Machine Learning

(1) GENERAL

SCHOOL	Ηλεκτρολόγων Μηχανικών και Μηχανικών Υπολογιστών		
SECOND SCHOOL			
LEVEL OF EDUCATION	Postgraduate		
COURSE CODE	INF905	**SEMESTER OF STUDIES**	2º
TEACHING ACTIVITIES	**WEEKLY TEACHING HOURS**		**CREDITS**
Lectures	4		
Total	4		7
COURSE TYPE	General background		
PREREQUISITE COURSES			
LANGUAGE OF TEACHING AND EXAMINATIONS	English		
THE COURSE IS OFFERED TO ERASMUS STUDENTS	Yes		
COURSE WEBSITE (URL)	https://www.eclass.tuc.gr/courses/MLDS109/		

(2) LEARNING OUTCOMES

Learning Outcomes

After completing this course the student will be able to:

- *Recognise* the potential of machine learning techniques in each problem
- *Apply* machine learning models adapted to the problem at hand
- *Combines* elements from different areas of Machine Learning and Artificial Intelligence in general
- *Manage* large volumes of data to meet machine learning needs (training, validation, testing)
- *Compare (Evaluate)* machine learning techniques and approaches
- *Use* modern software libraries for machine learning
- *Experiment* with different settings and techniques to optimize the result

Generic Skills

- Research, analysis and synthesis of data and information, using the necessary technologies
- Decision-making
- Autonomous work
- Production of new research ideas
- Promoting free, creative and inductive thinking
- Written communication
- Oral communication
- Alternative/ Innovative Thinking
- Time Management
- Computer Skill
- Problem Solving
- Numeracy

(3) COURSE CONTENT

Supervised learning: least mean squares (LMS), logistic regression, perceptron, Gaussian discriminant analysis, naïve Bayes, support vector machines, model selection and feature selection, ensemble methods (bagging, boosting). Deep Neural Networks & Modern Tools (e.g., Tensorflow, AutoML). Generative Adversarial Neural Networks (GANN) & Applications. Learning theory: bias/variance tradeoff, union and Chernoff/Hoeffding bounds, VC dimension. Unsupervised learning: clustering, k-means, EM, mixture of Gaussians, factor analysis, principal components analysis (PCA), independent component analysis (ICA). Reinforcement learning: Markov decision processes (MDPs), algorithms for POMDPs.

(4) TEACHING AND LEARNING METHODS - EVALUATION

LECTURE METHOD	Face to Face

USE OF INFORMATION AND COMMUNICATION TECHNOLOGIES	
In Teaching:	- use of digital presentations
In Laboratory Education:	- use of modern software libraries
In Communication with Students:	- support learning with eClass - distribution of digital material - use of electronic messaging

TEACHING ORGANIZATION	
Lectures	52.0 hours
Individual Project	70.0 hours
Research/ Study	30.0 hours
Self Studies	24.0 hours
Literature Review	12.0 hours
Total	188 hours

Course Material per Week (13 weeks) :
Probability
1. Random Variables, Expectations
2. Distributions, Densities

Parameter Estimation
3. Maximum A Posteriori, Maximum Likelihood
4. Bayesian Estimation, Discriminative Training

Supervised Learning
5. Bayesian Models, Linear Models, Discriminant Analysis
6. Deep Learning (Deep Neural Networks, GANNs)

Unsupervised Learning
7. Clustering, k-means, EM, Mixture of Gaussians
8. Expectation Maximization
9. Principal/Independent Component Analysis

Kernel Methods
10. Gaussian Processes
11. Support Vector Machines, Relevance Vector Machines

Reinforcement Learning
12. Sequential Decision Making
13. Value Function and Policy Learning

(5) STUDENTS ASSESSMENT

Collective / Concluding (for student degree) assessment		
Written Final Examination	40%	(Comparative evaluation of theoretical issues)
		(Short answer questions)
		(Problem solving questions)
Individual Project	30%	(Public Presentation)
		(Project Score)
Intermediate Exams	30%	

Comments about the Students Assessment :
Active class participation is taken into consideration and the midterm and final written examinations ensure sufficient breadth of study. To encourage deeper individual study on at least one topic, each student has to complete and present a semester project involving application of some method or algorithm covered in class to data drawn from a domain of interest related to their area of research.

(6) RECOMMENDED-BIBLIOGRAPHY

Kevin Patrick Murphy
Probabilistic Machine Learning: An Introduction, MIT Press, 2022
https://probml.github.io/pml-book/book1.html

Kevin Patrick Murphy
Probabilistic Machine Learning: Advanced Topics, MIT Press, 2023
https://probml.github.io/pml-book/book2.html

Christopher M. Bishop
Pattern Recognition and Machine Learning, Springer, 2006
http://research.microsoft.com/~cmbishop/PRML

Andreas Lindholm, Niklas Wahlström, Fredrik Lindsten, and Thomas B. Schön
Machine Learning - A First Course for Engineers and Scientists
http://smlbook.org/