Probabilistic Graphical Models

Instructor

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Goal

The course will provide students with an introduction to the theory and practice of graphical models, one of the most dominant frameworks in machine learning and artificial intelligence.

Recommended Textbook

Extensive course notes will be provided. Almost all of the material is covered in the book Probabilistic Graphical Models: Principles and Techniques, Daphne Koller & Nir Friedman

Grading

60% Homework, 4 assignment
20% Midterm Exam
20% Final Exam

Prerequisites

The course require the new class Mathematical Foundations of Machine Learning, and CSE6740/ISYE6740/CS7641 Advanced Introduction of Machine Learning as prerequisites. Students should have had exposure to the basics of linear algebra, probability, statistics, dynamic programming, graph algorithm and data structure. Student should also have basic programming skills.

Learning Objectives

As part of this course, students …

1. Become familiar with the most commonly used graphical model representation methods, learning and inference algorithms
2. Gain exposure to the application of graphical models to real world problems
3. Formulate a wide range of problems with very large number of variables using the unified language of graphical models

Course Educational Outcomes

Upon successful completion of this course, students should be able to …

1. Understand the conditional independence assumption in two major representations of graphical model, Bayes Networks and Markov Networks

2. Know how to perform exact inference in graphical models using variable elimination, message passing algorithms and junction tree algorithms
3. Know how to perform approximate inference in graphical models using variational inference
4. Know how to perform approximate inference using sampling algorithm, such as Gibbs sampling and MCMC.
5. Know the concept of latent variables and know how to perform learning in the presence of latent variables.
6. Know how to design graphical model structures based on real world problems
7. Know how to estimate graphical model structures from data
8. Know nonparametric Bayes models such as Gaussian processes and Dirichlet processes

Academic Integrity

Academic dishonesty will not be tolerated. This includes cheating, lying about course matters, plagiarism, or helping others commit a violation of the Honor Code. Plagiarism includes reproducing the words of others without both the use of quotation marks and citation. Students are reminded of the obligations and expectations associated with the Georgia Tech Academic Honor Code and Student Code of Conduct, available online at www.honor.gatech.edu.

Learning Accommodations

If needed, we will make classroom accommodations for students with documented disabilities. These accommodations must be arranged in advance and in accordance with the Office of Disability Services (http://disabilityservices.gatech.edu).

Outline of Topics

1. Bayesian networks
    a. Examples (HMM, diagnostic system, etc.)
    b. Separation and independence
    c. Markov properties and minimalism
    d. Applications to time series model, topic modeling and network modeling
2. Markov networks
    a. Examples (Boltzmann machine, Markov random field, etc.)
    b. Cliques and potentials
    c. Markov properties
    d. Applications to image modeling, and network modeling
3. Exact inference
    a. Complexity
    b. Variable elimination

    c. Belief propagation (message passing) on trees
    d. Sum- and Max-product algorithms
    e. Junction tree
    f. Application to HMM
4. Maximum likelihood for parameter learning
    a. Exponential family
    b. Expectation-Maximization (EM)
5. Approximate inference
    a. Mean field approach
    b. Loopy belief propagation
    c. Variational inference and optimization view of inference
    d. Characterization of solution spaces
    e. Advanced inference algorithm.
6. Bayesian learning and sampling methods
    a. Gibbs sampling
    b. MCMC method
7. Structure learning and causality
    a. Chow-Liu algorithm
    b. PC algorithm
    c. l1-regularized convex optimization for markov random fields
    d. Low-rank regularized learning of latent variable models
8. Nonparametric Bayes methods
    a. Gaussian processes
    b. Dirichlet processes
    c. Indian Buffet processes