EPFL

CS-434 **Unsupervised & reinforcement learning in neural networks**

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Cursus	Sem.	Type
Biocomputing minor	H	Opt.
Computational Neurosciences minor	H	Opt.
Computer science	MA1, MA3	Opt.
Neuroscience		Opt.
SC master EPFL	MA1, MA3	Opt.
Sciences du vivant	MA1, MA3	Opt.

Language of teaching	English
Credits	4
Session	Winter
Semester	Fall
Exam	Written
Workload	120h
Weeks	14
Hours	**4 weekly**
Courses	2 weekly
Exercises	2 weekly
Number of positions	

Summary

Learning is observable in animal and human behavior, but learning is also a topic of computer science. This course links algorithms from machine learning with biological phenomena of synaptic plasticity. The course covers unsupervised and reinforcement learning, but not supervised learning.

Content

I. unsupervised learning
1. Neurons and Synapses in the Brain. Synaptic Changes
2. Biology of unsupervised learning, Hebb rule and LTP .
3. Hebb rule in a linear neuron model and PCA
4. Analysis of Hebb rule and application to development
5. Plasticity and Independent Component Analysis (ICA)
6. Competitive Learning and Clustering
7. Kohonen networks

II. Reinforcement learning
8. The paradigm of reward-based learning
in biology and theoretical formalisation
9. Reinforcement learning in discrete spaces
10. Eligibity traces and reinforcement learning in continuous spaces and applications

III. Can the brain implement Unsupervised and Reinforcement learning?
11. Spiking neurons and learning: STDP
12. Neuromodulators and Learning
13. Long-term stability of synaptic memory
14. Unsupervised learning from an optimality
viewpoint: Information Maximization

Keywords

synaptic plasticity
learning rules
learning algorithms
neural networks

Learning Prerequisites

Required courses

Analysis I-III, linear algebra, probability and statistics

Recommended courses

Analysis I-III, linear algebra, probability and statistics

Important concepts to start the course

The student needs to be able to use mathematical abstrations as well as linear algebra, probability theory and statistics, analysis and calculus.

Learning Outcomes

By the end of the course, the student must be able to:

- Design learning algorithms
- Analyze learning algorithms and plasticity rules
- Classify learning algorithms and plasticity rules
- Prove convergence of batch learning rules
- Develop a learning rule based on optimization principles
- Formulate on-line plasticity rules
- Apply unsupervised and reinforcement learning rules

Transversal skills

- Write a scientific or technical report.
- Collect data.
- Negotiate effectively within the group.

Teaching methods

Classroom teaching, exercises and miniproject

Expected student activities

participate in class (slides are not self-contained)
solve paper and pencil exercises
write and run simulations for miniproject
write report

Assessment methods

The final grade is composed of two mini-projects and one exam.
The two mini-projects together count 1/3 of the final grade.
The final exam counts 2/3 of the final grade.
The exam will be written if the course has more than 40 students and oral otherwise.

Supervision

Office hours	No
Assistants	Yes
Forum	Yes

Resources

Bibliography

Dayan & Abbott : Theoretical Neuroscience, MIT Press 2001;
Gerstner & Kistler : Spiking Neuron Models, Cambridge Univ. Press
Sutton & Barto: Reinforcement learning, MIT Press1998,

Ressources en bibliothèque

- Theoretical Neuroscience / Dayan
- Spiking Neuron Models / Gerstner
- Reinforcement learning / Sutton

Websites

- http://moodle.epfl.ch/

Moodle Link

- http://moodle.epfl.ch/course/view.php?id=1241