APPLIED BAYESIAN METHODS

1. SYLLABUS INFORMATION

1.1. Course title
Applied Bayesian Methods

1.2. University
Universidad Autónoma de Madrid

1.3. Semester
First year, second semester

2. COURSE DETAILS

2.1. Course nature
Compulsory

2.2. ECTS Credit allotment
6

2.3. Recommendations
Knowledge of probability and statistics at an introductory level is useful to follow the course.

2.4. Faculty data

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3. COMPETENCES AND LEARNING OUTCOMES

3.1. Course objectives

The objective of this subject is to address machine learning problems from a Bayesian perspective. Graphical models (GMs) will be introduced as probabilistic models in which dependence and independence relations between random variables are described in terms of a graph. Similarly, Bayesian networks are a particular case of GMs that are especially useful for modelling conditional independences. Exact inference algorithms will be addressed (such as variable elimination, sum-product and junction tree) and the way they can be applied efficiently. These will be studied in this course alongside with the relation between inference and learning. More general approximate inference methods, either deterministic (e.g. variational inference or expectation propagation) or based on sampling and simulation (e.g. Monte Carlo methods based on Markov chains), will also be introduced in this course.

3.2. Course contents

The main references for each course item are given between parentheses. The reference is [1] when not explicitly specified.

1. Probabilistic Reasoning
   a. Introduction to probability theory: Bayes theorem, marginals, conditional probabilities (chapter 1).
   b. Introduction to probabilistic reasoning: Prior, likelihood and posterior (section 1.3).
   c. Bayesian Networks fundamentals (chapter 3)
   d. Markov Networks fundamentals (chapter 4)

2. Inference in Probabilistic Models
   a. Variable elimination (section 5.1)
   b. Sum-product algorithm (Bishop, sec. 8.4)
   c. Junction tree algorithm (chapter 6)

3. Learning in Probabilistic Models
    a. Maximum likelihood training of Bayesian Networks (section 9.3)
    b. Bayesian inference for Bayesian Networks (section 11.1)
    c. Expectation maximization, EM algorithm (section 11.1)

4. Approximate Inference
    a. Loopy Belief propagation
    b. Deterministic Methods
        i. The Laplace approximation (section 28.2).
        ii. Variational Inference (section 28.3).Expectation Propagation (section 28.8)
    c. Montecarlo methods

3.3. Course bibliography

1. David Barber. Bayesian Reasoning and Machine Learning. Cambridge University Press 2012
2. William M. Bostad. Introduction to Bayesian Statistics. Wiley-Interscience, 2007
3. Christopher M. Bishop. Pattern Recognition and Machine Learning. Springer, 2006
4. Koller, D. & Friedman, N. Probabilistic Graphical Models: Principles and Techniques MIT Press, 2009
5. Richard E. Neapolitan. Learning Bayesian Networks. Pearson Prentice Hall, 2004
6. David J. C. MacKay. Information Theory, Inference, and Learning Algorithms. Cambridge University Press, 2003.Introduction to time series and forecasting , P.J. Brockwell, R. A. Davis, Springer Texts in Statistics (1996)

4. TEACHING-AND-LEARNING METHODOLOGIES AND STUDENT WORKLOAD

4.1. Contact hours

	Hours
Classroom instruction (minimum 33%)	33%
Independent study time	67%

4.2. List of training activities

Activity	Hours
Lectures	28
Computer lab	14
Assessment activities	6

5. EVALUATION PROCEDURES AND WEIGHT OF COMPONENTS IN THE FINAL GRADE

5.1. Regular assessment

The course involves lectures, assignments, lab assignments and one final exam.
In both the ordinary and the extraordinary periods it is necessary to obtain a grade >= 5 in every part of the course in order to pass.

- In the ordinary exam period, the evaluation will be computed according to the following scheme:
- 50 % Lab assignments
- 50 % Exams

5.2. List of evaluation activities

Evaluatory activity	%
Final exam	50%
Programming assignments/classroom activities	50%