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University of Ruse “Angel Kanchev”

# MULTIAGENT SYSTEM WITH ARTIFICIAL INTELLIGENCE

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08,2022

Co-financed by the European Union
Connecting Europe Facility

This Master is run under the context of Action
No 2020-EU-IA-0087, co-financed by the EU CEF Telecom
under GA nr. INEA/CEF/ICT/A2020/2267423

LECTURE 6

# Cooperative Agents. Competing agents

1. Cooperative Agents
2. Competitive Agents
3. Major Open Topics
4. Problem Domains and Applications



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# Cooperative Agents

There are said to be two main categories of multi-agent cooperative learning approaches.

**Team training** - applies the search behavior of one learner to the entire team of agents. It is similar to traditional machine learning techniques, but may have scalability issues as team size increases. Team learning techniques can assign identical behavior to multiple team members in order to maintain scalability.

**Concurrent Learning** - Uses multiple concurrent learning processes. Adopts parallel learning approaches, typically using a learner for each team member, with the hope that this reduces the total space by designing it into N separate spaces.

This makes the environment non-stationary, which violates the premise of most traditional machine learning techniques. For this reason, concurrent learning requires new (or significantly modified versions of) machine learning methods

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# Team Learning

- Types
- **Homogeneous**
  - The assumption that all agents have the same behavior drastically reduces the learning search space. Research in this area includes analyses of the performance of the homogeneous team discovered by the learning process, comparisons of different learning paradigms, or the increased power added by indirect and direct communication abilities.
  - Learning rules for cellular automata is an oft-overlooked paradigm for homogeneous team learning

- **Purely-heterogeneous**
  - In heterogeneous team learning, the team is composed of agents with different behaviors, with a single learner trying to improve the team as a whole. This approach allows for more diversity in the team at the cost of increasing the search space. The bulk of research in heterogeneous team learning has concerned itself with the requirement for or the emergence of specialists. The results of Luke and Spector shows that restricted breeding (preventing cross-breeding of behaviors for different specialists) works better than unrestricted breeding, which suggests that the specialization allowed by the heterogeneous team representation conflicts with the inter-agent genotype mixture allowed by the free interbreeding. However, the question is not fully answered.



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# Team Learning

- **Hybrid Team Learning**
  - In hybrid team learning, the set of agents is split into several groups, with each agent belonging to exactly one group. All agents in a
  - group have the same behavior. One extreme (a single group), is equivalent to homogenous team learning, while the other extreme (one agent per group) is equivalent to heterogeneous team learning. Hybrid team learning thus permits the experimenter to achieve some of the advantages of each method.



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# Concurrent Learning

- The foremost common elective to team learning in cooperative multi-agent frameworks is concurrent learning, where numerous learning forms endeavor to concurrently move forward parts of the group. Most regularly, each operator has it claim unique learning handle to adjust its behavior.
- Credit Assignment
- Dynamics of learning
- Modeling other agents

- **Credit Assignment**
  - When managing with different learners, one is confronted with the assignment of divvying up among them the remunerate gotten through their joint activities. The only arrangement is to part the group remunerate similarly among each of the learners, or in a larger sense, isolate the compensate such that at whatever point a learner's compensate increases (or diminishes), all learners' rewards increment (diminish). This credit assignment approach is as a rule named global reward.

# Concurrent Learning

- **Dynamics of learning**
  - When applying single-agent learning to stationary situations, the operator tests with distinctive behaviors until ideally finding a universally ideal behavior. In energetic situations, the specialist may at best attempt to keep up with the changes within the environment and always track the moving ideal behavior. Things are indeed more complicated in multi-agent frameworks, where the operators may adaptively alter each others' learning situations.
  - Fully Cooperative Scenarios
  - General Sum Games

- **Modeling other agents (teammate modeling)**
  - Learning about other agents in the environment so as to make good guesses of their expected behavior, and to act accordingly (to cooperate with them more effectively for example)
  - Direct communications
  - Indirect communications



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# Competitive Agents

- **Opponent Modeling**
  - In a few settings, modeling the rival can be vital to urge great comes about from the amusement. In such models, (approximations of) adversary inclinations are spoken to, which can shape the basis for genuine specialist procedure. Typically especially vital when trade-offs can be made between amusement results between diverse players and a few sort of Pareto-efficiency is included, e.g. as in multi-issue transactions. Rival models can be characterized for a single adversary or for a course (sort) of opponents

- **Market and Strategy Modeling**
  - In other settings, models of adversary inclinations are less significant, and parameters concerning the products around which the market diversion is played, or the total (mysterious) showcase behavior (decided by a considerable sum of reasonably mysterious operators) is of more significance. In case of the fundamental great, one may think of a great of which its valuation can be decided from cooperation in numerous recreations.

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# Competitive Agents

- **Models of Application Settings**
- Application settings and models that go assist than the ordinary diversion theoretic stylizations are vital for this field. Advertise recreations are frequently considered related to more particular application models

- **Co-learning and Evaluation:**
- When applying versatile methods for competitive specialists in multiagent frameworks, the quality of an versatile procedure for an operator depends on the (versatile) techniques of other operators. Within the case that all operators utilize really versatile procedures as well, different shapes of colearning happens. Up to presently, such situations of different operators are still or maybe confined and basically address learning in agreeable frameworks and e.g. stochastic (general-sum) games



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# Major Open Topics

- **Scalability**
- Versatility is an issue for numerous learning strategies, but particularly for learning in multi-agent frameworks. The multidimensionality of the look space develops quickly with the number and complexity of operator behaviors, the number of operators included, and the measure of the organize of intelligent between them. In this way, the look space develops so quickly that it may not be conceivable to ponder the complete joint behavior of a huge, heterogeneous, profoundly communicating multiagent system.
- Effective learning in this complex space requires a few degree of give up: either by segregating the learned behavior between person operators, by decreasing the heterogeneity of operators, or by decreasing the complexity of the agents' capabilities. Procedures such as cross breed group preparing, behavior deterioration, or somewhat restricting the area of fortification give promising solutions in this course. It isn't however well portrayed beneath what imperatives and for which issue spaces these obliged strategies work well

# Major Open Topics

- **Adaptive Dynamics and Nash Equilibria**
- Multi-agent frameworks are ordinarily energetic situations, with different learning specialists competing for assets and tasks. This dynamism presents a special challenge not regularly found in single-agent learning: as the operators learn, their adjustment to one another changes the world situation. How do operators learn in an environment where the goalposts are continually and adaptively being moved?
- As said some time recently, this co-adaptation of learners to one another leads to a infringement of a essential suspicion of most machine learning methods; for this reason, completely modern multi-agent learning calculations may be required to bargain with this issue. Usually exacerbated by credit task schemes, which whereas regularly vital, can change over an conventional agreeable situation into a general-sum or indeed (accidentally) competitive environment.

# Major Open Topics

- **Problem Decomposition**
- The state space of a expansive, joint multi-agent errand can be overpowering. An self-evident way to handle this can be to utilize domain knowledge to rearrange the state space, regularly by giving a littler set of more “powerful” activities customized for the problem domain. For illustration, Mataric applies Q learning to choose from hand-coded responsive behaviors such as dodge, head-home, look or scatter for robot scavenging assignments. An elective has been to decrease complexity by heuristically breaking down the issue, and hence the joint behavior, into partitioned, less difficult behaviors for the specialists to memorize.
- Such deterioration may be done at different levels (breaking down group behaviors into sub-behaviors for each specialist; breaking down an agents’ behavior into sub-behaviors; etc.), and the behaviors may be learned independently, iteratively (each depending on the prior one), or in a bottom-up design (learning basic behaviors, at that point gathering into “complex” behaviors)



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# Problem Domains and Applications

- **Embodied Agents**
- The taken a toll of robots has diminished altogether, making it doable to buy and utilize a few (tens, hundreds, or indeed thousands of) robots for a assortment of assignments. This drop in fetched has impelled investigate in multi-agent agreeable robotics. Additionally, computer equipment is cheap sufficient that what cannot be performed with genuine robots can presently be exhausted reenactment; in spite of the fact that the mechanical technology community still emphatically energizes approval of comes about on genuine robots

- Predator-Prey Pursuit
- Foraging
- Box Pushing
- Box Pushing
- Keep-Away Soccer
- Cooperative Navigation
- Cooperative Target Observation
- Herding

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# Problem Domains and Applications

- **Game-Theoretic Environments**
- Many multi-agent systems may be cast in game-theoretic terms; essentially as strategy games consisting of matrices of payoffs for each agent based on their joint actions. In addition to game-theoretic analysis of multi-agent systems, some common problem domains are also taken from game theory.

- Coordination Games
- Social Dilemmas



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# Problem Domains and Applications

- **Real-World Applications**
- Numerous of the depicted issue spaces are coordination, arranging, and constraint-satisfaction issues requiring real-time, conveyed choice making. Since the applications are regularly exceptionally complex and profoundly dispersed, learning techniques have seldom been connected to them, and so they are displayed here fundamentally as case challenge issues for multi-agent learning.

- Distributed Vehicle Monitoring
- Air Traffic Control
- Network Management and Routing
- Electricity Distribution Management
- Distributed Medical Care
- Supply Chains
- Hierarchical Multi-Agent Systems Problems
- Models of Social Interaction
- Meeting Scheduling

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