Warsaw University of Technology

COURSE OFFERED IN THE DOCTORAL SCHOOL

Code of the course	4606-VL-ES-00014	Name of the course	Polish	**Probabilistyczne Uczenie Maszynowe**
			English	**Probabilistic Machine Learning**
Type of the course	Intensive			
Course coordinator	**Prof. Dharavath Ramesh (IIT Dhanbad, India)**	Course teacher	**Prof. Dharavath Ramesh (IIT Dhanbad, India)**	
Implementing unit	Wydział Mechatroniki	Scientific discipline / disciplines*	Automation, Electronics, Electrical Engineering and Space Technology Information and Communication Technology Mechanical Engineering Biomedical Engineering	

Level of education	Doctoral studies	Semester	Winter 2024		
Language of the course	English				
Type of assessment	Evaluation of submitted reports/ Assignments	Number of hours in a semester	18	ECTS credits	2
Minimum number of participants	Not applicable	Maximum number of participants	Not applicable	Available for students (BSc, MSc)	Yes

Type of classes		Lecture	Auditory classes	Project classes	Laboratory/Tutorial	Seminar
Number of hours	in a week	4			2	
	in a semester	12			6	
Estimated date for the implementation of the course	day of the week	1-1. 02-Dec-2024, Mon 10:15-12:00 1-2. 04-Dec-2024, Wed 10:15 12:00 1-3. 05-Dec-2024, Thu 10:15-12:00 2-1. 09-Dec-2024, Mon 10:15-12:00 2-2. 11-Dec-2024, Wed 10:15-12:00 2-3. 12-Dec-2024, Thu 10:15-12:00 3-1. 16-Dec-2024, Mon 10:15-12:00 3-2. 18-Dec-2024, Wed 10:15-12:00 3-3. 19-Dec-2024, Thu 10:15-12:00		Teaching location	Building	Room number
	hours	As mentioned above			**Stationary Mode**	

* Does not apply to the Researcher's Workshop

1. Prerequisites

No specific prerequisites are required, the student should:
Basic understanding of mathematical terminologies and logical thinking.
High School / UG level Calculus, Vector algebra, Linear algebra

2. Course objectives

To familiarize the students with Fundamentals of Machine Learning (ML) to start working on problem solving.
To familiarize the students with Fundamentals of Machine Learning to start working on applications.
Giving necessary knowledge to judiciously decide the ML algorithm to be applied in a given real-time problem scenario and analyze the performance of trained ML systems.

3. Course content (separate for each type of classes)

Lecture

Contents (planning)

The feature of this course is **Active learning with suitable examples**.
The procedure of each lecture is divided into two parts: <1> **Lecture**, and <2> **Tutorial/Hands-on**.
For every week - two days (Tuesday and Thursday):
<1> **Lecture** [5 lecture hours for two days]
- Lecture by the lecturer based on the lecture note.
- Exchanges of learning outcomes among students.
- Extracting contents related to topic of the day.
- Discussing applications.

<2> **Tutorial/Hands-on** [1 tutorial hour on Thursday]

- Summary of student learning outcomes for this unit.
- Submit the lecturer by e -mail within one day after the lecture.

The grading will be made based on the excellence of students' report, which is submitted as the outcome of post learning.

1. **Introduction and Learning**
   - Hypothesis space and inductive bias, and evaluation
   - Linear regression and Gradient descent algorithm
2. **Parameter Estimation in Probabilistic Models**
   - Likelihood, prior, posterior, marginal likelihood.
   - Parameter estimation via MLE, MAP, and fully Bayesian inference.
3. **Parameter Estimation for Gaussians, Probabilistic Linear Regression**
   - Probabilistic Linear Regression
   - Gaussian likelihood and Gaussian prior
4. **Laplace Approximation, Generalize Linear Models**
   - Perceptron, Multilayer network,
   - Back propagation, introduction to the DNN
5. **Probability and Bayes Learning**
   - Conditional Probability and m-estimate approach
   - Bayes Theorem (Generalized) and Example and Naïve Bayes Classifier and example
6. **Generative Models for Supervised Learning**
   - Wrap up GLM and testing conditional independence in directed graphical models
   - Inference in multi-parameter models, conditional posteriors, local conjugacy

Tutorial/Hands-on
1. Notions related to "Training" and "Testing" by considering algorithms like Decision Trees. 2. Experiment that demonstrates how SVM can yield a solution better than a simple linear separating solution. 3. Experiments on Back Propagation and modern library implementations. 4. Experiments on probability and Bayes learning and experiments related to K-Means, by varying in K, and initialization including Hierarchical clustering and types.

4. Learning outcomes			
Type of learning outcomes	Learning outcomes description	Reference to the learning outcomes of the WUT DS	Learning outcomes verification methods*
Knowledge			
K01	Familiarize the students with the concept of linear Regression and make them solve the related applications.	SDW_2, SD_W3	Through a quiz/test part.
K02	Assessing prospective growth opportunities. One of the applications of decision trees involves evaluating prospective growth opportunities for businesses based on historical data.	SDW_2, SD_W3	Through a quiz/test part.
K03	Familiarize the students using demographic data to find prospective clients.	SDW_2, SD_W3	Through a quiz/test part.
K04	Offering a powerful tool to navigate probabilistic situations and refine artificial models.	SDW_2, SD_W3	Through a quiz/test part.
K05	Familiarize to apply the concept of ANN for (i) Face Recognition, (ii) Neuro-Fuzzy Model and its Applications, and (iii) Data-intensive applications.	SDW_2, SD_W3	Through Tutorial part/test and discussions on research papers
Skills			
S01	Construct suitable training and testing methodologies for various applications.	SD_U7, SD_U8	Through Tutorial part (active participation during classes)
S02	Apply principles of statics and probabilistic models to analyze various applications including healthcare and agriculture.	SD_U7, SD_U8	Through Tutorial part (active participation during classes)

Social competencies			
SC01	Read and summarize literature in this area	SD_K2	As mentioned in the Literature
SC02	Explain the working of a few applications such as malaria prediction, heart disease prediction, etc.	SD_K2	Though discussions on research papers published (active participation during classes)

*Allowed learning outcomes verification methods: exam; oral exam; written test; oral test; project evaluation; report evaluation; presentation evaluation; active participation during classes; homework; tests

5. Assessment criteria

- ✓ Students will review a research paper in the field and summarize the content and key ideas and describe how the paper relates to content of the course. Students will have opportunities for self-assessment throughout the course through pop quizzes conducted for formative assessment.
- ✓ Depending on the content of the submitted reports, it is decided whether excellent, excellent, good, or acceptable.
- ✓ The contents of the submitted report are (1) learning content (especially new knowledge), (2) impressions and opinions (relationship with own research project).

6. Literature

Primary references:

[1]. Probabilistic Machine Learning: An Introduction - Kevin Murphy, MIT Press (March 22), ISBN: 9780262046824.
[2] The Elements of Statistical Learning - Trevor Hastie, Robert Tibshirani, Jerome Friedman, Springer New York, NY, ISBN: 9780387848570.
[3]. Machine Learning - Tom Mitchell, McGraw Hill, 1997, ISBN: 0070428077.
[4]. Pattern Recognition and Machine Learning - Christopher Bishop, Springer, ISBN: 9780387310732
[5]. Pattern Classification - Duda, Hart and Stork, 2nd Edition, Wiley, ISBN: 9780471056690.
[6]. Thakur, S., & Dharavath, R. (2019). Artificial neural network-based prediction of malaria abundances using big data: A knowledge capturing approach. Clinical Epidemiology and Global Health, 7(1), 121-126. https://www.sciencedirect.com/science/article/pii/S2213398417301240
[7]. Rao, G. Madhukar, Dharavath Ramesh, Vandana Sharma, Anurag Sinha, Md Mehedi Hassan, and Amir H. Gandomi. "AttGRU-HMSI: enhancing heart disease diagnosis using hybrid deep learning approach." Scientific Reports 14, no. 1 (2024): 7833. https://www.nature.com/articles/s41598-024-56931-4

Secondary references:

[1] Related materials will be shared and announced during the lectures.

7. PhD student's workload necessary to achieve the learning outcomes**

No.	Description	Number of hours
1	1) Prior learning / Self Study: # Review of basic learning with logical reasoning # Download the Document file to study, while watching the required files # Gathering information and making notes based on the main items presented	25H
2	Class hours (In-person for three weeks): # Lectures for 4H (Monday – 2H and Wednesday – 2H) # Tutorial/Problem-solving/Discussion session for 2H on Thursday	18H
	Total number of hours	43H
	ECTS credits	1~~2~~

** 1 ECTS = 25-30 hours of the PhD students work (2 ECTS = 60 hours; 4 ECTS = 110 hours, etc.)

8. Additional information

Number of ECTS credits for classes requiring direct participation of academic teachers	
Number of ECTS credits earned by a student in a practical course	
Please be careful when handling handouts for lectures. For example, please avoid publishing or sharing indiscriminately. Since many materials are used online, please be careful not to cause problems related to copyright.	

- Points 0 – 50: grade 2 (fail)
- Points 51 – 60: grade 3 (sufficient/fair)
- Points 61 – 70: grade 3.5 (more than sufficient)
- Points 71 – 80: grade 4 (good)
- Points 81 – 90: grade 4.5 (more than good)
- Points 91 – 100: grade 5 (very good)