EE-717: Probabilistic Graphical Models (Fall 2011)

Description: The course will focus on providing diverse mathematical tools for graduate students from statistical inference and learning; graph theory, signal processing and systems; coding theory and communications, and information theory. We will discuss exact and approximate statistical inference over large number of interacting variables, and develop probabilistic and optimization-based computational methods. We will cover hidden Markov models, belief propagation, and variational Bayesian methods (e.g., expectation maximization algorithm). We will read research papers and book chapters to understand the benefits and limitations of such algorithms.

Language: English

Class Timings: Mondays and Fridays : 10:00-12:00.

Room: BC 01 (Friday), BC 03 (Monday)

Credits: 4

Instructors: Prof. Volkan Cevher, ELE 233, volkan.cevher@epfl.ch
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Course Website: We use moodle to disseminate the course materials.

Honor Code: The EPFL honor code applies to the course:
http://wiki.epfl.ch/delegues/code.honneur

Grading: The grade is divided between homework assignments and class presentations as explained below. Furthermore all participants will have a bonus grade of **1.0**.
Final grade := min $\{6.0, 1.0 + \textit{homework\_grade} + \textit{presentation\_grade}\}$

Homeworks: There will be 10 homework assignments during the duration of the course. The homeworks are supposed to be done in either groups of 2 or 3. The group size is a question of choice, no special consideration will be given to groups of 2 students. The maximum grade associated with homeworks is **4.0** (*only upon completing all the homeworks*). The general grading policy for the homeworks is as follows.

- *[0 pts]* : No attempt/ Nonsensical answer.
- *[2 pts]* : Honest attempt but major mistakes.
- *[4 pts]* : Minor mistakes / full answer.

Each exercise is scored by a number of exercise points, depending on difficulty. There is a total of 192 exercise points over all 10 assignments, so that 48 exercise points translate to 1 grade point.
Assignments are made available on moodle on respective Mondays. They have to be handed in (written solutions, marked with names and matriculation numbers; no e-mails) at the beginning of the Friday lecture a week after. These are strict deadlines, late hand-ins will not be considered. Marked assignment sheets can be collected the subsequent Monday lecture.

Presentations: The group size for the presentations is the same as for the homeworks (however the group itself can be different). Each group is required to present a paper during the course. A list of papers has been put on moodle, however there is also the option of selecting a paper outside the list (as long as it is relevant to the course). All groups are required to have their choice of papers *approved* before 31st **October 2011**. Note that this is a strict deadline. The maximum grade for the presentations is **2.0**. Out of the maximum grade, 50% of the grade will be assigned by the instructors and the remaining grade will be assigned by another group. The criteria for grading presentations are as follows.

- *Understanding [0.8 pts]*: Does the group show that they understand the material?
- *Clarity and presentation [0.5 pts]*: Can they explain the difficult concepts? Are the slides well-made?
- *Star power [0.3 pts]*: Can they individually answer additional questions in a competent manner?
- *Knowing the unknown [0.2 pts]*: Do they know what they are NOT covering on the material? What are the future directions / extensions / applications of the presented work?
- *Wasting my time [0.2 pts]*: Is it too short or too long?

Textbooks:

Christopher M. Bishop, *Pattern Recognition and Machine Learning.*

S.L. Lauritzen, *Graphical Models.*

M.I. Jordan, *Learning in Graphical Models.*

Daphne Koller and Nir Friedman, *Probabilistic Graphical Models.*

J. Pearl, *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference.*

R. Cowell, *Introduction to Inference for Bayesian Networks.*

Recommended Reading:

W. Xu, Q. Zhu and M. I. Jordan, *The Junction Tree Algorithm*, Class notes, UC Berkeley, CS281A/Stat241A, Fall 2004.

F.R. Kschischang, B.J. Frey, and H.-A. Loeliger, *Factor Graphs and the Sum-Product Algorithm*, IEEE Transactions on Information Theory, Vol. 47, No. 2, February 2001.

M. I. Jordan, Z. Ghahramani, T. S. Jaakkola and L. K. Saul, *An Introduction to Variational Methods for Graphical Models*, Machine Learning vol. 37, 1999.

T. Minka, *Divergence Measures and Message Passing*, Microsoft Research Ltd. Tech. Report MSR-TR-2005-173, December 2005.

M.J. Wainwright and M.I. Jordan, *Grapical Models, exponential families, and variational inference*, 2003.

V. Cevher, M. Duarte, C. Hegde, and R. Baraniuk, *Sparse Signal Recovery Using Markov Random Fields*, 2008.

R.G. Baraniuk, V. Cevher, M.F. Duarte and C. Hegde, *Model-Based Compressive Sensing*, 2008.

V. Cevher, M.F. Duarte, C. Hegde and R.G. Baraniuk, *Sparse Signal Recovery Using Markov Random Fields*, 2008.

Seeger, M. and Wipf, D, *Variational Bayesian Inference Techniques*, IEEE SPM 2010.

Seeger, M., *Tutorial on Sparse Linear Models: Reconstruction and Approximate Inference* (http://lapmal.epfl.ch/teaching/dagm10/index.html).

Course Outline

Week 1:	Course introduction: Motivation and logistics
Week 2:	Introduction: Basic probability and Bayes Graphical Models Belief Propagation I
Week 3:	Graphical Models Belief Propagation II Gaussian distribution
Week 4:	Numerical mathematics / optimization Latent variable models
Week 5:	Expectation Maximization (EM) algorithm Dynamical state space models
Week 6:	Variational Inference Relaxations Loopy Belief Propagation
Week 7:	Class presentations Class presentations
Week 8:	Sparse linear models Compressible Priors
Week 9:	Sparse graphical model learning I Sparse graphical model learning II
Week 10:	Convex/lp Relaxations Continuous Variable Models
Week 11:	Expectation Propagation Advanced Variational Inference
Week 12:	Topic modeling / LDA Class presentations
Week 13:	No lectures this week.
Week 14:	Class presentations Class presentations