Course Specifications

From the academic year 2024-2025 up to and including the academic year

Probabilistic Graphical Models (E016340)

Course size *(nominal values; actual values may depend on programme)*

Credits 4.0 **Study time 120 h**

Course offerings and teaching methods in academic year 2024-2025

A (semester 2)	English	Gent	seminar lecture

Lecturers in academic year 2024-2025

Pizurica, Aleksandra	TW07	lecturer-in-charge

Offered in the following programmes in 2024-2025	crdts	offering
Bridging Programme Master of Science in Bioinformatics(main subject Engineering)	4	A
Master of Science in Bioinformatics(main subject Engineering)	4	A
Master of Science in Industrial Engineering and Operations Research(main subject Manufacturing and Supply Chain Engineering)	4	A
Master of Science in Industrial Engineering and Operations Research(main subject Transport and Mobility Engineering)	4	A
Master of Science in Computer Science Engineering	4	A
Master of Science in Computer Science Engineering	4	A
Master of Science in Industrial Engineering and Operations Research	4	A

Teaching languages

English

Keywords

Probabilistic graphical models, Bayesian networks, Causal models, Markov Random Fields, Conditional Random Fields, Bayesian inference, Markov Chain Monte Carlo samplers, Message passing, Belief propagation, Loopy belief propagation, Bethe approximation, Junction trees, Expectation propagation, Structure learning, Variational inference, Variational autoencoders, Diffusion models in AI (Diffusion probabilistic models)

Position of the course

Probabilistic graphical models (PGM) are powerful tools for representing complex inference problems and incorporating uncertainty into the reasoning process. As such, they find numerous applications in many domains, including machine learning, computer vision, natural language processing and computational biology. Incorporating uncertainties into reasoning and decision-making processes is especially important in high-stakes applications (e.g., health), where data is scarce, or the model structure is uncertain. The course gives a strong theoretical basis as well as practical insights into probabilistic graphical models and the corresponding inference mechanisms. The role of probabilistic graphical models in some of the latest developments in artificial intelligence (AI) is addressed (variational inference, variational autoencoders and diffusion probabilistic models).

Contents

- Recapitulation: basics of reasoning under uncertainty (including the concepts of random variables, discrete and continuous distributions, Monte Carlo approximations, foundations of Bayesian inference and its links to information theory)
- Bayesian statistics: MAP estimation, Expectation maximization (EM algorithm), Bayesian model selection, choice of prior, Latent variable models, Gaussian mixture models

- Directed graphical models (Bayesian networks): Markov and Hidden Markov Models, Causal models
- Non-directed graphical models (Markov Random Fields, Conditional Random Fields), Latent Linear models
- A unified treatment of probabilistic graphical models (directed and non-directed) as factor graphs; explaining connections to information-theoretic approaches.
- Inference approaches: Exact inference, Markov Chain Monte Carlo (MCMC) sampling, Belief propagation, Bethe approximation, Variational inference, Mean Field Approximation
- Structure learning
- Selected advanced topics (the role of PGM in modern artificial intelligence, Variational autoencoder, Diffusion Probabilistic models)

Initial competences

- The student has a good grasp of linear algebra, statistics, applied probability and general mathematical basis (mandatory)
- The student has a basic knowledge of machine learning (recommended) and basic knowledge of artificial intelligence foundations (recommended)
- The student is familiar with scientific programming and is able to program in Python.

Final competences

1 A very firm grasp of probability and information theory and how it is applied for learning
2 Be able to view a probabilistic model in its components (prior, likelihood, etc.) and how they interact with each other
3 Properly train a probabilistic model: choose a prior, inference method and likelihood for the problem at hand
4 Be able to represent a complex inference problem as a probabilistic graphical model and apply appropriate inference mechanisms to solve it (like message passing and sampling)
5 A strong foundation for comprehending unseen probabilistic techniques from literature and quickly notice their limitations
6 Good understanding of some of the latest developments in AI that are based on PGM (variational autoencoders, diffusin probabilistic models)

Conditions for credit contract

Access to this course unit via a credit contract is determined after successful competences assessment

Conditions for exam contract

This course unit cannot be taken via an exam contract

Teaching methods

Seminar, Lecture

Extra information on the teaching methods

Classroom lectures; Hands-on experience through a project

Study material

Type: Handbook

Name: Bayesian Reasoning and Machine Learning
Indicative price: Free or paid by faculty
Optional: yes
Language : English
Author : David Barber
ISBN : 0-521-51814-8
Number of Pages : 665
Online Available : Yes
Available in the Library : No
Available through Student Association : No
Usability and Lifetime within the Course Unit : regularly
Usability and Lifetime within the Study Programme : regularly
Usability and Lifetime after the Study Programme : regularly

Type: Slides

Name: Slides for the course Probabilistic Graphical Models
Indicative price: Free or paid by faculty
Optional: no
Language : English
Available on Ufora : Yes
Online Available : Yes
Available in the Library : No
Available through Student Association : Yes

Type: Handouts

Name: Slide notes for the course Probabilistic Graphical Models
Indicative price: Free or paid by faculty
Optional: yes
Language : English
Available on Ufora : Yes
Online Available : No
Available in the Library : No
Usability and Lifetime within the Course Unit : regularly
Usability and Lifetime within the Study Programme : regularly
Usability and Lifetime after the Study Programme : regularly

References

- [1] Daphne Koller and Nir Friedman, Probabilistic Graphical Models: Principles and Techniques
- [2] Christophe M. Bishop, Pattern Recognition and Machine Learning
- [3] David J.C. Mackay, Information Theory, Inference, and Learning Algorithms
- [4] Martin J. Wainwright and Michael I. Jordan, Graphical models, exponential families, and variational inference

Course content-related study coaching

Assessment moments

end-of-term and continuous assessment

Examination methods in case of periodic assessment during the first examination period

Oral assessment open-book

Examination methods in case of periodic assessment during the second examination period

Oral assessment open-book

Examination methods in case of permanent assessment

Participation, Assignment

Possibilities of retake in case of permanent assessment

examination during the second examination period is possible in modified form

Extra information on the examination methods

- During examination period: open-book oral exam.
- During semester: graded project report and participation. A project involving a research component (evaluated based on the code demonstration and written report).

Calculation of the examination mark

The oral exam counts for 2/3, and the project for 1/3 of the final grade, provided that all parts are above given minimum requirements as follows:

- oral exam is at least 9/20
- project is at least 9/20.

If these conditions are not met and the total score is still 10/20 or above, the final grade will be brought to the highest non-passing grade (9/20). Only the non-passing parts need to be retaken. Failing to participate in one or more parts of the evaluation results in the non-passing final grade.