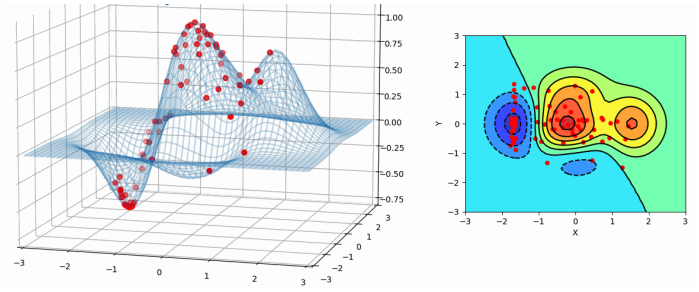
Particle Swarm Optimization

Learning Swarm Intelligence with RL

Collective Intelligence - Spring 2026

Teams of 2-3 students | 6-8 weeks



Overview

This project explores **learned particle swarm optimization (PSO)** using multi-agent reinforcement learning. Instead of hand-tuning hyperparameters like inertia weight ω, cognitive coefficient c_1, and social coefficient c_2, agents learn to dynamically adjust these parameters based on the current optimization landscape.

Your task is to extend the base implementation with **one of three research directions** below. Each task involves implementing new functionality, running rigorous experiments, and documenting results with visualizations and analysis.

What is already provided

- `src/envs/env.py` – TorchRL-based multi-agent PSO environment
- `src/envs/dynamic_functions.py` – Static and dynamic benchmark functions (Sphere, Rastrigin, Eggholder, etc.)
- `src/main.py` – Hydra-based training loop with PPO
- `src/eval.py` – Evaluation with 2D/3D visualization and GIF generation
- `src/visualizer.py` – SwarmVisualizer class for particle animation
- Docker containerization for reproducibility

Teams & Timeline

- **3 teams** of 2-3 students each
- **Deadline**: 6-8 weeks from start
- **Each team chooses ONE task** from the three options below

Task Options

Each team selects **one task**. All tasks have comparable scope and grading weight.

Task 1: Communication Topologies & Information Flow

Research Question: How do different swarm communication topologies (global best, local best, dynamic neighborhoods) affect convergence and diversity in learned PSO?

Hypothesis

Restricting information flow through local topologies (ring, von Neumann, dynamic k-nearest) will maintain diversity longer, improving performance on multimodal landscapes, while global best topology converges faster on unimodal functions.

Implementation Requirements

1. **Topology System** (`src/envs/topology.py` — new file):
   - Implement: Global Best (gBest), Local Best (lBest) with ring topology
   - Implement: Von Neumann (grid) neighborhood, k-Nearest dynamic neighbors
   - Topology abstraction: Topology.get_neighbors(particle_id) interface
   - Allow topology changes during optimization (learned or scheduled)
2. **Environment Extension** (`src/envs/env.py` modification):
   - Add topology-aware observation: include neighbor personal bests
   - Modify reward to use neighborhood best instead of global best
   - Config-driven topology selection via Hydra
3. **Diversity Metrics** (`src/eval/diversity.py` — new file):
   - Position diversity: mean pairwise distance, convex hull volume
   - Velocity diversity: velocity alignment coefficient
   - Information spread: how fast does best solution propagate?

Technical Guidance

- Use adjacency matrices for efficient neighbor queries
- Dynamic k-nearest: recompute neighbors every N steps (configurable)
- Configs: `src/configs/topology/` with global.yaml, ring.yaml, knearest.yaml
- Consider graph neural network observations for topology-aware policies

Expected Deliverables

- Working topology system with 4+ topology types
- Diversity metrics integrated into evaluation pipeline
- Comparison: 4 topologies × 3 landscapes (unimodal, multimodal, dynamic) × 5 seeds
- 4-6 plots: convergence curves, diversity over time, final fitness distributions, topology comparison heatmaps
- 2-3 GIFs: side-by-side topology comparison on same function
- Analysis: when does local topology help? Trade-offs between exploration and exploitation?

Task 2: Curriculum Learning & Adaptive Difficulty

Research Question: Can progressively increasing optimization difficulty (dimensionality, function complexity, landscape dynamics) improve sample efficiency and generalization?

Hypothesis

Starting training on simpler problems (low dimensions, unimodal functions) and gradually introducing complexity will produce policies that generalize better to hard problems compared to training directly on difficult tasks.

Implementation Requirements

1. **Curriculum Manager** (`src/training/curriculum.py` – new file):
   - Dimension curriculum: train 2D → 5D → 10D → 30D
   - Function curriculum: Sphere → Rosenbrock → Rastrigin → Eggholder
   - Dynamics curriculum: static → slow dynamics → fast dynamics
   - Progression criteria: performance threshold, training steps, or learned
2. **Generalization Testing** (`src/eval/generalization.py` – new file):
   - Zero-shot transfer: evaluate on unseen dimensions/functions
   - Performance gap: curriculum-trained vs direct-trained on hard problems
   - Learning curves: sample efficiency comparison
3. **Adaptive Difficulty** (bonus extension):
   - Automatic difficulty adjustment based on agent performance
   - Multi-armed bandit for curriculum stage selection
   - Self-paced learning: agents request harder problems

Technical Guidance

- Dimension-agnostic policy: use attention or recurrent networks for variable input sizes
- Function encoding: one-hot, learned embeddings, or meta-learning
- Configs: `src/configs/curriculum/` with dimension.yaml, function.yaml, combined.yaml
- Consider domain randomization as baseline comparison

Expected Deliverables

- Working curriculum system with 3+ curriculum types
- Generalization evaluation across unseen problems
- Comparison: curriculum vs direct training on final tasks (5 seeds each)
- 4-6 plots: learning curves, generalization matrices, curriculum progression, sample efficiency
- 2-3 GIFs: policy behavior on easy vs hard problems
- Analysis: optimal curriculum ordering? When does curriculum help/hurt? Transfer limits?

Task 3: Diversity-Preserving Reward Shaping

Research Question: Can auxiliary rewards for swarm diversity prevent premature convergence and improve global optimization on deceptive landscapes?

Hypothesis

Adding intrinsic motivation rewards for maintaining swarm diversity (position spread, velocity diversity, exploration bonuses) will improve performance on multimodal and deceptive functions where standard PSO suffers from premature convergence.

Implementation Requirements

1. **Diversity Rewards** (`src/envs/diversity_reward.py` — new file):
   - Position entropy: reward for spread in search space
   - Novelty bonus: reward for visiting unexplored regions (archive-based)
   - Velocity alignment penalty: discourage all particles moving same direction
   - Scalarization: $r = \alpha \cdot r_{\text{fitness}} + (1 - \alpha) \cdot r_{\text{diversity}}$
2. **Adaptive Weighting**:
   - Schedule: high diversity weight early, decay over optimization
   - Performance-based: increase diversity when stuck, decrease when improving
   - Learned: let the policy learn to balance via multi-objective heads
3. **Premature Convergence Detection** (`src/eval/convergence_analysis.py`):
   - Detect: when does swarm collapse? Distance to centroid metrics
   - Compare: baseline vs diversity-rewarded policies
   - Measure: escape rate from local optima

Technical Guidance

- Position entropy: $H = -\sum_i p_i \log p_i$ over discretized search space bins
- Novelty archive: store visited positions, reward distance to k-nearest archive points
- Configs: `src/configs/reward/` with baseline.yaml, diversity.yaml, adaptive.yaml
- Test on deceptive functions: Rastrigin, Schwefel, multimodal custom landscapes

Expected Deliverables

- 3+ diversity reward mechanisms with configurable weights
- Adaptive weighting system (at least 2 strategies)
- Comparison: baseline vs diversity rewards on 4+ functions (5 seeds each)
- 4-6 plots: diversity over time, convergence detection, α sensitivity, local optima escape rates
- 2-3 GIFs: baseline (premature convergence) vs diversity-rewarded (sustained exploration)
- Analysis: optimal diversity-fitness trade-off? Function-dependent tuning? Failure modes?

Shared Requirements (All Tasks)

All teams must follow these common guidelines to ensure quality and reproducibility.

Code Quality

- Follow existing code structure (TorchRL patterns, Hydra configs)
- Update relevant folder READMEs documenting new modules
- Add 2-3 unit tests for core functionality
- Hydra configs for all experiments

Experiments

- Run on both **low-dimensional** (2D-5D) and **high-dimensional** (10D-30D) problems
- Test on multiple function types: unimodal (Sphere), multimodal (Rastrigin), dynamic
- Use fixed seeds for reproducibility (report all seeds in README)
- Minimum 5 seeds per experimental condition

Documentation

- Update root README.md with new "Semester Contribution" section:
  - Research question & hypothesis
  - Implementation summary (what was added/modified)
  - Key results (embed 2-3 key plots/GIFs)
  - Conclusions & limitations
  - Future work
- Keep it concise (500-800 words max)

Grading Rubric

Total: 100 points

Each task has the same grading structure. All requirements must use Hydra configs and be reproducible.

Implementation (40 pts)

- Core functionality working (new modules/classes follow codebase conventions) **20 pts**
- Integration with existing system (configs, training loops, evaluation) **10 pts**
- Code quality (documentation, tests, readable) ..... **10 pts**

Experiments (30 pts)

- Rigorous experimental design (controls, baselines, multiple seeds) ... **10 pts**
- Sufficient scale (low-D + high-D, 5+ conditions) ..... **10 pts**
- Reproducibility (fixed seeds, configs, clear instructions) ..... **10 pts**

Results & Analysis (20 pts)

- Clear visualizations (4-6 plots + 2-3 GIFs with captions) ..... **10 pts**
- Insightful analysis (hypothesis testing, failure cases, limitations) . **10 pts**

Documentation (10 pts)

- Semester Contribution in root README (clear, well-structured) ..... **6 pts**
- Updated folder READMEs for modified modules ..... **4 pts**

Bonus (up to +10 pts)

- Novel extension beyond task requirements (e.g., new functions, theoretical analysis, hybrid approaches) ..... **+5 pts**
- Exceptional results (paper-quality plots, surprising insights, strong baselines) **+5 pts**

Presentation

Brief 10-minute presentation with slides covering: (1) Research question, (2) Implementation highlights, (3) Key results (3-4 plots/GIFs), (4) Failure analysis, (5) Future work. Live demo or pre-recorded GIF required.

Submission

- **GitHub**: Push all code, configs, and updated READMEs to repository
- **Canvas**: Submit PDF slides and link to GitHub branch/PR
- **Artifacts**: Include plots/GIFs in `images/semester_contribution/`
- **Team**: Document individual contributions in README

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Semester: 2025/26/2