AMRITA VISHWA VIDYAPEETHAM

DEEMED TO BE UNIVERSITY UNDER SECTION 3 OF UGC ACT, 1956

School of Computing

M.TECH ARTIFICIAL INTELLIGENCE

CURRICULUM 2024

M.TECH – Artificial Intelligence

Department of Computer Science and Engineering

M.Tech in Artificial Intelligence programme has been designed for students who aim to embark their career on Data intensive computing. The programme is a graduate degree that develops the skillsets and knowledge required in various paradigms of Artificial Intelligence such as Machine Learning, Big data analytics, and Deep Learning. The degree is suitable for students with a bachelor's degree in a computing related field as well as students who want to demonstrate computer science expertise in addition to a degree in another field. The curriculum has been designed to prepare students for highly prolific careers in industry. Some of the job profiles include: Application analyst, Data Scientist, Data analyst, Database administrator, Information systems manager, IT consultant, Multimedia analyst.

Artificial Intelligence has revolutionized the modern world. Technologies that we now use for granted - Internet, mobile phones, medical technology, has various paradigms of Artificial Intelligence inherently. This M.Tech programme offers an integrated course of study covering the theory, implementation and design of Artificial Intelligence systems with core focus on Machine learning and Deep learning systems. The programme has specialized courses in the streams of Computer Vision, IoT and High Performance Computing with significant focus on research. As a part of the programme during the period of study, students have the opportunity to intern at leading companies and R&D labs for a period of six months to one year. There are opportunities for the students to take up a semester or one-year study at International Universities like Virje University, Netherlands, UC Davis, UNM for an exchange programme or to pursue a dual degree programme.

Graduates of this programme are well represented in Oracle, IBM, HP, Cerner, Nokia, GE, Bosch, Intuit and other major MNCs as well as in research in premier academic institutions in India and abroad. The graduates are competent to take up R&D positions in Industry, academia and research labs.

Program Educational Objectives (PEOs)

1. Build strong foundations in Artificial Intelligence so that they can contribute significantly in the area of research and innovation.
2. Develop highly competent professionals in the field of AI to adapt with the latest trends and techniques.
3. Bring out professionals and entrepreneurs to design and develop solutions for real world inter- disciplinary problems having positive societal impacts.

Graduate Attributes prescribed by NBA for M-Tech Program

GA1: Scholarship of knowledge

GA2: Critical thinking

GA3: Problem solving

GA4: Research skill

GA5: Usage of modern tools

GA6: Collaborative and multidisciplinary work

GA7: Project management and finance

GA8: Communication

GA9: Lifelong learning

GA10: Ethical practices and social responsibility

GA11: Independent and reflective learning.

Program Outcomes (POs)

1. Enable graduates to understand, design and build novel concepts and algorithms to leverage the power of AI in various application domains. (GA1, GA2, GA3).
2. Develop the skillsets to support the requirements of current trends in industry. (GA3, GA5, GA7, GA9).
3. An ability to independently carry out research /investigation and development work to solve practical problems while adhering to professional ethics. (GA4, GA9, GA11).
4. 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. (GA4, GA6, GA7, GA10).
5. Build the ability to write and present a substantial technical report/document. (GA8, GA9).

Program Outcomes PO3 PO4 and PO5 have been adopted from NBA (Ref. https://www.nbaind.org/files/PG_Eng_Annexure/PG_Engineering_Manual.pdf). PO4 has been elaborated to suit our M.Tech AI program.

M.TECH - ARTIFICIAL INTELLIGENCE
CURRICULUM 2024

Semester I				
Course Code	**Type**	**Courses**	**L T P**	**Credit**
24AI601	FC	Foundations of Artificial Intelligence	3-0-2	4
24MA603	FC	Mathematical Foundations of Computing	3-1-0	4
24AI602	FC	Machine Learning	3-0-2	4
	SC	Soft Core - I	3-0-2	4
24RM605	FC	Research Methodology	2-0-0	2
22AVP103	HU	Mastery Over Mind (MAOM)	1-0-2	2
23AVP601	HU	Amrita Values Program*		P/F
23HU601	HU	Career Competency I	0 0 3	P/F
		Total Credits		**20**

*Non-credit course

Semester II				
Course Code	**Type**	**Courses**	**L T P**	**Credit**
	SC	Soft Core - II	3-0-2	4
	SC	Soft Core - III	3-0-2	4
	SC	Elective - I	2-0-2	3
	E	Elective - II	2-0-2	3
	E	Elective - III	2-0-2	3
24AI698	FC	Case Study	0-0-4	2
23HU611	HU	Career Competency II	0 0 3	1
		Total Credits		**20**

Semester III				
Course Code	**Type**	**Courses**	**L T P**	**Credit**
	E	Elective - IV	2 0 2	3
	E	Elective - V	3 0 0	3
24AI798		Dissertation Phase I		10
		Total Credits		**16**

Semester IV				
Course Code	**Type**	**Courses**	**L T P**	**Credit**
24AI799		Dissertation Phase II		16
		Total Credits		**16**

Sl. No	Type	Courses	Credit
1	FC	Foundation Core	16
2	SC	Soft Core	12
3	E	Elective	15
4	HU	Amrita Values Program / Career Competency / MAOM	3
5		Dissertation	26
		Total Credits	**72**

Foundation Core			
Course Code	**Courses**	**L T P**	**Credit**
24AI601	Foundations of Artificial Intelligence	3-0-2	4
24MA603	Mathematical Foundations of Computing	3-1-0	4
24AI602	Machine Learning	3-0-2	4
24RM605	Research Methodology	2 0 0	2
24AI698	Case Study	0 0 4	2

Soft Core			
Course Code	**Courses**	**L T P**	**Credit**
24AI631	Foundations of Data Science	3-0-2	4
24AI632	Advanced Algorithm Design	3-0-2	4
24AI633	Probabilistic Graphical Models	3-0-2	4
24AI634	Computational Statistics and Inference Theory	3-0-2	4
24AI635	Computational Intelligence	3-0-2	4
24AI636	Deep Learning	3-0-2	4
24AI637	Reinforcement Learning	3-0-2	4
24AI638	Mining of Massive Datasets	3-0-2	4
24AI639	Generative AI	3-0-2	4

Electives List			
Course Code	**Courses**	**L T P**	**Credit**
24AI731	Machine Learning for Big Data	2 0 2	3
24AI732	Applications of Machine Learning	2 0 2	3
24AI733	Evolutionary Machine Learning	2 0 2	3
24AI734	Applied Predictive Analytics	2 0 2	3
24AI735	Federated Learning	2 0 2	3
24AI736	Explainable AI	2 0 2	3
24AI737	Artificial Intelligence for Robotics	2 0 2	3
24AI738	Data Visualization	2 0 2	3
24AI739	Stochastic Modeling	2 0 2	3
24AI740	Networks and Spectral Graph Theory	2 0 2	3
24AI741	Parallel and Distributed Data Management	2 0 2	3
24AI742	Medical Signal Processing	2 0 2	3
24AI743	Computer Vision	2 0 2	3
24AI744	Natural Language Processing	2 0 2	3
24AI745	GPU Architecture and Programming	2 0 2	3
24AI746	Artificial Intelligence for IoT	2 0 2	3
24AI747	Quantum Artificial Intelligence	2 0 2	3
24AI748	Blockchain Technology	2 0 2	3
24AI749	Artificial Intelligence for Bioinformatics	2 0 2	3
24AI750	Cloud and Big Data Analytics	2 0 2	3

[*] Students can take Electives from other M.Tech branches in place of any one elective. Students can select online courses in place of Elective IV and Elective V as per the university norms with the consent and approval from the department.

24AI601 Foundations of Artificial Intelligence 3-0-2-4

Preamble

This course will deal with the fundamental principles of Artificial Intelligence including knowledge representation, reasoning, decision making and programming techniques. The course will also support developing an understanding of the theoretical relationships between these algorithms.

Course Objectives

- To understand basic principles of Artificial Intelligence.
- To understand the basic areas of artificial intelligence including problem solving, knowledge representation, reasoning, decision making, planning, perception and action.
- To understand automatic learning methods in artificial intelligence

Course Outcomes

COs	Description
CO1	Understand and apply formal methods of knowledge representation in AI systems.
CO2	Develop and utilize foundational principles, mathematical tools, and programming paradigms of AI.
CO3	Implement learning methods to solve real-world problems effectively.
CO4	Employ problem-solving techniques through search algorithms for various AI applications.
CO5	Communicate AI concepts and solutions effectively through technical reports and presentations.

Prerequisites

- None

Syllabus

Principles of search, uninformed search, informed (heuristic) search, genetic algorithms, game playing - Basic idea behind search algorithms. Complexity. Combinatorial explosion and NP completeness. Polynomial hierarchy. Uninformed Search - Depth-first. Breadth-first. Uniform-cost. Depth-limited. Iterative deepening. Informed search – Best-first. A* search. Heuristics. Hill climbing. Problem of local extrema. Simulated annealing. Genetic Algorithms.

Knowledge bases and inference; constraint satisfaction, logical reasoning - Fuzzy logic. Reasoning under uncertainty – probabilities, conditional independence, Markov blanket, Bayes Nets - Probabilistic inference, enumeration, variable elimination, approximate inference by stochastic simulation, Markov chain Monte Carlo, Gibbs sampling. Agents that reason logically – Knowledge-based agents. Logic and representation. Propositional (Boolean) logic, Inference in propositional logic. Syntax. Semantics. Probabilistic Reasoning over time: Temporal models, Hidden Markov Models, Kalman filters, Dynamic Bayesian Networks, Automata theory. Planning – Definition and goals. Basic representations for planning. Situation space and plan space.

Inductive learning, concept formation, decision tree learning, statistical approaches, probabilistic methods, learning from examples - neural networks - Probability-Based Learning: Probabilistic Models, Naïve Bayes Models, EM algorithm, Introductions to AI Ethics, Heterogeneous Data Acquisition techniques, Reinforcement Learning.

Text Book / References

1. Stuart Russell and Peter Norvig, Artificial Intelligence: A Modern Approach, Fourth edition, Pearson Education, 2021
2. Deepak Khemani. A First Course in Artificial Intelligence. McGraw Hill Education (India), 2013.
3. Denis Rothman. Artificial Intelligence by Example, Packt, 2020, 2nd Edition.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and apply formal methods of knowledge representation in AI systems.	3	3	2	-	-
CO2	Develop and utilize foundational principles, mathematical tools, and programming paradigms of AI.	3	3	-	2	-
CO3	Implement learning methods to solve real-world problems effectively.	3	-	3	3	-
CO4	Employ problem-solving techniques through search algorithms for various AI applications.	3	-	3	3	-
CO5	Communicate AI concepts and solutions effectively through technical reports and presentations.	-	-	2	-	3

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Quizzes - 20%
- Lab Assignments & Case Study – 30%
- End Semester Exam - 30%

24MA603 Mathematical Foundations of Computing 3-1-0-4

Course Objectives

- To equip students with advanced mathematical tools and techniques: This course aims to provide students with a comprehensive understanding of vector spaces, matrix decompositions, optimization methods, and statistical analysis, enabling them to solve engineering problems with precision and efficiency.
- To develop analytical and problem-solving skills in engineering contexts: This course focuses on enhancing students' ability to apply theoretical concepts in practical scenarios, including optimization, probabilistic analysis, and statistical inference, preparing them for research and professional practice in engineering and related fields.

Course Outcomes

COs	Description
CO1	Analyze and apply vector space concepts and matrix decompositions to solve engineering problems.
CO2	Demonstrate proficiency in using mathematical theorems and transformations to find solutions to engineering problems.
CO3	Solve optimization problems relevant to engineering contexts.
CO4	Analyze and interpret statistical data and apply probabilistic and Bayesian methods for rigorous analysis and parameter estimation.

Prerequisites

- Basic programming knowledge

Syllabus

Vector Space: Basis and Dimensions - Change of Basis, Orthogonality – Fundamental Vector Spaces Associated with a Matrix, Matrix Decompositions: LU, QR, Eigen Decomposition and SVD, Cayley Hamilton Theorem, Fourier Transform and Fourier Basis

Function Optimization – Constrained and Unconstrained Optimization - Linear Programming - Linear Regression – Ordinary Least Squares – Gradient Descent – Conjugate Gradient Descent – Lagrange Multipliers – KKT Multipliers – ADMM – SVM

Random Variables – Moments - Covariance and Correlation - Probability Distributions – Moment generating functions – Transforming a random variable and Jacobean- Central limit theorem. Bayes Theorem - Naïve Bayes Classification - Parameter Estimation: MLE – Statistical testing: Mean of two random variables and statistical testing for proportions.

Text Book / References

1. Gilbert Strang, Linear Algebra and Learning from Data, Wellesley-Cambridge Press, 2019.

2. William Flannery, Mathematical Modeling and Computational Calculus, Vol-1, Berkeley Science Books, 2013.

3. Stephen Boyd and Lieven Vandenberghe, Convex Optimization, Cambridge University Press, 2018.

4. Douglas C. Montgomery and George C. Runger, Applied Statistics and Probability for Engineers, John Wiley & Sons Inc., 2005.

5. Axler Sheldon, Linear Algebra Done Right, Springer Nature, 2024.

6. Howard Anton and Chris Rorrers, Elementary Linear Algebra, Tenth Edition, John Wiley & Sons, Inc., 2010.

7. David Forsyth, Probability and Statistics for Computer Science, Springer International Publishing, 2018.

8. Ernest Davis, Linear Algebra and Probability for Computer Science Applications, CRC Press, 2012.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Analyze and apply vector space concepts and matrix decompositions to solve engineering problems.	3	-	3	2	-
CO2	Demonstrate proficiency in using mathematical theorems and transformations to find solutions to engineering problems.	3	3	3	2	-
CO3	Solve optimization problems relevant to engineering contexts.	3	3	3	2	2
CO4	Analyze and interpret statistical data and apply probabilistic and Bayesian methods for rigorous analysis and parameter estimation.	2	-	3	1	3

Evaluation Pattern - 60:40

- Midterm Exam - 30%
- Continuous Assessment – 30%
- End Semester Exam - 40%

24AI602 Machine Learning 3-0-2-4

Preamble

This course deals with various algorithms to enable computers to learn data without being explicitly programmed. An insight into various types of machine learning algorithms, strategies for model generation and evaluation are given in this course. The fundamental machine learning algorithms required in industries are covered together with their concrete implementations.

Course Objectives

- To introduce the fundamental concepts and techniques of Machine Learning
- To become familiar with various classification and regression methods
- Apply neural networks, Bayes classifier and k nearest neighbor algorithms in machine learning.
- To develop skills using recent machine learning techniques and solving real world case study

Course Outcomes

COs	Description
CO1	Understand and apply the basic of ML, learning paradigms and concepts of regression
CO2	Design and develop classifier models and evaluate their performance
CO3	Acquire skills to build probabilistic model and deep network models for classification
CO4	Develop and build clustering models for real world applications
CO5	Understand and apply the concepts of dimensionality reduction and Reinforcement Learning

Prerequisites

- Basics of Linear Algebra, Probability Theory and Optimization: Vectors, Inner product, Outer product, Inverse of a matrix, Eigen analysis, Probability distributions – Discrete distributions and Continuous distributions; Independence of events, Conditional probability distribution and Joint probability distribution, Bayes theorem, Unconstrained optimization, Constrained optimization.

Syllabus

Introduction to machine learning - different forms of learning- Linear regression - Ridge and Lasso regression, Logistic regression, Discriminant Functions and models, Bayesian regression, regression with basic functions.

Classification - Perceptron –Multilayer Perceptron - Feed forward network - Backpropagation – Support vector machine - Decision trees - evaluation of classifiers – bias and variance. Gaussian mixture models -- Expectation-Maximization - Naive Bayes classifier - Ensemble

Methods - Bagging – Boosting -Time series Prediction and Markov Process - Introduction to deep learning - Convolutional neural networks - application of classification algorithm

Clustering - K-means – Hierarchical and Density Based Clustering – DBSCAN- Assessing Quality of Clustering - Dimensionality reduction - Principal Component Analysis. Understanding of Machine Learning Project Life Cycle - each stages of the cycle, Examples of ML projects.

Text Book / References

1. Alpaydin, Ethem. Introduction to machine learning. MIT press, 2020
2. Bishop, Christopher M. Pattern recognition and machine learning. springer, 2006.
3. Murphy, Kevin P. Machine learning: a probabilistic perspective. MIT press, 2012.
4. Tom Mitchell, "Machine Learning", McGraw-Hill, 1997
5. Duda, Richard O., and Peter E. Hart. Pattern classification. John Wiley & Sons, 2006.
6. Han, Jiawei, Micheline Kamber, and Jian Pei. "Data mining concepts and techniques third edition." The Morgan Kaufmann Series in Data Management Systems 5.4 (2011): 83-124.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and apply the basic of ML, learning paradigms and concepts of regression	3	1	-	2	-
CO2	Design and develop classifier models and evaluate their performance	3	3	2	-	1
CO3	Acquire skills to build probabilistic model and deep network models for classification	3	1	2	2	-
CO4	Develop and build clustering models for real world applications	3	3	-	-	1
CO5	Understand and apply the concepts of dimensionality reduction and Reinforcement Learning	3	1	-	2	-

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous Evaluation – 50%
- End Semester Exam - 30%

24RM605 Research Methodology 2-0-0-2

Course Objectives

- To enable students to define research problems, learn to evaluate literature and possibly to formulate effective solutions.
- To prepare students either for a research thesis or for an industry-based project.
- To provide oral and written communication skills.
- To inculcate a strict adherence to the principles of research ethics and values.

Course Outcomes

COs	Description
CO1	Understand the basic concepts related to Research and Research Methodology
CO2	Applying various tools for identifying, retrieving and organizing the literature.
CO3	Formulating a Research problem and follow the steps of a good research design to arrive at a solution.
CO4	Document writing using professional tools such as LaTeX, BibTeX, Medeley etc.

Syllabus

Meaning of Research, Types of Research, Research Process, Problem definition, Objectives of Research, Research Questions, Research design, Approaches to Research, Quantitative vs. Qualitative Approach, Understanding Theory, Building and Validating Theoretical Models, Exploratory vs. Confirmatory Research, Experimental vs Theoretical Research, Importance of reasoning in research.

Problem Formulation, Understanding Modeling & Simulation, Conducting Literature Review, Referencing, Information Sources, Information Retrieval, Role of libraries in Information Retrieval, Tools for identifying literatures, Indexing and abstracting services, Citation indexes

Experimental Research: Cause effect relationship, Development of Hypothesis, Measurement Systems Analysis, Error Propagation, Validity of experiments, Statistical Design of Experiments, Field Experiments, Data/Variable Types & Classification, Data collection, Numerical and Graphical Data Analysis: Sampling, Observation, Surveys, Inferential Statistics, and Interpretation of Results.

Preparation of Technical Reports and Research Papers, Tables and illustrations, Guidelines for writing the abstract, introduction, methodology, results and discussion, conclusion sections of a manuscript. References, Citation and listing system of documents.

Nature of Intellectual Property: Patents, Designs, Trade and Copyright. Process of Patenting and Development: technological research, innovation, patenting, development. International Scenario: International cooperation on Intellectual Property. Procedure for grants of patents, Patenting under PCT. Patent Rights: Scope of Patent Rights. Geographical Indications.

Text Book / References

1. Stuart Melville and Wayne Goddard, Research methodology: an introduction for science & engineering students, 2^{nd} Edition, 2014.

2. Bordens, K. S. and Abbott, B. B., “Research Design and Methods – A Process Approach”, 11thEdition, McGraw-Hill, 2022

3. Ron Iphofen (Ed), “Handbook of Research Ethics and Scientific Integrity”, Springer, 2020.

4. Ranjit Kumar, 4th Edition, Research Methodology: A Step by Step Guide for beginners, 2015

5. Davis, M., Davis K., and Dunagan M., “Scientific Papers and Presentations”, 3rd Edition, Elsevier Inc., 2013.

6. Robert P. Merges, Peter S. Menell, Mark A. Lemley, Intellectual Property in New Technological Age, 2016.

7. Design and Analysis of Experiments, Douglas C. Montgomery, Eight Edition, 2013

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understanding the work-flow of research, research types and research models.	-	2	1	2	3
CO2	Applying various tools for identifying, retrieving and organizing the literature.	-	2	3	1	2
CO3	Formulating a Research problem and follow the steps of a good research design to arrive at a solution.	1	2	1	2	2
CO4	Document writing using professional tools such as LaTeX, BibTeX, TikZ, PGF etc.	-	-	2	-	1

Evaluation Pattern - 60:40

- Internal – 60%
- External - 40%

24AI698 Case Study 0-0-4-2

Course Outcomes

COs	Description
CO1	To develop skills in doing project, technical presentation and report preparation.
CO2	To enable project identification and execution of preliminary works on final semester

Prerequisites

- None

Syllabus

This course is intended to give orientation towards research and innovation by developing skills in paper reading, programming and presentation skills. Each student can select an area for project in consultation with the faculty. This can be the initial phase of their dissertation as well. It should involve literature review, devising innovative solutions, implementation, testing and performance analysis in different application specific contexts. Students will be required to make an in-class presentation, project demonstration and a project report. The course will be evaluated by a panel of (at least) two faculty members.

Text Book / References

1. Relevant literature for the computing problem.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	To develop skills in doing project, technical presentation and report preparation.	1	1	1	2	3
CO2	To enable project identification and execution of preliminary works on the second year project	2	3	3	2	2

Evaluation Pattern - 80:20

- Internal - 80%
- External - 20%

24AI631 Foundations of Data Science 3-0-2-4

Preamble

Data Science is about drawing useful conclusions from large and diverse data sets through exploration, prediction, and inference. In this course, the students will learn the foundations of data science that focuses on pre-processing, exploration and visualization of data alongside the statistical and mathematical aspects of select techniques for prediction and classification using popular machine learning algorithms. The course also focuses on the associated inferencing techniques based on statistical models and tests for quantifying the degree of certainty of predictions.

Course Objectives

- To understand the important steps in drawing useful conclusions from data.
- To ask appropriate questions about data after data exploration using visualization and descriptive statistics
- To apply machine learning and optimization techniques to make predictions.
- To correctly interpret the answers generated by inferential and computational tools.

Course Outcomes

COs	Description
CO1	Understand the statistical foundations of data science
CO2	Learn techniques to pre-process raw data so as to enable further analysis
CO3	Conduct exploratory data analysis and create insightful visualizations to identify patterns
CO4	Apply machine learning algorithms for prediction/classification and to derive insights
CO5	Evaluate the degree of certainty of predictions using statistical test and models in Python

Prerequisites

- Basic Probability

Syllabus

Introduction to Data Science, Causality and Experiments, Data Pre-processing - Data cleaning - Data reduction - Data transformation, Visualization and Graphing: Visualizing Categorical Distributions - Visualizing Numerical Distributions - Overlaid Graphs and plots - Summary statistics of exploratory data analysis, Randomness, Probability, Introduction to Statistics, Sampling, Sample Means and Sample Sizes.

Probability distributions and density functions (univariate and multivariate), Error Probabilities; Expectations and moments; Covariance and correlation; Sampling and Empirical distributions; Permutation Testing, Statistical Inference; Hypothesis testing of means, proportions, variances and correlations - Assessing Models - Decisions and Uncertainty, Comparing Samples - A/B Testing, P-Values, Causality.

Estimation - Resampling and Bootstrap - Confidence Intervals, Properties of Mean - Central Limit Theorem - Variability of mean -Choosing Sample Size, Prediction - Regression - Method of Least Squares - Visual and Numerical Diagnostics - Inference for true slope - Prediction intervals, Classification - Nearest neighbors - accuracy of a classifier, Updating Predictions - Making Decisions - Bayes Theorem, Graphical Models

Text Book / References

1. Ani Adhikari and John DeNero, ”Computational and Inferential Thinking: The Foundations of Data Science”, e-book.
2. Joel Grus, ”Data Science from Scratch: First Principles with Python”, 2/e, O’Reilly Media, 2019.
3. Peter Bruce, Andrew Bruce and Peter Gedeck, ”Practical Statistics for Data Scientists: 50+ Essential Concepts Using R and Python”, 2/e, O’Reilly Media, 2020.
4. Allen B. Downey, “Think Stats: Probability and Statistics for Programmers”, 2/e, by O’Reilly Media, 2014.
5. Cathy O’Neil and Rachel Schutt, ”Doing Data Science”, O’Reilly Media, 2013.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the statistical foundations of data science	1	2	3	1	1
CO2	Learn techniques to pre-process raw data so as to enable further analysis	1	2	3	1	1
CO3	Conduct exploratory data analysis and create insightful visualizations to identify patterns	1	2	3	3	1
CO4	Apply machine learning algorithms for prediction and classification to derive insights	3	2	1	2	1
CO5	Evaluate the degree of certainty of predictions using statistical test and models	1	2	2	1	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous Evaluation – 50%
- End Semester Exam - 30%

24AI632 Advanced Algorithm Design 3-0-2-4

Preamble

This course builds upon the basic courses on data structures and algorithm design. It aims to enable students to design and adapt algorithms to solve complex problems especially relevant for AI domain. The focus will be on design and concrete implementations of various algorithmic techniques and their use in different application scenarios with proper analysis

Course Objectives

- To provide an understanding of algorithm design and analysis used in real life domain
- To solve complex problems by applying appropriate algorithmic design strategies
- To critically analyze the complexity of various algorithms
- To select appropriate design strategy to solve real world problems in AI domain

Course Outcomes

COs	Description
CO1	Explain the motivation behind the different algorithmic strategies and/or suitable data structures and their applications.
CO2	Articulate different algorithmic design techniques, compare and contrast them, and their application to real-world problems
CO3	Apply asymptotic and amortized analysis to determine the time and space complexities of an algorithm
CO4	Solve real world problems, especially in ML & AI domain, by identifying and applying appropriate design techniques
CO5	Concrete implementations of data structures and algorithms using Programming Language such as Java or Python

Prerequisites

- Basic Data Structures
- Basic Mathematics
- Basic Programming Language

Syllabus

Algorithm Analysis - Methodologies for Analyzing Algorithms, Asymptotic growth rates, Amortized Analysis. Array based structures, lists and. Number Theory: Preliminaries, FLT, Euclid's algorithm (extended), Totient function, Sieve for primes, Modular exponentiation.

Applications of Divide-and-Conquer, Greedy and Dynamic programming, Randomized techniques - Knapsack, Median finding, Scheduling algorithms, Party planning, bitonic TSP. String matching algorithms: Z Algorithm, KMP algorithm, Rabin-Karp, Universal hashing, consistent hashing, load balancing, power of two choices. Applications of graph algorithms: Topological sort, Strongly connected Components, Bi-connected Components, Bridges, Articulation points, All Pairs Shortest Paths, Single Source Shortest Paths.

Flow Networks: Ford-Fulkerson algorithm, Edmonds Karp algorithm, Applications of maximum flows - Maximum bipartite matching, minimum cost matching. Data Structures: Balanced binary trees, Suffix trees, Segment trees, Hash tables. Computational Geometry: Convex Hull, Closest pair of points. NP-Completeness: Important NP-Complete Problems, Polynomial time reductions, Approximation algorithms.

Text Book / References

1. Cormen T H, Leiserson CE, Rivest R L and Stein C, "Introduction to Algorithms", Prentice Hall of India Private Limited. Third Edition 2009.
2. Michael T Goodrich and Roberto Tamassia, "Algorithm Design and Applications", Wiley, 2014.
3. Goodrich M T, Tamassia R and Michael H. Goldwasser, “Data Structures and Algorithms in Python++”, Wiley publication, 2013.
4. Rajeev Motwani and Prabhakar Raghavan, "Randomized Algorithms", Cambridge University Press, 1995.
5. Vijay V. Vazirani, "Approximation Algorithm", Springer Science and Business Media, 2003.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Explain the motivation behind the different algorithmic strategies and/or suitable data structures and their applications.	3	3	1	-	1
CO2	Articulate different algorithmic design techniques, compare and contrast them, and their application to real-world problems	3	3	1	-	1
CO3	Apply asymptotic and amortized analysis to determine the time and space complexities of an algorithm	3	3	1	-	1
CO4	Solve real world problems, especially in ML & AI domain, by identifying and applying appropriate design techniques	3	3	3	-	1
CO5	Concrete implementations of data structures and algorithms using Programming Language such as Java or Python	3	3	3	1	1

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous Evaluation – 50%
- End Semester Exam - 30%

24AI633 Probabilistic Graphical Models 3-0-2-4

Preamble

Probabilistic graphical models use a graph-based representation for encoding complex distributions over a high-dimensional space. This course deals with representation, inference, and learning of probabilistic graphical models. Students will gain an in-depth understanding of several types of graphical models; basic ideas underlying exact inference in probabilistic graphical models and learning probabilistic models from data.

Course Objectives

- To enable students to model problems using graphical models
- To design inference algorithms
- To learn the structure of the graphical model from the data set

Course Outcomes

COs	Description
CO1	Understand the process of encoding probability distributions using graphs
CO2	Analyze the independence properties of the graph structure
CO3	Understand and analyze Markov networks for the graphical modeling of probability distributions
CO4	Familiarize methods that approximate joint distributions
CO5	Study and evaluate methods to learn the parameters of networks with known and unknown structures

Prerequisites

- Probability and Statistics
- Programming Languages
- Algorithm Design

Syllabus

Introduction: Probability distributions, random variables, joint distributions, random process, graphs, undirected and Directed Graphical Models. Representation: Bayesian Networks – Independence in graphs – d-separation, I-equivalence, minimal I-maps. Undirected Graphical models: Gibbs distribution and Markov Networks, Markov models and Hidden Markov Models. From Bayesian to Markov and Markov to Bayesian networks, Triangulation and Chordal Graphs. Directed Gaussian graphical models. Exponential Family Models. Factor Graph Representation. Conditional Random Fields. Other special Cases: Chains, Trees.

Inference: Variable Elimination (Sum Product and Max-Product). Junction Tree Algorithm. Forward Backward Algorithm (for HMMs). Loopy Belief Propagation. Markov Chain Monte Carlo Metropolis Hastings. Importance Sampling. Gibbs Sampling. Variational Inference.

Learning Graphical models: Discriminative vs. Generative Learning., Density estimation, learning as optimization, maximum likelihood estimation for Bayesian networks, structure learning in Bayesian networks, Parameter Estimation in Markov Networks. Structure Learning. Learning undirected models- EM: Handling Missing Data. Applications in Vision, Web/IR, NLP and Biology. Advanced Topics: Statistical Relational Learning, Markov Logic Networks .

Text Book / References

1. Daphne Koller and Nir Friedman, ”Probabilistic Graphical Models: Principles and Techniques”, First Edition, MIT Press, 2009.
2. Michael Jordan, ”Learning in Graphical Models”. MIT Press, 1998. Collection of Papers.
3. Judea Pearl, Morgan Kaufmann, ”Probabilistic Reasoning in Intelligent Systems”, 1988.
4. Kevin P. Murphy, “Machine Learning, a probabilistic perspective”, The MIT Press Cambridge, Massachusetts, 2012.
5. Darwiche Adnan, ”Modeling and reasoning with Bayesian networks”, Cambridge university press, 2009.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the process of encoding probability distributions using graphs	3	2	3	1	2
CO2	Analyze the independence properties of the graph structure	3	3	3	1	2
CO3	Understand and analyze Markov networks for the graphical modeling of probability distributions	3	2	3	2	2
CO4	Familiarize methods that approximate joint distributions	3	2	2	-	-
CO5	Study and evaluate methods to learn the parameters of networks with known and unknown structures using real life data sets	3	3	4	2	4

Evaluation Pattern - 70:30

- Midterm Exam - 30%
- Continuous Evaluation - 20%
- End Semester Exam - 50%

24AI634 Computational Statistics and Inference Theory 3-0-2-4

Preamble

This course mainly focuses on the methods of computational statistics and how these methods can be applied in real world data sets. It provides understanding in the basic ideas of statistics, sampling distributions, exploratory data analysis, approaches for simulating distributions, estimation of probability density functions, and algorithms for data analysis.

Course Objectives

- Introduce students to the importance of computation in data analysis.
- To familiarize students with computational methods and simulation techniques used in statistics.
- To enable the student to explore the features of high dimensional data sets.
- To choose suitable computational methods to identify statistical pattern in real world data.

Course Outcomes

COs	Description
CO1	Understand the need of computational methods in data analysis
CO2	Choose suitable computational methods to analyze real world high dimensional data
CO3	Sets
CO4	Identify statistical pattern in data using suitable algorithms

Prerequisites

- Probability and Statistics
- Linear Algebra

Syllabus

Probability concepts, Probability simulations, Sampling concepts - random sampling, sampling distribution-, Parameter estimation methods – Maximum Likelihood Estimation, Method of Moments- Random number generation - General techniques for generating Random Variables, Monte Carlo Algorithms-Buffon’s needle experiment,

Monte carlo integration, Monte Carlo Methods for Inferential Statistics - Monte Carlo Hypothesis Testing, Bootstrap Methods - Exploratory data analysis – Traditional statistics methods and computational statistics methods , Frequentist statistics and Bayesian statistics Linear models and regression analysis - Maximum likelihood estimation, Linear Regression, Polynomial Regression, Stepwise Regression, Ridge Regression, Lasso, ElasticNet - Statistical Pattern Recognition- Bayes Decision Theory Estimating Class-Conditional Probabilities, Bayes Decision Rule Classification and Regression Trees, Clustering

Classification trees, Algorithm for Normal Attributes, Information Theory and Information. Entropy, Highly-Branching Attributes, ID3 to c4.5, CHAID, CART, Regression Trees, Model Trees, Pruning. Preprocessing and Post processing in data mining – Steps in Preprocessing, Discretization, Manual Approach, Binning, Entropy- based Discretization, Gaussian Approximation, K-tile method, Chi Merge, Feature extraction, selection and construction, Feature extraction, Algorithms, Feature selection, Feature construction, Missing Data, Post processing.

Text Book / References

1. Wendy L. Martinez and Angel R Martinez, "Computational Statistics" ,Chapman & Hall/CRC, 2002.
2. Jiawei Han and Micheline Kamber, "Data Mining: Concepts and Techniques", Morgan Kauf- mann Publishers, 2001.
3. K. P. Soman, V. Ajay and Diwakar Shyam, "Insight into Data Mining: Theory and Practice", Prentice Hall India, 2005.
4. Murphy, Kevin P. Machine learning: a probabilistic perspective. MIT press, 2012.
5. Hastie, T., Tibshirani, R., & Friedman, J. H. The elements of statistical learning: data mining, inference, and prediction. 2nd ed. New York: Springer, 2009.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the need of computational methods in data analysis	3	3	2	-	-
CO2	Choose suitable computational methods to analyze real world high dimensional data sets	3	3	4	2	1
CO3	Identify statistical pattern in data using suitable algorithms	3	3	3	4	3
CO4	Use existing methods to develop new statistical tools	2	3	3	-	-

Evaluation Pattern - 70:30

- Midterm Exam - 30%
- Continuous Evaluation – 40%
- End Semester Exam - 30%

24AI635 Computational Intelligence 3-0-2-4

Preamble

This course covers the principles and applications of computational intelligence techniques, including artificial neural networks, evolutionary algorithms, and fuzzy systems. Students will gain theoretical knowledge and practical skills to design, implement, and analyze intelligent systems

Course Objectives

- Gain comprehensive knowledge of neural network architectures and training techniques, including backpropagation, gradient descent, and hyperparameter tuning.
- Develop proficiency in designing and implementing genetic algorithms and fuzzy logic systems, with a focus on real-world applications and hybrid computational intelligence systems.

Course Outcomes

COs	Description
CO1	Understand the foundational concepts of computational intelligence.
CO2	Apply computational intelligence techniques to solve real-world problems.
CO3	Develop the ability to critically analyze and compare different computational intelligence methods.
CO4	Gain hands-on experience with software tools and libraries for computational intelligence.

Prerequisites

- Basic programming knowledge (Python or MATLAB)
- Introductory courses in linear algebra, calculus, and probability

Syllabus

Introduction to Neural Networks: Biological inspiration, Perceptron and its limitations, Multilayer Perceptron, Training Neural Networks: Backpropagation algorithm, Gradient descent optimization, Overfitting and regularization, Hyper parameter tuning, Kohonen's Self-Organizing Networks - Hopfield Networks, Boltzmann Machine, Introduction to Advanced Architectures: CNN, RNN and Auto encoders

Introduction to Evolutionary Algorithms: Biological inspiration, Genetic algorithms (GA), Evolution strategies (ES), Genetic programming (GP), Genetic Algorithms: Representation and initialization, Selection, crossover, and mutation, Fitness evaluation, Convergence and diversity maintenance, Advanced Evolutionary Techniques: Differential evolution (DE), Particle swarm optimization (PSO)

Introduction to Fuzzy Logic: Fuzzy sets and membership functions, Fuzzy rules and reasoning, Fuzzy inference systems, Defuzzification methods, Designing Fuzzy Systems: Fuzzy controllers, Fuzzy clustering, Fuzzy decision making, Applications in control systems and data analysis

Hybrid Computational Intelligence Systems: Neuro-fuzzy systems, Genetic-fuzzy systems, Applications and case studies.

Text Book / References

1. R.C. Eberhart, “Computational Intelligence: Concept to Implementations”, Morgan Kaufmann Publishers, 2007.
2. Timothy J. Ross, "Fuzzy Logic with Engineering Applications," 4th Edition, Wiley, 2016
3. Laurence Fausett, “Fundamentals of Neural Networks”, Prentice Hall,1994
4. Nazmul Siddique, Hojjat Adeli, “Computational Intelligence: Synergies of Fuzzy Logic, Neural Networks and Evolutionary Computing”, Willey 2013

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the foundational concepts of computational intelligence.	3	-	-	-	-
CO2	Apply computational intelligence techniques to solve real-world problems.	-	3	-	-	-
CO3	Develop the ability to critically analyze and compare different computational intelligence methods.	3	-	2	2	-
CO4	Gain hands-on experience with software tools and libraries for computational intelligence.	-	3	3	-	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments & Case Study – 50%
- End Semester Exam - 30%

24AI636 Deep Learning 3-0-2-4

Preamble

With the advent of high-end computing facilities and with the availability of huge amount of data, deep learning became the de facto standard machine learning strategy to learn complicated patterns and is offering the state of the art results in diverse fields including but not limited to automatic language translation, speech processing, medical diagnoses and in almost all fields of computer vision. This course provides core understanding in different deep learning architectures, design principles, learning strategies and encourages the usage of many deep learning tools in designing and deploying solutions.

Course Objectives

- To introduce to students, different deep neural network architectures, training strategies/ algorithms, possible challenges, tools and techniques available in designing and deploying solutions to different practical/Engineering problems.

Course Outcomes

COs	Description
CO1	Understand and apply the basics of neural networks and address practical aspects of deep learning
CO2	Design and implement CNNs and apply them to real-world tasks such as object detection, face recognition
CO3	Develop and utilize RNNs, GRUs, LSTMs, and attention models for NLP applications including word embedding and speech processing
CO4	Understand and implement advanced deep learning models and apply them to solve complex problems

Prerequisites

- Computational Linear Algebra

Syllabus

Neural Networks basics – Linear Separable Problems and Perceptron – Multi layer neural networks and Back Propagation, Practical aspects of Deep Learning: Train/ Dev / Test sets, Bias/variance, Vanishing/exploding gradients, Gradient checking, Hyper Parameter Tuning

Convolutional Neural Networks – Basics and Evolution of Popular CNN architectures – Transfer Learning–Applications: Object Detection and Localization, Face Recognition, Neural Style Trans- fer Recurrent Neural Networks – GRU – LSTM – NLP – Word Embeddings – Transfer Learning – Attention Models – Applications: Sentinel Classification, Speech Recognition, Action Recognition

Restricted Boltzmann Machine – Deep Belief Network – Auto Encoders – Applications: Semi-Supervised classification, Noise Reduction, Non-linear Dimensionality Reduction. Goal

Oriented Decision Making – Policy and Target Networks – Deep Quality Network for Reinforcement Learning

Introduction to GAN – Encoder/Decoder, Generator/Discriminator architectures. Challenges in NN training – Data Augmentation – Hyper parameter Settings – Transfer Learning– Developing and Deploying ML Models (e.g., Matlab/Tensor Flow/PyTorch)

Text Book / References

1. Ian Goodfellow, YoshuaBengio and Aeron Courville,” Deep Learning”, MIT Press, First Edi- tion, 2016.
2. Adam Gibson and Josh Patterson,” Deep Learning, A practitioner’s approach”, O’Reilly, First Edition, 2017.
3. Francois Chollet,” Deep Learning with Python”, Manning Publications Co, First Edition, 2018.
4. Research Papers on Relevant Topics and Internet Resources

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and apply the basics of neural networks and address practical aspects of deep learning	3	1	-	2	-
CO2	Design and implement CNNs and apply them to real-world tasks such as object detection, face recognition	3	3	2	-	1
CO3	Develop and utilize RNNs, GRUs, LSTMs, and attention models for NLP applications including word embedding and speech processing	3	1	2	2	1
CO4	Understand and implement advanced deep learning models and apply them to solve complex problems	3	3	2	-	1

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments & Case Study – 50%
- End Semester Exam - 30%

24AI637 Reinforcement Learning 3-0-2-4

Preamble

Artificial intelligence techniques face challenges in learning from dynamic environment with minimal data. This course deals with various algorithms to learn such an environment. Elements of Reinforcement Learning, Model Based Learning, Temporal Difference Learning and Policy Search are the main focus topics of this course.

Course Objectives

- Good understanding of various types of algorithms for Reinforcement Learning
- Be able to design an RL system

Course Outcomes

COs	Description
CO1	Understand the fundamentals of reinforcement learning and recognize how it complements other ML techniques.
CO2	Acquire knowledge of different RL algorithms and apply them in practical applications
CO3	Learn to model tasks as reinforcement learning problems within the framework of Markov Decision Processes and develop solutions
CO4	Implement RL algorithms using a scientific programming language

Prerequisites

- Machine Learning basics
- Probability Theory basics
- Programming basics

Syllabus

Introduction to Machine Learning and its various types, Motivation and Introduction to Reinforcement Learning, Multi arm Bandits, Markov Decision Process, Value functions; Dynamic programming: Policy evaluation and improvement, Value iteration and Policy iteration algorithms

Value prediction problems: Temporal difference learning in finite state spaces Algorithms for large state spaces Control: Closed loop interactive learning, online and active learning in bandits, Q learning in finite MDPs, Q learning with function approximation,

On policy approximation of action values: Value Prediction with Function Approximation, Gradient- Descent Methods, Policy approximation: Actor critic methods, Monte Carlo Methods: Monte-carlo prediction, estimation of action values, off policy prediction via importance sampling,

Text Book / References

1. Sutton and Barto, Reinforcement Learning: An Introduction, The MIT Press Cambridge, Massachusetts London, England, 2015

2. Csaba Szepesvari, Algorithms for Reinforcement Learning, Morgan & Claypool, United States, 2010
3. Xiao, Z. (2024). Reinforcement Learning: Theory and Python Implementation. Springer, 2024, ISBN 9789811949326.
4. Li, S. E. Reinforcement Learning for Sequential Decision and Optimal Control. Springer. 2024, ISBN 9789811689093.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the fundamentals of reinforcement learning and recognize how it complements other ML techniques.	3	-	-	-	-
CO2	Acquire knowledge of different RL algorithms and apply them in practical applications	3	2	1	-	-
CO3	Learn to model tasks as reinforcement learning problems within the framework of Markov Decision Processes and develop solutions	3	3	3	3	-
CO4	Implement RL algorithms using a scientific programming language	3	3	3	3	3

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 25%
- Project – 25%
- End Semester Exam - 30%

24AI638 Mining of Massive Datasets 3-0-2-4

Preamble

With the rise of user-web interaction and networking, as well as technological advances in processing power and storage capability, the demand for effective and sophisticated knowledge discovery techniques has grown exponentially. Businesses need to transform large quantities of information into intelligence that can be used to make smart business decisions. The importance of data to business decisions, strategy and behavior has proven unparalleled in recent years. Predictive analytics, data mining and machine learning are tools giving us new methods for analyzing massive data sets. Companies place true value on individuals who understand and manipulate large data sets to provide informative outcomes.

Course Objectives

- To acquire knowledge of existing systems and approaches to handle large scale data science problems.
- Apply different data mining techniques to handle large amounts of data.
- Analyze the performance of various data mining techniques when applied to diverse data sets.
- To gain insights into the design of different machine learning algorithms applied for data mining.

Course Outcomes

COs	Description
CO1	Understand the importance of data to be applied for predictive analytics that considers data mining and machine learning as tools to analyze massive data sets.
CO2	Introduce the design and operation of various big-data systems like Hadoop, Spark and Hive.
CO3	Apply suitable data mining algorithms to handle huge document databases and infinite streams of data to mine large social networks and web graphs.
CO4	Use case studies as a powerful analytical tool that will provide first-hand insight into how big data problems and their solutions allow companies like Google to succeed in the market.
CO5	Design large scale machine learning algorithms with practical hands-on experience for analyzing very large amounts of data.

Prerequisites

- Machine Learning.

Syllabus

Basics of Data Mining - Computational Approaches - Statistical Limits on Data Mining - Bonferroni's Principle - Importance of Words in Documents - Hash Functions - Indexes - Secondary Storage - The Base of Natural Logarithms - Power Laws -MapReduce - Distributed

File Systems- Algorithms Using MapReduce . Extensions to MapReduce. Finding Similar Items - Applications of Near-Neighbor Search - Shingling of Documents - Similarity-Preserving Summaries of Sets - Locality- Sensitive Hashing for Documents - Distance Measures.

Mining Data Streams: The Stream Data Model - Sampling Data in a Stream - Filtering Streams – Blooms Filter. Link Analysis: PageRank - Efficient Computation of PageRank - Topic-Sensitive PageRank - Link Spam. Frequent Itemsets: The Market-Basket Model - Market Baskets and the A-Priori Algorithm - Handling Larger Datasets in Main Memory- The Algorithm of Park, Chen, and Yu - The Multistage Algorithm - The Multi-hash Algorithm.

Clustering: Introduction to Clustering Techniques -Points, Spaces, and Distances - Clustering Strategies - The Curse of Dimensionality. Hierarchical Clustering - K-means Algorithms – The Algorithm of Bradley, Fayyad, and Reina - CURE algorithm - Clustering in Non-Euclidean Spaces. Recommendation Systems: A Model for Recommendation Systems - Content-Based Recommendations - Collaborative Filtering – UV Decomposition. Dimensionality Reduction. Mining Social-Network Graphs: Social Networks as Graphs - Clustering of Social-Network Graphs - Direct Discovery of Communities - Partitioning of Graphs - Finding Overlapping Communities – Simrank. Dimensionality Reduction: Eigenvalues and Eigenvectors of Symmetric Matrices- Principal-Component Analysis - Singular-Value Decomposition

Text Book / References

1. Jeffrey David Ullman, Jure Leskovec, Anand Rajaraman, "Mining of Massive Data Sets", ebook, Cambridge University Press, 2020.
2. Jiawei Han, Micheline Kamber, Jian Pei, 'Data Mining. Concepts and Techniques', 3rd Edition (The Morgan Kaufmann Series in Data Management Systems), Elsevier, 2012.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the importance of data to be applied for predictive analytics that considers data mining and machine learning as tools to analyze massive data sets.	3	1	-	-	-
CO2	Introduce the design and operation of various big-data systems like Hadoop, Spark and Hive.	2	2	-	-	3
CO3	Apply suitable data mining algorithms to handle huge document databases and infinite streams of data to mine large social networks and web graphs.	3	-	3	3	2
CO4	Use case studies as a powerful analytical tool that will provide first-hand insight into how big data problems and their solutions allow companies like Google to succeed in the market.	2	3	2	2	2
CO5	Design large scale machine learning algorithms with practical hands-on experience for analyzing very large amounts of data.	3	3	3	-	3

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 25%
- Project – 25%
- End Semester Exam - 30%

24AI639 Generative AI 3-0-2-4

Preamble

This course offers an in-depth exploration of Generative AI, focusing on Generative Adversarial Networks (GANs) and Large Language Models (LLMs). Generative AI represents a cutting-edge field that aims to create models capable of generating realistic data, encompassing images, music, and text. Students will gain an understanding of generative models' principles and historical impact. The course covers GANs' architecture, and types like DCGANs and StyleGANs, and applications It also addresses performance challenges and improvement techniques. For LLMs, the course examines models like GPT-4 and BERT, their training on extensive text data, and applications in NLP tasks such as text generation, translation, and summarization. Students will learn to implement and fine-tune LLMs for specific purposes.

Course Objectives

- To understand basic principles of Artificial Intelligence.
- To understand the basic areas of artificial intelligence including problem solving, knowledge representation, reasoning, decision making, planning, perception and action.
- To understand automatic learning methods in artificial intelligence

Course Outcomes

COs	Description
CO1	To understand and design architectures for various Generative Adversarial Network (GAN) variants.
CO2	To implement and train GANs for practical real-world applications.
CO3	To apply techniques for assessing and improving the performance of GANs.
CO4	Apply the principles and optimization techniques of Large Language Models (LLMs) like GPT-4 and BERT for various downstream tasks
CO5	To implement and fine-tune LLMs for various natural language processing (NLP) tasks.

Prerequisites

- Basic knowledge of Deep Learning
- Familiarity with Python programming

Syllabus

Recap of Deep neural networks, Variational Autoencoders (VAEs), and attention mechanisms. Generative Adversarial Networks (GANs) GAN components, DCGANs using convolutional layers, control your GAN and build conditional GAN. Use GANs for data augmentation and privacy preservation, GANs applications, Pix2Pix and CycleGAN for image translation.

Comparison of generative models, FID method to assess GAN fidelity and diversity, Bias in GAN, StyleGAN techniques

Principles of Transformers, Word embeddings, Introduction to Large Language Models – Decoder-only LLMs: A deep dive into GPT, Encoder Only LLMs-BERT, Prompting – different prompting strategies – Instruction tuning – fine tuning – parameter efficient fine-tuning – quantized fine tuning. Small Language models. Training LLMs using reinforcement Learning.

Evaluating LLMs: Benchmarks, evaluation frameworks and popular leaderboards. Applications/Case study of Large Language Models - Text Generation, Translation, and Summarization - Question Answering, Sentiment Analysis, Chatbots, Application of LLMs in healthcare and Code generation, latest advancements in LLMs.

Text Book / References

1. Generative AI in Practice:Bernad Marr, Wiley,March 2024
2. Hands-On Large Language Models by Jay Alammar, Maarten Grootendorst, December 2024 Publisher(s): O'Reilly Media.
3. Ian Goodfellow, YoshuaBengio and Aeron Courville," Deep Learning", MIT Press,2016
4. 'Deep Learning for Natural Language Processing: Develop Deep Learning Models for your Natural Language Problems (Ebook)', Jason Browlee, Machine Learning Mastery, 2017.
5. Getting Started with Google BERT: Build and train state-of-the-art natural language processing models using BERT by Sudharsan Ravichandiran, Packt Publishing Limited January 2021.
6. Comprehensive Overview of LLMs- A survey paper: https://arxiv.org/pdf/2307.06435. Other research papers on LLM
7. 'Speech & language processing' , Daniel Jurafsky, James H Martin, preparation [cited 2020 June 1] Available from: https://web.stanford.edu/~jurafsky/slp3/

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	To understand and design architectures for various Generative Adversarial Network (GAN) variants.	3	1	-	-	-
CO2	To implement and train GANs for practical real-world applications.	2	3	2	-	-
CO3	To apply techniques for assessing and improving the performance of GANs.	3	2	2	-	-
CO4	Apply the principles and optimization techniques of Large Language Models (LLMs) like GPT-4 and BERT for various downstream tasks	3	1	-	2	-
CO5	To implement and fine-tune LLMs for various natural language processing (NLP) tasks.	3	1	-	2	1

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous Assessment - Theory - 10%
- Continuous Assessment - Lab – 40%
- End Semester Exam - 30%

24AI731 Machine Learning for Bigdata 2-0-2-3

Preamble

This course deals with two aspects of big data analytics. The first one is the infrastructure for big data analytics. Introduction to tools and algorithms that can be used to generate models from big data and to scale those models up to big data problems. Spark framework is the chosen platform. The second is the understanding and implementation of scalable and streaming algorithms to analyze voluminous data that is growing exponentially

Course Objectives

- To understand various scalable machine learning algorithms to solve big data problems.
- To understand the SPARK architecture
- To implement Machine Learning algorithms using PySpark

Course Outcomes

COs	Description
CO1	Understand and explain how machine learning algorithm is made scalable to solve big data problems.
CO2	Implement scalable Machine Learning algorithms using PySpark.
CO3	Apply and compare different strategies for big data analytics using various machine learning algorithms
CO4	Understand Streaming algorithms and Coreset concept to analyze high dimensional data

Prerequisites

- Machine Learning.

Syllabus

Introduction to Spark : Spark Architecture, Spark Jobs and APIs. Resilient Distributed Datasets- Creating RDDs, Transformation, Actions. Dataframes- Python to RDD communications, Creating Dataframes, Dataframe queries. MLlib -Loading and Transforming the data. Implementation of Machine Learning algorithms such as Classification and Clustering using the MLlib

Approaches to Modelling- Importance of Words in Documents - Hash Functions- Indexes - Secondary Storage -The Base of Natural Logarithms - Power Laws - Map Reduce. Finding similar items: Shingling – LSH - Distance Measures. Mining Data Streams: Stream data model - Sampling data - Filtering streams. Link Analysis: Page Rank, Link Spam.

Frequent Item Sets: Market Basket Analysis, A-Priori Algorithm - PCY Algorithm, Big data Clustering: Clustering in Non-Euclidean Spaces, BFR, CURE. Structured Streaming: Spark

Streaming, Application dataflow. Coresets: Coresets for K-means, K -median clustering

Text Book / References

1. Anand Raja Raman, Jure Leskovec and J.D. Ullman, "Mining of Massive Data sets", e-book, Publisher, 2014.
2. Kevin P. Murphey, "Machine Learning, a Probabilistic Perspective", The MIT Press Cambridge, Massachusetts, 2012.
3. Tomasz Drabas, Denny Lee , "Learning Pyspark", Packt, February 2017.
4. Jeff M. Phillips, "Coresets and Sketches", arXiv:1601.00617,2016

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and explain how machine learning algorithm is made scalable to solve big data problems.	3	-	-	-	-
CO2	Implement scalable Machine Learning algorithms using PySpark.	3	3	3	3	3
CO3	Apply and compare different strategies for big data analytics using various machine learning algorithms	3	2	1	1	-
CO4	Understand Streaming algorithms and Coreset concept to analyze high dimensional data	3	2	1	1	-

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 25%
- Project – 25%
- End Semester Exam - 30%

24AI732 Applications of Machine Learning 2-0-2-3

Preamble

Voluminous and high dimensional data persist in almost all domains. This course deals with applications of machine learning in various domains to solve complex optimization problems such as recommendation systems, web advertising, and customer segmentation. The entire life cycle of data analytics is dealt with in this course.

Course Objectives

- To understand the design and implementation strategies of various applications of machine learning
- To apply techniques of preprocessing, model generation and evaluation on a given dataset from a particular domain.
- To compare different strategies of machine learning on a particular application

Course Outcomes

COs	Description
CO1	Understand how Machine learning is applied to solve problems in various applications like game playing, recommendation systems, high dimensional analysis, and targeted web advertising
CO2	Present and Implement ML algorithms to solve real world problems
CO3	Apply and compare different types of Machine learning approaches for a given application problem in the context of performance
CO4	Design a machine learning system by incorporating various components of ML and evaluate the performance

Prerequisites

- Machine Learning.

Syllabus

Review of machine learning Concepts, Design of ML system – data cleaning, feature engineering, model selection, model building & fine tuning, and model deployment. Bias, variance, learning curves, and error analysis. Recommendation Systems – Model for Recommendation Systems, Utility Matrix, Content-Based Recommendations, Discovering Features of Documents, Collaborative Filtering. Usage of UV and NMF decomposition in Recommendation systems

Advertising on the Web: Issues in Online Advertising, Online and offline algorithms, The matching Problem, The AdWords Problem, The Balance Algorithm, A Lower Bound on Competitive Ratio for Balance. Customer segmentation – Subspace Clustering, Types of Subspace clustering, Top down and bottom-up approach: PROCLUS and, CLIQUE and their applications in Indexing in databases. Application of dimensionality reduction-SVD for Latent Semantic Indexing, CUR for approximate query processing from databases, PCA, for Image Processing – compression, identification and Visualization.

Sparse models, State space models, Markov Decision Process, Bellman equations, Value iteration and Policy iteration, Linear Quadratic Regulation (LQR), Non-linear dynamics to LQR, Linear Quadratic Gaussian (LQG), Independent component Analysis (ICA) for speech processing

Text Book / References

1. Anand Raja Raman, Jure Leskovec and J.D. Ullman, "Mining of Massive Data sets", e-book, Publisher, 2014.
2. Kevin P. Murphey, "Machine Learning, a Probabilistic Perspective", The MIT Press Cambridge, Massachusetts, 2012.
3. Selected Journal papers to be given as case study from each module.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand how Machine learning is applied to solve problems in various applications like game playing, recommendation systems, high dimensional analysis, and targeted web advertising	3	3	3	2	2
CO2	Present and Implement ML algorithms to solve real world problems	3	3	3	2	2
CO3	Apply and compare different types of Machine learning approaches for a given application problem in the context of performance	1	3	3	2	2
CO4	Design a machine learning system by incorporating various components of ML and evaluate the performance	3	3	3	2	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 25%
- Project – 25%
- End Semester Exam - 30%

24AI733 Evolutionary Machine Learning 2-0-2-3

Preamble

This course explores the intersection of evolutionary computation and machine learning. It provides an in-depth understanding of how evolutionary techniques can enhance machine learning methods. The course covers a wide range of topics, from fundamental concepts to advanced applications, and equips students with the skills to apply these techniques to real-world problems. It's a blend of theoretical knowledge and practical implementation, designed to prepare students for future academic or professional roles in this exciting field.

Course Objectives

- To understand the fundamental concepts of evolutionary algorithms and their applications in various learning paradigms in machine learning.
- To develop proficiency in implementing evolutionary computation techniques for clustering, classification, regression, and ensemble learning.
- To learn to enhance machine learning models through evolutionary approaches for data preparation, model parametrization, design, and validation.
- To critically evaluate and compare the effectiveness of evolutionary computation methods with traditional machine learning techniques.

Course Outcomes

COs	Description
CO1	Understand the principles and techniques of evolutionary computation in machine learning
CO2	Develop the ability to formulate and solve problems using evolutionary computation techniques.
CO3	Demonstrate the ability to apply evolutionary algorithms to solve problems in clustering, classification, regression, and ensemble learning
CO4	Design, validate, and optimize machine learning models using evolutionary computation.

Prerequisites

- Mathematical Foundations of Computing
- Machine Learning

Syllabus

Evolutionary Machine Learning Basics: Fundamentals of Evolutionary Machine Learning - Introduction to Evolutionary Computation, Biological Inspiration behind Evolutionary Algorithms. Evolutionary Supervised Machine Learning - Introduction to Supervised Learning, Evolutionary Algorithms for Regression and Classification, Feature Selection using Evolutionary Algorithms. Evolutionary Machine Learning for Unsupervised Learning - Introduction to Unsupervised Learning, Evolutionary Clustering Algorithms, Evolutionary

Dimensionality Reduction Techniques. Evolutionary Computation and the Reinforcement Learning Problem - Introduction to Reinforcement Learning, Evolutionary Algorithms for Policy Optimization, Balancing Exploration and Exploitation using Evolutionary Techniques.

Evolutionary Computation as Machine Learning: Evolutionary Regression and Modelling - Evolutionary Algorithms for Regression Problems, Model Selection and Optimization using Evolutionary Techniques. Evolutionary Clustering and Community Detection - Community Detection in Networks using Evolutionary Techniques. Evolutionary Classification - Evolutionary Algorithms for Binary and Multi-class Classification, Hyperparameter Tuning and Model Selection using Evolutionary Techniques. Evolutionary Ensemble Learning - Evolutionary Algorithms for Ensemble Model Construction, Diversity and Performance Optimization using Evolutionary Techniques.

Evolutionary Computation for Machine Learning: Genetic Programming as an Innovation Engine for Automated Machine Learning: The Tree-Based Pipeline Optimization Tool (TPOT), Evolutionary Model Validation—An Adversarial Robustness Perspective, Evolutionary Approaches to Explainable Machine Learning, Evolutionary Algorithms for Fair Machine Learning.

Text Book / References

1. Banzhaf, W., Machado, P., Zhang, M. (Eds.) (2023). Handbook of Evolutionary Machine Learning. Springer.
2. Song, T., Zheng, P., Wong, M. L. D., Wang, X. (2019). Bio-Inspired Computing Models and Algorithms. World Scientific.
3. Floreano, D., Mattiussi, C. (2008). Bio-Inspired Artificial Intelligence. MIT Press.
4. Mitchell, T. (1997). Machine Learning. McGraw Hill.
5. Eiben, A. E., Smith, J. E. (2015). Introduction to Evolutionary Computing. Springer.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the principles and techniques of evolutionary computation in machine learning	3	2	3	1	-
CO2	Develop the ability to formulate and solve problems using evolutionary computation techniques.	3	3	3	2	1
CO3	Demonstrate the ability to apply evolutionary algorithms to solve problems in clustering, classification, regression, and ensemble learning	3	3	3	2	1
CO4	Design, validate, and optimize machine learning models using evolutionary computation.	3	3	3	3	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 50%
- End Semester Exam - 30%

24AI734 Applied Predictive Analytics 2-0-2-3

Preamble

Predictive analytics is used to predict of future outcomes based on historical data using statistical and machine learning techniques. This course provides a comprehensive review of various analytics methods. Students will gain an in-depth understanding of supervised and unsupervised learning for predictive analytics. The course will also cover the principles of forecasting analytics.

Course Objectives

- To familiarize students with the methods for exploration and visualization of data
- To develop machine learning models for predictive tasks
- To choose suitable performance measures for predictive models
- To apply predictive modelling techniques in real world data

Course Outcomes

COs	Description
CO1	Understand and describe analytical methods used in predictive analytics
CO2	Evaluate the measures to access predictive performance of data mining tasks
CO3	Understand and design prediction, classification methods
CO4	Learn and identify appropriate methods for forecasting different types of time series data
CO5	Apply suitable predictive methods in real-life problems

Prerequisites

- Linear Algebra and Probability

Syllabus

Introduction and Overview of the Predictive Analytics – Building a Predictive Model - Predictive Power and Overfitting - Data Partitioning – Exploratory Data Analysis - Data Visualization - Dimension Reduction - Principal Components Analysis - Performance Evaluation - Evaluating Predictive Performance - Judging Classifier Performance – Lift and Decile Charts – Oversampling.

Prediction and Classification Methods - Multiple Linear Regression - Explanatory vs. Predictive Modeling - Estimating the Regression Equation and Prediction - The k-NN Classifier (Categorical Outcome) - The Naive Bayes Classifier - Classification and Regression Trees - Logistic Regression - Neural Nets - Discriminant Analysis - Combining Methods: Ensembles - Uplift Modeling - Association Rules and Collaborative Filtering - Clustering.

Forecasting Time Series – Components of a Time Series – Data Partitioning and Performance Evaluation for Time Series – Naive Forecasts - Smoothing Methods - Introduction - Moving Average - Simple Exponential Smoothing – Advanced Exponential Smoothing–Regression-Based Forecasting - Autocorrelation and ARIMA Models - Data Analytics - Social Network Analytics - - Text Mining - predictive analytics in business application - Other Case Studies.

Text Book / References

1. Max Kuhn and Kjell Johnson, "Applied Predictive Modeling", Springer, 2018.
2. Galit Shmueli, Peter Gedeck, Peter C. Bruce, Nitin R. Patel, "Data Mining for Business Analytics: Concepts, Techniques, and Applications in Python", Wiley, 2019.
3. Daniel T. Larose and Chantal D. Larose, "Data Mining and Predictive Analytics" (Wiley Series on Methods and Applications in Data Mining), Wiley, 2015.
4. Ratner Bruce, "Statistical and Machine-Learning Data Mining:: Techniques for Better Predictive Modeling and Analysis of Big Data", CRC Press, 2017.
5. Abbott Dean, "Applied predictive analytics: Principles and techniques for the professional data analyst", John Wiley & Sons, 2014.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and describe analytical methods used in predictive analytics	3	1	-	-	-
CO2	Evaluate the measures to access predictive performance of data mining tasks	3	3	2	-	-
CO3	Understand and design prediction, classification methods	3	3	3	1	-
CO4	Learn and identify appropriate methods for forecasting different types of time series data	3	2	2	1	-
CO5	Apply suitable predictive methods in real-life problems	3	3	3	3	3

Evaluation Pattern - 70:30

- Midterm Exam - 30%
- Continuous Evaluation – 40%
- End Semester Exam - 30%

24AI735 Federated Learning 2-0-2-3

Preamble

Federated Learning can improve the performance of models by leveraging the diversity of the data across different devices. In this course, students will learn basics of Federated Learning and will be able to apply the real-time updates of the model in various practical scenarios.

Course Objectives

- Get exposure to need for distributed model updates
- To understand the importance of privacy and security in machine learning techniques

Course Outcomes

COs	Description
CO1	Describe the key concepts and architecture of Federated Learning.
CO2	Apply different methods to develop federated learning systems.
CO3	Apply optimization techniques in Federated Learning
CO4	Construct and scale a simple federated system
CO5	Evaluate privacy and security concerns in Federated Learning and implement privacy-preserving techniques.

Prerequisites

- Machine Learning

Syllabus

Introduction to Federated Learning - Overview of Federated Learning: Definition, History, and Applications - Concepts and Terminology - Federated Learning Architecture -Machine Learning Perspective -Security & Privacy in Federated Learning - Federated Learning vs Centralized Learning: Comparison and Contrast

Horizontal Federated Learning (HFL) -Definition and Architecture of Horizontal Federated Learning - Federated Averaging (FedAvg) Algorithm - Improvements on the FedAvg Algorithm

Vertical Federated Learning (VFL) - Definition and Architecture of Vertical Federated Learning - VFL Algorithms: Secure Federated Linear Regression, Secure Federated Tree Boosting

Federated Learning with Non-IID Data - Heterogeneity in Federated Learning -Stratification and Local Updated Rules - Advanced Optimization Techniques in Federated Learning - Adaptive Learning Rate -Momentum and Weight Decay

Federated Transfer Learning (FTL) - Framework of Federated Transfer Learning - Homomorphic Encryption in FTL - FTL Training Process -FTL Prediction Process - Security Analysis of FTL - Secret Sharing based FTL

Security in Federated Learning - Protecting Against Data Leakage in FL -Private Parameter Aggregation for FL - Data Leakage in FL Advanced Security Issues -Dealing with Byzantine Threats to Neural Networks in FL

Practical Applications and Case Studies -Real-world Applications of Federated Learning

Text Book / References

1. Federated learning comprehensive overview of methods and applications Springer Nature Switzerland AG; 1st ed. 2022 edition By Heiko Ludwig (Editor), Nathalie Baracaldo.
2. Federated Learning, Morgan Claypool Publishers, By Qiang Yang, Yang Liu, Yong Cheng, Yan Kang, Tianjian Chen, and Han Yu.
3. Federated Learning with Python by Kiyoshi Nakayama PhD, George Jeno, O'Reilly Media, Inc. Pub.
4. What-is-federated learning? By Emily Glanz, Nova Fallen, O'Reilly Media, Inc. Pub.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Describe the key concepts and architecture of Federated Learning.	3	-	3	2	-
CO2	Apply different methods to develop federated learning systems.	3	2	1	-	2
CO3	Apply optimization techniques in Federated Learning	2	-	2	3	3
CO4	Construct and scale a simple federated system	2	3	2	3	-
CO5	Evaluate privacy and security concerns in Federated Learning and implement privacy-preserving techniques.	2	2	3	2	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous Evaluation – 50%
- End Semester Exam - 30%

24AI736 Explainable AI 2-0-2-3

Preamble

This course provides an Introduction to Explainable AI (XAI) through practical applications and real-world examples. Students will gain a basic proficiency in interpreting and explaining the decisions of ML and AI systems, in a transparent and understandable manner to humans. The course will cover various XAI techniques and algorithms, including rule-based models, feature importance analysis, model-agnostic approaches, and post-hoc explanations.

Course Objectives

- To understand how to explain machine learning models with various techniques.
- To explain various factors affecting the efficiency of machine learning models.
- To apply the explainability while applying ML models in practical applications.

Course Outcomes

COs	Description
CO1	Understand the concept and importance of explainability in AI models
CO2	Apply visual explanations techniques such as PDP, ICE, Surrogate Models, and Feature Importance
CO3	Explain structured data, images, and unstructured data using Deep Explainers and LLMs
CO4	Evaluate the application of explainability techniques in model development processes

Prerequisites

- Machine Learning, Python Programming

Syllabus

Explainability –What and Why, When not to use explainability; Types of explainability and Taxonomy, Explainability in the model development process.

Visual Explanations – Transparent models and RuleFit, Partial Dependency Plots, Partial Dependency plot (PDP), Individual conditional expectations (ICE), Applications of these plots, Global Explanations – Surrogate Models, Feature Importance; Local Explanations – LIME, Shapley values.

Explaining Structured Data, Explaining Images and Unstructured Data and Text Deep Explainers, Time Series Explainers, LLM, Foundation Models.

Text Book / References

1. Denis Rothman "Hands-On Explainable AI (XAI with Python", Packt Publishing, 2020
2. Explainable AI for Practitioners by Michael Munn, David Pitman, O'Reilly Media 2022, ISBN: 9781098119133
3. Explainable AI: Interpreting, Explaining and Visualizing Deep Learning, Lecture Notes in Artificial Intelligence, Springer Nature, 2019

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the concept and importance of explainability in AI models	2	2	1	2	-
CO2	Apply visual explanations techniques such as PDP, ICE, Surrogate Models, and Feature Importance	2	2	3	2	-
CO3	Explain structured data, images, and unstructured data using Deep Explainers and LLMs	3	2	2	3	1
CO4	Evaluate the application of explainability techniques in model development processes	1	1	3	2	3

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Quizzes - 20%
- Lab Assignments & Case Study – 30%
- End Semester Exam - 30%

24AI737 Artificial Intelligence for Robotics 2-0-2-3

Preamble

In recent years, several off-the-shelf robots have become available and some of them have made their way into our homes, offices, and factories. The ability to program robots has therefore become an important skill; e.g., for robotics research as well as in several companies (such as iRobot, ReThink Robotics, Willow Garage, medical robotics, and others). We study the problem of how a robot can learn to perceive its world well enough to act in it, to make reliable plans, and to learn from its own experience. The focus will be on algorithms and machine learning techniques for autonomous operation of robots.

Course Objectives

- To understand the principles of reinforcement learning which is one of the key learning techniques for robots.
- To understand uncertainty handling in robotics through probabilistic approaches.
- To learn how measurements work for robots.

Course Outcomes

COs	Description
CO1	Learn the foundations of reinforcement learning for robotics
CO2	Understand basic probabilistic principles behind Robotics intelligence
CO3	Learn different measurement techniques for robotics
CO4	Understand POMDP and its significance for robotics
CO5	Implement principles of robotics intelligence for solving real world problems

Prerequisites

- Data Structures and Algorithms
- Foundation of Data Science
- Linear Algebra and Optimization
- Principles of AI and ML

Syllabus

Overview: Robotics introduction, historical perspective on AI and Robotics, Uncertainty in Robotics Reinforcement Learning: Basic overview, examples, elements, Tabular Solution Methods - Multi- armed bandits, Finite Markov decision process, Dynamic programming (Policy Evaluation, Policy Iteration, Value Iteration), Monte Carlo Methods, Temporal-Difference Learning (Q-learning, SARSA).

Approximate Solution Methods - On-policy Prediction with Approximation, Value function approximation, Non-linear function approximation, Reinforcement Learning in robotics, Recursive state estimation: Robot Environment Interaction, Bayes filters, Gaussian filters – The Kalman filter, The Extended Kalman Filter, The information filter, The particle filter Robot motion: Velocity Motion Model, Odometry Motion Model, Motion and maps.

Measurement: Beam Models of Range Finders, Likelihood Fields for Range Finders, Correlation- Based Sensor Models, Feature-Based Sensor Models, Overview of POMDP.

Text Book / References

1. Sebastian Thrun, Wolfram Burgard, Dieter Fox, Probabilistic Robotics, MIT Press 2005
2. Richard S. Sutton, Andrew G. Barto, Reinforcement Learning: An Introduction", Second edition, MIT Press, 2018
3. Jens Kober, Jan Peters, Learning Motor Skills: From Algorithms to Robot Experiments, Springer, 2014
4. Francis X. Govers, Artificial Intelligence for Robotics, Packt, 2018

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Learn the foundations of reinforcement learning for robotics	3	1	3	-	1
CO2	Understand basic probabilistic principles behind Robotics intelligence	3	1	3	-	1
CO3	Learn different measurement techniques for robotics	3	-	3	-	1
CO4	Understand POMDP and its significance for robotics	3	-	3	-	1
CO5	Implement principles of robotics intelligence for solving real world problems	3	-	3	1	-

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 25%
- Project – 25%
- End Semester Exam - 30%

24AI738 Data Visualization 2-0-2-3

Preamble

Data visualization is an essential aspect of the data science portfolio and finds application across diverse disciplines which use visualization techniques to explore and present data. This course lays a road map to data-driven storytelling by focusing on the principles, methods, and techniques of scientific visualization that help to create powerful and engaging visuals, tailored to the needs of diverse stakeholders.

Course Objectives

- To understand the important role of visualization in the analysis of data.
- To apply data visualization best practices to choose the appropriate visualization tailored to the needs of the audience.
- To learn some of the latest tools and software to produce effective visuals that capture the stories within the data

Course Outcomes

COs	Description
CO1	Understand and explain the key techniques used in data visualization
CO2	Apply effective visualizations to explore and analyze input data
CO3	Present the insights and findings in engaging formats that produce compelling stories
CO4	Evaluate data visualization systems for their effectiveness
CO5	Design and build data visualization systems following the best practices using popular software tools for visualization such as Tableau/QlikView

Prerequisites

- Basic Data Science.

Syllabus

Value of Visualization – What is Visualization and Why do it: External representation – Interactivity – Difficulty in Validation. Data Abstraction: Dataset types – Attribute types – Semantics. Task Abstraction – Analyze, Produce, Search, Query. Four levels of validation – Validation approaches – Validation examples. Marks and Channels

Rules of thumb – Arrange tables: Categorical regions – Spatial axis orientation – Spatial layout density. Arrange spatial data: Geometry – Scalar fields – Vector fields – Tensor fields. Arrange networks and trees: Connections, Matrix views – Containment. Map color: Color theory, Color maps and other channels.

Manipulate view: Change view over time – Select elements – Changing viewpoint – Reducing attributes. Facet into multiple views: Juxtapose and Coordinate views – Partition into views

– Static and Dynamic layers – Reduce items and attributes: Filter – Aggregate. Focus and context: Elide – Superimpose - Distort, Case Studies using Tableau/Qlikview – Tabular Data - Graphs - Networks - Trees - Spatial Data - Text/Logs - Time Series Complex Combinations.

Text Book / References

1. Tamara Munzner, ”Visualization Analysis and Design”, A K Peters Visualization Series, CRC Press, 2014.
2. Claus O. Wilke, ”Fundamentals of Data Visualization: A primer for making informative and compelling figures”, O’Reilly, 2019.
3. Kieran Healy, ”Data Visualization: A Practical Introduction”, Princeton University Press, 2019.
4. Andy Kirk, ”Data Visualization, A Handbook for Data Driven Design”, 2nd ed, Sage Publi- cations, 2019.
5. Nathan Yau, ”Visualize This: The Flowing Data Guide to Design, Visualization and Statistics”, John Wiley & Sons, 2011.
6. Daniel Murray, ”Tableau Your Data!: Fast and Easy Visual Analysis with Tableau Software”, Wiley, 2016.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the key techniques and theory used in visualization of data	3	-	-	-	-
CO2	Apply effective visualizations to explore and analyze input data	3	-	-	1	-
CO3	Present the insights and findings in engaging formats that produce compelling stories	3	-	-	-	1
CO4	Evaluate data visualization systems for their effectiveness	3	2	-	-	-
CO5	Design and build data visualization systems following the best practices using popular software tools for visualization such as Tableau/QlikView	3	3	3	3	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 25%
- Project – 25%
- End Semester Exam - 30%

24AI739 | Stochastic Modeling | 2-0-2-3

Preamble

This course provides an in-depth exploration of stochastic processes with a focus on their applications in artificial intelligence.

Course Objectives

- Gain a foundational understanding of finite Markov chains in discrete time.
- Develop a comprehensive understanding of martingales in discrete time, covering fundamental theoretical concepts and their practical implications.
- Explore the essential principles of stochastic processes in continuous time, focusing on key examples such as the Poisson process and Brownian motion.
- Acquire insights into elementary stochastic calculus applied to Brownian motion, enhancing comprehension of its theoretical underpinnings.

Course Outcomes

COs	Description
CO1	Demonstrate a deep understanding of the theoretical foundations of finite Markov chains in discrete time.
CO2	Apply martingale theory to analyze algorithms and decision-making processes in AI.
CO3	Understand the essential principles of stochastic processes in continuous time, with a focus on the Poisson process.
CO4	Apply elementary stochastic calculus techniques to Brownian motion and related processes.

Prerequisites

- None.

Syllabus

Introduction to Stochastic Processes: Overview of stochastic processes - Introduction to conditional expectations. Conditional Expectations: Definition and properties of conditional expectations - Conditional expectations in the context of stochastic processes - Bayesian inference and decision theory.

Discrete Time Martingales: Definition and properties of martingales - Stopping times and optional stopping theorem - Discrete Time Markov Chains: Definition and properties of Markov chains - Classification of states, ergodicity - Stationary distributions and convergence - Markov decision processes (MDPs) and modelling sequential decision problems.

Poisson Process: Interarrival times and memory lessness - Poisson processes in queuing theory and AI applications - Brownian Motion: - Stochastic integration and differential equations - Geometric Brownian motion and its applications in finance and AI. Elements of Ito Stochastic

Calculus: Ito integral and Ito's lemma - Stochastic differential equations and models in continuous time.

Text Book / References

1. Lawler, G. F. (2006). *Introduction to Stochastic Processes* (2nd ed.). Cambridge University Press.
2. Del Moral, P. (2014). *Stochastic Processes: From Applications to Theory*, Springer.
3. Shreve, S. E. (2004). *Stochastic Calculus for Finance II: Continuous-Time Models* (1st ed.). Springer.
4. Brzezniak, Z., & Zastawniak, T. (1999). *Basic Stochastic Processes* (1st ed.). Springer.
5. Taylor, H. M., & Karlin, S. (2010). *An Introduction to Stochastic Modeling* (4th ed.). Academic Press.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Demonstrate a deep understanding of the theoretical foundations of finite Markov chains in discrete time.	2	2	2	1	2
CO2	Apply martingale theory to analyze algorithms and decision-making processes in AI.	2	1	2	2	2
CO3	Understand the essential principles of stochastic processes in continuous time, with a focus on the Poisson process.	2	2	2	2	1
CO4	Apply elementary stochastic calculus techniques to Brownian motion and related processes.	2	2	2	2	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Quiz – 20%
- Lab Continuous Assessment – 30%
- End Semester Exam / Project - 30%

24AI740 Networks and Spectral Graph Theory 2-0-2-3

Preamble

Network science is an inter disciplinary field that combines mathematics, social science, computer science and many other areas. This course is essentially bringing an understanding on the behavior of networked systems such as the Internet, social networks, and biological networks.

Course Objectives

- Exploring graph models in networked systems; understanding the structure and the behavior.
- Empirical study and hands-on experience on social networks and other systems

Course Outcomes

COs	Description
CO1	Understanding the key concepts in network graphs
CO2	Apply a range of measures and models for characterizing network structure
CO3	Define methodologies for analyzing networks of different fields
CO4	Apply graph algorithms to different networks
CO5	Demonstrate knowledge of network graphs with the help of software tools such NetworkX and Gephi

Prerequisites

- Primary knowledge of linear algebra and familiarity with graphs.
- Working knowledge in Python for data science.

Syllabus

Graphs and Networks- Review of basic graph theory, Mathematics of networks- Networks and their representation, Graph spectra, Graph Laplacian, Structure of complex networks, Clustering, Com- munity structures, Social networks - the web graph, the internet graph, citation graphs. Measures and metrics- Degree centrality, Eigenvector centrality, Katz centrality, PageRank, Hubs and authorities, Closeness centrality, Betweenness centrality, Transitivity, Reciprocity, Similarity, assortative mixing.

Networks models - Random graphs, Generalized random graphs, The small-world model, Exponential random graphs, The large-scale structure of networks- small world effect, Degree distributions, Power laws and scale-free networks; Structure of the Internet, Structure of the World Wide Web. Fundamental network algorithms- Graph partitioning, Maximum flows and minimum cuts, Spectral graph partitioning, Community detection, Girvan and Newman Algorithm, Simple modularity maximization, Spectral modularity maximization, Fast methods based on the modularity.

Models of network Formation-Preferential attachment, Model of Barabasi and Albert, Vertex copying models, Network optimization models; Epidemics on networks- Models of the spread of disease, SI model, SIR model, SIS model, SIRS model; Network Search-Web search, Searching distributed databases. Graph databases like Neo4j, Graph Convolutional Neural Networks, Graph algorithms and implementation using NetworkX and Gephi.

Text Book / References

1. M.E.J. Newman, "Networks: An Introduction", Oxford University Press, 2018.
2. Dougles West, "Introduction to Graph Theory", Third Edition, PHI Learning Private Limited, 2021.
3. Guido Caldarelli, "Scale-Free Networks - Complex Webs in Nature and Technology (2nd ed.)", Oxford University Press, 2020.
4. Alain Barrat, Marc Barthelemy and Alessandro Vespignani, "Dynamical processes on Complex networks", Cambridge University Press, 2008.
5. Reuven Cohen and Shlomo Havlin, "Complex Networks: Structure, Robustness and Function", Cambridge University Press, 2010.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understanding the key concepts in network graphs	-	3	-	1	-
CO2	Apply a range of measures and models for characterizing network structure	3	2	-	-	-
CO3	Define methodologies for analyzing networks of different fields	3	-	2	-	-
CO4	Apply graph algorithms to different networks	-	-	2	3	-
CO5	Demonstrate knowledge of network graphs with the help of software tools such NetworkX and Gephi	-	-	-	3	3

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 20%
- Project – 30%
- End Semester Exam - 30%

24AI741 Parallel and Distributed Data Management 2-0-2-3

Preamble

The improvements in Database Management System (DBMS) technology have resulted in significant developments in distributed computing and parallel processing technologies. This has led to the development of distributed database management systems and parallel database management systems that are now the dominant data management tools for highly data-intensive applications. In addition to an introduction to parallel and distributed database architectures and their implementation features, this course covers advanced query processing and optimization approaches for parallel and distributed systems. The students also gain knowledge in setting up a distributed database application using the latest technologies.

Course Objectives

- To provide an understanding of the distributed and parallel database architectures so as to make a choice while implementing a distributed application;
- To learn how a distributed database can be implemented for an application;
- To get trained in distributed query processing and optimization for various distributed or parallel database applications

Course Outcomes

COs	Description
CO1	Understand the need for different distributed and parallel database architectures and study its characteristics.
CO2	Design algorithms for distributed and parallel data processing.
CO3	Understand the concepts of fragmentation and allocation algorithms.
CO4	Implement optimized parallel and distributed queries for such a system.
CO5	Design and build an application using one of the latest distributed or parallel database technology.

Prerequisites

- DBMS
- Algorithms and Data Structures
- Advanced Java, Apache Spark

Syllabus

Introduction: Parallel and Distributed architectures, models, complexity measures, Communication aspects, A Taxonomy of Distributed Systems - Models of computation: shared memory and message passing systems, synchronous and asynchronous systems, Global state and snapshot algorithms.

Distributed and Parallel databases: Centralized versus Distributed Systems, Parallel versus Distributed Systems, Distributed Database Architectures-Shared disk, shared nothing, Distributed Database Design – Fragmentation and Allocation, Optimization.

Query Processing and Optimization – Parallel/ Distributed Sorting, Parallel/Distributed Join, Parallel/Distributed Aggregates, Network Partitions, Replication, Publish/Subscribe Systems-Case study on Apache Kafka Distributed Publish/Subscribe messaging Hadoop and Map Reduce – Data storage and analysis, Design and concepts of HDFS, YARN, Map Reduce workflows and Features, Setting up a Hadoop cluster.

Text Book / References

1. M. Tamer Özsu and Patrick Valduriez, "Principles of Distributed Database Systems", 4th Edition, 2020, Springer
2. Dimitri P. Bertsekas and John N. Tsitsiklis, "Parallel and distributed computation : Numerical methods", 3rd Edition, 2020
3. Andrew S. Tannenbaum and Maarten van Steen "Distributed Systems: Principles and Paradigms", Third Edition, Prentice Hall, October 2017.
4. Ajay D. Kshemkalyani and Mukesh Singhal, "Distributed Computing: Principles, Algorithms and Systems", Cambridge University Press, 2011.
5. Vijay K. Garg, "Elements of Distributed Computing", Wiley-IEEE Press, May 2002
6. David DeWitt and Jim Gray, "Parallel database systems: The future of high performance database systems", CACM, 1992
7. Tom White, "Hadoop-The Definitive Guide", 4th ed., O'Reilly, 2015

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the need for different distributed and parallel database architectures and study its characteristics.	3	-	-	-	-
CO2	Design algorithms for distributed and parallel data processing.	3	2	2	2	-
CO3	Understand the concepts of fragmentation and allocation algorithms.	3	2	-	-	-
CO4	Implement optimized parallel and distributed queries for such a system.	3	2	-	-	-
CO5	Design and build an application using one of the latest distributed or parallel database technology.	3	3	3	3	3

Evaluation Pattern - 70:30

- Midterm Exam - 30%
- Continuous Evaluation – 40%
- End Semester Exam - 30%

24AI742 Medical Signal Processing 2-0-2-3

Preamble

The development of Medical Imaging over the past four decades have been truly revolutionary. It is therefore essential to develop knowledge in Medical Signal Processing, stepping out of the conventional notion of extending the art of instrumentation in biomedicine. The course aims to provide the graduate students with a detailed background of state-of-the-art electrical engineering practices used in biomedical engineering. The course aims to provide an understanding of various image modalities captured based on various signal processing techniques. This course will also cover the application of various Deep learning techniques, for segmentation as well as classification problems.

Course Objectives

- To understand various signals and the image modalities in the field of Biomedical.
- To study origins and characteristics of some of the most commonly used biomedical signals like ECG.
- To explore research domain in biomedical signal processing.
- To understand various reconstruction techniques for CT and MRI.

Course Outcomes

COs	Description
CO1	Understand and explain various methods of acquiring bio signals.
CO2	Understand and compare various sources of bio signal distortions and its remedial techniques.
CO3	Analyze ECG and EEG signal with characteristic feature points.
CO4	Apply and implement deep learning techniques for medical image segmentation, clustering and classification problems.
CO5	Understand various volume reconstruction and volume rendering techniques for medical images.

Prerequisites

- None.

Syllabus

Signals and systems: Review, Medical Imaging Modalities and the need for different modalities (MRI, CT, OCT for Retinal Images, PET, X-Ray, Ultra Sound, Microscopy, Flow Cytometry, Imaging Flow Cytometry, etc. Pre-processing – Image Enhancement – Focus Analysis - Noise reduction

(Additive and Speckle Noise) – Image Quality Measures - Domain Transformation: Fourier Domain and Wavelet Domain- Thermal Imaging. Basic electrocardiography, ECG lead systems, ECG signal characteristics

Medical Image Segmentation – Deep Learning based Segmentation on 2D or 3D volume of Data Feature Extraction – Morphological Features – Textural Features –, Feature extraction for 1D Biomedical signals– Deep Features. Image Registration and Fusion — Key Point Matching - Geometric transformations. ECG data acquisition, ECG lead system, ECG signal characteristics (parameters and their estimation), Analog filters, ECG amplifier, and QRS detector, Power spectrum of the ECG, Band pass filtering techniques, Differentiation techniques, Template matching techniques, A QRS detection algorithm

Classification and Clustering– Examples of image classification for diagnostic/assistive technologies –Deep learning-based classifiers. 3D volume reconstruction – Reconstruction techniques for CT, MRI, Reconstruction of cell structure from focus stack of images - CT and MRI volume reconstruction – Wavelet based Volume Rendering, Applications of EEG.

Text Book / References

1. Klaus D. Toennies, ”Guide to Medical Image Analysis - Methods and Algorithms”, Advances in Computer Vision and Pattern Recognition, 2nd Edition, Springer-Verlag London, 2017, DOI: 10.1007/978-1-4471-7320-5, ISBN 978-1-4471-7318-2
2. Geoff Dougherty, “Medical Image Processing Techniques and application”, Springer New York 2011
3. Mostafa Analoui, Joseph D. Bronzino, Donald R. Peterson, “Medical Imaging: Principles and Practices”, Taylor and Francis group, 2012
4. Analyzing Neural Time Series Data-Theory and Practice (MIT Press) 2014

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and explain various methods of acquiring bio signals.	3	1	-	-	1
CO2	Understand and compare various sources of bio signal distortions and its remedial techniques.	3	2	-	-	2
CO3	Analyze ECG and EEG signal with characteristic feature points.	1	3	2	-	1
CO4	Apply and implement deep learning techniques for medical image segmentation, clustering and classification problems.	3	3	2	-	3
CO5	Understand various volume reconstruction and volume rendering techniques for medical images.	2	3	2	-	3

Evaluation Pattern - 50:50

- Midterm Exam - 30%
- Continuous Evaluation – 20%
- End Semester Exam - 50%

24AI743 Computer Vision 2-0-2-3

Preamble

Computer Vision is one of the fastest growing and most exciting AI (Artificial Intelligence) disciplines in today's academia and industry. This course is designed to open the doors for students who are interested in learning about the fundamental principles and important applications of computer vision. The course starts with the basic understanding of image formation and various image pre- processing techniques. It also deals with visual object detection and recognition algorithms. Object tracking and Motion segmentation from videos are also introduced as part of the course. The course also gives exposure to image reconstruction, camera calibration, stereo vision camera projection models etc. which enable students to understand the concepts required for implementing modern AI applications which can perceive understand and reconstruct complex visual world like robots navigating space and performing duties, smart cars which can drive safe etc.

Course Objectives

- To introduce students to the state-of-the-art algorithms in the area of image analysis and object recognition
- Give an exposure to video analysis techniques for object tracking and motion estimation
- To build good understanding on the computer vision concepts and techniques to be applied for robotic vision applications
- Enable students to apply the vision algorithms and develop applications in the domain of image analysis, robotic navigation

Course Outcomes

COs	Description
CO1	Understand and explain the different models of image formation
CO2	Understand and implement different techniques of image analysis through image feature extraction and object recognition.
CO3	Apply fundamental algorithms for video analysis such as object tracking, motion segmentation etc.
CO4	Analyze the major technical approaches involved in image registration, camera calibration, pose estimation, stereo vision etc. to be applied to develop vision algorithms for robotic applications.
CO5	Apply the algorithms and develop applications in the domain of image analysis and robotic vision

Prerequisites

- None.

Syllabus

Introduction to Image Processing-Basic mathematical concepts: Image enhancement: Grey level transforms, Spatial filtering. Extraction of special features: edge and corner detection. Morphological processing, Image transforms, Discrete Fourier Transform, Fast Fourier Transform. Frequency domain enhancement.

Image Segmentation Algorithms: contextual, non-contextual segmentation, texture segmentation. Feature Detectors and Descriptors, Feature Matching-Object Recognition, Face detection (Viola Jones), Face Recognition,

Modern computer vision architectures based on deep convolutional neural networks, The Use of Motion in Segmentation Optical Flow & Tracking Algorithms, YOLO, DeepSORT: Deep Learning to Track Custom Objects in a Video, Action classification with convolutional neural networks, RNN, LSTM

Image registration, 2D and 3D feature-based alignment, Pose estimation, Geometric intrinsic calibration, -Camera Models and Calibration: Camera Projection Models – orthographic, affine, perspective, projective models. Projective Geometry, transformation of 2-d and 3-d, Internal Parameters, Lens Distortion Models, Calibration Methods – linear, direct, indirect and multiplane methods. Geometry of Multiple views- Stereopsis, Camera and Epipolar Geometry, Fundamental matrix; Homography, Rectification, DLT, RANSAC, 3-D reconstruction framework; Auto-calibration., Introduction to SLAM (Simultaneous Localization and Mapping).

Text Book / References

1. Deep Learning (Adaptive Computation and Machine Learning series) Ian Goodfellow, Yoshua Bengio, Aaron Courville, Francis Bach, January 2017, MIT Press

2. Richard Szelinski, Computer Vision: Algorithms and Applications, 2010

3. E. Trucco and A. Verri, Prentice Hall, 1998.Introductory techniques for 3D Computer Vision.

4. Marco Treiber, “An Introduction to Object Recognition Selected Algorithms for a Wide Variety of Applications”, Springer, 2010.

5. Forsyth and Ponce, “Computer Vision – A Modern Approach”, Second Edition, Prentice Hall, 2011.

6. R. C. Gonzalez, R. E. Woods, ‘Digital Image Processing’, 4th edition Addison-Wesley,2016.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and explain the different models of image formation	3	3	1	-	-
CO2	Understand and implement different techniques of image analysis through image feature extraction and object recognition.	3	2	-	-	1
CO3	Apply fundamental algorithms for video analysis such as object tracking, motion segmentation etc.	3	3	2	-	-
CO4	Analyze the major technical approaches involved in image registration, camera calibration, pose estimation, stereo vision etc. to be applied to develop vision algorithms for robotic applications.	-	-	3	1	2
CO5	Apply the algorithms and develop applications in the domain of image analysis and robotic vision	-	-	-	3	3

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 25%
- Project – 25%
- End Semester Exam - 30%

24AI744 Natural Language Processing 2-0-2-3

Preamble

This course introduces the fundamental concepts and techniques of Natural Language Processing (NLP). Students will gain an in-depth understanding of the computational properties of natural languages and the commonly used algorithms for processing linguistic information. The course examines NLP models and algorithms using both the traditional symbolic and the more recent statistical approaches.

Course Objectives

- The objective of this course is to provide students with a comprehensive understanding of both the theoretical foundations and practical applications of NLP. Students will gain expertise in various NLP techniques, tools, and models, enabling them to address complex language-related challenges in diverse domains. The course aims to equip students with the skills needed to develop advanced NLP systems and conduct innovative research in the field

Course Outcomes

COs	Description
CO1	Understand and Apply Fundamental NLP Concepts
CO2	Develop and Implement Advanced Word Embeddings and Language Models
CO3	Apply Machine Learning and Deep Learning Techniques to NLP Tasks
CO4	Utilize NLP Toolkits and Develop Practical NLP Applications

Prerequisites

- Basics of Machine Learning
- Python Programming Language
- Basics of Probability

Syllabus

Foundations of NLP: Introduction to NLP: Syntax, Semantics, Morphology, Word Representation: One-hot Encoding, Bag-of-Words (BoW), Term Frequency – Inverse Document Frequency (TF-IDF), Language Models: n-grams, Neural Network-based Word Embedding Algorithms, Advanced Text Embeddings: Word2Vec, GloVe, FastText, Contextual Embeddings (BERT, ELMo, GPT, XLNet, RoBERTa, Sequences and Sequential Data

Machine Learning and Deep Learning for NLP: Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), Gated Recurrent Units (GRUs), Sequence to

Sequence Modelling, Encoder-Decoder Architectures, Attention Mechanism, Transformer Networks, Topic Modelling: LSA, LDA, Dynamic Topic Models

Practical Tools and Applications: NLP Toolkits (Eg. NLTK, SpaCy, Stanford NLP, OpenNLP) and case studies, Applications: Part-of-Speech Tagging, Named Entity Recognition (NER), Dependency Parsing, Sentiment Analysis, Machine Translation, Text Summarization, Evaluation Metrics, Visualization of Text Data, Emerging Trends: Zero-shot and Few-shot Learning, Multilingual and Cross-lingual Models, Explainable AI, Ethical Considerations

Text Book / References

1. Daniel Jurafsky, James H Martin, Speech & language processing, preparation [cited 2020 June 1] Available: from: https://web. stanford.edu/~ jurafsky/slp3 (2018).

2. Christopher Manning and Hinrich Schütze, Foundations of Statistical Natural Language Processing, MIT press, 1999.

3. Steven Bird, Ewan Klein and Edward Loper, Natural Language Processing with Python, O'Reilly Media, Inc., 2009.

4. Jason Browlee, Deep Learning for Natural Language Processing: Develop Deep Learning Models for your Natural Language Problems (Ebook), Machine Learning Mastery, 2017

5. Research papers and articles from recent NLP conferences (ACL, EMNLP, NAACL)

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and Apply Fundamental NLP Concepts	3	1	-	2	-
CO2	Develop and Implement Advanced Word Embeddings and Language Models	3	1	-	2	-
CO3	Apply Machine Learning and Deep Learning Techniques to NLP Tasks	3	1	2	-	-
CO4	Utilize NLP Toolkits and Develop Practical NLP Applications	-	3	1	-	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 25%
- Project – 25%
- End Semester Exam - 30%

24AI745 GPU Architecture and Programming 2-0-2-3

Preamble

GPU accelerated processors are being actively used nowadays in general purpose and scientific computing. These massively parallel, off-the shelf devices are used to run compute-intensive and time-consuming part of applications. This course introduces the students to the Single Instruction Multiple Thread (SIMT) architecture of modern GPUs and architecture-aware programming frameworks like Compute Unified Device Architecture (CUDA) and OpenCL. While CUDA programming model is a proprietary framework for the students to learn to interface with GPUs, OpenCL allows them to be familiarized with an open, heterogeneous parallel computing model. Modern day applications of GPUs are also introduced to the students through case studies.

Course Objectives

- To introduce the fundamentals of GPU computing architectures and programming models.
- To familiarize the student with GPU aware programming frameworks like proprietary NVIDIA CUDA(C) and open heterogeneous programming standards like OpenCL.
- To create GPGPU accelerated real world applications.

Course Outcomes

COs	Description
CO1	Understand and analyze parallel programming architectures, including SIMT architecture of modern GPUs, and their implications for AI and industry applications.
CO2	Master GPU-aware programming using NVIDIA CUDA and OpenCL frameworks to develop efficient GPU-accelerated applications.
CO3	Design and implement heterogeneous computing solutions across CPU/GPU architectures using OpenCL, emphasizing performance optimization and scalability.
CO4	Apply GPU computing techniques to real-world applications such as convolution, video processing, histogram analysis, and mixed particle simulations, and evaluate their performance metrics and scalability.

Prerequisites

- Computer Architecture
- Programming Fundamentals
- Data Structures

Syllabus

Introduction to Parallel Programming – Types of Parallelism – SIMD and SIMT – GPU architecture- Threads, Blocks and Grids- GPU Memory Organization- CUDA Programming Model- CUDA Mem- ory Model- Multidimensional thread management with CUDA- Basic CUDA Programming Examples -CUDA Streams – Synchronization and Warp Scheduling, Optimization.

Introduction to OpenCL - OpenCL Device Architectures - Basic OpenCL Programming Model – OpenCL Memory Model - Concurrency and Execution Model - Dissecting a CPU/GPU - OpenCL for Heterogeneous Computing - OpenCL Implementation – examples.

Case study: Convolution, Video Processing, Histogram and Mixed Particle Simulation - OpenCL Extensions - OpenCL Profiling and Debugging – WebCL, Applications of GPU Architecture like Gaming, Computer Vision, etc.

Text Book / References

1. David B. Kirk, Wenmei W. Hwu, Morgan Kaufmann, Programming Massively Parallel Processors: A Hands-on Approach, 2016
2. Benedict R. Gaster, Lee Howes, David, R. Kaeli, Perhaad Mistry and Dana Schaa, ”Heterogeneous Computing with OpenCL”, Elsevier, 2013.
3. Jason Sanders, Edward Kandrot, ”CUDA by Example: An Introduction to General-Purpose GPU Programming”, Addison-Wesley Professional, 2010
4. Shane Cook, ”CUDA Programming: A Developer’s Guide to Parallel Computing with GPUs”, Newnes, 2012
5. Aaftab Munshi, Benedict Gaster, Timothy G. Mattson, James Fung and Dan Ginsburg, ”OpenCL Programming Guide”, Addison-Wesley Professional, 2011.
6. Ryoji Tsuchiyama, Takashi Nakamura, Takuro Iizuka and Akihiro Asahara, ”The OpenCL Programming Book”, Fixstars Corporation, 2010.
7. Matthew Scarpio, ”OpenCL in Action: How to Accelerate Graphics and Computations”, Manning Publications, 2011.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and analyze parallel programming architectures, including SIMT architecture of modern GPUs, and their implications for AI and industry applications.	1	2	2	1	-
CO2	Master GPU-aware programming using NVIDIA CUDA and OpenCL frameworks to develop efficient GPU-accelerated applications.	1	3	2	-	-
CO3	Design and implement heterogeneous computing solutions across CPU/GPU architectures using OpenCL, emphasizing performance optimization and scalability.	1	3	3	1	1
CO4	Apply GPU computing techniques to real-world applications such as convolution, video processing, histogram analysis, and mixed particle simulations, and evaluate their performance metrics and scalability.	1	2	2	2	1

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 25%
- Project – 25%
- End Semester Exam - 30%

24AI746 Artificial Intelligence for IoT 2-0-2-3

Preamble

This course introduces the architectural overview and design principles of IoT, how to develop a machine learning application using Raspberry Pi and building Machine learning models for edge devices using Raspberry Pi. Deep learning models using TensorFlowLite is also discussed in this course.

Course Objectives

- Understand the general concepts in IoT and get familiar with the various hardware and software components of it
- Understand how to build real-life IoT based projects for different application domains
- Hands-on training to implement IoT with Raspberry Pi

Course Outcomes

COs	Description
CO1	Understand the architecture, the design principles and elements of IoT.
CO2	Gain the necessary skills needed to build Machine learning models for edge devices
CO3	Be able to design, deploy and evaluate scalable real-life IoT systems for different application domains
CO4	Understand and build scalable ML pipeline using Flask, Python, uWSGI, TensorFlow

Prerequisites

- Basic knowledge on Python Programming
- Basic knowledge on Machine Learning

Syllabus

Introduction to IoT, Architectural Overview and Design Principles, Elements of IoT (Arduino, Rasp- berry Pi, NodeMCU, Sensors & Actuators), IoT Applications, Sensing, Actuation, Networking Basics, Embedded OS, IoT and Cloud, Security aspects in IoT.

IoT Application Development, Introduction to Raspberry Pi, Integrating Sensors and Actuators with Raspberry Pi, Pushing and Managing Data in IoT Clouds, Programming APIs (Python/Node.js/Arduino) for communication protocols (MQTT, ZigBee, Bluetooth, UDP, TCP), Implementation of IoT with Raspberry Pi (lab - sensor, MQTT, visualization)

Introduction to ML and Deep learning models for IoT (challenges, opportunities, solutions), Sensor data classification using ML in Raspberry Pi (lab), Introduction to TensorFlowLite, Image classification on Raspberry Pi (lab), building scalable ML pipeline using Flask, Python, uWSGI, TensorFlow

Text Book / References

1. Vijay Madisetti, Arshdeep Bahga, ¨Internet of Things, "A Hands on Approach", University Press
2. Raj Kamal, "Internet of Things: Architecture and Design", McGraw Hill
3. Stuart Russell and Peter Norvig, "Artificial Intelligence: A Modern Approach", 3rd Edition, Prentice Hall
4. Sudip Misra, Anandarup Mukherjee, Arijit Roy, "Introduction to IoT", Cambridge University Press, 2020
5. Elaine Rich and Kevin Knight, "Artificial Intelligence", Tata McGraw Hill
6. Amita Kapoor, Hands-On Artificial Intelligence for IoT, 2019, Packt Publishing
7. https://www.tensorflow.org/lite/tutorials

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the architecture, the design principles and elements of IoT.	1	2	3	1	1
CO2	Gain the necessary skills needed to build Machine learning models for edge devices	3	2	2	-	1
CO3	Be able to design, deploy and evaluate scalable real-life IoT systems for different application domains	3	3	3	1	3
CO4	Understand and build scalable ML pipeline using Flask, Python, uWSGI, TensorFlow	1	3	3	1	3

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 25%
- Project – 25%
- End Semester Exam - 30%

24AI747 Quantum Artificial Intelligence 2-0-2-3

Preamble

This course deals with how to use quantum algorithms in artificial intelligence. The course also covers Quantum physics-based information and probability theory, and their relationships to artificial intelligence by associative memory and Bayesian networks. Students will get an introduction to the principles of quantum computation and its mathematical framework.

Course Objectives

- To understand how the physical nature, as described by quantum physics, can lead to algorithms that imitate human behavior
- To explore possibilities for the realization of artificial intelligence by means of quantum computation
- To learn computational algorithms as described by quantum computation

Course Outcomes

COs	Description
CO1	Understand the computation with Qubits
CO2	Apply Quantum algorithms - Fourier Transform and Grover's amplification
CO3	Apply Quantum problem solving using tree search
CO4	Understand and explore the models of Quantum Computer and Quantum Simulation tools
CO5	Explore open-source Quantum computer libraries for applications

Prerequisites

- Machine Learning
- Programming Languages
- Probability

Syllabus

Introduction - artificial intelligence - computation - Cantor's diagonal argument - complexity theory - Decision problems - P and NP - Church–Turing Thesis - Von Neumann architecture - Problem Solving - Rules - Logic-based operators - Frames - Categorial representation - Binary vector representation - Production System - Deduction systems - Reaction systems - Conflict resolution - Human problem-solving - Information and measurement - Reversible Computation - Reversible circuits - Toffoli gate

Introduction to quantum physics - Unitary Evolution - Quantum Mechanics - Hilbert space - Quan- tum Time Evolution - Von Neumann Entropy - Measurement - Heisenberg's uncertainty principle - Randomness - Computation with Qubits - Computation with m Qubit - Matrix Representation of Serial and Parallel Operations - Quantum Boolean Circuits - Periodicity - Quantum Fourier Transform - Unitary Transforms - Search and Quantum Oracle - Grover's Amplification - Circuit Representation - Speeding up the Traveling Salesman Problem - The Generate-and-Test Method - Quantum Problem-Solving - Heuristic Search - Quantum Tree Search - Tarrataca's Quantum Production System.

A General Model of a Quantum Computer - Cognitive architecture - Representation - Quantum Cognition - Decision making - Unpacking Effects - Quantum Walk on a graph - Quantum annealing - Optimization problems - Quantum Neural Computation - Applications on Quantum annealing Computer - Development libraries - Quantum Computer simulation tool kits.

Text Book / References

1. Andreas Wichert, Principles of Quantum Artificial Intelligence, First edition, World Scientific Publishing, 2014
2. Peter Wittek, Quantum Machine Learning, First edition, Academic Press, 2014.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the computation with Qubits	2	2	2	-	3
CO2	Apply Quantum algorithms - Fourier Transform and Grover's amplification	2	2	2	-	3
CO3	Apply Quantum problem solving using tree search	3	3	3	2	3
CO4	Understand and explore the models of Quantum Computer and Quantum Simulation tools	3	3	3	3	3
CO5	Explore open-source Quantum computer libraries for applications	3	3	2	2	3

Evaluation Pattern - 70:30

- Midterm Exam - 30%
- Continuous Evaluation – 40%
- End Semester Exam - 30%

24AI748 Blockchain Technology 2-0-2-3

Preamble

Blockchain is the latest technology in the domain of Computer security and is capable of contributing on security aspects of many segments in industry and society.

Course Objectives

- Understand how blockchain systems (mainly Bitcoin and Ethereum) work.
- Design, build, and deploy smart contracts and distributed applications.
- Integrate ideas from blockchain technology into their own projects

Course Outcomes

COs	Description
CO1	Understand the fundamental characteristics of Blockchain and cryptocurrency
CO2	Understand the basics concepts of Bitcoin and Ethereum Blockchain
CO3	Develop smart contracts using Solidity
CO4	Understand the architecture of distributed applications
CO5	Develop DApps for real-life use cases

Prerequisites

- None

Syllabus

Need for Distributed Record-Keeping, distributed ledger technology, Modeling faults and adversaries, Byzantine Generals problem, Nakamoto's concept with Blockchain-based cryptocurrency, Transaction: - syntax, structure and validation, Blocks- Structure, Genesis block, and Merkle tree. Mining: -target, hash rates, Consensus mechanisms, forking. Byzantine fault-tolerant distributed computing, coins, wallets, Bitcoin scripting language.

Ethereum smart contract architecture, contract transactions, comparing Bitcoin scripting vs. Ethereum Smart Contracts, Remix IDE, Solidity: - variables, data types, addresses and balances, strings in Solidity, global Msg-Object, mapping, structure, array, require, assert revert, constructor, fallback functions, View/Pure Getter functions. modifier, inheritance, importing of Files, events and return variables, ABI array, debugging libraries .

DApps architecture, blockchain server, Truffle suite: setup and test cases, Web3 SDK, Web3 provider, Ganache, MetaMask integration with web3, channel concept and micropayment channel, web interface for DApps, Deployment to public testnet and mainnet, Network ID, Infura API, private Blockchain, Go-Ethereum, Type of DApps, Oracles, Ethereum improvement proposal(EIP) framework, standard ERC 20 for token Dapps, ERC 721 for non-fungible tokens.

Hyperledger fabric, the plug and play platform and mechanisms in permissioned blockchain Privacy,

Textbooks / References:

1. Ramamurthy, Bina. *Blockchain in action*. Manning Publications, 2020.
2. https://web3js.readthedocs.io/en/v1.7.3/
3. Merunas Grincalaitis, "Mastering Ethereum: Implement Advanced Blockchain Applications Using Ethereum-supported Tools, Services, and Protocols", Packt Publishing.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the fundamental characteristics of Blockchain and cryptocurrency	-	3	-	-	-
CO2	Understand the basics concepts of Bitcoin and Ethereum Blockchain	-	3	-	-	-
CO3	Develop smart contracts using Solidity	-	3	-	-	-
CO4	Understand the architecture of distributed applications	-	3	-	-	1
CO5	Develop DApps for real-life use cases	-	3	1	-	1

Evaluation Pattern - 70:30

- Midterm Exam - 30%
- Continuous Evaluation – 40%
- End Semester Exam - 30%

24AI749 Artificial Intelligence for Bioinformatics 2-0-2-3

Preamble

This course exposes the students to apply AI technology in the domain of Bioinformatics.

Course Objectives

- To incorporate the concepts of bioinformatics using statistics.
- To enhance the application of programming for bioinformatics.
- To explore the challenges in bioinformatics and apply AI for solutions.

Course Outcomes

COs	Description
CO1	Understand and appreciate the role of bioinformatics in solving biological problems.
CO2	Demonstrate working proficiency with statistical techniques in Bioinformatics
CO3	Apply the concepts of deep learning problems in bioinformatics

Prerequisites

- Basic knowledge of Deep Learning
- Python programming

Syllabus

Introduction to the Basics of Molecular Biology - DNA,RNA, Genes and Proteins,Central Dogma of Molecular biology, Cell regulation, What is Bioinformatics, Challenges in Bioinformatics - Genome, Transcriptome, Proteome. –Python programming for bioinformatics.

AI in Bioinformatics Applications - Decision Trees, Neural Networks, Application guidelines, Genetic Algorithms, Probabilistic Graphical Models in Bioinformatics, Hybrid Models and Neural Network Parameterization of Graphical Models, Cellular Automata.

Internet Resources and Public Structure Databases in Molecular Biology, Sequences.

Text Book / References

1. Karthik Raman, an Introduction to Computational Systems Biology (Systems Level Modeling of Cellular Networks), CRC Press, 2021.
2. Bioinformatics algorithm, An active learning Approach', Phillip Compeauand Pavel PevznerVol.1. and Vol. 2 ,2015.
3. 'Essential Bioinformatics', JinXiong, Cambridge University Press, 2006
4. Edward Keedwell and Ajit Narayanan, Intelligent Bioinformatics, John Wiley & Sons Ltd, 2005

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and appreciate the role of bioinformatics in solving biological problems.	1	2	3	-	-
CO2	Demonstrate working proficiency with statistical techniques in Bioinformatics	-	2	2	3	-
CO3	Apply the concepts of deep learning problems in bioinformatics	3	3	2	2	2

Evaluation Pattern - 70:30

- Midterm Exam - 30%
- Continuous Evaluation – 40%
- End Semester Exam - 30%

24AI750 Cloud and Big Data Analytics 2-0-2-3

Preamble

There is an unprecedented amount of data that is generated in today's world by both humans and machines. Being able to store, manage, analyze, and building intelligent applications has a critical impact on business, scientific discovery, social and environmental challenges. This course helps students to use cloud platform with its tools and distributed computing techniques to quickly build prototypes and applications for scalable data and workloads.

Course Objectives

- To introduce principles of cloud computing and build applications on cloud platforms.
- To understand distributed computing paradigms and its implementations on cloud platform.
- To apply principles of Big Query for handling big data.

Course Outcomes

COs	Description
CO1	To introduce principles of cloud computing.
CO2	Develop and deploying applications on cloud platform.
CO3	Understand Distributed Machine learning with hadoop and spark.
CO4	Create data analytics applications on distributed cloud computing platforms for using Spark and its Tools.
CO5	Develop methods to handle Containers and Kubernetes in Google Cloud.

Prerequisites

- Basics of Machine Learning.

Syllabus

Cloud computing fundamentals - Principles of Cloud Computing Systems, Elastic Cloud Systems for Scalable Computing, Cloud Architectures Compared with Distributed Systems, Service Models, Ecosystems and Scalability Analysis, Building Compute Service - Storage Service – Databases Service - Serverless Models on Cloud.

Frameworks for Big data: Hadoop – Hadoop Framework – Hadoop Daemon - Map Reduce Programming- Hadoop Ecosystem - Spark - Framework – RDD – Advanced RDD - Structured data - SQL, Dataframes, and Datasets – Streaming in Spark - Spark Distributed Processing - Building Spark ML on Cloud platform.

Cloud dataflow – dataflow templates, data transformation with cloud dataflow, working with apache beam, cloud publisher subscriber - architecture, message flow, implementation. Cloud data processing. Introduction to Containers and Kubernetes in Google Cloud, Introduction to AI platform pipelines

Text Book / References

1. Kai Hwang, "Cloud Computing for Machine Learning and Cognitive Applications", MIT Press, 2017.
2. Murari Ramuka, "Data Analytics with Google Cloud Platform ", BPB PUBN, 2019.
3. Anand Deshpande, Manish Kumar, Vikram Chaudhari, "Hands-On Artificial Intelligence on Google Cloud Platform", Packt Publishing, 2020.
4. Jeffrey Jackovich, Ruze Richards, "Machine Learning with AWS", Packt Publishing, 2018.
5. Jules S. Damji, Brooke Wenig, Tathagata Das, Denny Lee, "Learning Spark Lightning fast data analysis", O'Reilly Media, Inc, 2020.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	To introduce principles of cloud computing.	2	1	-	-	-
CO2	Develop and deploying applications on cloud platform.	2	3	-	-	-
CO3	Understand Distributed Machine learning with hadoop and spark.	2	3	3	-	-
CO4	Create data analytics applications on distributed cloud computing platforms for using Spark and its Tools.	2	3	3	2	1
CO5	Develop methods to handle Containers and Kubernetes in Google Cloud.	2	3	3	2	1

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 25%
- Project – 25%
- End Semester Exam - 30%

24AI798 Dissertation Phase I 10

Course Objectives

The student is expected to carry out supervised research in this course. An intensive literature in the chosen area, should result in sound knowledge in the area and result in the identification of a suitable research problem, and its formulation and analysis. Study of relevant supplementary literature, mastering useful programming languages and tools for the problem, are also expected at this stage of the project. The student is expected to present three reports at different evaluation points during the semester, with clearly defined achievements and plans for further steps.

Course Outcomes

COs	Description
CO1	Demonstrate sound fundamentals in a chosen area of computing.
CO2	Identify and formulate a problem of research interest in the chosen area of computing.
CO3	Analyze the computing problem and propose solutions.
CO4	Effectively communicate the work at all stages of the project.

References

1. Relevant literature for the computing problem.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Demonstrate sound fundamentals in a chosen area of computing.	3	2	2	2	2
CO2	Identify and formulate a problem of research interest in the chosen area of computing	2	3	3	3	2
CO3	Analyze the computing problem and propose solutions.	3	3	3	2	2
CO4	Effectively communicate the work at all stages of the project.	2	3	3	2	2

Evaluation Pattern - 80:20

- Internal - 80%
- External - 20%

24AI799 Dissertation Phase II 16

Course Objectives

The student is expected to demonstrate the core competency aimed by this course, i.e., the development of enhancements to the knowledge base in the area of interest in computing. The secondary competencies include the management of time bound projects involving research, analysis of problem complexities, design and development of effective solutions and communication of the project's progress, adhering to ethical practices at every stage. This stage of the project evaluates the state of maturity of these competencies. The student is expected to present two reports at intermediate stages, as well as prepare and defend a thesis on his research work.

Course Outcomes

COs	Description
CO1	Reflectively analyze proposed solutions to the identified computing problem.
CO2	Design and develop solutions to the problem and analyze results.
CO3	Prepare a thesis report and defend the thesis on the work done.
CO4	Augment the knowledge base in the chosen area of computing, adhering to ethical practices at every stage.

Prerequisites

- Dissertation Phase I

References

1. Relevant literature for the computing problem.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Reflectively analyze proposed solutions to the identified computing problem	3	3	3	3	-
CO2	Design and develop solutions to the problem and analyze results.	3	3	3	3	2
CO3	Prepare a thesis report and defend the thesis on the work done.	3	3	3	2	2
CO4	Augment the knowledge base in the chosen area of computing, adhering to ethical practices at every stage.	3	3	3	2	3

Evaluation Pattern - 80:20

- Internal - 80%
- External - 20%

** Evaluations patterns mentioned in the syllabus are recommendations from BOS. Final decision on the same can be done at the class committee.

23HU601	Career Competency I	L-T-P-C: 0-0-3-P/F

Prerequisite:
An open mind and the urge for self-development, basic English language skills and knowledge of high school level arithmetic.

Course Objectives:

- Help students transit from campus to corporate and enhance their soft skills
- Enable students to understand the importance of goal setting and time management skills
- Support them in developing their problem solving and reasoning skills
- Inspire students to enhance their diction, grammar and verbal reasoning skills

Course Outcomes:
CO1: Soft Skills - To develop positive mindset, communicate professionally, manage time effectively and set personal goals and achieve them.
CO2: Soft Skills - To make formal and informal presentations with self-confidence.
CO3: Aptitude - To analyze, understand and employ the most suitable methods to solve questions on arithmetic and algebra.
CO4: Aptitude - To analyze, understand and apply suitable techniques to solve questions on logical reasoning and data analysis.
CO5: Verbal - To infer the meaning of words and use them in the right context. To have a better understanding of the nuances of English grammar and become capable of applying them effectively.
CO6: Verbal - To identify the relationship between words using reasoning skills. To understand and analyze arguments and use inductive/deductive reasoning to arrive at conclusions and communicate ideas/perspectives convincingly.

CO-PO Mapping

PO/CO	PO1	PO2	PO3
CO1	2	1	-
CO2	2	1	-
CO3	2	1	-
CO4	2	1	-
CO5	1	2	-
CO6	2	2	-

Syllabus:
Soft Skills
Introduction to 'campus to corporate transition':
Communication and listening skills: communication process, barriers to communication, verbal and non-verbal communications, elements of effective communication, listening skills, empathetic listening, role of perception in communication.
Assertiveness skills: the concept, assertiveness and self-esteem, advantages of being assertive, assertiveness and organizational effectiveness.
Self-perception and self-confidence: locus of control (internal v/s external), person perception, social perception, attribution theories-self presentation and impression management, the concept of self and self-confidence, how to develop self-confidence.
Goal setting: the concept, personal values and personal goals, goal setting theory, six areas of goal setting, process of goal setting: SMART goals, how to set personal goals
Time management: the value of time, setting goals/ planning and prioritizing, check the time killing

habits, procrastination, tools for time management, rules for time management, strategies for effective time management

Presentation skills: the process of presentation, adult learning principles, preparation and planning, practice, delivery, effective use of voice and body language, effective use of audio visual aids, dos and don’ts of effective presentation

Public speaking-an art, language fluency, the domain expertise (Business GK, Current affairs), self-confidence, the audience, learning principles, body language, energy level and conviction, student presentations in teams of five with debriefing

Verbal

Vocabulary: Familiarize students with the etymology of words, help them realize the relevance of word analysis and enable them to answer synonym and antonym questions. Create an awareness about the frequently misspelt words, commonly confused words and wrong form of words in English.

Grammar: Train students to understand the nuances of English Grammar and thereby enable them to spot grammatical errors and punctuation errors in sentences.

Reasoning: Stress the importance of understanding the relationship between words through analogy questions and learn logical reasoning through syllogism questions. Emphasize the importance of avoiding the gap (assumption) in arguments/ statements/ communication.

Oral Communication Skills: Aid students in using the gift of the gab to improve their debating skills.

Writing Skills: Introduce formal written communication and keep the students informed about the etiquettes of email writing. Make students practise writing emails especially composing job application emails.

Aptitude

Numbers: Types, Power Cycles, Divisibility, Prime, Factors & Multiples, HCF & LCM, Surds, Indices, Square roots, Cube Roots and Simplification.

Percentage: Basics, Profit, Loss & Discount, and Simple & Compound Interest.

Ratio, Proportion & Variation: Basics, Alligations, Mixtures, and Partnership.

Averages: Basics, and Weighted Average.

Time and Work: Basics, Pipes & Cistern, and Work Equivalence.

Time, Speed and Distance: Basics, Average Speed, Relative Speed, Boats & Streams, Races and Circular tracks.

Statistics: Mean, Median, Mode, Range, Variance, Quartile Deviation and Standard Deviation.

Data Interpretation: Tables, Bar Diagrams, Line Graphs, Pie Charts, Caselets, Mixed Varieties, and other forms of data representation.

Equations: Basics, Linear, Quadratic, Equations of Higher Degree and Problems on ages.

Logarithms, Inequalities and Modulus: Basics

References

Soft Skills:

Communication and listening skills:

- Andrew J DuRbin , “Applied Psychology: Individual and organizational effectiveness”, Pearson-Merril Prentice Hall, 2004
- Michael G Aamodt, “An Applied Approach, 6th edition”, Wadsworth Cengage Learning, 2010

Assertiveness skills:

- Robert Bolton, Dorothy Grover Bolton, “People Style at Work..and Beyond: Making Bad Relationships Good and Good”, Ridge Associates Inc., 2009
- John Hayes “Interpersonal skills at work”, Routledge, 2003
- Nord, W. R., Brief, A. P., Atieh, J. M., & Doherty, E. M., “Meanings of occupational work: A collection of essays (pp. 21- 64)”, Lexington, MA: Lexington Books, 1990

Self-perception and self-confidence:

- Mark J Martinko, “Attribution theory: an organizational perspective”, St. Lucie, 1995
- Miles Hewstone, “Attribution Theory: Social and Functional Extensions”, Blackwell, 1983

Time management:

- Stephen Covey, “The habits of highly effective people”, Free press Revised edition, 2004
- Kenneth H Blanchard , “The 25 Best Time Management Tools & Techniques: How to Get More Done Without Driving Yourself Crazy” , Peak Performance Press, 1st edition 2005

- Kenneth H. Blanchard and Spencer Johnson, "The One Minute Manager" , William Morrow, 1984

Verbal:

- Erica Meltzer, "The Ultimate Guide to SAT Grammar"
- Green, Sharon, and Ira K. Wolf, "Barron's New GRE", Barron's Educational Series, 2011
- Jeff Kolby, Scott Thornburg & Kathleen Pierce, "Nova's GRE Prep Course"
- Kaplan, "Kaplan New GRE Premier", 2011-2012
- Kaplan's GRE Comprehensive Programme
- Lewis Norman, "Word Power Made Easy", Goyal Publishers, Reprint edition, 1 June 2011
- Manhattan Prep, "GRE Verbal Strategies Effective Strategies Practice from 99th Percentile Instructors"
- Pearson- "A Complete Manual for CAT", 2013
- R.S. Aggarwal, "A Modern Approach to Verbal Reasoning"
- S. Upendran, "Know Your English", Universities Press (India) Limited, 2015
- Sharon Weiner Green, Ira K. Wolf, "Barron's New GRE, 19th edition (Barron's GRE)", 2019
- Wren & Martin, "English Grammar & Composition"
- www.bbc.co.uk/learningenglish
- www.cambridgeenglish.org
- www.englishforeveryone.org
- www.merriam-webster.com

Aptitude:

- Arun Sharma, "How to Prepare for Quantitative Aptitude for the CAT Common Admission Test", Tata Mc Graw Hills, 5th Edition , 2012
- Arun Sharma, "How to Prepare for Logical Reasoning for the CAT Common Admission Test", Tata Mc Graw Hills, 2nd Edition, 2014
- Arun Sharma, "How to Prepare for Data Interpretation for the CAT Common Admission Test", Tata Mc Graw Hills, 3nd Edition, 2015
- R.S. Aggarwal, "Quantitative Aptitude For Competitive Examinations", S. Chand Publishing, 2015
- R.S. Aggarwal, "A Modern Approach To Verbal & Non-Verbal Reasoning", S. Chand Publishing, Revised -2015
- Sarvesh Verma, "Quantitative Aptitude-Quantum CAT", Arihant Publications, 2016
- www.mbatious.com
- www.campusgate.co.in
- www.careerbless.com

<u>Evaluation Pattern</u>

Assessment	**Internal**	**External**
Continuous Assessment (CA)* – Soft Skills	30	-
Continuous Assessment (CA)* – Aptitude	10	25
Continuous Assessment (CA)* – Verbal	10	25
Total	50	50
Pass / Fail		

*CA - Can be **presentations, speaking activities and tests.**

23HU611	Career Competency II	L-T-P-C: 0-0-3-1

Pre-requisite: Willingness to learn, team spirit, basic English language and communication skills and knowledge of high school level arithmetic.

Course Objectives:

- Help students to understand the importance of interpersonal skills and team work
- Prepare the students for effective group discussions and interviews participation.
- Help students to sharpen their problem solving and reasoning skills
- Empower students to communicate effectively by using the correct diction, grammar and verbal reasoning skills

Course Outcomes:

CO1: Soft Skills - To demonstrate good interpersonal skills, solve problems and effectively participate in group discussions.

CO2: Soft Skills - To write technical resume and perform effectively in interviews.

CO3: Aptitude - To identify, investigate and arrive at appropriate strategies to solve questions on arithmetic by managing time effectively.

CO4: Aptitude - To investigate, understand and use appropriate techniques to solve questions on logical reasoning and data analysis by managing time effectively.

C05: Verbal - To be able to use diction that is more refined and appropriate and to be competent in knowledge of grammar to correct/improve sentences

C06: Verbal - To be able to examine, interpret and investigate passages and to be able to generate ideas, structure them logically and express them in a style that is comprehensible to the audience/recipient.

CO-PO Mapping

PO/CO	PO1	PO2	PO3
CO1	2	1	-
CO2	2	1	-
CO3	2	1	-
CO4	2	1	-
CO5	1	2	-
CO6	2	2	-

Syllabus

Soft Skills

Interpersonal skill: ability to manage conflict, flexibility, empathetic listening, assertiveness, stress management, problem solving, understanding one’s own interpersonal needs, role of effective team work in organizations

Group problem solving: the process, the challenges, the skills and knowledge required for the same.

Conflict management: the concept, its impact and importance in personal and professional lives, (activity to identify personal style of conflict management, developing insights that helps in future conflict management situations.)

Team building and working effectively in teams: the concept of groups (teams), different stages of group formation, process of team building, group dynamics, characteristics of effective team, role of leadership in team effectiveness. (Exercise to demonstrate the process of emergence of leadership in a group, debrief and reflection), group discussions.

Interview skills: what is the purpose of a job interview, types of job interviews, how to prepare for an interview, dos and don’ts of interview, One on one mock interview sessions with each student

Verbal

Vocabulary: Help students understand the usage of words in different contexts. Stress the importance of using refined language through idioms and phrasal verbs.

Grammar: Enable students to identify poorly constructed sentences or incorrect sentences and

improvise or correct them.
Reasoning: Facilitate the student to tap her/his reasoning skills through critical reasoning questions and logical ordering of sentences.
Reading Comprehension: Enlighten students on the different strategies involved in tackling reading comprehension questions.
Public Speaking Skills: Empower students to overcome glossophobia and speak effectively and confidently before an audience.
Writing Skills: Practice closet tests that assess basic knowledge and skills in usage and mechanics of writing such as punctuation, basic grammar and usage, sentence structure and rhetorical skills such as writing strategy, organization, and style.

Aptitude

Sequence and Series: Basics, AP, GP, HP, and Special Series.
Geometry: 2D, 3D, Coordinate Geometry, and Heights & Distance.
Permutations & Combinations: Basics, Fundamental Counting Principle, Circular Arrangements, and Derangements.
Probability: Basics, Addition & Multiplication Theorems, Conditional Probability and Bayes' Theorem.
Logical Reasoning I: Arrangements, Sequencing, Scheduling, Venn Diagram, Network Diagrams, Binary Logic, and Logical Connectives, Clocks, Calendars, Cubes, Non-Verbal reasoning and Symbol based reasoning.
Logical Reasoning II: Blood Relations, Direction Test, Syllogisms, Series, Odd man out, Coding & Decoding, Cryptarithmetic Problems and Input - Output Reasoning.
Data Sufficiency: Introduction, 5 Options Data Sufficiency and 4 Options Data Sufficiency.
Campus recruitment papers: Discussion of previous year question papers of all major recruiters of Amrita Vishwa Vidyapeetham.
Miscellaneous: Interview Puzzles, Calculation Techniques and Time Management Strategies.

References

Soft Skills

Team Building

- Thomas L.Quick, "Successful team building", AMACOM Div American Mgmt Assn, 1992
- **Brian Cole Miller, "Quick Team-Building Activities for Busy Managers: 50 Exercises That Get Results in Just 15 Minutes", AMACOM; 1 edition, 2003.**
- **Patrick Lencioni, "The Five Dysfunctions of a Team: A Leadership Fable", Jossey-Bass, 1st Edition, 2002**

Verbal

- "GMAT Official Guide" by the Graduate Management Admission Council, 2019
- Arun Sharma, "How to Prepare for Verbal Ability And Reading Comprehension For CAT"
- Joern Meissner, "Turbocharge Your GMAT Sentence Correction Study Guide", 2012
- Kaplan, "Kaplan GMAT 2012 & 13"
- Kaplan, "New GMAT Premier", Kaplan Publishing, U.K., 2013
- Manhattan Prep, "Critical Reasoning 6th Edition GMAT"
- Manhattan Prep, "Sentence Correction 6th Edition GMAT"
- Mike Barrett "SAT Prep Black Book The Most Effective SAT Strategies Ever Published"
- Mike Bryon, "Verbal Reasoning Test Workbook Unbeatable Practice for Verbal Ability, English Usage and Interpretation and Judgement Tests"
- www.bristol.ac.uk/arts/skills/grammar/grammar_tutorial/page_55.htm
- www.campusgate.co.in

Aptitude

- Arun Sharma, "How to Prepare for Quantitative Aptitude for the CAT Common Admission Test", Tata Mc Graw Hills, 5th Edition, 2012
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Tata Mc Graw Hills, 2nd Edition , 2014

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Total	50	50

*CA - Can be **presentations, speaking activities and tests.**

22AVP103 Mastery Over Mind (MAOM) 1-0-2 2

1. Course Overview

Master Over the Mind (MAOM) is an Amrita initiative to implement schemes and organize university-wide programs to enhance health and wellbeing of all faculty, staff, and students (UN SDG -3). This program as part of our efforts for sustainable stress reduction gives an introduction to immediate and long-term benefits and equips every attendee to manage stressful emotions and anxiety facilitating inner peace and harmony.

With a meditation technique offered by Amrita Chancellor and world-renowned humanitarian and spiritual leader, Sri Mata Amritanandamayi Devi (Amma), this course has been planned to be offered to all students of all campuses of AMRITA, starting off with all first years, wherein one hour per week is completely dedicated for guided practical meditation session and one hour on the theory aspects of MAOM. The theory section comprises lecture hours within a structured syllabus and will include invited guest lecture series from eminent personalities from diverse fields of excellence. This course will enhance the understanding of experiential learning based on university's mission: "Education for Life along with Education for Living", and is aimed to allow learners to realize and rediscover the infinite potential of one's true Being and the fulfilment of life's goals.

2. Course Syllabus

Unit 1 (4 hours)

Causes of Stress: The problem of not being relaxed. Need for meditation -basics of stress management at home and workplace. Traditions and Culture. Principles of
meditation– promote a sense of control and autonomy in the Universal Human Value System. Different stages of Meditation. Various Meditation Models. Various practices of Meditation techniques in different schools of philosophy and Indian Knowledge System.

Unit 2 (4 hours)

Improving work and study performance. Meditation in daily life. Cultivating compassion and good mental health with an attitude of openness and acceptance. Research and Science of Meditation: Significance of practising meditation and perspectives from diverse fields like science, medicine, technology. philosophy, culture, arts, management, sports, economics, healthcare, environment etc. The role of meditation for stress and anxiety reduction in one's life with insights based on recent cutting-edge technology. The effect of practicing meditation for the wholesome wellbeing of an individual.

Unit 3 (4 hours)

Communications: principles of conscious communication. Relationships and empathy: meditative approach in managing and maintaining better relationships in life during the interactions in the world, role of MAOM in developing compassion, empathy and responsibility, instilling interest, and orientation to humanitarian projects as a key to harness intelligence and compassion in youth. Methodologies to evaluate effective awareness and relaxation gained from meditation. Evaluating the global transformation through meditation by instilling human values which leads to service learning and compassion driven research.

TEXT BOOKS:

1.Mata Amritanandamayi Devi, "Cultivating Strength and vitality," published by Mata Amritanandamayi Math, Dec 2019

2.Swami Amritaswarupananda Puri ,"The Color of Rainbow " published by MAM, Amritapuri.

REFERENCES:

1.Craig Groeschel, "Winning the War in Your Mind: Change Your Thinking, Change Your Life" Zondervan Publishers, February 2019

2.R Nagarathna et al, "New Perspectives in Stress Management "Swami Vivekananda Yoga Prakashana publications, Jan 1986

3. Swami Amritaswarupananda Puri "Awaken Children Vol 1, 5 and 7 - Dialogues with Amma on Meditation", August 2019
4. Swami Amritaswarupananda Puri "From Amma's Heart - Amma's answer to questions raised during world tours" March 2018
5. Secret of Inner Peace- Swami Ramakrishnananda Puri, Amrita Books, Jan 2018.
6. Mata Amritanandamayi Devi "Compassion :The only way to Peace:Paris Speech", MA Center, April 2016.
7. Mata Amritanandamayi Devi "Understanding and collaboration between Religions", MA Center, April 2016.
8. Mata Amritanandamayi Devi "Awakening of Universal Motherhood: Geneva Speech" M A center, April 2016.

3. Evaluation and Grading

Internal			External	Total
Components	Weightage		Practical (attendance and class participation) 60%	100%
Quizzes(based on the reading material)	20%	40%		
Assignments (Based on webinars and lecture series)	20%			

4. Course Outcomes (CO)

CO1: Relate to the causes of stress in one's life.
CO2: Experiment with a range of relaxation techniques
CO3: Model a meditative approach to work, study, and life.
CO4: Develop appropriate practice of MA-OM technique that is effective in one's life
CO5: Inculcate a higher level of awareness and focus.
CO6: Evaluate the impact of a meditation technique

*__Program Outcomes (PO) (As given by NBA and ABET)__

PO1: Engineering Knowledge
PO2: Problem Analysis
PO3: Design/Development of Solutions
PO4: Conduct Investigations of complex problems
PO5: Modern tools usage

PO6: Engineer and Society
PO7: Environment and Sustainability
PO8: Ethics
PO9: Individual & Team work
PO10: Communication
PO11: Project management & Finance
PO12: Lifelong learning

CO – PO Affinity Map

P O/ C O	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PS01	PSO2	PSO3
CO 1	3	3	3	2		-	2	3	-	3	-	3	-	-	-
CO 2	3	3	3	2	2	_	2	3	3	3	-	3	-	-	-
CO 3	3	3	2	2	2	2	2	3	3	3	-	3	-	-	-
CO 4	3	3	3	2	-	2	3	3	3	3	-	3	-	-	-
CO 5	3	2	2	2	-	2	-	3	2	2	-	2	-	-	-
CO 6	3	2	2	2	3	2	_	3	2	2	-	2	-	-	-