NUS National University of Singapore | School of Computing

CS5340
Uncertainty Modeling in AI

Assoc. Prof. Lee Gim Hee

AY 2022/23

Semester 1

Course Information

Lecturer:

Dr. Lee Gim Hee

Department of Computer Science

Office: COM2-03-54

Email: gimhee.lee@comp.nus.edu.sg

Class Schedule:

Every Wednesday, **L1**: 1400hrs-1700hrs, **L2**: 1830hrs – 2130hrs

Venue:

COM1-02-12 (Seminar Room 3)

In-person Lectures; Only webcast for **L1**

Teaching Assistants

Chen Jinnan
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Low Weng Fei
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Lab: AS6-05-02

Mode of Assessments

- The grades of this module is based on **60% CA + 40% final exam**:

1. 4x coding assignments (15% each; individual work)

2. 40% final exam (**conducted in-person**, one-page A4 cheat sheet allowed)

Logistics: Assignments

- We will use Python as the programming language for the assignments.
- Nonetheless, you can use any programming language of your choice.
- But the helper functions and our support will be given only in Python.
- Ask my TAs on all questions regarding the assignments.

Assignment Late Policy

- All assignments are due at 2359hrs of the dates specified on the module schedule.
- 25% of the total marks will be deducted for each day of late submission.
- Deduction of marks does not apply to the late submissions with valid reasons. Please email me your reasons to seek for approval.

Honor Code

- **Assignments:** You may discuss and/or refer to online references, but plagiarism is strictly not allowed.

- **Violation of rules:** Zero will be given, and disciplinary actions that could lead to your expulsion from NUS will be taken!

Logistics: Final Exam

- The final exam is to be conducted in-person at a fixed date and time.
- Please arrange your schedule, and make sure you are present at NUS.
- **Format (more details later):**

1. Four questions
2. 2-hour exam
3. Students are allowed one-page A4 cheat sheet, written/typewritten on both sides.

Tutorials

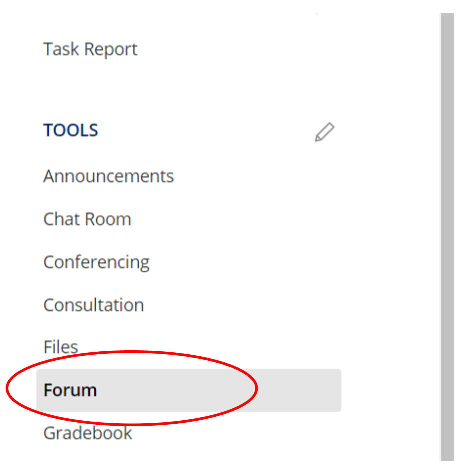
- No formal tutorials.
- Two sets of exercise questions and solutions will be provided.
- I will go through some of the solutions during the lectures if time permits or during the last lecture.

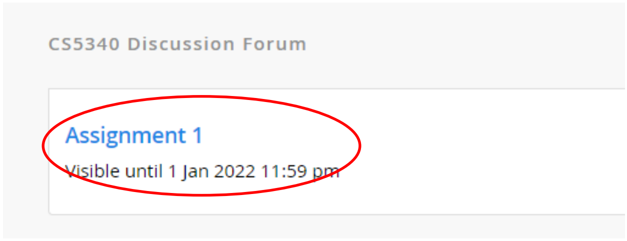
Consultations

- Please send all questions to me **via email or Luminus Forum** .
- To make sure your email gets my attention, use "[CS5340] xxx" as the title of your email.
- If necessary, we can arrange for consultation sessions too.
- I would prefer you to post your questions on Luminus Forum, so that your classmates can see too.

Consultations

- Please send all your questions on the assignments to my TAs.
- Use the discussion forum in Luminus.



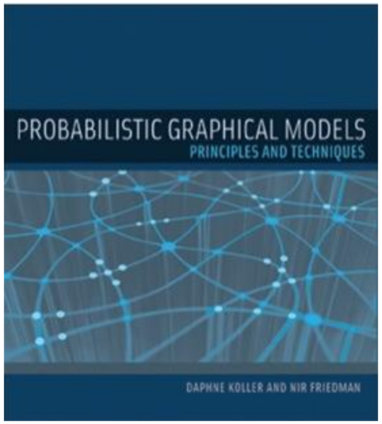


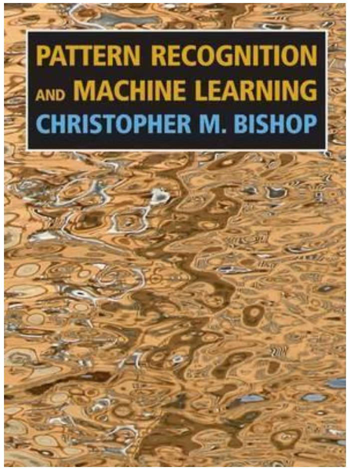
Course Schedule

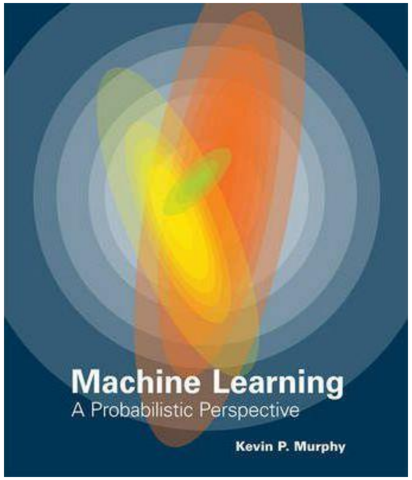
Week	Date	Topic	Remarks
1	10 Aug	Introduction to probabilistic reasoning	**Assignment 0:** Python Numpy Tutorial (Ungraded)
2	17 Aug	Bayesian networks (Directed graphical models)	
3	24 Aug	Markov random Fields (Undirected graphical models)	
4	31 Aug	Variable elimination and belief propagation	**Assignment 1:** Belief propagation and maximal probability (15%)
5	07 Sep	Factor graph and the junction tree algorithm	
6	14 Sep	Parameter learning with complete data	**Assignment 1:** Due **Assignment 2:** Junction tree and parameter learning (15%)
-	21 Sep	Recess week	**No lecture**
7	28 Sep	Mixture models and the EM algorithm	**Assignment 2:** Due
8	05 Oct	Hidden Markov Models (HMM)	**Assignment 3:** Hidden Markov model (15%)
9	12 Oct	Monte Carlo inference (Sampling)	
*	15 Oct	Variational inference	Makeup Lecture (Venue TBD) Time: 9.30am – 12.30pm (Saturday)
10	19 Oct	Variational Auto-Encoder and Mixture Density Networks	**Assignment 3:** Due **Assignment 4:** MCMC Sampling (15%)
11	26 Oct	No Lecture	I will be traveling
12	02 Nov	Graph-cut and alpha expansion	**Assignment 4:** Due
13	09 Nov	-	

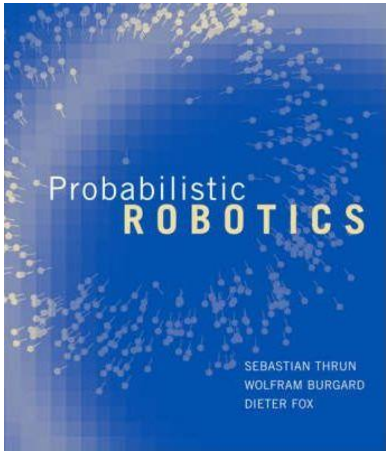
Final Exam: 21 Nov 2022

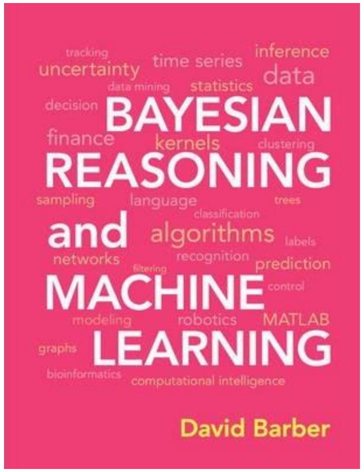
Recommended Readings (Not Compulsory)











Probabilistic Graphical Modeling

One of the most exciting advances in machine learning (AI, signal processing, coding, control, robotics, computer vision . . .) in the last decades.

Adapted from: "Probabilistic Graphical Modeling" Lectures NYU, David Sontag

Probabilistic Graphical Modeling

before deep learning

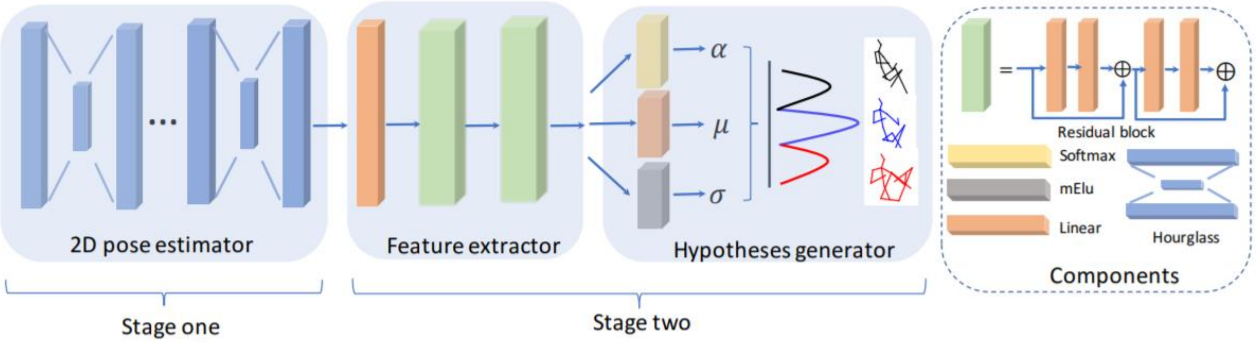
One of the most exciting advances in machine learning (AI, signal processing, coding, control, robotics, computer vision . . .) in the last decades.

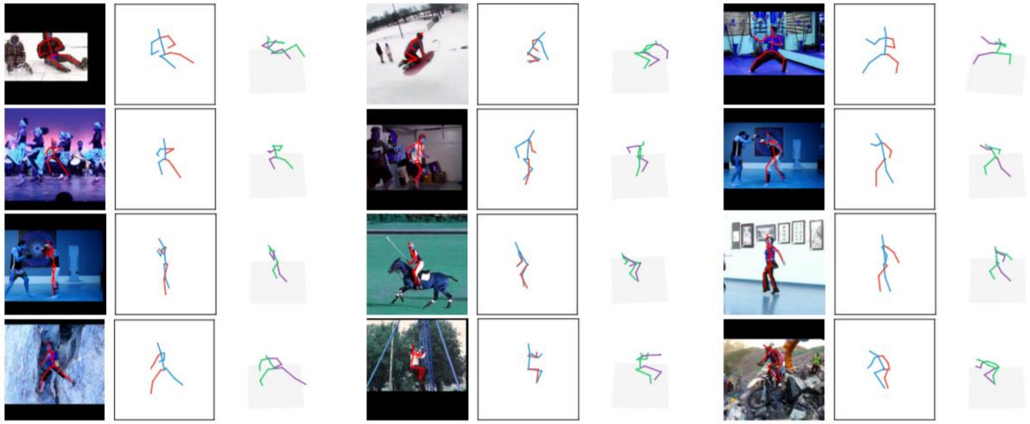
Knowledge on PGM helps formulate some of the most important deep networks, e.g., deep generative models (Lecture 11) !

Adapted from: "Probabilistic Graphical Modeling" Lectures NYU, David Sontag

PGM in Deep Learning

Example: Mixture density network for 3D human pose estimation





$$p(\mathbf{y} \mid \mathbf{x}, \mathbf{w}) = \sum_{i=1}^{M} \alpha_i(\mathbf{x}, \mathbf{w}) \phi_i(\mathbf{y} \mid \mathbf{x}, \mathbf{w}),$$

$$\phi_i(\mathbf{y} \mid \mathbf{x}, \mathbf{w}) = \frac{1}{(2\pi)^{d/2} \sigma_i(\mathbf{x}, \mathbf{w})^d} \exp - \frac{\|\mathbf{y} - \mu_i(\mathbf{x}, \mathbf{w})\|^2}{2\sigma_i(\mathbf{x}, \mathbf{w})^2}.$$

Chen Li, Gim Hee Lee, **Generating Multiple Hypotheses for 3D Human Pose Estimation with Mixture Density Network**, CVPR 2019

Probabilistic Graphical Modeling

How can we gain global insight based on local observations?

Adapted from: “Probabilistic Graphical Modeling” Lectures NYU, David Sontag

Probabilistic Graphical Modeling

How can we gain global insight based on local observations?

Example:

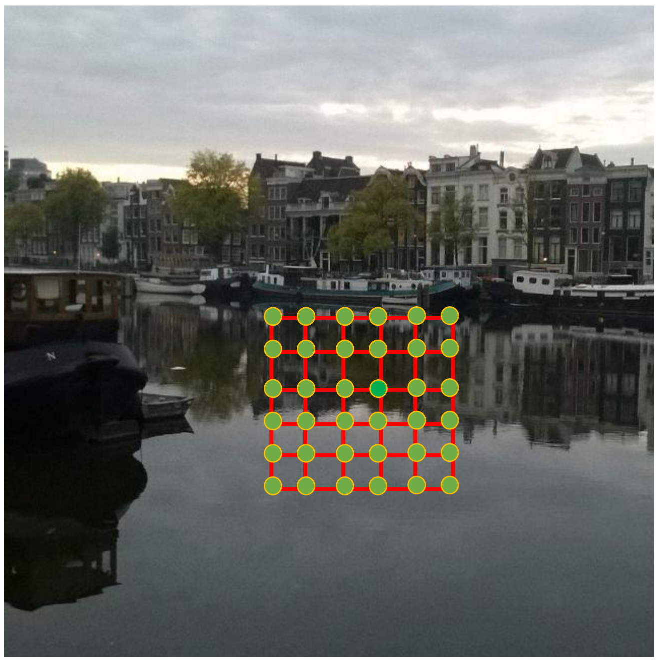


Photo Source:
G.H. Lee "Amsterdam"

Given: Local observations

- Each node takes 1-of-K labels and
- a smoothness prior, i.e, neighboring nodes linked by an edge should take the same label

We can find the label assignment of each pixel that is globally consistent!

Probabilistic Graphical Modeling

Key Ideas:

- Represent the world as a collection of random variables $X_1, \ldots, X_N$ with joint distribution $p(X_1, \ldots, X_N)$.
- Learn the distribution from data.
- Perform "inference" (compute conditional distributions $p(X_i \mid X_1 = x_1, \ldots, X_N = x_N)$).

Adapted from: "Probabilistic Graphical Modeling" Lectures NYU, David Sontag

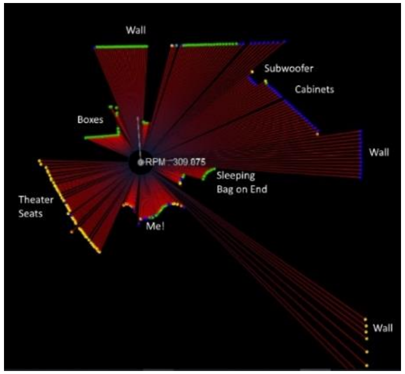
Reasoning Under Uncertainty

- As humans, we are continuously making predictions under uncertainty.
- Classical AI and ML research ignored this phenomena.
- Many of the ~~most recent~~ advances in technology are possible because of this probabilistic approach.

Adapted from: “Probabilistic Graphical Modeling” Lectures NYU, David Sontag

PGM: Applications

Markov Localization

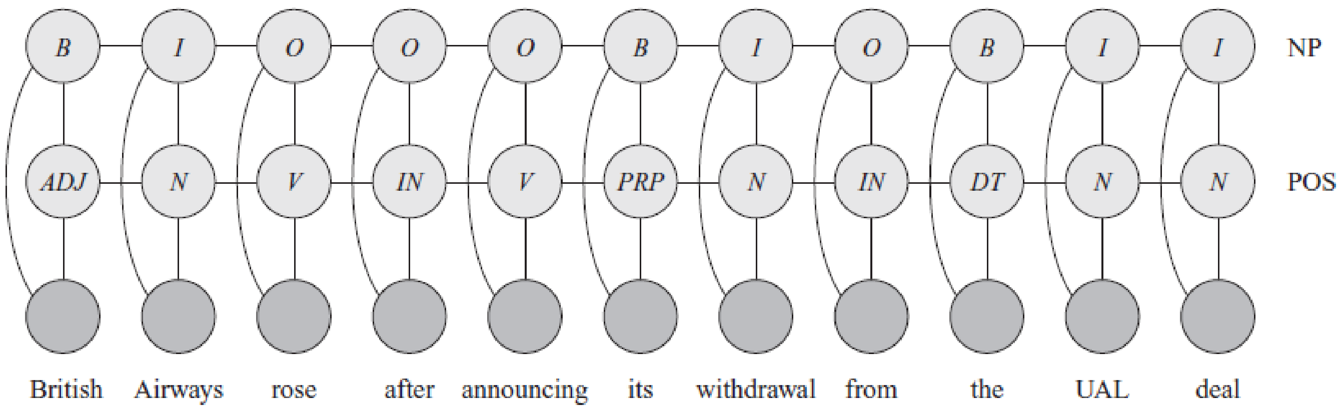


“ Monte Carlo Localization for Mobile Robots”, Frank Dellaert et. al., ICRA 1999

PGM: Applications

Part of Speech Tagging

A. Big hungry **bears** are coming.
B. Your friend **bears** gifts.



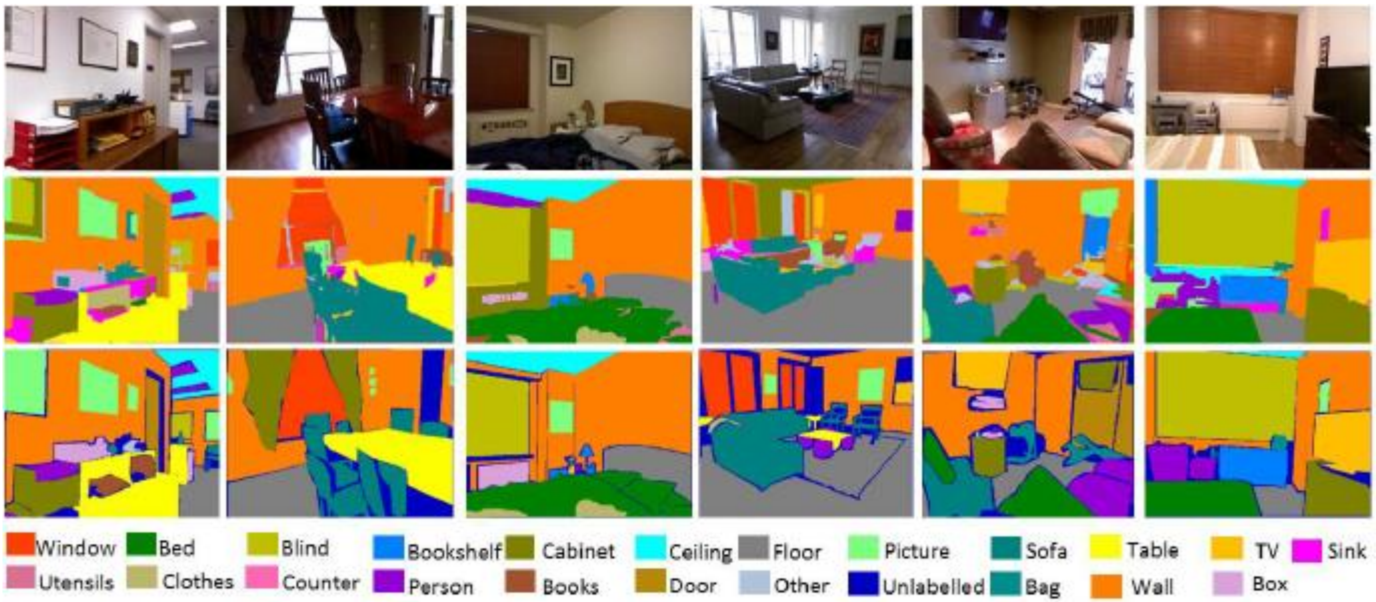
KEY

B	Begin noun phrase	*V*	Verb
I	Within noun phrase	*IN*	Preposition
O	Not a noun phrase	*PRP*	Possesive pronoun
N	Noun	*DT*	Determiner (e.g., a, an, the)
ADJ	Adjective		

D. Koller et. al. 2009

PGM: Applications

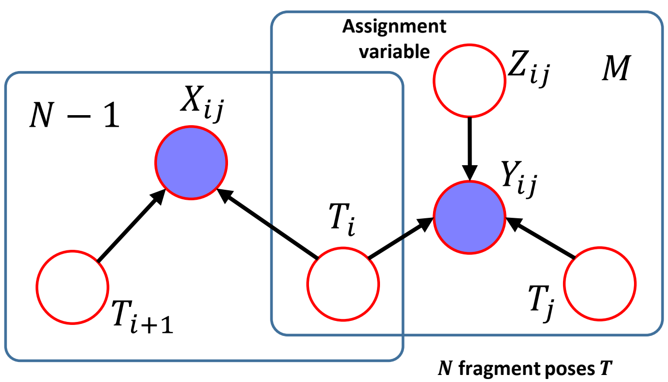
Scene Understanding

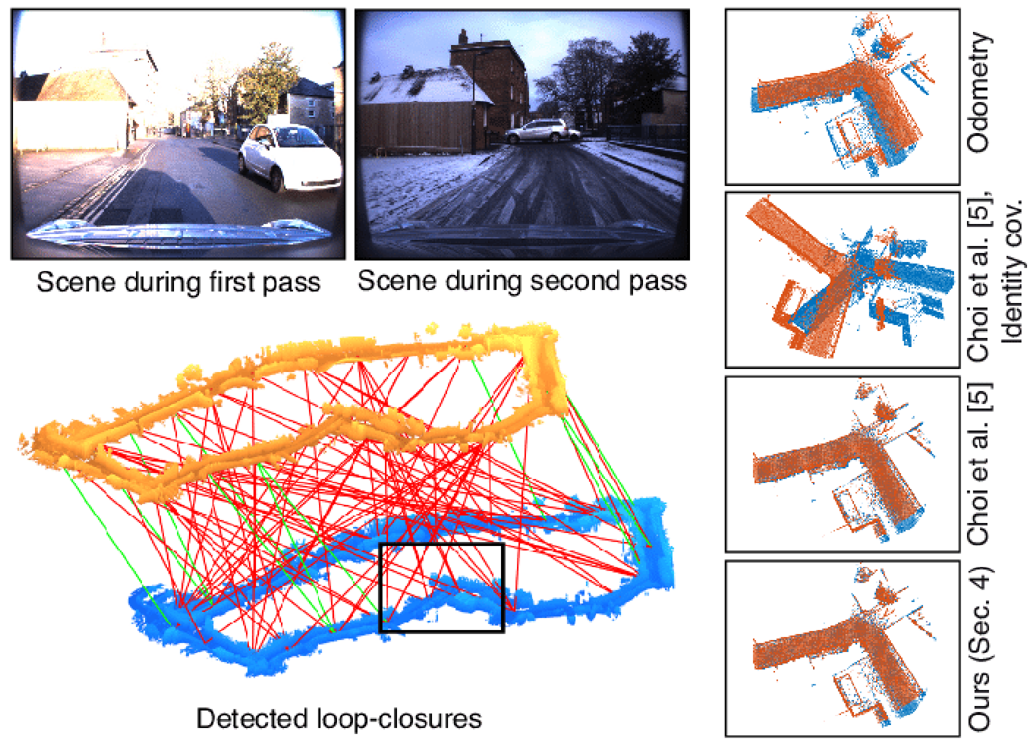


"Geometry Driven Semantic Labeling of Indoor Scenes", Salman Hameed Khan et. Al. ECCV 2014

PGM: Applications

Robust 3D Reconstruction





Ziquan Lan, Zi Jian Yew, Gim Hee Lee, "Robust Point Cloud Based Reconstruction of Large-Scale Outdoor Scenes", CVPR 2019