

ANNEX 2 – COURSE DESCRIPTION

Course Title	Machine Learning				
Course Code	ACSC468				
Course Type	Elective				
Level	BSc (Level 1)				
Year / Semester	4th, 7th - 8th				
Teacher's Name	Harris Papadopoulos				
ECTS	6	Lectures / week	3	Laboratories/week	0
Course Purpose	This course is intended as an introduction to the basics of machine learning. Its main purpose is to provide students with an understanding of the methodologies, technologies, mathematics and algorithms currently used in the area. By the end of the course students should be able to apply a variety of machine learning methods to a given target problem.				
Learning Outcomes	<ol style="list-style-type: none"> 1. Define and explain the fundamental concepts and terminology of machine learning and of its main areas. 2. Analyse and discuss a range of machine learning techniques and their theoretical background and recognize the situations where they could be applied successfully. 3. Examine, explain and propose ways of dealing with the issues involved in the use of machine learning methods. 4. Evaluate the strengths and limitations of learning procedures and identify the most appropriate learning algorithm for a given problem. 5. Apply machine learning methods to particular target problems and evaluate and report the results appropriately. 				
Prerequisites	None		Corequisites	None	
Course Content	<ul style="list-style-type: none"> • Introduction: Basic notions of learning; Unsupervised, semi-supervised and supervised learning; Goals and applications of machine learning; Aspects of developing a learning system: training data, concept representation, function approximation. • Concept Learning: The concept learning task; Concept learning as search through a hypothesis space; General-to-specific ordering of hypotheses; Finding maximally specific hypotheses; Version spaces and the candidate elimination algorithm; Inductive bias and its importance. • Decision Tree Learning: Decision tree representation; The ID3 algorithm; Picking the best splitting attribute: entropy and information gain; Searching for simple trees and computational complexity; Occams razor; Overfitting, noisy data, and pruning; Continuous attributes and missing values. 				

	<ul style="list-style-type: none"> • Artificial Neural Networks: Neurons and biological motivation; Neural network representation; Perceptrons: representational limitation and gradient descent training; Multilayer networks; The backpropagation learning algorithm; Early stopping. • Instance-Based Learning: Induction versus transduction; The k-nearest neighbour algorithm; Locally weighted regression; Radial basis functions; Case-based reasoning. • Evaluation: Issues: training, testing, tuning; Holdout; Cross-validation; Bootstrap; Loss functions: 0-1 loss, quadratic loss, informational loss (log loss); Confusion matrix; Evaluating numeric predictions: mean squared error, root mean-squared error, mean absolute error, relative squared error, relative absolute error, correlation coefficient.
Teaching Methodology	<p>The course is delivered through three hours of lectures per week, which include presentation of new material and demonstration of concepts and algorithms. Lectures also include in-class exercises to enhance the material learning process and to assess the student level of understanding and provide feedback accordingly.</p> <p>Furthermore a lot of work is in done through homework and private study by carrying out the computations of the different techniques for specific inputs and by experimenting in the WEKA data mining toolkit with the application of these techniques to benchmark datasets. This provides students with practical experience on the ideas and issues discussed in class.</p> <p>All lecture notes and other material is available to students through the course homepage.</p>
Bibliography	<p>(a) <u>Textbooks:</u></p> <ul style="list-style-type: none"> • Tom M. Mitchell, <i>Machine Learning</i>, McGraw Hill, 1997. • Ian Witten and Eibe Frank, <i>Data Mining: Practical Machine Learning Tools and Techniques</i>, Second Edition, Morgan Kaufmann, 2005. <p>(b) <u>References:</u></p> <ul style="list-style-type: none"> • Christopher Bishop, <i>Pattern Recognition and Machine Learning</i>, Springer, 2006. • Vladimir Vovk, Alex Gammerman, Glenn Shafer, <i>Algorithmic Learning in a Random World</i>, Springer, 2005.
Assessment	<p>The Students are assessed via continuous assessment throughout the duration of the Semester, which forms the Coursework grade and the final written exam. The coursework and the final exam grades are weighted 40% and 60%, respectively, and compose the final grade of the course. Various approaches are used for the continuous assessment of the students, such as class participation and in class exercises, assignments and tests. The assessment weight, date and time of each type of continuous assessment is being set at the beginning of the semester via</p>

	<p>the course outline. An indicative weighted continuous assessment of the course is shown below:</p> <ul style="list-style-type: none"> • Participation Activities (4% of total marks for module) • Three assignments (20% of total marks for module) • One closed-book test (16% of total marks for module) • One closed-book, 2-hour exam (60% of total marks for module) <p>Students are prepared for final exam, by revision on the matter taught, problem solving and concept testing and are also trained to be able to deal with time constraints and revision timetable.</p> <p>The criteria considered for the assessment of each type of the continuous assessment and the final exam of the course are: (i) the comprehension of the fundamental concepts and theory of each topic, (ii) the application of the theory in solving related problems and (iii) the ability to apply the above knowledge in complex real-life problems.</p> <p>The final assessment of the students is formative and summative and is assured to comply with the subject's expected learning outcomes and the quality of the course.</p>
Language	English