

**NATIONAL INSTITUTE OF TECHNOLOGY ANDHRA PRADESH**  
**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**

About the Department of CSE

The Department of Computer Science and Engineering at NIT Andhra Pradesh, offers a B.Tech. Undergraduate programme in Computer Science and Engineering, M. Tech in Computer Science and Data Analytics, M.S. (by research) and Ph.D. programmes. The department was incepted in the year 2015, the current sanctioned intake is 90 students for the B.Tech. (CSE) programme.

Vision of the Department of CSE

To attain and sustain eminence in teaching and research in Computer Science and Engineering.

Mission of the Department of CSE

M1: To adopt a teaching-learning process that imparts technical skills and state-of-the-art knowledge with a well-blended and balanced mix of theory and practice.

M2: To create functional centres of excellence that promote research and consultancy in the thrust sub-domains of theoretical computer science, systems and technology.

M3: To collaborate with industry and higher learning institutes of national/international repute by constituting Special Interest Groups and solve socially relevant problems.

Programme Educational Objectives (PEOs) for the M.Tech. (Computer Science and Data Analytics) Programme:

Within few years after the end of the M.Tech. in Computer Science and Data Analytics programme, graduates will be able to:

<b>PEO1</b>	Graduates will successfully pursue doctoral studies in institutes of repute and will make innovative contributions in terms of publications, patents and products.
<b>PEO2</b>	Graduates will have a successful career pertinent to teaching roles in academia and R&D roles in industry.
<b>PEO3</b>	Graduates will evolve into entrepreneurs and leaders who incubate and nurture companies to solve socially relevant problems.

Programme Articulation Matrix (PEO vs. Mission) for the B.Tech. (CSE) Programme:

<b>PEO\Mission</b>	<b>M1</b>	<b>M2</b>	<b>M3</b>
<b>PEO1</b>	S	S	S
<b>PEO2</b>	S	S	M
<b>PEO3</b>	M	S	S

S: Strong correlation, M: Medium correlation, L: Low correlation

Programme Outcomes (POs) for the M.Tech. (Computer Science and Data Analytics)  
Programme

At the end of the program, the student will be able to:

<b>PO1</b>	Scholarship of knowledge -Acquire in-depth knowledge of specific discipline or professional area, including wider and global perspective, with an ability to discriminate, evaluate, analyze and synthesize existing and new knowledge, and integration of the same for enhancement of knowledge.
<b>PO2</b>	Critical thinking - Analyze complex engineering problems critically, apply independent judgment for synthesizing information to make intellectual and/or creative advances for conducting research in a wider theoretical, practical and policy context.
<b>PO3</b>	Problem solving - Think laterally and originally, conceptualize and solve engineering problems, evaluate a wide range of potential solutions for those problems and arrive at feasible, optimal solutions after considering public health and safety, cultural, societal and environmental factors in the core areas of expertise.
<b>PO4</b>	Research skill - Extract information pertinent to unfamiliar problems through literature survey and experiments, apply appropriate research methodologies, techniques and tools, design, conduct experiments, analyze and interpret data, demonstrate higher order skill and view things in a broader perspective, contribute individually/in group(s) to the development of scientific/technological knowledge in one or more domains of engineering.
<b>PO5</b>	Usage of modern tools - Create, select, learn and apply appropriate techniques, resources, and modern engineering and IT tools, including prediction and modeling, to complex engineering activities with an understanding of the limitations.
<b>PO6</b>	Collaborative and multidisciplinary work - Possess knowledge and understanding of group dynamics, recognize opportunities and contribute positively to collaborative multidisciplinary scientific research, demonstrate a capacity for self-management and teamwork, decision-making based on open-mindedness, objectivity and rational analysis in order to achieve common goals and further the learning of themselves as well as others.
<b>PO7</b>	Project management and finance - Demonstrate knowledge and understanding of engineering and management principles and apply the same to one's own work, as a member and leader in a team, manage projects efficiently in respective disciplines and multidisciplinary environments after consideration of economical and financial factors.
<b>PO8</b>	Communication - Communicate with the engineering community, and with society at large, regarding complex engineering activities confidently and effectively, such as, being able to comprehend and write effective reports

	and design documentation by adhering to appropriate standards, make effective presentations, and give and receive clear instructions.
<b>PO9</b>	Lifelong learning - Recognize the need for and have the preparation and ability to engage in life-long learning independently, with a high level of enthusiasm and commitment to improve knowledge and competence continuously.
<b>PO10</b>	Ethical practices and social responsibility - Acquire professional and intellectual integrity, professional code of conduct, ethics of research and scholarship, consideration of the impact of research outcomes on professional practices and an understanding of responsibility to contribute to the community for sustainable development of society.
<b>PO11</b>	Independent and reflective learning - Observe and examine critically the outcomes of one's actions and make corrective measures subsequently and learn from mistakes without depending on external feedback.

Programme Specific Outcomes (PSO) for the M.Tech. (Computer Science and Data Analytics) Programme

At the end of the M.Tech. in Computer Science and Data Analytics programme, graduates will be able to:

<b>PSO1</b>	Apply the fundamentals of theoretical Computer Science, Systems and Technology to design scalable, efficient, robust, maintainable and secure systems to meet the given functional and non-functional requirements and the financial, social, cultural, ethical and safety constraints imposed.
<b>PSO2</b>	Work in interdisciplinary IT/Research teams and meet the team's objective with an understanding of one's role in the team through innovation, adaptability, inter-personal skills and smart work.
<b>PSO3</b>	Exhibit a drive for learning while keeping in pace with the rapidly evolving Computer Science and its related engineering application domains.

#### Credit Distribution

<b>Category</b>	<b>Category Description</b>	<b>Credits</b>
Professional Major Courses (PCC/DEC)	Professional Major Core Courses (PCC)	<b>18</b>
	Professional Major Core Courses Lab (PCC)	<b>4</b>
	Professional Major Department Electives (DEC)	<b>8</b>
Open/Free Electives(OEC)	Open Elective Courses (OEC) and DAC approved Free Electives (NPTEL, MOOCs, etc.)	<b>2</b>
HSC	Humanities Elective Course	<b>2</b>
PRC	Dissertation	<b>26</b>
	Total Credits	<b>60</b>

## M.Tech. Computer Science and Engineering Course Structure

### I Year M.Tech. Course Structure

S.No.	Course Code	Course Title	L	T	P	Credits	Cat. Code
1	25CS600	Advanced Algorithms	3	-	-	3	PCC
2	25CS601	Foundations of Data Science	3	-	-	3	PCC
3	25CS602	Machine Learning	3	-	-	3	PCC
4	25CS603	Data Science and Machine Learning Lab	3	-	-	3	PCC
5	25CS6xx	Department Elective	-	-	-	2	DEC
6	HSXXXX	Humanities Course	2	-	-	3	HSC
		Total				17	

  

S.No.	Course Code	Course Title	L	T	P	Credits	Cat. Code
1	25CS630	Reinforcement Learning	3	-	-	3	PCC
2	25CS631	Deep Learning for Computer Vision	3	-	-	3	PCC
3	25CS632	Deep Learning for Natural Language Processing	3	-	-	3	PCC
4	25CS633	Deep Learning Lab	-	1	2	2	PCC
5	25CS6xx	Department Elective	-	-	-	6	DEC
6	XXXX	MOOCS/Open Elective	2	-	-	2	OPC
		Total				19	

II Year M.Tech. CSE Course Structure

<b>II – Year: I – Semester</b>										
S.No	Course Code	Course Title	L	T	P	Credits	Cat. Code			
1	25CS698	Dissertation	-	-	26	13	PRC			
		Total				23				
<b>II – Year: II – Semester</b>										
S.No	Course Code	Course Title	L	T	P	Credits	Cat. Code			
1	25CS699	Dissertation	-	-	26	13	PRC			
		Total				21				
<b>II – Year: II – Semester, Department Electives*</b>										
S.No.	Faculty	Course Code	Course Title				L	T	P	Credits
1	CHS	25CS610	Data Warehousing and Data Mining	DE						3
2	KS	25CS611	Graph Algorithms	TCS						3
3	KS	25CS612	Design and Analysis of Parallel Algorithms	TCS						3
4	KS	25CS613	Advanced Data Structures	TCS						3
5	SNB	25CS614	Distributed Computing	DA						3
6	KHB	25CS615	Social Network Analytics	DA						3
7	SNB	25CS616	Information Retrieval and Web Search	DA/AI						3
8	KS	25CS617	Probabilistic Graphical Models	DA						3
9	SNB	25CS618	Generative AI	AI						3
10	KHB	25CS619	Explainable AI	AI						3
11	KS	25CS620	High Performance Computing	DA						3
12	SNB	25CS621	Game Theory							3
13	SNB	25CS622	Privacy Preserving Data Processing	SP						3
14	SNB	25CS623	Big Data Engineering	DA						3
15	CSP	25CS624	AI Ethics and Societal Challenges	AI						2
16	KS	25CS625	Applications of AI in Healthcare	AI						2

17	KS	25CS626	Advanced Computational Statistics	DA				3
18	CSP	25CS627	Computer Forensics & Cyber Security	SP				3

\*Additional titles can be offered as per the availability of faculty after BOS approval of the curriculum for additional titles

## Core courses

<b>25CS600</b>	<b>Advanced Algorithms</b>	<b>PCC</b>	<b>3 – 0 – 0</b>	<b>3 Credits</b>
----------------	----------------------------	------------	------------------	------------------

This course exposes a student to advanced algorithmic design and analysis techniques involving network flows, approximate and fixed-parameter algorithms, computational geometry, cache-efficiency, LP, online, streaming, external and parallel algorithms.

**Course Outcomes:** At the end of the course, the student will be able to:

CO1	Design and analyze algorithms for flow-based and computational geometry problems (Analyze)
CO2	Formulate and solve Linear Programming problems using simplex, interior-point, and ellipsoid algorithms (Analyze)
CO3	Develop and analyze algorithms for NP-hard problems using randomized, approximation, and fixed-parameter techniques (Analyze)
CO4	Construct and evaluate online, streaming, and external-memory algorithms for efficient data processing, including large-scale and real-time scenarios (Analyze)
CO5	Apply and analyze cache-oblivious and cache-efficient algorithms for memory-optimized computing (Analyze)

*Course Articulation Matrix:*

CO	PO/PSO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
CO1		S	S	S	M								S	S	
CO2		S	S	S	M								S	S	
CO3		S	S	S	M								S	S	
CO4		S	S	S	M								S	S	
CO5		S	S	S	M								S	S	

S: Strong correlation, M: Medium correlation, L: Low correlation

### Detailed Syllabus:

**Minimum Spanning Trees:** Fredman and Tarjan’s Algorithm, A linear time randomized algorithm, MST Verification, The Ackermann Function, Matroids

**Linear Programming:** Formulation of Problems as Linear Programs, Duality, Simplex, Interior Point, and Ellipsoid Algorithms.

**Directed Spanning Trees:** Arborescences, Chu-Liu/Edmonds/Bock Algorithm, Linear Programming methods, Matroid intersection

**Online Algorithms:** Ski Rental, Paging, The k-Server Problem.

**Randomized Algorithms:** *Models of Randomized Algorithms:* Classification-Las Vegas, Monte-Carlo (one-sided error, bounded-error and unbounded-error), Classification of Randomized Algorithms for Optimization problems.

*Design Paradigms:* Foiling the Adversary, Abundance of Witnesses, Fingerprinting, Random Sampling, Success Amplification, Random Rounding.

**Approximation Algorithms:** Hardness classes, Greedy Approximation Algorithms, Dynamic Programming and Weakly Polynomial-Time Algorithms, Linear Programming Relaxations, Randomized Rounding, Vertex Cover, Set Cover, Bin Packing and TSP, Approximation Algorithms through SDPs: Max-Cut, Coloring 3-colorable graphs.

**Fixed-Parameter Algorithms:** Coping with NP-Hardness, Parameterized Complexity, Kernelization, Vertex Cover, Edge Clique Cover, Crown decomposition, Expansion lemma, Kernels based on Linear Programming.

**External-Memory Algorithms:** Accounting for the Cost of Accessing Data from Slow Memory, Sorting, B-trees, Buffer Trees, Cache-oblivious Algorithms for indicative problems such as Matrix Multiplication and Binary Search.

**Computational Geometry:** Convex Hull, Line-segment Intersection, Sweep Lines, Voronoi Diagrams, Range Trees, Seidel's Low-dimensional LP Algorithm.

**Streaming Algorithms:** Computing Moments, Distinct and Frequent Elements.

#### **Reading List:**

1. Thomas H. Cormen, Charles E. Leiserson, Ronald L. Rivest and Clifford Stein, Introduction to Algorithms, Second Edition, PHI, 2009.
2. Motwani and Raghavan. *Randomized Algorithms*. Cambridge, UK: Cambridge University Press, 1995. ISBN: 0521474655.
3. Borodin, Allan, and Ran El-Yaniv. *Online Computation and Competitive Analysis*. Cambridge, UK: Cambridge University Press, 1998. ISBN: 0521563925.
4. Berg, Mark de, Marc van Kreveld, Mark Overmars, and Otfried Schwarzkopf. *Computational Geometry: Algorithms and Applications*. New York, NY: Springer-Verlag, 2000. ISBN: 3540656200.
5. VV Vazirani. *Approximation Algorithms*: Springer-Verlag, 2001. ISBN: 3-540-65367-8.
6. Marek Cygan et al., Parameterized Algorithms, Available at: <https://www.mimuw.edu.pl/~malcin/book/parameterized-algorithms.pdf>
7. Lecture Notes by the course instructor.

#### **Papers:**

1. Erik D. Demaine, Cache-Oblivious Algorithms and Data Structures, Available at: <https://erikdemaine.org/papers/BRICS2002/paper.pdf>
2. Gabow, H. N., Galil, Z., Spencer, T., and Tarjan, R. E. Efficient algorithms for finding minimum spanning trees in undirected and directed graphs. *Combinatorics* 6,2 (1986), 109-122.
3. Gabow, H. N., and Stallman, M. Efficient algorithms for the parity and intersection problems on graphic matroids. In *Automata, Languages, and Programming, 12th Colloquium, Lecture Notes in Computer Science, Vol. 194*, W. Brauer, Ed. Springer-Verlag, New York, 1985, pp. 210-220. 8.

4. Gabow, H. N., and Tarjan, R. E. Efficient algorithms for a family of matroid intersection problems. *J. Algorithms* 5, 1 (Mar. 1984), 80-131.
5. Y. J. Chu and T. H. Liu, "On the shortest arborescence of a directed graph", *Science Sinica*, v.14, 1965, pp.1396-1400.
6. F. Bock, An algorithm to construct a minimum spanning tree in a directed network, *Developments in Operations Research*, Gordon and Breach, NY, 1971, pp. 29-44.

<b>25CS601</b>	<b>Foundations of Data Science</b>	<b>PCC</b>	<b>3 – 0 – 0</b>	<b>3 Credits</b>
----------------	------------------------------------	------------	------------------	------------------

Students of this course upon completion will learn how to solve standard distributed computing problems. Students will also learn consensus algorithms. Further students shall also learn designing widely used algorithms for map-reduce/spark paradigms of distributed computing.

Course Outcomes: At the end of the course, the student will be able to:

<b>CO1</b>	Construction, analysis and evaluation of learning objectives for Regression (Analyze)
<b>CO2</b>	Analyze efficiency large scale matrix factorizations for different data science scenarios (Analyze)
<b>CO3</b>	Apply basic machine learning algorithms (Linear Regression, k-Nearest Neighbors (k-NN), k-means, Naive Bayes) for predictive modeling (Apply)
<b>CO4</b>	Designing Recommender System for different applications. (Analyze)
<b>CO5</b>	Designing feature reduction and clustering objectives using PCA. K-Means, Spectral Clustering (Apply)

Course Articulation Matrix:

PO/ PSO  CO	Program Outcomes												Program Specific Outcomes		
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
<b>CO1</b>	S	S	M										S	M	L
<b>CO2</b>	S	M	L										S	L	L
<b>CO3</b>	S	S	M										S	M	L
<b>CO4</b>	S	S	M										S	M	L
<b>CO5</b>	S	S	M										S	M	L

S: Strong correlation, M: Medium correlation, L: Low correlation

**Detailed Syllabus:** Basics of Optimization in Data Science: Linear Programming Objectives, Primal-Dual Methods, Quadratic Programming, Convex Optimization, Gradient Descent, Adaptive Learning Rate, Quasi Newton's method, Constrained Optimization, KKT Conditions for Optimization Problems

Probability theory including random variables, conditional probability, Bayes law, concentration of measure, linear algebra including eigenvalues, norms, elementary spectral graph theory.

Regression: Least Squares Objective for Multiple Linear Regression, Gauss-Markov Theorem, Statistical Tests, Weighted Least Squares, Box-Cox Transformation, Polynomial & Spline Regression, Ridge Regression, Bias-Variance Tradeoff, Subset Selection, LASSO, Adaptive LASSO, Elastic Net, Dantzig Selector, SLOPE and sorted penalties.

Matrix Factorizations used in Data Science:

Cholesky Decomposition and QR Factorization: Concepts, Applications

Eigen Vector Decomposition, Solving Large Scale Value Problems using Lanczos Method, Arnoldi's Iteration

SVD: Geometric Interpretation, Best Rank-K Approximation using SVD, Power Method for SVD, Efficient methods for SVD, Applications of SVD

PCA: PCA learning objective: Application of PCA for dimensionality reduction

Recommendation Systems: Collaborative Filtering using gradient Descent and Alternating Least Squares for recommender systems.

Classification: GLM methods for classification, SVM, Naïve Bayes, Evaluation of classification methods – Confusion matrix, Students T-tests and ROC curves, Feature Selection for Classification

Clustering: Choosing distance metrics – Different clustering approaches – hierarchical agglomerative clustering, k-means (Lloyd's algorithm), EM Algorithm for clustering, Spectral Clustering: Graph Laplacian, Properties of Graph Laplacian, Application of Spectral Clustering for Transfer-learning.

Link Analysis: Random Walks, Markov Chains, Stationary Distribution, Metro Polis Hastings Algorithm, Gibbs Sampling, Convergence of Random Walks on Undirected Graphs, Page Rank, HITS, combating spam, personalized page rank

High Dimensional Space High dimensional sphere, volumes of high dimensional solids, gaussians in high dimension, high dimensional point sets, Johnson-Lindenstrauss theorem.

### **Reading List:**

1. Avrim Blum, John Hopcroft, and Ravindran Kannan: Foundations of Data Science Cambridge University Press, 2020
2. Jianqing Fan, Runze Li, Cun-Hui Zhang, Hui Zou Statistical Foundations of Data Science, CRC Press 2020
3. Jure Leskovec, Anand Rajaraman, Jeff Ullman: Mining of Massive Datasets, Cambridge University Press, 2016

4. G. Strang. Introduction to Linear Algebra, Wellesley-Cambridge Press, Fifth edition, USA, 2016
5. Relevant Research articles shared by the instructor

<b>25CS602</b>	<b>Machine Learning</b>	<b>PCC</b>	<b>3 – 0 – 0</b>	<b>3 Credits</b>
----------------	-------------------------	------------	------------------	------------------

**Course Outcomes:** At the end of the course the student will be able to:

<b>CO1</b>	Design learning objectives for classification and regression problems
<b>CO2</b>	Design feature selection strategies using PCA/ SVD/ Spectral Clustering/EM
<b>CO3</b>	Design Sequence Learning Models using generative/discriminative approaches
<b>CO4</b>	Design neural network to solve classification and function approximation problems
<b>CO5</b>	Design efficient deep neural networks

### Course Articulation Matrix

CO \ PO/ PSO	Program Outcomes												Program Specific Outcomes		
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
<b>CO1</b>	M	S	S	M	M	-	S	-	-	S	-	-	M	S	M
<b>CO2</b>	M	S	M	M	M	-	S	-	-	S	-	-	M	M	M
<b>CO3</b>	M	S	S	M	M	-	S	-	-	S	-	-	M	M	M
<b>CO4</b>	M	M	M	M	M	S	M	-	-	S	S	-	M	M	L
<b>CO5</b>	M	S	S	M	M	-	S	-	-	S	-	-	M	M	M

S: Strong correlation, M: Medium correlation, L: Low correlation

### Detailed syllabus:

**Review of Probability and Statistics:** Gaussian Distribution, Poisson Distribution, Exponential Family Distributions, Conditional Multivariate Gaussian, Marginalization, Conjugacy

**Introduction:** Bayesian Learning – Bayes theorem, Bayes Optimal Classifier

**Regression:** Multi-Variate Linear Regression, Method of Least Squares, Model Selection, Evaluation of Regression Models, Regularization (Lasso & Ridge), Alternating Least Squares for solving recommendation systems

**Classification:** Likelihood vs Loss minimization for classifiers, Naïve Bayes, Multi-Class Logistic Regression, Regularization in Bayesian and Loss Minimization Scenarios, Gradient Descent vs Quasi-Newton methods for scaling the optimization

**Unsupervised Learning:** K-Means Clustering, Expectation Maximization for missing value problems, EM for clustering, EM for Gaussian Mixture Models, Spectral Clustering

**PCA for feature selection,** SVD, Spectral Clustering for dimensionality reduction, EM for PLSA

**Kernal Machines:** Support Vector Regression and Classification, hard-margin vs soft-margin classifiers, dual sparsity in SVMs, Multi-Class SVM, large-scale SVM learning

**Computational Learning Theory** – Sample Complexity for Finite Hypothesis spaces, Sample Complexity for Infinite Hypothesis spaces, The Mistake Bound Model of Learning;

**Sequence Labelling:** Hidden Markov Models, Parameter Estimation using EM, Conditional Random Fields

**Artificial Neural Networks** – Perceptrons, Multilayer networks, Activation Functions, Derivation of backpropagation rule-Backpropagation Algorithm- Dropout, Batch Normalization, Layer Norm, Recurrent Neural Network, Vanishing and Exploding Gradients and Gated Neural Networks

#### **Reading List:**

1. C Bishop – Pattern Recognition and Machine Learning – Springer, 2006.
2. Ian Goodfellow, Yoshua Bengio, Aaron Courville – Deep Learning, The MIT Press Cambridge, Massachusetts, London, England, 2016
3. Tom.M.Mitchell, Machine Learning, McGraw Hill International Edition, 1997.

25CS603	Data Science and Machine Learning Lab	PCC	3-0-0	3 Credits
---------	---------------------------------------	-----	-------	-----------

**Course Outcomes:** At the end of the course the student will be able to:

CO1	Design and implement algorithm using least means square, collaborative filtering
CO2	Design and implement classifiers using Naïve Bayes, Logistic Regression, SVM, Neural Networks
CO3	Design and implement EM for clustering, GMM, Sequence Learning.
CO4	Design and implement feature selection using PCA, SVD
CO5	Design and implement sequence labellers using HMM, CRF and LSTM

### Course Articulation Matrix

PO/ PSO  CO	Program Outcomes												Program Specific Outcomes		
	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3
CO1	M	S	S	M	M	-	S	-	-	S	-	-	M	S	M
CO2	M	S	M	M	M	-	S	-	-	S	-	-	M	S	M
CO3	M	S	S	M	M	-	S	-	-	S	-	-	S	S	S
CO4	M	M	S	M	M	S	M	-	-	S	S	-	M	M	M
CO5	M	M	S	M	M	S	M	-	-	S	S	-	M	M	M

S: Strong correlation, M: Medium correlation, L: Low correlation

### Detailed Syllabus:

**Case Studies:** Spam detection, stock-price prediction, whether forecast, face recognition, digit recognition,

**Regression:** Least Squares for regression, evaluation and model selection for regression, ALS for collaborative filtering, SVR

**Classification:** Design of Classifiers using Naïve Bayes, Logistic Regression, SVM and Neural Networks, Implementation of backpropagation for softmax, neural networks and weak supervision, Evaluation of Classifiers, Regularization, Error analysis through matplotlib, correlation plots, t-sne, heatmaps

Design of Classifiers for Semi-Supervised, Transfer Learning, EM for GMM,

**Feature Selection:** Feature Selection using PCA, Dimension reduction using SVD, Document Modelling through PLSA

**Sequence Labelling:** Design a sequence labellers using HMM, CRF, RNN and LSTM

Design a Convolutional network for handwritten character recognition problem for A to Z and 0 to 9 digits.

**Reading List:**

1. Tom M. Mitchell, "Machine Learning", Mc Graw Hill, Indian Edition, 2017.
2. Ethem Alpaydin, "Introduction to Machine Learning", MIT Press, Fourth Edition, 2020.
3. Sebastain Raschka, "Python Machine Learning", Packt publishing (open source).
4. M.A. Bramer, Logic Programming with PROLOG, Springer

<b>25CS630</b>	<b>REINFORCEMENT LEARNING</b>	<b>PCC</b>	<b>3 – 0 – 0</b>	<b>3 Credits</b>
----------------	-------------------------------	------------	------------------	------------------

This course introduces students to reinforcement learning techniques applicable in situations where trial and error attempts are required when explicit control signals are unavailable.

**Course Outcomes:** At the end of the course, the student will be able to:

CO1	Infer whether a given problem is amenable to be solved using RL as opposed to non-interactive vanilla ML and AI techniques. (Analyze)
CO2	Formulate a given problem as a RL problem with a specification of state space, action space, dynamics and reward model. (Analyze)
CO3	Infer which RL algorithm is best suited for addressing a given problem with justifications. (Analyze)
CO4	Implement and evaluate RL algorithms based on metrics such as regret, sample complexity, computational complexity, empirical performance, and convergence. (Analyze)
CO5	Infer suitable techniques for addressing the exploration vs. exploitation trade-off in terms of performance, scalability, complexity of implementation, and theoretical guarantees. (Analyze)

### Course Articulation Matrix

PO CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
CO1	S	S	S	M	M							S	S	S
CO2	S	S	S	M	M							S	S	S
CO3	S	S	S	M	M							S	S	S
CO4	S	S	S	M	M							S	S	S
CO5	S	S	S	M	M							S	S	S

S: Strong correlation, M: Medium correlation, L: Low correlation

### Detailed Syllabus:

**Introduction to Reinforcement Learning:** Examples, Elements of RL, Limitations and Scope.

### Tabular Solution Methods:

**Multi-armed Bandits:** A k-armed bandit problem, Action-value methods, tracking a non-stationary problem, Optimistic initial values, Upper Confidence Bound Action selection, Gradient bandit algorithms, Contextual bandits.

**Finite Markov Decision Processes:** the agent-environment interface, goals and rewards, returns and episodes, Unified notation for episodic and continuous tasks, policies and value functions, optimality and approximation

**Dynamic Programming:** Policy evaluation, policy improvement, policy iteration, value iteration, asynchronous dynamic programming, generalized policy iteration, efficiency of dynamic programming.

**Monte Carlo methods:** Prediction, estimation of action values, Control and control without exploring starts, Off-policy prediction through importance sampling, incremental implementation, Off-policy MC control, Discounting-aware importance sampling, Per-decision importance sampling.

**Temporal Difference Learning:** prediction, advantages, optimality of TD(0), Sarsa: On-policy TD control, Q-learning: off-policy TD control, Expected Sarsa, Maximization bias and double learning, Games, after-states and special cases.

### **n-Step bootstrapping, Techniques for planning and learning with tabular methods**

**Approximate-Solution methods:** On-policy prediction with approximation, On-policy control with approximation, Off-policy methods with approximation, Eligibility traces, Policy gradient methods.

**Applications and Case-studies:** TD-Gammon, Samuel's Checker Player, Watson's daily double wagering, Optimizing memory control, Human-level video game play, AlphaGo, Personalized web services, Thermal soaring.

### **Reading List:**

1. Sutton and Barto, Reinforcement Learning: An Introduction, 2nd Edition, MIT Press, 2018.
2. Marco Wiering and Martijn van Otterlo, Reinforcement Learning: State-of-the-Art, Springer, 2012.
3. Stuart J. Russell and Peter Norvig, Artificial Intelligence: A Modern Approach, fourth edition, Pearson, 2022.

25CS631	Deep Learning for Computer Vision	PCC	3 – 0 – 0	3 Credits
---------	-----------------------------------	-----	-----------	-----------

**Course Outcomes:** At the end of the course, the student will be able to:

<b>CO1</b>	Understand fundamental concepts of image processing and feature extraction techniques.
<b>CO2</b>	Application of deep learning techniques, including neural networks and optimization methods.
<b>CO3</b>	Convolutional neural networks (CNNs) are analyzed for classification, detection, and segmentation.
<b>CO4</b>	Evaluate attention-based models and transformers for vision applications
<b>CO5</b>	Development of generative and vision-language models for image synthesis and representation learning.

**Course Articulation Matrix:**

PO/ PSO	Program Outcomes												Program Specific Outcomes		
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
<b>CO1</b>	S	S	M	L									S	L	L
<b>CO2</b>	S	M	M	L									S	M	L
<b>CO3</b>	S	S	M	L									S	M	L
<b>CO4</b>	S	S	M	L									S	M	L
<b>CO5</b>	S	S	S	M									S	S	S

S: Strong correlation, M: Medium correlation, L: Low correlation

**Detailed Syllabus:**

**Introduction:** Introduction, Image Formation, Image Representation, Linear Filtering, Correlation, Convolution, Edge Detection, From Edges to Blobs and Corners, Scale Space, Image Pyramids and Filter Banks, SIFT and Variants, Human Visual System.

**Neural Networks:** A Review, linear classifiers, Stochastic gradient descent, Feedforward Neural Networks and Backpropagation, Gradient Descent and Variants, Regularization in Neural Networks, Improving Training of Neural Networks.

## **Convolutional Neural Networks**

Introduction, Backpropagation in CNNs, CNN Architecture for Image Classification, Evolution of CNN Architectures: VGG, Inception, ResNets, ResNet Variants, MobileNet, EfficientNet, Finetuning CNNs, Visualizing CNNs, CNNs for Object Detection: Two-stage Models, CNNs for Object Detection: Single-stage Models, CNNs for Segmentation, Camera Calibration, Epipolar Geometry, Structure from Motion. Recurrent Neural Networks: Introduction.

## **Attention Models and Transformers**

**Attention in Vision Models:** An Introduction, Soft and Hard Attention: Image Captioning, Self-Attention and Transformers, From Transformers to Vision Transformers, Transformers for Detection, Transformers for Segmentation.

### **Deep Generative Models**

**Deep Generative Models:** An Introduction, Generative Adversarial Networks, GAN Hacks and Improvements, Variational Autoencoders and Disentanglement, Introduction to Diffusion Models: DDPMs, Classifier and Classifier-Free Diffusion Guidance, Text-conditioned Diffusion Models, Under the Hood: Sampling, Prediction Space, Noise Schedules, Architectures.

## **Vision-Language Models and Recent Developments**

**Self-Supervised Learning:** SimCLR, Contrastive Learning, Vision-Language Models, CLIP, BLIP, BLIP-2.

### **Reading List:**

- 1) Ian Goodfellow, Yoshua Bengio, Aaron Courville, Deep Learning, 2016
- 2) Michael Nielsen, Neural Networks and Deep Learning, 2016
- 3) Yoshua Bengio, Learning Deep Architectures for AI, 2009
- 4) Richard Szeliski, Computer Vision: Algorithms and Applications, 2010.
- 5) Simon Prince, Computer Vision: Models, Learning, and Inference, 2012.
- 6) David Forsyth, Jean Ponce, Computer Vision: A Modern Approach, 2002.
- 7) Deep learning for Computer vision NPTEL: IIT Hyderabad
- 8) [https://onlinecourses.nptel.ac.in/noc24\\_cs89/preview](https://onlinecourses.nptel.ac.in/noc24_cs89/preview)

25CS632	Deep Learning for Natural Language Processing	PCC	3 – 0 – 0	3 Credits
---------	---	-----	-----------	-----------

**Course Outcomes:** At the end of the course the student will be able to:

CO1	Implement and critically evaluate word and sentence representation techniques using static and contextual embeddings for semantic understanding of language. <i>(Apply, Analyze, Evaluate)</i>
CO2	Design and compare recurrent and attention-based deep learning models for solving sequence modeling tasks such as language modeling, machine translation, and question answering. <i>(Create, Analyze, Evaluate)</i>
CO3	Develop and fine-tune large pre-trained language models (e.g., BERT, RoBERTa, GPT) for complex downstream tasks with domain-specific adaptation. <i>(Apply, Create, Evaluate)</i>
CO4	Critically analyze the limitations of deep learning models in NLP with respect to generalization, fairness, interpretability, and data efficiency. <i>(Analyze, Evaluate)</i>
CO5	Formulate and investigate novel research problems in NLP using state-of-the-art deep learning approaches, demonstrating the ability to synthesize literature and build effective solutions. <i>(Evaluate, Create)</i>

**Course Articulation Matrix:**

PO/ PSO CO	P O 1	P O 2	P O 3	P O 4	P O 5	P O 6	P O 7	P O 8	P O 9	P O 10	P O 11	P O 12	P S O 1	P S O 2	P S O 3
CO1	S	M	S	S	M	L							S	S	S
CO2	S	M	S	S	M	L							S	S	S
CO3	S	M	S	S	M	L							S	S	S
CO4	S	M	S	S	M	L							S	S	S

S: Strong correlation, M: Medium correlation, L: Low correlation

**Detailed syllabus:**

**N-Grams Language Models:** N-Grams, Evaluating Language Models: Training and Test Sets, Evaluating Language Models: Perplexity, Sampling sentences from a language model, Generalizing vs. overfitting the training set, Smoothing, Interpolation, and Backoff, Perplexity's Relation to Entropy

**Text Classification:** Naive Bayes Classifiers, Training the Naive Bayes Classifier,

Optimizing for Sentiment Analysis, Naive Bayes for other text classification tasks, Naive Bayes as a Language Model Evaluation: Precision, Recall, F-measure, Test sets and Cross-validation, Statistical Significance Testing, Avoiding Harms in Classification, Classification with Logistic Regression, Multinomial logistic regression, Interpreting models

**Vector Semantics and Embeddings:** Words and Vectors, Cosine for measuring similarity, TF-IDF: Weighing terms in the vector, Pointwise Mutual Information (PMI), Applications of the tf-idf or PPMI vector models, Word2vec, Visualizing Embeddings, Semantic properties of embeddings, Bias and Embeddings, Evaluating Vector Models,

**RRNs and LSTMs:** Recurrent Neural Networks, RNNs as Language Models, RNNs for other NLP tasks, Stacked and Bidirectional RNN architectures, The LSTM, Summary: Common RNN NLP Architectures, The Encoder-Decoder Model with RNNs, Attention

**The Transformer:** Attention, Transformer Blocks, Parallelizing computation using a single matrix, The input: embeddings for token and position, The Language Modeling Head

**Large Language Models:** Large Language Models with Transformers, Sampling for LLM Generation, Pretraining Large Language Models, Evaluating Large Language Models, Dealing with Scale, Potential Harms from Language Models

**Masked Language Models:** Bidirectional Transformer Encoders, Training Bidirectional Encoders, Contextual Embeddings, Fine-Tuning for Classification, Fine-Tuning for Sequence Labelling: Named Entity Recognition

**Model Alignment, Prompting, and In-Context Learning:** Prompting, Post-training and Model Alignment, Model Alignment: Instruction Tuning, Chain-of-Thought Prompting, Automatic Prompt Optimization, Evaluating Prompted Language Models, Model Alignment with Human Preferences: RLHF and DPO

### Reading List:

1. Speech and Language Processing, Dan Jurafsky and James H. Martin.
2. Deep Learning Ian Goodfellow, Yoshua Bengio, and Aaron Courville
3. Natural Language Processing with Transformers Lewis Tunstall, Leandro von Werra, and Thomas Wolf

25CS633	Deep Learning Lab	PCC	0 – 1 – 2	2 Credits
---------	-------------------	-----	-----------	-----------

**Course Outcomes:** At the end of the course the student will be able to:

<b>CO1</b>	Implement and evaluate deep learning models for computer vision tasks using convolutional neural networks (CNNs). ( <i>Apply, Analyze</i> )
<b>CO2</b>	Design and train sequence-based models such as RNNs, LSTMs, and Transformers for natural language processing tasks. ( <i>Apply, Create</i> )
<b>CO3</b>	Apply transfer learning and fine-tuning techniques to adapt pre-trained models for domain-specific vision and language applications. ( <i>Apply, Analyze</i> )
<b>CO4</b>	Develop and assess generative models such as GANs and autoencoders for image and text generation tasks. ( <i>Create, Analyze</i> )
<b>CO5</b>	Evaluate the performance of deep learning models using appropriate metrics and optimize them through regularization, tuning, and efficient training strategies. ( <i>Analyze, Evaluate</i> )

**Course Articulation Matrix:**

PO/ PSO CO	P O 1	P O 2	P O 3	P O 4	P O 5	P O 6	P O 7	P O 8	P O 9	P O 10	P O 11	P O 12	P S O 1	P S O 2	P S O 3
<b>CO1</b>	S	M	S	S		M							M	M	M
<b>CO2</b>	S	M	S	S		M							M	M	M
<b>CO3</b>	S	M	S	S		M							M	M	M
<b>CO4</b>	S	M	S	S		M							M	M	M
<b>CO5</b>	S	M	S	S		M							M	M	M

S: Strong correlation, M: Medium correlation, L: Low correlation

**List of Experiments:**

1. Develop a text classification system using Naive Bayes, Logistic Regression and Multinomial Logistic Regression
2. Develop a Neural Language Model
3. Develop a RNN based model for sequence labeling task
4. Develop a machine translation model using Attention and advanced RNNs (LSTM, GRU)
5. Develop a Transformer model for question answering

6. Develop a RAG based Chatbot using LLMs for answering questions on collection of documents
7. Implement image classification using given CNN architecture on the CIFAR-10 dataset.
8. Develop an object detection model using models such as YOLOv5 or Faster R-CNN
9. Build an image segmentation model using U-Net on medical imaging datasets.
10. Apply transfer learning using a pre-trained CNN (like ResNet or EfficientNet) on a custom image dataset.
11. Fine-tune CLIP or Vision Transformer (ViT) for a multi-modal classification task.
12. Implement a Variational Autoencoder (VAE) to generate synthetic handwritten digits.
13. Build a Generative Adversarial Network (GAN) to synthesize face images (e.g., using CelebA dataset).
14. Generate fake news headlines using a GPT-style language model or LSTM text generator.

**Reading List:**

1. Speech and Language Processing, Dan Jurafsky and James H. Martin.
2. Deep Learning Ian Goodfellow, Yoshua Bengio, and Aaron Courville
3. Natural Language Processing with Transformers Lewis Tunstall, Leandro von Werra, and Thomas Wolf

M.Tech. Department Electives Courses Syllabus

<b>25CS5610</b>	<b>Data Warehousing and Data Mining</b>	<b>DEC</b>	<b>3 – 0 – 0</b>	<b>3 Credits</b>
-----------------	---	------------	------------------	------------------

**Course Outcomes:** At the end of the course, the student will be able to:

<b>CO1</b>	Design and optimize data warehouse schemas, perform OLAP operations, and implement ETL pipelines to support analytical processing of large-scale data. <i>(Apply, Analyze)</i>
<b>CO2</b>	Implement and evaluate data preprocessing techniques and apply classical data mining methods such as association rule mining, classification, and clustering to discover patterns in structured data. <i>(Apply, Analyze, Evaluate)</i>
<b>CO3</b>	Develop and analyze advanced frequent pattern mining algorithms, including constraint-based and closed/maximal pattern mining, for discovering informative patterns efficiently. <i>(Analyze, Evaluate)</i>
<b>CO4</b>	Apply and compare graph-based frequent pattern mining techniques to extract substructures from complex data such as chemical compounds, social networks, and knowledge graphs. <i>(Apply, Analyze, Evaluate)</i>
<b>CO5</b>	Investigate real-world problems by formulating and solving data mining tasks on large datasets using appropriate models, mining strategies, and evaluation metrics. <i>(Evaluate, Create)</i>

**Course Articulation Matrix:**

PO/ PSO  CO	Program Outcomes												Program Specific Outcomes		
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO 1	PSO 2	PSO 3
CO1	S	S	S	M	M	L							S	S	S
CO2	S	S	S	M	M	L							S	S	S
CO3	S	S	S	M	M	L							S	S	S
CO4	S	S	S	M	M	L							S	S	S
CO5	S	S	S	M	M	L							S	S	S

S: Strong correlation, M: Medium correlation, L: Low correlation

**Detailed Syllabus:**

**Introduction:** Operational Databases, Data Warehouses, Building Data Warehouses, Using Data Warehouses

**Star Schema, Creating Facts and Dimensions:** Count Function, Average in the Fact, Outer Join, Creating Temporary Dimension Tables, Creating Temporary Tables in the Operational Database

**Hierarchies:** Hierarchy vs. Non-hierarchy, Hierarchy Versus Multiple Independent Dimensions, Separate vs. Combined Dimension, Linked Dimensions, Hierarchy Design Considerations, Bridge Tables, Temporal Data Warehousing Determinant Dimensions, Pivoted Fact Table, Junk Dimensions: Non-junk Dimension, Simple Join Queries, Nested Queries Dimension Keys, One- Attribute Dimensions

**Multi-Fact Star Schemas:** Multi-Fact or Single Fact with Multiple Fact Measure, Mutually Exclusive Star Schemas, Different Granularity Multi-Fact, Slicing a Fact, Multi-Input Operational Databases

**Data Mining:** Introduction, Basic concepts of Association Rule Mining, Frequent Item set mining, Mining various kinds of association rules, Classification by decision tree induction, Bayesian Classification, Rule-based Classification, Classification Back-propagation, Associative Classification, Lazy Learners. Clustering methods, Data Objects and Attribute Types, Basic Statistical Descriptions of Data, Measuring Data Similarity and Dissimilarity Partition based Clustering, Hierarchical based clustering, Density based clustering.

**Frequent Subgraph Mining:** Graph-based Substructure Pattern mining, FSG (Frequent Subgraph mining), Molecular Fragment Miner, Closed and Maximal Sub graph mining Compression based Mining, Discriminative Subgraph Mining, Constraint based Mining

**Advanced Concepts in Data Mining:** Mining imbalanced datasets and rare patterns, Mining complex data types: sequence, time-series, spatial, graph, fraud detection, recommender systems, social network analysis, Ethical, legal, and privacy issues. Scalability of datamining algorithms for large scale datasets

### **Reading List:**

1. Taniar, David, and Wenny Rahayu. Data warehousing and analytics: fueling the data engine. Springer Nature, 2022.
2. Inmon, William H., Derek Strauss, and Genia Neushloss. DW 2.0: The architecture for the next generation of data warehousing. Elsevier, 2010.
3. Grossmann, Wilfried, and Stefanie Rinderle-Ma. "Fundamentals of business intelligence". (2015): 348.
4. Sherif, Ahmed. Practical business intelligence. Packt Publishing Ltd, 2016.
5. Van Der Lans, Rick. Data Virtualization for business intelligence systems: revolutionizing data integration for data warehouses. Elsevier, 2012.

### **References:**

<https://www.coursera.org/learn/business-intelligence-data-warehousing>

<https://www.coursera.org/learn/data-warehousing-business-intelligence#modules>

BR1505297627176020D02\_Big\_data\_analytics\_IITKGP.pdf

[https://archive.nptel.ac.in/content/syllabus\\_pdf/106106361.pdf](https://archive.nptel.ac.in/content/syllabus_pdf/106106361.pdf)

<http://www.cs.iit.edu/~glavic/cs520/2022-spring/syllabus/>

[https://onlinecourses.nptel.ac.in/noc24\\_cs65/preview](https://onlinecourses.nptel.ac.in/noc24_cs65/preview)

<http://www.facweb.iitkgp.ac.in/~shamik/autumn2011/dwdm/dwdmautumn2011coursedtls.html>

<b>25CS611</b>	<b>Graph Algorithms</b>	<b>DEC</b>	<b>3 – 0 – 0</b>	<b>3 Credits</b>
----------------	-------------------------	------------	------------------	------------------

Students of this course upon completion will learn how to model problems as graph-based problems and to solve the problem. Students will also learn standard graph algorithms and notions in this course across a spectrum of problems from the conventional spanning trees, network flows to the contemporary social network analytics.

**Course Outcomes:** At the end of the course, the student will be able to:

<b>CO1</b>	Formulate a given problem as a suitable graph-theoretic problem. (Analyze)
<b>CO2</b>	Construct efficient algorithms for standard graph-theoretic problems with an analysis of their time and space requirements. (Analyze)
<b>CO3</b>	Construct an algorithm to solve a given graph-theoretic problem by applying a standard graph theoretic algorithm in isolation or by a combining multiple standard algorithms in a pipeline. (Analyze)
<b>CO4</b>	Analyze the properties of a given social network using standard graph-theoretic notions and algorithms. (Analyze)
<b>CO5</b>	Construct and analyze algorithms for solving network-flow-based problems with a comprehension of the relationship between cuts and flows. (Analyze)

### Course Articulation Matrix

CO \ PO	PO													
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
<b>CO1</b>	S	S	M	M								S	S	S
<b>CO2</b>	S	S	M	M								S	S	S
<b>CO3</b>	S	S	M	M								S	S	S
<b>CO4</b>	S	S	M	M								S	S	S
<b>CO5</b>	S	S	M	M								S	S	S

S: Strong correlation, M: Medium correlation, L: Low correlation

### Detailed Syllabus:

Basic definitions and notions in Graph theory, Representation of graphs – a review, Motivational examples for graphs: Web search engines and page rank algorithm, Web crawlers and social networks.

Strongly Connected Components, Biconnected components, Tarjan's algorithm, Invasion percolation with a case study on simulating river networks, Spanning Trees, Prim's algorithm, Kruskal's algorithm – a review, Prim-Dijkstra-Jarnik algorithm, Boruvka's algorithm.

Review: DFS-BFS algorithm, Applications of DFS-BFS, Directed Acyclic Graphs, Topological ordering, Algorithms to find single source shortest paths, All pair shortest paths.

Johnson's algorithm, Suurballe's Algorithm, Case studies on Map path planning, Landmark-based distance estimation, Widest path problems.

Eulerian graphs and standard results relating to characterization. Hamiltonian graphs, Dirac theorem, Chavathal theorem, closure of graph. Non-Hamiltonian graph with maximum number of edges. Self-centered graphs and related theorems.

Graph Coloring, Chromatic number, Greedy heuristic for Graph coloring, Interval graphs, Perfect graphs, Chordal graphs.

Planar graphs, Euler's formula, maximum number of edges in a planar graph. Five colour theorem. Graph Isomorphism.

Travelling Salesperson Problem, MST-doubling heuristic for finding TSP, Christofide's algorithm, Dynamic programming formulation for TSP.

Matching, Bipartite graphs, Hopcroft-Karp algorithm, Finding Vertex covers and Independent Sets using matching, Stable matching, Gale-Shapley algorithm for Stable matching.

Max flow-Min Cut theorem, Ford-Fulkerson's algorithm, Case Study: Bipartite maximum matching as a flow problem.

Social network analytics: Erdős numbers, the Oracle of Bacon, and the Milgram small-world experiment, Properties – sparsity and power law, centrality, degeneracy and k-cores, Network models - Erdős-Rényi model, ERGM, random graphs with fixed degrees, Barabási-Albert model, Kleinberg's model, Network Cliques, Bron-Kerbosch algorithm.

Case-studies from competitive programming venues.

### **Reading List:**

1. Douglas B. West, Introduction to Graph Theory, Second Edition, Pearson, 2000.
2. M. C. Golumbic, Algorithmic Graph Theory and Perfect Graphs, First Edition, Academic Press, 1997.
3. R. J. Wilson and J. J. Watkins, Graphs: An Introductory Approach, First Edition, Wiley, 1990.

<b>25CS612</b>	<b>Design and Analysis of Parallel Algorithms</b>	<b>DEC</b>	<b>3 – 0 – 0</b>	<b>3 Credits</b>
----------------	---	------------	------------------	------------------

Students of this course upon completion will learn design and analysis principles for constructing scalable parallel algorithms across various Flynn’s taxonomy of parallel computers. The course deals with problems from both numerical and non-numerical natures such as linear algebraic problems, graph theoretic problems, discrete optimization search related problems, and dynamic programming algorithms.

**Course Outcomes:** At the end of the course, the student will be able to:

CO1	Analyze the resource requirements of parallel algorithms with a comprehension of the parallel computer features and the underlying type of interconnection network. (Analyze)
CO2	Infer the most suitable parallel algorithm among a set of candidate algorithms to solve a given problem based on metrics such as cost, speed-up, efficiency and scalability. (Analyze)
CO3	Construct parallel algorithms for solving numerical problems from domains like Linear Algebra having representative problems such as matrix multiplication, transpose, and direct and iterative methods for solving systems of linear equations. (Apply)
CO4	Construct parallel algorithms for solving problems from non-numerical domains like graph theory, search in discrete optimization, and monadic and polyadic dynamic programming problems. (Apply)
CO5	Construct implementations of parallel algorithms on top of message-passing based parallel programming frameworks like Message Passing Interface. (Apply).

### Course Articulation Matrix

CO \ PO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
	CO1	S	S	M									S	M
CO2	S	S	M									S	M	M
CO3	S	M	L									S	M	M
CO4	S	M	L									S	M	M
CO5	S	M	L									S	S	M

S: Strong correlation, M: Medium correlation, L: Low correlation

### Detailed Syllabus:

**Introduction:** The need for parallel computers, Models of computation (SISD, MISD, SIMD, MIMD), Analyzing algorithms, Expressing Algorithms.

**Selection and Merging:** Introduction – Selection and Merging, The problem and a lower bound, A Sequential algorithm, Desirable properties for parallel algorithms, Broadcasting a datum, Computing

All Sums, An algorithm for parallel selection, A network for merging, Merging on CREW model, Merging on the EREW model.

**Sorting:** Introduction, A network for sorting, Sorting on a linear array, Sorting on the CRCW model, Sorting on CREW model, Sorting on the EREW model.

**Searching:** Introduction, Searching a sorted sequence, EREW, CREW, CRCW searching, Searching a random sequence, Searching on SM SIMD computers, Searching on a Tree, Searching on a Mesh.

**Performance Analysis:** Amdahl's Law, Gustafson Barsis's law- Karp Flatt metric- Iso efficiency metric.

**Numerical problems and implementation:** Matrix operations, Transposition, Mesh Transpose, Shuffle Transpose, EREW Transpose, Matrix by Matrix multiplication, Mesh multiplication, Cube multiplication, CRCW multiplication, Matrix by Vector multiplication, Linear Array multiplication, Tree multiplication, Convolution, Solving systems of linear equations (SIMD/MIMD), Finding roots of non-linear equations.

**Graph Theory:** connectivity matrix computation, finding connected components, computing all-pair shortest paths, minimum spanning trees, Traversals: Parallelizing breadth first and depth first searches.

**Optimization problems:** Job sequencing with deadlines, Knapsack problem.

**MPI primitives** with case-studies on implementation of parallel algorithms.

### Reading List:

1. S.G. Akl, "The design and analysis of parallel algorithms", Prentice Hall of India, 1989.
2. Michael Jay Quinn, "Parallel programming in C with MPI and OpenMP", McGraw-Hill Higher Education, 2004.
3. S. Lakshminarayanan and S.K. Dhall, "Analysis and design of parallel algorithms – Arithmetic and Matrix problems", McGraw Hill, 1990.

<b>25CS613</b>	<b>Advanced Data Structures</b>	<b>DEC</b>	<b>3 – 0 – 0</b>	<b>3 Credits</b>
----------------	---------------------------------	------------	------------------	------------------

This course exposes a student to data structures that support persistence, temporality, dynamic optimality, cache-efficiency and for designing optimal geometric, integer, and string structures.

**Course Outcomes:** At the end of the course, the student will be able to:

<b>CO1</b>	Design and analyze persistent and retroactive data structures under various temporal models, including partial and non-oblivious retroactivity, within the bounded-degree pointer machine framework ( <i>Analyze</i> )
<b>CO2</b>	Construct and evaluate data structures optimized for dynamic graph operations and dynamically optimal performance across varying workloads. ( <i>Analyze</i> )
<b>CO3</b>	Develop cache-efficient and cache-oblivious data structures for external memory and hierarchical memory models, ensuring performance portability. ( <i>Analyze</i> )
<b>CO4</b>	Design and analyze specialized data structures for string and integer data to enable efficient indexing, searching, and retrieval ( <i>Analyze</i> )
<b>CO5</b>	Apply suitable data structures to solve computational geometry problems involving spatial queries, range searching, and multidimensional data ( <i>Analyze</i> )

**Course Articulation Matrix:**

PO/ PSO  CO	Program Outcomes												Program Specific Outcomes		
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
CO1	S	S	S	M									S	S	
CO2	S	S	S	M									S	S	
CO3	S	S	S	M									S	S	
CO4	S	S	S	M									S	S	
CO5	S	S	S	M									S	S	

S: Strong correlation, M: Medium correlation, L: Low correlation

**Detailed Syllabus:**

**Persistence:** pointer machine model, partial persistence, full persistence, confluent persistence, functional.

**Temporality:** Partial retroactivity, full retroactivity, non-oblivious retroactivity.

**Computational Geometry:** Point location via persistence, dynamic via retroactive; orthogonal range queries, range trees, layered range trees, dynamizing augmentation via weight balance, fractional cascading, Quadtrees, Kinetic data structures.

**Dynamic optimal Structures:** Binary search trees, analytic bounds, splay trees, geometric view, greedy algorithm, Independent rectangle, wilber, and signed greedy lower bounds; key-independent optimality; Tango trees.

**Cache-oblivious structures:** Models, cache-oblivious B-trees, Ordered-file maintenance, list labeling, order queries, cache-oblivious priority queues, Distribution sweeping via lazy funnel sort; cache-oblivious orthogonal 2D range searching: batched and online.

**Tree Structures for Sets of Intervals:** Interval Graphs, Interval Trees, Segment Trees-Trees for union of intervals, Trees for sums of weighted intervals, Trees for interval restricted Maximum sum queries, Orthogonal Range Trees-Higher Dimensional Segment Trees, Other systems of building blocks, Range counting and the semi group model.

**Integer Structures:** Hashing: Perfect Hashing, Universal Hashing, Cuckoo Hashing; Models, predecessor problem, van Emde Boas, x-fast and y-fast trees, indirection, Fusion trees: sketching, parallel comparison, Predecessor lower bound via round elimination, Sorting in linear time for  $w = O(\lg^{2+\epsilon} n)$ -bit integers; Heaps: Heaps of optimal complexity, Double Ended Heap structures and Multi-dimensional Heaps, Heap related structures with Constant-Time updates.

**Data Structures for Strings:** Suffix Trees, Suffix Arrays, Linear Time construction of Suffix Trees, Aho-Corasick algorithm, Compact string structures.

**Dynamic Graphs:** Link-cut trees, heavy-light decomposition, Euler tour trees, decremental connectivity in trees in  $O(1)$ , fully dynamic connectivity in  $O(\lg^2 n)$ , survey,  $\Omega(\lg n)$  lower bound for dynamic connectivity.

### Reading List:

- 1) Mark Allen Weiss, Data Structures and Algorithm Analysis in C++, second Edition, Pearson, 2004.
- 2) Michael T. Goodrich, Roberto Tamassia, Algorithm Design, First Edition, Wiley, 2006.
- 3) Thomas H. Cormen, Charles E. Leiserson, Ronald L. Rivest and Clifford Stein, Introduction to Algorithms, Second Edition, PHI, 2009.
- 4) Peter Brass, Advanced Data Structures, First Edition, Cambridge University Press, 2008.
- 5) Reinhard Kuzelnigg, Random Graphs and Cuckoo Hashing, First Edition, Sudwestdeutscher Verlag Fur Hochschulschriften AG, 2009.
- 6) Research papers.

<b>25CS614</b>	<b>Distributed Computing</b>	<b>PCC</b>	<b>3 – 0 - 0</b>	<b>3 Credits</b>
----------------	------------------------------	------------	------------------	------------------

Students of this course upon completion will learn how to solve standard distributed computing problems. Students will also learn consensus algorithms. Further algorithms for global knowledge, recording distributed snapshots, distributed mutual exclusion with an emphasis to reduce communication cost are also studied.

**Course Outcomes:** At the end of the course, the student will be able to:

<b>CO1</b>	Construct efficient distributed algorithms for standard graph-theoretic problems with an analysis of their time, space and communication requirements (Apply)
<b>CO2</b>	Constructing efficient distributed algorithms for achieving stable properties (Apply)
<b>CO3</b>	Analyze the properties of various algorithms for fault tolerance/ consensus . (Analyze)
<b>CO4</b>	Construct and analyze algorithms for solving distributed mutual exclusion. (Apply)
<b>CO5</b>	Analyze the properties of distributed transaction processing/ concurrency algorithms (Apply)

**Course Articulation Matrix:**

PO/ PSO  CO	Program Outcomes												Program Specific Outcomes		
	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3
<b>CO1</b>	S	S	M										S	M	L
<b>CO2</b>	S	M	L										S	L	L
<b>CO3</b>	S	S	M										S	M	L
<b>CO4</b>	S	S	M										S	M	L
<b>CO5</b>	S	S	M										S	M	L

S: Strong correlation, M: Medium correlation, L: Low correlation

**Detailed Syllabus:**

Taxonomy of distributed systems, Failure Detection, Clocks and Time, Logical Time, Distributed Consistency Models,

Leader election in rings. Basic computational tasks in general synchronous networks: leader election. Breadth-first search. Shortest Path Algorithms, Floyd-Warshall's Algorithm, Minimal Spanning Trees, Maximal Independent Sets,

Stable property detection. Distributed termination. MultiCast Models, Distributed snapshot recording. Deadlock detection. Asynchronous shared-memory systems. The mutual exclusion problem, Distributed Mutual exclusion algorithms.

Fault-tolerant consensus, Link failures: the two generals' problem. Process failures (stopping, Byzantine). Algorithms for agreement with stopping and Byzantine failures. PBFT, Paxos, zookeeper, RAFT, A case study of Bitcoin consensus

Distributed Transaction Processing and Concurrency Control, 2PC, 3PC vs View Stamped Replication, 2PL, Distributed Deadlocks

Distributed Hash Tables, Key-Value Stores (Cassandra)

### **Reading List:**

- 1) A. Kshemkalyani and M. Singhal, Distributed Computing: Principles, Algorithms, and Systems Cambridge University Press 2008 ISBN: 978-0-521-87634-6
- 2) Lynch, Nancy. Distributed Algorithms. Burlington, MA: Morgan Kaufmann, 1996. ISBN:9781558603486.
- 3) Michel Raynal Distributed Algorithms for Message-Passing Systems ISBN 978-3-642-38122-5 © Springer-Verlag Berlin Heidelberg 2013
- 4) A Guided Tour on the Theory and Practice of State Machine Replication, Alysson Neves Bessani and Eduardo Alchieri Book Chapter
- 5) Relevant Research articles shared by the instructor.

<b>25CS615</b>	<b>Social Network Analytics</b>	<b>DEC</b>	<b>3 – 0 – 0</b>	<b>3 Credits</b>
----------------	---------------------------------	------------	------------------	------------------

**Course Outcomes:** At the end of the course the student will be able to:

<b>CO1</b>	Analyze the structure and connectivity of different graph models using traversal, shortest path, and network flow algorithms. (Analyze)
<b>CO2</b>	Evaluate and compare various network centrality measures to assess node importance in complex networks. (Apply)
<b>CO3</b>	Analyze real-world network models by evaluating their structural properties (Analyze)
<b>CO4</b>	Evaluate and compare community detection algorithms by analyzing their ability to capture evolving and overlapping communities in social networks. (Analyze)
<b>CO5</b>	Analyze diffusion and influence processes in social media by deconstructing cascade models and distinguishing between influence and homophily. (Analyze)

**Course Articulation Matrix:**

<b>PO/ PSO CO</b>	<b>P O 1</b>	<b>P O 2</b>	<b>P O 3</b>	<b>P O 4</b>	<b>P O 5</b>	<b>P O 6</b>	<b>P O 7</b>	<b>P O 8</b>	<b>P O 9</b>	<b>P O 10</b>	<b>P O 11</b>	<b>P O 12</b>	<b>P S O 1</b>	<b>P S O 2</b>	<b>P S O 3</b>
<b>CO1</b>	S	M	M	M	M								S	S	S
<b>CO2</b>	S	M	M	M	M								S	S	S
<b>CO3</b>	S	M	M	M	M								S	S	S
<b>CO4</b>	S	M	M	M	M								S	S	S
<b>CO5</b>	S	M	M	M	M								S	S	S

S: Strong correlation, M: Medium correlation, L: Low correlation

**Detailed syllabus:**

**Graph Models:**

Graph Essentials, Degree and Degree Distribution, Graph Representations, Types of Graphs, Connectivity in Graphs, Graph/Tree Traversal, Shortest Path Algorithms, Minimum Spanning Trees, Network Flow Algorithms

**Network Measures:**

Centrality, Degree Centrality, Eigenvector Centrality, Katz Centrality, PageRank, Topic-Specific PageRank, Betweenness Centrality, Closeness Centrality, Group Centrality,

Transitivity and Reciprocity, Balance and Status, Similarity, Structural Equivalence, Regular Equivalence

### **Network Models:**

Properties of Real-World Networks, Degree Distribution, Clustering Coefficient, Average Path Length, Random Graphs, Modeling Real-World Networks with Random Graphs, Small-World model, Modeling Real-World Networks with the Small-World Model, Preferential Attachment Model, Modeling Real-World Networks with the Preferential Attachment Model

### **Community Analysis:**

Community Detection, Community Detection Algorithms, Member-Based Community Detection, Group-Based Community Detection, Community Evolution, Community Detection in Evolving Networks.

### **Information Diffusion in social media:**

Information Cascades, Independent Cascade Model (ICM), Maximizing the Spread of Cascades, Diffusion of Innovations, Modeling Diffusion of Innovations, Epidemics, SI Model, SIR Model, SIS Model, SIRS Model

### **Influence and Homophily:**

Measuring Assortativity, Measuring Assortativity for Nominal Attributes, Measuring Assortativity for Ordinal Attributes, Influence, Homophily, Distinguishing Influence and Homophily

### **Recommendation in social media:**

Classical Recommendation Algorithms, Content-Based Methods, Collaborative Filtering (CF), Extending Individual Recommendation to Groups of Individuals, Recommendation Using Social Context, Extending Classical Methods with Social Context, Evaluating Recommendations, Evaluating Relevancy of Recommendations, Evaluating Ranking of Recommendations

**Behavior Analytics:** Individual Behavior, Collective Behavior

### **Reading List:**

1. Reza Zefarani, Mohammad Ali Abbasi, Huan Liu, "Social Media Mining: An Introduction." Cambridge University Press, 2014. ISBN: 978-1107018853.
2. Jure Leskovec, Anand Rajaraman and Jeffrey David Ullman, Mining of massive datasets, Cambridge University Press, 2014

25CS616	Information Retrieval and Web Search	DEC	3 – 0 - 0	3 Credits
---------	--------------------------------------	-----	-----------	-----------

**Course Outcomes:** At the end of the course, the student will be able to:

<b>CO1</b>	Analyze the components of an Information Retrieval system and deconstruct its architecture for effective document indexing and retrieval. (Analyze)
<b>CO2</b>	Analyze IR evaluation metrics to determine the effectiveness of search systems under various retrieval scenarios. (Analyze)
<b>CO3</b>	Analyze link analysis and crawling strategies in web search to understand how search engines index and rank content. (Analyze)
<b>CO4</b>	Evaluate the mechanisms of text classification and clustering algorithms to distinguish between supervised and unsupervised approaches in IR applications. (Evaluate)
<b>CO5</b>	Build a basic question answering system by applying question classification, information extraction, and answer retrieval techniques. (Apply)

**Course Articulation Matrix:**

CO \ PO/ PSO	Program Outcomes												Program Specific Outcomes		
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
<b>CO1</b>	S	M	L	L									S	M	L
<b>CO2</b>	S	M	M	L									S	M	L
<b>CO3</b>	S	M	M	L									S	M	L
<b>CO4</b>	S	S	M	M									S	S	M
<b>CO5</b>	S	S	M	M									S	S	M

S: Strong correlation, M: Medium correlation, L: Low correlation

**Detailed Syllabus:**

**Introduction to IR and Text pre-processing:**

Introduction, Data vs Information Retrieval, Logical view of the documents, Architecture of IR System, Web search system, Tokenization, Text Normalization, Stop-word removal, Morphological Analysis, Word Stemming, Lemmatization, Index term selection, Inverted indices, Positional Inverted index, Basic NLP tasks – POS tagging; shallow parsing.

**IR Models:** Classes of Retrieval Model, Boolean model, Term weighting mechanism – TF, IDF, TF-IDF weighting, Cosine Similarity, Vector space model, Probabilistic models, Non-Overlapping Lists, Proximal Nodes Model.

**Evaluation of IR:**

Precision, Recall, F-Measure, MAP (Mean Average Precision), Discounted Cumulative Gain, Known-item Search Evaluation.

**Query Operations and Languages:**

Relevance feedback and pseudo relevance feedback, Query expansion (with a thesaurus or WordNet and correlation matrix), Spelling correction, Query languages.

**Web Search:**

Search engines, Spidering (Structure of a spider, Simple spidering algorithm, multithreaded spidering, Bot), Directed spidering, Crawlers (Basic crawler architecture), Link analysis (HITS, Page ranking), Query log analysis, Handling “invisible” Web – Snippet generation, Cross Language Information Retrieval.

**Text Categorization and Clustering:**

Categorization, Learning for Categorization, General learning issues, Learning algorithms: Bayesian (naïve), Decision tree, KNN, Rocchio), Clustering algorithms (Hierarchical clustering, k-means, k-medoid, Expectation maximization (EM), Text shingling) .

**Recommender System:**

Personalization, Collaborative filtering recommendation, Content-based recommendation.

**Question Answering:**

Information bottleneck, Information Extraction, Ambiguities in IE, Architecture of QA system, Question processing, Paragraph retrieval, Answer processing.

**Reading List:**

- 1) Christopher D. Manning, Prabhakar Raghavan and Hinrich Schütze, Introduction to Information
- 2) Retrieval, Cambridge University Press. 2008. <http://nlp.stanford.edu/IR-book/information-retrieval-book.html>
- 3) Modern Information Retrieval. Baeza-Yates Ricardo and Berthier Ribeiro-Neto. 2nd edition, Addison-Wesley, 2011.

<b>25CS617</b>	<b>PROBABILISTIC GRAPHICAL MODELS</b>	<b>DEC</b>	<b>3 – 0 – 0</b>	<b>3 Credits</b>
----------------	---------------------------------------	------------	------------------	------------------

Probabilistic graphical models (PGMs) are helpful in characterizing complex relationships among many random variates by fusing graph theory and probability theory and providing a sound framework. PGMs are helpful in reasoning under uncertainty especially in application domains like Natural Language Processing, Computer Vision, and Computational Biology.

**Course Outcomes:** At the end of the course, the student will be able to:

<b>CO1</b>	Construct probabilistic graphical models to characterize uncertainty inherent in problem domains such as Natural Language Processing and Computer Vision. (Apply)
<b>CO2</b>	Construct fundamental algorithms for probabilistic inference in both directed (Bayesian) and Undirected (Markovian) probabilistic graphical models. (Apply)
<b>CO3</b>	Construct algorithms for learning the structure and parameters of probabilistic graphical models. (Apply)
<b>CO4</b>	Apply Bayesian principles to model domain knowledge under uncertainty. (Apply)
<b>CO5</b>	Construct algorithms to perform inference in statistical and causal models. (Apply)

### Course Articulation Matrix

CO \ PO	PO													
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
<b>CO1</b>	S	M	M	L								S	M	S
<b>CO2</b>	S	M	M	L								S	M	S
<b>CO3</b>	S	M	M	L								S	M	S
<b>CO4</b>	S	M	M	L								S	M	S
<b>CO5</b>	S	M	M	L								S	M	S

S: Strong correlation, M: Medium correlation, L: Low correlation

### Detailed Syllabus:

Introduction and Motivation: Probabilistic Graphical Models, Representation, Inference and Learning.

**Representation:**

Bayesian Networks: independence properties, D-separation Algorithm, I-equivalence, Minimal I-maps, Perfect maps.

Undirected graphical models: Parameterization, Gibbs distribution and Markov networks, Independencies in Markov networks, Conversion to/from Bayesian Networks to Markov Networks, partially directed models, Conditional Random Fields.

**Inference:**

Exact inference-variable elimination, Clique Trees, Message passing, Belief update, Clique tree construction.

Inference as Optimization: propagation-based approximation.

Particle-based approximate inference: forward sampling, likelihood weighting and importance sampling, Markov Chain Monte Carlo methods, Gibbs Sampling algorithm.

MAP Inference, Inference in hybrid networks and temporal models.

**Learning:**

Learning graphical models: goals, learning as optimization

Parameter estimation: Maximum Likelihood Estimation (MLE), MLE for Bayesian networks.

Structure Learning in Bayesian Networks: constraint-based approaches, structure search, scoring structures

**Reading List:**

1. Daphne Koller and Nir Friedman, Probabilistic Graphical Models, First Edition, MIT Press 2009.
2. Chris Bishop, Pattern Recognition and Machine Learning, First Edition, Springer 2006.

<b>25CS618</b>	<b>Generative AI</b>	<b>DEC</b>	<b>3 – 0 - 0</b>	<b>3 Credits</b>
----------------	----------------------	------------	------------------	------------------

**Course Outcomes: At the end of this course, students will be able to:**

<b>CO1</b>	Apply maximum likelihood estimation and variational inference techniques to train probabilistic generative models. (Apply)
<b>CO2</b>	Implement and train Variational Autoencoders (VAEs) and latent variable models for unsupervised representation learning. (Apply)
<b>CO3</b>	Implement and train Generative Adversarial Networks (GANs) and Normalizing Flows to generate high-dimensional data distributions. (Apply)
<b>CO4</b>	Apply diffusion-based generative modeling techniques for image generation, including score-based and denoising diffusion approaches. (Apply)
<b>CO5</b>	Develop conditional generative models for text-to-image or text-to-video generation tasks using large language models and transformer-based architectures. (Apply)

**Course Articulation Matrix**

PO/ PSO	Program Outcomes												Program Specific Outcomes		
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO 1	PSO 2	PSO 3
<b>CO1</b>	S	S	S	M	M	L							S	S	S
<b>CO2</b>	S	S	S	M	M	L							S	S	S
<b>CO3</b>	S	S	S	M	M	L							S	S	S
<b>CO4</b>	S	S	S	M	M	L							S	S	S
<b>CO5</b>	S	S	S	M	M	L							S	S	S

**Detailed Syllabus:**

Introduction to Probabilistic Deep Generative Modelling, Autoregressive Models and Large Language Models Introduction, Maximum Likelihood Learning, Variational AutoEncoders, Latent Variable Models, Variational Inference, Normalizing Flow Models, Generative Adversarial Networks (GANs), Introduction to Diffusion Models, Energy based Models, Score based models, Diffusion beyond Denoising, Discrete Diffusion, Evaluation Metrics for Generative Models. Text-to-Image/Video Generation, Conditional Generation.

**Reading List:**

1. Foster D. Generative deep learning. " O'Reilly Media, Inc.; 2023
2. Generative Modeling by Estimating Gradients of the Data Distribution Yang Song. Blog post on score-based generative models, May 2021.
3. How to Train Your Energy-Based Models. Yang Song and Diederik P. Kingma. February 2021.
4. Learning deep generative models. Ruslan Salakhutdinov. Annual Review of Statistics and Its Application, April 2015.
5. Stanford CS236 Lecture notes.
6. Y. Bengio, I. Goodfellow and A. Courville, "Deep Learning", MIT Press, 2016
7. C. M. Bishop, Pattern Recognition and Machine Learning, Springer, 2006.

**Resources used to prepare syllabus:**

1. <https://deepgenerativemodels.github.io/syllabus.html>
2. <https://cmu-dgm.github.io/schedule.html>
3. <https://user.ceng.metu.edu.tr/~gcinbis/courses/Spring24/CENG796/index.html>
4. <https://mit-6s978.github.io/schedule.html>
5. [https://study.iitm.ac.in/ds/course\\_pages/BSDA5002.html](https://study.iitm.ac.in/ds/course_pages/BSDA5002.html)
6. [https://github.com/davidADSP/Generative\\_Deep\\_Learning\\_2nd\\_Edition/tree/main/notebooks](https://github.com/davidADSP/Generative_Deep_Learning_2nd_Edition/tree/main/notebooks)

25CS619	Explainable AI	DEC	2 – 0 – 0	2 Credits
---------	----------------	-----	-----------	-----------

**Course Outcomes:** At the end of the course the student will be able to:

<b>CO1</b>	Apply perturbation-based feature attribution methods to interpret predictions from black-box models. (Apply)
<b>CO2</b>	Implement concept-based and propagation-based interpretability techniques to analyze and explain internal representations in deep neural networks. (Analyze)
<b>CO3</b>	Apply counterfactual explanation methods to generate diverse and actionable explanations for model decisions. (Apply)
<b>CO4</b>	Analyze interpretable architectures and neurosymbolic methods to build models with built-in explainability. (Analyze)
<b>CO5</b>	Apply evaluation techniques and human-centered criteria to assess the reliability and usability of explainable AI systems. (Apply)

**Course Articulation Matrix:**

PO/ PSO CO	P O 1	P O 2	P O 3	P O 4	P O 5	P O 6	P O 7	P O 8	P O 9	P O 10	P O 11	P O 12	P S O 1	P S O 2	P S O 3
<b>CO1</b>	S	M	M	M	M	M							S	S	S
<b>CO2</b>	S	M	M	M	M	M							S	S	S
<b>CO3</b>	S	M	M	M	M	M							S	S	S
<b>CO4</b>	S	M	M	M	M	M							S	S	S
<b>CO5</b>	S	M	M	M	M	M							S	S	S

S: Strong correlation, M: Medium correlation, L: Low correlation

**Detailed syllabus:**

Overview and taxonomy of XAI: need for explainable and responsible AI, definition of terms, taxonomy of the XAI space.

Perturbation-based feature attribution methods: LIME, SHAP and Anchors.

Propagation-based feature attribution methods: Relevance Propagation and Saliency methods.

Concept-based explainability methods: Net2Vec, T-CAV and ACE.

Interpretable architectures: CBMs and variants, Concept Whitening and SENNs.

Neurosymbolic methods: DeepProbLog and Neural Reasoners.

Sample-based explanations: Influence functions and ProtoPNets.

Counterfactual explanations: Diverse Counterfactual Explanation, Metrics for Evaluation of Counterfactual Generation Algorithms

Select-then-predict models: Rationalizing Neural Predictions

Mechanistic Interpretability: Circuit analysis, Activation patching, Induction Heads, Sparse Auto-Encoders

Evaluating XAI: Sanity Checks, Ground truth comparisons, Ablation metrics: Insertion/deletion, Remove and retrain, Additive proxy metrics, Sensitivity-n, Variable cardinality version etc

Human-centered design for AI explanations and real-world case studies, Fairness, Bias, and ethical considerations in XAI

### Reading List:

1. Christoph Molnar, "Interpretable Machine Learning". (2022): <https://christophm.github.io/interpretable-ml-book/>
2. Arrieta, Alejandro Barredo, et al. "Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI." Information fusion 58 (2020): 82-115.
3. Rudin, Cynthia, et al. "Interpretable machine learning: Fundamental principles and 10 grand challenges." Statistics Surveys 16 (2022): 1-85.
4. <https://courses.cs.washington.edu/courses/csep590b/22sp/files/lectures/lecture5.pdf>
5. <https://sites.google.com/view/aaai22-ximl-tutorial/home>
6. <https://jolt.law.harvard.edu/assets/articlePDFs/v31/Counterfactual-Explanations-without-Opening-the-Black-Box-Sandra-Wachter-et-al.pdf>
7. Wachter et al. (2018) "Counterfactual Explanations Without Opening the Black Box"
8. Karimi et al. (2020) "Algorithmic Recourse: From Counterfactual Explanations to Interventions,"
9. Lei et al. 2016 Rationalizing Neural Predictions, EMNLP
10. <https://www.neelnanda.io/mechanistic-interpretability/getting-started>

<b>25CS620</b>	<b>HIGH PERFORMANCE COMPUTING</b>	<b>DEC</b>	<b>3 – 0 – 0</b>	<b>3 Credits</b>
----------------	-----------------------------------	------------	------------------	------------------

This course introduces students to High-performance computing techniques to solve scientific, complex engineering and large-scale problems that are infeasible to be solved on a uniprocessor environment.

**Course Outcomes:** At the end of the course, the student will be able to:

<b>CO1</b>	Infer which HPC architecture is suitable for a given application or scientific workload, with a comprehension of the salient features of different HPC architectures. (Analyze)
<b>CO2</b>	Construct and evaluate the performance of parallel and distributed programs using techniques and platforms based on shared-memory and distributed-memory. (Analyze)
<b>CO3</b>	Analyze parallel and distributed HPC applications with an intent of identifying bottlenecks and enhancing scalability and efficiency. (Analyze)
<b>CO4</b>	Develop HPC applications by leveraging HPC frameworks, workload and resource managers, HPC Profilers and debuggers. (Analyze)
<b>CO5</b>	Construct power-aware HPC applications and architecture to reduce the carbon footprint of data centers without major adverse effects on the performance metrics. (Analyze)

### Course Articulation Matrix

PO \ CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
<b>CO1</b>	S	S	S	M	M								S	S	S
<b>CO2</b>	S	S	S	M	M								S	S	S
<b>CO3</b>	S	S	S	M	M								S	S	S
<b>CO4</b>	S	S	S	M	M								S	S	S
<b>CO5</b>	S	S	S	M	M	S	S	S					S	S	S

S: Strong correlation, M: Medium correlation, L: Low correlation

### Detailed Syllabus:

**Parallel Processing fundamentals;** Levels and model of parallelism: instruction, transaction, task, thread, memory, function, data flow models, demand-driven computation;

**Parallel architectures:** superscalar architectures, multi-core, multi-threaded, server and cloud;

**Fundamental design issues in HPC:** Load balancing, scheduling, synchronization and resource management;

Operating systems for scalable HPC

**Parallel languages and programming environments;** OpenMP, Pthread, MPI, java, Cilk;  
Performance analysis of parallel algorithms; Fundamental limitations in HPC: bandwidth, latency and latency hiding techniques.

**Benchmarking HPC:** scientific, engineering, commercial applications and workloads;

**Scalable storage systems:** RAID, SSD cache, SAS, SAN;

**HPC based on cluster, cloud, and grid computing:** economic model, infrastructure, platform, computation as service;

**Accelerated HPC:** architecture, programming and typical accelerated system with GPU, FPGA, Xeon Phi, Cell BE;

**Power-aware HPC Design:** computing and communication, processing, memory design, interconnect design, power management;

**Assorted topics:** peta scale computing; big data processing, optics in HPC, quantum computers.

### **Reading List:**

1. Georg Hager and Gerhard Wellein. Introduction to High Performance Computing for Scientists and Engineers (1st ed.). CRC Press, Chapman & Hall/CRC Computational Science, India, 2010.
2. Vipin Kumar, Ananth Grama, Anshul Gupta, George Karypis. Introduction to Parallel Computing, 2nd ed., Pearson India, 2003.
3. John L. Hennessy and David A. Patterson. Computer Architecture: A Quantitative Approach (5th ed.). Elsevier India Pvt. Ltd. 2011.
4. David B. Kirk and Wen-mei W. Hwu. Programming Massively Parallel Processors: A Hands-On Approach (1st ed.). Elsevier India Pvt. Ltd. 2010.

25CS621	Game Theory	DEC	3 – 0 - 0	3 Credits
---------	-------------	-----	-----------	-----------

**Course Outcomes:** At the end of the course, the student will be able to:

<b>CO1</b>	Apply solution concepts to analyze strategic interactions in normal-form games. (Apply and Analyze)
<b>CO2</b>	Implement algorithms to compute equilibria in two-player and n-player games. (Analyze)
<b>CO3</b>	Apply backward induction and subgame-perfect equilibrium concepts to solve extensive-form games with perfect and imperfect information. (Apply)
<b>CO4</b>	Apply game-theoretic principles to design and analyze simple mechanisms and auctions for resource allocation problems. (Apply and Analyze)
<b>CO5</b>	Apply concepts from coalitional game theory to analyze cooperative behavior in multi-agent systems. (Apply and Analyze)

**Course Articulation Matrix:**

PO/ PSO  CO	Program Outcomes												Program Specific Outcomes		
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
<b>CO1</b>	L	M	S	S	S		S			S			S	S	S
<b>CO2</b>	M	L	M	M	L			S		S		S	S	S	S
<b>CO3</b>	M	S	L	M	M	S	S		M		S	S	M	M	S
<b>CO4</b>	M	M	M	S	M	S	S		S	S			M	S	S
<b>CO5</b>	M	L	M	L	L	S		S	S			S	M	M	L

S: Strong correlation, M: Medium correlation, L: Low correlation

**Detailed Syllabus:**

**Noncooperative Game Theory:** Games in Normal Form - Preferences and utility, examples of normal-form, Analyzing games: Pareto optimality, Nash equilibrium, Max-min and minmax strategies, dominated strategies, Rationalizability, Correlated equilibrium

**Computing Solution Concepts of Normal-Form Games:** Computing Nash equilibria of two-player, zero-sum games, Computing Nash equilibria of two-player, general-sum games, Complexity of computing Nash equilibrium, Lemke–Howson algorithm, Searching the space of supports, Computing Nash equilibria of n-player, general-sum games, Computing max-

min and minmax strategies for two-player, general-sum games, Computing correlated equilibria

**Games with the Extensive Form:** Perfect-information extensive-form games, Subgame-perfect equilibrium, Computing equilibria, Imperfect-information extensive-form games, Sequential equilibrium

**Other Representations:** Repeated games: Finitely repeated games, Infinitely repeated games, automata, Stochastic games Bayesian games: Computing equilibria

**CoalitionalGameTheory:** Transferable Utility, Analyzing Coalitional Games, Shapley Value, the Core

**Mechanism Design:** Strategic voting, unrestricted preferences, Implementation, quasilinear setting, efficient mechanisms, and Computational applications of mechanism design, Task scheduling, Bandwidth allocation in computer networks

**Auctions:** Single-good auctions, Canonical auction families, Bayesian mechanisms, Multiunit auctions, combinatorial auctions

**Reading List:**

- 1) Shoham, Y. and Leyton–Brown, K. Multiagent Systems: Algorithmic, Game Theoretic, and Logical Foundations. Cambridge University Press, 2008.
- 2) Osborne, M. J., and Rubinstein, A. A Course in Game Theory. Cambridge, MA: MIT Press, 1994.
- 3) D. Fudenberg and J. Tirole, Game Theory, The MIT Press, 2005.

25CS622	Privacy Preserving Data Processing	DEC	3 – 0 - 0	3 Credits
---------	------------------------------------	-----	-----------	-----------

**Course Outcomes:** At the end of this course, students will be able to:

CO1	Apply privacy approaches to assess the privacy guarantees of datasets and systems. (Apply)
CO2	Implement mechanisms that satisfy differential privacy. (Apply)
CO3	Apply local differential privacy techniques to data collection and perform frequency or heavy hitter estimation. (Apply)
CO4	Apply convex optimization techniques to solve privacy-preserving machine learning problems. (Apply)
CO5	Apply relaxed differential privacy and statistical tools to improve the utility-privacy trade-off in ML systems. (Apply)

Course Articulation Matrix:

PO/ PSO  CO	Program Outcomes												Program Specific Outcomes		
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
CO1	S	S	M	L									S	S	S
CO2	S	M	L	L									S	S	S
CO3	S	M	L	L									S	S	S
CO4	S	M	L	L									S	S	S
CO5	S	M	L	L									S	S	S

S: Strong correlation, M: Medium correlation, L: Low correlation

### Detailed Syllabus:

**Introduction:** Why Data Privacy? Privacy definitions (k-anonymity,  $\ell$ -diversity).

**Foundation of Differential Privacy:** Formal definition, Properties: composition, invariance, postprocessing,  $(\epsilon, \delta)$ -DP.

**Local Privacy Models:** Differential privacy with untrusted curator, Randomized Response, Heavy hitter detection.

**Convex Optimization:** Basics of optimization, convex functions, Strong convexity, Lipschitz continuous, Gradient Descent

**Relaxations of Differential Privacy:** Moment accountant, Concentrated Differential Privacy, Renyi Differential Privacy, Concentration of measure, Chernoff bound, Hoeffding's inequality

**Statistical inference and machine learning under differential privacy:** Law & policy considerations, Tiered access models, Side-channel & randomness attacks on implementations, Combining differential privacy and cryptography

**Reading List:**

- 1) The Algorithmic Foundations of Differential Privacy, Cynthia Dwork and Aaron Roth. DOI: 10.1561/04000000042.
- 2) The Algorithmic Foundations of Differential Privacy by Cynthia Dwork and Aaron Roth, Publisher: Now Publisher, ISBN: 978-1-60198-818-8
- 3) Differential Privacy: A Primer for a Non-technical Audience by Nissim et al., Harvard University Privacy Tools Project
- 4) Elements of Statistical Learning, Hastie et al., Springer
- 5) Convex Optimization, Boyd and Vandenberghe, Cambridge

25CS623	Big Data Engineering	DEC	3 – 0 – 0	3 Credits
---------	----------------------	-----	-----------	-----------

**Course Outcomes:** At the end of the course, the students will be able to:

CO1	Analyze Map-Reduce programming model for data-intensive applications (Analyze)
CO2	Build a Big Data computing platform with distributed file system. (Apply)
CO3	Implement optimized join operations for a distributed environment. (Apply)
CO4	Perform exploratory data analysis on a distributed environment. (Apply)
CO5	Construct and evaluate ML models for Big Data. (Apply)

**Course Articulation Matrix:**

CO \ PO/ PSO	Program Outcomes												Program Specific Outcomes		
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
CO1	S	S	S	S	S				M	M		L	S	S	M
CO2	S	S	S	S	S				M	M		L	S	S	M
CO3	S	S	S	S	S				M	M		L	S	S	M
CO4	S	S	S	S	S				M	M		L	S	S	M
CO5	S	S	S	S	S				M	M		L	S	S	M
CO6	S	S	S	S	S				M	M		L	S	S	M

S: Strong correlation, M: Medium correlation, L: Low correlation

**Detailed Syllabus:**

**Big Data – An Introduction:** Big Data - Definition, an overview of Big Data; HPC & Big Data, Big Data Characteristics, Issues, and challenges of Big Data, Big data Technological approaches and Potential use cases for Big Data.

**MapReduce and the New Software Stack:** Hadoop Framework, Hadoop echo system, Distributed File Systems (HDFS and YARN), MapReduce, Algorithms Using MapReduce: Matrix-vector multiplication, Matrix multiplication, Relational Algebra operations, Join operations: optimization for join operations, theta join, skew aware join, Extensions to MapReduce, The Communication-Cost Model, Complexity Theory for MapReduce.

**Exploratory Data Analysis:** Visual data analysis techniques, interaction, techniques-Systems and applications.

**In memory processing:** Apache Spark, RDD programming, Spark SQL, Datasets and Dataframes, SparkML.

**Machine Learning for Big Data:** Selecting, Extracting and Transforming features, Basic statistics, ML pipelines, Supervised and Unsupervised models, Model selection and tuning.

**NoSQL:** CAP Theorem, Birth of NoSQL, Key-value databases, Document databases, Graph Databases, Column Databases, Distributed Data bases: Mango DB, Hive, Cassandra.

**Stream processing:** Introduction to Streams Concepts, Stream Data Model and Architecture, Sampling Data in a Stream, Filtering Streams, Algorithms for streams such as Counting Distinct Elements in a Stream, Estimating Moments, Counting Ones in a Window, Decaying Window.

### **Reading List:**

- 1) Jure Leskovec, Anand Rajaraman, Jeffrey D. Ullman, "Mining of Massive Datasets", Cambridge Universities Press, 3rd ed, 2020.
- 2) David Loshin, "Big Data Analytics: From Strategic Planning to Enterprise Integration with Tools, Techniques, NoSQL, and Graph", Elsevier, August 23, 2013.
- 3) Tom White, "Hadoop: The Definitive Guide: Storage and Analysis at Internet Scale", Orielly, 4th Edition, 2015.
- 4) Sandy Ryza, Uri Laserson, Sean Owen, Josh Wills, "Advanced Analytics with Spark: Patterns for Learning from Data at Scale", Orielly, 2015.
- 5) Dan Sullivan, "NoSQL for Mere Mortals", Addison-Wesley, 2015
- 6) <https://spark.apache.org/docs/latest/api/python/pyspark.html>
- 7) <https://github.com/adamjshook/mapreducepatterns>
- 8) <https://spark.apache.org/mllib/>

25CS624	AI Ethics and Societal Challenges	DEC	2 – 0 – 0	2 Credits
---------	-----------------------------------	-----	-----------	-----------

**Course Outcomes:** At the end of the course, the student will be able to:

<b>CO1</b>	Apply principles of AI risk assessment to analyze and categorize catastrophic risks such as AI race dynamics, rogue agents, and organizational failures. (Apply and Analyze)
<b>CO2</b>	Apply game-theoretic tools to analyze AI-related collective action problems. (Apply and Analyze).
<b>CO3</b>	Apply transparency and anomaly detection techniques to identify safety issues in single-agent AI systems, including emergent behaviors and Trojan attacks. (Apply)
<b>CO4</b>	Apply safety engineering methods to assess potential failure modes in AI systems. (Apply).
<b>CO5</b>	Apply ethical frameworks and social welfare models to evaluate the impact of AI systems on wellbeing, fairness, and moral tradeoffs. (Apply).

**Course Articulation Matrix:**

PO/ PSO  CO	Program Outcomes												Program Specific Outcomes		
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
<b>CO1</b>	M	S	M	L									S	M	L
<b>CO2</b>	S	M	S	M									S	S	M
<b>CO3</b>	S	S	M	S	M								S	S	M
<b>CO4</b>	S	S	S	S	S	M							S	S	S
<b>CO5</b>	S	S	S	S	S	S							S	S	S

S: Strong correlation, M: Medium correlation, L: Low correlation

**Detailed Syllabus:**

**Overview of Catastrophic AI Risks:** Malicious Use, AI race, Organizational Risks, Rogue AIS, Discussion of connections between risks.

**Artificial Intelligence Fundamentals:** Artificial Intelligence and its Types, Machine Learning and its Types, Deep Learning-Model Building Blocks, Training and Inference, Applications, History and Timeline of Key Architectures.

**Single-Agent Safety:** Monitoring-ML Systems are Opaque, Motivations for Transparency Research, Approaches to Transparency, Emergent Capabilities, Emergent Goal-Directed Behaviour, Tail Risk: Emergent Goals, Evaluations and Anomaly Detection, Trojan Attacks and Other Security Threats.

**Safety Engineering:** Risk Decomposition, Safe Design Principles, Component Failure Accident Models and Methods, Systemic Factors, Drift into Failure, and Existential Risks.

**Complex Systems:** Introduction To Complex Systems, Complex Systems For AI Safety- Puzzles, Problems, and Wicked Problems, Challenges With Interventionism.

**Ethics and Society:** Beneficial AI and Machine Ethics- Law, Fairness, The Economic Engine, Wellbeing, Preferences, Happiness, Social Welfare Functions, Moral Uncertainty.

**Collective Action Problems:** Game Theory- Game Theory Fundamentals, The Prisoner's Dilemma, The Iterated Prisoner's Dilemma, Collective Action Problems. Conflict- Bargaining Theory, Commitment Problems, Information Problems, Factors Outside of Bargaining Theory

**Reading List:**

- 1) Hendrycks, D. (2025). Introduction to AI safety, ethics, and society (p. 562). Taylor & Francis.

<b>25CS625</b>	<b>Applications of AI in Healthcare</b>	<b>DEC</b>	<b>2 – 0 – 0</b>	<b>2 Credits</b>
----------------	---	------------	------------------	------------------

**Course Outcomes:** At the end of the course, the student will be able to:

<b>CO1</b>	Apply healthcare entrepreneurship principles to develop business models addressing regulatory, legal, and consumer protection challenges in the Indian healthcare market. (Apply)
<b>CO2</b>	Implement responsible AI techniques and ethical frameworks to design AI-based healthcare solutions that address bias, privacy, and transparency concerns. (Apply)
<b>CO3</b>	Apply biomedical informatics and healthcare analytics methods to analyze healthcare data for improving patient outcomes and operational efficiencies. (Apply and Analyze)
<b>CO4</b>	Design and prototype healthcare technologies, including medical devices and digital health applications, integrating user feedback and regulatory standards. (Apply)
<b>CO5</b>	Apply digital health tools such as telemedicine and electronic health records while addressing interoperability, legal, and ethical challenges in healthcare delivery. (Apply)

### Course Articulation Matrix

CO \ PO	PO													
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
<b>CO1</b>	S	M	L	M		S		S				S	M	M
<b>CO2</b>	S	M	L	M		S		S				S	S	S
<b>CO3</b>	S	M	L	M	M	S		S				S	S	S
<b>CO4</b>	S	M	L	M	M	S		S				S	S	S
<b>CO5</b>	S	M	L	M	M	S		S				S	S	S

S: Strong correlation, M: Medium correlation, L: Low correlation

## Detailed Syllabus:

**Healthcare Entrepreneurship Fundamentals:** Overview of healthcare entrepreneurship, Understanding the intersection of technology, innovation, and healthcare, Differentiating between product and service in the healthcare sector, Understanding the importance of consumer protection in healthcare, Why B2B and not B2C in the Indian healthcare market, Addressing regulatory, legal, and compliance challenges in healthcare startups

**Fundamentals of Healthcare Systems and Preventive Care:** Key components of a healthcare system, Primary, secondary, and tertiary levels of healthcare, Understanding the difference between communicable and non-communicable diseases, Investigating the role of technology to improve healthcare affordability, Overview of healthcare financing models, Financial factors and healthcare access in India

**Intellectual Property and Regulatory Challenges in Healthcare:** Overview of intellectual property rights and their importance in healthcare innovation, Types of intellectual property: patents, copyrights, and trademarks, Role of intellectual property in protecting healthcare innovations, Understanding the regulatory approval process for medical devices, pharmaceuticals, and digital health solutions, Strategies for intellectual property protection and enforcement in healthcare startups, Ethical and legal standards in healthcare startups

**Responsible AI in Healthcare:** Responsible AI, The role of healthcare professionals in responsible AI, Challenges of gaining trust and acceptance in adopting AI technologies: Liability and accountability and legal responsibilities of healthcare providers, The ethical challenges of AI in healthcare, Bias in AI, Privacy and data protection in AI, The importance of transparency and accountability in AI, The future of regulation for AI in healthcare

**Biomedical Informatics:** Biomedical informatics, The use of information technology in healthcare, Applying data mining and machine learning for healthcare, ethical and legal issues in biomedical informatics, Privacy and confidentiality, Ownership of data, Informed consent

**Healthcare Technology and Innovation:** Medical device innovation and development process, needs assessment, prototyping, testing and design thinking, Understanding end-user needs and pain points, Strategies for gathering user feedback and incorporating it into design processes., Mobile health applications and wearable devices, Challenges and opportunities in implementing healthcare technology and innovation, Ethical considerations and challenges in the adoption of emerging technologies, IoT applications in healthcare monitoring, remote patient care, and chronic disease management, Virtual reality for medical training, simulation, and therapy, Augmented reality in surgical navigation and patient education, Blockchain applications for secure and interoperable healthcare data management

**Introduction to Digital Health:** Overview of the digital health ecosystem and its key components, Digital Health and their impact on healthcare transformation, Examining the benefits of telemedicine for patients, healthcare providers, and healthcare systems,

Analysing the barriers and challenges of implementing telemedicine in rural and underserved areas, Introduction to electronic health records and their role in digital health, Exploring the challenges of EHR implementation and interoperability, Addressing legal and regulatory considerations in telemedicine, including licensure and liability issues

**Role of Technologists in Designing Medical Devices and Implants:** Empowering Computer Science, Importance of design and engineering in developing safe and effective medical solutions, Regulatory landscape and standards for medical devices in India, Ethical considerations and patient safety in medical device design, Importance of engaging with healthcare professionals and patients in understanding their requirements, the challenges and the desired outcomes of a medical device or implant, Conducting usability studies and gathering feedback for iterative design improvements, Cost-effectiveness and affordability considerations for Indian healthcare systems, Integration of software and connectivity features in medical devices, Security and privacy considerations in connected healthcare systems, Leveraging data analytics and AI algorithms in medical device design

**Healthcare Analytics:** Definition and importance of healthcare analytics, Role of data-driven decision-making in improving healthcare outcomes, Descriptive analytics: summarizing and visualizing healthcare data, Diagnostic analytics: identifying patterns and correlations, Predictive analytics: forecasting and modelling future healthcare events, Prescriptive analytics: optimizing decision-making using predictive models, Using analytics to personalize treatment., Challenges and Opportunities in Healthcare Analytics, Ethical and Legal Implications of Healthcare Analytics, Scaling and implementing analytics solutions in healthcare organizations.

#### **Reading List:**

1. Adam Bohr, Kaveh Memarzadeh Artificial Intelligence in Healthcare. Elsevier Science, 2020.
2. Jyotir Moy Chatterjee, Vishal Jain Machine Learning with Health Care Perspective: Machine Learning and Healthcare. Springer International Publishing, 2020.
3. Ahmed A. Elngar, Akansha Singh, Krishna Kant Singh, Mohamed Elhoseny. Machine Learning and the Internet of Medical Things in Healthcare. Elsevier Science, 2021.
4. Pareras, Luis G.. Innovation and Entrepreneurship in the Healthcare Sector: From Idea to Funding to Launch. Greenbranch Publishing, 2011.
5. Govindarajan, Vijay., Ramamurti, Ravi. Reverse Innovation in Health Care: How to Make Value-based Delivery Work. Harvard Business Review Press, 2018.

<b>25CS626</b>	<b>Advanced Computational Statistics</b>	<b>DEC</b>	<b>3 – 0 – 0</b>	<b>3 Credits</b>
----------------	--	------------	------------------	------------------

Students of this course upon completion will gain a broad comprehension of the importance of computation in statistics and machine learning. Focus of this course will be on the mathematical and statistical underpinnings of why and how seminal modern statistical methods and inference works.

**Course Outcomes:** At the end of the course, the student will be able to:

<b>CO1</b>	Apply probability concepts to model and analyze random phenomena in practical scenarios. (Apply and Analyze)
<b>CO2</b>	Apply parametric and non-parametric estimation methods, including maximum likelihood and bootstrap techniques, for data-driven inference. (Apply)
<b>CO3</b>	Apply hypothesis testing procedures like Wald tests, likelihood ratio tests, and permutation tests to evaluate statistical hypotheses in empirical datasets. (Apply)
<b>CO4</b>	Apply Bayesian inference techniques to perform parameter estimation and hypothesis testing with prior information. (Apply)
<b>CO5</b>	Implement stochastic simulation and optimization algorithms for statistical inference and decision-making. (Apply)

### Course Articulation Matrix

PO CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PS01	PS02	PS03
<b>CO1</b>	S	M	L									S	S	S
<b>CO2</b>	S	M	L									S	S	S
<b>CO3</b>	S	M	L									S	S	S
<b>CO4</b>	S	M	L									S	S	S
<b>CO5</b>	M	M	L									M	M	M

S: Strong correlation, M: Medium correlation, L: Low correlation

### Detailed Syllabus:

#### Probability:

Review: Probability (Sample spaces, Conditional probability, Independent events, Bayes' theorem).

Review: Random variables (Distribution and probability functions, Discrete and continuous random variables, Bivariate, Marginal and conditional distributions, Multivariate distributions and IID samples, Expectation, Variance, Covariance, Conditional expectation, Moment generating functions).

Probability Inequalities, Convergence types of Random variables, Law of large numbers, Central limit theorem, The Delta method, L1 Convergence.

### **Statistical Inference:**

Parametric and non-parametric models, Point estimation, Confidence sets, Hypothesis testing – a review.

CDF estimation, Statistical functionals, Bootstrap: Simulation, Variance estimation, Confidence intervals, Percentile intervals.

Parametric inference: Method of moments, Maximum likelihood estimators: Properties, Consistency and Equivariance, Asymptotic normality, Optimality, Multiparameter models, Parametric bootstrap, Sufficiency, Exponential families and Conditional maximum likelihood estimators. Case study on Noise Contrastive Estimation.

Hypothesis testing and p-values: Wald test, Chi-square distribution, Pearson's Chi-square test for multinomial data, Permutation test, Likelihood ratio test, Multiple testing, Goodness-of-fit tests.

Bayesian Inference: Functions of parameters, Simulation, Large sample properties of Bayes' procedures, Flat priors, improper priors and non-informative priors, Multiparameter problems, Bayesian testing, Strengths and weaknesses of Bayesian inference.

Statistical Decision theory: comparing risk functions, Bayes estimators, Minmax rules, Admissibility, Stein's paradox.

Introduction to Variational Inference.

### **Statistical Processes and Methods:**

Stochastic Processes: Markov processes, Poisson processes, Birth-death processes.

Stochastic optimization: Robbins-Monro and Kiefer-Wolfowitz algorithms, simulated annealing, stochastic gradient methods.

Simulation methods: Monte Carlo methods: Rejection sampling, importance sampling, variance reduction methods (Rao-Blackwellization, stratified sampling).

MCMC methods: Gibbs sampling, Metropolis-Hastings, Langevin methods, Hamiltonian Monte Carlo, slice sampling. Implementation issues: burnin, monitoring convergence.

Sequential Monte Carlo (particle filtering)

**Reading List:**

1. Larry Wasserman, All of Statistics, First Edition, Springer-Verlag, 2004.
2. Geof H. Givens and Jennifer A. Hoeting, Computational Statistics, Second Edition, Wiley, 2005.
3. Christian P. Robert, George Casella, Monte Carlo Statistical Methods, Springer, First Edition, 2004.

25CS627	Computer Forensics & Cyber Security	DEC	3 – 0 – 0	3 Credits
---------	-------------------------------------	-----	-----------	-----------

**Pre-requisites:**

- i. Operating Systems (CS2021)
- ii. Cryptography and Network Security (CS3061)
- iii. Distributed Computing (CS3051)

**Course Outcomes:** At the end of the course, the student will be able to:

<b>CO1</b>	Apply standard forensic investigation methodologies to collect, preserve, and authenticate digital evidence while maintaining chain of custody. (Apply)
<b>CO2</b>	Apply forensic tools and imaging techniques to perform data recovery, duplication, and analysis across various digital devices including mobile, network, and storage systems.(Apply).
<b>CO3</b>	Apply network and email forensic procedures to analyze traffic, logs, and communications for identifying cyber incidents and evidence. (Analyze and Apply)
<b>CO4</b>	Analyze cybersecurity principles and cryptographic techniques to assess hardware-level and operating system vulnerabilities and countermeasures. (Analyze).
<b>CO5</b>	Apply malware analysis techniques and OS-level exploit detection to identify, analyze, and mitigate security breaches and side-channel attacks. (Apply)

**Course Articulation Matrix:**

PO/ PSO  CO	Program Outcomes												Program Specific Outcomes		
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
<b>CO1</b>	M	M	L	L	M								L		
<b>CO2</b>	S	M	M	M	M									M	
<b>CO3</b>	S	S	M	S	S									S	
<b>CO4</b>	S	S	S	S	S						S	S	S		
<b>CO5</b>	S	S	S	S	S						S	S	S	S	

S: Strong correlation, M: Medium correlation, L: Low correlation

**Detailed Syllabus:**

**Foundations of Computer Forensics: Introduction to Computer Forensics;** Definition, Scope, and Importance; Role in Law Enforcement and Human Resources; Professional Methodology and Services; Types of Computer Forensics Technologies; Business, Military and Law Enforcement Applications; Steps in a Forensic Investigation.

**Evidence Handling, Preservation, and Tools: Evidence and Data Capture:** Data Recovery: Backup and Recovery Concepts; Role of Backups in Forensic Context; Evidence Collection and Seizure: Types of Evidence, Collection Options, Obstacles, Rules of Evidence, Volatile Evidence, Chain of Custody; Duplication and Preservation of Digital Evidence, Imaging Techniques, Processing Steps, Legal Considerations; Verification and Authentication of Evidence; Overview of Forensic Tools: Software and Hardware Tools, Tool Evaluation, Validation, and Testing.

**Specialized Forensics Domains and Crime Scene Processing:** Forensic Analysis and Validation: Data Collection, Data-Hiding Techniques, Validation, Remote Acquisitions; Network Forensics: Live Acquisitions, Standard Procedures, Tools, Honeynet; Email Forensics: Structure, Investigation, Server/Client Roles; Mobile Device Forensics: Cell Phone Data Acquisition and Analysis; Windows and DOS System Forensics: File Systems, NTFS, Encryption, Registry, Boot Tasks; Processing Incident Scenes: Evidence Handling at Crime Scenes (Private and Law Enforcement), Search Preparation, Evidence Seizure, Hashing, Storage, Reviewing Cases.

**Cybersecurity Principles and Hardware-Level Security:** Introduction to Cybersecurity: CIA Triad (Confidentiality, Integrity, Availability), Threat Models and Risk Management: Cryptography Basics: AES, ECC; Hardware Security Threats: Hardware Trojans, PUFs, Power Analysis Attacks, Fault Attacks; Micro-architectural Attacks: Timing Attacks, Covert Channels, RAM-based Attacks, Cold Boot Attacks.

**Operating System Security and Malware Analysis:** Operating System-Level Attacks: Stack Smashing, Format String, ROP, Heap Attacks, Dynamic Memory Allocation Exploits: Countermeasures, Non-executable Stacks, Canaries, Capability-Based Systems, Malware Analysis Techniques, Side-Channel Attacks in Operating Systems.

### **Reading Lists:**

- 1) Computer Forensics and Investigations by Nelson, Phillips Enfinger, Steuart, CENGAGE Learning.
- 2) Computer Forensics, Computer Crime Investigation by John R, Vacca, Firewall Media, New Delhi.
- 3) "Introduction to Computer Security" by Matt Bishop, Pearson Publications
- 4) Swarup Bhunia and Mark Tehranipoor, Hardware Security: A Hands-on Learning Approach, Elsevier, 2019.
- 5) Michael E. Whitman, Herbert J. Mattord, (2018). Principles of Information Security, 6th edition, Cengage Learning, N. Delhi.