Predator–Prey Simulation with Swarm Intelligence

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Project Overview

➔ **Goal:** Analyze interactions between predator and prey and identify patterns in prey survival and predator efficiency.

➔ **Method:** Simulate an ecosystem environment using a swarm algorithm.

- Observe how they would naturally behave and how that behavior benefits their survival.

Why? Project Motivation

- ➔ Understanding ecological interactions and the dynamics of ecosystems
- ➔ Contribute to understanding key ecological areas
- ➔ Better predict species interactions that are otherwise difficult to observe directly
- ➔ Develop more methods for analyzing and modeling ecosystems.

Methodology

- **Swarm intelligence:** “Collective behavior of decentralized, self-organized systems, natural or artificial”.
  - Collective, group-like behavior of agents that interact with each other and their surrounding environment, exploring complex behaviors
- Our project models its predator and prey dynamics through an evolutionary machine learning system inspired by “A Framework for Learning Predator–Prey Agents from Simulation to Real World,” [1].

Methodology

- ➔ Our system is based on **NeuroEvolution of Augmenting Topologies (NEAT)** to learn the expected behaviors and evolve the neural controllers for both predator and prey agents.
- ➔ Combines principles of swarm intelligence (local decision making, emergent cooperation, etc.) with evolutionary machine learning.
  - ◆ Allows the agents to learn evasion strategies.

NEAT - Background

- **Neuroevolution (NE):** Evolving artificial neural networks using genetic algorithms - highly effective in RL tasks
- **NEAT:** NeuroEvolution of Augmenting Topologies
- Increased efficiency is due to:
  - Employing a principled method of crossover of different topologies
  - Protecting structural innovation using speciation
  - Incrementally growing from minimal structure

Implementation

- Environment & Agents
- Prey & Predator Models
- Swarm Mechanics
- Training Protocol
- Evaluation Methodology

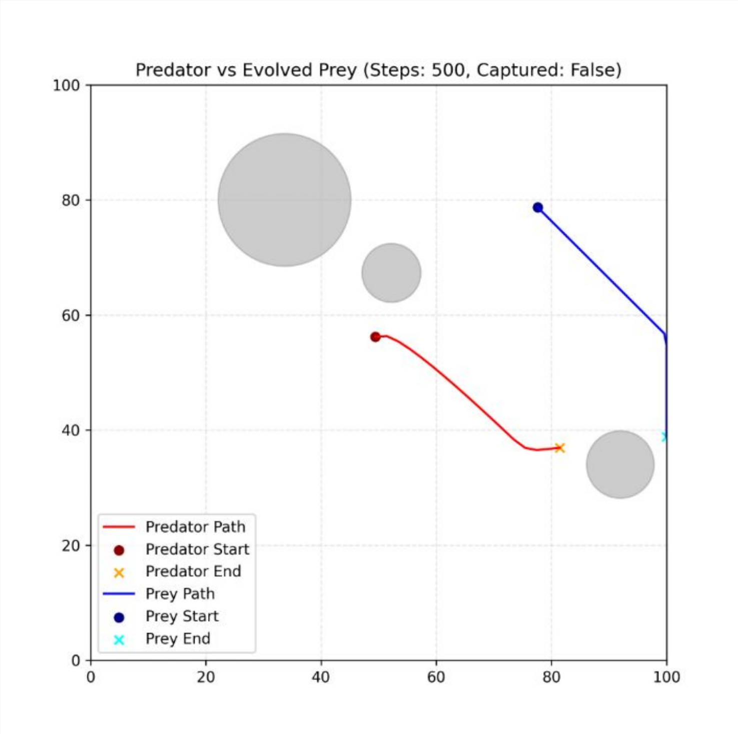
Environment & Agents

- **Simulation:**
  - 2 dimensional 100x100 board
  - Bound by walls and contains randomly placed obstacles
    - Constrains some movement
    - Encourages adaptive pathfinding
  - Predator and prey agents
    - Placed randomly and interact in the board
    - x, y (position), movement speed, radius (collisons)

Baseline Prey Strategy

- Heuristic prey controller
  - Uses simple hand-coded rules to decide movement
  - Always moves away from the predator's relative position
- Movement Behavior
  - Moves in the opposite direction of the predator
  - Does not account for obstacles or advanced tactics
- Limitations
  - Behavior is predictable and can be exploited
  - Cannot adapt to changes in predator strategy
- Purpose and role
  - Helps evaluate the performance of NEAT-evolved predators

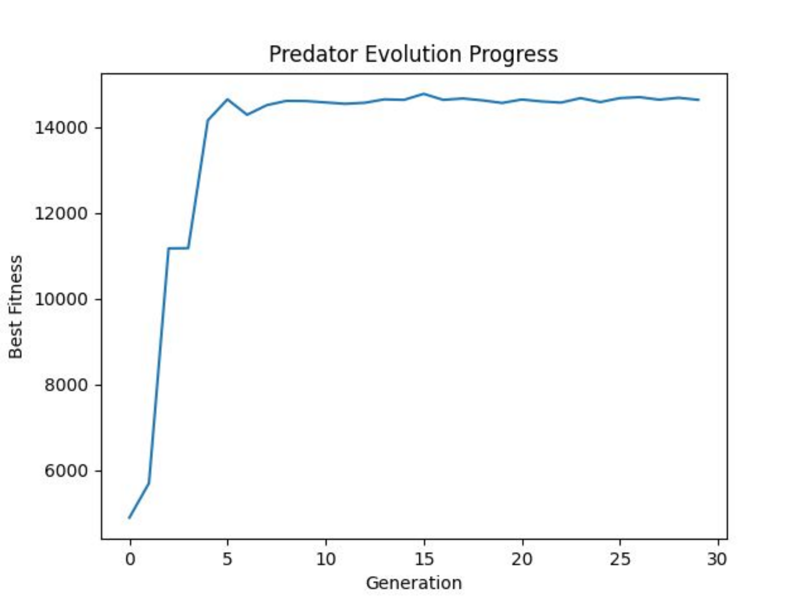
Evolved Prey Strategy



- NEAT-Evolved Prey Controller
  - Learns to evade predator using an evolved neural network
- Adaptive Movement
  - Zig-zag, loop, and sudden turns
  - Harder for predators to predict
- Purpose
  - Serves as a challenging opponent for evolved predators
  - Shows the effectiveness of coevolution

Predator Model

- ➔ Predator Agent
  - Tracks prey using relative direction and distance
  - Controlled by NEAT or simple heuristic
- ➔ Movement Behavior
  - Moves toward prey to reduce distance
  - Adjusts trajectory based on prey
- ➔ State Variables
  - Position (x, y), speed, and radius
- ➔ Purpose
  - Catch prey quickly
  - Drives coevolution with prey



Swarm Mechanics

Our simulation models predator-prey interactions on a 2D board bounded by walls and containing obstacles. Both agents are placed randomly, and obstacles constrain movement, encouraging adaptive pathfinding. Each agent only has limited local perception: they can sense the relative direction and distance of their opponent, which mimics real-world swarm systems. Agents move at a fixed speed in discrete time steps, and the simulation ends when the predator catches the prey.

- ➔ Limited local perception drives emergent chase and escape behaviors
- ➔ Obstacles and constrained movement encourage adaptive strategies

Training Protocol + Evolution Loop

1. **Train Predators** *(Prey stays fixed)*
2. **Train Prey** *(Against evolved predators; predator stays fixed)*
3. **Evolve Predators** *(Against evolved prey)*

- **Arms Race**
    - Predators evolve to chase better
    - Prey evolves to escape better

Evaluation Methodology

- **Metrics:** *Evaluation uses both success and trajectory-based metrics*
  - Capture rate
  - Time to capture
  - Average distance
  - Minimum distance
  - Movement efficiency

Evaluation Methodology

- **Baselines:**
  - Random, Greedy, Evolved, Dummy
- **Hyperparameters**
  - Population size
  - Episodes per genome
  - Episode length
  - Fitness scaling coefficients
  - Mutation probabilities & structural mutation rates

Qualitative Results

Key Behaviors Observed

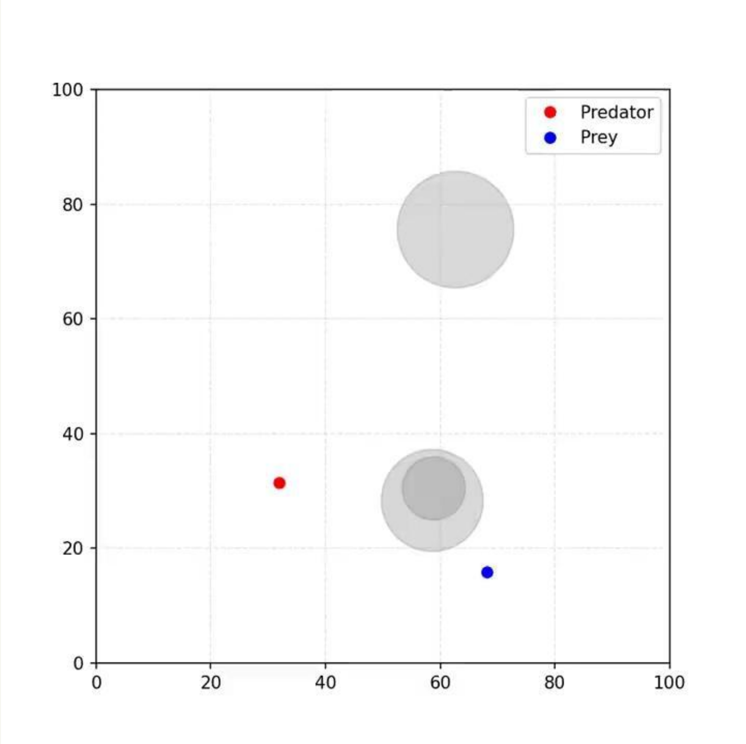
- Predator adjusts trajectory in real time
- Prey performs nonlinear escape maneuvers
- Both agents react to obstacles dynamically

Notable Emergent Patterns

- Curved interception paths
- Prey “probing” directions before committing
- Predator commits when within ~15-20 units

Takeaway

➔ Both agents exhibit coordinated, adaptive behavior not coded explicitly



Quantitative Results

Capture Rate:
• Against Dummy Prey: ~85% capture within 30 steps
• Against Evolved Prey: ~40–60% capture within 500 steps

Average Capture Time (successful runs):
• Dummy Prey: 17–25 steps
• Evolved Prey: 20–35 steps

Distance Reduction Efficiency:
• Median improvement: 30–50% reduction in predator–prey distance during successful chases

Training Stability:
• Predator fitness converged around 14.5k–14.7k
• Performance consistent across multiple random seeds

Future Steps

Add multi-agent swarm predators:

> Enable flanking, interception, herding behaviors

Fitness Shaping

> Add bonuses for using obstacles strategically

> Add penalties for entering obstacle danger zones

Generalization

> Randomize map layout and obstacle shapes

Thank You!

Reference: [1] Y. Chen and Y. Gao, “A Framework for Learning Predator–Prey Agents from Simulation to Real World,” *arXiv preprint* arXiv:2010.15792, 2020.