



S P Mandali's
R. A. PODAR COLLEGE OF COMMERCE AND ECONOMICS
(EMPOWERED AUTONOMOUS),
Matunga, Mumbai-400019

Course Structure

**Master of Science
(Data Science and Analytics)**

Semester I and II

College Website: www.rapodar.ac.in

Program Objectives

1. To equip learners with strong foundations in data science, including statistical analysis, computational mathematics, and data modeling techniques.
2. To develop the ability to analyze and extract meaningful insights from structured and unstructured data.
3. To train learners in designing intelligent systems using machine learning, neural networks, and adaptive algorithms.
4. To enable application of data science solutions in domains such as finance, marketing, IoT, and business analytics.
5. To provide exposure to emerging technologies such as web mining, IoT analytics, and large language models.
6. To strengthen mathematical and statistical foundations for building efficient and scalable models.
7. To develop skills in time series analysis and forecasting for predictive analytics.
8. To build expertise in domain-specific analytics such as financial and marketing analytics.
9. To inculcate research aptitude through research methodology, ethics, and academic writing.
10. To provide practical exposure through on-job training, internships, and field projects.
11. To develop problem-solving, critical thinking, and data-driven decision-making skills.
12. To instill professional ethics, communication skills, and teamwork abilities.
13. To encourage continuous learning and adaptability to evolving data science technologies.

Program Outcomes

1. Learners will be able to apply mathematical and statistical foundations to solve data science problems.
2. Learners will be able to perform data collection, preprocessing, and analysis using web mining and analytics techniques.
3. Learners will be able to design and implement machine learning and adaptive systems for intelligent decision-making.
4. Learners will be able to develop and apply neural network models for complex data-driven applications.
5. Learners will be able to analyze IoT data for real-time insights and predictive modeling.
6. Learners will be able to apply time series analysis and forecasting techniques for temporal data modeling.
7. Learners will be able to develop domain-specific analytics solutions in finance, marketing, and business intelligence.
8. Learners will be able to apply natural language processing and large language models for language intelligence tasks.
9. Learners will be able to use modern tools and technologies for data visualization and decision-making.
10. Learners will be able to conduct research using appropriate methodologies, ethical standards, and academic writing practices.

Master of Science (Data Science and Analytics) Programme
Syllabus as per National Education Policy 2020
Course Structure
M.Sc. (Data Science and Analytics) (Level 6)
(To be implemented from Academic Year 2026-27)

No of Courses	Course Code	Semester I	Credits	No of Courses	Course Code	Semester II	Credits
1	Major (16 Credits)			1	Major (16 Credits)		
1.A	Mandatory (08 Credits)			1.A	Mandatory (08 Credits)		
1.A.a	PPV101101	Web Mining	04	1.A.a	PPV102101	IoT Analytics	04
1.A.b	PPV101102	Machine Intelligence and Adaptive Systems	04	1.A.b	PPV102102	Neural Network Architectures	04
1.B	Major Elective (08 Credits)			1.B	Major Elective (08 Credits)		
1.B.a	PPV101103	Computational Mathematics	04	1.B.a	PPV102103	Statistical Computing	04
1.B.b	PPV101104	Time Series and Forecasting	04	1.B.b	PPV102104	Financial Analytics and Decision Making using Excel	04
1.B.c	PPV101105	Marketing Analytics and Customer Intelligence		1.B.c	PPV102105	Language Intelligence and Large Language Models	
2	Research Methodology (06 credits)			2	On Job Training/ Field Project (06 Credits)		
2.A.a	PPQ601101	Research Methodology	04	2.A.a	PPQ602101	On Job Training/ Field Project	06
2.A..b	PPQ601102	Research Ethics and Academic Writing	02				
TOTAL CUMULATIVE CREDITS			22	TOTAL CUMULATIVE CREDITS			22

Exit option at the end of the First year (on completion of semester I and semester II):

A Post Graduate Diploma in Data Science and Analytics will be awarded to a learner upon fulfillment of the following condition:

The learner must have acquired a total of 44 credits in Semesters I and II, considered together.

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R. A. PODAR COLLEGE OF COMMERCE AND ECONOMICS
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**Master of Science
(Data Science and Analytics)
First Year Semester I**

Syllabus
And
Question paper pattern of the Course

As per the National Education Policy 2020
To be implemented from Academic Year 2026- 2027

College Website: www.rapodar.ac.in

**M.Sc. (Data Science & Analytics) Programme
(With effect from the Academic Year 2026-2027)
Web Mining (4 Credits)**

1. Major	
1.A Mandatory	
Web Mining (4 Credits)	
Course Objectives and Course Outcomes	
Course Objectives	
CObj 1	To understand the fundamentals of web mining, data formats, and ethical data collection techniques.
CObj 2	To learn techniques for extracting meaningful information from web text using mining and NLP methods.
CObj 3	To understand graph-based web data representation and social network analysis techniques.
CObj 4	To explore user behavior analysis and applications like recommendation systems and personalization.
Course Outcomes	
COut 1	Learners will be able to apply web scraping techniques and data preprocessing methods to collect and store structured web data responsibly.
COut 2	Learners will be able to analyze web content using text mining, sentiment analysis, and topic modeling techniques.
COut 3	Learners will be able to evaluate web structures and social networks to identify influential nodes and detect link patterns.
COut 4	Learners will be able to design basic web usage mining applications such as recommendation systems using user interaction data.

Modules at a Glance

Web Mining		
Sr. No.	Modules	No. of Lectures
1	Introduction to Web Mining & Data Collection	15
2	Web Content Mining	15
3	Web Structure and Social Network Mining	15
4	Web Usage Mining and Applications	15
Total		60

Sr. No.	Modules
1	Introduction to Web Mining & Data Collection
	Introduction to Web Mining: definition, scope, applications, Types: Web Content, Web Structure, and Web Usage Mining, Web data formats (HTML, XML, JSON), Basics of Web Scraping (BeautifulSoup, Selenium, APIs), Data Cleaning, Parsing & Storage (CSV, MongoDB), Ethics, Legality, and Responsible Web Scraping, Case Study: Ethical scraping from job portals (e.g., Indeed), Mini Project: Build a small web crawler to collect product data from an e-commerce site
2	Web Content Mining
	Text Mining Fundamentals, Preprocessing Web Text (tokenization, stemming, TF-IDF), Keyword extraction and Topic modeling (LDA), Sentiment Analysis and Opinion Mining, Web Document Clustering and Classification (Naive Bayes, SVM), Metadata and Tag Analysis, Case Study: Sentiment analysis on tweets or product reviews, Mini Project: Extract blog data and perform keyword/topic extraction
3	Web Structure and Social Network Mining
	Link Analysis: PageRank, HITS, and centrality measures, Graph Representation of Web Data, Community Detection and Influence Propagation, Network APIs (Twitter, YouTube, Reddit), Web Spam and Link Fraud Detection, Case Study: Identify key influencers from Twitter network, Mini Project: Visualize and analyze a small social graph
4	Web Usage Mining and Applications
	Web Logs and Clickstream Data Analysis, User Behavior Modeling, Recommendation Systems (Collaborative & Content-based), Web Personalization and Targeted Advertising, Web Analytics Tools (Google Analytics, Tableau), Case Study: Recommendation system for news or product site, Group Discussion: Data privacy and personalization trade-offs

Practical Work

List of suggested Practicals	
1	Write a Python script to extract structured data from HTML pages using BeautifulSoup
2	Parse JSON data from a public REST API (e.g., weather, stock, news) and store in MongoDB.
3	Perform web text preprocessing and keyword extraction using TF-IDF or RAKE.
4	Conduct sentiment analysis on social media data (Twitter or Reddit).
5	Implement topic modeling (LDA) on blog or review data.
6	Construct a simple PageRank algorithm using NetworkX on a small web graph.
7	Build a recommendation engine using web usage data or user logs.
8	Analyze Google Analytics or log data for user behavior insights.
9	Integrate web scraping, text mining, and visualization into a mini project.
10	Build a domain-specific web mining prototype, e.g., “Social Sentiment Tracker for Brands.”

Question Paper Pattern (Academic Year: 2026-2027)
Web Mining
Semester End Examination and Practical Examination – 100 Marks
A] Semester End Examination (SEE) - 50 Marks

Maximum Marks: 50

Duration: 2 Hours

Note: (1) All questions are compulsory, subject to internal choice.

(2) Figures to the right indicate full marks.

Question No.	Particulars (Nature of Questions)	Marks (Given)	Marks (To Be Attempted)
Q-1	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-2	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-3	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-4	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q5.	Short notes	20	10
	Total	100	50

B] Practical Examination - 50 Marks**Maximum Marks: 50****Duration: 1 and a half hours.****All questions are compulsory.****A Certified copy of the journal is essential to appear for the practical examination.**

1.	Lab Work	30
2.	Journal	10
3.	Viva Voce	10

Books and References:

- Bing Liu, Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data, Springer.
- Raymond Kosala & Hendrik Blockeel, Web Mining Research: A Survey, ACM SIGKDD.
- Charu C. Aggarwal, Mining the Web: Discovering Knowledge from Hypertext Data, Springer.
- Jiawei Han, Micheline Kamber, Data Mining: Concepts and Techniques, Morgan Kaufmann.
- Leskovec, Rajaraman & Ullman, Mining of Massive Datasets, Cambridge University Press.

Teaching Pedagogy:

Lectures/ tutorials/ field work/ outreach activities/ project work/ vocational training/ viva/seminars/term papers/assignments/presentations/self-study/case studies, etc., or a combination of some of these. Sessions shall be interactive in nature to enable peer group learning

M.Sc. (Data Science & Analytics) Programme
(With effect from the Academic Year 2026-2027)
Machine Intelligence and Adaptive Systems (4 Credits)

1. Major	
1.A Mandatory	
1.A.b Machine Intelligence and Adaptive Systems (4 Credits)	
Course Objectives and Course Outcomes	
Course Objectives	
CObj 1	To understand the fundamentals of machine learning, including supervised and unsupervised learning, model evaluation, and feature engineering.
CObj 2	To learn ensemble methods and techniques for optimizing model performance and interpretability.
CObj 3	To understand adaptive and online learning systems, including incremental learning, concept drift, and transfer learning.
CObj 4	To explore the principles of reinforcement learning and intelligent agents for decision-making in dynamic environments.
Course Outcomes	
COut 1	Learners will be able to apply end-to-end machine learning pipelines, including data preprocessing, model building, and evaluation for real-world datasets.
COut 2	Learners will be able to analyze and evaluate different ensemble models and hyperparameter tuning strategies to improve predictive accuracy.
COut 3	Learners will be able to design adaptive learning systems that update with evolving data and maintain predictive performance.
COut 4	Learners will be able to apply reinforcement learning algorithms to develop agents that learn optimal strategies through interaction with an environment.

Modules at a Glance

Machine Intelligence and Adaptive Systems		
Sr. No.	Modules	No. of Lectures
1	Foundation of Machine Learning	15
2	Ensemble Learning and Model Optimization	15
3	Adaptive Systems and Online Learning	15
4	Reinforcement Learning and Intelligent Agents	15
Total		60

Sr. No.	Modules
1	Foundation of Machine Learning
	Introduction to Machine Intelligence – revisiting the difference between AI, ML, and DL, Supervised learning concepts: regression, classification, overfitting/underfitting, bias-variance trade-off, Unsupervised learning concepts: clustering (K-Means, Hierarchical), dimensionality reduction (PCA, t-SNE), Model evaluation metrics: accuracy, precision, recall, F1-score, ROC-AUC, silhouette score. Feature engineering, normalization, encoding categorical data, and data splitting strategies. Mini Case Study: Customer churn classification for a telecom company. Activity: Implement a complete ML pipeline (data cleaning → model → evaluation) as a bridge assignment.
2	Ensemble Learning and Model Optimization
	Concept of ensemble models — bagging, boosting, stacking. Random Forests, AdaBoost, Gradient Boosting, XGBoost, LightGBM, and CatBoost. Hyperparameter tuning using GridSearchCV, RandomizedSearchCV, and Bayesian Optimization. Model Interpretability: Feature Importance, SHAP, and LIME for Explainability. Mini Case Study: Credit scoring using ensemble models in financial risk prediction. Mini Project: Compare ensemble methods for tabular data (e.g., loan default dataset).
3	Adaptive Systems and Online Learning
	Concept of adaptability in intelligent systems. Online learning algorithms: perceptron, stochastic gradient descent (SGD), and adaptive boosting. Concept drift, incremental learning, and model retraining. Meta-learning and transfer learning (overview). Application in recommendation systems and predictive maintenance. Mini Case Study: Adaptive spam filtering system for evolving datasets. Activity: Build a lightweight adaptive learner that updates with new data streams.
4	Reinforcement Learning and Intelligent Agents
	Introduction to Reinforcement Learning (RL): agent, environment, reward, policy, value functions.

Exploration vs. exploitation, Markov Decision Processes (MDP). Q-Learning and SARSA algorithms. Applications: robotics, games, personalized recommendations, and traffic signal control. Mini Case Study: Q-learning for route optimization or dynamic pricing. Final Mini Project: Build a small RL-based simulation (e.g., grid-world navigation agent).

Practical Work

List of suggested Practicals	
1	Implement linear and logistic regression on a real-world dataset for prediction.
2	Apply K-Means and hierarchical clustering on customer segmentation data.
3	Build and evaluate Random Forest and Gradient Boosting models for classification tasks.
4	Perform hyperparameter tuning using GridSearchCV on an ensemble model.
5	Apply SHAP or LIME to interpret model decisions on tabular data.
6	Implement an online learning model that updates as new data arrives.
7	Build a transfer learning pipeline using pre-trained models (introductory).
8	Implement a Q-learning algorithm for a simple environment (maze or grid).
9	Integrate ensemble learning, adaptability, and reinforcement principles in a mini end-to-end project.
10	Develop an “Adaptive Credit Risk Prediction System” combining ensemble and online learning models.

Question Paper Pattern (Academic Year: 2026-2027)
Machine Intelligence and Adaptive Systems
Semester End Examination and Practical Examination – 100 Marks
A] Semester End Examination (SEE) - 50 Marks

Maximum Marks: 50

Duration: 2 Hours

Note: (1) All questions are compulsory, subject to internal choice.

(2) Figures to the right indicate full marks.

Question No.	Particulars (Nature of Questions)	Marks (Given)	Marks (To Be Attempted)
Q-1	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-2	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-3	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-4	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q5.	Short notes	20	10
	Total	100	50

BJ Practical Examination - 50 Marks**Maximum Marks: 50****Duration: 1 and a half hours.****All questions are compulsory.****A Certified copy of the journal is essential to appear for the practical examination.**

1.	Lab Work	30
2.	Journal	10
3.	Viva Voce	10

Books and References:

- Aurélien Géron — Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow (O'Reilly).
- Richard S. Sutton & Andrew G. Barto — Reinforcement Learning: An Introduction (MIT Press).
- Trevor Hastie, Robert Tibshirani, Jerome Friedman — The Elements of Statistical Learning.
- Sebastian Raschka & Vahid Mirjalili — Python Machine Learning: Machine Learning and Deep Learning with Python, Scikit-learn, and TensorFlow.

Teaching Pedagogy:

Lectures/ tutorials/ field work/ outreach activities/ project work/ vocational training/ viva/seminars/term papers/assignments/presentations/self-study/case studies, etc., or a combination of some of these. Sessions shall be interactive in nature to enable peer group learning.

**M.Sc. (Data Science & Analytics) Programme
(With effect from the Academic Year 2026-2027)
Computational Mathematics (4 Credits)**

1. Major	
1.B Elective	
1.B.a Computational Mathematics (4 Credits)	
Course Objectives and Course Outcomes	
Course Objectives	
CObj 1	To understand fundamental concepts of logic, relations, graph theory, and algorithmic traversals for computational problem-solving.
CObj 2	To gain knowledge of multivariable calculus, derivatives, and optimization techniques for functions of several variables.
CObj 3	To understand linear algebraic concepts, matrix factorizations, eigenvalue computations, and their applications in data analysis and algorithms.
CObj 4	To develop skills in numerical methods for solving equations, integration, linear systems, and differential equations with attention to error analysis.
Course Outcomes	
COut 1	Learners will be able to analyze and model discrete structures and apply traversal algorithms (BFS, DFS) to solve network and graph-related problems.
COut 2	Learners will be able to apply gradient-based methods and Lagrange multipliers to solve optimization problems in multivariate functions.
COut 3	Learners will be able to evaluate and implement numerical linear algebra techniques such as LU decomposition, SVD, and PCA for solving real-world problems like data compression and ranking algorithms.
COut 4	Learners will be able to design and implement computational methods (root-finding, numerical integration, ODE solvers) while assessing numerical stability and error propagation.

Modules at a Glance

Computational Mathematics		
Sr. No.	Modules	No. of Lectures
1	Discrete Mathematics and Logic	15
2	Multivariate Calculus	15
3	Linear Algebra	15
4	Numerical & Computational Methods	15
Total		60

Sr. No.	Modules
1	<p>Discrete Structures and Algorithms</p> <p>Propositional and predicate logic (applied and concise). Relations and equivalence relations. Partially ordered sets (posets), lattices, and Hasse diagrams. Recurrence relations and generating functions. Graph theory: Adjacency, incidence, and Laplacian matrices. Connectivity and traversal algorithms (BFS, DFS). Applications to networks and data graphs</p>
2	<p>Multivariate Calculus and Optimization</p> <p>Functions of several variables: differentiability and gradients. Partial derivatives, directional derivatives, and total derivatives. Jacobian and Hessian matrices: computation and interpretation. Taylor's theorem for multivariable functions. Optimization of multivariable functions. Introduction to constrained optimization using Lagrange multipliers.</p>
3	<p>Computational Linear Algebra</p> <p>Review of vector spaces, rank, and linear independence. Numerical solution of linear systems. Matrix factorizations: LU, QR, Cholesky, and SVD. Eigenvalue problems: Power method, Numerical diagonalization. Matrix norms, condition numbers, and numerical stability. Applications: PCA, Data compression, and dimensionality reduction. Google PageRank algorithm</p>
4	<p>Numerical & Computational Methods</p> <p>Error analysis: truncation and round-off errors. Root-finding methods: Bisection, Newton–Raphson, Secant method. Integration: Trapezoidal and Simpson's rules. Linear Systems: Jacobi and Gauss–Seidel Methods. Solution of ODE: Euler and Runge–Kutta methods.</p>

Practical Work

List of suggested Practicals	
1	Write a program to evaluate propositional logic expressions, generate truth tables, and verify logical equivalence, with interpretation in rule-based decision systems.
2	Represent relations using software, identify equivalence relations, and construct posets and Hasse diagrams, with applications to hierarchical and dependency structures.
3	Represent graphs using adjacency matrices and implement Breadth First Search (BFS) and Depth First Search (DFS), with applications to network and web data.
4	Solve simple recurrence relations (e.g., Fibonacci-type) using iterative methods and interpret results in growth and algorithmic analysis.
5	Compute partial derivatives and gradients of multivariable functions using software and interpret results in sensitivity analysis.
6	Find and classify critical points of multivariable functions using the gradient and Hessian matrix, with applications to cost and profit optimization.
7	Compute LU and QR decompositions of matrices using software and apply them to solve systems of linear equations.
8	Compute eigenvalues and eigenvectors of a matrix and determine the largest eigenvalue using the power method, with interpretation in ranking problems.
9	Perform PCA on a small numerical dataset using software and interpret dimensionality reduction and variance explained.
10	Solve a nonlinear equation using the Newton–Raphson method and solve an ordinary differential equation using Euler or Runge–Kutta methods, with interpretation in modeling and forecasting.

Question Paper Pattern (Academic Year: 2026-2027)
Computational Mathematics
Semester End Examination and Practical Examination – 100 Marks
A] Semester End Examination (SEE) - 50 Marks

Maximum Marks: 50

Duration: 2 Hours

Note: (1) All questions are compulsory, subject to internal choice.

(2) Figures to the right indicate full marks.

Question No.	Particulars (Nature of Questions)	Marks (Given)	Marks (To Be Attempted)
Q-1	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-2	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-3	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-4	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q5.	Short notes	20	10
	Total	100	50

BJ Practical Examination - 50 Marks**Maximum Marks: 50****Duration: 1 and a half hours.****All questions are compulsory.****A Certified copy of the journal is essential to appear for the practical examination.**

1.	Lab Work	30
2.	Journal	10
3.	Viva Voce	10

Books and References:

- Gilbert Strang – Linear Algebra and Its Applications (Cengage Learning).
- Erwin Kreyszig – Advanced Engineering Mathematics (Wiley).
- S. C. Chapra & R. P. Canale – Numerical Methods for Engineers (McGraw-Hill).
- Kenneth H. Rosen – Discrete Mathematics and Its Applications (McGraw-Hill).
- Sheldon Axler – Linear Algebra Done Right (Springer).

Teaching Pedagogy:

Lectures/ tutorials/ field work/ outreach activities/ project work/ vocational training/ viva/seminars/term papers/assignments/presentations/self-study/case studies, etc., or a combination of some of these. Sessions shall be interactive in nature to enable peer group learning

**Syllabus of courses of FY MSc (Data Science & Analytics) Programme
(With effect from the Academic Year 2026-2027)**

1.Major

1.B Elective

1.B.b Time Series and Forecasting (4 Credits)

Semester I

1. Major	
1.B Elective	
1.B.b Time Series and Forecasting	
Course Objectives and Course Outcomes	
Course Objectives	
CObj 1	To introduce learners to fundamental concepts of time-dependent data and its characteristics.
CObj 2	To develop skills in analyzing, visualizing, and modeling time series data.
CObj 3	To understand methods of forecasting using statistical and computational techniques.
CObj 4	To apply time series models to real-world data using Python, R, and Excel.
Course Outcomes	
COut 1	Understand the basic components, patterns, and visualization of time series data.
COut 2	Apply smoothing, trend, and decomposition techniques for time series analysis.
COut 3	Fit and interpret forecasting models such as ARIMA and Exponential Smoothing.
COut 4	Implement forecasting and model evaluation using statistical software tools.

Modules at a Glance

Time Series and Forecasting		
Sr. No.	Modules	No. of Lectures
1	Introduction to Time Series Data	15
2	Smoothing and Decomposition Techniques	15
3	ARIMA and Box–Jenkins Methodology	15
4	Advanced and Applied Forecasting	15
Total		60

Sr. No.	Modules
1	Introduction to Time Series Data
	Concept of time series and examples from business, finance, and environment. Components: trend, seasonality, cyclical, and irregular variations. Time series plots, transformations, and stationarity. Autocorrelation and partial autocorrelation – interpretation (no derivations).
2	Smoothing and Decomposition Techniques
	Moving averages and exponential smoothing (simple, double, and Holt’s method). Seasonal adjustment and decomposition of time series (additive/multiplicative). Trend estimation using least squares and growth models. Forecast accuracy measures: MSE, MAE, MAPE.
3	ARIMA and Box–Jenkins Methodology
	Concepts of AR, MA, and ARIMA models (no derivation). Identification using ACF and PACF plots. Model estimation, diagnostics, and forecasting. Seasonal ARIMA: concept and example.
4	Advanced and Applied Forecasting
	Introduction to regression-based forecasting and dummy variables for seasonality. Introduction to machine learning–based forecasting: Decision Trees, Random Forest (conceptual + demo). Forecast evaluation and model comparison. Case study: Sales, stock prices, or climate data.

Practical Work

List of Suggested Practicals to be Conducted	
1	Plot and visualize a time series using R/Python/Excel.
2	Identify trend and seasonal components from given data.
3	Apply moving average and exponential smoothing methods.
4	Fit Holt's linear and Holt-Winters models and evaluate accuracy.
5	Perform seasonal decomposition and interpret results.
6	Plot ACF and PACF for stationarity check.
7	Fit ARIMA model using R/Python and generate forecasts.
8	Compare ARIMA and Exponential Smoothing models using MAPE.
9	Apply regression-based forecasting for trend and seasonality.
10	Case study: Forecast monthly sales or stock data.
11	Mini project – develop a complete forecasting report for any real dataset.

Question Paper Pattern (Academic Year: 2026-2027)
Time Series and Forecasting
Semester End Examination and Practical Examination – 100 Marks
A] Semester End Examination (SEE) - 50 Marks

Maximum Marks: 50

Duration: 2 Hours

Note: (1) All questions are compulsory, subject to internal choice.

(2) Figures to the right indicate full marks.

Question No.	Particulars (Nature of Questions)	Marks (Given)	Marks (To Be Attempted)
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Q-3	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-4	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q5.	Short notes	20	10
	Total	100	50

B] Practical Examination - 50 Marks**Maximum Marks: 50****Duration: 1 and a half hours.****All questions are compulsory.****A Certified copy of the journal is essential to appear for the practical examination.**

1.	Lab Work	30
2.	Journal	10
3.	Viva Voce	10

Books and References:

- 📖 **Chatfield, C. (2000).** *Time-Series Forecasting*. Chapman & Hall/CRC.
- 📖 **Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2016).** *Time Series Analysis: Forecasting and Control*. Wiley.
- 📖 **Hyndman, R. J., & Athanasopoulos, G. (2021).** *Forecasting: Principles and Practice* (3rd Ed., free online).
- 📖 **Makridakis, S., Wheelwright, S. C., & Hyndman, R. J. (1998).** *Forecasting: Methods and Applications*. Wiley.
- 📖 **Cowpertwait, P. S. P., & Metcalfe, A. V. (2009).** *Introductory Time Series with R*. Springer.
- 📖 **Downey, A. (2014).** *Think Stats: Exploratory Data Analysis in Python*. O'Reilly.

Teaching Pedagogy:

Lectures/ tutorials/ field work/ outreach activities/ project work/ vocational training/ viva/ seminars / term papers/ assignments / presentations / self-study/case studies etc. or a combination of some of these. Sessions shall be interactive in nature to enable peer group learning

**Syllabus of courses of FY MSc (Data Science & Analytics) Programme
(With effect from the Academic Year 2026-2027)**

1.Major

1.B Elective

1.B.c Marketing Analytics and Customer Intelligence (4 Credits)

Semester I

1. Major	
1.B Elective	
1.B.c Marketing Analytics and Customer Intelligence	
Course Objectives and Course Outcomes	
Course Objectives	
CObj 1	To understand and apply R programming and fundamental concepts of customer value, segmentation, and targeting for marketing analysis.
CObj 2	To analyze and evaluate demand patterns, pricing strategies, and marketing effectiveness using analytical models.
CObj 3	To apply and analyze predictive techniques for understanding customer behavior, including recommendations, churn, and lifetime value.
CObj 4	To analyze and create insights from unstructured data and networks using text mining and social network analysis.
Course Outcomes	
COut 1	Learners will be able to analyze customer data and implement basic segmentation and targeting strategies using R.
COut 2	Learners will be able to evaluate pricing decisions and assess marketing campaign performance using forecasting and marketing mix models.
COut 3	Learners will be able to build and interpret predictive models such as recommender systems and churn models for customer decision-making.
COut 4	Learners will be able to design and develop advanced analytics solutions for sentiment analysis, product innovation, and network-based marketing strategies.

Modules at a Glance

Marketing Analytics and Customer Intelligence		
Sr. No.	Modules	No. of Lectures
1	Foundations of Marketing Analytics & R	15
2	Pricing, Demand & Marketing Effectiveness	15
3	Customer Analytics & Predictive Modeling	15
4	Advanced Analytics & Emerging Applications	15
Total		60

Sr. No.	Modules
1	Foundations of Marketing Analytics & R
	Introduction to R Programming, Data handling and visualization basics in R Understanding customer value Conjoint Analysis (measuring customer preferences) Customer segmentation techniques Targeting strategies using analytics
2	Pricing, Demand & Marketing Effectiveness
	Demand Forecasting methods Pricing strategies and optimization Marketing Mix Models (MMM) Advertising effectiveness models ROI measurement for marketing campaigns
3	Customer Analytics & Predictive Modeling
	Recommender Systems Market Basket Analysis RFM (Recency, Frequency, Monetary) Analysis Customer Churn prediction Customer Lifetime Value (CLV) modeling
4	Advanced Analytics & Emerging Applications
	Text Mining fundamentals Sentiment Analysis Text analytics for product innovation Social Network Analysis in marketing Applications of AI in marketing analytics

Practical Work

List of Suggested Practicals to be Conducted	
1	Customer segmentation using K-Means and Hierarchical clustering
2	Conjoint analysis to determine customer preferences
3	RFM (Recency, Frequency, Monetary) analysis using customer dataset
4	Customer churn prediction using logistic regression
5	Customer Lifetime Value (CLV) modeling
6	Market Basket Analysis (Apriori algorithm)
7	Building a recommender system (collaborative filtering)
8	Marketing Mix Modeling (MMM) using historical sales and advertising data
9	Text mining and sentiment analysis on social media or product reviews
10	Visualization of marketing insights using ggplot2 and Shiny dashboards

Question Paper Pattern (Academic Year: 2026-2027)
Marketing Analytics and Customer Intelligence
Semester End Examination and Practical Examination – 100 Marks
A] Semester End Examination (SEE) - 50 Marks

Maximum Marks: 50

Duration: 2 Hours

Note: (1) All questions are compulsory, subject to internal choice.

(2) Figures to the right indicate full marks.

Question No.	Particulars (Nature of Questions)	Marks (Given)	Marks (To Be Attempted)
Q-1	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-2	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-3	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-4	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q5.	Short notes	20	10
	Total	100	50

B] Practical Examination - 50 Marks**Maximum Marks: 50****Duration: 1 and a half hours.****All questions are compulsory.****A Certified copy of the journal is essential to appear for the practical examination.**

1.	Lab Work	30
2.	Journal	10
3.	Viva Voce	10

Books and References:

1. **R for Marketing Research and Analytics** – *Chris Chapman & Elea McDonnell Feit*
Publisher: Springer (Springer Nature)
2. **Applied Marketing Analytics Using R** – *Gokhan Yildirim & Raoul Kübler*
Publisher: SAGE Publications
3. **Marketing Analytics** – *Seema Gupta & Avadhoot Jathar*
Publisher: Wiley India
4. **Marketing Data Science: Modeling Techniques in Predictive Analytics with R and Python** – *Thomas W. Miller*
Publisher: Pearson Education
5. **Text Analytics in Marketing** – *Daniel Dan & Thomas Reutterer*
Publisher: Springer
6. **Marketing Analytics – IIT Kharagpur**
🔗 <https://onlinecourses.nptel.ac.in>

Teaching Pedagogy:

Lectures/ tutorials/ field work/ outreach activities/ project work/ vocational training/ viva/seminars/term papers/assignments/presentations/self-study/case studies, etc., or a combination of some of these. Sessions shall be interactive in nature to enable peer group learning.

M.Sc. (Data Science & Analytics) Programme
(With effect from the Academic Year 2026-2027)
Research Methodology (4 Credits)
Semester I

2. Research Methodology	
2.A.a Research Methodology(4 Credits)	
Course Objectives and Course Outcomes	
Course Objectives:	
CObj 1	Enable students to understand the conceptual foundations, types, and selection criteria of advanced research tools used in Commerce and Management studies.
CObj 2	Develop the ability to design structured and semi-structured research instruments aligned with specific research objectives.
CObj 3	Build competence in managing, organizing, and documenting research data ethically and systematically.
CObj 4	Foster critical interpretation of research findings using appropriate analytical tools and methodological rigor.
Course Outcomes:	
COut 1	Explain key research concepts, types of research, and components of a sound research design.
COut 2	Formulate research problems, objectives, and hypotheses based on literature review and research gaps.
COut 3	Apply appropriate data processing and statistical techniques for analysis and interpretation of research data.
COut 4	Prepare well-structured, ethical, and professionally written research reports using modern research practices.

Modules at a Glance

Research Methodology		
Module No.	Modules	No. of Lectures
1.	Foundations of Research	15
2.	Research Design and Process	15
3.	Data Processing and Statistical Analysis	15
4	Testing of hypotheses and Research Reporting	15
Total No. of Lectures:		60

Module No.	Modules
1	Foundations of Research
	<p>Introduction to Research- Meaning, objectives, and motivations of research; Characteristics and limitations of research; Components of research work; Criteria of good research; Types of research</p> <p>Literature Review- Purpose, sources, and Procedure for conducting a literature review</p> <p>Research Objectives- Meaning and definition of research objectives; Formulation of research objectives</p> <p>Research Problem and Hypothesis- Identification, selection, and analysis of the research problem; Formulation of the problem statement; Concept and formulation of research hypotheses</p>
2	Research Design and Process
	<p>Research Design- Definition and essentials of research design; Types of research design; Errors in research design; Stages of the Research Process- Sequential steps involved in conducting research</p> <p>Variables and Measurement- Types of variables in research; Measurement and scaling concepts; Types of measurement scales; Research Instruments- Construction of research instruments; Validity and reliability of instruments; Questionnaire design and validation</p> <p>Sampling- Significance of sampling; Sampling methods and techniques; Sample design; Factors determining sample size; Sample size determination</p> <p>Data Collection Methods- Primary and secondary data; Methods of data collection</p>
3	Data Processing and Statistical Analysis
	<p>Data Analysis Approaches- Concepts of qualitative research; Concepts of quantitative research;</p> <p>Qualitative vs. quantitative data analysis; Measurement, causality, generalization, and replication</p> <p>Data Processing- Editing, coding, and classification of data; Formation of statistical series</p> <p>Statistical Analysis-Tools and Techniques; Measures of Central Tendency; Measures of Dispersion; Correlation Analysis and Regression Analysis.</p>
4	Testing of hypotheses and Research Reporting
	<p>Parametric and Non-Parametric Test – Parametric Test-t test, f test, z test; Non-Parametric Test -Chi-square test, ANOVA, Factor Analysis</p> <p>Interpretation of data- Significance and Precautions in data interpretation</p> <p>Research Reporting- Types of research reports; Structure and contents of a research report; Executive summary; Chapterization and chapter contents; Report writing principles</p> <p>Role of the audience; Readability, comprehension, and tone; Final proofreading and formatting; Title of the research report</p>

Research Methodology
Question Paper Pattern
(Academic Year: 2026-27)

Internal Examination & Semester End Examination - 100 Marks

A] Internal Assessment: 50 Marks

B] Semester End Examination (SEE): 50 Marks

All questions are compulsory.

Duration - 2 Hours

Question No.	Particulars (Nature of Questions)	Marks (Given)	Marks (To Be Attempted)
Q-1	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-2	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-3	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-4	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q5.	Short notes	20	10
	Total	100	50

Continuous Internal Evaluation System:

Continuous Internal Evaluation (CIE) - 50 Marks

The internal evaluation of 50 marks for Honours each semester would be of tests and of class participation, project, case study analysis, Case lets, PowerPoint presentations, group discussion, book review, Research paper, article analysis and any other mode depending on the nature and scope of the course. Continuous Internal Evaluation (CIE), to be conducted by the subject teacher all through the semester. The total mark break up would be suitably divided and the total marks scored by the learner would be submitted to the Controller of Examination.

Reference Books:

1. Creswell, J.W. and Creswell, J.D., 2017. Research design: Qualitative, quantitative, and mixed methods approaches. Sage Publications.
2. Kothari, C.R., 2004. Research methodology: Methods and techniques. New Age International.
3. Sekaran, U. and Bougie, R., 2016. Research methods for business: A skill building approach. John Wiley & Sons.
4. Research Methodology – Text and Cases with SPSS Applications, by Dr. S.L. Gupta and Hitesh Gupta, International Book House Pvt Ltd
5. Business Research Methodology by T N Srivastava and Shailaja Rego, Tata McGraw-Hill Education Private Limited, New Delhi
6. Research Methods in Economics and Business by R. Gerber and P.J. Verdoom, The

M.Sc. (Data Science & Analytics) Programme
(With effect from the Academic Year 2026-2027)
2.A.b Research Ethics and Academic Writing (2 Credits)
Semester I

2. Research Methodology	
2.A.b Research Ethics and Academic Writing (2 Credits)	
Course Objectives and Course Outcomes	
Course Objectives:	
CObj 1	To familiarize learners with the principles of research ethics and academic integrity.
CObj 2	To sensitize learners to ethical issues in research, publication, and academic writing.
CObj 3	To develop responsible academic writing and ethical publication practices.
Course Outcomes:	
COut 1	Learners will be able to understand and apply ethical principles in research and academic practices.
COut 2	Learners will be able to identify and avoid unethical practices in academic writing and scholarly publication.

Modules at a Glance

Research Ethics and Academic Writing		
Module No.	Modules	No. of Lectures
1.	Research Ethics and Responsible Conduct of Research	15
2.	Academic Writing, Publication Practices, And Research Evaluation	15
Total No. of Lectures:		30

Module No.	Modules
1	Research Ethics and Responsible Conduct of Research
	Introduction to research ethics: meaning, nature, and importance Philosophy of ethics and moral reasoning in research Ethics in academics and academic integrity Research integrity and intellectual honesty Scientific misconduct: Fabrication, Falsification, and Plagiarism (FFP) Redundant publications: duplicate publication, salami slicing Selective reporting and misrepresentation of data Authorship and contributorship ethics Conflicts of interest in research Institutional mechanisms: complaints, appeals, and ethical accountability
2	Academic Writing, Publication Practices, And Research Evaluation
	Principles of academic writing: clarity, coherence, originality Review of literature and formulation of the research problem Integrating theory and data in academic writing Use of ICT tools in academic writing Publication ethics: COPE, WAME, CARE guidelines Predatory journals and publishers: identification and risks Plagiarism detection tools: Turnitin, Urkund, and open-source tools Introduction to open access publishing and self-archiving Academic databases: Web of Science, Scopus (overview) Research metrics: Impact Factor, CiteScore, h-index, altmetrics

Research Ethics and Academic Writing
Question Paper Pattern
(Academic Year: 2026-27)

Internal Examination & Semester End Examination - 50 Marks

A] Internal Assessment: 25 Marks

Continuous Internal Evaluation System:

Continuous Internal Evaluation (CIE) - 50 Marks

The internal evaluation of 50 marks for Honours each semester would be of tests and of class participation, project, case study analysis, Case lets, PowerPoint presentations, group discussion, book review, Research paper, article analysis and any other mode depending on the nature and scope of the course. Continuous Internal Evaluation (CIE), to be conducted by the subject teacher all through the semester. The total mark break up would be suitably divided and the total marks scored by the learner would be submitted to the Controller of Examination.

B] Semester End Examination (SEE): 50 Marks

All questions are compulsory.

Duration - 1 Hours

Question No.	Particulars	Marks
Q1. (Module I)	A) Practical/ Theory Question OR B) Practical/ Theory Question	10 Marks
Q2. (Module II)	A) Practical/ Theory Question OR B) Practical/ Theory Question	10 Marks
Q3. (Both Modules)	A) Practical/ Theory Question OR B) Practical/ Theory Question	5 Marks
Total		25 Marks

Reference Books:

1. Bird, A. (2006). *Philosophy of Science*. Routledge.
2. MacIntyre, A. (1967). *A Short History of Ethics*. London.
3. Chaddah, P. (2018). *Ethics in Competitive Research: Do Not Get Scooped, Do Not Get Plagiarized*. Springer.
4. National Academy of Sciences, National Academy of Engineering & Institute of Medicine. (2009). *On Being a Scientist: A Guide to Responsible Conduct in Research*. National Academies Press.
5. Resnik, D. B. (2011). *What Is Ethics in Research & Why Is It Important*. National Institute of Environmental Health Sciences.
6. Indian National Science Academy (INSA). (2019). *Ethics in Science Education, Research and Governance*. New Delhi.
7. Suber, P. (2012). *Open Access*. MIT Press.
8. Beall, J. (2012). Predatory publishers are corrupting open access. *Nature*, 489(7415), 179.
9. Das, A. K. (2015). *Research Evaluation Metrics*. UNESCO Curriculum for Researchers, Module 4.
10. UGC. (2020). *Good Academic Research Practices*. University Grants Commission, New Delhi.

S P Mandali's
R. A. PODAR COLLEGE OF COMMERCE AND ECONOMICS
(EMPOWERED AUTONOMOUS),
Matunga, Mumbai-400019

**Master of Science
(Data Science and Analytics)
First Year Semester II**

Syllabus
And
Question paper pattern of the Course

As per the National Education Policy 2020
To be implemented from Academic Year 2026- 2027

College Website: www.rapodar.ac.in

**M.Sc. (Data Science & Analytics) Programme
(With effect from the Academic Year 2026-2027)**

1.Major

1.A Mandatory

IoT Analytics (4 Credits)

1. Major	
1.A Mandatory	
1.A.a IoT Analytics	
Course Objectives and Course Outcomes	
Course Objectives	
CObj 1	To understand the architecture, components, and data ecosystem of IoT systems, and the role of analytics in IoT.
CObj 2	To learn methods for acquiring, transmitting, storing, and preprocessing IoT data efficiently.
CObj 3	To explore analytics techniques, machine learning applications, and anomaly detection in IoT data.
CObj 4	To understand visualization techniques and real-world applications of IoT analytics, including ethical and emerging trends.
Course Outcomes	
COut 1	Learners will be able to explain and classify IoT components, data types, and data flow in IoT ecosystems.
COut 2	Learners will be able to apply data collection, preprocessing, and pipeline techniques for structured and unstructured IoT data.
COut 3	Learners will be able to analyze IoT datasets using descriptive, predictive, and prescriptive analytics, and implement basic ML models for tasks like forecasting and anomaly detection.
COut 4	Learners will be able to design IoT dashboards and visualizations to derive actionable insights for decision-making in domains like healthcare, transportation, and smart cities.

Modules at a Glance

IoT Analytics		
Sr. No.	Modules	No. of Lectures
1	Fundamentals of IoT and Analytics	15
2	Data Collection and Processing in IoT	15
3	Analytical Models and Tools for IoT	15
4	Visualization and Applications of IoT Analytics	15
Total		60

Sr. No.	Modules
1	Fundamentals of IoT and Analytics
	<p>Overview of IoT systems: Devices, sensors, and data communication. IoT architecture and data life cycle. Role of analytics in IoT ecosystems. Types of IoT data: Structured, unstructured, and time-series. Case study: Smart city or smart home IoT data.</p>
2	Data Collection and Processing in IoT
	<p>IoT data acquisition and transmission protocols (MQTT, CoAP, HTTP). Data storage: Edge, fog, and cloud computing models. Stream vs. batch data processing. Preprocessing IoT data: Cleaning, filtering, normalization, and transformation. Use of data pipelines for IoT analytics.</p>
3	Analytical Models and Tools for IoT
	<p>Descriptive, predictive, and prescriptive analytics for IoT. Machine learning for IoT data analysis. Anomaly detection, trend analysis, and forecasting. Tools: Python libraries (NumPy, Pandas, Matplotlib), ThingSpeak, AWS IoT Analytics. Case study: Predictive maintenance using sensor data.</p>
4	Visualization and Applications of IoT Analytics
	<p>IoT dashboards and visualization tools (Grafana, Power BI, Tableau). Decision-making through IoT insights. Applications in healthcare, transportation, agriculture, and manufacturing. Ethical and privacy considerations in IoT analytics. Emerging trends: Edge AI, 5G-enabled analytics, and digital twins.</p>

Practical Work

List of suggested Practicals	
1	Collect and visualize data from IoT sensors using Python or ThingSpeak.
2	Perform data cleaning and preprocessing on an IoT dataset
3	Build a simple predictive model for sensor data (e.g., temperature forecasting).
4	Implement anomaly detection in IoT sensor readings.
5	Create a real-time dashboard using Power BI or Grafana.
6	Analyze IoT device performance using cloud-based analytics tools.
7	Case study presentation on IoT analytics in a chosen domain.
8	Mini project: Design an end-to-end IoT analytics pipeline.

Question Paper Pattern (Academic Year: 2026-2027)
IoT Analytics
Semester End Examination and Practical Examination – 100 Marks
A] Semester End Examination (SEE) - 50 Marks

Maximum Marks: 50

Duration: 2 Hours

Note: (1) All questions are compulsory, subject to internal choice.

(2) Figures to the right indicate full marks.

Question No.	Particulars (Nature of Questions)	Marks (Given)	Marks (To Be Attempted)
Q-1	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-2	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-3	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-4	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q5.	Short notes	20	10
	Total	100	50

B] Practical Examination - 50 Marks**Maximum Marks: 50****Duration: 1 and a half hours.****All questions are compulsory.****A Certified copy of the journal is essential to appear for the practical examination.**

1.	Lab Work	30
2.	Journal	10
3.	Viva Voce	10

Books and References:

- Pethuru Raj & Anupama C. Raman, The Internet of Things: Enabling Technologies, Platforms, and Use Cases, CRC Press.
- Andrew Minter, Analytics for the Internet of Things (IoT), Wiley.
- Arshdeep Bahga & Vijay Madisetti, Internet of Things: A Hands-On Approach, Universities Press.
- Honbo Zhou, The Internet of Things in the Cloud: A Middleware Perspective, CRC Press.
- Rajkumar Buyya & Amir Vahid Dastjerdi, Internet of Things: Principles and Paradigms, Morgan Kaufmann.

Teaching Pedagogy:

Lectures/ tutorials/ field work/ outreach activities/ project work/ vocational training/ viva/seminars/term papers/assignments/presentations/self-study/case studies, etc., or a combination of some of these. Sessions shall be interactive in nature to enable peer group learning.

**M.Sc. (Data Science & Analytics) Programme
(With effect from the Academic Year 2026-2027)**

1.Major

1.A Mandatory

Neural Network Architectures (4 Credits)

1. Major	
1.A Mandatory	
1.A.b Neural Network Architectures	
Course Objectives and Course Outcomes	
Course Objectives	
CObj 1	To understand the fundamental concepts of neural networks, including their biological inspiration, architecture, and basic learning mechanisms.
CObj 2	To learn the working of multilayer perceptrons, optimization techniques, and methods to improve generalization in deep networks.
CObj 3	To explore specialized deep learning architectures for image and sequential data, including CNNs, RNNs, LSTMs, and GRUs.
CObj 4	To explore advanced neural network architectures, including autoencoders, GANs, transformers, and graph-based models, along with ethical and interpretability considerations.
Course Outcomes	
COut 1	Learners will be able to explain and differentiate between single-layer and multilayer neural networks, activation functions, and learning processes.
COut 2	Learners will be able to apply and evaluate feedforward neural networks with optimization, regularization, and hyperparameter tuning for predictive tasks.
COut 3	Learners will be able to design and implement convolutional and recurrent neural networks for image recognition, text processing, and sequence prediction tasks.
COut 4	Learners will be able to analyze, design, and fine-tune advanced neural network models for complex tasks, comparing performance across architectures while considering ethical implications.

Modules at a Glance

Neural Network Architectures		
Sr. No.	Modules	No. of Lectures
1	Introduction to Neural Networks	15
2	Feedforward and Deep Neural Networks	15
3	Convolutional and Recurrent Architectures	15
4	Advanced and Emerging Neural Architectures	15
Total		60

Sr. No.	Modules
1	Introduction to Neural Networks
	<p>Historical evolution of neural networks and AI connection. Biological neuron vs. Artificial neuron – McCulloch-Pitts model. Basic architecture: Input, hidden, and output layers. Activation functions and their roles (Sigmoid, ReLU, Softmax, Tanh). Learning process: Gradient descent, cost functions, and backpropagation overview. Limitations of single-layer networks and need for multilayer architectures. Mini Case: Predicting student performance using a simple feedforward network.</p>
2	Feedforward and Deep Neural Networks
	<p>Structure and working of Multilayer Perceptron (MLP). Backpropagation algorithm – detailed mathematical derivation. Optimization algorithms: SGD, Momentum, Adam. Regularization and generalization: Dropout, L1/L2, Early stopping. Hyperparameter tuning, batch normalization, and model evaluation. Visualization of learning: Loss curves and accuracy trends. Case Study: Credit risk classification using MLP.</p>
3	Convolutional and Recurrent Architectures
	<p>Convolutional Neural Networks (CNN): Concept of convolution, filters, and feature extraction. Layers: Convolution, Pooling, Flatten, Fully Connected. Popular CNN models: LeNet, AlexNet, VGG, ResNet overview. Applications in image recognition and computer vision. Recurrent Neural Networks (RNN): Need for sequential learning. Vanishing gradient problem and solutions. LSTM and GRU architectures.</p>

Applications in text generation, sentiment analysis, and speech recognition.
 Practical Demo: Image classification using CNN and text sequence prediction using RNN.

4	Advanced and Emerging Neural Architectures
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Autoencoders: Structure, training, and dimensionality reduction.
 Generative Adversarial Networks (GANs): Concept, generator–discriminator mechanism, and applications.
 Transformer architectures: Attention mechanism, BERT, GPT, and their significance.
 Capsule Networks and Graph Neural Networks (GNNs): Basic intuition and use cases.
 Transfer learning and fine-tuning pre-trained models.
 Ethical and interpretability issues in neural networks (bias, transparency).
 Mini Project: Compare MLP vs. CNN vs. Transformer for a small dataset.

Practical Work

List of suggested Practicals

List of suggested Practicals	
1	Implement a single-layer perceptron for binary classification.
2	Implement a simple MLP from scratch for XOR problem or MNIST digits.
3	Compare performance using different activations (Sigmoid, ReLU, Tanh, Leaky ReLU).
4	Apply Dropout, L1/L2 regularization, and Batch Normalization on MLP.
5	Design and train a CNN on the MNIST / CIFAR-10 dataset.
6	Fine-tune a pretrained model (e.g., ResNet, VGG16, MobileNet) on a custom dataset.
7	Implement a simple RNN for text or time series prediction.
8	Use LSTM to predict stock prices or perform sentiment analysis.
9	Compare GRU and LSTM architectures on a sequence dataset.
10	Build an autoencoder to reconstruct images or remove noise.

Question Paper Pattern (Academic Year: 2026-2027)
Neural Network Architectures
Semester End Examination and Practical Examination – 100 Marks
A] Semester End Examination (SEE) - 50 Marks

Maximum Marks: 50

Duration: 2 Hours

Note: (1) All questions are compulsory, subject to internal choice.

(2) Figures to the right indicate full marks.

Question No.	Particulars (Nature of Questions)	Marks (Given)	Marks (To Be Attempted)
Q-1	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-2	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-3	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-4	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q5.	Short notes	20	10
	Total	100	50

BJ Practical Examination - 50 Marks**Maximum Marks: 50****Duration: 1 and a half hours.****All questions are compulsory.****A Certified copy of the journal is essential to appear for the practical examination.**

1.	Lab Work	30
2.	Journal	10
3.	Viva Voce	10

Books and References:

- Ian Goodfellow, Yoshua Bengio & Aaron Courville – Deep Learning, MIT Press.
- Michael Nielsen – Neural Networks and Deep Learning, Determination Press.
- Charu Aggarwal – Neural Networks and Deep Learning: A Textbook, Springer.
- François Chollet – Deep Learning with Python, Manning Publications.
- Simon Haykin – Neural Networks and Learning Machines, Pearson.

Teaching Pedagogy:

Lectures/ tutorials/ field work/ outreach activities/ project work/ vocational training/ viva/seminars/term papers/assignments/presentations/self-study/case studies, etc., or a combination of some of these. Sessions shall be interactive in nature to enable peer group learning.

**M.Sc. (Data Science & Analytics) Programme
(With effect from the Academic Year 2026-2027)**

1.Major

1.B Elective

Statistical Computing (4 Credits)

1. Major	
1.B Elective	
1.B.a Statistical Computing	
Course Objectives and Course Outcomes	
Course Objectives	
CObj 1	To learn techniques for cleaning, organizing, and visually exploring data to extract meaningful insights.
CObj 2	To understand probability concepts, random variables, and sampling distributions as the foundation for statistical inference.
CObj 3	To learn methods for estimating population parameters and testing statistical hypotheses using parametric and non-parametric techniques.
CObj 4	To understand simulation-based approaches for probability estimation and model validation using computational methods.
Course Outcomes	
COut 1	Learners will be able to apply data cleaning, transformation, and exploratory analysis methods using Python or R to prepare datasets for further analysis.
COut 2	Learners will be able to analyze probabilistic scenarios, compute probabilities, and describe sampling distributions for statistical modeling.
COut 3	Learners will be able to evaluate and perform hypothesis tests and confidence interval estimation to make data-driven decisions.
COut 4	Learners will be able to design and implement Monte Carlo simulations, bootstrap, and permutation methods for statistical inference and model validation.

Modules at a Glance

Statistical Computing		
Sr. No.	Modules	No. of Lectures
1	Data Handling and Exploratory Analysis	15
2	Probability and Sampling Distributions	15
3	Estimation and Hypothesis Testing	15
4	Computational and Simulation Techniques	15
Total		60

Sr. No.	Modules
1	Data Handling and Exploratory Analysis
	Types of data, measurement scales, missing values, and outliers. Data cleaning, reshaping, merging/joining datasets. Exploratory Data Analysis (EDA): summary statistics, boxplots, histograms, scatterplots, correlation, and pair plots. Software: R (dplyr, ggplot2) and Python (pandas, matplotlib, seaborn)
2	Probability and Sampling Distributions
	Probability axioms, conditional probability, Bayes' theorem. Random variables (discrete and continuous), PMF, PDF, CDF, expectation, variance, covariance, correlation. Common distributions: Binomial, Poisson, Normal, Exponential. Central Limit Theorem and sampling distributions (mean & proportion).
3	Estimation and Hypothesis Testing
	Point and interval estimation (mean, proportion, variance). Properties of estimators: unbiasedness, consistency, efficiency (conceptually). Parametric tests: z, χ^2 , t, and F tests. Analysis of Variance (ANOVA): One-way ANOVA, interpretation of F-statistic. Non-parametric tests: Sign test, Wilcoxon, Chi-square test of independence.
4	Computational and Simulation Techniques
	Monte Carlo simulation for probability estimation. Bootstrap and permutation methods for resampling. Random number generation and sampling from distributions. Application: Simulation-based inference and model validation.

Practical Work

List of suggested Practicals	
1	Importing, cleaning, and summarizing datasets (R/Python/Excel).
2	Data Visualization: histograms, scatterplots, boxplots, and a correlation matrix
3	Simulating random variables from standard distributions
4	Verifying the Central Limit Theorem via simulation
5	Point and interval estimation for mean and proportion
6	Hypothesis testing for a single mean and two-sample comparison
7	Chi-square test for independence using R/Python/Excel.
8	Perform One-way ANOVA using R/Python/Excel and interpret results with boxplots and post-hoc comparisons
9	Conducting nonparametric tests (Sign/Wilcoxon).
10	Bootstrap estimation of standard error or confidence interval. Monte Carlo simulation for probability or risk estimation. Mini project – analyze a real dataset and apply 3–4 statistical procedures computationally.

Question Paper Pattern (Academic Year: 2026-2027)
Statistical Computing
Semester End Examination and Practical Examination – 100 Marks
A] Semester End Examination (SEE) - 50 Marks

Maximum Marks: 50

Duration: 2 Hours

Note: (1) All questions are compulsory, subject to internal choice.

(2) Figures to the right indicate full marks.

Question No.	Particulars (Nature of Questions)	Marks (Given)	Marks (To Be Attempted)
Q-1	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-2	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-3	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-4	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q5.	Short notes	20	10
	Total	100	50

B] Practical Examination - 50 Marks**Maximum Marks: 50****Duration: 1 and a half hours.****All questions are compulsory.****A Certified copy of the journal is essential to appear for the practical examination.**

1.	Lab Work	30
2.	Journal	10
3.	Viva Voce	10

Books and References:

- **Montgomery, D. C., & Runger, G. C. (2018).**
Applied Statistics and Probability for Engineers (7th Ed.). Wiley.
- **Moore, D. S., McCabe, G. P., & Craig, B. A. (2017).**
Introduction to the Practice of Statistics (9th Ed.). W. H. Freeman.
- **Navidi, W. (2019).**
Statistics for Engineers and Scientists (6th Ed.). McGraw-Hill.
- **Dalgaard, P. (2008).**
Introductory Statistics with R (2nd Ed.). Springer.
- **Field, A., Miles, J., & Field, Z. (2012).**
Discovering Statistics Using R. Sage Publications..
- **Downey, A. (2014).**
Think Stats: Exploratory Data Analysis in Python. O'Reilly Media.

Teaching Pedagogy:

Lectures/ tutorials/ field work/ outreach activities/ project work/ vocational training/ viva/seminars/term papers/assignments/presentations/self-study/case studies, etc., or a combination of some of these. Sessions shall be interactive in nature to enable peer group learning

**Syllabus of courses of FY MSc (Data Science & Analytics) Programme
(With effect from the Academic Year 2026-2027)**

1.Major

1.B Elective

**1.B.c Financial Analytics and Decision Making using Excel (4 Credits)
Semester II**

1. Major	
1.B Elective	
1.B.c Financial Analytics and Decision Making using Excel	
Course Objectives and Course Outcomes	
Course Objectives	
CObj 1	To develop and apply Excel-based analytical skills to analyze, evaluate, and support financial decision-making in areas such as forecasting, investment, and budgeting.
CObj 2	To understand and apply Excel tools and basic financial concepts for decision-making.
CObj 3	To analyze and evaluate financial data using forecasting and investment techniques.
CObj 4	To apply and analyze valuation techniques and financial planning tools.
Course Outcomes	
COut 1	Learners will be able to build, interpret, and evaluate financial models and dashboards to support strategic business decisions.
COut 2	Learners will be able to perform break-even analysis and use Excel functions for financial data analysis.
COut 3	Learners will be able to assess investment decisions and forecast trends using time series and regression models.
COut 4	Learners will be able to develop business valuation models and design financial dashboards.

Modules at a Glance

Financial Analytics and Decision Making using Excel		
Sr. No.	Modules	No. of Lectures
1	Foundations of Excel and Financial Analytics	15
2	Forecasting and Investment Decisions	15
3	Valuation and Financial Planning	15
4	Budgeting and Data Analysis Tools	15
Total		60

Sr. No.	Modules
1	Foundations of Excel and Financial Analytics
	Introduction to Excel (functions, formulas, data handling) Basics of Financial Analytics Break-even analysis and decision-making
2	Forecasting and Investment Decisions
	Time Series Forecasting techniques Capital Budgeting (NPV, IRR, Payback) Regression Analysis for financial decision-making
3	Valuation and Financial Planning
	Business Valuation (Part I & II) Financial modeling concepts Financial dashboards and visualization in Excel
4	Budgeting and Data Analysis Tools
	Budget management and financial planning Pivot Tables (Part I & II) Advanced Excel tools for decision-making

Practical Work

List of Suggested Practicals to be Conducted	
1	Building break-even analysis models in Excel
2	Time series forecasting (moving average, exponential smoothing)
3	Regression analysis to predict sales or revenue
4	Capital budgeting decisions: NPV, IRR, Payback calculations
5	Business valuation (DCF method)
6	Creating interactive financial dashboards with charts and slicers
7	Budget planning and variance analysis
8	Pivot table creation for financial reporting
9	Scenario analysis and sensitivity testing for investment decisions
10	Portfolio performance evaluation and risk analysis

Question Paper Pattern (Academic Year: 2026-2027)
Financial Analytics and Decision Making using Excel
Semester End Examination and Practical Examination – 100 Marks
A] Semester End Examination (SEE) - 50 Marks

Maximum Marks: 50

Duration: 2 Hours

Note: (1) All questions are compulsory, subject to internal choice.

(2) Figures to the right indicate full marks.

Question No.	Particulars (Nature of Questions)	Marks (Given)	Marks (To Be Attempted)
Q-1	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-2	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-3	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-4	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q5.	Short notes	20	10
	Total	100	50

BJ Practical Examination - 50 Marks**Maximum Marks: 50****Duration: 1 and a half hours.****All questions are compulsory.****A Certified copy of the journal is essential to appear for the practical examination.**

1.	Lab Work	30
2.	Journal	10
3.	Viva Voce	10

Books and References:

- Financial Modeling in Excel** – Danielle Stein Fairhurst
Publisher: Wiley
- Excel for Finance** – John Carver
Publisher: Business Expert Press
- Principles of Corporate Finance** – Richard Brealey, Stewart Myers & Franklin Allen
Publisher: McGraw-Hill
- Business Analytics Using Excel** – Nitin K. Jaiswal
Publisher: Oxford University Press
- Financial Analytics (NPTEL – IIT Roorkee / IIT Kharagpur)**
- Introduction to Business Analytics using Excel (NPTEL)**
<https://onlinecourses.nptel.ac.in> (*Search relevant course titles*)

Teaching Pedagogy:

Lectures/ tutorials/ field work/ outreach activities/ project work/ vocational training/ viva/seminars/term papers/assignments/presentations/self-study/case studies, etc., or a combination of some of these. Sessions shall be interactive in nature to enable peer group learning.

**Syllabus of courses of FY MSc (Data Science & Analytics) Programme
(With effect from the Academic Year 2026-2027)**

1.Major

1.B Elective

1.B.c Language Intelligence and Large Language Models (4 Credits)

Semester II

1. Major	
1.B Elective	
1.B.c Language Intelligence and Large Language Models	
Course Objectives and Course Outcomes	
Course Objectives	
CObj 1	To understand and apply the basics of NLP, statistical language models, and deep learning for language tasks.
CObj 2	To apply and analyze word representations and neural language models for sequence prediction and text understanding.
CObj 3	To evaluate and implement pre-trained language models and instruction-based prompting techniques for advanced NLP applications.
CObj 4	To analyze and create solutions using knowledge graphs, parameter-efficient adaptation, and modern LLMs while addressing ethical concerns.
Course Outcomes	
COut 1	Learners will be able to analyze text data and implement basic NLP pipelines using PyTorch.
COut 2	Learners will be able to build neural language models, implement attention mechanisms, and apply transformers for language tasks.
COut 3	Learners will be able to fine-tune LLMs, design prompts, and perform retrieval-augmented generation tasks.
COut 4	Learners will be able to implement advanced LLM workflows, interpret model outputs, and assess ethical risks such as bias and toxicity.

Modules at a Glance

Language Intelligence and Large Language Models		
Sr. No.	Modules	No. of Lectures
1	Foundations of Language Intelligence	15
2	Representation and Neural Language Models	15
3	Large Language Models and Prompting	15
4	Advanced LLMs and Applications	15
Total		60

Sr. No.	Modules
1	Foundations of Language Intelligence
	Introduction to NLP and applications NLP pipeline Statistical language models Basics of deep learning (ANN, CNN) Introduction to PyTorch
2	Representation and Neural Language Models
	Word representations (Word2Vec, GloVe, fastText) Tokenization techniques Neural language models (RNN, LSTM, GRU, CNN) Sequence-to-sequence models and decoding strategies Attention mechanisms Introduction to Transformers
3	Large Language Models and Prompting
	Pre-trained models (BERT and variants) Hugging Face ecosystem Prompt-based learning and instruction tuning Reinforcement Learning with Human Feedback (RLHF) Retrieval-Augmented Generation (RAG)
4	Advanced LLMs and Applications
	Knowledge graphs and NLP Parameter-efficient fine-tuning (LoRA, prompt tuning) Model interpretability Overview of modern LLMs such as GPT-4, Llama 3, Claude 3, Gemini Ethical issues: bias and toxicity

Practical Work

List of Suggested Practicals to be Conducted	
1	Implement tokenization and text preprocessing pipelines
2	Build a simple statistical language model (unigram/bigram)
3	Implement a neural language model (RNN or LSTM) for text generation
4	Word embeddings with Word2Vec, GloVe, or fastText
5	Sequence-to-sequence model for machine translation or summarization
6	Attention mechanism implementation in a small Seq2Seq model
7	Fine-tune a pre-trained BERT model for text classification
8	Experiment with prompt-based learning on GPT or HuggingFace models
9	Implement retrieval-augmented generation (RAG) for question answering
10	Ethical evaluation: Detect bias or toxicity in LLM outputs

Question Paper Pattern (Academic Year: 2026-2027)
Language Intelligence and Large Language Models
Semester End Examination and Practical Examination – 100 Marks
A] Semester End Examination (SEE) - 50 Marks

Maximum Marks: 50

Duration: 2 Hours

Note: (1) All questions are compulsory, subject to internal choice.

(2) Figures to the right indicate full marks.

Question No.	Particulars (Nature of Questions)	Marks (Given)	Marks (To Be Attempted)
Q-1	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-2	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-3	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q-4	A) Practical/ Theory Question OR B) Practical/ Theory Question	20	10
Q5.	Short notes	20	10
	Total	100	50

B] Practical Examination - 50 Marks**Maximum Marks: 50****Duration: 1 and a half hours.****All questions are compulsory.****A Certified copy of the journal is essential to appear for the practical examination.**

1.	Lab Work	30
2.	Journal	10
3.	Viva Voce	10

Books and References:

1. **Natural Language Processing with PyTorch** – Delip Rao & Brian McMahan
Publisher: O'Reilly Media
2. **Deep Learning for NLP** – Palash Goyal, Sumit Pandey, Karan Jain
Publisher: Packt Publishing
3. **Transformers for Natural Language Processing** – Denis Rothman
Publisher: Packt Publishing
4. **Speech and Language Processing (3rd Edition, Draft)** – Daniel Jurafsky & James H. Martin
Publisher: Pearson
5. **Hands-On Natural Language Processing with Python** – Rajesh Arumugam & Rajalingappaa Shanmugamani
Publisher: Packt Publishing
6. **Natural Language Processing – IIT Madras / IIT Kharagpur**
Covers NLP pipeline, embeddings, language models, transformers
<https://onlinecourses.nptel.ac.in> *(Search: "Natural Language Processing")
7. **Deep Learning for NLP – IIT Kharagpur**
Covers neural language models, sequence modeling, attention, and LLMs
<https://onlinecourses.nptel.ac.in> *(Search: "Deep Learning for NLP")

Teaching Pedagogy:

Lectures/ tutorials/ field work/ outreach activities/ project work/ vocational training/ viva/seminars/term papers/assignments/presentations/self-study/case studies, etc., or a combination of some of these. Sessions shall be interactive in nature to enable peer group learning.

**M.Sc. (Data Science & Analytics) Programme
(With effect from the Academic Year 2026-2027)
On Job Training/ Field Project (6 Credits)**

Proposed Guidelines for

Introduction: Research Project Work Semester (06 Credits)

Inclusion of project work in the course curriculum is one of the ambitious aspects in the programme structure. The main objective of inclusion of project work is to inculcate the element of research work challenging the potential of the learner as regards to his/ her eagerness to enquire and ability to interpret particular aspects of the study in his/ her own words. It is expected that the guiding teacher should undertake the counselling sessions and make the learners about the methodology of formulation.

Preparation and Evaluation Pattern Of The Project Work.

There are two modes of preparation of project work

1. Project work based on research methodology in the study area
2. Project work based on internship in the study area

Guidelines for preparation of Project Work

· **Work Load**

Work load for Project Work is 01 (one) hour per batch of 15-20 learners per week for the teacher. The learner (of that batch) shall do field work and library work in the remaining 03 (three) hours per week.

1. General guidelines for preparation of project work based on research methodology

The project topic may be undertaken in any area of Elective Courses.

Each of the learners has to undertake a Project individually under the supervision of a teacher-guide.

The learner shall decide the topic and title which should be specific, clear and with definite scope in consultation with the teacher-guide concerned.

University/college shall allot a guiding teacher for guidance to the students based on her / his specialization.

The project report shall be prepared as per the broad guidelines given below:

♣ Font type: Times New Roman

- ♣ Font size: 12-For content, 14-for Title
- ♣ Line Space: 1.5-for content and 1-for in table work
- ♣ Paper Size: A4
- ♣ Margin: in Left-1.5, Up-Down-Right-1
- ♣ The Project Report shall be bound.
- ♣ The project report should be 60 to 80 pages

Structure to be followed to maintain the uniformity in formulation and presentation of Project Work:

(Model Structure of the Project Work)

Chapter No. 1: Introduction

In this chapter Selection and relevance of the problem, historical background of the problem, brief profile

of the study area, definition/s of related aspects, characteristics, different concepts pertaining to the problem

etc. can be incorporated by the learner.

Chapter No. 2: Research Methodology

This chapter will include Objectives, Hypothesis, Scope of the study, limitations of the study, significance

of the study, Selection of the problem, Sample size, Data collection, Tabulation of data, Techniques and

tools to be used, etc. can be incorporated by the learner.

Chapter No. 3: Literature Review

This chapter will provide information about studies done on the respective issue. This would specify how

the study undertaken is relevant and contribute for value addition in information/ knowledge/ application

of study area which ultimately helps the learner to undertake further study on the same issue.

Chapter No. 4: Data Analysis, Interpretation and Presentation

This chapter is the core part of the study. The analysis pertaining to collected data will be done by the

learner. The application of selected tools or techniques will be used to arrive at findings. In this, table of

information, presentation of graphs etc. can be provided with interpretation by the learner.

Chapter No. 5: Conclusions and Suggestions

In this chapter of project work, findings of work will be covered and suggestions will be enlisted to validate the objectives and hypotheses.

Note: If required more chapters of data analysis can be added.

- Bibliography
- Appendix

2. Guidelines for Internship based project work

Minimum 20 days/ 100 hours of Internship with an Organization/ NGO/ Charitable Organization/ Private firm.

- The theme of the internship should be based on any study area of the elective courses
- Project Report should be of minimum 50 pages
- Experience Certificate is Mandatory
- A project report has to be brief in content and must include the following aspects:

Executive Summary: A bird's eye view of your entire presentation has to be precisely offered under this category.

Introduction on the Company: A Concise representation of the company/ organization defining its scope, products/ services and its SWOT analysis.

Statement and Objectives: The mission and vision of the organization need to be stated enshrining its broad strategies.

Your Role in the Organization during the internship: The key aspects handled, the department under which you were deployed and brief summary report duly acknowledged by the reporting head.

Challenges: The challenges confronted while churning out theoretical knowledge into the practical world.

Conclusion: A brief overview of your experience and suggestions to bridge the gap between theory and practice.

The project report based on internship shall be prepared as per the broad guidelines given below:

- Font type: Times New Roman
- Font size: 12-For content, 14-for Title
- Line Space: 1.5-for content and 1-for in table work
- Paper Size: A4
- Margin: in Left-1.5, Up-Down-Right-1
- The Project Report shall be bounded

Evaluation pattern of the project work

The Project Report shall be evaluated in two stages viz.	
<i>Evaluation of Project Report (Bound Copy)</i>	60 Marks
Introduction and other areas covered	30 Marks
Research Methodology, Presentation, Analysis and interpretation of data	20 Marks
Conclusion & Recommendations	10 Marks
Conduct of Viva-voce	40 Marks
In the course of Viva-voce, the questions may be asked such as importance / relevance of the study, objective of the study, methodology of the study/ mode of Enquiry (question responses)	10 Marks
Ability to explain the analysis, findings, concluding observations, recommendation, limitations of the Study	20 Marks
Overall Impression (including Communication Skill)	10 Marks

Note:

The guiding teacher along with the external evaluator appointed by the University/ College for the evaluation of the project shall conduct the viva-voce examination as per the evaluation pattern.

Passing Standard

Minimum of Grade D in the project component

In case of failing in the project work, the same project can be revised for ATKT examination.

Absence of student for viva voce:

If any student fails to appear for the viva voce on the date and time fixed by the department such student shall appear for the viva voce on the date and time fixed by the Department, such student shall appear for the viva voce only along with students of the next batch.