2. Assignment - Pathfinding

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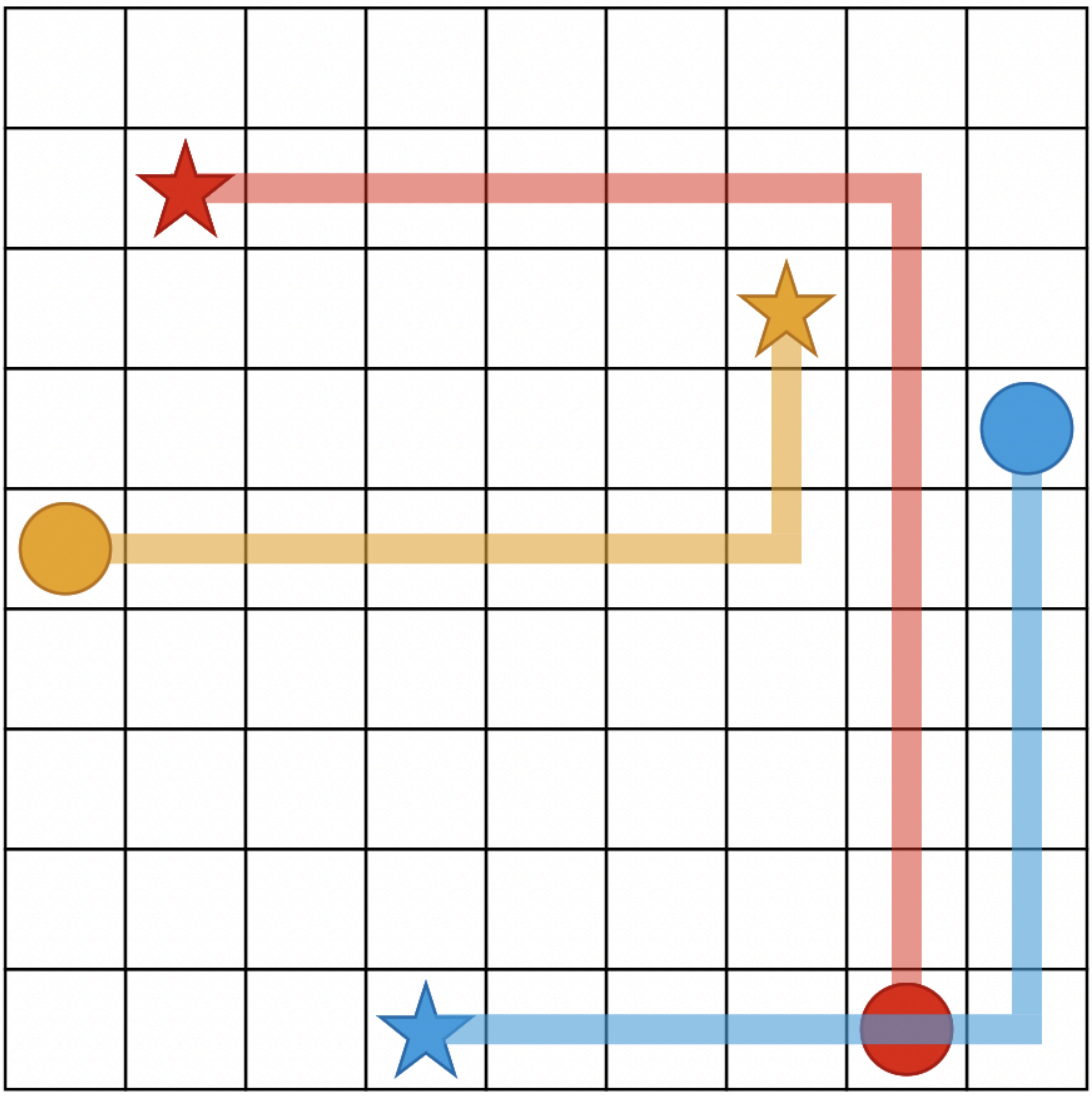
Collective Intelligence



This assignment focuses on implementing a **Multi-Agent Reinforcement Learning (MARL)** system using TorchRL, where agents must collaboratively **solve multi-agent pathfinding tasks** in complex, obstacle-rich environments. This assignment explores **adaptive coordination**, where agents must **navigate dynamically generated maps**, avoid hazards, and reach their targets in cooperation with teammates. These environments mimic real-world challenges such as **robot swarm navigation**, **emergency evacuation**, or **warehouse logistics**, where route planning is made harder by **changing layouts**, **moving goals**, and the presence of **other agents**.

Project GitHub Link (highly recommend MG'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

- The **Stable-Baselines3 PPO algorithm** for training shared policies. SB3 PPO
- 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. (**SB3** with **TensorBoard** Integration)

Agents must navigate from their spawn points to assigned targets while **avoiding obstacles**, minimizing **path length**, and **coordinating** to avoid collisions or deadlocks. The environment may be static or dynamic, with **changing obstacle layouts** or **moving goals**. 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.

Environment Phases

1. **Planning Phase (Warm-Up)**: Agents can scan the environment or explore without penalties.
2. **Execution Phase**: A timer starts and agents are evaluated based on path efficiency, collaboration, and avoidance of congestion.

Assignment Directions

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

- **Option 1: Incremental Migration**
  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 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)
- **MPE Environment (Optional)**: The Multi-Agent Particle Environment (MPE) can be retained, though you are also encouraged to consider reimplementing a simplified particle-based environment using native TorchRL. PettingZoo MPE
- **Core Objective**: The primary task remains, agents must collaboratively **solve multi-agent pathfinding tasks** in a complex, obstacle-rich environment.
- **Multi-Agent Setting**

Elements to Improve or Redesign:

- **Environmental Complexity**: Introduce walls, traps, moving hazards, or multi-room maps with choke points to increase coordination complexity.
- **Curriculum Learning**: Start with simple mazes or open maps, then gradually increase complexity (e.g., tighter corridors, dynamic targets, agent congestion). Curriculum Learning
- **Reward Design**: Develop a reward function that balances path efficiency, obstacle avoidance, goal completion, and collaborative movement (e.g., penalizing blocking teammates or deadlocks). Reward Shaping
- Your system should encourage behaviors like **traffic yielding**, **lane forming**, or **goal re-routing** when paths are blocked.
- **Evaluation Metrics**: Add custom metrics for training and evaluation, such as:
  - Average path length
  - Success rate (% agents reaching their goal)
  - Collision rate
  - Completion time variance
  - Congestion/delay penalties

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/
│       ├── 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/`:

```
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.

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