OSU CS 536
Probabilistic Graphical Models

Course Logistics

Scott Sanner
Instructors and Contact

- Scott Sanner (EECS)
  - Semi-official TA: Zahra Iman

- Office hours:
  - Immediately following class

- Questions:
  - Use Canvas Discussion Board link from course page
  - Questions to Scott (that cannot be posted to Canvas)
    - Strongly preferred after class
    - If necessary, send short email to scott.sanner@oregonstate.edu
Course Structure

• Representation:
  – Directed & Undirected Graphical Models
  – Factor Graphs

• Inference:
  – Message Passing
  – (MC)MC Sampling

• Learning
  – Parameter Learning
  – Structure Learning
  – Bayesian Inference Perspective

• Practical use and applications (what works where)
  – With Java implementation!

• Overview of state-of-the-art research topics
Learning Objectives

• Understand the motivations and probabilistic foundations for PGMs.

• Understand the importance of structured factor representations including trees and decision diagrams.

• Understand the semantics of directed and undirected PGMs and their unified representation as factor graphs.

• Understand message passing algorithms for PGMs and their computational and inferential characteristics.

• Understand (Markov Chain) Monte Carlo methods of inference in PGMs and their computational and inferential characteristics.

• Understand maximum (conditional) likelihood learning for both directed and undirected PGMs.

• Understand the use of PGMs for Bayesian learning and inference.

• Understand effective learning and inference algorithms for PGMs in applied settings.
Topics Not Covered

• Deep theory of join trees and I-maps
• Deep theory of structure learning
• Bayesian non-parametrics (NPs)
  – Dirichlet processes
  – Hierarchical NP processes

• Focus is on topics you might use as a practitioner or researcher
Assessment

• **Assessment:** (total: 100 points)

• **40 points: 4 assignments** (10 points each)
  – 20% deducted per day late (or fraction thereof), e.g.,
    - 1 minute late = 20% deduction
    - 1 day late = 20% deduction
    - 1 day 1 minute late = 40% deduction
    - 5 days late = 100% deduction = 0 points

• **15 points: independent mini-project**

• **15 points: midterm**

• **30 points: final exam**

See course web page for up-to-date schedule: [http://classes.engr.oregonstate.edu/eecs/winter2016/cs536/](http://classes.engr.oregonstate.edu/eecs/winter2016/cs536/)
Collaboration Policy

• Please learn from your fellow students and online web materials but

  (a) the code and written work you hand in must be your own *(plagiarism will result in immediate failure of the course)*, and

  (b) you should list all people you talked to and all web resources you used at the beginning of your assignment.
## Tentative Schedule

- **MWF 1300-1350, STAG 260**

- Tentative schedule at right (web page is definitive version)

- **Note the mid-term and final exams**

- Need to discuss assignment grading

- Submit assignments on Canvas

- Grades available on Canvas

<table>
<thead>
<tr>
<th>Week Starting</th>
<th>Monday</th>
<th>Wednesday</th>
<th>Friday</th>
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<tbody>
<tr>
<td>Jan 11</td>
<td>Factor Representations -- Tables, Trees, Decision Diagrams</td>
<td>Decision Diagram Algorithms -- Reduce and Apply</td>
<td>A1 due @ 1pm</td>
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<td>Jan 18</td>
<td>No class -- Martin Luther King, Jr. Day</td>
<td>Message Passing: (Loopy and Generalized) Belief Propagation, Join Trees</td>
<td>Monte Carlo Inference: Rejection Sampling, Likelihood Weighting, Importance Sampling</td>
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<td>Jan 25</td>
<td>Markov Chain Monte Carlo (MCMC): Introduction</td>
<td>MCMC: Metropolis-Hastings, Gibbs, Hamiltonian</td>
<td>Parameter Learning: Maximum Likelihood for Directed Models A2 due @ 1pm</td>
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<td>Feb 1</td>
<td>Parameter Learning: Maximum Likelihood for Undirected Models</td>
<td>Midterm review</td>
<td>Midterm (in class)</td>
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<td>Feb 8</td>
<td>Structure Learning: Chow-Liu Trees</td>
<td>Structure Learning: General Trees</td>
<td>Hidden Markov Models and CRFs A3 due @ 1pm</td>
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<td>Feb 15</td>
<td>Gaussian Processes</td>
<td>Continuous PGMs, Bayesian Inference, and Plates</td>
<td>Mixture Models and Bayesian Model Averaging</td>
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<td>Feb 22</td>
<td>Latent Dirichlet Allocation</td>
<td>Particle Filtering (for Localization and Tracking)</td>
<td>MAP with Mini-buckets and Graphcuts A4 due @ 1pm</td>
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<td>Feb 29</td>
<td>Knowledge Compilation</td>
<td>Relational Probabilistic Models -- MLNs and KBMC</td>
<td>Probabilistic Programming (with STAN) and PGMs</td>
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<td>Mar 7</td>
<td>Hybrid Models and Decision Diagrams</td>
<td>Symbolic Variable Elimination and Symbolic Gibbs</td>
<td>Course Review Mini-project due @ 1pm</td>
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<td>Mar 14</td>
<td>Finals Week</td>
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Book

  
  [https://mitpress.mit.edu/books/probabilistic-graphical-models](https://mitpress.mit.edu/books/probabilistic-graphical-models)
All Course Content

• Everything posted on web page or Canvas Discussion forum… nowhere else.

• Use the Canvas Forum
  – I will ask you to post your question to Canvas before it is answered
  – Others can answer your question
  – Others will have the same question