2. Assignment - Particle Swarm Optimization

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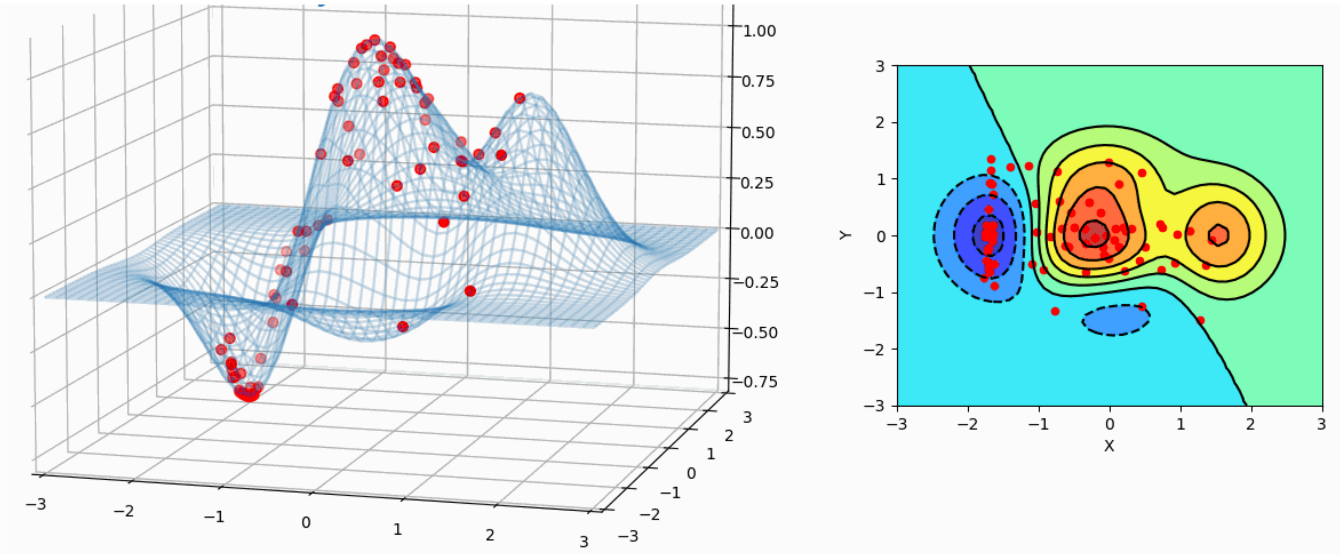
Collective Intelligence



This assignment focuses on implementing a **Multi-Agent Reinforcement Learning (MARL)** system using **TorchRL**. The goal is to design and train a **swarm of particles that collaboratively optimize a given objective function** in a multi-dimensional search space. While traditionally PSO relies on deterministic position and velocity updates, this assignment tries to explore a new angle: training particle agents using reinforcement learning to **learn optimization behavior** in a swarm setting. Agents are expected to mimic cooperative PSO-like behavior through interaction and learning, rather than rule-based updates.

Project GitHub Link

At this stage, the project is in its early **conceptual phase** - no implementation or starter code has been developed yet. The idea remains exploratory and has **not been successfully realized in previous semesters**. It represents an original contribution **within the context of the class**.

Agents must coordinate their movements to **converge efficiently toward the global optimum**, while preserving **diversity** and **even spatial distribution** across the search space. The system should adapt to both **static and dynamically changing objective landscapes**, simulating real-world conditions where optima may shift over time. This setting requires **cooperative behavior**, best addressed with a **Centralized Training with Decentralized Execution (CTDE)** approach, where policies are trained with access to global critic information but executed independently by each agent. An Introduction to Centralized Training for Decentralized Execution in Cooperative Multi-Agent Reinforcement Learning

While the final goal is to use **TorchRL**'s native environment structure (`EnvBase`, `TensorDict`, etc.), you may initially use **PettingZoo environments** with the official `PettingZooWrapper` provided by TorchRL, if helpful for bootstrapping.

Assignment Directions

You may choose between the following development directions for this assignment:

- **Option 1: Incremental Migration** (<u>not available for PSO</u>)
  Maintain the current implementation based on **Stable-Baselines3** (SB3), **Supersuit**, and **PettingZoo**, and gradually migrate the system to TorchRL. This approach involves adapting the environment and training loop to TorchRL-compatible components while preserving existing functionality. The migration should also include:
  - Integration of a **configuration management system** (e.g., Hydra or structured YAML)
  - **Preservation of logging** via both Weights & Biases (WandB) and TensorBoard
  - Docker for reproducibility and cross-platform compatibility
  - Structured **unit testing** (at least 2 components)

    - **Visualization** outputs (e.g., GIFs, performance plots)
    - A clear and well-maintained `README.md` with **setup and usage instructions**
- **Option 2: Reimplementation Using Native TorchRL**
  Build the project **from scratch using TorchRL's native APIs**. Instead of using PettingZoo, start from a TorchRL-compatible environment (e.g., based on `EnvBase`) or adapt an existing one. Design the training pipeline, agent interaction logic, and evaluation procedures entirely within the TorchRL framework. As with the first option, the final solution should support:
    - Centralized Training with Decentralized Execution (CTDE)
    - Configuration management
    - Docker deployment
    - WandB/TensorBoard logging
    - Visualization and reproducibility tools
    - Testing and documentation

Elements to Consider:

- Utilize **Proximal Policy Optimization**, specifically the clipped variant (PPO-Clip), as the core learning algorithm. PPO-Clip (Optionally, you could experiment with MADDPG, QMIX, VDN)
- **Custom Environment (Optional)**: While benchmark functions (e.g., Sphere, Rastrigin) are suitable, consider implementing a **custom dynamic optimization environment**, where the objective landscape shifts over time or incorporates constraints.
- Introduce **static or time-varying constraints**, such as obstacles or restricted zones in the search space.
- Each particle receives a **partial observation**: its own coordinates, velocity, personal best score, and optionally, a soft neighborhood summary (e.g., average position or fitness of nearby agents within a fixed radius).
- Integrate a **curriculum-based optimization** schedule, gradually increasing task complexity (e.g., moving from unimodal to multimodal landscapes, increasing dimensionality, or introducing shifting optima). Curriculum Learning
- Shape the reward function to promote desirable swarm behaviors - such as **spatial dispersion** (to maintain diversity) and **avoidance of premature convergence** (e.g., by penalizing stagnation or collapse into local optima) Reward Shaping. Can agents specialize into scouts, exploiters, or spreaders without being told to? Design your observation and reward schemes to allow such roles to emerge.
- **Design and track custom metrics** to evaluate the performance of your swarm, such as:
    - **Convergence speed**
    - **Global vs. local optima ratio**
    - **Diversity of particles** (e.g., average inter-particle distance)
    - **Stability in dynamic environments**

A Possible Structured Plan for Implementation Using Native TorchRL

0. Possible Directory Structure

```
marl-task/
├── configs/                        # Hydra or YAML configs for experiment control
│   ├── base.yaml
│   ├── env/
│   │   ├── task.yaml
│   ├── algo/
│   │   ├── ppo.yaml
│   ├── agent/
│   │   ├── default.yaml
│   └── experiment/
│       ├── exp.yaml
│
├── docker/                        # Dockerfile and entrypoints
│   ├── Dockerfile
│   └── entrypoint.sh
│
├── logs/                          # TensorBoard / WandB logs (auto-created)
│
```

```
├── outputs/                    # Visualizations (e.g., GIFs, videos)
│   ├── gifs/
│   └── metrics/
│
├── models/                     # Trained model checkpoints
│   ├── ppo/
│   │   ├── seed_1.pt
│   │   ├── seed_2.pt
│
├── src/                        # Source code
│   ├── envs/
│   │   ├── env.py
│   │   └── metrics.py          # Custom metrics
│   │
│   ├── agents/
│   │   ├── ppo_agent.py        # PPO policy/training logic
│   │   └── utils.py
│   │
│   ├── rollout/
│   │   ├── evaluator.py        # Evaluation logic
│   │   └── visualizer.py
│   │
│   └── main.py                 # Entry point: loads config and runs training
│
├── test/                       # Unit tests
│   ├── test_env.py
│   ├── test_metrics.py
│
├── .gitignore
├── requirements.txt
├── README.md
└── LICENSE
```

1. Environment Setup

Define a Custom TorchRL-Compatible Environment

Create a class `Env(EnvBase)` in `src/envs/env.py` with the following methods:

- `reset(self) -> TensorDict`
- `step(self, actions: TensorDict) -> TensorDict`

Define:

- `observation_spec`
- `action_spec`
- `reward_spec`
- `done_spec`

Ensure all I/O uses `TensorDict`. Observations should be partial and relative, including distance to the shape center and nearest neighbor. Use `torchrl.envs.transforms` for normalization or preprocessing.

Optional: PettingZoo Wrapper

Use `PettingZooWrapper` from `torchrl.envs.libs.pettingzoo` if adapting from existing environments:

```
from torchrl.envs.libs.pettingzoo import PettingZooWrapper
wrapped_env = PettingZooWrapper(pettingzoo_env)
```

2. Agent and Model Definition

Define Policy and Critic Modules

In `src/agents/ppo_agent.py`, implement:

- A shared `TensorDictModule` policy:

```
policy = TensorDictModule(network, in_keys=[...], out_keys=["action"])
```

- A centralized critic using `ValueOperator`:

```
critic = ValueOperator(critic_network, in_keys=[...])
```

This supports the CTDE paradigm: centralized critic with decentralized policy execution.

3. PPO Training Setup

Collector Configuration

Use `SyncDataCollector` or `MultiSyncDataCollector`:

```
collector = SyncDataCollector(
    create_env_fn=env_fn,
    policy=policy,
    frames_per_batch=2048,
    total_frames=...
)
```

Loss Function

Use `ClipPPOLoss`:

```
loss_module = ClipPPOLoss(
    actor=policy,
    critic=critic,
    clip_epsilon=0.2,
    entropy_coef=0.01
)
```

4. Training Loop

Training in `main.py`

Set up the training loop using `collector`, `replay_buffer`, `loss_module`, and `optimizer`:

```
for batch in collector:
    for _ in range(ppo_epochs):
        loss = loss_module(batch)
        loss.backward()
        optimizer.step()
        optimizer.zero_grad()
```

5. Evaluation and Logging

Logging

Use TensorBoard or W&B:

```
from torch.utils.tensorboard import SummaryWriter
writer = SummaryWriter(log_dir=...)
writer.add_scalar("reward/mean", mean_reward, step)
```

Evaluation

Run trained policies with local observations only (CTDE) and export GIFs using `pygame`, `matplotlib`, or `imageio`. Store results in `outputs/`.

6. Configuration Management

Hydra Integration

Use Hydra or structured YAML configs in `configs/`:

- `configs/env/task.yaml`
- `configs/algo/ppo.yaml`
- `configs/experiment/sweep.yaml`

Launch with:

```
python src/main.py +experiment=task +algo=ppo
```

7. Testing

Unit Tests

Place tests in `test/`:

```python
def test_env_reset():
    env = Env(...)
    td = env.reset()
    assert "observation" in td
```

8. CTDE Framework Details

- The shared policy is trained with access to a centralized value function.
- Execution uses only local observations per agent.
- During inference, policies should operate without access to the global state or other agents' observations.
- Ensure the actor's input keys are restricted to local observations, while the critic receives richer information.

9. Docker for Reproducibility

Add Docker Support

Create a `docker/` folder with the following:

- `Dockerfile`:

```dockerfile
FROM python:3.12-slim
WORKDIR /app
COPY . /app
RUN pip install -r requirements.txt
CMD ["python", "src/main.py"]
```

- `entrypoint.sh` (optional launcher script)

Build and run:

```bash
docker build -t marl-task .
docker run --rm marl-task
```

PowerPoint Presentation

While presenting your work is not mandatory, **not presenting will limit your maximum grade to 3**. The presentation serves as a concise overview of your project.

Duration

- Aim for **a few well-organized slides** that complement your documentation without repeating it verbatim.

Suggested Structure

1. **Title & Objective**
   - Briefly state the objective.
   - Mention which direction you chose (migration or reimplementation).
2. **System Architecture**
   - Give a high-level overview of your system (environment, agent setup, training loop).
   - Highlight the use of **TorchRL**, and explain your training logic (CTDE, PPO-Clip).
   - Optionally include a block diagram of the pipeline (env → collector → buffer → PPO → evaluation).
3. **Environment & Task Setup**
   - Describe the environment design:
     - Custom vs. PettingZoo-based
     - Agent count and spawn logic
     - Obstacles and dynamics (if any)
   - Explain how agents observe the world and what actions they take.
4. **Key Design Choices**
   - Discuss reward structure, curriculum learning, and logic.
   - Explain any metric(s) you implemented for evaluation
   - Mention logging strategy (WandB, TensorBoard) and how configuration and reproducibility are handled.
5. **Results & Visualizations**
   - Show GIFs or short clips of trained agents forming shapes.
   - Present reward curves, training stability plots, or metric graphs.
   - Provide insights into what worked, what didn't, and what improved after tuning.
6. **Conclusion & Future Work**
   - Summarize key takeaways.

Important Notes

- The **core of your submission is your documentation and code**, which will be the primary basis for grading.
- The presentation is an opportunity to highlight your contributions and insights.

Assignment Submission and General Rules

- All development must be carried out within a **GitHub repository**.
- If working as a **team**:
  - The **collaboration strategy** (e.g., shared or individual branches) can be determined by the team.
  - **Task division must be clearly defined** and documented in the project's `README.md` file (e.g., who worked on the environment, training logic, visualization, etc.).
- If working **individually**, each student must develop their solution on a **separate branch** within the repository.
- Once development is complete, you (or your team) must upload a **single ZIP file** to Canvas containing:
  - The **entire project repository** (excluding large model files or checkpoints to keep the size manageable).
  - The **presentation in PDF format**.
- **Collaboration is highly encouraged**, as this is a larger-scale assignment that benefits from cooperative design and debugging.

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