AC – 11/07/2022
Item No. – 6.8 (R)

University of Mumbai

Revised Syllabus for

Masters of Science

(Computer Science with specialization in Data Science)

Semester – III & IV

(Choice Based Credit System)

(With effect from the academic year 2022-23)

University of Mumbai

Syllabus for Approval

O: ______________ Title of Course	**M.Sc. (Computer Science with specialization in Data Science)**
O: ______________ Eligibility	**As per University regulations**
Passing Marks	**40%**
Ordinances / Regulations (if, any)	As applicable for all M.Sc. Courses
No. of years/Semesters:	Two years – Four Semesters
Level:	**P.G.** ~~**/ U.G./**~~ ~~Diploma / Certificate~~
Pattern:	~~Yearly~~ / **Semester**
Status:	~~New~~ / **Revised**
To be implemented from Academic Year :	**From the Academic Year 2022 – 2023**

Date:

Signature:
Name:
Chairman of Ad-hoc/BoS of

Signature:
Dr. Anuradha Majumdar
Dean, Science and Technology

Semester III

Course Code	Course Title	Course Type	Credits
PSDS301	Advanced Machine Learning	DSC	4
PSDS302	Predictive Modeling and Analytics	DSC	4
PSDS303	Data Engineering	DSC	4
Select anyone from the following electives			
PSDS304a	Deep Reinforcement Learning	DSE	4
PSDS304b	Healthcare Analytics	DSE	
PSDS304c	Social Media Analytics	DSE	
PSDS3P1	Advanced Machine Learning Practical	DSC Practical	2
PSDS3P2	Predictive Modeling and Analytics Practical	DSC Practical	2
PSDS3P3	Data Engineering Practical	DSC Practical	2
PSDS3P4	Research Paper – I	DSE Practical	2
		Total	24

M. Sc (Data Science)			**Semester –III**	
Course Name: Advanced Machine Learning			**Course Code: PSDS301**	
Periods per week **1 Period is 60 minutes**	**Lectures**		**4**	
	Credits		**4**	
			Hours	**Marks**
Evaluation System	**Theory Examination**		**2½**	**60**
	Theory Internal		**--**	**40**

Objectives	● Understanding Human learning aspects. ● Understanding primitives for learnable computers. ● Understanding real world problems solved with Advanced Machine Learning.

Pre requisites	Knowledge of Algorithms and mathematical foundation

Unit	Details	Lectures
I	**Introduction:** Machine learning, Examples of Machine Learning Problems, Structure of Learning, learning versus Designing, Training versus Testing, Characteristics of Machine learning tasks, Predictive and descriptive tasks, Machine learning Models: Geometric Models, Logical Models, Probabilistic Models. Features: Feature types, Feature Construction and Transformation, Feature Selection.	**12**
II	A Formal Learning Model, PAC Learning, A More General Learning Model. Learning via Uniform Convergence: Uniform Convergence Is Sufficient for Learnability, Finite Classes Are Agnostic PAC Learnable The VC-Dimension: Infinite-Size Classes Can Be Learnable, The VC-Dimension, Examples, The Fundamental Theorem of PAC learning	**12**

III	**Linear Predictors:** Halfspaces, Linear Regression , Logistic Regression Boosting: Weak Learnability, AdaBoost , Linear Combinations of Base Hypotheses , AdaBoost for Face Recognition Model Selection and Validation: Model Selection Using SRM, Validation, What to Do If Learning Fails Convex Learning Problems: Convexity, Lipschitzness, and Smoothness, Convex Learning Problems, Surrogate Loss Functions	**12**
IV	Rademacher Complexities: The Rademacher Complexity, Rademacher Complexity of Linear Classes, Generalization Bounds for SVM, Generalization Bounds for Predictors with Low Norm Covering Numbers: Covering, From Covering to Rademacher Complexity via Chaining Proof of the Fundamental Theorem of Learning Theory: The Upper Bound for the Agnostic Case, The Lower Bound for the Agnostic Case, The Upper Bound for the Realizable Case Multiclass Learnability: The Natarajan Dimension, The Multiclass Fundamental Theorem, Calculating the Natarajan Dimension, On Good and Bad ERMs	**12**
V	**Probabilistic Model:** Normal Distribution and Its Geometric Interpretations, Naïve Bayes Classifier, Discriminative learning with Maximum likelihood, Probabilistic Models with Hidden variables: Estimation-Maximization Methods, Gaussian Mixtures, and Compression based Models. **Trends In Machine Learning :** Model and Symbols- Bagging and Boosting, Multitask learning, Online learning and Sequence Prediction, Data Streams and Active Learning, Deep Learning, Reinforcement Learning.	**12**

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Books and References:

Sr. No.	**Title**	**Author/s**	**Publisher**	**Edition**	**Year**
01	Machine Learning: The Art and Science of Algorithms that Make Sense of Data	Peter Flach	Cambridge University Press		2012
02	UNDERSTANDING MACHINE LEARNING From Theory to Algorithms	Shai Shalev-Shwartz, Shai Ben-David	Cambridge University Press		2014
03	Introduction to Statistical Machine Learning with Applications in R	Hastie, Tibshirani, Friedman	Springer	2nd	2012
04	Introduction to Machine Learning	Ethem Alpaydin	PHI	2nd	2013

Course Outcome

CO1: Understand the key issues in Machine Learning and its associated applications in intelligent business and scientific computing.

CO2: Acquire the knowledge about different learning models where a learner will be able to explore his skill to generate data base knowledge using the prescribed techniques.

CO3: Understand and implement the techniques for extracting the knowledge using advanced machine learning methods.

CO4: Achieve adequate perspectives of Advanced Machine learning methods.

CO5: Understand the statistical approach related to machine learning. He will also Apply the algorithms to a real-world problem, optimize the models learned and report on the expected accuracy that can be achieved by applying the models.

M. Sc (Data Science)		**Semester – III**	
Course Name: Advanced Machine Learning Practical		**Course Code: PSDS3P1**	
Periods per week (1 Period is 60 minutes)		**4**	
Credits		**2**	
		Hours	**Marks**
Evaluation System	**Practical Examination**	**2**	**50**
	Internal	**--**	**-**

List of Practical:	
	Two Practical Assignments on each unit of the syllabus. Total 10 practical questions to be carried out.

M. Sc (Data Science)		**Semester – III**	
Course Name: Predictive Modeling and Analytics		**Course Code: PSDS302**	
Periods per week **1 Period is 60 minutes**	**Lectures**	**4**	
	Credits	**4**	
		Hours	**Marks**
Evaluation System	**Theory Examination**	**2½**	**60**
	Theory Internal	**--**	**40**

Objectives	● Develop an understanding of regression analysis and model building. ● Provide the ability to develop relationship between variables ● Investigate possible diagnostics in regression techniques ● Formulate feasible solution using regression model for real-life problems

Pre requisites	Knowledge of Algorithms and mathematical foundation

Unit	Details	Lectures
I	**Simple Regression Analysis:** Introduction to a linear and nonlinear model. Ordinary Least Square methods. Simple linear regression model, using simple regression to describe a linear relationship. Fitting a linear trend to time series data, Validating simple regression model using t, F and p test. Developing confidence interval. Precautions in interpreting regression results. **Multiple Regression Analysis:** Concept of Multiple regression model to describe a linear relationship, Assessing the fit of the regression line, inferences from multiple regression analysis, problem of overfitting of a model, comparing two regression model, prediction with multiple regression equation.	**12**

II	**Fitting Curves and Model Adequacy Checking:** Introduction, fitting curvilinear relationship, residual analysis, PRESS statistics, detection and treatment of outliers, lack of fit of the regression model, test of lack of fit, Problem of autocorrelation and heteroscedasticity. Estimation of pure errors from near neighbors. **Transformation techniques:** Introduction, variance stabilizing transformations, transformations to linearize the model, BoxCox methods, transformations on the repressor's variables, Generalized and weighted least squares, Some practical applications.	**12**
III	**Multicollinearity:** Introduction, sources of multicollinearity, effects of multicollinearity. Multicollinearity diagnostics: examination of correlation matrix, variance Inflation factors (VIF), Eigen system analysis of X1X. Methods of dealing with Multicollinearity: collecting additional data, model , re-specification, and ridge regression	**12**
IV	**Generalized Linear Models:** link functions and linear predictors, parameter estimation and inference in the GLM, prediction and estimation with the GLM, Residual Analysis, and concept of over dispersion.	**12**
V	**Model building and Nonlinear Regression:** Variable selection, model building, model misspecification. Model validation techniques: Analysis of model coefficients, and predicted values, data splitting method. Nonlinear regression model, nonlinear least squares, transformation to linear model, parameter estimation in nonlinear system, statistical inference in nonlinear regression. **Contemporary issues:** Research and Analytical problems on various applications of the regression analysis and predictive modeling	**12**

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Books and References:

Sr. No.	Title	Author/s	Publisher	Edition	Year
01	Introduction to Linear Regression Analysis	Douglas C. Montgomery, Elizabeth A. Peck, G. Geoffrey Vining	Wiley India Pvt. Ltd	3^{rd}	2016
02	Applied Regression Analysis	Norman R. Draper, Harry Smith	Wiley India Pvt. Ltd	3^{rd}	2016
03	Applied Multivariate Statistical Analysis	Johnson, R A., Wichern, D. W	PHI learning	2013	2013
04	Applied Regression Modeling	Iain Pardoe	John Wiley and Sons	2nd	2012

Course Outcome

CO1: Develop in-depth understanding of the linear and nonlinear regression model. • demonstrate the knowledge of regression modeling and model selection techniques.
CO2: Examine the relationships between dependent and independent variables.
CO3: Estimate the parameters and fit a model
CO4: Investigate possible diagnostics in regression modeling and analysis.
CO5: Validate the model using hypothesis testing and confidence interval approach understand the generalizations of the linear model to binary and count data.

M. Sc (Data Science)		**Semester – III**	
Course Name: Deep Reinforcement Learning Practical		**Course Code: PSDS3P2**	
Periods per week (1 Period is 60 minutes)		**4**	
Credits		**2**	
		Hours	**Marks**
Evaluation System	**Practical Examination**	**2**	**50**
	Internal	**--**	**-**

List of Practical:	
	Two Practical Assignments on each unit of the syllabus. Total 10 practical questions to be carried out.

M. Sc (Data Science)		**Semester – III**	
Course Name: Data Engineering		**Course Code: PSDS303**	
Periods per week **1 Period is 60 minutes**	**Lectures**	**4**	
	Credits	**4**	
		Hours	**Marks**
Evaluation System	**Theory Examination**	**2½**	**60**
	Theory Internal	**--**	**40**

Objectives	- To develop the skills of managing the data with respect to knowledge generation. - Provide the ability to design the data engineering process - To propose the data reliability models - To define how to use Machine learning models

Pre requisites	Knowledge of database concepts and big data

Unit	Details	Lectures
I	**Selecting Appropriate Storage Technologies:** From Buisness Requirements to Storage Systems, Technical Aspects of Data, Types Of Structure, Schema Design Consideration **Building and Operationalizing Storage Systems:** Cloud SQL, Cloud Spanner, Cloud Bigtable, Cloud Firestore, BigQuery, Cloud Memorystore, Cloud Storage, Unmanaged Databases	**12**
II	**Designing Data Pipelines:** Overview Of Data Pipelines, GCP Pipeline Components, Migrating Hadoop and Spark To GCP **Designing a Data Processing Solution:** Designing Infrastructure, Designing for Distributed Processing, Migrating a Data Warehouse	**12**
III	**Building and Operationalizing Processing Infrastructure:** Provisioning and Adjusting Processing Resources, Monitoring Processing Resources **Designing for Security and Compliance:** Identity and Access Management with Cloud IAM, Using IAM with Storage and Processing Services, Data Security, Ensuring Privacy with the Data Loss Prevention API, Legal Compliance	**12**
IV	**Designing Databases for Reliability, Scalability, and Availability:** Designing Cloud Bigtable Databases for Scalability and Reliability, Designing Cloud Spanner Databases for Scalability and Reliability, Designing BigQuery Databases for Data Warehousing **Understanding Data Operations for Flexibility and Portability:** Catloging and Discovery with Data Catalog, Data Preprocessing with Dataprep, Visualizing with Data Studio, Exploring Data with Cloud Datalab, Orchestrating Workflows with Cloud Composer **Deploying Machine Learning Pipelines:** Structure of ML Pipelines, GCP Options for Deploying Machine Learning Pipeline	**12**

V	**Choosing Training and Serving Infrastructure:** Hardware Accelerators, Distributed and Single Machine Infrastructure, Edge Computing with GCP **Measuring, Monitoring, and Troubleshooting Machine Learning Models:** Three Types of Machine Learning Algorithms, Deep Learning, Engineering Machine Learning Models, Common Sources of Error in Machine Learning Models **Leveraging Prebuilt Models as a Service:** Sight, Conversation, Language, Structured Data	**12**

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Books and References:					
Sr. No.	**Title**	**Author/s**	**Publisher**	**Edition**	**Year**
01	Professional Data Engineer	DAN SULLIVAN	Sybex - Wiley	3^{rd}	2020
02	Data Driven Science and Engineering	STEVEN L. BRUNTON, J. NATHAN KUTZ	Cambridge University Press	2nd	2019
03	Data Security in Cloud Computing	Vimal Kumar, Sivadon Chaisiri and Ryan Ko	The Institution of Engineering and Technology		2020
04	Data Engineering on Azure	Vlad Riscutia	Manning Publications		2021

Course Outcome

CO1: Building the storage system with appropriate data technologies
CO2: designing the data pipelines and data flow
CO3: Processing the data infrastructure
CO4: Investigate possible diagnostics by designing Databases for Reliability, Scalability, and Availability, Understanding Data Operations for Flexibility
CO5: Training and measuring the serving Infrastructure for Machine Learning Models

M. Sc (Data Science)		**Semester – III**	
Course Name: Data Engineering Practical		**Course Code: PSDS3P3**	
Periods per week (1 Period is 60 minutes)		**4**	
Credits		**2**	
		Hours	**Marks**
Evaluation System	**Practical Examination**	**2**	**50**
	Internal	**--**	**-**

List of Practical:	
	Two Practical Assignments on each unit of the syllabus. Total 10 practical questions to be carried out.

M. Sc (Data Science)		**Semester – III**	
Course Name: Deep Reinforcement Learning		**Course Code: PSDS304a**	
Periods per week **1 Period is 60 minutes**	**Lectures**	**4**	
	Credits	**4**	
		Hours	**Marks**
Evaluation System	**Theory Examination**	**2½**	**60**
	Theory Internal	**--**	**40**

Objectives	● To present the mathematical, statistical and computational challenges of building neural networks ● To study the concepts of deep learning ● To enable the students to know deep learning techniques to support real-time applications

Pre requisites	Knowledge of Machine learning Algorithms and mathematical concepts

Unit	Details	Lectures
I	**Applied Math and Machine Learning Basics:** Linear Algebra: Scalars, Vectors, Matrices and Tensors , Multiplying Matrices and Vectors , Identity and Inverse Matrices, Linear Dependence and Span, norms, special matrices and vectors, eigen decompositions. **Machine Learning Basics:** Learning Algorithms, Capacity, Overfitting and Underfitting, Hyperparameters and Validation Sets, Estimators, Bias and Variance, Maximum Likelihood Estimation, Bayesian Statistics, Supervised Learning Algorithms, Unsupervised Learning Algorithms, Stochastic Gradient Descent, building a Machine Learning Algorithm, Challenges Motivating Deep Learning	12
II	**Deep Networks:** Deep feedforward network , regularization for deep learning , Optimization for Training deep models	12
III	**Deep Networks:** Convolutional Networks, Advanced Convolution network, Sequence Modelling, Applications	12
IV	**Deep Learning Research:** Linear Factor Models, Autoencoders	12
V	**Fundamentals of Reinforcement Learning:** introduction, reinforcement learning as MDP, learnable functions in reinforcement learning, deep reinforcement learning algorithms, deep learning for reinforcement , reinforcement learning and supervised learning.	12

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Books and References:

Sr. No.	Title	Author/s	Publisher	Edition	Year
01	Deep Learning	Ian Goodfellow, Yoshua Bengio, Aaron Courvile	An MIT Press book	1st	2016
02	Fundamentals of Deep Learning	Nikhil Buduma	O’Reilly	1st	2017
03	Deep Learning: Methods and Applications	Deng & Yu	Now Publishers	1st	2013
04	Deep Learning CookBook	Douwe Osinga	O’Reilly	1st	2017

Course Outcome

At the end of successful completion of the course the student will be able to:

CO1: Describes basics of mathematical foundation that will help the learner to understand the concepts of Deep Learning.

CO2: Understand and describe model of deep learning

CO3: Design and implement various deep supervised learning architectures for text & image data.

CO4: Design and implement various deep learning models and architectures.

CO5: Fundamentals of Reinforcement learning

M. Sc (Data Science)		**Semester –III**	
Course Name: Healthcare Analytics		**Course Code: PSDS304b**	
Periods per week **1 Period is 60 minutes**	**Lectures**	**4**	
	Credits	**4**	
		Hours	**Marks**
Evaluation System	**Theory Examination**	**2½**	**60**
	Theory Internal	**--**	**40**

Objectives	To empower healthcare providers with effective analytical methods and tools that enable and assist them.

Unit	Details	Lectures
I	**Recent Development in Methodology for Gene Network Problems and Inferences** Introduction, Background, Genetic Data Available, Methodology, Search Algorithm, PC Algorithm, Application/Case Studies **Biomedical Analytics and Morphoproteomics: An Integrative Approach for Medical Decision Making for Recurrent or Refractory Cancers** Introduction, Backgrounds, Methodology, Case Studies **Characterization and Monitoring of Nonlinear Dynamics and Chaos in Complex Physiological Systems** Introduction, Backgrounds, Sensor-Based Chracterization and Modeling of Nonlinear Dynamics, HealthCare Application **Statistical Modeling of Electrocardiography Signal for Subject Monitoring and Diagnosis** Introduction, Basic Elements of ECG , Statistical Modeling of ECG for Disease Diagnosis, Detection of Obstructive Sleep Apnea from Single ECG Lead, Materials And Methods, Results.	**12**
II	**Modeling and Simulation of Measurement Uncertainty in Clinical Laboratories** Introduction, Background and Literature Review, Model Development Guidelines, Implementations of Guidelines: Enze Assay Uncertainty Model **Predictive Analytics: Classification in Medicine and Biology** Introduction, Background , Machine Learning with Discrete Support Vector Machine Predictive Models , Applying DAMIP to real World Application **Predictive Modeling in Radiation Oncology** Introduction, Predictive Modeling Techniques, Review of Recent Predictive Modeling Application in Radiation Oncology, Modeling Pathologic Response of Esophageal cancer to Chemoradiotherapy, Modeling Clinical Complications after Radiation Therapy , Modeling Tumor Motion with Respiratory Surrogates	**12**

III	**Mathematical Modeling of Innate Immunity Responses of Sepsis: Modeling and Computational Studies.** Background, System Dynamic Mathematics Model (SDMM), Pathogen Strain Selection, Mathematical Models od Innate Immunity of AIR, Discussion. **Systems Analytics: Modeling and Optimizing Clinic Workflow and Patient Care.** Introduction , Background , Challenges and Objectives, Methods and Design to Study , Computational Results, Implementation and ED Performance Comparison, Benefits and Impacts, Scientific Advances **A Multiobjective Simulation Optimization of the Macrolevel Patient Flow Distribution.** Introduction , Literature Review, Problem Description and Modeling , Methodology, Case Study: Adjusting Patient Flow for a Two-Level Healthcare System Centered on the Puth. **Analysis of Resource Intensive Activity Volumes in US Hospitals** Introduction, Structural Classification of Hospitals, ductivity Analysis of Hospitals, Resource and Activity Database for US Hospitals, Activity Based Modeling of Hospitals Operations , Resource use Profile of Hospitals from HUC Activity Data.	**12**
IV	**Discrete-Event Simulation for Primary Care Redesign: Review and a Case Study.** Introduction, Review of Relevant Literature, A Simulation Case Study at a Pediatric Clinic, What-If Analyses. **Temporal and Spatiotemporal Models for Ambulance Demand.** Introduction, Temporal Ambulance Demand Estimation, Spatiotemporal Ambulance Demand Estimation. **Mathematical Optimization and Simulation Analyses for Optimal Liver Allocation Boundaries.** Introduction, Methods, Results, **Predictive Analytics in 30-Day Hospital Readmissions for Heart Failure Patients.** Introduction, Analytics in Prediction Hospital Readmission Risk, Analytics in Recommending Intervention Strategies, Related Work.	**12**

V	**Heterogeneous Sensing and Predictive Modeling of Postoperative Outcomes.** Introduction, Research Background, Research Methodology, Materials and Experimental Design. **Analyzing Patient–Physician Interaction in Consultation for Shared Decision Making.** Introduction, Literature Review, Recent Data Mining Studies , Future Directions. **The History and Modern Applications of Insurance Claims Data in Healthcare Research.** Introduction, Healthcare Cost Predictions, Measuring Quality of Care. **Understanding the Role of Social Media in Healthcare via Analytics: a Health Plan Perspective.** Introduction, Literature Review, Case Study Description, Research Methods and Analytics Tools.	**12**

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Books and References:

Sr. No.	Title	Author/s	Publisher	Edition	Year
01	HealthCare Analytics from Data to Knowledge to Healthcare Improvement	Hui Yang, Eva K Lee	Wiley		2016
02	Analytics in Healthcare_ A Practical Introduction	Christo El Morr Hossam Ali-Hassan	Springer		2019
03	Machine Learning and AI for Healthcare_ Big Data for Improved Health Outcomes	Arjun Panesar	Apress		2019

Course Outcome

- To understand biomedical and health informatics
- To understand healthcare delivery systems, analyze physiological signals from patient monitoring systems.
- To understand predictive modeling and its applications to a broad variety of clinical and translational projects.
- To understand predictive usage within radiation oncology and disease modeling for sepsis.
- To understand dealing with physicians–patient interactions, Insurance claims, and the role of social media in healthcare.

M. Sc (Data Science)			**Semester –III**	
Course Name: Social Media Analytics			**Course Code: PSDS304c**	
Periods per week **1 Period is 60 minutes**	**Lectures**		**4**	
	Credits		**4**	
			Hours	**Marks**
Evaluation System	**Theory Examination**		**2½**	**60**
	Theory Internal		**--**	**40**

Objectives	To understand all the different parts of a problem and then be able to find improvement points from facts in the past, and to predict the future outcome of present decisions.

Unit	Details	Lectures
I	**Users: The Who of social media.** Measuring Variations in User Behavior in Wikipedia, Long Tails Everywhere: The 80/20 Rule (p/q Rule), Online Behavior on Twitter. **Networks: The How of Social Media.** Types and Properties of Social Networks, Visualizing Networks, Degrees: The Winner Takes All, Capturing Correlations: Triangles, Clustering, and Assortativity. **Temporal Processes: The When of Social Media**. What Traditional Models Tell You About Events in Time, Inter-Event, Bursty Activities of Individuals, Forecasting Metrics in Time.	12
II	**Content: The What of Social Media.** Defining Content: Focus on Text and Unstructured Data, Using Content Features to Identify Topics, Extracting Low-Dimensional Information from High-Dimensional Text. **Processing Large Datasets.** MapReduce: Structuring Parallel and Sequential Operations, Multi-Stage MapReduce Flows, Patterns in MapReduce Programming, Sampling and Approximations: Getting Results with Less Computation, Sampling and Approximations: Getting Results with Less Computation, Bloom Filter, Count-Min Sketch, Executing on a Hadoop Cluster (Amazon EC2).	12

III	**Learn, Map, and Recommend.** Social Media Services Online, Problem Formulation, Learning and Mapping, Prediction and Recommendation. **Social Media Data, From Data to Insights, Luis Madureira, Analytics in Social Media, Dedicated vs. Hybrid Tools.**	**12**
IV	**Alexander and Frederik Peiniger, Social Network Landscape, Tam Su, The Analytics Process, Armando Terribili, Metrics, Dashboards.**	**12**
V	**Reports, Milan Veverka, Strategy, Tactics , Michael Wu, Prescriptive Analytics, The Future of Social Media Analytics.**	**12**

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Books and References:

Sr. No.	Title	Author/s	Publisher	Edition	Year
01	Social Media Data Minning and Analytics	Gabor Szabo, Gungor Polatkan, Oscar Boykin, Antonios Chalkiopolos	John Wiley , & Sons		2019
02	Social Media Analytics Strategy	Alex Goncalves	Apress		2017

Course Outcome

- To understand and deal with any social media network, strategy, or campaign.
- Social media analytics integrates with and affects other areas of business.
- To give real-world context and insight.
- To present decisions.
- To learn and think in the field and reach a point where we can effortlessly approach any project with a sharp analytical mind.

M. Sc (Data Science)		**Semester – III**	
Course Name: Elective Practical		**Course Code: PSDS3P4**	
Periods per week (1 Period is 60 minutes)		**4**	
Credits		**2**	
		Hours	**Marks**
Evaluation System	**Examination**	**--**	**50**
	Internal	**--**	**-**

A quality research paper should be written under the guidance of the faculty. The paper is expected to be published in UGC Care Listed, Scopus, Web of Science, IEEE and the like journals. Plagiarism should be less than 10%.

Semester IV

Course Code	Course Title	Course Type	Credits
PSDS401	**Data Protection**	**SEC**	**4**
PSDS402	**Marketing Analytics**	**DSC**	**4**
PSDS403	**Internship**		**6**
PSDS404	**Project: Document and Viva Voce**	**DSC**	**6**
PSDS4P1	**Research Paper – II**		**2**
PSDS4P2	**Marketing Analytics Practical**		**2**
		Total	**24**

M. Sc (Data Science)		**Semester –IV**	
Course Name: Data Protection		**Course Code: PSDS401**	
Periods per week **1 Period is 60 minutes**	**Lectures**	**4**	
	Credits	**4**	
		Hours	**Marks**
Evaluation System	**Theory Examination**	**2½**	**60**
	Theory Internal	**--**	**40**

Objectives	To understand the data protection and various cases related to it around the world.

Unit	Details	Lectures
I	Mind the Air Group, Europe versus Facebook: An Imbroglio of EU Data Protection Issues, The Context-Dependence of Citizens' Attitudes and Preferences Regarding Privacy and Security, On Locational Privacy in the Absence of Anonymous Payments.	**12**

II	Development Towards a Learning Health System—Experiences with the Privacy Protection Model of the TRANSFORM Project, Could the CE Marking Be Relevant to Enforce Privacy by Design in the Internet of Things? Visions of Technology, Privacy and Innovation: From Disruption to Opportunities	**12**
III	Behavioural Advertising and the New 'EU Cookie Law's as a Victim of Business Resistance and a Lack of Official Determination, Forget About Being Forgotten, Do-It-Yourself Data Protection—Empowerment or Burden?	**12**
IV	Privacy Failures as Systems Failures: A Privacy-Specific Formal System Model, A Precautionary Approach to Big Data Privacy, The Impact of Domestic Robots on Privacy and Data Protection, and the Troubles with Legal Regulation by Design	**12**
V	Is the Human Rights Framework Still Fit for the Big Data Era? A Discussion of the ECTHR's Case Law on Privacy Violations Arising from Surveillance Activities, Metadata, Traffic Data, Communications Data, Service Use Information… What Is the Difference? Does the Difference Matter? An Interdisciplinary View from the UK, Global Views on Internet Jurisdiction and Trans-border Access.	**12**

Books and References:

Sr. No.	**Title**	**Author/s**	**Publisher**	**Edition**	**Year**
01	Data Protection on the Move	Serge Gutwirth , Ronald Leenes, Paul De Hert.	Springer		2016
02	Data Protection Act	UK Govt.	Uk Govt.		2018
03	IT Governance	Alan Calder, Steve Watkins	Kogan Page	6th	2015

Course Outcome

- To get the idea of the data protection and laws related to data protection around the world.
- To understand jurisdictional issues.
- To understand privacy by design and engineering privacy into the Internet.
- To understand the concepts of Anonymity and pseudonymity.
- To use privacy and data protection as a business opportunity.

M. Sc (Data Science)		**Semester – IV**	
Course Name: Research Paper – II		**Course Code: PSDS4P1**	
Periods per week (1 Period is 60 minutes)		**4**	
Credits		**2**	
		Hours	**Marks**
Evaluation System	**Practical Examination**	**--**	**50**
	Internal	**--**	**-**

A quality research paper should be written under the guidance of the faculty. The paper is expected to be published in UGC Care Listed, Scopus, Web of Science, IEEE and the like journals. Plagiarism should be less than 10%.

M. Sc (Data Science)		**Semester –IV**	
Course Name: Marketing Analytics		**Course Code: PSDS402**	
Periods per week **1 Period is 60 minutes**	**Lectures**	**4**	
	Credits	**4**	
		Hours	**Marks**
Evaluation System	**Theory Examination**	**2½**	**60**
	Theory Internal	**--**	**40**

Objectives	To understand and apply marketing analytics to different real-world scneraios.

Unit	Details	Lectures
I	**Introduction:** Slicing and Dicing Marketing Data with PivotTables, Using Excel Charts to Summarize Marketing Data, Using Excel Functions to	**12**

	Summarize Marketing Data, Estimating Demand Curves and Using Solver to Optimize Price, Price Bundling, Nonlinear Pricing.	
II	Price Skimming and Sales, Revenue Management, Simple Linear Regression and Correlation, Using Multiple Regression to Forecast Sales, Forecasting in the Presence of Special Events, Modeling Trend and Seasonality, Ratio to Moving Average Forecast Method, Winter's Method, Using Neural Networks to Forecast Sales	**12**
III	Conjoint Analysis, Logistic Regression, Discrete Choice Analysis, Calculating Lifetime Customer Value	**12**
IV	Using Customer Value to Value a Business, Customer Value, Monte Carlo Simulation, and Marketing Decision Making, Allocating Marketing Resources between Customer Acquisition and Retention, Cluster Analysis, Collaborative Filtering, Using Classification Trees for Segmentation, Using S Curves to Forecast Sales of a New Product, The Bass Diffusion Model, Using the Copernican Principle to Predict Duration of Future Sales	**12**
V	Market Basket Analysis and Lift, RFM Analysis and Optimizing Direct Mail Campaigns, Using the SCANPRO Model and Its Variants, Allocating Retail Space and Sales Resources, Forecasting Sales from Few Data Points, Measuring the Effectiveness of Advertising, Media Selection Models ,Pay Per Click (PPC) Online Advertising, Principal Component Analysis (PCA) ,Multidimensional Scaling (MDS), Classification Algorithms: Naive Bayes Classifier and Discriminant Analysis, Analysis of Variance: One-way ANOVA, Analysis of Variance: Two-way ANOVA, Networks ,The Mathematics Behind The Tipping Point ,Viral Marketing ,Text Mining.	**12**

Books and References:

Sr. No.	Title	Author/s	Publisher	Edition	Year
01	Marketing Analytics: Data-Driven Technique with Microsoft excel	Wayne L. Winston	WILEY		2012
02	Analytical Finance Volume 1: The Mathematics of Equity Derivatives, Markets, Risk and Valuation	Jan R. M. Röman	Palgrave Macmillan		2017
03	Analytical Finance Volume 2: The Mathematics of Equity Derivatives, Markets, Risk and Valuation	Jan R. M. Röman	Palgrave Macmillan		2017

Course Outcome

At the end of the course the students should

- apply their understanding of utility theory to measure customer preferences
- identify what customers' value in a product, and assess what they are willing to pay for it
- segment customers based on the differences in what they value, using different techniques, including state of the art latent class methods
- determine the most effective target markets, and how to market to those markets efficiently
- design a study that incorporates all of the above

M. Sc (Data Science)		**Semester – IV**	
Course Name: Marketing Analytics Practical		**Course Code: PSDS4P2**	
Periods per week (1 Period is 60 minutes)		**4**	
Credits		**2**	
		Hours	**Marks**
Evaluation System	**Practical Examination**	**2**	**50**
	Internal	**--**	**-**

List of Practical:	
	Two Practical Assignments on each unit of the syllabus. Total 10 practical questions to be carried out.

PSDS403: Internship

- Internship should be of 2 to 3 months with 8 to 12 weeks duration.
- A student is expected to find an internship by himself or herself. However, the institution should assist their students in getting internships in good organizations.
- The home institution cannot be taken as the place of internship.
- A student is expected to devote at least 300 hours physically at the organization.
- Internship can be on any topic covered in the syllabus mentioned in the syllabus, not restricted to the specialization.
- Internship can be done, in one of the following, but not restricted to, types of organizations:
- Software development firms
- Hardware/ manufacturing firms
- Any small scale industries, service providers like banks, clinics/ NGOs/professional institutions like that of CA, Advocate etc
- Civic Depts like Ward office/post office/police station/ punchayat.
- Research Centres/ University Depts/ College as research Assistant for research projects or similar capacities.

Guidelines for making Internship Report in Semester –IV

A student is expected to make a report based on the internship he or she has done in an organization. It should contain the following:

- Certificate: A certificate in the prescribed Performa (given in appendix 1) from the organization where the internship was done.
- Evaluation form: The form filled by the supervisor or to whom the intern was reporting, in the prescribed Performa (given in appendix 2).
- Title: A suitable title giving the idea about what work the student has performed during the internship.
- Description of the organization: A small description of 1 to 2 pages on the organization where the student has interned
- Description about the activities done by the section where the intern has worked: A description of 2 to 4 pages about the section or cell of the organization where the intern actually worked. This should give an idea about the type of activity a new employee is expected to do in that section of the organization.
- Description of work allotted and actually done by the intern: A detailed description of the work allotted and actual work performed by the intern during the internship period. Intern may give a weekly report of the work by him or her if needed. It shall be of around 7 to 10 pages.
- Self assessment: A self assessment by the intern on what he or she has learnt during the internship period. It shall contain both technical as well as interpersonal skills learned in the process. It shall be of around 2 to 3 pages.

PSDS404: Guidelines for Documentation of Project Proposal in Semester –IV

A Student should submit project implementation report with following details:

- Title: Title of the project (Same as the one proposed and evaluated at the semester II examination).
- Implementation details: A description of how the project has been implemented. It shall be of 2 to 4 pages.
- Experimental set up and results: A detailed explanation on how experiments were conducted, what software used and the results obtained. Details like screen shots, tables and graphs can come here. It shall be of 6 to 10 pages.
- Analysis of the results: A description on what the results means and how they have been arrived at. Different performing measures or statistical tools used etc may be part of this. It shall be of 4 to 6 pages.
- Conclusion: A conclusion of the project performed in terms of its outcome (May be half a page).
- Future enhancement: A small description on what enhancement can be done when more time and resources are available (May be half a page).
- Program code: The program code may be given as appendix. The proposal may be of around 20 pages (excluding program code), which needs to be signed by the teacher in charge and head of the Department.

Complete Project report of around 100 pages should be submitted.

Appendix 1

(Proforma for the certificate for internship in official letter head)

This is to certify that Mr/Ms________________________________ of ______________________College/Institution worked as an intern as part of her M.Sc. programe in Data Science of University of Mumbai. The particulars of internship are given below: Internship starting date: ________________ Internship ending date:_________________ Actual number of days worked:_______________ Tentative number of hours worked:___________ Hours Broad area of work:____ A small description of work done by the intern during the period:

____

____

____

____

____

____

Signature: Name:

Designation:

Contact number:

Email: (seal of the organization)

Appendix 2

(Proforma for the Evaluation of the intern by the supervisor/to whom the intern was reporting in the organization)

Professional Evaluation of intern

Name of intern:____

College/institution:____

[Note: Give a score in the 1-5 scale by putting √ in the respective cells]

Sr No	Particular	Excellent	Very Good	Good	Moderate	Satisfactory
1	Attendance					
2	Punctuality					
3	Adaptability					
4	Ability to shoulder responsibility					
5	Ability to work in a team					
6	Written and oral communication skills					
7	Problem solving skills					
8	Ability to grasp new concepts					
9	Ability to complete task					
10	Quality of work done					

Comments:

____

____

____

Signature:

Name:

Designation:

Contact number:

Email:

(seal of the organization)

Suggested format of Question paper of 30 marks for the Internal written test.

Q1.	**Attempt *any two* of the following:**	**16**
Q2.	**Attempt *any two* of the following:**	**14**

External Examination: (60 marks)

To be conducted by University as per other M.Sc. Programmes

	All questions are compulsory	
Q1	(Based on Unit 1) Attempt *__any two__* of the following:	12
Q2	(Based on Unit 2) Attempt *__any two__* of the following:	12
Q3	(Based on Unit 3) Attempt *__any two__* of the following:	12
Q4	(Based on Unit 4) Attempt *__any two__* of the following:	12
Q5	(Based on Unit 5) Attempt *__any two__* of the following:	12

Practical Evaluation (50 marks)

To be conducted by University as per other M.Sc. Programmes

A Certified copy journal is essential to appear for the practical examination.

	Practical Question 1	20
	Practical Question 2	20
	Journal	5
	Viva Voce	5

OR

	Practical Question	40
	Journal	5
	Viva Voce	5

UNIVERSITY OF MUMBAI

Syllabus for Semester-I and Semester -II

Program: M.Sc.

Course: M.Sc. Computer Science with Specialization in Data Science.

CHOICE BASED (REVISED)

With effect from the academic year

2021 – 2022

PROGRAMME OUTCOME

1. Students will attain proficiency with statistical analysis of Data.
2. Students will execute statistical analyses with professional statistical software.
3. Students will gain skills in Data management.
4. Students will develop the ability to build and assess Databased models.
5. Students will apply data science concepts and methods to solve problems in real-world contexts and will communicate these solutions effectively

PROGRAMME SPECIFIC OUTCOMES (PSOs)

On completion of M.Sc. Data Science programme, students will be able:

PO_01: To become a skilled Data Scientist in industry, academia, or government.

PO_02: To use specialised software tools for data storage, analysis and visualization.

PO_03: To independently carry out research/investigation to solve practical problems.

PO_04: To gain problem-solving ability- to assess social issues (ethical, financial, management, analytical and scientific analysis) and engineering problems.

PO_05: To have a clear understanding of professional and ethical responsibility.

PO_06: To collaborate virtually.

PO_07: To have critical thinking and innovative skills.

PO_08: To translate vast data into abstract concepts and to understand database reasoning.

PROGRAMME STRUCTURE

Semester – I		
Course Code	Course Title	Credits
PSDS101	Programming Paradigms	4
PSDS102	Database Technologies	4
PSDS103	Fundamentals of Data Science	4
PSDS104	Statistical Methods for Data Science	4
PSDS1P1	Programming Paradigms Practical	2
PSDS1P2	Database Technologies Practical	2
PSDS1P3	Fundamentals of Data Science Practical	2
PSDS1P4	Statistical Methods for Data Science Practical	2
	Total Credits	24

Semester – II		
Course Code	Course Title	Credits
PSDS201	Artificial Intelligence and Machine Learning	4
PSDS202	Soft Computing	4
PSDS203	Algorithms for Data Science	4
PSDS204	Optimization Techniques	4
PSDS2P1	Artificial Intelligence and Machine Learning Practical	2
PSDS2P2	Soft Computing Practical	2
PSDS2P3	Algorithms for Data Science Practical	2
PSDS2P4	Optimization Techniques Practical	2
	Total Credits	24

DETAILED SYLLABUS FOR SEMESTER - I & SEMESTER - II

Semester – 1

Programming Paradigms

M.Sc (Data Science)		Semester – I	
Course Name: **Programming Paradigms**		Course Code: PSDS101	
Periods per week (1 Period is 60 minutes)		4	
Credits		4	
		Hours	Marks
Evaluation System	Theory Examination	2½	60
	Internal	--	40

Course Objectives:

- To understand the basic building blocks of programming Languages.
- To Learn and understand various programming paradigms.

Unit	Details	Lectures
I	Foundations-Language design, why to study programming language, compilation and interpretation, programming environments. Programming language syntax – Specifying syntax: regular expressions and Context-Free grammar(Token and Regular expressions, Context Free grammar, Derivations and parse trees), Scanning(Generating Finite automation, Scanner code, Table-driven scanning, Lexical errors, pragmas), Parsing(Recursive Descent, Writing L1 grammar, Table driven top down parsing, Bottom up parsing, Syntax errors)	12
II	OBJECT ORIENTATION Basic concepts: objects, classes, methods, overloading methods, messages inheritance: overriding methods, single inheritance, multiple inheritance Interfaces, encapsulation, polymorphism.	12
III	FUNCTIONAL PROGRAMMING Definition of a function: domain and range, total and partial functions, strict functions. Recursion, Referential transparency, Side effects of functions	12
IV	LOGIC PROGRAMMING Basic constructs, Facts: queries, existential queries, conjunctive queries and rules. Definition and semantics of a logic program, Recursive programming: Computational model of logic programming, Goal reduction, Negation in logic programming	12
V	SCRIPTING LANGUAGE What is scripting language, Problem domain(Shell languages, Text processing and report generation, Mathematics and statistics, General	12

	purpose scripting, Extension languages), Scripting the world wide web(CGI scripts, Embedded server side script, client side script, Java Applets, XSLT)	

Books and References:					
Sr. No.	Title	Author/s	Publisher	Edition	Year
1.	Programming Language Pragmatics	Michael Scott	Morgan Kaufmann	4th Edition	2015
2.	The Craft of Functional Programming	Thompson, Simon. Haskell:	Addison-Wesley Professional	2ndEditon	2011
3.	"Foundations of Programming Languages Design & Implementation"	RoostaSeyed	Cenage learning	3rdEditon	2003
4.	Programming Languages: Concepts and Constructs	Sethi Ravi	Pearson Education	3rdEditon	2000

Programming Paradigms Practical

M. Sc. (Data Science)		Semester – I	
Course Name: **Programming Paradigms Practical**		Course Code: PSDS1P1	
Periods per week (1 Period is 60 minutes)		4	
Credits		2	
		Hours	Marks
Evaluation System	Practical Examination	2	50
	Internal	--	--

Practical:

Perform minimum ten practical based on the basic concepts of each programming paradigm covering the entire syllabus.

Course Outcomes:

- To explore a range of modern programming languages and programming techniques.
- To select appropriate software development tools for given application environments.

Database Technologies

M.Sc (Data Science)		Semester – I	
Course Name: **Database Technologies**		Course Code: PSDS102	
Periods per week (1 Period is 60 minutes)		4	
Credits		4	
		Hours	Marks
Evaluation System	Theory Examination	2½	60
	Internal	--	40

Course Objectives:
The objective of the course is to present an introduction to database management systems, with an emphasis on how to organize, maintain and retrieve - efficiently, and effectively - information from a DBMS.

Unit	Details	Lectures
I	Database Concepts:Why Databases?, Data versus Information, Introducing the Database, Why Database Design Is Important, Evolution of File System Data Processing, Problems with File System Data Processing, Database Systems Data Models:DataModeling and Data Models, The Importance of Data Models, Data Model Basic Building Blocks, Business Rules, The Evolution of Data Models, Degrees of Data Abstraction The Relational Database Model:A Logical View of Data, Keys, Integrity Rules, Relational Algebra, The Data Dictionary and the System Catalog, Relationships within the Relational Database, Data Redundancy Revisited Entity Relationship (ER) Modeling:The Entity Relationship Model, Developing an ER Diagram, Database Design Challenges: Conflicting Goals	12
II	Advanced Data Modelling:The Extended Entity Relationship Model, Entity Clustering, Design Cases: Learning Flexible Database Design Normalization of Database Tables:Database Tables and Normalization, The Need for Normalization, The Normalization Process, Improving the Design Introduction to Structured Query Language (SQL):Introduction to SQL, Basic SELECT Queries, SELECT Statement Options, FROM Clause Options, ORDER BY Clause Options, WHERE Clause Options, Aggregate Processing, Subqueries, SQL Functions, Relational Set Operators, Crafting SELECT Queries Advanced SQL:Data Definition Commands, Creating Table Structures, Altering Table Structures, Data Manipulation Commands, Virtual Tables: Creating a View, Sequences, Procedural SQL, Embedded SQL Transaction Management and Concurrency Control:What Is a	12

	Transaction?, Concurrency Control, Concurrency Control with Locking Methods, Concurrency Control with Time Stamping Methods, Concurrency Control with Optimistic Methods, ANSI Levels of Transaction Isolation, Database Recovery Management	
III	Three Database Revolutions: Early Database Systems, The First Database Revolution, The Second Database Revolution, The Third Database Revolution Google, Big Data, and Hadoop: The Big Data Revolution, Google: Pioneer of Big Data, Hadoop: Open-Source Google Stack Sharding, Amazon, and the Birth of NoSQL: Scaling Web 2.0, Amazon’s Dynamo Document Databases: XML and XML Databases, JSON Document Databases	12
IV	Tables are Not Your Friends: Graph Databases: What is a Graph?, RDBMS Patterns for Graphs, RDF and SPARQL, Property Graphs and Neo4j, Gremlin, Graph Database Internals, Graph Compute Engines Column Databases: Data Warehousing Schemas, The Columnar Alternative, Sybase IQ, C-Store, and Vertica, Column Database Architectures The End of Disk? SSD and In-Memory Databases: The End of Disk?, In-Memory Databases, Berkeley Analytics Data Stack and Spark Distributed Database Patterns: Distributed Relational Databases, Nonrelational Distributed Databases, MongoDB Sharding and Replication, HBase, Cassandra Consistency Models: Types of Consistency, Consistency in MongoDB, HBase Consistency, Cassandra Consistency	12
V	Data Models and Storage: Data Models, Storage Languages and Programming Interfaces: SQL, NoSQL APIs, The Return of SQL Databases of the Future: The Revolution Revisited, Counterrevolutionaries, Can We have it All?, Meanwhile, Back at Oracle HQ, Other Convergent Databases, Disruptive Database Technologies	12

Books and References:					
Sr. No.	Title	Author/s	Publisher	Edition	Year
1	Database System designs, Implementation & Management	Carlos Coronel, Steven Morris	Cengage	13th	2018
2	Next Generation Databases	Guy Harrison	Apress	1st	2015
3	Advanced Database Technology and Design	Mario Piattini, Oscar Díaz	Artech House	1st	2000

Database Technologies Practical

M. Sc. (Data Science)		Semester – I	
Course Name:**Database TechnologiesPractical**		Course Code: PSDS1P2	
Periods per week (1 Period is 60 minutes)		4	
Credits		2	
		Hours	Marks
Evaluation System	Practical Examination	2	50
	Internal	--	--

Practical:

Perform minimum ten practical based on the basic concepts of each programming paradigm covering the entire syllabus.

Course Outcomes:

Upon successful completion of this course, students should be able to:

- Describe the fundamental elements of relational database management systems
- Explain the basic concepts of relational data model, entity-relationship model, relational database design, relational algebra and SQL
- Design ER-models to represent simple database application scenarios
- Convert the ER-model to relational tables, populate relational database and formulate SQL queries on data.
- Improve the database design by normalization.

Fundamentals of Data Science

M.Sc (Data Science)		Semester – I	
Course Name: **Fundamentals of Data Science**		Course Code: PSDS103	
Periods per week (1 Period is 60 minutes)		4	
Credits		4	
		Hours	Marks
Evaluation System	Theory Examination	2½	60
	Internal	--	40

Course Objectives:
To provide strong foundation for data science and application in area related to it and understand the underlying core concepts and emerging technologies in data science.

Unit	Details	Lectures
I	Introduction to Data Science: ▪ What is Data? Kinds of data: e.g. static, spatial, temporal, text, media, ▪ Introduction to high level programming language + Integrated Development ▪ Environment (IDE) ○ Describing data: Exploratory Data Analysis (EDA) + Data Visualization - Summaries, aggregation, smoothing, distributions ▪ Data sources: e.g. relational databases, web/API, streaming, Data collection: e.g. sampling, design (observational vs experimental) and its impact on visualization, modeling and generalizability of results	12
II	Data analysis/modeling: ○ Question/problem formation along with EDA ○ Introduction to estimation and inference (testing and confidence intervals) including simulation and resampling ○ Scope of inference ○ Assessment and selection e.g. training and testing sets Data Curation, Management and Organization-I ▪ Query languages and operations to specify and transform data (e.g. projection, selection, join, aggregate/group, summarize) ▪ Structured/schema based systems as users and acquirers of data ○ Relational (SQL) databases, APIs and programmatic access, indexing ○ XML and XPath, APIs for accessing and querying structured data contained therein	12
III	Data Curation, Management and Organization-I	12

	▪ Semi-structured systems as users and acquirers of data
	    o Access through APIs yielding JSON to be parsed and structured
	▪ Unstructured systems in the acquisition and structuring of data
	    o Web Scraping
	    o Text/string parsing/processing to give structure
	
	Data Curation, Management and Organization-II
	▪ Security and ethical considerations in relation to authenticating and authorizing access to data on remote systems
	▪ Software development tools (e.g. github, version control)	

IV	Data Curation, Management and Organization-II
	▪ Large scale data systems
	    o Paradigms for distributed data storage
	    o Practical access to example systems (e.g. MongoDB, HBase, NoSQL systems)
	    o Amazon Web Services (AWS) provides public data sets in Landsat, genomics, multimedia
	Introduction to Statistical Models
	▪ Simple Linear Regression
	▪ Multiple Linear Regression
	▪ Logistic Regression
	▪ Review of hypothesis testing, confidence intervals, etc.
	▪ Estimation e.g. likelihood principle, Bayes,
		12

V	Introduction to Statistical Models
	▪ Linear models
	    o Regression theory i.e. least-squares: Introduction to estimation principles
	    o Multiple regression
	▪ Transformations, model selection
	▪ Interactions, indicator variables, ANOVA
	    o Generalized linear models e.g. logistic, etc.
	▪ Alternatives to classical regression e.g. trees, smoothing/splines
	▪ Introduction to model selection
	    o Regularization, bias/variance tradeoff e.g. parsimony, AIC, BIC
	    o Cross validation
	Ridge regressions and penalized regression e.g. LASSO
		12

Books and References:					
Sr. No.	Title	Author/s	Publisher	Edition	Year
1	Hands-On Programming with R	Garrett Grolemund	O'Reilly	1st	2014
2	Doing Data Science	Rachel Schutt, Cathy O'Neil	O'Reilly Media	1st	2013
3	AnIntroduction to Statistical Learning with Applications in R	Gareth James, Daniela Witten, Trevor Hastie, Robert Tibshirani:	Springer US	2^{nd}	2021
4	AppliedPredictive Modelling	M. Kuhn, K. Johnson	Springer New York	3^{rd}	2019
5	Mastering Machine Learning with R	Cory Lesmeister	Packt Publishing	2^{nd}	2015

Fundamentals of Data Science Practical

M. Sc (Data Science)		Semester – I	
Course Name: **Fundamentals of Data Science Practical**		Course Code: PSDS1P3	
Periods per week 1 Period is 60 minutes	Lectures	4	
	Credits	2	
		Hours	Marks
Evaluation System	Practical Examination	2	50

Practical:

Perform minimum ten practical based on the basic concepts of each programming paradigm covering the entire syllabus.

Course Outcomes:

- The students will be able to independently carry out research/investigation to solve practical problems
- The students should be able to understand & comprehend the problem; and should be able to define suitable statistical method to be adopted.

Statistical Methods for Data Science

M. Sc (Data Science)		Semester – I	
Course Name: **Statistical Methods for Data Science**		Course Code:PSDS104	
Periods per week 1 Period is 60 minutes	Lectures	4	
	Credits	4	
		Hours	Marks
Evaluation System	Theory Examination	2½	60
	Theory Internal	--	40

Pre requisites	Knowledge of statistics and mathematical concepts

Course Objectives:

1. To present the mathematical, statistical and computational challenges of building neural networks
2. To study the concepts of deep learning
3. To enable the students to know deep learning techniques to support real-time applications

Unit	Details	Lectures
I	Introduction to Applied Statistics: The Nature of Statistics and Inference, What is “Big Data”?, Statistical Modelling, Statistical Significance Testing and Error Rates, Simple Example of Inference Using a Coin,Statistics Is for Messy Situations, Type I versus Type II Errors, Point Estimates and Confidence Intervals, Variable Types, Sample Size, Statistical Power, and Statistical Significance, The Verdict on Significance Testing, Training versus Test Data.	12
II	Computational Statistics:Vectors and Matrices, The Inverse of a Matrix, Eigenvalues and Eigenvectors Means, Correlations, Counts: Drawing Inferences: Computing z and Related Scores, Statistical Tests, Plotting Normal Distributions, Correlation Coefficients, Evaluating Pearson’s r for Statistical Significance, Spearman’s Rho: A Nonparametric Alternative to Pearson, Tests of Mean Differences, t-Tests for One Sample, Two-Sample t-Test, Paired-Samples t-Test, Categorical Data, Binomial Test, Categorical Data Having More Than Two Possibilities.	12
III	Power Analysis and Sample Size Estimation:Power for t-Tests, Power for One-Way ANOVA, Power for Correlations. Analysis of Variance: Fixed Effects, Random Effects, Mixed Models,	12

	Introducing the Analysis of Variance (ANOVA), Performing the ANOVA, Random Effects ANOVA and Mixed Models, One-Way Random Effects ANOVA, Simple and Multiple Linear Regression,Simple Linear Regression, Multiple Regression Analysis, Hierarchical Regression, How Forward Regression Works,	
IV	Logistic Regression and the Generalized Linear Model:Logistic Regression, Logistic Regression, Predicting Probabilities, Multiple Logistic Regression, Training Error Rate Versus Test Error Rate. Multivariate Analysis of Variance (MANOVA) and Discriminant Analysis:Multivariate Tests of Significance, Example of MANOVA, Outliers, Homogeneity of Covariance Matrices, Linear Discriminant Function Analysis, Theory of Discriminant Analysis, Predicting Group Membership, Visualizing Separation	12
V	Principal Component Analysis: Principal Component Analysis Versus Factor Analysis, Properties of Principal Components, Component Scores, How Many Components to Keep?, Exploratory Factor Analysis, Common Factor Analysis Model, Factor Analysis Versus Principal Component Analysis on the Same, Initial Eigenvalues in Factor Analysis, Rotation in Exploratory Factor Analysis, Estimation in Factor Analysis Cluster Analysis:k-Means Cluster Analysis, Minimizing Criteria, Example of k-Means Clustering, Hierarchical Cluster Analysis, Why Clustering Is Inherently Subjective, Nonparametric Tests, Mann–Whitney U Test, Kruskal–Wallis Test, Nonparametric Test for Paired Comparisons and Repeated	12

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Books and References:					
Sr. No.	Title	Author/s	Publisher	Edition	Year
01	Univariate, Bivariate, and Multivariate Statistics Using R	Daniel J. Denis	Wiley	1st	2020
02	Practical Data Science	Andreas François Vermeulen	APress	1st	2018
03	Data Science from Scratch first Principle in python	Joel Grus	Shroff Publishers	1st	2017
04	Experimental Design in Data science with Least Resources	N C Das	Shroff Publishers	1st	2018

Statistical Methods for Data Science Practical

M. Sc (Data Science)		Semester – I	
Course Name: Statistical Methods for Data Science Practical		Course Code: PSDS1P4	
Periods per week 1 Period is 60 minutes	Lectures	4	
	Credits	2	
		Hours	Marks
Evaluation System	Practical Examination	2	40

Practical:

Perform minimum ten practical based on the basic concepts of each programming paradigm covering the entire syllabus.

Course Outcomes:

At the end of successful completion of the course the student will be able to:

- Describe basics of mathematical foundation that will help the learner to understand the concepts of Deep Learning.
- Understand and describe model of deep learning
- Design and implement various deep supervised learning architectures for text & image data.
- Design and implement various deep learning models and architectures.
- Apply various deep learning techniques to design efficient algorithms for real-world applications.

SEMESTER-II

Artificial Intelligence and Machine Learning

M. Sc (Data Science)		Semester – II	
Course Name: **Artificial Intelligence and Machine Learning**		Course Code: PSDS201	
Periods per week 1 Period is 60 minutes	Lectures	4	
	Credits	4	
		Hours	Marks
Evaluation System	Theory Examination	2½	60
	Theory Internal	--	40

Pre requisites	Knowledge of Algorithms and mathematical foundation

Course Objectives:

- To provide the foundations for AI problem-solving techniques and knowledge representation formalisms
- Understanding Human learning aspects.
- Understanding primitives in learning process by computer.
- Understanding nature of problems solved with Machine Learning

Unit	Details	Lectures
I	Introduction to AI: The AI problems, AI technique, philosophy and development of Artificial intelligence. Minimax algorithm, alpha-beta pruning, stochastic games, Constraint-satisfaction problems. Knowledge and Reasoning: Logical agents, Propositional logic, First-order logic, Inference in FoL: forward chaining, backward chaining, resolution, Knowledge representation: Frames, Ontologies, Semantic web and RDF.	12
II	Introduction to PROLOG: Facts and predicates, data types, goal finding, backtracking, simple object, compound objects, use of cut and fail predicates, recursion, lists, simple input/output, dynamic database. Machine Learning: Machine learning, Examples of Machine Learning Problems, Structure of Learning, learning versus Designing, Training versus Testing, Characteristics of Machine learning tasks, Predictive and descriptive tasks, Machine learning Models: Geometric Models, Logical Models, Probabilistic Models. Features: Feature types, Feature Construction and Transformation, Feature Selection	12
III	Classification and Regression: Classification: Binary Classification- Assessing Classification performance,	12

	Class probability Estimation Assessing class probability Estimates, Multiclass Classification. Regression: Assessing performance of Regression- Error measures, Overfitting- Catalysts for Overfitting, Case study of Polynomial Regression. Theory of Generalization: Effective number of hypothesis, Bounding the Growth function, VC Dimensions, Regularization theory.	
IV	Linear Models: Least Squares method, Multivariate Linear Regression, Regularized Regression, Using Least Square regression for Classification. Perceptron, Support Vector Machines, Soft Margin SVM, Obtaining probabilities from Linear classifiers, Kernel methods for non-Linearity. Logic Based and Algebraic Model: Distance Based Models:Neighbours and Examples, Nearest Neighbours Classification, Distance based clustering-K means Algorithm, Hierarchical clustering,	12
V	Rule Based Models: Rule learning for subgroup discovery, Association rule mining. Tree Based Models: Decision Trees, Ranking and Probability estimation Trees, Regression trees, Clustering Trees. Probabilistic Model: Normal Distribution and Its Geometric Interpretations, Naïve Bayes Classifier, Discriminative learning with Maximum likelihood, Probabilistic Models with Hidden variables: Estimation-Maximization Methods, Gaussian Mixtures, and Compression based Models.	12

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Books and References:

Sr. No.	Title	Author/s	Publisher	Edition	Year
01	Artificial Intelligence	Elaine Rich, Kevin Knight	Tata McGraw Hill	3rd	2017
02	Machine Learning: The Art and Science of Algorithms that Make Sense of Data	Peter Flach	Cambridge University Press	1st	2012
03	Introduction to Statistical Machine Learning with Applications in R	Hastie, Tibshirani, Friedman	Springer	2nd	2012
04	Introduction to Machine Learning	EthemAlpaydin	PHI	2nd	2013

Artificial Intelligence and Machine Learning Practical

M. Sc (Data Science)		Semester – II	
Course Name:Artificial Intelligence and Machine Learning Practical		Course Code: PSDS2P1	
Periods per week (1 Period is 60 minutes)		4	
Credits		2	
		Hours	Marks
Evaluation System	Practical Examination	2	50
	Internal	--	-

Practical:

Perform minimum ten practical based on the basic concepts of each programming paradigm covering the entire syllabus.

Course Outcomes:

- Understand the key issues and concepts in Artificial Intelligence.
- Acquire the knowledge about classification and regression techniques where a learner will be able to explore his skill to generate data base knowledge using the prescribed techniques.
- Understand and implement the techniques for extracting the knowledge using machine learning methods.
- Achieve adequate perspectives of big data analytics in various applications like recommender systems, social media applications etc.
- Understand the statistical approach related to machine learning. He will also apply the algorithms to a real-world problem, optimize the models learned and report on the expected accuracy that can be achieved by applying the mode

Soft Computing

M. Sc (Data Science)		Semester – II	
Course Name:**Soft Computing**		Course Code:PSDS202	
Periods per week 1 Period is 60 minutes	Lectures	4	
	Credits	4	
		Hours	Marks
Evaluation System	Theory Examination	2½	60
	Theory Internal	--	40

Course Objectives:

- Soft computing concepts like fuzzy logic, neural networks and genetic algorithm, where Artificial Intelligence is mother branch of all.

- All these techniques will be more effective to solve the problem efficiently

Unit	Details	Lectures
I	Artificial Neural Network:Fundamentalconcepts,Evolution of neural network, basic model of Artificial Neural Network, Important terminologies, McCulloch Pits neuron, linear separability, Hebb network Supervised Learning Network: Perceptron networks, Adaline, MAdaline, Backpropogation network, Radial Basis Function, Time Delay Network, Functional Link Networks, Tree Neural Network.	12
II	UnSupervised Learning Networks: Fixed weight competitive nets, Kohonen self-organizing feature maps, learning vectors quantization, counter propogation networks, adaptive resonance theory networks. Associative Memory Networks: Training algorithm for pattern Association, Autoassociative memory network, hetroassociative memory network, bi-directional associative memory, Hopfield networks, iterative autoassociative memory networks, temporal associative memory networks.	12
III	Special Networks: Simulated annealing, Boltzman machine, Gaussian Machine, Cauchy Machine, Probabilistic neural net, cascade correlation network, cognition network, neo-cognition network, cellular neural network, optical neural network Third Generation Neural Networks: Spiking Neural networks, convolutional neural networks, deep learning neural networks, extreme learning machine model.	12
IV	Introduction to Fuzzy Logic, Classical sets, Fuzzy sets, Classical Relations and Fuzzy Relations: Cartesian Product of relation, classical relation, fuzzy relations, tolerance and equivalence relations, non-iterative fuzzy sets. Membership Function: features of the membership functions, fuzzificationand methods of membership value assignments. Defuzzification: Lambda-cuts for fuzzy sets, Lambda-cuts for fuzzy relations, Defuzzification methods. Fuzzy Arithmetic and Fuzzy measures: fuzzy arithmetic, fuzzy measures, measures of fuzziness, fuzzy integrals.	12
V	Genetic Algorithm: Biological Background, Traditional optimization and search techniques, genetic algorithm and search space, genetic algorithm vs. traditional algorithms, basic terminologies, simple genetic algorithm, general genetic algorithm, operators in genetic algorithm, stopping condition for genetic algorithm flow, constraints	12

	in genetic algorithm, problem solving using genetic algorithm, the schema theorem, classification of genetic algorithm, Holland classifier systems, genetic programming, advantages and limitations and applications of genetic algorithm	

Books and References:

Sr. No.	Title	Author/s	Publisher	Edition	Year
1.	Artificial Intelligence and Soft Computing	Anandita Das Battacharya	SPD	3rd	2018
2.	Principles of Soft computing	S.N.Sivanandam S.N.Deepa	Wiley	3rd	2019
3.	Neuro-Fuzzy and Soft Computing	J.S.R.Jang, C.T.Sun and E.Mizutani	Prentice Hall of India	1st	2004
4.	Neural Networks, Fuzzy Logic and Genetic Algorithms: Synthesis & Applications	S.Rajasekaran, G. A. Vijayalakshami	Prentice Hall of India	1st	2004
5.	Fuzzy Logic with Engineering Applications	Timothy J.Ross	McGraw-Hill	1st	1997
6.	Genetic Algorithms: Search, Optimization and Machine Learning	Davis E.Goldberg	Addison Wesley	1st	1989
7.	Introduction to AI and Expert System	Dan W. Patterson	Prentice Hall of India	2nd	2009

Soft Computing Practical

M. Sc (Data Science)		Semester – II	
Course Name:Soft Computing Practical		Course Code:PSDS2P2	
Periods per week (1 Period is 60 minutes)		4	
Credits		2	
		Hours	Marks
Evaluation System	Practical Examination	2	50
	Internal	--	-

Practical:

Perform minimum ten practical based on the basic concepts of each programming paradigm covering the entire syllabus.

Course Outcome:

- Identify and describe soft computing techniques and their roles in building intelligent machines

- Recognize the feasibility of applying a soft computing methodology for a particular problem
- Apply fuzzy logic and reasoning to handle uncertainty and solve engineering problems and also Apply neural networks for classification and regression problems
- Apply genetic algorithms to combinatorial optimization problems
- Evaluate and compare solutions by various soft computing approaches for a given problem.

Algorithms for Data Science

M. Sc (Data Science)		Semester – II	
Course Name: **Algorithms for Data Science**		Course Code: PSDS203	
Periods per week (1 Period is 60 minutes)		4	
Credits		4	
		Hours	Marks
Evaluation System	Theory Examination	2½	60
	Internal	--	40

Course Objectives:

The course is aimed at:

- focussing on the principles of data reduction and core algorithms for analysing the data of data science
- providing many opportunities to develop and improve programming skills
- applying algorithms to real world data set
- Imparting design thinking capability to build big-data

Unit	Details	Lectures
I	Introduction: What Is Data Science?, Diabetes in America, Authors of the Federalist Papers, Forecasting NASDAQ Stock Prices, Algorithms, Python, R, Terminology and Notation Data Mapping and Data Dictionaries: Data Reduction, Political Contributions, Dictionaries, Tutorial: Big Contributors, Data Reduction, Election Cycle Contributions, Similarity Measures, Computing Similarity Scalable Algorithms and Associative Statistics: Introduction, Associative Statistics, Univariate Observations, Functions, Histogram Construction, Multivariate Data, Computing the Correlation Matrix, Linear Regression, Computing β	12
II	Hadoop and MapReduce: Introduction, The Hadoop Ecosystem, Medicare Payments, The Command Line Environment, Programming a MapReduce Algorithm, Using Amazon Web Services Data Visualization: Introduction, Principles of Data Visualization, Making Good Choices, Harnessing the Machine	12

III	Linear Regression Methods: Introduction, The Linear Regression Model, Introduction to R, Large Data Sets and R, Factors, Analysis of Residuals Healthcare Analytics: Introduction, The Behavioral Risk Factor Surveillance System, Diabetes Prevalence and Incidence, Predicting At-Risk Individuals, Identifying At-Risk Individuals, Unusual Demographic Attribute Vectors, Building Neighborhood Sets	12
IV	Cluster Analysis: Introduction, Hierarchical Agglomerative Clustering, Comparison of States, Hierarchical Clustering of States, The *k*-Means Algorithm *k*-Nearest Neighbor Prediction Functions: Introduction, Notation and Terminology, Distance Metrics, The *k*-Nearest Neighbor Prediction Function, Exponentially Weighted *k*-Nearest Neighbors, Digit Recognition, Accuracy Assessment, *k*-Nearest Neighbor Regression, Forecasting the S&P 500, Forecasting by Pattern Recognition, Cross-Validation The Multinomial Naïve Bayes Prediction Function: Introduction, The Federalist Papers, The Multinomial Naïve Bayes Prediction Function, Reducing the Federalist Papers, Predicting Authorship of the Disputed Federalist Papers, Customer Segmentation	12
V	Forecasting: Introduction, Working with Time, Analytical Methods, Computing $\rho\tau$, Drift and Forecasting, Holt-Winters Exponential Forecasting, Regression-Based Forecasting of Stock Prices, Time-Varying Regression Estimators Real-time Analytics: Introduction, Forecasting with a NASDAQ Quotation Stream, Forecasting the Apple Inc. Stream, The Twitter Streaming API, Sentiment Analysis, Sentiment Analysis of Hashtag Groups	12

Books and References:

Sr. No.	Title	Author/s	Publisher	Edition	Year
1	Algorithms for Data Science	Brian Steele, John Chandler,Swarna Reddy	Springer	1st	2016
2	Data Science Algorithms in a Week	David Natingga	Packt Publishing	1st	2017
3	Data Science: Theories, models, Algorithms and Analytics	SanjivRanjan Das	S.R. Das	1st	2017

Algorithms for Data Science Practical

M. Sc (Data Science)		Semester II	
Course Name:Algorithms for Data Science Practical		Course Code: PSDS2P3	
Periods per week (1 Period is 60 minutes)		4	
Credits		2	
		Hours	Marks
Evaluation System	Practical Examination	2	50
	Internal	--	

Practical:

Perform minimum ten practical based on the basic concepts of each programming paradigm covering the entire syllabus.

Course Outcomes:
At the end of the course the student should be able to:

- Understand fundamentals of data science
- Apply data visualisation in big-data analytics
- Apply Hadoop and map-reduce algorithm to big data
- Apply different algorithms to data sets
- Perform real-time analytics

Optimization Techniques

M. Sc (Data Science)		Semester – II	
Course Name: **Optimization Techniques**		Course Code: PSDS204	
Periods per week (1 Period is 60 minutes)		4	
Credits		4	
		Hours	Marks
Evaluation System	Theory Examination	2½	60
	Internal	--	40

Course Objectives:

- To familiarize the students with some basic concepts of optimization techniques and approaches.
- To formulate a real-world problem as a mathematical programming model.
- To develop the model formulation and applications are used in solving decision problems.
- To solve specialized linear programming problems like the transportation and assignment Problems.

Unit	Details	Lectures
I	Mathematical Foundations: Functions and Continuity, Review of Calculus, Vectors, Matrix Algebra, Eigenvalues and Eigenvectors, Optimization and Optimality, General Formulation of Optimization Problems Algorithms, Complexity, and Convexity: What Is an Algorithm?, Order Notations, Convergence Rate, Computational Complexity, Convexity, Stochastic Nature in Algorithms	12
II	Optimization: Unconstrained Optimization, Gradient-Based Methods, Gradient-Free Nelder–MeadMethod Constrained Optimization: Mathematical Formulation, Lagrange Multipliers, Slack Variables, Generalized Reduced GradientMethod, KKT Conditions, PenaltyMethod Optimization Techniques: Approximation Methods: BFGS Method, Trust-Region Method, Sequential Quadratic Programming, Convex Optimization, Equality Constrained Optimization, Barrier Functions, Interior-PointMethods, Stochastic and Robust Optimization	12
III	Linear Programming: Introduction, SimplexMethod, Worked Example by	12

	Simplex Method, Interior-PointMethod for LP Integer Programming: Integer Linear Programming, LP Relaxation, Branch and Bound, Mixed Integer Programming, Applications of LP, IP, and MIP Regression and Regularization: SampleMean and Variance, Regression Analysis, Nonlinear Least Squares, Over-fitting and Information Criteria, Regularization and Lasso Method, Logistic Regression, Principal Component Analysis	
IV	Machine Learning Algorithms: Data Mining, Data Mining for Big Data, Artificial Neural Networks, Support Vector Machines, Deep Learning Queueing Theory and Simulation: Introduction, Arrival Model, Service Model, Basic QueueingModel, Little’s Law, Queue Management and Optimization Multiobjective Optimization: Introduction, Pareto Front and Pareto Optimality, Choice and Challenges, Transformation to Single Objective Optimization, The □Constraint Method, Evolutionary Approaches	12
V	Constraint-Handling Techniques: Introduction and Overview, Method of Lagrange Multipliers, Barrier Function Method, PenaltyMethod, Equality Constraints via Tolerance, Feasibility Criteria, Stochastic Ranking, Multiobjective Constraint-Handling and Ranking Evolutionary Algorithms: Evolutionary Computation, Evolutionary Strategy, Genetic Algorithms, Simulated Annealing, Differential Evolution Nature-Inspired Algorithms: Introduction to SI, Ant and Bee Algorithms, Particle Swarm Optimization, Firefly Algorithm, Cuckoo Search, Bat Algorithm, Flower Pollination Algorithm, Other Algorithms	12

Books and References:

Sr. No.	Title	Author/s	Publisher	Edition	Year
1	Optimization Techniques and Applications with Examples	Xin-She Yang	Wiley	3rd	2018
2	Optimization Techniques	A.K. Malik, S.K. Yadav, S.R. Yadav	I.K. International Publishing House	1st	2012
3	**Optimization methods: from theory to design**	Marco Cavazzuti	Springer	1st	2012
4	**Optimization Techniques**	Chander Mohan, Kusum Deep	New Age International	1st	2009

Optimization Techniques Practical

M. Sc (Data Science)		Semester II	
Course Name: Optimization Techniques Practical		Course Code: PSDS2P4	
Periods per week (1 Period is 60 minutes)		4	
Credits		2	
		Hours	Marks
Evaluation System	Practical Examination	2	50
	Internal	--	

Practical:

Perform minimum ten practical based on the basic concepts of each programming paradigm covering the entire syllabus.

Course Outcomes:
Learner will be able to

- Apply operations research techniques like linear programming problem in industrial optimization problems.
- Solve allocation problems using various OR methods.
- Understand the characteristics of different types of decision making environment and the appropriate decision making approaches and tools to be used in each type.
- Recognize competitive forces in the marketplace and develop appropriate reactions based on existing constraints and resources.

Evaluation Scheme

The External Examination and Practical Examination will be held by University of Mumbai in accordance with the M.Sc. guidelines for all the courses.

Internal Evaluation (40 Marks)

The internal assessment marks shall be awarded as follows:

1. 30 marks (Any one of the following):
   a. Written Test or
   b. SWAYAM (Advanced Course) of minimum 20 hours and certification exam completed or
   c. NPTEL (Advanced Course) of minimum 20 hours and certification exam completed or

   d. Valid International Certifications (Prometric, Pearson, Certiport, Coursera, Udemy and the like)
   e. One certification marks shall be awarded one course only. For four courses, the students will have to complete four certifications.
2. 10 marks: Class participation, Question answer sessions during lectures, Discussions

Suggested format of Question paper of 30 marks for the Internal written test.

Q1.	**Attempt *any two* of the following:**	**16**
a.		
b.		
c.		
d.		
Q2.	**Attempt *any two* of the following:**	**14**
a.		
b.		
c.		
d.		

External Examination: (60 marks)

To be conducted by University as per other M.Sc. Programmes

	All questions are compulsory	
Q1	(Based on Unit 1) Attempt *any two* of the following:	12
a.		
b.		
c.		
d.		
Q2	(Based on Unit 2) Attempt *any two* of the following:	12
Q3	(Based on Unit 3) Attempt *any two* of the following:	12
Q4	(Based on Unit 4) Attempt *any two* of the following:	12
Q5	(Based on Unit 5) Attempt *any two* of the following:	12

Practical Evaluation (50 marks)

To be conducted by University as per other M.Sc. Programmes

A Certified copy journal is essential to appear for the practical examination.

1.	Practical Question 1	20
2.	Practical Question 2	20

3.	Journal	5
4.	Viva Voce	5

OR

1.	Practical Question	40
2.	Journal	5
3.	Viva Voce	5