Course guides
270715 - ATCI - Advanced Topics in Computational Intelligence

Unit in charge: Barcelona School of Informatics
Teaching unit: 723 - CS - Department of Computer Science.

Degree: MASTER'S DEGREE IN ARTIFICIAL INTELLIGENCE (Syllabus 2017). (Optional subject).

Academic year: 2021  ECTS Credits: 4.0  Languages: English

LECTURER

Coordinating lecturer: MARIO MARTÍN MUÑOZ

Others: Segon quadrimestre: MARIO MARTÍN MUÑOZ - 10

PRIOR SKILLS

Basic concepts of Deep Learning.

DEGREE COMPETENCES TO WHICH THE SUBJECT CONTRIBUTES

Specific:
- CEA11. Capability to understand the advanced techniques of Computational Intelligence, and to know how to design, implement and apply these techniques in the development of intelligent applications, services or systems.
- CEA3. Capability to understand the basic operation principles of Machine Learning main techniques, and to know how to use on the environment of an intelligent system or service.
- CEA9. Capability to understand Multiagent Systems advanced techniques, and to know how to design, implement and apply these techniques in the development of intelligent applications, services or systems.
- CEP2. Capability to solve the decision making problems from different organizations, integrating intelligent tools.
- CEP3. Capacity for applying Artificial Intelligence techniques in technological and industrial environments to improve quality and productivity.
- CEP8. Capability to respect the surrounding environment and design and develop sustainable intelligent systems.

General:
- CG3. Capacity for modeling, calculation, simulation, development and implementation in technology and company engineering centers, particularly in research, development and innovation in all areas related to Artificial Intelligence.
- CG4. Capacity for general management, technical management and research projects management, development and innovation in companies and technology centers in the area of Artificial Intelligence.

Transversal:
- CT3. TEAMWORK: Being able to work in an interdisciplinary team, whether as a member or as a leader, with the aim of contributing to projects pragmatically and responsibly and making commitments in view of the resources that are available.
TEACHING METHODOLOGY

Theory classes will introduce the knowledge, techniques and concepts required to apply them in practice during the laboratory classes. Theory classes will be mainly of the type magisterial lecture, but some of them may be of the type exposition-participation, with the participation of the students in solving problems or exercises.

Laboratory classes have as objective that the students work with software tools which allow the application to real problems of the techniques presented in theory classes. Students will use these tools to develop their practical work of the course, which will consist of a part of autonomous individual work and a part of cooperative work in a team of 2/3 people. Some time of the laboratory classes will be devoted to the orientation and supervision by the professor of these autonomous and cooperative works.

LEARNING OBJECTIVES OF THE SUBJECT

1. To understand the need, fundamentals, and particularities of behavior learning and the differences it has from supervised and unsupervised machine learning.
2. To distinguish the kind of problems can be modeled as a reinforcement learning problem and identify the techniques that can be applied to solve them.
3. To understand the most important algorithms and state of the art in the area of learning by reinforcement.
4. To know how to computationally formalize a real world problem as learning by reinforcement and know how to implement in the most current environments the learning algorithms that solve them.
5. To understand the most advanced and recent techniques in the field of Multi-Agent learning to cooperate and compete.
6. To understand the difficulties and inefficiencies of the reinforcement learning approach and propose the techniques and approaches that could solve them.

STUDY LOAD

<table>
<thead>
<tr>
<th>Type</th>
<th>Hours</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Self study</td>
<td>64,0</td>
<td>64.00</td>
</tr>
<tr>
<td>Theory classes</td>
<td>20,0</td>
<td>20.00</td>
</tr>
<tr>
<td>Laboratory classes</td>
<td>16,0</td>
<td>16.00</td>
</tr>
</tbody>
</table>

Total learning time: 100 h

CONTENTS

Introduction: Behavior Learning in Agents and description of main elements in Reinforcement Learning

Description:
Intuition, motivation and definition of the reinforcement learning (RL) framework. Key elements in RL.

Finding optimal policies using Dynamic Programming

Description:
How to learn the optimal policy with full knowledge of the world model: algebraic solution, policy iteration and value iteration.

Introduction to Model-Free approaches.

Description:
Basic algorithms for reinforcement learning: Monte-Carlo, Q-learning, Sarsa, TD(lambda). The need for Exploration. Differences between On-policy and Off-policy methods.
<table>
<thead>
<tr>
<th><strong>Function approximation in Reinforcement Learning</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Description:</strong> Need for function approximation and Incremental methods in RL. The Gradient Descent approach. RL with Linear function approximation. The deadly triad for function approximation in RL. Batch methods and Neural Networks for function Approximation.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Deep Reinforcement Learning (DRL)</strong></th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th><strong>Advanced topics: Model Based Reinforcement Learning (MBRL)</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Description:</strong> Separating the learning of the policy from the learning of a model of the world has some benefits and some problems. Sample efficiency in RL by hallucination and imagination.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Policy gradient methods</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Description:</strong> What to do in continuous action spaces. How probabilistic policies allow to apply the gradient method directly in the policy network. The REINFORCE algorithm. The Actor-Critic algorithms. State-of-the-art algorithms in continuous action spaces: DDPG, TD3 and SAC.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Advanced Topics: How to deal with sparse rewards</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Description:</strong> The problem of the sparse reward. Introduction to advanced exploration techniques: curiosity and empowerment in RL. Introduction to curriculum learning to easy the learning of the goal. Hierarchical RL to learn complex tasks. The learning of Universal Value Functions and Hindsight Experience Replay (HER).</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Advanced Topics: Towards Long-life learning in agents</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Description:</strong> Is RL a way to obtain a General Artificial Intelligence? Multi-task learning in RL, Transfer learning in RL and Meta-learning in RL. State-of-the-art approaches.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Reinforcement Learning in the multi-agent framework</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Description:</strong> Learning of behaviors in environment where several agents act. Learning of cooperative behaviors, Learning of competitive behaviors, and mixed cases. State-of-the-art algorithms. The special case of games: The AlfaGo case and the extension to Alfa-Zero.</td>
</tr>
</tbody>
</table>
### ACTIVITIES

<table>
<thead>
<tr>
<th>Activity</th>
<th>Description</th>
<th>Specific objectives</th>
<th>Full-or-part-time</th>
<th>Theory classes</th>
<th>Laboratory classes</th>
<th>Self study</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Introduction, motivation and examples of successful applications in RL</strong></td>
<td>Development of the corresponding topic and laboratory exercises</td>
<td>1, 2</td>
<td>2h</td>
<td>1h</td>
<td>1h</td>
<td></td>
</tr>
<tr>
<td><strong>Definition of the RL framework. Key elements in RL. Finding the optimal policy using Value Iteration and Policy Iteration</strong></td>
<td>Development of the corresponding topic and laboratory exercises</td>
<td>1, 2, 3</td>
<td>9h</td>
<td>2h</td>
<td>1h</td>
<td>6h</td>
</tr>
<tr>
<td><strong>Introduction to Model-Free approaches. Monte-Carlo, Q-learning, Sarsa, TD(lambda)</strong></td>
<td>Development of the corresponding topic</td>
<td>1, 2, 3</td>
<td>7h</td>
<td>2h</td>
<td>1h</td>
<td>4h</td>
</tr>
<tr>
<td><strong>Function approximation in RL</strong></td>
<td>Development of the corresponding topic and laboratory exercises</td>
<td>3, 4, 7</td>
<td>5h</td>
<td>2h</td>
<td>1h</td>
<td>2h</td>
</tr>
</tbody>
</table>
Deep Reinforcement Learning (DRL)

Description:
Development of the corresponding topic and laboratory exercises

Specific objectives:
3, 4, 7

Full-or-part-time: 12h
Theory classes: 3h
Laboratory classes: 1h
Self study: 8h

Policy gradient methods

Description:
Presentation of the corresponding course topic and lab exercises

Specific objectives:
3, 7

Full-or-part-time: 12h 30m
Theory classes: 3h
Laboratory classes: 0h 30m
Self study: 9h

Tutorized practical works

Specific objectives:
2, 4, 5

Full-or-part-time: 12h
Guided activities: 2h
Self study: 10h

Final exam

Specific objectives:
1, 2, 3, 4, 5, 7

Full-or-part-time: 7h
Guided activities: 3h
Self study: 4h

Study of the state-of-the-art in an advanced topic work

Specific objectives:
4, 5, 7

Full-or-part-time: 10h
Self study: 10h
Advanced topics on behavior learning: Increasing sample efficiency

Specific objectives:
3, 4, 7

Full-or-part-time: 16h
Theory classes: 6h
Laboratory classes: 2h
Self study: 8h

Multiagent RL

Specific objectives:
5

Full-or-part-time: 6h
Theory classes: 2h
Self study: 4h

GRADING SYSTEM

The mark (M) is calculated as follows:

M = 0.20 * Quiz + 0.30 * Practical + 0.5 * Theoretical

where

*Quiz* refers to a Quiz with theoretical and conceptual questions about the first part of the course
*Practical* refers to an implementation of a RL algorithm on a problem done in Python
*Theoretical* refers to a study of the state-of-the art in an advanced topic work to be chosen by the student

BIBLIOGRAPHY

Basic:

Complementary:

RESOURCES

Hyperlink:
- https://www.cs.upc.edu/~mmartin/ATCI-RL.html