M.TECH ARTIFICIAL INTELLIGENCE

CURRICULUM & SYLLABUS 2021

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, Computational statistics, and Deep Learning systems. The programme has specialized courses in the streams of Data Science, Computer Vision, IoT and High Performance Computing with significant focus onresearch. As a part of the programme during the period of study, students have the opportunityto 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, 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. Obtain expertise to turn actionable insights and cutting-edge technology into innovative products to solve real world problems. (GA4, GA6, GA7, GA10).

4. Build the ability to write and present a substantial technical report/document. (GA8, GA9).

5. Inculcate independent research ability that addresses state-of-the-art problems. (GA4, GA9, GA11)

M.TECH - ARTIFICIAL INTELLIGENCE

CURRICULUM 2021

Semester I				
Course Code	**Type**	**Courses**	**L T P**	**Cr**
21AI601	FC	Advanced Data Structures and Algorithms	3-0-2	4
21MA613	FC	Linear Algebra and Probability	2-1-0	3
21AI602	FC	Computational Methods for Optimisation	2-1-0	3
21AI603	FC	Foundations of Artificial Intelligence	3-0-2	4
21AI604	FC	Machine Learning	3-0-2	4
21HU601	HU	Amrita Values Program*		P/F
21HU602	HU	Career Competency I		P/F
		Total Credits		**18**

*Non-credit course

Semester II				
Course Code	**Type**	**Courses**	**L T P**	**Cr**
	SC	Soft Core - I	3-0-2	4
	SC	Soft Core - II	3-0-2	4
	E	Elective - I	2-0-2	3
	E	Elective - II	2-0-2	3
21AI698	SC	Case Study	0-0-4	2
21RM618	SC	Research Methodology	2-0-0	2
21HU603	HU	Career Competency II	0-0-2	1
		Total Credits		19

Semester III				
Course Code	**Type**	**Courses**	**L T P**	**Cr**
	E	Elective - III	2-0-2	3
21AI723	E	Negotiated Studies/Online Course	3-0-0	3
21AI798		Dissertation Phase I		10
		Total Credits		**16**

Semester IV				
Course Code	**Type**	**Courses**	**L T P**	**Cr**
21AI799		Dissertation Phase II		16
		Total Credits		**16**

S.No	**Type**	**Course Category**	**Credits**
1.	FC	Foundation Core	18
2.	SC	Soft Core	12
3.	E	Electives	12
4.	HU	Amrita Values Program/Career Competency	1
6.		Dissertation	26
		Total Credits	69

Foundation Core			
Course Code	**Courses**	**L T P**	**Cr**
21AI601	Advanced Data Structures and Algorithms	3-0-2	4
21MA613	Linear Algebra and Probability	2-1-0	3
21AI602	Computational Methods for Optimisation	2-1-0	3
21AI603	Foundations of Artificial Intelligence	3-0-2	4
21AI604	Machine Learning	3-0-2	4

Soft Core			
Course Code	**Courses**	**L T P**	**Cr**
21AI631	Foundation of Data Science	3-0-2	4
21AI632	Statistical Learning Theory	3-0-2	4
21AI633	Probabilistic Graphical Models	3-0-2	4
21AI634	Computational Statistics and Inference Theory	3-0-2	4
21AI635	Multi Agent Systems	3-0-2	4
21AI636	Computational Intelligence	3-0-2	4
21AI637	Deep Learning	3-0-2	4
21AI638	Reinforcement Learning	3-0-2	4
21AI639	Computer Vision	3-0-2	4
21AI640	Data Engineering	3-0-2	4
21AI641	Mining of Massive Datasets	3-0-2	4
21AI642	Natural Language Processing	3-0-2	4
21AI643	Cloud and Big Data Analytics	3-0-2	4
21AI698	Case Study	0-0-4	2
21RM618	Research Methodology	2-0-0	2

Electives List			
Course Code	**Courses**	**L T P**	**Cr**
21AI701	Machine Learning for Big Data	2-0-2	3
21AI702	Applications of Machine Learning	2-0-2	3
21AI703	Representation Learning	2-0-2	3
21AI704	Applied Predictive Analytics	2-0-2	3
21AI705	Artificial Intelligence for Robotics	2-0-2	3
21AI706	Introduction to Game Theory	2-0-2	3
21AI707	Modeling and Simulation	2-0-2	3
21AI708	Information Retrieval	2-0-2	3
21AI709	Web Intelligence and Big Data	2-0-2	3
21AI710	Data Visualization	2-0-2	3
21AI711	Networks and Spectral Graph Theory	2-0-2	3
21AI712	Parallel and Distributed Data Management	2-0-2	3
21AI713	Medical Signal Processing	2-0-2	3
21AI714	Parallel and Distributed Computing	2-0-2	3
21AI715	Modern Computer Architecture	2-0-2	3
21AI716	GPU Architecture and Programming	2-0-2	3
21AI717	IoT for AI	2-0-2	3
21AI718	Neuroevolution	2-0-2	3
21AI719	Quantum Artificial Intelligence	2-0-2	3
21AI720	Knowledge Graphs	2-0-2	3
21AI721	Integer Programming: Theory and Computations	2-0-2	3
21AI722	Data Pre-processing and Feature Engineering	2-0-2	3
21AI723	Negotiated Studies/Online Course	3-0-0	3

*Students can take Electives from other M.Tech branches in place of any one elective.

SYLLABUS

21AI601 Advanced Data Structures and Algorithms 3-0-2-4

Preamble

This course builds upon the basic data structures and algorithms. It aims to enable students to design data structures and algorithms to solve complex problems specially relevant for AI domain. The main focus will be on concrete implementations of various data structures and their use in non-trivial algorithms with proper analysis.

Course Objectives

- To provide an understanding of Data structures and algorithms used in real life domain
- To solve complex problems by applying appropriate Data structures and algorithms
- 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	Understand advanced data structures and their advanced applications
CO2	Understand wide range of algorithmic design techniques, their relations and variants, and application to real-world problems.
CO3	Understand Amortized analysis associated with a data structure and various ways of analyzing a given algorithm
CO4	Solve real world problems, especially in 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. Number Theory: Preliminaries, FLT, Euclid's algorithm (extended), Totient function, Sieve for primes, Modular exponentiation, Applications of graph algorithms: Topological sort, Strongly connected Components, Bi-connected Components, Bridges, Articulation points, All Pairs Shortest Paths, Single Source Shortest Paths. Computational Geometry: Convex Hull, Closest pair of points.

Applications of Divide-and-Conquer, Greedy and Dynamic programming 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

B-trees, Suffix trees, Segment trees, Flow Networks: Ford-Fulkerson algorithm, Edmonds Karp algorithm, Applications of maximum flows - Maximum bipartite matching, minimum cost matching,. 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. Rajeev Motwani and PrabhakarRaghavan, ”Randomized Algorithms”, Cambridge University Press, 1995.
4. Vijay V. Vazirani, ”Approximation Algorithm”, Springer Science and Business Media, 2003.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand advanced data structures and their advanced applications	3	3	1	–	1
CO2	Understand wide range of algorithmic design techniques, their relations and variants, and application to real-world problems.	3	3	1	–	1
CO3	Understand Amortized analysis associated with a data structure and various ways of analyzing a given algorithm	3	3	1	-	1
CO4	Solve real world problems, especially in 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

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation - 40%
End Semester Exam- 30%

21MA613 Linear Algebra and Probability 2-1-0-3

Preamble

Linear algebra is central to almost all fields of engineering fields particularly in AI & ML as it allows efficient computational models when dealing with high dimensional data. The probability& statistics provide the formal basis for analyzing uncertainties and risks that are important when designing solutions based on data. This course is designed to impart core concepts and techniques on Linear Algebra and Probability with special focus on computational experiments.

Course Objectives

- Provide strong theoretical foundations on linear algebra and probability theory.
- Through properly designed computational experiments, make students confident enough to apply tools and techniques on linear algebra, probability and statistical testing in research and development.

Course Outcomes

After completing this course, the students will be able to

COs	Description
CO1	Use computational techniques and algebraic skills essential for the study of systems of linear equations, matrix algebra, vector spaces, eigenvalues and Eigenvectors, orthogonality and diagonalization.
CO2	Understand the importance of probability distribution and statistical testing in data modelling and data analytics
CO3	Should be able to wisely choose tools and techniques in Linear algebra and Statistical testing for building and evaluating solutions to different Engineering problems.

Syllabus

Geometry of linear equations, Gaussian elimination, vector spaces and subspaces, Fundamental vector spaces associated with a matrix, Bases and dimension. Projections and ordinary least squares, Eigenvalues and Eigenvectors, Matrix decompositions and applications: LU, QR, $Q\Lambda Q'$, SVD, Positive definite matrices - minima, maxima and saddle points, Introduction to special matrices and applications: Fourier transform, Sine and Cosine transforms.

Review of probability theory, Conditional probability, Baye’s rule, Random variables and probability Distributions - Moments and moment-generating function, Joint probability distributions, Sampling from probability distributions, Covariance and Correlation, Central limit theorem, Parameter estimations: Maximum likelihood estimation, Expectation-Maximisation, Introduction to statistical testing - Z Test and Test on Proportions

Text Book / References

1. Gene H. Golub and V. Van Loan, Matrix Computations, Third Edition, John Hopkins University Press, Baltimore, 1996.
2. Strang, Gilbert. Linear algebra and learning from data. Cambridge: Wellesley-Cambridge Press, 2019.
3. Douglas C. Montgomery and George C. Runger, “Applied Statistics and Probability for Engineers”, Third Edition, John Wiley & Sons Inc., 2003.
4. David Forsyth, “Probability and Statistics for Computer Science”, Springer international publishing, 2018

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Use computational techniques and algebraic skills essential for the study of systems of linear equations, matrix algebra, vector spaces, eigenvalues and Eigenvectors, orthogonality and diagonalization.	3	3	3	2	3
CO2	Understand the importance of probability distribution and statistical testing in data modelling and data analytics.	3	3	3	3	3
CO3	Should be able to wisely choose tools and techniques in Linear algebra and Statistical testing for building and evaluating solutions to different Engineering problems.	3	3	3	3	3

Evaluation Pattern - 70:30

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

21AI602 Computational Methods for Optimisation 2-1-0-3

Preamble

This course is designed to teach core concepts and techniques for Mathematical optimisation with special focus to convex optimisation. Each technique should be taught by designing computational experiments by selecting relevant Engineering AI& ML Application.

Course Objectives

- The course will lay down the basic concepts and techniques of optimization theory needed for subsequent study.
- The course provides a thorough understanding of how optimization problems are solved, and some experience in solving them.
- The course will provide the background required to use the methods in research work and/or applications.

Course Outcomes

After completing this course, the students will be able to

COs	Description
CO1	Should be able to understand and appreciate the necessary theory behind solutions to optimisation problems and develop skills to understand research papers in the domain
CO2	Should be able to use different tools and techniques to find solutions to Optimisation problems
CO3	Should gain necessary skill to pose engineering problem as an optimisation problem wherever possible.

Syllabus

Theory of Optimization – Regression and Least Square – Batch gradient descent – Conjugate Gradi- ent method – Linear programming and Simplex method and Applications to Engineering Problems – Direct methods for convex functions, Newton methods for non-convex functions. Constrained Con- vex Optimization problems, Formulating problems as LP and QP, solving by packages (CVXOPT) – Need for Unconstrained optimization methods – Lagrangian multiplier method, KKT conditions – Alternating direction method of multipliers (ADMM) and Applications– Optimization methods for sparsity – Introduction to Variational Methods in Optimisation: Calculus of variations and Applica- tions – Optimization methods for Neural Networks: Stochastic gradient descent, ADAM (Adaptive Moment), Contrastive Divergence

Text Book / References

1. Stephen Boyd and Lieven Vandenberghe, ‘Convex Optimization’, Cambridge University Press, 2018
2. Fletcher R., ‘Practical Methods of Optimization’, John Wiley, 2000.
3. Kalyanmoy, Deb. Optimization for engineering design: Algorithms and examples. Prentice-Hall of India Pvt. Limited, 2012.
4. Chong, Edwin KP, and Stanislaw H. Zak. An introduction to optimization. John Wiley & Sons, 2004.
5. Bhatti, M. Asghar. Practical Optimization Methods: With Mathematica® Applications. Springer Science & Business Media, 2012.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Should be able to understand and appreciate the necessary theory behind solutions to optimisa- tion problems and develop skills to understand research papers in the domain.	3	3	2	2	2
CO2	Should be able to use different tools and tech- niques to find solutions to Optimisation problems.	3	3	3	2	2
CO3	Should gain necessary skill to pose engineering problem as an optimisation problem wherever possible.	3	3	3	2	3

Evaluation Pattern - 70:30

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

21AI603 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 learn and design intelligent agents
- To understand the basic areas of artificial intelligence including problem solving, knowledge representation, reasoning, decision making, planning, perception and action

Course Outcomes

COs	Description
CO1	Understand formal methods of knowledge representation
CO2	Understand foundational principles, mathematical tools and program paradigms of AI.
CO3	Apply intelligent agents for Artificial Intelligence programming techniques
CO4	Apply problem solving through search for AI applications
CO5	Apply logic and reasoning techniques to AI applications.

Prerequisites

- None

Syllabus

Logic and Knowledge Representation - Knowledge base - Ontology - Commonsense Knowledge - Representation of Commonsense knowledge – Graphical models – Belief networks - State space representation – Vector representation - Propositional logic and predicate logic - Propositional and predicate logic - Syntax - Informal and formal semantics - Validity, satisfiability - Semantic en- tailment - Equivalence - De Morgan's laws - Decidable problems - Many-sorted logic - first-order, aspects of higher-order logic

Automated Reasoning– Formal program techniques: specification by pre- and post-conditions, derivation and verification of programs, invariants. Strategic Reasoning in AI - Agents, strate- gic behaviours of agents in multiagent systems (MAS) by using the language of alternating-time temporal logic (ATL), an extension of the temporal logics CTL and LTL which allows to express game-theoretical notions such as the existence of a winning strategy for a group of agents - Expert system-based reasoning - Production system, semantic network, and frame - Soft computing based reasoning – Fuzzy logic

Decision Theory Decision-Making: basics of utility theory, decision theory, sequential decision problems, decision networks, elementary game theory, sample applications; Problem-solving through Search: forward and backward, state-space, blind, heuristic, hill climbing, best-first, A, A*, AO*, minimax, constraint propagation, intelligent search, meta-heuristics, problem-reduction, neural and stochastic; Intelligent agents - reactive, deliberative, goal-driven, utility-driven, and learning agentsArtificial Intelligence programming techniques; Planning: planning as search, partial order planning, construction and use of planning graph.

Text Book / References

1. Russell, Norvig, Artifificial Intelligence: A Modern Approach, Third edition, Prentice Hall, 2010
2. Tsang. Foundations of constraint satisfaction, Academic press, 1993
3. Gendreau, Michel, and Jean-Yves Potvin, Handbook of metaheuristics, Springer, 2010.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand formal methods of knowledge representation	2	2	1	2	2
CO2	Understand foundational principles, mathematical tools and program paradigms of AI	2	2	1	2	2
CO3	Apply intelligent agents for Artificial Intelligence programming techniques	2	2	2	1	1
CO4	Apply problem solving through search for AI applications	2	2	2	3	3
CO5	Apply logic and reasoning techniques to AI applications	2	1	2	3	3

Evaluation Pattern - 70:30

Periodical 1 - 10%
Periodical 2 - 10%
Lab Assignments & Case Study – 50%
End Semester Exam - 30%

21AI604 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 understand fundamental concepts of machine learning and its various algorithms
- To understand various strategies of generating models from data and evaluating them
- To apply ML algorithms on given data and interpret the results obtained
- To design appropriate ML solution to solve real world problems in AI domain

Course Outcomes

COs	Description
CO1	Develop a good understanding of fundamental principles of machine learning
CO2	Formulation of a Machine Learning problem
CO3	Develop a model using supervised/unsupervised machine learning algorithms for classification/prediction/clustering
CO4	Evaluate performance of various machine learning algorithms on various data sets of a domain.
CO5	Design and Concrete implementations of various machine learning algorithms to solve a given problem using languages such as Python

Prerequisites

- Basics of Algorithms
- Basics of Linear Algebra
- Basics of Python Programming Language

Syllabus

Introduction: Machine learning, Terminologies in machine learning, Types of machine learning: supervised, unsupervised, semi-supervised learning. Discriminative Models: Least Square Regres- sion, Gradient Descent Algorithm, Univariate and Multivariate Linear Regression, Prediction Model, probabilistic interpretation, Regularization, Logistic regression, multi class classification, Support Vector Machines- Large margin classifiers, Nonlinear SVM, kernel functions, SMO algorithm.

Model evaluation and improvement, Regularization, Bias Variance, Hyper-parameter Tuning. Computational Learning theory- Sample complexity, ϵ- exhausted version space, PAC Learning, agnostic learner, VC dimensions, Sample complexity - Mistake bounds. Gaussian models: Multivariate Gaussian distributions, Maximum Likelihood Estimate, Inferring parameters, Mixture models, EM algorithm for clustering and learning with latent variables.

Generative models : Linear Discriminative Analysis,Na¨ıve Bayes classifier, Decision trees, Ensemble models – Bagging and Boosting. Unsupervised Learning Algorithms: Dimensionality Reduction - Principal Component Analysis (PCA), Singular Value Decomposition (SVD). Clustering – Hierarchical, Partitioned clustering : K-means, PAM, eXplainable AI (XAI), Approaching an ML problem

Text Book / References

1. Tom Mitchell, “Machine Learning”, McGraw Hill, 1997
2. E. Alpaydin, “Introduction to Machine Learning”, PHI, 2005.
3. Andrew Ng, Machine learning yearning, https://www.deeplearning.ai/machine-learning-yearning/
4. AurolienGeron, ”Hands-On Machine Learning with Scikit-Learn and TensorFlow, Shroff/O’Reilly”, 2017
5. Andreas Muller and Sarah Guido, ”Introduction to Machine Learning with Python: A Guide for Data Scientists”, Shroff/O’Reilly, 2016
6. Alejandro Barredo Arrieta, Natalia Díaz-Rodríguez, Javier Del Ser, et.al., ”Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI, Information Fusion”, Volume 58, 2020, Pages 82-115,ISSN 1566-2535, https://doi.org/10.1016/j.inffus.2019.12.012.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Develop a good understanding of fundamental principles of machine learning	3	3	1	1	-
CO2	Formulation of a Machine Learning problem	3	3	2	1	1
CO3	Develop a model using supervised/unsupervised machine learning algorithms for classification/prediction/clustering	3	3	3	2	2
CO4	Evaluate performance of various machine learning algorithms on various data sets of a domain	3	3	3	3	2
CO5	Design and Concrete implementations of various machine learning algorithms to solve a given problem using languages such as Python	3	3	3	3	1

Evaluation Pattern - 70:30

Periodical 1 - 10%
Periodical 2 - 10%
Lab Assignments – 50%
End Semester Exam - 30%

21AI631 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 ma- chine learning algorithms. The course also focuses on the associated inferencing techniques basedon 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 Distri- butions - 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%

21AI632 Statistical Learning Theory 3-0-2-4

Preamble

This course teaches fundamental theory of statistical learning. It enables the students to choose suitable computational models for real world data analysis and to develop machine learning algorithms. The main focus is to provide understanding of linear models for prediction, model selection and inference techniques.

Course Objectives

- To provide theoretical foundations required to develop effective machine learning solutions to real world problems.
- To choose suitable computational methods to analyze high dimensional data sets

Course Outcomes

COs	Description
CO1	Understand linear methods for regression and classification
CO2	Analyze prediction methods focusing on statistical and computational aspects
CO3	Analyze statistical methods to identify and characterize nonlinearity in data
CO4	Apply suitable computational methods to analyze real world high dimensional data sets
CO5	Explore tools for statistical learning

Prerequisites

- Machine Learning
- Programming languages
- Probability

Syllabus

Overview of Supervised Learning, Linear methods for Regression, Linear methods for Classification, Basis Expansions and Regularization, Kernel smoothing.

Model assessment and Selection, Model Inference and Averaging, Additive Models, Trees & Related Methods, Boosting and Additive Trees, Random Forests, Ensemble Learning.

Support Vector Machines and Flexibilities, Prototype methods and Nearest Neighbors, Unsuper- vised Learning, Undirected graphical Models, High dimensional Problems.

Text Book / References

1. Trevor Hastie, Robert Tibshirani and Jerome Friedman, "Elements of Statistical Learning" Second Edition, Springer, 2008.

2. Devroye L, L Gyorfi, and G. Lugosi, "A Probabilistic Theory of Pattern Recognition", Springer, 1997.

3. V. N. Vapnik, "Statistical Learning Theory", Wiley, 1998.

4. Michael J. Kearns and Umesh Vazirani, "An Introduction to Computational Learning Theory", The MIT Press, 1994.

5. E. Alpaydin, "Introduction to Machine Learning", PHI, 2005.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand linear methods for regression and classification	3	3	1	1	-
CO2	Analyze prediction methods focusing on statistical and computational aspects	4	3	3	1	2
CO3	Analyze statistical methods to identify and characterize non-linearity in data	3	3	4	1	2
CO4	Apply suitable computational methods to analyze real world high dimensional data sets	3	3	3	3	2
CO5	Explore tools for statistical learning	2	4	3	2	-

Evaluation Pattern - 70:30

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation - 40%
End Semester Exam- 30%

21AI633 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 - 50:50

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation - 20%
End Semester Exam- 50%

21AI634 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 Sets
CO3	Identify statistical pattern in data using suitable algorithms
CO4	Use existing methods to develop new statistical tools

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 Kaufmann Publishers, 2001.
3. K. P. Soman, V. Ajay and DiwakarShyam, "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

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation - 40%
End Semester Exam- 30%

21AI635 Multi Agent Systems 3-0-2-4

Preamble

Agents are programs that sense their environment, make decisions based on these sensations, and execute actions. Multiagent systems are collections of multiple agents that interact with one another. This course provides a broad introduction to multiagent systems including agent architectures, inter-agent communication, rational decision making,agent modeling and multiagent learning.

Course Objectives

- To understand key concepts, methods, and algorithms that form the core of multiagent systems
- To designing agent systems as complex distributed software systems
- Understand various application where agent programs can be leveraged

Course Outcomes

COs	Description
CO1	Develop a good understanding of fundamental concepts of agent systems and requirement of multi agent systems.
CO2	Formulate and design an agent system for a given problem
CO3	Concrete implementations of agent systems

Prerequisites

- None

Syllabus

Intelligent Agents - Abstract architectures for Intelligent agents - Concrete architectures for Intel- ligent agents - Agent communications - Agent interaction protocols - Societies of Agents - Search algorithms for agents - Constraint satisfaction problems - Path-Finding Problem

Distributed Problem solving and Planning - Task and Result sharing - Planning representations and execution - Learning in Multiagent systems - Credit assignment problem - Interactive Reinforcement Learning of coordination -Learning and communication - Partial Order Planning – Graphs – Non deterministic Domains Conditional Planning - Continuous Planning – Multi Agent Planning.

Higher level Agents, Knowledge in Learning- Statistical Learning Methods -Logics for Multiagent systems - Possible-Worlds Semantics for Modal Logics - Normal Modal Logics - Epistemic Logicfor Multiagent Systems. Industrial and Practical Applications - Agents for Workflow and Business Process Management - Agents for Electronic Commerce - Agents for Human-Computer Interfaces - Agents for Virtual Environments - Agents for Social Simulation

Text Book / References

1. Stuart Russell and Peter Norvig, “Artificial Intelligence - A Modern Approach”, 2nd Edition, Prentice Hall, 2002.

2. Multiagent Systems A Modern Approach to Distributed Modern Approach to Artificial Intelligence, MIT Press, 2000

3. Gerhard Weiss, ”Multiagent Systems”, Second Edition, MIT Press, 2016

4. Michael Wooldridge, “An Introduction to Multi Agent System”, John Wiley, 2002.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Develop a good understanding of fundamental concepts of agent systems and requirement of multi agent systems	3	2			
CO2	Formulate and design an agent system for a given problem	3	2	2		3
CO3	Concrete implementations of agent systems	3	3			

Evaluation Pattern - 70:30

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation - 40%
End Semester Exam- 30%

21AI636 Computational Intelligence 3-0-2-4

Preamble

Computational Intelligence (CI) is a relatively new area which is becoming more and more important in society today and in the future, especially due to the growing possibilities of gathering data and the need for intelligent systems It is a set of nature-inspired computational methodologies and approaches to address complex real-world problems. This course is designed around five paradigms of the Computational Intelligence, namely, artificial immune systems (AIS), evolutionary computing, fuzzy systems, neural networks (NNs), and swarm intelligence. This course will also give an insight into a variety of applications in which various CI techniques will be applicable.

Course Objectives

- Become familiar with basic principles of Computational Intelligence techniques.

- Understand various CI paradigms like neural networks, fuzzy systems and optimization techniques.

- At the end of the course students should be able to identify and select a suitable CI principle to solve engineering or real life problems.

Course Outcomes

COs	Description
CO1	Understanding of basic principles of Computational Intelligence techniques.
CO2	Understand various neural network architectures
CO3	Understand and define various fuzzy systems
CO4	Identify and select a suitable CI principle to solve engineering or real life

Prerequisites

- None

Syllabus

Computational intelligence (CI): Linear Separable Problems and Perceptron, Multi-Layer neural networks – Back Propagation-radial basis function based multilayer perceptron - Kohonen's Self-Organizing Networks - Hopfield Networks, ART networks, Boltzmann Machine.

Fuzzy systems: Fuzzy sets – properties - membership functions - fuzzy operations, Applications, Implementation, Hybrid systems.

Evolutionary computing: - Genetic algorithm – Schema theorem - Advances in the theory GA. Genetic Programming, Particle swarm optimization, Ant colony optimization, Artificial immune Systems. Applications: case studies may include image processing, digital systems, control, fore- casting and time-series predictions.

Text Book / References

1. R.C. Eberhart, "Computational Intelligence: Concept to Implementations", Morgan Kaufmann Publishers, 2007.
2. Laurence Fausett, "Fundamentals of Neural Networks", Prentice Hall,1994
3. Timothy J Rose, "Fuzzy Logic with Engineering Applications", Third Edition, Wiley, 1995.
4. NazmulSiddique, HojjatAdeli, "Computational Intelligence: Synergies of Fuzzy Logic, Neural Networks and Evolutionary Computing", Willey 2013

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understanding of basic principles of Computational Intelligence techniques	3	2	-	-	1
CO2	Understand various neural network architectures	3	1	2	-	2
CO3	Understand and define various fuzzy systems	3	2	2	-	2
CO4	Identify and select a suitable CI principle to solve engineering or real life	3	3	3	-	3

Evaluation Pattern - 70:30

Periodical 1 - 10%
Periodical 2 - 10%
Lab Assignments & Case Study – 50%
End Semester Exam - 30%

21AI637 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 patternsand 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 deployingsolutions.

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	Be able to design, train, deploy neural networks for solving different practical/engineering problems and analyse and report its efficacy
CO2	Have a good level of knowledge (Both Conceptual and Mathematical) on different neural network settings to pursue Research in this Field
CO3	Build skills in using established ML tools/libraries and in building self-learning skills in the field

Prerequisites

- Computational Linear Algebra
- Computational Methods for Optimization

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 Transfer 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 Edition, 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	Be able to design, train, deploy neural networks for solving different practical/engineering problems and analyse & report its efficacy	5	5	5	5	3
CO2	Have a good level of knowledge (Conceptual & Mathematical) on different neural network settings to pursue Research in this Field	5	5	5	3	5
CO3	Build skills in using established ML tools/libraries and in building self-learning skills in the field	5	5	5	3	5

Evaluation Pattern - 70:30

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

21AI638 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 relevance of Reinforcement Learning and how does it complement other ML techniques.
CO2	Understand various RL algorithms.
CO3	Formulate a problem as a Reinforcement Learning problem and solve it
CO4	Implement RL algorithms using Python

Prerequisites

- Machine Learning basics
- Linear Algebra and Probability theory basics
- Python Programming

Syllabus

Introduction to Machine Learning and its various types, Motivation and Introduction to Reinforcement Learning, Multi arm Bandits ; Markov Decision Process, Value functions; Dynamic program- ming : 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

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the relevance of Reinforcement Learning and how does it complement other ML techniques.	3	2	1	–	–
CO2	Understand various RL algorithms	3	1	1	–	1
CO3	Formulate a problem as a Reinforcement Learning problem and solve it	1	3	2	-	1
CO4	Implement RL algorithms using Python	3	3	3	-	-

Evaluation Pattern - 70:30

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

21AI639 Computer Vision 3-0-2-4

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	To build an understanding on detailed models of image formation
CO2	To expose the students to techniques of image analysis through image feature extraction and object recognition.
CO3	To introduce fundamental algorithms for video analysis such as object tracking, motion segmentation etc.
CO4	Become familiar with 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. Morpholog- ical 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, perspec- tive, projective models. Projective Geometry, transformation of 2-d and 3-d, Internal Parameters, Lens Distortion Models, Calibration Methods – linear, direct, indirect and multiplane methods. Ge- ometry of Multiple views- Stereopsis, Camera and Epipolar Geometry, Fundamental matrix; Homog- raphy, 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. Introduction to Computer Vision and its Application, Richard Szelinski,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	To build an understanding on detailed models of image formation	3	3	1	-	-
CO2	To expose the students to techniques of image analysis through image feature extraction and object recognition.	3	2	-	-	1
CO3	To introduce fundamental algorithms for video analysis such as object tracking, motion segmentation etc.	3	3	2	-	-
CO4	Become familiar with 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%

21AI640 Data Engineering 3-0-2-4

Preamble

Data engineering helps to build large-scale data processing systems for maintaining data for usage in many digital applications. A data engineer must be able to install continuous pipelines that run to and from huge pools of filtered information from which data scientists can pull relevant data sets for their analyses. The course introduces students to the different types of data, models, databases and to the area of data processing. It gives an understanding of languages used for data handling. It also helps the student to get a clear idea of how to use different data sources in a scalable way. This course covers common elements of data engineering pipelines a data engineer can build to run repetitive tasks and schedule complex dependencies between applications.

Course Objectives

- To understand different types of data, databases, models and extraction techniques depending on the type.
- To study and compare various tools to do ETL and data processing
- To gain knowledge in building and scheduling data pipelines

Course Outcomes

COs	Description
CO1	To get trained in data modeling and design
CO2	Practice SQL for data processing
CO3	Understand the usage of different types of databases
CO4	Python programming in pySpark and Comparison of Pyspark with other frameworks such as H2O, Dask and Vaex
CO5	To build and schedule data pipelines preferably in Apache Airflow

Prerequisites

- Understanding of DBMS
- Knowledge of SQL
- Python programming

Syllabus

Data modeling, relational data models, ER models – Graph models - Normalization and de-normalization, OLTP and OLAP - Big data – Data Science – Processing big data – Languages – SQL, Cypher, Embedded SQL, Constraints – Data Consistency – Query optimization – Object-oriented databases - NoSQL data models – schema migrations - PostgreSQL, Apache Cassandra, Presto

Spark and data lakes: Python programming in Spark; Data wrangling – Sparkql, spark data frames - SparkSQL, ETL in Spark, SparkMlLib,Comparison of Pyspark with H2O, Dask and Vaex

Data Pipeline – Apache Airflow - Set up task dependencies- Create data connections using hooks - Track data lineage - Set up data pipeline schedules - Partition data to optimize pipelines - Write tests to ensure data quality - Backfill data - Build reusable and maintainable pipelines -Implement subDAGs - Set up task boundaries - Monitor data pipelines

Text Book / References

1. Database System Concepts, Abraham Silberschatz, Henry F. Korth, S. Sudarshan, McGraw-Hill Education, 2011
2. NoSQL Distilled: Pramod J. Sadalage, Martin Fowler, Addison-Wesley, 2012
3. Learning Spark: Lightning-Fast Big Data Analysis, Holden Karau, Andy Konwinski, Patrick Wendell, MateiZaharia, O'Reilly Media, Inc., 2015
4. Practical Machine Learning with H2O: Powerful, Scalable Techniques for Deep Learning and AI, Darren Cook, O'Reilly Media, Inc., 2016
5. Learning PySpark, Tomasz Drabas, Denny Lee, Packt, 2017
6. https://medium.com/plotly/interactive-and-scalable-dashboards-with-vaex-and-dash-9b104b2dc9f0

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	To get trained in data modeling and design	1	3	3	1	1
CO2	Practice SQL for data processing	1	3	3	1	1
CO3	Understand the usage of different types of databases	1	3	3	1	1
CO4	Python programming in pySpark and Comparison of Pyspark with other frameworks such as H2O, Dask and Vaex	3	3	3	2	2
CO5	To build and schedule data pipelines preferably in Apache Airflow	2	3	3	2	2

Evaluation Pattern - 70:30

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

21AI641 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 introduce systems and approaches for large scale datascience problems

- Focus on data mining of very large amounts of data, that is, data so large it does not fit in main memory.
- To understand the techniques of handling large and varied types of data sets.
- To understand algorithmic point of view: data mining is about applying algorithms to data , rather than using data to "train" a machine-learning engine of some sort.

Course Outcomes

COs	Description
CO1	Understand the importance of data to business decisions, strategy and behavior. Predictive analytics, data mining and machine learning as tools give new methods for analyzing massive data sets.
CO2	Expose the students to Big data systems like Hadoop, Spark and Hive.
CO3	Explore means to deal with huge document databases and infinite streams of data to mining large social networks and web graphs. Also, learn Algorithms suitable for large scale mining.
CO4	As a useful analytic tool, case studies 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 Multihash 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. Anand Rajaraman, Jure Leskovec and J.D. Ullman, "Mining of Massive Data Sets", ebook, Cambridge University Press, 2014.

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 business decisions, strategy and behavior. Predictive analytics, data mining and machine learning as tools give new methods for analyzing massive data sets.	3	1			
CO2	Expose the students to Big data systems like Hadoop, Spark and Hive.	2	3			3
CO3	Explore means to deal with huge document databases and infinite streams of data to mining large social networks and web graphs. Also, learn Algorithms suitable for large scale mining.	3		3	3	2
CO4	As a useful analytic tool, case studies 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%

21AI642 Natural Language Processing 3-0-2-4

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

- Understand leading trends and systems in natural language processing.
- Describe concepts of morphology, syntax, semantics and pragmatics of the language.
- Understand Language Models and its evaluation.
- Writing programs in Python to carry out natural language processing.
- Implement deep learning algorithms in Python and learn how to train deep networks for NLP applications.

Course Outcomes

COs	Description
CO1	Understand the basic processes and representations used in syntax, semantics, and other components of natural language processing.
CO2	Understand how machine learning and deep learning algorithms are used for Natural Language Processing applications.
CO3	Understand and explore the models used for word/sentence representations for various NLP applications.
CO4	Understand the tools for performing text analytics in a variety of contexts.

Prerequisites

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

Syllabus

Introduction - terminologies -basic techniques in natural language processing, including tokenization, part-of-speech tagging, chunking, syntax parsing, Dependency parsing, named entity recognition, Coreference Resolution Wordsense Disambiguation. Text representations and embeddings: One-hot encoding, Bag-of-Words (BoW) Dictionary: Term Frequency – Inverse Document Frequency (TF-IDF), N-gram. Introduction to various nlp toolkits such as nltk, Spacy etc.

Introduction to Deep Learning: Neural Networks Basics, Feedforward Neural Network, Recurrent Neural Networks, LSTM, An Introduction to Transform- ers and Sequence-to-Sequence Learning. Neural Networks for NLP – Vector Representation of words – Contextual Understanding of text – Co-occurrence of matrix – N-grams – Dense Word Vector. Word2Vec – CBOW and Skip- gram Models – One-word learning architecture- Forward pass for Word2Vec – Reduction of complexity – sub-sampling and negative sampling. Continuous Skip-Gram Model, GloVe, BERT,XLNet.

NLP Challenges: Word sense Disambiguation NER. Named Entity Recognition, Sentiment anal- ysis, Text categorization: Basic supervised text categorization algorithms, including Naive Bayes, k Nearest Neighbor (kNN) and Logistic Regression. Topic modeling: SVD and Latent semantic Indexing, Probabilistic Latent Semantic Indexing (pLSI) and Latent Dirichlet Allocation (LDA). Introduce Mathematical and programming tools to visualize a large collection of text documents.

Text Book / References

1. C.D. Manning et al, “Foundations of Statistical Natural Language Processing,” MitPress. MIT Press, 1999. isbn: 9780262133609.
2. James Allen, “Natural Language Processing with Python”, O’Reilly Media, July 2009.
3. Ian Goodfellow, YoshuaBengio, and Aaron Courville, Deep Learning, http://www.deeplearningbook.org. MIT Press, 2016.
4. Daniel Jurafsky and James H. Martin ”Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition,” 1st. Upper Saddle River, NJ, USA: Prentice Hall PTR, 2000. isbn: 0130950696.
5. Jacob Perkins, ”Python 3 text processing with NLTK 3 cookbook,” Packet Publishing Ltd, 2014.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the basic processes and representations used in syntax, semantics, and other components of natural language processing.	2	2	2	–	3
CO2	Understand how machine learning and deep learning algorithms are used for Natural Language Processing applications.	2	2	1	–	–
CO3	Understand and explore the models used for word/sentence representations for various NLP applications.	1	3	3	1	3
CO4	Understand the tools for performing text analytics in a variety of contexts.	1	3	2	1	3

Evaluation Pattern - 70:30

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

21AI643 Cloud and Big Data Analytics 3-0-2-4

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 Systemsfor 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%

21AI698 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 project.

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 panelof (at least) two faculty members.

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%

21RM618 Research Methodology 2-0-0-2

Course Outcomes

COs	Description
CO1	Understanding the work-flow of research, research types and research models.
CO2	Applying various tools for identifying, retrieving and organizing the literature.
CO3	Understanding experimental and data-driven approaches in research.
CO4	Document writing using professional tools such as LaTeX, BibTeX, TikZ, PGF etc.

Syllabus

Research problem, Sources of research problem, Criteria Characteristics of a good research problem, Errors in selecting a research problem, Scope and objectives of research problem. Approaches of investigation of solutions for research problem, data collection, analysis, interpretation, Necessary instrumentations.

Effective literature studies approaches, Bibliography management. Plagiarism, Research ethics. Effective technical writing, how to write report, Paper. Technical writing tools. Developing a Re- search Proposal, Format of research proposal, a presentation and assessment by a review committee.

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. Licensing and transfer of technology. Patent informa- tion and databases. Geographical Indications.

New Developments in IPR: Administration of Patent System. New developments in IPR; IPRof Biological Systems, Computer Software etc. Traditional knowledge Case Studies, IPR and IITs.

Text Book / References

1. Stuart Melville and Wayne Goddard, Research methodology: an introduction for science & engineering students.
2. Wayne Goddard and Stuart Melville, Research Methodology: An Introduction.
3. Ranjit Kumar, 2nd Edition, Research Methodology: A Step by Step Guide for beginners.
4. Halbert, Resisting Intellectual Property, Taylor & Francis Ltd, 2007.
5. Mayall, Industrial Design, McGraw Hill, 1992.
6. Niebel, Product Design, McGraw Hill, 1974.
7. Asimov, Introduction to Design, Prentice Hall, 1962.
8. Robert P. Merges, Peter S. Menell, Mark A. Lemley, Intellectual Property in New Technological Age, 2016.
9. T. Ramappa, Intellectual Property Rights Under WTO, S. Chand, 2008.

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	Understanding experimental and data-driven ap- proaches in research.	1	2	1	2	2
CO4	Document writing using professional tools such as LaTeX, BibTeX, TikZ, PGF etc.			2		1

Evaluation Pattern - 80:20

Internal – 80%
External - 20%

21AI701 Machine Learning for Big Data 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 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 voluminous and 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. AnandRajaRaman, 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 PressCambridge, 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 how Machine learning algorithm is made scalable to solve big data problems.	2	3	3	-	-
CO2	Implement scalable Machine Learning algorithms using PySpark	1	3	3	-	-
CO3	Apply and compare different strategies for big data analytics using various machine learning algorithms	2	3	3	1	2
CO4	Understand Streaming algorithms and Coreset concept to analyze voluminous and high dimensional data	3	3	2	-	2

Evaluation Pattern - 70:30

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

21AI702 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 approximatequery processing from databases, PCA, for Image Processing – compression, identification and Vi- sualization.

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. AnandRajaRaman, 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 PressCambridge, 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%

21AI703 Representation Learning 2-0-2-3

Preamble

This course introduces the concept of representation learning, especially unsupervised feature learning and deep learning, covering probabilistic models, auto-encoders, manifold learning, and deep networks. How to learn good representations, for inference, and the geometrical connections between representation learning,density estimation and manifold learning is also dealt with.

Course Objectives

- To understand the requirements for representation learning
- To understand various strategies for representation learning
- To understand and compare the mathematical aspects in each of the representation learning strategies.

Course Outcomes

COs	Description
CO1	Understand why Representation Learning is required in various real world domains
CO2	Present and implement Representation learning algorithms
CO3	Apply and compare different types of Representation learning approaches for data in a given domain
CO4	Design a represenation learning algorithm by incorporating various processes involved in it for a specific domain dataset

Prerequisites

- Machine Learning

Syllabus

Introduction : Overview of Representation Learning and its motivation, Priors for Representation Learning in AI. Basic Representation Learning using Unsupervised strategies- Dimensionality reduction - Principal Component Analysis (PCA), Non-linear PCA, sparse PCA, Independent Component Analysis, Singular Value Decomposition. Clustering Strategies to extract features in high dimensional space - Subspace Learning: Top down subspace clustering – PROCLUS, FINDIT, Bottom up subspace clustering – CLIQUE, MAFIA.

Manifold Learning: Kernel K-means, kernel PCA, similarity-based clustering. Deep Learning: Stochastic optimization, stochastic approximation algorithms. Restricted Boltzmann machines, auto encoders, deep belief networks, convolutional neural networks, Multi-view Learning: Partial least squares, canonical correlation analysis (CCA), Kernel CCA, Deep CCA. State of the art models in applications such as text classification, speech recognition and image classification

Transfer Learning and Domain adaptation. Spectral Learning: Spectral methods, spectral clus- tering, co-training, spectral learning of Hidden Markov Models (HMMs), tensor factorization, latent variable PCFGs, multivariate latent tree structures.

Text Book / References

1. Jeremy Watt, Reza Borhani, Aggelos K. Katsaggelos, “Machine Learning Refined: Foundations, Algorithms, and Applications”. Cambridge University Press.
2. Shiliang Sun, Liang Mao, Ziang Dong, Lidan Vu, “Multiview Machine Learning”. Springer
3. Ian Goodfellow, YoshuaBengio and Aaron Courville, “Deep Learning”, MIT Press
4. Yoshua Bengio and Aaron Courville and Pascal Vincent, ”Representation Learning: A Review and New Perspectives”,arXiv:1206.5538, 2012
5. https://www.deeplearningbook.org/contents/representation.html

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand why Representation Learning is required in various real world domains	1	2	2	-	2
CO2	Present and implement Representation learning algorithms	3	3	3	1	1
CO3	Apply and compare different types of Representation learning approaches for data in a given domain	1	3	3	2	1
CO4	Design a representation learning algorithm by incorporating various processes involved in it for a specific domain dataset	3	3	3	-	2

Evaluation Pattern - 70:30

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation - 40%
End Semester Exam- 30%

21AI704 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 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	Study approaches for forecating 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 - Dimen- sion 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 – Na¨ıve 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. GalitShmueli, Peter C. Bruce, InbalYahav, Nitin R. Patel, Kenneth C. LichtendahlJr"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 Pre-dictive 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 analytical methods used in predictive analytics	3	3	2	1	1
CO2	Evaluate the measures to access predictive performance of data mining tasks	3	4	4	1	1
CO3	Understand and design prediction, classification methods	3	3	2	2	2
CO4	Study approaches for forecating time series data	3	3	2	1	1
CO5	Apply suitable predictive methods in real life problems	3	3	3	4	4

Evaluation Pattern - 70:30

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation - 40%
End Semester Exam- 30%

21AI705 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, ReThinkRobotics, Willow Garage, medical robotics, and others). We study the problem of how a robot canlearn 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, Pol- icy Iteration, Value Iteration), Monte Carlo Methods, Temporal-Difference Learning (Q-learning, SARSA).

Approximate Solution Methods - On-policy Prediction with Approximation, Value function approx- imation, 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%

21AI706 Introduction to Game Theory 2-0-2-3

Preamble

This course is an introduction to game theory. It focuses on fundamentals of game theory including basic concepts and techniques, various ways of describing and solving games, and various applications. Students will gain a detailed background about the mathematical modelling of strategic games.

Course Objectives

- Introduce students to the basics of game theory
- Introduce students to analyse decision making process
- To enable students to recognize and model strategic situations

Course Outcomes

COs	Description
CO1	Understand the theory of Nash equilibrium in a strategic game
CO2	Identify real life strategic situations and formulate as games
CO3	Study variant of Nash equilibrium in a strategic game with different configurations
CO4	Solve real world problems with different approaches in game theory

Prerequisites

- Basics of probability and graph theory
- Formal reasoning

Syllabus

Games with Perfect Information: Strategic Games: Concepts and Examples. Nash Equilibrium and Existence Properties. Market Equilibrium and Pricing: Cournot and Bertrand Games. Games with Perfect Information Continued: Electoral Competition: Median Voter Theorem.

Auctions: Definitions and The role of knowledge. Decision Making and utility Theory: Mixed Strategy Equilibrium: Extensive Frame Game with Perfect Information Theory: Stackelberg Modelof Duopoly.

Buying Votes.Committee Decision-Making. Repeated games: The Prisoner's Dilemma General Result-Super Modular Game and Potential Game

Text Book / References

1. Martin Osbome, "An Introduction to Game Theory", Oxford University Press,2003
2. Gibbons, R," Game Theory for Applied Economists", Princeton university press,1992.
3. Dixit A, B. Nalebuff, "The Art of Strategy", WWW Norton,2008(Hereafter DN).
4. Dixit A, B.Nalebuff," Thinking Strategically", WW Norton, 1991.
5. PrajitDatta," Strategies and Games", MIT press.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the theory of Nash equilibrium in a strategic game	3	3	2	-	-
CO2	Identify real life strategic situations and formulate as games	3	3	2	1	1
CO3	Study variant of Nash equilibrium in a strategic game with different configurations	3	3	2	-	-
CO4	Solve real world problems with different approaches in game theory	3	3	4	2	4

Evaluation Pattern - 50:50

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation - 20%
End Semester Exam- 50%

21AI707 Modeling and Simulation 2-0-2-3

Preamble

Modeling and Simulation is a course which provides insights into various types of simulation techniques. The course starts with basic concepts of Monte Carlo simulation and subsequently covers topics related to Discrete Event Simulation. Given a problem, the students will learn how to model the input data, fit a suitable distribution, and conduct an output analysis of the simulation. Oncea model is built, it must go through verification and validation techniques. Thus a student can actually go through all the steps of building a simulator for a particular problem. Additionally, the course covers basic statistical probability distributions, hypothesis testing and application of these concepts in practical problems.

Course Objectives

- To make the students familiar with the basic steps of building a simulator;
- To fit a specific probability distribution for a given data set;
- To analyze the data quality of output of a simulation.

Course Outcomes

COs	Description
CO1	Understand fundamental concepts of modeling and simulation
CO2	Develop simulators to find out performance of simple application scenarios
CO3	Learn the techniques for random number generation and their properties
CO4	Understand and apply input modeling techniques
CO5	Understand and apply different statistical models in simulation
CO6	Perform output analysis of simulation and apply techniques for verification and validation of simulation models

Prerequisites

- Basic Probability and Statistics

Syllabus

Introduction to Simulation: System and system environment, Component System, Type of systems, Types of models, Steps in simulation study, Advantages and disadvantages of Simulation. Types of Simulation: Discrete Event Simulation, Simulation of a single server queuing system, Simulation of an Inventory system, Continuous Simulation, Predator-prey system, Combined Discrete-Continuous Simulation, Monte Carlo Simulation. Statistical Models in Simulation: Useful statistical model, Discrete and Continuous Probability distributions, Poisson process and Empirical distribution.

Random Numbers Generation: Properties of random numbers, Generation of pseudo random numbers, Techniques for generating random numbers, Tests for random numbers. Random Variate Generation: Inverse Transform technique, Convolution method, Acceptance Rejection Techniques. Input Modeling: Data Collection, Identifying the distribution of data, Parameter Estimation, Good- ness of fit tests, Selection input model without data, Multivariate and Time series input models.

Verification and Validation of Simulation Model: Model Building, Verification and Validation, Verification of Simulation models, Calibration and Validation of models. Output Analysis: Stochastic nature of output data, Measure of performance and their estimation, Output analysis of terminating simulators, Output Analysis of steady state simulation. Comparison and Evaluation of Alternate System Design: Comparison of two system design, Comparison of several system design, Confidence interval for the difference between expected responses of two systems.

Text Book / References

1. Jerry Banks, John S. Carson, Barry L. Nelson, ”Discrete-Event-System Simulation”, 5/e, Pearson Education, 2010.
2. Averill M. Law, ”Simulation Modeling and Analysis”, 4/e, Tata McGraw-Hill, 2017.

3. Lawrence M. Leemis and Stephen K. Park, ”Discrete – Event Simulation: A First Course”, Pearson Education, 2006.

4. Bernard Zeigler, Alexandre Muzy and Ernesto Kofman, ”Theory of Modeling and Simulation: Discrete Event & Iterative System Computational Foundations”, 3/e, Academic Press, 2018.

5. John A. Sokolowski and Catherine M. Banks, ”Principles Of Modeling And Simulation”, John Wiley, 2014.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Develop simulators to find out performance of simple application scenarios	-	2	-	-	-
CO2	Apply effective visualizations to explore and analyze input data	-	2	3	-	-
CO3	Learn the techniques for random number generation and their properties	-	-	1	-	2
CO4	Understand and apply input modeling techniques	2	2	3	-	1
CO5	Understand and apply different statistical models in simulation	-	2	3	-	2
CO6	Perform output analysis of simulation and apply techniques for verification and validation of simulation models	1	-	3	-	2

Evaluation Pattern - 70:30

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation – 40%
End Semester Exam - 30%

21AI708 Information Retrieval 2-0-2-3

Preamble

The amount of data available in the web has been increasing beyond limits and automatic methods of information retrieval has gained remarkable significance. IR is an important problem in natural language processing (NLP) also. The purpose of this course is the study of the indexing, processing, and querying of textual data.

Course Objectives

- To study the fundamentals of information retrieval (IR)
- To elaborate on indexing, search, relevance, classification, organization and storage of information
- To focus on prominent computer algorithms and methods used in IR

Course Outcomes

COs	Description
CO1	Gain insights to different retrieval models like Boolean and vector space models
CO2	Back end construction of an IR system by designing data structures and maintaining different types of indexes
CO3	Learn different ways of user query handling techniques
CO4	Understand evaluation measures of an IR system
CO5	Be able to improve an IR system through feedback mechanisms and ranking through ML algorithms

Prerequisites

- Algorithms, Data structures and DBMS
- Machine Learning
- Basic Probability, Statistics and Linear Algebra

Syllabus

Introduction to IR: Retrieval Models - Ranked Retrieval - Text Similarity Metrics - Tokenizing-Stemming-Evaluations on benchmark text collections - Components of an information retrieval system.

Indexing for IR: Inverted Indices - Postings lists - Optimizing indices with skip lists - Proximity and phrase queries - Positional indices - Dictionaries and tolerant retrieval - Dictionary data struc- tures - Wild-card queries- n-gram indices - Spelling correction and synonyms - Edit distance - Index construction - Dynamic indexing - Distributed indexing - real-world issues.

Relevance in IR: Parametric or fielded search - Document zones - Vector space retrieval model - tf.idf weighting - queries as vectors - Computing scores in a complete search system - Efficient scoring and ranking - Evaluation in information retrieval: User happiness- Creating test collections:kappa measure-interjudge agreement - Relevance feedback and query expansion: Query expansion - Automatic thesaurus generation - Sense-based retrieval. Understanding the working and usage of Google Analytics, Lucene, Elasticsearch, Solr

Case study in topics like Image retrieval, search optimization, QDD, Learning to rank, Cross and multi-lingual IR, Privacy Preservation, IR Techniques for the Web

Text Book / References

1. C. Manning, P. Raghavan, and H. Schütze, “Introduction to Information Retrieval”, Cambridge University Press, 2008.
2. R. Baeza-Yates and B. RibeiroNeto, “Modern Information Retrieval: The Concepts and Technology behind Search”, Second Edition, Addison Wesley, 2011.
3. David A. Grossman and OphirFrieder “Information Retrieval: Algorithms and Heuristics”, Second Edition, Springer 2004.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Gain insights to different retrieval models like Boolean and vector space models	3	3	3	1	1
CO2	Back end construction of an IR system by designing data structures and maintaining different types of indexes	3	3	3	1	1
CO3	Learn different ways of user query handling techniques	1	3	3	1	1
CO4	Understand evaluation measures of an IR system	1	2	2	-	-
CO5	Be able to improve an IR system through feedback mechanisms and ranking through ML algorithms	3	3	3	1	1

Evaluation Pattern - 70:30

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation – 40%
End Semester Exam - 30%

21AI709 Web Intelligence and Big Data 2-0-2-3

Preamble

Web Intelligence explores the fundamental roles as well as practical impacts of artificial intelligence and advanced information technology for the Web-empowered systems, services, and environments. This course brings out new trends in web in terms of user behavior, opinion mining, and recommender systems.

Course Objectives

- Introduce basic concepts of information retrieval and semantic web
- Develop skills in processing web data for applications or systems such as search engine, recommender systems.

Course Outcomes

COs	Description
CO1	Understand fundamentals of IR and knowledge extraction from Web
CO2	Develop skills for content and user mining techniques of web data
CO3	Applying machine learning techniques on web data for web-powered systems
CO4	Study models to interpret the structure of Web and Social networks
CO5	Apply technical and analytic skills to develop a research project, with the opportunity to submit the results for publication

Prerequisites

- A fare understanding of internet and web services.

- The course requires basic knowledge in linear algebra, and programming skills in Python and R.

Syllabus

Introduction to Web Intelligence: Ingredients of Web Intelligence, Topics of Web Intelligence. Information Retrieval - Document Representation, Retrieval Models, Evaluation of Retrieval Performance.

Semantic Web: The Layered-Language Model, Metadata and Ontologies, Ontology Languages for the Web. Web Usage Mining: Web-Log Processing, Analyzing Web Logs, Applications of Web Usage Mining, Clustering of Web Users, Classification Modeling of Web Users, Association Mining of Web Usages, Sequence-Pattern Analysis of Web Logs.

Web Content Mining- Web Crawlers, Search Engines, Personalization of Web Content. Web Structure Mining- Modeling Web Topology, PageRank Algorithm, Hyperlink-Induced Topic Search (HITS) Random Walks on the Web, Social Networks & Graphs

Text Book / References

1. GautamShroff, The Intelligent Web: Search, Smart Algorithms, and Big Data, Oxford Press,2019
2. Akerkar, R. & Lingras, P. (2008). Building an Intelligent Web: Theory and Practice. Jones and Bartlett Publishers, Sudbury, Massachusetts. ISBN-13: 978-0-7637-4137-2
3. Bing Liu: Web Data Mining, Springer, 2nd ed. 2011
4. Marmanis & Babenko: Algorithms of the Intelligent Web, Manning Publications, 2009, ISBN: 978-1933988665
5. Manning, Raghavan and Schuetze: Introduction to Information Retrieval, Cambridge University Press, 2008

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand fundamentals of IR and knowledge extraction from Web	3				
CO2	Develop skills for content and user mining techniques of web data	3	2	2		
CO3	Applying machine learning techniques on web data for web-powered systems	3	3	3		
CO4	Study models to interpret the structure Web graph and Social network graphs	3	3			
CO5	Apply technical and analytic skills to develop a research project, with the opportunity to submit the results for publication				3	3

Evaluation Pattern - 70:30

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation – 40%
End Semester Exam - 30%

21AI710 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 the key techniques and theory used in visualization of data
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 Publications, 2019.
5. Nathan Yau, ”Visualize This: The FlowingData 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	1	2	3	3	2
CO2	Apply effective visualizations to explore and analyze input data	1	2	3	3	2
CO3	Present the insights and findings in engaging formats that produce compelling stories	1	2	3	3	1
CO4	Evaluate data visualization systems for their effectiveness	1	2	2	2	1
CO5	Design and build data visualization systems following the best practices using popular software tools for visualization such as Tableau/QlikView	1	3	3	3	2

Evaluation Pattern - 70:30

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

21AI711 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 brings 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, Community structures, Social networks - the web graph, the internet graph, citation graphs. Measures and metrics- Degree centrality, Eigenvector centrality, Katz centrality, PageRank, Hubs and author- ities, Closeness centrality, Betweenness centrality, Transitivity, Reciprocity, Similarity, assortative mixing.

Networks models - Random graphs, Generalized random graphs, The small-world model, Exponen- tial 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 copy- ing 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, 2010.
2. Dougles West, “Introduction to Graph Theory”, Second Edition, PHI Learning Private Limited, 2011.
3. Guido Caldarelli, “Scale-Free Networks”, Oxford University Press, 2007.
4. Alain Barrat, Marc Barthelemy and Alessandro Vespignani, “Dynamical processes on Complex networks”, Cambridge University Press, 2008.
5. Reuven Cohen and ShlomoHavlin, “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%

21AI712 Parallel and Distributed Data Management 2-0-2-3

Preamble

The improvements in Database Management System (DBMS) technology has 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 mes- sage passing systems, synchronous and asynchronous systems, Global state and snapshot algorithms.

Distributed and Parallel databases: Centralized versus Distributed Systems, Parallel versus Dis- tributed 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 Ozsu and Patrick Valduriez, "Principles of Distributed Database Systems", 3rd ed. 2011 Edition, Springer
2. Dimitri P. Bertsekas and John N. Tsitsiklis, ”Parallel and distributed computation : Numerical methods”,
3. Andrew S. Tannenbaum and Maarten van Steen ”Distributed Systems: Principles and Paradigms”, Second Edition, Prentice Hall, October 2006.
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	2	2	-	2
CO2	Design algorithms for distributed and parallel data processing	3	2	2	1	3
CO3	Understand the concepts of fragmentation and allocation algorithms	3	2	2	-	2
CO4	Implement optimized parallel and distributed queries for such a system	2	2	2	-	3
CO5	Design and build an application using one of the latest distributed or parallel database technology	3	3	3	1	3

Evaluation Pattern - 70:30

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation – 40%
End Semester Exam - 30%

21AI713 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	The student will be able to understand various methods of acquiring bio signals.
CO2	The student will be able to understand various sources of bio signal distortions and its remedial techniques.
CO3	The students will be able to analyse ECG and EEG signal with characteristic feature points.
CO4	The student will have a basic understanding of applying deep learning techniques for medical image segmentation, clustering and classification problems.
CO5	Understand various volume reconstruction and volume rendering techniques for Med- ical 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, Imag- ing 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, AQRS 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, 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. MostafaAnaloui, Joseph D. Bronzino, Donald R. Peterson, "Medical Imaging: Principles and Practices", Taylor and Francis group, 2012

4. Analysing Neural Time Series Data-Theory and Practice (MIT Press) 2014

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	The student will be able to understand various methods of acquiring bio signals	3	1	-	-	1
CO2	The student will be able to understand various sources of bio signal distortions and its remedial techniques	3	2	-	-	2
CO3	The students will be able to analyse ECG and EEG signal with characteristic feature points	1	3	2	-	1
CO4	The student will have a basic understanding of applying 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

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation – 20%
End Semester Exam - 50%

21AI714 Parallel and Distributed Computing 2-0-2-3

Preamble

This course is organized around various parallel and distributed computing models. Within each model, we develop and analyze sample algorithms, study practical issues such as programming language and hardware support, and undertake performance prediction and experimental performance analysis.

Course Objectives

- To introduce the fundamentals of parallel and distributed programming and application development in different parallel programming environments;
- To develop and execute basic parallel and distributed applications using basic programming models;
- To learn tools such as CUDA for developing applications for multi-core processors;

Course Outcomes

COs	Description
CO1	Understand the requirements for programming parallel and distributed systems .
CO2	Knowledge of parallel and distributed computing techniques and methodologies.
CO3	Understand the architecture of Graphics Processing Units(GPU)
CO4	Understand the memory hierarchy and evaluate cost-performance tradeoffs.
CO5	Design, develop and analyze performance of parallel and distributed applications.

Prerequisites

- Computer Architecture
- Algorithms and Data Structures
- Programming Fundamentals

Syllabus

Introduction - Asynchronous and synchronous computation, Fault tolerance and recovery: basic concepts, fault models, agreement problems and its applications, commit protocols, voting protocols, check pointing and recovery, reliable communication, heterogeneity, interconnection topologies, load balancing, memory consistency model, memory hierarchies, Models of computation: shared memory and message passing systems

GPU Programming Model, GPU Hardware and Parallel Communication, Fundamental Parallel Algorithms, Optimizing GPU Programs,, Parallel Computing Patterns

Multithreaded programming, parallel algorithms and architectures, parallel I/O, performance anal- ysis and tuning, power, programming models (data parallel, task parallel, process-centric, shared/ distributed memory), scalability and performance studies, scheduling, storage systems, synchronization.

Text Book / References

1. Kai Hwang, Jack Dongarra and Geoffrey C. Fox, ”Distributed and Cloud Computing: Clusters, Grids, Clouds, and the Future Internet (DCC)”, 2012.

2. Andrew S. Tanenbaum and Maarten van Steen, ”Distributed Systems: Principles and Paradigms”, Prentice Hall, 2017.

3. Ajay D Kshemkalyani and Mukesh Singhal, ”Distributed computing: principles algorithms and systems”, Cambridge University Press 2011.

4. David B. Kirk and Wen-mei W. Hwu, ”Programming Massively Parallel Processors: A Hands-on Approach”, Elsevier Science, 2016.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the requirements for programming parallel and distributed systems	1	3	3	2	2
CO2	Knowledge of parallel and distributed computing techniques and methodologies	2	2	3	3	2
CO3	Understand the architecture of Graphics Processing Units(GPU)	3	3	2	2	2
CO4	Understand the memory hierarchy and evaluate cost-performance tradeoffs	1	3	2	3	3
CO5	Design, develop and analyze performance of parallel and distributed applications	1	2	3	3	3

Evaluation Pattern - 70:30

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation – 40%
End Semester Exam - 30%

21AI715 Modern Computer Architecture 2-0-2-3

Preamble

This course attempts to provide an understanding on design issues of computer systems, through quantitative approach, where performance is a main issue.

Course Objectives

- To develop an understanding on the performance aspects of computer systems
- A deeper understanding of multi core, multiprocessor, and GPGPU architectures.

Course Outcomes

COs	Description
CO1	Understanding quantitative analysis on the performance of computer systems
CO2	Develop design skills of pipelined instruction set architecture
CO3	Understanding data and control path of advanced processors
CO4	Analyzing various aspects for parallelism
CO5	Demonstrating the knowledge on recent research in processor architecture through technical writing and presentations.

Prerequisites

- Assembly language programming and basics of computer organization.
- A working knowledge in programming languages such as C, C^{++}/Java is desirable.

Syllabus

Introduction-Fundamentals of computer design, evaluating performance -Pipelining-Instruction set design principles. Caches and memory hierarchy. Design-Review of memory Hierarchy-Advanced memory hierarchy design concepts.

Instruction level parallelism and its Exploitation-Limits on instruction level parallelism. Multiprocessors and Thread-level Parallelism-Models of parallel computation, network topologies, consistency models.

Simultaneous Multi-Threading (SMT), Chip Multi-Processors (CMP), General Purpose Graphics Processing Units (GPGPU). VLSI Scaling issues, data speculation, dynamic compilation, communication architectures, near data processing, and other advanced topics.

Text Book / References

1. L. Hennessy & David A. Patterson, Morgan Kaufmann," Computer Architecture: A Quantitative Approach", 5th Edition, 2011, , ISBN: 978-0-12-383872-8
2. David A Patterson & John L. Hennessy, Morgan Kaufmann, "Computer Organization and Design", the Hardware/Software Interface, 5th Edition.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understanding quantitative analysis on the performance of computer systems		3			
CO2	Develop design skills of pipelined instruction set		3	3		
CO3	Understanding data and control path of advanced processors		3	3		
CO4	Analyzing various aspects of parallelism in computing		3	3		
CO5	Demonstrating the knowledge on recent research in processor architecture through technical writing and presentations				3	3

Evaluation Pattern - 70:30

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation – 40%
End Semester Exam - 30%

21AI716 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 Multi- ple Thread (SIMT) architecture of modern GPUs and architecture-aware programming frameworks like Compute Unified Device Architecture (CUDA) and OpenCL. While CUDA programming modelis a proprietary framework for the students to learn to interface with GPUs, OpenCL allows themto 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 the difference between different parallel programming architectures.
CO2	Knowledge of GPU aware programming using CUDA and OpenCL frameworks.
CO3	Design and develop GPU accelerated real-world simulations and applications.

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 Memory 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. Benedict R. Gaster, Lee Howes, David, R. Kaeli, PerhaadMistry and Dana Schaa, ”Heterogeneous Computing with OpenCL”, Elsevier, 2013.

2. Jason Sanders, Edward Kandrot, ”CUDA by Example: An Introduction to General-Purpose GPU Programming”, Addison-Wesley Professional, 2010

3. Shane Cook, ”CUDA Programming: A Developer’s Guide to Parallel Computing with GPUs”, Newnes, 2012

4. AaftabMunshi, Benedict Gaster, Timothy G. Mattson, James Fung and Dan Ginsburg, ”OpenCL Programming Guide”, Addison-Wesley Professional, 2011.

5. Ryoji Tsuchiyama, Takashi Nakamura, TakuroIizuka and Akihiro Asahara, ”The OpenCL Programming Book”, Fixstars Corporation, 2010.

6. 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 the difference between different parallel programming architectures.	1	3	3	-	-
CO2	Knowledge of GPU aware programming using CUDA and OpenCL frameworks.	3	3	3	-	2
CO3	Design and develop GPU accelerated real-world simulations and applications.	3	3	3	3	3

Evaluation Pattern - 70:30

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

21AI717 IoT for AI 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, Raspberry 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), object detection on Raspberry Pi (optional 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. Elaine Rich and Kevin Knight, “Artificial Intelligence”, Tata McGraw Hill
5. 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 differentapplication domains	3	3	3	1	3
CO4	Understand and build scalable ML pipeline using Flask, Python, uWSGI, Ten-sorFlow	1	3	3	1	3

Evaluation Pattern - 70:30

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

21AI718 Neuroevolution 2-0-2-3

Preamble

Current neural network research is predominantly focused in the fields of deep learning and deep reinforcement learning. In these fields, the neural network weights are typically trained through variants of stochastic gradient descent. This method has provided remarkable results both in supervised and reinforcement learning. An alternative approach, inspired by the fact that natural brains themselves are the products of an evolutionary process, harnesses evolutionary algorithms to train neural networks. This field is called Neuroevolution. Neuroevolution enables important capabilities that were not hitherto available to stochastic gradient methods. Such capabilities include learning neural network building blocks (for example activation functions), hyperparameters, architectures and even the algorithms for learning themselves.

Course Objectives

- To introduce to students the state-of-the-art in simulated evolution of complex systems.
- To introduce sophisticated encoding techniques inspired from generative and developmental systems to realize complexity.
- To provide comprehensive overview of neuroevolution algorithms that demonstrates alternative way (i.e. search) to produce controllers for a diversified range of tasks.

Course Outcomes

COs	Description
CO1	Understand the Evolutionary Computation paradigm
CO2	Understand sophisticated encoding techniques (i.e. generative and developmental systems)
CO3	Understand the theory and working of neuroevolution algorithms
CO4	Apply the neuroevolution algorithms for real-world learning tasks

Prerequisites

- Data Structures and Algorithms
- Programming
- Linear Algebra

Syllabus

Topics in Evolutionary Computation (EC): Canonical Evolutionary Algorithms (EAs), Unified View of Simple EAs, Components of EAs, Working with EAs, Interactive EAs, Coevolutionary Systems, Evolutionary Algorithms as problem solvers.

Neuroevolution: Classic Neuroevolution – combining ANNs and EC, classic obstacles, NeuroEvolution of Augmenting Topologies (NEAT), Post-NEAT methods, Generative and Developmental Systems – CPNNs, Novelty Search, Quality Diversity.

Neuroevolution at scale: Evolutionary Algorithms as scalable alternative to Reinforcement/deep learning, Meta-learning and Architecture Search. Evolving Plastic Artificial Neural Networks (EPANNs) – Evolutionary discovery of learning, Evolving neuromodulation, evolving plasticity.

Text Book / References

1. A.E. Eiben and J. E. Smith, Introduction to Evolutionary Computing 2nd Edition, Springer (Natural Computing Series), 2015.
2. Gene I Sher, Handbook of Neuroevolution through Erlang, Springer, 2012.
3. Kenneth A. De Jong, Evolutionary Computation A Unified Approach, MIT Press, March 2016 (Paperback Edition)
4. Ian Goodfellow, Yoshua Bengio and Aaron Courville, Deep Learning, MIT Press, 2016.
5. Richard S. Sutton and Andrew G. Barto, Reinforcement Learning – An Introduction, MIT Press, Second Edition, 2018.
6. Dario Floreano and Stefano Nolfi, Evolutionary Robotics – The Biology, Intelligence, and Technology of Self-Organizing Machines, MIT Press, 2004 (Paperback Edition)

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the Evolutionary Computation paradigm	1	-	1	-	-
CO2	Understand sophisticated encoding techniques (i.e. generative and developmental systems)	2	-	1	-	1
CO3	Understand the theory and working of neuroevolution algorithms	2	-	1	-	2
CO4	Apply the neuroevolution algorithms for real-world learning tasks	3	-	3	-	1

Evaluation Pattern - 70:30

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation – 40%
End Semester Exam - 30%

21AI719 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 - CircuitRepresentation - Speeding up the Traveling Salesman Problem - The Generate-and-Test Method - Quantum Problem-Solving - Heuristic Search - Quantum Tree Search - Tarrataca's Quantum Pro- duction 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

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation – 40%
End Semester Exam - 30%

21AI720 Knowledge Graphs 2-0-2-3

Preamble

This course focuses on foundations of knowledge graphs, building knowledge graphs, and querying & analysing large real world graphs.

Course Objectives

- Exploring knowledge graphs.
- Empirical study and hands-on experience on real world knowledge graphs

Course Outcomes

COs	Description
CO1	Understanding the key concepts in network & knowledge graphs
CO2	Study the building of knowledge graphs; crawling web sites, structured data extraction, and information extraction from unstructured text.
CO3	Understand the foundations and techniques of the Semantic Web, including RDF, ontology, SPARQL, and linked data.
CO4	Gaining experience to work with graph databases, organizing the data for efficient access, and query the contents.
CO5	Apply the big data tools and infrastructure such as *Spark* to build and query knowledge graphs.

Prerequisites

- Fundamental knowledge on machine learning and deep learning techniques.
- Working knowledge in *Python for data science*.

Syllabus

Properties of Graphs- Networks and their representation,Structure of complex networks, Clustering, Measures and metrics- Degree centrality, Eigenvector centrality, Katz centrality, PageRank, Hubs and authorities, Graph spectra, Graph Laplacian, Structure of WWW & Web Graphs, Query pro- cessing on graph structures.

Knowledge Graph Fundamentals, Building knowledge graphs- algorithms for crawling web sites, structured data extraction, and information extraction from unstructured text, Knowledge repre- sentation & entity linking. Basics of semantic web, Graph Representation, RDF, RDF Schema, ontology and RDF mapping tools, SPARQL, and linked data.

Knowledge Graph Applications- Reasoning over knowledge graphs- rule induction based, distributed representation and neural network based reasoning. Querying knowledge graphs, knowledge graphs and search engine, Graph embedding and probabilistic models, machine learning for graph em- bedding. Working with graph databases-Neo4j, Large and real world knowledge graphs: Google's Knowledge Graph, Knowledge Vault, DBPedia and Freebase.

Text Book / References

1. Manning, Christopher D., Hinrich Schütze, and Prabhakar Raghavan. Introduction to information retrieval. Cambridge university press, 2008.

2. Fensel, Dieter, Umutcan Şimşek, Kevin Angele, Elwin Huaman, Elias Kärle, Oleksandra Panasiuk, Ioan Toma, Jürgen Umbrich, and Alexander Wahler. Knowledge Graphs. Springer International Publishing, 2020.

3. Pan, J.Z., Vetere, G., Gomez-Perez, J.M. and Wu, H. eds., 2017. Exploiting linked data and knowledge graphs in large organisations (p. 281). Heidelberg: Springer.

4. Tiddi, I., Lécué, F. and Hitzler, P. eds., 2020. Knowledge Graphs for eXplainable Artificial Intelligence: Foundations, Applications and Challenges (Vol. 47). IOS Press.

5. **Additional References**

    - Hogan, A., Blomqvist, E., Cochez, M., d'Amato, C., de Melo, G., Gutierrez, C., Gayo, J.E.L., Kirrane, S., Neumaier, S., Polleres, A. and Navigli, R., 2020. Knowledge graphs. arXiv preprint arXiv:2003.02320.
    - Nickel, M., Murphy, K., Tresp, V. and Gabrilovich, E., 2015. A review of relational machine learning for knowledge graphs. Proceedings of the IEEE, 104(1), pp.11-33.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understanding the key concepts in network & knowledge graphs		2		3	
CO2	Study the building of knowledge graphs; crawling web sites, structured data extraction, and information extraction from unstructured text.	1	2			
CO3	Understand the foundations and techniques of the Semantic Web, including RDF, ontologies, SPARQL, and linked data.	2		3		
CO4	Gaining experience to work with graph databases, organizing the data for efficient access, and query the contents.			1	2	
CO5	Apply the big data tools and infrastructure such as *Spark* to build and query knowledge graphs.				2	3

Evaluation Pattern - 70:30

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation – 40%
End Semester Exam - 30%

21AI721 Integer Programming: Theory and Computations 2-0-2-3

Course Outcomes

After completing this course, the students will be able to

COs	Description
CO1	Understand and appreciate the necessary theory behind solutions to different integer programming problems and develop skills to understand research papers in the domain.
CO2	Rightly formulate different engineering problems, wherever applicable, as Integer programming problem.
CO3	Develop skills to use different tools available for finding solutions to Integer programming problems.

Syllabus

Effective modeling in integer programming-Modeling with integer variables: correct formulations, Optimality, relaxation, bounds, search: branch–and–bound, Choices in modeling: strong formulations, extended formulations, Preprocessing of formulations. Relaxation and decomposition methods for large–scale problems-Describing polyhedra with extreme points and extreme rays, Connections between integer programming and polyhedral, Lagrangian relaxation, Subgradient optimization-Applications: traveling salesman problem, facility location problems, generalized assignment problem, Dantzig–Wolfe decomposition, column generation, Applications: generalized assignment and multicommodity flow problems, Benders decomposition, Applications: facility location, networkdesign problems. Cutting plane methods for unstructured problems-Integer and mixed–integer rounding, Gomory cuts, disjunctive cuts. Cutting plane methods for structured problems-Affineindependence, dimension and faces of polyhedral Strong valid inequalities, facets, Valid inequali- ties for set packing and 0–1 knapsack problems and their separation, Sequential lifting, Sequence independent lifting, Applications: airline crew scheduling, production lot–sizing, facility locationproblems, network design.

Text Book / References

1. G. L. Nemhauser and L. A. Wolsey, Integer and Combinatorial Optimization, Wiley, 1999.
2. L. A. Wolsey, Integer Programming, Wiley, 1998
3. A. Schrijver, Theory of Linear and Integer Programming, Wiley, 1998.
4. Y. Pochet and L.A. Wolsey, Production Planning by Mixed Integer Programming, Springer, 2006.
5. D. Bertsimas and R. Weismantel, Optimization over Integers, Dynamics Ideas, 2005.

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and appreciate the necessary theory behind solutions to different integer programming problems and develop skills to understand research papers in the domain	3	3	2	2	2
CO2	Rightly formulate different engineering problems, wherever applicable, as Integer programming problem.	3	3	3	2	2
CO3	Develop skills to use different tools available for finding solutions to Integer programming problems.	3	3	3	2	3

CO-PO Mapping

Evaluation Pattern - 70:30

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation – 40%
End Semester Exam - 30%

21AI722 Data Pre-processing and Feature Engineering 2-0-2-3

Course Outcomes

COs	Description
CO1	Understand the structure and quality of datasets and its impact on the outcomes of learning algorithms.
CO2	Develop an in-depth and comprehensive knowledge of techniques related to extracting features from raw data.
CO3	Develop the skill to build data pipelines by collecting, cleaning, and validating datasets and assessing data quality.
CO4	Perform processing of the features and still obtain improved performance while reducing the cost of computation.
CO5	Study the tools/libraries/frameworks needed for feature extraction and processing from both structured and unstructured data.

Syllabus

Data – Representation of data, Imbalanced data, Data level approach, Algorithmic Ensemble Techniques, Bias in Data, Interpreting models- LIME, SHAP, ELI5, Identifying outliers in data, Discretization of data, Locality Sensitive Hashing (LSH). Dimensionality Reduction, Visualising high-dimensional datasets using t-SNE.

Quantitative and Qualitative data types, Missing data imputation, Feature scaling, Normalization, Standardization, Encoding Categorical Data – Encoding techniques, combine multiple categorical variables. Correlation, Collinearity & Multicollinearity. Structured data - Generating polynomial features, Feature selection techniques.

Unstructured Data. Text Data - Web scraping, Parsing, Tokenization, Distance measures, Spelling correction, n-gram, Text normalization, Stop word removal, Stemming & Lemmatization, syntactic similarity vs semantic similarity, Sentiment analysis, Text models, Word embedding techniques. Image/Video Data - Invariance, pre-processing techniques. Audio Data - Fast Fourier transform, Speed perturbation, Time-Frequency analysis, Vibration analysis, Mel Frequency Cepstral Coefficients (MFCCs), Noise suppression, Echo cancellation.

Text Book / References

1. Data Preparation for Machine Learning: Data Cleaning, Feature Selection, and Data Transforms in Python, by Jason Brownlee.
2. Feature Engineering and Selection: A Practical Approach for Predictive Models, by Max Kuhn and Kjell Johnson.
3. The Art of Feature Engineering: Essentials for Machine Learning, by Pablo Duboue.
4. Bad Data Handbook: Cleaning Up The Data So You Can Get Back To Work 1st Edition by Q. Ethan McCallum.
5. Data Wrangling with Python: Tips and Tools to Make Your Life Easier, by Jacqueline Kazil & Katharine Jarmul.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the structure and quality of datasets and its impact on the outcomes of learning algorithms.	3	3	1	–	1
CO2	Develop an in-depth and comprehensive knowledge of techniques related to extracting features from raw data.	3	3	1	–	1
CO3	Develop the skill to build data pipelines by collecting, cleaning, and validating datasets and assessing data quality.	3	3	1	-	1
CO4	Perform processing of the features and still obtain improved performance while reducing the cost of computation.	3	3	3	-	1
CO5	Study the tools/libraries/frameworks needed for feature extraction and processing from both structured and unstructured data.	3	3	3	1	1

Evaluation Pattern - 70:30

Periodical 1 - 15%
Periodical 2 - 15%
Continuous Evaluation – 40%
End Semester Exam - 30%

21AI723 Negotiated Studies/Online Course 3-0-0-3

Preamble

This course is a self-study course and offered as an elective during third semester.

Course Outcomes

COs	Description
CO1	To acquire knowledge and skills by aggravating the self-learning abilities of the students.
CO2	To enhance the quality of learning by doing courses from global online platforms.

Syllabus

The syllabus includes course objectives, topics of study and references such as books, research articles (thesis, review articles, published articles in journals and book chapters), online study materials. The study can also involve programming, implementation, testing and performance analysis. Besides, students can do courses from online platforms (Coursera, EdX, NPTEL, SWAYAM etc) related to their field of study, for acquiring knowledge and skills. Students will be required to make two in-class presentation and prepare an article (or report), possibly with a publishable quality. The seminars, article and skills achieved through online courses will be evaluated for grading purposes. The evaluation will be done by a panel of at least two Faculty members. It should be ensured that the area or the topic chosen for the Negotiated studies is not the same as the Thesis topic during third and fourth semester.

Department can also decide to evaluate this course completely based on an online course with a minimum duration of 8 weeks.

The faculty member/ class committee has the flexibility of choosing an apt evaluation method depending upon the course objectives and syllabus as per the University norms.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	To acquire knowledge and skills by aggravating the self-learning abilities of the students.	1	1	1	2	3
CO2	To enhance the quality of learning by doing courses from global online platforms.	2	3	3	2	2

21AI798 Dissertation Phase I 10

Course Objectives

The student is expected to carry out supervised research in this course. An intensive literaturein the chosen area, should result in sound knowledge in the area and result in the identificationof 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%

21AI799 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.