INDIAN INSTITUTE OF TECHNOLOGY JODHPUR

M.Tech (DCS)
Program Course Curriculum
July-2025

Department of Mathematics

Department of Mathematics
Proposed Curriculum
M.Tech. (DCS)

Cat.	*Course Number, Course Title*		*L-T-P*	*Credits*		*Cat.*	*Course Number, Course Title*		*L-T-P*	*Credits*
I Semester						**II Semester**				
C	MAL7XX0	Foundations of Data Science	3-0-0	3		C	CSL7XX0	*Deep Learning*	3-0-0	3
C	CSL7XX0	Machine Learning	3-0-0	3		E	Xxxxx	*Elective*	3-0-0	3
C	MAL7XX0	Data Analytics	2-0-2	3		E	Xxxxx	*Elective*	3-0-0	3
E	Xxxxx	Elective	3-0-0	3		E	Xxxxx	*Elective*	3-0-0	3
NG1	HSN7XX0	Technical Communication	1-0-0	S/X		NG2	HSN7XX0	*Professional Ethics*	1-0-0	S/X
			Total	**12**					*Total*	**12**
III Semester						**IV Semester**				
T	MAT8XXo	Thesis		16		T	MAT8XX0	Thesis		16
			Total	**16**					*Total*	**16**

Electives

S.No.	Course Number	*Course Title*		
1	MAL7XX0	Financial Engineering	3-0-0	3
2	MAL8XX0	Computational Game Theory	3-0-0	3
3	CSL7XX0	Natural Language Understanding	3-0-0	3
4	CSL7XX0	Artificial Intelligence	3-0-0	3
5	MAL7XX0	Time Series Analysis	3-0-0	3
6	CSL7XX0	Cryptography	3-0-0	3
7	CSL7XX0	Graph Theory and Applications	3-0-0	3
8	CSL7XX0	Algorithm for Big Data	3-0-0	3
9	MAL7XX0	Multi-Objective Optimization	3-0-0	3
10	CSL7XX0	*Digital Image Analysis*	3-0-0	3
11	QCL7XX0	*Quantum Cryptography and Coding*	3-0-0	3
12	QCL7XXX	*Quantum Inspired Optimization*	2-0-2	3

S.No.	*Category*	*Course Category Title*	*Total Courses*	*Total Credits*
1	C	*COMPULSORY*	4	12
2	E	*ELECTIVES*	4	12
3	NG	*Non-Graded*	2	2
3	T	Thesis	**2 (16+16)**	32
		Total		**58**

Note: 1. The department should retain only the relevant courses as electives for the M.Tech. program. The courses that are either irrelevant or not attracting more than 10 students should be removed from the PG booklet.

Course (Credit) Requirements for PhD students

S.No.	Ph.D. in	With	Minimum courses required
1.	Engineering discipline	M.Tech., M.E. or M.Sc. (Engineering) in an Engineering discipline	4 Compulsory
		M.Sc. degree in a Science discipline	4 Compulsory (Same as M.Tech. Compulsory) + 4 Electives
		B.Tech., B.S., B.E. or B.Sc. (Engineering) in an Engineering discipline	4 Compulsory (Same as M.Tech. Compulsory) + 4 Electives
2.	Science, Humanities or Social Science discipline	M.Sc., M.A. and M.Phil. degree in a Science, Humanities or Social Science discipline	4 Compulsory
3.	Management, Design	As per approved norms after 2 years of Masters degree in appropriate discipline	4 Compulsory

Note:

1. Departments can design various sets of compulsory courses based on their research themes. These courses can either be existing ones or new courses introduced by the department.
2. The four compulsory courses account for a minimum of 12 credits as per the current regulations.
3. Direct Ph.D. students holding a B.Tech. degree can choose to pursue an additional M.Tech. degree by fulfilling the M.Tech. thesis requirements. The M.Tech. thesis work must be separate from the Ph.D. thesis. The additional degree will be awarded alongside the Ph.D. degree only upon the completion of the Ph.D. program.

Content of Core courses:

Title	**Foundations of Data Science**	Number	MAL7XX0
Department	Mathematics	L-T-P-D [C]	3–0–0-0 [3]
Offered for	M.Tech. (DCS)	Type	Compulsory
Prerequisite			

Objectives

The Instructor will:

1. Provide an understanding statistical concepts for data scientist.
2. Train the student to do Matrix Computations for implementing various numerical linear algebra algorithms.
3. Train student in the domain of linear and non-linear programming.

Learning Outcomes

The students are expected to have the ability to:

4. Derive distributional results needed for the statistical hypothesis testing and perform the hypothesis testing for the parameters of the normal population.
5. Understand the numerical linear algebraic methods and their usage for data analysis.
6. Apply programming concepts for further applications in different areas of interest.

Contents:

Statistical Techniques:

Probability Models and Sampling Techniques [3 Lectures]: Normal, Chi-Square and t distributions, Basic concepts of random sampling, sampling from normal distribution, properties of sample mean and sample variance.

Estimation [5 Lectures]: Problem of point estimation, Unbiased estimation, Maximum likelihood estimators, Shortest length confidence intervals for mean and variance of normal population

Tests of Hypotheses [5 Lectures]: Basic concepts of statistical hypotheses testing, critical regions, Type-I and Type-II errors, size and power of a test, tests for one-sample and two-sample problems from normal populations.

Matrix Computations:

Matrix Algebra [3 Lectures]: Matrix operations and type of matrices, Rank of Matrix, Eigenvalues, Eigenvectors and Diagonalizable matrices, Vector Norms, Matrix Norms.

Decompositions [8 Lectures]: Spectral decomposition, Schur Decomposition, QR Factorization, Singular value decomposition (SVD), Polar Decomposition, Pseudo Inverse.

Approximations [2 Lectures]: Least square approximations, Low-Rank Approximation.

Optimization Techniques:

Unconstrained Optimization [7 Lectures]: Convex set, Convex function, First and second order conditions, Gradient descent method, Application in linear and nonlinear regression

Constrained Optimization [6 Lectures]: Karush-Kuhn-Tucker conditions, Lagrange multiplier method, Interior point method, Application in SVM.

Text Books

1. Casella, G. and Berger, R. (2002), Statistical Inference, Cengage Learning.
2. Ross, S.M. (1996), Stochastic Processes, Wiley.
3. Mayer, C.D. (2000) Matrix Analysis and Applied Linear Algebra, SIAM.
4. Kambo, N. S., *Mathematical Programming Techniques*, Second Edition, Affiliated East West Press, 2005
5. Beck, Amir: *First-order methods in optimization*. Society for Industrial and Applied Mathematics, 2017.

Reference Books

1. Rohatgi, V.K. and Saleh, A.K.M.E. (2018). An Introduction to Probability and Statistics, Wiley.
2. Ross, S.M. (2010). An Introduction to Probability Models, Elsevier.
3. M Goloub, G.H. and Charles, F.V.L. (2013) Matrix Computations, JHU Press.
4. Lancaster, P. and Tismenetsky, M. (1985) The Theory of Matrices: With Applications, Academic Press.
5. Bazaraa, M. S., Sherali, H.D., and Shetty, C. M., Nonlinear *Programming: Theory and Algorithms*, Third Edition, Wiley publications, 2006

Online course Material

1. Agrawal, P.N., Numerical Linear Algebra, NPTEL course material, Department of Mathematics, Indian Institute of Technology Roorkee, https://nptel.ac.in/courses/111107106/
2. Goswami A., Chakraborty D., *Optimization,* NPTEL Course Material, Department of Mathematics, Indian Institute of Technology Kharagpur, https://nptel.ac.in/courses/111105039/

Title	Machine Learning	Number	CSL7XX0
Department	Computer Science and Engineering	L-T-P [C]	3-0-0 [3]
Offered for	M.Tech. (DCS)	Type	Compulsory
Prerequisite	Introduction to Computer Sc., Probability, Statistics and Stochastic Processes, Linear Algebra	Antirequisite	IML, PRML

Objectives

1. To understand various key paradigms for machine learning approaches
2. To familiarize with the mathematical and statistical techniques used in machine learning.
3. To understand and differentiate among various machine learning techniques.

Learning Outcomes

The students are expected to have the ability to:

1. To formulate a machine learning problem
2. Select an appropriate pattern analysis tool for analyzing data in a given feature space.
3. Apply pattern recognition and machine learning techniques such as classification and feature selection to practical applications and detect patterns in the data.

Contents:

Introduction [6 Lectures]: Definitions, Datasets for Machine Learning, Different Paradigms of Machine Learning,
Data Normalization, Hypothesis Evaluation, VC-Dimensions and Distribution, Bias-Variance Tradeoff, Regression (Linear)
Bayes Decision Theory [5 Lectures]: Bayes decision rule, Minimum error rate classification, Normal density and discriminant functions
Parameter Estimation [2 Lectures]: Maximum Likelihood and Bayesian Parameter Estimation
Discriminative Methods [5 Lectures]: Distance-based methods, Linear Discriminant Functions, Decision Tree, Random Decision Forest and Boosting
Feature Selection and Dimensionality Reduction [4 Lectures]: PCA, LDA, ICA, SFFS, SBFS
Clustering [4 Lectures]: k-means clustering, Gaussian Mixture Modeling, EM-algorithm
Kernel Machines [5 Lectures]: Kernel Tricks, SVMs (primal and dual forms), K-SVR, K-PCA
Artificial Neural Networks [4 Lectures]: MLP , Backprop, and RBF-Net
Foundations of Deep Learning [4 lectures]: DNN, CNN, Autoencoders

Text Books

1. Shalev-Shwartz,S., Ben-David,S., (2014), Understanding Machine Learning: From Theory to Algorithms, Cambridge University Press
2. R. O. Duda, P . E. Hart, D. G. Stork (2000), Pattern Classification, Wiley-Blackwell, 2nd Edition.

Reference Books

1. Mitchell Tom (1997). Machine Learning, Tata McGraw-Hill
2. C. M. BISHOP (2006), Pattern Recognition and Machine Learning, Springer-Verlag New York, 1st Edition.

Online course Material

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

Title	**Data Analytics**	Number	MAL7XX0
Department	Mathematics	L-T-P-D [C]	2–0–2-0 [3]
Offered for	M.Tech.(DCS)	Type	Compulsory
Prerequisite			

Objectives
The Instructor will:
1. Introduce the basics of data science and its underlying concepts.
2. Introduce data processing, manipulation and cleaning techniques.
3. Enable students to be able to analyze the data using R.

Learning Outcomes
The students are expected to have the ability to:
1. Acquire familiarity with the basic concepts of data science.
2. Distinguish between different kinds of data and data governance.
3. Understand the preparation and processing of the data.
4. Comprehend What R is and how it's used to perform data analysis.

Contents
Data Analysis [12 Lectures]: Data preparation, Data pre-processing, Data Cleaning, Data Integration, Data Transformation, Data Reduction, Redundancy Removal, Data storage, Data Handling, Querying Data, Data Representation and Exploration, Big Data.

Central tendency of data and Variation in data [7 Lectures]: Arithmetic Mean, Median, Quantiles, Mode, Geometric Mean and Harmonic Mean, Range, Interquartile Range and Quartile Deviation, Absolute Deviation and Absolute Mean Deviation, Mean Squared Error, Variance and Standard Deviation, Coefficient of Variation and Boxplots.

Moments, Association of Variables [7 Lectures]: Central Moments, Absolute Moments and Computation of Moments, Skewness and Kurtosis, Univariate and Bivariate Scatter Plots, Quantile in 3D plots, Correlation Coefficient, Rank Correlation Coefficient, Measure of Association for Discrete and Counting Variables, Least Squares Method.

Lab using R: Implementation of concepts learnt using R.

Text Books
1. Kotu, V. and Deshpande, B. (2018) Data Science: Concepts and Practice, Morgan Kaufmann.
2. Saltz, J.S. and Stanton, J.M. (2017) An Introduction to Data Science, SAGE Publications.
3. Wickham, H. and Grolemund, G. (2016) R for Data Science: Import, Tidy, Transform, Visualize, and Model Data, 'O'Reilly Media, Inc.
4. Toomey, D. (2014) R for Data Science, Packt Publishing Ltd.

Reference Books
1. Kelleher, J.D., and Tierney, B. (2018) Data Science, MIT Press.
2. Moreira, J., Carvalho, A. and Horvath, T. (2018) A General Introduction to Data Analytics, John Wiley & Sons.
3. Mayer-Schonberger, V. and Cukier, K., (2013) Big data: The essential guide to work, life and learning in the age of insight, John Murray Publications.
4. Knell, R.J. (2014) Introductory R: A Beginner's Guide to Data Visualization

Online course Material
Not Available

Title	Deep Learning	Number	CSL7XX0
Department	Computer Science and Engineering	L-T-P [C]	3-0-0 [3]
Offered for	M.Tech. (DCS)	Type	Compulsory
Prerequisite	Machine Learning	Antirequisite	Deep Learning (400)-CSL4xx

Objectives

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

Learning Outcomes

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 DL-based applications and products

Contents:

Deep Networks [7 Lectures]: CNN, RNN, LSTM, Attention layers, Applications

Techniques to improve deep networks [6 Lectures]: DNN Optimization, Regularization, AutoML

Representation Learning [7 Lectures]: Unsupervised pre-training, transfer learning, and domain adaptation, distributed representation, discovering underlying causes

Auto-DL [6 Lectures]: Neural architecture search, network compression, graph neural networks (6 lectures)

Probabilistic Generative Models [3 Lectures]: DBN, RBM

Deep Generative Models [10 Lectures]: Encoder-Decoder, Variational Autoencoder, Generative Adversarial Network (GAN), Deep Convolutional GAN, Variants and Applications of GANs

Text Books

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

Reference Books

1. Charniak, E. (2019), Introduction to deep learning, The MIT Press.
2. Research literature.

Online course Material

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

Content of Elective courses:

Title	**Financial Engineering**	Number	MAL7XX0
Department	Mathematics	L-T-P-D [C]	3–0–0-0 [3]
Offered for	M.Tech. (DCS)	Type	Elective
Prerequisite			

Objectives
The Instructor will:

1. Securities Pricing Securities, Risk Management Assessment, prediction and decision making, under uncertainty, regarding future events and their consequences
2. Portfolio Optimization Balancing risk and return
3. Modeling Pricing of derivatives and Itos calculus

Learning Outcomes
The students are expected to have the ability to:

1. Valuation of financial portfolio
2. Pricing of financial derivatives (options and contracts)
3. Understanding risk and return

Contents

[18 lectures] Introduction to financial markets and financial instruments, financial derivatives, risk and return, risky and risk free assets, interest rates, bonds, bonds pricing, spot and forward rates, investment portfolio, mean-variance analysis, capital asset pricing model, arbitrage pricing theory.

[21 lectures] Discrete time models, stock and money market models, principle of no arbitrage, pricing of contracts (forward and future), options, put-call parity, option pricing, martingales, Binomial model, CRR model, Black-Scholes formula, Greeks, random walk, Brownian motion, stochastic process, Itos integral and Ito-Deoblins formula.

Textbook

1. M. Capinski and T. Zastawniak (2010). Mathematics for finance: an introduction to financial engineering, Springer.
2. S.N. Neftci (2009). Principles of financial engineering. Academic Press/Elsevier.

Reference Books

1. J.C. Hull (2011). Options, futures and other derivatives. Pearson India.
2. S.E. Shreve (2000). Stochastic calculus for finance I: The binomial asset pricing model, Springer

Online Course Material
Not Available

Title	**Computational Game Theory**	Number	MAL7XX0
Department	Mathematics	L-T-P [C]	3–0–0–0 [3]
Offered for	M.Tech. (DCS)	Type	Elective
Prerequisite	Basics of Optimization Theory		

Objectives

1. Provide background in the area of computational game theory.
2. Provide sufficient knowledge of the subject which can be used by students for further applications in their respective domains of interest.

Learning Outcomes

1. Understanding of fundamentals like Nash equilibrium, dominant strategies and their applications.
2. Basic understanding of the Co-operative games, iterated games and mixed strategies.
3. Knowledge of non-co-operative games, Zermelo's algorithm and their applications.

Contents

[11 lectures]: Von Neumann and Morgenstern utility functions, expected utility and expected utility maximization, Paradoxes of expected utility maximization, Compact representations for preference relations, Dichotomous preferences and goals. Representations for specifying goals, Strategic Form Non-Cooperative Games, Basic model and solution concepts, pure strategy Nash equilibrium, dominant strategies, notable games, coordination games and focal points, complexity of pure strategy Nash equilibrium.

[13 Lectures]: Mixed strategies: Nash's theorem and Nash equilibrium, Computing mixed strategy Nash equilibria, Lemke-Howson algorithm, Zero sum games, Minimax Theorem, Compact representations for strategic form games, Boolean games, congestion games, Iterated Games: Finitely repeated games and backward induction, Infinitely repeated games, measuring utility over infinite plays modelling strategies as finite state machines with output (Moore machines); The Folk theorems, Iterated Boolean games, Axelrod's tournament, the Hawk-Dove game, evolutionary game theory, evolutionarily stable strategies.

[15 lectures]: Extensive Form Non-Cooperative Games: Zermelo's algorithm and backward induction, subgame perfect equilibrium, Zermelo's theorem, Compact representations for extensive form games, PEEK games and EXPTIME-completeness results, the Game Description Language (GDL), Imperfect information games, PEEK games with incomplete information, Cooperative Games: Transferable utility (TU) characteristic function games, basic model, stability & fairness solution concepts, cost of stability, Shapley value, Banzhaf index, induced subgraph representation, marginal contribution nets, Simple TU games, swap and trade robustness, weighted voting games, vector weighted voting games, network flow games, NTU games and their representations

Textbooks

1. G. Chalkiadakis, E. Elkind, and M Wooldridge, Computational Aspects of Cooperative Game Theory, Morgan-Claypool, 2011.
2. Machler, E. Solan, S. Zamir, Game Theory, Cambridge U.P., 2013.
3. M. J. Osborne, An Introduction to Game Theory, Oxford U.P., 2004.

Reference Books

1. R. D. Luce and H. Raiffa, Games and Decisions, Wiley, 1958
2. M. J. Osborne and A. Rubinstein, A Course in Game Theory, 1994.

Online course Material

Not Available

Title	Natural Language Understanding	Number	CSL7XX0
Department	Computer Science and Engineering	L-T-P [C]	3-0-0 [3]
Offered for	M.Tech. (DCS)	Type	Elective
Prerequisite	Deep Learning	Antirequisite	None

Objectives

The Instructor will:

1. To provide insights into fundamental concepts and algorithms related to Natural Language Understanding
2. Impart working expertise by introducing practical problems.

Learning Outcomes

The students are expected to have the ability to:

1. Formulate natural language understanding tasks
2. Design and implement basic applications of NLU

Contents:

Traditional NLU [13 Lectures]: Introduction to NLU, Motivation, Morphology, Parts-of-Speech, Language Models, Word Sense Disambiguation, Anaphora Resolution, Basics of Supervised and Semi-supervised Learning for NLU, Hidden Markov Models for language modeling, EM Algorithm, Structured Prediction, Dependency Parsing, Topic Models, Semantic Parsing, Sentiment analysis.

Deep Learning for NLU [20 Lectures]: Intro to Neural NLU, Word Vector representations, Neural Networks and backpropagation -- for named entity recognition, Practical tips: gradient checks, overfitting, regularization, activation functions, Recurrent neural networks -- for language modeling and other tasks, GRUs and LSTMs -- for machine translation, Recursive neural networks -- for parsing, Convolutional neural networks -- for sentence classification, Question answering and dialogue system, Graph Neural Network for NLU, Natural Language Generation, Analysis and Interpretability of Neural NLU.

Knowledge Graphs [6 Lectures]: Knowledge graph embedding techniques, Inference on knowledge graphs.

Text Books

1. C. MANNING, H. SCHÜTZE (1999), Foundations of Statistical Natural Language Processing, MIT Press.
2. D. JURAFSKY, J.H. MARTIN, Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics and Speech Recognition (3rd Edition Draft), 2019.

Reference Books

1. E. BENDER (2013), Linguistic Fundamentals for NLP , Morgan Claypool Publishers..
2. J. ALLEN (1995), Natural Language Understanding, Pearson Education, 1995.
3. Research Literature.

Online course Material

1. http://web.stanford.edu/class/cs224n/index.html#schedule (Deep learning for NLP)

Title	Artificial Intelligence	Number	CSL7XX0
Department	Computer Science and Engineering	L-T-P [C]	3-0-0 [3]
Offered for	M.Tech. (DCS)	Type	Compulsory (AI)
Prerequisite	Data Structures and Algorithms	Antirequisite	Artificial Intelligence (300) -CSL3XX

Objectives

The Instructor will:

1. Cover various paradigms that come under the broad umbrella of AI.

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 [9 Lectures]: Uninformed search strategies, Greedy best-first search, And-Or search, Uniform cost search, A* search, Memory-bounded heuristic search, Local and evolutionary searches

Constraint Satisfaction Problems [3 Lectures]: Backtracking search for CSPs, Local search for CSPs

Adversarial Search [4 Lectures]: Optimal Decision in Games, The minimax algorithm, Alpha-Beta pruning, Expectimax search

Knowledge and Reasoning [8 Lectures]: Propositional Logic, Reasoning Patterns in propositional logic; First order logic: syntax, semantics, Inference in First order logic, unification and lifting, backward chaining, resolution

Planning [3 Lectures]: Situation Calculus, Deductive planning, STRIPES, sub-goal, Partial order planner

Bayesian Network, Causality, and Uncertain Reasoning [5 lectures]: Probabilistic models, directed and undirected models, inferencing, causality, Introduction to Probabilistic reasoning

Reinforcement Learning [7 Lectures]: MDP , Policy, Q-value, Passive RL, Active RL, Policy Search

Text Books

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

Reference Books

1. Research literature

Online course 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	Time Series Analysis	Number	MAL7XXX
Department	Mathematics	L-T-P [3]	3-0-0 [3]
Offered for	M.Tech.(DCS)	Type	Elective
Prerequisite	Probability, Statistics and Random Processes		

Objectives

1. To provide working knowledge of time series techniques and forecasting methods
2. To provide with techniques and receipts for estimation and assessment of quality of econometric models with time series data

Learning Outcomes

1. To develop the skills needed to do empirical research in "elds operating with time series data sets

Contents:

Models for Time Series [8 Lectures] Time series data, trend, seasonality, cycles and residuals, strong and weak stationarity, autocorrelation function, linear processes, estimation of mean and covariance functions, Wold decomposition Theorem.

Models of stationary process [8 Lectures] ARMA (p, q) processes, ACF and PACF, Modeling using ARMA processes, estimation of parameters, testing model adequacy, Order estimation.

Univariate Forecasting Models [7 Lectures] Prediction in stationery processes, special reference to ARMA processes, Frequency domain analysis – spectral density and its estimation, transfer functions.

Multivariate Forecasting Models [7 Lectures] Single equation models, Vector AR and ARMA models, econometric models

Non-stationary Models [9 Lectures] Stationarity through differencing, ARIMA model, ARMAX, ARIMAX models and introduction to ARCH models. Indicative Assignments: Analysis of real data (namely, NEON data, IMD data, etc.) using different
time series models

Text Books

1. Blockwell, P. J. and Davis, R. A. (2017). Introduction to Time Series and Forecasting, 2nd Edition, Springer.
2. Chat"eld, C. (2004) The Analysis of Time Series – An Introduction, Chapman and Hall / CRC, 4 th ed.

Reference Books

1. Box, G.E.P., Jenkins, G. and Reinsel, G. (1994) Time Series Analysis-Forecasting and Control, 3rd ed., Pearson Education

Online course Material

1. Mikusheva, Anna, Time Series Analysis, Department of Economics, Massachusetts Institute ofTechnology, MIT OpenCourseware Course Material, https://ocw.mit.edu/courses/economics/14-384-time-series-analysis-fall-2013/recitations/

Title	Cryptography	Number	CSL 7480
Department	Computer Science	L-T-P [C]	3-0-0 [3]
Offered for	M.Tech. (DCS)	Type	Elective
Prerequisite	None		

Objectives

1. Introduce students to the domain of Symmetric and Asymmetric Cryptography, and develop an appreciation for some applications in which Cryptography is used in real-life.

Learning Outcomes

1. Learn to model security of various cryptographic primitives as an adversarial game.
2. Learn the design principles of Block ciphers, stream ciphers, hash functions, MAC's, public key encryption, and digital signatures.
3. Identify novel and significant open research questions in the field.
4. Using cryptographic primitives to design some real life protocols, such as ZKP, coin tossing over insecure-channel, and MPC.

Contents:

Foundations [9 lectures): Attacking Toy ciphers, Kerchofs law, Perfect security, OWE, PRG, PRF, PRP

Symmetric key cryptography [11 lectures]: Block ciphers, stream ciphers, hash functions, MAC, authenticated encryption.

Asymmetric Key cryptography [11 lectures]: DKHE, RSA, El Gamal cryptosystems (with required mathematical foundations), Elliptic Curve Cryptography, Digital signatures, Public Key Infrastructure and Digital certificates.

Cryptographic protocols [8 lectures]: Secure multiparty computation, Zero knowledge proofs, Oblivious transfer etc.

Text Books

1. Katz, Lindell: Theory of modern cryptography, CRC Press, 3rd Edition.
2. Hoffstein, Pfipher, Silverman: Introduction to mathematical cryptography

Reference Books

NA

Online course Material

https://nptel.ac.in/courses/106106221

Title	**Graph Theory and Applications**	Number	CSL7XX0
Department	Computer Science and Engineering	L-T-P [C]	3-0-0 [3]
Offered for	M.Tech. (DCS)	Type	Elective
Prerequisite	None	Antirequisite	None

Objectives

The Instructor will:

1. Introduce various terminologies, concepts and algorithms related to graphs, and discuss their applications in real-world scenarios.

Learning Outcomes

The students are expected to have the ability to:

1. Formulate and solve real-world problems using the mathematical foundations of graph theory.

Contents:

Preliminaries [3 lectures]: Graphs, Isomorphism, Subgraphs, Matrix representations, Degree, Operations on graphs, Degree sequences
Connected graphs and shortest paths [4 lectures]: Walks, Trails, Paths, Connected graphs, Distance, Cut-vertices, Cut-edges, Blocks, Connectivity, Weighted graphs, Shortest path algorithms
Trees [3 lectures]: Characterizations, Number of trees, Minimum spanning trees
Special classes of graphs [2 lectures]: Bipartite graphs, Line graphs, Chordal graphs
Eulerian graphs [2 lectures]: Characterization, Fleury's algorithm, Chinese-postman-problem
Hamilton graphs [3 lectures]: Necessary conditions and sufficient conditions
Independent sets, coverings, matchings [5 lectures]: Basic equations, Matchings in bipartite graphs, Perfect matchings, Greedy and approximation algorithms
Vertex colorings [2 lectures]: Chromatic number and cliques, Greedy coloring algorithm, Coloring of chordal graphs, Brook's theorem
Edge colorings [4 lectures]: Gupta-Vizing theorem, Class-1 graphs and Class-2 graphs, Equitable edge-coloring
Planar graphs [3 lectures]: Basic concepts, Euler's formula, Polyhedrons and planar graphs, Characterizations, Planarity testing, 5-color-theorem
Directed graphs [4 lectures]: Out-degree, In-degree, Connectivity, Orientation, Eulerian directed graphs, Hamilton directed graphs
Applications [4 lectures]: Biology, Social Sciences, Engineering, Computer Science

Text Books

1. West,D.B., (2002), Introduction to Graph Theory, 2nd Edition, Prentice Hall of India
2. Deo,N., (2003), Graph Theory: With Application to Engineering and Computer Science, Prentice Hall of India

Reference Books

2. Research literature

Online course Material

NPTEL: Graph Theory (for CSE), https://nptel.ac.in/courses/106108054/39
NPTEL: Graph Theory (for Mathematics), https://nptel.ac.in/courses/111106050/

Title	Algorithm for Big Data	Number	CSL7XX0
Department	Computer Science and Engineering	L-T-P [3]	3-0-0 [3]
Offered for	M.Tech. (DCS)	Type	Elective
Prerequisite	None	Antirequisite	None

Objectives
The Instructor will:

1. Introduce some algorithmic techniques developed for handling large amounts of data.
2. Emphasize both theoretical as well as practical aspects of such algorithms.

Learning Outcomes
Students are expected to have the ability to:

1. Design and Analyzing existing algorithms as well as design novel algorithms pertaining to big data.

Contents:
Introduction [7 lectures]: Randomized algorithms, Universal hash family, Probabilistic algorithm analysis, Approximation algorithms, ε-Approximation schemes, Sublinear time complexity, Sublinear Algorithms.

Property Testing [10 lectures]: Testing list's sortedness or monotonicity, Distribution testing Testing properties of bounded degree graphs, Dense graphs and General graphs.

Sketching and Streaming [10 lectures]: Extremely Small-Space Data Structures, CountMin Sketch, Count Sketch, Linear Sketching, AMS Sketch, Turnstile Streaming, Graph Sketching, Graph Connectivity

MapReduce [6 lectures]: MapReduce Algorithms in Constrains Settings such as small memory, few machines, few rounds, and small total work, Efficient Parallel Algorithms

External memory and cache-obliviousness [6 lectures]: Minimizing I/O for large datasets, Algorithms and data structures such as B-trees, Buffer trees, Multiway merge sort

Text Books
NA

Reference Books
NA

Online course Material
NA

Self Learning Material

1. Department of Computer Science, Harvard University, Algorithms for Big Data
2. https://www.sketchingbigdata.org/
3. "Introduction to Property Testing" (link) by Oded Goldreich
4. http://grigory.us/big-data.html

Title	**Multi-objective Optimization**	Number	MAL7XXX
Department	Mathematics	L-T-P [C]	3-0-0 [3]
Offered for	M.Tech. (DCS)	Type	Elective
Prerequisite			

Objectives

1. Introduce multi-objective optimization.
2. Introduce evolutionary computations and using these to solve nonlinear optimization problems.
3. Application of multi-objective optimization.

Learning Outcomes

1. Understand the ideas of evolutionary computations and multi-objective optimization.
2. Understand the advantages of multi-objective optimization.
3. Solving single and multi-objective optimization problems using evolutionary computations.
4. Implementation of multi-objectvie optimization in some engineering problems.

Contents:

Evolutionary optimization [10 lectures]: Introduction to evolutionary optimization, genetic algorithms, mathematical models of genetic algorithms. Evolutionary programming and evolution strategies, antcolony optimization and particle swarm optimization

Multi-objective Optimization [6 lectures]: Partial ordering with respect to a pointed cone, non dominated sorting, introduction to multi-objective optimization, applications of multi objective optimization, solution of a multi-objective optimization problem, efficient, week efficient proper efficient solution, ideal and nadir vector. Multi-objective decision making

Classical methods for solving multi objective optimization [6 lectures]: Weighted sum method, ϵ-constrained method, goal programming technique, weighted metric methods, lexicographic ordering method. Advantages and limitations of classical methods

Multi-objective optimization using evolutionary algorithm [7 lectures]: Evolutionary algorithms for multi-obicative optimization - binary and real coded genetic algorithm NSGA-II, NSGA-III, particle swarm optimization for multi objective optimization, implementation of evolutionary algorithms

Application of Multi-objective optimization in polynomial time problems [5 lectures]: shortest path problems, spanning trees, assignment problems

Application of Multi-objective optimization in NP hard problems [5 lectures]: Knapsack problems, branch and bound problems, and travelling salesman problems, application of multi-objective optimization in engineering

Text Books

1. Dan Simon, Evolutionary Optimization Algorithms, Wiley, 2013
2. K. Deb, Multiobjective optimization using evolutionary algorithms, Wiley, 2003
3. M. Ehrgott, Multicriteria optimization, Springer, 2005

Reference Books

1. R Fletcher, Practical Methods of Optimization, 2nd Edition, Wiley, 2000
2. K. Miettinen, Nonlinear Multiobjective Optimization, Kluer Academic Publications, 1999.

Online course Material

1. D. Sharma, Evolutionary Computation for Single and Multiobjective Optimization, Department of Mechanical Engineering, IIT Guwahati , NPTEL course materials, https://nptel.ac.in/ courses/112/103/112103301/
2. K. Deb, Introduction to Optimization and its Scope in Practice, GIAN - MHRD, IIT Kharagpur video lectures, https://www.youtube.com/watch?v=4mZp_-SApks&list=PLBNAhOTc16q9CyTPoJzrklUQE3zPujwyf&t=2s

Title	*Digital Image Analysis*	Number	CSL7XX0
Department	Computer Science and Engineering, EE	L-T-P [C]	3-0-0 [3]
Offered for	M.Tech. (DCS)	Type	Elective
Prerequisite	Linear Algebra	Antirequisite	None

Objectives
The Instructor will:
1. To introduce the origin and formation of digital imaging.
2. To develop the understanding of different types of imaging techniques for different purposes.
3. To equip the students with various possible applications of image analysis.

Learning Outcomes
Students are expected to have the ability to:
1. Enhance image in spatial and frequency domain.
2. Implement various aspects of image segmentation and compression.

Contents:
Digital Image Fundamentals [3 Lectures]: Image modeling, Sampling and Quantization, Imaging Geometry, Digital Geometry, Image Acquisition Systems, Different types of digital images

Image Transforms [7 Lectures]: Basic transforms: Spatial and Frequency Domain Transforms

Image Enhancement [7 Lectures]: Point processing, interpolation, enhancement in spatial domain, enhancement in frequency domain

Color Image Processings [3 Lectures]: Color Representation, Laws of color matching, chromaticity diagram, color enhancement, color image segmentation, color edge detection

Image compression [4 Lectures]: Lossy and lossless compression schemes, prediction based compression schemes, vector quantization, sub-band encoding schemes, JPEG compression standard

Morphology [5 Lectures]: Dilation, erosion, opening, closing, hit and miss transform, thinning, extension to grayscale morphology, Euler technique

Segmentation [5 Lectures]: Segmentation of grey level images, Watershed algorithm for segmenting grey level image

Feature Detection [5 Lectures]:Fourier descriptors, shape features, object matching/features

Text Books

1. C. GONZALEZ, R.E. WOODS (2018), Digital Image Processing, Prentice Hall, 4th Edition.
2. A.K. JAIN (1989), Fundamentals of Digital Image Processing, Prentice Hall.

Reference Books
NA

Online course Material
1. https://nptel.ac.in/courses/117104020/

Title	Quantum Cryptography and Coding	Number	QCL7XX0
Department	IDRP-QIC	L-T-P [C]	3–0–0 [3]
Offered for	M.Tech (DCS)	Type	Elective
Prerequisite			

Objectives

The Instructor will:

1. Introduce the students to the fascinating field of cryptography and coding, with specific emphasis on the quantum aspects of it.
2. Highlight a number of facets of these theories having some parallel with the more familiar classical world.

Learning Outcomes

The students are expected to have the ability to:

1. Understand the fundamental principles of quantum cryptography and coding.
2. Become familiar with the modern aspects of the theory, including its experimental implementation.

Contents:

Cryptography [10 Lectures]: Various aspects of modern cryptography; number theoretic concepts

Classical Coding Theory [6 Lectures]: Concepts of entropy, mutual information and related aspects; Shannon's coding theorem.

Basic concepts of Quantum Mechanics [5 Lectures]: From the perspective of information and cryptography: Hilbert space, states, operators: Hermitian and Unitary, simple measurements.

Some basic no-go theorems [2 Lectures]: With implications to cryptography.

Some basic applications pertinent to quantum cryptography [12 Lectures]: Entanglement, teleportation, dense coding, Quantum Key Distribution protocols: BB84, B92, Ekert protocol, Goldenberg-Vaidman, counterfactual quantum cryptography; protocols of quantum dialogue; Quantum secret sharing protocol; Quantum cheating and cryptography; Protecting information and QKA (quantum key agreement); Shor's factoring algorithm and modern cryptography; Experimental progress in quantum cryptography.

Quantum Coding [4 Lectures]: Quantum aspects of Shannon coding theorem. (4 Lectures)

Text Books

1. Nielsen Michael, A. and Chuang Isaac , I., (2010), Quantum Computation and Quantum Information, Cambridge University Press, 2010.

Reference Books

1. Benenti, G., Casati, G., and Strini, G., (2004) Principles of Quantum Computation and Information, World Scientific Press, 2004
2. Bouwmeester, D., Ekert, A. and Zeilinger, A., (2000) The Physics of Quantum Information, 2nd edition, Springer, 2000

Online course Material

1. Shor, P., Quantum Computation,MIT Open Course, 18.435J Fall 2003, Link https://ocw.mit.edu/courses/mathematics/18-435j-quantum-computation-fall-2003/

Title	**Quantum Inspired Optimization**	Number	MAL7XXX
Department	Mathematics	L-T-P [C]	2-0-2 [3]
Offered for	MSc, M.Tech and Ph. D. Students	Type	Elective
Prerequisite	Any nonlinear optimization course and basic concepts of quantum introduction.		

Objectives

1. Introduce quantum computing in optimization.
2. Formulation and solution of different optimization problems in quantum way.
3.

Learning Outcomes

1. Learn to solve different optimization problems using quantum annealers and digital quantum computer
2. Learn about more general optimization problems and about the Variational Quantum Eigen-solver

Contents:

Introduction of optimization [2 lecture]: General optimization problem, local/global solution, integer programming, binary knapsack programming and applications

Quadratic unconstrained binary optimization problems [5 lectures]: Max cut problem and Ising model, Formulating the problem in quantum way, Moving from Ising to QUBO and back, Combinatorial optimization problems with QUBO model, Application in Knapsack problems, Graph colouring etc.

Adiabatic Quantum computing and quantum annealing [5 lectures]: Adiabatic quantum computing, Quantum annealing, Constrained quadratic models in Ocean, Running constrained problem on quantum annealing

Quantum approximate optimization algorithm [3 lectures]: From adiabatic to QAOA,Using QAOA with Qiskit, Using QAOA with PennyLane

Grover adaptive search [3 lectures]: Grover's algorithm, Quantum oracles for combinatorial optimization, Using GAS with Qiskit

Quantum computing for Pseudo-Boolean Optimization [4 lectures]: Basic transformations,Hadamard transform, σx transform, k-local Hamiltonian Problems,Graph structures and optimization problems

Variational Quantum Eigensolver [5 lectures]: Hamiltonians, observables, and their expectation values, Introduction of Variational Quantum Eigensolver, Using VQE with Qiskit, Using VQE and PennyLane

Text Books

1. Elias F. Combarro, Samuel Gonzalez-Castillo: A Practical Guide to Quantum Machine Learning and Quantum Optimization, Pact Publishing Ltd., Birmingham, 2023.
2. W. Cruz-Santos, G. Morales-Luna: Approximability of Optimization Problems through Adiabatic Quantum Computation, Morgan & Claypool Publishers, California, USA

Reference Books

NA

Online course Material

1. Advances for Quantum-Inspired Optimization by INFORMS https://www.youtube.com/watch?v=qdrXL8HL3cQ