

GAIL Pipeline Implementation

Clean, modular implementation of Generative Adversarial Imitation Learning (GAIL) using the [HumanCompatibleAI/imitation](#) library.

Under Development

For environments without pre-trained HuggingFace experts, custom expert training will be added in future versions.

Currently tested environments:

- CartPole-v0 
 - MountainCar-v0 
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Features

- **Pre-trained Expert Loading:** Automatically loads pre-trained experts from HuggingFace
- **Vectorized Environments:** Parallel environment execution for faster training
- **Modular Pipeline:** Clear separation of setup → expert loading → demonstration collection → GAIL training
- **CLI Interface:** Easy configuration without code changes
- **Vector Observations Only:** Supports standard Gym environments (CartPole, MountainCar, etc.)

Installation & Setup

Windows (Command Prompt)

First-time setup:

```
# 1. Install Python 3.12 from python.org (if not installed)
python --version
```

```

# Should show: Python 3.12.x

# 2. Navigate to your GAIL folder
cd C:\Users\YourUsername\GAIL

# 3. Create a virtual environment
python -m venv venv

# 4. Activate environment
venv\Scripts\activate

# 5. Set version variable
set SETUPTOOLS_SCM_PRETEND_VERSION_FOR_IMITATION=0.0.0

# 6. Install the package
pip install -e .

# 7. Run your first test
python gail_pipeline.py --env CartPole-v0

```

Subsequent runs:

```

# 1. Navigate to your GAIL folder
cd C:\Users\YourUsername\GAIL

# 2. Activate environment (previously installed)
venv\Scripts\activate

# 3. Run your first test
python gail_pipeline.py --env CartPole-v0

```

AWS/Cloud Environments [!! Read the Note !!]

Note: Untested - based on typical AWS EC2 setup patterns.

First-time setup (Amazon Linux 2 / Ubuntu):

```

# 1. Connect to your EC2 instance
ssh -i your-key.pem ec2-user@your-instance-ip

# 2. Install Python 3.12 (if not available, use Python 3.11)
sudo yum update -y                               # Amazon Linux

```

```

# OR
sudo apt update && sudo apt upgrade      # Ubuntu

# For Amazon Linux 2
sudo amazon-linux-extras install python3.11 -y
# OR for Ubuntu
sudo apt install python3.12 python3.12-venv -y

# 3. Upload your GAIL package to EC2 (from local machine)
# scp -i your-key.pem -r GAIL/ ec2-user@your-instance-ip:~/

# 4. Navigate to GAIL folder
cd ~/GAIL

# 5. Create virtual environment
python3.12 -m venv venv
# OR
python3.11 -m venv venv

# 6. Activate environment
source venv/bin/activate

# 7. Set environment variable
export SETUPTOOLS_SCM_PRETEND_VERSION_FOR_IMITATION=0.0.0

# 8. Install package
pip install -e .

# 9. Run test (use nohup for long training)
nohup python gail_pipeline.py --env CartPole-v0

```

Subsequent runs:

```

ssh -i your-key.pem ec2-user@your-instance-ip
cd ~/GAIL
source venv/bin/activate
export SETUPTOOLS_SCM_PRETEND_VERSION_FOR_IMITATION=0.0.0

# Run in background
nohup python gail_pipeline.py --env CartPole-v0

```

Quick Start

Basic Usage (Default Settings)

```
python gail_pipeline.py --env CartPole-v0
```

What happens:

1. Loads pre-trained CartPole expert from HuggingFace
 2. Collects 60 expert demonstration episodes
 3. Trains GAIL for 100,000 timesteps
 4. Evaluates learner performance on 100 episodes

Expected output:

=====
=====

GAIL Pipeline - CartPole-v0

[1/4] Setting up environment: CartPole-v0

✓ Environment ready: seals:seals/CartPole-v0 (8 parallel envs)

[2/4] Loading expert policy from HuggingFace

✓ Expert loaded | Mean reward: 500.00 ± 0.00

[3/4] Collecting 60 expert demonstrations

✓ Collected 64 episodes, 32064 transitions

[4 / 4] Setting up GAIL trainer

✓ GAIL trainer initialized

→ Minimum training timesteps: 8192

Training GAIL (100000 steps)

Mean reward before GAIL training: 100.35 ± 14.77

round: 100% |



Learner reward after: 29.20 + 6.62

Improvement: -71.15

Pipeline complete!

'Note that this run results in an under-trained learner model and is just for demonstration.'

CLI Parameters

Environment & Basic Settings

Parameter	Default	Description
--env	CartPole-v0	Gym environment name (CartPole-v0)
--seed	42	Random seed for reproducibility
--n-envs	8	Number of parallel environments

Demonstration Collection

Parameter	Default	Description
--demo-episodes	60	Number of expert episodes to collect for training dataset

What it means: More episodes = better representation of expert behavior, but diminishing returns after ~100 episodes.

GAIL Training

Parameter	Default	Description
--gail-steps	100000	Total training timesteps for GAIL
--demo-batch-size	2048	Batch size for demonstration samples
--gen-buffer-capacity	512	Generator replay buffer capacity
--n-disc-updates	16	Discriminator updates per training round

Minimum timesteps: `demo_batch_size × n-disc-updates` (default: $2048 \times 16 = 32,768$)

Evaluation

Parameter	Default	Description
--n-eval-episodes	100	Number of episodes for performance evaluation

What it means: Used only for measuring reward before/after training. More episodes = more accurate estimate.

Usage Examples

Example 1: Quick Test Run

Test GAIL with minimal training:

```
python gail_pipeline.py --env CartPole-v0 --gail-steps 50000 --demo-epis
```

```
python gail_pipeline.py --env MountainCar-v0 --gail-steps 50000 --demo-epis
```

Use case: Fast prototyping, debugging, or verifying setup works.

Example 2: Full Training to Match Expert

Train until the learner matches the expert performance:

```
python gail_pipeline.py --env CartPole-v0 --gail-steps 800000 --demo-epis
```

Expected results:

- Expert reward: 500 ± 0.00
- Learner before: 100.35 ± 14.77
- Learner after: 500.00 ± 0.00

```
python gail_pipeline.py --env MountainCar-v0 --gail-steps 2000000 --demo-epis
```

Expected results:

- Expert reward: -98.94 ± 7.61
- Learner before: -200.00 ± 0.00
- Learner after: -120.70 ± 18.75

Use case: Production-quality imitation learning.

Example 3: Custom GAIL Configuration

Adjust GAIL hyperparameters:

```
python gail_pipeline.py \
--seed 32
--n-envs 10
--env CartPole-v0 \
--demo-episodes 100
--gail-steps 500000 \
--demo-batch-size 1024 \
--gen-buffer-capacity 2048 \
--n-disc-updates 8
```

Note: Minimum timesteps becomes $2048 \times 8 = 16,384$ [Check]

Use case: Hyperparameter tuning for specific environments.

Example 4: More Parallel Environments [Not Tested]

Speed up training with more parallel environments:

```
python gail_pipeline.py --env CartPole-v0 --n-envs 16 --gail-steps 100000
```

Use case: Faster training on multi-core systems.

Understanding the Output

Stage 1: Environment Setup

[1/4] Setting up environment: CartPole-v0

✓ Environment ready: seals:seals/CartPole-v0 (8 parallel envs)

- Creates vectorized environment for parallel execution
- Wraps with `RolloutInfoWrapper` for demonstration collection

Stage 2: Expert Loading

[2/4] Loading expert policy from HuggingFace

✓ Expert loaded | Mean reward: 500.00 ± 0.00

- Loads pre-trained expert from HuggingFace Hub

- Expert reward shows the performance goal for GAIL

Stage 3: Demonstration Collection

[3/4] Collecting 60 expert demonstrations

✓ Collected 67 episodes, 33500 transitions

- Collects expert trajectories (observations, actions, next_obs, done)
- May collect more episodes than requested to reach minimum timesteps
- Transitions = individual (state, action, next_state) tuples

Stage 4: GAIL Setup

[4/4] Setting up GAIL trainer

✓ GAIL trainer initialized

→ Minimum training timesteps: 32768

- Initializes learner policy (untrained PPO)
- Creates a reward network for GAIL
- Shows minimum timesteps required (auto-calculated)

Training & Evaluation

Training GAIL (100000 steps)

Mean reward before GAIL training: 100.35 ± 14.77

Training for 100000 timesteps...

Learner reward after: 29.20 ± 6.62

Improvement: -71.15

Interpreting results:

- **Before training:** Random/untrained policy performance (~20-100 for CartPole)
- **After training:** Learned policy performance (should approach expert ~500)
- **Improvement:** Difference showing learning effectiveness
- **Standard deviation (\pm):** Variance across evaluation episodes

Success criteria:

- ✓ After training \approx Expert reward (within ~10%)

- ✓ Improvement > 80% of gap between before and expert
- ✗ After training << Expert reward → Need more training steps or demos

Troubleshooting

Error: Timesteps too low

AssertionError: No updates (need at least 16384 timesteps, have only total_timesteps=10000)!

Solution: Increase `--gail-steps` to at least the minimum shown in setup:

```
python gail_pipeline.py --env CartPole-v0 --gail-steps 16384
```

Performance doesn't match the expert

Possible causes:

1. **Not enough training:** Increase `--gail-steps` (try 1-2M)
2. **Not enough demos:** Increase `--demo-episodes` (try 100+)
3. **Evaluation variance:** Increase `--n-eval-episodes` to 100+

Advanced: Loading Custom Experts [Under Development]

For environments without pre-trained HuggingFace experts, use the separate loader:

```
from load_cheetah_expert import train_cheetah_expert

# Train custom expert
expert, env = train_cheetah_expert(
    total_timesteps=1_000_000,
    save_path="my_expert.zip"
)

# Integrate with pipeline
pipeline = GAILPipeline(env_name="HalfCheetah-v3")
```

```
pipeline.venv = env
pipeline.expert = expert
pipeline.collect_demonstrations()
pipeline.setup_gail()
pipeline.train_gail()
```

Key Concepts

Demo Episodes vs Eval Episodes

- **Demo Episodes** (`--demo-episodes`): Training data for GAIL
 - Used to teach the learner what expert behavior looks like
 - More = better training signal
- **Eval Episodes** (`--n-eval-episodes`): Testing/measurement only
 - Used to calculate performance metrics
 - More = more stable/accurate estimates
 - Does NOT affect training

GAIL Hyperparameters

- **demo_batch_size**: How many expert transitions per batch
 - Larger = more stable discriminator training
 - Should be > 1024 for most environments
- **gen_replay_buffer_capacity**: Buffer size for learner experience
 - Larger = more diverse training data
 - Trade-off with memory usage
- **n_disc_updates**: Discriminator training frequency
 - Higher = better reward learning, but slower
 - Typical range: 8-32

Citation

```
@misc{gleave2022imitation,  
author = {Gleave, Adam and Taufeeque, Mohammad and Rocamonde, Juan and  
title = {imitation: Clean Imitation Learning Implementations},  
year = {2022},  
howPublished = {arXiv:2211.11972v1 [cs.LG]},  
archivePrefix = {arXiv},  
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url = {https://arxiv.org/abs/2211.11972},  
}
```

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