M. Tech. Data Science

Under Regulations (R-2025)

(w.e.f. 2025-26 admitted batch)

Course Structure and Syllabi

THE APOLLO UNIVERSITY

MURUKAMBATTU - CHITTOOR (Dt) 517127

ANDHRA PRADESH

PROGRAM OUTCOMES (PO)

PO 1: Engineering knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialisation for the solution of complex engineering problems.

PO 2: Problem analysis: Identify, formulate, research literature, and analyse complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

PO 3: Design/Development of Solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for public health and safety, and cultural, societal, and environmental considerations.

PO 4: Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

PO 5: Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modelling to complex engineering activities with an understanding of the limitations.

PO 6: The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

PO 7: Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and the need for sustainable development.

PO 8: Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

PO 9: Individual and team work: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

PO 10: Communication: Communicate effectively on complex engineering activities with the engineering community and with the society at large, such as being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

PO 11: Project management and finance: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

PO 12: Life-long learning: Recognise the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

PROGRAM EDUCATIONAL OBJECTIVES (PEO):

PEO1: Technical Mastery: Graduates will develop a deep understanding of data science methodologies, tools, and techniques to excel in data-driven problem-solving and innovation in various industries.

PEO2: Research Excellence: Graduates will engage in advanced research, contributing to the development of novel data science solutions, publishing their findings, and pushing the boundaries of the field.

PEO3: Ethical Leadership: Graduates will exhibit strong ethical principles, effective communication skills, and leadership capabilities, enabling them to make informed decisions and lead diverse teams in professional settings.

PROGRAM SPECIFIC OUTCOMES (PSO):

After successful completion of the program the graduates will be able to:

PSO 1: Advanced Data Analytics: Graduates will be proficient in applying advanced statistical, machine learning, and artificial intelligence techniques to analyse and interpret complex datasets, deriving actionable insights.

PSO2: Big Data Management: Graduates will have expertise in using big data technologies and frameworks (e.g., Hadoop, Spark) to efficiently manage, process, and analyse large-scale data, ensuring high performance and scalability.

PSO3: Domain-Specific Applications: Graduates will be able to apply data science principles to specific domains, such as healthcare, finance, and cybersecurity, creating impactful solutions tailored to the unique challenges of each field.

THE APOLLO UNIVERSITY

ACADEMIC REGULATIONS

SCOPE:

This Academic regulation provide a framework for the regulatory guidelines of all programs offered by The Apollo University. It includes procedures and practices that are to be followed to ensure academic standards in the University. The regulations are approved by the Academic Council. These regulations may be amended from time to time with the approval of the Academic council for the benefit of students or some times to reflect the changes suggested by the statutory bodies.

Information regarding amendments (if any) to the regulations will be communicated to the students by publishing in the University website. Students must follow the amended regulations as they might impact the process for the award of degree. The decision of the Vice Chancellor shall be the final in case of any discrepancy. These regulations apply to all students, despite the program of study.

1. ADMISSION INTO THE PROGRAM

The University admits the students in two modes. One through the convenor quota as per the Andhra Pradesh Private Universities Act, for which the admissions will be carried out through the convener quota by the Govt of Andhra Pradesh. The other is through University quota for which the following procedure will be followed:

A. The applicant shall satisfy the entrance requirements specified by The Apollo University and in accordance with guidelines of statutory councils for Under-graduation.
B. The Applicant shall be qualified in the qualifying examination for a particular program.
C. The Applicant secures a rank in national level entrance exam or suitable such test conducted by The Apollo University / professional body.
D. The Applicant qualifies in the specified state or national level examinations prescribed by The Apollo University.

The Apollo University will widely notify the counselling schedule for admissions into the academic programs in the media. The provisional admission will be given to the eligible students during the counseling scheduled by The Apollo University. The selected candidates will be provisionally admitted into the program of his/her choice if the candidate meets the program specific requirements in addition to academic performance qualifying exam. Admission is purely based on merit and so merely meeting the requirements will not ensure admission. The University does not discriminate based on gender, race, region, religion, disability or nationality. The University reserves the right to make admissions based on various criteria which is specified in the admission brochure.

2. ELIGIBILITY CRITERIA

Undergraduate programs

The qualifying exam eligibility for each program is given Annexure 1. The student should have passed the qualifying exam either in the year the student is seeking admission or the previous year.

Convener Quota: The student seeking admission to any program under convener quota shall qualify in the relevant entrance exam conducted by the Government of Andhra Pradesh.

University Quota: For getting admission under University quota, percentage of marks obtained in the qualifying exam, the rank obtained in TAU entrance exam or any recognized national level examination in the year of admission will be considered.

Counselling

All the eligible students need to apply for admission and have to attend counselling conducted by TAU as per the schedule for the university quota

3. PROGRAMS

The Apollo University offers variety of programs which includes certificate, undergraduate, postgraduate, and Research. The list of programs on offer for the academic year 2022-23 are annexed in Annexure 2 and those of 2023-24 are annexed in Annexure 3.

Minimum duration of the program

The minimum duration of each program depends on the type of program, viz., undergraduate, postgraduate, integrated programs, etc., and the faculty which offers the program. The maximum duration of the program is N+2 years, where N stands for the minimum duration of the program as mentioned in Annexure 2 and 3. If the student has not obtained the minimum number of credits within the stipulated time, the Vice-Chancellor may extend the maximum duration in extenuating circumstances upon receiving a request along with reasons from the student for not completing the program on time.

4. CHOICE BASED CREDIT SYSTEM

The choice-based credit system (CBCS) facilitates the education student-centric. It provides the opportunity for the learner to choose the courses from a basket of core, elective, and skill enhanced courses. All programs of study are designed to meet the specified number of credit requirements. The courses taken by the student in each semester as part of program are allotted some credit points based on the number of hours assigned. Upon successful completion of the course, the student secures the number of credits allotted for that course. Once the minimum number of credits of the program is achieved, the degree can be awarded, subject to fulfilment of all other relevant conditions.

5. STRUCTURE OF THE PROGRAM

The Program structure Consists of

i) University Courses
   A. University Core
   B. University Electives

ii) Faculty Courses
   A. Faculty Core
   B. Faculty Electives

iii) Program Courses
   A. Program Core
   B. Program electives

Each course* is assigned a certain number of credits depending upon the number of contact hours (lectures/tutorials/practical) per week. (*one course means one subject)

Core Courses = 3 Credits /4 Credits Elective =3 Credits

In general, credits are assigned to the courses as detailed below:

- A classroom lecture/ tutorial of 60 min (1 hr) duration per week, spread over the entire semester, shall be considered as one credit.
- A laboratory session of minimum of 120 min (2 hr) per week shall be considered as one credit.
- A project work/ Internship session of 60 minutes (1 hr) carried out per week shall be considered as one credit.

6. MEDIUM OF INSTRUCTION

The medium of instruction (including examinations and project reports) shall be English.

7. REGISTRATION

Any of the following student must register for the courses opted in a particular semester during the scheduled registration period.

i. a new student who enrolls into any program
ii. an existing student who is continuing on rolls from the preceding regular semester
iii. a former student, i.e., who has not enrolled in the preceding regular semester or who has availed academic break or detained and got readmission

Each newly admitted student shall attend an induction/ orientation program prior to commencement of the first semester. During this program academic advisors assist the students in choosing the courses. Existing student may register online by using their registration number and mail ID through the Apollo ERP portal. Class schedules are available approximately two weeks before the beginning of every semester for each program. The concerned head of the department must approve class schedule.

8. ATTENDANCE REQUIREMENTS

- Students should earn a minimum of 80% attendance in the current semester to become eligible to write the Semester End Examinations.
- The monthly statement of attendance will be displayed on the Department Notice Board/ Apollo ERP by the respective departments within the first five working days of the following month.
- Candidates who are falling short of 80% attendance will be detained on the recommendation of the HoD and are not eligible to appear for the current semester examinations. The students who are detained in the current semester will not be allowed to register for the next semester and they have to repeat the same semester by paying the tuition fee prescribed. However, they can write arrear subjects, if any.

9. EVALUATION

The assessment of the student's performance in a Theory course shall be based on two components: Continuous Evaluation (40 marks) and Semester-end examination (60 marks). A student has to secure an aggregate of 40% in the course in the two components put together to be declared to have passed the course, subject to the condition that the candidate must have secured a minimum of 24 marks (i.e. 40%) in the theory component at the semester-end examination. Practical/ Project Work/ Industrial Training/ Viva voce/ Seminar etc. are completely assessed under Continuous Evaluation for a maximum of 100 marks, and a student has to obtain a minimum of 50% to secure Pass Grade. For courses having both theory and practical components, 60% of the weightage will be given for theory component and 40% weightage for practical component. The student must secure 40% (Theory + Practical) with 24 marks minimum in theory to attain pass grade.

Details of Assessment Procedure are furnished below in Table 1.

Table 1: Assessment Procedure

S. No.	Component of Assessment	Marks Allotted	Type of Assessment	Scheme of Evaluation
1	Theory	40	Continuous Evaluation	i) Twenty (20) marks for mid examinations. Three mid examinations shall be conducted for 20 marks each; average of the best two performances shall be taken into consideration. ii) Ten (10) marks for Quizzes, Assignments and Presentations. iii) Ten (10) marks for periodic evaluation, case studies and projects
		60	Semester-end Examination	iv) Sixty (60) marks for Semester-end examinations
	Total	**100**		
2	Laboratory	100	Continuous Evaluation	1) 80 marks with equal weightage to all experiments subject to conduct of minimum of 10 experiments 2) 20marks for the end exam (with one of our university teachers as external other than course teacher)

3	Internship	100	Continuous Evaluation	i) (80) marks for periodic evaluation of Internship report by the Project Supervisor. ii) Twenty (20) marks for final Report presentation and Viva-voce, by a panel of internal examiners. iii) Students shall undergo TWO internships during the course of time and the evaluation shall be done during final semester.
4	Project work	100	Continuous Evaluation	iv) (80) marks for periodic evaluation and technical report writing by the Project Supervisor. ii) Twenty (20) marks for final Report presentation and Viva-voce, by a panel of internal examiners
5	Students Seminars	100	Continuous Evaluation	Each student has to give a seminar on any topic in consultation with the faculty member in charge A detailed report shall be submitted to the in charge. 60 marks for periodic evaluation including report preparation and 40 marks for viva voce by a panel of examiners.

10. GRADING SYSTEM

Based on the student performance during a given semester, a final letter grade will be awarded at the end of the semester in each course. The letter grades and the corresponding grade points are as given inTable2.

Table 2: Grades & Grade Points

Sl. No.	Grade	Grade Points	Absolute Marks
1	O(Outstanding)	10	90 and above
2	A+(Excellent)	9	80 to 89
3	A (Very Good)	8	70 to 79

4	B+(Good)	7	60 to 69
5	B (Above Average)	6	50 to 59
6	C(Average)	5	45 to 49
7	P(Pass)	4	40 to 44
8	F(Fail)	0	Less than 40
9	Ab. (Absent)	0	-

SEMESTER GRADEPOINTAVERAGE (SGPA)

A Semester Grade Point Average (SGPA) for the semester will be calculated according to the formula:

$$SGPA = \frac{\sum [C \times G]}{\sum C}$$

Where

C=number of credits for the course,

G=grade points obtained by the student in the course.

A student who earns a minimum of 4 grade points (P grade) in a course is declared to have successfully completed the course, and is deemed to have earned the credits assigned to that course.

CUMULATIVE GRADE POINT AVEARGE (CGPA)

A similar formula is used to arrive at Cumulative Grade Point Average (CGPA), considering the student's performance in all the courses taken in all the semesters up to the particular point of time.

Table 3 shows the CGPA required for the award of class after the successful completion of the program.

Table3: CGPA required for award of Class

Class	**CGPA Required**
First Class with Distinction	≥8.0*
First Class	≥6.5
Second Class	≥5.5
Pass Class	≥5.0

*In addition to the required CGPA of 8.0 or more, the student must have necessarily passed all the courses of every semester in first attempt.

11. REAPPEARANCE

a. A student who has secured 'F' grade in a Theory course shall have to reappear at the subsequent Semester end examination held for that course.
b. A student who has secured 'F' grade in a Practical course shall have to attend Special Instruction Classes scheduled by the Department for securing pass.
c. A student who has secured 'F' Grade in Internship /Project work / Industrial Training etc shall have to reappear for Viva – voce scheduled by the department.
d. A student who is declared fail (F) in a course/s can apply for revaluation within one week from the date of publication of results with a fee prescribed by the university. The marks /grade awarded in the revaluation is final.

11.1 Procedure for revaluation

- The students who have not satisfied with the marks awarded by the examiner can apply for revaluation of his/her answer script/s
- The students have to apply through proper channel for revaluation and to pay the revaluation fee per paper to the university towards revaluation fee.
- Students have to apply for revaluation within 7 days from the date publication of result.
- The scripts will get valued by second examiner and if the difference is more than 15 marks, they will get valued by the third examiner. The average of the nearest two marks will be declared as the final marks.

11.2 ASSESSMENT MECHANISM

The Apollo University offers a student the benefits of Choice Based Credit System. Every paper is allotted a certain number of credits as per the UGC norms. A student is awarded the specified credits on obtaining a pass in the respective paper.

The Choice Based Credit System (CBCS) has been adopted for UG Course from the year 2021-22 onwards as per the recommendations of the A.P. State Council for Higher Education (APSCHE). The structure of undergraduate programmes provides a wide range of choice for students to opt for courses based on their eligibility, aptitude and career goals.

11.3 Semester End Examination

The End semester examination will be a comprehensive examination of 3 hours duration. Two

End Semester examinations are conducted in a year-

Odd semester examinations in November/ December and

Even semester examination in May/June

Practical examination / Project viva will be held 2 weeks prior to the theory semester end examinations.

PG-Graduation Programs

Course	Continuous Assessment	End semester	Aggregate in End semester Examinations
All PG Courses	No passing minimum	50%	50%

11.4 Post Evaluation Programme:

Under the Post Evaluation Programme there are three menus:

- Provision for improvement
- Re-totaling and Revaluation of answer scripts
- Restrictions to appear for the examinations

11.5 Provision for improvement

A student who passes a paper in the first attempt can reappear for the same paper in the succeeding End-of-Semester examination only, for improving his/her marks. Re-appearance for improvement is allowed for theory and practical subjects of all semesters, except for the final semester subjects. Revised mark statement will be issued after withdrawing the previous one, if the marks obtained in improvement are higher than the marks awarded earlier. When there is no improvement, there shall not be any change in the original marks already awarded. The improved marks shall be considered for classification but not for ranking.

Provision for Re-totaling and Revaluation of valued answer scripts

- PG candidates may apply for re-totaling / revaluation of valued answer scripts, to the Controller of Examinations through the Heads of Departments and Principal / Dean, in the prescribed forms, remitting the prescribed fee within 7 days from the date of publication of results. Revaluation of answer scripts is permissible only for the current semester papers and not for any arrear paper.

- Those wish to apply for revaluation of final semester papers can do so within five days from the date of publication of results. In re-valuation, the answer papers will be valued by an external examiner and if there is a difference of 15 marks between the two evaluations then the script will be sent for third valuation which is final and the mark awarded by the third examiner will be taken into the account.
- Revised mark statement will be issued after withdrawing the previous one, if the marks obtained in revaluation / retotalling are higher than the marks obtained earlier. In other cases, the original marks obtained earlier will be retained and the matter will be intimated to the student concerned as 'No change'.
- A candidate who applies for revaluation should not apply for retotalling.

Restrictions to appear for the examinations

Candidates who fail in any of the papers in the PG End semester examinations shall complete the paper concerned within N+2 years from the date of admission to the particular course. If they fail to do so, they shall re-register their names and take the examination in the texts/revised regulations/syllabus of the paper prescribed for the subsequent batch of candidates, in force at the time of their reappearance. In the event of removal of that paper consequent to change of regulation and/or curriculum after N+2 years period, the candidate shall have to take up an equivalent paper in the revised syllabus as suggested by the Chairman, Board of Studies concerned.

12. BETTERMENT OF GRADES

A student who has secured only a Pass or Second class and desires to improve his/her Class can appear for Betterment Examinations only in Theory courses of any Semester of his/her choice, conducted in the Summer Vacation along with the Special Examinations. Betterment of Grades is permitted 'only once' immediately after completion of the program of study.

13. DETENTION AND RE-ADMISSION

If a student fails to meet the minimum attendance requirement or minimum standards for academic progression, the concerned academic head will recommend for detention and it will be notified by the concerned Dean of the School. The students who are detained in the current semester will not be allowed to register for the next semester and they have to repeat the same semester.

The candidates who are detained or availed academic break or suspended in the previous semester/academic year and want to continue their study shall apply for re-admission to the university. The candidates shall request for re-admission to the respective Head of the Department, with details viz., Full Name, Registration Number, Department, School, Fee payment particulars with proofs and reasons for discontinuations. The concerned academic head will forward it to the Registrar with specific comments. The Registrar will notify the decision of re-admission which shall include the prescribed fee particulars, semester/ year into which readmission is granted and additional courses to be completed by the student (if any). The candidates should apply for re-admission in advance, that is before the commencement of the semester.

14. GROOMING AND ATTIRE FOR STUDENTS

Grooming and Etiquette is of great significance in the dynamic of shaping one's Personality. The Apollo University stands by a *Code of Grooming, Attire and Etiquette* that promotes a professional standard: Academic Day; Campus Placements and Non-Academic Hours on Campus.

The Dress Code to be in compliance on academic premises while attending: Formal Functions of the Institution / Lectures / Practicals / Dining Area / Library / Labs / Office Areas.

Students shall follow appropriate attire during Academic and Non-Academic hours on the campus. Students shall wear clean, neat, pressed and presentable clothing, and command respect by dressing in accordance with responsible personal norms. Students shall always wear The Apollo University ID Card with the Lanyard.

Grooming and Formal Wear - Boys:

Formal Shirts / T-Shirts with a Collar should preferably be tucked in with a Formal pair of Pants Shoes and Socks to complete the Formal Attire. Personal Hygiene should be followed and Hair should be well groomed.

Smart Casuals for Boys:

Long Kurtas / Formals / Semi-Formal Shirts with Jeans.

Grooming and Formal Wear - Girls: Sarees / Salwar Suits / Leggings or Jeggings with Long Kurtis / Long Frocks / Long Skirts / Palazzos. Complement the outfit with proper footwear. Personal Hygiene should be followed and Hair should be well groomed.

Smart Casuals for Girls:

Jeans with long Kurtis / Long Skirts / Long Frocks.

Attire for Non-Academic Hours On Campus:

The students should be neatly attired during Non-Academic Hours on Campus.

Dress Code for Boys:

Jeans / Track Suits / T-Shirts / Trousers / Shirts.

Dress Code for Girls:

Jeans / T-Shirts or Blouses / Salwar Suits / Palazzos / Leggings or Jeggings with Long Tops / Sarees / Long Skirts / Track Suits.

DO’S AND DO’NTS FOR BOYS AND GIRL STUDENTS OF THE UNIVERSITY:

- To wear modest clothing that reflects the essence of good personal grooming standards.
- To refrain from wearing Sleeveless Clothing; Shorts; Short Tops, etc.,

PLEASE NOTE: The decision as to what constitutes Appropriate Attire vests with the Authorities of The Apollo University.

15. ELIGIBILITY FOR AWARD OF THE DEGREE

The undergraduate degree will be of 4-years/ 3-years (Lateral Entry) of duration. A student shall be declared as eligible for the award of the degree if the candidate has successfully secured the minimum number of required credits as specified in the curriculum corresponding to the branch of his/her study within the stipulated time.

After successful completion of the program, a provisional certificate cum memorandum of grades (PCMG) will be issued to the students. The PCMG includes the secured grades and class achieved in the chosen program and specialization, if any, along with grades and CGPA secured by the student. The original degree will be presented in the subsequent convocation.

16. DISCRETION POWER

Not with-standing anything contained in the above sections, the Vice Chancellor may review all exceptional cases, and give his decision, which will be final and binding.

ANNEXURE 1

ELIGIBILITY FOR QUALIFYING EXAM FOR POST GRADUATE PROGRAM

Program Type	**Program Name**	**Eligibility**
Masters	**M.Tech. Data Science**	Pass with 50% aggregate marks (45% for reserved categories) in B.Tech. (Computer Science and Engineering or Information Technology or Electronics and Communication Engineering or Electrical and Electronics Engineering) or MCA or M.Sc. (Information Technology or Computer Science) or equivalent.

ANNEXURE 2

PROGRAMS OFFERED BY THE SCHOOL OF TECHNOLOGY

FROM ACADEMIC YEAR 2022-23

Sl. No.	Program	Expanded	Level	Minimum Duration in Years (N)
1	B. Tech. CSE	Computer Science and Engineering	Bachelor’s	4*
2.	B. Tech. CSE (AI& DS)	Computer Science and Engineering (Artificial Intelligence and Data Structures)	Bachelor’s	4*

* Engineering programs (UG) under Lateral Entry will be with a minimum duration of 3 years

ANNEXURE 3

PROGRAMS OFFERED BY THE SCHOOL OF TECHNOLOGY

FROM ACADEMIC YEAR 2023-24

Sl. No.	**Program**	**Expanded**	**Level**	**Minimum Duration in Years (N)**
1	B. Tech. CSE	Computer Science and Engineering	Bachelor’s	4
2.	B. Tech. CSE (AI& DS)	Computer Science and Engineering (Artificial Intelligence and Data Structures)	Bachelor’s	4
3	B. Tech. CSE (AI& ML)	Computer Science and Engineering (Artificial Intelligence and Machine Learning)	Bachelor’s	4
4	B. Tech CSE (Cybersecurity)	Computer Science and Engineering (Cybersecurity)	Bachelor’s	4
5	B.Tech Computer Engineering (Software Engineering)	Computer Engineering (Software Engineering) with Kalium	Bachelor’s	4
6	M. Tech (VLSI design & ES)	Master of Technology in Very Large-Scale Integration design and Embedded Systems	Masters	2

* Engineering programs (UG) under Lateral Entry will be with the Minimum duration of 3 years

ANNEXURE 3

PROGRAMS OFFERED BY THE SCHOOL OF TECHNOLOGY

FROM ACADEMIC YEAR 2024-25

Sl. No.	Program	Expanded	Level	Minimum Duration in Years (N)
1	B. Tech. CSE	Computer Science and Engineering	Bachelor’s	4
2.	B. Tech. CSE (AI& DS)	Computer Science and Engineering (Artificial Intelligence and Data Structures)	Bachelor’s	4
3	B. Tech. CSE (AI& ML)	Computer Science and Engineering (Artificial Intelligence and Machine Learning)	Bachelor’s	4
4	B. Tech CSE (Cybersecurity)	Computer Science and Engineering (Cybersecurity)	Bachelor’s	4
5	B.Tech Computer Engineering (Software Engineering)	Computer Engineering (Software Engineering) with Kalium	Bachelor’s	4
6	M. Tech (VLSI design & ES)	Master of Technology in Very Large-Scale Integration design and Embedded Systems	Masters	2

* Engineering programs (UG) under Lateral Entry will be with the Minimum duration of 3 years

I - Semester

3 Week Induction Program						
Course Code	**Course Name**	**Periods per week**			**Credits**	**Hours per week**
		L	**T**	**P**		
MTDT6501	Mathematical Foundations of Data Science	2	1	0	3	3
SOTT6301	Advanced Data Structures and Algorithms	2	1	0	3	3
Program Elective-I						
MTDT6601a	Programming for Data Science	3	0	0	3	3
MTDT6601b	Data Engineering and Databases					
MTDT6601c	Machine Learning and AI					
Program Elective-II						
MTDT6602a	AI and Decision-Making Models	3	0	0	3	3
MTDT6602b	Data Preparation and Analysis					
MTDT6602c	Data Visualization and Communication					
SOTT6302	Research Methodology and IPC	2	0	0	2	2
SOTT6303	Human Values & Professional Ethics (Audit Course – I)	2	0	0	0	2
MTDS6501/ MTDC6501	Technical Seminar/Case Study -1	1	0	0	1	1
SOTL6301	Advanced Data Structures and Algorithms Lab	0	0	4	2	4
MTDL6501	Programming for Data Science Lab	0	0	4	2	4
--	Mentoring	0	0	0	0	1
--	Library	0	0	0	0	2
--	Physical Activity	0	0	0	0	2
--	Extra-curricular activities	0	0	0	0	2
--	Co-curricular activity	0	0	0	0	2
--	Self-Learning	0	0	0	0	2
TOTAL		**15**	**2**	**8**	**19**	**36**

II - Semester

Course Code	Course Name	Periods per week			Credits	Hours per week
		L	T	P		
SOTT6304	Advanced Machine Learning	2	1	0	3	3
MTDT6504	Big Data Analytics	2	1	0	3	3
Program Elective-III						
MTDT6603a	Ethical AI and Decision Making	3	0	0	3	3
MTDT6603b	Time Series Analysis					
MTDT6603c	Text Analytics					
Program Elective-IV						
MTDT6604a	Predictive and Perspective Analytics	3	0	0	3	3
MTDT6604b	Edge AI and IoT Analytics					
MTDT6604c	Data Privacy and Security					
SOTT6305	English for Research Paper Writing (Audit Course-2)	2	0	0	0	2
MTDP6501	Mini project	0	0	8	4	8
SOTL6302	Advanced Machine Learning Lab	0	0	4	2	4
MTDL6502	Big Data Analytics Lab	0	0	4	2	4
--	Mentoring	0	0	0	0	1
--	Co-curricular activity	0	0	0	0	1
--	Self-Learning	0	0	0	0	1
--	Extra-curricular activities	0	0	0	0	2
--	Library	0	0	0	0	1
TOTAL		**12**	**2**	**16**	**18**	**36**

III - Semester

Course Code	Course Name	Periods per week			Credits	Hours per week
		L	T	P		
MTDM7501	MOOC-1	3	0	0	3	3
MTDM7502	MOOC -2	3	0	0	3	3
MTDP7501	Dissertation I / Industrial Project	0	0	20	10	20
--	Mentoring	0	0	0	0	1
--	Co-curricular activity	0	0	0	0	2
--	Self-Learning	0	0	0	0	1
--	Physical Activity	0	0	0	0	2
--	Extra-curricular activities	0	0	0	0	2
--	Soft Skills Training	0	0	0	0	1
--	Certification Course	0	0	0	0	1
TOTAL		**6**	**0**	**20**	**16**	**36**

IV - Semester

Course Code	Course Name	Periods per week			Credits	Hours per week
		L	T	P		
MTDP7502	Dissertation Phase II	0	0	32	16	32
TOTAL		**0**	**0**	**32**	**16**	**32**

I SEMESTER

MTDT6501 **Mathematical Foundations of Data Science**

L	T	P	C
2	1	0	3

Course Description

This course provides a rigorous mathematical foundation essential for advanced data science. Topics include linear algebra, calculus, probability, statistics, and optimization. Emphasis is placed on theoretical concepts and computational techniques that underpin algorithms in data analysis, machine learning, and AI.

Course Objectives

- To develop a strong mathematical background for understanding data science algorithms.
- To introduce linear algebra, calculus, probability, and optimization concepts with practical applications.
- To enable students to derive and analyze mathematical models used in data science.
- To build proficiency in mathematical reasoning and problem solving relevant to real-world data challenges.
- To prepare students for advanced studies in machine learning, AI, and computational methods.

Unit 1: Linear Algebra for Data Science **9 Hrs**

Vectors, matrices, and operations-Matrix factorizations (LU, QR, SVD)-Eigenvalues, eigenvectors, and spectral analysis-Applications in dimensionality reduction (PCA, LDA)

Unit 2: Calculus and Multivariate Calculus **9 Hrs**

Limits, continuity, and differentiation-Partial derivatives, gradients, and Hessians-Optimization basics: gradient descent and second-order methods-Chain rule and Taylor series approximations.

Unit 3: Probability Theory and Statistics **9 Hrs**

Basic probability concepts, random variables, and distributions- Expectation, variance, covariance, and correlation- Common distributions (Gaussian, Binomial, Poisson)-Central Limit Theorem and Law of Large Numbers

Unit 4: Optimization Techniques **9 Hrs**

Convex sets and convex functions- Unconstrained and constrained optimization- Lagrange multipliers and duality- Linear programming and gradient-based methods

Unit 5: Mathematical Tools and Applications in Data Science **9 Hrs**

Numerical methods and error analysis- Introduction to graph theory and network models- Information theory basics (entropy, KL-divergence)

Case studies: Mathematical modeling for machine learning applications

Course Outcomes

After completing the course, students will be able to:

1. Apply linear algebra and calculus concepts to model and solve data problems.
2. Use probability theory and statistics to analyze uncertainty in data.
3. Formulate and solve optimization problems common in machine learning.
4. Interpret mathematical models and algorithms used in data science.
5. Develop proofs and analytical arguments for algorithmic performance and convergence.

Textbooks & References

1. Strang, G. – *Introduction to Linear Algebra*, 5th Edition, Wellesley–Cambridge Press, 2016.
2. Boyd, S. & Vandenberghe, L. – *Convex Optimization*, 1st Edition, Cambridge University Press, 2004.
3. Papoulis, A. & Pillai, S.U. – *Probability, Random Variables, and Stochastic Processes*, 4th Edition, McGraw-Hill, 2002.
4. Lay, D.C., Lay, S.R., & McDonald, J.J. – *Linear Algebra and Its Applications*, 5th Edition, Pearson, 2015.
5. Strang, G. – *Calculus*, (Selected chapters), Various editions for supplemental material.

SOTT6301 **Advanced-Data Structures**

L	T	P	C
2	1	0	3

Course Description:

This course provides an in-depth study of advanced data structures and algorithmic techniques essential for efficient problem-solving in data science. It covers key topics such as balanced trees, hash-based structures, graphs, dynamic programming, and approximation algorithms. The course emphasizes the application of these concepts in large-scale data processing, optimization, and machine learning. Students will also explore parallel and distributed algorithms, along with performance analysis and complexity optimization strategies. Hands-on implementation and real-world problem-solving are integral parts of this course.

Course Objectives:

1. Understand and implement advanced data structures for efficient data handling.
2. Apply graph algorithms to solve real-world network and optimization problems.
3. Develop efficient algorithmic solutions using dynamic programming, greedy, and divide-and-conquer techniques.
4. Analyze NP-completeness and design approximation and randomized algorithms for intractable problems.
5. Implement and optimize parallel and distributed algorithms for large-scale data processing.

UNIT I **9 Hrs**

Advanced Data Structures

Algorithms, Performance analysis- time complexity and space complexity, Asymptotic Notation- Big Oh, Omega and Theta notations, Complexity Analysis Examples; Review of basic data structures (arrays, linked lists, stacks, queues), Trees: AVL Trees, Red-Black Trees, B-Trees, Segment Trees, Fenwick Trees, Hashing: Hash functions, collision resolution techniques, perfect hashing, Disjoint Set Union (Union-Find) and applications

UNIT II **9 Hrs**

Graph Algorithms

Graph representations (adjacency list, adjacency matrix), Traversal algorithms: BFS, DFS, Topological Sorting, Shortest path algorithms: Dijkstra’s, Bellman-Ford, Floyd-Warshall, Minimum spanning tree: Prim’s and Kruskal’s algorithms, Network flow algorithms: Max-flow (Ford-Fulkerson, Edmonds-Karp)

UNIT III **9 Hrs**

Algorithmic Techniques

Divide and Conquer: Applications in searching and sorting (Merge Sort, Quick Sort), Greedy Algorithms: Huffman Coding, Activity Selection, Job Scheduling, Dynamic Programming:

Knapsack problem, Matrix Chain Multiplication, LCS, LIS, Backtracking and Branch & Bound: N-Queens, Traveling Salesman Problem

UNIT IV **9 Hrs**

Approximation and Randomized Algorithms

NP-Completeness and NP-Hard problems, Approximation algorithms: Vertex Cover, TSP, Set Cover, Randomized algorithms: Monte Carlo and Las Vegas algorithms, Probabilistic data structures: Bloom Filters, Skip Lists

UNIT V **9 Hrs**

Parallel and Distributed Algorithms

Parallel sorting and searching algorithms, MapReduce and distributed graph algorithms, Concurrent data structures and synchronization, GPU-based algorithms and parallel computing techniques

Course Outcomes:

After completion of course, students would be able to:

1. Design and implement advanced data structures for complex applications.
2. Solve graph-related problems using efficient algorithms.
3. Apply advanced algorithmic techniques to real-world computational challenges.
4. Evaluate algorithmic performance and optimize computational complexity.
5. Implement scalable parallel and distributed solutions for big data applications..

Text Books:

1. Cormen, T. H., Leiserson, C. E., Rivest, R. L., & Stein, C. – *Introduction to Algorithms*, 4th Edition, MIT Press, 2022.
2. Sedgewick, R., & Wayne, K. – *Algorithms*, 4th Edition, Addison-Wesley, 2011.
3. Aho, A. V., Hopcroft, J. E., & Ullman, J. D. – *Data Structures and Algorithms*, Pearson Education, 2002.
4. Goodrich, M. T., & Tamassia, R. – *Algorithm Design and Applications*, Wiley, 2014.
5. Dasgupta, S., Papadimitriou, C., & Vazirani, U. – *Algorithms*, McGraw-Hill, 2006.

Reference Books:

1. Tarjan, R. E. – Data Structures and Network Algorithms, SIAM, 1983.
2. Kleinberg, J., & Tardos, E. – Algorithm Design, Pearson, 2006.
3. Mehta, D. P., & Sahni, S. – Handbook of Data Structures and Applications, Chapman & Hall/CRC, 2018.
4. Skiena, S. S. – The Algorithm Design Manual, 3rd Edition, Springer, 2020.
5. Motwani, R., & Raghavan, P. – Randomized Algorithms, Cambridge University Press, 1995.

Online Resources:

1. MIT Open Course Ware – Advanced Data Structures and Algorithms
2. Stanford Online – Algorithms Specialization by Tim Roughgarden (Coursera)

Program Elective - I

MTDT6601a **Programming for Data Science**

L	T	P	C
3	0	0	3

Course Description

This course introduces programming fundamentals and advanced techniques using languages and tools widely adopted in data science, particularly Python. It covers core programming constructs, data structures, libraries for data manipulation, visualization, and best practices for writing efficient, readable, and maintainable code.

Course Objectives

- To provide a solid grounding in programming concepts with a focus on Python.
- To teach the use of programming for data manipulation, analysis, and visualization.
- To introduce software development best practices including modularity, testing, and debugging.
- To equip students with the ability to write efficient code for handling large datasets.
- To foster problem-solving skills applicable to real-world data science challenges.

Unit 1: Fundamentals of Programming with Python **9 Hrs**

Basic syntax, variables, data types, and operators-Control structures: loops, conditionals, and error handling-Functions, recursion, and lambda expressions- Introduction to scripting and automation.

Unit 2: Data Structures and Built-in Libraries **9 Hrs**

Lists, tuples, dictionaries, and sets-String manipulation and regular expressions-File I/O operations and data serialization (JSON, CSV)-Introduction to Python’s standard libraries (os, sys, datetime)

Unit 3: Data Manipulation and Analysis **9 Hrs**

NumPy for numerical computations-Pandas for data manipulation and analysis cleaning, transformation, and aggregation techniques with time series and missing data.

Unit 4: Data Visualization and Exploratory Analysis **9 Hrs**

Plotting with Matplotlib and Seaborn-Creating interactive visualizations with Plotly-Exploratory data analysis techniques and best practices-Integrating visualizations into reports and dashboards

Unit 5: Advanced Programming Concepts and Best Practices **9 Hrs**

Object-oriented programming and design patterns-Functional programming approaches in Python-Performance optimization and debugging techniques-Introduction to parallel and asynchronous programming.

Course Outcomes

After completing the course, students will be able to:

1. Develop Python programs utilizing control structures, functions, and modules.
2. Manipulate and analyze data using libraries such as NumPy and Pandas.
3. Create data visualizations with Matplotlib, Seaborn, and Plotly.
4. Apply object-oriented and functional programming paradigms in data science projects.
5. Write clean, efficient, and well-documented code with testing and debugging practices.

Textbooks & References

1. McKinney, W. – *Python for Data Analysis*, 2nd Edition, O'Reilly Media, 2017.
2. Sweigart, A. – *Automate the Boring Stuff with Python*, 2nd Edition, No Starch Press, 2019.
3. Lutz, M. – *Learning Python*, 5th Edition, O'Reilly Media, 2013.
4. Ramalho, L. – *Fluent Python*, 1st Edition, O'Reilly Media, 2015.
5. Downey, A. – *Think Python: How to Think Like a Computer Scientist*, 2nd Edition, Green Tea Press, 2015.

MTDT6601b **Data Engineering and Databases**

L	T	P	C
3	0	0	3

Course Description: This course covers the principles of data engineering and database management systems, focusing on data storage, management, retrieval, and processing using various tools and technologies.

Course Objectives:

1. Understand the fundamentals of data engineering.
2. Learn to design and manage databases.
3. Gain proficiency in data storage and retrieval techniques.
4. Develop skills to process and transform large datasets.
5. Apply data engineering principles to real-world problems.

Unit 1: Introduction to Data Engineering **9 Hrs**

Fundamentals of Data Engineering- Role of Data Engineers in modern data ecosystems- Data Engineering vs Data Science- The Data Engineering Lifecycle- Overview of key tools (Apache Airflow, Spark, Hadoop, Kafka).

Unit 2: Database Management Systems **9 Hrs**

Introduction to DBMS- Relational Database Concepts- Entity-Relationship (ER) Modeling- SQL Queries: DDL, DML, DQL- Normalization and Database Design

Unit 3: NoSQL Databases **9 Hrs**

Introduction to NoSQL and its need- Types of NoSQL Databases: Key-Value Stores (e.g., Redis), Document Stores (e.g., MongoDB), Column Family Stores (e.g., Cassandra), Graph Databases (e.g., Neo4j)-Use-cases comparison with relational DBs

Unit 4: Data Storage and Retrieval **9 Hrs**

Data Storage Techniques: Local vs Cloud- File formats (CSV, JSON, Parquet, Avro)- Indexing Techniques- Query Optimization Techniques- Introduction to Data Warehousing- Concepts of OLAP and OLTP

Unit 5: Data Pipelines and Workflows **9 Hrs**

ETL (Extract, Transform, Load) Process-ELT and streaming pipelines- Data integration from multiple sources- Workflow Automation using Apache Airflow-Monitoring and logging of pipelines

Course Outcomes:

1. Ability to design and manage relational and non-relational databases.
2. Proficiency in data storage and retrieval using SQL and NoSQL databases.
3. Skills to process and transform large datasets using data engineering tools.
4. Capability to manage data pipelines and workflows.
5. Understanding of data engineering best practices.

Text Books and References:

- "Designing Data-Intensive Applications" by Martin Kleppmann
- "Database System Concepts" by Abraham Silberschatz, Henry F. Korth, and S. Sudarshan
- "NoSQL Distilled" by Pramod J. Sadalage and Martin Fowler

MTDT6601b **Machine Learning**

L	T	P	C
3	0	0	3

Course Description: This course introduces machine learning algorithms and artificial intelligence techniques for predictive modeling and data analysis. Students will learn to implement and evaluate various models.

Course Objectives:

1. Understand the fundamentals of machine learning and AI.
2. Learn to implement and evaluate machine learning models.
3. Develop skills to select appropriate algorithms for different problems.
4. Apply machine learning techniques to real-world data.
5. Gain proficiency in using machine learning tools and libraries.

Unit 1: Introduction to Machine Learning **9 Hrs**

Machine Learning Fundamentals- Applications and scope - Types of learning: Supervised, Unsupervised, Reinforcement Learning- Overview of ML pipeline and major algorithms- Bias-variance tradeoff.

Unit 2: Supervised Learning **9 Hrs**

Regression: Linear regression, regularization (Ridge, Lasso)- Classification: k-NN, Decision Trees, Logistic Regression, SVM- Model Evaluation: Train/test split, cross-validation, confusion matrix, precision, recall, F1-score, ROC curves.

Unit 3: Unsupervised Learning **9 Hrs**

Clustering: k-Means, Hierarchical Clustering, DBSCAN- Dimensionality Reduction: PCA, t-SNE- Anomaly Detection techniques

Unit 4: Advanced Machine Learning **9 Hrs**

Ensemble Methods: Bagging, Boosting (Random Forests, AdaBoost, Gradient Boosting)- Neural Networks: Perceptron, MLPs- Introduction to Deep Learning: CNNs, RNNs

Unit 5: Machine Learning Tools and Libraries **9 Hrs**

Overview of ML toolchain- scikit-learn: Pipelines, preprocessing, feature selection- TensorFlow and Keras: Model building and training- PyTorch: Tensors, neural network modules, autograd.

Course Outcomes:

1. Ability to implement various machine learning algorithms.
2. Proficiency in evaluating and tuning machine learning models.
3. Skills to select appropriate models for specific problems.
4. Capability to apply machine learning techniques to real-world datasets.
5. Understanding of machine learning tools and libraries.

Text Books and References:

- "Pattern Recognition and Machine Learning" by Christopher M. Bishop
- "Machine Learning: A Probabilistic Perspective" by Kevin P. Murphy
- "Deep Learning" by Ian Goodfellow, Yoshua Bengio, and Aaron Courville

Program Elective-II

MTDT6602a **AI and Decision-Making Models**

L	T	P	C
3	0	0	3

Course Description

This course delves into advanced decision-making frameworks that integrate AI techniques with classical decision theory. Topics include probabilistic reasoning, optimization, simulation, and reinforcement learning. The course emphasizes the development of decision support systems that operate under uncertainty and complexity in dynamic environments.

Course Objectives

- To introduce decision theory and its application in AI.
- To develop probabilistic models for decision-making under uncertainty.
- To explore optimization and simulation techniques in decision processes.
- To integrate AI methods (e.g., reinforcement learning) into decision support systems.
- To analyze real-world case studies in finance, supply chain, and operations research.

Unit 1: Fundamentals of Decision Theory 9 Hrs

Overview of decision-making frameworks and utility theory-Decision trees, risk analysis, and cost-benefit analysis-multi-criteria decision-making methods.

Case studies in business and economics

Unit 2: Probabilistic Models and Bayesian Decision Making 9 Hrs

Basics of probability and statistical inference-Bayesian networks and probabilistic graphical models-Markov decision processes (MDP) and dynamic programming-Applications in healthcare, finance, and logistics

Unit 3: Optimization Techniques in Decision Making 9 Hrs

Linear, integer, and nonlinear programming fundamentals-Heuristic and metaheuristic optimization methods-Simulation and Monte Carlo methods for risk assessment-Software tools for optimization (e.g., MATLAB, Python libraries).

Unit 4: Reinforcement Learning and Adaptive Decision Systems 9 Hrs

Fundamentals of reinforcement learning and policy gradients-Q-learning, SARSA, and deep reinforcement learning-Integration of RL with traditional decision-making applications in robotics, finance, and operational research.

Unit 5: Case Studies and Emerging Trends **9 Hrs**

Real-world decision support system implementations- Dynamic, real-time decision making with AI- Ethical and societal considerations in AI-driven decisions- Future directions: hybrid models and data-driven strategic decision-making

Course Outcomes

After completing the course, students will be able to:

1. Model decision-making problems using probabilistic and statistical methods.
2. Apply optimization techniques and simulation models to evaluate decisions.
3. Utilize reinforcement learning for dynamic decision-making scenarios.
4. Build integrated decision support systems that leverage AI.
5. Critically assess and compare various decision-making frameworks for complex problems.

Textbooks & References

1. Goodwin, P. & Wright, G. – *Decision Analysis for Management Judgment*, 5th Edition, Wiley, 2014.
2. Sutton, R.S. & Barto, A.G. – *Reinforcement Learning: An Introduction*, 2nd Edition, MIT Press, 2018.
3. Hillier, F.S. & Lieberman, G.J. – *Introduction to Operations Research*, 10th Edition, McGraw-Hill, 2015.
4. Barber, D. – *Bayesian Reasoning and Machine Learning*, 1st Edition, Cambridge University Press, 2012.
5. Russell, S. & Norvig, P. – *Artificial Intelligence: A Modern Approach*, 4th Edition, Pearson, 2020.

MTDT6602b **Data Preparation and Analysis**

L	T	P	C
3	0	0	3

Course Description

This course focuses on the critical steps of data preparation, cleaning, transformation, and exploratory analysis. Emphasis is placed on practical techniques to handle noisy, incomplete, or unstructured data and to extract meaningful insights through statistical analysis and feature engineering.

Course Objectives

- To introduce data collection, cleaning, and transformation methodologies.
- To develop proficiency in exploratory data analysis and statistical inference.
- To teach feature engineering techniques for improving model performance.
- To provide hands-on experience with data wrangling using modern tools.
- To prepare students to tackle real-world data challenges through rigorous analysis.

Course Outcomes

After completing the course, students will be able to:

1. Collect, clean, and preprocess diverse datasets effectively.
2. Apply statistical techniques to explore and analyze data.
3. Engineer and select features to enhance predictive modeling.
4. Utilize Python/R libraries for data manipulation and analysis.
5. Communicate data insights and prepare data for machine learning pipelines.

Unit 1: Data Collection and Cleaning 9 Hrs

Data acquisition techniques and sources-Handling missing values, outlier detection, and imputation-Data quality assessment and error correction-Introduction to data cleaning tools and libraries.

Unit 2: Data Transformation and Feature Engineering 9 Hrs

Data normalization, scaling, and encoding techniques-Feature extraction and creation-Dimensionality reduction methods (PCA, t-SNE)-Handling categorical and time-series data

Unit 3: Exploratory Data Analysis (EDA) **9 Hrs**

Descriptive statistics and data summarization visualization for EDA (histograms, scatter plots, box plots)-Correlation analysis and hypothesis testing- Tools: Pandas, Matplotlib, Seaborn.

Unit 4: Statistical Analysis and Inference **9 Hrs**

Probability distributions and statistical tests- Confidence intervals and significance testing-Regression analysis and correlation measures

Case studies in inferential statistics for business and science

Unit 5: Tools and Technologies for Data Preparation **9 Hrs**

Data wrangling with Python (Pandas, NumPy) and R (dplyr, tidyr)-Introduction to SQL for data extraction- Integrating data pipelines and automation of data cleaning tasks-

Mini project: End-to-End data preparation workflow.

Textbooks & References

1. McKinney, W. – *Python for Data Analysis*, 2nd Edition, O'Reilly Media, 2017.
2. Pyle, D. – *Data Preparation for Data Mining*, 1st Edition, Morgan Kaufmann, 1999.
3. Bruce, P. & Bruce, A. – *Practical Statistics for Data Scientists*, 1st Edition, O'Reilly Media, 2017.
4. Kazil, J. & Jarmul, K. – *Data Wrangling with Python*, 1st Edition, O'Reilly Media, 2016.
5. James, G., Witten, D., Hastie, T., & Tibshirani, R. – *An Introduction to Statistical Learning*, 2nd Edition, Springer, 2021.

MTDT6602c **Data Visualization and Communication**

L	T	P	C
3	0	0	3

Course Description: This course teaches methods for visualizing data effectively and communicating findings to different stakeholders. Students will learn to create compelling visualizations and reports.

Course Objectives:

1. Understand the principles of data visualization.
2. Learn techniques for creating effective visualizations.
3. Gain proficiency in using visualization tools and libraries.
4. Develop skills to communicate data insights effectively.
5. Apply visualization techniques to real-world datasets.

Unit 1: Introduction to Data Visualization **9 Hrs**

Data visualization- History and evolution- Key principles of design: clarity, accuracy, aesthetics- Importance of context and audience- Cognitive aspects of visual perception

Unit 2: Visualization Techniques **9 Hrs**

Basic chart types: bar, line, pie, scatter, histogram, box plots- Multivariate visualizations: heatmaps, bubble charts- Temporal and hierarchical data visualization- Color theory, labeling, and layout.

Unit 3: Visualization Tools and Libraries **9 Hrs**

Python-based libraries: Matplotlib, Seaborn- R-based tools: ggplot2- Introduction to Tableau: interface, data import, basic dashboards- Comparative strengths and limitations.

Unit 4: Storytelling with Data **9 Hrs**

Elements of narrative in data- Structuring stories with visual elements- Designing dashboards for different audiences- Writing reports with embedded visuals

Unit 5: Advanced Visualization Techniques **9 Hrs**

Interactive visualizations using Plotly, Bokeh, or D3.js- Geospatial data visualization: maps, choropleths (using Folium, GeoPandas)- Real-time data visualization techniques and tools.

Course Outcomes:

1. Ability to create effective visualizations.

2. Proficiency in using visualization tools and libraries.
3. Skills to communicate data insights to stakeholders.
4. Capability to design and present data reports.
5. Understanding of data visualization best practices.

Text Books and References:

- "Storytelling with Data" by Cole Nussbaumer Knaflic
- "The Visual Display of Quantitative Information" by Edward R. Tufte
- "Python Data Visualization Cookbook" by Igor Milovanovic, Dimitry Foures, and Giuseppe Vettigli

SOTT6302 **Research Methodology and IPC**

L	T	P	C
2	0	0	2

Course Description

This course provides a comprehensive overview of research methodology tailored for data science. It covers the entire research process—from problem formulation and literature review to data collection, analysis, and reporting. In addition, the course introduces aspects of Intellectual Property and Communication (IPC), including publication ethics, academic writing, and effective dissemination of research outcomes. Emphasis is placed on both theoretical foundations and practical applications to prepare students for rigorous academic or industrial research.

Course Objectives

- To develop the ability to formulate research problems and design appropriate methodologies.
- To familiarize students with qualitative and quantitative research methods and data analysis techniques.
- To guide students in the preparation of literature reviews, research proposals, and research reports.
- To introduce the ethical, legal, and intellectual property issues related to research.
- To enhance communication skills for effective dissemination of research findings.

Unit 1: Introduction to Research Methodology **6 Hrs**

Definition, scope, and importance of research in data science of research (exploratory, descriptive, explanatory, experimental and applied)-Steps in the research process and research design-Formulating research questions and hypotheses-Overview of literature review techniques

Unit 2: Research Design and Data Collection Methods **6 Hrs**

Qualitative vs. quantitative research methodologies- sampling techniques and research instruments (surveys, interviews, observations)-Experimental design and case study approaches-Data collection methods and tools-Reliability, validity, and bias in research.

Unit 3: Data Analysis and Interpretation **6 Hrs**

Statistical techniques and data analysis methods tools for data analysis (SPSS, R, Python)-Interpreting quantitative and qualitative data (ATLAS.ti) -Reporting results and drawing conclusions to data visualization for research findings

Unit 4: Intellectual Property, Publication Ethics, and Communication **6 Hrs**

Overview of intellectual property rights (patents, copyrights, trademarks)-Publication ethics and academic integrity- Preparing research proposals, manuscripts, and technical reports-Communication skills for oral presentations and poster sessions for submitting to journals and conferences.

Unit 5: Research Project and Practical Communication **6 Hrs**

Designing a mini research project in data science evaluation of research literature and case studies and peer-review exercises-Workshop on effective oral and poster presentations-Discussion on current trends and future challenges in research

Course Outcomes

Upon completion of this course, students will be able to:

1. Formulate and refine research questions and hypotheses relevant to data science.
2. Design research studies using appropriate methodologies and tools.
3. Conduct comprehensive literature reviews and critically evaluate academic sources.
4. Analyze data using both qualitative and quantitative methods.
5. Prepare research proposals, technical reports, and academic papers while adhering to ethical and intellectual property standards.

Textbooks & References

1. **Kothari, C.R.** – *Research Methodology: Methods and Techniques*, 2nd Edition, New Age International, 2004.
2. **Creswell, J.W.** – *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*, 4th Edition, SAGE Publications, 2014.
3. **Cooper, D.R. & Schindler, P.S.** – *Business Research Methods*, 12th Edition, McGraw-Hill, 2014.
4. **Silverman, D.** – *Interpreting Qualitative Data*, 5th Edition, SAGE Publications, 2016.

5. **Day, R.A. & Gastel, B.** – *How to Write and Publish a Scientific Paper*, 7th Edition, Cambridge University Press, 2012.
6. **Hennink, Monique, Inge Hutter, and Ajay Bailey**. *Qualitative research methods*. Sage, 2020.

SOTT6303 **Human Values & Professional Ethics**

(Audit Course- I)

L	T	P	C
2	0	0	0

Course Description

This course examines the role of human values and professional ethics in the context of data science and technology. It discusses ethical theories, professional responsibilities, and the societal impacts of technology. Special emphasis is placed on understanding ethical dilemmas, maintaining professional integrity, and fostering social responsibility in both academic and industrial environments.

Course Objectives

1. To introduce fundamental ethical theories and their relevance to professional practice.
2. To analyse ethical dilemmas and decision-making frameworks in modern workplaces.
3. To cultivate an understanding of professional responsibility and integrity.
4. To explore the legal and ethical standards governing technology and data use.
5. To prepare students to address ethical challenges in their professional careers.

UNIT I: Fundamentals of Human Values and Ethics **6 Hrs**

Introduction to ethics and human values- Overview of ethical theories: utilitarianism, deontology, virtue ethics-Importance of ethics in personal and professional life.
Case studies on ethical decision-making.

UNIT II: Professional Ethics and Responsibilities **6 Hrs**

Codes of conduct and professional ethics in various industries-Role of accountability, transparency, and integrity in the workplace-Ethical issues in information technology and data science-Legal frameworks and standards influencing professional practice.

UNIT III: Ethical Dilemmas **6 Hrs**

Data privacy, security, and bias in AI applications-Intellectual property, plagiarism, and research misconduct-Conflict of interest, corporate governance, and whistleblowing-Analysis of real-world ethical dilemmas through case studies.

UNIT IV: Social Responsibility and Impact of Technology **6 Hrs**

Corporate Social Responsibility (CSR) and sustainable development- The societal impact of data-driven decision-making- Global and multicultural perspectives on ethics- Role of ethics in innovation and technological advancement.

UNIT V: Ethics in Research and Professional Practice **6 Hrs**

Academic integrity and research ethics- Collaborative work, interdisciplinary ethics, and professional accountability- Workshops, role plays, and discussions on ethical decision-making- Developing a personal ethical framework and professional development plan.

Course Outcomes

Upon completion of this course, students will be able to:

1. Explain key ethical theories and apply them to real-world professional scenarios.
2. Identify and analyse ethical issues in data science, including privacy, bias, and intellectual property.
3. Demonstrate professional responsibility and integrity in academic and workplace settings.
4. Apply ethical frameworks to resolve conflicts and dilemmas in practice.
5. Appreciate the social and global impacts of technological innovations.

Textbooks & References

1. Velasquez, M.G. et al. – Ethical Issues in Business, 6th Edition, Pearson, 2015.
2. Ferrell, O.C., Fraedrich, J., & Ferrell, L. – Business Ethics: Ethical Decision Making & Cases, 11th Edition, Cengage Learning, 2019.
3. Solomon, R.C. & Flores, F. – A Passion for Justice: Embracing Human Rights, Diversity, and Ethics in the Workplace, 1st Edition, Wiley, 2012.
4. Beauchamp, T.L. & Childress, J.F. – Principles of Biomedical Ethics, 7th Edition, Oxford University Press, 2013.
5. Singer, P. – Practical Ethics, 3rd Edition, Cambridge University Press, 2011.

MTDS6501/MTDC6501 Technical Seminar/Case Study -1

L	T	P	C
1	0	0	1

SOTL6301 **Advanced Data Structures and Algorithms Lab**

L	T	P	C
0	0	4	2

Course Description:

This laboratory course is designed to provide hands-on experience in implementing, testing, and optimizing advanced data structures and algorithms. Through a series of practical exercises and projects, students will translate theoretical concepts into efficient, real-world code using programming languages such as C++, Java, or Python.

Course Objectives:

1. To reinforce the theoretical concepts of advanced data structures and algorithms through practical coding exercises.
2. To develop the ability to analyze algorithm performance using complexity analysis and benchmarking.
3. To enhance coding proficiency and optimization skills.
4. To enable students to design and implement complex data-driven solutions.
5. To encourage collaborative problem solving and project-based learning in a lab setting.

List of Experiments

1. Implementation of the following:
    - Revision of fundamental data structures (arrays, linked lists, stacks, queues)
    - Analysis and Big-O notation
2. Implementation of basic sorting and searching algorithms
    - Lab activity: performance measurement and benchmarking of simple algorithms
3. Illustration of Advanced Tree Structures and Graph Algorithms
    - Implementation of balanced trees (AVL, Red-Black Trees)
4. Illustration of tree-based search and graph traversal algorithms
5. Performance analysis and optimization discussions
6. Demonstration of Dynamic Programming and Greedy Algorithms

    A) Implementation of dynamic programming solutions for classic problems (e.g., knapsack, longest common subsequence),

    B) Exercises comparing dynamic programming and greedy approaches

7. Randomized Algorithms and Approximation Techniques
    - Coding randomized algorithms (e.g., quickselect, random graph generation)
    - Implementation of heuristic and approximation algorithms
8. Lab activity: performance evaluation and variability analysis
    - Discussion on the robustness of randomized vs. deterministic approaches
9. Design and implementation of an end-to-end project integrating advanced data structures, Code profiling, memory management, and optimization techniques
10. Collaborative project development and peer review
    - Final presentation and demonstration of project outcomes

Course Outcomes

After completing the lab, students will be able to:

1. Implement advanced data structures (e.g., balanced trees, heaps, graphs) in a programming language.
2. Analyze and compare the efficiency of different algorithms using Big-O notation and empirical testing.
3. Develop solutions for complex algorithmic problems using dynamic programming, greedy methods, and randomized algorithms.
4. Optimize code performance through profiling and iterative improvement.
5. Collaborate effectively on programming projects and present their solutions.

Textbooks & References

1. Cormen, T.H., Leiserson, C.E., Rivest, R.L., & Stein, C. – *Introduction to Algorithms*, 3rd Edition, MIT Press, 2009.
2. Sedgewick, R. & Wayne, K. – *Algorithms*, 4th Edition, Addison-Wesley, 2011.
3. Goodrich, M.T., Tamassia, R., & Goldwasser, M.H. – *Data Structures and Algorithms in Java*, 6th Edition, Wiley, 2014.
4. Skiena, S.S. – *The Algorithm Design Manual*, 2nd Edition, Springer, 2008.
5. Aho, A.V., Hopcroft, J.E., & Ullman, J.D. – *Data Structures and Algorithms*, 1st Edition, Addison-Wesley, 1983.

MTDL6501 **Programming for Data Science Lab**

L	T	P	C
0	0	4	2

Course Description

This lab course aims to equip students with essential programming skills and practical experience in data manipulation, analysis, and visualization using modern data science tools. Students will explore real-world datasets, perform statistical operations, build basic models, and communicate insights effectively.

Course Objectives

1. To develop proficiency in Python programming for data science applications.
2. To apply data wrangling, cleaning, and preprocessing techniques.
3. To visualize data and uncover insights using popular libraries.
4. To explore machine learning basics through practical exercises.
5. To foster a hands-on approach to solving data-centric problems.

Recommended Tools

- **Programming Language**: Python 3.x
- **IDE**: Jupyter Notebook / Google Colab / VS Code
    - **Libraries**: Data Handling: pandas, numpy, Visualization: matplotlib, seaborn, plotly, Machine Learning: scikit-learn, Others: statsmodels, scipy, openpyxl, json

Lab Exercises

1. Basic syntax, control structures, functions, and file handling.
2. Load, explore, slice, filter, and summarize data using pandas and numpy.
3. Handle missing values, duplicates, data types, and outliers; normalize or scale features.
4. Perform statistical summaries, correlation analysis, and feature distributions.
5. Create bar plots, histograms, heatmaps, pair plots, box plots using matplotlib and seaborn.
6. Use datasets from Kaggle or UCI; perform initial cleaning, EDA, and visualization.
7. Apply statistical tests, confidence intervals, regression analysis using scipy and statsmodels.
8. Implement Linear Regression and K-Nearest Neighbors using scikit-learn.
9. Implement classification (Logistic Regression or Decision Trees) and evaluate using accuracy, precision, recall, and confusion matrix.
10. Mini- Project: Choose a dataset, perform EDA, build a basic predictive model, visualize results, and document in Jupyter Notebook or presentation.

Course Outcomes

Upon successful completion of the lab, students will be able to:

1. Write efficient Python code for data acquisition, cleaning, and transformation.
2. Analyze datasets using descriptive and inferential statistics.
3. Visualize data using various charts and plots.
4. Build and evaluate basic predictive models.
5. Apply Jupyter Notebooks for documenting and presenting data science workflows.

Textbooks and References

1. Joel Grus, Title: Data Science from Scratch: First Principles with Python, 2nd Edition, O'Reilly Media, 2019
2. Jake VanderPlas, Python Data Science Handbook: Essential Tools for Working with Data, 1st Edition, O'Reilly Media, 2016.
3. Wes McKinney, Python for Data Analysis: Data Wrangling with pandas, NumPy, and IPython, 3rd Edition, O'Reilly Media, 2022.

II Semester

SOTT6304 **Advanced Machine Learning**

L	T	P	C
2	1	0	3

Course Description:

This course covers advanced machine learning (ML) techniques beyond traditional supervised and unsupervised learning. It includes deep learning, ensemble methods, reinforcement learning, probabilistic models, and generative adversarial networks (GANs). The course emphasizes theoretical foundations, algorithmic implementation, and real-world applications.

Course Objectives:

1. Understand the principles of advanced ML techniques, including deep learning and reinforcement learning.
2. Learn ensemble methods, Bayesian approaches, and probabilistic graphical models.
3. Develop skills to implement ML models using modern frameworks such as TensorFlow and PyTorch.
4. Explore ethical considerations and interpretability of ML models.
5. Apply ML techniques to real-world applications in healthcare, finance, and other domain

Unit 1: Advanced Supervised and Unsupervised Learning **9 Hrs**

Advanced Decision Trees and Random Forests-Support Vector Machines (SVM) - Optimization and Kernels- Clustering Techniques (Spectral Clustering, DBSCAN, Gaussian Mixture Models)- Anomaly Detection using ML

Unit 2: Deep Learning and Neural Networks **9 Hrs**

Neural Network Architectures (MLP, CNN, RNN)- Backpropagation and Optimization Techniques (Adam, RMSprop)- Autoencoders and Variational Autoencoders (VAE)- Attention Mechanism and Transformers

Unit 3: Probabilistic and Bayesian Learning **9 Hrs**

Bayesian Networks and Probabilistic Graphical Models- Hidden Markov Models (HMM) and Gaussian Processes-Markov Chain Monte Carlo (MCMC) Methods- Variational Inference Techniques

Unit 4: Reinforcement Learning and Generative Models **9 Hrs**

Markov Decision Processes (MDP)-Q-Learning and Policy Gradient Methods-Deep Reinforcement Learning (DQN, PPO)-Generative Adversarial Networks (GANs) and Applications.

Unit 5: Advanced Topics and Applications **9 Hrs**

Fairness and Bias in Machine Learning-Explainable AI (XAI) and Interpretability Techniques-Scalable ML with Big Data (Spark ML, Federated Learning)-ML Applications in Healthcare, Finance, and Autonomous Systems

Course Outcomes:

After completing this course, students will be able to:

1. Develop and optimize advanced ML models.
2. Implement deep learning architectures such as CNNs, RNNs, and GANs.
3. Apply reinforcement learning techniques for decision-making problems.
4. Analyze large-scale datasets using scalable ML methods.
5. Evaluate and interpret ML models for explainability and fairness.

Textbooks & References

1. Ian Goodfellow, Yoshua Bengio, Aaron Courville - *Deep Learning*, MIT Press
2. Kevin P. Murphy - *Machine Learning: A Probabilistic Perspective*, MIT Press
3. Sutton & Barto - *Reinforcement Learning: An Introduction*, MIT Press
4. Christopher Bishop - *Pattern Recognition and Machine Learning*, Springer
5. François Chollet - *Deep Learning with Python*, Manning Publications

MTDT6504 **Big Data Analytics**

L	T	P	C
2	1	0	3

Course Description:

This course focuses on the fundamental concepts, frameworks, and tools used in big data analytics. It covers the Hadoop ecosystem, distributed computing, real-time data processing, and big data machine learning. The course also explores practical applications in domains like healthcare, finance, and cybersecurity.

Course Objectives:

1. Understand the principles of big data storage, processing, and analytics.
2. Learn distributed computing frameworks such as Hadoop and Spark.
3. Explore real-time big data processing with Apache Kafka and Flink.
4. Implement big data machine learning techniques.
5. Work with cloud-based big data solutions such as AWS, Azure, and Google Cloud.

Unit 1: Introduction to Big Data and Distributed Systems **9 Hrs**

Introduction to Big Data: Characteristics, Challenges, and Applications-Big Data Ecosystem: Overview of Hadoop, Spark, and NoSQL Databases-Distributed File Systems: HDFS, Google File System (GFS)-Parallel Processing: MapReduce Programming Model

Unit 2: Data Storage and Processing Frameworks **9 Hrs**

Apache Hadoop: HDFS, YARN, and MapReduce- Apache Spark: RDDs, Data Frames, and Spark SQL- NoSQL Databases: MongoDB, Cassandra, HBase- Distributed Data Warehousing: Apache Hive and Impala.

Unit 3: Real-time Data Processing and Streaming Analytics **9 Hrs**

Real-time Data Processing: Apache Kafka and Apache Flink-Stream Processing Frameworks: Apache Storm, Spark Streaming-Case Studies: Real-time Analytics in Social Media, Finance, and IoT.

Unit 4: Machine Learning on Big Data **9 Hrs**

ML Techniques for Large Datasets: Feature Engineering and Model Training-Scalable ML with Spark MLlib and TensorFlow on Big Data-Deep Learning on Big Data using Horovod and TensorFlowOnSpark

Case Studies: Big Data ML Applications in Healthcare and Cybersecurity

Unit 5: Big Data on Cloud and Ethical Considerations **9 Hrs**

Cloud-based Big Data Analytics: AWS, Azure, Google Cloud-Serverless Computing for Big Data: AWS Lambda, Azure Functions-Data Privacy and Security in Big Data-Ethical AI and Bias in Big Data Analytics.

Course Outcomes:

After completing this course, students will be able to:

1. Design scalable big data architectures using Hadoop and Spark.
2. Implement MapReduce and Spark programs for large-scale data processing.
3. Analyze streaming data using real-time analytics frameworks.
4. Develop big data ML models for predictive analytics.
5. Evaluate cloud-based big data solutions for different use cases.

Textbooks & References

1. Tom White - *Hadoop: The Definitive Guide*, O'Reilly Media
2. Holden Karau, Andy Konwinski - *Learning Spark: Lightning-Fast Data Analytics*, O'Reilly
3. Bill Chambers, Matei Zaharia - *Spark: The Definitive Guide*, O'Reilly
4. Benjamin Bengfort, Jenny Kim - *Data Analytics with Hadoop*, O'Reilly
5. Avrim Blum, John Hopcroft - *Foundations of Data Science*, Cambridge University Press

PROGRAM ELECTIVE - III

MTDT6603a **Ethical AI and Decision Making**

L	T	P	C
3	0	0	3

Course Description:

This course explores ethical considerations in artificial intelligence (AI) and data-driven decision-making. It covers fairness, bias, accountability, transparency, and regulatory frameworks in AI systems. The course also examines real-world case studies in AI ethics and responsible AI design.

Course Objectives:

1. Understand the ethical challenges in AI and machine learning.
2. Analyze biases in datasets and algorithms and mitigate them.
3. Explore legal and regulatory frameworks for AI governance.
4. Learn decision-making frameworks in AI-driven systems.
5. Develop strategies for designing responsible and interpretable AI models.

Unit 1: Introduction to AI Ethics and Responsible AI **9 Hrs**

Ethics in AI: Overview and Need for Ethical AI-Key Ethical Principles: Fairness, Accountability, Transparency, and Ethics (FATE)-Case Studies: AI Failures and Ethical Dilemmas.

Unit 2: Bias, Fairness, and Interpretability in AI **9 Hrs**

Algorithmic Bias: Types and Causes-Techniques for Bias Mitigation in Machine Learning-Explainability and Interpretability in AI Models-Tools for Explainable AI: SHAP, LIME, Model Cards.

Unit 3: Decision-Making in AI and Human-AI Collaboration **9 Hrs**

Decision-Making Under Uncertainty-AI-Driven Decision Support Systems-Human-in-the-Loop (HITL) AI-Ethical Considerations in Autonomous Systems.

Unit 4: AI Regulations, Policies, and Governance 9 Hrs

Global AI Regulations: GDPR, AI Act, IEEE Standards-Data Privacy and Protection: Compliance with AI Policies-Ethical Guidelines for AI Development and Deployment-AI Ethics in Industry: Healthcare, Finance, and Autonomous Systems.

Unit 5: Future of Ethical AI and Emerging Trends 9 Hrs

AI for Social Good and Ethical AI Frameworks-AI and Sustainability: Green AI and Environmental Impact-AI in Warfare and Surveillance: Ethical Implications-Case Studies on Ethical AI Practices in Industry

Course Outcomes:

After completing this course, students will be able to:

1. Identify ethical risks and biases in AI systems.
2. Apply fairness and accountability principles in AI models.
3. Understand global AI regulations and compliance frameworks.
4. Develop interpretable and explainable AI solutions.
5. Assess ethical implications in real-world AI applications.

Textbooks & References

1. Virginia Eubanks - *Automating Inequality*, St. Martin’s Press
2. Kate Crawford - *Atlas of AI*, Yale University Press
3. Cathy O’Neil - *Weapons of Math Destruction*, Crown Publishing
4. Brian Christian - *The Alignment Problem*, W.W. Norton & Company
5. Markus D. Dubber - *The Oxford Handbook of Ethics of AI*, Oxford University Press

MTDT6603b **Time Series Analysis**

L	T	P	C
3	0	0	3

Course Description:

This course explores fundamental and advanced techniques for analyzing time-dependent data. It covers statistical and machine learning approaches for forecasting, anomaly detection, and modeling complex temporal patterns. The course includes hands-on implementation using Python and R.

Course Objectives:

1. Understand the characteristics and components of time series data.
2. Learn classical statistical models such as ARIMA and Exponential Smoothing.
3. Apply deep learning techniques for time series forecasting.
4. Develop skills for real-world applications like stock market prediction and anomaly detection.
5. Implement time series models using Python and R libraries such as Statsmodels, Prophet, and TensorFlow.

Unit 1: Introduction to Time Series Data and Forecasting **9 Hrs**

Time Series Data: Components, Trends, and Seasonality-Stationarity and Differencing Techniques-Exploratory Data Analysis for Time Series-Time Series Decomposition.

Unit 2: Classical Time Series Models **9 Hrs**

Autoregressive (AR), Moving Average (MA), and ARMA Models-ARIMA and Seasonal ARIMA (SARIMA) Models-Exponential Smoothing and Holt-Winters Method-Model Evaluation Metrics: RMSE, MAPE, AIC, BIC.

Unit 3: Machine Learning for Time Series **9 Hrs**

Feature Engineering for Time Series-Regression-based Approaches (Random Forest, XGBoost)-Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU)-Facebook Prophet Model for Forecasting.

Unit 4: Anomaly Detection and Advanced Forecasting **9 Hrs**

Time Series Anomaly Detection Techniques-Hidden Markov Models (HMM) for Time Series-Variational Autoencoders (VAE) for Anomaly Detection-Transfer Learning for Time Series Forecasting.

Unit 5: Applications and Case Studies **9 Hrs**

Financial Time Series Analysis: Stock Market and Cryptocurrency Prediction-Healthcare Time Series: Patient Monitoring and Epidemic Forecasting-IoT and Sensor Data Analytics-Real-time Forecasting with Cloud Platforms (AWS, Google Cloud AI).

Course Outcomes:

After completing this course, students will be able to:

1. Preprocess and analyze time series data.
2. Implement traditional and machine learning-based forecasting models.
3. Handle seasonality, trends, and noise in time series datasets.
4. Evaluate and optimize time series models for accuracy and performance.
5. Apply time series analytics to real-world domains like finance, healthcare, and IoT.

Textbooks & References

1. Hyndman, R.J., & Athanasopoulos, G. - *Forecasting: Principles and Practice*, 3rd Edition, OTexts, 2021.
2. Box, G.E.P., Jenkins, G.M., & Reinsel, G.C. - *Time Series Analysis: Forecasting and Control*, 5th Edition, Wiley, 2015.
3. Shumway, R.H., & Stoffer, D.S. - *Time Series Analysis and Its Applications*, 4th Edition, Springer, 2017.
4. Montgomery, D.C., Jennings, C.L., & Kulahci, M. - *Introduction to Time Series Analysis and Forecasting*, 2nd Edition, Wiley, 2015.
5. Goodfellow, I., Bengio, Y., & Courville, A. - *Deep Learning*, 1st Edition, MIT Press, 2016 (For Deep Learning in Time Series).

MTDT6603c **Text Analytics**

L	T	P	C
3	0	0	3

Course Description:

This course covers the fundamental and advanced techniques of text analytics, focusing on natural language processing (NLP), text mining, sentiment analysis, and deep learning models for textual data. It provides hands-on experience with modern NLP tools and frameworks such as NLTK, SpaCy, and Transformer-based models.

Course Objectives:

1. Understand the fundamental concepts of text analytics and NLP.
2. Learn text preprocessing techniques such as tokenization, stemming, and lemmatization.
3. Apply statistical and machine learning models for text classification, topic modeling, and sentiment analysis.
4. Implement deep learning-based NLP techniques, including Transformer models.
5. Work with real-world applications such as chatbots, recommender systems, and information retrieval.

Unit 1: Introduction to Text Analytics and NLP **9 Hrs**

Basics of Text Analytics and Natural Language Processing (NLP)-Text Preprocessing: Tokenization, Stopwords Removal, Stemming, Lemmatization-Regular Expressions for Text Processing-Word Embeddings: Word2Vec, GloVe, FastText.

Unit 2: Text Classification and Sentiment Analysis **9 Hrs**

Bag of Words (BoW) and Term Frequency-Inverse Document Frequency (TF-IDF)-Machine Learning for Text Classification (Naïve Bayes, SVM, Random Forest)-Sentiment Analysis using Lexicon-Based and ML Approaches-Multilingual Text Processing Challenges.

Unit 3: Topic Modeling and Information Retrieval **9 Hrs**

Latent Semantic Analysis (LSA)-Latent Dirichlet Allocation (LDA)-Named Entity Recognition (NER) and Part-of-Speech (POS) Tagging-Information Retrieval: TF-IDF, BM25, and Search Algorithms

Unit 4: Deep Learning for Text Analytics **9 Hrs**

Introduction to Recurrent Neural Networks (RNNs), LSTMs, and GRUs-Transformer Models: BERT, GPT, and T5-Sequence-to-Sequence Models for Machine Translation and Chatbots-Text Summarization and Question Answering Systems

Unit 5: Applications and Advanced Topics **9 Hrs**

Text Analytics in Healthcare, Finance, and E-Commerce-Fake News Detection and Cybersecurity Applications-Large-Scale Text Processing using Spark NLP-Ethics and Bias in NLP Models.

Course Outcomes:

After completing this course, students will be able to:

1. Process and analyze textual data efficiently.
2. Build and evaluate text classification and sentiment analysis models.
3. Implement deep learning models like BERT, GPT, and LSTMs for NLP tasks.
4. Develop real-world text analytics applications.
5. Integrate NLP techniques with large-scale datasets for meaningful insights.

Textbooks & References

1. Jurafsky, D., & Martin, J.H. - *Speech and Language Processing*, 3rd Edition (Draft), Pearson, 2021.
2. Bird, S., Klein, E., & Loper, E. - *Natural Language Processing with Python*, 1st Edition, O'Reilly Media, 2009.
3. Manning, C.D., Raghavan, P., & Schütze, H. - *Introduction to Information Retrieval*, 1st Edition, Cambridge University Press, 2008.
4. Vaswani, A., et al. - *Attention Is All You Need* (Research Paper on Transformers), 2017.
5. O'Reilly Team - *Practical Natural Language Processing: A Comprehensive Guide to Building Real-World NLP Systems*, 1st Edition, O'Reilly, 2020.

PROGRAM ELECTIVE - IV

MTDT6604a **Predictive and Prescriptive Analytics**

L	T	P	C
3	0	0	3

Course Description:

This course covers predictive modeling techniques and prescriptive analytics to support data-driven decision-making. It focuses on statistical approaches, machine learning, and optimization techniques to extract insights and make actionable recommendations.

Course Objectives:

1. Understand the principles of predictive analytics and prescriptive analytics.
2. Learn regression-based, machine learning, and deep learning techniques for predictive modeling.
3. Explore decision optimization and simulation methods for prescriptive analytics.
4. Apply advanced forecasting techniques for business and industry applications.
5. Implement predictive and prescriptive models using Python and R.

Unit 1: Introduction to Predictive and Prescriptive Analytics **9 Hrs**

Overview of Predictive and Prescriptive Analytics-Importance of Predictive Modeling in Business and Industry-Machine Learning for Predictive Analytics-Decision Science and Optimization in Prescriptive Analytics.

Unit 2: Predictive Analytics Techniques **9 Hrs**

Regression Analysis (Linear, Logistic, Ridge, Lasso)-Decision Trees, Random Forest, and Gradient Boosting (XGBoost, LightGBM)-Time Series Forecasting with ARIMA, SARIMA, and Prophet-Deep Learning for Predictive Analytics (LSTMs, CNNs).

Unit 3: Prescriptive Analytics and Decision Optimization **9 Hrs**

Decision Analysis: Linear Programming, Integer Programming-Heuristic and Metaheuristic Optimization (Genetic Algorithms, Simulated Annealing)-Monte Carlo Simulation for Risk Analysis-Reinforcement Learning for Decision Optimization

Unit 4: Applications of Predictive and Prescriptive Analytics **9 Hrs**

Predictive Maintenance in Manufacturing and IoT-Customer Segmentation and Churn Prediction in Marketing-Supply Chain Optimization and Demand Forecasting-Healthcare Analytics: Disease Prediction and Treatment Optimization.

Unit 5: Tools and Ethical Considerations **9 Hrs**

Implementation using Python (Scikit-learn, TensorFlow, PyTorch) and R-Cloud-based Predictive Analytics Platforms (AWS SageMaker, Google Vertex AI, Azure ML)-Ethical Considerations in Predictive and Prescriptive Analytics.

Case Studies on Predictive and Prescriptive Analytics in Real-World Applications

Course Outcomes:

After completing this course, students will be able to:

1. Build and evaluate predictive models for forecasting and classification.
2. Optimize decision-making using prescriptive analytics techniques.
3. Apply Monte Carlo simulation and reinforcement learning in real-world scenarios.
4. Develop prescriptive models for strategic decision-making.
5. Use analytics tools like Python, R, and cloud-based AI services for predictive and prescriptive analytics.

Textbooks & References

1. Eric Siegel - Predictive Analytics: The Power to Predict Who Will Click, Buy, Lie, or Die, 2nd Edition, Wiley, 2016.
2. James, G., Witten, D., Hastie, T., & Tibshirani, R. - An Introduction to Statistical Learning, 2nd Edition, Springer, 2021.
3. Trevor Hastie, Robert Tibshirani, & Jerome Friedman - The Elements of Statistical Learning, 2nd Edition, Springer, 2009.
4. Dorian Pyle - Data Preparation for Data Mining, 1st Edition, Morgan Kaufmann, 1999.
5. Dimitris Bertsimas & John Tsitsiklis - Introduction to Linear Optimization, 1st Edition, Athena Scientific, 1997.

MTDT6604b **Edge AI and IoT Analytics**

L	T	P	C
3	0	0	3

Course Description:

This course explores the integration of artificial intelligence (AI) and analytics with the Internet of Things (IoT), focusing on Edge AI, real-time data processing, and low-latency AI models. It covers distributed computing frameworks, hardware acceleration, and industry applications in smart cities, healthcare, and industrial automation.

Course Objectives:

1. Understand the fundamentals of IoT data generation, collection, and processing.
2. Learn Edge AI frameworks and their role in low-latency analytics.
3. Explore lightweight deep learning models for edge devices.
4. Implement real-time IoT data analytics and decision-making.
5. Develop scalable IoT solutions using cloud-edge hybrid architectures.

Unit 1: Introduction to IoT and Edge AI **9 Hrs**

Fundamentals of IoT: Architecture, Sensors, and Communication Protocols-Overview of Edge Computing and Edge AI-Edge vs. Cloud AI: Trade-offs and Challenges-IoT Data Lifecycle: Collection, Storage, and Processing.

Unit 2: AI for IoT Analytics **9 Hrs**

Machine Learning and Deep Learning for IoT Data-TinyML and Lightweight AI Models (MobileNet, SqueezeNet)-Federated Learning for Distributed IoT Devices-Case Study: Predictive Maintenance in Industrial IoT.

Unit 3: Edge AI Hardware and Frameworks **9 Hrs**

Edge AI Hardware: NVIDIA Jetson, Google Coral, Intel Movidius-Edge AI Frameworks: TensorFlow Lite, ONNX Runtime, OpenVINO-Optimization Techniques for Edge AI Models (Quantization, Pruning, Distillation).

Case Study: AI-powered Smart Surveillance Systems

Unit 4: Real-time Data Processing and Security in IoT **9 Hrs**

Streaming Data Analytics with Apache Kafka and Apache Flink-Secure Data Transmission in IoT Networks-Blockchain for IoT Security and Privacy-Case Study: Healthcare Monitoring with Wearable IoT Devices

Unit 5: Edge-to-Cloud Integration and Industry Applications **9 Hrs**

Hybrid Edge-Cloud AI Architectures-Serverless Computing for IoT (AWS Lambda, Azure Functions)-IoT Applications in Smart Cities, Transportation, and Retail-Ethical AI and Privacy Concerns in IoT Analytics.

Course Outcomes:

After completing this course, students will be able to:

1. Design and implement AI models optimized for edge devices.
2. Process real-time sensor data using Edge AI frameworks.
3. Deploy lightweight deep learning models on IoT devices.
4. Integrate cloud and edge computing for scalable IoT analytics.
5. Apply Edge AI to real-world applications like smart homes, healthcare monitoring, and predictive maintenance.

Textbooks & References

1. Amita Kapoor - Hands-On Artificial Intelligence for IoT, 1st Edition, Packt Publishing, 2019.
2. Pethuru Raj, Anupama C. Raman - The Internet of Things: Enabling Technologies, Platforms, and Use Cases, 1st Edition, CRC Press, 2017.
3. Joseph Barry, David Williston, Junhang Shi - Edge AI: Deep Learning on Embedded Systems, 1st Edition, O'Reilly Media, 2022.
4. Shyam Varan Nath, Ann Dunkin, Mahesh Chowdhary - Industrial Digital Transformation: Accelerate Digitalization with Business Automation, AI, and Data Analytics, 1st Edition, Packt Publishing, 2021.
5. Mingon Kang, Taehyun Kim - Machine Learning for the Internet of Things, 1st Edition, Springer, 2022.

MTDT6604c **Data Privacy and Security**

L	T	P	C
3	0	0	3

Course Description:

This course provides an in-depth understanding of data privacy, security, and compliance in the digital age. It covers cryptographic techniques, privacy-preserving machine learning, regulatory frameworks, and ethical considerations in data protection. Students will gain practical experience in securing data systems and implementing privacy-enhancing technologies.

Course Objectives:

1. Understand fundamental principles of data privacy and security.
2. Learn cryptographic methods for securing data.
3. Explore privacy-preserving techniques for machine learning and big data.
4. Analyze global data protection laws such as GDPR, CCPA, and HIPAA.
5. Implement secure data storage, transmission, and access control mechanisms.

Unit 1: Fundamentals of Data Privacy and Security **9 Hrs**

Introduction to Data Security and Privacy Concepts-Data Threats: Cyber Attacks, Data Breaches, and Ransomware-Security Models: Confidentiality, Integrity, and Availability (CIA)-Privacy by Design and Default.

Unit 2: Cryptographic Techniques for Data Security **10 Hrs**

Symmetric and Asymmetric Encryption (AES, RSA, ECC)-Hashing and Digital Signatures (SHA, MD5)-Homomorphic Encryption for Secure Computation-Secure Multi-Party Computation (SMPC).

Unit 3: Privacy-Preserving Data Analytics **8 Hrs**

Differential Privacy and Noise Injection-Federated Learning for Secure AI Training-Zero-Knowledge Proofs and Secure Data Sharing.

Case Study: Privacy in Healthcare and Financial Data

Unit 4: Legal, Ethical, and Compliance Aspects **9 Hrs**

Global Data Protection Regulations (GDPR, CCPA, HIPAA)-Data Governance and Ethical AI Practices-Risk Management and Compliance Audits

Case Study: Data Privacy Challenges in Cloud Computing

Unit 5: Emerging Trends in Data Privacy and Security **9 Hrs**

Blockchain for Secure Data Transactions-AI-driven Threat Detection and Cybersecurity Analytics-Quantum Cryptography and Post-Quantum Security-Future Challenges in Privacy and Data Protection

Course Outcomes:

After completing this course, students will be able to:

1. Identify vulnerabilities and risks in data systems.
2. Implement cryptographic techniques for data security.
3. Apply privacy-preserving AI techniques like differential privacy and federated learning.
4. Comply with legal and ethical standards for data protection.
5. Secure data infrastructures in cloud, IoT, and enterprise environments.

Textbooks & References

1. **Bruce Schneier -** *Applied Cryptography: Protocols, Algorithms, and Source Code in C*, 20th Anniversary Edition, Wiley, 2015.
2. **Joseph Migga Kizza -** *Guide to Computer Network Security*, 4th Edition, Springer, 2020.
3. **Mike Chapple, James Michael Stewart, Darril Gibson -** *CISSP (ISC)² Certified Information Systems Security Professional Official Study Guide*, 9th Edition, Wiley, 2021.
4. **Arvind Narayanan, Joseph Bonneau, Edward Felten, Andrew Miller, & Steven Goldfeder -** *Bitcoin and Cryptocurrency Technologies: A Comprehensive Introduction,* 1st Edition, Princeton University Press, 2016.
5. **O'Reilly Team -** *Data Privacy: A Runbook for Engineers*, 1st Edition, O'Reilly Media, 2021.

SOTT6305 **ENGLISH FOR RESEARCH PAPER WRITING**

(Audit Course- II)

L	T	P	C
2	0	0	0

Course Description

This course is designed to help postgraduate students develop essential academic and technical writing skills for effective communication of research. It focuses on the structure and style of scientific writing, including clarity, conciseness, coherence, and correctness. Students will learn how to plan, draft, revise, and finalize various components of a research paper such as abstracts, introductions, literature reviews, methods, results, and conclusions. Emphasis is placed on ethical writing practices, including proper citation and avoiding plagiarism, ultimately guiding students to produce publication-ready manuscripts.

Course Objectives

By the end of this course, students will be able to:

1. Understand the principles of academic and technical writing specific to research papers.
2. Learn to structure sentences, paragraphs, and sections to achieve clarity and logical flow.
3. Develop skills to write major components of research papers including abstract, introduction, and conclusion.
4. Apply ethical writing practices such as paraphrasing, referencing, and avoiding plagiarism.
5. Enhance their ability to revise and polish manuscripts for effective journal submission.

Unit -1 **6 Hrs**

Planning and Preparation, Word Order, Breaking up long sentences, Structuring Paragraphs and Sentences, Being Concise and Removing, Redundancy, Avoiding Ambiguity and Vagueness

Unit -2 **5 Hrs**

Clarifying Who Did What, Highlighting Your Findings, Hedging and Criticising, Paraphrasing and Plagiarism, Sections of a Paper, Abstracts.

Unit -3 **8 Hrs**

Review of the Literature, Methods, Results, Discussion, Conclusions, The Final Check. key skills are needed when writing a Title, key skills are needed when writing an Abstract, key skills are needed when writing an Introduction, skills needed when writing a Review of the Literature,

Unit -4 **7 Hrs**

Skills are needed when writing the Methods, skills needed when writing the Results, skills are needed when writing the Discussion, skills are needed when writing the Conclusions

Unit -5 **4 Hrs**

Useful phrases, how to ensure paper is as good as it could possibly be the first- time submission.

Course Outcomes

After successful completion of the course, students will be able to:

1. Demonstrate the ability to write clearly, concisely, and precisely in academic English.
2. Structure research papers according to scientific conventions with logical flow and coherence.
3. Write each section of a research paper using appropriate academic style and tone.
4. Avoid redundancy, ambiguity, and plagiarism using effective paraphrasing and referencing techniques.
5. Prepare a complete, well-written technical or scientific manuscript ready for submission to academic journals.

Text Books and References

1. Goldbort R (2006) Writing for Science, Yale University Press.
2. 2. Day R (2006) How to Write and Publish a Scientific Paper, Cambridge University Press.
3. 3. Highman N (1998), Handbook of Writing for the Mathematical Sciences, SIAM. Highman'sbook.
4. 4. Adrian Wallwork, English for Writing Research Papers, Springer New York Dordrecht Heidelberg London, 2011

SOTL6302 **Advanced Machine Learning Lab**

L	T	P	C
0	0	4	2

Course Description:

This lab course provides hands-on experience with advanced machine learning techniques, focusing on deep learning, generative models, and scalable ML frameworks. Students will implement models using TensorFlow, PyTorch, and cloud-based AI services, applying them to real-world datasets in image processing, NLP, and time series forecasting.

Course Objectives:

1. Implement advanced machine learning models using Python and ML libraries.
2. Explore deep learning architectures such as CNNs, RNNs, and Transformers.
3. Work with generative models like GANs and VAEs.
4. Optimize ML models using hyperparameter tuning and transfer learning.
5. Deploy machine learning models on cloud and edge platforms.

Recommended Tools for Advanced Machine Learning Lab

Programming Languages & IDEs

- Python 3.x – Primary language for ML and deep learning
- Jupyter Notebook – Interactive development environment
- Google Colab – Cloud-based notebook with free GPU/TPU access
- PyCharm – IDE for Python development

Deep Learning Frameworks

- TensorFlow 2.x – Deep learning library for training and deploying ML models
- PyTorch – Flexible deep learning framework
- Keras – High-level API for building deep learning models
- ONNX (Open Neural Network Exchange) – Model format for interoperability

Machine Learning & Optimization

- Scikit-learn – Library for machine learning algorithms
- XGBoost / LightGBM – Gradient boosting libraries
- Optuna / Hyperopt – Hyperparameter optimization frameworks

NLP & Computer Vision

- NLTK / spaCy – Libraries for NLP processing
- Transformers (Hugging Face) – Pretrained models for NLP tasks
- OpenCV – Computer vision and image processing library

Data Processing & Visualization

- Pandas / NumPy – Data manipulation libraries
- Matplotlib / Seaborn / Plotly – Data visualization tools

Cloud & Edge AI Deployment

- AWS SageMaker / Google Vertex AI / Azure ML – Cloud ML services
- TensorFlow Lite / OpenVINO – Optimizing ML models for edge deployment

List of Experiments

1: Introduction to Advanced Machine Learning Libraries

- Working with TensorFlow and PyTorch
- Model building, training, and evaluation basics

2: Deep Learning for Image Processing

- Implementing Convolutional Neural Networks (CNNs)
- Transfer Learning with Pretrained Models (ResNet, VGG, EfficientNet)

3: Recurrent Neural Networks and Time Series Analysis

- Implementing RNNs, LSTMs, and GRUs for sequence data
- Forecasting with Transformer-based models (TFT, BERT for Time Series)

4: Natural Language Processing with Deep Learning

- Training custom word embeddings (Word2Vec, FastText)
- Implementing Transformer-based models (BERT, GPT)

5: Generative Models and Unsupervised Learning

- Implementing Variational Autoencoders (VAEs)
- Training Generative Adversarial Networks (GANs)

6: Hyperparameter Optimization and Model Fine-Tuning

- Grid search, Bayesian optimization, and automated ML (AutoML)
- Experimenting with dropout, batch normalization, and learning rate scheduling

7: Scalable Machine Learning with Big Data

- Training ML models on Apache Spark (MLlib)
- Using distributed computing frameworks for large-scale AI

8: Deploying ML Models on Cloud and Edge Devices

- ML model deployment using AWS SageMaker, Google Vertex AI, and Azure ML

- Optimizing models for edge deployment (TensorFlow Lite, OpenVINO)

9: Explainable AI and Model Interpretability

- Visualizing and interpreting ML models (SHAP, LIME)
- Analyzing bias and fairness in AI models

10: Case Study and Project Implementation

- Students work on a real-world project integrating various ML techniques

Course Outcomes:

After completing this course, students will be able to:

1. Develop and train deep learning models for structured and unstructured data.
2. Implement generative models for synthetic data generation.
3. Optimize and fine-tune models for performance and efficiency.
4. Deploy ML models in cloud and IoT environments.
5. Work with scalable ML frameworks for big data processing.

Textbooks & References

1. Ian Goodfellow, Yoshua Bengio, Aaron Courville - Deep Learning, 1st Edition, MIT Press, 2016.
2. François Chollet - Deep Learning with Python, 2nd Edition, Manning Publications, 2021.
3. Aurélien Géron - Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, 3rd Edition, O'Reilly Media, 2022.
4. Sebastian Raschka, Vahid Mirjalili - Python Machine Learning, 3rd Edition, Packt Publishing, 2019.
5. Zahid Hossain, Scott Haines - Scalable Machine Learning with Spark, 1st Edition, O’Reilly Media, 2023.

MTDL6502 **Big Data Analytics Lab**

L	T	P	C
0	0	4	2

Course Description:

This lab course provides hands-on experience with big data processing, storage, and analytics using frameworks like Hadoop, Spark, and cloud-based solutions. Students will work with large datasets, explore distributed computing, and implement machine learning models at scale.

Course Objectives:

1. Understand big data frameworks and processing techniques.
2. Implement distributed computing using Hadoop and Spark.
3. Work with NoSQL databases for big data storage.
4. Develop scalable machine learning models using big data tools.
5. Deploy big data applications in cloud environments.

Recommended Tools:

Big Data Frameworks

- **Apache Hadoop – Distributed storage and processing framework**
- **Apache Spark – Fast big data processing and analytics engine**
- **Apache Flink – Stream processing framework**

Data Storage & NoSQL Databases

- **HDFS (Hadoop Distributed File System) – Big data storage**
- **MongoDB / Cassandra / HBase – NoSQL databases for large-scale data storage**

Distributed Computing & Stream Processing

- **Apache Kafka – Real-time data streaming platform**
- **Apache Storm / Flink – Real-time analytics processing**

Cloud-Based Big Data Services

- **AWS EMR / Google BigQuery / Azure HDInsight – Managed cloud big data services**

- **Databricks – Unified analytics platform for big data and AI**

Graph Analytics

- **Neo4j – Graph database for network analytics**
- **Apache Giraph – Graph processing on big data**

Security & Privacy Tools

- **Apache Ranger – Security and access control for big data**
- **Apache Knox – Securing Hadoop clusters**

List of Experiments

1: Introduction to Big Data and Hadoop Ecosystem

- Setting up a Hadoop cluster
- Working with HDFS (Hadoop Distributed File System)

2: Batch Processing with MapReduce

- Implementing MapReduce programs in Java/Python
- Analyzing large-scale datasets using MapReduce

3: Apache Spark for Distributed Data Processing

- Setting up Spark and running applications
- RDDs (Resilient Distributed Datasets) and DataFrames

4: Real-Time Stream Processing with Apache Kafka and Spark Streaming

- Streaming data ingestion with Kafka
- Real-time analytics with Spark Streaming

5: NoSQL Databases for Big Data Storage

- Working with MongoDB, Cassandra, and HBase
- Querying and analyzing big data in NoSQL databases

6: Scalable Machine Learning with MLlib and Spark

- Training ML models on large datasets using Spark MLlib
- Hyperparameter tuning and model optimization

7: Cloud-Based Big Data Analytics

- Using AWS EMR, Google BigQuery, and Azure HDInsight
- Running analytics on cloud-based data lakes

8: Graph Analytics with Apache Giraph and Neo4j

- Implementing graph-based data analytics
- Real-world applications in social networks and fraud detection

9: Big Data Security and Privacy

- Implementing access control and encryption in Hadoop and Spark
- Data anonymization and privacy-preserving analytics

10: Minor Project on Big Data Analytics

- Students work on an end-to-end big data analytics project

Course Outcomes:

After completing this course, students will be able to:

1. Set up and configure big data frameworks like Hadoop and Spark.
2. Process large datasets using distributed computing.
3. Implement big data storage solutions using NoSQL databases.
4. Train and deploy machine learning models on big data platforms.
5. Work with cloud-based big data services.

Textbooks & References

1. **Tom White** - *Hadoop: The Definitive Guide*, 4th Edition, O'Reilly Media, 2015.
2. **Holden Karau, Andy Konwinski, Patrick Wendell, Matei Zaharia** - *Learning Spark: Lightning-Fast Data Analytics*, 2nd Edition, O'Reilly Media, 2020.
3. **Benjamin Bengfort, Jenny Kim** - *Data Analytics with Hadoop: An Introduction for Data Scientists*, 1st Edition, O'Reilly Media, 2016.
4. **Bill Chambers, Matei Zaharia** - *Spark: The Definitive Guide*, 1st Edition, O'Reilly Media, 2018.
5. **Pramod J. Sadalage, Martin Fowler** - *NoSQL Distilled: A Brief Guide to the Emerging World of Polyglot Persistence*, 1st Edition, Addison-Wesley, 2013.

III SEMESTER

MTDM7501 **MOOC-1**

L	T	P	C
3	0	0	3

MTDM7502 **MOOC-2**

L	T	P	C
3	0	0	3

MTDP7501 **Dissertation I / Industrial Project**

L	T	P	C
3	0	0	3

IV SEMESTER

MTDP7502 **Dissertation Phase II**

L	T	P	C
0	0	32	16