Technical University of Crete
School of Electronic and Computer Engineering, Fall 2013

Introduction to Probabilistic Graphical Models & Inference Algorithms (Graduate Course)

Probabilistic Graphical Models (PGMs) are based on graph, probability, estimation, and information theory, as well as elements of machine learning and offer a fascinating unifying theoretical framework exploited in a rich variety of (challenging) engineering applications, including: communications, computer vision, natural language processing, bioinformatics, social networks and big data analysis. They are particularly useful in problems that can be described as graphs of random variables, and their theory is currently an active topic of research. This class will offer an introduction in representation with PGMs, algorithms for exact inference, approximate inference and learning (estimation). Term projects will thoroughly study application examples in diverse domains.

Instructor: Aggelos Bletsas (aggelos@telecom.tuc.gr)

Lectures: Thursday and Friday, 16.00-18.00, ECE Conference Room.
Recitation: Wednesday, 16.00-18.00, Room TBD.
Projects: Tuesday, 16.00-18.00, Room TBD.
Grading: 30% Midterm and Psets, 40% Term Project, 30% Final.

Books and Course Notes: The syllabus will be based on Koller and Friedman textbook, as well as selected material:

D. Koller and N. Friedman, Probabilistic Graphical Models: Principles and Techniques, MIT Press, 2009 (**required**).

C. M. Bishop, Pattern Recognition and Machine Learning, Springer Verlag, 2006.

D. Barber, Bayesian Reasoning and Machine Learning, Cambridge University Press, 2012.

M. Mézard and A. Montanari, Information, Physics, and Computation, Oxford University Press, 2009.

R. G. Cowell, A. P. Dawid, S. L. Lauritzen and D. J. Spiegelhalter, Probabilistic Networks and Expert Systems, Springer Verlag, 1999.

J. Pearl, Probabilistic Reasoning in Intelligent Systems, Morgan Kaufmann, 1988.

D. J. C. MacKay, Information Theory, Inference and Learning Algorithms, Cambridge University Press, 2003.

S. Lauritzen, Graphical models, Oxford University Press, 1996.

Tentative schedule (similar to MIT 6.438 Inference class)

Lecture #	Topic
1,2	Introduction, overview, logistics, probability theory review
3,4	Directed Acyclic Graphs (DAGs) (Bayesian Nets) Factorization Theorem
5,6	Directed Acyclic Graph Semantics (I-map, d-separation, P-map)
7,8	Undirected Graphs (Markov Networks: Markov Blanket, Hammersley-Clifford Theorem)
9	Factor Graphs: techniques for converting graphs
10	Gaussian Graphical Models
11	Exact Inference: Elimination Algorithm
12	Exact Inference on Trees: Sum-Product (BP), Sum-product vs Max-product in Factor Graphs
13,14	Examples in Dynamic Models: HMMs and Kalman Filtering
15,16	Exact Inference: Junction Tree Algorithm
17,18	Approximate Inference: Loopy BP
19,20	Approximate Inference: Sampling (MC, MH, Gibbs)
21-24	Approximate Inference: Intro to Variational Methods (Bethe Energy, Mean Field)
25	Learning in Directed Graphs Intro: BIC
25	Learning in Undirected Graphs Intro: IPF
26	Learning with missing data: EM
27	Project Presentations

Εισαγωγή στα Πιθανοτικά Γραφικά Μοντέλα και σε Αλγορίθμους Συμπερασμάτων: Κατευθυνόμενοι μη-κυκλικοί Γράφοι, Θεώρημα Παραγοντοποίησης, μη Κατευθυνόμενοι Γράφοι, Markov Blanket, Θεώρημα Hammersley-Clifford, Γράφοι Παραγόντων και τεχνικές μετατροπής μεταξύ διαφορετικών ειδών Γράφων. Ακριβής Εξαγωγή Συμπερασμάτων: Αλγόριθμος Elimination, Belief Propagation (Sum-Product), Max-Product, Junction Tree. Εφαρμογές σε δυναμικά μοντέλα. Προσεγγιστική Εξαγωγή Συμπερασμάτων: Loopy Belief Propagation, Μέθοδοι Δειγματοληψίας (Monte Carlo, Metropolis-Hastings, Gibbs), Μεταβολικές Μέθοδοι (Bethe, Mean Field). Εισαγωγή σε τεχνικές μάθησης για Πιθανοτικούς Γράφους.