IMITATION: Clean Imitation Learning Implementations

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Abstract

IMITATION provides open-source implementations of imitation and reward learning algorithms in PyTorch. We include three inverse reinforcement learning (IRL) algorithms, three imitation learning algorithms and a preference comparison algorithm. The implementations have been benchmarked against previous results, and automated tests cover 98\% of the code. Moreover, the algorithms are implemented in a modular fashion, making it simple to develop novel algorithms in the framework. Our source code, including documentation and examples, is available at \url{https://github.com/HumanCompatibleAI/imitation}.

Keywords: Imitation Learning, Reward Learning, Software, Python, PyTorch

1. Introduction

Reinforcement learning (RL) has surpassed human performance in domains with clearly-defined reward functions, such as games (Berner et al., 2019). Unfortunately, it is difficult or impossible to procedurally specify the reward function for many real-world tasks. We must instead learn a reward function or policy directly from user feedback. Moreover, even when we can write down a reward function, such as if the agent wins a game, the resulting objective might be so sparse that RL cannot efficiently solve it. State-of-the-art results in RL therefore often use imitation learning to initialize the policy (Vinyals et al., 2019).

We introduce IMITATION: a library providing high-quality, reliable and modular implementations of seven reward and imitation learning algorithms. Crucially, our algorithms follow a consistent interface, making it simple to train and compare a range of algorithms. Furthermore, IMITATION is built using modern backends such as PyTorch and Stable Baselines\textsuperscript{3}. By contrast, prior libraries typically support only a handful of algorithms, are no longer actively maintained, and are built on top of deprecated frameworks.

A key use case of IMITATION is as an experimental baseline. Prior work has shown that small implementation details in imitation learning algorithms can have significant impacts on performance (Orsini et al., 2021). This could lead to spurious positive results being...
reported if a weak experimental baseline were used. To address this challenge, our algorithms have been carefully benchmarked and compared to prior implementations (see Figure 1 and Table 2). Additionally, our test suite covers 98% of our code, and we also perform static type checking.

In addition to providing reliable baselines, IMITATION aims to simplify developing novel reward and imitation learning algorithms. Our implementations are modular: users can freely change the reward or policy network architecture, RL algorithm and optimizer without any changes to the code. Algorithms can be extended by subclassing and overriding the relevant methods. Moreover, to support the development of entirely novel algorithms, IMITATION provides utility methods to handle common tasks such as collecting rollouts.

2. Features

**Comprehensive** IMITATION implements seven algorithms spanning a range of reward and imitation learning styles. Our IRL algorithms consist of 1) the seminal tabular method Maximum Causal Entropy IRL (MCE IRL; Ziebart et al., 2010), 2) a baseline based on density estimation, and 3) the state-of-the-art approach Adversarial IRL (AIRL; Fu et al., 2018). For imitation learning, we include 1) the simple Behavioral Cloning (BC) algorithm, 2) a variant DAgger (Ross et al., 2011) that learns from interactive demonstrations, and 3) the state-of-the-art Generative Adversarial Imitation Learning (Ho and Ermon, 2016) algorithm. Finally, we also include Deep RL from Human Preferences (DRLHP; Christiano et al., 2017) that infers a reward function from comparisons between trajectory fragments.

**Consistent Interface** We provide a unified API for all algorithms, inheriting from a common base class `BaseImitationAlgorithm`. Algorithms diverge only where strictly necessary (e.g. a different feedback modality). This makes it simple to automatically test a wide range of algorithms against a benchmark suite.

**Experimental Framework** We provide scripts to train and evaluate the algorithms, making it easy to use the library without writing a single line of code. The scripts follow a consistent interface, and we include examples to run all algorithms on a suite of commonly used environments. To ensure replicable experiments we use Sacred (Greff et al., 2017) for configuration and logging.

**Modularity** To support the variety of use cases that arise in research, we have designed our implementations to be modular and highly configurable. For example, algorithms can be configured to use any of the seven Stable Baselines3 RL algorithms (or a custom algorithm matching this interface). By contrast, prior implementations often implemented imitation learning algorithms by subclassing a specific RL algorithm, requiring substantial code modification to be ported to new RL algorithms.

We have also designed the code to be easy to extend in order to implement novel algorithms. Each algorithm is implemented by a class with instance methods corresponding to each logical step of the algorithm. New algorithms can be implemented simply by subclassing an existing algorithm and overriding a subset of methods. This power is illustrated by our implementations of GAIL and AIRL, which both subclass `AdversarialTrainer`. They differ only in the choice of discriminator, with most training logic shared.
Figure 1: Returns of our algorithms normalized so that 1 is the returns of an expert policy and 0 is that of a random policy. Our algorithms reach close to expert performance on most environments. Detailed results, including confidence intervals, can be found in Table 2.

Documentation  IMITATION comes with extensive documentation available at https://imitation.readthedocs.io. We include installation instructions, a quickstart guide and a contribution guide for prospective developers as well as an API reference. We also provide tips for evaluation of imitation and reward learning algorithms, including avoiding variable-horizon environments which has confounded prior evaluation (Kostrikov et al., 2019).

High-Quality Implementations  We take great care to provide reliable implementations of algorithms. Our test suite covers 98% of the entire codebase. Additionally, we use type annotations throughout, and statically check our code using pytype and mypy.

While our thorough testing and code review help avoid bugs, even apparently minor implementation details can have significant impacts on algorithm performance (Engstrom et al. 2020). Therefore, we have also benchmarked our algorithms on environments that have been commonly used in prior work, including in the original papers of the algorithms.

We find in Figure 1 that our algorithms reach expert-level performance on these environments, with the exception of AIRL in the Ant and Walker environments, and DAgger in the Hopper environment. AIRL and DAgger were not originally tested on the Walker and Hopper environments, respectively, so it is possible these algorithms just do not perform well on these environments. The AIRL paper did report positive results on an Ant environment, whereas our implementation performs close to random. However, the AIRL paper used a custom version of the Ant environment, whereas we use the standard Gym environment (see Table 3 for a description of the environments used for benchmarking).

3. Comparison to Other Software

A key advantage of IMITATION is the breadth of reward and imitation learning algorithms implemented. IMITATION includes a total of seven algorithms, whereas Table 1 shows most other software packages include only one or two. This broad coverage allows users to easily test a large number of baselines, without needing to find and integrate multiple libraries.
Another benefit of imitation is that it is built on modern frameworks like PyTorch and Stable Baselines3. By contrast, many extant implementations of imitation and reward learning algorithms were released many years ago and have not been actively maintained. This is particularly true for reference implementations released with original papers, such as the GAIL (Ho and Hesse, 2016) and AIRL (Fu, 2018) codebases. However, even popular libraries like Stable Baselines2 are no longer under active development\(^1\).

We compare alternative libraries on a variety of metrics in Table 1. Although it is not feasible to include every implementation of imitation and reward learning algorithms, to the best of our knowledge this table includes all widely-used imitation learning libraries. We find that imitation equals or surpasses alternatives in all metrics. APRel (Bıyık et al., 2021) also scores highly but focuses on preference comparison algorithms learning from low-dimensional features. This is complementary to imitation, which provides a broader range of algorithms and emphasizes scalability, at the cost of greater implementation complexity.

| Backend          | imitation | APReL | OpenAI Baselines | Stable Baselines2 | Intel COACH | GAIL Paper | AIRL Paper |
|-------------------|-----------|-------|------------------|-------------------|-------------|------------|------------|
| # imitation       | PyTorch   | NumPy | TF1              | TF1               | TF1/MxNet   | Theano     | TF1        |
| algorithms        | 7         | 1*    | 1                | 1                 | 2           | 2          | 4          |
| Last Commit (age) | <1w       | <1m   | >2.5y            | >3m               | 1m          | >4y        | >4y        |
| Approved PRs (6 months) | 103       | 0     | 0                | 0                 | 1           | 7          | 0          | 0          |
| PEP8              | ✓         | ✗     | ✓                | ✓                 | ✗           | ✓          | ✓          | ✓          |
| Type Annotations  | ✓         | ✗     | ✗                | ✓                 | ✓           | ✗          | ✗          | ✗          |
| Type Checking     | ✓         | ✗     | ✗                | ✓                 | ✗           | ✓          | ✓          | ✓          |
| Test Coverage     | 98%       | ✗     | 49%**            | 89%**             | >58%**      | ✗          | ✗          | ✗          |
| Documentation     | ✓         | ✓     | ✗                | ✓                 | ✓           | ✗          | ✗          | ✓          |
| Custom RL Agent   | ✓         | N/A†  | ✗§               | ✗§                | N/A†        | ✗§         | ✗§         | ✗         |
| Custom Optimizer  | ✓         | ✓     | ✗                | ✗                 | ✗           | ✗          | ✓          | ✓          |

Table 1: Imitation compares favourably to alternative libraries in terms of number of imitation learning algorithms implemented, project activity, implementation quality and flexibility. Only imitation, APReL and COACH use modern backends.

Key: * Is a single Bayesian algorithm, but supports different feedback formats (e.g. preference ranking and comparisons) and methods for querying feedback. ** coverage not officially reported, estimated by us from running test suite; † does not use RL; § TRPO is the only RL algorithm supported; ¶ configurable but limited to Adam, RMSProp and LBFGS.

\(^1\) The successor to Stable Baselines2, Stable Baselines3, has dropped support for imitation algorithms in favour of imitation’s own implementation (Raffin et al. 2021).
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Author contributions

Adam Gleave managed the project, performed code reviews and made a variety of minor code contributions. Mohammad Taufeeque benchmarked the algorithms, improved the documentation and made other minor code contributions. Juan Rocamonde edited the manuscript, added MyPy typing support, and made other minor code improvements. Erik Jenner added the initial implementation of our preference comparison algorithm. Steven H. Wang was the primary developer of the original, TensorFlow codebase. Nora Belrose improved the documentation, added new algorithmic features, and made minor code improvements. Sam Toyer implemented initial versions of several algorithms and assisted with the PyTorch port. Scott Emmons led the initial port to PyTorch and Stable Baselines3. Stuart Russell provided research advice.

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Appendix A. Detailed benchmarking results

The table below contains a more detailed account of the results obtained during benchmarking, including confidence intervals. The hyperparameters used to train these algorithms can be found on the benchmarking folder of the v0.3.2 release of imitation.

|                  | Ant   | Half Cheetah | Hopper | Swimmer | Walker |
|------------------|-------|--------------|--------|---------|--------|
| Random           | $-356 \pm 22$ | $-272 \pm 36$ | $-60 \pm 59$ | $1 \pm 7$ | $-22 \pm 63$ |
| Expert           | $2408 \pm 110$ | $3465 \pm 162$ | $2631 \pm 19$ | $298 \pm 1$ | $2673 \pm 112$ |
| GAIL             | $2126 \pm 119$ | $3010 \pm 157$ | $2671 \pm 27$ | $294 \pm 2$ | $2643 \pm 98$ |
| AIRL             | $-110 \pm 37$ | $3444 \pm 189$ | $2675 \pm 24$ | $276 \pm 6$ | $722 \pm 81$ |
| BC               | $1953 \pm 123$ | $3446 \pm 130$ | $2243 \pm 20$ | $283 \pm 1$ | $2512 \pm 86$ |
| DAgger           | $2321 \pm 127$ | $4172 \pm 104$ | $442 \pm 9$ | $289 \pm 2$ | $2669 \pm 110$ |

Table 2: Benchmarking results for different algorithms and environments, in addition to random and expert policies. Each cell contains the estimate of the mean returns and a 95% confidence interval for a t-distribution $t_{n-1}(\hat{\mu}, \hat{\sigma}^2, n-1)$, where $\hat{\mu}$ is the mean returns, $\hat{\sigma}^2$ is an estimate of the variance of $\hat{\mu}$, and $n$ is the number of experiments that were run, each with different seeds. In our benchmarks, $n = 5$, and for each experiment, $\approx 50$ trajectories were collected.

Appendix B. Environments used for benchmarking

All the environments used for benchmarking are standard Gym environments with some modifications to the default configuration. These ship within the Seals package (Gleave et al., 2020). MuJoCo environments from Seals are configured to always include position in the observation and prevent early termination when environments are unhealthy. The Half Cheetah and Swimmer environments naturally do not terminate early, whereas the Hopper, Ant, and Walker environments are explicitly configured to behave in this way.

The table below lists the Gym IDs of the environments, and can be loaded by first installing Seals from PyPI.

| Name            | ID                | Base                  |
|-----------------|-------------------|-----------------------|
| Ant             | seals/Ant-v0      | Ant-v3                |
| Half Cheetah    | seals/HalfCheetah-v0 | HalfCheetah-v3        |
| Hopper          | seals/Hopper-v0   | Hopper-v3             |
| Swimmer         | seals/Swimmer-v0  | Swimmer-v3            |
| Walker          | seals/Walker2d-v0 | Walker2d-v3           |

Table 3: Environments used for benchmarking, including the Gym ID, and the Gym ID of the base environment (from gym.envs.mujoco).