Tonic: A Deep Reinforcement Learning Library for Fast Prototyping and Benchmarking

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Abstract
Deep reinforcement learning has been one of the fastest growing fields of machine learning over the past years and numerous libraries have been open sourced to support research. However, most codebases have a steep learning curve or limited flexibility that do not satisfy a need for fast prototyping in fundamental research. This paper introduces Tonic, a Python library allowing researchers to quickly implement new ideas and measure their importance by providing: 1) general-purpose configurable modules 2) several baseline agents: A2C, TRPO, PPO, MPO, DDPG, D4PG, TD3 and SAC built with these modules 3) support for TensorFlow 2 and PyTorch 4) support for continuous-control environments from OpenAI Gym, DeepMind Control Suite and PyBullet 5) scripts to experiment in a reproducible way, plot results, and play with trained agents 6) a benchmark of the provided agents on 70 continuous-control tasks. Evaluation is performed in fair conditions with identical seeds, training and testing loops, while sharing general improvements such as non-terminal timeouts and observation normalization. Finally, to demonstrate how Tonic simplifies experimentation, a novel agent called TD4 is implemented and evaluated.

1. Introduction
Supported by the deep learning revolution (LeCun et al., 2015; Goodfellow et al., 2016), reinforcement learning (RL) (Sutton & Barto, 2018) has grown in popularity and been at the heart of many of the recent milestones in artificial intelligence. Programs are now able to surpass the best humans at ancient board games (Silver et al., 2017) and video games (Mnih et al., 2015; Vinyals et al., 2019; Berner et al., 2019). While those achievements are impressive, they often rely on a number of simple fundamental research ideas that were originally developed independently such as Q-learning (Watkins & Dayan, 1992), policy gradient (Sutton et al., 2000) or Monte Carlo tree search (Coulom, 2006; Kocsis & Szepesvári, 2006).

An almost systematic pattern in deep RL research is: 1) the combination of novel general purpose ideas incorporated into agents 2) performance comparison with known baseline agents on simulated environments. While writing code from scratch has formative qualities, it is usually desirable to use a simple and flexible codebase. A large number of libraries exist with diverse goals such as large scale heavily distributed training (e.g. Liang et al., 2017), simple and pedagogical code (e.g. Achiam, 2018), fundamental research in pixel-based domains (e.g. Castro et al., 2018) or based on specific deep learning frameworks such as Keras (e.g. Plappert, 2016), TensorFlow (e.g. Dhariwal et al., 2017; Guadarrama et al., 2018), and PyTorch (e.g. Stooke & Abbeel, 2019; D’Eramo et al., 2020). While much effort has been made to build those libraries, we found that there was a need for a simple yet modular codebase designed to quickly try fundamental research ideas and evaluate them in a controlled and fair way, in particular in continuous control domains.

In this article, we introduce Tonic, a library for deep reinforcement learning research, written in Python and supporting both TensorFlow 2 (Abadi et al., 2016) and PyTorch (Passke et al., 2019). Tonic includes modules such as deep learning models, replay buffers or exploration strategies. Those modules are written to be easily configured and plugged into compatible agents. Furthermore, Tonic implements a number of popular continuous control baseline agents: A2C (Mnih et al., 2016), TRPO (Schulman et al., 2015), PPO (Schulman et al., 2017), MPO (Abdolmaleki et al., 2018), DDPG (Lillicrap et al., 2016), D4PG...
(Barth-Maron et al., 2018), TD3 (Fujimoto et al., 2018) and SAC (Haarnoja et al., 2018). Those agents are written with minimal abstractions to simplify readability and modification, emphasizing core ideas while moving other details into modules and sharing general improvements such as non-terminal timeouts (Pardo et al., 2018) and observation normalization. Tonic also includes three essential scripts to 1) train and test agents in a controlled way 2) plot results against baselines and 3) play with trained policies. Finally, Tonic includes a large-scale benchmark with training logs and model weights of the baseline agents for 10 seeds on 70 popular environments from OpenAI Gym (Brockman et al., 2016), DeepMind Control Suite (Tassa et al., 2018) and PyBullet (Coumans & Bai, 2016), representing a large and diverse set of domains based on Box2D (Catto, 2011), MuJoCo (Todorov et al., 2012) and Bullet (Coumans, 2010) physics engines. Table 1 in the Appendix, lists a number of differences between Tonic and other popular existing RL libraries.

The paper is organized as follows: Section 2 presents the configuration-based philosophy underlying most of Tonic’s components, Section 3 presents the training pipeline, Section 4 describes the different agents implemented using the previously introduced modules, Section 5 describes the supported environments and how they are adapted to work with the Tonic agents, Section 6 presents the benchmark, some of the results and shows how a new agent called TD4 can be easily implemented and evaluated, and Section 7 presents the three essential scripts provided with Tonic to simplify running experiments, interpret the results and play with the trained policies.

Before diving into the description of the library and the results, here is a minimal usage example:

```python
from tonic import environments, logger, Trainer
from tonic.tensorflow import agents

agent = agents.MPO()

env_fn = lambda: environments.Gym('Humanoid-v3')
env = environments.distribute(env_fn, 10, 10)
test_env = environments.distribute(env_fn)

logger.initialize('Humanoid-v3/MPO-10x10/42')

trainer = Trainer()
trainer.initialize(agent, env, test_env, 42)
trainer.run()
```

2. Library of Modules

Many libraries tend to put all the parameters of an experiment at the same level, calling an agent function with an environment name and all the relevant parameters. This prevents modularity and readability. Tonic tries as much as possible to move the configurable parts into modules. This has a number of advantages: 1) it clarifies the parameter targets, avoiding confusing long lists of parameters in input 2) different compatible modules with their own specific parameters can be used 3) new capabilities can be added without modifying agents.

In Tonic, the configuration of modules happens in two stages. First, when an experiment is described, agent modules are configured with general purpose parameters such as hidden layer sizes, exploration noise scale and trace decay used in λ-returns. Then, when the environment is selected, some specific values such as the observation and action space sizes are known and the modules are finally initialized. An illustration of the hierarchy of parameterized modules corresponding to the previous code snippet is shown in Figure 2.

Before describing the different modules, here is a minimal usage example showing how modules can be configured and initialized:

```python
model = models.ActorCritic(
    actor=models.Actor(
        encoder=models.ObservationEncoder(),
        torso=models.MLP((64, 64), 'tanh'),
        head=models.DetachedScaleGaussianPolicyHead()),
    critic=models.Critic(
        encoder=models.ObservationEncoder(),
        torso=models.MLP((64, 64), 'tanh'),
        head=models.ValueHead()),
    observation_normalizer=normalizers.MeanStd())

actor_updater = updaters.ClippedRatio(
    optimizer=optimizers.Adam(3e-4, epsilon=1e-8),
    ratio_clip=0.2, kl_threshold=0.015,
    entropy_coeff=0.01, gradient_clip=40)

model.initialize(env.observation_space, env.action_space)
actor_updater.initialize(model)
```

Models

For TensorFlow 2 and PyTorch models, smaller modules are assembled. For example, an actor-critic accepts an actor and a critic network. Actors and critics are built with an encoder, a torso and a head module. An encoder processes inputs, for example concatenating observations and actions for an action-dependent critic or normalizing observations using statistics from perceived observations so far. A torso is typically a multilayer perceptron (MLP) or a recurrent network. A head produces the outputs, such as values or distributions.

Replays

Different kinds of replays can be used for different types of agents. For example, a traditional Buffer can be used to randomly sample past transitions for off-policy training and a Segment can be used to store contiguous transitions for an on-policy agent. Since those replays are configurable modules, they hold parameters like the dis-
Figure 2. A hierarchy of configured modules are used to specify experiments in Tonic. Modules written for both TensorFlow 2 and PyTorch are shown with their respective logos.

**3. Trainer**

The `tonic.Trainer` module is in charge of the training loop in Tonic. It takes care of the communication between the agent and the environment, testing the agent on the test environment, logging data via the logger and periodically saving the model parameters in checkpoints for future reload.

Distributed training has been shown to greatly accelerate the training of RL agents with respect to wall clock time (Mnih et al., 2016; Espeholt et al., 2018). Instead of interacting with a single environment at a time, the agent interacts with a set of differently seeded copies of the environment to diversify experience and increase throughput. For simplicity and to ensure reproducibility, Tonic uses a synchronous training loop illustrated in Figure 3. At training step $t$, the trainer first sends a tensor $O_t$ of observations to the agent via the agent's step function which returns a tensor $A_t$ of actions and keeps track of some values such as $O_t$ or the log probabilities of the actions. The actions are transmitted to the environment module via the environment.step function which returns multiple values. First, the ones describing the current transitions caused by the actions $A_t$; the tensor $O_t'$, of next observations, the vectors $r_t$ of rewards, $\tau_t$ of terminations and $\rho_t$ of resets. The terminations indicate true environmental terminations, the ones caused for example by falling on the floor in a locomotion task or reaching a target state. Agents can use those to know when bootstrapping is possible. The resets vector signals the end of episodes, from terminations and timeouts and can be used by agents to know the boundaries of episodes, for example for $\lambda$-return calculations. When using non-terminal time-
outs, partial-episode bootstrapping (Pardo et al., 2018) is used to bootstrap from the values in $O'_t$, and it is therefore important to know that a reset happened without an environmental termination. When an environment resets, a new observation is generated and has to be used to select the next action, therefore, the environment also returns a tensor $O_{i+1}$ of observations to use next. For a sub-environment $i$, $o'_i = o_{i+1}$ if $\rho_i = \text{False}$. Finally, the transition values are given to the actor via the actor.update function which takes care of registering the transitions in a replay and performing updates, while the new observations $O_{i+1}$ are used to generate the new actions $A_{i+1}$ at the next step.

4. Agents

A number of reinforcement learning agents have been proposed over the years. Tonic contains 8 popular baseline agents, some are simple and foundational while others are more complicated state of the art algorithms.

Basic agents Especially useful for debugging, the simple non-parametric agents are NormalRandom, UniformRandom, OrnsteinUhlenbeck, and Constant.

Advantage Actor-Critic (A2C) This agent, also called Vanilla Policy Gradient (VPG) in some libraries, uses advantages from $\lambda$-returns and a learned value function to update a stochastic policy via policy gradient (Sutton et al., 2000; Schulman et al., 2016; Mnih et al., 2016). It is stable but learns slowly because it can use the latest collected transitions only once to update its actor.

Trust Region Policy Optimization (TRPO) This agent uses a conjugate gradient optimizer to take a large update step of policy gradient while satisfying a KL constraint between the new and previous policies (Schulman et al., 2015).

Proximal Policy Optimization (PPO) This agent approximates TRPO by using clipped ratios between the old policy which generated the latest transitions and the currently optimized policy (Schulman et al., 2017).

Maximum a Posteriori Policy Optimisation (MPO) This agent uses a complex relative-entropy objective taking advantage of the duality between control and estimation (Abdolmaleki et al., 2018). It can be very powerful if carefully tuned but its complexity made it very challenging to implement and Acme’s code (Hoffman et al., 2020) was the only reliable source when Tonic was created.

Deep Deterministic Policy Gradient (DDPG) This agent uses a deterministic actor trained via deterministic policy gradient (Silver et al., 2014; Lillicrap et al., 2016). It is data-efficient because it learns off-policy an approximation to the optimal value function used to locally optimize the actor.

Distributed Distributional Deep Deterministic Policy Gradient (D4PG) This agent uses a distributional critic head, n-step returns and prioritized experience replay (Barth-Maron et al., 2018). Tonic does not currently include a prioritized replay buffer but as pointed in the original paper, this is a less critical component and can lead to unstable updates.

Twin Delayed Deep Deterministic Policy Gradient (TD3) This agent stabilizes DDPG using a pair of critics, action noise in the target actor and a delay to update the actor network less often (Fujimoto et al., 2018).

Soft Actor-Critic (SAC) This agent uses an entropy based reward augmentation, a squared Gaussian policy and a pair of critics (Haarnoja et al., 2018).

5. Environments

OpenAI Gym, PyBullet and DeepMind Control Suite Tonic includes builders for continuous-control environments from OpenAI Gym (Brockman et al., 2016), DeepMind Control Suite (Tassa et al., 2018) and PyBullet (Coumans & Bai, 2016), representing a large and diverse set of domains based on Box2D (Catto, 2011), MuJoCo (Todorov et al., 2012) and Bullet (Coumans, 2010) physics engines. For simplicity and to match Gym and PyBullet environments,
Figure 4. Subset of the benchmark results. For each agent, 5 test episodes are collected after each training epoch and averaged. The solid lines represent the average over 10 runs for each agent. The [minimum, maximum] range is shown with transparent areas and a sliding window of size 5 is used for smoothing. A large palette of environments are represented across the supported domains. The best performing agents are mostly TD3, SAC, MPO and D4PG (Control Suite tasks) but significant variations exist for each agent.

Figure 5. Dictionary observations are flattened and concatenated in vectors.

**Non-terminal timeouts** All of these environments are wrapped to enable the synchronous interaction described in Section 3. The TimeLimit wrapper is removed from the Gym and PyBullet environments while in the case of Control Suite environments, task terminations are detected from `task.get_termination(physics)`. Moreover, when `terminal_timeouts` is set to `True`, it is recommended to also set `time_feature` to `True` to use a `tonic.environments.TimeFeature` wrapper, adding a representation of the remaining time in observation. This is known as time-awareness (Pardo et al., 2018) and allows environments to stay Markovian.

**Action scaling** Agents are all expected to act in a $[-1, 1]^d$ action space where $d$ is the number of dimensions. This facilitates action noise scaling and learning for agents relying on deterministic policies. Environments use a `tonic.environments.ActionRescaler` wrapper by default.

**Distributed training** Finally, for distributed training, the set of environment copies is maintained in parallel groups of sequential workers. Each parallel group is allocated to a different process and communication is done via pipes. Since this communication method adds some time overhead, using multiple sequential environments in each group can increase throughput.

### 6. Benchmark

When evaluating novel ideas in the literature, it is sometimes difficult to measure the significance of results as baselines can be poorly tuned or evaluated in unfair conditions. Benchmarks of popular RL agents on popular RL environments (e.g. Duan et al., 2016; Huang et al., 2020) evaluated in identical conditions are essential to provide reliable lower bounds in fundamental research.

**Methods** Tonic contains a large-scale benchmark of the 8 provided deep RL agents on 70 popular continuous-control tasks: 17 from OpenAI Gym (2 classic control, 3 Box2D, 12 MuJoCo), 10 from PyBullet and 43 from the benchmark.
subset in DeepMind Control Suite. The exact same 10 seeds (0, 1, 2, ..., 9) are used for all agents with default parameters on all environments with single-worker training (not distributed). D4PG was only run on DeepMind Control Suite environments because known reward boundaries are required for distributional value functions. Therefore, the total number of runs contained in the benchmark is $70 \times 10 \times 7 + 43 \times 10 = 5330$. These runs were all generated with \texttt{tonic.tensorflow} which was significantly faster with off-policy agents than \texttt{tonic.torch}. This difference could be due to a more efficient graph tracing mechanism provided by TensorFlow’s \texttt{tf.function} decorator. A speed comparison is provided in Appendix Figure 9. The runs were started by only specifying the environment, the agent and the seed, without any other argument. This means that all the hyperparameters used are the default ones.

**Results** Some of the results can be seen in Figure 4 while the full benchmark plots can be found in Appendix Figure 7. Environments from OpenAI Gym (names starting with an uppercase) and PyBullet (names with “PybulletEnv”) are mostly “solved” with best agents getting scores similar to the best performances reported in the literature. However, many environments from DeepMind Control Suite seem much harder to learn and most results reported for those environments can be found in the literature with distributed training and many more training steps. Nevertheless, it is important to note that better hyper parameters could certainly be found for those agents, and especially better ones for each environment specifically.

**Comparison to Spinning Up in Deep RL** To prove that the results for A2C, TRPO, PPO, DDPG, TD3 and SAC can be used as valid baselines, another benchmark was generated with TensorFlow 1 implementations of those agents from Spinning Up in Deep RL (Achiam, 2018). The library was slightly modified to use a test environment for each agent, a frequency and number of test episodes and seeds identical to the ones used in the Tonic benchmark and VPG was renamed A2C. Results on the original 5 environments used in the benchmark of this library can be found in Appendix Figure 8. The results from Spinning Up in Deep RL are compatible with the ones found on the website. The agents from Tonic perform significantly better on four of the five environments. This difference can be explained by some of the improvements in Tonic, such as observation normalization, non-terminal timeouts and action-scaling, even though Spinning Up in Deep RL partially implements non-terminal timeouts for the off-policy methods by ignoring environmental terminations at timeout.

**Ablations and variants** To measure the effectiveness of non-terminal timeouts and observation normalization in particular, PPO was trained with different variants. Results shown in Figure 5 demonstrate that those improvements indeed improve performance of PPO. Finally, supplementary experiments validated the effectiveness of these improvements on the other agents and environments.

**Prototyping and benchmarking a novel agent** To demonstrate how Tonic can accelerate the development and the evaluation of ideas, a new agent called TD4, combining features of TD3 and D4PG is proposed. The source code consisting of 93 clean lines of code can be found in Appendix Section E.1. It contains three elements. The first one is a new model based on \texttt{ActorTwinCriticWithTargets}...
with a DistributionalValueHead for the twin critic. The second element is a new updater similar to TwinCriticDeterministicQLearning but adapted to use a pair of critics. The third element is the agent itself, based on TD3 and D4PG and using the two previous elements. The command lines needed to train the proposed agent and using the two previous elements. The command lines needed to train the proposed agent and directly compare its performance to D4PG and TD3 can be found in E.2. The results on 10 tasks are shown in Figure 6 and demonstrate that TD4 is an excellent agent combining advantages from TD3 and D4PG and was particularly simple to implement and evaluate.

7. Scripts

The modules and agents described above can easily be used in a standalone experiment Python script or integrated in another codebase. However, for convenience, Tonic includes three essential scripts to take care of the most important things: training, plotting and playing.

**tonic.train** A script used to launch training experiments. Since any agent could be configured with any compatible modules and launched on any configured environment, a simple list of parsed parameters would not give enough flexibility. Therefore, Tonic uses the interpreted nature of the Python language to directly evaluate Python snippets describing the agent, the environment and the trainer configurations. The script saves the experiment script and arguments and automatically configures the logger to use a particular checkpoint can be chosen. While rendering the policy interacting with the environment, the episode lengths, scores, min and max rewards are printed on the terminal.

```
python3 -m tonic.train \ 
--header "import tonic.torch" \ 
--agent "tonic.torch.agents.PPO()" \ 
--environment "tonic.environments.Gym('Ant-v3')" \ 
--seed 0
```

**tonic.plot** A script to load and display results from multiple experiments together. The script expects a list of csv or pkl files to load data from. Regular expressions like BipedalWalker-v3/PPO-X/6, BipedalWalker-v3/(PPO*,DDPG*) or *Bullet* can be used to point to different sets of logs. Multiple sub-figures are generated, one per environment, aggregating results of agents across runs. The script can be configured in many ways. For example, the figure can be saved in different file formats such as PDF and PNG. A non-GUI backend such as agg can be used. If the seconds argument is used, plotting is performed regularly in real time. The baseline argument can be used to load logs from the benchmark saved in the /data/logs folder at the root of Tonic. For example, --baselines all uses all agents while --baselines A2C PPO TRPO will use logs from A2C, PPO and TRPO. Different parameters allow the user to customize the x and y axes, change the smoothing window size, specify the type of interval shown, display individual runs, select the minimum and maximum values of the x axis, and do many other things. Finally, the legend is shown at the bottom of the figure, regrouping all agents across environments with a mechanism to automatically detect the ideal number of legend columns to use. Usage example:

```
python3 -m tonic.plot --path Ant-v3 --baselines all
```

**tonic.play** A script to reinstantiate the environment and agent from an experiment folder, reloading weights from a checkpoint and rendering the policy acting in the environment. The path to the experiment must be specified and a particular checkpoint can be chosen. While rendering the policy interacting with the environment, the episode lengths, scores, min and max rewards are printed on the terminal. Gym environments are simply rendered while PyBullet and DeepMind Control Suite viewers allow users to add pertur-
bations to the bodies in the simulation. Usage example:

```python
python3 -m tonic.play --path BipedalWalker-v3/PPO/0
```

**Adding new modules, agents and environments** When using `tonic.train`, new components can be added using the `header` field which is evaluated first. For example, if the components are installed or accessible from the current directory, they can directly be imported. If necessary, the path to the required files can also be added to the `sys.path` before importing them. Finally, for OpenAI Gym, PyBullet and DeepMind Control Suite environments, it is recommended to register new tasks at import time in the packages themselves. For example, the `__init__.py` at the root of a package containing new tasks could use `register(id='Cat-v0', entry_point=CatEnv)` for Gym and PyBullet, and `suite._DOMAINS['cat'] = cat_tasks` for Control Suite. Usage example:

```python
python3 -m tonic.train \
--header "import animal_envs, tonic.tensorflow" \
--environment "tonic.environments.Gym('Cat-v0')" \
--agent "tonic.tensorflow.agents.TD3()" \
--seed 0
```

8. Conclusion and Future Work

This paper introduced Tonic, a library designed for fast prototyping and benchmarking of deep RL algorithms. It contains a number of configurable modules, agents, supported environments, three essential scripts and a large-scale continuous-control benchmark. Future work will include support for discrete action spaces and pixel-based observations, better handling of dictionary-based observations, benchmark results with improved hyper-parameters, new modules and agents. In particular, some of the new agents will rely on discretization of continuous-action spaces as this alternative has proven to be competitive with continuous-control methods (Metz et al., 2017; Tavakoli et al., 2018; Van de Wiele et al., 2020). Hopefully researchers will use Tonic, contribute to it and will find easier to release the source code of their papers.

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References

Martin Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, Manjunath Kudlur, Josh Levenberg, Rajat Monga, Sherry Moore, Derek G. Murray, Benoit Steiner, Paul Tucker, Vijay Vasudevan, Pete Warden, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. Tensorflow: A system for large-scale machine learning. In 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16), pp. 265–283, 2016.

Abbas Abdolmaleki, Jost Tobias Springenberg, Yuval Tassa, Remi Munos, Nicolas Heess, and Martin Riedmiller. Maximum a posteriori policy optimisation. In International Conference on Learning Representations, 2018.

Joshua Achian. Spinning Up in Deep Reinforcement Learning. GitHub repository, 2018. URL https://github.com/openai/spinningup.

Gabriel Barth-Maron, Matthew W Hoffman, David Budden, Will Dabney, Dan Horgan, Dhruva Tb, Alistair Muldal, Nicolas Heess, and Timothy Lillicrap. Distributed distributional deterministic policy gradients. arXiv preprint arXiv:1804.08617, 2018.

Christopher Berner, Greg Brockman, Brooke Chan, Vicki Cheung, Przemyslaw Dębiak, Christy Dennison, David Farhi, Quirin Fischer, Shariq Hashme, Chris Hesse, et al. Dota 2 with large scale deep reinforcement learning. arXiv preprint arXiv:1912.06680, 2019.

Greg Brockman, Vicki Cheung, Ludwig Pettersson, Jonas Schneider, John Schulman, Jie Tang, and Wojciech Zaremba. OpenAI Gym. arXiv preprint arXiv:1606.01540, 2016.

Pablo Samuel Castro, Subhodeep Moitra, Carles Gelada, Saurabh Kumar, and Marc G Bellemare. Dopamine: A research framework for deep reinforcement learning. arXiv preprint arXiv:1812.06110, 2018.

Erin Catto. Box2D: a 2D physics engine for games. GitHub repository, 2011. URL https://github.com/erincatto/box2d.

Rémi Coulom. Efficient selectivity and backup operators in monte-carlo tree search. In International conference on computers and games, pp. 72–83. Springer, 2006.

Erwin Coumans. Bullet physics engine. 2010. URL http://pybullet.org.

Erwin Coumans and Yunfei Bai. PyBullet, a Python module for physics simulation for games, robotics and machine learning. 2016. URL https://pybullet.org.
Carlo D’Eramo, Davide Tateo, Andrea Bonarini, Marcello Restelli, and Jan Peters. Mushroomrl: Simplifying reinforcement learning research. arXiv preprint arXiv:2001.01102, 2020. URL https://github.com/mushroomrl/mushroom-rl.

Prafulla Dhariwal, Christopher Hesse, Oleg Klimov, Alex Nichol, Matthias Plappert, Alec Radford, John Schulman, Szymon Sidor, Yuhuai Wu, and Peter Zhokhov. Openai baselines. GitHub repository, 2017. URL https://github.com/openai/baselines.

Yan Duan, Xi Chen, Rein Houthooft, John Schulman, and Pieter Abbeel. Benchmarking deep reinforcement learning for continuous control. In International Conference on Machine Learning, pp. 1329–1338, 2016.

Lasse Espeholt, Hubert Soyer, Remi Munos, Karen Simonyan, Volodymyr Mnih, Tom Ward, Yotam Doron, Vlad Firoiu, Tim Harley, Iain Dunning, et al. Impala: Scalable distributed deep-rl with importance weighted actor-learner architectures. arXiv preprint arXiv:1802.01561, 2018.

Scott Fujimoto, Herke Van Hoof, and David Meger. Addressing function approximation error in actor-critic methods. volume 80 of Proceedings of Machine Learning Research, pp. 1587–1596. PMLR, 2018.

Ian Goodfellow, Yoshua Bengio, and Aaron Courville. Deep learning. MIT press, 2016.

Sergio Guadarrama, Anoop Korattikara, Oscar Ramirez, Pablo Castro, Ethan Holly, Sam Fishman, Ke Wang, Ekaterina Gonina, Neal Wu, Chris Harris, et al. TFD-Agents: A library for reinforcement learning in tensorflow. GitHub repository, 2018. URL https://github.com/tensorflow/agents.

Tuomas Haaranoja, Aurick Zhou, Pieter Abbeel, and Sergey Levine. Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor. arXiv preprint arXiv:1801.01290, 2018.

Matt Hoffman, Bobak Shakirari, John Aslanides, Gabriel Barth-Maron, Feryal Behbahani, Tamara Norman, Abbas Abdolmaleki, Albin Cassirer, Fan Yang, Kate Baumli, et al. Acme: A research framework for distributed reinforcement learning. arXiv preprint arXiv:2006.00979, 2020. URL https://github.com/deepmind/acme.

Shengyi Huang, Rousslan Dossa, and Chang Ye. Cleanrl: High-quality single-file implementation of deep reinforcement learning algorithms. GitHub repository, 2020. URL https://github.com/vwxyzjn/cleanrl.

Levente Kocsis and Csaba Szepesvári. Bandit based monte-carlo planning. In European conference on machine learning, pp. 282–293. Springer, 2006.

Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. nature, 521(7553):436–444, 2015.

Eric Liang, Richard Liaw, Philipp Moritz, Robert Nishihara, Roy Fox, Ken Goldberg, Joseph E Gonzalez, Michael I Jordan, and Ion Stoica. Rllib: Abstractions for distributed reinforcement learning. arXiv preprint arXiv:1712.09381, 2017.

Timothy P Lillicrap, Jonathan J Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. Continuous control with deep reinforcement learning. In Proceedings of the International Conference on Learning Representations (ICLR), 2016.

Luke Metz, Julian Ibarz, Navdeep Jaitly, and James Davidson. Discrete sequential prediction of continuous actions for deep rl. arXiv preprint arXiv:1705.05035, 2017.

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. Nature, 518(7540):529–533, 2015.

Volodymyr Mnih, Adria Puigdomenech Badia, Mehdi Mirza, Alex Graves, Timothy Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous methods for deep reinforcement learning. In International conference on machine learning, pp. 1928–1937, 2016.

Fabio Pardo, Arash Tavakoli, Vitaly Levdkiv, and Petar Kormushev. Time limits in reinforcement learning. volume 80 of Proceedings of Machine Learning Research, pp. 4045–4054. PMLR, 2018.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. In Advances in Neural Information Processing Systems, pp. 8024–8035, 2019.

Matthias Plappert. Keras-RL. GitHub repository, 2016. URL https://github.com/keras-rl/keras-rl.

John Schulman, Sergey Levine, Pieter Abbeel, Michael Jordan, and Philipp Moritz. Trust region policy optimization. In International conference on machine learning, pp. 1889–1897, 2015.
John Schulman, Philipp Moritz, Sergey Levine, Michael Jordan, and Pieter Abbeel. High-dimensional continuous control using generalized advantage estimation. In Proceedings of the International Conference on Learning Representations (ICLR), 2016.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. arXiv preprint arXiv:1707.06347, 2017.

David Silver, Guy Lever, Nicolas Heess, Thomas Degris, Daan Wierstra, and Martin Riedmiller. Deterministic policy gradient algorithms. volume 32 of Proceedings of Machine Learning Research, pp. 387–395. PMLR, 2014.

David Silver, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert, Lucas Baker, Matthew Lai, Adrian Bolton, et al. Mastering the game of go without human knowledge. Nature, 550(7676):354–359, 2017.

Adam Stooke and Pieter Abbeel. rlpyt: A research code base for deep reinforcement learning in pytorch. arXiv preprint arXiv:1909.01500, 2019.

Richard S Sutton and Andrew G Barto. Reinforcement learning: An introduction. MIT press, 2018.

Richard S Sutton, David A McAllester, Satinder P Singh, and Yishay Mansour. Policy gradient methods for reinforcement learning with function approximation. In Advances in neural information processing systems, pp. 1057–1063, 2000.

Yuval Tassa, Yotam Doron, Alistair Muldal, Tom Erez, Yazhe Li, Diego de Las Casas, David Budden, Abbas Abdolmaleki, Josh Merel, Andrew Lefrancq, et al. DeepMind Control Suite. arXiv preprint arXiv:1801.00690, 2018.

Arash Tavakoli, Fabio Pardo, and Petar Kormushev. Action branching architectures for deep reinforcement learning. In AAAI Conference on Artificial Intelligence, pp. 4131–4138, 2018.

Emanuel Todorov, Tom Erez, and Yuval Tassa. MuJoCo: a physics engine for model-based control. In 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 5026–5033. IEEE, 2012.

Tom Van de Wiele, David Warde-Farley, Andriy Mnih, and Volodymyr Mnih. Q-learning in enormous action spaces via amortized approximate maximization. arXiv preprint arXiv:2001.08116, 2020.

Oriol Vinyals, Igor Babuschkin, Wojciech M Czarnecki, Michaël Mathieu, Andrew Dudzik, Junyoung Chung, David H Choi, Richard Powell, Timo Ewalds, Petko Georgiev, et al. Grandmaster level in StarCraft II using multi-agent reinforcement learning. Nature, 575(7782):350–354, 2019.

Christopher JCH Watkins and Peter Dayan. Q-learning. Machine learning, 8(3-4):279–292, 1992.
A. Benchmark Results

Figure 7. Full benchmark results on 70 tasks, for 5 million time steps over 10 seeds. Intervals indicate minimum and maximum values. Curves are smoothed with a sliding window of size 5. A few runs diverged catastrophically, especially on Striker-v2 and Thrower-v2.
B. Comparison with Spinning Up in Deep RL

Figure 8. Comparison with Spinning Up in Deep RL using the same training, evaluation and agent parameters.
C. TensorFlow 2 vs PyTorch

![Graph showing speed comparison between TensorFlow 2 and PyTorch agents trained on walker-walk.](image)

**Figure 9.** Speed comparison between TensorFlow 2 and PyTorch agents trained on walker-walk. Agents were trained for 1 million steps, using the same parameters as for the benchmark. The time spent to run the last 250,000 steps is used to measure the average number of steps per second indicated by bars. The agents were fully trained in turn on the same 6-core processor running at 3.8 GHz without GPU. The figure on the left used the default number of threads while the figure on right shows the impact of setting the number of interop and intraop threads for DDPG. The difference between the two frameworks might be due to a better optimization mechanism provided by TensorFlow’s `tf.function` decorator.

D. Comparison to Existing Libraries

**Table 1.** Comparison between Tonic and other popular existing RL libraries.

| LIBRARY          | ACTIVE | FRAMEWORKS | MODULES | TRAINER | DISTRIBUTED | BENCH  | SCRIPTS |
|------------------|--------|------------|---------|---------|-------------|--------|---------|
| **Tonic (ours)** | ✓      | TF 2 AND PT| ✓       | ✓       | SYNC WITH PEB| LARGE | ✓       |
| RLLIB            | ✓      | TF 1 AND PT| ✓       | ✓       | SYNC AND ASYNC| SMALL |         |
| Baselines        |         | TF 1       | ✓       | ✓       | SOME SYNC (MPI) |       |         |
| Stable Baselines |         | TF 1       | ✓       | ✓       | SOME SYNC (MPI) |       |         |
| Stable Baselines 3| ✓      | PT         | ✓       | ✓       |             |       |         |
| Spinning Up      |         | TF 1 AND PT| ✓       | ✓       | SOME SYNC (MPI) | SMALL|         |
| ACME             | ✓      | TF 2 AND JAX| ✓       | ✓       | ASYNC       |       |         |
| RLGraph          |         | TF 1 AND PT| ✓       | ✓       | SYNC AND ASYNC|     |         |
| COACH            |         | TF 1       | ✓       | ✓       | SYNC AND ASYNC| SMALL|         |

Repositories that have not received any major update during the past year are marked as not active. With MPI (Message Passing Interface) each worker has its own environment and a copy of the networks, computes gradients based on its own experience and a synchronous averaging of the gradients is required for each update. This approach does not easily scale to a large number of workers. Asynchronous distributed training does not guarantee reproducible experiments and provides significantly different results on machines with different compute power. Tonic is the only library properly handling timeout terminations and providing three essential scripts to train, plot and play easily.
E. The Proposed TD4 Agent

E.1. Full Source Code

```python
import tensorflow as tf
from tonic import replays
from tonic.tensorflow import agents, models, normalizers, updaters

def default_model():
    return models.ActorTwinCriticWithTargets(
        actor=models.Actor(
            encoder=models.ObservationEncoder(),
            torso=models.MLP((256, 256), 'relu'),
            head=models.DeterministicPolicyHead()),
        critic=models.Critic(
            encoder=models.ObservationActionEncoder(),
            torso=models.MLP((256, 256), 'relu'),
            head=models.DistributionalValueHead(-150., 150., 51)),
        observation_normalizer=normalizers.MeanStd())

class TwinCriticDistributionalDeterministicQLearning:
    def __init__(self, optimizer=None, target_action_noise=None, gradient_clip=0):
        self.optimizer = optimizer or tf.keras.optimizers.Adam(lr=1e-3, epsilon=1e-8)
        self.target_action_noise = target_action_noise or updaters.TargetActionNoise(scale=0.2, clip=0.5)
        self.gradient_clip = gradient_clip

    def initialize(self, model):
        self.model = model
        variables_1 = self.model.critic_1.trainable_variables
        variables_2 = self.model.critic_2.trainable_variables
        self.variables = variables_1 + variables_2

    @tf.function
    def __call__(self, observations, actions, next_observations, rewards, discounts):
        next_actions = self.model.target_actor(next_observations)
        next_actions = self.target_action_noise(next_actions)
        next_value_distributions_1 = self.model.target_critic_1(next_observations, next_actions)
        next_value_distributions_2 = self.model.target_critic_2(next_observations, next_actions)
        values = next_value_distributions_1.values
        returns = rewards[:, None] + discounts[:, None] * values
        targets_1 = next_value_distributions_1.project(returns)
        targets_2 = next_value_distributions_2.project(returns)
        next_values_1 = next_value_distributions_1.mean()
        next_values_2 = next_value_distributions_2.mean()
        twin_next_values = tf.concat([next_values_1[None], next_values_2[None]], axis=0)
        indices = tf.argmin(twin_next_values, axis=0, output_type=tf.int32)
        twin_targets = tf.concat([targets_1[None], targets_2[None]], axis=0)
        batch_size = tf.shape(observations)[0]
        indices = tf.stack([indices, tf.range(batch_size)], axis=-1)
        targets = tf.gather_nd(twin_targets, indices)
        with tf.GradientTape() as tape:
```

value_distributions_1 = self.model.critic_1(observations, actions)
losses_1 = tf.nn.softmax_cross_entropy_with_logits(
    logits=value_distributions_1.logits, labels=targets)
value_distributions_2 = self.model.critic_2(observations, actions)
losses_2 = tf.nn.softmax_cross_entropy_with_logits(
    logits=value_distributions_2.logits, labels=targets)
loss = tf.reduce_mean(losses_1) + tf.reduce_mean(losses_2)
gradients = tape.gradient(loss, self.variables)
if self.gradient_clip > 0:
    gradients = tf.clip_by_global_norm(
        gradients, self.gradient_clip)[0]
self.optimizer.apply_gradients(zip(gradients, self.variables))
return dict(loss=loss)

class TD4(agents.TD3):
    def __init__(self, model=None, replay=None, exploration=None, actor_updater=None, critic_updater=None, delay_steps=2):
        model = model or default_model()
        replay = replay or replays.Buffer(num_steps=5)
        actor_updater = actor_updater or \
            updaters.DistributionalDeterministicPolicyGradient()
        critic_updater = critic_updater or \
            TwinCriticDistributionalDeterministicQLearning()
        super().__init__(model=model, replay=replay, exploration=exploration, actor_updater=actor_updater, critic_updater=critic_updater, delay_steps=delay_steps)

E.2. Command Lines

Training can be started using:

python3 -m tonic.train \
    --header "import td4, tonic.tensorflow" \
    --environment "tonic.environments.ControlSuite('humanoid-walk')" \
    --agent "td4.TD4()" \
    --seed 0

The agent can be evaluated against D4PG and TD3 using:

python3 -m tonic.plot --path humanoid-walk --baselines D4PG TD3