POZNAN UNIVERSITY OF TECHNOLOGY

EUROPEAN CREDIT TRANSFER AND ACCUMULATION SYSTEM (ECTS)

COURSE DESCRIPTION CARD - SYLLABUS

Course name
Data prcoessing and Machine Learning [S2Teleinf2>PDiUM]

Course

Field of study
Teleinformatics

Year/Semester
1/1

Area of study (specialization)
–

Profile of study
general academic

Level of study
second-cycle

Course offered in
Polish

Form of study
full-time

Requirements
compulsory

Number of hours

Lecture
14

Laboratory classes
24

Other
14

Tutorials
0

Projects/seminars
0

Number of credit points

3,00

Coordinators

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Lecturers

Prerequisites

Basic Mathematical Knowledge: Students should have a solid foundational knowledge of mathematics, including linear algebra, differential and integral calculus, and statistics. Machine learning often relies on mathematical fundamentals such as differential equations, statistical formulas, and matrix algebra. Programming: Proficiency in basic programming is crucial, especially in languages like Python or R, which are commonly used in machine learning. Students should be able to write and understand code, create functions, and analyze data using programming tools. Statistics and Data Analysis: Understanding fundamental statistical concepts and the ability to analyze data are essential for working in machine learning. Students should be capable of data exploration, assessing probability distributions, and conducting hypothesis testing. Basic Algorithmic Knowledge: Grasping fundamental concepts related to algorithms is important because many machine learning algorithms are based on optimization algorithms, graph algorithms, and other algorithmic structures.

Course objective

The subject is an advanced study program focused on the theory, algorithms, and practical applications of machine learning. Students in this subject gain in-depth knowledge of data analysis and machine learning techniques, including supervised and unsupervised learning, deep learning, and artificial intelligence. A characteristic feature of this subject is its practical approach, which includes designing models, experimenting with data, and solving real-world problems using various tools and frameworks. This course prepares students for careers in fields such as data analysis, pattern recognition, and the development of advanced machine learning-based applications.

Course-related learning outcomes

Knowledge:
Understanding of machine learning theory and algorithms: Students will gain an in-depth understanding of the different types of machine learning algorithms, both supervised and unsupervised, and be able to choose the appropriate method to solve different types of problems. K2_W06, , K2_W11
Knowledge of advanced concepts in deep learning: Students will be familiar with deep neural networks, network architectures and artificial intelligence techniques, allowing them to perform advanced model design and solve complex problems. K2_W06, K2_W07, K2_W11
Awareness of the ethical aspects of machine learning: Students will gain an understanding of the ethical and social implications of machine learning, including bias, discrimination and data privacy.

Skills:
Practical experience in the implementation of machine learning models: Students will be able to implement machine learning models using tools and frameworks, such as TensorFlow or PyTorch, and adapt them to specific applications.
Data analysis and model evaluation skills: Students will learn to analyse data, evaluate the performance of models and adjust parameters to get the best results. K2_U06, K2_U07, K2_U10, K2_U16
Problem solving using machine learning: Students will acquire the ability to identify problems that can be solved using machine learning, and to design and implement solutions in practice. K2_U01, K2_U14

Social competences:
Teamwork in machine learning projects: Students will work in teams on machine learning projects, allowing them to develop their communication skills, ability to collaborate and work effectively in a group. K2_K03
Scientific and business communication: Students will learn how to clearly and effectively communicate the results of their projects in both academic and business settings, facilitating collaboration with different stakeholders. K2_K06
Ethical awareness and social responsibility: Students will develop ethical and social awareness, which will enable them to make responsible decisions in the use of machine learning and data management. K2_K04

Methods for verifying learning outcomes and assessment criteria

Learning outcomes presented above are verified as follows:

1. Lecture
Problem-solving task: case studies that require working together in teams to analyse and solve problems. Assessment of the ability to collaborate, prioritise and propose effective solutions.
Assessment of critical thinking, problem solving skills and team dynamics.
The pass mark is 50%.
In the case of written and oral credit, the points are totalled.
Grading scale: <50% - 2.0 (ndst); 50% to 59% - 3.0 (dst); 60% to 69% - 3.5 (dst+) ; 70% to 79% - 4.0 (db); 80% to 89% - 4.5 (db+); 90% to 100% - 5.0 (bdb).
2 Laboratory
The skills achieved in the laboratory are determined on the basis of reports (reports) from laboratory exercises (OL) and a final mark (ZK) in the form of an independently carried out exercise or project.
Social competence (KS) is assessed on the basis of an evaluation of active listening skills, the ability to cooperate and participate effectively in team discussions and the level of involvement in problem-solving processes .
A weighted average is determined: OK = 0.5 x OL + 0.3 x ZK + 0.2 x KS and grades are given:
5.0 for OK > 4.75;

4,5 for 4,75 > OK > 4,25;
4,0 for 4,25 > OK > 3,75;
3,5 for 3,75 > OK > 3,25;
3,0 for 3,25 > OK > 2,75;
2,0 for OK < 2,75.

Programme content

Fundamentals of machine learning (History and development of machine learning. Concept of training, validation and test sets. Classification of machine learning problems: supervised, unsupervised and reinforcement learning).
Machine learning methods (Supervised learning algorithms: linear regression, decision trees, ensemble algorithms (e.g. Random Forest, Gradient Boosting). Unsupervised learning algorithms: clustering, principal component analysis (PCA), dimensionality reduction. Reinforcement learning algorithms: Q-learning, exploratory strategies).
Deep machine learning (Neural networks: architectures, layers, activation functions. Deep learning: convolutional neural networks (CNNs), recurrent neural networks (RNNs). Image processing and natural language processing using deep networks).
Data mining and data preparation (Data cleaning: removing missing data, handling outliers. Feature extraction: selecting appropriate features for modelling. Feature engineering: creating new features from existing data.)
Model validation and optimisation (Cross-validation: evaluating model performance. Hyper-parameterisation: fine-tuning of model parameters. Evaluating model performance in the context of overfitting and underfitting.)
Ethics and Responsibility in Machine Learning (Ethical issues in machine learning: bias, discrimination, data privacy. Social and ethical responsibility when designing and implementing machine learning models. Practical guidance on ethics in machine learning and regulations.)

Course topics

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Teaching methods

1 Active learning techniques: Active learning strategies such as group discussions, problem solving and case studies to actively engage students in the learning process. Encouraging collaborative learning and interaction to foster critical thinking and application of knowledge.
2 Technology integration: Using technology tools and platform to enhance learning. Using online collaboration tools for brainstorming sessions, virtual simulations for problem solving and multimedia presentations to deliver engaging content. In addition, using online discussion forums or learning management systems for asynchronous learning and resource sharing.
3 Case-based learning: incorporate real-life case studies into lectures and labs to demonstrate the practical application of creative thinking in solving technical problems. This will encourage analysis and

discussion of cases, identification of creative solutions and reflection on decision-making.
4 Feedback and teaching from students: Introduce student feedback mechanisms where students provide constructive feedback on the problem-solving approaches or design solutions of their peers. Encourage student teaching sessions where students can share their knowledge and creative techniques with their peers.
5 Project-based learning: Incorporate project-based learning into the curriculum, where students work on real-world problems or design challenges that require creative thinking. This approach allows them to apply their skills, conduct in-depth research and develop innovative solutions through practical, experiential learning.

Bibliography

Basic:
Christopher M. Bishop, "Pattern Recognition and Machine Learning", Springer, 2006
Trevor Hastie, Robert Tibshirani, Jerome Friedman, "The Elements of Statistical Learning: Data Mining, Inference, and Prediction", Springer, 2009
Ian Goodfellow, Yoshua Bengio, Aaron Courville, "Deep Learning", MIT Press, 2016
Richard S. Sutton, Andrew G. Barto, "Reinforcement Learning: An Introduction", The MIT Press, 2018
Peter Flach, "Machine Learning: The Art and Science of Algorithms that Make Sense of Data", Cambridge University Press, 2012

Additional:
J. Redmon and A. Farhadi, "YOLOv4: Optimal Speed and Accuracy of Object Detection," Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020.
A. Rosebrock, "Deep Learning for Computer Vision with Python," 2nd ed., PyImageSearch, 2020.
R. Girshick, "Fast R-CNN," Proceedings of the IEEE International Conference on Computer Vision, 2015.

Breakdown of average student's workload

	Hours	ECTS
Total workload	78	3,00
Classes requiring direct contact with the teacher	38	1,50
Student's own work (literature studies, preparation for laboratory classes/ tutorials, preparation for tests/exam, project preparation)	40	1,50