obs • mb_actions • mb_mus • mb_dones • mb_rewards • actions • states • mus • clipped_actions • obs • rewards • dones	From timestep 1
• steps • masks	From timestep `n_step+1`
• names_ops • values_ops	From timestep `2 * n_step+1`
• samples_number	After replay_start steps, when replay_ratio > 0 and buffer is not None

1.21 ACKTR

Actor Critic using Kronecker-Factored Trust Region (ACKTR) uses Kronecker-factored approximate curvature (K-FAC) for trust region optimization.

1.21.1 Notes

- Original paper: https://arxiv.org/abs/1708.05144
- Baselines blog post: https://blog.openai.com/baselines-acktr-a2c/
- `python -m stable_baselines.acktr.run_atari` runs the algorithm for 40M frames = 10M timesteps on an Atari game. See help (`-h`) for more options.

1.21.2 Can I use?

- Recurrent policies: ✓
- Multi processing: ✓
- Gym spaces:

Space	Action	Observation
Discrete	✓	✓
Box	✓	✓
MultiDiscrete		✓
MultiBinary		✓

1.21.3 Example

```
import gym

from stable_baselines.common.policies import MlpPolicy, MlpLstmPolicy, MlpLnLstmPolicy
from stable_baselines.common import make_vec_env
from stable_baselines import ACKTR

# multiprocess environment
env = make_vec_env('CartPole-v1', n_envs=4)

model = ACKTR(MlpPolicy, env, verbose=1)
model.learn(total_timesteps=25000)
model.save("acktr_cartpole")

del model # remove to demonstrate saving and loading

model = ACKTR.load("acktr_cartpole")

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

1.21.4 Parameters

class stable_baselines.acktr.**ACKTR**(*policy*, *env*, *gamma=0.99*, *nprocs=None*, *n_steps=20*, *ent_coef=0.01*, *vf_coef=0.25*, *vf_fisher_coef=1.0*, *learning_rate=0.25*, *max_grad_norm=0.5*, *kfac_clip=0.001*, *lr_schedule='linear'*, *verbose=0*, *tensorboard_log=None*, *_init_setup_model=True*, *async_eigen_decomp=False*, *kfac_update=1*, *gae_lambda=None*, *policy_kwargs=None*, *full_tensorboard_log=False*, *seed=None*, *n_cpu_tf_sess=1*)

The ACKTR (Actor Critic using Kronecker-Factored Trust Region) model class, https://arxiv.org/abs/1708.05144

Parameters

- **policy** – (ActorCriticPolicy or str) The policy model to use (MlpPolicy, CnnPolicy, CnnLstmPolicy, . . .)
- **env** – (Gym environment or str) The environment to learn from (if registered in Gym, can be str)
- **gamma** – (float) Discount factor
- **nprocs** – (int) The number of threads for TensorFlow operations

  Deprecated since version 2.9.0: Use *n_cpu_tf_sess* instead.
- **n_steps** – (int) The number of steps to run for each environment
- **ent_coef** – (float) The weight for the entropy loss
- **vf_coef** – (float) The weight for the loss on the value function
- **vf_fisher_coef** – (float) The weight for the fisher loss on the value function
- **learning_rate** – (float) The initial learning rate for the RMS prop optimizer
- **max_grad_norm** – (float) The clipping value for the maximum gradient
- **kfac_clip** – (float) gradient clipping for Kullback-Leibler
- **lr_schedule** – (str) The type of scheduler for the learning rate update ('linear', 'constant', 'double_linear_con', 'middle_drop' or 'double_middle_drop')
- **verbose** – (int) the verbosity level: 0 none, 1 training information, 2 tensorflow debug
- **tensorboard_log** – (str) the log location for tensorboard (if None, no logging)
- **_init_setup_model** – (bool) Whether or not to build the network at the creation of the instance
- **async_eigen_decomp** – (bool) Use async eigen decomposition
- **kfac_update** – (int) update kfac after kfac_update steps
- **policy_kwargs** – (dict) additional arguments to be passed to the policy on creation
- **gae_lambda** – (float) Factor for trade-off of bias vs variance for Generalized Advantage Estimator If None (default), then the classic advantage will be used instead of GAE
- **full_tensorboard_log** – (bool) enable additional logging when using tensorboard WARNING: this logging can take a lot of space quickly
- **seed** – (int) Seed for the pseudo-random generators (python, numpy, tensorflow). If None (default), use random seed. Note that if you want completely deterministic results, you must set *n_cpu_tf_sess* to 1.

- **n_cpu_tf_sess** – (int) The number of threads for TensorFlow operations If None, the number of cpu of the current machine will be used.

action_probability(*observation*, *state=None*, *mask=None*, *actions=None*, *logp=False*)
If `actions` is `None`, then get the model's action probability distribution from a given observation.

Depending on the action space the output is:

- Discrete: probability for each possible action
- Box: mean and standard deviation of the action output

However if `actions` is not `None`, this function will return the probability that the given actions are taken with the given parameters (observation, state, …) on this model. For discrete action spaces, it returns the probability mass; for continuous action spaces, the probability density. This is since the probability mass will always be zero in continuous spaces, see http://blog.christianperone.com/2019/01/ for a good explanation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **actions** – (np.ndarray) (OPTIONAL) For calculating the likelihood that the given actions are chosen by the model for each of the given parameters. Must have the same number of actions and observations. (set to None to return the complete action probability distribution)
- **logp** – (bool) (OPTIONAL) When specified with actions, returns probability in log-space. This has no effect if actions is None.

Returns (np.ndarray) the model's (log) action probability

get_env()
returns the current environment (can be None if not defined)

Returns (Gym Environment) The current environment

get_parameter_list()
Get tensorflow Variables of model's parameters

This includes all variables necessary for continuing training (saving / loading).

Returns (list) List of tensorflow Variables

get_parameters()
Get current model parameters as dictionary of variable name -> ndarray.

Returns (OrderedDict) Dictionary of variable name -> ndarray of model's parameters.

get_vec_normalize_env() → Optional[stable_baselines.common.vec_env.vec_normalize.VecNormalize]
Return the `VecNormalize` wrapper of the training env if it exists.

Returns Optional[VecNormalize] The `VecNormalize` env.

learn(*total_timesteps*, *callback=None*, *log_interval=100*, *tb_log_name='ACKTR'*, *reset_num_timesteps=True*)
Return a trained model.

Parameters

- **total_timesteps** – (int) The total number of samples to train on

- **callback** – (Union[callable, [callable], BaseCallback]) function called at every steps with state of the algorithm. It takes the local and global variables. If it returns False, training is aborted. When the callback inherits from BaseCallback, you will have access to additional stages of the training (training start/end), please read the documentation for more details.
- **log_interval** – (int) The number of timesteps before logging.
- **tb_log_name** – (str) the name of the run for tensorboard log
- **reset_num_timesteps** – (bool) whether or not to reset the current timestep number (used in logging)

Returns (BaseRLModel) the trained model

classmethod load(*load_path*, *env=None*, *custom_objects=None*, ***kwargs*)
Load the model from file

Parameters

- **load_path** – (str or file-like) the saved parameter location
- **env** – (Gym Environment) the new environment to run the loaded model on (can be None if you only need prediction from a trained model)
- **custom_objects** – (dict) 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.
- **kwargs** – extra arguments to change the model when loading

load_parameters(*load_path_or_dict*, *exact_match=True*)
Load model parameters from a file or a dictionary

Dictionary keys should be tensorflow variable names, which can be obtained with `get_parameters` function. If `exact_match` is True, dictionary should contain keys for all model's parameters, otherwise RunTimeError is raised. If False, only variables included in the dictionary will be updated.

This does not load agent's hyper-parameters.

> **Warning:** This function does not update trainer/optimizer variables (e.g. momentum). As such training after using this function may lead to less-than-optimal results.

Parameters

- **load_path_or_dict** – (str or file-like or dict) Save parameter location or dict of parameters as variable.name -> ndarrays to be loaded.
- **exact_match** – (bool) If True, expects load dictionary to contain keys for all variables in the model. If False, loads parameters only for variables mentioned in the dictionary. Defaults to True.

predict(*observation*, *state=None*, *mask=None*, *deterministic=False*)
Get the model's action from an observation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)

- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray, np.ndarray) the model's action and the next state (used in recurrent policies)

pretrain (*dataset*, *n_epochs=10*, *learning_rate=0.0001*, *adam_epsilon=1e-08*, *val_interval=None*)
Pretrain a model using behavior cloning: supervised learning given an expert dataset.

NOTE: only Box and Discrete spaces are supported for now.

Parameters

- **dataset** – (ExpertDataset) Dataset manager
- **n_epochs** – (int) Number of iterations on the training set
- **learning_rate** – (float) Learning rate
- **adam_epsilon** – (float) the epsilon value for the adam optimizer
- **val_interval** – (int) Report training and validation losses every n epochs. By default, every 10th of the maximum number of epochs.

Returns (BaseRLModel) the pretrained model

save (*save_path*, *cloudpickle=False*)
Save the current parameters to file

Parameters

- **save_path** – (str or file-like) The save location
- **cloudpickle** – (bool) Use older cloudpickle format instead of zip-archives.

set_env (*env*)
Checks the validity of the environment, and if it is coherent, set it as the current environment.

Parameters **env** – (Gym Environment) The environment for learning a policy

set_random_seed (*seed: Optional[int]*) → None

Parameters **seed** – (Optional[int]) Seed for the pseudo-random generators. If None, do not change the seeds.

setup_model ()
Create all the functions and tensorflow graphs necessary to train the model

1.21.5 Callbacks - Accessible Variables

Depending on initialization parameters and timestep, different variables are accessible. Variables accessible from "timestep X" are variables that can be accessed when `self.timestep==X` from the `on_step` function.

Variable	Availability
• self • total_timesteps • callback • log_interval • tb_log_name • reset_num_timesteps • new_tb_log • writer • tf_vars • is_uninitialized • new_uninitialized_vars • t_start • coord • enqueue_threads • old_uninitialized_vars • mb_obs • mb_rewards • mb_actions • mb_values • mb_dones • mb_states • ep_infos • _ • actions • values • states • clipped_actions • obs • rewards • dones • infos	From timestep 1
• info • maybe_ep_info	From timestep 2
• update • rollout • returns • masks • true_reward	From timestep `n_steps+1`
• policy_loss • value_loss • policy_entropy • n_seconds • fps	From timestep `2*n_steps+1`

1.22 DDPG

Deep Deterministic Policy Gradient (DDPG)

Note: DDPG requires *OpenMPI*. If OpenMPI isn't enabled, then DDPG isn't imported into the `stable_baselines` module.

Warning: The DDPG model does not support `stable_baselines.common.policies` because it uses q-value instead of value estimation, as a result it must use its own policy models (see *DDPG Policies*).

Available Policies

`MlpPolicy`	Policy object that implements actor critic, using a MLP (2 layers of 64)
`LnMlpPolicy`	Policy object that implements actor critic, using a MLP (2 layers of 64), with layer normalisation
`CnnPolicy`	Policy object that implements actor critic, using a CNN (the nature CNN)
`LnCnnPolicy`	Policy object that implements actor critic, using a CNN (the nature CNN), with layer normalisation

1.22.1 Notes

- Original paper: https://arxiv.org/abs/1509.02971
- Baselines post: https://blog.openai.com/better-exploration-with-parameter-noise/
- `python -m stable_baselines.ddpg.main` runs the algorithm for 1M frames = 10M timesteps on a Mujoco environment. See help (`-h`) for more options.

1.22.2 Can I use?

- Recurrent policies:
- Multi processing: ✓ (using MPI)
- Gym spaces:

Space	Action	Observation
Discrete		✓
Box	✓	✓
MultiDiscrete		✓
MultiBinary		✓

1.22.3 Example

```python
import gym
import numpy as np

from stable_baselines.ddpg.policies import MlpPolicy
from stable_baselines.common.noise import NormalActionNoise,␣
↪OrnsteinUhlenbeckActionNoise, AdaptiveParamNoiseSpec
from stable_baselines import DDPG

env = gym.make('MountainCarContinuous-v0')

# the noise objects for DDPG
n_actions = env.action_space.shape[-1]
param_noise = None
action_noise = OrnsteinUhlenbeckActionNoise(mean=np.zeros(n_actions), sigma=float(0.
↪5) * np.ones(n_actions))

model = DDPG(MlpPolicy, env, verbose=1, param_noise=param_noise, action_noise=action_
↪noise)
model.learn(total_timesteps=400000)
model.save("ddpg_mountain")

del model # remove to demonstrate saving and loading

model = DDPG.load("ddpg_mountain")

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

1.22.4 Parameters

class stable_baselines.ddpg.**DDPG**(*policy, env, gamma=0.99, memory_policy=None, eval_env=None, nb_train_steps=50, nb_rollout_steps=100, nb_eval_steps=100, param_noise=None, action_noise=None, normalize_observations=False, tau=0.001, batch_size=128, param_noise_adaption_interval=50, normalize_returns=False, enable_popart=False, observation_range=(-5.0, 5.0), critic_l2_reg=0.0, return_range=(-inf, inf), actor_lr=0.0001, critic_lr=0.001, clip_norm=None, reward_scale=1.0, render=False, render_eval=False, memory_limit=None, buffer_size=50000, random_exploration=0.0, verbose=0, tensorboard_log=None, _init_setup_model=True, policy_kwargs=None, full_tensorboard_log=False, seed=None, n_cpu_tf_sess=1*)

Deep Deterministic Policy Gradient (DDPG) model

DDPG: https://arxiv.org/pdf/1509.02971.pdf

Parameters

- **policy** – (DDPGPolicy or str) The policy model to use (MlpPolicy, CnnPolicy, LnMlpPolicy, . . .)

- **env** – (Gym environment or str) The environment to learn from (if registered in Gym, can be str)
- **gamma** – (float) the discount factor
- **memory_policy** – (ReplayBuffer) the replay buffer (if None, default to baselines.deepq.replay_buffer.ReplayBuffer)

  Deprecated since version 2.6.0: This parameter will be removed in a future version
- **eval_env** – (Gym Environment) the evaluation environment (can be None)
- **nb_train_steps** – (int) the number of training steps
- **nb_rollout_steps** – (int) the number of rollout steps
- **nb_eval_steps** – (int) the number of evaluation steps
- **param_noise** – (AdaptiveParamNoiseSpec) the parameter noise type (can be None)
- **action_noise** – (ActionNoise) the action noise type (can be None)
- **param_noise_adaption_interval** – (int) apply param noise every N steps
- **tau** – (float) the soft update coefficient (keep old values, between 0 and 1)
- **normalize_returns** – (bool) should the critic output be normalized
- **enable_popart** – (bool) enable pop-art normalization of the critic output (https://arxiv.org/pdf/1602.07714.pdf), normalize_returns must be set to True.
- **normalize_observations** – (bool) should the observation be normalized
- **batch_size** – (int) the size of the batch for learning the policy
- **observation_range** – (tuple) the bounding values for the observation
- **return_range** – (tuple) the bounding values for the critic output
- **critic_l2_reg** – (float) l2 regularizer coefficient
- **actor_lr** – (float) the actor learning rate
- **critic_lr** – (float) the critic learning rate
- **clip_norm** – (float) clip the gradients (disabled if None)
- **reward_scale** – (float) the value the reward should be scaled by
- **render** – (bool) enable rendering of the environment
- **render_eval** – (bool) enable rendering of the evaluation environment
- **memory_limit** – (int) the max number of transitions to store, size of the replay buffer

  Deprecated since version 2.6.0: Use *buffer_size* instead.
- **buffer_size** – (int) the max number of transitions to store, size of the replay buffer
- **random_exploration** – (float) Probability of taking a random action (as in an epsilon-greedy strategy) This is not needed for DDPG normally but can help exploring when using HER + DDPG. This hack was present in the original OpenAI Baselines repo (DDPG + HER)
- **verbose** – (int) the verbosity level: 0 none, 1 training information, 2 tensorflow debug
- **tensorboard_log** – (str) the log location for tensorboard (if None, no logging)
- **_init_setup_model** – (bool) Whether or not to build the network at the creation of the instance

- **policy_kwargs** – (dict) additional arguments to be passed to the policy on creation
- **full_tensorboard_log** – (bool) enable additional logging when using tensorboard WARNING: this logging can take a lot of space quickly
- **seed** – (int) Seed for the pseudo-random generators (python, numpy, tensorflow). If None (default), use random seed. Note that if you want completely deterministic results, you must set *n_cpu_tf_sess* to 1.
- **n_cpu_tf_sess** – (int) The number of threads for TensorFlow operations If None, the number of cpu of the current machine will be used.

action_probability(*observation*, *state=None*, *mask=None*, *actions=None*, *logp=False*)

If `actions` is `None`, then get the model's action probability distribution from a given observation.

Depending on the action space the output is:

- Discrete: probability for each possible action
- Box: mean and standard deviation of the action output

However if `actions` is not `None`, this function will return the probability that the given actions are taken with the given parameters (observation, state, ...) on this model. For discrete action spaces, it returns the probability mass; for continuous action spaces, the probability density. This is since the probability mass will always be zero in continuous spaces, see http://blog.christianperone.com/2019/01/ for a good explanation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **actions** – (np.ndarray) (OPTIONAL) For calculating the likelihood that the given actions are chosen by the model for each of the given parameters. Must have the same number of actions and observations. (set to None to return the complete action probability distribution)
- **logp** – (bool) (OPTIONAL) When specified with actions, returns probability in log-space. This has no effect if actions is None.

Returns (np.ndarray) the model's (log) action probability

get_env()

returns the current environment (can be None if not defined)

Returns (Gym Environment) The current environment

get_parameter_list()

Get tensorflow Variables of model's parameters

This includes all variables necessary for continuing training (saving / loading).

Returns (list) List of tensorflow Variables

get_parameters()

Get current model parameters as dictionary of variable name -> ndarray.

Returns (OrderedDict) Dictionary of variable name -> ndarray of model's parameters.

get_vec_normalize_env() → Optional[stable_baselines.common.vec_env.vec_normalize.VecNormalize]

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

Returns Optional[VecNormalize] The `VecNormalize` env.

is_using_her() → bool
Check if is using HER

Returns (bool) Whether is using HER or not

learn(*total_timesteps*, *callback=None*, *log_interval=100*, *tb_log_name='DDPG'*, *reset_num_timesteps=True*, *replay_wrapper=None*)
Return a trained model.

Parameters

- **total_timesteps** – (int) The total number of samples to train on
- **callback** – (Union[callable, [callable], BaseCallback]) function called at every steps with state of the algorithm. It takes the local and global variables. If it returns False, training is aborted. When the callback inherits from BaseCallback, you will have access to additional stages of the training (training start/end), please read the documentation for more details.
- **log_interval** – (int) The number of timesteps before logging.
- **tb_log_name** – (str) the name of the run for tensorboard log
- **reset_num_timesteps** – (bool) whether or not to reset the current timestep number (used in logging)

Returns (BaseRLModel) the trained model

classmethod load(*load_path*, *env=None*, *custom_objects=None*, ***kwargs*)
Load the model from file

Parameters

- **load_path** – (str or file-like) the saved parameter location
- **env** – (Gym Environment) the new environment to run the loaded model on (can be None if you only need prediction from a trained model)
- **custom_objects** – (dict) 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.
- **kwargs** – extra arguments to change the model when loading

load_parameters(*load_path_or_dict*, *exact_match=True*)
Load model parameters from a file or a dictionary

Dictionary keys should be tensorflow variable names, which can be obtained with `get_parameters` function. If `exact_match` is True, dictionary should contain keys for all model's parameters, otherwise RunTimeError is raised. If False, only variables included in the dictionary will be updated.

This does not load agent's hyper-parameters.

> **Warning:** This function does not update trainer/optimizer variables (e.g. momentum). As such training after using this function may lead to less-than-optimal results.

Parameters

- **load_path_or_dict** – (str or file-like or dict) Save parameter location or dict of parameters as variable.name -> ndarrays to be loaded.

- **exact_match** – (bool) If True, expects load dictionary to contain keys for all variables in the model. If False, loads parameters only for variables mentioned in the dictionary. Defaults to True.

predict(*observation*, *state=None*, *mask=None*, *deterministic=True*)
Get the model's action from an observation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray, np.ndarray) the model's action and the next state (used in recurrent policies)

pretrain(*dataset*, *n_epochs=10*, *learning_rate=0.0001*, *adam_epsilon=1e-08*, *val_interval=None*)
Pretrain a model using behavior cloning: supervised learning given an expert dataset.

NOTE: only Box and Discrete spaces are supported for now.

Parameters

- **dataset** – (ExpertDataset) Dataset manager
- **n_epochs** – (int) Number of iterations on the training set
- **learning_rate** – (float) Learning rate
- **adam_epsilon** – (float) the epsilon value for the adam optimizer
- **val_interval** – (int) Report training and validation losses every n epochs. By default, every 10th of the maximum number of epochs.

Returns (BaseRLModel) the pretrained model

replay_buffer_add(*obs_t*, *action*, *reward*, *obs_tp1*, *done*, *info*)
Add a new transition to the replay buffer

Parameters

- **obs_t** – (np.ndarray) the last observation
- **action** – ([float]) the action
- **reward** – (float) the reward of the transition
- **obs_tp1** – (np.ndarray) the new observation
- **done** – (bool) is the episode done
- **info** – (dict) extra values used to compute the reward when using HER

save(*save_path*, *cloudpickle=False*)
Save the current parameters to file

Parameters

- **save_path** – (str or file-like) The save location
- **cloudpickle** – (bool) Use older cloudpickle format instead of zip-archives.

set_env(*env*)
Checks the validity of the environment, and if it is coherent, set it as the current environment.

Parameters **env** – (Gym Environment) The environment for learning a policy

set_random_seed(*seed: Optional[int]*) → None

Parameters **seed** – (Optional[int]) Seed for the pseudo-random generators. If None, do not change the seeds.

setup_model()

Create all the functions and tensorflow graphs necessary to train the model

1.22.5 DDPG Policies

class stable_baselines.ddpg.**MlpPolicy**(*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *reuse=False*, ***_kwargs*)

Policy object that implements actor critic, using a MLP (2 layers of 64)

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

action_ph

tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state

The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete

bool: is action space discrete.

make_actor(*obs=None*, *reuse=False*, *scope='pi'*)

creates an actor object

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name of the actor

Returns (TensorFlow Tensor) the output tensor

make_critic(*obs=None*, *action=None*, *reuse=False*, *scope='qf'*)

creates a critic object

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)

- **action** – (TensorFlow Tensor) The action placeholder (can be None for default placeholder)
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name of the critic

Returns (TensorFlow Tensor) the output tensor

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step(*obs*, *state=None*, *mask=None*)
Returns the action probability for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) the action probability

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step(*obs*, *state=None*, *mask=None*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) actions

value(*obs*, *action*, *state=None*, *mask=None*)
Returns the value for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **action** – ([float] or [int]) The taken action
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) The associated value of the action

class stable_baselines.ddpg.**LnMlpPolicy**(*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *reuse=False*, ***_kwargs*)
Policy object that implements actor critic, using a MLP (2 layers of 64), with layer normalisation

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment

- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

action_ph
tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state
The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete
bool: is action space discrete.

make_actor(*obs=None*, *reuse=False*, *scope='pi'*)
creates an actor object

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name of the actor

Returns (TensorFlow Tensor) the output tensor

make_critic(*obs=None*, *action=None*, *reuse=False*, *scope='qf'*)
creates a critic object

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **action** – (TensorFlow Tensor) The action placeholder (can be None for default placeholder)
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name of the critic

Returns (TensorFlow Tensor) the output tensor

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step(*obs*, *state=None*, *mask=None*)
Returns the action probability for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) the action probability

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step (*obs*, *state=None*, *mask=None*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) actions

value (*obs*, *action*, *state=None*, *mask=None*)
Returns the value for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **action** – ([float] or [int]) The taken action
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) The associated value of the action

class stable_baselines.ddpg.**CnnPolicy** (*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *reuse=False*, ***_kwargs*)
Policy object that implements actor critic, using a CNN (the nature CNN)

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

action_ph
tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state
The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete
bool: is action space discrete.

make_actor (*obs=None*, *reuse=False*, *scope='pi'*)
creates an actor object

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name of the actor

Returns (TensorFlow Tensor) the output tensor

make_critic (*obs=None*, *action=None*, *reuse=False*, *scope='qf'*)
creates a critic object

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **action** – (TensorFlow Tensor) The action placeholder (can be None for default placeholder)
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name of the critic

Returns (TensorFlow Tensor) the output tensor

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step (*obs*, *state=None*, *mask=None*)
Returns the action probability for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) the action probability

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step (*obs*, *state=None*, *mask=None*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) actions

value (*obs*, *action*, *state=None*, *mask=None*)
Returns the value for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **action** – ([float] or [int]) The taken action
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) The associated value of the action

class stable_baselines.ddpg.**LnCnnPolicy**(*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *reuse=False*, ***_kwargs*)

Policy object that implements actor critic, using a CNN (the nature CNN), with layer normalisation

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

action_ph

tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state

The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete

bool: is action space discrete.

make_actor(*obs=None*, *reuse=False*, *scope='pi'*)

creates an actor object

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name of the actor

Returns (TensorFlow Tensor) the output tensor

make_critic(*obs=None*, *action=None*, *reuse=False*, *scope='qf'*)

creates a critic object

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **action** – (TensorFlow Tensor) The action placeholder (can be None for default placeholder)
- **reuse** – (bool) whether or not to reuse parameters

- **scope** – (str) the scope name of the critic

Returns (TensorFlow Tensor) the output tensor

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step (*obs*, *state=None*, *mask=None*)
Returns the action probability for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) the action probability

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step (*obs*, *state=None*, *mask=None*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) actions

value (*obs*, *action*, *state=None*, *mask=None*)
Returns the value for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **action** – ([float] or [int]) The taken action
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) The associated value of the action

1.22.6 Action and Parameters Noise

class stable_baselines.ddpg.**AdaptiveParamNoiseSpec** (*initial_stddev=0.1*, *desired_action_stddev=0.1*, *adoption_coefficient=1.01*)
Implements adaptive parameter noise

Parameters

- **initial_stddev** – (float) the initial value for the standard deviation of the noise

- **desired_action_stddev** – (float) the desired value for the standard deviation of the noise
- **adoption_coefficient** – (float) the update coefficient for the standard deviation of the noise

adapt (*distance*)
update the standard deviation for the parameter noise

Parameters **distance** – (float) the noise distance applied to the parameters

get_stats ()
return the standard deviation for the parameter noise

Returns (dict) the stats of the noise

class stable_baselines.ddpg.**NormalActionNoise** (*mean*, *sigma*)
A Gaussian action noise

Parameters

- **mean** – (float) the mean value of the noise
- **sigma** – (float) the scale of the noise (std here)

reset () → None
call end of episode reset for the noise

class stable_baselines.ddpg.**OrnsteinUhlenbeckActionNoise** (*mean*, *sigma*, *theta=0.15*, *dt=0.01*, *initial_noise=None*)
A 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** – (float) the mean of the noise
- **sigma** – (float) the scale of the noise
- **theta** – (float) the rate of mean reversion
- **dt** – (float) the timestep for the noise
- **initial_noise** – ([float]) the initial value for the noise output, (if None: 0)

reset () → None
reset the Ornstein Uhlenbeck noise, to the initial position

1.22.7 Custom Policy Network

Similarly to the example given in the examples page. You can easily define a custom architecture for the policy network:

```
import gym

from stable_baselines.ddpg.policies import FeedForwardPolicy
from stable_baselines import DDPG

# Custom MLP policy of two layers of size 16 each
class CustomDDPGPolicy(FeedForwardPolicy):
    def __init__(self, *args, **kwargs):
```

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```
        super(CustomDDPGPolicy, self).__init__(*args, **kwargs,
                                               layers=[16, 16],
                                               layer_norm=False,
                                               feature_extraction="mlp")


model = DDPG(CustomDDPGPolicy, 'Pendulum-v0', verbose=1)
# Train the agent
model.learn(total_timesteps=100000)
```

1.22.8 Callbacks - Accessible Variables

Depending on initialization parameters and timestep, different variables are accessible. Variables accessible from "timestep X" are variables that can be accessed when `self.timestep==X` from the `on_step` function.

Variable	Availability
• self • total_timesteps • callback • log_interval • tb_log_name • reset_num_timesteps • replay_wrapper • new_tb_log • writer • rank • eval_episode_rewards_history • episode_rewards_history • episode_successes • obs • eval_obs • episode_reward • episode_step • episodes • step • total_steps • start_time • epoch_episode_rewards • epoch_episode_steps • epoch_actor_losses • epoch_critic_losses • epoch_adaptive_distances • eval_episode_rewards • eval_qs • epoch_actions • epoch_qs • epoch_episodes • epoch • action • q_value • unscaled_action • new_obs • reward • done • info	From timestep 1
• obs_ • new_obs_ • reward_	From timestep 2
• t_train	After nb_rollout_steps+1
• distance • critic_loss • actor_loss	After nb_rollout_steps*ceil(nb_rollout_steps/batch_size)‘‘‘
• maybe_is_success	After episode termination

1.23 DQN

Deep Q Network (DQN) and its extensions (Double-DQN, Dueling-DQN, Prioritized Experience Replay).

Warning: The DQN model does not support `stable_baselines.common.policies`, as a result it must use its own policy models (see *DQN Policies*).

Available Policies

MlpPolicy	Policy object that implements DQN policy, using a MLP (2 layers of 64)
LnMlpPolicy	Policy object that implements DQN policy, using a MLP (2 layers of 64), with layer normalisation
CnnPolicy	Policy object that implements DQN policy, using a CNN (the nature CNN)
LnCnnPolicy	Policy object that implements DQN policy, using a CNN (the nature CNN), with layer normalisation

1.23.1 Notes

- DQN paper: https://arxiv.org/abs/1312.5602
- Dueling DQN: https://arxiv.org/abs/1511.06581
- Double-Q Learning: https://arxiv.org/abs/1509.06461
- Prioritized Experience Replay: https://arxiv.org/abs/1511.05952

Note: By default, the DQN class has double q learning and dueling extensions enabled. See Issue #406 for disabling dueling. To disable double-q learning, you can change the default value in the constructor.

1.23.2 Can I use?

- Recurrent policies:
- Multi processing:
- Gym spaces:

Space	Action	Observation
Discrete	✓	✓
Box		✓
MultiDiscrete		✓
MultiBinary		✓

1.23.3 Example

```
import gym

from stable_baselines.common.vec_env import DummyVecEnv
from stable_baselines.deepq.policies import MlpPolicy
from stable_baselines import DQN

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

model = DQN(MlpPolicy, env, verbose=1)
model.learn(total_timesteps=25000)
model.save("deepq_cartpole")

del model # remove to demonstrate saving and loading

model = DQN.load("deepq_cartpole")

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

With Atari:

```
from stable_baselines.common.atari_wrappers import make_atari
from stable_baselines.deepq.policies import MlpPolicy, CnnPolicy
from stable_baselines import DQN

env = make_atari('BreakoutNoFrameskip-v4')

model = DQN(CnnPolicy, env, verbose=1)
model.learn(total_timesteps=25000)
model.save("deepq_breakout")

del model # remove to demonstrate saving and loading

model = DQN.load("deepq_breakout")

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

1.23.4 Parameters

class stable_baselines.deepq.**DQN**(*policy, env, gamma=0.99, learning_rate=0.0005, buffer_size=50000, exploration_fraction=0.1, exploration_final_eps=0.02, exploration_initial_eps=1.0, train_freq=1, batch_size=32, double_q=True, learning_starts=1000, target_network_update_freq=500, prioritized_replay=False, prioritized_replay_alpha=0.6, prioritized_replay_beta0=0.4, prioritized_replay_beta_iters=None, prioritized_replay_eps=1e-06, param_noise=False, n_cpu_tf_sess=None, verbose=0, tensorboard_log=None, _init_setup_model=True, policy_kwargs=None, full_tensorboard_log=False, seed=None*)

The DQN model class. DQN paper: https://arxiv.org/abs/1312.5602 Dueling DQN: https://arxiv.org/abs/1511.06581 Double-Q Learning: https://arxiv.org/abs/1509.06461 Prioritized Experience Replay: https://arxiv.org/abs/1511.05952

Parameters

- **policy** – (DQNPolicy or str) The policy model to use (MlpPolicy, CnnPolicy, LnMlpPolicy, . . .)
- **env** – (Gym environment or str) The environment to learn from (if registered in Gym, can be str)
- **gamma** – (float) discount factor
- **learning_rate** – (float) learning rate for adam optimizer
- **buffer_size** – (int) size of the replay buffer
- **exploration_fraction** – (float) fraction of entire training period over which the exploration rate is annealed
- **exploration_final_eps** – (float) final value of random action probability
- **exploration_initial_eps** – (float) initial value of random action probability
- **train_freq** – (int) update the model every *train_freq* steps. set to None to disable printing
- **batch_size** – (int) size of a batched sampled from replay buffer for training
- **double_q** – (bool) Whether to enable Double-Q learning or not.
- **learning_starts** – (int) how many steps of the model to collect transitions for before learning starts
- **target_network_update_freq** – (int) update the target network every *target_network_update_freq* steps.
- **prioritized_replay** – (bool) if True prioritized replay buffer will be used.
- **prioritized_replay_alpha** – (float)alpha parameter for prioritized replay buffer. It determines how much prioritization is used, with alpha=0 corresponding to the uniform case.
- **prioritized_replay_beta0** – (float) initial value of beta for prioritized replay buffer
- **prioritized_replay_beta_iters** – (int) number of iterations over which beta will be annealed from initial value to 1.0. If set to None equals to max_timesteps.
- **prioritized_replay_eps** – (float) epsilon to add to the TD errors when updating priorities.

- **param_noise** – (bool) Whether or not to apply noise to the parameters of the policy.
- **verbose** – (int) the verbosity level: 0 none, 1 training information, 2 tensorflow debug
- **tensorboard_log** – (str) the log location for tensorboard (if None, no logging)
- **_init_setup_model** – (bool) Whether or not to build the network at the creation of the instance
- **full_tensorboard_log** – (bool) enable additional logging when using tensorboard WARNING: this logging can take a lot of space quickly
- **seed** – (int) Seed for the pseudo-random generators (python, numpy, tensorflow). If None (default), use random seed. Note that if you want completely deterministic results, you must set *n_cpu_tf_sess* to 1.
- **n_cpu_tf_sess** – (int) The number of threads for TensorFlow operations If None, the number of cpu of the current machine will be used.

action_probability(*observation*, *state=None*, *mask=None*, *actions=None*, *logp=False*)

If `actions` is `None`, then get the model's action probability distribution from a given observation.

Depending on the action space the output is:

- Discrete: probability for each possible action
- Box: mean and standard deviation of the action output

However if `actions` is not `None`, this function will return the probability that the given actions are taken with the given parameters (observation, state, ...) on this model. For discrete action spaces, it returns the probability mass; for continuous action spaces, the probability density. This is since the probability mass will always be zero in continuous spaces, see http://blog.christianperone.com/2019/01/ for a good explanation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **actions** – (np.ndarray) (OPTIONAL) For calculating the likelihood that the given actions are chosen by the model for each of the given parameters. Must have the same number of actions and observations. (set to None to return the complete action probability distribution)
- **logp** – (bool) (OPTIONAL) When specified with actions, returns probability in log-space. This has no effect if actions is None.

Returns (np.ndarray) the model's (log) action probability

get_env()

returns the current environment (can be None if not defined)

Returns (Gym Environment) The current environment

get_parameter_list()

Get tensorflow Variables of model's parameters

This includes all variables necessary for continuing training (saving / loading).

Returns (list) List of tensorflow Variables

get_parameters()

Get current model parameters as dictionary of variable name -> ndarray.

Returns (OrderedDict) Dictionary of variable name -> ndarray of model's parameters.

get_vec_normalize_env() → Optional[stable_baselines.common.vec_env.vec_normalize.VecNormalize]
Return the `VecNormalize` wrapper of the training env if it exists.

Returns Optional[VecNormalize] The `VecNormalize` env.

is_using_her() → bool
Check if is using HER

Returns (bool) Whether is using HER or not

learn(*total_timesteps*, *callback=None*, *log_interval=100*, *tb_log_name='DQN'*, *reset_num_timesteps=True*, *replay_wrapper=None*)
Return a trained model.

Parameters

- **total_timesteps** – (int) The total number of samples to train on
- **callback** – (Union[callable, [callable], BaseCallback]) function called at every steps with state of the algorithm. It takes the local and global variables. If it returns False, training is aborted. When the callback inherits from BaseCallback, you will have access to additional stages of the training (training start/end), please read the documentation for more details.
- **log_interval** – (int) The number of timesteps before logging.
- **tb_log_name** – (str) the name of the run for tensorboard log
- **reset_num_timesteps** – (bool) whether or not to reset the current timestep number (used in logging)

Returns (BaseRLModel) the trained model

classmethod load(*load_path*, *env=None*, *custom_objects=None*, ***kwargs*)
Load the model from file

Parameters

- **load_path** – (str or file-like) the saved parameter location
- **env** – (Gym Environment) the new environment to run the loaded model on (can be None if you only need prediction from a trained model)
- **custom_objects** – (dict) 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.
- **kwargs** – extra arguments to change the model when loading

load_parameters(*load_path_or_dict*, *exact_match=True*)
Load model parameters from a file or a dictionary

Dictionary keys should be tensorflow variable names, which can be obtained with `get_parameters` function. If `exact_match` is True, dictionary should contain keys for all model's parameters, otherwise RunTimeError is raised. If False, only variables included in the dictionary will be updated.

This does not load agent's hyper-parameters.

Warning: This function does not update trainer/optimizer variables (e.g. momentum). As such training after using this function may lead to less-than-optimal results.

Parameters

- **load_path_or_dict** – (str or file-like or dict) Save parameter location or dict of parameters as variable.name -> ndarrays to be loaded.
- **exact_match** – (bool) If True, expects load dictionary to contain keys for all variables in the model. If False, loads parameters only for variables mentioned in the dictionary. Defaults to True.

predict(*observation*, *state=None*, *mask=None*, *deterministic=True*)

Get the model's action from an observation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray, np.ndarray) the model's action and the next state (used in recurrent policies)

pretrain(*dataset*, *n_epochs=10*, *learning_rate=0.0001*, *adam_epsilon=1e-08*, *val_interval=None*)

Pretrain a model using behavior cloning: supervised learning given an expert dataset.

NOTE: only Box and Discrete spaces are supported for now.

Parameters

- **dataset** – (ExpertDataset) Dataset manager
- **n_epochs** – (int) Number of iterations on the training set
- **learning_rate** – (float) Learning rate
- **adam_epsilon** – (float) the epsilon value for the adam optimizer
- **val_interval** – (int) Report training and validation losses every n epochs. By default, every 10th of the maximum number of epochs.

Returns (BaseRLModel) the pretrained model

replay_buffer_add(*obs_t*, *action*, *reward*, *obs_tp1*, *done*, *info*)

Add a new transition to the replay buffer

Parameters

- **obs_t** – (np.ndarray) the last observation
- **action** – ([float]) the action
- **reward** – (float) the reward of the transition
- **obs_tp1** – (np.ndarray) the new observation
- **done** – (bool) is the episode done
- **info** – (dict) extra values used to compute the reward when using HER

save(*save_path*, *cloudpickle=False*)

Save the current parameters to file

Parameters

- **save_path** – (str or file-like) The save location

- **cloudpickle** – (bool) Use older cloudpickle format instead of zip-archives.

set_env(*env*)
Checks the validity of the environment, and if it is coherent, set it as the current environment.

Parameters env – (Gym Environment) The environment for learning a policy

set_random_seed(*seed: Optional[int]*) → None

Parameters seed – (Optional[int]) Seed for the pseudo-random generators. If None, do not change the seeds.

setup_model()
Create all the functions and tensorflow graphs necessary to train the model

1.23.5 DQN Policies

class stable_baselines.deepq.**MlpPolicy**(*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *reuse=False*, *obs_phs=None*, *dueling=True*, ***_kwargs*)
Policy object that implements DQN policy, using a MLP (2 layers of 64)

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **obs_phs** – (TensorFlow Tensor, TensorFlow Tensor) a tuple containing an override for observation placeholder and the processed observation placeholder respectively
- **dueling** – (bool) if true double the output MLP to compute a baseline for action scores
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

action_ph
tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state
The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete
bool: is action space discrete.

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step(*obs*, *state=None*, *mask=None*)
Returns the action probability for a single step

Parameters

- **obs** – (np.ndarray float or int) The current observation of the environment

- **state** – (np.ndarray float) The last states (used in recurrent policies)
- **mask** – (np.ndarray float) The last masks (used in recurrent policies)

Returns (np.ndarray float) the action probability

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step (*obs*, *state=None*, *mask=None*, *deterministic=True*)
Returns the q_values for a single step

Parameters

- **obs** – (np.ndarray float or int) The current observation of the environment
- **state** – (np.ndarray float) The last states (used in recurrent policies)
- **mask** – (np.ndarray float) The last masks (used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray int, np.ndarray float, np.ndarray float) actions, q_values, states

class stable_baselines.deepq.**LnMlpPolicy** (*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *reuse=False*, *obs_phs=None*, *dueling=True*, ***_kwargs*)
Policy object that implements DQN policy, using a MLP (2 layers of 64), with layer normalisation

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **obs_phs** – (TensorFlow Tensor, TensorFlow Tensor) a tuple containing an override for observation placeholder and the processed observation placeholder respectively
- **dueling** – (bool) if true double the output MLP to compute a baseline for action scores
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

action_ph
tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state
The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete
bool: is action space discrete.

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step (*obs*, *state=None*, *mask=None*)
Returns the action probability for a single step

Parameters

- **obs** – (np.ndarray float or int) The current observation of the environment
- **state** – (np.ndarray float) The last states (used in recurrent policies)
- **mask** – (np.ndarray float) The last masks (used in recurrent policies)

Returns (np.ndarray float) the action probability

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step (*obs*, *state=None*, *mask=None*, *deterministic=True*)
Returns the q_values for a single step

Parameters

- **obs** – (np.ndarray float or int) The current observation of the environment
- **state** – (np.ndarray float) The last states (used in recurrent policies)
- **mask** – (np.ndarray float) The last masks (used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray int, np.ndarray float, np.ndarray float) actions, q_values, states

class stable_baselines.deepq.**CnnPolicy** (*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *reuse=False*, *obs_phs=None*, *dueling=True*, ***_kwargs*)
Policy object that implements DQN policy, using a CNN (the nature CNN)

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **obs_phs** – (TensorFlow Tensor, TensorFlow Tensor) a tuple containing an override for observation placeholder and the processed observation placeholder respectively
- **dueling** – (bool) if true double the output MLP to compute a baseline for action scores
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

action_ph
tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state
The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete
bool: is action space discrete.

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step(*obs*, *state=None*, *mask=None*)
Returns the action probability for a single step

Parameters

- **obs** – (np.ndarray float or int) The current observation of the environment
- **state** – (np.ndarray float) The last states (used in recurrent policies)
- **mask** – (np.ndarray float) The last masks (used in recurrent policies)

Returns (np.ndarray float) the action probability

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step(*obs*, *state=None*, *mask=None*, *deterministic=True*)
Returns the q_values for a single step

Parameters

- **obs** – (np.ndarray float or int) The current observation of the environment
- **state** – (np.ndarray float) The last states (used in recurrent policies)
- **mask** – (np.ndarray float) The last masks (used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray int, np.ndarray float, np.ndarray float) actions, q_values, states

class stable_baselines.deepq.**LnCnnPolicy**(*sess*, *ob_space*, *ac_space*, *n_env*, *n_steps*, *n_batch*, *reuse=False*, *obs_phs=None*, *dueling=True*, ***_kwargs*)
Policy object that implements DQN policy, using a CNN (the nature CNN), with layer normalisation

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **obs_phs** – (TensorFlow Tensor, TensorFlow Tensor) a tuple containing an override for observation placeholder and the processed observation placeholder respectively
- **dueling** – (bool) if true double the output MLP to compute a baseline for action scores
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

action_ph
tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state
The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete
bool: is action space discrete.

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step (*obs*, *state=None*, *mask=None*)
Returns the action probability for a single step

Parameters

- **obs** – (np.ndarray float or int) The current observation of the environment
- **state** – (np.ndarray float) The last states (used in recurrent policies)
- **mask** – (np.ndarray float) The last masks (used in recurrent policies)

Returns (np.ndarray float) the action probability

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step (*obs*, *state=None*, *mask=None*, *deterministic=True*)
Returns the q_values for a single step

Parameters

- **obs** – (np.ndarray float or int) The current observation of the environment
- **state** – (np.ndarray float) The last states (used in recurrent policies)
- **mask** – (np.ndarray float) The last masks (used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray int, np.ndarray float, np.ndarray float) actions, q_values, states

1.23.6 Custom Policy Network

Similarly to the example given in the examples page. You can easily define a custom architecture for the policy network:

```
import gym

from stable_baselines.deepq.policies import FeedForwardPolicy
from stable_baselines.common.vec_env import DummyVecEnv
from stable_baselines import DQN

# Custom MLP policy of two layers of size 32 each
class CustomDQNPolicy(FeedForwardPolicy):
    def __init__(self, *args, **kwargs):
        super(CustomDQNPolicy, self).__init__(*args, **kwargs,
```

(continues on next page)

(continued from previous page)

```
                                           layers=[32, 32],
                                           layer_norm=False,
                                           feature_extraction="mlp")

# Create and wrap the environment
env = gym.make('LunarLander-v2')
env = DummyVecEnv([lambda: env])

model = DQN(CustomDQNPolicy, env, verbose=1)
# Train the agent
model.learn(total_timesteps=100000)
```

1.23.7 Callbacks - Accessible Variables

Depending on initialization parameters and timestep, different variables are accessible. Variables accessible from "timestep X" are variables that can be accessed when `self.timestep==X` from the `on_step` function.

Variable	Availability
• self • total_timesteps • callback • log_interval • tb_log_name • reset_num_timesteps • replay_wrapper • new_tb_log • writer • episode_rewards • episode_successes • reset • obs • _ • kwargs • update_eps • update_param_noise_threshold • action • env_action • new_obs • rew • done • info	From timestep 1
• obs_ • new_obs_ • reward_ • can_sample • mean_100ep_reward • num_episodes	From timestep 2
• maybe_is_success	After the first episode
• obses_t • actions • rewards • obses_tp1 • dones • weights • batch_idxes • td_errors	After at least `max(batch_size, learning_starts)` and every *train_freq* steps

1.24 GAIL

The Generative Adversarial Imitation Learning (GAIL) uses expert trajectories to recover a cost function and then learn a policy.

Learning a cost function from expert demonstrations is called Inverse Reinforcement Learning (IRL). The connection between GAIL and Generative Adversarial Networks (GANs) is that it uses a discriminator that tries to seperate expert trajectory from trajectories of the learned policy, which has the role of the generator here.

Note: GAIL requires *OpenMPI*. If OpenMPI isn't enabled, then GAIL isn't imported into the `stable_baselines` module.

1.24.1 Notes

- Original paper: https://arxiv.org/abs/1606.03476

Warning: Images are not yet handled properly by the current implementation

1.24.2 If you want to train an imitation learning agent

Step 1: Generate expert data

You can either train a RL algorithm in a classic setting, use another controller (e.g. a PID controller) or human demonstrations.

We recommend you to take a look at *pre-training* section or directly look at `stable_baselines/gail/dataset/` folder to learn more about the expected format for the dataset.

Here is an example of training a Soft Actor-Critic model to generate expert trajectories for GAIL:

```
from stable_baselines import SAC
from stable_baselines.gail import generate_expert_traj

# Generate expert trajectories (train expert)
model = SAC('MlpPolicy', 'Pendulum-v0', verbose=1)
# Train for 60000 timesteps and record 10 trajectories
# all the data will be saved in 'expert_pendulum.npz' file
generate_expert_traj(model, 'expert_pendulum', n_timesteps=60000, n_episodes=10)
```

Step 2: Run GAIL

In case you want to run Behavior Cloning (BC)

Use the `.pretrain()` method (cf guide).

Others

Thanks to the open source:

- @openai/imitation
- @carpedm20/deep-rl-tensorflow

1.24.3 Can I use?

- Recurrent policies:
- Multi processing: ✓ (using MPI)
- Gym spaces:

Space	Action	Observation
Discrete	✓	✓
Box	✓	✓
MultiDiscrete		✓
MultiBinary		✓

1.24.4 Example

```
import gym

from stable_baselines import GAIL, SAC
from stable_baselines.gail import ExpertDataset, generate_expert_traj

# Generate expert trajectories (train expert)
model = SAC('MlpPolicy', 'Pendulum-v0', verbose=1)
generate_expert_traj(model, 'expert_pendulum', n_timesteps=100, n_episodes=10)

# Load the expert dataset
dataset = ExpertDataset(expert_path='expert_pendulum.npz', traj_limitation=10,␣
↪verbose=1)

model = GAIL('MlpPolicy', 'Pendulum-v0', dataset, verbose=1)
# Note: in practice, you need to train for 1M steps to have a working policy
model.learn(total_timesteps=1000)
model.save("gail_pendulum")

del model # remove to demonstrate saving and loading

model = GAIL.load("gail_pendulum")

env = gym.make('Pendulum-v0')
obs = env.reset()
while True:
  action, _states = model.predict(obs)
  obs, rewards, dones, info = env.step(action)
  env.render()
```

1.24.5 Parameters

class stable_baselines.gail.**GAIL**(*policy, env, expert_dataset=None, hidden_size_adversary=100, adversary_entcoeff=0.001, g_step=3, d_step=1, d_stepsize=0.0003, verbose=0, _init_setup_model=True, **kwargs*)

Generative Adversarial Imitation Learning (GAIL)

Warning: Images are not yet handled properly by the current implementation

Parameters

- **policy** – (ActorCriticPolicy or str) The policy model to use (MlpPolicy, CnnPolicy, CnnLstmPolicy, . . .)
- **env** – (Gym environment or str) The environment to learn from (if registered in Gym, can be str)
- **expert_dataset** – (ExpertDataset) the dataset manager
- **gamma** – (float) the discount value
- **timesteps_per_batch** – (int) the number of timesteps to run per batch (horizon)
- **max_kl** – (float) the Kullback-Leibler loss threshold
- **cg_iters** – (int) the number of iterations for the conjugate gradient calculation
- **lam** – (float) GAE factor
- **entcoeff** – (float) the weight for the entropy loss
- **cg_damping** – (float) the compute gradient dampening factor
- **vf_stepsize** – (float) the value function stepsize
- **vf_iters** – (int) the value function's number iterations for learning
- **hidden_size** – ([int]) the hidden dimension for the MLP
- **g_step** – (int) number of steps to train policy in each epoch
- **d_step** – (int) number of steps to train discriminator in each epoch
- **d_stepsize** – (float) the reward giver stepsize
- **verbose** – (int) the verbosity level: 0 none, 1 training information, 2 tensorflow debug
- **_init_setup_model** – (bool) Whether or not to build the network at the creation of the instance
- **full_tensorboard_log** – (bool) enable additional logging when using tensorboard WARNING: this logging can take a lot of space quickly

action_probability(*observation*, *state=None*, *mask=None*, *actions=None*, *logp=False*)

If `actions` is `None`, then get the model's action probability distribution from a given observation.

Depending on the action space the output is:

- Discrete: probability for each possible action
- Box: mean and standard deviation of the action output

However if `actions` is not `None`, this function will return the probability that the given actions are taken with the given parameters (observation, state, . . .) on this model. For discrete action spaces, it returns the probability mass; for continuous action spaces, the probability density. This is since the probability mass will always be zero in continuous spaces, see http://blog.christianperone.com/2019/01/ for a good explanation

Parameters

- **observation** – (np.ndarray) the input observation

- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **actions** – (np.ndarray) (OPTIONAL) For calculating the likelihood that the given actions are chosen by the model for each of the given parameters. Must have the same number of actions and observations. (set to None to return the complete action probability distribution)
- **logp** – (bool) (OPTIONAL) When specified with actions, returns probability in log-space. This has no effect if actions is None.

Returns (np.ndarray) the model's (log) action probability

get_env()
returns the current environment (can be None if not defined)

Returns (Gym Environment) The current environment

get_parameter_list()
Get tensorflow Variables of model's parameters

This includes all variables necessary for continuing training (saving / loading).

Returns (list) List of tensorflow Variables

get_parameters()
Get current model parameters as dictionary of variable name -> ndarray.

Returns (OrderedDict) Dictionary of variable name -> ndarray of model's parameters.

get_vec_normalize_env() → Optional[stable_baselines.common.vec_env.vec_normalize.VecNormalize]
Return the `VecNormalize` wrapper of the training env if it exists.

Returns Optional[VecNormalize] The `VecNormalize` env.

learn(*total_timesteps*, *callback=None*, *log_interval=100*, *tb_log_name='GAIL'*, *reset_num_timesteps=True*)
Return a trained model.

Parameters

- **total_timesteps** – (int) The total number of samples to train on
- **callback** – (Union[callable, [callable], BaseCallback]) function called at every steps with state of the algorithm. It takes the local and global variables. If it returns False, training is aborted. When the callback inherits from BaseCallback, you will have access to additional stages of the training (training start/end), please read the documentation for more details.
- **log_interval** – (int) The number of timesteps before logging.
- **tb_log_name** – (str) the name of the run for tensorboard log
- **reset_num_timesteps** – (bool) whether or not to reset the current timestep number (used in logging)

Returns (BaseRLModel) the trained model

classmethod load(*load_path*, *env=None*, *custom_objects=None*, ***kwargs*)
Load the model from file

Parameters

- **load_path** – (str or file-like) the saved parameter location

- **env** – (Gym Environment) the new environment to run the loaded model on (can be None if you only need prediction from a trained model)
- **custom_objects** – (dict) 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.
- **kwargs** – extra arguments to change the model when loading

load_parameters (*load_path_or_dict*, *exact_match=True*)

Load model parameters from a file or a dictionary

Dictionary keys should be tensorflow variable names, which can be obtained with `get_parameters` function. If `exact_match` is True, dictionary should contain keys for all model's parameters, otherwise RunTimeError is raised. If False, only variables included in the dictionary will be updated.

This does not load agent's hyper-parameters.

> **Warning:** This function does not update trainer/optimizer variables (e.g. momentum). As such training after using this function may lead to less-than-optimal results.

Parameters

- **load_path_or_dict** – (str or file-like or dict) Save parameter location or dict of parameters as variable.name -> ndarrays to be loaded.
- **exact_match** – (bool) If True, expects load dictionary to contain keys for all variables in the model. If False, loads parameters only for variables mentioned in the dictionary. Defaults to True.

predict (*observation*, *state=None*, *mask=None*, *deterministic=False*)

Get the model's action from an observation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray, np.ndarray) the model's action and the next state (used in recurrent policies)

pretrain (*dataset*, *n_epochs=10*, *learning_rate=0.0001*, *adam_epsilon=1e-08*, *val_interval=None*)

Pretrain a model using behavior cloning: supervised learning given an expert dataset.

NOTE: only Box and Discrete spaces are supported for now.

Parameters

- **dataset** – (ExpertDataset) Dataset manager
- **n_epochs** – (int) Number of iterations on the training set
- **learning_rate** – (float) Learning rate
- **adam_epsilon** – (float) the epsilon value for the adam optimizer

- **val_interval** – (int) Report training and validation losses every n epochs. By default, every 10th of the maximum number of epochs.

Returns (BaseRLModel) the pretrained model

save (*save_path*, *cloudpickle=False*)
Save the current parameters to file

Parameters

- **save_path** – (str or file-like) The save location
- **cloudpickle** – (bool) Use older cloudpickle format instead of zip-archives.

set_env (*env*)
Checks the validity of the environment, and if it is coherent, set it as the current environment.

Parameters env – (Gym Environment) The environment for learning a policy

set_random_seed (*seed: Optional[int]*) → None

Parameters seed – (Optional[int]) Seed for the pseudo-random generators. If None, do not change the seeds.

setup_model ()
Create all the functions and tensorflow graphs necessary to train the model

1.25 HER

Hindsight Experience Replay (HER)

HER is a method wrapper that works with Off policy methods (DQN, SAC, TD3 and DDPG for example).

Note: HER was re-implemented from scratch in Stable-Baselines compared to the original OpenAI baselines. If you want to reproduce results from the paper, please use the rl baselines zoo in order to have the correct hyperparameters and at least 8 MPI workers with DDPG.

Warning: HER requires the environment to inherits from gym.GoalEnv

Warning: you must pass an environment or wrap it with `HERGoalEnvWrapper` in order to use the predict method

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 wrapped model (DQN, SAC, TD3 or DDPG) for that section.

1.25.3 Example

```
from stable_baselines import HER, DQN, SAC, DDPG, TD3
from stable_baselines.her import GoalSelectionStrategy, HERGoalEnvWrapper
from stable_baselines.common.bit_flipping_env import BitFlippingEnv

model_class = DQN  # works also with SAC, DDPG and TD3

env = BitFlippingEnv(N_BITS, continuous=model_class in [DDPG, SAC, TD3], max_steps=N_
↪BITS)

# Available strategies (cf paper): future, final, episode, random
goal_selection_strategy = 'future' # equivalent to GoalSelectionStrategy.FUTURE

# Wrap the model
model = HER('MlpPolicy', env, model_class, n_sampled_goal=4, goal_selection_
↪strategy=goal_selection_strategy,
                                                verbose=1)
# Train the model
model.learn(1000)

model.save("./her_bit_env")

# WARNING: you must pass an env
# or wrap your environment with HERGoalEnvWrapper to use the predict method
model = HER.load('./her_bit_env', env=env)

obs = env.reset()
for _ in range(100):
    action, _ = model.predict(obs)
    obs, reward, done, _ = env.step(action)

    if done:
        obs = env.reset()
```

1.25.4 Parameters

class `stable_baselines.her.`**HER**(*policy*, *env*, *model_class*, *n_sampled_goal=4*, *goal_selection_strategy='future'*, **args*, ***kwargs*)

Hindsight Experience Replay (HER) https://arxiv.org/abs/1707.01495

Parameters

- **policy** – (BasePolicy or str) The policy model to use (MlpPolicy, CnnPolicy, CnnLstmPolicy, . . .)
- **env** – (Gym environment or str) The environment to learn from (if registered in Gym, can be str)
- **model_class** – (OffPolicyRLModel) The off policy RL model to apply Hindsight Experience Replay currently supported: DQN, DDPG, SAC
- **n_sampled_goal** – (int)
- **goal_selection_strategy** – (GoalSelectionStrategy or str)

action_probability(*observation*, *state=None*, *mask=None*, *actions=None*, *logp=False*)

If `actions` is `None`, then get the model's action probability distribution from a given observation.

Depending on the action space the output is:

- Discrete: probability for each possible action
- Box: mean and standard deviation of the action output

However if `actions` is not `None`, this function will return the probability that the given actions are taken with the given parameters (observation, state, ...) on this model. For discrete action spaces, it returns the probability mass; for continuous action spaces, the probability density. This is since the probability mass will always be zero in continuous spaces, see http://blog.christianperone.com/2019/01/ for a good explanation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **actions** – (np.ndarray) (OPTIONAL) For calculating the likelihood that the given actions are chosen by the model for each of the given parameters. Must have the same number of actions and observations. (set to None to return the complete action probability distribution)
- **logp** – (bool) (OPTIONAL) When specified with actions, returns probability in log-space. This has no effect if actions is None.

Returns (np.ndarray) the model's (log) action probability

get_env()

returns the current environment (can be None if not defined)

Returns (Gym Environment) The current environment

get_parameter_list()

Get tensorflow Variables of model's parameters

This includes all variables necessary for continuing training (saving / loading).

Returns (list) List of tensorflow Variables

learn(*total_timesteps*, *callback=None*, *log_interval=100*, *tb_log_name='HER'*, *reset_num_timesteps=True*)

Return a trained model.

Parameters

- **total_timesteps** – (int) The total number of samples to train on
- **callback** – (Union[callable, [callable], BaseCallback]) function called at every steps with state of the algorithm. It takes the local and global variables. If it returns False, training is aborted. When the callback inherits from BaseCallback, you will have access to additional stages of the training (training start/end), please read the documentation for more details.
- **log_interval** – (int) The number of timesteps before logging.
- **tb_log_name** – (str) the name of the run for tensorboard log
- **reset_num_timesteps** – (bool) whether or not to reset the current timestep number (used in logging)

Returns (BaseRLModel) the trained model

classmethod load(*load_path*, *env=None*, *custom_objects=None*, ***kwargs*)
Load the model from file

Parameters

- **load_path** – (str or file-like) the saved parameter location
- **env** – (Gym Environment) the new environment to run the loaded model on (can be None if you only need prediction from a trained model)
- **custom_objects** – (dict) 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.
- **kwargs** – extra arguments to change the model when loading

predict(*observation*, *state=None*, *mask=None*, *deterministic=True*)
Get the model's action from an observation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray, np.ndarray) the model's action and the next state (used in recurrent policies)

save(*save_path*, *cloudpickle=False*)
Save the current parameters to file

Parameters

- **save_path** – (str or file-like) The save location
- **cloudpickle** – (bool) Use older cloudpickle format instead of zip-archives.

set_env(*env*)
Checks the validity of the environment, and if it is coherent, set it as the current environment.

Parameters env – (Gym Environment) The environment for learning a policy

setup_model()
Create all the functions and tensorflow graphs necessary to train the model

1.25.5 Goal Selection Strategies

class stable_baselines.her.**GoalSelectionStrategy**
The strategies for selecting new goals when creating artificial transitions.

1.25.6 Goal Env Wrapper

class stable_baselines.her.**HERGoalEnvWrapper**(*env*)
A wrapper that allow to use dict observation space (coming from GoalEnv) with the RL algorithms. It assumes that all the spaces of the dict space are of the same type.

Parameters env – (gym.GoalEnv)

convert_dict_to_obs (*obs_dict*)

Parameters **obs_dict** – (dict<np.ndarray>)

Returns (np.ndarray)

convert_obs_to_dict (*observations*)
Inverse operation of convert_dict_to_obs

Parameters **observations** – (np.ndarray)

Returns (OrderedDict<np.ndarray>)

1.25.7 Replay Wrapper

class stable_baselines.her.**HindsightExperienceReplayWrapper** (*replay_buffer*, *n_sampled_goal*, *goal_selection_strategy*, *wrapped_env*)

Wrapper around a replay buffer in order to use HER. This implementation is inspired by to the one found in https://github.com/NervanaSystems/coach/.

Parameters

- **replay_buffer** – (ReplayBuffer)
- **n_sampled_goal** – (int) The number of artificial transitions to generate for each actual transition
- **goal_selection_strategy** – (GoalSelectionStrategy) The method that will be used to generate the goals for the artificial transitions.
- **wrapped_env** – (HERGoalEnvWrapper) the GoalEnv wrapped using HERGoalEnvWrapper, that enables to convert observation to dict, and vice versa

add (*obs_t*, *action*, *reward*, *obs_tp1*, *done*, *info*)
add a new transition to the buffer

Parameters

- **obs_t** – (np.ndarray) the last observation
- **action** – ([float]) the action
- **reward** – (float) the reward of the transition
- **obs_tp1** – (np.ndarray) the new observation
- **done** – (bool) is the episode done
- **info** – (dict) extra values used to compute reward

can_sample (*n_samples*)
Check if n_samples samples can be sampled from the buffer.

Parameters **n_samples** – (int)

Returns (bool)

1.26 PPO1

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: PPO1 requires *OpenMPI*. If OpenMPI isn't enabled, then PPO1 isn't imported into the `stable_baselines` module.

Note: PPO1 uses MPI for multiprocessing unlike PPO2, which uses vectorized environments. PPO2 is the implementation OpenAI made for GPU.

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/
- `mpirun -np 8 python -m stable_baselines.ppo1.run_atari` runs the algorithm for 40M frames = 10M timesteps on an Atari game. See help (`-h`) for more options.
- `python -m stable_baselines.ppo1.run_mujoco` runs the algorithm for 1M frames on a Mujoco environment.
- Train mujoco 3d humanoid (with optimal-ish hyperparameters): `mpirun -np 16 python -m stable_baselines.ppo1.run_humanoid --model-path=/path/to/model`
- Render the 3d humanoid: `python -m stable_baselines.ppo1.run_humanoid --play --model-path=/path/to/model`

1.26.2 Can I use?

- Recurrent policies:
- Multi processing: ✓ (using MPI)
- Gym spaces:

Space	Action	Observation
Discrete	✓	✓
Box	✓	✓
MultiDiscrete	✓	✓
MultiBinary	✓	✓

1.26.3 Example

```
import gym

from stable_baselines.common.policies import MlpPolicy
from stable_baselines import PPO1

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

model = PPO1(MlpPolicy, env, verbose=1)
model.learn(total_timesteps=25000)
model.save("ppo1_cartpole")

del model # remove to demonstrate saving and loading

model = PPO1.load("ppo1_cartpole")

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

1.26.4 Parameters

class stable_baselines.ppo1.**PPO1**(*policy, env, gamma=0.99, timesteps_per_actorbatch=256, clip_param=0.2, entcoeff=0.01, optim_epochs=4, optim_stepsize=0.001, optim_batchsize=64, lam=0.95, adam_epsilon=1e-05, schedule='linear', verbose=0, tensorboard_log=None, _init_setup_model=True, policy_kwargs=None, full_tensorboard_log=False, seed=None, n_cpu_tf_sess=1*)

Proximal Policy Optimization algorithm (MPI version). Paper: https://arxiv.org/abs/1707.06347

Parameters

- **env** – (Gym environment or str) The environment to learn from (if registered in Gym, can be str)
- **policy** – (ActorCriticPolicy or str) The policy model to use (MlpPolicy, CnnPolicy, CnnLstmPolicy, . . .)
- **timesteps_per_actorbatch** – (int) timesteps per actor per update
- **clip_param** – (float) clipping parameter epsilon
- **entcoeff** – (float) the entropy loss weight
- **optim_epochs** – (float) the optimizer's number of epochs
- **optim_stepsize** – (float) the optimizer's stepsize # 每个stepsize降低学习率(乘以gamma)
- **optim_batchsize** – (int) the optimizer's the batch size
- **gamma** – (float) discount factor
- **lam** – (float) advantage estimation
- **adam_epsilon** – (float) the epsilon value for the adam optimizer

- **schedule** – (str) The type of scheduler for the learning rate update ('linear', 'constant', 'double_linear_con', 'middle_drop' or 'double_middle_drop')
- **verbose** – (int) the verbosity level: 0 none, 1 training information, 2 tensorflow debug
- **tensorboard_log** – (str) the log location for tensorboard (if None, no logging)
- **_init_setup_model** – (bool) Whether or not to build the network at the creation of the instance 添加自定义网络？
- **policy_kwargs** – (dict) additional arguments to be passed to the policy on creation
- **full_tensorboard_log** – (bool) enable additional logging when using tensorboard WARNING: this logging can take a lot of space quickly
- **seed** – (int) Seed for the pseudo-random generators (python, numpy, tensorflow). If None (default), use random seed. Note that if you want completely deterministic results, you must set *n_cpu_tf_sess* to 1.
- **n_cpu_tf_sess** – (int) The number of threads for TensorFlow operations If None, the number of cpu of the current machine will be used.

action_probability(*observation*, *state=None*, *mask=None*, *actions=None*, *logp=False*)

If `actions` is `None`, then get the model's action probability distribution from a given observation.

Depending on the action space the output is:

- Discrete: probability for each possible action
- Box: mean and standard deviation of the action output

However if `actions` is not `None`, this function will return the probability that the given actions are taken with the given parameters (observation, state, ...) on this model. For discrete action spaces, it returns the probability mass; for continuous action spaces, the probability density. This is since the probability mass will always be zero in continuous spaces, see http://blog.christianperone.com/2019/01/ for a good explanation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **actions** – (np.ndarray) (OPTIONAL) For calculating the likelihood that the given actions are chosen by the model for each of the given parameters. Must have the same number of actions and observations. (set to None to return the complete action probability distribution)
- **logp** – (bool) (OPTIONAL) When specified with actions, returns probability in log-space. This has no effect if actions is None.

Returns (np.ndarray) the model's (log) action probability

get_env()

returns the current environment (can be None if not defined)

Returns (Gym Environment) The current environment

get_parameter_list()

Get tensorflow Variables of model's parameters

This includes all variables necessary for continuing training (saving / loading).

Returns (list) List of tensorflow Variables

get_parameters()
Get current model parameters as dictionary of variable name -> ndarray.

Returns (OrderedDict) Dictionary of variable name -> ndarray of model's parameters.

get_vec_normalize_env() → Optional[stable_baselines.common.vec_env.vec_normalize.VecNormalize]
Return the `VecNormalize` wrapper of the training env if it exists.

Returns Optional[VecNormalize] The `VecNormalize` env.

learn(*total_timesteps*, *callback=None*, *log_interval=100*, *tb_log_name='PPO1'*, *reset_num_timesteps=True*)
Return a trained model.

Parameters

- **total_timesteps** – (int) The total number of samples to train on
- **callback** – (Union[callable, [callable], BaseCallback]) function called at every steps with state of the algorithm. It takes the local and global variables. If it returns False, training is aborted. When the callback inherits from BaseCallback, you will have access to additional stages of the training (training start/end), please read the documentation for more details.
- **log_interval** – (int) The number of timesteps before logging.
- **tb_log_name** – (str) the name of the run for tensorboard log
- **reset_num_timesteps** – (bool) whether or not to reset the current timestep number (used in logging)

Returns (BaseRLModel) the trained model

classmethod load(*load_path*, *env=None*, *custom_objects=None*, ***kwargs*)
Load the model from file

Parameters

- **load_path** – (str or file-like) the saved parameter location
- **env** – (Gym Environment) the new environment to run the loaded model on (can be None if you only need prediction from a trained model)
- **custom_objects** – (dict) 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.
- **kwargs** – extra arguments to change the model when loading

load_parameters(*load_path_or_dict*, *exact_match=True*)
Load model parameters from a file or a dictionary

Dictionary keys should be tensorflow variable names, which can be obtained with `get_parameters` function. If `exact_match` is True, dictionary should contain keys for all model's parameters, otherwise RunTimeError is raised. If False, only variables included in the dictionary will be updated.

This does not load agent's hyper-parameters.

> **Warning:** This function does not update trainer/optimizer variables (e.g. momentum). As such training after using this function may lead to less-than-optimal results.

Parameters

- **load_path_or_dict** – (str or file-like or dict) Save parameter location or dict of parameters as variable.name -> ndarrays to be loaded.
- **exact_match** – (bool) If True, expects load dictionary to contain keys for all variables in the model. If False, loads parameters only for variables mentioned in the dictionary. Defaults to True.

predict(*observation*, *state=None*, *mask=None*, *deterministic=False*)
Get the model's action from an observation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray, np.ndarray) the model's action and the next state (used in recurrent policies)

pretrain(*dataset*, *n_epochs=10*, *learning_rate=0.0001*, *adam_epsilon=1e-08*, *val_interval=None*)
Pretrain a model using behavior cloning: supervised learning given an expert dataset.

NOTE: only Box and Discrete spaces are supported for now.

Parameters

- **dataset** – (ExpertDataset) Dataset manager
- **n_epochs** – (int) Number of iterations on the training set
- **learning_rate** – (float) Learning rate
- **adam_epsilon** – (float) the epsilon value for the adam optimizer
- **val_interval** – (int) Report training and validation losses every n epochs. By default, every 10th of the maximum number of epochs.

Returns (BaseRLModel) the pretrained model

save(*save_path*, *cloudpickle=False*)
Save the current parameters to file

Parameters

- **save_path** – (str or file-like) The save location
- **cloudpickle** – (bool) Use older cloudpickle format instead of zip-archives.

set_env(*env*)
Checks the validity of the environment, and if it is coherent, set it as the current environment.

Parameters **env** – (Gym Environment) The environment for learning a policy

set_random_seed(*seed: Optional[int]*) → None

Parameters **seed** – (Optional[int]) Seed for the pseudo-random generators. If None, do not change the seeds.

setup_model()
Create all the functions and tensorflow graphs necessary to train the model

1.26.5 Callbacks - Accessible Variables

Depending on initialization parameters and timestep, different variables are accessible. Variables accessible "From timestep X" are variables that can be accessed when `self.timestep==X` in the `on_step` function.

Variable	Availability
• self • total_timesteps • callback • log_interval • tb_log_name • reset_num_timesteps • new_tb_log • writer • policy • env • horizon • reward_giver • gail • step • cur_ep_ret • current_it_len • current_ep_len • cur_ep_true_ret • ep_true_rets • ep_rets • ep_lens • observations • true_rewards • rewards • vpreds • episode_starts • dones • actions • states • episode_start • done • vpred • _ • i • clipped_action • reward • true_reward • info • action • observation	From timestep 0
• maybe_ep_info	After the first episode termination

1.27 PPO2

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: PPO2 is the implementation of OpenAI made for GPU. For multiprocessing, it uses vectorized environments compared to PPO1 which uses MPI.

Note: PPO2 contains several modifications from the original algorithm not documented by OpenAI: value function is also clipped and advantages are normalized.

1.27.1 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/
- **`python -m stable_baselines.ppo2.run_atari` runs the algorithm for 40M** frames = 10M timesteps on an Atari game. See help (`-h`) for more options.
- **`python -m stable_baselines.ppo2.run_mujoco` runs the algorithm for 1M** frames on a Mujoco environment.

1.27.2 Can I use?

- Recurrent policies: ✓
- Multi processing: ✓
- Gym spaces:

Space	Action	Observation
Discrete	✓	✓
Box	✓	✓
MultiDiscrete	✓	✓
MultiBinary	✓	✓

1.27.3 Example

Train a PPO agent on *CartPole-v1* using 4 processes.

```
import gym

from stable_baselines.common.policies import MlpPolicy
from stable_baselines.common import make_vec_env
```

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```
from stable_baselines import PPO2

# multiprocess environment
env = make_vec_env('CartPole-v1', n_envs=4)

model = PPO2(MlpPolicy, env, verbose=1)
model.learn(total_timesteps=25000)
model.save("ppo2_cartpole")

del model # remove to demonstrate saving and loading

model = PPO2.load("ppo2_cartpole")

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

1.27.4 Parameters

class stable_baselines.ppo2.**PPO2**(*policy, env, gamma=0.99, n_steps=128, ent_coef=0.01, learning_rate=0.00025, vf_coef=0.5, max_grad_norm=0.5, lam=0.95, nminibatches=4, noptepochs=4, cliprange=0.2, cliprange_vf=None, verbose=0, tensorboard_log=None, _init_setup_model=True, policy_kwargs=None, full_tensorboard_log=False, seed=None, n_cpu_tf_sess=None*)

Proximal Policy Optimization algorithm (GPU version). Paper: https://arxiv.org/abs/1707.06347

Parameters

- **policy** – (ActorCriticPolicy or str) The policy model to use (MlpPolicy, CnnPolicy, CnnLstmPolicy, . . .)
- **env** – (Gym environment or str) The environment to learn from (if registered in Gym, can be str)
- **gamma** – (float) Discount factor
- **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)
- **ent_coef** – (float) Entropy coefficient for the loss calculation
- **learning_rate** – (float or callable) The learning rate, it can be a function
- **vf_coef** – (float) Value function coefficient for the loss calculation
- **max_grad_norm** – (float) The maximum value for the gradient clipping
- **lam** – (float) Factor for trade-off of bias vs variance for Generalized Advantage Estimator
- **nminibatches** – (int) Number of training minibatches per update. For recurrent policies, the number of environments run in parallel should be a multiple of nminibatches.
- **noptepochs** – (int) Number of epoch when optimizing the surrogate
- **cliprange** – (float or callable) Clipping parameter, it can be a function

- **cliprange_vf** – (float or callable) Clipping parameter for the value function, it can be a function. This is a parameter specific to the OpenAI implementation. If None is passed (default), then *cliprange* (that is used for the policy) will be used. IMPORTANT: this clipping depends on the reward scaling. To deactivate value function clipping (and recover the original PPO implementation), you have to pass a negative value (e.g. -1).
- **verbose** – (int) the verbosity level: 0 none, 1 training information, 2 tensorflow debug
- **tensorboard_log** – (str) the log location for tensorboard (if None, no logging)
- **_init_setup_model** – (bool) Whether or not to build the network at the creation of the instance
- **policy_kwargs** – (dict) additional arguments to be passed to the policy on creation
- **full_tensorboard_log** – (bool) enable additional logging when using tensorboard WARNING: this logging can take a lot of space quickly
- **seed** – (int) Seed for the pseudo-random generators (python, numpy, tensorflow). If None (default), use random seed. Note that if you want completely deterministic results, you must set *n_cpu_tf_sess* to 1.
- **n_cpu_tf_sess** – (int) The number of threads for TensorFlow operations If None, the number of cpu of the current machine will be used.

action_probability(*observation*, *state=None*, *mask=None*, *actions=None*, *logp=False*)

If `actions` is `None`, then get the model's action probability distribution from a given observation.

Depending on the action space the output is:

- Discrete: probability for each possible action
- Box: mean and standard deviation of the action output

However if `actions` is not `None`, this function will return the probability that the given actions are taken with the given parameters (observation, state, …) on this model. For discrete action spaces, it returns the probability mass; for continuous action spaces, the probability density. This is since the probability mass will always be zero in continuous spaces, see http://blog.christianperone.com/2019/01/ for a good explanation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **actions** – (np.ndarray) (OPTIONAL) For calculating the likelihood that the given actions are chosen by the model for each of the given parameters. Must have the same number of actions and observations. (set to None to return the complete action probability distribution)
- **logp** – (bool) (OPTIONAL) When specified with actions, returns probability in log-space. This has no effect if actions is None.

Returns (np.ndarray) the model's (log) action probability

get_env()

returns the current environment (can be None if not defined)

Returns (Gym Environment) The current environment

get_parameter_list()
Get tensorflow Variables of model's parameters

This includes all variables necessary for continuing training (saving / loading).

Returns (list) List of tensorflow Variables

get_parameters()
Get current model parameters as dictionary of variable name -> ndarray.

Returns (OrderedDict) Dictionary of variable name -> ndarray of model's parameters.

get_vec_normalize_env() → Optional[stable_baselines.common.vec_env.vec_normalize.VecNormalize]
Return the `VecNormalize` wrapper of the training env if it exists.

Returns Optional[VecNormalize] The `VecNormalize` env.

learn(*total_timesteps*, *callback=None*, *log_interval=1*, *tb_log_name='PPO2'*, *reset_num_timesteps=True*)
Return a trained model.

Parameters

- **total_timesteps** – (int) The total number of samples to train on
- **callback** – (Union[callable, [callable], BaseCallback]) function called at every steps with state of the algorithm. It takes the local and global variables. If it returns False, training is aborted. When the callback inherits from BaseCallback, you will have access to additional stages of the training (training start/end), please read the documentation for more details.
- **log_interval** – (int) The number of timesteps before logging.
- **tb_log_name** – (str) the name of the run for tensorboard log
- **reset_num_timesteps** – (bool) whether or not to reset the current timestep number (used in logging)

Returns (BaseRLModel) the trained model

classmethod load(*load_path*, *env=None*, *custom_objects=None*, ***kwargs*)
Load the model from file

Parameters

- **load_path** – (str or file-like) the saved parameter location
- **env** – (Gym Environment) the new environment to run the loaded model on (can be None if you only need prediction from a trained model)
- **custom_objects** – (dict) 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.
- **kwargs** – extra arguments to change the model when loading

load_parameters(*load_path_or_dict*, *exact_match=True*)
Load model parameters from a file or a dictionary

Dictionary keys should be tensorflow variable names, which can be obtained with `get_parameters` function. If `exact_match` is True, dictionary should contain keys for all model's parameters, otherwise RunTimeError is raised. If False, only variables included in the dictionary will be updated.

This does not load agent's hyper-parameters.

> **Warning:** This function does not update trainer/optimizer variables (e.g. momentum). As such training after using this function may lead to less-than-optimal results.

Parameters

- **load_path_or_dict** – (str or file-like or dict) Save parameter location or dict of parameters as variable.name -> ndarrays to be loaded.
- **exact_match** – (bool) If True, expects load dictionary to contain keys for all variables in the model. If False, loads parameters only for variables mentioned in the dictionary. Defaults to True.

predict (*observation*, *state=None*, *mask=None*, *deterministic=False*)

Get the model's action from an observation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray, np.ndarray) the model's action and the next state (used in recurrent policies)

pretrain (*dataset*, *n_epochs=10*, *learning_rate=0.0001*, *adam_epsilon=1e-08*, *val_interval=None*)

Pretrain a model using behavior cloning: supervised learning given an expert dataset.

NOTE: only Box and Discrete spaces are supported for now.

Parameters

- **dataset** – (ExpertDataset) Dataset manager
- **n_epochs** – (int) Number of iterations on the training set
- **learning_rate** – (float) Learning rate
- **adam_epsilon** – (float) the epsilon value for the adam optimizer
- **val_interval** – (int) Report training and validation losses every n epochs. By default, every 10th of the maximum number of epochs.

Returns (BaseRLModel) the pretrained model

save (*save_path*, *cloudpickle=False*)

Save the current parameters to file

Parameters

- **save_path** – (str or file-like) The save location
- **cloudpickle** – (bool) Use older cloudpickle format instead of zip-archives.

set_env (*env*)

Checks the validity of the environment, and if it is coherent, set it as the current environment.

Parameters **env** – (Gym Environment) The environment for learning a policy

set_random_seed (*seed: Optional[int]*) → None

Parameters **seed** – (Optional[int]) Seed for the pseudo-random generators. If None, do not change the seeds.

setup_model()

Create all the functions and tensorflow graphs necessary to train the model

1.27.5 Callbacks - Accessible Variables

Depending on initialization parameters and timestep, different variables are accessible. Variables accessible "From timestep X" are variables that can be accessed when `self.timestep==X` in the `on_step` function.

Variable	Availability
• self • total_timesteps • callback • log_interval • tb_log_name • reset_num_timesteps • cliprange_vf • new_tb_log • writer • t_first_start • n_updates • mb_obs • mb_rewards • mb_actions • mb_values • mb_dones • mb_neglogpacs • mb_states • ep_infos • actions • values • neglogpacs • clipped_actions • rewards • infos	From timestep 1
• info • maybe_ep_info	From timestep 1

1.28 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.

> **Warning:** The SAC model does not support `stable_baselines.common.policies` because it uses double q-values and value estimation, as a result it must use its own policy models (see *SAC Policies*).

Available Policies

MlpPolicy	Policy object that implements actor critic, using a MLP (2 layers of 64)
LnMlpPolicy	Policy object that implements actor critic, using a MLP (2 layers of 64), with layer normalisation
CnnPolicy	Policy object that implements actor critic, using a CNN (the nature CNN)
LnCnnPolicy	Policy object that implements actor critic, using a CNN (the nature CNN), with layer normalisation

1.28.1 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

1.28.2 Can I use?

- Recurrent policies:
- Multi processing:
- Gym spaces:

Space	Action	Observation
Discrete		✓
Box	✓	✓
MultiDiscrete		✓
MultiBinary		✓

1.28.3 Example

```python
import gym
import numpy as np

from stable_baselines.sac.policies import MlpPolicy
from stable_baselines import SAC

env = gym.make('Pendulum-v0')

model = SAC(MlpPolicy, env, verbose=1)
model.learn(total_timesteps=50000, log_interval=10)
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)
    obs, rewards, dones, info = env.step(action)
    env.render()
```

1.28.4 Parameters

class stable_baselines.sac.**SAC**(*policy, env, gamma=0.99, learning_rate=0.0003, buffer_size=50000, learning_starts=100, train_freq=1, batch_size=64, tau=0.005, ent_coef='auto', target_update_interval=1, gradient_steps=1, target_entropy='auto', action_noise=None, random_exploration=0.0, verbose=0, tensorboard_log=None, _init_setup_model=True, policy_kwargs=None, full_tensorboard_log=False, seed=None, n_cpu_tf_sess=None*)

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) and from the Softlearning repo (https://github.com/rail-berkeley/softlearning/) Paper: https://arxiv.org/abs/1801.01290 Introduction to SAC: https://spinningup.openai.com/en/latest/algorithms/sac.html

Parameters

- **policy** – (SACPolicy or str) The policy model to use (MlpPolicy, CnnPolicy, LnMlpPolicy, . . .)
- **env** – (Gym environment or str) The environment to learn from (if registered in Gym, can be str)
- **gamma** – (float) the discount factor
- **learning_rate** – (float or callable) 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 (from 1 to 0)
- **buffer_size** – (int) size of the replay buffer
- **batch_size** – (int) Minibatch size for each gradient update

- **tau** – (float) the soft update coefficient ("polyak update", between 0 and 1)
- **ent_coef** – (str or 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)
- **train_freq** – (int) Update the model every *train_freq* steps.
- **learning_starts** – (int) how many steps of the model to collect transitions for before learning starts
- **target_update_interval** – (int) update the target network every *target_network_update_freq* steps.
- **gradient_steps** – (int) How many gradient update after each step
- **target_entropy** – (str or float) target entropy when learning ent_coef (ent_coef = 'auto')
- **action_noise** – (ActionNoise) the action noise type (None by default), this can help for hard exploration problem. Cf DDPG for the different action noise type.
- **random_exploration** – (float) Probability of taking a random action (as in an epsilon-greedy strategy) This is not needed for SAC normally but can help exploring when using HER + SAC. This hack was present in the original OpenAI Baselines repo (DDPG + HER)
- **verbose** – (int) the verbosity level: 0 none, 1 training information, 2 tensorflow debug
- **tensorboard_log** – (str) the log location for tensorboard (if None, no logging)
- **_init_setup_model** – (bool) Whether or not to build the network at the creation of the instance
- **policy_kwargs** – (dict) additional arguments to be passed to the policy on creation
- **full_tensorboard_log** – (bool) enable additional logging when using tensorboard Note: this has no effect on SAC logging for now
- **seed** – (int) Seed for the pseudo-random generators (python, numpy, tensorflow). If None (default), use random seed. Note that if you want completely deterministic results, you must set *n_cpu_tf_sess* to 1.
- **n_cpu_tf_sess** – (int) The number of threads for TensorFlow operations If None, the number of cpu of the current machine will be used.

action_probability(*observation*, *state=None*, *mask=None*, *actions=None*, *logp=False*)

If `actions` is `None`, then get the model's action probability distribution from a given observation.

Depending on the action space the output is:

- Discrete: probability for each possible action
- Box: mean and standard deviation of the action output

However if `actions` is not `None`, this function will return the probability that the given actions are taken with the given parameters (observation, state, ...) on this model. For discrete action spaces, it returns the probability mass; for continuous action spaces, the probability density. This is since the probability mass will always be zero in continuous spaces, see http://blog.christianperone.com/2019/01/ for a good explanation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)

- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **actions** – (np.ndarray) (OPTIONAL) For calculating the likelihood that the given actions are chosen by the model for each of the given parameters. Must have the same number of actions and observations. (set to None to return the complete action probability distribution)
- **logp** – (bool) (OPTIONAL) When specified with actions, returns probability in log-space. This has no effect if actions is None.

Returns (np.ndarray) the model's (log) action probability

get_env()
returns the current environment (can be None if not defined)

Returns (Gym Environment) The current environment

get_parameter_list()
Get tensorflow Variables of model's parameters

This includes all variables necessary for continuing training (saving / loading).

Returns (list) List of tensorflow Variables

get_parameters()
Get current model parameters as dictionary of variable name -> ndarray.

Returns (OrderedDict) Dictionary of variable name -> ndarray of model's parameters.

get_vec_normalize_env() → Optional[stable_baselines.common.vec_env.vec_normalize.VecNormalize]
Return the `VecNormalize` wrapper of the training env if it exists.

Returns Optional[VecNormalize] The `VecNormalize` env.

is_using_her() → bool
Check if is using HER

Returns (bool) Whether is using HER or not

learn(*total_timesteps*, *callback=None*, *log_interval=4*, *tb_log_name='SAC'*, *reset_num_timesteps=True*, *replay_wrapper=None*)
Return a trained model.

Parameters

- **total_timesteps** – (int) The total number of samples to train on
- **callback** – (Union[callable, [callable], BaseCallback]) function called at every steps with state of the algorithm. It takes the local and global variables. If it returns False, training is aborted. When the callback inherits from BaseCallback, you will have access to additional stages of the training (training start/end), please read the documentation for more details.
- **log_interval** – (int) The number of timesteps before logging.
- **tb_log_name** – (str) the name of the run for tensorboard log
- **reset_num_timesteps** – (bool) whether or not to reset the current timestep number (used in logging)

Returns (BaseRLModel) the trained model

classmethod load(*load_path*, *env=None*, *custom_objects=None*, ***kwargs*)
Load the model from file

Parameters

- **load_path** – (str or file-like) the saved parameter location
- **env** – (Gym Environment) the new environment to run the loaded model on (can be None if you only need prediction from a trained model)
- **custom_objects** – (dict) 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.
- **kwargs** – extra arguments to change the model when loading

load_parameters (*load_path_or_dict*, *exact_match=True*)
Load model parameters from a file or a dictionary

Dictionary keys should be tensorflow variable names, which can be obtained with `get_parameters` function. If `exact_match` is True, dictionary should contain keys for all model's parameters, otherwise RunTimeError is raised. If False, only variables included in the dictionary will be updated.

This does not load agent's hyper-parameters.

> **Warning:** This function does not update trainer/optimizer variables (e.g. momentum). As such training after using this function may lead to less-than-optimal results.

Parameters

- **load_path_or_dict** – (str or file-like or dict) Save parameter location or dict of parameters as variable.name -> ndarrays to be loaded.
- **exact_match** – (bool) If True, expects load dictionary to contain keys for all variables in the model. If False, loads parameters only for variables mentioned in the dictionary. Defaults to True.

predict (*observation*, *state=None*, *mask=None*, *deterministic=True*)
Get the model's action from an observation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray, np.ndarray) the model's action and the next state (used in recurrent policies)

pretrain (*dataset*, *n_epochs=10*, *learning_rate=0.0001*, *adam_epsilon=1e-08*, *val_interval=None*)
Pretrain a model using behavior cloning: supervised learning given an expert dataset.

NOTE: only Box and Discrete spaces are supported for now.

Parameters

- **dataset** – (ExpertDataset) Dataset manager
- **n_epochs** – (int) Number of iterations on the training set
- **learning_rate** – (float) Learning rate
- **adam_epsilon** – (float) the epsilon value for the adam optimizer

- **val_interval** – (int) Report training and validation losses every n epochs. By default, every 10th of the maximum number of epochs.

Returns (BaseRLModel) the pretrained model

replay_buffer_add(*obs_t*, *action*, *reward*, *obs_tp1*, *done*, *info*)
Add a new transition to the replay buffer

Parameters

- **obs_t** – (np.ndarray) the last observation
- **action** – ([float]) the action
- **reward** – (float) the reward of the transition
- **obs_tp1** – (np.ndarray) the new observation
- **done** – (bool) is the episode done
- **info** – (dict) extra values used to compute the reward when using HER

save(*save_path*, *cloudpickle=False*)
Save the current parameters to file

Parameters

- **save_path** – (str or file-like) The save location
- **cloudpickle** – (bool) Use older cloudpickle format instead of zip-archives.

set_env(*env*)
Checks the validity of the environment, and if it is coherent, set it as the current environment.

Parameters **env** – (Gym Environment) The environment for learning a policy

set_random_seed(*seed: Optional[int]*) → None

Parameters **seed** – (Optional[int]) Seed for the pseudo-random generators. If None, do not change the seeds.

setup_model()
Create all the functions and tensorflow graphs necessary to train the model

1.28.5 SAC Policies

class stable_baselines.sac.**MlpPolicy**(*sess*, *ob_space*, *ac_space*, *n_env=1*, *n_steps=1*, *n_batch=None*, *reuse=False*, ***_kwargs*)
Policy object that implements actor critic, using a MLP (2 layers of 64)

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

action_ph
tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state
The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete
bool: is action space discrete.

make_actor(*obs=None*, *reuse=False*, *scope='pi'*)
Creates an actor object

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name of the actor

Returns (TensorFlow Tensor) the output tensor

make_critics(*obs=None*, *action=None*, *reuse=False*, *scope='values_fn'*, *create_vf=True*, *create_qf=True*)
Creates the two Q-Values approximator along with the Value function

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **action** – (TensorFlow Tensor) The action placeholder
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name
- **create_vf** – (bool) Whether to create Value fn or not
- **create_qf** – (bool) Whether to create Q-Values fn or not

Returns ([tf.Tensor]) Mean, action and log probability

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step(*obs*, *state=None*, *mask=None*)
Returns the action probability params (mean, std) for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float], [float])

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step (*obs*, *state=None*, *mask=None*, *deterministic=False*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns ([float]) actions

class stable_baselines.sac.**LnMlpPolicy** (*sess*, *ob_space*, *ac_space*, *n_env=1*, *n_steps=1*, *n_batch=None*, *reuse=False*, ***_kwargs*)
Policy object that implements actor critic, using a MLP (2 layers of 64), with layer normalisation

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

action_ph
tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state
The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete
bool: is action space discrete.

make_actor (*obs=None*, *reuse=False*, *scope='pi'*)
Creates an actor object

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name of the actor

Returns (TensorFlow Tensor) the output tensor

make_critics (*obs=None*, *action=None*, *reuse=False*, *scope='values_fn'*, *create_vf=True*, *create_qf=True*)
Creates the two Q-Values approximator along with the Value function

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **action** – (TensorFlow Tensor) The action placeholder
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name
- **create_vf** – (bool) Whether to create Value fn or not
- **create_qf** – (bool) Whether to create Q-Values fn or not

Returns ([tf.Tensor]) Mean, action and log probability

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step (*obs*, *state=None*, *mask=None*)
Returns the action probability params (mean, std) for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float], [float])

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step (*obs*, *state=None*, *mask=None*, *deterministic=False*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns ([float]) actions

class stable_baselines.sac.**CnnPolicy** (*sess*, *ob_space*, *ac_space*, *n_env=1*, *n_steps=1*, *n_batch=None*, *reuse=False*, ***_kwargs*)
Policy object that implements actor critic, using a CNN (the nature CNN)

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)

- **reuse** – (bool) If the policy is reusable or not
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

action_ph
tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state
The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete
bool: is action space discrete.

make_actor(*obs=None*, *reuse=False*, *scope='pi'*)
Creates an actor object

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name of the actor

Returns (TensorFlow Tensor) the output tensor

make_critics(*obs=None*, *action=None*, *reuse=False*, *scope='values_fn'*, *create_vf=True*, *create_qf=True*)
Creates the two Q-Values approximator along with the Value function

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **action** – (TensorFlow Tensor) The action placeholder
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name
- **create_vf** – (bool) Whether to create Value fn or not
- **create_qf** – (bool) Whether to create Q-Values fn or not

Returns ([tf.Tensor]) Mean, action and log probability

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step(*obs*, *state=None*, *mask=None*)
Returns the action probability params (mean, std) for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float], [float])

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step(*obs*, *state=None*, *mask=None*, *deterministic=False*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns ([float]) actions

class stable_baselines.sac.**LnCnnPolicy**(*sess*, *ob_space*, *ac_space*, *n_env=1*, *n_steps=1*, *n_batch=None*, *reuse=False*, ***_kwargs*)
Policy object that implements actor critic, using a CNN (the nature CNN), with layer normalisation

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

action_ph
tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state
The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete
bool: is action space discrete.

make_actor(*obs=None*, *reuse=False*, *scope='pi'*)
Creates an actor object

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name of the actor

Returns (TensorFlow Tensor) the output tensor

make_critics(*obs=None, action=None, reuse=False, scope='values_fn', create_vf=True, create_qf=True*)
Creates the two Q-Values approximator along with the Value function

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **action** – (TensorFlow Tensor) The action placeholder
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name
- **create_vf** – (bool) Whether to create Value fn or not
- **create_qf** – (bool) Whether to create Q-Values fn or not

Returns ([tf.Tensor]) Mean, action and log probability

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step(*obs, state=None, mask=None*)
Returns the action probability params (mean, std) for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float], [float])

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step(*obs, state=None, mask=None, deterministic=False*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns ([float]) actions

1.28.6 Custom Policy Network

Similarly to the example given in the examples page. You can easily define a custom architecture for the policy network:

```python
import gym

from stable_baselines.sac.policies import FeedForwardPolicy
from stable_baselines.common.vec_env import DummyVecEnv
from stable_baselines import SAC

# Custom MLP policy of three layers of size 128 each
class CustomSACPolicy(FeedForwardPolicy):
    def __init__(self, *args, **kwargs):
        super(CustomSACPolicy, self).__init__(*args, **kwargs,
                                           layers=[128, 128, 128],
                                           layer_norm=False,
                                           feature_extraction="mlp")

# Create and wrap the environment
env = gym.make('Pendulum-v0')
env = DummyVecEnv([lambda: env])

model = SAC(CustomSACPolicy, env, verbose=1)
# Train the agent
model.learn(total_timesteps=100000)
```

1.28.7 Callbacks - Accessible Variables

Depending on initialization parameters and timestep, different variables are accessible. Variables accessible "From timestep X" are variables that can be accessed when `self.timestep==X` in the `on_step` function.

Variable	Availability
• self • total_timesteps • callback • log_interval • tb_log_name • reset_num_timesteps • replay_wrapper • new_tb_log • writer • current_lr • start_time • episode_rewards • episode_successes • obs • n_updates • infos_values • step • unscaled_action • action • new_obs • reward • done • info	From timestep 1
• obs_ • new_obs_ • reward_ • maybe_ep_info • mean_reward • num_episodes	From timestep 2
• mb_infos_vals • grad_step	After timestep train_freq steps
• frac	After timestep train_freq steps After at least batch_size and learning_starts steps
• maybe_is_success	After the first episode

1.29 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.

Warning: The TD3 model does not support `stable_baselines.common.policies` because it uses double q-values estimation, as a result it must use its own policy models (see *TD3 Policies*).

Available Policies

MlpPolicy	Policy object that implements actor critic, using a MLP (2 layers of 64)
LnMlpPolicy	Policy object that implements actor critic, using a MLP (2 layers of 64), with layer normalisation
CnnPolicy	Policy object that implements actor critic, using a CNN (the nature CNN)
LnCnnPolicy	Policy object that implements actor critic, using a CNN (the nature CNN), with layer normalisation

1.29.1 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

1.29.2 Can I use?

- Recurrent policies:
- Multi processing:
- Gym spaces:

Space	Action	Observation
Discrete		✓
Box	✓	✓
MultiDiscrete		✓
MultiBinary		✓

1.29.3 Example

```
import gym
import numpy as np

from stable_baselines import TD3
from stable_baselines.td3.policies import MlpPolicy
from stable_baselines.common.vec_env import DummyVecEnv
from stable_baselines.ddpg.noise import NormalActionNoise,␣
↪OrnsteinUhlenbeckActionNoise
```

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```
env = gym.make('Pendulum-v0')

# 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=50000, log_interval=10)
model.save("td3_pendulum")

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()
```

1.29.4 Parameters

class `stable_baselines.td3.`**`TD3`**(*policy, env, gamma=0.99, learning_rate=0.0003, buffer_size=50000, learning_starts=100, train_freq=100, gradient_steps=100, batch_size=128, tau=0.005, policy_delay=2, action_noise=None, target_policy_noise=0.2, target_noise_clip=0.5, random_exploration=0.0, verbose=0, tensorboard_log=None, _init_setup_model=True, policy_kwargs=None, full_tensorboard_log=False, seed=None, n_cpu_tf_sess=None*)

Twin Delayed DDPG (TD3) Addressing Function Approximation Error in Actor-Critic Methods.

Original implementation: https://github.com/sfujim/TD3 Paper: https://arxiv.org/pdf/1802.09477.pdf Introduction to TD3: https://spinningup.openai.com/en/latest/algorithms/td3.html

Parameters

- **policy** – (TD3Policy or str) The policy model to use (MlpPolicy, CnnPolicy, LnMlpPolicy, . . .)
- **env** – (Gym environment or str) The environment to learn from (if registered in Gym, can be str)
- **gamma** – (float) the discount factor
- **learning_rate** – (float or callable) learning rate for adam optimizer, the same learning rate will be used for all networks (Q-Values and Actor networks) it can be a function of the current progress (from 1 to 0)
- **buffer_size** – (int) size of the replay buffer
- **batch_size** – (int) Minibatch size for each gradient update
- **tau** – (float) the soft update coefficient ("polyak update" of the target networks, between 0 and 1)

- **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).
- **action_noise** – (ActionNoise) the action noise type. Cf DDPG for the different action noise type.
- **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.
- **train_freq** – (int) Update the model every *train_freq* steps.
- **learning_starts** – (int) how many steps of the model to collect transitions for before learning starts
- **gradient_steps** – (int) How many gradient update after each step
- **random_exploration** – (float) Probability of taking a random action (as in an epsilon-greedy strategy) This is not needed for TD3 normally but can help exploring when using HER + TD3. This hack was present in the original OpenAI Baselines repo (DDPG + HER)
- **verbose** – (int) the verbosity level: 0 none, 1 training information, 2 tensorflow debug
- **tensorboard_log** – (str) the log location for tensorboard (if None, no logging)
- **_init_setup_model** – (bool) Whether or not to build the network at the creation of the instance
- **policy_kwargs** – (dict) additional arguments to be passed to the policy on creation
- **full_tensorboard_log** – (bool) enable additional logging when using tensorboard Note: this has no effect on TD3 logging for now
- **seed** – (int) Seed for the pseudo-random generators (python, numpy, tensorflow). If None (default), use random seed. Note that if you want completely deterministic results, you must set *n_cpu_tf_sess* to 1.
- **n_cpu_tf_sess** – (int) The number of threads for TensorFlow operations If None, the number of cpu of the current machine will be used.

action_probability(*observation*, *state=None*, *mask=None*, *actions=None*, *logp=False*)

If `actions` is `None`, then get the model's action probability distribution from a given observation.

Depending on the action space the output is:

- Discrete: probability for each possible action
- Box: mean and standard deviation of the action output

However if `actions` is not `None`, this function will return the probability that the given actions are taken with the given parameters (observation, state, . . .) on this model. For discrete action spaces, it returns the probability mass; for continuous action spaces, the probability density. This is since the probability mass will always be zero in continuous spaces, see http://blog.christianperone.com/2019/01/ for a good explanation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)

- **actions** – (np.ndarray) (OPTIONAL) For calculating the likelihood that the given actions are chosen by the model for each of the given parameters. Must have the same number of actions and observations. (set to None to return the complete action probability distribution)
- **logp** – (bool) (OPTIONAL) When specified with actions, returns probability in log-space. This has no effect if actions is None.

Returns (np.ndarray) the model's (log) action probability

get_env()
returns the current environment (can be None if not defined)

Returns (Gym Environment) The current environment

get_parameter_list()
Get tensorflow Variables of model's parameters

This includes all variables necessary for continuing training (saving / loading).

Returns (list) List of tensorflow Variables

get_parameters()
Get current model parameters as dictionary of variable name -> ndarray.

Returns (OrderedDict) Dictionary of variable name -> ndarray of model's parameters.

get_vec_normalize_env() → Optional[stable_baselines.common.vec_env.vec_normalize.VecNormalize]
Return the `VecNormalize` wrapper of the training env if it exists.

Returns Optional[VecNormalize] The `VecNormalize` env.

is_using_her() → bool
Check if is using HER

Returns (bool) Whether is using HER or not

learn(*total_timesteps*, *callback=None*, *log_interval=4*, *tb_log_name='TD3'*, *reset_num_timesteps=True*, *replay_wrapper=None*)
Return a trained model.

Parameters

- **total_timesteps** – (int) The total number of samples to train on
- **callback** – (Union[callable, [callable], BaseCallback]) function called at every steps with state of the algorithm. It takes the local and global variables. If it returns False, training is aborted. When the callback inherits from BaseCallback, you will have access to additional stages of the training (training start/end), please read the documentation for more details.
- **log_interval** – (int) The number of timesteps before logging.
- **tb_log_name** – (str) the name of the run for tensorboard log
- **reset_num_timesteps** – (bool) whether or not to reset the current timestep number (used in logging)

Returns (BaseRLModel) the trained model

classmethod load(*load_path*, *env=None*, *custom_objects=None*, ***kwargs*)
Load the model from file

Parameters

- **load_path** – (str or file-like) the saved parameter location

- **env** – (Gym Environment) the new environment to run the loaded model on (can be None if you only need prediction from a trained model)
- **custom_objects** – (dict) 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.
- **kwargs** – extra arguments to change the model when loading

load_parameters (*load_path_or_dict*, *exact_match=True*)
Load model parameters from a file or a dictionary

Dictionary keys should be tensorflow variable names, which can be obtained with `get_parameters` function. If `exact_match` is True, dictionary should contain keys for all model's parameters, otherwise RunTimeError is raised. If False, only variables included in the dictionary will be updated.

This does not load agent's hyper-parameters.

> **Warning:** This function does not update trainer/optimizer variables (e.g. momentum). As such training after using this function may lead to less-than-optimal results.

Parameters

- **load_path_or_dict** – (str or file-like or dict) Save parameter location or dict of parameters as variable.name -> ndarrays to be loaded.
- **exact_match** – (bool) If True, expects load dictionary to contain keys for all variables in the model. If False, loads parameters only for variables mentioned in the dictionary. Defaults to True.

predict (*observation*, *state=None*, *mask=None*, *deterministic=True*)
Get the model's action from an observation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray, np.ndarray) the model's action and the next state (used in recurrent policies)

pretrain (*dataset*, *n_epochs=10*, *learning_rate=0.0001*, *adam_epsilon=1e-08*, *val_interval=None*)
Pretrain a model using behavior cloning: supervised learning given an expert dataset.

NOTE: only Box and Discrete spaces are supported for now.

Parameters

- **dataset** – (ExpertDataset) Dataset manager
- **n_epochs** – (int) Number of iterations on the training set
- **learning_rate** – (float) Learning rate
- **adam_epsilon** – (float) the epsilon value for the adam optimizer

- **val_interval** – (int) Report training and validation losses every n epochs. By default, every 10th of the maximum number of epochs.

Returns (BaseRLModel) the pretrained model

replay_buffer_add(*obs_t*, *action*, *reward*, *obs_tp1*, *done*, *info*)
Add a new transition to the replay buffer

Parameters

- **obs_t** – (np.ndarray) the last observation
- **action** – ([float]) the action
- **reward** – (float) the reward of the transition
- **obs_tp1** – (np.ndarray) the new observation
- **done** – (bool) is the episode done
- **info** – (dict) extra values used to compute the reward when using HER

save(*save_path*, *cloudpickle=False*)
Save the current parameters to file

Parameters

- **save_path** – (str or file-like) The save location
- **cloudpickle** – (bool) Use older cloudpickle format instead of zip-archives.

set_env(*env*)
Checks the validity of the environment, and if it is coherent, set it as the current environment.

Parameters **env** – (Gym Environment) The environment for learning a policy

set_random_seed(*seed: Optional[int]*) → None

Parameters **seed** – (Optional[int]) Seed for the pseudo-random generators. If None, do not change the seeds.

setup_model()
Create all the functions and tensorflow graphs necessary to train the model

1.29.5 TD3 Policies

class stable_baselines.td3.**MlpPolicy**(*sess*, *ob_space*, *ac_space*, *n_env=1*, *n_steps=1*, *n_batch=None*, *reuse=False*, ***_kwargs*)
Policy object that implements actor critic, using a MLP (2 layers of 64)

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

action_ph
tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state
The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete
bool: is action space discrete.

make_actor(*obs=None*, *reuse=False*, *scope='pi'*)
Creates an actor object

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name of the actor

Returns (TensorFlow Tensor) the output tensor

make_critics(*obs=None*, *action=None*, *reuse=False*, *scope='values_fn'*)
Creates the two Q-Values approximator

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **action** – (TensorFlow Tensor) The action placeholder
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name

Returns ([tf.Tensor]) Mean, action and log probability

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step(*obs*, *state=None*, *mask=None*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) actions

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step(*obs*, *state=None*, *mask=None*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) actions

class stable_baselines.td3.**LnMlpPolicy**(*sess*, *ob_space*, *ac_space*, *n_env=1*, *n_steps=1*, *n_batch=None*, *reuse=False*, ***_kwargs*)

Policy object that implements actor critic, using a MLP (2 layers of 64), with layer normalisation

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

action_ph

tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state

The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete

bool: is action space discrete.

make_actor(*obs=None*, *reuse=False*, *scope='pi'*)

Creates an actor object

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name of the actor

Returns (TensorFlow Tensor) the output tensor

make_critics(*obs=None*, *action=None*, *reuse=False*, *scope='values_fn'*)

Creates the two Q-Values approximator

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **action** – (TensorFlow Tensor) The action placeholder
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name

Returns ([tf.Tensor]) Mean, action and log probability

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step (*obs*, *state=None*, *mask=None*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) actions

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step (*obs*, *state=None*, *mask=None*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) actions

class stable_baselines.td3.**CnnPolicy** (*sess*, *ob_space*, *ac_space*, *n_env=1*, *n_steps=1*, *n_batch=None*, *reuse=False*, ***_kwargs*)
Policy object that implements actor critic, using a CNN (the nature CNN)

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

action_ph
tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state
The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete
bool: is action space discrete.

make_actor (*obs=None*, *reuse=False*, *scope='pi'*)
Creates an actor object

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name of the actor

Returns (TensorFlow Tensor) the output tensor

make_critics (*obs=None*, *action=None*, *reuse=False*, *scope='values_fn'*)
Creates the two Q-Values approximator

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **action** – (TensorFlow Tensor) The action placeholder
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name

Returns ([tf.Tensor]) Mean, action and log probability

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step (*obs*, *state=None*, *mask=None*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) actions

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step (*obs*, *state=None*, *mask=None*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) actions

class stable_baselines.td3.**LnCnnPolicy** (*sess*, *ob_space*, *ac_space*, *n_env=1*, *n_steps=1*, *n_batch=None*, *reuse=False*, ***_kwargs*)
Policy object that implements actor critic, using a CNN (the nature CNN), with layer normalisation

Parameters

- **sess** – (TensorFlow session) The current TensorFlow session
- **ob_space** – (Gym Space) The observation space of the environment
- **ac_space** – (Gym Space) The action space of the environment
- **n_env** – (int) The number of environments to run
- **n_steps** – (int) The number of steps to run for each environment
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **reuse** – (bool) If the policy is reusable or not
- **_kwargs** – (dict) Extra keyword arguments for the nature CNN feature extraction

action_ph
tf.Tensor: placeholder for actions, shape (self.n_batch,) + self.ac_space.shape.

initial_state
The initial state of the policy. For feedforward policies, None. For a recurrent policy, a NumPy array of shape (self.n_env,) + state_shape.

is_discrete
bool: is action space discrete.

make_actor(*obs=None*, *reuse=False*, *scope='pi'*)
Creates an actor object

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name of the actor

Returns (TensorFlow Tensor) the output tensor

make_critics(*obs=None*, *action=None*, *reuse=False*, *scope='values_fn'*)
Creates the two Q-Values approximator

Parameters

- **obs** – (TensorFlow Tensor) The observation placeholder (can be None for default placeholder)
- **action** – (TensorFlow Tensor) The action placeholder
- **reuse** – (bool) whether or not to reuse parameters
- **scope** – (str) the scope name

Returns ([tf.Tensor]) Mean, action and log probability

obs_ph
tf.Tensor: placeholder for observations, shape (self.n_batch,) + self.ob_space.shape.

proba_step(*obs*, *state=None*, *mask=None*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment

- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) actions

processed_obs
tf.Tensor: processed observations, shape (self.n_batch,) + self.ob_space.shape.

The form of processing depends on the type of the observation space, and the parameters whether scale is passed to the constructor; see observation_input for more information.

step (*obs*, *state=None*, *mask=None*)
Returns the policy for a single step

Parameters

- **obs** – ([float] or [int]) The current observation of the environment
- **state** – ([float]) The last states (used in recurrent policies)
- **mask** – ([float]) The last masks (used in recurrent policies)

Returns ([float]) actions

1.29.6 Custom Policy Network

Similarly to the example given in the examples page. You can easily define a custom architecture for the policy network:

```
import gym
import numpy as np

from stable_baselines import TD3
from stable_baselines.td3.policies import FeedForwardPolicy
from stable_baselines.common.vec_env import DummyVecEnv
from stable_baselines.ddpg.noise import NormalActionNoise,␣
↪OrnsteinUhlenbeckActionNoise

# Custom MLP policy with two layers
class CustomTD3Policy(FeedForwardPolicy):
    def __init__(self, *args, **kwargs):
        super(CustomTD3Policy, self).__init__(*args, **kwargs,
                                              layers=[400, 300],
                                              layer_norm=False,
                                              feature_extraction="mlp")

# Create and wrap the environment
env = gym.make('Pendulum-v0')
env = DummyVecEnv([lambda: env])

# 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(CustomTD3Policy, env, action_noise=action_noise, verbose=1)
# Train the agent
model.learn(total_timesteps=80000)
```

1.29.7 Callbacks - Accessible Variables

Depending on initialization parameters and timestep, different variables are accessible. Variables accessible "From timestep X" are variables that can be accessed when `self.timestep==X` in the `on_step` function.

Variable	Availability
• self • total_timesteps • callback • log_interval • tb_log_name • reset_num_timesteps • replay_wrapper • new_tb_log • writer • current_lr • start_time • episode_rewards • episode_successes • obs • n_updates • infos_values • step • unscaled_action • action • new_obs • reward • done • info	From timestep 1
• obs_ • new_obs_ • reward_ • maybe_ep_info • mean_reward • num_episodes	From timestep 2
• mb_infos_vals • grad_step	After timestep train_freq steps
• frac	After timestep train_freq steps After at least batch_size and learning_starts steps
• maybe_is_success	After the first episode

1.30 TRPO

Trust Region Policy Optimization (TRPO) is an iterative approach for optimizing policies with guaranteed monotonic improvement.

Note: TRPO requires *OpenMPI*. If OpenMPI isn't enabled, then TRPO isn't imported into the `stable_baselines` module.

1.30.1 Notes

- Original paper: https://arxiv.org/abs/1502.05477
- OpenAI blog post: https://blog.openai.com/openai-baselines-ppo/
- `mpirun -np 16 python -m stable_baselines.trpo_mpi.run_atari` runs the algorithm for 40M frames = 10M timesteps on an Atari game. See help (`-h`) for more options.
- `python -m stable_baselines.trpo_mpi.run_mujoco` runs the algorithm for 1M timesteps on a Mujoco environment.

1.30.2 Can I use?

- Recurrent policies:
- Multi processing: ✓ (using MPI)
- Gym spaces:

Space	Action	Observation
Discrete	✓	✓
Box	✓	✓
MultiDiscrete	✓	✓
MultiBinary	✓	✓

1.30.3 Example

```
import gym

from stable_baselines.common.policies import MlpPolicy
from stable_baselines import TRPO

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

model = TRPO(MlpPolicy, env, verbose=1)
model.learn(total_timesteps=25000)
model.save("trpo_cartpole")

del model # remove to demonstrate saving and loading

model = TRPO.load("trpo_cartpole")
```

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

1.30.4 Parameters

class stable_baselines.trpo_mpi.**TRPO**(*policy, env, gamma=0.99, timesteps_per_batch=1024, max_kl=0.01, cg_iters=10, lam=0.98, entcoeff=0.0, cg_damping=0.01, vf_stepsize=0.0003, vf_iters=3, verbose=0, tensorboard_log=None, _init_setup_model=True, policy_kwargs=None, full_tensorboard_log=False, seed=None, n_cpu_tf_sess=1*)

Trust Region Policy Optimization (https://arxiv.org/abs/1502.05477)

Parameters

- **policy** – (ActorCriticPolicy or str) The policy model to use (MlpPolicy, CnnPolicy, CnnLstmPolicy, . . .)
- **env** – (Gym environment or str) The environment to learn from (if registered in Gym, can be str)
- **gamma** – (float) the discount value
- **timesteps_per_batch** – (int) the number of timesteps to run per batch (horizon)
- **max_kl** – (float) the Kullback-Leibler loss threshold
- **cg_iters** – (int) the number of iterations for the conjugate gradient calculation
- **lam** – (float) GAE factor
- **entcoeff** – (float) the weight for the entropy loss
- **cg_damping** – (float) the compute gradient dampening factor
- **vf_stepsize** – (float) the value function stepsize
- **vf_iters** – (int) the value function's number iterations for learning
- **verbose** – (int) the verbosity level: 0 none, 1 training information, 2 tensorflow debug
- **tensorboard_log** – (str) the log location for tensorboard (if None, no logging)
- **_init_setup_model** – (bool) Whether or not to build the network at the creation of the instance
- **policy_kwargs** – (dict) additional arguments to be passed to the policy on creation
- **full_tensorboard_log** – (bool) enable additional logging when using tensorboard WARNING: this logging can take a lot of space quickly
- **seed** – (int) Seed for the pseudo-random generators (python, numpy, tensorflow). If None (default), use random seed. Note that if you want completely deterministic results, you must set *n_cpu_tf_sess* to 1.
- **n_cpu_tf_sess** – (int) The number of threads for TensorFlow operations If None, the number of cpu of the current machine will be used.

action_probability(*observation*, *state=None*, *mask=None*, *actions=None*, *logp=False*)
If `actions` is `None`, then get the model's action probability distribution from a given observation.

Depending on the action space the output is:

- Discrete: probability for each possible action
- Box: mean and standard deviation of the action output

However if `actions` is not `None`, this function will return the probability that the given actions are taken with the given parameters (observation, state, …) on this model. For discrete action spaces, it returns the probability mass; for continuous action spaces, the probability density. This is since the probability mass will always be zero in continuous spaces, see http://blog.christianperone.com/2019/01/ for a good explanation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **actions** – (np.ndarray) (OPTIONAL) For calculating the likelihood that the given actions are chosen by the model for each of the given parameters. Must have the same number of actions and observations. (set to None to return the complete action probability distribution)
- **logp** – (bool) (OPTIONAL) When specified with actions, returns probability in log-space. This has no effect if actions is None.

Returns (np.ndarray) the model's (log) action probability

get_env()
returns the current environment (can be None if not defined)

Returns (Gym Environment) The current environment

get_parameter_list()
Get tensorflow Variables of model's parameters

This includes all variables necessary for continuing training (saving / loading).

Returns (list) List of tensorflow Variables

get_parameters()
Get current model parameters as dictionary of variable name -> ndarray.

Returns (OrderedDict) Dictionary of variable name -> ndarray of model's parameters.

get_vec_normalize_env() → Optional[stable_baselines.common.vec_env.vec_normalize.VecNormalize]
Return the `VecNormalize` wrapper of the training env if it exists.

Returns Optional[VecNormalize] The `VecNormalize` env.

learn(*total_timesteps*, *callback=None*, *log_interval=100*, *tb_log_name='TRPO'*, *reset_num_timesteps=True*)
Return a trained model.

Parameters

- **total_timesteps** – (int) The total number of samples to train on
- **callback** – (Union[callable, [callable], BaseCallback]) function called at every steps with state of the algorithm. It takes the local and global variables. If it returns False, training is aborted. When the callback inherits from BaseCallback, you will have access

to additional stages of the training (training start/end), please read the documentation for more details.

- **log_interval** – (int) The number of timesteps before logging.
- **tb_log_name** – (str) the name of the run for tensorboard log
- **reset_num_timesteps** – (bool) whether or not to reset the current timestep number (used in logging)

Returns (BaseRLModel) the trained model

classmethod load(*load_path*, *env=None*, *custom_objects=None*, ***kwargs*)
Load the model from file

Parameters

- **load_path** – (str or file-like) the saved parameter location
- **env** – (Gym Environment) the new environment to run the loaded model on (can be None if you only need prediction from a trained model)
- **custom_objects** – (dict) 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.
- **kwargs** – extra arguments to change the model when loading

load_parameters(*load_path_or_dict*, *exact_match=True*)
Load model parameters from a file or a dictionary

Dictionary keys should be tensorflow variable names, which can be obtained with `get_parameters` function. If `exact_match` is True, dictionary should contain keys for all model's parameters, otherwise RunTimeError is raised. If False, only variables included in the dictionary will be updated.

This does not load agent's hyper-parameters.

Warning: This function does not update trainer/optimizer variables (e.g. momentum). As such training after using this function may lead to less-than-optimal results.

Parameters

- **load_path_or_dict** – (str or file-like or dict) Save parameter location or dict of parameters as variable.name -> ndarrays to be loaded.
- **exact_match** – (bool) If True, expects load dictionary to contain keys for all variables in the model. If False, loads parameters only for variables mentioned in the dictionary. Defaults to True.

predict(*observation*, *state=None*, *mask=None*, *deterministic=False*)
Get the model's action from an observation

Parameters

- **observation** – (np.ndarray) the input observation
- **state** – (np.ndarray) The last states (can be None, used in recurrent policies)
- **mask** – (np.ndarray) The last masks (can be None, used in recurrent policies)
- **deterministic** – (bool) Whether or not to return deterministic actions.

Returns (np.ndarray, np.ndarray) the model's action and the next state (used in recurrent policies)

pretrain(*dataset*, *n_epochs=10*, *learning_rate=0.0001*, *adam_epsilon=1e-08*, *val_interval=None*)
Pretrain a model using behavior cloning: supervised learning given an expert dataset.

NOTE: only Box and Discrete spaces are supported for now.

Parameters

- **dataset** – (ExpertDataset) Dataset manager
- **n_epochs** – (int) Number of iterations on the training set
- **learning_rate** – (float) Learning rate
- **adam_epsilon** – (float) the epsilon value for the adam optimizer
- **val_interval** – (int) Report training and validation losses every n epochs. By default, every 10th of the maximum number of epochs.

Returns (BaseRLModel) the pretrained model

save(*save_path*, *cloudpickle=False*)
Save the current parameters to file

Parameters

- **save_path** – (str or file-like) The save location
- **cloudpickle** – (bool) Use older cloudpickle format instead of zip-archives.

set_env(*env*)
Checks the validity of the environment, and if it is coherent, set it as the current environment.

Parameters env – (Gym Environment) The environment for learning a policy

set_random_seed(*seed: Optional[int]*) → None

Parameters seed – (Optional[int]) Seed for the pseudo-random generators. If None, do not change the seeds.

setup_model()
Create all the functions and tensorflow graphs necessary to train the model

1.30.5 Callbacks - Accessible Variables

Depending on initialization parameters and timestep, different variables are accessible. Variables accessible "From timestep X" are variables that can be accessed when `self.timestep==X` in the `on_step` function.

Variable	Availability
• total_timesteps • callback • log_interval • tb_log_name • reset_num_timesteps • new_tb_log • writer • self • policy • env • horizon • reward_giver • gail • step • cur_ep_ret • current_it_len • current_ep_len • cur_ep_true_ret • ep_true_rets • ep_rets • ep_lens • observations • true_rewards • rewards • vpreds • episode_starts • dones • actions • states • episode_start • done • vpred • clipped_action • reward • true_reward • info • action • observation • maybe_ep_info	From timestep 0

1.31 Probability Distributions

Probability distributions used for the different action spaces:

- `CategoricalProbabilityDistribution` -> Discrete
- `DiagGaussianProbabilityDistribution` -> Box (continuous actions)
- `MultiCategoricalProbabilityDistribution` -> MultiDiscrete
- `BernoulliProbabilityDistribution` -> MultiBinary

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 `CategoricalProbabilityDistribution` allows to sample from it, computes the entropy, the negative log probability (`neglogp`) 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 `DiagGaussianProbabilityDistribution`).

class `stable_baselines.common.distributions.`**`BernoulliProbabilityDistribution`**(*logits*)

`entropy`()
Returns Shannon's entropy of the probability

Returns (float) the entropy

`flatparam`()
Return the direct probabilities

Returns ([float]) the probabilities

classmethod `fromflat`(*flat*)
Create an instance of this from new Bernoulli input

Parameters **`flat`** – ([float]) the Bernoulli input data

Returns (ProbabilityDistribution) the instance from the given Bernoulli input data

`kl`(*other*)
Calculates the Kullback-Leibler divergence from the given probability distribution

Parameters **`other`** – ([float]) the distribution to compare with

Returns (float) the KL divergence of the two distributions

`mode`()
Returns the probability

Returns (Tensorflow Tensor) the deterministic action

`neglogp`(*x*)
returns the of the negative log likelihood

Parameters **`x`** – (str) the labels of each index

Returns ([float]) The negative log likelihood of the distribution

`sample`()
returns a sample from the probability distribution

Returns (Tensorflow Tensor) the stochastic action

class `stable_baselines.common.distributions.`**`BernoulliProbabilityDistributionType`**(*size*)

`param_shape`()
returns the shape of the input parameters

Returns ([int]) the shape

`proba_distribution_from_latent`(*pi_latent_vector*, *vf_latent_vector*, *init_scale=1.0*, *init_bias=0.0*)
returns the probability distribution from latent values

Parameters

- **pi_latent_vector** – ([float]) the latent pi values
- **vf_latent_vector** – ([float]) the latent vf values
- **init_scale** – (float) the initial scale of the distribution
- **init_bias** – (float) the initial bias of the distribution

Returns (ProbabilityDistribution) the instance of the ProbabilityDistribution associated

probability_distribution_class()
returns the ProbabilityDistribution class of this type

Returns (Type ProbabilityDistribution) the probability distribution class associated

sample_dtype()
returns the type of the sampling

Returns (type) the type

sample_shape()
returns the shape of the sampling

Returns ([int]) the shape

class stable_baselines.common.distributions.**CategoricalProbabilityDistribution**(*logits*)

entropy()
Returns Shannon's entropy of the probability

Returns (float) the entropy

flatparam()
Return the direct probabilities

Returns ([float]) the probabilities

classmethod fromflat(*flat*)
Create an instance of this from new logits values

Parameters **flat** – ([float]) the categorical logits input

Returns (ProbabilityDistribution) the instance from the given categorical input

kl(*other*)
Calculates the Kullback-Leibler divergence from the given probability distribution

Parameters **other** – ([float]) the distribution to compare with

Returns (float) the KL divergence of the two distributions

mode()
Returns the probability

Returns (Tensorflow Tensor) the deterministic action

neglogp(*x*)
returns the of the negative log likelihood

Parameters **x** – (str) the labels of each index

Returns ([float]) The negative log likelihood of the distribution

sample()
returns a sample from the probability distribution

Returns (Tensorflow Tensor) the stochastic action

class stable_baselines.common.distributions.**CategoricalProbabilityDistributionType**(*n_cat*)

param_shape()
returns the shape of the input parameters

Returns ([int]) the shape

proba_distribution_from_latent(*pi_latent_vector*, *vf_latent_vector*, *init_scale=1.0*, *init_bias=0.0*)
returns the probability distribution from latent values

Parameters

- **pi_latent_vector** – ([float]) the latent pi values
- **vf_latent_vector** – ([float]) the latent vf values
- **init_scale** – (float) the initial scale of the distribution
- **init_bias** – (float) the initial bias of the distribution

Returns (ProbabilityDistribution) the instance of the ProbabilityDistribution associated

probability_distribution_class()
returns the ProbabilityDistribution class of this type

Returns (Type ProbabilityDistribution) the probability distribution class associated

sample_dtype()
returns the type of the sampling

Returns (type) the type

sample_shape()
returns the shape of the sampling

Returns ([int]) the shape

class stable_baselines.common.distributions.**DiagGaussianProbabilityDistribution**(*flat*)

entropy()
Returns Shannon's entropy of the probability

Returns (float) the entropy

flatparam()
Return the direct probabilities

Returns ([float]) the probabilities

classmethod fromflat(*flat*)
Create an instance of this from new multivariate Gaussian input

Parameters flat – ([float]) the multivariate Gaussian input data

Returns (ProbabilityDistribution) the instance from the given multivariate Gaussian input data

kl(*other*)
Calculates the Kullback-Leibler divergence from the given probability distribution

Parameters other – ([float]) the distribution to compare with

Returns (float) the KL divergence of the two distributions

mode()
Returns the probability

Returns (Tensorflow Tensor) the deterministic action

neglogp(*x*)
returns the of the negative log likelihood

Parameters **x** – (str) the labels of each index

Returns ([float]) The negative log likelihood of the distribution

sample()
returns a sample from the probability distribution

Returns (Tensorflow Tensor) the stochastic action

class stable_baselines.common.distributions.**DiagGaussianProbabilityDistributionType**(*size*)

param_shape()
returns the shape of the input parameters

Returns ([int]) the shape

proba_distribution_from_flat(*flat*)
returns the probability distribution from flat probabilities

Parameters **flat** – ([float]) the flat probabilities

Returns (ProbabilityDistribution) the instance of the ProbabilityDistribution associated

proba_distribution_from_latent(*pi_latent_vector*, *vf_latent_vector*, *init_scale=1.0*, *init_bias=0.0*)
returns the probability distribution from latent values

Parameters

- **pi_latent_vector** – ([float]) the latent pi values
- **vf_latent_vector** – ([float]) the latent vf values
- **init_scale** – (float) the initial scale of the distribution
- **init_bias** – (float) the initial bias of the distribution

Returns (ProbabilityDistribution) the instance of the ProbabilityDistribution associated

probability_distribution_class()
returns the ProbabilityDistribution class of this type

Returns (Type ProbabilityDistribution) the probability distribution class associated

sample_dtype()
returns the type of the sampling

Returns (type) the type

sample_shape()
returns the shape of the sampling

Returns ([int]) the shape

class stable_baselines.common.distributions.**MultiCategoricalProbabilityDistribution**(*nvec*, *flat*)

entropy()
Returns Shannon's entropy of the probability

Returns (float) the entropy

flatparam()
Return the direct probabilities

Returns ([float]) the probabilities

classmethod fromflat(*flat*)
Create an instance of this from new logits values

Parameters **flat** – ([float]) the multi categorical logits input

Returns (ProbabilityDistribution) the instance from the given multi categorical input

kl(*other*)
Calculates the Kullback-Leibler divergence from the given probability distribution

Parameters **other** – ([float]) the distribution to compare with

Returns (float) the KL divergence of the two distributions

mode()
Returns the probability

Returns (Tensorflow Tensor) the deterministic action

neglogp(*x*)
returns the of the negative log likelihood

Parameters **x** – (str) the labels of each index

Returns ([float]) The negative log likelihood of the distribution

sample()
returns a sample from the probability distribution

Returns (Tensorflow Tensor) the stochastic action

class stable_baselines.common.distributions.**MultiCategoricalProbabilityDistributionType**(*n_v*

param_shape()
returns the shape of the input parameters

Returns ([int]) the shape

proba_distribution_from_flat(*flat*)
Returns the probability distribution from flat probabilities flat: flattened vector of parameters of probability distribution

Parameters **flat** – ([float]) the flat probabilities

Returns (ProbabilityDistribution) the instance of the ProbabilityDistribution associated

proba_distribution_from_latent(*pi_latent_vector*, *vf_latent_vector*, *init_scale=1.0*, *init_bias=0.0*)
returns the probability distribution from latent values

Parameters

- **pi_latent_vector** – ([float]) the latent pi values
- **vf_latent_vector** – ([float]) the latent vf values
- **init_scale** – (float) the initial scale of the distribution
- **init_bias** – (float) the initial bias of the distribution

Returns (ProbabilityDistribution) the instance of the ProbabilityDistribution associated

probability_distribution_class()
returns the ProbabilityDistribution class of this type

Returns (Type ProbabilityDistribution) the probability distribution class associated

sample_dtype()
returns the type of the sampling

Returns (type) the type

sample_shape()
returns the shape of the sampling

Returns ([int]) the shape

class stable_baselines.common.distributions.**ProbabilityDistribution**
Base class for describing a probability distribution.

entropy()
Returns Shannon's entropy of the probability

Returns (float) the entropy

flatparam()
Return the direct probabilities

Returns ([float]) the probabilities

kl(*other*)
Calculates the Kullback-Leibler divergence from the given probability distribution

Parameters **other** – ([float]) the distribution to compare with

Returns (float) the KL divergence of the two distributions

logp(*x*)
returns the of the log likelihood

Parameters **x** – (str) the labels of each index

Returns ([float]) The log likelihood of the distribution

mode()
Returns the probability

Returns (Tensorflow Tensor) the deterministic action

neglogp(*x*)
returns the of the negative log likelihood

Parameters **x** – (str) the labels of each index

Returns ([float]) The negative log likelihood of the distribution

sample()
returns a sample from the probability distribution

Returns (Tensorflow Tensor) the stochastic action

class stable_baselines.common.distributions.**ProbabilityDistributionType**
Parametrized family of probability distributions

param_placeholder(*prepend_shape*, *name=None*)
returns the TensorFlow placeholder for the input parameters

Parameters

- **prepend_shape** – ([int]) the prepend shape
- **name** – (str) the placeholder name

Returns (TensorFlow Tensor) the placeholder

param_shape()
returns the shape of the input parameters

Returns ([int]) the shape

proba_distribution_from_flat(*flat*)
Returns the probability distribution from flat probabilities flat: flattened vector of parameters of probability distribution

Parameters **flat** – ([float]) the flat probabilities

Returns (ProbabilityDistribution) the instance of the ProbabilityDistribution associated

proba_distribution_from_latent(*pi_latent_vector*, *vf_latent_vector*, *init_scale=1.0*, *init_bias=0.0*)
returns the probability distribution from latent values

Parameters

- **pi_latent_vector** – ([float]) the latent pi values
- **vf_latent_vector** – ([float]) the latent vf values
- **init_scale** – (float) the initial scale of the distribution
- **init_bias** – (float) the initial bias of the distribution

Returns (ProbabilityDistribution) the instance of the ProbabilityDistribution associated

probability_distribution_class()
returns the ProbabilityDistribution class of this type

Returns (Type ProbabilityDistribution) the probability distribution class associated

sample_dtype()
returns the type of the sampling

Returns (type) the type

sample_placeholder(*prepend_shape*, *name=None*)
returns the TensorFlow placeholder for the sampling

Parameters

- **prepend_shape** – ([int]) the prepend shape
- **name** – (str) the placeholder name

Returns (TensorFlow Tensor) the placeholder

sample_shape()
returns the shape of the sampling

Returns ([int]) the shape

stable_baselines.common.distributions.**make_proba_dist_type**(*ac_space*)
return an instance of ProbabilityDistributionType for the correct type of action space

Parameters **ac_space** – (Gym Space) the input action space

Returns (ProbabilityDistributionType) the appropriate instance of a ProbabilityDistributionType

stable_baselines.common.distributions.**shape_el**(*tensor*, *index*)
get the shape of a TensorFlow Tensor element

Parameters

- **tensor** – (TensorFlow Tensor) the input tensor
- **index** – (int) the element

Returns ([int]) the shape

1.32 Tensorflow Utils

stable_baselines.common.tf_util.**avg_norm**(*tensor*)
Return an average of the L2 normalization of the batch

Parameters **tensor** – (TensorFlow Tensor) The input tensor

Returns (TensorFlow Tensor) Average L2 normalization of the batch

stable_baselines.common.tf_util.**batch_to_seq**(*tensor_batch*, *n_batch*, *n_steps*, *flat=False*)
Transform a batch of Tensors, into a sequence of Tensors for recurrent policies

Parameters

- **tensor_batch** – (TensorFlow Tensor) The input tensor to unroll
- **n_batch** – (int) The number of batch to run (n_envs * n_steps)
- **n_steps** – (int) The number of steps to run for each environment
- **flat** – (bool) If the input Tensor is flat

Returns (TensorFlow Tensor) sequence of Tensors for recurrent policies

stable_baselines.common.tf_util.**calc_entropy**(*logits*)
Calculates the entropy of the output values of the network

Parameters **logits** – (TensorFlow Tensor) The input probability for each action

Returns (TensorFlow Tensor) The Entropy of the output values of the network

stable_baselines.common.tf_util.**check_shape**(*tensors*, *shapes*)
Verifies the tensors match the given shape, will raise an error if the shapes do not match

Parameters

- **tensors** – ([TensorFlow Tensor]) The tensors that should be checked
- **shapes** – ([list]) The list of shapes for each tensor

stable_baselines.common.tf_util.**flatgrad**(*loss*, *var_list*, *clip_norm=None*)
calculates the gradient and flattens it

Parameters

- **loss** – (float) the loss value
- **var_list** – ([TensorFlow Tensor]) the variables
- **clip_norm** – (float) clip the gradients (disabled if None)

Returns ([TensorFlow Tensor]) flattened gradient stable_baselines.common.tf_util.**function**(*inputs*, *outputs*, *updates=None*, *givens=None*)

Take a bunch of tensorflow placeholders and expressions computed based on those placeholders and produces f(inputs) -> outputs. Function f takes values to be fed to the input's placeholders and produces the values of the expressions in outputs. Just like a Theano function.

Input values can be passed in the same order as inputs or can be provided as kwargs based on placeholder name (passed to constructor or accessible via placeholder.op.name).

Example:

```
>>> x = tf.placeholder(tf.int32, (), name="x")
>>> y = tf.placeholder(tf.int32, (), name="y")
>>> z = 3 * x + 2 * y
>>> lin = function([x, y], z, givens={y: 0})
>>> with single_threaded_session():
>>>     initialize()
>>>     assert lin(2) == 6
>>>     assert lin(x=3) == 9
>>>     assert lin(2, 2) == 10
```

Parameters

- **inputs** – (TensorFlow Tensor or Object with make_feed_dict) list of input arguments
- **outputs** – (TensorFlow Tensor) list of outputs or a single output to be returned from function. Returned value will also have the same shape.
- **updates** – ([tf.Operation] or tf.Operation) list of update functions or single update function that will be run whenever the function is called. The return is ignored.
- **givens** – (dict) the values known for the output

stable_baselines.common.tf_util.**get_globals_vars**(*name*)

returns the trainable variables

Parameters name – (str) the scope

Returns ([TensorFlow Variable])

stable_baselines.common.tf_util.**get_trainable_vars**(*name*)

returns the trainable variables

Parameters name – (str) the scope

Returns ([TensorFlow Variable])

stable_baselines.common.tf_util.**gradient_add**(*grad_1*, *grad_2*, *param*, *verbose=0*)

Sum two gradients

Parameters

- **grad_1** – (TensorFlow Tensor) The first gradient
- **grad_2** – (TensorFlow Tensor) The second gradient
- **param** – (TensorFlow parameters) The trainable parameters
- **verbose** – (int) verbosity level

Returns (TensorFlow Tensor) the sum of the gradients

stable_baselines.common.tf_util.**huber_loss**(*tensor*, *delta=1.0*)

Reference: https://en.wikipedia.org/wiki/Huber_loss

Parameters

- **tensor** – (TensorFlow Tensor) the input value
- **delta** – (float) Huber loss delta value

Returns (TensorFlow Tensor) Huber loss output

`stable_baselines.common.tf_util.`**`in_session`**(*func*)
Wraps a function so that it is in a TensorFlow Session

Parameters **func** – (function) the function to wrap

Returns (function)

`stable_baselines.common.tf_util.`**`initialize`**(*sess=None*)
Initialize all the uninitialized variables in the global scope.

Parameters **sess** – (TensorFlow Session)

`stable_baselines.common.tf_util.`**`intprod`**(*tensor*)
calculates the product of all the elements in a list

Parameters **tensor** – ([Number]) the list of elements

Returns (int) the product truncated

`stable_baselines.common.tf_util.`**`is_image`**(*tensor*)
Check if a tensor has the shape of a valid image for tensorboard logging. Valid image: RGB, RGBD, GrayScale

Parameters **tensor** – (np.ndarray or tf.placeholder)

Returns (bool)

`stable_baselines.common.tf_util.`**`make_session`**(*num_cpu=None*, *make_default=False*, *graph=None*)
Returns a session that will use <num_cpu> CPU's only

Parameters

- **num_cpu** – (int) number of CPUs to use for TensorFlow
- **make_default** – (bool) if this should return an InteractiveSession or a normal Session
- **graph** – (TensorFlow Graph) the graph of the session

Returns (TensorFlow session)

`stable_baselines.common.tf_util.`**`mse`**(*pred*, *target*)
Returns the Mean squared error between prediction and target

Parameters

- **pred** – (TensorFlow Tensor) The predicted value
- **target** – (TensorFlow Tensor) The target value

Returns (TensorFlow Tensor) The Mean squared error between prediction and target

`stable_baselines.common.tf_util.`**`numel`**(*tensor*)
get TensorFlow Tensor's number of elements

Parameters **tensor** – (TensorFlow Tensor) the input tensor

Returns (int) the number of elements

`stable_baselines.common.tf_util.`**`outer_scope_getter`**(*scope*, *new_scope=''*)
remove a scope layer for the getter

Parameters

- **scope** – (str) the layer to remove
- **new_scope** – (str) optional replacement name

Returns (function (function, str, *args, **kwargs): Tensorflow Tensor)

`stable_baselines.common.tf_util.`**`q_explained_variance`**(*q_pred*, *q_true*)

Calculates the explained variance of the Q value

Parameters

- **q_pred** – (TensorFlow Tensor) The predicted Q value
- **q_true** – (TensorFlow Tensor) The expected Q value

Returns (TensorFlow Tensor) the explained variance of the Q value

`stable_baselines.common.tf_util.`**`sample`**(*logits*)

Creates a sampling Tensor for non deterministic policies when using categorical distribution. It uses the Gumbel-max trick: http://amid.fish/humble-gumbel

Parameters **logits** – (TensorFlow Tensor) The input probability for each action

Returns (TensorFlow Tensor) The sampled action

`stable_baselines.common.tf_util.`**`seq_to_batch`**(*tensor_sequence*, *flat=False*)

Transform a sequence of Tensors, into a batch of Tensors for recurrent policies

Parameters

- **tensor_sequence** – (TensorFlow Tensor) The input tensor to batch
- **flat** – (bool) If the input Tensor is flat

Returns (TensorFlow Tensor) batch of Tensors for recurrent policies

`stable_baselines.common.tf_util.`**`single_threaded_session`**(*make_default=False*, *graph=None*)

Returns a session which will only use a single CPU

Parameters

- **make_default** – (bool) if this should return an InteractiveSession or a normal Session
- **graph** – (TensorFlow Graph) the graph of the session

Returns (TensorFlow session)

`stable_baselines.common.tf_util.`**`total_episode_reward_logger`**(*rew_acc*, *rewards*, *masks*, *writer*, *steps*)

calculates the cumulated episode reward, and prints to tensorflow log the output

Parameters

- **rew_acc** – (np.array float) the total running reward
- **rewards** – (np.array float) the rewards
- **masks** – (np.array bool) the end of episodes
- **writer** – (TensorFlow Session.writer) the writer to log to
- **steps** – (int) the current timestep

Returns (np.array float) the updated total running reward

Returns (np.array float) the updated total running reward `stable_baselines.common.tf_util.`**`var_shape`**(*tensor*)

get TensorFlow Tensor shape

Parameters **`tensor`** – (TensorFlow Tensor) the input tensor

Returns ([int]) the shape

1.33 Command Utils

Helpers for scripts like run_atari.py.

`stable_baselines.common.cmd_util.`**`arg_parser`**()

Create an empty argparse.ArgumentParser.

Returns (ArgumentParser)

`stable_baselines.common.cmd_util.`**`atari_arg_parser`**()

Create an argparse.ArgumentParser for run_atari.py.

Returns (ArgumentParser) parser {'–env': 'BreakoutNoFrameskip-v4', '–seed': 0, '–num-timesteps': int(1e7)}

`stable_baselines.common.cmd_util.`**`make_atari_env`**(*env_id*, *num_env*, *seed*, *wrapper_kwargs=None*, *start_index=0*, *allow_early_resets=True*, *start_method=None*, *use_subprocess=False*)

Create a wrapped, monitored VecEnv for Atari.

Parameters

- **`env_id`** – (str) the environment ID
- **`num_env`** – (int) the number of environment you wish to have in subprocesses
- **`seed`** – (int) the initial seed for RNG
- **`wrapper_kwargs`** – (dict) the parameters for wrap_deepmind function
- **`start_index`** – (int) start rank index
- **`allow_early_resets`** – (bool) allows early reset of the environment
- **`start_method`** – (str) method used to start the subprocesses. See SubprocVecEnv doc for more information
- **`use_subprocess`** – (bool) Whether to use *SubprocVecEnv* or *DummyVecEnv* when *num_env* > 1, *DummyVecEnv* is usually faster. Default: False

Returns (VecEnv) The atari environment

`stable_baselines.common.cmd_util.`**`make_mujoco_env`**(*env_id*, *seed*, *allow_early_resets=True*)

Create a wrapped, monitored gym.Env for MuJoCo.

Parameters

- **`env_id`** – (str) the environment ID
- **`seed`** – (int) the initial seed for RNG
- **`allow_early_resets`** – (bool) allows early reset of the environment

Returns (Gym Environment) The mujoco environment `stable_baselines.common.cmd_util.`**`make_robotics_env`**`(`*env_id*, *seed*, *rank=0*, *allow_early_resets=True*`)`

Create a wrapped, monitored gym.Env for MuJoCo.

Parameters

- **`env_id`** – (str) the environment ID
- **`seed`** – (int) the initial seed for RNG
- **`rank`** – (int) the rank of the environment (for logging)
- **`allow_early_resets`** – (bool) allows early reset of the environment

Returns (Gym Environment) The robotic environment

`stable_baselines.common.cmd_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*`)`

Create a wrapped, monitored *VecEnv*. By default it uses a *DummyVecEnv* which is usually faster than a *SubprocVecEnv*.

Parameters

- **`env_id`** – (str or Type[gym.Env]) the environment ID or the environment class
- **`n_envs`** – (int) the number of environments you wish to have in parallel
- **`seed`** – (int) the initial seed for the random number generator
- **`start_index`** – (int) start rank index
- **`monitor_dir`** – (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`** – (gym.Wrapper or callable) 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`** – (dict) Optional keyword argument to pass to the env constructor
- **`vec_env_cls`** – (Type[VecEnv]) A custom *VecEnv* class constructor. Default: None.
- **`vec_env_kwargs`** – (dict) Keyword arguments to pass to the *VecEnv* class constructor.

Returns (VecEnv) The wrapped environment

`stable_baselines.common.cmd_util.`**`mujoco_arg_parser`**`()`

Create an argparse.ArgumentParser for run_mujoco.py.

Returns (ArgumentParser) parser {'–env': 'Reacher-v2', '–seed': 0, '–num-timesteps': int(1e6), '–play': False}

`stable_baselines.common.cmd_util.`**`robotics_arg_parser`**`()`

Create an argparse.ArgumentParser for run_mujoco.py.

Returns (ArgumentParser) parser {'–env': 'FetchReach-v0', '–seed': 0, '–num-timesteps': int(1e6)}

1.34 Schedules

Schedules are used as hyperparameter for most of the algorithms, in order to change value of a parameter over time (usually the learning rate).

This file is used for specifying various schedules that evolve over time throughout the execution of the algorithm, such as:

- learning rate for the optimizer
- exploration epsilon for the epsilon greedy exploration strategy
- beta parameter for beta parameter in prioritized replay

Each schedule has a function *value(t)* which returns the current value of the parameter given the timestep t of the optimization procedure.

class `stable_baselines.common.schedules.`**`ConstantSchedule`**(*value*)

Value remains constant over time.

Parameters **`value`** – (float) Constant value of the schedule

`value`(*step*)

Value of the schedule for a given timestep

Parameters **`step`** – (int) the timestep

Returns (float) the output value for the given timestep

class `stable_baselines.common.schedules.`**`LinearSchedule`**(*schedule_timesteps*, *final_p*, *initial_p=1.0*)

Linear interpolation between initial_p and final_p over schedule_timesteps. After this many timesteps pass final_p is returned.

Parameters

- **`schedule_timesteps`** – (int) Number of timesteps for which to linearly anneal initial_p to final_p
- **`initial_p`** – (float) initial output value
- **`final_p`** – (float) final output value

`value`(*step*)

Value of the schedule for a given timestep

Parameters **`step`** – (int) the timestep

Returns (float) the output value for the given timestep

class `stable_baselines.common.schedules.`**`PiecewiseSchedule`**(*endpoints*, *interpolation=<function linear_interpolation>*, *outside_value=None*)

Piecewise schedule.

Parameters

- **`endpoints`** – ([(int, int)]) list of pairs *(time, value)* meaning that schedule should output *value* when *t==time*. All the values for time must be sorted in an increasing order. When t is between two times, e.g. *(time_a, value_a)* and *(time_b, value_b)*, such that *time_a* <= *t* < *time_b* then value outputs *interpolation(value_a, value_b, alpha)* where alpha is a fraction of time passed between *time_a* and *time_b* for time *t*.

- **interpolation** – (lambda (float, float, float): float) a function that takes value to the left and to the right of t according to the *endpoints*. Alpha is the fraction of distance from left endpoint to right endpoint that t has covered. See linear_interpolation for example.
- **outside_value** – (float) if the value is requested outside of all the intervals specified in *endpoints* this value is returned. If None then AssertionError is raised when outside value is requested.

value (*step*)
Value of the schedule for a given timestep

Parameters **step** – (int) the timestep

Returns (float) the output value for the given timestep

stable_baselines.common.schedules.**constant** (_)
Returns a constant value for the Scheduler

Parameters _ – ignored

Returns (float) 1

stable_baselines.common.schedules.**constfn** (*val*)
Create a function that returns a constant It is useful for learning rate schedule (to avoid code duplication)

Parameters **val** – (float)

Returns (function)

stable_baselines.common.schedules.**double_linear_con** (*progress*)
Returns a linear value (x2) with a flattened tail for the Scheduler

Parameters **progress** – (float) Current progress status (in [0, 1])

Returns (float) 1 - progress*2 if (1 - progress*2) >= 0.125 else 0.125

stable_baselines.common.schedules.**double_middle_drop** (*progress*)
Returns a linear value with two drops near the middle to a constant value for the Scheduler

Parameters **progress** – (float) Current progress status (in [0, 1])

Returns (float) if 0.75 <= 1 - p: 1 - p, if 0.25 <= 1 - p < 0.75: 0.75, if 1 - p < 0.25: 0.125

stable_baselines.common.schedules.**get_schedule_fn** (*value_schedule*)
Transform (if needed) learning rate and clip range to callable.

Parameters **value_schedule** – (callable or float)

Returns (function)

stable_baselines.common.schedules.**linear_interpolation** (*left*, *right*, *alpha*)
Linear interpolation between *left* and *right*.

Parameters

- **left** – (float) left boundary
- **right** – (float) right boundary
- **alpha** – (float) coeff in [0, 1]

Returns (float)

stable_baselines.common.schedules.**linear_schedule** (*progress*)
Returns a linear value for the Scheduler

Parameters **progress** – (float) Current progress status (in [0, 1])

Returns (float) 1 - progress

`stable_baselines.common.schedules.`**`middle_drop`**(*progress*)

Returns a linear value with a drop near the middle to a constant value for the Scheduler

Parameters **`progress`** – (float) Current progress status (in [0, 1])

Returns (float) 1 - progress if (1 - progress) >= 0.75 else 0.075

1.35 Evaluation Helper

`stable_baselines.common.evaluation.`**`evaluate_policy`**(*model: BaseRLModel, env: Union[gym.core.Env, stable_baselines.common.vec_env.base_vec_env.VecEnv], n_eval_episodes: int = 10, deterministic: bool = True, render: bool = False, callback: Optional[Callable] = None, reward_threshold: Optional[float] = None, return_episode_rewards: bool = False*) → Union[Tuple[float, float], Tuple[List[float], List[int]]]

Runs policy for `n_eval_episodes` episodes and returns average reward. This is made to work only with one env.

Parameters

- **`model`** – (BaseRLModel) The RL agent you want to evaluate.
- **`env`** – (gym.Env or VecEnv) The gym environment. In the case of a `VecEnv` this must contain only one 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`** – (callable) callback function to do additional checks, called after each step.
- **`reward_threshold`** – (float) Minimum expected reward per episode, this will raise an error if the performance is not met
- **`return_episode_rewards`** – (Optional[float]) If True, a list of reward per episode will be returned instead of the mean.

Returns (float, float) Mean reward per episode, std of reward per episode returns ([float], [int]) when `return_episode_rewards` is True

1.36 Gym Environment Checker

`stable_baselines.common.env_checker.`**`check_env`**(*env: gym.core.Env, warn: bool = True, skip_render_check: bool = True*) → None

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** – (gym.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)

1.37 Monitor Wrapper

class stable_baselines.bench.monitor.**Monitor**(*env: gym.core.Env, filename: Optional[str], allow_early_resets: bool = 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** – (gym.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) extra keywords for the reset call, if extra parameters are needed at reset
- **info_keywords** – (tuple) extra information to log, from the information return of environment.step

close()

Closes the environment

get_episode_lengths() → List[int]

Returns the number of timesteps of all the episodes

Returns ([int])

get_episode_rewards() → List[float]

Returns the rewards of all the episodes

Returns ([float])

get_episode_times() → List[float]

Returns the runtime in seconds of all the episodes

Returns ([float])

get_total_steps() → int

Returns the total number of timesteps

Returns (int)

reset(***kwargs*) → numpy.ndarray

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

Returns (np.ndarray) the first observation of the environment

step(*action: numpy.ndarray*) → Tuple[numpy.ndarray, float, bool, Dict[Any, Any]]
Step the environment with the given action

Parameters **action** – (np.ndarray) the action

Returns (Tuple[np.ndarray, float, bool, Dict[Any, Any]]) observation, reward, done, information

`stable_baselines.bench.monitor.`**get_monitor_files**(*path: str*) → List[str]
get all the monitor files in the given path

Parameters **path** – (str) the logging folder

Returns ([str]) the log files

`stable_baselines.bench.monitor.`**load_results**(*path: str*) → pandas.core.frame.DataFrame
Load all Monitor logs from a given directory path matching `*monitor.csv` and `*monitor.json`

Parameters **path** – (str) the directory path containing the log file(s)

Returns (pandas.DataFrame) the logged data

1.38 Changelog

For download links, please look at Github release page.

1.38.1 Pre-Release 2.10.2a0 (WIP)

Breaking Changes:

New Features:

Bug Fixes:

Deprecations:

Others:

Documentation:

- Added stable-baselines-tf2 link on Projects page. (@sophiagu)

1.38.2 Release 2.10.1 (2020-08-05)

Bug fixes release

Breaking Changes:

- `render()` method of `VecEnvs` now only accept one argument: `mode`

New Features:

- Added momentum parameter to A2C for the embedded RMSPropOptimizer (@kantneel)
- ActionNoise is now an abstract base class and implements `__call__`, `NormalActionNoise` and `OrnsteinUhlenbeckActionNoise` have return types (@PartiallyTyped)
- HER now passes info dictionary to compute_reward, allowing for the computation of rewards that are independent of the goal (@tirafesi)

Bug Fixes:

- Fixed DDPG sampling empty replay buffer when combined with HER (@tirafesi)
- Fixed a bug in `HindsightExperienceReplayWrapper`, where the openai-gym signature for `compute_reward` was not matched correctly (@johannes-dornheim)
- Fixed SAC/TD3 checking time to update on learn steps instead of total steps (@PartiallyTyped)
- Added `**kwarg` pass through for `reset` method in `atari_wrappers.FrameStack` (@PartiallyTyped)
- Fix consistency in `setup_model()` for SAC, `target_entropy` now uses `self.action_space` instead of `self.env.action_space` (@PartiallyTyped)
- Fix reward threshold in `test_identity.py`
- Partially fix tensorboard indexing for PPO2 (@enderdead)
- Fixed potential bug in `DummyVecEnv` where `copy()` was used instead of `deepcopy()`
- Fixed a bug in `GAIL` where the dataloader was not available after saving, causing an error when using `CheckpointCallback`
- Fixed a bug in `SAC` where any convolutional layers were not included in the target network parameters.
- Fixed `render()` method for `VecEnvs`
- Fixed `seed()`` method for `SubprocVecEnv`
- Fixed a bug `callback.locals` did not have the correct values (@PartiallyTyped)
- Fixed a bug in the `close()` method of `SubprocVecEnv`, causing wrappers further down in the wrapper stack to not be closed. (@NeoExtended)
- Fixed a bug in the `generate_expert_traj()` method in `record_expert.py` when using a non-image vectorized environment (@jbarsce)
- Fixed a bug in CloudPickleWrapper's (used by VecEnvs) `__setstate____` where loading was incorrectly using `pickle.loads` (@shwang).
- Fixed a bug in `SAC` and `TD3` where the log timesteps was not correct(@YangRui2015)
- Fixed a bug where the environment was reset twice when using `evaluate_policy`

Deprecations:

Others:

- Added `version.txt` to manage version number in an easier way
- Added `.readthedocs.yml` to install requirements with read the docs
- Added a test for seeding `SubprocVecEnv`` and rendering

Documentation:

- Fix typos (@caburu)
- Fix typos in PPO2 (@kvenkman)
- Removed `stable_baselines\deepq\experiments\custom_cartpole.py` (@aakash94)
- Added Google's motion imitation project
- Added documentation page for monitor
- Fixed typos and update `VecNormalize` example to show normalization at test-time
- Fixed `train_mountaincar` description
- Added imitation baselines project
- Updated install instructions
- Added Slime Volleyball project (@hardmaru)
- Added a table of the variables accessible from the `on_step` function of the callbacks for each algorithm (@PartiallyTyped)
- Fix typo in README.md (@ColinLeongUDRI)

1.38.3 Release 2.10.0 (2020-03-11)

Callback collection, cleanup and bug fixes

Breaking Changes:

- `evaluate_policy` now returns the standard deviation of the reward per episode as second return value (instead of `n_steps`)
- `evaluate_policy` now returns as second return value a list of the episode lengths when `return_episode_rewards` is set to `True` (instead of `n_steps`)
- Callback are now called after each `env.step()` for consistency (it was called every `n_steps` before in algorithm like `A2C` or `PPO2`)
- Removed unused code in `common/a2c/utils.py` (`calc_entropy_softmax`, `make_path`)
- **Refactoring, including removed files and moving functions.**
  - Algorithms no longer import from each other, and `common` does not import from algorithms.
  - `a2c/utils.py` removed and split into other files:
    * common/tf_util.py: `sample`, `calc_entropy`, `mse`, `avg_norm`, `total_episode_reward_logger`, `q_explained_variance`, `gradient_add`, `avg_norm`, `check_shape`, `seq_to_batch`, `batch_to_seq`.
    * common/tf_layers.py: `conv`, `linear`, `lstm`, `_ln`, `lnlstm`, `conv_to_fc`, `ortho_init`.
    * a2c/a2c.py: `discount_with_dones`.
    * acer/acer_simple.py: `get_by_index`, `EpisodeStats`.
    * common/schedules.py: `constant`, `linear_schedule`, `middle_drop`, `double_linear_con`, `double_middle_drop`, `SCHEDULES`, `Scheduler`.

  - `trpo_mpi/utils.py` functions moved (`traj_segment_generator` moved to `common/runners.py`, `flatten_lists` to `common/misc_util.py`).
  - `ppo2/ppo2.py` functions moved (`safe_mean` to `common/math_util.py`, `constfn` and `get_schedule_fn` to `common/schedules.py`).
  - `sac/policies.py` function `mlp` moved to `common/tf_layers.py`.
  - `sac/sac.py` function `get_vars` removed (replaced with `tf.util.get_trainable_vars`).
  - `deepq/replay_buffer.py` renamed to `common/buffers.py`.

New Features:

- Parallelized updating and sampling from the replay buffer in DQN. (@flodorner)
- Docker build script, *scripts/build_docker.sh*, can push images automatically.
- Added callback collection
- Added `unwrap_vec_normalize` and `sync_envs_normalization` in the `vec_env` module to synchronize two VecNormalize environment
- Added a seeding method for vectorized environments. (@NeoExtended)
- Added extend method to store batches of experience in ReplayBuffer. (@PartiallyTyped)

Bug Fixes:

- Fixed Docker images via `scripts/build_docker.sh` and `Dockerfile`: GPU image now contains `tensorflow-gpu`, and both images have `stable_baselines` installed in developer mode at correct directory for mounting.
- Fixed Docker GPU run script, `scripts/run_docker_gpu.sh`, to work with new NVidia Container Toolkit.
- Repeated calls to `RLModel.learn()` now preserve internal counters for some episode logging statistics that used to be zeroed at the start of every call.
- Fix *DummyVecEnv.render* for `num_envs > 1`. This used to print a warning and then not render at all. (@shwang)
- Fixed a bug in PPO2, ACER, A2C, and ACKTR where repeated calls to `learn(total_timesteps)` reset the environment on every call, potentially biasing samples toward early episode timesteps. (@shwang)
- **Fixed by adding lazy property `ActorCriticRLModel.runner`. Subclasses now use lazily-generated**
  `self.runner` instead of reinitializing a new Runner every time `learn()` is called.
- Fixed a bug in `check_env` where it would fail on high dimensional action spaces
- Fixed `Monitor.close()` that was not calling the parent method
- Fixed a bug in `BaseRLModel` when seeding vectorized environments. (@NeoExtended)
- Fixed `num_timesteps` computation to be consistent between algorithms (updated after `env.step()`) Only `TRPO` and `PPO1` update it differently (after synchronization) because they rely on MPI
- Fixed bug in `TRPO` with NaN standardized advantages (@richardwu)
- Fixed partial minibatch computation in ExpertDataset (@richardwu)
- Fixed normalization (with `VecNormalize`) for off-policy algorithms
- Fixed `sync_envs_normalization` to sync the reward normalization too

- Bump minimum Gym version (>=0.11)

Deprecations:

Others:

- Removed redundant return value from `a2c.utils::total_episode_reward_logger`. (@shwang)
- Cleanup and refactoring in `common/identity_env.py` (@shwang)
- Added a Makefile to simplify common development tasks (build the doc, type check, run the tests)

Documentation:

- Add dedicated page for callbacks
- Fixed example for creating a GIF (@KuKuXia)
- Change Colab links in the README to point to the notebooks repo
- Fix typo in Reinforcement Learning Tips and Tricks page. (@mmcenta)

1.38.4 Release 2.9.0 (2019-12-20)

Reproducible results, automatic ``VecEnv`` wrapping, env checker and more usability improvements

Breaking Changes:

- The `seed` argument has been moved from *learn()* method to model constructor in order to have reproducible results
- `allow_early_resets` of the `Monitor` wrapper now default to `True`
- `make_atari_env` now returns a `DummyVecEnv` by default (instead of a `SubprocVecEnv`) this usually improves performance.
- Fix inconsistency of sample type, so that mode/sample function returns tensor of tf.int64 in CategoricalProbabilityDistribution/MultiCategoricalProbabilityDistribution (@seheevic)

New Features:

- Add `n_cpu_tf_sess` to model constructor to choose the number of threads used by Tensorflow
- Environments are automatically wrapped in a `DummyVecEnv` if needed when passing them to the model constructor
- Added `stable_baselines.common.make_vec_env` helper to simplify VecEnv creation
- Added `stable_baselines.common.evaluation.evaluate_policy` helper to simplify model evaluation
- `VecNormalize` changes:
  - Now supports being pickled and unpickled (@AdamGleave).
  - New methods `.normalize_obs(obs)` and *normalize_reward(rews)* apply normalization to arbitrary observation or rewards without updating statistics (@shwang)

- `.get_original_reward()` returns the unnormalized rewards from the most recent timestep
- `.reset()` now collects observation statistics (used to only apply normalization)

- Add parameter `exploration_initial_eps` to DQN. (@jdossgollin)
- Add type checking and PEP 561 compliance. Note: most functions are still not annotated, this will be a gradual process.
- DDPG, TD3 and SAC accept non-symmetric action spaces. (@Antymon)
- Add `check_env` util to check if a custom environment follows the gym interface (@araffin and @justinkterry)

Bug Fixes:

- Fix seeding, so it is now possible to have deterministic results on cpu
- Fix a bug in DDPG where `predict` method with *deterministic=False* would fail
- Fix a bug in TRPO: mean_losses was not initialized causing the logger to crash when there was no gradients (@MarvineGothic)
- Fix a bug in `cmd_util` from API change in recent Gym versions
- Fix a bug in DDPG, TD3 and SAC where warmup and random exploration actions would end up scaled in the replay buffer (@Antymon)

Deprecations:

- `nprocs` (ACKTR) and `num_procs` (ACER) are deprecated in favor of `n_cpu_tf_sess` which is now common to all algorithms
- `VecNormalize`: `load_running_average` and `save_running_average` are deprecated in favour of using pickle.

Others:

- Add upper bound for Tensorflow version (<2.0.0).
- Refactored test to remove duplicated code
- Add pull request template
- Replaced redundant code in load_results (@jbulow)
- Minor PEP8 fixes in dqn.py (@justinkterry)
- Add a message to the assert in `PPO2`
- Update replay buffer doctring
- Fix `VecEnv` docstrings

Documentation:

- Add plotting to the Monitor example (@rusu24edward)
- Add Snake Game AI project (@pedrohbtp)
- Add note on the support Tensorflow versions.

- Remove unnecessary steps required for Windows installation.
- Remove `DummyVecEnv` creation when not needed
- Added `make_vec_env` to the examples to simplify VecEnv creation
- Add QuaRL project (@srivatsankrishnan)
- Add Pwnagotchi project (@evilsocket)
- Fix multiprocessing example (@rusu24edward)
- Fix `result_plotter` example
- Add JNRR19 tutorial (by @edbeeching, @hill-a and @araffin)
- Updated notebooks link
- Fix typo in algos.rst, "containes" to "contains" (@SyllogismRXS)
- Fix outdated source documentation for load_results
- Add PPO_CPP project (@Antymon)
- Add section on C++ portability of Tensorflow models (@Antymon)
- Update custom env documentation to reflect new gym API for the `close()` method (@justinkterry)
- Update custom env documentation to clarify what step and reset return (@justinkterry)
- Add RL tips and tricks for doing RL experiments
- Corrected lots of typos
- Add spell check to documentation if available

1.38.5 Release 2.8.0 (2019-09-29)

MPI dependency optional, new save format, ACKTR with continuous actions

Breaking Changes:

- OpenMPI-dependent algorithms (PPO1, TRPO, GAIL, DDPG) are disabled in the default installation of stable_baselines. `mpi4py` is now installed as an extra. When `mpi4py` is not available, stable-baselines skips imports of OpenMPI-dependent algorithms. See *installation notes* and Issue #430.
- SubprocVecEnv now defaults to a thread-safe start method, `forkserver` when available and otherwise `spawn`. This may require application code be wrapped in `if __name__ == '__main__'`. You can restore previous behavior by explicitly setting `start_method = 'fork'`. See PR #428.
- Updated dependencies: tensorflow v1.8.0 is now required
- Removed `checkpoint_path` and `checkpoint_freq` argument from `DQN` that were not used
- Removed `bench/benchmark.py` that was not used
- Removed several functions from `common/tf_util.py` that were not used
- Removed `ppo1/run_humanoid.py`

New Features:

- **important change** Switch to using zip-archived JSON and Numpy `savez` for storing models for better support across library/Python versions. (@Miffyli)
- ACKTR now supports continuous actions
- Add `double_q` argument to `DQN` constructor

Bug Fixes:

- Skip automatic imports of OpenMPI-dependent algorithms to avoid an issue where OpenMPI would cause stable-baselines to hang on Ubuntu installs. See *installation notes* and Issue #430.
- Fix a bug when calling `logger.configure()` with MPI enabled (@keshaviyengar)
- set `allow_pickle=True` for numpy>=1.17.0 when loading expert dataset
- Fix a bug when using VecCheckNan with numpy ndarray as state. Issue #489. (@ruifeng96150)

Deprecations:

- Models saved with cloudpickle format (stable-baselines<=2.7.0) are now deprecated in favor of zip-archive format for better support across Python/Tensorflow versions. (@Miffyli)

Others:

- Implementations of noise classes (`AdaptiveParamNoiseSpec`, `NormalActionNoise`, `OrnsteinUhlenbeckActionNoise`) were moved from *stable_baselines.ddpg.noise* to `stable_baselines.common.noise`. The API remains backward-compatible; for example `from stable_baselines.ddpg.noise import NormalActionNoise` is still okay. (@shwang)
- Docker images were updated
- Cleaned up files in `common/` folder and in *acktr/* folder that were only used by old ACKTR version (e.g. *filter.py*)
- Renamed *acktr_disc.py* to *acktr.py*

Documentation:

- Add WaveRL project (@jaberkow)
- Add Fenics-DRL project (@DonsetPG)
- Fix and rename custom policy names (@eavelardev)
- Add documentation on exporting models.
- Update maintainers list (Welcome to @Miffyli)

1.38.6 Release 2.7.0 (2019-07-31)

Twin Delayed DDPG (TD3) and GAE bug fix (TRPO, PPO1, GAIL)

Breaking Changes:

New Features:

- added Twin Delayed DDPG (TD3) algorithm, with HER support
- added support for continuous action spaces to `action_probability`, computing the PDF of a Gaussian policy in addition to the existing support for categorical stochastic policies.
- added flag to `action_probability` to return log-probabilities.
- added support for python lists and numpy arrays in `logger.writekvs`. (@dwiel)
- the info dict returned by VecEnvs now include a `terminal_observation` key providing access to the last observation in a trajectory. (@qxcv)

Bug Fixes:

- fixed a bug in `traj_segment_generator` where the `episode_starts` was wrongly recorded, resulting in wrong calculation of Generalized Advantage Estimation (GAE), this affects TRPO, PPO1 and GAIL (thanks to @miguelrass for spotting the bug)
- added missing property `n_batch` in `BasePolicy`.

Deprecations:

Others:

- renamed some keys in `traj_segment_generator` to be more meaningful
- retrieve unnormalized reward when using Monitor wrapper with TRPO, PPO1 and GAIL to display them in the logs (mean episode reward)
- clean up DDPG code (renamed variables)

Documentation:

- doc fix for the hyperparameter tuning command in the rl zoo
- added an example on how to log additional variable with tensorboard and a callback

1.38.7 Release 2.6.0 (2019-06-12)

Hindsight Experience Replay (HER) - Reloaded | get/load parameters

Breaking Changes:

- **breaking change** removed `stable_baselines.ddpg.memory` in favor of `stable_baselines.deepq.replay_buffer` (see fix below)

Breaking Change: DDPG replay buffer was unified with DQN/SAC replay buffer. As a result, when loading a DDPG model trained with stable_baselines<2.6.0, it throws an import error. You can fix that using:

```python
import sys
import pkg_resources

import stable_baselines

# Fix for breaking change for DDPG buffer in v2.6.0
if pkg_resources.get_distribution("stable_baselines").version >= "2.6.0":
    sys.modules['stable_baselines.ddpg.memory'] = stable_baselines.deepq.replay_buffer
    stable_baselines.deepq.replay_buffer.Memory = stable_baselines.deepq.replay_
↪buffer.ReplayBuffer
```

We recommend you to save again the model afterward, so the fix won't be needed the next time the trained agent is loaded.

New Features:

- **revamped HER implementation**: clean re-implementation from scratch, now supports DQN, SAC and DDPG
- add `action_noise` param for SAC, it helps exploration for problem with deceptive reward
- The parameter `filter_size` of the function `conv` in A2C utils now supports passing a list/tuple of two integers (height and width), in order to have non-squared kernel matrix. (@yutingsz)
- add `random_exploration` parameter for DDPG and SAC, it may be useful when using HER + DDPG/SAC. This hack was present in the original OpenAI Baselines DDPG + HER implementation.
- added `load_parameters` and `get_parameters` to base RL class. With these methods, users are able to load and get parameters to/from existing model, without touching tensorflow. (@Miffyli)
- added specific hyperparameter for PPO2 to clip the value function (`cliprange_vf`)
- added `VecCheckNan` wrapper

Bug Fixes:

- bugfix for `VecEnvWrapper.__getattr__` which enables access to class attributes inherited from parent classes.
- fixed path splitting in `TensorboardWriter._get_latest_run_id()` on Windows machines (@PatrickWalter214)
- fixed a bug where initial learning rate is logged instead of its placeholder in `A2C.setup_model` (@sc420)
- fixed a bug where number of timesteps is incorrectly updated and logged in `A2C.learn` and `A2C._train_step` (@sc420)
- fixed `num_timesteps` (total_timesteps) variable in PPO2 that was wrongly computed.
- fixed a bug in DDPG/DQN/SAC, when there were the number of samples in the replay buffer was lesser than the batch size (thanks to @dwiel for spotting the bug)
- **removed** `a2c.utils.find_trainable_params` please use `common.tf_util.get_trainable_vars` instead. `find_trainable_params` was returning all trainable variables, discarding the scope argument. This bug was causing the model to save duplicated parameters (for DDPG and SAC) but did not affect the performance.

Deprecations:

- **deprecated** `memory_limit` and `memory_policy` in DDPG, please use `buffer_size` instead. (will be removed in v3.x.x)

Others:

- **important change** switched to using dictionaries rather than lists when storing parameters, with tensorflow Variable names being the keys. (@Miffyli)
- removed unused dependencies (tdqm, dill, progressbar2, seaborn, glob2, click)
- removed `get_available_gpus` function which hadn't been used anywhere (@Pastafarianist)

Documentation:

- added guide for managing `NaN` and `inf`
- updated ven_env doc
- misc doc updates

1.38.8 Release 2.5.1 (2019-05-04)

Bug fixes + improvements in the VecEnv

Warning: breaking changes when using custom policies

- doc update (fix example of result plotter + improve doc)
- fixed logger issues when stdout lacks `read` function
- fixed a bug in `common.dataset.Dataset` where shuffling was not disabled properly (it affects only PPO1 with recurrent policies)
- fixed output layer name for DDPG q function, used in pop-art normalization and l2 regularization of the critic
- added support for multi env recording to `generate_expert_traj` (@XMaster96)
- added support for LSTM model recording to `generate_expert_traj` (@XMaster96)
- `GAIL`: remove mandatory matplotlib dependency and refactor as subclass of `TRPO` (@kantneel and @AdamGleave)
- added `get_attr()`, `env_method()` and `set_attr()` methods for all VecEnv. Those methods now all accept `indices` keyword to select a subset of envs. `set_attr` now returns `None` rather than a list of `None`. (@kantneel)
- `GAIL`: `gail.dataset.ExpertDataset` supports loading from memory rather than file, and `gail.dataset.record_expert` supports returning in-memory rather than saving to file.
- added support in `VecEnvWrapper` for accessing attributes of arbitrarily deeply nested instances of `VecEnvWrapper` and `VecEnv`. This is allowed as long as the attribute belongs to exactly one of the nested instances i.e. it must be unambiguous. (@kantneel)
- fixed bug where result plotter would crash on very short runs (@Pastafarianist)
- added option to not trim output of result plotter by number of timesteps (@Pastafarianist)

- clarified the public interface of `BasePolicy` and `ActorCriticPolicy`. **Breaking change** when using custom policies: `masks_ph` is now called `dones_ph`, and most placeholders were made private: e.g. `self.value_fn` is now `self._value_fn`
- support for custom stateful policies.
- fixed episode length recording in `trpo_mpi.utils.traj_segment_generator` (@GerardMaggiolino)

1.38.9 Release 2.5.0 (2019-03-28)

Working GAIL, pretrain RL models and hotfix for A2C with continuous actions

- fixed various bugs in GAIL
- added scripts to generate dataset for gail
- added tests for GAIL + data for Pendulum-v0
- removed unused `utils` file in DQN folder
- fixed a bug in A2C where actions were cast to `int32` even in the continuous case
- added addional logging to A2C when Monitor wrapper is used
- changed logging for PPO2: do not display NaN when reward info is not present
- change default value of A2C lr schedule
- removed behavior cloning script
- added `pretrain` method to base class, in order to use behavior cloning on all models
- fixed `close()` method for DummyVecEnv.
- added support for Dict spaces in DummyVecEnv and SubprocVecEnv. (@AdamGleave)
- added support for arbitrary multiprocessing start methods and added a warning about SubprocVecEnv that are not thread-safe by default. (@AdamGleave)
- added support for Discrete actions for GAIL
- fixed deprecation warning for tf: replaces `tf.to_float()` by `tf.cast()`
- fixed bug in saving and loading ddpg model when using normalization of obs or returns (@tperol)
- changed DDPG default buffer size from 100 to 50000.
- fixed a bug in `ddpg.py` in `combined_stats` for eval. Computed mean on `eval_episode_rewards` and `eval_qs` (@keshaviyengar)
- fixed a bug in `setup.py` that would error on non-GPU systems without TensorFlow installed

1.38.10 Release 2.4.1 (2019-02-11)

Bug fixes and improvements

- fixed computation of training metrics in TRPO and PPO1
- added `reset_num_timesteps` keyword when calling train() to continue tensorboard learning curves
- reduced the size taken by tensorboard logs (added a `full_tensorboard_log` to enable full logging, which was the previous behavior)
- fixed image detection for tensorboard logging

- fixed ACKTR for recurrent policies
- fixed gym breaking changes
- fixed custom policy examples in the doc for DQN and DDPG
- remove gym spaces patch for equality functions
- fixed tensorflow dependency: cpu version was installed overwritting tensorflow-gpu when present.
- fixed a bug in `traj_segment_generator` (used in ppo1 and trpo) where `new` was not updated. (spotted by @junhyeokahn)

1.38.11 Release 2.4.0 (2019-01-17)

Soft Actor-Critic (SAC) and policy kwargs

- added Soft Actor-Critic (SAC) model
- fixed a bug in DQN where prioritized_replay_beta_iters param was not used
- fixed DDPG that did not save target network parameters
- fixed bug related to shape of true_reward (@abhiskk)
- fixed example code in documentation of tf_util:Function (@JohannesAck)
- added learning rate schedule for SAC
- fixed action probability for continuous actions with actor-critic models
- added optional parameter to action_probability for likelihood calculation of given action being taken.
- added more flexible custom LSTM policies
- added auto entropy coefficient optimization for SAC
- clip continuous actions at test time too for all algorithms (except SAC/DDPG where it is not needed)
- added a mean to pass kwargs to policy when creating a model (+ save those kwargs)
- fixed DQN examples in DQN folder
- added possibility to pass activation function for DDPG, DQN and SAC

1.38.12 Release 2.3.0 (2018-12-05)

- added support for storing model in file like object. (thanks to @erniejunior)
- fixed wrong image detection when using tensorboard logging with DQN
- fixed bug in ppo2 when passing non callable lr after loading
- fixed tensorboard logging in ppo2 when nminibatches=1
- added early stoppping via callback return value (@erniejunior)
- added more flexible custom mlp policies (@erniejunior)

1.38.13 Release 2.2.1 (2018-11-18)

- added VecVideoRecorder to record mp4 videos from environment.

1.38.14 Release 2.2.0 (2018-11-07)

- Hotfix for ppo2, the wrong placeholder was used for the value function

1.38.15 Release 2.1.2 (2018-11-06)

- added `async_eigen_decomp` parameter for ACKTR and set it to `False` by default (remove deprecation warnings)
- added methods for calling env methods/setting attributes inside a VecEnv (thanks to @bjmuld)
- updated gym minimum version

1.38.16 Release 2.1.1 (2018-10-20)

- fixed MpiAdam synchronization issue in PPO1 (thanks to @brendenpetersen) issue #50
- fixed dependency issues (new mujoco-py requires a mujoco license + gym broke MultiDiscrete space shape)

1.38.17 Release 2.1.0 (2018-10-2)

> **Warning:** This version contains breaking changes for DQN policies, please read the full details

Bug fixes + doc update

- added patch fix for equal function using *gym.spaces.MultiDiscrete* and *gym.spaces.MultiBinary*
- fixes for DQN action_probability
- re-added double DQN + refactored DQN policies **breaking changes**
- replaced `async` with `async_eigen_decomp` in ACKTR/KFAC for python 3.7 compatibility
- removed action clipping for prediction of continuous actions (see issue #36)
- fixed NaN issue due to clipping the continuous action in the wrong place (issue #36)
- documentation was updated (policy + DDPG example hyperparameters)

1.38.18 Release 2.0.0 (2018-09-18)

> **Warning:** This version contains breaking changes, please read the full details

Tensorboard, refactoring and bug fixes

- Renamed DeepQ to DQN **breaking changes**
- Renamed DeepQPolicy to DQNPolicy **breaking changes**
- fixed DDPG behavior **breaking changes**
- changed default policies for DDPG, so that DDPG now works correctly **breaking changes**
- added more documentation (some modules from common).

- added doc about using custom env
- added Tensorboard support for A2C, ACER, ACKTR, DDPG, DeepQ, PPO1, PPO2 and TRPO
- added episode reward to Tensorboard
- added documentation for Tensorboard usage
- added Identity for Box action space
- fixed render function ignoring parameters when using wrapped environments
- fixed PPO1 and TRPO done values for recurrent policies
- fixed image normalization not occurring when using images
- updated VecEnv objects for the new Gym version
- added test for DDPG
- refactored DQN policies
- added registry for policies, can be passed as string to the agent
- added documentation for custom policies + policy registration
- fixed numpy warning when using DDPG Memory
- fixed DummyVecEnv not copying the observation array when stepping and resetting
- added pre-built docker images + installation instructions
- added `deterministic` argument in the predict function
- added assert in PPO2 for recurrent policies
- fixed predict function to handle both vectorized and unwrapped environment
- added input check to the predict function
- refactored ActorCritic models to reduce code duplication
- refactored Off Policy models (to begin HER and replay_buffer refactoring)
- added tests for auto vectorization detection
- fixed render function, to handle positional arguments

1.38.19 Release 1.0.7 (2018-08-29)

Bug fixes and documentation

- added html documentation using sphinx + integration with read the docs
- cleaned up README + typos
- fixed normalization for DQN with images
- fixed DQN identity test

1.38.20 Release 1.0.1 (2018-08-20)

Refactored Stable Baselines

- refactored A2C, ACER, ACTKR, DDPG, DeepQ, GAIL, TRPO, PPO1 and PPO2 under a single constant class
- added callback to refactored algorithm training

- added saving and loading to refactored algorithms
- refactored ACER, DDPG, GAIL, PPO1 and TRPO to fit with A2C, PPO2 and ACKTR policies
- added new policies for most algorithms (Mlp, MlpLstm, MlpLnLstm, Cnn, CnnLstm and CnnLnLstm)
- added dynamic environment switching (so continual RL learning is now feasible)
- added prediction from observation and action probability from observation for all the algorithms
- fixed graphs issues, so models wont collide in names
- fixed behavior_clone weight loading for GAIL
- fixed Tensorflow using all the GPU VRAM
- fixed models so that they are all compatible with vectorized environments
- fixed `set_global_seed` to update `gym.spaces`'s random seed
- fixed PPO1 and TRPO performance issues when learning identity function
- added new tests for loading, saving, continuous actions and learning the identity function
- fixed DQN wrapping for atari
- added saving and loading for Vecnormalize wrapper
- added automatic detection of action space (for the policy network)
- fixed ACER buffer with constant values assuming n_stack=4
- fixed some RL algorithms not clipping the action to be in the action_space, when using `gym.spaces.Box`
- refactored algorithms can take either a `gym.Environment` or a `str` ([if the environment name is registered](https://github.com/openai/gym/wiki/Environments))
- Hoftix in ACER (compared to v1.0.0)

Future Work :

- Finish refactoring HER
- Refactor ACKTR and ACER for continuous implementation

1.38.21 Release 0.1.6 (2018-07-27)

Deobfuscation of the code base + pep8 and fixes

- Fixed `tf.session().__enter__()` being used, rather than `sess = tf.session()` and passing the session to the objects
- Fixed uneven scoping of TensorFlow Sessions throughout the code
- Fixed rolling vecwrapper to handle observations that are not only grayscale images
- Fixed deepq saving the environment when trying to save itself
- Fixed `ValueError: Cannot take the length of Shape with unknown rank.` in `acktr`, when running `run_atari.py` script.
- Fixed calling baselines sequentially no longer creates graph conflicts
- Fixed mean on empty array warning with deepq
- Fixed kfac eigen decomposition not cast to float64, when the parameter use_float64 is set to True
- Fixed Dataset data loader, not correctly resetting id position if shuffling is disabled

- Fixed `EOFError` when reading from connection in the `worker` in `subproc_vec_env.py`
- Fixed `behavior_clone` weight loading and saving for GAIL
- Avoid taking root square of negative number in `trpo_mpi.py`
- Removed some duplicated code (a2cpolicy, trpo_mpi)
- Removed unused, undocumented and crashing function `reset_task` in `subproc_vec_env.py`
- Reformated code to PEP8 style
- Documented all the codebase
- Added atari tests
- Added logger tests

Missing: tests for acktr continuous (+ HER, rely on mujoco…)

1.38.22 Maintainers

Stable-Baselines is currently maintained by Ashley Hill (aka @hill-a), Antonin Raffin (aka @araffin), Maximilian Ernestus (aka @erniejunior), Adam Gleave (@AdamGleave) and Anssi Kanervisto (aka @Miffyli).

1.38.23 Contributors (since v2.0.0):

In random order…

Thanks to @bjmuld @iambenzo @iandanforth @r7vme @brendenpetersen @huvar @abhiskk @JohannesAck @EliasHasle @mrakgr @Bleyddyn @antoine-galataud @junhyeokahn @AdamGleave @keshaviyengar @tperol @XMaster96 @kantneel @Pastafarianist @GerardMaggiolino @PatrickWalter214 @yutingsz @sc420 @Aaahh @billtubbs @Miffyli @dwiel @miguelrass @qxcv @jaberkow @eavelardev @ruifeng96150 @pedrohbtp @srivatsankrishnan @evilsocket @MarvineGothic @jdossgollin @SyllogismRXS @rusu24edward @jbulow @Antymon @seheevic @justinkterry @edbeeching @flodorner @KuKuXia @NeoExtended @PartiallyTyped @mmcenta @richardwu @tirafesi @caburu @johannes-dornheim @kvenkman @aakash94 @enderdead @hardmaru @jbarsce @ColinLeongUDRI @shwang @YangRui2015 @sophiagu

1.39 Projects

This is a list of projects using stable-baselines. Please tell us, if you want your project to appear on this page ;)

1.39.1 Stable Baselines for TensorFlow 2

A fork of the original stable-baselines repo that works with TF2.x.

Author: Sophia Gu (@sophiagu)
Github repo: https://github.com/sophiagu/stable-baselines-tf2

1.39.2 Slime Volleyball Gym Environment

A simple environment for benchmarking single and multi-agent reinforcement learning algorithms on a clone of the Slime Volleyball game. Only dependencies are gym and numpy. Both state and pixel observation environments are available. The motivation of this environment is to easily enable trained agents to play against each other, and also facilitate the training of agents directly in a multi-agent setting, thus adding an extra dimension for evaluating an agent's performance.

Uses stable-baselines to train RL agents for both state and pixel observation versions of the task. A tutorial is also provided on modifying stable-baselines for self-play using PPO.

Author: David Ha (@hardmaru)
Github repo: https://github.com/hardmaru/slimevolleygym

1.39.3 Learning to drive in a day

Implementation of reinforcement learning approach to make a donkey car learn to drive. Uses DDPG on VAE features (reproducing paper from wayve.ai)

Author: Roma Sokolkov (@r7vme)
Github repo: https://github.com/r7vme/learning-to-drive-in-a-day

1.39.4 Donkey Gym

OpenAI gym environment for donkeycar simulator.

Author: Tawn Kramer (@tawnkramer)
Github repo: https://github.com/tawnkramer/donkey_gym

1.39.5 Self-driving FZERO Artificial Intelligence

Series of videos on how to make a self-driving FZERO artificial intelligence using reinforcement learning algorithms PPO2 and A2C.

Author: Lucas Thompson
Video Link

1.39.6 S-RL Toolbox

S-RL Toolbox: Reinforcement Learning (RL) and State Representation Learning (SRL) for Robotics. Stable-Baselines was originally developped for this project.

Authors: Antonin Raffin, Ashley Hill, René Traoré, Timothée Lesort, Natalia Díaz-Rodríguez, David Filliat
Github repo: https://github.com/araffin/robotics-rl-srl

1.39.7 Roboschool simulations training on Amazon SageMaker

"In this notebook example, we will make HalfCheetah learn to walk using the stable-baselines [. . .]"

Author: Amazon AWS
Repo Link

1.39.8 MarathonEnvs + OpenAi.Baselines

Experimental - using OpenAI baselines with MarathonEnvs (ML-Agents)

Author: Joe Booth (@Sohojoe)
Github repo: https://github.com/Sohojoe/MarathonEnvsBaselines

1.39.9 Learning to drive smoothly in minutes

Implementation of reinforcement learning approach to make a car learn to drive smoothly in minutes. Uses SAC on VAE features.

Author: Antonin Raffin (@araffin)
Blog post: https://towardsdatascience.com/learning-to-drive-smoothly-in-minutes-450a7cdb35f4
Github repo: https://github.com/araffin/learning-to-drive-in-5-minutes

1.39.10 Making Roboy move with elegance

Project around Roboy, a tendon-driven robot, that enabled it to move its shoulder in simulation to reach a pre-defined point in 3D space. The agent used Proximal Policy Optimization (PPO) or Soft Actor-Critic (SAC) and was tested on the real hardware.

Authors: Alexander Pakakis, Baris Yazici, Tomas Ruiz
Email: FirstName.LastName@tum.de
GitHub repo: https://github.com/Roboy/DeepAndReinforced
DockerHub image: deepandreinforced/rl:latest
Presentation: https://tinyurl.com/DeepRoboyControl
Video: https://tinyurl.com/DeepRoboyControlVideo
Blog post: https://tinyurl.com/mediumDRC
Website: https://roboy.org/

1.39.11 Train a ROS-integrated mobile robot (differential drive) to avoid dynamic objects

The RL-agent serves as local planner and is trained in a simulator, fusion of the Flatland Simulator and the crowd simulator Pedsim. This was tested on a real mobile robot. The Proximal Policy Optimization (PPO) algorithm is applied.

Author: Ronja Güldenring

Email: 6guelden@informatik.uni-hamburg.de

Video: https://www.youtube.com/watch?v=laGrLaMaeT4

GitHub: https://github.com/RGring/drl_local_planner_ros_stable_baselines

1.39.12 Adversarial Policies: Attacking Deep Reinforcement Learning

Uses Stable Baselines to train *adversarial policies* that attack pre-trained victim policies in a zero-sum multi-agent environments. May be useful as an example of how to integrate Stable Baselines with Ray to perform distributed experiments and Sacred for experiment configuration and monitoring.

Authors: Adam Gleave, Michael Dennis, Neel Kant, Cody Wild

Email: adam@gleave.me

GitHub: https://github.com/HumanCompatibleAI/adversarial-policies

Paper: https://arxiv.org/abs/1905.10615

Website: https://adversarialpolicies.github.io

1.39.13 WaveRL: Training RL agents to perform active damping

Reinforcement learning is used to train agents to control pistons attached to a bridge to cancel out vibrations. The bridge is modeled as a one dimensional oscillating system and dynamics are simulated using a finite difference solver. Agents were trained using Proximal Policy Optimization. See presentation for environment detalis.

Author: Jack Berkowitz

Email: jackberkowitz88@gmail.com

GitHub: https://github.com/jaberkow/WaveRL

Presentation: http://bit.ly/WaveRLslides

1.39.14 Fenics-DRL: Fluid mechanics and Deep Reinforcement Learning

Deep Reinforcement Learning is used to control the position or the shape of obstacles in different fluids in order to optimize drag or lift. Fenics is used for the Fluid Mechanics part, and Stable Baselines is used for the DRL.

Authors: Paul Garnier, Jonathan Viquerat, Aurélien Larcher, Elie Hachem

Email: paul.garnier@mines-paristech.fr

GitHub: https://github.com/DonsetPG/openFluid

Paper: https://arxiv.org/abs/1908.04127

Website: https://donsetpg.github.io/blog/2019/08/06/DRL-FM-review/

1.39.15 Air Learning: An AI Research Platform Algorithm Hardware Benchmarking of Autonomous Aerial Robots

Aerial robotics is a cross-layer, interdisciplinary field. Air Learning is an effort to bridge seemingly disparate fields.

Designing an autonomous robot to perform a task involves interactions between various boundaries spanning from modeling the environment down to the choice of onboard computer platform available in the robot. Our goal through building Air Learning is to provide researchers with a cross-domain infrastructure that allows them to holistically study and evaluate reinforcement learning algorithms for autonomous aerial machines. We use stable-baselines to train UAV agent with Deep Q-Networks and Proximal Policy Optimization algorithms.

Authors: Srivatsan Krishnan, Behzad Boroujerdian, William Fu, Aleksandra Faust, Vijay Janapa Reddi
Email: srivatsan@seas.harvard.edu
Github: https://github.com/harvard-edge/airlearning
Paper: https://arxiv.org/pdf/1906.00421.pdf
Video: https://www.youtube.com/watch?v=oakzGnh7Llw (Simulation),
https://www.youtube.com/watch?v=cvO5YOzI0mg (on a CrazyFlie Nano-Drone)

1.39.16 Snake Game AI

AI to play the classic snake game. The game was trained using PPO2 available from stable-baselines and then exported to tensorflowjs to run directly on the browser

Author: Pedro Torres (@pedrohbtp)
Repository: https://github.com/pedrohbtp/snake-rl
Website: https://www.pedro-torres.com/snake-rl/

1.39.17 Pwnagotchi

Pwnagotchi is an A2C-based “AI” powered by bettercap and running on a Raspberry Pi Zero W that learns from its surrounding WiFi environment in order to maximize the crackable WPA key material it captures (either through passive sniffing or by performing deauthentication and association attacks). This material is collected on disk as PCAP files containing any form of handshake supported by hashcat, including full and half WPA handshakes as well as PMKIDs.

Author: Simone Margaritelli (@evilsocket)
Repository: https://github.com/evilsocket/pwnagotchi
Website: https://pwnagotchi.ai/

1.39.18 Quantized Reinforcement Learning (QuaRL)

QuaRL is a open-source framework to study the effects of quantization broad spectrum of reinforcement learning algorithms. The RL algorithms we used in this study are from stable-baselines.

Authors: Srivatsan Krishnan, Sharad Chitlangia, Maximilian Lam, Zishen Wan, Aleksandra Faust, Vijay Janapa Reddi

Email: srivatsan@seas.harvard.edu
Github: https://github.com/harvard-edge/quarl
Paper: https://arxiv.org/pdf/1910.01055.pdf

1.39.19 PPO_CPP: C++ version of a Deep Reinforcement Learning algorithm PPO

Executes PPO at C++ level yielding notable execution performance speedups. Uses Stable Baselines to create a computational graph which is then used for training with custom environments by machine-code-compiled binary.

Author: Szymon Brych
Email: szymon.brych@gmail.com
GitHub: https://github.com/Antymon/ppo_cpp

1.39.20 Learning Agile Robotic Locomotion Skills by Imitating Animals

Learning locomotion gaits by imitating animals. It uses PPO1 and AWR.

Authors: Xue Bin Peng, Erwin Coumans, Tingnan Zhang, Tsang-Wei Lee, Jie Tan, Sergey Levine
Website: https://xbpeng.github.io/projects/Robotic_Imitation/index.html
Github: https://github.com/google-research/motion_imitation
Paper: https://arxiv.org/abs/2004.00784

1.39.21 Imitation Learning Baseline Implementations

This project aims to provide clean implementations of imitation learning algorithms. Currently we have implementations of AIRL and GAIL, and intend to add more in the future.

Authors: Adam Gleave, Steven Wang, Nevan Wichers, Sam Toyer
Github: https://github.com/HumanCompatibleAI/imitation

1.40 Plotting Results

`stable_baselines.results_plotter.main()`

Example usage in jupyter-notebook

```
from stable_baselines import results_plotter
%matplotlib inline
results_plotter.plot_results(["./log"], 10e6, results_plotter.X_TIMESTEPS,
↪"Breakout")
```

Here ./log is a directory containing the monitor.csv files

`stable_baselines.results_plotter.plot_curves(xy_list, xaxis, title)`

plot the curves

Parameters

- **xy_list** – ([(np.ndarray, np.ndarray)]) the x and y coordinates to plot
- **xaxis** – (str) the axis for the x and y output (can be X_TIMESTEPS='timesteps', X_EPISODES='episodes' or X_WALLTIME='walltime_hrs')
- **title** – (str) the title of the plot

`stable_baselines.results_plotter.`**`plot_results`**(*dirs*, *num_timesteps*, *xaxis*, *task_name*)
plot the results

Parameters

- **dirs** – ([str]) the save location of the results to plot
- **num_timesteps** – (int or None) only plot the points below this value
- **xaxis** – (str) the axis for the x and y output (can be X_TIMESTEPS='timesteps', X_EPISODES='episodes' or X_WALLTIME='walltime_hrs')
- **task_name** – (str) the title of the task to plot

`stable_baselines.results_plotter.`**`rolling_window`**(*array*, *window*)
apply a rolling window to a np.ndarray

Parameters

- **array** – (np.ndarray) the input Array
- **window** – (int) length of the rolling window

Returns (np.ndarray) rolling window on the input array

`stable_baselines.results_plotter.`**`ts2xy`**(*timesteps*, *xaxis*)
Decompose a timesteps variable to x ans ys

Parameters

- **timesteps** – (Pandas DataFrame) the input data
- **xaxis** – (str) the axis for the x and y output (can be X_TIMESTEPS='timesteps', X_EPISODES='episodes' or X_WALLTIME='walltime_hrs')

Returns (np.ndarray, np.ndarray) the x and y output

`stable_baselines.results_plotter.`**`window_func`**(*var_1*, *var_2*, *window*, *func*)
apply a function to the rolling window of 2 arrays

Parameters

- **var_1** – (np.ndarray) variable 1
- **var_2** – (np.ndarray) variable 2
- **window** – (int) length of the rolling window
- **func** – (numpy function) function to apply on the rolling window on variable 2 (such as np.mean)

Returns (np.ndarray, np.ndarray) the rolling output with applied function

CHAPTER 2

Citing Stable Baselines

To cite this project in publications:

```
@misc{stable-baselines,
  author = {Hill, Ashley and Raffin, Antonin and Ernestus, Maximilian and Gleave,␣
↪Adam and Kanervisto, Anssi and Traore, Rene and Dhariwal, Prafulla and Hesse,␣
↪Christopher and Klimov, Oleg and Nichol, Alex and Plappert, Matthias and Radford,␣
↪Alec and Schulman, John and Sidor, Szymon and Wu, Yuhuai},
  title = {Stable Baselines},
  year = {2018},
  publisher = {GitHub},
  journal = {GitHub repository},
  howpublished = {\url{https://github.com/hill-a/stable-baselines}},
}
```

CHAPTER 3

Contributing

To any interested in making the rl baselines better, there are still some improvements that need to be done. A full TODO list is available in the roadmap.

If you want to contribute, please read CONTRIBUTING.md first.

CHAPTER 4

Indices and tables

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- search
- modindex

Python Module Index

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