Subject: Applied Bayesian Methods (ABM)
Code: 32421
Institution: Escuela Politécnica Superior
Degree: Master's program in Research and Innovation in Information and Communications Technologies (I^2-ICT)
Level: Master
Type: Elective [computational intelligence]
ECTS: 6

COURSE GUIDE: Applied Bayesian Methods (ABM)

Academic year:	2017-2018
Program:	Master's program in Research and Innovation in Information and Communications Technologies (I^2-ICT)
Center:	Escuela Politécnica Superior
University:	Universidad Autónoma de Madrid
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1. ASIGNATURA / COURSE (ID)

Métodos Bayesianos Aplicados
Applied Bayesian Methods (ABM)

1.1. Programa / program

Máster Universitario en Investigación e Innovación en Tecnologías de la Información y las Comunicaciones (I^2-TIC)

Master in Research and Innovation in Information and Communications Technologies (I^2-ICT) [Officially certified]

1.2. Course code

32421

1.3. Course areas

Computer Science and Artificial Intelligence

1.4. Tipo de asignatura / Course type

Optativa [itinerario: Inteligencia computacional]
Elective [itinerary: Computational Intelligence]

1.5. Semester

Second semester

1.6. Credits

6 ETCS

1.7. Language of instruction

The lecture notes are in English. The lectures are mostly in Spanish. Some of the lectures and seminars can be in English.

1.8. Recommendations / Related subjects

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

Related subjects are:

- Aprendizaje Automático: teoría y aplicaciones [Machine Learning: theory and applications]
- Procesamiento de información temporal [Temporal Information Processing]

1.9. Lecturers

Add @uam.es to all email addresses below.

Lectures and labs:

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1.10. Objetivos de la asignatura / Course objectives

El objetivo de esta asignatura es abordar problemas de aprendizaje automático desde un punto de vista Bayesiano. Partiendo de una interpretación Bayesiana de las probabilidades, se analizará la modelización de dependencias e inferencia en redes Bayesianas y de Markov. En esta asignatura se describirán algoritmos para de inferencia exacta en estos modelos gráficos como: eliminación de variables, algoritmo sum-product y juntion tree. Realizar inferencia exacta puede ser computacionalmente costoso. En esta asignatura se describirá cómo poder llevarla a cabo de forma eficiente y se estudiarán las relaciones entre inferencia y aprendizaje. Siguiendo un enfoque más aplicado, se mostrarán varios métodos de inferencia aproximada de carácter general, tanto deterministas (ej. inferencia variacional o el algoritmo de propagación de esperanzas) como basados en muestreo y simulación (ej. métodos Montecarlo basados en cadenas de Markov).

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.

At the end of each unit, the student should be able to:

UNIT BY UNIT SPECIFIC OBJECTIVES	
UNIT 1.- Probabilistic Reasoning.	
1.1.	Distinguish between frequentist and Bayesian probabilities.
1.2.	Calculate posterior probabilities by means of Bayes' formula.
1.3.	Get familiar with the operations between factor product, marginalization and reduction.
UNIT 2.- Inference in Probabilistic Models.	
2.1.	Use Bayesian networks to represent statements about independence of variables in a probabilistic model.
2.2.	Compare Bayesian networks with Markov Models.
2.3.	Make efficient exact inference in a Bayesian network by means of variable elimination.
2.4.	Make efficient exact inference in a Bayesian network by means of The sum-product algorithm.
2.5.	Make efficient exact inference in a Bayesian network by means of the junction tree algorithm.
UNIT 3.- Learning in Probabilistic Models.	
3.1.	Train Bayesian networks by maximum likelihood
3.2.	Train Bayesian networks by Bayesian inference.
3.3.	Apply Expectation Maximization to maximize likelihoods under missing data and/or hidden variables.
UNIT 4.- Approximate Inference.	

4.1.	Understand and correctly apply deterministic inference methods.
4.2.	Understand and correctly apply sampling inference methods.
4.3	Know the advantages and disadvantages of each approximate inference method.
4.5.	Determine which inference method is the most appropriate for a given problem.

1.11. 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

1.12. 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)

1.13. Coursework and evaluation

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

  The grades of the individual parts are kept for the extraordinary exam period.

- In case of a fail grade in the ordinary evaluation period, in the extraordinary evaluation period, the student has the opportunity to
  - Turn-in again all the exercises with corrections.
  - Turn-in again all the lab assignments with corrections.
  - Re-take the exam(s)

  The grade will be determined using the same percentages as in the ordinary evaluation period.