Technical University of Crete
School of Electrical and Computer Engineering, Fall 2017

TEL606 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: Tuesday and Thursday, 18.00-20.00, ECE Conference Room.
Recitation: Friday, 10.00-12.00.
Grading: 30% Midterm and Psets, 40% Term Project, 30% Final.

Books and Course Notes: The syllabus will be based on Koller and Friedman textbook, MIT 6.438 notes, papers, as well as selected material:

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

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

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

MIT “Algorithms for Inference” 2014 graduate course notes (also given as 6.438), MITOPENCOURSEWARE (OCW), available at http://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-438-algorithms-for-inference-fall-2014/

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: Intro to AMP/GAMP
21-22	Approximate Inference: Sampling Methods (Particle Filtering, Metropolis-Hastings)
23-25	Intro to Learning: known or unknown structure, missing data
26	Project Presentations