*CSXX02*67: Probabilistic Graphical Models
L-T-P-Cr: 3-0-0-3

Prerequisites: Linear Algebra, Probability Theory, Statistics, Algorithms, Machine Learning

Course Description:

- Probabilistic graphical models are a powerful framework for representing complex domains using probability distributions, with numerous applications in machine learning, computer vision, natural language processing and computational biology. Graphical models bring together graph theory and probability theory, and provide a flexible framework for modelling large collections of random variables with complex interactions. This course will provide a comprehensive survey of the topic, introducing the key formalisms and main techniques used to construct them, make predictions, and support decision-making under uncertainty.
- The aim of this course is to develop the knowledge and skills necessary to design, implement and apply these models to solve real problems. The course will cover: (1) Bayesian networks, undirected graphical models and their temporal extensions; (2) exact and approximate inference methods; (3) estimation of the parameters and the structure of graphical models.

Course Objectives

1. To introduce students to the foundational concepts in probabilistic graphical models (PGMs).
2. To develop an understanding of directed and undirected graphical models.
3. To analyze inference algorithms for exact and approximate reasoning.
4. To explore parameter learning in supervised and unsupervised settings.
5. To apply PGMs to real-world problems and implement them computationally.

Course Outcomes (COs)

CO Code	Description
CO1	Understand the foundational principles of probabilistic graphical models.
CO2	Model real-world problems using Bayesian and Markov networks.
CO3	Apply exact and approximate inference algorithms in PGMs.
CO4	Learn and estimate model parameters from data using various techniques.
CO5	Implement PGMs and analyze their performance on real datasets.

PO Mapping (Program Outcomes)

CO → PO	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO10	PO11	PO12	PSO 1	PSO 2
CO1	3	3										2	2	1
CO2	3	3	2	2	2						1	2	3	2
CO3	3	2	3	2					2	1	2	2	3	3
CO4	3	3	3	2	3	1	1	2	3	2	2	2	3	3
CO5	2	2	2		3	2	2	3	2	2	2	3	3	3

Detailed Syllabus

Module 1: Introduction to Probabilistic Graphical Models [7]

Motivation and real-world examples, Probability theory review (Bayesian vs. Frequentist), Conditional independence and d-separation

Module 2: Directed Graphical Models (Bayesian Networks) [8]

Structure, semantics, and factorization, Conditional independence properties, Learning with complete data, Structure learning and scoring metrics

Module 3: Undirected Graphical Models (Markov Random Fields) [7]

MRFs and conditional independence, Factor graphs and log-linear models, CRFs: Conditional Random Fields, Parameter estimation and inference

Module 4: Inference Algorithms [8]

Variable elimination, Belief propagation, Junction tree algorithm, Monte Carlo methods: Gibbs sampling, Metropolis-Hastings, Variational inference and mean field

Module 5: Learning in PGMs [7]

MLE, MAP estimation, Expectation Maximization (EM), Learning structures from data, Discriminative vs generative models

Module 6: Applications [5]

NLP: POS tagging, Named Entity Recognition, Vision: Image segmentation, Bioinformatics: Gene network inference, Time-series: HMMs and Dynamic Bayesian Networks

Lab Component

- Python-based implementation of inference algorithms
- Hands-on exercises with sampling and EM
- Real-world case studies
- Mini-project involving end-to-end PGM modeling

Required Textbook: *Probabilistic Graphical Models: Principles and Techniques* by Daphne Koller and Nir Friedman. MIT Press.

Further Readings:

- *Modeling and Reasoning with Bayesian networks* by Adnan Darwiche.
- *Pattern Recognition and Machine Learning* by Chris Bishop.
- *Machine Learning: a Probabilistic Perspective* by Kevin P. Murphy.
- *Information Theory, Inference, and Learning Algorithms* by David J. C. Mackay. Available online.
- *Bayesian Reasoning and Machine Learning* by David Barber. Available online.
- *Graphical models, exponential families, and variational inference* by Martin J. Wainwright and Michael I. Jordan. Available online.