Multiagent Behaviors in Neural Network

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Motivation

- Most of works so far (i.e. reinforcement learning, neuroevolution) focused exclusively on single agents we can extend reinforcement learning straightforwardly to multiple agents if they are all independent.
- Intuitive idea: Multiple agents together will outperform any single agent due to the fact that they have more resources and a better chance of receiving rewards.
- Today, we will touch a broad area

"Multiagent System" (M.A.S.).

Introduction

What is multiple agent system?

- Unfortunately, it is not formally defined by M.A.S. community.
- Employment of multiple agents (10 to thousands).
- Intelligent mechanisms to address interactions between agents.

When is it proposed?

- a relatively new sub-field of computer science
- has only been studied since about 1980
- only gained widespread recognition since about the mid-1990s

M.A.S. Environments

The agents in a multi-agent system have several important characteristics:

- Autonomy: the agents are at least partially independent, self-aware, autonomous.
- Local views: no agent has a full global view of the system, or the system is too complex for an agent to make practical use of such knowledge.
- Decentralization: there is no designated controlling agent (or the system is effectively reduced to a monolithic system).

Applications/Simulations

- Crowd Simulation / Crowd Collision Avoidance
- ClearPath: Highly Parallel Collision Avoidance for Multi-agent Simulation
- MATISSE: A Multi-Agent based Traffic Simulation System

Main topics of M.A.S.

Currently active research areas of M.A.S. are as follows:

- **Communication**
- Cooperation and Coordination
- Negotiation
- Distributed Problem Solving
- **Multi-agent Learning**
- Fault Tolerance

Communication

Communication is defined as altering the state of the environment such that other agents can perceive the modification and decode information from it.

- Direct Communication: share information with one another in explicit way.
- Indirect Communication: implicit transfer of information from agent to agent through modification of the world environment.
- Stegmergic Communication: no shared information at all.

Independent v.s. Cooperative Agents

Tang Ming (1993) [**1**] studied the performance of cooperative agents, using independent agents as a benchmark. Here are the discoveries:

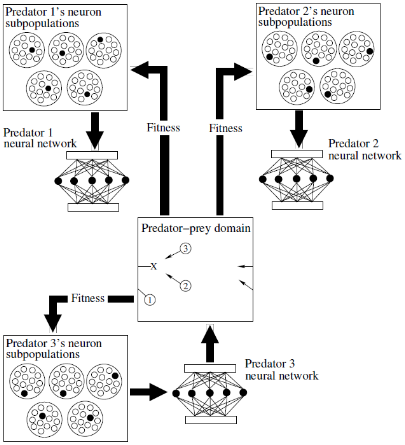
- Additional sensation from another agent is beneficial if it can be used efficiently.
- Sharing learned policies or episodes among agents speeds up learning at the cost of communication.
- For joint tasks, agents engaging in partnership can significantly outperform independent agents although they may learn slowly in the beginning.

Predator / Prey

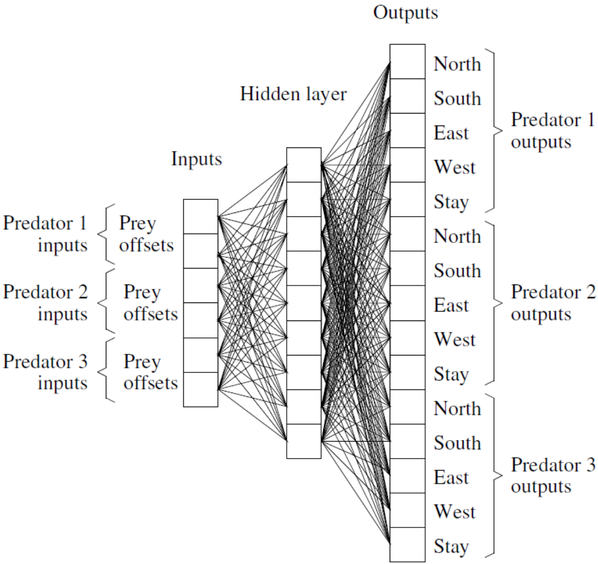
Three different examples:

- Centralized network
- Autonomous networks with communication
- Autonomous networks *without* communication

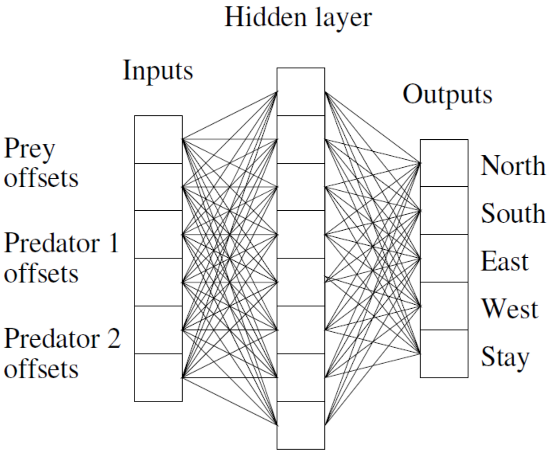
All are trained using ESP or **Multi-Agent ESP**



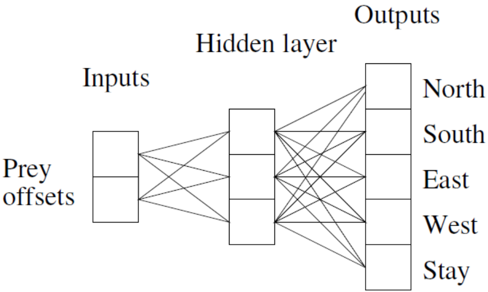
Centralized Network



Communicating Network

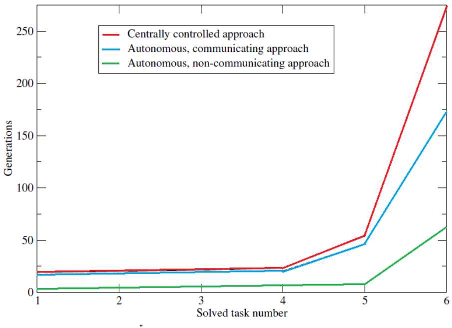


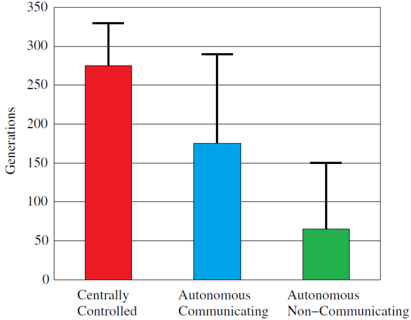
Non-communicating Network



Predator / Prey Results

How long does it take these networks to become successful?



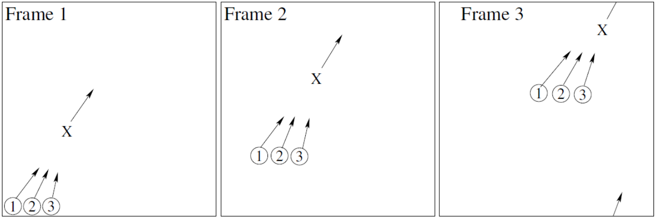


Conclusion: The predators are able to cooperate using **stigmergy** – indirect coordination based on the environment

- What if the environment is more complicated?

Predator / Prey Conclusion

- What happens if we use homogeneous networks? (All predators have the same network weights)
- Communication becomes a necessity



Even with communication, homogeneous networks do poorly, catching the prey only 3% of the time

Homogeneous Networks

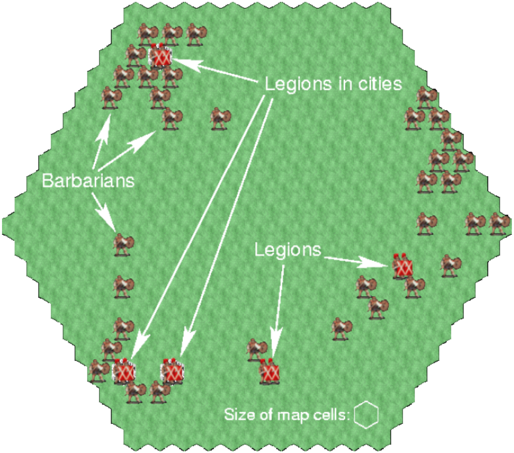
- Thus far, all multi-agent solutions have used heterogeneous networks
- In the predator prey, homogeneous networks performed very poorly
- Can we evolve agents with identical networks, which nevertheless cooperate by adopting different strategies?

Legion Game

The Legion game consists of:

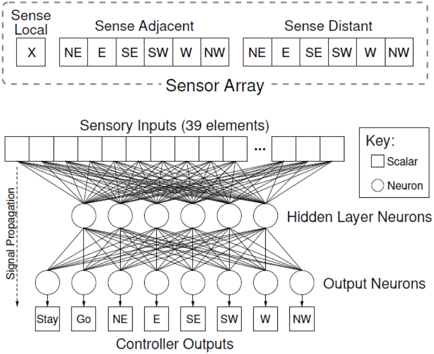
- A hexagonal grid
- Randomly placed cities
- Legions (defenders)
- Barbarian attackers

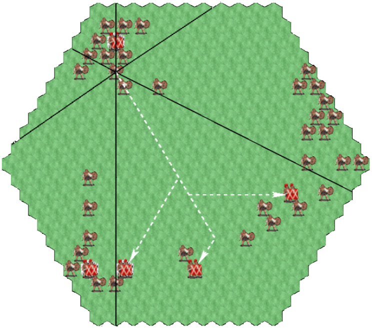
At every game tick, legions are penalized for each barbarian on the board



Legion Network

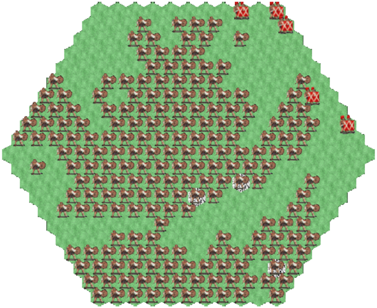
- Each legion has six sensors for each of the six directions



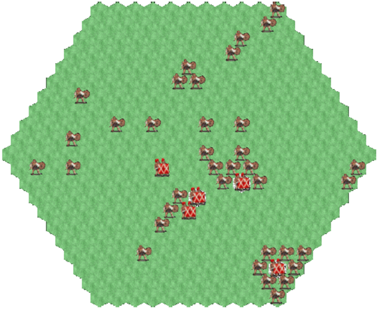


Legion Results

- Legions were trained with ESP neuroevolution
- Successfully learned to divide labor between "guard duty" and search and destroy" behavior



Before training



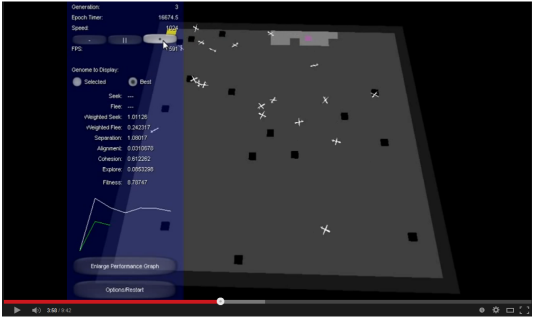
After training

Social Learning

- In **social learning**, agents improve their performance by learning from other members of the population
- Traditionally, agents are partitioned into students and teachers, where teachers are chosen to be high fitness members of the population
- **Problem**: How to decide which agents should be teachers and which the students?

Cooperative search

- In this example, agents are **Unmanned Aerial Vehicles** (**UAVs**) searching a grid of airspace

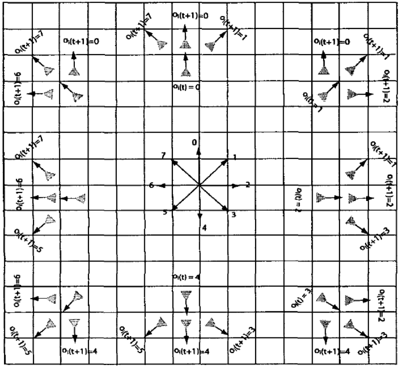


UAV Example: Goals

- Compare a *centralized* approach, where agents share a network, to a *decentralized* approach
- Determine whether opportunistic sharing of network weights improves the speed and accuracy of learning

UAV Example: Setup

- UAVs trained via Reinforcement Learning
- Each cell in the search space is given a *certainty* value between 0 and 1
- UAVs are rewarded for reducing uncertainty



UAV Example

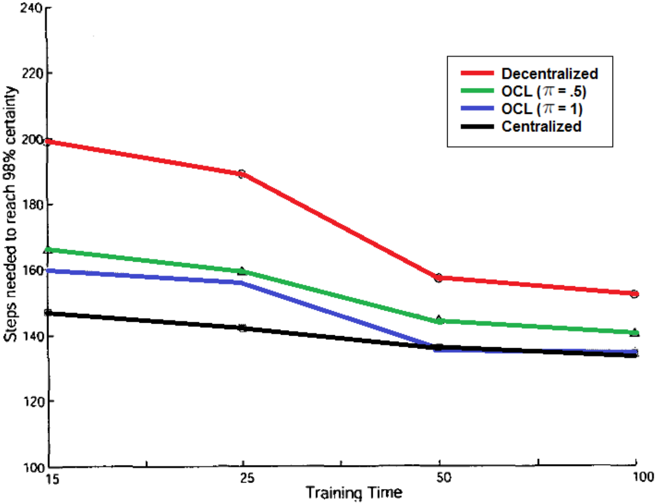
- Diminishing returns for searching the same cell, as well as having multiple agents search the same cell
- At each time-step, an agent only has three options (turn left, turn right, keep straight)
- Neural networks are used to estimate the benefit of each course

UAV Experiment

Compare these three architectures:

- **Centralized Learning**: shared networks receive input from all agents
- **Decentralized Learning**: each agent has its own three networks
- **Opportunistic Cooperative Learning**: each agent has its own three networks. Additionally, when two agents come close together, the less successful one copies the other's network with probability π

UAV Example: Results

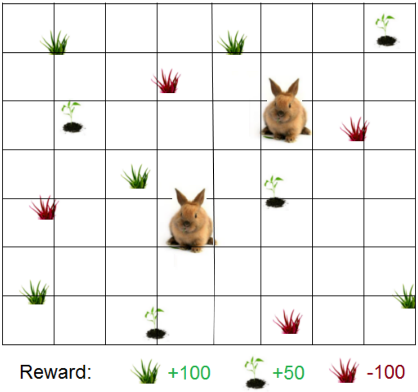


Egaltarian Social Learning

- In **Egaltarian Social Learning** (**ESL**), agents learn from each other instead without any designated "teachers"
- The population of agents is partitioned into subcultures at the start of each generation
- An agent may probabilistically learn from any other agent in the same subculture

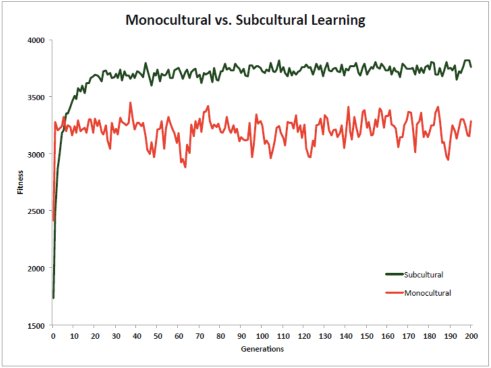
ESL Example: Foraging

- Agents move independently across a continuous world filled with several types of plants
- Plants are automatically consumed when an agent draws close enough; some types of plant give positive reward, others negative reward

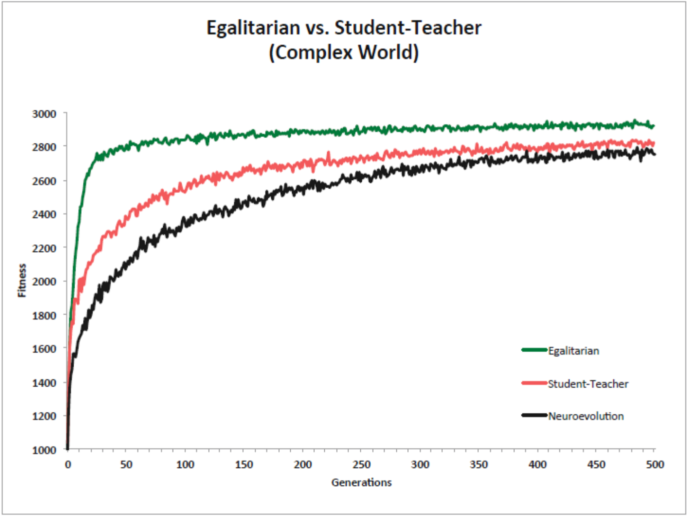


ESL Example: Foraging (Results)

- Backpropagation networks trained with NEAT
- ESL without subcultures performs worse than plain neuroevolution
- Adding subcultures results in a significant improvement



ESL Example: Foraging (Results)



ESL Example: Foraging (Conclusion)

- In the foraging example, ESL performed better than the Student-Teacher model
- ESL is advantageous because it promotes diversity and avoids premature convergence

- **Takeaway**: Social learning techniques improve learning speed and performance

Questions, Suggestions or Some Other Ideas?

Our Research Project

- Motivations: Multiagent Learning
  - Faster Convergence
  - Flexible Architectures
  - Collectively Robust
- Where to start?
  - Begin from implementing ESP for Roombas in Opennero Platform
- Suggestions?

Further Readings: Books

- W. Michael. *An introduction to multiagent systems*. John Wiley & Sons, 2009.
- S. Yoav, and K. L. Brown. *Multiagent systems: Algorithmic, game-theoretic, and logical foundations*. Cambridge University Press, 2008.
- W, Gerhard, ed. *Multiagent systems: a modern approach to distributed artificial intelligence*. MIT press, 1999.

Further Readings: Courses and Labs

- Stanford CS224M: Multi Agent Systems (Spring 2013-14). HERE
- MIT CPSC689: Special Topics in Multi-Agent Systems (Spring 2006). HERE
- Stanford Multiagent Research Group. HERE
- CMU Advanced Agent-Robotics Technology Lab. HERE
- MIT Robust Open Multi-Agent Systems (ROMA) Research Group. HERE

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[1] Bobby D. Bryant and Risto Miikkulainen (2003). Neuroevolution for Adaptive Teams. *Proceedings of the 2003 Congress on Evolutionary Computation* 1:2194-2201.

[2] Tan, Ming. "Multi-agent reinforcement learning: Independent vs. cooperative agents." *Proceedings of the Tenth International Conference on Machine Learning*. Vol. 337. 1993.

[3] Rawal, A.; Rajagopalan, P.; Miikkulainen, R., "Constructing competitive and cooperative agent behavior using coevolution," *Computational Intelligence and Games (CIG), 2010 IEEE Symposium on*, vol., no., pp.107,114, 18-21 Aug. 2010

[4] Rajagopalan, P.; Rawal, A.; Miikkulainen, R.; Wiseman, M.A.; Holekamp, K.E., "The role of reward structure, coordination mechanism and net return in the evolution of cooperation," *Computational Intelligence and Games (CIG), 2011 IEEE Conference on*, vol., no., pp.258,265, Aug. 31 2011-Sept. 3 2011

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[5] Risto Miikkulainen and Eliana Feasley and Leif Johnson and Igor Karpov and Padmini Rajagopalan and Aditya Rawal and Wesley Tansey (2012). *Multiagent Learning through Neuroevolution. Advances in Computational Intelligence* LNCS 7311:24-46.

[6] Yanli Yang; Polycarpou, M.M.; Minai, A.A., "Opportunistically cooperative neural learning in mobile agents," *Neural Networks, 2002. IJCNN '02. Proceedings of the 2002 International Joint Conference on*, vol.3, no., pp.2638,2643, 2002

[7] Yong, C.H.; Miikkulainen, R., "Coevolution of Role-Based Cooperation in Multiagent Systems," *Autonomous Mental Development, IEEE Transactions on*, vol.1, no.3, pp.170,186, Oct. 2009

Acknowledgement

Thanks.