**MSc in Artificial Intelligence and Data Analytics**

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| **ΜΑΘΗΜΑ “Probabilistic Modeling and Reasoning” AIDA 101** | |
| **code** | AIDA 101 |
| **title** | **Probabilistic Modeling and Reasoning** |
| **type (compulsory/optional)** | compulsory |
| **cycle (first/second/third)** | second |
| **year of study when the component is delivered (if applicable)** | 1 |
| **semester/trimester when the component is delivered** | Fall |
| **number of ECTS credits allocated** | 7,5 |
| **name of lecturer(s), with information about how, when and where to contact them.** | Prof. Dimitrios Hristu-Varsakelis (Office: 432, [dcv@uom.edu.gr)](mailto:dcv@uom.edu.gr))  Office hours TBA |
| **learning outcomes** | Upon successful completion of the course, students will be able to:   1. Model and solve a variety of inference problems starting from basic principles. 2. Understand maximum likelihood and Bayesian methods for parameter estimation, and write down the relevant equations for specific problems. 3. Understand the difference between various latent variable models, write down the corresponding EM equations and perform the necessary computations. 4. Design, estimate and evaluate belief network models.   Perform experimental investigations using specific models and data, and draw useful conclusions. |
| **mode of delivery (face-to-face/distance learning etc.)** | Face to face |
| **prerequisites and co-requisites (if applicable)** | Undergraduate coursework in probability theory (discrete and continuous random variables, expectation, variance, joint and conditional distributions). Linear Algebra and Analysis. Programming experience in a high-level language such as Python and/or MATLAB. |
| **course content** | Probability (events, discrete random variables, joint and conditional distributions).  Belief networks, inference.  Parameter estimation: Maximum likelihood.  Latent variable models (mixture models, EM algorithm, factor analysis, ICA)  Dynamic models with hidden variables (Hidden Markov models, Kalman filters)  Information theory: Entropy, mutual information, source coding, Kullback-Leibler divergence  Approximate inference: MCMC, Variational Methods  Sampling methods  Bayesian methods for parameter inference and model comparisons. |
| **recommended or required reading and other learning resources/tools** | Required: “Bayesian Reasoning and Machine Learning”, David Barber, Cambridge University Press, 2012.  Additional reading from: “Pattern Recognition and Machine Learning”, C. M. Bishop, Springer, 2006. |
| **planned learning activities and teaching methods** | Lectures, homework and programming assignments |
| **assessment methods and criteria** | The final grade will be the sum of the following:  \* Final written exam: 50 points  \* Midterm exam: 30 points  \* Homework: 20 points  Homework grades will be taken into account only if the sum of points from the written exams (midterm and final) is at least 40 out of the possible 80.  Homework will be assigned on an approximately weekly basis and will be returned electronically to the instructor. The lowest homework grade will be discarded.  No late homework will be accepted. |
| **language of instruction** | English |