EECS 474: Probabilistic Graphical Models

Fall 2016

Introductions

Professor: Doug Downey

- Course web site:
 - www.cs.northwestern.edu/~ddowney/courses/474_Fall2016/
 - (linked off prof. home page very soon)

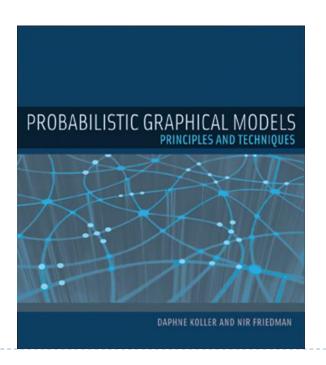
Logistics

- Grading
 - ► Homework (50%)
 - ▶ Handed out in weeks 1, 2, 4, 6, 8
 - Exercises and programming
 - Midterms (50%)
 - Weeks 5 & 9
 - ▶ A lot like the homework



Textbook

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





Motivation

- Artificial Intelligence
 - tremendous success in domains without a lot of uncertainty (e.g. chess)
 - But in the real world, uncertainty reigns
- We are awash in data
 - A crisis and an opportunity
- How can we deal with uncertainty? And how can we exploit massive bodies of data?



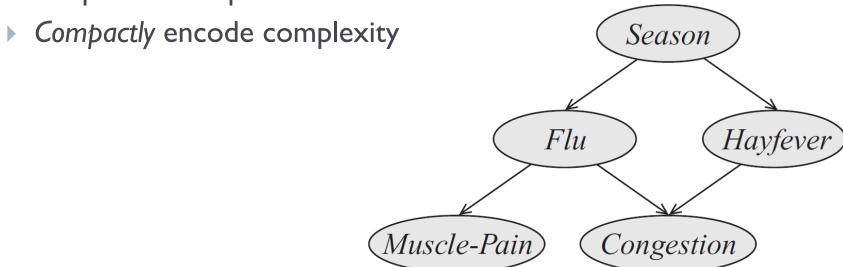
What the course is about

Probabilistic Models

 Deal with uncertainty: assign degree of confidence that different events will occur

Probabilistic Graphical Models

Graph-based representation





Goals

- Learn how to:
 - Build probabilistic models from data
 - Use the models to do work
 - Recognize opportunities for using models



Compared to Other Courses (1 of 2)

▶ EECS 349 is a prerequisite for this class

EECS 349	This class
Studies methods for learning functions	Studies methods for learning distributions
More algorithmic	More mathematical
Surveys many approaches	Dives deep into a few approaches



Compared to Other Courses (2 of 2)

- Statistics vs. this class
 - A few variables vs. tens of thousands
 - Continuous vs. discrete variables
 - Our focus: computational issues and applications
 - ▶ How can we scale to huge, multivariate data sets?
 - When and where are graphical models useful?



Applications

- Almost anything!
- ▶ E.g.,
 - Computational Biology
 - Robotics
 - Vision
 - Human-Computer Interaction
 - Networks and Systems
 - Information Retrieval/Web Search
 - Etc., etc.



Topics

- Basics of Probability and Statistical Estimation (briefly)
- Representing Probability Distributions as Graphs
 - Directed ("Bayes Nets") and Undirected ("Markov Nets")
- Working with Probabilistic Graphical Models
 - Inference: making predictions with a model
 - Learning: acquiring models from data
- Restricted Boltzmann Machines (a "deep network")
- Statistical Language Models: Hidden Markov Models, Recurrent Neural Networks, Long Short-term Memory Networks

