**COEP Technological University, Pune**

**School of Engineering and Technology**

**Department of Computer Science and Engineering**

**M. Tech in AIML**

**Curriculum Structure**

**w.e.f AY 2025-26**

## INDEX

## Program Educational Objectives (PEOs)

PEO 1. To make students eligible to take up higher studies/research

PEO 2. To build competency among students to take up jobs that require technical expertise and problem-solving ability

PEO 3. To inculcate readiness among students for self-learning

PEO 4. To build competency among students in applying technology to solve real-life socio-economic problems

**Program Outcomes (POs)**

The post-graduate students will demonstrate:

PO 1. An ability to independently carry out research /investigation and development work to solve practical problems

PO 2. An ability to write and present a substantial technical report/document

PO 3. Students should be able to demonstrate a degree of mastery over the area as per the specialization of the program. The mastery should be at a level higher than the requirements in the appropriate bachelor program

PO 4. Ability to manage/work in teams with diverse backgrounds in different aspects (such as language, region, technical proficiency, engineering discipline etc.) and communicate effectively

PO 5. Ability to life-long self-learning and to keep oneself up to date in the field of technology

PO 6. Understand intellectual property rights and the ability to apply them in an appropriate manner

**Correlation between the PEOs and the POs**

| | PO 1 | PO 2 | PO 3 | PO 4 | PO 5 | PO 6 |
|---|---|---|---|---|---|---|
| **PEO 1** | √ | √ | √ | | √ | √ |
| **PEO 2** | √ | | √ | √ | √ | |
| **PEO 3** | | | √ | | √ | |
| **PEO 4** | √ | √ | √ | | √ | |

## List of Abbreviations

| Abbreviation | Title | No of courses | Credits | % of Credits |
|---|---|---|---|---|
| PSMC | Program Specific Mathematics Course | 1 | 4 | 5.88% |
| PSBC | Program Specific Bridge Course | 1 | 3 | 4.41% |
| PCC | Program Core Course | 6 | 18 | 26.47% |
| PEC | Program Specific Elective Course | 3 | 9 | 13.24% |
| LC | Laboratory Course | 4 | 4 | 7.35% |
| VSEC | Vocational and Skill Enhancement Course | 2 | 18 | 26.47% |
| OE | Open Elective | 1 | 3 | 4.41% |
| SLC | Self-Learning Course | 2 | 6 | 8.82% |
| AEC | Ability Enhancement Course | 1 | 1 | 1.47% |
| MLC | Mandatory Learning Course | 2 | -- | -- |
| CCA | Co-curricular and Extracurricular Activities | 1 | 1 | 1.47% |
| | **Total** | **25** | **68** | **100%** |

**Semester I**

| Sr. No. | Course Type | Course Code | Course Name | Teaching Scheme | | | | Credits |
|---|---|---|---|---|---|---|---|---|
| | | | | L | T | P | S | |
| 1 | PSMC | | Probability, Statistics and Queuing Theory | 3 | 1 | 0 | 1 | 4 |
| 2 | PSBC | | Advance Data Structure &Algorithms | 3 | 0 | 0 | 1 | 3 |
| 3 | PCC& LC | | Artificial Intelligence | 3 | 0 | 2 | 1 | 4 |
| 4 | PCC | | Machine Learning | 3 | 0 | 0 | 1 | 3 |
| 5 | PCC | | Data Visualization Techniques | 3 | 1 | 0 | 1 | 4 |
| 6 | AEC | | Mini Project/ Seminar | 0 | 0 | 2 | 1 | 1 |
| 7 | PEC | | Program Specific Elective Course-I<br>1. Time Series Analysis<br>2. Probabilistic Graphical Model<br>3. Data Analytics | 3 | 0 | 0 | 1 | 3 |
| 8 | MLC | | Research Methodology and Intellectual Property Rights | 0 | 0 | 0 | 2 | - |
| 9 | MLC | | Effective Technical Communication Skills | 0 | 0 | 0 | 1 | - |
| | | | | **Total Credits** | | | | **22** |

Legends: L-Lecture, T-Tutorial, P-Practical, S-Self Study

**Semester II**

| Sr. | Course | Course | Course Name | Teaching Scheme | Credits |
|---|---|---|---|---|---|

| No. | Type | Code | | L | T | P | S | |
|---|---|---|---|---|---|---|---|---|
| 1 | OE | | Open Elective | 3 | 0 | 0 | 1 | 3 |
| 2 | PCC & LC | | Deep Learning | 3 | 0 | 2 | 1 | 4 |
| 3 | PCC & LC | | Generative Adversarial Network (GAN) | 3 | 0 | 2 | 1 | 4 |
| 4 | PCC &LC | | Optimization Techniques | 3 | 0 | 2 | 1 | 4 |
| 5 | PEC | | Program Specific Elective –II<br>1. Reinforcement Learning<br>2. EAI<br>3. ML-OPS | 3 | 0 | 0 | 1 | 3 |
| 6 | PEC | | Program Specific Elective –III<br>1. NLP<br>2. Graph Nural Network<br>3. Federated AI | 3 | 0 | 0 | 1 | 3 |
| 7 | CCA | | Liberal Learning Course | 0 | 0 | 2 | 2 | 1 |
| | | | | | **Total Credits** | | | **22** |

- The department offers “Data Structures” as Open Elective for students of other departments

## Semester III

| Sr. No. | Course Type | Course Code | Course Name | Teaching Scheme | | | | Credits |
|---|---|---|---|---|---|---|---|---|
| | | | | **L** | **T** | **P** | **S** | |
| 1 | SLC | | Massive Open Online Course –I | 3 | -- | -- | - | 3 |
| 2 | SLC | | Massive Open Online Course –II | 3 | -- | -- | - | 3 |
| 3 | VSEC | | Dissertation Phase – I | -- | -- | 12 | 18 | 6 |
| | | | | | **Total Credits** | | | **12** |

## Semester IV

| Sr. No. | Course Type | Course Code | Course Name | Teaching Scheme | | | | Credits |
|---|---|---|---|---|---|---|---|---|
| | | | | **L** | **T** | **P** | **S** | |
| 1 | VSEC | | Dissertation Phase – II | -- | -- | 24 | 12 | 12 |
| | | | | | **Total Credits** | | | **12** |
| | | | | | | | | |

**Probability and Statistics foundation**

| **Teaching Scheme** | **Examination Scheme** |
|---|---|
| Lectures: 3 hours/week | Theory: MSE: 30 Marks |
| Self-Study: 1 hour/week | TA: 20, ESE: 50 marks |
| Tutorial:1Hrs | |

**Course Outcomes:**

Students will be able to:

1. Solve various problems on probability and statistics.
2. Analyze the given probabilistic model of the problem.
3. Use the techniques studied in probability and statistics to solve problems in domains such as data mining, machine learning, network analysis.

**Unit 1: Basic Probability Theory [2 Hrs]**

Probability axioms, conditional probability, independence of events, Bayes' rule, Bernoulli trials

**Unit 2: Random Variables and Expectation [10 Hrs]**

Discrete random variables: Random variables and their event spaces, Probability Mass Function, Discrete Distributions such as Binomial, Poisson, Geometric etc., Indicator random variables, Continuous random variables: Distributions such as Exponential, Erlang, Gamma, Normal etc., Functions of a random variable, Expectation: Moments, Expectation based on multiple random variables, transform methods, Moments and Transforms of some distributions such as Binomial, Geometric, Poisson, Gamma, Normal

**Unit 3: Stochastic Processes [6 Hrs]**

Introduction and classification of stochastic processes, Bernoulli process, Poisson process, Renewal processes

**Unit 4: Markov chains [8 Hrs]**

Discrete-Time Markov chains: computation of n-step transition probabilities, state classification and limiting probabilities, distribution of time between time changes, M/G/1 queuing system. Continuous-Time Markov chains: Birth-Death process (M/M/1 and M/M/m queues), non-birthdeath processes, Petri nets

**Unit 5: Statistical Inference [8 Hrs]**

Parameter Estimation – sampling from normal distribution, exponential distribution, estimation related to Markov chains, Hypothesis testing.

**Unit 6: Regression and Analysis of Variance [6 Hrs]**

Least square curve fitting, Linear and non-linear regression, Analysis of variance.

**Textbooks:**

1. Ronald Walpole, Probability and Statistics for Engineers and Scientists, Pearson, ISBN13: 978-0321629111

**References:**

1. Kishor Trivedi, Probability and Statistics with Reliability, Queuing, and Computer Science Ap

## Advanced Data Structure and Algorithm

| **Teaching Scheme** | **Examination Scheme** |
|---|---|
| Lectures: 3 hrs/week | Mid Sem – 30 Marks |
| Self-Study:1Hrs | ESE–50 Marks |
| | TA – 20 Marks |

**Course Outcomes:**

Students will be able to:

1. To understand the advanced concepts of data structures and their applications in AI/ML domains.
2. To analyze and design efficient algorithms using appropriate data structures for AI/ML-related problem solving.
3. Optimize algorithmic solutions with consideration of space-time trade-offs.
4. Apply AI-inspired algorithms to practical, real-world scenarios.

**Review of Fundamentals [6 Hrs]**

Time complexity and space complexity, Asymptotic analysis (Big-O, Omega, Theta), recurrence relations, amortized analysis. Review of linear and nonlinear data structures.

**Advanced Trees and Graphs: [6 Hrs]**

Balanced Search Trees: AVL, Red-Black Trees, B-Trees, Splay Trees, Segment Trees, Interval Trees, Fenwick Tree (Binary Indexed Tree), Trie and Suffix Trees, Disjoint Set Union (DSU), Graph representations, DFS/BFS, shortest paths (Dijkstra, Floyd-Warshall), MST (Kruskal, Prim).

**Advanced Algorithms and Techniques: [8 Hrs]**

Greedy algorithms and dynamic programming, Divide and Conquer algorithms, Backtracking and Branch & Bound, Bit Manipulation and Sliding Window Techniques, String Matching Algorithms: KMP, Rabin-Karp, Z-algorithm, Suffix Arrays.

**Heuristic and Approximation Algorithms: [8 Hrs]**

A* Search Algorithm, Hill Climbing, Simulated Annealing, Genetic Algorithms and Evolutionary Computing, Approximation Algorithms for NP-Hard Problems, Applications in AI planning, pathfinding, and optimization.

**Algorithms for Data Science and Machine Learning: [6 Hrs]**

KD-Trees, Ball Trees for high-dimensional data indexing, Locality-Sensitive Hashing (LSH), Graph algorithms for social networks and recommendation systems, Time series indexing structures, Streaming algorithms.

**Case Studies and Applications in AIML [6 Hrs]**

Graph-based algorithms in Knowledge Graphs and Recommendation Systems. Dynamic programming in Reinforcement Learning. Data structures for neural network optimization and sparse matrix operations.

**Textbooks:**

1. "Introduction to Algorithms" by Cormen, Leiserson, Rivest, and Stein (CLRS) – MIT Press
2. "Data Structures and Algorithms in Python" by Michael T. Goodrich, Roberto Tamassia, and Michael H. Goldwasser.

## Artificial Intelligence

| **Teaching Scheme** | **Examination Scheme** |
|---|---|
| Lectures: 3 hours/week | Theory: MSE: 30 Marks |
| Self-Study: 1 hour/week | TA: 20, ESE: 50 marks |

**Course Objectives:**

1. Gain the basic principles of AI problem solving, inference, perception, and learning.
2. Investigate applications of AI techniques in intelligent agents, ANN, ML and DL models.
3. Experience AI development tools such as a problem solver, Pytorch, TensorFlow, etc.
4. Experiment with AI techniques for design and analysis of real-world problems.
5. Explore the current scope, potential, limitations, and implications of AI systems.

**Unit 1:** **[6 Hrs]**

What Is AI? The Foundations of Artificial Intelligence, The History of Artificial Intelligence, The State of the Art, Risks and Benefits of AI, Intelligent Agents: Agents and Environments, The Concept of Rationality, The Nature of Environments, The Structure of Agents

**Unit 2:** **[6 Hrs]**

Solving Problems by Searching, Problem Solving Agents, Search Algorithms, Uninformed Search Strategies, Informed Search Strategies, Heuristic Functions, Constraint Satisfaction Problems (CSP): Defining CPSs, Constraint Propagation, Backtracking Search, Local Search for CSPs, Adversarial Search and Games: Game Theory, Optimal Decisions in Games, Heuristic Alpha–Beta Tree Search

**Unit 3:** **[8 Hrs]**

Artificial Neural Network: Biological Neural Networks, Artificial Neural Model, McCulloch – Pitts Neuron Model, Single Layer Perceptrons, Multilayer Perceptrons, Activation Functions, Loss Functions, Backpropagation Algorithm, Gradient Descent.

**Unit 4:** **[8 Hrs]**

Machine Learning: Supervised Learning, Learning Decision Trees, Model Selection and Optimization, Linear Regression and Classification, Nonparametric Models, Ensemble Learning

**Unit 5:** **[8 Hrs]**

Deep Learning: Simple Feedforward Networks, Computation Graphs for Deep Learning, Convolutional Networks, Learning Algorithms, Generalization, Recurrent Neural Networks, Unsupervised Learning and Transfer Learning

**Unit 6:** **[Self Learning]**

Deep Learning for NLP: Word Embeddings, Recurrent Neural Networks for NLP, Sequence-to-Sequence Models, The Transformer Architecture, Pretraining and Transfer Learning, Computer Vision: Image Formation, Simple Image Features, Classifying Images, Detecting Objects

**Textbook:**

1. S. Russel and P. Norvig, "Artificial Intelligence – A Modern Approach", Fourth Edition, 2021 Pearson Education

**Reference Books:**

1. David L. Poole, Alan K. Mackworth, "Artificial Intelligence: Foundations of Computational Agents", Third Edition, 2023, Cambridge University Press.
2. Wolfgang Ertel, "Introduction to Artificial Intelligence", Second Edition, 2022, Springer.
3. Perry Xiao, "Artificial Intelligence Programming with Python", First Edition, 2022, Wiley.

## Machine Learning

| **Teaching Scheme** | **Evaluation Scheme** |
|---|---|
| Lectures: 3 hrs/week | TA: 20 Marks |
| Self-Study: 1 hr./week | MSE: 30 Marks |
| | ESE: 50 Marks |

**Course Outcomes:** Students will be able to

1. Understand the foundational concepts and types of Machine Learning and their applications in real-world scenarios.
2. Apply regression and classification algorithms to solve predictive modeling problems.
3. Analyze various clustering methods, feature selection techniques, and dimensionality reduction approaches to uncover patterns and optimize models.
4. Evaluate the performance of machine learning models using metrics, cross-validation, model selection criteria, and understand the tradeoffs
5. Design complete ML workflows using appropriate learning paradigms, ensemble methods, and inference techniques to address complex data-driven problems.

**Course Contents**

**Introduction:** Overview of Artificial Intelligence and Machine Learning, Key Applications of Machine Learning across domains, Design perspectives and challenges in building ML systems, Categories of Machine Learning: Supervised Learning, Unsupervised Learning, Semi-supervised Learning, Reinforcement Learning, Inductive vs Transductive Learning. [4 hrs]

**Regression and Probabilistic Models:** Linear Regression: Assumptions, Least Squares Estimation, Logistic Regression: Formulation, Maximum Likelihood Estimation (MLE), MAP Estimation, Naive Bayes Classifier: Generative model and independence assumptions

**Model Evaluation and Selection:** Cross-Validation Techniques, Subset Selection Methods, Regularization Techniques (L1, L2), Linear Basis Function Models, Model Interpretability and Importance of Variables. [6 hrs]

**Classification and Hypothesis Testing:** Hypothesis Space and Inductive Bias, Variable Types and Measurement Scales, Constructing Hypotheses: Null and Alternative Hypotheses, Hypothesis Testing, p-values, Type I and Type II Errors, Classification Algorithms: Linear Discriminant Analysis (LDA), Perceptron Algorithm, Large Margin Classifiers and Support Vector Machines SVM: Dual Problem, KKT Conditions, Kernel Trick, Multilayer Perceptron (MLP) and Backpropagation, Decision Trees and Classification and Regression Trees (CART), Kernel Methods and Optimality Conditions. [10 hrs]

**Decision Trees and Clustering:** Decision Trees: Tree Construction and Representation, Splitting Criteria (Gini, Entropy), Overfitting and Pruning Strategies, Rule Extraction from Trees, Clustering Methods: Partitional Clustering: k-means, k-medoids, Hierarchical Clustering: Agglomerative, Divisive, Distance Measures and Linkage Criteria. [8 hrs]

**Instance-Based and Feature Learning:** Instance-Based Learning: k-Nearest Neighbors (k-NN), Curse of Dimensionality, Feature Selection: Forward and Backward Selection, Univariate vs Multivariate Feature Selection, Feature Reduction: Principal Component Analysis (PCA), Dimensionality Reduction Techniques. [6 hrs]

**Graphical and Ensemble Methods:** Probabilistic Graphical Models: Bayesian Belief Networks, Markov Random Fields, Exact and Approximate Inference (e.g., Belief Propagation, Sampling),

**Ensemble Methods:** Bagging and Random Forests, Boosting: AdaBoost, Gradient Boosting, Bias-Variance Reduction in Ensembles. [6 hrs]

**Self-Study:** Confidence Intervals and Statistical Significance, Bias-Variance Tradeoff: Concepts of Overfitting and Underfitting, Density-Based Clustering: DBSCAN, OPTICS, Spectral Clustering Techniques, Gaussian Mixture Models (GMM) and Expectation-Maximization.

**Text Books**

1. Tom M. Mitchell, “Machine Learning”, First Edition, McGraw Hill Education, ISBN 97812-5909-695-2
2. Andreas C. Müller and Sarah Guido , “Introduction to Machine Learning with Python: A Guide for Data Scientists”, First Edition, O'Reilly Media, ISBN 978-14-4936-941-5
3. Ethem Alpaydin, Introduction to Machine Learning, PHI, 2005
4. K.P. Soman, R. Longonathan and V. Vijay, Machine Learning with SVM and Other Kernel Methods, PHI-2009
5. Reference Books
6. Christopher M. Bishop, “Pattern Recognition and Machine Learning”, Second Edition, Springer, 978-03-8731-073-2
7. Hadley Wickham and Garrett Grolemund, “R for Data Science: Import, Tidy, Transform, Visualize, and Model Data”, First Edition, O'Reilly, ISBN 978-14-9191-0399

## Data Visualization

| **Teaching Scheme** | **Examination Scheme** |
|---|---|
| Lectures: 3 hrs/week | Mid Sem – 30 Marks |
| | ESE–50 Marks |
| | TA – 20 Marks |

**Course Outcomes:**
Students will be able to:
1. Understand the fundamentals of Data Visualization.
2. Study and apply data collection and preprocessing techniques for visualizing data.
3. Identify and apply suitable visualizations techniques to represent distributions, amounts, and proportions in data.
4. Apply advanced visualization techniques to get a deeper understanding of data.
5. Apply visualization techniques to text data to interpret and communicate insights effectively.

**Purpose of Data Visualization [6 Hrs]**
Data, Data Taxonomy: 1D, temporal, 2D, 3D, 4D, ND, Trees, Graphs, Nominal, Ordinal, Quantitative; Visualization, Importance of Data Visualization, Goals of Visualization, Characteristics of Good Visualizations; Exploratory Data Analysis; Time series data and Visualization; Text and Visualization; Tools for Visualization.

**Collecting, pre-processing and Visualizing Data: [6 Hrs]**
Collection: Single source, Multiple sources, Web scraping; Data Cleaning and Aggregation; Mapping data onto aesthetics: Aesthetics and types of data, Scales map data values onto aesthetics; Coordinate systems and axes: Cartesian coordinates, Nonlinear axes, Coordinate systems with curved axes.

**Visualizing Amounts, Distributions, Proportions: [8 Hrs]**

Visualizing amounts: Bar plots; Grouped and stacked bars; Dot plots and heat maps; Visualizing distributions: Histograms and density plots, visualizing a single distribution, Visualizing multiple distributions at the same time, Empirical cumulative distribution functions and q-q plots, Empirical cumulative distribution functions, highly skewed distributions, Quantile–quantile plots.

**Advanced Visualization Design** **[8 Hrs]**

Visualizing many distributions at once: Visualizing distributions along the vertical axis, Visualizing distributions along the horizontal axis; Visualizing proportions: pie charts, side-by-side bars, stacked bars and stacked densities, Visualizing proportions separately as parts of the total; Visualizing nested proportions; Visualizing associations among two or more quantitative variables: Scatter plots, Correlograms, Dimension reduction, Paired data.

**Visualizing time series, trends and geospatial data** **[6 hrs]**

Time series: Individual time series, Multiple time series and dose–response curves, Time series of two or more response variables; Trends: Smoothing, Showing trends with a defined functional form, Detrending and time-series decomposition; Geospatial data: Projections, Layers, Choropleth mapping, Cartograms.

**Text Data and Visualization** **[6 Hrs]**

Text Data, n-gram, techniques for text data visualization: word cloud, bar chart, Bigram Network, Word frequency distribution plot, network graph, case study for text data visualization

**Textbooks:**


1. Kieran Healy, "Data Visualization: A Practical Introduction". Princeton University Press, with ISBN-13: 978-0691185064
2. Claus O. Wilke, "*Fundamentals of Data Visualization: A Primer on Making Informative and Compelling Figures",* O'Reilly Media. The ISBN-13: 978-1492031086


**Reference Books:**


1. Edward R. Tufte, "The Visual Display of Quantitative Information", Graphics Pr, ISBN-13: 978-1930824133
2. Alberto Cairo – The Functional Art: An Introduction to Information Graphics and Visualizatio, New Riders, ISBN-13: 978-0321834737


## [AEC] Mini Project/Seminar

| **Teaching Scheme** | **Examination Scheme** |
| --- | --- |
| Laboratory: 2 hours/week | CIE: 50 marks, |
| Self-Study: 1 hour/week | ESE (Orals): 50 Marks |

**Course Outcomes**

Students will be able to:
1. Create links across different areas of knowledge and develop ideas to apply the problem-solving skills to a project task.
2. Do independent learning, and critical thinking and develop an attitude of innovation.
3. Identify a methodology for solving the project task and apply engineering knowledge to solve it
4. Communicate effectively and present ideas clearly in both written and oral forms.

**Guidelines**

Each student shall carry out a Mini Project task jointly in constant consultation with an internal guide assigned by the department. The project task may consider product development, prototype development, simulation development, statistical analysis, etc. The guide will continuously assess the progress of the work. Finally, a project report will be submitted as per the norms of avoiding plagiarism and the presentations will be taken.

## Data Analytics

| **Teaching Scheme** | **Examination Scheme** |
|---|---|
| Lectures: 3 hrs/week | Mid Sem – 30 Marks |
| Self-Study:1Hrs | TA:20 |
| | ESE:50 Marks |

**Course Outcomes:**

Student will be able to:

1. Identify and assess the opportunities, needs and constraints for data collection, and explore various types of datasets and features.
2. Analyze the business issues that data science and analytics can address and resolve.
3. Identify the methods by which data can be collected, stored, secured, analyzed, interpreted, forecasted, visualized, reported and applied in a business environment
4. Describe how data can be interpreted beyond its basic analysis to tell a story relevant and meaningful to its organization, and how these stories can be utilized to gain competitive advantage through strategic application
5. Design case studies on social media analytics.

**Unit I: Fundamentals of Data Analytics [8Hrs]**

Data Analytics Basics, Data Types, Analytics Types, Data Analytics Steps: Data Pre-Processing, Data Imputation, Data Cleaning, Data Transformation, Data Visualization, and Data Engineering. Descriptive, Predictive, and Prescriptive Analytics.

**Unit II: Data Analytics with Python [8 Hrs]**

Data Analytics using Python, Statistical Procedures, Web Scraping in Python, Advanced analytics, NumPy, Pandas, SciPy, Matplotlib.

**Unit III: Correlated Data Analysis** **[7 Hrs]**

Analysis of Variance and Co-Variance, ANOVA results, Chi-Square Statistical Test, Examine Regression results, Regressing Analysis, Linear Regression and its analysis, Logistic Regression and its analysis.

**Unit IV: DecisionTrees and Cluster Analysis** **[9Hrs]**
Decision Tree Problem Analysis, Decision tree Construction, Decision Tree Algorithms; Applications of Cluster Analysis, Definition of Cluster, representing clusters, Clustering Techniques, K-Means Algorithm for Clustering, Advantages and Disadvantages of K-Means Clustering.

**Unit V: Social Media Analytics** **[8 Hrs]**

Datasets, Analysis of Social Network Dataset Features, Learning Models and Validation, Association Rule Mining, artificial Neural Networks for web analytics.

**Textbooks:**

1. Anil Maheshwari,"Data Analytics made accessible,"Amazon Digital Publication, 2014.
2. Song, PeterX.-K,"Correlated DataAnalysis: Modeling, Analytics, and Applications", Springer-Verlag New York 2007.
3. Glenn J.Myatt,Wayne P.Johnson,"Making Sense of Data I: A Practical Guide to Exploratory Data Analysis and Data Mining", Wiley 2009.

**Reference Books:**

1. Thomas H. Davenport, Jeanne G. Harris and Robert Morison,"Analytics at Work: Smarter Decisions, Better Results", Harvard Business Press, 2010
2. Rachel Schutt, Cathy O'Neil, "Doing Data Science", O'REILLY, 2006.
3. Shamanth Kumar Fred Morstatter Huan Liu "Twitter Data Analytics", Springer-Verlag, 2014.

## [ MLC] Research Methodology and Intellectual Property Rights

| **Teaching Scheme** | **Examination Scheme** |
|---|---|
| Self-Study: 2 hrs/week | CIE–90 Marks |
| | TA – 10 Marks |

**Course Outcomes:**

1. Understand research problem formulation and approaches of investigation of solutions for research problems
2. Learn ethical practices to be followed in research
3. Discover how IPR is regarded as a source of national wealth and the mark of economic leadership in the context of the global market scenario
4. Study the national & International IP system

**Unit 1:** **[5 hrs]**
Meaning of research problem, Sources of research problem, Criteria Characteristics of a good research problem, Errors in selecting a research problem, Scope and objectives of research problem. Approaches of investigation of solutions for research problem, data collection, analysis, interpretation, and necessary instrumentations.

**Unit 2:** **[5 hrs]**
Effective literature studies approaches, analysis Use Design of Experiments /Taguchi Method to plan a set of experiments or simulations or build prototype Analyze your results and draw conclusions or Build Prototype, Test and Redesign

**Unit 3:** **[5 hrs]**
Plagiarism, Research ethics Effective technical writing, how to write report, Paper. Developing a Research Proposal, Format of research proposal, a presentation and assessment by a review committee

**Unit 4:** **[4 hrs]**
Introduction to the concepts Property and Intellectual Property, Nature and Importance of Intellectual Property Rights, Objectives and Importance of understanding Intellectual Property Rights

**Unit 5:** **[7 hrs]**
Understanding the types of Intellectual Property Rights: -Patents-Indian Patent Office and its Administration, Administration of Patent System – Patenting under Indian Patent Act, Patent Rights and its Scope, Licensing and transfer of technology, Patent information and database. Provisional and Non-Provisional Patent Application and Specification, Plant Patenting, Idea Patenting, Integrated Circuits, Industrial Designs, Trademarks (Registered and unregistered trademarks), Copyrights, Traditional Knowledge, Geographical Indications, Trade Secrets, Case Studies

**Unit 6:** **[4 hrs]**
New Developments in IPR, Process of Patenting and Development: technological research, innovation, patenting, development, International Scenario: WIPO, TRIPs, Patenting under PCT

**Reference Books:**

1. B L Wadehra, Law Relating to Patents, Trademarks, Copyright, Designs and Geographical Indications, 2004
2. Satyawrat Ponkse, The Management of Intellectual Property, 1991.
3. Manual of Patent Office Practice and Procedure, 2019
4. W.H. Mayall, Industrial Design for Engineers, liffe Books, 1967

5. Niebel, Benjamin W, Product Design and Process Engineering, McGraw-Hill, 1974
6. Asimow, Morris, Introduction to Design, Prentice Hall, 1962

## [ MLC] Effective Technical Communication

**Teaching Scheme**
Self-Study: 1 hour/week

**Examination Scheme**
Theory: CIE: 90 Marks,

TA: 10 marks

**Course Outcomes (COs):**
Students will be able to
1. Produce effective dialogue for business related situations
2. Use listening, speaking, reading and writing skills for communication purposes and attempt tasks by using functional grammar and vocabulary effectively
3. Analyze critically different concepts/principles of communication skills
4. To appreciate, analyze, and evaluate business reports and research papers

**Unit 1: Fundamentals of Communication** **[4 hrs]**
7 Cs of communication, common errors in English, enriching vocabulary, styles, and registers

**Unit 2: Aural-Oral Communication** **[4 hrs]**
The art of listening, stress and intonation, group discussion, oral presentation skills

**Unit 3: Reading and Writing** **[4 hrs]**
Types of reading, effective writing, business correspondence, interpretation of technical reports and research papers

**Text Books**
1. Raman Sharma, "Technical Communication", Oxford University Press.
2. Raymond Murphy "Essential English Grammar" (Elementary & Intermediate) Cambridge University Press.
3. Mark Hancock "English Pronunciation in Use" Cambridge University Press.
4. Shirley Taylor, "Model Business Letters, Emails and Other Business Documents" (seventh edition), Prentice Hall
5. Thomas Huckin, Leslie Olsen "Technical writing and Professional Communications for Non-native speakers of English", McGraw Hill.

**Reference books/paper(s):**
1. D.J.C. MacKay, Information Theory, Inference, and Learning Algorithms, Cambridge University Press
2. C. E. Shannon, A Mathematical Theory of Communication, Bell Sys. Tech Journ, 1948.

**Web Resources:**
1. NPTEL Course (Information Theory and Coding– IIT, Bombay): http://nptel.ac.in/syllabus/117101053/

2. MIT OpenCourseWare (Information Theory): http://ocw.mit.edu/courses/electrical-engineering-and- computer-science/6-441- information-theory-spring-2010/index.htm

**Detailed Syllabus - Semester III**

**[OE] Data Structures**

(offered to students of other departments)

**Teaching Scheme**
Lectures: 3 hours/week
Study: 1 hour/week

**Examination Scheme**
MSE: 30 Marks, TA: 20 marks Self-
ESE: 50 marks

**Course Outcomes**

Students will be able to:

1. Decide appropriate data structures such as B-trees, heaps, etc that are best suits for solving a real-life problem
2. Implement advanced data structures, such as B-trees, multi-way trees, balanced trees, heaps, and priority queues, to solve computational problems
3. Analyze the time and space complexity of advanced data structures and their supported operations
4. Compare the time and space tradeoff of different advanced data structures and their common operations

**Unit 1** **[6 hrs]**

Review of Basic Concepts: Abstract data types, Data structures, Algorithms, Big Oh, Small Oh, Omega and Theta notations, Solving recurrence equations, Master theorems, Generating function techniques, Constructive induction.

**Unit 2** **[8 hrs]**

Advanced Search Structures for Dictionary ADT: Splay trees, Amortized analysis, 2-3 trees, 2-3-4 trees, Red-black trees, Randomized structures, Skip lists, Treaps, Universal hash functions.

**Unit 3** **[6 hrs]**

Advanced Structures for Priority Queues and Their Extensions: Binary Heap, Min Heap, Max Heap, Binomial heaps, Leftist heaps, Skewed heaps, Fibonacci heaps and its amortized analysis, Applications to minimum spanning tree algorithms

**Unit 4** **[6 hrs]**

Data Structures for Partition ADT: Weighted union and path compression, Applications to finite state automata minimization, Code optimization.

**Unit 5** **[6 hrs]**

Graph Algorithms: DFS, BFS, Biconnected components, cut vertices, Matching, Network flow; Maximum-Flow / Minimum-Cut; Ford–Fulkerson algorithm, Augmenting Path.

**Unit 6** **[8 hrs]**

Computational Geometry: Geometric data structures, Plane sweep paradigm, Concurrency, Java Threads, Critical Section Problem, Race Conditions, Re-entrant code, Synchronization; Multiple Readers/Writers Problem.

**Text Books**


1. Thomas H. Cormen, Charles E. Leiserson, Ronald L. Rivest and Clifford Stein, Introduction to Algorithms, 3rd Edition, PHI Learning Pvt. Ltd.; ISBN-13: 978-0262033848 ISBN-10: 0262033844
2. Robert Sedgewick and Kevin Wayne, Algorithms, Pearson Education, 4th Edition, ISBN-13: 978-0321573513


**Reference Books**


1. S. Dasgupta, C.H. Papadimitriou, and U. V. Vazirani, Algorithms, McGraw-Hill, 2006; ISBN-13: 978-0073523408 ISBN-10: 007352340.

2. J. Kleinberg and E. Tardos, Algorithm Design, Addison-Wesley, 2006; ISBN-13: 978-0321295354 ISBN-10: 0321295358


## Deep Learning

| **Teaching Scheme** | **Examination Scheme** |
|---|---|
| Lectures: 3 hours/week | MSE: 30, TA: 20 marks |
| Self-Study: 1 hour/week | ESE: 50 marks |

**Course Outcomes**

Students will be able to:

1. Understand the fundamentals of neural networks.
2. Design feed-forward networks with backpropagation.
3. Apply attention mechanism to the neural network.
4. Solve the real-time problem statements using Deep Learning Architectures

**Unit 1: Basic** **[4 hrs]**

Biological Neuron, Idea of computational units, McCulloch–Pitts unit and Thresholding logic, Linear Perceptron, Perceptron Learning Algorithm, Linear separability. Convergence theorem for Perceptron Learning Algorithm.

**Unit 2: Feedforward Networks** **[6 hrs]**

Introduction to the neural network and multilayer perceptron (MLPs) representation power of MLPs, sigmoid neurons, gradient descent, feed-forward neural networks representation, Backpropagation.

**Unit 3: Optimization Techniques** **[8 hrs]**

Gradient Descent, Batch Optimization, Momentum Based GD, Nesterov Accelerated GD, Stochastic GD, AdaGrad, RMSProp, Adam, Saddle point problem in neural networks, Regularization methods (dropout, drop connect, batch normalization).

**Unit 4: Autoencoders** **[10 hrs]**

Autoencoders, Regularization in autoencoders, Denoising autoencoders, Sparse autoencoders, Contractive autoencoders, Regularization: Bias Variance Tradeoff, L2 regularization, Early stopping, Dataset augmentation, Parameter sharing and tying, Injecting noise at input, Ensemble methods, Dropout, Greedy Layer wise Pre-training, Better activation functions, better weight initialization methods, Batch Normalization.

**Unit 5: Convolutional Neural Networks (CNN)** **[8 hrs]**

Introduction to CNN, Building blocks of CNN, Transfer Learning, LeNet, AlexNet, ZF- Net, VGGNet, GoogLeNet, ResNet, Visualizing CNNs, Guided Backpropagation, Fooling Convolutional Neural Networks.

**Unit 6: Recurrent Neural Networks (RCNN)** **[4 hrs]**

Introduction to RCNN, Backpropagation through time (BPTT), Vanishing and Exploding Gradients, Truncated BPTT

**Self-Study:** **[4 Hrs]**

Long Short Term Memory, Gated Recurrent Units Bidirectional LSTM, RNNs, Encoder Decoder Models, Attention Mechnism

**Textbook:**

1. Ian Goodfelllow, Yoshua Benjio and Aaron Courville, Deep Learning, The MIT Press, 2016.
2. François Chollet, Deep Learning with Python, Manning, Second Edition, 2021.
3. Josh Patterson and Adam Gibson, Deep Learning: A Practitioner’s Approach, O'Reilly Media, Inc., 2017.

**Reference Books**

1. Raúl Rojas, Neural Networks: A Systematic Introduction, Springer, 1996.
2. Christopher Bishop, Pattern Recognition and Machine Learning, Springer, 2007.

**Generative Adversarial Networks**

| | |
|---|---|
| **Teaching Scheme:** | **Examination Scheme:** |
| Lectures: 3 Hrs/week | MSE: 30 Marks |
| Self-Study: 1Hrs | TA:20, ESE: 50 Marks |

**Course Outcomes:**

Students will be able to:

1. Understand various clocks of Generative Adversarial Networks (GANs)
2. Analyse and understand Deep convolution architecture with its challenges pertaining to GANs.
3. Design various structure of GANs while optimizing the various training challenges.
4. Study, implement and understand various application of GANs for image, text, and speech datasets.

**Contents:**

**Unit I: Introduction to GANs: [8 Hrs]**

Generative Adversarial Networks (GANs), mathematics underpinning, Random noise vector, Generator network, Discriminator network, Iterative training/tuning, Adversarial training, Nash equilibrium, Introduction to generative modelling, Encoder network, Latent space, Decoder network, Generation using an autoencoder, Variational autoencoder

**Unit II: Deep Convolutional GAN: [8 Hrs]**

Convolutional neural networks, Convolutional filters, Parameter sharing, Batch normalization, Training challenges (Mode collapse, Slow convergence, Overgeneralization), Non-Saturating GAN

**Unit III: Various types of GANs: [14 Hrs]**

Semi-Supervised GAN: Introduction to Semi-Supervised GAN, Architecture, Training process, Training objective Conditional GAN: Motivation, CGAN Generator, CGAN Discriminator, Architecture of CGAN CycleGAN: Image-to-image translation, Cycle-consistency loss, Adversarial loss, Identity loss, CycleGAN architecture: building the network Object-oriented design of GANs

**Unit IV: Real-World Applications for GANs: [12 Hrs]**

Human Faces Generation, Deep Fake, Image-to-Image Translation/Restoration, Text to Image Generation, Enhancing Image Resolution, Semantic Image Inpainting, Text to Speech, Speech Enhancement with GANs

**Reference Books**

1. Foster, D., 2019. Generative Deep Learning. Teaching Machines to Paint, Write, Compose and Play (2019). Beijing-Boston-Farnham-Sebastopol-Tokyo, OREILLY, p.330.
2. Bok, Vladimir, and Jakub Langr. GANs in action: deep learning with generative adversarial networks. Simon and Schuster, 2019.
3. Ganguly, Kuntal. Learning generative adversarial networks: next generation deep learning simplified. Packt Publishing, 2017.
4. Valle, Rafael. Hands-On Generative Adversarial Networks with Keras: Your guide to implementing next-generation generative adversarial networks. Packt Publishing Ltd.

## Optimization Techniques

| **Teaching Scheme:** | **Examination Scheme:** |
|---|---|
| Lectures: 3 Hrs/week | MSE: 30 Marks |
| Self-Study: 1Hrs | TA: 20, ESE: 50 Marks |

**Course Outcomes:**

After successful completion of the course, students will be able to:

1. Illustrate the concepts of optimization and its terminologies.
2. Apply and compare bio-inspired and physics-based optimization techniques.
3. Solve constrained and unconstrained optimization problems.
4. Design efficient hybrid and parallel algorithms for real-world problems.
5. Formulate and solve multi-objective optimization problems.
6. Analyse the performance of algorithms in various engineering and ML applications

**Contents:**

**Unit I: Introduction to Optimization** **[6 Hrs]**

Problem formulation, Global and Local optima, Optimality criteria, Basic calculus for optimization

**Unit II: Classical & Convex Optimization** **[6 Hrs]**

Unconstrained and constrained optimization, KKT conditions, Duality, Convex functions and sets

**Unit III: Biology-Inspired Algorithms** **[6 Hrs]**

Bee Algorithm, Cuckoo Search, Teaching–Learning Based Optimization (TLBO), applications

**Unit IV: Physics-Inspired & Swarm Algorithms** **[6 Hrs]**

Simulated Annealing, Particle Swarm Optimization (PSO), Harmony Search, Firefly Algorithm

**Unit V: Multi-objective & Hybrid Optimization** **[6 Hrs]**

Pareto optimality, NSGA-II, MOEA/D, Hybrid algorithms, constraint handling techniques

**Unit VI: Applications & Case Studies in AI/ML** **[6 Hrs]**

Real-world engineering/ML applications, Benchmark functions, Algorithm comparison, ML use cases

**Reference Books**


1. Boyd, Stephen, and Lieven Vandenberghe. Convex Optimization. Cambridge University Press, 2004.
2. Beck, Amir. Introduction to Nonlinear Optimization: Theory, Algorithms, and Applications with MATLAB. SIAM, 2014.
3. Rao, Singiresu S. Engineering Optimization: Theory and Practice, 4th Edition. Wiley, 2009.
4. Bertsekas, Dimitri P. Nonlinear Programming, 3rd Edition. Athena Scientific, 2016.
5. Deb, Kalyanmoy. Multi-Objective Optimization Using Evolutionary Algorithms. Wiley, 2001.


## (PEC-02) Reinforcement Learning

**Teaching Scheme:** **Examination Scheme:**

Lectures: 3 Hrs/week TA: 20 Marks

Self-Study: 1Hrs/Week Midsem: 30 Mark, ESE - 50 marks

**Course Outcomes**

Students will be able to:

1. Discuss the process of Reinforcement Learning
2. Apply the RL algorithms for decision making in uncertain conditions
3. Evaluate the performance of solution and optimal strategy
4. Interpret the fine tuning the target to have better learning performance
5. Elaborate the approximation methods and algorithms for optimizing the problem
6. Decompose the RL problem into hierarchy of sub problems

**Course contents**

**Introduction** **[6 Hrs]**

Supervised learning of Behaviours, Reinforcement Learning, Bandit algorithms – UCB, PAC, Bandit algorithms –Median Elimination, Multi-armed bandits

**Policy Gradient** **[6 Hrs]**

Policy Gradient Methods, Actor Critic Algorithm, Contextual Bandits, Value function Methods, Deep RL, Q functions, Deep RL with Q Functions, Advanced Policy Gradients

**Optimal Control** **[8 Hrs]**

Finite Markov Decision Process, Bellman Optimality, Dynamic Programming and TD Methods, Policy Iteration, Value Iteration, Monte carlo methods

**Model Based Reinforcement Learning** **[6 Hrs]**

Temporal Difference Learning, n-step Bootstrapping, Eligibility Traces, Exploration, Model Based Policy Learning

**Planning** **[6 Hrs]**

On-policy prediction with function approximation - on-policy control with function approximation - off-policy control with function approximation, least square Methods, Fitted Q, DQN and Policy Gradient for Full RL

**Hierarchical RL** **[6 Hrs]**

Full RL, - POMDPs - inverse-RL - Exploration in RL - Offline RL, Inverse RL, Transfer and Multi-task learning, Meta-learning

**Self-Study topics:**

Explore-exploit dilemma, Binary Bandits, Learning automata, exploration schemes Dynamic programming: value iteration, policy iteration, asynchronous DP, generalized policy iteration, forward and backward views, Q(lambda), SARSA(lambda), replacing traces and accumulating trace, MAXQ framework, Options framework, HAM framework, Option discovery algorithms Case studies: Elevator dispatching, Samuel's checker player, TDgammon, Acrobot, Helicopter piloting, Computational Neuroscience

**[14 hrs]**

**Text Books**

1. Rich Sutton and Andrew Barto. *Reinforcement Learning: An Introduction*. Available free online.
2. [Szepesvari] Csaba Szepesvari. *Algorithms for Reinforcement Learning*. Available free online
3. [BT] Dimitri Berstekas and John Tsitsiklis. *Neuro-Dynamic Programming*

**Reference Books**

1. Marco Wiering and Martijn van Otterlo, Eds. Reinforcement Learning: State-of-the-Art. Sprinkler.
2. Stuart J. Russell and Peter Norvig. Artificial Intelligence: A Modern Approach. Pearson.
3. Ian Goodfellow, Yoshua Bengio,and Aaron Courville. Deep Learning. MIT Press.Milan Milenkovic; Operating Systems; Tata McGraw Hill; Second Edition. ISBN: 0-07-044700-4

## (PEC-02) Explainable AI

**Teaching Scheme:**
Lectures: 3 Hrs/week
Self-Study: 1Hrs/Week

**Examination Scheme:**
TA: 20 Marks
Midsem: 30 Marks
End Sem Exam - 50 marks
Mode: Open Book, Online/Offline

**Course Outcomes**

Students will be able to:

1. Discuss the process of XAI
2. Apply interpretability and explainability techniques using case studies
3. Evaluate interpretability of models
4. Measure the model interpretability
5. Elaborate the black box models and its vulnerabilities
6. Discuss the reasoning in large language models

**Course contents**

**Introduction** **[6 Hrs]**

Transparency: motivations and challenges, Interpretability in Intelligent System, Model Understanding, Inherently Interpretable Models vs Post-hoc Explanations, Properties of interpretable models, Defining and understanding interpretability

**Learning Inherently Interpretable Models** **[6 Hrs]**

Rule based Approaches, Interpretable decision sets, Submodular maximization, local search, smooth local search, Intelligible models for healthcare, feature shaping vs Expert discretization, prototype-based approaches: Deep learning for case-based reasoning through prototypes, Gradient based Attribution methods, Layer-wise relevance propagation, Explaining and interpreting LSTM

**Evaluating Interpretability** **[8 Hrs]**

Practitioner Interpretability needs, Human factors in Model Interpretability: Industry practices, challenges and needs, Human Evaluation of models built for interpretability: Decision Sets, Regularizers, Types of Complexity, Statistical Analysis, Manipulating and measuring model interpretability, gradient based vs propagation-based explanations

**Black Box models and their vulnerabilities**: Attention and concept-based explanations, Influence function, Equitable valuation of data, Explainable active learning, Unified Framework for Model Explanations, Latent space of GAN, GANSpace

**[6 Hrs]**

**Adversarial robustness, fairness, DP** **[8 Hrs]**

Discriminative Features, Explainability for Fair Machine Learning, Mechanistic Interpretability, variables and importance of Interpretable Bias, OpenXAI, Vertex XAI

**Understanding and reasoning in Large Language Models** **[6 Hrs]**

Foundation Models, concept probing, UNet Architecture, Visuo-syntactic Analysis, Visuo-semantic Analysis, Applications of XAI

**Self Study topics** **[14 hrs]**

Explainability Consumers :Practitioners—Data Scientists and ML Engineers, Observers—Business Stakeholders and Regulators, End Users—Domain Experts and Affected Users; Types of Explanations: Premodeling Explainability, Intrinsic Versus Post Hoc Explainability, Local, Cohort, and Global Explanations, Attributions, Counterfactual, and Example-Based Explanations: Themes Throughout Explainability: Feature Attributions, Surrogate Models, Activation, Permutation Feature Importance: Permutation Feature Importance from Scratch, Permutation Feature Importance in scikit-learn; Shapley Values: SHAP (SHapley Additive exPlanations), Visualizing Local Feature Attributions, Visualizing Global Feature Attributions,Interpreting Feature Attributions from Shapley Values, Managed Shapley Values, Explaining Tree-Based Models: From Decision Trees to Tree Ensembles, SHAP's TreeExplainer; Partial Dependence Plots and Related Plots: Partial Dependence Plots (PDPs), Individual Conditional Expectation Plots (ICEs) Accumulated Local Effects (ALE)

**Text Books**

1. Pethuru Raj, Utku Kose, Usha Sakthivel, Susila Nagarajan, Vijanth S, Asirvadam, "Explainable Artificial Intelligence(XAI): Concepts, enabling tools, technologies and applications", ISBN: 978183953695
2. Wojciech Samek, Gregoire Montavon, Andrea Vedaldi, Lars Kai Hansen, Klaus Robert Muller, "Explainable AI: Interpreting, Explaining and Visualizing Deep Learning", Springer
3. Michael Munn, David Pitman, "Explainable AI for Practitioners: Designing and implementing Explainable ML solutions", O'Reilly Media, Inc., ISBN: 9781098119133

**Reference Books**

1. Mayuri Mehta Vasile Palade Indranath Chatterjee, "Explainable AI: Foundations, Methodologies and Applications", Springer, ISBN 978-3-031-12806-6
2. Guide to explainability in Artificial Intelligence, TIC Salut Social Foundation

## (PEC) MLOps and Systems

| **Teaching Scheme:** | **Examination Scheme:** |
|---|---|
| Lectures: 3 Hrs/week | MSE: 30 Marks |
| Self-Study: 1Hrs | TA:20 |
| | ESE: 50 Marks |

**Course Outcomes:**

Students will be able to:

1. Build and validate well known ML/DL model prototypes on a variety of ML use cases such as Data Streams

2. Apply transfer learning for ML Model deployment on cloud platforms.
3. Understand the impact of data drift and concept drift in ML pipelines.
4. Apply AutoML and collaborative frameworks such as MLflow.
5. Build and maintain CI/CD pipelines for cloud-based ML-Model Deployments.
6. Apply production-specific software services using Prometheus, grafana cloud, elk stack (AWS), fluentD and cloudwatch (AWS)

**Unit I: Statistical ML Models for Data Streams [8 Hrs]**

Classification, Regression, Unsupervised learning, AutoML: autosklearn, TPOT, Linear and nonLinear Models: linear regression, Random Forest, SVM, kNN, k-means, logistic regression, Visualization using D3, Tableau.

**Unit II: ML API Development and Deployment on GCP and AWS [6 Hrs]**

Flask, FastApi, Tensorflow serving, Tensorflow lite for optimization latency

**Unit III: Cloud-based APIs [6 Hrs]**

Intro to Kubeflow, Collaborative platforms: MLflow, AutoML in GCP, Azure, AWS, Hyper parameter optimization

**Unit IV: ML Deployment and MLOps Pipelines [8 Hrs]**

ML Deployment : Docker Containers, Kubernetes, FluentD, Elk Stack
MLOps Pipelines : CI/CD Pipelines, Gitlab, Jenkins, YAML/XML, Profiler

**Unit V: Application Production Testing on Google Optimize [6 Hrs]**

Canary pattern, A/B Pattern, Shadow Pattern

**Unit VI: Production Software Build and Analytics [8 Hrs]**

Prometheus, Grafana Cloud, Cloudwatch, Special Topics: Building models from scratch, Hyperparameterization, optimization, quantization

**Suggested Assignments:**

1. E-commerce use-case for data wrangling, compression, meta-data tagging, metrics and visualization
2. ML API Development and Deployment on GCP and AWS: Rapid Prototyping for NLP usecase

3. Computer Vision use case: Hyper-parameterization using MLflow
4. Study of ML Deployment use case
5. Study of MLOps Pipelines Deployment use case
6. Application Production Testing on Google Optimize Deployment use case
7. Production Software Build and Analytics Deployment use case

**Books:**

1. Mark Treveil, CL Stenac, L Dreyfus-Schmidt, Kenji LeFevre, Nicolas Omont, Introducing MLOps: How to Scale Machine Learning in the Enterprise, O'REILLY, 2021
2. Noah Gift and Alfredo Deza, Practical MLOps: Operationalizing Machine Learning Models, O'REILLY, 2021.
3. Hannes Hapke and Catherine Nelson, Building Machine Learning Pipelines: Automating Model Life Cycles with TensorFlow, O'REILLY, 2020

## (PEC) Natural Language Processing

| **Teaching Scheme:** | **Examination Scheme:** |
|---|---|
| Lectures: 3 hours/week | MSE: 30 Marks, TA:20 |
| Self-Study 1 Hrs | End-Sem Exam: 50 Marks |

**Course Outcomes:**

Students will be able to:

1. Demonstrate the understanding of basic text processing techniques in NLP.
2. Design, implement and evaluate part-of-speech taggers and parsers for a language.
3. Build language models and demonstrate Word Sense Disambiguation using WordNet.
4. Analyze and build word embeddings for different languages.

**Unit 1: Introduction** **[6 hrs]**

What is NLP, Fundamental and Scientific goals, Engineering goals, stages of NLP, problems in NLP, Applications of NLP, Empirical Laws of language, zipf's law, Heap's law.

**Unit 2: Basic Text Processing** **[8 hrs]**

Tokenization, word token, word type, sentence segmentation, feature extraction, issues in tokenization for different languages, word segmentation, text segmentation, normalization, case folding, Spelling Correction, Morphology, Stemming, Porters Algorithm, , lemmatization, spelling correction – dynamic programming approach for finding edit distance, N-gram Language Modeling- context sensitive spelling correction, probabilistic language model, auto completion prediction, Evaluation and perplexity, Smoothing techniques.

**Unit 3: POS Tagging** **[8 hrs]**

Sequence labeling tasks of NLP, POS tagging, POS tag sets, Hidden Markov Model-Introduction, Markov Processes, HMM characterization -Likelihood of a sequence (Forward Procedure, Backward Procedure), Best state sequence (Viterbi Algorithm), Re-estimation(Baum-Welch - Forward-Backward Algorithm) , Models for Sequential tagging – Maximum Entropy, Conditional Random Field.

**Unit 4: Syntax** **[10 hrs]**

Constituency and dependency parsing, Constituency parser -Syntactic structure, Parsing methodology, Different parsing algorithms, Parsing in case of ambiguity, Probabilistic parsing, CKY algorithm, Issues in parsing, Dependency parsing- Syntactic structure, Parsing methodology, Transition-Based Dependency Parsing, Graph-Based dependency parsing, Evaluation, Co-reference resolution, Namedentity recognition.

**Unit 5: Knowledge Base and Semantics** **[6 hrs]**

WordNet: Word Senses, Word relations, Word similarity and thesaurus methods, Word sense disambiguation, WordNet. Lexical and Distributional Semantics - Introduction, models of semantics, applications.

**Unit 6: Word Embeddings** **[6 hrs]**

Introduction, one-hot vectors, methods of generating word embeddings, Skip-gram, CBOW, Glove model, Fast Text model, evaluation measures-rough scores.

**Text Books:**

1. Daniel Jurafsky and James H. Martin, “Speech and Language Processing”, Second Edition, Prentice Hall, 2008, ISBN: 978-0131873216.
2. Allen James, “Natural Language Understanding”, Second Edition, Benjamin/Cumming, 1994,
ISBN: 978-0805303346.
3. Chris Manning and Hinrich Schuetze, “Foundations of Statistical Natural Language Processing”, MIT Press, ISBN: 978-0262133609.

**Reference Books:**

1. Journals: Computational Linguistics, Natural Language Engineering, Machine Learning, Machine Translation, Artificial Intelligence.
2. Conferences: Annual Meeting of the Association of Computational Linguistics (ACL), Computational Linguistics (COLING), European ACL (EACL), Empirical Methods in NLP (EMNLP), Annual Meeting of the Special Interest Group in Information Retrieval (SIGIR), Human Language Technology (HLT).

## (PEC) Graph Neural Network

| **Teaching Scheme:** | **Examination Scheme:** |
|---|---|
| Lectures: 3 Hrs/week | Mid Sem: 30 Marks, TA: 20 Marks |
| Self-Study: 1Hrs | ESE: 50 Marks |

**Course Outcomes:**

Students will be able to:

1. Understand the fundamentals of graphs, graph representations, and their applications in AI/ML.
2. Analyze and implement traditional graph algorithms and their limitations.
3. Design, train, and evaluate various Graph Neural Network (GNN) architectures.
4. Apply GNNs to real-world problems such as social networks, recommendation systems, and bioinformatics.
5. Compare different GNN models and understand their theoretical foundations.

**Module 1: Introduction to Graphs & GNNs** **[06 hrs.]**

Graph Basics: Types of graphs (directed, undirected, weighted, heterogeneous). Graph representations (adjacency matrix, edge list, Laplacian). Traditional Graph Algorithms:

PageRank, Shortest Path, Community Detection. Why GNNs? Limitations of CNNs/RNNs on graph data.

Message Passing Framework.

**Module 2: Core GNN Architectures [08 hrs.]**

Graph Convolutional Networks (GCN), ChebNet, Graph Fourier Transform. Graph Attention Networks (GAT), GraphSAGE. Spectral vs. spatial approaches.

**Module 3: Advanced GNN Models [06 hrs.]**

Graph Auto encoders (GAE, VGAE). Dynamic GNNs (Temporal Graphs). Heterogeneous GNNs (RGCN, HAN). Explainability in GNNs.

**Module 4: Applications of GNNs (DP) [06 hrs.]**

Social Network Analysis: Link prediction, Community detection. Recommendation Systems: Collaborative filtering with GNNs. Bioinformatics: Molecular property prediction, Drug discovery. Computer Vision & NLP: Scene graphs, Knowledge graphs.

**Module 5: Scalability & Optimization [06 hrs.]**

Large-scale GNN training Sampling Techniques (Node, Edge, Subgraph). Distributed GNN Training. Hardware Acceleration (GPU/TPU).

**Module 6: Recent Trends & Tools in GNN [06 hrs.]**

State-of-the-art research: Self-supervised GNNs, Heterogeneous Graphs, Dynamic GNNs.
Popular GNN frameworks: PyTorch Geometric, DGL, GraphGym.
GNN explainability and interpretability, Limitations & Open Problems.

**Books:**


1. Zhou, Jie, et al. "Graph neural networks: A review of methods and applications." AI Open 1 (2020): 57-81.
2. Hamilton, Will. *Graph Representation Learning*. Morgan & Claypool Publishers, 2020.
3. Wu, Zonghan, et al. "A Comprehensive Survey on Graph Neural Networks." IEEE Transactions on Neural Networks and Learning Systems, 2021.


**Reference Books:**


1. Bronstein, Michael M., et al. "Geometric Deep Learning: Grids, Groups, Graphs, Geodesics, and Gauges." (arXiv:2104.13478)
2. Kipf, Thomas, and Max Welling. "Semi-Supervised Classification with Graph Convolutional Networks." ICLR, 2017.
3. Velickovic, Petar, et al. "Graph Attention Networks." ICLR, 2018.


**Research Resources:**

1. Conferences: NeurIPS, ICLR, ICML, KDD, AAAI
2. Journals: IEEE TNNLS, JMLR, ACM TKDD
3. Libraries: PyTorch Geometric, Deep Graph Library (DGL), Stellar

## (PEC)Federated AI

| **Teaching Scheme** | **Examination Scheme** |
|---|---|
| Lectures: 3 hours/week | MSE: 30 Marks, TA: 20 marks |
| Self-Study: 1 hour/week | ESE: 50 marks |

**Course Outcomes**

Students will be able to:

1. Apply basic search techniques for problem solving.

2. Explain how to represent the Knowledge required for problem solving.

3. Apply reasoning to sift through data.

4. Utilize AI for application in real world.

**Unit 1:** **[6 hrs]**

Introduction to Federated and Edge AI, Overview of Edge Computing and AI at the Edge, Motivation for Federated Learning (FL), Differences between centralized, distributed, and federated learning, Applications of Federated and Edge AI

**Unit 2:** **[6 hrs]**

Fundamentals of Federated Learning, Federated Learning Architecture & System Design, Types of Federated Learning: Cross-device vs Cross-silo, Basic algorithms: Federated Averaging (FedAvg), Data heterogeneity and non-IID data challenges, Communication efficiency and compression techniques.

**Unit 3:** **[6 hrs]**

Privacy and Security in Federated Learning, Privacy risks in distributed learning, Differential Privacy (DP), Secure Multi-Party Computation (SMPC), Homomorphic Encryption, Adversarial attacks and robustness in FL. Optimization and Algorithms, Optimization challenges in FL, Gradient aggregation and client selection strategies, Handling stragglers and fault tolerance Personalization in federated learning.

**Unit 4:** **[6 hrs]**

Edge AI Fundamentals, Hardware constraints and AI model design for Edge devices, Model compression techniques: Pruning, Quantization, Knowledge Distillation, Lightweight neural network architectures (MobileNet, TinyML), Edge inference and deployment strategies.

**Unit 5:** **[6 hrs]**

Case Studies and Applications, Federated learning in healthcare, finance, and IoT, Edge AI in autonomous vehicles, smart cameras, and wearable devices, Real-world frameworks: TensorFlow Federated, PySyft, Flower.

**Unit 6:** **[6 hrs]**

Emerging Trends and Research Directions, Federated Transfer Learning, Cross-modal Federated Learning, Federated Learning with Blockchain, Future challenges in scalability and fairness

**Text Books**

1. Federated Learning: Collaborative Machine Learning with Privacy — Qiang Yang et al.

2. Edge AI: On-Demand Accelerated Deep Learning Inference via Edge Computing — Yu Shi et al.

## [CCA] Liberal Learning Course

| Teaching Scheme | Examination Scheme |
|---|---|
| Lectures: 1 hour/week | CIE: 90 marks, TA: 10 marks |

**Guidelines:**

Liberal Learning Courses began aims with a vision of expanding the horizons of knowledge in a variety of areas beyond Engineering. It provides opportunities to students of Engineering to foray into areas of their interest, to contribute to their overall personality development. The students are required to go through the areas of agriculture, Clay Art & Pottery, Dance (Contemporary), Dance (Indian), Film Appreciation, French, Geography, Holistic Health, Interior Design, Introduction to Indian Armed Forces, Music (Instrumental), Music (Vocal), Painting, Photography, Political Science, Theatre & Dramatics, Wood & Metal Art etc. Experts from respective areas conduct classes for each area on campus through activities, discussions, presentations, and lecture methods, and an evaluation out of 100 per area is done for each area throughout the semester. Evaluation patterns may differ according to the nature of each area. Although there is no pre-defined syllabus for LLC areas, there is an outline that experts normally develop and follow for the classes. However, students may approach the faculty to cover certain topics of their interest in that area during classes based on students' interests and experts' areas of expertise.

**Detailed Syllabus: Semester III**

**[ SLC] Massive Open Online Course – I**

| **Teaching Scheme** | **Examination Scheme** |
|---|---|
| Lectures: 3 hours/week | Theory: |
| CIE: 40 Marks Self-Study: 1hour / Week | |
| | ESE: 60 |
| marks | |

**Course Outcome**

Students will able to:

1. Acquire new skills or knowledge to enhance their personal and professional development
2. Receive a flexible learning environment, allowing one to study at own pace and convenience
3. Opportunity for lifelong learning
4. Foster collaboration and networking among participants

The students in consultation with the faculty advisor opt for a single course of 12 weeks offered by the NPTEL in the current semester. The students need to register for the examination conducted by the NPTEL. For the students who secured a passing score in the NPTEL examination, the marks obtained for assignments (in 25 marks) will be upscaled to out of 40 marks of CIE and the marks obtained from the certificate examination (in 75 marks) will be downscaled 60 marks of ESE assessments.

## [ SLC] Massive Open Online Course – II

**Teaching Scheme** | **Examination Scheme**

Lectures: 3 hours/week | Theory:

CIE: 40 Marks Self-Study: 1hour / Week

ESE: 60

marks

**Course Outcome**

Students will able to:

1. Acquire new skills or knowledge to enhance their personal and professional development
2. Receive a flexible learning environment, allowing one to study at own pace and convenience
3. Opportunity for lifelong learning
4. Foster collaboration and networking among participants

The students in consultation with the faculty advisor opt for a single course of 12 weeks offered by the NPTEL in the current semester. The students need to register for the examination conducted by the NPTEL. For the students who secured a passing score in the NPTEL examination, the marks obtained for assignments (in 25 marks) will be upscaled to out of 40 marks of CIE and the marks obtained from the certificate examination (in 75 marks) will be downscaled 60 marks of ESE assessments.

## [VSEC] Dissertation Phase – I

**Teaching Scheme** | **Examination Scheme**

Laboratory: 12 hours/week | Theory: CIE: 50 Marks

Self-Study: 18 hour / Week | ESE: 50 marks

**Course Outcomes**

Students will be able to:

1. Demonstrate how to search the existing literature to gather information about a specific problem or domain.
2. Identify the state-of-the-art technologies and research in the chosen domain and highlight open problems that are relevant to societal or industrial needs.
3. Evaluate various solution techniques to determine the most feasible solution within given constraints for the chosen dissertation problem.
4. Apply software engineering principles related to requirements gathering and design to produce relevant documentation.

5. Write a dissertation report that details the research problem, objectives, literature review, and solution architecture.
6. Deliver effective oral presentations to communicate the findings and outcomes of the research work.

**Guidelines**
The dissertation is a year-long project, conducted and evaluated in two phases. It can be carried out either in-house or within an industry as assigned by the department. The project topic and internal advisor (a faculty member from the department) are determined at the beginning of Phase I.

Student is expected to complete the following activities in Phase-I:
1. Literature survey
2. Problem Definition
3. Motivation for study and Objectives
4. Preliminary design / feasibility / modular approaches

**Deliverables**
1. A report having following details: Abstract, Problem statement, Requirements specification, Literature survey, Proposed solution, High level design description, Plan for implementation

   and testing in Phase-II
2. A presentation that covers the major points covered in the report.
3. A proof of concept (preferable but not mandatory)

**Evaluation**
Two independent assessments (Mid-Semester and End-Semester evaluations) will be done:
1. The internal guide will evaluate his/her student for 40 marks
2. A panel of External Examiner(s) and two senior faculty of the department will evaluate the work for 60 marks

The marks obtained in these two assessments will be combined to get final evaluation out of 100 marks. The course grading, like other courses, will be relative in nature.

The evaluation will take place based on criteria such as literature survey and well-defined project problem statement, proposed high level system design, concrete plan for implementation and result generation, presentation etc.

The panel (external examiner(s) and senior faculty) will provide a report about suggestions/changes to be incorporated during phase-II.

**Detailed Syllabus: Semester IV**

**[VSEC] Dissertation Phase – II**

| **Teaching Scheme** | **Examination Scheme** |
|---|---|
| Laboratory: 24 hours/week | Theory: CIE: 50 Marks |
| Self-Study: 12 hour / Week | ESE: 50 marks |

**Course Outcomes**

Students will be able to

1. Achieve proficiency in the languages, tools, libraries, and technologies used in the dissertation work.
2. Apply project planning principles and techniques to ensure effective and efficient project execution.
3. Demonstrate an understanding of the entire lifecycle of a software product or solution.
4. Produce artifacts such as source code, test plans, and test results based on the dissertation work.
5. Write research paper(s) and a thesis in accordance with publication ethics.
6. Exhibit the presentation skills needed to effectively present the work at various platforms.

**Guidelines**

Student is expected to complete the following activities in Phase-II:

1. Implementation of the proposed approach in the first stage
2. Testing and verification of the implemented solution

3. Writing of a report and presentation
4. Publish the work done at suitable conference/in a journal

**Deliverables**

1. Source code (if the project is in-house)
2. Dissertation report that gives overview of the problem statement, literature survey, design, implementation details, testing strategy and results of testing
3. All the artifacts created throughout the duration of dissertation such as requirements specification, design, project plan, test cases etc
4. Presentation based on the dissertation report
5. Research Paper(s) based on the dissertation work

**Evaluation**

Evaluation will be done in two steps: Mid-Semester evaluation and End-Semester evaluation.

- Mid-Semester evaluation:

Evaluation will be done by the internal guide and a qualified external examiner The internal guide will evaluate his/her student for 20 marks.
External Examiner will provide evaluation for 30 marks

The assessment is done on the criteria such as concrete system design, implementation status and concrete plan for completion of remaining tasks, presentation etc.

The purpose of Mid-Semester evaluation is also to check preparedness of students for the End- Semester evaluation. Examiners may give suggestions for changes/corrections to be incorporated before the final evaluation. If the work done till then may not lead to successful completion of the dissertation in the remaining time, student may be asked to take extension in time to complete the course.

- End-Semester evaluation:

The internal guide and one external examiner will carry out the final evaluation. The guide will provide evaluation for 20 marks and the external examiner for 30 marks.

The assessment will be done based on the criteria such as quality of implementation, result analysis, project outcomes (publications, patent, copyright, contribution to opensource community, participation in project competition etc.), quality of report, presentation etc.

The total assessment of phase-II work is for 100 marks (Mid-Semester evaluation for 50 marks and End-Semester evaluation for 50 marks) and the grading, like other courses, will be relative.