جامعة الملك عبدالله
للعلوم والتقنية
King Abdullah University of
Science and Technology

Course Syllabus: Probabilistic Graphical Models - CS 320

Division	Computer, Electrical and Mathematical Sciences & Engineering
Course Number	CS 320
Course Title	Probabilistic Graphical Models
Academic Semester	Spring
Academic Year	2017/2018
Semester Start Date	01/28/2018
Semester End Date	05/24/2018
Class Schedule (Days & Time)	02:30 PM - 05:30 PM | Wed

Instructor(s)

Name	Email	Phone	Office Location	Office Hours
Xin Gao	Xin.Gao@kaust.edu.sa	+966128080323	4217, 3, Ibn Sina (bldg. 3)	Wednesday 1-2pm. Building 3, sea side, Room 4217.

Teaching Assistant(s)

Name	Email
TBD	

Course Information

Comprehensive Course Description

Probabilistic graphical models (PGMs) have been one of the most important emerging subareas of statistical machine learning in the past twenty years. Michael Jordan commented in 1998 that "Graphical models are a marriage between probability theory and graph theory. They provide a natural tool for dealing with two problems that occur throughout applied mathematics and engineering -- uncertainty and complexity -- and in particular they are playing an increasingly important role in the design and analysis of machine learning algorithms. Fundamental to the idea of a graphical model is the notion of modularity -- a complex system is built by combining simpler parts. Probability theory provides the glue whereby the parts are combined, ensuring that the system as a whole is consistent, and providing ways to interface models to data. The graph theoretic side of graphical models provides both an intuitively appealing interface by which humans can model highly-interacting sets of variables as well as a data structure that lends itself naturally to the design of efficient general-purpose algorithms."

PGMs have become the basis for the state-of-the-art methods in various areas in computer science, such as graphics (e.g., image segmentation), natural language processing (e.g., speech recognition), computer vision (e.g., object tracking), and bioinformatics (e.g., gene finding). Since these areas are well aligned with the research in CEMSE Division and the missions of KAUST, an advanced graduate-level course for PGMs is timely needed.

This is a research-oriented graduate-level course on PGMs. The course will cover two main types of PGMs, i.e., directed PGMs and undirected PGMs. For directed PGMs, we will cover Bayesian networks, with one of its most important variants, hidden Markov models. For undirected PGMs, we will cover Markov networks (or Markov random fields), with one of its most important variants, conditional random fields. Therefore, the course contains four parts: Bayesian networks, hidden Markov models, Markov networks, and conditional random fields.

In each part, I will introduce motivations, ideas, definitions, examples, properties, representations, inference algorithms, and applications for the corresponding PGM. This is done through lectures by the instructor. In the next two lectures, the students will present recommended research papers and lead in-class discussions. The last lecture of each part will be an in-class quiz, the purpose of which is not to judge their ability of calculation or memorization, but to push them to think more and deeper about the contents introduced in lectures. The course will finish by a final exam lecture and two project presentation lectures. The projects are expected to be a real application or a serious theoretical work of PGMs on real research problems.

Course Description from Program Guide	This is a research-oriented graduate-level course on PGMs. The course will cover two (2) main types of PGMs, i.e., directed PGMs and undirected PGMs. For directed PGMs, we will cover Bayesian networks, with one (1) of its most important variants, hidden Markov models. For undirected PGMs, we will cover Markov networks (or Markov random fields), with one (1) of its most important variants, conditional random fields. Therefore, the course contains four (4) parts: Bayesian networks, hidden Markov models, Markov networks, and conditional random fields. In each part, I will introduce motivations, ideas, definitions, examples, properties, representations, inference algorithms, and applications for the corresponding PGM. This is done through lectures by the instructor. In the next two (2) lectures, the students will present recommended research papers and lead in-class discussions. The last lecture of each part will be an in-class quiz, the purpose of which is not to judge their ability of calculation or memorization, but to push them to think more and deeper about the contents introduced in lectures. The course will finish by a final exam lecture and two (2) project presentation lectures. The projects are expected to be a real application or a serious theoretical work of PGMs on real research problems.
Goals and Objectives	The goal of this course is to give a systematic and timely overview of the most important PGMs with their applications in various research areas, so that students can master and apply such techniques in their own research. For students who are interested in theory of PGMs, the goal is to introduce the state-of-the-art and open problems of PGMs, and to motivate them to pursue theoretical work in this area. The objectives of this course are as follows: 1. Introduce the motivations, definitions, representations, properties, and inference algorithms of both directed and undirected PGMs to the students. 2. Link the PGM techniques with the real applications in various research areas and show students how such techniques can lead to the state-of-the-art methods. 3. Deepen students understanding by research paper reading and presentation, in-class discussion, quiz, and assignments. 4. Provide students an opportunity to explore how to link PGMs with their own research through the semester-long course project. “Toy” projects are not acceptable.
Required Knowledge	Students are expected to be familiar with probability theory, algorithms, machine learning and programming language.
Reference Texts	There will be no textbook required for this course. The lectures and slides are self-contained. The reference book is “Probabilistic graphical models – Principles and techniques” by Daphne Koller and Nir Friedman, the MIT press.
Method of evaluation	**30.00**% - Research Project **30.00**% - Scientific review article presentation **10.00**% - Quiz(zes) **10.00**% - Homework /Assignments **20.00**% - Final exam
Nature of the assignments	The final grade is composed of 10% assignment, 10% in-class quiz, 20% final exam, 30% research paper presentation and in-class discussion, and 30% semester-long project.
Course Policies	Attendance is required since this is a research-oriented and seminar-based course. Student discussions and participations in class is expected and highly encouraged.
Additional Information	

Tentative Course Schedule *(Time, topic/emphasis & resources)*		
Week	**Lectures**	**Topic**
1	Wed 01/31/2018	Introduction
2	Wed 02/07/2018	Review of probability theory
3	Wed 02/14/2018	Bayesian network: representation and independence
4	Wed 02/21/2018	Bayesian network: Bayes ball algorithm and variable elimination algorithm
5	Wed 02/28/2018	Journal club: student presentation of research papers on Bayesian networks
6	Wed 03/07/2018	Hidden Markov models: representation and evaluation algorithm
7	Wed 03/14/2018	Hidden Markov models: decoding and learning algorithms
8	Wed 03/21/2018	Journal club: student presentation of research papers on HMMs
9	Wed 03/28/2018	Markov random field: representation and Gibbs distribution
10	Wed 04/04/2018	Markov random field: induced MRF and factorization
11	Wed 04/11/2018	Markov random field: independence
12	Wed 04/18/2018	Journal club: student presentation of research papers on Markov random fields
13	Wed 04/25/2018	Conditional random field: representation and cluster graphs
14	Wed 05/02/2018	Message passing: belief propagation
15	Wed 05/09/2018	Cluster graph properties and construction
16	Wed 05/16/2018	Journal club: student presentation of research papers on conditional random fields
17	Wed 05/23/2018	Research project presentation
18		Final exam

Note

The instructor reserves the right to make changes to this syllabus as necessary.