NATIONAL INSTITUTE OF TECHNOLOGY WARANGAL



Minor in

APPLIED AND COMPUTATIONAL MATHEMATICS

SCHEME OF INSTRUCTION AND SYLLABI

(for all B.Tech. students)

(Effective from 2021-22)

DEPARTMENT OF MATHEMATICS

SCHEME OF INSTRUCTION

Minor Program – Applied and Computational Mathematics

S. No.	Course Code		L	T	P	Credits	Sem.
1	MAM01	Mathematical Foundations for Machine Learning	3	0	0	3	III
2	MAM02	Statistics for Data Science	3	0	0	3	IV
3	MAM03	Computational Methods and Design of Experiments	3	0	0	3	V
4	MAM04	Search Methods in Artificial Intelligence	3	0	0	3	VI
5	MAM05	Fuzzy Logic and Applications	3	0	0	3	VII
6	MAM06	Mathematics with Applications in Finance	3	0	0	3	VIII
		Total	**16**	**0**	**4**	**18**	

Course Code: MAM01	Mathematical Foundations for Machine Learning	Credits 3-0-0: 3

Course Outcomes:

At the end of the course, the student will be able to:

CO1	Understand the concepts of Vector space and inner-product spaces
CO2	Apply the linear algebra concepts in approximations and matrix decompositions
CO3	Understand functions of several variables, gradients relevant for machine learning
CO4	Apply optimization techniques in real life problems
CO5	Acquire sound mathematical aspects of machine learning

Syllabus:

Linear Algebra: Vector spaces, linear independence, basis, linear transformations, coordinates, matrix representation of linear transformations, affine spaces, affine mappings; inner-product spaces – inner products and norms on a vector space, lengths, angles, orthogonal complements, projections, least square approximations, Gram-Schmidt process, rotations; matrix decompositions – Cholesky decomposition, eigen decomposition and diagonalization, singular value decomposition;

Calculus and Optimization: Functions of several variables, gradients of matrices, useful identities for computing gradients, backpropagation and automatic differentiation, gradients in a deep network, linearization and multivariate Taylor series; optimization using gradient descent, constrained optimization using Lagrange multipliers, convex optimization - convex sets, convex functions, linear programming, quadratic programming, Legendre-Fenchel Transform and convex conjugates

Mathematical aspects in Machine Learning: Linear Regression and parameter estimation; Dimensionality reduction - Principal Component Analysis, linear discriminant analysis; Density estimation with Gaussian mixture models; classification with support vector machines – separating hyperplanes, primal and dual support vector machines, kernels;

Learning Resources:

Text Books:

1. Mathematics for Machine Learning, **Mark Peter Deisenroth, A. Aldo Faisal and Cheng Soon Ong**, Cambridge University Press, 2020

Reference Books:

1. Linear Algebra, **Stephen H. Friedberg, Arnold J. Insel and Lawrence E. Spence**, Pearson, 2019, Fifth Edition
2. Linear Algebra and Learning from Data, **Gilbert Strang**, Wellesley-Cambridge Press, 2019
3. Linear Algebra and Optimization for Machine Learning, **Charu C. Aggarwal**, Springer, 2020

Course Code: MAM02	Statistics for Data Science	Credits 3-0-0: 3

Course Outcomes:

At the end of the course, the student will be able to:

CO1	Understand functions of one random variable, functions of multiple random variables with all relevant parameters
CO2	Utilize the knowledge of random variables, distributions in multivariate analysis
CO3	Apply the concepts of regression in predictive models
CO4	Understand the concept of dimension reduction and PCA
CO5	Learn the concepts about KKN, K-means clustering and Naïve Baye's classifier

Syllabus:

Random Variables: Brief overview of random variables, known special probability distributions; Functions of one random variable – mean, variance, moments;

Multivariate Analysis: Two random variables – bivariate distributions, joint distributions; functions of multiple random variables - Expectation, Scatter plots and spread, Variance and standard deviation, Covariance and correlation, Inequalities; Multiple continuous random variables; Averages of random variables, Jointly Gaussian random variables;

Regression: Brief overview of simple linear regression; Multiple linear regression; logistic regression;

Multivariate Description and Dimension Reduction: Overfitting, Principal component analysis, log-linear models;

Brief Introduction to: K Nearest Neighbours, K means clustering, Naïve Baye's classifier

Learning Resources:

Text Books:

1. Probability, Random Variables, and Stochastic Processes, **Athanasios Papoulis and S. Unnikrishnan Pillai**, Mc-Graw Hill, 2002, Fourth Edition
2. Applied Statistics and Probability for Engineers, **Douglas C. Montgomery and George C. Runger**, John Wiley & Sons, 2018, Seventh Edition
3. Machine Learning: An Applied Mathematics Introduction, **Paul Wilmott**, Panda Ohana Publishing, 2019

Reference Books:

1. Probability and Statistics for Data Science: Math + R + Data, **Norman Matloff**, CRC Press, 2020
2. Univariate, Bivariate, and Multivariate Statistics using R, **Daniel J. Denis**, John Wiley & Sons, 2020

Course Code: MAM03	Computational Methods and Design of Experiments	Credits 3-0-0: 3

Course Outcomes:

At the end of the course, the student will be able to:

CO1	Understand the concepts of statistical learning
CO2	Apply Monte Carlo methods
CO3	Discover the concepts behind supervised and unsupervised learning
CO4	Learn the concepts connected with regularization methods and classification
CO5	Design and analyse single-factor and multi-factors experiments

Syllabus:

Statistical Learning: Supervised and unsupervised learning; Modelling data – linear, multivariate Gaussian and Bayesian models; collinearity; multicollinearity; auto-correlation;

Monte Carlo Methods: Monte Carlo sampling – generating random numbers, simulating random variables, random vectors; Monte Carlo estimation – bootstrap method, variance reduction; Monte Carlo optimization – simulated annealing, cross-entropy method, splitting for optimization;

Unsupervised Learning: Expectation-Maximization algorithm; clustering via mixture models; clustering via vector quantization – K-means; hierarchical clustering;

Brief Introduction to: regularization and Kernel methods – kernel Hilbert spaces; Classification – metrics, classification via Baye's rule, K-Nearest Neighbors classification;

Design of Experiments: Design and analysis of single-factor experiments - completely randomized single factor experiment; the analysis of variance; the random effects model; randomized complete block design – latin squares design and related designs; Design of experiments with several factors – factorial and general factorial experiments; 2^k-factorial designs;

Learning Resources:

Text Books:

1. Data Science and Machine Learning: Mathematical and Statistical Methods, **Dirk P. Kroese, Zdravko I. Botev, Thomas Taimre, Radislav Vaisman**, CRC Press, 2020
2. Applied Statistics and Probability for Engineers, **Douglas C. Montgomery and George C. Runger**, John Wiley & Sons, 2018, Seventh Edition

Reference Books:

1. Statistical Design and Analysis of Experiments with Applications to Engineering and Science, **Robert Mason, Richard F. Gunst and James L. Hess**, Wiley-Interscience, 2003, Second Edition
2. Design and Analysis of Experiments, **Douglas C. Montgomery**, John Wiley & Sons, 2001, Fifth Edition

Course Code: MAM04	Search Methods in Artificial Intelligence	Credits 3-0-0: 3

Course Outcomes:

At the end of the course, the student will be able to:

CO1	Apply search-based algorithms to solve problems
CO2	Construct decomposition and rule-based methods
CO3	Explain the relation between search methods and other with other formulations
CO4	Solve problems using stochastic, local, and population-based search algorithms
CO5	Implement game playing algorithms

Syllabus:

Introduction: History and philosophy. The Turing Test. The Winograd Schema Challenge. State space search. Depth first, breadth First, DFID, comparison

Heuristic Search: Heuristic functions. Solution space search. Escaping local optima, Stochastic local search. Population based methods. Genetic algorithms, emergent systems, ant colony optimization

Finding Optimal Paths: Algorithm A*. Admissibility of A*. The monotone condition. Space saving versions of A*. Sequence alignment

Game Playing: Board games. Algorithms Minimax, Alpha-Beta, and SSS*. Automated domain independent planning. Goal Stack Planning, Partial Order Planning. Algorithm Graphplan. Problem decomposition with goal trees. Algorithm AO*

Inference Systems: Pattern directed inference systems. Forward chaining inference engine. The Rete algorithm. Deduction as search. Logic. Forward chaining, backward chaining. Incompleteness

Constraint Processing: Waltz algorithm. Model based diagnosis. Arc consistency. Combining search and reasoning

Learning Resources:

Text Books:

1. A First Course in Artificial Intelligence, **Deepak Khemani**, McGraw Hill Education, 2013 (Chapters 1 – 8, some parts from Chapters 9 and 10)

Reference Books:

1. Artificial Intelligence: The Very Idea, A Bradford Book, **John Haugeland**, The MIT Press, 1985
2. Machines Who Think: A Personal Inquiry into the History and Prospects of Artificial Intelligence, **Pamela McCorduck**, A K Peters/CRC Press, 2004, Second Edition
3. How to Solve It: Modern Heuristics, **Zbigniew Michalewicz and David B. Fogel**, Springer, 2004, Second Edition
4. Artificial Intelligence: A Modern Approach, **Stuart Russell and Peter Norvig**, Prentice Hall, 2009, Third Edition

Course Code: MAM05	Fuzzy Logic and Applications	Credits 3-0-0: 3

Course Outcomes:

At the end of the course, the student will be able to:

CO1	Explain real-world imprecision using fuzzy logic
CO2	Compare Propositional Logics for inference rules
CO3	Define Fuzzy Relations
CO4	Construct fuzzy-logic based approximate reasonings
CO5	Apply fuzzy rule-based methods to engineering problems

Syllabus:

Crisp set theory (CST): Introduction, Relations between sets, Operations on sets, Characteristic functions, Cartesian products of crisp sets, crisp relations on sets.

Fuzzy set theory (FST): Introduction, concept of fuzzy set (FS), Relation between FS, operations on FS, properties of standard operations, certain numbers associated with a FS, certain crisp sets associated with FS, Certain FS associated with given FS, Extension principle.

Propositional Logic (PL1): Introduction, Syntax of PL1, Semantics of PL1, certain properties satisfied by connectives, inference rules, Derivation, Resolution.

Predicate Logic (PL2): Introduction, Syntax of PL2, Semantics of PL2, certain properties satisfied by connectives and quantifiers, inference rules, Derivation, Resolution

Fuzzy Relations (FR): Introduction, Operations on FR, Alpha-cuts of FR, Composition of FR, Projections of FR, Cylindrical extensions, cylindrical closure, FR on a domain.

Fuzzy Logic (FL): Introduction, Three-valued logics, N-valued logics and infinite valued logics, Fuzzy logics, Fuzzy propositions and their interpretations in terms of fuzzy sets, Fuzzy rules and their interpretations in terms of FR, fuzzy inference, More on fuzzy inference, Generalizations of FL Switching functions (SF) and Switching circuits (SC): Introduction, SF, Disjunctive normal form, SC, Relation between SF and SC, Equivalence and simplification of circuits, Introduction of Boolean Algebra BA, Identification, Complete Disjunctive normal form.

Applications: Introduction to fuzzy logic controller (FLC), Fuzzy expert systems, classical control theory versus fuzzy control, examples, working of FLC through examples, Details of FLC, Mathematical formulation of FLC, Introduction of fuzzy methods in decision making.

Learning Resources:

Text Books:

1. Introduction to Fuzzy Sets and Fuzzy Logic, **M. Ganesh**, PHI, 2009, First Edition (Reprint)
2. Fuzzy set theory and its applications, **H. J. Zimmermann**, Springer Science & Business Media, 2011, Fourth Edition

Reference Books:

1. Fuzzy Modeling and Genetic Algorithms for Data Mining and Exploration, **Earl Cox,** Elsevier

– Morgan Kaufmann Publishers, 2005
2. Knowledge Discovery and Data Mining: The Info-Fuzzy Network (IFN) Methodology, **Oded Maimon and Mark Last**, Springer, 2001
3. Fuzzy Sets and Fuzzy Logic: Theory and Applications, **G. J. Klir and B. Yuan**, Prentice-Hall of India Pvt. Limited, 2008, First Edition (Reprint)

Course Code: MAM06	Mathematics with Applications in Finance	Credits 3-0-0: 3

Course Outcomes:

At the end of the course, the student will be able to:

CO1	Understand the Simplest financial Model
CO2	Understand Central Limit Theorem Brownian Motion
CO3	Apply Black–Scholes Formula
CO4	Estimate the Volatility Parameter
CO5	Evaluate the Deterministic and Probabilistic Optimization Models

Syllabus:

Introduction: Probability - Random Variables- Central Limit Theorem- Brownian Motion.

Interest Rates and Present Value Analysis: Pricing Contracts via Arbitrage- The Arbitrage Theorem- The Black–Scholes Formula- Additional Results on Options: Call Options on Dividend-Paying Securities-Adding Jumps to Geometric Brownian Motion-Estimating the Volatility Parameter-Valuing by Expected Utility

Optimization Models: A Deterministic Optimization Model-A General Solution Technique Based on Dynamic Programming -A Solution Technique for Concave- Return Functions -The Knapsack Problem- Probabilistic Optimization Problems-A Gambling Model with Unknown Win Probabilities -An Investment Allocation Model

Data-Driven Finance: Fundamentals of data reduction and clustering applied specifically to financial data; derivative pricing – discretized and continuous approach

Learning Resources:

Text Books:

1. An Elementary Introduction to Mathematical Finance - Options and Other Topics, **Sheldon M. Ross,** Cambridge University Press, 2002
2. Mathematical Techniques in Finance: Tools for Incomplete Markets, **Ales Cerny**, Princeton University Press, 2009

Reference Books:

1. Introduction to Mathematical Finance: Discrete Time Models, **S. R. Pliska,** Blackwell Publishers Inc, 2002