2. Assignment - Sorting & Clustering

Tamás Takács, PhD student, Department of Artificial Intelligence

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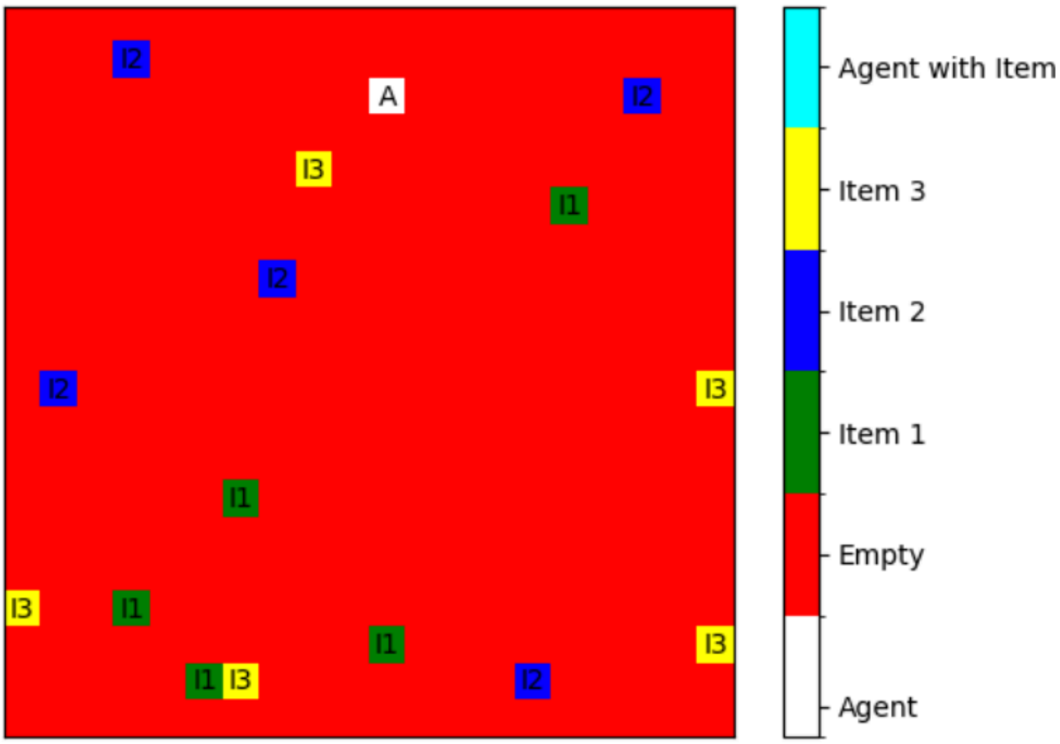
Collective Intelligence



This assignment focuses on implementing a **Multi-Agent Reinforcement Learning (MARL)** system using **TorchRL**, where multiple agents (ants) interact in a shared 2D environment containing scattered items of different categories. Items are scattered randomly at spawn and do not have predefined destinations. Agents must dynamically form spatial clusters based on category, rather than placing items at fixed goal locations. The agents must learn to pick up, **sort and cluster these items into coherent spatial groups** across the map, based on their types.

Project GitHub Link (highly recommend TA's work)

The current project versions utilize:

- A **PettingZoo AEC (Agent Environment Cycle) environment**, customized to simulate 2D pathfinding with discrete grid or continuous motion. AEC API
- A TensorFlow based **PPO** implementation.
- Real-time **visual rendering using** *pygame* and post-processed visualizations.
- **Centralized Training and Centralized Execution** model. A **single shared policy is trained** alongside a centralized value function that has access to shared information across agents. During evaluation, this same centralized policy is used by all agents, meaning that each **agent's behavior is determined by a common model**, rather than acting independently based on purely local observations.
- A simple agent evaluation framework.

Agents must learn to:

- **Perceive local item types** and neighborhood density.
- Decide **which item to move** and where to place it.
- **Avoid interfering with teammates** while cooperatively building category-specific clusters.
- Adapt to **varying map layouts**, object types, and dynamic item spawning conditions.

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.

> **Note**: This task is loosely inspired by **ant-based clustering** models, where agents interact locally with their environment to collectively sort objects into piles without explicit coordination or global knowledge.

Assignment Directions

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

- **Option 1: Incremental Migration**
  Maintain the current implementation based on **TensorFlow** (SB3) 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)
  - **Inclusion 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**. 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 Preserve:

- **PPO Algorithm**: Continue using Proximal Policy Optimization, specifically the clipped variant (PPO-Clip), as the core learning algorithm. PPO-Clip (Optionally, you could experiment with MADDPG, QMIX, VDN)
- **Core Objective**: The primary task remains, agents must learn to pick up, **sort and cluster categorized items into coherent spatial groups** across the map, based on their types.
- **Multi-Agent Setting**

Elements to Improve or Redesign:

- **Environmental Complexity**: Add **multiple item types** (e.g., red, green, blue blocks) with varying spawn locations. Include **distractors**, **obstacles**, or **limited pickup range**. Optionally allow agents to **pick up**, **carry**, or **drop** items in 2D space. Consider map setups with **limited clustering zones** or **spatial constraints**.
- **PettingZoo Support (Optional)**: Leverage existing tools or port environments to TorchRL format.
- **Curriculum Learning**: Start with simple and small maps, then gradually increase complexity (e.g., more item categories, obstacles). Curriculum Learning
- **Reward Design**: Develop a reward function that balances sorting efficiency (sorting items in their respective cluster), obstacle avoidance, time efficiency, and collaborative movement (e.g., penalizing blocking teammates or deadlocks) Reward Shaping. Reward shaping should encourage correct placement (item ends up near similar items), penalize misplacement (e.g., placing a red item in a blue cluster), and incentivize space-efficient clustering.
- **Evaluation Metrics**: Add custom metrics for training and evaluation, such as:
  - Clustering purity
  - Mean sorting accuracy

    - Conflict rate
    - Idle time
- For clustering purity or accuracy, you can calculate the **mean intra-cluster distance** or use **DBSCAN-style heuristics** over item positions after an episode.

A Possible Structured Plan for Reimplementation 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/
│       ├── sphere_spawn.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/`:

```
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`:

```
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:

```
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.

👤 Tamás Takács

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