COURSE DESCRIPTION CARD - SYLLABUS

Course name
Deep learning [S1SI1E>DEEPL]

Course

Field of study
Artificial Intelligence

Year/Semester
3/5

Area of study (specialization)
–

Profile of study
general academic

Level of study
first-cycle

Course offered in
English

Form of study
full-time

Requirements
compulsory

Number of hours

Lecture
30

Laboratory classes
30

Other
0

Tutorials
0

Projects/seminars
0

Number of credit points

5,00

Coordinators

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Lecturers

Prerequisites

Basic mathematical knowledge of mathematical analysis and linear algebra. Knowledge acquired during the courses on Introduction to AI, Statistics, and Machine learning. Programming skills in Python (preferably including the familiarity with the Numpy library).

Course objective

1. To make students knowledgeable about selected issues of deep learning, neural networks, representation learning and related aspects of machine learning. 2. To develop students' ability to solve machine learning problems and tasks using deep learning models, including deep neural networks, especially classification, regression and representation learning. 3. To acquire general experience and know-how in using these skills in selected practical applications. 4. To teach students work effectively on small project-programming projects in deep learning, including cooperation in project groups.

Course-related learning outcomes

Knowledge:

The student has a structured, theoretically grounded general knowledge of deep learning models, especially neural networks [K2st_W2].
Has knowledge related to selected issues in computer science, such as deep learning, neural networks, machine learning, representation learning, feature engineering [K2st_W3].
Has advanced and detailed knowledge of the processes occurring in the life cycle of hardware or software information systems used to solve selected tasks specific to deep learning [K2st_W5].
Is familiar with methods, techniques and tools used in solving complex engineering tasks and conducting research work typical of classification, regression, and representation learning using deep learning [K2st_W6].

Skills:
The student can formulate and test hypotheses related to problems solved with deep learning models and simple research problems specific to this area of artificial intelligence [K2st_U3].
Can use experimental methods to formulate and solve tasks in the area of deep learning applications, especially deep neural networks, and simple research problems [K2st_U4].
Can - when formulating and solving typical deep learning and neural networks - integrate knowledge from different areas of computer science (and, if necessary, knowledge from other scientific disciplines) [K2st_U5].
Can evaluate the usefulness and applicability of new developments in deep learning and related issues and techniques of artificial intelligence [K2st_U6].
Can propose improvements (enhancements) to existing technical solutions in the area of deep learning, especially based on existing libraries and development environments such as TensorFlow and PyTorch [K2st_U8].

Social competences:
Social competencies
The student understands that in the field of deep learning, knowledge and skills become obsolete very quickly [K2st_K1].
Understands the importance of using the latest knowledge of deep learning, neural networks and related approaches of machine learning and artificial intelligence in solving research and practical problems [K2st_K2].

Methods for verifying learning outcomes and assessment criteria

Learning outcomes presented above are verified as follows:

Formative assessment:
1. lectures
a. asking student questions pertaining to the material presented in previous lectures,
2. laboratory classes:
a. evaluation of progress in project realization (checkpointing)
b. checking knowledge and skills through homeworks
Total assessment:
1. verification of assumed learning objectives related to lectures:
a. Evaluation of acquired knowledge in the form of a written exam (5-8 open questions pertaining to lecture contents). Roughly half of the questions are theoretical (define, describe, characterize, etc.), the other half are practical and require manual calculations. Maximum total score: 25 points, of which 13 are required to obtain a positive grade.
2. verification of assumed learning objectives related to laboratory classes:
a. Evaluation of progress along the semester classes, based on 2 projects carried out by students and based on its documentation; students work on the project in part during the classes, and partially individually. The assigned grade reflects also student’s teamwork skills.
b. The final grade is computed as a weighted average from the individual marks.
Additional assessment elements include:
● Student’s capability of applying the acquired knowledge to the problem posed in the project.
● Student’s remarks aimed at improving the quality of teaching material.

● Indications of students’ problems at acquisition and understanding of the knowledge presented at the lectures, aimed at improving the overall quality of the teaching process.

Programme content

Lecture:
The overall goal is to learn the theoretical and practical aspects of deep learning and artificial neural networks, in particular: 1) Master the basics of deep learning and artificial neural networks as machine learning and optimization methods. 2) Acquire knowledge about algorithms and methods for learning deep models, with particular emphasis on representation learning. 3) Acquire the skills of applying deep learning models and artificial neural networks to solve problems of classification, detection, regression, computer vision, and sequence interpretation.
To achieve the above objectives, the lecture program includes: Introduction. Definition of deep learning as a specific paradigm for machine learning, optimization and modeling. Definition of parameters and hyperparameters of models. Discussion of the modular characteristics of deep learning models. Description of the most important and commonly used deep learning components, including dense layers, convolutional layers, pooling layers, reductions and residual connections. Nonlinear components and normalizing components. Taxonomy of loss functions and characteristics of the most commonly used loss functions. Neural architectures for solving classification, regression and auto-association tasks. Deep architectures for processing sequences, in particular recurrent layers. Adversarial learning. Review of milestone architectures: AlexNet, VGG, ResNet, GoogleLeNet, UNet, LSTM, GRU, GAN, selected autoencoder architectures and transformers.
Lab: The laboratory program includes the following topics:
● Introduction (2h): Presentation of the objectives of the laboratory part of the course and basic computer tools used in the laboratory part (programming libraries, programming environments).
● Instructional session (4h): Exercises involving the implementation of selected neural network models in popular environments (Python, Keras, Tensorflow, Pytorch). Testing of implemented algorithms on real and artificial data. Evaluation of the correctness and efficiency of algorithms. Good practices for designing and implementing neural networks; common mistakes and how to avoid them.
● Implementation of projects in groups (24h): Implementation, in groups of two students, of two half-semester programming projects aimed at accomplishing specific tasks.

Course topics

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Teaching methods

Teaching methodology
Lecture: multimedia presentation, illustrated by examples given on the blackboard, demonstration.
Laboratory exercises: solving tasks, designing systems individually and in small groups (typically two people), implementing neural network models, conducting computational experiments, discussion, presentation of results of computational experiments and operation of implemented methods.

Bibliography

Basic:
1. Josh Patterson, Adam Gibson, Deep Learning: A Practitioner’s Approach. O’Reilly, 2017.
2. Ian Goodfellow, Yoshua Bengio, Aaron Courville, Deep learning. The MIT Press, 2016.
3. Francois Chollet, Deep Learning with Python, Manning Publications, 2017.

Additional:
1. Valentino Zocca, Gianmario Spacagna, Daniel Slater, Peter Roelants, Python Deep Learning, Packt Publishing Ltd, 2017.
2. Krzysztof Krawiec, Jerzy Stefanowski. Machine learning and neural networks. Poznan University of Technology. Publishing House, 2004 (in Polish).

Breakdown of average student's workload

	Hours	ECTS
Total workload	125	5,00
Classes requiring direct contact with the teacher	62	2,50
Student's own work (literature studies, preparation for laboratory classes/ tutorials, preparation for tests/exam, project preparation)	63	2,50