Gujarat University

Master in Science (Artificial Intelligence and Machine Learning)

(M.Sc. – II (AI & ML))

Syllabus

Semester – II

(Effective from 2019 – 20)

NEW SCHEME FOR M. Sc. (Artificial Intelligence and Machine Learning)

SEMESTER - II (M.Sc. (AI & ML)) Applicable from January 2020 onwards

			TEACHING SCHEME			EXAMINATION SCHEME							
SR. NO.	SUBJECT NO.	NAME OF THE SUBJECT	THEORY HR	TUTO HR.	PRACT. HR.	SESSIONAL M.	SESSIONAL HR.	THEORY M.	THEORY HR	PRACT. M	PRACT. H	T.W.	TOTAL MARKS
1	MSCAI 121	Numerical Optimization	3	1	-	25	2	100	3	-	0	25	150
2	MSCAI 122	Advanced Python	4	-	3	25	2	100	3	50	3	25	200
3.	MSCAI 123	Machine Learning	4	0	3	25	2	100	3	50	3	25	200
4	MSCAI 124	Computer Vision	3	1	3	25	2	100	3	50	3	25	200
	MSCAI 125	Statistical Foundation	4	-	-	25	2	100	3	-	-	25	150
	MSCAI 126	Project - II	-	-	6	25	-	-	-	100	3	25	150
	TOTAL		18	2	12	150	-	500	-	250	-	150	1050

Course Name: Numerical Optimization

Course Code: MSCAI 121

Objectives:

To teach the student fundamental concepts of optimization both from the point of view of theory as well as practical implementation of algorithms relevant to Machine Learning applications.

Prerequisites:

- Undergraduate level course in Linear Algebra
- Undergraduate level course in Multivariable Calculus

Contents:

1. **Review of Multivariable Calculus**
   Multivariable functions, Partial Derivatives, Total Derivative, Vector Functions, Gradient, Physical interpretation of Gradient, Existence of Minimum and a Maximum, Continuity of Functions, Taylor's Theorem, Convex Functions

2. **Optimization Problem Formulation**
   Statement of an Optimization problem, Historical development, Classification of Optimization problems and techniques, Single variable optimization problem, Iterative algorithmic approach

3. **One Dimensional Unconstrained Optimization**
   Unimodality and bracketing, Fibonacci Method, Golden Section Method, Line search

4. **Unconstrained Optimization**
   Necessary and Sufficient conditions for optimality, Convexity, Steepest Descent Method, Hessian Matrix, Conjugate Gradient Method, Newton's Method, Quasi-Newton Method, Approximate Line Search

5. **Constrained Optimization**
   Necessary conditions for optimality, sufficient conditions for optimality, sensitivity of solution, Sequential Quadratic Programming, Duality, Exterior penalty functions, interior penalty functions

6. **Direct Search methods**
   Hooke-Jeeves Pattern Search, Powell's Methods of Conjugate directions, Nelder-Mead's, Simplex methods, Simulated Annealing, Genetic Algorithms

Reference Books:

1. "Optimization Concepts and Applications in Engineering"; Belegundu
2. "Engineering Optimization"; 2nd Edition; Ravindran & Reklaits
3. "Practical Methods of Optimization"; R. Fletcher

Accomplishments of the student after completing the Course:

After completion of this course, students will be able to formulate optimization problem and apply appropriate method and corresponding algorithm to obtain optimum value

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Course Name: Advanced Python

Course Code: MSCAI 122

Objectives:

This course will introduce advanced concepts of python implementations and the latest Machine Learning and Data analysis libraries such as NumPy, Pandas, Scikit-Learn, MatplotLib and TensorFlow to students. This course will be hands on with major focus on practical implementation of these concepts

- To understand and use functionality of various Python libraries for various scientific and mathematical tasks
- To gain basic insight of implementation of advanced concepts and use of various libraries for applying Machine Learning for problem solving

Prerequisites:

Fundamentals of Computers and basic Python

Contents:

1. Introduction

Review of Important Python Concepts, Overview of Advanced techniques in Python: Lambdas, Filter and map, is and id, Decorators, Iterators and Generators, Garbage Collector, environment, Exception handling, Interop module, Pickle, Marshal, Networking Concepts, Process and Threads, Sockets, Regular Expression

2. Scientific and Numerical Computing with Python

Introduction to Scientific and Numerical computing, Introduction to various modules used for Scientific and Numerical programming: NumPy; SciPy; Scikit-Learn; MatplotLib and Keras & Pandas, Introduction of Internal Statistics, overview of common approaches to multivariate statistics, Introduction to IPython

3. Implementation of Machine Learning concepts in Python

Introduction to Machine Learning Approaches, Overview of ML tasks: Supervised Learnings: Classifications; Regression, Unsupervised Learnings: Clustering, Semi-supervised Learning, Basics of implementation of Machine Learning modules using Python

4. **Introduction to Frameworks used with Python – TensorFlow**
   Concept of Computational Graph and Nodes, Virtual Environment and Anaconda, Installing TensorFlow with GPU support on a Linux System, TF Datatypes, Placeholders, TF Variables, TF Session, Softmax, One Hot Encoding, Dropout, building hidden layers, Batching, Stochastic Gradient Descent, Building an Optimizer, Training and displaying outcome, Overview of various python frameworks

5. **Introduction to Processing of Data Sets**
   Overview of various Data sets, Data handling Techniques: using Structured and unstructured Files; Excel Files and SQL Files; Data Preparation, Data munging and Data Analysis (using Pandas); Data Visualization (using MatplotLib, Pandas and Seaborn, Exploring duplicate data and missing data, Data fitting concepts, Introduction to collection modules, counter, data storage offline

Reference Books:

1. Rao N.R., "Core Python Programming", Dreamtech Publication India
2. Sarker M.O.F., "Python Network Programming Cookbook", Packt Publication
3. Sebastian Raschka, "Python Machine Learning", Packt Publication
4. Willi Richert, "Building Machine Learning Systems with Python", Packt publication
5. Fredrik Lundh, "Python Standard Library", O'Reilly Publications
6. Halterman R.,"Fundamentals of Python Programming", Southern Adventist University
7. Guttag J.V., "Introduction to Computation and Programming Using Python", Prentice Hall India
8. Chun W., "Core Python Programming", Prentice Hall India

Accomplishments of the student after completing the Course:

After completion of this course, students will be able to gain awareness about various libraries and able to solve challenging problems using Python programming language

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Course Name: Machine Learning

Course Code: MSCAI 123

Objectives:

Introduce the concept of learning patterns from data and develop a strong theoretical foundation for understanding of state of the art Machine Learning algorithms. To enable students to identify, formulate and solve machine learning problems that arise in practical applications.

Prerequisites:

- Undergraduate level course in Linear Algebra
- Undergraduate level course in Calculus

Contents:

1. Overview of Machine Learning

Introduction to Machine learning from data, Types of Machine Learning: Supervised, Unsupervised, Reinforcement, concepts of regression, classification, clustering

2. Linear Regression

Scatter diagram, Model representation for single variable, Single variable Cost Function, Least Square line fit, Normal Equations, Gradient Descent method for Linear Regression, Assumptions in linear regression, properties of regression line, Model Performance through R^2, Multivariable model representation, Multivariable cost function, multiple linear regression, Normal Equations and non-invertibility , Gradient Descent method for multiple linear regression , Overfitting, Underfitting, Bias and variance , Regularization

3. Logistic Regression

Issues of using Linear Regression in Classification, Sigmoid function, odds of an event, Logit function, Decision Boundary, Maximum Likelihood function, Linear regression verses Logistic Regression, Cost function, Multi-classification , confusion matrix, statistical measures to measure binary classification : Recall, sensitivity, specificity, precision, accuracy, pros and cons of logistic regression

4. Supervised Learning

Classification problems; decision boundaries; K nearest neighbour methods, Linear classifiers, Bayes' Rule and Naive Bayes Model, SVM - Introduction, Support Vectors & Margin, Optimization Objective, Linear & Non-Linear SVM, Hard Margin & Soft

Margin in, Large Margin Classifiers, Kernels, SVM practical considerations, Ensemble methods for classification and regression: Bagging, Random Forests, Boosting, Decision Tree

5. **Unsupervised learning**

Cluster Analysis, Classification and Clustering , Definition of Clusters ,Clustering Applications , Distance measures, Proximity Measures for Discrete Variables, Proximity Measures for Mixed Variables, Partitional Clustering, Clustering Criteria, K-Means Algorithm, Fuzzy Clustering , Hierarchical Clustering, Agglomerative Hierarchical Clustering, Divisive Hierarchical Clustering, Cluster Validity, External Criteria, Internal Criteria

Reference Books:

1. "Building Machine Learning Systems with Python"; Richert & Coelho; Packt Publishing Ltd.
2. "Data Science from Scratch"; Joel Grus; O'Reilly Publications
3. "MACHINE LEARNING: An Algorithmic Perspective; Stephen Marsland; CRC Press
4. "Clustering"; Rui Xu & Donald C. Wunsch II; IEEE Press
5. "Machine Learning"; Tom M. Mitchell; McGraw-Hill publications
6. "Machine Learning with SVM and other Kernel methods"; K.P. Soman R.Loganathan
7. "Introduction to Machine Learning"; Ethem Alpaydın; The MIT Press

Accomplishments of the student after completing the course:

After completion of the course, students should be able to:

- Develop an appreciation for what is involved in learning models from data
- Understand a wide variety of learning algorithms
- Understand how to evaluate models generated from data
- Understand and develop application involving computer vision and Natural Language Processing

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Course Name: Introduction to Computer Vision

Course Code: MSCAI 124

Objectives:

A.I. has major applications in Computer Vision, especially in object detection, recognition & classification. This course covers fundamentals of Image Processing and Computer Vision which plays an important role in fields such as Machine and Robot Intelligence. It provides means for machines and robots to interact intelligently with the outside world through visual perception like human vision. This course will provide sufficient background to prepare students for plentiful challenging applications in automation.

Prerequisites:

- Introductory course in Linear Algebra
- Introductory course in Calculus
- Introductory course in Probability

Contents:

1. **Introduction**
   Overview, Smoothing, Image Morphology, Flood Fill, Resize, Image Pyramids, Thresholding operation
2. **Image Transforms**
   Convolution, Gradients and Sobel Derivatives, Laplace, Canny & Hough Transforms, Remap, Stretch, Shrink, Warp, and Rotate, Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT), Integral Images, Distance Transform, Histogram Equalization
3. **Image Parts and Segmentation**
   Parts and Segments, Background Subtraction, Watershed Algorithm, Image Repair by Inpainting, Mean-Shift Segmentation, Delaunay Triangulation, Voronoi Tessellation
4. **Tracking and Motion**
   The Basics of Tracking, Corner Finding, Subpixel Corners, Invariant Features, Optical Flow, Mean-Shift & Camshift Tracking, Motion Templates, Estimators, Lucas-Kanade algorithm for optical flow, Multi-scale Lucas-Kanade algorithm, Comparison of Horn-Shunck and Lucas-Kanade algorithms, Applications of optical flow

5. Camera Models and Calibration

Developing Camera Model, Calibration -Concept of camera calibration and basic aim of camera calibration, Motivation for camera calibration - implications for 3D reconstruction using two calibrated cameras, Un-distortion, Putting Calibration Together, Rodrigues Transform

Reference Books:

1. "Image Processing: Analysis and Machine Vision"; Sonka & Hlavac
2. "Digital Image Processing"; Gonzalez
3. "Computer Vision: Algorithms and Applications"; Richard Szeliski; Springer-Verlag London Limited 2011

Accomplishments of the student after completing the course:

After completion of the course, students will:

- Have foundation of image formation, processing and analysis.
- Understand the geometric aspects of images in spatial and frequency domain.
- Gain exposure to object and image recognition with feature extraction, pattern analysis and geometric modeling
- Develop practical skills necessary to build computer vision applications including mining of visual content, image rendering, camera surveillance etc.

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Course Name: Probability and Statistics

Course Code: MSCAI 125

Objectives:

With the current deployment of computer technology and tools, it is very important to understand the concepts of Probability and Statistics to implement efficiency of algorithms for solving problems in science, engineering, technology, insurance & banking. Thus, the objective of this course is to enable students to obtain an intuitive and working understanding of probability and methods for the problems of analysis and prediction. Students will gain experience in the implementation of methods for data analysis and prediction using a computer. They would also gain an appreciation of the concept of error in these methods and the need to analyze and predict it.

Prerequisites:

Basic knowledge of Mathematics

Contents:

1. **Introduction to Probability**
   Basic probability concepts (Experiment, sample space, events, exclusive events, exhaustive events, independent events, dependent events), methods for assigning probability (Classical method, relative frequency method, subjective method, axiomatic method), events and their probability, addition rule, multiplication rule, conditional probability Posterior Probability, Bayes's theorem, Conditional Independence, concept of measure and sigma algebra

2. **Probability Distributions**
   Random variable, Discrete and continuous random variable, expected value and variance of random variable, *Probability distribution*: Joint probability distribution, Marginal Probability distribution, Conditional Probability distribution, *Standard Distributions:* Bernoulli distribution, Binomial distribution, Continuous probability distribution, Normal distribution

3. **Probabilistic Graphical Models**
   Bayesian Networks, Markov Models, Independencies, MAP Inference

4. Descriptive Statistics

Introduction to statistics, Data, Scales of measurements, Sample vs. population, Introduction to frequency distribution, *Measures of central tendency:* Mean, median, mode, weighted mean, *Measures of dispersion*: absolute and relative measures of range, quartile deviation, standard deviation, basic mathematical properties and applications of the measures, *Measures based on shape of distribution*: Skewness and Kurtosis (basic concepts only, introduction using curve, possible values of these measures, relationship (distance) between mean, median, mode, *Measures of association between two variables* (Correlation: for paired observations only): Covariance, *Types of correlation*: (+ve, -ve, 0), (Linear, non-linear), Karl Pearson's correlation coefficient, its mathematical properties, regression line

5. Statistical Inference

Sampling methods, Sampling distribution, central limit theorem (statement only), Hypothesis testing: Null & alternative hypothesis, Type I & II errors, one and two tailed test, rejection rule using p-value and critical value approach, Analysis of variance (1-way, two-way), Chi-square test for goodness of fit and independence

Reference Books:

1. "Numerical A First Course in Probability"; 9th Edition; Sheldon Ross
2. "An Introduction to Probability and Statistics"; 2nd Edition; Rohatgi & Saleh
3. "Probabilistic Graphical Models"; Daphne Koller & Nir Friedman
4. "Statistics for Management", Richard I Levin & David S Rubin, Pearson
5. " Introduction to Probability and Statistics", J. Susan Milton & Jesse C Arnold, McGraw Hill Publication

Accomplishments of the student after completing the course:

After completion of the course, students will be able to apply probability and statistical concepts for analysis and prediction from data and able to infer the result

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