Title	**Data structures and practices**	Number	CSXXX
Department	Computer Science and Engineering	L-T-P [C]	0–0–2 [1]
Offered for	M.Tech. 1st Year	Type	Compulsory
Prerequisite	Computer Programming		

Objectives

The Instructor will:

1. Explain various data structures and provide details to implement and use them in different algorithms

Learning Outcomes

The students are expected to have the ability to:

1. Write, debug and rectify the programs using different data structures
2. Expertise in transforming coding skills into algorithm design and implementation

Contents

Laboratory Experiments

Exercises based on

Abstract Data Types: Arrays, linked-list/list, hash tables, dictionaries, structures, *stack, queues* (4 labs)

Data Structures: Heap, Sets, Sparse matrix, Binary Search Tree, B-Tree/ B+ Tree, Graph (4 labs)

Algorithm implementation: Quick or Merge sort, Breadth or Depth first search or Dijkstra's Shortest Path First algorithm, Dynamic programming (6 labs)

Textbook

1. Weiss, M. A. (2007), Data Structures and Algorithm Analysis in C++, Addison-Wesley.
2. Lipschutz, S. (2017), Data Structures with C, McGraw Hill Education.
3. Cormen, T. H., Leiserson, C. E., Rivest, R. L. and Stein, C., (2009), Introduction to Algorithms, MIT Press

Title	**Artificial Intelligence-1**	Number	CSXXXX
Department	Computer Science and Engineering	L-T-P [C]	3–0–0 [3]
Offered for	M.Tech. 1st Year, Ph.D. 1st Year	Type	Compulsory
Prerequisite	None		

Objectives

The Instructor will:

1. Cover various paradigms that come under the broad umbrella of AI, with some of them being covered in depth

Learning Outcomes

The students are expected to have the ability to:

1. Develop an understanding of where and how AI can be used

Contents

Introduction (1 lecture)
Propositional logic (8 lectures)
Search: Uninformed strategies (BFS, DFS, Dijkstra), Informed strategies (A* search, heuristic functions, hill-climbing), Adversarial search (Minimax algorithm, Alpha-beta pruning) (10 lectures)
Predicate logic: Knowledge representation, Resolution (6 lectures)
Rule-based systems: Natural language parsing, Context free grammar (3 lectures)
Constraint satisfaction problems (4 lectures)
Planning: State space search, Planning Graphs, Partial order planning (4 lectures)
Uncertain Reasoning: Probabilistic reasoning, Bayesian Networks, Dempster-Shafer theory, Fuzzy logic (6 lectures)

Textbook

1. Russel,S., and Norvig,P., (2015), *Artificial Intelligence: A Modern Approach*, 3rd Edition, Prentice Hall

Reference Books

1. Research literature

Self Learning Material

1. Department of Computer Science, University of California, Berkeley, http://www.youtube.com/playlist?list=PLD52D2B739E4D1C5F
2. NPTEL: Artificial Intelligence, https://nptel.ac.in/courses/106105077/

Title	**Artificial Intelligence-2**	Number	CSXXXX
Department	Computer Science and Engineering	L-T-P [C]	3–0–0 [3]
Offered for	M.Tech. 1st Year, Ph.D. 1st Year	Type	Compulsory
Prerequisite	Artificial Intelligence-1		

Objectives

The Instructor will:

1. Cover modern paradigms of AI that go beyond traditional learning

Learning Outcomes

The students are expected to have the ability to:

1. Develop an understanding of modern concepts in AI and where they can be used
2. Design, implement and apply novel AI techniques based on emerging real-world requirements

Contents

(fractal 1) *Probabilistic Reasoning over time:* Hidden Markov Models, Kalman Filters, Dynamic Bayesian Networks (7 lectures)
Knowledge Representation: Ontological engineering, Semantic Networks, Description Logics (7 lectures)
(fractal 2) *Making decisions:* Utility theory, utility functions, decision networks, sequential decision problems, Partially Observable MDPs, Game Theory (14 lectures)
(fractal 3) *Reinforcement Learning:* Passive RL, Active RL, Generalization in RL, Policy Search, Deep Reinforcement Learning (14 lectures)

Textbook

1. Russel,S., and Norvig,P., (2015), *Artificial Intelligence: A Modern Approach*, 3rd Edition, Prentice Hall

Reference Books

1. Research literature

Title	**Machine Learning-1**	Number	CSXXXX
Department	Computer Science and Engineering	L-T-P [C]	3–0–0 [3]
Offered for	M.Tech. 1st Year, Ph.D. 1st Year	Type	Compulsory
Prerequisite	None		

Objectives

The Instructor will:

1. Provide motivation and understanding of the need and importance of Machine Learning in today's world
2. Provide details about various algorithms in Machine Learning

Learning Outcomes

The students are expected to have the ability to:

1. Develop a sense of Machine Learning in the modern context, and independently work on problems relating to Machine Learning
2. Design and program efficient algorithms related to Machine Learning, train models, conduct experiments, and deliver ML-based applications

Contents

(fractal 1) *Introduction:* Motivation, Different types of learning, Linear regression, Logistic regression (2 lectures)
Gradient Descent: Introduction, Stochastic Gradient Descent, Subgradients, Stochastic Gradient Descent for risk minimization (2 lectures)
Support Vector Machines: Hard SVM, Soft SVM, Optimality conditions, Duality, Kernel trick, Implementing Soft SVM with Kernels (4 lectures)
Decision Trees: Decision Tree algorithms, Random forests (2 lectures)
Nearest Neighbour: k-nearest neighbour, Curse of dimensionality (1 lecture)
Neural Networks: Feedforward neural networks, Expressive power of neural networks, SGD and Backpropagation (3 lectures)
(fractal 2) *Clustering:* Linkage-based clustering algorithms, k-means algorithm, Spectral clustering (2 lectures)
Dimensionality reduction: Principal Component Analysis, Random projections, Compressed sensing (2 lectures)
Generative Models: Maximum likelihood estimator, Naive Bayes, Linear Discriminant Analysis, Latent variables and Expectation-maximization algorithm, Bayesian learning (4 lectures)
Feature Selection and Generation: Feature selection, Feature transformations, Feature learning (3 lectures)
Model selection and validation: Validation for model selection, k-fold cross-validation, Training-Validation-Testing split, Regularized loss minimization (3 lectures)
(fractal 3) *Statistical Learning Framework:* PAC learning, Agnostic PAC learning, Bias-complexity tradeoff, No free lunch theorem, VC dimension, Structural risk minimization, Adaboost (7 lectures)
Foundations of Deep Learning: DNN, CNN, RNN, Autoencoders (7 lectures)

Textbook

1. Shalev-Shwartz,S., Ben-David,S., (2014), *Understanding Machine Learning: From Theory to Algorithms*, Cambridge University Press

Reference Books

1. Mitchell Tom (1997). *Machine Learning,* Tata McGraw-Hill

Self Learning Material

1. Department of Computer Science, Stanford University, https://see.stanford.edu/Course/CS229

Title	**Machine Learning-2**	Number	CSXXXX
Department	Computer Science and Engineering	L-T-P [C]	3–0–0 [3]
Offered for	M.Tech. 1st Year, Ph.D. 1st Year	Type	Compulsory
Prerequisite	Machine Learning-1		

Objectives

The Instructor will:

1. Provide technical details about various recent algorithms and software platforms related to Machine Learning with specific focus on Deep Learning.

Learning Outcomes

The students are expected to have the ability to:

1. Design and program efficient algorithms related to recent machine learning techniques, train models, conduct experiments, and develop real-world ML-based applications and products

Contents

(fractal 1) *Model Search:* Optimization, Regularization, AutoML (4 lectures)
Deep Networks: Attention layers, Gated CNNs, Graph Neural Networks (8 lectures)
Applications: Neural language models (2 lectures)
(fractal 2) *Representation Learning:* Unsupervised pre-training, transfer learning and domain adaptation, distributed representation, discovering underlying causes (7 lectures)
Structured models: learning about dependencies, inference and approximate inference, sampling and Monte Carlo Methods, Importance Sampling, Gibbs Sampling, Partition Function, MAP inference and Sparse Coding, Variational Inference (7 lectures)
(fractal 3) *Deep Generative Models:* Deep Belief Networks, Variational Autoencoder, Generative Adversarial Network (GAN), Deep Convolutional GAN, Autoencoder GANs, iGAN, pix2pix, CycleGAN, Conditional GANs, StackGAN (14 lectures)

Laboratory Experiments

Overview of Deep Learning platforms such Tensorflow and PyTorch.

Textbook

1. Goodfellow,I., Bengio.,Y., and Courville,A., (2016), *Deep Learning*, The MIT Press

Reference Books

1. Research literature

Self Learning Material

1. https://www.deeplearningbook.org/