Year : 2019/20

24019 - Probabilistic Graphical Models

Syllabus Information

Academic Course: 2019/20
Academic Center: 337 - Polytechnic School
Study: 3379 - Bachelor's (degree) programme in Telecommunications Network Engineering
Subject: 24019 - Probabilistic Graphical Models
Credits: 5.0
Course: 3
Teaching languages: Theory: Grup 1: English Practice: Grup 101: English
Grup 102: English
Seminar: Grup 101: English
Grup 102: English

Teachers: Vicente Gomez Cerda
Teaching Period: Second Quarter
Schedule: ---

Presentation

Probabilistic graphical models (PGMs) are powerful modeling tools for reasoning and decision making under uncertainty. PGMs have many application domains, including computer vision, natural language processing, efficient coding, and computational biology. PGMs connects graph theory and probability theory, and provide a flexible framework for modeling large collections of random variables with complex interactions.

This is an introductory course which focuses on two main principles: (1) emphasizing the role of PGMs as a unifying language in machine learning that allows a natural specification of many problem domains with inherent uncertainty, and (2) providing a set of computational tools for probabilistic inference (making predictions that can be used to aid decision making), and learning (estimating the graph structure and their parameters from data).

Associated skills

Basic Competences

- That the students can apply their knowledge to their work or vocation of a professional form in a professional way and possess the competences which are usually proved by means of the elaboration and defense of arguments and solving the solution of problems within their study area.
- That the students have the ability of collecting and interpreting relevant data (normally within their study area) to issue judgements which include a reflection about relevant topics of social, scientific or ethical nature.

Transversal Competences

- Applying with flexibility and creativity the acquired knowledge and adapting it to new contexts and situations.
- Applying leadership and coordination and proving initiative.

Specific Competences

- Solving the mathematical problems which can be set out in the engineering and apply the knowledge on: probability and statistics; graph algorithms; inference and learning; optimization.
- Ability to communicate effectively using the technical vocabulary of the field in English.

Learning outcomes

- Understanding the mathematical framework of probabilistic graphical models
- Implementing the basic algorithms for probabilistic inference in graphical models
- Implementing the basic algorithms for learning graphical models

- Recognizing and applying Bayesian principles behind modeling domain knowledge under uncertainty
- Understand the difference between statistical and causal models

Prerequisites

The student is expected to have taken the courses

- Introduction to Network Science
- Statistical Models
- Artificial Intelligence

Contents

Block 1: **Representation**

- Directed Graphical Models
- Undirected Graphical Models
- Factor Graphs

Block 2: **Probabilistic Inference**

- Exact Inference: variable elimination
- Message passing algorithms. Belief Propagation
- The Junction Tree Algorithm
- Temporal Models
- Approximate Inference

Block 3: **Learning**

- Maximum Likelihood and Structural Learning
- Learning Temporal Models
- Introduction to Causality

Teaching Methods

The course comprises 12 theory lectures where the core theoretical concepts are introduced, and 10 problem-solving sessions in smaller groups (both analytical and programming). The programming sessions will use a variety of software tools such as the BRML toolbox (in Matlab) [1] or the Python Library for Probabilistic Graphical Models (https://github.com/pgmpy/pgmpy).

Evaluation

There will be several deliverables for both practicals and seminars. For the practicals, students must submit a report and code, and will be evaluated according to their clarity and quality. The evaluation for the seminars will consist of exercises and will be based on the correctness and clarity of the submitted solutions.

The final grade is obtained by doing the following weighted average:

Final grade = 0.4 * Exam + 0.3 * Practicals + 0.3 * Seminars.

To pass the course, Exam, average Practicals and average Seminars must have a grade of 5 or higher, otherwise the course will be failed.

If failed, there is a resit exam in July. A grade of 5 or higher is required to pass the resit exam and the course. The final grade will be

Grade July = Maximum { ExamJuly, 0.4 * ExamJuly + 0.3 * Practicals + 0.3 * Seminars }.

Bibliography and information resources

[1] *Bayesian Reasoning and Machine Learning.* David Barber. Cambridge University Press. 2012.
[2] *Probabilistic Graphical Models: Principles and Techniques.* Daphne Koller and Nir Friedman. MIT Press. 2009.
[3] *Bayesian networks and decision graphs.* Finn B. Jensen and Thomas Graven-Nielsen. Series: Information Science and Statistics. Springer. 2007.
[4] *Pattern Recognition and Machine Learning* (Chap. 8). Chris Bishop. Springer. 2006.
[5] *Information Theory, Inference, and Learning Algorithms*. David Mackay. Cambridge university press. 2003.

All the material will be available through the Aula Global