| Course Code | Course Name | Credits (TH+P+TUT) |
|---|---|---|
| CEDLC5054 | **Probabilistic Graphical Model** | 3 - 0 - 0 |

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| **Prerequisite:** | 1. Discrete Structure<br>2. Engineering Mathematics |
| **Course Objectives:** | 1. To give comprehensive introduction of probabilistic graphical models.<br>2. To make inferences, learning, actions and decisions while applying these models.<br>3. To introduce real-world trade offs when using probabilistic graphical models in practice.<br>4. To develop the knowledge and skills necessary to apply these models to solve real world problems. |
| **Course Outcomes:** | **After the successful completion of this course, learner will be able to:**<br>1. Describe basic concepts of probabilistic graphical modelling.<br>2. Model and extract inference from various graphical models like Bayesian Network model and inference.<br>3. Perform learning and take actions and decisions using probabilistic graphical models - Markov Model.<br>4. Devise learning and take actions and decisions using probabilistic graphical models - Hidden Markov Model<br>5. Represent real world problems using graphical models; design inference algorithms; and learn the structure of the graphical model from data<br>6. Design real life applications using probabilistic graphical models. |

| Module No. & Name | Sub Topics | CO mapped | Hrs / Sub topics | Total Hrs/ Module |
|---|---|---|---|---|
| **i. Prerequisites and Course Outline** | Prerequisite Concepts and Course Introduction. | - | 02 | 02 |
| **1. Introduction to Probabilistic Graphical Modeling** | Introduction to Probability Theory: Probability Theory, Basic Concepts in Probability, Random Variables and Joint Distribution, Independence and Conditional Independence, Continuous Spaces, Expectation and Variances Theory of Predicate Calculus, Mathematical Induction. | CO1 | 02 | 05 |
| | Introduction to Graphs: Nodes and Edges, Subgraphs, Paths and Trails, Cycles and Loops | | 01 | |
| | Introduction to Probabilistic Graph Models: Bayesian Network, Markov Model, Hidden Markov Model | | 01 | |
| | Applications of PGM | | 01 | |
| **2. Bayesian Network Model and Inference** | 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. | CO2 | 04 | 10 |

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|---|---|---|---|---|
| | Modelling: Picking variables, Picking Structure, Picking Probabilities, D-separation | | | |
| | Local Probabilistic Models: Tabular CPDs, Deterministic CPDs, Context Specific CPDs, Generalized Linear Models | | **02** | |
| | Exact inference variable elimination: Analysis of Complexity, Variable Elimination, Conditioning, Inference with Structured CPDs | | **04** | |
| **3. Markov Network Model and Inference** | 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 | **CO3** | **04** | **08** |
| | Exact inference variable elimination: Graph Theoretic Analysis for Variable Elimination, Conditioning | | **04** | |
| **4. Hidden Markov Model and Inference** | Template Based Graph Model : HMM- Temporal Models, Template Variables and Template Factors, | **CO4** | **03** | **06** |
| | Directed Probabilistic Models, Undirected Representation, Structural Uncertainty | | **03** | |
| **5. Learning and Taking Actions and Decisions** | 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 | **CO5** | **03** | **06** |
| | 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 | | **03** | |
| **6. Applications** | Application of Bayesian Networks: Classification, Forecasting, Decision Making | **CO6** | **01** | **04** |
| | Application of Markov Models: Cost Effectiveness Analysis, Relational Markov Model and its Applications, Application in Portfolio Optimization | | **02** | |
| | Application of HMM: Speech Recognition, Part of Speech Tagging, Bioinformatics | | **01** | |
| **ii.Course Conclusion** | Recap of Modules, Outcomes, Applications, and Summarization. | **--** | **01** | **01** |
| **Total Hours** | | | | **42** |

**Books:**

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

**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/ Draft Copy
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

**Assessment:**

**Continuous Assessment for 40 marks:**

1. Test 1– 30 marks
2. Test 2– 30 marks
3. Internal assessment --10 marks

Internal assessment will be based on assignments/quizzes /case study/activity conducted by the faculty

**End Semester Theory Examination will be of 60-Marks for 02 hrs 30 min duration.**

| Lab Code | Lab Name | Credits (P+TUT) |
|---|---|---|
| **CEDLL5054** | **Probabilistic Graphical Model Lab** | **1- 0** |

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| **Lab Prerequisite:** | 1.Engineering Mathematics<br>2.Discrete Structure |
| **Lab Objectives:** | 1.To give comprehensive introduction of probabilistic graphical models.<br>2. To make inferences, learning, actions and decisions while applying these models<br>3. To introduce real-world trade offs when using probabilistic graphical models in practice<br>4. To develop the knowledge and skills necessary to apply these models to solve real world problems. |
| **Lab Outcomes (LOs):** | **At the end of the course, the student will be able to**<br>1. Explore probability theory and it uses.<br>2. Devise the functionality of Graph Theory<br>3. Implement Bayesian Network modelling.<br>4. Implement Markov Chain and HMM modelling<br>5. Implement the decision tree, maximum likelihood estimation.<br>6. Explore the problem of learning with optimization<br>7. Apply ethical principles like timeliness and adhere to the rules of the laboratory |

| Lab No | Experiment Title | LO mapped | Hrs/Lab |
|---|---|---|---|
| **0** | Prerequisite | **-** | **02** |
| **1.** | Experiment on Probability Theory | **LO1, LO7** | **02** |
| **2.** | Experiment on Graph Theory | **LO2, LO7** | **02** |
| **3.** | Experiment on Bayesian Network Modelling | **LO3, LO7** | **02** |
| **4.** | Experiment on Markov Chain Modeling | **LO4, LO7** | **02** |
| **5.** | Experiment on HMM | **LO4, LO7** | **02** |
| **6.** | Experiment on Maximum Likelihood Estimation | **LO5, LO7** | **02** |
| **7.** | Decision Making using Decision Trees | **LO5, LO7** | **02** |
| **8.** | Case Study on Learning with Optimization | **LO6, LO7** | **02** |

**Term work:**

1. Term work should consist of minimum 08 experiments

2. Journal must include at least 2 assignments on content of theory and practical of the course “Probabilistic Graphical Model”
3. The final certification and acceptance of term work ensures that satisfactory performance of laboratory work and minimum passing marks in term work.
4. Total 25 Marks (Experiments: 20-marks, Assignments: 05-marks)