Course Code:	Course Title	Credit
CSDO501	Probabilistic Graphical Models	3

Prerequisite: Engineering Mathematics, Discrete Structure	
Course Objectives:	
1.	To give comprehensive introduction of probabilistic graphical models
2.	To make inferences, learning, actions and decisions while applying these models
3.	To introduce real-world trade offs when using probabilistic graphical models in practice
4.	To develop the knowledge and skills necessary to apply these models to solve real world problems.
Course Outcomes: On successful completion of course, learners will be able to	
1.	understand basic concepts of probabilistic graphical modelling
2.	model and extract inference from various graphical models like Bayesian Networks, Markov Models
3.	perform learning and take actions and decisions using probabilistic graphical models
4.	represent real world problems using graphical models; design inference algorithms; and learn the structure of the graphical model from data.
5.	design real life applications using probabilistic graphical models.

Module		Content	Hrs
1.		**Introduction to Probabilistic Graphical Modeling**	**5**
	1.1	Introduction to Probability Theory: Probability Theory, Basic Concepts in Probability, Random Variables and Joint Distribution, Independence and Conditional Independence, Continuous Spaces, Expectation and Variances	
	1.2	Introduction to Graphs: Nodes and Edges, Subgraphs, Paths and Trails, Cycles and Loops	
	1.3	Introduction to Probabilistic Graph Models: Bayesian Network, Markov Model, Hidden Markov Model	
	1.4	Applications of PGM	
2.		**Bayesian Network Model and Inference**	**10**

	2.1	Directed Graph Model: Bayesian Network-Exploiting Independence Properties, Naive Bayes Model, Bayesian Network Model, Reasoning Patterns, Basic Independencies in Bayesian Networks, Bayesian Network Semantics, Graphs and Distributions. Modelling: Picking variables, Picking Structure, Picking Probabilities, D-separation	
	2.2	Local Probabilistic Models: Tabular CPDs, Deterministic CPDs, Context Specific CPDs, Generalized Linear Models.	
	2.3	Exact inference variable elimination: Analysis of Complexity, Variable Elimination, Conditioning, Inference with Structured CPDs.	
3.		**Markov Network Model and Inference**	**8**
	3.1	**Undirected Graph Model :** Markov Model-Markov Network, Parameterization of Markov Network, Gibb's distribution, Reduced Markov Network, Markov Network Independencies, From Distributions to Graphs, Fine Grained Parameterization, Over Parameterization	
	3.2	Exact inference variable elimination: Graph Theoretic Analysis for Variable Elimination, Conditioning	
4.		**Hidden Markov Model and Inference**	**6**
	4.1	Template Based Graph Model : HMM- Temporal Models, Template Variables and Template Factors, Directed Probabilistic Models, Undirected Representation, Structural Uncertainty.	
5.		**Learning and Taking Actions and Decisions**	**6**
	5.1	Learning Graphical Models: Goals of Learning, Density Estimation, Specific Prediction Tasks, Knowledge Discovery. Learning as Optimization: Empirical Risk, Over fitting, Generalization, Evaluating Generalization Performance, Selecting a Learning Procedure, Goodness of fit, Learning Tasks. Parameter Estimation: Maximum Likelihood Estimation, MLE for Bayesian Networks	
	5.2	Causality: Conditioning and Intervention, Correlation and Causation, Causal Models, Structural Causal Identifiability, Mechanisms and Response Variables, Learning Causal Models. Utilities and Decisions: Maximizing Expected Utility, Utility Curves, Utility Elicitation. Structured Decision Problems: Decision Tree	
6.		**Applications**	**4**
	6.1	Application of Bayesian Networks: Classification, Forecasting, Decision Making	
	6.2	Application of Markov Models: Cost Effectiveness Analysis, Relational Markov Model and its Applications, Application in Portfolio Optimization	
	6.3	Application of HMM: Speech Recognition, Part of Speech Tagging, Bioinformatics.	

Textbooks:	
1.	Daphne Koller and Nir Friedman, **"Probabilistic Graphical Models: Principles and Techniques"**, Cambridge, MA: The MIT Press, 2009 (ISBN 978-0-262-0139-2).
2.	David Barber, **"Bayesian Reasoning and Machine Learning"**, Cambridge University Press, 1st edition, 2011.
References:	
1.	Finn Jensen and Thomas Nielsen, **"Bayesian Networks and Decision Graphs (Information Science and Statistics**)", 2nd Edition, Springer, 2007.
2.	Kevin P. Murphy, **"Machine Learning: A Probabilistic Perspective"**, MIT Press, 2012.
3.	Martin Wainwright and Michael Jordan, M., **"Graphical Models, Exponential Families, and Variational Inference"**, 2008.

Assessment:	
Internal Assessment:	
Assessment consists of two class tests of 20 marks each. The first class test is to be m onducted when approx. 40% syllabus is completed and second class test when additional 40% syllabus is completed. Duration of each test shall be one hour.	
End Semester Theory Examination:	
1.	Question paper will comprise of total six questions.
2.	All question carries equal marks
3.	Questions will be mixed in nature (for example supposed Q.2 has part (a) from module 3 then part (b) will be from any module other than module 3)
4.	Only Four question need to be solved.
5.	In question paper weightage of each module will be proportional to number of respective lecture hours as mention in the syllabus.
Useful Links	
1.	https://www.coursera.org/specializations/probabilistic-graphical-models
2.	https://www.mooc-list.com/tags/probabilistic-graphical-models
3.	https://scholarship.claremont.edu/cgi/viewcontent.cgi?referer=https://www.google.com/&httpsredir=1&article=2690&context=cmc_theses
4.	https://www.upgrad.com/blog/bayesian-networks/

5.	https://www.utas.edu.au/__data/assets/pdf_file/0009/588474/TR_14_BNs_a_resource_guide.pdf
6.	https://math.libretexts.org/Bookshelves/Applied_Mathematics/Book%3A_Applied_Finite_Mathematics_(Sekhon_and_Bloom)/10%3A_Markov_Chains/10.02%3A_Applications_of_Markov_Chains/10.2.01%3A_Applications_of_Markov_Chains_(Exercises)
7.	https://link.springer.com/chapter/10.1007/978-3-319-43742-2_24
8.	https://homes.cs.washington.edu/~pedrod/papers/kdd02a.pdf
9.	https://core.ac.uk/download/pdf/191938826.pdf
10.	https://cs.brown.edu/research/pubs/theses/ugrad/2005/dbooksta.pdf
11.	https://web.ece.ucsb.edu/Faculty/Rabiner/ece259/Reprints/tutorial%20on%20hmm%20and%20applications.pdf
12.	https://mi.eng.cam.ac.uk/~mjfg/mjfg_NOW.pdf
13.	http://bioinfo.au.tsinghua.edu.cn/member/jgu/pgm/materials/Chapter3-LocalProbabilisticModels.pdf

Suggested List of Experiments:

Sr. No	Experiment
1.	Experiment on Probability Theory
2.	Experiment on Graph Theory
3.	Experiment on Bayesian Network Modelling
4.	Experiment on Markov Chain Modeling
5.	Experiment on HMM
6.	Experiment on Maximum Likelihood Estimation
7.	Decision Making using Decision Trees
8.	Learning with Optimization

** Laboratory work based on above syllabus can be incorporated along with mini project in CSM501: Mini-Project.